Epipolar Geometry

EECS 442 – David Fouhey
Fall 2019, University of Michigan

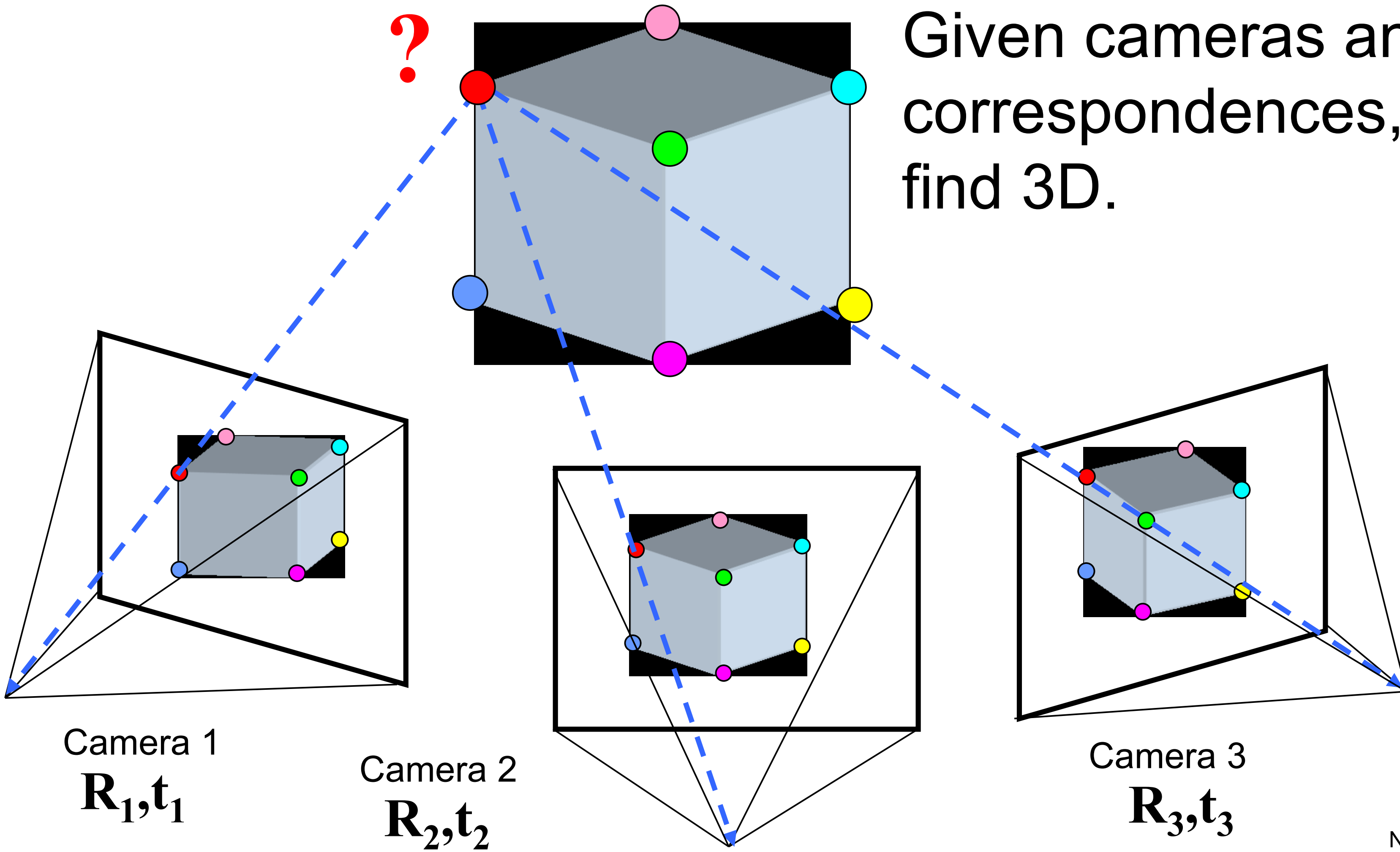
http://web.eecs.umich.edu/~fouhey/teaching/EECS442_F19/

Multi-view geometry

Image Credit: S. Lazebnik

Multi-view geometry problems

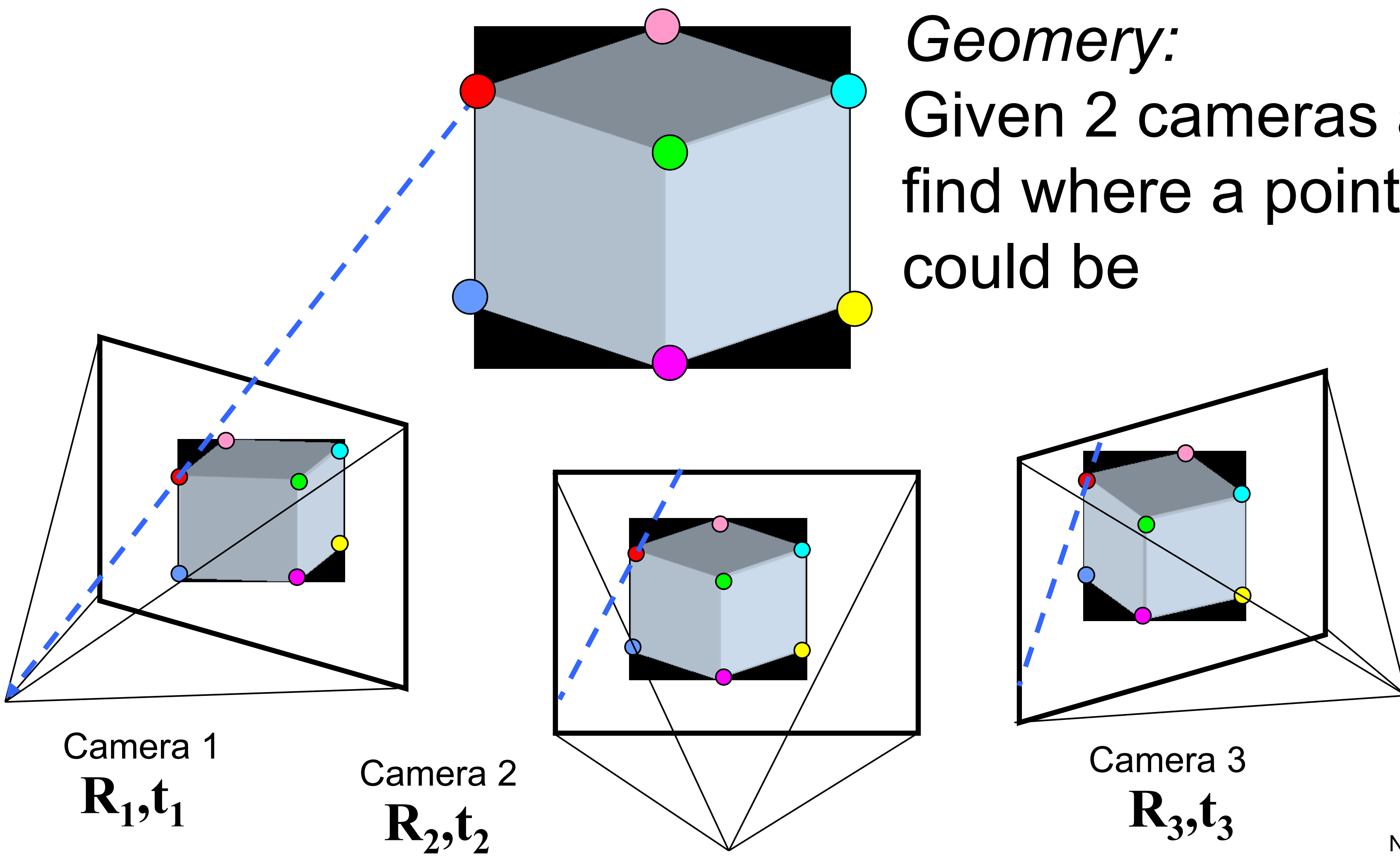
Recovering structure: Given cameras and correspondences, find 3D.



Slide credit: Noah Snavely

Multi-view geometry problems

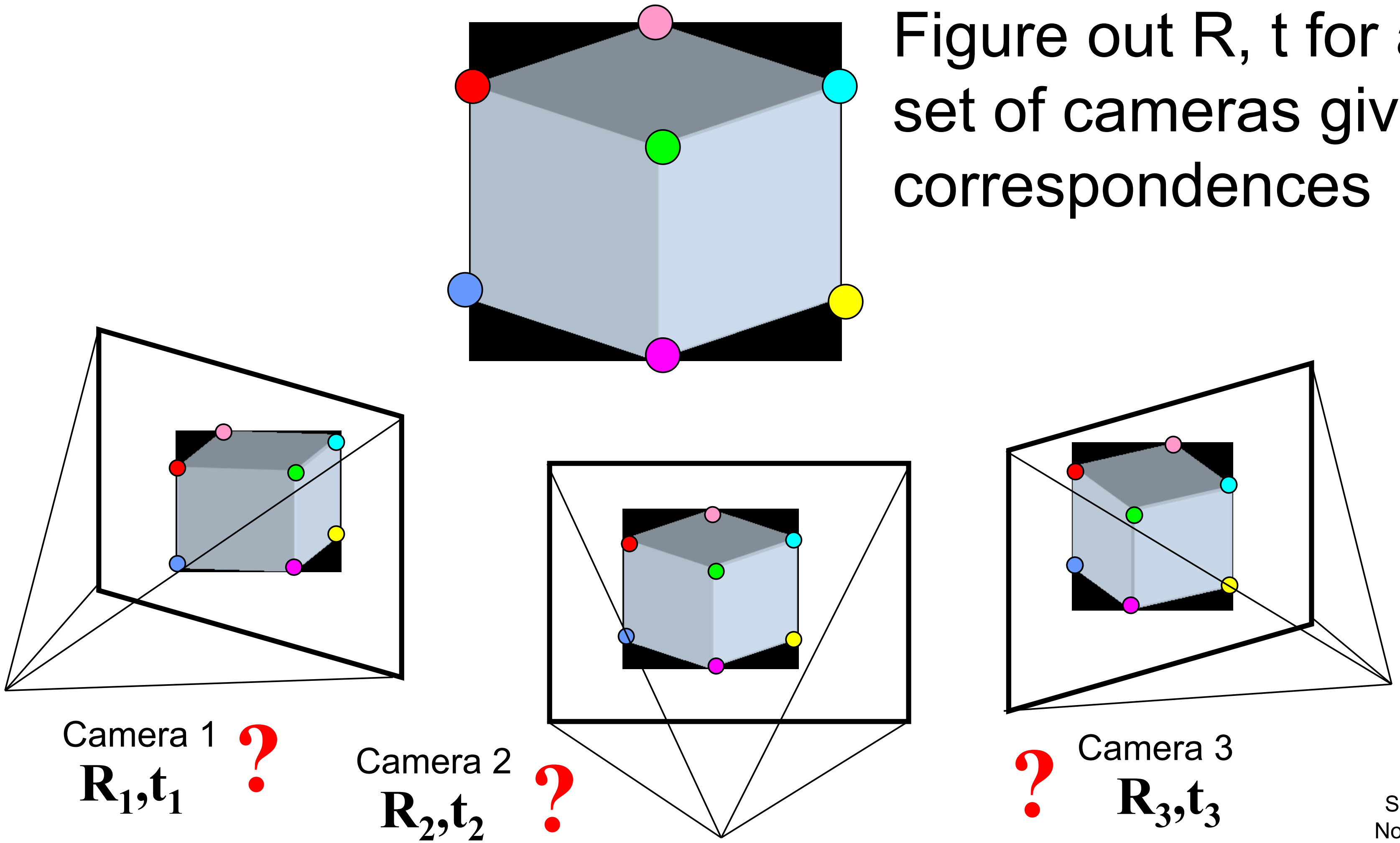
Stereo/Epipolar Geomery:
Given 2 cameras and find where a point could be



