

# Professors and Grants

## 1. INTRODUCTION

This note is intended as a compliment and complement to B. Zhang's very enjoyable "Coconuts and Islanders", which motivates the Boltzmann distribution in the case where every nonnegative integer is a possible energy-level. Here, our initial focus is, instead, on Boltzmann distributions where 0 and 1 and 10 are the only possible energy-levels. Taking our cue from "Coconuts and Islanders", we motivate by story.

From §3 to §12, we analyze **three systems** for dispensing grant money to  $N$  professors. Congress allocates  $N$  dollars to award to the  $N$  professors. The grant rules stipulate: each professor receives \$0 or \$1 or \$10. Each professor is identified by a number, from 1 to  $N$ . By a **dispensation**, we mean a full complement of awards, with a specific amount (\$0 or \$1 or \$10) to Professor#1, a specific amount (\$0 or \$1 or \$10) to Professor#2, *etc.*, up to and including Professor# $N$ , such that the total of the awards is the  $N$  allocated by Congress.

The **first system** (see §3) for awarding grants is very simple: There are many possible dispensations, and, among all of them, one is selected randomly, giving equal probability to each possible dispensation. The **main problem** is to figure out: Using this first system, for a given professor, what is the probability of being awarded \$0? \$1? \$10?

Later (see §5), we describe second and third probabilistic award systems. Both of them depends on three parameters  $p, q, r$  satisfying  $p, q, r > 0$  and  $p + q + r = 1 = q + 10r$ .

The **second system** uses an iid system of random-variables,  $X_1, \dots, X_N$  such that,  $\forall \ell$ ,  $\Pr[X_\ell = 0] = p$ ,  $\Pr[X_\ell = 1] = q$ ,  $\Pr[X_\ell = 10] = r$ .

$$\Pr[X_\ell = 10] = r.$$

For all  $\ell$ , the second system awards  $X_\ell$  dollars to Professor  $\# \ell$ .

The total dollar payout  $X_1 + \dots + X_N$  is then random;

if  $X_1 = \dots = X_N = 0$ , it could be as small as 0 dollars,

and if  $X_1 = \dots = X_N = 10$ , it could be as large as  $10N$  dollars.

The **third system** is obtained from the second

by conditioning on the event  $X_1 + \dots + X_N = N$ ,

so that the total payout is exactly the  $\$N$  allocated by Congress.

KEY POINT: With exactly the right choice of  $p, q, r$ ,

the first and third systems are shown to be equivalent.

In §6 and §7, we show that this parameter choice is Boltzmann,

meaning:  $(p, q, r)$  is, for some real number  $\beta$ ,

a scalar multiple of  $(e^{-0\cdot\beta}, e^{-1\cdot\beta}, e^{-10\cdot\beta})$ .

That is,  $\exists \beta, C \in \mathbb{R}$  s.t.  $(p, q, r) = (C, Ce^{-\beta}, Ce^{-10\beta})$ .

The second and third systems are

accessible by basic tools of probability theory,

while our main problem involves the first system.

However, once we know the first and third systems are equivalent,

we can bring these probabilistic tools to bear on the main problem.

Thanks to J. Steif, for pointing out to me that

the Discrete Local Limit Theorem, which is described in §9,

is the right tool for the main problem, which is solved in §12.

Boltzmann distributions are often motivated by entropy, but,

from our perspective,

what's special about  $(p, q, r) = (C, Ce^{-\beta}, Ce^{-10\beta})$  is:

For any  $i, j, k \geq 0$ , we have

$$p^i q^j r^k = C^{i+j+k} \cdot e^{-\beta \cdot (j+10k)},$$

so  $p^i q^j r^k$  depends only on:  $i + j + k$  and  $j + 10k$ .

In the third system of grant awards,

there exists a normalizing constant  $S > 0$  s.t.,

for any dispensation in which

$i$  professors receive \$ 0,

$j$  professors receive \$ 1,

$k$  professors receive \$10,

the probability of that dispensation is  $p^i q^j r^k / S$ ,

which is equal to  $C^{i+j+k} \cdot e^{-\beta \cdot (j+10k)} / S$ .

That probability, then, depends only on

$i + j + k$ , which is the number of professors,

and  $j + 10k$ , which is the total dollar payout.

So, since the number of professors is  $= N$

and the total dollar payout is also  $= N$ ,

we conclude: each award-dispensation has probability  $C^N \cdot e^{-\beta \cdot N} / S$ ,  
so they are all equally likely, which exactly describes the first system.

Therefore, under the Boltzmann assumption,

the first and third systems are equivalent.

In §14, we expose the inequitablity of the first system.

In fact, assuming  $N$  is sufficiently large, we show that:

with probability  $> 99\%$ , over half of the professors receive \$0.

Thanks to V. Reiner for suggesting

applying Chebyshev's inequality to a sum of indicator variables,  
to transition from individual statistics to population statistics.

In §15 and §16 and §17, we extend the theory to handle cases

where the award-sets are finite sets of rational numbers.

In §18, we show that

irrational award amounts can lead to non-Boltzmann statistics.

In §19 and §20 and §21, we extend our earlier results to include

degenerate energy-levels, with a finite set of states.

In §22 through §28, we extend these results further to include

cases that involve a countably infinite set of states.

Thanks to C. Prouty for help with many calculations.

For some of his Python code, see §29.

## 2. SOME NOTATION

A box around an expression indicates that it is global,

meaning that it is fixed to the end of these notes.

Unboxed variables are freed at the end of each section, if not earlier.

**Let**  $\boxed{\mathbb{R}^*} := \{-\infty\} \cup \mathbb{R} \cup \{\infty\}$ ,  $\boxed{\mathbb{Z}^*} := \{-\infty\} \cup \mathbb{Z} \cup \{\infty\}$ .

For any  $s, t \in \mathbb{R}^*$ , **let**

$\boxed{(s; t)} := \{x \in \mathbb{R}^* \mid s < x < t\}$ ,  $\boxed{[s; t]} := \{x \in \mathbb{R}^* \mid s \leq x < t\}$ ,

$$\boxed{(s;t]} := \{x \in \mathbb{R}^* \mid s < x \leq t\}, \quad \boxed{[s;t]} := \{x \in \mathbb{R}^* \mid s \leq x \leq t\}.$$

$$\text{For any } s, t \in \mathbb{R}^*, \quad \text{let } \boxed{(s..t)} := (s;t) \cap \mathbb{Z}^*, \quad \boxed{[s..t]} := [s;t] \cap \mathbb{Z}^*, \\ \boxed{(s..t]} := (s;t] \cap \mathbb{Z}^*, \quad \boxed{[s..t]} := [s;t] \cap \mathbb{Z}^*.$$

Let  $\boxed{\mathbb{N}} := [1..\infty)$  be the set of positive integers.

For any finite set  $F$ , let  $\boxed{\#F}$  be the number of elements in  $F$ .

For any infinite set  $F$ , let  $\boxed{\#F} := \infty$ . Then  $\#\mathbb{Z} = \infty = \#\mathbb{R}$ .

For all  $t \in \mathbb{R}$ , let  $\boxed{[t]}$  :=  $\max\{n \in \mathbb{N} \mid n \leq t\}$  be the **floor of  $t$** .

For any sets  $S, T$ , for any function  $f : S \rightarrow T$ ,

the **image of  $f$**  is:  $\boxed{\mathbb{I}_f} := \{f(x) \mid x \in S\} \subseteq T$ .

For any sets  $S, T$ , for any function  $f : S \rightarrow T$ ,

for any set  $A$ , we **define**:  $\boxed{f^*A} := \{x \in S \mid f(x) \in A\}$ .

By convention, in these notes, we define  $\boxed{0^0} := 1$ .

By “ $C^\omega$ ” we mean: “real-analytic”.

### 3. FIRST SYSTEM OF GRANT AWARDS

Let  $\boxed{N} \in \mathbb{N}$ . Think of  $N$  as large.

Whenever we need to

formulate and prove precise mathematical statements,  
we will “pass to the thermodynamic limit”, which means:

we replace  $N$  by a variable  $n \in \mathbb{N}$ , and let  $n \rightarrow \infty$ .

((Alternatively, within nonstandard analysis, the variable  $N$   
could be taken as an infinite integer,

and the various approximations involving  $N$ ,

could be taken as equality-modulo-infinitesimals.))

Suppose there are  $N$  professors, numbered 1 to  $N$ ,

who apply, once per year, to the GFA (Grant Funding Agency),

seeking funding for the very important work they are doing.

Each year, Congress authorizes  $\$N$  for the GFA to dispense

to the  $N$  professors.

The GFA has the rule: every award is 0 or 1 or 10 dollars.

The set of grant-dispensions is represented by:

$$\boxed{\Omega} := \left\{ \omega : [1..N] \rightarrow \{0, 1, 10\} \mid \sum_{\ell=1}^N [\omega(\ell)] = N \right\}.$$

The GFA has set aside  $\#\Omega$  pieces of paper,

and has written down all possible dispensations,

one on each piece of paper.

So, for example, there is a piece of paper that says:

Professors 1 to  $N$  each get \$1.

Another piece of paper says:

Professors 1 to  $N - 10$  each get \$1 and

Professors  $N - 9$  to  $N - 1$  each get \$0 and

Professor  $N$  gets \$10.

Since  $N$  is large, it follows that  $\#\Omega$  is large, and so there are many, many, many other pieces of paper.

Each year, a GFA bureaucrat

places all the pieces of paper in a big bin,

then selects one at random and

makes the awards as indicated on that piece of paper.

Under this **first system** of awarding grants, we have:

$\forall \omega \in \Omega$ , the probability that

the selected grant-dispensation is  $\omega$

is equal to  $1 / (\#\Omega)$ .

Suppose I am one of the professors. Here is our **main problem**:

Calculate my probability of getting \$0.

Then calculate my probability of getting \$1.

Then calculate my probability of getting \$10.

Approximate answers are acceptable.

In §5 to §12 of this note,

we reformulate and then solve this problem.

Spoiler: It's a Boltzmann distribution, approximately.

#### 4. PARTICLES AND ENERGY

Recall that  $N \in \mathbb{N}$ . Think of  $N$  as large.

Suppose there are  $N$  particles, numbered 1 to  $N$ ,

each of which has a certain amount of energy.

Suppose the total energy is  $N$ , dispensed among the  $N$  particles.

Suppose physicists have somehow determined that, for any particle,

its possible energy-levels are: 0 or 1 or 10.

Recall:  $\Omega = \left\{ \omega : [1..N] \rightarrow \{0, 1, 10\} \mid \sum_{\ell=1}^N [\omega(\ell)] = N \right\}$ .

Then  $\Omega$  represents the set of energy-dispensations.

Assume that physicists have somehow determined

that this system of particles has a random energy-dispensation

and that all energy-dispensations in  $\Omega$  are equally probable.

That is, physicists tell us:

$\forall \omega \in \Omega$ , the probability that  
the energy-dispensation is  $\omega$   
is equal to  $1 / (\#\Omega)$ .

The equal probability of all energy-dispensations  
is a recurring theme in microcanonical-ensemble thermodynamics,  
and can often be motivated through  
rules of random energy transfer between random pairs of particles.  
For examples of this, either see §19 below or  
search for “Coconuts and Islanders” by B. Zhang,  
and, in particular, see the work leading up to  
the last paragraph of §3.2 therein.

In §19 below,  
instead of particles exchanging energy,  
there are professors exchanging dollars,  
but the principle is exactly the same.

In Zhang’s exposition,  
instead of particles exchanging energy,  
there are islanders exchanging coconuts,  
but the principle is exactly the same.

Returning to our  $N$  particles, pick any one of them.

Problem: Calculate its probability of having energy-level 0.

Then calculate its probability of having energy-level 1.

Then calculate its probability of having energy-level 10.

Approximate answers are acceptable.

Spoiler: It’s a Boltzmann distribution, approximately.

Except for terminology, this problem is the same as  
the main problem (end of §3) about professors and grants.

We will go back to professors and grants.

Mathematically it makes no difference, but it’s more fun.

## 5. SECOND AND THIRD SYSTEMS OF GRANT AWARDS

In an effort to go paperless, the GFA changes to a new system:

In this **second system**, instead of all those pieces of paper,

the GFA chooses  $p, q, r > 0$  s.t.  $p + q + r = 1$ ,

and then, for each of the  $N$  professors,

awards \$ 0 with probability  $p$ ,

\$ 1 with probability  $q$ ,  
 \$10 with probability  $r$ .

No professor's award depends in any way on any other professor's;  
 the awards are independent.

The expected payout, for any professor, is  $p \cdot 0 + q \cdot 1 + r \cdot 10$  dollars.

Under this second system,

there is no guarantee that the total payout will be  $\$N$ ,  
 which is a difficulty that we will discuss later.

However, recognizing that the average award is *intended* to be \$1,

the GFA chooses the numbers  $p, q, r$  subject to the constraint that

$$p \cdot 0 + q \cdot 1 + r \cdot 10 = 1, \quad i.e., \quad q + 10r = 1.$$

For each function  $\omega : [1..N] \rightarrow \{0, 1, 10\}$ , **let**

$$\boxed{i_\omega} := \#\{ \ell \in [1..N] \mid \omega(\ell) = 0 \},$$

$$\boxed{j_\omega} := \#\{ \ell \in [1..N] \mid \omega(\ell) = 1 \},$$

$$\boxed{k_\omega} := \#\{ \ell \in [1..N] \mid \omega(\ell) = 10 \};$$

that is,  $i_\omega$  is the number of professors awarded \$ 0 and

$j_\omega$  is the number of professors awarded \$ 1 and

$k_\omega$  is the number of professors awarded \$10.

Then,  $\forall \omega : [1..N] \rightarrow \{0, 1, 10\}$ , we have:

the total number of awards is  $i_\omega + j_\omega + k_\omega$

and the total dollar payout is  $i_\omega \cdot 0 + j_\omega \cdot 1 + k_\omega \cdot 10$ ,

$$i.e., \quad j_\omega + 10k_\omega.$$

Then,  $\forall \omega : [1..N] \rightarrow \{0, 1, 10\}$ , we have:

$$i_\omega + j_\omega + k_\omega = N \quad \text{and} \quad j_\omega + 10k_\omega = \sum_{\ell=1}^N [\omega(\ell)].$$

Recall:  $\Omega = \left\{ \omega : [1..N] \rightarrow \{0, 1, 10\} \mid \sum_{\ell=1}^N [\omega(\ell)] = N \right\}$ .

That is,  $\Omega$  is the set of all payout functions

$$\omega : [1..N] \rightarrow \{0, 1, 10\}$$

s.t. the total dollar payout is  $N$ .

Then:  $\forall \omega : [1..N] \rightarrow \{0, 1, 10\}$ , we have:

$$\omega \in \Omega \quad \text{iff} \quad j_\omega + 10k_\omega = N.$$

For every  $i, j, k \in [0..N]$ ,

if  $i + j + k = N$  and  $j + 10k = N$ ,

then  $\exists \omega \in \Omega$  s.t.  $(i, j, k) = (i_\omega, j_\omega, k_\omega)$ ;

indeed, one such  $\omega : [1..N] \rightarrow \{0, 1, 10\}$  is described by:

$$\omega = 0 \text{ on } [1..i], \quad \omega = 1 \text{ on } (i..i+j], \quad \omega = 10 \text{ on } (i+j..N].$$

**Let**  $\boxed{A} := \{(i_\omega, j_\omega, k_\omega) \mid \omega \in \Omega\}$ .

Then  $A$  is the set of all  $(i, j, k)$  s.t.  $i, j, k \in [0..N]$  and

$$i + j + k = N \quad \text{and} \quad j + 10k = N.$$

Under the second system,

each \$ 0 award happens with probability  $p$  and

each \$ 1 award happens with probability  $q$  and

each \$10 award happens with probability  $r$ .

So,  $\forall \omega : [1..N] \rightarrow \{0, 1, 10\}$ , under the second system,

the probability that the grant-dispensation is equal to  $\omega$

is  $p^{i\omega} q^{j\omega} r^{k\omega}$ .

**Let**  $S := \sum_{\omega \in \Omega} p^{i\omega} q^{j\omega} r^{k\omega}$ .

Then  $S$  is the probability (using the second system) that  $\omega \in \Omega$ ,

*i.e.*, the probability that the total payout is exactly  $N$  dollars.

Assuming  $N$  is large, it turns out that  $S$  is close to zero.

So, under this second system,

the probability of paying out exactly  $N$  dollars

is very small.

Congress only allocates  $\$N$  per year for the  $N$  professors.

So, using this second system, each year,

with probability  $1 - S \approx 1$ , the GFA will run a surplus or a deficit.

On the other hand, since  $q + 10r = 1$ , we see that,

each year, the expected payout is \$1 per professor,

so, each year, the expected total payout is  $\$N$ .

So these surpluses and deficits should, over time, cancel one another.

Unfortunately, Congress is a paragon of fiscal responsibility, and,

as soon as it finds out about the GFA's second system,

it insists that the GFA never again underspend or overspend.

So the GFA changes its system one more time, as follows.

Under its **third system**, each year,

before announcing any of the awards publicly,

the GFA writes out, in an *internal* memo,

a *tentative* proposal of awards that,

independently, for each of the  $N$  professors,

awards \$ 0 with probability  $p$ ,

\$ 1 with probability  $q$ ,

\$10 with probability  $r$ .

If the memo's total award payout is NOT equal to  $\$N$ ,

the GFA deems the memo as unacceptable,

deletes it, and starts over, making memo after memo,

until an acceptable one (meaning payout exactly  $\$N$ ) appears.



Each memo has a probability  $S$  of being acceptable, so, each year, the GFA will likely need to repeat the memo process many times to get to a memo with total payout exactly equal to  $\$N$ . However, as soon as that happens, the GFA uses that first acceptable memo, and publicizes its dispensation of awards.

Mathematically, we are conditioning on the event  $\omega \in \Omega$ .

So, using the third system, the probability that  $\omega \notin \Omega$  is 0.

Also, for this third system,  $\forall \omega \in \Omega$ , the probability of  $\omega$  is  $p^{i\omega} q^{j\omega} r^{k\omega} / S$ .

The sum of these probabilities is 1:

$$\sum_{\omega \in \Omega} \frac{p^{i\omega} q^{j\omega} r^{k\omega}}{S} = \frac{1}{S} \cdot \sum_{\omega \in \Omega} p^{i\omega} q^{j\omega} r^{k\omega} = \frac{1}{S} \cdot S = 1.$$

This third system is not necessarily equivalent to the first, because

in the first system, all the probabilities were  $1 / (\#\Omega)$ , whereas, in the third system, they are  $p^{i\omega} q^{j\omega} r^{k\omega} / S$ .

So a **new question** arises:

Is it possible to choose  $p, q, r > 0$  in such a way that

$$p + q + r = 1 \quad \text{and} \quad q + 10r = 1 \quad \text{and} \\ \forall \omega \in \Omega, \quad p^{i\omega} q^{j\omega} r^{k\omega} / S = 1 / (\#\Omega) \quad ?$$

If yes, then, using that  $(p, q, r)$ ,

the first and third systems are equivalent.

We will see that the answer to this new question, in fact, *is* yes.

In the next two sections, assuming  $N \geq 10$ ,

we will show how to compute the only  $(p, q, r)$  that works.

Spoiler: It's a Boltzmann distribution, exactly.

## 6. COMPUTING $p, q, r$ À LA BOLTZMANN

As in the preceding section, **let**  $p, q, r > 0$ ,  $S := \sum_{\omega \in \Omega} p^{i\omega} q^{j\omega} r^{k\omega}$ .

We assume:  $p + q + r = 1$  and  $q + 10r = 1$ .

We also assume:  $\forall \omega \in \Omega, \quad p^{i\omega} q^{j\omega} r^{k\omega} / S = 1 / (\#\Omega)$ .

**We will prove** that, if  $N \geq 10$ , then

there is at most one  $(p, q, r)$  that satisfies these conditions,

$$\text{specifically, } (p, q, r) = \frac{(1, 9^{-1/10}, 9^{-1})}{1 + 9^{-1/10} + 9^{-1}}.$$

**Define** the dot product,  $\odot$ , on  $\mathbb{R}^3$ , by:

$$\forall x, y, z, X, Y, Z \in \mathbb{R}, \quad (x, y, z) \odot (X, Y, Z) = xX + yY + zZ.$$

For all  $u \in \mathbb{R}^3$ , **let**  $u^\perp := \{v \in \mathbb{R}^3 \mid u \odot v = 0\}$ ;

then  $u^\perp$  is a vector subspace of  $\mathbb{R}^3$ .

Also,  $\forall u \in \mathbb{R}^3, u \in u^{\perp\perp}$ .

For all  $U \subseteq \mathbb{R}^3$ , **let**  $U^\perp := \{v \in \mathbb{R}^3 \mid \forall u \in U, u \odot v = 0\}$ ;  
then  $U^\perp$  is a vector subspace of  $\mathbb{R}^3$ .

Also,  $\forall T, U \subseteq \mathbb{R}^3, (T \subseteq U) \Rightarrow (T^\perp \supseteq U^\perp)$ .

For all  $u, v \in \mathbb{R}^3$ , **let**  $\langle u, v \rangle_{\text{span}}$  denote the  $\mathbb{R}$ -span of  $\{u, v\}$ , *i.e.*,

**let**  $\langle u, v \rangle_{\text{span}} := \{su + tv \mid s, t \in \mathbb{R}\}$ ;

then  $\langle u, v \rangle_{\text{span}}$  is a vector subspace of  $\mathbb{R}^3$ .

Recall (§3):  $\Omega = \left\{ \omega : [1..N] \rightarrow \{0, 1, 10\} \mid \sum_{\ell=1}^N [\omega(\ell)] = N \right\}$ .

Recall (§5):  $A = \{(i_\omega, j_\omega, k_\omega) \mid \omega \in \Omega\}$ .

Recall (§5):  $A$  is the set of all  $(i, j, k)$  s.t.  $i, j, k \in [0..N]$  and  
 $i + j + k = N$  and  $j + 10k = N$ .

Then:  $A$  is the set of all  $(i, j, k)$  s.t.  $i, j, k \in [0..N]$  and  
 $(1, 1, 1) \odot (i, j, k) = N$  and  $(0, 1, 10) \odot (i, j, k) = N$ .

For all  $a, b \in A$ , we have

$$(1, 1, 1) \odot a = N = (1, 1, 1) \odot b \quad \text{and}$$

$$(0, 1, 10) \odot a = N = (0, 1, 10) \odot b,$$

so we get

$$(1, 1, 1) \odot (a - b) = 0 \quad \text{and} \quad (0, 1, 10) \odot (a - b) = 0,$$

so  $a - b \in (1, 1, 1)^\perp \cap (0, 1, 10)^\perp$ .

**Let**  $V := (1, 1, 1)^\perp \cap (0, 1, 10)^\perp$ .

Then:  $\forall a, b \in A, a - b \in V$ .

**Let**  $D := \{a - b \mid a, b \in A\}$ . Then  $D \subseteq V$ .

Also, we have:  $V \subseteq (1, 1, 1)^\perp$  and  $V \subseteq (0, 1, 10)^\perp$ .

Then:  $V^\perp \supseteq (1, 1, 1)^{\perp\perp}$  and  $V^\perp \supseteq (0, 1, 10)^{\perp\perp}$ .

Since  $(1, 1, 1) \in (1, 1, 1)^{\perp\perp} \subseteq V^\perp$  and  $(0, 1, 10) \in (0, 1, 10)^{\perp\perp} \subseteq V^\perp$ ,

we get:  $\langle (1, 1, 1), (0, 1, 10) \rangle_{\text{span}} \subseteq V^\perp$ .

**Let**  $W := \langle (1, 1, 1), (0, 1, 10) \rangle_{\text{span}}$ . Then:  $W \subseteq V^\perp$ .

Assume  $N \geq 10$ . **Let**  $a_1 := (0, N, 0)$ ,  $a_2 := (9, N - 10, 1)$ .

Then  $a_1, a_2 \in A$ . **Let**  $d_1 := a_2 - a_1$ . Then  $d_1 \in D$ .

Since  $d_1 \neq (0, 0, 0)$ , we get:  $\dim d_1^\perp = 2$ .

Since  $W = \langle (1, 1, 1), (0, 1, 10) \rangle_{\text{span}}$ , we get:  $\dim W = 2$ .

Since  $d_1 \in D \subseteq V$  and  $W \subseteq V^\perp$ , we get:  $d_1^\perp \supseteq D^\perp \supseteq V^\perp \supseteq W$ .

So, since  $\dim d_1^\perp = 2 = \dim W$ , we get:  $d_1^\perp = D^\perp = V^\perp = W$ .

Then  $D^\perp = W$ . Recall:  $\forall \omega \in \Omega, p^{i_\omega} q^{j_\omega} r^{k_\omega} / S = 1 / (\#\Omega)$ .

So, since  $A = \{(i_\omega, j_\omega, k_\omega) \mid \omega \in \Omega\}$ , we get:

$$\forall (i, j, k) \in A, p^i q^j r^k / S = 1 / (\#\Omega).$$

Equivalently,  $\forall (i, j, k) \in A$ ,

$$i \cdot (\ln p) + j \cdot (\ln q) + k \cdot (\ln r) - (\ln S) = -(\ln(\#\Omega)).$$

Equivalently,  $\forall (i, j, k) \in A$ ,

$$(i, j, k) \odot (\ln p, \ln q, \ln r) = (\ln S) - (\ln(\#\Omega)).$$

Then:  $\forall a, b \in A$ ,

$$a \odot (\ln p, \ln q, \ln r) = (\ln S) - (\ln(\#\Omega)) = b \odot (\ln p, \ln q, \ln r),$$

so we get:  $(a - b) \odot (\ln p, \ln q, \ln r) = 0$ .

Then:  $\forall d \in D$ ,  $d \odot (\ln p, \ln q, \ln r) = 0$ .

Then:  $(\ln p, \ln q, \ln r) \in D^\perp$ .

Since  $(\ln p, \ln q, \ln r) \in D^\perp = W = \langle (1, 1, 1), (0, 1, 10) \rangle_{\text{span}}$ ,

**choose** a real number  $C > 0$  and  $\beta \in \mathbb{R}$  s.t.

$$(\ln p, \ln q, \ln r) = (\ln C) \cdot (1, 1, 1) - \beta \cdot (0, 1, 10).$$

Then  $(\ln p, \ln q, \ln r) = (\ln C, (\ln C) - \beta, (\ln C) - 10\beta)$ .

Then  $(p, q, r) = (C, Ce^{-\beta}, Ce^{-10\beta})$ .

Then  $(p, q, r) = C \cdot (1, e^{-\beta}, e^{-10\beta})$ .

So, since  $p + q + r = 1$ , we get:  $C \cdot (1 + e^{-\beta} + e^{-10\beta}) = 1$ .

Then  $C = \frac{1}{1 + e^{-\beta} + e^{-10\beta}}$ . Then  $(p, q, r) = \frac{(1, e^{-\beta}, e^{-10\beta})}{1 + e^{-\beta} + e^{-10\beta}}$ .

So, since  $q + 10r = 1$ , we get:  $\frac{e^{-\beta} + 10e^{-10\beta}}{1 + e^{-\beta} + e^{-10\beta}} = 1$ .

Then  $e^{-\beta} + 10e^{-10\beta} = 1 + e^{-\beta} + e^{-10\beta}$ . Then  $9e^{-10\beta} = 1$ .

Then  $e^{-10\beta} = 9^{-1}$ . Then  $e^{-\beta} = 9^{-1/10}$ . Then  $(p, q, r) = \frac{(1, 9^{-1/10}, 9^{-1})}{1 + 9^{-1/10} + 9^{-1}}$ .

So this is the only  $(p, q, r)$  that can possibly work.

In the next section, we show that it *does* work.

## 7. SHOWING THE BOLTZMANN $p, q, r$ WORK

In this section, we prove

the converse of the result from the preceding section.

That is, we **let**  $(p, q, r) := \frac{(1, 9^{-1/10}, 9^{-1})}{1 + 9^{-1/10} + 9^{-1}}$  and  $S := \sum_{\omega \in \Omega} p^{i_\omega} q^{j_\omega} r^{k_\omega}$ ,  
and **we wish to show**:  $p + q + r = 1$  and  $q + 10r = 1$  and  
 $\forall \omega \in \Omega$ ,  $p^{i_\omega} q^{j_\omega} r^{k_\omega} / S = 1 / (\#\Omega)$ .

**Let**  $\beta := (\ln 9)/10$ . Then  $e^{-\beta} = 9^{-1/10}$ . Then  $e^{-10\beta} = 9^{-1}$ .

Then  $(p, q, r) = \frac{(1, e^{-\beta}, e^{-10\beta})}{1 + e^{-\beta} + e^{-10\beta}}$ . **Let**  $C := \frac{1}{1 + e^{-\beta} + e^{-10\beta}}$ .

Then  $(p, q, r) = C \cdot (1, e^{-\beta}, e^{-10\beta})$ . Then  $(p, q, r) = (C, Ce^{-\beta}, Ce^{-10\beta})$ .

**Let**  $K := C^N \cdot e^{-\beta \cdot N}$ .

Recall (§3):  $\Omega = \left\{ \omega : [1..N] \rightarrow \{0, 1, 10\} \mid \sum_{\ell=1}^N [\omega(\ell)] = N \right\}$ .

*Claim:*  $\forall \omega \in \Omega, p^{i_\omega} q^{j_\omega} r^{k_\omega} = K$ .

*Proof of Claim:* **Given**  $\omega \in \Omega$ , **want:**  $p^{i_\omega} q^{j_\omega} r^{k_\omega} = K$ .

Recall (§5):  $i_\omega + j_\omega + k_\omega = N$  and  $j_\omega + 10k_\omega = \sum_{\ell=1}^N [\omega(\ell)]$ .

By definition of  $\Omega$ , since  $\omega \in \Omega$ , we get:  $\sum_{\ell=1}^N [\omega(\ell)] = N$ .

Then:  $j_\omega + 10k_\omega = N$ . Recall:  $(p, q, r) = (C, Ce^{-\beta}, Ce^{-10\beta})$ .

Then:  $p^{i_\omega} q^{j_\omega} r^{k_\omega} = C^{i_\omega} \cdot (Ce^{-\beta})^{j_\omega} \cdot (Ce^{-10\beta})^{k_\omega}$   
 $= C^{i_\omega + j_\omega + k_\omega} \cdot e^{-\beta \cdot (j_\omega + 10k_\omega)} = C^N \cdot e^{-\beta \cdot N} = K$ .

*End of proof of Claim.*

By definition of  $S$ , we have:  $S = \sum_{\omega \in \Omega} p^{i_\omega} q^{j_\omega} r^{k_\omega}$ .

So, by the Claim, we get:  $S = (\#\Omega) \cdot K$ . Then  $K/S = 1/(\#\Omega)$ .

We have  $10/9 = 1 + (1/9)$ . That is,  $10 \cdot 9^{-1} = 1 + 9^{-1}$ .

So, since  $e^{-10\beta} = 9^{-1}$ , we get:  $10e^{-10\beta} = 1 + e^{-10\beta}$ .

Then:  $e^{-\beta} + 10e^{-10\beta} = 1 + e^{-\beta} + e^{-10\beta}$ .

By definition of  $C$ , we get:  $C \cdot (1 + e^{-\beta} + e^{-10\beta}) = 1$ .

Recall:  $(p, q, r) = C \cdot (1, e^{-\beta}, e^{-10\beta})$ .

Since  $p + q + r = C \cdot (1 + e^{-\beta} + e^{-10\beta}) = 1$

and since  $q + 10r = C \cdot (e^{-\beta} + 10e^{-10\beta}) = C \cdot (1 + e^{-\beta} + e^{-10\beta}) = 1$ ,

**it remains only to show:**  $\forall \omega \in \Omega, p^{i_\omega} q^{j_\omega} r^{k_\omega} / S = 1/(\#\Omega)$ .

**Given**  $\omega \in \Omega$ , **want:**  $p^{i_\omega} q^{j_\omega} r^{k_\omega} / S = 1/(\#\Omega)$ .

By the Claim, we get:  $p^{i_\omega} q^{j_\omega} r^{k_\omega} = K$ .

Recall:  $K/S = 1/(\#\Omega)$ .

Then:  $p^{i_\omega} q^{j_\omega} r^{k_\omega} / S = K/S = 1/(\#\Omega)$ .

## 8. COUNTABLE MEASURE THEORY

**Let**  $S$  be a set, and **let**  $f : S \rightarrow [0; \infty]$ . **Let**  $\mathcal{F} := \{A \subseteq S \mid \#A < \infty\}$ .

Then:  $\boxed{\sum_{x \in S} [f(x)]} := \sup_{A \in \mathcal{F}} \sum_{x \in A} [f(x)]$ .

**Let**  $S$  be a set, and **let**  $f : S \rightarrow \mathbb{R}$ . Assume:  $\sum_{x \in S} |f(x)| < \infty$ .

Then:  $\boxed{\sum_{x \in S} [f(x)]} := \left( \sum_{x \in S} |f(x)| \right) - \left( \sum_{x \in S} [|f(x)| - (f(x))] \right)$ .

By convention, in this note,

any countable set is given its discrete Borel structure.

A measure  $\mu$  on a countable set  $\Theta$

is completely determined by

the function  $t \mapsto \mu\{t\} : \Theta \rightarrow [0; \infty]$ ,

because:  $\forall \Theta_0 \subseteq \Theta$ , we have  $\mu(\Theta_0) = \sum_{t \in \Theta_0} [\mu\{t\}]$ .

**DEFINITION 8.1.** Let  $\Theta$  be a countable set.

Then  $\mathcal{M}_\Theta$  denotes the set of measures on  $\Theta$ ,

and  $\mathcal{FM}_\Theta := \{\mu \in \mathcal{M}_\Theta \mid \mu(\Theta) < \infty\}$ ,

and  $\mathcal{FM}_\Theta^\times := \{\mu \in \mathcal{M}_\Theta \mid 0 < \mu(\Theta) < \infty\}$ ,

and  $\mathcal{P}_\Theta := \{\mu \in \mathcal{M}_\Theta \mid \mu(\Theta) = 1\}$ .

Then  $\mathcal{M}_\Theta$  is the set of measures on  $\Theta$

and  $\mathcal{FM}_\Theta$  is the set of finite measures on  $\Theta$

and  $\mathcal{FM}_\Theta^\times$  is the set of nonzero finite measures on  $\Theta$

and  $\mathcal{P}_\Theta$  is the set of probability measures on  $\Theta$ .

The only measure on  $\emptyset$  is the zero measure.

Therefore:  $\mathcal{FM}_\emptyset^\times = \emptyset = \mathcal{P}_\emptyset$ .

**DEFINITION 8.2.** Let  $\Theta$  be a countable set,  $\mu \in \mathcal{FM}_\Theta$ .

Let  $n \in \mathbb{N}$ . Then  $\mu^n \in \mathcal{FM}_{\Theta^n}$  is defined by:

$$\forall x \in \Theta^n, \quad \mu^n\{x\} = (\mu\{x_1\}) \cdots (\mu\{x_n\}).$$

The following is a basic fact, whose proof we omit:

Let  $\Theta$  be a countable set,  $\mu \in \mathcal{FM}_\Theta$ ,  $n \in [2.. \infty)$ .

Let  $Z \subseteq \Theta^n$ ,  $X \subseteq \Theta^{n-1}$ ,  $Y \subseteq \Theta$ . Assume that:

under the standard bijection  $\Theta^n \longleftrightarrow \Theta^{n-1} \times \Theta$ ,

we have:  $Z \longleftrightarrow X \times Y$ .

Then:  $\mu^n(Z) = (\mu^{n-1}(X)) \cdot (\mu(Y))$ .

It is common to identify  $Z$  with  $X \times Y$ , in which case we have:

$$\mu^n(X \times Y) = (\mu^{n-1}(X)) \cdot (\mu(Y)).$$

We also omit proof of:

Let  $\Theta$  be a countable set,  $\mu \in \mathcal{FM}_\Theta$ ,  $n \in [2.. \infty)$ .

Then:  $\mu^n(\Theta^n) = (\mu(\Theta))^n$ .

In particular,  $(\mu \in \mathcal{P}_\Theta) \Rightarrow (\mu^n \in \mathcal{P}_{\Theta^n})$ .

The countable sets that are of interest in this note

all carry the discrete topology. We therefore define:

**DEFINITION 8.3.** Let  $\Theta$  be a countable set,  $\mu \in \mathcal{M}_\Theta$ .

Then the **support of  $\mu$**  is:  $S_\mu := \{ t \in \Theta \mid \mu\{t\} \neq 0 \}$ .

**DEFINITION 8.4.** Let  $\Theta \subseteq \mathbb{R}$  be countable,  $\mu \in \mathcal{M}_\Theta$ .

Let  $\rho \geq 1$  be real. Then:  $|\mu|_\rho := (\sum_{t \in \Theta} [|t|^\rho \cdot (\mu\{t\})])^{1/\rho}$ .

Note:  $\forall$ countable  $\Theta \subseteq \mathbb{R}$ ,  $\forall \mu \in \mathcal{FM}_\Theta$ ,

if  $\#S_\mu < \infty$ , then:  $\forall$ real  $\rho \geq 1$ ,  $|\mu|_\rho < \infty$ .

**DEFINITION 8.5.** Let  $\Theta \subseteq \mathbb{R}$  be countable.

Let  $\mu \in \mathcal{P}_\Theta$ . Assume:  $|\mu|_1 < \infty$ .

Then the **mean of  $\mu$**  is:  $M_\mu := \sum_{t \in \Theta} [t \cdot (\mu\{t\})]$ .

Also, the **variance of  $\mu$**  is:  $V_\mu := \sum_{t \in \Theta} [(t - M_\mu)^2 \cdot (\mu\{t\})]$ .

Let  $\Theta \subseteq \mathbb{R}$  be countable,  $\mu \in \mathcal{P}_\Theta$ . Assume:  $|\mu|_1 < \infty$ .

Then, by subadditivity of absolute value, we get  $|M_\mu| \leq |\mu|_1$ .

In particular,  $|M_\mu| < \infty$ , i.e.,  $-\infty < M_\mu < \infty$ .

Also, by expanding the square in the formula for  $V_\mu$ ,

$$\text{we get } V_\mu = |\mu|_2^2 - M_\mu^2.$$

In particular,  $(V_\mu < \infty) \Leftrightarrow (|\mu|_2 < \infty)$ .

Let  $\Theta \subseteq \mathbb{R}$  be countable and let  $X$  be a  $\Theta$ -valued random-variable.

Let  $\mu$  denote the distribution on  $\Theta$  of  $X$ ,

i.e., **define**  $\mu \in \mathcal{P}_\Theta$  by:  $\forall t \in \Theta$ ,  $\mu\{t\} = \Pr[X = t]$ .

Then,  $\forall$ real  $\rho \geq 1$ , we have:  $|\mu|_\rho$  is the  $L^\rho$ -norm of  $X$ .

Then,  $\forall$ real  $\rho \geq 1$ , we have:  $(|\mu|_\rho < \infty) \Leftrightarrow (X \text{ is } L^\rho)$ .

In particular,  $(|\mu|_1 < \infty) \Leftrightarrow (X \text{ is } L^1)$ .

Also, if  $X$  is  $L^1$ , then  $M_\mu = E[X]$  and  $V_\mu = \text{Var}[X]$ .

That is, if  $X$  is  $L^1$ , then

$M_\mu$  is the mean (aka expected value, aka average value) of  $X$   
and  $V_\mu$  is the variance of  $X$ .

**THEOREM 8.6.** Let  $\Theta \subseteq \mathbb{R}$  be countable,  $\mu \in \mathcal{P}_\Theta$ .

Assume:  $|\mu|_1 < \infty$ . Then:  $(\#S_\mu \geq 2) \Leftrightarrow (V_\mu > 0)$ .

The preceding result is a measure-theoretic analogue of the statement:

An  $L^1$  random-variable is non-deterministic iff its variance is positive.

We omit proof.

Because  $\forall t \in \mathbb{Z}$ ,  $|t| \leq t^2$ , we conclude:

for any  $\mathbb{Z}$ -valued random-variable  $X$ ,  $E[|X|] \leq E[X^2]$ .

It follows that for any  $\mathbb{Z}$ -valued  $L^2$  random-variable  $X$ , we have:

$$X \text{ is } L^1, \quad \text{and so } E[X] \text{ is defined and finite.}$$

Because  $\forall t \in \mathbb{Z}, |t| \leq t^2$ , we conclude:

$$\forall \Theta \subseteq \mathbb{Z}, \forall \mu \in \mathcal{M}_\Theta, \quad |\mu|_1 \leq |\mu|_2^2 ;$$

it follows that if  $|\mu|_2 < \infty$ , then

$$|\mu|_1 < \infty, \quad \text{and so } M_\mu \text{ is defined and finite.}$$

**DEFINITION 8.7.** Let  $\Theta$  be a countable set.

Let  $\mu_1, \mu_2, \dots \in \mathcal{P}_\Theta$  and let  $\lambda \in \mathcal{P}_\Theta$ .

By  $\boxed{\mu_1, \mu_2, \dots \rightarrow \lambda}$ , we mean:  $\forall \Theta_0 \subseteq \Theta, \mu_1(\Theta_0), \mu_2(\Theta_0), \dots \rightarrow \lambda(\Theta_0)$ .

Recall (§2):  $\forall$ function  $f$ , the notation:  $\mathbb{I}_f$ .

Recall (§2):  $\forall$ function  $f, \forall$ set  $A$ , the notation:  $f^*A$ .

For any countable set  $S$ , for any set  $T$ ,

for any function  $f : S \rightarrow T$ , for any  $\mu \in \mathcal{M}_S$ ,

we define  $\boxed{f_*\mu} \in \mathcal{M}_{\mathbb{I}_f}$  by:  $\forall A \subseteq \mathbb{I}_f, (f_*\mu)(A) = \mu(f^*A)$ .

Let  $S$  be a countable set,  $T$  a set,  $f : S \rightarrow T$ . Let  $n \in \mathbb{N}$ .

Define  $f^n : S^n \rightarrow T^n$  by:  $\forall x \in S^n, f^n(x) = (f(x_1), \dots, f(x_n))$ .

Then:  $(f^n)_*\mu^n = (f_*\mu)^n$ .

For any nonempty countable set  $\Theta$ , for any  $\mu \in \mathcal{FM}_\Theta^\times$ ,

let  $\boxed{\mathcal{N}(\mu)} := \frac{\mu}{\mu(\Theta)} \in \mathcal{P}_\Theta$ ; then  $\forall \Theta_0 \subseteq \Theta, (\mathcal{N}(\mu))(\Theta_0) = \frac{\mu(\Theta_0)}{\mu(\Theta)}$ ,

and  $\mathcal{N}(\mu)$  is called the **normalization of  $\mu$** .

Let  $\hat{\Theta}$  be a countable set. Let  $\mu \in \mathcal{M}_{\hat{\Theta}}$ . Let  $\Theta \subseteq \hat{\Theta}$ .

Then the **restriction of  $\mu$  to  $\Theta$** , denoted  $\boxed{\mu|_\Theta} \in \mathcal{M}_\Theta$ ,

is **defined by**:  $\forall \Theta_0 \subseteq \Theta, (\mu|_\Theta)(\Theta_0) = \mu(\Theta_0)$ .

