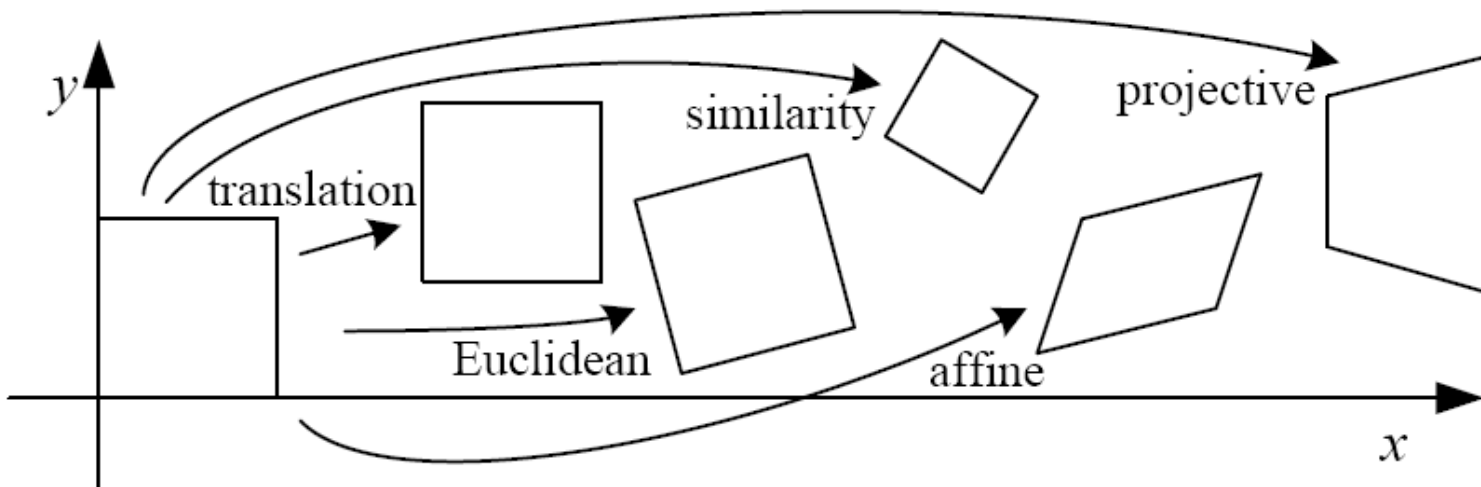


CSCI 497P/597P: Computer Vision



Lecture 16

Fitting Transformations with Outliers:
RANdom **SA**mple **C**onsensus (RANSAC)

Announcements

- P2 is out
- Do you want the option to work in pairs?

Goals

- Understand the Random Sample Consensus (RANSAC) algorithm.
- Be prepared to implement RANSAC to fitting image coordinate transforms using matches that may contain outliers.

Warping



We've found correspondence.

How do we fit a **transformation** to a given set of **matches**?

Warping



We've found correspondence.

How do we fit a **transformation** to a given set of **matches**?

Analogy: fit a **line** to a given set of **points**?

Warping

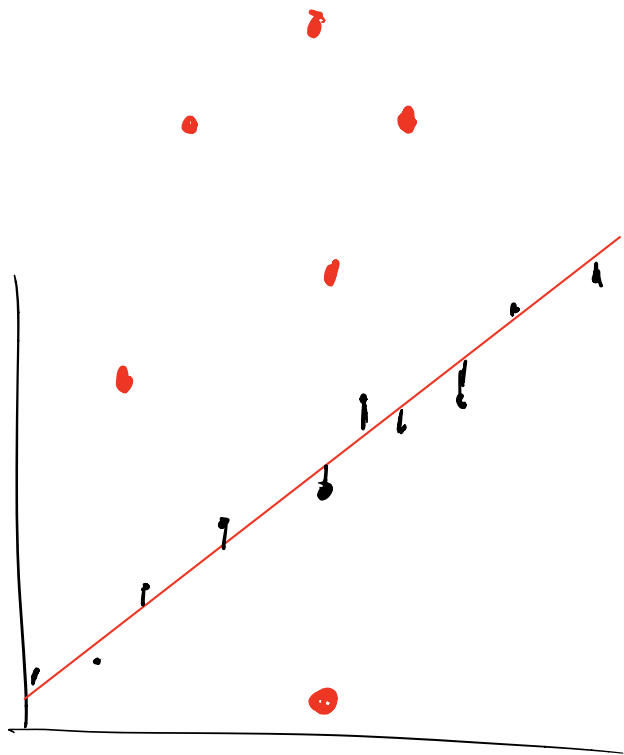


We've found correspondence.

