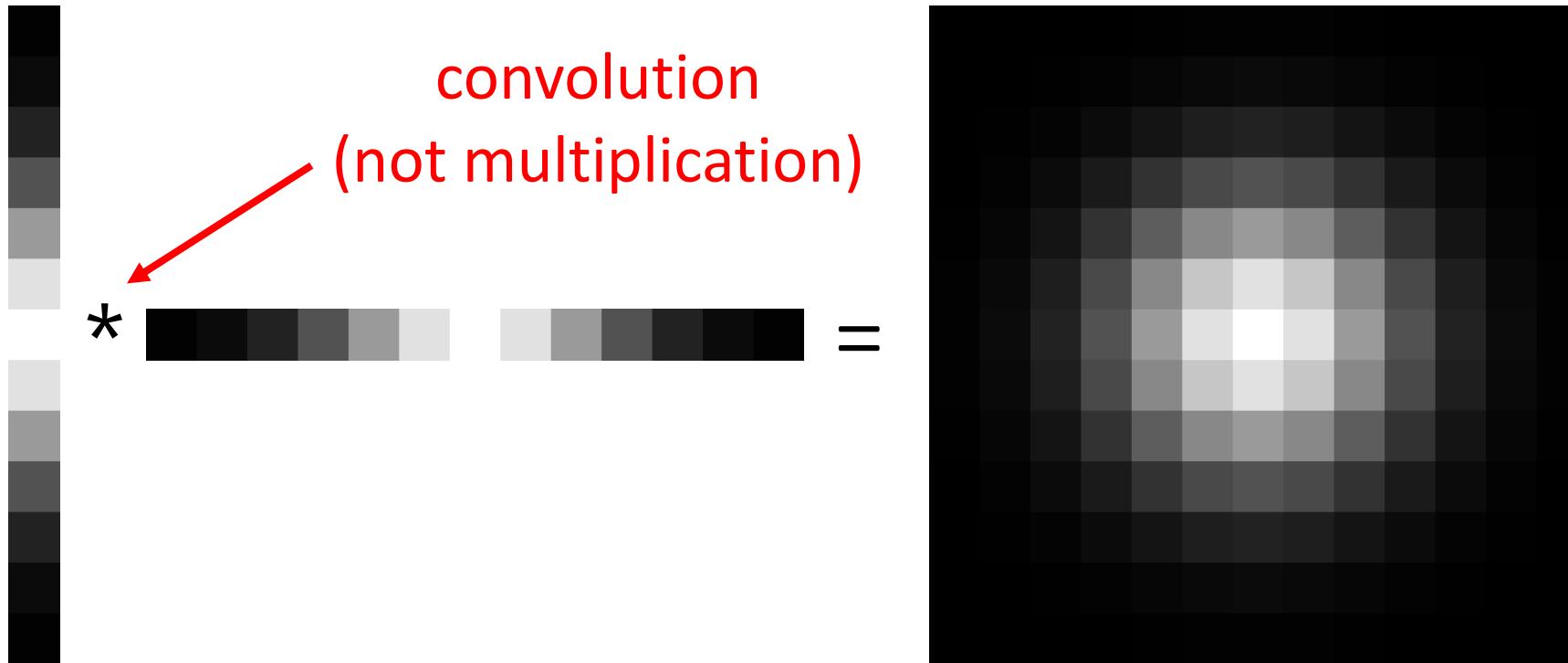


# Camera Calibration and Epipolar Geometry

CS5330, Huaizu Jiang

Fall 2021, Northeastern University

# Separability of the Gaussian filter

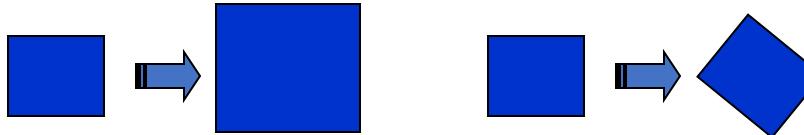


# Unit Tests in PA2

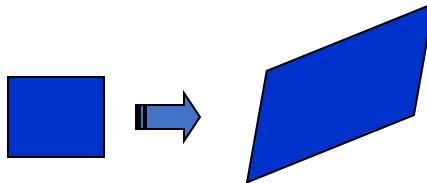
- 1.7
  - The confidence value should be ~4.8
  - The one that is used in the current unit test is local minimum
- 4.4
  - Working on it
- The deadline extended by two days until midnight of Oct 14
  - Start early, more challenging than pa1
  - Use your late days if necessary

# 2D transformation models

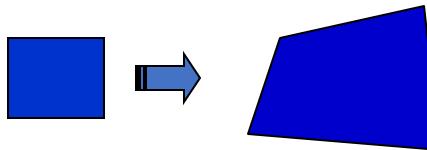
- Similarity  
(translation,  
scale, rotation)



- Affine

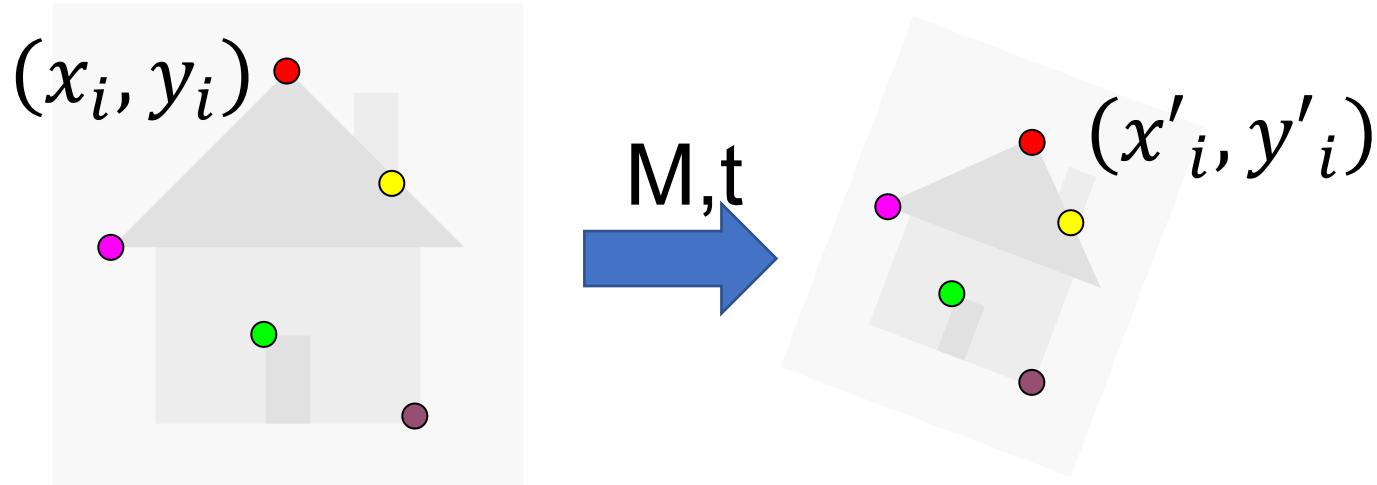


- Projective  
(homography)



# Fitting Transformations

Setup: have pairs of correspondences



$$\begin{bmatrix} x_i' \\ y_i' \end{bmatrix} = M \begin{bmatrix} x_i \\ y_i \end{bmatrix} + t$$

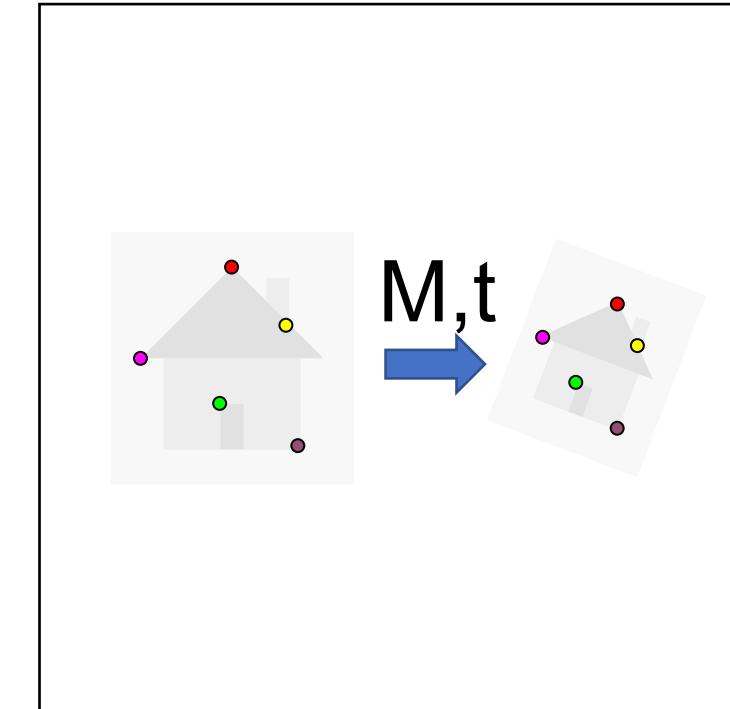
# Fitting Transformation

Affine Transformation:  $M, t$

Data:  $(x_i, y_i, x'_i, y'_i)$  for  
 $i=1, \dots, k$

Model:  
 $[x'_i, y'_i] = M[x_i, y_i] + t$

Objective function:  
 $\| [x'_i, y'_i] - (M[x_i, y_i] + t) \|_2^2$



# Fitting Transformations

Given correspondences:  $[x'_i, y'_i] \leftrightarrow [x_i, y_i]$

$$\begin{bmatrix} x'_i \\ y'_i \end{bmatrix} = \begin{bmatrix} m_1 & m_2 \\ m_3 & m_4 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

Set up two equations per point

$$\begin{bmatrix} \vdots \\ x'_i \\ y'_i \\ \vdots \end{bmatrix} = \begin{bmatrix} & & & \dots & & \\ x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ & & & \dots & & \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_x \\ t_y \end{bmatrix}$$

# Fitting Transformations

$$\begin{array}{c} \boxed{2k} \\ \uparrow \\ \left[ \begin{array}{c} \vdots \\ x_i' \\ y_i' \\ \vdots \end{array} \right] = \left[ \begin{array}{cccccc} x_i & y_i & 0 & 0 & 1 & 0 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ \dots & & \dots & & & \end{array} \right] \left[ \begin{array}{c} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_x \\ t_y \end{array} \right] \end{array}$$

**6**       $\longleftrightarrow$

2 equations per point, 6 unknowns

How many points do we need to properly constrain the problem?

# Fitting Transformations

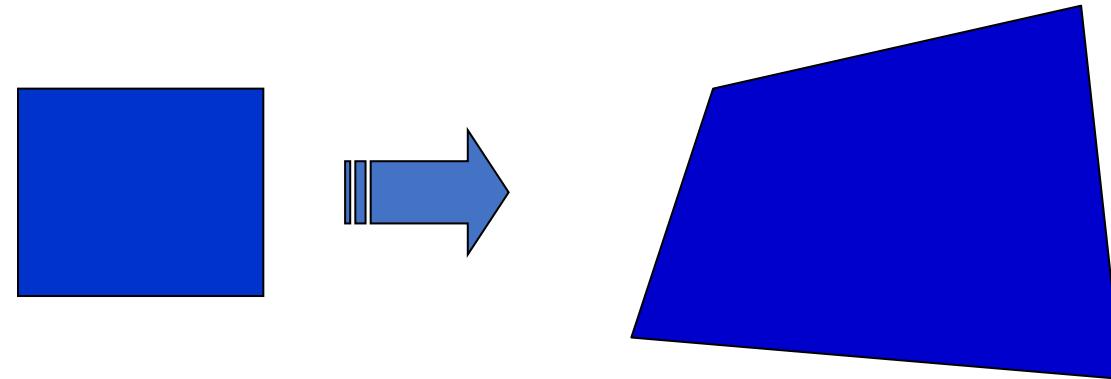
$$\begin{matrix} \boxed{2k} \\ \uparrow \\ \boxed{\begin{bmatrix} \vdots \\ x'_i \\ y'_i \\ \vdots \end{bmatrix}} \end{matrix} = \boxed{\begin{bmatrix} & & 0 & 0 & 1 & 0 \\ x_i & y_i & 0 & 0 & 0 & 1 \\ 0 & 0 & x_i & y_i & 0 & 1 \\ \vdots & & & & & \end{bmatrix}} \boxed{\begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ t_x \\ t_y \end{bmatrix}}$$

Diagram illustrating the matrix equation  $b = Ax$  for fitting transformations. The vector  $b$  (containing  $x'_i$  and  $y'_i$ ) has dimension  $2k$ . The matrix  $A$  is a  $2k \times 6$  matrix with columns corresponding to the transformation parameters  $m_1, m_2, m_3, m_4, t_x, t_y$ . The vector  $x$  contains these parameters.

Want:  $b = Ax$  ( $x$  contains all parameters)  
Overconstrained, so solve  $\arg \min |Ax - b|$   
How?

# Fitting a plane projective transformation

- **Homography:** plane projective transformation (transformation taking a quad to another arbitrary quad)



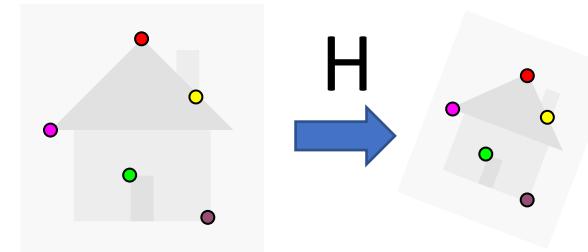
# Fitting Transformation

Homography:  $H$

Data:  $(x_i, y_i, x'_i, y'_i)$  for  
 $i=1, \dots, k$

Model:  
 $[x'_i, y'_i, 1] \equiv H[x_i, y_i, 1]$

Objective function:  
It's complicated



**Want:**

$$\begin{bmatrix} x'_i \\ y'_i \\ w'_i \end{bmatrix} \equiv \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ w_i \end{bmatrix}$$

$$p_i = \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ w_i \end{bmatrix} \equiv H p_i \equiv \begin{bmatrix} h_1^T \\ h_2^T \\ h_3^T \end{bmatrix} p_i \equiv \begin{bmatrix} h_1^T p_i \\ h_2^T p_i \\ h_3^T p_i \end{bmatrix}$$

**Recall:**  $a \equiv b \rightarrow a = \lambda b$     **Fun Fact:**  $\rightarrow a \times b = 0$

**In the end  
want:**

$$\begin{bmatrix} x'_i \\ y'_i \\ w'_i \end{bmatrix} \times \begin{bmatrix} h_1^T p_i \\ h_2^T p_i \\ h_3^T p_i \end{bmatrix} = 0$$

Why?

Cross products have  
explicit forms

# Fitting Transformation

$k$  points  $\rightarrow$

$$\begin{array}{c} \text{2k} \\ \uparrow \\ \boxed{9} \\ \leftarrow \quad \rightarrow \end{array}$$

$$\begin{bmatrix} \mathbf{0}^T & -w'_1 \mathbf{p}_1^T & y'_1 \mathbf{p}_1^T \\ w'_1 \mathbf{p}_1^T & \mathbf{0}^T & -x'_1 \mathbf{p}_1^T \\ \vdots & & \vdots \\ \mathbf{0}^T & -w'_n \mathbf{p}_n^T & y'_n \mathbf{p}_n^T \\ w'_n \mathbf{p}_n^T & \mathbf{0}^T & -x'_n \mathbf{p}_n^T \end{bmatrix} \begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \\ \mathbf{h}_3 \end{bmatrix} = \mathbf{0}$$

$A\mathbf{h} = \mathbf{0}$

$$p_i = \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}$$

If  $h$  is up to scale, what do we use from last time?

$$h^* = \arg \min_{\|h\|=1} \|Ah\|^2 \rightarrow \text{Eigenvector of } A^T A \text{ with smallest eigenvalue}$$

# Fitting Transformation – In Practice

The diagram illustrates the linear system  $A\mathbf{h} = 0$  for fitting transformation. On the left, an orange box labeled "N points" has arrows pointing up to "2n" and down to "9". To the right of "9" is a double-headed orange arrow. Below "2n" is a large matrix equation. The matrix has 2n rows and 9 columns. The first column contains  $\mathbf{0}^T$  and  $\mathbf{p}_1^T$ . The second column contains  $-\mathbf{p}_1^T$  and  $\mathbf{0}^T$ . The third column contains  $y'_1 \mathbf{p}_1^T$  and  $-x'_1 \mathbf{p}_1^T$ . This pattern repeats for n rows, with the last row containing  $\mathbf{0}^T$  and  $\mathbf{p}_n^T$  in the first two columns, and  $y'_n \mathbf{p}_n^T$  and  $-x'_n \mathbf{p}_n^T$  in the third and fourth columns respectively. The matrix is multiplied by a vector  $\mathbf{h}$  (with components  $\mathbf{h}_1, \mathbf{h}_2, \mathbf{h}_3$ ) and equals zero. A blue bracket underlines the last four columns of the matrix, and a blue curly brace groups the last four entries of the vector  $\mathbf{h}$ , both labeled  $A\mathbf{h} = 0$ .

$$N \text{ points} \rightarrow \boxed{2n} \quad \boxed{9} \quad \boxed{\mathbf{p}_i = \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}}$$
$$\begin{bmatrix} \mathbf{0}^T & -\mathbf{p}_1^T & y'_1 \mathbf{p}_1^T \\ \mathbf{p}_1^T & \mathbf{0}^T & -x'_1 \mathbf{p}_1^T \\ \vdots & \vdots & \vdots \\ \mathbf{0}^T & -\mathbf{p}_n^T & y'_n \mathbf{p}_n^T \\ \mathbf{p}_n^T & \mathbf{0}^T & -x'_n \mathbf{p}_n^T \end{bmatrix} \begin{bmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \\ \mathbf{h}_3 \end{bmatrix} = \mathbf{0}$$
$$A\mathbf{h} = 0$$

**What is the minimum number of matches needed for a solution?**

**Four:**  $A$  has 8 degrees of freedom (9 parameters, but scale is arbitrary), one match gives us two linearly independent equations

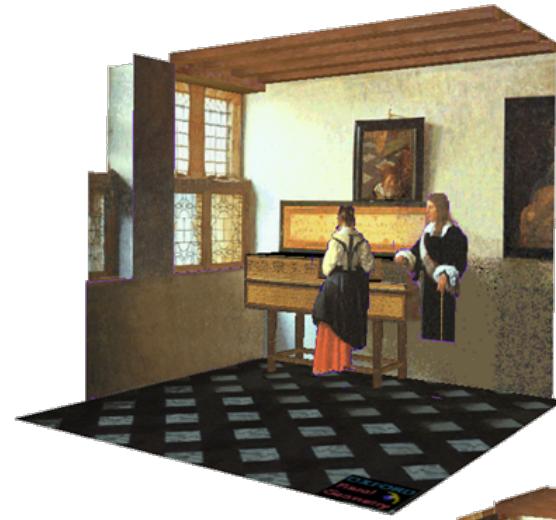
# Perspective & 3D Geometry

Perspective and 3D Geometry		
Week 4	Thur, Oct 7	Camera Calibration, Epipolar Geometry
	Mon, Oct 11	No class, Indigenous Peoples Day
Week 5	Thu, Oct 14	Stereo Vision
	Mon, Oct 18	Optical Flow
Week 6	Thu, Oct 21	Structure from Motion

# Our goal: Recovery of 3D structure

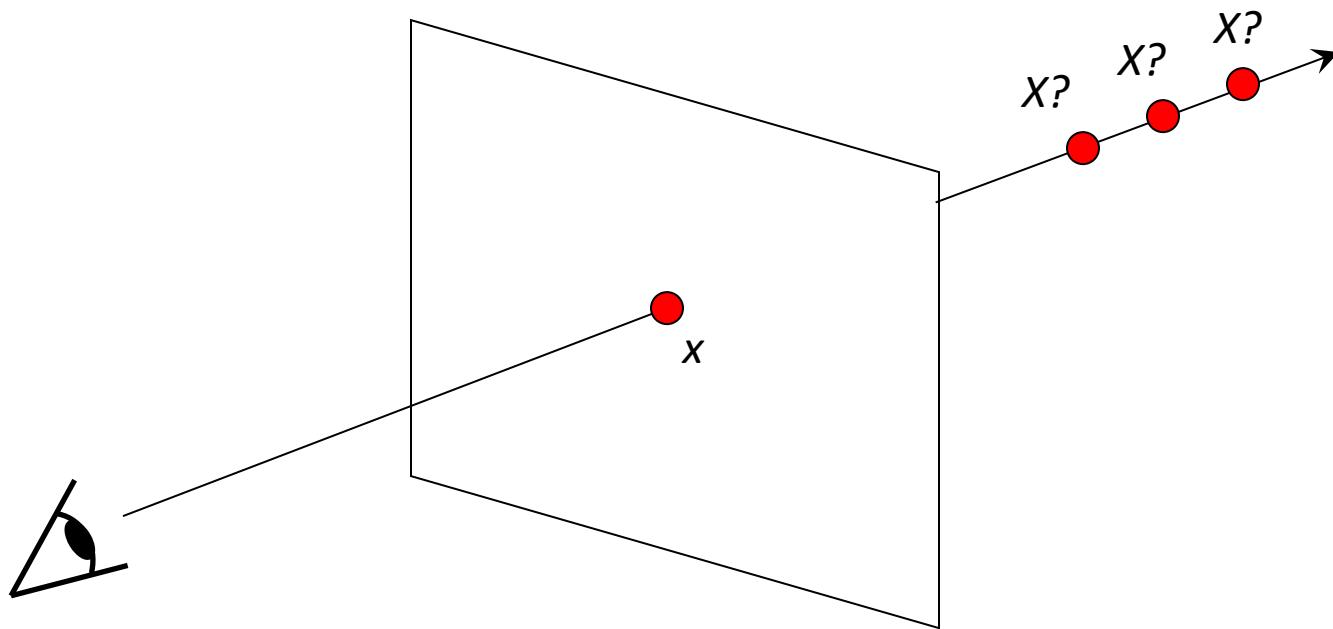


J. Vermeer, *Music Lesson*, 1662

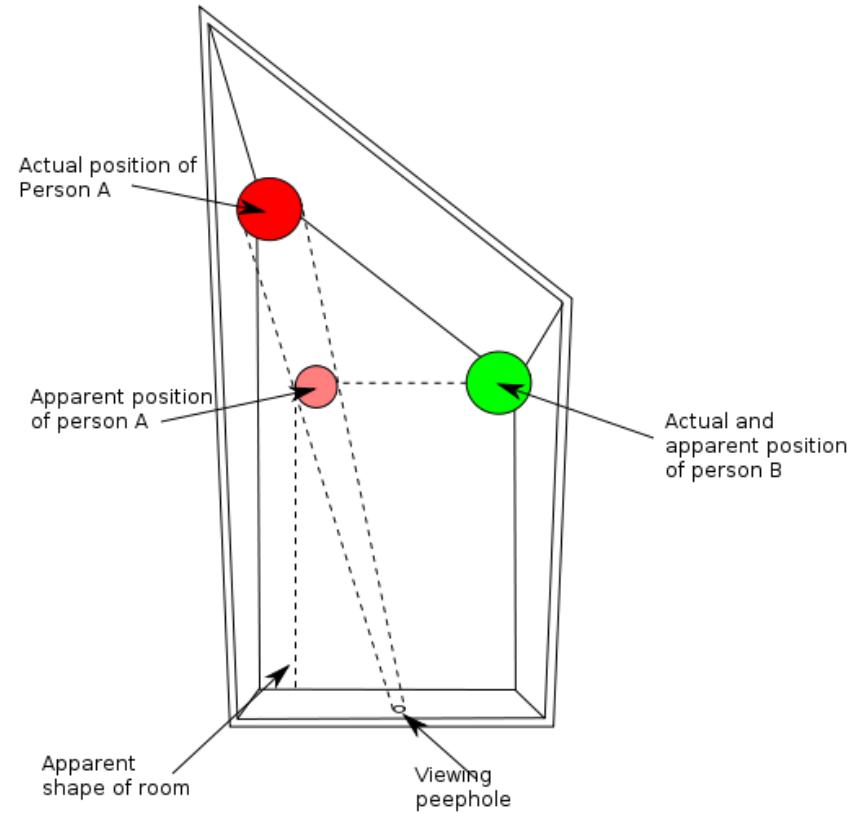


A. Criminisi, M. Kemp, and A. Zisserman, [Bringing Pictorial Space to Life: computer techniques for the analysis of paintings](#), Proc. Computers and the History of Art, 2002

