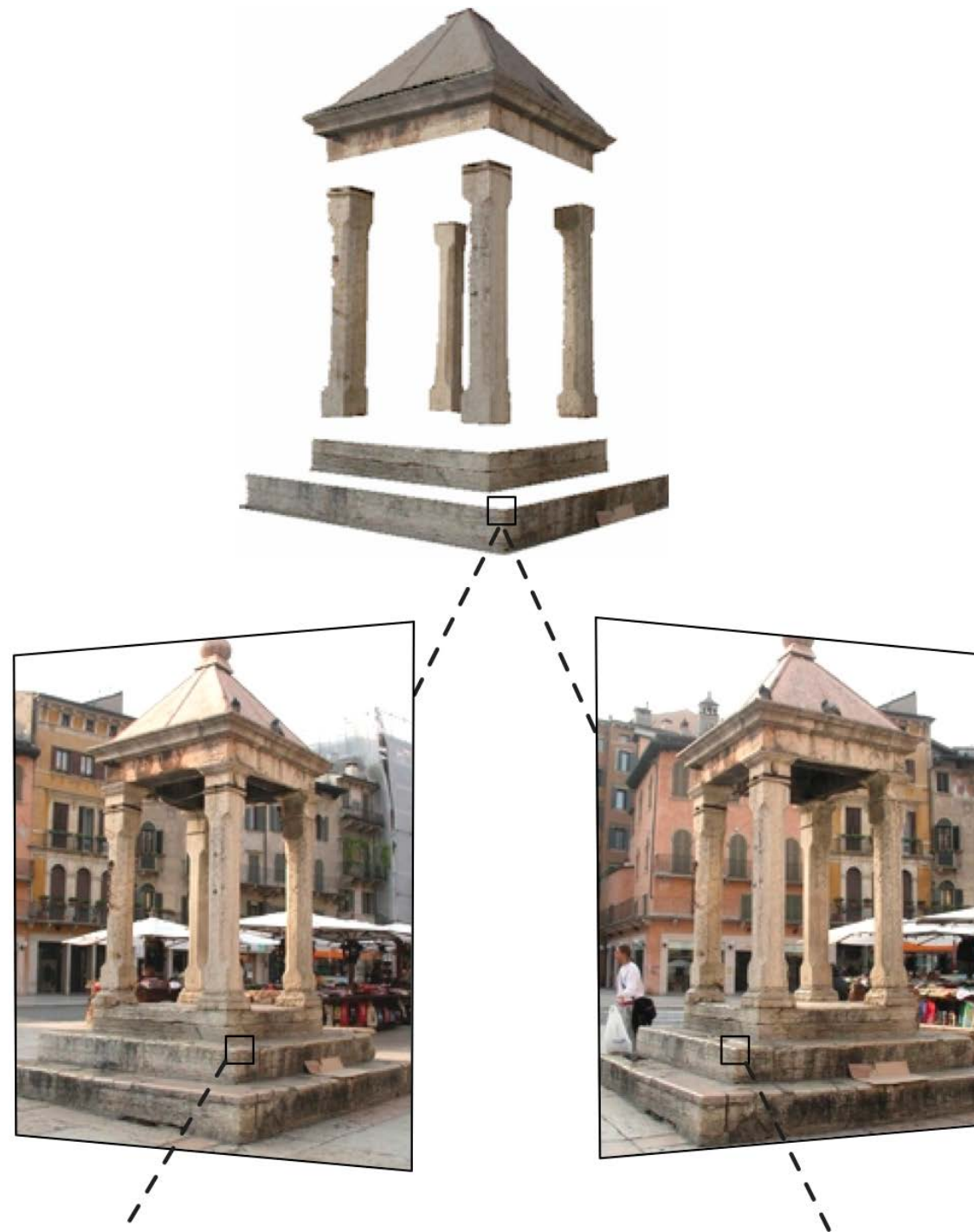


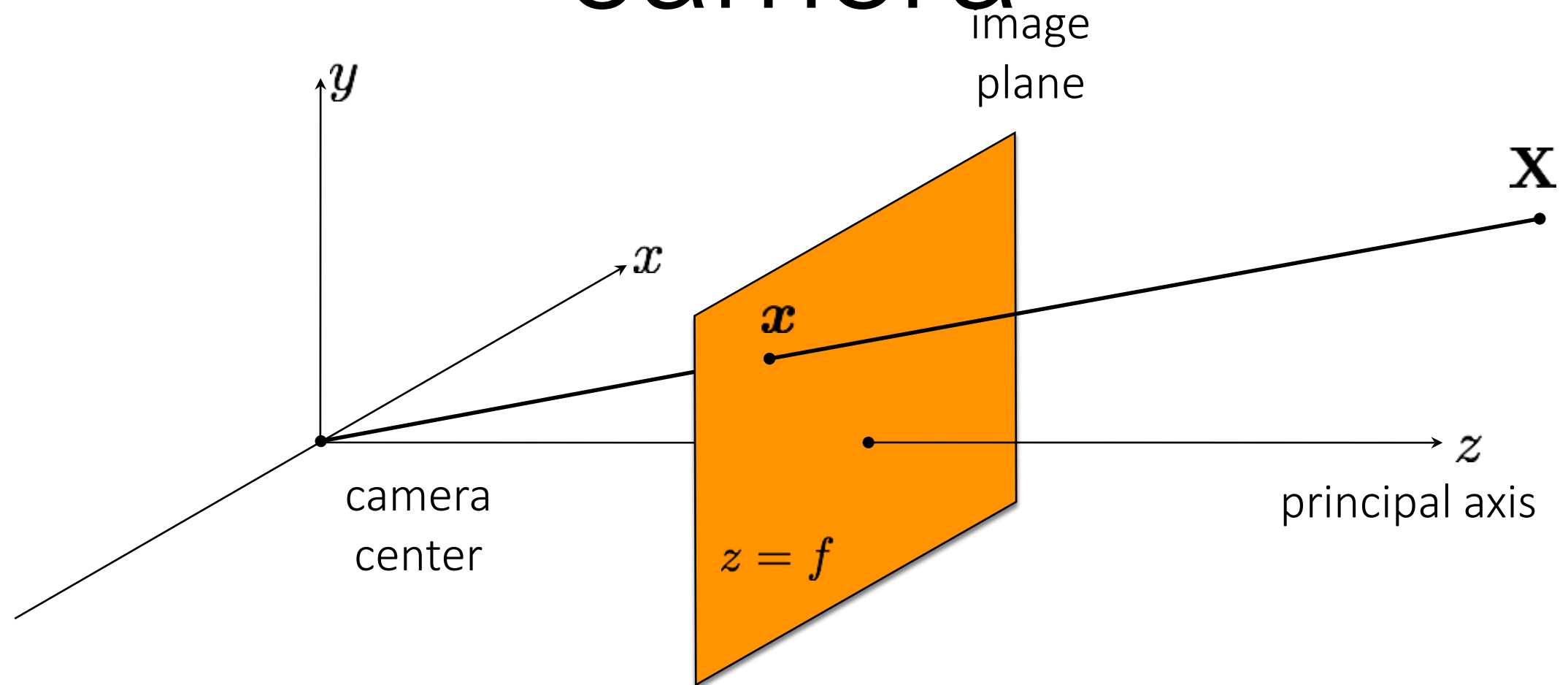
Two-view geometry



Overview of today's lecture

- Leftover from previous lecture: camera calibration.
- Triangulation.
- Epipolar geometry.
- Essential matrix.
- Fundamental matrix.
- 8-point algorithm.

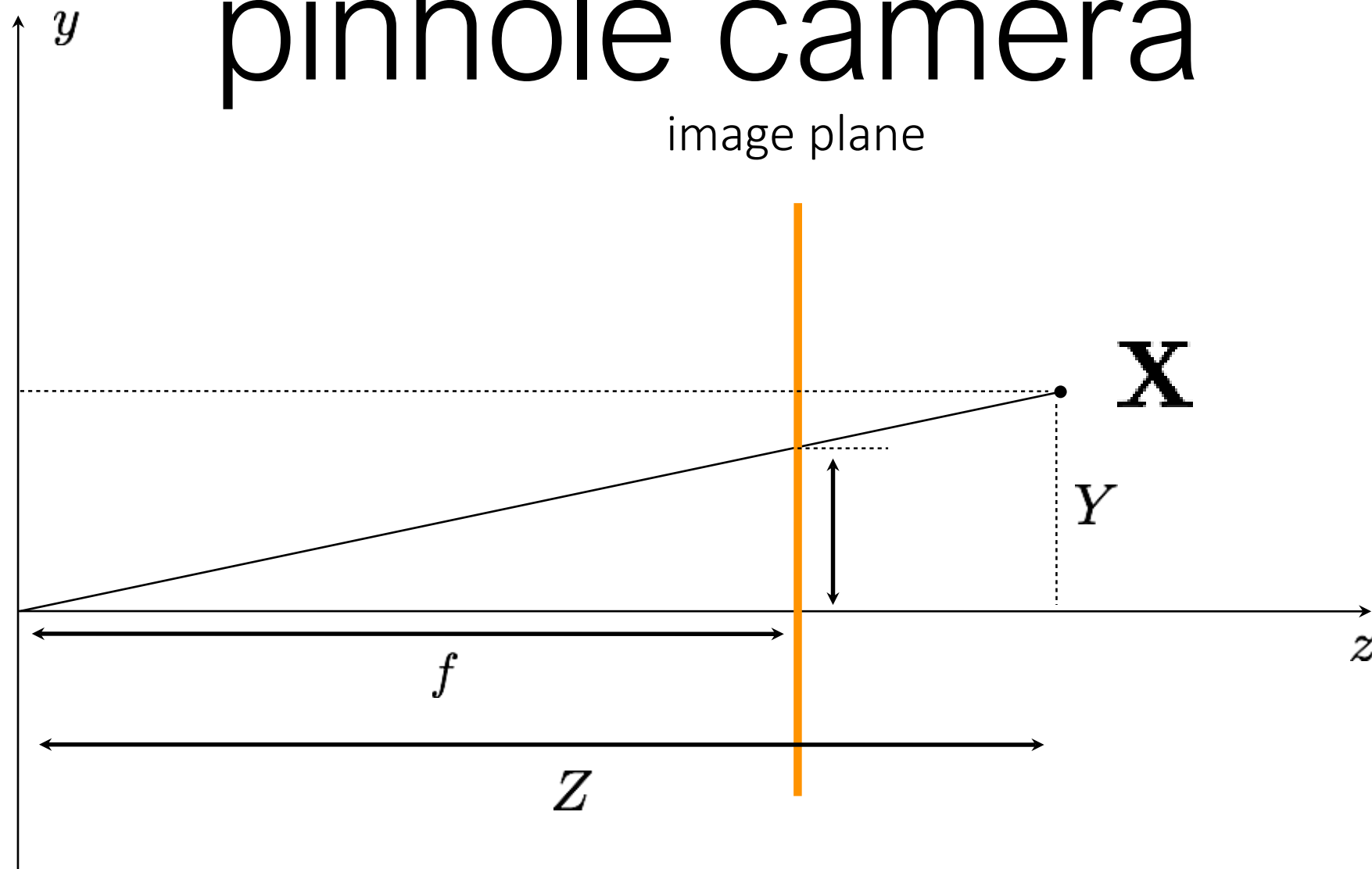
The (rearranged) pinhole camera



Perspective projection in 3D

$$\mathbf{x} = \mathbf{P}\mathbf{X}$$

The 2D view of the (rearranged) pinhole camera



Perspective projection in 2D

$$\begin{bmatrix} X & Y & Z \end{bmatrix}^T \mapsto \begin{bmatrix} fX/Z & fY/Z \end{bmatrix}^T$$

The pinhole camera matrix

Relationship from similar triangles:

$$\begin{bmatrix} X & Y & Z \end{bmatrix}^\top \mapsto \begin{bmatrix} fX/Z & fY/Z \end{bmatrix}^\top$$

General camera model:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

What does the pinhole camera projection look like?

$$\mathbf{P} = \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

General pinhole camera matrix

$$\mathbf{P} = \mathbf{K}[\mathbf{R}|\mathbf{t}]$$

$$\mathbf{P} = \begin{bmatrix} f & 0 & p_x \\ 0 & f & p_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_1 & r_2 & r_3 & | & t_1 \\ r_4 & r_5 & r_6 & | & t_2 \\ r_7 & r_8 & r_9 & | & t_3 \end{bmatrix}$$

intrinsic
parameters

extrinsic
parameters

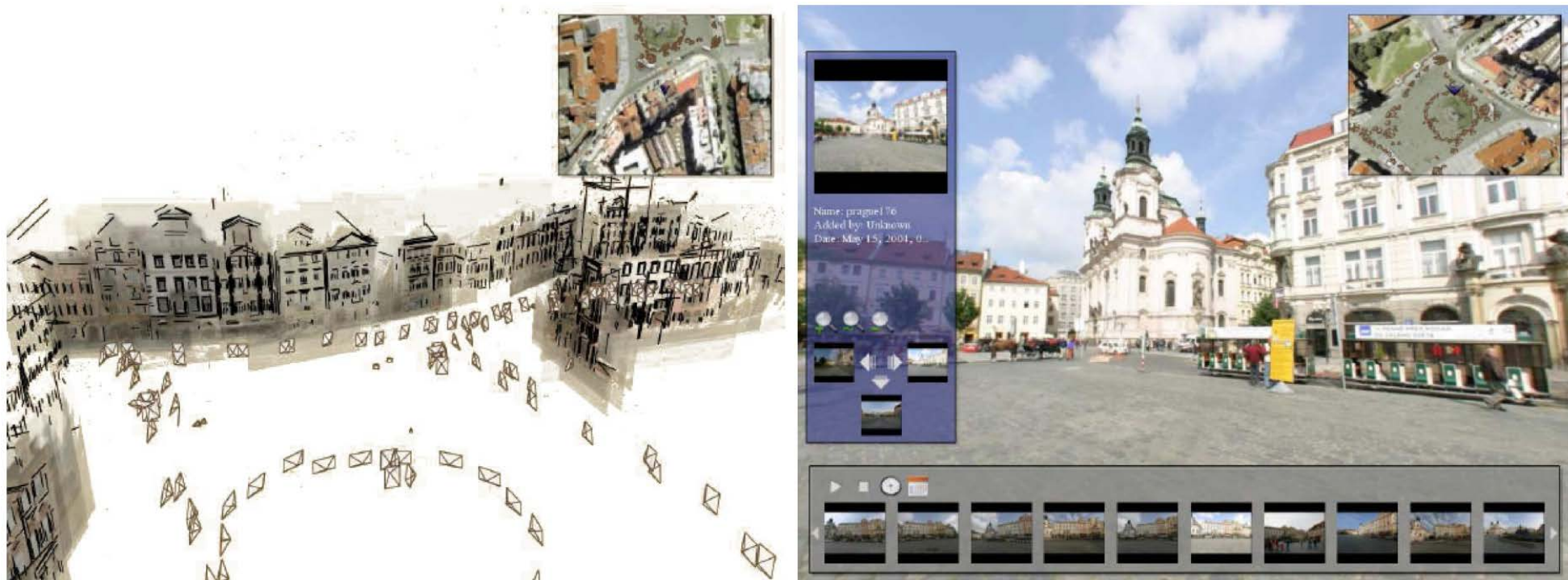
$$\mathbf{R} = \begin{bmatrix} r_1 & r_2 & r_3 \\ r_4 & r_5 & r_6 \\ r_7 & r_8 & r_9 \end{bmatrix} \quad \mathbf{t} = \begin{bmatrix} t_1 \\ t_2 \\ t_3 \end{bmatrix}$$

3D rotation

3D translation

	Structure (scene geometry)	Motion (camera geometry)	Measurements
Camera Calibration (a.k.a. Pose Estimation)	known	estimate	3D to 2D correspondences
Triangulation	estimate	known	2D to 2D coorespondences
Reconstruction	estimate	estimate	2D to 2D coorespondences

Pose Estimation



Given a single image,
estimate the exact position of the photographer

Geometric camera calibration

Given a set of matched points

$$\{\mathbf{X}_i, \mathbf{x}_i\}$$

point in 3D
space

point in the
image

and camera model

$$\mathbf{x} = \mathbf{f}(\mathbf{X}; \mathbf{p}) = \mathbf{P}\mathbf{X}$$

projection
model

parameters

Camera
matrix

Find the (pose) estimate of

P

We'll use a **perspective** camera
model for pose estimation

Same setup as homography estimation
(slightly different derivation here)

Mapping between 3D point and image points

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

What are the unknowns?

Mapping between 3D point and image points

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \text{---} & \mathbf{p}_1^\top & \text{---} \\ \text{---} & \mathbf{p}_2^\top & \text{---} \\ \text{---} & \mathbf{p}_3^\top & \text{---} \end{bmatrix} \begin{bmatrix} | \\ \mathbf{X} \\ | \end{bmatrix}$$

Heterogeneous coordinates

$$x' = \frac{\mathbf{p}_1^\top \mathbf{X}}{\mathbf{p}_3^\top \mathbf{X}} \quad y' = \frac{\mathbf{p}_2^\top \mathbf{X}}{\mathbf{p}_3^\top \mathbf{X}}$$

(non-linear relation between coordinates)

How can we make these relations linear?

How can we make these relations linear?

$$x' = \frac{\mathbf{p}_1^\top \mathbf{X}}{\mathbf{p}_3^\top \mathbf{X}} \quad y' = \frac{\mathbf{p}_2^\top \mathbf{X}}{\mathbf{p}_3^\top \mathbf{X}}$$

Make them linear with algebraic manipulation...

$$\mathbf{p}_2^\top \mathbf{X} - \mathbf{p}_3^\top \mathbf{X} y' = 0$$

$$\mathbf{p}_1^\top \mathbf{X} - \mathbf{p}_3^\top \mathbf{X} x' = 0$$

Now we can setup a system of linear equations with multiple point correspondences

$$\mathbf{p}_2^\top \mathbf{X} - \mathbf{p}_3^\top \mathbf{X} y' = 0$$

$$\mathbf{p}_1^\top \mathbf{X} - \mathbf{p}_3^\top \mathbf{X} x' = 0$$

How do we proceed?

$$\mathbf{p}_2^\top \mathbf{X} - \mathbf{p}_3^\top \mathbf{X} y' = 0$$

$$\mathbf{p}_1^\top \mathbf{X} - \mathbf{p}_3^\top \mathbf{X} x' = 0$$

In matrix form ...

$$\begin{bmatrix} \mathbf{X}^\top & \mathbf{0} & -x' \mathbf{X}^\top \\ \mathbf{0} & \mathbf{X}^\top & -y' \mathbf{X}^\top \end{bmatrix} \begin{bmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \mathbf{p}_3 \end{bmatrix} = \mathbf{0}$$

How do we proceed?

12x 1



$$\mathbf{p}_2^\top \mathbf{X} - \mathbf{p}_3^\top \mathbf{X} y' = 0$$

$$\mathbf{p}_1^\top \mathbf{X} - \mathbf{p}_3^\top \mathbf{X} x' = 0$$

In matrix form ...

$$\begin{bmatrix} \mathbf{X}^\top & \mathbf{0} & -x' \mathbf{X}^\top \\ \mathbf{0} & \mathbf{X}^\top & -y' \mathbf{X}^\top \end{bmatrix} \begin{bmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \mathbf{p}_3 \end{bmatrix} = \mathbf{0}$$

For N points ...

$$\begin{bmatrix} \mathbf{X}_1^\top & \mathbf{0} & -x' \mathbf{X}_1^\top \\ \mathbf{0} & \mathbf{X}_1^\top & -y' \mathbf{X}_1^\top \\ \vdots & \vdots & \vdots \\ \mathbf{X}_N^\top & \mathbf{0} & -x' \mathbf{X}_N^\top \\ \mathbf{0} & \mathbf{X}_N^\top & -y' \mathbf{X}_N^\top \end{bmatrix} \begin{bmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \mathbf{p}_3 \end{bmatrix} = \mathbf{0}$$

*How do we solve
this system?*

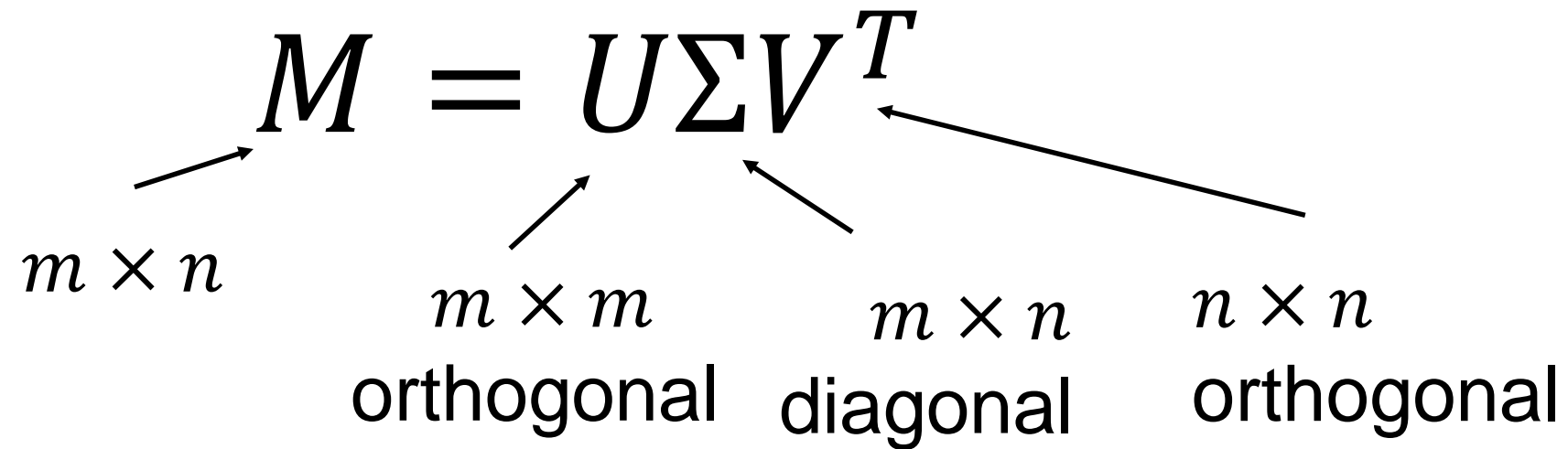
Solve for camera matrix by

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{A}\mathbf{x}\|^2 \text{ subject to } \|\mathbf{x}\|^2 = 1$$

$$\mathbf{A} = \begin{bmatrix} \mathbf{X}_1^\top & \mathbf{0} & -x' \mathbf{X}_1^\top \\ \mathbf{0} & \mathbf{X}_1^\top & -y' \mathbf{X}_1^\top \\ \vdots & \vdots & \vdots \\ \mathbf{X}_N^\top & \mathbf{0} & -x' \mathbf{X}_N^\top \\ \mathbf{0} & \mathbf{X}_N^\top & -y' \mathbf{X}_N^\top \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}$$

SVD!

SVD (singular value decomposition)

$$M = U \Sigma V^T$$


$m \times n$ $m \times m$ $m \times n$ $n \times n$
orthogonal diagonal orthogonal

The diagonal entries of Σ are known as the singular values
The number of non-zero singular values is equal to the rank of M

Eigen value decomposition:

$$M^T M = V \Sigma^2 V^T$$

Solve for camera matrix by

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{A}\mathbf{x}\|^2 \text{ subject to } \|\mathbf{x}\|^2 = 1$$

$$\mathbf{A} = \begin{bmatrix} \mathbf{X}_1^\top & \mathbf{0} & -x' \mathbf{X}_1^\top \\ \mathbf{0} & \mathbf{X}_1^\top & -y' \mathbf{X}_1^\top \\ \vdots & \vdots & \vdots \\ \mathbf{X}_N^\top & \mathbf{0} & -x' \mathbf{X}_N^\top \\ \mathbf{0} & \mathbf{X}_N^\top & -y' \mathbf{X}_N^\top \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}$$

Solution \mathbf{x} is the column of \mathbf{V}
corresponding to smallest singular
value of

$$\mathbf{A} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^\top$$

Solve for camera matrix by

$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \|\mathbf{A}\mathbf{x}\|^2 \text{ subject to } \|\mathbf{x}\|^2 = 1$$

$$\mathbf{A} = \begin{bmatrix} \mathbf{X}_1^\top & \mathbf{0} & -x' \mathbf{X}_1^\top \\ \mathbf{0} & \mathbf{X}_1^\top & -y' \mathbf{X}_1^\top \\ \vdots & \vdots & \vdots \\ \mathbf{X}_N^\top & \mathbf{0} & -x' \mathbf{X}_N^\top \\ \mathbf{0} & \mathbf{X}_N^\top & -y' \mathbf{X}_N^\top \end{bmatrix} \quad \mathbf{x} = \begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}$$

solution \mathbf{x} is the Eigenvector
corresponding to smallest
Eigenvalue of

$$\mathbf{A}^\top \mathbf{A}$$

Now we have:

$$\mathbf{P} = \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix}$$

Are we done?

Almost there ...

$$\mathbf{P} = \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix}$$

How do you get the intrinsic and extrinsic parameters from the projection matrix?

Decomposition of the Camera Matrix

$$\mathbf{P} = \left[\begin{array}{ccc|c} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{array} \right]$$

Decomposition of the Camera Matrix

$$\mathbf{P} = \left[\begin{array}{ccc|c} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{array} \right]$$

$$\begin{aligned} \mathbf{P} &= \mathbf{K}[\mathbf{R}|\mathbf{t}] \\ &= \mathbf{K}[\mathbf{R} | -\mathbf{R}\mathbf{c}] \\ &= [\mathbf{M} | -\mathbf{M}\mathbf{c}] \end{aligned}$$

Decomposition of the Camera Matrix

$$\mathbf{P} = \left[\begin{array}{ccc|c} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{array} \right]$$

$$\begin{aligned} \mathbf{P} &= \mathbf{K}[\mathbf{R}|\mathbf{t}] \\ &= \mathbf{K}[\mathbf{R} | -\mathbf{R}\mathbf{c}] \\ &= [\mathbf{M} | -\mathbf{M}\mathbf{c}] \end{aligned}$$

Find the camera center \mathbf{C}

What is the projection of the camera center?

Find intrinsic \mathbf{K} and rotation \mathbf{R}

Decomposition of the Camera Matrix

$$\mathbf{P} = \left[\begin{array}{ccc|c} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{array} \right]$$

$$\begin{aligned} \mathbf{P} &= \mathbf{K}[\mathbf{R}|\mathbf{t}] \\ &= \mathbf{K}[\mathbf{R} | -\mathbf{R}\mathbf{c}] \\ &= [\mathbf{M} | -\mathbf{M}\mathbf{c}] \end{aligned}$$

Find the camera center \mathbf{c}

$$\mathbf{P}\mathbf{c} = \mathbf{0}$$

How do we compute the camera center from this?

Find intrinsic \mathbf{K} and rotation \mathbf{R}

Decomposition of the Camera Matrix

$$\mathbf{P} = \left[\begin{array}{ccc|c} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{array} \right]$$

$$\begin{aligned} \mathbf{P} &= \mathbf{K}[\mathbf{R}|\mathbf{t}] \\ &= \mathbf{K}[\mathbf{R} | -\mathbf{R}\mathbf{c}] \\ &= [\mathbf{M} | -\mathbf{M}\mathbf{c}] \end{aligned}$$

Find the camera center \mathbf{c}

$$\mathbf{P}\mathbf{c} = \mathbf{0}$$

SVD of \mathbf{P} !

\mathbf{c} is the singular vector corresponding
to smallest singular value

Find intrinsic \mathbf{K} and rotation \mathbf{R}

Decomposition of the Camera Matrix

$$\mathbf{P} = \left[\begin{array}{ccc|c} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{array} \right]$$

$$\begin{aligned} \mathbf{P} &= \mathbf{K}[\mathbf{R}|\mathbf{t}] \\ &= \mathbf{K}[\mathbf{R} | -\mathbf{R}\mathbf{c}] \\ &= [\mathbf{M} | -\mathbf{M}\mathbf{c}] \end{aligned}$$

Find the camera center \mathbf{c}

$$\mathbf{P}\mathbf{c} = \mathbf{0}$$

SVD of \mathbf{P} !

\mathbf{c} is the singular vector corresponding
to smallest singular value

Find intrinsic \mathbf{K} and rotation \mathbf{R}

$$\mathbf{M} = \mathbf{K}\mathbf{R}$$

*Any useful properties of K
and R we can use?*

Decomposition of the Camera Matrix

$$\mathbf{P} = \left[\begin{array}{ccc|c} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{array} \right]$$

$$\begin{aligned} \mathbf{P} &= \mathbf{K}[\mathbf{R}|\mathbf{t}] \\ &= \mathbf{K}[\mathbf{R} | -\mathbf{R}\mathbf{c}] \\ &= [\mathbf{M} | -\mathbf{M}\mathbf{c}] \end{aligned}$$

Find the camera center \mathbf{c}

$$\mathbf{P}\mathbf{c} = \mathbf{0}$$

SVD of \mathbf{P} !

\mathbf{c} is the Eigenvector corresponding to
smallest Eigenvalue

Find intrinsic \mathbf{K} and rotation \mathbf{R}

$$\mathbf{M} = \mathbf{K}\mathbf{R}$$

right upper
triangle

orthogonal

*How do we find K
and R ?*

Decomposition of the Camera Matrix

$$\mathbf{P} = \left[\begin{array}{ccc|c} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{array} \right]$$

$$\begin{aligned} \mathbf{P} &= \mathbf{K}[\mathbf{R}|\mathbf{t}] \\ &= \mathbf{K}[\mathbf{R} | -\mathbf{R}\mathbf{c}] \\ &= [\mathbf{M} | -\mathbf{M}\mathbf{c}] \end{aligned}$$

Find the camera center \mathbf{c}

$$\mathbf{P}\mathbf{c} = \mathbf{0}$$

SVD of P!