How do we fit a **transformation** to a given set of **matches**?

Analogy: fit a **line** to a given set of **points**?

This is a model-fitting problem.



Problem Statement: Last time

(imperfect)

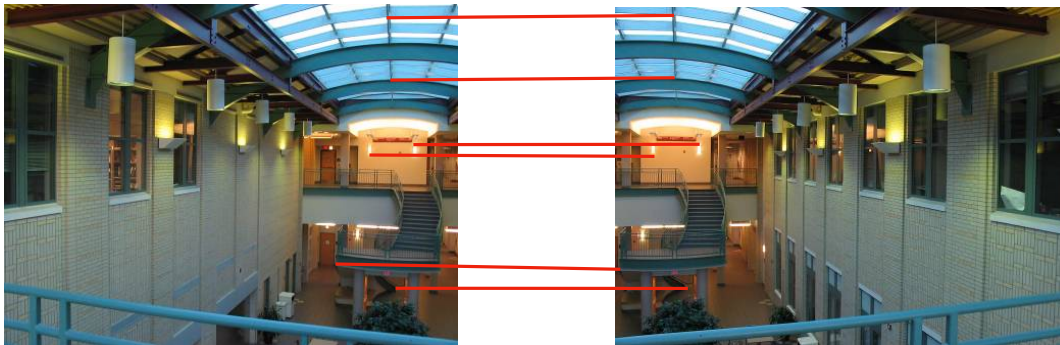
Given a set of feature matches, how do I **find** the **transformation** that relates the two images?

translation?

affine?

homography?

** all points may be off by a little*



Fitting a Homography: TL;DM

$$\begin{bmatrix}
 x_1 & y_1 & 1 & 0 & 0 & 0 & -x'_1 x_1 & -x'_1 y_1 & -x'_1 \\
 0 & 0 & 0 & x_1 & y_1 & 1 & -y'_1 x_1 & -y'_1 y_1 & -y'_1 \\
 & & & & & & \vdots & & \\
 x_n & y_n & 1 & 0 & 0 & 0 & -x'_n x_n & -x'_n y_n & -x'_n \\
 0 & 0 & 0 & x_n & y_n & 1 & -y'_n x_n & -y'_n y_n & -y'_n
 \end{bmatrix}
 \begin{bmatrix}
 h_{00} \\
 h_{01} \\
 h_{02} \\
 h_{10} \\
 h_{11} \\
 h_{12} \\
 h_{20} \\
 h_{21} \\
 h_{22}
 \end{bmatrix}
 =
 \begin{bmatrix}
 0 \\
 0 \\
 \vdots \\
 0 \\
 0
 \end{bmatrix}$$

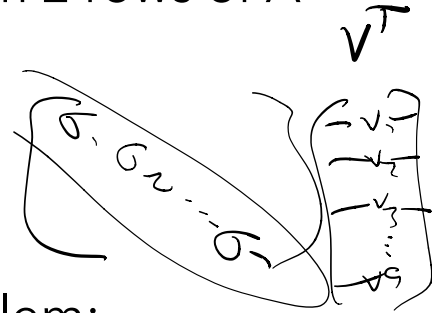
A
 $2n \times 9$

h = **0**
 $9 \quad 2n$

Fitting a Homography: TL;DM

- For each feature match $(x_i, y_i) \rightarrow (x_i', y_i')$, fill in 2 rows of A as in:

$$\begin{matrix}
 \nearrow \\
 \nearrow \\
 \nearrow \\
 \nearrow
 \end{matrix}
 \begin{bmatrix}
 x_1 & y_1 & 1 & 0 & 0 & 0 & -x_1'x_1 & -x_1'y_1 & -x_1' \\
 0 & 0 & 0 & x_1 & y_1 & 1 & -y_1'x_1 & -y_1'y_1 & -y_1' \\
 & & & & & \vdots & & & \\
 x_n & y_n & 1 & 0 & 0 & 0 & -x_n'x_n & -x_n'y_n & -x_n' \\
 0 & 0 & 0 & x_n & y_n & 1 & -y_n'x_n & -y_n'y_n & -y_n'
 \end{bmatrix}$$



- Solve the homogeneous least squares problem:

$$\min_h \|Ah\|^2$$

$S \rightarrow 9 \times 1$
 Σ

➔ Take the SVD of A to get U , S , and V

- ~~Let h = the right singular vector of A whose singular value is smallest.~~
- Let h = the column of V (row of V^T) whose column (row) index is the same as that of the smallest diagonal entry of S .

