Feature-based Alignment
Chapter 6 R. Szelisky

Guido Gerig

CS 6320 Spring 2012

Slide Credits: Trevor Darrell, Berkeley (C280 CV Course), Steve Seitz, Kristen Grauman, Alyosha Efros, L. Lazebnik, Marc Pollefeys

Original Slides Prof. Trevor Darrel (08Alignment, 06LocalFeatures): please visit http://www.eecs.berkeley.edu/~trevor/CS280Notes/

Today: Alignment

(a)

(b)

(c)

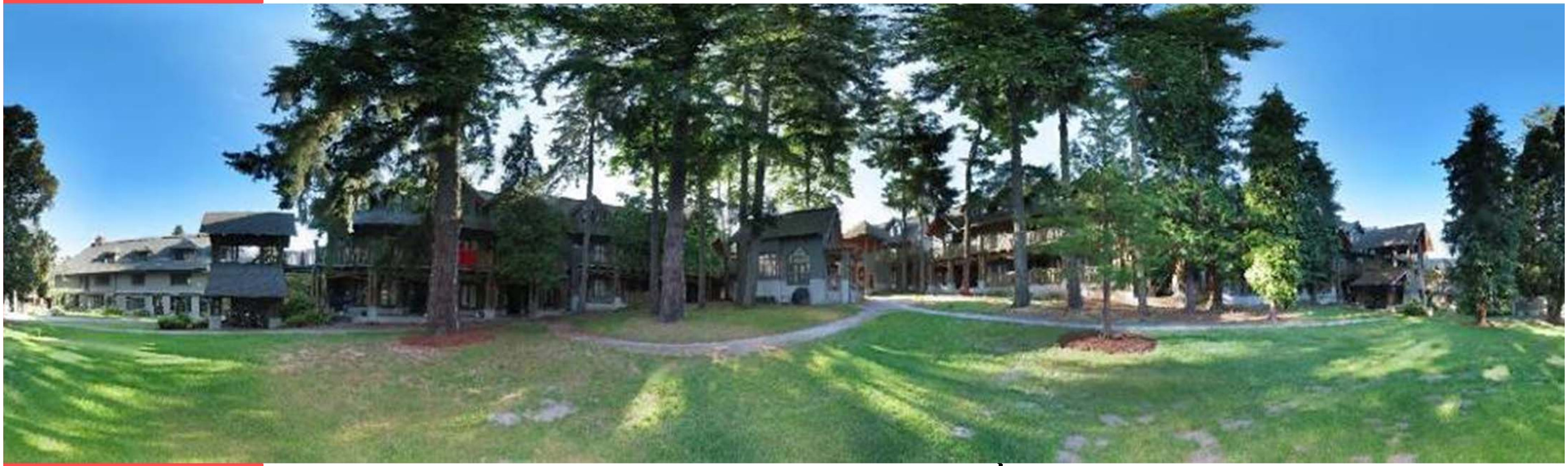
Motivation: Mosaics

- Getting the whole picture
  - Consumer camera: 50˚ x 35˚

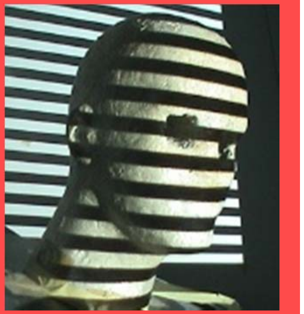
Slide from Brown & Lowe 2003

Motivation: Mosaics

- Getting the whole picture
  - Consumer camera: 50˚ x 35˚
  - Human Vision: 176˚ x 135˚



Slide from Brown & Lowe 2003



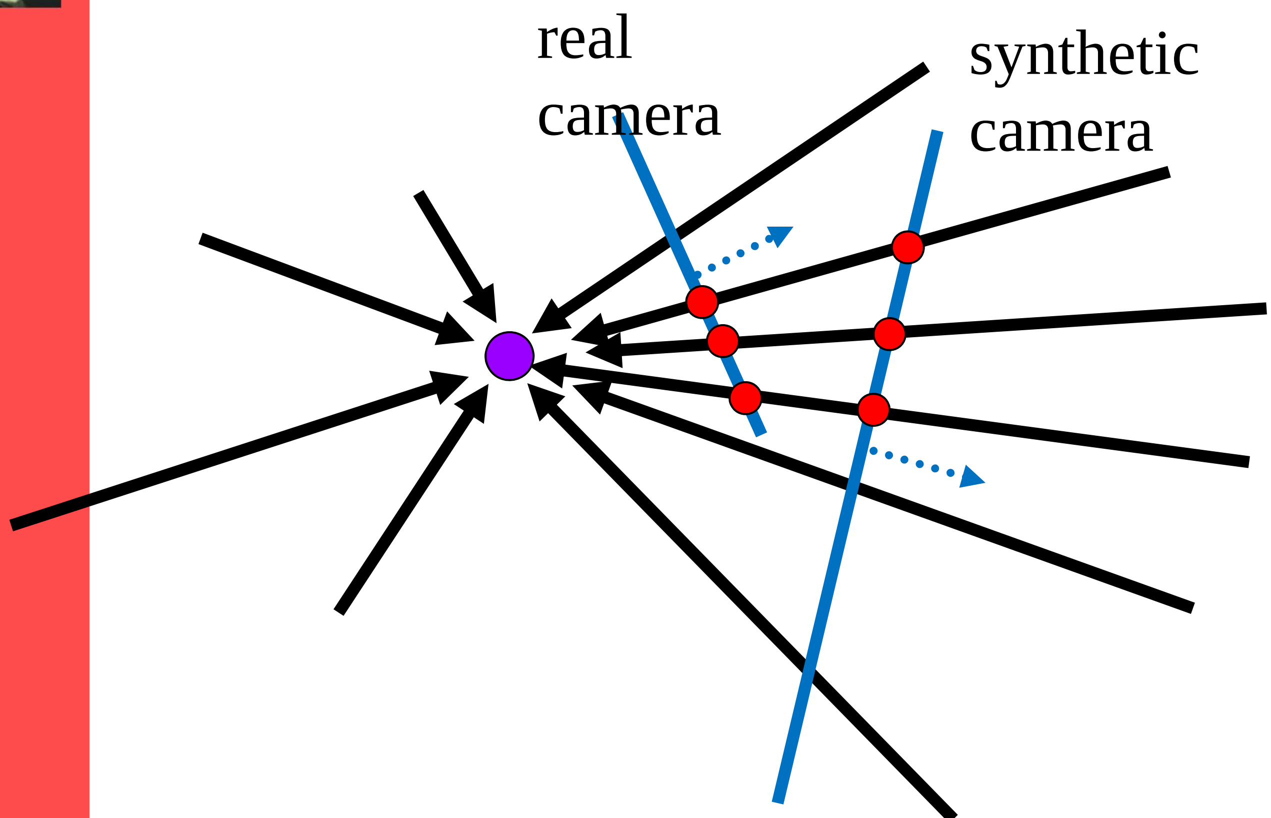
Motion models

Motion models

- What happens when we take two images with a camera and try to align them?
- translation?
- rotation?
- scale?
- affine?
- perspective?

Szelis

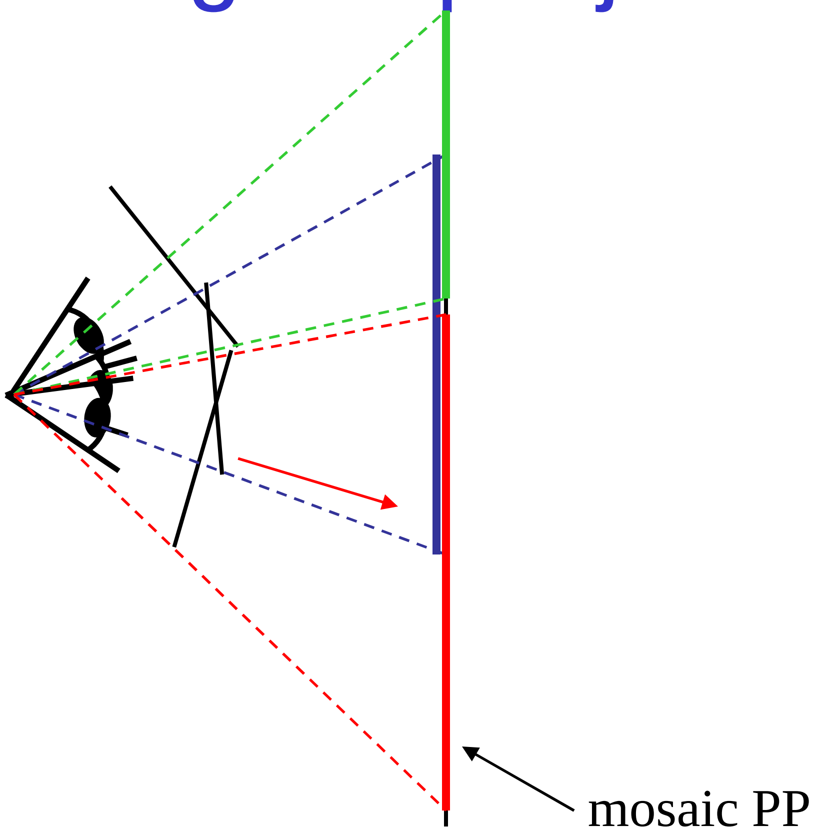
Panoramas: generating synthetic views



Can generate any synthetic camera view
as long as it has **the same center of projection**!

Source: Alyosha Efros

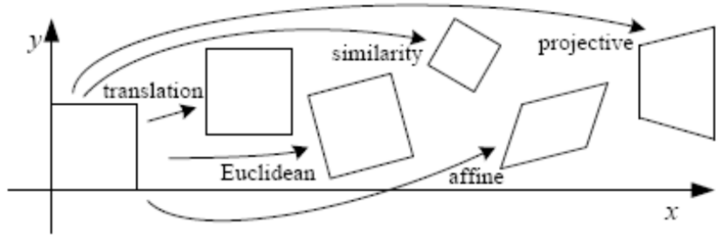
Image reprojection



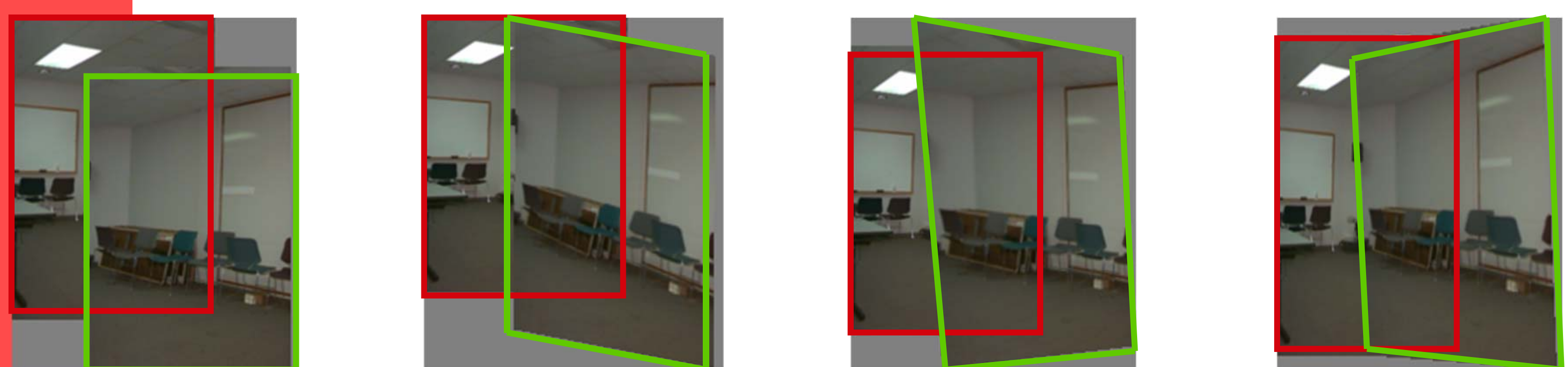
- The mosaic has a natural interpretation in 3D
  - The images are reprojected onto a common plane
  - The mosaic is formed on this plane
  - Mosaic is a *synthetic wide-angle camera*

Source: Steve Seitz

Motion models



Translation | Affine | Perspective | 3D rotation



2 unknowns | 6 unknowns | 8 unknowns | 3 unknowns

Szeliski

2D coordinate transformations

- translation: $\boldsymbol{x'} = \boldsymbol{x} + \boldsymbol{t}$ $\quad \boldsymbol{x} = (x,y)$
- rotation: $\boldsymbol{x'} = \boldsymbol{R}\,\boldsymbol{x} + \boldsymbol{t}$
- similarity: $\boldsymbol{x'} = s\,\boldsymbol{R}\,\boldsymbol{x} + \boldsymbol{t}$
- affine: $\boldsymbol{x'} = \boldsymbol{A}\,\boldsymbol{x} + \boldsymbol{t}$
- perspective: $\underline{\boldsymbol{x}}' \cong \boldsymbol{H}\,\underline{\boldsymbol{x}}$ $\quad \underline{\boldsymbol{x}} = (x,y,1)$
  ($\underline{\boldsymbol{x}}$ is a *homogeneous* coordinate)
- These all form a nested *group* (closed w/ inv.)