\mathbf{c} is the Eigenvector corresponding to
smallest Eigenvalue

Find intrinsic \mathbf{K} and rotation \mathbf{R}

$$\mathbf{M} = \mathbf{K}\mathbf{R}$$

QR decomposition

Geometric camera calibration

Given a set of matched points

$$\{\mathbf{X}_i, \mathbf{x}_i\}$$

point in 3D
space

point in the
image

*Where do we get these
matched points from?*

and camera model

$$\mathbf{x} = \mathbf{f}(\mathbf{X}; \mathbf{p}) = \mathbf{P}\mathbf{X}$$

projection
model

parameters

Camera
matrix

Find the (pose) estimate of

P

We'll use a **perspective** camera
model for pose estimation

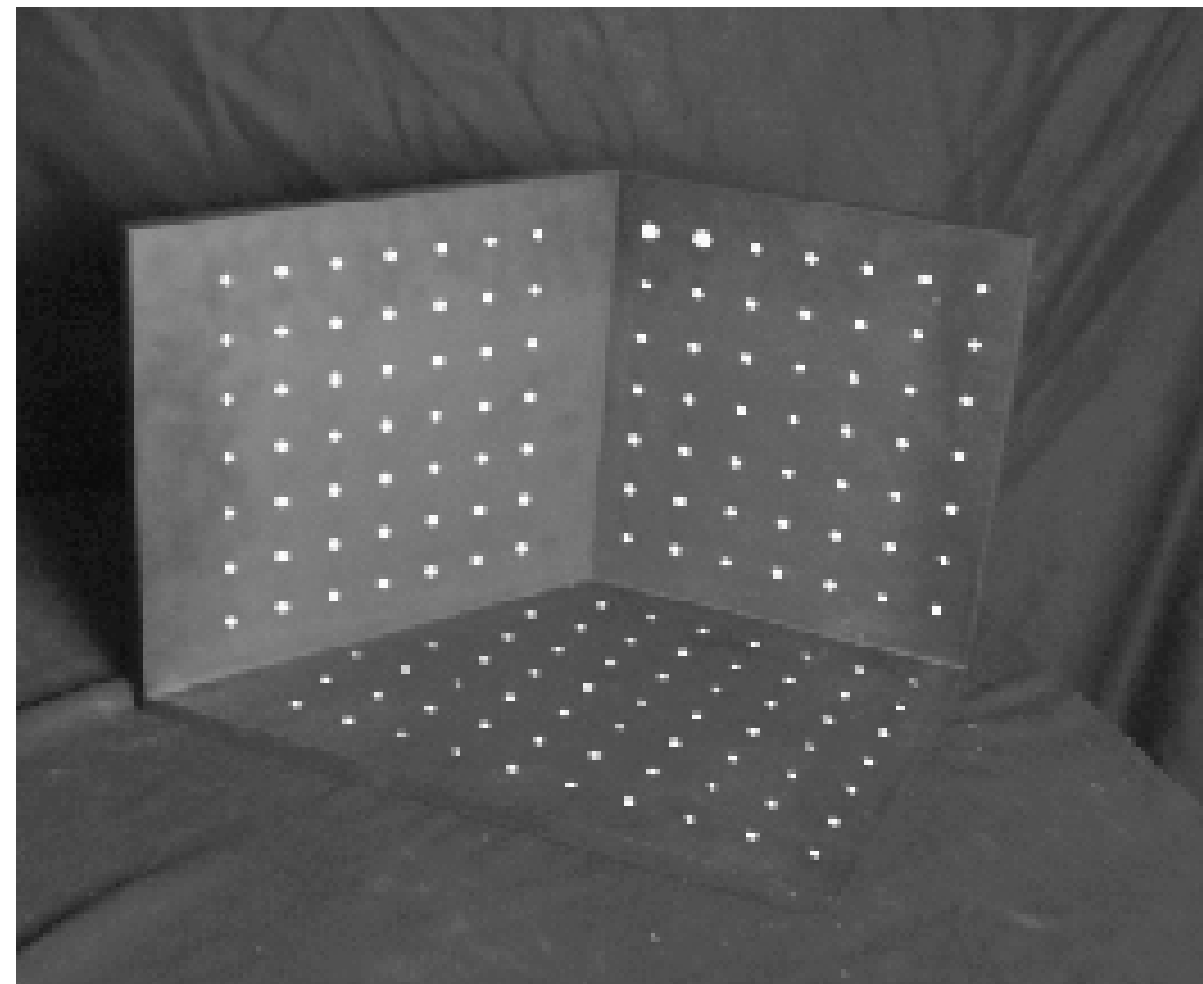
Calibration using a reference object

Place a known object in the scene:

- identify correspondences between image and scene
- compute mapping from scene to image

Issues:

- must know geometry very accurately
- must know 3D->2D correspondence



Geometric camera calibration

Advantages:

- Very simple to formulate.
- Analytical solution.

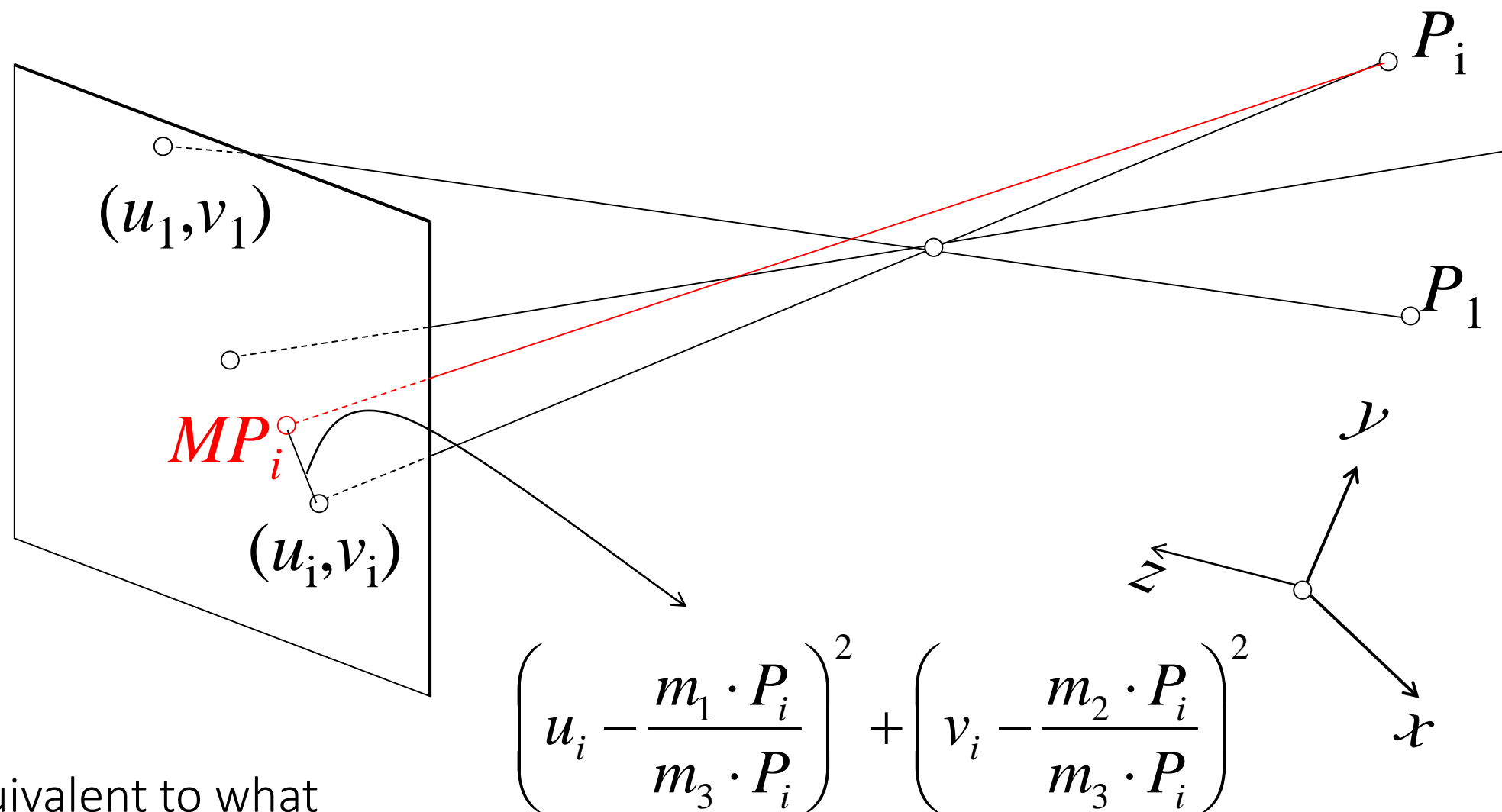
Disadvantages:

- Doesn't model radial distortion.
- Hard to impose constraints (e.g., known f).
- Doesn't minimize the correct error function.

For these reasons, *nonlinear methods* are preferred

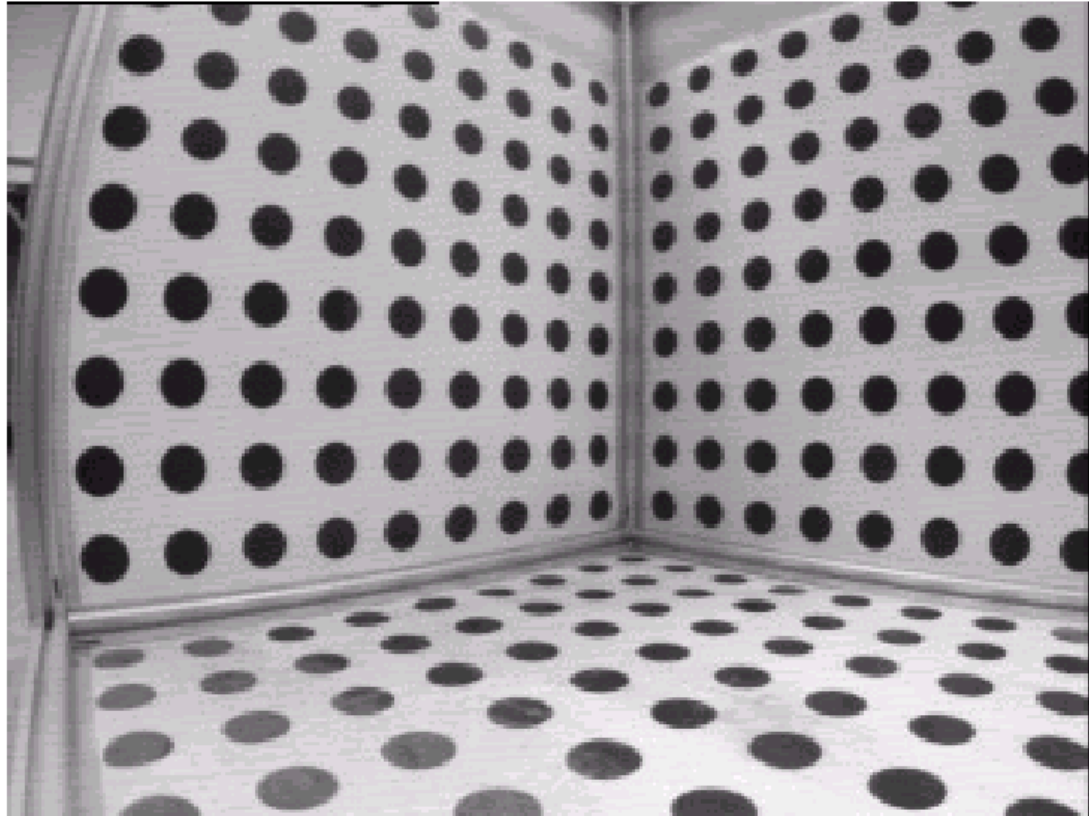
- Define error function E between projected 3D points and image positions
 - E is nonlinear function of intrinsics, extrinsics, radial distortion
- Minimize E using nonlinear optimization techniques

Minimizing reprojection error

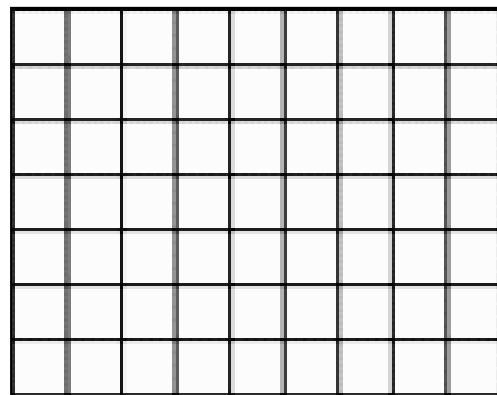


Is this equivalent to what we were doing previously?

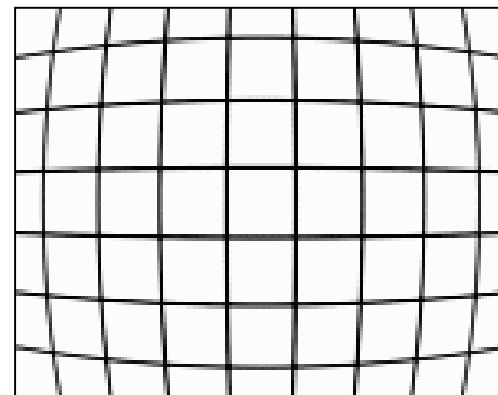
Radial distortion



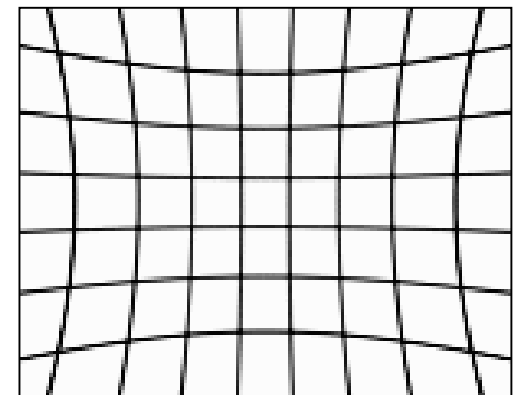
What causes this distortion?



no distortion



barrel distortion



pincushion distortion

Correcting radial distortion

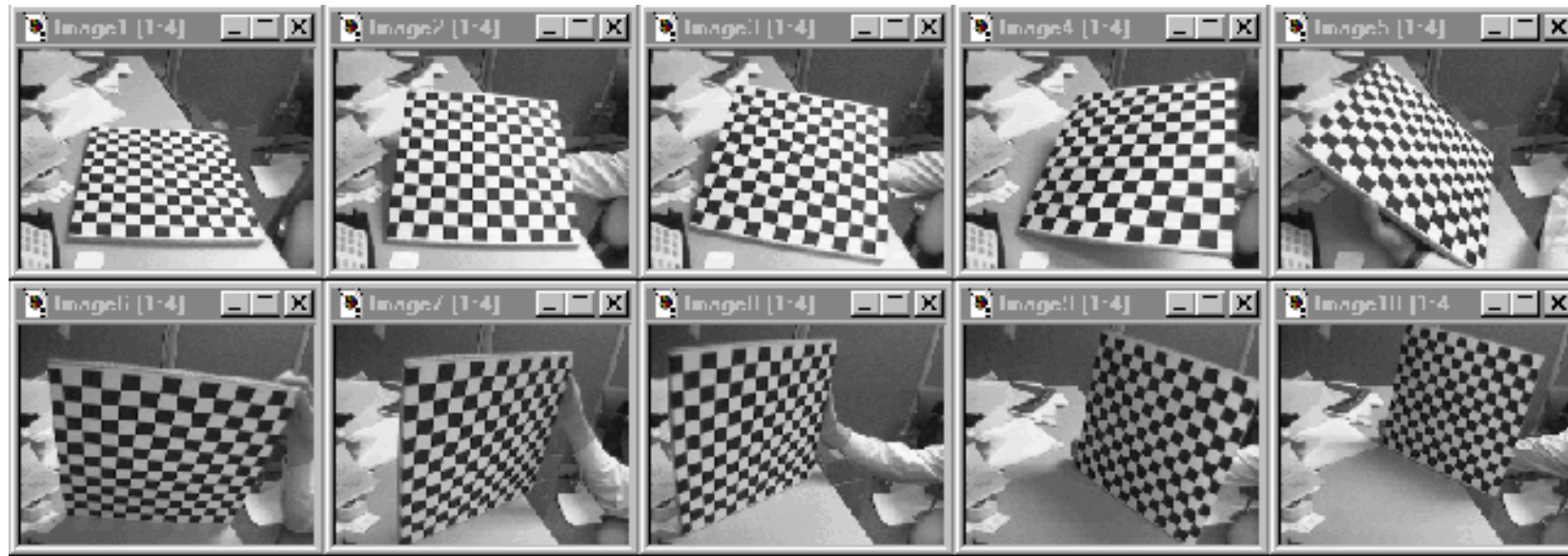


before



after

Alternative: Multi-plane calibration

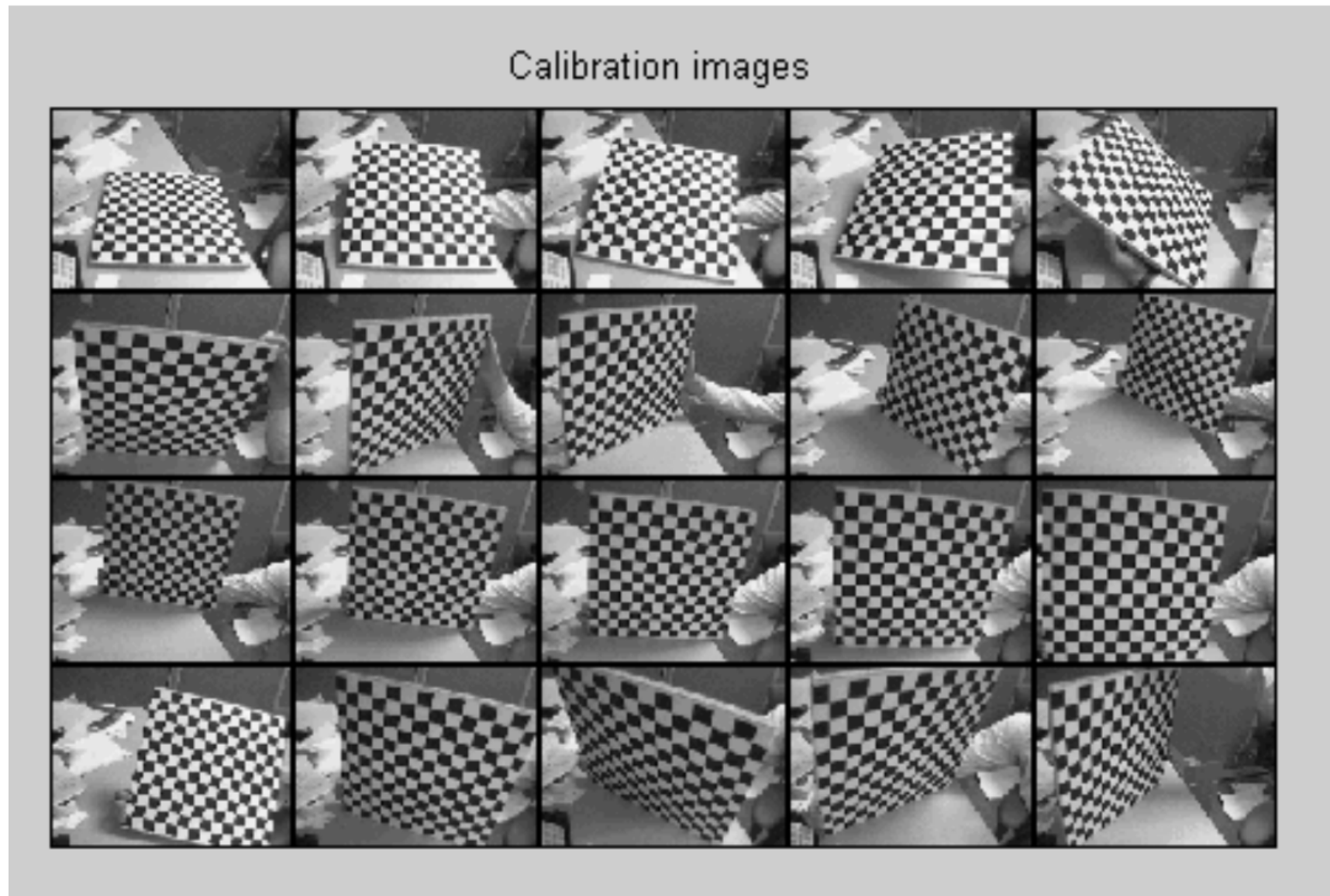


Advantages:

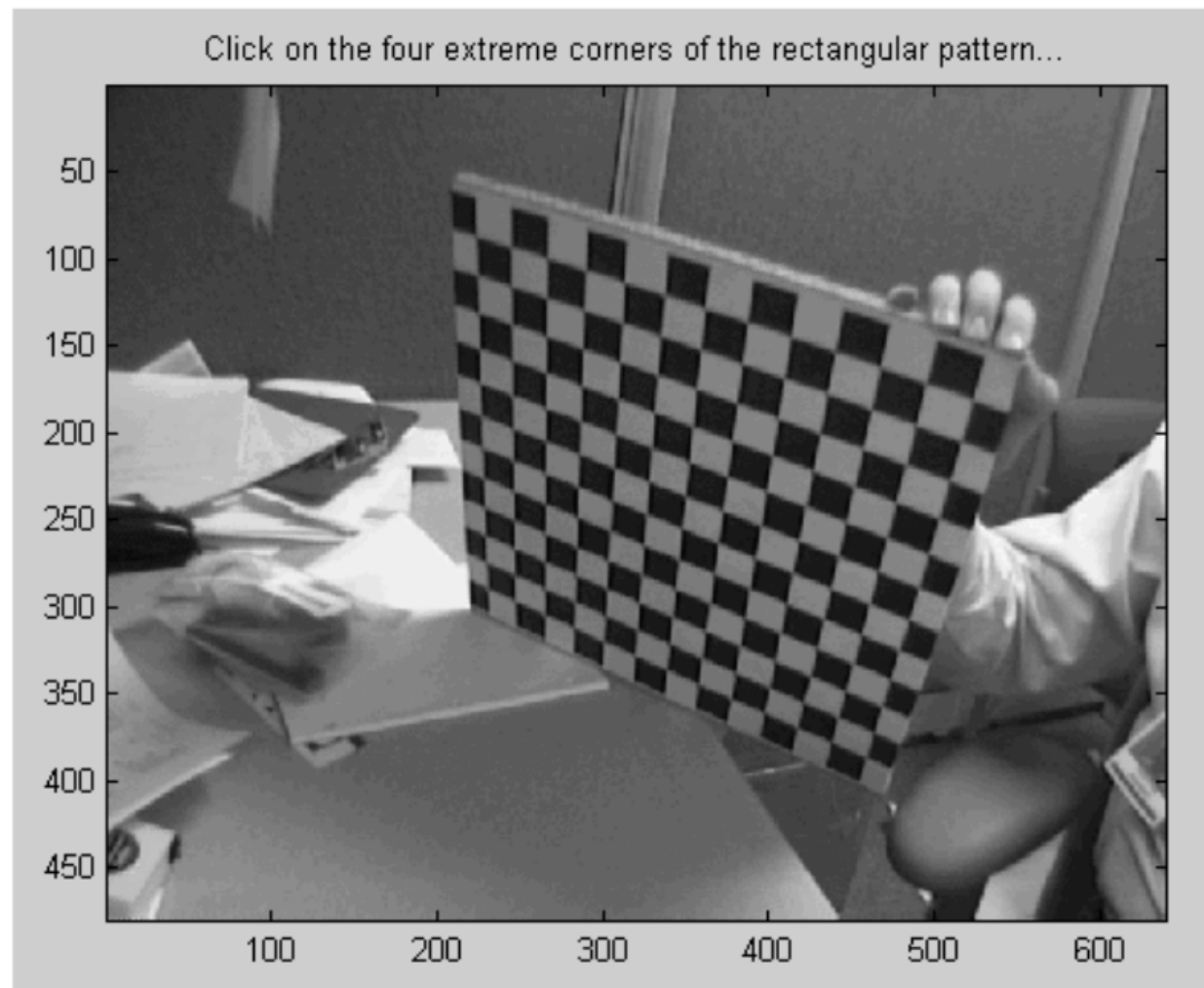
- Only requires a plane
- Don't have to know positions/orientations
- Great code available online!
 - Matlab version: http://www.vision.caltech.edu/bouguetj/calib_doc/index.html
 - Also available on OpenCV.

Disadvantage: Need to solve non-linear optimization problem.

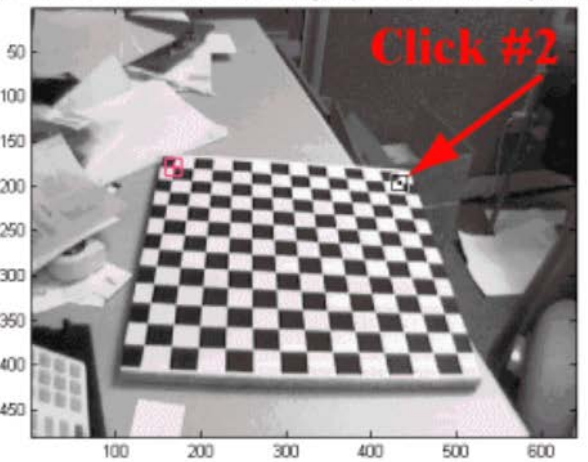
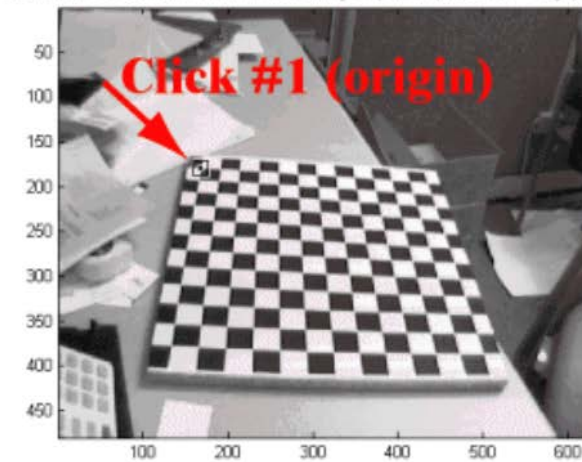
Step-by-step demonstration



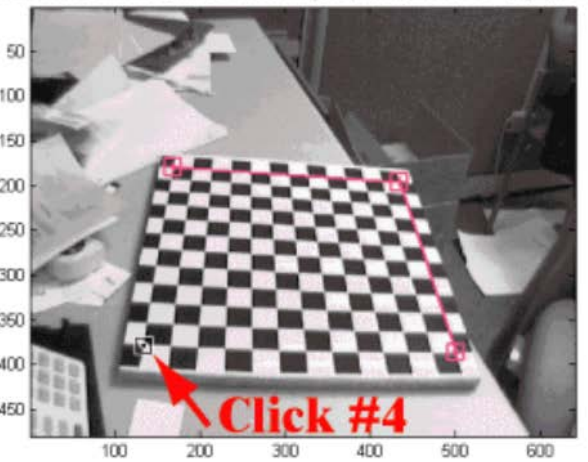
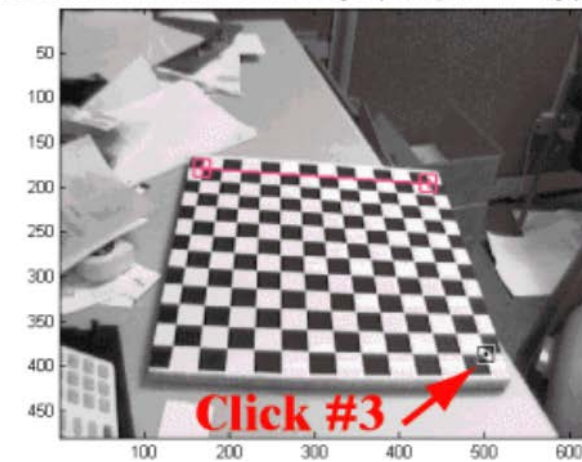
Step-by-step demonstration



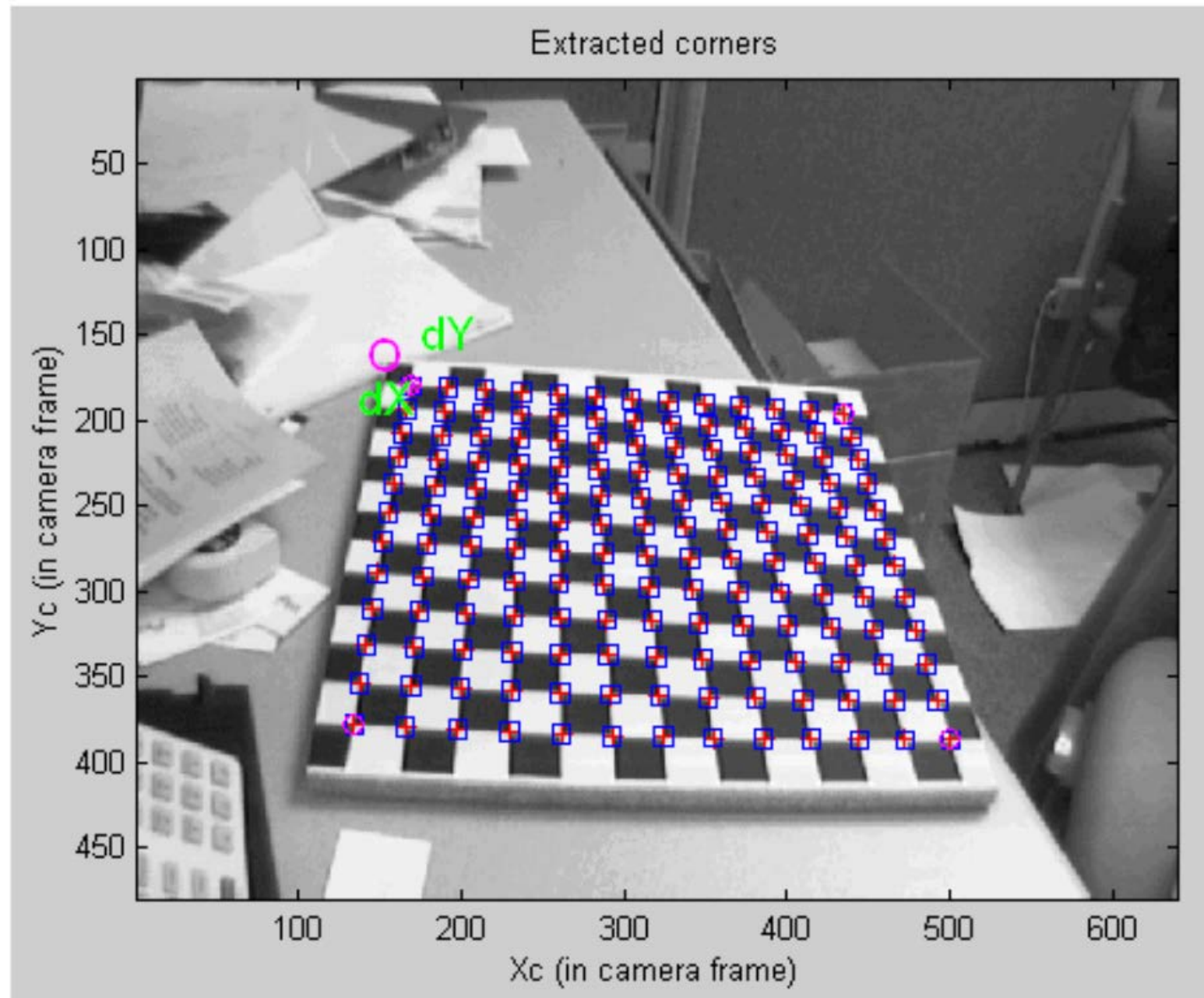
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



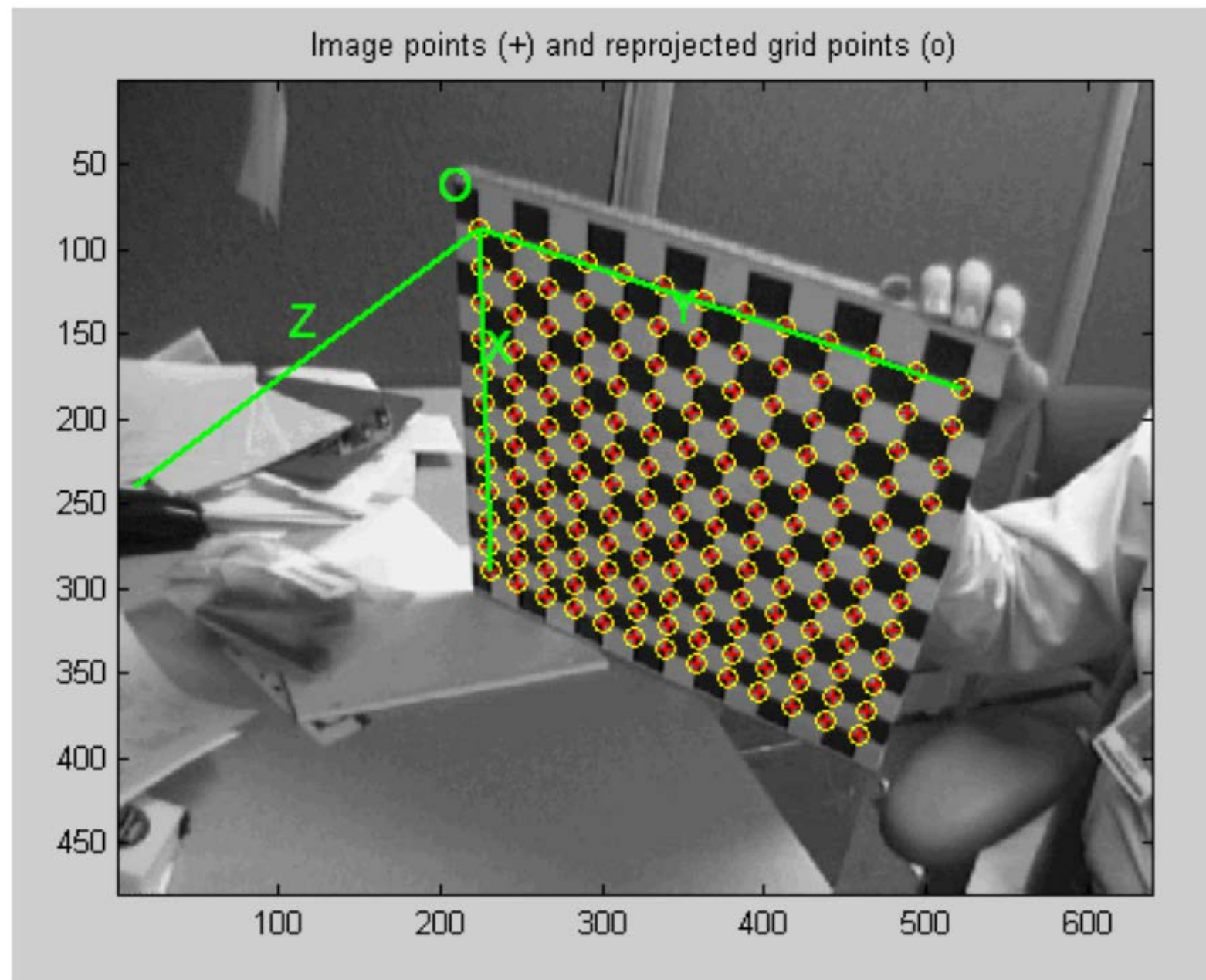
Click on the four extreme corners of the rectangular pattern (first corner = origin)... Image 1