- Reshape h into $H_{3 \times 3}$ and divide by the bottom-right entry.

Problem Statement: Last time

(imperfect*)

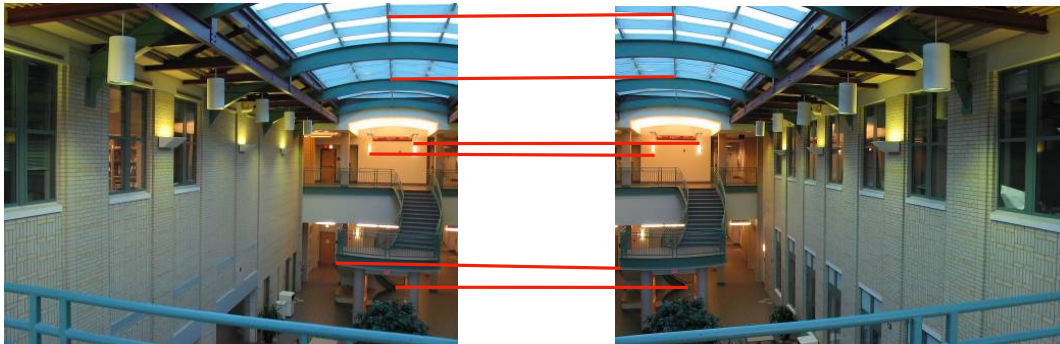
Given a set of feature matches, how do I **find** the **transformation** that relates the two images?

translation?

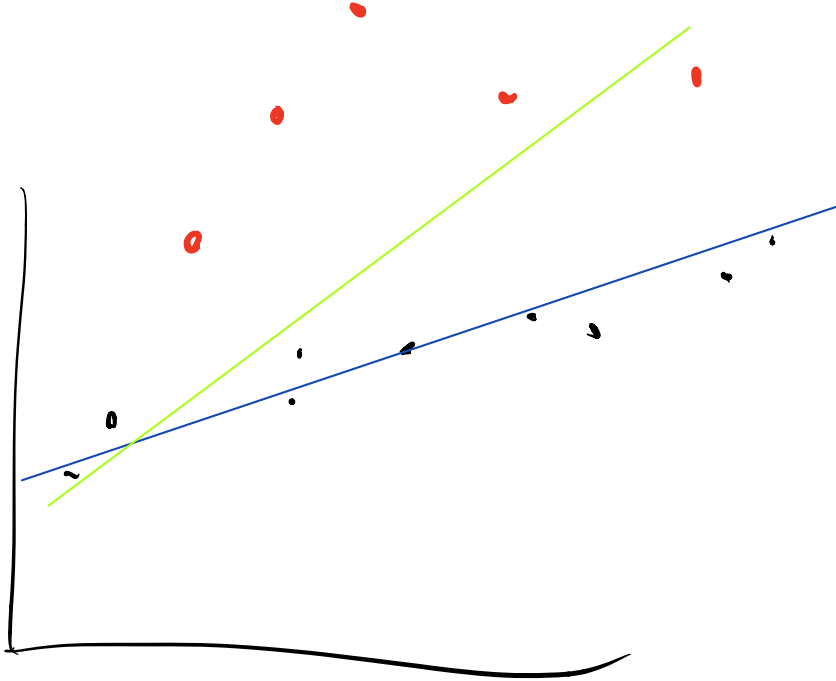
affine?

homography?