Slide credit: Noah Snavely

Multi-view geometry problems

Motion:
Figure out R, t for a set of cameras given correspondences



Slide credit: Noah Snavely

Two-view geometry

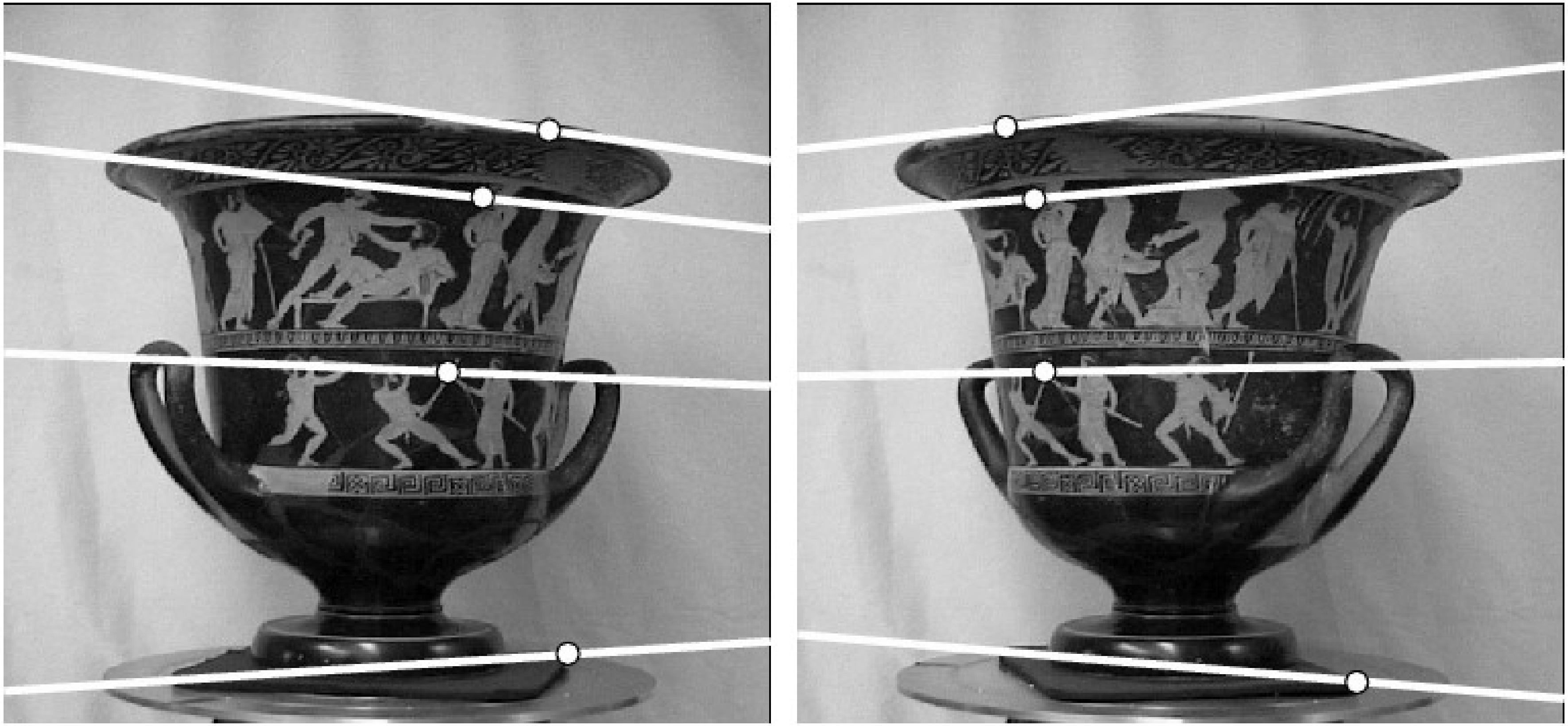
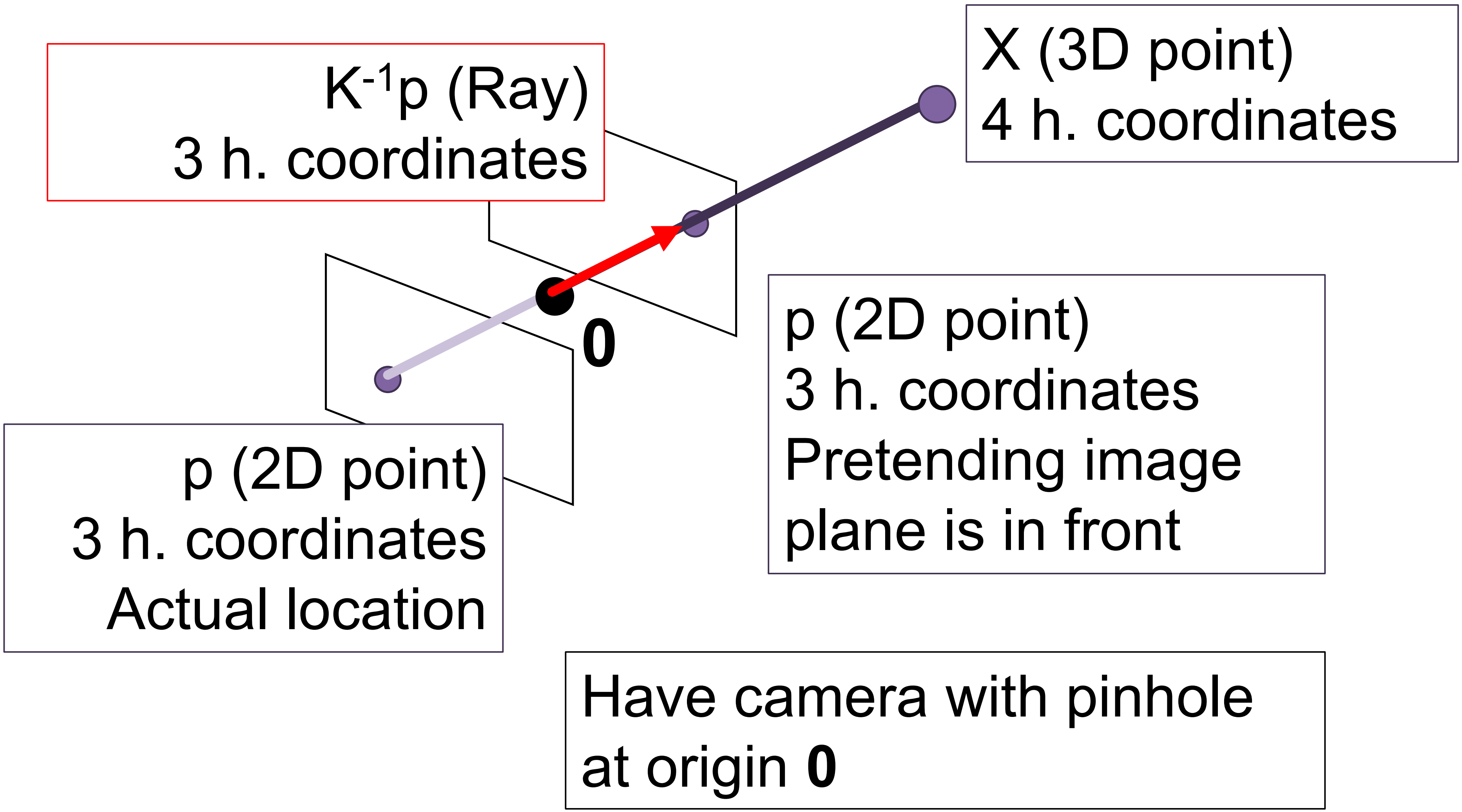
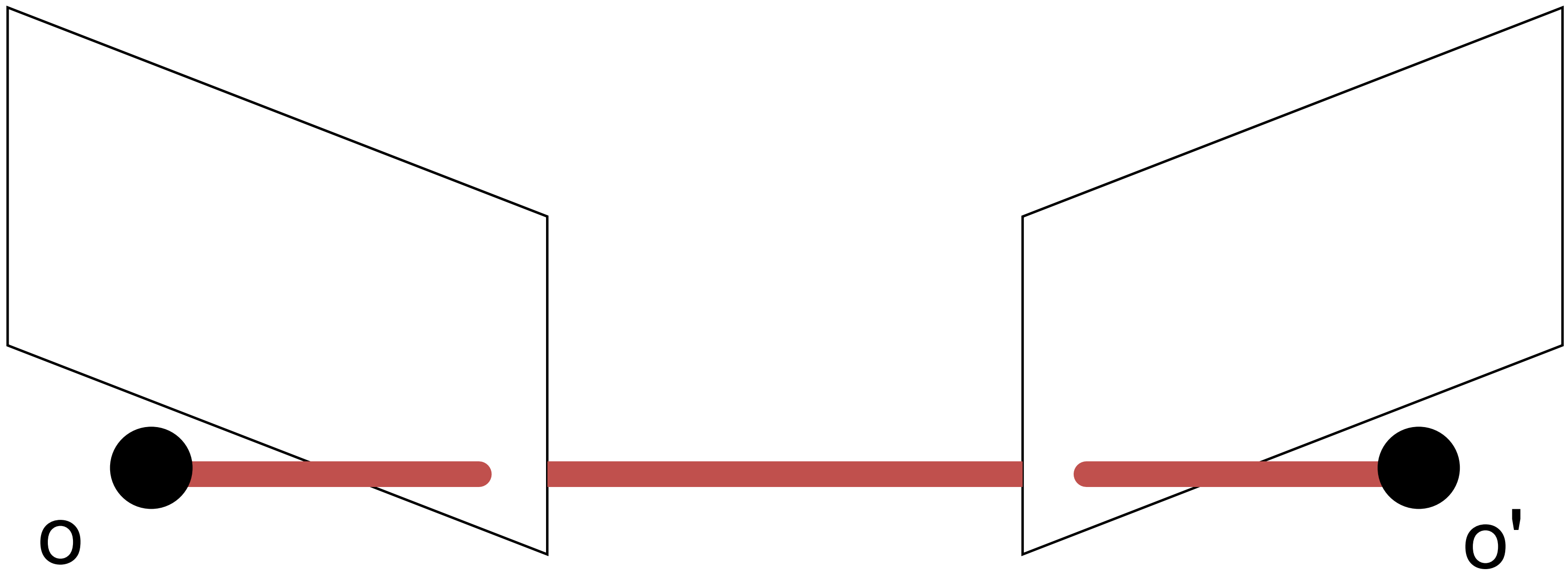


Image Credit: Hartley & Zisserman

Camera Geometry Reminder



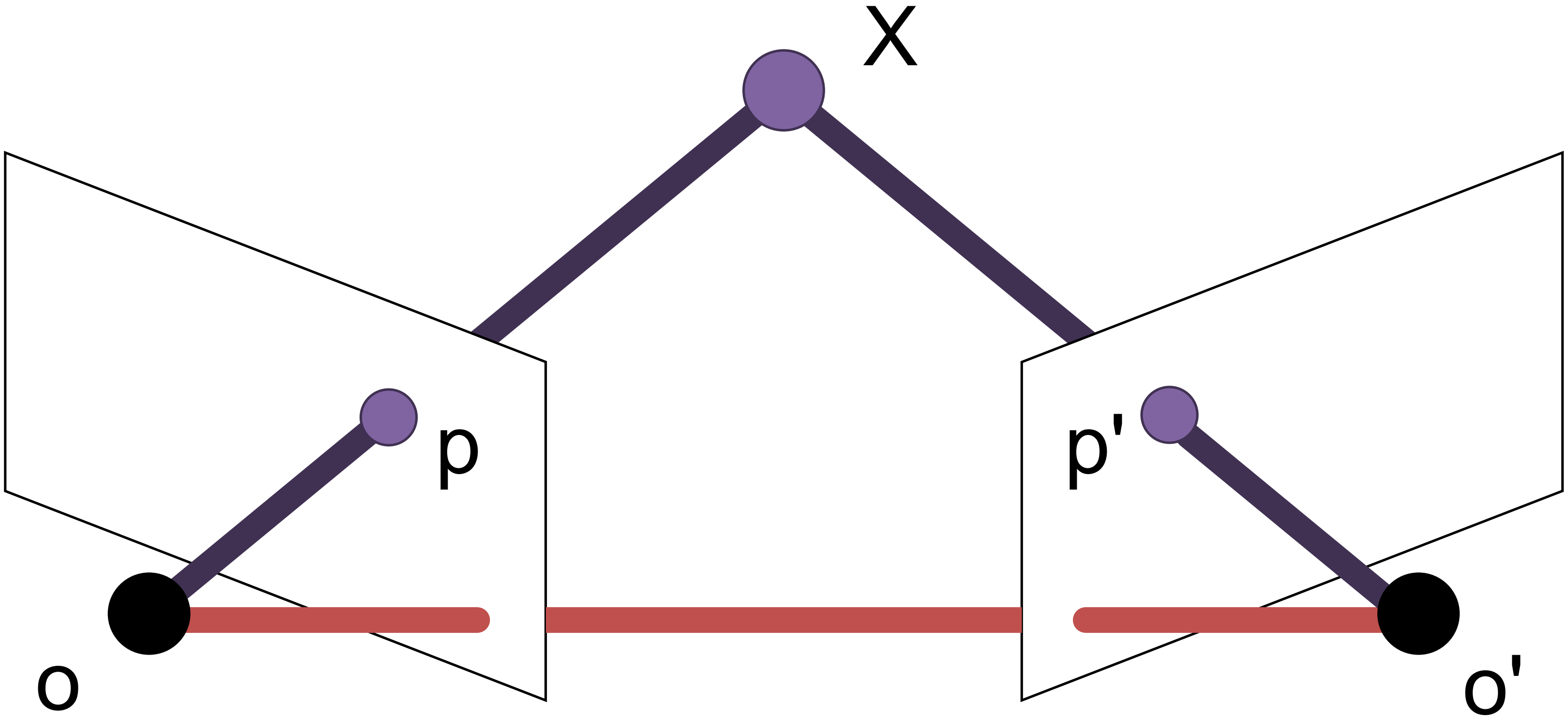
Epipolar Geometry



Suppose we have two cameras at origins o, o’

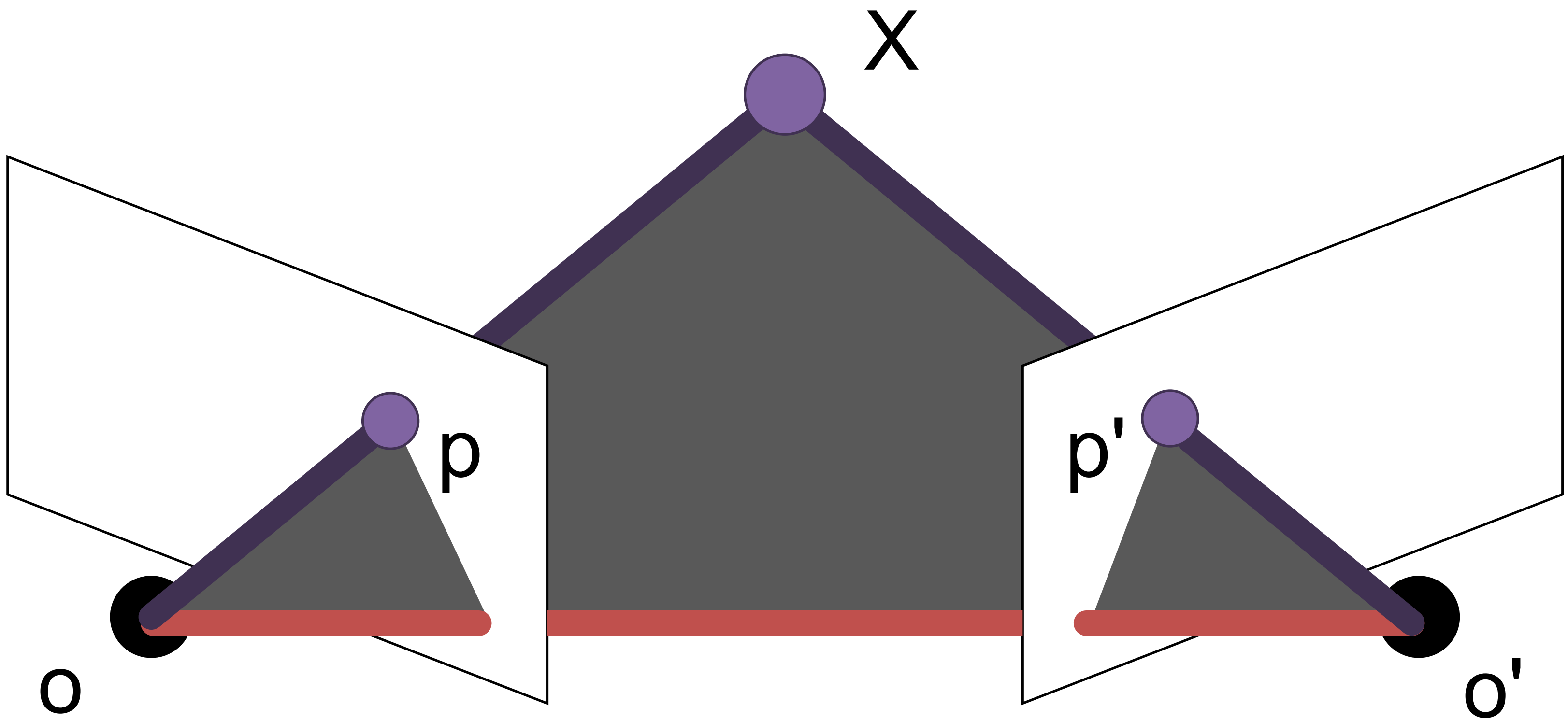
Baseline is the line connecting the origins

