



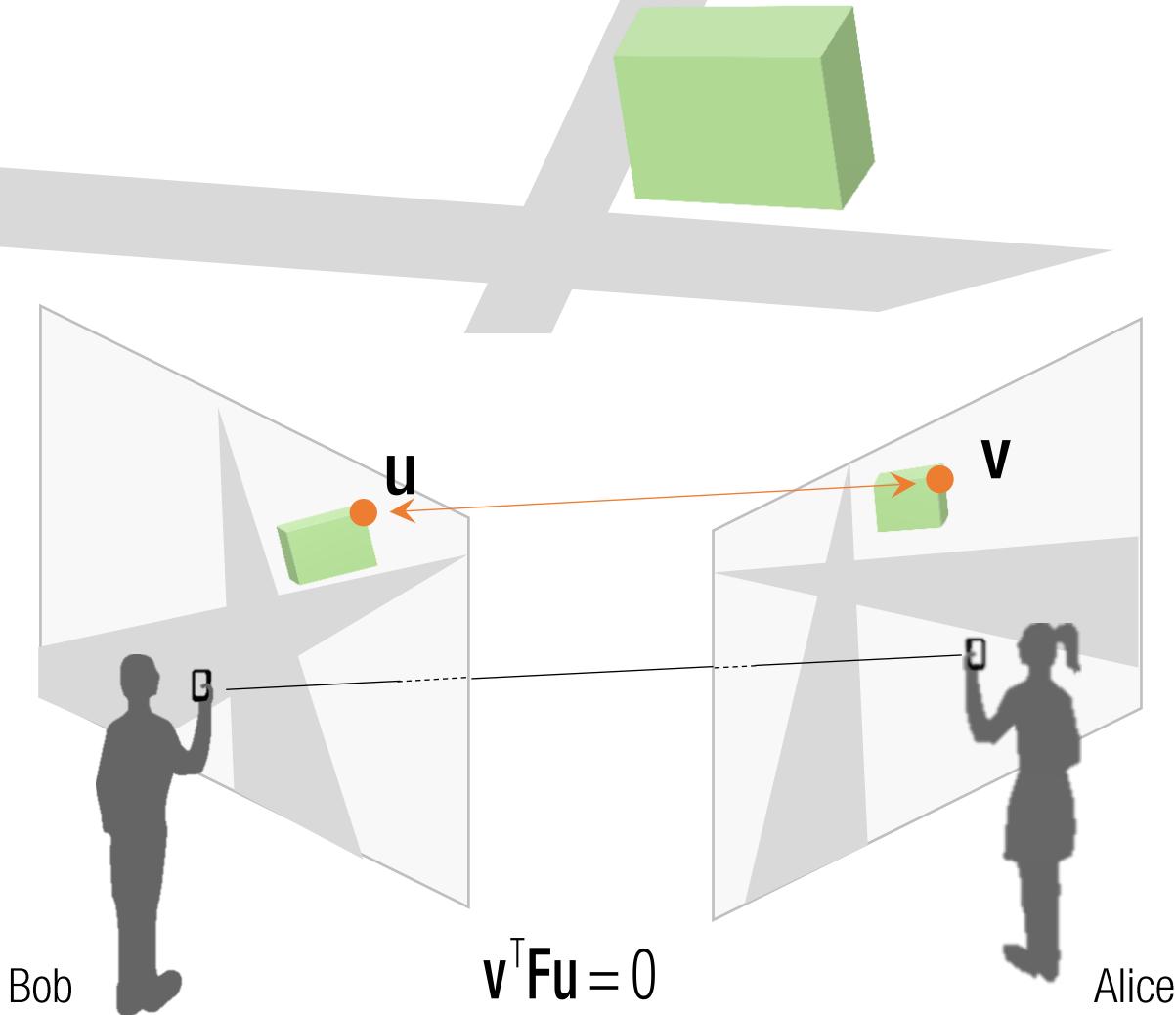
Two View (Epipolar) Geometry

Announcement

- HW #4 is out (start early)
- HW #5 grading is done

Daniel Wedge "The Fundamental Matrix Song"

Fundamental Matrix Estimation

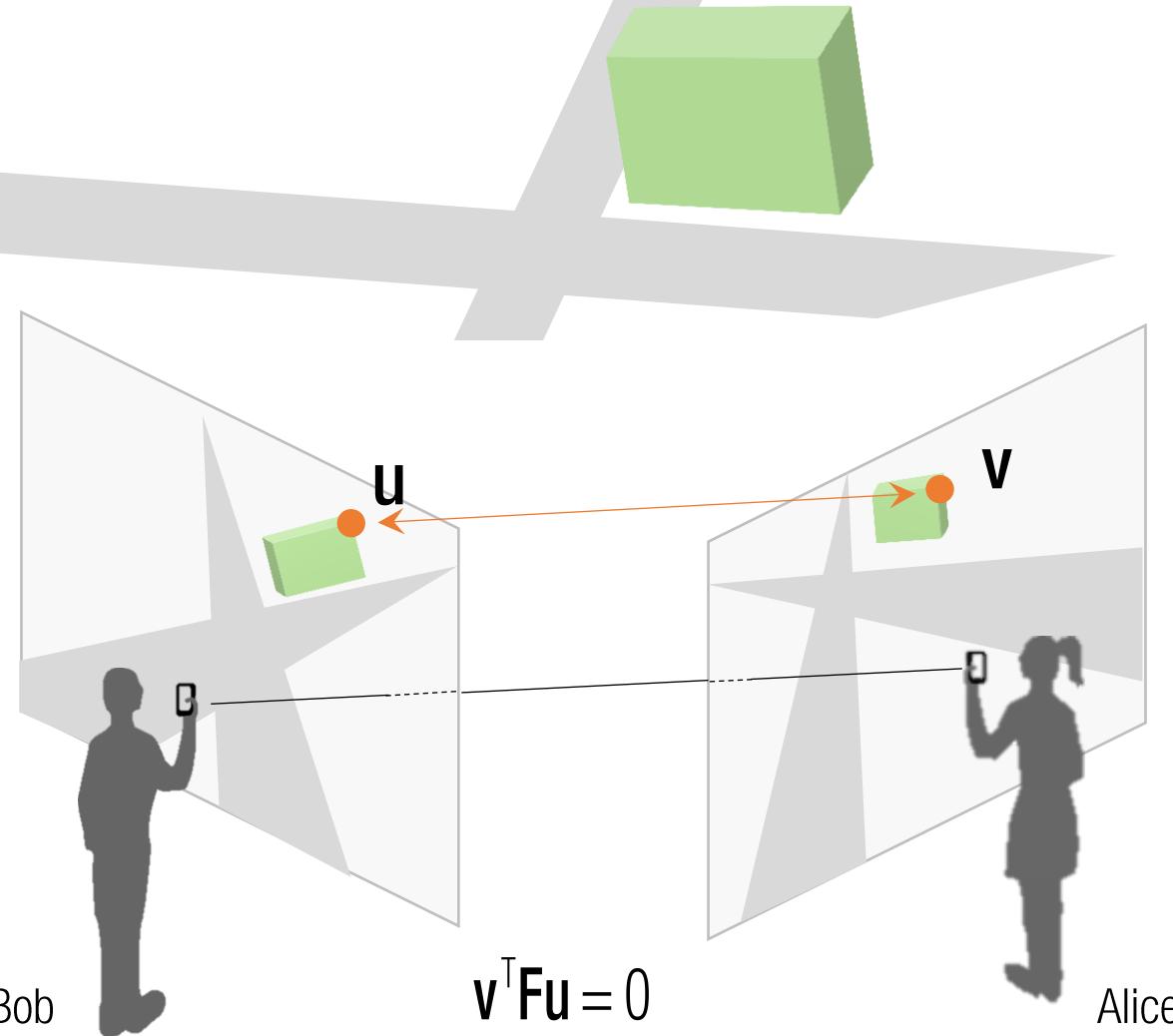


$$\mathbf{F} = \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix}$$

Degree of freedom of fundamental matrix:
7 = 9 (3x3 matrix) – 1 (scale) – 1 (rank 2)

We will estimate fundamental matrix with 8 parameter by ignoring rank constraint and then project onto rank 2 matrix:

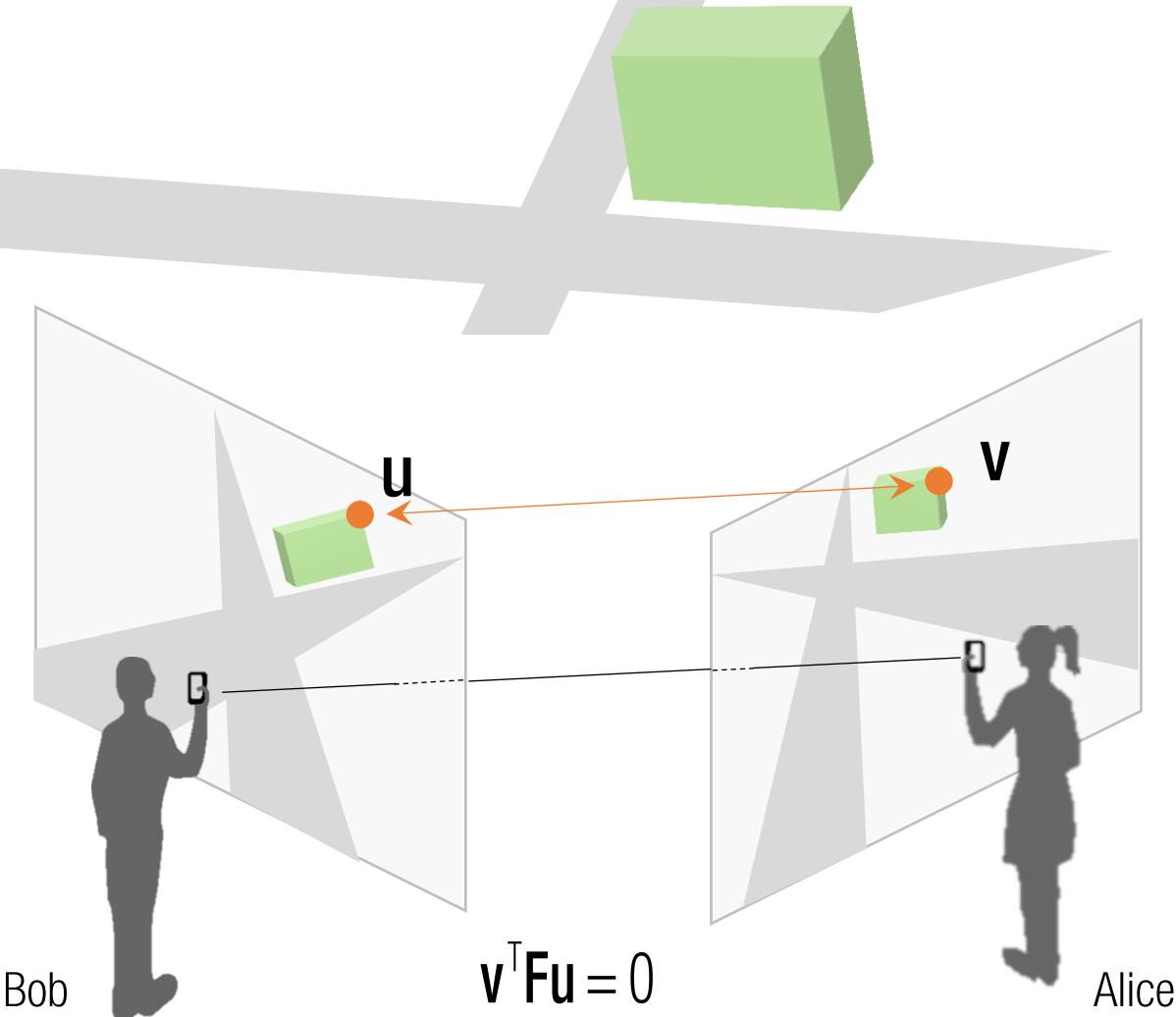
Fundamental Matrix Estimation



$$\begin{aligned} v^T \mathbf{F} u &= \begin{bmatrix} v^x & v^y & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^x \\ u^y \\ 1 \end{bmatrix} \\ &= f_{11}u^xv^x + f_{12}u^yv^x + f_{13}v^x + f_{21}u^xv^y + f_{22}u^yv^y + f_{23}v^y + f_{31}u^x + f_{32}u^y + f_{33} \\ &= 0 \end{aligned}$$

Linear in \mathbf{F} .

Fundamental Matrix Estimation



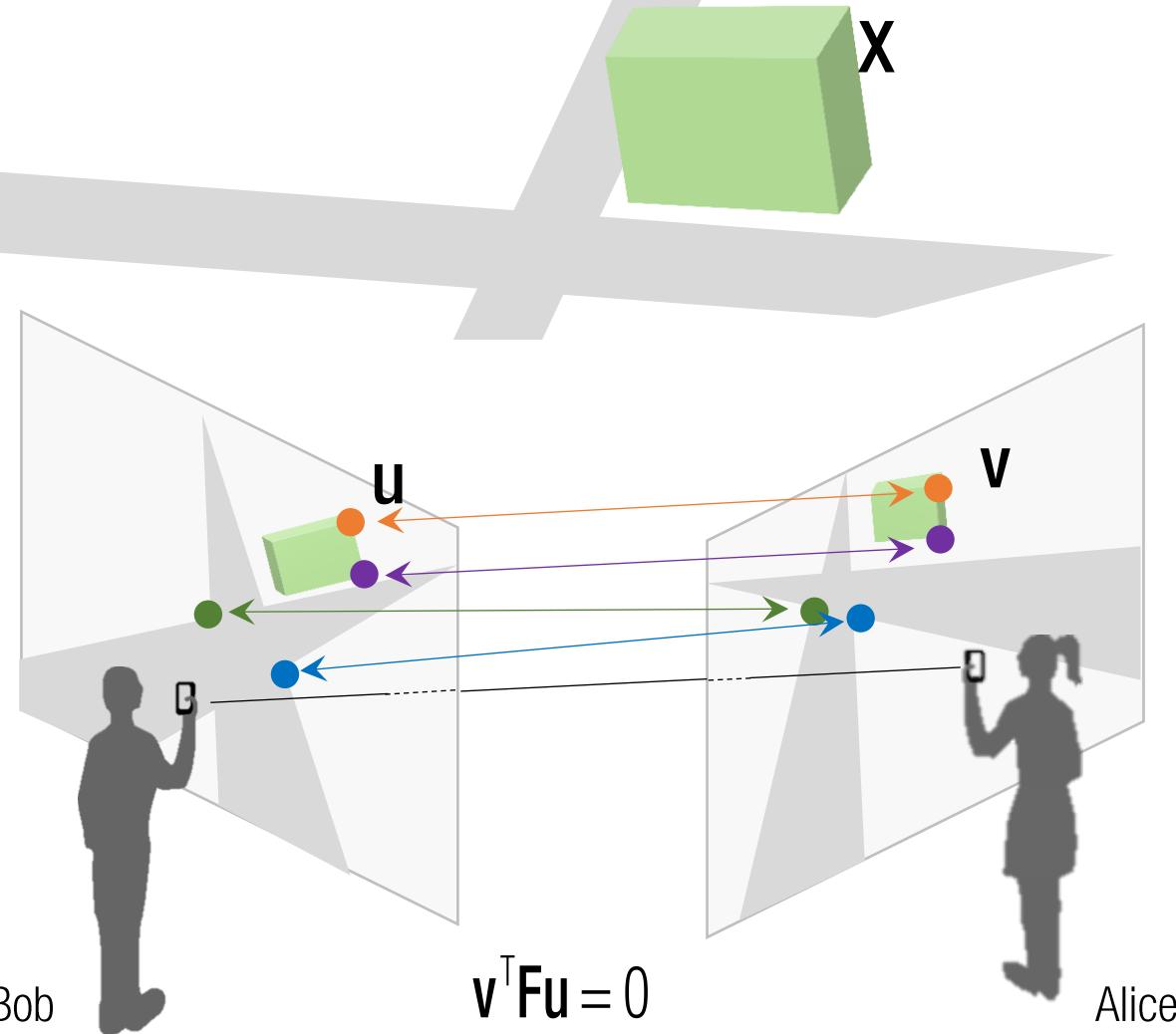
$$v^T F u = \begin{bmatrix} v^x & v^y & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^x \\ u^y \\ 1 \end{bmatrix}$$
$$= f_{11}u^xv^x + f_{12}u^yv^x + f_{13}v^x + f_{21}u^xv^y + f_{22}u^yv^y + f_{23}v^y + f_{31}u^x + f_{32}u^y + f_{33}$$
$$= 0$$

Linear in \mathbf{F} .

$$\rightarrow \begin{bmatrix} u^xv^x & u^yv^x & v^x & u^xv^y & u^yv^y & v^y & u^x & u^y & 1 \end{bmatrix} \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{31} \\ f_{32} \\ f_{33} \end{bmatrix} = 0$$

of unknowns: 9
of equations per correspondence: 1

Fundamental Matrix Estimation



$$v^T F u = \begin{bmatrix} v^x & v^y & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^x \\ u^y \\ 1 \end{bmatrix}$$

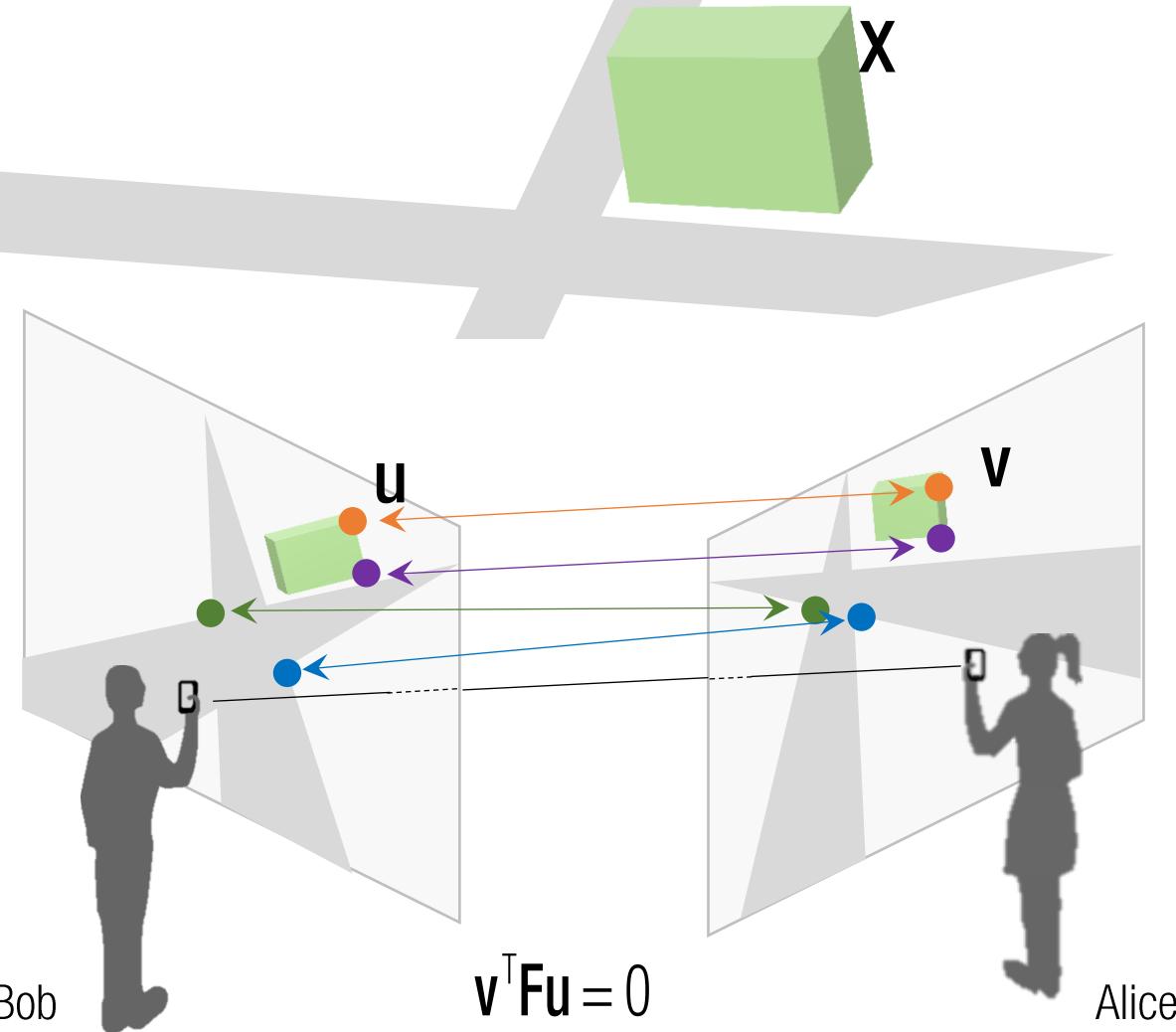
$$= f_{11}u^xv^x + f_{12}u^yv^x + f_{13}v^x + f_{21}u^xv^y + f_{22}u^yv^y + f_{23}v^y + f_{31}u^x + f_{32}u^y + f_{33}$$

Linear in \mathbf{F} .

$$\rightarrow \begin{bmatrix} u_1^x v_1^x & u_1^y v_1^x & v_1^x & u_1^x v_1^y & u_1^y v_1^y & v_1^y & u_1^x & u_1^y & 1 \\ \vdots & \vdots \\ u_m^x v_m^x & u_m^y v_m^x & v_m^x & u_m^x v_m^y & u_m^y v_m^y & v_m^y & u_m^x & u_m^y & 1 \end{bmatrix} = \mathbf{0}_{m \times 1}$$

What is minimum m ?

Fundamental Matrix Estimation



$$v^T F u = \begin{bmatrix} v^x & v^y & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u^x \\ u^y \\ 1 \end{bmatrix}$$

$$= f_{11}u^xv^x + f_{12}u^yv^x + f_{13}v^x + f_{21}u^xv^y + f_{22}u^yv^y + f_{23}v^y + f_{31}u^x + f_{32}u^y + f_{33}$$

$$= 0$$

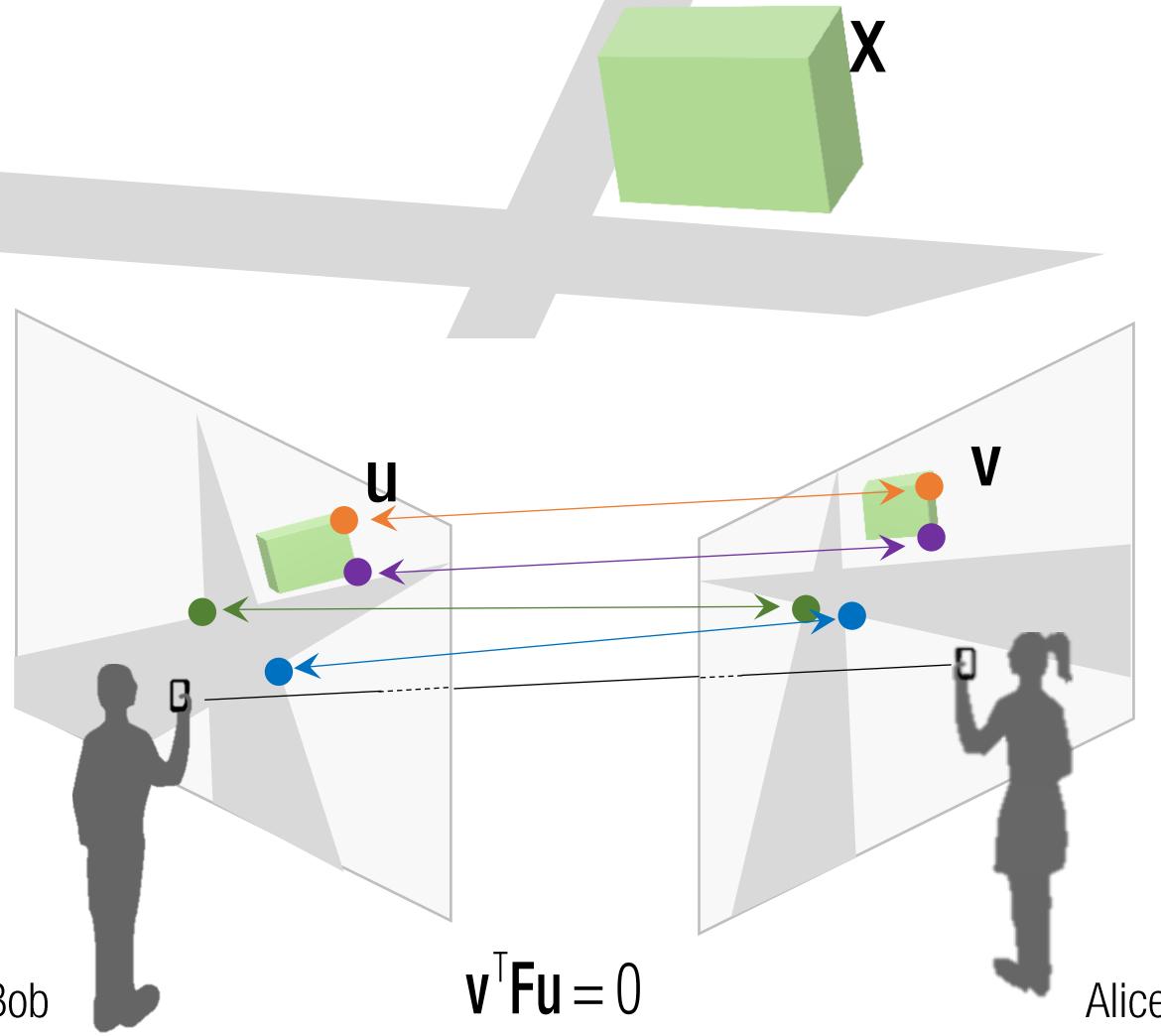
Linear in \mathbf{F} .

→

$$\begin{bmatrix} u_1^x v_1^x & u_1^y v_1^x & v_1^x & u_1^x v_1^y & u_1^y v_1^y & v_1^y & u_1^x & u_1^y & 1 \\ \vdots & \vdots \\ u_m^x v_m^x & u_m^y v_m^x & v_m^x & u_m^x v_m^y & u_m^y v_m^y & v_m^y & u_m^x & u_m^y & 1 \end{bmatrix} \mathbf{A} \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{31} \\ f_{32} \\ f_{33} \end{bmatrix} = \mathbf{0}$$

What is minimum m ?

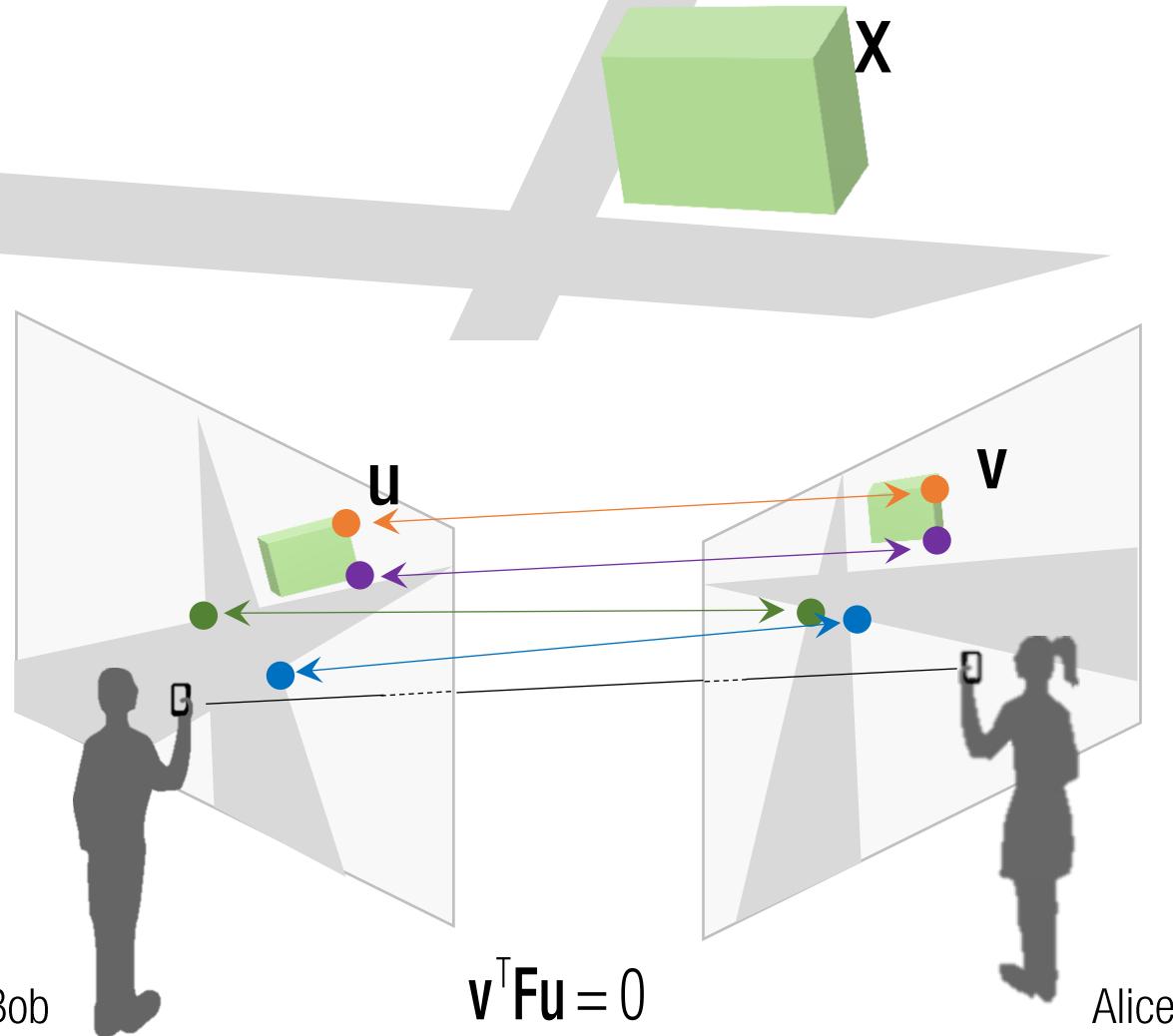
Fundamental Matrix Estimation



$$\begin{matrix} A & X & 0 \end{matrix}$$

The solution is not necessarily satisfy rank 2 constraint.

Fundamental Matrix Estimation

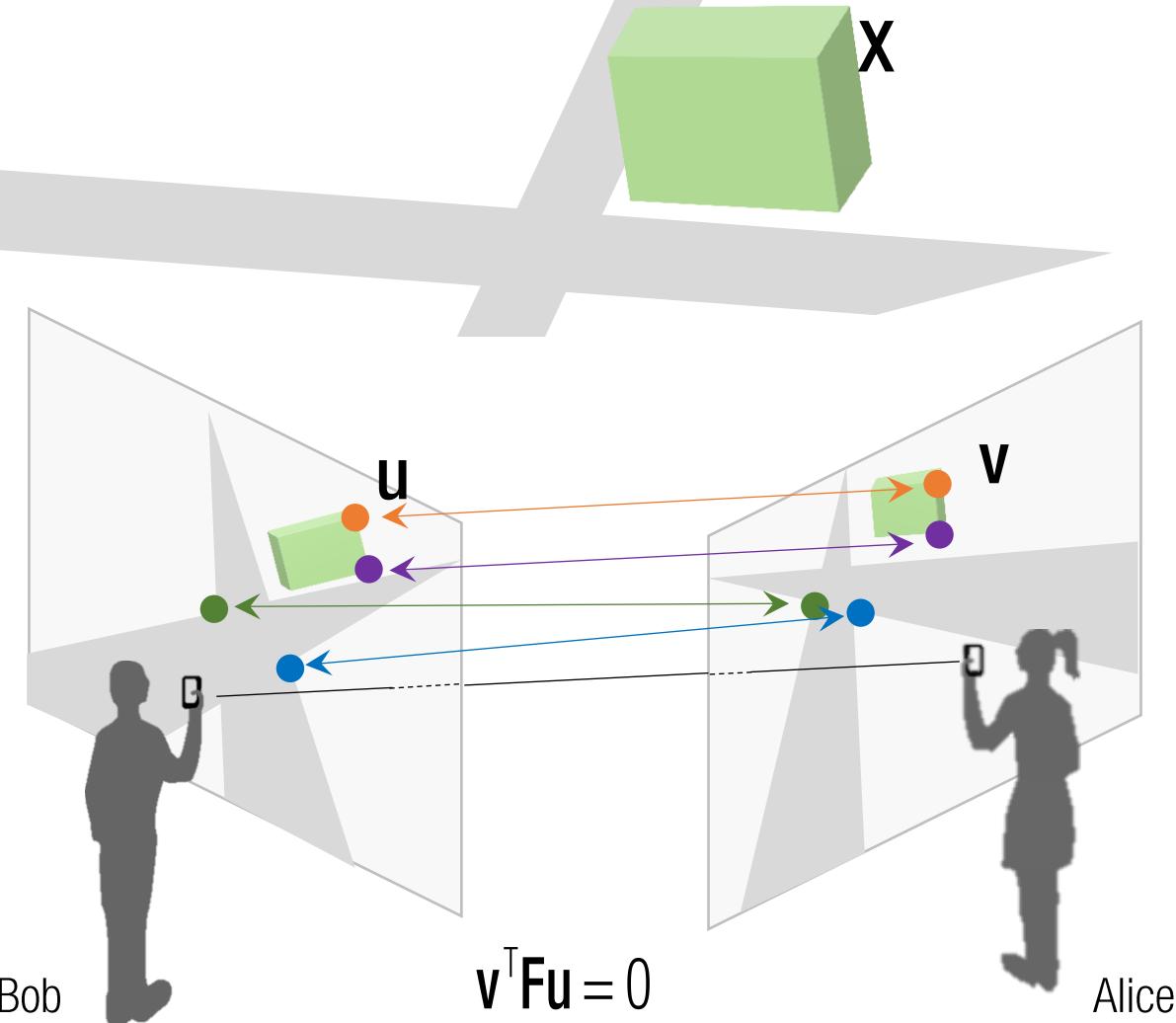


$$\begin{matrix} A & X & 0 \end{matrix}$$

The solution is not necessarily satisfy rank 2 constraint.

$$\begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} = \begin{matrix} U \end{matrix} \begin{matrix} D \end{matrix} \begin{matrix} V^T \end{matrix}$$

Fundamental Matrix Estimation



$$\begin{matrix} A & X & 0 \end{matrix}$$

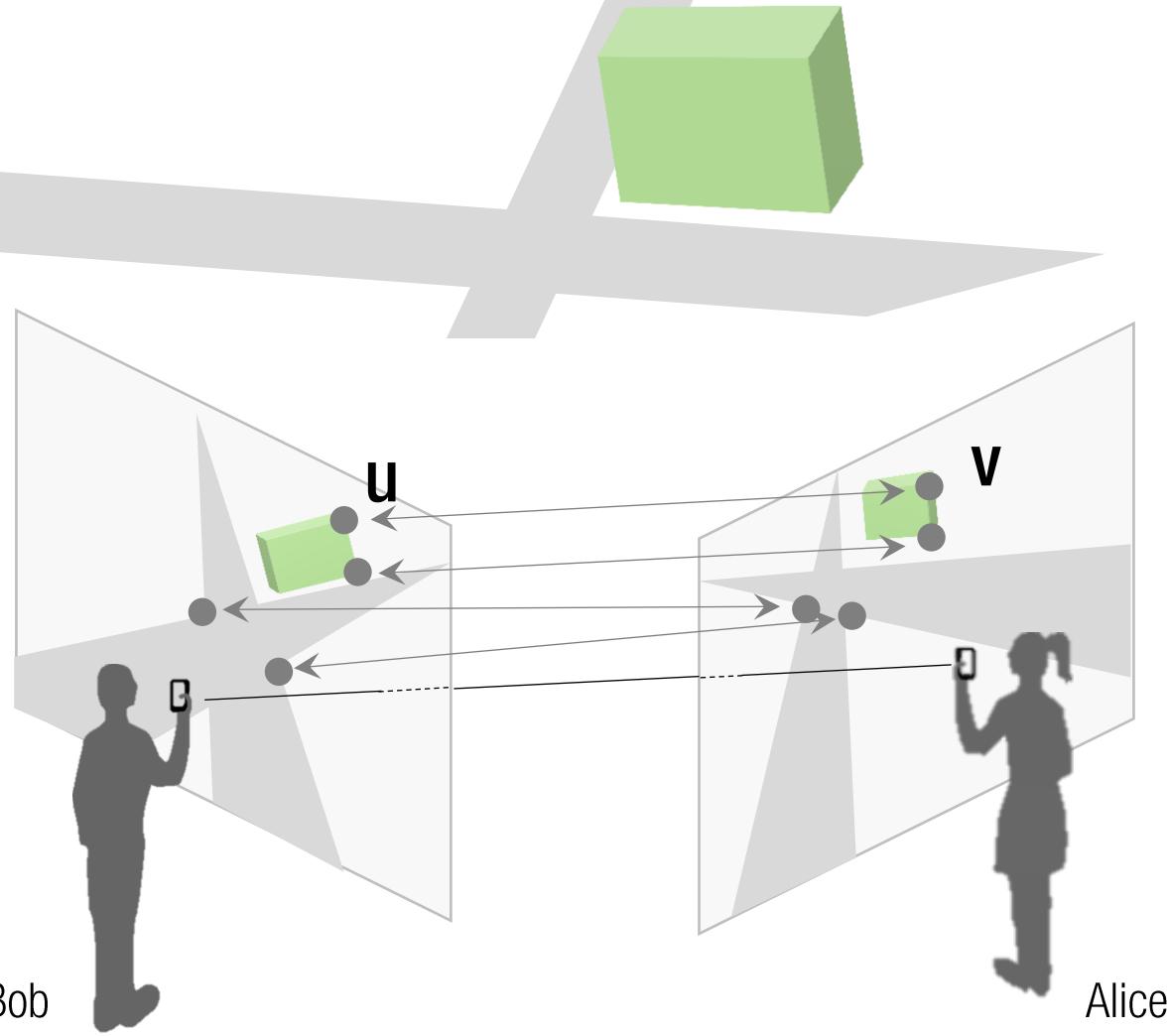
The solution is not necessarily satisfy rank 2 constraint.

