

RANSAC

RANdom SAmple Consensus

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Talk Outline

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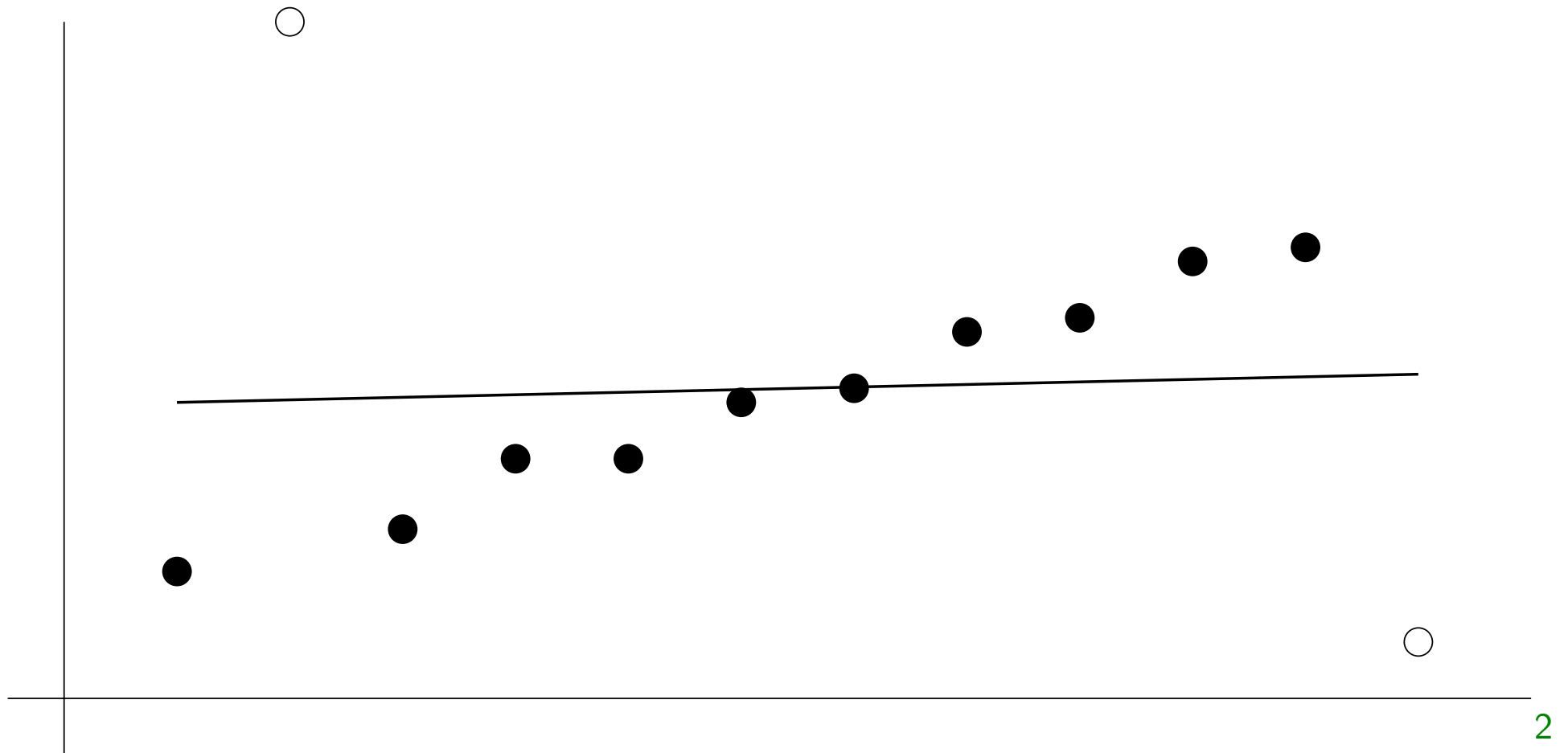
- ◆ importance for computer vision
- ◆ principle
- ◆ line fitting
- ◆ epipolar geometry

Importance for Computer Vision

- ◆ published in 1981 as a model fitting method [2]
- ◆ one of the most cited papers in computer vision and related fields
- ◆ widely accepted as a method that works even for difficult computer vision problems
- ◆ recent advancement presented at the “25-years of RANSAC” [workshop](http://cmp.felk.cvut.cz/ransac-cvpr2006)¹. Look at the R. Bowless’ presentation.

¹<http://cmp.felk.cvut.cz/ransac-cvpr2006>

LSQ does not work for gross errors . . .



RANSAC motivations for computer vision

- ◆ gross errors (outliers) spoil LSQ estimation
- ◆ detection (localization) algorithms in computer vision and recognition
do have gross error
- ◆ in difficult problems the portion of good data may be even less than $1/2$
- ◆ standard robust estimation techniques hardly applicable to data with less than $1/2$ good

RANSAC inputs and output

In:	$U = \{x_i\}$	set of data points, $ U = N$
	$f(S) : S \rightarrow \theta$	function f computes model parameters θ given a sample S from U
	$\rho(\theta, x)$	the cost function for a single data point x
Out:	θ^*	θ^* , parameters of the model maximizing the cost function

RANSAC algorithm

$k := 0$

Repeat until $P\{\text{better solution exists}\} < \eta$ (a function of C^* and no. of steps k)

