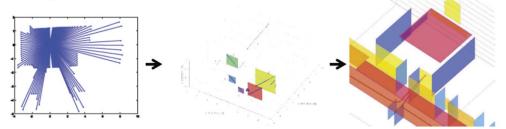
## CMPE 185 Autonomous Mobile Robots

Perception: Feature Extraction Based on Range Data

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#### Line Extraction Problem

- Given range data, how do we extract line segments (or planes)?
- These features (line segments) can be used to build maps or be compared with an existing map.
- Three main problems in line extraction in unknown environments
  - How many lines are there?
  - Segmentation: Which points belong to which line?
  - Line Fitting/Extraction: Given points that belong to a line, how to estimate the line parameters?



#### Line Extraction: Representing a line

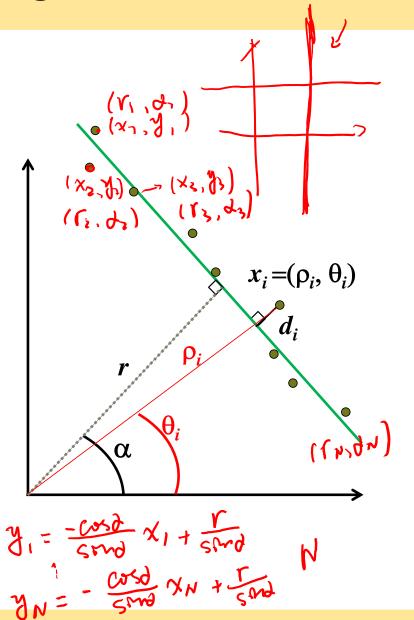
A line can be represented by

$$y = ax + b$$

- Q: how to represent a vertical line?
- Polar coordinate  $\mathbf{x} = (r, \alpha)$ 
  - r: distance from the origin to the close point on the line
  - α: angle of the line
  - $r = x * cos\alpha + y * sin\alpha$
- The line can represented by

$$y = \frac{-\cos\alpha}{\sin\alpha} * x + \frac{r}{\sin\alpha}$$

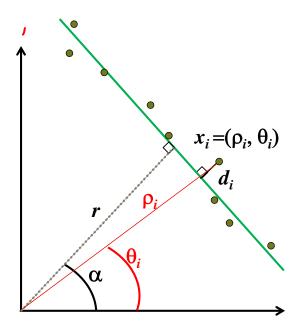
for  $\alpha \in [0,180]$  and  $r \in \mathbf{R}$  or  $\alpha \in [0,360]$  and  $r \ge 0$ 



#### Line Extraction Problem

• Given a measurement vector of N range and bearing measurements  $\mathbf{x_i} = (\rho_i, \theta_i)$ , what are the parameters  $(r, \alpha)$  that define a line feature for these measurements.

	pointing angle of sensor $\theta_i$ [deg]	range $\rho_i$ [m]
10,05797	0 5 5	0.5197
10, 5311	<b>)</b> X i 5	0.4404
	10	0.4850
	15	0.4222
	20	0.4132
	25	0.4371
	30	0.3912
	35	0.3949
	40	0.3919
	<b>4</b> 5	0.4276
	<b>71</b> 50	0.4075
160,0.4053	55	0.3956
1. 1013	60	0.4053
160,0,000	65	0.4752
. •	70	0.5032
	75	0.5273
	80	0.4879



#### Line Extraction

- Polar measurement  $x_i = (\rho_i, \theta_i)$
- The corresponding Euclidean coordinate:

• 
$$x_i = \rho_i cos \theta_i$$

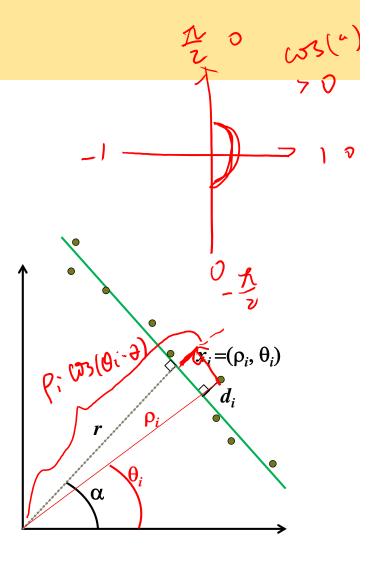
• 
$$y_i = \rho_i sin\theta_i$$

Point-Line distance

$$\rho_i \cos(\theta_i - \alpha) - r = d_i$$

• If each measurement is equally uncertain, the sum of squared errors:

$$S = \sum_{i} d_i^2 = \sum_{i} (\rho_i \cos(\theta_i - \alpha) - r)^2$$



#### Line Extraction

$$y = \frac{1}{2}(x-2)^2$$
ford x, that minimize  $y^2$ 

• Each sensor measurement may have its own, unique uncertainty  $\sigma_{\rm i}^{\,2}$ 

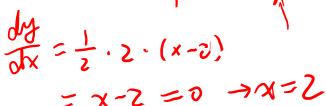
$$S = \sum w_i d_i^2 = \sum w_i (\rho_i \cos(\theta_i - \alpha) - r)^2$$

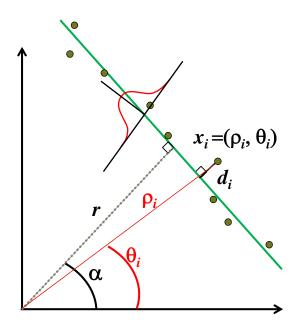
$$w_i = \frac{1}{\sigma_i^2}$$

• Goal: minimize S when selecting  $(r, \alpha)$ 

$$\frac{\partial S}{\partial \alpha} = 0 \qquad \frac{\partial S}{\partial r} = 0$$

- "Unweighted Least Squares"
- "Weighted Least Squares"





Line Extraction
$$N = 4$$

$$\lambda = \frac{1}{2} \operatorname{atom} \left( \frac{2P_{1} \leq n \geq 0}{1 + P_{1} \leq n \geq 0}, \frac{1}{2} \operatorname{cos} 0, \frac{1}{2} \operatorname{cos}$$

 Weighted least squares and solving the equations

$$\frac{\partial S}{\partial \alpha} = 0 \qquad \frac{\partial S}{\partial r} = 0$$

The line parameters are

$$\alpha = \frac{1}{2} \operatorname{atan} \left[ \frac{\sum w_i \rho_i^2 \sin 2\theta_i - \frac{2}{\sum w_i} \sum \sum w_i w_j \rho_i \rho_j \cos \theta_i \sin \theta_{j_{0.1}}}{\sum w_i \rho_i^2 \cos 2\theta_i - \frac{1}{\sum w_i} \sum \sum w_i w_j \rho_i \rho_j \cos (\theta_i + \theta_j)} \right]_{-0.1}$$

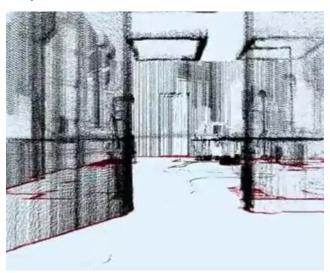
$$r = \frac{\sum w_i \rho_i \cos(\theta_i - \alpha)}{\sum w_i}$$

The uncertainty  $\sigma_i$  of each

measurement is proportional to the measured distance  $\rho_i$ 

#### Line Extraction from a Point Cloud

- Extract lines from a point cloud (e.g. range scan)
- Three main problems:
  - How many lines are there?
  - Segmentation: Which points belong to which line?
  - Line Fitting/Extraction: Given points that belong to a line, how to estimate the line parameters?
- Algorithms we will see:
  - Split-and-merge
  - Linear regression
  - RANSAC
  - Hough-Transform

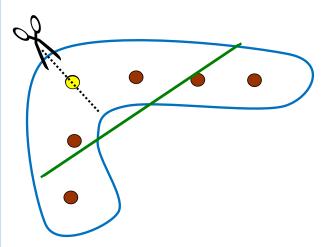


#### Line Extraction – Split and Merge (standard)

- Popular algorithm, originates from Computer Vision.
- A recursive procedure of fitting and splitting.