NOTE: We have  $(\mu|_\Theta)(\Theta) = \mu(\Theta)$ . So, if  $0 < \mu(\Theta) < \infty$ , then:

$$\begin{aligned} \mu|_\Theta \in \mathcal{FM}_\Theta^\times \quad \text{and} \quad \mathcal{N}(\mu|_\Theta) &= \frac{\mu|_\Theta}{\mu(\Theta)} \\ \text{and} \quad \forall \Theta_0 \subseteq \Theta, (\mathcal{N}(\mu|_\Theta))(\Theta_0) &= \frac{\mu(\Theta_0)}{\mu(\Theta)}. \end{aligned}$$

**DEFINITION 8.8.** Let  $F$  be a nonempty finite set.

Then we define  $\boxed{\nu_F} \in \mathcal{P}_F$  by:  $\forall f \in F, \nu_F\{f\} = 1/(\#F)$ .

Also, we define  $\boxed{\nu_\emptyset} : \{\emptyset\} \rightarrow \{-1\}$  by:  $\nu_\emptyset(\emptyset) = -1$ .

**THEOREM 8.9.** Let  $F$  be a nonempty finite set. Let  $\theta \in \mathcal{P}_F$ .  
 Assume:  $\forall f, g \in F, \theta\{f\} = \theta\{g\}$ . Then:  $\theta = \nu_F$ .

*Proof.* Since  $F$  is nonempty, choose  $g_0 \in F$ . Let  $b := \theta\{g_0\}$ .  
 Then:  $\forall f \in F, \theta\{f\} = b$ . Then:  $\sum_{f \in F} (\theta\{f\}) = (\#F) \cdot b$ .  
 Since  $\theta \in \mathcal{P}_F$ , we get:  $\theta(F) = 1$ .  
 Since  $(\#F) \cdot b = \sum_{f \in F} (\theta\{f\}) = \theta(F) = 1$ , we get:  $b = 1/(\#F)$ .  
 Since  $\forall f \in F, \theta\{f\} = b = 1/(\#F) = \nu_F\{f\}$ , we get:  $\theta = \nu_F$ .  $\square$

## 9. THE DISCRETE LOCAL LIMIT THEOREM

**DEFINITION 9.1.** Let  $E \subseteq \mathbb{Z}$ .

By  $E$  is **residue-constrained**, we mean:  
 $\exists m \in [2.. \infty), \exists n \in \mathbb{Z} \quad \text{s.t.} \quad E \subseteq m\mathbb{Z} + n$ .

By  $E$  is **residue-unconstrained**, we mean:  
 $E$  is not residue-constrained.

Since  $\emptyset \subseteq 2 \cdot \mathbb{Z} + 1$ , we get:  $\emptyset$  is residue-constrained.

For all  $b \in \mathbb{Z}$ , since  $\{b\} \subseteq 2 \cdot \mathbb{Z} + b$ , we get:  $\{b\}$  is residue-constrained.

Then:  $\forall$  residue-unconstrained  $E \subseteq \mathbb{Z}, \#E \geq 2$ .

We have:  $\{0, 3, 9\} \subseteq 3\mathbb{Z} + 0$  and  $\{2, 5, 11\} \subseteq 3\mathbb{Z} + 2$ ,  
 so  $\{0, 3, 9\}$  and  $\{2, 5, 11\}$  are both residue-constrained.

Here is a test for residue-unconstrainedness:

Let  $E \subseteq \mathbb{Z}$ . Assume  $\#E \geq 2$ . Let  $\varepsilon_0 \in E$ .

Then: (  $E$  is residue-unconstrained ) iff (  $\gcd(E - \varepsilon_0) = 1$  ).

By this test, we see that:

$\{0, 1, 10\}$  and  $\{2, 4, 8, 9\}$  and  $\{3, 9, 13, 18\}$  are all residue-unconstrained.

**DEFINITION 9.2.** For all  $\alpha \in \mathbb{R}$ , for all real  $v > 0$ ,  
 define  $\Phi_\alpha^v : \mathbb{R} \rightarrow (0; \infty)$  by:  $\forall t \in \mathbb{R}, \Phi_\alpha^v(t) = \frac{\exp(- (t - \alpha)^2 / (2v))}{\sqrt{2\pi v}}$ .

Note:  $\Phi_\alpha^v$  is a PDF of a normal variable with mean  $\alpha$  and variance  $v$ .

The next result is a version of the Discrete Local Limit Theorem;

this one is stated in probability-theoretic terms:

**THEOREM 9.3.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $X_1, X_2, \dots$  be an iid sequence of  $\mathbb{Z}$ -valued  $L^2$  random-variables.

Assume:  $\forall n \in \mathbb{N}, \{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} = E$ .

Let  $\alpha \in \mathbb{R}, v \in [0; \infty]$ . Assume:  $\forall n \in \mathbb{N}, \mathbb{E}[X_n] = \alpha$  and  $\text{Var}[X_n] = v$ .



Then:  $0 < v < \infty$ , and,  $\forall t_1, t_2, \dots \in \mathbb{Z}$ ,  
as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot [(\Pr[X_1 + \dots + X_n = t_n]) - (\Phi_{n\alpha}^{nv}(t_n))] \rightarrow 0$ .

For a good exposition of this theorem and its proof,  
search on “Terence Tao Local Limit Theorem”.

Visit the website, and then expand “read the rest of this entry”,  
and then scroll down to “– 2. Local limit theorems –”.

In Theorem 9.3, since  $E \subseteq \mathbb{Z}$ , we have, for each  $n \in \mathbb{N}$ ,  
 $|X_n| \leq X_n^2$  a.s., so  $E[|X_n|] \leq E[X_n^2]$ ,  
so, since  $X_n$  is  $L^2$ , we get  $X_n$  is  $L^1$ ,  
and so  $E[X_n]$  and  $\text{Var}[X_n]$  are both defined.

Moreover,  $\forall n \in \mathbb{N}$ ,

since  $E[X_n] \leq E[|X_n|] \leq E[X_n^2] < \infty$ , we get:  $E[X_n]$  is finite.

In Theorem 9.3, the proof that  $v > 0$  is relatively simple:

Since  $E$  is residue-unconstrained, we get:  $\#E \geq 2$ .

Then,  $\forall n \in \mathbb{N}$ ,  $\#\{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} \geq 2$ ,  
which implies that  $\text{Var}[X_n] > 0$ ,

and so  $v > 0$ .

In Theorem 9.3, the proof that  $v < \infty$  is relatively simple:

$$\forall n \in \mathbb{N}, \quad \text{Var}[X_n] = E[X_n^2] - (E[X_n])^2 \leq E[X_n^2] < \infty,$$

and so  $v < \infty$ .

Next is another version of the Discrete Local Limit Theorem;

this one is stated in measure-theoretic terms:

**THEOREM 9.4.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $\mu \in \mathcal{P}_E$ . Assume:  $S_\mu = E$ . Assume:  $|\mu|_2 < \infty$ .

Let  $\alpha := M_\mu$ ,  $v := V_\mu$ . Then:  $0 < v < \infty$ , and,  $\forall t_1, t_2, \dots \in \mathbb{Z}$ ,  
as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot [(\mu^n\{f \in E^n \mid f_1 + \dots + f_n = t_n\}) - (\Phi_{n\alpha}^{nv}(t_n))] \rightarrow 0$ .

In Theorem 9.4, since  $E \subseteq \mathbb{Z}$  we get:  $|\mu|_1 \leq |\mu|_2^2$ .

Since  $|\mu|_1 \leq |\mu|_2^2 < \infty$ , we get:  $M_\mu$  and  $V_\mu$  are both defined.

Moreover, since  $|M_\mu| \leq |\mu|_1 \leq |\mu|_2^2 < \infty$ , we get:  $M_\mu$  is finite.

In Theorem 9.4, the proof that  $v > 0$  is relatively simple:

Since  $E$  is residue-unconstrained, we get:  $\#E \geq 2$ .

Since  $\#S_\mu = \#E \geq 2$ , by Theorem 8.6, we get:  $v > 0$ .

In Theorem 9.4, the proof that  $v < \infty$  is relatively simple:

$$v = V_\mu = |\mu|_2^2 - M_\mu^2 \leq |\mu|_2^2 < \infty.$$

Here is an application of Theorem 9.3:

**THEOREM 9.5.** *Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.*

*Let  $X_1, X_2, \dots$  be an iid sequence of  $\mathbb{Z}$ -valued  $L^2$  random-variables.*

*Assume:  $\forall n \in \mathbb{N}, \{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} = E$ .*

*Let  $\alpha \in \mathbb{R}, v \in [0; \infty]$ . Assume:  $\forall n \in \mathbb{N}, \mathbb{E}[X_n] = \alpha$  and  $\text{Var}[X_n] = v$ .*

*Then:  $0 < v < \infty$ . Also,  $\forall t_1, t_2, \dots \in \mathbb{Z}$ ,*

*if  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded,*

*then, as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Pr[X_1 + \dots + X_n = t_n]) \rightarrow 1/\sqrt{2\pi v}$ .*

*Proof.* By Theorem 9.3, we get  $0 < v < \infty$ .

**Given**  $t_1, t_2, \dots \in \mathbb{Z}$ , assume  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded,

**want:** as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Pr[X_1 + \dots + X_n = t_n]) \rightarrow 1/\sqrt{2\pi v}$ .

By Theorem 9.3, **it suffices to show:**

as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Phi_{n\alpha}^{nv}(t_n)) \rightarrow 1/\sqrt{2\pi v}$ .

We have:  $\forall n \in \mathbb{N}, \quad \Phi_{n\alpha}^{nv}(t_n) = \frac{\exp(-(t_n - n\alpha)^2 / (2nv))}{\sqrt{2\pi nv}}$ .

Since  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded and since  $0 < v < \infty$ , we get:

as  $n \rightarrow \infty$ ,  $-(t_n - n\alpha)^2 / (2nv) \rightarrow 0$ .

Then: as  $n \rightarrow \infty$ ,  $\exp(-(t_n - n\alpha)^2 / (2nv)) \rightarrow 1$ .

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Phi_{n\alpha}^{nv}(t_n)) \rightarrow 1/\sqrt{2\pi v}$ .  $\square$

We record a measure-theoretic version of Theorem 9.5:

**THEOREM 9.6.** *Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.*

*Let  $\mu \in \mathcal{P}_E$ . Assume:  $S_\mu = E$  and  $|\mu|_2 < \infty$ .*

*Let  $\alpha := M_\mu, v := V_\mu$ . Then:  $0 < v < \infty$ .*

*Also,  $\forall t_1, t_2, \dots \in \mathbb{Z}$ ,*

*if  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded,*

*then, as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\mu^n \{f \in E^n \mid f_1 + \dots + f_n = t_n\}) \rightarrow 1/\sqrt{2\pi v}$ .*

We also record the  $t_n = t_0 + n\alpha$  special case of the past two theorems:

**THEOREM 9.7.** *Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.*

*Let  $X_1, X_2, \dots$  be an iid sequence of  $\mathbb{Z}$ -valued  $L^2$  random-variables.*

*Assume:  $\forall n \in \mathbb{N}, \{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} = E$ .*

*Let  $t_0, \alpha \in \mathbb{Z}, v \in [0; \infty]$ . Assume:  $\forall n \in \mathbb{N}, \mathbb{E}[X_n] = \alpha$  and  $\text{Var}[X_n] = v$ .*

*Then:  $0 < v < \infty$ , and,*

*as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Pr[X_1 + \dots + X_n = t_0 + n\alpha]) \rightarrow 1/\sqrt{2\pi v}$ .*

**THEOREM 9.8.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $\mu \in \mathcal{P}_E$ . Assume:  $S_\mu = E$ . Assume:  $|\mu|_2 < \infty$ .

Let  $\alpha := M_\mu$ ,  $v := V_\mu$ . Assume:  $\alpha \in \mathbb{Z}$ . Let  $t_0 \in \mathbb{Z}$ .

Then:  $0 < v < \infty$ , and,

$$\text{as } n \rightarrow \infty, \quad \sqrt{n} \cdot (\mu^n \{f \in E^n \mid f_1 + \cdots + f_n = t_0 + n\alpha\}) \rightarrow 1/\sqrt{2\pi v}.$$

We also record the  $t_0 = 0$  special case of the past two theorems:

**THEOREM 9.9.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $X_1, X_2, \dots$  be an iid sequence of  $\mathbb{Z}$ -valued  $L^2$  random-variables.

Assume:  $\forall n \in \mathbb{N}, \quad \{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} = E$ .

Let  $\alpha \in \mathbb{Z}, v \in [0; \infty]$ . Assume:  $\forall n \in \mathbb{N}, \mathbb{E}[X_n] = \alpha$  and  $\text{Var}[X_n] = v$ .

Then:  $0 < v < \infty$ , and,

$$\text{as } n \rightarrow \infty, \quad \sqrt{n} \cdot (\Pr[X_1 + \cdots + X_n = n\alpha]) \rightarrow 1/\sqrt{2\pi v}.$$

**THEOREM 9.10.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $\mu \in \mathcal{P}_E$ . Assume:  $S_\mu = E$ . Assume:  $|\mu|_2 < \infty$ .

Let  $\alpha := M_\mu$ ,  $v := V_\mu$ . Assume:  $\alpha \in \mathbb{Z}$ .

Then:  $0 < v < \infty$ , and,

$$\text{as } n \rightarrow \infty, \quad \sqrt{n} \cdot (\mu^n \{f \in E^n \mid f_1 + \cdots + f_n = n\alpha\}) \rightarrow 1/\sqrt{2\pi v}.$$

## 10. AVERAGE EVENTS HAVE LOW INFORMATION, PARTICULAR CASE

Suppose, in secret, I flip a coin 1000 times,

then reveal to you that

the total number of heads was 1000,

and then ask you to guess the last flip.

The answer is that, since *all* the coin flips were heads,

the last flip must have been a head.

Similarly, if I had told you that

the total number of heads was 0,

then you would have known that the last flip was a tail.

By contrast, if I had told you that

the total number of heads was 500,

it seems intuitively clear that

you'd have had very little information about the last flip.

We wish to generalize and formalize that intuition,

and then provide rigorous proof of the resulting formal statement.

Our main theorem is Theorem 11.5, in the next section.

In this section, we go carefully through a special case:

**Let**  $X_1, X_2 \dots$  be  $\mathbb{Z}$ -valued iid random-variables s.t.,

$$\begin{aligned} \forall n \in \mathbb{N}, \quad \Pr[X_n = -1] &= 1/2, \\ &\Pr[X_n = 0] = 1/3, \\ &\Pr[X_n = 3] = 1/6. \end{aligned}$$

Then,  $\forall n \in \mathbb{N}$ ,  $X_n$  is  $L^1$  and  $X_n$  is  $L^2$ .

Also,  $\forall n \in \mathbb{N}$ ,  $E[X_n] = 0$  and  $\text{Var}[X_n] = 2$ .

Also,  $\forall n \in \mathbb{N}$ ,  $-1 \leq X_n \leq 3$  a.s.

For all  $n \in \mathbb{N}$ , **let**  $T_n := X_1 + \dots + X_n$ .

Then:  $\forall n \in \mathbb{N}$ ,  $-n \leq T_n \leq 3n$  a.s.

Then:  $-1000 \leq T_{1000} \leq 3000$  a.s.

Also,  $[T_{1000} = -1000] \Rightarrow [X_1 = \dots = X_{1000} = -1]$ ,

and so  $\Pr[X_{1000} = -1 | T_{1000} = -1000] = 1$ .

Similarly,  $\Pr[X_{1000} = 3 | T_{1000} = 3000] = 1$ .

By contrast, the event  $T_{1000} = 0$

would seem to give very little information about  $X_{1000}$ .

It therefore seems reasonable to expect that

$$\begin{aligned} \Pr[X_{1000} = -1 | T_{1000} = 0] &\approx 1/2 \quad \text{and} \\ \Pr[X_{1000} = 0 | T_{1000} = 0] &\approx 1/3 \quad \text{and} \\ \Pr[X_{1000} = 3 | T_{1000} = 0] &\approx 1/6. \end{aligned}$$

To make this precise, we will work “in the thermodynamic limit”,

which means: we replace 1000 by a variable  $n \in \mathbb{N}$ , and let  $n \rightarrow \infty$ .

That is, more precisely, we expect that, as  $n \rightarrow \infty$ ,

$$\begin{aligned} \Pr[X_n = -1 | T_n = 0] &\rightarrow 1/2 \quad \text{and} \\ \Pr[X_n = 0 | T_n = 0] &\rightarrow 1/3 \quad \text{and} \\ \Pr[X_n = 3 | T_n = 0] &\rightarrow 1/6. \end{aligned}$$

We will focus on proving the third of these limits;

proofs of the other two are similar.

By definition of conditional probability,

$$\text{we wish to prove:} \quad \text{As } n \rightarrow \infty, \quad \frac{\Pr[(X_n = 3) \& (T_n = 0)]}{\Pr[T_n = 0]} \rightarrow 1/6.$$

*Claim: Let*  $n \in [2.. \infty)$ .

Then:  $\Pr[(X_n = 3) \& (T_n = 0)] = (1/6) \cdot (\Pr[T_{n-1} = -3])$ .

*Proof of Claim:* We have:  $T_n = X_1 + \dots + X_{n-1} + X_n$ .

Since  $\Pr[(X_n = 3) \& (T_n = 0)]$

$$\begin{aligned} &= \Pr[(X_n = 3) \& (X_1 + \dots + X_{n-1} + X_n = 0)] \\ &= \Pr[(X_n = 3) \& (X_1 + \dots + X_{n-1} + 3 = 0)] \end{aligned}$$

$$= \Pr[(X_n = 3) \& (X_1 + \cdots + X_{n-1} = -3)],$$

it follows, from independence of  $X_1, \dots, X_n$ , that

$$\Pr[(X_n = 3) \& (T_n = 0)] \\ = (\Pr[X_n = 3]) \cdot (\Pr[X_1 + \cdots + X_{n-1} = -3]).$$

So, since  $\Pr[X_n = 3] = 1/6$  and  $X_1 + \cdots + X_{n-1} = T_{n-1}$ , we get:  $\Pr[(X_n = 3) \& (T_n = 0)] = (1/6) \cdot (\Pr[T_{n-1} = -3])$ .

*End of proof of Claim.*

By the claim, we wish to prove:

$$\text{As } n \rightarrow \infty, \quad \frac{(1/6) \cdot (\Pr[T_{n-1} = -3])}{\Pr[T_n = 0]} \rightarrow 1/6.$$

**We wish to prove:** As  $n \rightarrow \infty$ ,

$$\frac{\Pr[T_{n-1} = -3]}{\Pr[T_n = 0]} \rightarrow 1.$$

That is, we wish to prove:

$$\text{As } n \rightarrow \infty, \quad \Pr[T_{n-1} = -3] \text{ is asymptotic to } \Pr[T_n = 0].$$

So the question becomes:

How do we get a handle on the asymptotics, as  $n \rightarrow \infty$ , of both  $\Pr[T_{n-1} = -3]$  and  $\Pr[T_n = 0]$  ?

The Discrete Local Limit Theorem turns out to be just what we need.

Recall:  $\forall n \in \mathbb{N}$ ,  $E[X_n] = 0$  and  $\text{Var}[X_n] = 2$ .

**Let**  $\alpha := 0$  and  $v := 2$ . Then: ( $\forall n \in \mathbb{N}$ ,  $n\alpha = 0$ ) and ( $2\pi v = 4\pi$ ).

Also,  $\forall n \in \mathbb{N}$ ,  $E[X_n] = \alpha$  and  $\text{Var}[X_n] = v$ .

**Let**  $E := \{-1, 0, 3\}$ . Then  $E$  is residue-unconstrained.

Also, we have:  $\forall n \in \mathbb{N}$ ,  $\{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} = E$ .

By Theorem 9.9, as  $n \rightarrow \infty$ ,

$$\sqrt{n} \cdot (\Pr[X_1 + \cdots + X_n = n\alpha]) \rightarrow 1/\sqrt{2\pi v},$$

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Pr[T_n = 0]) \rightarrow 1/\sqrt{4\pi}$ ,

so, as  $n \rightarrow \infty$ ,  $\Pr[T_n = 0]$  is asymptotic to  $1/\sqrt{4\pi n}$ .

**Want:** as  $n \rightarrow \infty$ ,  $\Pr[T_{n-1} = -3]$  is asymptotic to  $1/\sqrt{4\pi n}$ .

**Let**  $t_0 := -3$ . Then,  $\forall n \in \mathbb{N}$ ,  $t_0 + n\alpha = -3$ .

By Theorem 9.7, as  $n \rightarrow \infty$ ,

$$\sqrt{n} \cdot (\Pr[X_1 + \cdots + X_n = t_0 + n\alpha]) \rightarrow 1/\sqrt{2\pi v}.$$

Recall:  $\forall n \in \mathbb{N}$ ,  $T_n = X_1 + \cdots + X_n$ .

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Pr[T_n = -3]) \rightarrow 1/\sqrt{4\pi}$ .

Then, as  $n \rightarrow \infty$ ,  $\sqrt{n-1} \cdot (\Pr[T_{n-1} = -3]) \rightarrow 1/\sqrt{4\pi}$ .

Then, as  $n \rightarrow \infty$ ,  $\Pr[T_{n-1} = -3]$  is asymptotic to  $1/\sqrt{4\pi(n-1)}$ , which is asymptotic to  $1/\sqrt{4\pi n}$ .

## 11. AVERAGE EVENTS HAVE LOW INFORMATION, GENERAL RESULT

We now seek to generalize our work in §10;

in the example at the end of this section, we show that

Theorem 11.5 reproduces the result of §10.

**THEOREM 11.1.** *Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.*

**Let  $X_1, X_2, \dots$  be an iid sequence of  $\mathbb{Z}$ -valued  $L^2$  random-variables.**

*Assume:  $\forall n \in \mathbb{N}, \{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} = E.$       **Let  $\alpha, P \in \mathbb{R}.$***

*Assume:  $\forall n \in \mathbb{N}, E[X_n] = \alpha$  and  $\Pr[X_n = \varepsilon_0] = P.$       **Let  $\varepsilon_0 \in E.$***

**Let  $t_1, t_2, \dots \in \mathbb{Z}.$       Assume:  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded.**

*Then: as  $n \rightarrow \infty,$   $\Pr[X_n = \varepsilon_0 \mid X_1 + \dots + X_n = t_n] \rightarrow P.$*

I don't know whether “ $L^2$ ” can be replaced by “ $L^1$ ”.

Part of the content of Theorem 11.1 is:

$$\forall \text{sufficiently large } n \in \mathbb{N}, \quad \Pr[X_1 + \dots + X_n = t_n] > 0.$$

*Proof.* Since  $X_1, X_2, \dots$  are all  $\mathbb{Z}$ -valued and  $L^2$ , we get:

$$X_1, X_2, \dots \text{ are } L^1.$$

Since  $X_1, X_2, \dots$  is an identically distributed sequence,

$$\text{choose } v \in [0; \infty] \text{ s.t., } \forall n \in \mathbb{N}, \text{Var}[X_n] = v.$$

By Theorem 9.5, we have:  $0 < v < \infty$  and

$$\text{as } n \rightarrow \infty, \sqrt{n} \cdot (\Pr[X_1 + \dots + X_n = t_n]) \rightarrow 1/\sqrt{2\pi v}.$$

For all  $n \in \mathbb{N},$  **let  $T_n := X_1 + \dots + X_n.$**

Then: as  $n \rightarrow \infty,$   $\sqrt{n} \cdot (\Pr[T_n = t_n]) \rightarrow 1/\sqrt{2\pi v}.$

**Want:** as  $n \rightarrow \infty,$   $\Pr[X_n = \varepsilon_0 \mid T_n = t_n] \rightarrow P.$

**Let  $D_1 := \{t_n - n\alpha \mid n \in \mathbb{N}\}.$       By hypothesis,  $D_1$  is bounded.**

**Let  $D_2 := \{t_n - n\alpha \mid n \in [2.. \infty)\}.$       Then  $D_2 \subseteq D_1.$**

**Let  $D_3 := \{t_{n+1} - (n+1) \cdot \alpha \mid n \in \mathbb{N}\}.$       Then  $D_3 = D_2.$**

For all  $n \in \mathbb{N},$  **let  $\tilde{t}_n := t_{n+1} - \varepsilon_0.$**

**Let  $D_4 := \{\tilde{t}_n - n\alpha \mid n \in \mathbb{N}\}.$**

$$\begin{aligned} \text{Since } D_4 - \alpha + \varepsilon &= \{ \tilde{t}_n - n\alpha - \alpha + \varepsilon \mid n \in \mathbb{N} \} \\ &= \{ t_{n+1} - \varepsilon_0 - (n+1) \cdot \alpha + \varepsilon \mid n \in \mathbb{N} \} \\ &= \{ t_{n+1} - (n+1) \cdot \alpha \mid n \in \mathbb{N} \} \\ &= D_3 = D_2 \subseteq D_1, \end{aligned}$$

and since  $D_1$  is bounded,

we get  $D_4 - \alpha + \varepsilon$  is bounded.

Then:  $D_4 - \alpha + \varepsilon + (\alpha - \varepsilon)$  is bounded.

Then:  $D_4$  is bounded.

Then, by Theorem 9.5, we have:

$$\text{as } n \rightarrow \infty, \quad \sqrt{n} \cdot (\Pr[T_n = \tilde{t}_n]) \rightarrow 1/\sqrt{2\pi v}.$$

$$\text{Then, as } n \rightarrow \infty, \quad \sqrt{n-1} \cdot (\Pr[T_{n-1} = \tilde{t}_{n-1}]) \rightarrow 1/\sqrt{2\pi v}.$$

$$\text{We have: } \forall n \in [2..\infty), \quad \tilde{t}_{n-1} = t_n - \varepsilon_0.$$

$$\text{So, as } n \rightarrow \infty, \quad \sqrt{n-1} \cdot (\Pr[T_{n-1} = t_n - \varepsilon_0]) \rightarrow 1/\sqrt{2\pi v}.$$

$$\text{Recall: as } n \rightarrow \infty, \quad \sqrt{n} \cdot (\Pr[T_n = t_n]) \rightarrow 1/\sqrt{2\pi v}.$$

Dividing the last two limits, we get:

$$\text{as } n \rightarrow \infty, \quad \frac{\sqrt{n-1} \cdot (\Pr[T_{n-1} = t_n - \varepsilon_0])}{\sqrt{n} \cdot (\Pr[T_n = t_n])} \rightarrow 1.$$

$$\text{Also, as } n \rightarrow \infty, \quad \frac{\sqrt{n}}{\sqrt{n-1}} \rightarrow 1.$$

Multiplying the last two limits together, we get:

$$\text{as } n \rightarrow \infty, \quad \frac{\Pr[T_{n-1} = t_n - \varepsilon_0]}{\Pr[T_n = t_n]} \rightarrow 1.$$

Since,  $\forall n \in [2..\infty)$ ,

$$\begin{aligned} \Pr[X_n = \varepsilon_0 | T_n = t_n] &= \frac{\Pr[(X_n = \varepsilon_0) \& (T_n = t_n)]}{\Pr[T_n = t_n]} \\ &= \frac{\Pr[(X_n = \varepsilon_0) \& (T_{n-1} + X_n = t_n)]}{\Pr[T_n = t_n]} \\ &= \frac{\Pr[(X_n = \varepsilon_0) \& (T_{n-1} + \varepsilon_0 = t_n)]}{\Pr[T_n = t_n]} \\ &= \frac{\Pr[(X_n = \varepsilon_0) \& (T_{n-1} = t_n - \varepsilon_0)]}{\Pr[T_n = t_n]} \\ &= \frac{(\Pr[X_n = \varepsilon_0]) \cdot (\Pr[T_{n-1} = t_n - \varepsilon_0])}{\Pr[T_n = t_n]} \\ &= P \cdot \frac{\Pr[T_{n-1} = t_n - \varepsilon_0]}{\Pr[T_n = t_n]}, \end{aligned}$$

and since, as  $n \rightarrow \infty$ ,

$$\frac{\Pr[T_{n-1} = t_n - \varepsilon_0]}{\Pr[T_n = t_n]} \rightarrow 1,$$

we get: as  $n \rightarrow \infty$ ,

$$\Pr[X_n = \varepsilon_0 | T_n = t_n] \rightarrow P. \quad \square$$

Recall (§8):  $\forall$ countable set  $\Theta$ ,

$\mathcal{FM}_\Theta^\times$  is the set of nonzero finite measures on  $\Theta$

and  $\mathcal{P}_\Theta$  is the set of probability measures on  $\Theta$ .

Recall (§8):  $\forall$ nonempty countable set  $\Theta$ ,  $\forall \mu \in \mathcal{FM}_\Theta^\times$ ,

$\mathcal{N}(\mu)$  is the normalization of  $\mu$ .

Here is a measure-theoretic version of the preceding theorem:

**THEOREM 11.2.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $\mu \in \mathcal{P}_E$ . Assume:  $S_\mu = E$ . Assume:  $|\mu|_2 < \infty$ .

Let  $\alpha := M_\mu$ . Let  $\varepsilon_0 \in E$ ,  $P := \mu\{\varepsilon_0\}$ .

Let  $t_1, t_2, \dots \in \mathbb{Z}$ . Assume:  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded.

For all  $n \in \mathbb{N}$ , let  $\Omega_n := \{f \in E^n \mid f_1 + \dots + f_n = t_n\}$ .

Then: as  $n \rightarrow \infty$ ,  $(\mathcal{N}(\mu^n | \Omega_n))\{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow P$ .

I don't know whether " $|\mu|_2 < \infty$ " can be replaced by " $|\mu|_1 < \infty$ ".

Part of the content of Theorem 11.2 is:

$\forall$ sufficiently large  $n \in \mathbb{N}$ ,  $\mu^n(\Omega_n) > 0$ ,

since, otherwise,  $\mu^n | \Omega_n$  would be the zero measure on  $\Omega_n$ ,

and so  $\mathcal{N}(\mu^n | \Omega_n)$  would not be defined.

We record the  $t_n = t_0 + n\alpha$  special case of the past two theorems:

**THEOREM 11.3.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $X_1, X_2, \dots$  be an iid sequence of  $\mathbb{Z}$ -valued  $L^2$  random-variables.

Assume:  $\forall n \in \mathbb{N}$ ,  $\{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} = E$ . Let  $t_0, \alpha \in \mathbb{Z}$ ,  $P \in \mathbb{R}$ .

Let  $\varepsilon_0 \in E$ . Assume:  $\forall n \in \mathbb{N}$ ,  $E[X_n] = \alpha$  and  $\Pr[X_n = \varepsilon_0] = P$ .

Then: as  $n \rightarrow \infty$ ,  $\Pr[X_n = \varepsilon_0 \mid X_1 + \dots + X_n = t_0 + n\alpha] \rightarrow P$ .

**THEOREM 11.4.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $\mu \in \mathcal{P}_E$ . Assume:  $S_\mu = E$ . Assume:  $|\mu|_2 < \infty$ .

Let  $\alpha := M_\mu$ . Assume:  $t_0, \alpha \in \mathbb{Z}$ . Let  $\varepsilon_0 \in E$ ,  $P := \mu\{\varepsilon_0\}$ .

For all  $n \in \mathbb{N}$ , let  $\Omega_n := \{f \in E^n \mid f_1 + \dots + f_n = t_0 + n\alpha\}$ .

Then: as  $n \rightarrow \infty$ ,  $(\mathcal{N}(\mu^n | \Omega_n))\{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow P$ .

We record the  $t_0 = 0$  special case of the past two theorems:

**THEOREM 11.5.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $X_1, X_2, \dots$  be an iid sequence of  $\mathbb{Z}$ -valued  $L^2$  random-variables.

Assume:  $\forall n \in \mathbb{N}$ ,  $\{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} = E$ . Let  $\alpha \in \mathbb{Z}$ ,  $P \in \mathbb{R}$ .

Let  $\varepsilon_0 \in E$ . Assume:  $\forall n \in \mathbb{N}$ ,  $E[X_n] = \alpha$  and  $\Pr[X_n = \varepsilon_0] = P$ .

Then: as  $n \rightarrow \infty$ ,  $\Pr[X_n = \varepsilon_0 \mid X_1 + \dots + X_n = n\alpha] \rightarrow P$ .

**THEOREM 11.6.** Let  $E \subseteq \mathbb{Z}$  be residue-unconstrained.

Let  $\mu \in \mathcal{P}_E$ . Assume:  $S_\mu = E$ . Assume:  $|\mu|_2 < \infty$ .

Let  $\alpha := M_\mu$ . Assume:  $\alpha \in \mathbb{Z}$ . Let  $\varepsilon_0 \in E$ ,  $P := \mu\{\varepsilon_0\}$ .

For all  $n \in \mathbb{N}$ , let  $\Omega_n := \{f \in E^n \mid f_1 + \dots + f_n = n\alpha\}$ .

Then: as  $n \rightarrow \infty$ ,  $(\mathcal{N}(\mu^n | \Omega_n))\{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow P$ .



*Example:* **Let**  $E := \{-1, 0, 3\}$ .

Then:  $E \subseteq \mathbb{Z}$  and  $E$  is residue-unconstrained.

**Let**  $X_1, X_2, \dots$  be  $\mathbb{Z}$ -valued iid random-variables s.t.,  
 $\forall n \in \mathbb{N}, \quad \Pr[X_n = -1] = 1/2,$   
 $\Pr[X_n = 0] = 1/3,$   
 $\Pr[X_n = 3] = 1/6.$

Then:  $\forall n \in \mathbb{N}, \quad E = \{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\}.$

**Let**  $\varepsilon_0 = 3, \quad P := 1/6.$

Then:  $\forall n \in \mathbb{N}, \quad \Pr[X_n = \varepsilon_0] = P.$

We have:  $\forall n \in \mathbb{N}, \quad \mathbb{E}[X_n] = 0. \quad \mathbf{Let} \quad \alpha := 0.$

Then,  $\forall n \in \mathbb{N}, \quad \mathbb{E}[X_n] = \alpha.$

Then, by Theorem 11.5, we have:

as  $n \rightarrow \infty, \quad \Pr[X_n = \varepsilon_0 \mid X_1 + \dots + X_n = n\alpha] \rightarrow P.$

Then: as  $n \rightarrow \infty, \quad \Pr[X_n = 3 \mid X_1 + \dots + X_n = 0] \rightarrow 1/6.$

For all  $n \in \mathbb{N}, \quad \mathbf{let} \quad T_n := X_1 + \dots + X_n.$

Then: as  $n \rightarrow \infty, \quad \Pr[X_n = 3 \mid T_n = 0] \rightarrow 1/6.$

Thus Theorem 11.5 reproduces the result of §10.

## 12. SOLVING THE MAIN PROBLEM

We finally have all we need to solve the main problem (end of §3).

**Let**  $(p, q, r) := \frac{(1, 9^{-1/10}, 9^{-1})}{1 + 9^{-1/10} + 9^{-1}}.$

We compute  $(p, q, r) \approx (0.5225, 0.4194, 0.0581),$

all accurate to four decimal places.

Again, let's say I am one of the professors applying to the GFA.

**We will show:** Under the GFA's *first* system (§3),

my probability of getting \$ 0 is  $p$ , approximately and

my probability of getting \$ 1 is  $q$ , approximately and

my probability of getting \$10 is  $r$ , approximately.

Recall:  $\Omega = \left\{ \omega : [1..N] \rightarrow \{0, 1, 10\} \mid \sum_{\ell=1}^N [\omega(\ell)] = N \right\}.$

Recall (§5): the notations  $i_\omega, j_\omega, k_\omega.$

**Let**  $S := \sum_{\omega \in \Omega} p^{i_\omega} q^{j_\omega} r^{k_\omega}.$

By the work in §7,  $p + q + r = 1$  and  $q + 10r = 1$  and

$\forall \omega \in \Omega, \quad p^{i_\omega} q^{j_\omega} r^{k_\omega} / S = 1 / (\#\Omega).$

**Let**  $X_1, X_2, \dots$  be  $\mathbb{Z}$ -valued iid random-variables s.t.,  $\forall n \in \mathbb{N},$

$\Pr[X_n = 0] = p,$

$$\begin{aligned}\Pr[X_n = 1] &= q, \\ \Pr[X_n = 10] &= r.\end{aligned}$$

Then  $X_1, X_2, \dots$  is a sequence of  $L^2$  random-variables.

Also,  $\forall n \in \mathbb{N}, \quad \mathbb{E}[X_n] = q + 10r.$

So, since  $q + 10r = 1,$  we get:

$$\forall n \in \mathbb{N}, \quad \mathbb{E}[X_n] = 1.$$

We model the GFA's *second* system (§5) by:  $\forall \ell \in [1..N],$

Professor# $\ell$  receives  $X_\ell$  dollars.

For all  $n \in \mathbb{N},$  **let**  $T_n := X_1 + \dots + X_n.$

We model the GFA's *third* system (§5) by:  $\forall \ell \in [1..N],$

Professor# $\ell$  receives  $X_\ell$  dollars, conditioned on  $T_N = N.$

Since  $\forall \omega \in \Omega, \quad p^{i\omega} q^{j\omega} r^{k\omega} / S = 1 / (\#\Omega),$

it follows that: the third system is equivalent to the first.

For definiteness, let's assume that I am Professor# $N.$

Then, assuming  $N$  is large, **we wish to show:**

$$\begin{aligned}\Pr[X_N = 0 | T_N = N] &\approx p && \text{and} \\ \Pr[X_N = 1 | T_N = N] &\approx q && \text{and} \\ \Pr[X_N = 10 | T_N = N] &\approx r.\end{aligned}$$

To be more precise, **we wish to show:** as  $n \rightarrow \infty,$

$$\begin{aligned}\Pr[X_n = 0 | T_n = n] &\rightarrow p && \text{and} \\ \Pr[X_n = 1 | T_n = n] &\rightarrow q && \text{and} \\ \Pr[X_n = 10 | T_n = n] &\rightarrow r.\end{aligned}$$

**Let**  $E := \{0, 1, 10\}.$  Then:  $E$  is residue-unconstrained.

$$\textbf{Given } \varepsilon_0 \in E, \textbf{ let } P := \begin{cases} p, & \text{if } \varepsilon_0 = 0 \\ q, & \text{if } \varepsilon_0 = 1 \\ r, & \text{if } \varepsilon_0 = 10, \end{cases}$$

**want:** as  $n \rightarrow \infty, \quad \Pr[X_n = \varepsilon_0 | T_n = n] \rightarrow P.$

By definition of  $X_1, X_2, \dots,$  we get:  $\forall n \in \mathbb{N}, \quad \Pr[X_n = \varepsilon_0] = P.$

**Let**  $\alpha := 1.$  Then:  $\alpha \in \mathbb{Z}$  and  $\forall n \in \mathbb{N}, \quad \mathbb{E}[X_n] = \alpha.$

Also,  $\forall n \in \mathbb{N}, \quad \{t \in \mathbb{Z} | \Pr[X_n = t] > 0\} = E.$

Then, by Theorem 11.5, we have:

$$\text{as } n \rightarrow \infty, \quad \Pr[X_n = \varepsilon_0 | X_1 + \dots + X_n = n\alpha] \rightarrow P.$$

Then: as  $n \rightarrow \infty, \quad \Pr[X_n = \varepsilon_0 | T_n = n] \rightarrow P.$

### 13. PROBABILITY OF TWO PROFESSORS GETTING ZERO

Under the GFA's first system, since  $N$  is large, one would expect:  
the award amounts of two different professors

are almost independent.

Then, for example, one would expect:

the probability that two professors both receive zero dollars should be very close to the square of

the probability that one professor receives zero dollars.

We will formalize this statement and prove it, below.

For definiteness, we will assume that

the two professors are Professor  $\#(N - 1)$  and Professor  $\#N$ .

**Let**  $(p, q, r) := \frac{(1, 9^{-1/10}, 9^{-1})}{1 + 9^{-1/10} + 9^{-1}}$ . Then (§7):  $p + q + r = 1$ .

**Let**  $X_1, X_2, \dots$  be  $\mathbb{Z}$ -valued iid random-variables s.t.,  $\forall n \in \mathbb{N}$ ,

$$\Pr[X_n = 0] = p,$$

$$\Pr[X_n = 1] = q,$$

$$\Pr[X_n = 10] = r.$$

Then  $X_1, X_2, \dots$  is a sequence of  $L^2$  random-variables.

For all  $n \in \mathbb{N}$ , **let**  $T_n := X_1 + \dots + X_n$ .

Assuming  $N$  is large, our goal is to prove:

$$\Pr[X_{N-1} = 0 = X_N \mid T_N = N] \approx p^2.$$

To be more precise, **we will prove:**

$$\text{as } n \rightarrow \infty, \quad \Pr[X_{n-1} = 0 = X_n \mid T_n = n] \rightarrow p^2.$$

For all  $n \in \mathbb{N}$ , **define**  $\psi_n : \mathbb{Z} \rightarrow \mathbb{R}$  by:

$$\forall t \in \mathbb{Z}, \quad \psi_n(t) = \Pr[T_n = t].$$

For all  $n \in \mathbb{N}$ , **let**  $a_n := \psi_n(n + 2)$ ,  $z_n := \psi_n(n)$ .

Since,  $\forall n \in \mathbb{N}$ , we have  $\psi_n(n) = \Pr[T_n = n] = \Pr[X_1 + \dots + X_n = n]$   
 $\geq \Pr[X_1 = \dots = X_n = 1] = q^n > 0$ ,

we conclude:  $\forall n \in \mathbb{N}$ ,  $z_n > 0$ .

*Claim:* **Let**  $n \in [3, \infty)$ . Then  $\Pr[X_{n-1} = 0 = X_n \mid T_n = n] = p^2 \cdot \frac{a_{n-2}}{z_n}$ .

*Proof of Claim:* We have  $T_n = X_1 + \dots + X_{n-2} + X_{n-1} + X_n$ .

$$\begin{aligned} \text{Since } & \Pr[(X_{n-1} = 0 = X_n) \& (T_n = n)] \\ &= \Pr[(X_{n-1} = 0 = X_n) \& (X_1 + \dots + X_{n-2} + X_{n-1} + X_n = n)] \\ &= \Pr[(X_{n-1} = 0 = X_n) \& (X_1 + \dots + X_{n-2} + 0 + 0 = n)] \\ &= \Pr[(X_{n-1} = 0 = X_n) \& (X_1 + \dots + X_{n-2} = n)], \end{aligned}$$

it follows, from independence of  $X_1, \dots, X_n$ , that

$$\begin{aligned} & \Pr[(X_{n-1} = 0 = X_n) \& (T_n = n)] \\ &= (\Pr[X_{n-1} = 0]) \cdot (\Pr[X_n = 0]) \cdot (\Pr[X_1 + \dots + X_{n-2} = n]). \end{aligned}$$

So, since  $\Pr[X_{n-1} = 0] = p = \Pr[X_n = 0]$

and since  $X_1 + \dots + X_{n-2} = T_{n-2}$ ,

we get:  $\Pr[(X_{n-1} = 0 = X_n) \& (T_n = n)] = p^2 \cdot (\Pr[T_{n-2} = n])$ .

$$\begin{aligned} \text{Then } \Pr[X_{n-1} = 0 = X_n \mid T_n = n] &= \frac{\Pr[(X_{n-1} = 0 = X_n) \& (T_n = n)]}{\Pr[T_n = n]} \\ &= \frac{p^2 \cdot (\Pr[T_{n-2} = n])}{\Pr[T_n = n]} = p^2 \cdot \frac{\psi_{n-2}(n)}{\psi_n(n)} = p^2 \cdot \frac{a_{n-2}}{z_n}. \end{aligned}$$

*End of proof of Claim.*

Because of the Claim, **we want to show:** as  $n \rightarrow \infty$ ,  $p^2 \cdot \frac{a_{n-2}}{z_n} \rightarrow p^2$ .

