Photogrammetry & Robotics Lab

RANSAC – Random Sample Consensus

Cyrill Stachniss

5 Minute Preparation for Today

https://www.ipb.uni-bonn.de/5min/

Notre-Dame

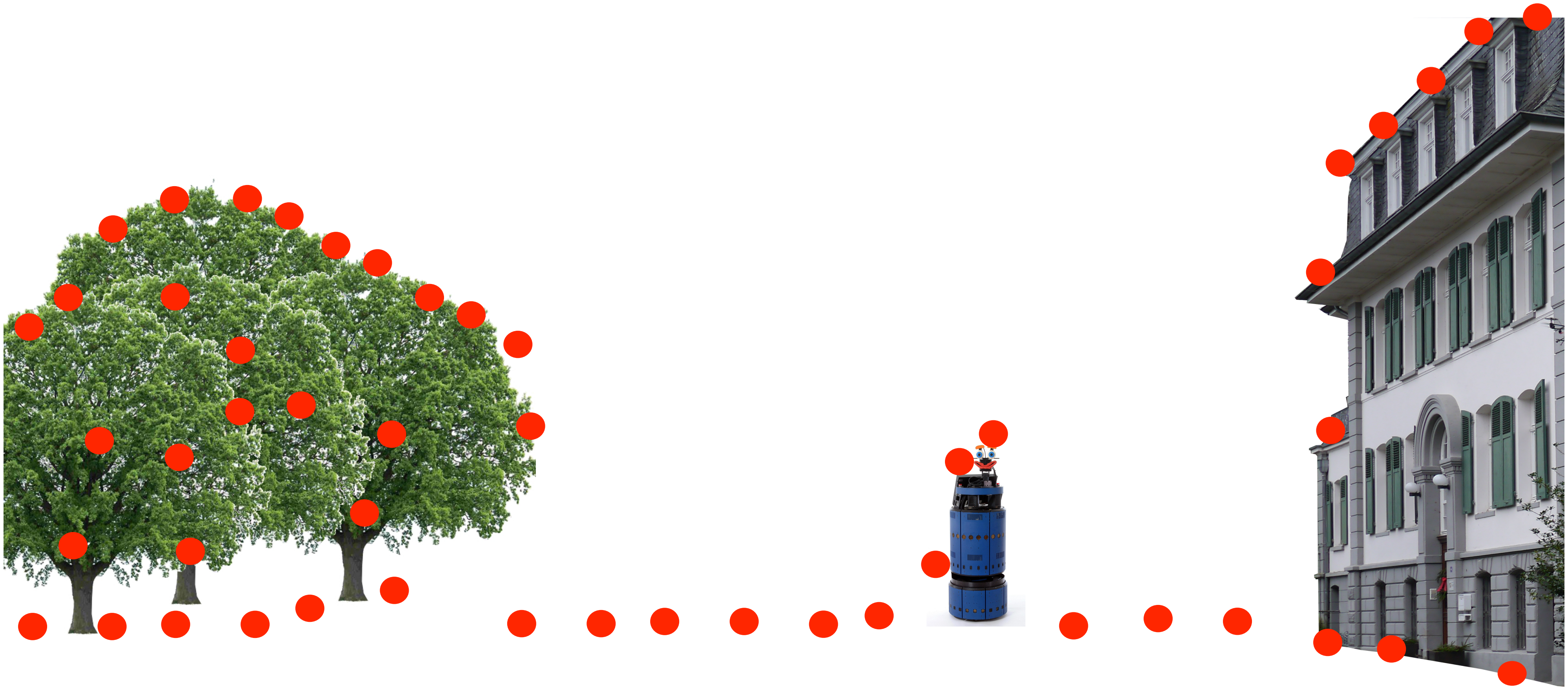
Notre-Dame: SIFT All Matches

[Image courtesy: Barulic]

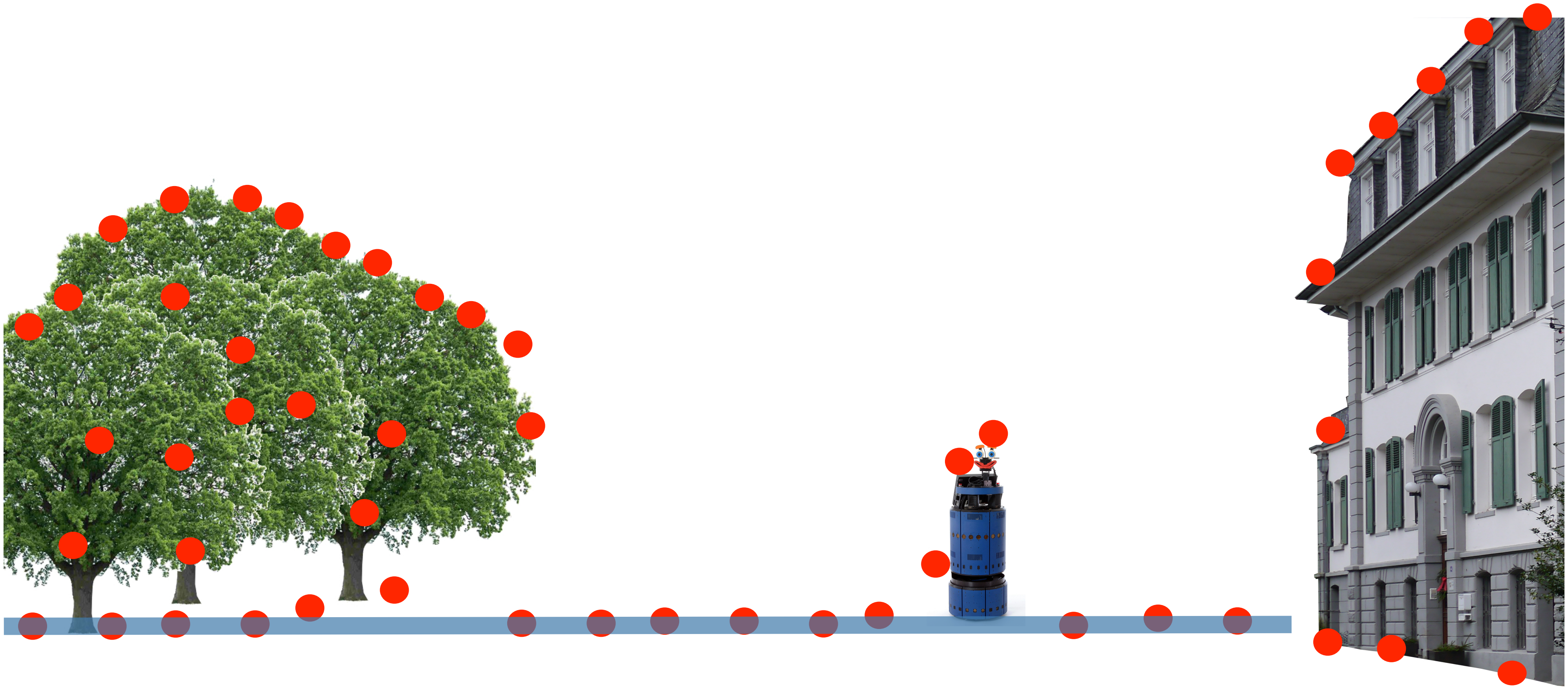
Notre-Dame: SIFT Inliers

[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

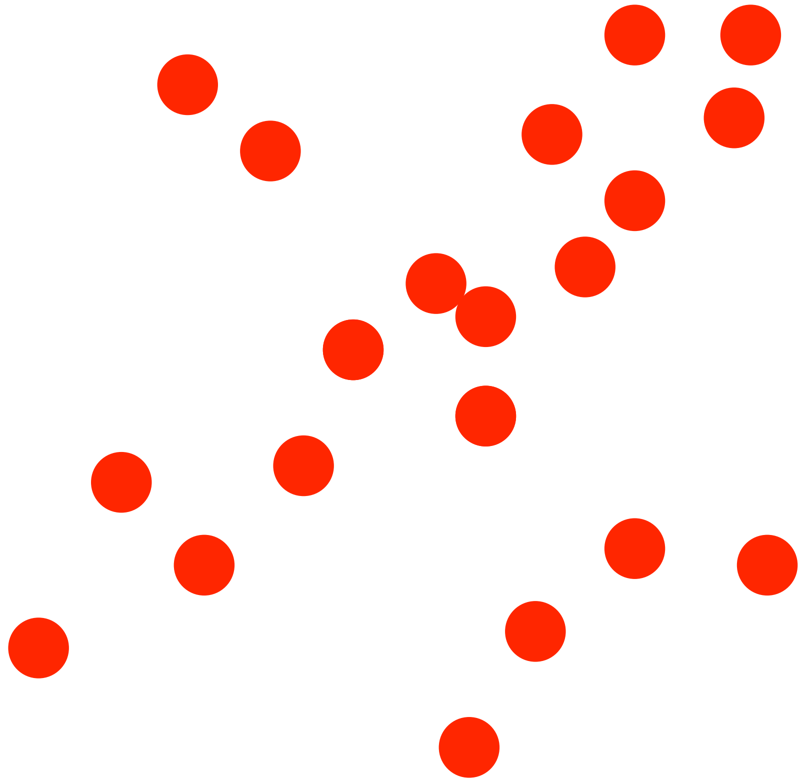
- Trial-and-error approach
- Approach to deal with high fractions of outliers in the data
- **Key idea:** Find the best partition of points in inlier set and outlier and estimate the model from the inlier set
- **Standard approach** for fitting in the presence of outliers

