

Financial Mathematics

Principal component analysis

Also: $\text{dist} (v_p , \langle v_1, \dots, v_{p-1} \rangle) = |v_p|$

For most matrices, to know if one row is nearly a linear combination of the rest is a hard problem. Not so if the rows are pw-orthog.

Discussion:

Can a collection of pw-orthogonal vectors be linearly dependent?

Yes, if some of them are zero . . .

How about if they're all nonzero? NO.

$$c_1 v_1 + \cdots + c_p v_p = 0$$

$$(c_1 v_1 + \cdots + c_p v_p) \cdot v_j = 0$$

$$c_j (\cancel{v_j \cdot v_j}) = 0$$

$$c_j = 0$$

Principal Component Analysis

Singular Value Decomposition

(a.k.a. Singular Value Decomposition)

Principal Component Analysis Theorem:

Let $M \in \mathbb{R}^{p \times q}$.

Then there are rotation matrices

$K \in \mathbb{R}^{p \times p}$ and $L \in \mathbb{R}^{q \times q}$

s.t. KML is “diagonal”.

but not square
 $p \times q$

$$\begin{bmatrix} K \\ M \end{bmatrix} = \begin{bmatrix} D \\ DL^{-1} \end{bmatrix} \begin{bmatrix} L^{-1} \\ \text{top } p \text{ rows of } L^{-1} \text{ multiplied by entries on "diagonal" of } D \end{bmatrix}$$

rotation matrix

rotation matrix

“diagonal” matrix

pw orthogonal rows

$\forall M$,
 \exists rot'n K
s.t.
rows of KM
are
pw-orthog.

(a.k.a. Singular Value Decomposition)

Principal Component Analysis Theorem:

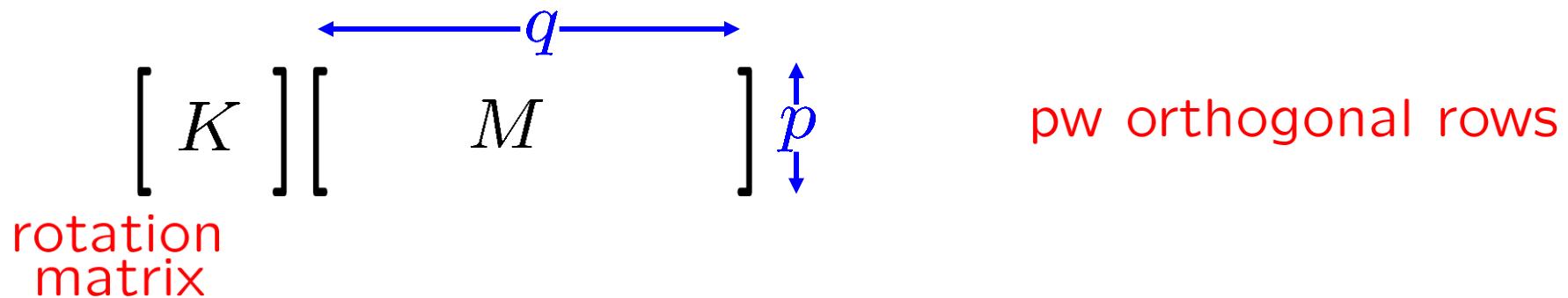
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Any matrix, after some post-processing, can be made to have pw orthogonal rows.

(a.k.a. Singular Value Decomposition)

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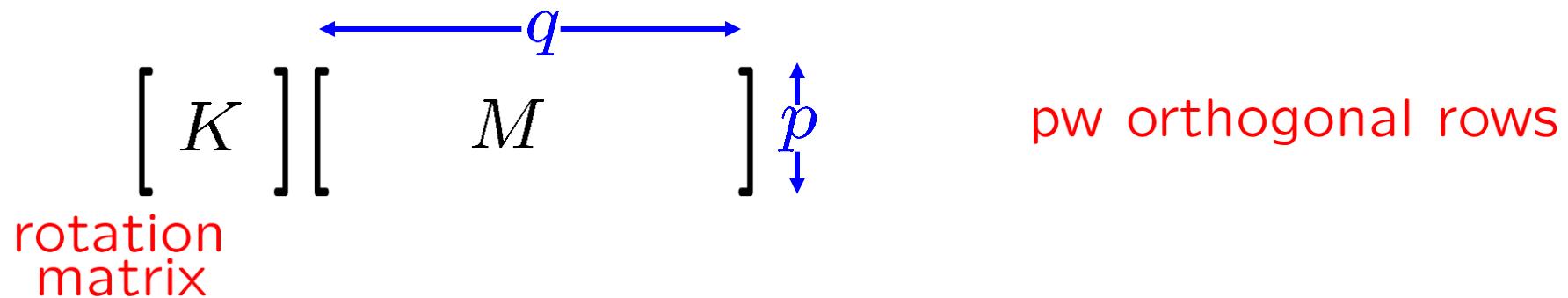
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$\forall M$,
 \exists rot'n K
s.t.
rows of KM
are
pw-orthog.

