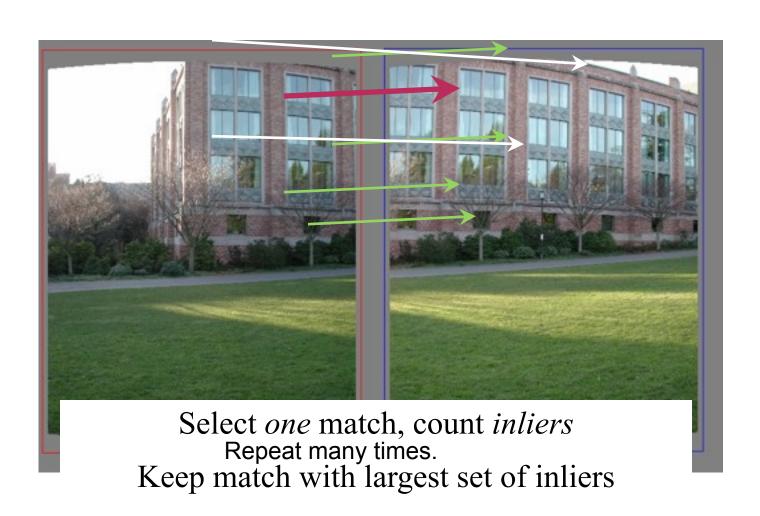
M. A. Fischler, R. C. Bolles. Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography. Comm. of the ACM, Vol 24, pp 381-395, 1981.

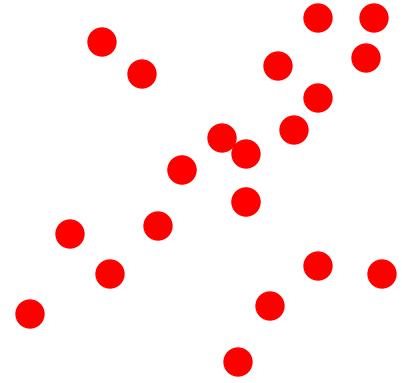
RANdom SAmple Consensus



Basic Philosophy (voting scheme)

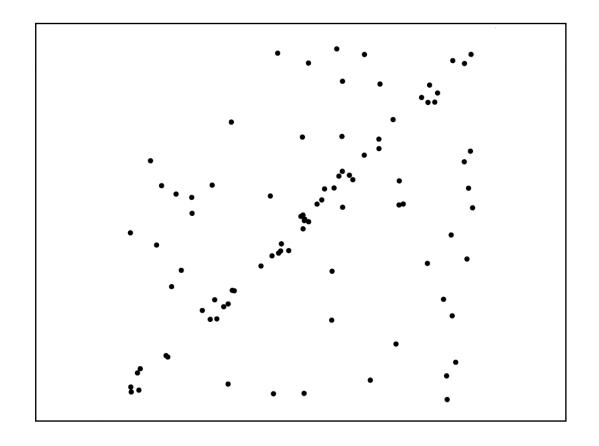
- Elemental subset (minimum number of points) randomly picked up for each hyphotesis.
- The standard deviation of the inlier noise has to be given before by the user!
- Assumption1: Outlier features will not vote consistently for any single model.
- Assumption 2: There are enough features to agree on a good model.