# Single-view ambiguity



# Things aren't always as they appear...



[http://en.wikipedia.org/wiki/Ames\\_room](http://en.wikipedia.org/wiki/Ames_room)

# Single-view ambiguity

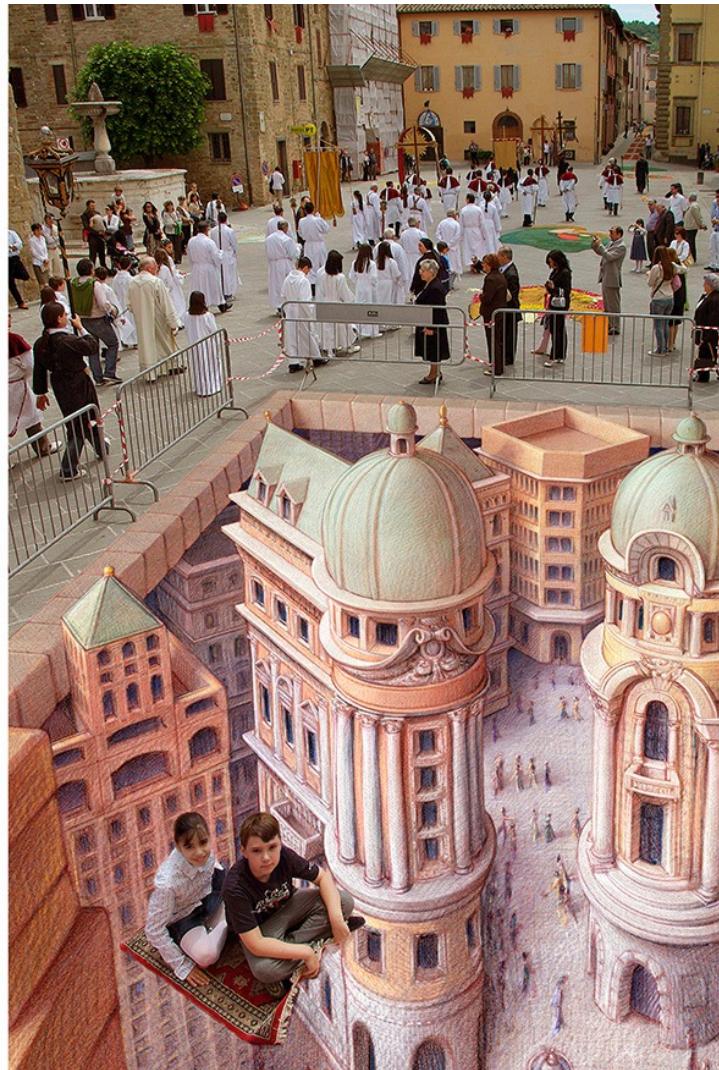


# Single-view ambiguity



Rashad Alakbarov shadow sculptures

# Anamorphic perspective



# Resolving Single-view Ambiguity



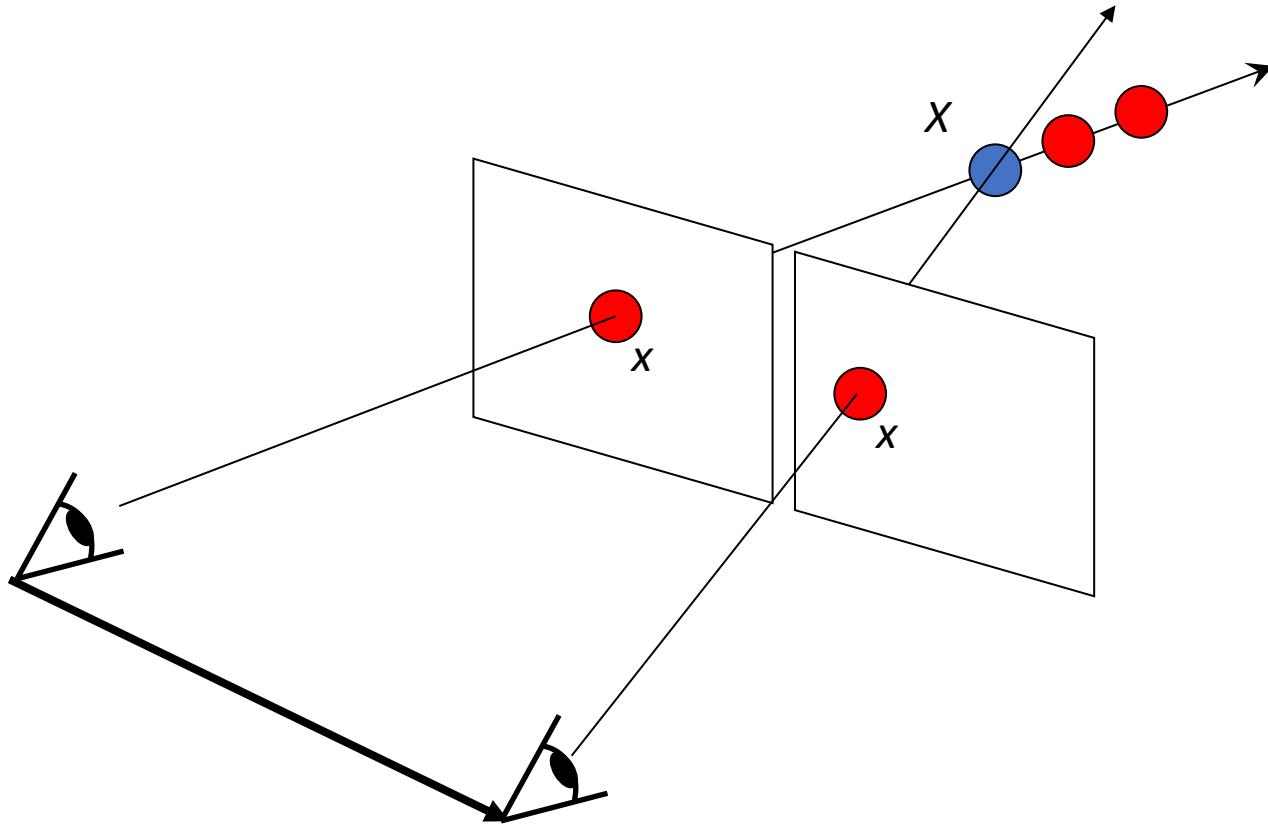
- Shoot light (lasers etc.) out of your eyes!
- Con: not so biologically plausible, dangerous?

# Resolving Single-view Ambiguity



- Shoot light (lasers etc.) out of your eyes!
- Con: not so biologically plausible, dangerous?

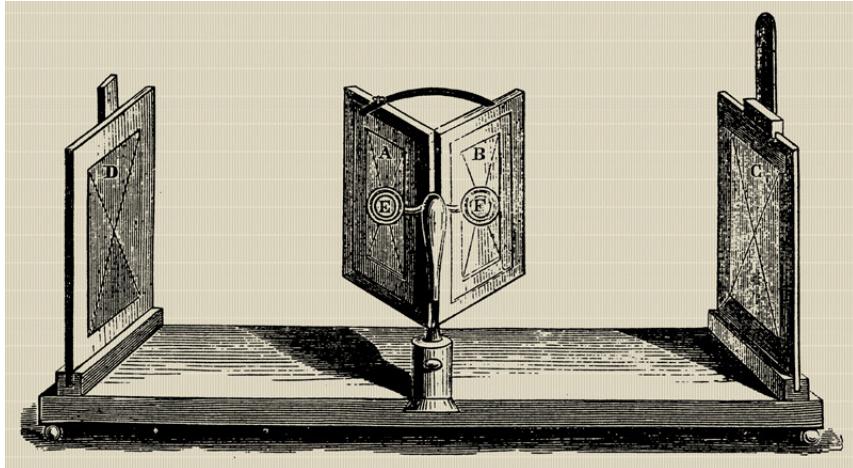
# Resolving Single-view Ambiguity



- Stereo: given 2 calibrated cameras in different views and correspondences, can solve for  $X$

# Stereo photography and stereo viewers

Take two pictures of the same subject from two slightly different viewpoints and display so that each eye sees only one of the images.



Invented by Sir Charles Wheatstone, 1838

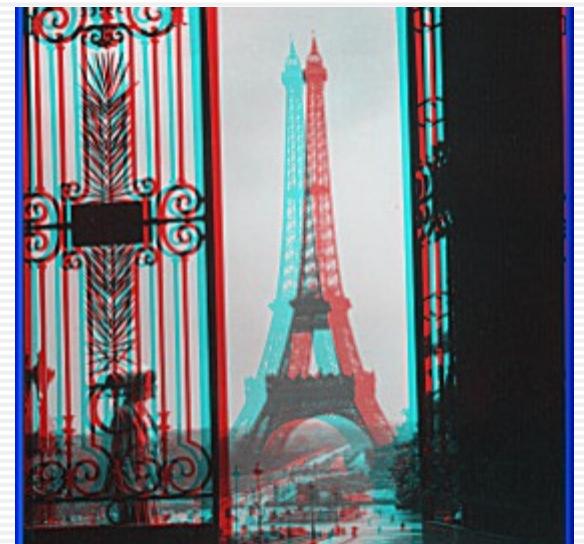


Slide credit: J. Hays



Image from fisher-price.com





© Copyright 2001 Johnson-Shaw Stereoscopic Museum



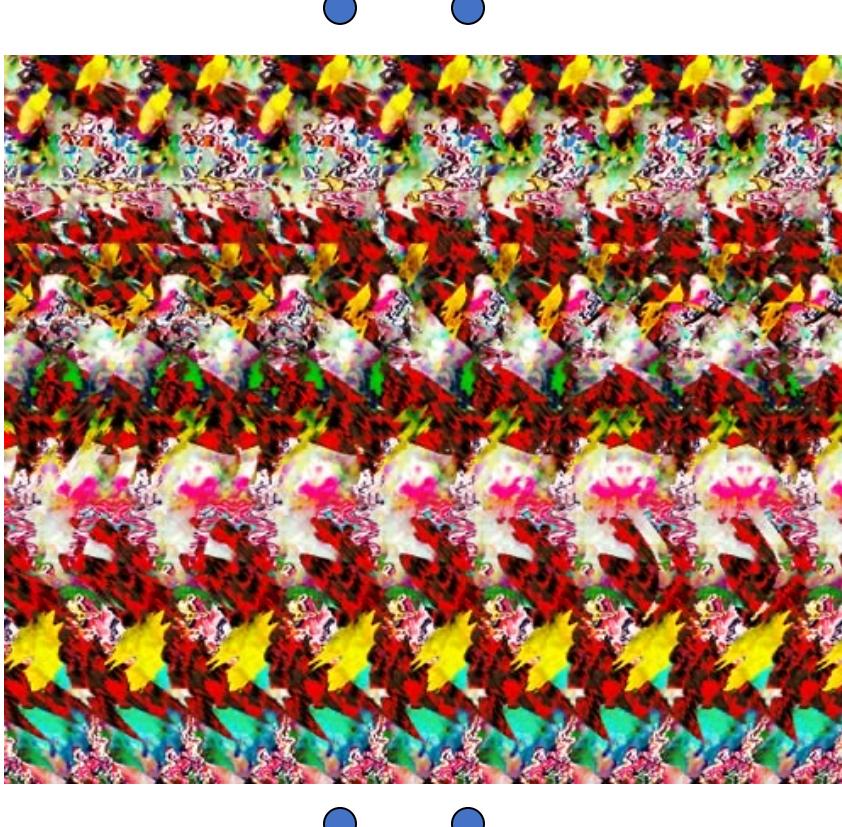


[http://www.well.com/~jimg/stereo/stereo\\_list.html](http://www.well.com/~jimg/stereo/stereo_list.html)



[http://www.well.com/~jimg/stereo/stereo\\_list.html](http://www.well.com/~jimg/stereo/stereo_list.html)

# Autostereograms



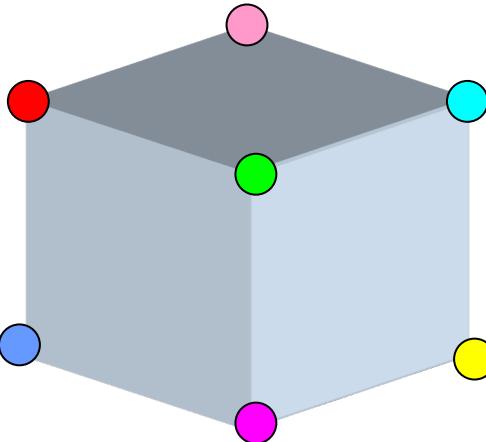
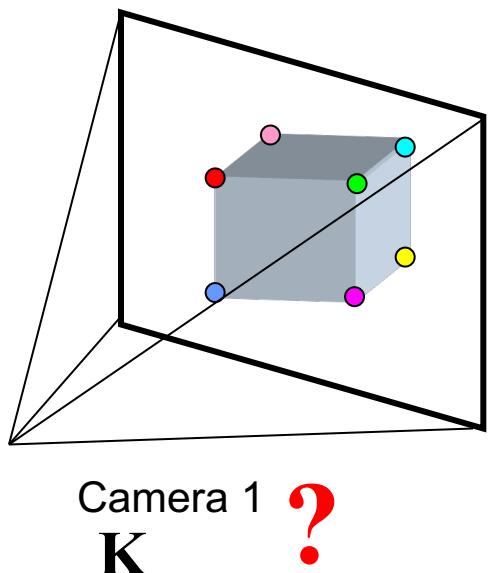
Exploit disparity as  
depth cue using single  
image.

(Single image random  
dot stereogram, Single  
image stereogram)

# Autostereograms



# Multi-view geometry problems

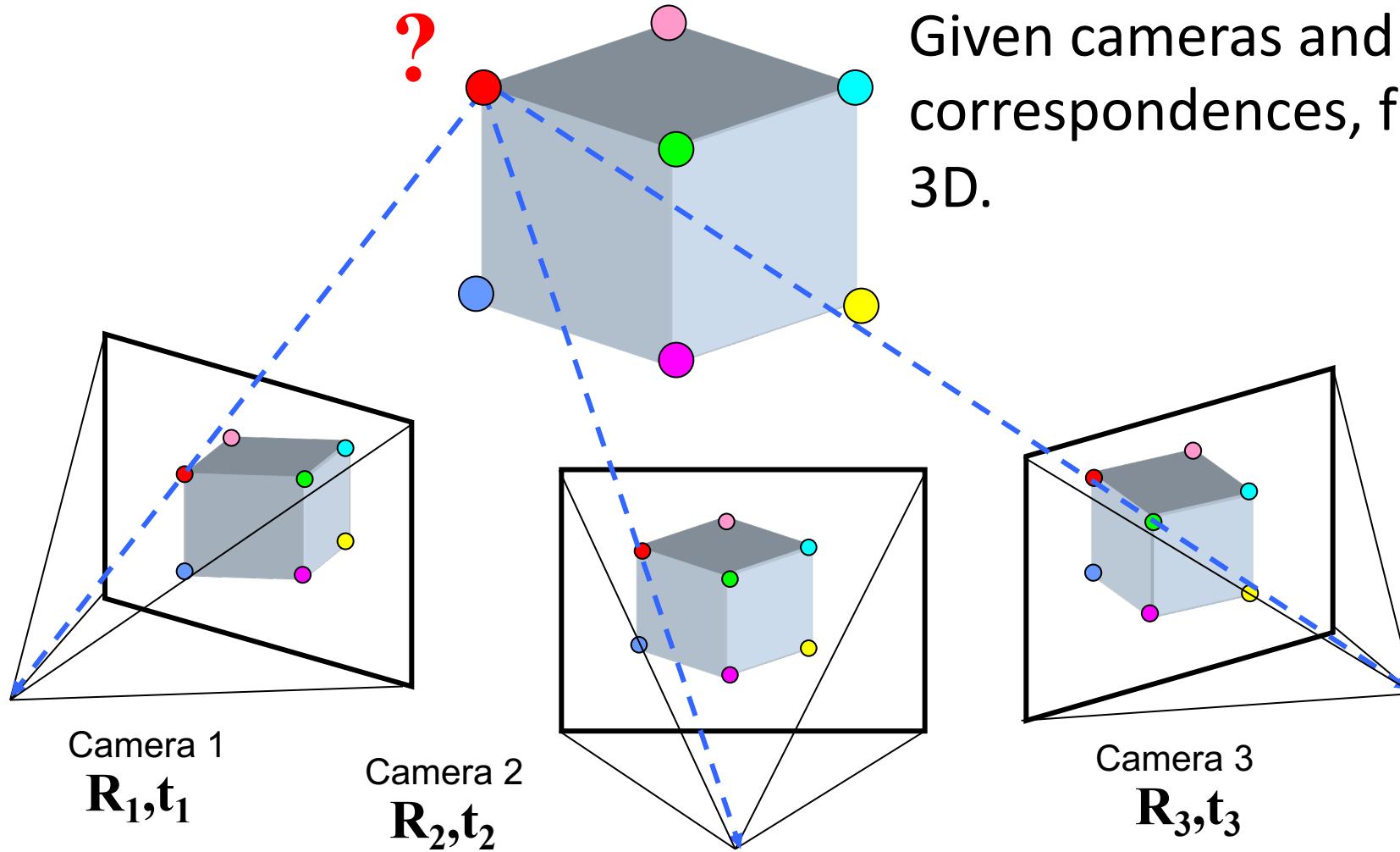


*Calibration:*

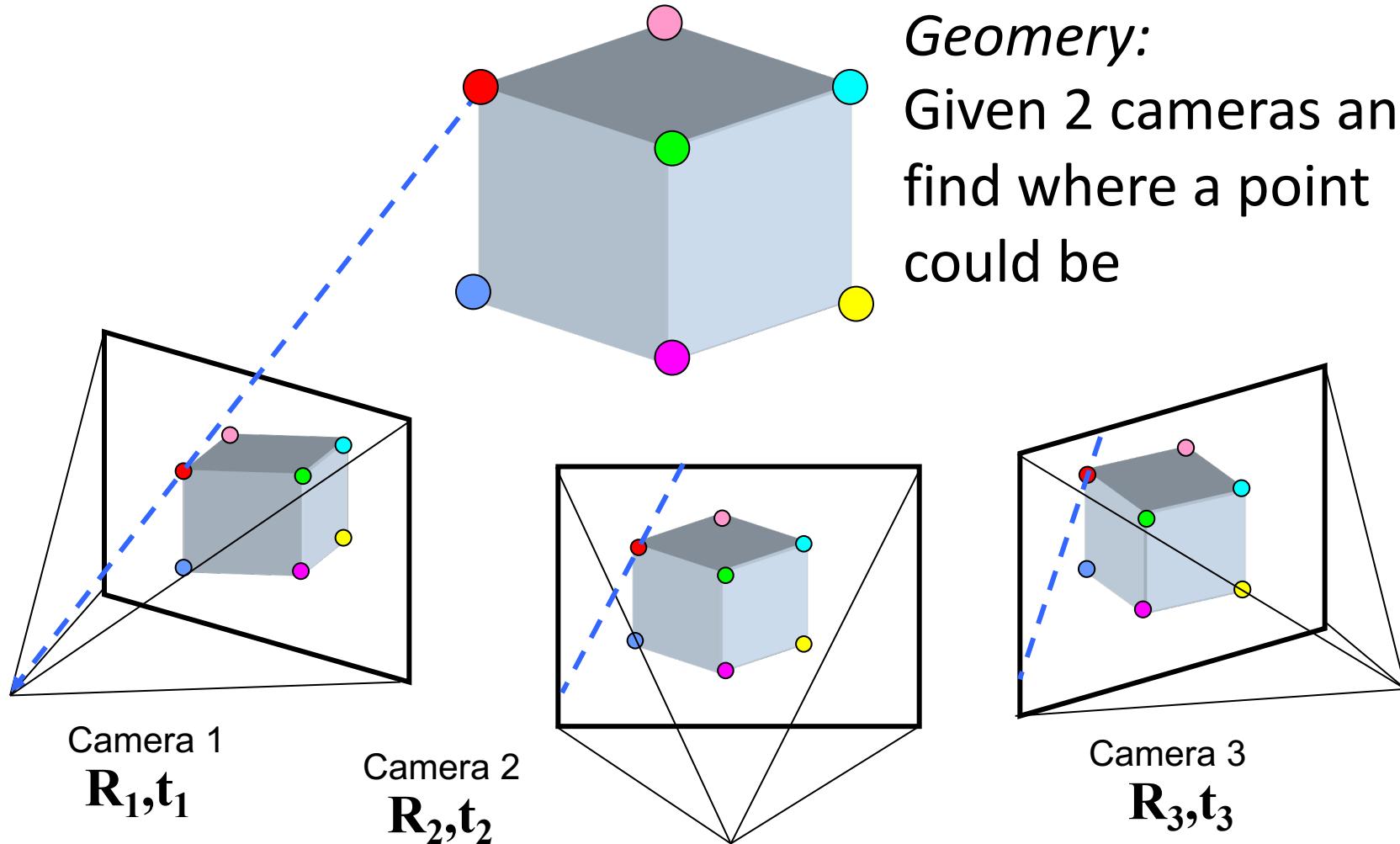
Figure out intrinsics of camera ( $K$ ).

