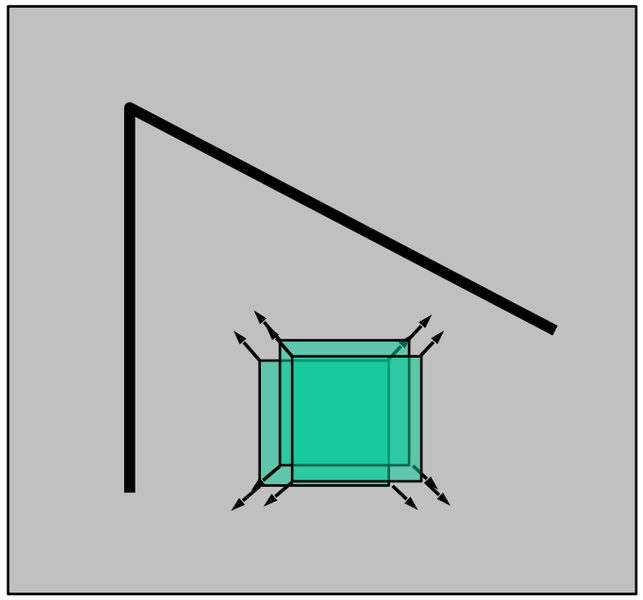
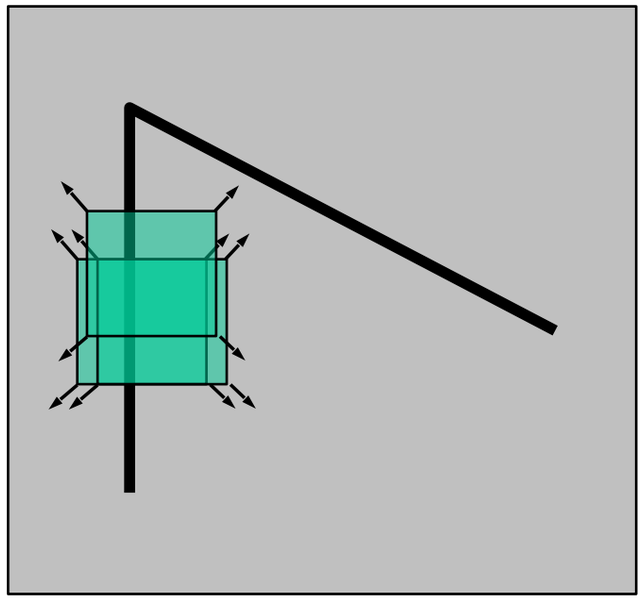
Matching and Image Alignment

Computer Vision
Fall 2019
Columbia University

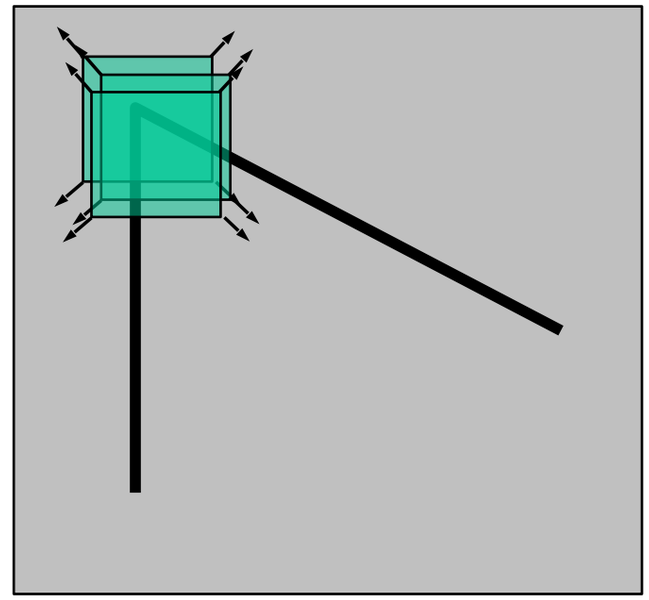
Corner Detector: Basic Idea



“flat” region:
no change in any direction



“edge”:
no change along the edge direction



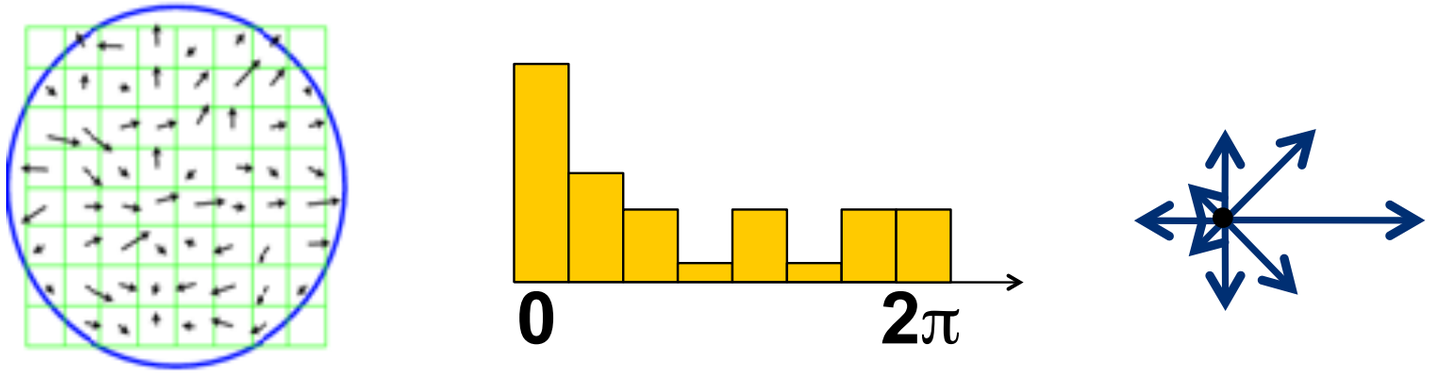
“corner”:
significant change in all directions

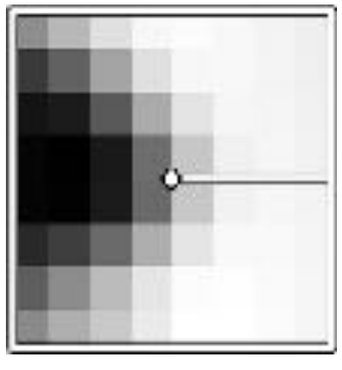
Defn: points are “matchable” if small shifts always produce a large SSD error

Source: Deva Ramanan

Find dominant orientation

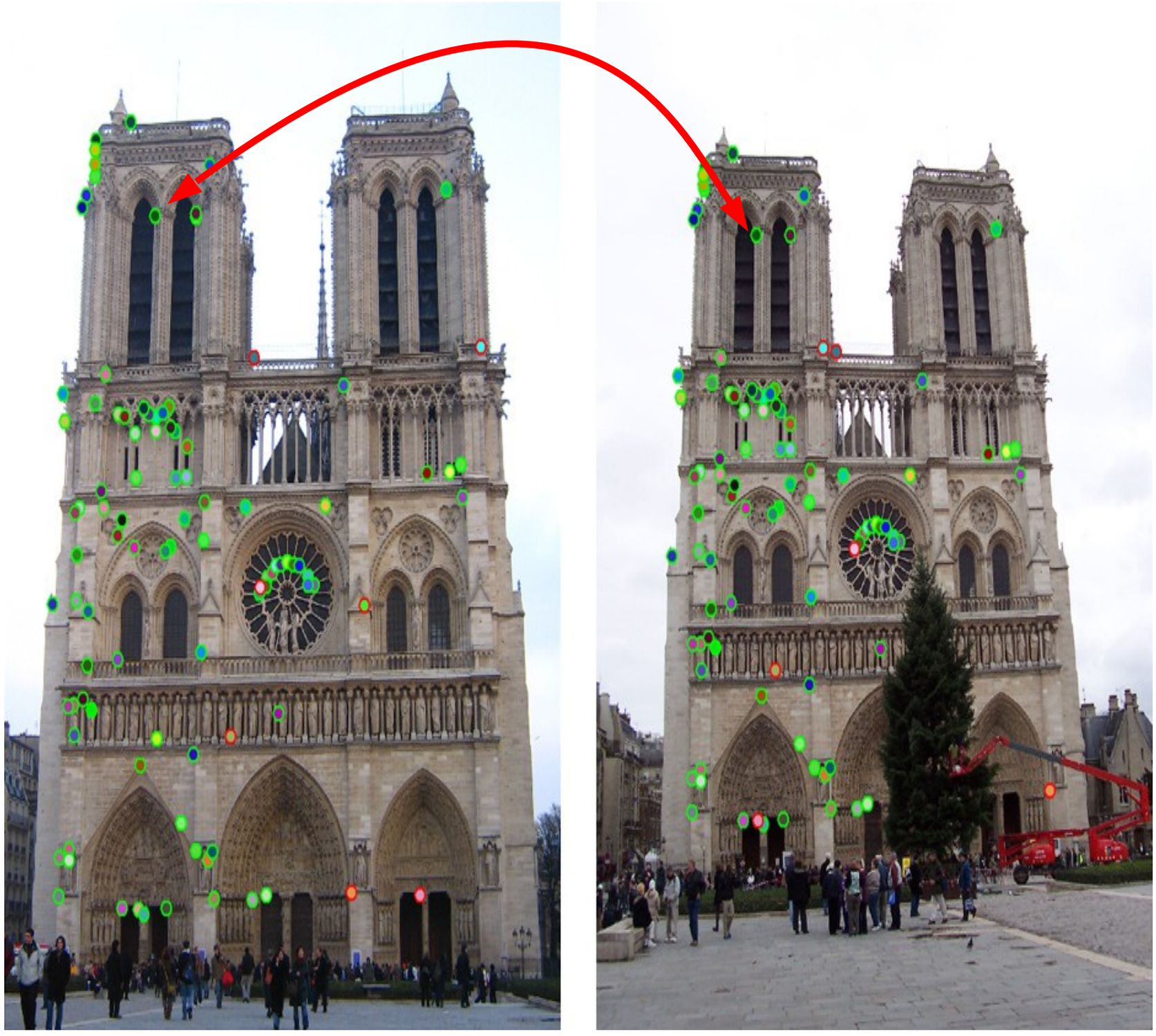
Compute gradients for all pixels in patch. Histogram (bin) gradients by orientation





Source: Deva Ramanan

Feature Matching



1. Find a set of distinctive key-points
2. Define a region around each keypoint
3. Extract and normalize the region content
4. Compute a local descriptor from the normalized region
5. Match local descriptors

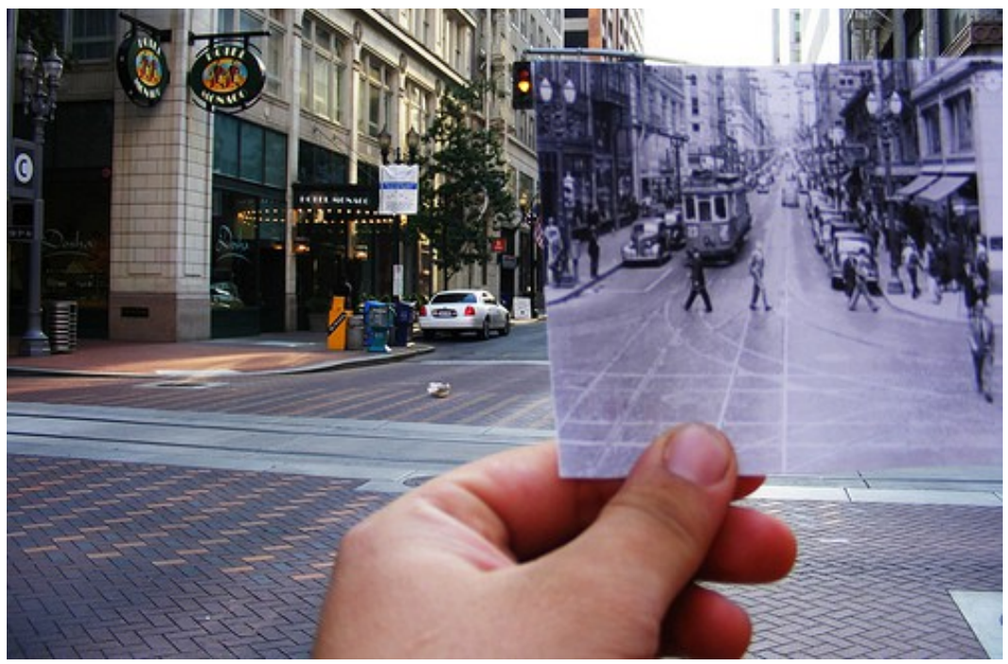
Slide credit: James Hays

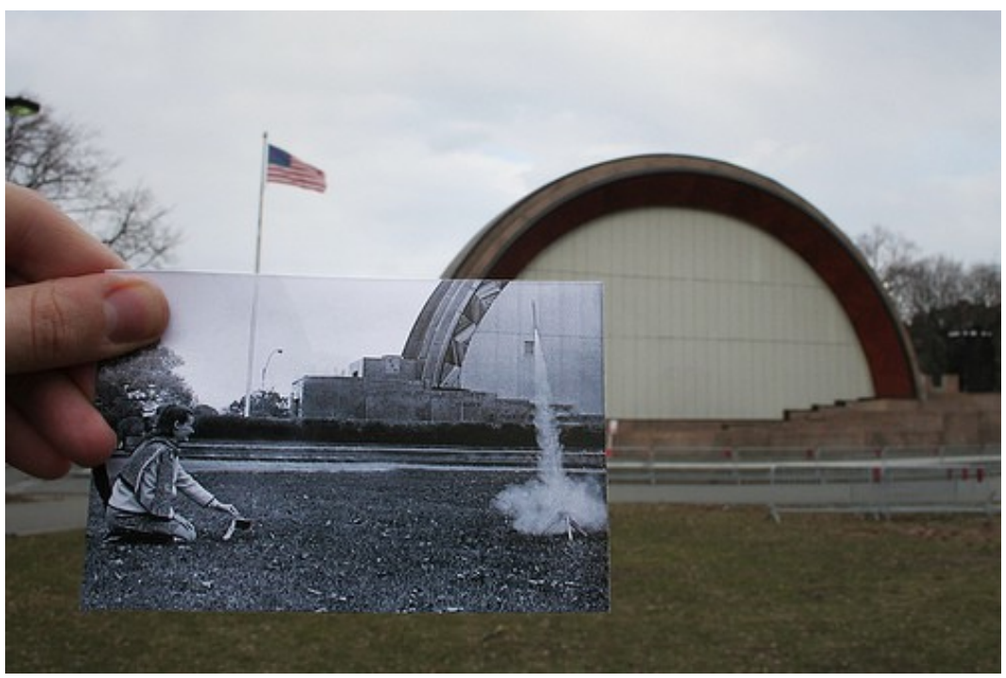
Panoramas

Slide credit: Olga Russakovsky

Gigapixel Images

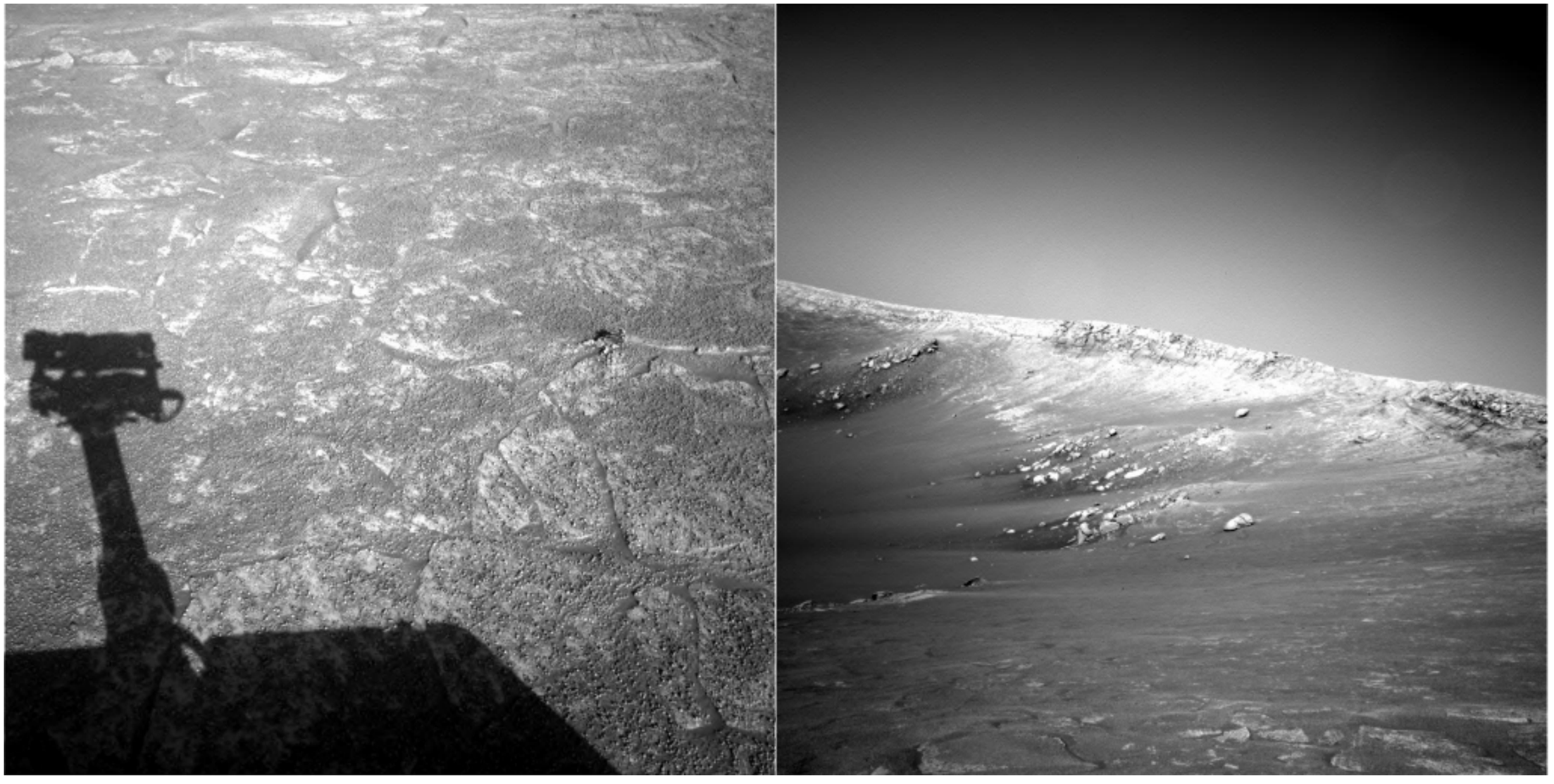
Look into the Past





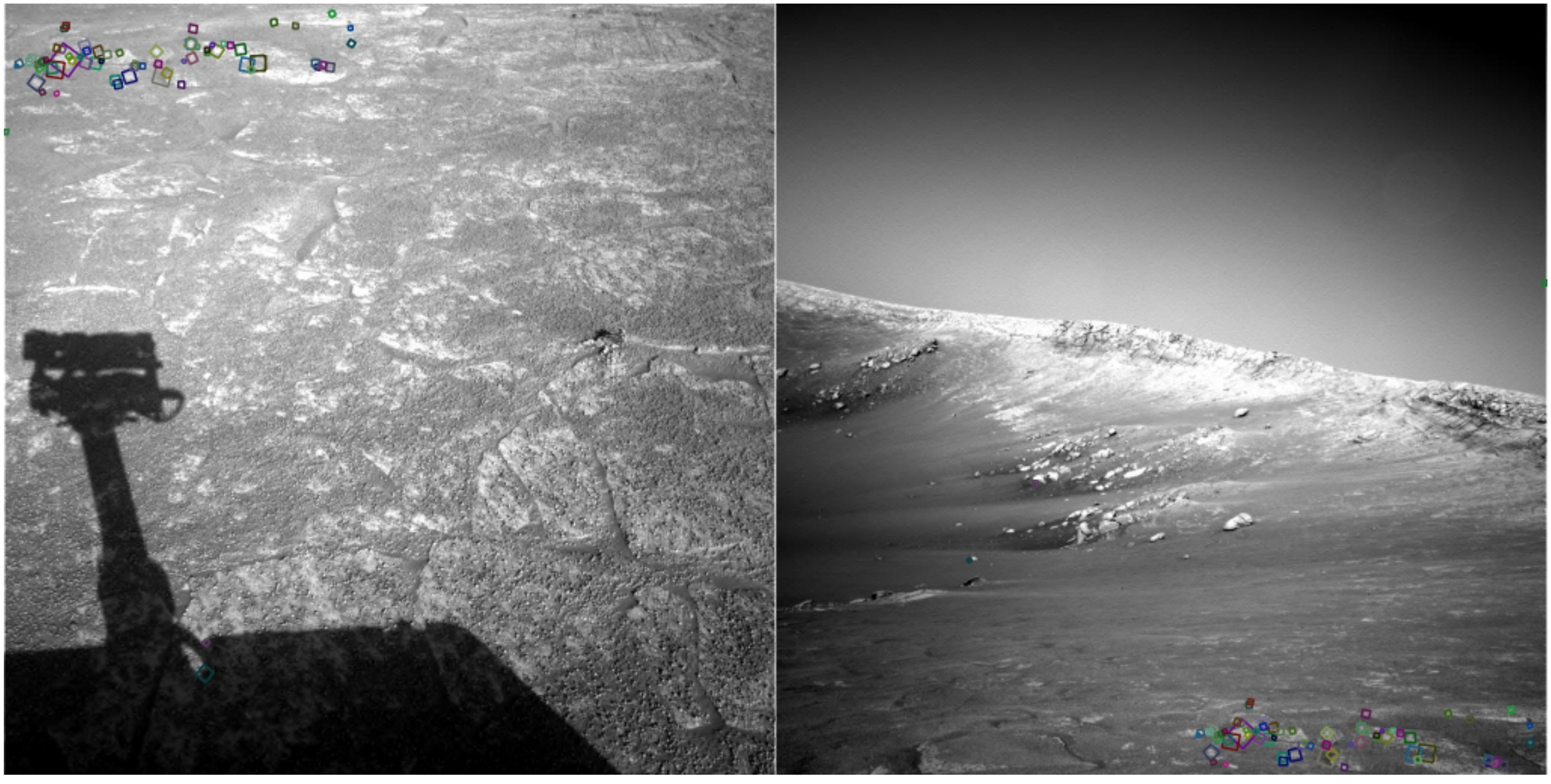
Slide credit: Olga Russakovsky

Can you find the matches?