$k := k + 1$

I. Hypothesis

(1) select randomly set $S_k \subset U$, $|S_k| = s$

(2) compute parameters $\theta_k = f(S_k)$

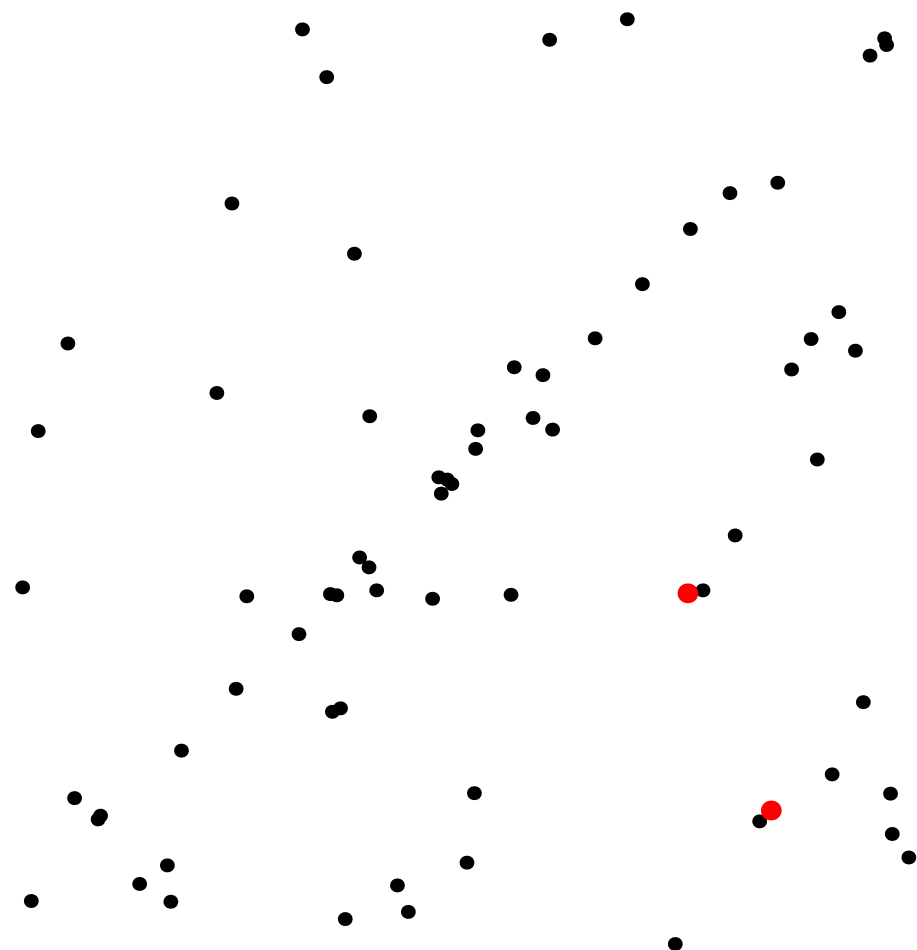
II. Verification

(3) compute cost $C_k = \sum_{x \in U} \rho(\theta_k, x)$

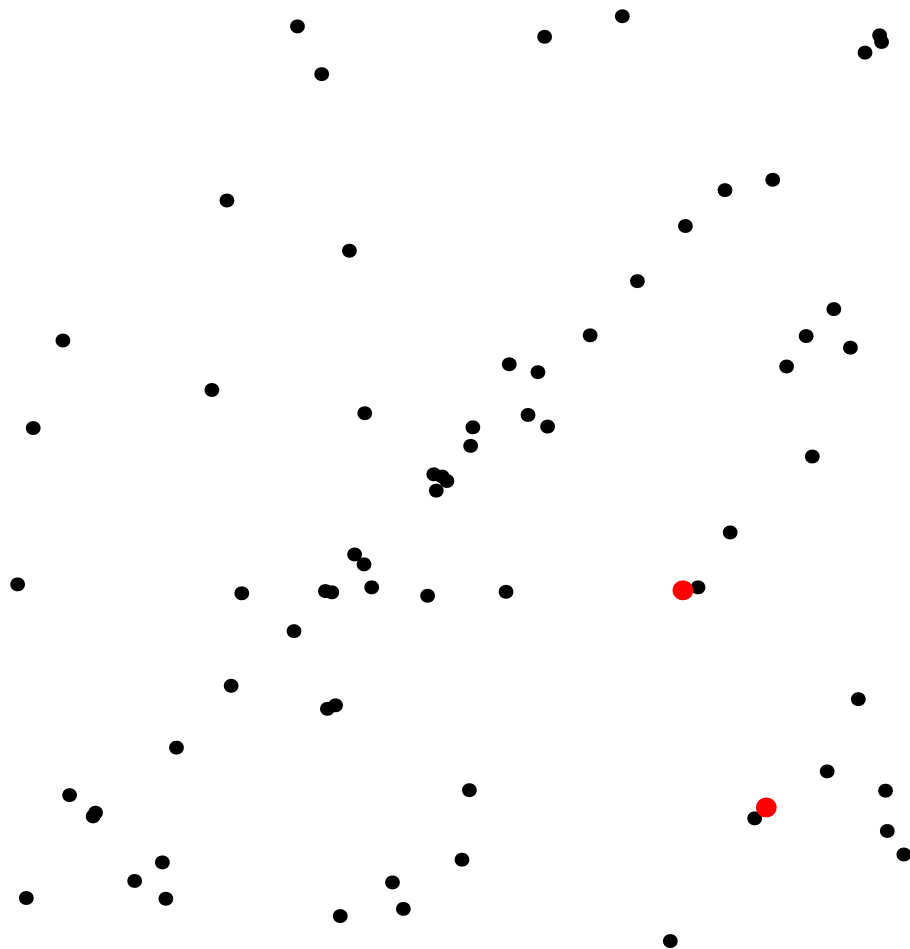
(4) if $C^* < C_k$ then $C^* := C_k$, $\theta^* := \theta_k$

