Robust Model Fitting

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Learning objectives

After this lecture you should be able to:

- explain how the Hough transform works
- understand and implement RANSAC

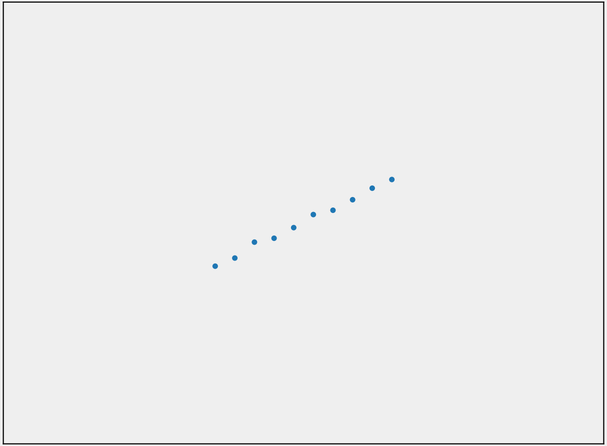
Presentation topics

Hough Transform

RANSAC

Fitting models

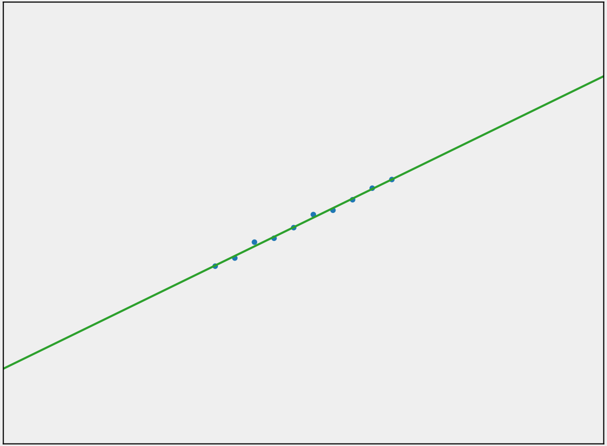
Can we fit a straight line?



Fitting models

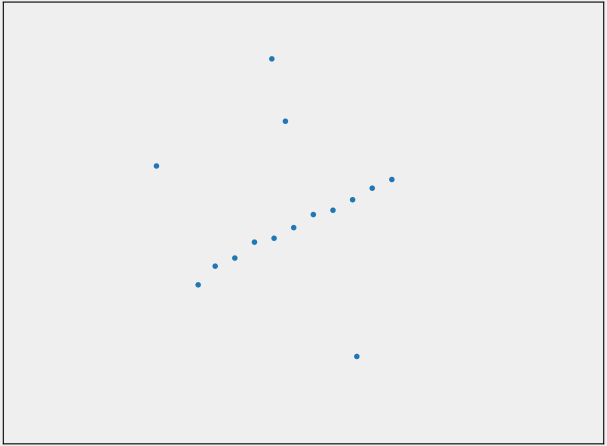
Can we fit a straight line?

Yes we can!



Fitting models

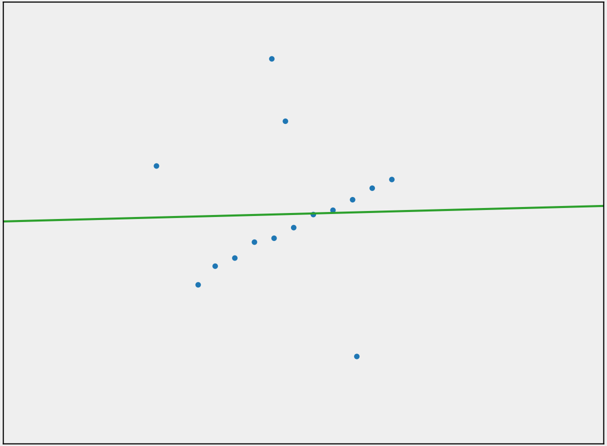
Can we fit a straight line when there are a few outliers?



Fitting models

Can we fit a straight line when there are a few outliers?

Not really...
We get a very bad fit.
We need robust ways to fit models!