“post-processing” =
left multiplication by
a rotation matrix

Any matrix, after some
post-processing, can be made
to have pw orthogonal rows.

(a.k.a. Singular Value Decomposition)

Principal Component Analysis Theorem:

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Say we make 17 measurements at time 0,
then again at time 1, then again at time 2,
etc., until time 4,999.
dimensionless

Assemble data into a matrix $M \in \mathbb{R}^{17 \times 5000}$.

Each row is a “time series”.

If we changed our instruments to produce KM ,
then the 17 “time series” would be pw orthog.

(uncorrelated)

If 12 of the 17 are zero, or close to zero,
we'd say that the other 5
are the “important factors”.

Principal Component Analysis Theorem:

Let $M \in \mathbb{R}^{p \times q}$.

Then there are rotation matrices

$K \in \mathbb{R}^{p \times p}$ and $L \in \mathbb{R}^{q \times q}$

s.t. KML is “diagonal”.

but not square
 $p \times q$

Say we track 17 asset returns at time 0,
 then again at time 1, then again at time 2,
 etc., until time 4,999.

Assemble data into a matrix $M \in \mathbb{R}^{17 \times 5000}$.

Each row of K describes an index.

If we watch the returns of the 17 indexes,
 then the 17 “time series” would be pw orthog.
 (uncorrelated)

If 12 of the 17 are zero, or close to zero,
 we’d say that the other 5
 are the “important factors”.

PCA / SVD Theorem: Let $M \in \mathbb{R}^{p \times q}$.

Then \exists rotation matrices

$K \in \mathbb{R}^{p \times p}$ and $L \in \mathbb{R}^{q \times q}$

s.t. KML is “diagonal”.

e.g.:

$$\begin{bmatrix} -0.98 & 0.01 & 1.03 & -9.21 & 3.43 \\ -1.02 & -0.03 & 1 & -9.24 & 3.42 \end{bmatrix}$$

ordinary row & col. operations

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}$$

We'll see, via PCA/SVD, in a moment...

rotational left & right multiplications

$$\begin{bmatrix} \alpha & 0 & 0 & 0 & 0 \\ 0 & \varepsilon & 0 & 0 & 0 \end{bmatrix}$$

□ $\alpha \approx \sqrt{\sum_{i=1}^{10} (\dots)^2}$

$$\varepsilon \approx 0$$

$$M := \begin{bmatrix} -0.98 & 0.01 & 1.03 & -9.21 & 3.43 \\ -1.02 & -0.03 & 1 & -9.24 & 3.42 \end{bmatrix}$$

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$$M := \begin{bmatrix} -0.98 & 0.01 & 1.03 & -9.21 & 3.43 \\ -1.02 & -0.03 & 1 & -9.24 & 3.42 \end{bmatrix}$$

$$K \approx \begin{bmatrix} 0.71 & 0.71 \\ -0.71 & 0.71 \end{bmatrix}$$

Let's try to use this to show that the data in M is driven by only one "factor", but distorted by "noise" . . .

$$L \approx \begin{bmatrix} -0.1 & -0.56 & -0.09 & -0.8 & 0.19 \\ 0 & -0.6 & -0.54 & 0.37 & -0.46 \\ 0.1 & -0.49 & 0.83 & 0.2 & -0.17 \\ -0.93 & -0.1 & 0.05 & 0.24 & 0.26 \\ 0.34 & -0.28 & -0.13 & 0.36 & 0.81 \end{bmatrix}$$

L and K are rotation matrices.

$$KML \approx \begin{bmatrix} 14.06 & 0 & 0 & 0 & 0 \\ 0 & 0.05 & 0 & 0 & 0 \end{bmatrix}$$