end

Explanation example: line detection

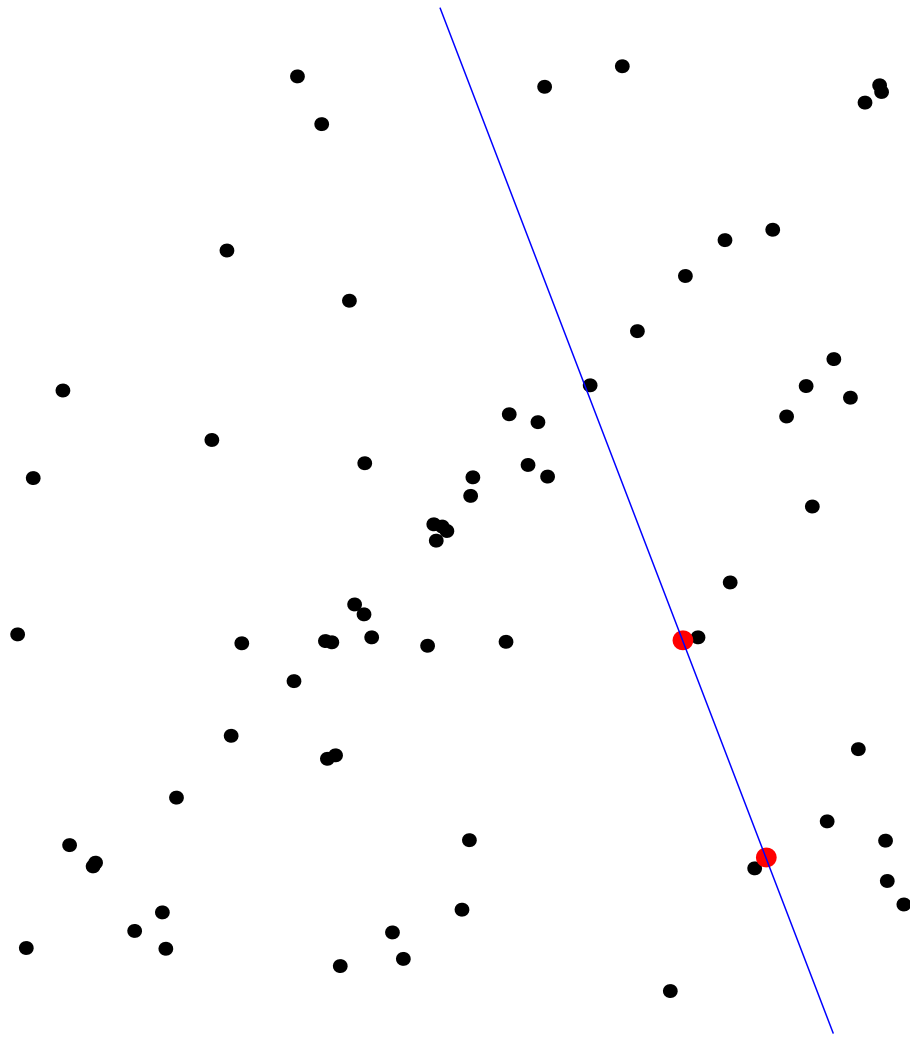


Explanation example: line detection



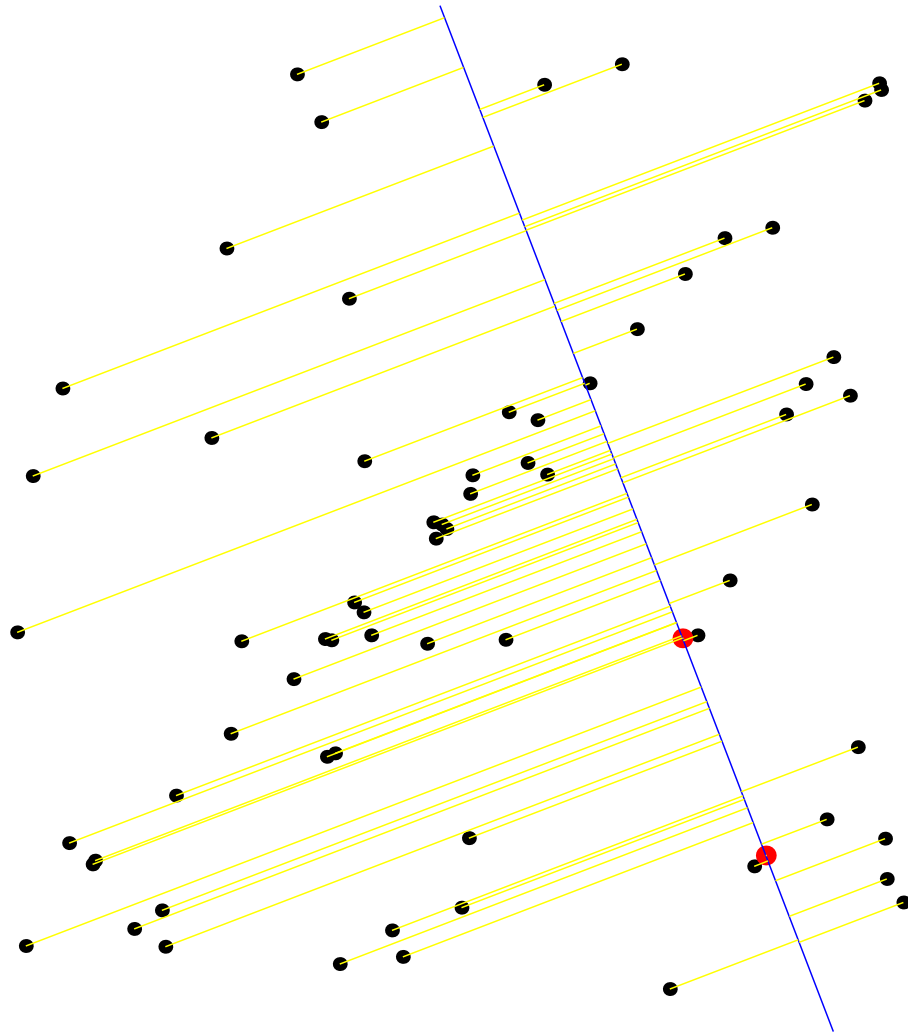
- Randomly select two points

Explanation example: line detection



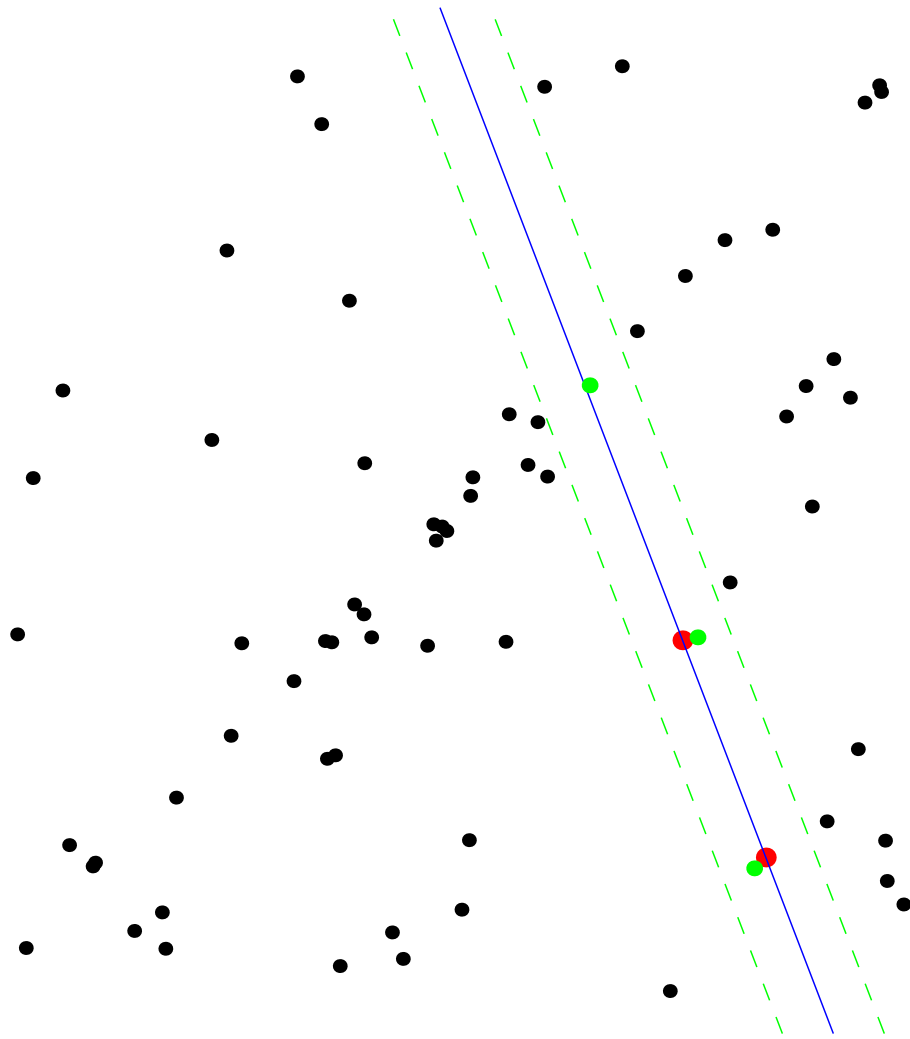
- ◆ Randomly select two points
- The hypothesised model is the line passing through the two points

Explanation example: line detection



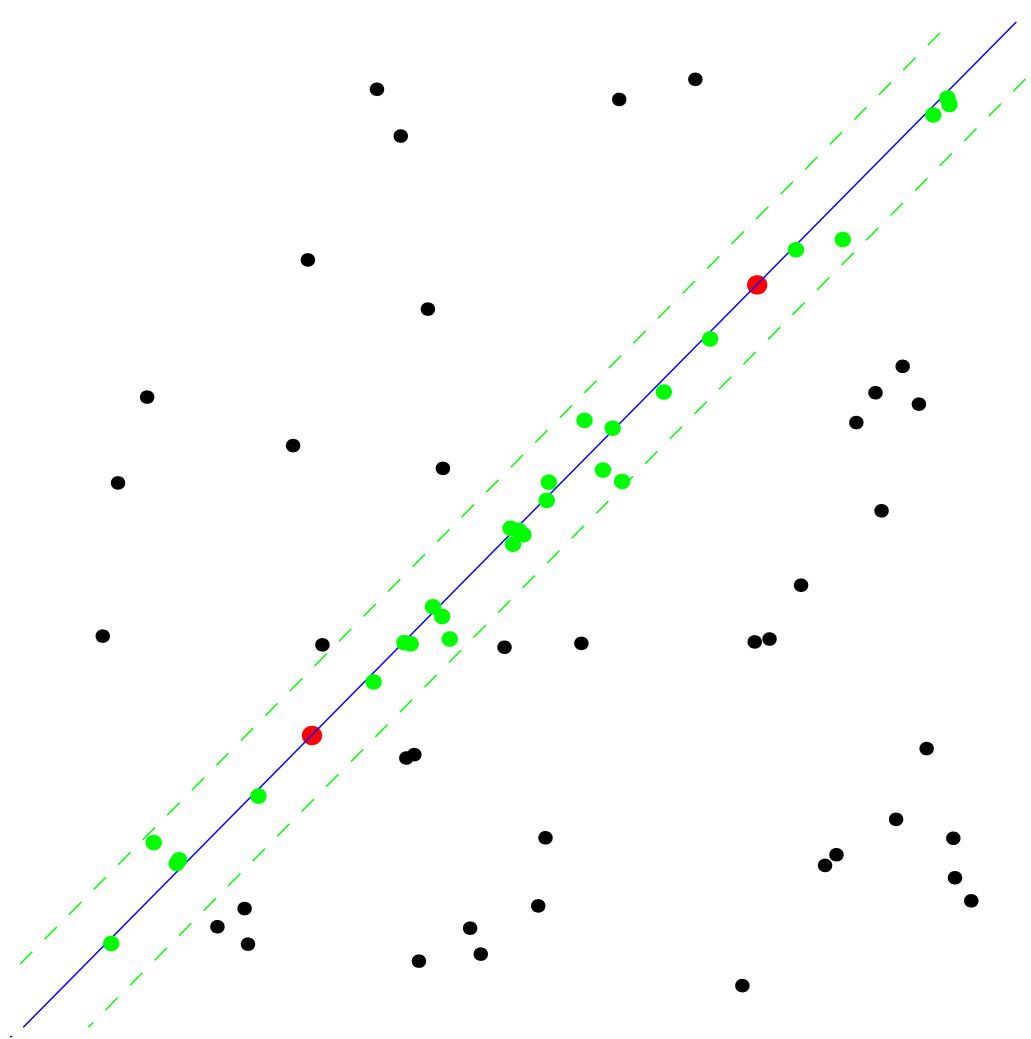
- ◆ Randomly select two points
- ◆ The hypothesised model is the line passing through the two points
- The error function is a distance from the line