$$\begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} = \begin{matrix} U & D & V^T \end{matrix}$$

$$\approx F_{\text{rank } 2} = \begin{matrix} U & \tilde{D} & V^T \end{matrix}$$

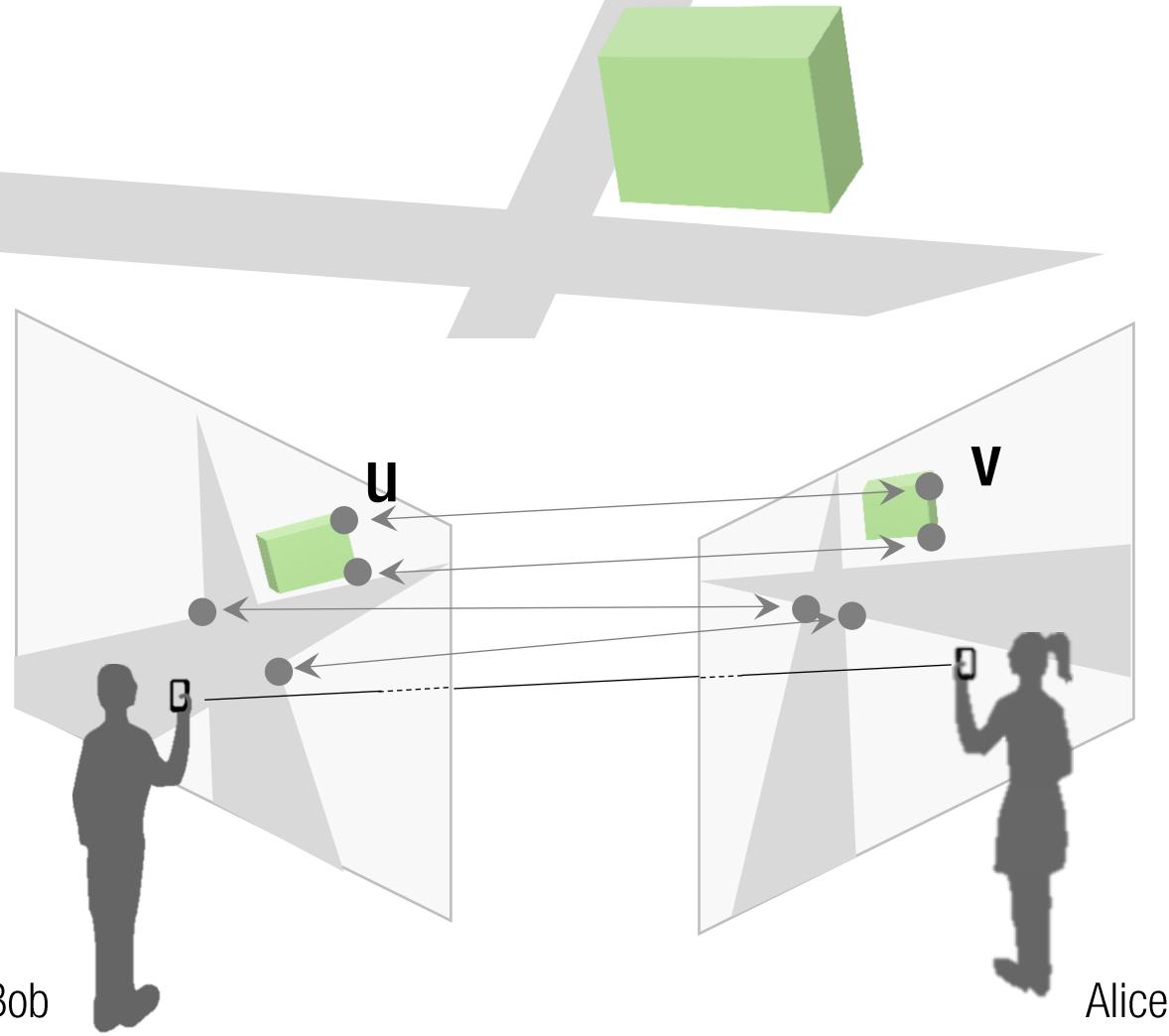
SVD cleanup

Essential Matrix



$$\begin{aligned} F &= F(R, t) \\ &= K^{-T} [t]_x R K^{-1} = K^{-T} E K^{-1} \end{aligned}$$

Essential Matrix



Essential Matrix:

$$F = F(R, t)$$

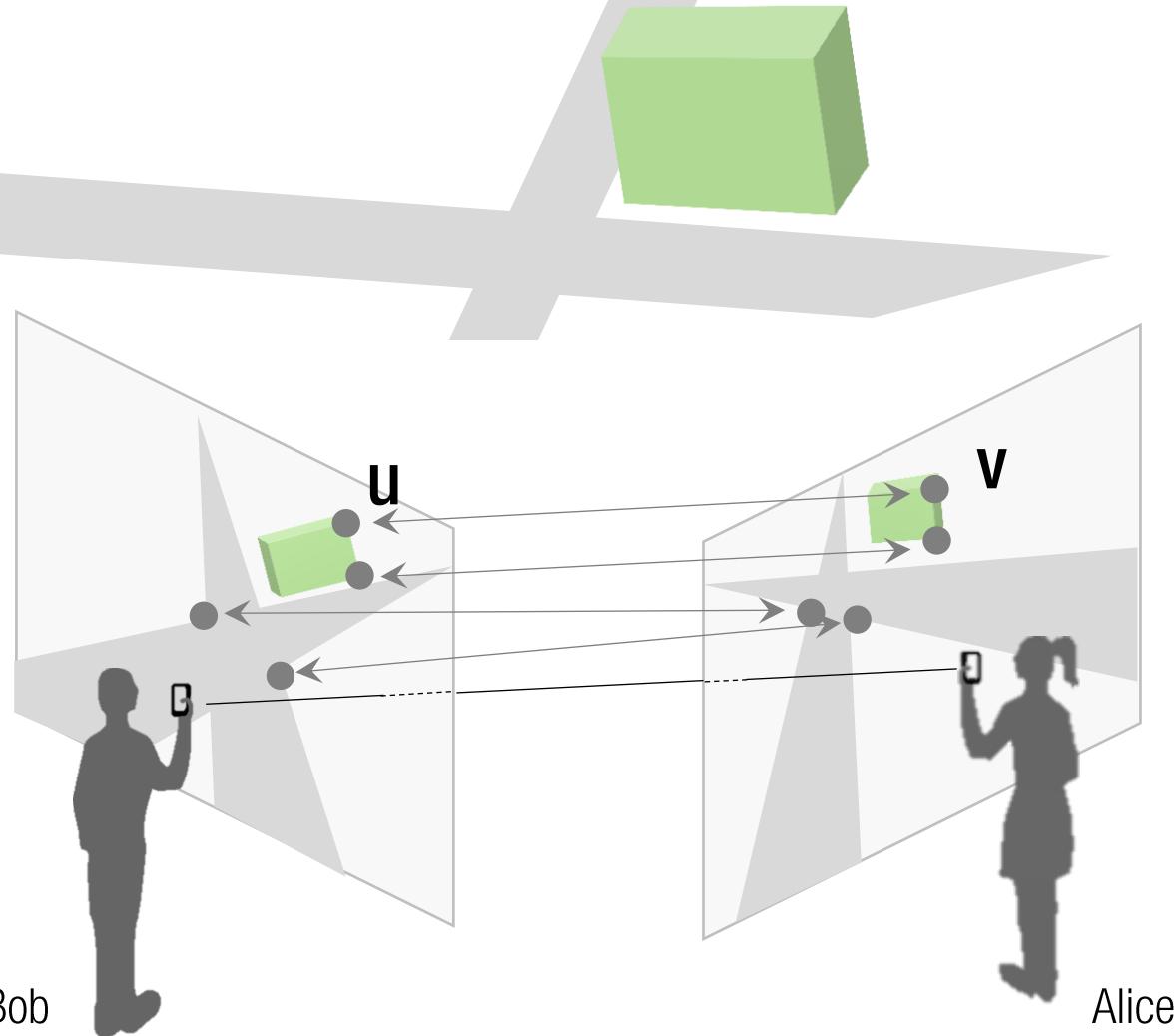
$$= K^{-T} \begin{bmatrix} t \end{bmatrix}_x R K^{-1} = K^{-T} E K^{-1}$$

$$\rightarrow E = K^T F K$$

Calibrated fundamental matrix

where $E = \begin{bmatrix} t \end{bmatrix}_x R$

Essential Matrix



Essential Matrix:

$$F = F(R, t)$$

$$= K^{-T} [t]_x R K^{-1} = K^{-T} E K^{-1}$$

$$\rightarrow E = K^T F K$$

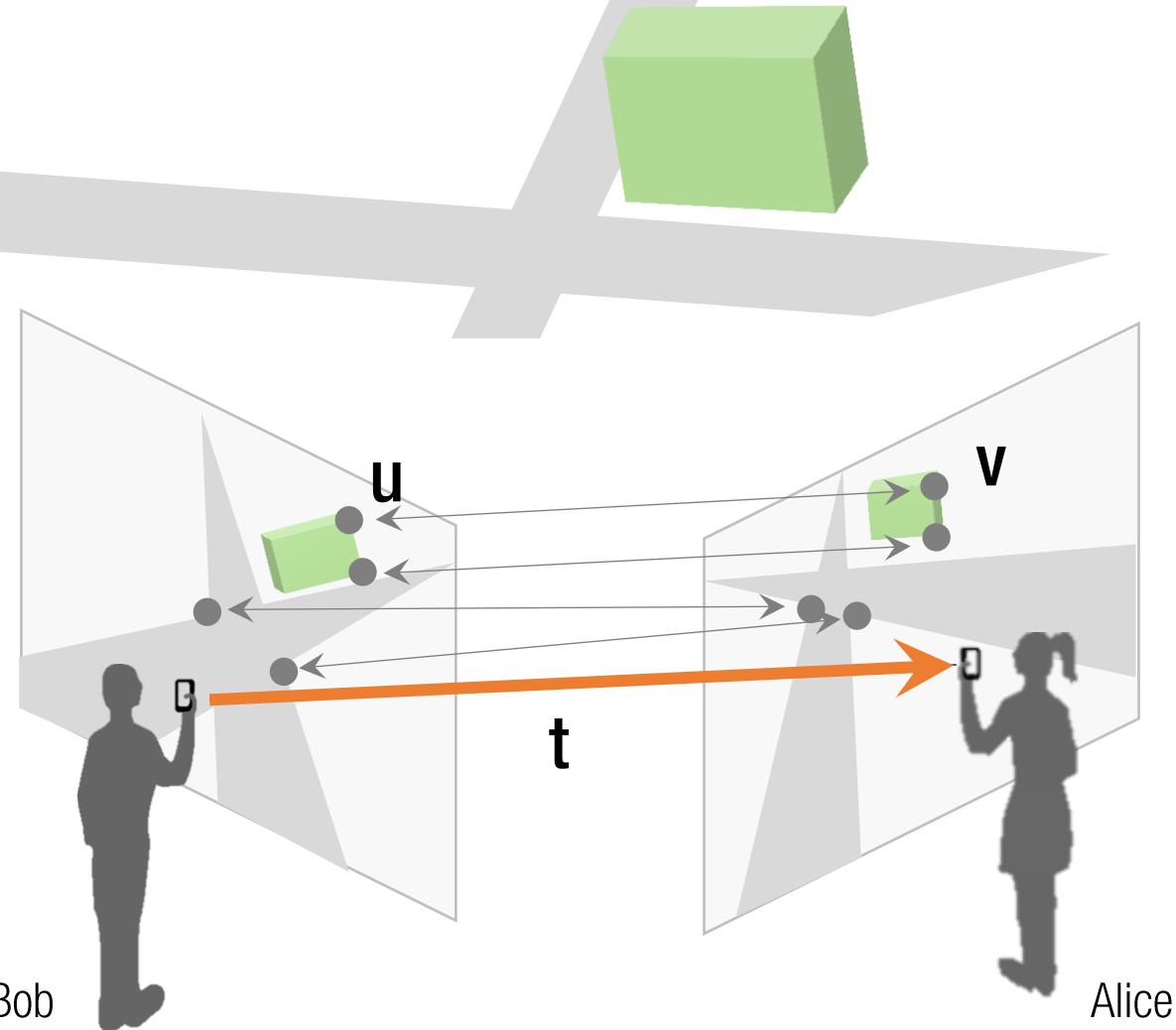
where $E = [t]_x R$

Calibrated fundamental matrix

Property of essential matrix:

$$E = UDV^T = \begin{matrix} 1 & \\ & 1 \\ & & 0 \end{matrix} \quad \boxed{\begin{matrix} 1 & \\ & 1 \\ & & 0 \end{matrix}} \quad V^T$$

Camera Pose from Essential Matrix (Translation)



Essential Matrix:

$$F = F(R, t)$$

$$= K^{-T} \begin{bmatrix} t \end{bmatrix}_x R K^{-1} = K^{-T} E K^{-1}$$

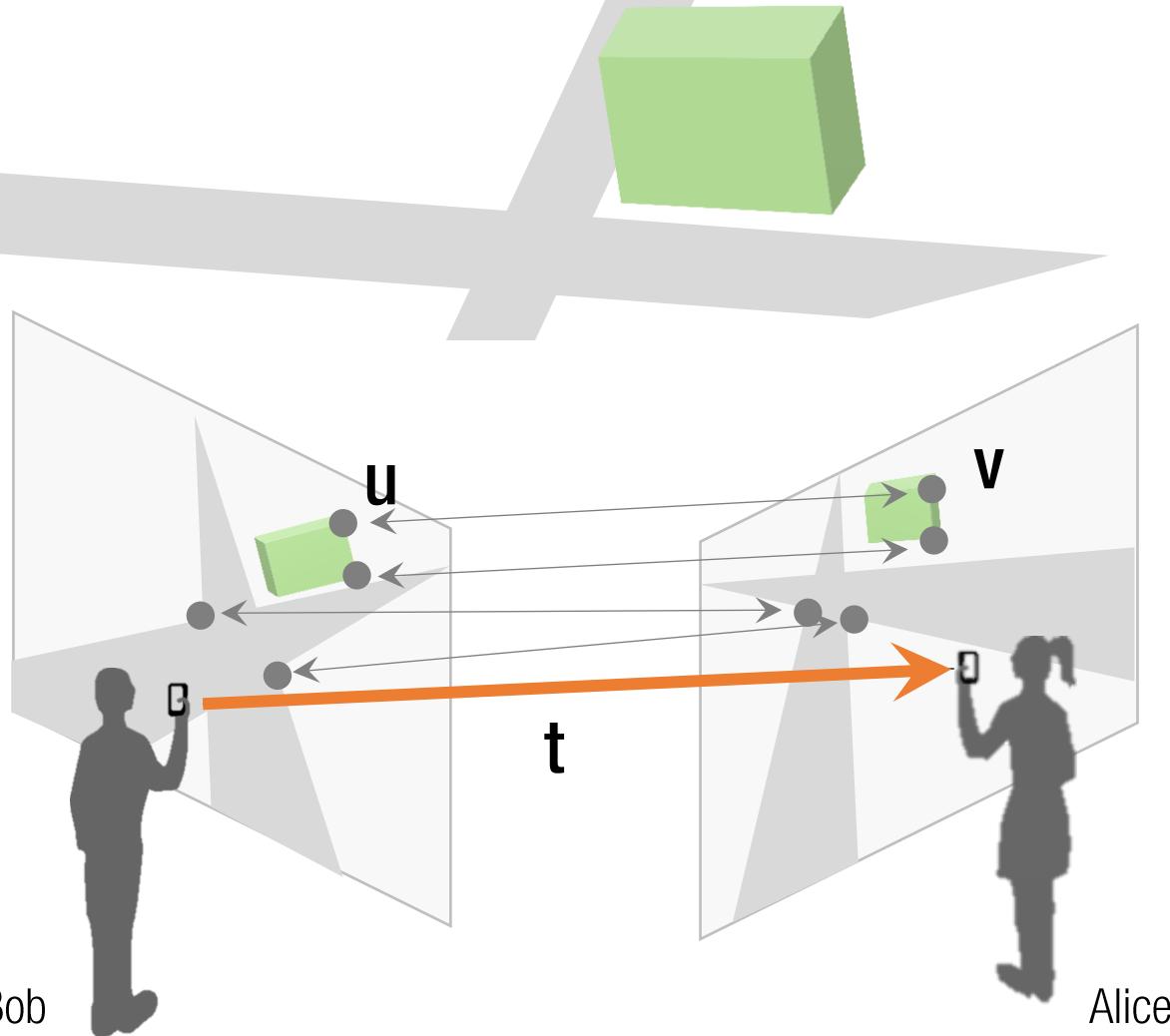
$$\rightarrow E = K^T F K$$

Calibrated fundamental matrix

where $E = \begin{bmatrix} t \end{bmatrix}_x R$

$$t =$$

Camera Pose from Essential Matrix (Translation)



Essential Matrix:

$$F = F(R, t)$$

$$= K^{-T} \begin{bmatrix} t \end{bmatrix}_x R K^{-1} = K^{-T} E K^{-1}$$

$$\rightarrow E = K^T F K$$

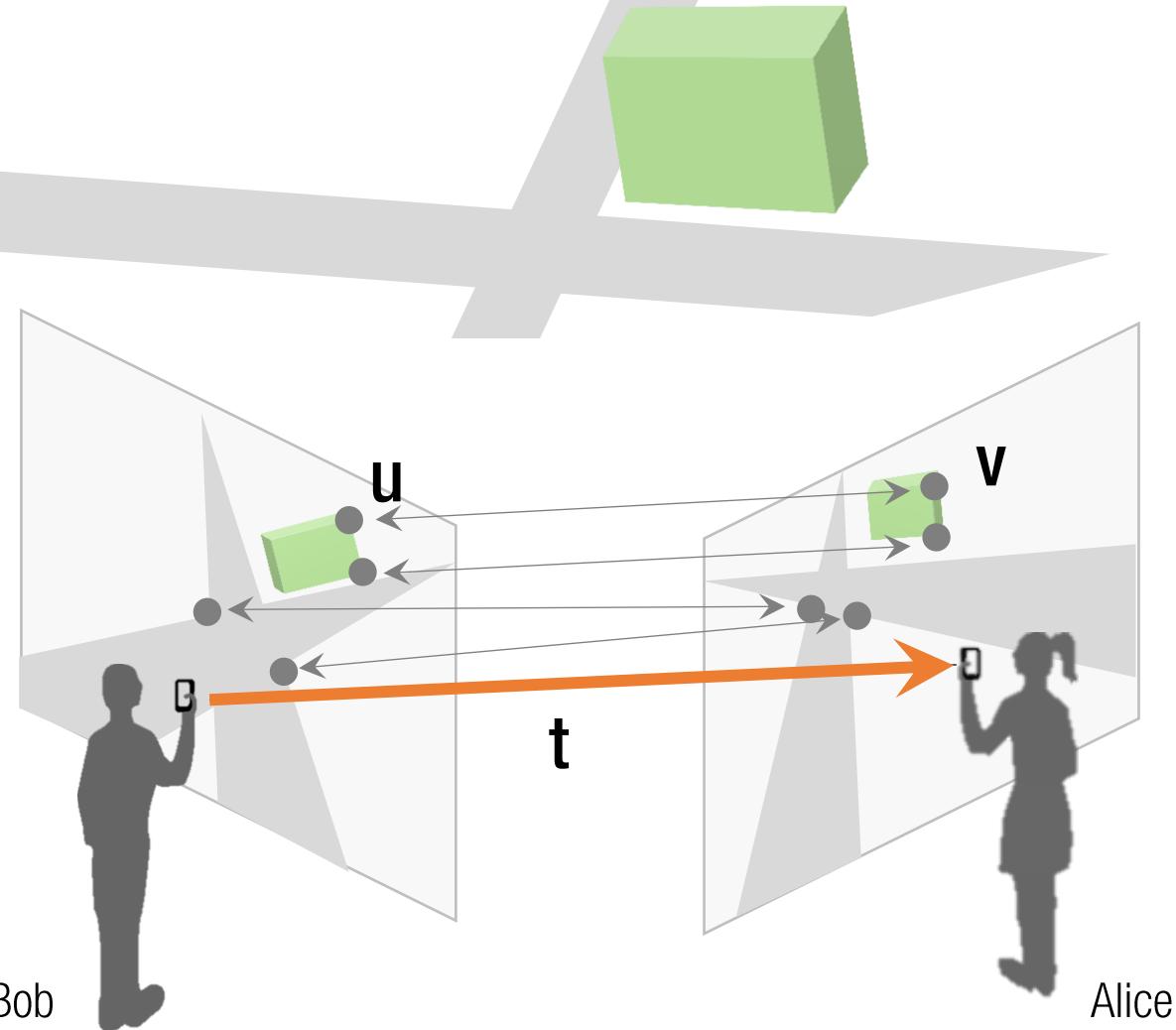
$$\text{where } E = \begin{bmatrix} t \end{bmatrix}_x R$$

Calibrated fundamental matrix

Left null space of E is translation vector, t :

$$t =$$

Camera Pose from Essential Matrix (Translation)



Essential Matrix:

$$F = F(R, t)$$

$$= K^{-T} \begin{bmatrix} t \end{bmatrix}_x R K^{-1} = K^{-T} E K^{-1}$$

$$\rightarrow E = K^T F K$$

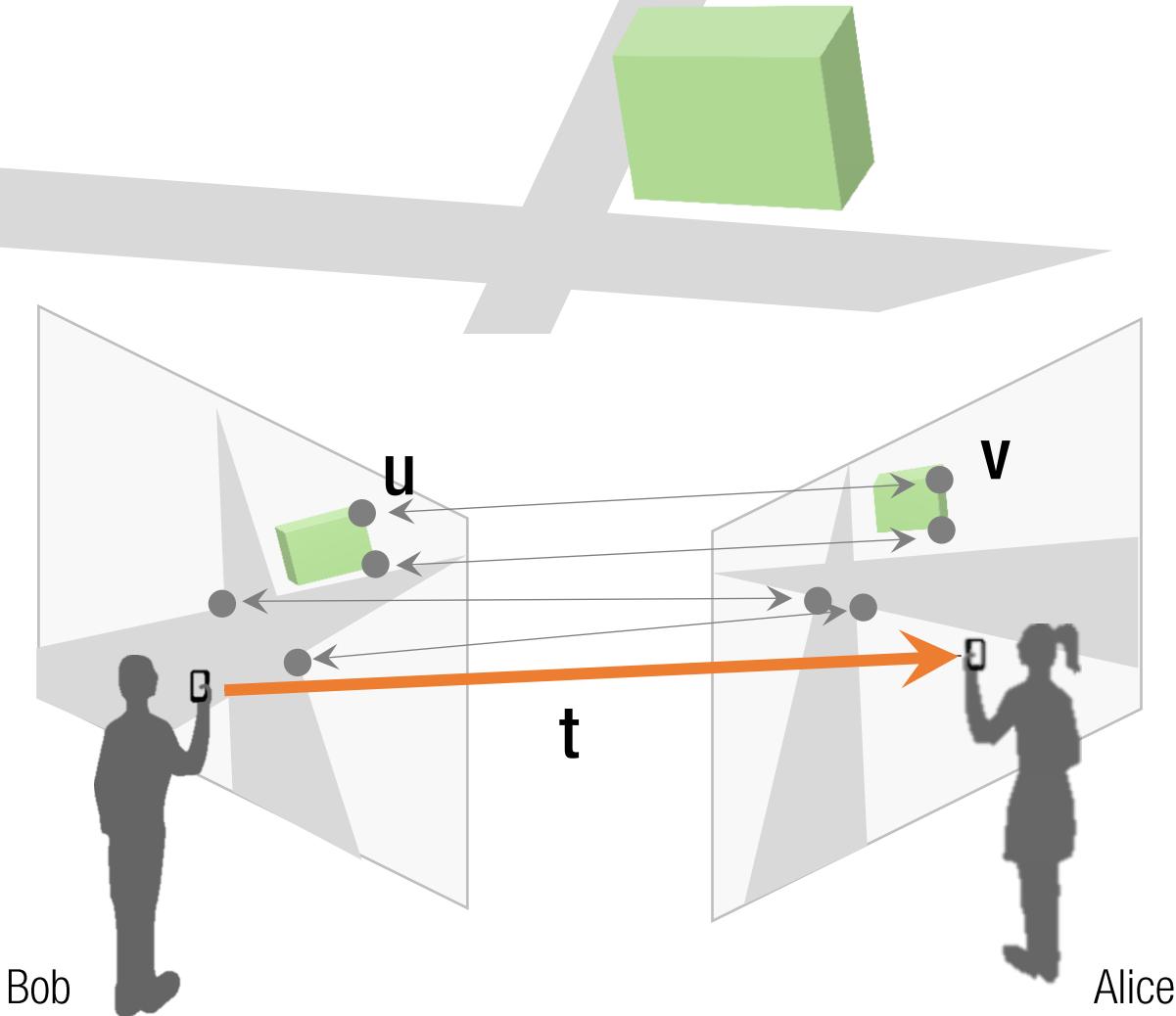
$$\text{where } E = \begin{bmatrix} t \end{bmatrix}_x R$$

Calibrated fundamental matrix

Left null space of E is translation vector, t :

$$t = \pm \text{null}(E^T) = \pm \text{null}(\begin{bmatrix} t \end{bmatrix}_x R)^T$$

Camera Pose from Essential Matrix (Translation)



Essential Matrix:

$$F = F(R, t)$$

$$= K^{-T} \begin{bmatrix} t \end{bmatrix}_x R K^{-1} = K^{-T} E K^{-1}$$

$$\rightarrow E = K^T F K$$

$$\text{where } E = \begin{bmatrix} t \end{bmatrix}_x R$$

Calibrated fundamental matrix

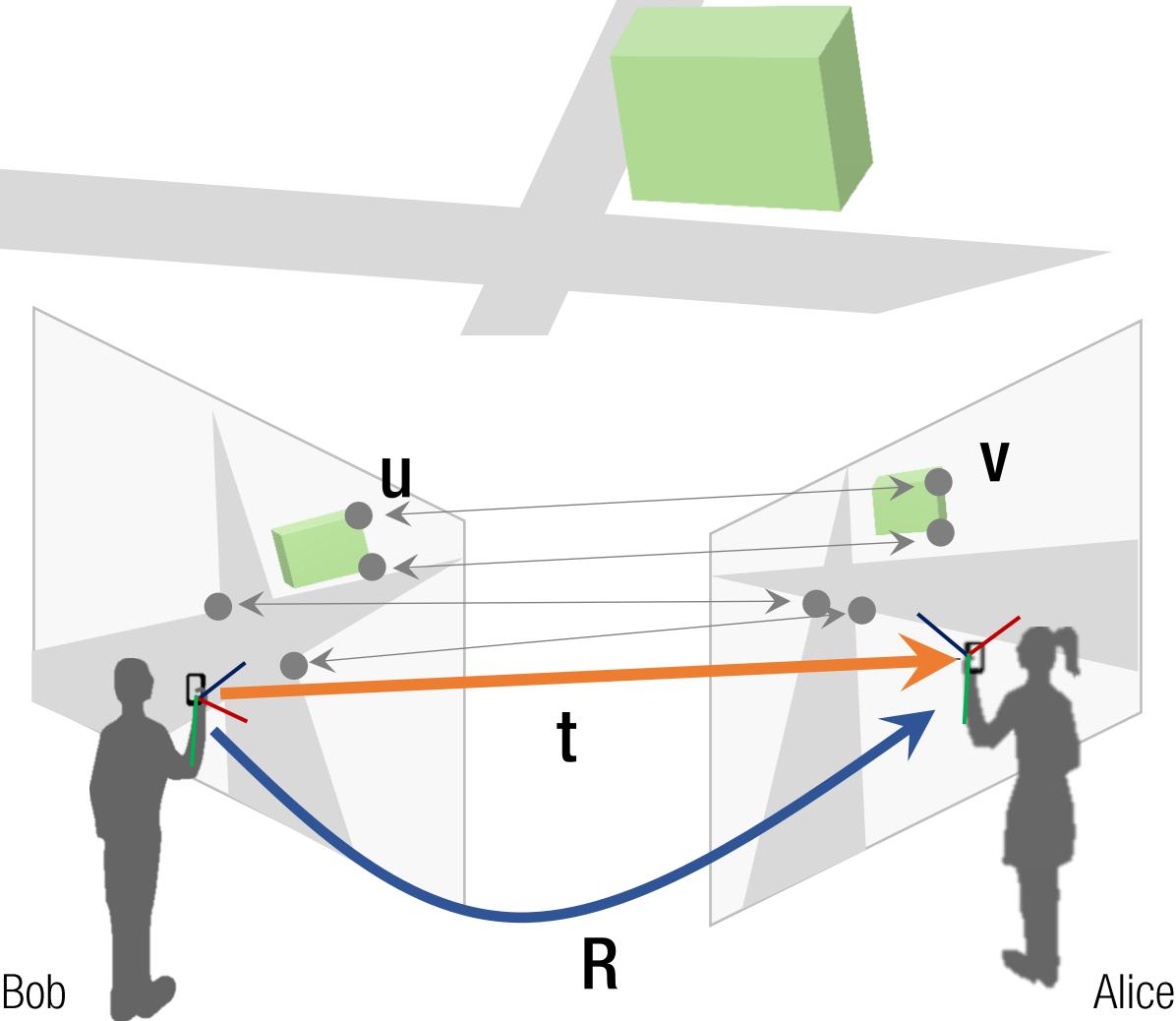
Left null space of E is translation vector, t :

$$t = \pm \text{null}(E^T) = \pm \text{null}(\begin{bmatrix} t \end{bmatrix}_x R)^T$$

$$\therefore t^T \begin{bmatrix} t \end{bmatrix}_x R = -(\begin{bmatrix} t \end{bmatrix}_x t)^T R = -(\underline{t \times t})^T R = 0$$

Self-cross product

Essential Matrix Decomposition



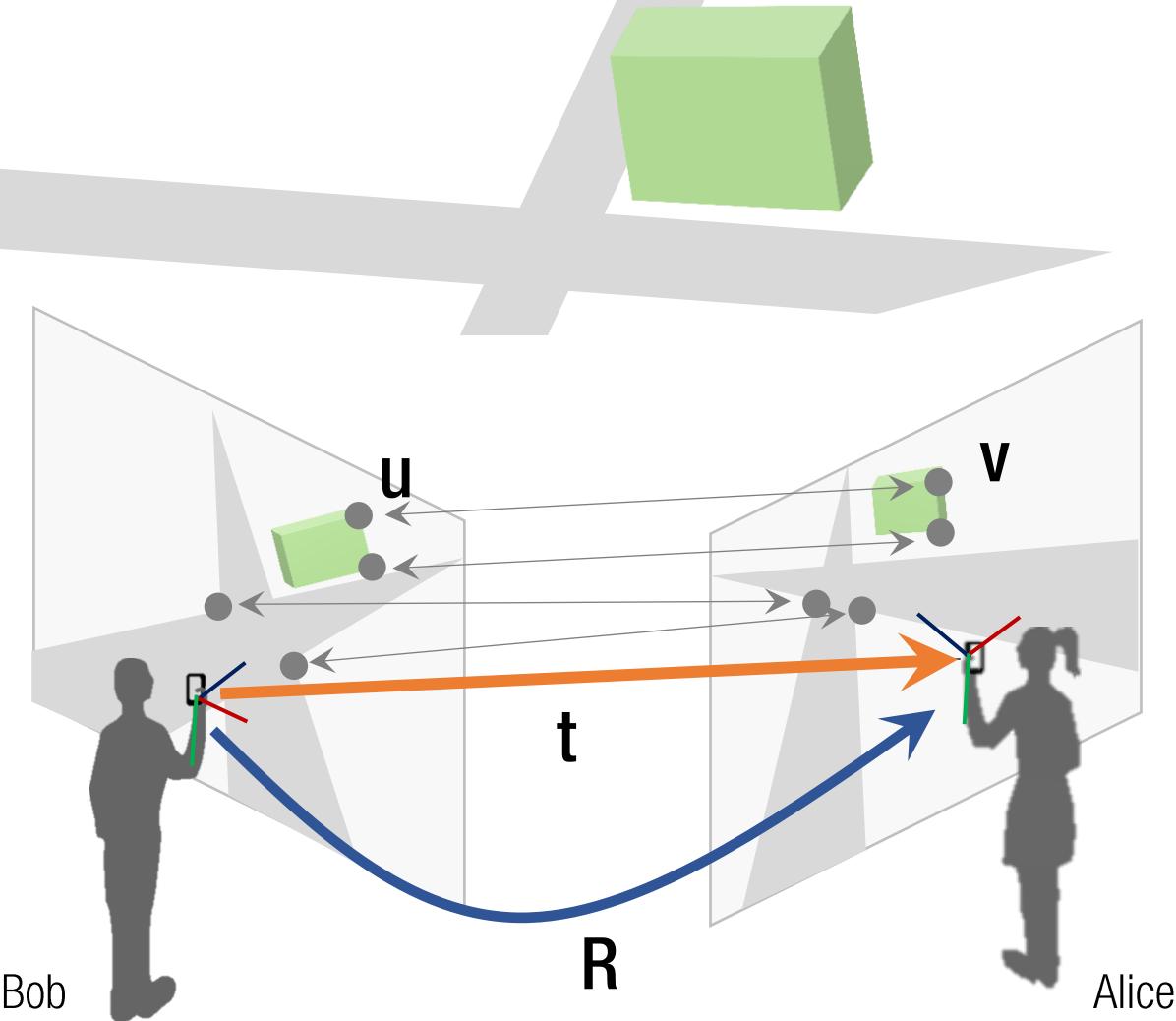
Left null space of E is translation vector, t :

$$t = \text{null}(E^T) = \text{null}(\begin{bmatrix} t \\ R \end{bmatrix}^T)$$

$$\rightarrow t = u_3 \quad \text{where } U = [u_1 \ u_2 \ u_3]$$

$$E = UDV^T = U \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} V^T$$

Essential Matrix Decomposition



Left null space of E is translation vector, \mathbf{t} :

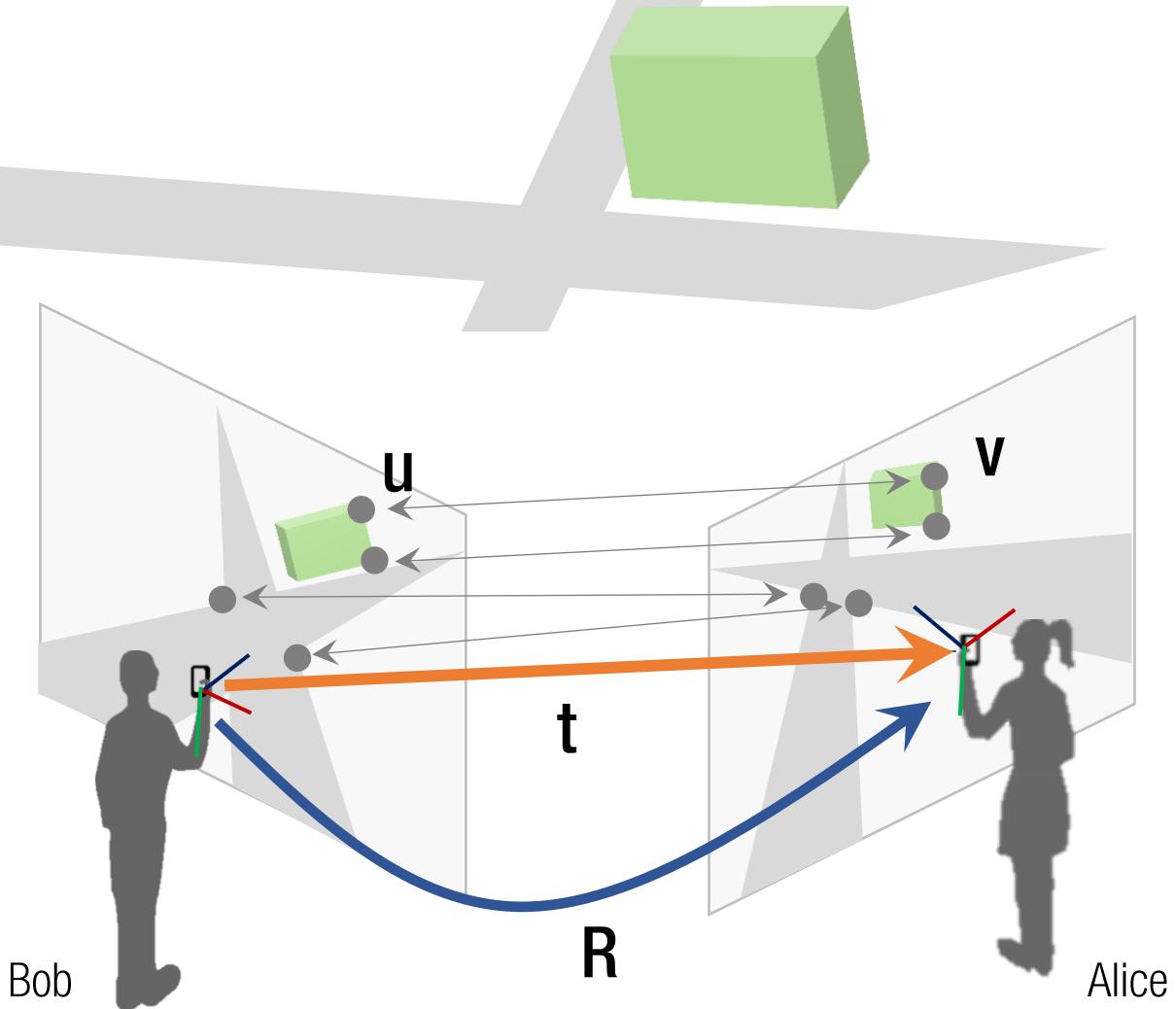
$$\mathbf{t} = \text{null}(\mathbf{E}^T) = \text{null}\left(\begin{bmatrix} \mathbf{t} \\ \mathbf{R} \end{bmatrix}^T\right)$$

$$\rightarrow \mathbf{t} = \mathbf{u}_3 \quad \text{where } \mathbf{U} = \begin{bmatrix} \mathbf{u}_1 & \mathbf{u}_2 & \mathbf{u}_3 \end{bmatrix}$$

$$\mathbf{E} = \mathbf{UDV}^T = \mathbf{U} \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} \mathbf{V}^T$$

$$\rightarrow \mathbf{t} = \mathbf{u}_1 \times \mathbf{u}_2 \quad (\text{orthogonal matrix, } \mathbf{U})$$

Essential Matrix Decomposition



Left null space of E is translation vector, \mathbf{t} :

$$\mathbf{t} = \text{null}(\mathbf{E}^T) = \text{null}(\begin{bmatrix} \mathbf{t} \\ \mathbf{R} \end{bmatrix}^T)$$

$$\rightarrow \mathbf{t} = \mathbf{u}_3 \quad \text{where } \mathbf{U} = [\mathbf{u}_1 \ \mathbf{u}_2 \ \mathbf{u}_3]$$

