
The Ancient
Secrets
Computer Vision

Logistics:

- Homework 2 out! Due a week from Thursday
  - Little longer than past ones, start early
- Google group
-

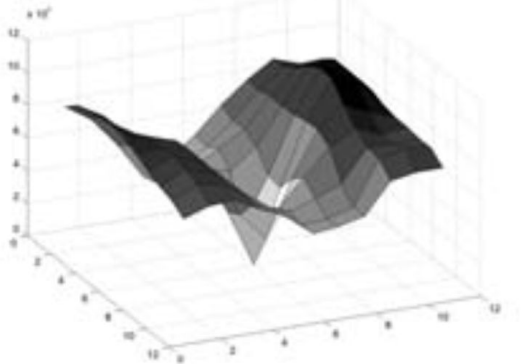

Previously
On
the
Ancient Secrets
of Computer Vision

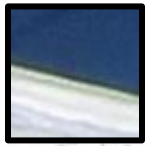
Self-difference

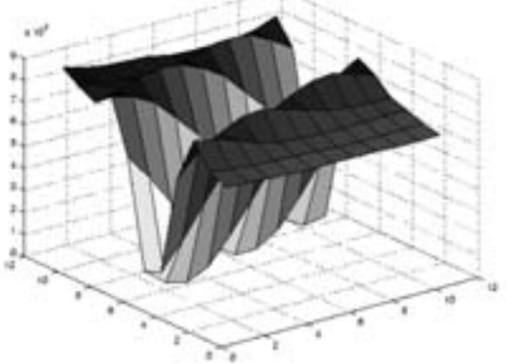
Sky: low everywhere

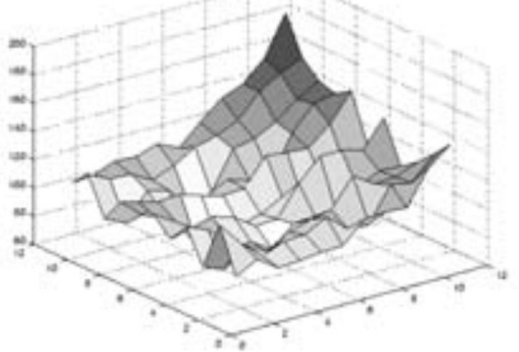
Edge: low along edge

Corner: mostly high









Self-difference is still expensive

- $\Sigma_{\mathbf{d}}\Sigma_{x,y}\ (I(x,y) - I(x+\mathbf{d}_x, y+\mathbf{d}_y))^2$
- Lots of summing
- Need an approximation
  - If you want the mathy details, Szeliski pg 212

Structure matrix

- Weighted sum of gradient information
  - $| \Sigma_i w_i I_x(i) I_x(i) \quad \Sigma_i w_i I_x(i) I_y(i) |$
  - $| \Sigma_i w_i I_x(i) I_y(i) \quad \Sigma_i w_i I_y(i) I_y(i) |$
- Can use Gaussian weighting (so many gaussians)
- Eigen vectors/values of this matrix summarize the distribution of the gradients nearby
- λ_1 and λ_2 are eigenvalues
  - λ_1 and λ_2 both small: no gradient
  - $\lambda_1 >> \lambda_2$: gradient in one direction
  - λ_1 and λ_2 similar: multiple gradient directions, corner

Estimating smallest eigen value

- A few methods:
  - $\det(S) = \lambda_1 * \lambda_2$
  - $\text{trace}(S) = \lambda_1 + \lambda_2$
- $\det(S) - \alpha\ \text{trace}(S)^2 = \lambda_1\lambda_2 - \alpha(\lambda_1+\lambda_2)^2$
- $\det(S) / \text{trace}(S) = \lambda_1\lambda_2/(\lambda_1+\lambda_2)$
- If these estimates are large, λ_2 is large

Harris Corner Detector

- Calculate derivatives I_x and I_y
- Calculate 3 measures I_xI_x, I_yI_y, I_xI_y
- Calculate weighted sums
  - Want a weighted sum of nearby pixels, guess what this is?
  - Gaussian!
- Estimate response based on smallest eigen value
- Non-max suppression (just like canny)

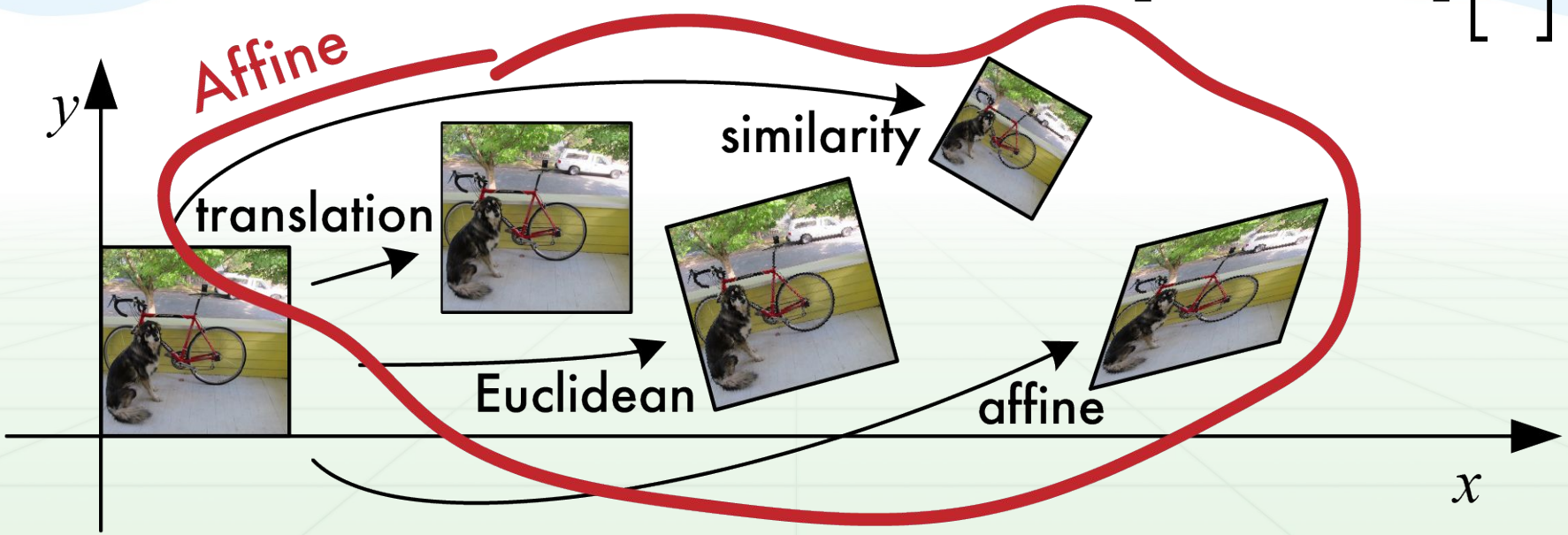
Matching patches: descriptors!

- We want a way to represent an image patch
- Can be very simple, just pixels!
- Finding matching patch is easy, distance metric:
  - $\Sigma_{x,y}\ (I(x,y) - J(x,y))^2$
  - What problems are there with just using pixels?
- Descriptors can be more complex
  - Gradient information
  - How much context?
  - Edges, etc. we'll talk more about descriptors later!

Affine: scale, rotate, translate, shear

General case of 2x3 matrix

$$\mathbf{x}' = \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$



Combinations are still affine

Say you want to translate, then rotate, then translate back, then scale.

$\mathbf{x'} = \mathbf{S}\ \mathbf{t}\ \mathbf{R}\ \mathbf{t}\ \bar{\mathbf{x}} = \mathbf{M}\ \bar{\mathbf{x}}$,

If $\mathbf{M} = (\mathbf{S}\ \mathbf{t}\ \mathbf{R}\ \mathbf{t})$

$\mathbf{M}$ is still affine transformation

Wait, but these are all 2x3, how to we multiply them together?

Added row to transforms

$$\bar{\mathbf{x}}' = \begin{bmatrix} 1 & 0 & dx \\ 0 & 1 & dy \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

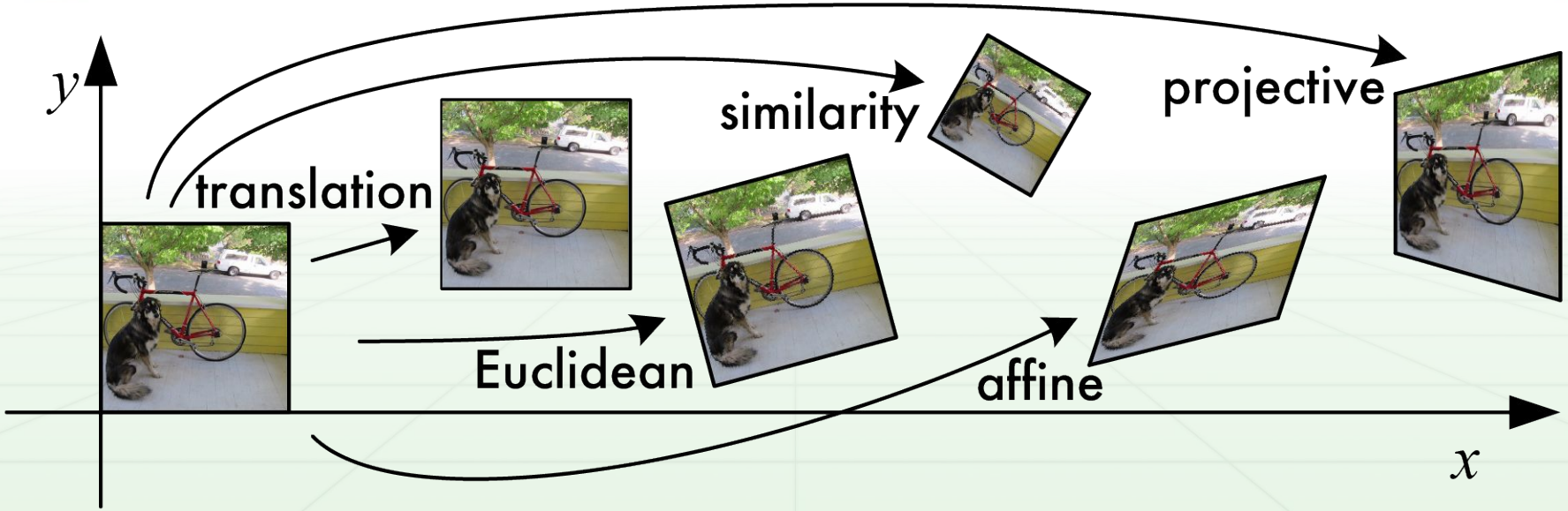
$$\bar{\mathbf{x}}' = \begin{bmatrix} \cos\theta & -\sin\theta & dx \\ \sin\theta & \cos\theta & dy \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$\bar{\mathbf{x}}' = \begin{bmatrix} a & -b & dx \\ b & a & dy \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$$\bar{\mathbf{x}}' = \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Projective transform

- AKA perspective transform or homography
- Wait but affine was any 2x3 matrix...



Projective transform

- AKA perspective transform or homography
- Wait but affine was any 2x3 matrix...
- Homography is general 3x3 matrix
- Multiplication by scalar: equivalent projection
  - 3*H ~ H

$$\tilde{\mathbf{x}}' = \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{w} \end{bmatrix}$$

$$\tilde{\mathbf{x}}' = \tilde{\mathbf{H}}\,\tilde{\mathbf{x}}$$

Using homography to project point

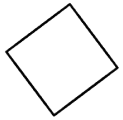
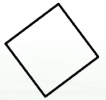
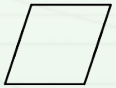
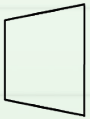
- Multiply **x~** by **H~** to get **x'~**
- Convert to **x'** by dividing by **w'~**

$$\tilde{\mathbf{x}}' = \tilde{\mathbf{H}}\,\tilde{\mathbf{x}}$$

$$\begin{bmatrix} \tilde{x}' \\ \tilde{y}' \\ \tilde{w}' \end{bmatrix} = \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{w} \end{bmatrix}$$

$$\bar{\mathbf{x}} = \tilde{\mathbf{x}} / \tilde{w}$$

Lots to choose from

Transformation	Matrix	# DoF	Preserves	Icon
translation	$\begin{bmatrix} \mathbf{I} \mid \mathbf{t} \end{bmatrix}_{2\times3}$	2	orientation	
rigid (Euclidean)	$\begin{bmatrix} \mathbf{R} \mid \mathbf{t} \end{bmatrix}_{2\times3}$	3	lengths	
similarity	$\begin{bmatrix} s\mathbf{R} \mid \mathbf{t} \end{bmatrix}_{2\times3}$	4	angles	
affine	$\begin{bmatrix} \mathbf{A} \end{bmatrix}_{2\times3}$	6	parallelism	
projective	$\begin{bmatrix} \tilde{\mathbf{H}} \end{bmatrix}_{3\times3}$	8	straight lines	

Say we want affine transformation

- Have our matched points
- Want to estimate **A** that maps from **x** to **x’**
- **xA = x’**
- How many degrees of freedom?
  - 6
- How many knowns do we get with one match? **mA = n**
  - 2
  - $n_x = a_{00}*m_x + a_{01}*m_y + a_{02}*1$
  - $n_y = a_{10}*m_x + a_{11}*m_y + a_{12}*1$

$$\mathbf{x'} = \begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$


Chapter
Seven
Stitching, RANSAC
SIFT, and HOG

Say we want affine transformation

- How many knowns do we get with one match? **mA = n**
  - $n_x = a_{00} * m_x + a_{01} * m_y + a_{02} * 1$
  - $n_y = a_{10} * m_x + a_{11} * m_y + a_{12} * 1$
  - Solve **M a = b**
    - $M^T M a = M^T b$
    - $a = (M^T M)^{-1} M^T b$
  - Still works if overdetermined
    - WHY???

$$\underset{\mathbf{M}}{\begin{bmatrix} m_{x1} & m_{y1} & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & m_{x1} & m_{y1} & 1 \\ m_{x2} & m_{y2} & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & m_{x2} & m_{y2} & 1 \\ m_{x3} & m_{y3} & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & m_{x3} & m_{y3} & 1 \\ & & & \cdots & & \\ & & & \cdots & & \end{bmatrix}} \underset{\mathbf{a}}{\begin{bmatrix} a_{00} \\ a_{01} \\ a_{02} \\ a_{10} \\ a_{11} \\ a_{12} \end{bmatrix}} = \underset{\mathbf{b}}{\begin{bmatrix} n_{x1} \\ n_{y1} \\ n_{x2} \\ n_{y2} \\ n_{x3} \\ n_{y3} \end{bmatrix}}$$

Linear least squares

Want to solve overdetermined linear system:

- $M\ a = b$

Want to minimize squared error:

$|| b - M\ a ||^2 =$

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Want to minimize squared error:

$$|| b - M a ||^2 =$$

$$(b - M a)^T(b - M a) =$$

$$b^Tb - a^TM^Tb - b^TMa + a^TM^TMa =$$

$$b^Tb - 2a^TM^Tb + a^TM^TMa$$

Linear least squares

Want to minimize squared error: $|| b - M a ||^2 =$

$b^T b - 2a^T M^T b + a^T M^T M a$

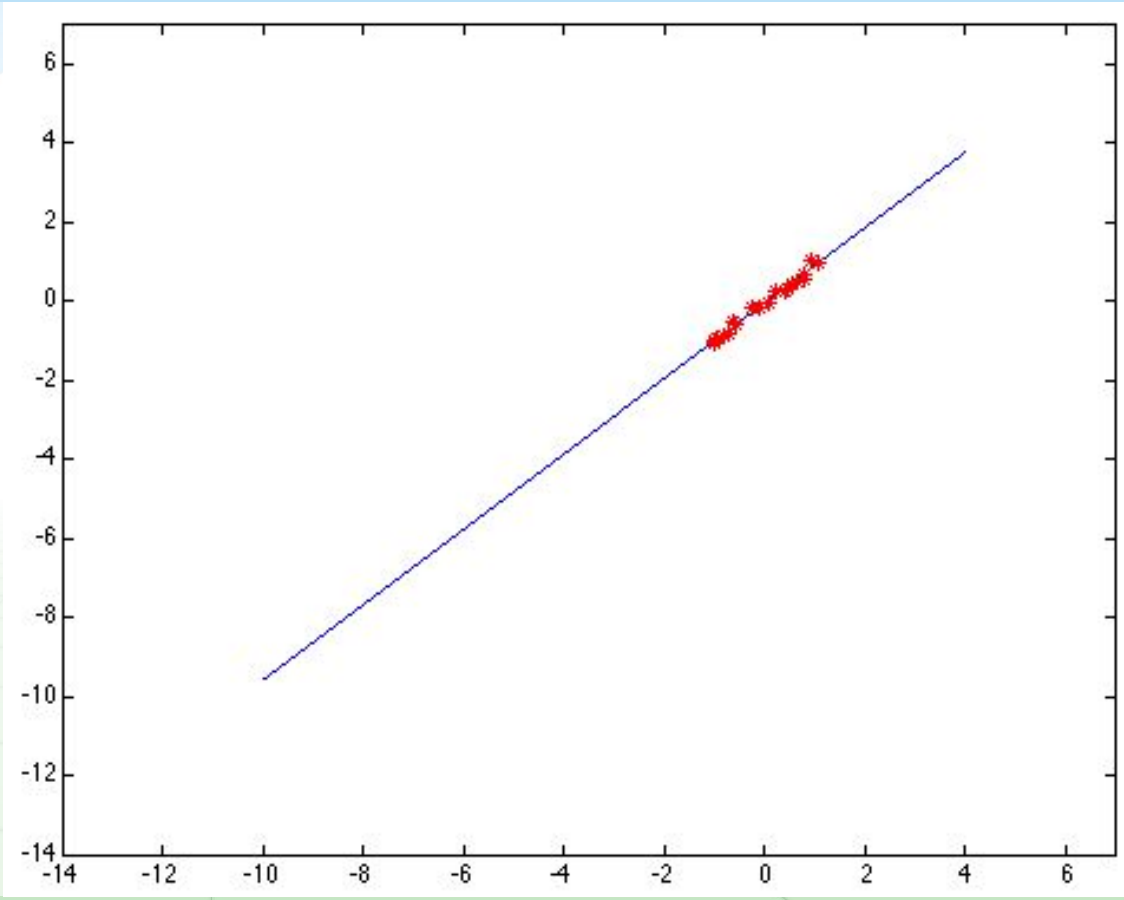
This is convex and minimized when gradient = 0. So we take the derivative wrt a and set = 0.

$-M^T b + (M^T M)a = 0$

$(M^T M)a = M^T b$

$a = (M^T M)^{-1} M^T b$ yay!!!!

So how does least squares do?

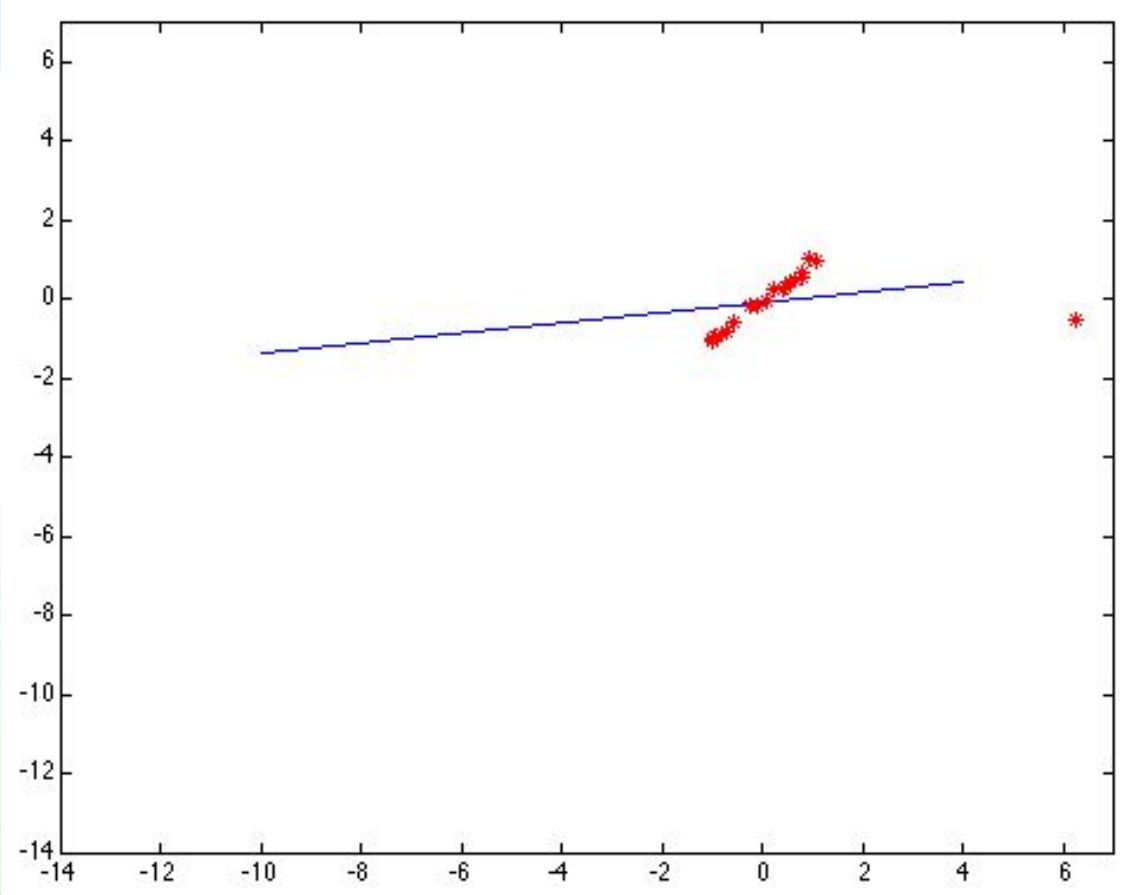


So how does least squares do?

Error based on **squared** residual

Very scared of being wrong, even for just one point

Very bad at handling outliers in data



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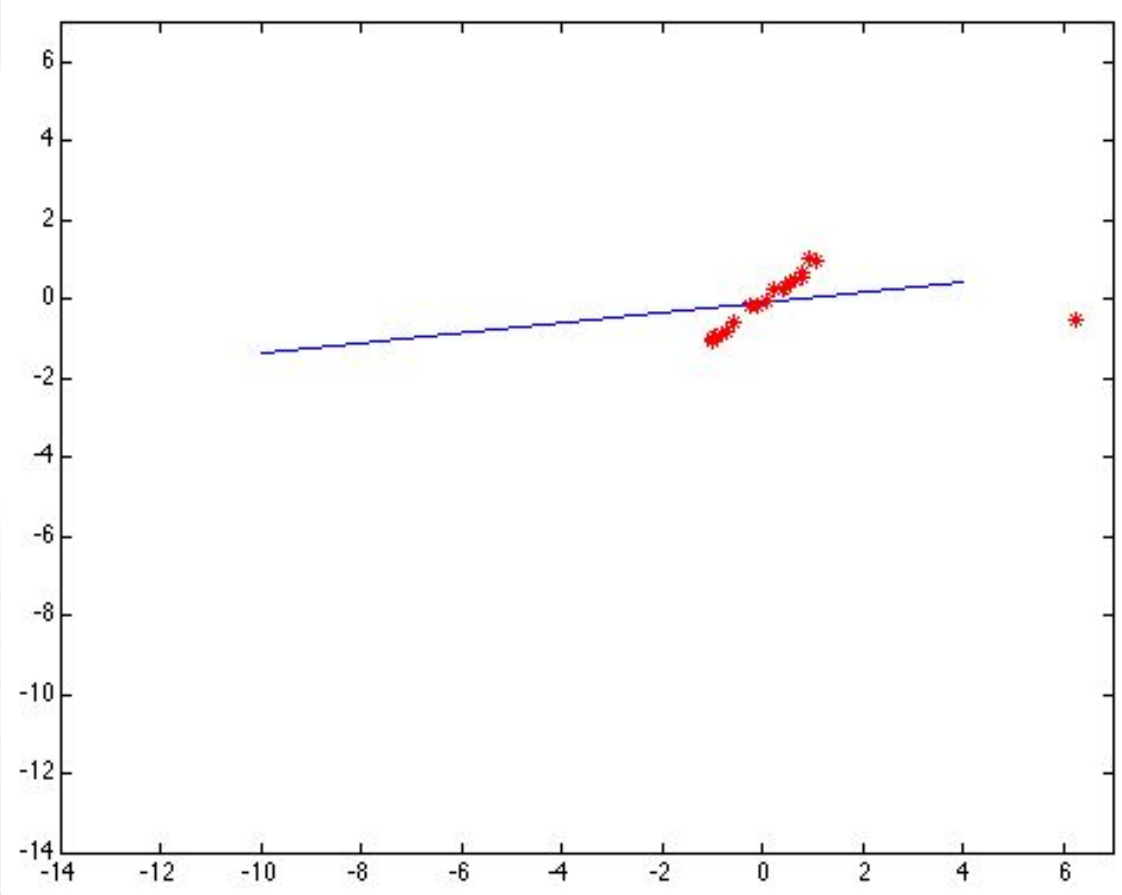
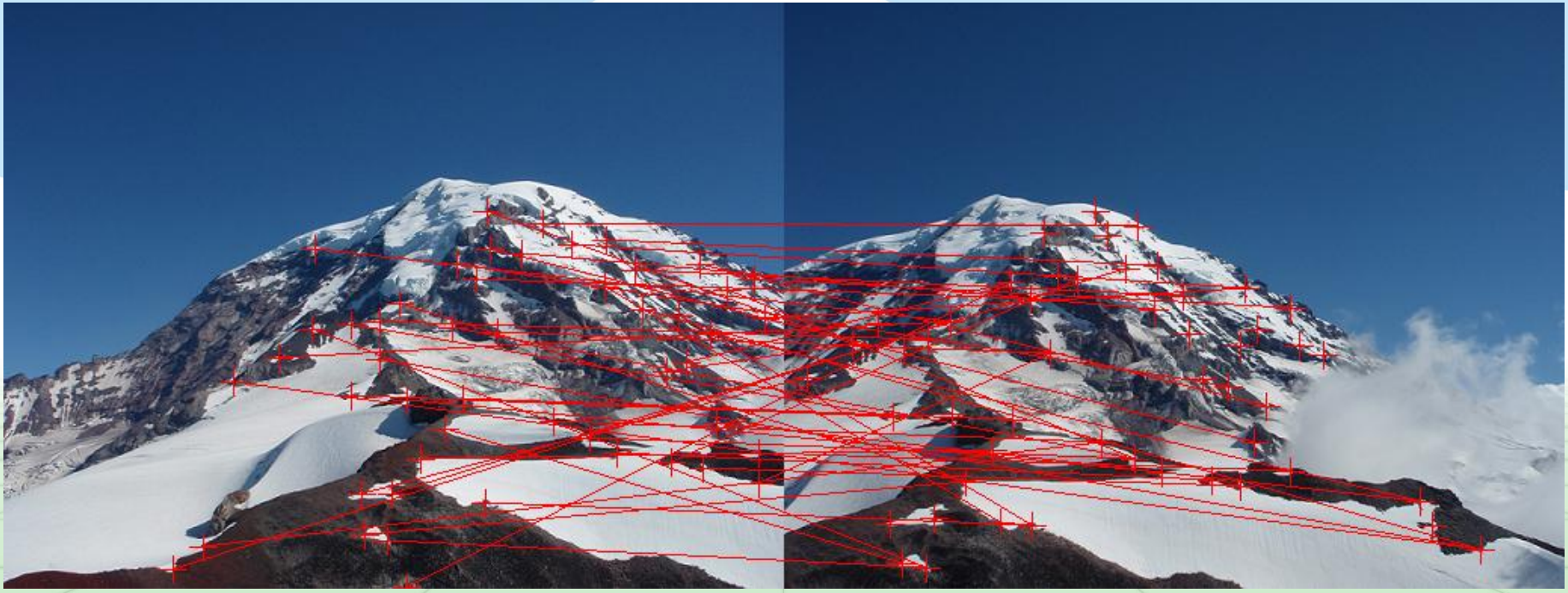