Epipolar Geometry



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

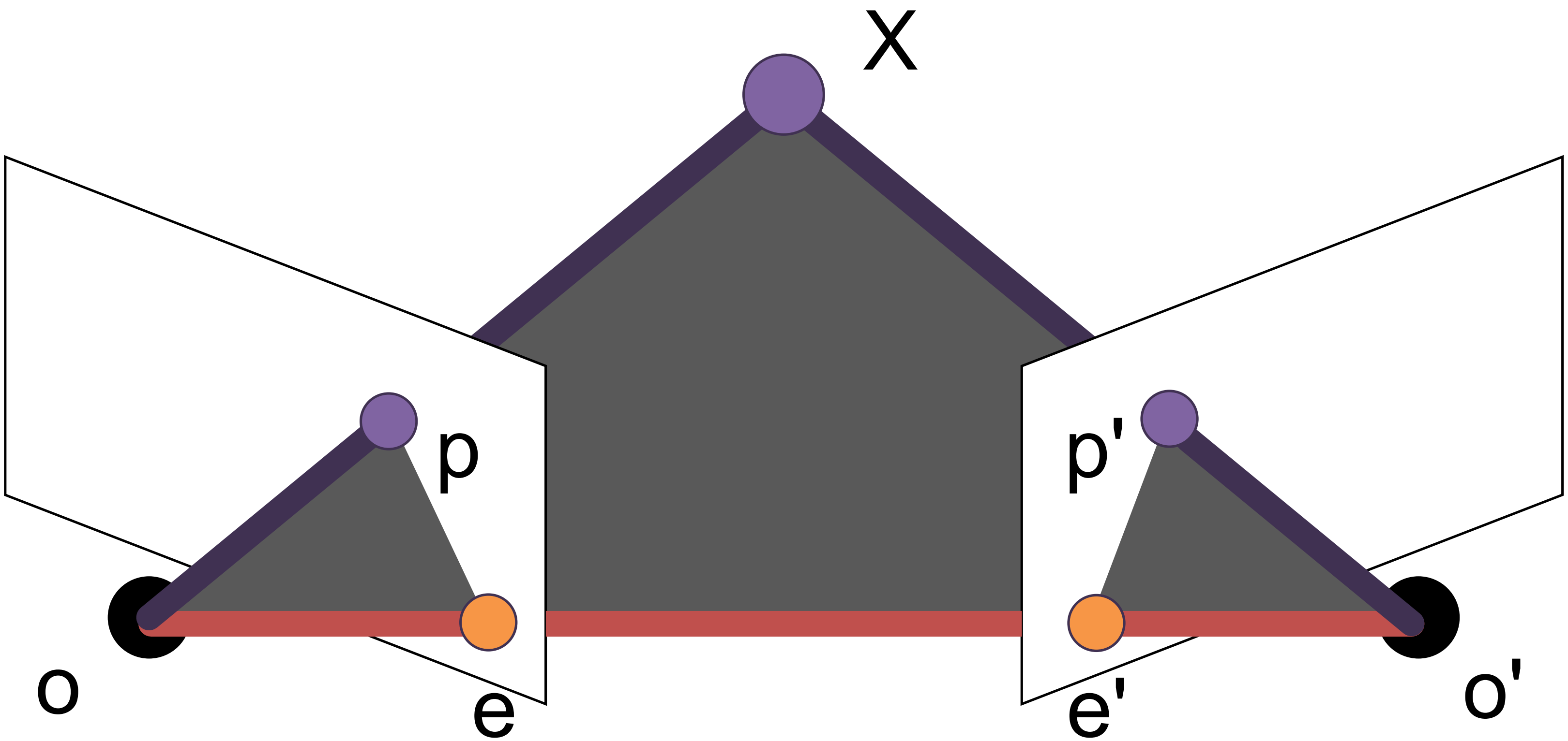
Epipolar Geometry



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

There is a family of planes per o, o’

Epipolar Geometry

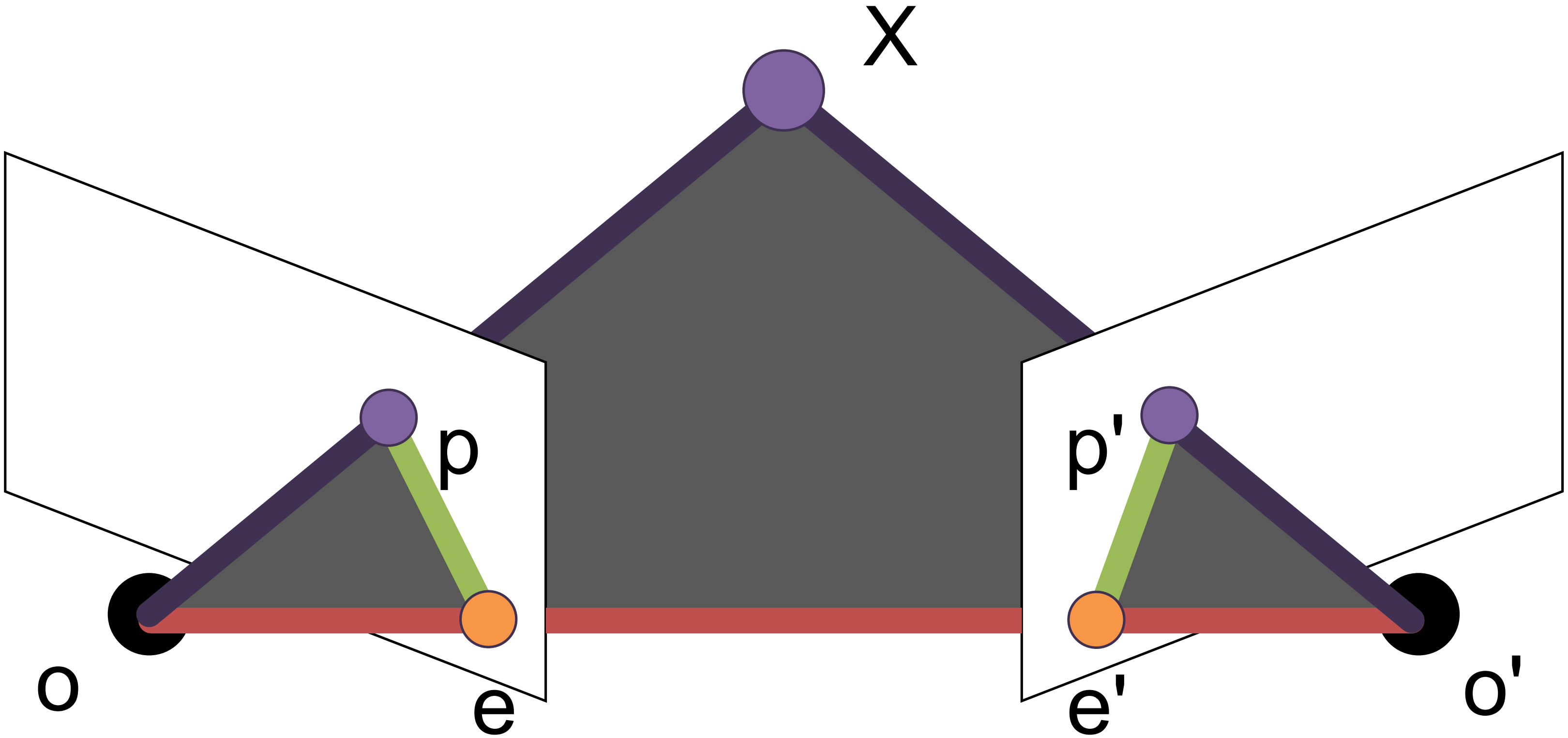


- Epipoles e, e’ are where the baseline intersects the image planes
- Projection of other camera in the image plane

The Epipole

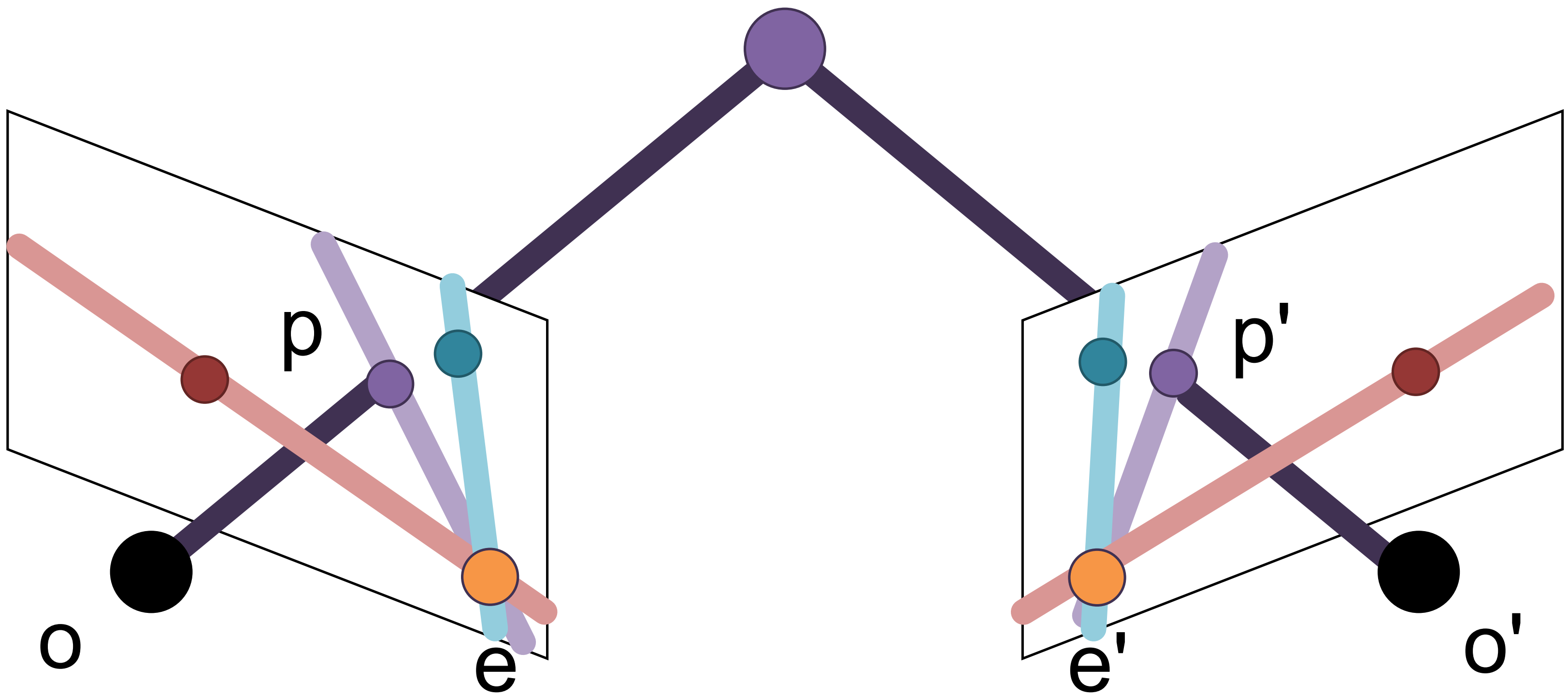
Photo by Frank Dellaert

Epipolar Geometry



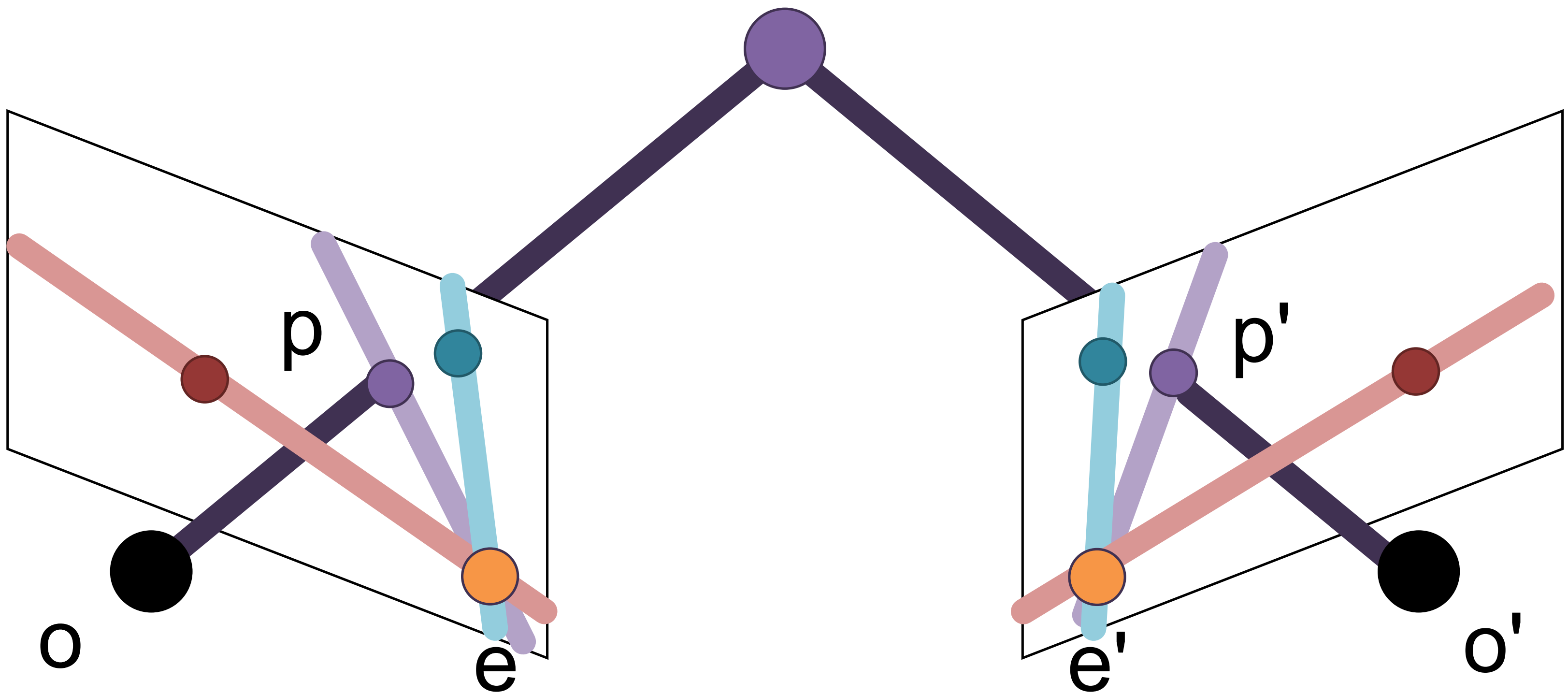
- Epipolar lines go between the epipoles and the projections of the points.
- Intersection of epipolar plane with image plane

