

# DMIP - Exercise:

## RANSAC

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Pattern Recognition Lab (CS 5)



**FAU**

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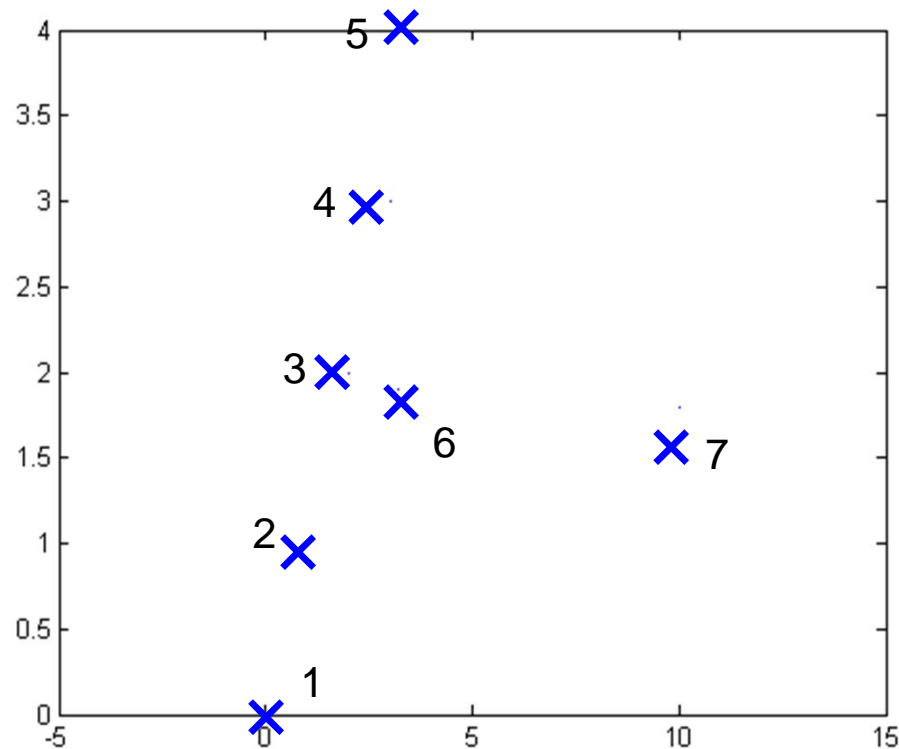
TECHNISCHE FAKULTÄT