Basic 2D Transformations

- Basic 2D transformations as 3x3 matrices

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & t_x \\ 0 & 1 & t_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Translate

$$\begin{bmatrix} \boldsymbol{x}' \\ \boldsymbol{y}' \\ 1 \end{bmatrix} = \begin{bmatrix} \boldsymbol{s}_x & 0 & 0 \\ 0 & \boldsymbol{s}_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{y} \\ 1 \end{bmatrix}$$

Scale

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} \cos\Theta & -\sin\Theta & 0 \\ \sin\Theta & \cos\Theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Rotate

$$\begin{bmatrix} \boldsymbol{x}' \\ \boldsymbol{y}' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & \boldsymbol{sh}_x & 0 \\ \boldsymbol{sh}_y & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \boldsymbol{x} \\ \boldsymbol{y} \\ 1 \end{bmatrix}$$

Shear

Source: Alyosha Efros

2D Affine Transformations

$$\begin{bmatrix} x' \\ y' \\ w \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ w \end{bmatrix}$$

- Affine transformations are combinations of …
  - Linear transformations, and
  - Translations
- Parallel lines remain parallel

Grauman

Projective Transformations

$$\begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x \\ y \\ w \end{bmatrix}$$

- Projective transformations:
  - Affine transformations, and
  - Projective warps
- Parallel lines do not necessarily remain parallel

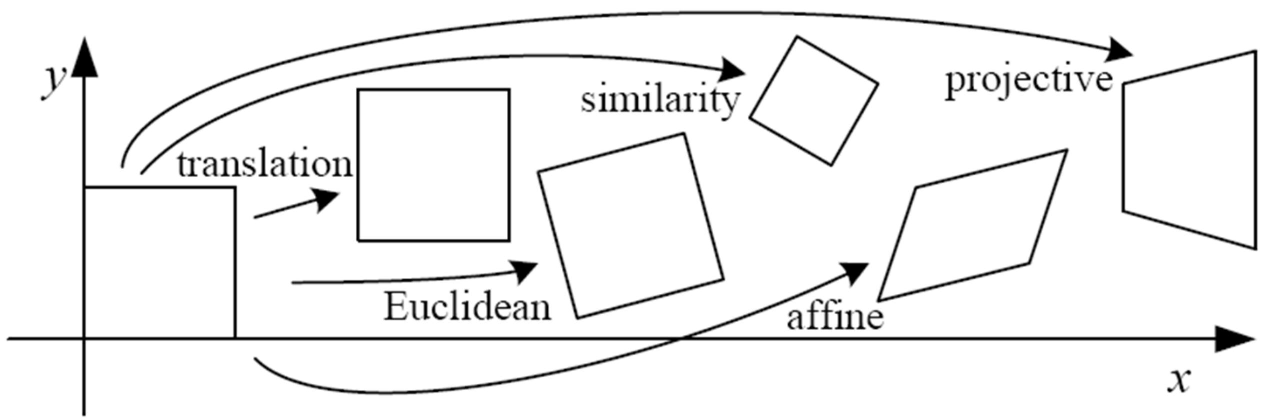


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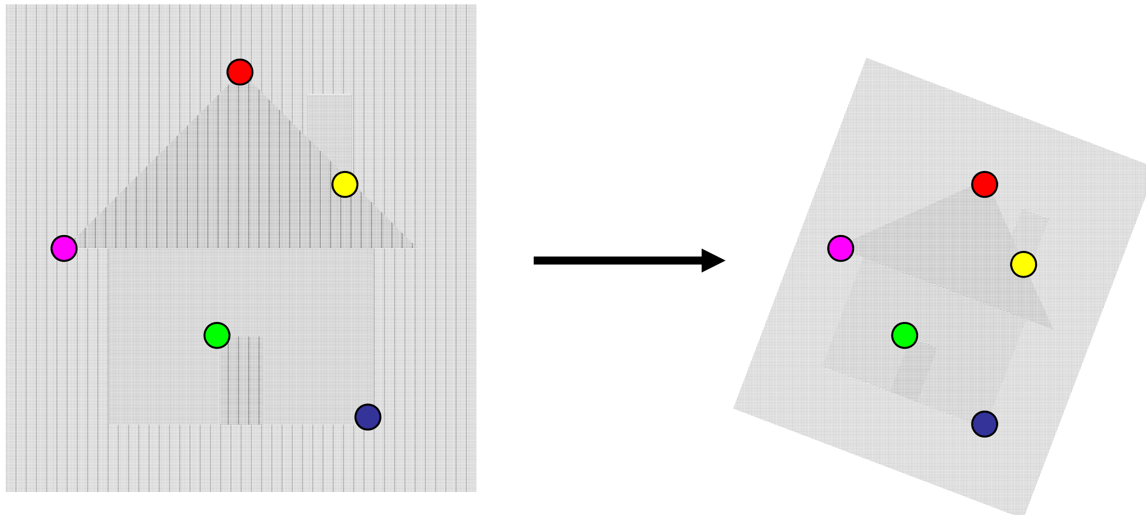
Image alignment

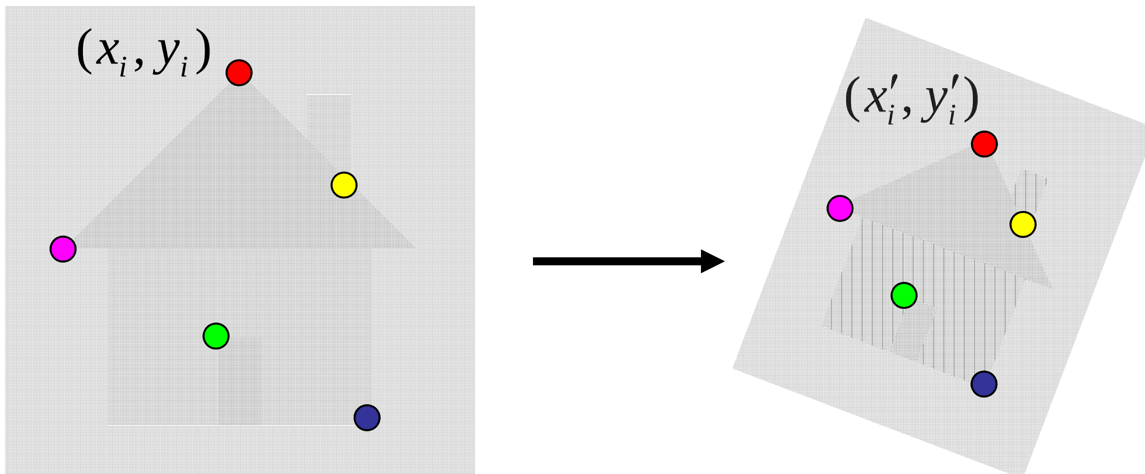


- Two broad approaches:
  - Direct (pixel-based) alignment
    - Search for alignment where most pixels agree
  - Feature-based alignment
    - Search for alignment where *extracted features* agree
    - Can be verified using pixel-based alignment

Source: L. Lazebnik

Fitting an affine transformation

- Assuming we know the correspondences, how do we get the transformation?

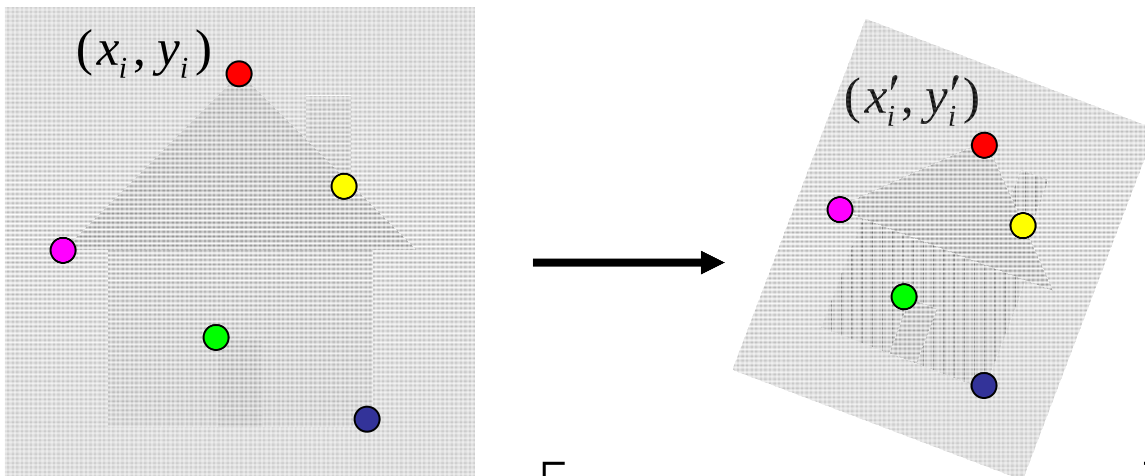


$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

Grauman

Fitting an affine transformation

- Assuming we know the correspondences, how do we get the transformation?



$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_1 \\ t_2 \end{bmatrix}$$

$$\begin{bmatrix} & & \\ & & \\ & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \\ \\ \end{bmatrix}$$

Fitting an affine transformation

$$\begin{bmatrix} & & \cdots & & & \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ & & \cdots & & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_1 \\ t_2 \end{bmatrix} = \begin{bmatrix} \cdots \\ x_i' \\ y_i' \\ \cdots \end{bmatrix}$$

- How many matches (correspondence pairs) do we need to solve for the transformation parameters?
- Once we have solved for the parameters, how do we compute the coordinates of the corresponding point for (x_{new}, y_{new}) ?

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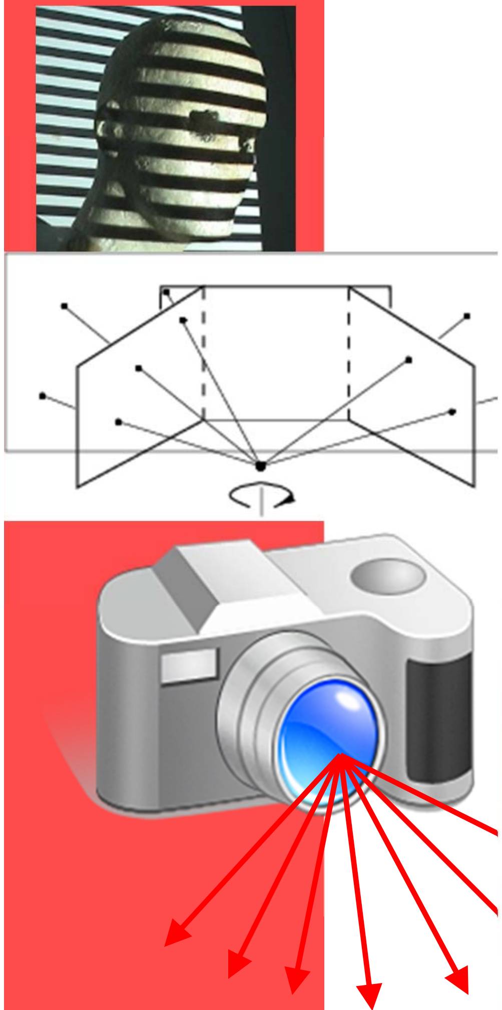
Panoramas