We need camera intrinsics /  $K$  in order to figure out where the rays are

# Multi-view geometry problems



# Multi-view geometry problems

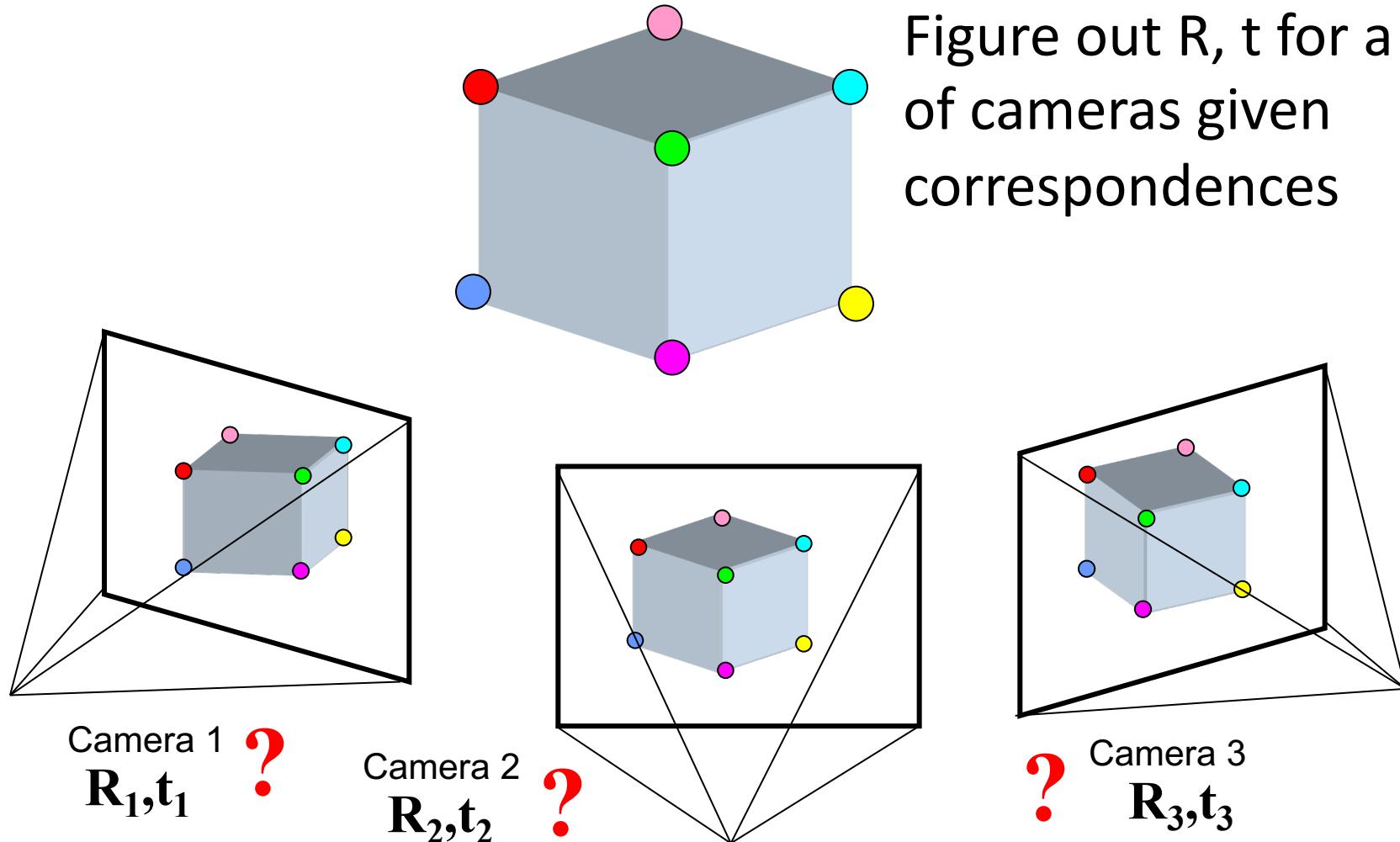


*Stereo/Epipolar*

*Geomery:*

Given 2 cameras and  
find where a point  
could be

# Multi-view geometry problems

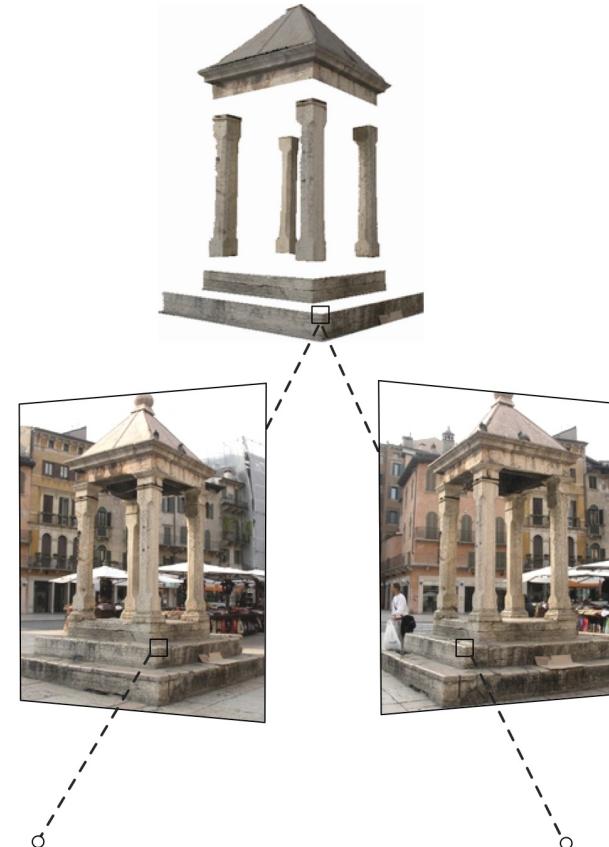


# Outline

- (Today) Calibration:
  - Getting intrinsic matrix/K
- (Today) Epipolar geometry:
  - 2 pictures -> depth map
- Stereo
  - Rectified 2 pictures -> depth map
- Optical flow
  - Finding correspondences in 2 pictures (similar to stereo)
- Structure from motion (SfM):
  - 2+ pictures -> cameras, pointcloud

# Our goal: Recovery of 3D structure

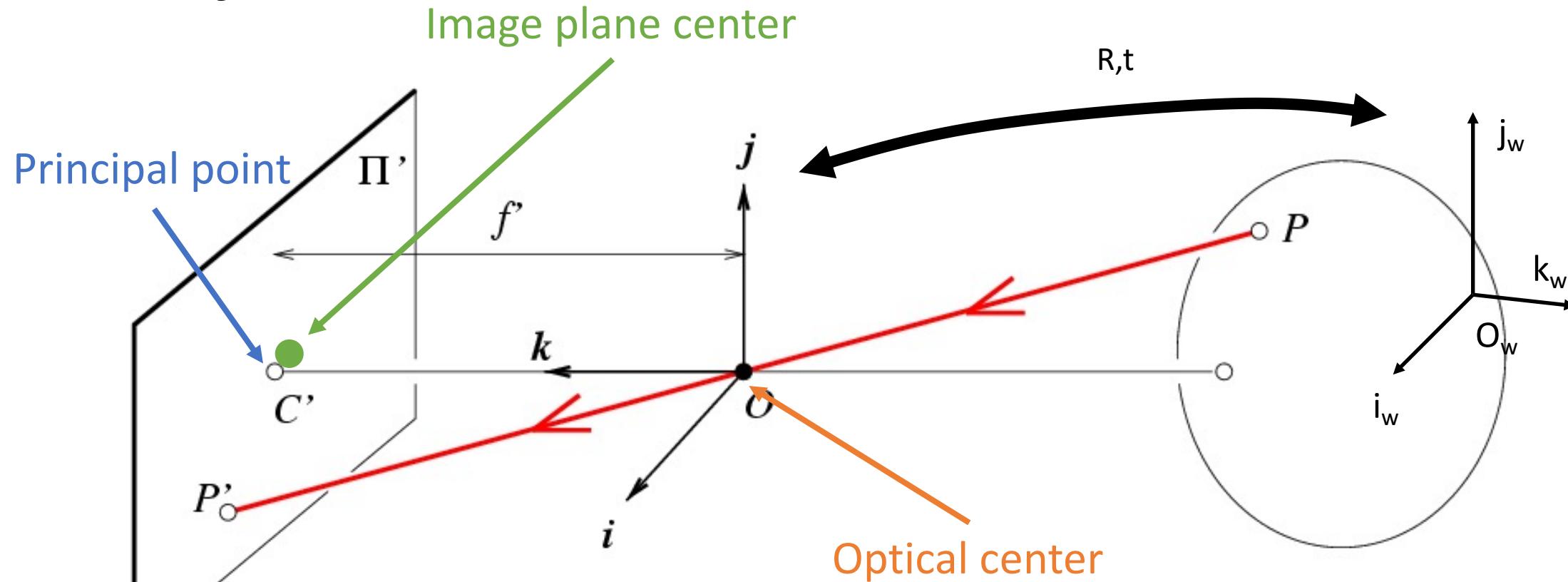
- When certain assumptions hold, we can recover structure from a single view
- In general, we need *multi-view geometry*



[Image source](#)

- But first, we need to understand the geometry of a single camera...

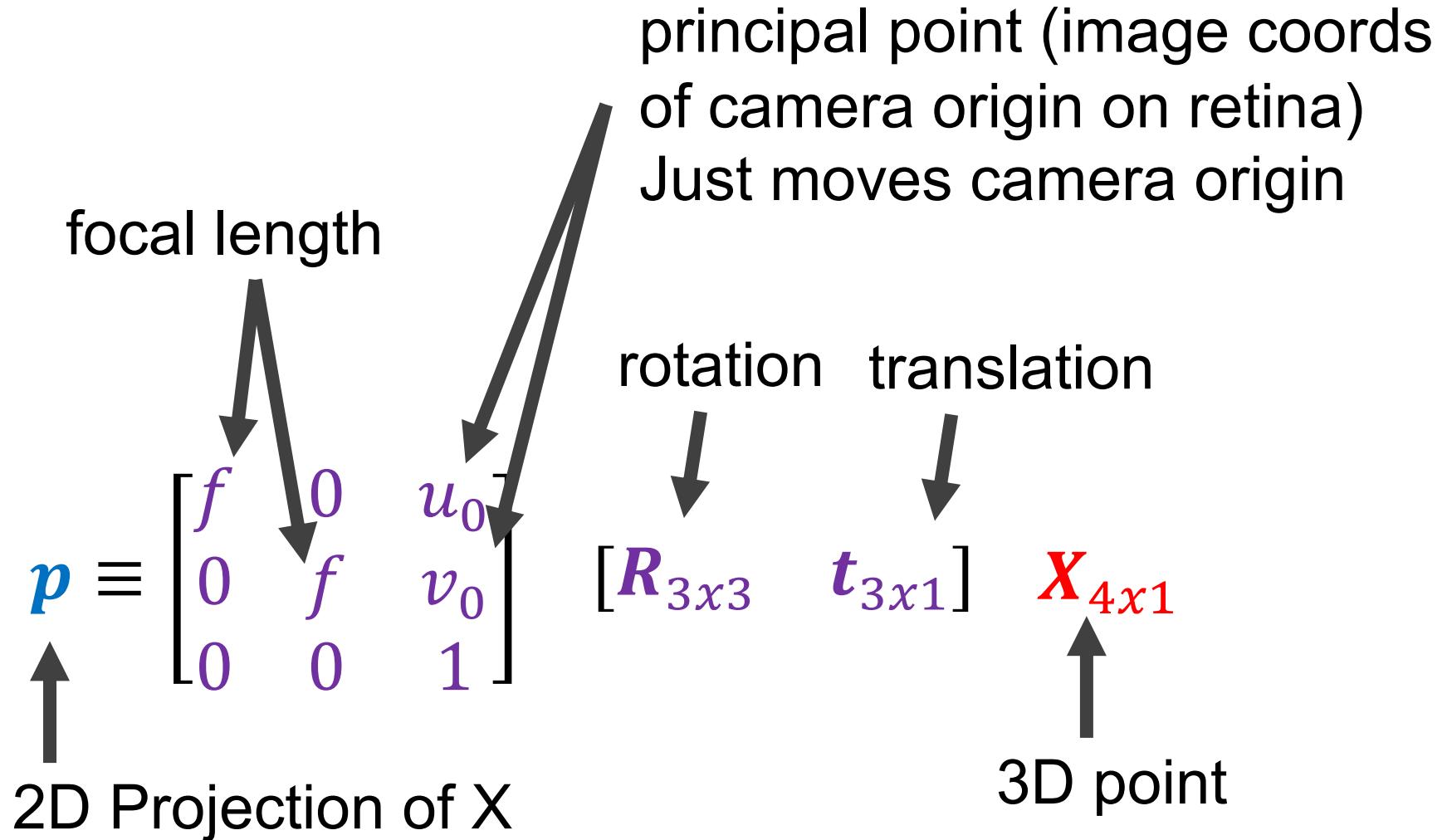
# Projection matrix



$$\mathbf{x} = \mathbf{K}[\mathbf{R} \quad \mathbf{t}] \mathbf{X}$$

$\mathbf{x}$ : Image Coordinates:  $(u, v, 1)$   
 $\mathbf{K}$ : Intrinsic Matrix (3x3)  
 $\mathbf{R}$ : Rotation (3x3)  
 $\mathbf{t}$ : Translation (3x1)  
 $\mathbf{X}$ : World Coordinates:  $(X, Y, Z, 1)$

# Typical Perspective Model



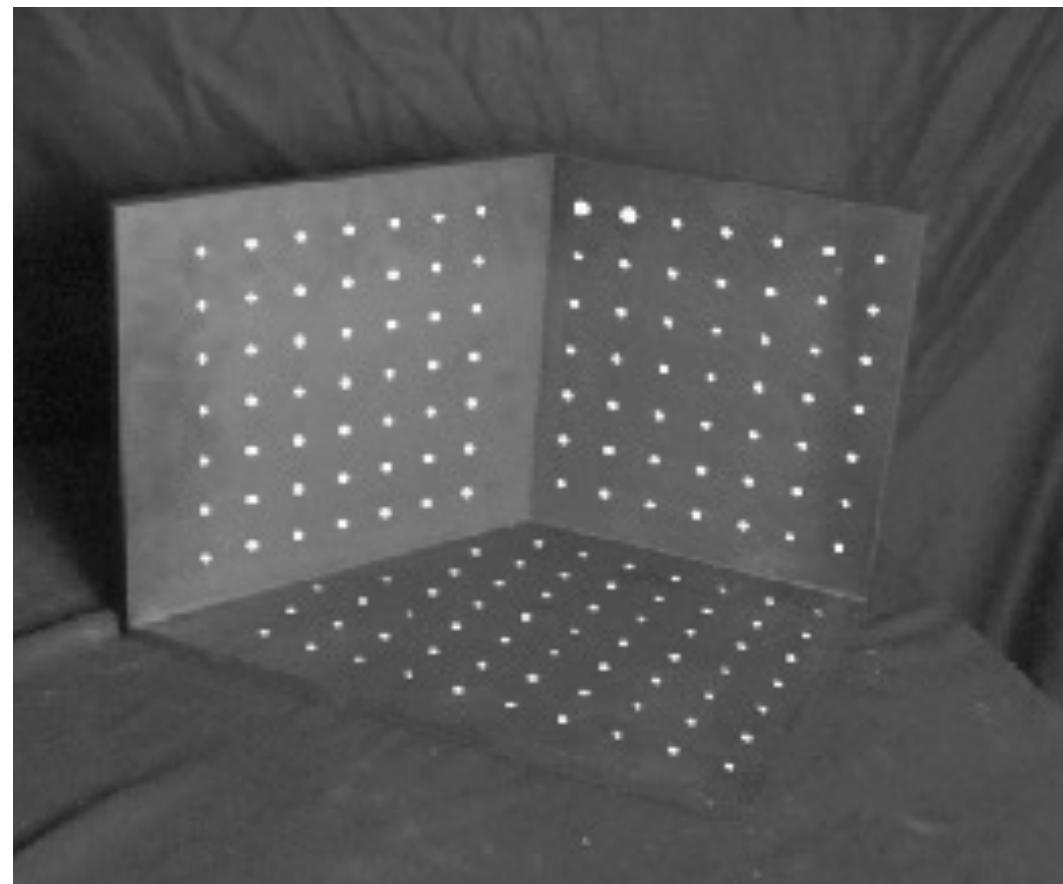
# Camera Calibration

$$\mathbf{p} = \begin{bmatrix} f & 0 & u_0 \\ 0 & f & v_0 \\ 0 & 0 & 1 \end{bmatrix} \quad [\mathbf{R}_{3x3} \quad \mathbf{t}_{3x1}] \quad \mathbf{X}_{4x1}$$
$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \mathbf{M}_{3x4} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

Pairs of  $[X, Y, Z]$  and  $[u, v]$   $\rightarrow$  eqns to constrain  $\mathbf{M}$   
How do I get  $[X, Y, Z]$ ,  $[u, v]$ ?

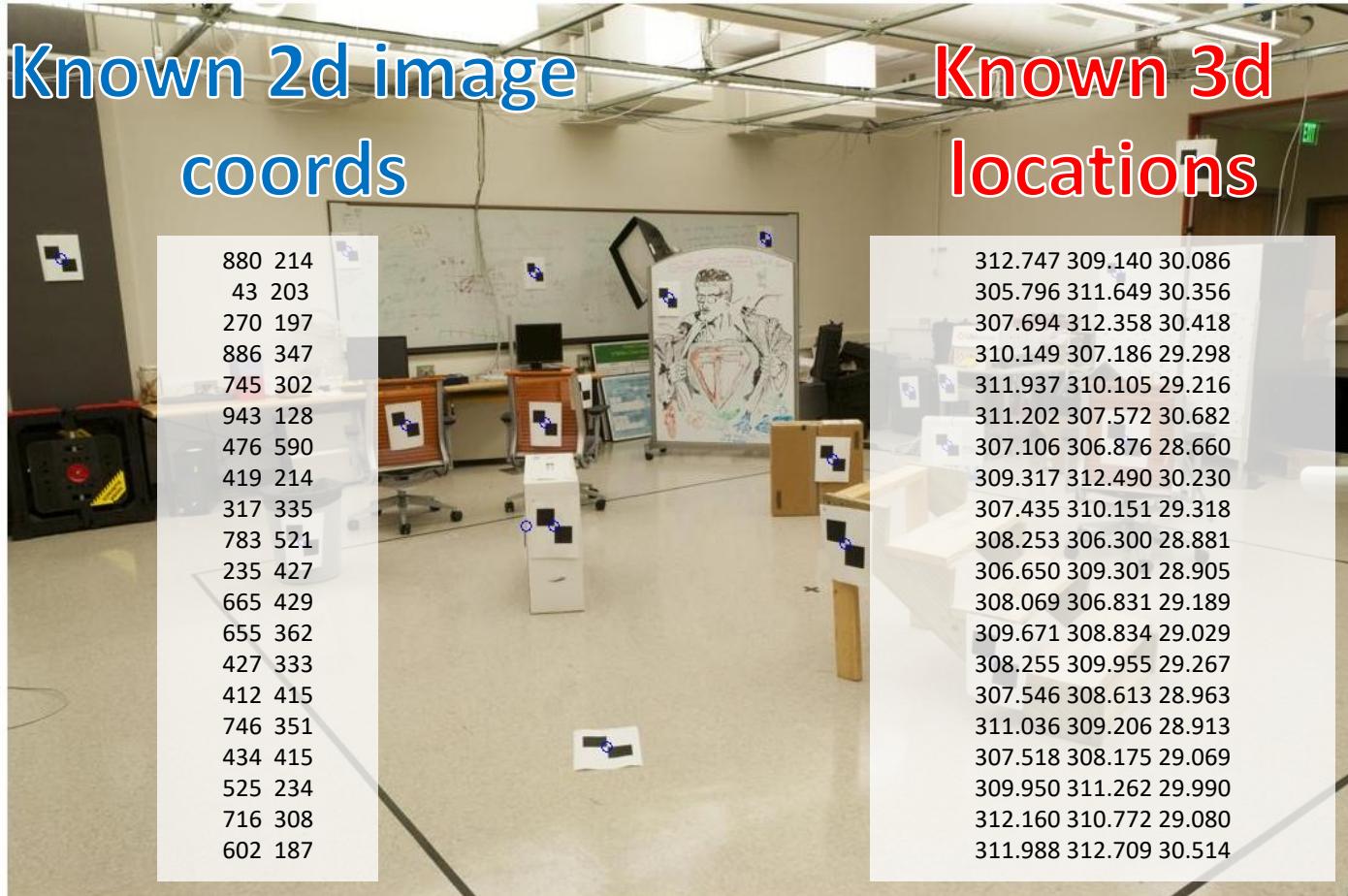
# Camera Calibration

A funny object with multiple planes.