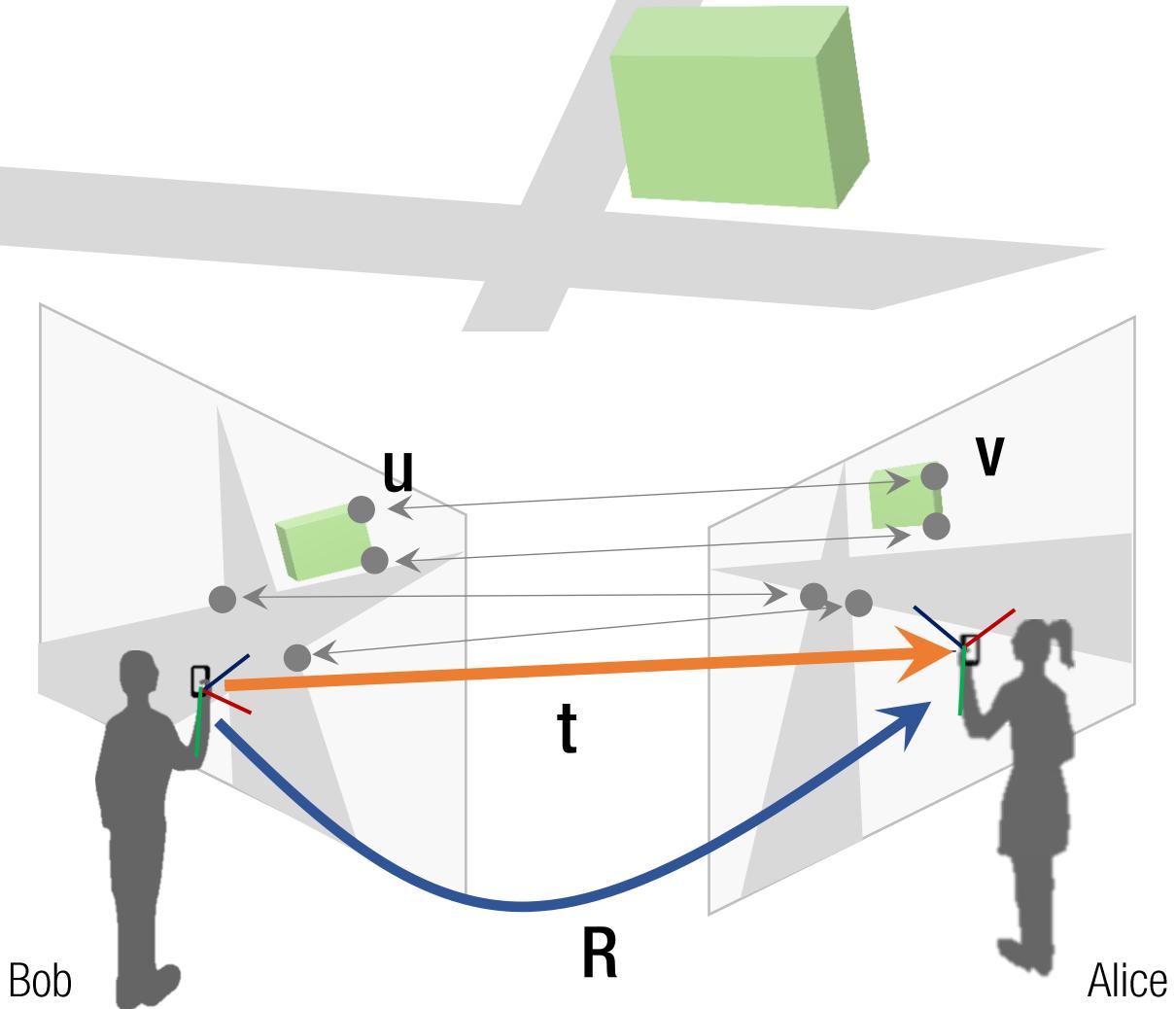
$$\mathbf{E} = \mathbf{UDV}^T = \mathbf{U} \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} \mathbf{V}^T$$

$$\rightarrow \mathbf{t} = \mathbf{u}_1 \times \mathbf{u}_2 \quad (\text{orthogonal matrix, } \mathbf{U})$$

$$[\mathbf{t}]_x = [\mathbf{u}_1 \times \mathbf{u}_2]_x = \mathbf{u}_2 \mathbf{u}_1^T - \mathbf{u}_1 \mathbf{u}_2^T$$

:

Essential Matrix Decomposition



Left null space of E is translation vector, \mathbf{t} :

$$\mathbf{t} = \text{null}(\mathbf{E}^T) = \text{null}(\begin{bmatrix} \mathbf{t} \\ \mathbf{R} \end{bmatrix}^T)$$

$$\rightarrow \mathbf{t} = \mathbf{u}_3 \quad \text{where } \mathbf{U} = [\mathbf{u}_1 \ \mathbf{u}_2 \ \mathbf{u}_3]$$

$$\mathbf{E} = \mathbf{UDV}^T = \mathbf{U} \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} \mathbf{V}^T$$

$$\rightarrow \mathbf{t} = \mathbf{u}_1 \times \mathbf{u}_2 \quad (\text{orthogonal matrix, } \mathbf{U})$$

$$[\mathbf{t}]_x = [\mathbf{u}_1 \times \mathbf{u}_2]_x = \mathbf{u}_2 \mathbf{u}_1^T - \mathbf{u}_1 \mathbf{u}_2^T$$

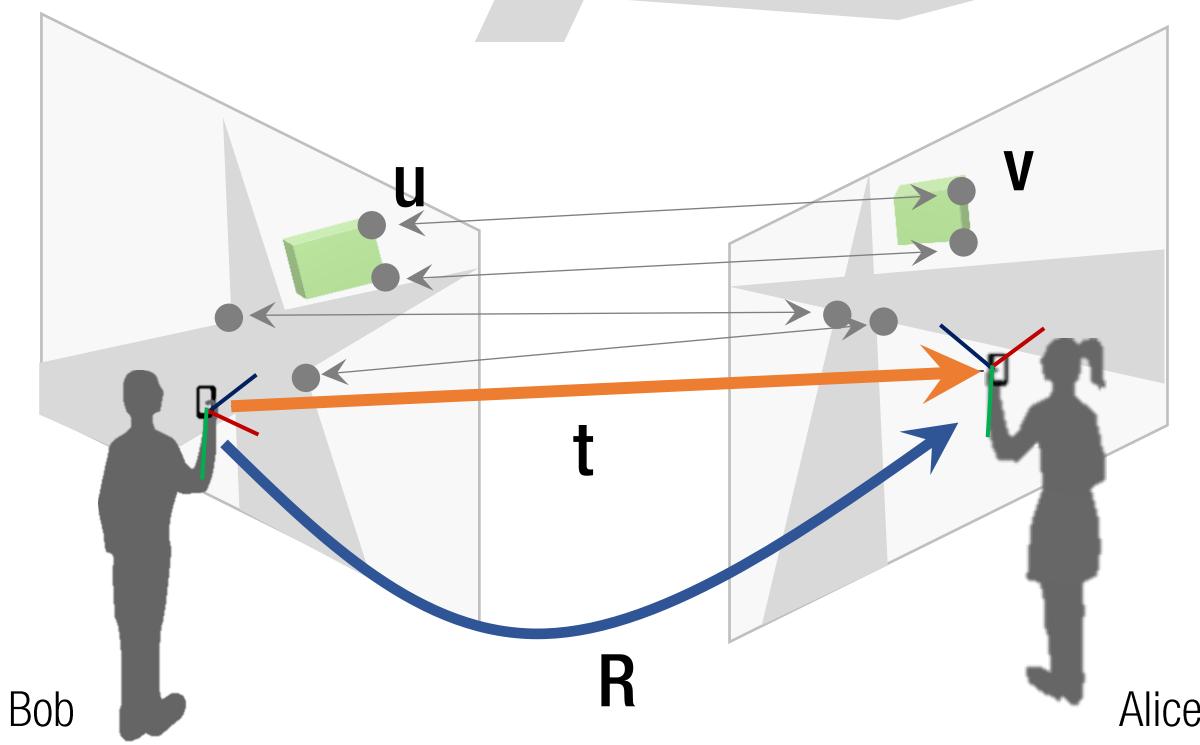
$$= \mathbf{U} \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{U}^T$$

Prove!

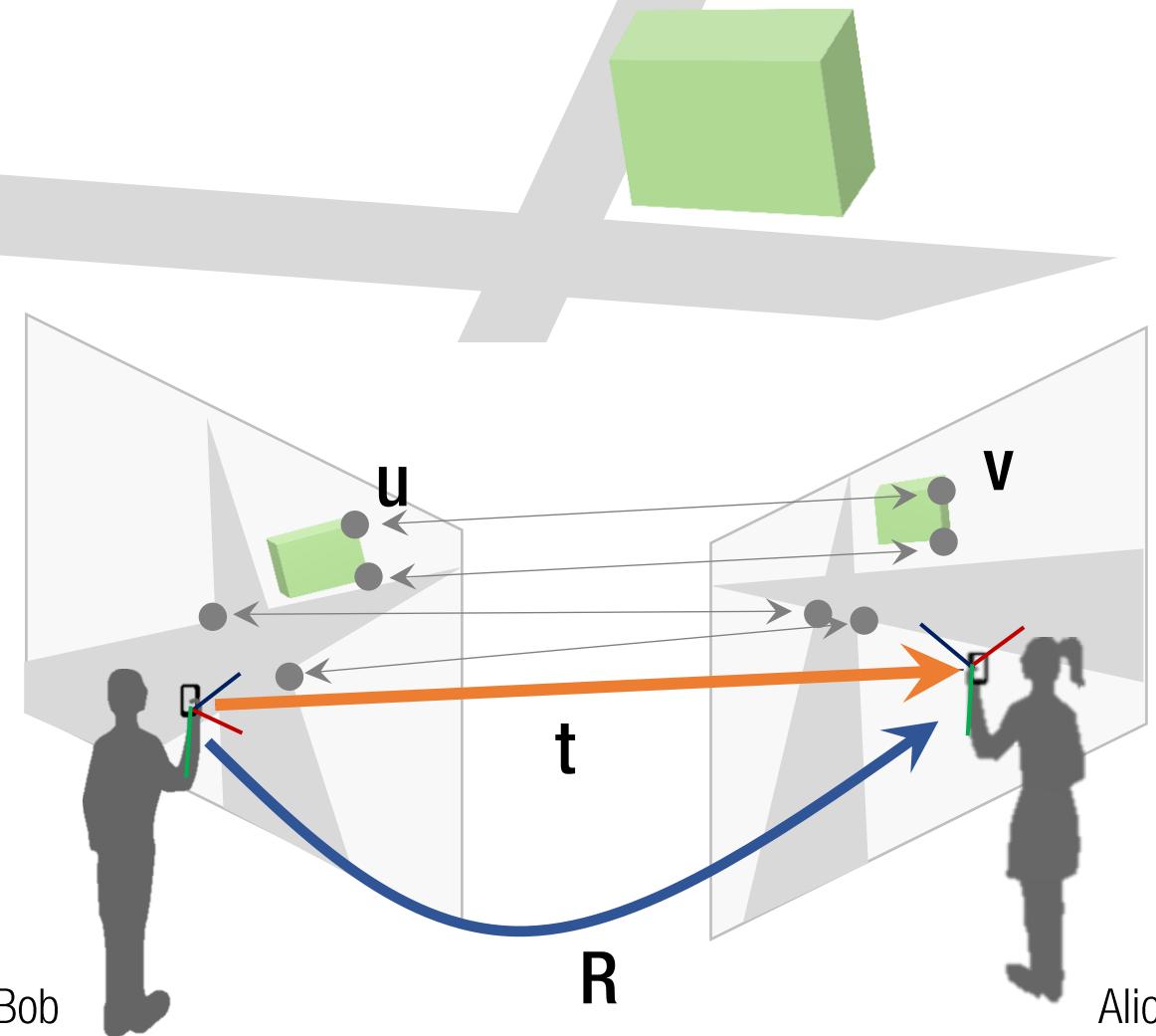
Essential Matrix Decomposition

$$E = \begin{bmatrix} t \\ \times \end{bmatrix} R = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} U^T R$$

where $R \in SO(3)$



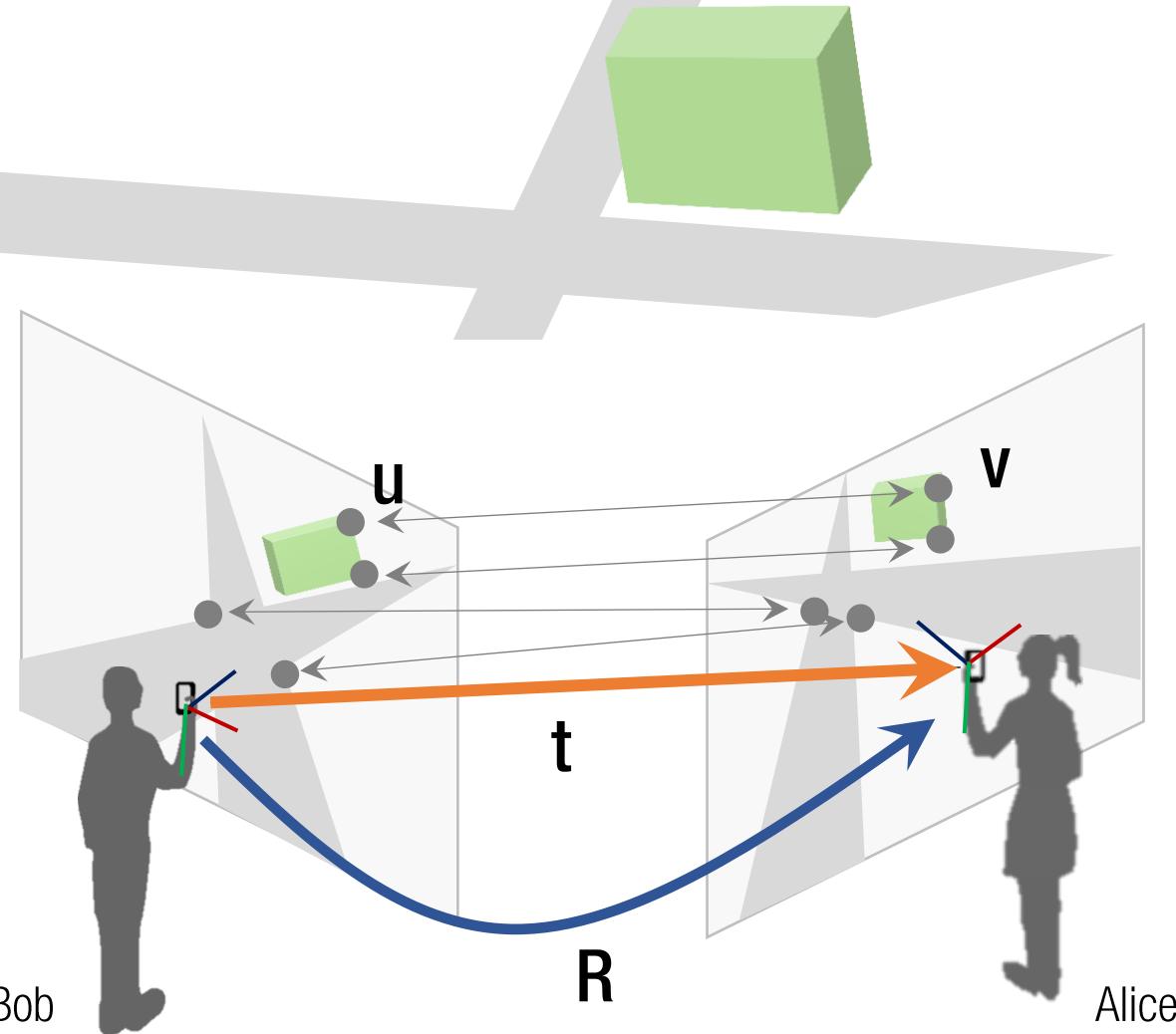
Essential Matrix Decomposition



$$E = [t]_x R = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} U^T R = U \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} V^T$$

where $R \in SO(3)$

Essential Matrix Decomposition



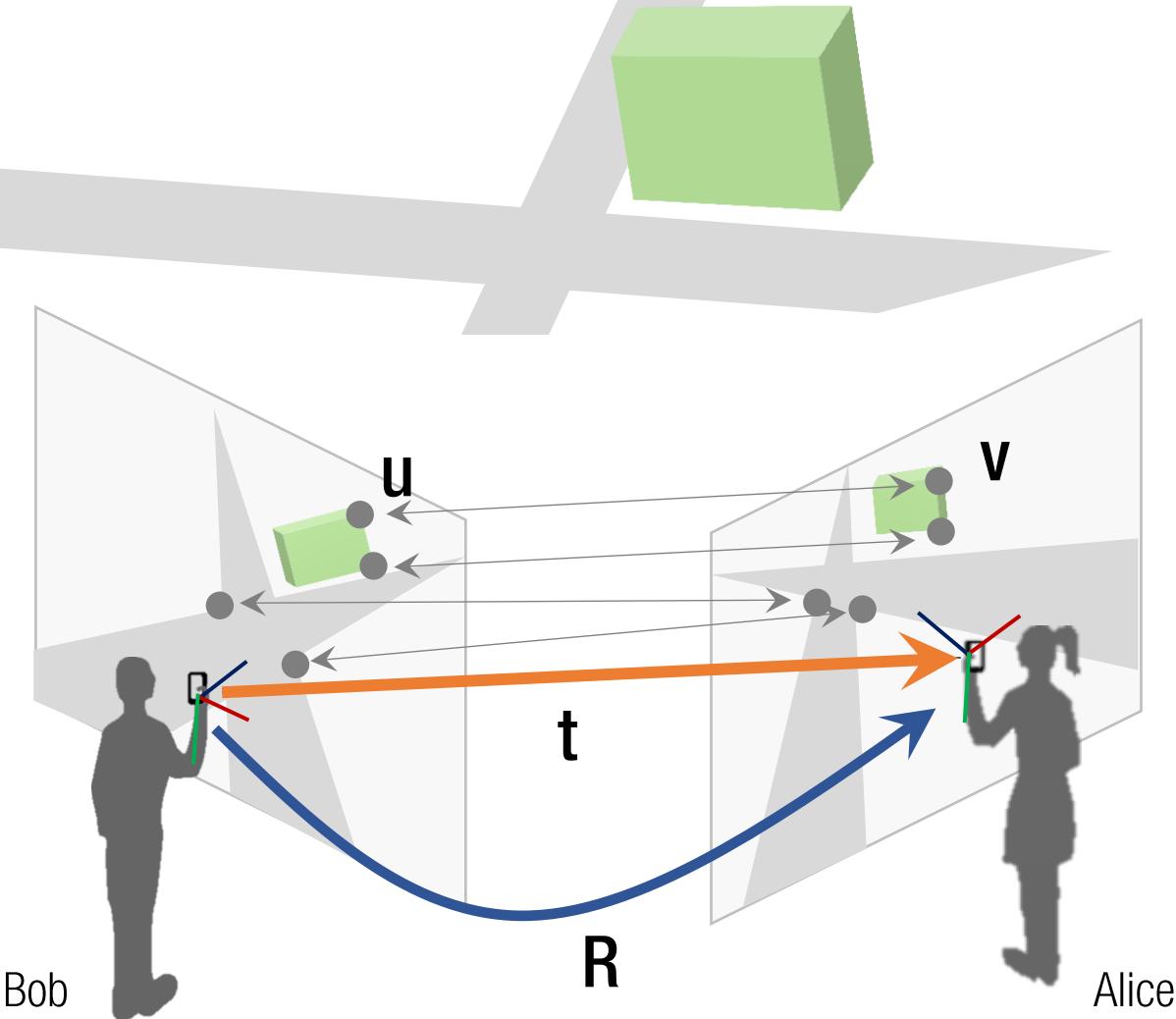
$$E = \begin{bmatrix} t \end{bmatrix}_x R = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} U^T R = U \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} V^T$$

where $R \in SO(3)$

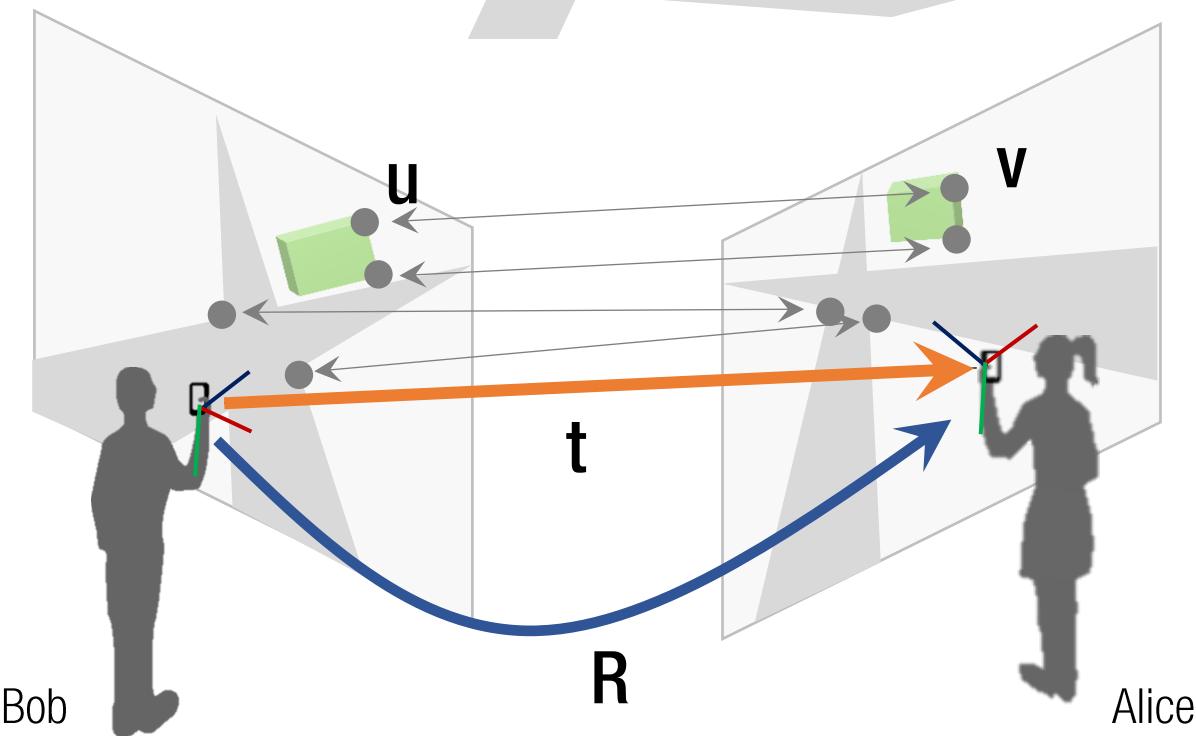
$$\text{Define } R = \underline{U} \underline{W} \underline{V}^T$$

$$E = \begin{bmatrix} t \end{bmatrix}_x R = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} U^T U \underline{W} \underline{V}^T = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \underline{W} \underline{V}^T$$

Essential Matrix Decomposition



Essential Matrix Decomposition



$$E = [t]_x R = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} U^T R = U \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} V^T$$

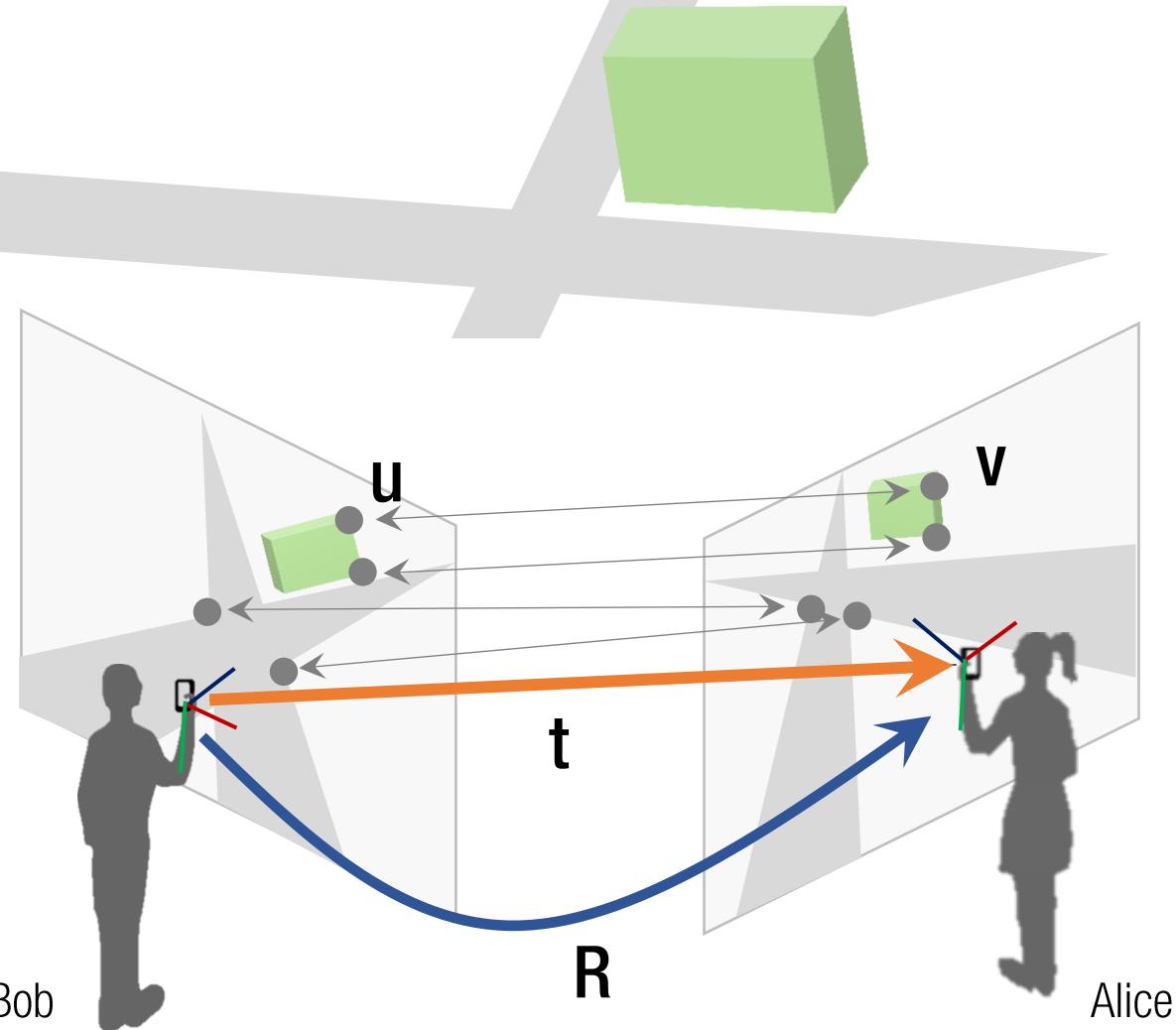
where $R \in SO(3)$

$$\text{Define } R = \underline{U W V^T}$$

$$E = [t]_x R = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} U^T U W V^T = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} W V^T$$

$$\rightarrow \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} W \quad W = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \text{ or } \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Camera Pose from Essential Matrix (Rotation)

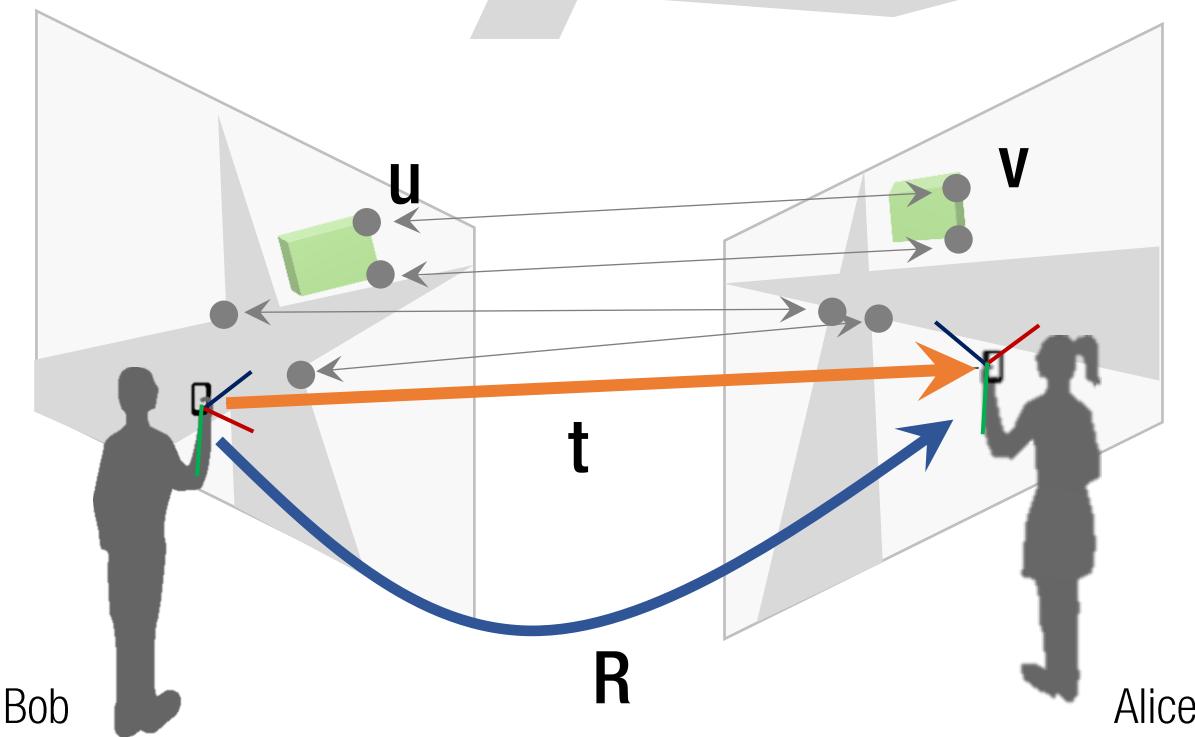


$$E = \begin{bmatrix} t \\ \times \end{bmatrix} R = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} U^T R = U \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} V^T$$

where $R \in SO(3)$

$$R = U \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} V^T, \text{ or } U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} V^T$$

Where Am I?



$$E = [t]_x R = U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} U^T R = U \begin{bmatrix} 1 & & \\ & 1 & \\ & & 0 \end{bmatrix} V^T$$

$$t = \pm u_3$$

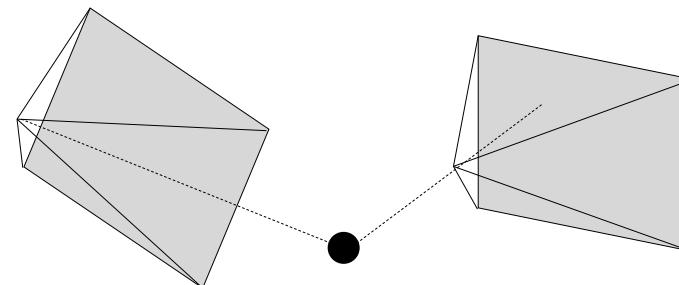
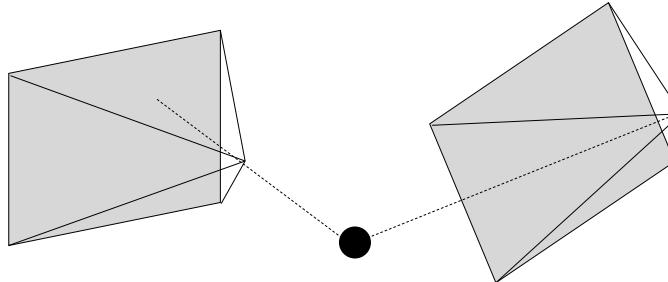
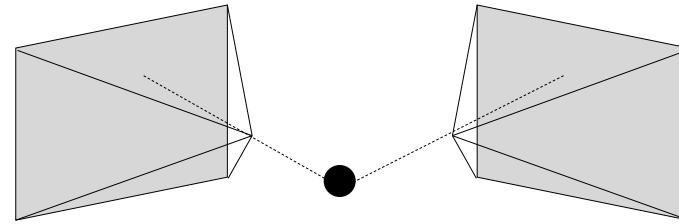
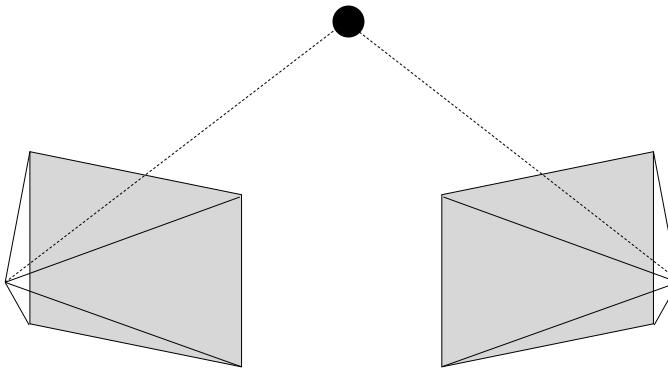
$$R = U \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} V^T, \text{ or } U \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} V^T$$

→ Four configurations

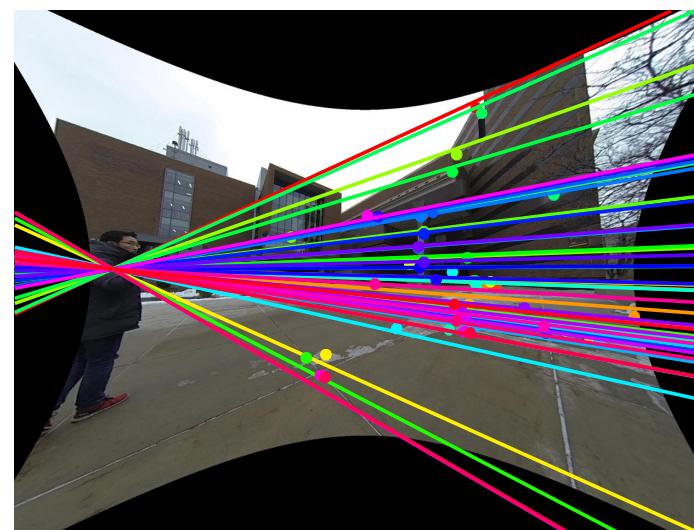
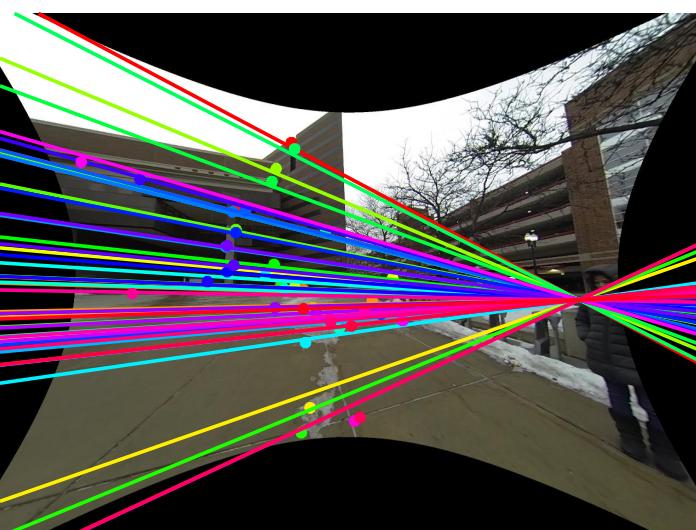
$$\mathbf{t} = \pm \mathbf{u}_3$$

$$\mathbf{R} = \mathbf{U} \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{v}^T, \text{ or } \mathbf{U} \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{v}^T$$

Four Configurations



Camera Pose Estimation



$$E = K^T F K$$

```
function E = ComputeEssentialMatrix(F, K)
```

```
E = K' * F * K;
```

```
[u d v] = svd(E);
```

```
d(1,1) = 1;
```

```
d(2,2) = 1;
```

```
d(3,3) = 0;
```

SVD cleanup

```
E = u * d * v';
```

D =

1.0468	0	0
0	0.9975	0
0	0	0.0000

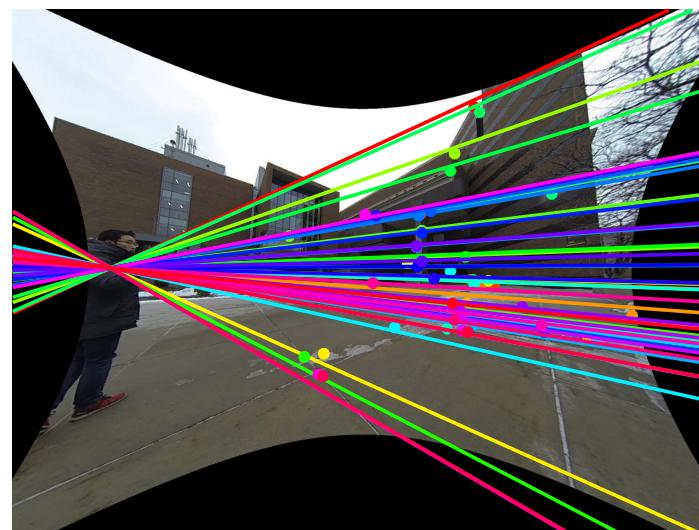
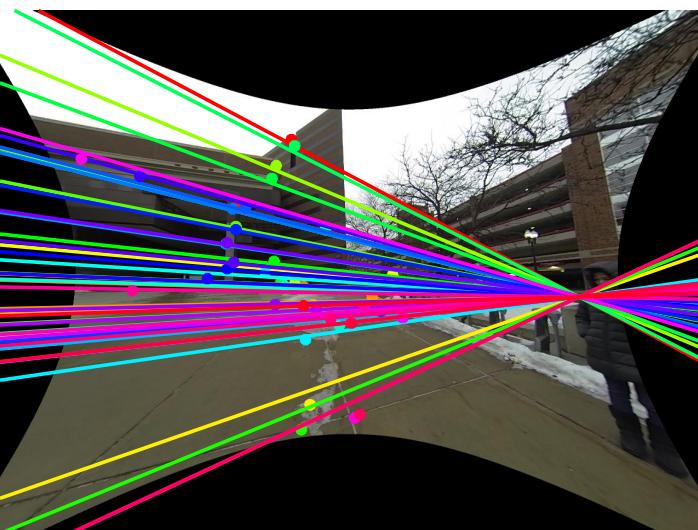
Before cleanup

D =

1.0000	0	0
0	1.0000	0
0	0	0.0000

After cleanup

Camera Pose Estimation



$$\mathbf{t} = \pm \mathbf{u}_3$$

$$\mathbf{R} = \mathbf{U} \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^T, \text{ or } \mathbf{U} \begin{bmatrix} 0 & 1 & 0 \\ -1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix} \mathbf{V}^T$$

```
function [R1 t1, R2, t2, R3, t3, R4, t4] = ...
CameraPoseFromEssentialMatrix(E)
```