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

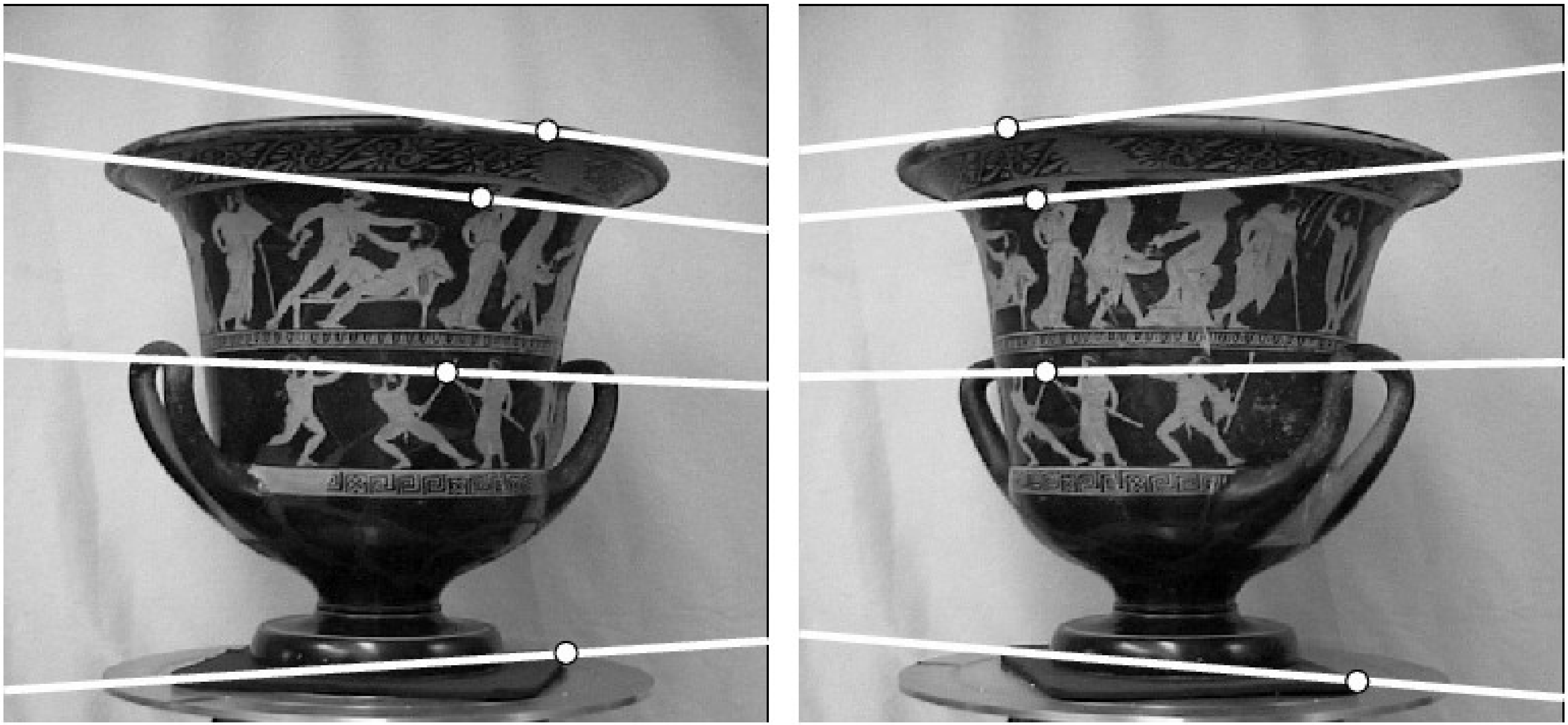
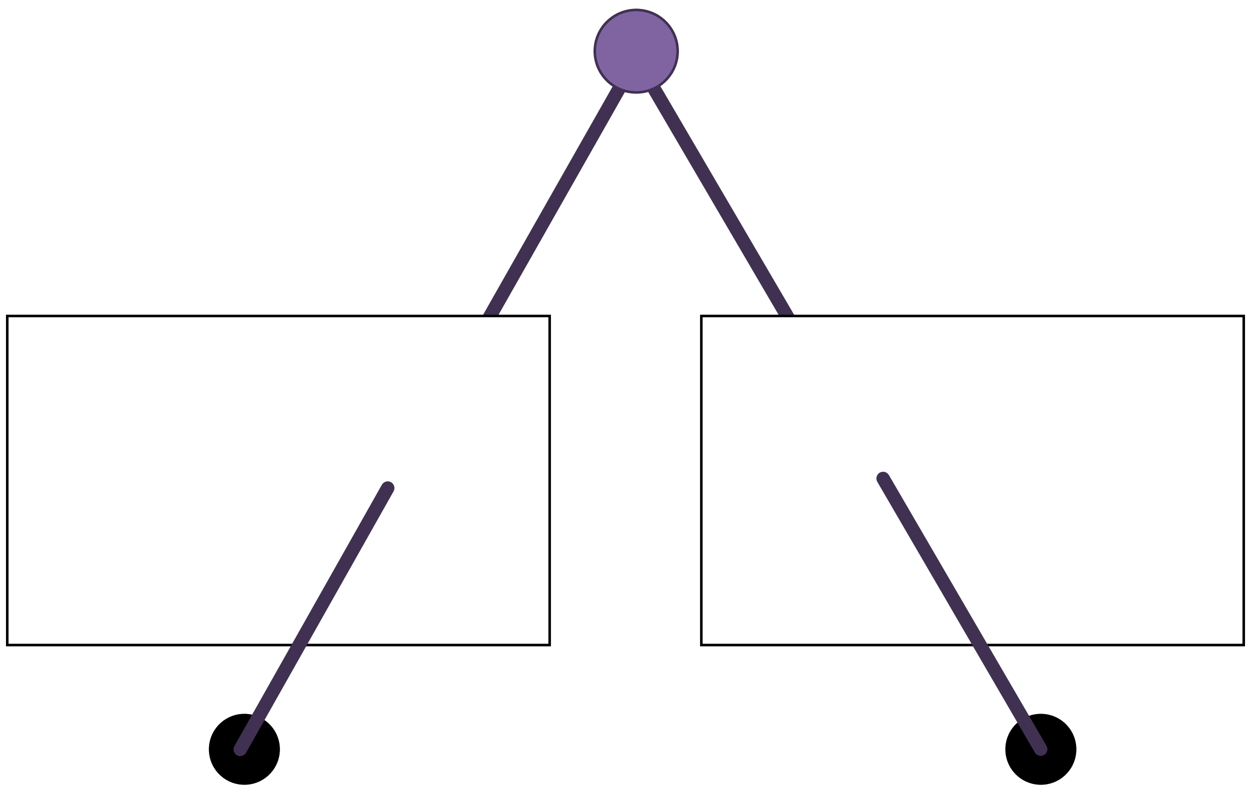