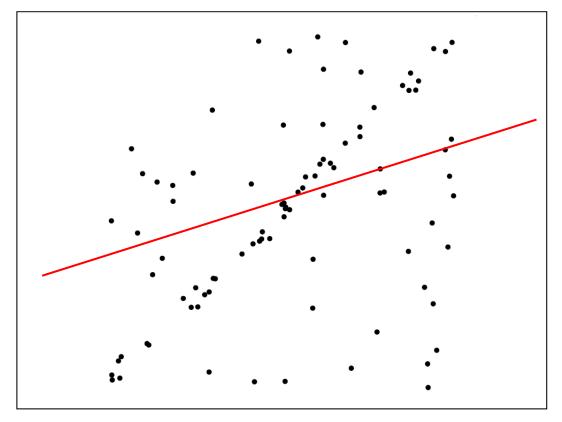
RANSAC



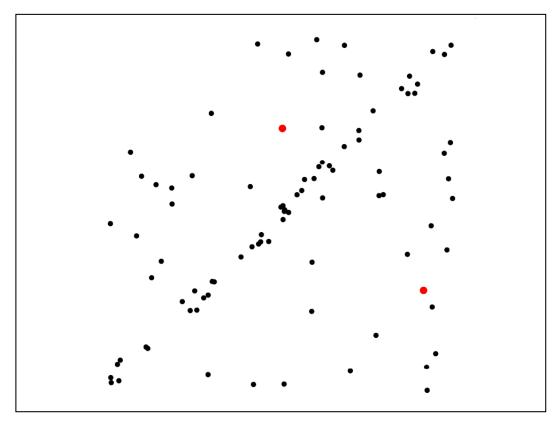
Sample set = set of points in 2D

- 1. Select random sample of minimum required size to fit model
- 2. Compute a putative model from sample set
- 3. Compute the set of inliers to this model from whole data set Repeat 1-3 until model with the most inliers over all samples is found

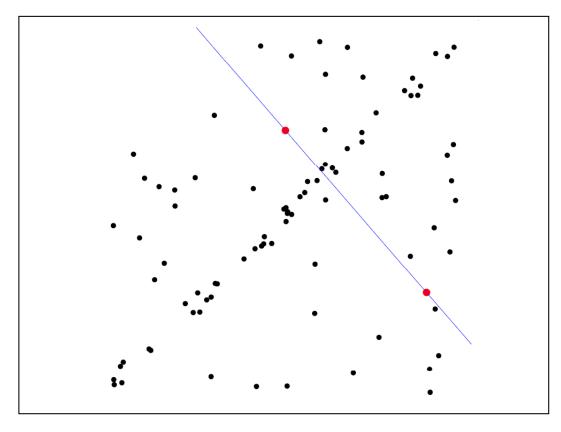




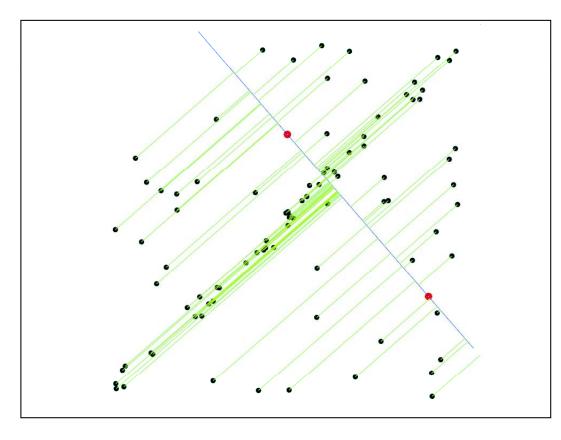
Least-squares fit



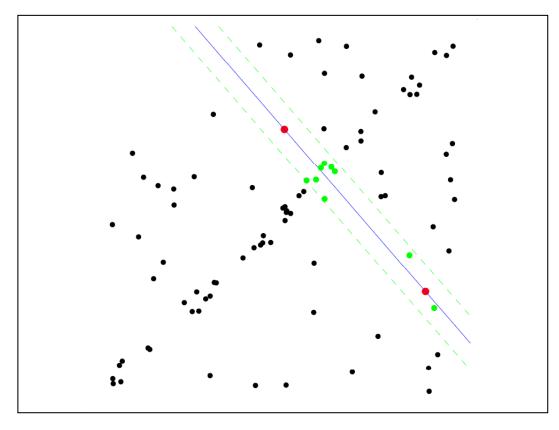
 Randomly select minimal subset of points



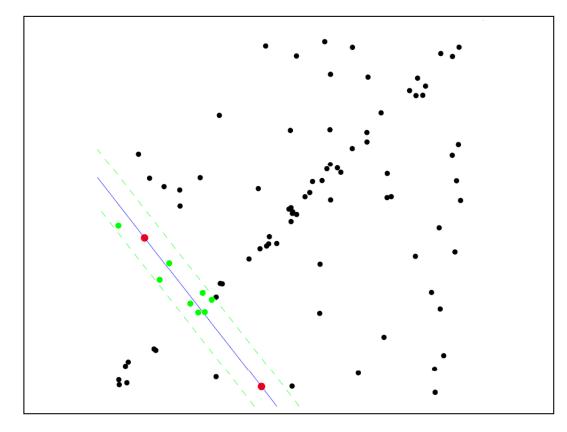
- Randomly select minimal subset of points
- 2. Hypothesize a model