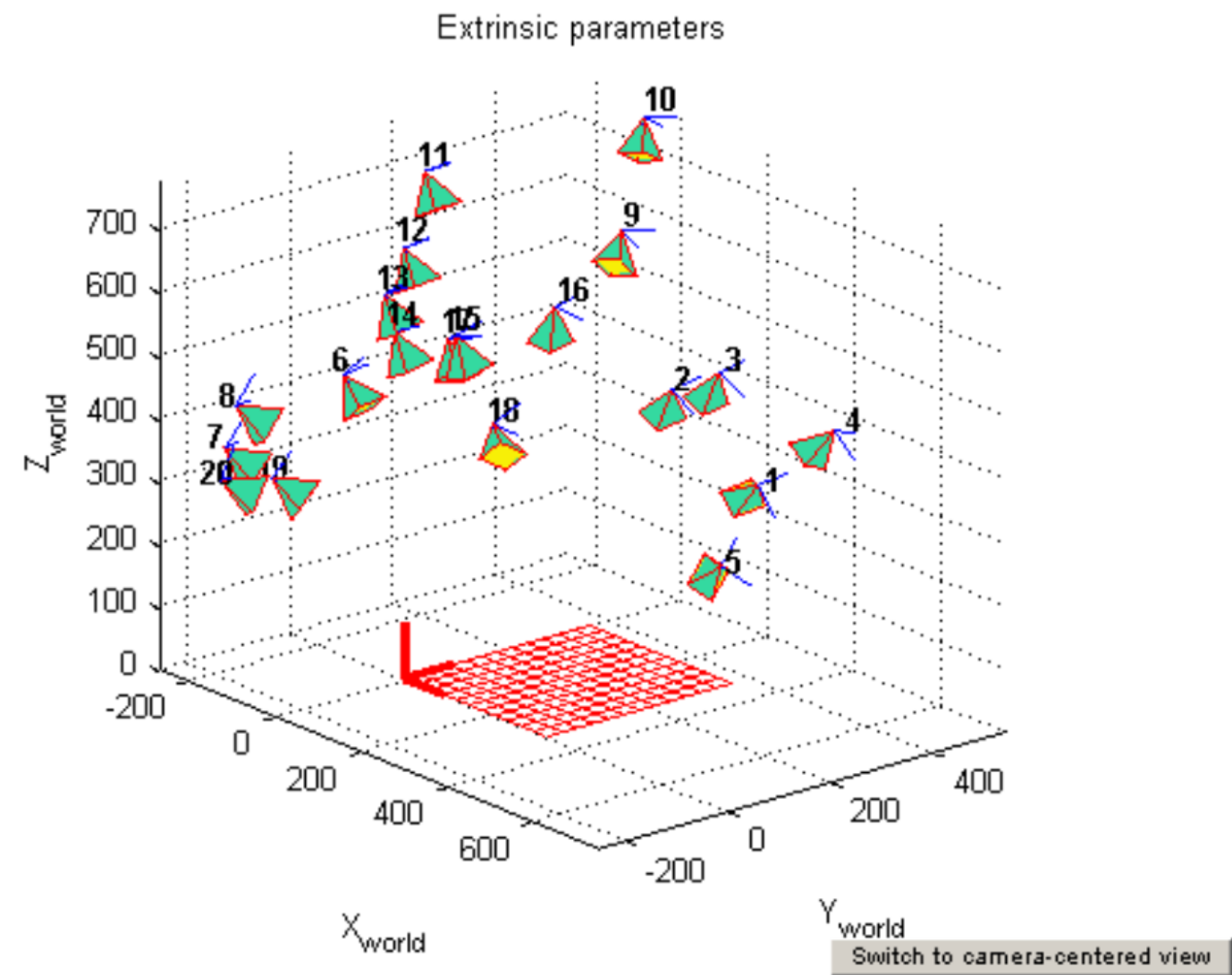
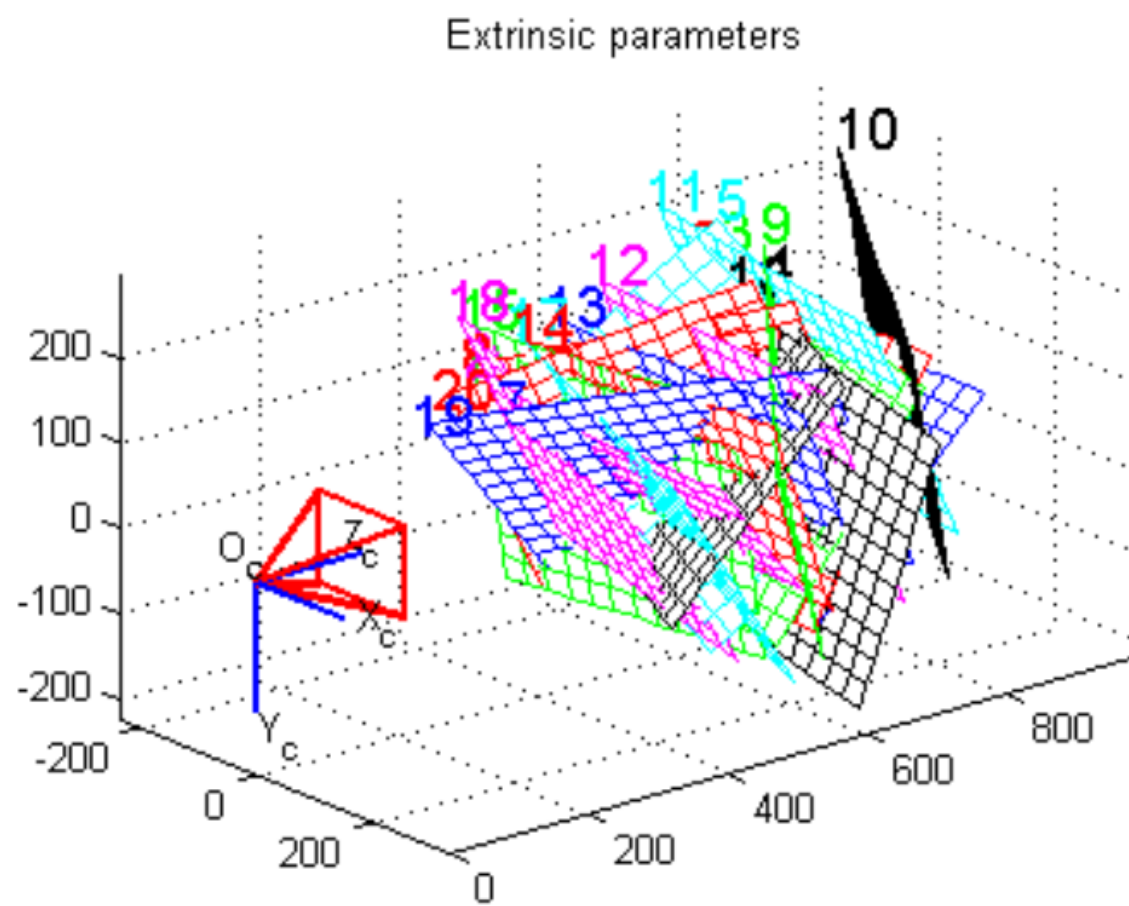
Step-by-step demonstration



Step-by-step demonstration



Step-by-step demonstration



What does it mean to “calibrate a camera”?

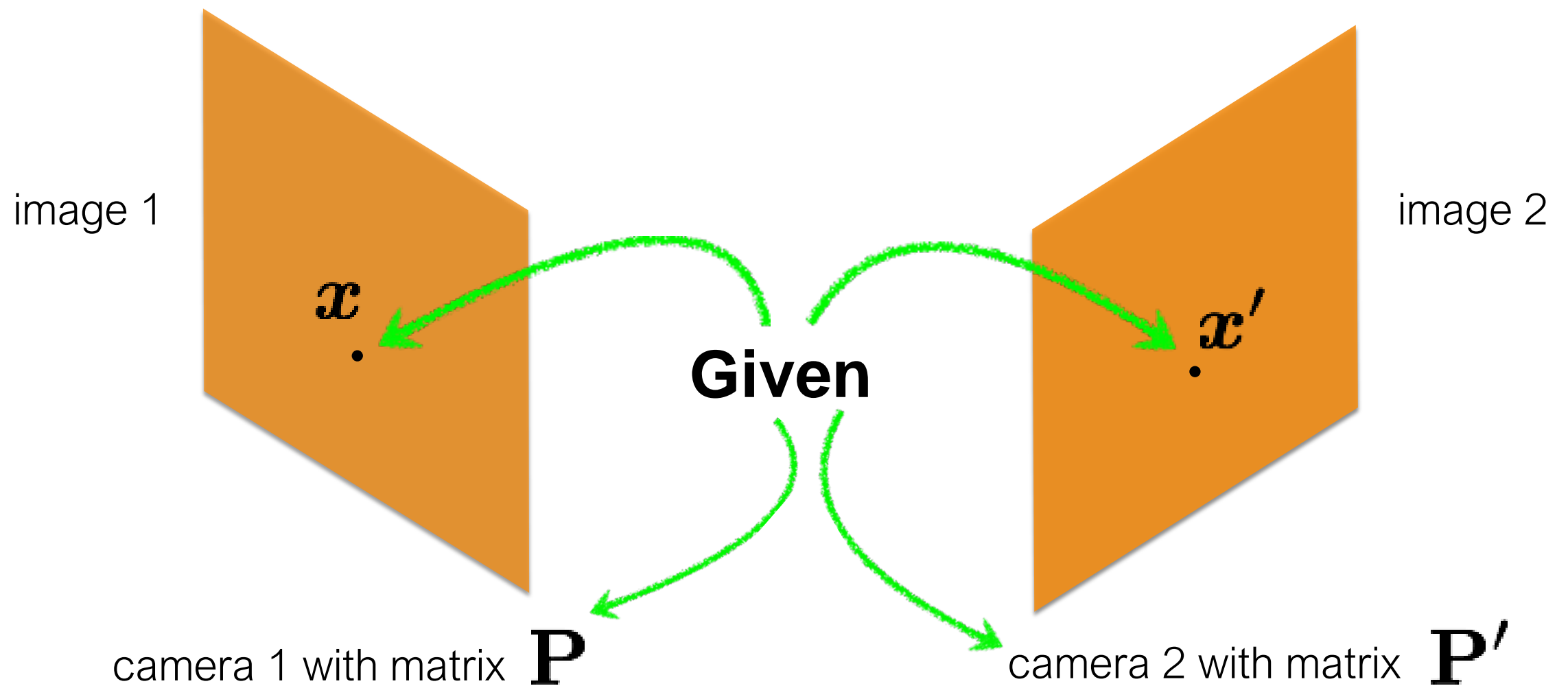
Many different ways to calibrate a camera:

- Radiometric calibration.
- Color calibration.
- Geometric calibration.
- Noise calibration.
- Lens (or aberration) calibration.

Triangulation

	Structure (scene geometry)	Motion (camera geometry)	Measurements
Pose Estimation	known	estimate	3D to 2D correspondences
Triangulation	estimate	known	2D to 2D coorespondences
Reconstruction	estimate	estimate	2D to 2D coorespondences

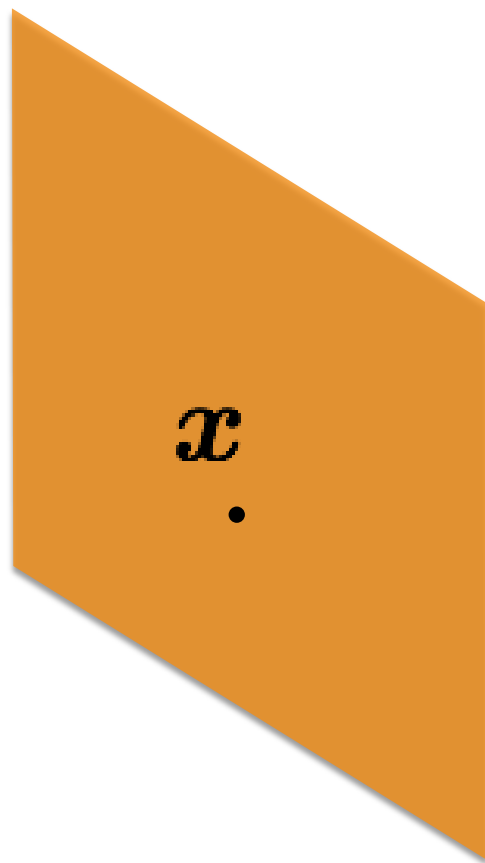
Triangulation



Triangulation

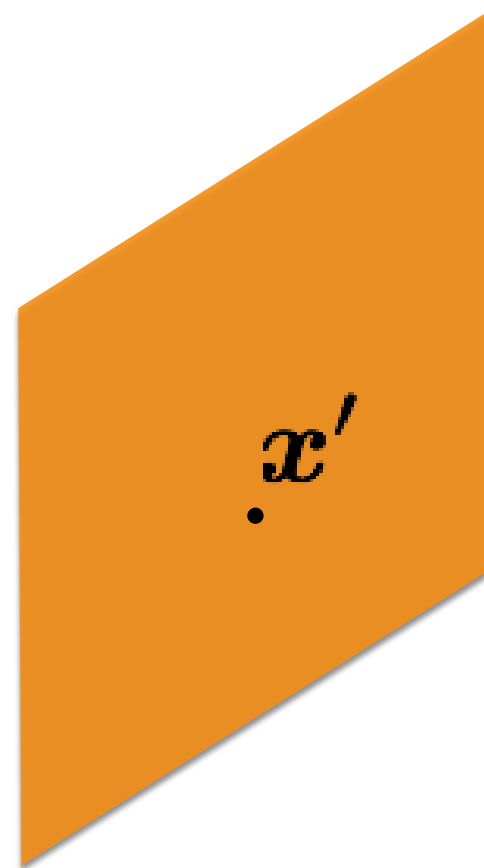
Which 3D points map
to \mathbf{x} ?

image 1



camera 1 with matrix \mathbf{P}

image 2

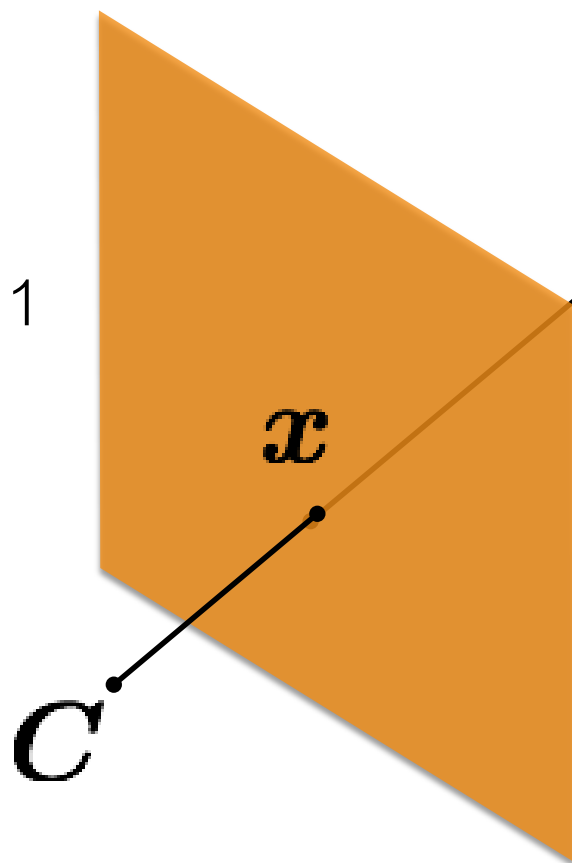


camera 2 with matrix \mathbf{P}'

Triangulation

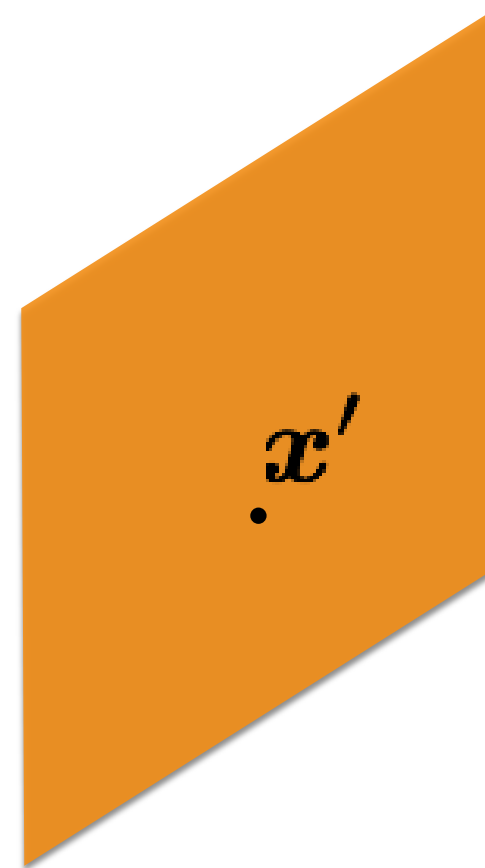
How can you compute
this ray?

image 1



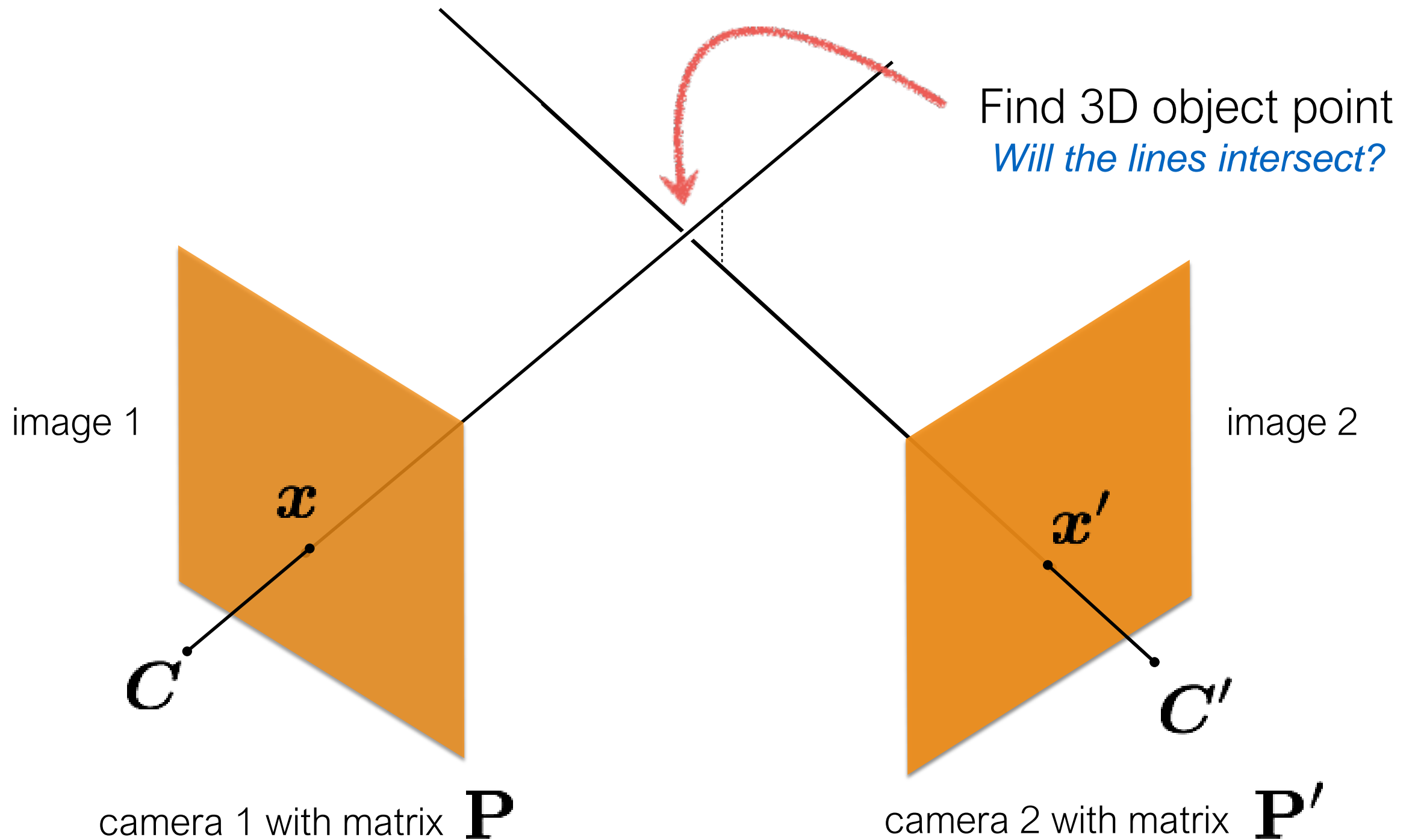
camera 1 with matrix \mathbf{P}

image 2

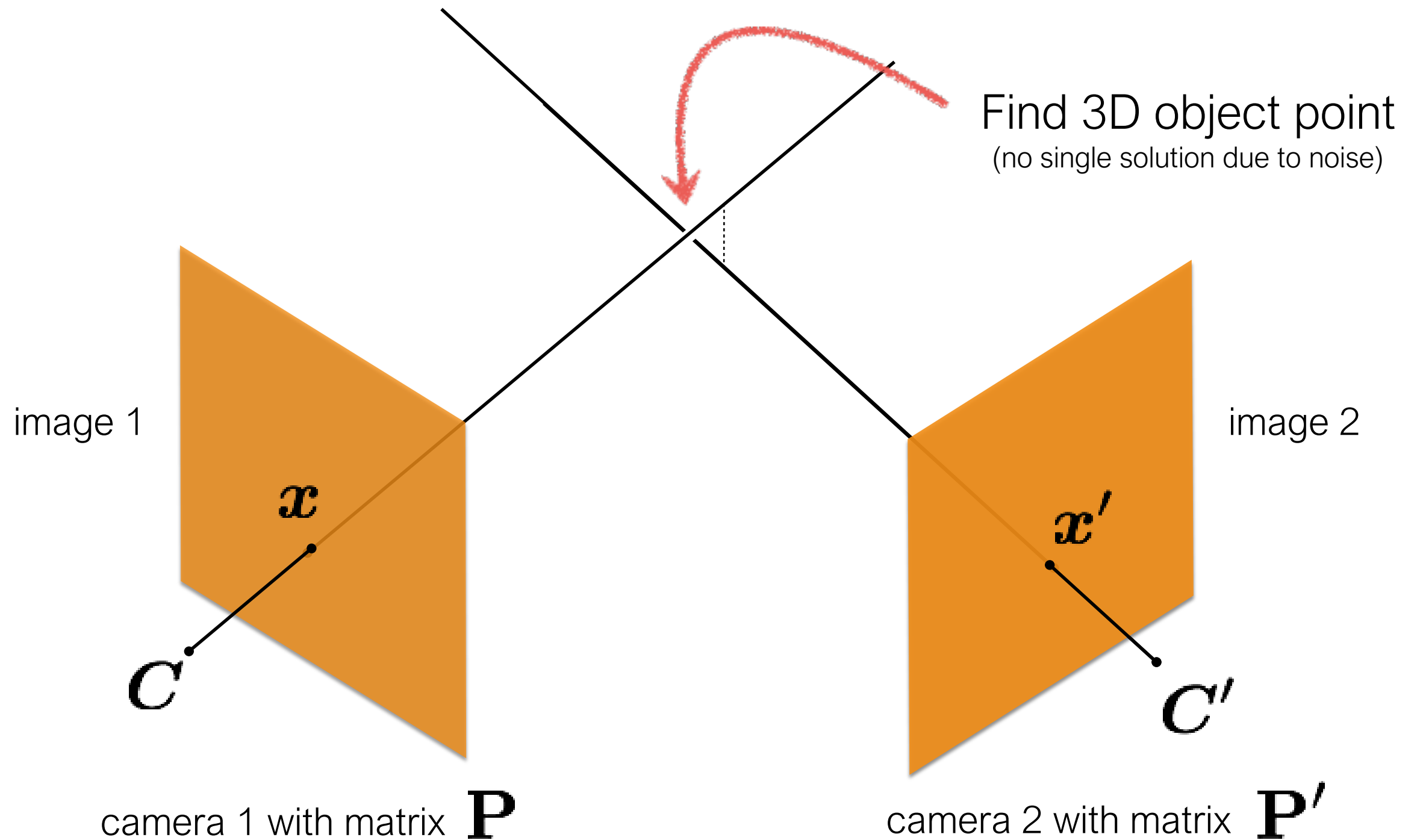


camera 2 with matrix \mathbf{P}'

Triangulation



Triangulation



Triangulation

Given a set of (noisy) matched points

$$\{\mathbf{x}_i, \mathbf{x}'_i\}$$

and camera matrices

$$\mathbf{P}, \mathbf{P}'$$

Estimate the 3D point

$$\mathbf{X}$$

$$\mathbf{x} = \mathbf{P}\mathbf{X}$$

(homogeneous
coordinate)

Also, this is a similarity relation because it involves homogeneous coordinates

$$\mathbf{x} = \alpha \mathbf{P}\mathbf{X}$$

(homogeneous
coordinate)

Same ray direction but differs by a scale factor

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

How do we solve for unknowns in a similarity relation?

$$\mathbf{x} = \mathbf{P}\mathbf{X}$$

(homogeneous
coordinate)

Also, this is a similarity relation because it involves homogeneous coordinates

$$\mathbf{x} = \alpha \mathbf{P}\mathbf{X}$$

(homogeneous
coordinate)

Same ray direction but differs by a scale factor

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

How do we solve for unknowns in a similarity relation?

Remove scale factor, convert to linear system and solve with



$$\mathbf{x} = \mathbf{P}\mathbf{X}$$

(homogeneous
coordinate)

Also, this is a similarity relation because it involves homogeneous coordinates

$$\mathbf{x} = \alpha \mathbf{P}\mathbf{X}$$

(homogeneous
coordinate)

Same ray direction but differs by a scale factor

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

How do we solve for unknowns in a similarity relation?

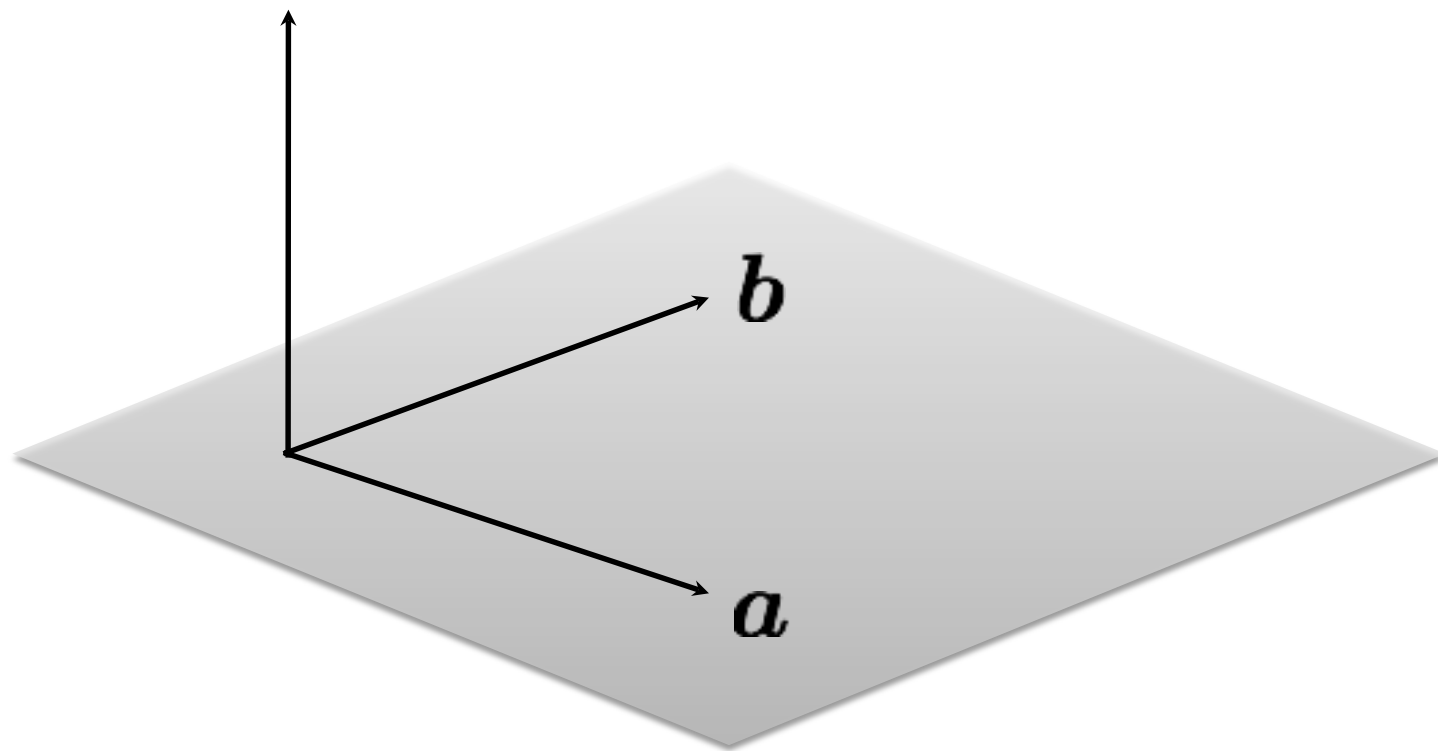
Remove scale factor, convert to linear system and solve with SVD!