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

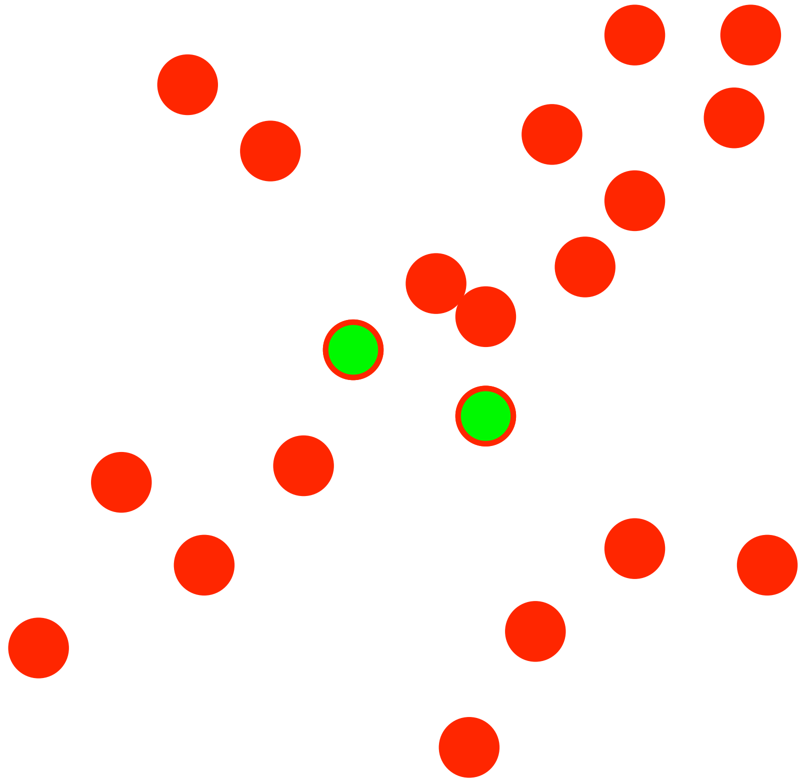
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found

Illustration by Savarese

RANSAC

Line fitting example



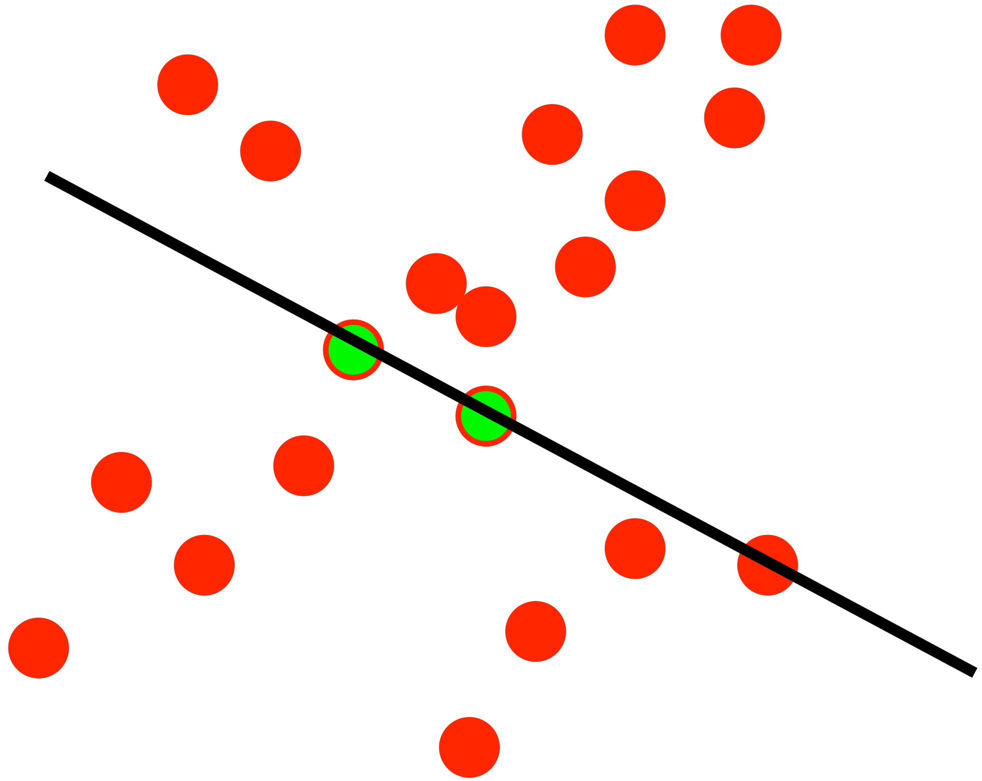
1. **Sample** the number of data points required to fit the model (here: 2 points)
2. **Compute** model parameters using the samples
3. **Score** by the fraction of inliers within a preset threshold of the model

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)

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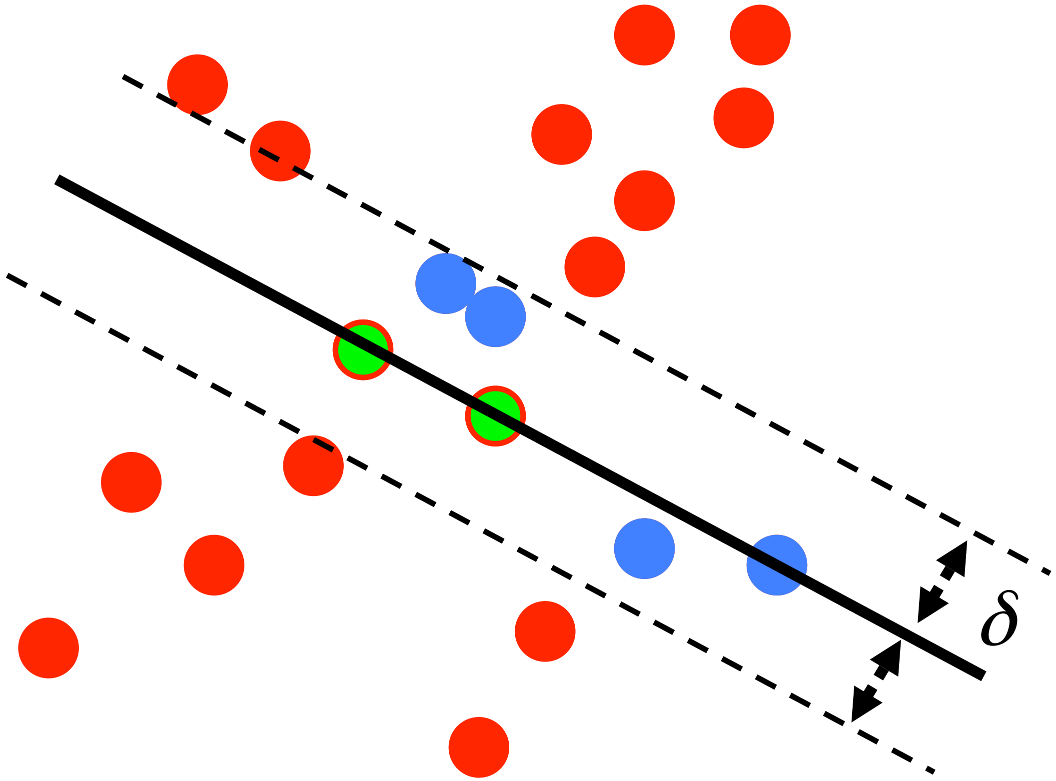
Illustration by Savarese