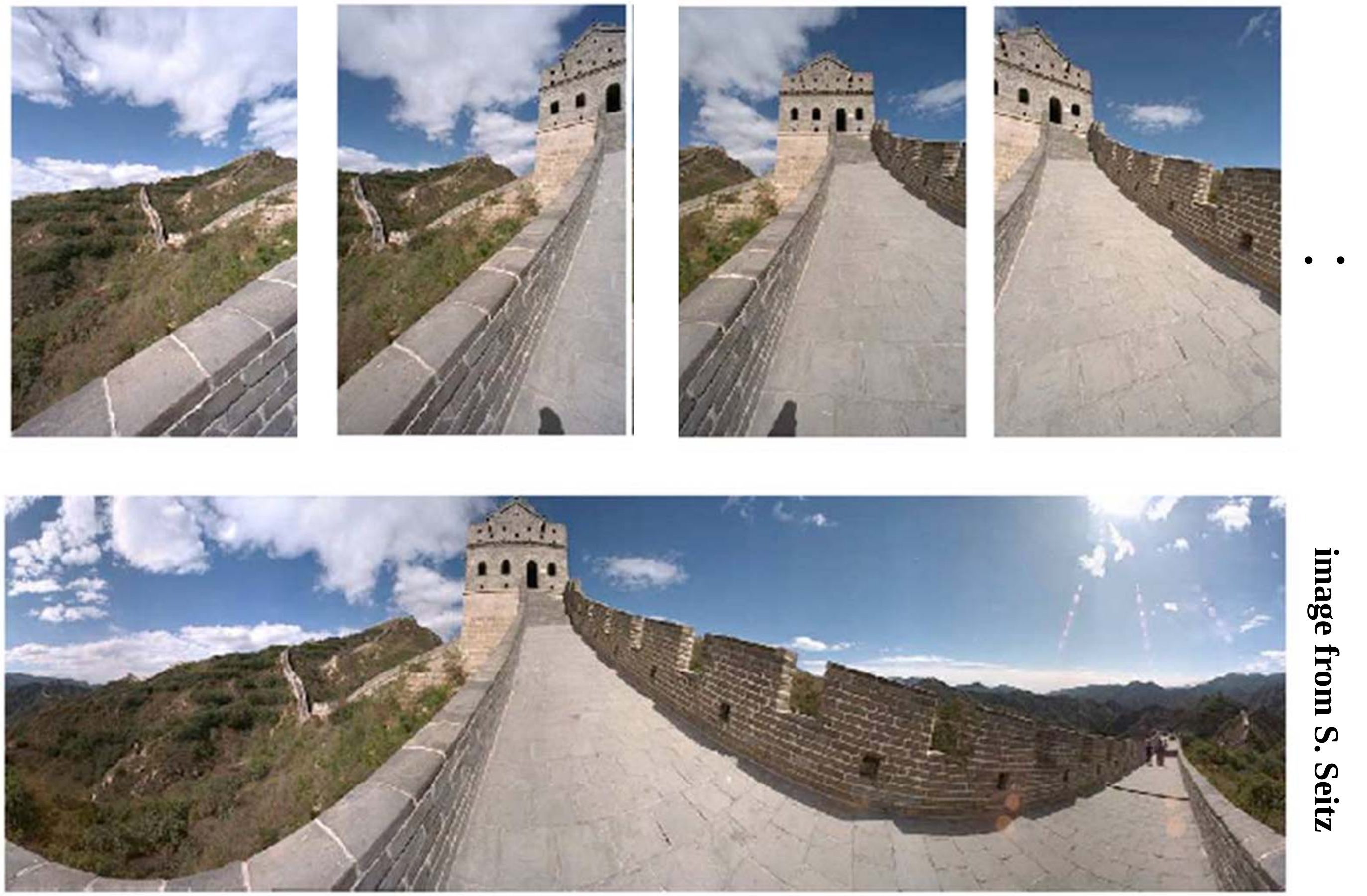
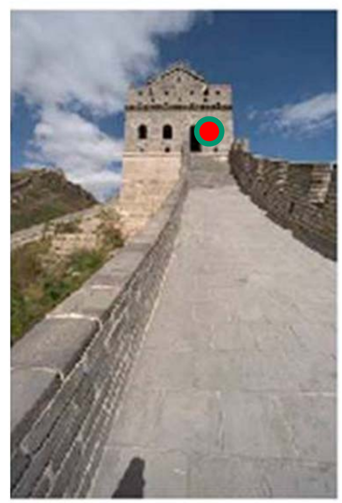


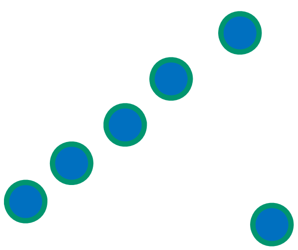
image from S. Seitz

Obtain a wider angle view by combining multiple images.

Outliers

- **Outliers** can hurt the quality of our parameter estimates, e.g.,
  - an erroneous pair of matching points from two images
  - an edge point that is noise, or doesn't belong to the line we are fitting.





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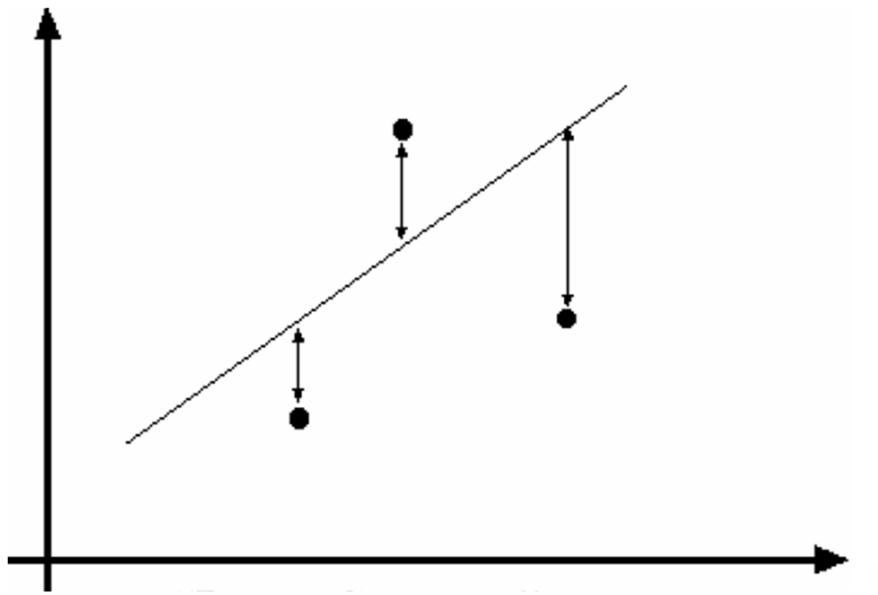
Example: least squares line fitting

- Assuming all the points that belong to a particular line are known



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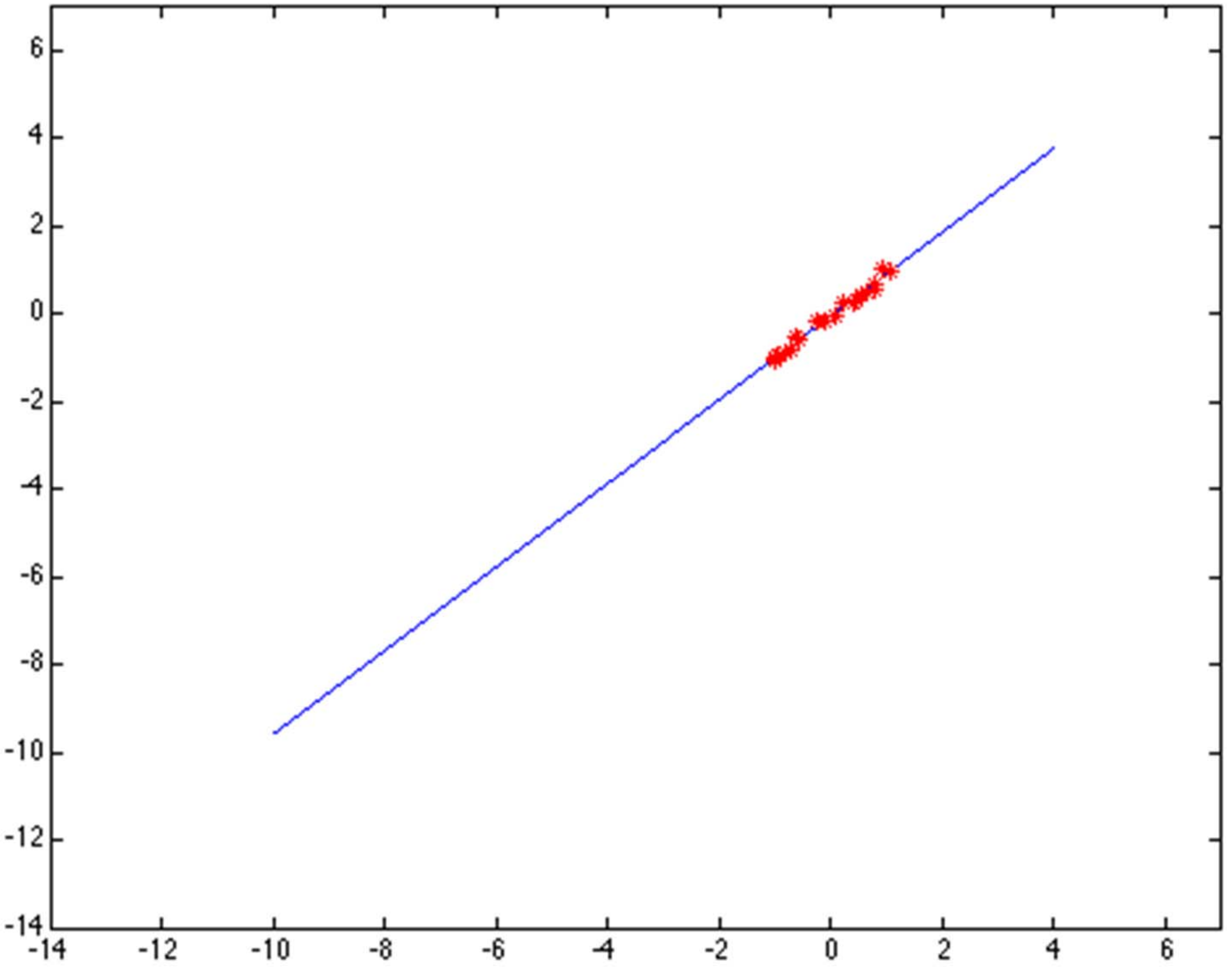
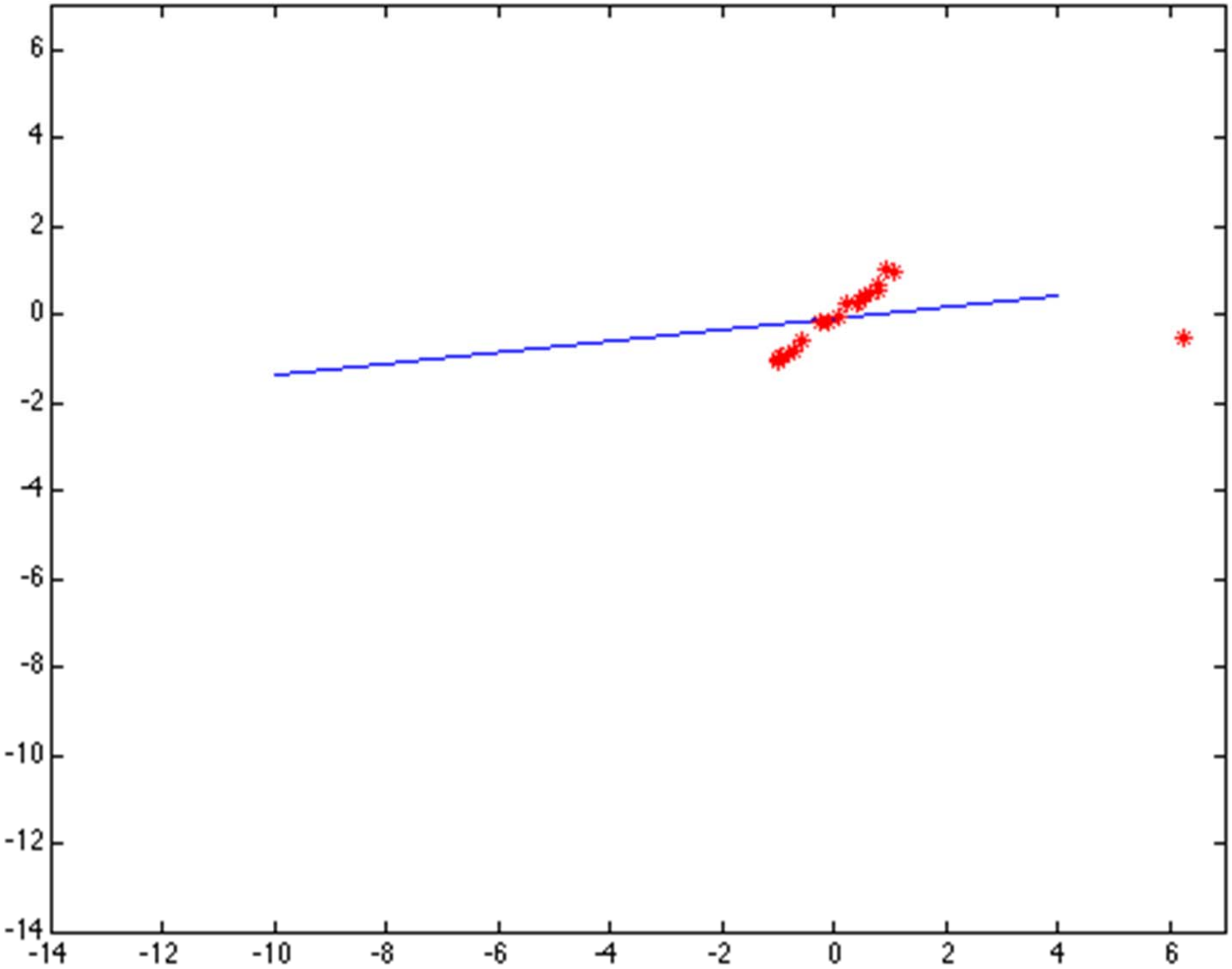
Outliers affect least squares fit