** all points off by a bit*



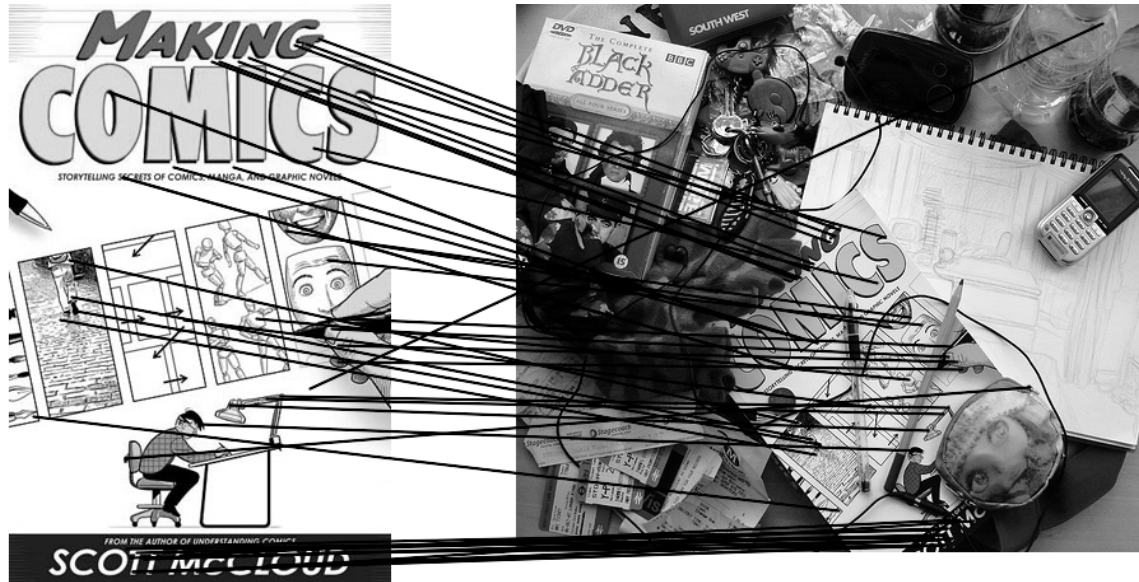
When does least squares work well?



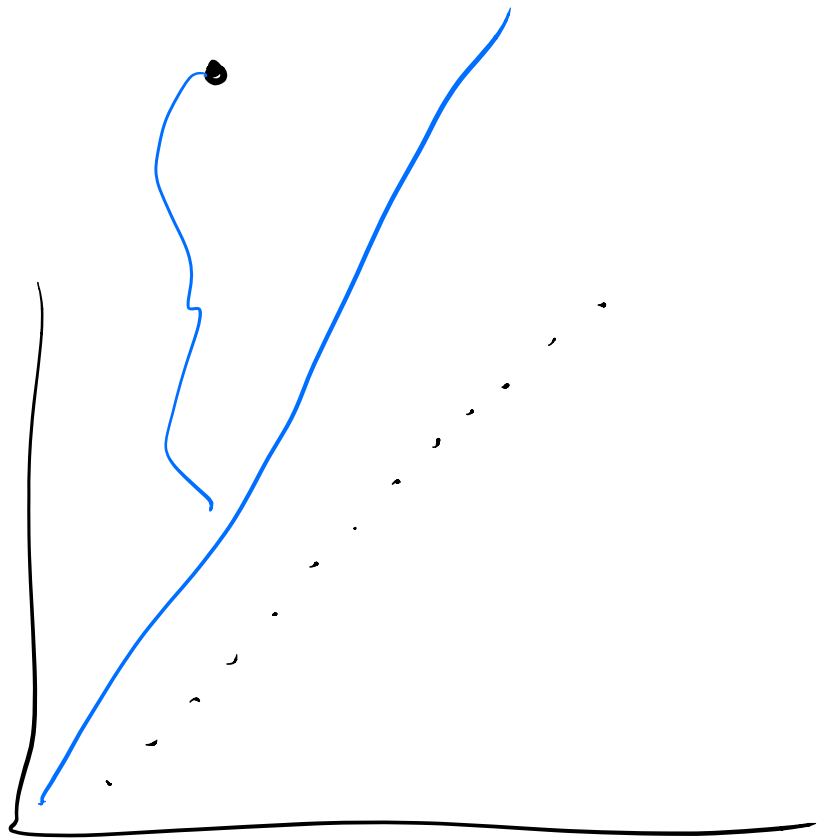
Problem Statement: Today

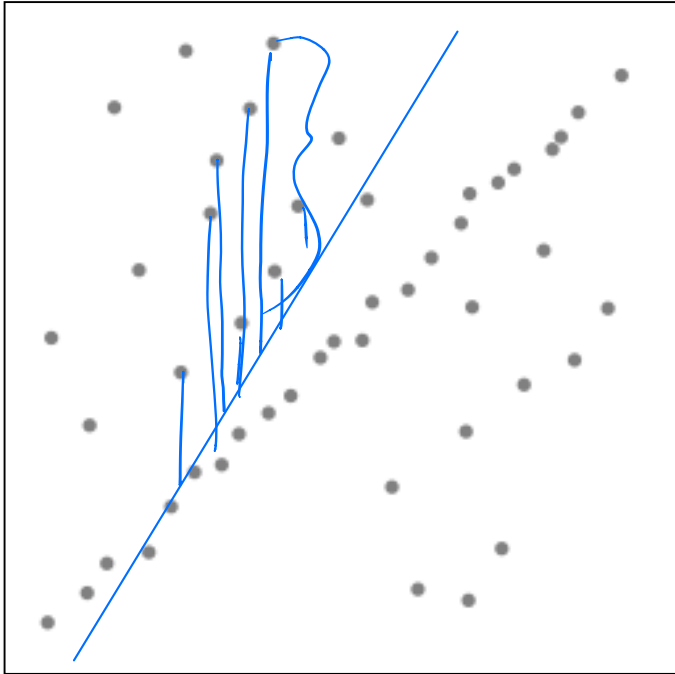
(imperfect*)

Given a set of feature matches, how do I **find** the **transformation** that relates the two images?