Thanks to Carl Hagen

$$M := \begin{bmatrix} -0.98 & 0.01 & 1.03 & -9.21 & 3.43 \\ -1.02 & -0.03 & 1 & -9.24 & 3.42 \end{bmatrix}$$

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Let's try to use this to show that the data in M is driven by only one "factor", but distorted by "noise" . . .

$$KM \approx \begin{bmatrix} -1.42 & -0.01 & 1.44 & -13.10 & 4.86 \\ -0.03 & -0.03 & -0.02 & -0.02 & -0.01 \end{bmatrix}$$

zero out the small rows

$$\approx \begin{bmatrix} -1.42 & -0.01 & 1.44 & -13.10 & 4.86 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$M \approx K^{-1} \begin{bmatrix} -1.42 & -0.01 & 1.44 & -13.10 & 4.86 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} -1.01 & -0.01 & 1.02 & -9.30 & 3.45 \\ -1.01 & -0.01 & 1.02 & -9.30 & 3.45 \end{bmatrix}$$

$$M := \begin{bmatrix} -0.98 & 0.01 & 1.03 & -9.21 & 3.43 \\ -1.02 & -0.03 & 1 & -9.24 & 3.42 \end{bmatrix}$$

$$M \approx \begin{bmatrix} -1.01 & -0.01 & 1.02 & -9.30 & 3.45 \\ -1.01 & -0.01 & 1.02 & -9.30 & 3.45 \end{bmatrix}$$

Rows only span one dimension.

$$M \approx$$

$$\begin{bmatrix} -1.01 & -0.01 & 1.02 & -9.30 & 3.45 \\ -1.01 & -0.01 & 1.02 & -9.30 & 3.45 \end{bmatrix}$$

$$M := \begin{bmatrix} -0.98 & 0.01 & 1.03 & -9.21 & 3.43 \\ -1.02 & -0.03 & 1 & -9.24 & 3.42 \end{bmatrix}$$

$$M \approx \begin{bmatrix} -1.01 & -0.01 & 1.02 & -9.30 & 3.45 \\ -1.01 & -0.01 & 1.02 & -9.30 & 3.45 \end{bmatrix}$$

Rows only span one dimension.
Only “factor” is important;
everything else is “noise”.

PCA (SVD) Theorem: Let $M \in \mathbb{R}^{p \times q}$.

Then \exists rotation matrices

$K \in \mathbb{R}^{p \times p}$ and $L \in \mathbb{R}^{q \times q}$

s.t. KML is “diagonal”.

Easier version: Let $M \in \mathbb{R}^{p \times q}$.

Then \exists a rotation matrix $K \in \mathbb{R}^{p \times p}$

s.t. KM has pairwise orthogonal rows.

Pf of easier version:

MM^t is symmetric.

Spectral
Theorem

Choose a rotation matrix K
s.t. $K(MM^t)K^t$ is diagonal.

$K(MM^t)K^t$
// diagonal

All off-diagonal entries of $(KM)(KM)^t$ are 0.

If $j, k \in [1, p]$ are integers, and $j \neq k$,

then $[j\text{th row of } KM] \cdot [k\text{th col. of } (KM)^t] = 0$,

so $[j\text{th row of } KM] \cdot [k\text{th row of } KM] = 0$.

KM has pw-orthogonal rows.

QED

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Easier version: Let $M \in \mathbb{R}^{p \times q}$.

Then \exists a rotation matrix $K \in \mathbb{R}^{p \times p}$

s.t. KM has pairwise orthogonal rows,
with all zero rows at bottom.

rotation

e.g.: Say

$K_0 M =$

$$\begin{bmatrix} -1 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 2 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} K_0 M =$$

$$\begin{bmatrix} -1 & 0 & 1 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$K \leftarrow$ orthogonal, but not rotation

PCA (SVD) Theorem: Let $M \in \mathbb{R}^{p \times q}$.

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with all zero rows at bottom.

rotation

e.g.: Say $K_0 M =$

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & -1 & 0 \end{bmatrix}$$

$$\begin{bmatrix} -1 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 2 & 0 \end{bmatrix}$$

$$K_0 M =$$

$$\begin{bmatrix} -1 & 0 & 1 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$K \leftarrow$ rotation

QED

PCA (SVD) Theorem: Let $M \in \mathbb{R}^{p \times q}$.

