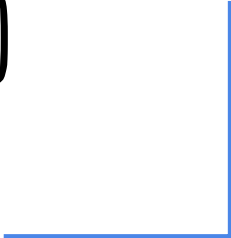


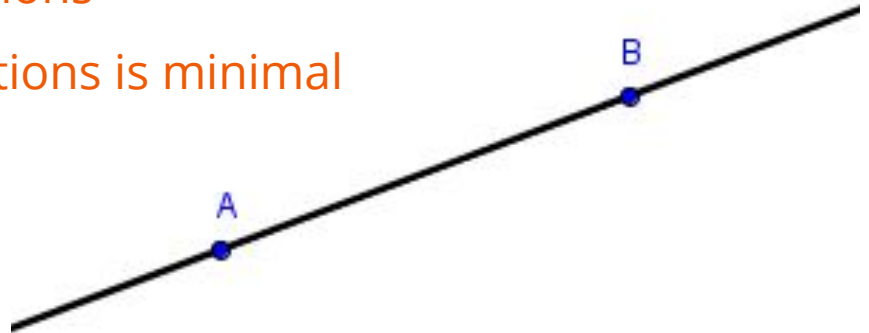
Robust Geometry Estimation (RANSAC)



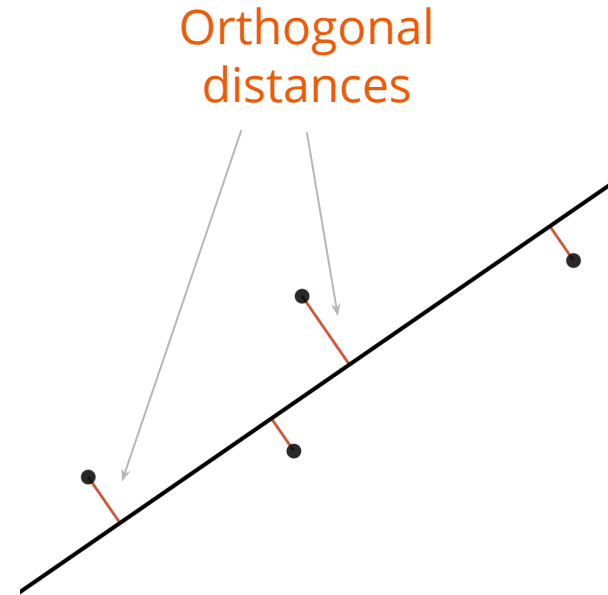
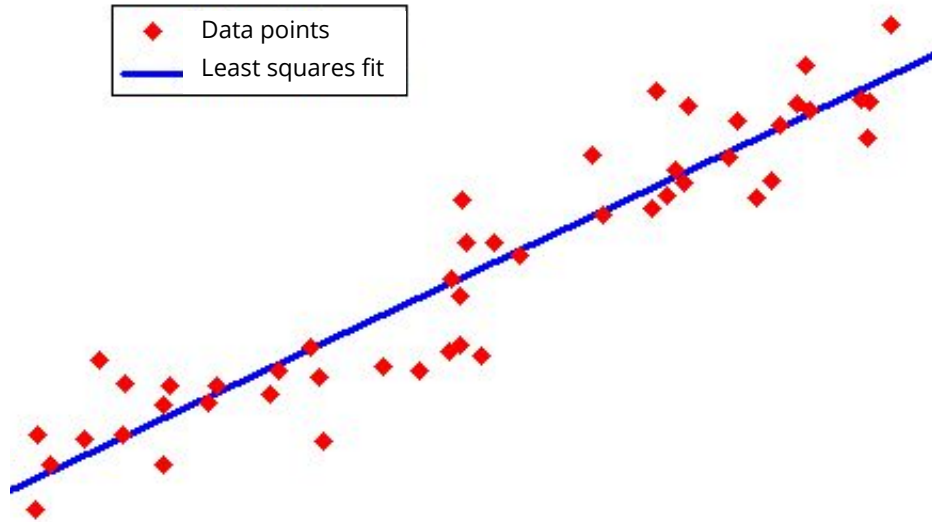
Line Fitting Example

Exact solution to $ax + by + c = 0$

- Line has **2** degrees of freedom (DoF)
- **1** point introduces **1** independent constraint equation
- Thus we need at least **2** points
- **2** is a **minimal** number of observations
- The solution to the system of equations is minimal
- Also called a **minimal solver**