NASA Mars Rover images

Slide credit: S. Lazebnik

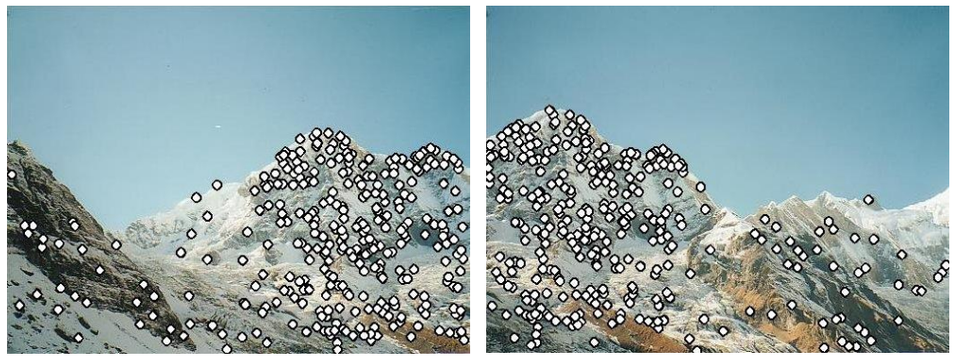


NASA Mars Rover images
with SIFT feature matches
Figure by Noah Snavely

Slide credit: S. Lazebnik

Discussion

- *Design a feature point matching scheme.*
- Two images, I_1 and I_2



- Two sets X_1 and X_2 of feature points
  - Each feature point $\mathbf{x_1}$ has a descriptor $\mathbf{x}_1 = [x_1^{(1)}, \ldots, x_d^{(1)}]$

- Distance, bijective/injective/surjective, noise, confidence, computational complexity, generality…

Slide credit: James Hays

Distance Metric

- Euclidean distance:

$$\mathrm{d}(\mathbf{p}, \mathbf{q}) = \mathrm{d}(\mathbf{q}, \mathbf{p}) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2}$$

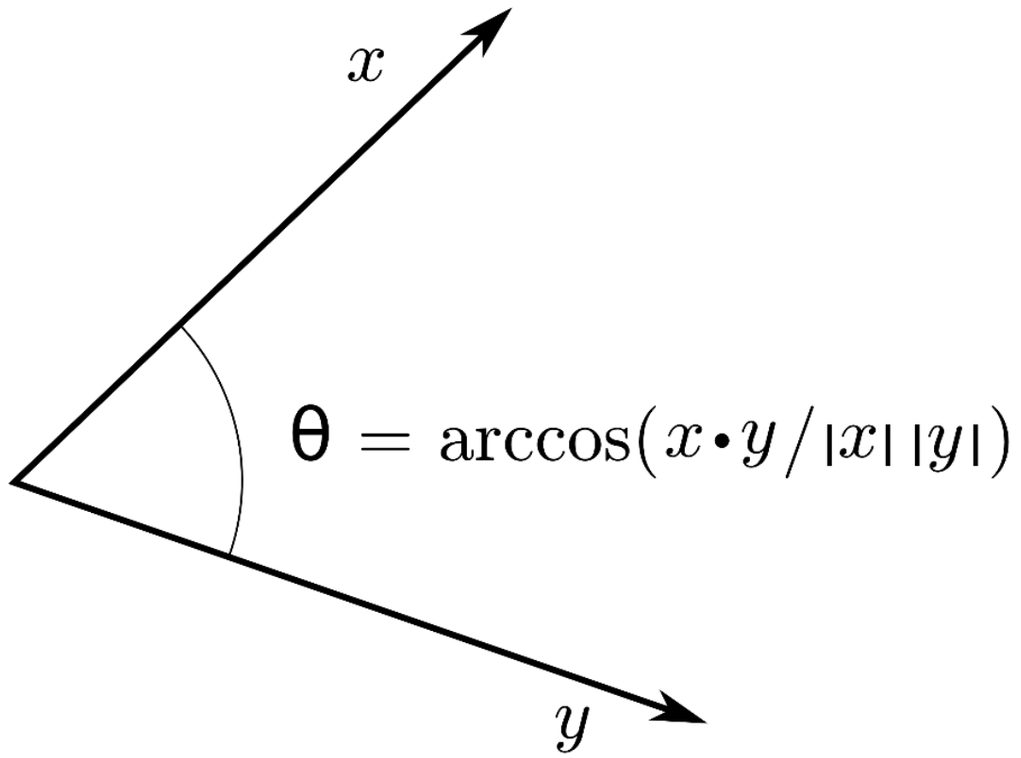
$$= \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}.$$

$$\|\mathbf{q} - \mathbf{p}\| = \sqrt{(\mathbf{q} - \mathbf{p}) \cdot (\mathbf{q} - \mathbf{p})}.$$

- Cosine similarity:

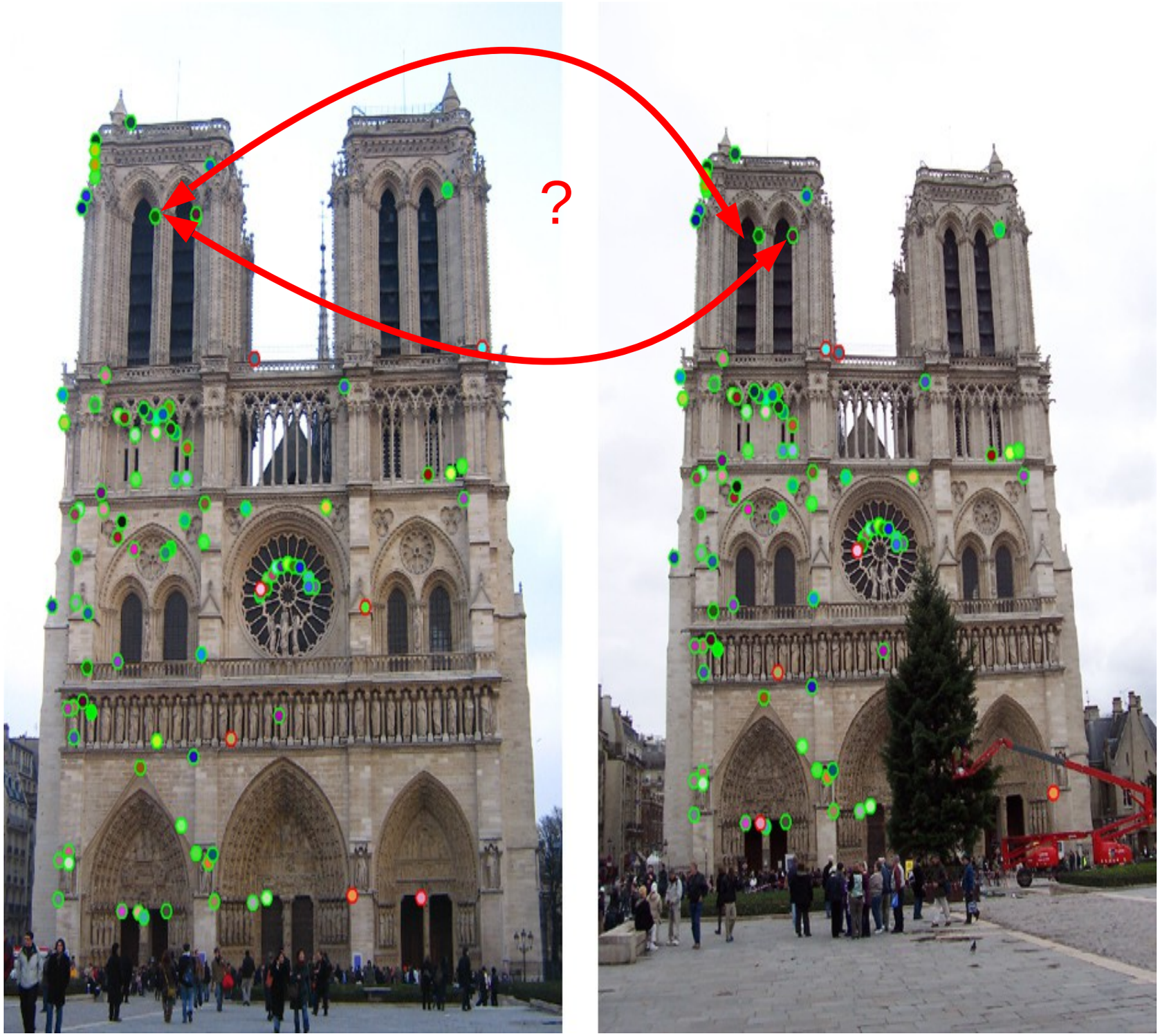
$$\mathbf{a} \cdot \mathbf{b} = \|\mathbf{a}\|_2 \|\mathbf{b}\|_2 \cos\theta$$

$$\mathbf{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|_2 \|\mathbf{B}\|_2}$$



Wikipedia

Matching Ambiguity



Locally, feature matches are ambiguous

=> need to fit a **model** to find globally consistent matches

Slide credit: James Hays

Feature Matching

- Criteria 1:
  - Compute distance in feature space, e.g., Euclidean distance between 128-dim SIFT descriptors
  - Match point to lowest distance (nearest neighbor)

- Problems:
  - Does everything have a match?

Slide credit: James Hays

Feature Matching

- Criteria 2:
  - Compute distance in feature space, e.g., Euclidean distance between 128-dim SIFT descriptors
  - Match point to lowest distance (nearest neighbor)
  - Ignore anything higher than threshold (no match!)

- Problems:
  - Threshold is hard to pick
  - Non-distinctive features could have lots of close matches, only one of which is correct

Slide credit: James Hays

Nearest Neighbor Distance Ratio

Compare distance of closest (NN1) and second-closest (NN2) feature vector neighbor.

- If NN1 ≈ NN2, ratio $\frac{NN1}{NN2}$ will be ≈ 1 -> matches too close.
- As NN1 << NN2, ratio $\frac{NN1}{NN2}$ tends to 0.

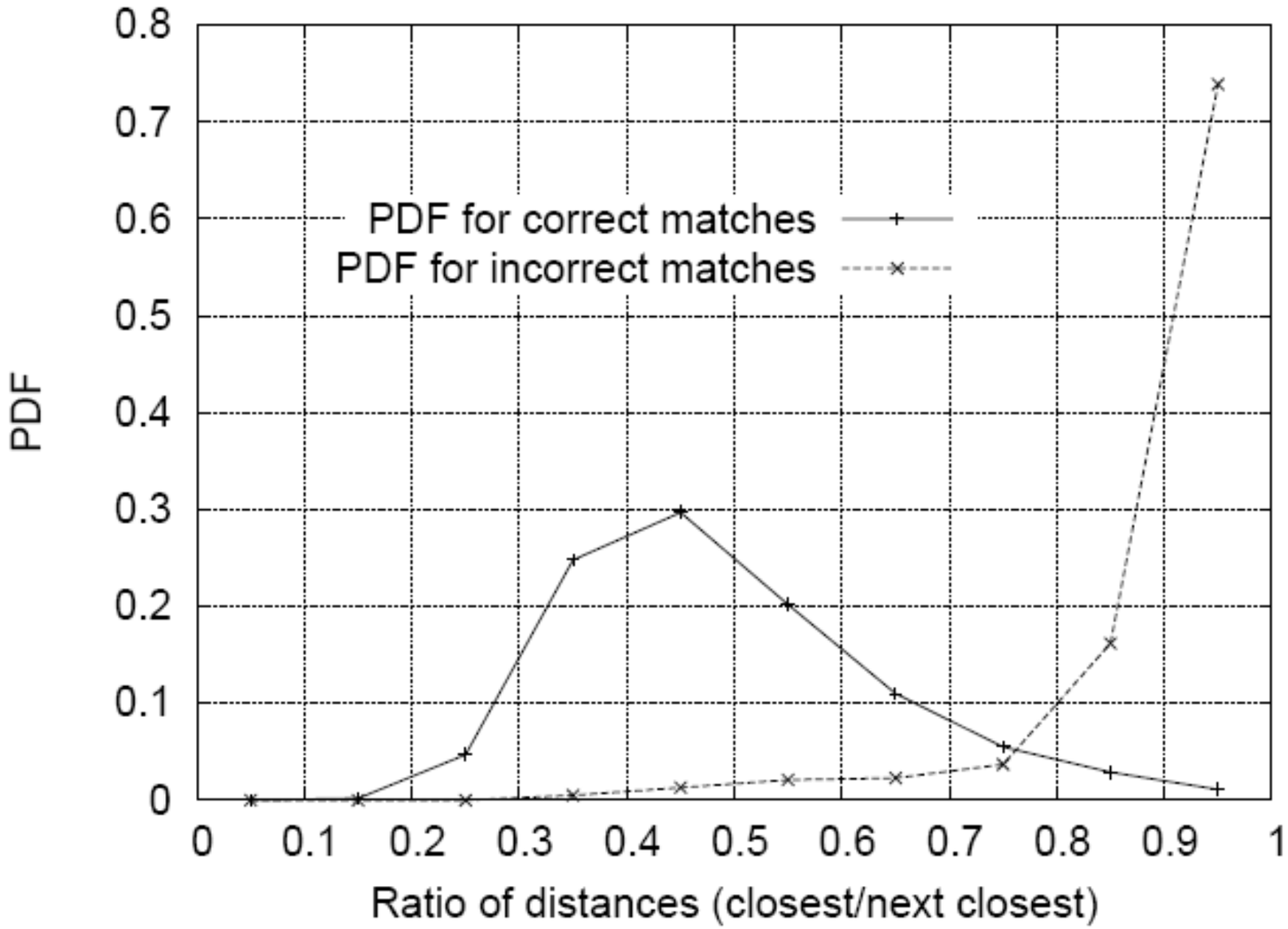
Sorting by this ratio puts matches in order of confidence.

Threshold ratio – but how to choose?

Slide credit: James Hays

Nearest Neighbor Distance Ratio

- Lowe computed a probability distribution functions of ratios
- 40,000 keypoints with hand-labeled ground truth



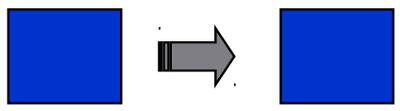
Ratio threshold depends on your application's view on the trade-off between the number of false positives and true positives!

Lowe IJCV 2004

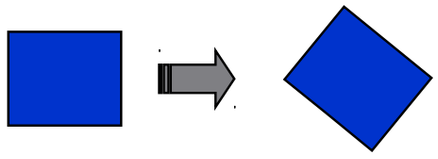
What is the transformation between these images?

Transformation Models

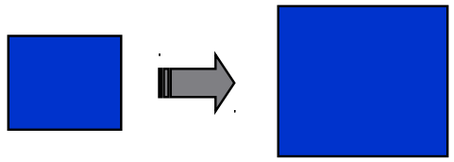
- Translation only



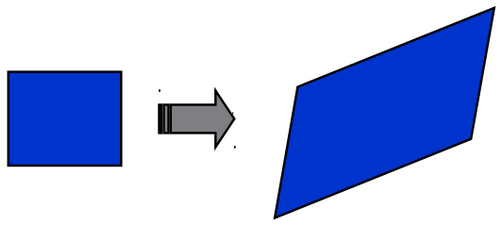
- Rigid body (translate+rotate)



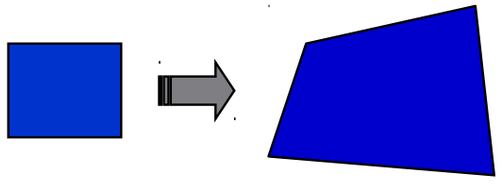
- Similarity (translate+rotate+scale)



- Affine



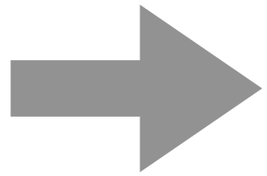
- Homography (projective)



Homogenous Coordinates

Cartesian:

$$P = (x, y)$$



Homogenous:

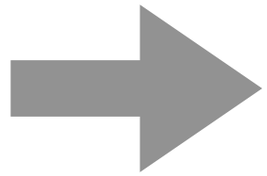
$$\tilde{P} = (x, y, 1)$$

Slide credit: Peter Corke

Homogenous Coordinates

Cartesian:

$$P = (x, y)$$



Homogenous:

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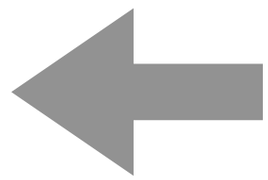
Homogenous:



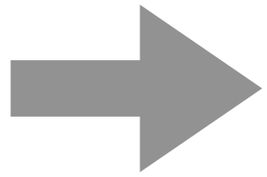
$$\tilde{P} = (\tilde{x}, \tilde{y}, \tilde{z})$$

Slide credit: Peter Corke

Homogenous Coordinates

Cartesian:

$$P = (x, y)$$

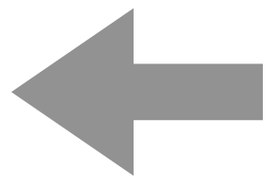


Homogenous:

$$\tilde{P} = (x, y, 1)$$

Cartesian:

$$P = \left(\frac{\tilde{x}}{\tilde{z}}, \frac{\tilde{y}}{\tilde{z}} \right)$$

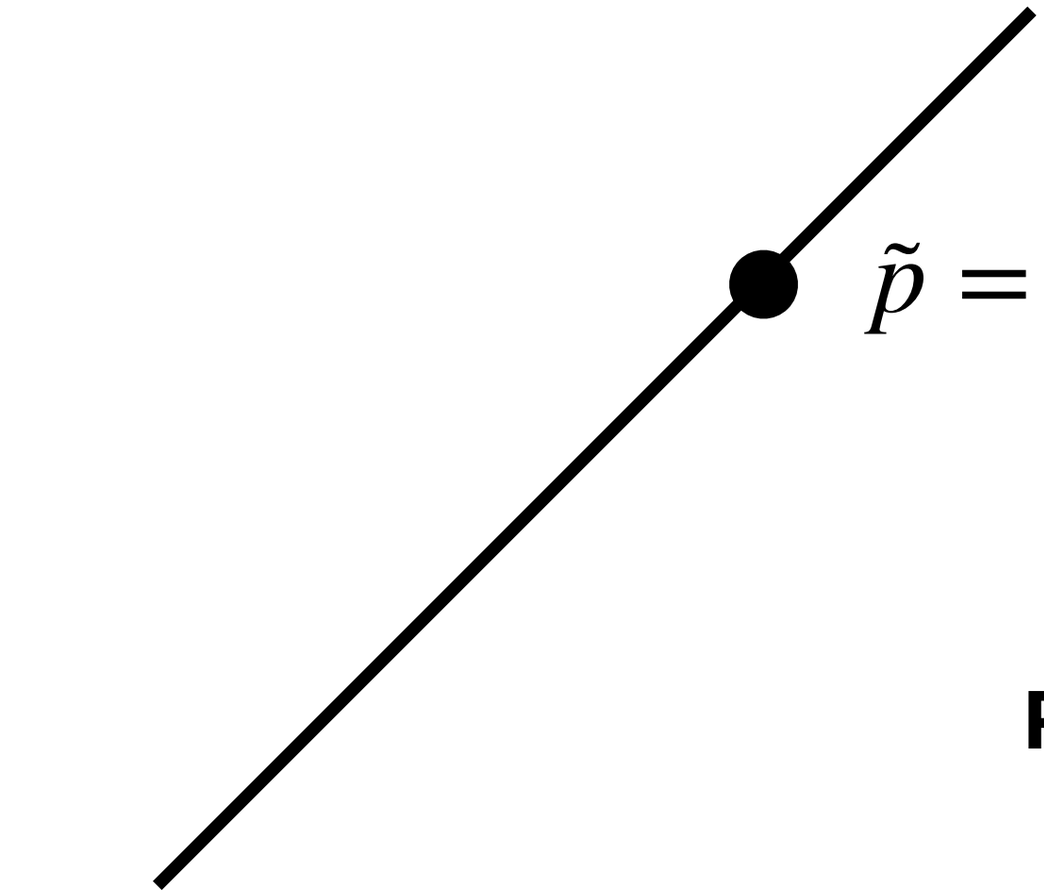


Homogenous:

$$\tilde{P} = (\tilde{x}, \tilde{y}, \tilde{z})$$

Slide credit: Peter Corke

Lines and Points are Duals

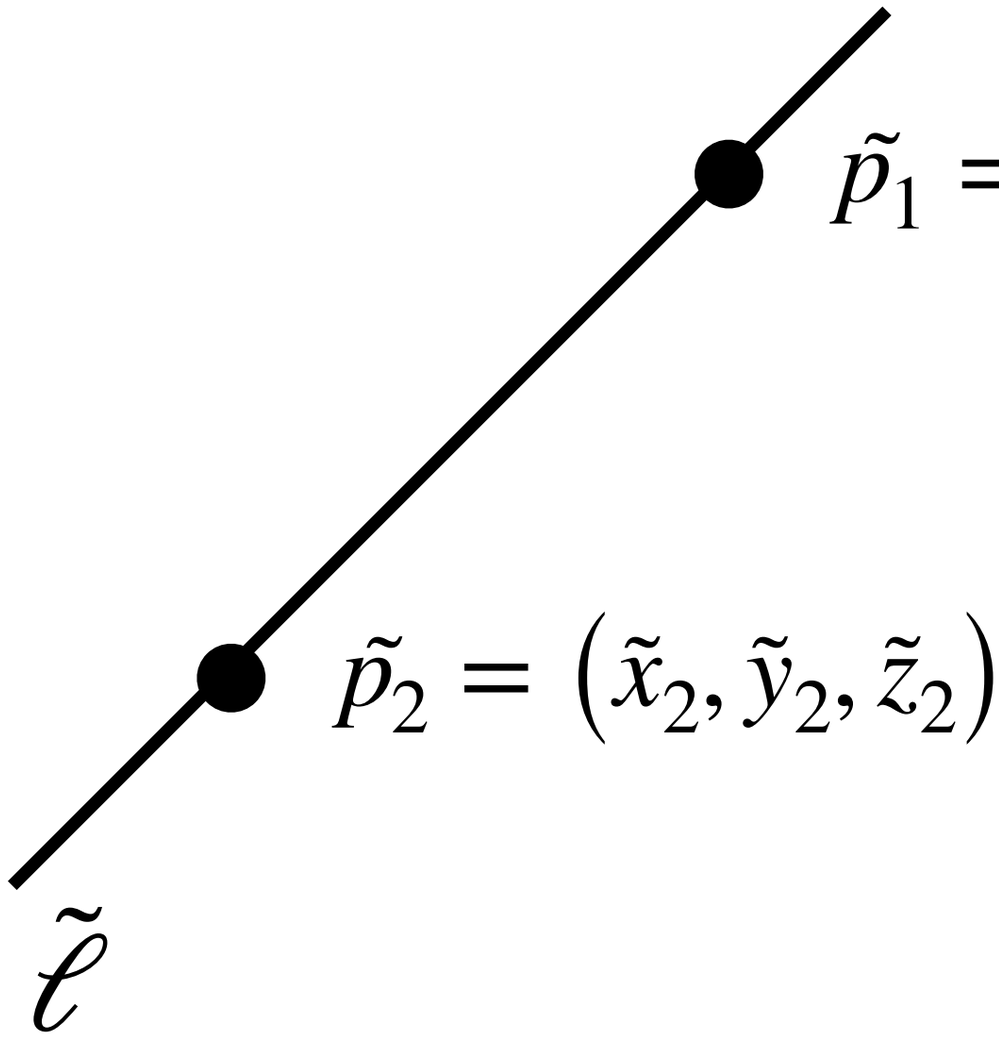


Point Equation of a Line:

$$\tilde{\ell}^T \tilde{p} = 0$$

$$l_1 \tilde{x} + l_2 \tilde{y} + l_3 \tilde{z} = 0$$

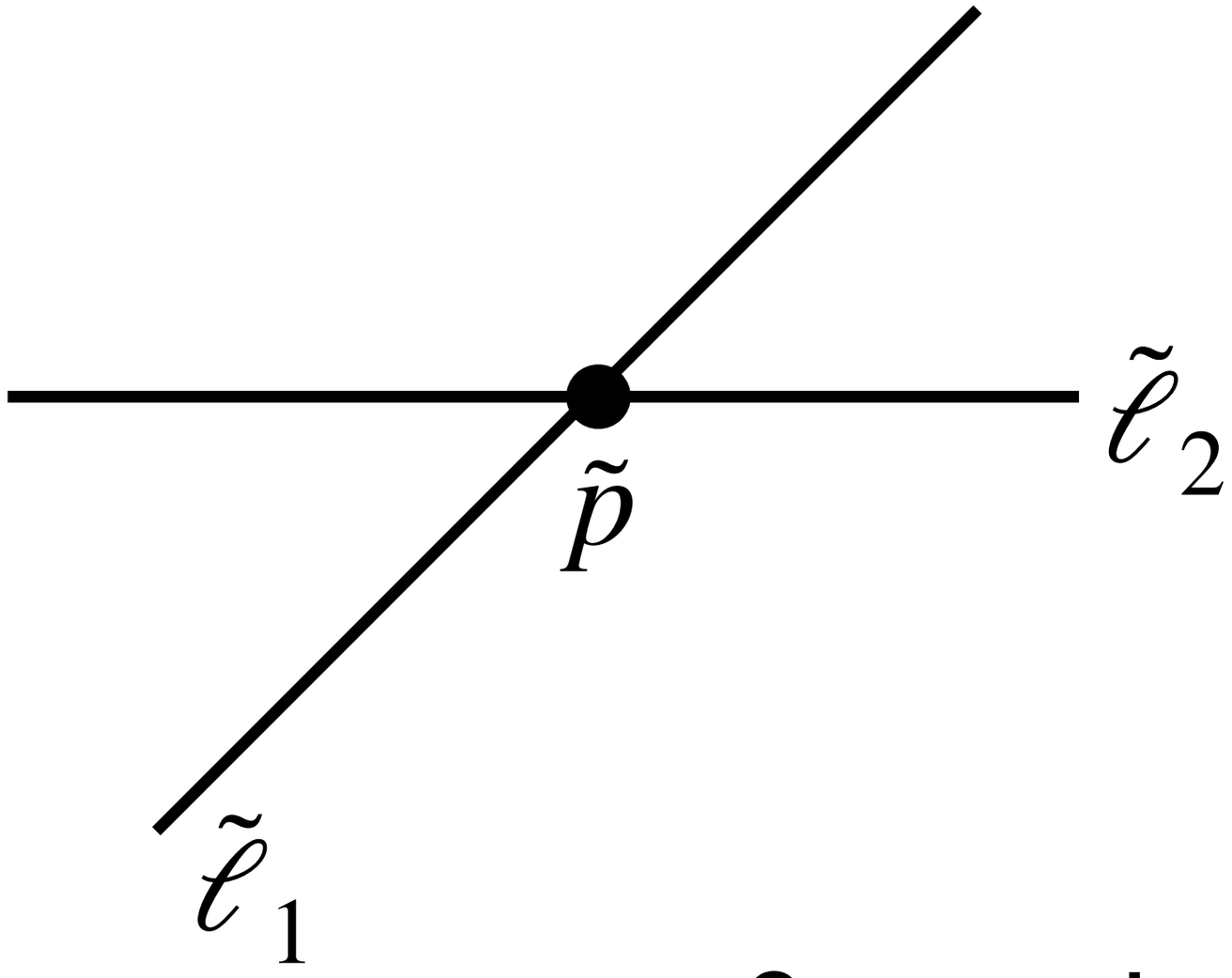
Slide credit: Peter Corke



Cross product of two points is a line:

$$\tilde{\ell} = \tilde{p}_1 \times \tilde{p}_2$$

Slide credit: Peter Corke

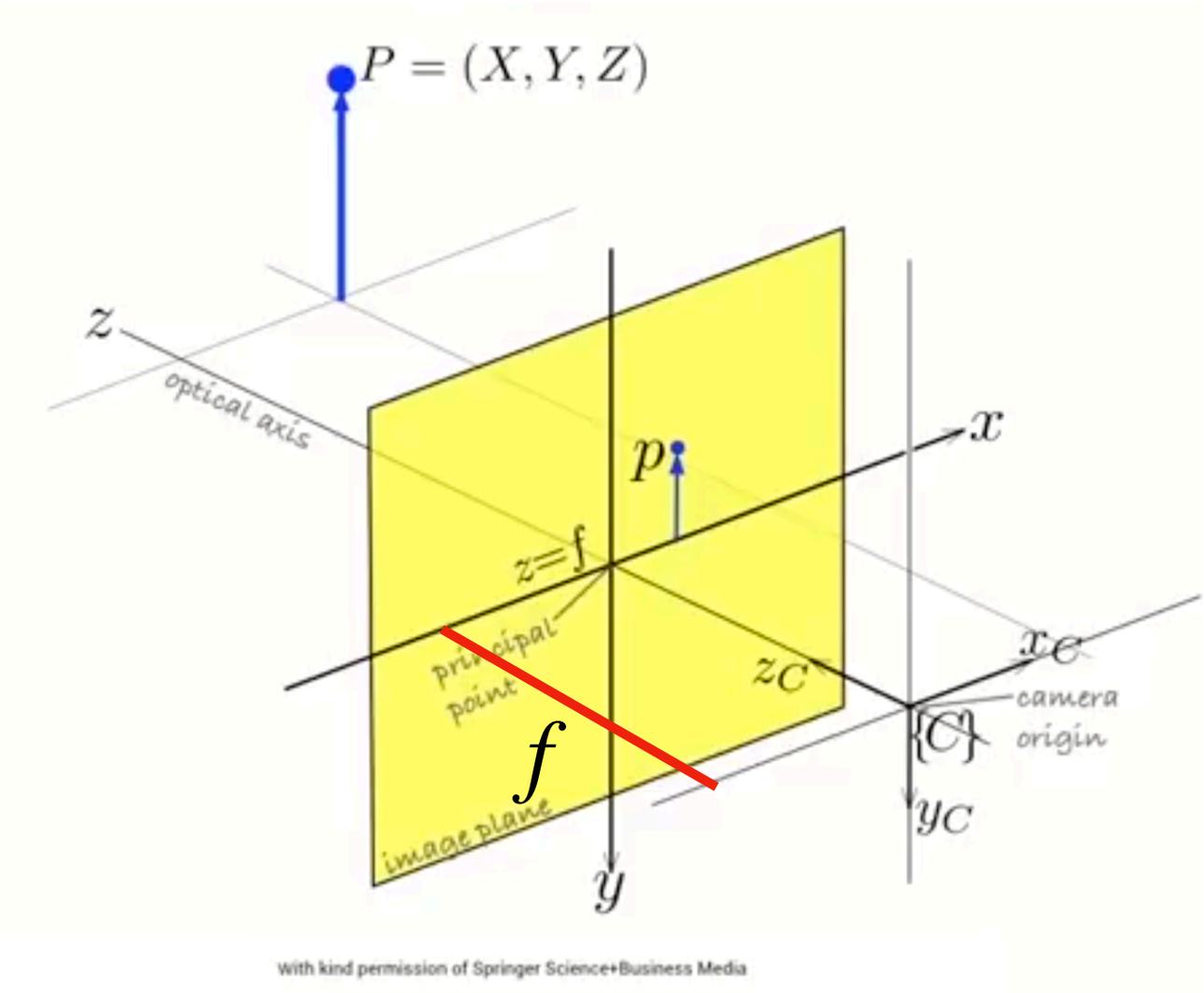


Cross product of two lines is a point:

$$\tilde{p} = \tilde{\ell}_1 \times \tilde{\ell}_2$$

Slide credit: Peter Corke

Central Projection Model



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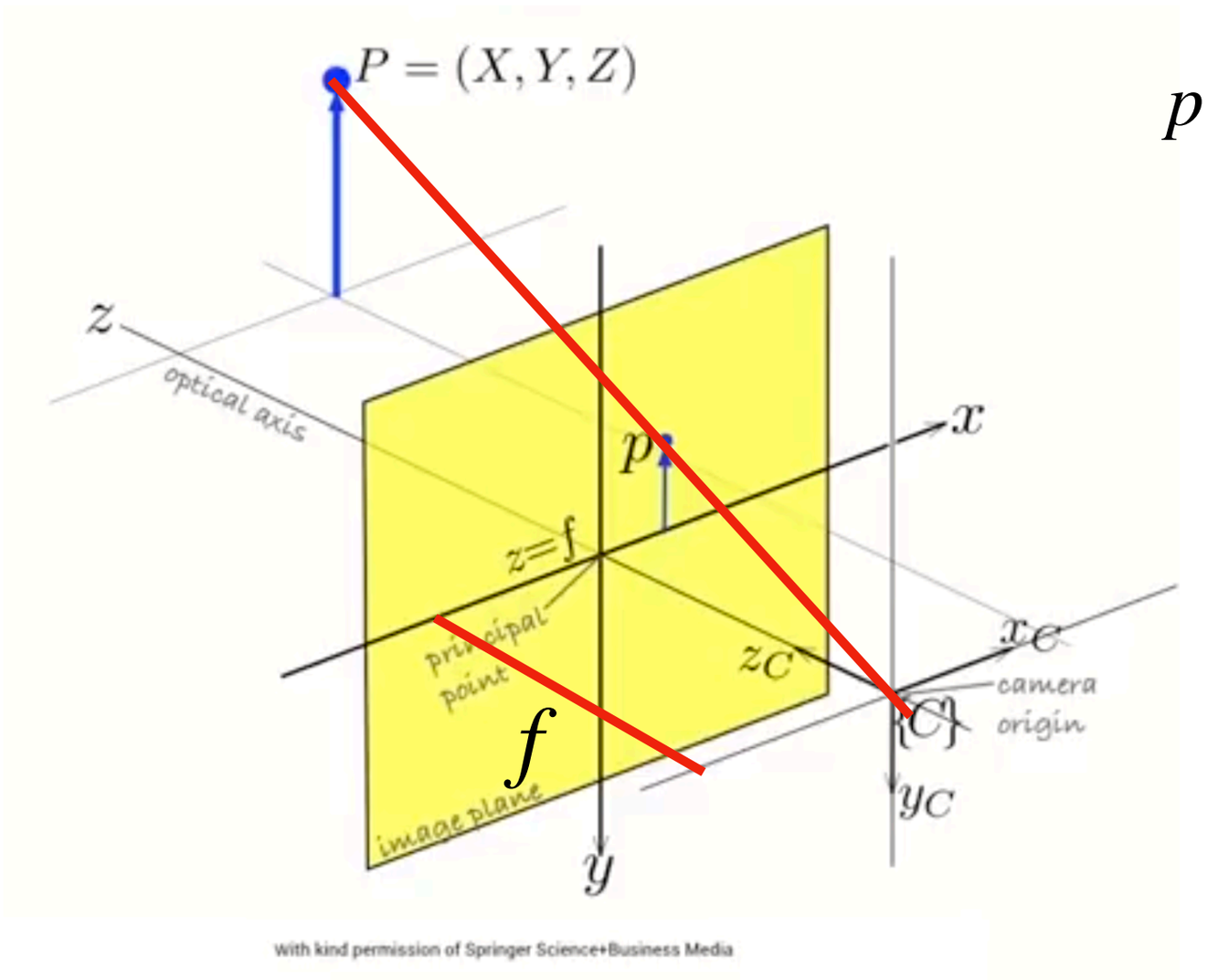
Central Projection Model



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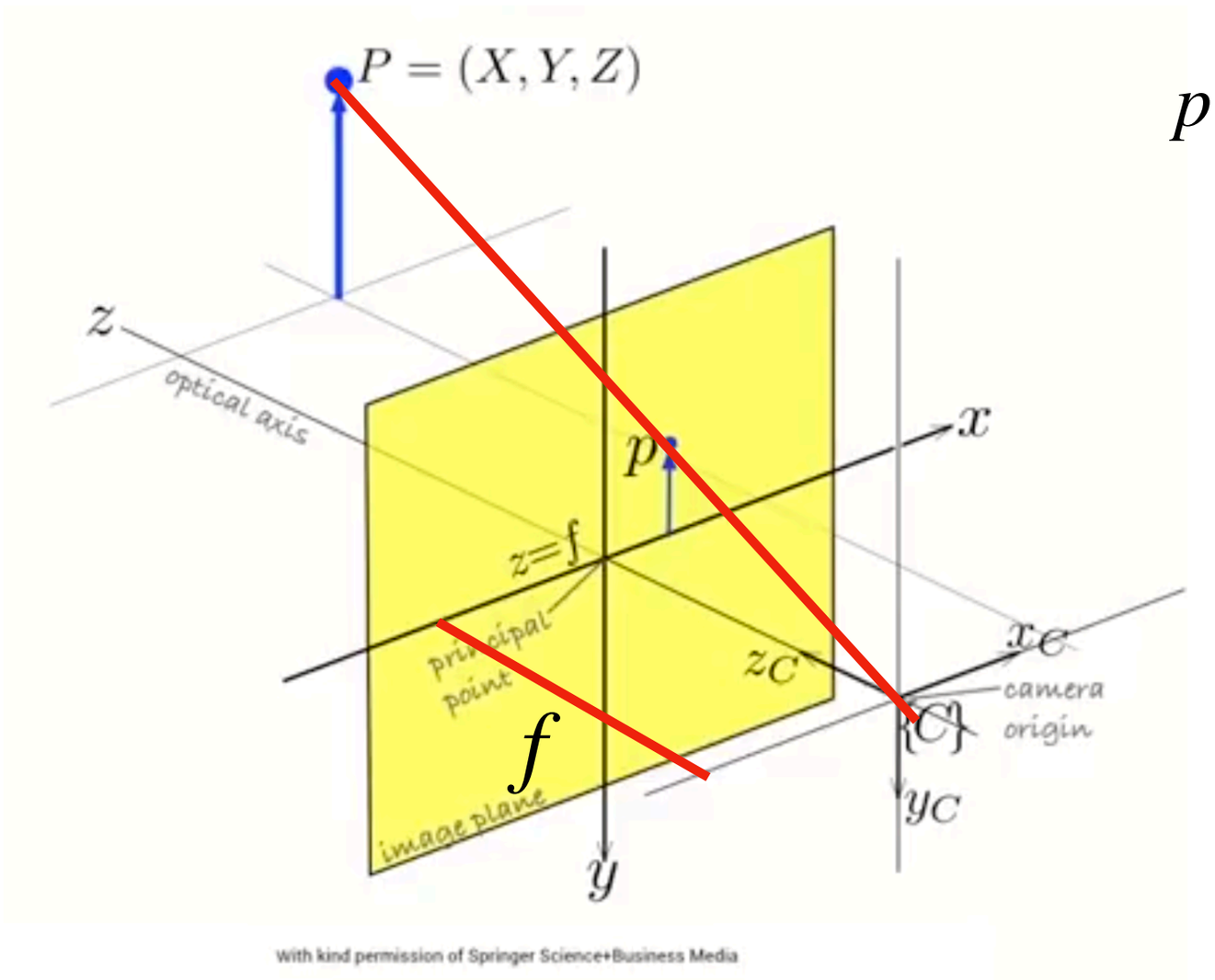
$$p = \begin{pmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$$

Slide credit: Peter Corke

Central Projection Model



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$$p = \begin{pmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \end{pmatrix}$$

What if the camera moves?