# Let S be the set of all data points Split Merge If two consecutive segments are collinear enough, obtain

- If two consecutive segments are collinear enough, obtain the common line and find the most distant point
- If distance <= threshold, merge both segments



#### Line Extraction – Split and Merge (standard)

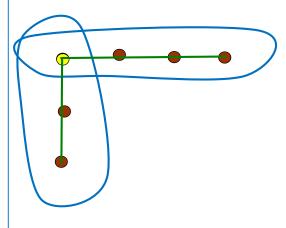
Let **S** be the set of all data points

#### **Split**

- •
- •
- If distance > threshold ⇒ split set & repeat with left and right point sets

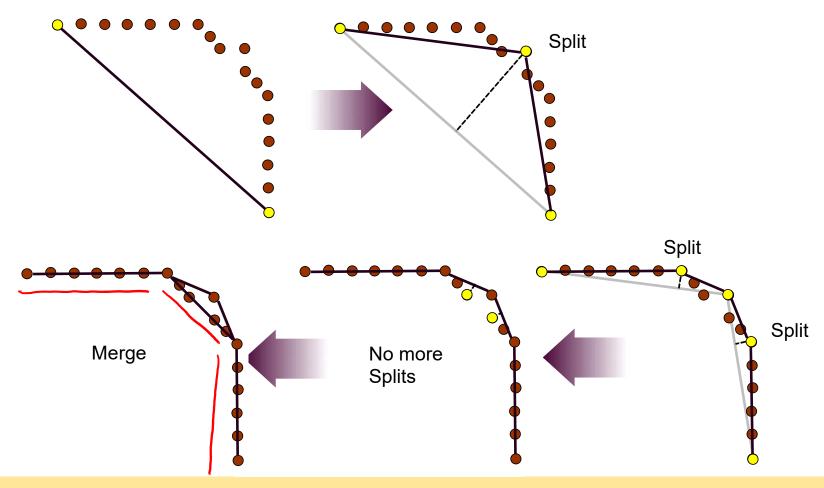
#### Merge

- If two consecutive segments are collinear enough, obtain the common line and find the most distant point
- If distance <= threshold, merge both segments



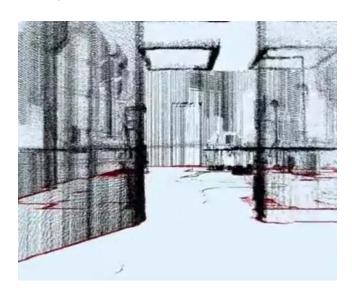
### Line Extraction – Split and Merge (iterative end-point-fit)

 Iterative end-point-fit: simply connects the end points for line fitting



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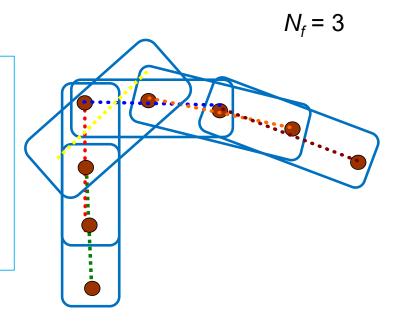


#### Line Extraction – Line Regression

- "Sliding window" of size  $N_f$  points
- Fit line-segment to all points in each window

#### **Line-Regression**

- Initialize sliding window size  $N_f$
- Fit a line to every  $N_f$  consecutive points (i.e. in each window)
- Merge overlapping line segments + re-compute line parameters for each segment