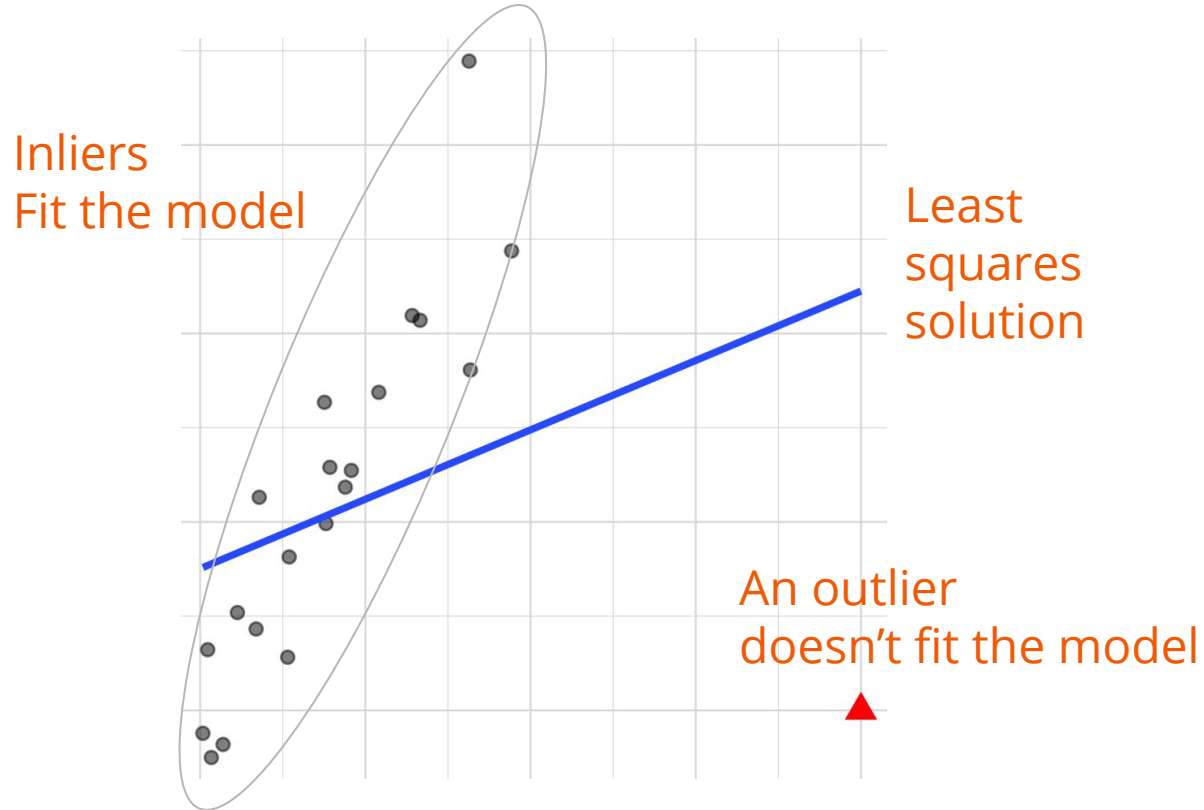
Lots of Noisy Points -> MLE -> Least Squares



Total Least Squares (TLS)

Both x- and y- coordinates are observed subject to error. Solution — eigenvector corresponding to the smallest eigenvalue of $\mathbf{A}^T \mathbf{A}$, where \mathbf{A} is $\mathbf{K} \times 2$ data matrix.

Outliers?