Explanation example: line detection



- ◆ Randomly select two points
- ◆ The hypothesised model is the line passing through the two points
- ◆ The error function is a distance from the line
- Points consistent with the model

Probability of selecting uncontaminated sample in K trials



Uncontaminated sample

- ◆ N - number of data points
- ◆ w - fraction of inliers
- ◆ s - size of the sample

Prob. of selecting a sample with all inliers³: $\approx w^s$

Prob. of **not** selecting a sample with all inliers: $1 - w^s$

Prob. of **not** selecting a good sample K times: $(1 - w^s)^K$

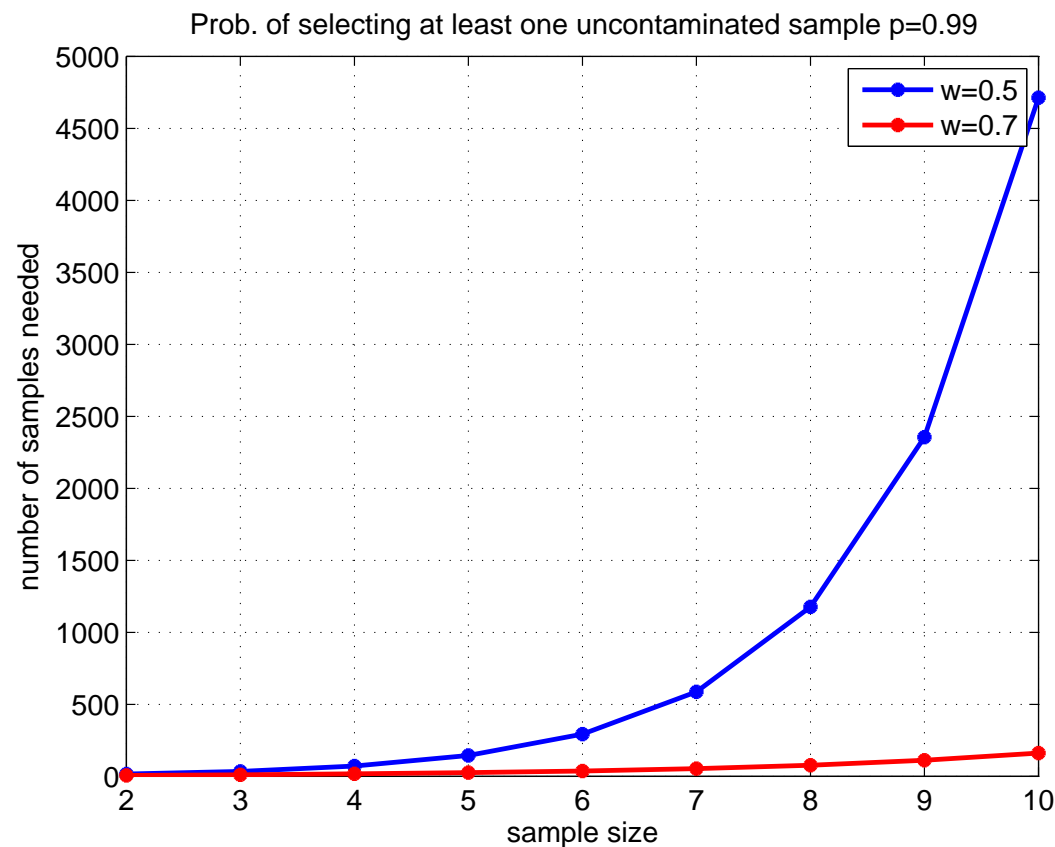
The sought probability of selecting uncontaminated sample in K trials at least once: $P = 1 - (1 - w^s)^K$

³Approximation valid for $s \ll N$, see the [lecture notes](#)

How many samples are needed, $K = ?$

How many trials is needed to select an uncontaminated sample with a given probability P ? We derived $P = 1 - (1 - w^s)^K$. Log the both sides to get

$$K = \frac{\log(1 - P)}{\log(1 - w^s)}$$



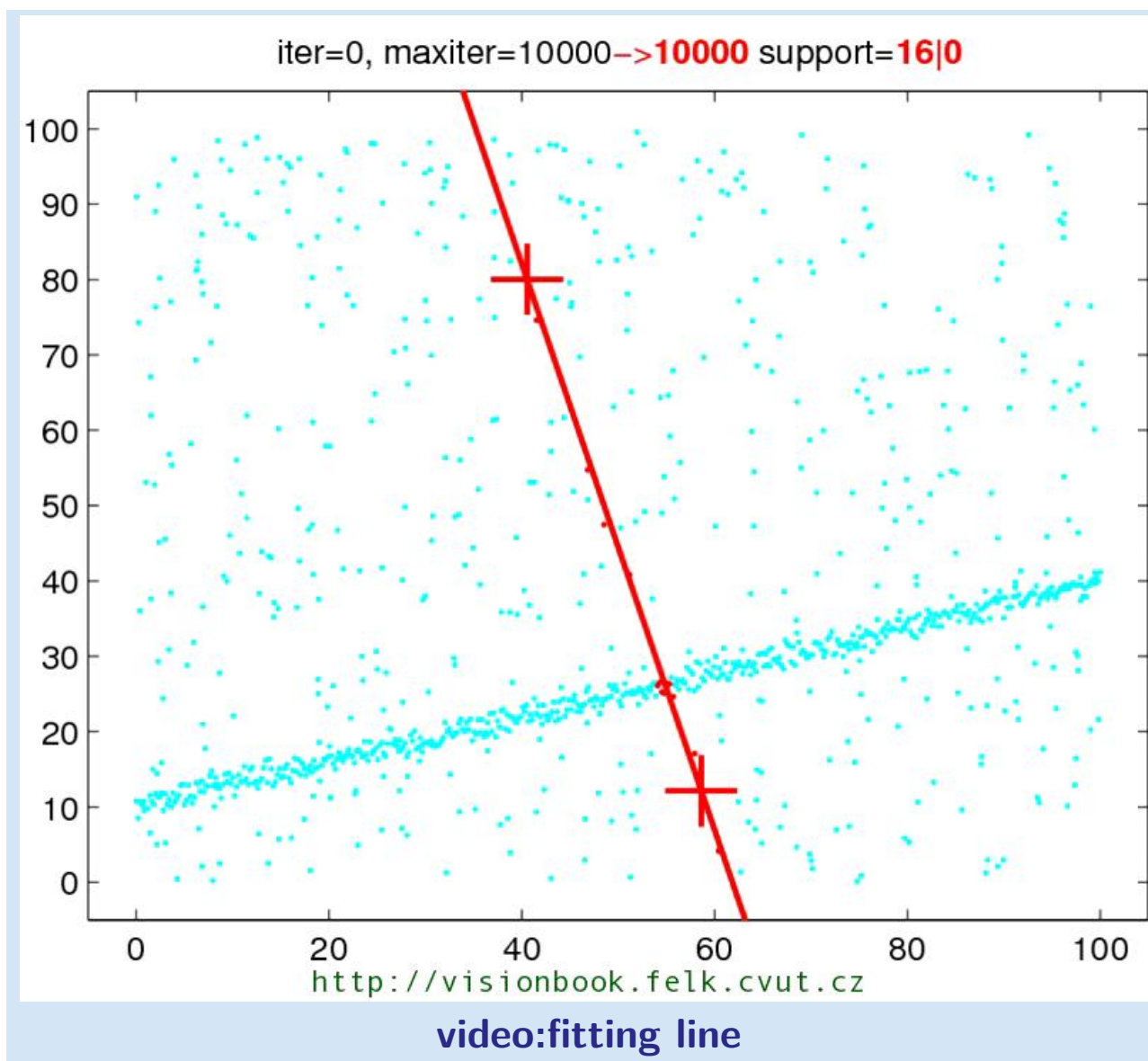
Real problem— w unknown

Often, the proportion of inliers in data cannot be estimated in advance.