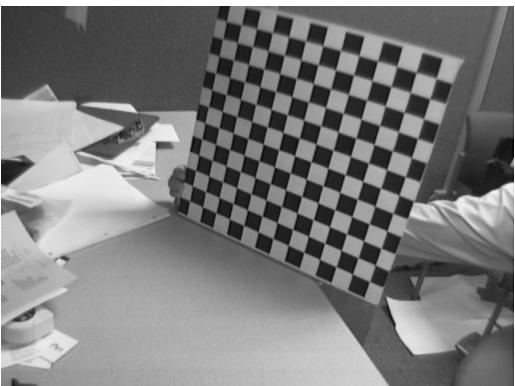
# Camera Calibration Targets

Using a tape measure

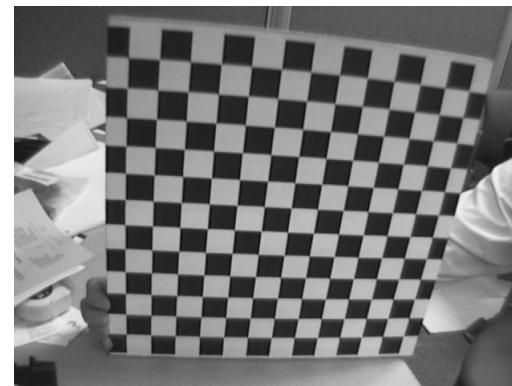


# Camera Calibration Targets

A set of views of a plane (not covered today)

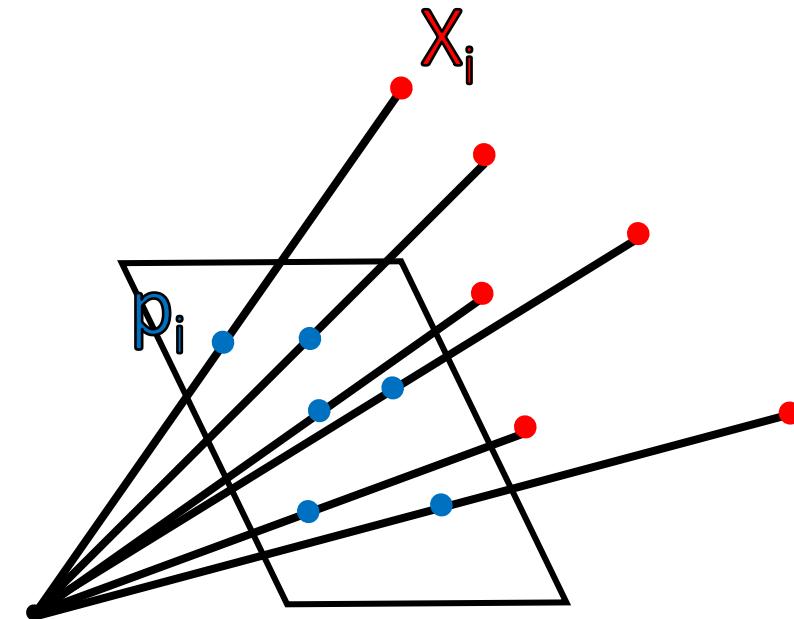
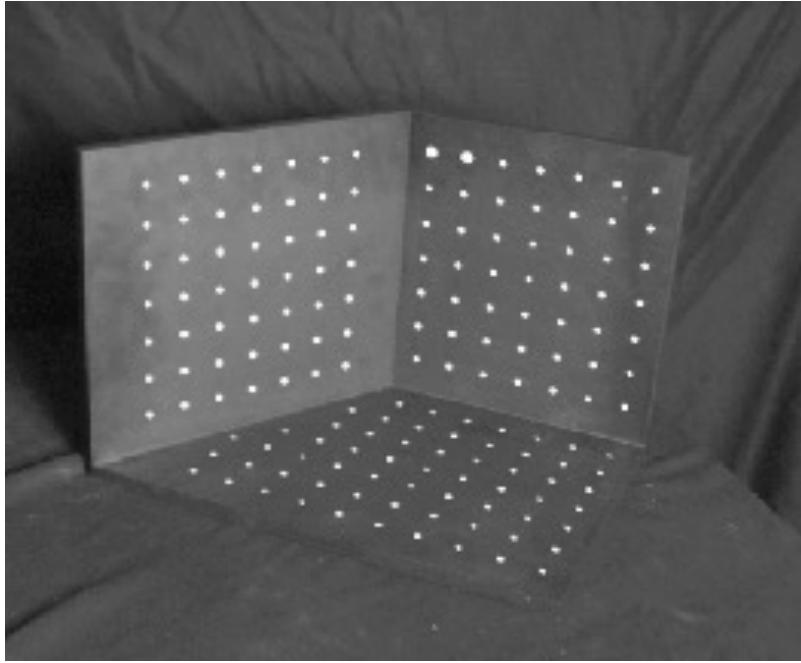


• • •



# Camera calibration

- Given  $n$  points with known 3D coordinates  $\mathbf{X}_i$  and known image projections  $\mathbf{p}_i$ , estimate the camera parameters



# Camera Calibration: Linear Method

$$\mathbf{p}_i \equiv \mathbf{M}\mathbf{X}_i$$

Remember (from geometry): this implies  $\mathbf{M}\mathbf{X}_i$  &  $\mathbf{p}_i$  are proportional/scaled copies of each other

$$\mathbf{p}_i = \lambda \mathbf{M}\mathbf{X}_i, \lambda \neq 0$$

Remember (from homography fitting): this implies their cross product is 0

$$\mathbf{p}_i \times \mathbf{M}\mathbf{X}_i = 0$$

# Camera Calibration: Linear Method

$$\mathbf{p}_i \times \mathbf{M} \mathbf{X}_i = 0$$

$$\begin{bmatrix} u_i \\ v_i \\ 1 \end{bmatrix} \times \begin{bmatrix} \mathbf{M}_1 \mathbf{X}_i \\ \mathbf{M}_2 \mathbf{X}_i \\ \mathbf{M}_3 \mathbf{X}_i \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

...Some tedious math occurs...  
(see Homography derivation)

$$\begin{bmatrix} \mathbf{0}^T & -\mathbf{X}_i^T & v_i \mathbf{X}_i^T \\ \mathbf{X}_i^T & \mathbf{0}^T & -u_i \mathbf{X}_i^T \\ -v_i \mathbf{X}_i^T & u_i \mathbf{X}_i^T & \mathbf{0}^T \end{bmatrix} \begin{bmatrix} \mathbf{M}_1^T \\ \mathbf{M}_2^T \\ \mathbf{M}_3^T \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

# Camera Calibration: Linear Method

$$\begin{bmatrix} \mathbf{0}^T & -\mathbf{X}_i^T & v_i \mathbf{X}_i^T \\ \mathbf{X}_i^T & \mathbf{0}^T & -u_i \mathbf{X}_i^T \\ -v_i \mathbf{X}_i^T & u_i \mathbf{X}_i^T & \mathbf{0}^T \end{bmatrix} \begin{bmatrix} \mathbf{M}_1^T \\ \mathbf{M}_2^T \\ \mathbf{M}_3^T \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

How many linearly independent equations?

2

How many equations per  $[\mathbf{u}, \mathbf{v}] + [\mathbf{X}, \mathbf{Y}, \mathbf{Z}]$  pair?

2

If  $\mathbf{M}$  is  $3 \times 4$ , how many degrees of freedom?

11

# Camera Calibration: Linear Method

$$\begin{bmatrix} \mathbf{0}^T & \mathbf{X}_1^T & -v_1 \mathbf{X}_1^T \\ \mathbf{X}_1^T & \mathbf{0}^T & -u_1 \mathbf{X}_1^T \\ \dots & \dots & \dots \\ \mathbf{0}^T & \mathbf{X}_n^T & -v_n \mathbf{X}_n^T \\ \mathbf{X}_n^T & \mathbf{0}^T & -u_n \mathbf{X}_n^T \end{bmatrix} \begin{bmatrix} M_1^T \\ M_2^T \\ M_3^T \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

How do we solve problems of the form

$$\arg \min \|A\mathbf{n}\|_2^2, \|\mathbf{n}\|_2^2 = 1 ?$$

Eigenvector of  $\mathbf{A}^T \mathbf{A}$  with smallest eigenvalue

# Camera calibration: Linear method

$$\begin{bmatrix} \mathbf{0}^T & \mathbf{X}_1^T & -v_1 \mathbf{X}_1^T \\ \mathbf{X}_1^T & \mathbf{0}^T & -u_1 \mathbf{X}_1^T \\ \dots & \dots & \dots \\ \mathbf{0}^T & \mathbf{X}_n^T & -v_n \mathbf{X}_n^T \\ \mathbf{X}_n^T & \mathbf{0}^T & -u_n \mathbf{X}_n^T \end{bmatrix} \begin{bmatrix} M_1^T \\ M_2^T \\ M_3^T \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

- Note: for coplanar points that satisfy  $\Pi^T \mathbf{X} = 0$ , we will get degenerate solutions  $(\Pi, 0, 0)$ ,  $(0, \Pi, 0)$ , or  $(0, 0, \Pi)$

# Camera calibration: Linear vs. nonlinear

- Linear calibration is easy to formulate and solve, but it doesn't directly tell us the camera parameters

$$\begin{bmatrix} \lambda_x \\ \lambda_y \\ \lambda \end{bmatrix} = \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} \quad \text{vs.} \quad \mathbf{x} = \mathbf{K}[\mathbf{R} \quad \mathbf{t}] \mathbf{X}$$

- In practice, non-linear methods are preferred
  - Write down objective function in terms of intrinsic and extrinsic parameters
  - Define error as sum of squared distances between measured 2D points and estimated projections of 3D points
  - Minimize error using Newton's method or other non-linear optimization
  - Can model radial distortion and impose constraints such as known focal length and orthogonality

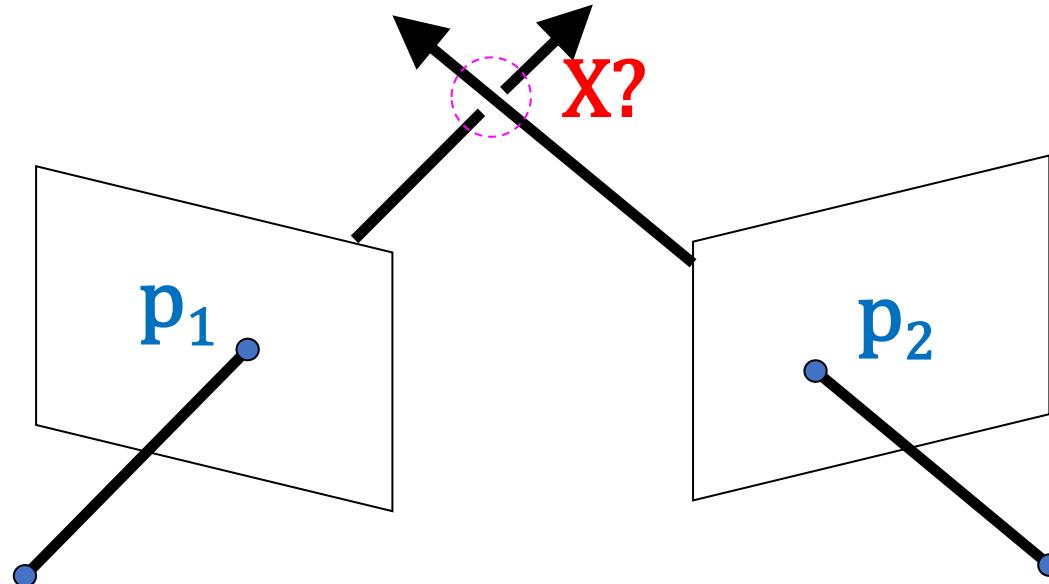
# What Does This Get You?

Given projection  $\mathbf{p}_i$  of unknown 3D point  $\mathbf{X}$  in two or more images (with known cameras  $\mathbf{M}_i$ ), find  $\mathbf{X}$



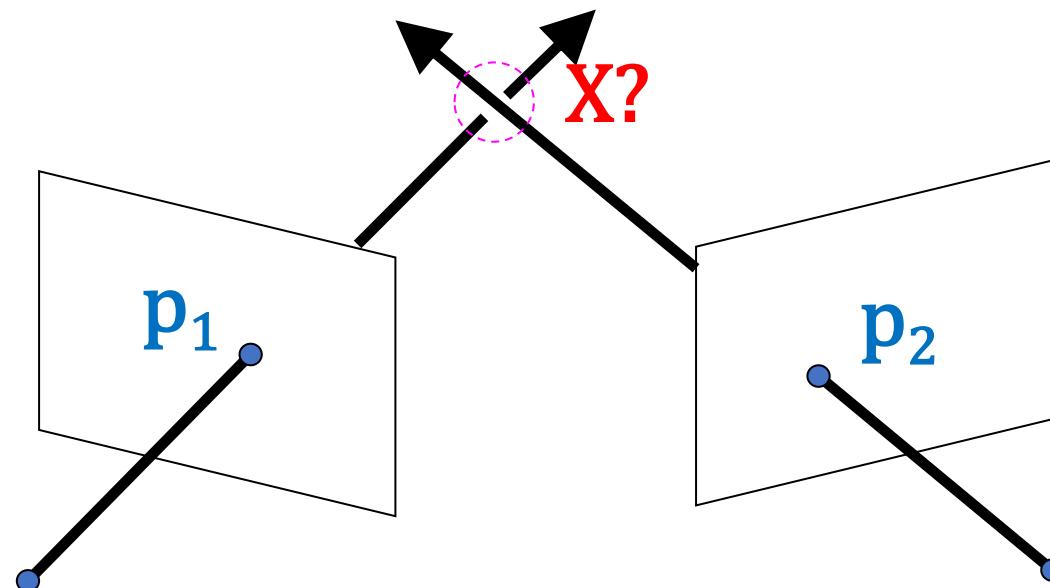
# Triangulation

Given projection  $p_i$  of unknown 3D point  $\mathbf{X}$  in two or more images (with known cameras  $M_i$ ), find  $\mathbf{X}$   
**Why is the calibration here important?**



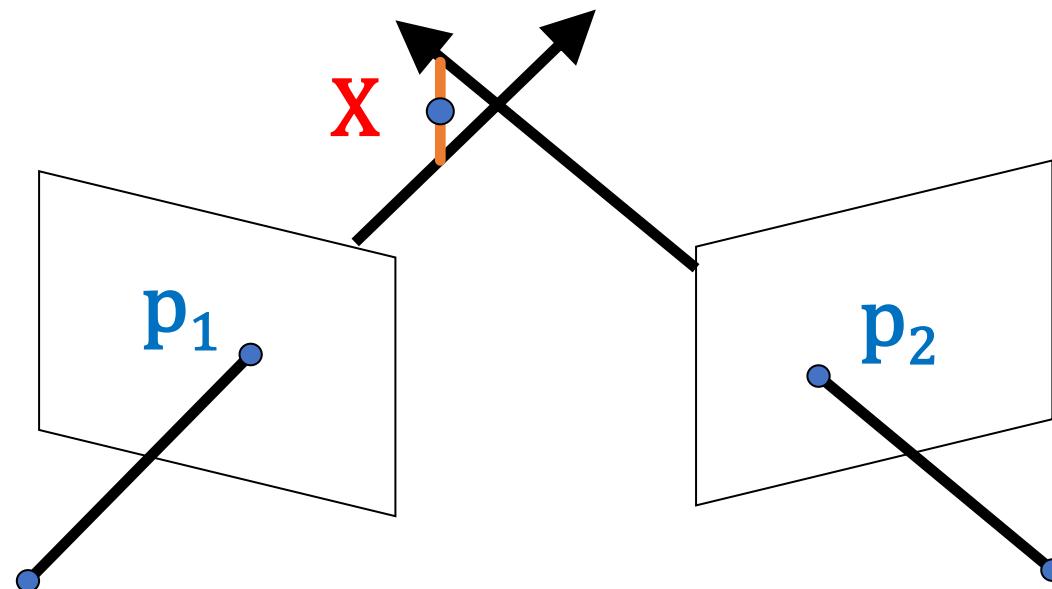
# Triangulation

Rays in principle should intersect, but in practice usually don't exactly due to noise, numerical errors.



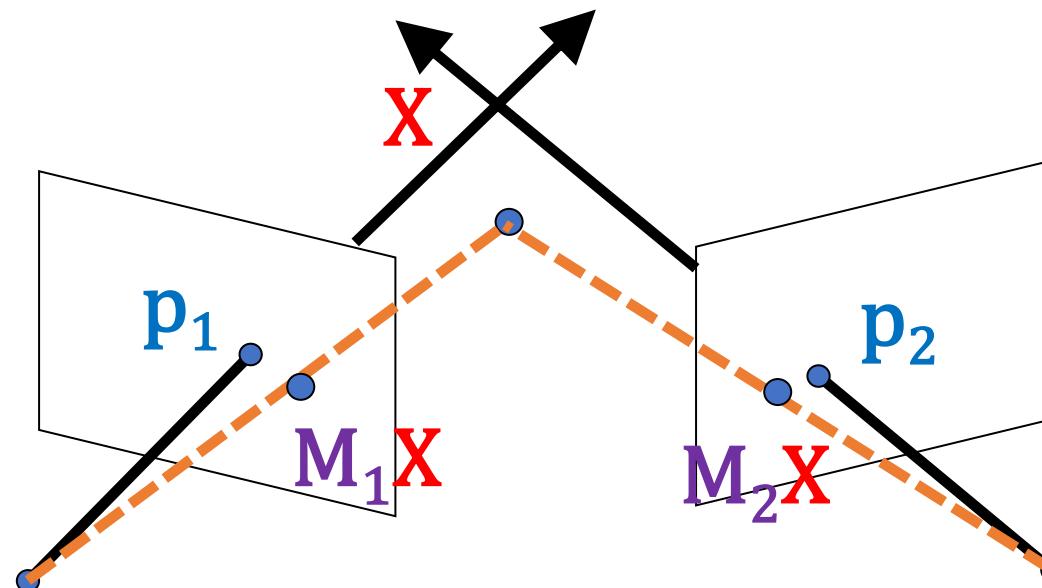
# Triangulation – Geometry

Find shortest segment between viewing rays, set **X** to be the midpoint of the segment.



# Triangulation – Non-linear Optim.

Find  $\mathbf{X}$  minimizing  $d(\mathbf{p}_1, \mathbf{M}_1 \mathbf{X})^2 + d(\mathbf{p}_2, \mathbf{M}_2 \mathbf{X})^2$



# Triangulation – Linear Optimization

$$\begin{aligned} \mathbf{p}_1 &\equiv \mathbf{M}_1 \mathbf{X} & \mathbf{p}_1 \times \mathbf{M}_1 \mathbf{X} = 0 \\ \mathbf{p}_2 &\equiv \mathbf{M}_2 \mathbf{X} & \mathbf{p}_2 \times \mathbf{M}_2 \mathbf{X} = 0 \end{aligned}$$

Cross Prod.  
as matrix

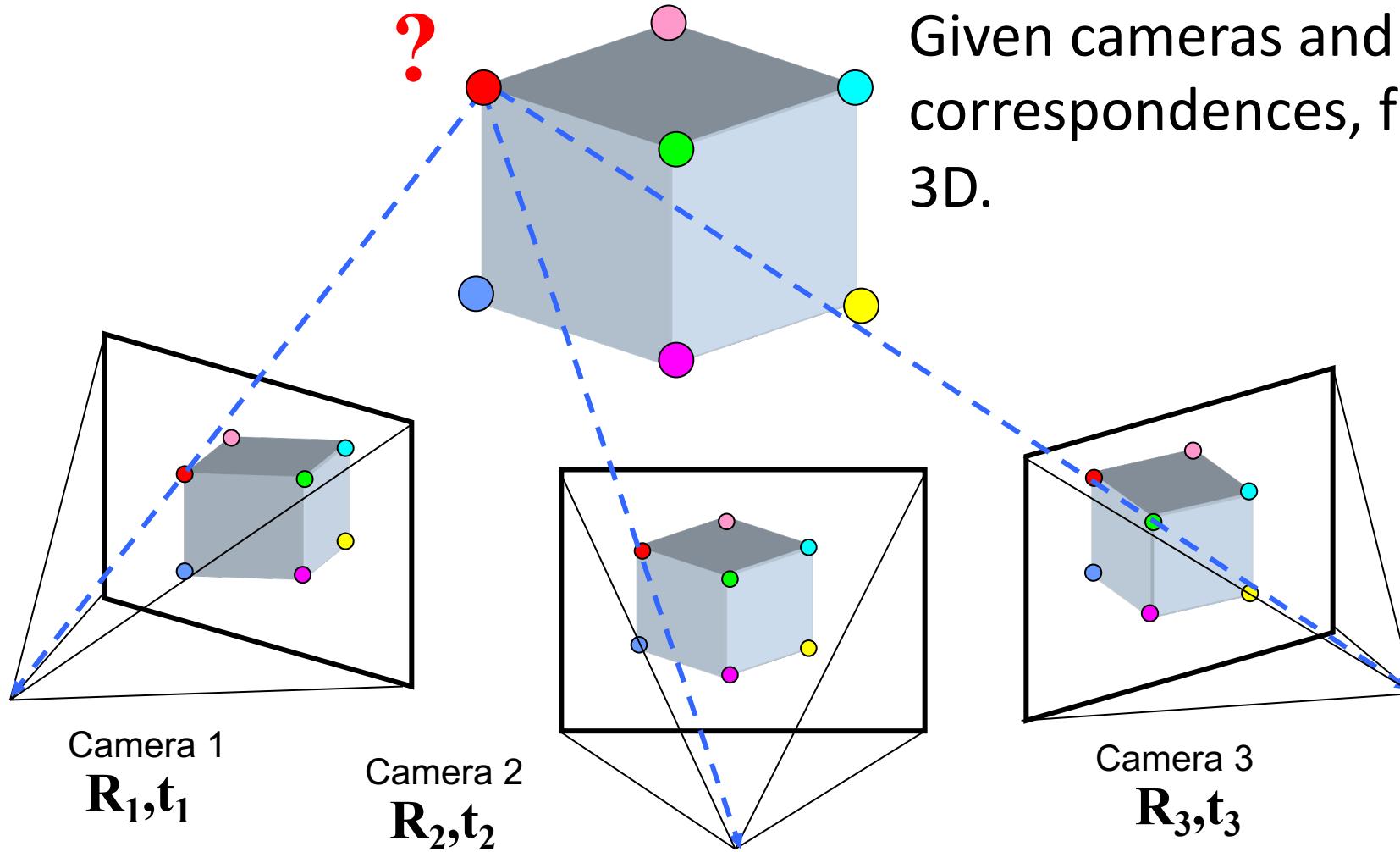
$$\mathbf{a} \times \mathbf{b} = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix} \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} = [\mathbf{a}_x] \mathbf{b}$$

$$\begin{aligned} [\mathbf{p}_{1x}] \mathbf{M}_1 \mathbf{X} &= 0 \\ [\mathbf{p}_{2x}] \mathbf{M}_2 \mathbf{X} &= 0 \end{aligned}$$

$$\begin{aligned} ([\mathbf{p}_{1x}] \mathbf{M}_1) \mathbf{X} &= 0 \\ ([\mathbf{p}_{2x}] \mathbf{M}_2) \mathbf{X} &= 0 \end{aligned}$$