Outliers affect least squares fit



RANSAC

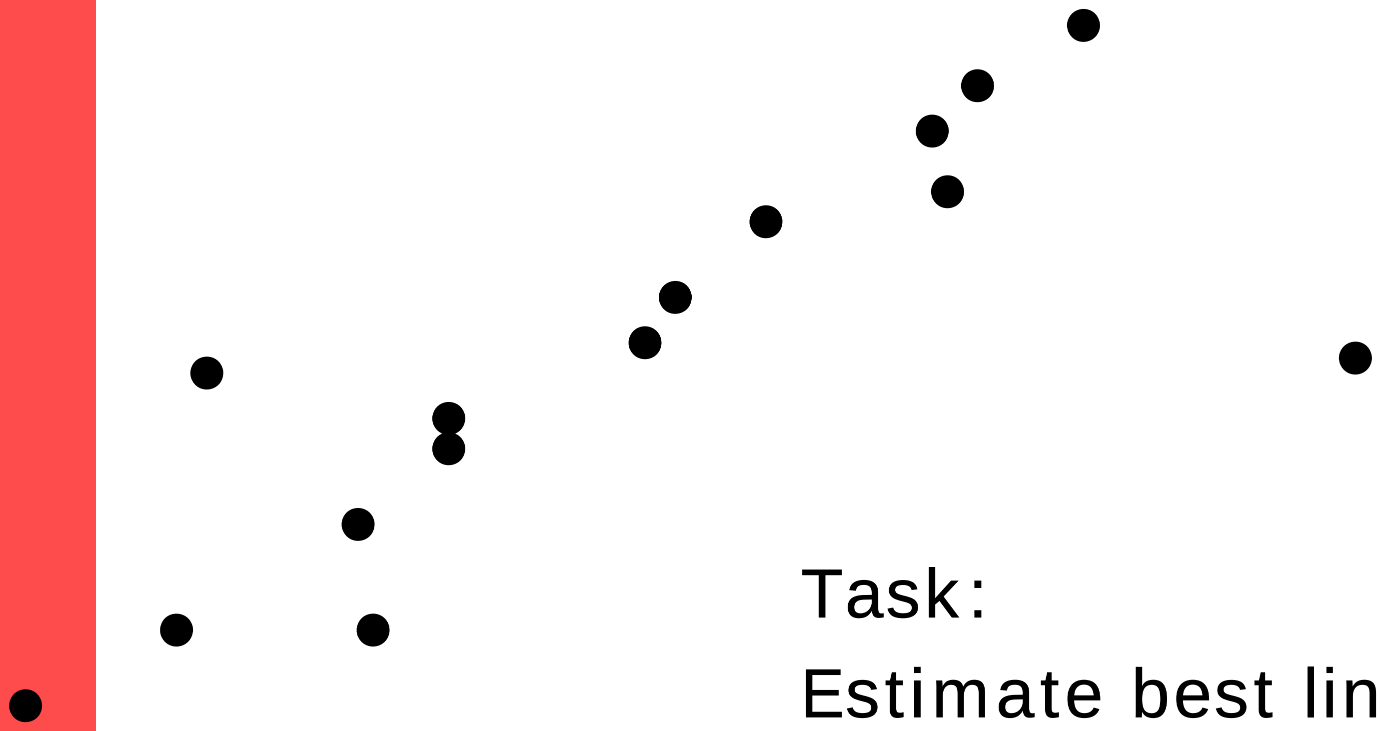
- RANdom Sample Consensus
- Approach: we want to avoid the impact of outliers, so let’s look for “inliers”, and use those only.
- Intuition: if an outlier is chosen to compute the current fit, then the resulting line won’t have much support from rest of the points.

RANSAC

- <u>RANSAC loop</u>:
  1. Randomly select a *seed group* of points on which to base transformation estimate (e.g., a group of matches)
  2. Compute transformation from seed group
  3. Find *inliers* to this transformation
  4. If the number of inliers is sufficiently large, re-compute least-squares estimate of transformation on all of the inliers

- Keep the transformation with the largest number of inliers

RANSAC Line Fitting Example

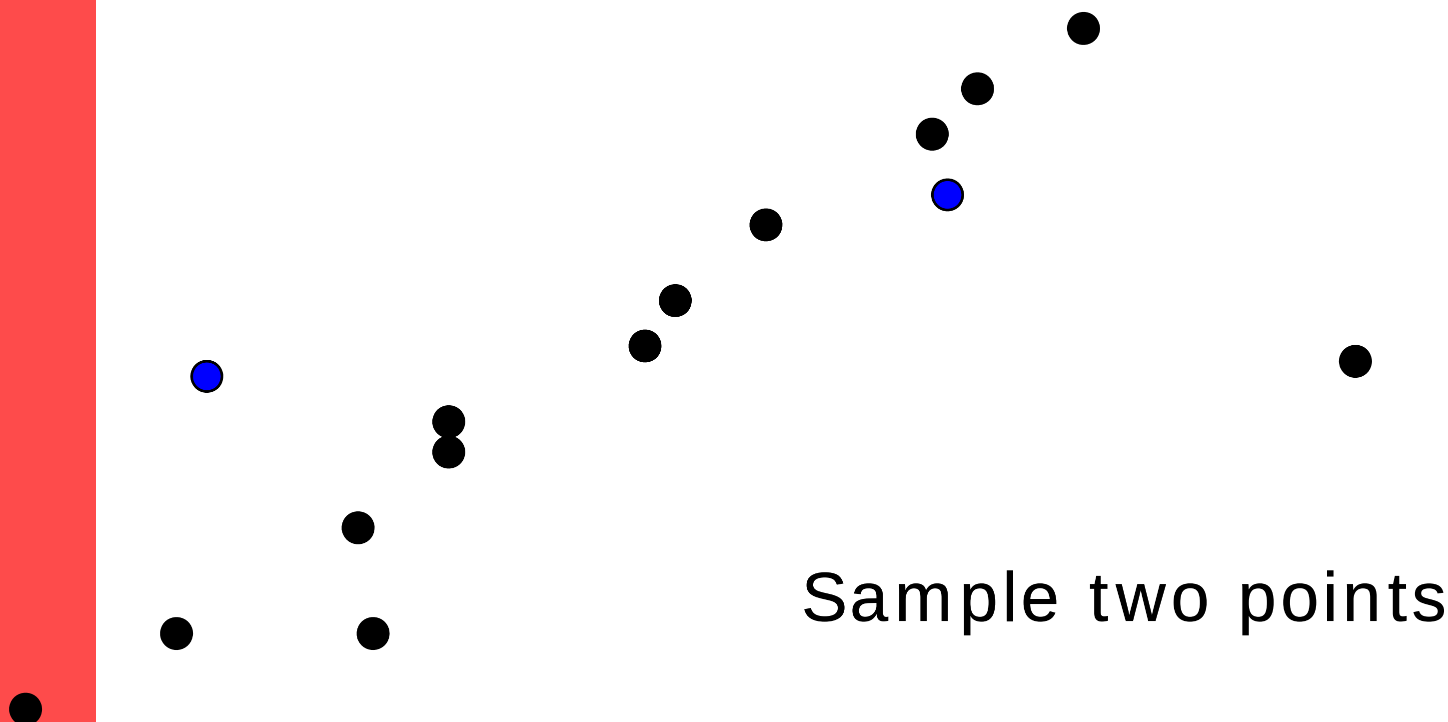


Task:

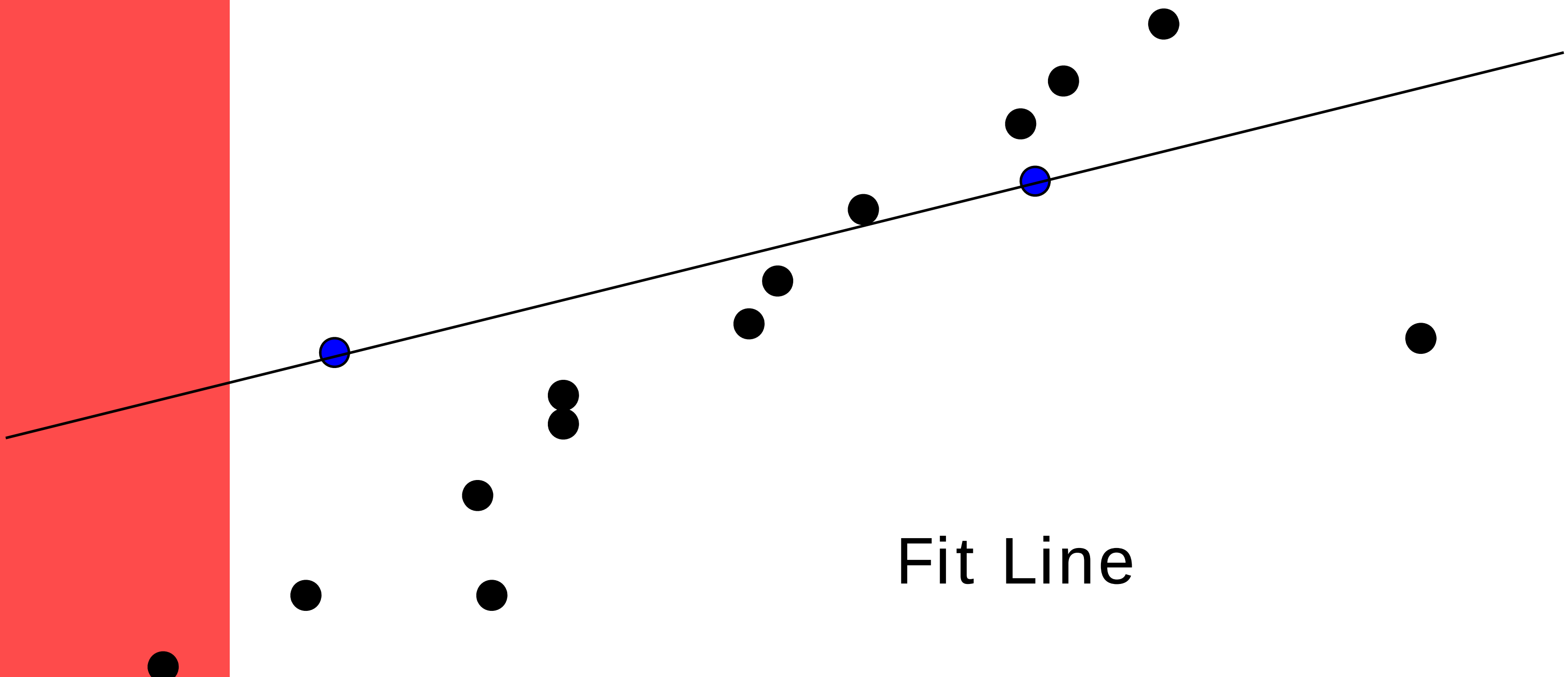
Estimate best line

Slide credit: Jinxiang Chai, CMU

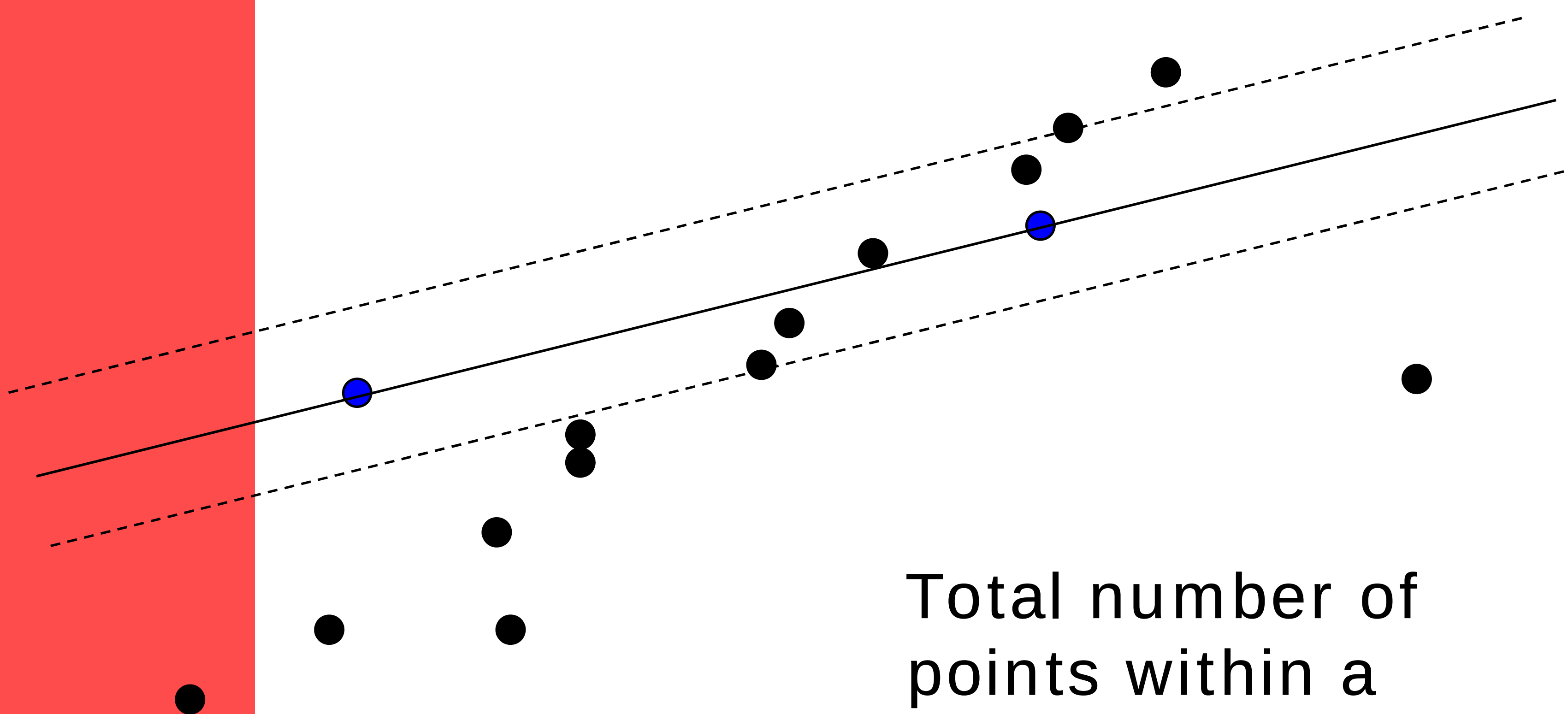
RANSAC Line Fitting Example



RANSAC Line Fitting Example

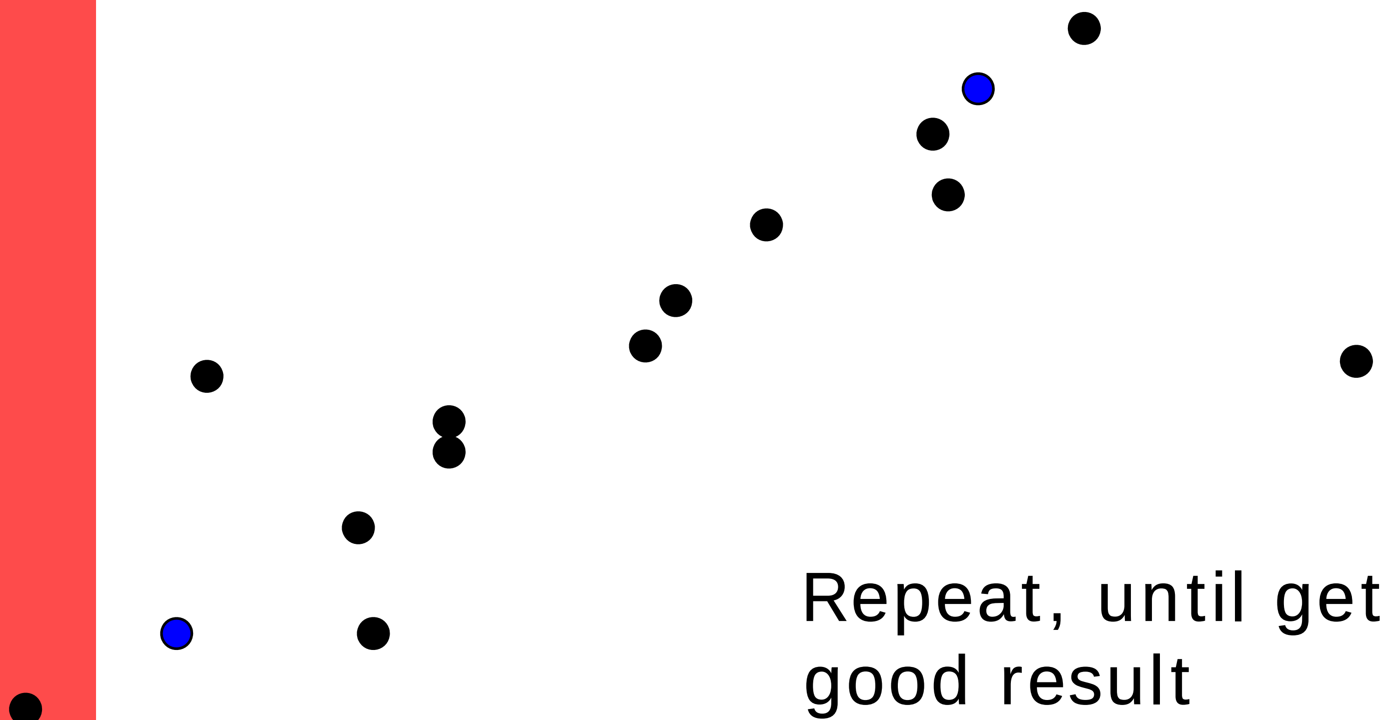


RANSAC Line Fitting Example



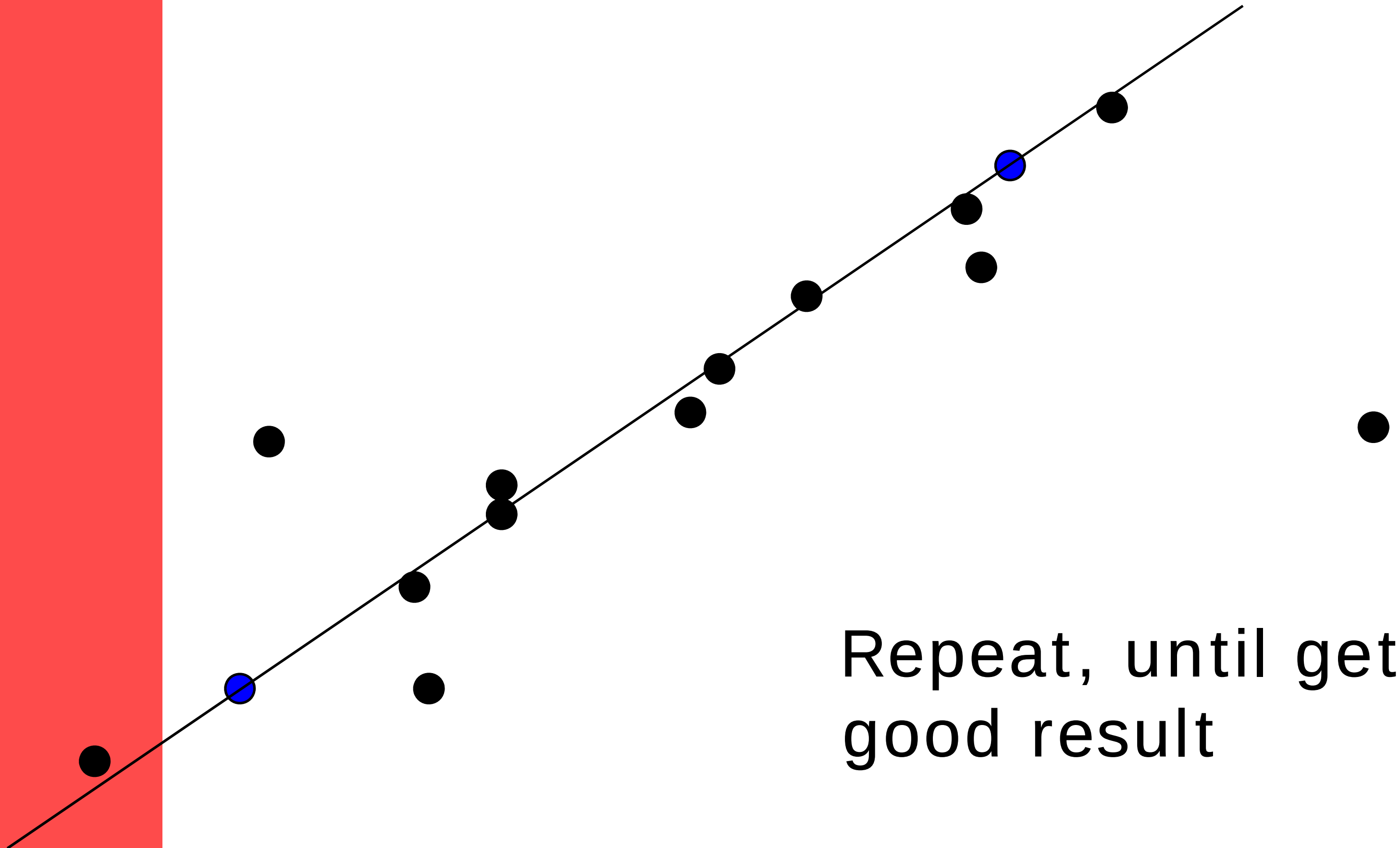
Total number of points within a threshold of line.