RANSAC

Line fitting example



#inliers: 4

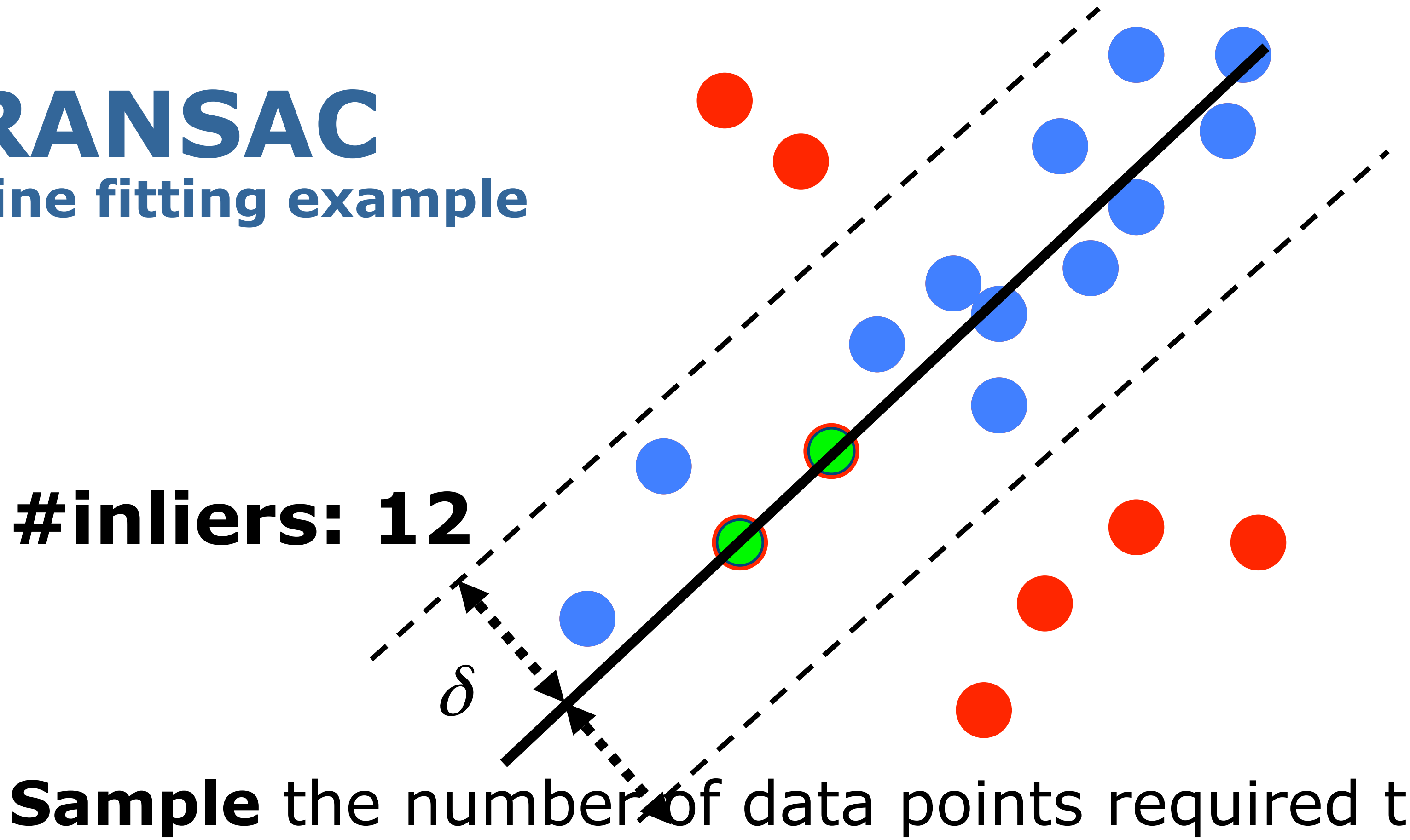
1. **Sample** the number of data points required to fit the model (here: 2 points)
2. **Compute** model parameters using the samples
3. **Score** by the fraction of inliers within a preset threshold of the model

Repeat 1-3 until the best model is found

Illustration by Savarese

RANSAC

Line fitting example



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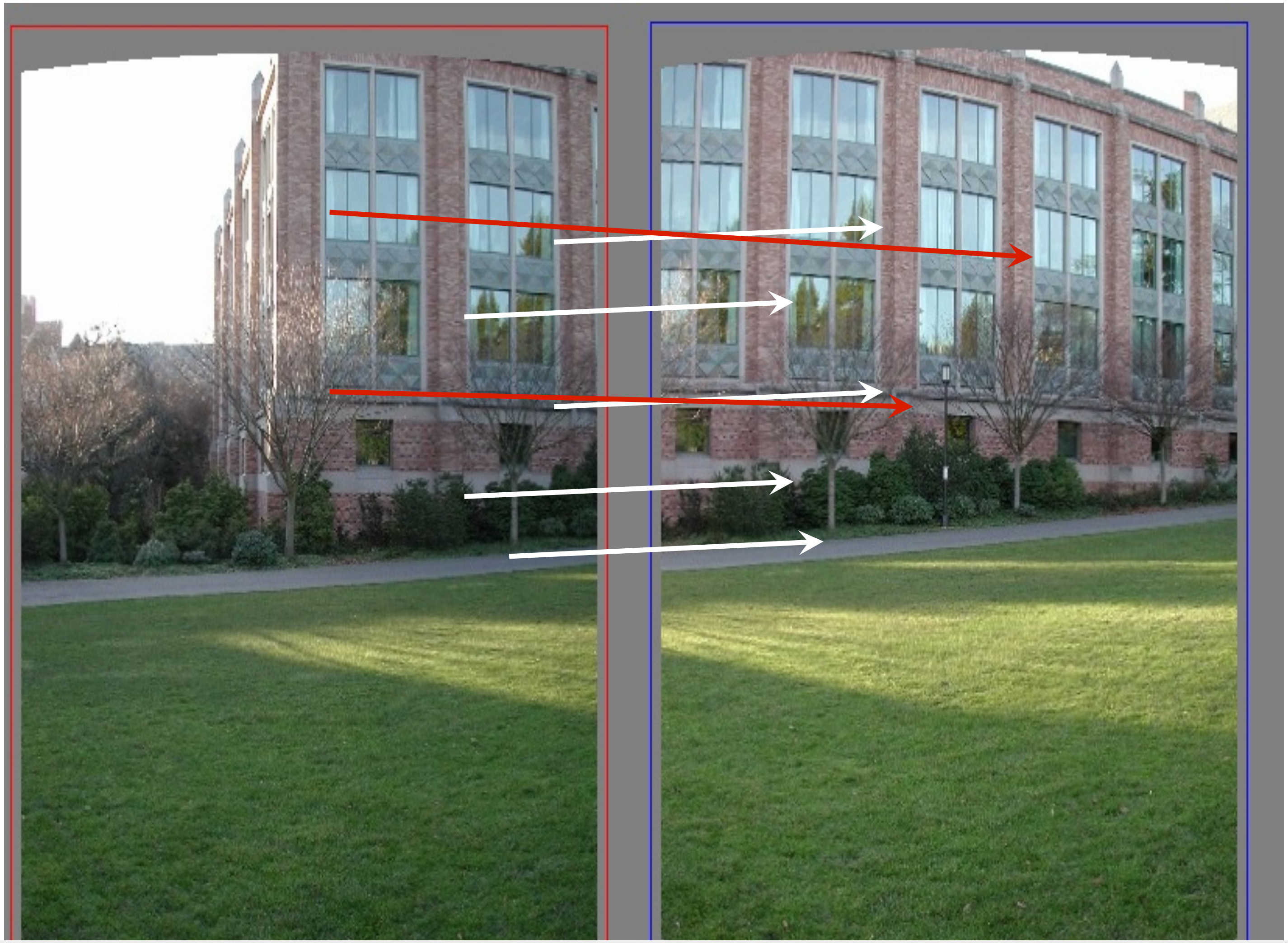
Repeat 1-3 until the best model is found