Two eqns per camera  
for 3 unkn. in X

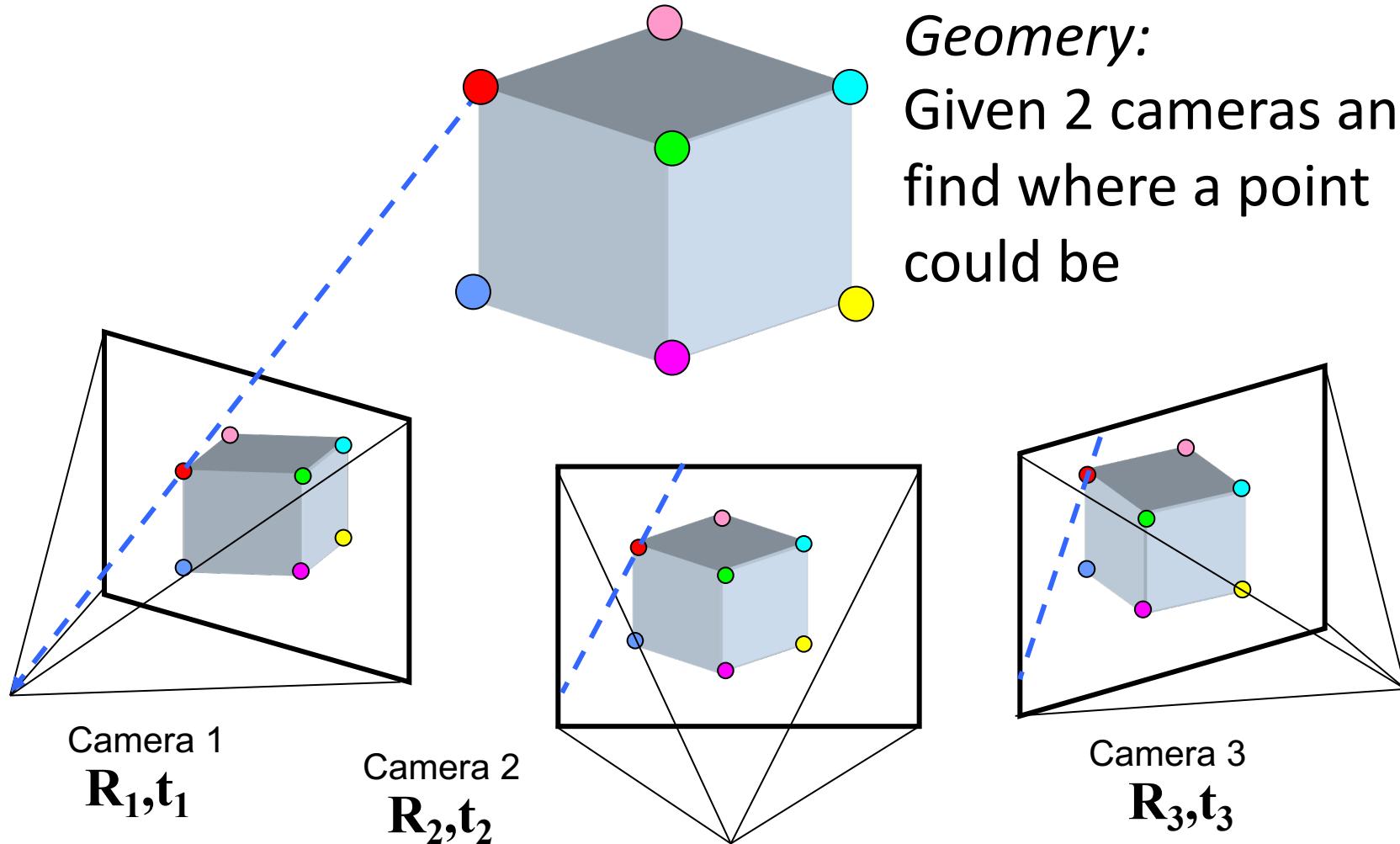
# Multi-view geometry problems



*Recovering structure:*

Given cameras and correspondences, find 3D.

# Multi-view geometry problems



*Stereo/Epipolar*

*Geomery:*

Given 2 cameras and  
find where a point  
could be

# Two-view geometry

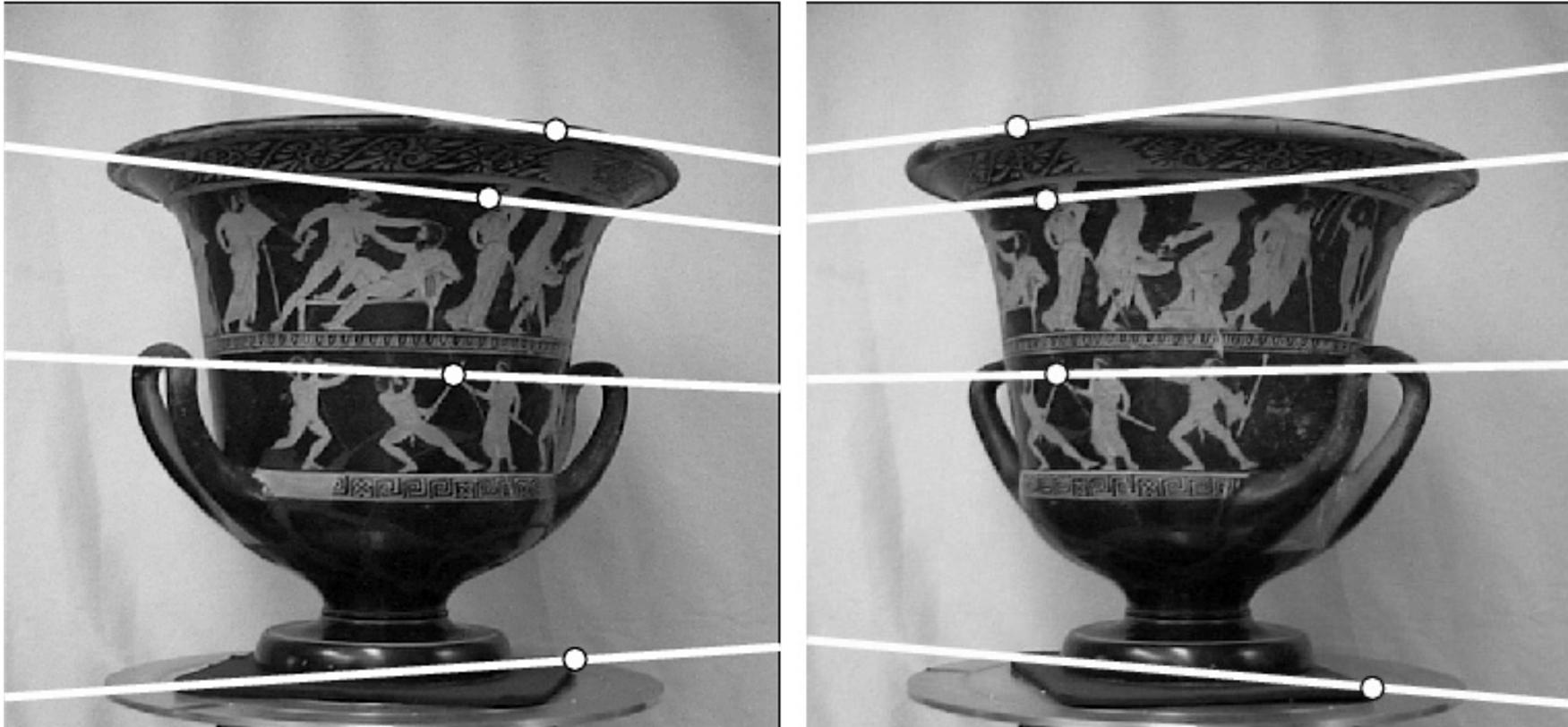
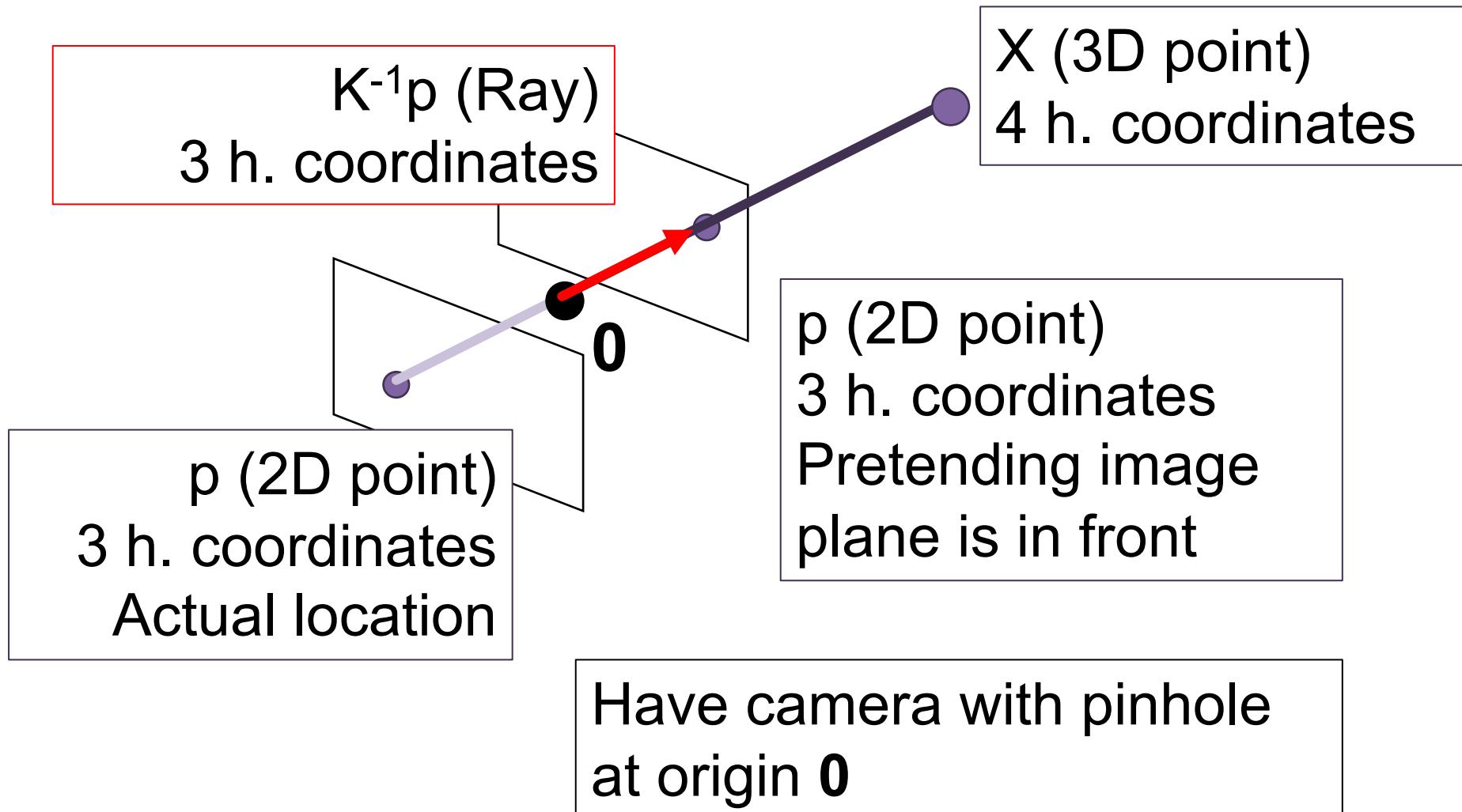
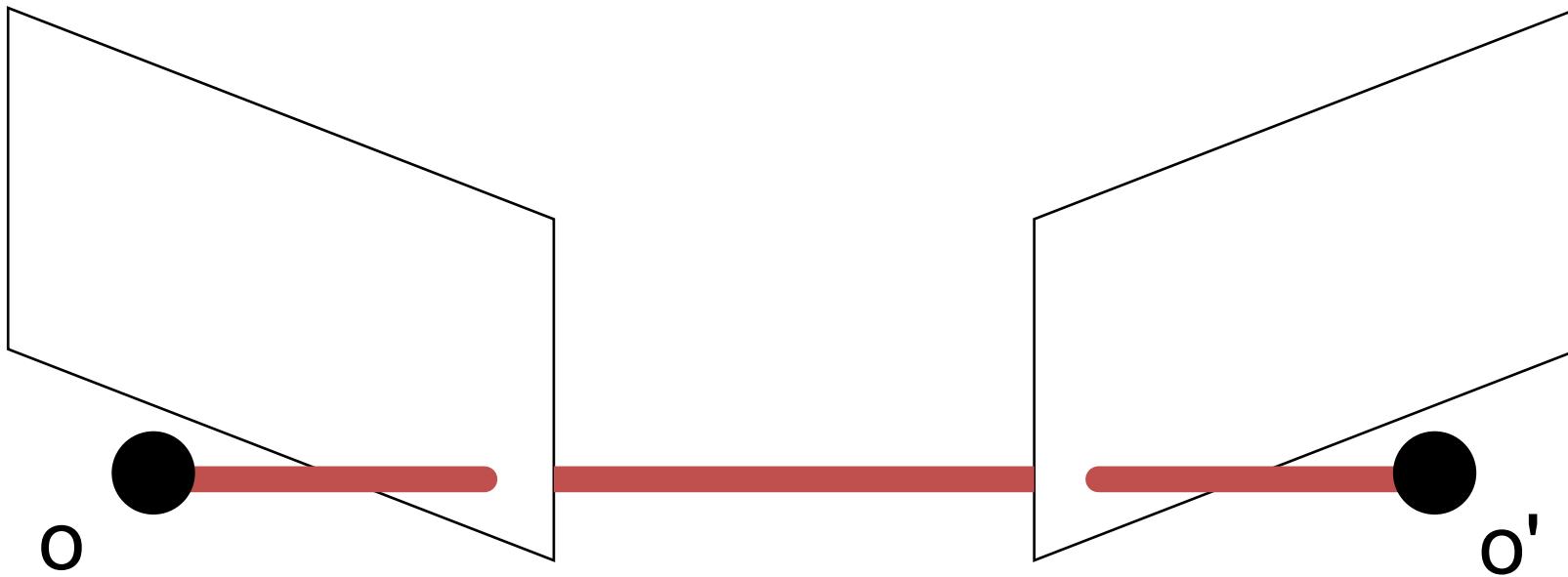


Image Credit: Hartley & Zisserman

# Camera Geometry Reminder

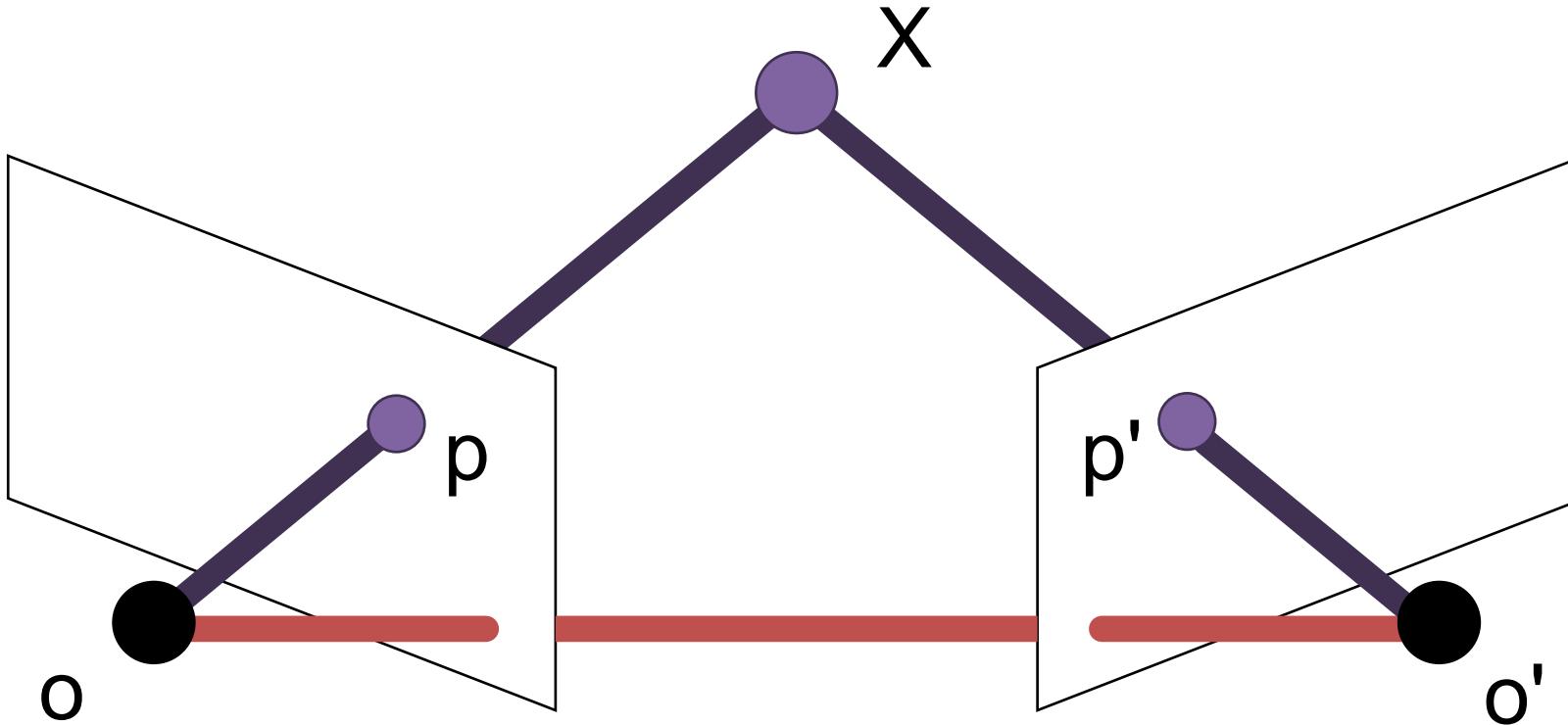


# Epipolar Geometry



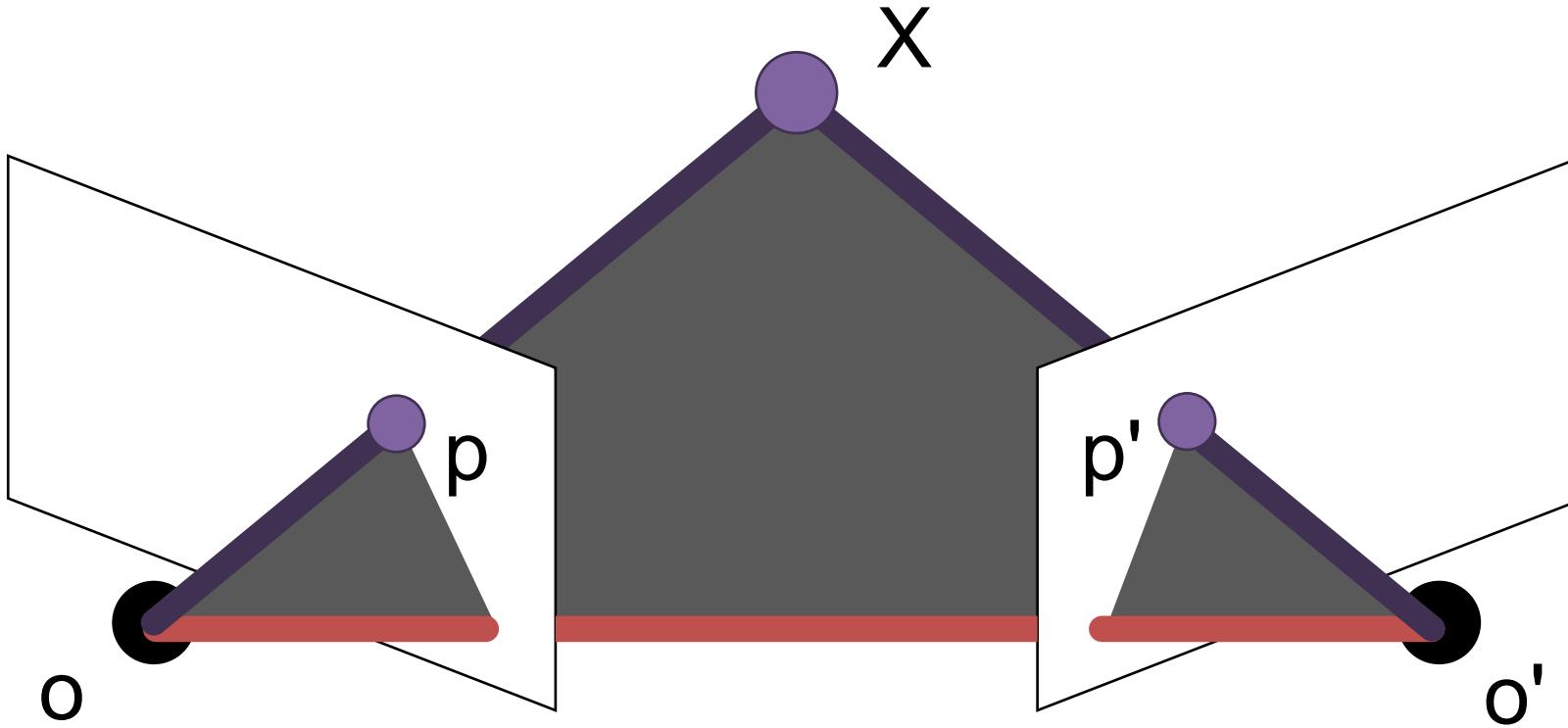
Suppose we have two cameras at origins  $o$ ,  $o'$   
**Baseline** is the line connecting the origins

