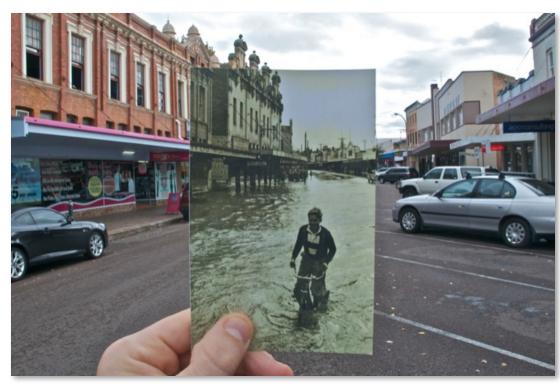
## CS5760: Computer Vision

#### RANSAC



http://www.wired.com/gadgetlab/2010/07/camera-software-lets-you-see-into-the-past/

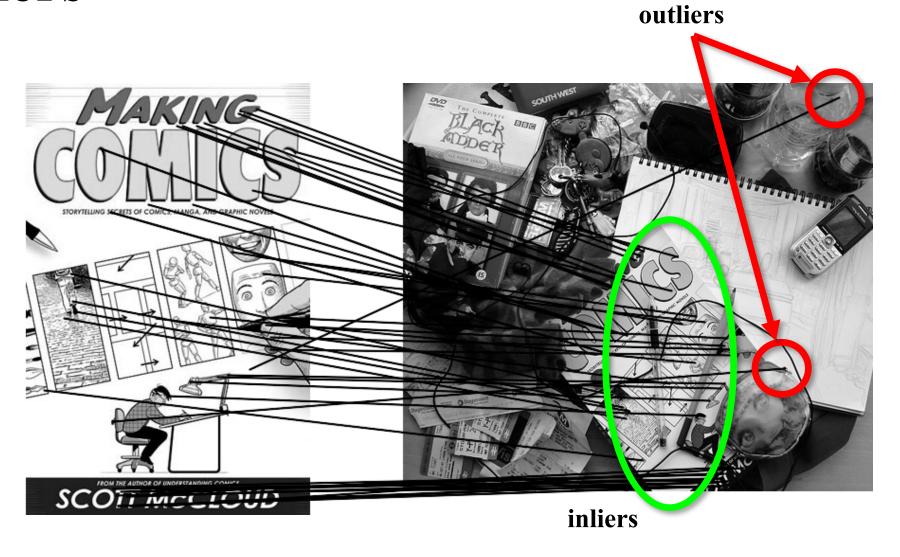
## Reading

• Szeliski: Chapter 6.1

#### **Announcements**

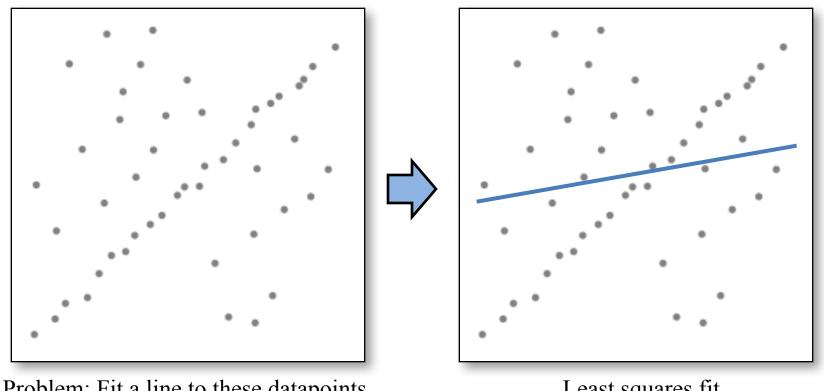
- Vote for Project 1 artifacts by Friday, 11:59pm
- Project 2: code due on Monday, March 2 at 11:59pm
  - Report due Wednesday, March 4 at 11:59pm
- Midterm
  - Plan to release in-class next Wednesday, March 4
  - Due at the beginning of class, Monday, March 9

## **Outliers**



#### Robustness

• Let's consider the problem of linear regression



Problem: Fit a line to these datapoints

Least squares fit

• How can we fix this?