About lines

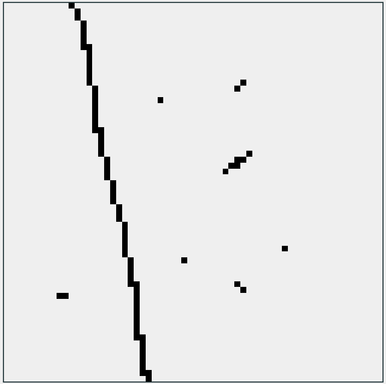
- This presentation will uses fitting straight lines to data for all examples.
- The same principles generalize to other models!

Hough Transform

Hough Transform

Is a transformation of an edge image where lines can be extracted.

Example image



Hough transform of image

Hough Transform

How to represent a line?

- $y = ax + b$?
  - Has singularities for vertical lines
- Homogeneous coordinates?
  - Is over-parametrized

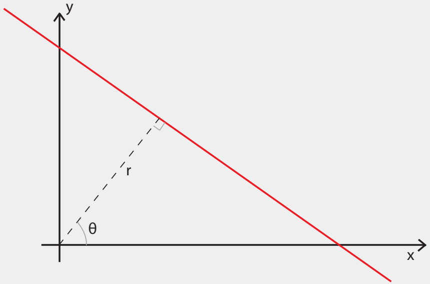
Hough Transform - r, θ representation

Represent using:

- θ angle of the line
- r closest distance from origin to line

Closely related to the homogeneous line representation

$$\boldsymbol{l} = \begin{bmatrix} \cos(\theta) & \sin(\theta) & -r \end{bmatrix}$$



Hough Transform

We can discretize all possible lines within an image on a 2D grid.

- θ is between 0 and 2π
- r is between 0 and the length of the image diagonal.

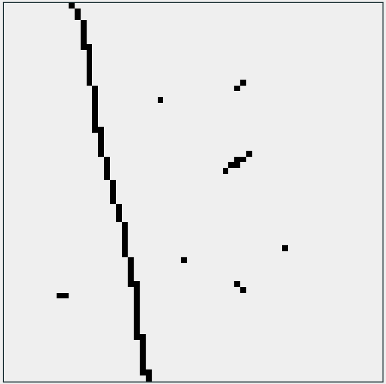
Hough Transform

Idea: Let points vote on which line is the best!

- Each point can be part of (infinitely) many lines.
- All potential lines going through this point are of interest
- Each point votes on all lines that go through its
  - This corresponds to a line in Hough space
- Repeat for all points