Image Credit: Hartley & Zisserman

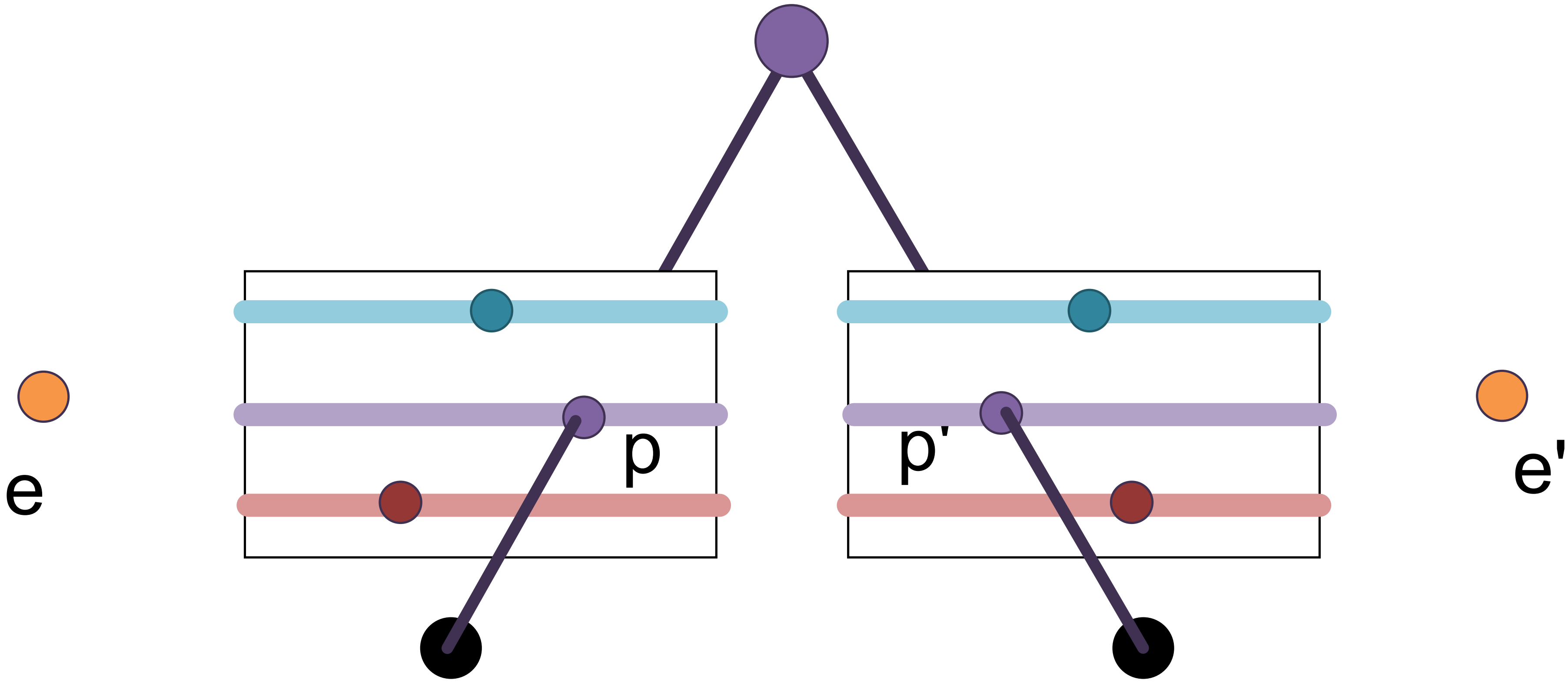
Example: Parallel to Image Plane



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

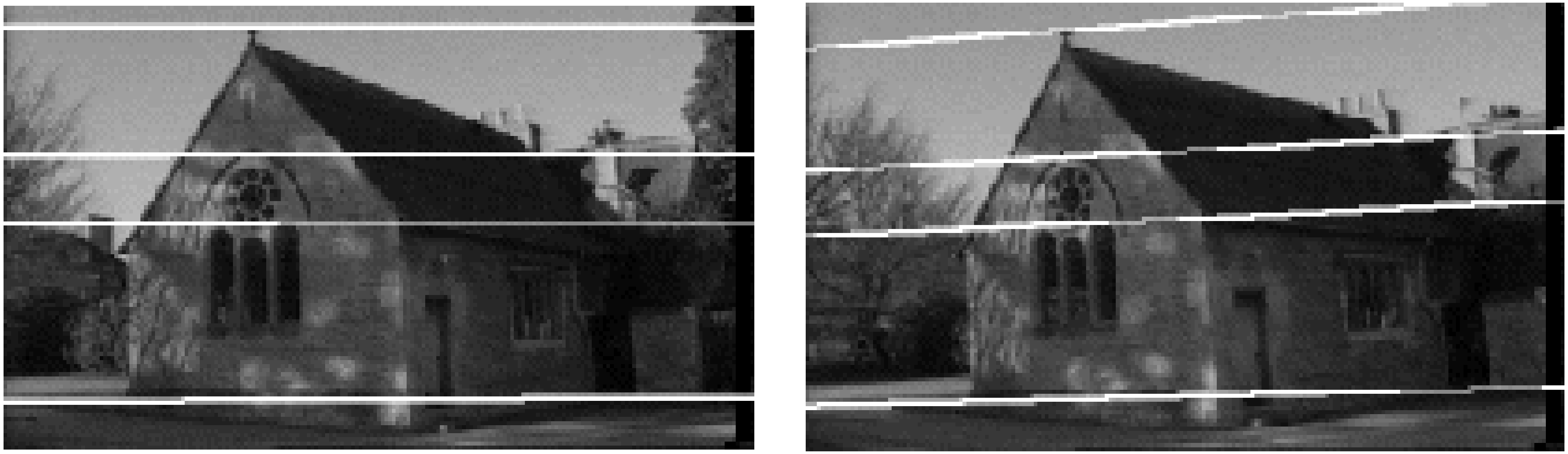


Image Credit: Hartley & Zisserman

Example: Forward Motion

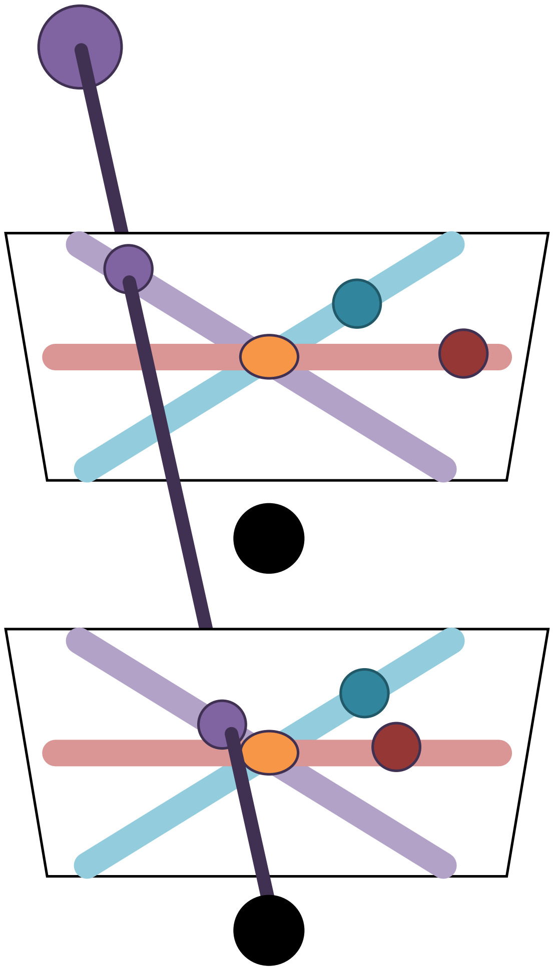
Image Credit: Hartley & Zisserman

Example: Forward Motion

Image Credit: Hartley & Zisserman

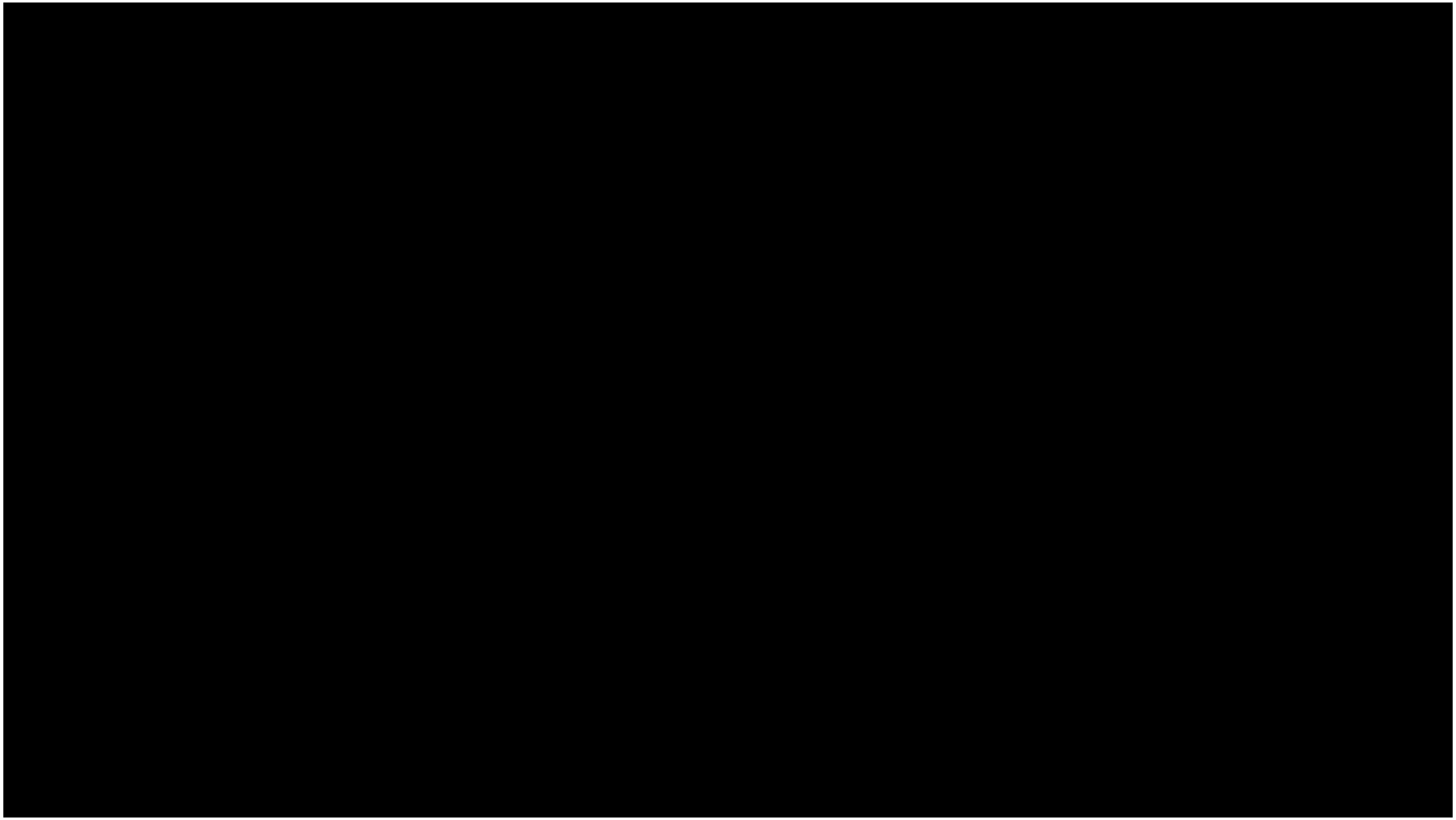
Example: Forward Motion

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



Epipolar lines go out from principal point

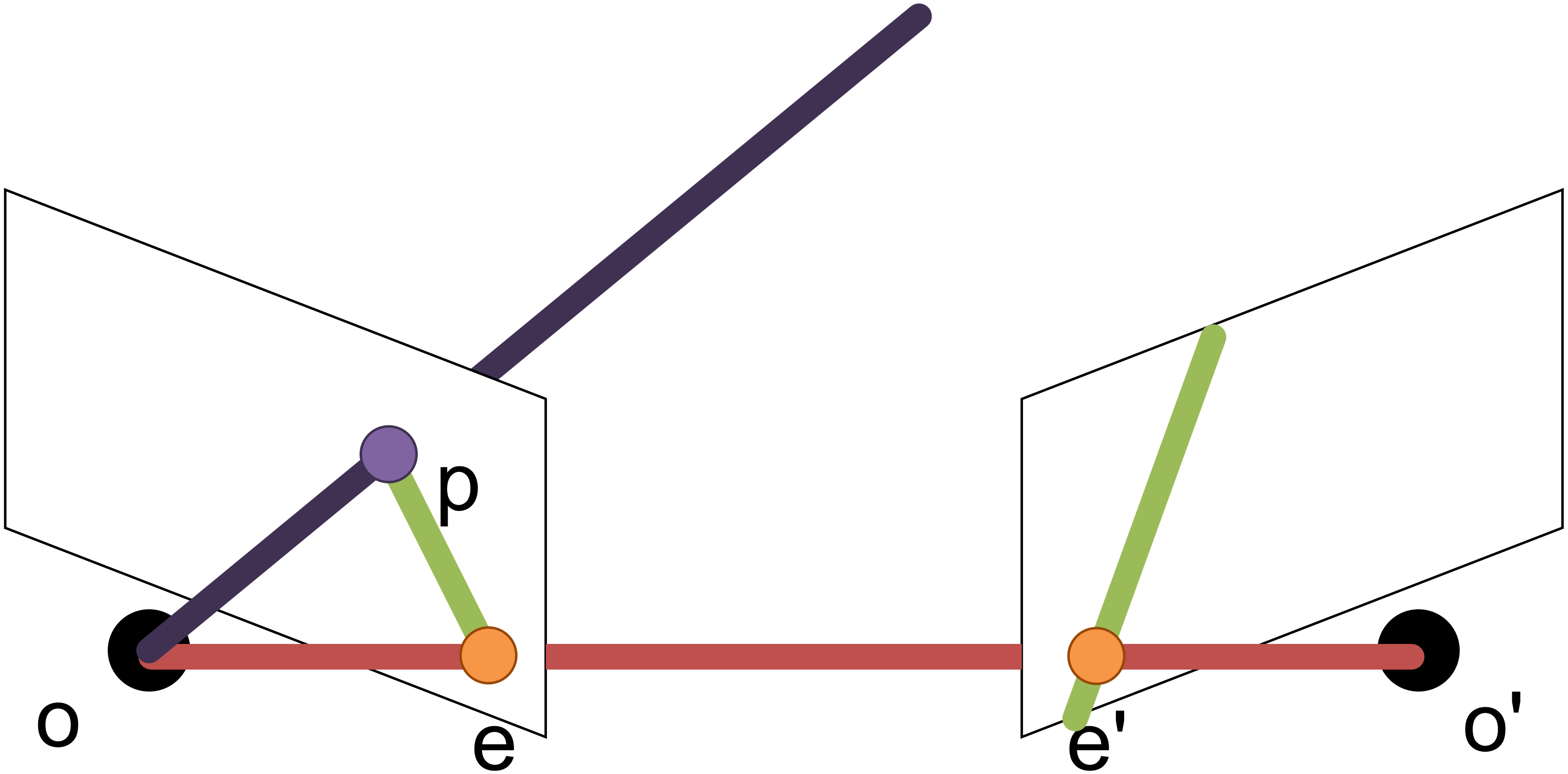
Motion perpendicular to image plane



http://vimeo.com/48425421

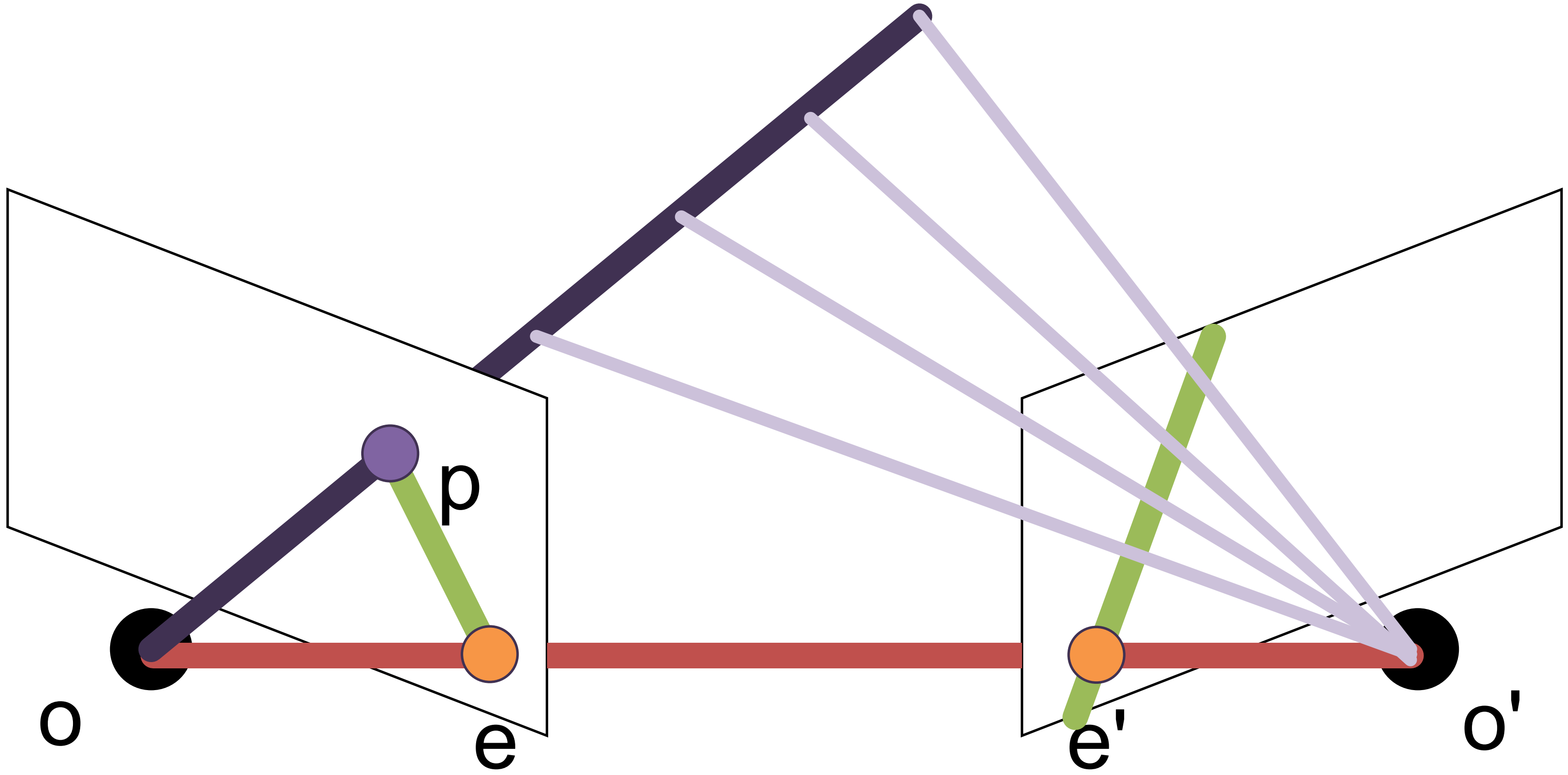
So?

Epipolar Geometry



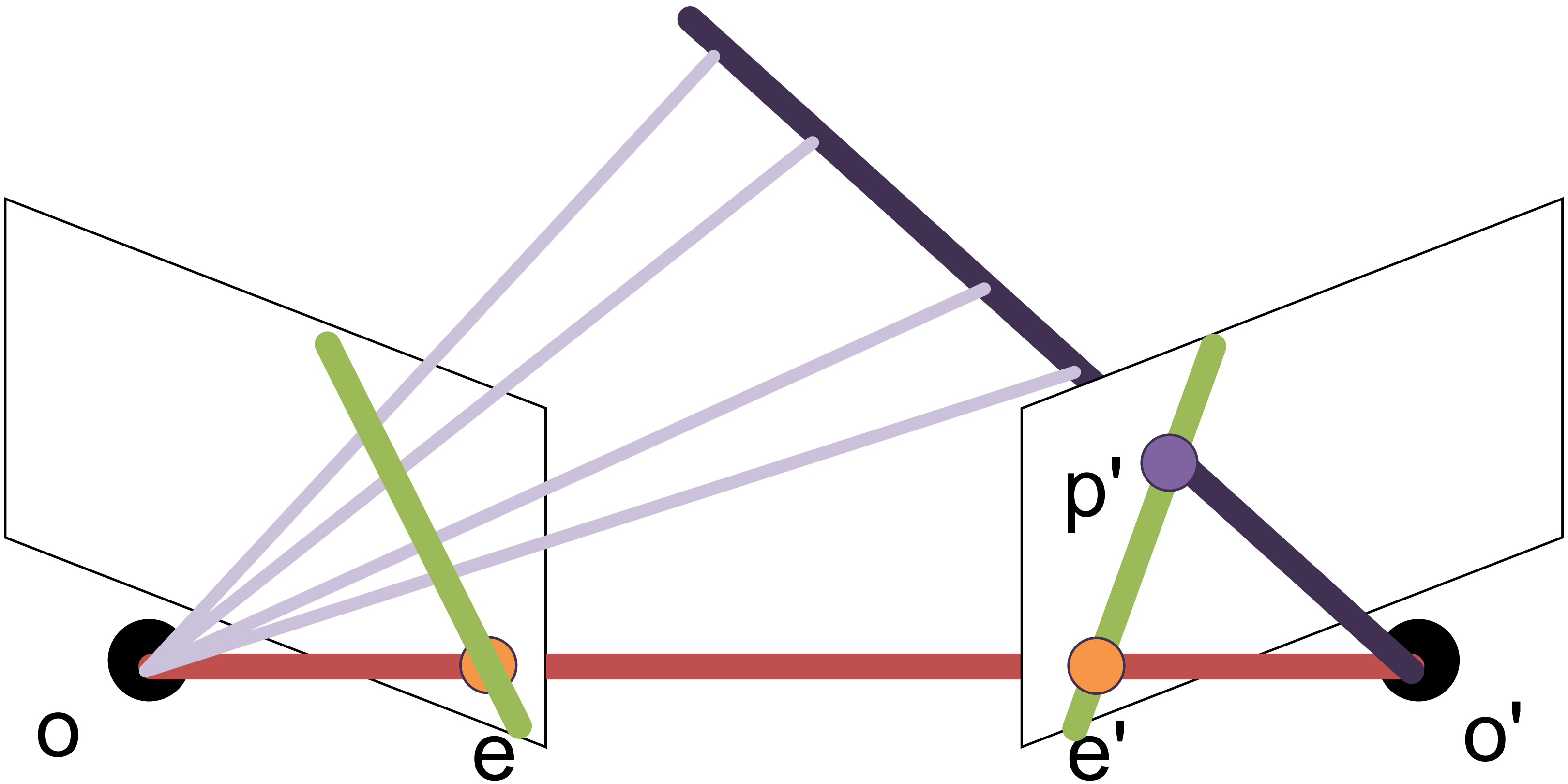
- Suppose we don't know X and just have p
- Can construct the epipolar line in the other image

Epipolar Geometry



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

Epipolar Geometry

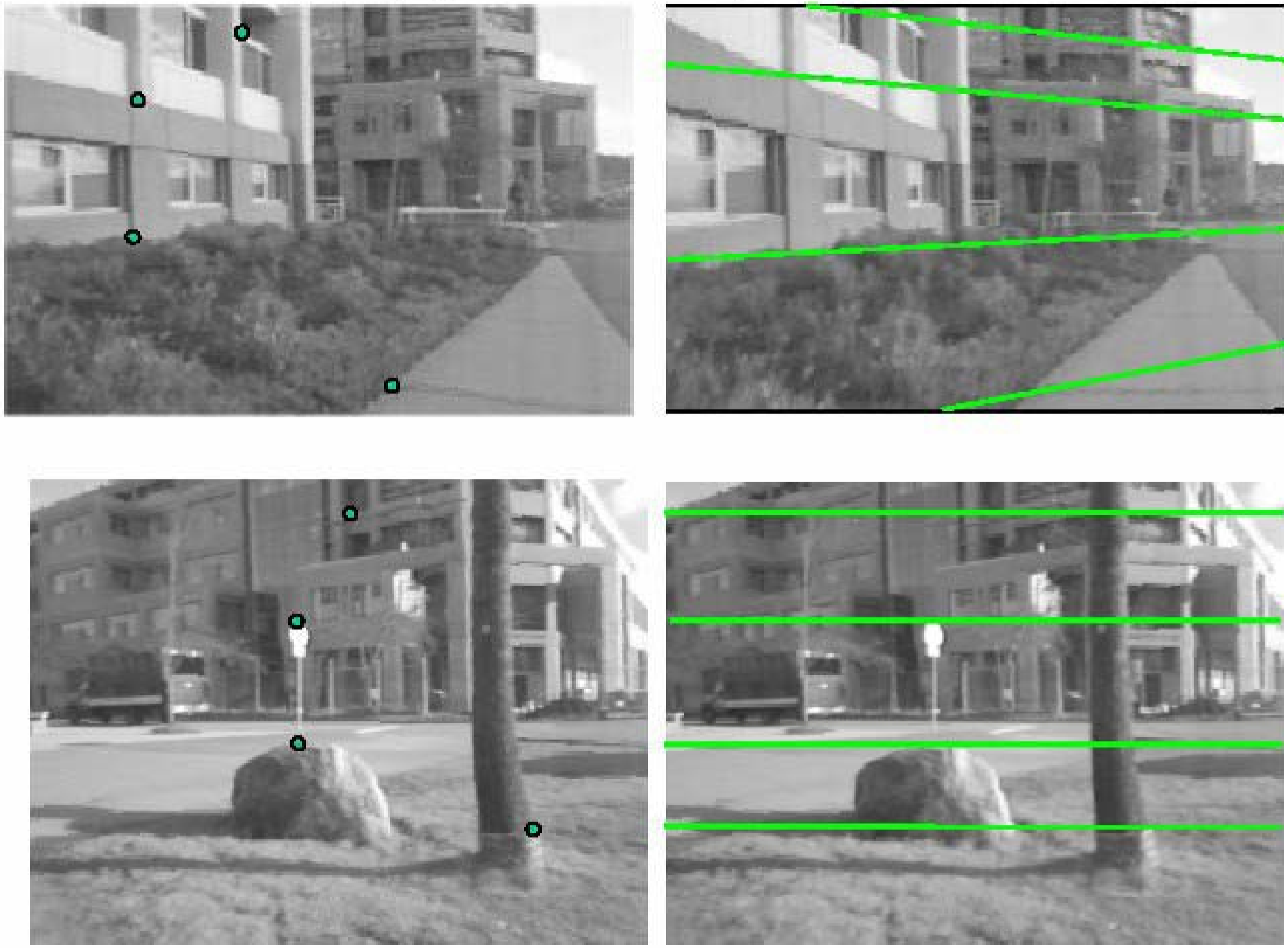


- Suppose we don’t know X and just have p’
- Corresponding p is on corresponding epipolar line