#### We need a better cost function...

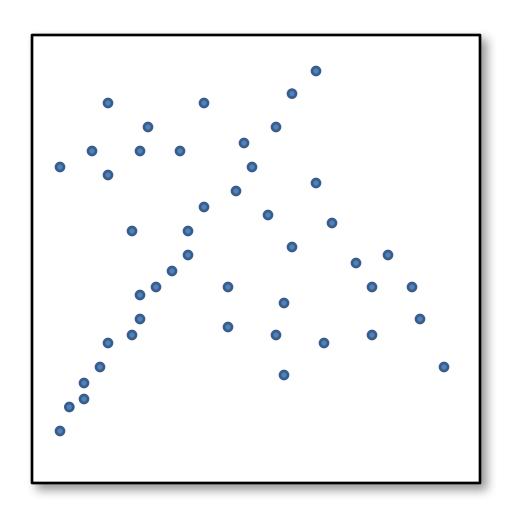
• Suggestions?

#### Idea

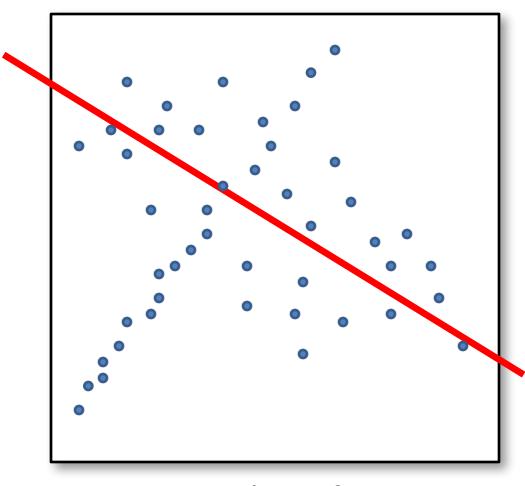
- Given a hypothesized line
- Count the number of points that "agree" with the line
  - "Agree" = within a small distance of the line
  - I.e., the **inliers** to that line