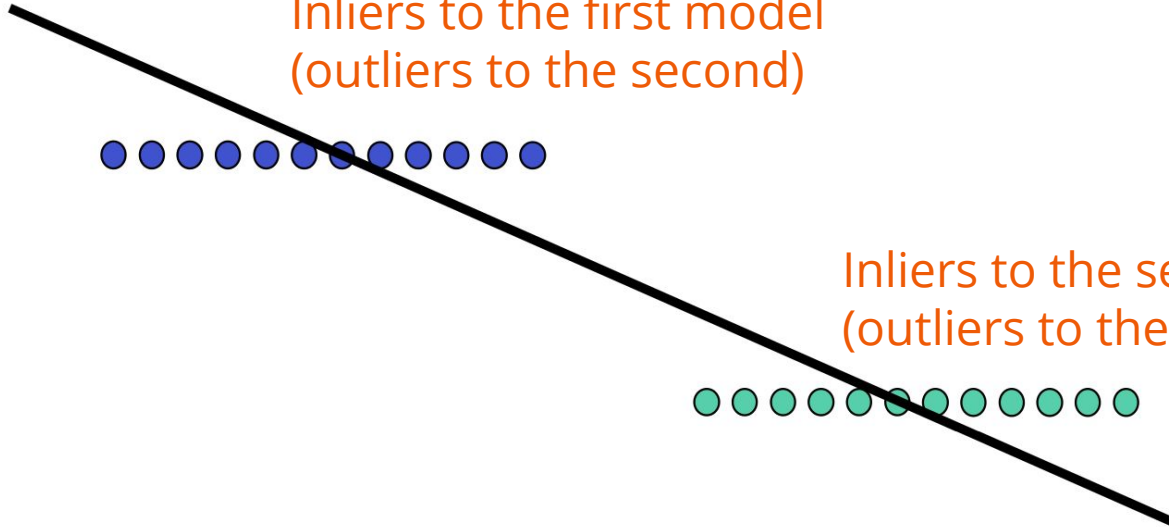
Multiple Models (e.g. Lines) ?

Least
squares
solution

Inliers to the first model
(outliers to the second)



Inliers to the second model
(outliers to the first)

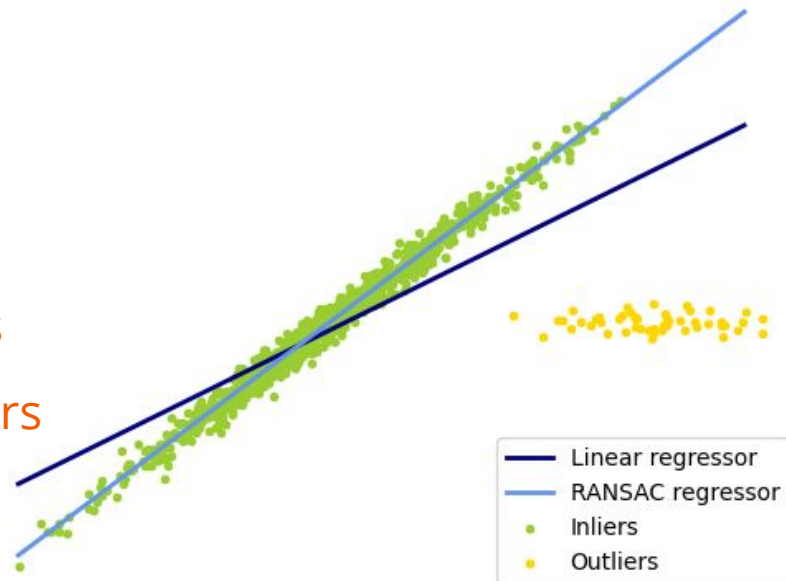


RANSAC: Robust to Outliers

*(**RAN**dom **SA**mple **C**onsensus)*

Two “stages”:

- (1) Classify data points as outliers or inliers
- (2) Fit model to inliers while ignoring outliers



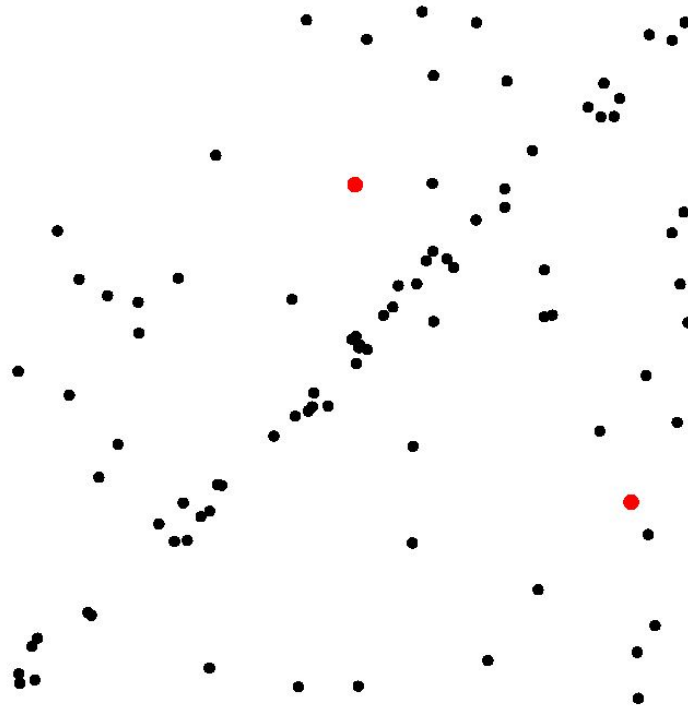
[1] M. A. Fischler and R. C. Bolles. Random Sample Consensus: A Paradigm for Model Fitting with Applications to Image Analysis and Automated Cartography (1981)