Not a problem for us, our data is perfect…

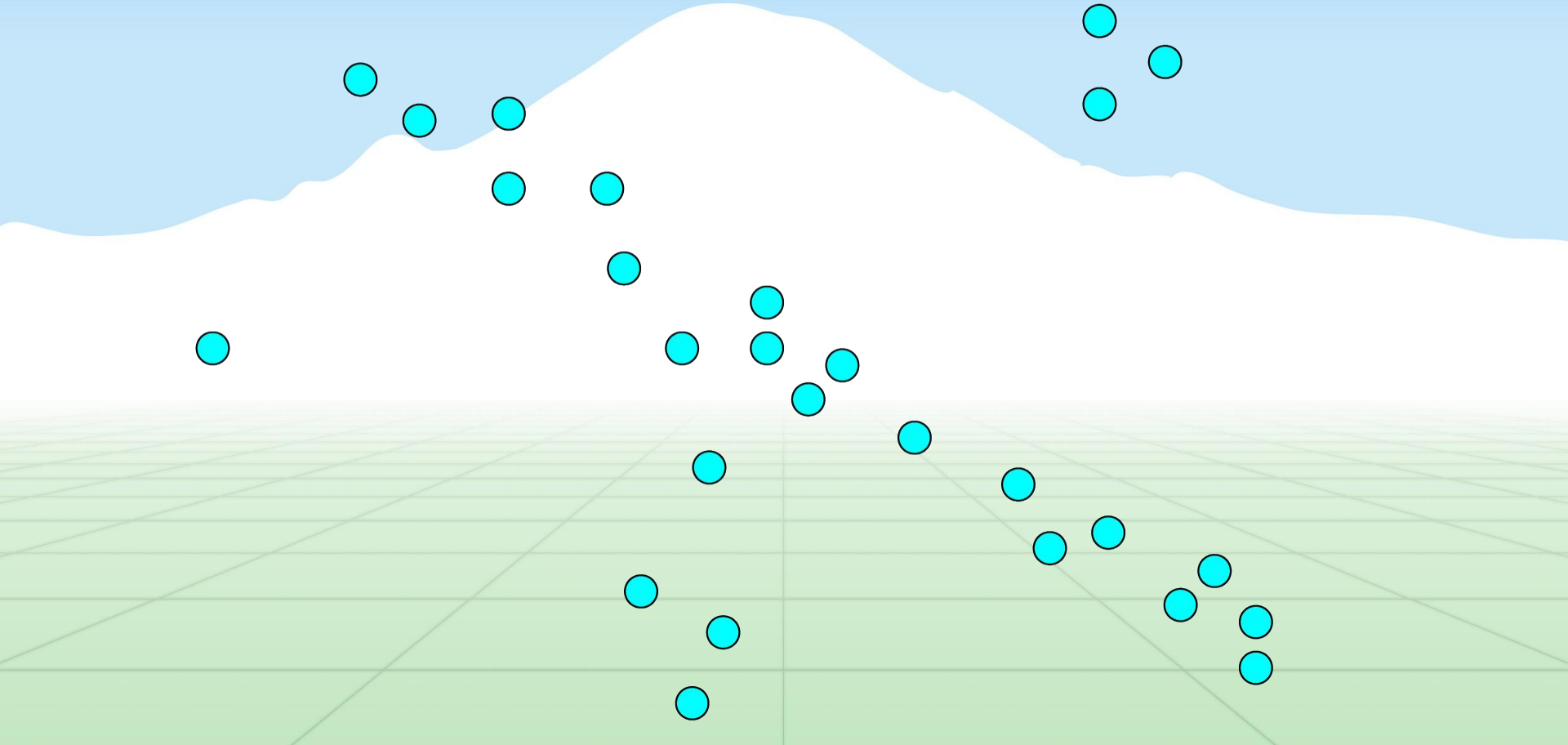


Oh wait…

RANSAC: RANdom **SA**mple **C**onsensus

- How can we fit model to inliers but ignore outliers?
- Try a bunch of models, see which ones are best!
- Inliers will all agree on a model
- Outliers are basically random, will not agree

RANSAC: RANdom SAmple Consensus



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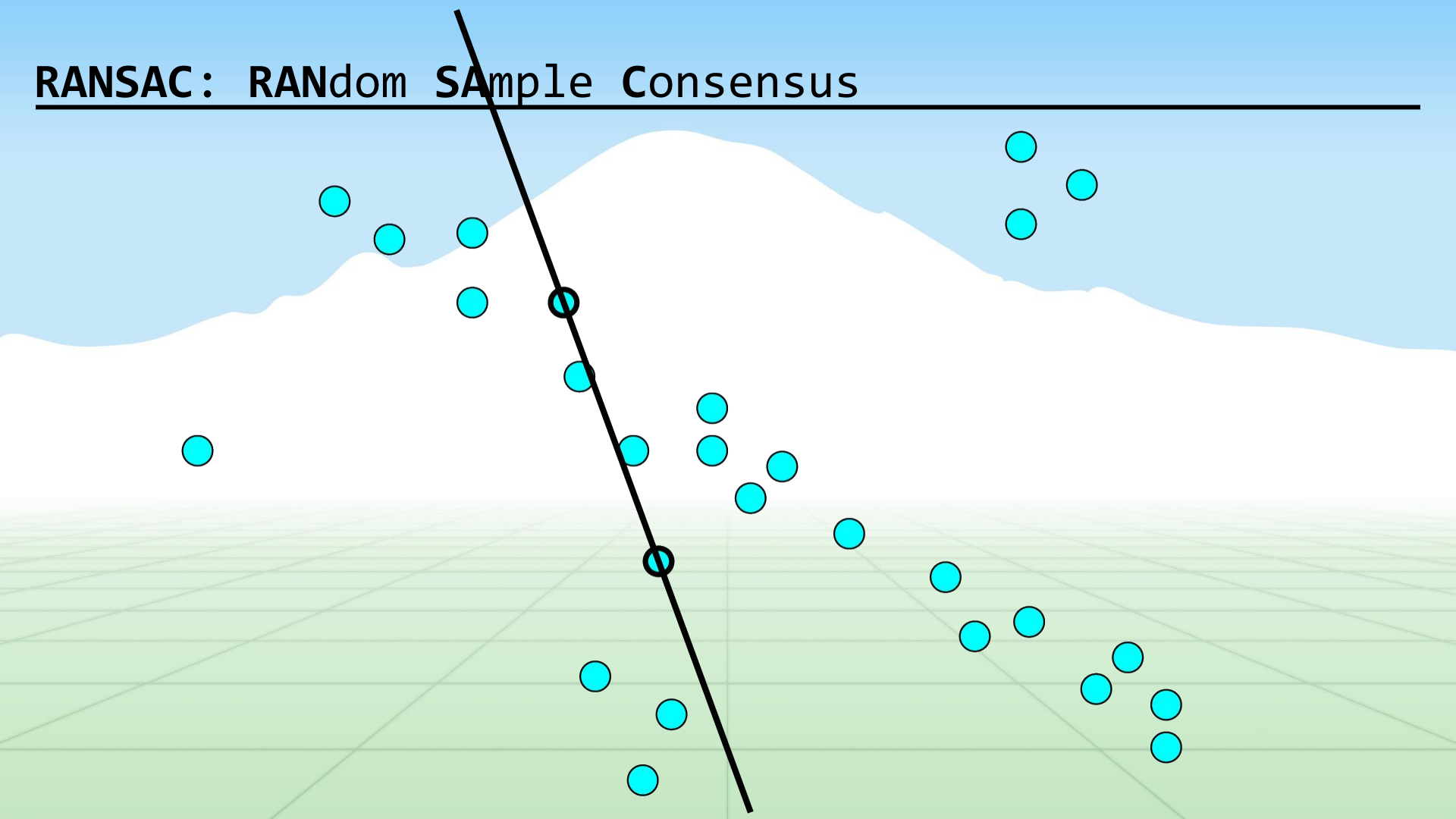
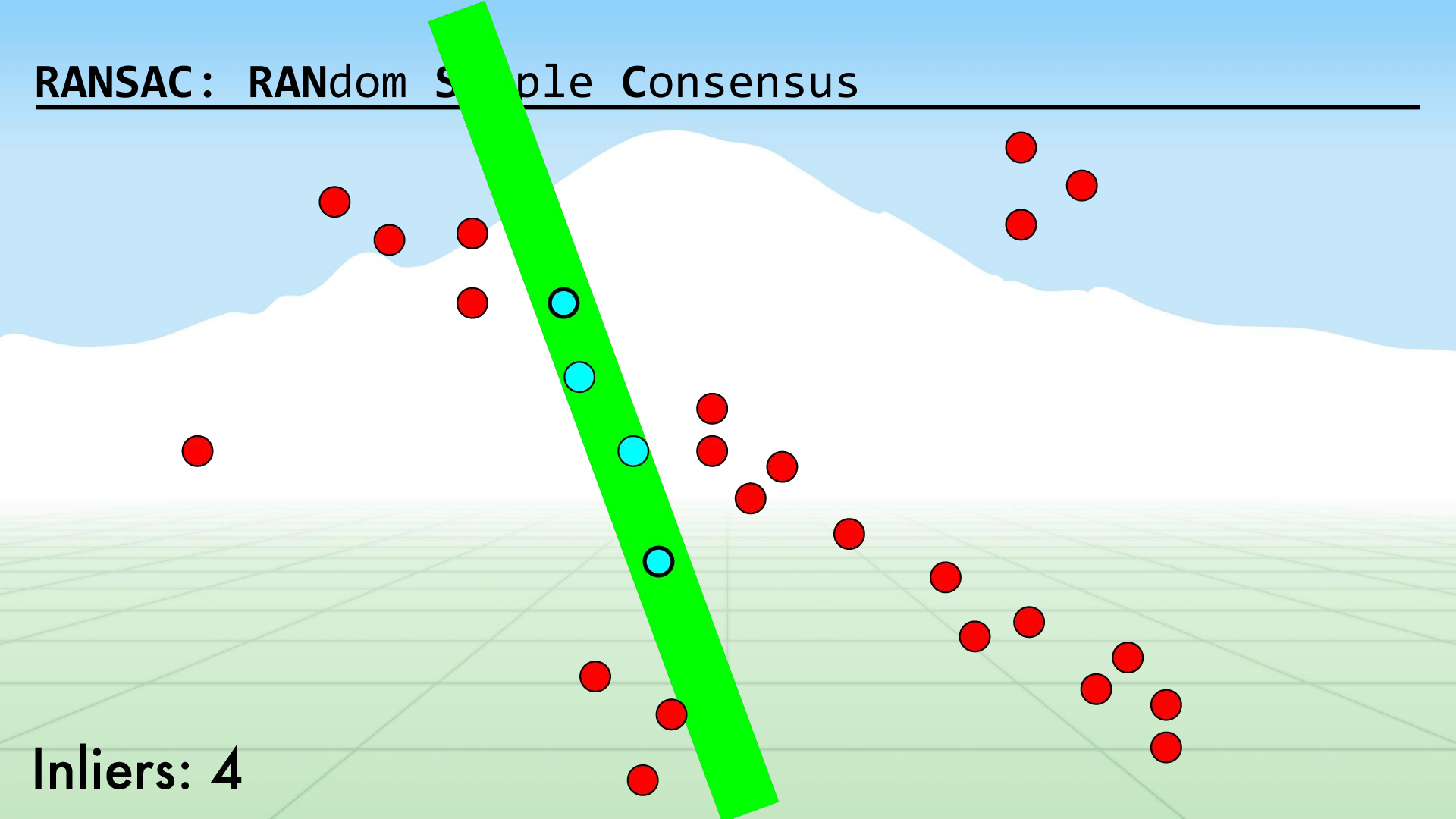
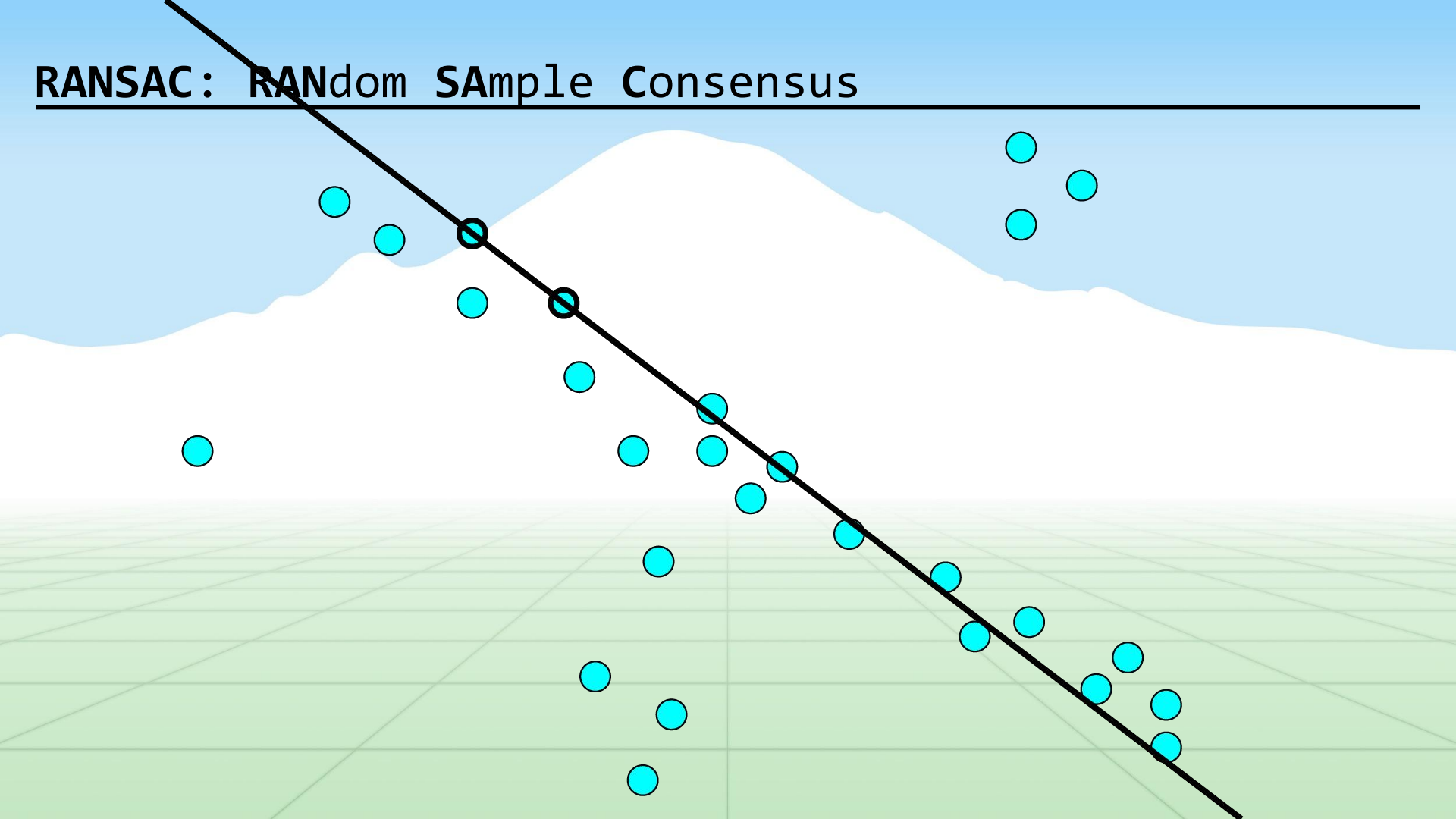