• For all possible lines, select the one with the largest number of inliers

# **Counting inliers**

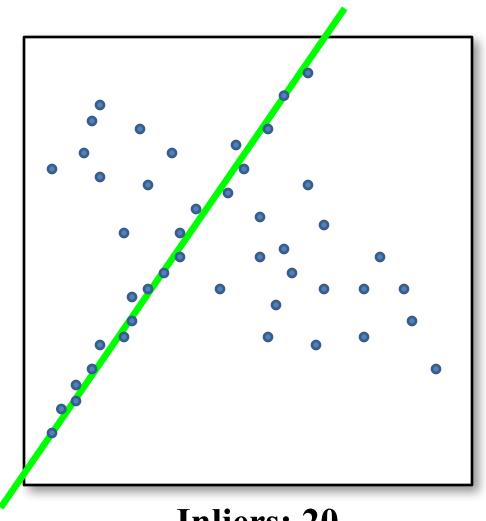


## **Counting inliers**



**Inliers: 3** 

## **Counting inliers**



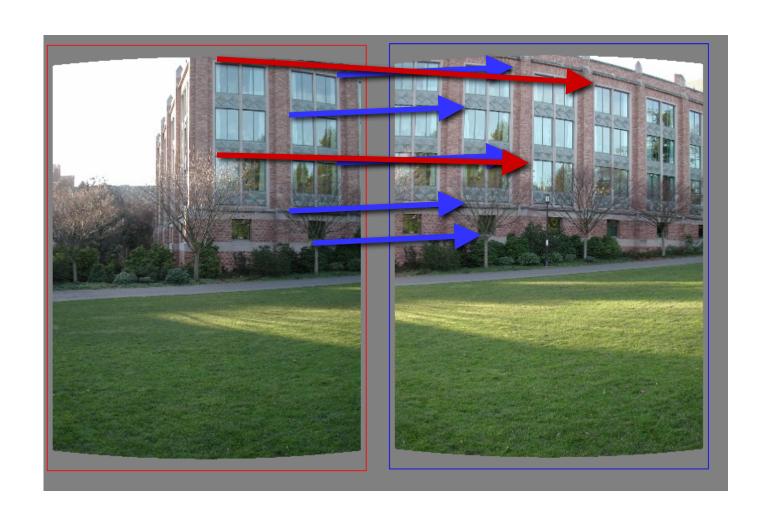
**Inliers: 20** 

#### How do we find the best line?

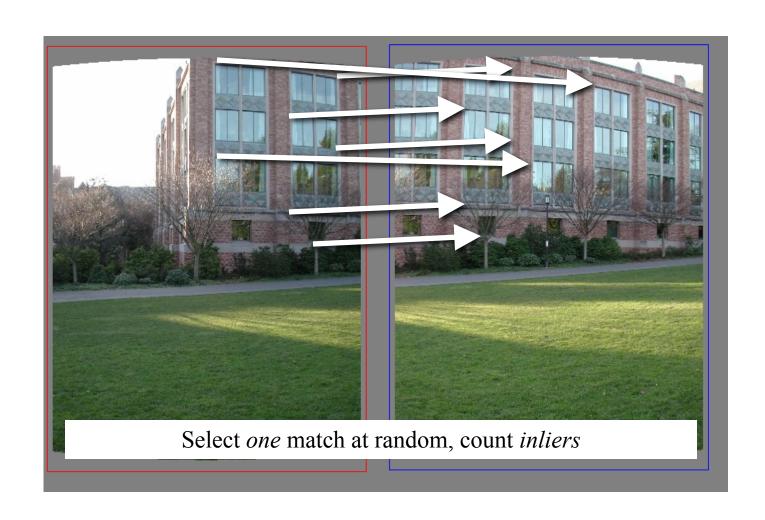
• Unlike least-squares, no simple closed-form solution

- Hypothesize-and-test
  - Try out many lines, keep the best one
  - Which lines?