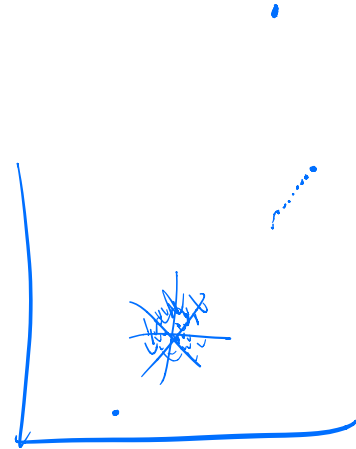
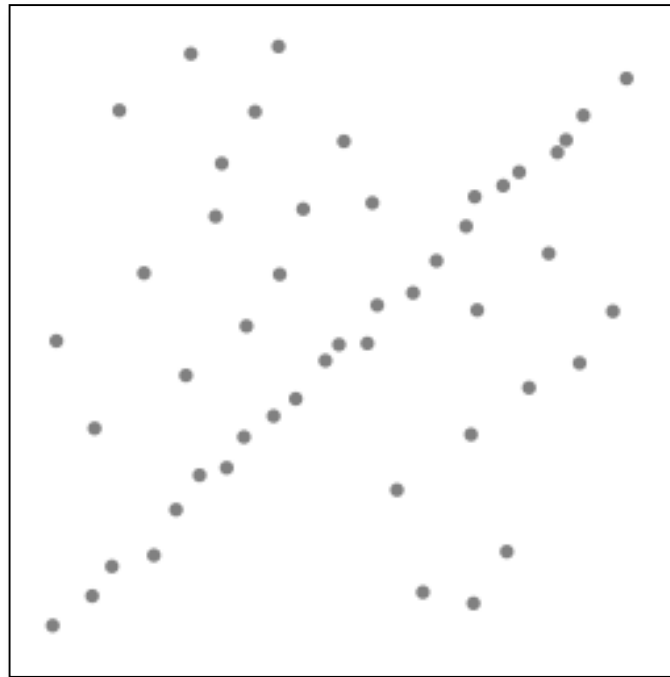
* a few points are outliers





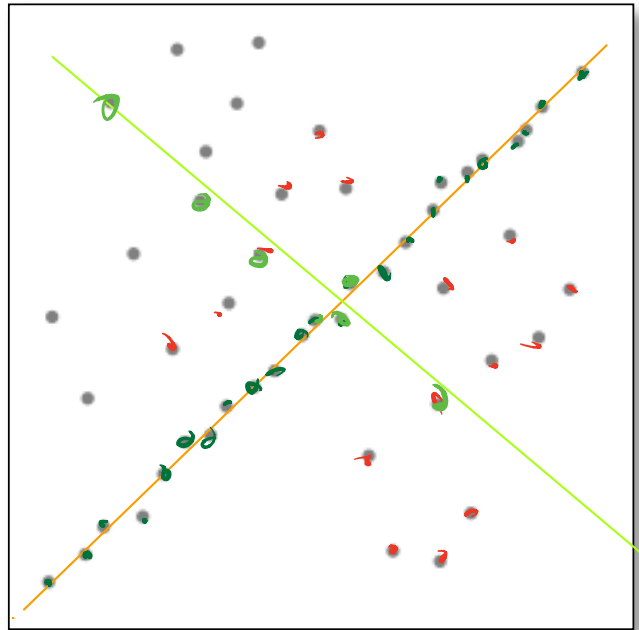
1

How could we fit a line to this data?