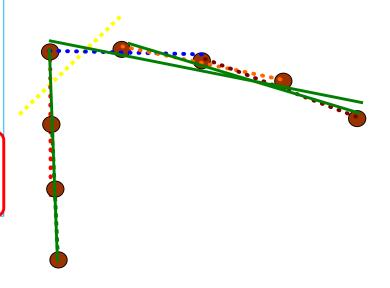


#### Line Extraction – Line Regression

 $N_f = 3$ 

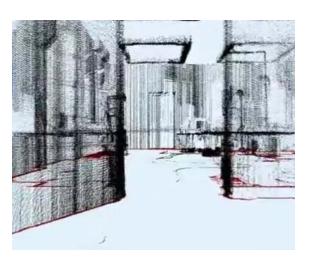
#### **Line-Regression**

- Initialize sliding window size N<sub>f</sub>
- Fit a line to every  $N_f$  consecutive points (i.e. in each window)
- Merge overlapping line segments + re-compute line parameters for each segment



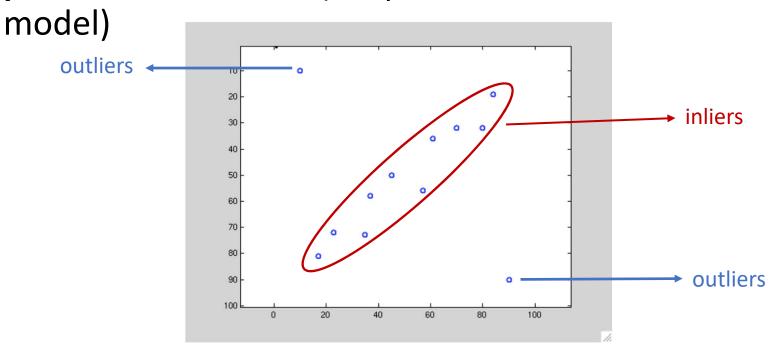
#### Line Extraction from a Point Cloud

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RANSAC = RANdom Sample Consensus

 A generic & robust fitting algorithm of models in the presence of outliers (i.e. points which do not satisfy a

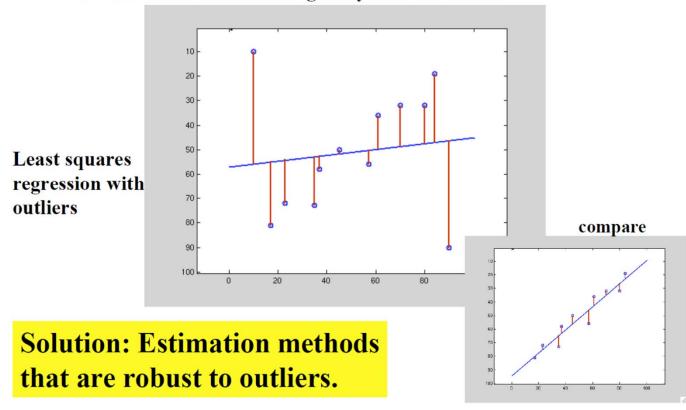


M. Fischler & R. C. Bolles. RANndom SAmple Consensus:

A paradigm for model fitting with applications to image analysis and automated cartography. Graphics and Image Processing, 1981.