**Want:** as  $n \rightarrow \infty$ ,  $\frac{z_n}{a_{n-2}} \rightarrow 1$ .

We compute:  $\forall n \in \mathbb{N}$ ,  $\mathbb{E}[X_n] = q + 10r$ .

Recall (§7):  $q + 10r = 1$ . Then:  $\forall n \in \mathbb{N}$ ,  $\mathbb{E}[X_n] = 1$ .

We compute:  $\forall n \in \mathbb{N}$ ,  $\text{Var}[X_n] = q + 100r - 1$ .

**Let**  $v := q + 100r - 1$ . Then:  $\forall n \in \mathbb{N}$ ,  $\text{Var}[X_n] = v$ .

Since  $v = (q + 10r - 1) + 90r = 0 + 90r = 90r$ , and since  $0 < r < \infty$ ,  
we get:  $0 < v < \infty$ . **Let**  $\tau := 1/\sqrt{2\pi v}$ . Then:  $\tau > 0$ .

**Let**  $\alpha := 1$ . Then,  $\alpha \in \mathbb{Z}$  and  $\forall n \in \mathbb{N}$ ,  $\mathbb{E}[X_n] = \alpha$ .

**Let**  $E := \{0, 1, 10\}$ . Then,  $\forall n \in \mathbb{N}$ ,  $\{t \in \mathbb{Z} \mid \Pr[X_n = t] > 0\} = E$ .

Also,  $E$  is residue-unconstrained.

By Theorem 9.9, as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Pr[T_n = n\alpha]) \rightarrow 1/\sqrt{2\pi v}$ .

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Pr[T_n = n]) \rightarrow \tau$ .

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\psi_n(n)) \rightarrow \tau$ .

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot z_n \rightarrow \tau$ .

**Let**  $t_0 := 2$ . Then  $t_0 \in \mathbb{Z}$  and  $\forall n \in \mathbb{N}$ ,  $t_0 + n\alpha = n + 2$ .

By Theorem 9.7, as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Pr[T_n = t_0 + n\alpha]) \rightarrow 1/\sqrt{2\pi v}$ .

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\Pr[T_n = n + 2]) \rightarrow \tau$ .

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\psi_n(n + 2)) \rightarrow \tau$ .

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot a_n \rightarrow \tau$ .

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n-2} \cdot a_{n-2} \rightarrow \tau$ .

Recall: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot z_n \rightarrow \tau$ .

Dividing the last two limits, we get:

$$\text{as } n \rightarrow \infty, \quad \frac{\sqrt{n-2} \cdot a_{n-2}}{\sqrt{n} \cdot z_n} \rightarrow 1.$$

$$\text{Also, as } n \rightarrow \infty, \quad \frac{\sqrt{n}}{\sqrt{n-2}} \rightarrow 1.$$

Multiplying these last two limits, we get:

$$\text{as } n \rightarrow \infty, \quad \frac{a_{n-2}}{z_n} \rightarrow 1.$$

#### 14. FRACTION OF PROFESSORS GETTING A ZERO AWARD

**Let**  $(p, q, r) := \frac{(1, 9^{-1/10}, 9^{-1})}{1 + 9^{-1/10} + 9^{-1}}.$

We compute  $(p, q, r) \approx (0.5225, 0.4194, 0.0581),$

all accurate to four decimal places.

**Let**  $X_1, X_2, \dots$  be  $\mathbb{Z}$ -valued iid random-variables s.t.,  $\forall n \in \mathbb{N},$

$$\Pr[X_n = 0] = p,$$

$$\Pr[X_n = 1] = q,$$

$$\Pr[X_n = 10] = r.$$

For all  $n \in \mathbb{N},$  **let**  $T_n := X_1 + \dots + X_n.$

For all  $n \in \mathbb{N},$  **let**  $I_n$  be the indicator variable of the event:  $X_n = 0.$

For all  $n \in \mathbb{N},$  **let**  $J_n := (I_1 + \dots + I_n)/n.$

Using the GFA's first (or third) awards system, the random-variable

$$J_N \quad \text{conditioned on} \quad T_N = N$$

represents the fraction of professors receiving a \$0 award.

In this section, **we will prove the following:**

*Claim:*  $\forall \varepsilon > 0,$  as  $n \rightarrow \infty,$   $\Pr [ p - \varepsilon < J_n < p + \varepsilon \mid T_n = n ] \rightarrow 1.$

Assume, for a moment, that this Claim is true.

Then: as  $n \rightarrow \infty,$   $\Pr [ p - 0.02 < J_n < p + 0.02 \mid T_n = n ] \rightarrow 1.$

From this, it follows that, if  $N$  is sufficiently large, then

$$\Pr [ p - 0.02 < J_N < p + 0.02 \mid T_N = N ] > 0.99,$$

so  $\Pr [ p - 0.02 < J_N \mid T_N = N ] > 0.99,$

so  $\Pr [ J_N > p - 0.02 \mid T_N = N ] > 0.99.$

Since  $p \approx 0.5225,$  accurate to four decimal places, we get

$$p - 0.02 > 0.5,$$

so  $[ J_N > p - 0.02 ] \Rightarrow [ J_N > 0.5 ],$

so  $\Pr [ J_N > p - 0.02 \mid T_N = N ]$

$$\leq \Pr [ J_N > 0.5 \mid T_N = N ].$$

Therefore, for  $N$  is sufficiently large, since

$$\Pr [ J_N > 0.5 \mid T_N = N ]$$

$$\geq \Pr [ J_N > p - 0.02 \mid T_N = N ] > 0.99,$$

we conclude: under the GFA's first system, with probability  $> 99\%,$

over  $50\%$  of the professors receive \$0.

*Proof of Claim:*

**Given**  $\varepsilon > 0$ , **want:** as  $n \rightarrow \infty$ ,  $\Pr[p - \varepsilon < J_n < p + \varepsilon | T_n = n] \rightarrow 1$ .

**Let**  $E := \{0, 1, 10\}$ . Then  $E$  is residue-unconstrained.

Also,  $\forall n \in \mathbb{N}$ ,  $\{t \in \mathbb{Z} | \Pr[X_n = t] > 0\} = E$ .

**Let**  $\alpha := 1$ . Then:  $\alpha \in \mathbb{Z}$  and  $\forall n \in \mathbb{N}$ ,  $\mathbb{E}[X_n] = \alpha$ .

For all  $n \in \mathbb{N}$ , **let**  $\kappa_n := \mathbb{E}[I_n | T_n = n]$ .

Then:  $\forall n \in \mathbb{N}$ ,  $\kappa_n = \Pr[X_n = 0 | T_n = n]$ .

By Theorem 11.5, we get:

$$\text{as } n \rightarrow \infty, \Pr[X_n = 0 | X_1 + \dots + X_n = n\alpha] \rightarrow p.$$

That is, as  $n \rightarrow \infty$ ,  $\Pr[X_n = 0 | T_n = n] \rightarrow p$ .

Then: as  $n \rightarrow \infty$ ,  $\kappa_n \rightarrow p$ .

So,  $\exists n_0 \in \mathbb{N}$  s.t.,  $\forall n \in [n_0.. \infty)$ ,

$$\text{we have } p - (\varepsilon/2) < \kappa_n < p + (\varepsilon/2),$$

and so both  $p - \varepsilon < \kappa_n - (\varepsilon/2)$  and  $\kappa_n + (\varepsilon/2) < p + \varepsilon$ ,

and so  $[\kappa_n - (\varepsilon/2) < J_n < \kappa_n + (\varepsilon/2)] \Rightarrow [p - \varepsilon < J_n < p + \varepsilon]$ ,

$$\begin{aligned} \text{and so } & \Pr[\kappa_n - (\varepsilon/2) < J_n < \kappa_n + (\varepsilon/2) | T_n = n] \\ & \leq \Pr[p - \varepsilon < J_n < p + \varepsilon | T_n = n]. \end{aligned}$$

**It therefore suffices to show:**

$$\text{as } n \rightarrow \infty, \Pr[\kappa_n - (\varepsilon/2) < J_n < \kappa_n + (\varepsilon/2) | T_n = n] \rightarrow 1.$$

We have:  $\forall n \in \mathbb{N}$ ,  $T_n$  is invariant under permutation of  $X_1, \dots, X_n$ ,  
as is the joint-distribution of  $X_1, \dots, X_n$ .

Then:  $\forall n \in \mathbb{N}$ ,  $\forall i \in [1..n]$ ,  $\mathbb{E}[I_i | T_n = n] = \mathbb{E}[I_n | T_n = n]$ .

Then:  $\forall n \in \mathbb{N}$ ,  $\forall i \in [1..n]$ ,  $\mathbb{E}[I_i | T_n = n] = \kappa_n$ .

Since,  $\forall n \in \mathbb{N}$ ,  $J_n = (I_1 + \dots + I_n)/n$ , we get:

$$\forall n \in \mathbb{N}, \mathbb{E}[J_n | T_n = n] = (\sum_{i=1}^n \mathbb{E}[I_i | T_n = n]) / n.$$

Then:  $\forall n \in \mathbb{N}$ ,  $\mathbb{E}[J_n | T_n = n] = (\sum_{i=1}^n \kappa_n) / n$ .

Then:  $\forall n \in \mathbb{N}$ ,  $\mathbb{E}[J_n | T_n = n] = (n\kappa_n) / n$ .

Then:  $\forall n \in \mathbb{N}$ ,  $\mathbb{E}[J_n | T_n = n] = \kappa_n$ .

For all  $n \in \mathbb{N}$ , **let**  $v_n := \text{Var}[J_n | T_n = n]$ .

Then, by Chebyshev's inequality, we have:  $\forall n \in \mathbb{N}$ ,

$$\Pr[\kappa_n - (\varepsilon/2) < J_n < \kappa_n + (\varepsilon/2) | T_n = n] \geq 1 - (v_n/(\varepsilon/2)^2).$$

**It therefore suffices to show:** as  $n \rightarrow \infty$ ,  $v_n \rightarrow 0$ .

For all  $n \in \mathbb{N}$ , **let**  $v_n := \text{Var}[J_n | T_n = n]$ .

Recall: as  $n \rightarrow \infty$ ,  $\kappa_n \rightarrow p$ .

$$\begin{aligned} \text{Since } \forall n \in \mathbb{N}, \quad v_n &= \text{Var}[J_n | T_n = n] \\ &= (\mathbb{E}[J_n^2 | T_n = n]) - (\mathbb{E}[J_n | T_n = n])^2 \\ &= (\mathbb{E}[J_n^2 | T_n = n]) - \kappa_n^2. \end{aligned}$$

and since, as  $n \rightarrow \infty$ ,  $\kappa_n^2 \rightarrow p^2$ ,

**we want:** as  $n \rightarrow \infty$ ,  $E [ J_n^2 | T_n = n ] \rightarrow p^2$ .

For all  $n \in [2..\infty)$ , **let**  $\lambda_n := E [ I_{n-1} \cdot I_n | T_n = n ]$ .

Then:  $\forall n \in [2..\infty)$ ,  $\lambda_n = \Pr [ X_{n-1} = 0 = X_n | T_n = n ]$ .

So, by the result of §13, we get: as  $n \rightarrow \infty$ ,  $\lambda_n \rightarrow p^2$ .

For all  $n \in \mathbb{N}$ , since  $I_n$  is an indicator variable, we get:  $I_n \in \{0, 1\}$  a.s.

Then:  $\forall n \in \mathbb{N}$ ,  $I_n = I_n^2$  a.s.

Then:  $\forall n \in \mathbb{N}$ ,  $E [ I_n | T_n = n ] = E [ I_n^2 | T_n = n ]$ .

Recall:  $\forall n \in \mathbb{N}$ ,  $E [ I_n | T_n = n ] = \kappa_n$ .

Then:  $\forall n \in \mathbb{N}$ ,  $\kappa_n = E [ I_n^2 | T_n = n ]$ .

For all  $n \in \mathbb{N}$ , for all  $i, j \in [1..n]$ , **let**  $c_{ijn} := E [ I_i \cdot I_j | T_n = n ]$ .

We have:  $\forall n \in \mathbb{N}$ ,  $T_n$  is invariant under permutation of  $X_1, \dots, X_n$ ,  
as is the joint-distribution of  $X_1, \dots, X_n$ .

Then  $\forall n \in \mathbb{N}$ ,  $\forall i \in [1..n]$ ,  $E [ I_i^2 | T_n = n ] = E [ I_n^2 | T_n = n ]$ ,

so,  $\forall n \in \mathbb{N}$ ,  $\forall i \in [1..n]$ ,  $E [ I_i^2 | T_n = n ] = \kappa_n$ ,

so,  $\forall n \in \mathbb{N}$ ,  $\forall i \in [1..n]$ ,  $c_{iin} = \kappa_n$ .

Similarly,  $\forall n \in [2..\infty)$ ,  $\forall i, j \in [1..n]$ , if  $i \neq j$ , then

$$E [ I_i \cdot I_j | T_n = n ] = E [ I_{n-1} \cdot I_n | T_n = n ],$$

so,  $\forall n \in [2..\infty)$ ,  $\forall i, j \in [1..n]$ , if  $i \neq j$ , then

$$E [ I_i \cdot I_j | T_n = n ] = \lambda_n.$$

so,  $\forall n \in [2..\infty)$ ,  $\forall i, j \in [1..n]$ , if  $i \neq j$ , then

$$c_{ijn} = \lambda_n.$$

Then:  $\forall n \in \mathbb{N}$ ,  $\forall i, j \in [1..n]$ ,  $c_{ijn} = \begin{cases} \kappa_n, & \text{if } i = j \\ \lambda_n, & \text{if } i \neq j. \end{cases}$

Then:  $\forall n \in \mathbb{N}$ ,  $\sum_{i=1}^n \sum_{j=1}^n c_{ijn} = n \cdot \kappa_n + (n^2 - n) \cdot \lambda_n$ .

Recall: as  $n \rightarrow \infty$ ,  $\kappa_n \rightarrow p$  and  $\lambda_n \rightarrow p^2$ .

Since  $\forall n \in \mathbb{N}$ ,  $J_n = (I_1 + \dots + I_n)/n$ ,

we get:  $\forall n \in \mathbb{N}$ ,  $J_n^2 = ( \sum_{i=1}^n \sum_{j=1}^n [ I_i \cdot I_j ] ) / n^2$ .

Then:  $\forall n \in \mathbb{N}$ ,  $E [ J_n^2 | T_n = n ] = ( \sum_{i=1}^n \sum_{j=1}^n c_{ijn} ) / n^2$ .

Then:  $\forall n \in \mathbb{N}$ ,  $E [ J_n^2 | T_n = n ] = (1/n) \cdot \kappa_n + (1 - (1/n)) \cdot \lambda_n$ .

Then: as  $n \rightarrow \infty$ ,  $E [ J_n^2 | T_n = n ] \rightarrow 0 \cdot p + 1 \cdot p^2$ .

Then: as  $n \rightarrow \infty$ ,  $E [ J_n^2 | T_n = n ] \rightarrow p^2$ .

*End of proof of Claim.*

## 15. BOLTZMANN DISTRIBUTIONS ON NONEMPTY FINITE SETS

Recall (§8):  $\forall$  countable set  $\Theta$ ,

$\mathcal{M}_\Theta$  is the set of measures on  $\Theta$

and  $\mathcal{FM}_\Theta^\times$  is the set of nonzero finite measures on  $\Theta$   
 and  $\mathcal{P}_\Theta$  is the set of probability measures on  $\Theta$ .  
 Recall (§8):  $\forall$  nonempty countable set  $\Theta$ ,  $\forall \mu \in \mathcal{FM}_\Theta^\times$ ,  
 $\mathcal{N}(\mu)$  is the normalization of  $\mu$ .

**DEFINITION 15.1.** Let  $E \subseteq \mathbb{R}$  be nonempty and finite,  $\beta \in \mathbb{R}$ .  
 The unnormalized- $\beta$ -Boltzmann distribution on  $E$  is

the measure  $\widehat{B}_\beta^E$   $\in \mathcal{FM}_E^\times$  defined by:

$$\forall \varepsilon \in E, \quad \widehat{B}_\beta^E\{\varepsilon\} = e^{-\beta \cdot \varepsilon}.$$

Also, the  $\beta$ -Boltzmann distribution on  $E$  is

$$\boxed{B_\beta^E} := \mathcal{N}(\widehat{B}_\beta^E) \in \mathcal{P}_E.$$

Then:  $\forall \varepsilon \in E$ , we have:  $B_\beta^E\{\varepsilon\} = (\widehat{B}_\beta^E\{\varepsilon\}) / (\widehat{B}_\beta^E(E))$ .

*Example:* Let  $E := \{0, 1, 10\}$  and let  $\beta \in \mathbb{R}$ .

$$\text{Then: } \widehat{B}_\beta^E\{0\} = 1, \quad \widehat{B}_\beta^E\{1\} = e^{-\beta}, \quad \widehat{B}_\beta^E\{10\} = e^{-10\beta}.$$

$$\text{Let } C := 1/(1 + e^{-\beta} + e^{-10\beta}).$$

$$\text{Then: } B_\beta^E\{0\} = C, \quad B_\beta^E\{1\} = Ce^{-\beta}, \quad B_\beta^E\{10\} = Ce^{-10\beta}.$$

*Example:* Let  $E := \{2, 4, 8, 9\}$  and let  $\beta \in \mathbb{R}$ .

$$\text{Then: } \widehat{B}_\beta^E\{2\} = e^{-2\beta}, \quad \widehat{B}_\beta^E\{4\} = e^{-4\beta},$$

$$\widehat{B}_\beta^E\{8\} = e^{-8\beta}, \quad \widehat{B}_\beta^E\{9\} = e^{-9\beta}.$$

$$\text{Let } C := 1/(e^{-2\beta} + e^{-4\beta} + e^{-8\beta} + e^{-9\beta}).$$

$$\text{Then: } B_\beta^E\{2\} = Ce^{-2\beta}, \quad B_\beta^E\{4\} = Ce^{-4\beta},$$

$$B_\beta^E\{8\} = Ce^{-8\beta}, \quad B_\beta^E\{9\} = Ce^{-9\beta}.$$

Recall (§8): For any countable set  $\Theta$ , for any  $\mu \in \mathcal{M}_\Theta$ ,

$S_\mu$  is the support of  $\mu$ .

Note:  $\forall$  nonempty finite  $E \subseteq \mathbb{R}$ ,  $\forall \beta \in \mathbb{R}$ , we have:  $S_{\widehat{B}_\beta^E} = E = S_{B_\beta^E}$ .

**THEOREM 15.2.** Let  $E \subseteq \mathbb{R}$  be nonempty and finite.

Let  $\varepsilon_0 \in E$ ,  $\beta, \xi \in \mathbb{R}$ . Then:  $B_\beta^{E-\xi}\{\varepsilon_0 - \xi\} = B_\beta^E\{\varepsilon_0\}$ .

$$\begin{aligned} \text{Proof. We have: } B_\beta^{E-\xi}\{\varepsilon_0 - \xi\} &= \frac{e^{-\beta \cdot (\varepsilon_0 - \xi)}}{\sum_{\varepsilon \in E} [e^{-\beta \cdot (\varepsilon - \xi)}]} \\ &= \frac{e^{-\beta \cdot \varepsilon_0} \cdot e^{\beta \cdot \xi}}{\sum_{\varepsilon \in E} [e^{-\beta \cdot \varepsilon} \cdot e^{\beta \cdot \xi}]} \end{aligned}$$



$$\begin{aligned}
&= \frac{e^{\beta \cdot \xi} \cdot e^{-\beta \cdot \varepsilon_0}}{e^{\beta \cdot \xi} \cdot \sum_{\varepsilon \in E} [e^{-\beta \cdot \varepsilon}]} \\
&= \frac{e^{-\beta \cdot \varepsilon_0}}{\sum_{\varepsilon \in E} [e^{-\beta \cdot \varepsilon}]} = B_\beta^E \{\varepsilon_0\}. \quad \square
\end{aligned}$$

Recall (§8): **Let**  $\Theta \subseteq \mathbb{R}$  be countable,  $\mu \in \mathcal{P}_\Theta$ . Assume  $\#S_\mu < \infty$ . Then  $|\mu|_1 < \infty$  and  $M_\mu$  is the mean of  $\mu$  and  $V_\mu$  is the variance of  $\mu$ .

**Let**  $E \subseteq \mathbb{R}$  be nonempty and finite. **Let**  $\beta \in \mathbb{R}$ . We define:

$$\begin{aligned}
\boxed{\Gamma_\beta^E} &:= \sum_{\varepsilon \in E} [\varepsilon \cdot e^{\beta \cdot \varepsilon}], \\
\boxed{\Delta_\beta^E} &:= \sum_{\varepsilon \in E} [e^{\beta \cdot \varepsilon}], \\
\boxed{A_\beta^E} &:= \Gamma_\beta^E / \Delta_\beta^E.
\end{aligned}$$

Then:  $\Gamma_\beta^E = \sum_{\varepsilon \in E} [\varepsilon \cdot (\widehat{B}_\beta^E \{\varepsilon\})]$ .

Also,  $\Delta_\beta^E = \sum_{\varepsilon \in E} [\widehat{B}_\beta^E \{\varepsilon\}]$ , and so  $\Delta_\beta^E = \widehat{B}_\beta^E(E)$ .

Since  $\frac{\Gamma_\beta^E}{\Delta_\beta^E} = \frac{\sum_{\varepsilon \in E} [\varepsilon \cdot (\widehat{B}_\beta^E \{\varepsilon\})]}{\widehat{B}_\beta^E(E)} = \sum_{\varepsilon \in E} [\varepsilon \cdot (B_\beta^E \{\varepsilon\})]$ ,

we conclude:  $A_\beta^E = M_{B_\beta^E}$ .

Then:  $A_\beta^E$  is the average value of any  $E$ -valued random-variable whose distribution in  $E$  is  $B_\beta^E$ .

**THEOREM 15.3.** **Let**  $E \subseteq \mathbb{R}$  be nonempty and finite. **Let**  $\beta, \xi \in \mathbb{R}$ .

Then:  $A_\beta^{E-\xi} = A_\beta^E - \xi$ .

*Proof.*

**Want:**  $M_{B_\beta^{E-\xi}} = M_{B_\beta^E} - \xi$ .

**Let**  $\lambda := B_\beta^{E-\xi}$ ,  $\mu := B_\beta^E$ .

**Want:**  $M_\lambda = M_\mu - \xi$ .

We have:  $\lambda \in \mathcal{P}_{E-\xi}$  and  $\mu \in \mathcal{P}_E$ .

By Theorem 15.2, we have:  $\forall \varepsilon \in E$ ,  $B_\beta^{E-\xi} \{\varepsilon - \xi\} = B_\beta^E \{\varepsilon\}$ .

Then:  $\forall \varepsilon \in E$ ,  $\lambda \{\varepsilon - \xi\} = \mu \{\varepsilon\}$ .

Since  $\mu \in \mathcal{P}_E$ , we get:  $\mu(E) = 1$ .

$$\begin{aligned}
\text{Then: } M_\lambda &= \sum_{\varepsilon \in E} [(\varepsilon - \xi) \cdot (\lambda \{\varepsilon - \xi\})] \\
&= \sum_{\varepsilon \in E} [(\varepsilon - \xi) \cdot (\mu \{\varepsilon\})] \\
&= \sum_{\varepsilon \in E} [\varepsilon \cdot (\mu \{\varepsilon\}) - \xi \cdot (\mu \{\varepsilon\})] \\
&= (\sum_{\varepsilon \in E} [\varepsilon \cdot (\mu \{\varepsilon\})]) - (\sum_{\varepsilon \in E} [\xi \cdot (\mu \{\varepsilon\})]) \\
&= (\sum_{\varepsilon \in E} [\varepsilon \cdot (\mu \{\varepsilon\})]) - \xi \cdot (\sum_{\varepsilon \in E} [\mu \{\varepsilon\}]) \\
&= M_\mu - \xi \cdot (\mu(E)) = M_\mu - \xi \cdot 1 = M_\mu - \xi. \quad \square
\end{aligned}$$

**THEOREM 15.4.** Let  $E \subseteq \mathbb{R}$  be nonempty and finite. Then:

$$\begin{aligned} & \text{as } \beta \rightarrow \infty, \quad A_\beta^E \rightarrow \min E \\ \text{and} \quad & \text{as } \beta \rightarrow -\infty, \quad A_\beta^E \rightarrow \max E. \end{aligned}$$

The proof is a matter of bookkeeping, best explained by example:

Let  $E := \{2, 4, 8, 9\}$ . Then  $\min E = 2$  and  $\max E = 9$ .

$$\text{Since,} \quad \forall \beta \in \mathbb{R}, \quad A_\beta^E = \frac{2e^{-2\beta} + 4e^{-4\beta} + 8e^{-8\beta} + 9e^{-9\beta}}{e^{-2\beta} + e^{-4\beta} + e^{-8\beta} + e^{-9\beta}},$$

$$\text{we get} \quad \text{as } \beta \rightarrow \infty, \quad A_\beta^E \rightarrow 2/1$$

$$\text{and} \quad \text{as } \beta \rightarrow -\infty, \quad A_\beta^E \rightarrow 9/1,$$

$$\text{and so} \quad \text{as } \beta \rightarrow \infty, \quad A_\beta^E \rightarrow \min E$$

$$\text{and} \quad \text{as } \beta \rightarrow -\infty, \quad A_\beta^E \rightarrow \max E.$$

For all nonempty, finite  $E \subseteq \mathbb{R}$ , define  $\boxed{A_\bullet^E} : \mathbb{R} \rightarrow \mathbb{R}$  by:

$$\forall \beta \in \mathbb{R}, \quad A_\bullet^E(\beta) = A_\beta^E.$$

**THEOREM 15.5.** Let  $E \subseteq \mathbb{R}$ . Assume:  $2 \leq \#E < \infty$ .

Then:  $A_\bullet^E$  is a strictly-decreasing  $C^\omega$ -diffeomorphism

from  $\mathbb{R}$  onto  $(\min E; \max E)$ .

*Proof.* Let  $\kappa := \#E$ . Choose  $\varepsilon_1, \dots, \varepsilon_\kappa \in \mathbb{R}$  s.t.  $E = \{\varepsilon_1, \dots, \varepsilon_\kappa\}$ .

Then:  $2 \leq \kappa < \infty$  and  $\varepsilon_1, \dots, \varepsilon_\kappa$  are distinct.

Then:  $\forall \beta \in \mathbb{R}, A_\bullet^E(\beta) = \frac{\sum_{i=1}^\kappa [\varepsilon_i \cdot e^{-\beta \cdot \varepsilon_i}]}{\sum_{j=1}^\kappa [e^{-\beta \cdot \varepsilon_j}]}$ . Then  $A_\bullet^E : \mathbb{R} \rightarrow \mathbb{R}$  is  $C^\omega$ .

So, by Theorem 15.4 and the  $C^\omega$ -Inverse Function Theorem and the Mean Value Theorem, it suffices to show:  $(A_\bullet^E)' < 0$  on  $\mathbb{R}$ .

Given  $\beta \in \mathbb{R}$ , want:  $(A_\bullet^E)'(\beta) < 0$ .

Let  $P := \sum_{i=1}^\kappa [\varepsilon_i \cdot e^{-\beta \cdot \varepsilon_i}]$ ,  $P' := \sum_{i=1}^\kappa [(-\varepsilon_i^2) \cdot e^{-\beta \cdot \varepsilon_i}]$ .

Let  $Q := \sum_{j=1}^\kappa [e^{-\beta \cdot \varepsilon_j}]$ ,  $Q' := \sum_{j=1}^\kappa [(-\varepsilon_j) \cdot e^{-\beta \cdot \varepsilon_j}]$ .

Then  $Q > 0$ . Also, by the Quotient Rule,  $(A_\bullet^E)'(\beta) = [QP' - PQ']/Q^2$ .

Want:  $QP' - PQ' < 0$ .

We have:  $QP' = \sum_{i=1}^\kappa \sum_{j=1}^\kappa [(-\varepsilon_i^2) \cdot e^{-\beta \cdot (\varepsilon_i + \varepsilon_j)}]$ .

We have:  $PQ' = \sum_{i=1}^\kappa \sum_{j=1}^\kappa [(-\varepsilon_i \varepsilon_j) \cdot e^{-\beta \cdot (\varepsilon_i + \varepsilon_j)}]$ .

Then:  $QP' - PQ' = \sum_{i=1}^\kappa \sum_{j=1}^\kappa [(-\varepsilon_i^2 + \varepsilon_i \varepsilon_j) \cdot e^{-\beta \cdot (\varepsilon_i + \varepsilon_j)}]$ .

Interchanging  $i$  and  $j$ , we get:

$$QP' - PQ' = \sum_{j=1}^\kappa \sum_{i=1}^\kappa [(-\varepsilon_j^2 + \varepsilon_j \varepsilon_i) \cdot e^{-\beta \cdot (\varepsilon_j + \varepsilon_i)}].$$

By commutativity of addition and multiplication,

adding the last two equations gives:

$$2 \cdot (QP' - PQ') = \sum_{i=1}^\kappa \sum_{j=1}^\kappa [(-\varepsilon_i^2 - \varepsilon_j^2 + 2\varepsilon_i \varepsilon_j) \cdot e^{-\beta \cdot (\varepsilon_i + \varepsilon_j)}].$$

Then:  $2 \cdot (QP' - PQ') = \sum_{i=1}^{\kappa} \sum_{j=1}^{\kappa} [ -(\varepsilon_i - \varepsilon_j)^2 \cdot e^{-\beta \cdot (\varepsilon_i + \varepsilon_j)} ]$ .  
 Then:  $2 \cdot (QP' - PQ') < 0$ . Then:  $QP' - PQ' < 0$ .  $\square$

**DEFINITION 15.6.** Let  $E \subseteq \mathbb{R}$ .  
 Assume:  $2 \leq \#E < \infty$ . Let  $\alpha \in (\min E; \max E)$ .

The  $\alpha$ -Boltzmann-parameter on  $E$  is:  $\boxed{\text{BP}_{\alpha}^E} := (A_{\bullet}^E)^{-1}(\alpha)$ .

So the  $\alpha$ -Boltzmann-parameter on  $E$  is the unique  $\beta \in \mathbb{R}$  s.t.  $A_{\beta}^E = \alpha$ .

*Example:* Computations at the end of §6 show:

$$\begin{aligned} \forall \beta \in \mathbb{R}, \quad & \text{if } \frac{e^{-\beta} + 10e^{-10\beta}}{1 + e^{-\beta} + 10e^{-10\beta}} = 1, \text{ then } e^{-\beta} = 9^{-1/10}. \\ \text{Then, } \forall \beta \in \mathbb{R}, \quad & \text{if } A_{\bullet}^{\{0,1,10\}}(\beta) = 1, \text{ then } \beta = (\ln 9)/10. \\ & \text{Then: } (A_{\bullet}^{\{0,1,10\}})^{-1}(1) = (\ln 9)/10. \\ & \text{Then: } \text{BP}_1^{\{0,1,10\}} = (\ln 9)/10. \end{aligned}$$

*Example:* Let  $E := \{2, 4, 8, 9\}$ ,  $\alpha := 5$ ,  $\beta := \text{BP}_{\alpha}^E$ .

To compute  $\beta$ , we need to solve  $A_{\beta}^E = 5$  for  $\beta$ .

Since  $A_{\bullet}^E$  is strictly-decreasing, there are iterative methods of solution,  
 and we get:  $\beta \approx 0.0918$ , accurate to four decimal places.

(Thanks to C. Prouty for these calculations. See §29.)

**THEOREM 15.7.** Let  $E \subseteq \mathbb{R}$ . Assume:  $2 \leq \#E < \infty$ .  
 Let  $\alpha \in (\min E; \max E)$ . Let  $\xi \in \mathbb{R}$ . Then:  $\text{BP}_{\alpha-\xi}^{E-\xi} = \text{BP}_{\alpha}^E$ .

*Proof.* Let  $\beta := \text{BP}_{\alpha}^E$ . **Want:**  $\text{BP}_{\alpha-\xi}^{E-\xi} = \beta$ .

Since  $\beta = \text{BP}_{\alpha}^E = (A_{\bullet}^E)^{-1}(\alpha)$ , we get:  $(A_{\bullet}^E)(\beta) = \alpha$ .

By Theorem 15.3,  $A_{\beta}^{E-\xi} = A_{\beta}^E - \xi$ .

Since  $(A_{\bullet}^{E-\xi})(\beta) = A_{\beta}^{E-\xi} = A_{\beta}^E - \xi = ((A_{\bullet}^E)(\beta)) - \xi = \alpha - \xi$ ,

we get:  $\beta = (A_{\bullet}^{E-\xi})^{-1}(\alpha - \xi)$ .

So, since  $\text{BP}_{\alpha-\xi}^{E-\xi} = (A_{\bullet}^{E-\xi})^{-1}(\alpha - \xi)$ , we get:  $\text{BP}_{\alpha-\xi}^{E-\xi} = \beta$ .  $\square$

## 16. RESIDUE-UNCONSTRAINED FINITE SETS

In the next three theorems, we generalize our work in §12

from  $\{0, 1, 10\}$  to arbitrary finite residue-unconstrained sets.

In the example at the end of this section,

we show that Theorem 16.3 below reproduces the result of §12.

Recall (§8):  $\forall$  countable set  $\Theta$ ,

$\mathcal{FM}_\Theta$  is the set of finite measures on  $\Theta$   
 and  $\mathcal{FM}_\Theta^\times$  is the set of nonzero finite measures on  $\Theta$   
 and  $\mathcal{P}_\Theta$  is the set of probability measures on  $\Theta$ .

Recall (§8):  $\forall$  nonempty finite set  $F$ ,  $\forall f \in F$ ,  $\nu_F\{f\} = 1/(\#F)$ .

Recall (Definition 8.2):  $\forall$  countable set  $\Theta$ ,  $\forall \mu \in \mathcal{FM}_\Theta$ ,

$$\forall x \in \Theta^n, \quad \mu^n\{x\} = (\mu\{x_1\}) \cdots (\mu\{x_n\}).$$

**THEOREM 16.1.** *Let  $E \subseteq \mathbb{Z}$  be finite and residue-unconstrained.*

**Let**  $\alpha \in (\min E; \max E)$ . **Let**  $\beta := \text{BP}_\alpha^E$ .

**Let**  $t_1, t_2, \dots \in \mathbb{Z}$ . *Assume:  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded.*

*For all  $n \in \mathbb{N}$ , let  $\Omega_n := \{f \in E^n \mid f_1 + \cdots + f_n = t_n\}$ .*

**Let**  $\varepsilon_0 \in E$ . *Then: as  $n \rightarrow \infty$ ,  $\nu_{\Omega_n}\{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow B_\beta^E\{\varepsilon_0\}$ .*

Recall (§8):  $\nu_\emptyset(\emptyset) = -1$ .

So, since  $B_\beta^E\{\varepsilon_0\} > 0$ , part of the content of this theorem is:

$$\forall \text{sufficiently large } n \in \mathbb{N}, \quad \Omega_n \neq \emptyset.$$

See Claim 2 in the proof below.

*Proof.* **Let**  $\mu := B_\beta^E$ . Then:  $\mu \in \mathcal{P}_E$  and  $S_\mu = E$ .

By hypothesis,  $E$  is finite. Then  $S_\mu$  is finite.

So, since  $\mu \in \mathcal{P}_E \subseteq \mathcal{FM}_E$ , we get:  $|\mu|_1 < \infty$  and  $|\mu|_2 < \infty$ .

Since  $\beta = \text{BP}_\alpha^E = (A_\bullet^E)^{-1}(\alpha)$ , we get:  $(A_\bullet^E)(\beta) = \alpha$ .

So, since  $(A_\bullet^E)(\beta) = A_\beta^E = M_{B_\beta^E} = M_\mu$ , we get:  $M_\mu = \alpha$ .

For all  $n \in \mathbb{N}$ , **define**  $\psi_n : \mathbb{Z} \rightarrow \mathbb{R}$  by:

$$\forall t \in \mathbb{Z}, \quad \psi_n(t) = \mu^n\{f \in E^n \mid f_1 + \cdots + f_n = t\}.$$

Then:  $\forall n \in \mathbb{N}$ ,  $\psi_n(t_n) = \mu^n(\Omega_n)$ .

Since  $E$  is finite and residue-unconstrained, we get:  $2 \leq \#E < \infty$ .

Since  $\#S_\mu = \#E \geq 2$ , by Theorem 8.6, we get:  $V_\mu > 0$ .

So, since  $V_\mu = |\mu|_2^2 - M_\mu^2 \leq |\mu|_2^2 < \infty$ , we conclude:

$$0 < V_\mu < \infty.$$

**Let**  $v := V_\mu$ . Then  $0 < v < \infty$ . Then  $1/\sqrt{2\pi v} > 0$ .

**Let**  $\tau := 1/\sqrt{2\pi v}$ . Then  $\tau > 0$ .

*Claim 1:* As  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\psi_n(t_n)) \rightarrow \tau$ .

*Proof of Claim 1:* By Theorem 9.6, we get:

$$\text{as } n \rightarrow \infty, \quad \sqrt{n} \cdot (\mu^n\{f \in E^n \mid f_1 + \cdots + f_n = t_n\}) \rightarrow 1/\sqrt{2\pi v}.$$

Then: as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\psi_n(t_n)) \rightarrow \tau$ .

*End of proof of Claim 1.*

Since  $\tau > 0$ , by Claim 1, **choose**  $n_0 \in \mathbb{N}$  s.t.

$$\forall n \in [n_0.. \infty), \quad \sqrt{n} \cdot (\psi_n(t_n)) > 0.$$

*Claim 2:* Let  $n \in [n_0.. \infty)$ . Then:  $\mu^n(\Omega_n) > 0$ .

*Proof of Claim 2:* Recall:  $\psi_n(t_n) = \mu^n(\Omega_n)$ . **Want:**  $\psi_n(t_n) > 0$ .

By the choice of  $n_0$ , we get:  $\sqrt{n} \cdot (\psi_n(t_n)) > 0$ . Then:  $\psi_n(t_n) > 0$ .

*End of proof of Claim 2.*

Recall:  $\mu \in \mathcal{P}_E$ .  
 Then:  $\forall n \in \mathbb{N}, \mu^n \in \mathcal{P}_{E^n}$ , so  $\mu^n(\Omega_n) \leq 1$ .  
 So, by Claim 2,  $\forall n \in [n_0.. \infty)$ ,  $0 < \mu^n(\Omega_n) \leq 1$ .  
 Also, we have:  $\forall n \in \mathbb{N}$ ,  $(\mu^n | \Omega_n)(\Omega_n) = \mu^n(\Omega_n)$ .  
 Then:  $\forall n \in [n_0.. \infty)$ ,  $0 < (\mu^n | \Omega_n)(\Omega_n) \leq 1$ .  
 Then:  $\forall n \in [n_0.. \infty)$ ,  $\mu^n | \Omega_n \in \mathcal{FM}_{\Omega_n}^\times$ .  
 Then:  $\forall n \in [n_0.. \infty)$ ,  $\mathcal{N}(\mu^n | \Omega_n) \in \mathcal{P}_{\Omega_n}$ .

*Claim 3:* Let  $n \in [n_0.. \infty)$ . Then:  $\mathcal{N}(\mu^n | \Omega_n) = \nu_{\Omega_n}$ .

*Proof of Claim 3:* Let  $\theta := \mathcal{N}(\mu^n | \Omega_n)$ ,  $F := \Omega_n$ . Then  $\theta \in \mathcal{P}_F$ .

**Want:**  $\theta = \nu_F$ . By Theorem 8.9, given  $f, g \in F$ , **want:**  $\theta\{f\} = \theta\{g\}$ .

By Claim 2, we have:  $\mu^n(\Omega_n) > 0$ .

Since  $(\mu^n | \Omega_n)(\Omega_n) = \mu^n(\Omega_n)$  and  $\theta = \mathcal{N}(\mu^n | \Omega)$ , we get:  $\theta = \frac{\mu^n | \Omega_n}{\mu^n(\Omega_n)}$ .

**Want:**  $\frac{(\mu^n | \Omega_n)\{f\}}{\mu^n(\Omega_n)} = \frac{(\mu^n | \Omega_n)\{g\}}{\mu^n(\Omega_n)}$ .

**Want:**  $(\mu^n | \Omega_n)\{f\} = (\mu^n | \Omega_n)\{g\}$ .

Since  $f, g \in F = \Omega_n$ , we get:

$$(\mu^n | \Omega_n)\{f\} = \mu^n\{f\} \quad \text{and} \quad (\mu^n | \Omega_n)\{g\} = \mu^n\{g\}.$$

**Want:**  $\mu^n\{f\} = \mu^n\{g\}$ .

Since  $\#E \geq 2$ , we get:  $E \neq \emptyset$ . Then  $\widehat{B}_\beta^E(E) > 0$ .

Let  $C := 1/(\widehat{B}_\beta^E(E))$ . Then  $\mathcal{N}(\widehat{B}_\beta^E) = C \cdot \widehat{B}_\beta^E$ .

By definition of  $\widehat{B}_\beta^E$ , we have:  $\forall \varepsilon \in E, \widehat{B}_\beta^E\{\varepsilon\} = e^{-\beta \cdot \varepsilon}$ .

So, since  $\mu = B_\beta^E = \mathcal{N}(\widehat{B}_\beta^E) = C \cdot \widehat{B}_\beta^E$ ,

$$\text{we get:} \quad \forall \varepsilon \in E, \quad \mu\{\varepsilon\} = C e^{-\beta \cdot \varepsilon}.$$

Since  $f \in F = \Omega_n$ , by definition of  $\Omega_n$ , we get:  $f_1 + \dots + f_n = t_n$ .

Since  $g \in F = \Omega_n$ , by definition of  $\Omega_n$ , we get:  $g_1 + \dots + g_n = t_n$ .

Since  $f_1 + \dots + f_n = t_n = g_1 + \dots + g_n$ ,

$$\text{we get:} \quad C^n e^{-\beta \cdot (f_1 + \dots + f_n)} = C^n e^{-\beta \cdot (g_1 + \dots + g_n)}.$$

Then:  $(C e^{-\beta \cdot f_1}) \dots (C e^{-\beta \cdot f_n}) = (C e^{-\beta \cdot g_1}) \dots (C e^{-\beta \cdot g_n})$ .

Then:  $(\mu\{f_1\}) \dots (\mu\{f_n\}) = (\mu\{g_1\}) \dots (\mu\{g_n\})$ .

Then:  $\mu^n\{f\} = \mu^n\{g\}$ .

*End of proof of Claim 3.*

By hypothesis,  $E$  is residue-unconstrained and  $\varepsilon_0 \in E$  and  $t_1, t_2, \dots \in \mathbb{Z}$  and  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded.

Recall:  $\mu \in \mathcal{P}_E$  and  $S_\mu = E$  and  $|\mu|_2 < \infty$  and  $M_\mu = \alpha$ .

**Let**  $P := \mu\{\varepsilon_0\}$ . Then, since  $\mu = B_\beta^E$ , we get:  $P = B_\beta^E\{\varepsilon_0\}$ .

**We want:** as  $n \rightarrow \infty$ ,  $\nu_{\Omega_n}\{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow P$ .

By Theorem 11.2, as  $n \rightarrow \infty$ ,  $(\mathcal{N}(\mu^n | \Omega_n))\{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow P$ .

So, by Claim 3, as  $n \rightarrow \infty$ ,  $\nu_{\Omega_n}\{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow P$ .  $\square$

Recall (§2):  $\forall t \in \mathbb{R}$ ,  $\lfloor t \rfloor$  is the floor of  $t$ .