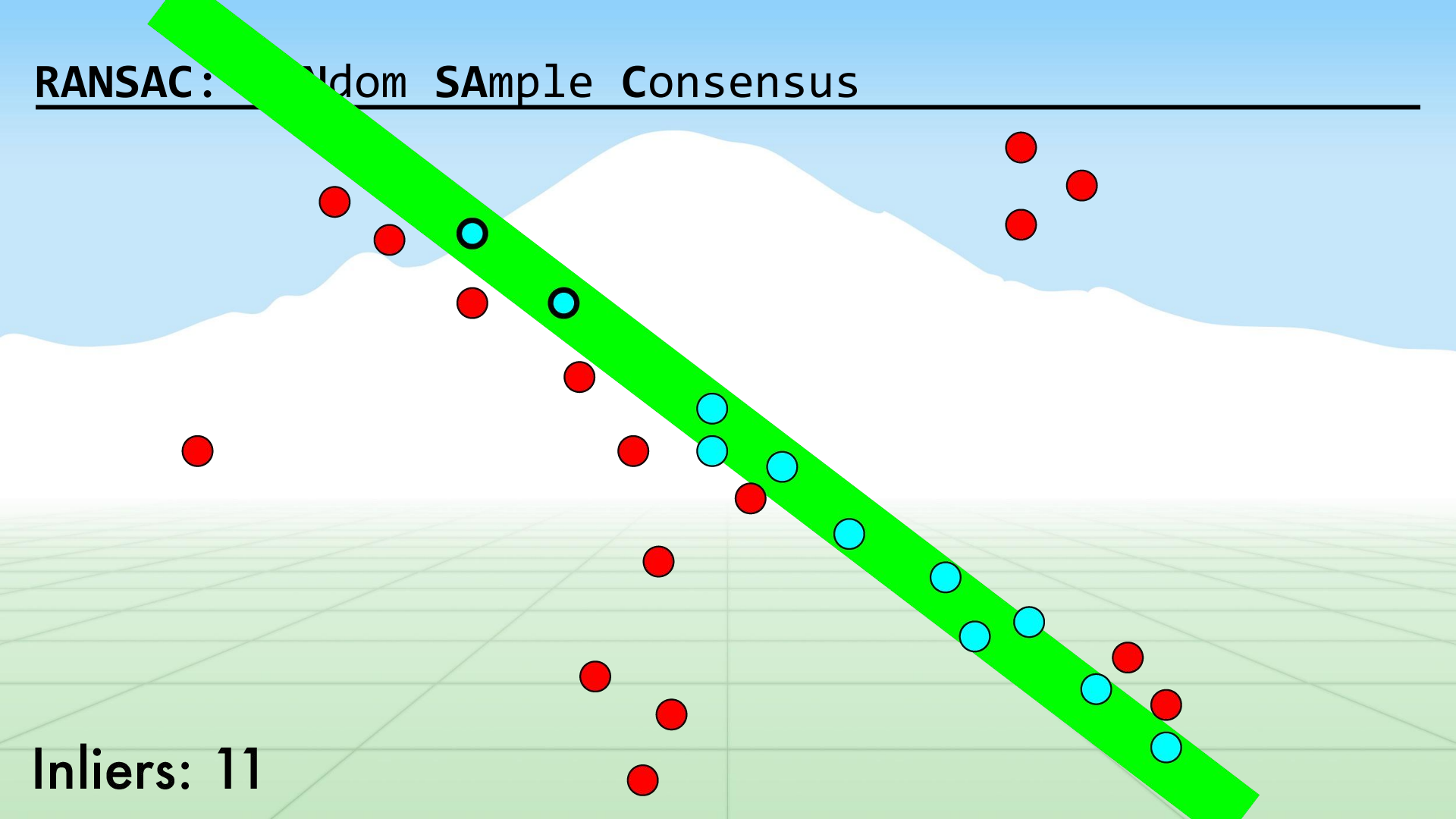
RANSAC: RANdom Sample Consensus



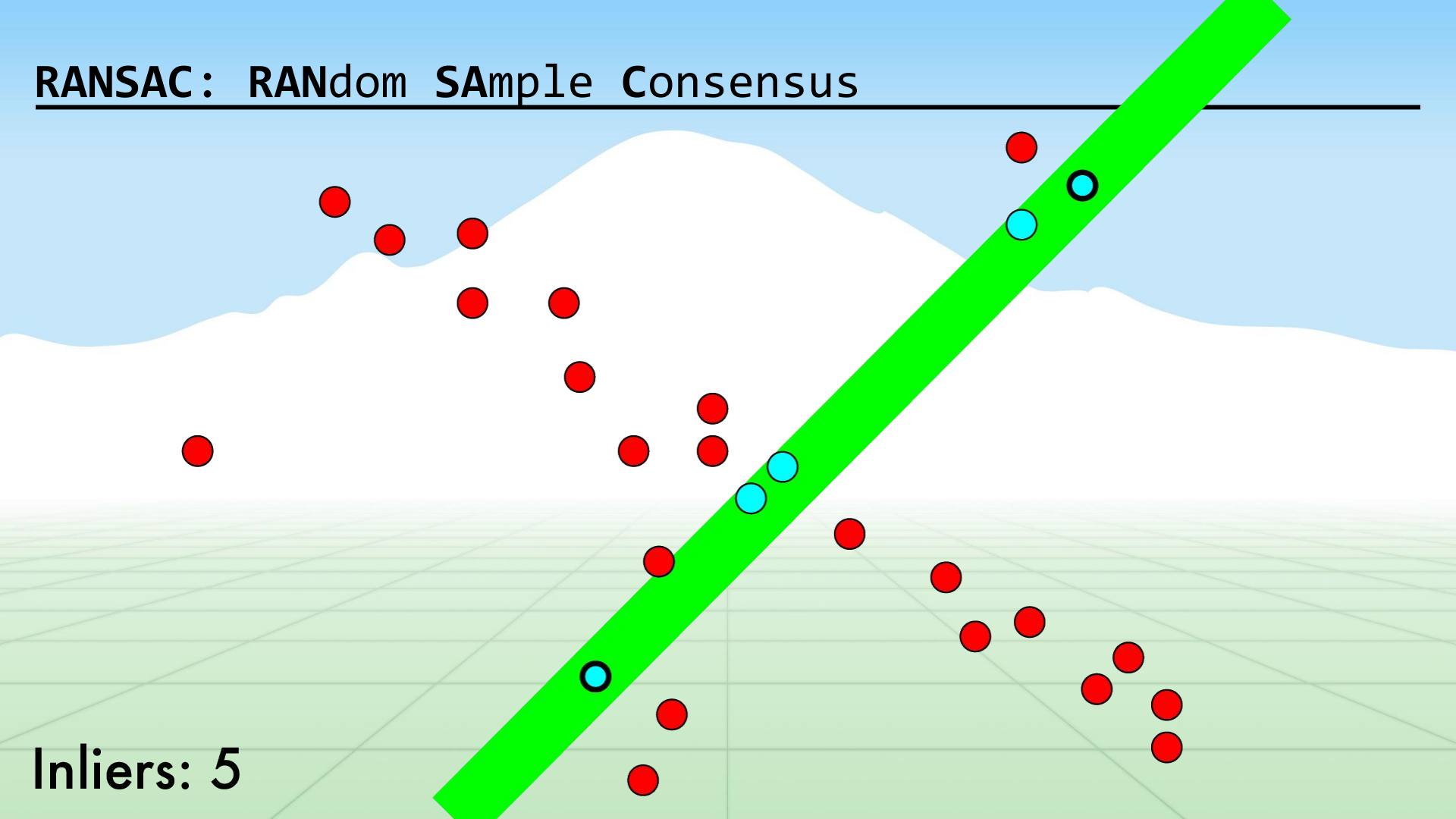
Inliers: 4

RANSAC: RANdom SAmple Consensus



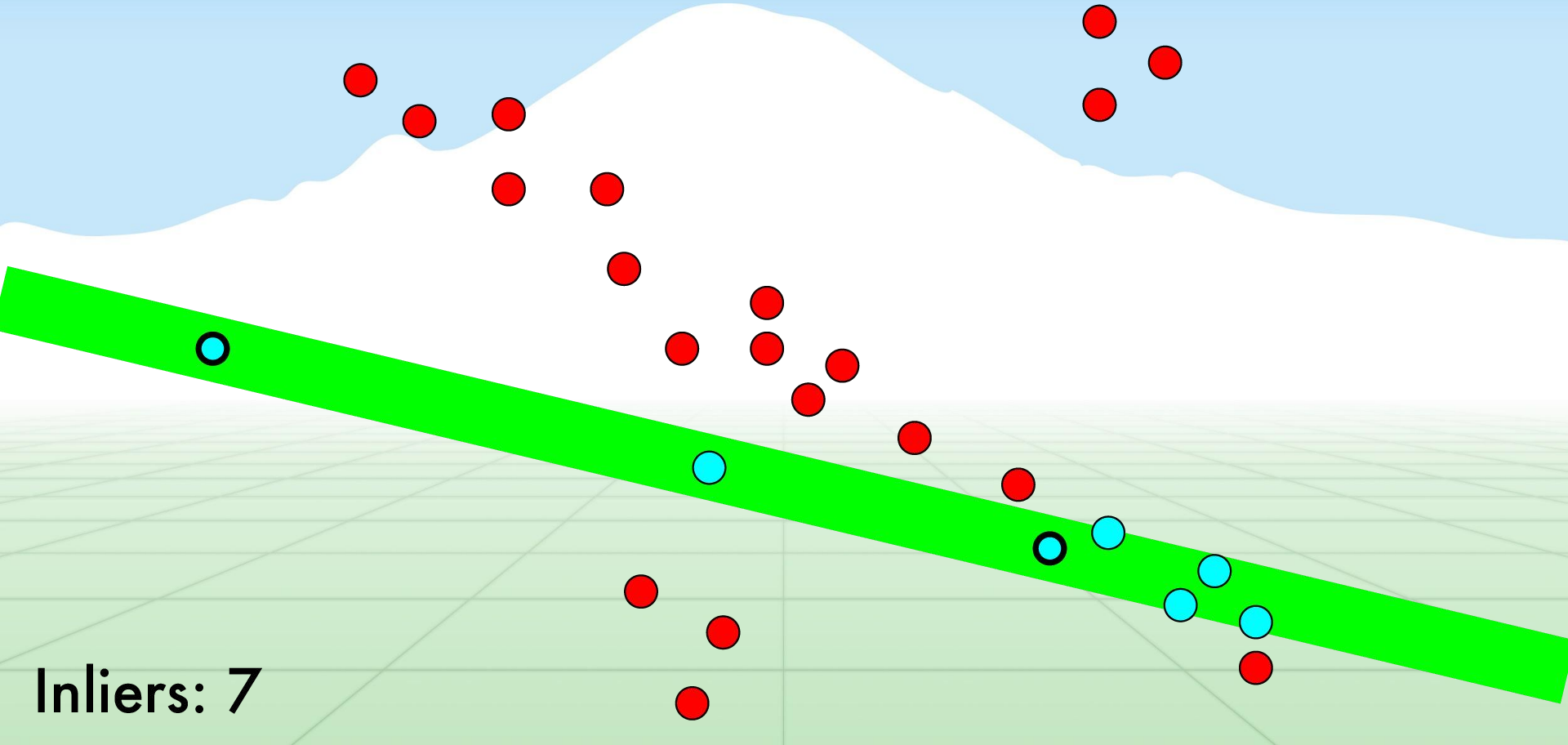

RANSAC: RANdom SAmple Consensus
Inliers: 11

RANSAC: RANdom SAmple Consensus



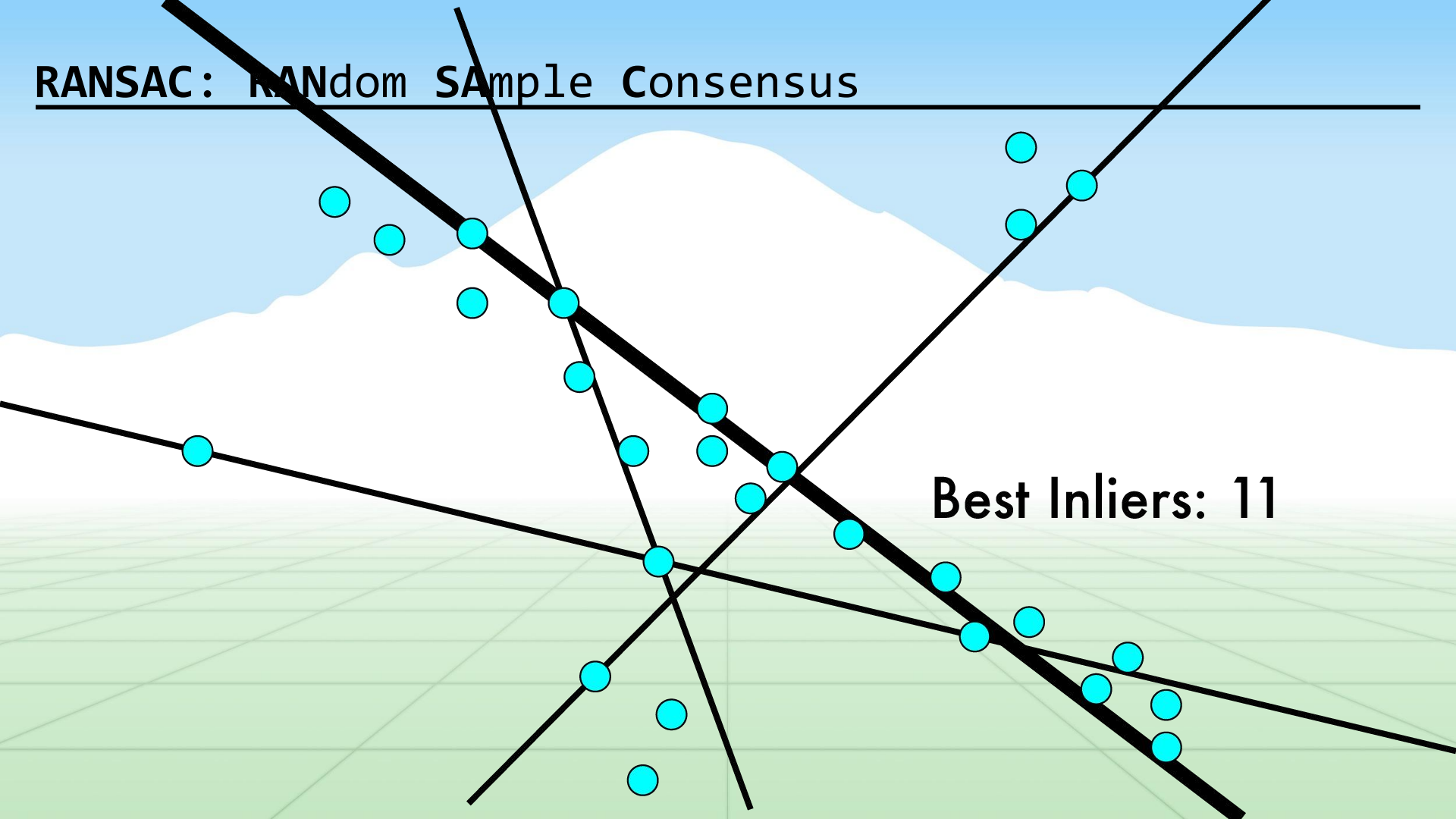
Inliers: 5

RANSAC: RANdom SAmple Consensus



Inliers: 7

RANSAC: RANdom SAmple Consensus



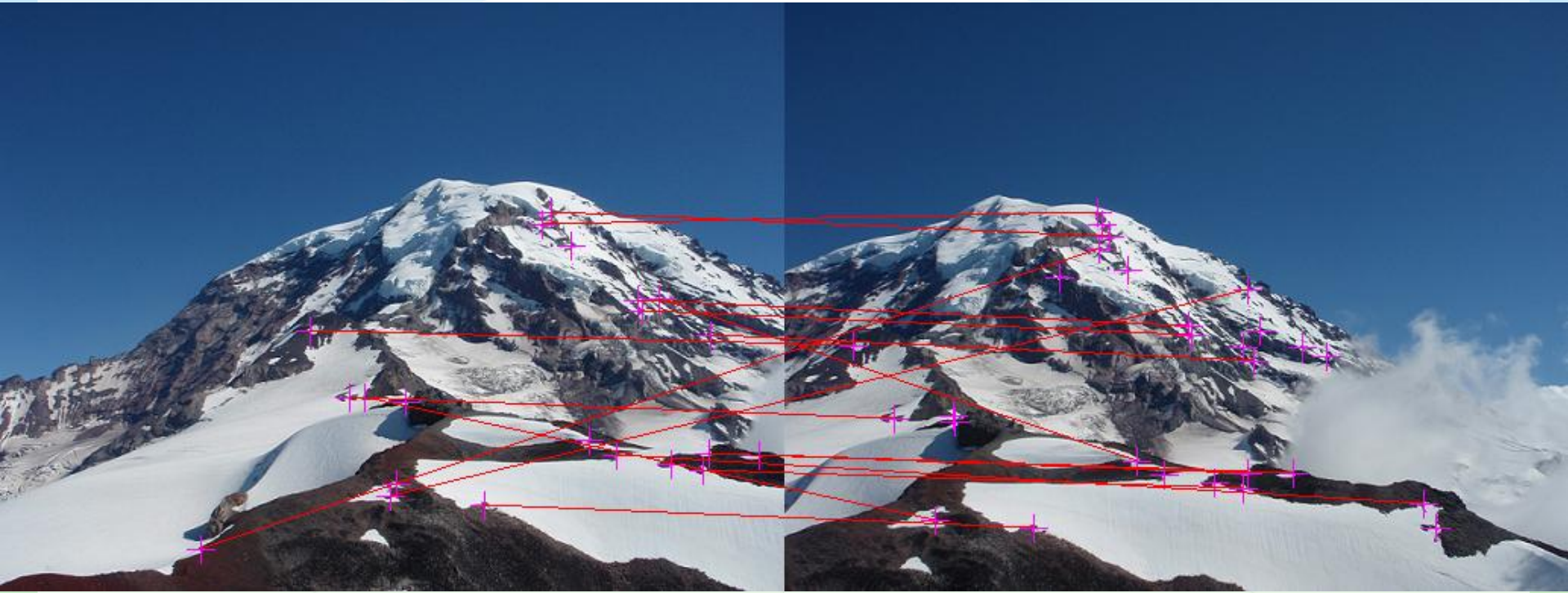
RANSAC: RANdom SAmple Consensus

- Parameters: data, model, n points to fit model, k iterations, t threshold, d “good” fit cutoff

```
bestmodel = None
bestfit = INF
While i < k:
     sample = draw n random points from data
     Fit model to sample
     inliers = data within t of model
     if inliers > bestfit:
          Fit model to all inliers
          bestfit = fit
          bestmodel = model
          if inliers > d:
               return model
return bestmodel
```

RANSAC: RANdom **SA**mple **C**onsensus

- Works well even with extreme noise.



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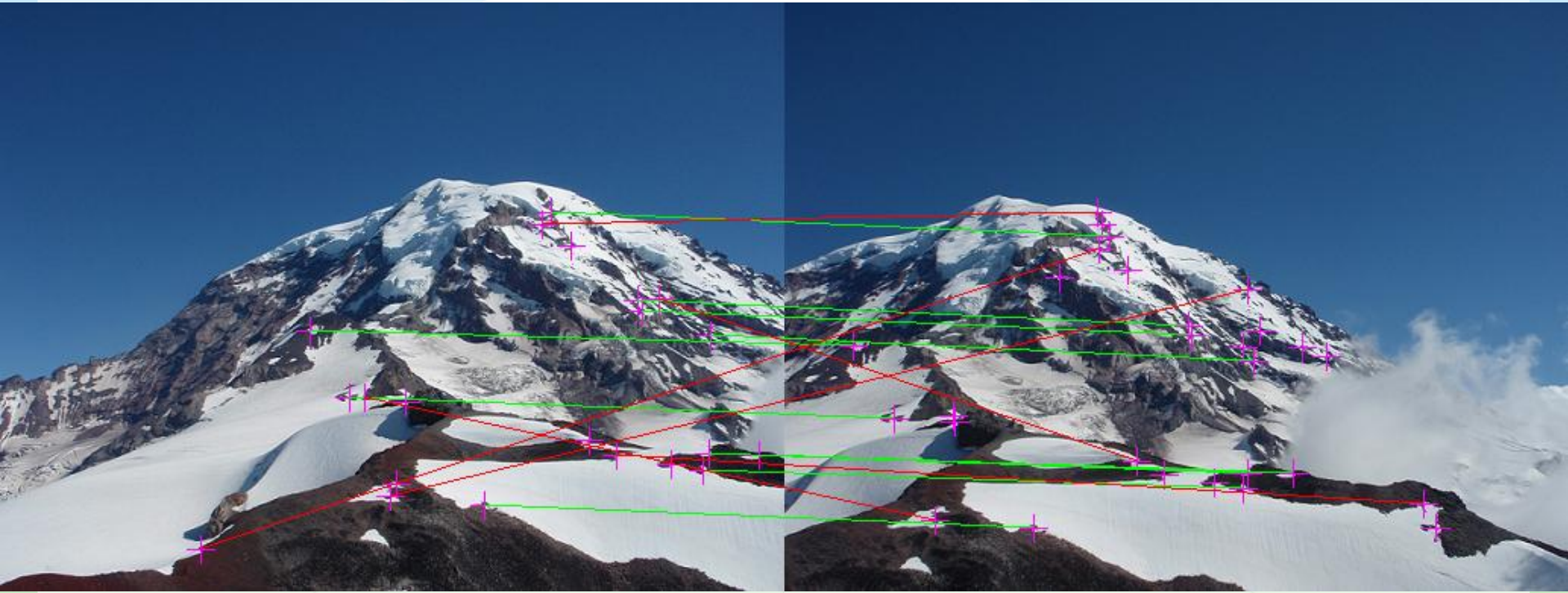

RANSAC: RANdom SAmple Consensus

- Parameters: data, model, n points to fit model, k iterations, t threshold, d “good” fit cutoff
- Lots of tunable parameters
- Want high probability of recovering “right” model
- t: often quite small, assume “good” inliers
- n: should be just enough to fit model, no extra
- k: can be very high
- d: should be >> n

We can estimate affine...

- How many knowns do we get with one match? **mA = n**
  - $n_x = a_{00} * m_x + a_{01} * m_y + a_{02} * 1$
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  - Solve **M a = b**
    - $M^T M\ a = M^T\ b$
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We want projective (homography)

- What are our equations now?
  - $n_x = (h_{00}*m_x + h_{01}*m_y + h_{02}*m_w) / (h_{20}*m_x + h_{21}*m_y + h_{22}*m_w)$
  - $n_y = (h_{10}*m_x + h_{11}*m_y + h_{12}*m_w) / (h_{20}*m_x + h_{21}*m_y + h_{22}*m_w)$

$$\begin{bmatrix} \tilde{x}' \\ \tilde{y}' \\ \tilde{w}' \end{bmatrix} = \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{w} \end{bmatrix}$$

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  - $n_y = (h_{10}*m_x + h_{11}*m_y + h_{12}*m_w) / (h_{20}*m_x + h_{21}*m_y + h_{22}*m_w)$
- Assume h_{22} and m_w are 1, now 8 DOF
  - $n_x = (h_{00}*m_x + h_{01}*m_y + h_{02}) / (h_{20}*m_x + h_{21}*m_y + 1)$
  - $n_y = (h_{10}*m_x + h_{11}*m_y + h_{12}) / (h_{20}*m_x + h_{21}*m_y + 1)$

$$\begin{bmatrix} \tilde{x}' \\ \tilde{y}' \\ \tilde{w}' \end{bmatrix} = \begin{bmatrix} h_{00} & h_{01} & h_{02} \\ h_{10} & h_{11} & h_{12} \\ h_{20} & h_{21} & h_{22} \end{bmatrix} \begin{bmatrix} \tilde{x} \\ \tilde{y} \\ \tilde{w} \end{bmatrix}$$

We want projective (homography)

- What are our equations now?