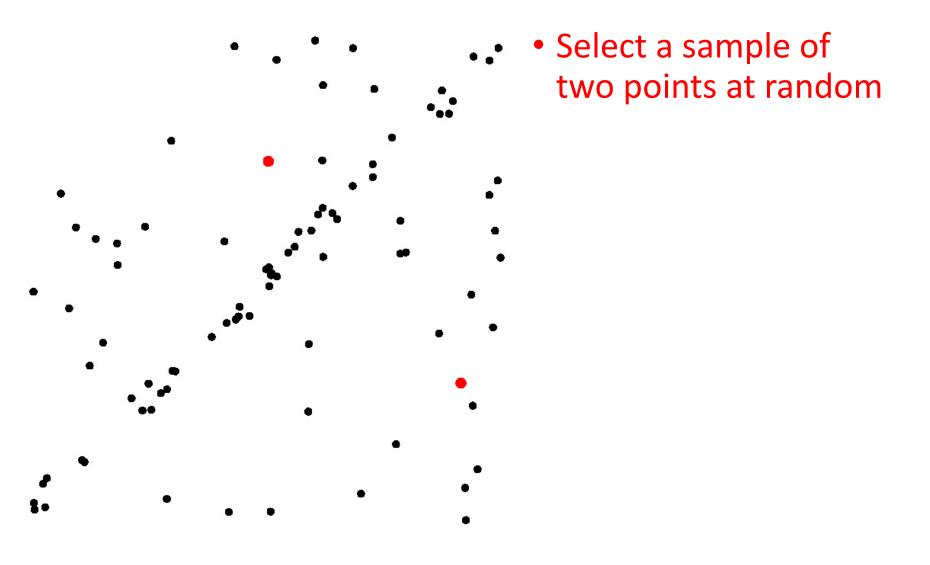
RANSAC = RANdom Sample Consensus

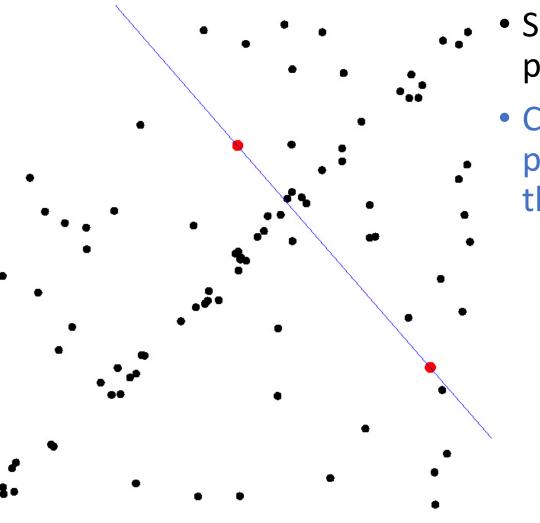
Least squares estimation is sensitive to outliers, so that a few outliers can greatly skew the result.



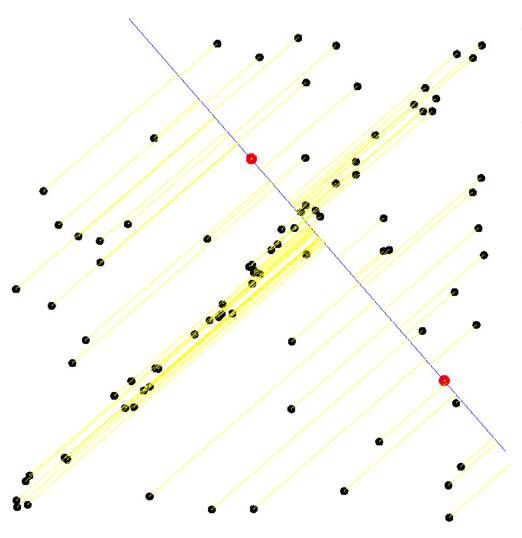
- RANSAC = RANdom Sample Consensus
- Can be applied in general to any problem, where the goal is to identify the inliers which satisfy a predefined model.
- Typical applications in robotics are: line extraction from 2D range data, plane extraction from 3D data, feature matching, structure from motion, camera calibration, homography estimation, etc.
- RANSAC is iterative and non-deterministic: the probability to find a set free of outliers increases as more iterations are used
- Drawback: a non-deterministic method, results are different between runs.