Recall: Cross Product

Vector (cross) product

takes two vectors and returns a vector perpendicular to both

$$\mathbf{c} = \mathbf{a} \times \mathbf{b}$$



$$\mathbf{c} \cdot \mathbf{a} = 0$$

$$\mathbf{c} \cdot \mathbf{b} = 0$$

$$\mathbf{a} \times \mathbf{b} = \begin{bmatrix} a_2b_3 - a_3b_2 \\ a_3b_1 - a_1b_3 \\ a_1b_2 - a_2b_1 \end{bmatrix}$$

cross product of two vectors in the same direction is zero

$$\mathbf{a} \times \mathbf{a} = 0$$

remember this!!!

$$\mathbf{x} = \alpha \mathbf{P} \mathbf{X}$$

Same direction but differs by a scale factor

$$\mathbf{x} \times \mathbf{P} \mathbf{X} = \mathbf{0}$$

Cross product of two vectors of same direction is zero
(this equality removes the scale factor)

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} \text{---} & \mathbf{p_1^\top} & \text{---} \\ \text{---} & \mathbf{p_2^\top} & \text{---} \\ \text{---} & \mathbf{p_3^\top} & \text{---} \end{bmatrix} \begin{bmatrix} | \\ \mathbf{X} \\ | \end{bmatrix}$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} \mathbf{p_1^\top X} \\ \mathbf{p_2^\top X} \\ \mathbf{p_3^\top X} \end{bmatrix}$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} \text{---} & \mathbf{p_1^\top} & \text{---} \\ \text{---} & \mathbf{p_2^\top} & \text{---} \\ \text{---} & \mathbf{p_3^\top} & \text{---} \end{bmatrix} \begin{bmatrix} | \\ \mathbf{X} \\ | \end{bmatrix}$$

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} \mathbf{p_1^\top X} \\ \mathbf{p_2^\top X} \\ \mathbf{p_3^\top X} \end{bmatrix}$$

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \times \begin{bmatrix} \mathbf{p_1^\top X} \\ \mathbf{p_2^\top X} \\ \mathbf{p_3^\top X} \end{bmatrix} = \begin{bmatrix} yp_3^\top X - p_2^\top X \\ p_1^\top X - xp_3^\top X \\ xp_2^\top X - yp_1^\top X \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Using the fact that the cross product should be zero

$$\mathbf{x} \times \mathbf{P}\mathbf{X} = \mathbf{0}$$

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \times \begin{bmatrix} \mathbf{p}_1^\top \mathbf{X} \\ \mathbf{p}_2^\top \mathbf{X} \\ \mathbf{p}_3^\top \mathbf{X} \end{bmatrix} = \begin{bmatrix} y\mathbf{p}_3^\top \mathbf{X} - \mathbf{p}_2^\top \mathbf{X} \\ \mathbf{p}_1^\top \mathbf{X} - x\mathbf{p}_3^\top \mathbf{X} \\ x\mathbf{p}_2^\top \mathbf{X} - y\mathbf{p}_1^\top \mathbf{X} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Third line is a linear combination of the first and second lines.
(x times the first line plus y times the second line)

One 2D to 3D point correspondence give you  equations

Using the fact that the cross product should be zero

$$\mathbf{x} \times \mathbf{P}\mathbf{X} = \mathbf{0}$$

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \times \begin{bmatrix} \mathbf{p}_1^\top \mathbf{X} \\ \mathbf{p}_2^\top \mathbf{X} \\ \mathbf{p}_3^\top \mathbf{X} \end{bmatrix} = \begin{bmatrix} y\mathbf{p}_3^\top \mathbf{X} - \mathbf{p}_2^\top \mathbf{X} \\ \mathbf{p}_1^\top \mathbf{X} - x\mathbf{p}_3^\top \mathbf{X} \\ x\mathbf{p}_2^\top \mathbf{X} - y\mathbf{p}_1^\top \mathbf{X} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

Third line is a linear combination of the first and second lines.
(x times the first line plus y times the second line)

One 2D to 3D point correspondence give you 2 equations

$$\begin{bmatrix} yp_3^\top X - p_2^\top X \\ p_1^\top X - xp_3^\top X \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} yp_3^\top - p_2^\top \\ p_1^\top - xp_3^\top \end{bmatrix} X = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\mathbf{A}_i X = \mathbf{0}$$

Now we can make a system of linear equations
(two lines for each 2D point correspondence)

Concatenate the 2D points from both images

$$\begin{bmatrix} y\mathbf{p}_3^\top - \mathbf{p}_2^\top \\ \mathbf{p}_1^\top - x\mathbf{p}_3^\top \\ y'\mathbf{p}'_3{}^\top - \mathbf{p}'_2{}^\top \\ \mathbf{p}'_1{}^\top - x'\mathbf{p}'_3{}^\top \end{bmatrix} \mathbf{X} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

sanity check! dimensions?

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

How do we solve homogeneous linear system?

Concatenate the 2D points from both images

$$\begin{bmatrix} y\mathbf{p}_3^\top - \mathbf{p}_2^\top \\ \mathbf{p}_1^\top - x\mathbf{p}_3^\top \\ y'\mathbf{p}'_3{}^\top - \mathbf{p}'_2{}^\top \\ \mathbf{p}'_1{}^\top - x'\mathbf{p}'_3{}^\top \end{bmatrix} \mathbf{X} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

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

How do we solve homogeneous linear system?

S V D !

Recall: Total least squares

(**Warning:** change of notation. \mathbf{x} is a vector of parameters!)

$$\begin{aligned} E_{\text{TLS}} &= \sum_i (\mathbf{a}_i \mathbf{x})^2 \\ &= \|\mathbf{A}\mathbf{x}\|^2 && \text{(matrix form)} \\ \|\mathbf{x}\|^2 &= 1 && \text{constraint} \end{aligned}$$

$$\begin{array}{ll} \text{minimize} & \|\mathbf{A}\mathbf{x}\|^2 \\ \text{subject to} & \|\mathbf{x}\|^2 = 1 \end{array} \quad \rightarrow \quad \begin{array}{l} \text{minimize} \quad \frac{\|\mathbf{A}\mathbf{x}\|^2}{\|\mathbf{x}\|^2} \\ \text{(Rayleigh quotient)} \end{array}$$

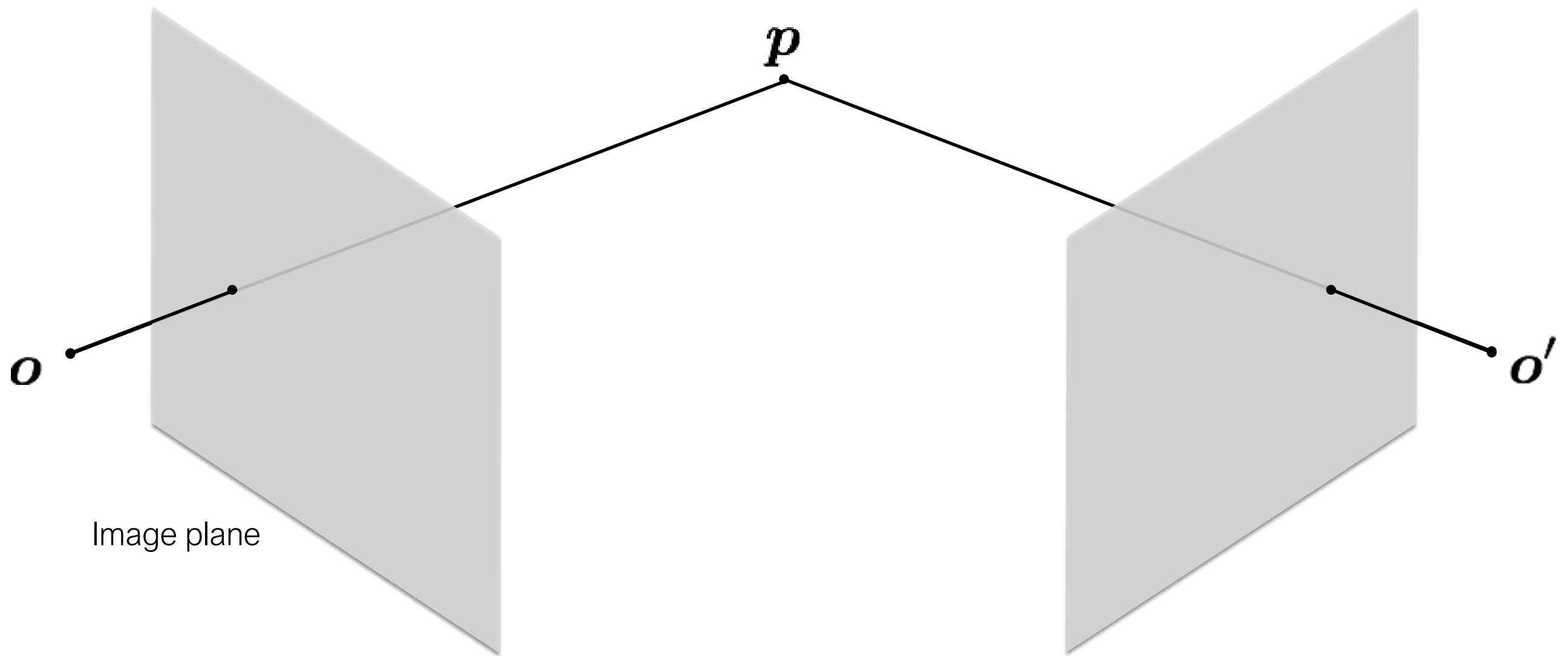
Solution is the eigenvector
corresponding to smallest eigenvalue of

$$\mathbf{A}^\top \mathbf{A}$$

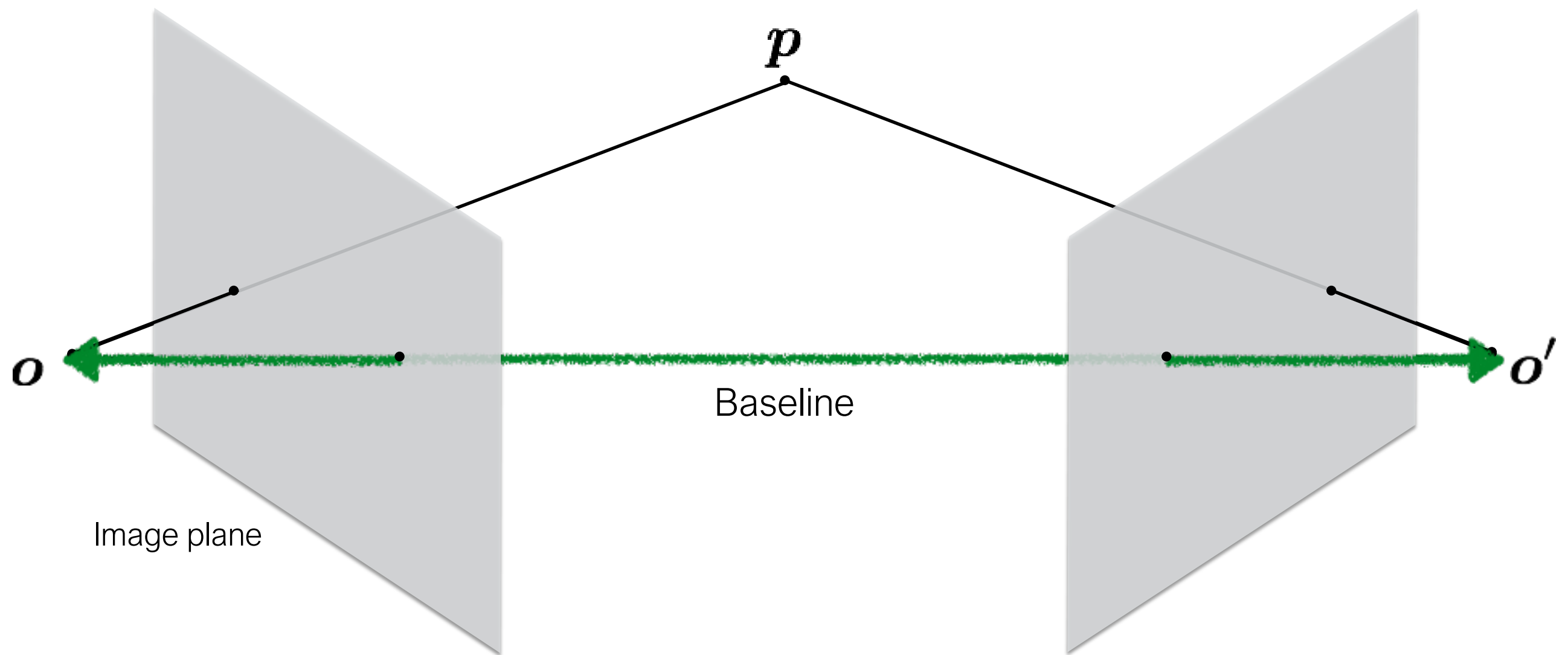
	Structure (scene geometry)	Motion (camera geometry)	Measurements
Pose Estimation	known	estimate	3D to 2D correspondences
Triangulation	estimate	known	2D to 2D coorespondences
Reconstruction	estimate	estimate	2D to 2D coorespondences