Slide credit: Peter Corke

Review: 3D Transformations

3D translations

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} + T = \begin{bmatrix} X + t_x \\ Y + t_y \\ Z + t_z \end{bmatrix}$$

3D rotations

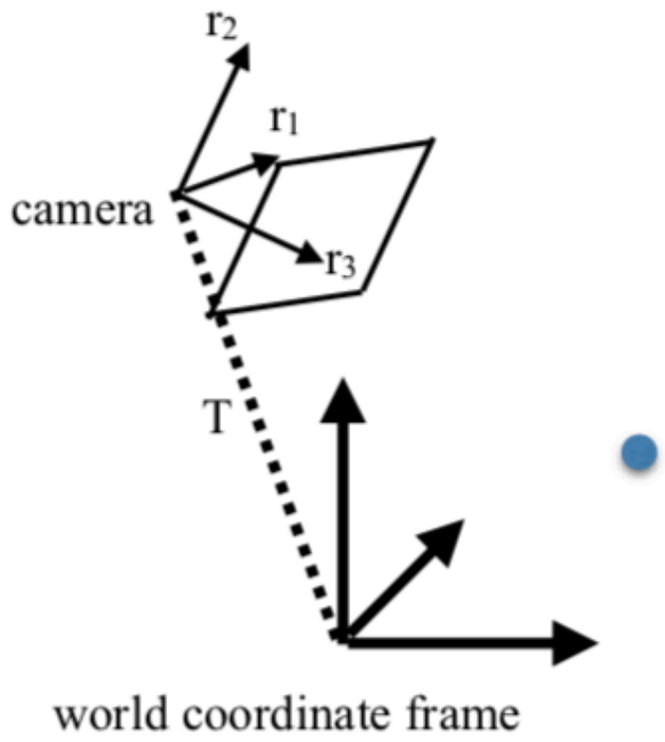
$$R \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

$$R \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} + T = \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Slide credit: Deva Ramanan

Change of Coordinate System

$$R\begin{bmatrix}X\\Y\\Z\end{bmatrix}+T=\begin{bmatrix}r_{11} & r_{12} & r_{13} & t_x\\ r_{21} & r_{22} & r_{23} & t_y\\ r_{31} & r_{32} & r_{33} & t_z\end{bmatrix}\begin{bmatrix}X\\Y\\Z\\1\end{bmatrix}$$



Slide credit: Deva Ramanan

Camera Projection

$$\begin{pmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_x \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

Camera Intrinsics

Camera Extrinsics

World Coordinates

Camera Matrix

Mapping points from the world to image coordinates is matrix multiplication in homogenous coordinates

$$\begin{pmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} C_{11} & C_{12} & C_{13} & C_{14} \\ C_{21} & C_{22} & C_{23} & C_{24} \\ C_{31} & C_{32} & C_{33} & C_{34} \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

Scale Invariance

$$\begin{pmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{pmatrix} = \lambda \begin{pmatrix} C_{11} & C_{12} & C_{13} & C_{14} \\ C_{21} & C_{22} & C_{23} & C_{24} \\ C_{31} & C_{32} & C_{33} & C_{34} \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

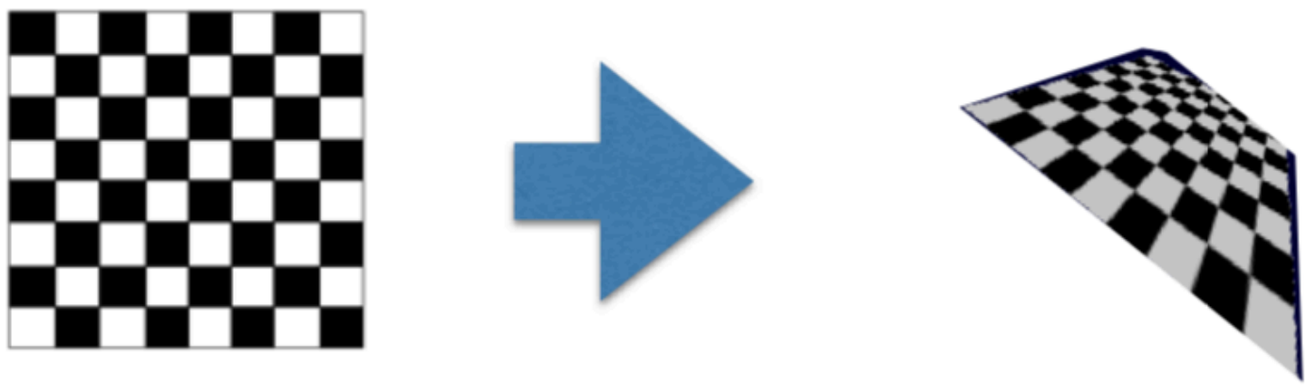
$$x = \frac{\tilde{x}}{\tilde{z}} = \frac{\lambda \tilde{x}}{\lambda \tilde{z}} \qquad y = \frac{\tilde{y}}{\tilde{z}} = \frac{\lambda \tilde{y}}{\lambda \tilde{z}}$$

Normalized Camera Matrix

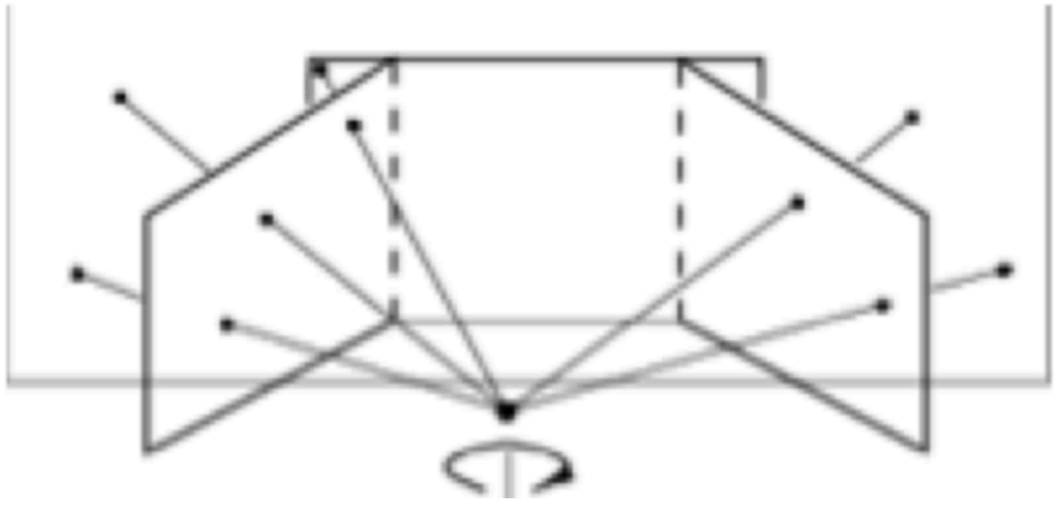
$$\begin{pmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} C_{11} & C_{12} & C_{13} & C_{14} \\ C_{21} & C_{22} & C_{23} & C_{24} \\ C_{31} & C_{32} & C_{33} & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

Homography

1. Models perspective effects for a planar scene

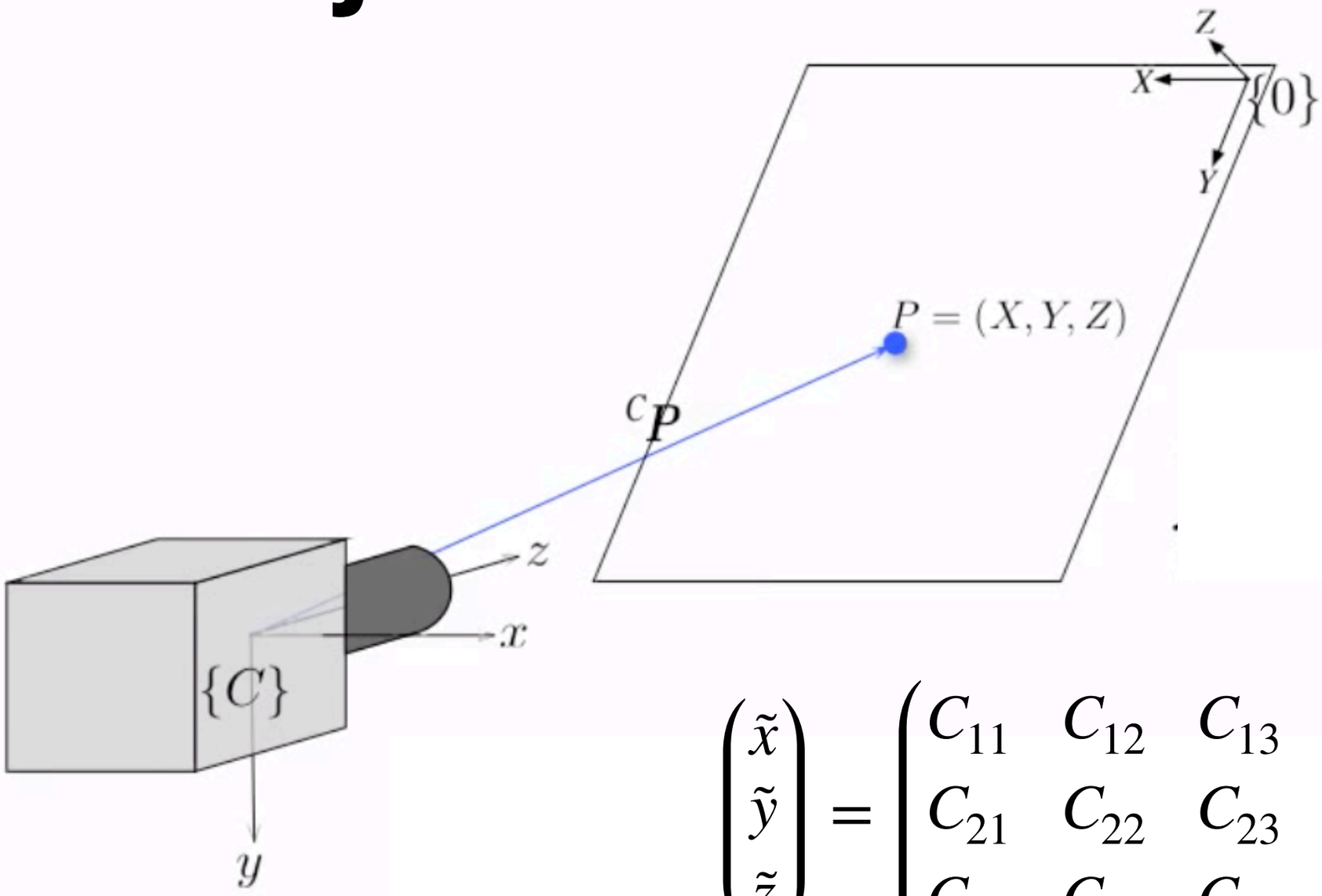


2. Models perspective effects from camera rotations



Slide credit: Deva Ramanan

Projection of 3D Plane

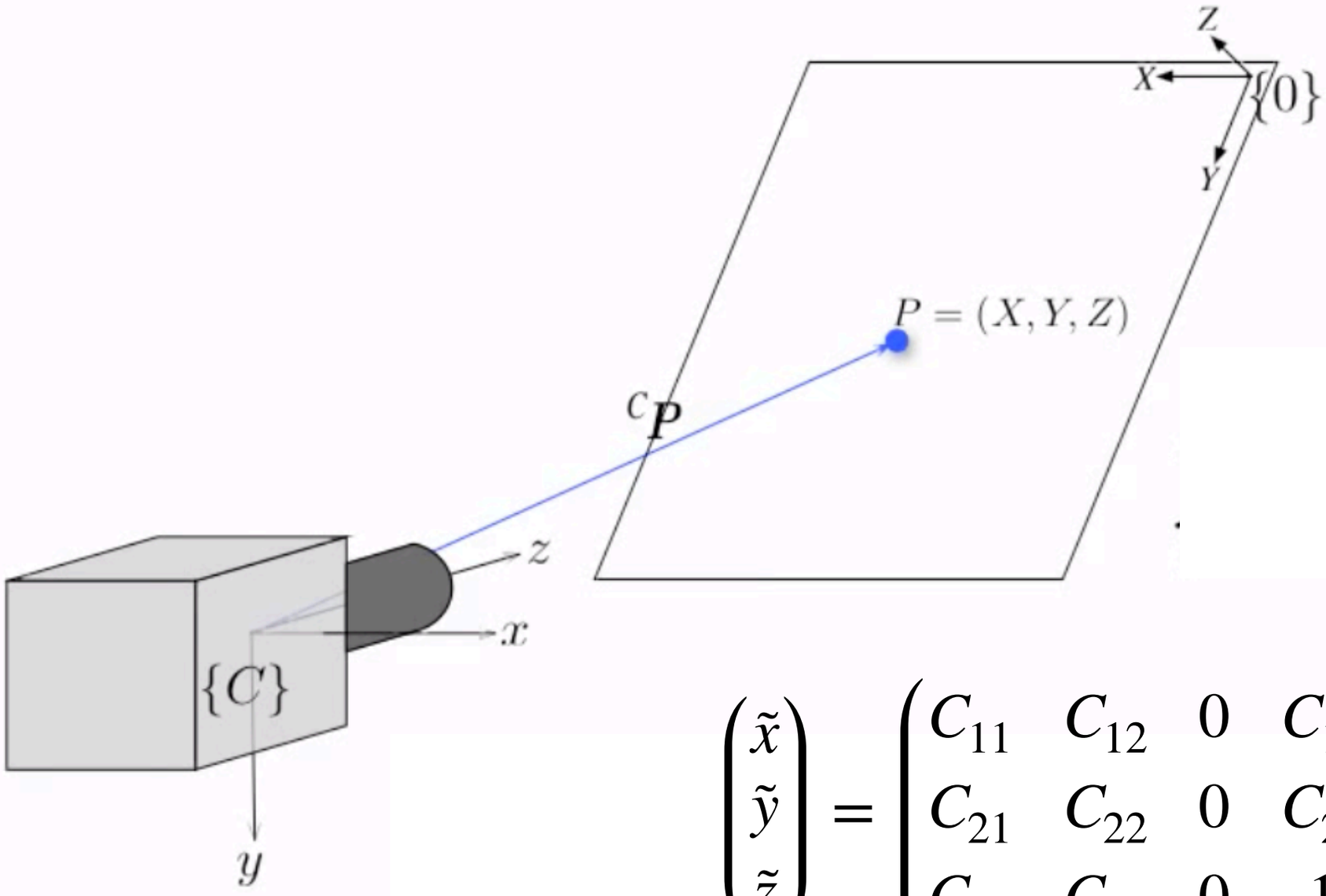


All points on the plane have Z = 0

$$\begin{pmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} C_{11} & C_{12} & C_{13} & C_{14} \\ C_{21} & C_{22} & C_{23} & C_{24} \\ C_{31} & C_{32} & C_{33} & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ 0 \\ 1 \end{pmatrix}$$

Slide credit: Peter Corke

Proiection of 3D Plane

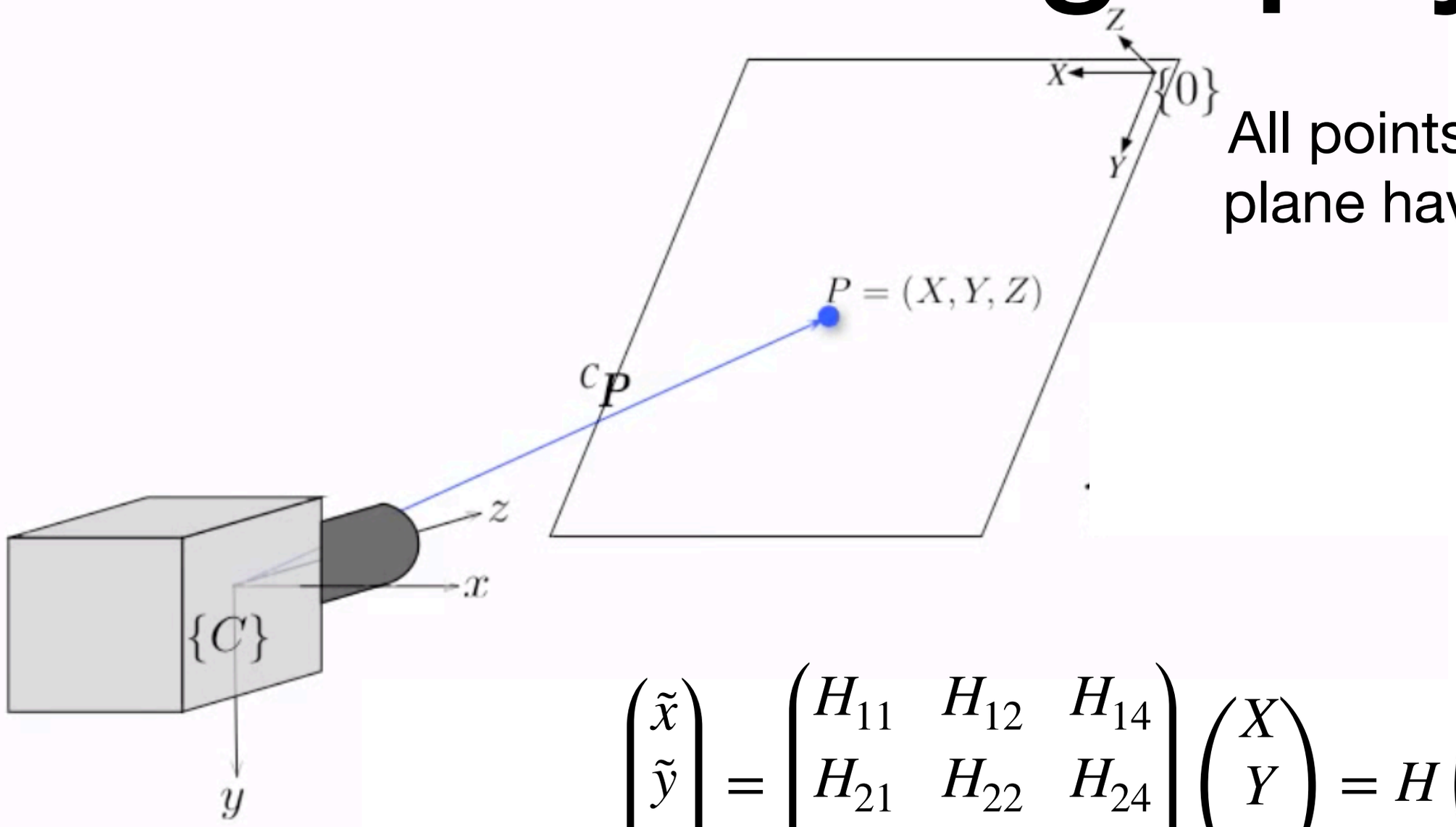


All points on the plane have Z = 0

$$\begin{pmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} C_{11} & C_{12} & 0 & C_{14} \\ C_{21} & C_{22} & 0 & C_{24} \\ C_{31} & C_{32} & 0 & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ 0 \\ 1 \end{pmatrix}$$

Slide credit: Peter Corke

Planar Homography

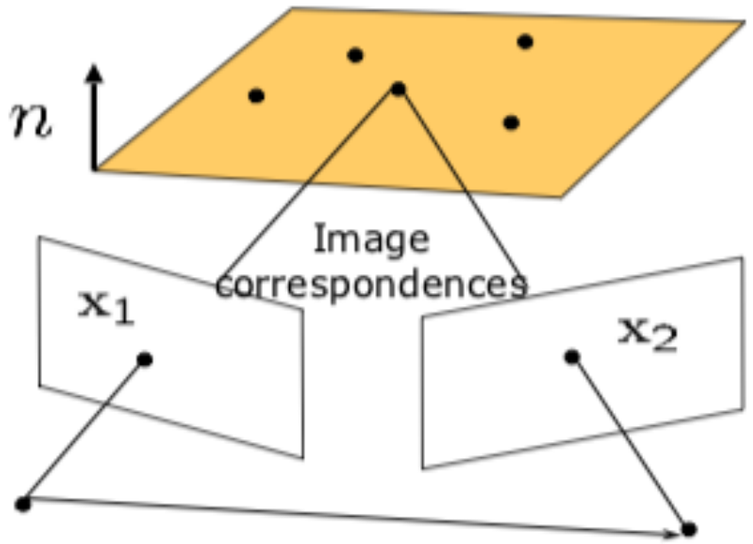


All points on the plane have Z = 0

$$\begin{pmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{z} \end{pmatrix} = \begin{pmatrix} H_{11} & H_{12} & H_{14} \\ H_{21} & H_{22} & H_{24} \\ H_{31} & H_{32} & 1 \end{pmatrix} \begin{pmatrix} X \\ Y \\ 1 \end{pmatrix} = H \begin{pmatrix} X \\ Y \\ 1 \end{pmatrix}$$

Slide credit: Peter Corke

Two-views of Plane

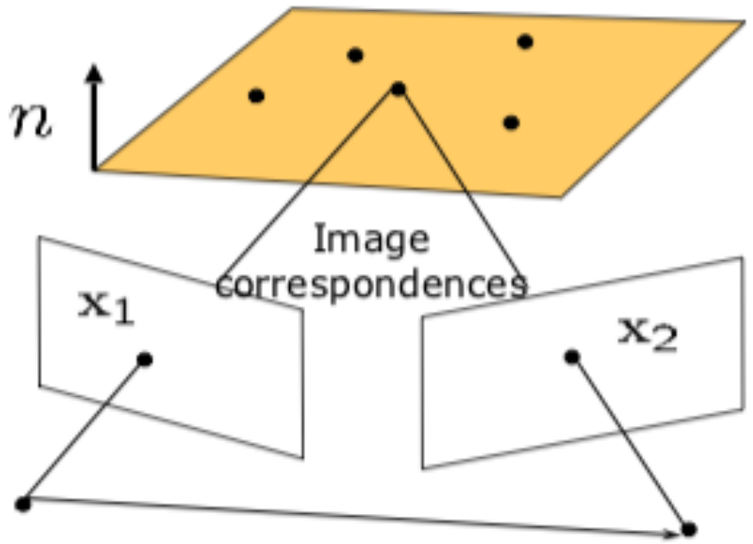


$$\begin{pmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \tilde{z}_1 \end{pmatrix} = H_1 \begin{pmatrix} X \\ Y \\ 1 \end{pmatrix} \qquad \begin{pmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{pmatrix} = H_2 \begin{pmatrix} X \\ Y \\ 1 \end{pmatrix}$$

If you know both H and (x1, y1),
what is (x2, y2)?