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

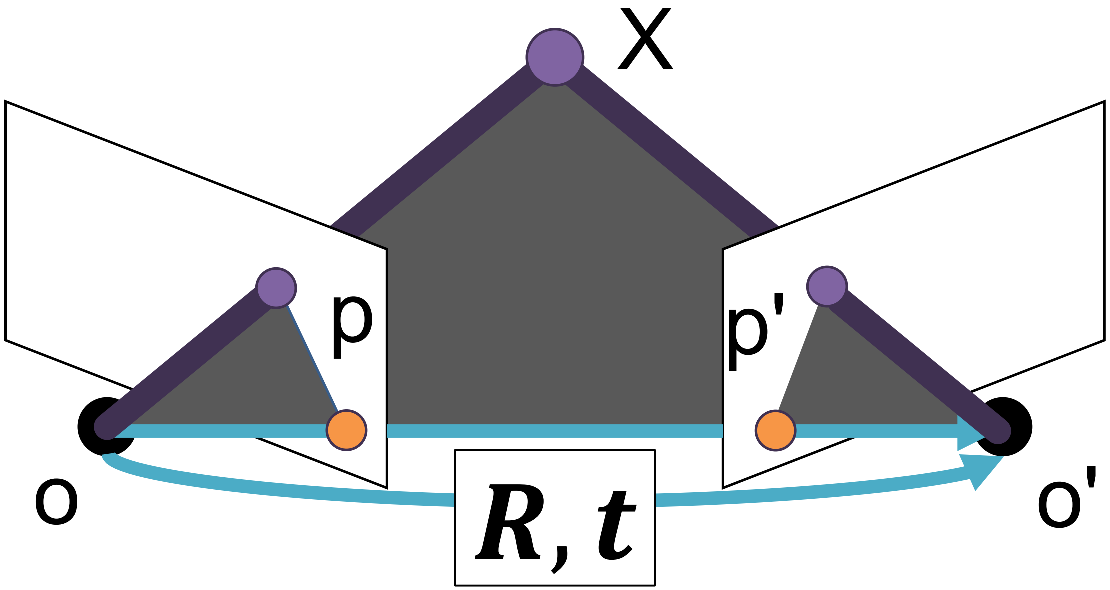


Slide Credit: S. Lazebnik

Epipolar Constraint: One Note

- If you look around for other reading, you'll find derivations with p, p' flipped and constraints derived in a flipped way
- It all works the same

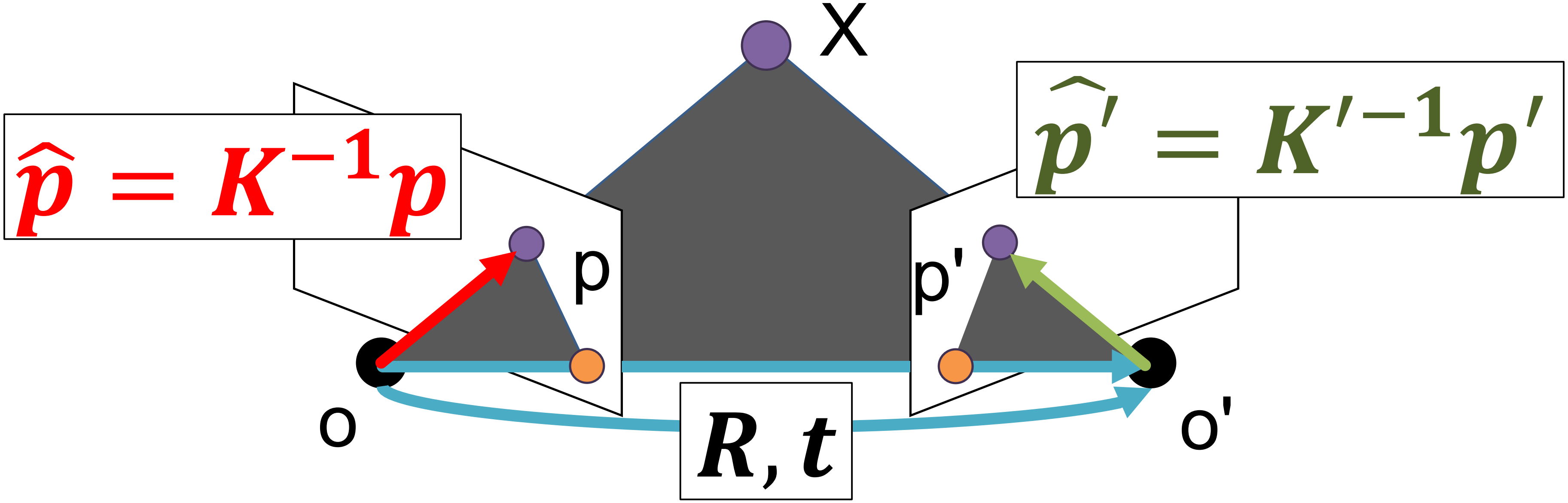
Epipolar Constraint: Calibrated Case



- If we know intrinsic and extrinsic parameters, set coordinate system to first camera
- Projection matrices: $\mathbf{P}_1 = \boldsymbol{K}[\boldsymbol{I}, \mathbf{0}]$ and $\boldsymbol{P}_2 = \boldsymbol{K}'[\boldsymbol{R}, \boldsymbol{t}]$
- **What are:**

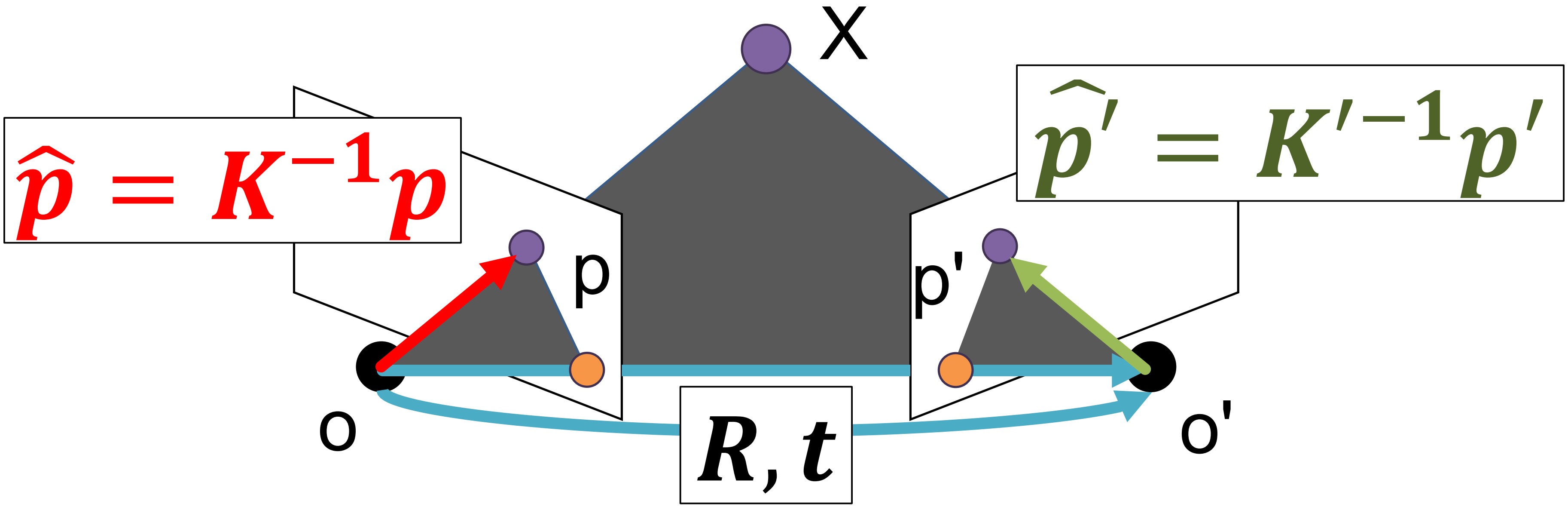
$$\boldsymbol{P}_1\boldsymbol{X} \qquad \boldsymbol{P}_2\boldsymbol{X} \qquad \boldsymbol{K}^{-1}\boldsymbol{p} \qquad \boldsymbol{K'}^{-1}\boldsymbol{p}'$$

Epipolar Constraint: Calibrated Case



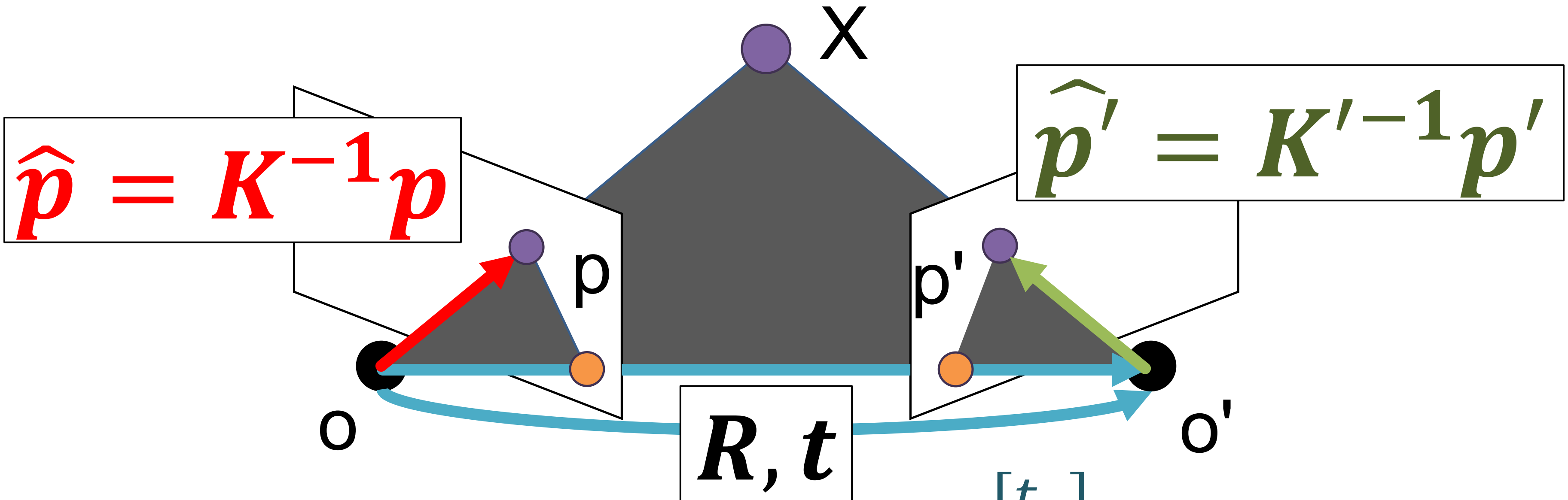
- Given calibration, $\hat{p} = K^{-1}p$ and $\widehat{p'} = K'^{-1}p'$ are "normalized coordinates"
- Note that $\widehat{p'}$ is actually translated and rotated

Epipolar Constraint: Calibrated Case



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

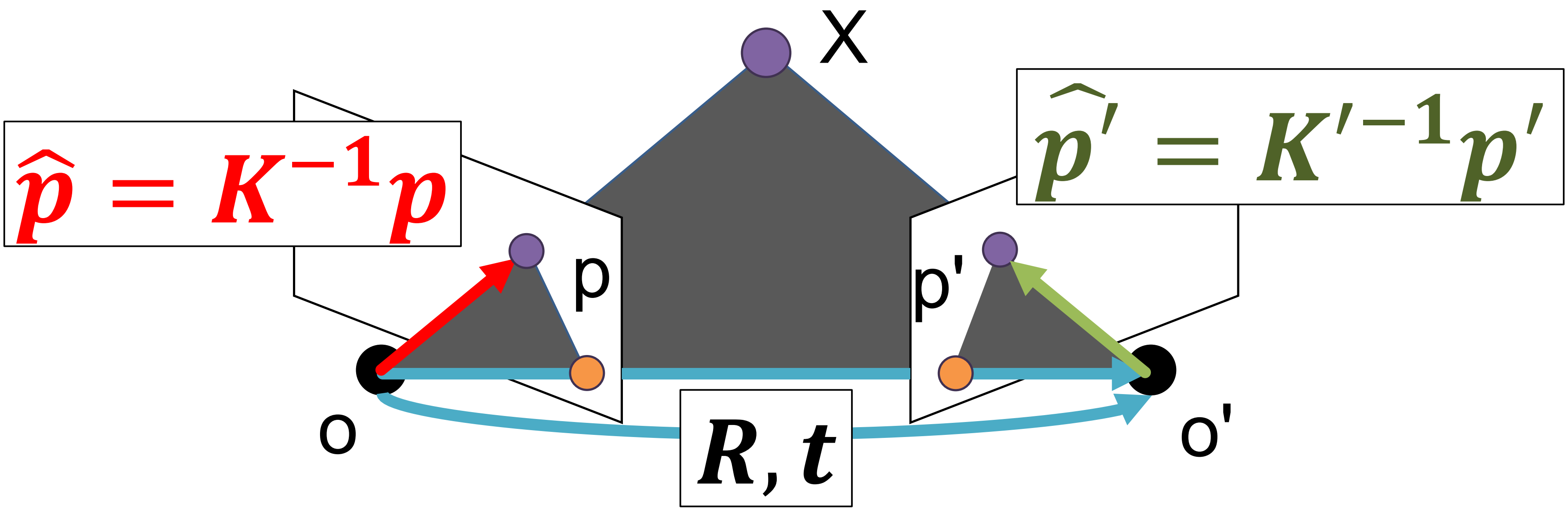
Epipolar Constraint: Calibrated Case



$$\hat{p}^T (t \times R \hat{p}') = 0 \rightarrow \hat{p}^T \underbrace{\begin{bmatrix} 0 & -t_3 & t_2 \\ t_3 & 0 & -t_1 \\ -t_2 & t_1 & 0 \end{bmatrix}}_{[t_x]} R \hat{p}' = 0$$