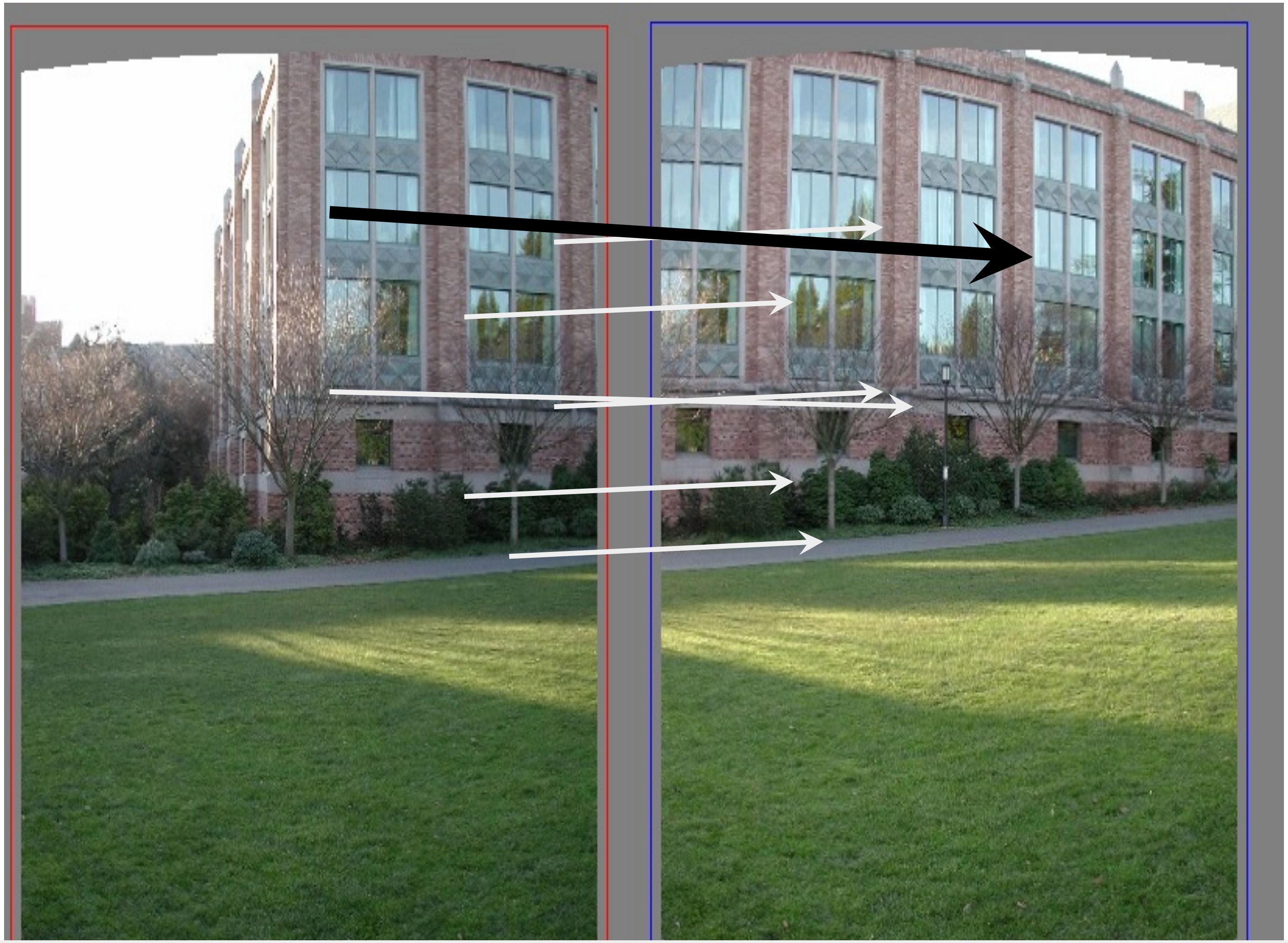
Illustration by Savarese

RANSAC Example: Translation



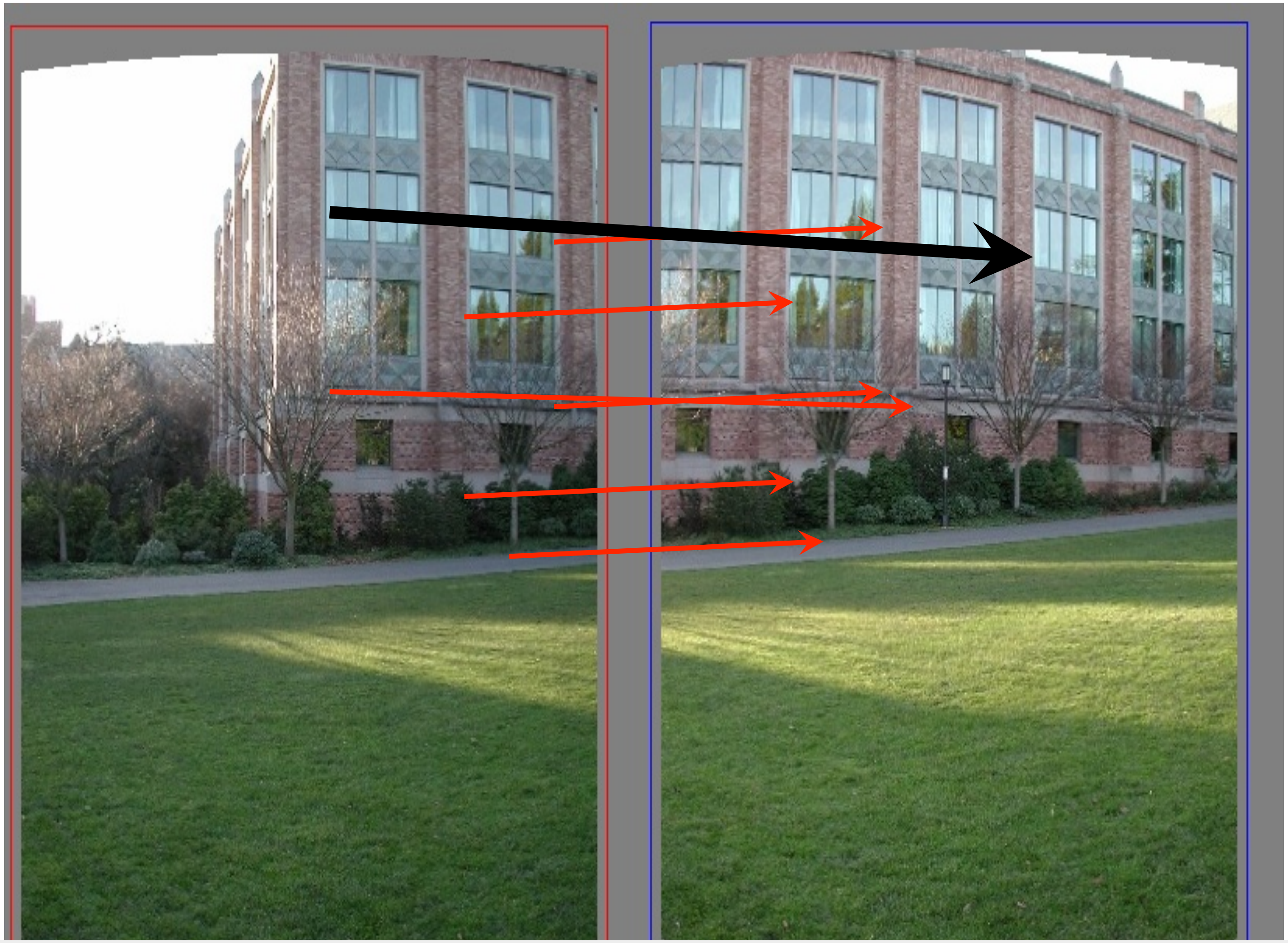
extracted features correspondences

RANSAC Example: Translation



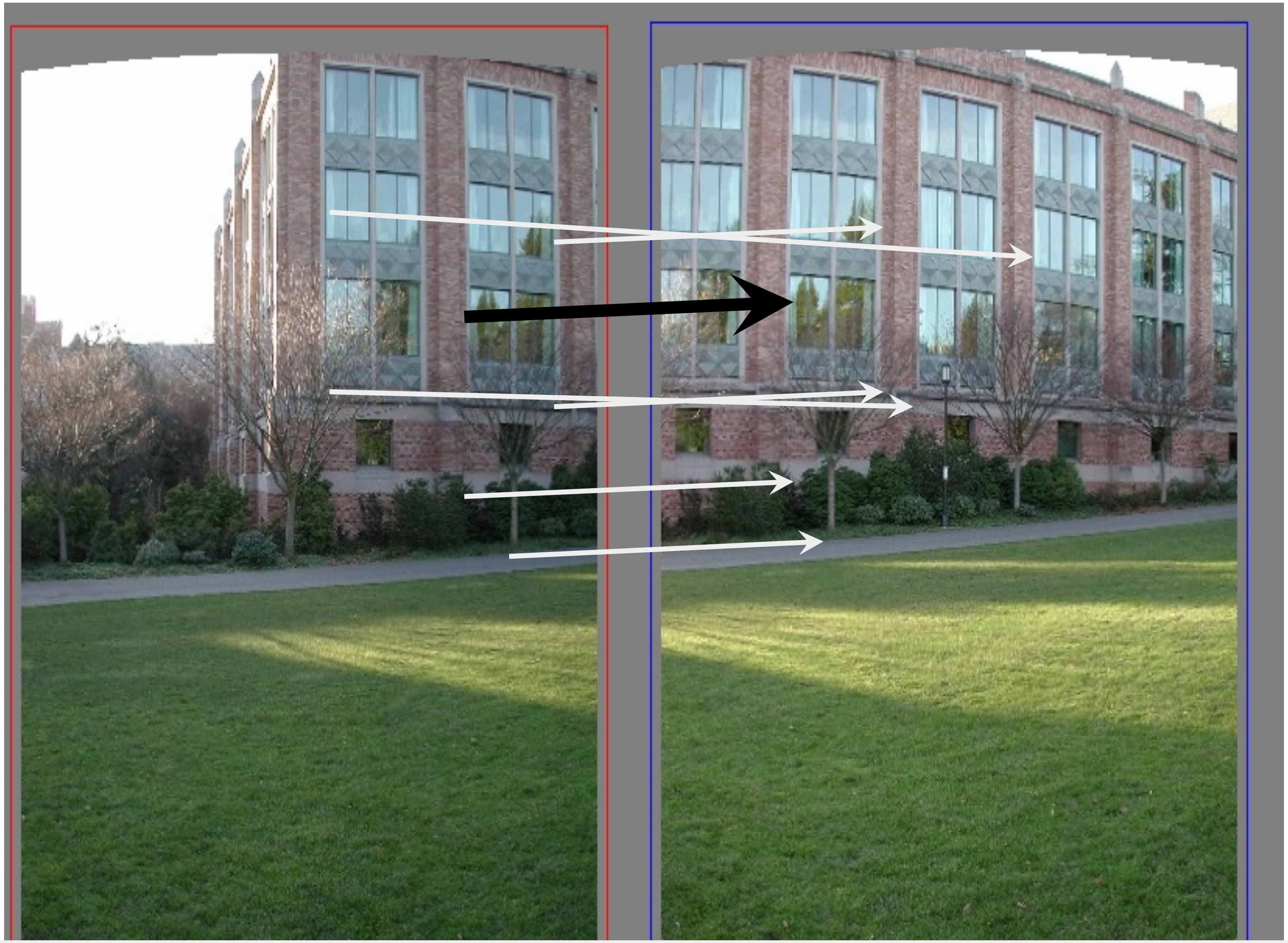