RANSAC Line Fitting Example



Repeat, until get a good result

RANSAC Line Fitting Example



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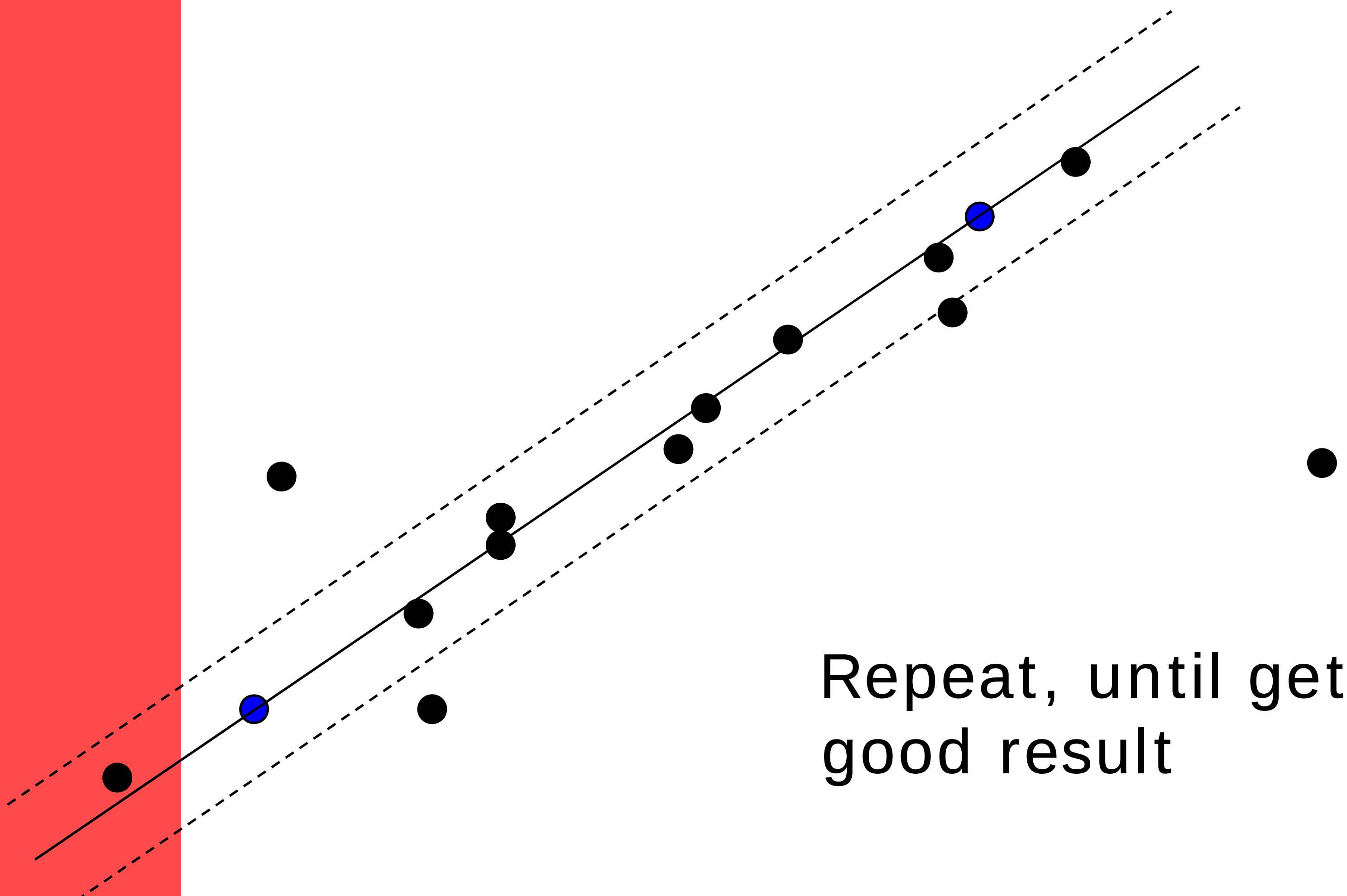
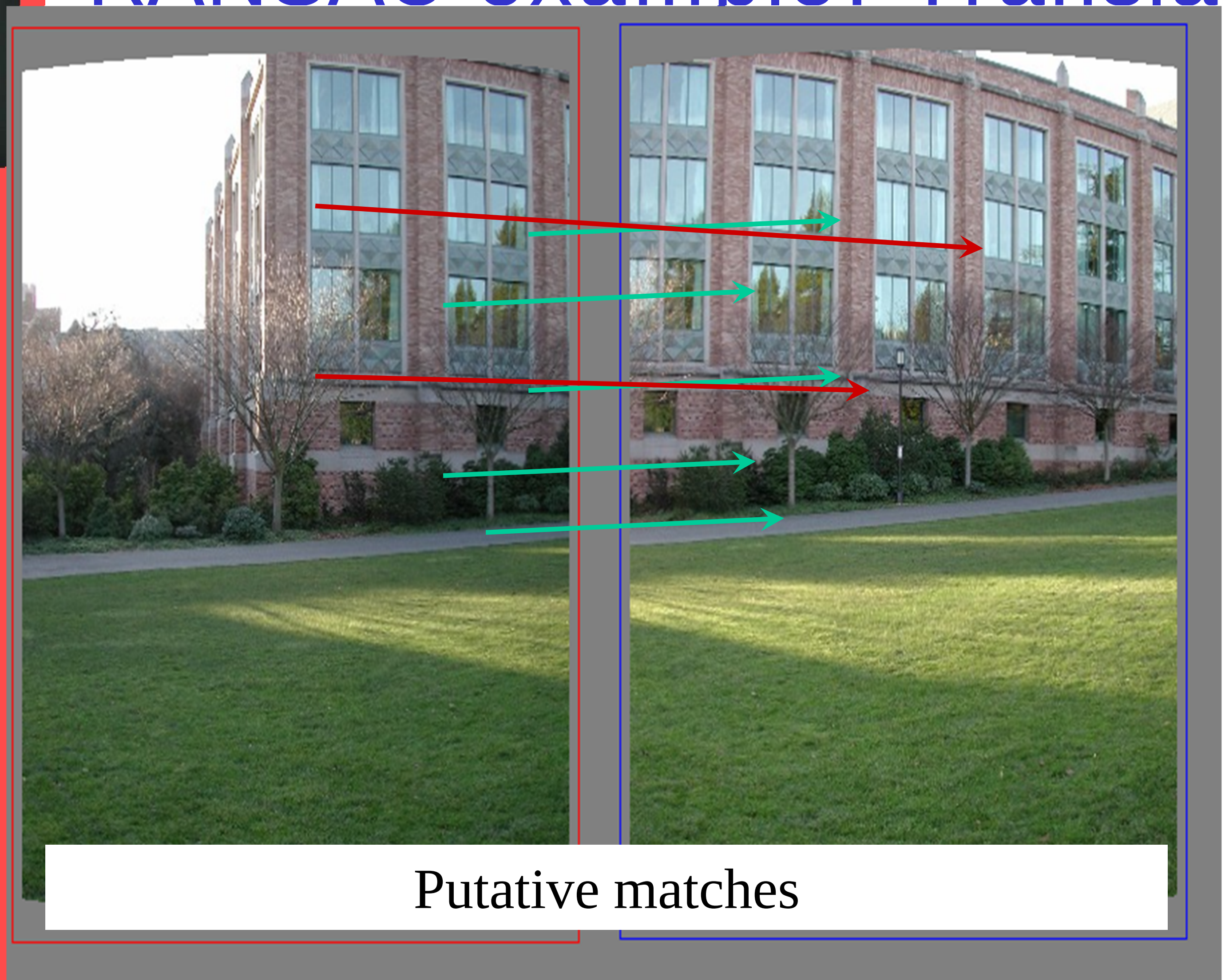