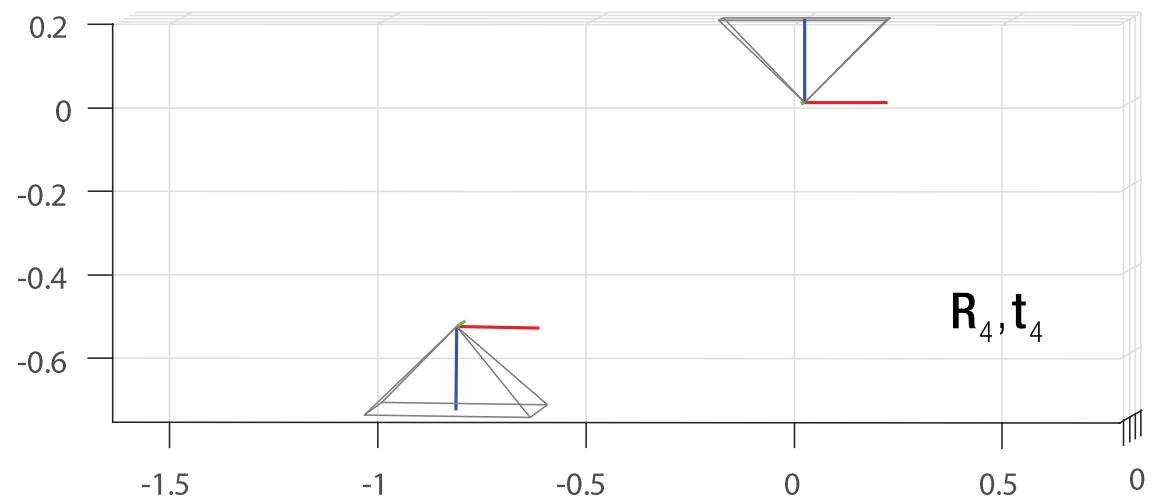
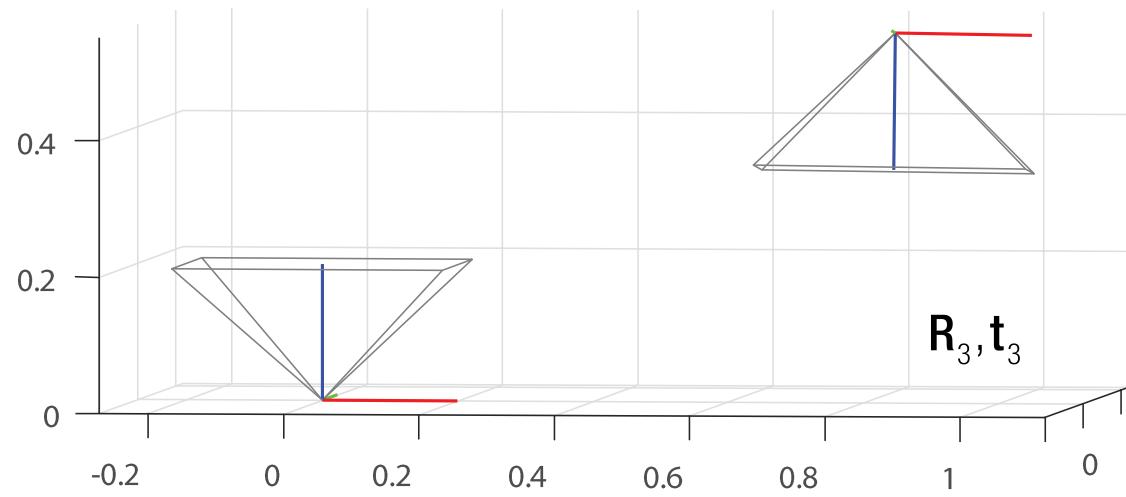
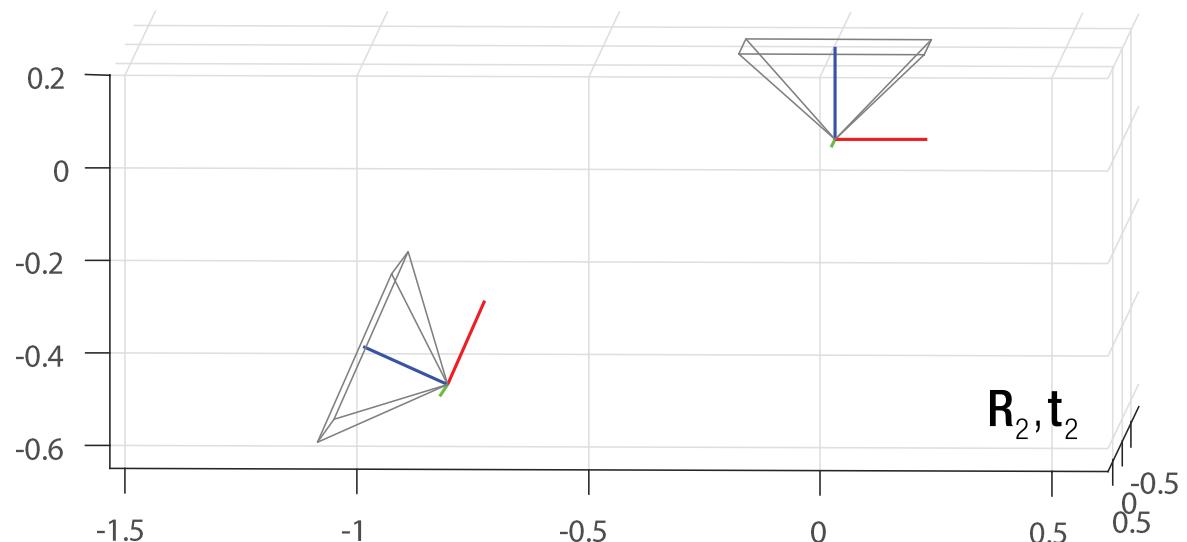
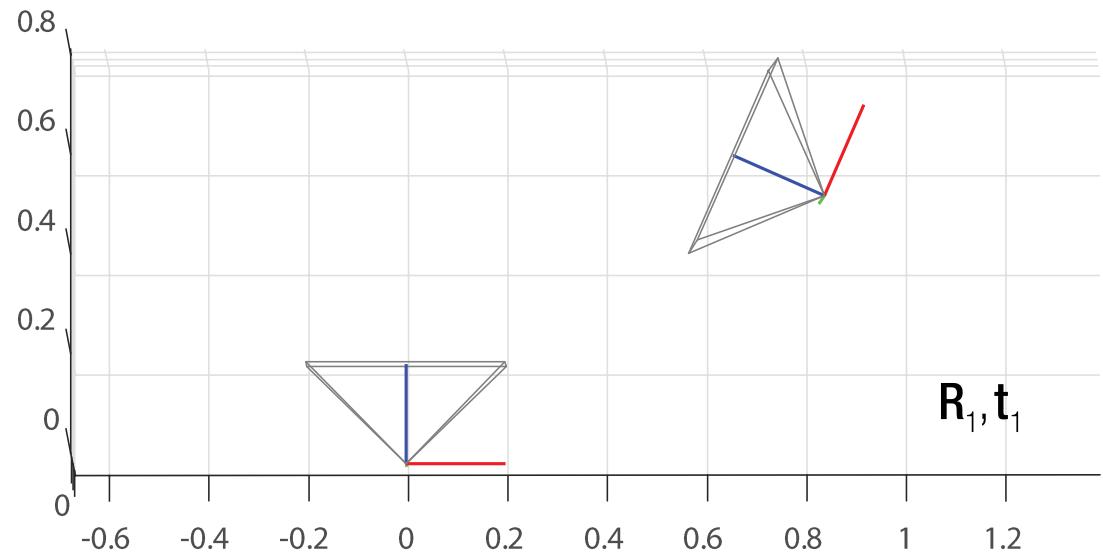
```
[U D V] = svd(E);
```

```
W = [0 -1 0;
      1 0 0;
      0 0 1];
```

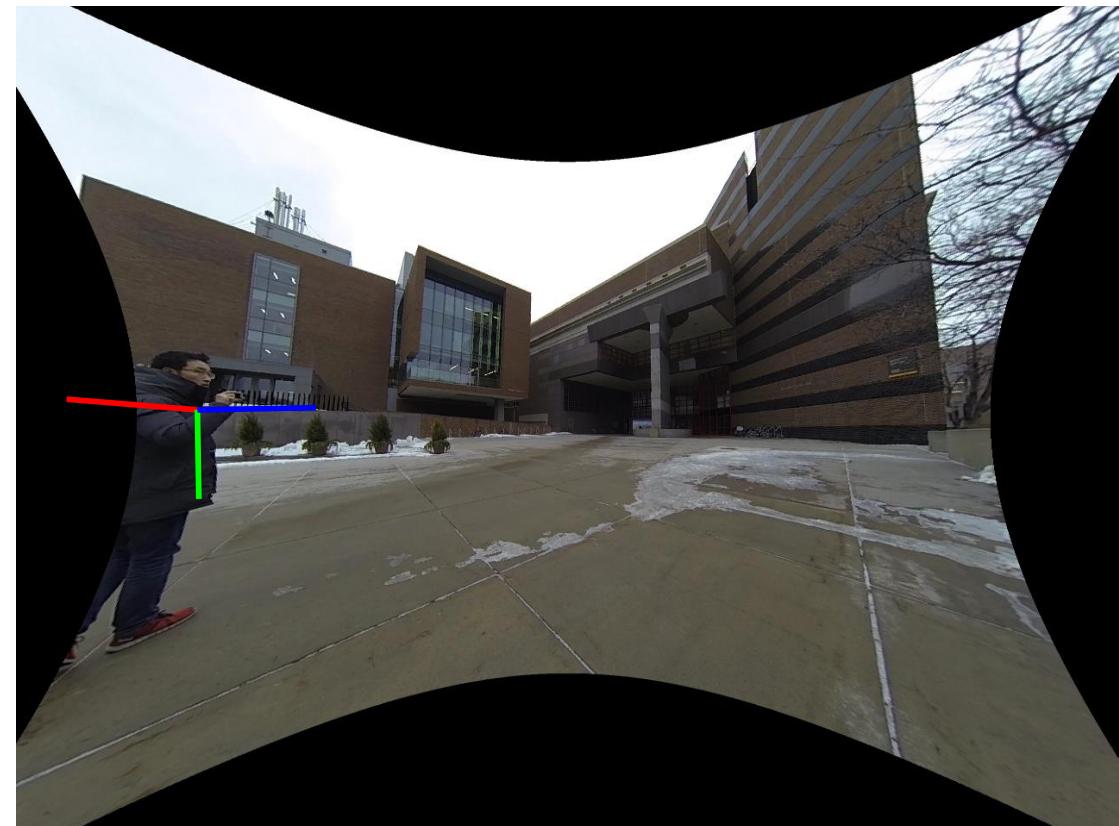
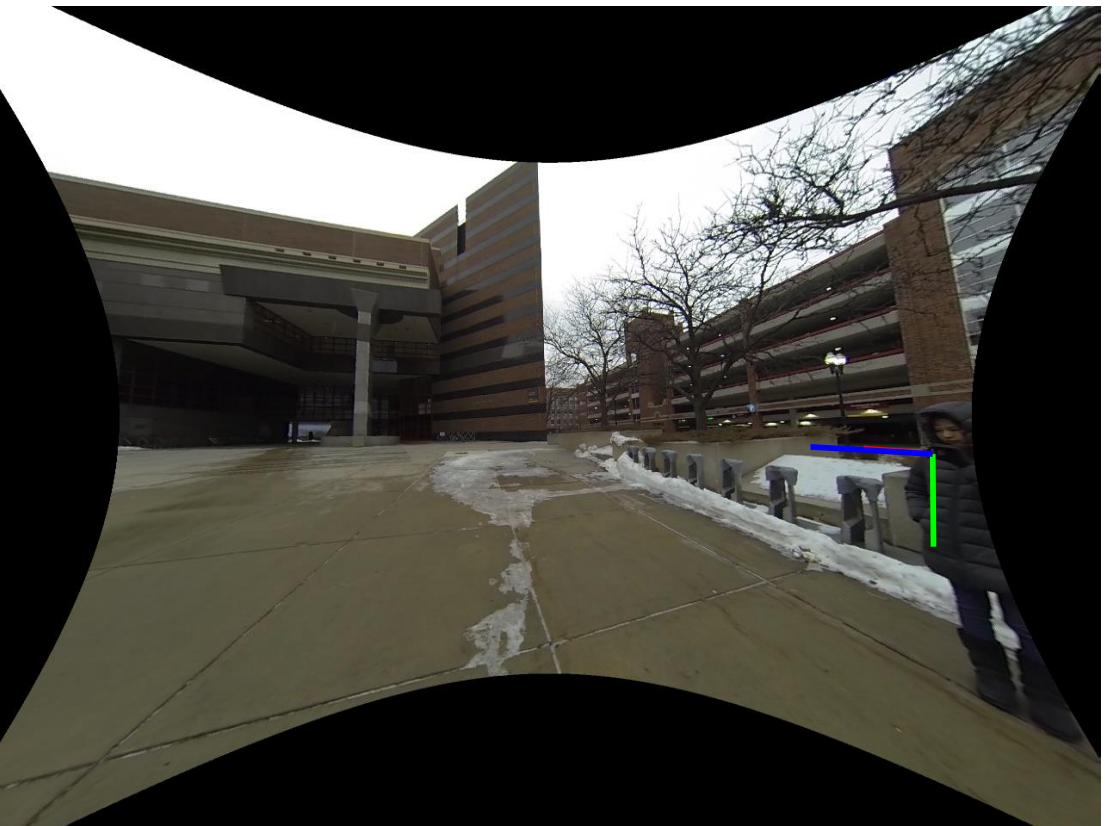
```
t1 = U(:,3);
R1 = U * W * V';
if det(R1) < 0
    t1 = -t1; R1 = -R1;
end
```

$$\det(\mathbf{R}) = 1$$

...



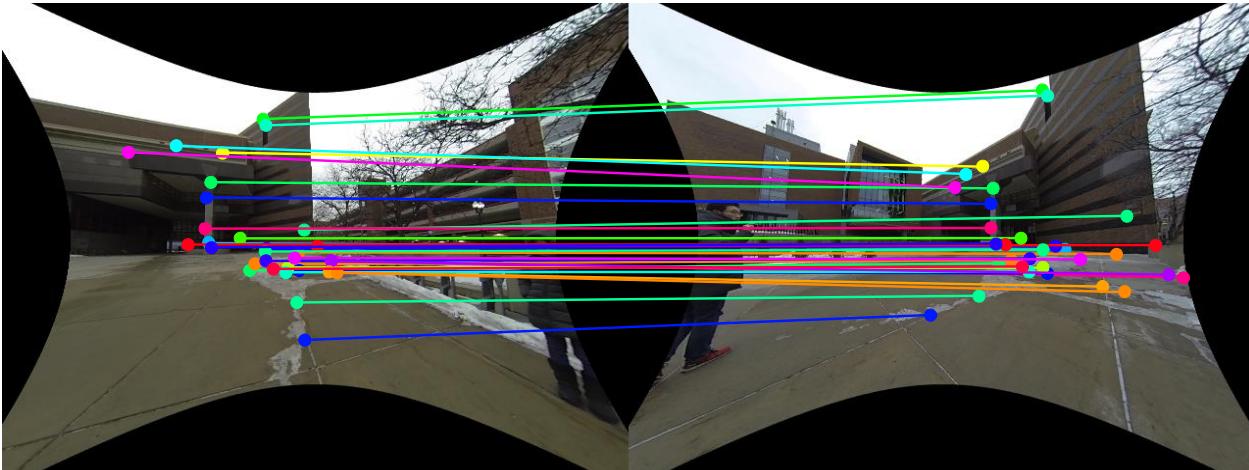
Camera Image Projection





Feature Matching

How Many Correspondences?



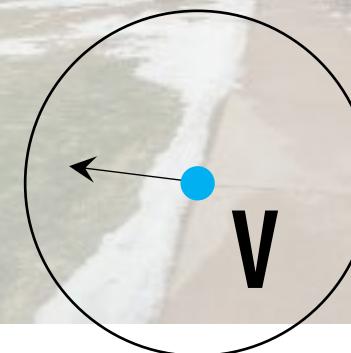
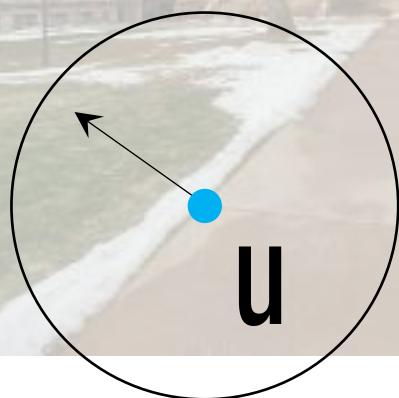
$$\begin{bmatrix} u_1^x v_1^x & u_1^y v_1^x & v_1^x & u_1^x v_1^y & u_1^y v_1^y & v_1^y & u_1^x & u_1^y & 1 \\ \vdots & \vdots \\ u_m^x v_m^x & u_m^y v_m^x & v_m^x & u_m^x v_m^y & u_m^y v_m^y & v_m^y & u_m^x & u_m^y & 1 \end{bmatrix} \mathbf{A} \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{31} \\ f_{32} \\ f_{33} \end{bmatrix} = \mathbf{0}$$

What is minimum m?



Local Scale Invariant Feature Transform (SIFT)

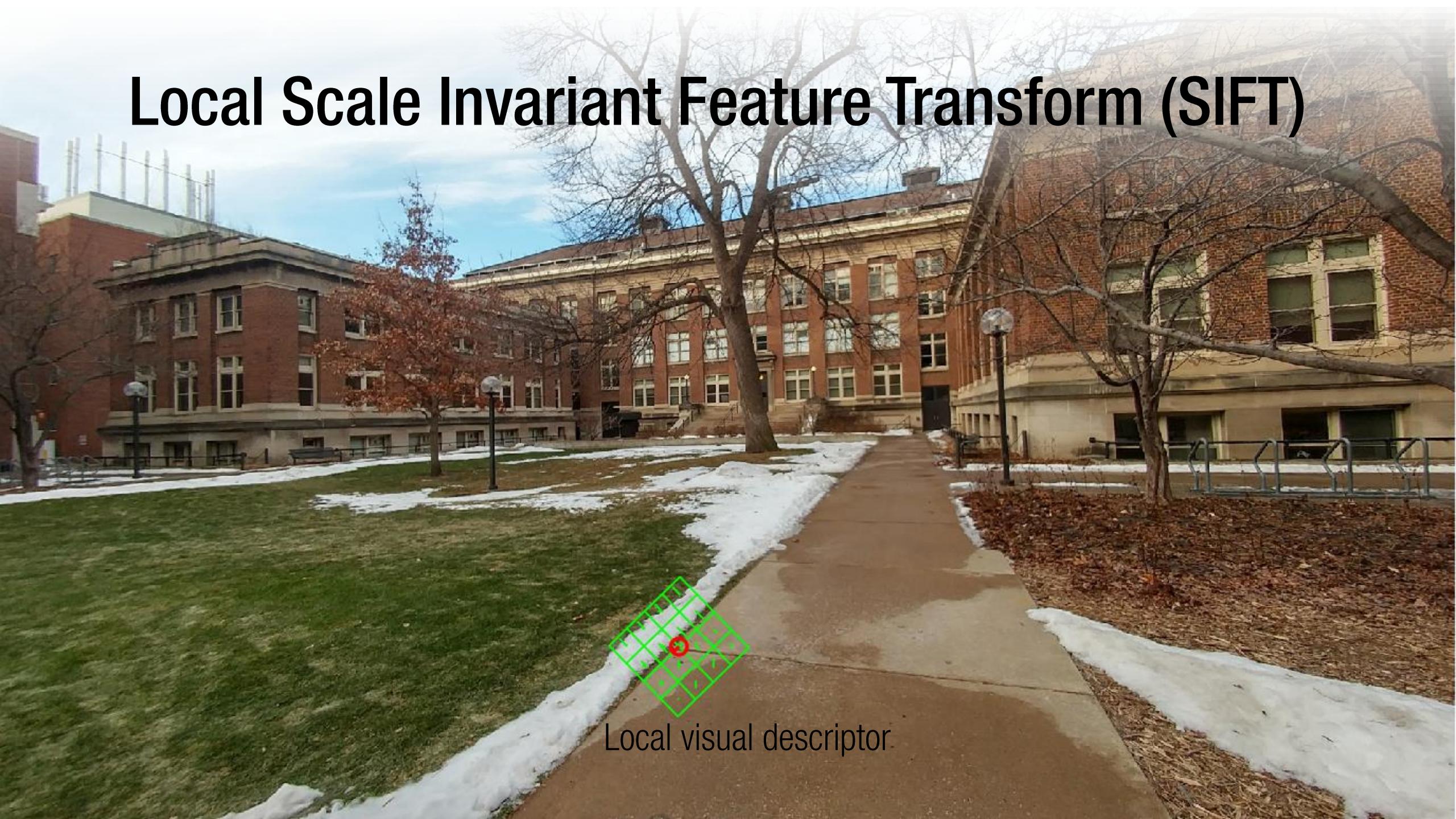
SIFT automatically finds the optimal scale of feature point and its orientation.



Desired properties:

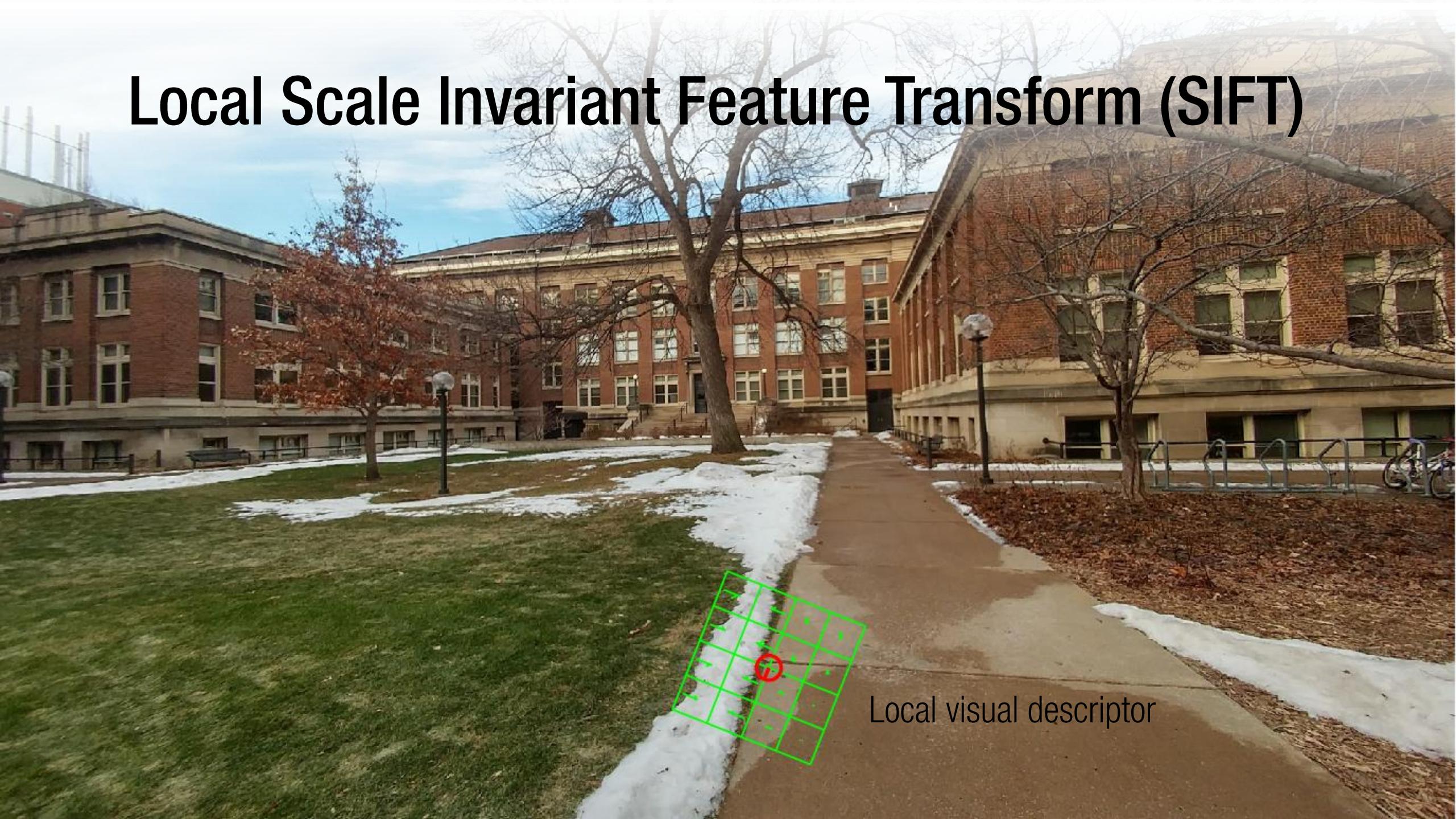
- Repeatability: the same point is repeatedly detected.
- Discriminativity: the point is unique.
- Orientation aware

Local Scale Invariant Feature Transform (SIFT)



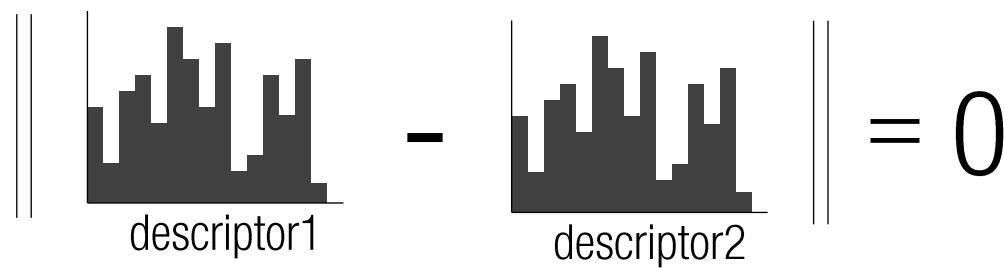
Local visual descriptor

Local Scale Invariant Feature Transform (SIFT)

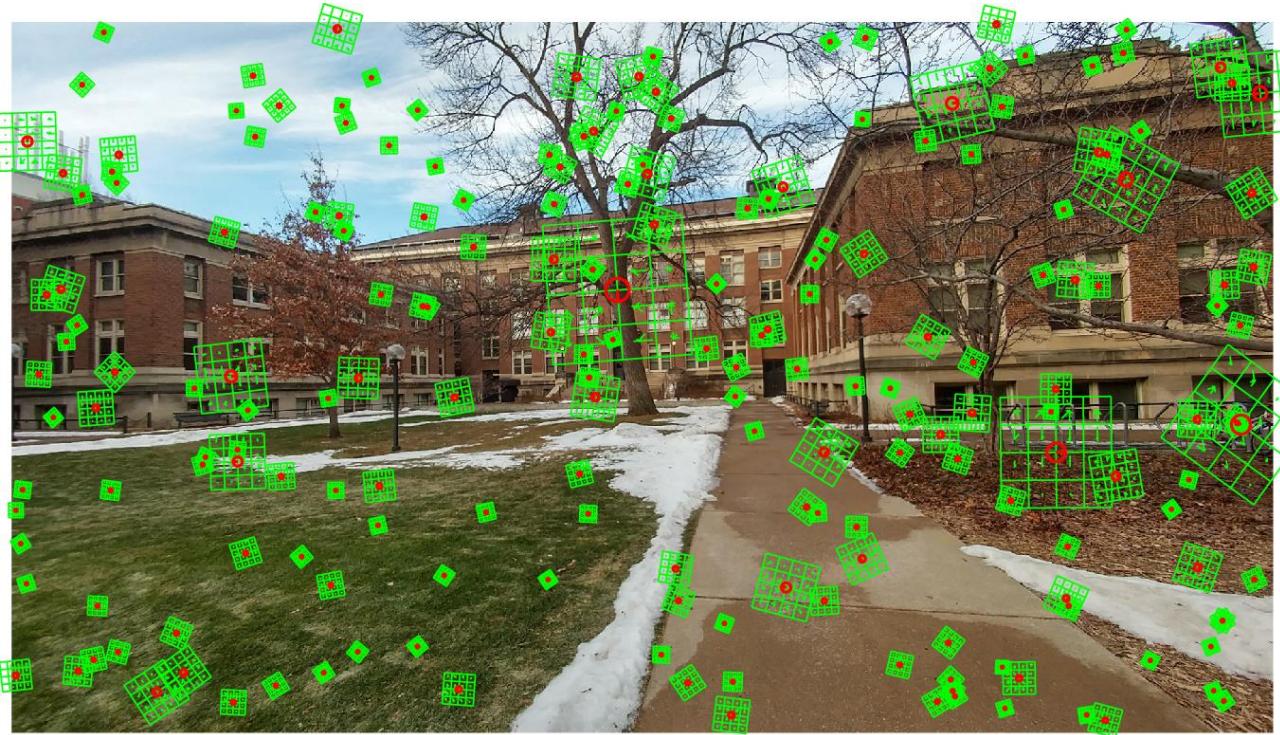


Local visual descriptor

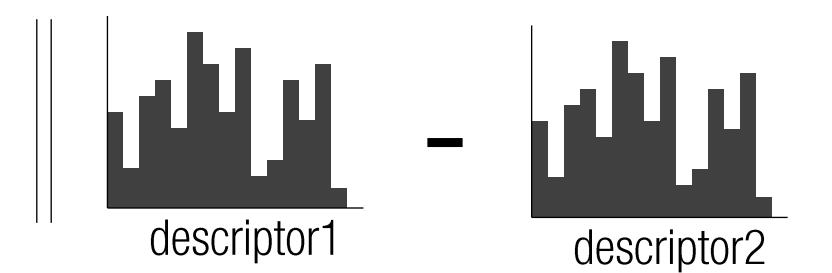
Local Scale Invariant Feature Transform (SIFT)



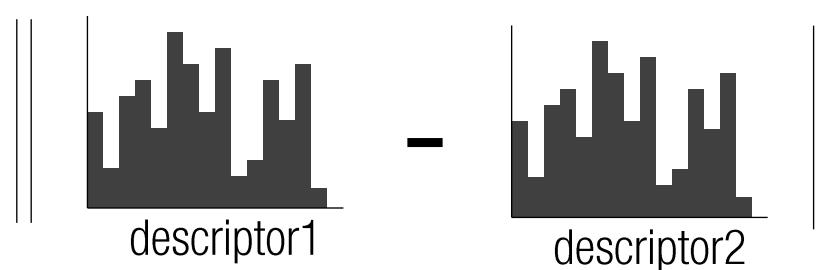
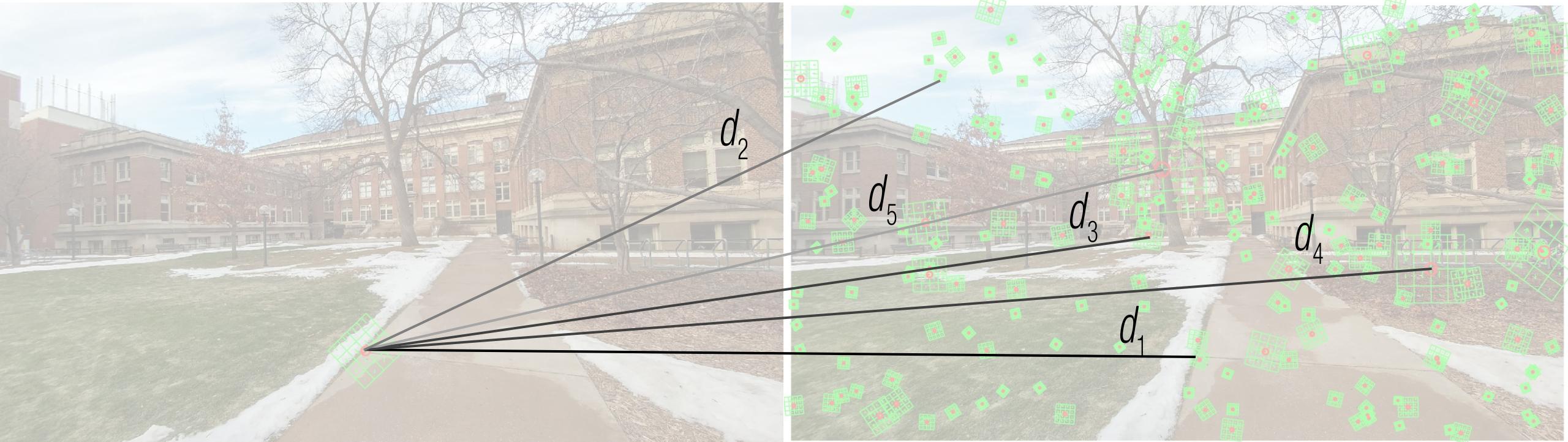
Local Scale Invariant Feature Transform (SIFT)



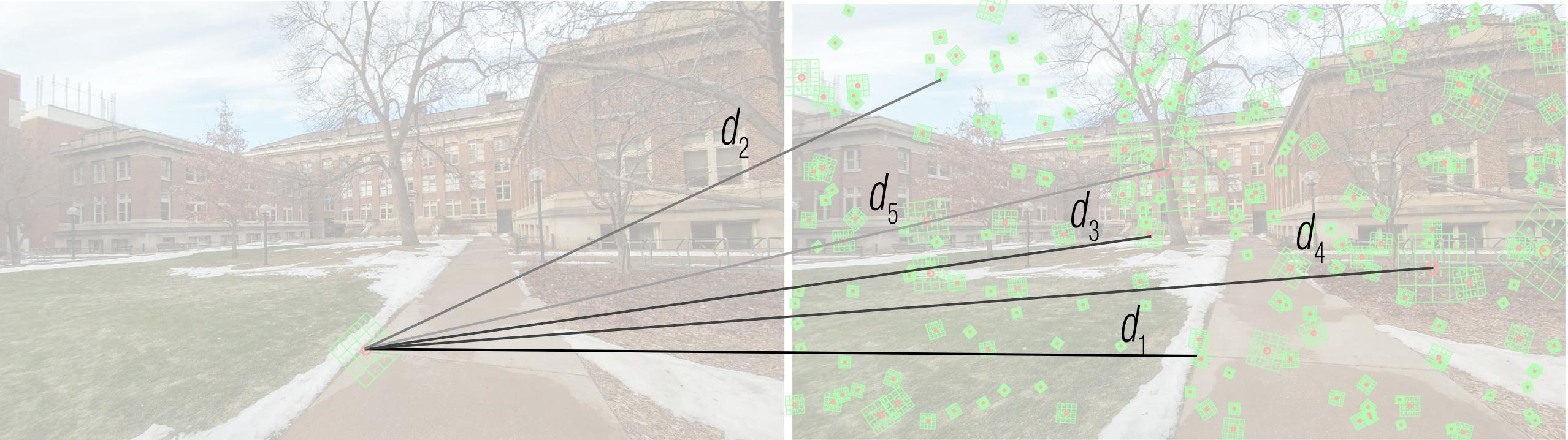
Feature match candidates



Nearest Neighbor Search



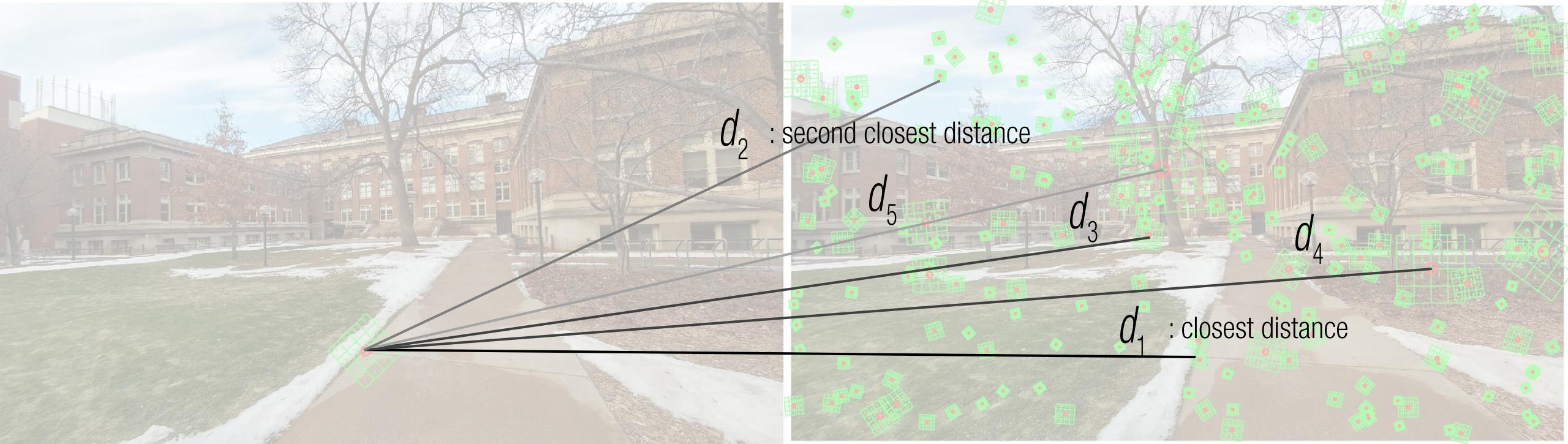
Nearest Neighbor Search



Discriminativity: how is the feature point unique?

Feature match candidates

Nearest Neighbor Search w/ Ratio Test

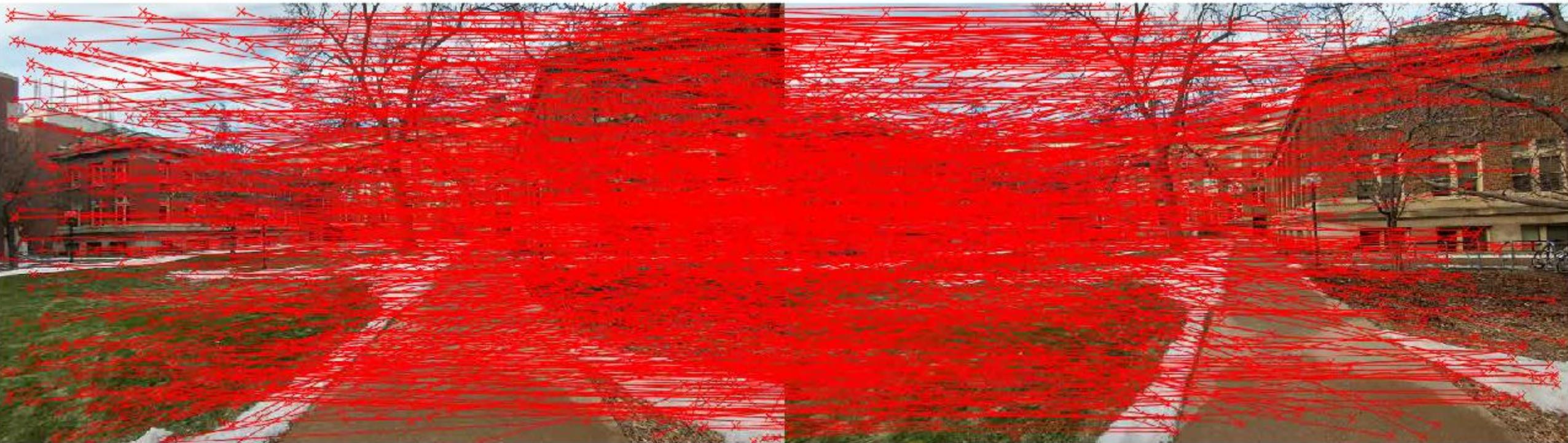


Discriminativity: how is the feature point unique?

$$\frac{d_1}{d_2} < 0.7$$

Feature match candidates

Nearest Neighbor Search w/o Ratio Test



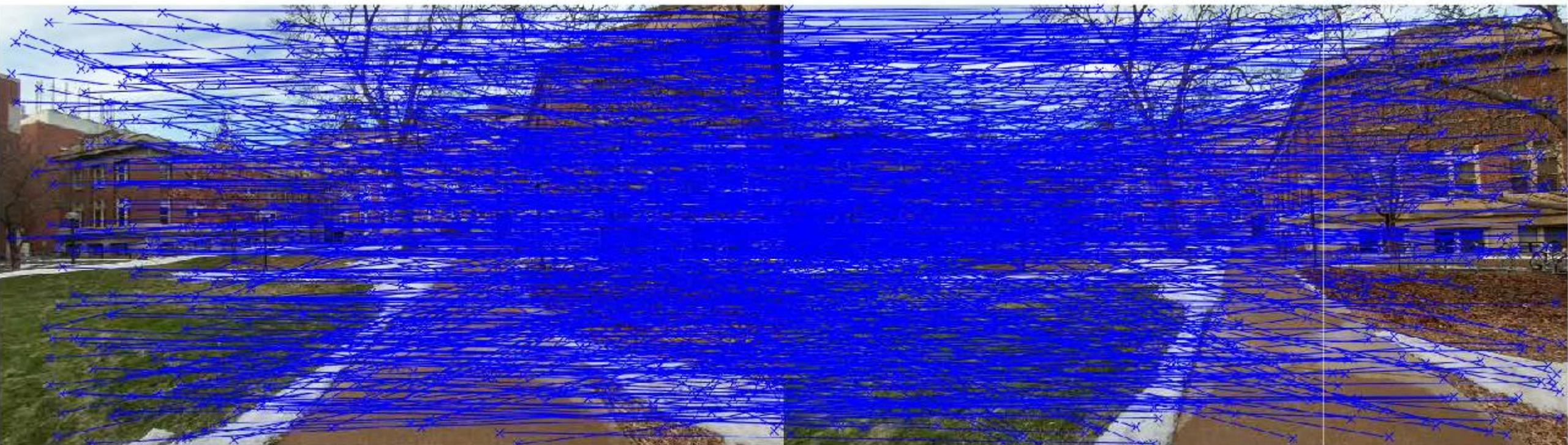
Left image → right image

Nearest Neighbor Search w/ Ratio Test



Left image → right image

Nearest Neighbor Search w/o Ratio Test



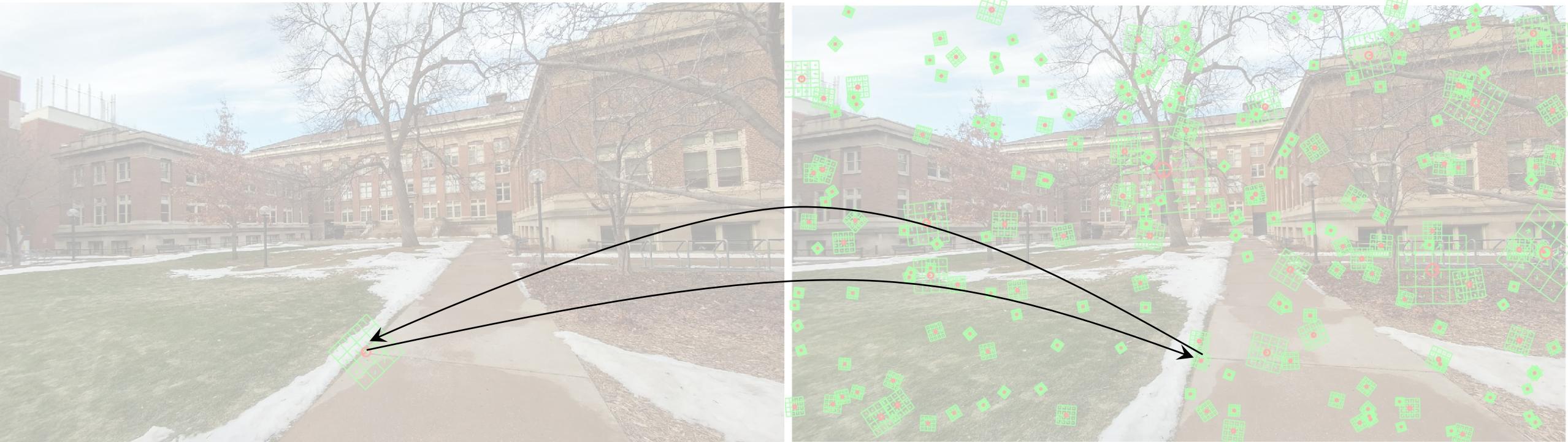
Left image ← right image

Nearest Neighbor Search w/ Ratio Test



Left image ← right image

Bi-directional Consistency Check



Consistency: would a feature match correspond to each other?