select random match

RANSAC Example: Translation



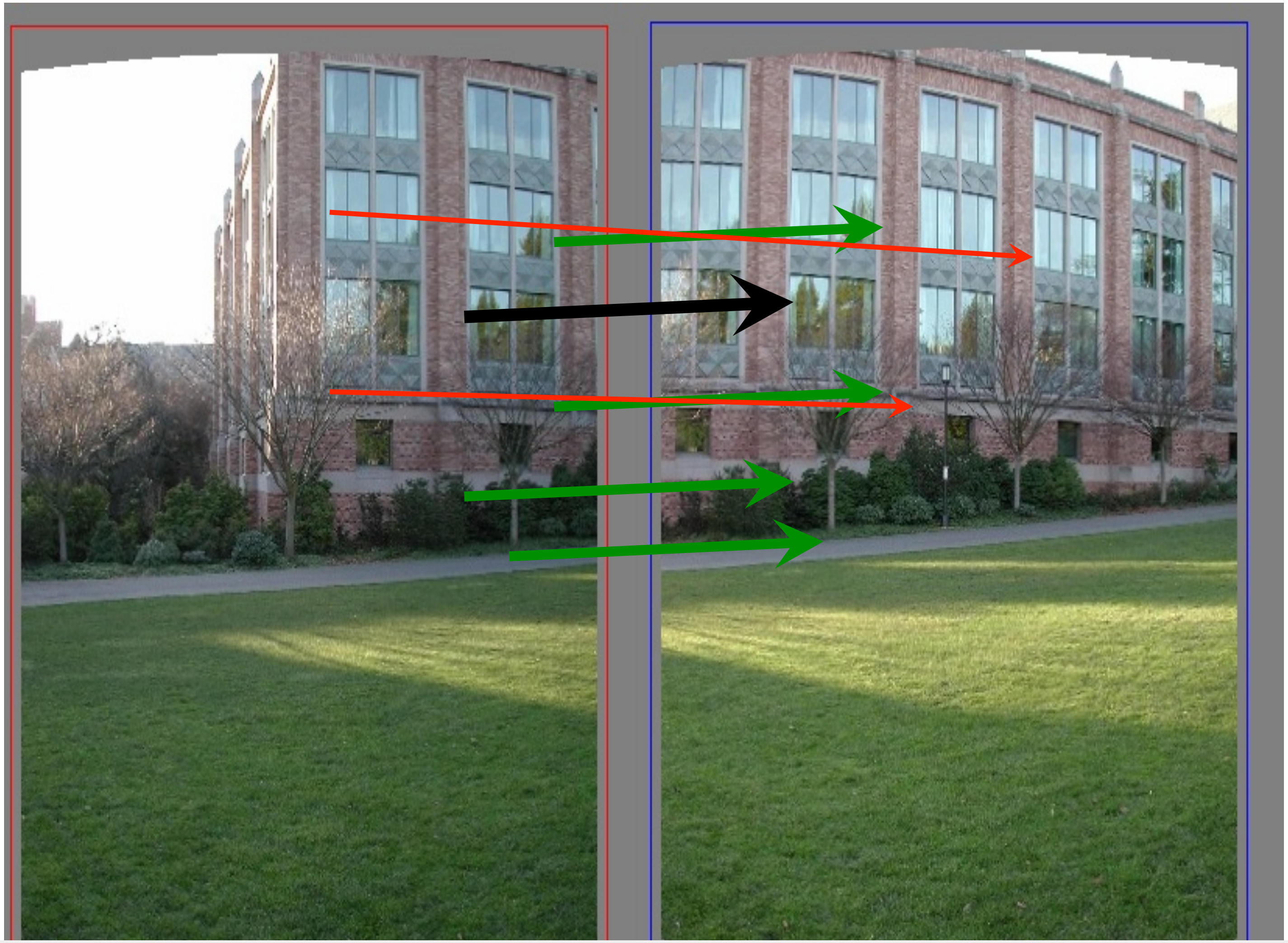
count inliers (0)

RANSAC Example: Translation



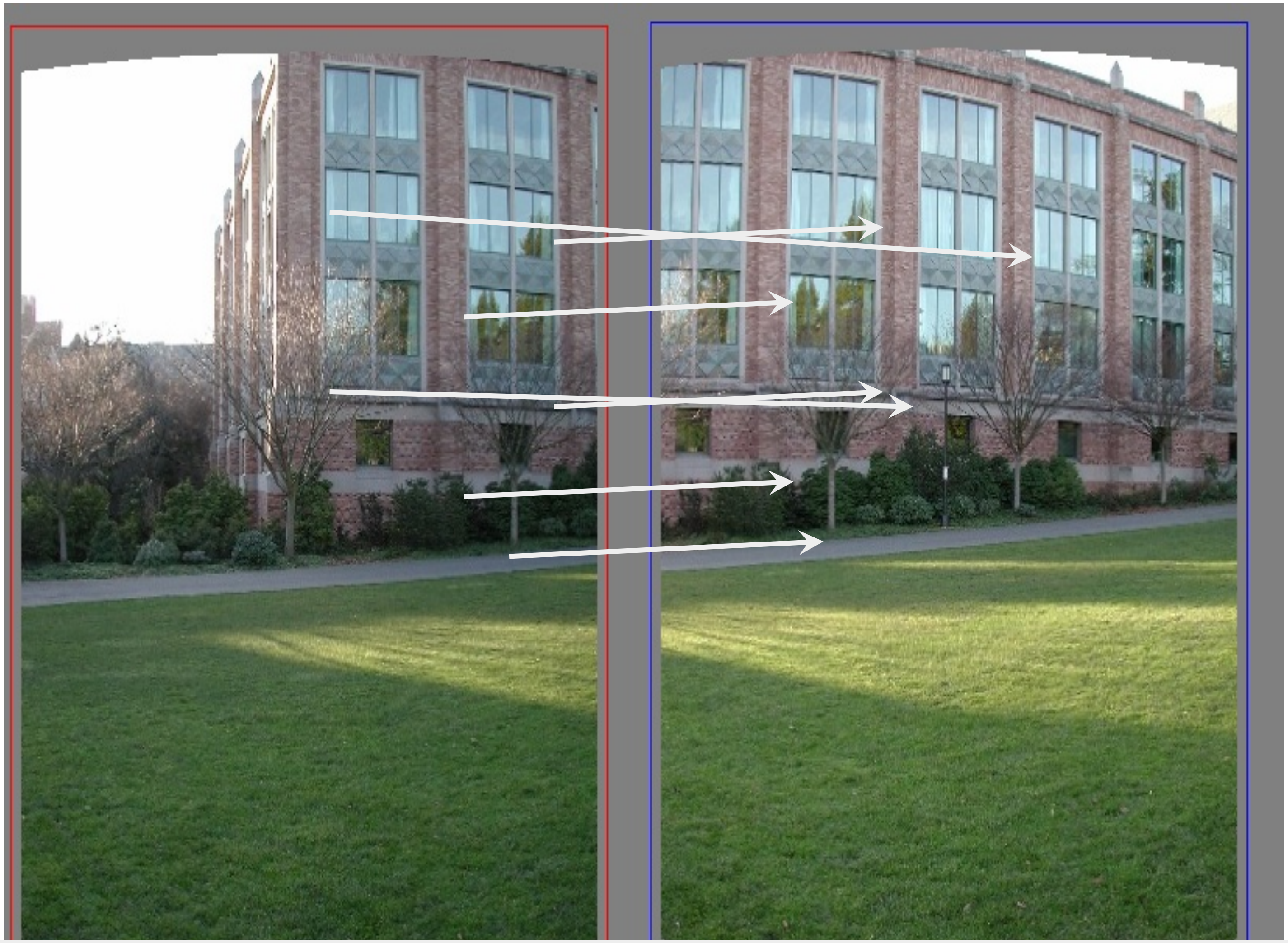
select another random match

RANSAC Example: Translation



count inliers (4)

