Photogrammetry & Robotics Lab

# RANSAC – Random Sample Consensus

**Cyrill Stachniss**

# Notre-Dame

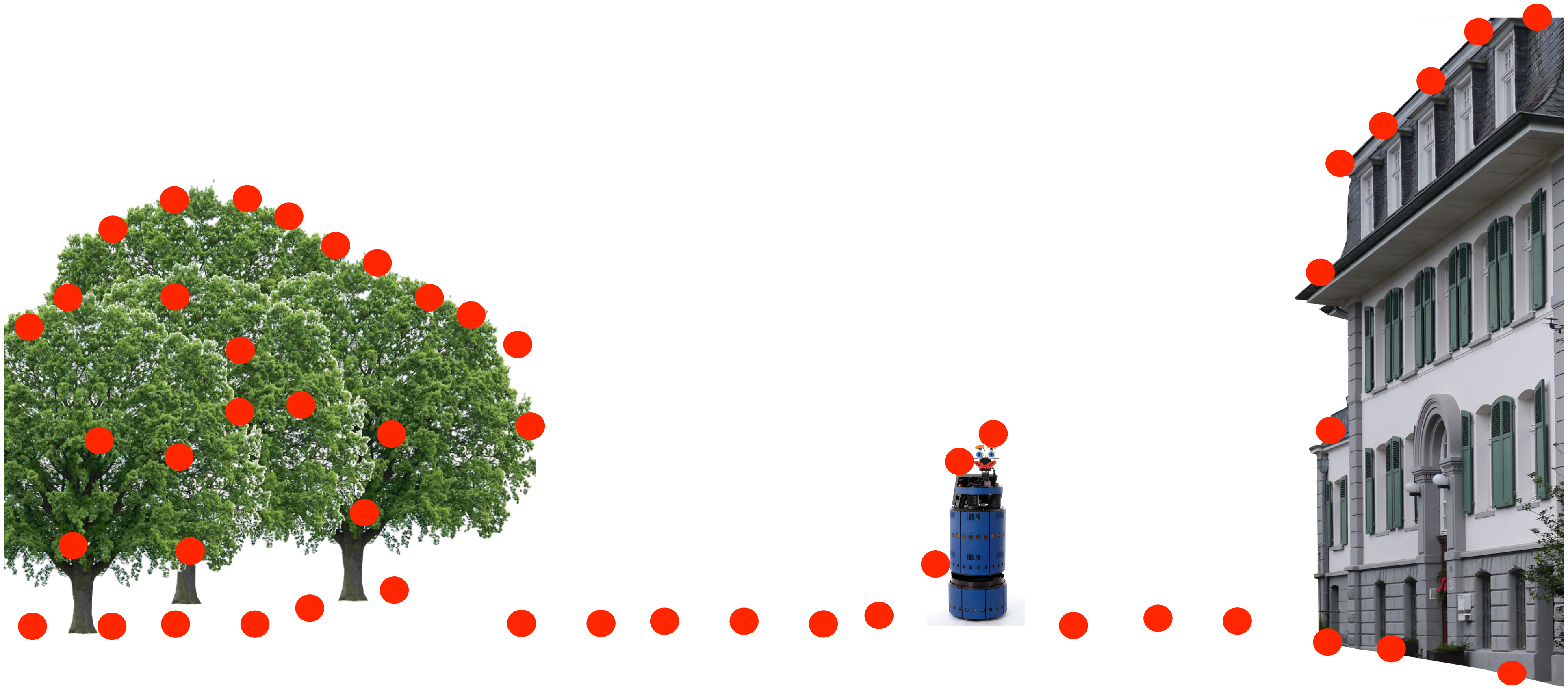
# Notre-Dame: SIFT All Matches

[Image courtesy: Barulic]

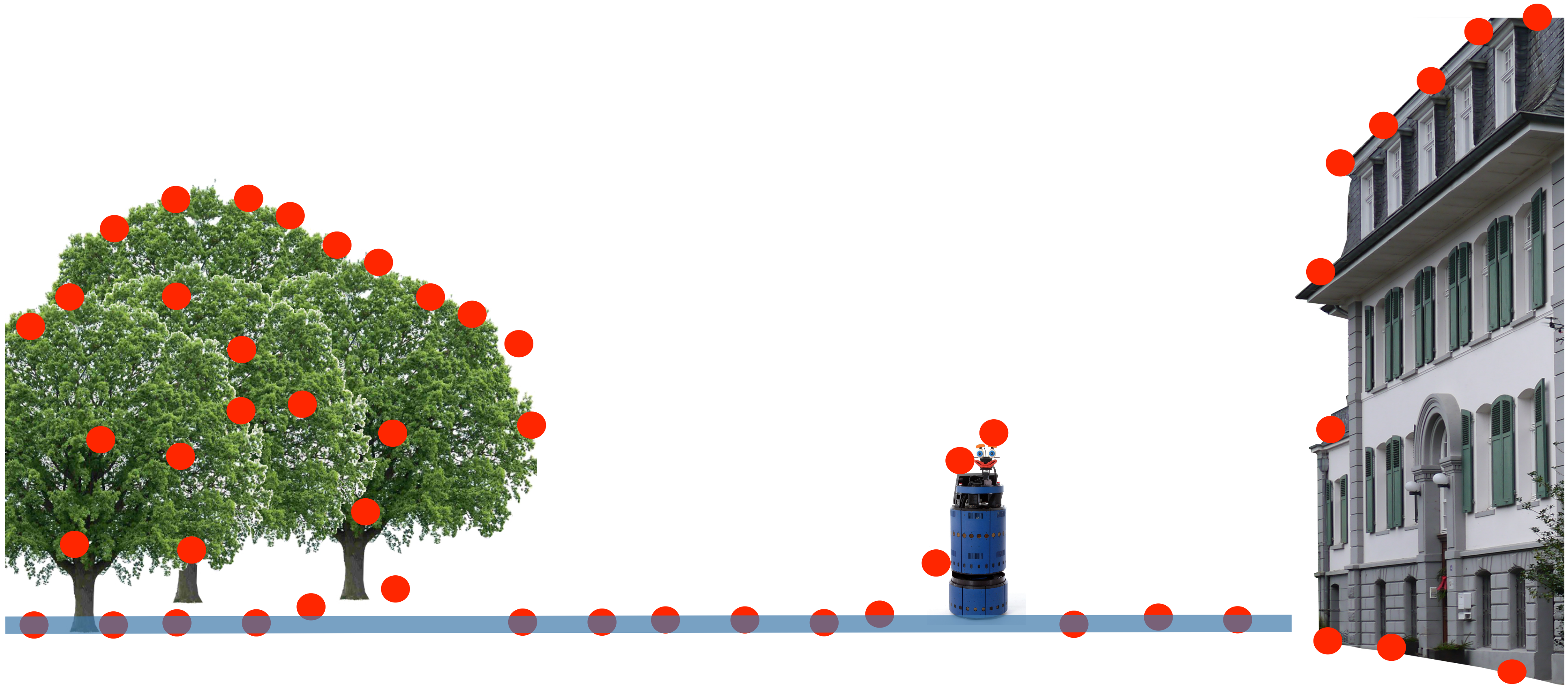
# Notre-Dame: SIFT Inliers

[Image courtesy: Barulic]

# Fitting Example: Ground Plane From Aerial Laser Scans



# Fitting Example: Ground Plane From Aerial Laser Scans



# RANSAC
# RANdom SAmple Consensus

[Fischler & Bolles 81]

# RANdom SAmple Consensus

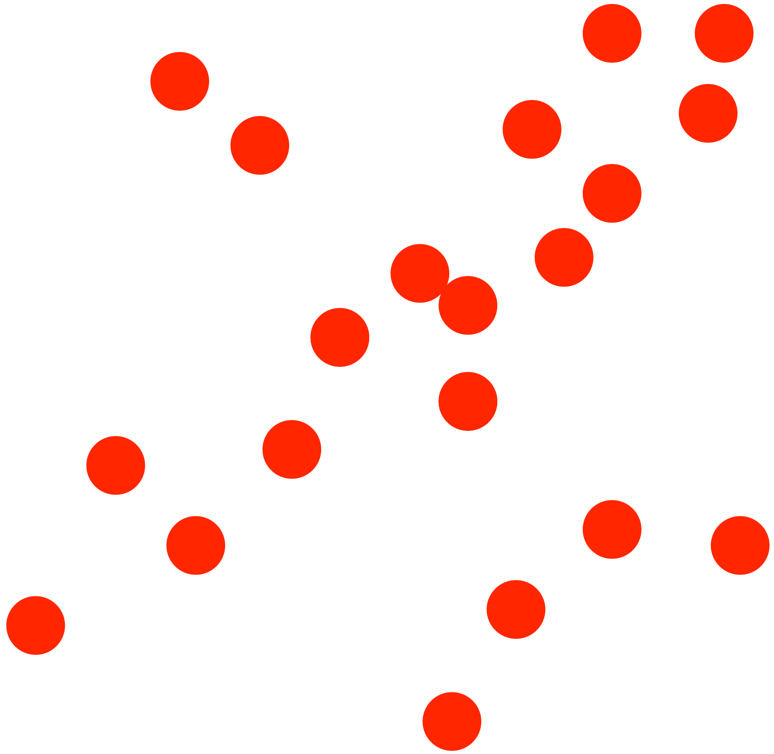
- Trial-and-error approach
- Approach to deal with high fractions of outliers in the data
- **Key idea:** Find the best partition of points in inlier set and outlier and estimate the model from the inlier set
- **Standard approach** for fitting in the presence of outliers

# RANSAC Algorithm

1. **Sample** the number of data points required to fit the model
2. **Compute** model parameters using the sampled data points
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