Slide credit: Deva Ramanan

Two-views of Plane

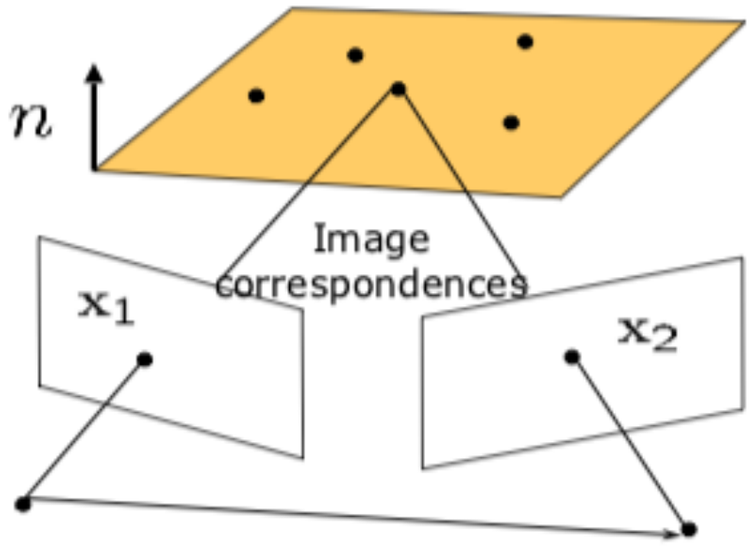


$$\begin{pmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \tilde{z}_1 \end{pmatrix} = H_1 \begin{pmatrix} X \\ Y \\ 1 \end{pmatrix} \qquad \begin{pmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{pmatrix} = H_2 \begin{pmatrix} X \\ Y \\ 1 \end{pmatrix}$$

$$\begin{pmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{pmatrix} = H_2 H_1^{-1} \begin{pmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \tilde{z}_1 \end{pmatrix}$$

Slide credit: Deva Ramanan

Estimating Homography



How many corresponding points do you need to estimate H?

$$\begin{pmatrix} \tilde{x}_2 \\ \tilde{y}_2 \\ \tilde{z}_2 \end{pmatrix} = H \begin{pmatrix} \tilde{x}_1 \\ \tilde{y}_1 \\ \tilde{z}_1 \end{pmatrix}$$

Slide credit: Deva Ramanan

Estimating Homography (details)

$$\begin{bmatrix} {\scriptstyle \mathrm{w}} x_i' \\ {\scriptstyle \mathrm{w}} y_i' \\ {\scriptstyle \mathrm{w}} \end{bmatrix} \cong \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}$$

$$x_i' = \frac{h_{00}x_i + h_{01}y_i + h_{02}}{h_{20}x_i + h_{21}y_i + h_{22}}$$

$$y_i' = \frac{h_{10}x_i + h_{11}y_i + h_{12}}{h_{20}x_i + h_{21}y_i + h_{22}}$$

$$\begin{aligned} x_i'(h_{20}x_i + h_{21}y_i + h_{22}) &= h_{00}x_i + h_{01}y_i + h_{02} \\ y_i'(h_{20}x_i + h_{21}y_i + h_{22}) &= h_{10}x_i + h_{11}y_i + h_{12} \end{aligned}$$

$$\begin{bmatrix} x_i & y_i & 1 & 0 & 0 & 0 & -x_i'x_i & -x_i'y_i & -x_i' \\ 0 & 0 & 0 & x_i & y_i & 1 & -y_i'x_i & -y_i'y_i & -y_i' \end{bmatrix} \begin{bmatrix} h_{00} \\ h_{01} \\ h_{02} \\ h_{10} \\ h_{11} \\ h_{12} \\ h_{20} \\ h_{21} \\ h_{22} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

Slide credit: Antonio Torralba

Estimating Homography (details)

$$\begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 & -x'_1x_1 & -x'_1y_1 & -x'_1 \\ 0 & 0 & 0 & x_1 & y_1 & 1 & -y'_1x_1 & -y'_1y_1 & -y'_1 \\ & & & & & \vdots & & & \\ x_n & y_n & 1 & 0 & 0 & 0 & -x'_nx_n & -x'_ny_n & -x'_n \\ 0 & 0 & 0 & x_n & y_n & 1 & -y'_nx_n & -y'_ny_n & -y'_n \end{bmatrix} \begin{bmatrix} h_{00} \\ h_{01} \\ h_{02} \\ h_{10} \\ h_{11} \\ h_{12} \\ h_{20} \\ h_{21} \\ h_{22} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

$$\underset{2n \times 9}{\mathbf{A}} \qquad \underset{9}{\mathbf{h}} \qquad \underset{2n}{\mathbf{0}}$$

Defines a least squares problem: $\text{minimize } \|\mathbf{Ah} - \mathbf{0}\|^2$

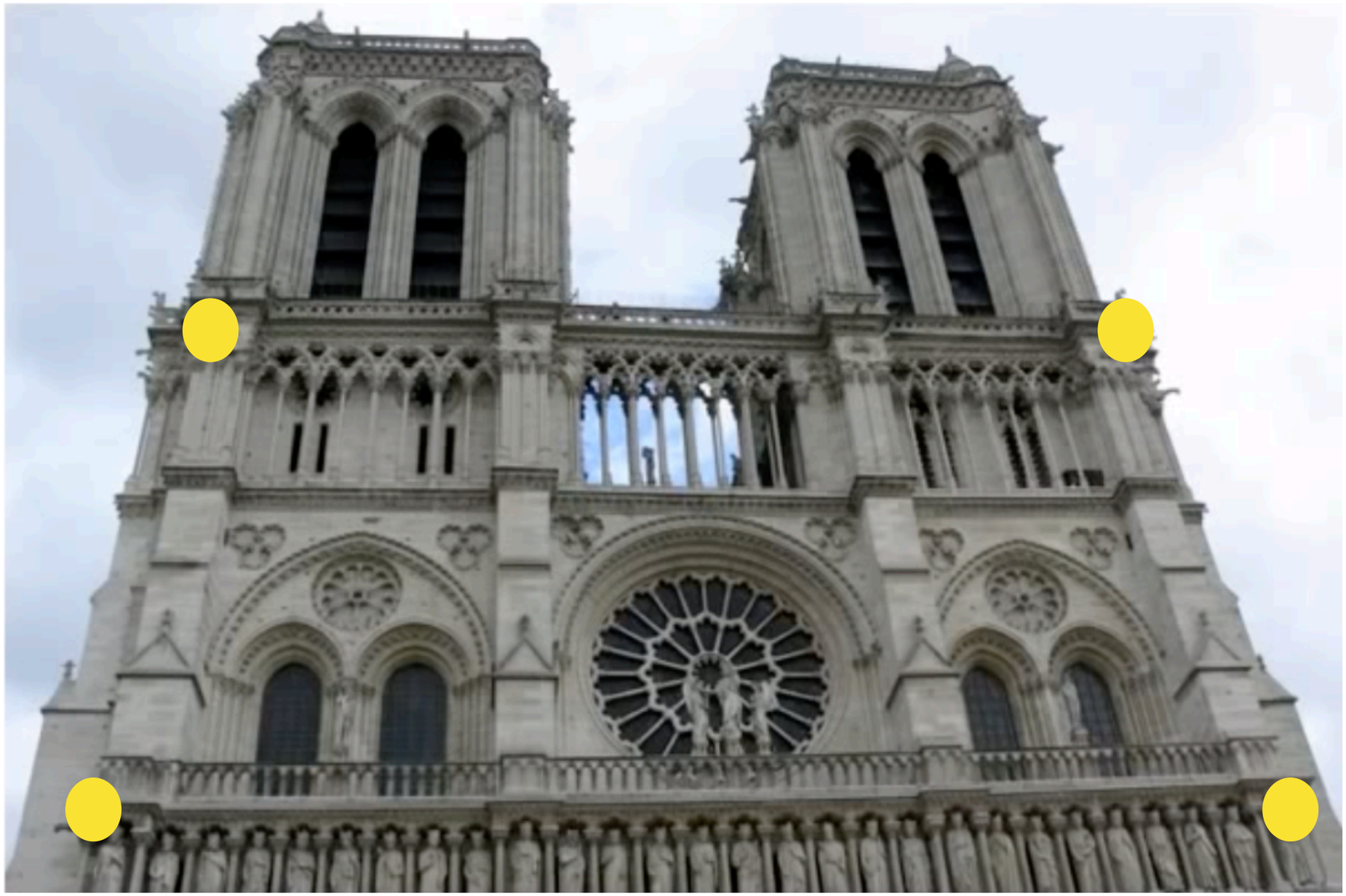
- Since h is only defined up to scale, solve for unit vector $\hat{h}$
- Solution: $\hat{h}$ = eigenvector of A^TA with smallest eigenvalue
- Works with 4 or more points

Slide credit: Antonio Torralba

Rectification

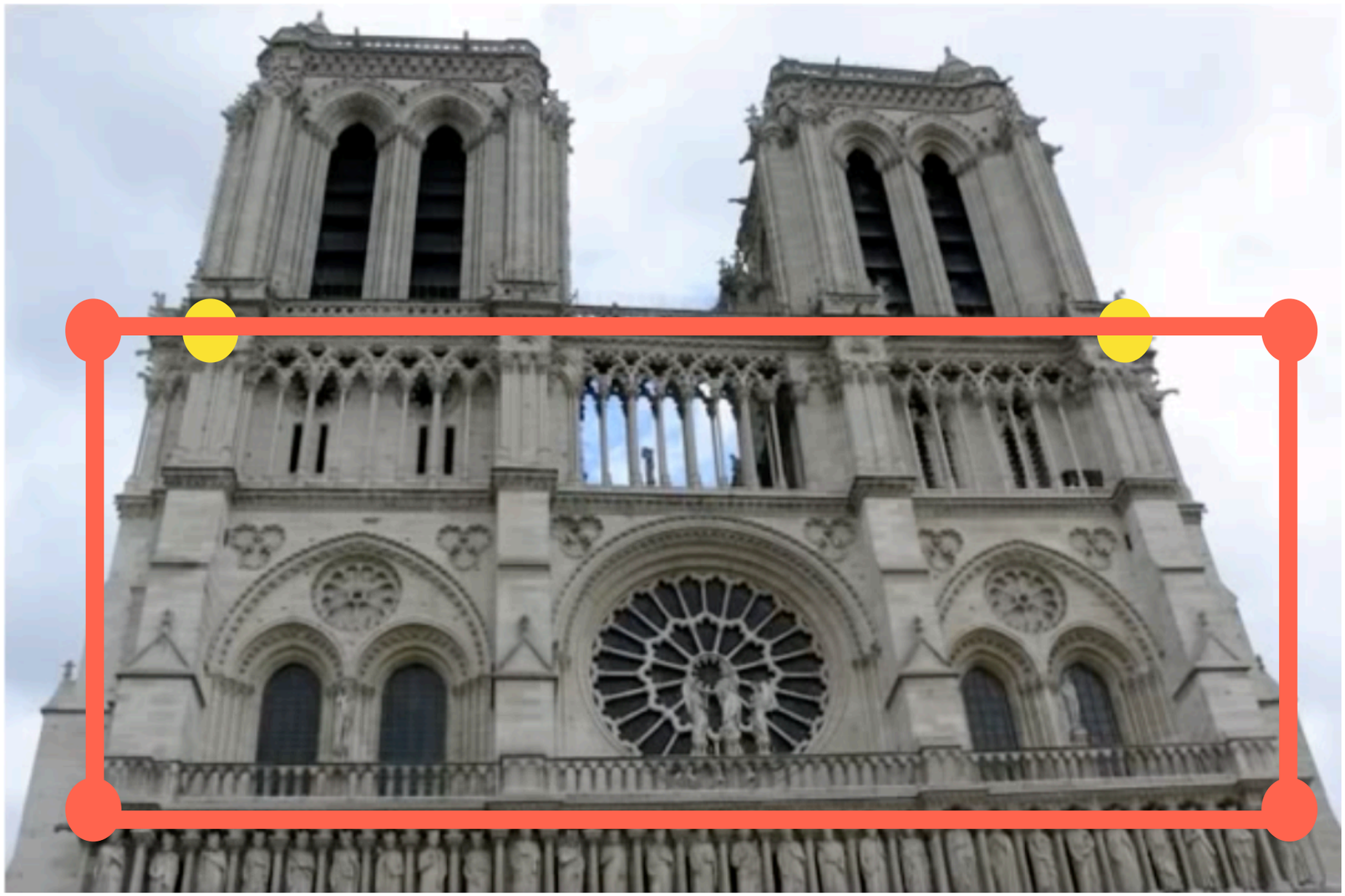
Slide credit: Peter Corke

Rectification



Slide credit: Peter Corke

Rectification

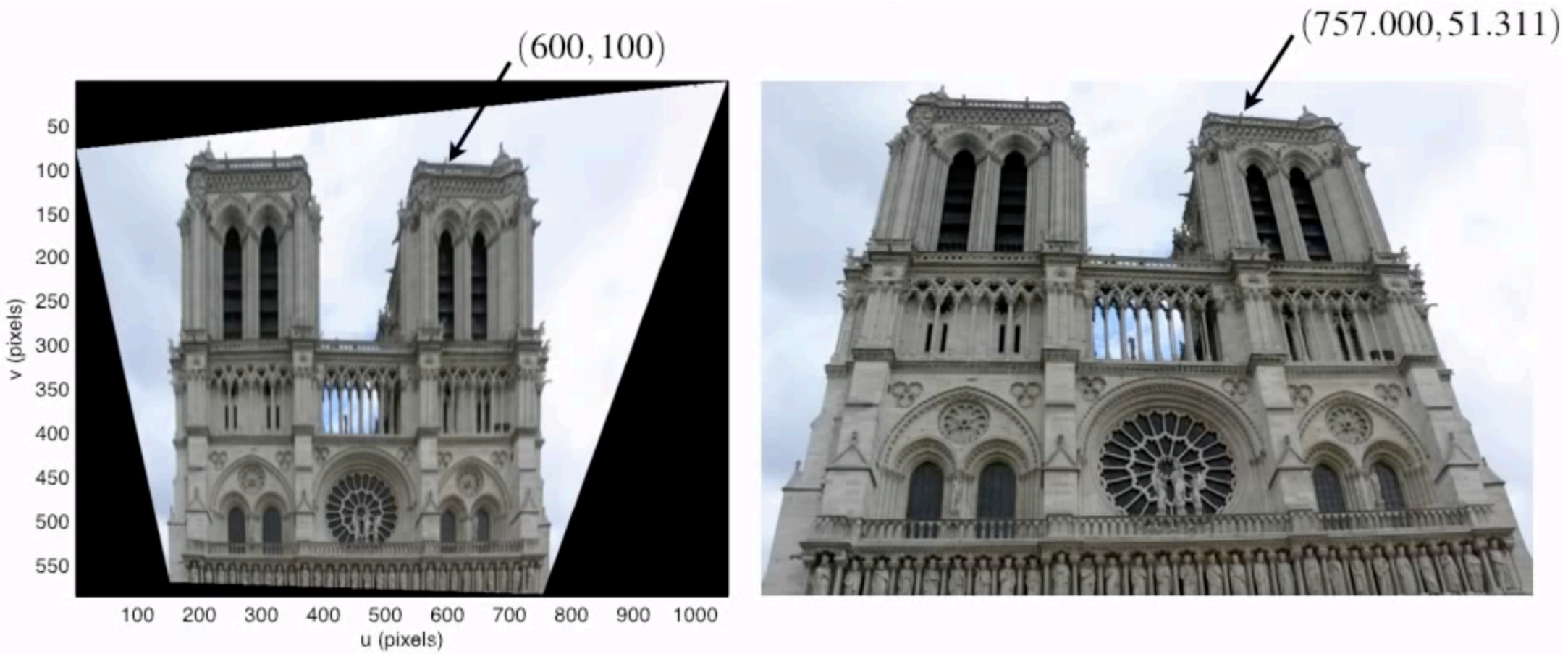


Slide credit: Peter Corke

Rectification

Slide credit: Peter Corke

Warping



$$\mathbf{H}\begin{pmatrix}600\\100\\1\end{pmatrix} = \begin{pmatrix}741.86\\50.285\\0.98\end{pmatrix}$$

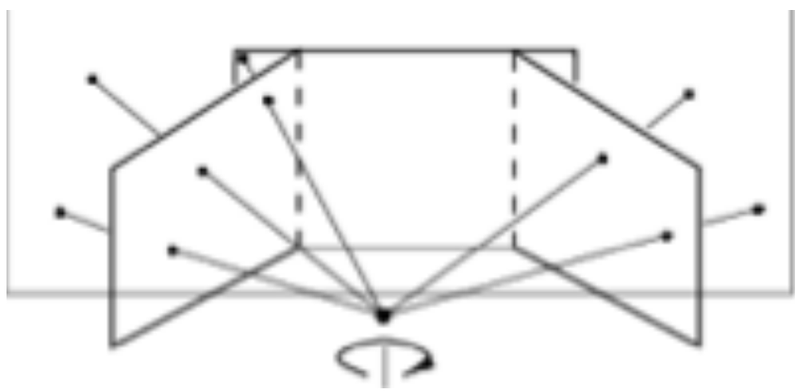
$$u = 757.000, v = 51.311$$

Slide credit: Peter Corke

Panoramas

Slide credit: Olga Russakovsky

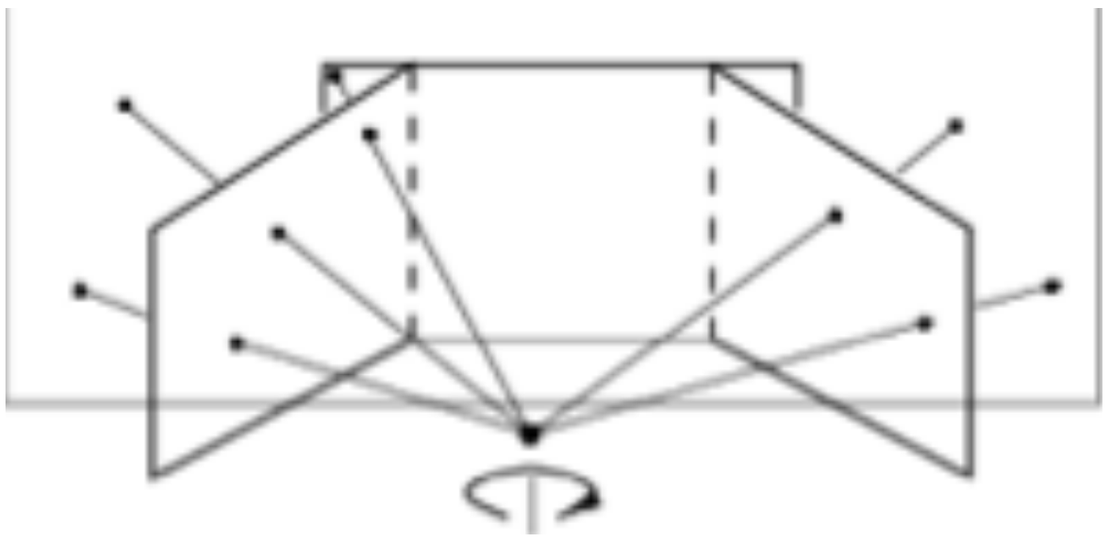
Special case of 2 views: rotations about camera center



Can be modeled as planar transformations, regardless of scene geometry!

Slide credit: Deva Ramanan

Derivation



Relation between 3D camera coordinates: $\begin{bmatrix} X_2 \\ Y_2 \\ Z_2 \end{bmatrix} = R \begin{bmatrix} X_1 \\ Y_1 \\ Z_1 \end{bmatrix}$ K_2

3D->2D projection: $\lambda_2 \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} f_2 & 0 & 0 \\ 0 & f_2 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_2 \\ Y_2 \\ Z_2 \end{bmatrix}$

Combining both: $\lambda \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = K_2 R K_1^{-1} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix}$

Slide credit: Deva Ramanan

Take-home points for homographies

$$\lambda \begin{bmatrix} x_2 \\ y_2 \\ 1 \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x_1 \\ y_1 \\ 1 \end{bmatrix}$$

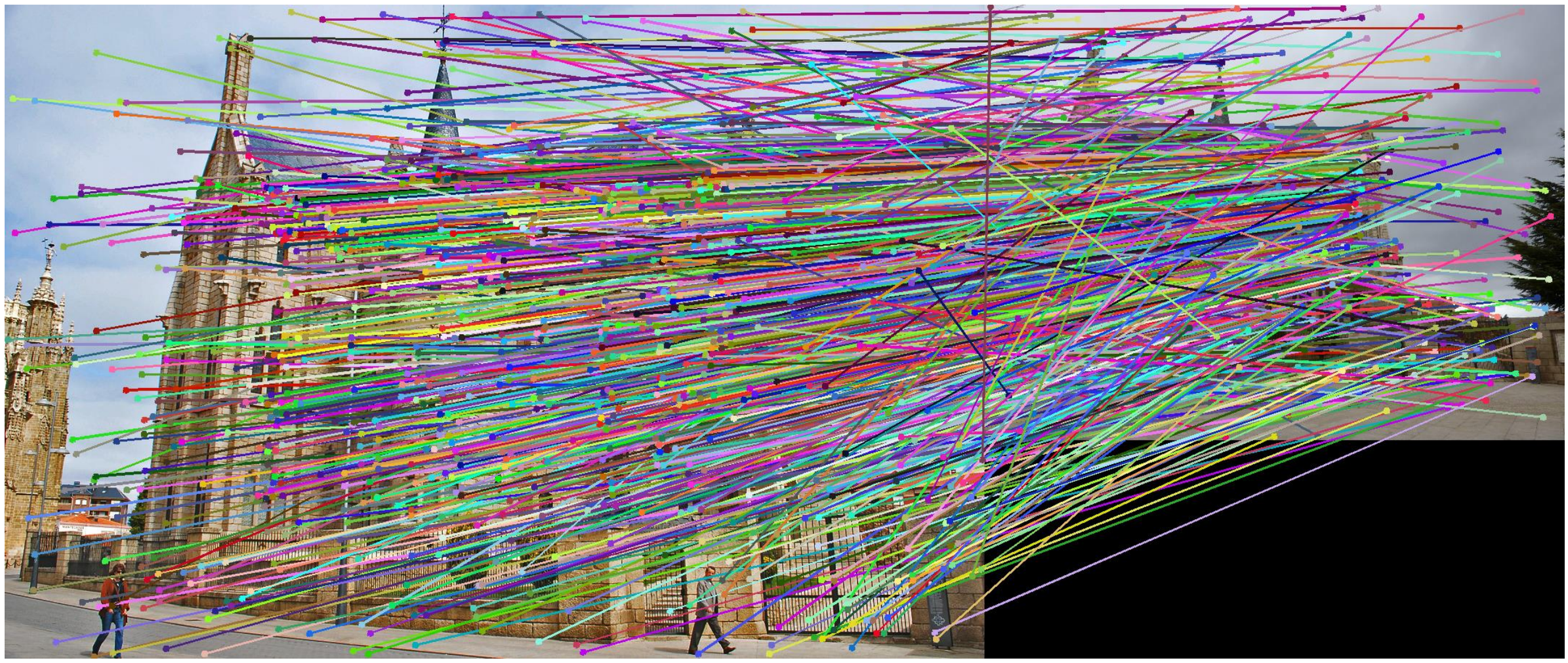
- If camera rotates about its center, then the images are related by a homography irrespective of scene depth.

- If the scene is planar, then images from any two cameras are related by a homography.

- Homography mapping is a 3x3 matrix with 8 degrees of freedom.