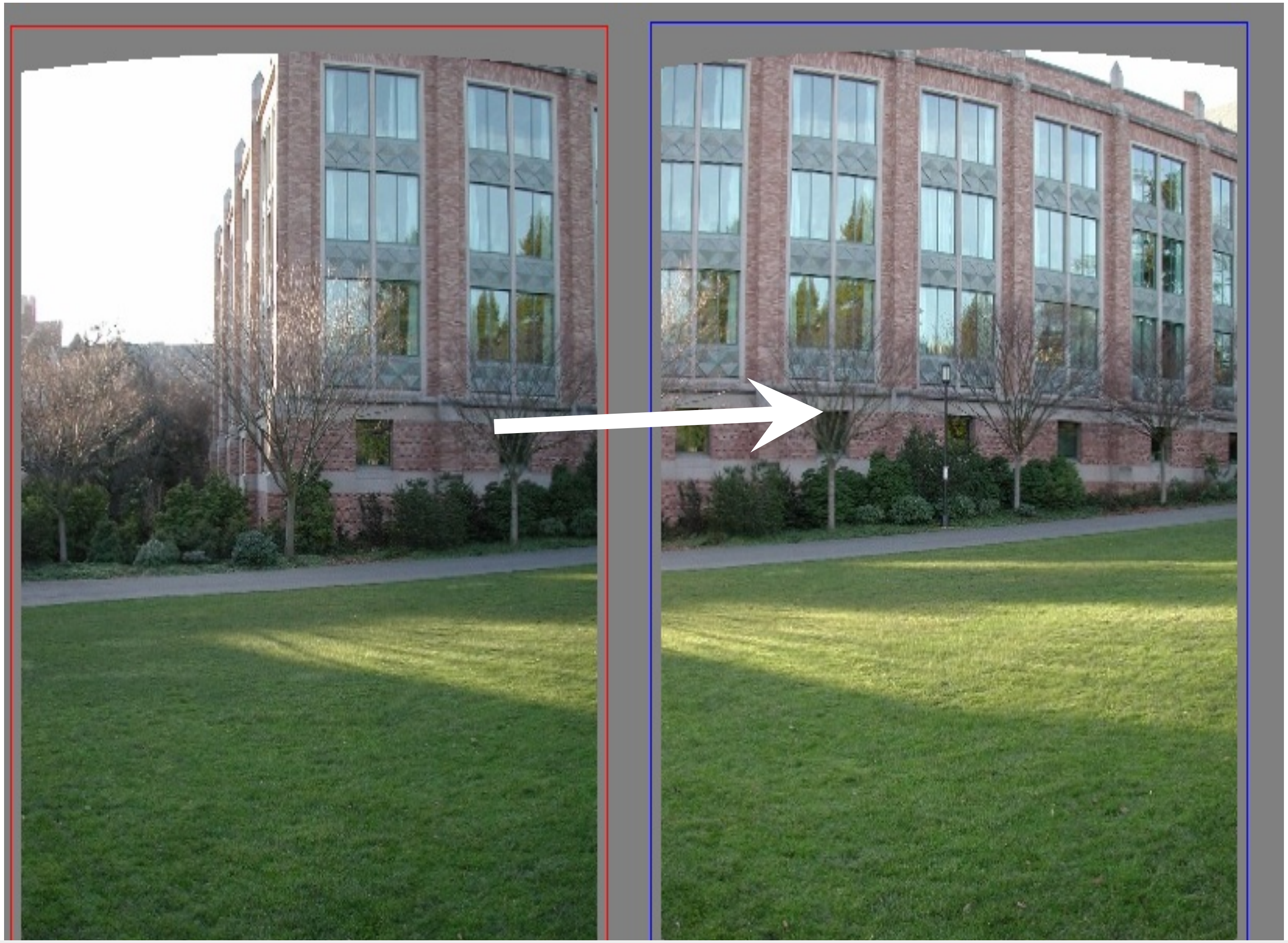
RANSAC Example: Translation



Repeat N times: select match, count inliers

Slide courtesy: Snavely/Efros

RANSAC Example: Translation



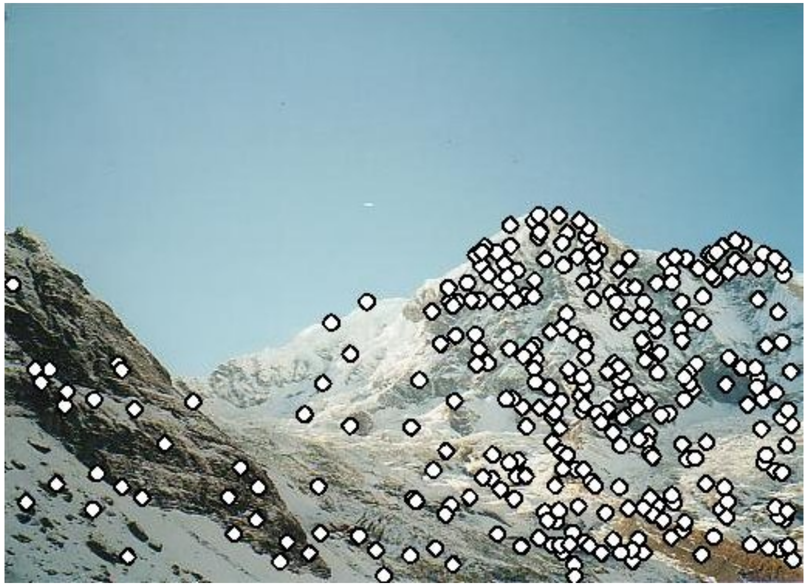
Return translation with the most inliers