Repeat, until get a good result

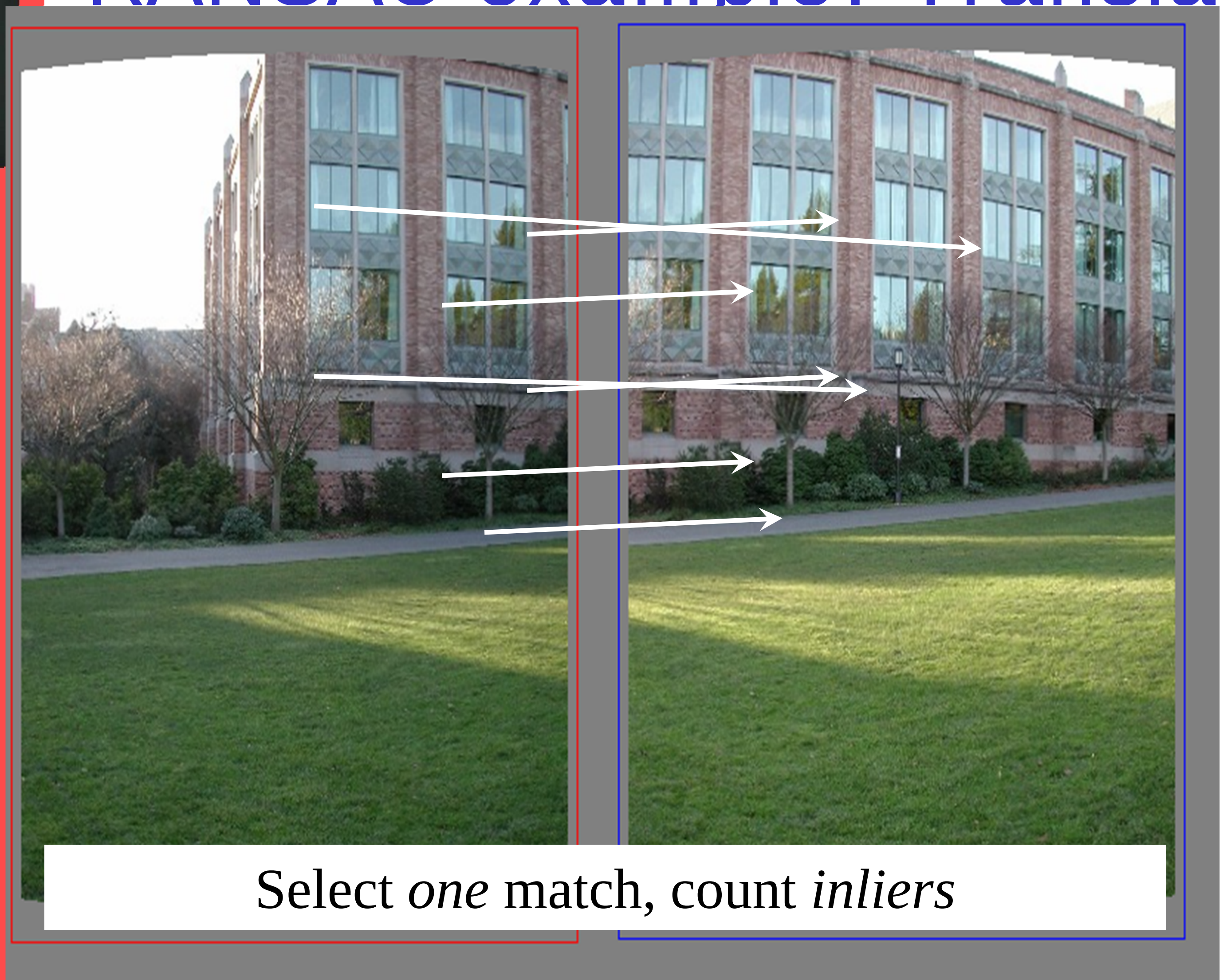
RANSAC example: Translation



Putative matches

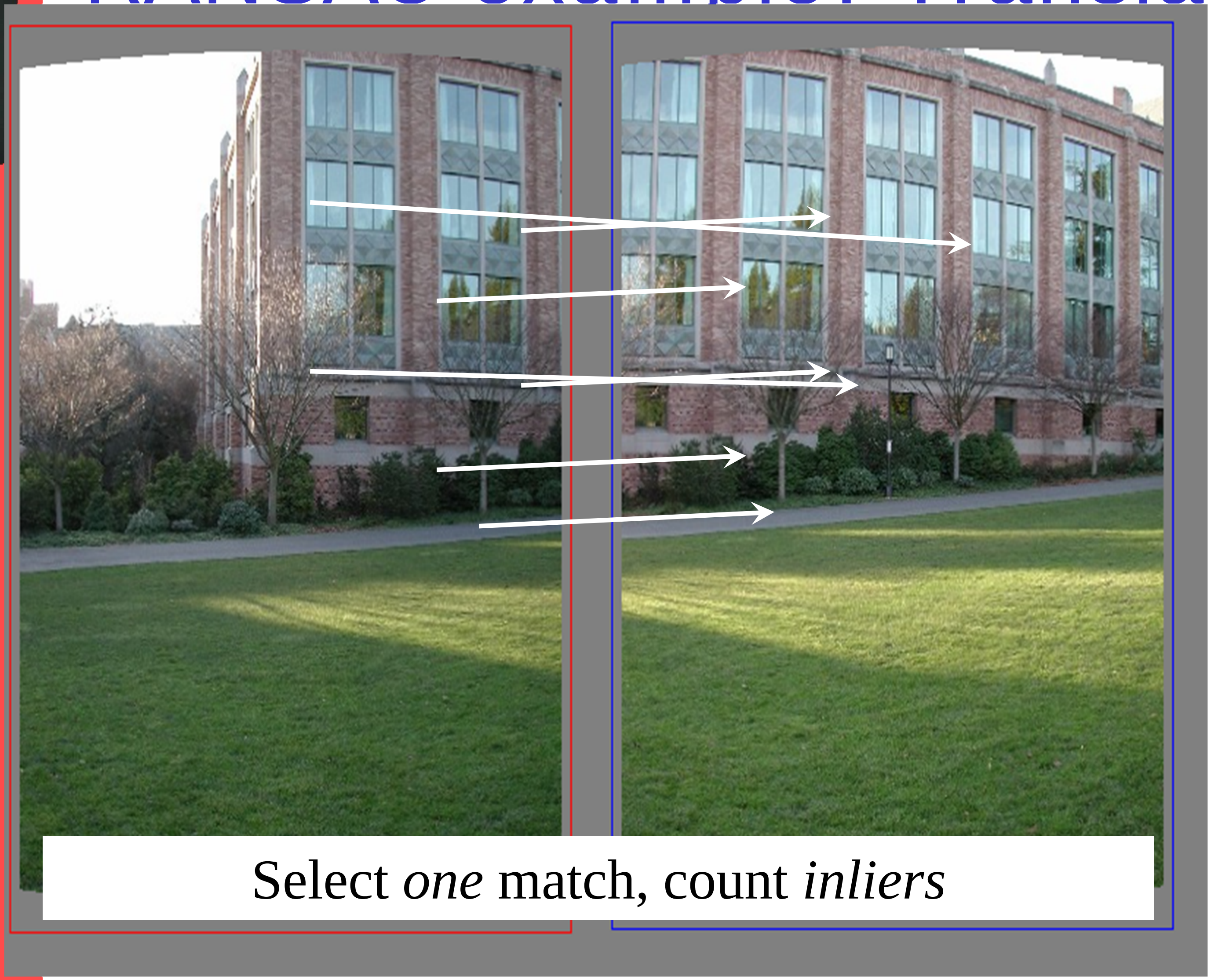
Source: Rick Szeliski

RANSAC example: Translation



Select *one* match, count *inliers*

RANSAC example: Translation



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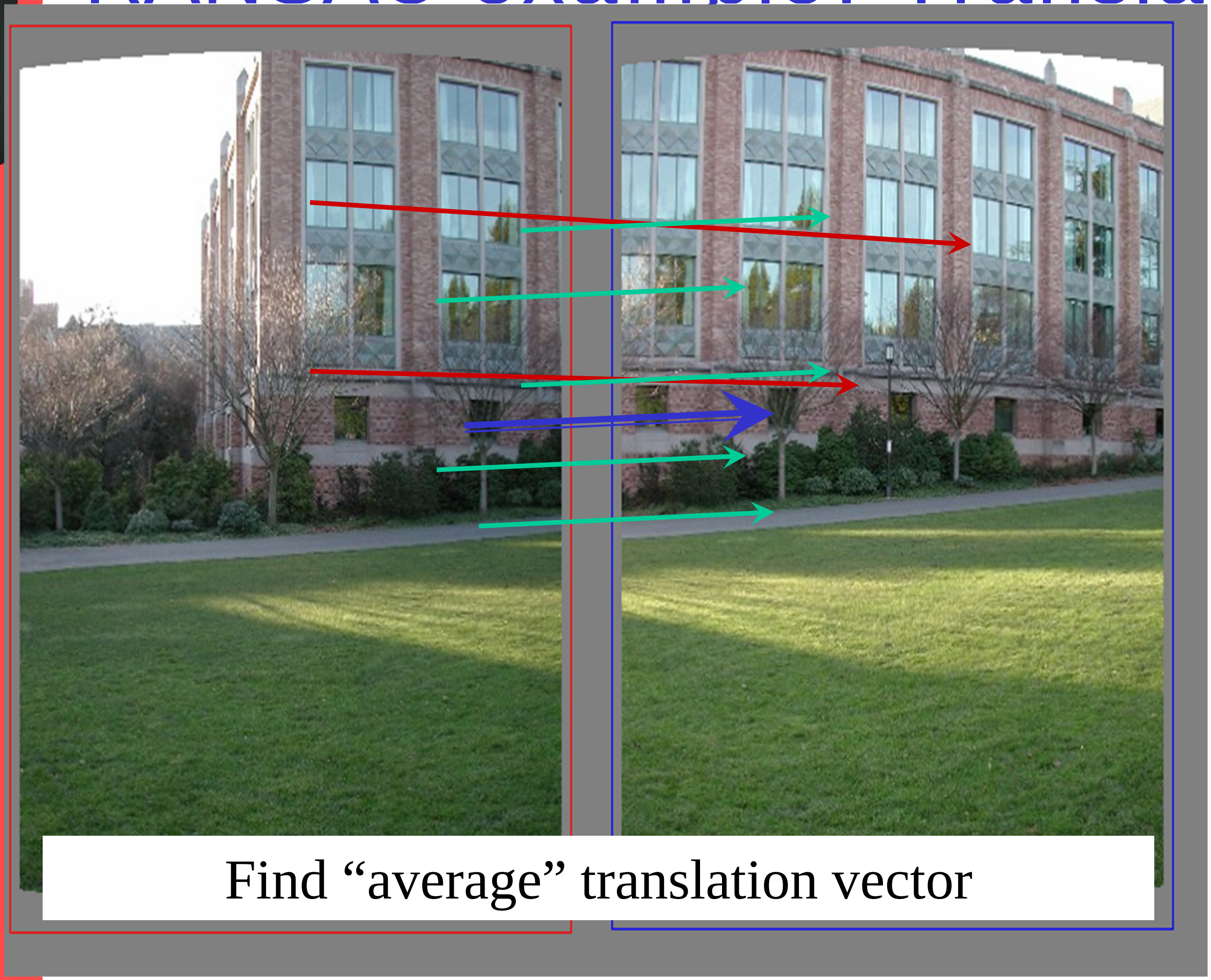
RANSAC example: Translation



Find "average" translation vector

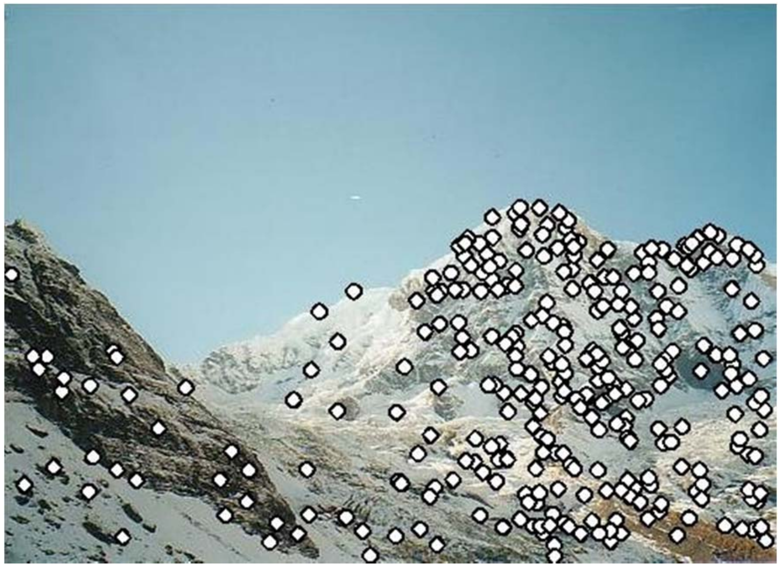
Towards large-scale mosaics…

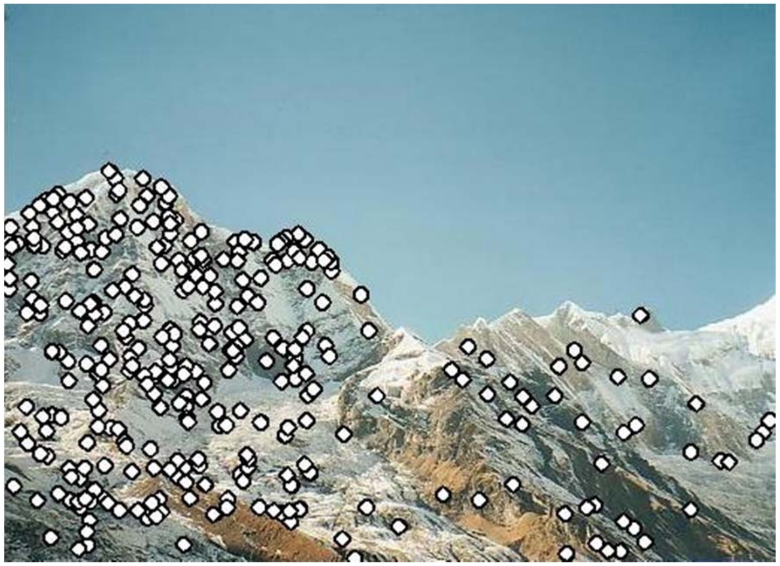
Feature-based alignment outline

Source: L. Lazebnik

Feature-based alignment outline





- Extract features

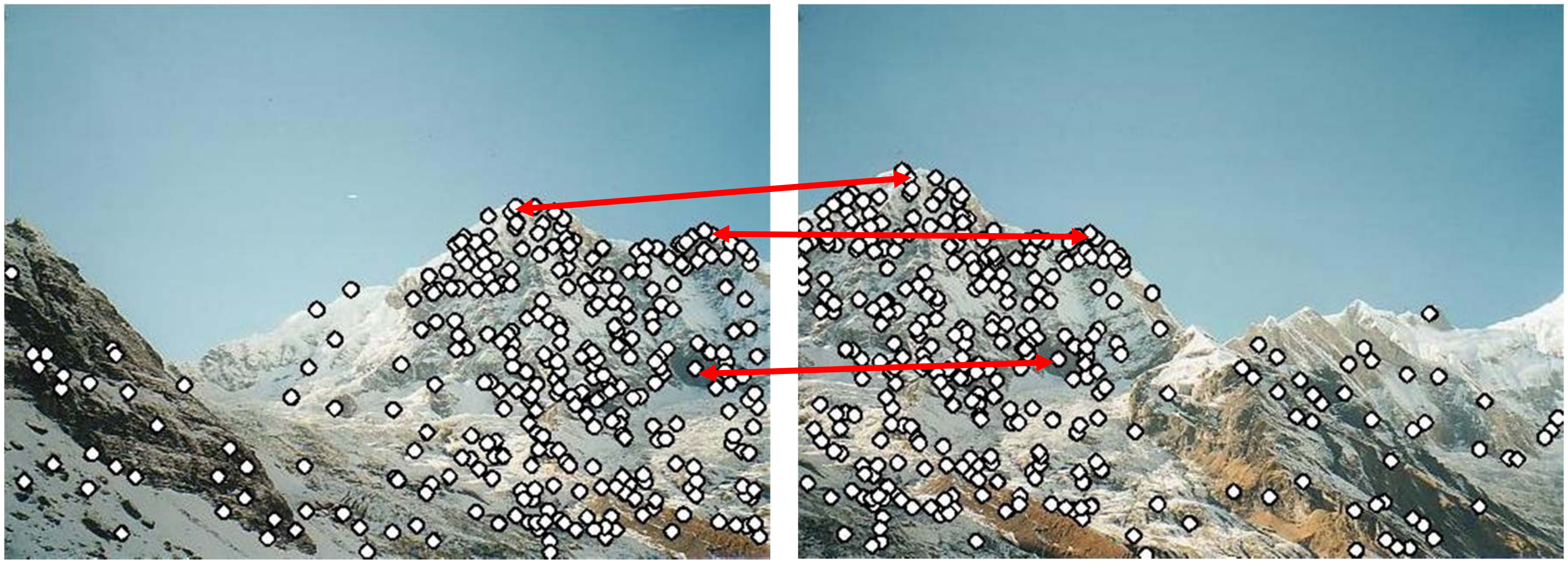
Source: L. Lazebnik

Feature-based alignment outline

- Extract features
- Compute *putative matches*

Source: L. Lazebnik

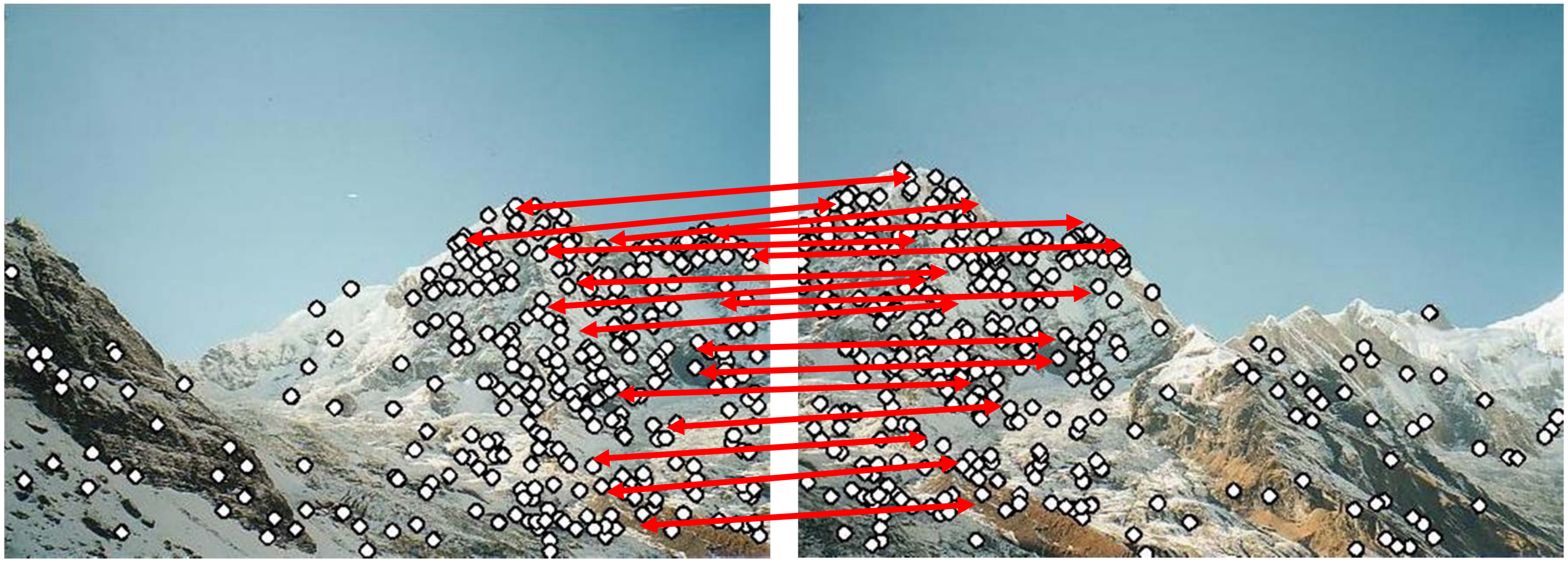
Feature-based alignment outline



- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T* (small group of putative matches that are related by *T*)