# RANSAC

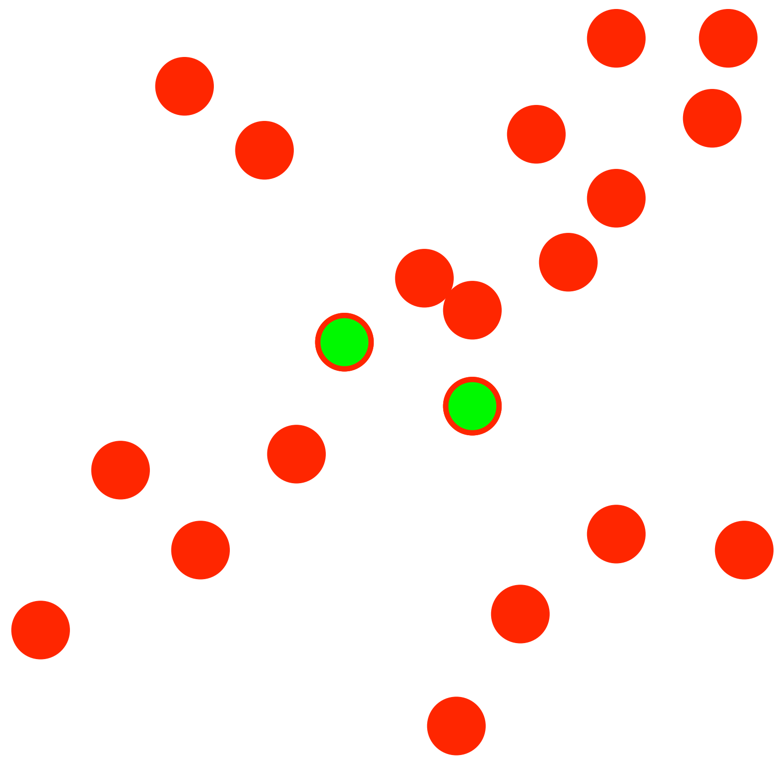


1. **Sample** the number of data points required to fit the model
2. **Compute** model parameters using the samples
3. **Score** by the fraction of inliers within a preset threshold of the model

**Repeat** 1-3 until the best model is found

Illustration by Savarese

# RANSAC
## Line fitting example

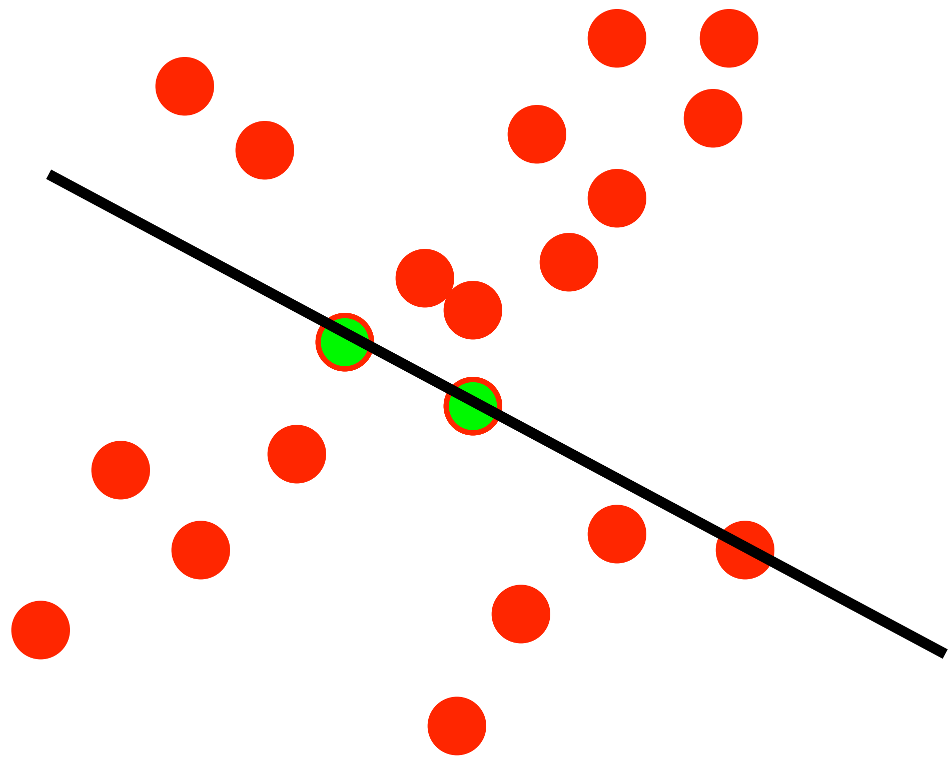


1. **Sample** the number of data points required to fit the model (here: 2 points)
2. **Compute** model parameters using the samples
3. **Score** by the fraction of inliers within a preset threshold of the model

**Repeat** 1-3 until the best model is found

Illustration by Savarese 

# RANSAC
## Line fitting example



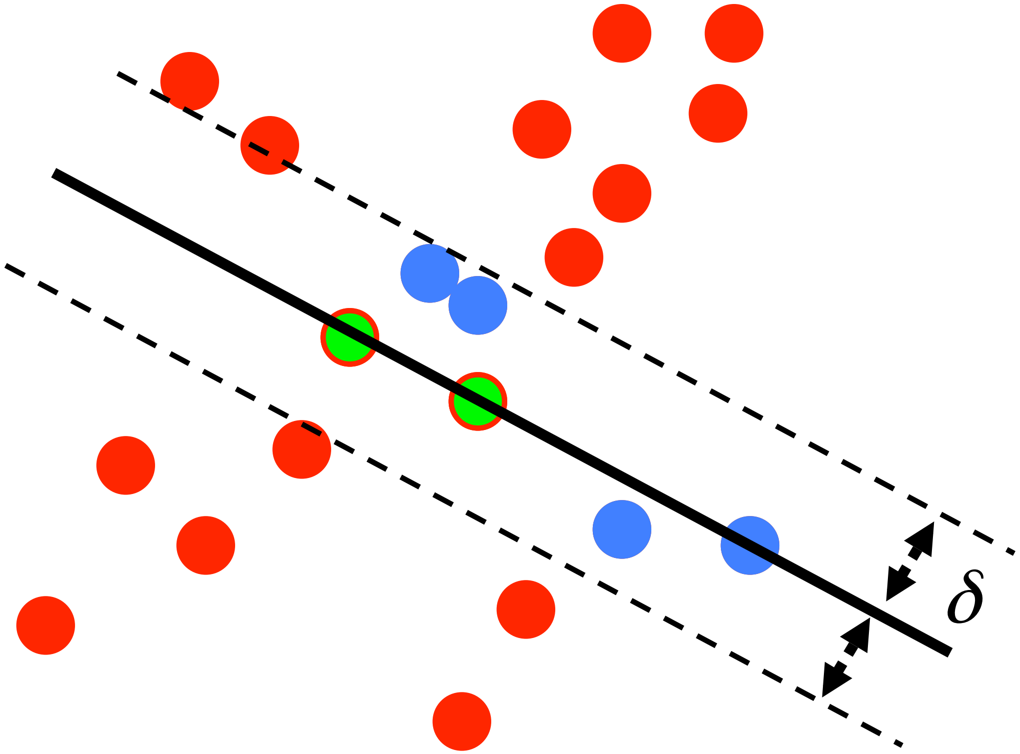
1. **Sample** the number of data points required to fit the model (here: 2 points)
2. **Compute** model parameters using the samples
3. **Score** by the fraction of inliers within a preset threshold of the model

**Repeat** 1-3 until the best model is found

Illustration by Savarese

# RANSAC

## Line fitting example




**#inliers: 4**

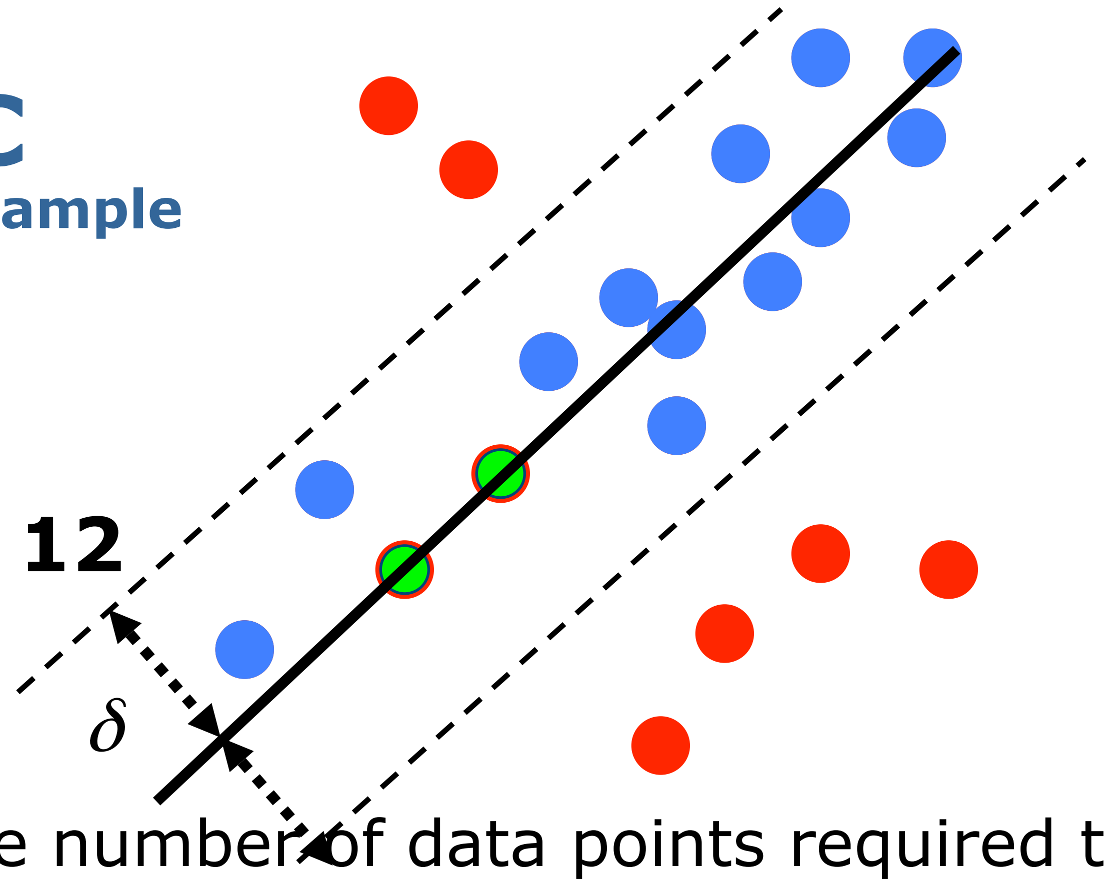
1. **Sample** the number of data points required to fit the model (here: 2 points)
2. **Compute** model parameters using the samples
3. **Score** by the fraction of inliers within a preset threshold of the model