Feature match candidates

Bi-directional Consistency Check

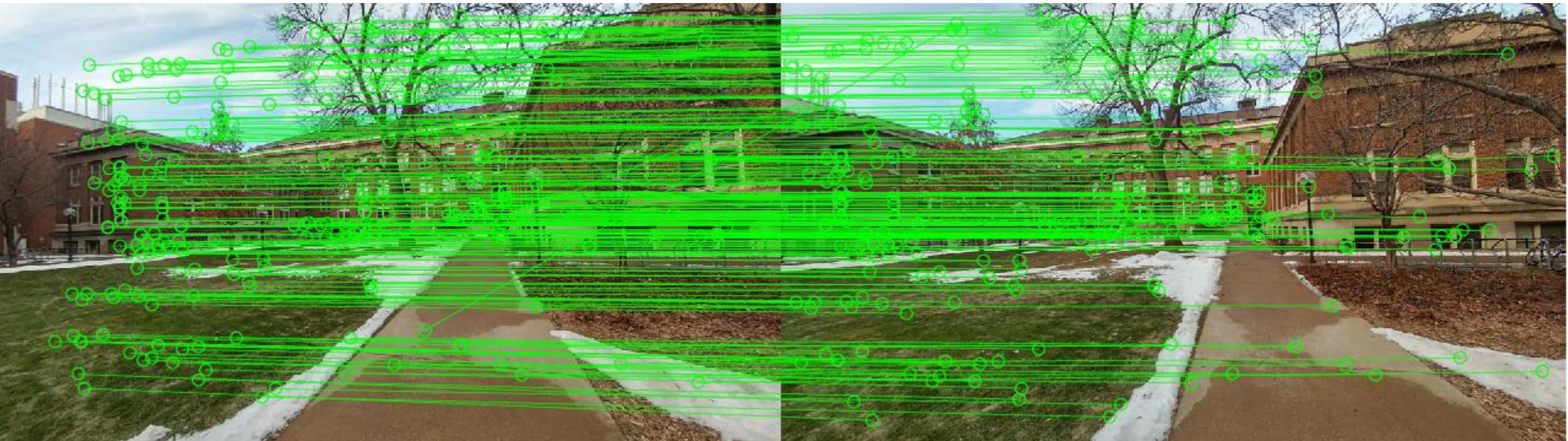


RANSAC: Random Sample Consensus



Fundamental Matrix Computation: Linear Least Squares

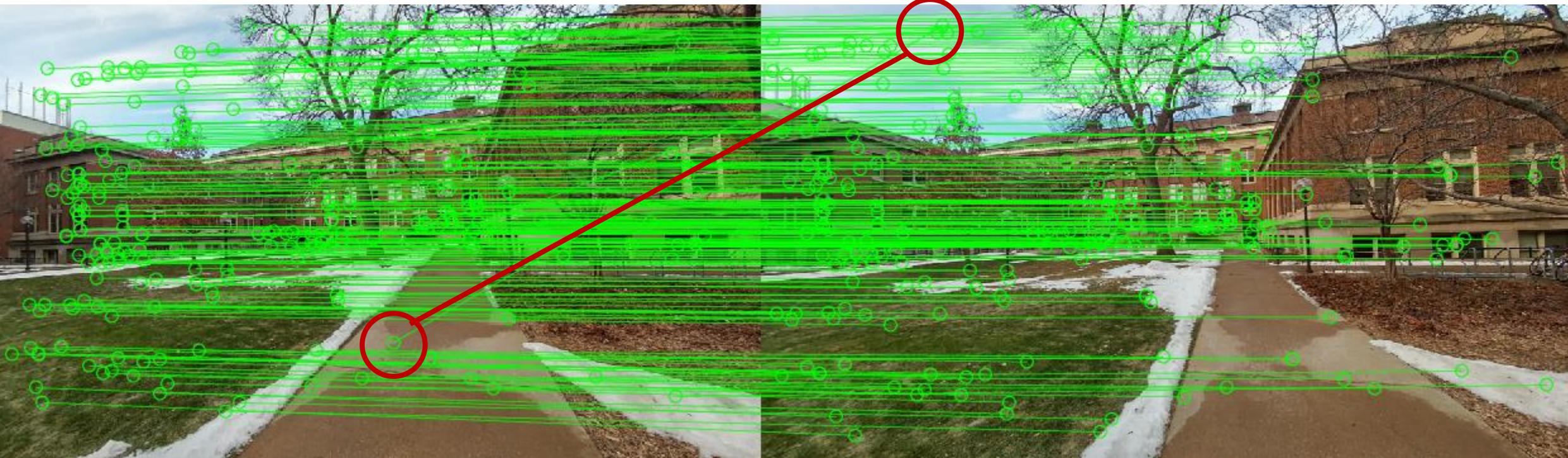
$$\begin{bmatrix} u_1^x v_1^x & u_1^y v_1^x & v_1^x & u_1^x v_1^y & u_1^y v_1^y & v_1^y & u_1^x & u_1^y & 1 \\ \vdots & \vdots \\ u_m^x v_m^x & u_m^y v_m^x & v_m^x & u_m^x v_m^y & u_m^y v_m^y & v_m^y & u_m^x & u_m^y & 1 \end{bmatrix} \mathbf{A} \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{23} \\ f_{31} \\ f_{32} \\ f_{33} \end{bmatrix} = \mathbf{0}$$



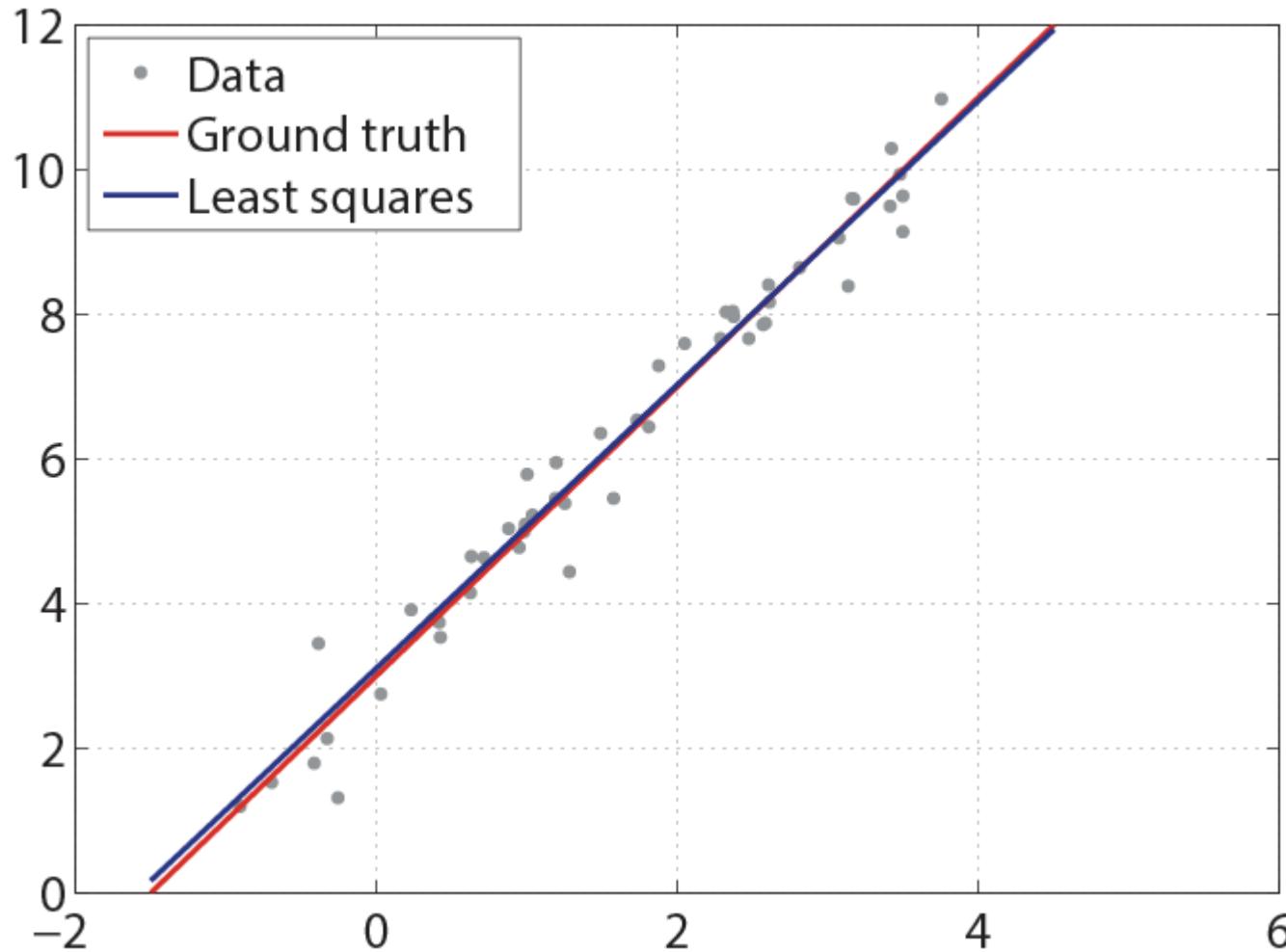
Fundamental Matrix Computation: Linear Least Squares

$$\begin{bmatrix} u_1^x v_1^x & u_1^y v_1^x & v_1^x & u_1^x v_1^y & u_1^y v_1^y & v_1^y & u_1^x & u_1^y & 1 \\ \vdots & \vdots \\ u_m^x v_m^x & u_m^y v_m^x & v_m^x & u_m^x v_m^y & u_m^y v_m^y & v_m^y & u_m^x & u_m^y & 1 \end{bmatrix} \mathbf{A} \quad \mathbf{X} = \mathbf{0}$$

Outlier?



Recall: Line Fitting ($Ax=b$)

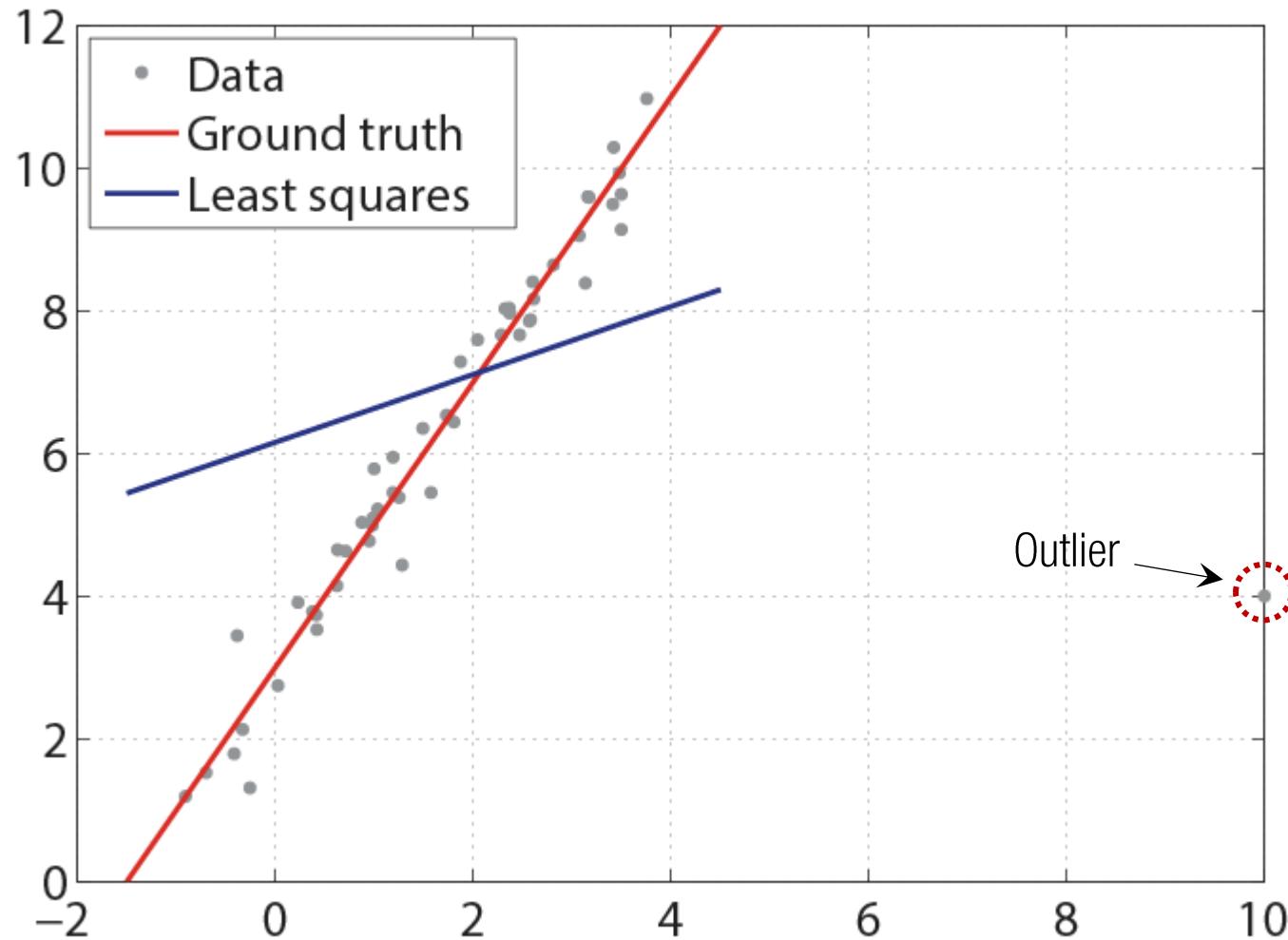


$$\begin{bmatrix} u_1 & 1 \\ u_2 & 1 \\ \vdots & \vdots \\ u_n & 1 \end{bmatrix} \mathbf{A} \begin{bmatrix} m \\ d \end{bmatrix} \approx \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} \mathbf{b}$$

$$\mathbf{A}^T \quad \mathbf{A} \quad \mathbf{x} = \mathbf{A}^T \quad \mathbf{b}$$

$$\mathbf{x} = \left[\mathbf{A}^T \quad \mathbf{A} \right]^{-1} \mathbf{A}^T \quad \mathbf{b}$$

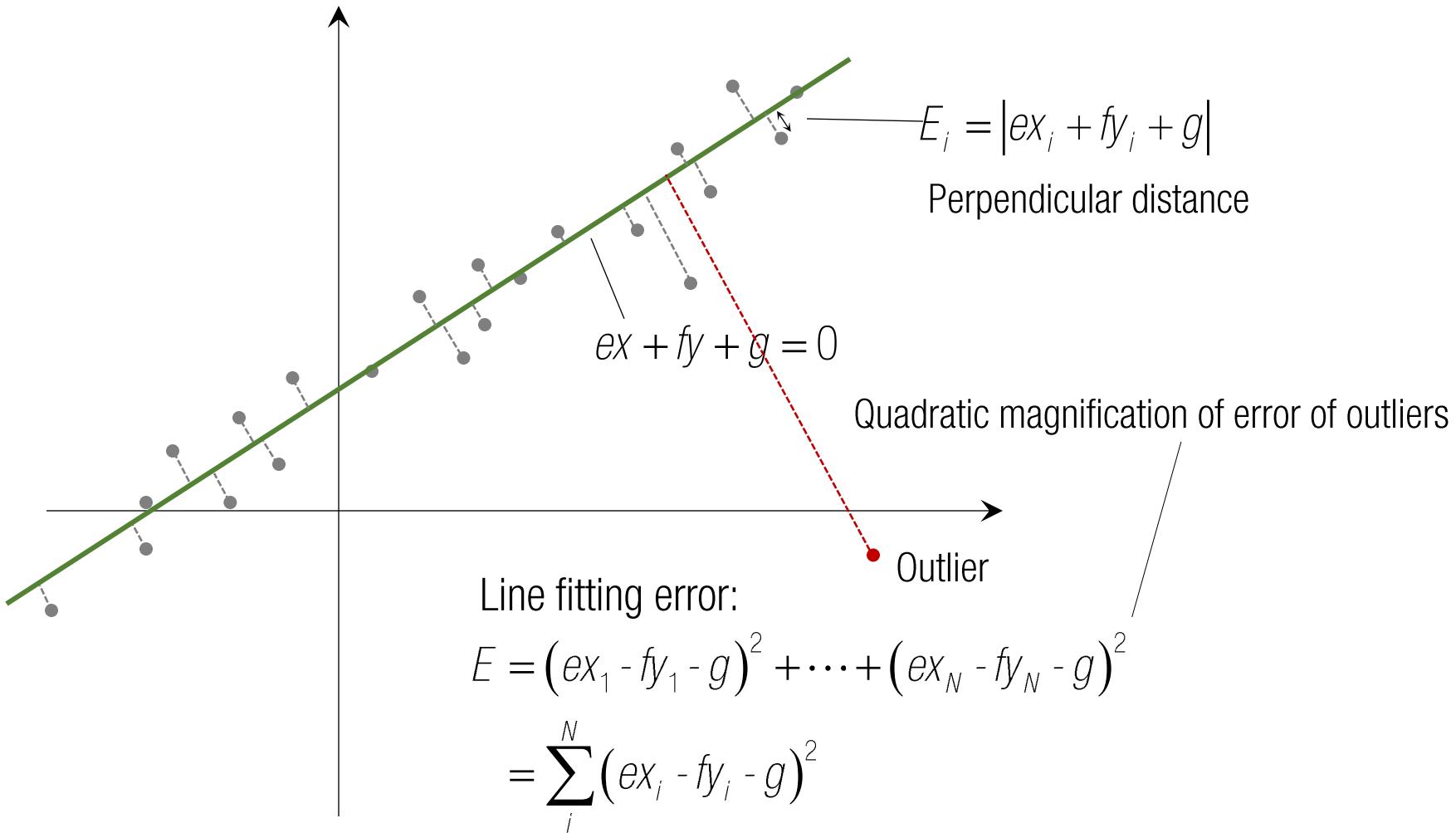
Outlier

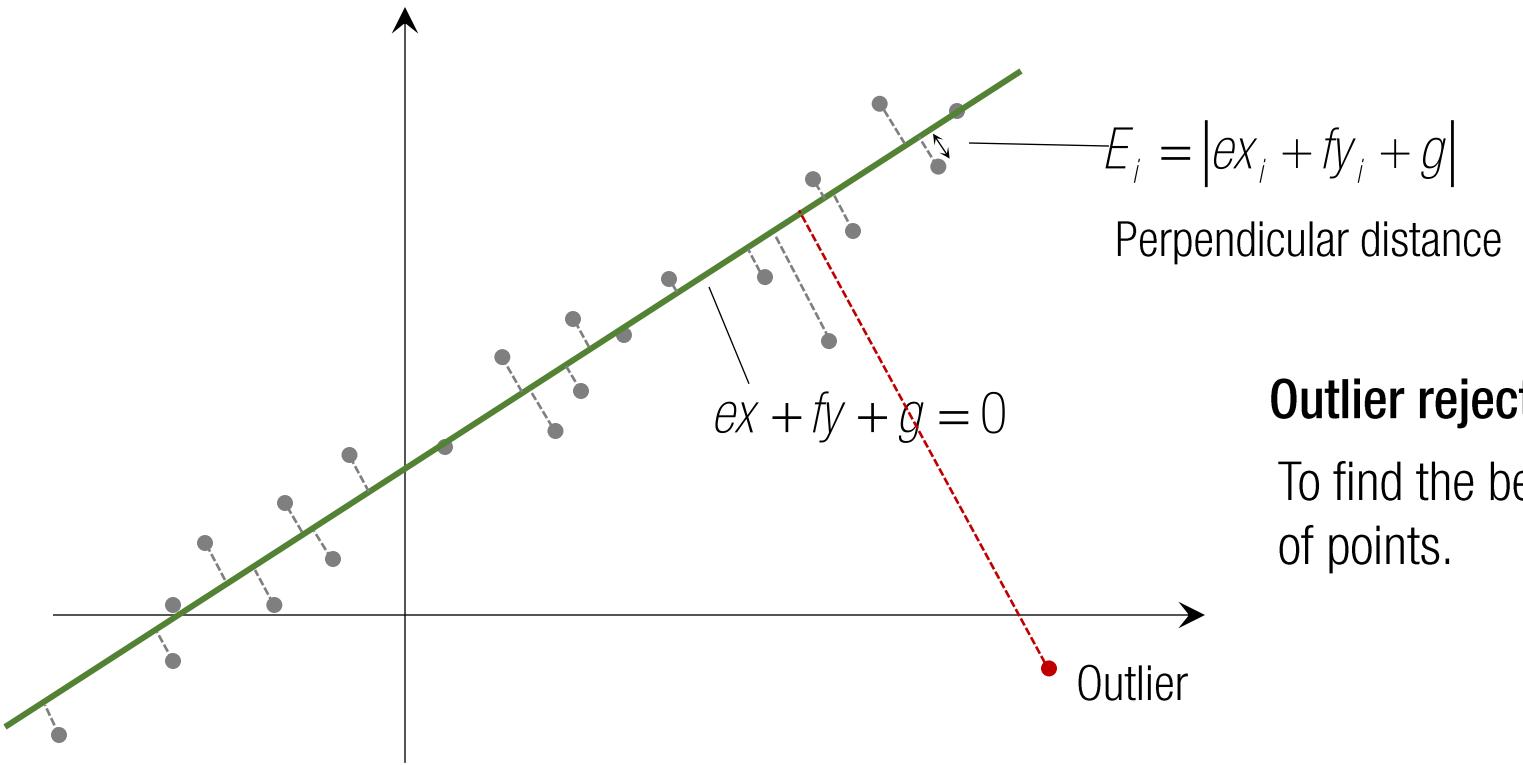


$$\begin{bmatrix} u_1 & 1 \\ u_2 & 1 \\ \vdots & \vdots \\ u_n & 1 \end{bmatrix} \mathbf{A} \begin{bmatrix} m \\ d \end{bmatrix} \approx \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix} \mathbf{b}$$

$$\mathbf{A}^T \quad \mathbf{A} \quad \mathbf{x} = \mathbf{A}^T \quad \mathbf{b}$$

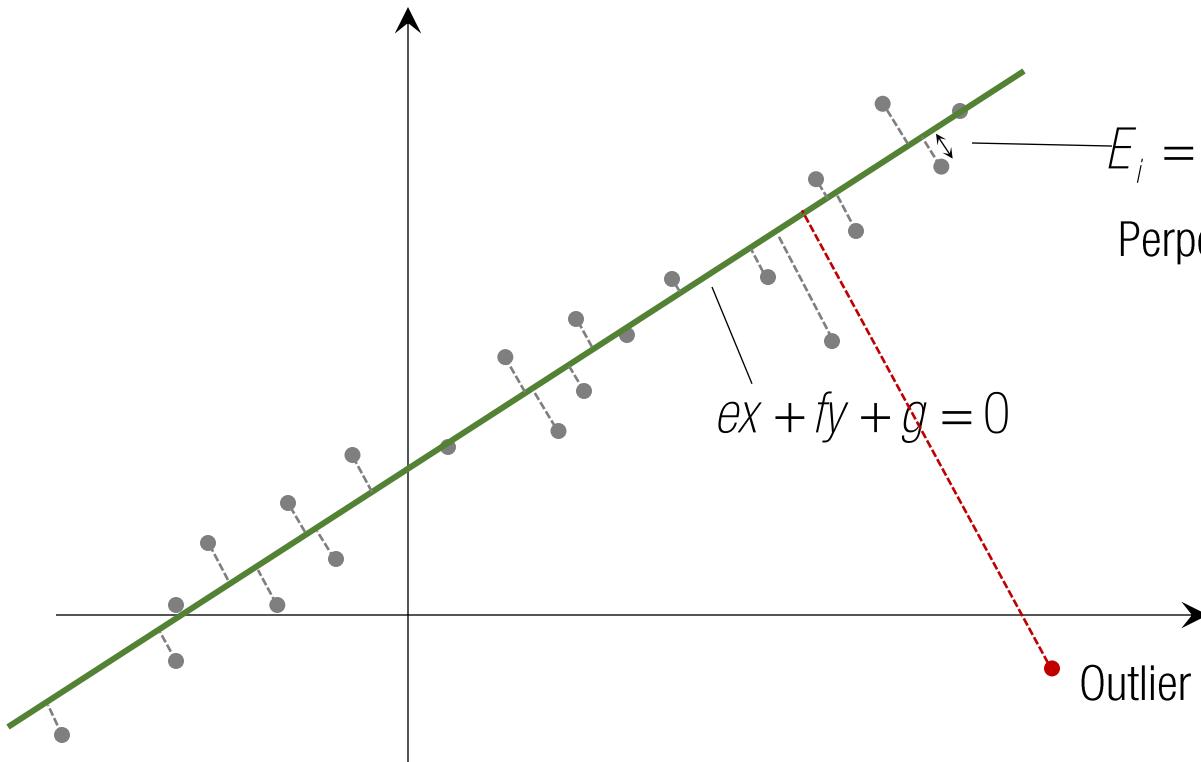
$$\mathbf{x} = \left[\mathbf{A}^T \quad \mathbf{A} \right]^{-1} \mathbf{A}^T \quad \mathbf{b}$$





Outlier rejection strategy:

To find the best line that explains the maximum number of points.



$$E_i = |ex_i + fy_i + g|$$

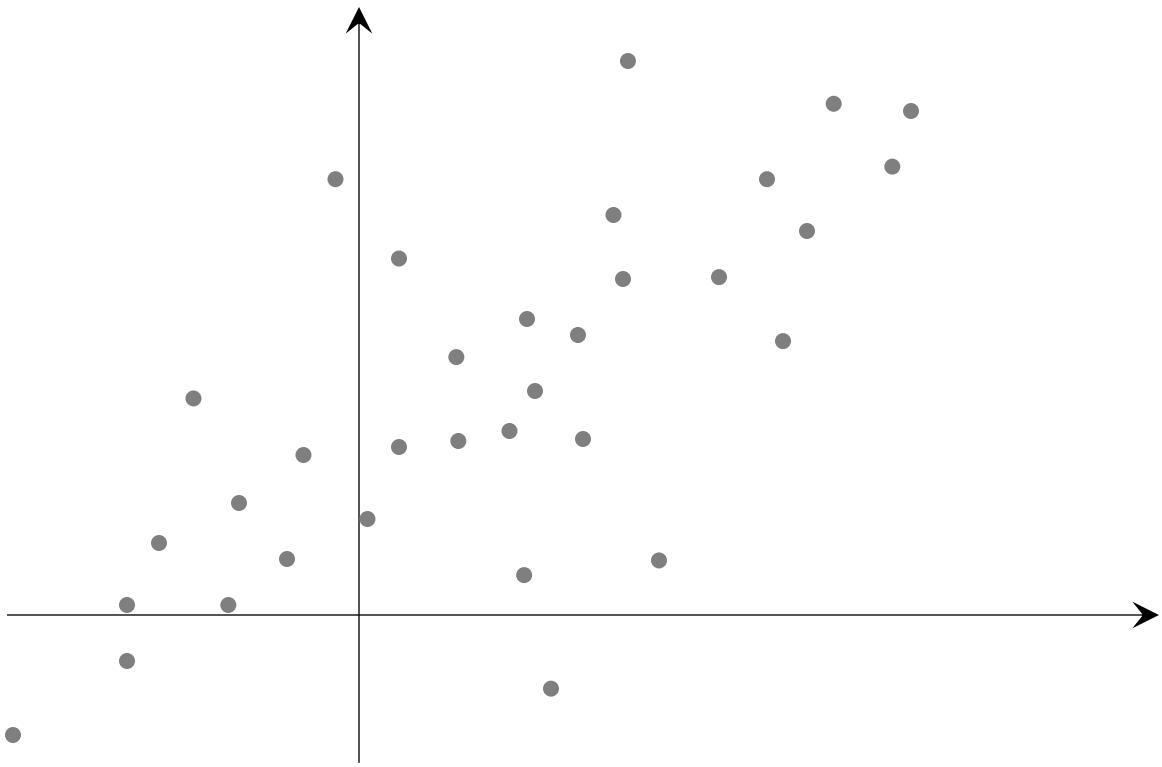
Perpendicular distance

Outlier rejection strategy:

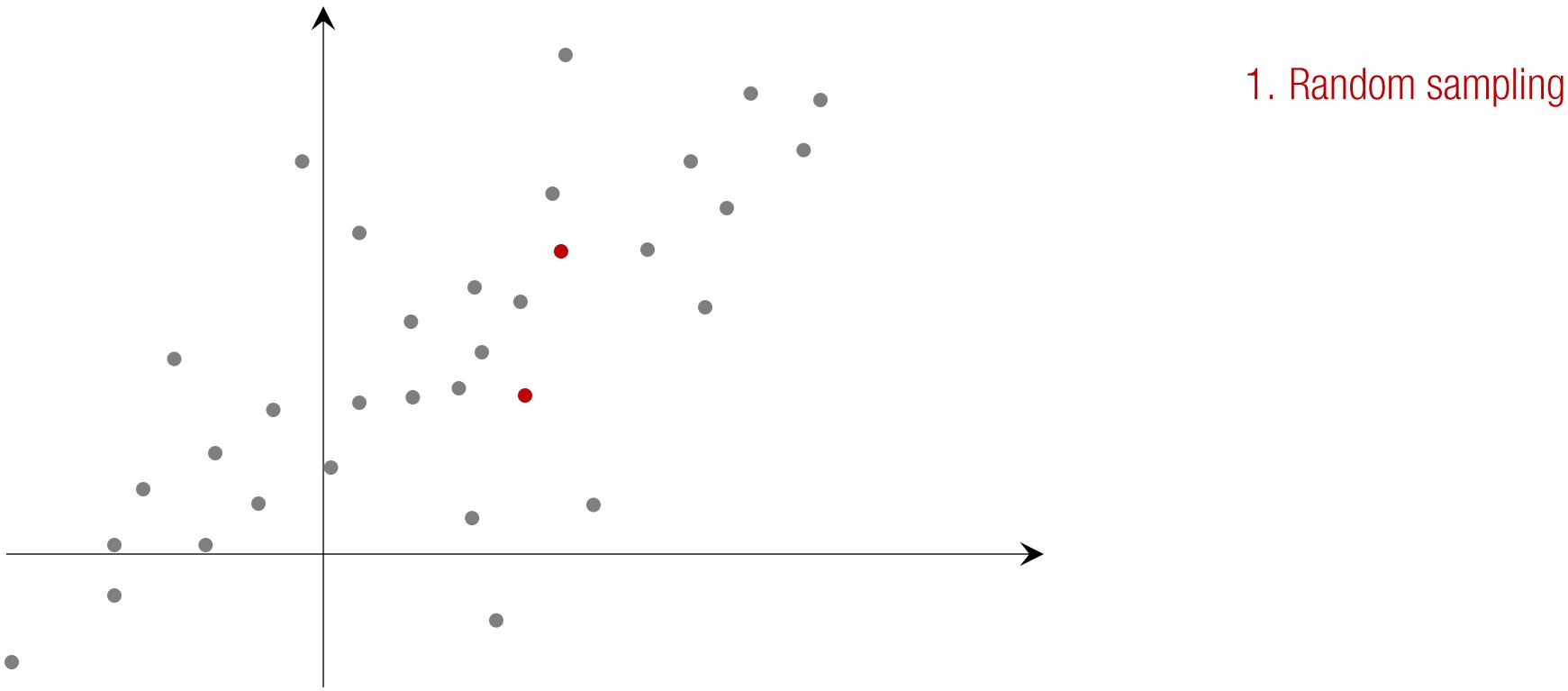
To find the best line that explains the maximum number of points.

Assumptions:

1. Majority of good samples agree with the underlying model (good apples are same and simple.).
2. Bad samples does not consistently agree with a single model (all bad apples are different and complicated.).