Slide credit: Deva Ramanan

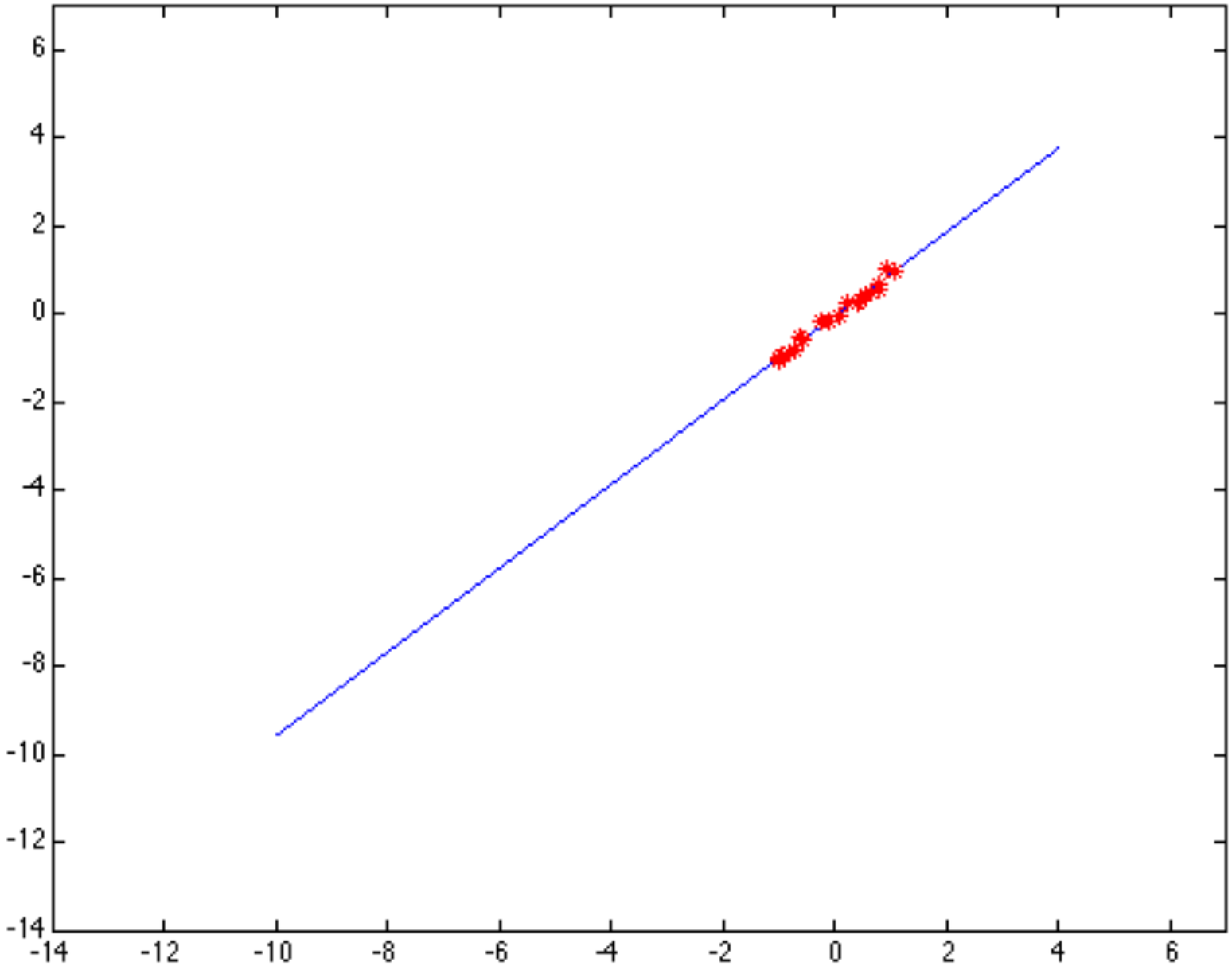
VLFeat’s 800 most confident matches among 10,000+ local features.



Which matches should we use to estimate homography?

Least squares: Robustness to noise

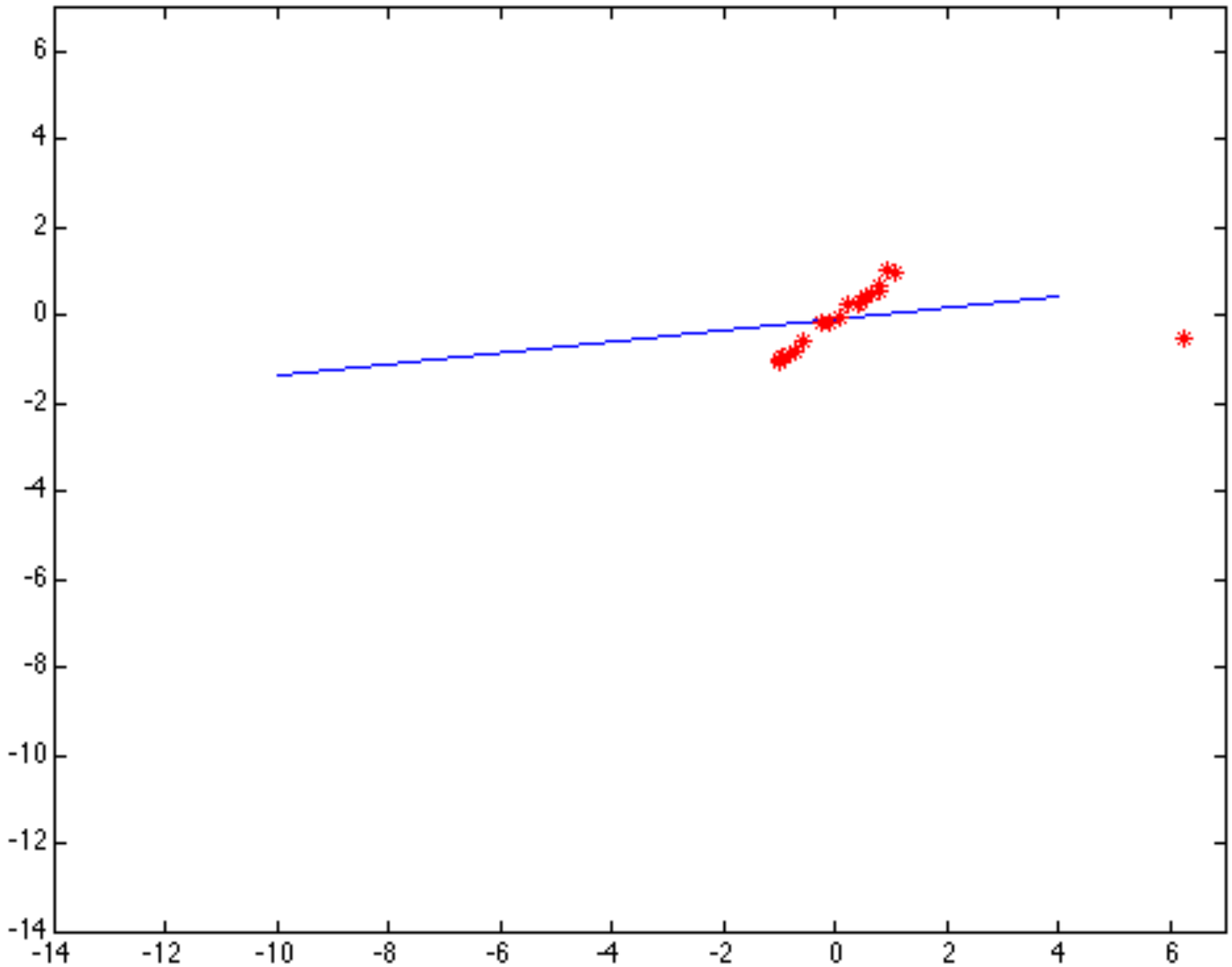
- Least squares fit to the red points:



Slide credit: James Hays

Least squares: Robustness to noise

- Least squares fit with an outlier:



Problem: squared error heavily penalizes outliers

Slide credit: James Hays

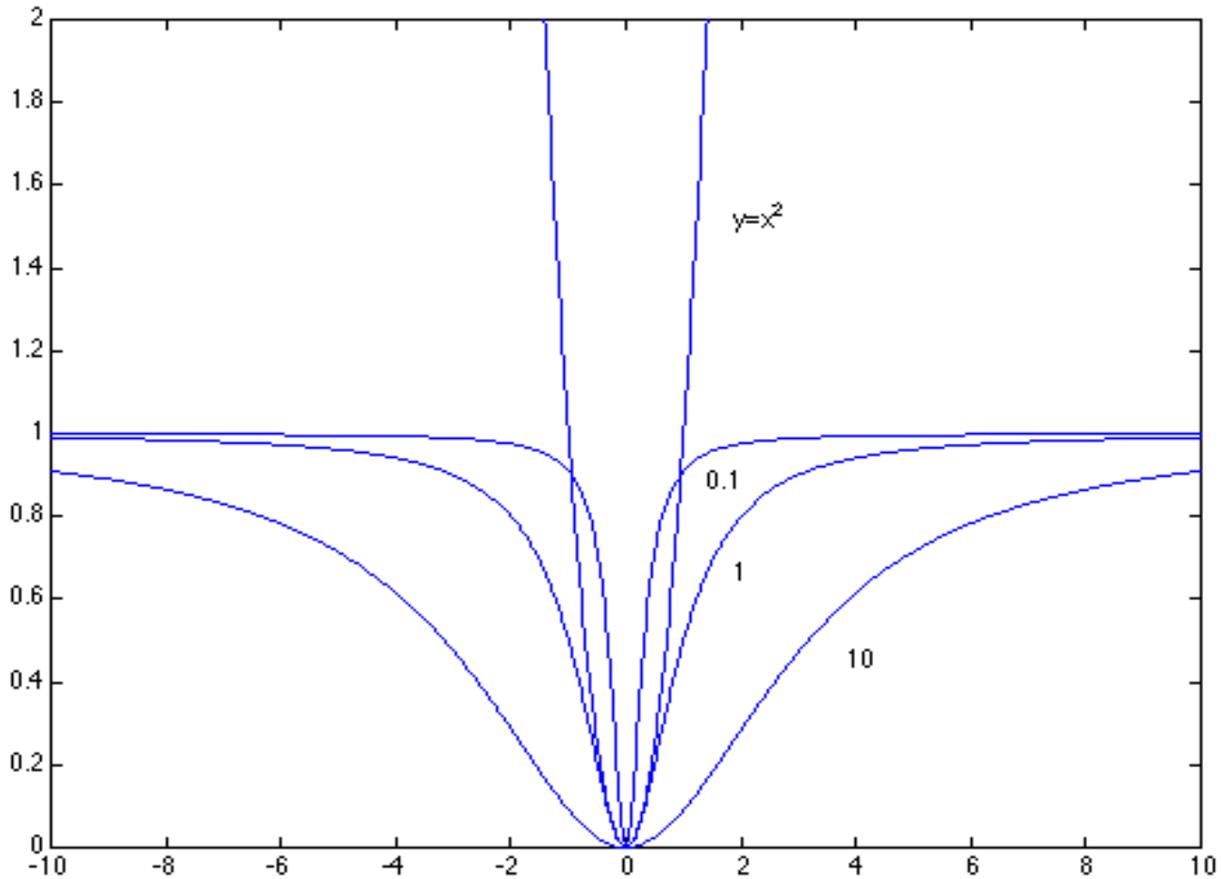
Robust least squares (to deal with outliers)

General approach:

minimize $\sum_i \rho\left(u_i\left(x_i, \theta\right); \sigma\right)$ $\qquad u^2 = \sum_{i=1}^{n} (y_i - mx_i - b)^2$

$u_i(x_i, \theta)$ – residual of i[th] point w.r.t. model parameters Θ

ρ – robust function with scale parameter σ



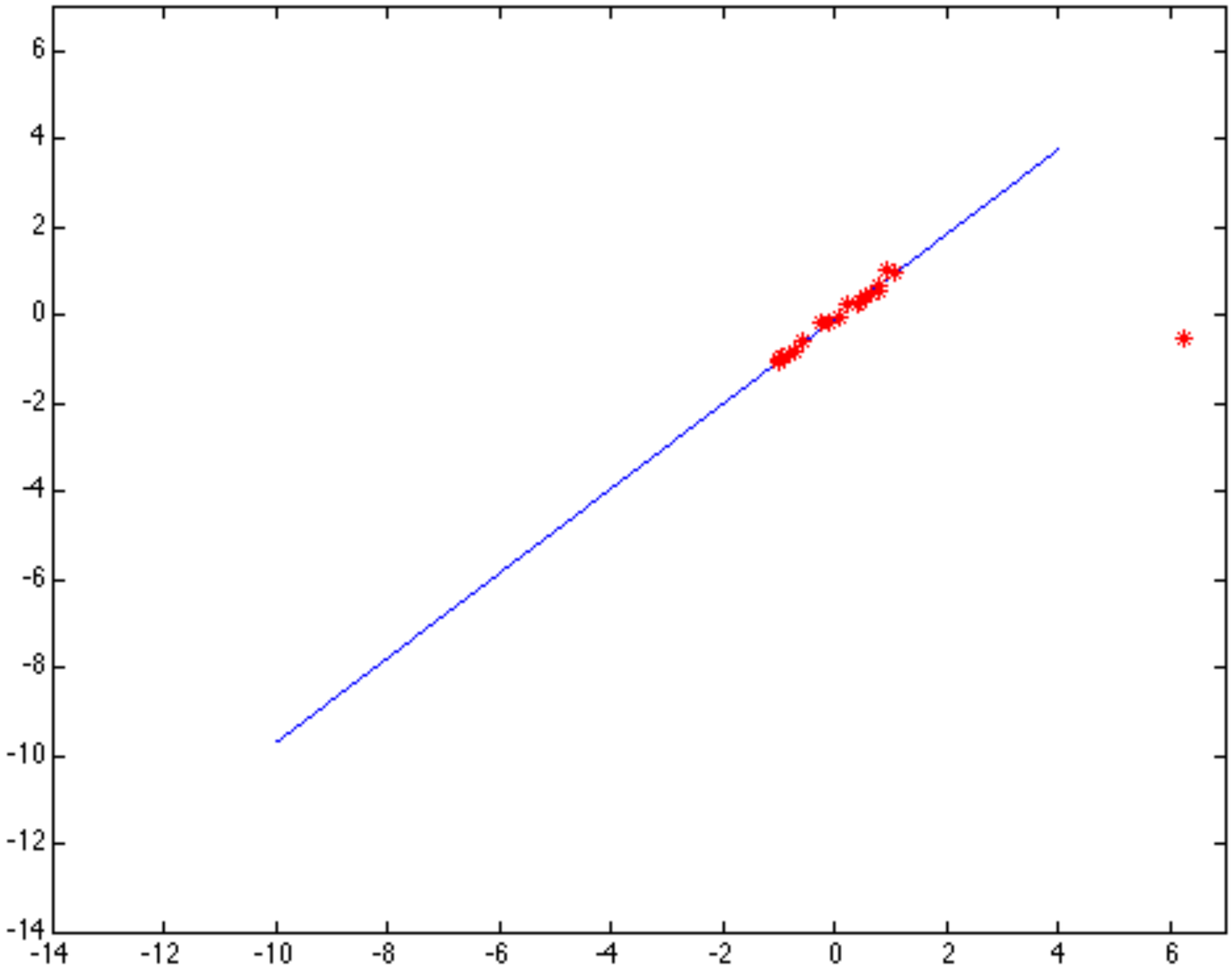
The robust function ρ

- Favors a configuration with small residuals
- Constant penalty for large residuals