## Problem in calibration: inaccuracies in observations and outliers.

- Badly localized points (noise)
- Wrong correspondence

### Linear Regression

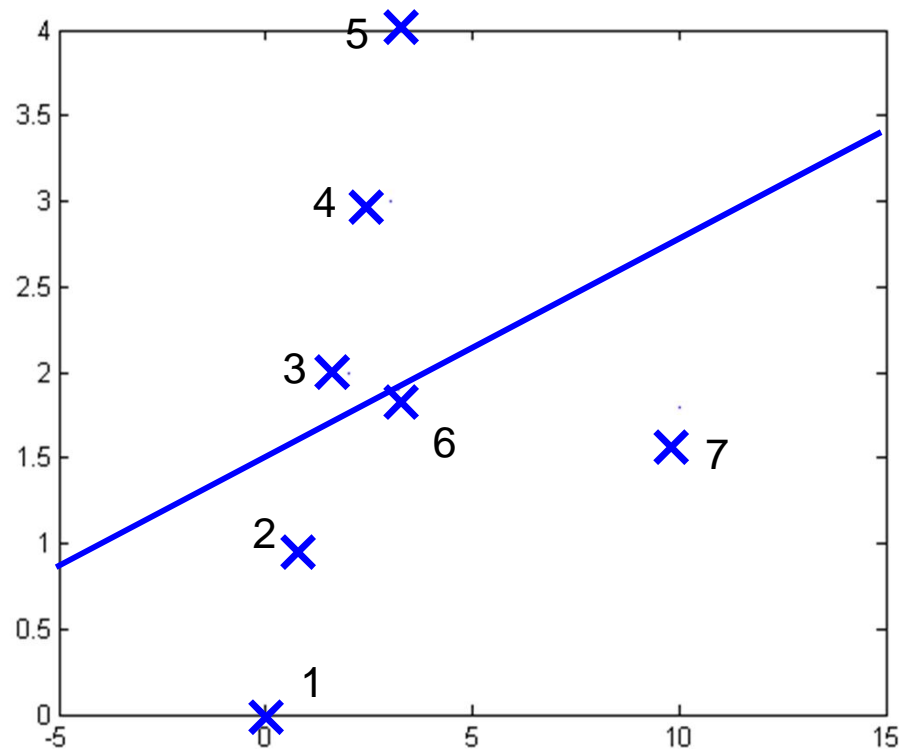




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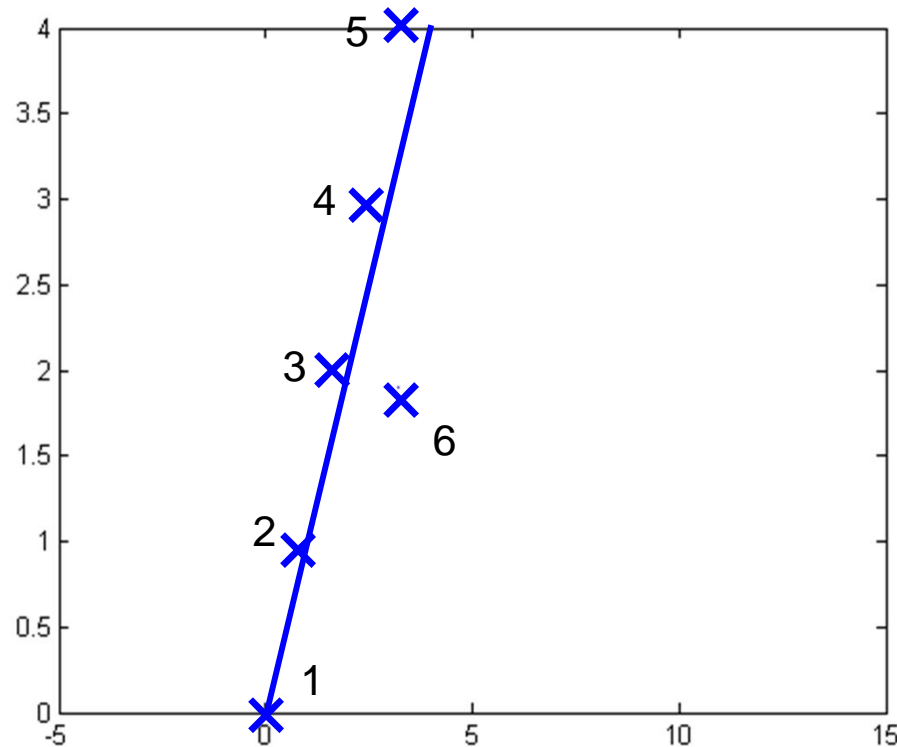




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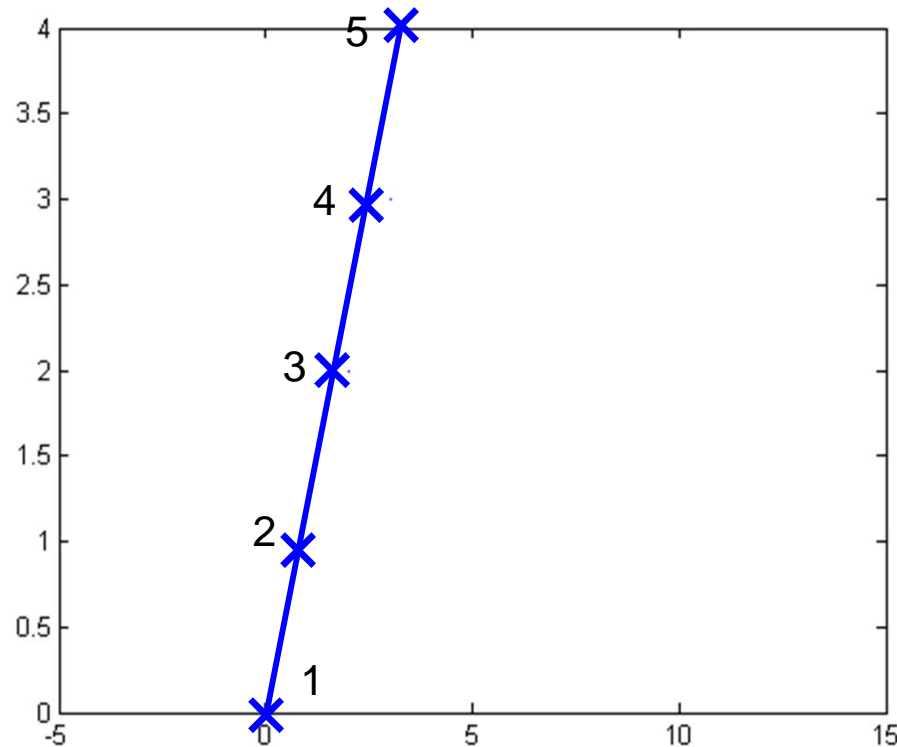