An idea

- If I have a hypothesis, I can tell how "good" it is:
 - Count the number of points that are close to the line (**inliers**)



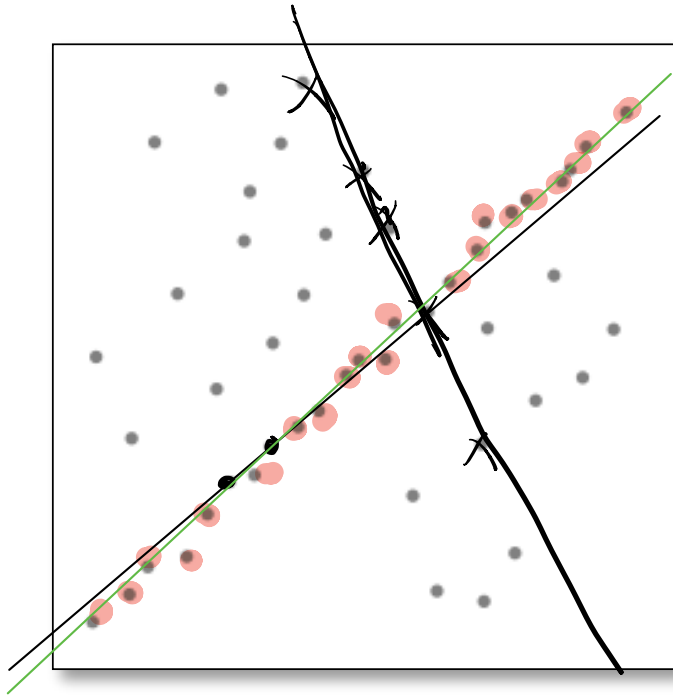
An idea

- If I have a hypothesis, I can tell how "good" it is:
 - Count the number of points that are close to the line (**inliers**)
- Algorithm: generate all possible lines and pick the one with the most inliers
- Runtime: $O(\infty)$

Another idea

- If I have a hypothesis, I can tell how "good" it is:
 - Count the number of points that are close to the line (**inliers**)
- Algorithm: generate **many random** lines and pick the one with the most inliers.
- Questions:
 - How many lines? Which ones? How do I measure "inlierness"?

$$s = z$$



The key

- Points that fit the model will agree.
- Points that don't fit the model will all be wrong in their own unique ways, and there won't be a very large set of them that agree with each other.

"All good matches are alike; every bad match is bad in its own way."

-Tolstoy, as misquoted by Alyosha Efros

RANSAC

The Algorithm

for $i = 0 \dots K$:

$d_i \leftarrow \mathcal{S}$ random data points

$M_i \leftarrow \text{fit_model}(d_i)$

$\text{inlier_count} \leftarrow \sum \left(\underset{\substack{\text{model} \\ \text{prediction}}}{\mathbb{1}(M(x_i) - y_i)} \leq \underset{\substack{\text{observation}}}{\sigma} \right)$

if $\text{inlier_count} > \text{best_count}$:

$\text{best_count} \leftarrow \text{inlier_count}$

$\text{best_M} \leftarrow M_i$

$\text{best_data} \leftarrow \{ x_i, y_i : |M(x_i) - y_i| < \sigma \}$

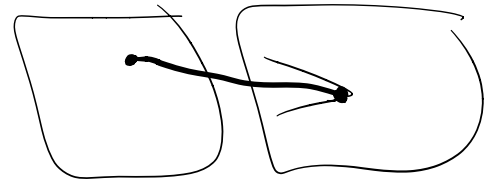
$M_{\text{final}} \leftarrow \text{fit_model}(\text{best_data})$

Choose Parameters:

δ - inlier threshold

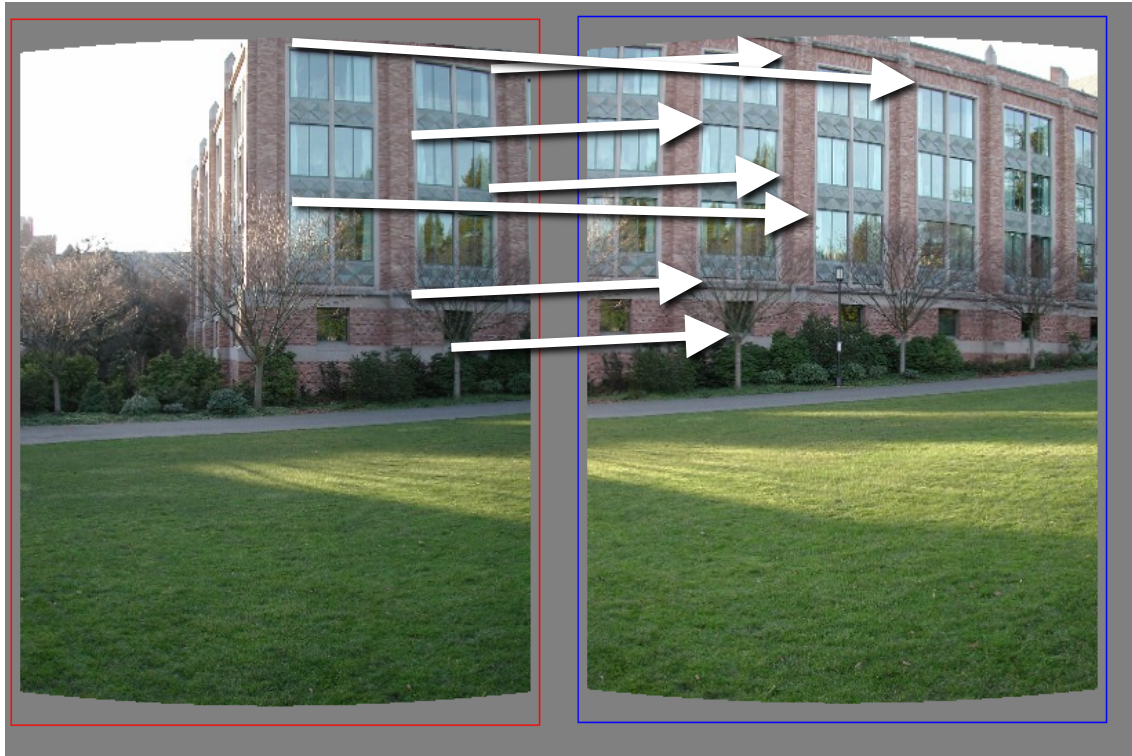
assume Gaussian noise $\delta \in [5, 25]$

K : iterations - guess, or assume fraction of inliers and acceptable probability of picking a set of all inliers.



Questions Remain

- How do we generate a hypothesis for transformations?

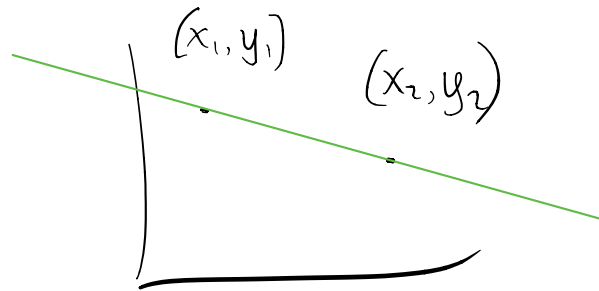


Questions Remain

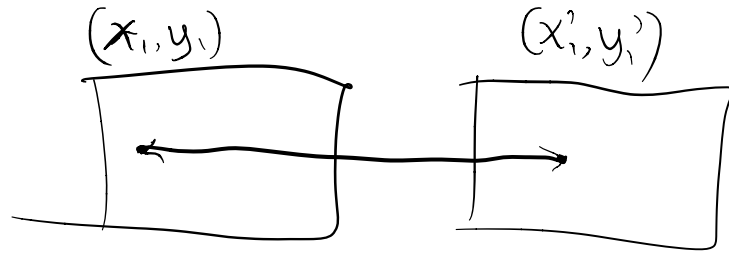
- How do we generate a hypothesis for transformations?

S: smallest number of points that can fully determine your model. Or: # of degrees of Freedom.

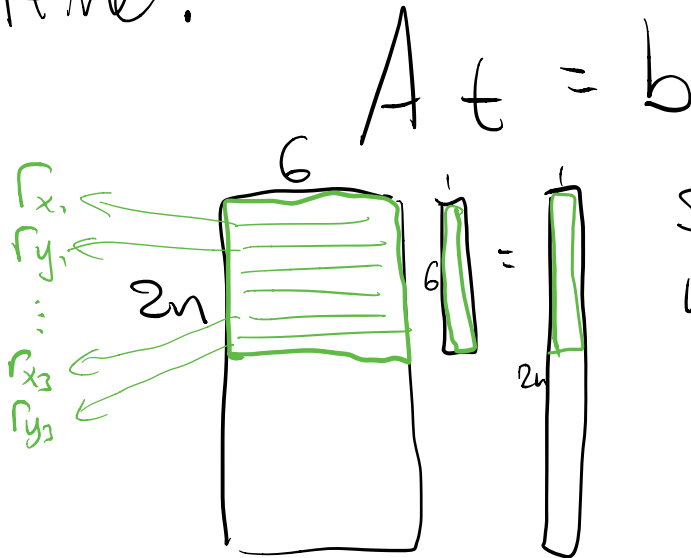
Linear Regression? 2 points fit a line.