Want something like $x^T M y = 0$. **What's M?**

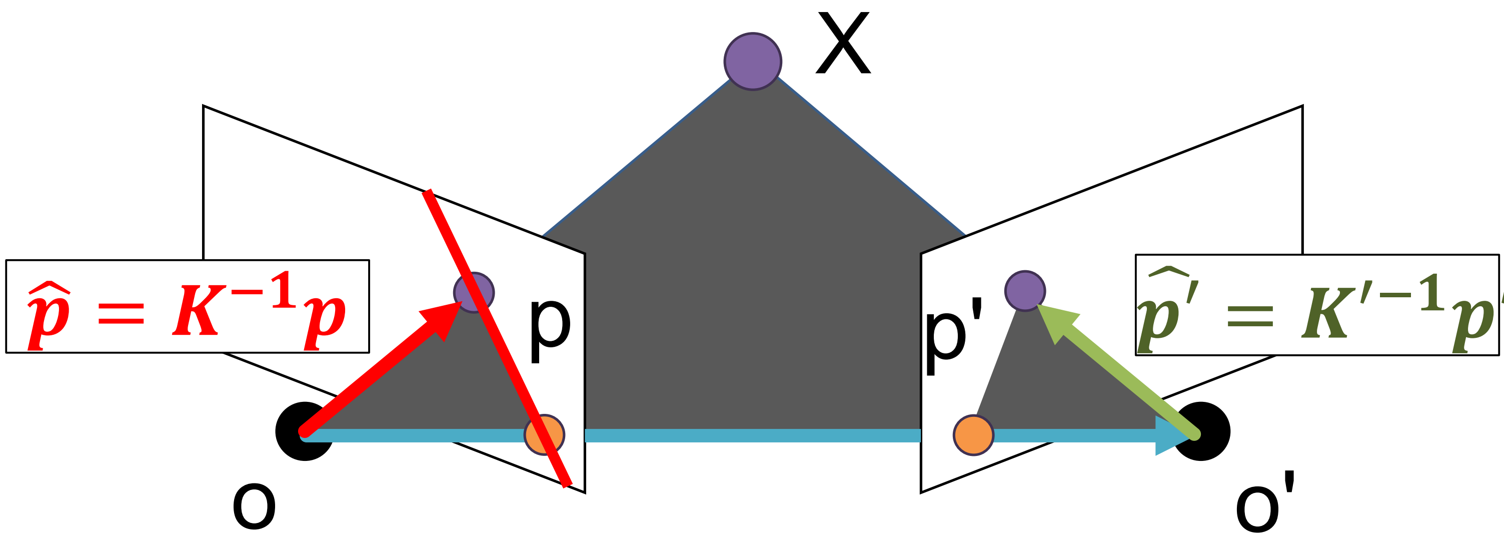
Epipolar Constraint: Calibrated Case



Essential matrix (Longuet-Higgins, 1981): $E = [t_x]R$

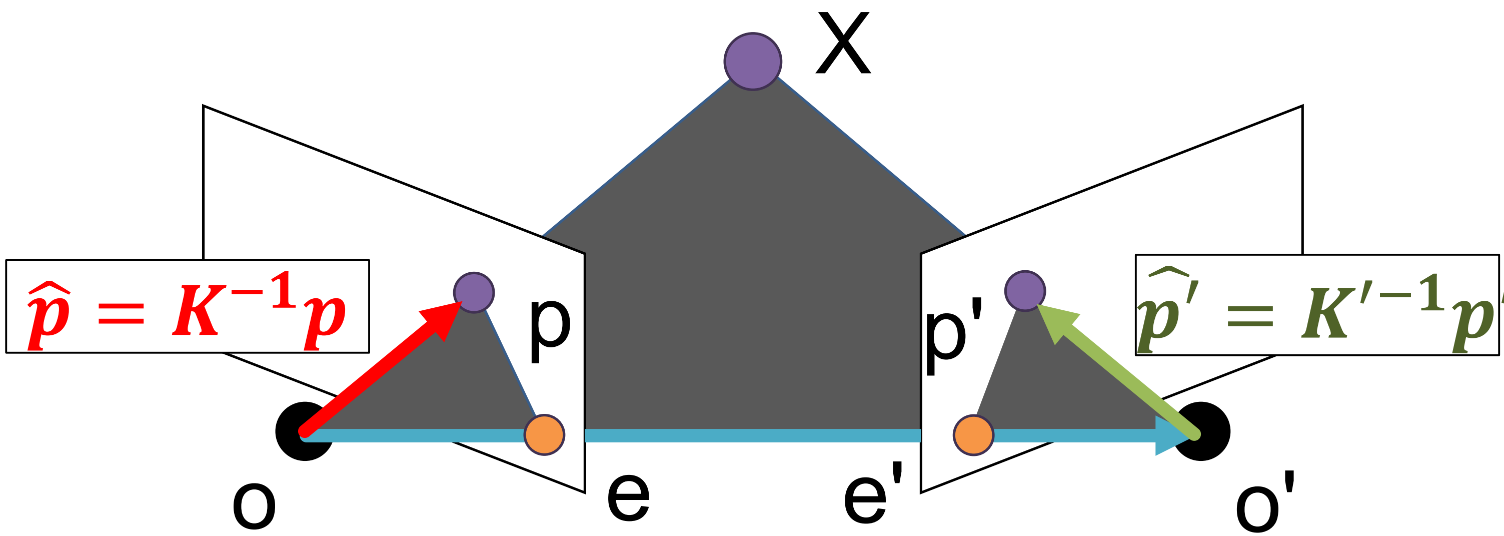
If you have a normalized point $\hat{p}$, its correspondence $\widehat{p}'$ **must** satisfy $\hat{p}^T E \widehat{p'} = 0$

Essential Essential Matrix Facts



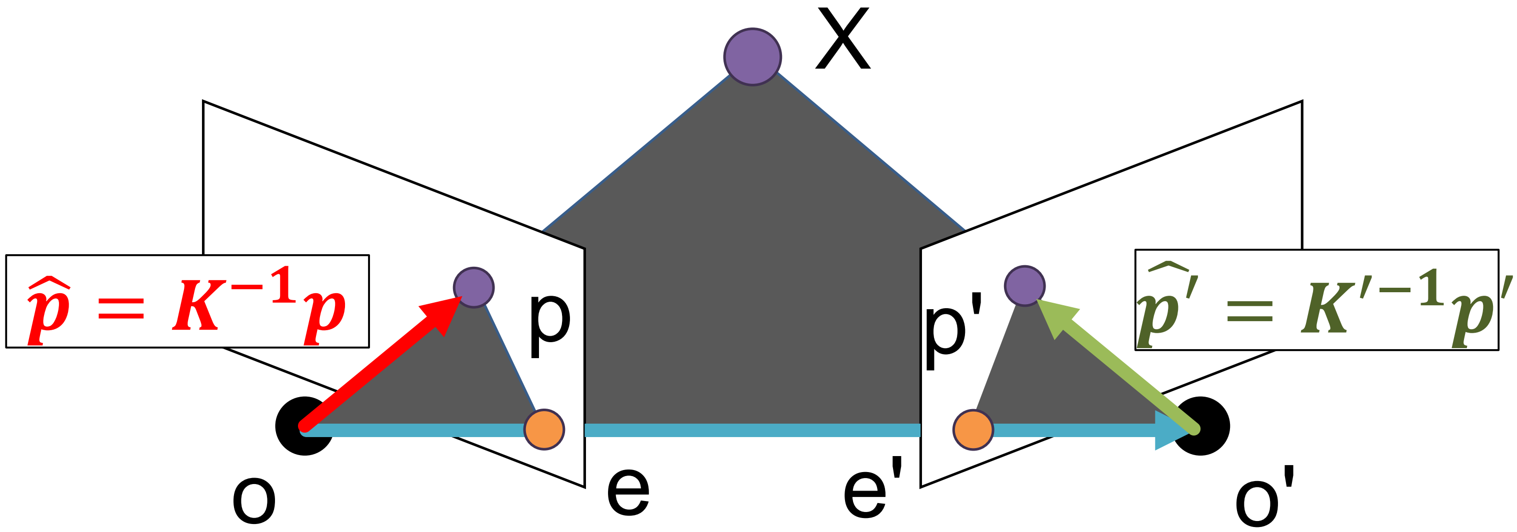
- Suppose we know **E** and $\widehat{\boldsymbol{p}}^T \boldsymbol{E} \widehat{\boldsymbol{p}'} = 0$. What is the set $\{\boldsymbol{x}: \boldsymbol{x}^T \boldsymbol{E} \widehat{\boldsymbol{p}'} = \boldsymbol{0}\}$?
- $\boldsymbol{E}\widehat{\boldsymbol{p}}$ gives equation of the epipolar line (in ax+by+c=0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

Essential Essential Matrix Facts



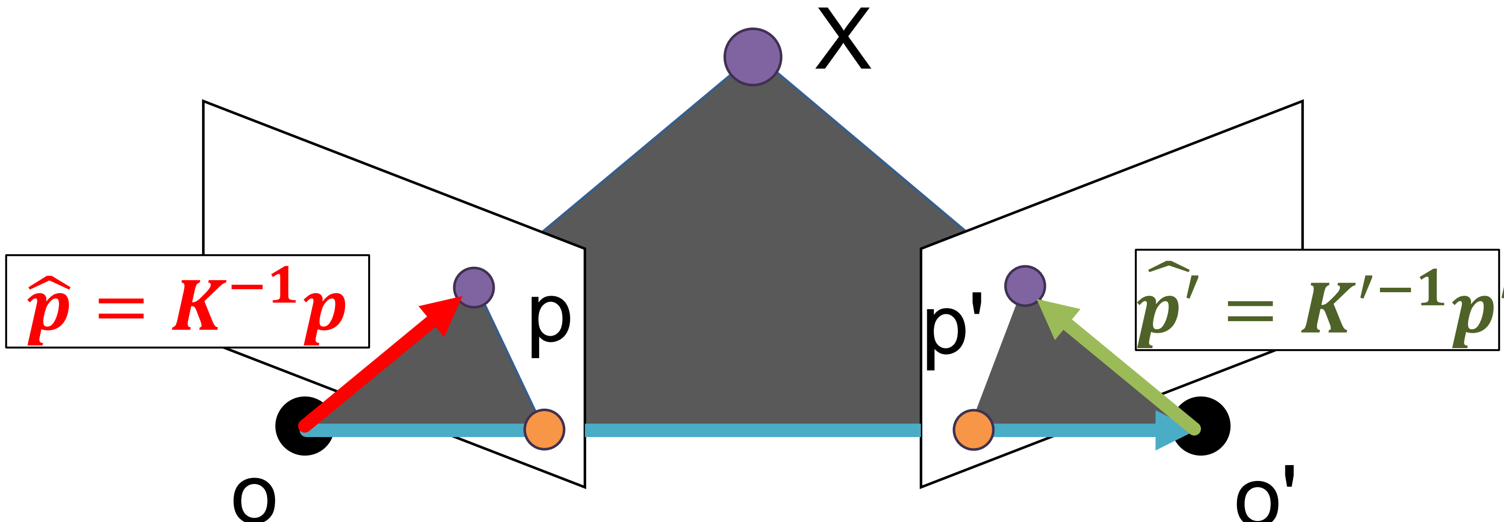
- $E\hat{e}' = 0$ and $E^T\hat{e} = 0$ (epipoles are the nullspace of E – note all epipolar lines pass through epipoles)
- **Degrees of freedom (Recall $E = [t_x]R$)?**
- 5 – 3 (R)+ 3 (t) – 1 due to scale ambiguity
- E is singular (rank 2); it has two non-zero and *identical* singular values

Essential Essential Matrix Facts



- One nice thing: if I estimate E from two images (more on this later), it's unique up to easy symmetries

What if we don't know K?



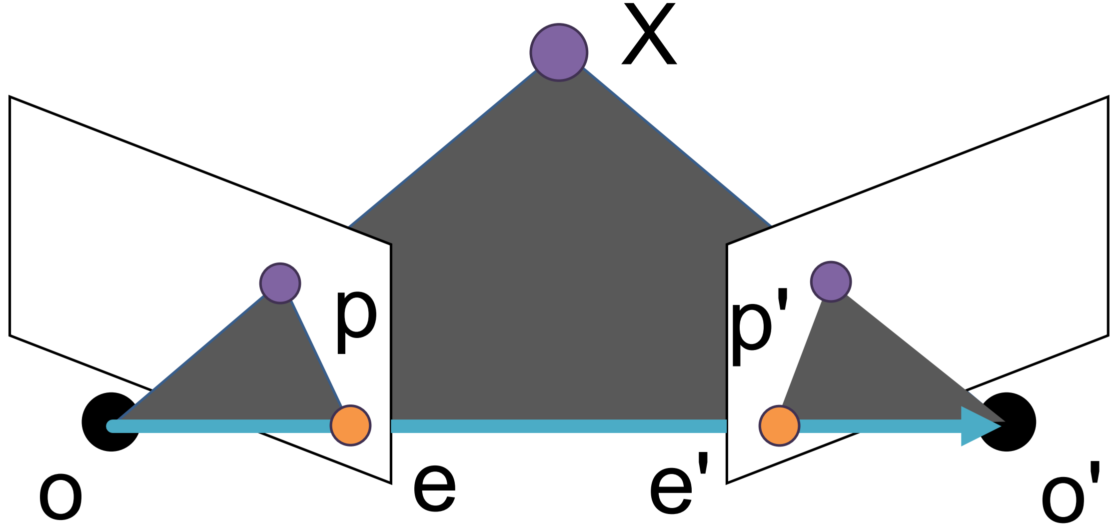
Have: $\hat{p} = K^{-1}p$, $\hat{p}' = K'^{-1}p'$, $\hat{p}^T E \hat{p}' = 0$

$$\left(K^{-1}p\right)^T E\left(K'^{-1}p'\right) = \mathbf{0} \;\Rightarrow\; p^T K^{-T} E K'^{-1} p' = 0$$