We record the  $t_n = \lfloor n\alpha \rfloor$  version of the preceding theorem:

**THEOREM 16.2.** **Let**  $E \subseteq \mathbb{Z}$  be finite and residue-unconstrained.

**Let**  $\alpha \in (\min E; \max E)$ . **Let**  $\beta := \text{BP}_\alpha^E$ .

For all  $n \in \mathbb{N}$ , **let**  $\Omega_n := \{f \in E^n \mid f_1 + \dots + f_n = \lfloor n\alpha \rfloor\}$ .

**Let**  $\varepsilon_0 \in E$ . *Then:* as  $n \rightarrow \infty$ ,  $\nu_{\Omega_n}\{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow B_\beta^E\{\varepsilon_0\}$ .

We record the  $\alpha \in \mathbb{Z}$  special case of the preceding theorem:

**THEOREM 16.3.** **Let**  $E \subseteq \mathbb{Z}$  be finite and residue-unconstrained.

**Let**  $\alpha \in (\min E; \max E)$ . **Let**  $\beta := \text{BP}_\alpha^E$ . Assume  $\alpha \in \mathbb{Z}$ .

For all  $n \in \mathbb{N}$ , **let**  $\Omega_n := \{f \in E^n \mid f_1 + \dots + f_n = n\alpha\}$ .

**Let**  $\varepsilon_0 \in E$ . *Then:* as  $n \rightarrow \infty$ ,  $\nu_{\Omega_n}\{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow B_\beta^E\{\varepsilon_0\}$ .

*Example:* Suppose  $E = \{0, 1, 10\}$  and  $\alpha = 1$ .

Then  $\Omega_N = \{f \in E^N \mid f_1 + \dots + f_N = N\}$ ,

so  $\Omega_N$  represents the set of all GFA dispensations,

as described in §3.

The measure  $\nu_{\Omega_N}$  gives equal probability to each dispensation,

so  $\nu_{\Omega_N}$  represents the GFA's first system for awarding grants,

also described in §3.

Since  $\beta = \text{BP}_\alpha^E = \text{BP}_1^{\{0,1,10\}}$ , we calculate:  $\beta = (\ln 9)/10$ .

More calculation gives:  $(B_\beta^E\{0\}, B_\beta^E\{1\}, B_\beta^E\{10\}) = \frac{(1, 9^{-1/10}, 9^{-1})}{1 + 9^{-1/10} + 9^{-1}}$ .

Since  $N$  is large, by Theorem 16.3, we get:

$$\nu_{\Omega_N}\{f \in \Omega_N \mid f_N = \varepsilon_0\} \approx B_\beta^E\{\varepsilon_0\}.$$

So, if I am the  $N$ th professor, then, under the first system,

my probability of receiving  $\varepsilon_0$  dollars

is approximately equal to  $B_\beta^E\{\varepsilon_0\}$ .

Thus Theorem 16.3 reproduces the result of §12.

## 17. RATIONAL AWARD SETS

In this section, we investigate what happens if  
the set of awards is an arbitrary set of rational numbers.  
Recall that, on our Earth, which is Earth-1218,  
grants are \$0, \$1, \$10, with average grant \$1.

*Example:* **Let**  $N_0$  be a positive integer.

In a parallel universe, on Earth-googol-plex,  
there are  $N_0$  professors, and  
grants are \$10, \$14.45, \$54, with average grant \$13.37,  
Earth-googol-plex has its own GFA.

This GFA there is using the “first system” for awarding grants,  
in which every dispensation is equally likely.

*Question:* Under this system, for any professor,  
what is the approximate probability of receiving \$10? \$14.45? \$54?

To simplify this problem, we can imagine that  
the GFA makes two rounds of awards.

In the first round, it simply dispenses \$10 to each professor.

In the second round, using the first system, it dispenses  
additional grants of \$0, \$4.45, \$44, with average grant \$3.37.

We seek the approximate probability of the additional grant being  
each of the numbers \$0, \$4.45, \$44.

To simplify this problem still more, we can

change monetary units so that the grant amounts are all integers:  
Additional grants, in pennies, are 0, 445, 4400, with average grant 337,  
and we seek the approximate probability of receiving 0, 445, 4400.

Unfortunately,  $\{0, 445, 4400\} \subseteq 5\mathbb{Z} + 0$ ,

so  $\{0, 445, 4400\}$  is not residue-unconstrained,

making it difficult to apply the Discrete Local Limit Theorem.

Since  $\gcd\{0, 445, 4400\} = 5$ , we can change monetary units again:

Additional grants, in nickels, are 0, 89, 880, with average grant  $337/5$ ,

and we seek the approximate probability of receiving 0, 89, 880.

**Let**  $E := \{0, 89, 880\}$  and **let**  $\alpha := 337/5$ .

Since  $0 \in E$  and  $\gcd(E) = 1$ , we get:  $E$  is residue-unconstrained.

The amount of money (in nickels) allocated by Congress is  $N_0\alpha$ ,

to be dispensed among the  $N_0$  professors.

Unfortunately, a census reveals that:  $N_0$  is not divisible by 5.

Recall:  $\alpha = 337/5$ . Then  $N_0\alpha \notin \mathbb{Z}$ , while  $0, 89, 880 \in \mathbb{Z}$ .

It is therefore *impossible* to dispense the grant money.

The bureaucracy seizes up, there is pandemonium in the streets,  
and the military steps in to impose order.

The superheros of Earth-googol-plex are committed to democracy,  
and so they reverse time and select a different time-line.

On this new time-line,  $E$  and  $\alpha$  are unchanged, but  
the number,  $N_1$ , of professors

is now blissfully divisible by 5, so  $N_1\alpha \in \mathbb{Z}$ .

**Let**  $\varepsilon_0 \in E$  **be given.**

**We want:** the approximate probability of receiving  $\varepsilon_0$  nickels.

Recall (§2):  $\forall t \in \mathbb{R}$ ,  $\lfloor t \rfloor$  is the floor of  $t$ .

For all  $n \in \mathbb{N}$ , **let**  $\Omega_n := \{f \in E^n \mid f_1 + \cdots + f_n = \lfloor n\alpha \rfloor\}$ .

Since  $N_1\alpha \in \mathbb{Z}$ , we get:  $\Omega_{N_1} = \{f \in E^{N_1} \mid f_1 + \cdots + f_{N_1} = N_1\alpha\}$ .

**We want:** an approximation to  $\nu_{\Omega_{N_1}} \{f \in \Omega_{N_1} \mid f_{N_1} = \varepsilon_0\}$ .

Since  $0 \in E$  and  $\gcd(E) = 1$ , we get:  $E$  is residue-unconstrained.

**Let**  $\beta := \text{BP}_\alpha^E$ . By Theorem 16.2, we have:

$$\text{as } n \rightarrow \infty, \nu_{\Omega_n} \{f \in \Omega_n \mid f_n = \varepsilon_0\} \rightarrow B_\beta^E \{\varepsilon_0\}.$$

So, assuming  $N_1$  is large, we get

$$\nu_{\Omega_{N_1}} \{f \in \Omega_{N_1} \mid f_{N_1} = \varepsilon_0\} \approx B_\beta^E \{\varepsilon_0\}.$$

For each  $\varepsilon_0 \in \{0, 89, 880\}$ , **we want** to compute  $B_\beta^E \{\varepsilon_0\}$ .

**We therefore want** to compute  $(B_\beta^E \{0\}, B_\beta^E \{89\}, B_\beta^E \{880\})$ .

Since  $\beta = \text{BP}_\alpha^E = \text{BP}_{337/5}^{\{0,89,880\}}$ , we see that:

to evaluate  $\beta$ , we must solve  $A_{\bullet}^{\{0,89,880\}}(\beta) = 337/5$  for  $\beta$ .

Since, by Theorem 15.5,  $A_{\bullet}^{\{0,89,880\}}$  is strictly-decreasing,

there are simple iterative methods to do this.

We calculate  $\beta = 0.003144$ , accurate to six decimals.

We also calculate  $(B_\beta^E \{0\}, B_\beta^E \{89\}, B_\beta^E \{880\}) = (0.5498, 0.4156, 0.0345)$ ,  
all accurate to four decimals.

(Thanks to C. Prouty for this calculation. See §29.)

Recall (§3):  $N$  is a large positive integer.

More generally: Imagine a parallel universe with  $N$  professors.

**Let**  $E_0$  denote the set of grant-awards.

Assume  $E_0 \subseteq \mathbb{Q}$  and  $2 \leq \#E_0 < \infty$ .

**Let**  $\alpha_0$  denote the average award.

Since  $\#E_0 \geq 2$ , we get:  $E_0 \neq \emptyset$ . **Choose**  $\varepsilon_0 \in E_0$ . Then  $\varepsilon_0 \in \mathbb{Q}$ .



**Let**  $E_1 := E_0 - \varepsilon_0$ ,  $\alpha_1 := \alpha_0 - \varepsilon_0$ . Then  $0 \in E_1$ .

So, by giving out awards in two rounds (first  $\varepsilon_0$ , then the remainder),

we are reduced to a case where  $0$  is a possible grant-award.

Since  $E_1 = E_0 - \varepsilon_0 \subseteq \mathbb{Q}$ , **choose**  $m \in \mathbb{N}$  s.t.  $mE_1 \subseteq \mathbb{Z}$ .

**Let**  $E_2 := mE_1$ ,  $\alpha_2 := m\alpha_1$ . Then:  $0 \in E_2 \subseteq \mathbb{Z}$ .

So, by change of monetary unit,

we are reduced to a case where every grant-award is an integer

and where  $0$  is a possible grant-award.

**Let**  $g := \gcd(E_2)$ ,  $E := E_2/g$ ,  $\alpha := \alpha_2/g$ .

Then  $0 \in E$  and  $\gcd(E) = 1$ , so  $E$  is residue-unconstrained.

So, by change of monetary unit, we are reduced to a case where

the set of grant-awards is a residue-unconstrained set of integers.

Since every grant-award is an integer,

if  $N\alpha \notin \mathbb{Z}$ , then no dispensation is possible, leading to

your typical military dictatorship and superhero intervention.

On the other hand, since  $N$  is large,

if  $N\alpha \in \mathbb{Z}$ , then, using Theorem 16.2,

we can compute the approximate probability of each award.

## 18. IRRATIONAL AWARDS

In this section, we briefly discuss the case where

NOT every grant award is a rational number.

Here, we only present an example to show that

the award probabilities may NOT follow a Boltzmann distribution.

*Example:* On Earth-aleph-1, the GFA gives

grants of  $0$ ,  $\sqrt{2}$ ,  $\sqrt{3}$ ,  $10 - \sqrt{2} - \sqrt{3}$  dollars,

with an average grant of  $1$  dollar,

giving equal probability to every possible dispensation.

Assume:  $N$  is the number of professors and  $N$  is divisible by 10.

**Let**  $M := N/10$ . Then  $M \in \mathbb{N}$  and there are  $10M$  professors.

Moreover, since the average grant is 1 dollar, we get:

there are  $10M$  dollars to dispense among the  $10M$  professors.

*Claim:* On Earth-aleph-1, every dispensation of awards has

$7M$  grants of  $0$  dollars,

$M$  grants of  $\sqrt{2}$  dollars,

$M$  grants of  $\sqrt{3}$  dollars,

$M$  grants of  $10 - \sqrt{2} - \sqrt{3}$  dollars.

*Proof of Claim:* **Given** a dispensation,

**let**  $w$  be the number of 0 dollar grants and

**let**  $x$  be the number of  $\sqrt{2}$  dollar grants and

**let**  $y$  be the number of  $\sqrt{3}$  dollar grants and

**let**  $z$  be the number of  $10 - \sqrt{2} - \sqrt{3}$  dollar grants,

**want:**  $w = 7M$  and  $x = y = z = M$ .

Because the total money dispensed is  $10M$  dollars, we get:

$$w \cdot 0 + x \cdot \sqrt{2} + y \cdot \sqrt{3} + z \cdot (10 - \sqrt{2} - \sqrt{3}) = 10M.$$

Then:  $(10z - 10M) \cdot 1 + (x - z) \cdot \sqrt{2} + (y - z) \cdot \sqrt{3} = 0$ .

So, since  $1, \sqrt{2}, \sqrt{3}$  are linearly independent over  $\mathbb{Q}$ , we get:

$$10z - 10M = 0 \quad \text{and} \quad x - z = 0 \quad \text{and} \quad y - z = 0.$$

Then  $z = M$  and  $x = z$  and  $y = z$ . Then  $x = y = z = M$ .

**It remains only to show:**  $w = 7M$ .

Because there are  $10M$  professors, we get:  $w + x + y + z = 10M$ .

Then:  $w + M + M + M = 10M$ . Then:  $w = 7M$ .

*End of proof of Claim.*

Of the four grant amounts, the largest is  $10 - \sqrt{2} - \sqrt{3}$ .

So, if I am one of the  $10M$  professors, then I would hope to be among the lucky  $M$  who receive  $10 - \sqrt{2} - \sqrt{3}$  dollars.

My probability of being so lucky is:  $M/(10M)$ , *i.e.*, 10%.

That is, we obtain a probability of:

10% for  $10 - \sqrt{2} - \sqrt{3}$  dollars.

Extending this reasoning, we obtain probabilities of:

70% for 0 dollars,

10% for  $\sqrt{2}$  dollars,

10% for  $\sqrt{3}$  dollars,

10% for  $10 - \sqrt{2} - \sqrt{3}$  dollars.

In a Boltzmann distribution, depending on whether  $\beta = 0$  or  $\beta \neq 0$ , either the probabilities are all equal

or the probabilities are all distinct from one another.

The numbers 70,10,10,10 are neither all equal nor all distinct.

Thus, the 70-10-10-10 distribution above is NOT Boltzmann.

## 19. EARTH-MINIMUM-MAHLO-CARDINAL AND THE BUA

Next, we wish to handle thermodynamic systems in which many states may have a single energy-level.

One says that such an energy-level is “degenerate”.  
 In this section, we develop a whimsical example.  
 In §20 and §21, we will develop a general theory.

Recall that  $N \in \mathbb{N}$  is large.

In a parallel universe, on Earth-minimum-Mahlo-cardinal,  
 the BUA (Best University Anywhere) employs  $N$  professors.

Each professor has a number, from 1 to  $N$ .

Each professor wanders the campus,  
 carrying two bags: one red, one blue.

Each bag is closed from view, but has money in it or is empty.

The “state” of a professor is the pair  $\sigma = (\sigma_1, \sigma_2)$  such that

$\sigma_1$  is the number of dollars in the professor’s red bag,

$\sigma_2$  is the number of dollars in the professor’s blue bag;

the professor’s “wealth” is  $\sigma_1 + \sigma_2$  dollars.

So, if I am one of the professors, and if my state is  $(3, 2)$ ,

then I have: \$3 in my red bag and \$2 in my blue bag,

and my wealth is \$5.

By BUA rules, the amount of money in any bag is always

\$0 or \$1 or \$2 or \$3 or \$4,

and each professor’s wealth is always  $\leq$  \$7.

Therefore, the set of allowable states is

$([0..4] \times [0..4]) \setminus \{(4, 4)\}$ .

**Let**  $\Sigma := ([0..4] \times [0..4]) \setminus \{(4, 4)\}$ .

Since  $\#[0..4] \times [0..4] = 5 \cdot 5 = 25$ , we get:  $\#\Sigma = 24$ .

**Define**  $\varepsilon : \Sigma \rightarrow [0..7]$  by:  $\forall \sigma \in \Sigma, \varepsilon(\sigma) = \sigma_1 + \sigma_2$ .

For convenience of notation,  $\forall \sigma \in \Sigma$ , **let**  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

If I am one of the professors,

and if my state is  $\sigma = (\sigma_1, \sigma_2) \in \Sigma$ ,

then I have:  $\$\sigma_1$  in my red bag and  $\$\sigma_2$  in my blue bag,

and my wealth is  $\$\varepsilon_\sigma$ .

Since  $\varepsilon_{(3,2)} = 5 = \varepsilon_{(1,4)}$ , we see that  $\varepsilon$  is not one-to-one,

and we have a so-called “degeneracy” at 5.

This function  $\varepsilon$  has many other degeneracies, as well.

Recall: The professors are numbered, from 1 to  $N$ .

At random moments,

random pairs of wandering professors cross paths, and interact.

Each interaction involves three steps:

a game and then  
 a verbal offer and then  
 a rejection or a money transfer.

The first step, the game, is played as follows:

one of the two professors flips a fair coin and  
 if heads, then the lower-numbered professor wins and  
 if tails, then the higher-numbered professor wins.

Next, without touching any money,

the losing professor verbally offers \$1 to the winning professor.

The losing professor then flips a fair coin, and  
 if heads, then the loser's red bag is opened and  
 if tails, then the loser's blue bag is opened.

If the loser's open bag is empty, then

then the winner gallantly rejects the \$1 offer and  
 the opened bag is closed, the interaction is over, and  
 the professors continue their wanderings.

On the other hand, if the loser's open bag is NOT empty, then,  
 both of the winner's bags are opened.

Recall that, by BUA rules, every professor's wealth must be  $\leq$  \$7.

If the winner's wealth is \$7,

then the winner rejects the \$1 offer and  
 the opened bags are closed, the interaction is over, and  
 the professors continue their wanderings.

On the other hand, if the winner's wealth is  $\leq$  \$6,

then the winner flips a fair coin, and  
 if heads, then the winner's red bag is closed and  
 if tails, then the winner's blue bag is closed.

At this point, the winner has one open bag, as does the loser.

Moreover, the loser's open bag is NOT empty.

Recall that no bag may have more than \$4.

If the winner's open bag has \$4,

then the winner rejects the \$1 offer and  
 the opened bags are closed, the interaction is over, and  
 the professors continue their wanderings.

On the other hand, if the winner's open bag has  $\leq$  \$3,  
 then \$1 is transferred

from the losing professor's open bag

to the winning professor's open bag;  
then the opened bags are closed, the interaction is over, and  
the professors continue their wanderings.

Because of these interactions,

the wealth of an individual professor may change over time,  
but the sum of the wealths of all of them is constant;  
there is "conservation of (total) wealth".

An audit reveals that, at the BUA, that total wealth is always  $N$ .

A "state-dispensation" is a function  $[1..N] \rightarrow \Sigma$ ,  
representing the states of all  $N$  professors.

So, if, at some point in time, the state-dispensation is  $\omega : [1..N] \rightarrow \Sigma$ ,

then, for every  $\ell \in [1..N]$ , the state of Professor  $\#\ell$  is  $\omega(\ell)$ ,  
and the wealth of Professor  $\#\ell$  is  $\varepsilon_{\omega(\ell)}$ ;

therefore, the total wealth of all the professors is  $\sum_{\ell=1}^N \varepsilon_{\omega(\ell)}$ .

As we mentioned, at the BUA, that total wealth is  $N$ .

**Let**  $\Omega^* := \left\{ \omega : [1..N] \rightarrow \Sigma \mid \sum_{\ell=1}^N \varepsilon_{\omega(\ell)} = N \right\}$ .

Then  $\Omega^*$  represents the set of all state-dispensations at the BUA.

The random interactions, described above,

induce a discrete Markov-chain on  $\Omega^*$ .

This, in turn, induces a map  $\Pi : \mathcal{P}_{\Omega^*} \rightarrow \mathcal{P}_{\Omega^*}$ .

**Let**  $T := \#\Omega^*$ . Fix an ordering of  $\Omega^*$ , *i.e.*, a bijection  $[1..T] \leftrightarrow \Omega^*$ .

The Markov-chain then has a  $T \times T$  transition-matrix  $\Phi$ ,

with entries in  $[0; 1]$ , whose column-sums are all  $= 1$ .

For every  $\phi, \psi \in \Omega^*$ , the probability of transitioning from  $\phi$  to  $\psi$

is equal to

the probability of transitioning from  $\psi$  to  $\phi$ .

That is, the transition-matrix  $\Phi$  is symmetric.

So, since the column-sums of  $\Phi$  are all 1,

we get: the row-sums of  $\Phi$  are all 1.

**Let**  $v$  be a  $T \times 1$  column vector whose entries are all 1. Then  $\Phi v = v$ .

**Let**  $w := v/T$ . Then: all the entries of  $w$  are  $1/T$  and  $\Phi w = w$ .

Recall that the probability-distribution  $\nu_{\Omega^*} \in \mathcal{P}_{\Omega^*}$

assigns equal probability to each state-dispensation in  $\Omega^*$ .

That is,  $\forall \omega \in \Omega^*, \nu_{\Omega^*}\{\omega\} = 1/T$ .

Since the entries of  $w$  are equal to these  $\nu_{\Omega^*}$ -probabilities,

and since  $\Phi w = w$ , we get:  $\Pi(\nu_{\Omega^*}) = \nu_{\Omega^*}$ .

We will say that two state-dispensations  $\phi, \psi \in \Omega^*$  are “adjacent”,  
if there is an interaction that carries  $\phi$  to  $\psi$ .

For any  $\phi, \psi \in \Omega^*$ ,

$\exists$  a finite sequence of interactions that carries  $\phi$  to  $\psi$ .

That is:  $\forall \phi, \psi \in \Omega^*, \exists m \in \mathbb{N}, \exists \omega_0, \dots, \omega_m \in \Omega^*$

s.t.  $\phi = \omega_0$  and  $\omega_m = \psi$

and s.t.  $\forall i \in [1..m], \omega_{i-1}$  is adjacent to  $\omega_i$ .

That is, any two state-dispensations

are connected by an adjacency-path.

That is, the Markov-chain is irreducible.

Recall that some interactions result in a rejection;

such interactions do not change the state-dispensation.

So, a state-dispensation is sometimes adjacent to itself.

That is, there are adjacency-cycles of length 1.

It follows that the Markov-chain is aperiodic.

So, since the Markov-chain is irreducible and since  $\Pi(\nu_{\Omega^*}) = \nu_{\Omega^*}$ ,

by the Perron-Frobenius Theorem, we get:

$$\forall \mu \in \mathcal{P}_{\Omega^*}, \mu, \Pi(\mu), \Pi(\Pi(\mu)), \Pi(\Pi(\Pi(\mu))), \dots \rightarrow \nu_{\Omega^*}.$$

That is, for any starting probability-distribution on  $\Omega^*$ ,

after enough random interactions,

the resulting probability-distribution on  $\Omega^*$

will be approximately equal to  $\nu_{\Omega^*}$ ,

to any desired level of accuracy.

**Problem:** Suppose I am Professor # $N$  at the BUA.

Suppose that the probability-distribution  $\mu$  of state-dispensations

is approximately equal to  $\nu_{\Omega^*}$ .

For each  $\sigma \in \Sigma$ , compute my probability of being in state  $\sigma$ .

That is,  $\forall \sigma \in \Sigma$ , compute  $\mu\{\omega \in \Omega^* \mid \omega(N) = \sigma\}$ .

Since  $\#\Sigma = 24$ , there will be 24 answers.

Approximate answers are acceptable.

To make a precise mathematical problem,

we, in fact, assume that  $\mu$  is *exactly* equal to  $\nu_{\Omega^*}$ ,

and we seek the exact “thermodynamic limit”, meaning  
we replace  $N$  with a variable  $n \in \mathbb{N}$ , and let  $n \rightarrow \infty$ .

In the next two sections, we will develop a theory  
to solve problems like this one.  
We need only adapt our earlier methods to allow for degeneracies.

Our main theorems are  
Theorem 21.1 and Theorem 21.2 and Theorem 21.3,  
and the solution to the above “precise mathematical problem”  
appears in the example at the end of §21.

## 20. BOLTZMANN DISTRIBUTIONS ON FINITE SETS WITH DEGENERACY

We begin by adapting our work on Boltzmann distributions  
to allow for degeneracies.

**DEFINITION 20.1.** Let  $\Sigma$  be a nonempty finite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ . Let  $\beta \in \mathbb{R}$ .

Then  $\widehat{B}_\beta^\varepsilon \in \mathcal{FM}_\Sigma^\times$  is **defined** by:  $\forall \sigma \in \Sigma$ ,  $\widehat{B}_\beta^\varepsilon\{\sigma\} = e^{-\beta \cdot (\varepsilon(\sigma))}$ .

Also, we **define**:  $B_\beta^\varepsilon := \mathcal{N}(\widehat{B}_\beta^\varepsilon) \in \mathcal{P}_\Sigma$ .

Then:  $\forall$  nonempty finite set  $\Sigma$ ,  $\forall \varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\forall \beta \in \mathbb{R}$ ,  
 $\widehat{B}_\beta^\varepsilon(\Sigma) > 0$  and  $\forall \sigma \in \Sigma$ ,  $B_\beta^\varepsilon\{\sigma\} = (\widehat{B}_\beta^\varepsilon\{\sigma\}) / (\widehat{B}_\beta^\varepsilon(\Sigma))$   
and  $S_{\widehat{B}_\beta^\varepsilon} = \Sigma = S_{B_\beta^\varepsilon}$ .

*Example:* Let  $\Sigma := \{0, 1, 10\}$  and let  $\beta \in \mathbb{R}$ .

**Define**  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:  $\forall \sigma \in \Sigma$ ,  $\varepsilon(\sigma) = \sigma$ .

Then:  $\widehat{B}_\beta^\varepsilon\{0\} = 1$ ,  $\widehat{B}_\beta^\varepsilon\{1\} = e^{-\beta}$ ,  $\widehat{B}_\beta^\varepsilon\{10\} = e^{-10\beta}$ .

**Let**  $C := 1/(1 + e^{-\beta} + e^{-10\beta})$ .

Then:  $B_\beta^\varepsilon\{0\} = C$ ,  $B_\beta^\varepsilon\{1\} = Ce^{-\beta}$ ,  $B_\beta^\varepsilon\{10\} = Ce^{-10\beta}$ .

*Example:* Let  $\Sigma := \{2, 4, 8, 9\}$  and let  $\beta \in \mathbb{R}$ .

**Define**  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:  $\forall \sigma \in \Sigma$ ,  $\varepsilon(\sigma) = \sigma$ .

Then:  $\widehat{B}_\beta^\varepsilon\{2\} = e^{-2\beta}$ ,  $\widehat{B}_\beta^\varepsilon\{4\} = e^{-4\beta}$ ,

$\widehat{B}_\beta^\varepsilon\{8\} = e^{-8\beta}$ ,  $\widehat{B}_\beta^\varepsilon\{9\} = e^{-9\beta}$ .

**Let**  $C := 1/(e^{-2\beta} + e^{-4\beta} + e^{-8\beta} + e^{-9\beta})$ .

Then:  $B_\beta^\varepsilon\{2\} = Ce^{-2\beta}$ ,  $B_\beta^\varepsilon\{4\} = Ce^{-4\beta}$ ,

$$B_\beta^\varepsilon\{8\} = Ce^{-8\beta}, \quad B_\beta^\varepsilon\{9\} = Ce^{-9\beta}.$$

*Example:* **Let**  $\Sigma := \{1, 2, 3, 4\}$  and **let**  $\beta \in \mathbb{R}$ .

**Define**  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:

$$\varepsilon(1) = 2, \quad \varepsilon(2) = 4, \quad \varepsilon(3) = 8, \quad \varepsilon(4) = 9.$$

$$\begin{aligned} \text{Then: } \widehat{B}_\beta^\varepsilon\{1\} &= e^{-2\beta}, & \widehat{B}_\beta^\varepsilon\{2\} &= e^{-4\beta}, \\ & \widehat{B}_\beta^\varepsilon\{3\} &= e^{-8\beta}, & \widehat{B}_\beta^\varepsilon\{4\} &= e^{-9\beta}. \end{aligned}$$

**Let**  $C := 1/(e^{-2\beta} + e^{-4\beta} + e^{-8\beta} + e^{-9\beta})$ .

$$\begin{aligned} \text{Then: } B_\beta^\varepsilon\{1\} &= Ce^{-2\beta}, & B_\beta^\varepsilon\{2\} &= Ce^{-4\beta}, \\ & B_\beta^\varepsilon\{3\} &= Ce^{-8\beta}, & B_\beta^\varepsilon\{4\} &= Ce^{-9\beta}. \end{aligned}$$

In the preceding three examples,  $\varepsilon$  is one-to-one.

That is,  $\varepsilon$  has no degeneracies.

In the next,  $\varepsilon$  has one degeneracy, at energy-level 9.

*Example:* **Let**  $\Sigma := \{1, 2, 3, 4\}$  and **define**  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:

$$\varepsilon(1) = 2, \quad \varepsilon(2) = 4, \quad \varepsilon(3) = 9, \quad \varepsilon(4) = 9.$$

$$\begin{aligned} \text{Then: } \widehat{B}_\beta^\varepsilon\{1\} &= e^{-2\beta}, & \widehat{B}_\beta^\varepsilon\{2\} &= e^{-4\beta}, \\ & \widehat{B}_\beta^\varepsilon\{3\} &= e^{-9\beta}, & \widehat{B}_\beta^\varepsilon\{4\} &= e^{-9\beta}. \end{aligned}$$

**Let**  $C := 1/(e^{-2\beta} + e^{-4\beta} + 2 \cdot e^{-9\beta})$ .

$$\begin{aligned} \text{Then: } B_\beta^\varepsilon\{1\} &= Ce^{-2\beta}, & B_\beta^\varepsilon\{2\} &= Ce^{-4\beta}, \\ & B_\beta^\varepsilon\{3\} &= Ce^{-9\beta}, & B_\beta^\varepsilon\{4\} &= Ce^{-9\beta}. \end{aligned}$$

In the next example,  $\varepsilon$  has many degeneracies.

*Example:* **Let**  $\Sigma := ([0..4] \times [0..4]) \setminus \{(4, 4)\}$ .

**Let**  $\beta \in \mathbb{R}$  and **define**  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:  $\forall \sigma \in \Sigma, \varepsilon(\sigma) = \sigma_1 + \sigma_2$ .

$$\text{Then: } \widehat{B}_\beta^\varepsilon\{(3, 2)\} = e^{-5\beta}, \quad \widehat{B}_\beta^\varepsilon\{(1, 4)\} = e^{-5\beta}, \quad \widehat{B}_\beta^\varepsilon\{(0, 0)\} = 1.$$

$$\text{Generally, } \forall \sigma \in \Sigma, \widehat{B}_\beta^\varepsilon\{\sigma\} = e^{-(\sigma_1 + \sigma_2) \cdot \beta}.$$

**Let**  $C := 1/(\sum_{\sigma \in \Sigma} [e^{-(\sigma_1 + \sigma_2) \cdot \beta}])$ .

$$\text{Then: } B_\beta^\varepsilon\{(3, 2)\} = Ce^{-5\beta}, \quad B_\beta^\varepsilon\{(1, 4)\} = Ce^{-5\beta}, \quad B_\beta^\varepsilon\{(0, 0)\} = C.$$

$$\text{Generally, } \forall \sigma \in \Sigma, B_\beta^\varepsilon\{\sigma\} = Ce^{-(\sigma_1 + \sigma_2) \cdot \beta}.$$

**THEOREM 20.2.** **Let**  $\Sigma$  be a nonempty finite set.

$$\text{Let } \varepsilon : \Sigma \rightarrow \mathbb{R}, \quad \xi, \beta \in \mathbb{R}. \quad \text{Then: } B_\beta^\varepsilon = B_\beta^{\varepsilon - \xi}.$$

*Proof.* For all  $\sigma \in \Sigma$ , **let**  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

$$\text{Since, } \forall \sigma \in \Sigma, \widehat{B}_\beta^\varepsilon\{\sigma\} = e^{-\beta \cdot \varepsilon_\sigma} = e^{-\beta \cdot \xi} \cdot e^{-\beta \cdot (\varepsilon_\sigma - \xi)} = e^{-\beta \cdot \xi} \cdot (\widehat{B}_\beta^{\varepsilon - \xi}\{\sigma\}),$$



we get:  $\widehat{B}_\beta^\varepsilon = e^{-\beta \cdot \xi} \cdot \widehat{B}_\beta^{\varepsilon - \xi}$ .  
 Since  $e^{-\beta \cdot \xi} > 0$ , we get:  $\mathcal{N}(e^{-\beta \cdot \xi} \cdot \widehat{B}_\beta^{\varepsilon - \xi}) = \mathcal{N}(\widehat{B}_\beta^{\varepsilon - \xi})$ .  
 Then:  $B_\beta^\varepsilon = \mathcal{N}(\widehat{B}_\beta^\varepsilon) = \mathcal{N}(e^{-\beta \cdot \xi} \cdot \widehat{B}_\beta^{\varepsilon - \xi}) = \mathcal{N}(\widehat{B}_\beta^{\varepsilon - \xi}) = B_\beta^{\varepsilon - \xi}$ .  $\square$

**DEFINITION 20.3.** Let  $\Sigma$  be a nonempty finite set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .  
 For all  $\beta \in \mathbb{R}$ , let  $\boxed{\Gamma_\beta^\varepsilon} := \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot e^{-\beta \cdot \varepsilon_\sigma}]$ ,  
 $\boxed{\Delta_\beta^\varepsilon} := \sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}]$ ,  
 $\boxed{A_\beta^\varepsilon} := \Gamma_\beta^\varepsilon / \Delta_\beta^\varepsilon$ .

Let  $\Sigma$  be a nonempty finite set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Then:  $\Gamma_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (\widehat{B}_\beta^\varepsilon\{\sigma\})]$ .  
 Then:  $\Gamma_\beta^\varepsilon$  is the integral of  $\varepsilon$  wrt  $\widehat{B}_\beta^\varepsilon$ .  
 Since  $\Delta_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [\widehat{B}_\beta^\varepsilon\{\sigma\}]$ ,  
 we get:  $\Delta_\beta^\varepsilon = \widehat{B}_\beta^\varepsilon(\Sigma)$ .  
 Since  $\frac{\Gamma_\beta^\varepsilon}{\Delta_\beta^\varepsilon} = \frac{\sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (\widehat{B}_\beta^\varepsilon\{\sigma\})]}{\widehat{B}_\beta^\varepsilon(\Sigma)}$ ,  
 we get:  $A_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})]$ .  
 Then:  $A_\beta^\varepsilon$  is the average value of  $\varepsilon$  wrt  $B_\beta^\varepsilon$ .

Recall (§2) the notations  $\mathbb{I}_f$ ,  $f^*A$ . Recall (§8) the notation  $\varepsilon_*\mu$ .  
 Recall (Definition 8.5) the notation  $M_\mu$ .

**THEOREM 20.4.** Let  $\Sigma$  be a nonempty finite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta \in \mathbb{R}$ . Then:  $M_{\varepsilon_* B_\beta^\varepsilon} = A_\beta^\varepsilon$ .

*Proof.* For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

Because  $\Sigma$  is the disjoint union, over  $t \in \mathbb{I}_\varepsilon$ , of  $\varepsilon^*\{t\}$ ,

we get:  $\sum_{t \in \mathbb{I}_\varepsilon} \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})] = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})]$ .

Also,  $A_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})]$ .

Then:  $\sum_{t \in \mathbb{I}_\varepsilon} \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})] = A_\beta^\varepsilon$ .

So, since  $\sum_{t \in \mathbb{I}_\varepsilon} [t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\})] = M_{\varepsilon_* B_\beta^\varepsilon}$ ,

**we want:**  $\sum_{t \in \mathbb{I}_\varepsilon} [t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\})] = \sum_{t \in \mathbb{I}_\varepsilon} \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})]$ .

**Want:**  $\forall t \in \mathbb{I}_\varepsilon$ ,  $t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\}) = \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})]$ .

**Given**  $t \in \mathbb{I}_\varepsilon$ , **want:**  $t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\}) = \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})]$ .

For all  $\sigma \in \varepsilon^*\{t\}$ , since  $\varepsilon_\sigma = \varepsilon(\sigma) \in \{t\}$ , we get:  $t = \varepsilon_\sigma$ .

**Want:**  $t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\}) = \sum_{\sigma \in \varepsilon^*\{t\}} [t \cdot (B_\beta^\varepsilon\{\sigma\})]$ .

Because  $\varepsilon^*\{t\}$  is the disjoint union, over  $\sigma \in \varepsilon^*\{t\}$ , of  $\{\sigma\}$ ,

we get:  $B_\beta^\varepsilon(\varepsilon^*\{t\}) = \sum_{\sigma \in \varepsilon^*\{t\}} [B_\beta^\varepsilon\{\sigma\}]$ .  
 Also,  $(\varepsilon_* B_\beta^\varepsilon)\{t\} = B_\beta^\varepsilon(\varepsilon^*\{t\})$ .  
 Then:  $t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\}) = t \cdot (B_\beta^\varepsilon(\varepsilon^*\{t\})) = \sum_{\sigma \in \varepsilon^*\{t\}} [t \cdot (B_\beta^\varepsilon\{\sigma\})]$ .  $\square$

**THEOREM 20.5.** Let  $\Sigma$  be a nonempty finite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta, \xi \in \mathbb{R}$ . Then:  $A_\beta^{\varepsilon-\xi} = A_\beta^\varepsilon - \xi$ .

*Proof.* We have:  $B_\beta^\varepsilon(\Sigma) = \sum_{\sigma \in \Sigma} [B_\beta^\varepsilon\{\sigma\}]$ .  
 Since  $B_\beta^\varepsilon \in \mathcal{P}_\Sigma$ , we get:  $B_\beta^\varepsilon(\Sigma) = 1$ .  
 By Theorem 20.2, we have:  $B_\beta^\varepsilon = B_\beta^{\varepsilon-\xi}$ .  
 For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .  
 Then:  $A_\beta^{\varepsilon-\xi} = \sum_{\sigma \in \Sigma} [(\varepsilon_\sigma - \xi) \cdot (B_\beta^{\varepsilon-\xi}\{\sigma\})]$   
 $= \sum_{\sigma \in \Sigma} [(\varepsilon_\sigma - \xi) \cdot (B_\beta^\varepsilon\{\sigma\})]$   
 $= (\sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})]) - (\sum_{\sigma \in \Sigma} [\xi \cdot (B_\beta^\varepsilon\{\sigma\})])$   
 $= (\sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})]) - \xi \cdot (\sum_{\sigma \in \Sigma} [B_\beta^\varepsilon\{\sigma\}])$   
 $= A_\beta^\varepsilon - \xi \cdot (B_\beta^\varepsilon(\Sigma)) = A_\beta^\varepsilon - \xi \cdot 1 = A_\beta^\varepsilon - \xi$ .  $\square$

**THEOREM 20.6.** Let  $\Sigma$  be a nonempty finite set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Then: as  $\beta \rightarrow \infty$ ,  $A_\beta^\varepsilon \rightarrow \min \mathbb{I}_\varepsilon$   
 and as  $\beta \rightarrow -\infty$ ,  $A_\beta^\varepsilon \rightarrow \max \mathbb{I}_\varepsilon$ .

The proof is a matter of bookkeeping, best explained by example:

Let  $\Sigma := \{1, 2, 3, 4\}$  and define  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:

$$\varepsilon(1) = 2, \quad \varepsilon(2) = 4, \quad \varepsilon(3) = 9, \quad \varepsilon(4) = 9.$$

Then  $\mathbb{I}_\varepsilon = \{2, 4, 9\}$ , so  $\min \mathbb{I}_\varepsilon = 2$  and  $\max \mathbb{I}_\varepsilon = 9$ .

Since  $\forall \beta \in \mathbb{R}$ ,  $A_\beta^\varepsilon = \frac{2e^{-2\beta} + 4e^{-4\beta} + 9e^{-9\beta} + 9e^{-9\beta}}{e^{-2\beta} + e^{-4\beta} + e^{-9\beta} + e^{-9\beta}}$ ,  
 $= \frac{2e^{-2\beta} + 4e^{-4\beta} + 18e^{-9\beta}}{e^{-2\beta} + e^{-4\beta} + 2e^{-9\beta}}$ ,

we get as  $\beta \rightarrow \infty$ ,  $A_\beta^\varepsilon \rightarrow 2/1$   
 and as  $\beta \rightarrow -\infty$ ,  $A_\beta^\varepsilon \rightarrow 18/2$ ,  
 and so as  $\beta \rightarrow \infty$ ,  $A_\beta^\varepsilon \rightarrow \min \mathbb{I}_\varepsilon$   
 and as  $\beta \rightarrow -\infty$ ,  $A_\beta^\varepsilon \rightarrow \max \mathbb{I}_\varepsilon$ .

For any nonempty finite set  $\Sigma$ , for any  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,

define  $\boxed{A_\bullet^\varepsilon} : \mathbb{R} \rightarrow \mathbb{R}$  by:  $\forall \beta \in \mathbb{R}$ ,  $A_\bullet^\varepsilon(\beta) = A_\beta^\varepsilon$ .

Recall (§2): “ $C^\omega$ ” means “real-analytic”.

**THEOREM 20.7.** Let  $\Sigma$  be a finite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ . Assume:  $\#\mathbb{I}_\varepsilon \geq 2$ .

Then:  $A_{\bullet}^{\varepsilon}$  is a strictly-decreasing  $C^{\omega}$ -diffeomorphism  
from  $\mathbb{R}$  onto  $(\min \mathbb{I}_{\varepsilon}; \max \mathbb{I}_{\varepsilon})$ .

*Proof.* For all  $\sigma \in \Sigma$ , let  $\varepsilon_{\sigma} := \varepsilon(\sigma)$ .

We have:  $\forall \beta \in \mathbb{R}$ ,  $A_{\bullet}^{\varepsilon}(\beta) = \frac{\sum_{\sigma \in \Sigma} [\varepsilon_{\sigma} \cdot e^{-\beta \cdot \varepsilon_{\sigma}}]}{\sum_{\tau \in \Sigma} [e^{-\beta \cdot \varepsilon_{\tau}}]}$ . Then  $A_{\bullet}^{\varepsilon} : \mathbb{R} \rightarrow \mathbb{R}$  is  $C^{\omega}$ .

So, by Theorem 20.6 and the  $C^{\omega}$ -Inverse Function Theorem and the Mean Value Theorem, it suffices to show:  $(A_{\bullet}^{\varepsilon})' < 0$  on  $\mathbb{R}$ .

**Given**  $\beta \in \mathbb{R}$ , **want:**  $(A_{\bullet}^{\varepsilon})'(\beta) < 0$ .

**Let**  $P := \sum_{\sigma \in \Sigma} [\varepsilon_{\sigma} \cdot e^{-\beta \cdot \varepsilon_{\sigma}}]$ ,  $P' := \sum_{\sigma \in \Sigma} [(-\varepsilon_{\sigma}^2) \cdot e^{-\beta \cdot \varepsilon_{\sigma}}]$ .

**Let**  $Q := \sum_{\tau \in \Sigma} [e^{-\beta \cdot \varepsilon_{\tau}}]$ ,  $Q' := \sum_{\tau \in \Sigma} [(-\varepsilon_{\tau}) \cdot e^{-\beta \cdot \varepsilon_{\tau}}]$ .

Then  $Q > 0$ . Also, by the Quotient Rule,  $(A_{\bullet}^{\varepsilon})'(\beta) = [QP' - PQ']/Q^2$ .

**Want:**  $QP' - PQ' < 0$ .

We have:  $QP' = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [(-\varepsilon_{\sigma}^2) \cdot e^{-\beta \cdot (\varepsilon_{\sigma} + \varepsilon_{\tau})}]$ .

We have:  $PQ' = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [(-\varepsilon_{\sigma} \varepsilon_{\tau}) \cdot e^{-\beta \cdot (\varepsilon_{\sigma} + \varepsilon_{\tau})}]$ .

Then:  $QP' - PQ' = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [(-\varepsilon_{\sigma}^2 + \varepsilon_{\sigma} \varepsilon_{\tau}) \cdot e^{-\beta \cdot (\varepsilon_{\sigma} + \varepsilon_{\tau})}]$ .