  - $n_x = (h_{00}*m_x + h_{01}*m_y + h_{02}*m_w) / (h_{20}*m_x + h_{21}*m_y + h_{22}*m_w)$
  - $n_y = (h_{10}*m_x + h_{11}*m_y + h_{12}*m_w) / (h_{20}*m_x + h_{21}*m_y + h_{22}*m_w)$
- Assume h_{22} and m_w are 1, now 8 DOF
  - $n_x = (h_{00}*m_x + h_{01}*m_y + h_{02}) / (h_{20}*m_x + h_{21}*m_y + 1)$
  - $n_y = (h_{10}*m_x + h_{11}*m_y + h_{12}) / (h_{20}*m_x + h_{21}*m_y + 1)$
- More algebra on n_x
  - $n_x * (h_{20}*m_x + h_{21}*m_y + 1) = (h_{00}*m_x + h_{01}*m_y + h_{02})$
  - $n_x*h_{20}*m_x + n_x*h_{21}*m_y + n_x = h_{00}*m_x + h_{01}*m_y + h_{02}$
  - $n_x = h_{00}*m_x + h_{01}*m_y + h_{02} - n_x*h_{20}*m_x - n_x*h_{21}*m_y$
- Similar for n_y

We want projective (homography)

- What are our equations now?
  - $n_x = h_{00}*m_x + h_{01}*m_y + h_{02} - n_x*h_{20}*m_x - n_x*h_{21}*m_y$
  - $n_y = h_{10}*m_x + h_{11}*m_y + h_{12} - n_x*h_{20}*m_x - n_x*h_{21}*m_y$
- New matrix equations:

$$\underset{\mathbf{M}}{\begin{bmatrix} m_{x1} & m_{y1} & 1 & 0 & 0 & 0 & -m_{x1}n_{x1} & -m_{y1}n_{x1} \\ 0 & 0 & 0 & m_{x1} & m_{y1} & 1 & -m_{x1}n_{y1} & -m_{y1}n_{y1} \\ m_{x2} & m_{y2} & 1 & 0 & 0 & 0 & -m_{x2}n_{x2} & -m_{y2}n_{x2} \\ 0 & 0 & 0 & m_{x2} & m_{y2} & 1 & -m_{x2}n_{y2} & -m_{y2}n_{y2} \\ m_{x3} & m_{y3} & 1 & 0 & 0 & 0 & -m_{x3}n_{x3} & -m_{y3}n_{x3} \\ 0 & 0 & 0 & m_{x3} & m_{y3} & 1 & -m_{x3}n_{y3} & -m_{y3}n_{y3} \\ m_{x4} & m_{y4} & 1 & 0 & 0 & 0 & -m_{x4}n_{x4} & -m_{y4}n_{x4} \\ 0 & 0 & 0 & m_{x4} & m_{y4} & 1 & -m_{x4}n_{y4} & -m_{y4}n_{y4} \end{bmatrix}} \underset{\mathbf{a}}{\begin{bmatrix} h_{00} \\ h_{01} \\ h_{02} \\ h_{10} \\ h_{11} \\ h_{12} \\ h_{20} \\ h_{21} \end{bmatrix}} = \underset{\mathbf{b}}{\begin{bmatrix} n_{x1} \\ n_{y1} \\ n_{x2} \\ n_{y2} \\ n_{x3} \\ n_{y3} \\ n_{x4} \\ n_{y4} \end{bmatrix}}$$

We want projective (homography)

- New matrix equations:

$$\underbrace{\begin{bmatrix} m_{x1} & m_{y1} & 1 & 0 & 0 & 0 & -m_{x1}n_{x1} & -m_{y1}n_{x1} \\ 0 & 0 & 0 & m_{x1} & m_{y1} & 1 & -m_{x1}n_{y1} & -m_{y1}n_{y1} \\ m_{x2} & m_{y2} & 1 & 0 & 0 & 0 & -m_{x2}n_{x2} & -m_{y2}n_{x2} \\ 0 & 0 & 0 & m_{x2} & m_{y2} & 1 & -m_{x2}n_{y2} & -m_{y2}n_{y2} \\ m_{x3} & m_{y3} & 1 & 0 & 0 & 0 & -m_{x3}n_{x3} & -m_{y3}n_{x3} \\ 0 & 0 & 0 & m_{x3} & m_{y3} & 1 & -m_{x3}n_{y3} & -m_{y3}n_{y3} \\ m_{x4} & m_{y4} & 1 & 0 & 0 & 0 & -m_{x4}n_{x4} & -m_{y4}n_{x4} \\ 0 & 0 & 0 & m_{x4} & m_{y4} & 1 & -m_{x4}n_{y4} & -m_{y4}n_{y4} \end{bmatrix}}_{\mathbf{M}} \underbrace{\begin{bmatrix} h_{00} \\ h_{01} \\ h_{02} \\ h_{10} \\ h_{11} \\ h_{12} \\ h_{20} \\ h_{21} \end{bmatrix}}_{\mathbf{a}} = \underbrace{\begin{bmatrix} n_{x1} \\ n_{y1} \\ n_{x2} \\ n_{y2} \\ n_{x3} \\ n_{y3} \\ n_{x4} \\ n_{y4} \end{bmatrix}}_{\mathbf{b}}$$

- Same procedure, Solve **M a = b**
  - Exact if #rows of M = 8
  - Least squares if #rows of M > 8

Are there any problems with this??