RANSAC Procedure



RANSAC Procedure

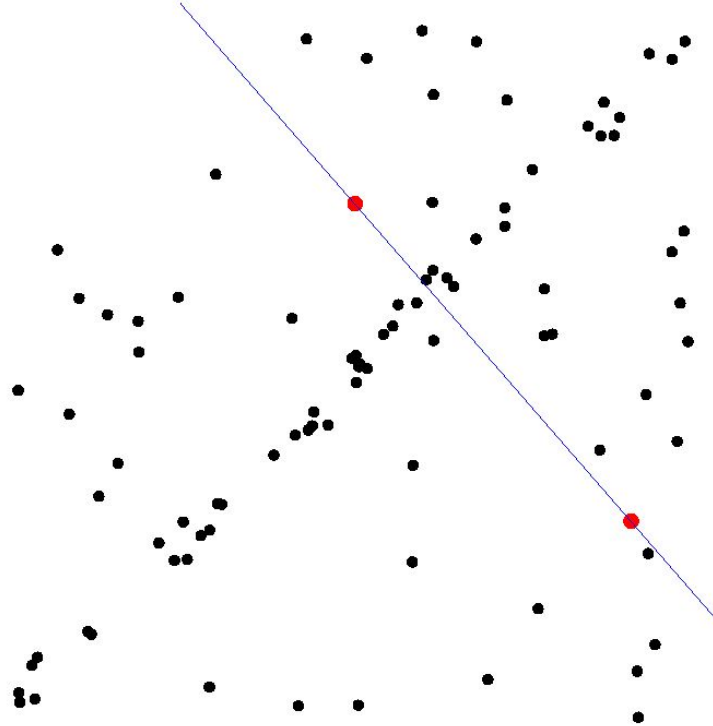
Randomly pick the
minimal number of
observations — the
minimal sample