Hough Transform – Example

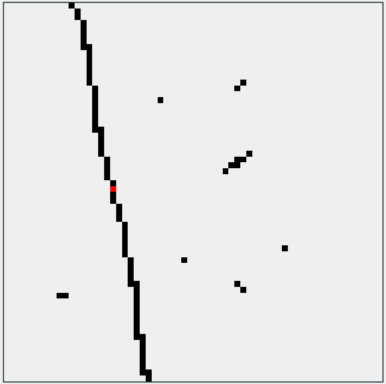
Image



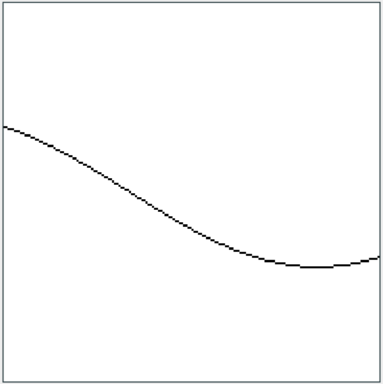
Hough Space

Hough Transform – Example

Image

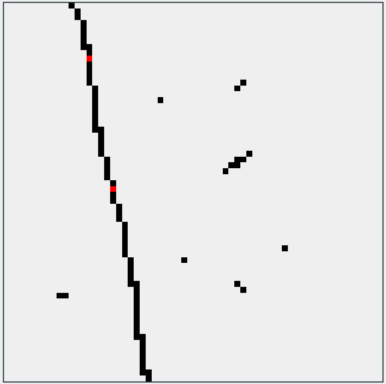


Hough Space

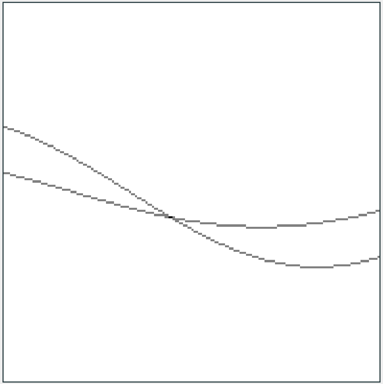


Hough Transform – Example

Image

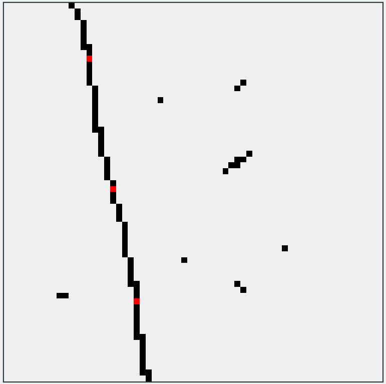


Hough Space

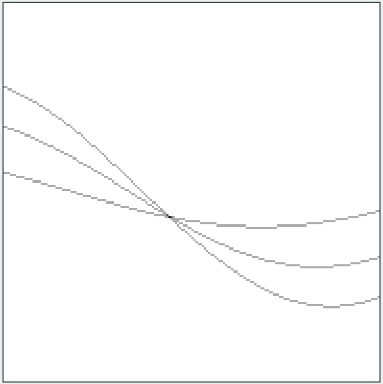


Hough Transform – Example

Image

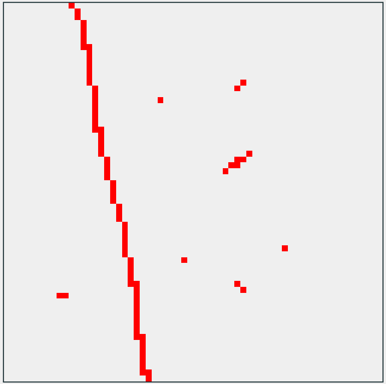


Hough Space



Hough Transform – Example

Image



Hough Space

Hough Transform

- A peak in Hough space corresponds to a line in the image.
- Can be found using non-maximum suppression.

Generalized Hough Transform

- We can generalize the Hough transform for more complex models.
  - e.g. for circles, the Hough space is now in 3D and each point becomes a conic.
- Hough space has same number of dimensions as the model we fit has degrees of freedom.
- Impractical for more than three degrees of freedom

RANSAC

Random sample consensus (RANSAC)

Idea!

Instead of computing the Hough space, what if we could sample points directly in Hough space?

Random sample consensus (RANSAC)

Idea!

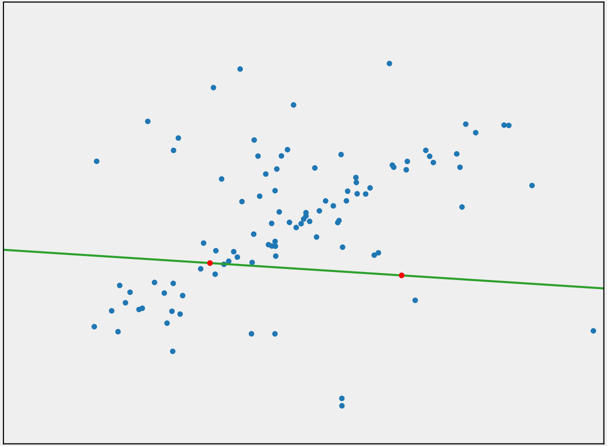
Instead of computing the Hough space, what if we could sample points directly in Hough space?

What if we could sample with the value in hough space being proportional to the probability of sampling the point?

RANSAC

- Randomly sample the minimum number of points we need to fit our model
- Fit the model to these samples

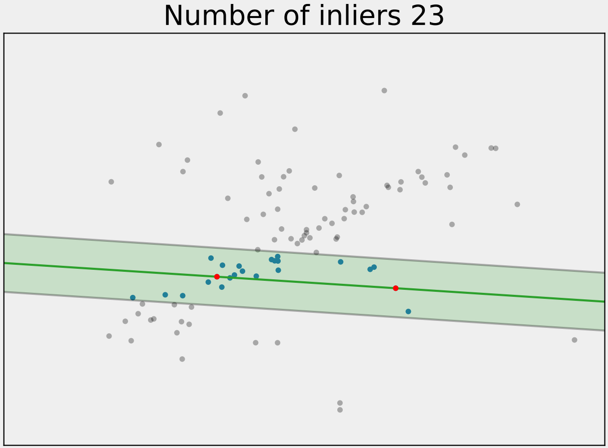
Does this line fit the data well?