Interchanging  $\sigma$  and  $\tau$ , we get:

$$QP' - PQ' = \sum_{\tau \in \Sigma} \sum_{\sigma \in \Sigma} [(-\varepsilon_{\tau}^2 + \varepsilon_{\tau} \varepsilon_{\sigma}) \cdot e^{-\beta \cdot (\varepsilon_{\tau} + \varepsilon_{\sigma})}].$$

By commutativity of addition and multiplication,

adding the last two equations gives:

$$2 \cdot (QP' - PQ') = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [(-\varepsilon_{\sigma}^2 - \varepsilon_{\tau}^2 + 2\varepsilon_{\sigma} \varepsilon_{\tau}) \cdot e^{-\beta \cdot (\varepsilon_{\sigma} + \varepsilon_{\tau})}].$$

Then:  $2 \cdot (QP' - PQ') = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [-(\varepsilon_{\sigma} - \varepsilon_{\tau})^2 \cdot e^{-\beta \cdot (\varepsilon_{\sigma} + \varepsilon_{\tau})}]$ .

Then:  $2 \cdot (QP' - PQ') < 0$ . Then:  $QP' - PQ' < 0$ .  $\square$

**DEFINITION 20.8.** Let  $\Sigma$  be a finite set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\#\mathbb{I}_{\varepsilon} \geq 2$ . Let  $\alpha \in (\min \mathbb{I}_{\varepsilon}; \max \mathbb{I}_{\varepsilon})$ .

The  $\alpha$ -Boltzmann-parameter on  $\varepsilon$  is:  $\boxed{\text{BP}_{\alpha}^{\varepsilon}} := (A_{\bullet}^{\varepsilon})^{-1}(\alpha)$ .

So the  $\alpha$ -Boltzmann-parameter on  $\varepsilon$  is the unique  $\beta \in \mathbb{R}$  s.t.  $A_{\beta}^{\varepsilon} = \alpha$ .

*Example:* Let  $\Sigma := \{0, 1, 10\}$ , and define  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:

$$\forall \sigma \in \Sigma, \quad \varepsilon(\sigma) = \sigma.$$

Computation shows:  $A_{(\ln 9)/10}^{\varepsilon} = 1$ . Then:  $\text{BP}_1^{\varepsilon} = (\ln 9)/10$ .

*Example:* Let  $\Sigma := \{2, 4, 8, 9\}$ , and define  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:

$$\forall \sigma \in \Sigma, \quad \varepsilon(\sigma) = \sigma.$$

To evaluate  $\text{BP}_5^{\varepsilon}$ , we must solve  $A_{\beta}^{\varepsilon} = 5$  for  $\beta$ ,

and, since, by Theorem 20.7,  $A_{\bullet}^{\varepsilon}$  is strictly-decreasing,

there are simple iterative methods to do this.

We compute:  $\text{BP}_5^{\varepsilon} \approx 0.0918$ , accurate to four decimal places.

(Thanks to C. Prouty for this calculation. See §29.)

Next, let  $\bar{\Sigma} := \{1, 2, 3, 4\}$ , and define  $\bar{\varepsilon} : \bar{\Sigma} \rightarrow \mathbb{R}$  by:

$$\bar{\varepsilon}(1) = 2, \quad \bar{\varepsilon}(2) = 4, \quad \bar{\varepsilon}(3) = 8, \quad \bar{\varepsilon}(4) = 9.$$

Then  $A_{\bullet}^{\bar{\varepsilon}} = A_{\bullet}^{\varepsilon}$ , so  $\text{BP}_5^{\bar{\varepsilon}} = \text{BP}_5^{\varepsilon}$ .

Then  $\text{BP}_5^{\bar{\varepsilon}} \approx 0.0918$ , accurate to four decimal places.

*Example:* Let  $\Sigma := \{1, 2, 3, 4\}$  and define  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:

$$\varepsilon(1) = 2, \quad \varepsilon(2) = 4, \quad \varepsilon(3) = 9, \quad \varepsilon(4) = 9.$$

To evaluate  $\text{BP}_5^{\varepsilon}$ , we must solve  $A_{\bullet}^{\varepsilon}(\beta) = 5$  for  $\beta$ ,

and, since, by Theorem 20.7,  $A_{\bullet}^{\varepsilon}$  is strictly-decreasing,  
there are simple iterative methods to do this.

We compute:  $\text{BP}_5^{\varepsilon} \approx 0.1060$ , accurate to four decimal places.

(Thanks to C. Prouty for this calculation. See §29.)

*Example:* Let  $\Sigma := ([0..4] \times [0..4]) \setminus \{(4, 4)\}$ .

Define  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:  $\forall \sigma \in \Sigma, \varepsilon(\sigma) = \sigma_1 + \sigma_2$ .

To evaluate  $\text{BP}_1^{\varepsilon}$ , we must solve  $A_{\bullet}^{\varepsilon}(\beta) = 1$  for  $\beta$ ,

and, since, by Theorem 20.7,  $A_{\bullet}^{\varepsilon}$  is strictly-decreasing,  
there are simple iterative methods to do this.

We compute:  $\text{BP}_1^{\varepsilon} \approx 1.0670$ , accurate to four decimal places.

(Thanks to C. Prouty for this calculation. See §29.)

**THEOREM 20.9.** Let  $\Sigma$  be a finite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ . Assume:  $\#\mathbb{I}_{\varepsilon} \geq 2$ .

Let  $\alpha \in (\min \mathbb{I}_{\varepsilon}; \max \mathbb{I}_{\varepsilon})$ . Let  $\xi \in \mathbb{R}$ . Then:  $\text{BP}_{\alpha-\xi}^{\varepsilon-\xi} = \text{BP}_{\alpha}^{\varepsilon}$ .

*Proof.* Let  $\beta := \text{BP}_{\alpha}^{\varepsilon}$ .

**Want:**  $\text{BP}_{\alpha-\xi}^{\varepsilon-\xi} = \beta$ .

Since  $\beta = \text{BP}_{\alpha}^{\varepsilon} = (A_{\bullet}^{\varepsilon})^{-1}(\alpha)$ , we get:  $(A_{\bullet}^{\varepsilon})(\beta) = \alpha$ .

By Theorem 20.5,  $A_{\beta}^{\varepsilon-\xi} = A_{\beta}^{\varepsilon} - \xi$ .

Since  $(A_{\bullet}^{\varepsilon-\xi})(\beta) = A_{\beta}^{\varepsilon-\xi} = A_{\beta}^{\varepsilon} - \xi = ((A_{\bullet}^{\varepsilon})(\beta)) - \xi = \alpha - \xi$ ,

we get:  $\beta = (A_{\bullet}^{\varepsilon-\xi})^{-1}(\alpha - \xi)$ .

So, since  $\text{BP}_{\alpha-\xi}^{\varepsilon-\xi} = (A_{\bullet}^{\varepsilon-\xi})^{-1}(\alpha - \xi)$ , we get:  $\text{BP}_{\alpha-\xi}^{\varepsilon-\xi} = \beta$ .  $\square$

## 21. DEGENERATE ENERGY LEVELS

Recall (§2): the notations  $\mathbb{I}_f$  and  $f^*A$ .

Recall (§8): the notation  $\nu_F$ .

**THEOREM 21.1.** Let  $\Sigma$  be a finite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$ . Assume  $\mathbb{I}_{\varepsilon}$  is residue-unconstrained.

**Let**  $\alpha \in (\min \mathbb{I}_\varepsilon; \max \mathbb{I}_\varepsilon)$ . **Let**  $\beta := \text{BP}_\alpha^\varepsilon$ .  
**Let**  $t_1, t_2, \dots \in \mathbb{Z}$ . Assume:  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded.  
For all  $n \in \mathbb{N}$ , **let**  $\Omega_n := \{f \in \Sigma^n \mid (\varepsilon(f_1)) + \dots + (\varepsilon(f_n)) = t_n\}$ .  
**Let**  $\sigma_0 \in \Sigma$ . Then: as  $n \rightarrow \infty$ ,  $\nu_{\Omega_n} \{f \in \Omega_n \mid f_n = \sigma_0\} \rightarrow B_\beta^\varepsilon \{\sigma_0\}$ .

Recall (§8):  $\nu_\emptyset(\emptyset) = -1$ .

So, since  $B_\beta^\varepsilon \{\sigma_0\} > 0$ , part of the content of Theorem 21.1 is:

$$\forall \text{sufficiently large } n \in \mathbb{N}, \quad \Omega_n \neq \emptyset.$$

See Claim 2 in the proof below.

*Proof.* Since  $\mathbb{I}_\varepsilon$  is residue-unconstrained, we get:  $\mathbb{I}_\varepsilon \neq \emptyset$ .  
So, since  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$ , we conclude:  $\Sigma \neq \emptyset$ .  
By hypothesis,  $\Sigma$  is finite. Then:  $\Sigma$  is a nonempty finite set.  
Since  $\beta = \text{BP}_\alpha^\varepsilon = (A_\bullet^\varepsilon)^{-1}(\alpha)$ , we get:  $A_\bullet^\varepsilon(\beta) = \alpha$ .  
By Theorem 20.4, we have:  $M_{\varepsilon_* B_\beta^\varepsilon} = A_\beta^\varepsilon$ .  
So, since  $A_\beta^\varepsilon = A_\bullet^\varepsilon(\beta) = \alpha$ , we get:  $M_{\varepsilon_* B_\beta^\varepsilon} = \alpha$ .  
**Let**  $\mu := B_\beta^\varepsilon$ . Then:  $\mu \in \mathcal{P}_\Sigma$  and  $M_{\varepsilon_* \mu} = \alpha$ .  
**Let**  $E := \mathbb{I}_\varepsilon$ ,  $\tilde{\mu} := \varepsilon_* \mu$ . Then:  $\tilde{\mu} \in \mathcal{P}_E$  and  $M_{\tilde{\mu}} = \alpha$ .  
By hypothesis,  $E$  is residue-unconstrained.

Since  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$ , we get:  $E \subseteq \mathbb{Z}$ .

Since  $\Sigma$  is finite, we get:  $E$  is finite.

So, since  $\tilde{\mu} \in \mathcal{P}_E \subseteq \mathcal{FM}_E$ , we get:  $|\tilde{\mu}|_1 < \infty$  and  $|\tilde{\mu}|_2 < \infty$ .

For all  $\sigma \in \Sigma$ , **let**  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

Then:  $\forall n \in \mathbb{N}$ ,  $\Omega_n = \{f \in \Sigma^n \mid \varepsilon_{f_1} + \dots + \varepsilon_{f_n} = t_n\}$ .

For all  $n \in \mathbb{N}$ , **define**  $\varepsilon^n : \Sigma^n \rightarrow E^n$  by:

$$\forall f_1, \dots, f_n \in \Sigma, \quad \varepsilon^n(f_1, \dots, f_n) = (\varepsilon_{f_1}, \dots, \varepsilon_{f_n}).$$

Then, since  $\varepsilon_* \mu = \tilde{\mu}$ , we get:  $\forall n \in \mathbb{N}$ ,  $(\varepsilon^n)_*(\mu^n) = \tilde{\mu}^n$ .

For all  $n \in \mathbb{N}$ , **let**  $\tilde{\Omega}_n := \{\tilde{f} \in E^n \mid \tilde{f}_1 + \dots + \tilde{f}_n = t_n\}$ ;

$$\text{then } (\varepsilon^n)^* \tilde{\Omega}_n = \Omega_n.$$

Then:  $\forall n \in \mathbb{N}$ ,  $\mu^n((\varepsilon^n)^* \tilde{\Omega}_n) = \mu^n(\Omega_n)$ .

Then:  $\forall n \in \mathbb{N}$ ,  $((\varepsilon^n)_* \mu^n)(\tilde{\Omega}_n) = \mu^n(\Omega_n)$ .

Then:  $\forall n \in \mathbb{N}$ ,  $\tilde{\mu}^n(\tilde{\Omega}_n) = \mu^n(\Omega_n)$ .

For all  $n \in \mathbb{N}$ , **define**  $\psi_n : \mathbb{Z} \rightarrow \mathbb{R}$  by:

$$\forall t \in \mathbb{Z}, \quad \psi_n(t) = \tilde{\mu}^n \{f \in E^n \mid \tilde{f}_1 + \dots + \tilde{f}_n = t\}.$$

Then:  $\forall n \in \mathbb{N}$ ,  $\psi_n(t_n) = \tilde{\mu}^n(\tilde{\Omega}_n)$ .

Since  $E$  is finite and residue-unconstrained, we get:  $2 \leq \#E < \infty$ .

Since  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$ , we get:  $S_{B_\beta^\varepsilon} = \Sigma$ .

So, since  $\mu = B_\beta^\varepsilon$ , we get:  $S_\mu = \Sigma$ .

So, since  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$ , we get:  $S_{\varepsilon_* \mu} = \mathbb{I}_\varepsilon$ .

So, since  $\varepsilon_*\mu = \tilde{\mu}$  and  $\mathbb{I}_\varepsilon = E$ , we get:  $S_{\tilde{\mu}} = E$ .

Since  $E$  is finite, we get:  $E$  is countable.

So, since  $\tilde{\mu} \in \mathcal{P}_E$  and  $|\tilde{\mu}|_1 < \infty$  and  $\#S_{\tilde{\mu}} = \#E \geq 2$ ,

by Theorem 8.6, we get:  $V_{\tilde{\mu}} > 0$ .

So, since  $V_{\tilde{\mu}} = |\tilde{\mu}|_2^2 - M_{\tilde{\mu}}^2 \leq |\tilde{\mu}|_2^2 < \infty$ , we conclude:

$$0 < V_{\tilde{\mu}} < \infty.$$

**Let**  $v := V_{\tilde{\mu}}$ . Then  $0 < v < \infty$ . Then  $1/\sqrt{2\pi v} > 0$ .

**Let**  $\tau := 1/\sqrt{2\pi v}$ . Then  $\tau > 0$ .

*Claim 1:* As  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\psi_n(t_n)) \rightarrow \tau$ .

*Proof of Claim 1:* Recall:  $E \subseteq \mathbb{Z}$ ,  $E$  is residue-unconstrained,

$$\tilde{\mu} \in \mathcal{P}_E, \quad S_{\tilde{\mu}} = E, \quad |\tilde{\mu}|_2 < \infty, \quad \alpha = M_{\tilde{\mu}}, \quad v = V_{\tilde{\mu}}.$$

By hypothesis,  $t_1, t_2, \dots \in \mathbb{Z}$  and  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded.

Then, by Theorem 9.6, we get:

$$\text{as } n \rightarrow \infty, \quad \sqrt{n} \cdot (\tilde{\mu}^n \{f \in E^n \mid \tilde{f}_1 + \dots + \tilde{f}_n = t_n\}) \rightarrow 1/\sqrt{2\pi v}.$$

Then, as  $n \rightarrow \infty$ ,  $\sqrt{n} \cdot (\psi_n(t_n)) \rightarrow \tau$ .

*End of proof of Claim 1.*

Since  $\tau > 0$ , by Claim 1, **choose**  $n_0 \in [2..\infty)$  s.t.  
 $\forall n \in [n_0..\infty), \quad \sqrt{n} \cdot (\psi_n(t_n)) > 0$ .

*Claim 2:* **Let**  $n \in [n_0..\infty)$ . Then:  $\mu^n(\Omega_n) > 0$ .

*Proof of Claim 2:* Recall:  $\tilde{\mu}^n(\tilde{\Omega}_n) = \mu^n(\Omega_n)$  and  $\psi_n(t_n) = \tilde{\mu}^n(\tilde{\Omega}_n)$ .

By the choice of  $n_0$ , we get:  $\sqrt{n} \cdot (\psi_n(t_n)) > 0$ . Then:  $\psi_n(t_n) > 0$ .

$$\text{Then: } \mu^n(\Omega_n) = \tilde{\mu}^n(\tilde{\Omega}_n) = \psi_n(t_n) > 0.$$

*End of proof of Claim 2.*

Recall:  $\Sigma \neq \emptyset$  and  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$ . Then  $\widehat{B}_\beta^\varepsilon(\Sigma) > 0$ .

**Let**  $C := 1/(\widehat{B}_\beta^\varepsilon(\Sigma))$ . Then  $\mathcal{N}(\widehat{B}_\beta^\varepsilon) = C \cdot \widehat{B}_\beta^\varepsilon$

By definition of  $\widehat{B}_\beta^\varepsilon$ , we have:  $\forall \sigma \in \Sigma, \quad \widehat{B}_\beta^\varepsilon\{\sigma\} = e^{-\beta \cdot \varepsilon \sigma}$ .

So, since  $\mu = B_\beta^\varepsilon = \mathcal{N}(\widehat{B}_\beta^\varepsilon) = C \cdot \widehat{B}_\beta^\varepsilon$ ,  
we get:  $\forall \sigma \in \Sigma, \quad \mu\{\sigma\} = C e^{-\beta \cdot \varepsilon \sigma}$ .

Since  $\mu \in \mathcal{P}_\Sigma$ , we get:  $\forall n \in \mathbb{N}, \mu^n \in \mathcal{P}_{\Sigma^n}$ , so  $\mu^n(\Omega_n) \leq 1$ .

So, by Claim 2,  $\forall n \in [n_0..\infty), \quad 0 < \mu^n(\Omega_n) \leq 1$ .

Also, we have:  $\forall n \in \mathbb{N}, \quad (\mu^n | \Omega_n)(\Omega_n) = \mu^n(\Omega_n)$ .

Then:  $\forall n \in [n_0..\infty), \quad 0 < (\mu^n | \Omega_n)(\Omega_n) \leq 1$ .

Then:  $\forall n \in [n_0..\infty), \quad \mu^n | \Omega_n \in \mathcal{FM}_{\Omega_n}^\times$ .

Then:  $\forall n \in [n_0..∞)$ ,  $\mathcal{N}(\mu^n | \Omega_n) \in \mathcal{P}_{\Omega_n}$ .  
Also,  $\forall n \in \mathbb{N}, \forall S \subseteq \Omega_n$ ,  $(\mu^n | \Omega_n)(S) = \mu^n(S)$ .  
Then:  $\forall n \in \mathbb{N}$ ,  $(\mu^n | \Omega_n)(\Omega_n) = \mu^n(\Omega_n)$ .  
For all  $n \in \mathbb{N}$ , **let**  $z_n := \mu^n(\Omega_n)$ .  
Then:  $\forall n \in [n_0..∞)$ ,  $(\mu^n | \Omega_n)(\Omega_n) = z_n$  and  $0 < z_n \leq 1$ .  
For all  $n \in [n_0..∞)$ , **let**  $\lambda_n := \mathcal{N}(\mu^n | \Omega_n)$ .  
Then:  $\forall n \in [n_0..∞)$ ,  $\lambda_n = (\mu^n | \Omega_n) / z_n$ .  
Then:  $\forall n \in [n_0..∞)$ ,  $\forall S \subseteq \Omega_n$ ,  $\lambda_n(S) = (\mu^n(S)) / z_n$ .

*Claim 3: Let*  $n \in [n_0..∞)$ . **Then:**  $\lambda_n = \nu_{\Omega_n}$ .

*Proof of Claim 3: Let*  $F := \Omega_n$ . **Want:**  $\lambda_n = \nu_F$ .

Since  $\lambda_n = \mathcal{N}(\mu^n | \Omega_n) = \mathcal{N}(\mu^n | F)$ , we get:  $\lambda_n \in \mathcal{P}_F$ .

By Theorem 8.9, **given**  $f, g \in F$ , **want:**  $\lambda_n\{f\} = \lambda_n\{g\}$ .

**Want:**  $(\mu^n\{f\})/z_n = (\mu^n\{g\})/z_n$ . **Want:**  $\mu^n\{f\} = \mu^n\{g\}$ .

For all  $i \in [1..n]$ , **let**  $\tilde{f}_i := \varepsilon_{f_i}$  and  $\tilde{g}_i := \varepsilon_{g_i}$ .

Recall:  $\forall \sigma \in \Sigma$ ,  $\mu\{\sigma\} = Ce^{-\beta \cdot \varepsilon_\sigma}$ .

Then:  $\forall i \in [1..n]$ ,  $\mu\{f_i\} = Ce^{-\beta \cdot \tilde{f}_i}$  and  $\mu\{g_i\} = Ce^{-\beta \cdot \tilde{g}_i}$ .

Since  $f \in F = \Omega_n$ , we get:  $\varepsilon_{f_1} + \dots + \varepsilon_{f_n} = t_n$ .

Since  $g \in F = \Omega_n$ , we get:  $\varepsilon_{g_1} + \dots + \varepsilon_{g_n} = t_n$ .

Since  $\tilde{f}_1 + \dots + \tilde{f}_n = \varepsilon_{f_1} + \dots + \varepsilon_{f_n} = t_n$   
 $= \varepsilon_{g_1} + \dots + \varepsilon_{g_n} = \tilde{g}_1 + \dots + \tilde{g}_n$ ,

we get:  $C^n e^{-\beta \cdot (\tilde{f}_1 + \dots + \tilde{f}_n)} = C^n e^{-\beta \cdot (\tilde{g}_1 + \dots + \tilde{g}_n)}$ .

Then:  $(Ce^{-\beta \cdot \tilde{f}_1}) \dots (Ce^{-\beta \cdot \tilde{f}_n}) = (Ce^{-\beta \cdot \tilde{g}_1}) \dots (Ce^{-\beta \cdot \tilde{g}_n})$ .

Then:  $(\mu\{f_1\}) \dots (\mu\{f_n\}) = (\mu\{g_1\}) \dots (\mu\{g_n\})$ .

Then:  $\mu^n\{f\} = \mu^n\{g\}$ .

*End of proof of Claim 3.*

*Claim 4: Let*  $\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}$ . **Then:**  $\mu\{\sigma\} = \mu\{\sigma_0\}$ .

*Proof of Claim 4:* Since  $\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}$ , we get:  $\varepsilon(\sigma) \in \{\varepsilon_{\sigma_0}\}$ .

Since  $\varepsilon_\sigma = \varepsilon(\sigma) \in \{\varepsilon_{\sigma_0}\}$ , we get:  $\varepsilon_\sigma = \varepsilon_{\sigma_0}$ .

Then:  $\mu\{\sigma\} = Ce^{-\beta \cdot \varepsilon_\sigma} = Ce^{-\beta \cdot \varepsilon_{\sigma_0}} = \mu\{\sigma_0\}$ .

*End of proof of Claim 4.*

Since  $\varepsilon(\sigma_0) = \varepsilon_{\sigma_0} \in \{\varepsilon_{\sigma_0}\}$ , we get:  $\sigma_0 \in \varepsilon^*\{\varepsilon_{\sigma_0}\}$ .

Then  $\varepsilon^*\{\varepsilon_{\sigma_0}\} \neq \emptyset$ , so  $\#(\varepsilon^*\{\varepsilon_{\sigma_0}\}) \geq 1$ .

**Let**  $k := \#(\varepsilon^*\{\varepsilon_{\sigma_0}\})$ . **Then:**  $k \geq 1$ .

*Claim 5:*  $\mu(\varepsilon^*\{\varepsilon_{\sigma_0}\}) = k \cdot (\mu\{\sigma_0\})$ .

*Proof of Claim 5:* Since  $\varepsilon^*\{\varepsilon_{\sigma_0}\}$  is equal to  
the disjoint union, over  $\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}$ , of  $\{\sigma\}$ ,  
we get:  $\mu(\varepsilon^*\{\varepsilon_{\sigma_0}\}) = \sum_{\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}} [\mu\{\sigma\}]$ ,  
So, by Claim 4, we get:  $\mu(\varepsilon^*\{\varepsilon_{\sigma_0}\}) = \sum_{\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}} [\mu\{\sigma_0\}]$ .  
So, since  $k = \#(\varepsilon^*\{\varepsilon_{\sigma_0}\})$ , we get:  $\mu(\varepsilon^*\{\varepsilon_{\sigma_0}\}) = k \cdot (\mu\{\sigma_0\})$ .  
*End of proof of Claim 5.*

*Claim 6: Let*  $n \in [2..\infty)$ . **Let**  $\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}$ .  
Then:  $\mu^n\{f \in \Omega_n \mid f_n = \sigma\} = \mu^n\{f \in \Omega_n \mid f_n = \sigma_0\}$ .

*Proof of Claim 6:*

**Let**  $X := \{f \in \Sigma^{n-1} \mid \varepsilon_{f_1} + \cdots + \varepsilon_{f_{n-1}} = t_n - \varepsilon_\sigma\}$ .

Recall:  $\Omega_n = \{f \in \Sigma^n \mid \varepsilon_{f_1} + \cdots + \varepsilon_{f_{n-1}} + \varepsilon_{f_n} = t_n\}$ .

Since  $\{f \in \Omega_n \mid f_n = \sigma\}$   
 $= \{f \in \Sigma^n \mid [\varepsilon_{f_1} + \cdots + \varepsilon_{f_{n-1}} + \varepsilon_{f_n} = t_n] \& [f_n = \sigma]\}$   
 $= \{f \in \Sigma^n \mid [\varepsilon_{f_1} + \cdots + \varepsilon_{f_{n-1}} + \varepsilon_\sigma = t_n] \& [f_n = \sigma]\}$   
 $= \{f \in \Sigma^n \mid [\varepsilon_{f_1} + \cdots + \varepsilon_{f_{n-1}} = t_n - \varepsilon_\sigma] \& [f_n = \sigma]\}$ ,

it follows that, under the standard bijection  $\Sigma^n \leftrightarrow \Sigma^{n-1} \times \Sigma$ , we have:

$$\{f \in \Omega_n \mid f_n = \sigma\} \subseteq \Sigma^n$$

corresponds to  $X \times \{\sigma\} \subseteq \Sigma^{n-1} \times \Sigma$ .

Then:  $\mu^n\{f \in \Omega_n \mid f_n = \sigma\} = (\mu^{n-1}(X)) \cdot (\mu\{\sigma\})$ .

**Want:**  $\mu^n\{f \in \Omega_n \mid f_n = \sigma_0\} = (\mu^{n-1}(X)) \cdot (\mu\{\sigma\})$ .

By Claim 4, we have:  $\mu\{\sigma\} = \mu\{\sigma_0\}$ .

**Want:**  $\mu^n\{f \in \Omega_n \mid f_n = \sigma_0\} = (\mu^{n-1}(X)) \cdot (\mu\{\sigma_0\})$ .

Since  $\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}$ , we get:  $\varepsilon(\sigma) \in \{\varepsilon_{\sigma_0}\}$ .

Since  $\varepsilon_\sigma = \varepsilon(\sigma) \in \{\varepsilon_{\sigma_0}\}$ , we get:  $\varepsilon_\sigma = \varepsilon_{\sigma_0}$ .

Then  $X = \{f \in \Sigma^{n-1} \mid \varepsilon_{f_1} + \cdots + \varepsilon_{f_{n-1}} = t_n - \varepsilon_{\sigma_0}\}$ .

Since  $\{f \in \Omega_n \mid f_n = \sigma_0\}$   
 $= \{f \in \Sigma^n \mid [\varepsilon_{f_1} + \cdots + \varepsilon_{f_{n-1}} + \varepsilon_{f_n} = t_n] \& [f_n = \sigma_0]\}$   
 $= \{f \in \Sigma^n \mid [\varepsilon_{f_1} + \cdots + \varepsilon_{f_{n-1}} + \varepsilon_{\sigma_0} = t_n] \& [f_n = \sigma_0]\}$   
 $= \{f \in \Sigma^n \mid [\varepsilon_{f_1} + \cdots + \varepsilon_{f_{n-1}} = t_n - \varepsilon_{\sigma_0}] \& [f_n = \sigma_0]\}$ ,

it follows that, under the standard bijection  $\Sigma^n \leftrightarrow \Sigma^{n-1} \times \Sigma$ , we have:

$$\{f \in \Omega_n \mid f_n = \sigma_0\} \subseteq \Sigma^n$$

corresponds to  $X \times \{\sigma_0\} \subseteq \Sigma^{n-1} \times \Sigma$ .

Then:  $\mu^n\{f \in \Omega_n \mid f_n = \sigma_0\} = (\mu^{n-1}(X)) \cdot (\mu\{\sigma_0\})$ .

*End of proof of Claim 6.*

*Claim 7: Let*  $n \in [2..\infty)$ .

Then:  $\tilde{\mu}^n\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \varepsilon_{\sigma_0}\} = k \cdot (\mu^n\{f \in \Omega_n \mid f_n = \sigma_0\})$ .



*Proof of Claim 7:* Recall:  $\tilde{\mu}^n = (\varepsilon^n)_*(\mu^n)$ . Recall:  $(\varepsilon^n)^*\tilde{\Omega}_n = \Omega_n$ .

Then  $(\varepsilon^n)^*\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \varepsilon_{\sigma_0}\} = \{f \in \Omega_n \mid f_n \in \varepsilon^*\{\varepsilon_{\sigma_0}\}\}$ ,

and so  $\mu^n((\varepsilon^n)^*\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \varepsilon_{\sigma_0}\}) = \mu^n\{f \in \Omega_n \mid f_n \in \varepsilon^*\{\varepsilon_{\sigma_0}\}\}$ .

Then:  $((\varepsilon^n)_*(\mu^n))\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \varepsilon_{\sigma_0}\} = \mu^n\{f \in \Omega_n \mid f_n \in \varepsilon^*\{\varepsilon_{\sigma_0}\}\}$ .

Then:  $\tilde{\mu}^n\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \varepsilon_{\sigma_0}\} = \mu^n\{f \in \Omega_n \mid f_n \in \varepsilon^*\{\varepsilon_{\sigma_0}\}\}$ .

**Want:**  $\mu^n\{f \in \Omega_n \mid f_n \in \varepsilon^*\{\varepsilon_{\sigma_0}\}\} = k \cdot (\mu^n\{f \in \Omega_n \mid f_n = \sigma_0\})$ .

Since  $\{f \in \Omega_n \mid f_n \in \varepsilon^*\{\varepsilon_{\sigma_0}\}\}$

is the disjoint union, over  $\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}$ , of

$$\{f \in \Omega_n \mid f_n = \sigma\},$$

we get:  $\mu^n\{f \in \Omega_n \mid f_n \in \varepsilon^*\{\varepsilon_{\sigma_0}\}\} = \sum_{\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}} [\mu^n\{f \in \Omega_n \mid f_n = \sigma\}]$ .

Then, by Claim 6, we conclude:

$$\mu^n\{f \in \Omega_n \mid f_n \in \varepsilon^*\{\varepsilon_{\sigma_0}\}\} = \sum_{\sigma \in \varepsilon^*\{\varepsilon_{\sigma_0}\}} [\mu^n\{f \in \Omega_n \mid f_n = \sigma_0\}].$$

So, since  $k = \#(\varepsilon^*\{\varepsilon_{\sigma_0}\})$ , we get:

$$\mu^n\{f \in \Omega_n \mid f_n \in \varepsilon^*\{\varepsilon_{\sigma_0}\}\} = k \cdot (\mu^n\{f \in \Omega_n \mid f_n = \sigma_0\}).$$

*End of proof of Claim 7.*

Recall:  $\forall n \in \mathbb{N}$ ,  $\mu^n(\Omega_n) = \tilde{\mu}^n(\tilde{\Omega}_n)$ .

Recall:  $\forall n \in [n_0.. \infty)$ ,  $0 < \mu^n(\Omega_n) \leq 1$ .

Then:  $\forall n \in [n_0.. \infty)$ ,  $0 < \tilde{\mu}^n(\tilde{\Omega}_n) \leq 1$ .

Also,  $\forall n \in \mathbb{N}$ ,  $\forall S \subseteq \tilde{\Omega}_n$ ,  $(\tilde{\mu}^n|_{\tilde{\Omega}_n})(S) = \tilde{\mu}^n(S)$ .

Then:  $\forall n \in \mathbb{N}$ ,  $(\tilde{\mu}^n|_{\tilde{\Omega}_n})(\tilde{\Omega}_n) = \tilde{\mu}^n(\tilde{\Omega}_n)$ .

By dividing the last two equations, we get:

$$\forall n \in [n_0.. \infty), \forall S \subseteq \tilde{\Omega}_n, (\mathcal{N}(\tilde{\mu}^n|_{\tilde{\Omega}_n}})(S) = (\tilde{\mu}^n(S))/(\tilde{\mu}^n(\tilde{\Omega}_n)).$$

For all  $n \in [n_0.. \infty)$ , let  $\tilde{\lambda}_n := \mathcal{N}(\tilde{\mu}^n|_{\tilde{\Omega}_n})$ .

Then:  $\forall n \in [n_0.. \infty)$ ,  $\forall S \subseteq \tilde{\Omega}_n$ ,  $\tilde{\lambda}_n(S) = (\tilde{\mu}^n(S))/(\tilde{\mu}^n(\tilde{\Omega}_n))$ .

So, since  $\forall n \in \mathbb{N}$ ,  $z_n = \mu^n(\Omega_n) = \tilde{\mu}^n(\tilde{\Omega}_n)$ , we get:

$$\forall n \in [n_0.. \infty), \forall S \subseteq \tilde{\Omega}_n, \tilde{\lambda}_n(S) = (\tilde{\mu}^n(S))/z_n.$$

Recall:  $\forall n \in [n_0.. \infty)$ ,  $\lambda_n = \mathcal{N}(\mu^n|_{\Omega_n})$ .

Recall:  $\forall n \in [n_0.. \infty)$ ,  $\forall S \subseteq \Omega_n$ ,  $\lambda_n(S) = (\mu^n(S))/z_n$ .

**Claim 8: Let**  $n \in [n_0.. \infty)$ .

Then:  $\tilde{\lambda}_n\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \varepsilon_{\sigma_0}\} = k \cdot (\lambda_n\{f \in \Omega_n \mid f_n = \sigma_0\})$ .

*Proof of Claim 8:* By choice of  $n_0$ , we have:  $n_0 \in [2.. \infty)$ .

Then  $[n_0.. \infty) \subseteq [2.. \infty)$ , so, since  $n \in [n_0.. \infty)$ , we get:  $n \in [2.. \infty)$ .

Then, by Claim 7,  $\tilde{\mu}^n\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \varepsilon_{\sigma_0}\} = k \cdot (\mu^n\{f \in \Omega_n \mid f_n = \sigma_0\})$ .

Dividing this last equation by  $z_n$  yields

$$\tilde{\lambda}_n\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \varepsilon_{\sigma_0}\} = k \cdot (\lambda_n\{f \in \Omega_n \mid f_n = \sigma_0\}).$$

End of proof of Claim 8.

**Let**  $P := \mu\{\sigma_0\}$  and  $\tilde{P} := \tilde{\mu}\{\varepsilon_{\sigma_0}\}$ . Recall:  $k \geq 1$ .

By Claim 5, we have:  $\mu(\varepsilon^*\{\varepsilon_{\sigma_0}\}) = k \cdot (\mu\{\sigma_0\})$ .

Recall:  $\tilde{\mu} = \varepsilon_*\mu$ .

Since  $\tilde{P} = \tilde{\mu}\{\varepsilon_{\sigma_0}\} = (\varepsilon_*\mu)\{\varepsilon_{\sigma_0}\} = \mu(\varepsilon^*\{\varepsilon_{\sigma_0}\}) = k \cdot (\mu\{\sigma_0\}) = k \cdot P$ ,  
we get:  $\tilde{P}/k = P$ .

Recall:  $M_{\tilde{\mu}} = \alpha$  and  $\tilde{\mu} \in \mathcal{P}_E$  and  $S_{\tilde{\mu}} = E$ .

Recall:  $E$  is residue-unconstrained and  $|\tilde{\mu}|_2 < \infty$ .

Since  $\varepsilon_{\sigma_0} = \varepsilon(\sigma_0) \in \mathbb{I}_\varepsilon = E$ , we get:  $\varepsilon_{\sigma_0} \in E$ .

**Let**  $\tilde{\varepsilon}_0 := \varepsilon_{\sigma_0}$ . Then:  $\tilde{\varepsilon}_0 \in E$  and  $\tilde{P} = \tilde{\mu}\{\tilde{\varepsilon}_0\}$ .

Recall:  $\forall n \in \mathbb{N}$ ,  $\tilde{\Omega}_n := \{\tilde{f} \in E^n \mid \tilde{f}_1 + \dots + \tilde{f}_n = t_n\}$ .

By hypothesis,  $t_1, t_2, \dots \in \mathbb{Z}$  and  $\{t_n - n\alpha \mid n \in \mathbb{N}\}$  is bounded.

By Theorem 11.2, as  $n \rightarrow \infty$ ,  $\mathcal{N}(\tilde{\mu}^n | \tilde{\Omega}_n)\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \tilde{\varepsilon}_0\} \rightarrow \tilde{P}$ .

Recall:  $\forall n \in [n_0.. \infty)$ ,  $\tilde{\lambda}_n = \mathcal{N}(\tilde{\mu}^n | \tilde{\Omega}_n)$ .

Then: as  $n \rightarrow \infty$ ,  $\tilde{\lambda}_n\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \tilde{\varepsilon}_0\} \rightarrow \tilde{P}$ .

Then: as  $n \rightarrow \infty$ ,  $\tilde{\lambda}_n\{\tilde{f} \in \tilde{\Omega}_n \mid \tilde{f}_n = \varepsilon_{\sigma_0}\} \rightarrow \tilde{P}$ .

So, by Claim 8, as  $n \rightarrow \infty$ ,  $k \cdot (\lambda_n\{f \in \Omega_n \mid f_n = \sigma_0\}) \rightarrow \tilde{P}$ .

Then: as  $n \rightarrow \infty$ ,  $\lambda_n\{f \in \Omega_n \mid f_n = \sigma_0\} \rightarrow \tilde{P}/k$ .

So, by Claim 3, as  $n \rightarrow \infty$ ,  $\nu_{\Omega_n}\{f \in \Omega_n \mid f_n = \sigma_0\} \rightarrow \tilde{P}/k$ .

Recall:  $\mu = B_\beta^\varepsilon$ .

Then, since  $\tilde{P}/k = P = \mu\{\sigma_0\} = B_\beta^\varepsilon\{\sigma_0\}$ , we get:

$$\text{as } n \rightarrow \infty, \quad \nu_{\Omega_n}\{f \in \Omega_n \mid f_n = \sigma_0\} \rightarrow B_\beta^\varepsilon\{\sigma_0\}. \quad \square$$

The possibility of degeneracy at  $\tilde{\varepsilon}_0$  (i.e., the possibility that  $k \neq 1$ ) causes a number of complications in the preceding proof.

Here is another approach to proving Theorem 21.1:

By density of the set of injective functions  $\Sigma \rightarrow \mathbb{R}$  in the topological space of all functions  $\Sigma \rightarrow \mathbb{R}$ , we reduce to the case where  $\varepsilon$  is injective.

Then the proof can follow the proof of Theorem 16.1, avoiding the degeneracy complications in the preceding proof.

Recall (§2):  $\forall t \in \mathbb{R}$ ,  $\lfloor t \rfloor$  is the floor of  $t$ .

Next, we record the  $t_n = \lfloor n\alpha \rfloor$  version of the preceding theorem:

**THEOREM 21.2.** Let  $\Sigma$  be a finite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$ . Assume  $\mathbb{I}_\varepsilon$  is residue-unconstrained.

Let  $\alpha \in (\min \mathbb{I}_\varepsilon; \max \mathbb{I}_\varepsilon)$ . Let  $\beta := \text{BP}_\alpha^\varepsilon$ .

For all  $n \in \mathbb{N}$ , **let**  $\Omega_n := \{f \in \Sigma^n \mid (\varepsilon(f_1)) + \cdots + (\varepsilon(f_n)) = \lfloor n\alpha \rfloor\}$ .  
**Let**  $\sigma_0 \in \Sigma$ . *Then:* as  $n \rightarrow \infty$ ,  $\nu_{\Omega_n} \{f \in \Omega_n \mid f_n = \sigma_0\} \rightarrow B_\beta^\varepsilon\{\sigma_0\}$ .

We record the  $\alpha \in \mathbb{Z}$  special case of the preceding theorem:

**THEOREM 21.3.** **Let**  $\Sigma$  be a finite set.

**Let**  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$ . Assume  $\mathbb{I}_\varepsilon$  is residue-unconstrained.

**Let**  $\alpha \in (\min \mathbb{I}_\varepsilon; \max \mathbb{I}_\varepsilon)$ . Assume  $\alpha \in \mathbb{Z}$ . **Let**  $\beta := \text{BP}_\alpha^\varepsilon$ .

For all  $n \in \mathbb{N}$ , **let**  $\Omega_n := \{f \in \Sigma^n \mid (\varepsilon(f_1)) + \cdots + (\varepsilon(f_n)) = n\alpha\}$ .

**Let**  $\sigma_0 \in \Sigma$ . *Then:* as  $n \rightarrow \infty$ ,  $\nu_{\Omega_n} \{f \in \Omega_n \mid f_n = \sigma_0\} \rightarrow B_\beta^\varepsilon\{\sigma_0\}$ .

*Example:* Suppose  $\Sigma = \{0, 1, 10\}$  and  $\alpha = 1$ .

Suppose, also,  $\forall \sigma \in \Sigma$ ,  $\varepsilon(\sigma) = \sigma$ .

Then  $\Omega_N$  represents

the set of all GFA dispensations to the  $N$  professors.

Since  $\nu_{\Omega_N}$  gives equal probability to each dispensation,

$\nu_{\Omega_N}$  represents the GFA's first system for awarding grants.

Since  $\beta = \text{BP}_\alpha^\varepsilon = \text{BP}_1^\varepsilon$ , we calculate:  $\beta = (\ln 9)/10$ .

More calculation gives:  $(B_\beta^\varepsilon\{0\}, B_\beta^\varepsilon\{1\}, B_\beta^\varepsilon\{10\}) = \frac{(1, 9^{-1/10}, 9^{-1})}{1 + 9^{-1/10} + 9^{-1}}$ .

Since  $N$  is large, by Theorem 21.3, we get:

$$\nu_{\Omega_N} \{f \in \Omega_N \mid f_N = \sigma_0\} \approx B_\beta^\varepsilon\{\sigma_0\}.$$

So, if I am the  $N$ th professor, then, under the first system,

my probability of receiving  $\sigma_0$  dollars

is approximately equal to  $B_\beta^\varepsilon\{\sigma_0\}$ .

Thus Theorem 21.3 reproduces the result of §12.

*Example:* Suppose  $\Sigma = ([0..4] \times [0..4]) \setminus \{(4, 4)\}$ .

Suppose, also,  $\alpha = 1$  and  $\forall \sigma \in \Sigma$ ,  $\varepsilon(\sigma) = \sigma_1 + \sigma_2$ .

Then  $\Omega_N$  represents

the set of all state-distributions at the BUA. (See §19.)

Since  $\beta = \text{BP}_\alpha^\varepsilon = \text{BP}_1^\varepsilon$ , we calculate:

$\beta \approx 1.0670$ , accurate to four decimal places.

**Let**  $M \in \mathbb{R}^{5 \times 5}$  be the matrix defined by:  $M_{55} = 0$  and

$$\forall (i, j) \in ([1..5] \times [1..5]) \setminus \{(5, 5)\}, \quad M_{ij} = B_\beta^\varepsilon\{(i-1, j-1)\}.$$

$$\text{Then } M \approx \begin{bmatrix} 0.4345 & 0.1495 & 0.0514 & 0.0177 & 0.0061 \\ 0.1495 & 0.0514 & 0.0177 & 0.0061 & 0.0021 \\ 0.0514 & 0.0177 & 0.0061 & 0.0021 & 0.0007 \\ 0.0177 & 0.0061 & 0.0021 & 0.0007 & 0.0002 \\ 0.0061 & 0.0021 & 0.0007 & 0.0002 & 0 \end{bmatrix}$$

all accurate to four decimal places.