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

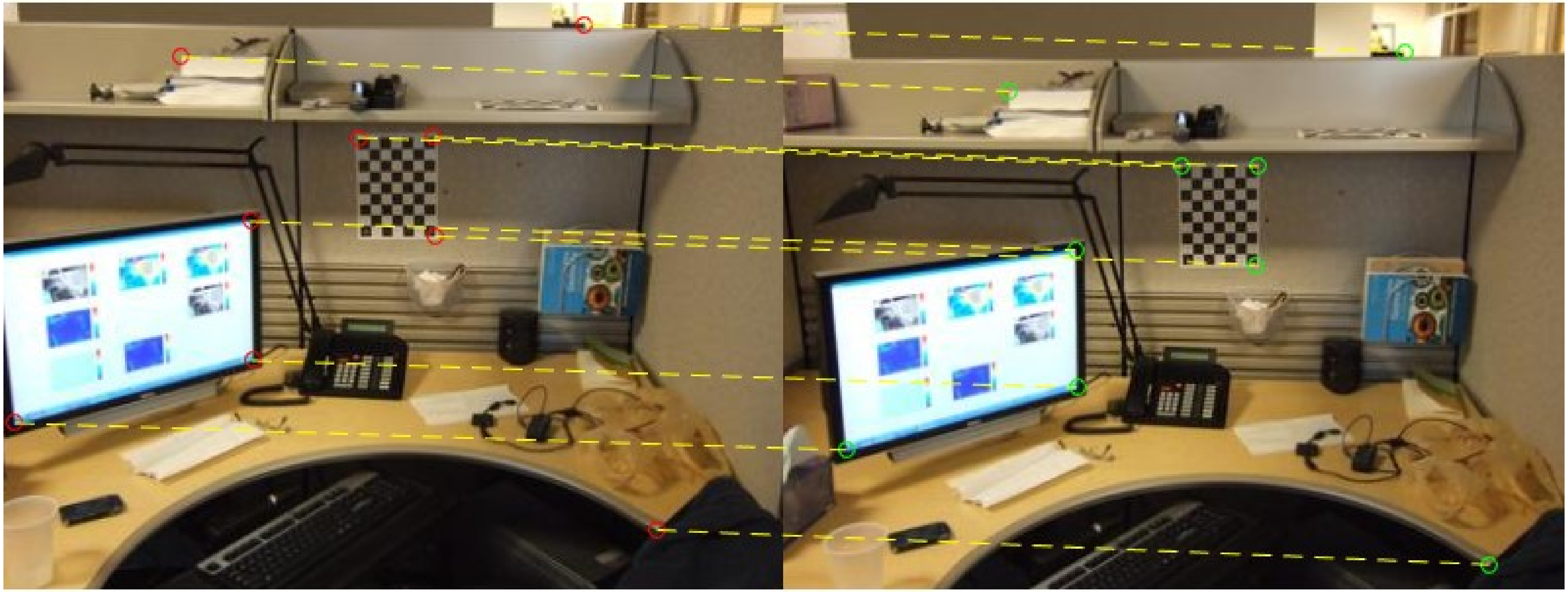
Fundamental Matrix (Faugeras and Luong, 1992)

Fundamental Matrix Fundamentals



- $\boldsymbol{Fp'}, \boldsymbol{F^T p}$ are epipolar lines for p’, p
- $\boldsymbol{Fe'} = 0, \boldsymbol{F^T e} = 0$
- F is singular (rank 2)
- F has seven degrees of freedom
- F definitely not unique

Estimating the fundamental matrix



Slide Credit: S. Lazebnik

Estimating the fundamental matrix

- F has 7 degrees of freedom so it’s in principle possible to fit F with seven correspondences, but it’s a slightly more complex and typically not taught in regular vision classes

Estimating the fundamental matrix

Given correspondences $\boldsymbol{p} = [u, v, 1]$ and $\boldsymbol{p}' = [u', v', 1]$ (e.g., via SIFT) we know: $\boldsymbol{p}^{\boldsymbol{T}}\boldsymbol{F}\boldsymbol{p}' = 0$

$$[u, v, 1] \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} = 0$$

$$\begin{matrix} [uu', uv', u, vu', vv', v, u', v', 1] \cdot \\ [f_{11}, f_{12}, f_{13}, f_{21}, f_{22}, f_{23}, f_{31}, f_{32}, f_{33}] \end{matrix} = 0$$

How do we solve for f?

How many correspondences do we need?

Leads to the **eight point algorithm**

Eight Point Algorithm

Each point gives an equation:

$$[uu', uv', u, vu', vv', v, u', v', 1] \cdot [f_{11}, f_{12}, f_{13}, f_{21}, f_{22}, f_{23}, f_{31}, f_{32}, f_{33}] = 0$$

Stack equations to yield **U**:

$$\boldsymbol{U} = \begin{bmatrix} & & & & \vdots & & & & \\ u_i u_i' & u_i v_i' & u_i & v_i u_i' & v_i v_i' & v_i & u_i' & v_i' & 1 \\ & & & & \vdots & & & & \end{bmatrix}$$

Usual eigenvalue stuff to find **f** (**F** unrolled):

$$\arg\min_{\|\boldsymbol{f}\|=1} \|\boldsymbol{U}\boldsymbol{f}\|_2^2 \rightarrow$$ Eigenvector of $\boldsymbol{U}^{\boldsymbol{T}}\boldsymbol{U}$ with smallest eigenvalue

Eight Point Algorithm – Difficulty 1

If we estimate F, we get some 3x3 matrix F.
We know F needs to be singular/rank 2. How do we force F to be singular?

$$U\Sigma V^T = F_{init}$$

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & \cancel{\sigma_3} \end{bmatrix} \rightarrow \Sigma' = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$F = U\Sigma' V^T$$

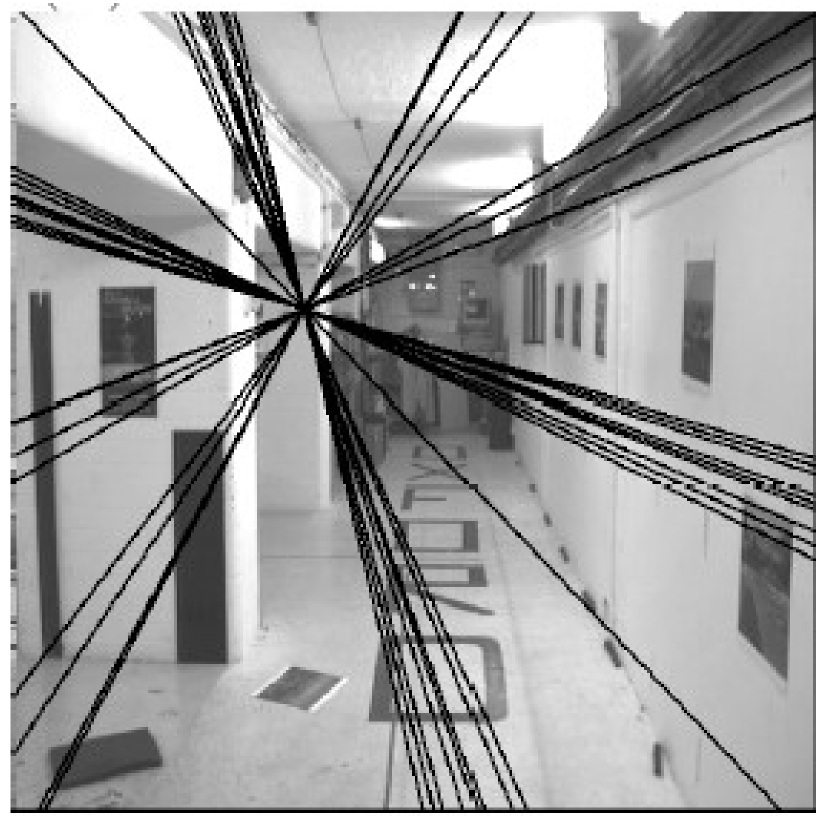
Open it up with SVD, mess with singular values, put it back together.

See Eckart–Young–Mirsky theorem if you're interested

Eight Point Algorithm – Difficulty 1

Estimated F
(Wrong)

Estimated+SVD'd F
(Correct)



Slide Credit: S. Lazebnik

Eight Point Algorithm – Difficulty 2

$$[uu', uv', u, vu', vv', v, u', v', 1] \cdot [f_{11}, f_{12}, f_{13}, f_{21}, f_{22}, f_{23}, f_{31}, f_{32}, f_{33}]^T = 0$$

Recall: u,u' are in pixels. Suppose image is 1Kx1K

How big might uu' be? How big might u be?

Each row looks like:

$$\boldsymbol{U} = \begin{bmatrix} & & & & \vdots & & & & \\ 10^6 & 10^6 & 10^3 & 10^6 & 10^6 & 10^3 & 10^3 & 10^3 & 1 \\ & & & & \vdots & & & & \end{bmatrix}$$

Then: $\boldsymbol{U^T U_{1,1}}$ is ~10^{12}, $\boldsymbol{U^T U_{2,9}}$ is ~10^3

Eight Point Algorithm – Difficulty 2

Numbers of varying magnitude → instability

Remember: a floating point number (float/double) isn't a "real" number: for sign, coefficient, exponent integers

$(-1)^{sign} * coefficient * 2^{exponent}$

Exercise to see how this screws up: add up Gaussian noise (mean=100, std=10), divide by number you added up

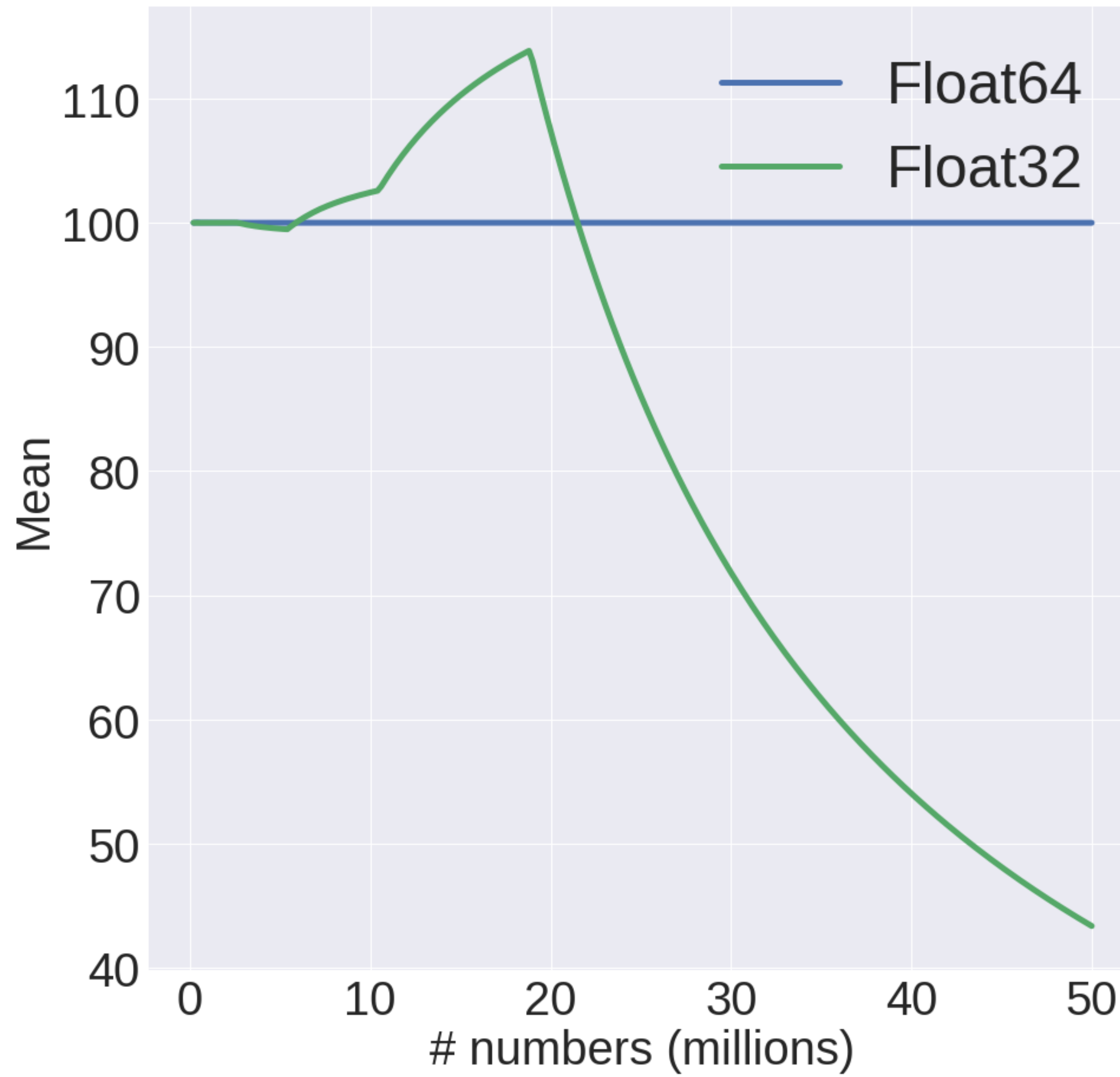
Remember Numerical Instability?

Code:

```
x += N(100,10)
i += 1
mean = x/I
```

Only change is the # of bits in accumulator x

Note: 50M is 50 1Kx1K images



Solution: Normalized 8-point

- Center the image data at the origin, and scale it so the mean squared distance between the origin and the data points is 2 pixels
- Use the eight-point algorithm to compute $\boldsymbol{F}$ from the normalized points
- Enforce the rank-2 constraint (for example, take SVD of $\boldsymbol{F}$ and throw out the smallest singular value)
- Transform fundamental matrix back to original units: if $\boldsymbol{T}$ and $\boldsymbol{T'}$ are the normalizing transformations in the two images, than the fundamental matrix in original coordinates is $\boldsymbol{T'^{T} F T}$

Slide Credit:
S. Lazebnik

R. Hartley
In defense of the eight-point algorithm TPAMI 1997

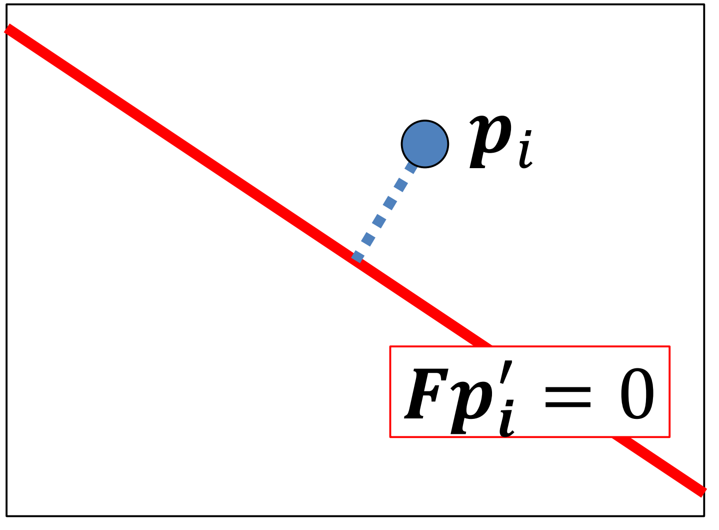
Last Trick

Minimizing via U^TU minimizes sum of squared *algebraic* distances between points $\boldsymbol{p}_i$ and epipolar lines $\boldsymbol{Fp'}_i$ (or points $\boldsymbol{p'}_i$ and epipolar lines $\boldsymbol{F}^T\boldsymbol{p}_i$):

$$\sum_i \left(p_i^T F p_i'\right)^2$$

May want to minimize *geometric* distance:

$$\sum_i \begin{matrix} d(p_i, Fp'_i)^2 + \\ d(p_i', F^T p_i)^2 \end{matrix}$$



Slide Credit: S. Lazebnik

Comparison

	8-point	Normalized 8-point	Nonlinear least squares
Av. Dist. 1	2.33 pixels	0.92 pixel	0.86 pixel
Av. Dist. 2	2.18 pixels	0.85 pixel	0.80 pixel

Slide Credit: S. Lazebnik

The Fundamental Matrix Song

http://danielwedge.com/fmatrix/

From Epipolar Geometry to Calibration

- Estimating the fundamental matrix is known as "weak calibration"
- If we know the calibration matrices of the two cameras, we can estimate the essential matrix: $\boldsymbol{E} = \boldsymbol{K}'^{T}\boldsymbol{F}\boldsymbol{K}$
- The essential matrix gives us the relative rotation and translation between the cameras, or their extrinsic parameters
- Alternatively, if the calibration matrices are known, the five-point algorithm can be used to estimate relative camera pose

Slide Credit: S. Lazebnik