Then \exists rotation matrices

$$K \in \mathbb{R}^{p \times p} \text{ and } L \in \mathbb{R}^{q \times q}$$

s.t. KML is “diagonal”.

Easier version: Let $M \in \mathbb{R}^{p \times q}$.

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s.t. KM has pairwise orthogonal rows,
with all zero rows at bottom.

Remark: $X \in \mathbb{R}^{p \times q}$ has pw orthog. **non0** rows

$\Rightarrow \exists$ diagonal $D \in \mathbb{R}^{p \times p}$, $\exists Y \in \mathbb{R}^{p \times q}$

s.t. Y has orthonormal rows and $X = DY$.

e.g.: X

\parallel

$$\begin{bmatrix} -1 & 0 & 1 \\ 0 & 2 & 0 \end{bmatrix}$$

D

$$\underbrace{\begin{bmatrix} \sqrt{2} & 0 \\ 0 & 2 \end{bmatrix}}_{\parallel}$$

Y

$$\underbrace{\begin{bmatrix} -1/\sqrt{2} & 0 & 1/\sqrt{2} \\ 0 & 1 & 0 \end{bmatrix}}_{\parallel}$$

QED

PCA (SVD) Theorem: Let $M \in \mathbb{R}^{p \times q}$.

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$\Rightarrow \exists$ “diagonal” $D_1 \in \mathbb{R}^{p \times q}$, $\exists Y_1 \in \mathbb{R}^{q \times q}$

s.t. Y_1 has orthonormal rows **and** $X = D_1 Y_1$.
 Y_1 is orthogonal.

$$\begin{bmatrix} -1 & 0 & 1 \\ 0 & 2 & 0 \end{bmatrix} = \begin{bmatrix} \sqrt{2} & 0 \\ 0 & 2 \end{bmatrix} \underbrace{\begin{bmatrix} \sqrt{2} & 0 & 0 \\ 0 & 2 & 0 \end{bmatrix}}_{D_1} \underbrace{\begin{bmatrix} -1/\sqrt{2} & 0 & 1/\sqrt{2} \\ 0 & 1 & 0 \\ -1/\sqrt{2} & 0 & 1/\sqrt{2} \\ 0 & 1 & 0 \\ 1/\sqrt{2} & 0 & 1/\sqrt{2} \end{bmatrix}}_{Y_1}$$

Remark: $X \in \mathbb{R}^{p \times q}$ has pw orthog. **non0** rows
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$$\begin{bmatrix} -1 & 0 & 1 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} -\sqrt{2} & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} +1/\sqrt{2} & 0 & -1/\sqrt{2} \\ 0 & 1 & 0 \\ 1/\sqrt{2} & 0 & 1/\sqrt{2} \end{bmatrix}$$

Remark: $X \in \mathbb{R}^{p \times q}$ has pw orthog. **non0** rows
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Remark: $X \in \mathbb{R}^{p \times q}$ has pw orthog. **non0** rows
with all zero rows at bottom
 $\Rightarrow \exists$ “diagonal” $D_1 \in \mathbb{R}^{p \times q}$, $\exists Y_1 \in \mathbb{R}^{q \times q}$
s.t. Y_1 has orthonormal rows and $X = D_1 Y_1$.
 Y_1 is orthogonal.

Can choose Y_1 to be a rotation matrix.

PCA (SVD) Theorem: Let $M \in \mathbb{R}^{p \times q}$.

Then \exists rotation matrices

$K \in \mathbb{R}^{p \times p}$ and $L \in \mathbb{R}^{q \times q}$

s.t. KML is “diagonal”.

Pf of PCA Theorem: $[KM =: X = D_1 Y_1] \times Y_1^{-1}$

$$KML = KMY_1^{-1} = D_1$$

$$L := Y_1^{-1}$$

QED

Easier version: Let $M \in \mathbb{R}^{p \times q}$.

Then \exists a rotation matrix $K \in \mathbb{R}^{p \times p}$

s.t. KM has pairwise orthogonal rows,

with all zero rows at bottom.