Translation? 1 match determines (t_x, t_y)



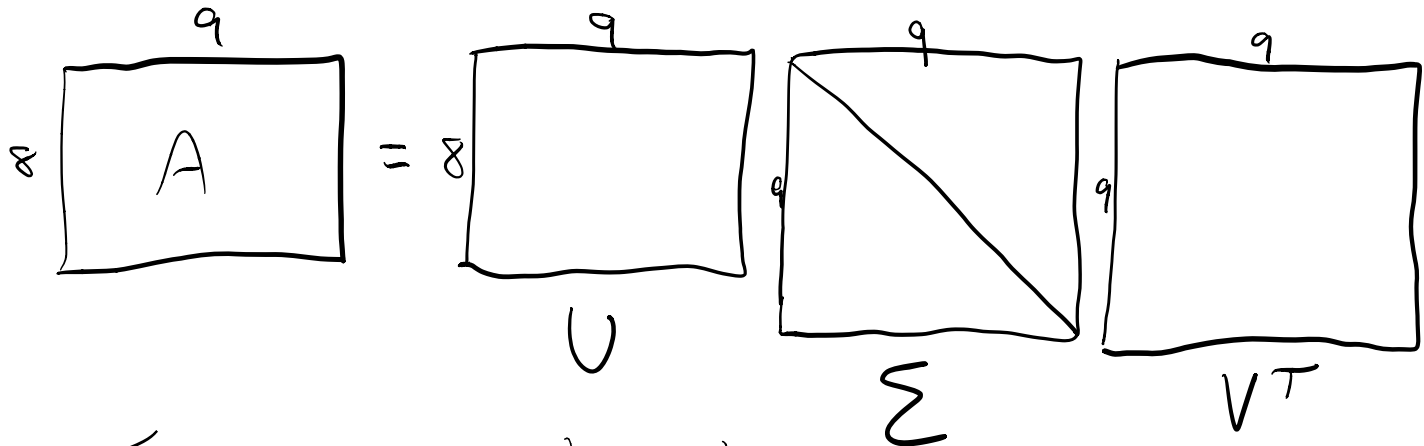
Affine?



Smallest n without being underdetermined: 3

Homography? Awkward: A is $2n \times 9$
but has only 8 DOF

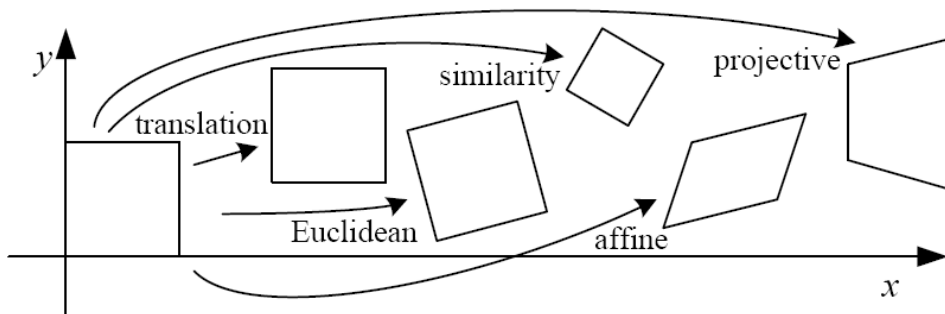
Turns out: SVD works on 8×9 A :








Same argument applies, so

$A_{8 \times 9}$ uses 4 matches, 2 residuals per match.

TLiDM: $s = \lceil \text{DOF} / 2 \rceil$



| Name | Matrix | # D.O.F. | Preserves: | Icon |
|-------------------|---|----------|-------------------|---|
| translation | $\begin{bmatrix} \mathbf{I} & & \mathbf{t} \end{bmatrix}_{2 \times 3}$ | 2 | orientation + ... |  |
| rigid (Euclidean) | $\begin{bmatrix} \mathbf{R} & & \mathbf{t} \end{bmatrix}_{2 \times 3}$ | 3 | lengths + ... |  |
| similarity | $\begin{bmatrix} s\mathbf{R} & & \mathbf{t} \end{bmatrix}_{2 \times 3}$ | 4 | angles + ... |  |
| affine | $\begin{bmatrix} \mathbf{A} \end{bmatrix}_{2 \times 3}$ | 6 | parallelism + ... |  |
| projective | $\begin{bmatrix} \tilde{\mathbf{H}} \end{bmatrix}_{3 \times 3}$ | 8 | straight lines |  |

Questions^{do not!} Remain

- How do we choose the parameters?
 - k (# iterations)
 - s (# data points needed to fit a model)
 - δ (inlier threshold)

(See above - page 22 for δ, k
25-28 for s)