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# RANSAC – RANdOm Sample Consensus

RANSAC assumes that a model built with a minimum number of data points for this model **does not contain outliers**.

## Algorithm:

- Determine the minimum number  $n_{\text{mdl}}$  of data points required to build the model  
→ A line is completely defined by two points →  $n_{\text{mdl}} = 2$
- For  $n_{\text{it}}$  iterations do
  - a) Choose randomly  $n_{\text{mdl}}$  points out of your data to estimate the model
  - b) Determine the error of the current model using all data points
- Choose model with lowest error



# RANSAC

**Task:** complete the function `fitline`: This will be used for fitting a line through a set of points.

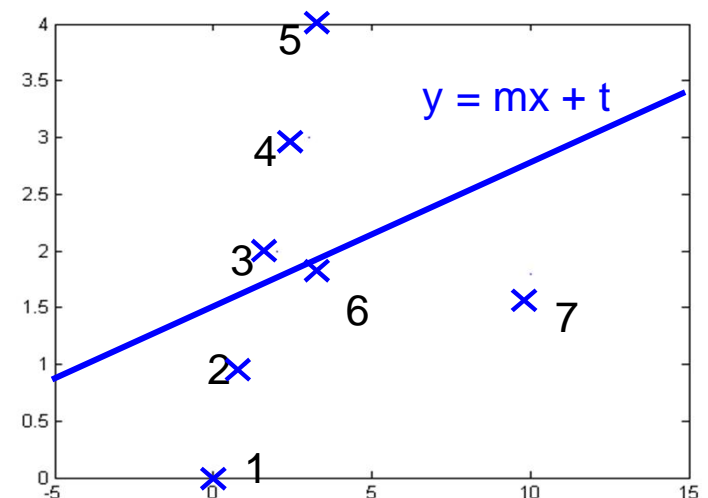
Find the line parameter  $m$  and  $t$ , so that all points  $(x_i, y_i)$ ,  $i = 1, \dots, 7$ , approximately fulfill the line equation  $y_i = mx_i + t$

→ Solve the following optimization problem

$$\left\| [X \ 1] \cdot \begin{pmatrix} m \\ t \end{pmatrix} - Y \right\| = \left\| M \cdot \begin{pmatrix} m \\ t \end{pmatrix} - Y \right\| \rightarrow 0$$

The least square solution of this equation is given (**Moore-Penrose pseudo-inverse**)