Adaptive estimation: start with worst case and update the estimate as the computation progress

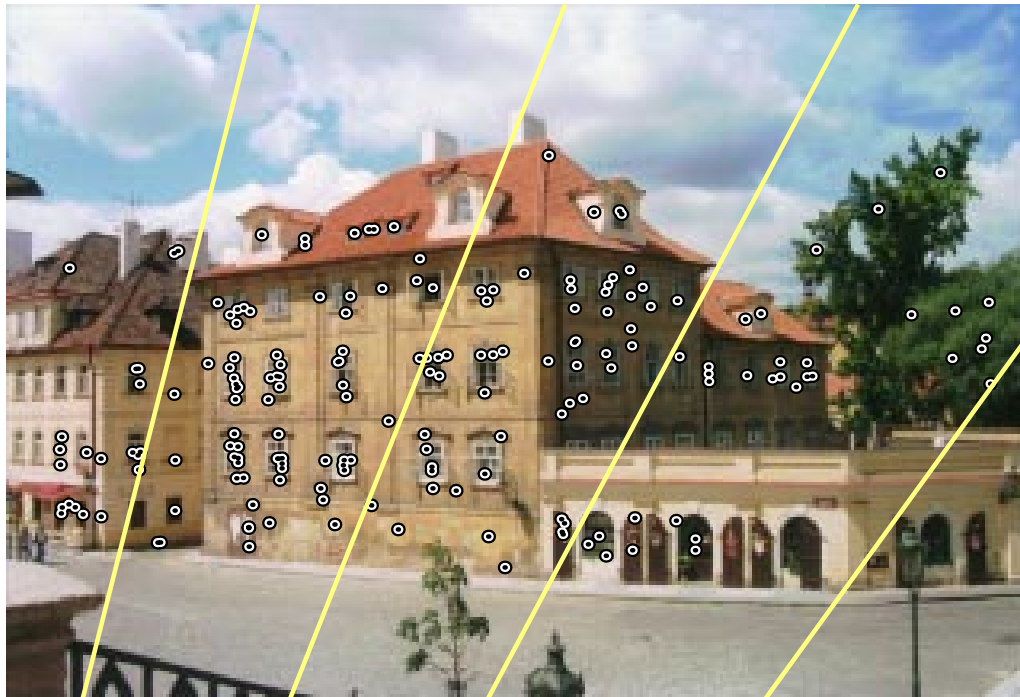
- ◆ set $K = \infty$, $\#samples = 0$, P very conservative, say $P = 0.99$
- ◆ while $K > \#samples$ repeat
 - choose a random sample, compute the model and count inliers
 - $w = \frac{\#inliers}{\#data\ points}$
 - $K = \frac{\log(1-P)}{\log(1-w^s)}$
 - increment $\#samples$
- ◆ terminate

Fitting line via RANSAC



Epipolar geometry estimation by RANSAC

- ◆ U : a set of correspondences, i.e. pairs of 2D points data points
- ◆ $s = 7$ sample size
- ◆ f : seven-point algorithm - gives 1 to 3 independent solutions model parameters
- ◆ ρ : thresholded Sampson's error cost function