- New matrix equations:

$$\underset{\mathbf{M}}{\begin{bmatrix} m_{x1} & m_{y1} & 1 & 0 & 0 & 0 & -m_{x1}n_{x1} & -m_{y1}n_{x1} \\ 0 & 0 & 0 & m_{x1} & m_{y1} & 1 & -m_{x1}n_{y1} & -m_{y1}n_{y1} \\ m_{x2} & m_{y2} & 1 & 0 & 0 & 0 & -m_{x2}n_{x2} & -m_{y2}n_{x2} \\ 0 & 0 & 0 & m_{x2} & m_{y2} & 1 & -m_{x2}n_{y2} & -m_{y2}n_{y2} \\ m_{x3} & m_{y3} & 1 & 0 & 0 & 0 & -m_{x3}n_{x3} & -m_{y3}n_{x3} \\ 0 & 0 & 0 & m_{x3} & m_{y3} & 1 & -m_{x3}n_{y3} & -m_{y3}n_{y3} \\ m_{x4} & m_{y4} & 1 & 0 & 0 & 0 & -m_{x4}n_{x4} & -m_{y4}n_{x4} \\ 0 & 0 & 0 & m_{x4} & m_{y4} & 1 & -m_{x4}n_{y4} & -m_{y4}n_{y4} \end{bmatrix}} \underset{\mathbf{a}}{\begin{bmatrix} h_{00} \\ h_{01} \\ h_{02} \\ h_{10} \\ h_{11} \\ h_{12} \\ h_{20} \\ h_{21} \end{bmatrix}} = \underset{\mathbf{b}}{\begin{bmatrix} n_{x1} \\ n_{y1} \\ n_{x2} \\ n_{y2} \\ n_{x3} \\ n_{y3} \\ n_{x4} \\ n_{y4} \end{bmatrix}}$$

- Same procedure, Solve **M a = b**
  - Exact if #rows of M = 8
  - Least squares if #rows of M > 8

Panorama algorithm:

Find corners in both images

Calculate descriptors

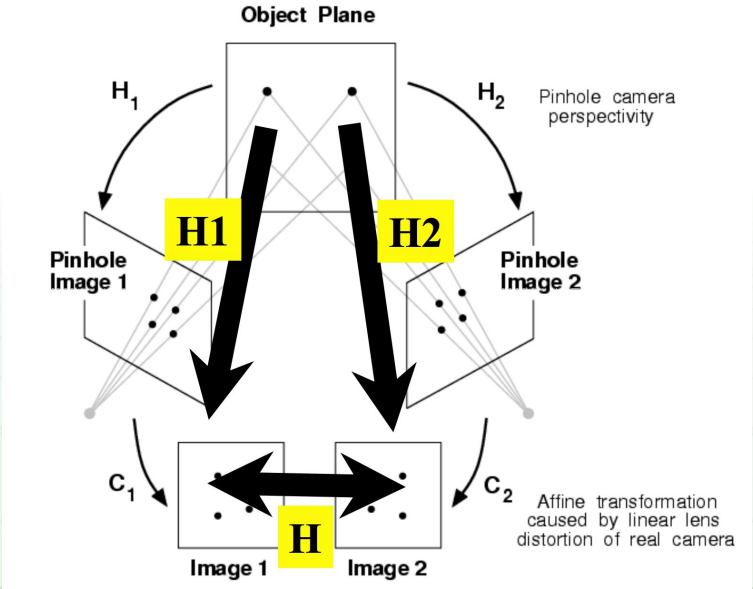
Match descriptors

RANSAC to find homography

Stitch together images with homography

Stitching panoramas:

- We know homography is right choice under certain assumption:
  - Assume we are taking multiple images of planar object



In practice:

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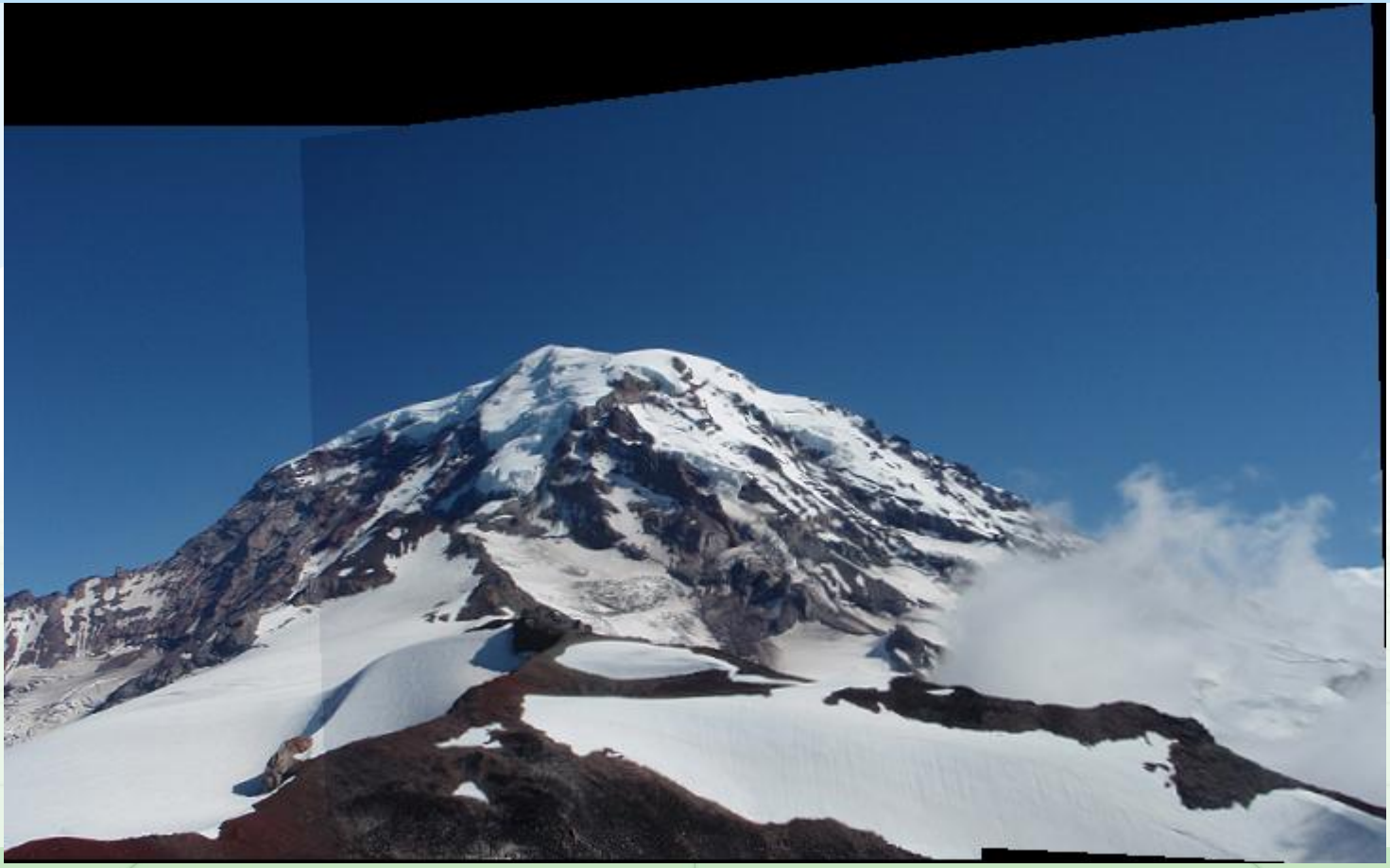
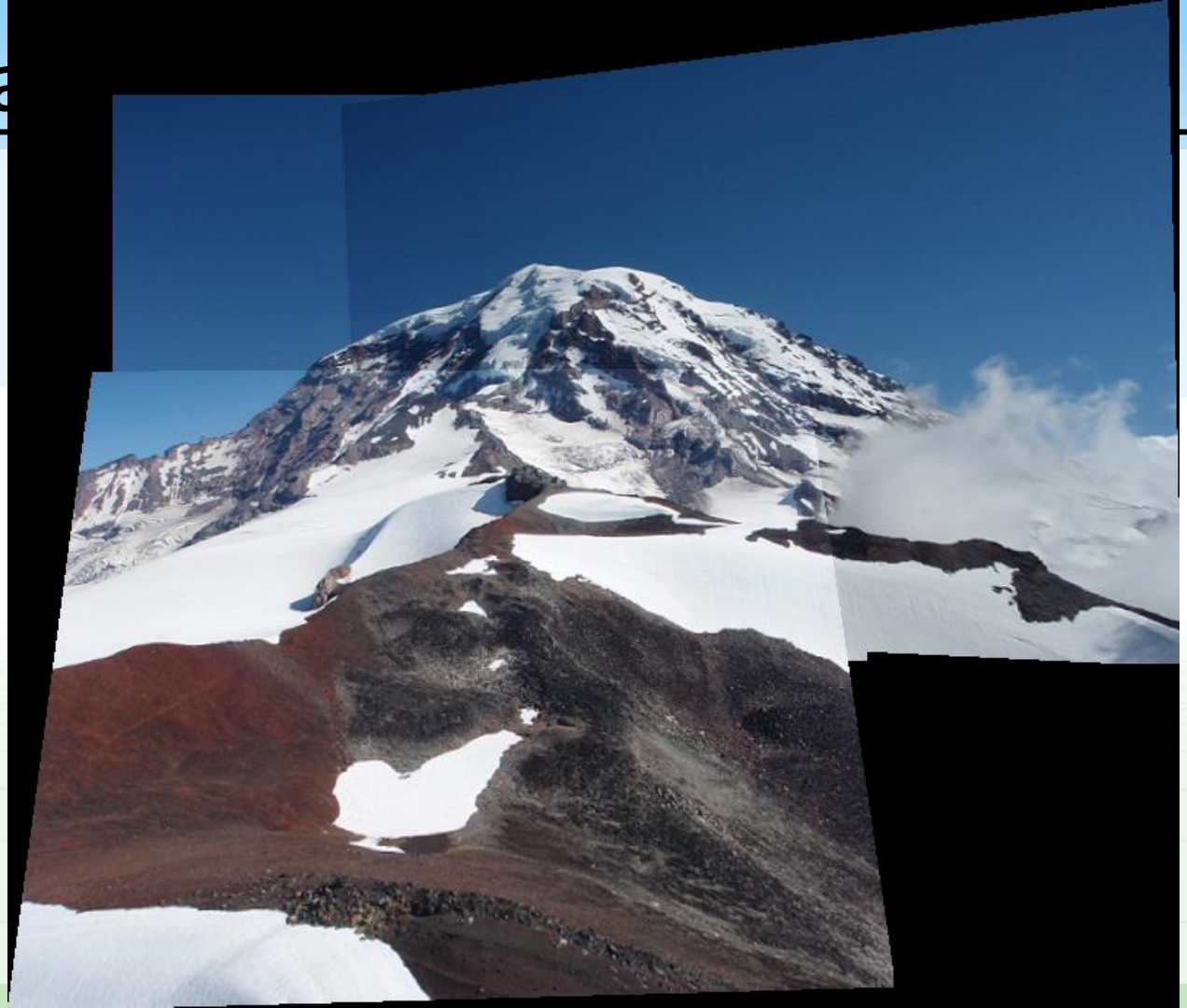
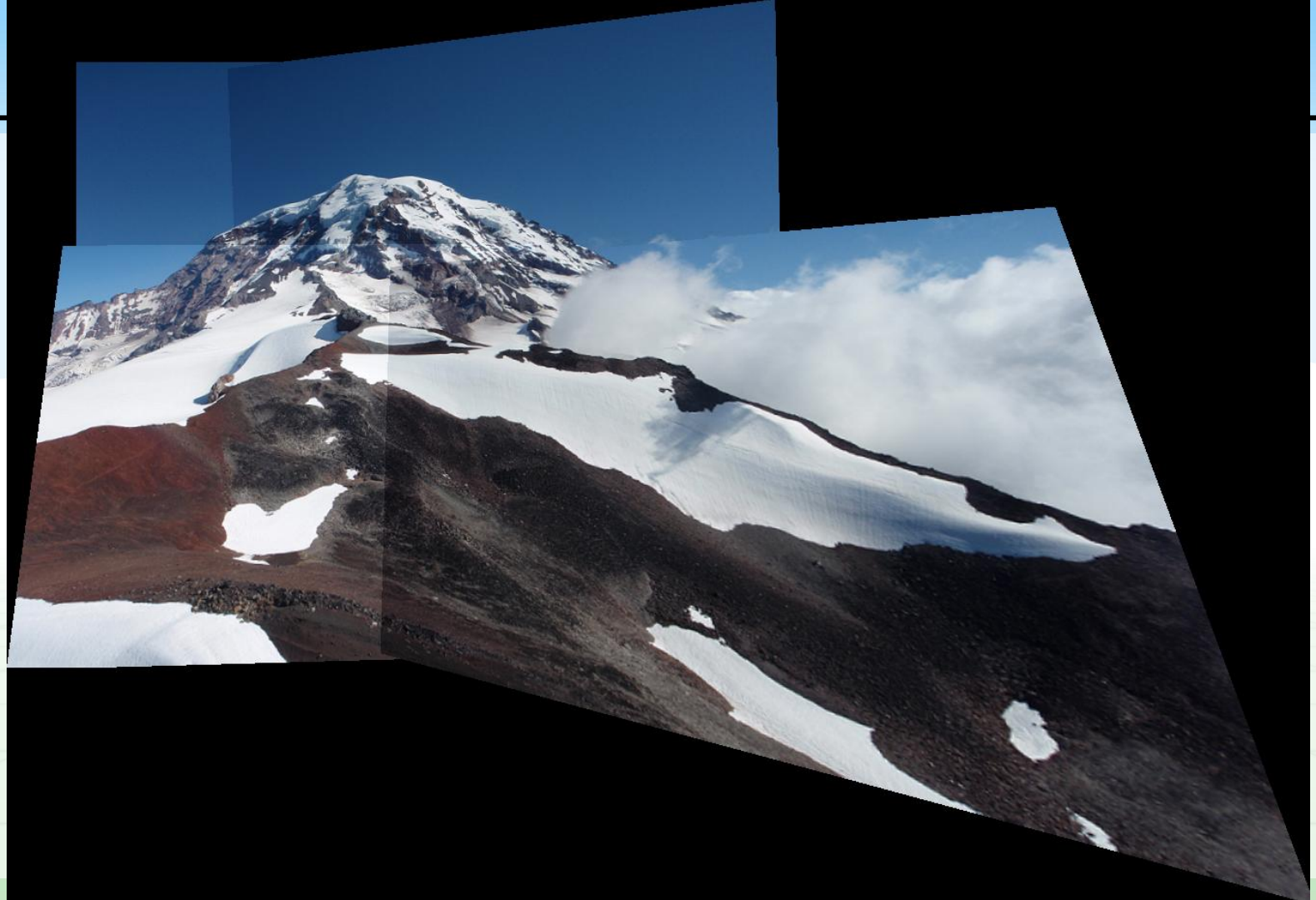
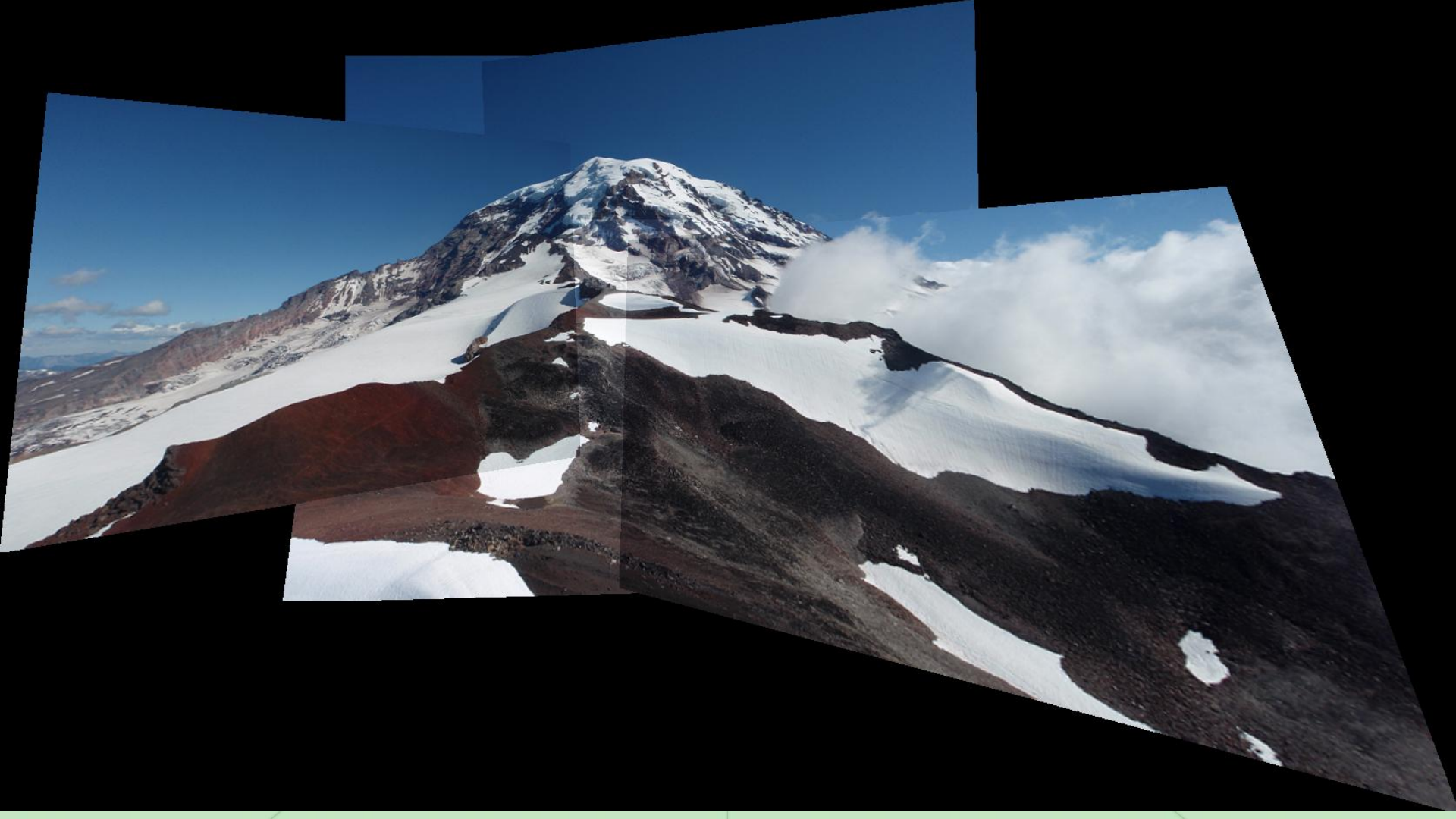