(Thanks to C. Prouty for these calculations. See §29.)

According to Theorem 21.3, this answers

the problem formulated near the end of §19.

Since  $B_\beta^\varepsilon\{(0,0)\} = M_{11} = 0.4345$ , it is possible (cf. §14) to prove:

If  $N$  is sufficiently large, then, more than 99% of the time,  
over 43% of the BUA professors have \$0 wealth.

## 22. $\infty$ -PROPERNESS AND $(-\infty)$ -PROPERNESS

Recall (§2): the notations  $\mathbb{I}_f$  and  $f^*A$ .

**DEFINITION 22.1.** Let  $\Sigma$  be a set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

By  $\varepsilon$  is  $\infty$ -proper, we mean:  $\forall t \in \mathbb{R}, \#\{\sigma \in \Sigma \mid \varepsilon(\sigma) \leq t\} < \infty$ .

That is,  $\forall t \in \mathbb{R}, \#(\sigma^*(-\infty; t]) < \infty$ .

Note that, for any finite set  $\Sigma$ , for any  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  
we have:  $\varepsilon$  is  $\infty$ -proper.

**THEOREM 22.2.** Let  $\Sigma$  be a nonempty set.

If  $\exists \varepsilon : \Sigma \rightarrow \mathbb{R}$  s.t.  $\varepsilon$  is  $\infty$ -proper, then  $\Sigma$  is countable.

The next result asserts that, for a nonempty set  $\Sigma$ ,

if  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  is  $\infty$ -proper,

then its image  $\mathbb{I}_\varepsilon$  has a minimal element, i.e.,  $\min \mathbb{I}_\varepsilon$  exists.

**THEOREM 22.3.** Let  $\Sigma$  be a set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper.

Assume:  $\Sigma \neq \emptyset$ . Then:  $\exists t_0 \in \mathbb{I}_\varepsilon$  s.t.,  $\forall t \in \mathbb{I}_\varepsilon, t \geq t_0$ .

**THEOREM 22.4.** Let  $\Sigma$  be a set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper.

Then:  $\mathbb{I}_\varepsilon$  is bounded below and  $\forall t \in \mathbb{I}_\varepsilon, \varepsilon^*\{t\}$  is finite.

The preceding three theorems are basic; we omit the proofs.

When  $\varepsilon$  is  $\mathbb{Z}$ -valued, the converse of Theorem 22.4 is also true:

**THEOREM 22.5.** Let  $\Sigma$  be a set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$ .

Then:  $[\varepsilon \text{ is } \infty\text{-proper}]$

$\Leftrightarrow [(\mathbb{I}_\varepsilon \text{ is bounded below}) \ \& \ (\forall t \in \mathbb{I}_\varepsilon, \varepsilon^*\{t\} \text{ is finite})].$

The preceding is basic; we omit the proof.

The following two results are corollaries of Theorem 22.5:

**THEOREM 22.6.** Let  $\Sigma$  be a set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$  be injective.

Then:  $[\varepsilon \text{ } \infty\text{-proper}] \Leftrightarrow [\mathbb{I}_\varepsilon \text{ is bounded below}].$

**THEOREM 22.7.** Let  $\Sigma \subseteq \mathbb{Z}$ .

**Define**  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:  $\forall \sigma \in \Sigma, \varepsilon(\sigma) = \sigma$ .

*Then:*  $[\varepsilon \text{ } \infty\text{-proper}] \Leftrightarrow [\Sigma \text{ is bounded below}]$ .

**DEFINITION 22.8.** Let  $\Sigma$  be a set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

By  $\varepsilon$  is  $\boxed{(-\infty)\text{-proper}}$ , we mean:  $\forall t \in \mathbb{R}, \#\{\sigma \in \Sigma \mid \varepsilon(\sigma) \geq t\} < \infty$ .

**THEOREM 22.9.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

*Then:*  $(\varepsilon \text{ is } (-\infty)\text{-proper}) \Leftrightarrow (-\varepsilon \text{ is } \infty\text{-proper})$ .

**THEOREM 22.10.** Let  $\Sigma$  be a finite set.

*Then:*  $\forall \varepsilon : \Sigma \rightarrow \mathbb{R}, \varepsilon$  is both  $\infty$ -proper and  $(-\infty)$ -proper.

**THEOREM 22.11.** Let  $\Sigma$  be a set.

*Assume:*  $\exists \varepsilon : \Sigma \rightarrow \mathbb{R}$  s.t.  $\varepsilon$  is both  $\infty$ -proper and  $(-\infty)$ -proper.

*Then:*  $\Sigma$  is finite.

The preceding three theorems are basic; we omit the proofs.

### 23. BOLTZMANN DISTRIBUTIONS ON COUNTABLE SETS

In the next few sections,

we generalize our earlier work on Boltzmann distributions (§20) to allow for a countably infinite set of states.

Recall (§8) the notations:  $\mathcal{M}_\Theta, \mathcal{FM}_\Theta^\times, \mathcal{P}_\Theta, \mathcal{N}(\mu)$ .

**DEFINITION 23.1.** Let  $\Sigma$  be a countable set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}, \beta \in \mathbb{R}$ .

*Then*  $\boxed{\hat{B}_\beta^\varepsilon} \in \mathcal{M}_\Sigma$  is defined by:  $\forall \sigma \in \Sigma, \hat{B}_\beta^\varepsilon\{\sigma\} = e^{-\beta \cdot (\varepsilon(\sigma))}$ .

**DEFINITION 23.2.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}, \beta \in \mathbb{R}$ .

*For all*  $\sigma \in \Sigma$ , **let**  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

*Then:*  $\boxed{\Delta_\beta^\varepsilon} := \sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}] \in [0; \infty]$ .

We have:  $\forall$  nonempty set  $\Sigma, \forall \varepsilon : \Sigma \rightarrow \mathbb{R}, \forall \beta \in \mathbb{R}, \Delta_\beta^\varepsilon > 0$ .

**Let**  $\Sigma$  be a countable set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}, \beta \in \mathbb{R}$ .

Since  $\Delta_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [\hat{B}_\beta^\varepsilon\{\sigma\}]$ , we get:  $\Delta_\beta^\varepsilon = \hat{B}_\beta^\varepsilon(\Sigma)$ .

**DEFINITION 23.3.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

*Then the*  $\boxed{\text{Delta-finite-set}}$  of  $\varepsilon$  is:  $\boxed{\text{DF}_\varepsilon} := \{\beta \in \mathbb{R} \mid \Delta_\beta^\varepsilon < \infty\}$ .

We have:  $\forall$ finite set  $\Sigma$ ,  $\forall \varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\forall \beta \in \mathbb{R}$ ,  $\Delta_\beta^\varepsilon < \infty$ .  
 Then:  $\forall$ finite set  $\Sigma$ ,  $\forall \varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\text{DF}_\varepsilon = \mathbb{R}$ .

**Let**  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Since  $\forall \beta \in \mathbb{R}$ ,  $\Delta_{-\beta}^{-\varepsilon} = \Delta_\beta^\varepsilon$ , we get:  $\text{DF}_{-\varepsilon} = -\text{DF}_\varepsilon$ .

**Let**  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\xi \in \mathbb{R}$ .

Since  $\forall \beta \in \mathbb{R}$ ,  $\Delta_\beta^{\varepsilon+\xi} = e^{-\beta \cdot \xi} \cdot \Delta_\beta^\varepsilon$ , we get:  $\text{DF}_{\varepsilon+\xi} = \text{DF}_\varepsilon$ .

For any countable set  $\Sigma$ , for any  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ , for any  $\beta \in \mathbb{R}$ ,

$$\begin{aligned} & (\Sigma \neq \emptyset \text{ and } \beta \in \text{DF}_\varepsilon) \Leftrightarrow \\ & (0 < \Delta_\beta^\varepsilon < \infty) \Leftrightarrow (0 < \widehat{B}_\beta^\varepsilon(\Sigma) < \infty) \Leftrightarrow (\widehat{B}_\beta^\varepsilon \in \mathcal{FM}_\Sigma^\times). \end{aligned}$$

**DEFINITION 23.4.** **Let**  $\Sigma$  be a countable set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta \in \mathbb{R}$ .

Assume:  $0 < \Delta_\beta^\varepsilon < \infty$ . Then:  $\boxed{B_\beta^\varepsilon} := \mathcal{N}(\widehat{B}_\beta^\varepsilon) \in \mathcal{P}_\Sigma$ .

**Let**  $\Sigma$  be a countable set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

If  $\text{DF}_\varepsilon = \emptyset$ , then, for all  $\beta \in \mathbb{R}$ , since  $\widehat{B}_\beta^\varepsilon(\Sigma) = \Delta_\beta^\varepsilon = \infty$ ,

we see that  $\widehat{B}_\beta^\varepsilon$  cannot be normalized, *i.e.*, there is no  $B_\beta^\varepsilon$ .

So, if  $\text{DF}_\varepsilon = \emptyset$ , then we have no Boltzmann distributions to study.

So, going forward, we generally focus on cases where  $\text{DF}_\varepsilon \neq \emptyset$ .

**Let**  $\Sigma$  be a countable set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

In case  $\Sigma = \emptyset$ ,  $\varepsilon$  is the empty function, and there is nothing to say.

In case  $\Sigma$  is nonempty and finite,

we already developed a satisfactory Boltzmann theory, in §20.

So, going forward, we generally focus on cases where  $\Sigma$  is infinite.

Recall (§2): the notations  $\mathbb{I}_f$  and  $f^*A$ .

**Let**  $\Sigma$  be an infinite set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ . Then:  $\varepsilon^*\mathbb{R} = \Sigma$ ,

We have:  $(-\infty; 0] \cup [0; \infty) = \mathbb{R}$ .

Since  $(\varepsilon^*(-\infty; 0]) \cup (\varepsilon^*[0; \infty)) = \varepsilon^*\mathbb{R} = \Sigma$ ,

we get either  $\varepsilon^*(-\infty; 0]$  is infinite or  $\varepsilon^*[0; \infty)$  is infinite,

and the Boltzmann theory splits into those two cases.

Also, by Theorem 23.7 below, if  $\text{DF}_\varepsilon \neq \emptyset$ ,

then only one of the two cases can happen.

**THEOREM 23.5.** **Let**  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\varepsilon^*[0; \infty)$  is infinite. Then:  $\text{DF}_\varepsilon \subseteq (0; \infty)$ .

*Proof.* **Given**  $\beta \in \text{DF}_\varepsilon$ , **want:**  $\beta \in (0; \infty)$ .  
 Since  $\text{DF}_\varepsilon \subseteq \mathbb{R}$ , we get:  $\beta \in \mathbb{R}$ .  
**Want:**  $\beta > 0$ . Assume:  $\beta \leq 0$ . **Want:** Contradiction.  
 For all  $\sigma \in \Sigma$ , **let**  $\varepsilon_\sigma := \varepsilon(\sigma)$ .  
 For all  $\sigma \in \varepsilon^*[0; \infty)$ , since  $\varepsilon_\sigma = \varepsilon(\sigma) \in [0; \infty)$ , we get:  $\varepsilon_\sigma \geq 0$ .  
 So, since  $\beta \leq 0$ , we get:  $\forall \sigma \in \varepsilon^*[0; \infty)$ ,  $-\beta \cdot \varepsilon_\sigma \geq 0$ .  
 Then:  $\forall \sigma \in \varepsilon^*[0; \infty)$ ,  $e^{-\beta \cdot \varepsilon_\sigma} \geq 1$ .  
 So, since  $\varepsilon^*[0; \infty)$  is infinite, we get:  $\sum_{\sigma \in \varepsilon^*[0; \infty)} [e^{-\beta \cdot \varepsilon_\sigma}] = \infty$ .  
 Since  $\Delta_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}] \geq \sum_{\sigma \in \varepsilon^*[0; \infty)} [e^{-\beta \cdot \varepsilon_\sigma}] = \infty$ ,  
 we get:  $\beta \notin \text{DF}_\varepsilon$ . Contradiction.  $\square$

**THEOREM 23.6.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\varepsilon^*(-\infty; 0]$  is infinite. Then:  $\text{DF}_\varepsilon \subseteq (-\infty; 0)$ .

*Proof.* Since  $(-\varepsilon)^*[0; \infty) = \varepsilon^*(-\infty; 0]$ , we get:  $(-\varepsilon)^*[0; \infty)$  is infinite.  
 Then, by Theorem 23.5, we get:  $\text{DF}_{-\varepsilon} \subseteq (0; \infty)$ .  
 Then  $\text{DF}_\varepsilon = -\text{DF}_{-\varepsilon} \subseteq -(0; \infty) = (-\infty; 0)$ .  $\square$

**THEOREM 23.7.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\varepsilon^*(-\infty; 0]$  and  $\varepsilon^*[0; \infty)$  are both infinite. Then:  $\text{DF}_\varepsilon = \emptyset$ .

*Proof.* By Theorem 23.5, we get:  $\text{DF}_\varepsilon \subseteq (0; \infty)$ .  
 By Theorem 23.6, we get:  $\text{DF}_\varepsilon \subseteq (-\infty; 0)$ .  
 Since  $\text{DF}_\varepsilon \subseteq (-\infty; 0) \cap (0; \infty) = \emptyset$ , we get:  $\text{DF}_\varepsilon = \emptyset$ .  $\square$

**THEOREM 23.8.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\text{DF}_\varepsilon \cap [0; \infty) \neq \emptyset$ . Then:  $\varepsilon$  is  $\infty$ -proper.

*Proof.* **Given**  $t \in \mathbb{R}$ , **let**  $\Sigma_0 := \{\sigma \in \Sigma \mid \varepsilon(\sigma) \leq t\}$ , **want:**  $\#\Sigma_0 < \infty$ .  
 Since  $\text{DF}_\varepsilon \cap [0; \infty) \neq \emptyset$ , **choose**  $\beta \in \text{DF}_\varepsilon \cap [0; \infty)$ .  
 Then  $\beta \in \text{DF}_\varepsilon$  and  $\beta \in [0; \infty)$ .  
 Since  $\beta \in \text{DF}_\varepsilon$ , we get:  $\Delta_\beta^\varepsilon < \infty$ . Then:  $e^{\beta \cdot t} \cdot \Delta_\beta^\varepsilon < \infty$ .  
 For all  $\sigma \in \Sigma$ , **let**  $\varepsilon_\sigma := \varepsilon(\sigma)$ . Then:  $\Delta_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}]$ .  
 By definition of  $\Sigma_0$ , we have:  $\forall \sigma \in \Sigma_0$ ,  $\varepsilon(\sigma) \leq t$ .  
 Since  $\beta \in [0; \infty)$  and since  $\forall \sigma \in \Sigma_0$ ,  $t \geq \varepsilon(\sigma) = \varepsilon_\sigma$ ,  
 we get:  $\forall \sigma \in \Sigma_0$ ,  $-\beta \cdot t \leq -\beta \cdot \varepsilon_\sigma$ .  
 Then:  $\forall \sigma \in \Sigma_0$ ,  $e^{-\beta \cdot t} \leq e^{-\beta \cdot \varepsilon_\sigma}$ .  
 Then:  $\#\Sigma_0 = \sum_{\sigma \in \Sigma_0} [1] = e^{\beta \cdot t} \cdot \sum_{\sigma \in \Sigma_0} [e^{-\beta \cdot t}] \leq e^{\beta \cdot t} \cdot \sum_{\sigma \in \Sigma_0} [e^{-\beta \cdot \varepsilon_\sigma}]$   
 $\leq e^{\beta \cdot t} \cdot \sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}] = e^{\beta \cdot t} \cdot \Delta_\beta^\varepsilon < \infty$ .  $\square$

**THEOREM 23.9.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\text{DF}_\varepsilon \cap (-\infty; 0] \neq \emptyset$ . Then:  $\varepsilon$  is  $(-\infty)$ -proper.

*Proof.* Since  $-(DF_\varepsilon \cap (-\infty; 0]) \neq \emptyset$ ,  
we get:  $DF_{-\varepsilon} \cap [0; \infty) \neq \emptyset$ .

Then, by Theorem 23.8,  $-\varepsilon$  is  $\infty$ -proper, and so  $\varepsilon$  is  $(-\infty)$ -proper.  $\square$

**THEOREM 23.10.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $DF_\varepsilon \neq \emptyset$ . Then:  $\Sigma$  is countable.

*Proof.* Since  $(DF_\varepsilon \cap (-\infty; 0]) \cup (DF_\varepsilon \cap [0; \infty)) = DF_\varepsilon \neq \emptyset$ ,  
it follows that: either  $DF_\varepsilon \cap (-\infty; 0] \neq \emptyset$  or  $DF_\varepsilon \cap [0; \infty) \neq \emptyset$ .  
Then, by Theorem 23.9 or Theorem 23.8,  
we get: either  $\varepsilon$  is  $(-\infty)$ -proper or  $\varepsilon$  is  $\infty$ -proper.  
Then: either  $-\varepsilon$  is  $\infty$ -proper or  $\varepsilon$  is  $\infty$ -proper.  
In either case, by Theorem 22.2, we get:  $\Sigma$  is countable.  $\square$

**THEOREM 23.11.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $DF_\varepsilon \cap (-\infty; 0] \neq \emptyset \neq DF_\varepsilon \cap [0; \infty)$ . Then:  $\Sigma$  is finite.

*Proof.* By Theorem 23.8, we get:  $\varepsilon$  is  $\infty$ -proper.

By Theorem 23.9, we get:  $\varepsilon$  is  $(-\infty)$ -proper.

Then, by Theorem 22.11, we get:  $\Sigma$  is finite.  $\square$

**THEOREM 23.12.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\varepsilon^*[0; \infty)$  is infinite and  $DF_\varepsilon \neq \emptyset$ . Then:  $\varepsilon$  is  $\infty$ -proper.

*Proof.* By Theorem 23.5, we have:  $DF_\varepsilon \subseteq (0; \infty)$ .

Since  $DF_\varepsilon \subseteq (0; \infty) \subseteq [0; \infty)$ , we get:  $DF_\varepsilon \cap [0; \infty) = DF_\varepsilon$ .

Since  $DF_\varepsilon \cap [0; \infty) = DF_\varepsilon \neq \emptyset$ , by Theorem 23.8,

we get:  $\varepsilon$  is  $\infty$ -proper.  $\square$

**THEOREM 23.13.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\varepsilon^*(-\infty; 0]$  is infinite and  $DF_\varepsilon \neq \emptyset$ . Then:  $\varepsilon$  is  $(-\infty)$ -proper.

*Proof.* Since  $(-\varepsilon)^*[0; \infty) = \varepsilon^*(-\infty; 0]$ , we get:  $(-\varepsilon)^*[0; \infty)$  is infinite.

Since  $DF_{-\varepsilon} = -DF_\varepsilon$ , we get:  $DF_{-\varepsilon} \neq \emptyset$ .

Then, by Theorem 23.12,  $-\varepsilon$  is  $\infty$ -proper, so  $\varepsilon$  is  $(-\infty)$ -proper.  $\square$

**DEFINITION 23.14.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta \in \mathbb{R}$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

Then,  $\forall$  real  $\rho \geq 0$ , the  $\rho$ -exponent  $(\beta, \varepsilon)$ -absolute-sum is:

$$\overline{X}^\rho S_\beta^\varepsilon := \sum_{\sigma \in \Sigma} [|\varepsilon_\sigma|^\rho \cdot |e^{-\beta \cdot \varepsilon_\sigma}|] \in [0; \infty).$$

Also,  $\forall \rho \in [0; \infty)$ , if  $\overline{X}^\rho S_\beta^\varepsilon < \infty$ ,



then the  $\boxed{\rho\text{-exponent } (\beta, \varepsilon)\text{-sum}}$  is:

$$\boxed{X^\rho S_\beta^\varepsilon} := \sum_{\sigma \in \Sigma} [\varepsilon_\sigma^\rho \cdot e^{-\beta \cdot \varepsilon_\sigma}] \in [0; \infty].$$

Recall our convention (§2):  $0^0 = 1$ . Then:  $\bar{X}^0 S_\beta^\varepsilon = X^0 S_\beta^\varepsilon = \Delta_\beta^\varepsilon$ .

Also, if  $\bar{X}^\rho S_\beta^\varepsilon < \infty$ , then, by subadditivity of absolute value,

$$\text{we get: } |X^\rho S_\beta^\varepsilon| \leq \bar{X}^\rho S_\beta^\varepsilon.$$

Also, if  $\bar{X}^1 S_\beta^\varepsilon < \infty$ , then  $X^1 S_\beta^\varepsilon = \Gamma_\beta^\varepsilon$ .

**THEOREM 23.15.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\text{DF}_\varepsilon \neq \emptyset$  and  $\mathbb{I}_\varepsilon$  is bounded below. Let  $\rho \geq 0$  be real.

Let  $\beta_0 := \inf \text{DF}_\varepsilon$  and let  $\gamma > \beta_0$  be real. Then:  $\bar{X}^\rho S_\gamma^\varepsilon < \infty$ .

We cannot replace “ $\gamma > \beta$ ” with “ $\gamma \geq \beta$ ”, see Theorem 23.18 below.

*Proof.* Since  $\gamma > \beta_0 = \inf \text{DF}_\varepsilon$ , choose  $\beta \in \text{DF}_\varepsilon$  s.t.  $\gamma > \beta$ .

Since  $\mathbb{I}_\varepsilon$  is bounded below, choose  $t_0 \in \mathbb{R}$  s.t.  $\forall \sigma \in \Sigma, \varepsilon(\sigma) \geq t_0$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ . Then:  $\forall \sigma \in \Sigma, \varepsilon_\sigma \geq t_0$ .

Let  $\delta := \gamma - \beta$ . Then  $\delta > 0$ , so, as  $t \rightarrow \infty$ ,  $|t|^\rho \cdot e^{-\delta \cdot t} \rightarrow 0$ .

So, since  $t \mapsto |t|^\rho \cdot e^{-\delta \cdot t} : [t_0; \infty) \rightarrow \mathbb{R}$  is continuous,

by the Extreme Value Theorem, choose  $M \in \mathbb{R}$  s.t.,

$$\forall \text{real } t \geq t_0, \quad |t|^\rho \cdot e^{-\delta \cdot t} \leq M.$$

Then:  $\forall \sigma \in \Sigma, \quad |\varepsilon_\sigma|^\rho \cdot e^{-\delta \cdot \varepsilon_\sigma} \leq M$ .

By definition of  $\bar{X}^\rho S_\gamma^\varepsilon$ , we get:  $\bar{X}^\rho S_\gamma^\varepsilon = \sum_{\sigma \in \Sigma} [|\varepsilon_\sigma|^\rho \cdot e^{-\gamma \cdot \varepsilon_\sigma}]$ .

So, since  $-\gamma = -\delta - \beta$ , we get:  $\bar{X}^\rho S_\gamma^\varepsilon = \sum_{\sigma \in \Sigma} [(|\varepsilon_\sigma|^\rho \cdot e^{-\delta \cdot \varepsilon_\sigma}) \cdot (e^{-\beta \cdot \varepsilon_\sigma})]$ .

Since  $\beta \in \text{DF}_\varepsilon$ , we get:  $\Delta_\beta^\varepsilon < \infty$ . Then:  $M \cdot \Delta_\beta^\varepsilon < \infty$ .

$$\begin{aligned} \text{Then: } \bar{X}^\rho S_\gamma^\varepsilon &= \sum_{\sigma \in \Sigma} [(|\varepsilon_\sigma|^\rho \cdot e^{-\delta \cdot \varepsilon_\sigma}) \cdot (e^{-\beta \cdot \varepsilon_\sigma})] \\ &\leq \sum_{\sigma \in \Sigma} [M \cdot (e^{-\beta \cdot \varepsilon_\sigma})] \\ &= M \cdot (\sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}]) = M \cdot \Delta_\beta^\varepsilon < \infty. \quad \square \end{aligned}$$

**THEOREM 23.16.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\mathbb{I}_\varepsilon$  is bounded below and  $\text{DF}_\varepsilon \neq \emptyset$ .

Let  $\beta_0 := \inf \text{DF}_\varepsilon$  and let  $\gamma > \beta_0$  be real. Then:  $\gamma \in \text{DF}_\varepsilon$ .

*Proof.* By Theorem 23.15, we have:  $\bar{X}^0 S_\gamma^\varepsilon < \infty$ .

Since  $\Delta_\gamma^\varepsilon = \bar{X}^0 S_\gamma^\varepsilon < \infty$ , we get:  $\gamma \in \text{DF}_\varepsilon$ .  $\square$

**THEOREM 23.17.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta, \rho \in \mathbb{R}$ .

Assume:  $\rho \geq 0$ ,  $\varepsilon$  is  $\infty$ -proper,  $\bar{X}^\rho S_\beta^\varepsilon < \infty$ . Then:  $\beta \in \text{DF}_\varepsilon$ .

The assumption of  $\infty$ -properness is needed, see Theorem 23.19 below.

*Proof.* **Want:**  $\Delta_\beta^\varepsilon < \infty$ .

**Let**  $F := \{\sigma \in \Sigma \mid \varepsilon(\sigma) \leq 1\}$ . Since  $\varepsilon$  is  $\infty$ -proper, we get:  $F$  is finite.

For all  $\sigma \in \Sigma$ , **let**  $\varepsilon_\sigma := \varepsilon(\sigma)$ . Then:  $F = \{\sigma \in \Sigma \mid \varepsilon_\sigma \leq 1\}$ .

Since  $F$  is finite, we get:  $\sum_{\sigma \in F} [e^{-\beta \cdot \varepsilon_\sigma}] < \infty$ .

So, since  $\Delta_\beta^\varepsilon = (\sum_{\sigma \in F} [e^{-\beta \cdot \varepsilon_\sigma}]) + (\sum_{\sigma \in \Sigma \setminus F} [e^{-\beta \cdot \varepsilon_\sigma}])$ ,

**it suffices to show:**  $\sum_{\sigma \in \Sigma \setminus F} [e^{-\beta \cdot \varepsilon_\sigma}] < \infty$ .

Since  $F = \{\sigma \in \Sigma \mid \varepsilon_\sigma \leq 1\}$ ,

we get:  $\forall \sigma \in \Sigma \setminus F$ ,  $\varepsilon_\sigma > 1$ .

Then:  $\forall \sigma \in \Sigma \setminus F$ , since  $\varepsilon_\sigma > 1 > 0$ ,

we get:  $\varepsilon_\sigma = |\varepsilon_\sigma|$ .

Since  $\forall \sigma \in \Sigma \setminus F$ ,  $1 < \varepsilon_\sigma = |\varepsilon_\sigma|$ ,

we get:  $\forall \sigma \in \Sigma \setminus F$ ,  $1^\rho \leq |\varepsilon_\sigma|^\rho$ .

Then:  $\forall \sigma \in \Sigma \setminus F$ ,  $1^\rho \cdot e^{-\beta \cdot \varepsilon_\sigma} \leq |\varepsilon_\sigma|^\rho \cdot e^{-\beta \cdot \varepsilon_\sigma}$ .

Then:  $\sum_{\sigma \in \Sigma \setminus F} [e^{-\beta \cdot \varepsilon_\sigma}] = \sum_{\sigma \in \Sigma \setminus F} [1^\rho \cdot e^{-\beta \cdot \varepsilon_\sigma}] \leq \sum_{\sigma \in \Sigma \setminus F} [|\varepsilon_\sigma|^\rho \cdot e^{-\beta \cdot \varepsilon_\sigma}]$   
 $\leq \sum_{\sigma \in \Sigma} [|\varepsilon_\sigma|^\rho \cdot e^{-\beta \cdot \varepsilon_\sigma}] = \bar{X}^\rho S_\beta^\varepsilon < \infty$ .  $\square$

**THEOREM 23.18.** Let  $\Sigma := [3.. \infty)$ .

**Define**  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:  $\forall k \in \Sigma$ ,  $\varepsilon(k) = (\ln k) + 2 \cdot (\ln(\ln k))$ .

**Let**  $\beta := 1$ ,  $\rho := 1$ . Then:  $\beta \in \text{DF}_\varepsilon$  and  $\bar{X}^\rho S_\beta^\varepsilon = \infty$ .

*Proof.* For all  $k \in \Sigma$ , **let**  $\varepsilon_k := \varepsilon(k)$ .

Then:  $\forall k \in [3.. \infty)$ ,  $\varepsilon_k = (\ln k) + 2 \cdot (\ln(\ln k))$ .

Since  $\Delta_\beta^\varepsilon = \sum_{k \in \Sigma} [e^{-\beta \cdot \varepsilon_k}] = \sum_{k \in \Sigma} [e^{-\varepsilon_k}] = \sum_{k=3}^\infty [e^{-\varepsilon_k}]$

$$= \sum_{k=3}^\infty \left[ \frac{1}{e^{\varepsilon_k}} \right] = \sum_{k=3}^\infty \left[ \frac{1}{e^{(\ln k) + 2(\ln(\ln k))}} \right] = \sum_{k=3}^\infty \left[ \frac{1}{k \cdot (\ln k)^2} \right] < \infty,$$

we get:  $\beta \in \text{DF}_\varepsilon$ . **It remains only to show:**  $\bar{X}^\rho S_\beta^\varepsilon = \infty$ .

We have:  $\forall k \in [3.. \infty)$ ,  $k > e$ , so  $\ln k > 1$ , so  $\ln(\ln k) > 0$ .

For all  $k \in [3.. \infty)$ , since  $\varepsilon_k = (\ln k) + 2 \cdot (\ln(\ln k)) > 1 + 2 \cdot 0 = 1 > 0$ ,

we get:  $|\varepsilon_k| = \varepsilon_k$ .

$$\begin{aligned} \text{Since } \bar{X}^\rho S_\beta^\varepsilon &= \bar{X}^1 S_1^\varepsilon = \sum_{k \in \Sigma} [|\varepsilon_k| \cdot e^{-\varepsilon_k}] \\ &= \sum_{k=3}^\infty [|\varepsilon_k| \cdot e^{-\varepsilon_k}] \\ &= \sum_{k=3}^\infty [\varepsilon_k \cdot e^{-\varepsilon_k}] \\ &= \sum_{k=3}^\infty \left[ \frac{\varepsilon_k}{e^{\varepsilon_k}} \right] = \sum_{k=3}^\infty \left[ \frac{(\ln k) + 2 \cdot (\ln(\ln k))}{e^{(\ln k) + 2(\ln(\ln k))}} \right] \\ &= \sum_{k=3}^\infty \left[ \frac{(\ln k) + 2 \cdot (\ln(\ln k))}{k \cdot (\ln k)^2} \right] \\ &\geq \sum_{k=3}^\infty \left[ \frac{\ln k}{k \cdot (\ln k)^2} \right] \end{aligned}$$

$$= \sum_{k=3}^{\infty} \left[ \frac{1}{k \cdot (\ln k)} \right] = \infty,$$

we get:  $\bar{X}^{\rho} S_{\beta}^{\varepsilon} = \infty$ . □

**THEOREM 23.19.** Let  $\Sigma := \mathbb{N}$ .

Define  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:  $\forall k \in \Sigma, \varepsilon(k) = 1/k^2$ .

Let  $\beta := 1, \rho := 1$ . Then:  $\bar{X}^{\rho} S_{\beta}^{\varepsilon} < \infty$  and  $\beta \notin \text{DF}_{\varepsilon}$ .

*Proof.* For all  $k \in \Sigma$ , let  $\varepsilon_k := \varepsilon(k)$ . Then:  $\forall k \in \Sigma, \varepsilon_k = 1/k^2$ .

We have:  $\forall k \in \Sigma$ , both  $|\varepsilon_k| = 1/k^2$  and  $-\varepsilon_k = -1/k^2$ .

$$\begin{aligned} \text{Since } \bar{X}^{\rho} S_{\beta}^{\varepsilon} &= \bar{X}^1 S_1^{\varepsilon} = \sum_{k \in \Sigma} [|\varepsilon_k| \cdot e^{-\varepsilon_k}] \\ &= \sum_{k=1}^{\infty} [(1/k^2) \cdot e^{-1/k^2}] \\ &\leq \sum_{k=1}^{\infty} [(1/k^2) \cdot 1] \\ &= \sum_{k=1}^{\infty} [1/k^2] < \infty, \end{aligned}$$

it remains only to show:  $\beta \notin \text{DF}_{\varepsilon}$       **Want:**  $\Delta_{\beta}^{\varepsilon} = \infty$ .

We have: as  $k \rightarrow \infty, e^{-1/k^2} \rightarrow 1$ . Then:  $\sum_{k=1}^{\infty} [e^{-1/k^2}] = \infty$ .

Then:  $\Delta_{\beta}^{\varepsilon} = \Delta_1^{\varepsilon} = \sum_{k \in \Sigma} [e^{-\varepsilon_k}] = \sum_{k=1}^{\infty} [e^{-\varepsilon_k}] = \sum_{k=1}^{\infty} [e^{-1/k^2}] = \infty$ . □

**THEOREM 23.20.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\varepsilon^*[0; \infty)$  is infinite and  $\text{DF}_{\varepsilon} \neq \emptyset$ . Let  $\beta_0 := \inf \text{DF}_{\varepsilon}$ .

Then:  $0 \leq \beta_0 < \infty$  and  $(\beta_0; \infty) \subseteq \text{DF}_{\varepsilon}$ .

*Proof.* By Theorem 23.5,  $\text{DF}_{\varepsilon} \subseteq (0; \infty)$ . Then:  $\inf \text{DF}_{\varepsilon} \geq \inf(0; \infty)$ .

Since  $\text{DF}_{\varepsilon} \neq \emptyset$ , we get:  $\inf \text{DF}_{\varepsilon} < \infty$ .

Since  $\beta_0 = \inf \text{DF}_{\varepsilon} \geq \inf(0; \infty) = 0$  and since  $\beta_0 = \inf \text{DF}_{\varepsilon} < \infty$ ,

we get:  $0 \leq \beta_0 < \infty$ .

**It remains to show:**  $(\beta_0; \infty) \subseteq \text{DF}_{\varepsilon}$ .

**Given**  $\gamma \in (\beta_0; \infty)$ , **want:**  $\gamma \in \text{DF}_{\varepsilon}$ .

By Theorem 23.12,  $\varepsilon$  is  $\infty$ -proper.

Then, by Theorem 22.4, we have:  $\mathbb{I}_{\varepsilon}$  is bounded below.

Since  $\gamma > \beta_0 = \inf \text{DF}_{\varepsilon}$ , **choose**  $\beta \in \text{DF}_{\varepsilon}$  s.t.  $\gamma > \beta$ .

Then, by Theorem 23.16, we get:  $\gamma \in \text{DF}_{\varepsilon}$ . □

**THEOREM 23.21.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\varepsilon^*[0; \infty)$  is infinite and  $\text{DF}_{\varepsilon} \neq \emptyset$ . Let  $\beta_0 := \inf \text{DF}_{\varepsilon}$ .

Then either  $(\text{DF}_{\varepsilon} = [\beta_0; \infty)$  and  $0 < \beta_0 < \infty$ )

or  $(\text{DF}_{\varepsilon} = (\beta_0; \infty)$  and  $0 \leq \beta_0 < \infty$ ).

*Proof.* By Theorem 23.20, we get:  $0 \leq \beta_0 < \infty$  and  $(\beta_0; \infty) \subseteq \text{DF}_{\varepsilon}$ .

Since  $\beta_0 = \inf \text{DF}_{\varepsilon}$ , we get:  $\text{DF}_{\varepsilon} \subseteq [\beta_0; \infty)$ .

By Theorem 23.5, we get:  $\text{DF}_{\varepsilon} \subseteq (0; \infty)$ .

*Case 1:*  $\beta_0 \in \text{DF}_\varepsilon$ .      **Want:**  $\text{DF}_\varepsilon = [\beta_0; \infty)$  and  $0 < \beta_0 < \infty$ .  
Recall:  $(\beta_0; \infty) \subseteq \text{DF}_\varepsilon$  and  $\text{DF}_\varepsilon \subseteq [\beta_0; \infty)$  and  $\text{DF}_\varepsilon \subseteq (0; \infty)$ .  
Since  $\beta_0 \in \text{DF}_\varepsilon$  and  $(\beta_0; \infty) \subseteq \text{DF}_\varepsilon$ ,  
we get:  $\{\beta_0\} \cup (\beta_0; \infty) \subseteq \text{DF}_\varepsilon$ .  
Since  $[\beta_0; \infty) = \{\beta_0\} \cup (\beta_0; \infty) \subseteq \text{DF}_\varepsilon$  and since  $\text{DF}_\varepsilon \subseteq [\beta_0; \infty)$ ,  
we get:  $\text{DF}_\varepsilon = [\beta_0; \infty)$ .  
**It remains only to show:**  $0 < \beta_0 < \infty$ .  
Recall:  $0 \leq \beta_0 < \infty$ .      Then:  $\beta_0 < \infty$ .  
**It remains only to show:**  $0 < \beta_0$ .  
Since  $\beta_0 \in [\beta_0; \infty) = \text{DF}_\varepsilon \subseteq (0; \infty)$ ,      we get:  $0 < \beta_0$ .  
*End of Case 1.*

*Case 2:*  $\beta_0 \notin \text{DF}_\varepsilon$ .      **Want:**  $\text{DF}_\varepsilon = (\beta_0; \infty)$  and  $0 \leq \beta_0 < \infty$ .  
Recall:  $0 \leq \beta_0 < \infty$ .  
**It remains only to show:**  $\text{DF}_\varepsilon = (\beta_0; \infty)$ .  
Recall:  $\text{DF}_\varepsilon \subseteq [\beta_0; \infty)$ ,  
Since  $\beta_0 \notin \text{DF}_\varepsilon$  and  $\text{DF}_\varepsilon \subseteq [\beta_0; \infty)$ ,  
we get:  $\text{DF}_\varepsilon \subseteq [\beta_0; \infty) \setminus \{\beta_0\}$ .      Recall:  $(\beta_0; \infty) \subseteq \text{DF}_\varepsilon$ .  
Since  $\text{DF}_\varepsilon \subseteq [\beta_0; \infty) \setminus \{\beta_0\} = (\beta_0; \infty)$  and  $(\beta_0; \infty) \subseteq \text{DF}_\varepsilon$ ,  
we get:  $\text{DF}_\varepsilon = (\beta_0; \infty)$ .  
*End of Case 2.* □

Replacing  $\varepsilon$  by  $-\varepsilon$  in Theorem 23.21 yields:

**THEOREM 23.22.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .  
Assume:  $\varepsilon^*(-\infty; 0]$  is infinite and  $\text{DF}_\varepsilon \neq \emptyset$ .      Let  $\beta_0 := -\sup \text{DF}_\varepsilon$ .  
Then one of the following holds:  
Either  $(\text{DF}_\varepsilon = (-\infty; -\beta_0])$  and  $0 < \beta_0 < \infty$  )  
or  $(\text{DF}_\varepsilon = (-\infty; -\beta_0))$  and  $0 \leq \beta_0 < \infty$  ).

**THEOREM 23.23.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ . Assume:  $\text{DF}_\varepsilon \neq \emptyset$ .  
Then one of the following is true:  
(i)  $\text{DF}_\varepsilon = \mathbb{R}$ .  
(ii)  $\exists$  real  $\beta_0 \geq 0$  s.t.  $\text{DF}_\varepsilon = (\beta_0; \infty)$ .  
(iii)  $\exists$  real  $\beta_0 > 0$  s.t.  $\text{DF}_\varepsilon = [\beta_0; \infty)$ .  
(iv)  $\exists$  real  $\beta_0 \geq 0$  s.t.  $\text{DF}_\varepsilon = (-\infty; -\beta_0]$ .  
(v)  $\exists$  real  $\beta_0 > 0$  s.t.  $\text{DF}_\varepsilon = (-\infty; -\beta_0)$ .

*Proof.* Since  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ , we get:  $\varepsilon^*\mathbb{R} = \Sigma$ .

Since  $(-\infty; 0] \cup [0; \infty) = \mathbb{R}$ , we get:  $\varepsilon^*(-\infty; 0] \cup \varepsilon^*[0; \infty) = \varepsilon^*\mathbb{R}$ .

In case  $\#\Sigma < \infty$ , we get: (i) holds. We therefore assume  $\#\Sigma = \infty$ .

**Want:** (ii) or (iii) or (iv) or (v) holds.

Because  $\varepsilon^*(-\infty; 0] \cup \varepsilon^*[0; \infty) = \varepsilon^*\mathbb{R} = \Sigma$ ,

and because  $\Sigma$  is infinite, we get:

either  $\varepsilon^*(-\infty; 0]$  is infinite or  $\varepsilon^*[0; \infty)$  is infinite.

Then, by Theorem 23.22 or Theorem 23.21, we get:

either (iv) or (v) holds or (ii) or (iii) holds.  $\square$

**THEOREM 23.24.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Then all of the following are true:

- (i)  $(\text{DF}_\varepsilon = \mathbb{R}) \Rightarrow (\Sigma \text{ is finite})$   
 $\Rightarrow (\varepsilon \text{ is both } \infty\text{-proper and } (-\infty)\text{-proper}).$
- (ii)  $(\exists \text{ real } \beta_0 \geq 0 \text{ s.t. } \text{DF}_\varepsilon = (\beta_0; \infty)) \Rightarrow (\varepsilon \text{ is } \infty\text{-proper}).$
- (iii)  $(\exists \text{ real } \beta_0 > 0 \text{ s.t. } \text{DF}_\varepsilon = [\beta_0; \infty)) \Rightarrow (\varepsilon \text{ is } \infty\text{-proper}).$
- (iv)  $(\exists \text{ real } \beta_0 \geq 0 \text{ s.t. } \text{DF}_\varepsilon = (-\infty; -\beta_0)) \Rightarrow (\varepsilon \text{ is } (-\infty)\text{-proper}).$
- (v)  $(\exists \text{ real } \beta_0 > 0 \text{ s.t. } \text{DF}_\varepsilon = (-\infty; -\beta_0]) \Rightarrow (\varepsilon \text{ is } (-\infty)\text{-proper}).$

*Proof.* Proof of (i): By Theorem 23.11,  $(\text{DF}_\varepsilon = \mathbb{R}) \Rightarrow (\Sigma \text{ is finite})$ .