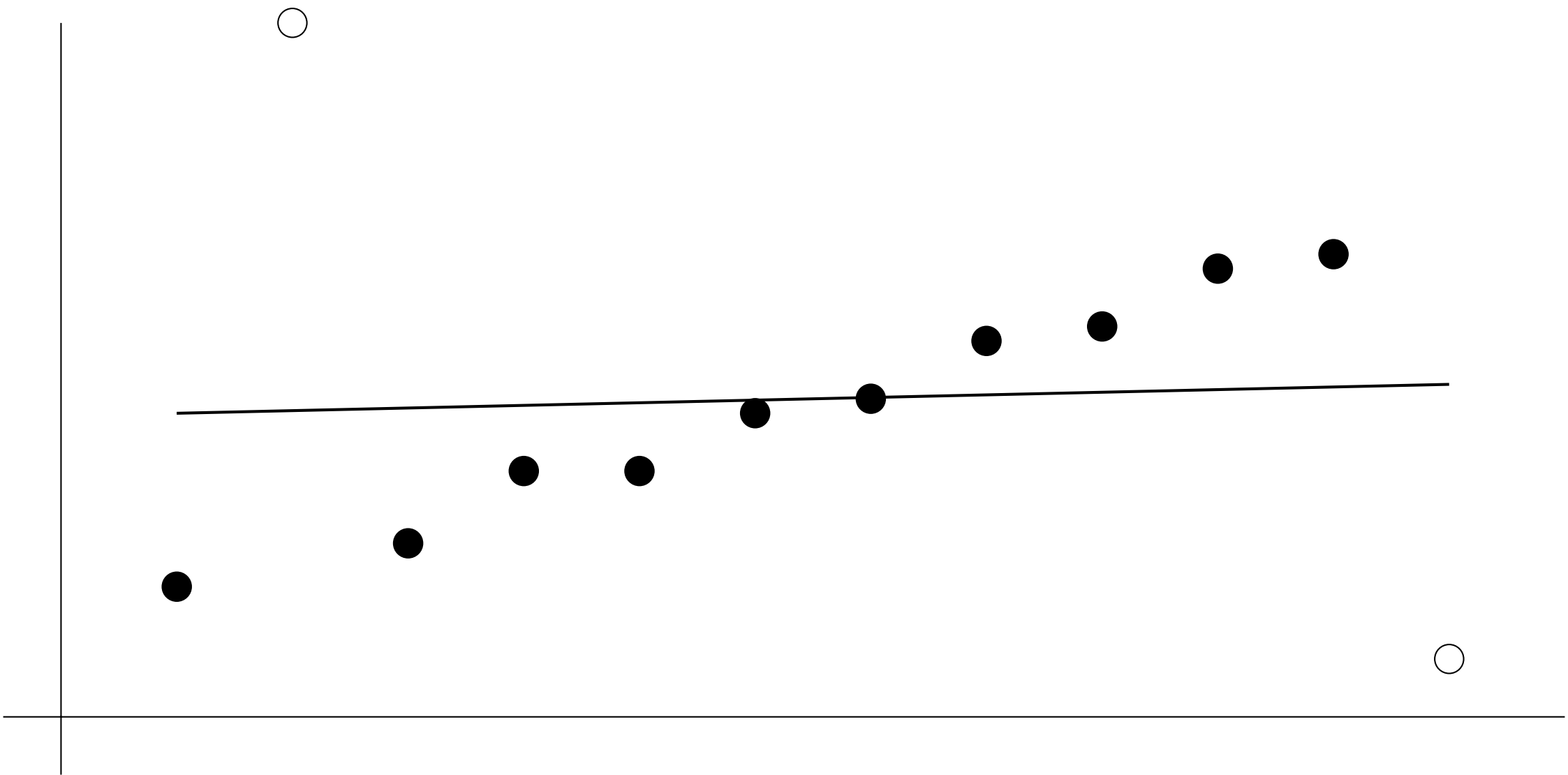
References

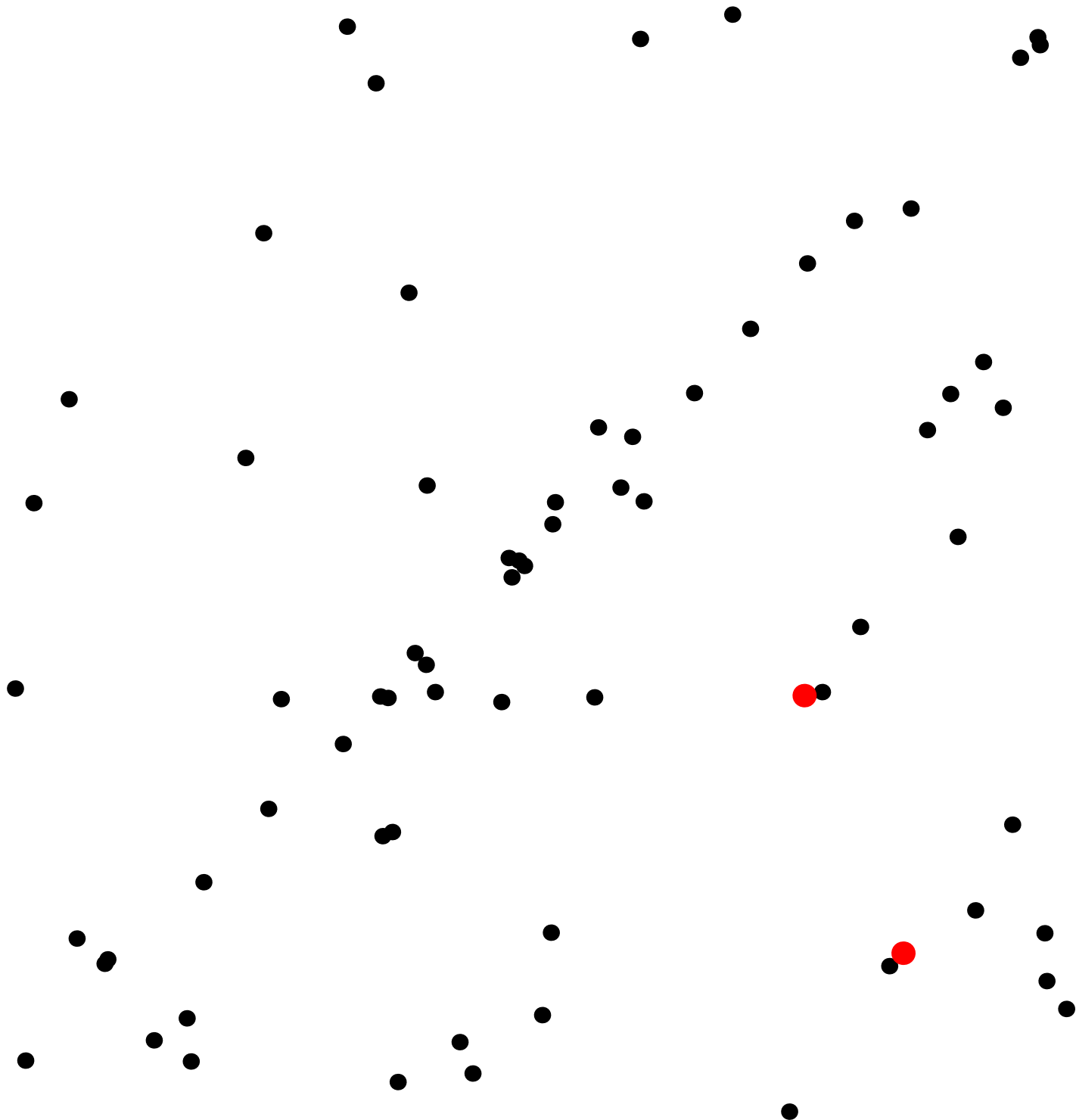
Besides the main reference [2] the Huber's book [5] about robust estimation is also widely recognized. The RANSAC algorithm recieved several essential improvements in recent years [1, 6, 7]

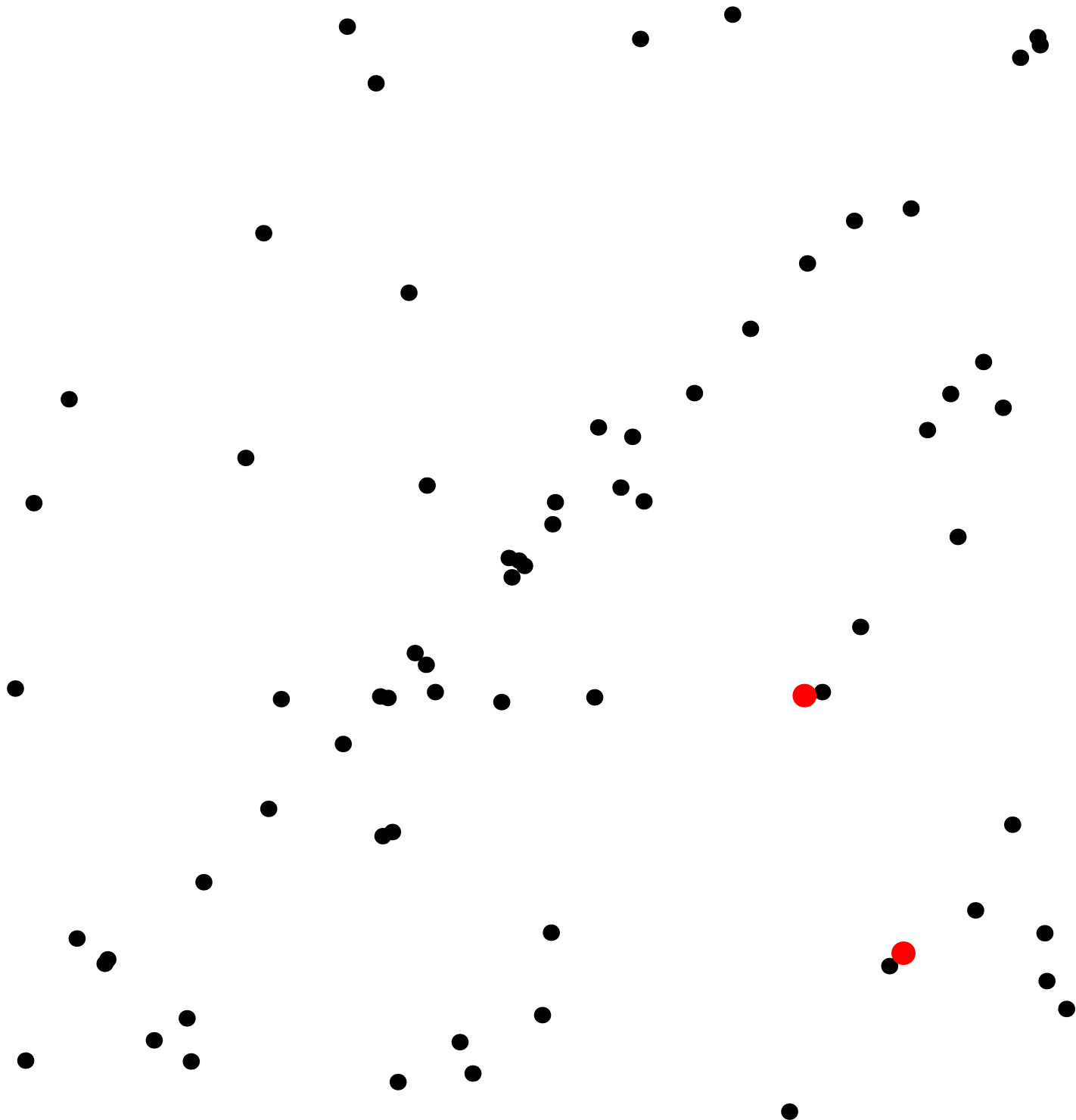
For the seven-point algorithm and Sampson's error, see [4]