Hypothesize

RANSAC Procedure

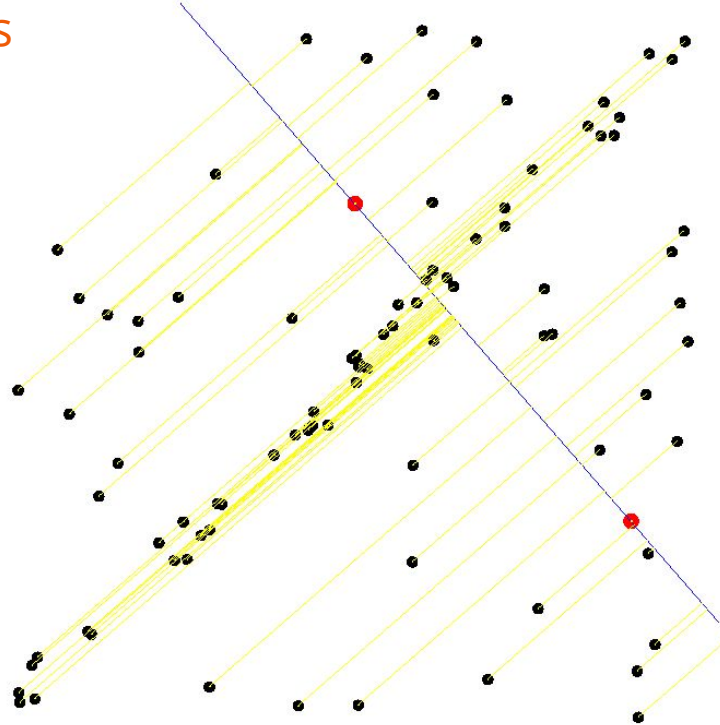
Fit the model exactly



Hypothesize

RANSAC Procedure

Calculate the residuals



Verify

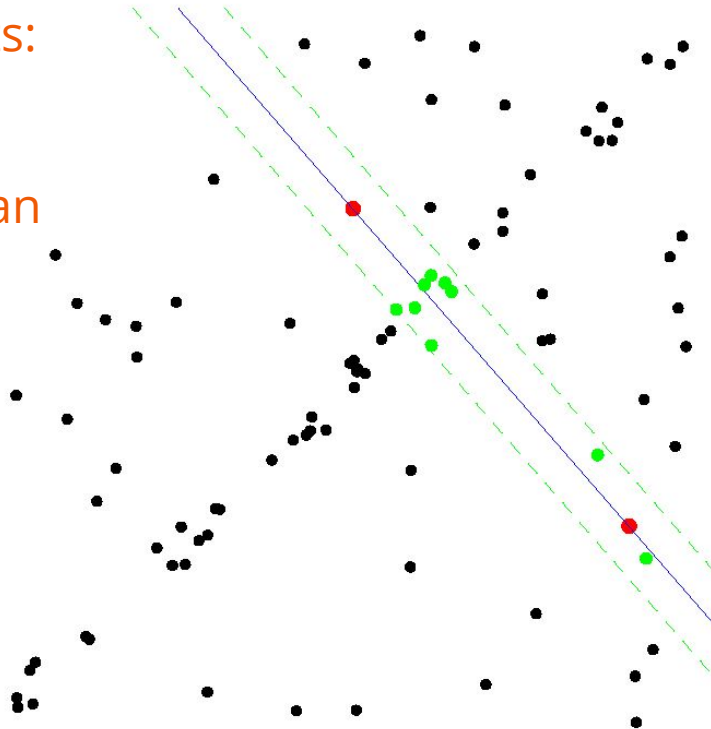
RANSAC Procedure

Classify the data points:

- **inlier** if the residual is less than threshold
- **outlier** otherwise

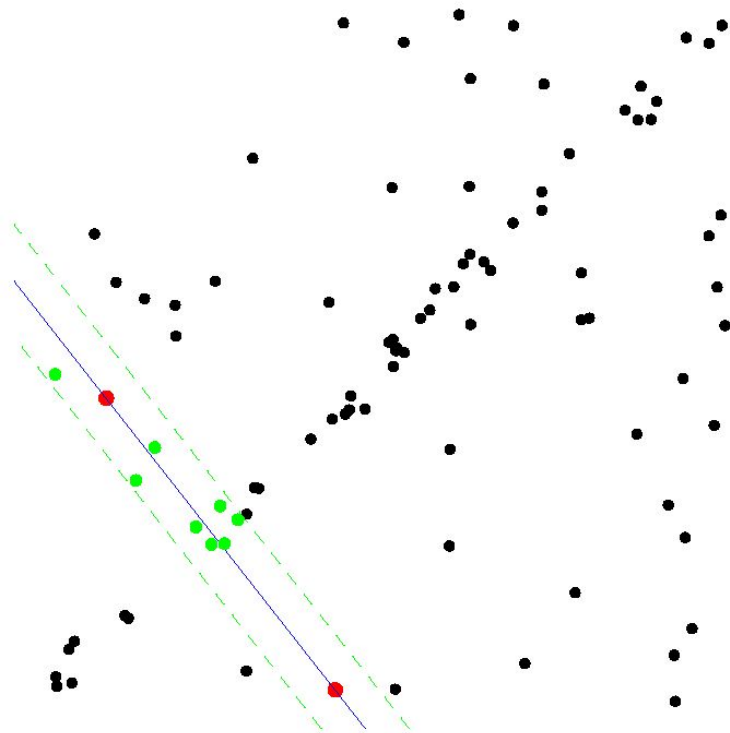
Compute the number of inliers — the **consensus set**