Remark: $X \in \mathbb{R}^{p \times q}$ has pw orthog. ~~nonzero~~ rows

with all zero rows at bottom

$\Rightarrow \exists$ “diagonal” $D_1 \in \mathbb{R}^{p \times q}$, $\exists Y_1 \in \mathbb{R}^{q \times q}$

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$$\forall A, B \in \mathbb{R}^{p \times q}, \text{dist}(A, B) := \sqrt{\sum_{i,j} (A_{ij} - B_{ij})^2}$$

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$K \in \mathbb{R}^{p \times p}$ orthogonal

$$\Rightarrow \forall A, B \in \mathbb{R}^{p \times q}, \text{dist}(KA, KB) = \text{dist}(A, B)$$

$M' := KM$ has pairwise orthogonal rows

uncorrelated
 \forall integers $i \in [1, p]$, $s_i := \sqrt{\sum_j (M'_{ij})^2}$ the singular values of M

e.g.: $M = \begin{bmatrix} -0.98 & 0.01 & 1.03 & -9.21 & 3.43 \\ -1.02 & -0.03 & 1 & -9.24 & 3.42 \end{bmatrix}$

Thanks to Carl Hagen:
Singular values are 14.06, 0.05.

Easier version: Let $M \in \mathbb{R}^{p \times q}$.

Then \exists a rotation matrix $K \in \mathbb{R}^{p \times p}$
s.t. KM has pairwise orthogonal rows.

$$\forall A, B \in \mathbb{R}^{p \times q}, \text{dist}(A, B) := \sqrt{\sum_{i,j} (A_{ij} - B_{ij})^2}$$

$K \in \mathbb{R}^{p \times p}$ orthogonal

$$\Rightarrow \forall A, B \in \mathbb{R}^{p \times q}, \text{dist}(KA, KB) = \text{dist}(A, B)$$

$M' := KM$ has pairwise ^{uncorrelated} orthogonal rows

$$\forall \text{integers } i \in [1, p], s_i := \sqrt{\sum_j (M'_{ij})^2} \text{ the singular values of } M$$

\tilde{M}' obtained from M' by zeroing “small” rows
 $\text{dist}(M', \tilde{M}')$ small ^{noise}

$$\text{dist}(K^{-1}M', K^{-1}\tilde{M}') \text{ small}$$

$p_0 :=$ number of
non0 rows in \tilde{M}'

\parallel
 M

\parallel
 \tilde{M}

p_0 uncorrelated
“factors”

KRL “diag”

		movie 0	movie 1	movie 2	movie 3	...	movie q
person 0	??	r_{01}	r_{02}	r_{03}	\cdots	r_{0q}	
person 1	r_{10}	r_{11}	r_{12}	r_{13}	\cdots	r_{1q}	
person 2	r_{20}	r_{21}	r_{22}	r_{23}	\cdots	r_{2q}	
person 3	r_{30}	r_{31}	r_{32}	r_{33}	\cdots	r_{3q}	$=: R$
⋮	⋮	⋮	⋮	⋮		⋮	
person p	r_{p0}	r_{p1}	r_{p2}	r_{p3}	\cdots	r_{pq}	

$$\begin{aligned} \text{person' } t &:= \sum_i K_{ti} \cdot (\text{person } i) & r'_{0u} &:= \sum_j (r_{0j}) \cdot L_{ju} \\ t = 1, \dots, p & & & \\ \text{movie' } u &:= \sum_j (\text{movie } j) \cdot L_{ju} & & \\ u = 1, \dots, q & & & \end{aligned}$$

KRL “diag”

$$R' = KRL$$

	movie 0	movie 1	movie 2	movie 3	...	movie' q
person 0	??	r'_{01}	r'_{02}	r'_{03}	...	r'_{0q}
person' 1	r'_{10}	r'_{11}	r'_{12}	r'_{13}	...	r'_{1q}
person' 2	r'_{20}	r'_{21}	r'_{22}	r'_{23}	...	r'_{2q}
person' 3	r'_{30}	r'_{31}	r'_{32}	r'_{33}	...	r'_{3q}
:	:	:	:	:		:
person' p	r'_{p0}	r'_{p1}	r'_{p2}	r'_{p3}	...	r'_{pq}

$$\begin{aligned} \text{person' } t &:= \sum_i K_{ti} \cdot (\text{person } i) & r'_{0u} &:= \sum_j (r_{0j}) \cdot L_{ju} \\ t = 1, \dots, p & & & \\ r'_{t0} &:= \sum_i K_{ti} \cdot (r_{i0}) & \text{movie' } u &:= \sum_j (\text{movie } j) \cdot L_{ju} \\ u = 1, \dots, q & & & \end{aligned}$$

		movie 0	movie' 1	movie' 2	movie' 3	...	movie' q
person 0	??	r'_{01}	r'_{02}	r'_{03}	...	r'_{0q}	
person' 1	r'_{10}	s_1	0	0	...	0	
person' 2	r'_{20}	0	s_2	0	...	0	
person' 3	r'_{30}	0	0	s_3	...	0	
:	:	:	:	:		:	
person' p	r'_{p0}	0	0	0	...	??	