$$\rho(u; \sigma) = \frac{u^2}{\sigma^2 + u^2}$$

Slide from S. Savarese

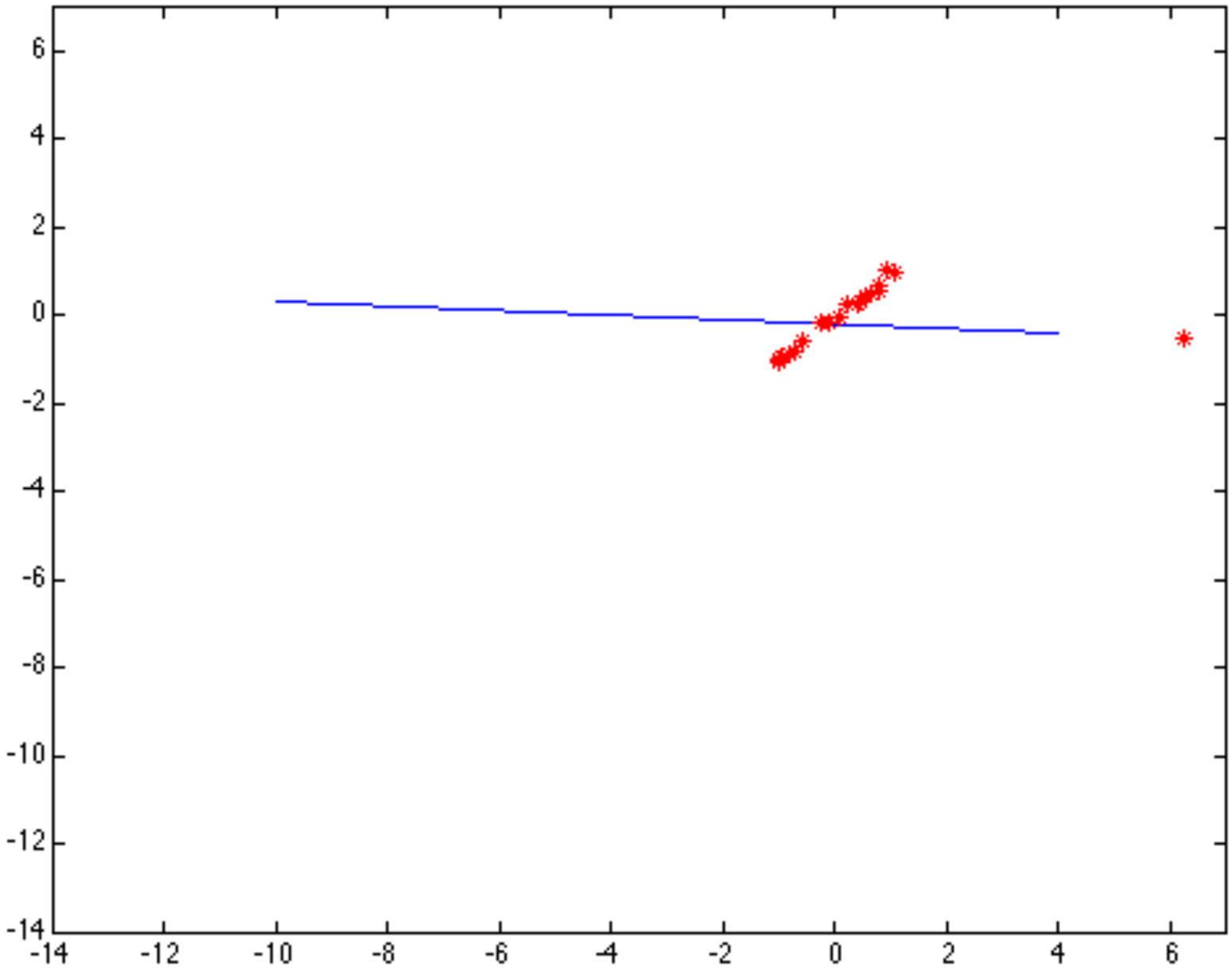
Choosing the scale: Just right



The effect of the outlier is minimized

Slide credit: James Hays

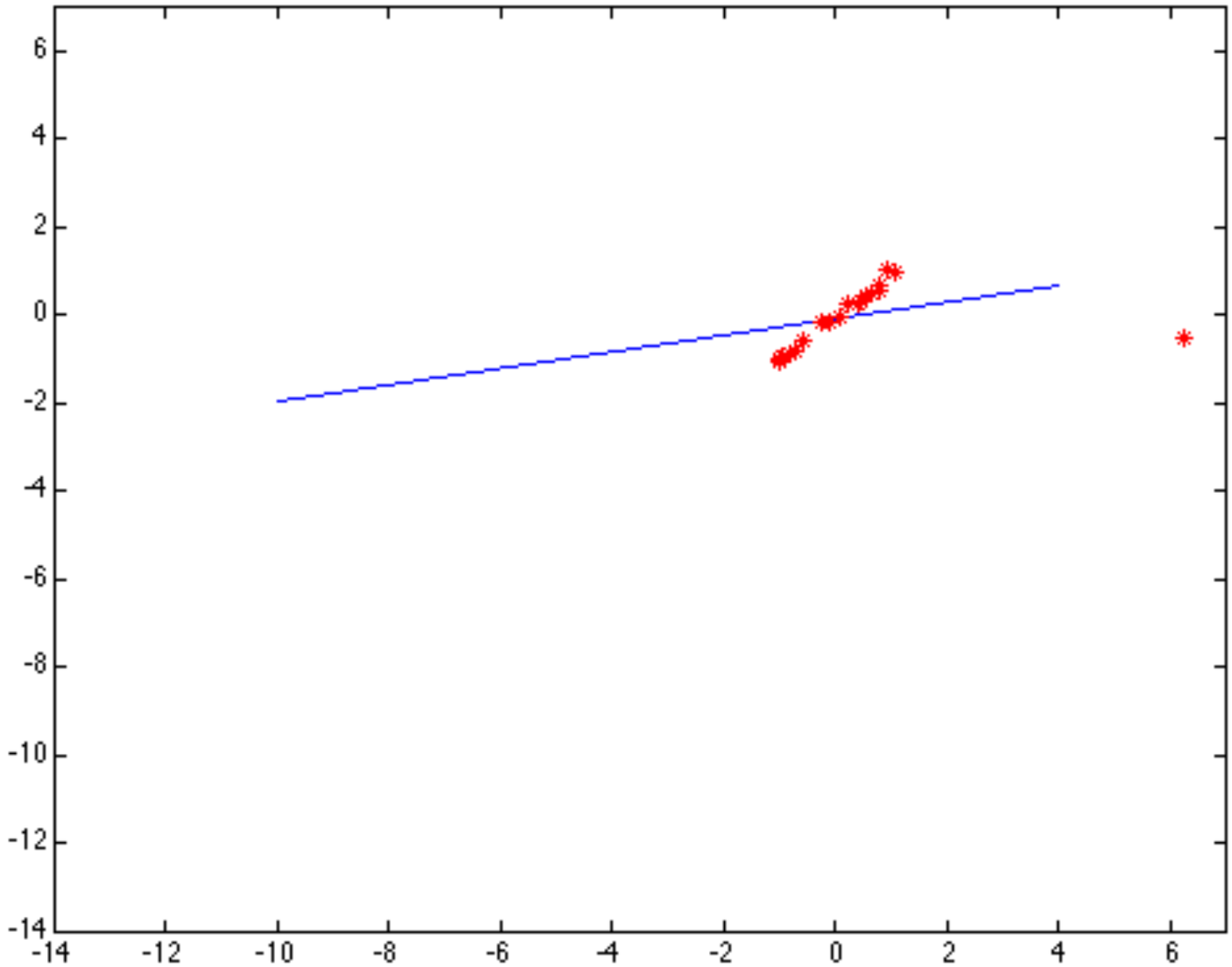
Choosing the scale: Too small



The error value is almost the same for every point and the fit is very poor

Slide credit: James Hays

Choosing the scale: Too large



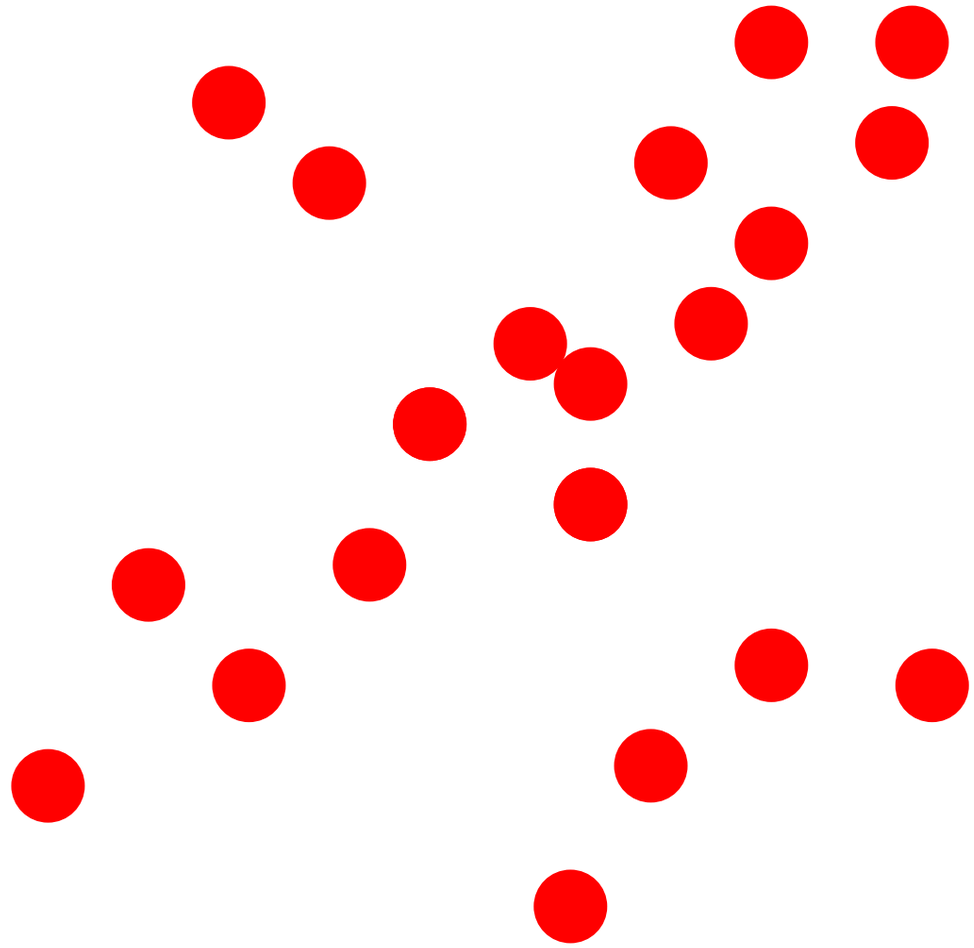
Behaves much the same as least squares

Slide credit: James Hays

RANSAC

(RANdom SAmple Consensus) :

Fischler & Bolles in ‘81.

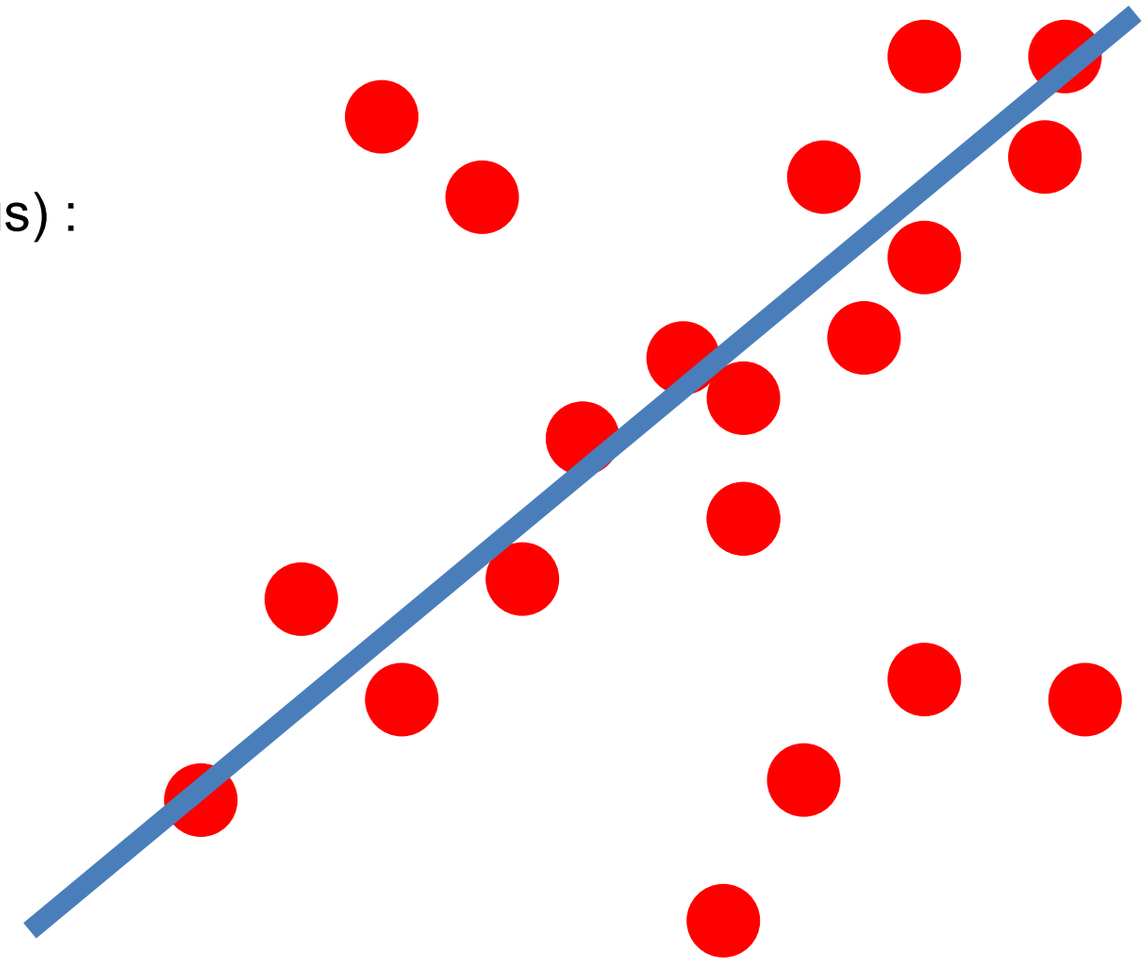


Slide credit: James Hays

RANSAC

(RANdom SAmple Consensus) :

Fischler & Bolles in ‘81.



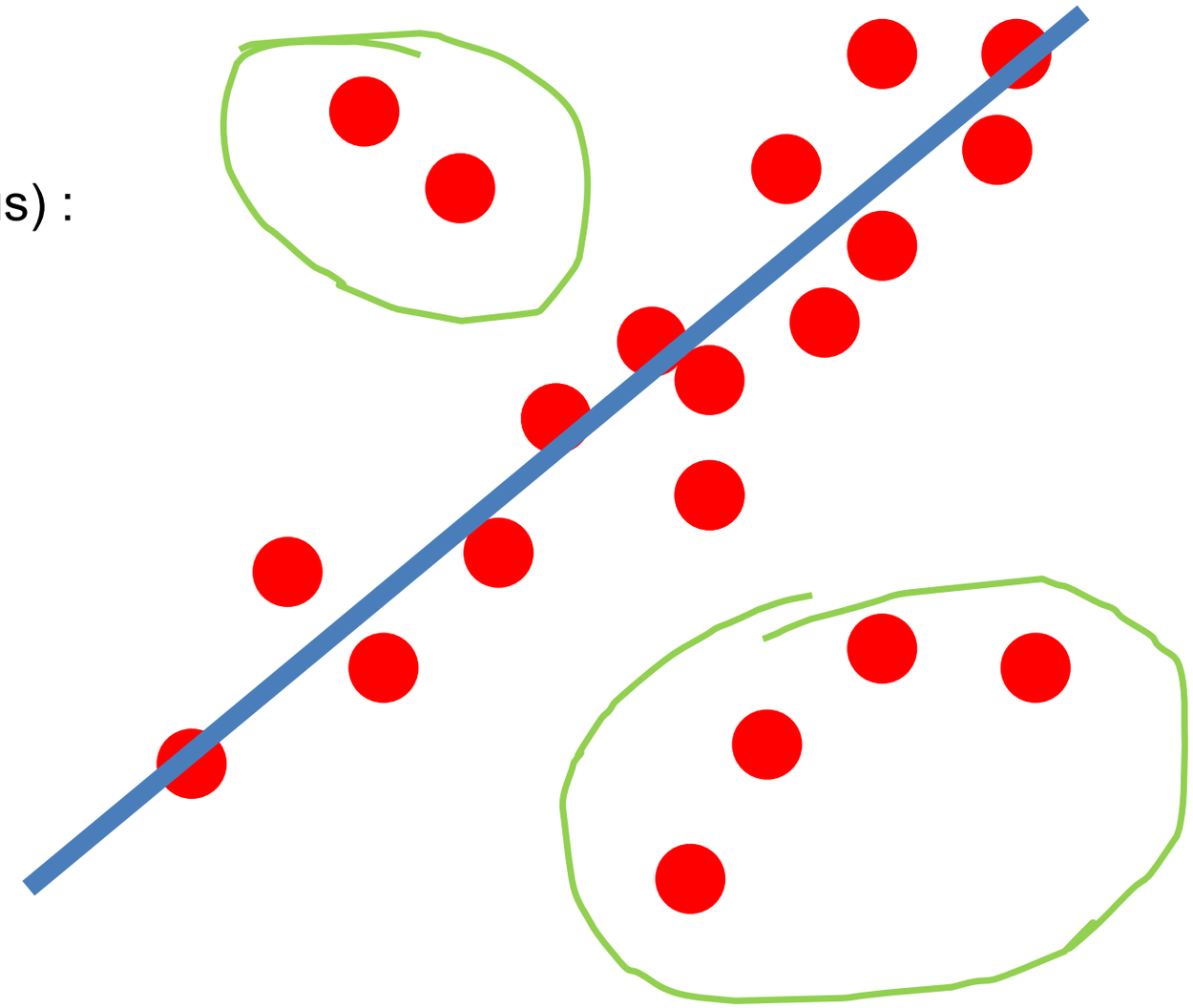
This data is noisy, but we expect a good fit to a known model.

Slide credit: James Hays

RANSAC

(RANdom SAmple Consensus) :

Fischler & Bolles in ‘81.



This data is noisy, but we expect a good fit to a known model.

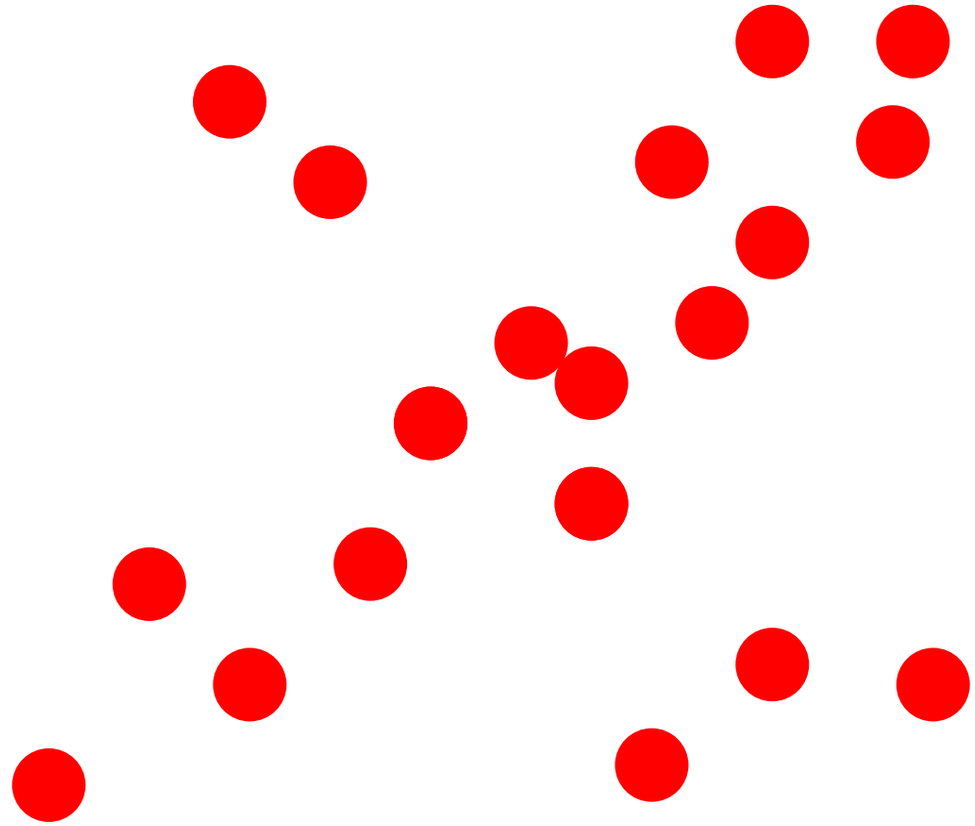
Here, we expect to see a line, but least-squares fitting will produce the wrong result due to strong outlier presence.

Slide credit: James Hays

RANSAC

(RANdom SAmple Consensus) :

Fischler & Bolles in ‘81.



Algorithm:

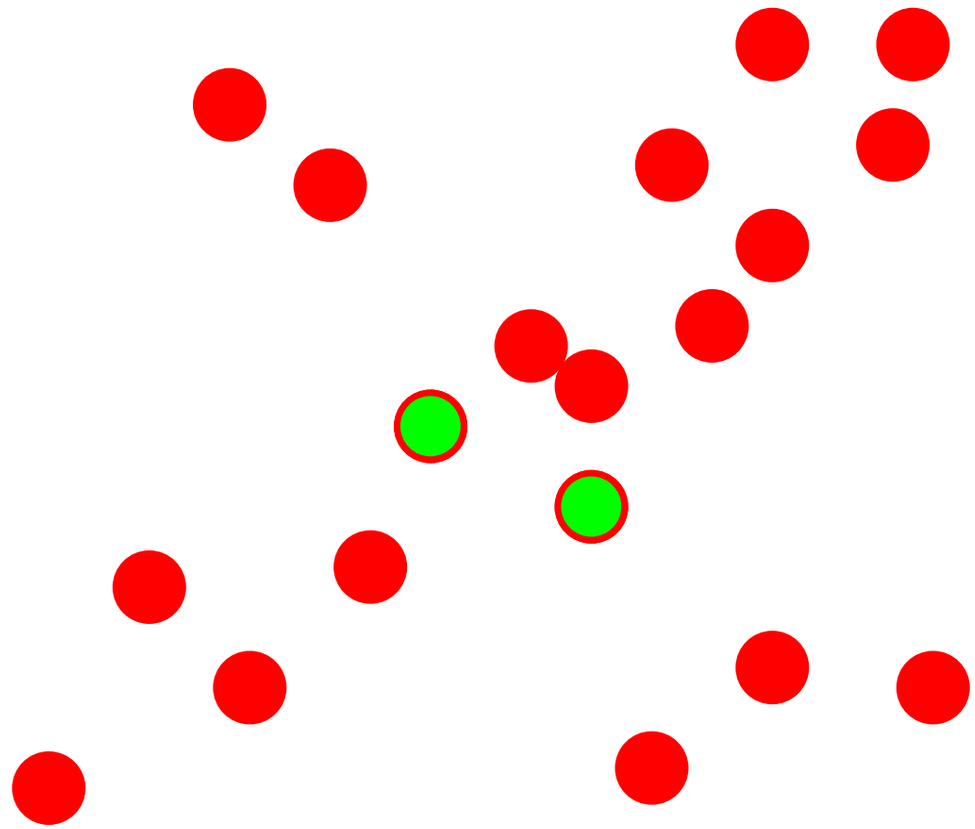
1. **Sample** (randomly) the number of points *s* required to fit the model
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Slide credit: James Hays

RANSAC

Line fitting example



Algorithm:

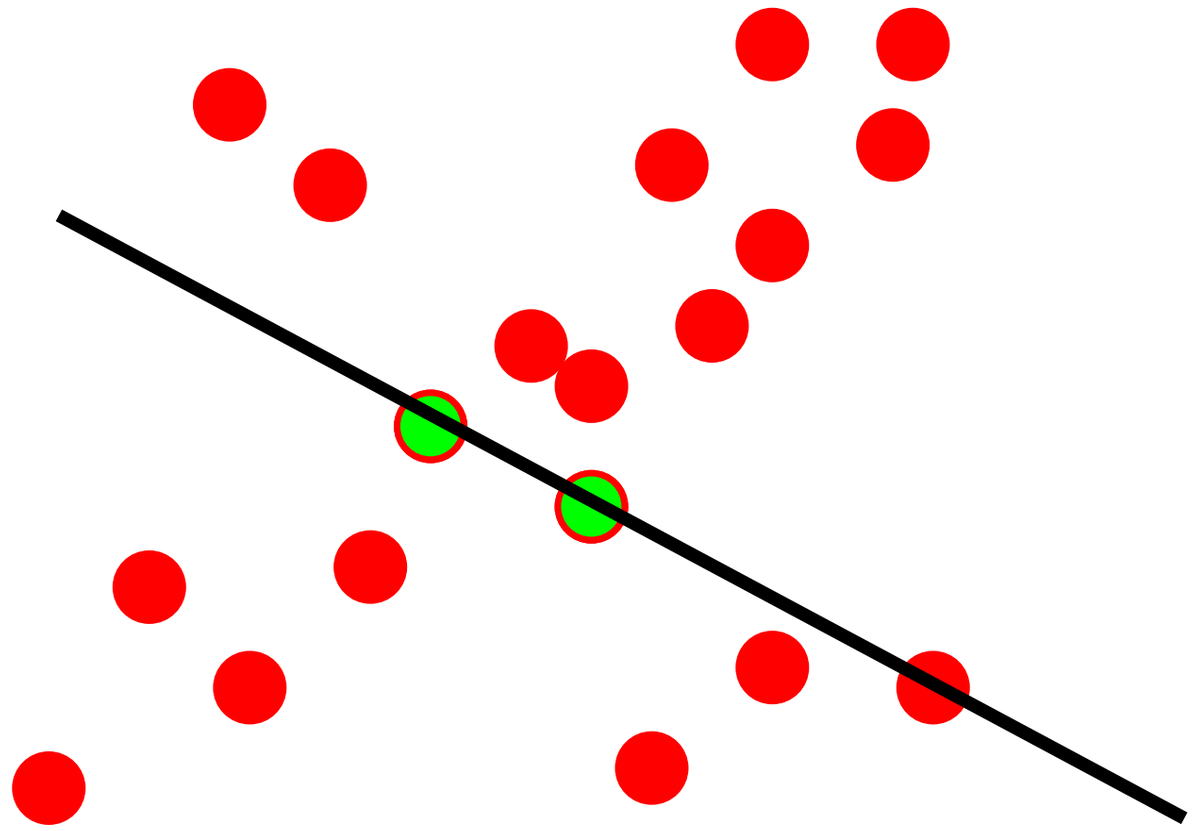
1. **Sample** (randomly) the number of points required to fit the model (s=2)
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Illustration by Savarese

RANSAC

Line fitting example



Algorithm:

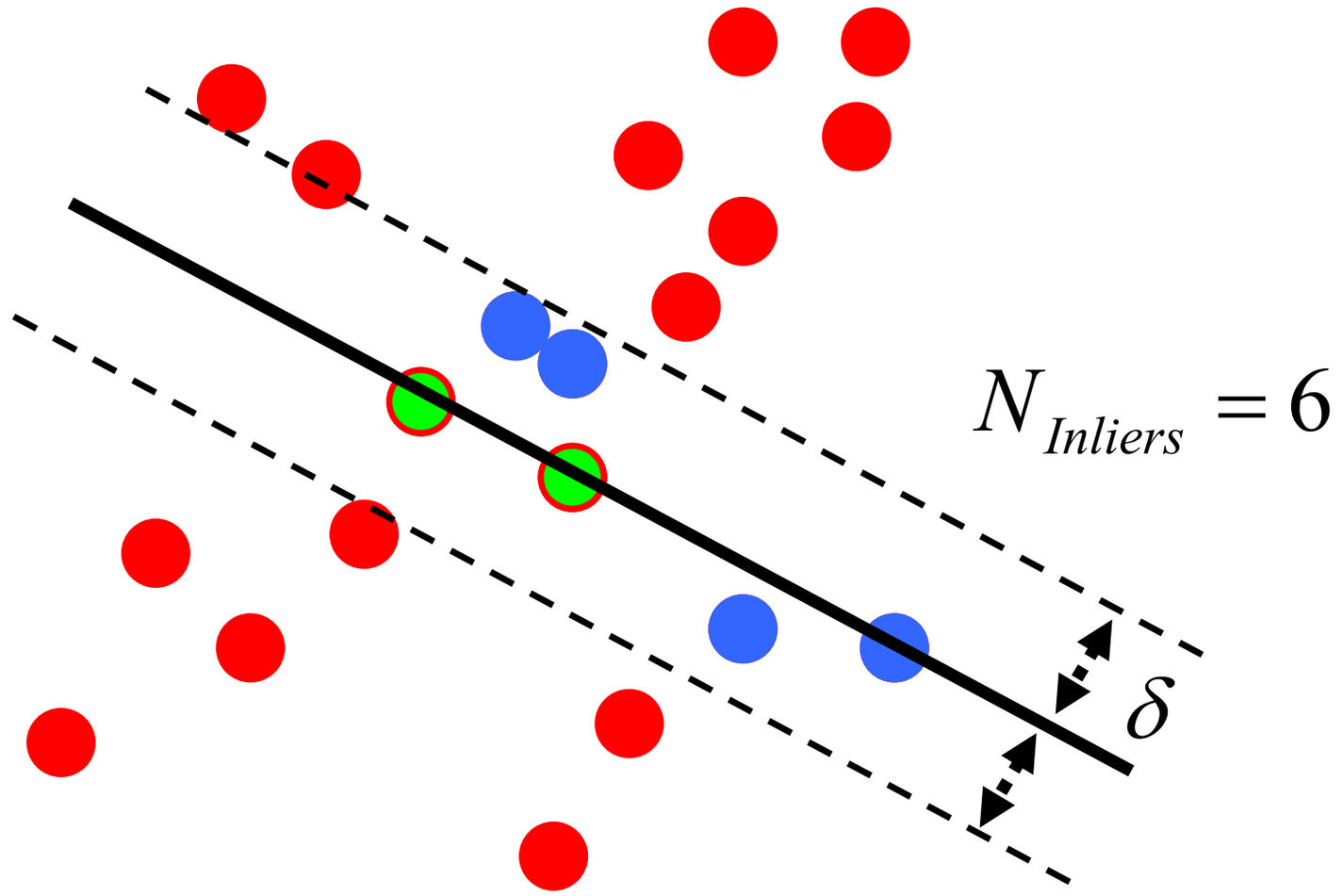
1. **Sample** (randomly) the number of points required to fit the model (s=2)
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Slide credit: James Hays

RANSAC

Line fitting example



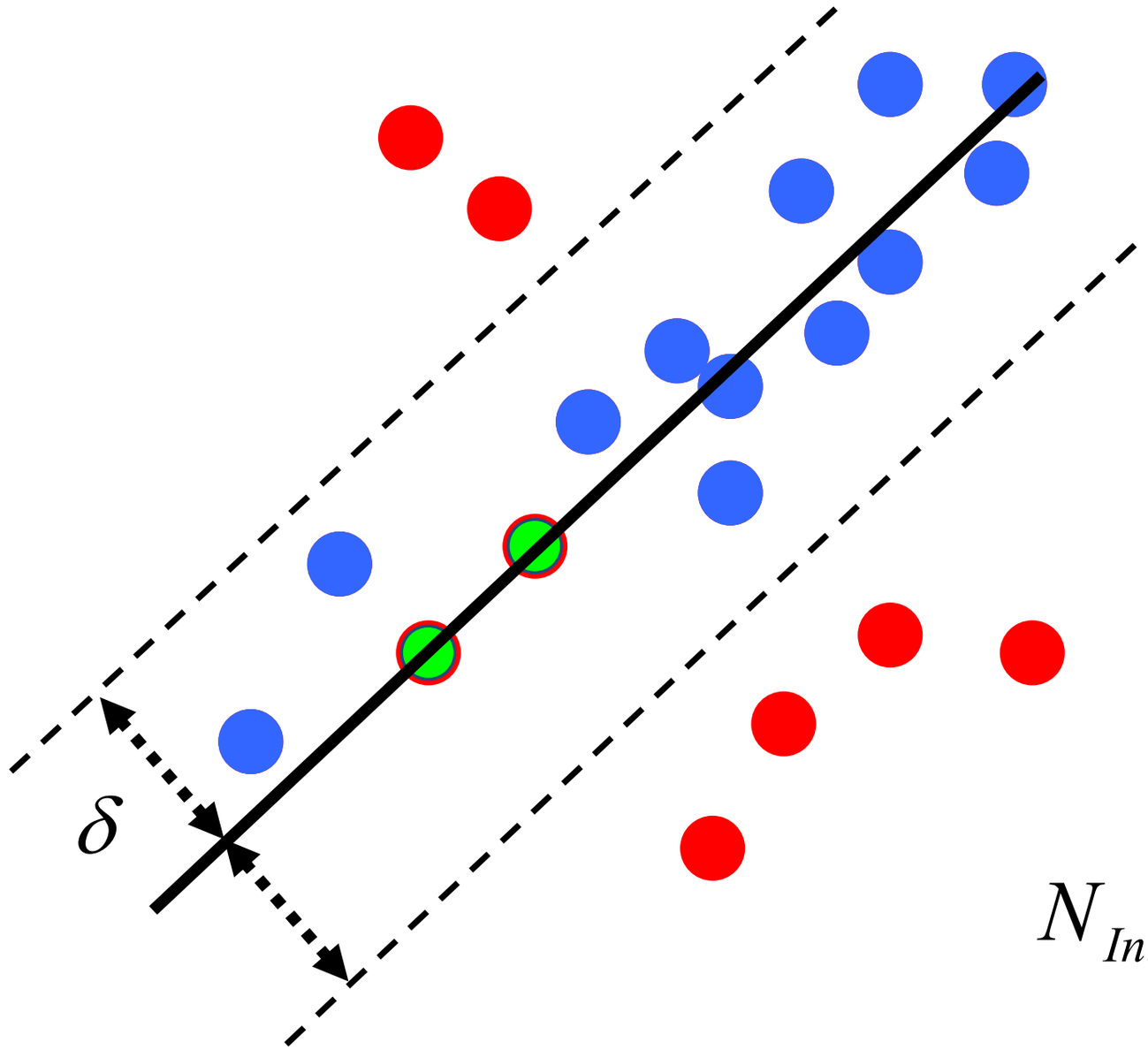
Algorithm:

1. **Sample** (randomly) the number of points required to fit the model (*s*=2)
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Slide credit: James Hays

RANSAC



$$N_{Inliers} = 14$$

Algorithm:

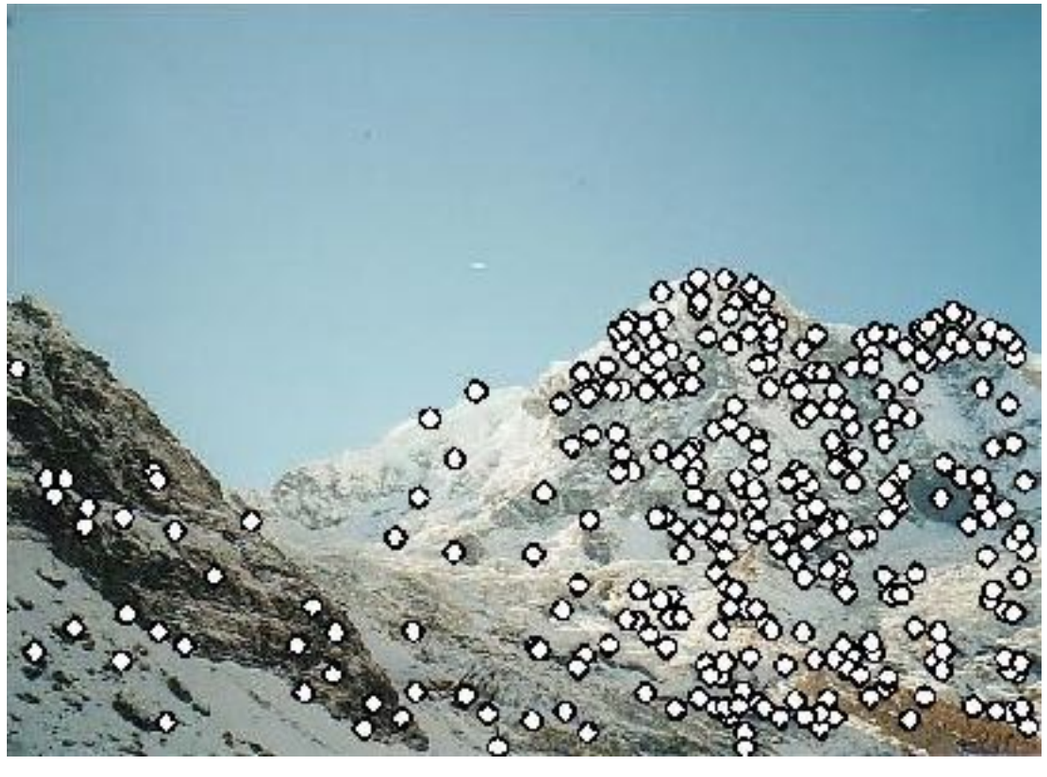
1. **Sample** (randomly) the number of points required to fit the model (*s*=2)
2. **Solve** for model parameters using samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found with high confidence

Slide credit: James Hays

RANSAC for alignment

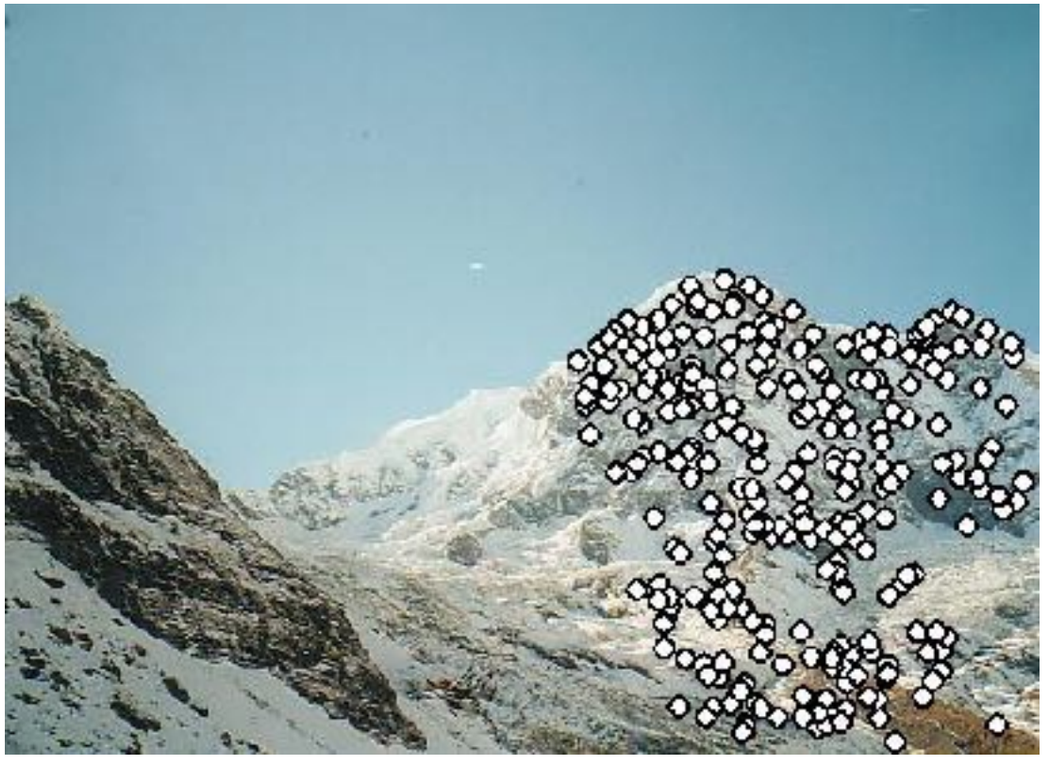
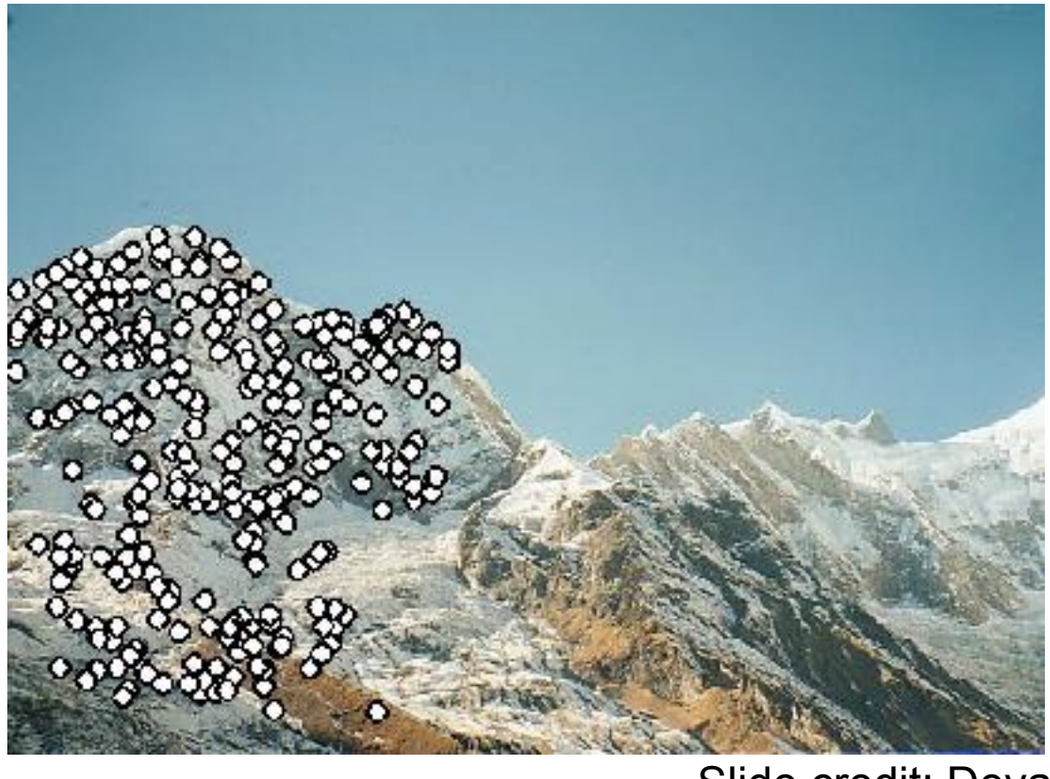





Slide credit: Deva Ramanan

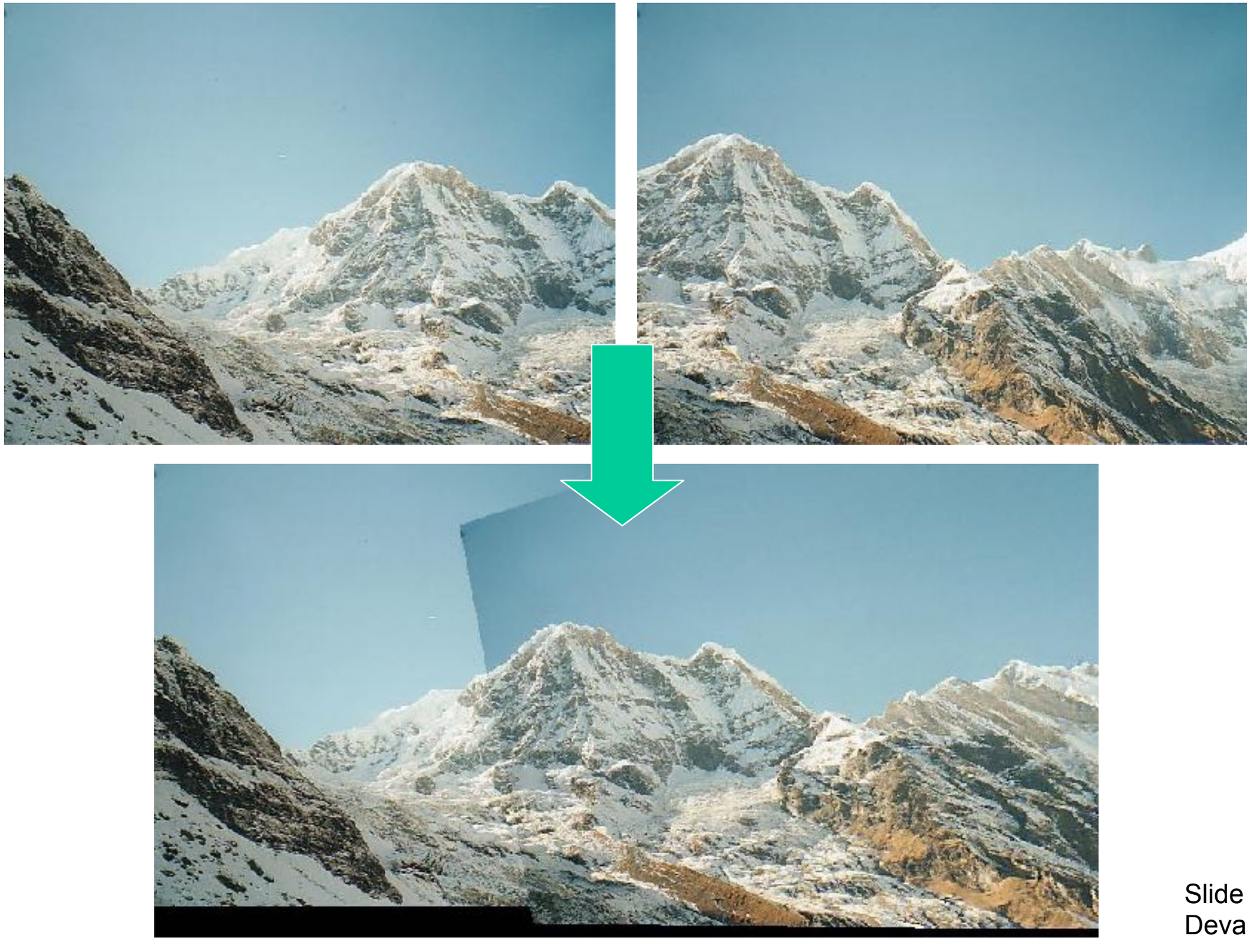
RANSAC for alignment



Slide credit: Deva Ramanan

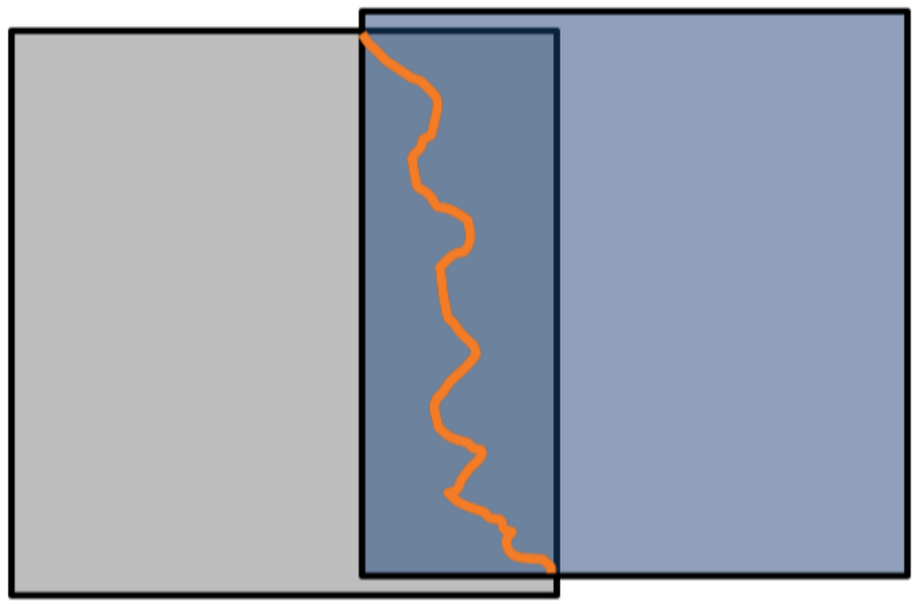
RANSAC for alignment



Slide credit:
Deva Ramanan

Blending

Instead of blending high frequencies along a straight line, blend along line of minimum differences in image intensities



Slide credit: Olga Russakovsky

Blending

Moving object, simple blending => blur

Slide credit: Davis ‘98

Blending

Minimum-cost cut ⛁ no blur

Slide credit: Davis ‘98


THIS IS YOUR MACHINE LEARNING SYSTEM?
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.
WHAT IF THE ANSWERS ARE WRONG?
JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.
DATA
ANSWERS

Next Class