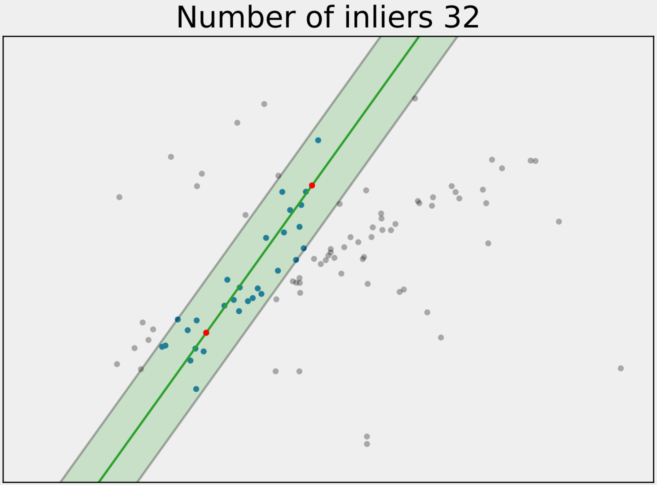
Measure inliers

Points closer than a certain threshold to the line are inliers!

Number of inliers is indication of how well the line fits.

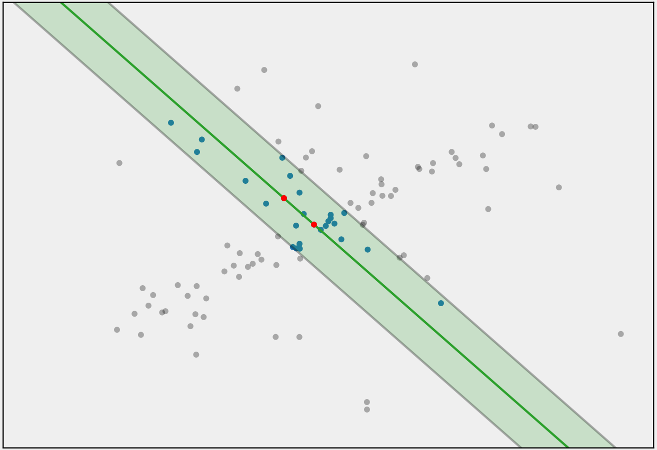


Example line

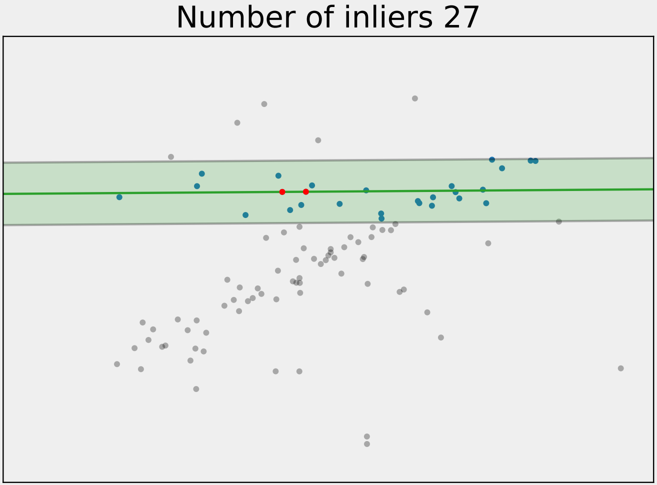


Example line

Number of inliers 26

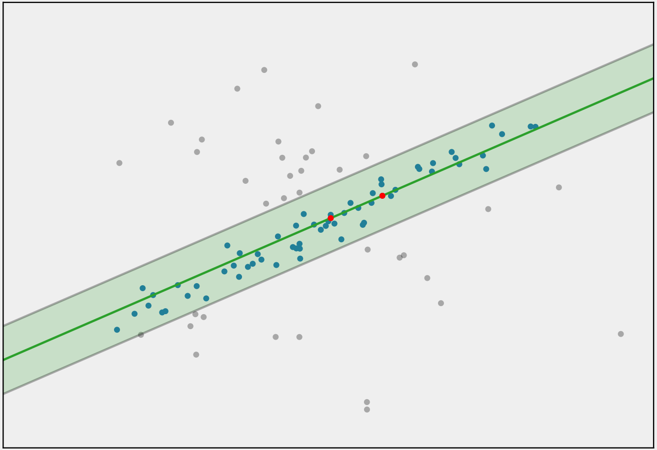


Example line



Example line

Number of inliers 62



The RANSAC algorithm

Keep track of which line had the most inliers so far, and update this if a line with more inliers are found

The RANSAC algorithm

- Sample minimum number of points required to fit model
  - Fit model to these
- Data points with an error less than τ are inliers with respect to fitted model
  - If number of inliers is higher than the highest number of inliers seen so far, update best model.

The RANSAC algorithm

- Sample minimum number of points required to fit model
  - Fit model to these
- Data points with an error less than τ are inliers with respect to fitted model
  - If number of inliers is higher than the highest number of inliers seen so far, update best model.
- Repeat for N iterations.
- Final step:
  - Re-fit model to all inliers of the best model

Implementation details

- Represent lines with homogeneous coordinates
    - Makes it easy to compute distance to line
    - The first two coordinates should have norm 1
- Recall that distance to line is given by: $|\boldsymbol{l} \cdot \Pi^{-1}(\boldsymbol{p})|$

RANSAC

- Sample in Hough space without computing it.
- Useful for fitting models when outliers are present.
- We must select the threshold for inliers and the number of iterations carefully.
- Being able to fit a model to the least amount of data points is of interest

How many iterations?

- We can come with some idea of how many iterations we need
- Assume fraction of outliers is ϵ, for example $\epsilon = 0.1$