M. Fischler & R. C.Bolles. RANndom SAmple Consensus:
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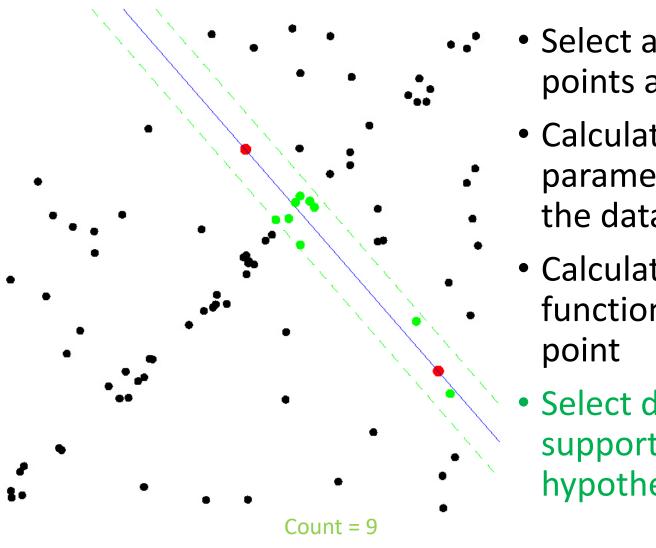




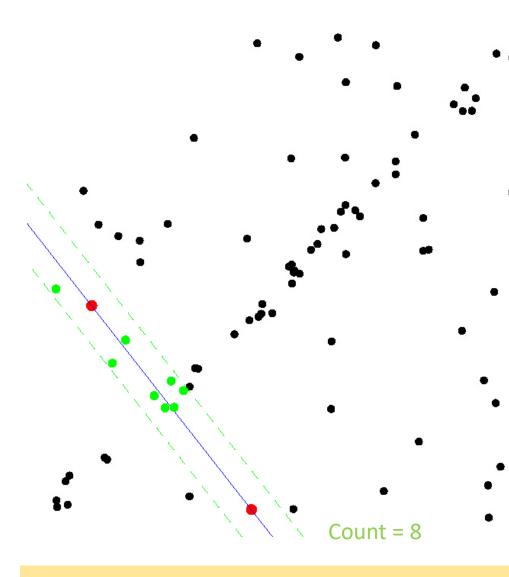
- Select a sample of two points at random
- Calculate model
   parameters that fit
   the data in the sample



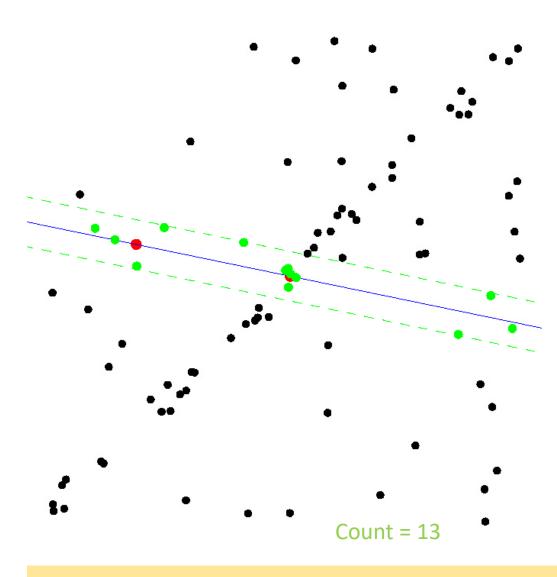
- Select a sample of two points at random
- Calculate model
   parameters that fit
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- Calculate error function for each data point