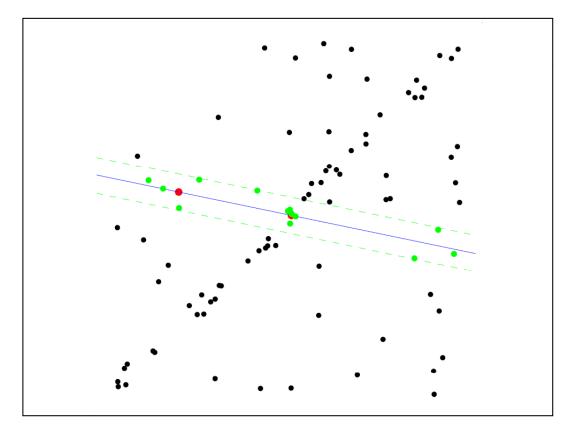
- Randomly select minimal subset of points
- 2. Hypothesize a model
- 3. Compute error function



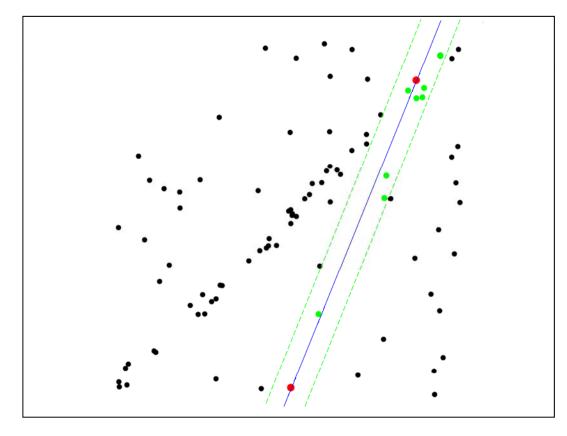
- Randomly select minimal subset of points
- 2. Hypothesize a model
- 3. Compute error function
- 4. Select points consistent with model



- Randomly select minimal subset of points
- 2. Hypothesize a model
- 3. Compute error function
- 4. Select points consistent with model
- 5. Repeat hypothesize-andverify loop

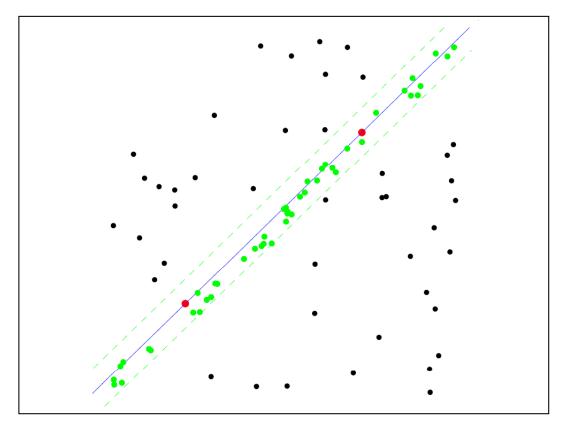


- Randomly select minimal subset of points
- Hypothesize a model
- 3. Compute error function
- 4. Select points consistent with model
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- Randomly select minimal subset of points
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- 3. Compute error function
- 4. Select points consistent with model
- 5. Repeat hypothesize-andverify loop

The best inlier structure



- Randomly select minimal subset of points
- 2. Hypothesize a model
- 3. Compute error function
- 4. Select points consistent with model
- 5. Repeat hypothesize-andverify loop

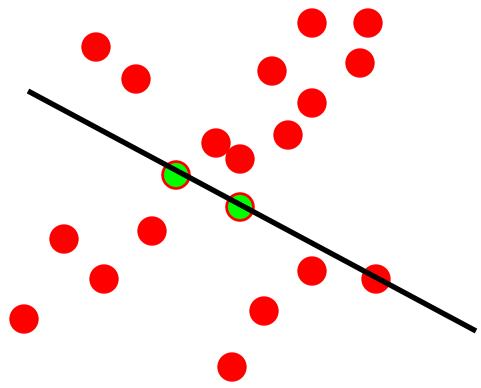
Do least-square fit on the inliers.