# Epipolar Geometry



Now add a **point  $X$** , which projects to  $p$  and  $p'$

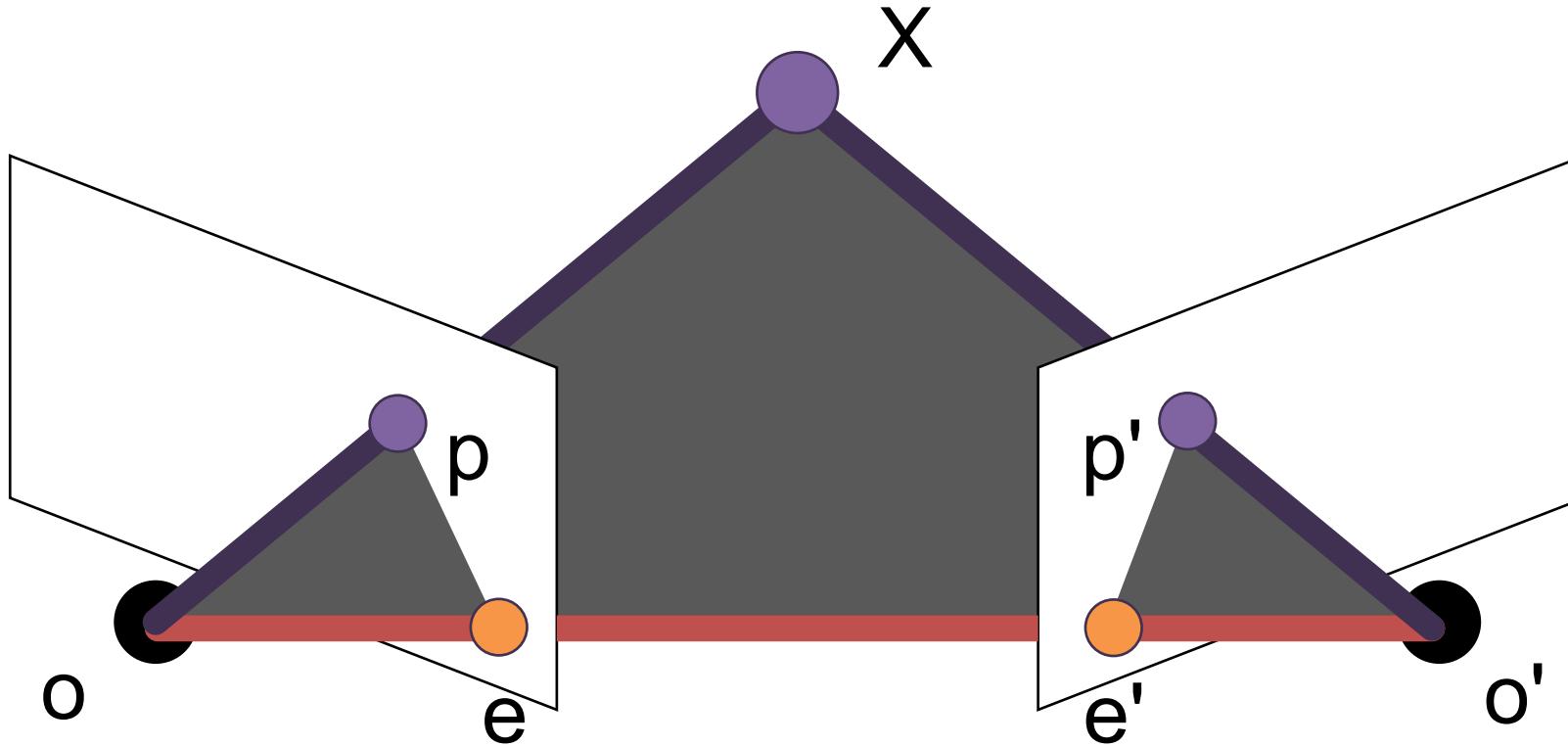
# Epipolar Geometry



The plane formed by  $X$ ,  $o$ , and  $o'$  is called the epipolar plane

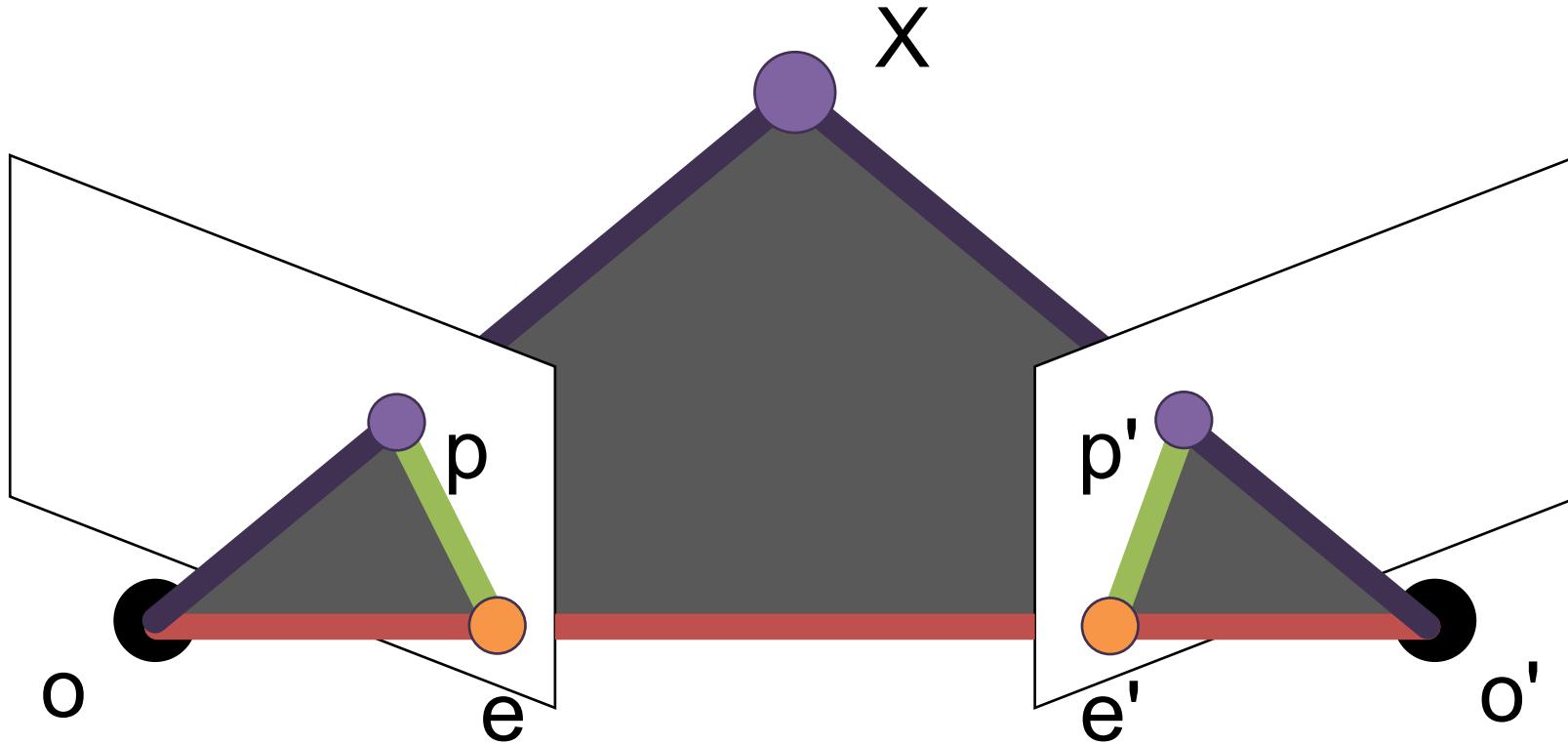
There is a family of planes per  $o$ ,  $o'$

# Epipolar Geometry



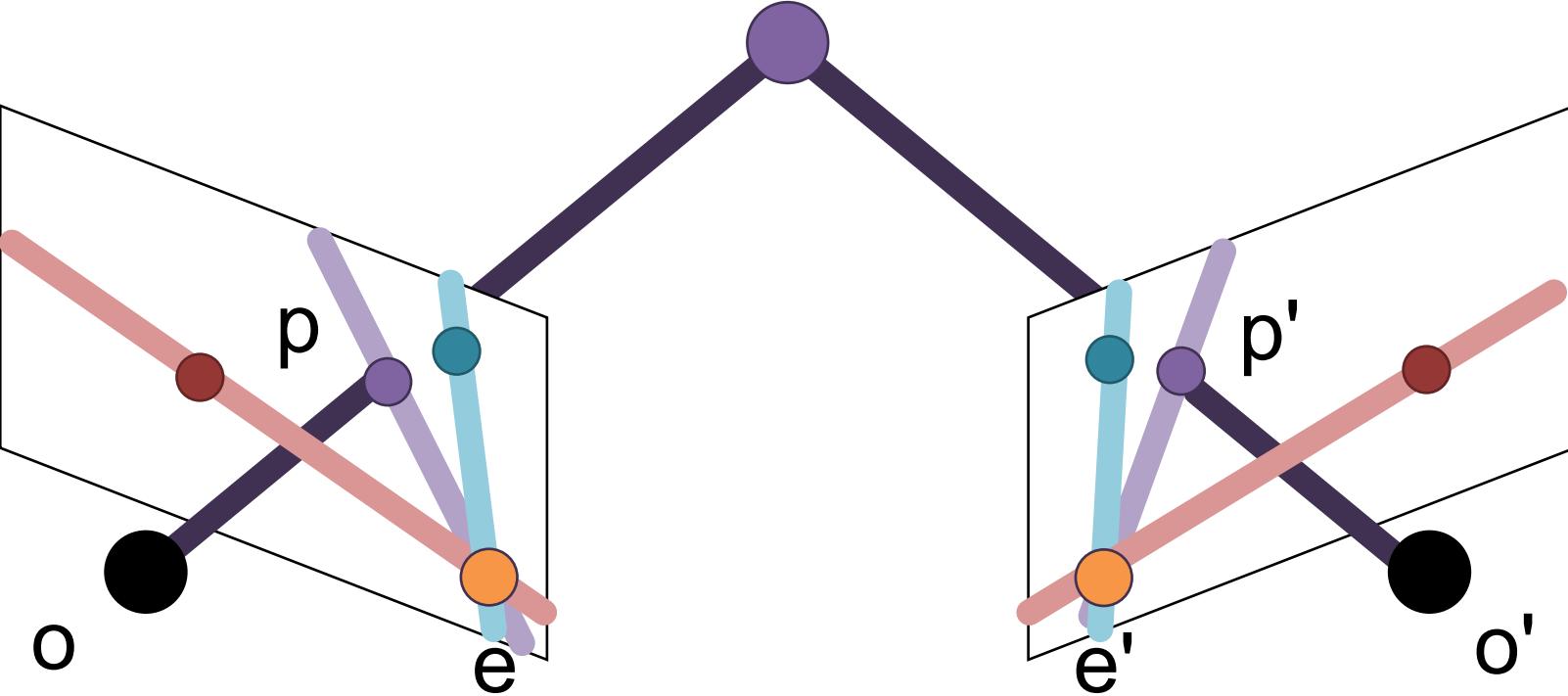
- Epipoles  $e, e'$  are where the baseline intersects the image planes
- Projection of other camera in the image plane

# Epipolar Geometry



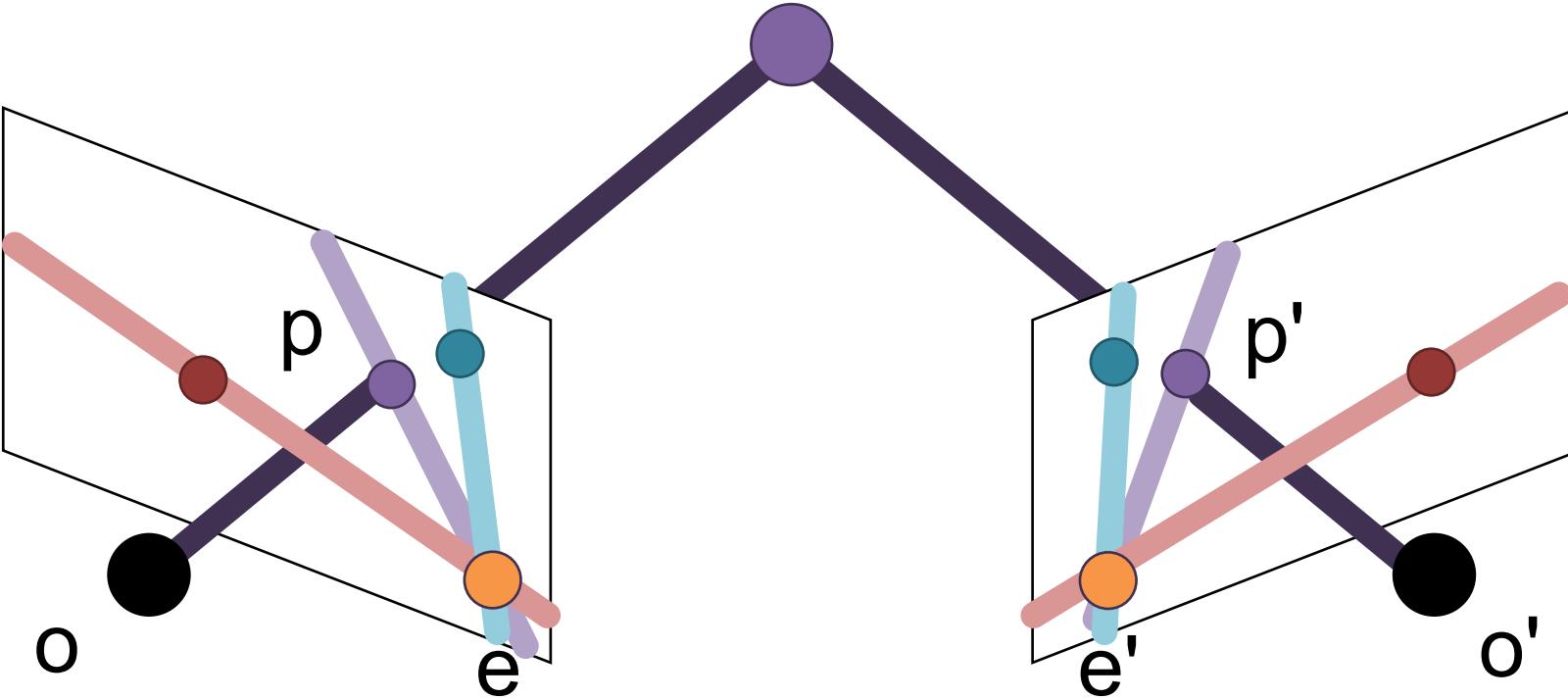
- Epipolar lines go between the epipoles and the projections of the points.
- Intersection of epipolar plane with image plane

# Example: Converging Cameras



Epipoles finite, maybe in image; epipolar lines converge

# Example: Converging Cameras



Epipolar lines come in pairs: given a point  $p$ , we can construct the epipolar line for  $p'$ .

# Example 1: Converging Cameras

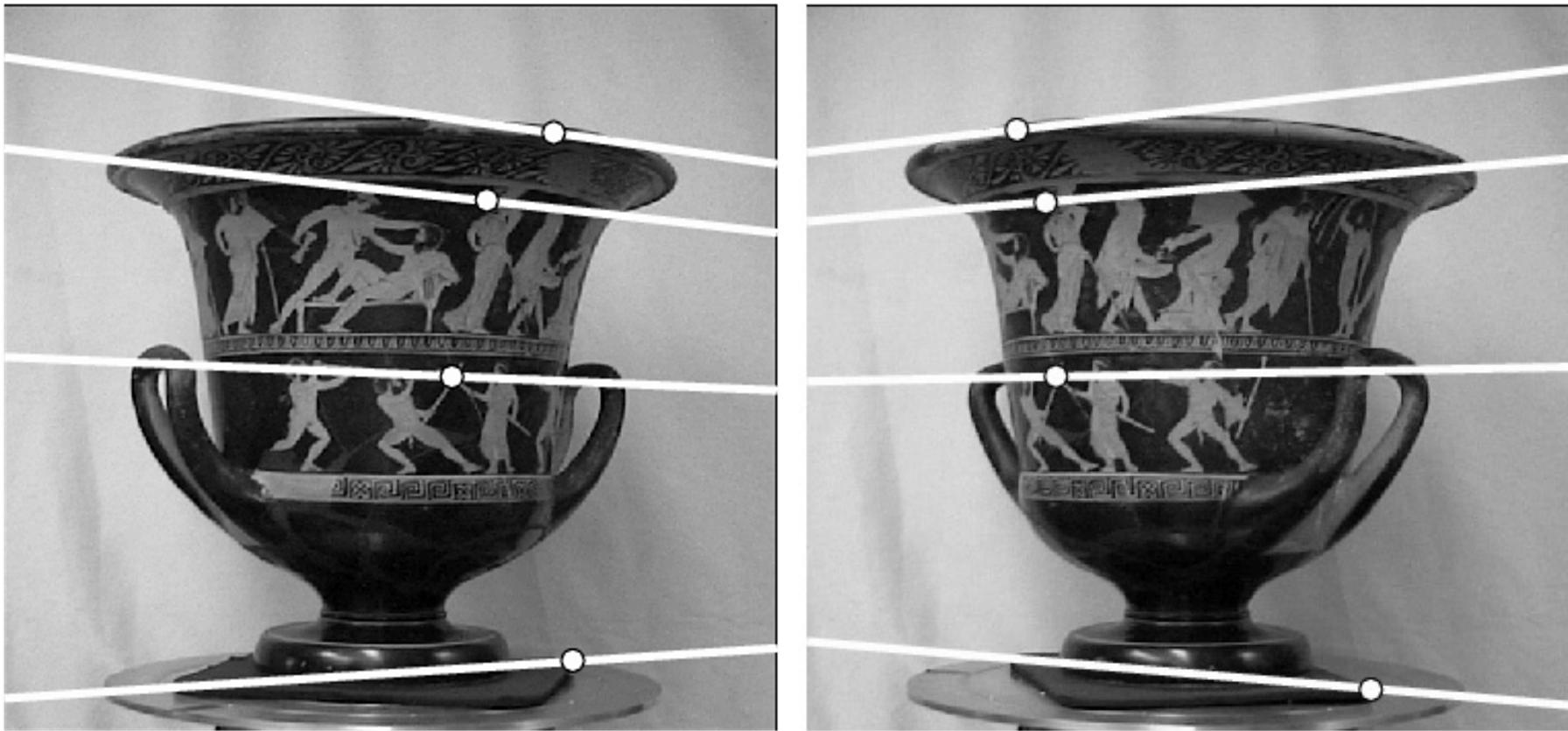
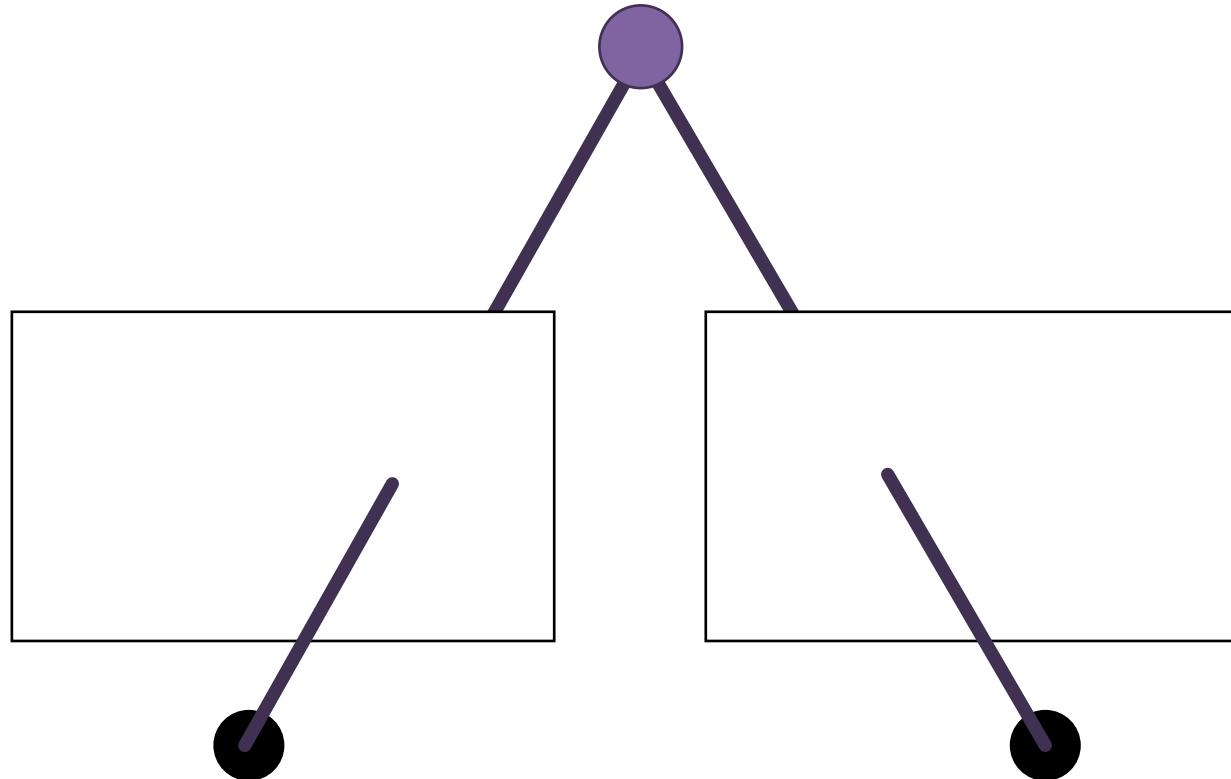