Epipolar geometry

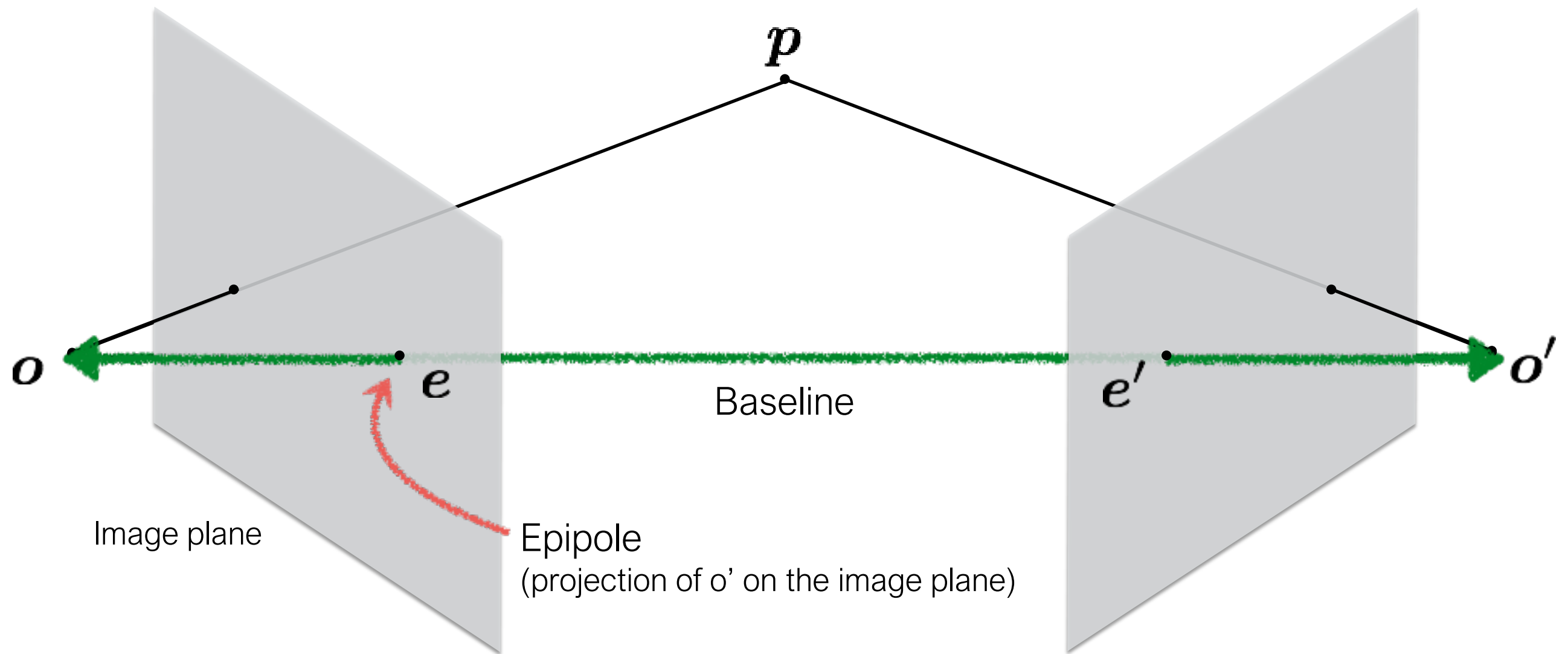
Epipolar geometry



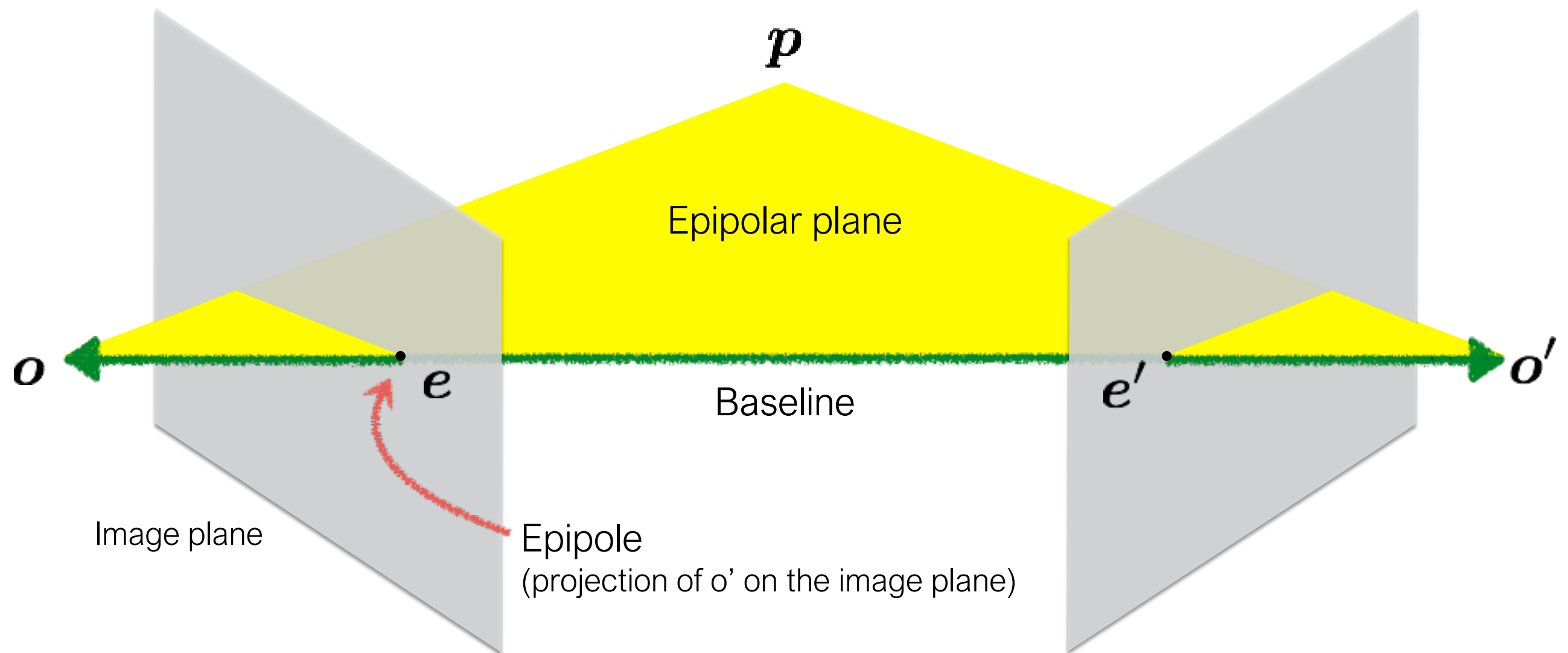
Epipolar geometry



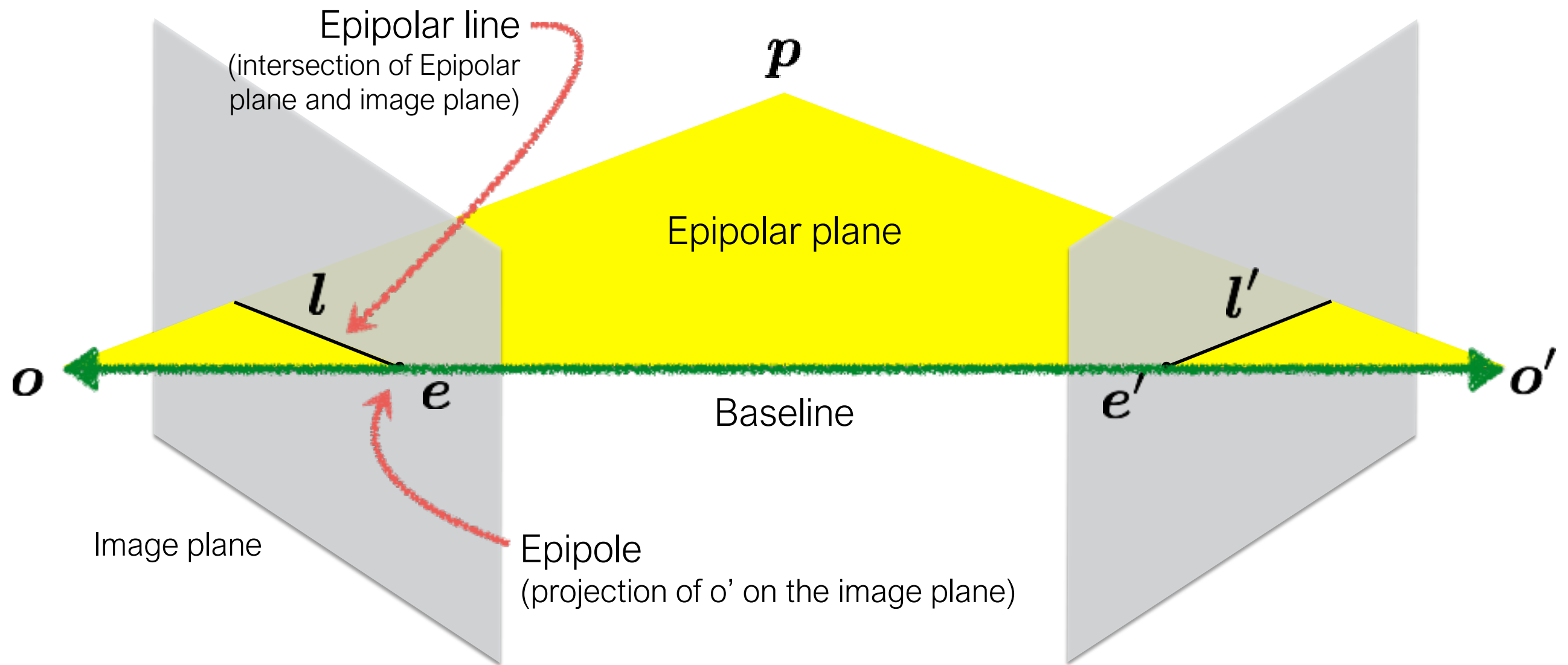
Epipolar geometry



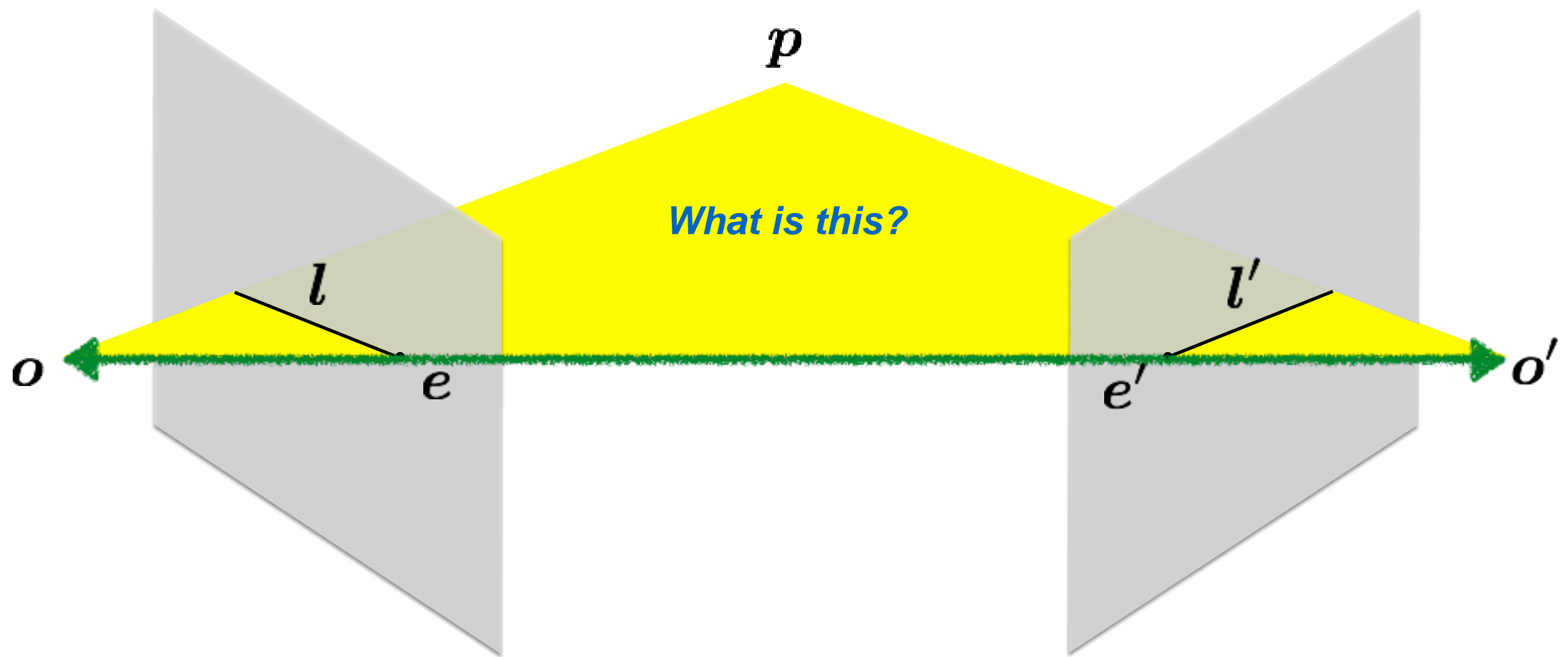
Epipolar geometry



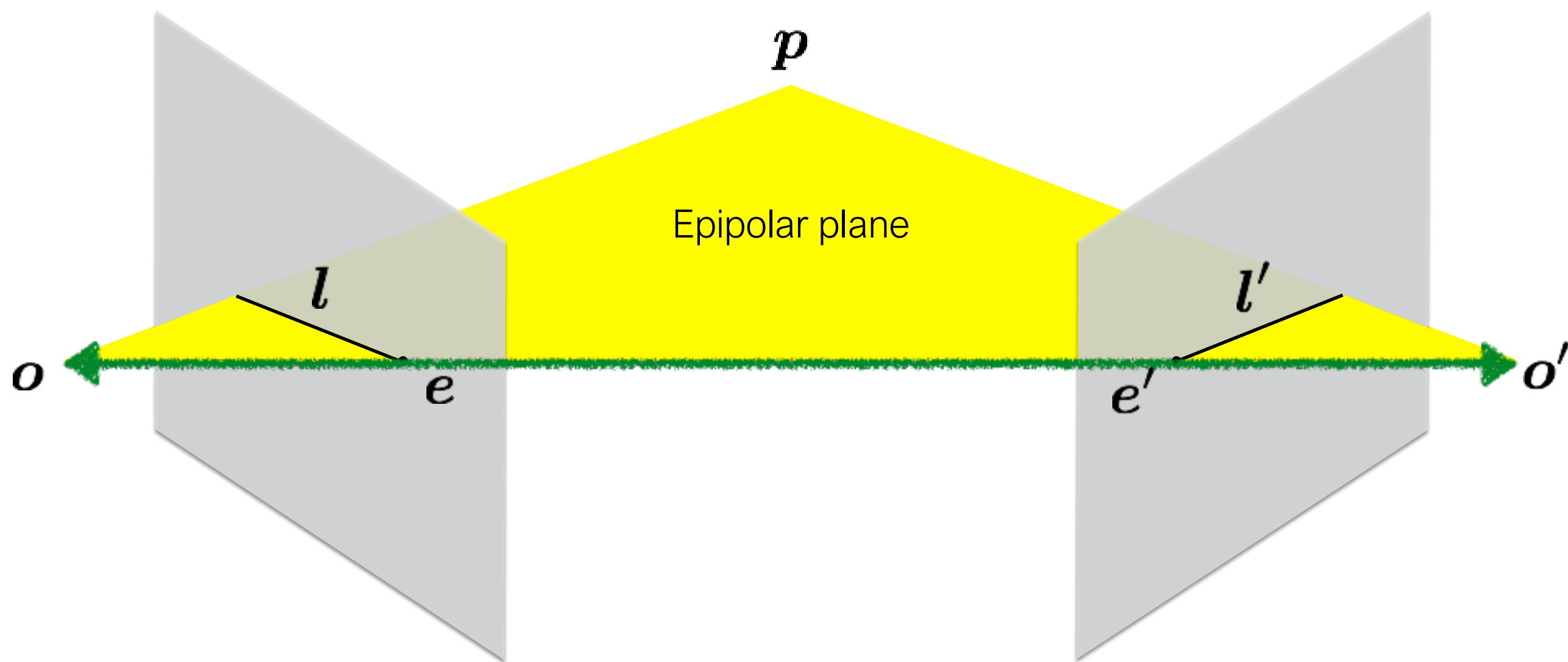
Epipolar geometry



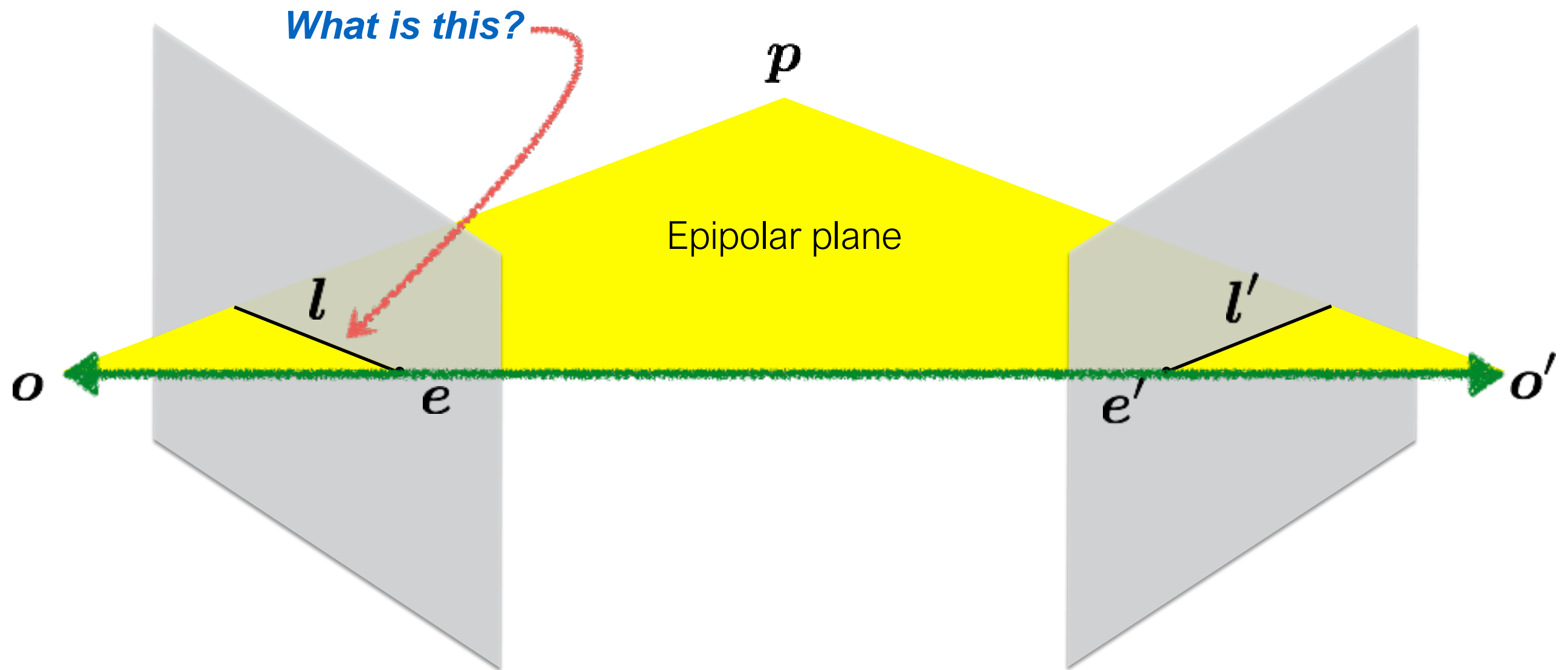
Quiz



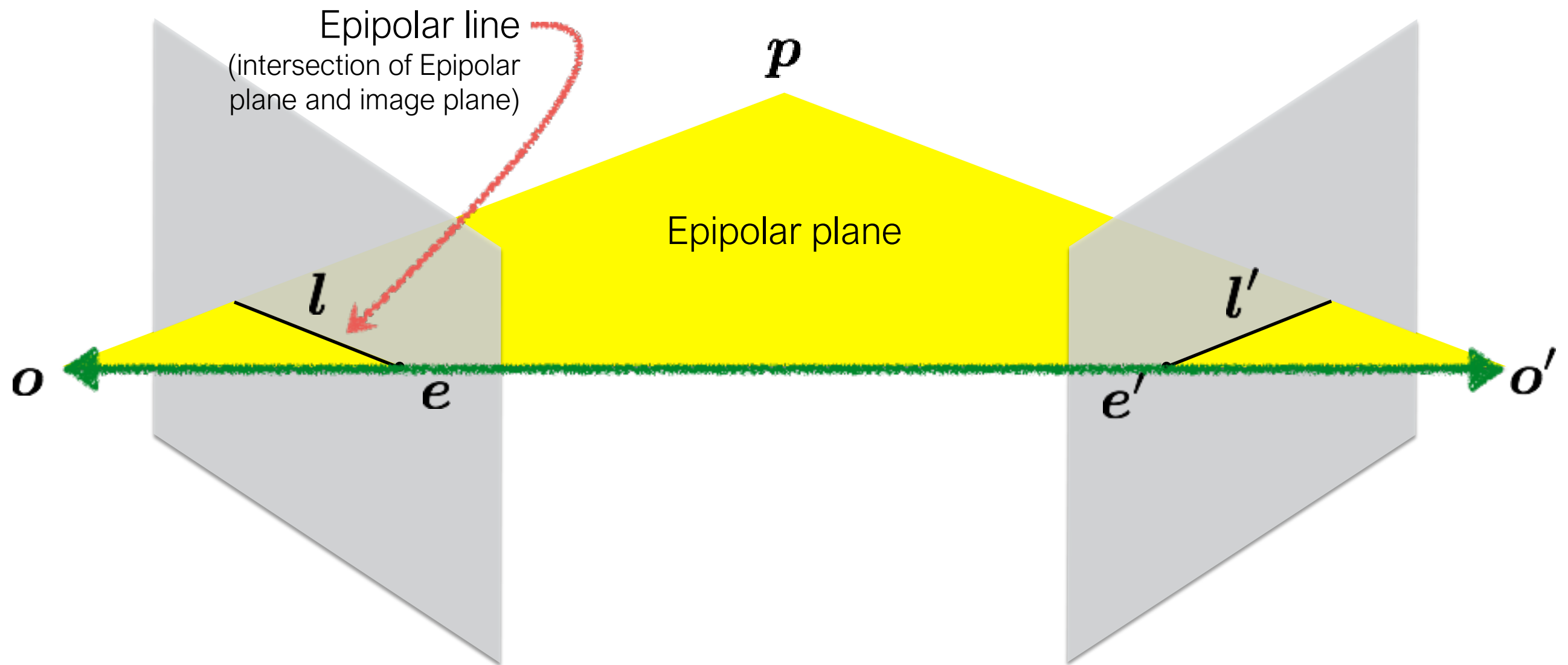
Quiz



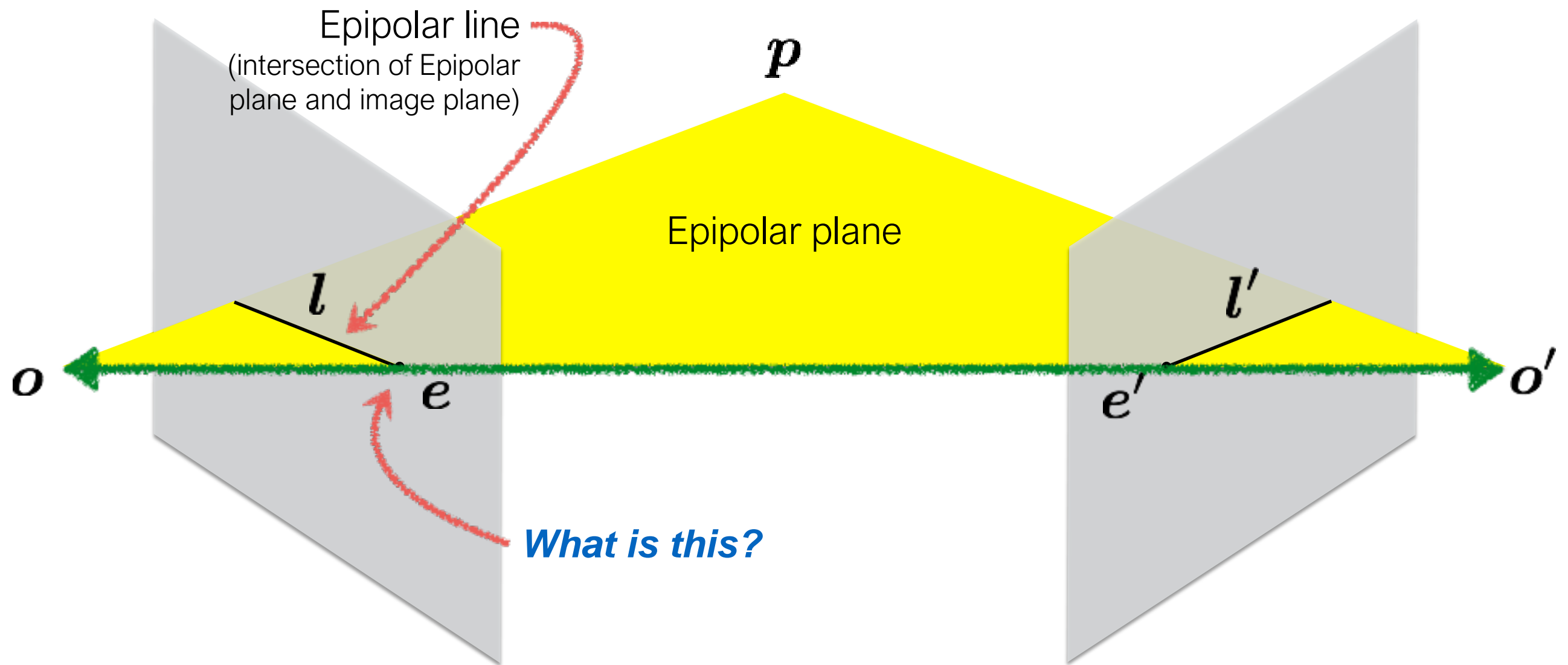
Quiz



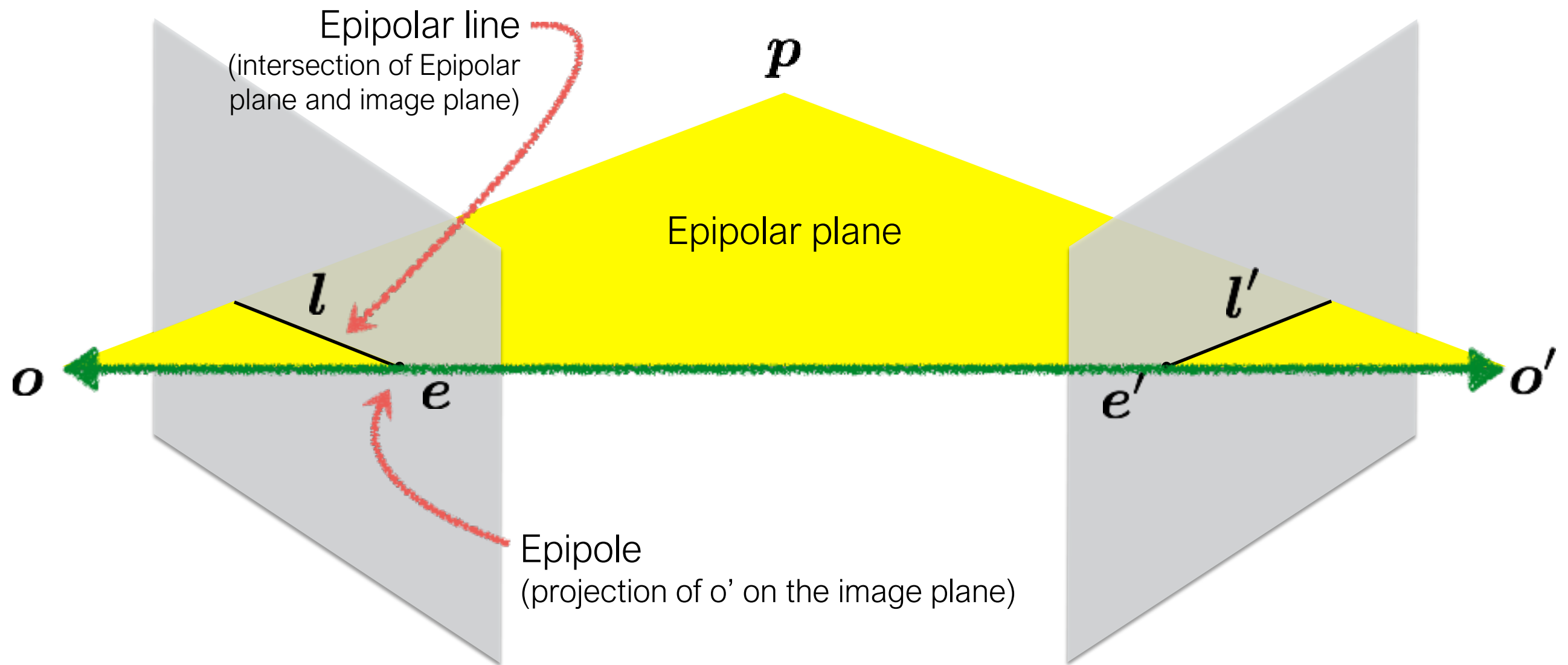
Quiz



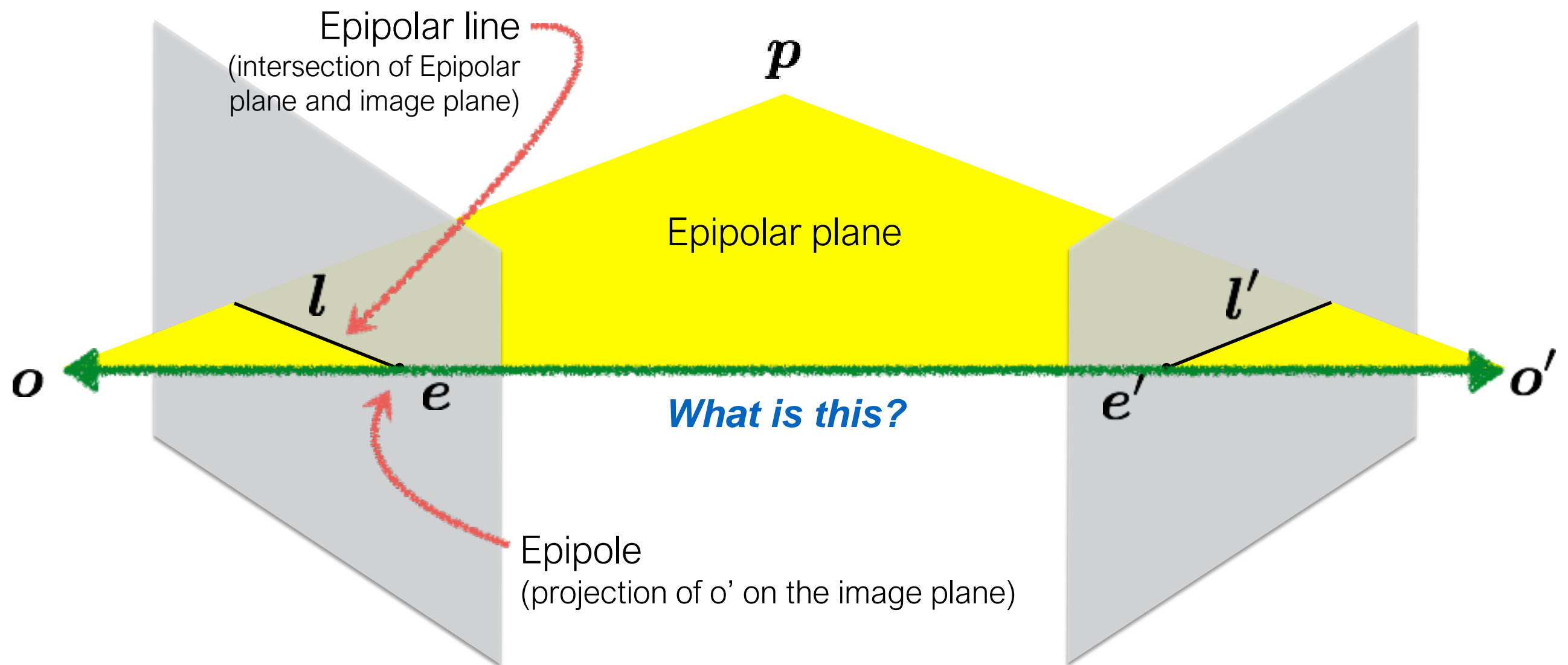
Quiz



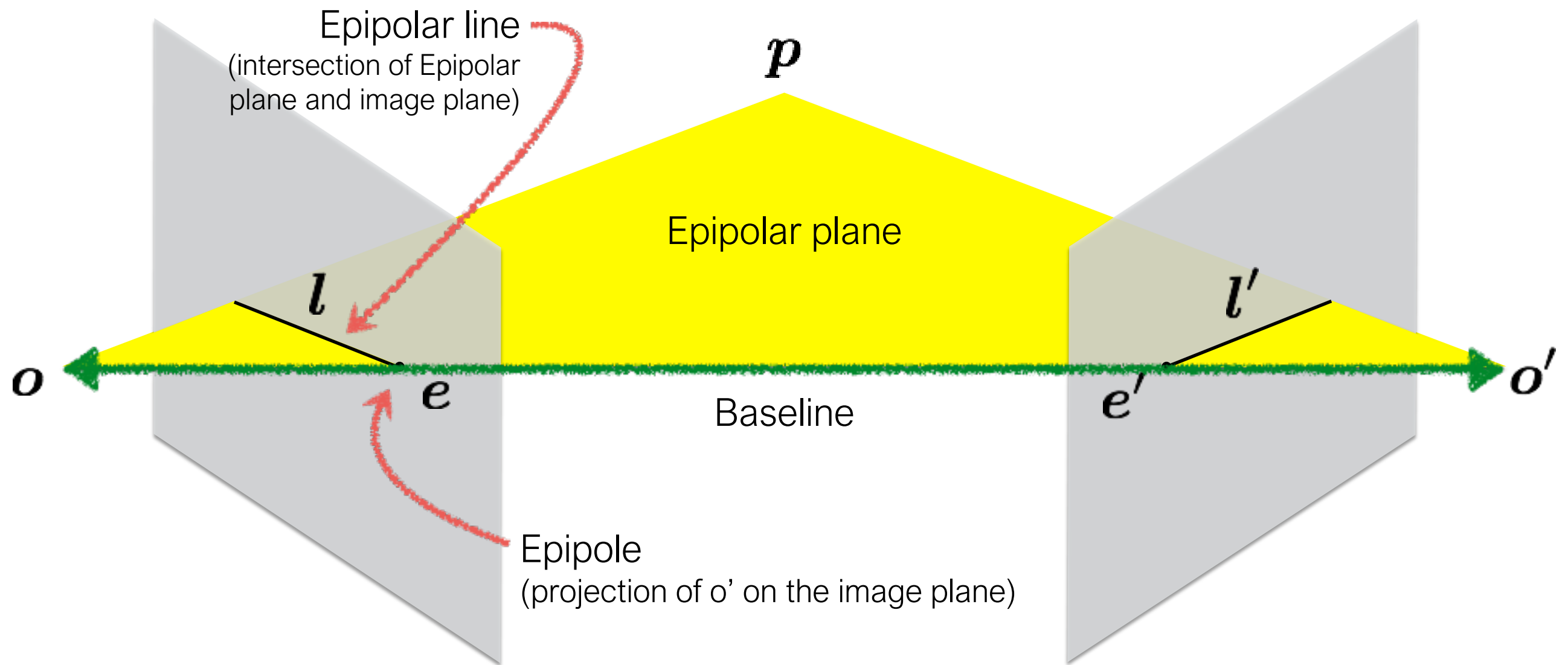
Quiz



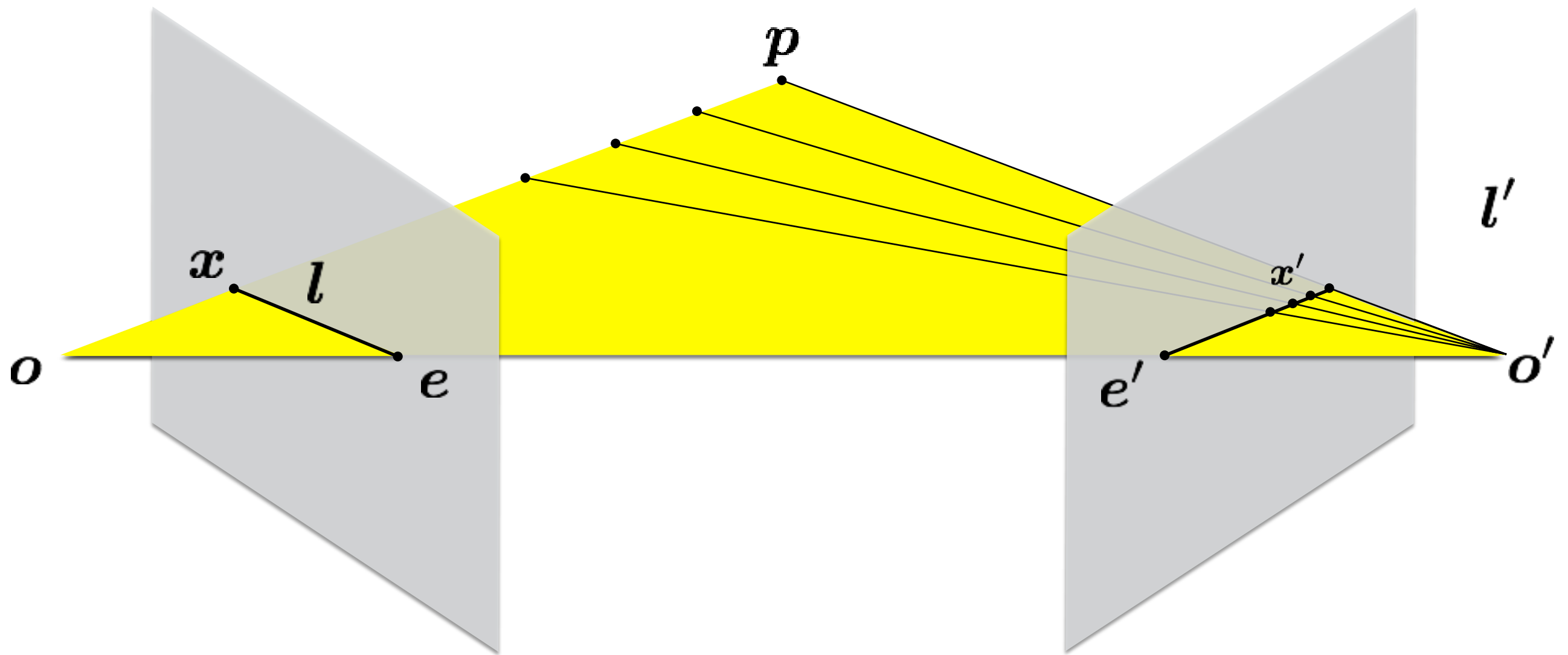
Quiz



Quiz

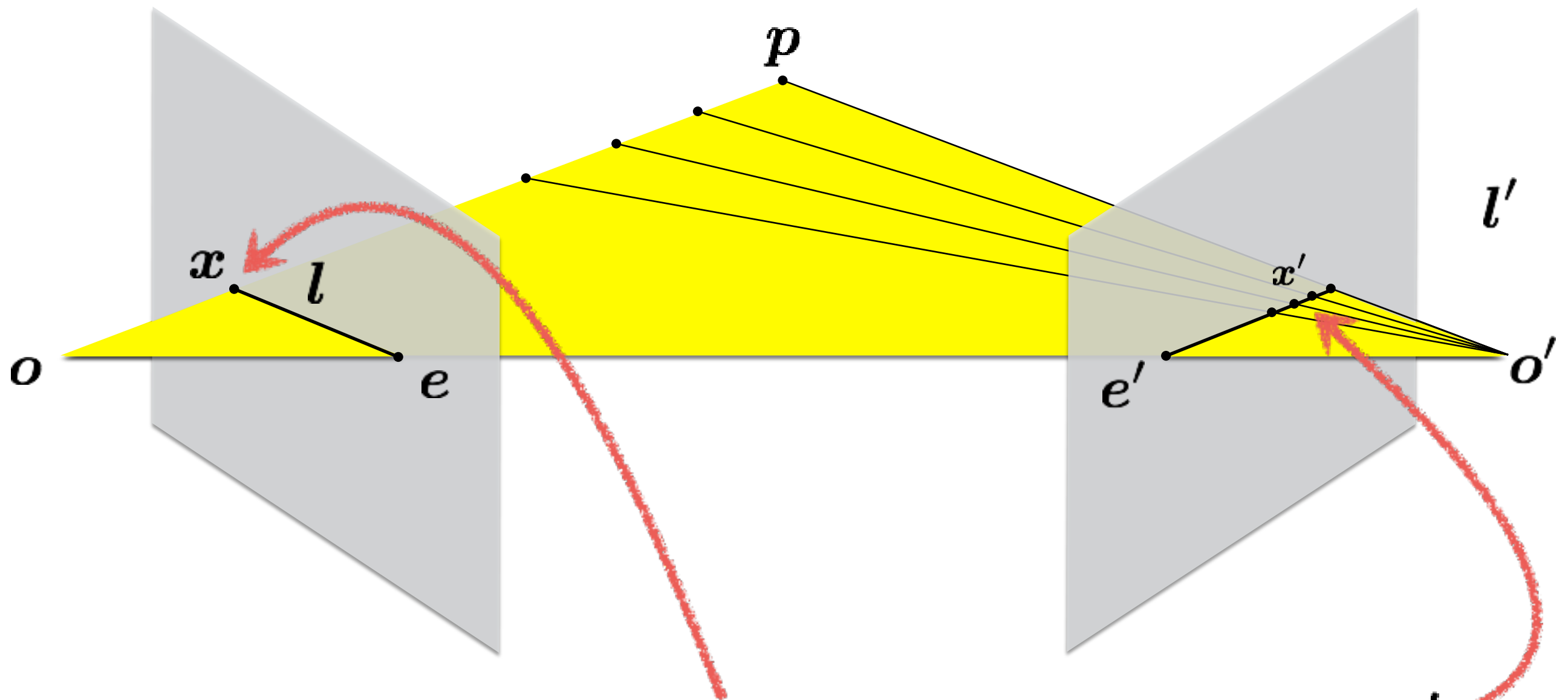


Epipolar constraint

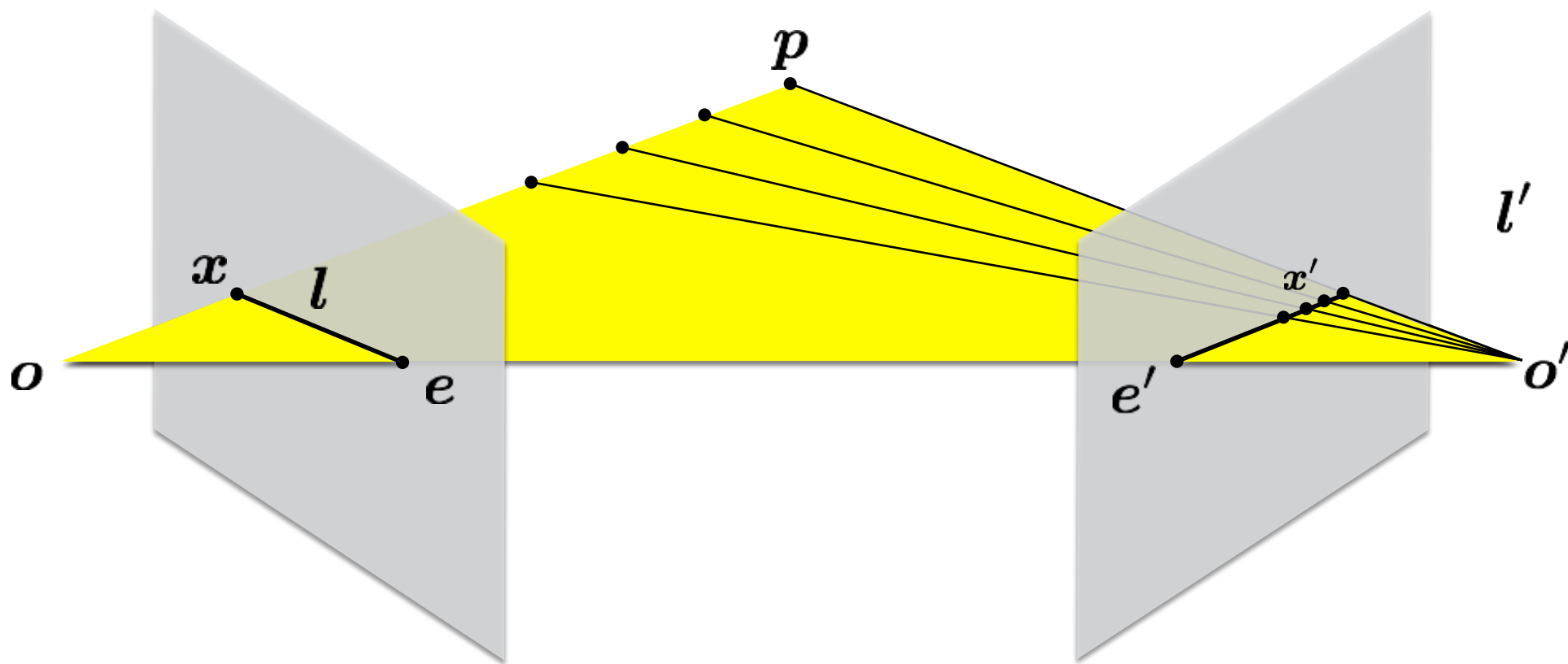


Potential matches for x lie on the epipolar line l'

Epipolar constraint



Potential matches for x lie on the epipolar line l'



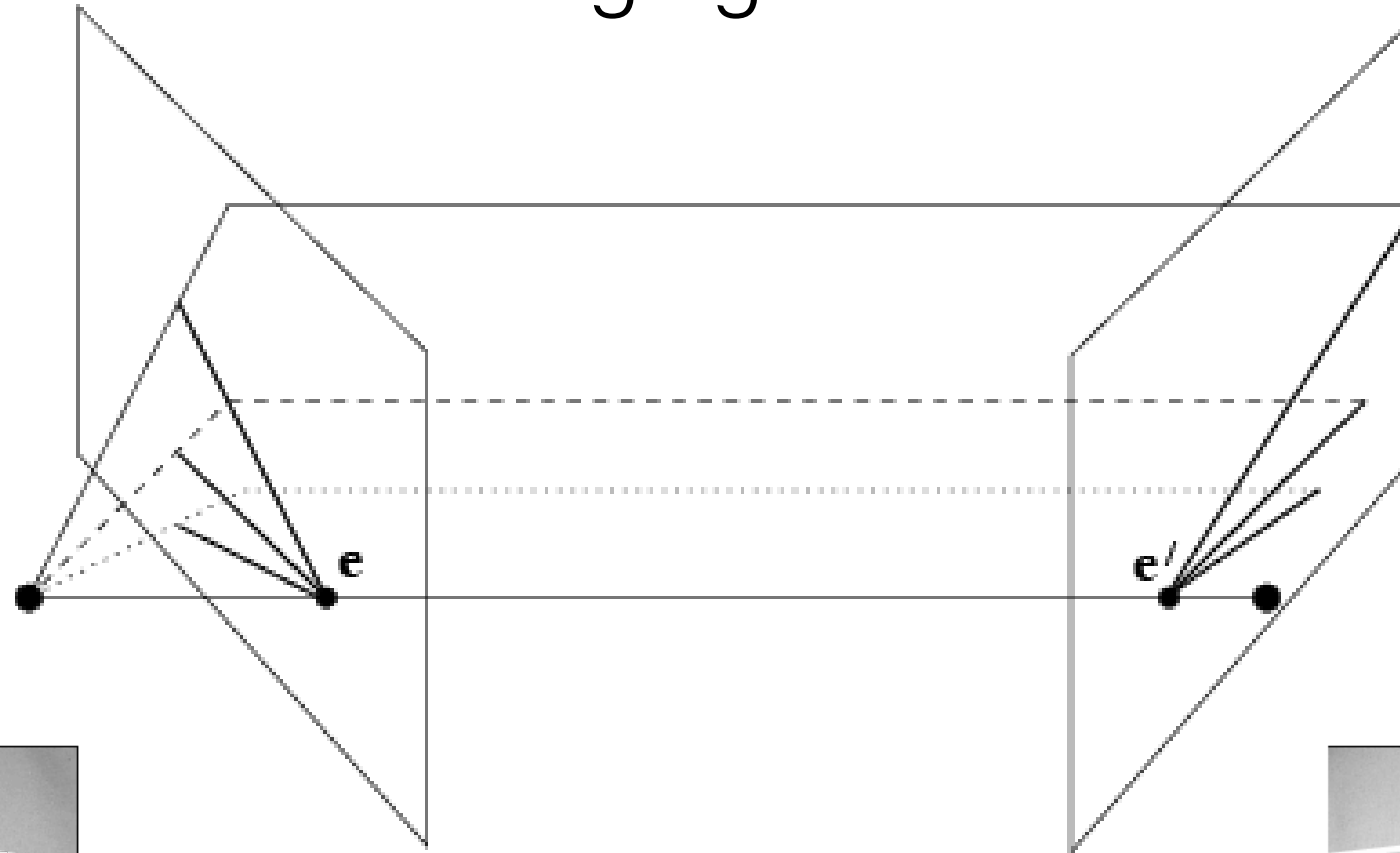
The point **x** (left image) maps to a Epipolar line in the right image

The baseline connects the Camera centers and epipols

An epipole **e** is a projection of the Camera center O' on the image plane

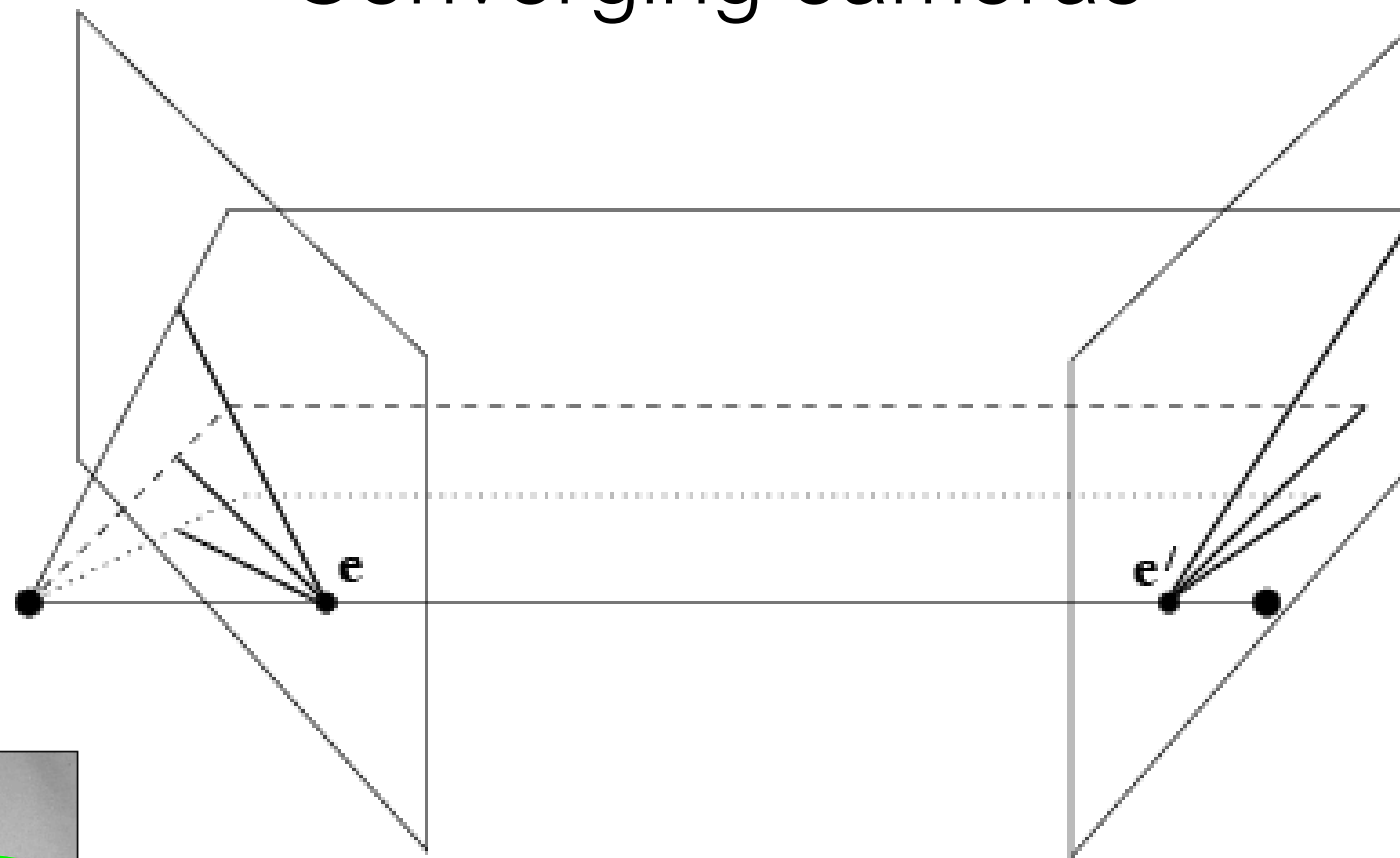
All epipolar lines in an image intersect at the epipole

Converging cameras



Where is the epipole in this image?