RANSAC RANdom SAmple Consensus

Sample set = set of points in 2D

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RANSAC

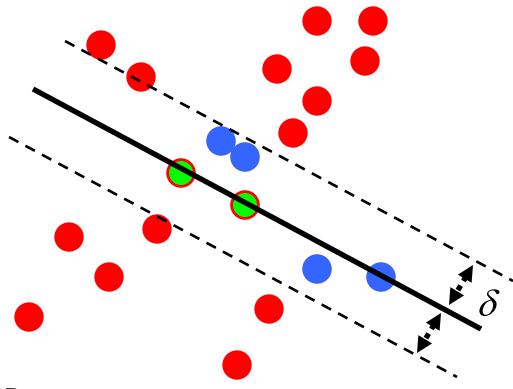


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RANSAC

standard deviation of the inlier noise has to be given



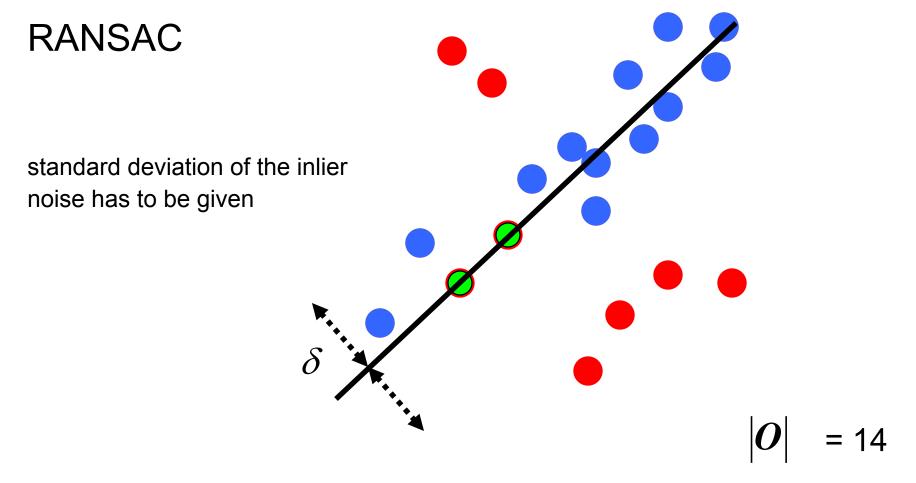
Sample set = set of points in 2D

$$|O| = 6$$

Algorithm:

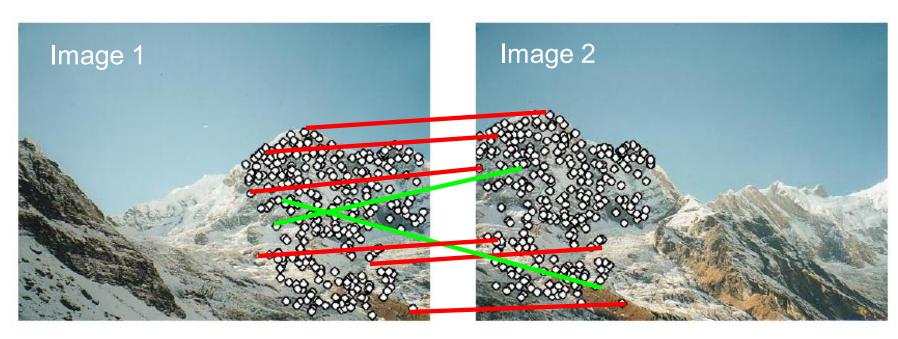
- 1. Select random sample of minimum required size to fit model
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- 1. Select random sample of minimum required size to fit model
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An example:



Matches:

Red: good matches Green: bad matches

- By RANSAC fit a homography (later...) mapping features from image 1 to 2.
- Bad matches will be labeled as outliers (hence rejected).

Fitting helps matching.



this is a robust fit

RANSAC conclusions

a better robust estimator exist already

Good

- Robust to outliers.
- The number of hyphotesis N is taken sufficiently large (hundreds to thousands) that RANSAC gives very similar results every time.

Bad

- Computational time grows quickly with fraction of outliers and number of parameters.
- Not good for getting multiple inlier structures.

Common applications

- Computing a homography (e.g., image stitching)
- Estimating fundamental matrix (relating two views)