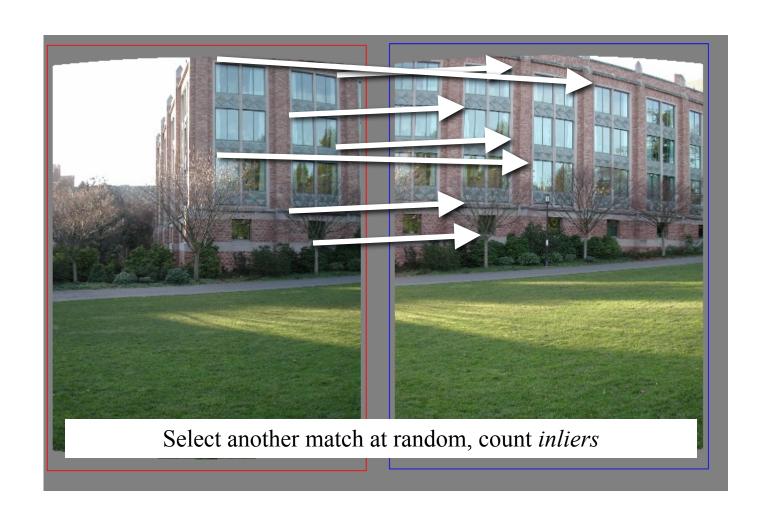
## **Translations**



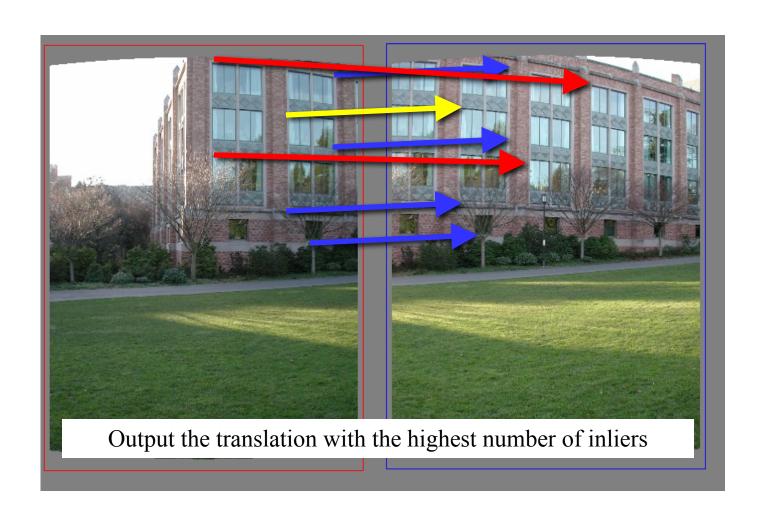
## RAndom SAmple Consensus



## RAndom SAmple Consensus



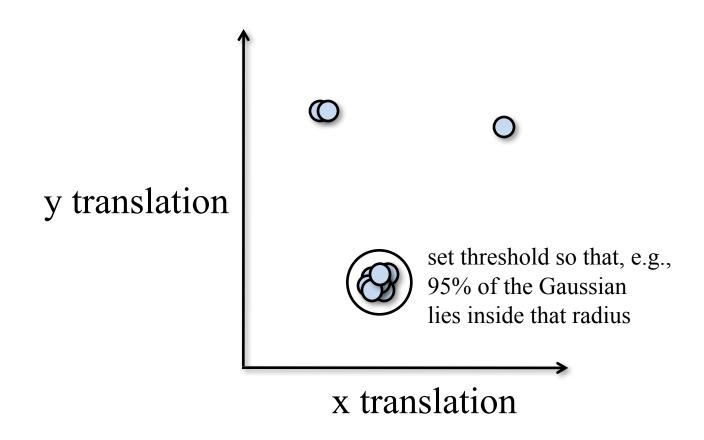
## RAndom SAmple Consensus



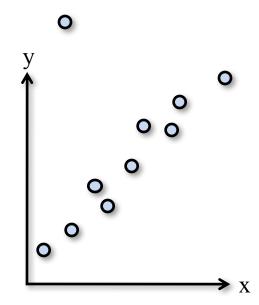
- Idea:
  - All the inliers will agree with each other on the translation vector; the (hopefully small) number of outliers will (hopefully) disagree with each other
    - RANSAC only has guarantees if there are < 50% outliers
  - "All good matches are alike; every bad match is bad in its own way."
    - Tolstoy via Alyosha Efros

- Inlier threshold related to the amount of noise we expect in inliers
  - Often model noise as Gaussian w/ some standard deviation (e.g. 3 pixels)
- Number of rounds related to the percentage of outliers we expect, and the probability of success we'd like to guarantee
  - Suppose there are 20% outliers, and we want to find the correct answer with 99% probability
  - How many rounds do we need?

#### **RANSAC:** Another view



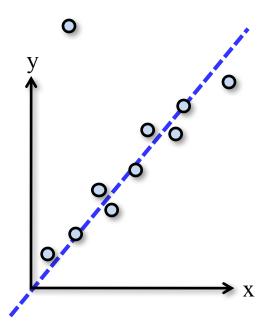
- Back to linear regression
- How do we generate a hypothesis?



0

• Back to linear regression

• How do we generate a hypothesis?



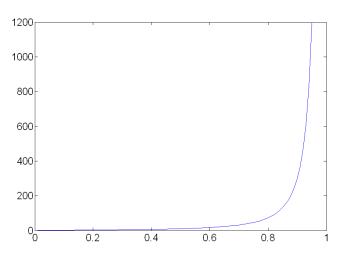
- General version:
  - 1. Randomly choose *s* samples
    - Typically s = minimum sample size that lets you fit a model
  - 2. Fit a model (e.g., line) to those samples
  - 3. Count the number of inliers that approximately fit the model
  - 4. Repeat *N* times
  - 5. Choose the model that has the largest set of inliers

## How many rounds?

- If we have to choose s samples each time
  - with an outlier ratio e
  - and we want the right answer with probability p

$$N \ge \frac{\log(1-p)}{\log(1-(1-e)^s)}$$

	proportion of outliers <i>e</i>							
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	

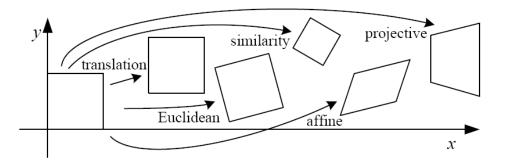


p = 0.99

Source: M. Pollefeys

## How big is s?

- For alignment, depends on the motion model
  - Here, each sample is a correspondence (pair of matching points)



Name	Matrix	# D.O.F.	Preserves:	Icon
translation	$egin{bmatrix} ig[ egin{array}{c c} ig[ oldsymbol{I} ig  oldsymbol{t} ig]_{2 imes 3} \end{array}$	2	orientation $+\cdots$	
rigid (Euclidean)	$egin{bmatrix} ig[ m{R}  ig   m{t}  ig]_{2 imes 3} \end{split}$	3	lengths + · · ·	$\Diamond$
similarity	$\left[\begin{array}{c c} sR & t\end{array}\right]_{2\times 3}$	4	$angles + \cdots$	$\Diamond$
affine	$\left[egin{array}{c} oldsymbol{A} \end{array} ight]_{2 imes 3}$	6	parallelism $+\cdots$	
projective	$igg   ilde{H} igg _{_{3 imes 3}}$	8	straight lines	

## RANSAC pros and cons

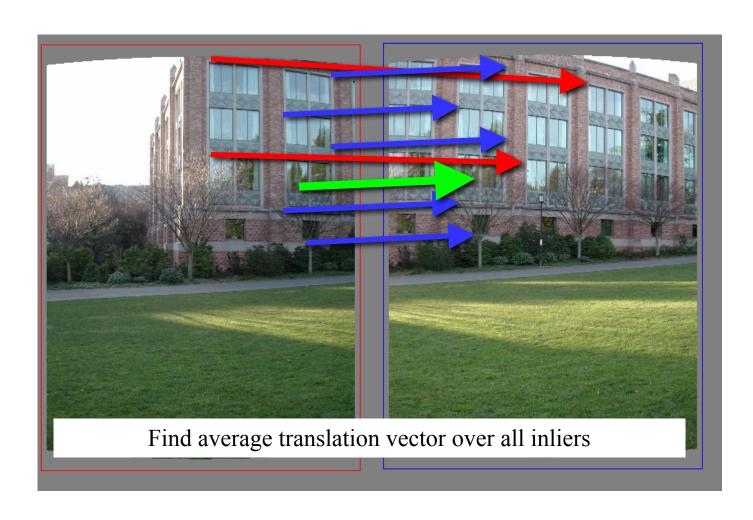
#### Pros

- Simple and general
- Applicable to many different problems
- Often works well in practice