**Repeat** 1-3 until the best model is found

Illustration by Savarese 

# RANSAC

## Line fitting example



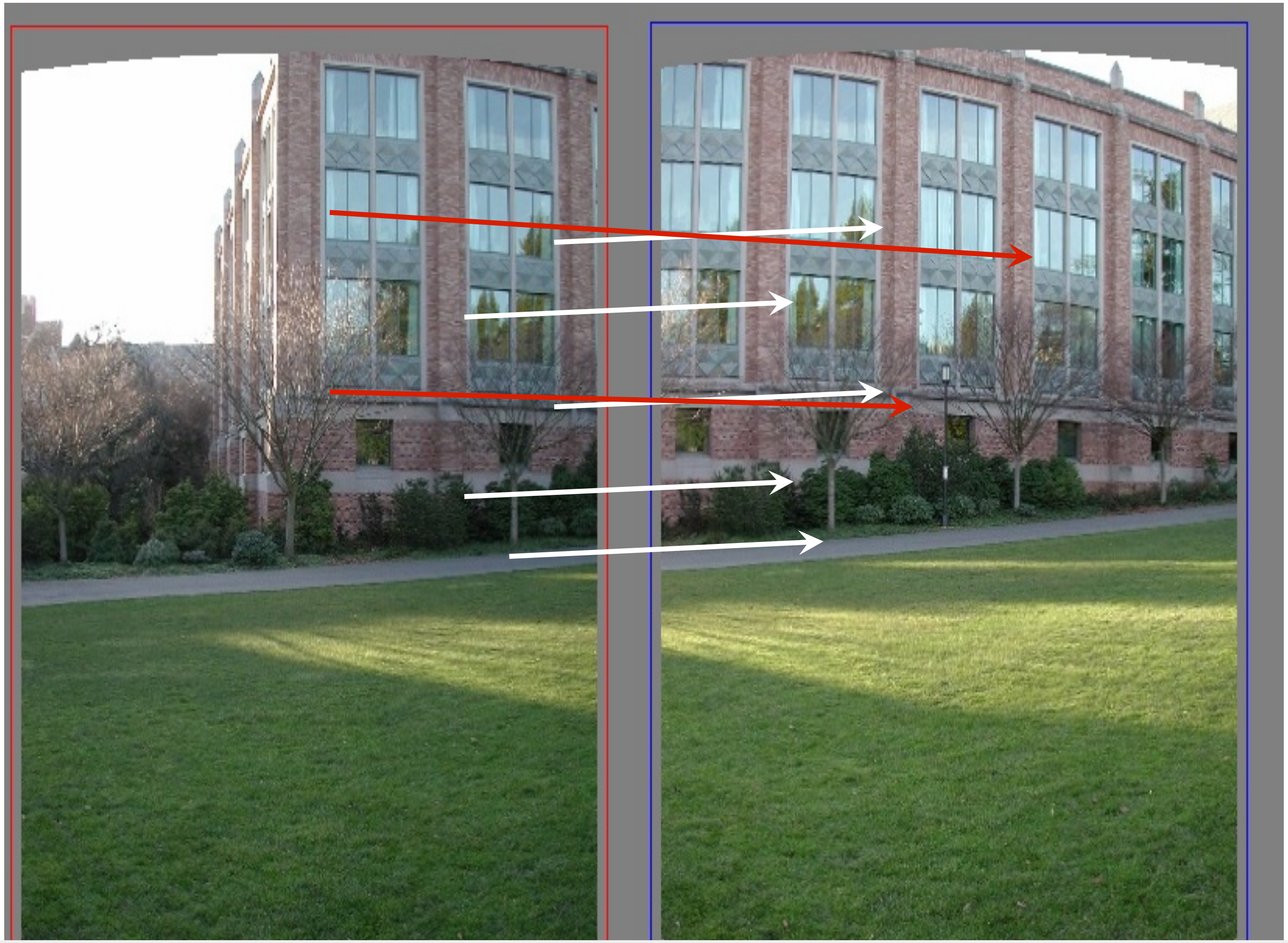

**#inliers: 12**

1. **Sample** the number of data points required to fit the model (here: 2 points)
2. **Compute** model parameters using the samples
3. **Score** by the fraction of inliers within a preset threshold of the model