Source: L. Lazebnik

Feature-based alignment outline



- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T* (small group of putative matches that are related by *T*)
  - *Verify* transformation (search for other matches consistent with *T*)

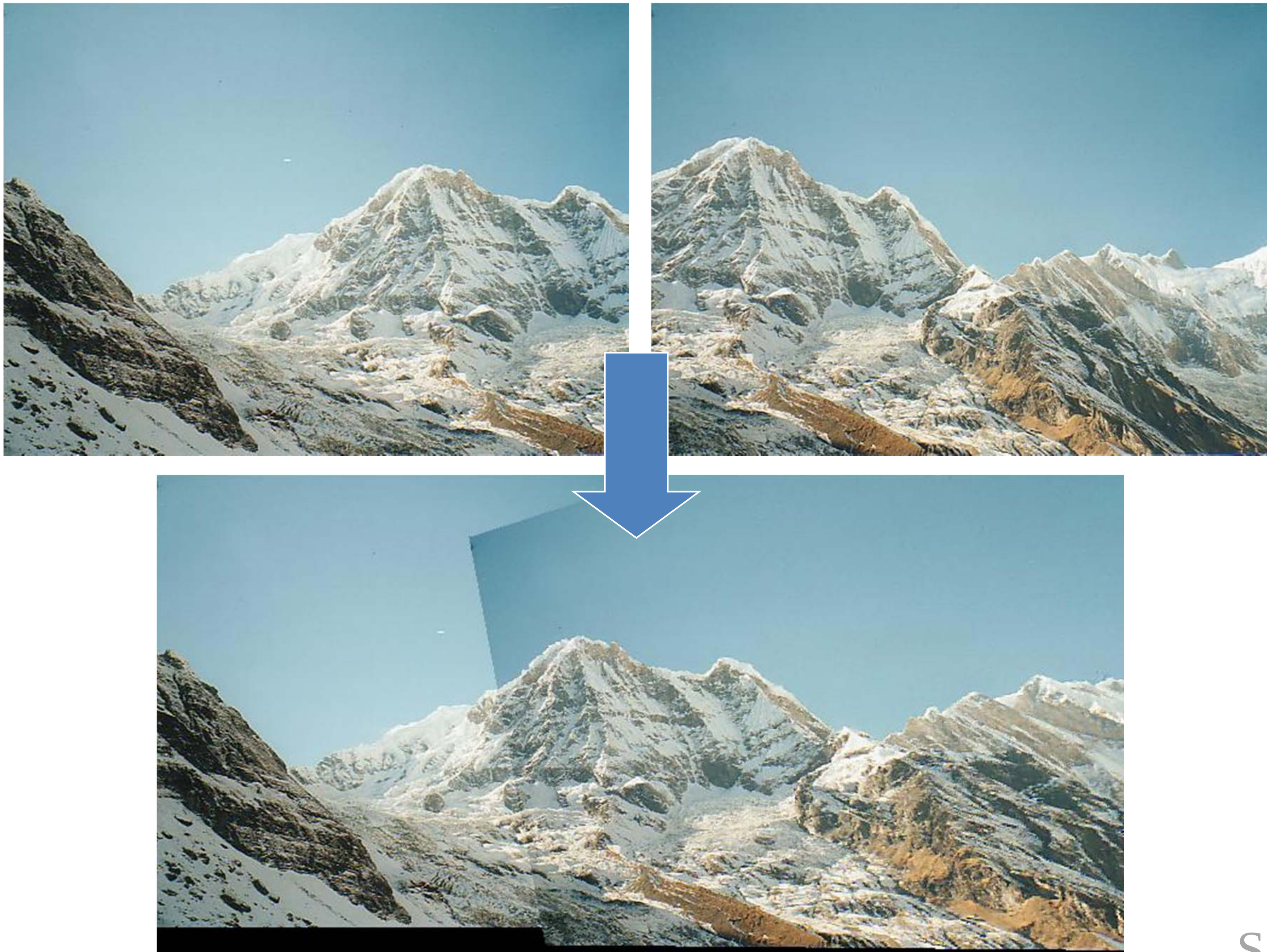
Source: L. Lazebnik

Feature-based alignment outline

- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T* (small group of putative matches that are related by *T*)
  - *Verify* transformation (search for other matches consistent with *T*)

Source: L. Lazebnik

RANSAC motion model



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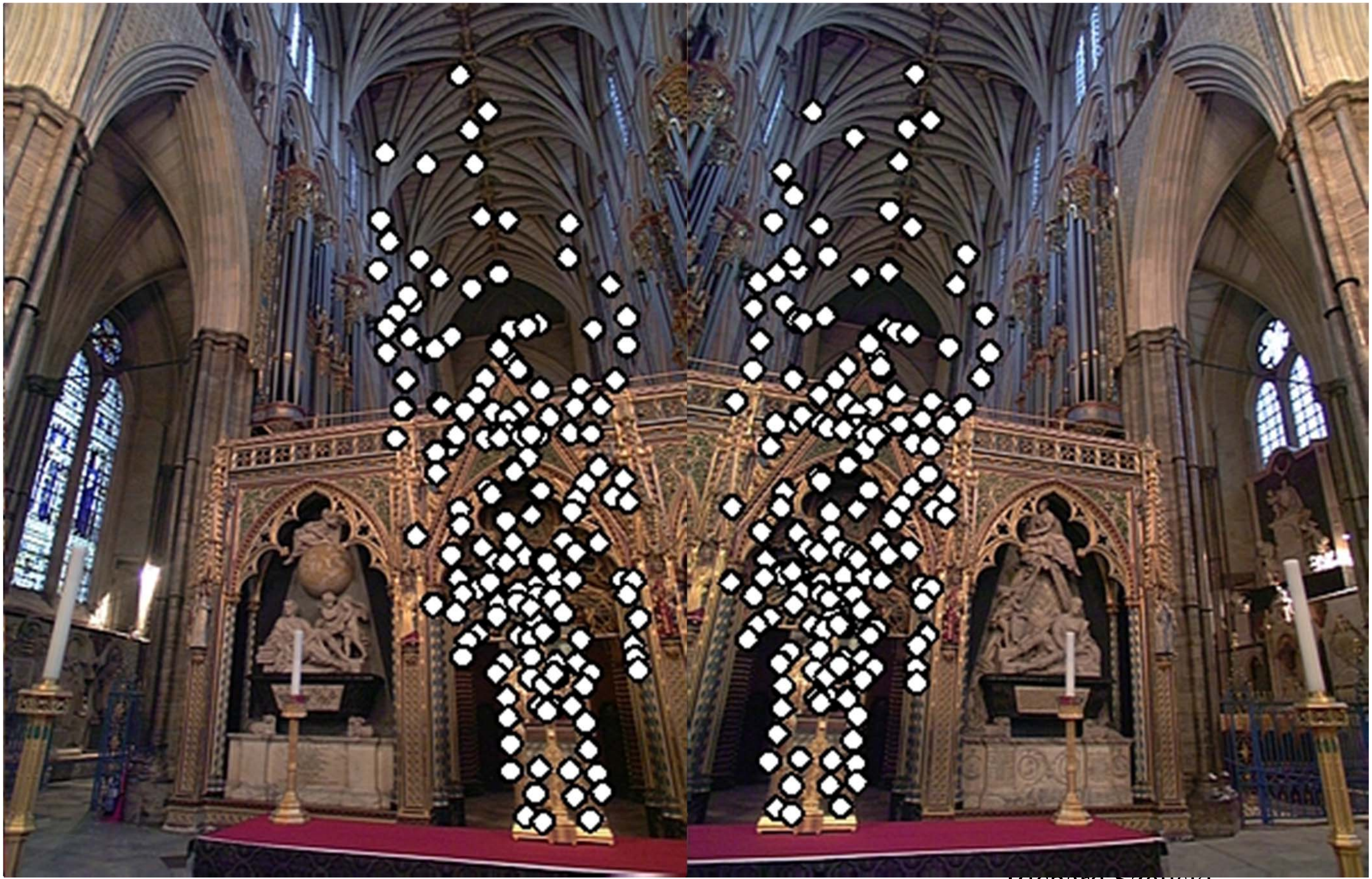
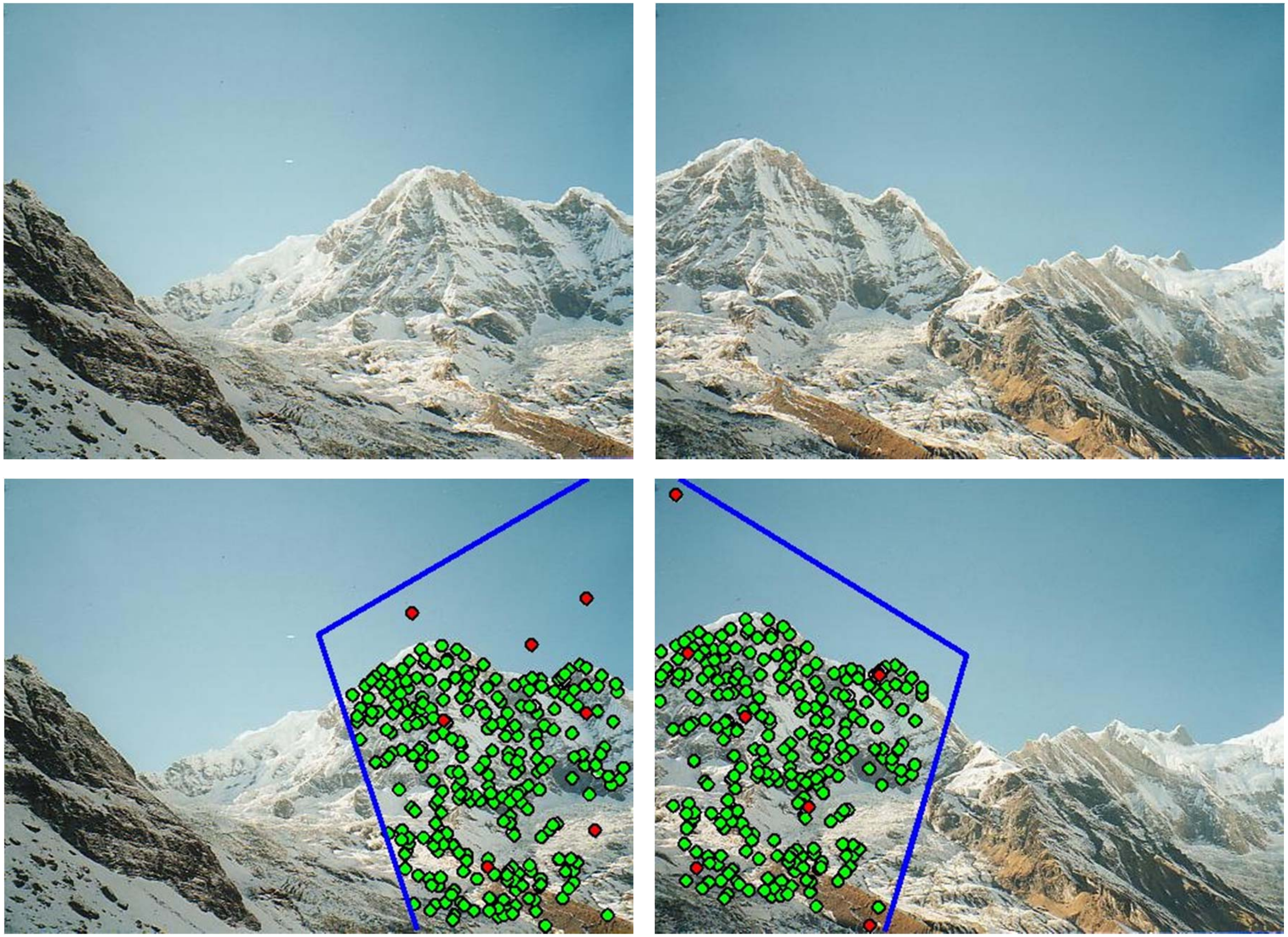
Towards large-scale mosaics…

Probabilistic Feature Matching



Richard Szeliski

Probabilistic model for verification



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Other types of mosaics

- Can mosaic onto *any* surface if you know the geometry
  - See NASA's [Visible Earth project]for some stunning earth mosaics
    - http://earthobservatory.nasa.gov/Newsroom/BlueMarble/

Final thought: What is a “panorama”?

- Tracking a subject

- Repeated (best) shots
- Multiple exposures

- “Infer” what photographer wants?

Szeliski

Next time: 6.2 Pose Estimation

- 6.2 Pose Estimation
- Chapter 7: Structure from Motion