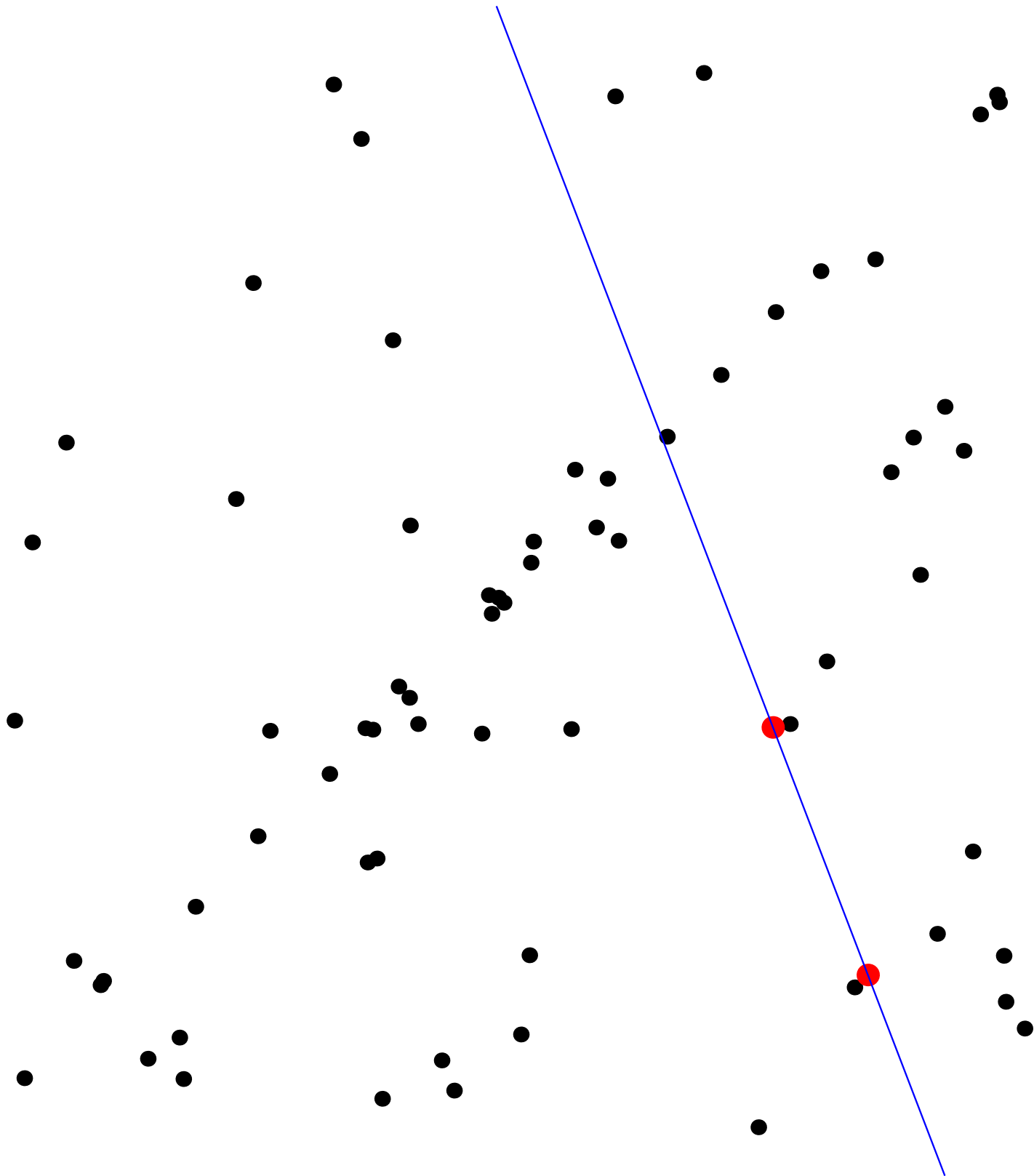
- [1] Ondřej Chum and Jiří Matas. Matching with PROSAC - progressive sample consensus. In Cordelia Schmid, Stefano Soatto, and Carlo Tomasi, editors, *Proc. of Conference on Computer Vision and Pattern Recognition (CVPR)*, volume 1, pages 220–226, Los Alamitos, USA, June 2005. IEEE Computer Society.
- [2] M.A. Fischler and R.C. Bolles. Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM*, 24(6):381–395, June 1981.
- [3] R. Hartley and A. Zisserman. *Multiple View Geometry in Computer Vision*. Cambridge University Press, Cambridge, UK, 2000. On-line resources at:
<http://www.robots.ox.ac.uk/~vgg/hzbook/hzbook1.html>.
- [4] Richard Hartley and Andrew Zisserman. *Multiple view geometry in computer vision*. Cambridge University, Cambridge, 2nd edition, 2003.
- [5] Peter J. Huber. *Robust Statistics*. Willey series in probability and mathematical statistics. John Willey and Sons, 1981.
- [6] Jiří Matas and Ondřej Chum. Randomized RANSAC with $T_{d,d}$ test. *Image and Vision Computing*, 22(10):837–842, September 2004.
- [7] Jiří Matas and Ondřej Chum. Randomized ransac with sequential probability ratio test. In Songde Ma and Heung-Yeung Shum, editors, *Proc. IEEE International Conference on Computer Vision (ICCV)*, volume II, pages 1727–1732, New York, USA, October 2005. IEEE Computer Society Press.

