Robust model estimation from data contaminated by outliers

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Fitting a Line





• Select sample of m points at random



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• Calculate model parameters that fit the data in the sample



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On average

N	number of point
Ι	number of inliers
т	size of the sample

$$P(\text{good}) = \frac{\binom{I}{m}}{\binom{N}{m}} = \prod_{j=0}^{m-1} \frac{I-j}{N-j}$$

mean time before the success E(k) = 1 / P(good)

With confidence p

How large k?

... to hit at least one pair of points on the line l with probability larger than p (0.95)

Equivalently

... the probability of not hitting any pair of points on l is $\leq 1-p$

With confidence *p*

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Ι	number of inliers
т	size of the sample

$$P(\text{good}) = \frac{\binom{I}{m}}{\binom{N}{m}} = \prod_{j=0}^{m-1} \frac{I-j}{N-j}$$

P(bad) = 1 - P(good)

P(bad *k* times) =
$$(1 - P(good))^k$$

With confidence *p*

P(bad *k* times) =
$$(1 - P(\text{good}))^k \le 1 - p$$

$$k \log (1 - P(\text{good})) \le \log(1 - p)$$

$$k \ge \log(1-p) / \log(1-P(\text{good}))$$

I/N[%]

Ш		15%	20%	30%	40%	50%	70%
mple	2	132	73	32	17	10	4
	4	5916	1871	368	116	46	11
sai	7	$1.75 \cdot 10^{6}$	$2.34 \cdot 10^{5}$	$1.37 \cdot 10^{4}$	1827	382	35
f the	8	$1.17\cdot 10^7$	$1.17 \cdot 10^{6}$	$4.57\cdot 10^4$	4570	765	50
	12	$2.31 \cdot 10^{10}$	$7.31 \cdot 10^{8}$	$5.64 \cdot 10^{6}$	$1.79 \cdot 10^{5}$	$1.23 \cdot 10^4$	215
0	18	$2.08 \cdot 10^{15}$	$1.14 \cdot 10^{13}$	$7.73 \cdot 10^{9}$	$4.36 \cdot 10^{7}$	$7.85 \cdot 10^{5}$	1838
ize	30	∞	∞	$1.35 \cdot 10^{16}$	$2.60 \cdot 10^{12}$	$3.22 \cdot 10^{9}$	$1.33 \cdot 10^{5}$
S	40	∞	∞	∞	$2.70 \cdot 10^{16}$	$3.29 \cdot 10^{12}$	$4.71 \cdot 10^{6}$



$$k = \frac{\log(1-p)}{\log\left(1-\frac{I}{N}\frac{I-1}{N-1}\right)}$$

- *k* ... number of samples drawn
 - $N \dots$ number of data points
 - $I \dots$ time to compute a
 - single model
 - *p* ... confidence in the solution (.95)

RANSAC [Fischler, Bolles '81]

In: $U = \{x_i\}$ set of data points, |U| = N

 $f(S) : S \to p$ function f computes model parameters p given a sample S from U

 $\rho(p, x)$ the cost function for a single data point x

Out: p^{*} p^{*}, parameters of the model maximizing the cost function

k := 0

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

k := k + 1

I. Hypothesis

- (1) select randomly set $S_k \subset U$, sample size $|S_k| = m$
- (2) compute parameters $p_k = f(S_k)$
- II. Verification
- (3) compute cost $C_k = \sum_{x \in U} \rho(p_k, x)$ (4) if $C^* < C_k$ then $C^* := C_k$, $p^* := p_k$ end

PROSAC – PROgressive SAmple Consensus

- Not all correspondences are created equally
- Some are better than others
- Sample from the best candidates first

$$1 2 3 4 5 \dots N-2 N-1 N$$

Sample from here

PROSAC Samples

$$\cdots l - 1 l l + 1 l + 2 \cdots$$

Draw T_l samples from $(1 \dots l)$ Draw T_{l+1} samples from $(1 \dots l+1)$

Samples from $(1 \dots l)$ that are not from $(1 \dots l+1)$ contain



Draw T_{l+1} - T_l samples of size *m*-1 and add