**Repeat** 1-3 until the best model is found

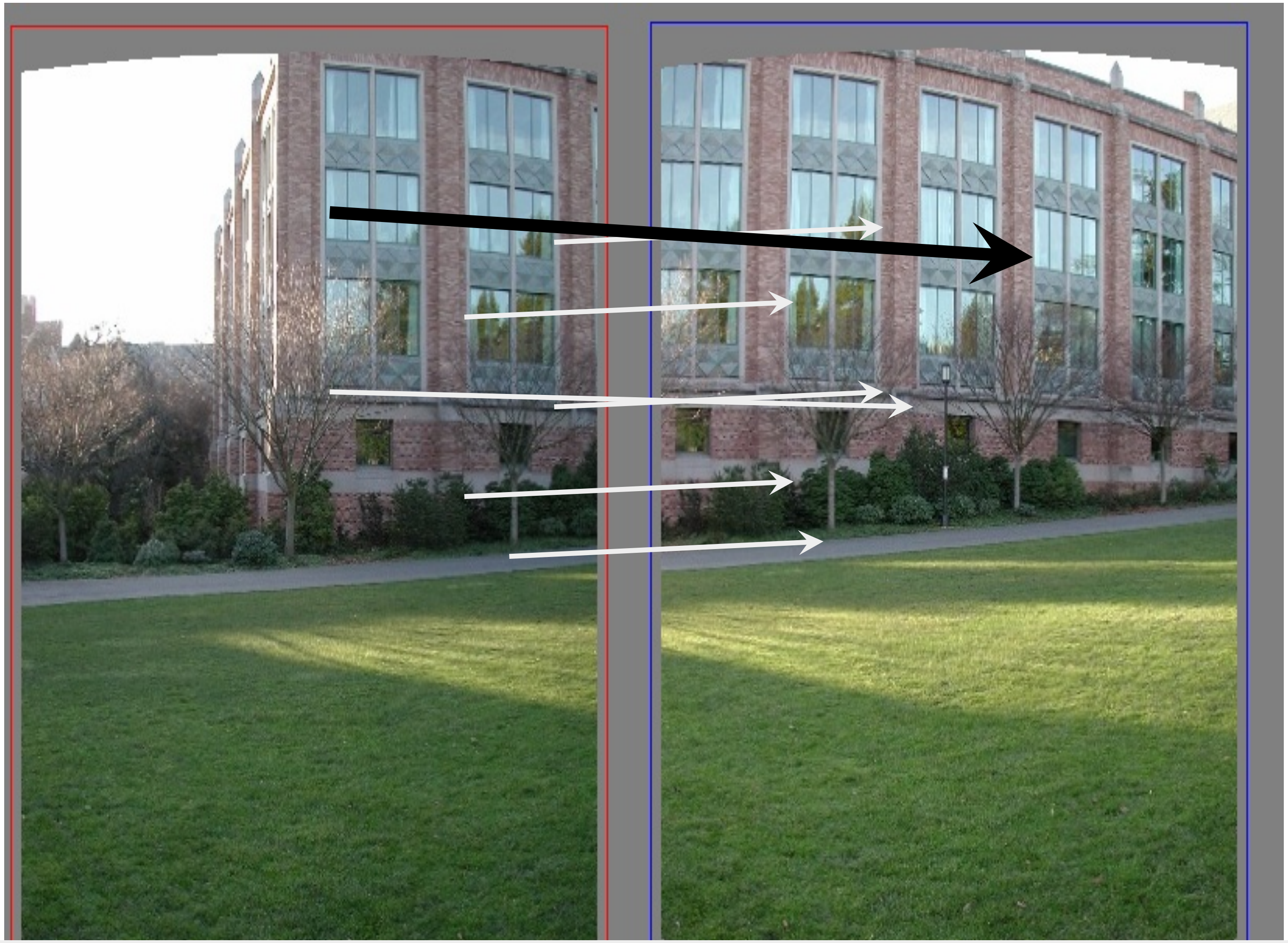
Illustration by Savarese 

# RANSAC Example: Translation



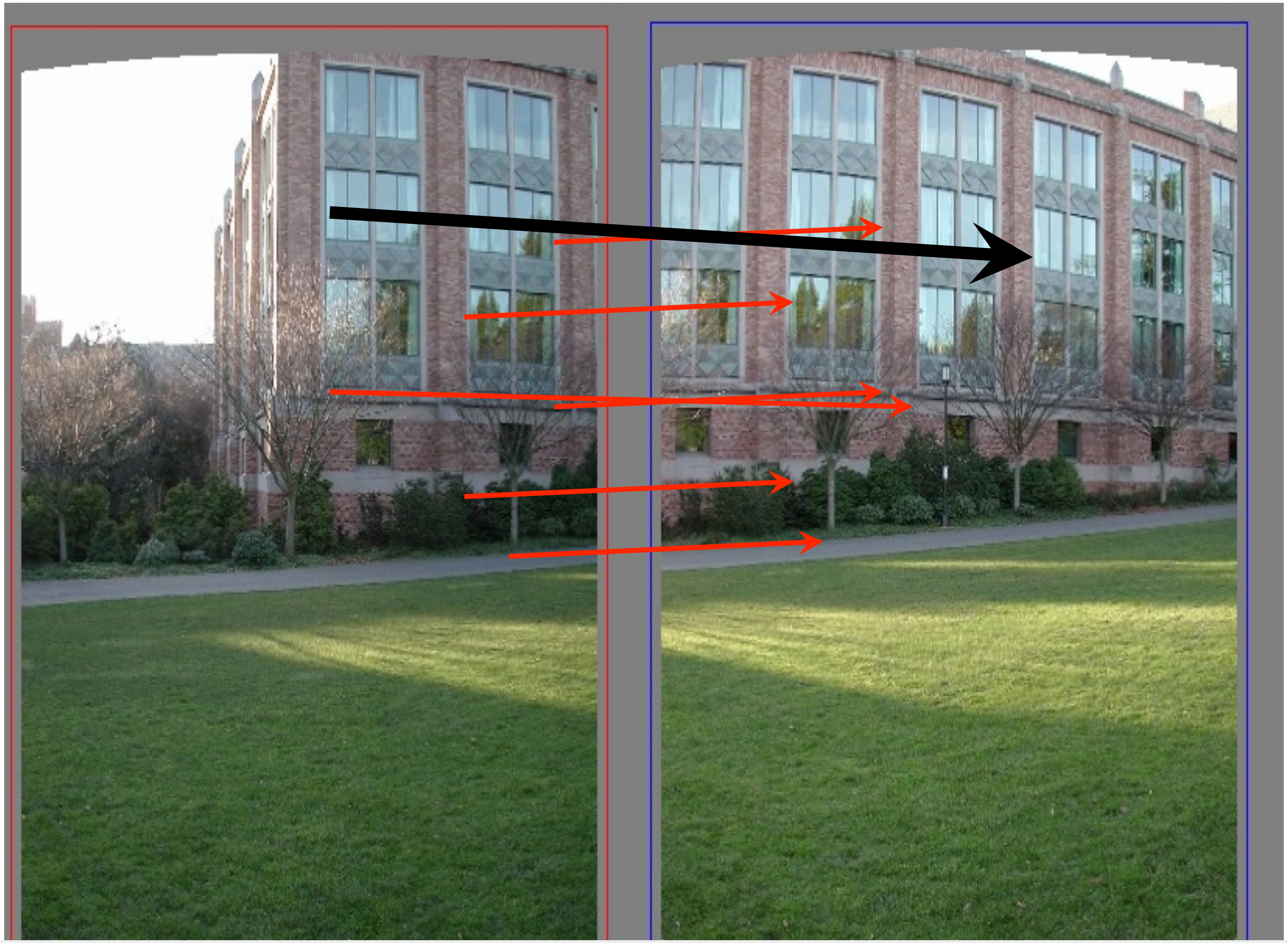
extracted features correspondences

# RANSAC Example: Translation



select random match

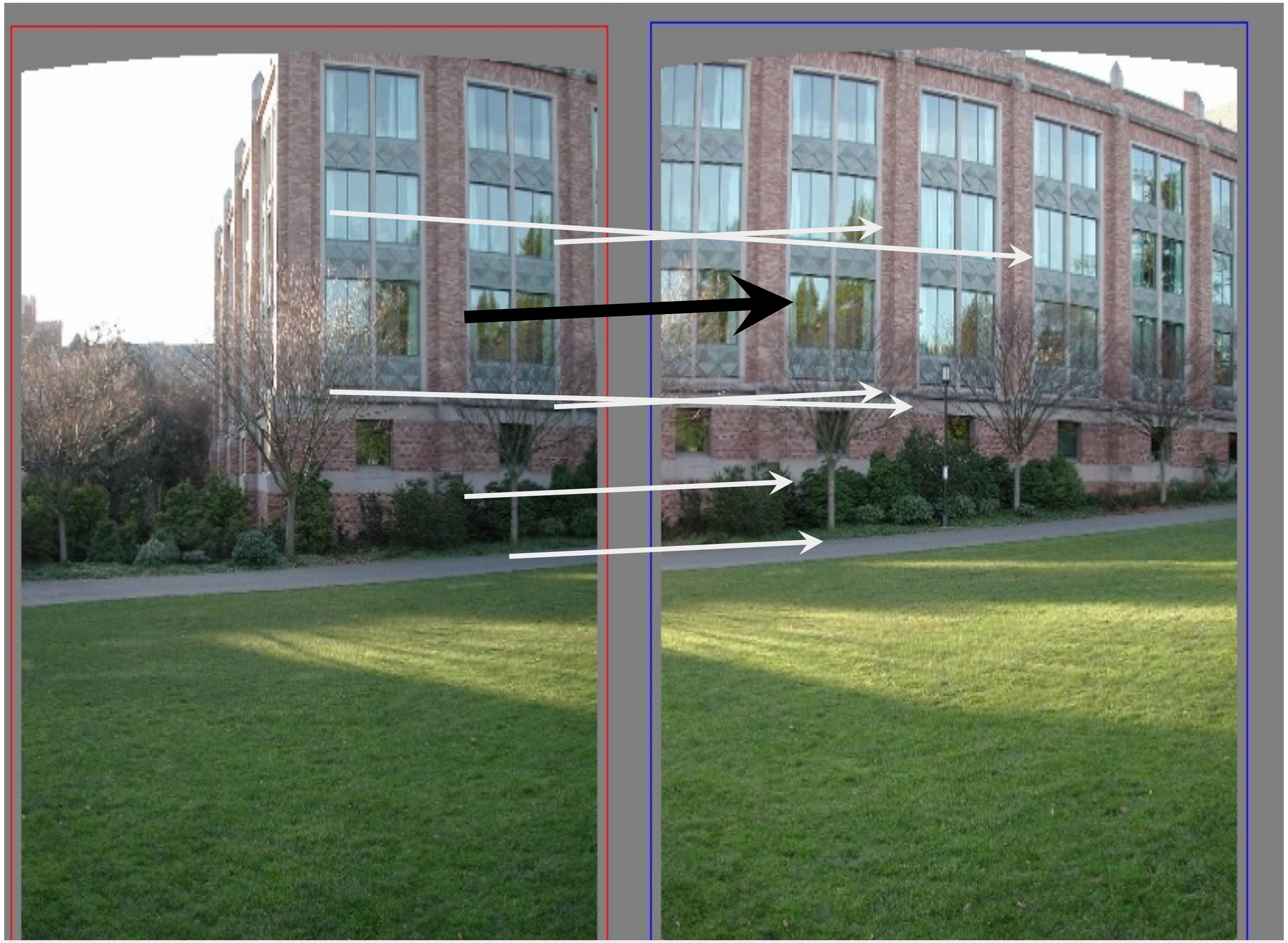
# RANSAC Example: Translation



count inliers (0)