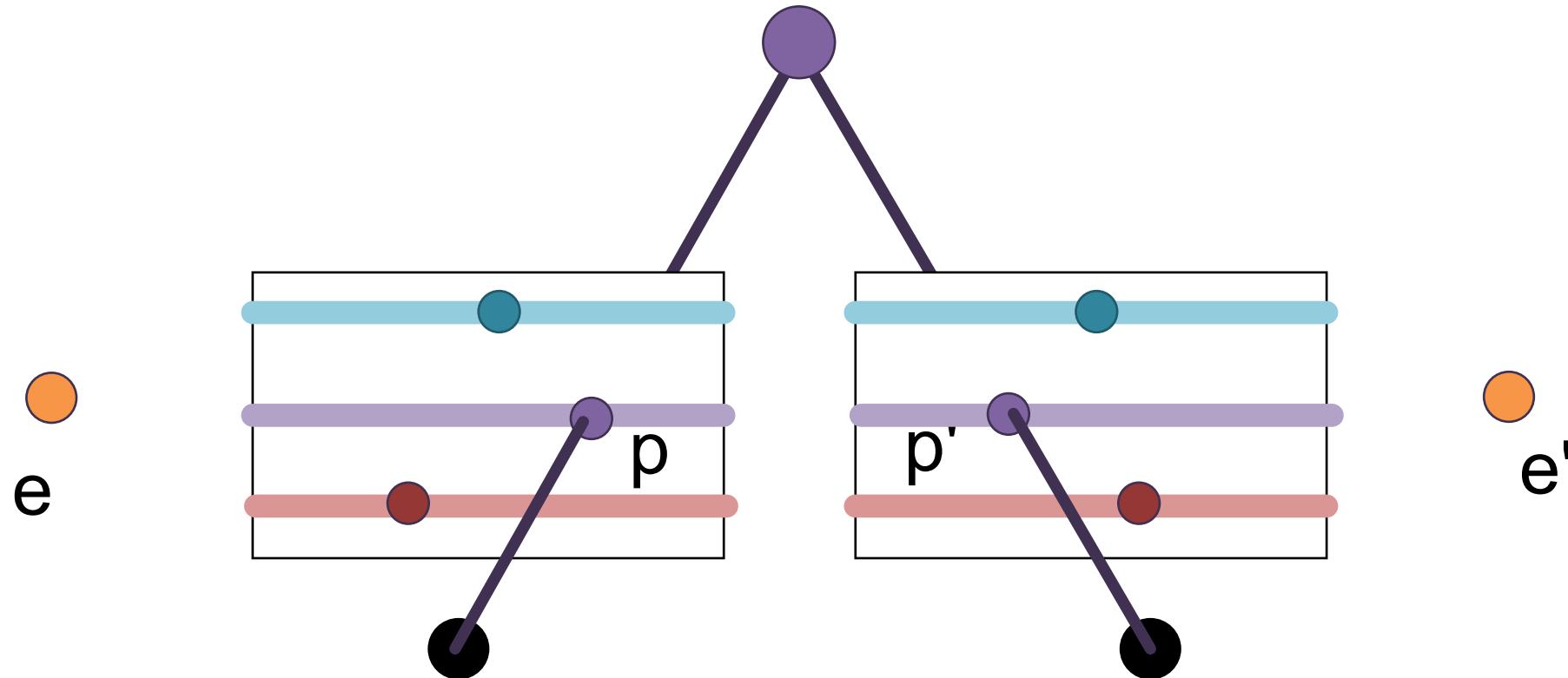
Image Credit: Hartley & Zisserman

# Example: Parallel to Image Plane



Suppose the cameras are both facing outwards.  
**Where are the epipoles (proj. of other camera)?**

# Example: Parallel to Image Plane



Epipoles *infinitely* far away, epipolar lines parallel

# Example: Parallel to Image Plane

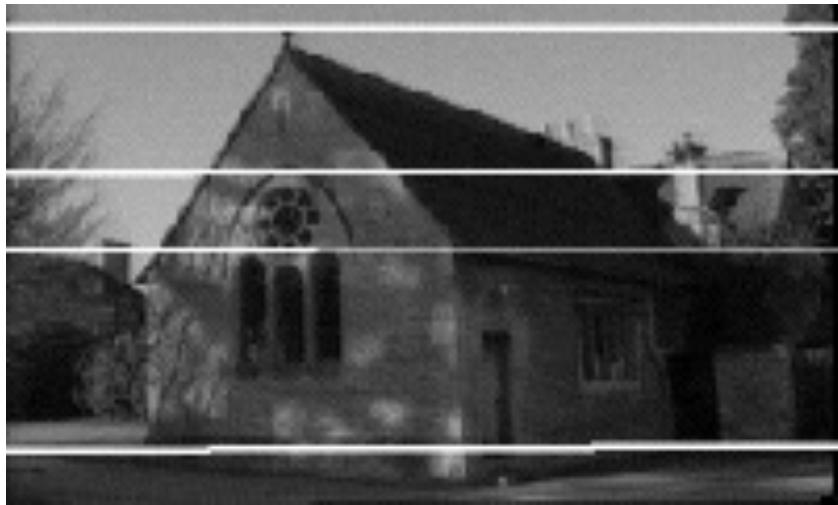


Image Credit: Hartley & Zisserman

# Example: Forward Motion



Image Credit: Hartley & Zisserman

# Example: Forward Motion

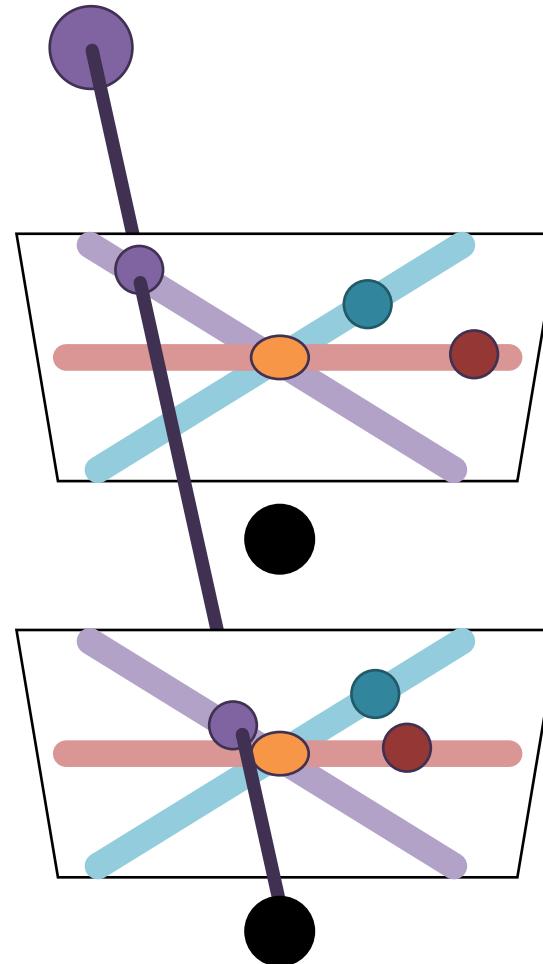


Image Credit: Hartley & Zisserman

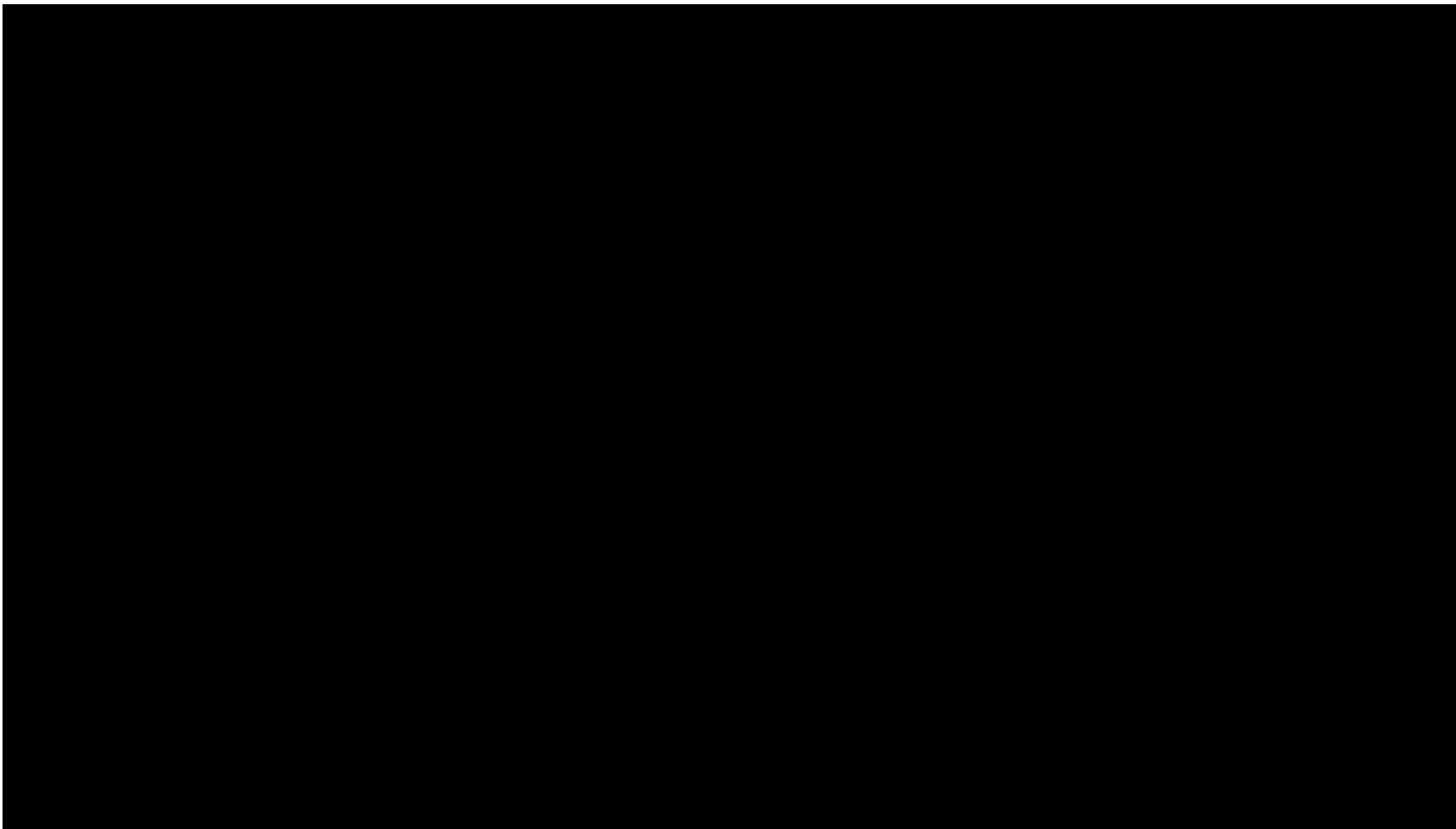
# Example: Forward Motion

Epipole is focus  
of expansion /  
principal point of  
the camera.

Epipolar lines go  
out from  
principal point

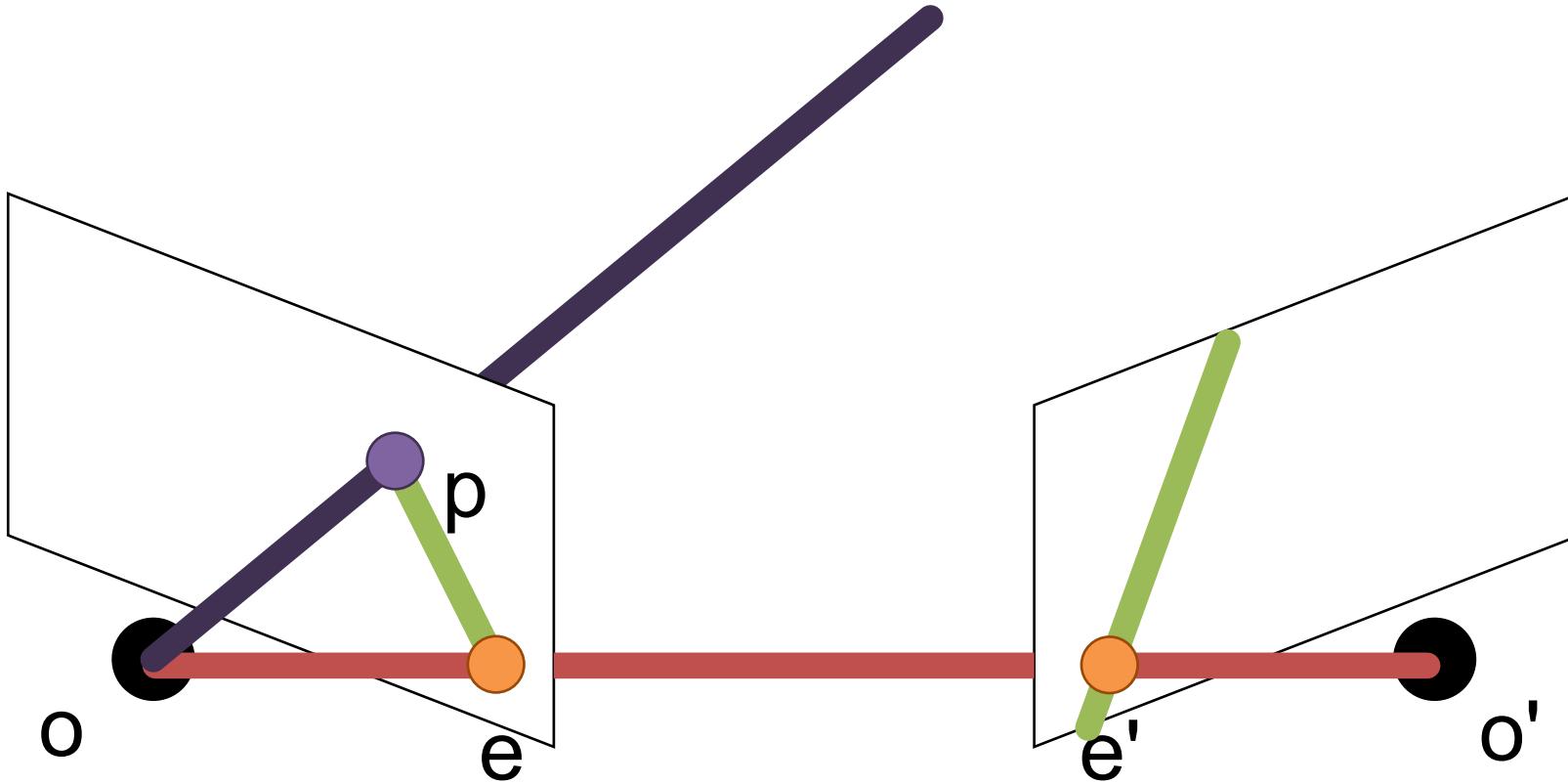


# Motion perpendicular to image plane



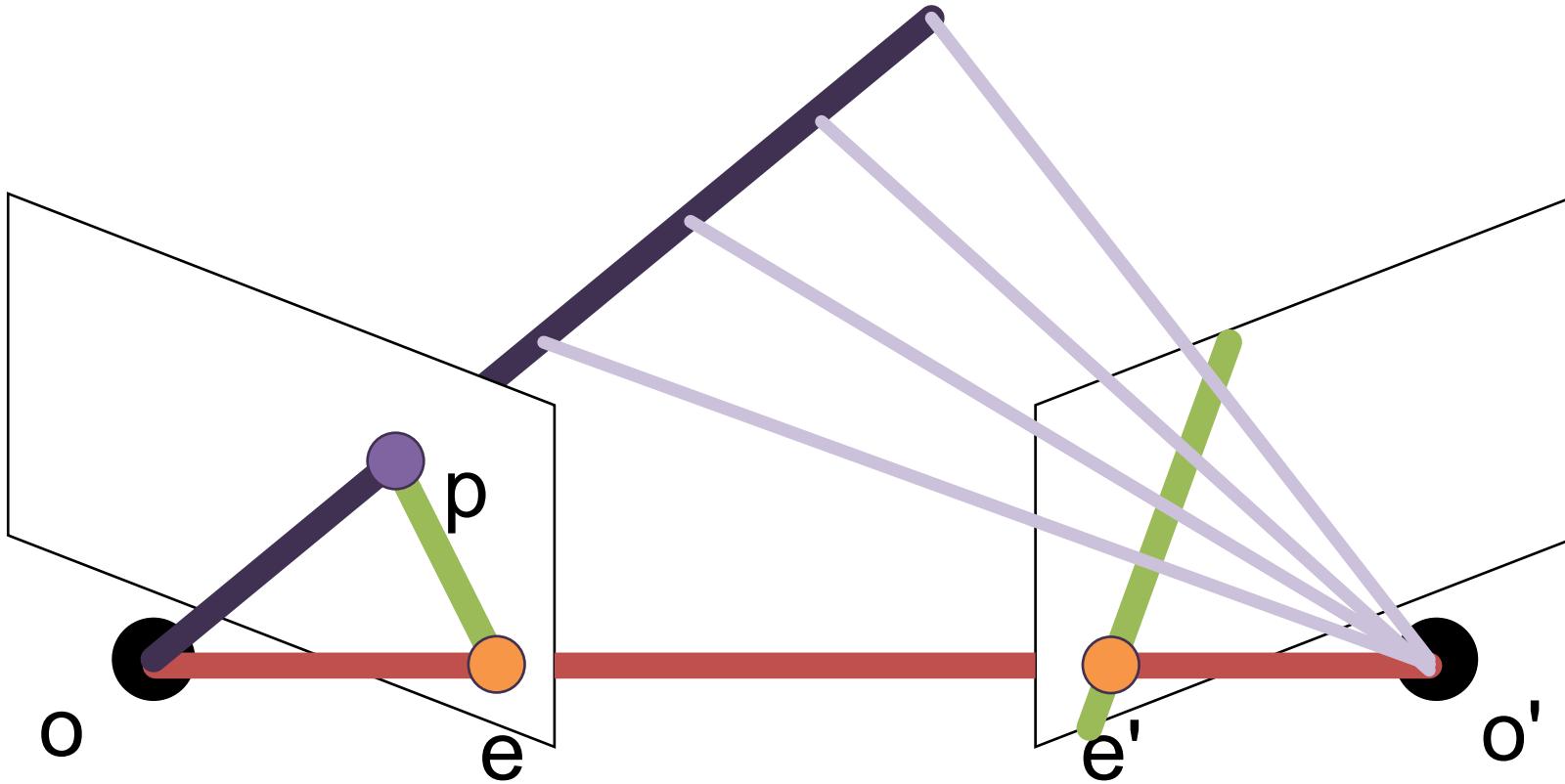
<http://vimeo.com/48425421>

# Epipolar Geometry



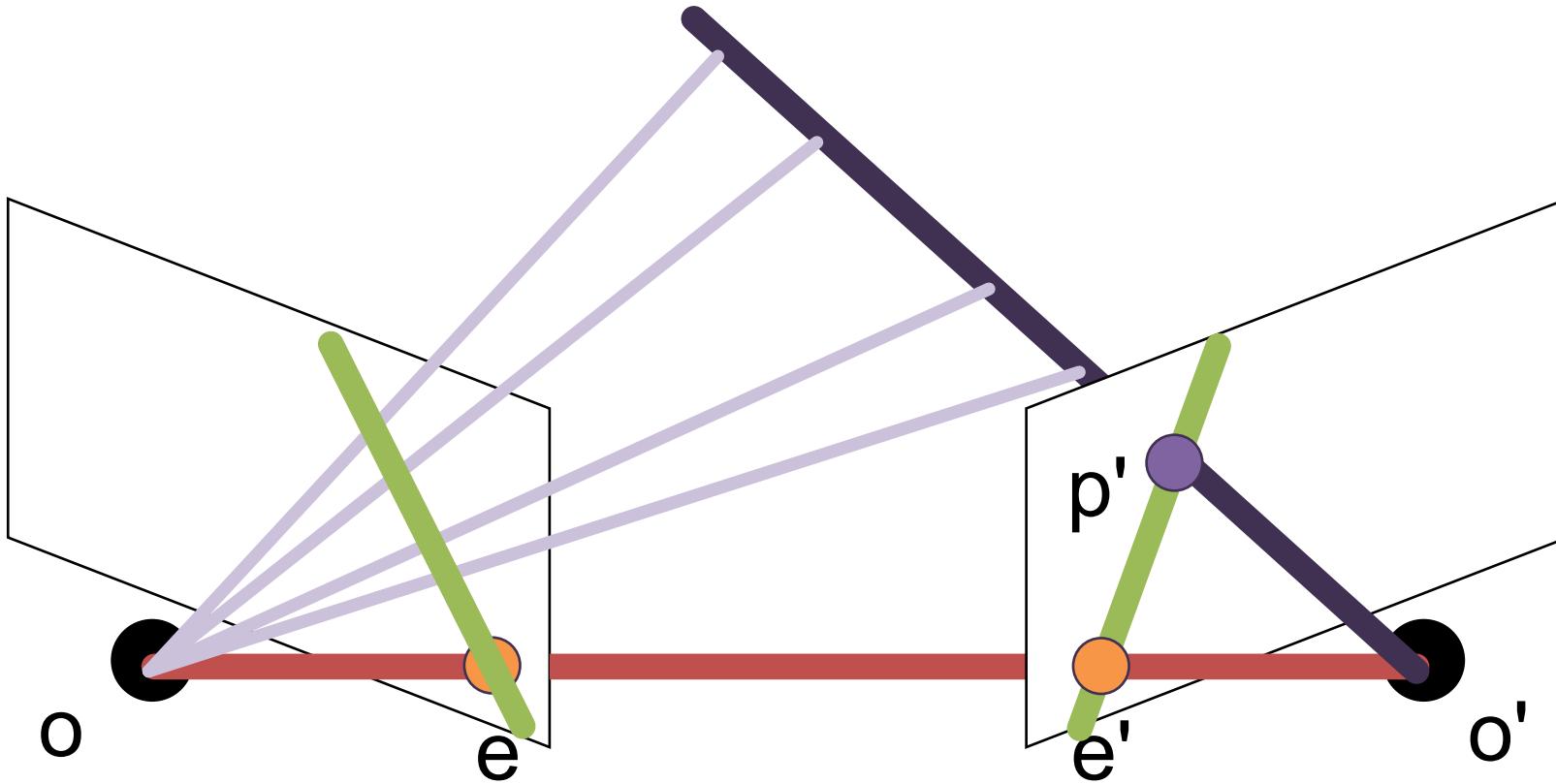
- Suppose we don't know  $X$  and just have  $p$
- Can construct the epipolar line in the other image

# Epipolar Geometry



- Suppose we don't know  $X$  and just have  $p$
- Corresponding  $p'$  is on corresponding epipolar line