**It remains to show:**

$(\Sigma \text{ is finite}) \Rightarrow (\varepsilon \text{ is both } \infty\text{-proper and } (-\infty)\text{-proper}).$

By Theorem 22.10,

$(\Sigma \text{ is finite}) \Rightarrow (\varepsilon \text{ is both } \infty\text{-proper and } (-\infty)\text{-proper}).$

*End of proof of (i).*

*Proof of (ii) and (iii):*

By Theorem 23.8, we have:

$(\exists \text{ real } \beta_0 \geq 0 \text{ s.t. } \text{DF}_\varepsilon = (\beta_0; \infty)) \Rightarrow (\varepsilon \text{ is } \infty\text{-proper})$

and  $(\exists \text{ real } \beta_0 > 0 \text{ s.t. } \text{DF}_\varepsilon = [\beta_0; \infty)) \Rightarrow (\varepsilon \text{ is } \infty\text{-proper}).$

*End of proof of (ii) and (iii).*

*Proof of (iv) and (v):*

By Theorem 23.9, we have:

$(\exists \text{ real } \beta_0 \geq 0 \text{ s.t. } \text{DF}_\varepsilon = (-\infty; -\beta_0)) \Rightarrow (\varepsilon \text{ is } (-\infty)\text{-proper})$

and  $(\exists \text{ real } \beta_0 > 0 \text{ s.t. } \text{DF}_\varepsilon = (-\infty; -\beta_0]) \Rightarrow (\varepsilon \text{ is } (-\infty)\text{-proper}).$

*End of proof of (iv) and (v).*  $\square$

Below, after each of

Theorem 23.27, Theorem 23.28, Theorem 23.29,

we give examples of  $\infty$ -proper  $\varepsilon : \Sigma \rightarrow \mathbb{Z}$  such that:

$$\text{DF}_\varepsilon = \emptyset, \quad \text{DF}_\varepsilon = (\beta_0; \infty), \quad \text{DF}_\varepsilon = [\beta_0; \infty), \quad \text{respectively.}$$

It follows that:  $-\varepsilon$  is  $(-\infty)$ -proper and

$$\text{DF}_{-\varepsilon} = \emptyset, \quad \text{DF}_{-\varepsilon} = (-\infty; -\beta_0), \quad \text{DF}_{-\varepsilon} = (-\infty; -\beta_0], \quad \text{respectively.}$$

**THEOREM 23.25.** Let  $n_1, n_2, \dots \in [0.. \infty)$ .

Let  $\Sigma := \{(k, j) \in \mathbb{N} \times \mathbb{N} \mid j \leq n_k\}$ .

Define  $\varepsilon : \Sigma \rightarrow [0.. \infty)$  by:  $\forall (k, j) \in \Sigma, \quad \varepsilon(k, j) = k - 1$ .

Then:  $\forall k \in \mathbb{N}, \quad \#(\varepsilon^*[k - 1; k]) = n_k$ .

*Proof.* Given  $k \in \mathbb{N}$ , want:  $\#(\varepsilon^*[k - 1; k]) = n_k$ .

$$\begin{aligned} \text{Since } \varepsilon^*[k - 1; k] &= \{(\ell, j) \in \Sigma \mid \varepsilon(\ell, j) \in [k - 1; k]\} \\ &= \{(\ell, j) \in \Sigma \mid \ell - 1 \in [k - 1; k]\} \\ &= \{(\ell, j) \in \Sigma \mid \ell - 1 = k - 1\} \\ &= \{(\ell, j) \in \Sigma \mid \ell = k\} \\ &= \{(\ell, j) \in \mathbb{N} \times \mathbb{N} \mid \ell = k, j \leq n_\ell\} \\ &= \{(\ell, j) \in \mathbb{N} \times \mathbb{N} \mid \ell = k, j \leq n_k\} \\ &= \{(k, 1), \dots, (k, n_k)\}, \end{aligned}$$

we get:  $\#(\varepsilon^*[k - 1; k]) = n_k$ . □

**THEOREM 23.26.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow [0; \infty)$ .

For all  $k \in \mathbb{N}$ , let  $n_k := \#(\varepsilon^*[k - 1; k])$ .

Let  $\beta \in [0; \infty)$ . Then:  $(\beta \in \text{DF}_\varepsilon) \Leftrightarrow (\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty)$ .

*Proof.* For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

*Proof of  $\Rightarrow$ :* Assume:  $\beta \in \text{DF}_\varepsilon$ . **Want:**  $\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty$ .

Since  $\beta \in \text{DF}_\varepsilon$ , we get:  $\Delta_\beta^\varepsilon < \infty$ .

Because  $\Sigma$  is the disjoint union, over  $k = 1$  to  $\infty$ , of  $\varepsilon^*[k - 1; k)$ ,

$$\text{we get: } \sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}] = \sum_{k=1}^{\infty} \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot \varepsilon_\sigma}].$$

For all  $k \in \mathbb{N}$ , for all  $\sigma \in \varepsilon^*[k - 1; k)$ , since  $\varepsilon_\sigma = \varepsilon(\sigma) \in [k - 1; k)$ ,

$$\text{we have: } k > \varepsilon_\sigma.$$

Since  $\beta \in [0; \infty)$ , we get:  $-\beta \leq 0$ .

For all  $k \in \mathbb{N}$ , for all  $\sigma \in \varepsilon^*[k - 1; k)$ , we have:  $-\beta \cdot k \leq -\beta \cdot \varepsilon_\sigma$ .

For all  $k \in \mathbb{N}$ , for all  $\sigma \in \varepsilon^*[k - 1; k)$ , we have:  $e^{-\beta \cdot k} \leq e^{-\beta \cdot \varepsilon_\sigma}$ .

Then:  $\forall k \in \mathbb{N}, \quad \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot k}] \leq \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot \varepsilon_\sigma}]$ .

Also,  $\forall k \in \mathbb{N}, \quad \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot k}] = n_k e^{-\beta \cdot k}$ .

Then:  $\forall k \in \mathbb{N}, \quad n_k e^{-\beta \cdot k} \leq \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot \varepsilon_\sigma}]$ .

Then:  $\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] \leq \sum_{k=1}^{\infty} \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot \varepsilon_\sigma}]$   
 $= \sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}] = \Delta_\beta^\varepsilon < \infty$ .

End of proof of  $\Rightarrow$ .

*Proof of  $\Leftarrow$ :* Assume:  $\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty$ . **Want:**  $\beta \in \text{DF}_{\varepsilon}$ .

Because  $\Sigma$  is the disjoint union, over  $k = 1$  to  $\infty$ , of  $\varepsilon^*[k-1; k)$ ,

$$\text{we get: } \sum_{\sigma \in \Sigma} [e^{-\beta \cdot (\varepsilon_{\sigma} + 1)}] = \sum_{k=1}^{\infty} \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot (\varepsilon_{\sigma} + 1)}].$$

For all  $k \in \mathbb{N}$ , for all  $\sigma \in \varepsilon^*[k-1; k)$ , since  $\varepsilon_{\sigma} = \varepsilon(\sigma) \in [k-1; k)$ ,

$$\text{we have: } \varepsilon_{\sigma} \geq k-1.$$

For all  $k \in \mathbb{N}$ , for all  $\sigma \in \varepsilon^*[k-1; k)$ , we have:  $\varepsilon_{\sigma} + 1 \geq k$ .

Since  $\beta \in [0; \infty)$ , we get:  $-\beta \leq 0$ .

For all  $k \in \mathbb{N}$ , for all  $\sigma \in \varepsilon^*[k-1; k)$ , we have:  $-\beta \cdot (\varepsilon_{\sigma} + 1) \leq -\beta \cdot k$ .

For all  $k \in \mathbb{N}$ , for all  $\sigma \in \varepsilon^*[k-1; k)$ , we have:  $e^{-\beta \cdot (\varepsilon_{\sigma} + 1)} \leq e^{-\beta \cdot k}$ .

Then:  $\forall k \in \mathbb{N}$ ,  $\sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot (\varepsilon_{\sigma} + 1)}] \leq \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot k}]$ .

Also,  $\forall k \in \mathbb{N}$ ,  $n_k e^{-\beta \cdot k} = \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot k}]$ .

Then:  $\forall k \in \mathbb{N}$ ,  $\sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot (\varepsilon_{\sigma} + 1)}] \leq n_k e^{-\beta \cdot k}$ .

Then:  $\sum_{k=1}^{\infty} \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot (\varepsilon_{\sigma} + 1)}] \leq \sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}]$ .

By assumption,  $\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty$ . Then  $e^{\beta} \cdot \sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty$ .

Since  $\Delta_{\beta}^{\varepsilon} = \sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_{\sigma}}]$

$$= \sum_{\sigma \in \Sigma} [e^{\beta} \cdot e^{-\beta \cdot (\varepsilon_{\sigma} + 1)}]$$

$$= e^{\beta} \cdot \sum_{\sigma \in \Sigma} [e^{-\beta \cdot (\varepsilon_{\sigma} + 1)}]$$

$$= e^{\beta} \cdot \sum_{k=1}^{\infty} \sum_{\sigma \in \varepsilon^*[k-1; k)} [e^{-\beta \cdot (\varepsilon_{\sigma} + 1)}]$$

$$\leq e^{\beta} \cdot \sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty,$$

we get:  $\beta \in \text{DF}_{\varepsilon}$ .

End of proof of  $\Leftarrow$ .  $\square$

**THEOREM 23.27.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow [0; \infty)$ .

For all  $k \in \mathbb{N}$ , let  $n_k := \#(\varepsilon^*[k-1; k))$ .

Assume:  $\forall k \in \mathbb{N}$ ,  $n_k \geq e^{k^2}$ . Then:  $\text{DF}_{\varepsilon} = \emptyset$ .

*Proof.* Since  $\forall k \in \mathbb{N}$ ,  $n_k \geq e^{k^2} > 1$ , we get:  $\sum_{k=1}^{\infty} n_k = \infty$ .

Since  $\#(\varepsilon^*[0; \infty)) = \sum_{k=1}^{\infty} [\#(\varepsilon^*[k-1; k))] = \sum_{k=1}^{\infty} n_k = \infty$ ,

it follows, from Theorem 23.5, that:  $\text{DF}_{\varepsilon} \subseteq (0; \infty)$ .

**It therefore suffices to show:**  $\forall \beta \in (0; \infty)$ ,  $\beta \notin \text{DF}_{\varepsilon}$ .

**Given**  $\beta \in (0; \infty)$ , **want:**  $\beta \notin \text{DF}_{\varepsilon}$ .

Since, as  $k \rightarrow \infty$ ,  $e^{k^2 - \beta \cdot k} \rightarrow \infty$ , we get:  $\sum_{k=1}^{\infty} [e^{k^2 - \beta \cdot k}] = \infty$ .

Since  $\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] \geq \sum_{k=1}^{\infty} [e^{k^2} e^{-\beta \cdot k}] = \sum_{k=1}^{\infty} [e^{k^2 - \beta \cdot k}] = \infty$ ,

and since  $\beta \in (0; \infty) \subseteq [0; \infty)$ ,

by Theorem 23.26, we get:  $\beta \notin \text{DF}_{\varepsilon}$ .  $\square$

Recall (§2):  $\forall t \in \mathbb{R}$ ,  $[t]$  denotes the floor of  $t$ .

*Example:* For all  $k \in \mathbb{N}$ , let  $n_k := \lfloor e^{k^2} + 1 \rfloor$ .

Then:  $\forall k \in \mathbb{N}, n_k \geq e^{k^2}$ . Let  $\Sigma := \{(k, j) \in \mathbb{N} \times \mathbb{N} \mid j \leq n_k\}$ .

**Define**  $\varepsilon : \Sigma \rightarrow [0.. \infty)$  by:  $\forall (k, j) \in \Sigma, \varepsilon(k, j) = k - 1$ .

Then, by Theorem 23.25 and Theorem 23.27, we get:  $\text{DF}_\varepsilon = \emptyset$ .

**THEOREM 23.28.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow [0; \infty)$ .

For all  $k \in \mathbb{N}$ , let  $n_k := \#(\varepsilon^*[k - 1; k])$ . Let  $\beta_0 \in [0; \infty)$ .

Assume: as  $k \rightarrow \infty, n_k e^{-\beta_0 \cdot k} \rightarrow 1$ . Then:  $\text{DF}_\varepsilon = (\beta_0; \infty)$ .

*Proof.* Since as  $k \rightarrow \infty, n_k e^{-\beta_0 \cdot k} \rightarrow 1$ , we get:

$$\#\{k \in \mathbb{N} \mid n_k e^{-\beta_0 \cdot k} = 0\} < \infty.$$

Then:  $\#\{k \in \mathbb{N} \mid n_k = 0\} < \infty$ .

Then  $\#\{k \in \mathbb{N} \mid n_k \geq 1\} = \infty$ , and so  $\sum_{k=1}^{\infty} n_k = \infty$ .

Since  $\#(\varepsilon^*[0; \infty)) = \sum_{k=1}^{\infty} [\#(\varepsilon^*[k - 1; k])] = \sum_{k=1}^{\infty} n_k = \infty$ ,

it follows, from Theorem 23.5, that:  $\text{DF}_\varepsilon \subseteq (0; \infty)$ .

Since  $\text{DF}_\varepsilon \subseteq (0; \infty) \subseteq [0; \infty)$ , we get:  $\text{DF}_\varepsilon \cap [0; \infty) = \text{DF}_\varepsilon$ .

Since  $\beta_0 \in [0; \infty)$ , we get:  $(\beta_0; \infty) \subseteq (0; \infty)$ .

Since  $(\beta_0; \infty) \subseteq (0; \infty) \subseteq [0; \infty)$ , we get:  $(\beta_0; \infty) \cap [0; \infty) = (\beta_0; \infty)$ .

We have:  $\forall \beta \in \mathbb{R}, \forall k \in \mathbb{N}, [n_k e^{-\beta \cdot k}] / [e^{-(\beta - \beta_0) \cdot k}] = n_k e^{-\beta_0 \cdot k}$ .

By hypothesis, as  $k \rightarrow \infty, n_k e^{-\beta_0 \cdot k} \rightarrow 1$ .

Then:  $\forall \beta \in \mathbb{R},$  as  $k \rightarrow \infty, [n_k e^{-\beta \cdot k}] / [e^{-(\beta - \beta_0) \cdot k}] \rightarrow 1$ .

Then:  $\forall \beta \in \mathbb{R}, (\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty) \Leftrightarrow (\sum_{k=1}^{\infty} [e^{-(\beta - \beta_0) \cdot k}] < \infty)$ .

Also,  $\forall \beta \in \mathbb{R}, (\beta > \beta_0) \Leftrightarrow (\sum_{k=1}^{\infty} [e^{-(\beta - \beta_0) \cdot k}] < \infty)$ .

Then:  $\forall \beta \in \mathbb{R}, (\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty) \Leftrightarrow (\beta > \beta_0)$ .

Then, by Theorem 23.26,

$$\forall \beta \in [0; \infty), (\beta \in \text{DF}_\varepsilon) \Leftrightarrow (\beta > \beta_0).$$

Then  $\text{DF}_\varepsilon \cap [0; \infty) = (\beta_0; \infty) \cap [0; \infty)$ .

Then  $\text{DF}_\varepsilon = \text{DF}_\varepsilon \cap [0; \infty) = (\beta_0; \infty) \cap [0; \infty) = (\beta_0; \infty)$ .  $\square$

*Example:* Let  $\beta_0 \in [0; \infty)$ . For all  $k \in \mathbb{N}$ , let  $n_k := \lfloor e^{\beta_0 \cdot k} \rfloor$ .

Then: as  $k \rightarrow \infty, n_k e^{-\beta_0 \cdot k} \rightarrow 1$ . Let  $\Sigma := \{(k, j) \in \mathbb{N} \times \mathbb{N} \mid j \leq n_k\}$ .

**Define**  $\varepsilon : \Sigma \rightarrow [0.. \infty)$  by:  $\forall (k, j) \in \Sigma, \varepsilon(k, j) = k - 1$ .

Then, by Theorem 23.25 and Theorem 23.28, we get:  $\text{DF}_\varepsilon = (\beta_0; \infty)$ .

**THEOREM 23.29.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow [0; \infty)$ ,  $p \in (1; \infty)$ .

For all  $k \in \mathbb{N}$ , let  $n_k := \#(\varepsilon^*[k - 1; k])$ . Let  $\beta_0 \in (0; \infty)$ .

Assume: as  $k \rightarrow \infty, k^p n_k e^{-\beta_0 \cdot k} \rightarrow 1$ . Then:  $\text{DF}_\varepsilon = [\beta_0; \infty)$ .

*Proof.* Since as  $k \rightarrow \infty, k^p n_k e^{-\beta_0 \cdot k} \rightarrow 1$ , we get:

$$\#\{k \in \mathbb{N} \mid k^p n_k e^{-\beta_0 \cdot k} = 0\} < \infty.$$

Then  $\#\{k \in \mathbb{N} \mid n_k = 0\} < \infty$ .



Then  $\#\{k \in \mathbb{N} \mid n_k \geq 1\} = \infty$ , and so  $\sum_{k=1}^{\infty} n_k = \infty$ .

Since  $\#(\varepsilon^*[0; \infty)) = \sum_{k=1}^{\infty} [\#(\varepsilon^*[k-1; k])] = \sum_{k=1}^{\infty} n_k = \infty$ ,

it follows, from Theorem 23.5, that:  $\text{DF}_\varepsilon \subseteq (0; \infty)$ .

Since  $\text{DF}_\varepsilon \subseteq (0; \infty) \subseteq [0; \infty)$ , we get:  $\text{DF}_\varepsilon \cap [0; \infty) = \text{DF}_\varepsilon$ .

Since  $\beta_0 \in (0; \infty)$ , we get:  $[\beta_0; \infty) \subseteq (0; \infty)$ .

Since  $[\beta_0; \infty) \subseteq (0; \infty) \subseteq [0; \infty)$ , we get:  $[\beta_0; \infty) \cap [0; \infty) = [\beta_0; \infty)$ .

We have:  $\forall \beta \in \mathbb{R}, \forall k \in \mathbb{N}, [n_k e^{-\beta \cdot k}] / [k^{-p} e^{-(\beta - \beta_0) \cdot k}] = k^p n_k e^{-\beta_0 \cdot k}$ .

By hypothesis, as  $k \rightarrow \infty$ ,  $k^p n_k e^{-\beta_0 \cdot k} \rightarrow 1$ .

Then:  $\forall \beta \in \mathbb{R}$ , as  $k \rightarrow \infty$ ,  $[n_k e^{-\beta \cdot k}] / [k^{-p} e^{-(\beta - \beta_0) \cdot k}] \rightarrow 1$ .

Then:  $\forall \beta \in \mathbb{R}, (\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty) \Leftrightarrow (\sum_{k=1}^{\infty} [k^{-p} e^{-(\beta - \beta_0) \cdot k}] < \infty)$ .

Also, since  $p \in (1; \infty)$ , we get:

$$\forall \beta \in \mathbb{R}, (\beta \geq \beta_0) \Leftrightarrow (\sum_{k=1}^{\infty} [k^{-p} e^{-(\beta - \beta_0) \cdot k}] < \infty).$$

Then:  $\forall \beta \in \mathbb{R}, (\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty) \Leftrightarrow (\beta \geq \beta_0)$ .

Then, by Theorem 23.26,

$$\forall \beta \in [0; \infty), (\beta \in \text{DF}_\varepsilon) \Leftrightarrow (\beta \geq \beta_0).$$

Then  $\text{DF}_\varepsilon \cap [0; \infty) = [\beta_0; \infty) \cap [0; \infty)$ .

Then  $\text{DF}_\varepsilon = \text{DF}_\varepsilon \cap [0; \infty) = [\beta_0; \infty) \cap [0; \infty) = [\beta_0; \infty)$ .  $\square$

*Example:* **Let**  $\beta_0 \in (0; \infty)$ . For all  $k \in \mathbb{N}$ , **let**  $n_k := \lfloor k^{-2} e^{\beta_0 \cdot k} \rfloor$ .

Then: as  $k \rightarrow \infty$ ,  $k^2 n_k e^{-\beta_0 \cdot k} \rightarrow 1$ . **Let**  $\Sigma := \{(k, j) \in \mathbb{N} \times \mathbb{N} \mid j \leq n_k\}$ .

**Define**  $\varepsilon : \Sigma \rightarrow [0; \infty)$  by:  $\forall (k, j) \in \Sigma, \varepsilon(k, j) = k - 1$ .

Then, by Theorem 23.25 and Theorem 23.29, we get:  $\text{DF}_\varepsilon = [\beta_0; \infty)$ .

**Let**  $\Sigma$  be an infinite set,  $\varepsilon : \Sigma \rightarrow [0; \infty)$ .

For all  $k \in \mathbb{N}$ , **let**  $n_k := \#(\varepsilon^*[k-1; k])$ .

In many applications, the sequence  $n_1, n_2, \dots$  is subexponential.

By the next theorem, whenever that happens, we get:  $\text{DF}_\varepsilon = (0; \infty)$ .

**THEOREM 23.30.** **Let**  $\Sigma$  be an infinite set,  $\varepsilon : \Sigma \rightarrow [0; \infty)$ .

For all  $k \in \mathbb{N}$ , **let**  $n_k := \#(\varepsilon^*[k-1; k])$ .

*Assume:*  $\forall \beta \in (0; \infty)$ , as  $k \rightarrow \infty$ ,  $n_k e^{-\beta \cdot k} \rightarrow 0$ .

*Then:*  $\text{DF}_\varepsilon = (0; \infty)$ .

*Proof.* Since  $\varepsilon : \Sigma \rightarrow [0; \infty)$ , we get:  $\varepsilon^*[0; \infty) = \Sigma$ .

So, since  $\Sigma$  is infinite, we get:  $\varepsilon^*[0; \infty)$  is infinite.

It follows, from Theorem 23.5, that:  $\text{DF}_\varepsilon \subseteq (0; \infty)$ .

**Want:**  $(0; \infty) \subseteq \text{DF}_\varepsilon$ .

**Given**  $\beta \in (0; \infty)$ , **want:**  $\beta \in \text{DF}_\varepsilon$ .

Since  $\beta \in (0; \infty) \subseteq [0; \infty)$ , by Theorem 23.26,

**it suffices to show:**  $\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] < \infty$ .

**Let**  $\beta' := \beta/2$ . Since  $\beta \in (0; \infty)$ , we get:  $\beta' \in (0; \infty)$ .  
 Then, by hypothesis, we have: as  $k \rightarrow \infty$ ,  $n_k e^{-\beta' \cdot k} \rightarrow 0$ .

It follows that:  $\{n_k e^{-\beta' \cdot k} \mid k \in \mathbb{N}\}$  is bounded.

**Choose**  $M \in \mathbb{R}$  s.t.,  $\forall k \in \mathbb{N}$ ,  $n_k e^{-\beta' \cdot k} \leq M$ .

Since  $\beta' \in (0; \infty)$ , it follows that  $1 - e^{-\beta'} > 0$

$$\text{and that } e^{-\beta'} + e^{-2\beta'} + e^{-3\beta'} + \dots = e^{-\beta'} / (1 - e^{-\beta'}).$$

Then:  $e^{-\beta'} + e^{-2\beta'} + e^{-3\beta'} + \dots < \infty$ .

Then:  $M \cdot (e^{-\beta'} + e^{-2\beta'} + e^{-3\beta'} + \dots) < \infty$ .

Then  $\sum_{k=1}^{\infty} [n_k e^{-\beta \cdot k}] = \sum_{k=1}^{\infty} [n_k e^{-2\beta' \cdot k}]$   
 $= \sum_{k=1}^{\infty} [(n_k e^{-\beta' \cdot k}) \cdot e^{-\beta' \cdot k}] \leq \sum_{k=1}^{\infty} [M e^{-\beta' \cdot k}] = M \cdot \sum_{k=1}^{\infty} [e^{-\beta' \cdot k}]$   
 $= M \cdot (e^{-\beta'} + e^{-2\beta'} + e^{-3\beta'} + \dots) < \infty. \quad \square$

*Example:* **Let**  $\Sigma := [0; \infty)$ . **Define**  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  by:  $\forall \sigma \in \Sigma$ ,  $\varepsilon(\sigma) = \sigma$ .  
 Then,  $\forall k \in \mathbb{N}$ ,  $\varepsilon^*[k-1; k] = \{k-1\}$ , and so  $\#(\varepsilon^*[k-1; k]) = 1$ .  
 Then, by Theorem 23.30, we get:  $\text{DF}_\varepsilon = (0; \infty)$ .

**DEFINITION 23.31.** **Let**  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

**Let**  $\boxed{\text{IDF}_\varepsilon}$  denote the interior in  $\mathbb{R}$  of  $\text{DF}_\varepsilon$ .

**THEOREM 23.32.** **Let**  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ . Assume:  $\text{IDF}_\varepsilon \neq \emptyset$ .

Then one of the following is true:

- (i)  $\text{IDF}_\varepsilon = \mathbb{R}$ .
- (ii)  $\exists$  real  $\beta_0 \geq 0$  s.t.  $\text{IDF}_\varepsilon = (\beta_0; \infty)$ .
- (iii)  $\exists$  real  $\beta_0 \geq 0$  s.t.  $\text{IDF}_\varepsilon = (-\infty; -\beta_0)$ .

*Proof.* MORE LATER □

**THEOREM 23.33.** **Let**  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Then all of the following are true:

- (i)  $(\text{IDF}_\varepsilon = \mathbb{R}) \Rightarrow (\Sigma \text{ is finite})$   
 $\Rightarrow (\varepsilon \text{ is both } \infty\text{-proper and } (-\infty)\text{-proper}).$
- (ii)  $(\exists \text{ real } \beta_0 \geq 0 \text{ s.t. } \text{IDF}_\varepsilon = (\beta_0; \infty)) \Rightarrow (\varepsilon \text{ is } \infty\text{-proper}).$
- (iii)  $(\exists \text{ real } \beta_0 \geq 0 \text{ s.t. } \text{IDF}_\varepsilon = (-\infty; -\beta_0)) \Rightarrow (\varepsilon \text{ is } (-\infty)\text{-proper}).$

*Proof.* MORE LATER □

## 24. BOLTZMANN AVERAGES ON COUNTABLE SETS

**DEFINITION 24.1.** **Let**  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta \in \mathbb{C}$ .

For all  $\sigma \in \Sigma$ , **let**  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

Then,  $\forall$  real  $\rho \geq 0$ , the  $\boxed{\rho\text{-exponent } (\beta, \varepsilon)\text{-absolute-sum}}$  is:

$$\boxed{\bar{X}^\rho S_\beta^\varepsilon} := \sum_{\sigma \in \Sigma} [|\varepsilon_\sigma|^\rho \cdot |e^{-\beta \cdot \varepsilon_\sigma}|] \in [0; \infty].$$

Also,  $\forall \rho \in [0.. \infty)$ , if  $\bar{X}^\rho S_\beta^\varepsilon < \infty$ ,

then the  $\boxed{\rho\text{-exponent } (\beta, \varepsilon)\text{-sum}}$  is:

$$\boxed{X^\rho S_\beta^\varepsilon} := \sum_{\sigma \in \Sigma} [\varepsilon_\sigma^\rho \cdot e^{-\beta \cdot \varepsilon_\sigma}] \in [0; \infty].$$

**DEFINITION 24.2.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta \in \mathbb{R}$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

Assume:  $\bar{X}^1 S_\beta^\varepsilon < \infty$ . Then:  $\boxed{\Gamma_\beta^\varepsilon} := \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot e^{-\beta \cdot \varepsilon_\sigma}]$ .

We have:

$$\bar{X}^1 S_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [|\varepsilon_\sigma| \cdot e^{-\beta \cdot \varepsilon_\sigma}],$$

So, by subadditivity of absolute value, if  $\bar{X}^1 S_\beta^\varepsilon < \infty$ , then  $|\Gamma_\beta^\varepsilon| \leq \bar{X}^1 S_\beta^\varepsilon$ .

**Let**  $\Sigma$  be a countable set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta \in \mathbb{R}$ .

If  $\bar{X}^1 S_\beta^\varepsilon < \infty$ , then  $\Gamma_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (\hat{B}_\beta^\varepsilon\{\sigma\})]$ ,

and so  $\Gamma_\beta^\varepsilon$  is the integral of  $\varepsilon$  wrt  $\hat{B}_\beta^\varepsilon$ .

In the next definition, in order that  $\Gamma_\beta^\varepsilon / \Delta_\beta^\varepsilon$  is defined,

we need: both  $\Gamma_\beta^\varepsilon$  is defined and  $0 < \Delta_\beta^\varepsilon < \infty$ .

We therefore assume  $\bar{X}^1 S_\beta^\varepsilon < \infty$ , to ensure that  $\Gamma_\beta^\varepsilon$  is defined.

We also assume  $\Sigma$  is nonempty, to ensure that  $\Delta_\beta^\varepsilon > 0$ .

Finally, we assume  $\beta \in \text{DF}_\varepsilon$ , to ensure that  $\Delta_\beta^\varepsilon < \infty$ .

**DEFINITION 24.3.** Let  $\Sigma$  be a nonempty set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta \in \mathbb{R}$ .

Assume:  $\bar{X}^1 S_\beta^\varepsilon < \infty$  and  $\beta \in \text{DF}_\varepsilon$ . Then:  $\boxed{A_\beta^\varepsilon} := \Gamma_\beta^\varepsilon / \Delta_\beta^\varepsilon$ .

Note that, by Theorem 23.17, if  $\varepsilon$  is  $\infty$ -proper, then

$$(\bar{X}^1 S_\beta^\varepsilon < \infty) \Rightarrow (\beta \in \text{DF}_\varepsilon).$$

Without  $\infty$ -properness, this fails, see Theorem 23.19.

By Theorem 23.18, even with  $\infty$ -properness,

$$(\beta \in \text{DF}_\varepsilon) \not\Rightarrow (\bar{X}^1 S_\beta^\varepsilon < \infty).$$

## 25. UNIFORM CONVERGENCE AND DIFFERENTIATION RESULTS

Recall (§2): the notations  $\mathbb{I}_f$  and  $f^*A$ .

Fix an element of  $\{z \in \mathbb{C} \mid z^2 = -1\}$  and **denote** it by  $\boxed{\sqrt{-1}}$ .

**Define**  $\boxed{\Re} : \mathbb{C} \rightarrow \mathbb{R}$  and  $\boxed{\Im} : \mathbb{C} \rightarrow \mathbb{R}$  by:

$$\forall x, y \in \mathbb{R}, \quad \Re(x + y\sqrt{-1}) = x \quad \text{and} \quad \Im(x + y\sqrt{-1}) = y.$$

Then:  $\forall z \in \mathbb{C}, |e^z| = e^{\Re(z)}$ .

Also,  $\forall S \subseteq \mathbb{R}, \Re^* S = \{x + y\sqrt{-1} \mid x \in S\}$ .

Let  $S$  be a set, and let  $f : S \rightarrow \mathbb{C}$ . Assume:  $\sum_{x \in S} |f(x)| < \infty$ .

Then:  $\boxed{\sum_{x \in S} [f(x)]} := \left( \sum_{x \in S} [\Re(f(x))] \right) - \left( \sum_{x \in S} [\Im(f(x))] \right) \cdot \sqrt{-1}$ .

**THEOREM 25.1.** Let  $S$  be a countably infinite set.

Let  $S_1, S_2, \dots \subseteq \Sigma$ . Assume:  $S_1 \subseteq S_2 \subseteq \dots$  and  $S_1 \cup S_2 \cup \dots = S$ .

Let  $f : S \rightarrow [0; \infty]$ .

Then: as  $n \rightarrow \infty, \sum_{x \in S_n} [f(x)] \rightarrow \sum_{x \in S} [f(x)]$ .

*Proof.* For all  $n \in \mathbb{N}$ , let  $T_n := \sum_{x \in S_n} [f(x)]$ . Let  $T := \sum_{x \in S} [f(x)]$ .

**Want:** as  $n \rightarrow \infty, T_n \rightarrow T$ . Let  $X := \sup\{T_n \mid n \in \mathbb{N}\}$ .

Since  $T_1 \leq T_2 \leq \dots$ , we get: as  $n \rightarrow \infty, T_n \rightarrow X$ . **Want:**  $X = T$ .

Since,  $\forall n \in \mathbb{N}, T_n = \sum_{x \in S_n} [f(x)] \leq \sum_{x \in S} [f(x)] = T$ , we get:

$$\sup\{T_n \mid n \in \mathbb{N}\} \leq T. \quad \text{Then: } X \leq T.$$

**Want:**  $X \geq T$ . Assume:  $X < T$ . **Want:** Contradiction.

Let  $\mathcal{F} := \{A \subseteq S \mid \#A < \infty\}$ .

Since  $X = \sup\{T_n \mid n \in \mathbb{N}\} < T = \sum_{x \in S} [f(x)] = \sup_{A \in \mathcal{F}} \sum_{x \in A} [f(x)]$ ,

**choose**  $A \in \mathcal{F}$  s.t.  $X < \sum_{x \in A} [f(x)]$ .

Since  $A$  is finite, choose  $n_0 \in \mathbb{N}$  s.t.  $S_{n_0} \supseteq A$ .

Since  $S_{n_0} \supseteq A$ , we get  $\sum_{x \in S_{n_0}} [f(x)] \geq \sum_{x \in A} [f(x)]$ .

However,  $\sum_{x \in S_{n_0}} [f(x)] = T_{n_0} \leq \sup\{T_n \mid n \in \mathbb{N}\} = X < \sum_{x \in A} [f(x)]$ .

Contradiction.  $\square$

**THEOREM 25.2.** Let  $S$  be a countably infinite set.

Let  $S_1, S_2, \dots \subseteq \Sigma$ . Assume:  $S_1 \subseteq S_2 \subseteq \dots$  and  $S_1 \cup S_2 \cup \dots = S$ .

Let  $f : S \rightarrow \mathbb{R}$ . Assume:  $\sum_{x \in S} |f(x)| < \infty$ .

Then: as  $n \rightarrow \infty, \sum_{x \in S_n} [f(x)] \rightarrow \sum_{x \in S} [f(x)]$ .

*Proof.* By Theorem 25.1, as  $n \rightarrow \infty$ , we have both:

$$\begin{aligned} \sum_{x \in S_n} |f(x)| &\rightarrow \sum_{x \in S} |f(x)| \\ \text{and } \sum_{x \in S_n} [ |f(x)| - (f(x)) ] &\rightarrow \sum_{x \in S} [ |f(x)| - (f(x)) ]. \end{aligned}$$

Subtracting the preceding limit from the one before it,

we see that, as  $n \rightarrow \infty$ , we have:

$$\sum_{x \in S_n} [f(x)] \rightarrow \sum_{x \in S} [f(x)]. \quad \square$$

**THEOREM 25.3.** Let  $U$  be an open subset of  $\mathbb{C}$ ,  $g, h : U \rightarrow \mathbb{C}$ .

Let  $f_1, f_2, \dots : U \rightarrow \mathbb{C}$  all be complex differentiable on  $U$ .

Assume, as  $n \rightarrow \infty$ , we have:

both  $f_n \rightarrow g$  pointwise on  $U$  and  $f'_n \rightarrow h$  uniformly on  $U$ .  
Then  $g' = h$  on  $U$ .

Theorem 25.3 is a basic result on commutation of limits and derivatives.  
We omit the proof.

**DEFINITION 25.4.** Let  $\Sigma$  be a set. Let  $\rho \in [0; \infty)$ .

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper,  $\beta_0 := \inf \text{DF}_\varepsilon$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

Then  $\boxed{X^\rho S_\bullet^\varepsilon} : (\beta_0; \infty) \rightarrow \mathbb{R}$  is defined by:

$$\forall \beta \in (\beta_0; \infty), \quad (X^\rho S_\bullet^\varepsilon)(\beta) = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma^\rho \cdot e^{-\beta \cdot \varepsilon_\sigma}].$$

Also,  $\boxed{X^\rho S_{\bullet, \mathbb{C}}^\varepsilon} : \mathfrak{R}^*(\beta_0; \infty) \rightarrow \mathbb{C}$  is defined by:

$$\forall z \in \mathfrak{R}^*(\beta_0; \infty), \quad (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)(z) = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma^\rho \cdot e^{-z \cdot \varepsilon_\sigma}].$$

**THEOREM 25.5.** Let  $\Sigma$  be an infinite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper,  $\beta_0 := \inf \text{DF}_\varepsilon$ ,  $\beta_1 \in (\beta_0; \infty)$ .

For all  $n \in \mathbb{N}$ , let  $\Sigma_n := \varepsilon^*(-\infty; n]$  and let  $\varepsilon_n := \varepsilon|_{\Sigma_n}$ .

Then:  $(\overline{X}^\rho S_{\beta_1}^\varepsilon < \infty)$  and  $(\text{as } n \rightarrow \infty, X^\rho S_{\beta_1}^{\varepsilon_n} \rightarrow X^\rho S_{\beta_1}^\varepsilon)$ .

*Proof.* Since  $\beta_1 \in (\beta_0; \infty)$ , by Theorem 23.15,

$$\text{we get: } \overline{X}^\rho S_{\beta_1}^\varepsilon < \infty.$$

**It remains to show:** as  $n \rightarrow \infty$ ,  $X^\rho S_{\beta_1}^{\varepsilon_n} \rightarrow X^\rho S_{\beta_1}^\varepsilon$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

**Define**  $f : \Sigma \rightarrow \mathbb{R}$  by:  $\forall \sigma \in \Sigma$ ,  $f(\sigma) = \varepsilon_\sigma^\rho \cdot e^{-\beta_1 \cdot \varepsilon_\sigma}$ .

By Theorem 25.2, as  $n \rightarrow \infty$ ,  $\sum_{\sigma \in \Sigma_n} [f(\sigma)] \rightarrow \sum_{\sigma \in \Sigma} [f(\sigma)]$ .

So, since  $\forall n \in \mathbb{N}$ ,  $\sum_{\sigma \in \Sigma_n} [f(\sigma)] = X^\rho S_{\beta_1}^{\varepsilon_n}$

$$\text{and since } \sum_{\sigma \in \Sigma} [f(\sigma)] = X^\rho S_{\beta_1}^\varepsilon,$$

$$\text{we get: as } n \rightarrow \infty, X^\rho S_{\beta_1}^{\varepsilon_n} \rightarrow X^\rho S_{\beta_1}^\varepsilon. \quad \square$$

**THEOREM 25.6.** Let  $\Sigma$  be an infinite set. Let  $\rho \in [0; \infty)$ .

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper,  $\beta_0 := \inf \text{DF}_\varepsilon$ ,  $\beta_1 \in (\beta_0; \infty)$ .

For all  $n \in \mathbb{N}$ , let  $\Sigma_n := \varepsilon^*(-\infty; n]$  and let  $\varepsilon_n := \varepsilon|_{\Sigma_n}$ .

Then: as  $n \rightarrow \infty$ ,  $X^\rho S_{\bullet, \mathbb{C}}^{\varepsilon_n} \rightarrow X^\rho S_{\bullet, \mathbb{C}}^\varepsilon$  uniformly on  $\mathfrak{R}^*(\beta_1; \infty)$ .

*Proof.* MORE LATER □

**THEOREM 25.7.** Let  $\Sigma$  be a finite set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\rho \in [0; \infty)$ ,  $z \in \mathbb{C}$ .

Then  $X^\rho S_{\bullet, \mathbb{C}}^\varepsilon$  is complex-differentiable at  $z$

$$\text{and } (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)'(z) = -(X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon)(z).$$

*Proof.* For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

$$\text{We have: } \forall \zeta \in \mathbb{C}, \quad (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)(\zeta) = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma^\rho \cdot e^{-\zeta \cdot \varepsilon_\sigma}]$$

Since  $\Sigma$  is finite, by differentiating this, we get:

$$\forall \zeta \in \mathbb{C}, \quad (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)'(\zeta) = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma^\rho \cdot e^{-\zeta \cdot \varepsilon_\sigma} \cdot (-\varepsilon_\sigma)]$$

Thus  $X^\rho S_{\bullet, \mathbb{C}}^\varepsilon$  is complex-differentiable at  $z$

$$\text{and} \quad (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)'(z) = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma^\rho \cdot e^{-z \cdot \varepsilon_\sigma} \cdot (-\varepsilon_\sigma)].$$

It remains to show:  $\sum_{\sigma \in \Sigma} [\varepsilon_\sigma^\rho \cdot e^{-z \cdot \varepsilon_\sigma} \cdot (-\varepsilon_\sigma)] = -(X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon)(z)$ .

$$\begin{aligned} \text{We have } \sum_{\sigma \in \Sigma} [\varepsilon_\sigma^\rho \cdot e^{-z \cdot \varepsilon_\sigma} \cdot (-\varepsilon_\sigma)] &= -\sum_{\sigma \in \Sigma} [\varepsilon_\sigma^{\rho+1} \cdot e^{-z \cdot \varepsilon_\sigma}] \\ &= -(X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon)(z). \end{aligned} \quad \square$$

**THEOREM 25.8.** *Let  $\Sigma$  be an infinite set.*

*Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper,  $\beta_0 := \inf \text{DF}_\varepsilon$ .*

*Let  $\rho \in [0; \infty)$ . Then:  $X^\rho S_{\bullet, \mathbb{C}}^\varepsilon$  is complex-differentiable on  $\mathfrak{R}^*(\beta_0; \infty)$*

$$\text{and} \quad (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon \text{ on } \mathfrak{R}^*(\beta_0; \infty).$$

*Proof.* For all  $n \in \mathbb{N}$ , let  $\Sigma_n := \varepsilon^*(-\infty; n]$  and let  $\varepsilon_n := \varepsilon|_{\Sigma_n}$ .

**Given**  $z \in \mathfrak{R}^*(\beta_0; \infty)$ , **want:**  $X^\rho S_{\bullet, \mathbb{C}}^\varepsilon$  is complex-differentiable at  $z$

$$\text{and} \quad (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)'(z) = -(X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon)(z).$$

**Let**  $\beta := \Re(z)$ . **Let**  $\beta_1 := (\beta_0 + \beta)/2$ . Then  $\beta_0 < \beta_1 < \beta$ .

**It suffices to show:**  $X^\rho S_{\bullet, \mathbb{C}}^\varepsilon$  is complex-differentiable on  $\mathfrak{R}^*(\beta_1; \infty)$

$$\text{and} \quad (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon \text{ on } \mathfrak{R}^*(\beta_1; \infty).$$

By Theorem 25.6, as  $n \rightarrow \infty$ , we have both

$$X^\rho S_{\bullet, \mathbb{C}}^{\varepsilon_n} \rightarrow X^\rho S_{\bullet, \mathbb{C}}^\varepsilon \quad \text{uniformly on } \mathfrak{R}^*(\beta_1; \infty)$$

$$\text{and} \quad X^{\rho+1} S_{\bullet, \mathbb{C}}^{\varepsilon_n} \rightarrow X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon \quad \text{uniformly on } \mathfrak{R}^*(\beta_1; \infty).$$

For all  $n \in \mathbb{N}$ , since  $\Sigma_n$  is finite, by Theorem 25.7, we see that

$X^\rho S_{\bullet, \mathbb{C}}^{\varepsilon_n}$  is complex-differentiable at  $z$

$$\text{and} \quad (X^\rho S_{\bullet, \mathbb{C}}^{\varepsilon_n})' = -X^{\rho+1} S_{\bullet, \mathbb{C}}^{\varepsilon_n} \text{ on } \mathfrak{R}^*(\beta_0; \infty).$$

Then, as  $n \rightarrow \infty$ , we have both

$$X^\rho S_{\bullet, \mathbb{C}}^{\varepsilon_n} \rightarrow X^\rho S_{\bullet, \mathbb{C}}^\varepsilon \quad \text{pointwise on } \mathfrak{R}^*(\beta_1; \infty)$$

$$\text{and} \quad (X^\rho S_{\bullet, \mathbb{C}}^{\varepsilon_n})' \rightarrow -X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon \quad \text{uniformly on } \mathfrak{R}^*(\beta_1; \infty).$$

Then, by Theorem 25.3, we get:

$$X^\rho S_{\bullet, \mathbb{C}}^\varepsilon \text{ is complex-differentiable on } \mathfrak{R}^*(\beta_1; \infty)$$

$$\text{and} \quad (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon \text{ on } \mathfrak{R}^*(\beta_1; \infty). \quad \square$$

**THEOREM 25.9.** *Let  $\Sigma$  be an infinite set.*

*Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper,  $\beta_0 := \inf \text{DF}_\varepsilon$ .*

*Let  $\rho \in [0; \infty)$ . Then:  $X^\rho S_{\bullet, \mathbb{C}}^\varepsilon$  is  $C^\omega$  on  $(\beta_0; \infty)$*

$$\text{and} \quad (X^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon \text{ on } (\beta_0; \infty).$$

*Proof.* MORE LATER □

## 26. UNNAMED SECTION

**DEFINITION 26.1.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

For all  $\beta \in \text{DF}_\varepsilon^{\mathbb{C}}$ , let  $\Delta_\beta^\varepsilon := \sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}] \in \mathbb{C}$ .