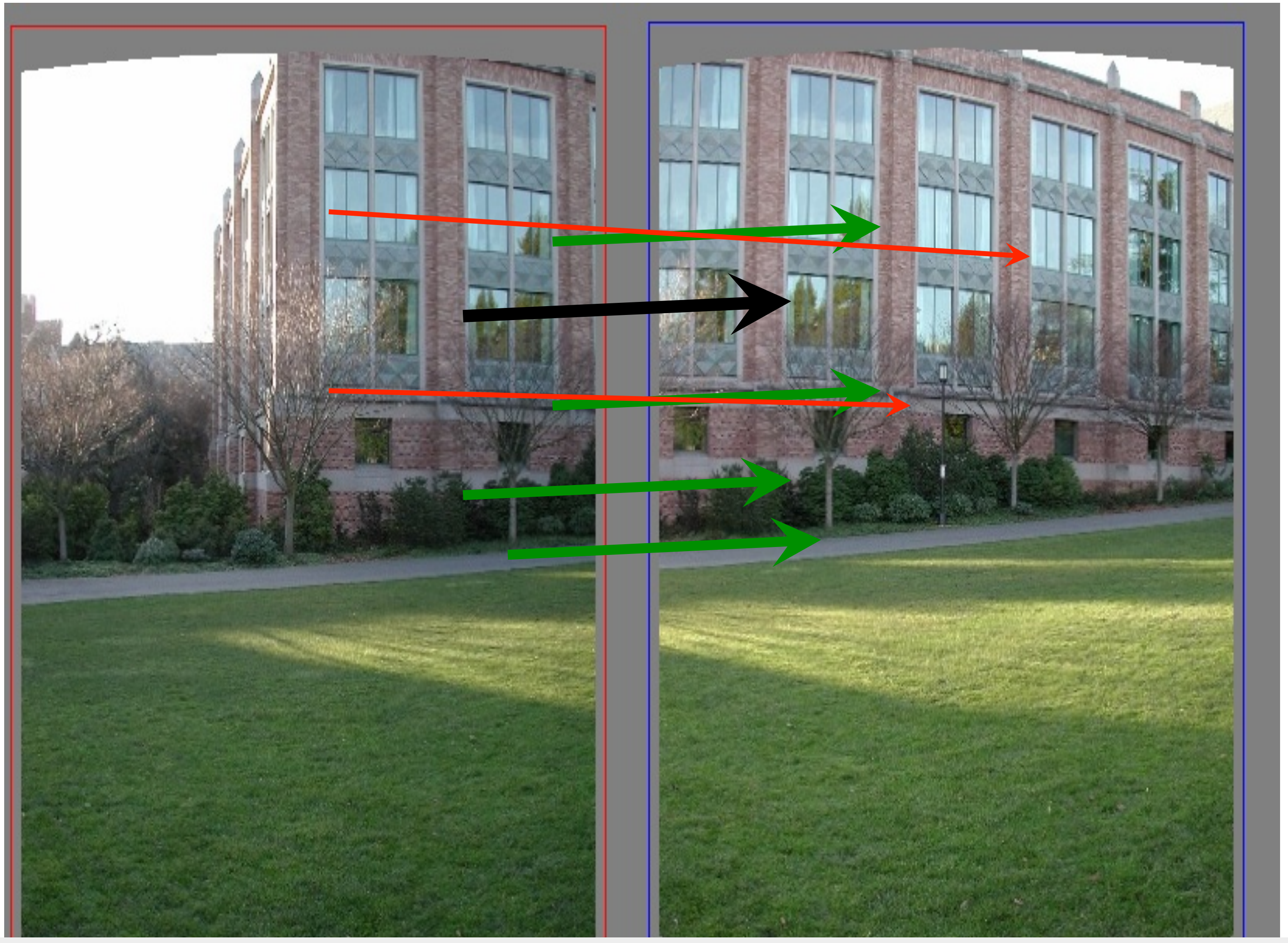
Slide courtesy: Snavely/Efros

# RANSAC Example: Translation



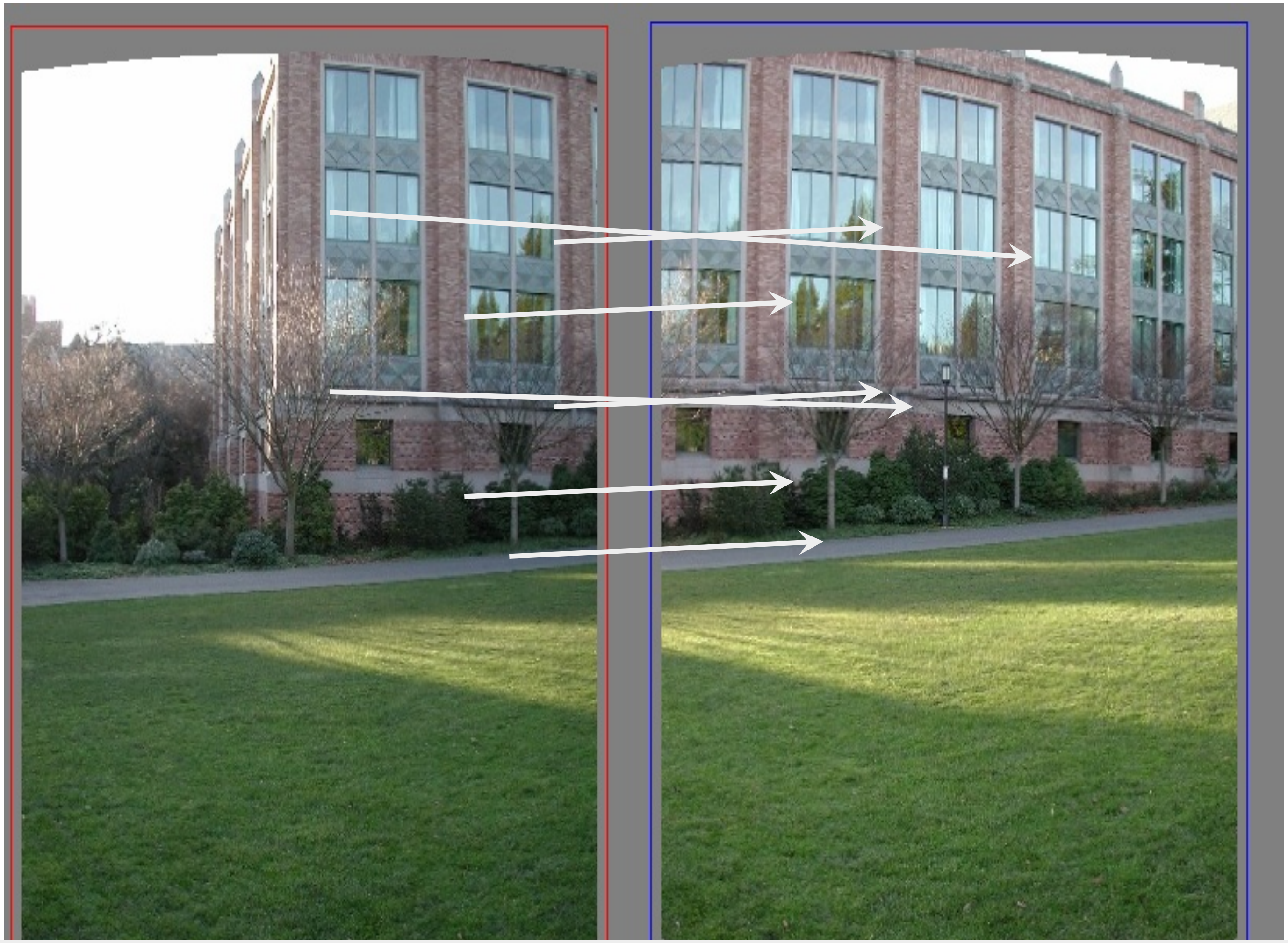
select another random match

# RANSAC Example: Translation



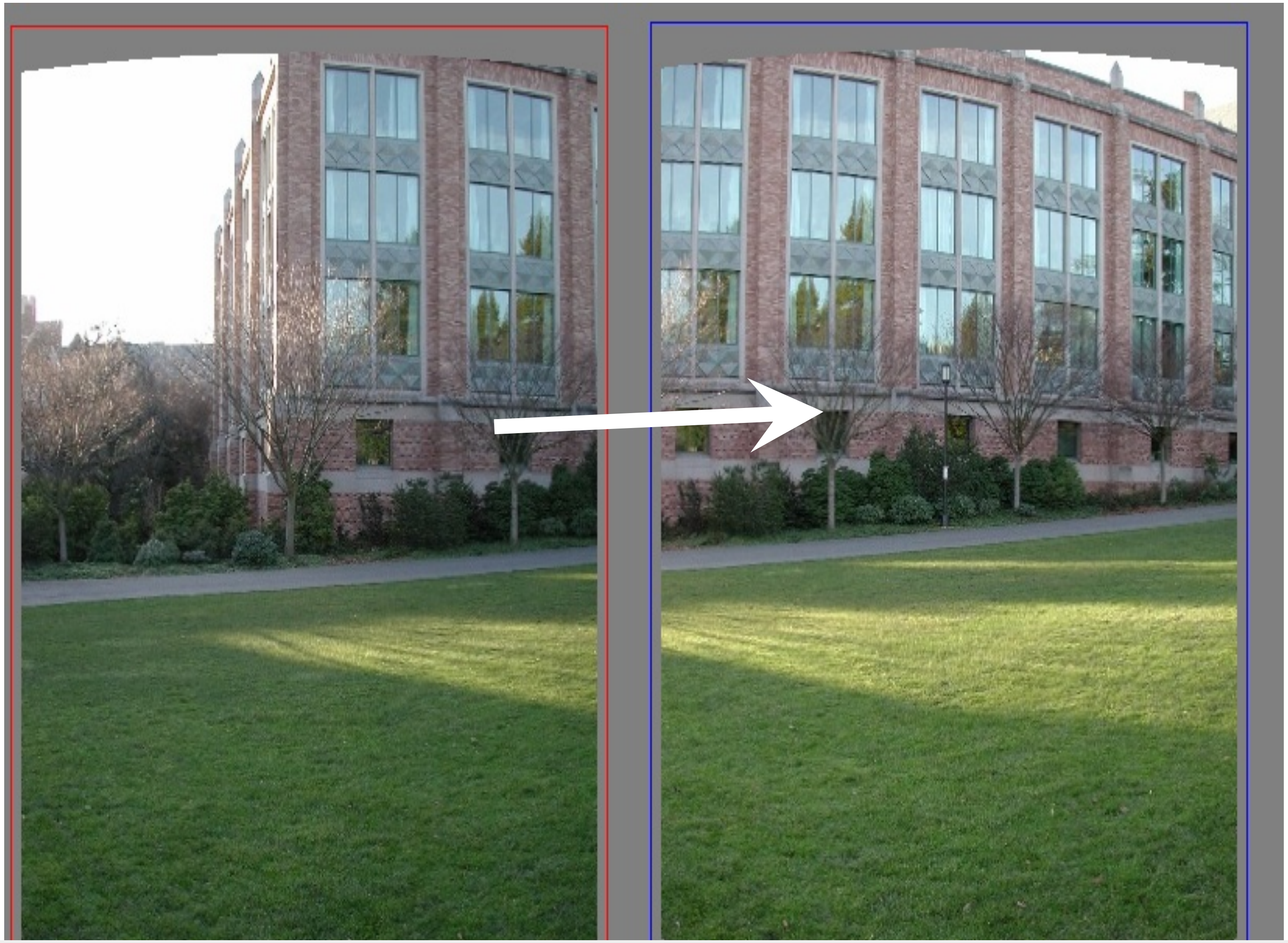
count inliers (4)