$$\begin{pmatrix} m \\ t \end{pmatrix} = M^\dagger Y$$

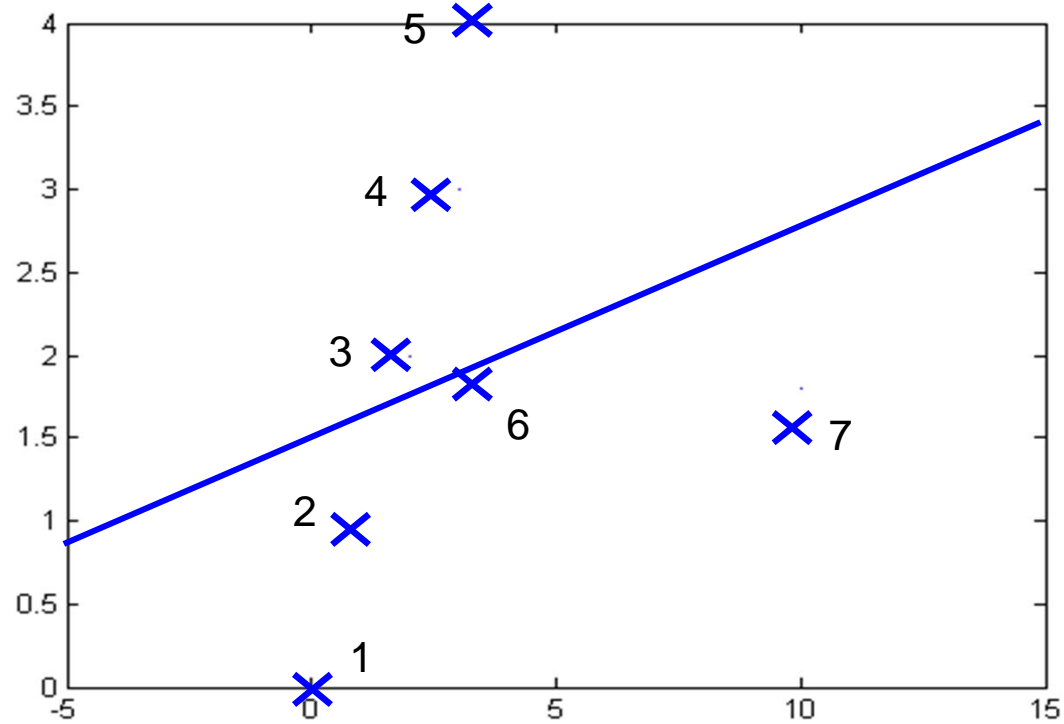


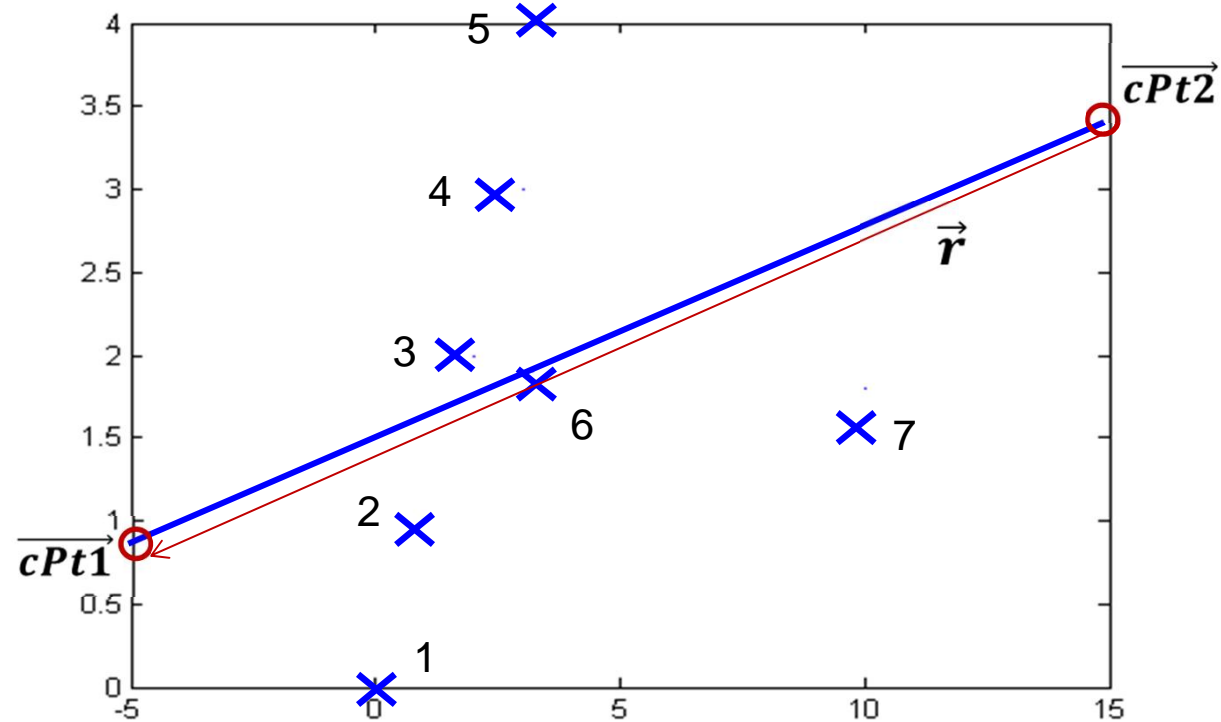


# RANSAC

**Task:** `lineerror`: This will be our specialized `errFct` for our line model `mdl` considering all samples in `pts`. Think about a proper error metric.