# Epipolar Geometry

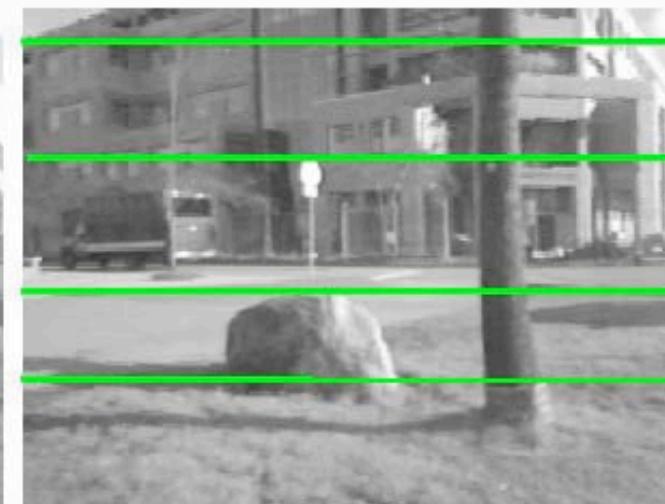
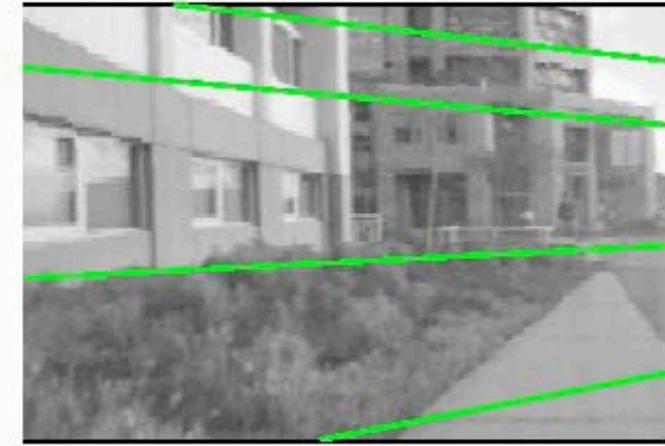


- Suppose we don't know  $X$  and just have  $p'$
- Corresponding  $p$  is on corresponding epipolar line

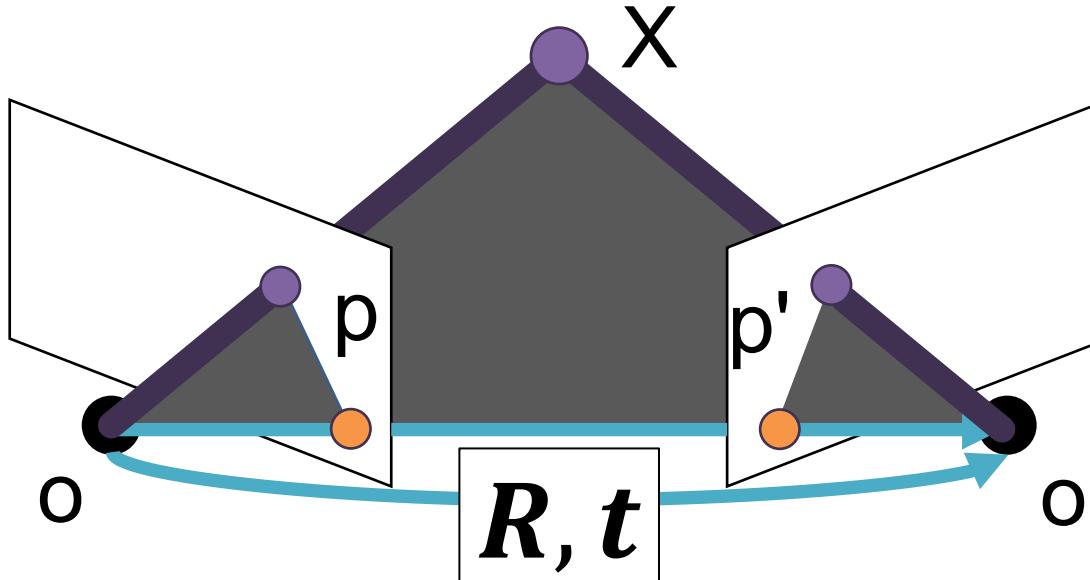
# Epipolar Geometry

- If I want to do stereo, I want to find a corresponding pixel for each pixel in the image:
- Naïve search:
  - For each pixel, search every other pixel
- With epipolar geometry:
  - For each pixel, search along each line (1D search)

# Epipolar constraint example



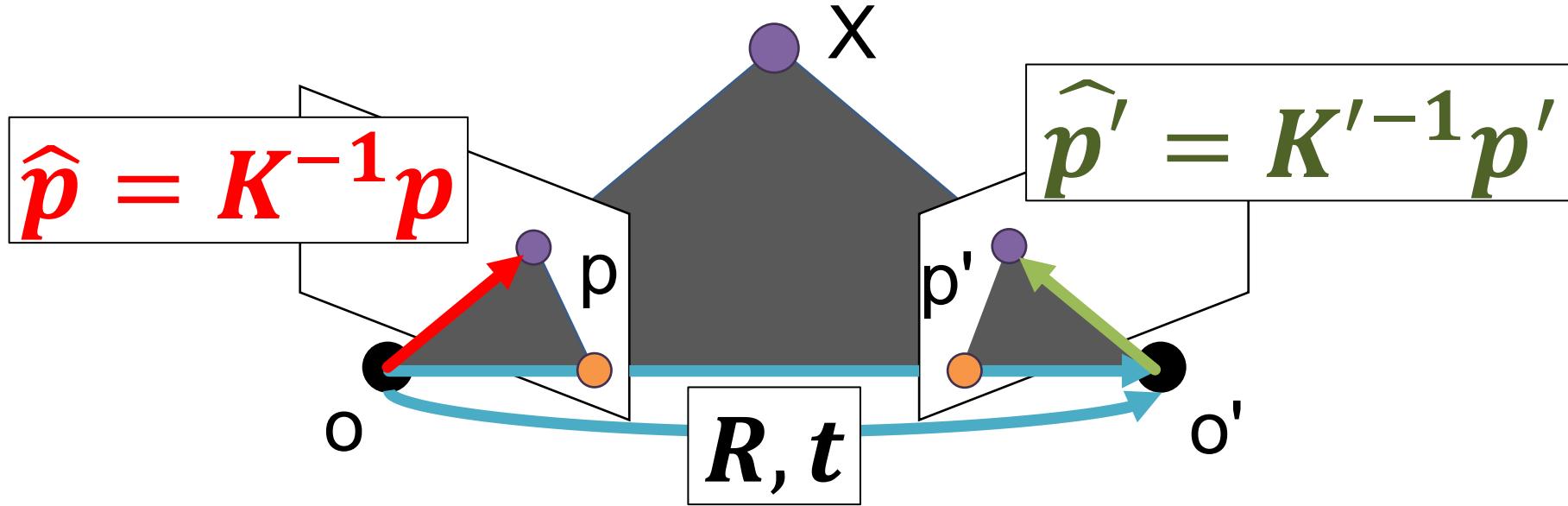
# Epipolar Constraint: Calibrated Case



- If we know intrinsic and extrinsic parameters, set coordinate system to first camera
- Projection matrices:  $M_1 = K[I, \mathbf{0}]$  and  $M_2 = K'[R, t]$
- **What are:**

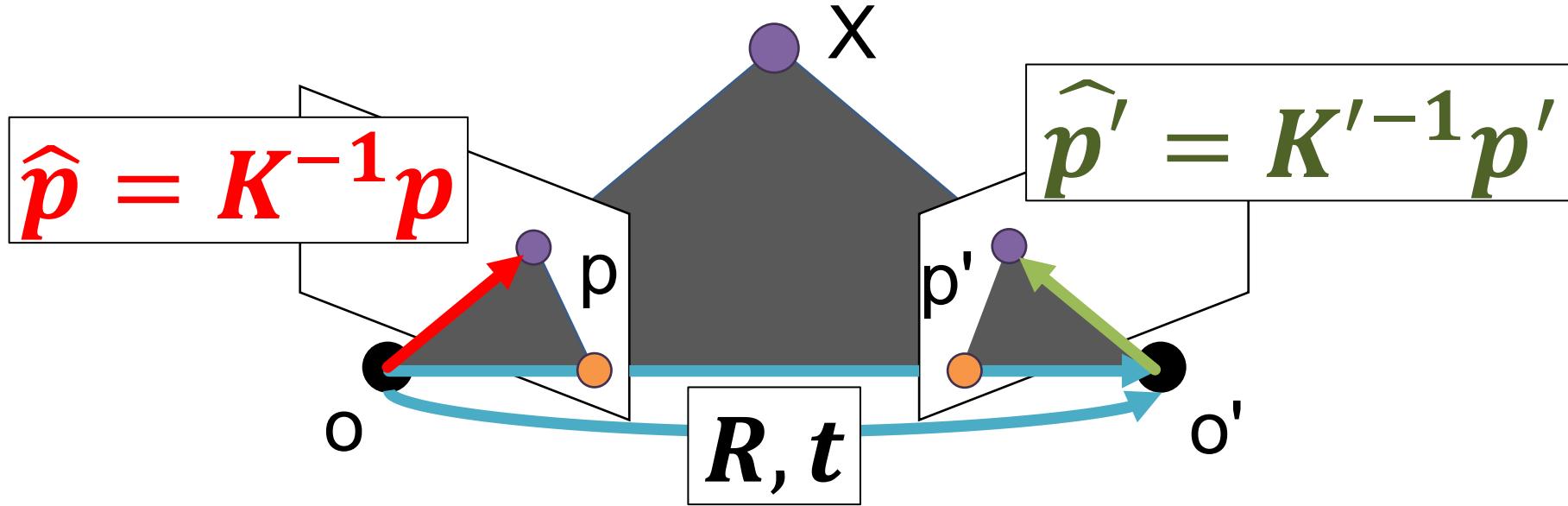
$$M_1 X \quad M_2 X \quad K^{-1} p \quad K'^{-1} p'$$

# Epipolar Constraint: Calibrated Case



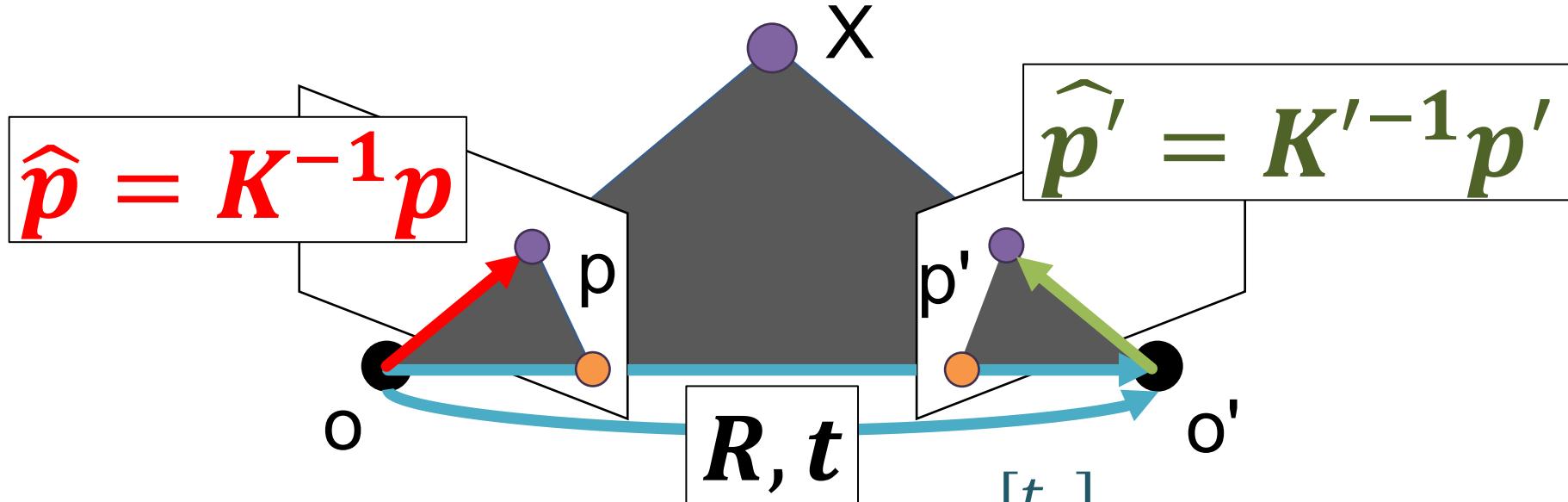
- Given calibration,  $\hat{p} = K^{-1}p$  and  $\hat{p}' = K'^{-1}p'$  are “normalized coordinates”
- Note that  $\hat{p}'$  is actually translated and rotated to  $o'$

# Epipolar Constraint: Calibrated Case



- The following are all co-planar:  $\mathbf{R}\hat{p}$ ,  $\mathbf{t}$ ,  $\hat{p}'$  (can ignore translation for co-planarity here)
- One way to check co-planarity (triple product):  
$$\hat{p}'^T(\mathbf{t} \times \mathbf{R}\hat{p}) = 0$$

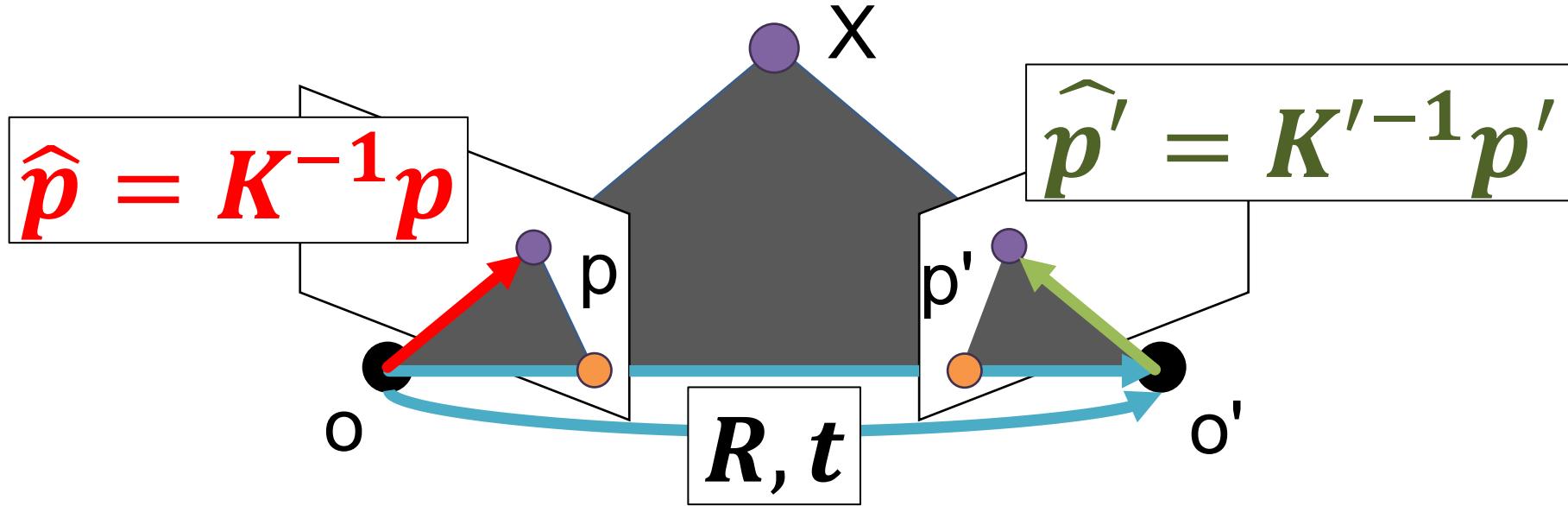
# Epipolar Constraint: Calibrated Case



$$\hat{p}'^T (\mathbf{t} \times R \hat{p}) = 0 \quad \rightarrow \quad \hat{p}'^T \begin{bmatrix} 0 & -t_3 & t_2 \\ t_3 & 0 & -t_1 \\ -t_2 & t_1 & 0 \end{bmatrix} R \hat{p} = 0$$

Want something like  $\mathbf{x}^T \mathbf{A} \mathbf{y} = 0$ . What's  $\mathbf{A}$ ?

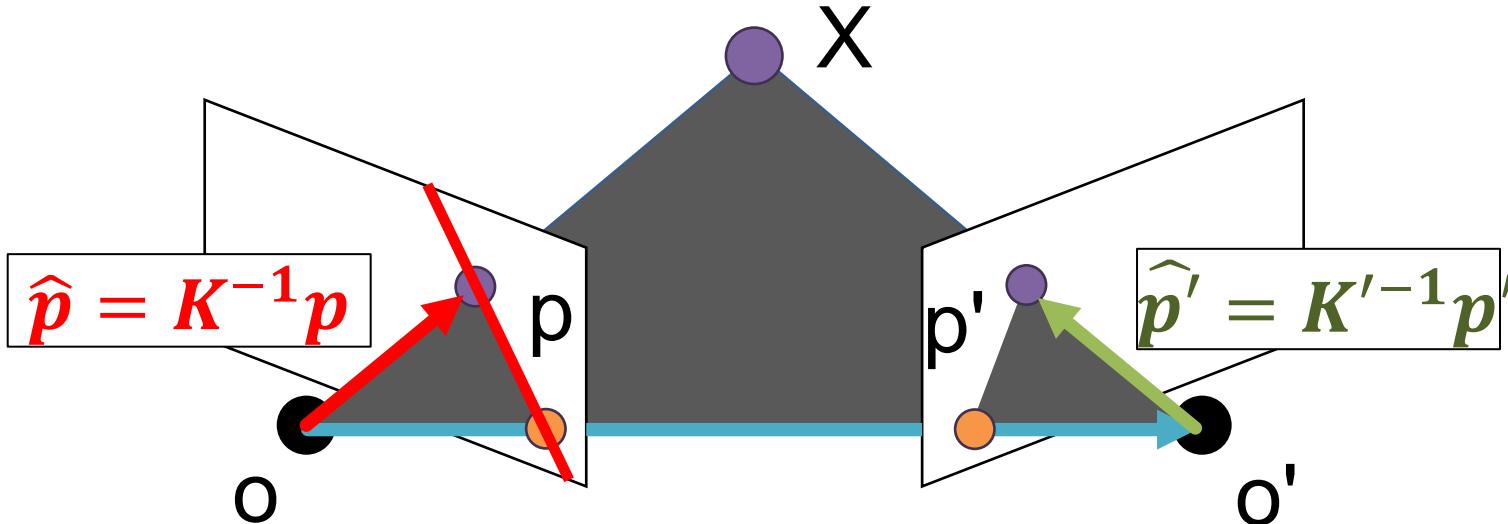
# Epipolar Constraint: Calibrated Case



Essential matrix (Longuet-Higgins, 1981):  $E = [\mathbf{t}_x]R$

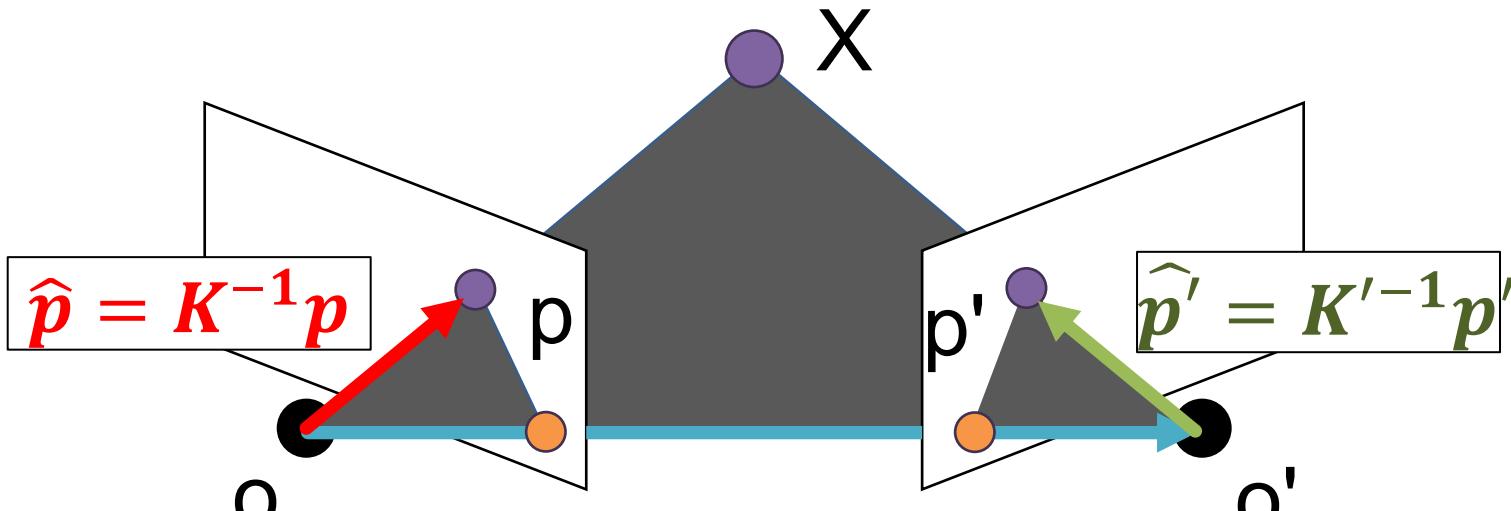
If you have a normalized point  $\hat{p}$ , its correspondence  $\hat{p}'$  must satisfy  $\hat{p}'^T E \hat{p} = 0$

# Essential Essential Matrix Facts



- Suppose we know  $E$  and  $\hat{p}'^T E \hat{p} = 0$ . What is the set  $\{\mathbf{x}: \hat{p}'^T E \mathbf{x} = 0\}$ ?
- $\hat{p}'^T E$  gives equation of the epipolar line (in  $ax+by+c=0$  form) in image for  $o$ .
- What's  $E^T \hat{p}'$  ?

# What if we don't know K?



Have:  $\hat{p} = K^{-1}p$ ,  $\hat{p}' = K'^{-1}p'$ ,  $\hat{p}'^T E \hat{p} = 0$

$$(K'^{-1}p')^T E (K^{-1}p) = 0 \rightarrow p'^T K'^{-T} E K^{-1} p = 0$$

Set:  $F = K'^{-T} E K^{-1}$       Then:  $p'^T F p = 0$

Fundamental Matrix (Faugeras and Luong, 1992)

# The Fundamental Matrix Song



<http://danielwedge.com/fmatrix/>

# Next class

- A bit more about epipolar geometry
  - Properties of the essential and fundamental matrices
  - How to estimate the fundamental matrix from images
- Stereo vision