# RANSAC Example: Translation



Repeat N times: select match, count inliers

# RANSAC Example: Translation



Return translation with the most inliers

Slide courtesy: Snavely/Efros

# Feature-Based Alignment

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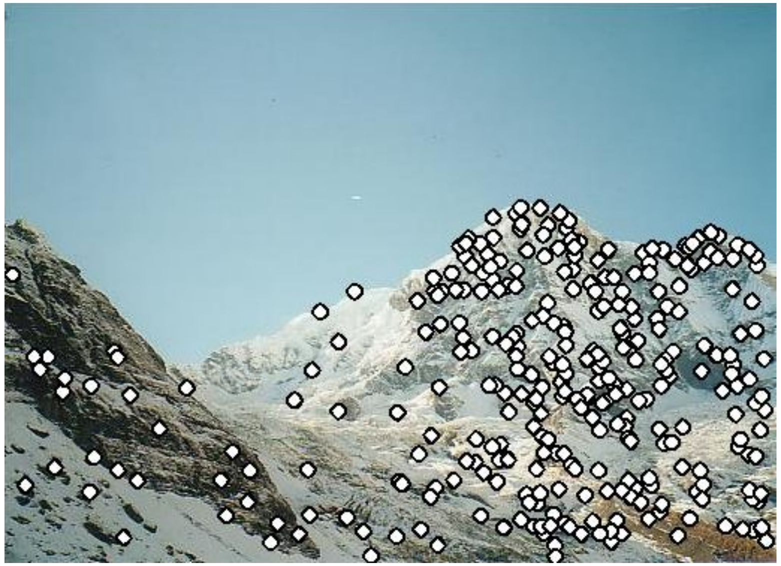
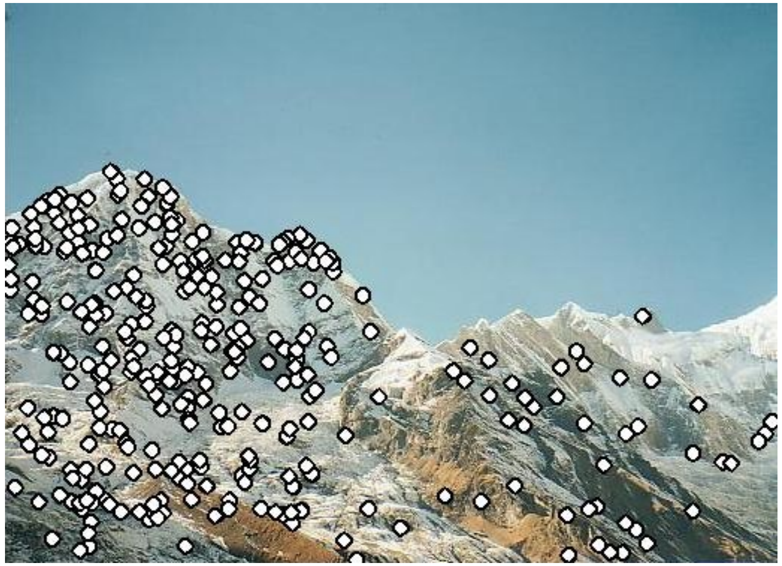
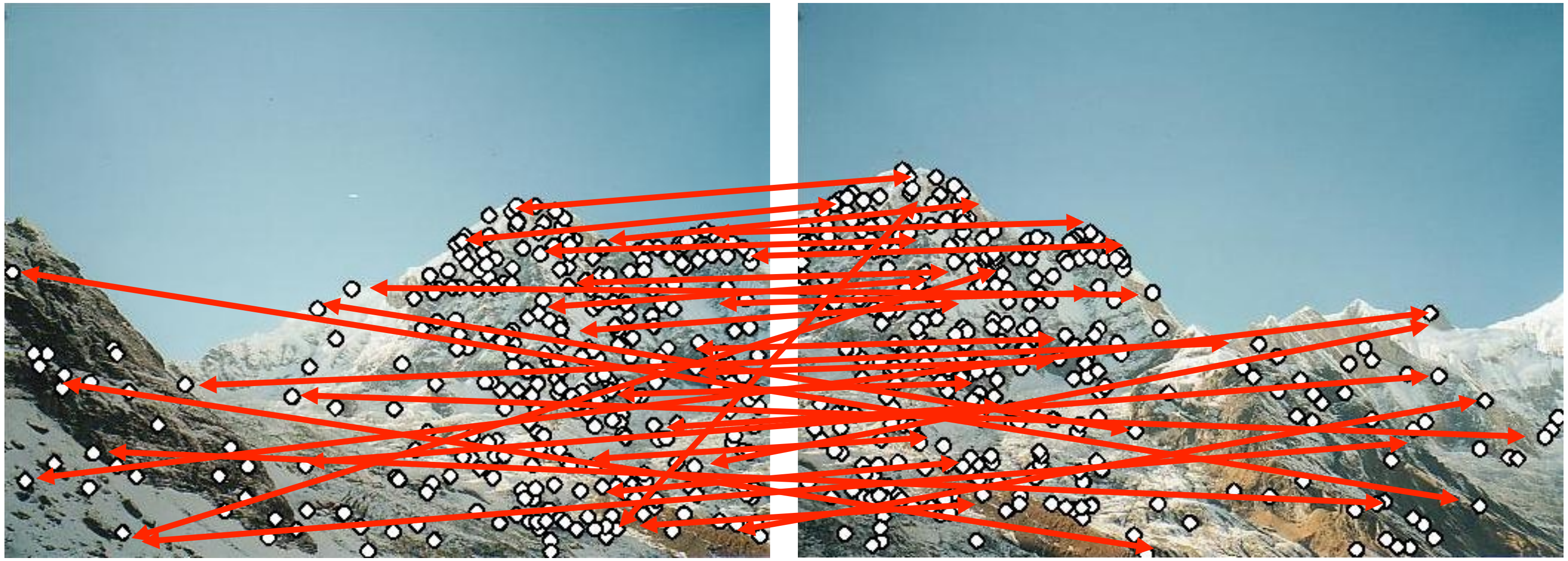




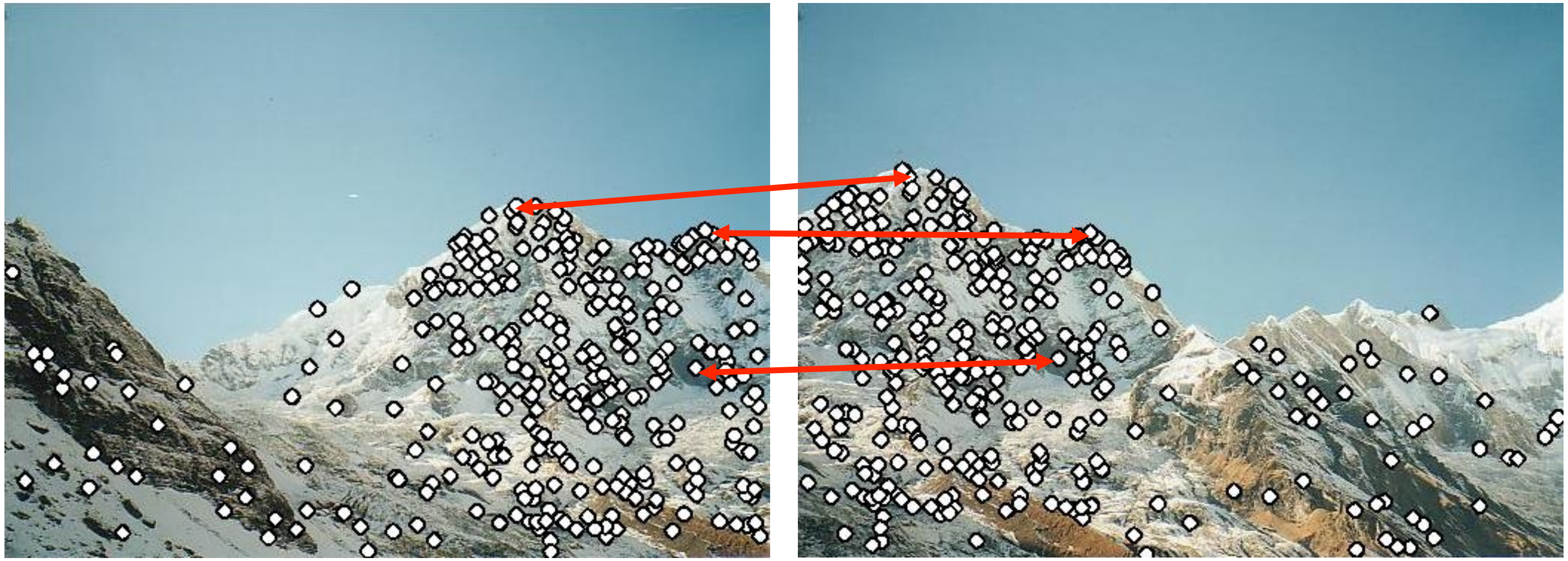
- Extract features

# Feature-Based Alignment



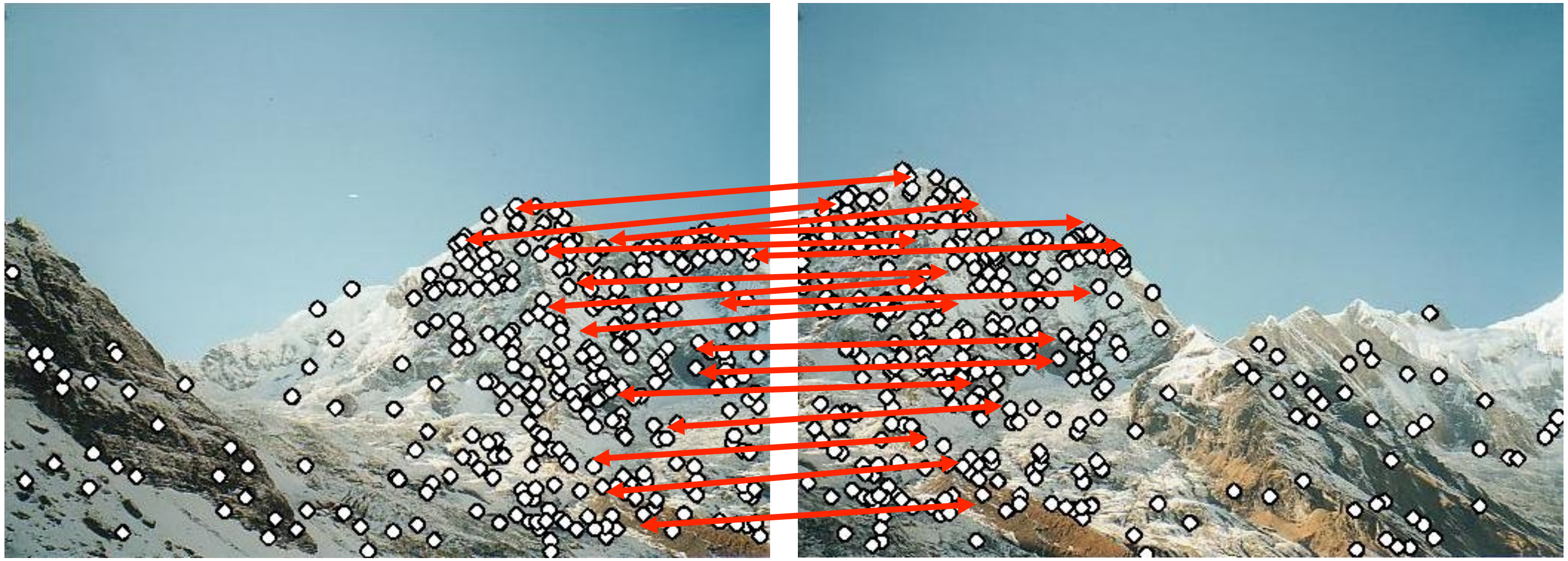
- Extract features
- Compute *putative matches*