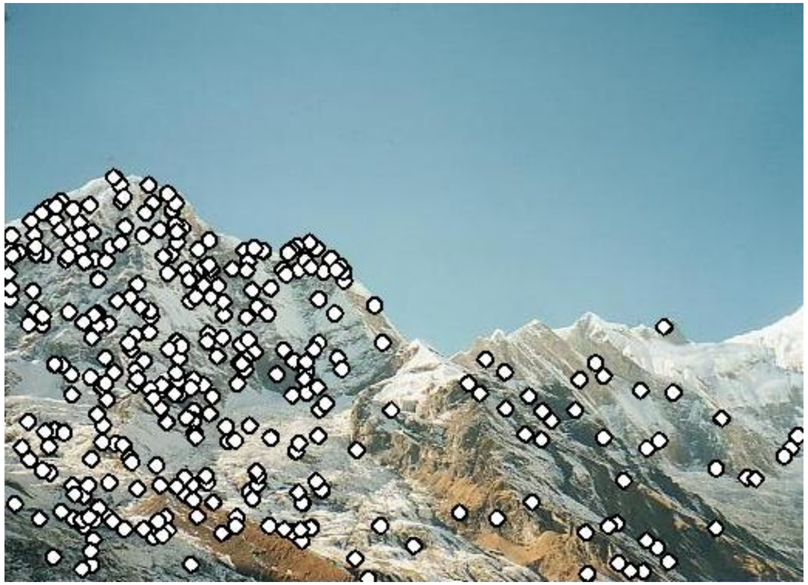
Slide courtesy: Snavely/Efros

Feature-Based Alignment

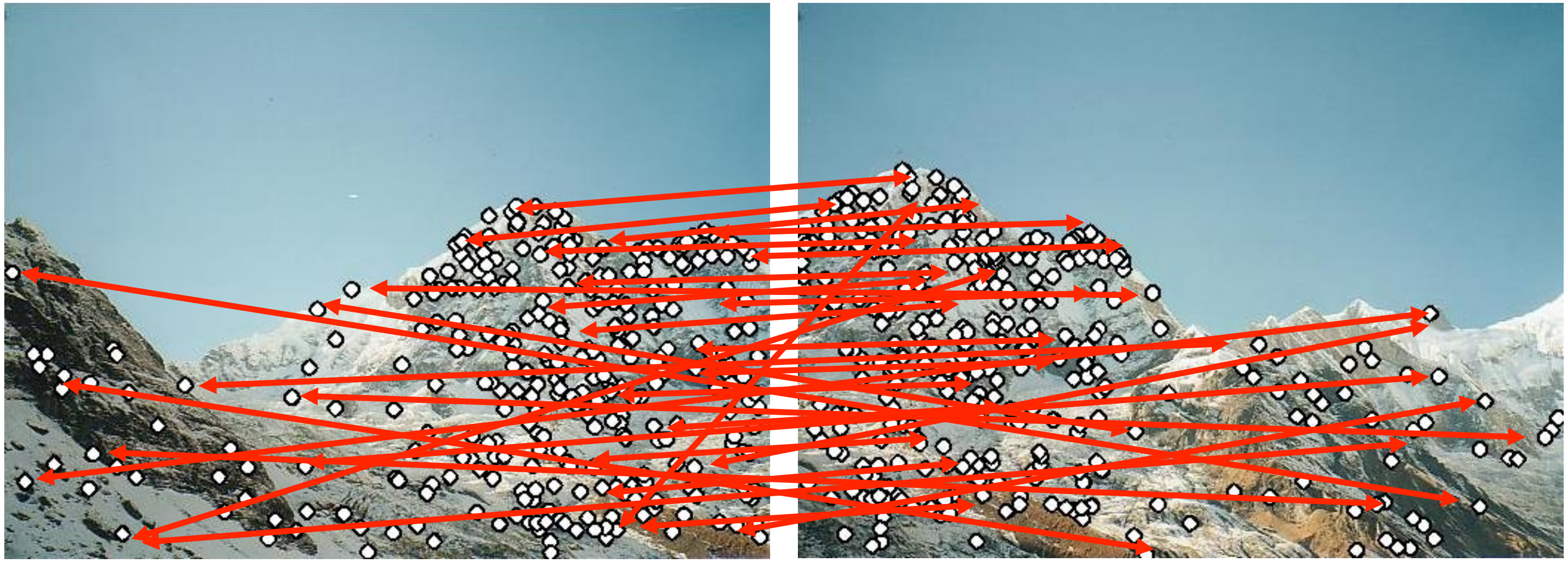
Feature-Based Alignment





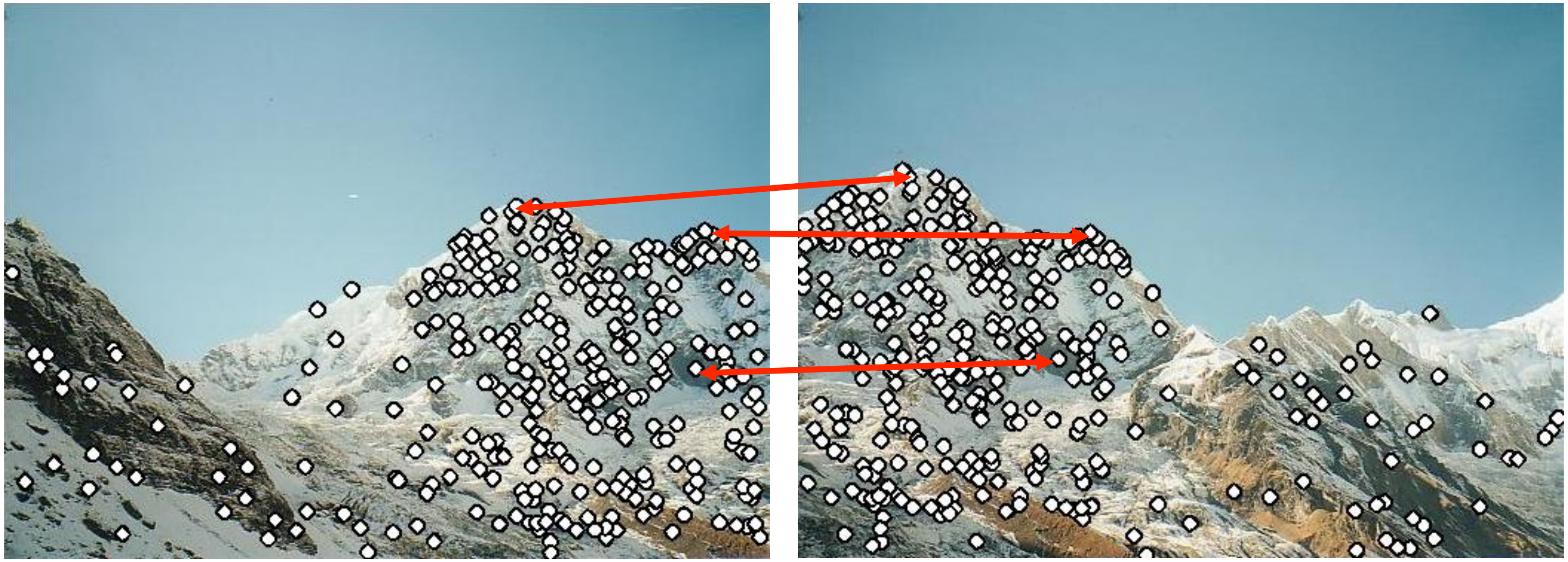
- Extract features

Feature-Based Alignment



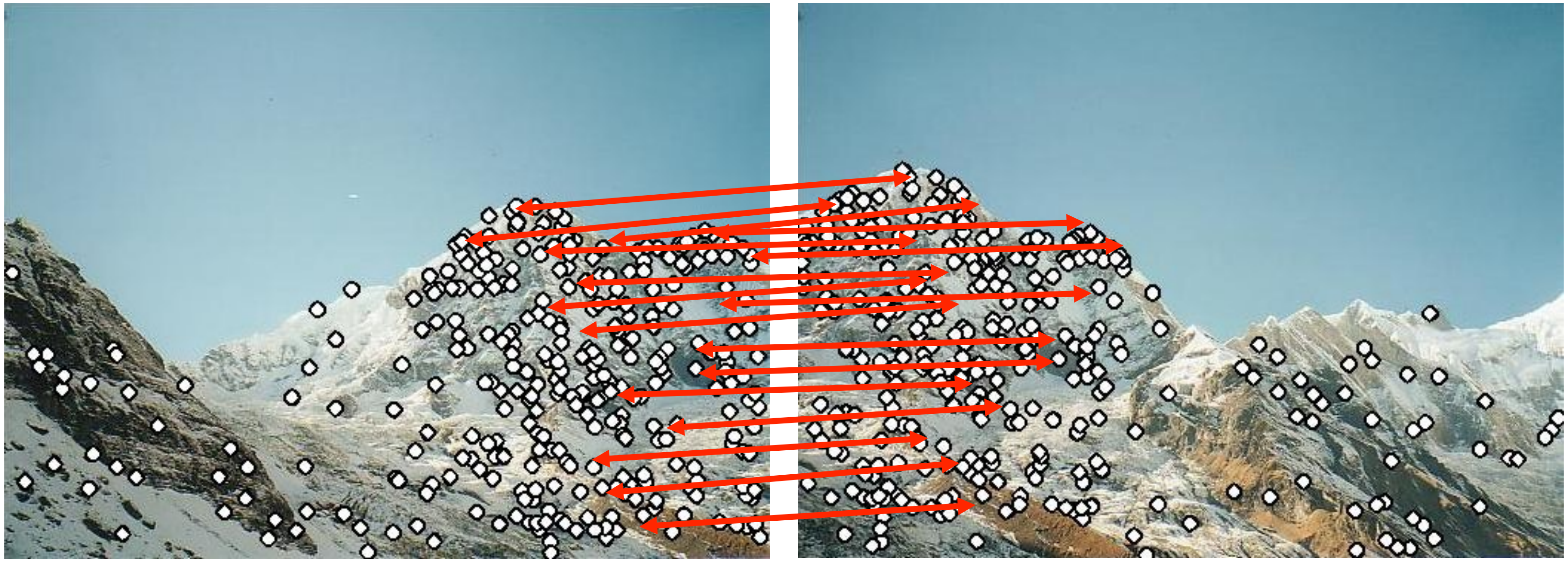
- Extract features
- Compute *putative matches*

Feature-Based Alignment



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

Feature-Based Alignment



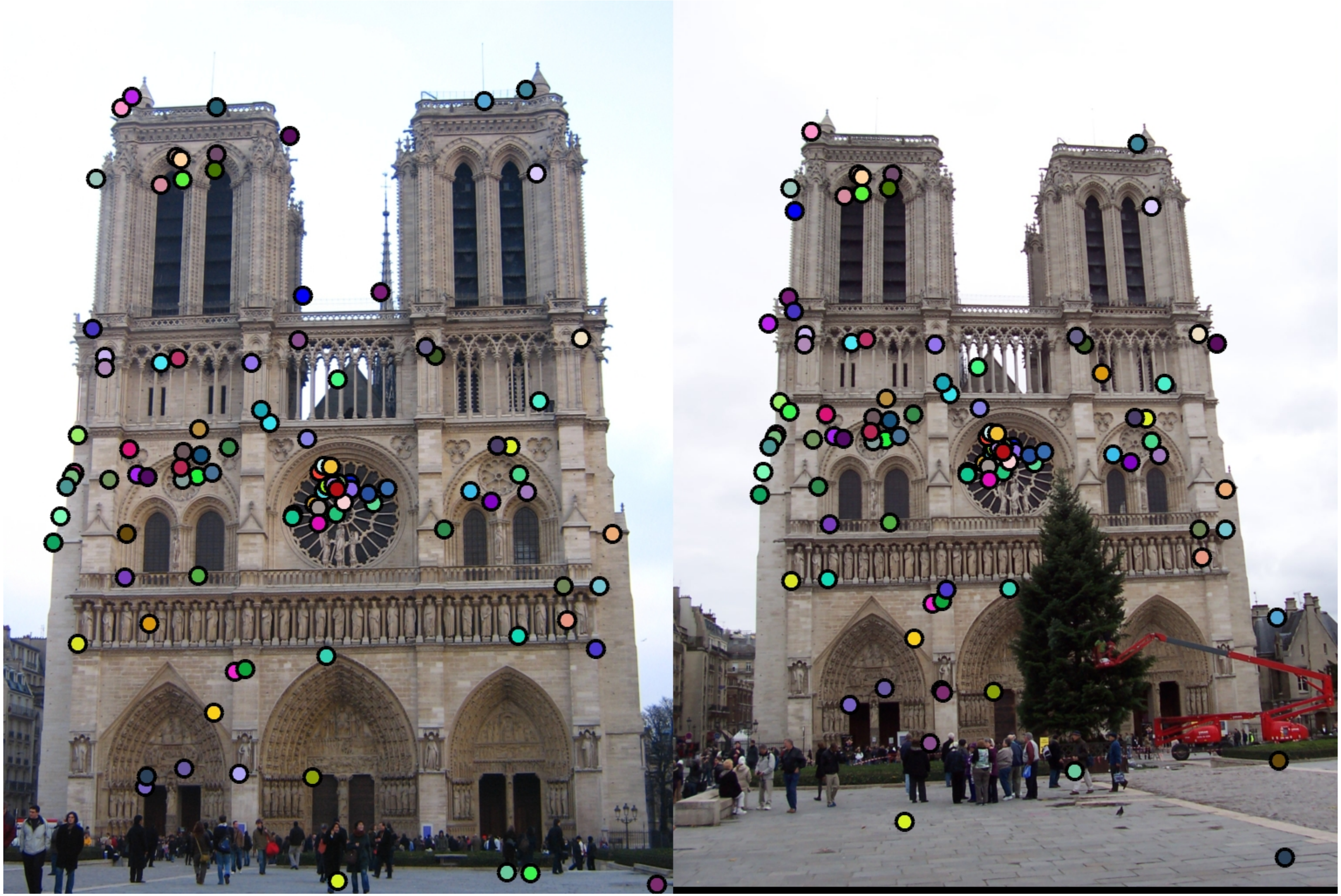
- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation *T*
  - *Verify* transformation (search for other matches consistent with *T*)