Converging cameras



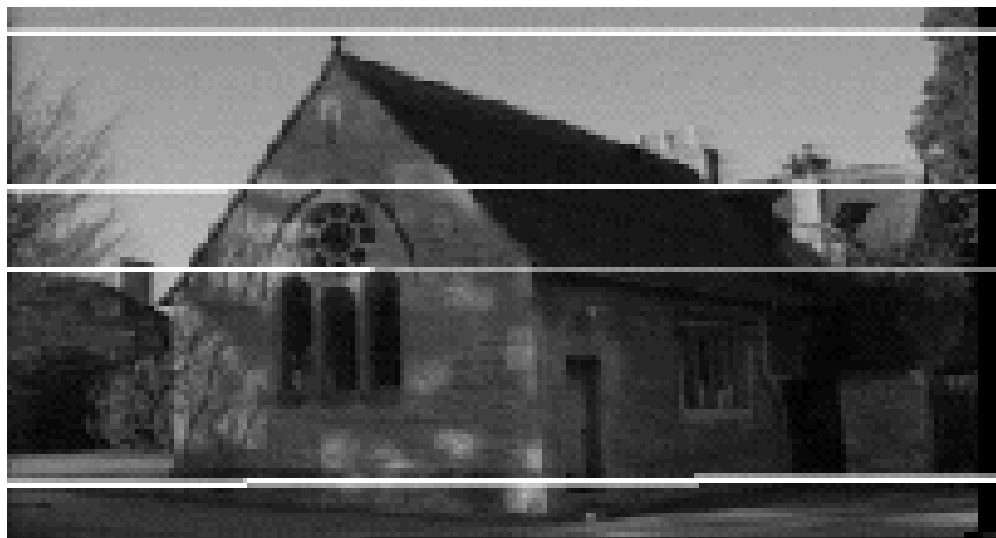
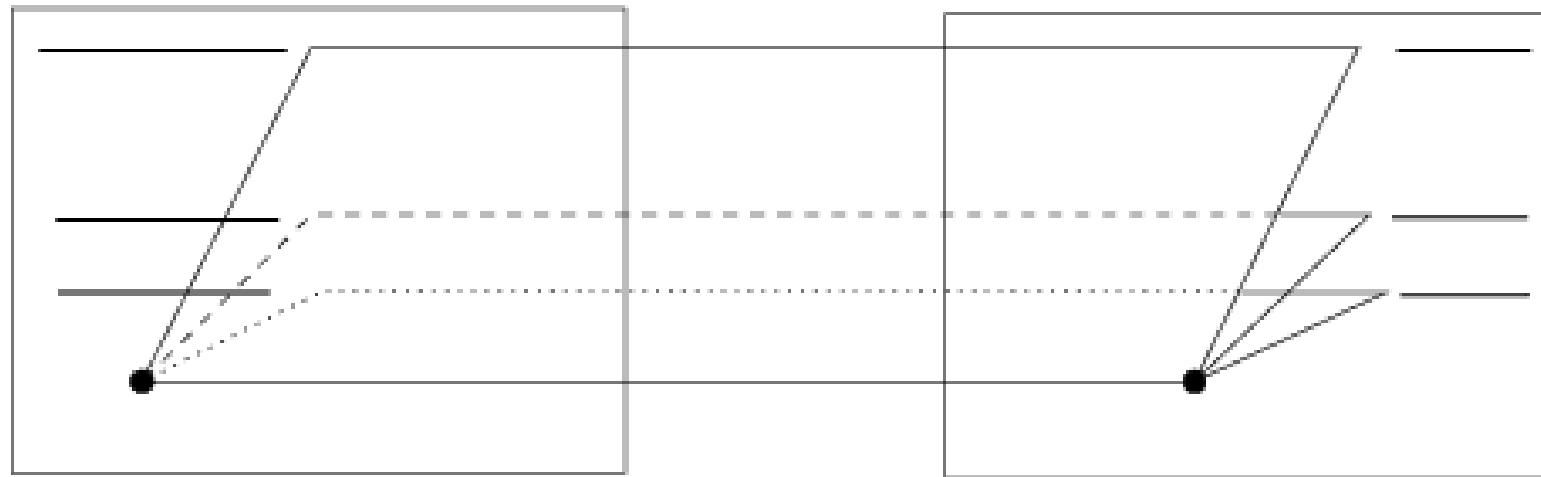
here!



Where is the epipole in this image?

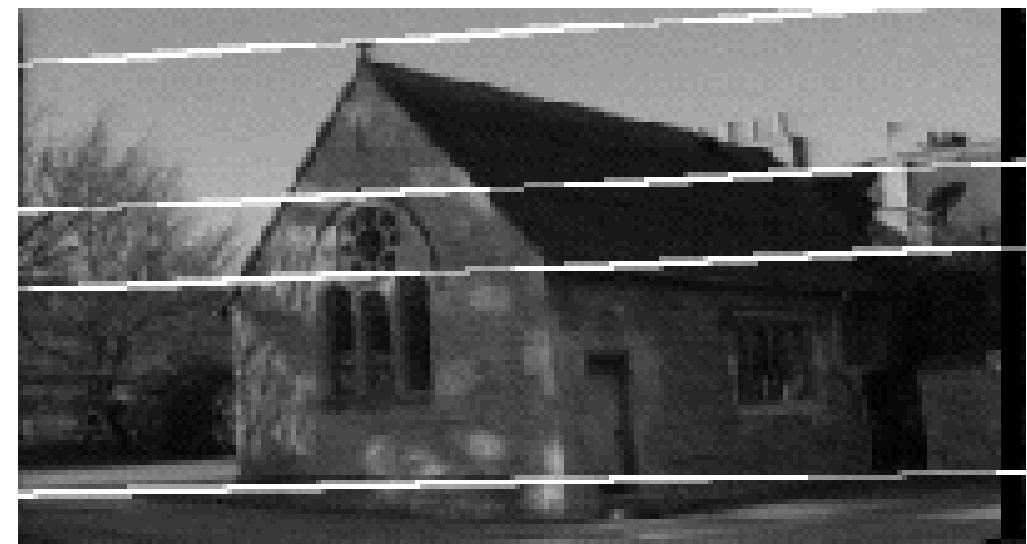
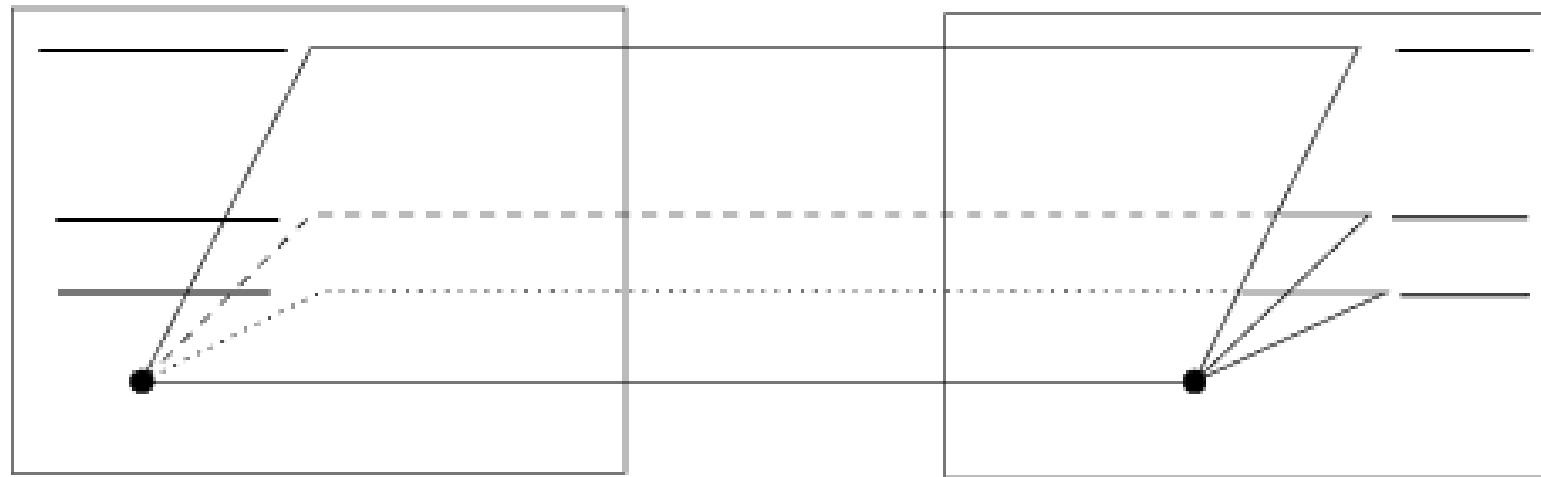
It's not always in the image

Parallel cameras



Where is the epipole?

Parallel cameras



epipole at infinity

Forward moving camera



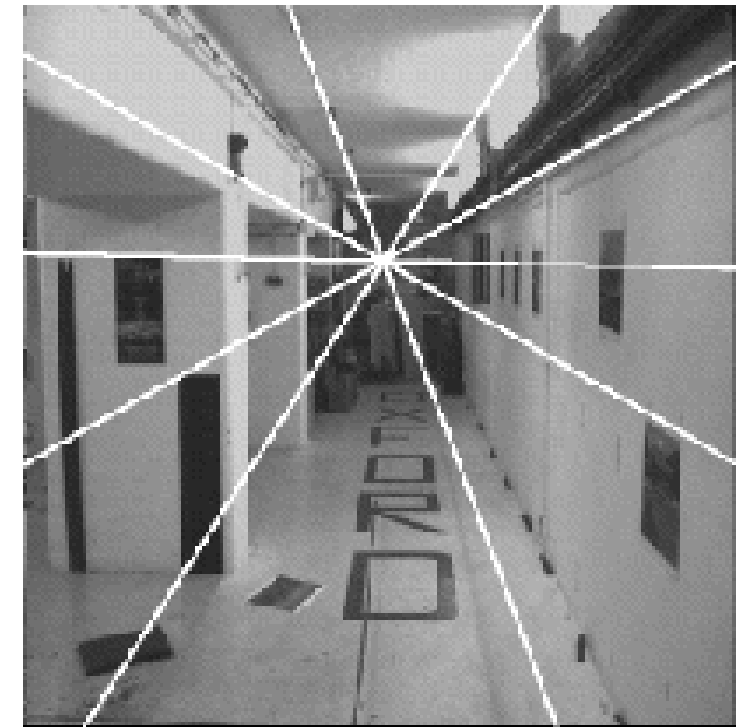
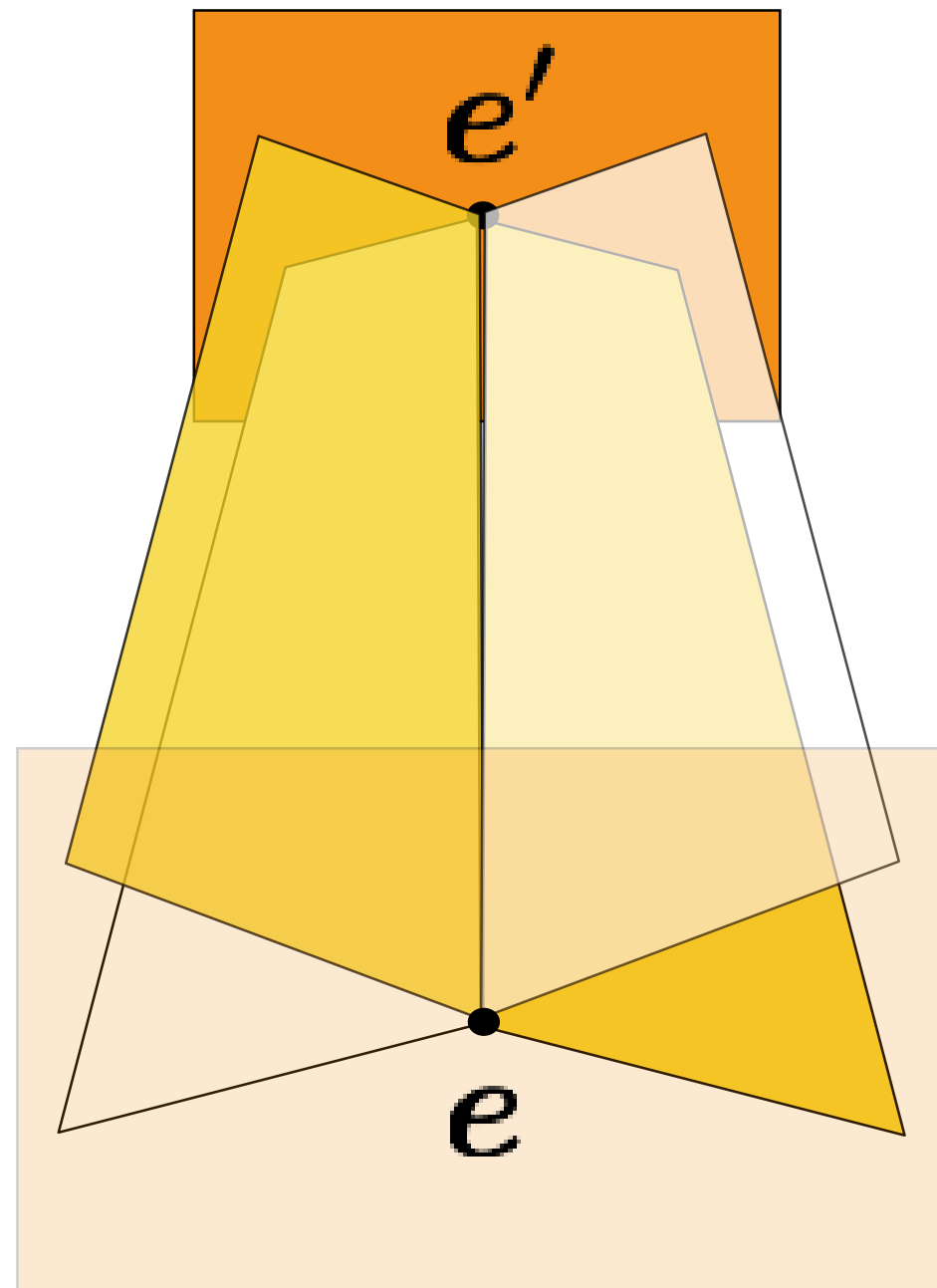
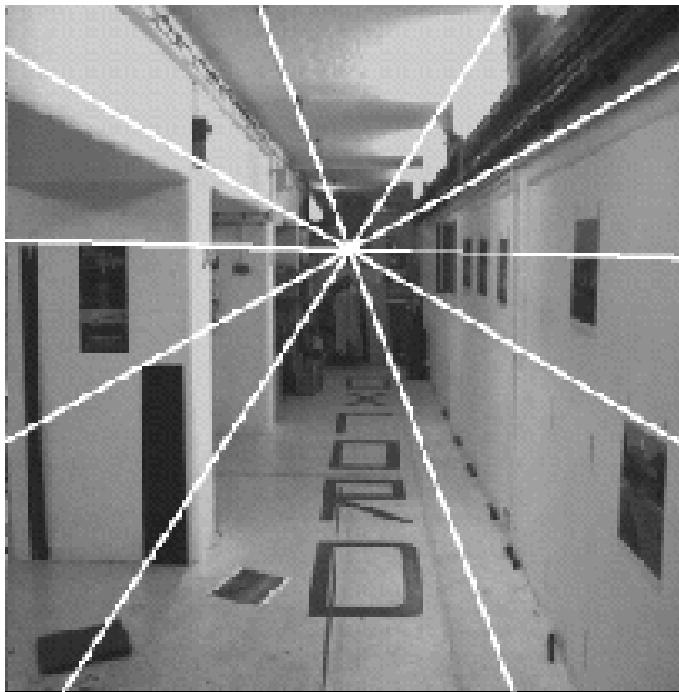
Forward moving camera



Where is the epipole?

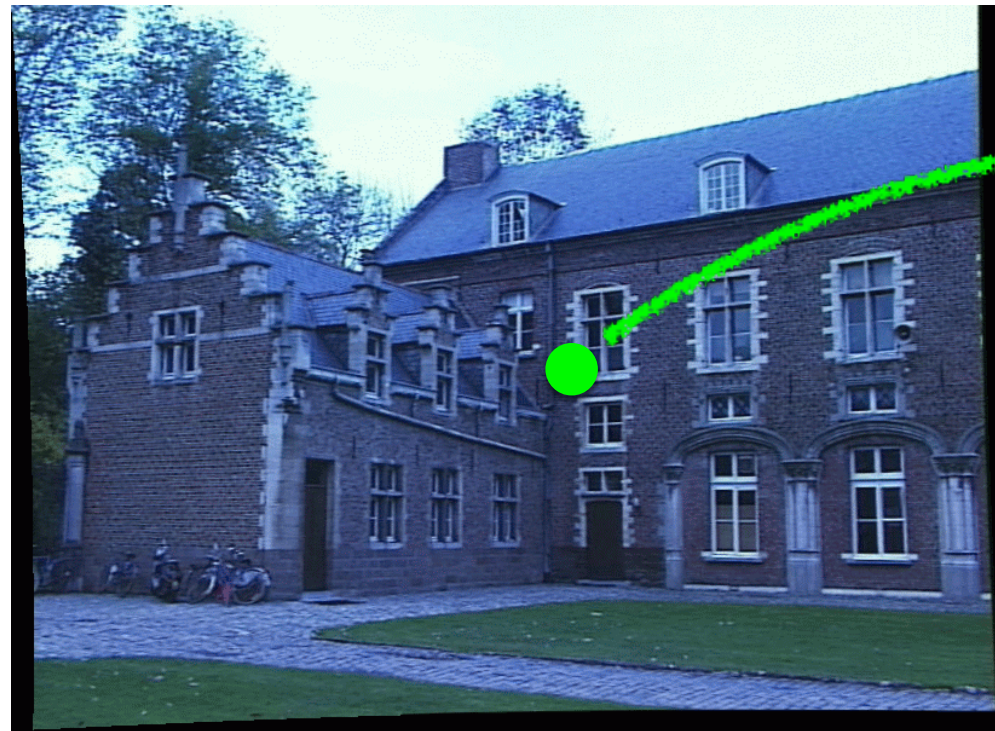
What do the epipolar lines look like?

Epipole has same coordinates in both images.
Points move along lines radiating from “Focus of expansion”

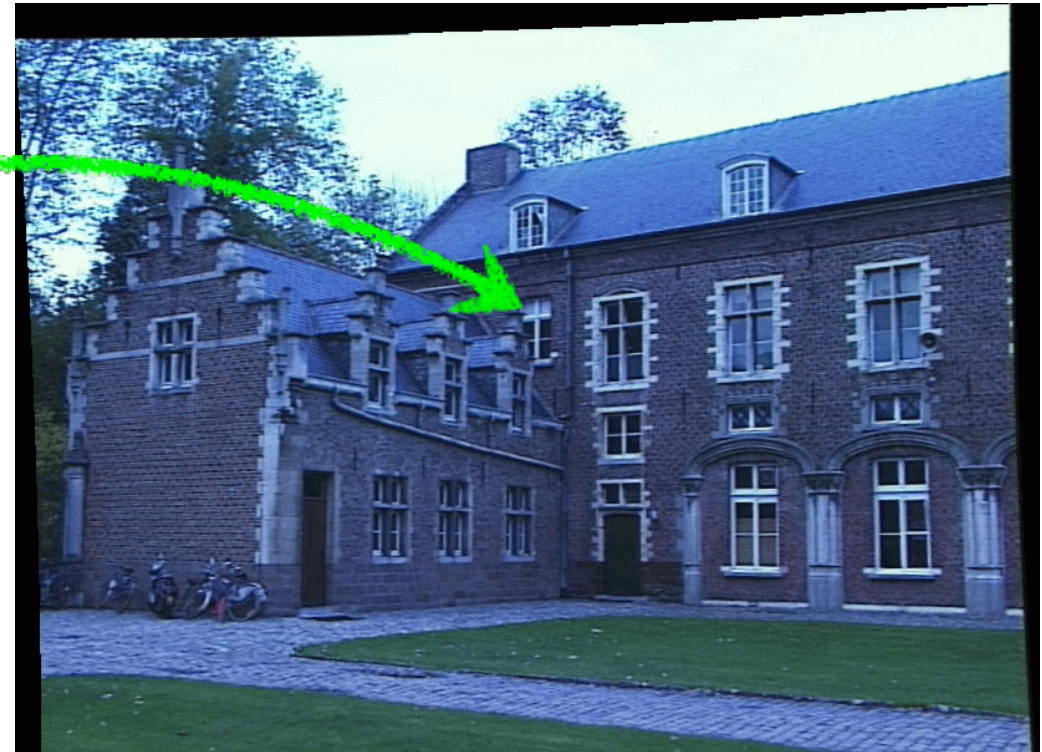


The epipolar constraint is an important concept for stereo vision

Task: Match point in left image to point in right image



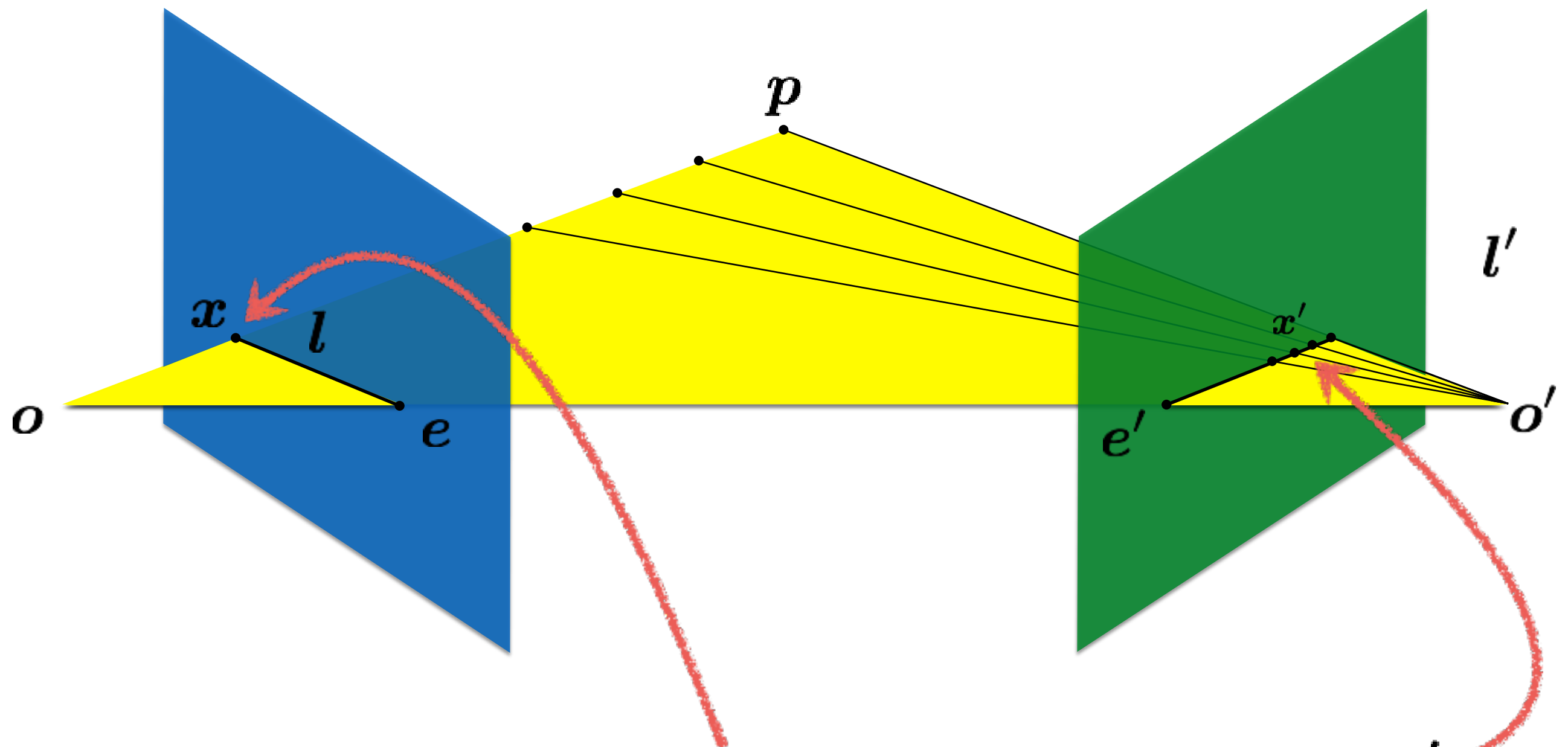
Left image



Right image

How would you do it?

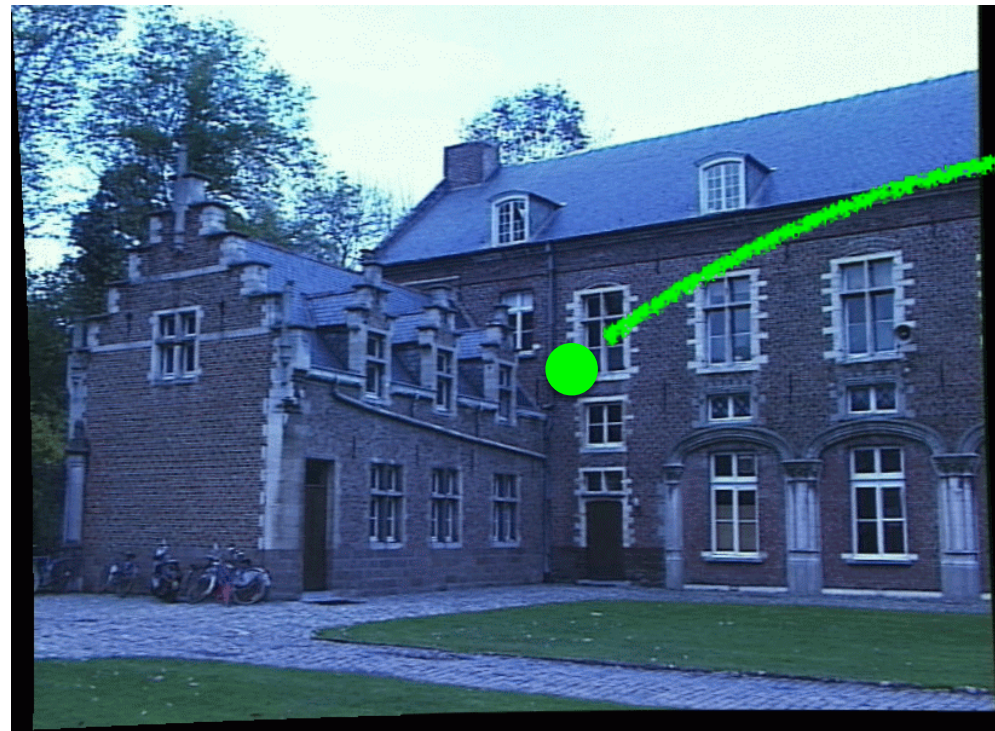
Recall: Epipolar constraint



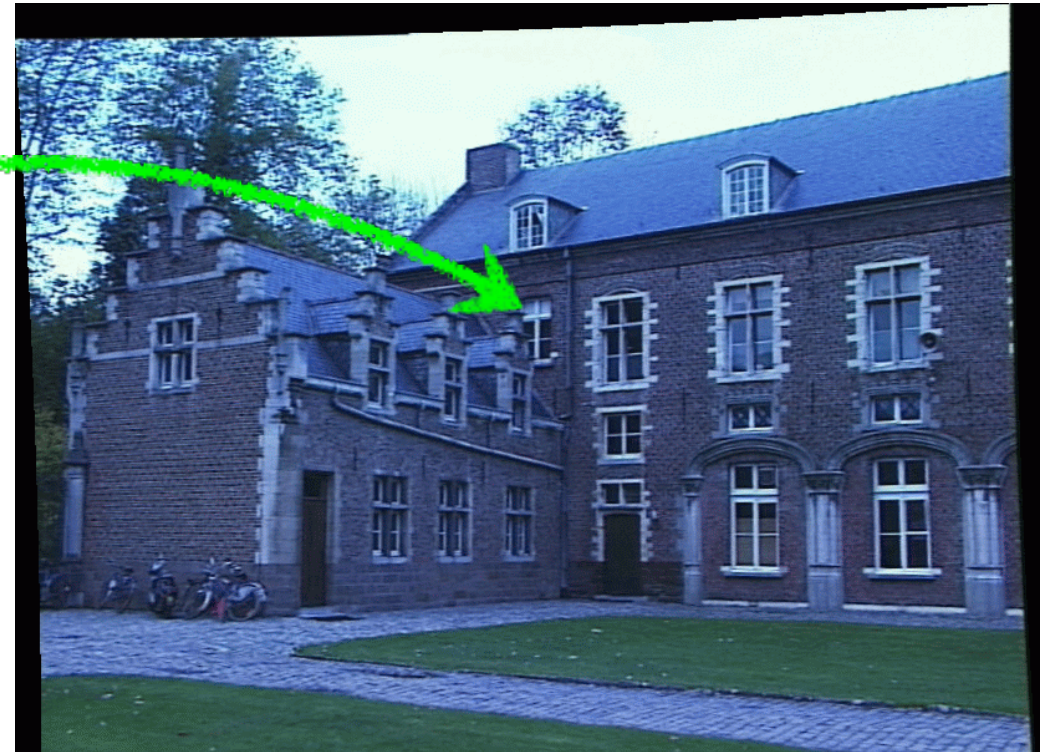
Potential matches for x lie on the epipolar line l'