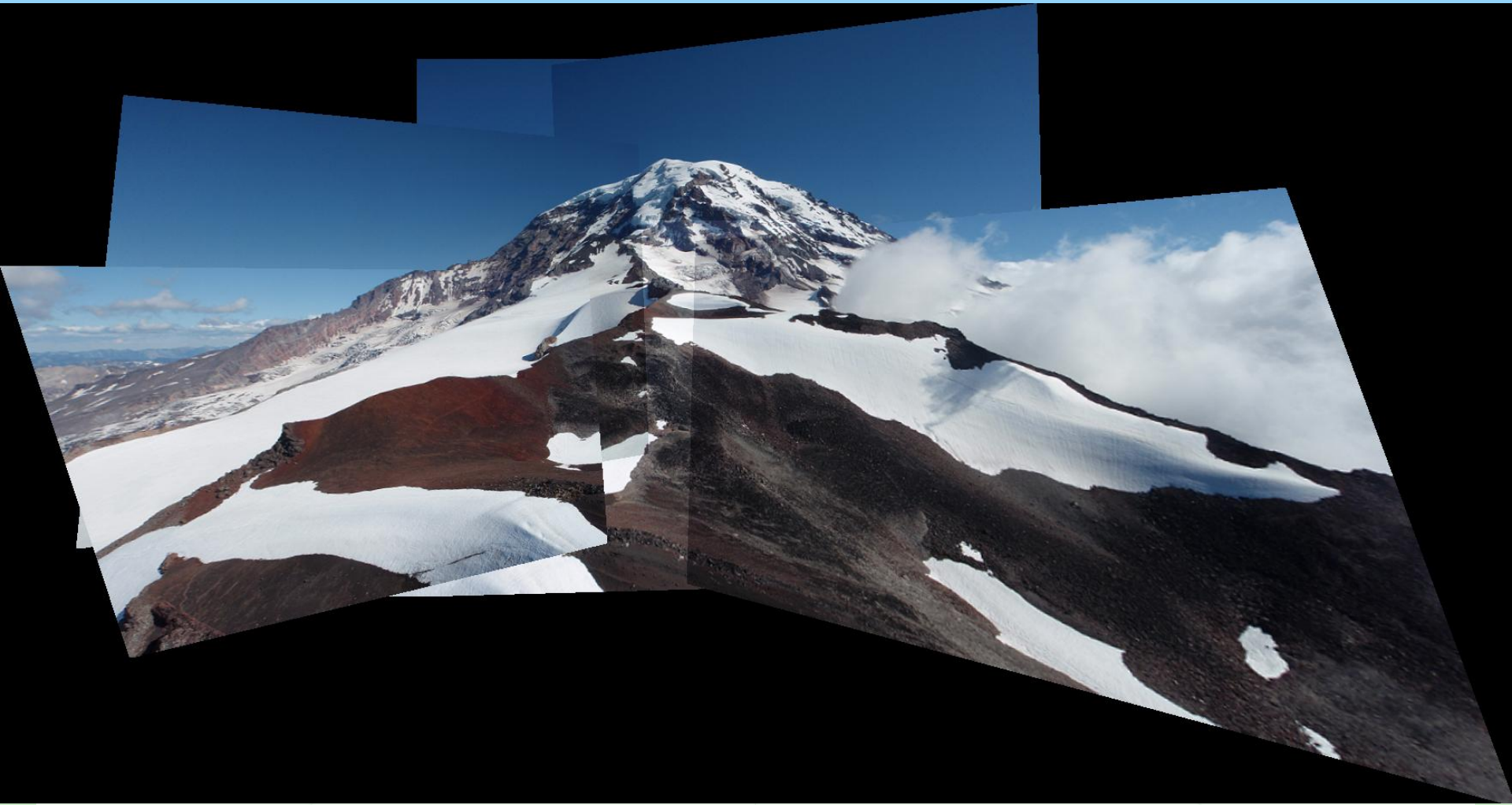
In pra



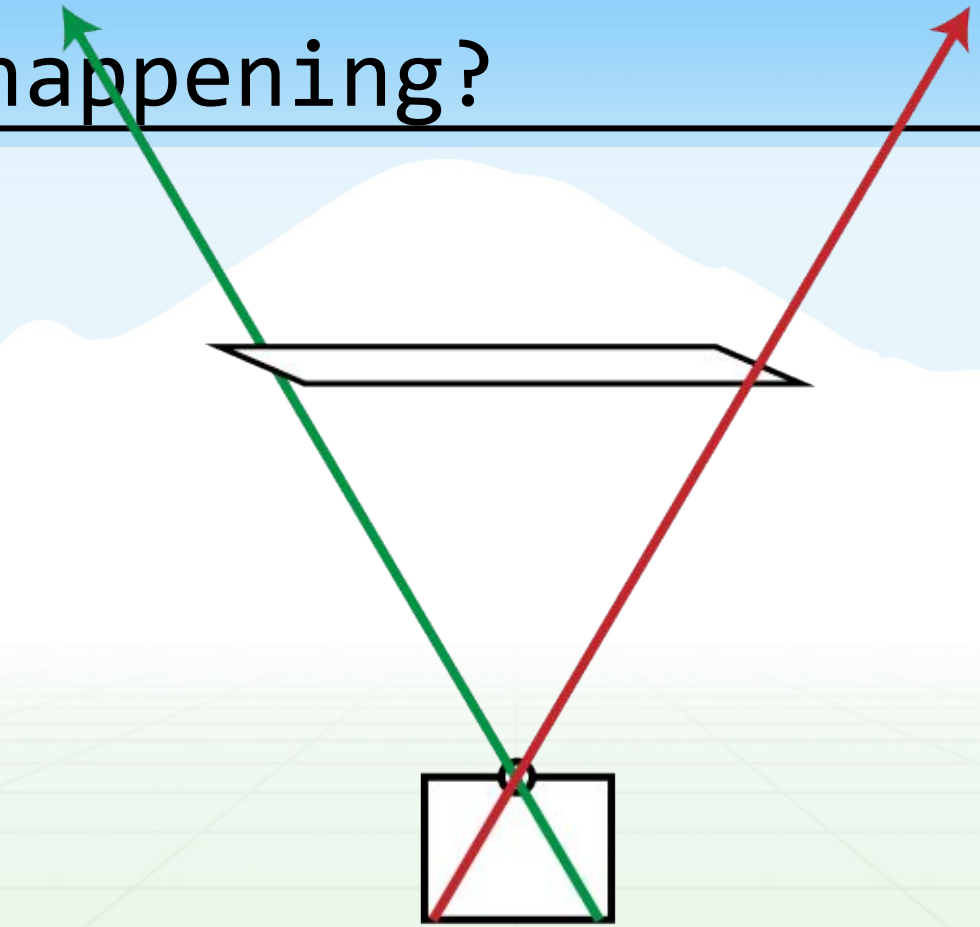
In



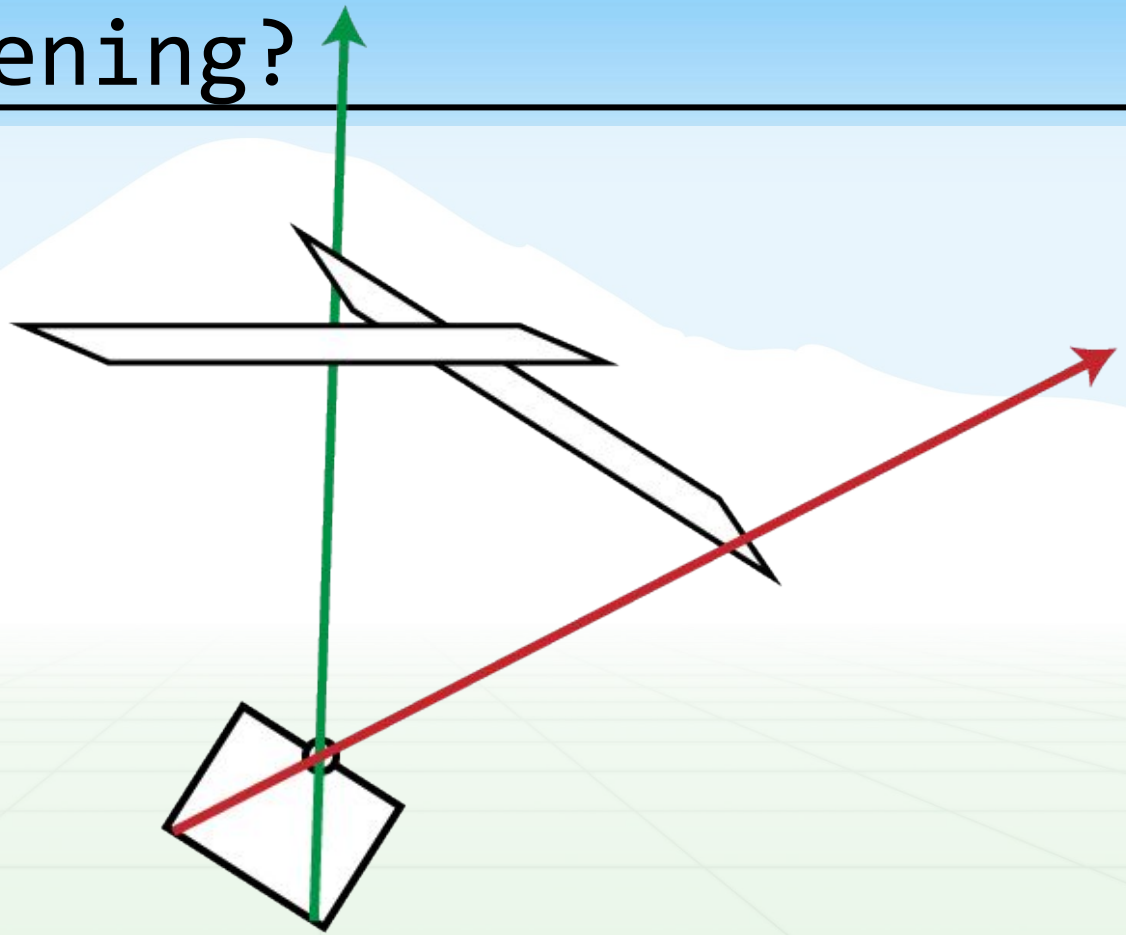




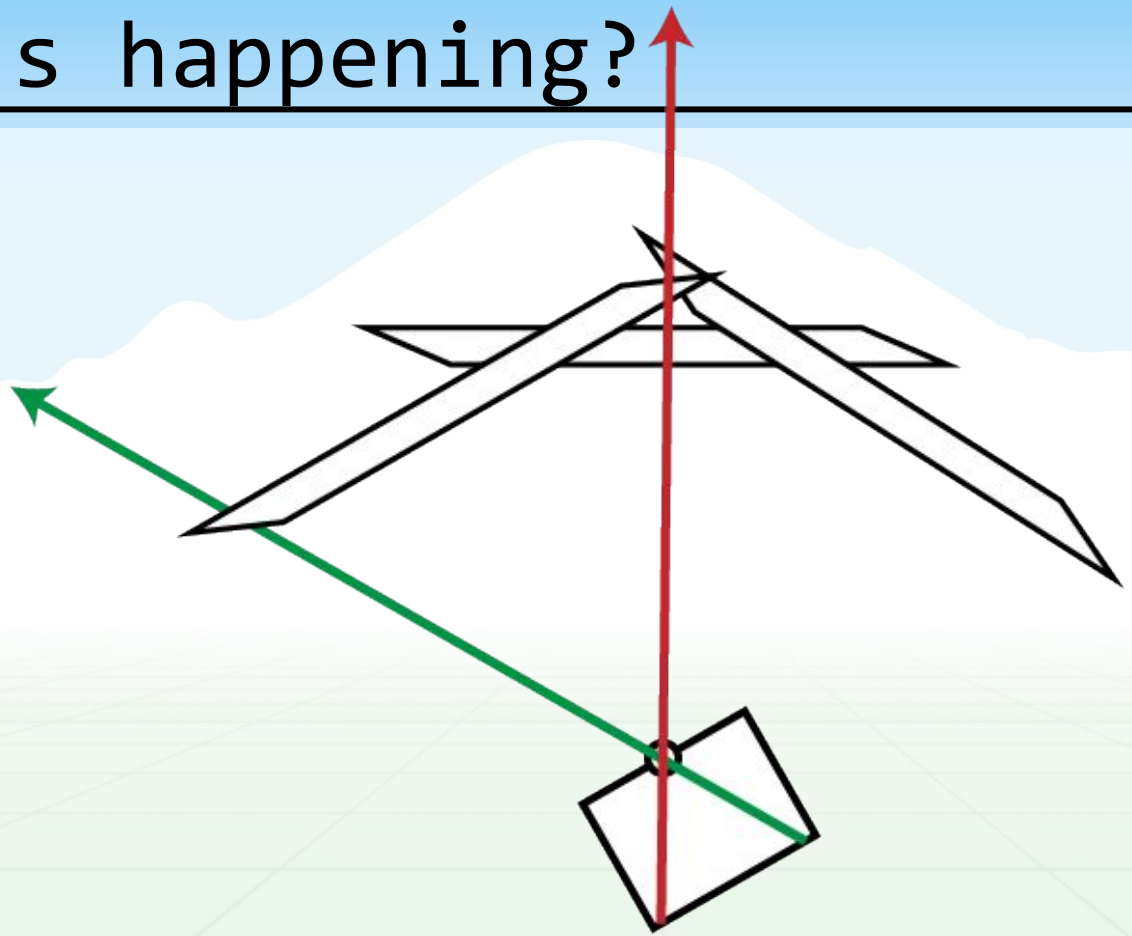
What’s happening?