# Feature-Based Alignment



- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T*
  - *Verify* transformation (search for other matches consistent with *T*)

# Feature-Based Alignment



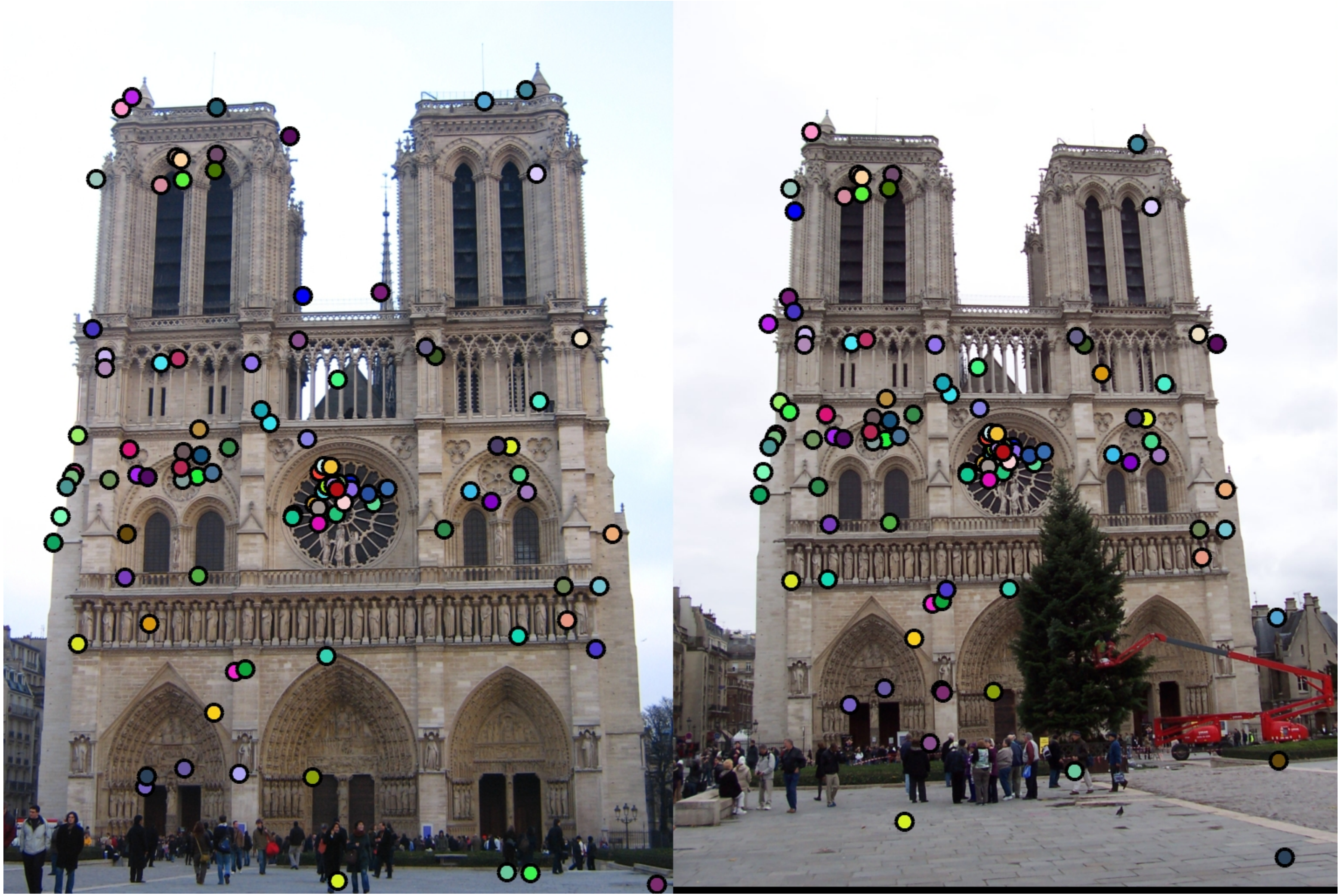
- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation $T$
  - *Verify* transformation (search for other matches consistent with $T$)

# Feature-Based Alignment

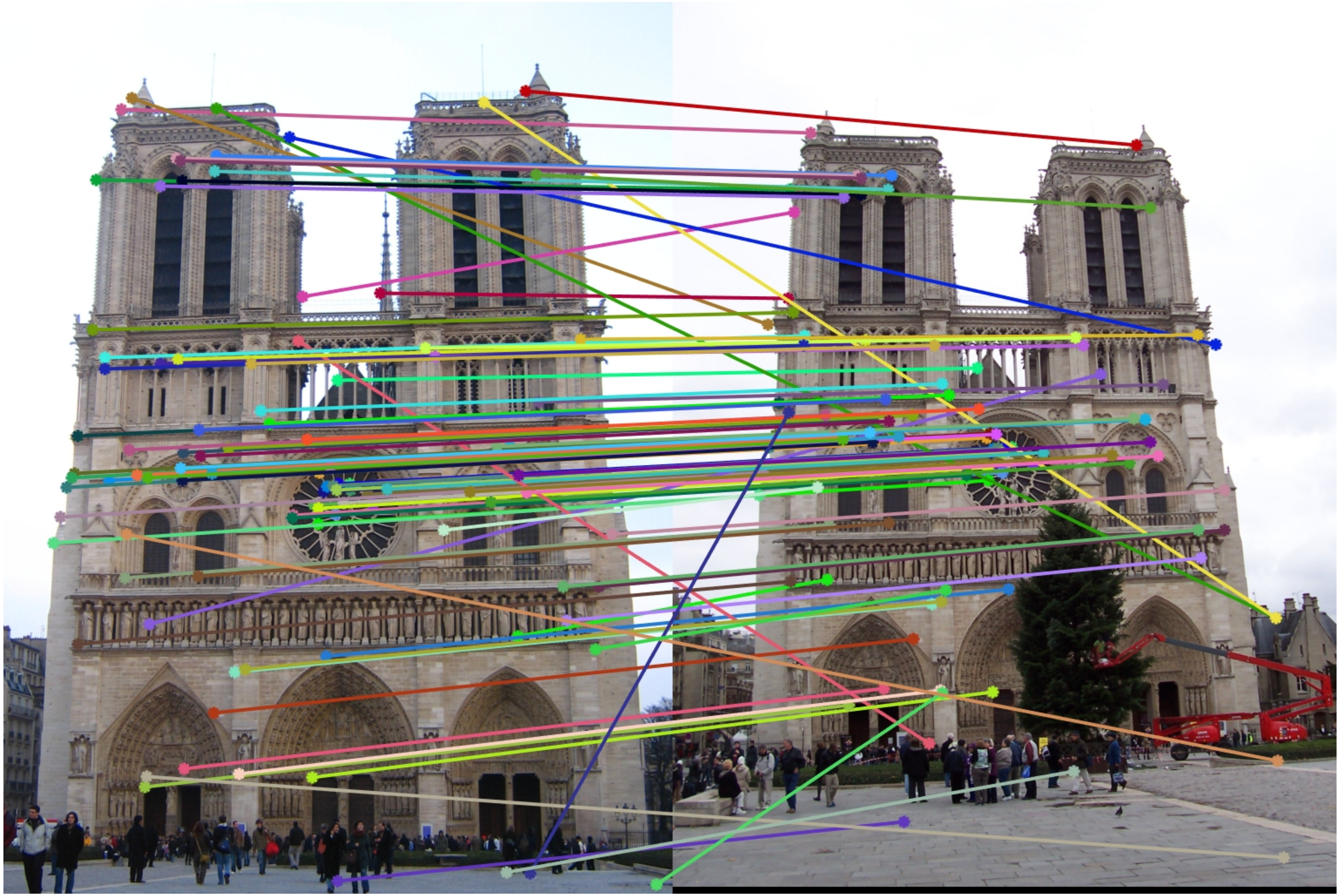
- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T*
  - *Verify* transformation (search for other matches consistent with *T*)