The epipolar constraint is an important concept for stereo vision

Task: Match point in left image to point in right image



Left image



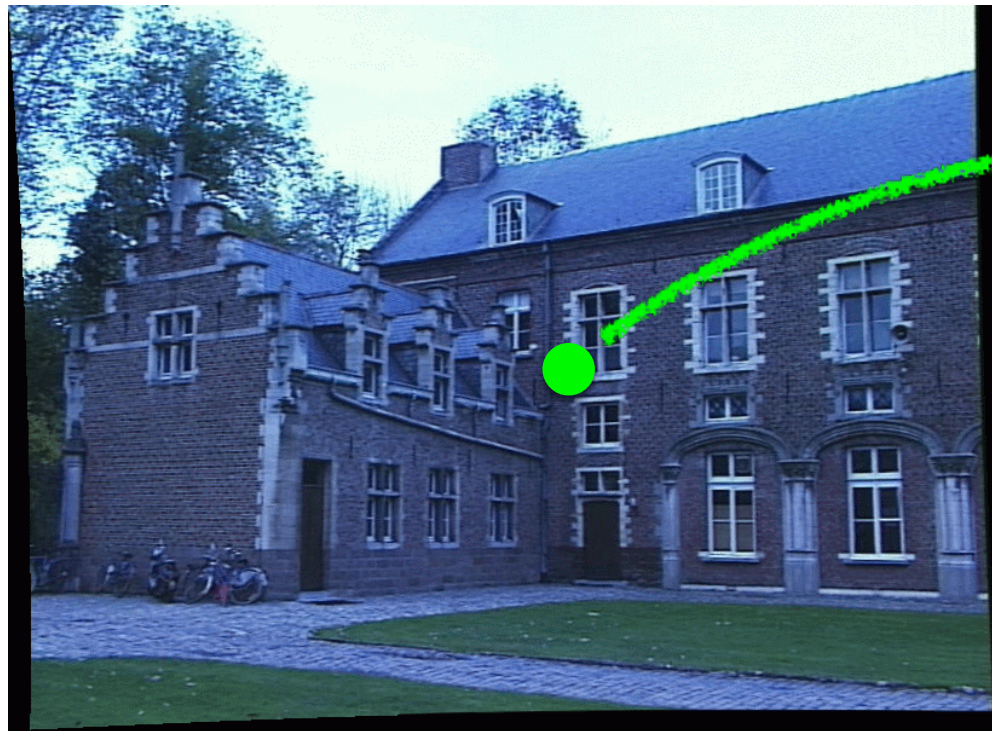
Right image

Want to avoid search over entire image

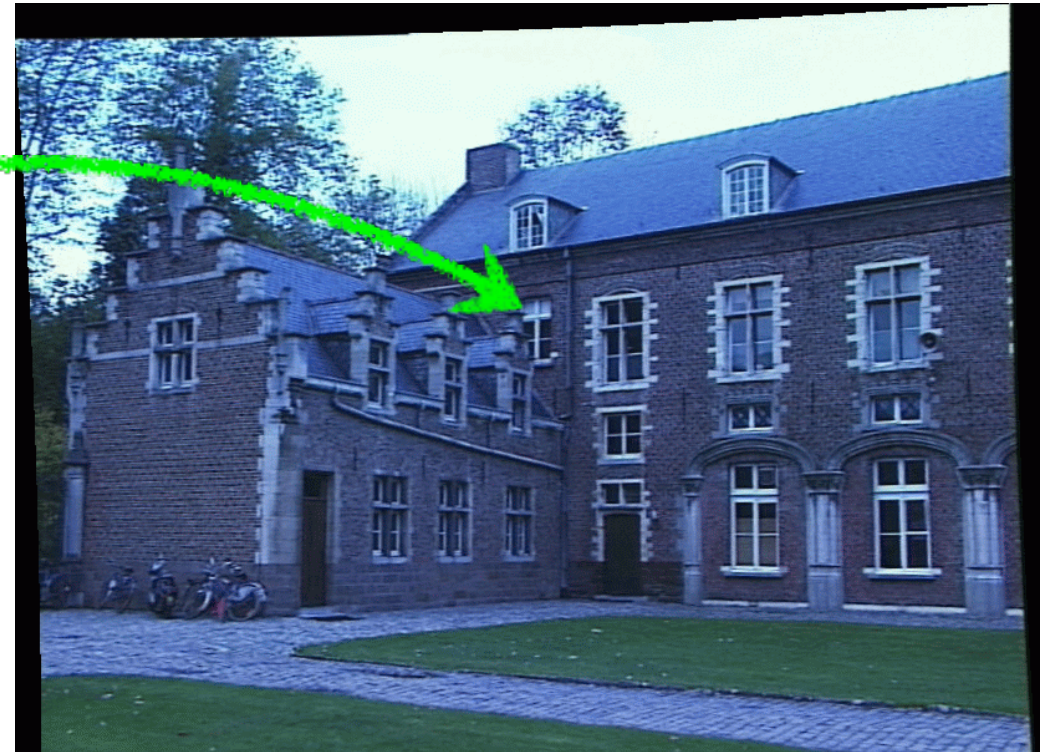
Epipolar constraint reduces search to a single line

The epipolar constraint is an important concept for stereo vision

Task: Match point in left image to point in right image



Left image



Right image

Want to avoid search over entire image

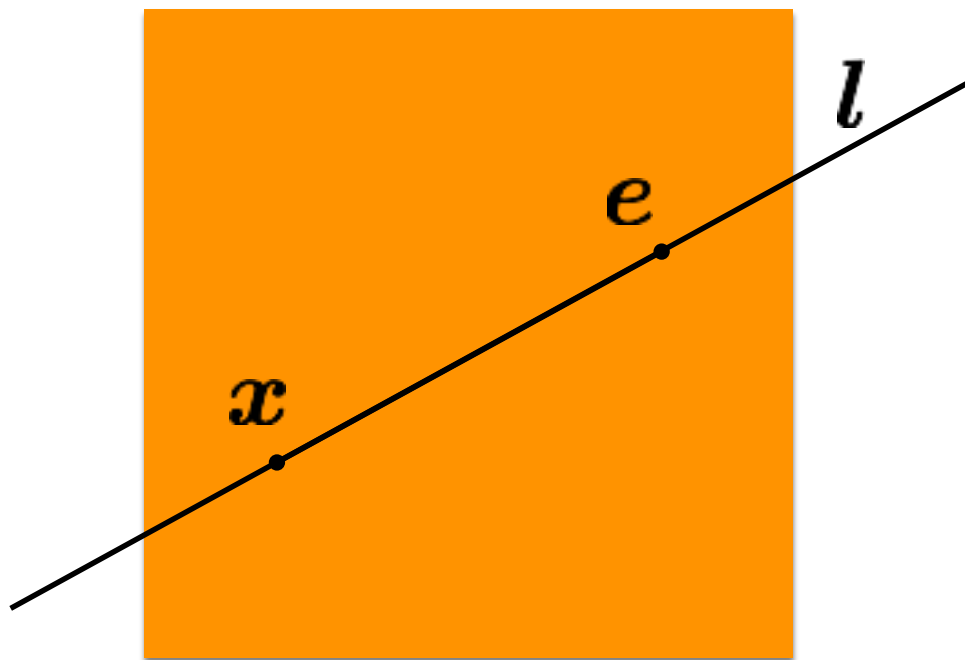
Epipolar constraint reduces search to a single line

How do you compute the epipolar line?

Representing the ...

Epipolar Line

$$ax + by + c = 0 \quad \text{in vector form} \quad \boldsymbol{l} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

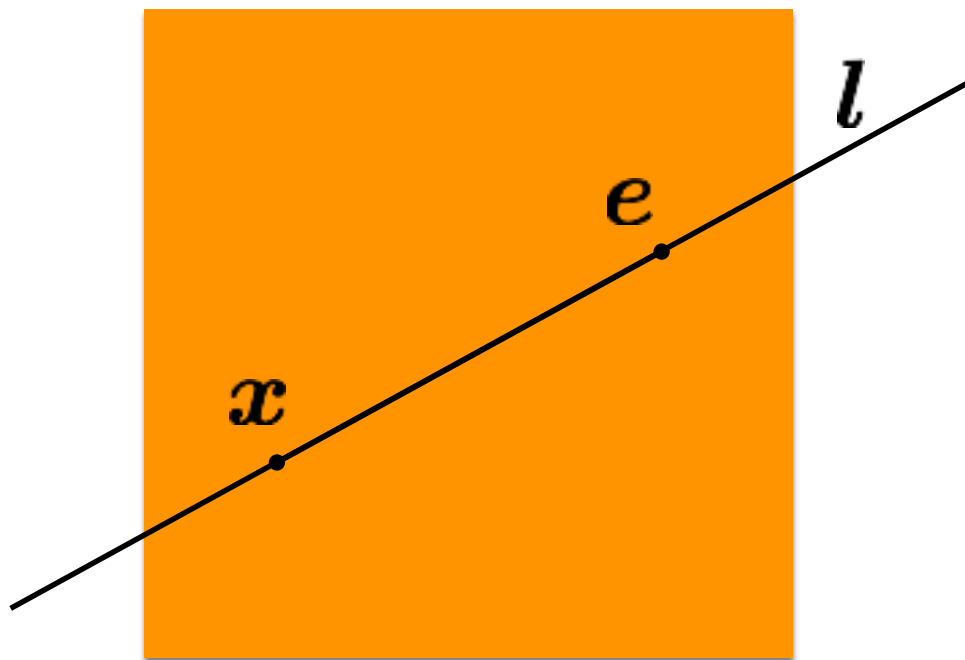


If the point \boldsymbol{x} is on the epipolar line \boldsymbol{l} then

$$\boldsymbol{x}^\top \boldsymbol{l} = ?$$

Epipolar Line

$$ax + by + c = 0 \quad \text{in vector form} \quad \mathbf{l} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$



If the point \mathbf{x} is on the epipolar line \mathbf{l} then

$$\mathbf{x}^\top \mathbf{l} = 0$$

vector representing the line is
normal (orthogonal) to the plane

$$l = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

O

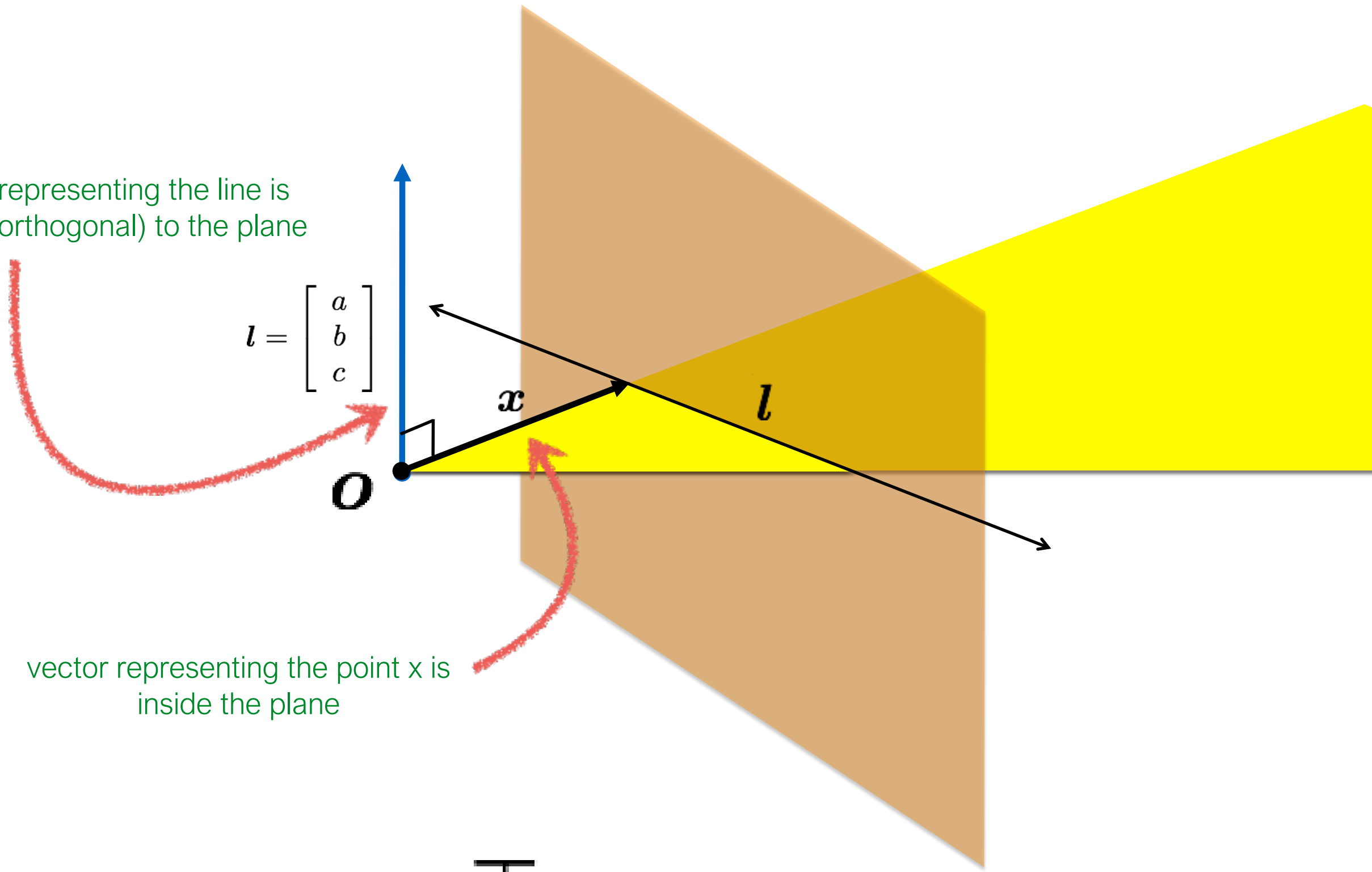
x

l

vector representing the point x is
inside the plane

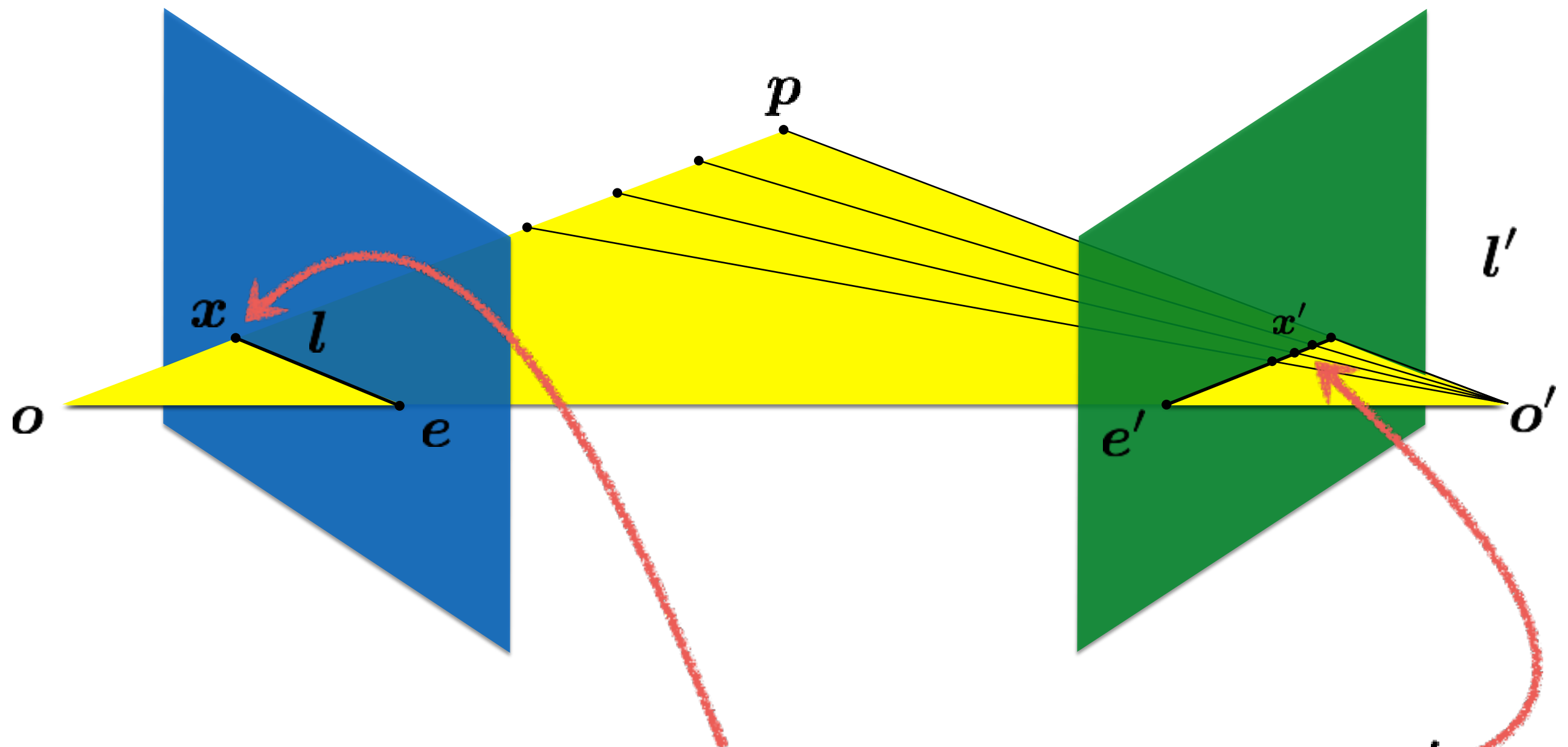
Therefore:

$$x^T l = 0$$



The essential matrix

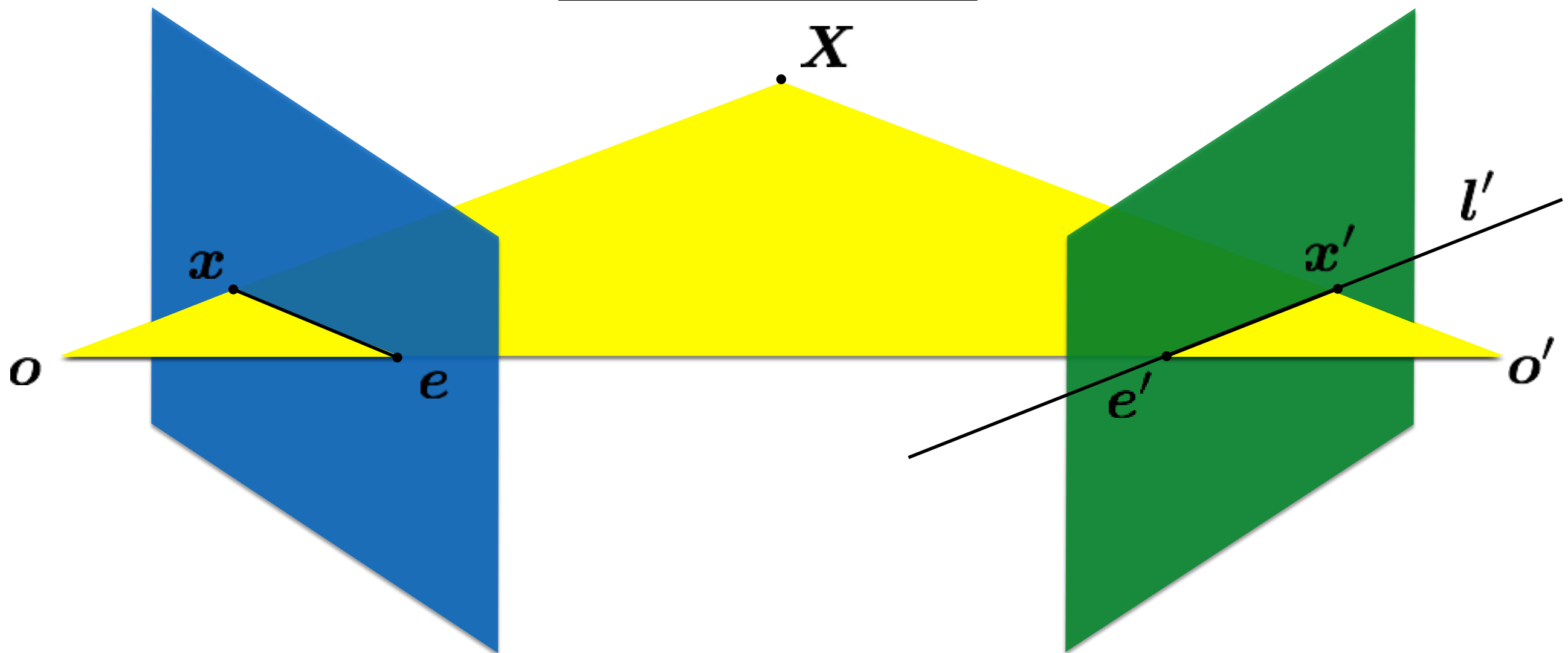
Recall: Epipolar constraint



Potential matches for x lie on the epipolar line l'

Given a point in one image,
multiplying by the **essential matrix** will tell us
the **epipolar line** in the second view.

$$\mathbf{E}x = l'$$

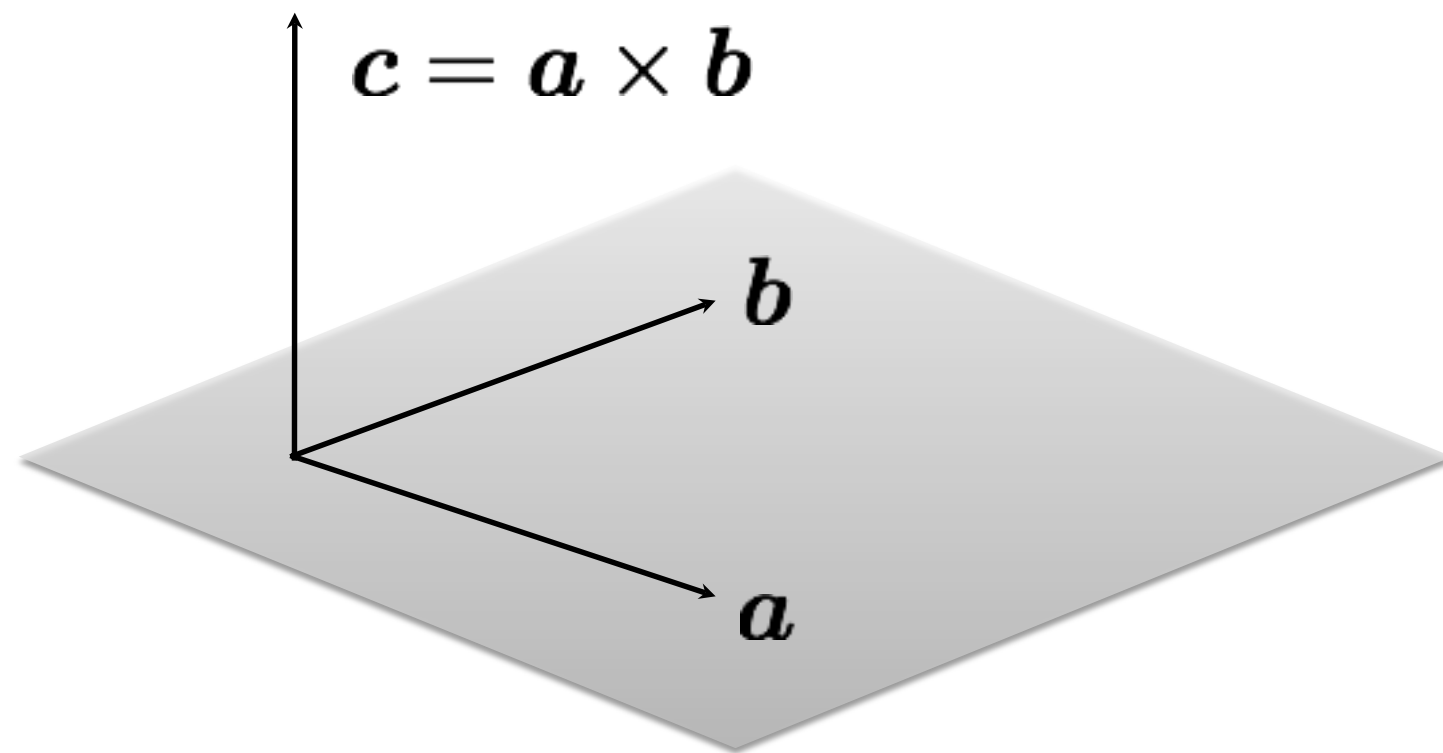


Motivation

The Essential Matrix is a 3×3 matrix that encodes **epipolar geometry**

Given a point in one image,
multiplying by the **essential matrix** will tell us
the **epipolar line** in the second view.

Recall: Dot Product



$$c \cdot a = 0$$

$$c \cdot b = 0$$

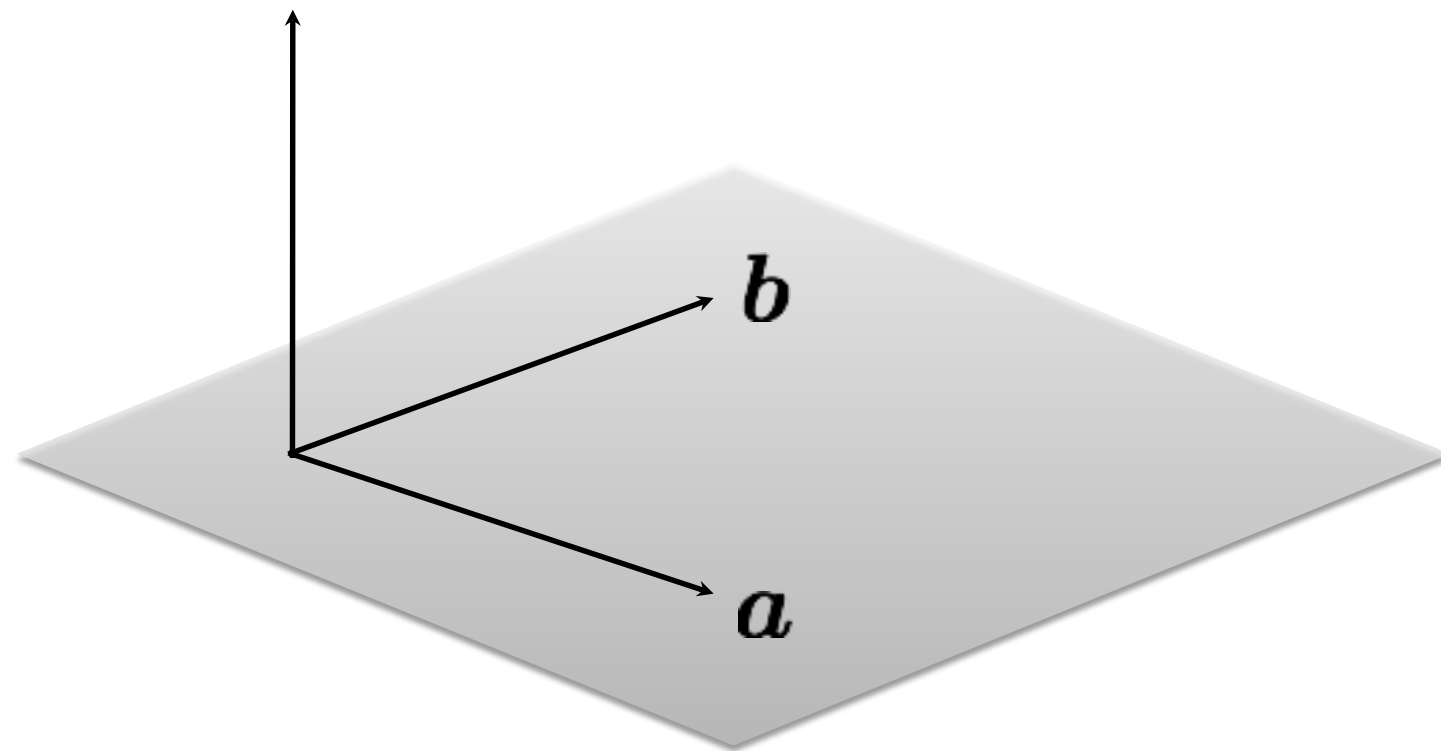
dot product of two orthogonal vectors is zero

Recall: Cross Product

Vector (cross) product

takes two vectors and returns a vector perpendicular to both

$$\mathbf{c} = \mathbf{a} \times \mathbf{b}$$



$$\mathbf{c} \cdot \mathbf{a} = 0$$

$$\mathbf{c} \cdot \mathbf{b} = 0$$

Cross product

$$\mathbf{a} \times \mathbf{b} = \begin{bmatrix} a_2 b_3 - a_3 b_2 \\ a_3 b_1 - a_1 b_3 \\ a_1 b_2 - a_2 b_1 \end{bmatrix}$$

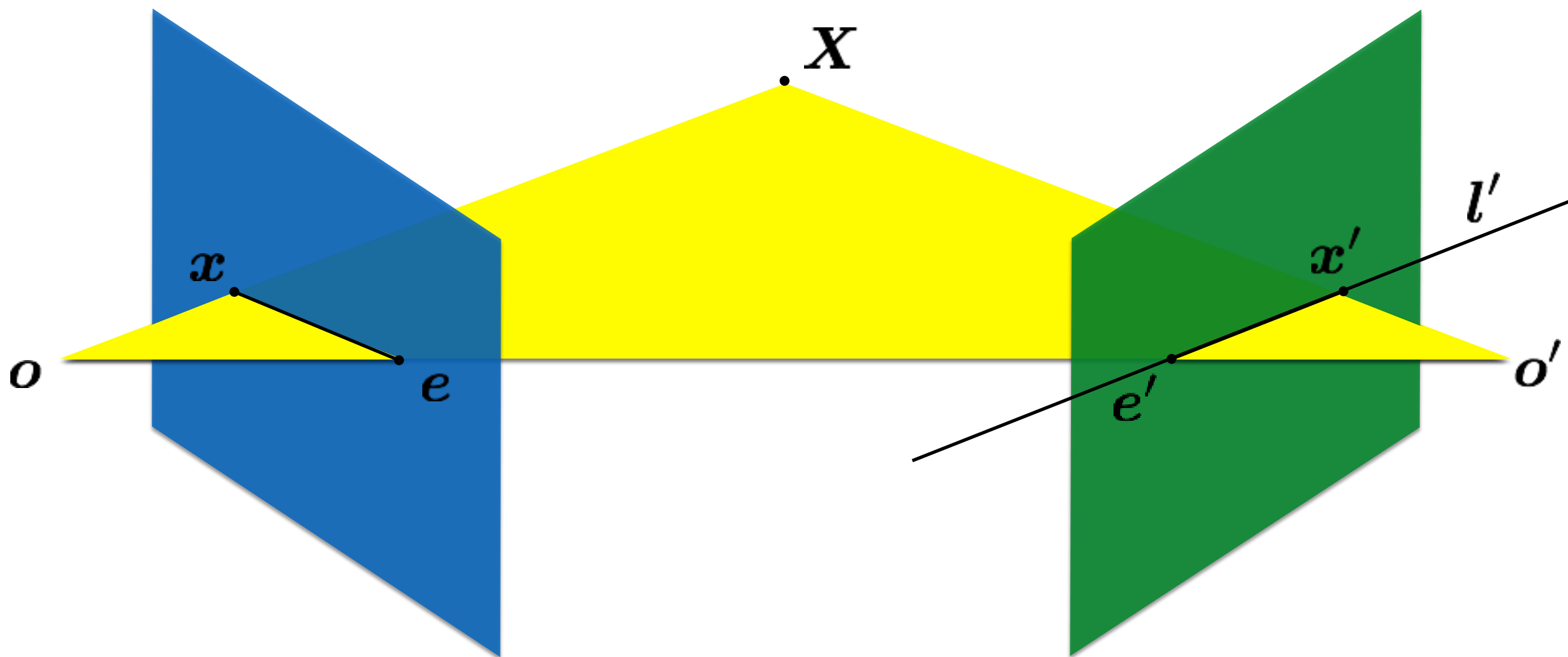
Can also be written as a matrix multiplication

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

Skew symmetric

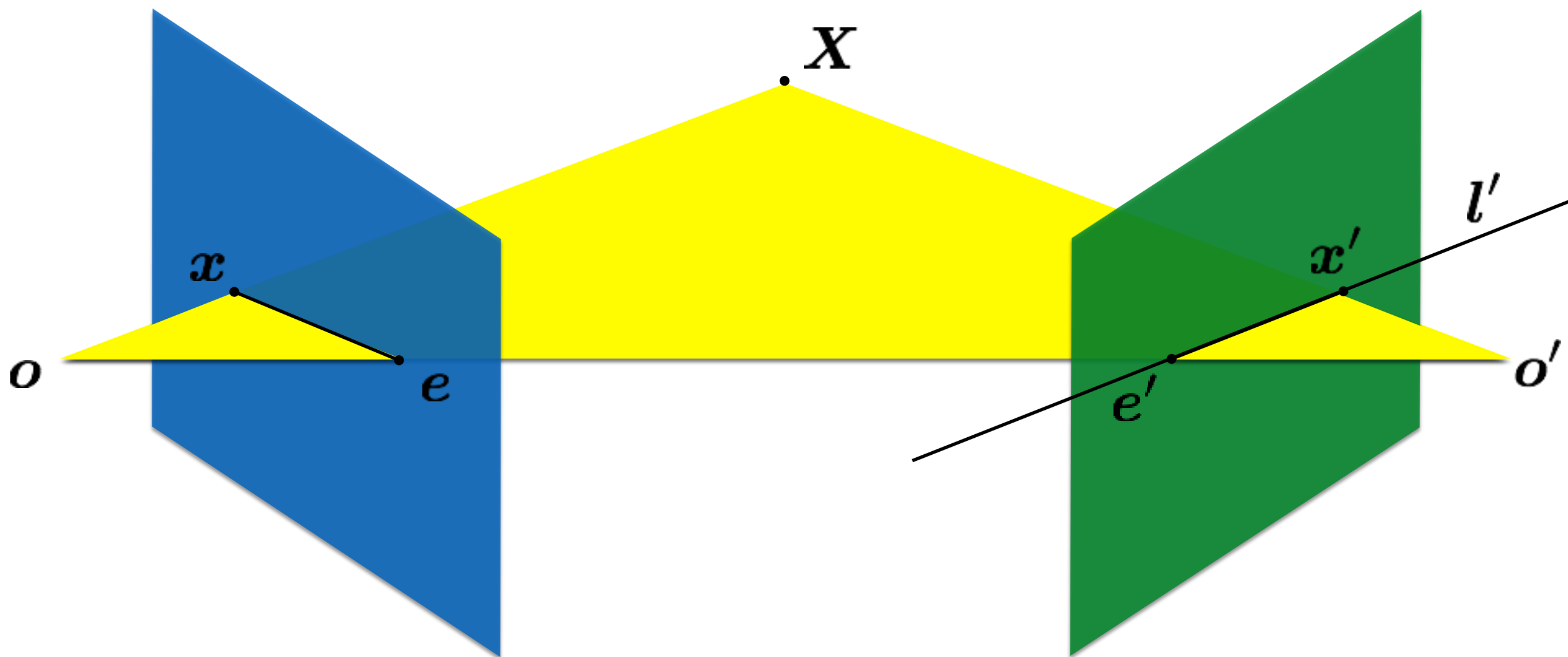
So if $\mathbf{x}^\top \mathbf{l} = 0$ and $\mathbf{E}\mathbf{x} = \mathbf{l}'$ then

$$\mathbf{x}'^\top \mathbf{E}\mathbf{x} = ?$$



So if $\mathbf{x}^\top \mathbf{l} = 0$ and $\mathbf{E}\mathbf{x} = \mathbf{l}'$ then

$$\mathbf{x}'^\top \mathbf{E}\mathbf{x} = 0$$



Essential Matrix vs Homography

What's the difference between the essential matrix and a homography?