Feature-Based Alignment

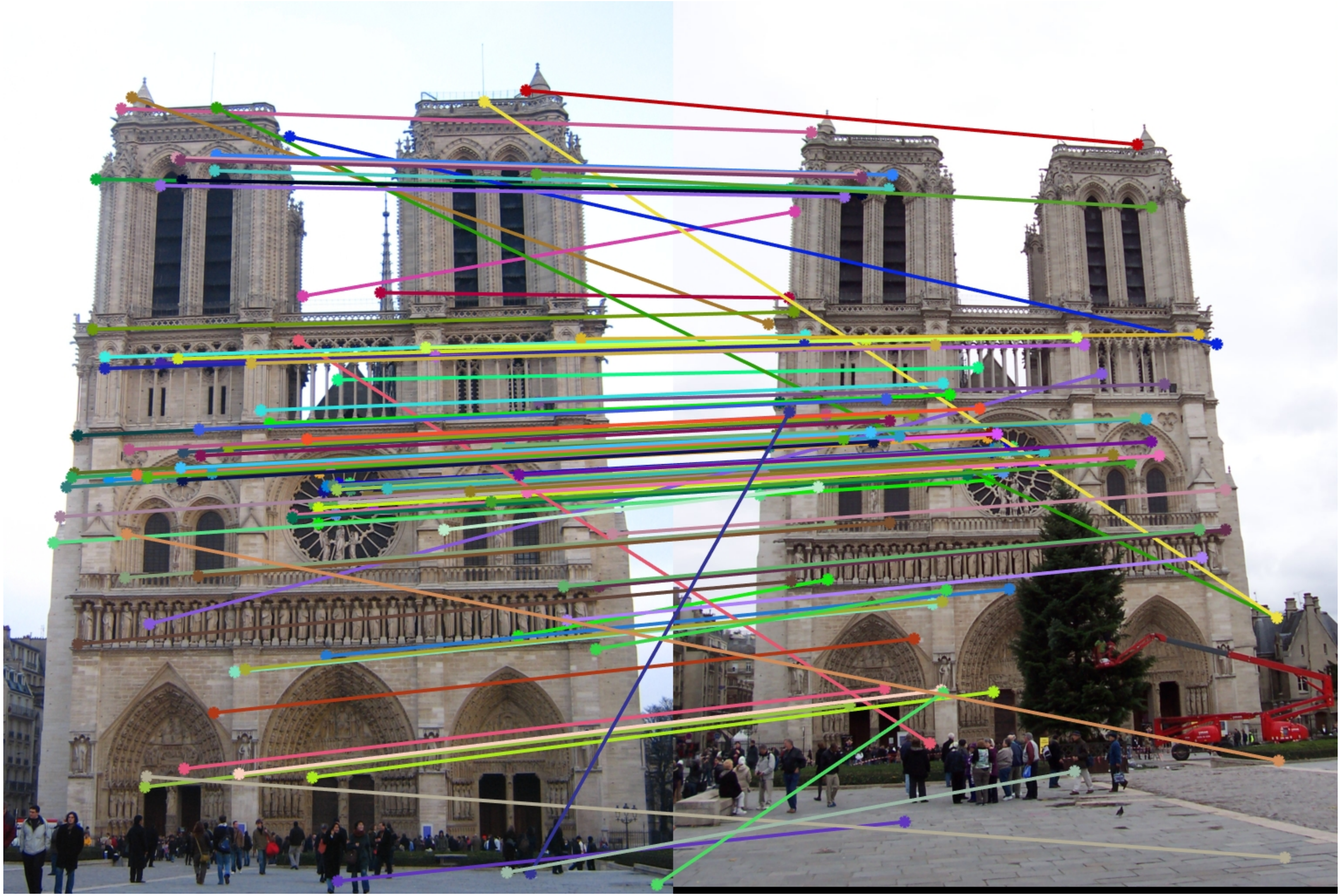
- Extract features
- Compute *putative matches*
- Loop:
  - *Hypothesize* transformation T
  - *Verify* transformation (search for other matches consistent with T)

Notre-Dame

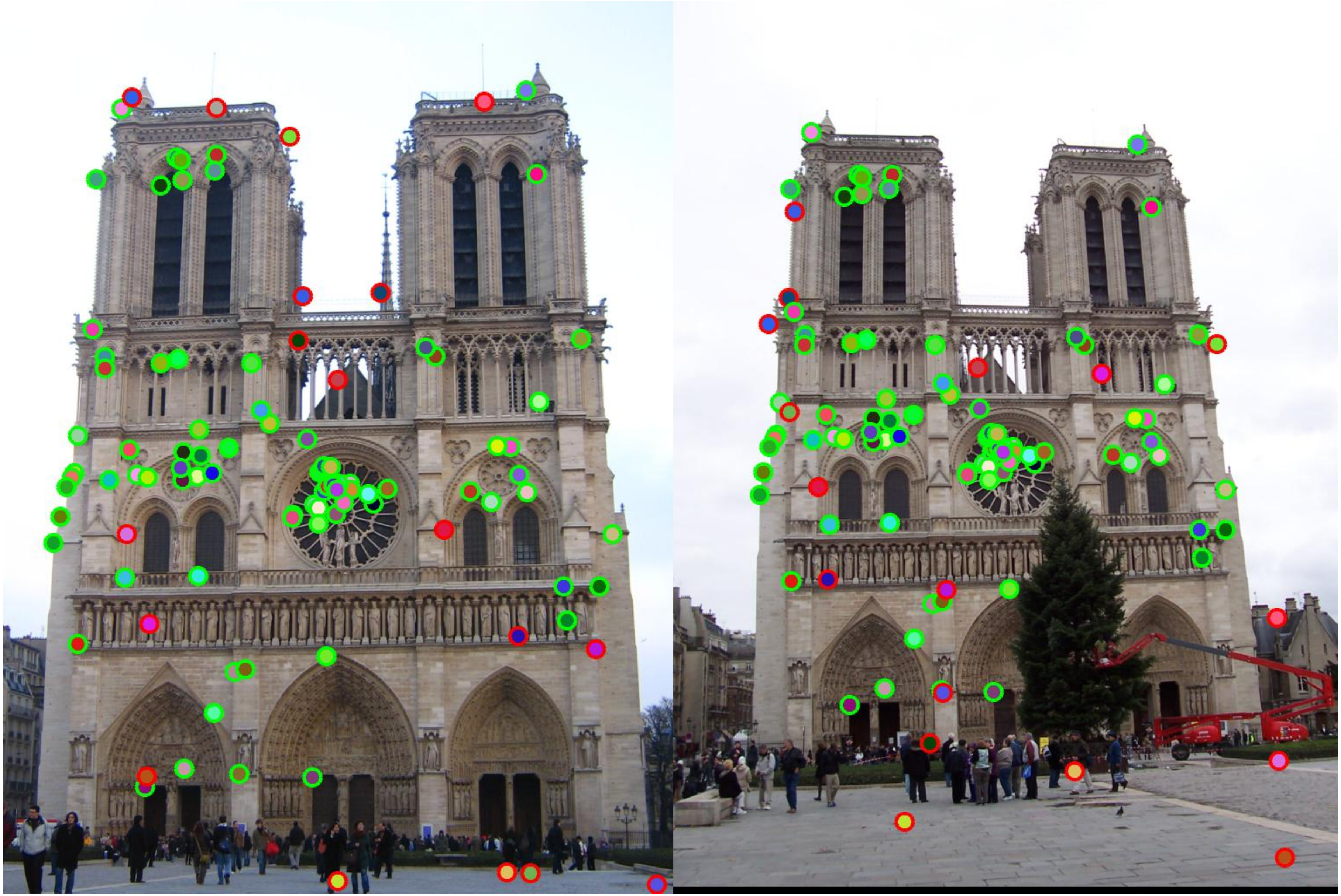
Notre-Dame: Harris Keypoints



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

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

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