# Notre-Dame

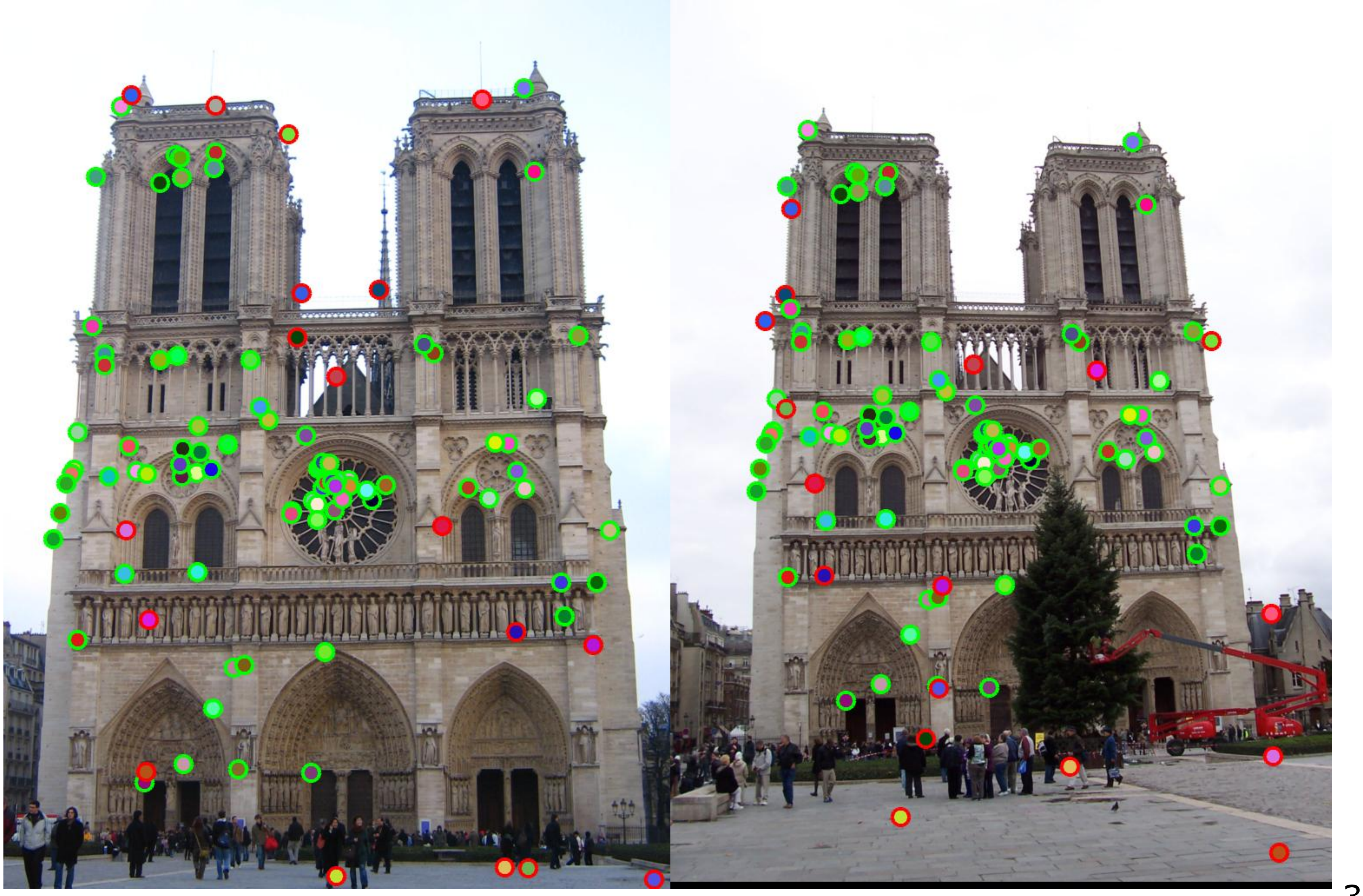
# Notre-Dame: Harris Keypoints



# Notre-Dame: Keypoint Matches



# Notre-Dame: After RANSAC



# How Often Do We Need to Try?

# How to Choose the Parameters?

- Number of sampled points **s**
  (minimum number needed to fit the model)
- Outlier ratio **e** (e=#outliers/#datapoints)

**How many trials to we need?**

# How to Choose the Parameters?

- Number of sampled points **s**
  (minimum number needed to fit the model)
- Outlier ratio **e** (e=#outliers/#datapoints)
- Number of trials **T**
  Choose T so that, with probability p, at least one random sample set is free from outliers

# How to Choose the Parameters?

- Number of sampled points **s**
  (minimum number needed to fit the model)
- Outlier ratio **e** (e=#outliers/#datapoints)
- Number of trials **T**
  Choose T so that, with probability p, at least one random sample set is free from outliers

$$1 - p = 1 - (1 - e)^s$$

p(fail **once**) = do not select only inliers

# How to Choose the Parameters?

- Number of sampled points **s**
  (minimum number needed to fit the model)
- Outlier ratio **e** (e=#outliers/#datapoints)
- Number of trials **T**
  Choose T so that, with probability p, at least one random sample set is free from outliers

$$1 - p = \left(1 - (1 - e)^s\right)^T$$

p(fail **T times**) = select at least one outlier in all T trials

# How to Choose the Parameters?

- Number of sampled points **s**
  (minimum number needed to fit the model)
- Outlier ratio **e** (e=#outliers/#datapoints)
- Number of trials **T**
  Choose T so that, with probability p, at least one random sample set is free from outliers

$$1 - p = (1 - (1 - e)^s)^T$$

$$\Downarrow$$

$$\log(1 - p) = T \log(1 - (1 - e)^s)$$

# How to Choose the Parameters?

- Number of sampled points **s**
  (minimum number needed to fit the model)
- Outlier ratio **e** (e=#outliers/#datapoints)
- Number of trials **T**
  Choose T so that, with probability p, at least one random sample set is free from outliers

$$\boxed{T = \frac{\log(1-p)}{\log\left(1-(1-e)^s\right)}}$$

# Required Number of Trials

| p | s | 2 | 3 | 4 | 5 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|---|
| 0,1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| 0,5 | 1 | 1 | 1 | 1 | 2 | 4 | 6 |
| 0,75 | 1 | 2 | 2 | 2 | 4 | 7 | 11 |
| 0,9 | 2 | 2 | 3 | 3 | 6 | 10 | 18 |
| 0,95 | 2 | 3 | 3 | 4 | 7 | 13 | 24 |
| 0,99 | 3 | 4 | 5 | 6 | 11 | 20 | 36 |
| 0,999 | 5 | 6 | 7 | 8 | 17 | 30 | 54 |
| 0,9999 | 6 | 8 | 9 | 11 | 22 | 40 | 72 |
| | | | | | | | |
| | | | | | | | |
| | | | | | | | |
| | | | | | | | |
| | 0,1 | Outlier Ratio | | | | | |

# Required Number of Trials

| p \| s | 2 | 3 | 4 | 5 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|---|
| 0,1 | 1 | 1 | 1 | 1 | 4 | 23 | 132 |
| 0,5 | 2 | 2 | 3 | 4 | 25 | 146 | 869 |
| 0,75 | 3 | 4 | 6 | 8 | 49 | 292 | 1737 |
| 0,9 | 4 | 6 | 9 | 13 | 81 | 484 | 2885 |
| 0,95 | 5 | 8 | 11 | 17 | 105 | 630 | 3753 |
| 0,99 | 7 | 11 | 17 | 26 | 161 | 968 | 5770 |
| 0,999 | 11 | 17 | 26 | 38 | 242 | 1452 | 8654 |
| 0,9999 | 14 | 22 | 34 | 51 | 322 | 1936 | 11539 |

0,3 Outlier Ratio

# Required Number of Trials

| p \| s | 2 | 3 | 4 | 5 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|---|
| 0,1 | 1 | 1 | 2 | 4 | 108 | 3453 | 110479 |
| 0,5 | 3 | 6 | 11 | 22 | 710 | 22713 | 726818 |
| 0,75 | 5 | 11 | 22 | 44 | 1419 | 45426 | 1453635 |
| 0,9 | 9 | 18 | 36 | 73 | 2357 | 75450 | 2414435 |
| 0,95 | 11 | 23 | 47 | 95 | 3067 | 98163 | 3141252 |
| 0,99 | 17 | 35 | 72 | 146 | 4714 | 150900 | 4828869 |
| 0,999 | 25 | 52 | 108 | 218 | 7071 | 226350 | 7243303 |
| 0,9999 | 33 | 69 | 143 | 291 | 9427 | 301800 | 9657738 |

| | | |
|---|---|---|
| 0,5 | Outlier Ratio | |

# Required Number of Trials

| p \| s | 2 | 3 | 4 | 5 | 10 | 15 | 20 |
|---|---|---|---|---|---|---|---|
| 0,1 | 3 | 14 | 66 | 330 | 1028912 | 3,215E+09 | 1,01E+13 |
| 0,5 | 17 | 87 | 433 | 2166 | 6769016 | 2,115E+10 | 6,642E+13 |
| 0,75 | 34 | 173 | 866 | 4332 | 13538031 | 4,231E+10 | 1,328E+14 |
| 0,9 | 57 | 287 | 1438 | 7195 | 22486182 | 7,027E+10 | 2,206E+14 |
| 0,95 | 74 | 373 | 1871 | 9361 | 29255197 | 9,142E+10 | 2,871E+14 |
| 0,99 | 113 | 574 | 2876 | 14389 | 44972363 | 1,405E+11 | 4,413E+14 |
| 0,999 | 170 | 861 | 4314 | 21584 | 67458545 | 2,108E+11 | 6,619E+14 |
| 0,9999 | 226 | 1147 | 5752 | 28778 | 89944726 | 2,811E+11 | 8,825E+14 |
| | | | | | | | |
| | | | | | | | |
| | | | | | | | |
| | | | | | | | |
| 0,8 | Outlier Ratio | | | | | | |

# Number of Sampled Points (s) Matter

- Estimation algorithms require different numbers of sampled points
- 8-point vs. 5-point algorithm (Nister)
- The small s, the better, especially with high outlier ratios

# How to Choose the Parameters?

- Number of sampled points **s**
  (minimum number needed to fit the model)
- Outlier ratio **e** (e=#outliers/#datapoints)
- Number of trials **T**
  Choose T so that, with probability p, at least one random sample set is free from outliers
- Distance threshold **δ**
  Choose δ so that a good point with noise is likely (e.g., prob=0.95) within threshold

# RANSAC: Pros and Cons

## Pros

- Robustly deal with outliers
- Works well for 1 to roughly 10 parameters (depending on the number of outliers)
- Easy to implement and understand

## Cons

- Computational time grows quickly with fraction of outliers and number of parameters needed to fit the model
- Not good for getting multiple fits

# Common RANSAC Applications

- Finding point correspondences
- Estimating fundamental matrix (relating two views)
- Visual odometry
- Computing a homography (e.g., image stitching)
- Laser scan matching
- …

## Summary

- RANSAC – the standard tool for model fitting with outliers
- Trial-and-error approach

**"RANSAC in 30 seconds"**

- Guess inliers
- Compute model given guess
- Score the model by testing the data points and model for consistency
- Repeat