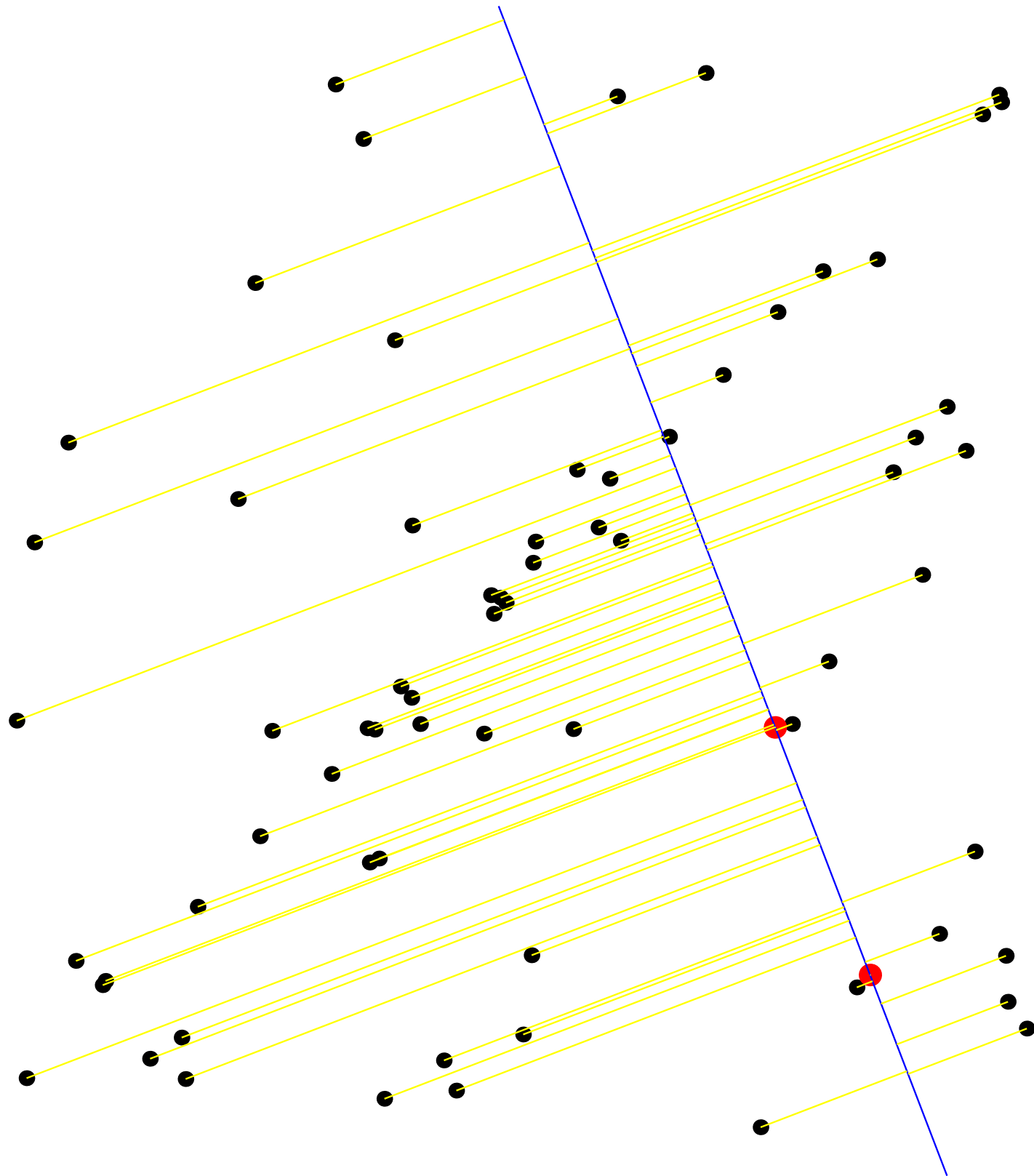
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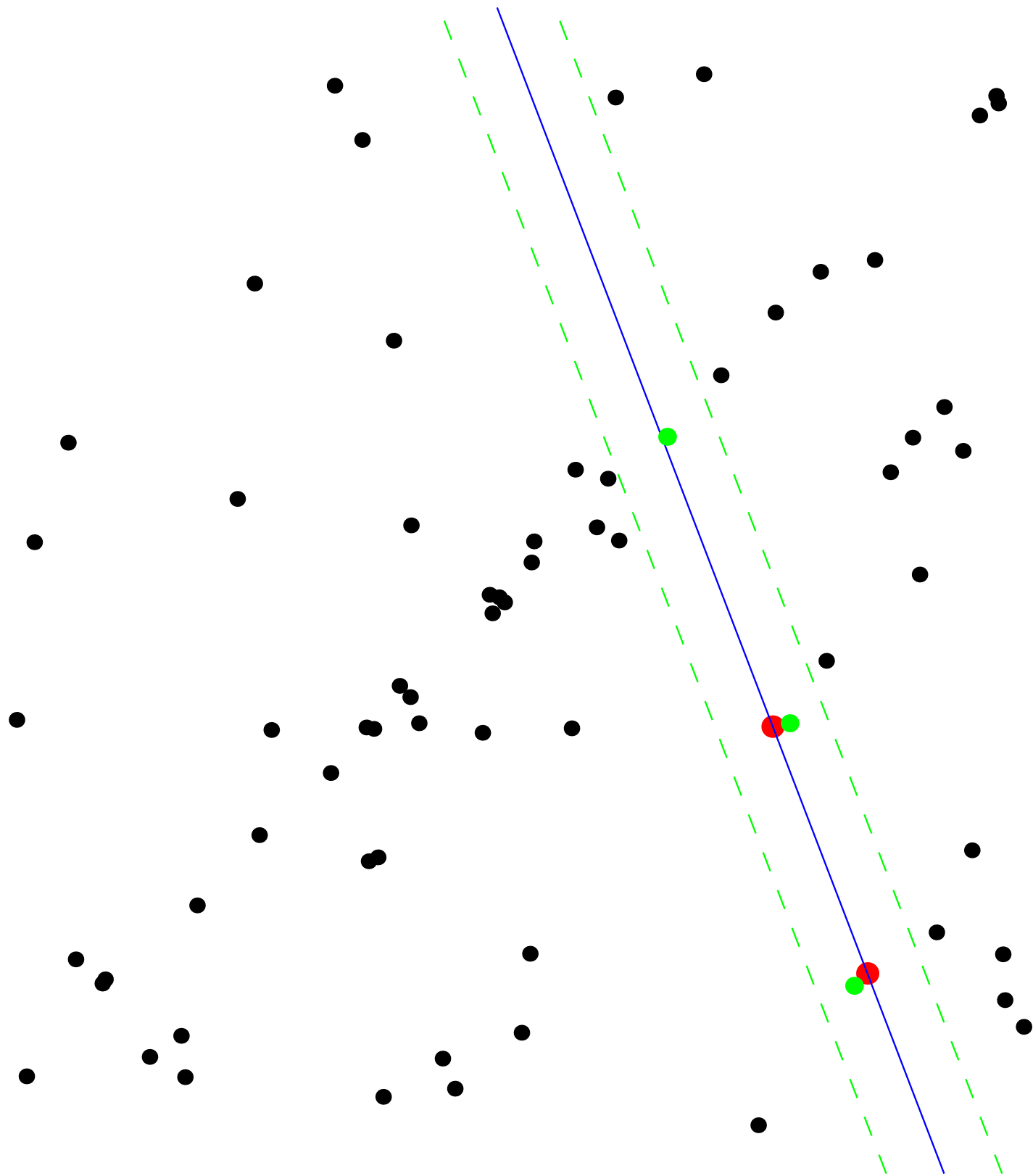


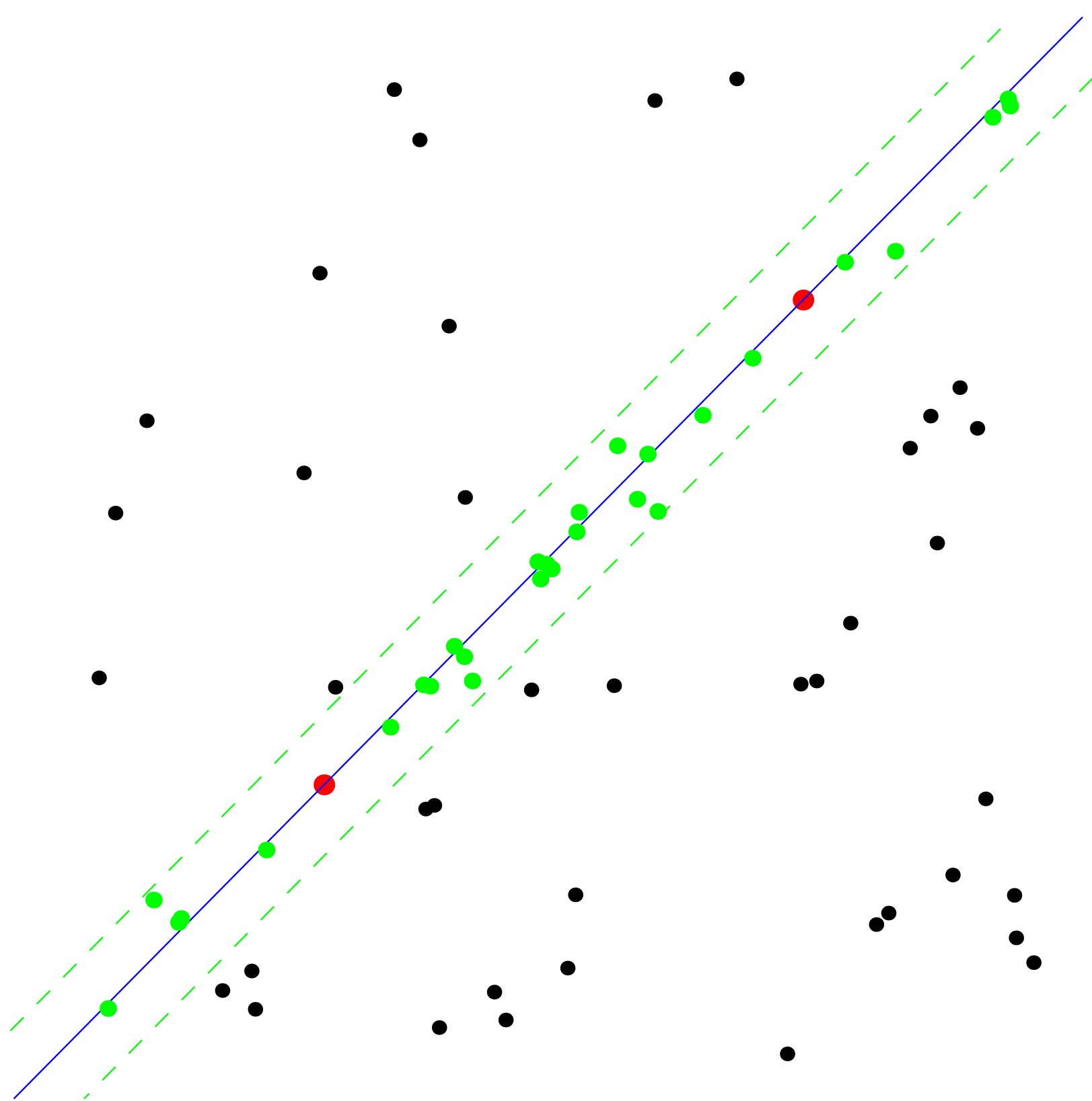












Prob. of selecting at least one uncontaminated sample $p=0.99$