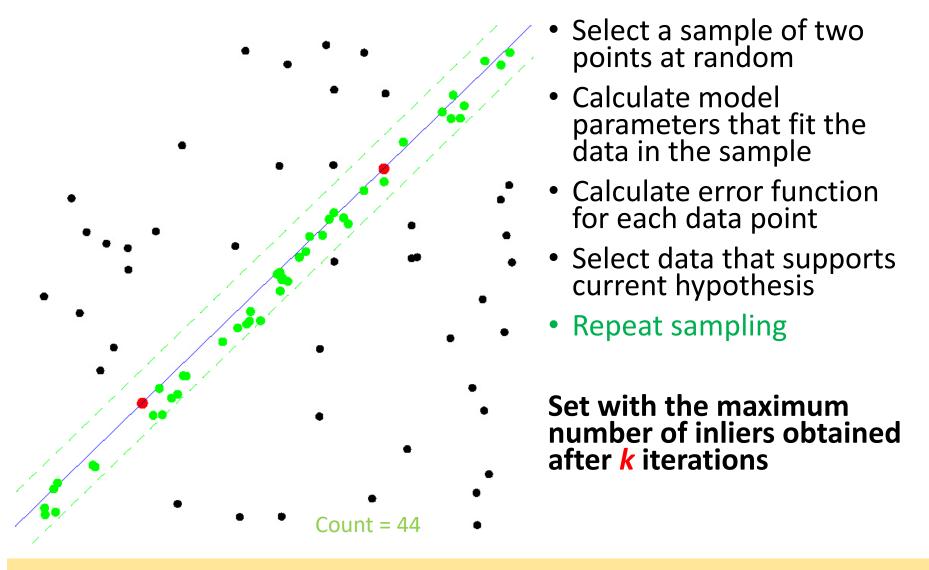
- Select a sample of two points at random
- Calculate model parameters that fit the data in the sample
- Calculate error function for each data point
- Select data that supports current hypothesis



- Select a sample of two points at random
- Calculate model parameters that fit the data in the sample
- Calculate error function for each data point
  - Select data that supports current hypothesis
  - Repeat sampling



- Select a sample of two points at random
- Calculate model parameters that fit the data in the sample
- Calculate error function for each data point
- Select data that supports current hypothesis
- Repeat sampling



#### How many iterations does RANSAC need? k = ?

- Ideally: check all possible combinations of 2 points in a dataset of N points
- Number of all pairwise combinations: N(N-1)/2
  - computationally infeasible if N is too large.
     example:
     10'000 points to fit a line through a need to check all 10'000 x
     9'999/2 = 50 million combinations!
- Do we really need to check all combinations or can we stop after some iterations?
  - Checking a subset of combinations is enough if we have a rough estimate of the percentage of inliers in our dataset
- This can be done in a probabilistic way

#### How many iterations does RANSAC need? k = ?

- N: total number of data points
- w: number of inliers / N
  - w is the fraction of inliers in the dataset, the probability of selecting an inlier-point out of the dataset
- p: the desired probability of success
- The number of RANSAC iterations needed is

$$k = \frac{\log(1-p)}{\log(1-w^2)}$$

- **Example:** if we want a probability of success p = 99%, and we know that  $w = 50\% \rightarrow k = 16$  iterations
  - dramatically fewer than the number of all possible combinations!
- In practice, we need only a rough estimate of w. There are more advanced variants of RANSAC

#### RANSAC is not only for line extraction

```
Given:
    data - a set of observations
    model - a model to explain observed data points
    n - minimum number of data points required to estimate model parameters
    k - maximum number of iterations allowed in the algorithm
   t - threshold value to determine data points that are fit well by model
    d - number of close data points required to assert that a model fits well to data
Return:
    bestFit - model parameters which best fit the data (or nul if no good model is found)
iterations = 0
bestFit = nul
bestErr = something really large
while iterations < k {
    maybeInliers = n randomly selected values from data
    maybeModel = model parameters fitted to maybeInliers
    alsoInliers = empty set
    for every point in data not in maybeInliers {
        if point fits maybeModel with an error smaller than t
             add point to alsoInliers
   if the number of elements in alsoInliers is > d {
        % this implies that we may have found a good model
        % now test how good it is
        betterModel = model parameters fitted to all points in maybeInliers and alsoInliers
        thisErr = a measure of how well betterModel fits these points
        if thisErr < bestErr {
            bestFit = betterModel
            bestErr = thisErr
    increment iterations
                                                                      wikipedia
return bestFit
```

• Thank you!