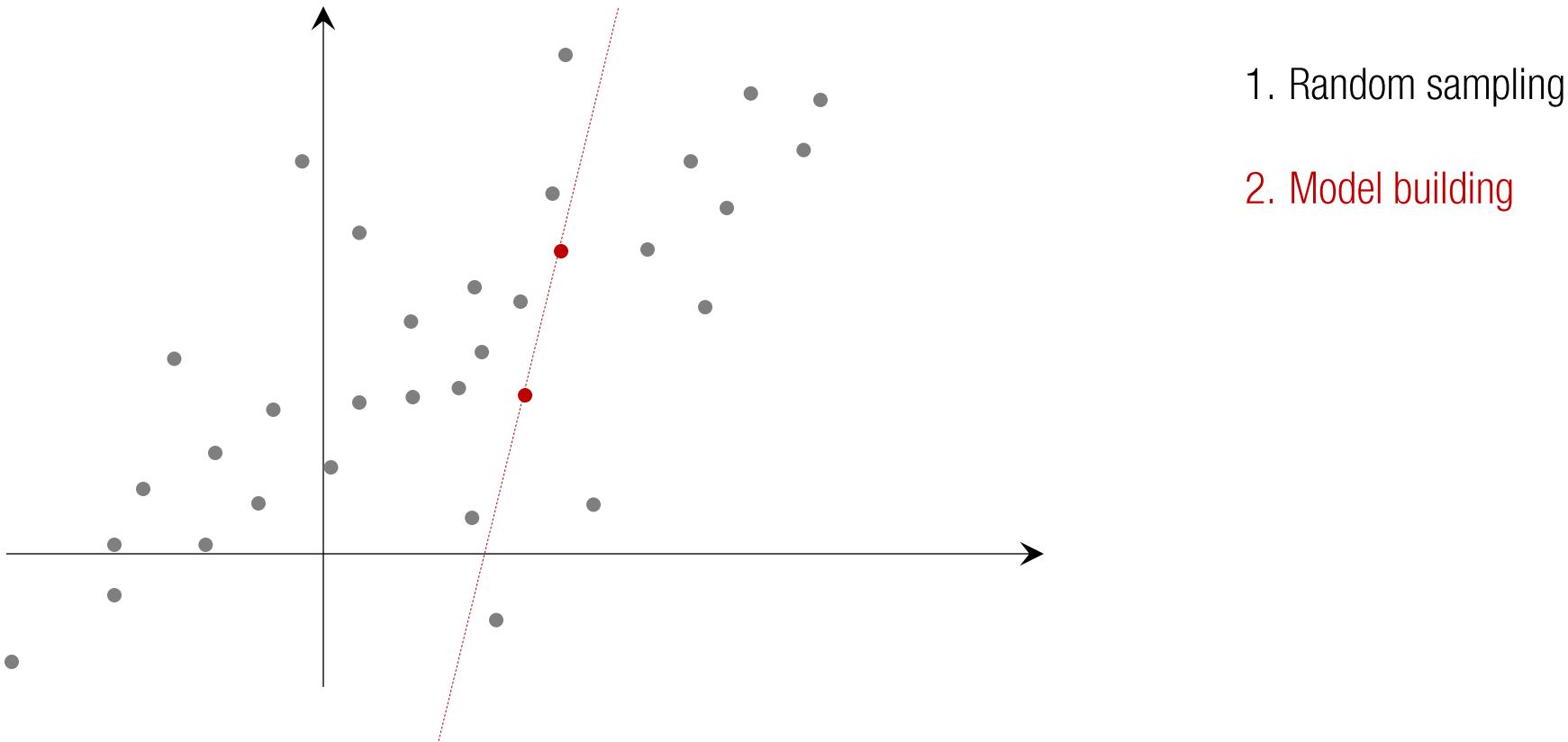


RANSAC: Random Sample Consensus

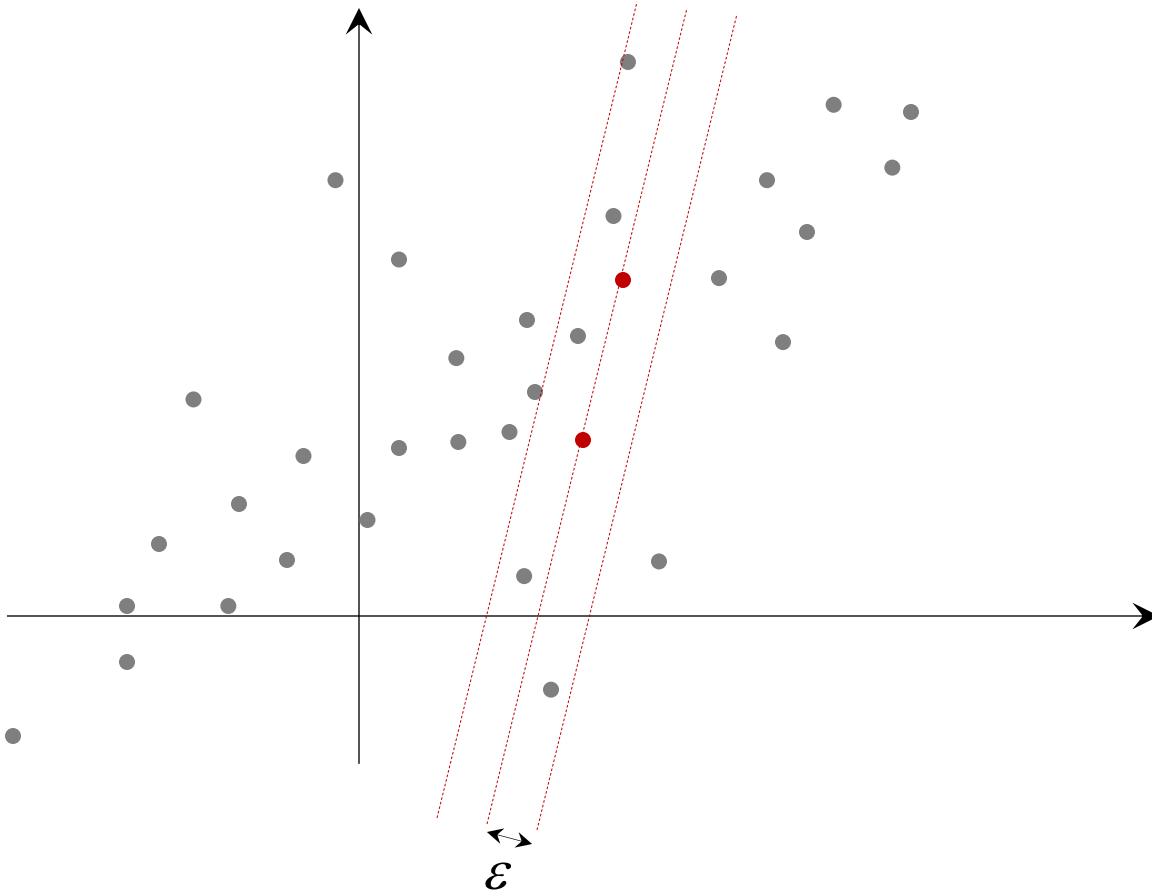


1. Random sampling

RANSAC: Random Sample Consensus

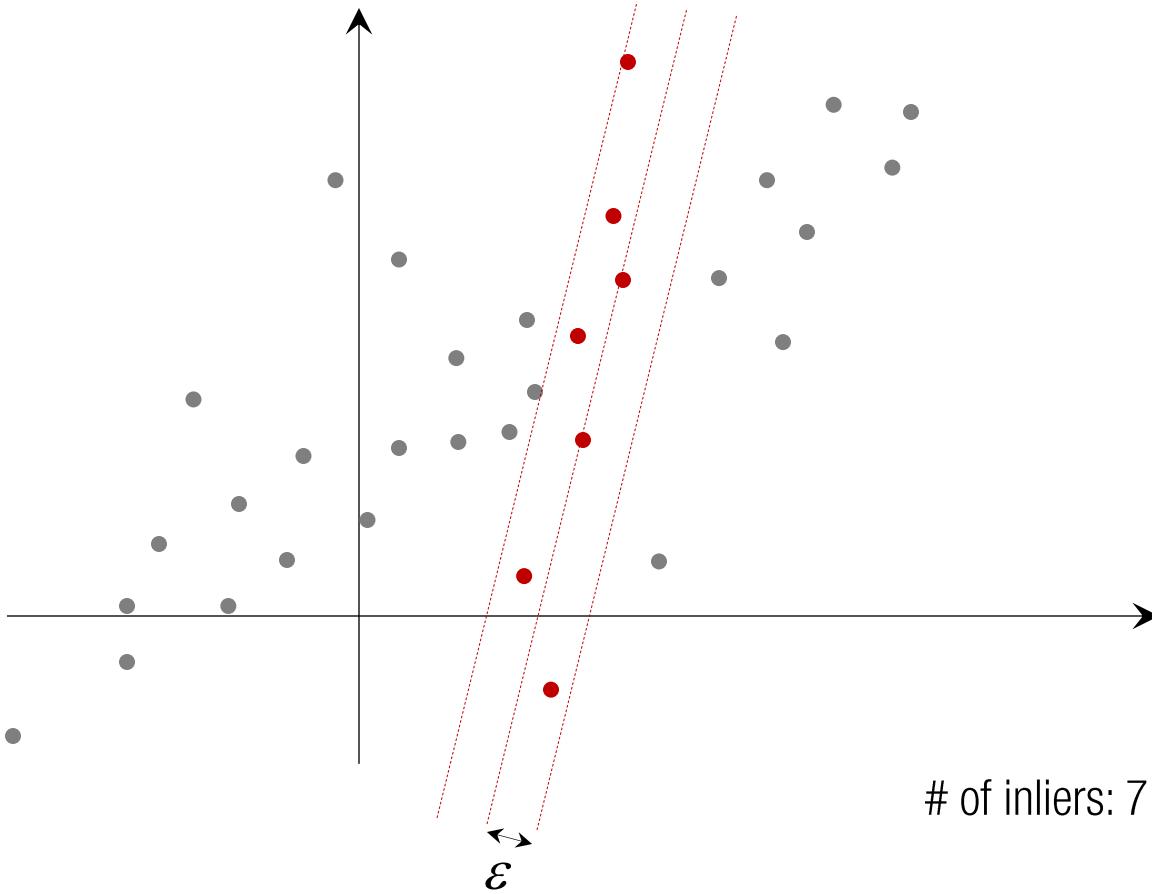


RANSAC: Random Sample Consensus



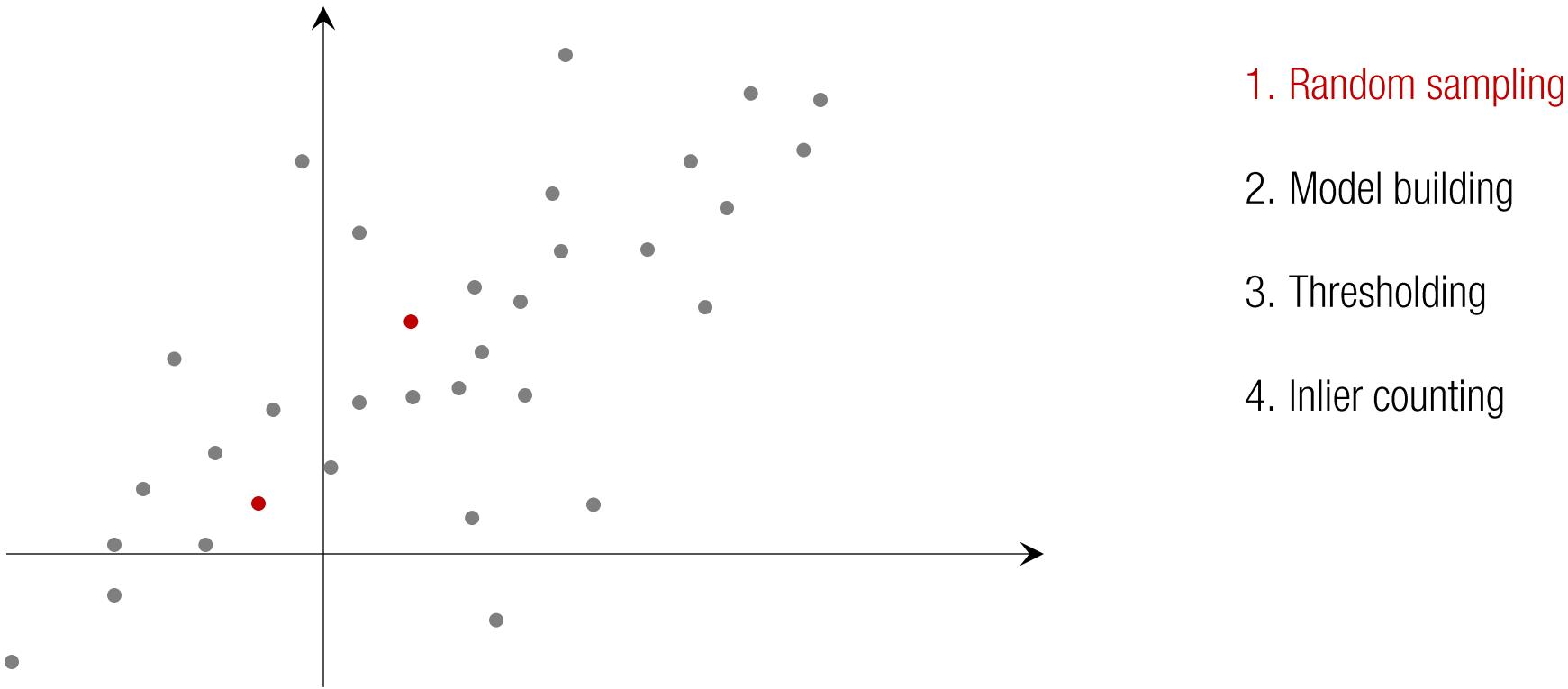
RANSAC: Random Sample Consensus

1. Random sampling
2. Model building
3. Thresholding

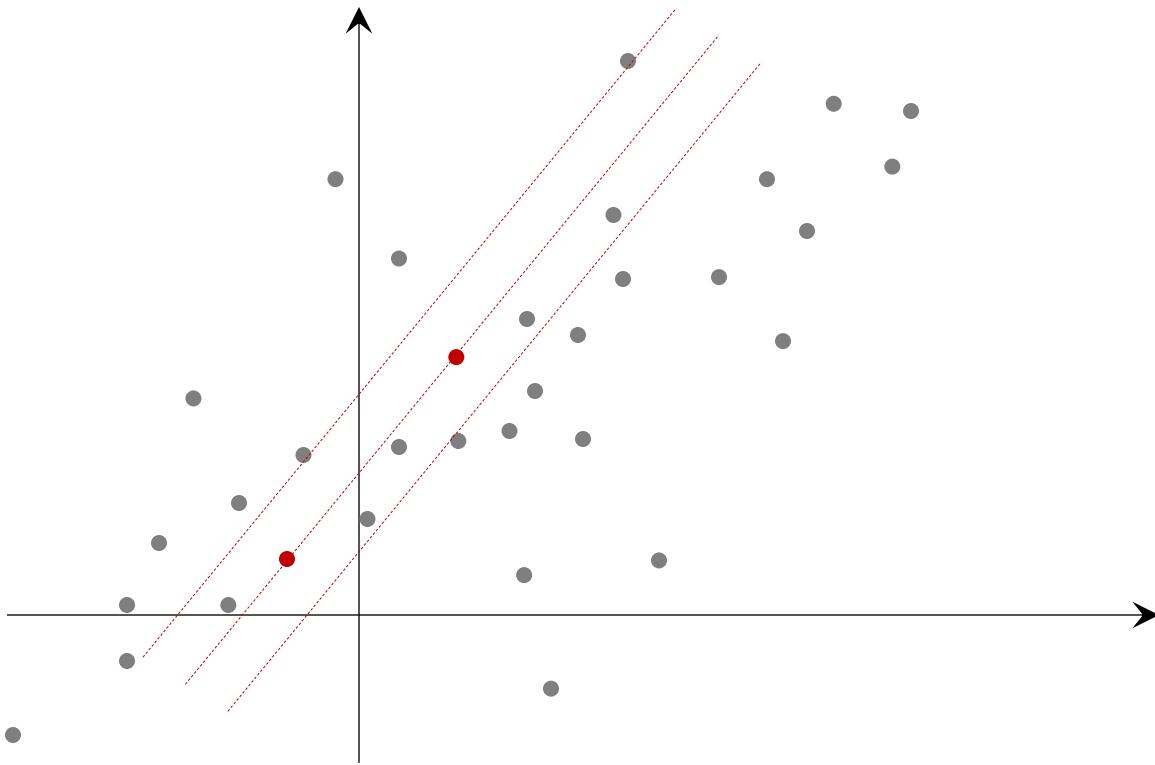


1. Random sampling
2. Model building
3. Thresholding
4. Inlier counting

RANSAC: Random Sample Consensus

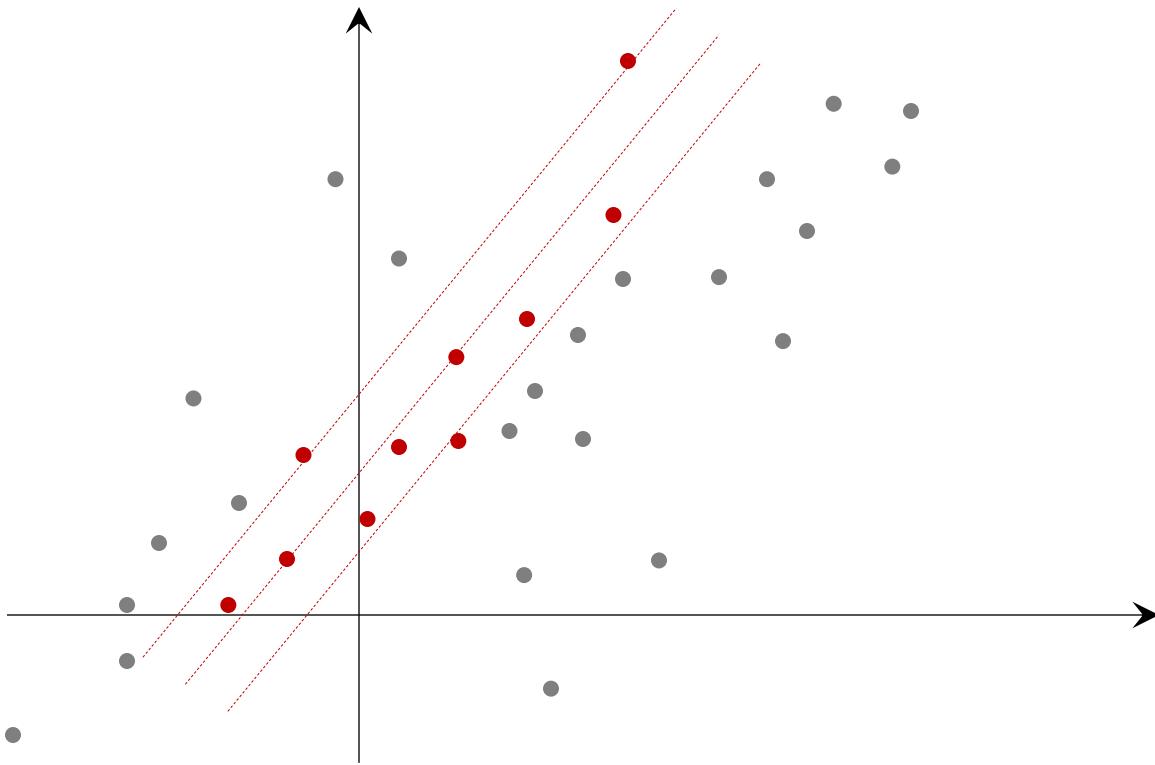


RANSAC: Random Sample Consensus



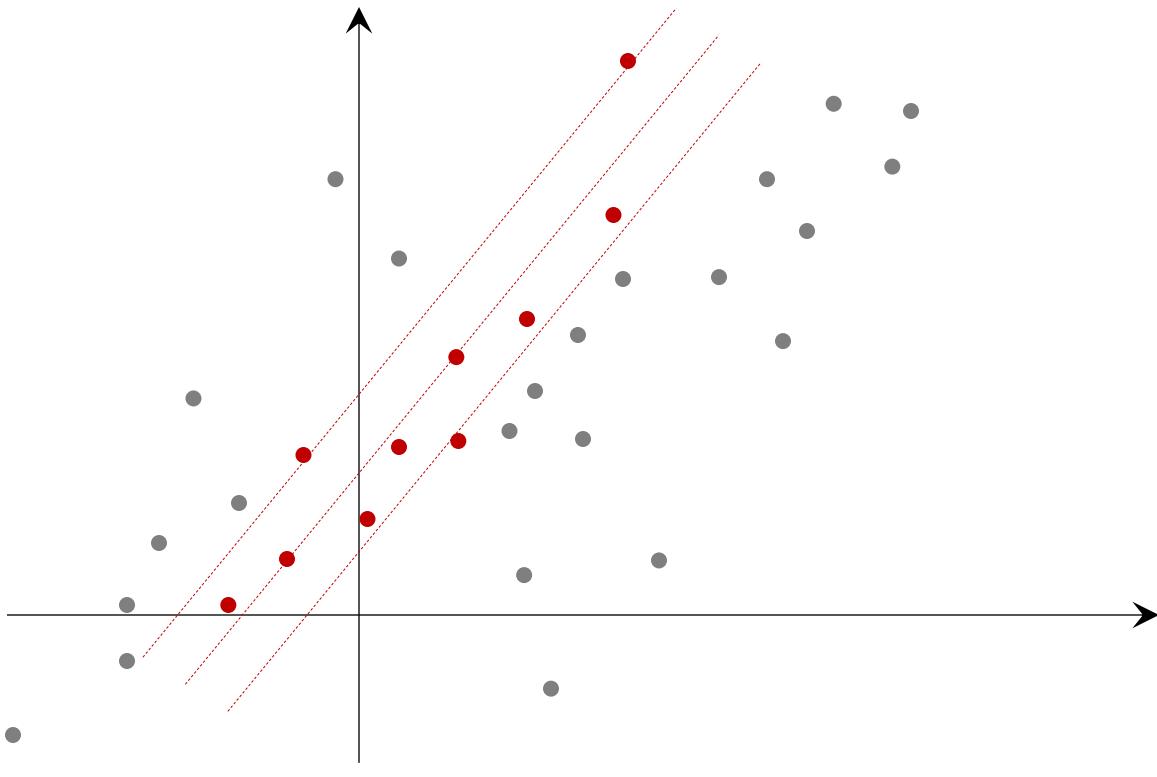
RANSAC: Random Sample Consensus

1. Random sampling
2. Model building
3. Thresholding
4. Inlier counting



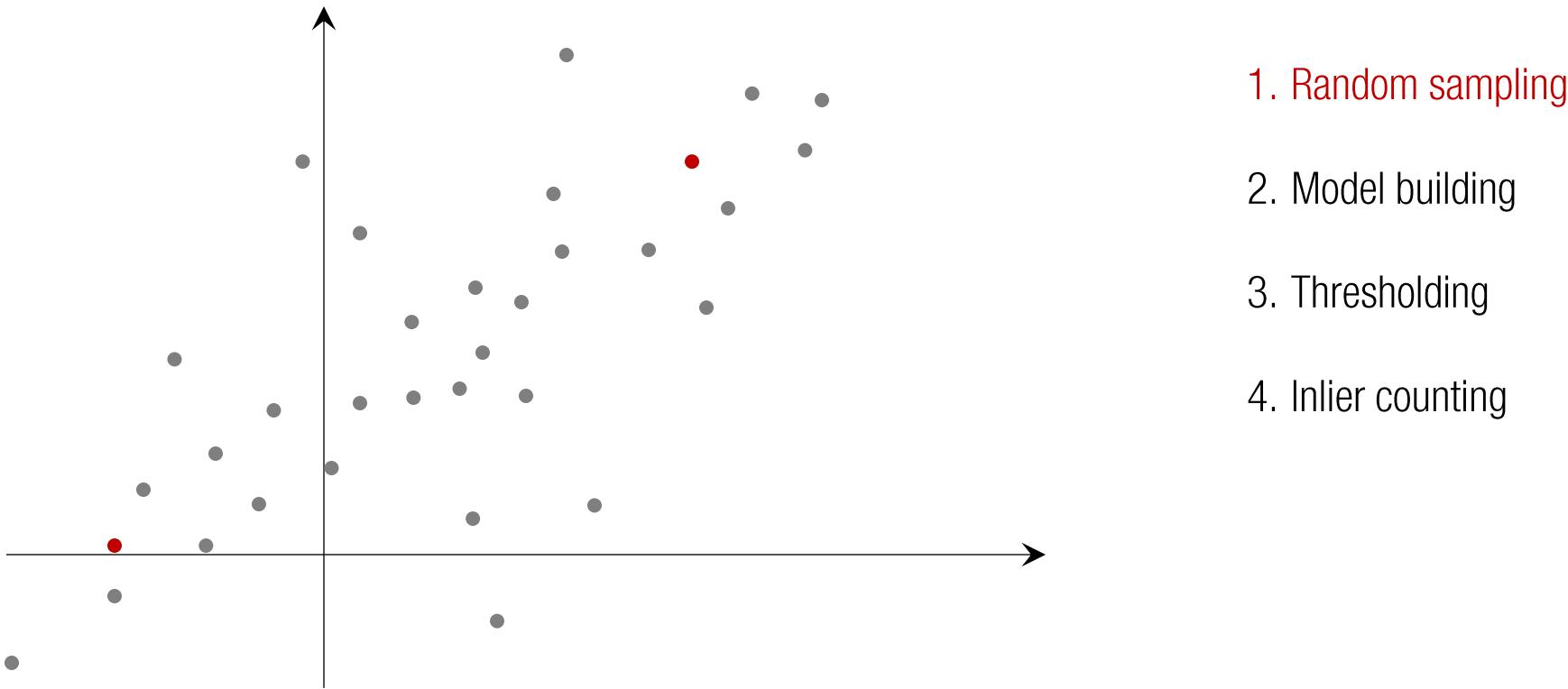
1. Random sampling
2. Model building
3. Thresholding
4. Inlier counting

RANSAC: Random Sample Consensus

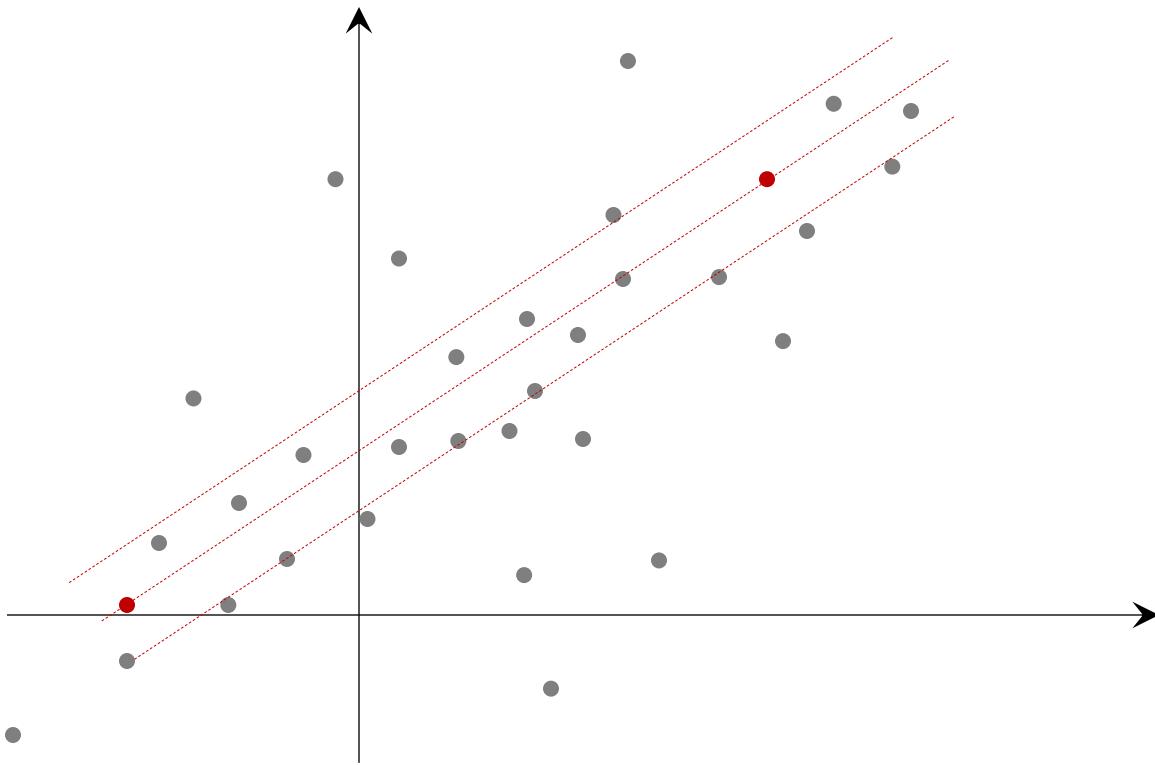


1. Random sampling
2. Model building
3. Thresholding
4. Inlier counting

RANSAC: Random Sample Consensus

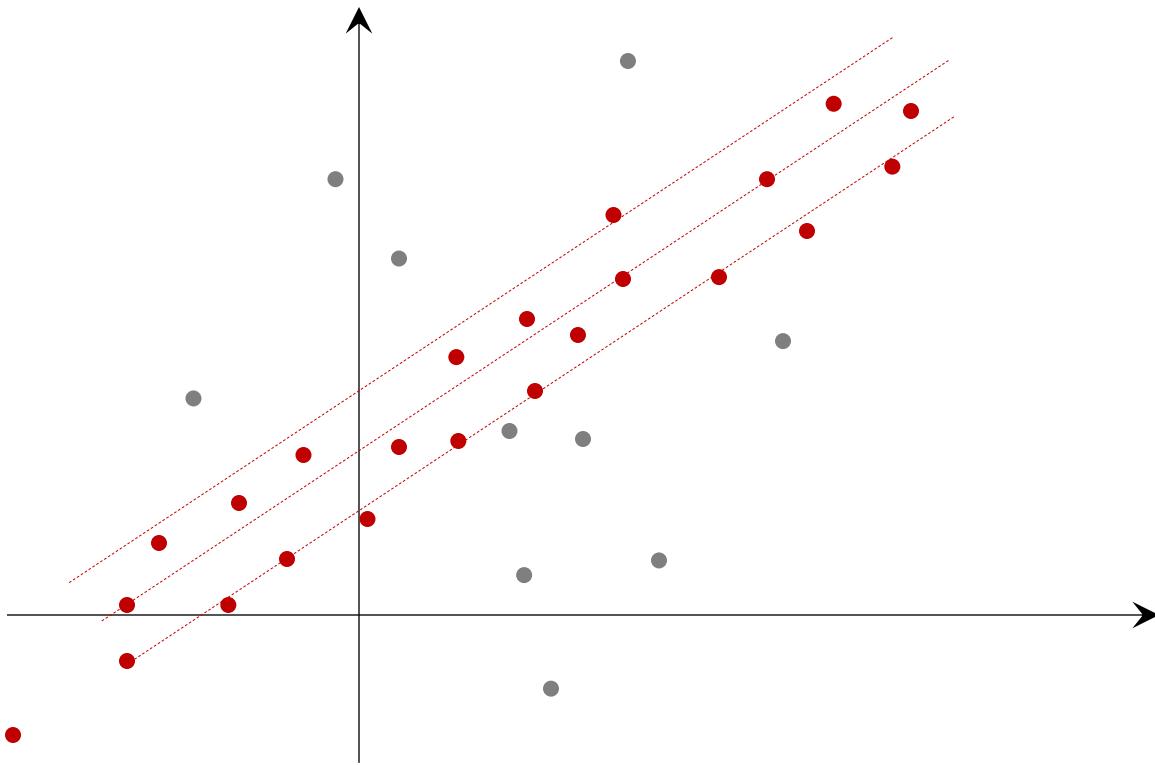


RANSAC: Random Sample Consensus



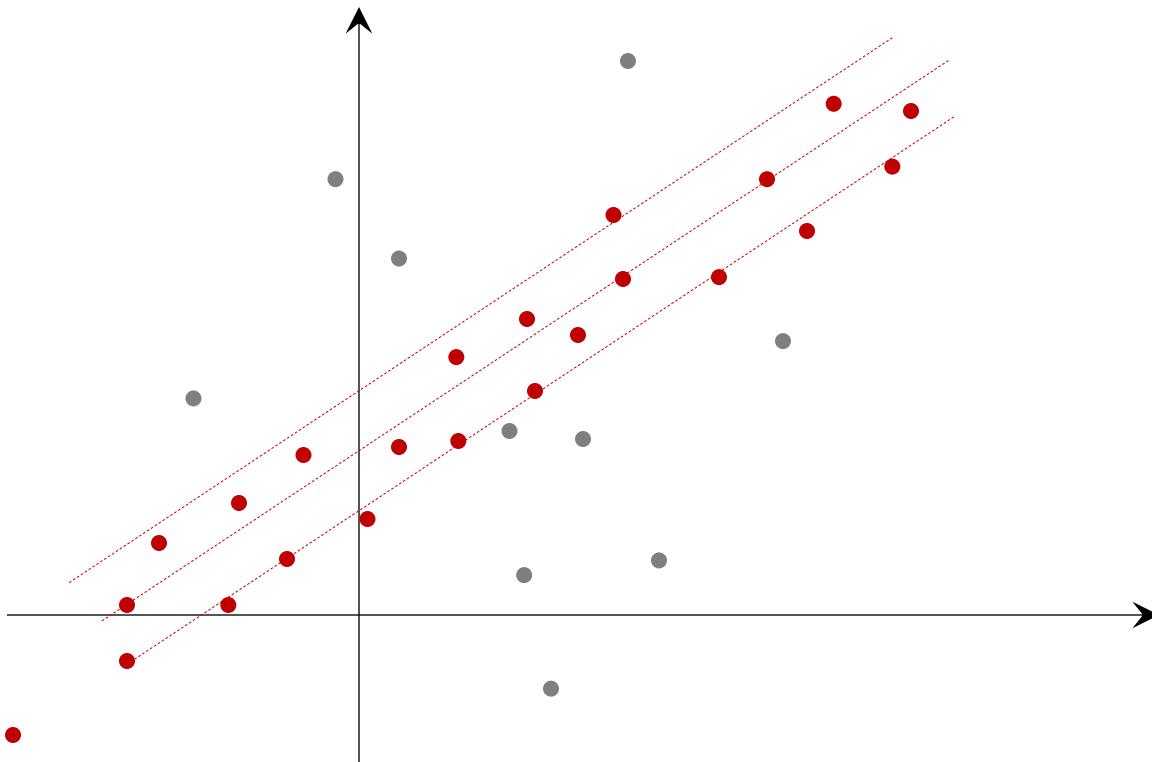
1. Random sampling
2. Model building
3. Thresholding
4. Inlier counting

RANSAC: Random Sample Consensus



RANSAC: Random Sample Consensus

1. Random sampling
2. Model building
3. Thresholding
4. Inlier counting

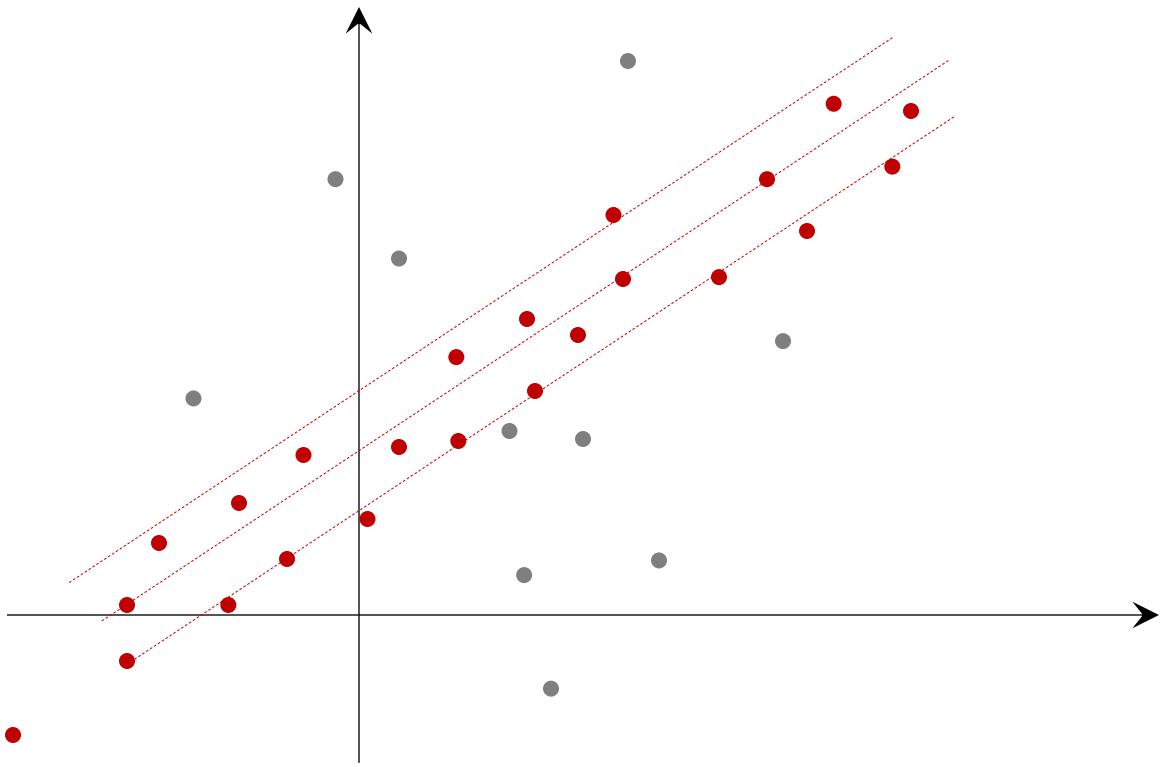


of inliers: 23

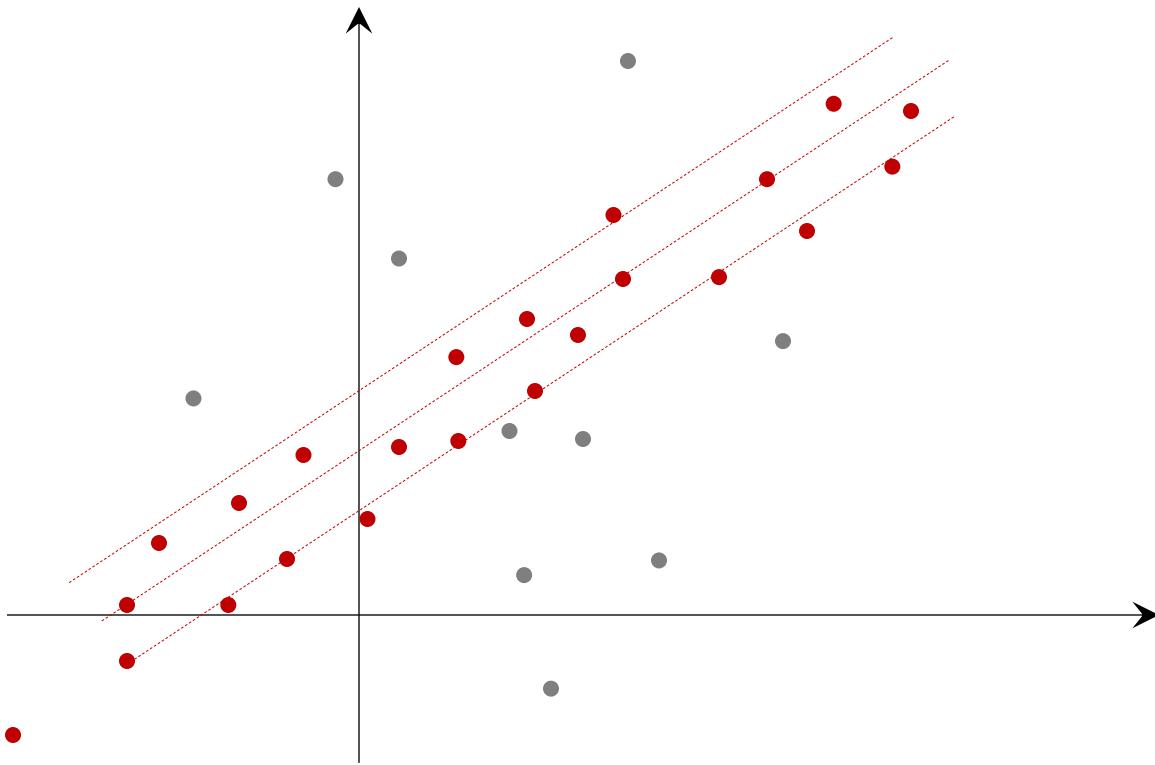
Maximum number of inliers

1. Random sampling
2. Model building
3. Thresholding
4. Inlier counting

RANSAC: Random Sample Consensus



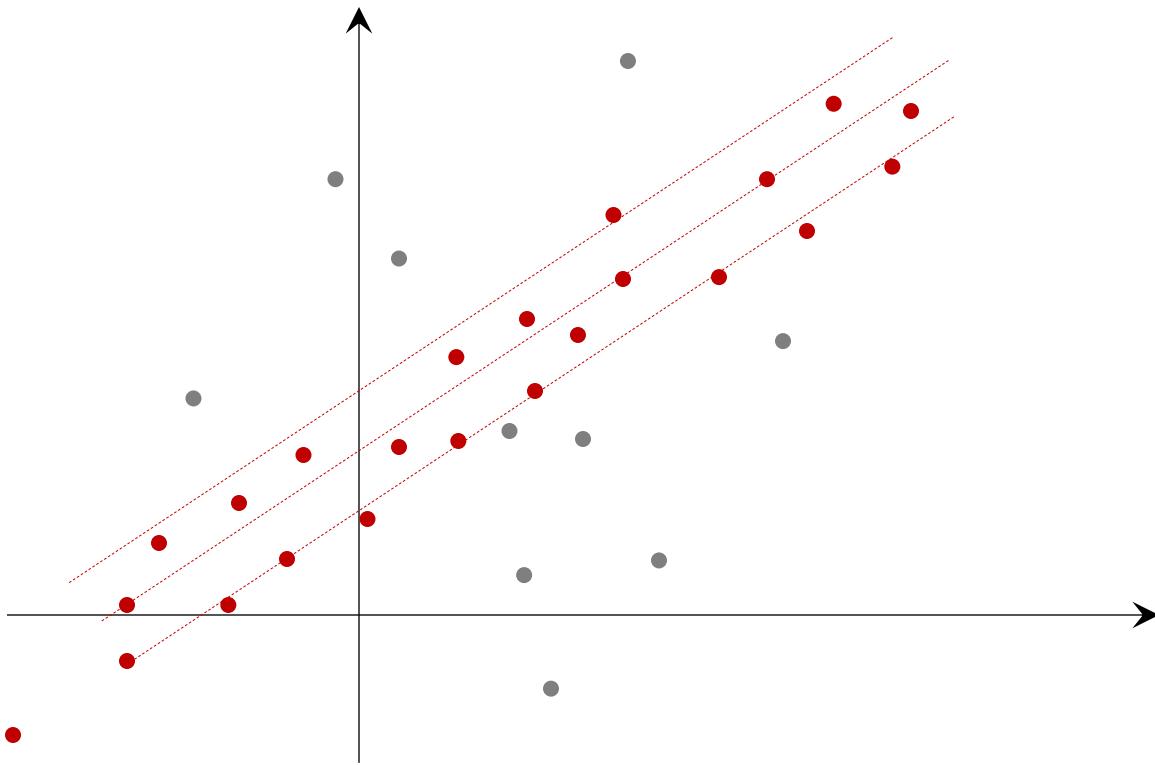
Required number of iterations with p success rate:



Probability of choosing an inlier:

Required number of iterations with p success rate:

$$W = \frac{\text{\# of inliers}}{\text{\# of samples}}$$

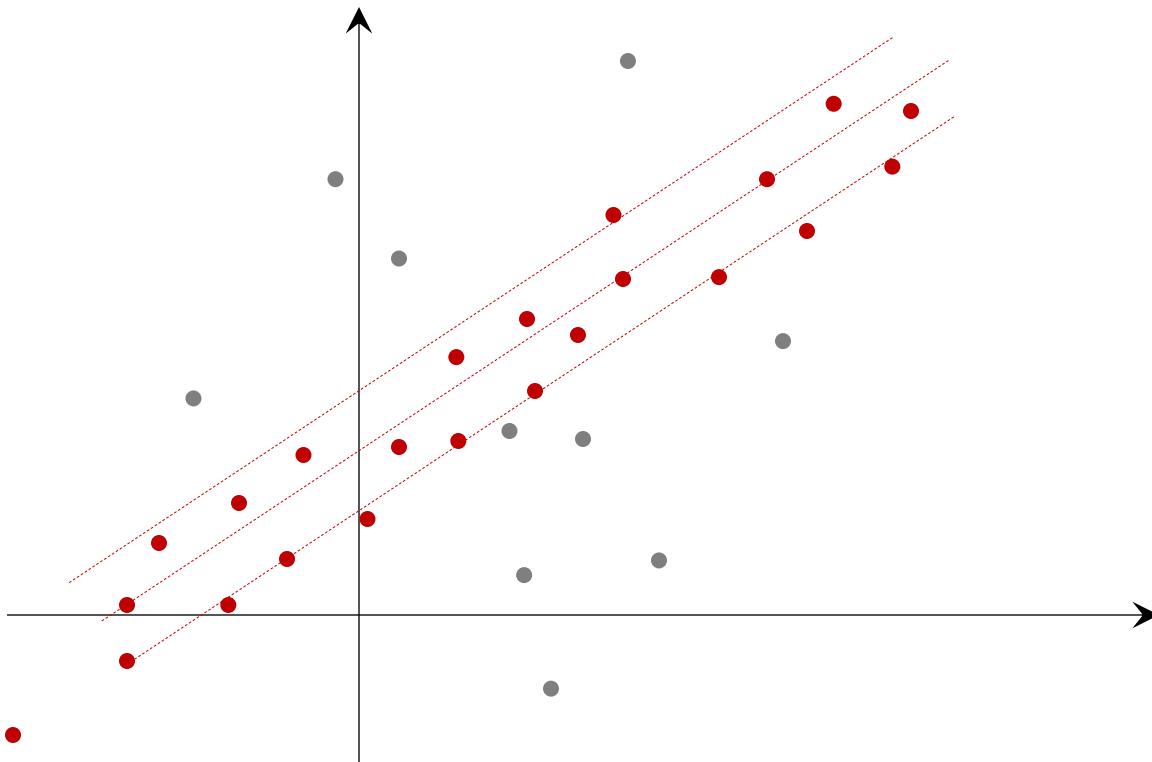


Required number of iterations with p success rate:

$$W = \frac{\# \text{ of inliers}}{\# \text{ of samples}}$$

Probability of choosing an inlier:

Probability of building a correct model: W^n where n is the number of samples to build a model.