$$\text{person' } t := \sum_i K_{ti} \cdot (\text{person } i) \quad [K, L \text{ rotation}]$$

$$\text{movie' } u := \sum_j (\text{movie } j) \cdot L_{ju}$$

	movie 0	movie' 1	movie' 2	movie' 3	...	movie' q
person 0	??	r'_{01}	r'_{02}	r'_{03}	...	r'_{0q}
person' 1	r'_{10}	s_1	0	0	...	0
person' 2	r'_{20}	0	s_2	0	...	0
person' 3	r'_{30}	0	0	s_3	...	0
:	:	:	:	:	⋮	⋮
person' p	r'_{p0}	0	0	0	...	??

$$\underbrace{\text{person 0}}_{r'_{0u}} \underbrace{\text{on movie' } u}_{?} = \sum_t \frac{r'_{0t}}{s_t} \cdot \underbrace{\left(\begin{array}{l} \text{person' } t \\ \text{on movie' } u \end{array} \right)}_{s_t \delta_t^u}$$

	movie 0	movie' 1	movie' 2	movie' 3	...	movie' q
person 0	??	r'_{01}	r'_{02}	r'_{03}	...	r'_{0q}
person' 1	r'_{10}	s_1	0	0	...	0
person' 2	r'_{20}	0	s_2	0	...	0
person' 3	r'_{30}	0	0	s_3	...	0
:	:	:	:	:		:
person' p	r'_{p0}	0	0	0	...	??

person 0
 on movie' u $\stackrel{?}{=}$ $\sum_t \frac{r'_{0t} \cdot s_t \delta_t^u}{s_t} = r'_{0u}$

QED

r'_{0u} $\xrightarrow{\quad}$ $s_t \delta_t^u$

	movie 0	movie' 1	movie' 2	movie' 3	...	movie' q
person 0	??	r'_{01}	r'_{02}	r'_{03}	...	r'_{0q}
person' 1	r'_{10}	s_1	0	0	...	0
person' 2	r'_{20}	0	s_2	0	...	0
person' 3	r'_{30}	0	0	s_3	...	0
:	:	:	:	:		:
person' p	r'_{p0}	0	0	0	...	??

person 0
on movie' $\boxed{u} = \sum_t \frac{r'_{0t}}{s_t} \cdot \begin{pmatrix} \text{person' } t \\ \text{on movie' } \boxed{u} \end{pmatrix}$

$u = 1, \dots, q$

$u \rightarrow 0$

	movie 0	movie' 1	movie' 2	movie' 3	...	movie' q
person 0	??	r'_{01}	r'_{02}	r'_{03}	...	r'_{0q}
person' 1	r'_{10}	s_1	0	0	...	0
person' 2	r'_{20}	0	s_2	0	...	0
person' 3	r'_{30}	0	0	s_3	...	0
:	:	:	:	:	...	:
person' p	r'_{p0}	0	0	0	...	??

person 0
on movie 0 $\approx \sum_t \frac{r'_{0t}}{s_t} \cdot \underbrace{\left(\begin{array}{l} \text{person' } t \\ \text{on movie 0} \end{array} \right)}_{r'_{t0}}$

		movie 0	movie' 1	movie' 2	...	movie' q
person 0	??	r'_{01}	r'_{02}	r'_{03}	...	r'_{0q}
person' 1	r'_{10}	0	0	...	0	0
person' 2	r'_{20}	0	s_2	0	...	0
person' 3	r'_{30}	0	0	s_3	...	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮
person p	r'_{p0}	0	0	0	...	??

person 0
on movie 0 $\approx \sum_t \frac{r'_{0t}}{s_t} \cdot r'_{t0}$

??
DONE!

What if some $s_t = 0$?
What if some $s_t \approx 0$?