Verify



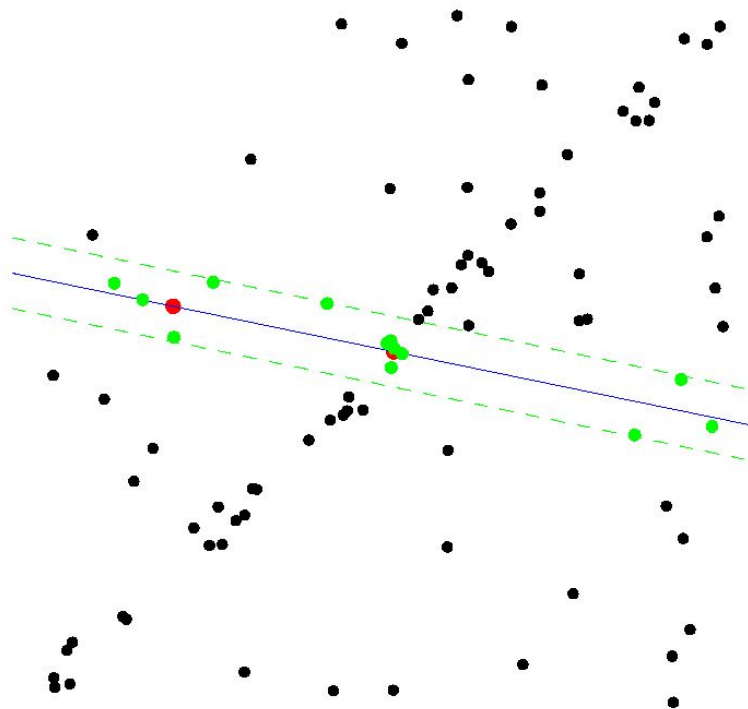
RANSAC Procedure

Repeat



RANSAC Procedure

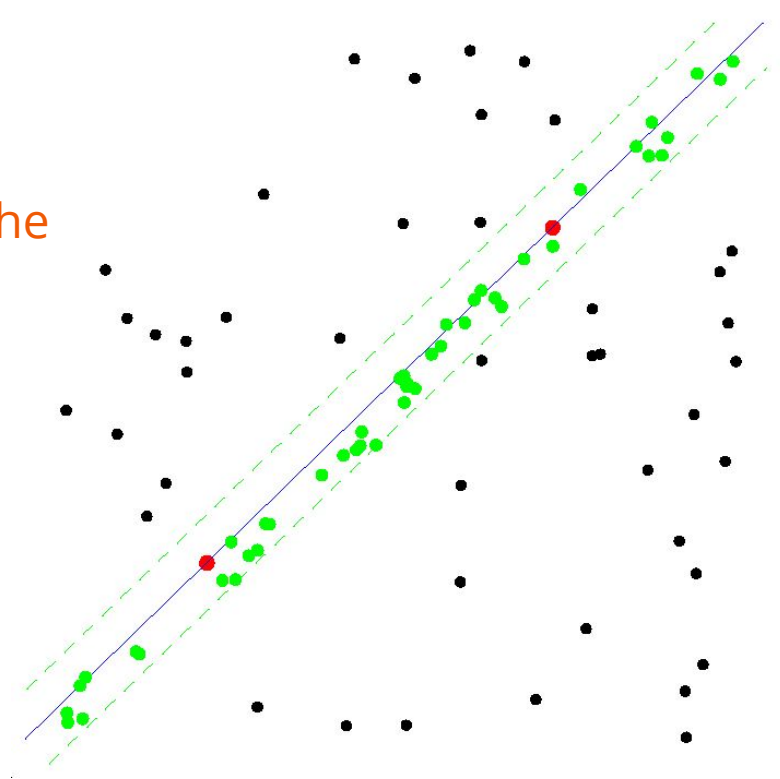
Repeat



RANSAC Procedure

Repeat

Goal: to maximize the
consensus set



Number of Iterations (Samples)

Sample all models? That's a lot..

$$k = \binom{K}{2} = \frac{K!}{2(K-2)!} = \frac{K(K-1)}{2} = \Theta(K^2)$$

K — number of all data points

k — number of samples

Number of Iterations

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

p — desired probability of success

w — inlier ratio — number of inliers in data / number of points in data

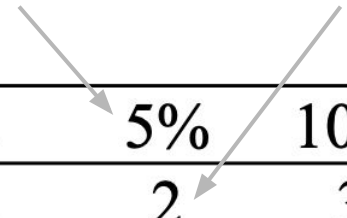
n — minimal sample size

k — number of samples

Number of Iterations

Percentage
of outliers

Number of
samples



s	5%	10%	20%	25%	30%	40%	50%
2	2	3	5	6	7	11	17
3	3	4	7	9	11	19	35
4	3	5	9	13	17	34	72
5	4	6	12	17	26	57	146
6	4	7	16	24	37	97	293
7	4	8	20	33	54	163	588
8	5	9	26	44	78	272	1177

Minimal
sample
size