How many iterations?

- We need n data points to fit a single model

$$P(\text{one sample has only inliers}) = (1-\epsilon)^n$$

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How many iterations?

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$$
\begin{aligned}
P(\text{one sample has only inliers}) &= (1-\epsilon)^n \\
P(\text{one sample has outliers}) &= 1-(1-\epsilon)^n \\
P(\text{each of N samples has outliers}) &= (1-(1-\epsilon)^n)^N \\
P(\text{at least one of N samples has only inliers}) &= 1-(1-(1-\epsilon)^n)^N
\end{aligned}
$$

How many iterations?

- We need n data points to fit a single model

$$
\begin{aligned}
P(\text{one sample has only inliers}) &= (1-\epsilon)^n \\
P(\text{one sample has outliers}) &= 1-(1-\epsilon)^n \\
P(\text{each of N samples has outliers}) &= (1-(1-\epsilon)^n)^N \\
P(\text{at least one of N samples has only inliers}) &= 1-(1-(1-\epsilon)^n)^N = p \\
\Leftrightarrow N &= \frac{\log(1-p)}{\log\left((1-(1-\epsilon)^n)\right)}
\end{aligned}
$$

- Set p to a high value such as $p = 0.99$. Useful if we know ϵ.

Determining number of iterations adaptively

- We can estimate an upper bound of ϵ while running RANSAC.
- Let be s the largest amount of inliers seen, and m the number of data points.
- $\hat{\epsilon} = 1 - \frac{s}{m}$

Determining number of iterations adaptively

- We can estimate an upper bound of ϵ while running RANSAC.
- Let be s the largest amount of inliers seen, and m the number of data points.
- $\hat{\epsilon} = 1 - \frac{s}{m}$
- We can now estimate an upper bound on the number of iterations required
- $\hat{N} = \frac{\log(1-p)}{\log\left((1-(1-\hat{\epsilon})^n)\right)}$
- Terminate once we have done more than $\hat{N}$ iterations.

Learning objectives

After this lecture you should be able to:

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- understand and implement RANSAC

Exercise time!