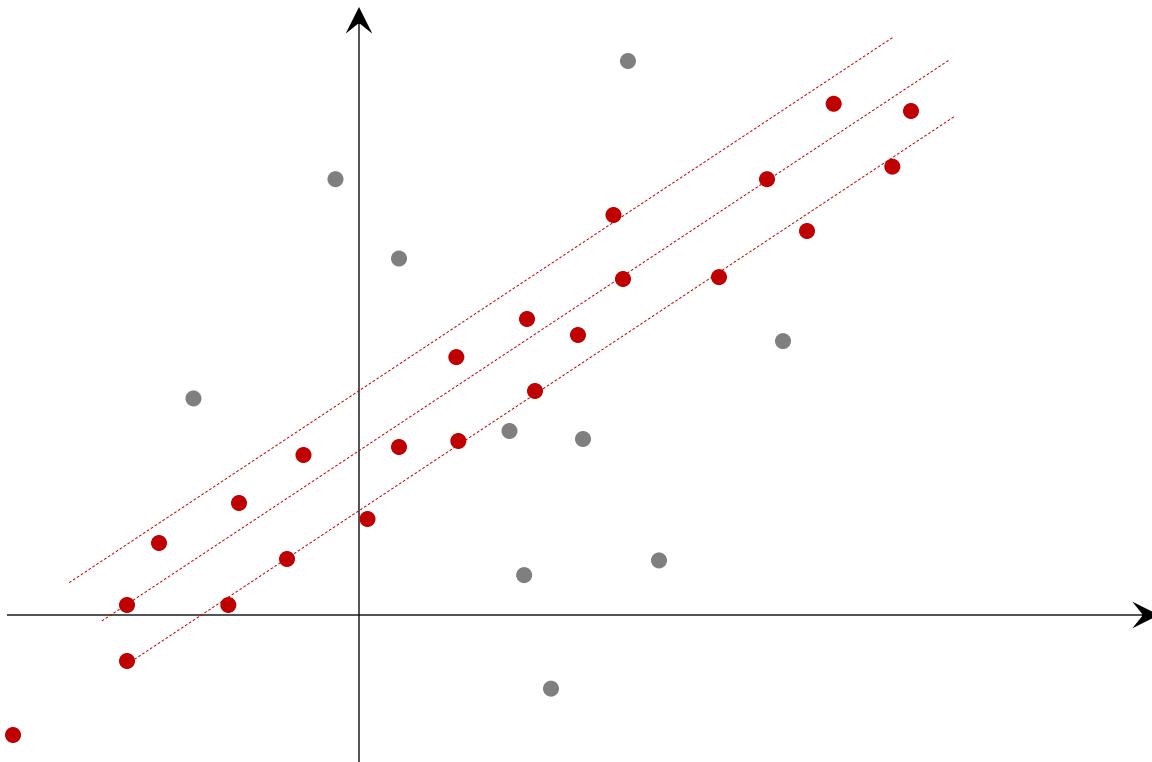
Probability of choosing an inlier:

$$w = \frac{\text{\# of inliers}}{\text{\# of samples}}$$

Probability of building a correct model: w^n where n is the number of samples to build a model.

Probability of not building a correct model during k iterations: $(1-w^n)^k$

Required number of iterations with p success rate:



Required number of iterations with p success rate:

Probability of choosing an inlier:

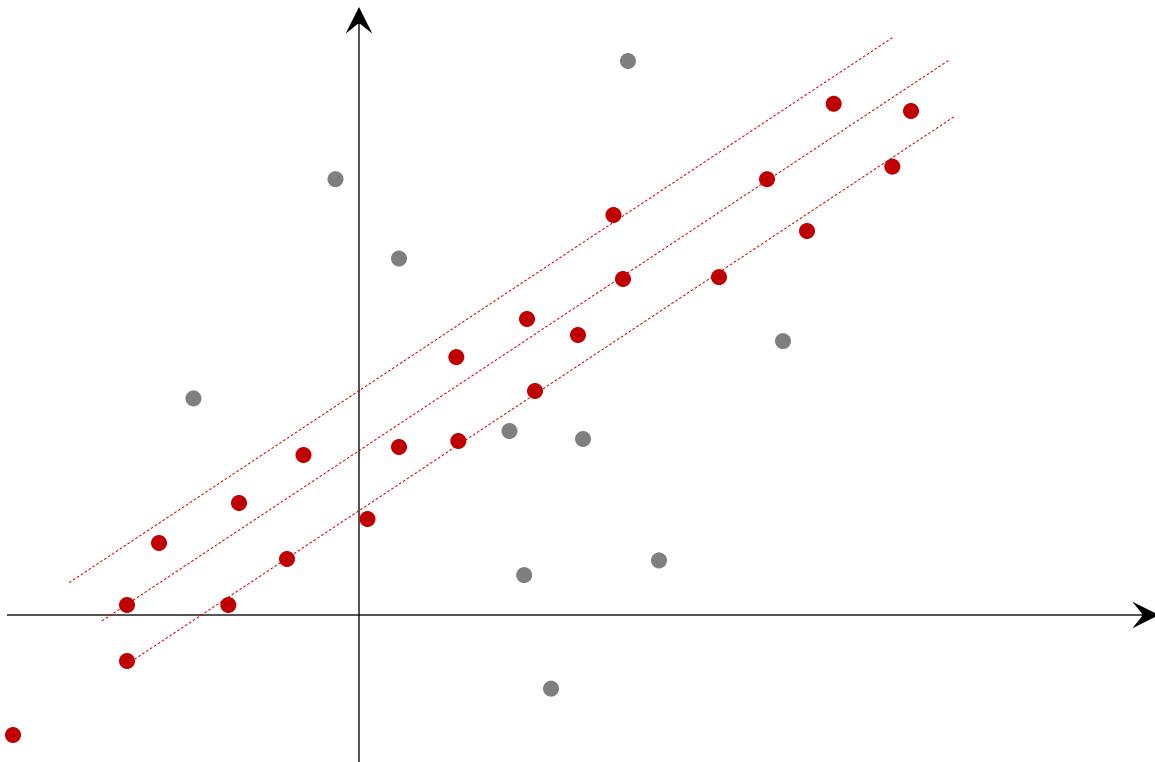
$$w = \frac{\text{\# of inliers}}{\text{\# of samples}}$$

Probability of building a correct model: w^n where n is the number of samples to build a model.

Probability of not building a correct model during k iterations: $(1-w^n)^k$

$$(1-w^n)^k = 1-p \quad \text{where } p \text{ is desired RANSAC success rate.}$$

$$k = \frac{\log(1-p)}{\log(1-w^n)}$$



Probability of choosing an inlier:

$$w = \frac{\text{\# of inliers}}{\text{\# of samples}}$$

Probability of building a correct model: w^n where n is the number of samples to build a model.

Probability of not building a correct model during k iterations: $(1-w^n)^k$

$$(1-w^n)^k = 1-p \quad \text{where } p \text{ is desired RANSAC success rate.}$$

Required number of iterations with p success rate:

$$k = \frac{\log(1-p)}{\log(1-w^n)}$$

where $w = \frac{\text{\# of inliers}}{\text{\# of samples}}$

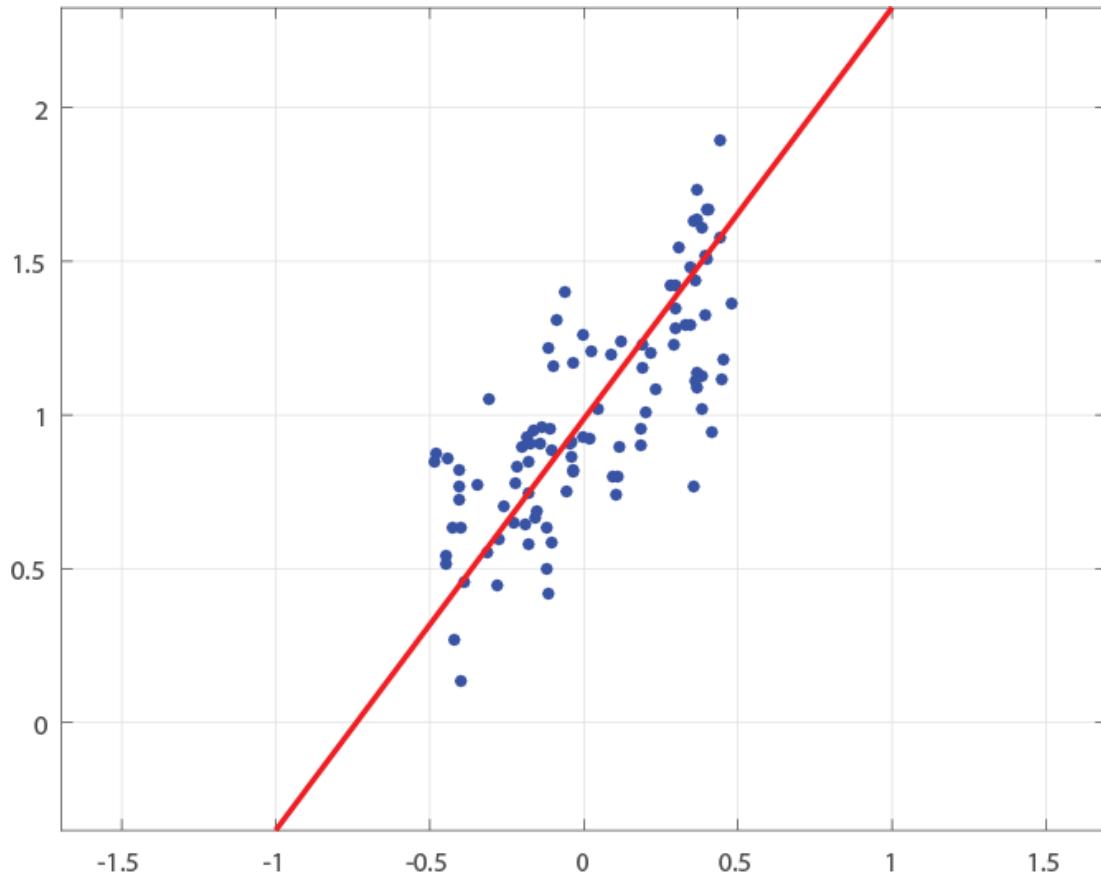
$$k = \frac{\log(1-p)}{\log(1-w^n)}$$

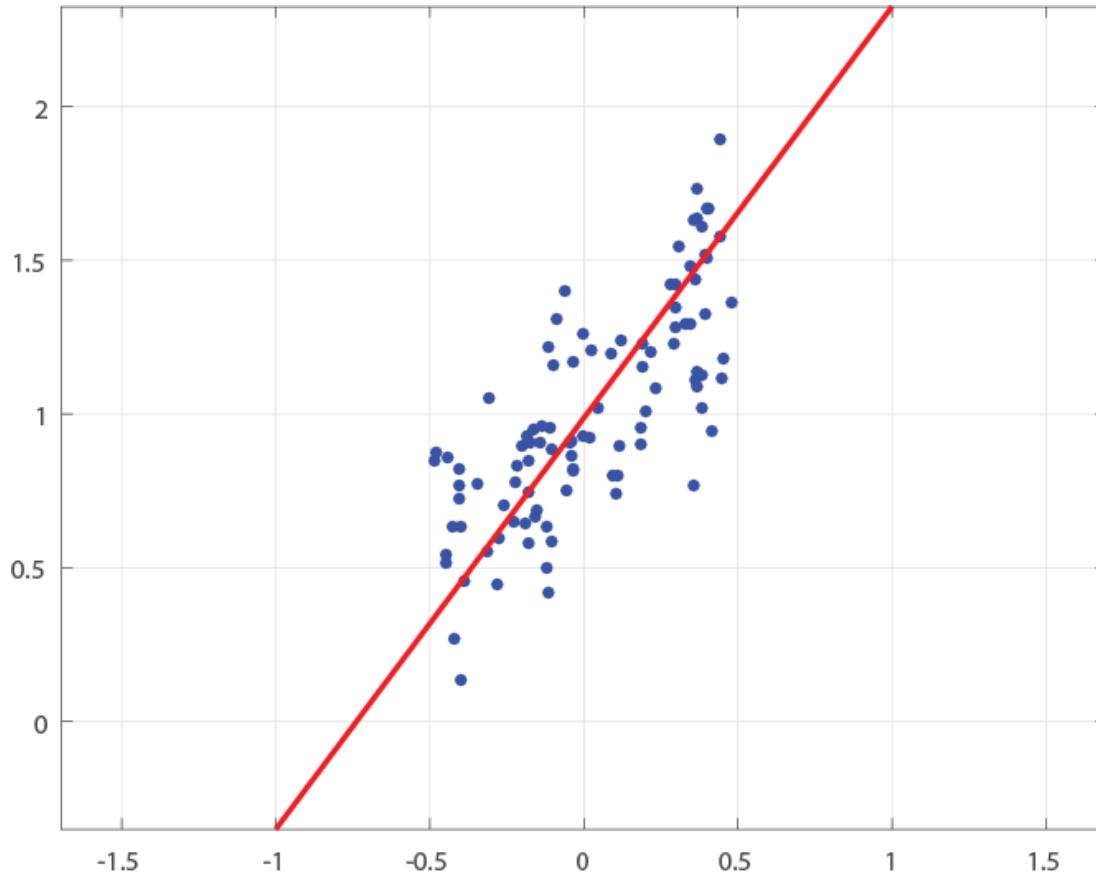
function RANSAC_line

```
a = 1;  
b = 1;
```

```
nPoints = 100;  
x = rand(nPoints,1)-0.5;  
y = a*x + b + 0.2*randn(nPoints,1);
```

Generating samples





function RANSAC_line

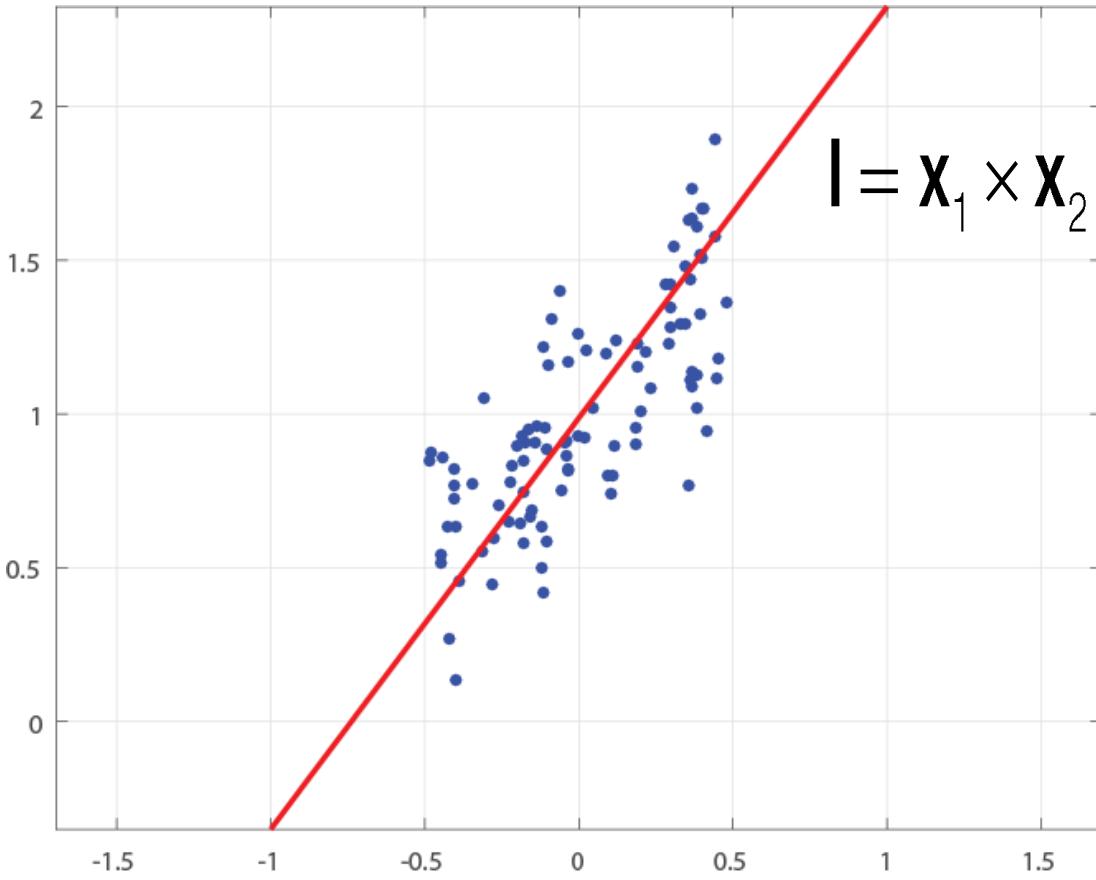
```
a = 1;  
b = 1;
```

```
nPoints = 100;  
x = rand(nPoints,1)-0.5;  
y = a*x + b + 0.2*randn(nPoints,1);
```

```
nRansacIter = 500;  
threshold = 0.1;  
max_nInliers = 0;  
for i = 1 : nRansacIter  
    r = randperm(nPoints);  
    s1 = [x(r(1)); y(r(1)); 1];  
    s2 = [x(r(2)); y(r(2)); 1];
```

Generating samples

Random sampling



function RANSAC_line

a = 1;
b = 1;

nPoints = 100;
x = rand(nPoints,1)-0.5;
y = a*x + b + 0.2*randn(nPoints,1);

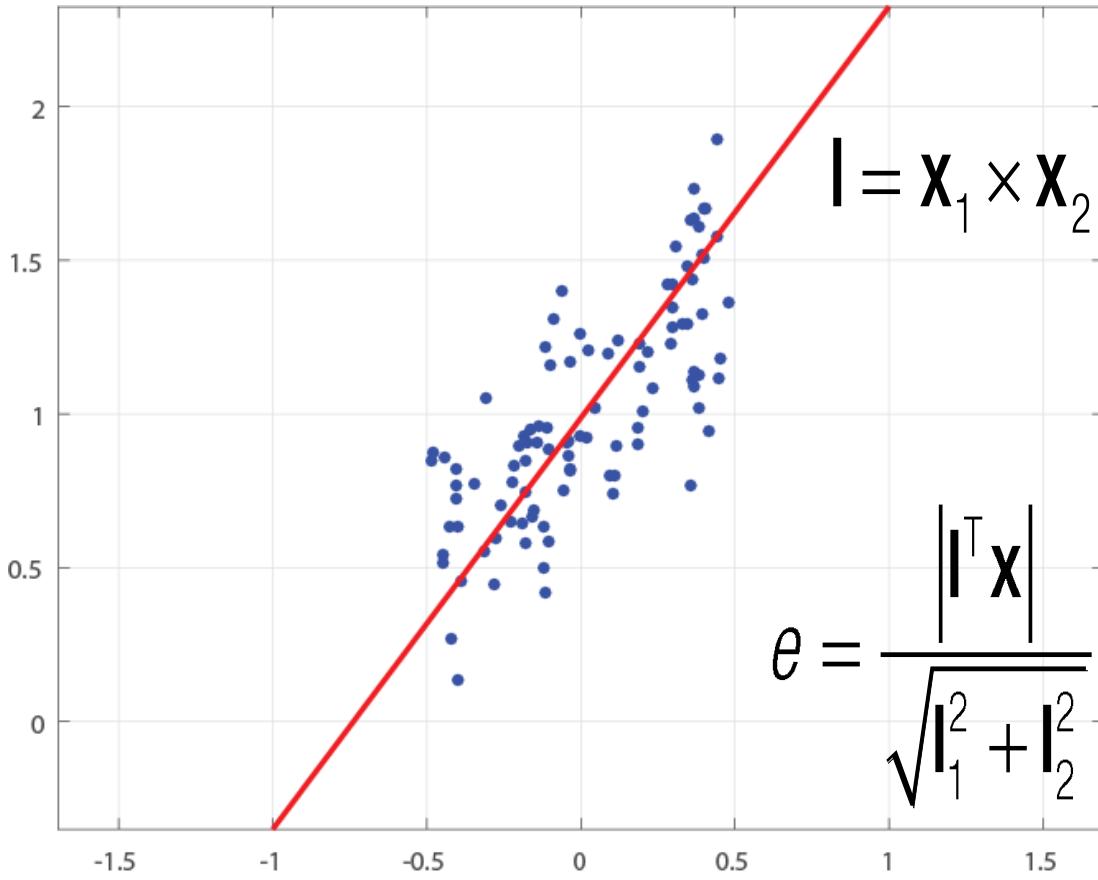
nRansacIter = 500;
threshold = 0.1;
max_nInliers = 0;
for i = 1 : nRansacIter
r = randperm(nPoints);
s1 = [x(r(1)); y(r(1)); 1];
s2 = [x(r(2)); y(r(2)); 1];

$l = \text{GetLineFromTwoPoints}(s1, s2);$

Generating samples

Random sampling

Model building



function RANSAC_line

```
a = 1;
b = 1;
```

```
nPoints = 100;
x = rand(nPoints,1)-0.5;
y = a*x + b + 0.2*randn(nPoints,1);
```

```
nRansacIter = 500;
threshold = 0.1;
max_nInliers = 0;
for i = 1 : nRansacIter
    r = randperm(nPoints);
    s1 = [x(r(1)); y(r(1)); 1];
    s2 = [x(r(2)); y(r(2)); 1];
```

```
l = GetLineFromTwoPoints(s1, s2);
```

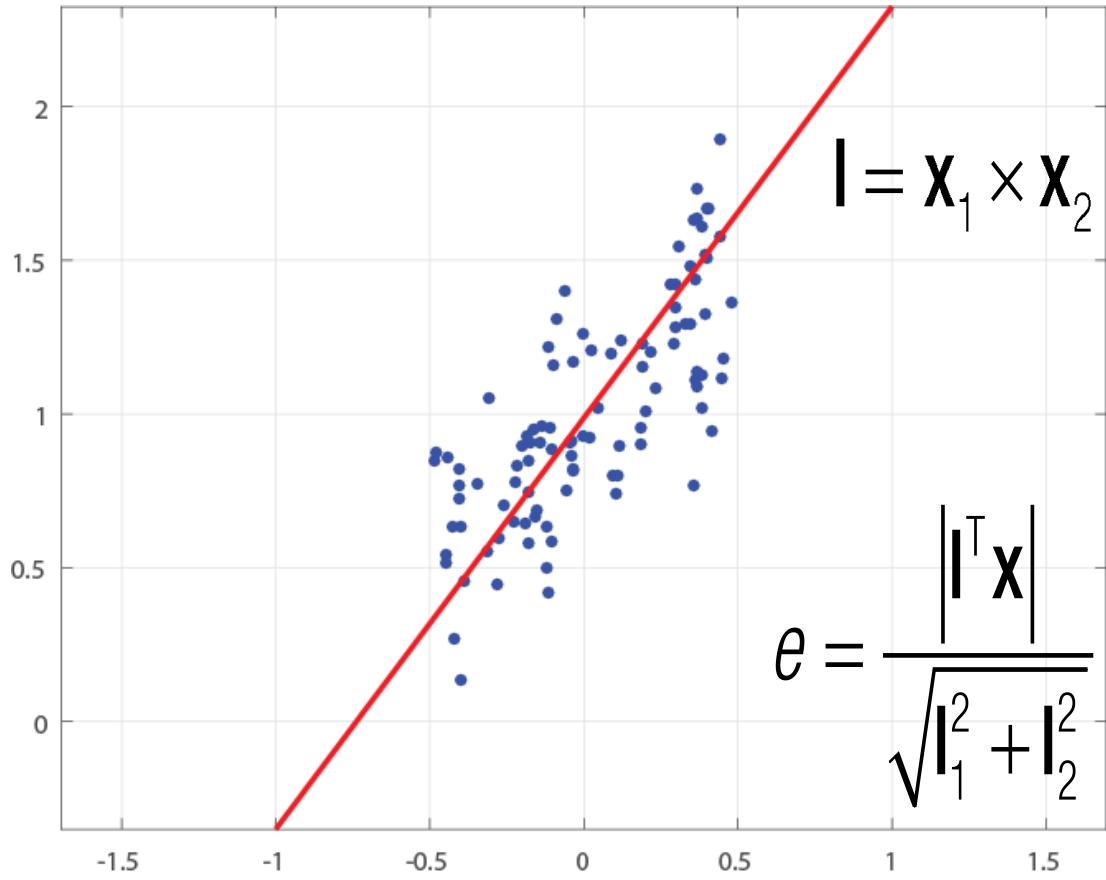
```
nInliers = 0;
for j = 1 : nPoints
    e = abs(l' * [x(j); y(j); 1])/norm(l(1:2));
    if (e < threshold)
        nInliers = nInliers + 1;
    end
end
```

Generating samples

Random sampling

Model building

Thresholding
Inlier counting



function RANSAC_line

a = 1;
b = 1;

nPoints = 100;
x = rand(nPoints,1)-0.5;
y = a*x + b + 0.2*randn(nPoints,1);

nRansacIter = 500;
threshold = 0.1;
max_nInliers = 0;
for i = 1 : nRansacIter
 r = randperm(nPoints);
 s1 = [x(r(1)); y(r(1)); 1];
 s2 = [x(r(2)); y(r(2)); 1];

$l = \text{GetLineFromTwoPoints}(s1, s2);$

nInliers = 0;
for j = 1 : nPoints
 e = abs($l^T [x(j); y(j); 1]$) / norm($l(1:2)$);
 if (e < threshold)
 nInliers = nInliers + 1;
 end

end
if (nInliers > max_nInliers)
 max_nInliers = nInliers;
 L = l ;

end
end

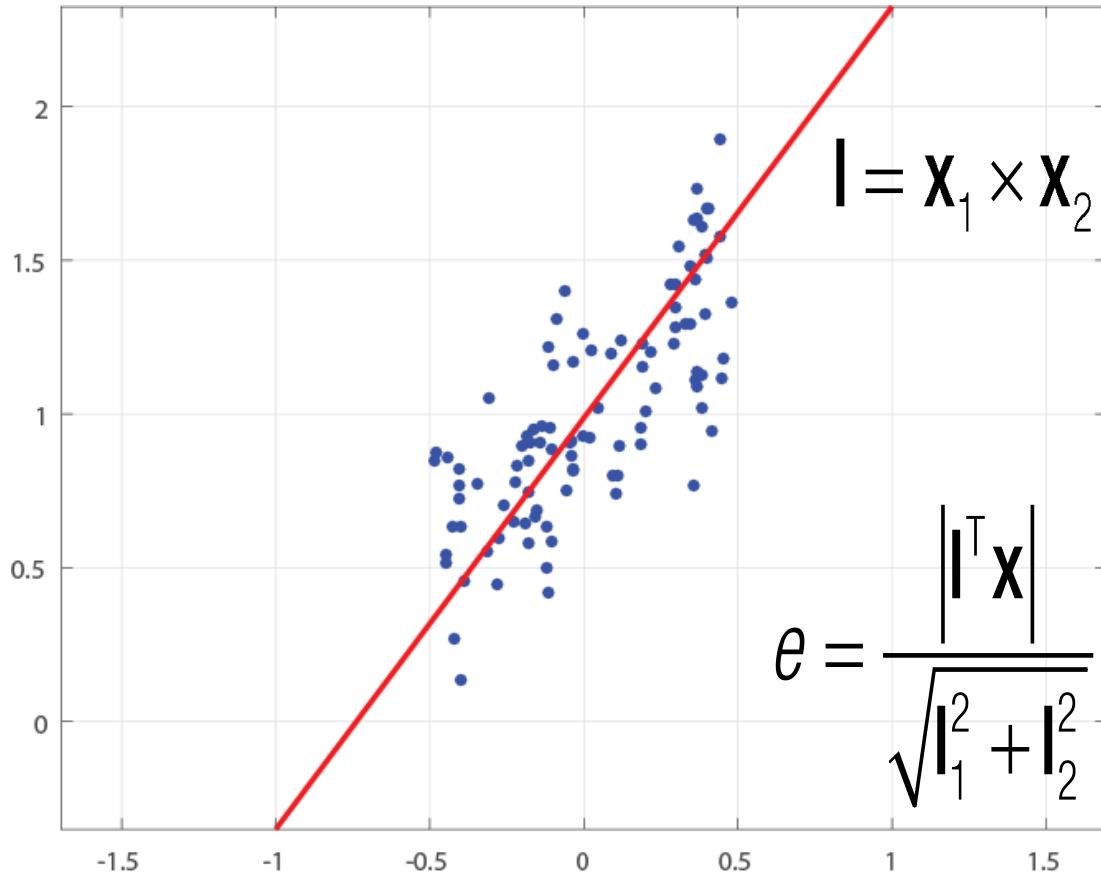
Generating samples

Random sampling

Model building

Thresholding
Inlier counting

Model updating



function RANSAC_line

a = 1;
b = 1;

nPoints = 100;
x = rand(nPoints,1)-0.5;
y = a*x + b + 0.2*randn(nPoints,1);

nRansacIter = 500;
threshold = 0.1;
max_nInliers = 0;
for i = 1 : nRansacIter
 r = randperm(nPoints);
 s1 = [x(r(1)); y(r(1)); 1];
 s2 = [x(r(2)); y(r(2)); 1];

$l = \text{GetLineFromTwoPoints}(s1, s2);$

nInliers = 0;
for j = 1 : nPoints
 e = abs($l^T [x(j); y(j); 1]$) / norm($l(1:2)$);
 if (e < threshold)
 nInliers = nInliers + 1;
 end
end
if (nInliers > max_nInliers)
 max_nInliers = nInliers;
 L = l ;
end
end

Generating samples

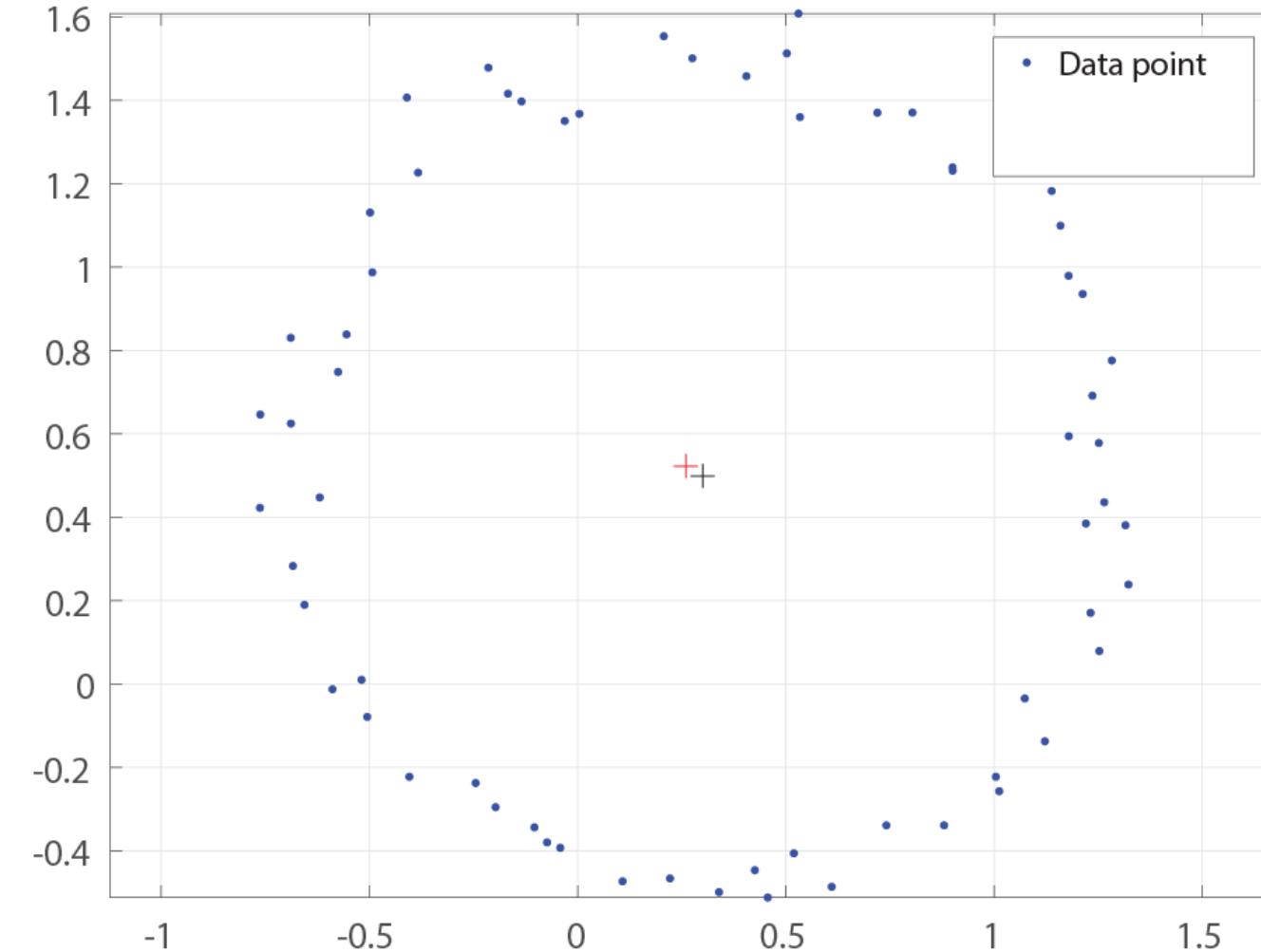
Random sampling

Model building

Thresholding
Inlier counting

Model updating

Recall: Circle Fitting ($Ax=b$)



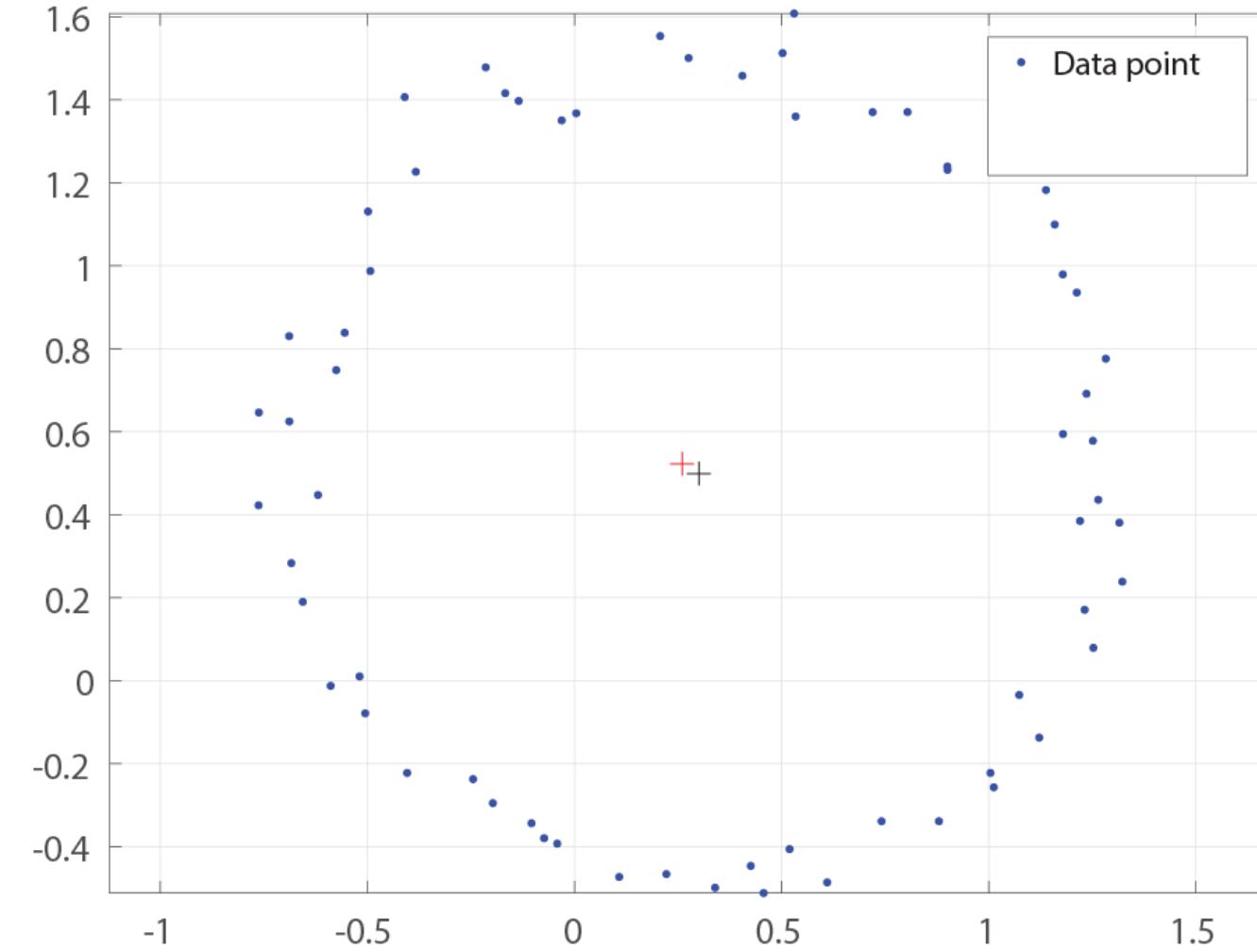
$$(x_1 - C_x)^2 + (y_1 - C_y)^2 = r^2$$

⋮

$$(x_n - C_x)^2 + (y_n - C_y)^2 = r^2$$

Unknowns: C_x, C_y, r

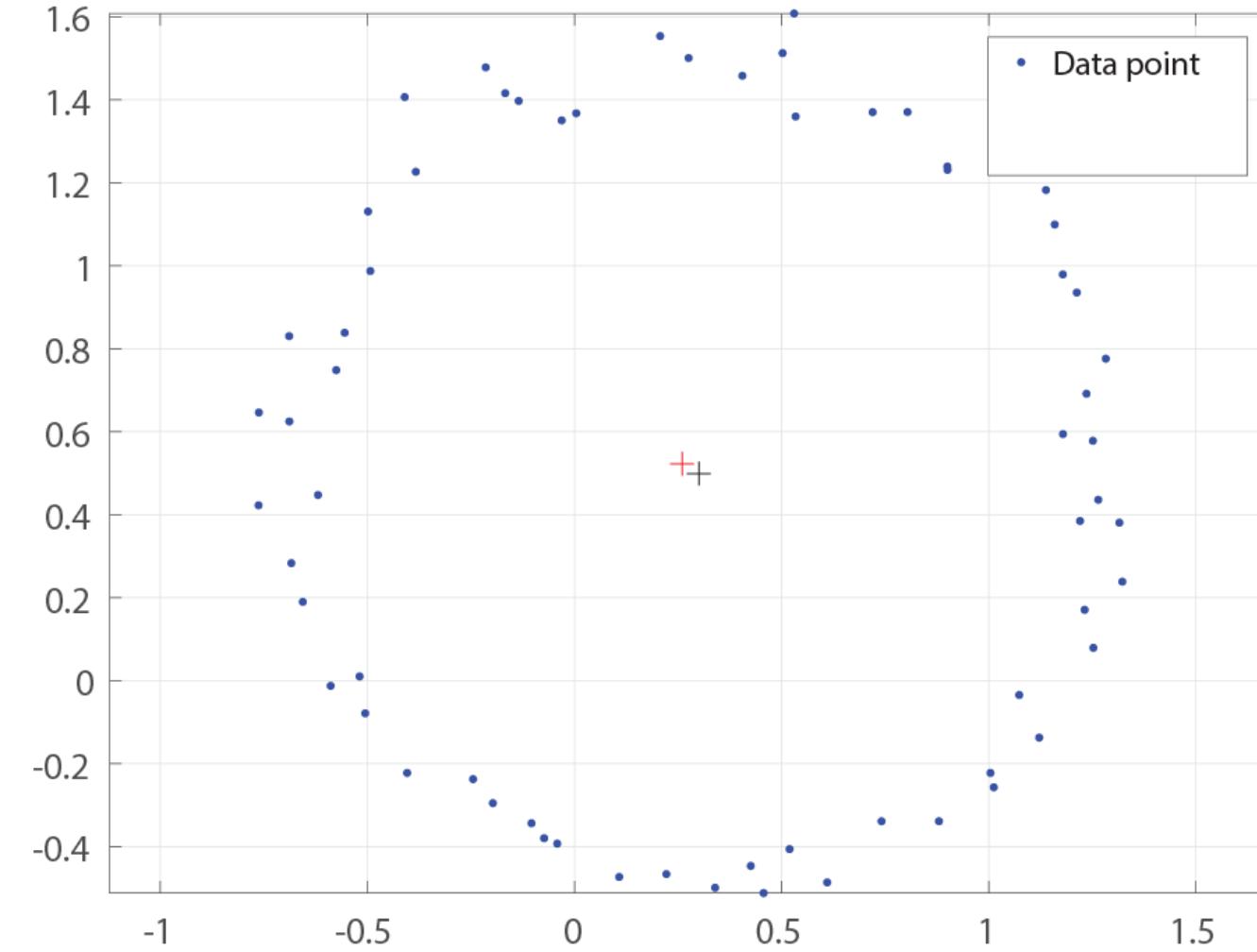
Recall: Circle Fitting ($Ax=b$)