Essential Matrix vs Homography

What's the difference between the essential matrix and a homography?

They are both 3 x 3 matrices but ...

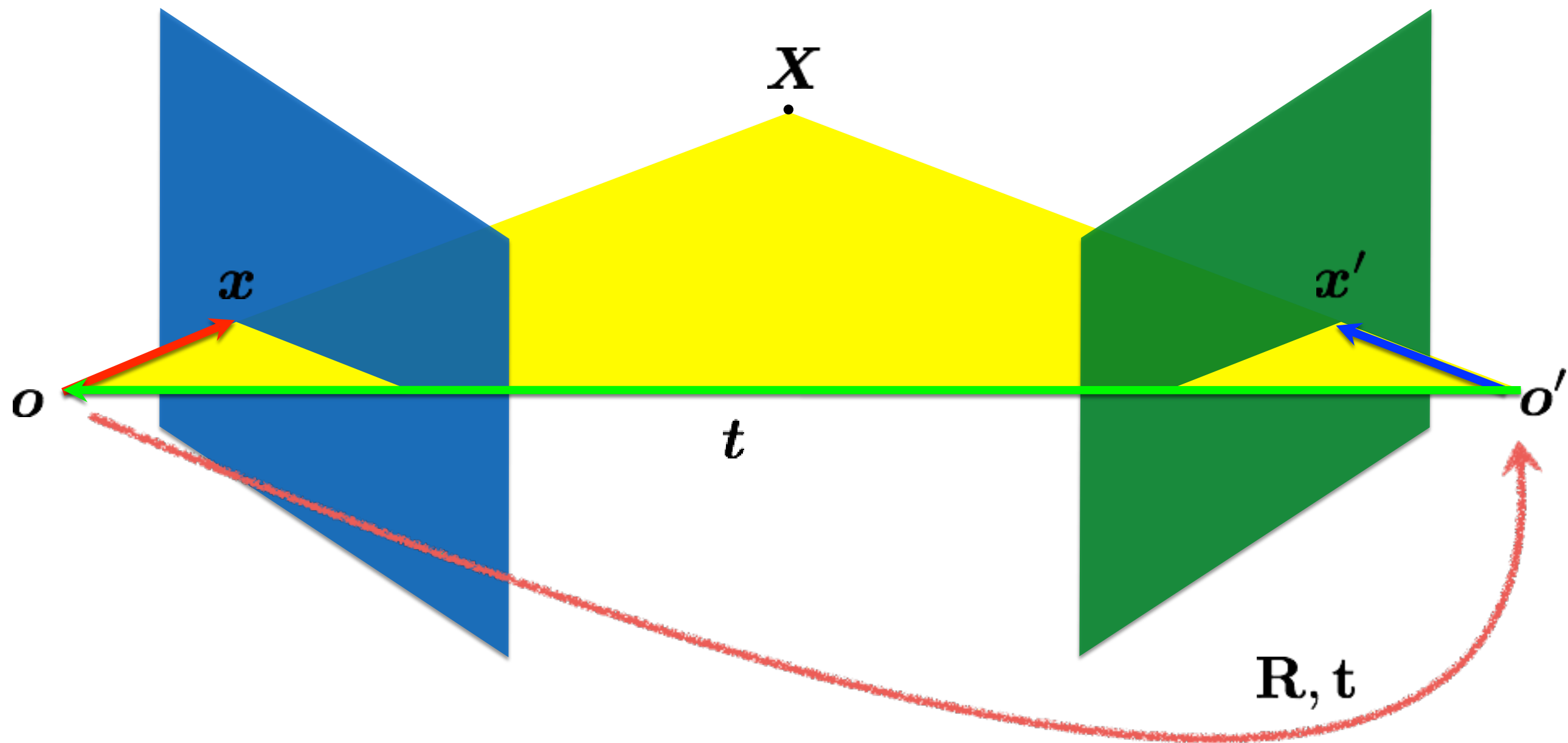
$$l' = Ex$$

Essential matrix maps a
point to a **line**

$$x' = Hx$$

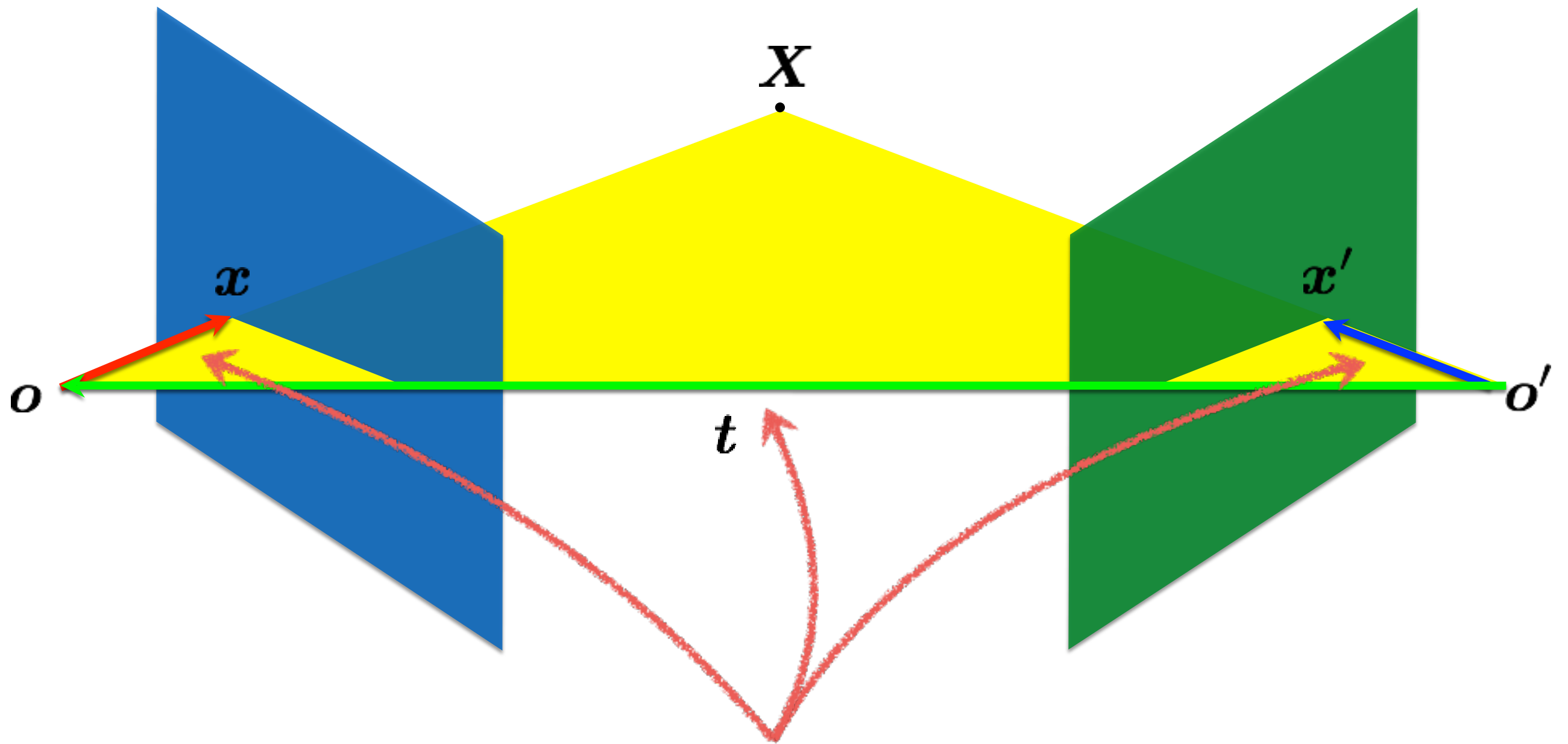
Homography maps a
point to a **point**

Where does the Essential matrix come from?



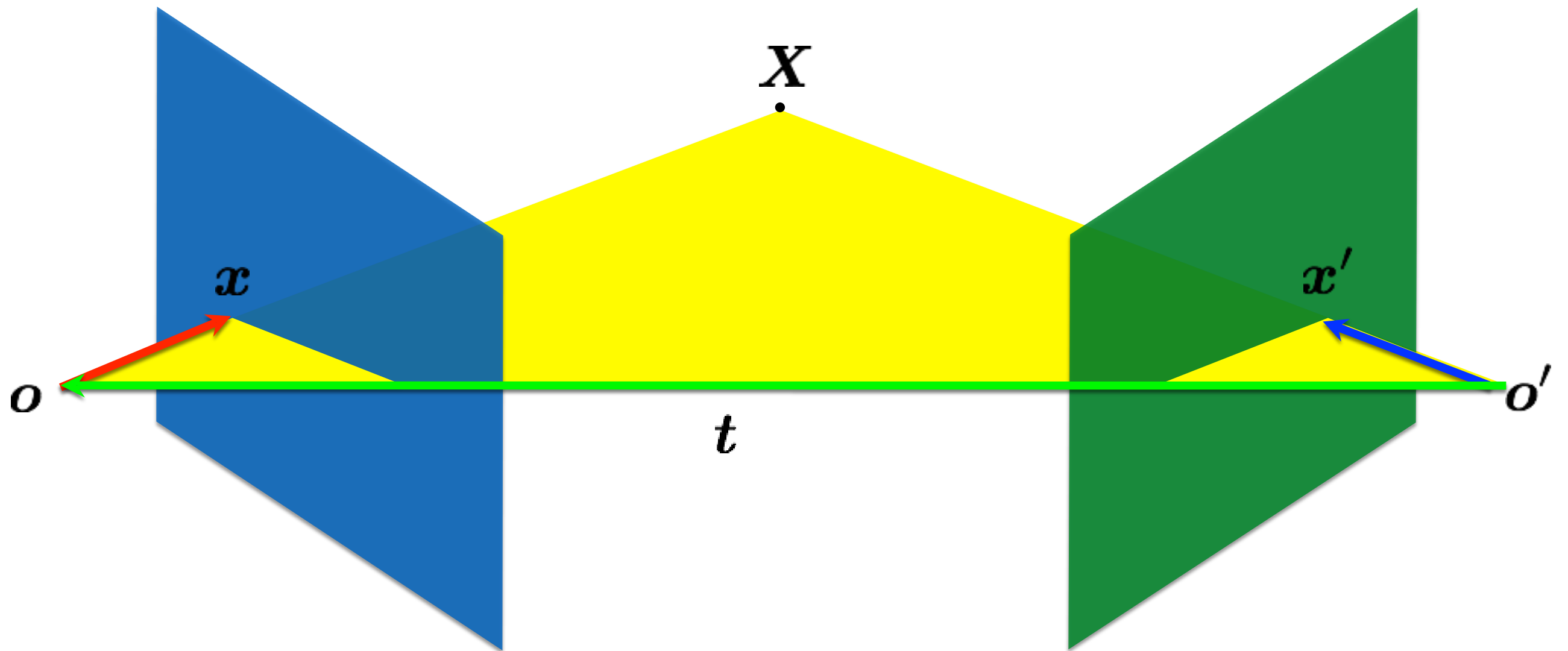
$$x'_{\text{coordinate frame 1}} = R^T x' - t$$

Camera-camera transform just like **world-camera** transform



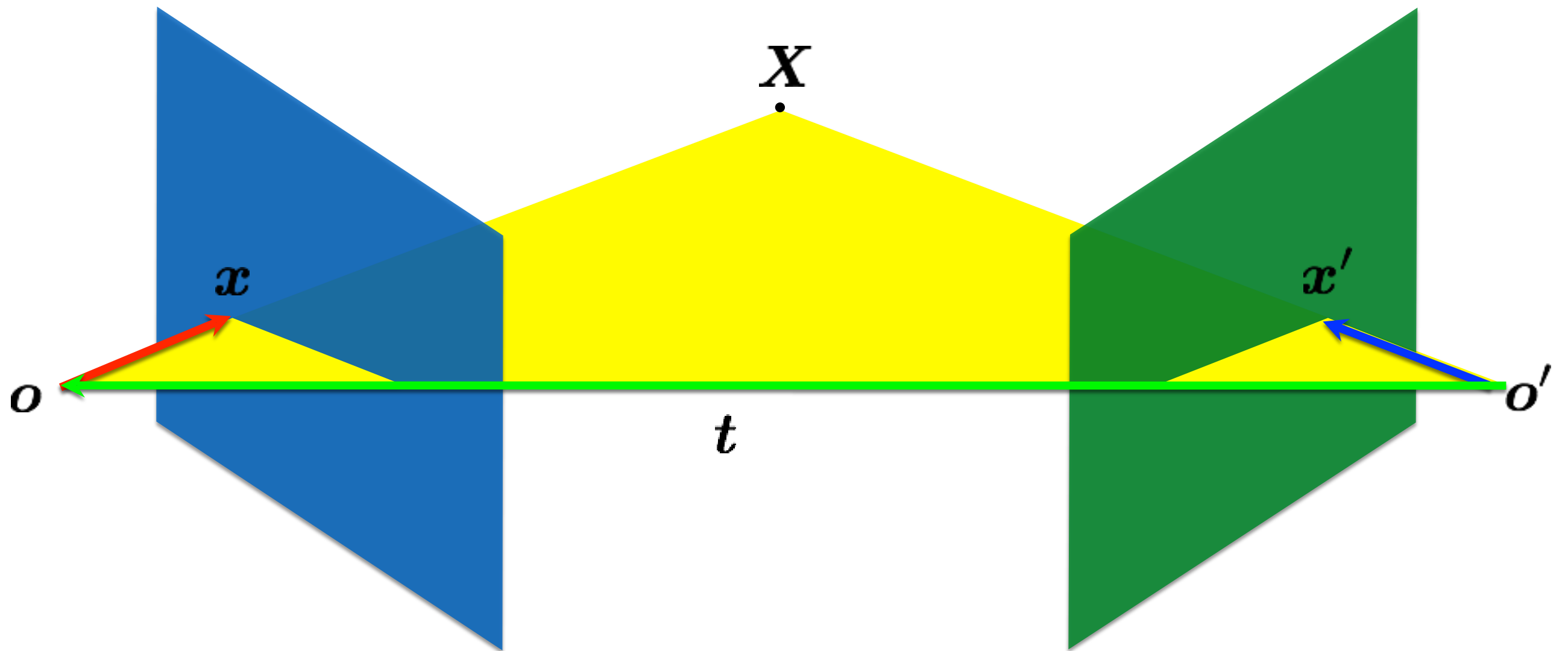
These three vectors are coplanar

x, t, x' coordinate frame 1



If these three vectors are coplanar x, t, x' coordinate frame 1

$$(x'_{\text{coordinate frame 1}})^T (t \times x) = ?$$



If these three vectors are coplanar x, t, x' coordinate frame 1

$$(x'_{\text{coordinate frame 1}})^T (t \times x) = 0$$

putting it together

coplanarity

$$(x'_{\text{coordinate frame 1}})^T (t \times x) = 0$$

rigid motion

$$x'_{\text{coordinate frame 1}} = R^T x' - t$$

$$(R^T x' - t)^T (t \times x) = 0$$

$$(R^T x')^T (t \times x) = 0$$

$$(x')^T R (t \times x) = 0$$

putting it together

coplanarity

$$(x'_{\text{coordinate frame } 1})^T (t \times x) = 0$$

rigid motion

$$x'_{\text{coordinate frame } 1} = R^T x' - t$$

$$(R^T x' - t)^T (t \times x) = 0$$

$$(x')^T R (t \times x) = 0$$

$$\mathbf{x}'^\top (\mathbf{R}[\mathbf{t}_\times]) \mathbf{x} = 0$$

putting it together

coplanarity

$$(x'_{\text{coordinate frame 1}})^T (t \times x) = 0$$

rigid motion

$$x'_{\text{coordinate frame 1}} = R^T x' - t$$

$$(R^T x' - t)^T (t \times x) = 0$$

$$(x')^T R (t \times x) = 0$$

$$\mathbf{x}'^\top (\mathbf{R}[\mathbf{t}_\times]) \mathbf{x} = 0$$

$$\mathbf{x}'^\top \mathbf{E} \mathbf{x} = 0$$

putting it together

coplanarity

$$(x'_{\text{coordinate frame 1}})^T (t \times x) = 0$$

rigid motion

$$x'_{\text{coordinate frame 1}} = R^T x' - t$$

$$(R^T x' - t)^T (t \times x) = 0$$

$$(x')^T R (t \times x) = 0$$

$$x'^{\top} (\mathbf{R}[\mathbf{t}_{\times}]) \mathbf{x} = 0$$

$$\boxed{x'^{\top} \mathbf{E} \mathbf{x} = 0}$$

Essential Matrix
[Longuet-Higgins 1981]

properties of the E matrix

Longuet-Higgins equation

$$\mathbf{x}'^{\top} \mathbf{E} \mathbf{x} = 0$$

properties of the E matrix

Longuet-Higgins equation

$$\mathbf{x}'^\top \mathbf{E} \mathbf{x} = 0$$

Epipolar lines

$$\mathbf{x}^\top \mathbf{l} = 0$$

$$\mathbf{l}' = \mathbf{E} \mathbf{x}$$

$$\mathbf{x}'^\top \mathbf{l}' = 0$$

$$\mathbf{l} = \mathbf{E}^\top \mathbf{x}'$$

properties of the \mathbf{E} matrix

Longuet-Higgins equation

$$\mathbf{x}'^\top \mathbf{E} \mathbf{x} = 0$$

Epipolar lines

$$\mathbf{x}^\top \mathbf{l} = 0$$

$$\mathbf{l}' = \mathbf{E} \mathbf{x}$$

$$\mathbf{x}'^\top \mathbf{l}' = 0$$

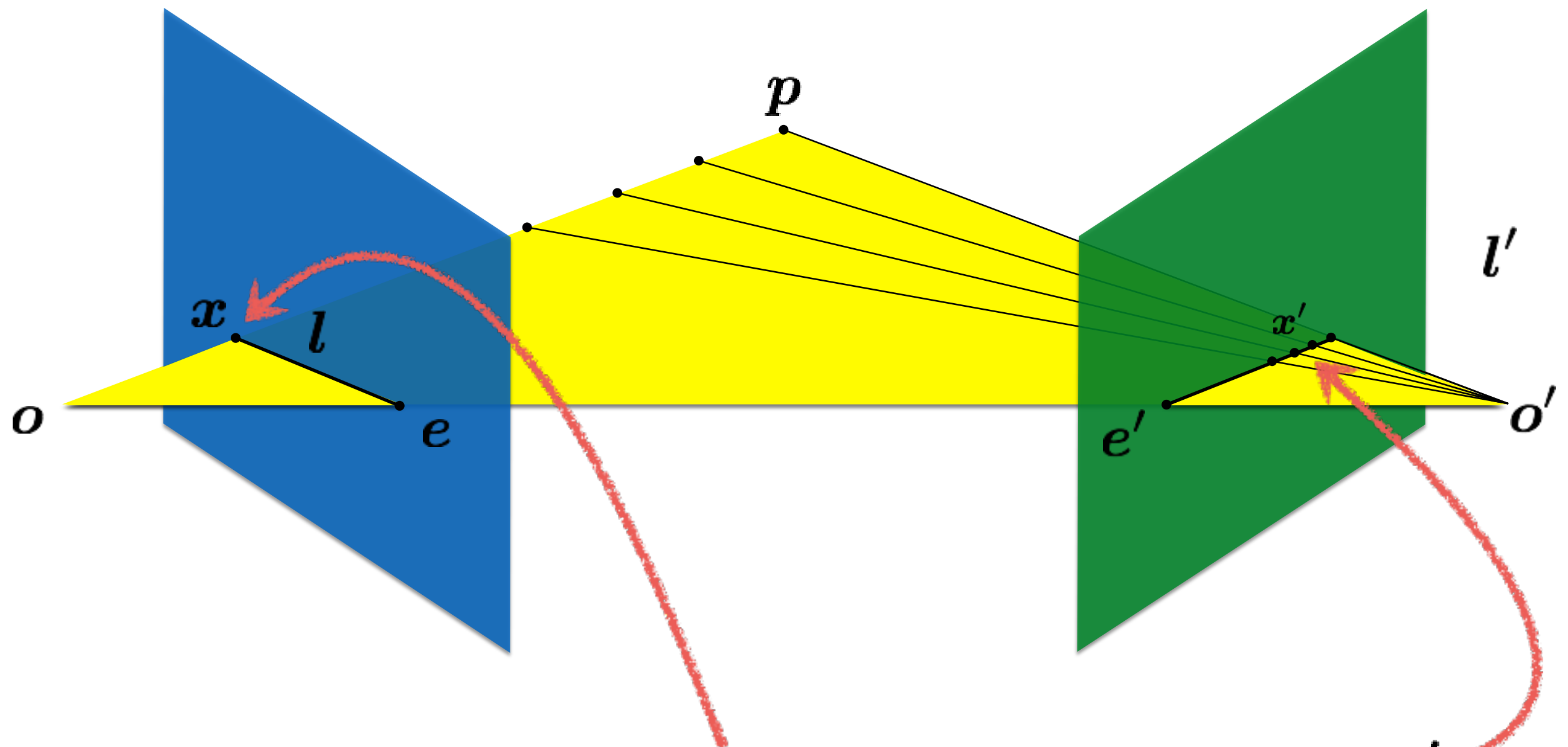
$$\mathbf{l} = \mathbf{E}^\top \mathbf{x}'$$

Epipoles

$$\mathbf{e}'^\top \mathbf{E} = \mathbf{0}$$

$$\mathbf{E} \mathbf{e} = \mathbf{0}$$

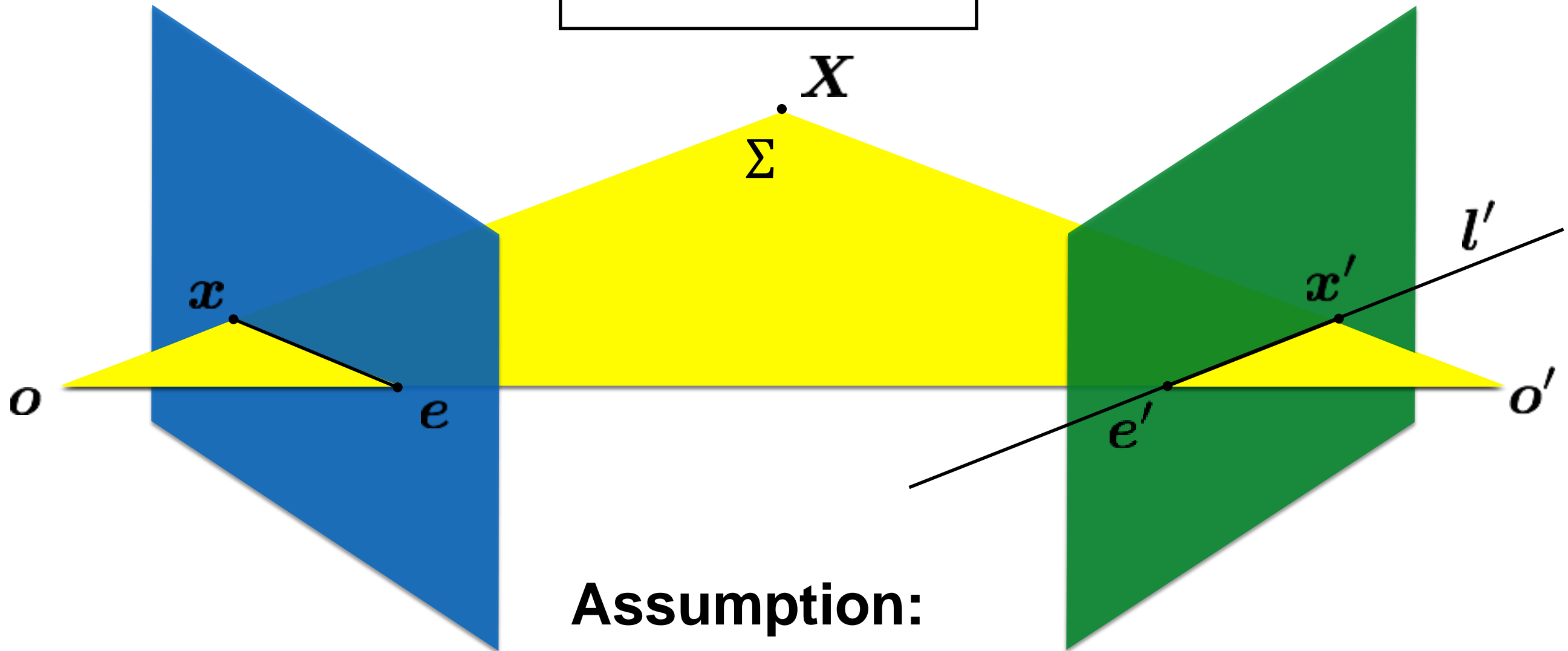
Recall: Epipolar constraint



Potential matches for x lie on the epipolar line l'

Given a point in one image,
multiplying by the **essential matrix** will tell us
the **epipolar line** in the second view.

$$\mathbf{E}x = l'$$



Assumption:

points aligned to camera coordinate axis (calibrated camera)
(internal matrix K was pre-applied)

Putting it all together


We can write everything into a single projection:

$$\mathbf{x} = \mathbf{P}\mathbf{X}_w$$


The camera matrix now looks like:

$$\mathbf{P} = \begin{bmatrix} f & 0 & p_x \\ 0 & f & p_y \\ 0 & 0 & 1 \end{bmatrix} \left[\mathbf{R} \mid -\mathbf{RC} \right]$$

intrinsic parameters (3 x 3):
correspond to camera internals
(sensor not at $f = 1$ and origin shift)



extrinsic parameters (3 x 4):
correspond to camera externals
(world-to-image transformation)



More general camera matrices

Finite projective camera: sensor be skewed.

$$\mathbf{P} = \begin{bmatrix} \alpha_x & s & p_x \\ 0 & \alpha_y & p_y \\ 0 & 0 & 1 \end{bmatrix} \left[\mathbf{R} \mid -\mathbf{RC} \right]$$

How many degrees of freedom?

How do you generalize to
uncalibrated cameras?

The fundamental matrix

The
Fundamental matrix
is a
generalization
of the
Essential matrix,
where the assumption of
calibrated cameras
is removed

$$\hat{x}'^T \mathbf{E} \hat{x} = 0$$

The Essential matrix operates on image points expressed in
normalized coordinates
(points have been aligned (normalized) to camera coordinates)

$$\hat{x}' = \mathbf{K}^{-1} x'$$

$$\hat{x} = \mathbf{K}^{-1} x$$

camera point image point

$$\hat{x}'^T \mathbf{E} \hat{x} = 0$$

The Essential matrix operates on image points expressed in
normalized coordinates
 (points have been aligned (normalized) to camera coordinates)

$$\hat{x}' = \mathbf{K}^{-1} x' \qquad \hat{x} = \mathbf{K}^{-1} x$$

camera point image point

Writing out the epipolar constraint in terms of image coordinates

$$x'^T \mathbf{K}'^{-T} \mathbf{E} \mathbf{K}^{-1} x = 0$$

$$x'^T (\mathbf{K}'^{-T} \mathbf{E} \mathbf{K}^{-1}) x = 0$$

$$x'^T \mathbf{F} x = 0$$

Same equation works in image coordinates!

$$\mathbf{x}'^T \mathbf{F} \mathbf{x} = 0$$

it maps pixels to epipolar lines

properties of the ~~F~~ \mathbf{E} matrix

Longuet-Higgins equation

$$\mathbf{x}'^\top \mathbf{E} \mathbf{x} = 0$$

Epipolar lines

$$\mathbf{x}^\top \mathbf{l} = 0$$

$$\mathbf{l}' = \mathbf{E} \mathbf{x}$$

$$\mathbf{x}'^\top \mathbf{l}' = 0$$

$$\mathbf{l} = \mathbf{E}^\top \mathbf{x}'$$

Epipoles

$$\mathbf{e}'^\top \mathbf{E} = \mathbf{0}$$

$$\mathbf{E} \mathbf{e} = \mathbf{0}$$

(points in **image** coordinates)

Breaking down the fundamental matrix

$$\mathbf{F} = \mathbf{K}'^{-\top} \mathbf{E} \mathbf{K}^{-1}$$

$$\mathbf{F} = \mathbf{K}'^{-\top} [\mathbf{t}_x] \mathbf{R} \mathbf{K}^{-1}$$

Depends on both intrinsic and extrinsic parameters

Breaking down the fundamental matrix

$$\mathbf{F} = \mathbf{K}'^{-\top} \mathbf{E} \mathbf{K}^{-1}$$

$$\mathbf{F} = \mathbf{K}'^{-\top} [\mathbf{t}_x] \mathbf{R} \mathbf{K}^{-1}$$

Depends on both intrinsic and extrinsic parameters

How would you solve for F ?

$$\mathbf{x}_m'^{\top} \mathbf{F} \mathbf{x}_m = 0$$

References

Basic reading:

- Szeliski textbook, Sections 7.1, 7.2, 11.1.
- Hartley and Zisserman, Chapters 9, 11, 12.