For all  $\beta \in \text{IDF}_\varepsilon^{\mathbb{C}}$ , let  $\Gamma_\beta^\varepsilon := \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot e^{-\beta \cdot \varepsilon_\sigma}] \in \mathbb{C}$ .

**DEFINITION 26.2.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

For all real  $\rho \geq 0$ ,

define  $\overline{X^\rho S_\bullet^\varepsilon} : \text{IDF}_\varepsilon \rightarrow \mathbb{R}$  by:  $\forall \beta \in \text{IDF}_\varepsilon, \overline{X^\rho S_\bullet^\varepsilon}(\beta) = \overline{X^\rho S_\beta^\varepsilon}$ .

Define  $\Delta_\bullet^\varepsilon : \text{IDF}_\varepsilon \rightarrow \mathbb{R}$  by:  $\forall \beta \in \text{IDF}_\varepsilon, \Delta_\bullet^\varepsilon(\beta) = \Delta_\beta^\varepsilon$ .

Define  $\Gamma_\bullet^\varepsilon : \text{IDF}_\varepsilon \rightarrow \mathbb{R}$  by:  $\forall \beta \in \text{IDF}_\varepsilon, \Gamma_\bullet^\varepsilon(\beta) = \Gamma_\beta^\varepsilon$ .

*Proof.* MORE LATER □

## 27. UNNAMED SECTION

**DEFINITION 27.1.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

For all real  $\rho \geq 0$ ,

define  $\overline{X^\rho S_{\bullet\mathbb{C}}^\varepsilon} : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  by:  $\forall \beta \in \text{IDF}_\varepsilon^{\mathbb{C}}, \overline{X^\rho S_{\bullet\mathbb{C}}^\varepsilon}(\beta) = \overline{X^\rho S_\beta^\varepsilon}$ .

Define  $\Delta_{\bullet\mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  by:  $\forall \beta \in \text{IDF}_\varepsilon^{\mathbb{C}}, \Delta_{\bullet\mathbb{C}}^\varepsilon(\beta) = \Delta_\beta^\varepsilon$ .

Define  $\Gamma_{\bullet\mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  by:  $\forall \beta \in \text{IDF}_\varepsilon^{\mathbb{C}}, \Gamma_{\bullet\mathbb{C}}^\varepsilon(\beta) = \Gamma_\beta^\varepsilon$ .

**DEFINITION 27.2.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Let  $\boxed{\text{DF}_\varepsilon^{\mathbb{C}}} := \mathfrak{R}^*(\text{DF}_\varepsilon)$  and let  $\boxed{\text{IDF}_\varepsilon^{\mathbb{C}}} := \mathfrak{R}^*(\text{IDF}_\varepsilon)$ .

**THEOREM 27.3.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta \in \text{DF}_\varepsilon^{\mathbb{C}}$ .  
For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ . Then:  $\sum_{\sigma \in \Sigma} |e^{-\beta \cdot \varepsilon_\sigma}| < \infty$ .

*Proof.* MORE LATER □

**THEOREM 27.4.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta \in \text{IDF}_\varepsilon^{\mathbb{C}}$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

Then:  $\forall \rho \geq 0, \overline{X^\rho S_\beta^\varepsilon} < \infty$ .

*Proof.* MORE LATER □

By “**unif-on-cpta on**” we mean: “uniformly on compact subsets of”.

**THEOREM 27.5.** Let  $\Sigma$  be an infinite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper.

For all  $t \in \mathbb{R}$ , let  $\Sigma^t := \varepsilon^*(-\infty; t]$  and  $\varepsilon^t := \varepsilon|_{\Sigma^t}$ .

Assume  $\text{DF}_\varepsilon \neq \emptyset$ . Let  $\rho \geq 0$  be real.

Then: as  $t \rightarrow \infty$ ,  $X^\rho S_{\bullet\mathbb{C}}^{\varepsilon^t} \rightarrow X^\rho S_{\bullet\mathbb{C}}^\varepsilon$  unif-on-cpta on  $\text{IDF}_\varepsilon^{\mathbb{C}}$ .

*Proof.* MORE LATER □

**THEOREM 27.6.** Let  $\Sigma$  be an infinite set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper.

Let  $\rho \geq 0$  be real.

Then  $\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  is complex-differentiable

$$\text{and } (\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -\bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon.$$

*Proof.* For all  $t \in \mathbb{R}$ , let  $\Sigma^t := \varepsilon^*(-\infty; t]$  and  $\varepsilon^t := \varepsilon|_{\Sigma^t}$ .

Then:  $\forall t \in \mathbb{R}$ ,  $X^\rho S_{\bullet, \mathbb{C}}^{\varepsilon^t} : \text{IDF}_{\varepsilon^t}^{\mathbb{C}} \rightarrow \mathbb{C}$  is complex-differentiable

$$\text{and } (X^\rho S_{\bullet, \mathbb{C}}^{\varepsilon^t})' = -X^{\rho+1} S_{\bullet, \mathbb{C}}^{\varepsilon^t}.$$

By Theorem 27.5, as  $t \rightarrow \infty$ , we have

$$\text{both } X^\rho S_{\bullet, \mathbb{C}}^{\varepsilon^t} \rightarrow X^\rho S_{\bullet, \mathbb{C}}^\varepsilon \text{ unif-on-cpta on } \text{IDF}_\varepsilon^{\mathbb{C}}$$

$$\text{and } X^{\rho+1} S_{\bullet, \mathbb{C}}^{\varepsilon^t} \rightarrow X^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon \text{ unif-on-cpta on } \text{IDF}_\varepsilon^{\mathbb{C}}.$$

Then  $\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  is complex-differentiable

$$\text{and } (\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -\bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon. \quad \square$$

**THEOREM 27.7.** Let  $\Sigma$  be an infinite set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $(-\infty)$ -proper.

Let  $\rho \geq 0$  be real.

Then  $\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  is complex-differentiable

$$\text{and } (\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -\bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon.$$

*Proof.* By Theorem 27.6,  $\bar{X}^\rho S_{\bullet, \mathbb{C}}^{-\varepsilon} : \text{IDF}_{-\varepsilon}^{\mathbb{C}} \rightarrow \mathbb{C}$  is complex-differentiable

$$\text{and } (\bar{X}^\rho S_{\bullet, \mathbb{C}}^{-\varepsilon})' = -\bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^{-\varepsilon}.$$

Then  $-\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  is complex-differentiable

$$\text{and } (-\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -(-\bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon).$$

Then  $\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  is complex-differentiable

$$\text{and } (\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -\bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon. \quad \square$$

**THEOREM 27.8.** Let  $\Sigma$  be an infinite set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Let  $\rho \geq 0$  be real.

Then  $\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  is complex-differentiable

$$\text{and } (\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon)' = -\bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon.$$

*Proof.* By Theorem 23.32, there are four cases to consider:

$$\text{IDF}_\varepsilon = \emptyset, \text{IDF}_\varepsilon = \mathbb{R}, \text{IDF}_\varepsilon = (\beta_0; \infty), \text{IDF}_\varepsilon = (-\infty; -\beta_0).$$

MORE LATER □

**THEOREM 27.9.** Let  $\Sigma$  be a set. Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$  be  $\infty$ -proper.

Let  $\rho \geq 0$  be real. Then  $\bar{X}^\rho S_{\bullet}^\varepsilon : \text{IDF}_\varepsilon \rightarrow \mathbb{R}$  is  $C^\omega$

$$\text{and } (\bar{X}^\rho S_{\bullet}^\varepsilon)' = \bar{X}^{\rho+1} S_{\bullet}^\varepsilon.$$



*Proof.* Since complex-differentiable implies complex-analytic, by Theorem 27.6, we see that  $\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C}$  is complex-analytic. So, since  $\bar{X}^\rho S_{\bullet}^\varepsilon : \text{IDF}_\varepsilon \rightarrow \mathbb{R}$  is the restriction to  $\text{IDF}_\varepsilon$  of

$$\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C},$$

it follows that  $\bar{X}^\rho S_{\bullet}^\varepsilon : \text{IDF}_\varepsilon \rightarrow \mathbb{R}$  is  $C^\omega$ .

**Want:**  $(\bar{X}^\rho S_{\bullet}^\varepsilon)' = \bar{X}^{\rho+1} S_{\bullet}^\varepsilon$ .

**Given**  $\beta \in \text{IDF}_\varepsilon$ , **want:**  $(\bar{X}^\rho S_{\bullet}^\varepsilon)'(\beta) = \bar{X}^{\rho+1} S_{\bullet}^\varepsilon(\beta)$ .

By Theorem 27.6, we see that  $(\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon)'(\beta) = \bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon(\beta)$ .

Since  $\bar{X}^\rho S_{\bullet}^\varepsilon : \text{IDF}_\varepsilon \rightarrow \mathbb{R}$  is the restriction to  $\text{IDF}_\varepsilon$  of

$$\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon : \text{IDF}_\varepsilon^{\mathbb{C}} \rightarrow \mathbb{C},$$

we get:  $(\bar{X}^\rho S_{\bullet}^\varepsilon)'(\beta) = (\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon)'(\beta)$ .

Since  $\bar{X}^{\rho+1} S_{\bullet}^\varepsilon : \text{IDF}_\varepsilon \rightarrow \mathbb{R}$  is the restriction to  $\text{IDF}_\varepsilon$  of

we get:  $(\bar{X}^{\rho+1} S_{\bullet}^\varepsilon)(\beta) = (\bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon)(\beta)$ .

Then:  $(\bar{X}^\rho S_{\bullet}^\varepsilon)'(\beta) = (\bar{X}^\rho S_{\bullet, \mathbb{C}}^\varepsilon)'(\beta) = \bar{X}^{\rho+1} S_{\bullet, \mathbb{C}}^\varepsilon(\beta) = \bar{X}^{\rho+1} S_{\bullet}^\varepsilon(\beta)$ .  $\square$

**THEOREM 27.10.** Let  $\Sigma$  be a nonempty countable set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Let  $\beta \in \text{DF}_\varepsilon$ . Assume  $\bar{X}^1 S_\beta^\varepsilon < \infty$ . Then  $\bar{X}^1 S_\beta^\varepsilon = |\varepsilon_* B_\beta^\varepsilon|_1$ .

*Proof.* CHECK (Copied from Theorem 20.4):

Since  $\beta \in \text{DF}_\varepsilon$ , we get:  $\text{DF}_\varepsilon \neq \emptyset$ . Then  $\Sigma$  is countable.

Since  $\Sigma \neq \emptyset$ , we get:  $\Delta_\beta^\varepsilon > 0$ .

Since  $\beta \in \text{DF}_\varepsilon$ , we get:  $\Delta_\beta^\varepsilon < \infty$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ ,  $\bar{\varepsilon}_\sigma := |\varepsilon(\sigma)|$ .

Because  $\Sigma$  is the disjoint union, over  $t \in \mathbb{I}_{\bar{\varepsilon}}$ , of  $\bar{\varepsilon}^* \{t\}$ ,

$$\text{we get: } \sum_{t \in \mathbb{I}_{\bar{\varepsilon}}} \sum_{\sigma \in \bar{\varepsilon}^* \{t\}} [\bar{\varepsilon}_\sigma \cdot (B_\beta^{\bar{\varepsilon}} \{\sigma\})] = \sum_{\sigma \in \Sigma} [\bar{\varepsilon}_\sigma \cdot (B_\beta^{\bar{\varepsilon}} \{\sigma\})].$$

$$\text{Also, } A_\beta^{\bar{\varepsilon}} = \sum_{\sigma \in \Sigma} [\bar{\varepsilon}_\sigma \cdot (B_\beta^{\bar{\varepsilon}} \{\sigma\})].$$

$$\text{Then: } \sum_{t \in \mathbb{I}_{\bar{\varepsilon}}} \sum_{\sigma \in \bar{\varepsilon}^* \{t\}} [\bar{\varepsilon}_\sigma \cdot (B_\beta^{\bar{\varepsilon}} \{\sigma\})] = A_\beta^{\bar{\varepsilon}}.$$

$$\text{So, since } \sum_{t \in \mathbb{I}_{\bar{\varepsilon}}} [t \cdot ((\bar{\varepsilon}_* B_\beta^{\bar{\varepsilon}}) \{t\})] = M_{\bar{\varepsilon}_* B_\beta^{\bar{\varepsilon}}},$$

$$\text{we want: } \sum_{t \in \mathbb{I}_{\bar{\varepsilon}}} [t \cdot ((\bar{\varepsilon}_* B_\beta^{\bar{\varepsilon}}) \{t\})] = \sum_{t \in \mathbb{I}_{\bar{\varepsilon}}} \sum_{\sigma \in \bar{\varepsilon}^* \{t\}} [\bar{\varepsilon}_\sigma \cdot (B_\beta^{\bar{\varepsilon}} \{\sigma\})].$$

$$\text{Want: } \forall t \in \mathbb{I}_{\bar{\varepsilon}}, \quad t \cdot ((\bar{\varepsilon}_* B_\beta^{\bar{\varepsilon}}) \{t\}) = \sum_{\sigma \in \bar{\varepsilon}^* \{t\}} [\bar{\varepsilon}_\sigma \cdot (B_\beta^{\bar{\varepsilon}} \{\sigma\})].$$

$$\text{Given } t \in \mathbb{I}_{\bar{\varepsilon}}, \text{ want: } t \cdot ((\bar{\varepsilon}_* B_\beta^{\bar{\varepsilon}}) \{t\}) = \sum_{\sigma \in \bar{\varepsilon}^* \{t\}} [\bar{\varepsilon}_\sigma \cdot (B_\beta^{\bar{\varepsilon}} \{\sigma\})].$$

For all  $\sigma \in \bar{\varepsilon}^* \{t\}$ , since  $\bar{\varepsilon}_\sigma = \bar{\varepsilon}(\sigma) \in \{t\}$ , we get:  $t = \bar{\varepsilon}_\sigma$ .

$$\text{Want: } t \cdot ((\bar{\varepsilon}_* B_\beta^{\bar{\varepsilon}}) \{t\}) = \sum_{\sigma \in \bar{\varepsilon}^* \{t\}} [t \cdot (B_\beta^{\bar{\varepsilon}} \{\sigma\})].$$

Because  $\bar{\varepsilon}^* \{t\}$  is the disjoint union, over  $\sigma \in \bar{\varepsilon}^* \{t\}$ , of  $\{\sigma\}$ ,

$$\text{we get: } B_\beta^{\bar{\varepsilon}}(\bar{\varepsilon}^* \{t\}) = \sum_{\sigma \in \bar{\varepsilon}^* \{t\}} [B_\beta^{\bar{\varepsilon}} \{\sigma\}].$$

$$\text{Also, } (\bar{\varepsilon}_* B_\beta^{\bar{\varepsilon}}) \{t\} = B_\beta^{\bar{\varepsilon}}(\bar{\varepsilon}^* \{t\}).$$

$$\text{Then: } t \cdot ((\bar{\varepsilon}_* B_\beta^{\bar{\varepsilon}}) \{t\}) = t \cdot (B_\beta^{\bar{\varepsilon}}(\bar{\varepsilon}^* \{t\})) = \sum_{\sigma \in \bar{\varepsilon}^* \{t\}} [t \cdot (B_\beta^{\bar{\varepsilon}} \{\sigma\})]. \quad \square$$

**THEOREM 27.11.** Let  $\Sigma$  be a nonempty countable set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ . Let  $\beta \in \text{DF}_\varepsilon$ . Assume  $\bar{X}^1 S_\beta^\varepsilon < \infty$ . Then  $|\varepsilon_* B_\beta^\varepsilon|_1 < \infty$  and  $A_\beta^\varepsilon = M_{\varepsilon_* B_\beta^\varepsilon}$ .

*Proof.* CHECK (Copied from Theorem 20.4):

Since  $\beta \in \text{DF}_\varepsilon$ , we get:  $\text{DF}_\varepsilon \neq \emptyset$ . Then  $\Sigma$  is countable.

Since  $\Sigma \neq \emptyset$ , we get:  $\Delta_\beta^\varepsilon > 0$ .

Since  $\beta \in \text{DF}_\varepsilon$ , we get:  $\Delta_\beta^\varepsilon < \infty$ .

For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

Because  $\Sigma$  is the disjoint union, over  $t \in \mathbb{I}_\varepsilon$ , of  $\varepsilon^*\{t\}$ ,

$$\text{we get: } \sum_{t \in \mathbb{I}_\varepsilon} \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})] = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})].$$

$$\text{Also, } A_\beta^\varepsilon = \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})].$$

$$\text{Then: } \sum_{t \in \mathbb{I}_\varepsilon} \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})] = A_\beta^\varepsilon.$$

$$\text{So, since } \sum_{t \in \mathbb{I}_\varepsilon} [t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\})] = M_{\varepsilon_* B_\beta^\varepsilon},$$

$$\text{we want: } \sum_{t \in \mathbb{I}_\varepsilon} [t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\})] = \sum_{t \in \mathbb{I}_\varepsilon} \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})].$$

$$\text{Want: } \forall t \in \mathbb{I}_\varepsilon, \quad t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\}) = \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})].$$

$$\text{Given } t \in \mathbb{I}_\varepsilon, \text{ want: } t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\}) = \sum_{\sigma \in \varepsilon^*\{t\}} [\varepsilon_\sigma \cdot (B_\beta^\varepsilon\{\sigma\})].$$

For all  $\sigma \in \varepsilon^*\{t\}$ , since  $\varepsilon_\sigma = \varepsilon(\sigma) \in \{t\}$ , we get:  $t = \varepsilon_\sigma$ .

$$\text{Want: } t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\}) = \sum_{\sigma \in \varepsilon^*\{t\}} [t \cdot (B_\beta^\varepsilon\{\sigma\})].$$

Because  $\varepsilon^*\{t\}$  is the disjoint union, over  $\sigma \in \varepsilon^*\{t\}$ , of  $\{\sigma\}$ ,

$$\text{we get: } B_\beta^\varepsilon(\varepsilon^*\{t\}) = \sum_{\sigma \in \varepsilon^*\{t\}} [B_\beta^\varepsilon\{\sigma\}].$$

$$\text{Also, } (\varepsilon_* B_\beta^\varepsilon)\{t\} = B_\beta^\varepsilon(\varepsilon^*\{t\}).$$

$$\text{Then: } t \cdot ((\varepsilon_* B_\beta^\varepsilon)\{t\}) = t \cdot (B_\beta^\varepsilon(\varepsilon^*\{t\})) = \sum_{\sigma \in \varepsilon^*\{t\}} [t \cdot (B_\beta^\varepsilon\{\sigma\})]. \quad \square$$

**THEOREM 27.12.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\varepsilon^*[0; \infty)$  is infinite and  $\text{DF}_\varepsilon \neq \emptyset$ . Let  $\beta_0 := \inf \text{DF}_\varepsilon$ .

Then:  $\forall \text{real } \gamma > \beta_0, \forall \text{real } \rho > 0, \bar{X}^\rho S_\gamma^\varepsilon < \infty$ .

*Proof.* Given a real  $\gamma > \beta_0$  and a real  $\rho > 0$ , want:  $\bar{X}^\rho S_\gamma^\varepsilon < \infty$ .

Since  $\gamma > \beta_0 = \inf \text{DF}_\varepsilon$ , choose  $\beta \in \text{DF}_\varepsilon$  s.t.  $\gamma > \beta$ .

By Theorem 23.15, we have:  $\bar{X}^\rho S_\gamma^\varepsilon < \infty$ . □

**DEFINITION 27.13.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Then  $\boxed{A_\bullet^\varepsilon} : \text{IDF}_\varepsilon \rightarrow \mathbb{R}$  is defined by:  $\forall \beta \in \text{IDF}_\varepsilon, A_\bullet^\varepsilon(\beta) = A_\beta^\varepsilon$ .

**THEOREM 27.14.** Let  $\Sigma$  be a set.

Let  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ . Assume:  $\#\mathbb{I}_\varepsilon \geq 2$ .

Then:  $A_\bullet^\varepsilon$  is a strictly-decreasing  $C^\omega$ -diffeomorphism

from  $\text{IDF}_\varepsilon$  onto  $(\inf \mathbb{I}_{A_\bullet^\varepsilon}; \sup \mathbb{I}_{A_\bullet^\varepsilon})$ .

*Proof.* (MODIFY!) For all  $\sigma \in \Sigma$ , let  $\varepsilon_\sigma := \varepsilon(\sigma)$ .

We have:  $\forall \beta \in$

$$IDF_\varepsilon, A_\bullet^\varepsilon(\beta) = \frac{\sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot e^{-\beta \cdot \varepsilon_\sigma}]}{\sum_{\tau \in \Sigma} [e^{-\beta \cdot \varepsilon_\tau}]}.$$

Then  $A_\bullet^\varepsilon : IDF_\varepsilon \rightarrow \mathbb{R}$  is  $C^\omega$ .

We have:  $\forall \beta \in$

$$IDF_\varepsilon, A_\bullet^\varepsilon(\beta) = \frac{\sum_{\sigma \in \Sigma} [\Gamma_\bullet^\varepsilon(\beta)]}{\sum_{\tau \in \Sigma} [\Delta_\bullet^\varepsilon(\beta)]}.$$

We have:  $\forall \beta \in$

$$IDF_\varepsilon, A_\bullet^\varepsilon(\beta) = \frac{\sum_{\sigma \in \Sigma} [X^1 S_\bullet^\varepsilon(\beta)]}{\sum_{\tau \in \Sigma} [X^0 S_\bullet^\varepsilon(\beta)]}.$$

So, by Theorem 20.6 and the  $C^\omega$ -Inverse Function Theorem and the Mean Value Theorem, **it suffices to show:**  $(A_\bullet^\varepsilon)' < 0$  on  $IDF_\varepsilon$ .

**Given**  $\beta \in IDF_\varepsilon$ , **want:**  $(A_\bullet^\varepsilon)'(\beta) < 0$ .

$$\text{Let } P := \sum_{\sigma \in \Sigma} [\varepsilon_\sigma \cdot e^{-\beta \cdot \varepsilon_\sigma}], \quad P' := \sum_{\sigma \in \Sigma} [(-\varepsilon_\sigma^2) \cdot e^{-\beta \cdot \varepsilon_\sigma}].$$

$$\text{Let } Q := \sum_{\tau \in \Sigma} [e^{-\beta \cdot \varepsilon_\tau}], \quad Q' := \sum_{\tau \in \Sigma} [(-\varepsilon_\tau) \cdot e^{-\beta \cdot \varepsilon_\tau}].$$

Then  $Q > 0$ . Also, by the Quotient Rule,  $(A_\bullet^\varepsilon)'(\beta) = [QP' - PQ']/Q^2$ .

**Want:**  $QP' - PQ' < 0$ .

$$\text{We have: } QP' = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [(-\varepsilon_\sigma^2) \cdot e^{-\beta \cdot (\varepsilon_\sigma + \varepsilon_\tau)}].$$

$$\text{We have: } PQ' = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [(-\varepsilon_\sigma \varepsilon_\tau) \cdot e^{-\beta \cdot (\varepsilon_\sigma + \varepsilon_\tau)}].$$

$$\text{Then: } QP' - PQ' = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [(-\varepsilon_\sigma^2 + \varepsilon_\sigma \varepsilon_\tau) \cdot e^{-\beta \cdot (\varepsilon_\sigma + \varepsilon_\tau)}].$$

Interchanging  $\sigma$  and  $\tau$ , we get:

$$QP' - PQ' = \sum_{\tau \in \Sigma} \sum_{\sigma \in \Sigma} [(-\varepsilon_\tau^2 + \varepsilon_\tau \varepsilon_\sigma) \cdot e^{-\beta \cdot (\varepsilon_\tau + \varepsilon_\sigma)}].$$

By commutativity of addition and multiplication,

adding the last two equations gives:

$$2 \cdot (QP' - PQ') = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [(-\varepsilon_\sigma^2 - \varepsilon_\tau^2 + 2\varepsilon_\sigma \varepsilon_\tau) \cdot e^{-\beta \cdot (\varepsilon_\sigma + \varepsilon_\tau)}].$$

$$\text{Then: } 2 \cdot (QP' - PQ') = \sum_{\sigma \in \Sigma} \sum_{\tau \in \Sigma} [-(\varepsilon_\sigma - \varepsilon_\tau)^2 \cdot e^{-\beta \cdot (\varepsilon_\sigma + \varepsilon_\tau)}].$$

$$\text{Then: } 2 \cdot (QP' - PQ') < 0. \quad \text{Then: } QP' - PQ' < 0. \quad \square$$

Recall (Theorem 22.3):

If  $\varepsilon$  is  $\infty$ -proper, then  $\mathbb{I}_\varepsilon$  has a minimum element, *i.e.*,  $\min \mathbb{I}_\varepsilon$  exists.

**THEOREM 27.15.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ .

Assume:  $\varepsilon^*[0; \infty)$  is infinite and  $DF_\varepsilon \neq \emptyset$ .

Then:  $\varepsilon$  is  $\infty$ -proper and as  $\beta \rightarrow \infty$ ,  $A_\beta^\varepsilon \rightarrow \min \mathbb{I}_\varepsilon$ .

*Proof.* By Theorem 23.12,  $\varepsilon$  is  $\infty$ -proper.

**It remains to show:** as  $\beta \rightarrow \infty$ ,  $A_\beta^\varepsilon \rightarrow \min \mathbb{I}_\varepsilon$ .

**Let**  $t_0 := \min \mathbb{I}_\varepsilon$ . **Want:**  $A_\beta^\varepsilon \rightarrow t_0$ .

**Let**  $\Sigma' := \Sigma \setminus (\varepsilon^*\{t_0\})$ . **Let**  $n_0 := \#(\varepsilon^*\{t_0\})$ .

Since  $\{t_0\} \subseteq (-\infty; t_0]$ , we get  $\varepsilon^*\{t_0\} \subseteq \varepsilon^*(-\infty; t_0]$ .

Since  $\varepsilon$  is  $\infty$ -proper, we get:  $\varepsilon^*(-\infty; t_0]$  is finite.

Then  $\varepsilon^*\{t_0\}$  is finite. That is,  $n_0 < \infty$ .

Since  $t_0 \in \mathbb{I}_\varepsilon$ , we get  $\varepsilon^*\{t_0\} \neq \emptyset$ , and so  $n_0 > 0$ . Then  $0 < n_0 < \infty$ .

For all  $\beta \in (\beta_0; \infty)$ , we have:

$$\begin{aligned} A_\beta^\varepsilon &= \frac{n_0 \cdot t_0 \cdot e^{-\beta \cdot t_0} + \sum_{\sigma \in \Sigma'} [\varepsilon_\sigma \cdot e^{-\beta \cdot \varepsilon_\sigma}]}{n_0 \cdot e^{-\beta \cdot t_0} + \sum_{\sigma \in \Sigma'} [e^{-\beta \cdot \varepsilon_\sigma}]} \\ &= \frac{n_0 \cdot t_0 \cdot e^{-\beta \cdot t_0} + \sum_{\sigma \in \Sigma'} [\varepsilon_\sigma \cdot e^{-\beta \cdot \varepsilon_\sigma}]}{n_0 \cdot e^{-\beta \cdot t_0} + \sum_{\sigma \in \Sigma'} [e^{-\beta \cdot \varepsilon_\sigma}]} \cdot \frac{e^{\beta \cdot t_0}}{e^{\beta \cdot t_0}} \\ &= \frac{n_0 \cdot t_0 + \sum_{\sigma \in \Sigma'} [\varepsilon_\sigma \cdot e^{-\beta \cdot (\varepsilon_\sigma - t_0)}]}{n_0 + \sum_{\sigma \in \Sigma'} [e^{-\beta \cdot (\varepsilon_\sigma - t_0)}]}. \end{aligned}$$

**Let**  $\beta_1 := \beta_0 + 1$ .

Then, for all  $\beta \in [\beta_1; \infty)$ , for all  $\sigma \in \Sigma$ , we have

$$|\varepsilon_\sigma \cdot e^{-\beta \cdot (\varepsilon_\sigma - t_0)}| = |\varepsilon_\sigma| \cdot e^{-\beta_1 \cdot (\varepsilon_\sigma - t_0)}$$

$$\text{and} \quad |e^{-\beta \cdot (\varepsilon_\sigma - t_0)}| = e^{-\beta_1 \cdot (\varepsilon_\sigma - t_0)}.$$

We have:  $\sum_{\sigma \in \Sigma} [|\varepsilon_\sigma| \cdot e^{-\beta_1 \cdot (\varepsilon_\sigma - t_0)}] = \bar{X}^1 S_{\beta_1}^\varepsilon$ .

Also,  $\sum_{\sigma \in \Sigma} [e^{-\beta_1 \cdot (\varepsilon_\sigma - t_0)}] = \bar{X}^0 S_{\beta_1}^\varepsilon$ .

By Theorem 27.12, we have:  $\bar{X}^1 S_{\beta_1}^\varepsilon < \infty$  and  $\bar{X}^0 S_{\beta_1}^\varepsilon < \infty$ .

So, by the Dominated Convergence Theorem, as  $\beta \rightarrow \infty$ ,

$$\begin{aligned} \sum_{\sigma \in \Sigma'} [\varepsilon_\sigma \cdot e^{-\beta \cdot (\varepsilon_\sigma - t_0)}] &\rightarrow 0 \\ \text{and} \quad \sum_{\sigma \in \Sigma'} [e^{-\beta \cdot (\varepsilon_\sigma - t_0)}] &\rightarrow 0. \end{aligned}$$

Then: as  $\beta \rightarrow \infty$ ,  $A_\beta^\varepsilon \rightarrow \frac{n_0 \cdot t_0 + 0}{n_0 + 0}$ .

Then: as  $\beta \rightarrow \infty$ ,  $A_\beta^\varepsilon \rightarrow t_0$ . □

**Let**  $\Sigma$  be an infinite set and **let**  $\varepsilon : \Sigma \rightarrow \mathbb{N}$  be  $\infty$ -proper.

Then  $\sup \mathbb{I}_\varepsilon = \infty$ . Assume  $\text{DF}_\varepsilon \neq \emptyset$ . **Let**  $\beta_0 := \inf \text{DF}_\varepsilon$ .

By Theorem 23.20,  $(\beta_0; \infty) \subseteq \text{DF}_\varepsilon$ .

Even though  $\sup \mathbb{I}_\varepsilon = \infty$ ,

it does NOT necessarily follow that: as  $\beta \rightarrow (\beta_0)^+$ ,  $A_\beta^\varepsilon \rightarrow \infty$ .

Here is an example:

For all  $k \in \mathbb{N}$ , **let**  $n_k := \lfloor e^k/k^3 \rfloor$ .

**Let**  $\Sigma := \{(k, j) \in \mathbb{N} \times \mathbb{N} \mid k \in \mathbb{N}, j \in [1..n_k]\}$ .

**Define**  $\varepsilon : \Sigma \rightarrow [0..\infty)$  by:  $\forall k \in \mathbb{N}, \forall j \in [1..n_k], \varepsilon(k, j) = k - 1$ .

Then  $\text{DF}_\varepsilon = [1; \infty)$ , so  $\inf \text{DF}_\varepsilon = 1$ .

Also,  $\Gamma_1^\varepsilon < \infty$  and  $0 < \Delta_1^\varepsilon < \infty$ , so  $A_1^\varepsilon < \infty$ .

Also, by the Dominated Convergence Theorem, we have:

$$\text{as } \beta \rightarrow 1^+, \text{ both } \Gamma_\beta^\varepsilon \rightarrow \Gamma_1^\varepsilon \text{ and } \Delta_\beta^\varepsilon \rightarrow \Delta_1^\varepsilon.$$

Then, as  $\beta \rightarrow 1^+$ ,  $A_\beta^\varepsilon \rightarrow A_1^\varepsilon < \infty$ .

This, then, leads to an **Open Problem**, as follows:

For all  $k \in \mathbb{N}$ , **let**  $n_k := \lfloor e^k/k^3 \rfloor$ .

**Let**  $\Sigma := \{(k, j) \in \mathbb{N} \times \mathbb{N} \mid k \in \mathbb{N}, j \in [1..n_k]\}$ .

**Define**  $\varepsilon : \Sigma \rightarrow \mathbb{N}$  by:  $\forall k \in \mathbb{N}, \forall j \in [1..n_k], \varepsilon(k, j) = k$ .

By Theorem 27.14,  $A_\bullet^\varepsilon$  is strictly-decreasing, and so

and since as  $\beta \rightarrow 1^+$ ,  $A_\beta^\varepsilon \rightarrow A_1^\varepsilon$ , we get:

$\mathbb{I}_{A_\bullet^\varepsilon}$  is bounded above by  $A_1^\varepsilon$ .

**Let**  $\alpha \in \mathbb{N}$ . Assume:  $\alpha > A_1^\varepsilon$ . Then:  $\alpha \notin \mathbb{I}_{A_\bullet^\varepsilon}$ .

Suppose  $N$  professors, numbered 1 to  $N$ , have states in  $\Sigma$ .

Suppose each state  $\sigma \in \Sigma$  has wealth  $\varepsilon(\sigma)$ .

Suppose the total wealth of all professors is  $N\alpha$ .

Give equal probability to every dispensation of states.

For each  $\sigma_0 \in \Sigma$ , we seek a method to approximate  
the probability that Professor# $N$  is in state  $\sigma_0$ .

More precisely: For all  $n \in \mathbb{N}$ ,

**let**  $\Omega_n := \{\omega : [1..n] \rightarrow \Sigma \mid \sum_{\ell=1}^n [\varepsilon(\omega(\ell))] = n\alpha\}$ .

Then  $\Omega_N$  represents the set of all state-dispensations.

**Open Problem:** For each  $\sigma_0 \in \Sigma$ ,

determine whether

the limit, as  $n \rightarrow \infty$ , of  $\nu_{\Omega_n} \{\omega \in \Omega_n \mid \omega(n) = \sigma_0\}$  exists,

and, if it does, compute it.

This is a well-defined mathematical problem.

However, since  $\alpha \notin \mathbb{I}_{A_\bullet^\varepsilon}$ , we cannot solve  $A_\beta^\varepsilon = \alpha$  for  $\beta$ ,

so our earlier techniques do not immediately apply.

**THEOREM 27.16.** **Let**  $\beta_0 \in \mathbb{R}$ ,  $I := (\beta_0; \infty)$ ,  $g : I \rightarrow \mathbb{R}$ .

*Assume:*  $g$  is differentiable on  $I$  and  $g'$  is semi-decreasing on  $I$ .

*Assume:* as  $\beta \rightarrow (\beta_0)^+$ ,  $g(\beta) \rightarrow -\infty$ .

*Then:* as  $\beta \rightarrow (\beta_0)^+$ ,  $g'(\beta) \rightarrow \infty$ .

*Proof.* **Let**  $M := \sup \mathbb{I}_{g'} \in (-\infty; \infty]$ .

Since  $g'$  is strictly-decreasing, we get: as  $\beta \rightarrow (\beta_0)^+$ ,  $g'(\beta) \rightarrow M$ .

**Want:**  $M = \infty$ . Assume  $M < \infty$ . **Want:** Contradiction.

**Let**  $\beta_1 := \beta_0 + 1$ .

Since as  $\beta \rightarrow (\beta_0)^+$ ,  $g(\beta) \rightarrow -\infty$ ,

**choose**  $\beta \in (\beta_0; \beta_1)$  s.t.  $g(\beta) < (g(\beta_1)) - M$ .

By the Mean Value Theorem, choose  $\xi \in (\beta; \beta_0 + 1)$  s.t.

$$\frac{(g(\beta_1) - g(\beta))}{\beta_1 - \beta} = g'(\xi).$$

Since  $M = \sup \mathbb{I}_{g'}$ , we get:  $g'(\xi) \leq M$ .

Since  $\beta \in (\beta_0; \beta_1)$ , we get:  $\beta_1 - \beta > 0$ .

Then  $(g'(\xi)) \cdot (\beta_1 - \beta) \leq M \cdot (\beta_1 - \beta)$ .

Since  $(g(\beta_1) - (g(\beta))) = (g'(\xi)) \cdot (\beta_1 - \beta) \leq M \cdot (\beta_1 - \beta)$ ,

we get:  $g(\beta) \geq (g(\beta_1)) - M \cdot (\beta_1 - \beta)$ .

By the choice of  $\beta$ , we get:  $(g(\beta_1)) - M > g(\beta)$ .

Since  $(g(\beta_1)) - M > g(\beta) \geq (g(\beta_1)) - M \cdot (\beta_1 - \beta)$ ,

we get:  $M < M \cdot (\beta_1 - \beta)$ .

Then  $M \cdot (\beta_1 - \beta) < 0$ .

So, since  $\beta_1 = \beta_0 + 1$ , we get  $M \cdot (\beta_1 - \beta_0) < 0$ .

So, since  $\beta \in (\beta_0; \beta_1)$ , we get  $M < 0$ .

So, since  $M = \sup \mathbb{I}_{g'}$ , we get:  $g' < 0$  on  $(\beta_0; \infty)$ .

Then, by the Mean Value Theorem, we get:

$g$  is strictly-decreasing on  $(\beta_0; \infty)$ .

We conclude:  $\forall \beta \in (\beta_0; \beta_1)$ ,  $g(\beta) > g(\beta_1)$ .

This contradicts the hypothesis that as  $\beta \rightarrow (\beta_0)^+$ ,  $g(\beta) \rightarrow -\infty$ .  $\square$

**THEOREM 27.17.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta_0 \in \mathbb{R}$ .

Assume:  $\text{DF}_\varepsilon = (\beta_0; \infty)$ . Then: as  $\beta \rightarrow (\beta_0)^+$ ,  $\Delta_\beta^\varepsilon \rightarrow \infty$ .

*Proof.* Otherwise, since  $\beta \mapsto \Delta_\beta^\varepsilon$  is strictly-decreasing,

we get  $\{\Delta_\beta^\varepsilon \mid \beta \in \text{DF}_\varepsilon\}$  is bounded.

Let  $M$  be an upper bound.

Since  $\beta_0 \notin (\beta_0; \infty) = \text{DF}_\varepsilon$ , we get:  $\Delta_{\beta_0}^\varepsilon = \infty$ .

That is,  $\sum_{\sigma \in \Sigma} [e^{-\beta \cdot \varepsilon_\sigma}] = \infty$ .

Choose a finite subsum that is  $> M$ .

Perturb  $\beta_0$  to a slightly larger  $\beta$ .

If the perturbation is small enough, then the subsum stays  $> M$ .

This implies  $\Delta_\beta^\varepsilon > M$ , contradicting that  $M$  is an upper bound.  $\square$

**THEOREM 27.18.** Let  $\Sigma$  be a set,  $\varepsilon : \Sigma \rightarrow \mathbb{R}$ ,  $\beta_0 \in \mathbb{R}$ .

Assume:  $\text{DF}_\varepsilon = (\beta_0; \infty)$ . Then: as  $\beta \rightarrow (\beta_0)^+$ ,  $A_\beta^\varepsilon \rightarrow \infty$ .

*Proof.* Let  $I := (\beta_0; \infty)$ . Define  $f : I \rightarrow \mathbb{R}$  by:  $\forall \beta \in I$ ,  $f(\beta) = \Delta_\beta^\varepsilon$ .

We have:  $\forall \beta \in I$ ,  $f'(\beta) = \Gamma_\beta^\varepsilon$ .

Define  $g : I \rightarrow \mathbb{R}$  by:  $\forall \beta \in I$ ,  $g(\beta) = -(\ln(f(\beta)))$ .

Then:  $g$  is differentiable on  $I$  and  $\forall \beta \in I$ ,  $g'(\beta) = A_\beta^\varepsilon$ .

**Want:** as  $\beta \rightarrow (\beta_0)^+$ ,  $g'(\beta) \rightarrow \infty$ .

By Theorem 27.14, we get:  $g$  is strictly-decreasing on  $I$ .

By Theorem 27.17, we get: as  $\beta \rightarrow (\beta_0)^+$ ,  $\Delta_\beta^\varepsilon \rightarrow \infty$ .

Then: as  $\beta \rightarrow (\beta_0)^+$ ,  $f(\beta) \rightarrow \infty$ .

Then: as  $\beta \rightarrow (\beta_0)^+$ ,  $\ln(f(\beta)) \rightarrow \infty$ .

Then: as  $\beta \rightarrow (\beta_0)^+$ ,  $g(\beta) \rightarrow -\infty$ .

Then, by Theorem 27.16, we get: as  $\beta \rightarrow (\beta_0)^+$ ,  $g'(\beta) \rightarrow \infty$ .  $\square$

## 28. COUNTABLY INFINITE SETS OF STATES

MORE LATER

## 29. APPENDIX: PYTHON CODE

Thanks once again to C. Prouty, for writing the Python code to do the Boltzmann computations in this paper:

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First code: The GFA and 0, 2, 20 dollar awards, with average 3 dollars.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
def F(beta):
    z = np.zeros(3)
    z[0] = 1
    z[1] = np.exp(-2 * beta)
    z[2] = np.exp(-20 * beta)
    return z
def G(beta):
    z = np.zeros(3)
    z[0] = 0
    z[1] = 2 * np.exp(-2 * beta)
    z[2] = 20 * np.exp(-20 * beta)
    return z
def f(beta):
    return np.sum(F(beta))
def g(beta):
    return np.sum(G(beta))
def bisection(minval, maxval, y, fn):
    mid = (maxval + minval) / 2
    while((fn(mid) - y) ** 2 > 0.0000001):
        if(fn(mid) < y):
            maxval = mid
        else:
            minval = mid
    mid = (maxval + minval) / 2
    return mid
fn = lambda x: g(x) / f(x)
```



```

target = bisection(-25, 25, 3, fn)
b = 0.07410049 # hard-coded result of bisection
r = F(b) / f(b)
df = pd.DataFrame(r)
df.to_excel("results2.xlsx", index=False)
betas = np.linspace(-25,25,100000)
z = np.zeros(len(betas))
for i in range(len(betas)):
    z[i] = fn(betas[i])
plt.plot(betas,z)
plt.show()

```

---

Second code: The BUA and red bags and blue bags

```

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
def F(beta):
    z = np.zeros(25).reshape(5,5)
    for i in range(5):
        for j in range(5):
            z[i,j] = np.exp(-(i+j)*beta)
    z[4,4] = 0
    return z
def G(beta):
    z = np.zeros(25).reshape(5,5)
    for i in range(5):
        for j in range(5):
            z[i,j] = (i+j) * np.exp(-(i+j)*beta)
    z[4,4] = 0
    return z
def f(beta):
    return np.sum(F(beta))
def g(beta):
    return np.sum(G(beta))
def bisection(minval, maxval, y, fn):

```

```
mid = (maxval + minval) / 2
while((fn(mid) - y) ** 2 > 0.0000001):
if(fn(mid) < y):
maxval = mid
else:
minval = mid
mid = (maxval + minval) / 2
return mid
fn = lambda x: g(x) / f(x)
target = bisection(-25, 25, 1, fn)
b = 1.06697083 # hard-coded result of bisection
r = F(b) / f(b)
df = pd.DataFrame(r)
df.to_excel("results5.xlsx", index=False)
betas = np.linspace(-25,25,100000)
z = np.zeros(len(betas))
for i in range(len(betas)):
z[i] = fn(betas[i])
plt.plot(betas, z)
plt.show()
```

---