#### • Cons

- Parameters to tune
- Sometimes too many iterations are required
- Can fail for extremely low inlier ratios
- We can often do better than brute-force sampling

## Final step: least squares fit



- An example of a "voting"-based fitting scheme
- Each hypothesis gets voted on by each data point, best hypothesis wins

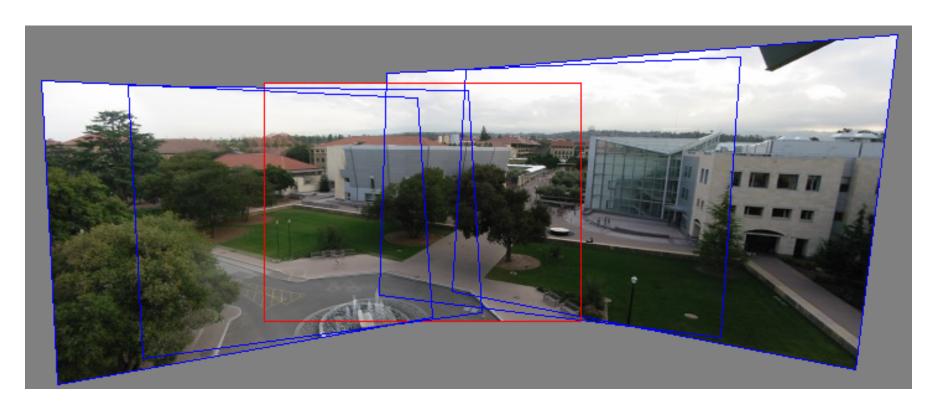
- There are many other types of voting schemes
  - E.g., Hough transforms...

#### **Panoramas**

Now we know how to create panoramas!

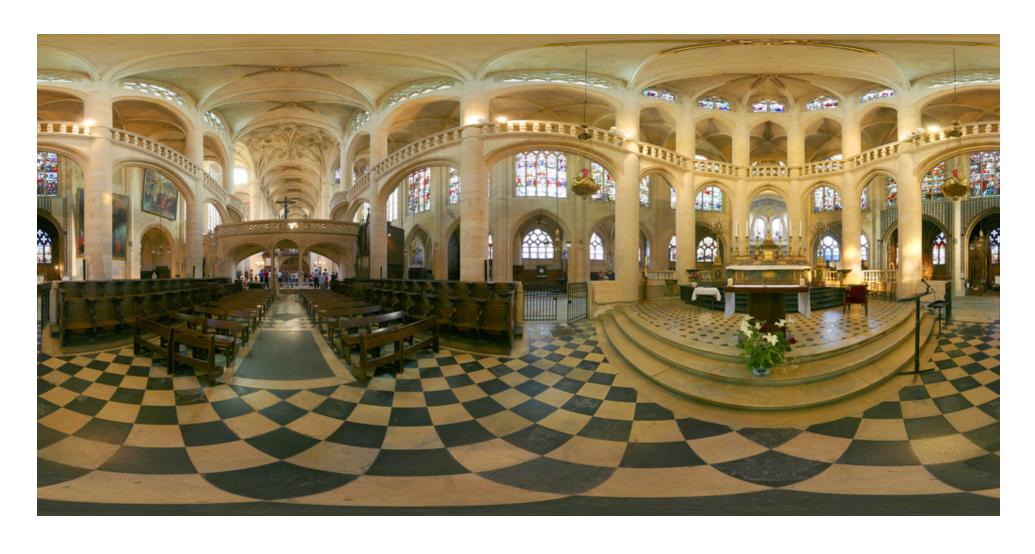
- Given two images:
  - Step 1: Detect features
  - Step 2: Match features
  - Step 3: Compute a homography using RANSAC
  - Step 4: Combine the images together (somehow)
- What if we have more than two images?

# Can we use homographies to create a 360 panorama?



• In order to figure this out, we need to learn what a camera is

## 360 panorama



## **Questions?**