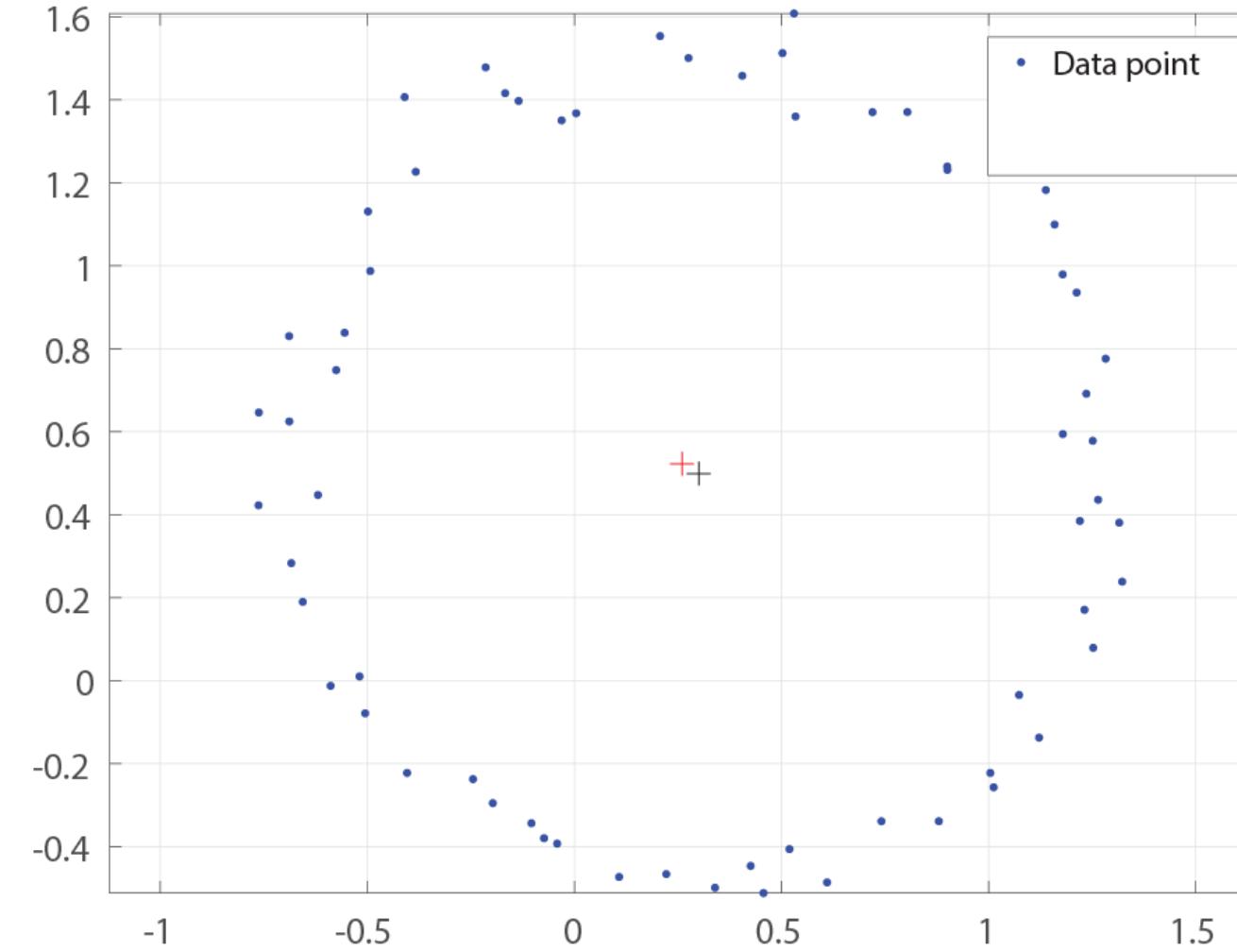
$$x_1^2 - 2x_1 C_x + C_x^2 + y_1^2 - 2y_1 C_y + C_y^2 = r^2$$

$$x_n^2 - 2x_n C_x + C_x^2 + y_n^2 - 2y_n C_y + C_y^2 = r^2$$

Recall: Circle Fitting ($Ax=b$)



Recall: Circle Fitting ($Ax=b$)



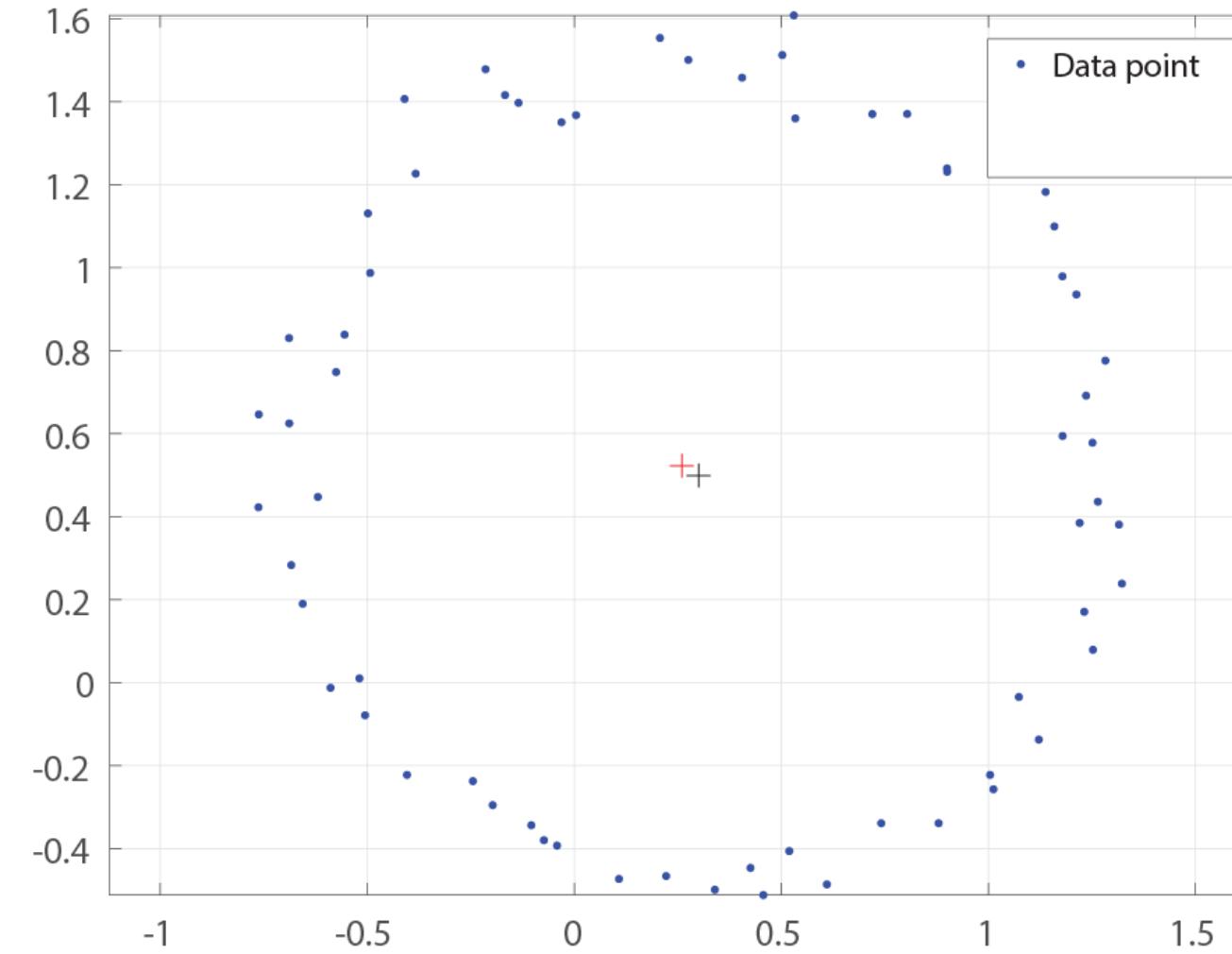
$$x_1^2 - 2x_1 C_x + C_x^2 + y_1^2 - 2y_1 C_y + C_y^2 = r^2$$

$$x_n^2 - 2x_n C_x + C_x^2 + y_n^2 - 2y_n C_y + C_y^2 = r^2$$

$$x_i^2 - x_1^2 - 2C_x(x_i - x_1) + y_i^2 - y_1^2 - 2(y_i - y_1)C_y = 0$$

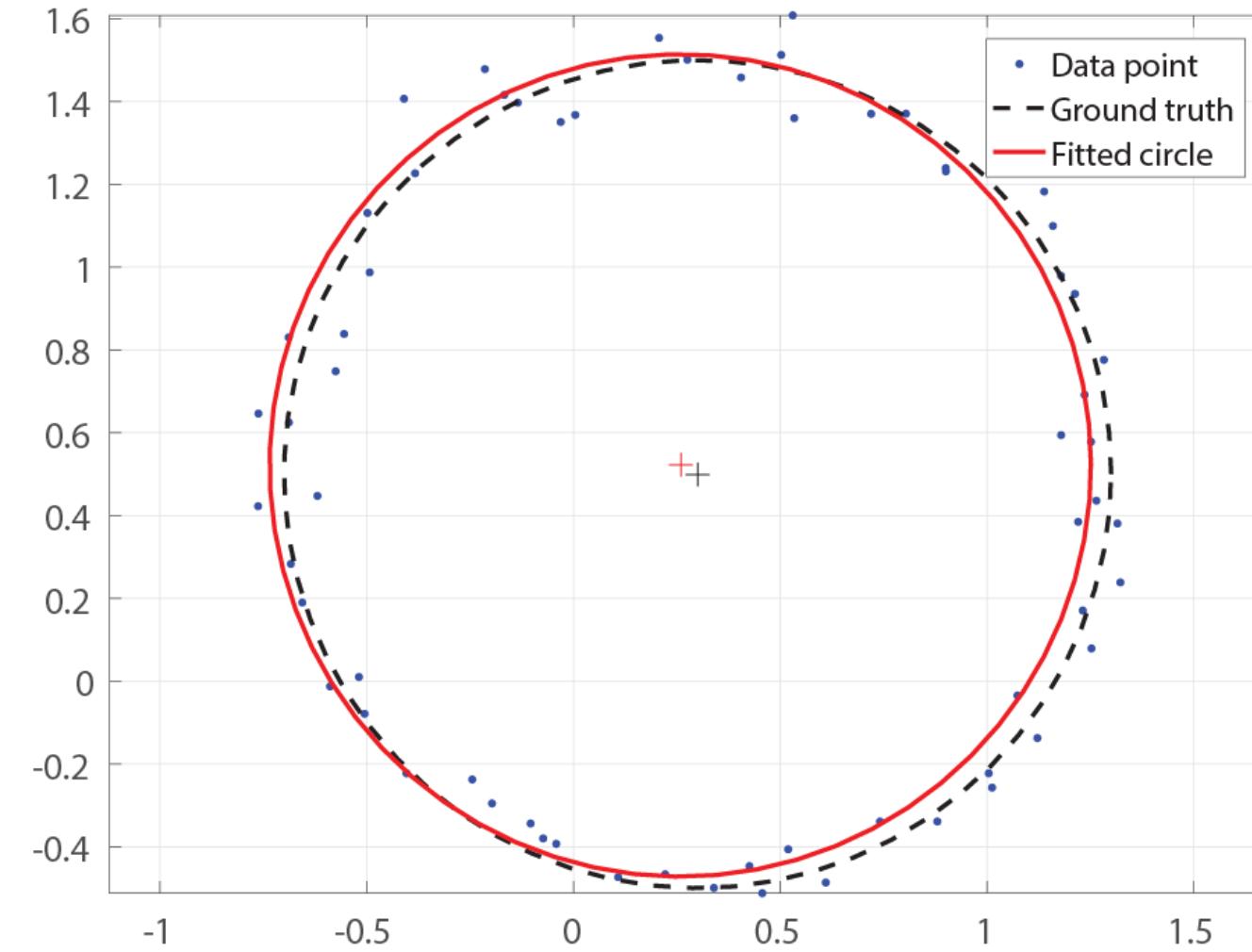
$$\begin{bmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ \vdots & \vdots \\ 2(x_n - x_1) & 2(y_n - y_1) \end{bmatrix} \begin{bmatrix} C_x \\ C_y \end{bmatrix} = \begin{bmatrix} x_2^2 - x_1^2 + y_2^2 - y_1^2 \\ \vdots \\ x_n^2 - x_1^2 + y_n^2 - y_1^2 \end{bmatrix}$$

Circle Fitting ($Ax=b$)



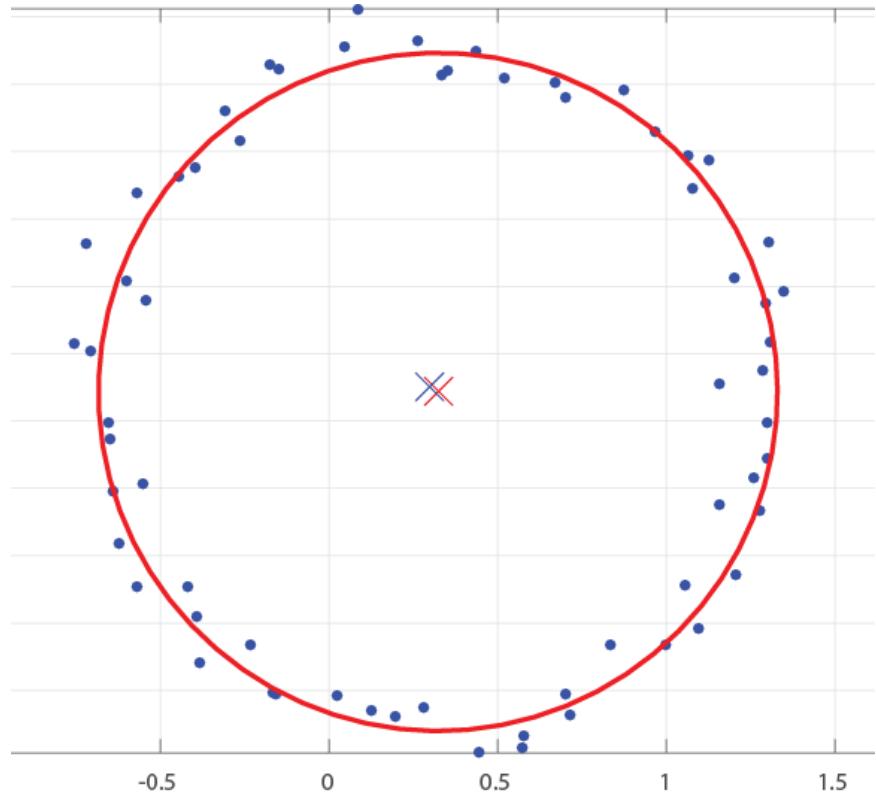
$$x_1^2 - 2x_1 C_x + C_x^2 + y_1^2 - 2y_1 C_y + C_y^2 = r^2$$
$$\vdots \quad \vdots$$
$$x_n^2 - 2x_n C_x + C_x^2 + y_n^2 - 2y_n C_y + C_y^2 = r^2$$
$$\downarrow$$
$$x_i^2 - x_1^2 - 2C_x(x_i - x_1) + y_i^2 - y_1^2 - 2(y_i - y_1)C_y = 0$$
$$\downarrow$$
$$\begin{bmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ \vdots & \vdots \\ 2(x_n - x_1) & 2(y_n - y_1) \end{bmatrix} \begin{bmatrix} C_x \\ C_y \end{bmatrix} = \begin{bmatrix} x_2^2 - x_1^2 + y_2^2 - y_1^2 \\ \vdots \\ x_n^2 - x_1^2 + y_n^2 - y_1^2 \end{bmatrix}$$

Recall: Circle Fitting ($Ax=b$)



$$\begin{aligned} x_1^2 - 2x_1 C_x + C_x^2 + y_1^2 - 2y_1 C_y + C_y^2 &= r^2 \\ \vdots & \\ x_n^2 - 2x_n C_x + C_x^2 + y_n^2 - 2y_n C_y + C_y^2 &= r^2 \\ \downarrow & \\ x_i^2 - x_1^2 - 2C_x(x_i - x_1) + y_i^2 - y_1^2 - 2(y_i - y_1)C_y &= 0 \\ \downarrow & \\ \begin{bmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ \vdots & \vdots \\ 2(x_n - x_1) & 2(y_n - y_1) \end{bmatrix} \begin{bmatrix} C_x \\ C_y \end{bmatrix} &= \begin{bmatrix} x_2^2 - x_1^2 + y_2^2 - y_1^2 \\ \vdots \\ x_n^2 - x_1^2 + y_n^2 - y_1^2 \end{bmatrix} \end{aligned}$$

Circle Fitting RANSAC



$$\begin{bmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) \\ \vdots & \vdots \\ 2(x_n - x_1) & 2(y_n - y_1) \end{bmatrix} \begin{bmatrix} C_x \\ C_y \end{bmatrix} = \begin{bmatrix} x_2^2 - x_1^2 + y_2^2 - y_1^2 \\ \vdots \\ x_n^2 - x_1^2 + y_n^2 - y_1^2 \end{bmatrix}$$

function RANSAC_circle

```
cx = 0.3;
cy = 0.5;
r = 1;
```

Download [RANSAC_circle.m](#)

```
theta = 0:0.1:2*pi+0.1;
theta = theta';
x = cos(theta) + cx + 0.05*randn(size(theta));
y = sin(theta) + cy + 0.05*randn(size(theta));
```

```
figure(1)
clf;
plot(x,y, 'b.');
axis equal
grid on
```

```
nRansacIter = 500;
threshold = 0.1;
max_nInliers = 0;
%% RANSAC circle
% U: Estimated center of circle
% R: Radius
```

```
%%
hold on
plot(R*cos(theta)+U(1), R*sin(theta)+U(2), 'r-');
hold on
plot(U(1), U(2), 'rx');
hold on
plot(cx, cy, 'bx');
```

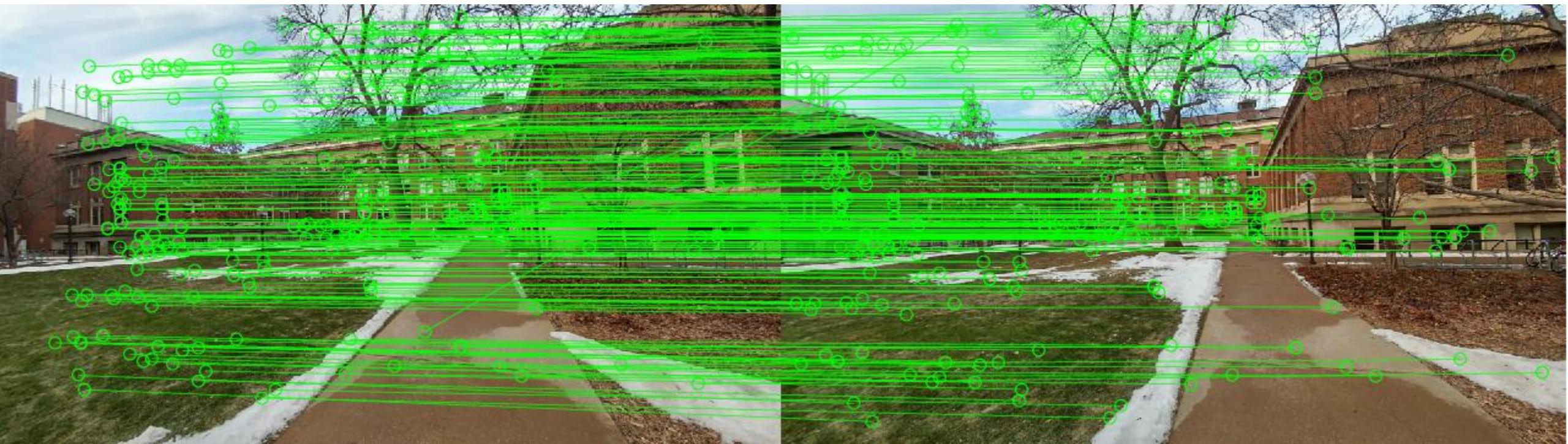
Fill out this part

HW #4 RANSAC Fundamental matrix

Algorithm 1 GetInliersRANSAC

```
1:  $n \leftarrow 0$ 
2: for  $i = 1 : M$  do
3:   Choose 8 correspondences,  $\mathbf{u}_r$  and  $\mathbf{v}_r$ , randomly from  $\mathbf{u}$  and  $\mathbf{v}$ .
4:    $\mathbf{F}_r = \text{ComputeFundamentalMatrix}(\mathbf{u}_r, \mathbf{v}_r)$ 
5:   Compute the number of inliers,  $n_r$ , with respect to  $\mathbf{F}$ .
6:   if  $n_r > n$  then
7:      $n \leftarrow n_r$ 
8:      $\mathbf{F} = \mathbf{F}_r$ 
9:   end if
10: end for
```

Fundamental Matrix Computation via RANSAC



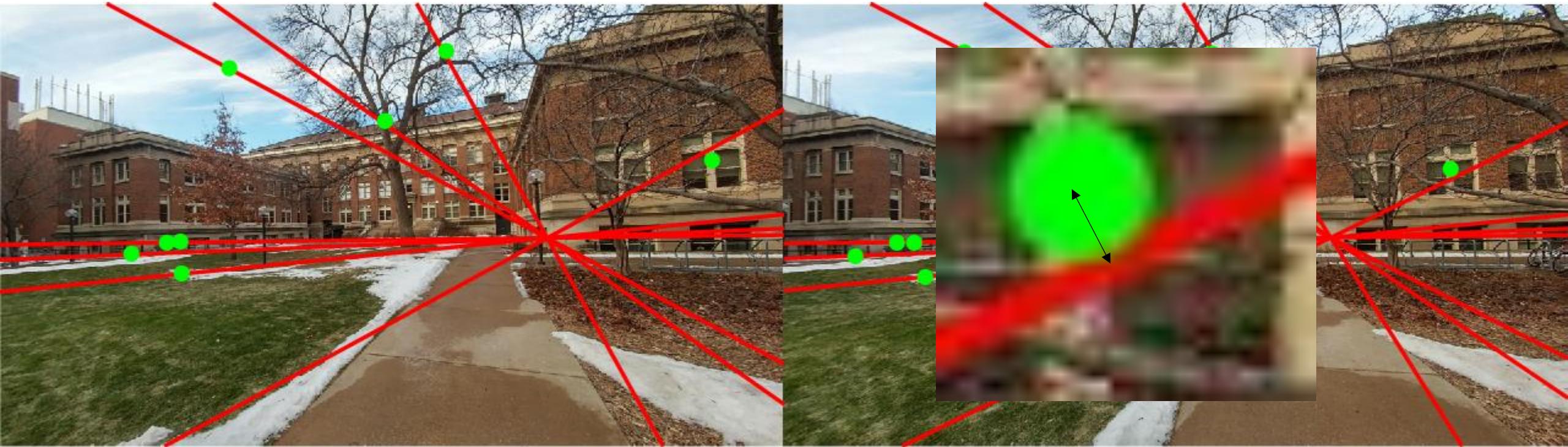
Fundamental Matrix Computation via RANSAC



$$\begin{bmatrix} u_1^x v_1^x & u_1^y v_1^x & v_1^x & u_1^x v_1^y & u_1^y v_1^y & v_1^y & u_1^x & u_1^y & 1 \\ \vdots & \vdots \\ u_m^x v_m^x & u_m^y v_m^x & v_m^x & u_m^x v_m^y & u_m^y v_m^y & v_m^y & u_m^x & u_m^y & 1 \end{bmatrix} \mathbf{A} = \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{31} \\ f_{32} \\ f_{33} \end{bmatrix}$$

$\mathbf{X} = \mathbf{0}$

Fundamental Matrix Computation via RANSAC



Epipolar line:

$$\mathbf{I}_u = \mathbf{F}\mathbf{u}$$

Distance:

$$d = \frac{|au_x + bu_y + c|}{\sqrt{a^2 + b^2}} = \frac{|\mathbf{F}\mathbf{u}|}{\sqrt{(\mathbf{F}_{1,:}\mathbf{u})^2 + (\mathbf{F}_{2,:}\mathbf{u})^2}}$$

Fundamental Matrix Computation via RANSAC



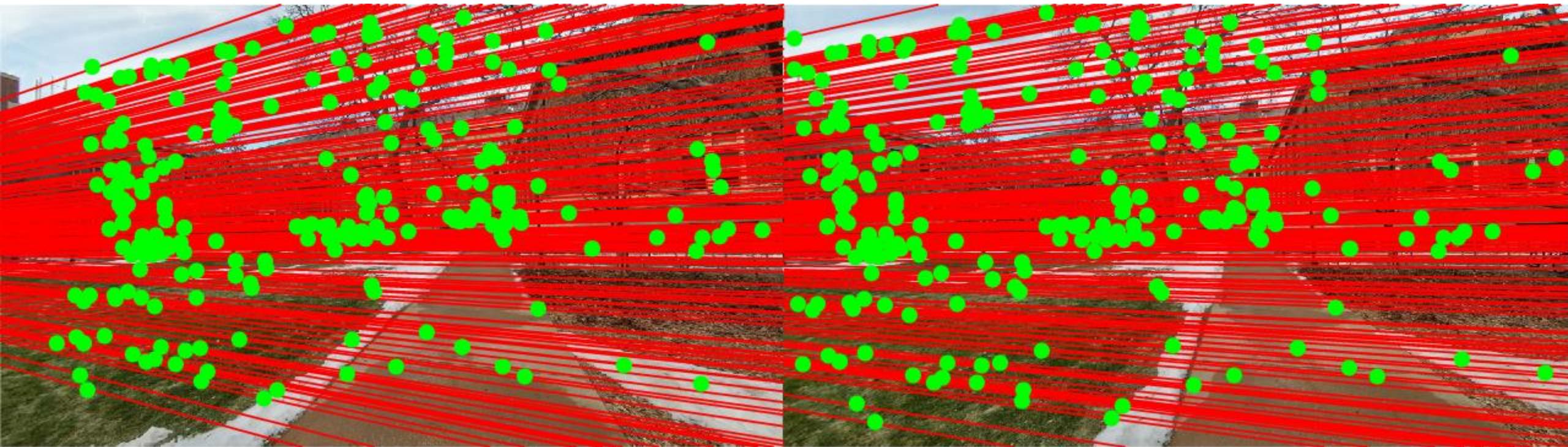
of inliers: 65 out of 260

Fundamental Matrix Computation via RANSAC



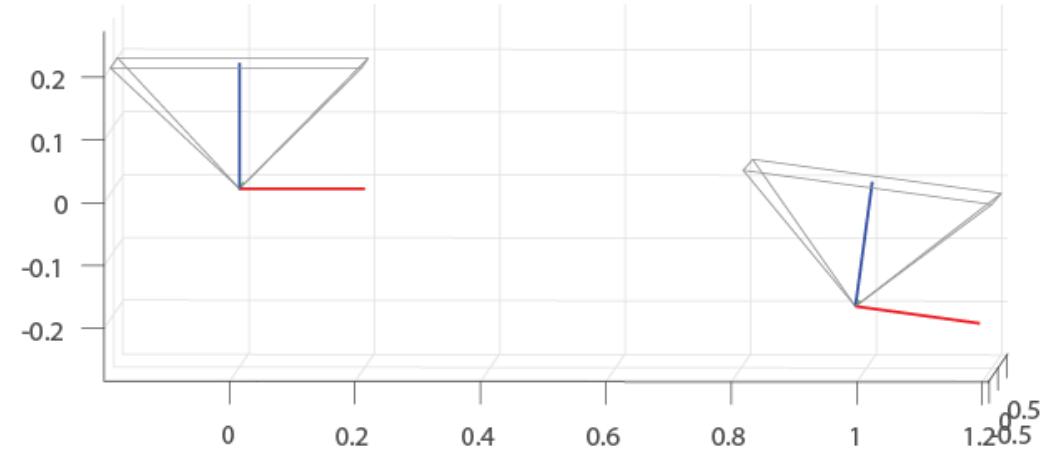
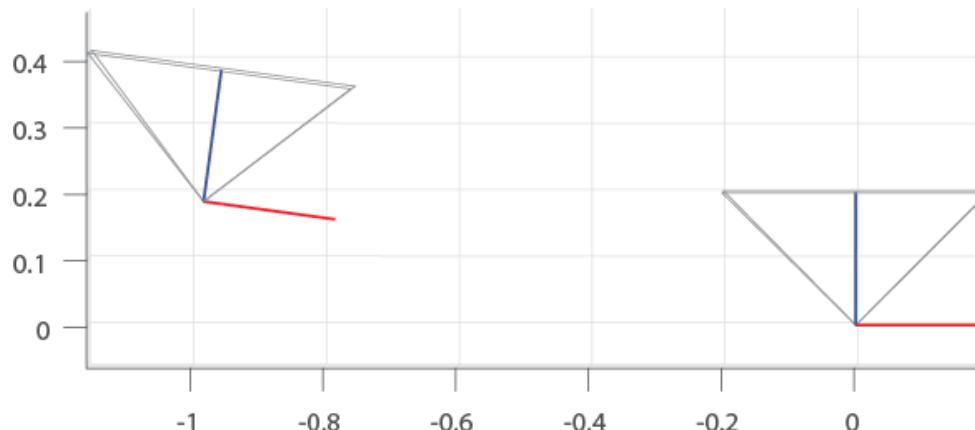
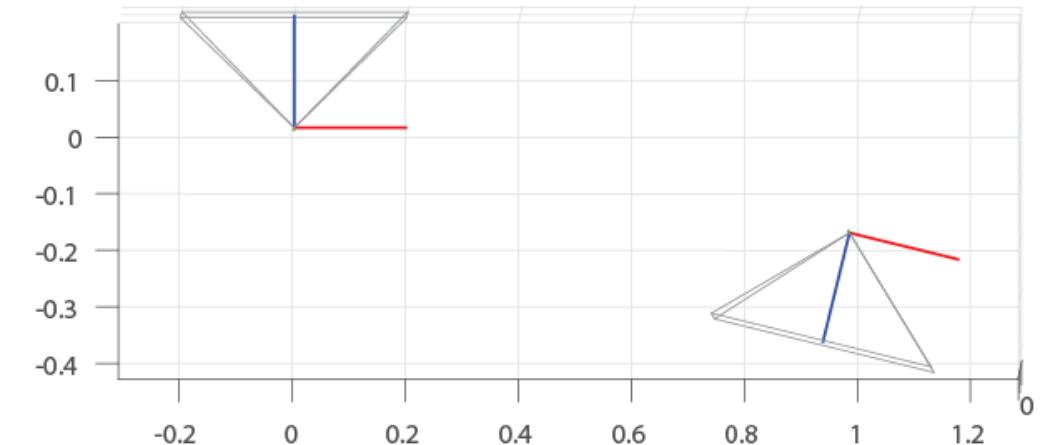
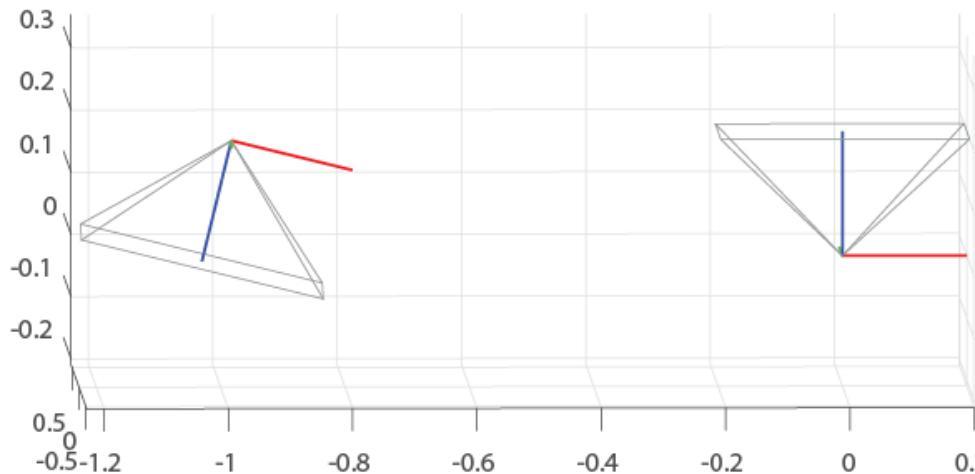
of inliers: 65 out of 260

Fundamental Matrix Computation via RANSAC

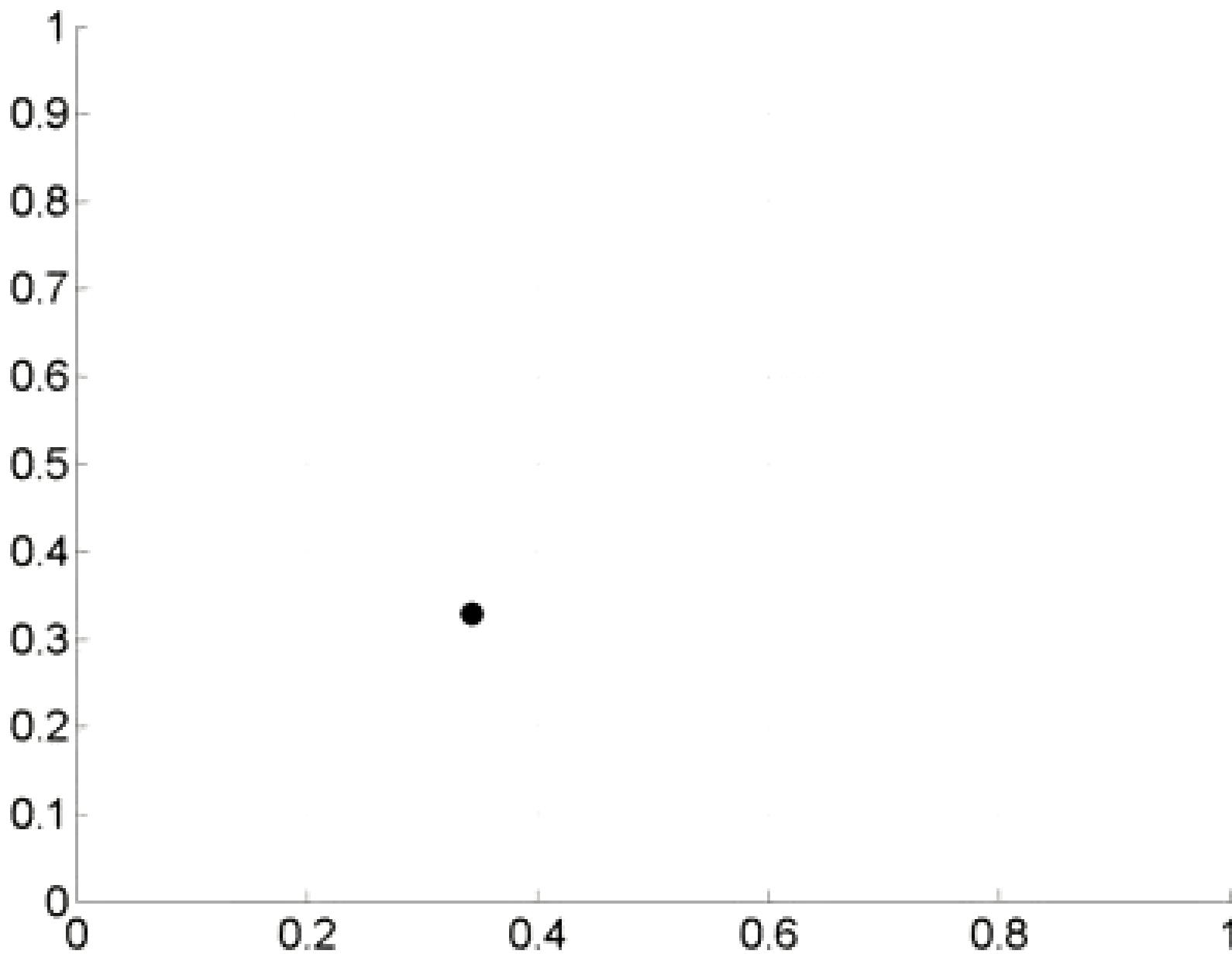


of inliers: 186 out of 260

Four Camera Pose Config. From Essential Matrix



Fit a straight line to this data



Daniel Wedge "The RANSAC Song"