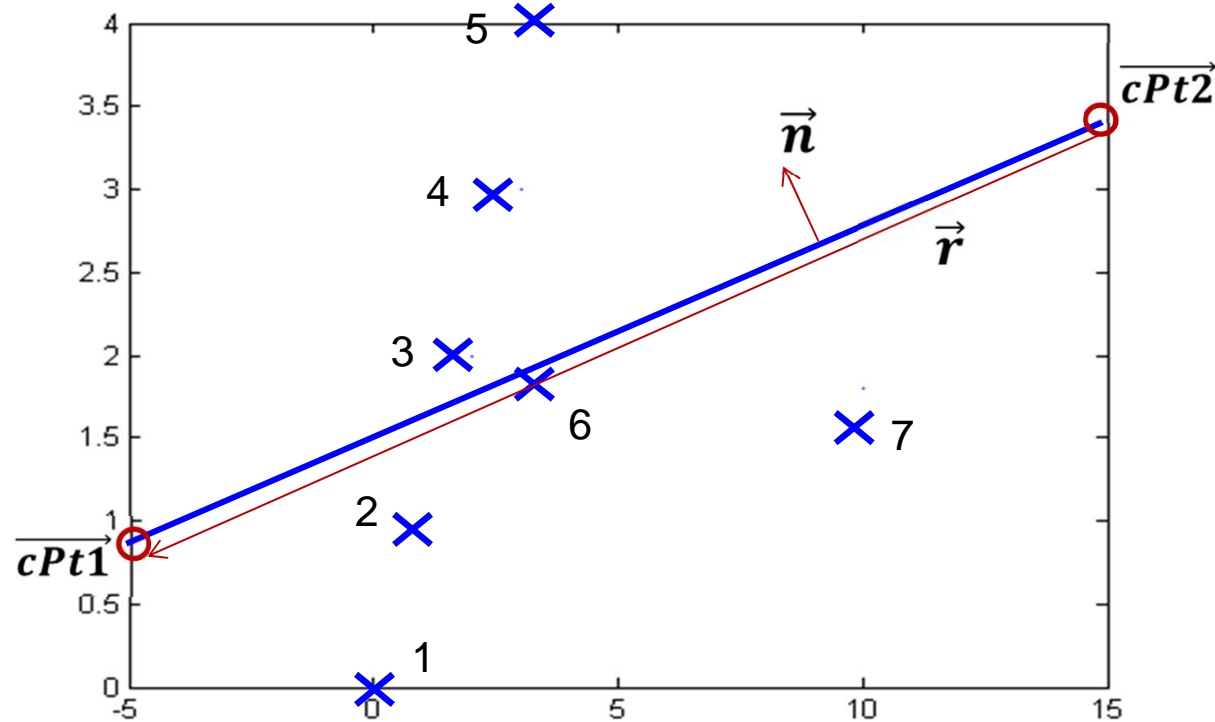






1) Pick two points on the line and calculate direction:

$$\vec{r} = c\vec{Pt}2 - c\vec{Pt}1$$



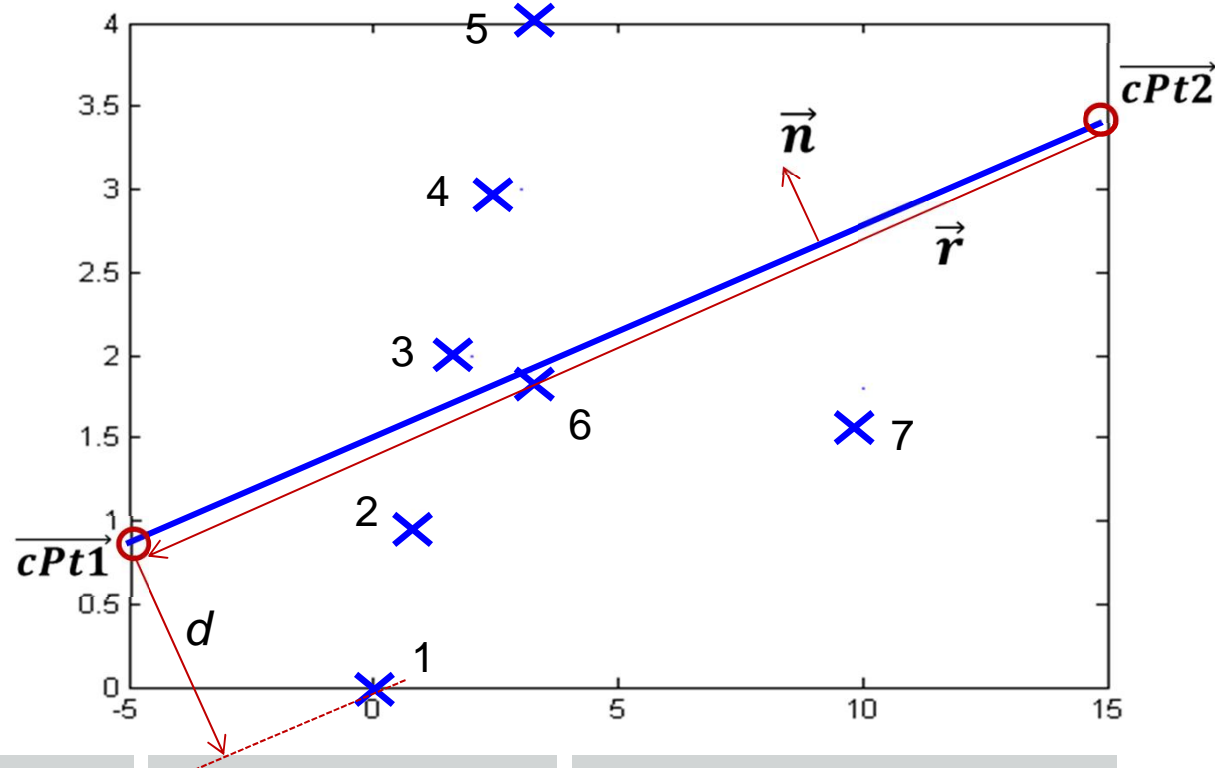
1) Pick two points on the line and calculate direction:

$$\vec{r} = c\vec{Pt2} - c\vec{Pt1}$$

2) Calculate normal vector to direction and normalize it:

$$\vec{n} = \begin{pmatrix} -y_{\vec{r}} \\ x_{\vec{r}} \end{pmatrix}$$

$$\vec{n} = \vec{n} / \text{norm}(\vec{n})$$



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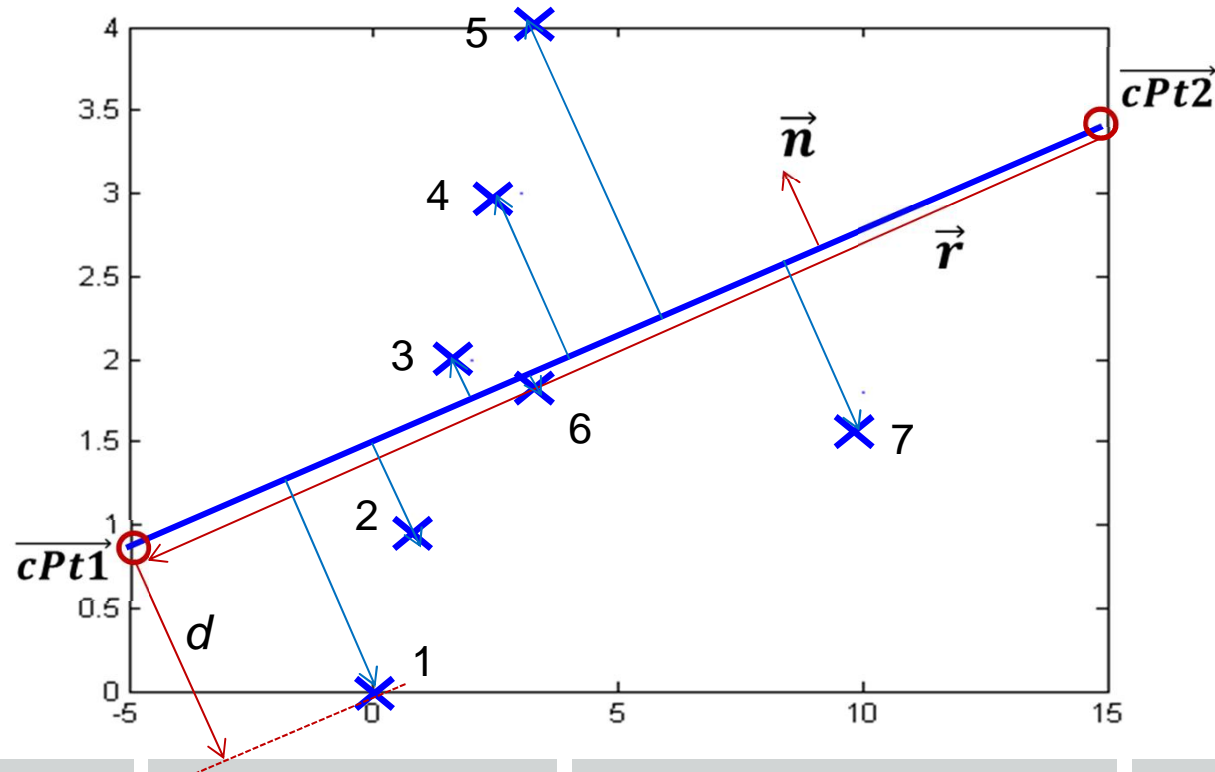
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3) Distance to origin is given by the scalar product of some point on the line and the normal:

$$d = c\vec{Pt1}^T \cdot \vec{n}$$



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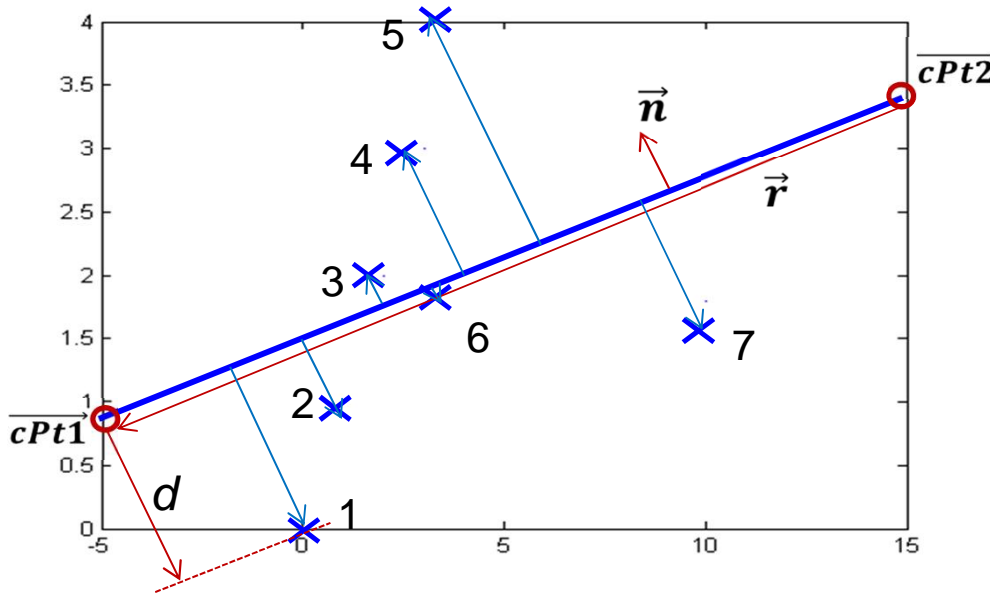
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4) Hesse normal form

$$\vec{d}s = p\vec{t}s_i^T \cdot \vec{n} - d$$



## Implementation hints:



- How to pick two points and compute  $\vec{r}$   
 $x = [-\min(\text{pts}(:, 1)) - 5 \quad \max(\text{pts}(:, 1)) + 5];$   
 $y = m * x + t;$   
 $cPt1 = [x(1) \quad y(1)]; \quad cPt2 = [x(2) \quad y(2)];$   
 $r = cPt2 - cPt1;$
- Use \* for scalar product! Do not use loop!
- Dimension size:  $\vec{n}$  : 2x1 vector  
 $d$  : 1x1 scalar  
 $\vec{d}s$  : nx1 vector

1) Pick two points on the line and calculate direction:

$$\vec{r} = cPt2 - cPt1$$

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4) Hesse normal form

$$\vec{d}s = p\vec{t}s_i^T \cdot \vec{n} - d$$

$$\text{err} = \text{sum}(\vec{d}s > \text{thr}) / n$$



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## Number of iterations

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Estimate probability for an outlier using relative frequencies. Minimum number of points for the model is given.

→ Choose probability for having at least one iteration without outliers



# RANSAC

**Task:** `commonransac`: In `it` iterations choose randomly `mn` points out of `data`. Use them to estimate the model with `mdlEstFct`. Estimate the error for this model using `errFct`.

For each iteration, do

1. Randomly choose `mn` points from data  
→ could use `randperm()`
2. Use them to estimate the model with `mdlEstFct()`
3. Compute the error for this model using `errFct()`