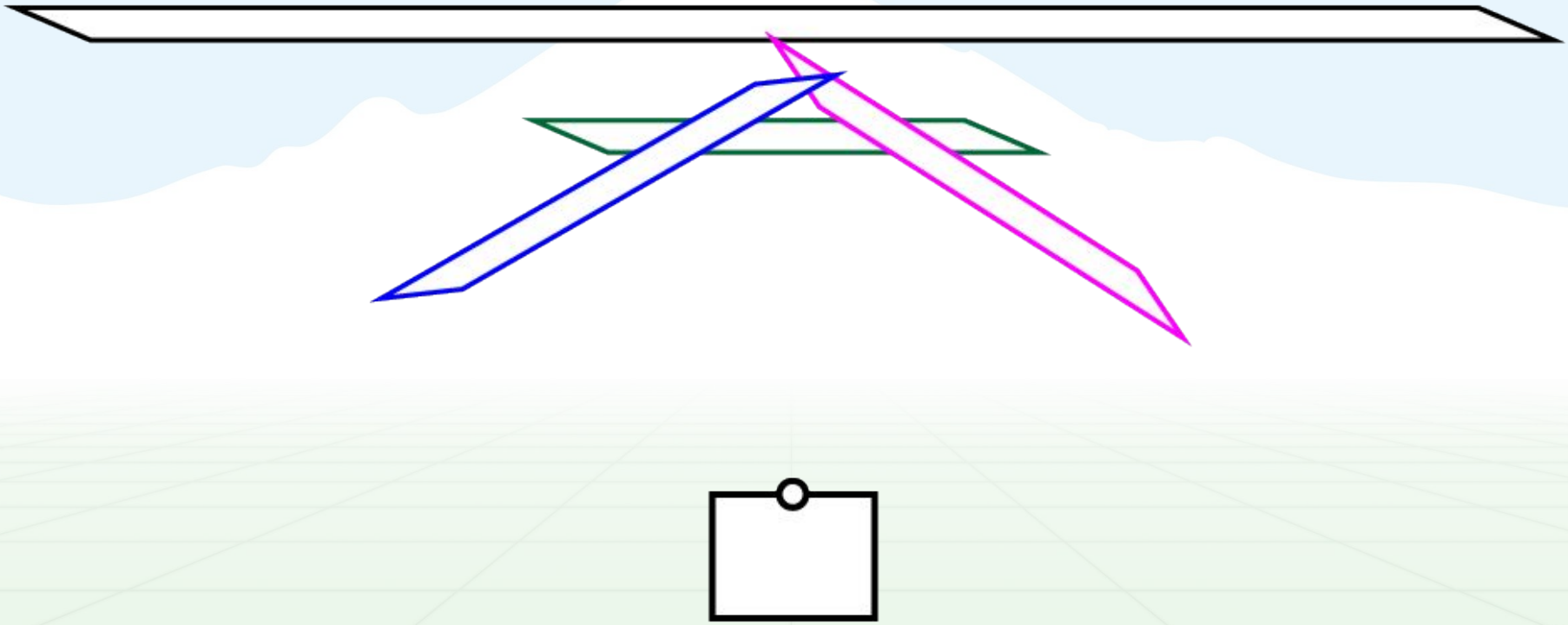
What’s happening?



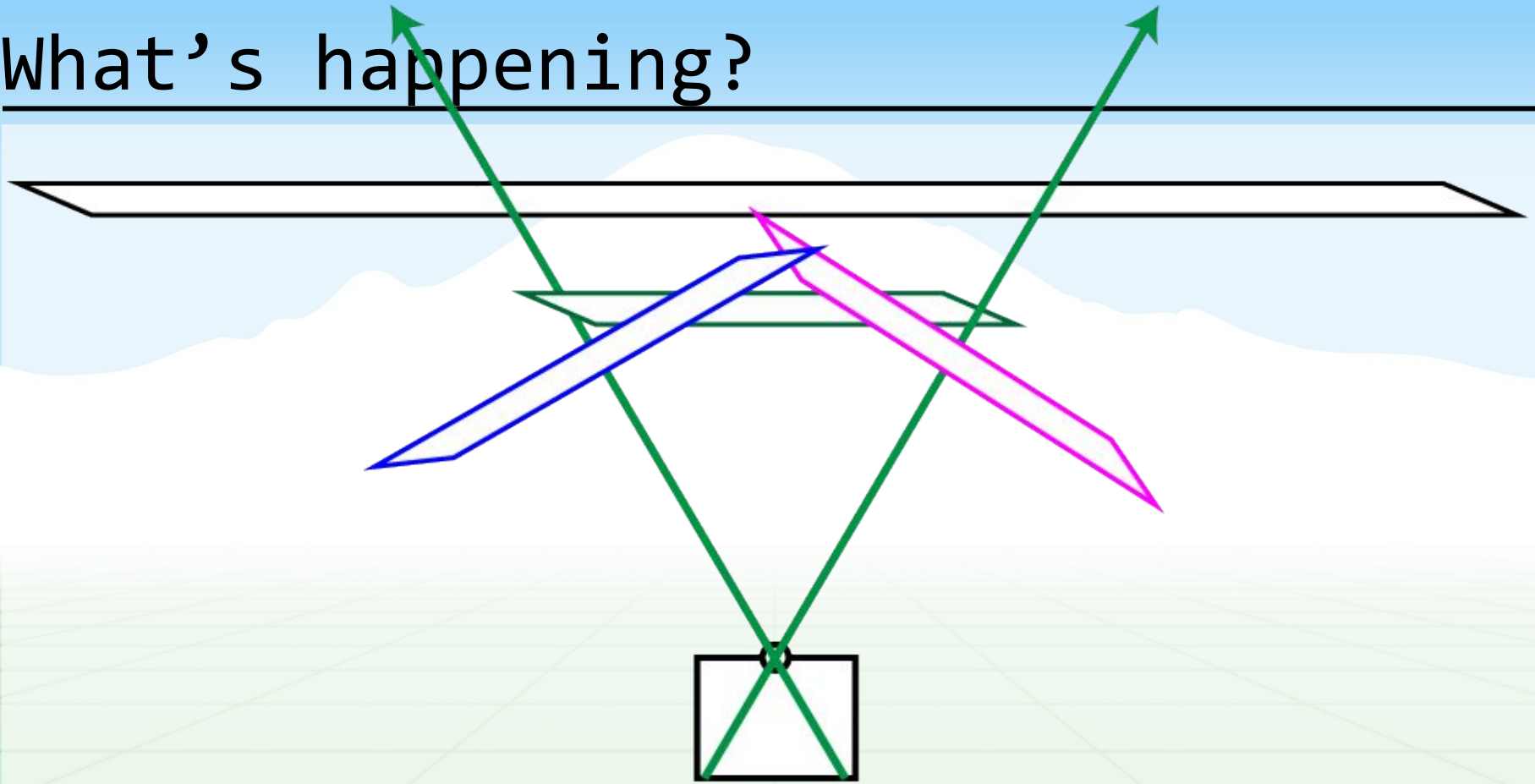
What’s happening?



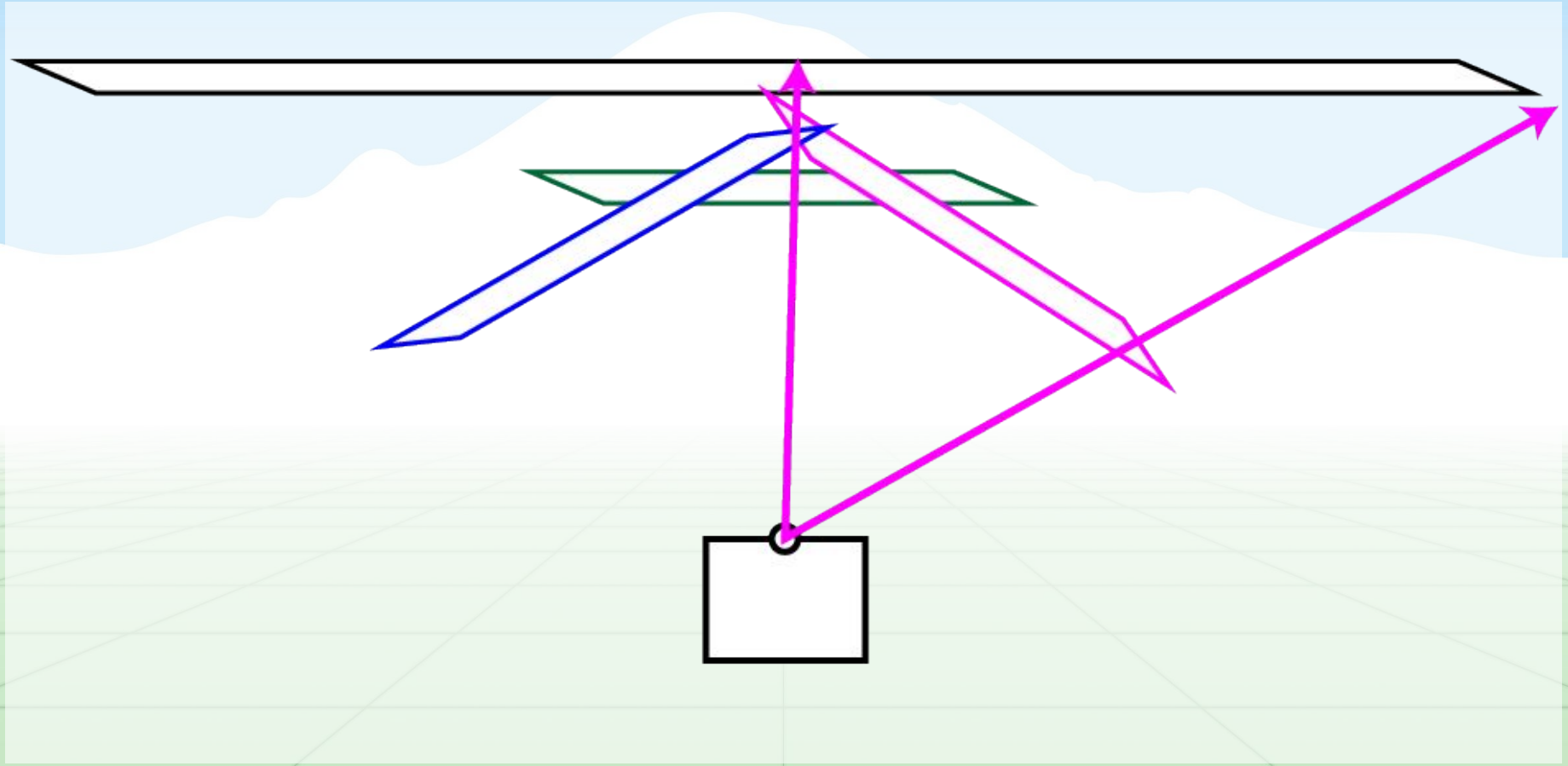
What’s happening?



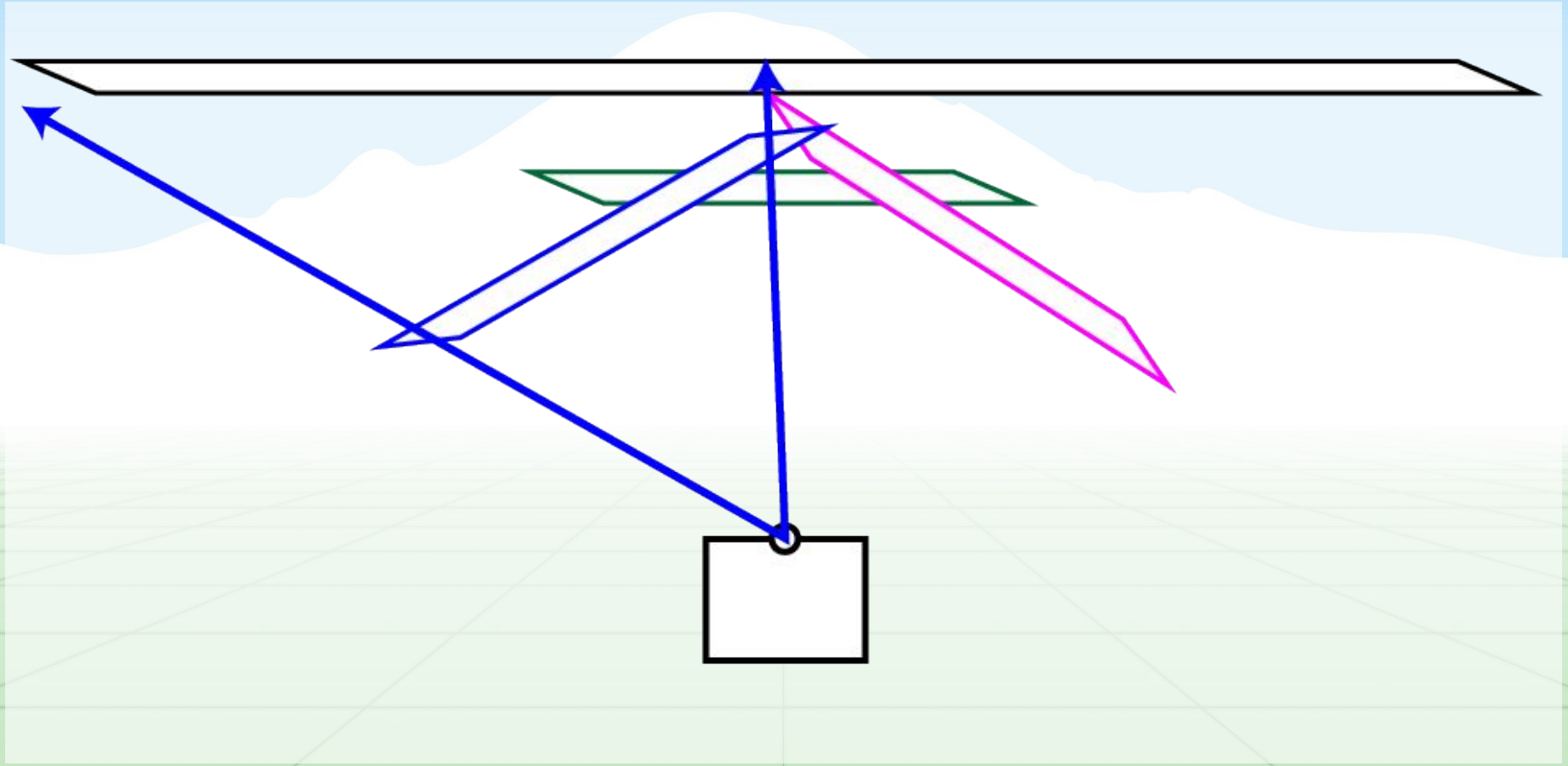
What’s happening?



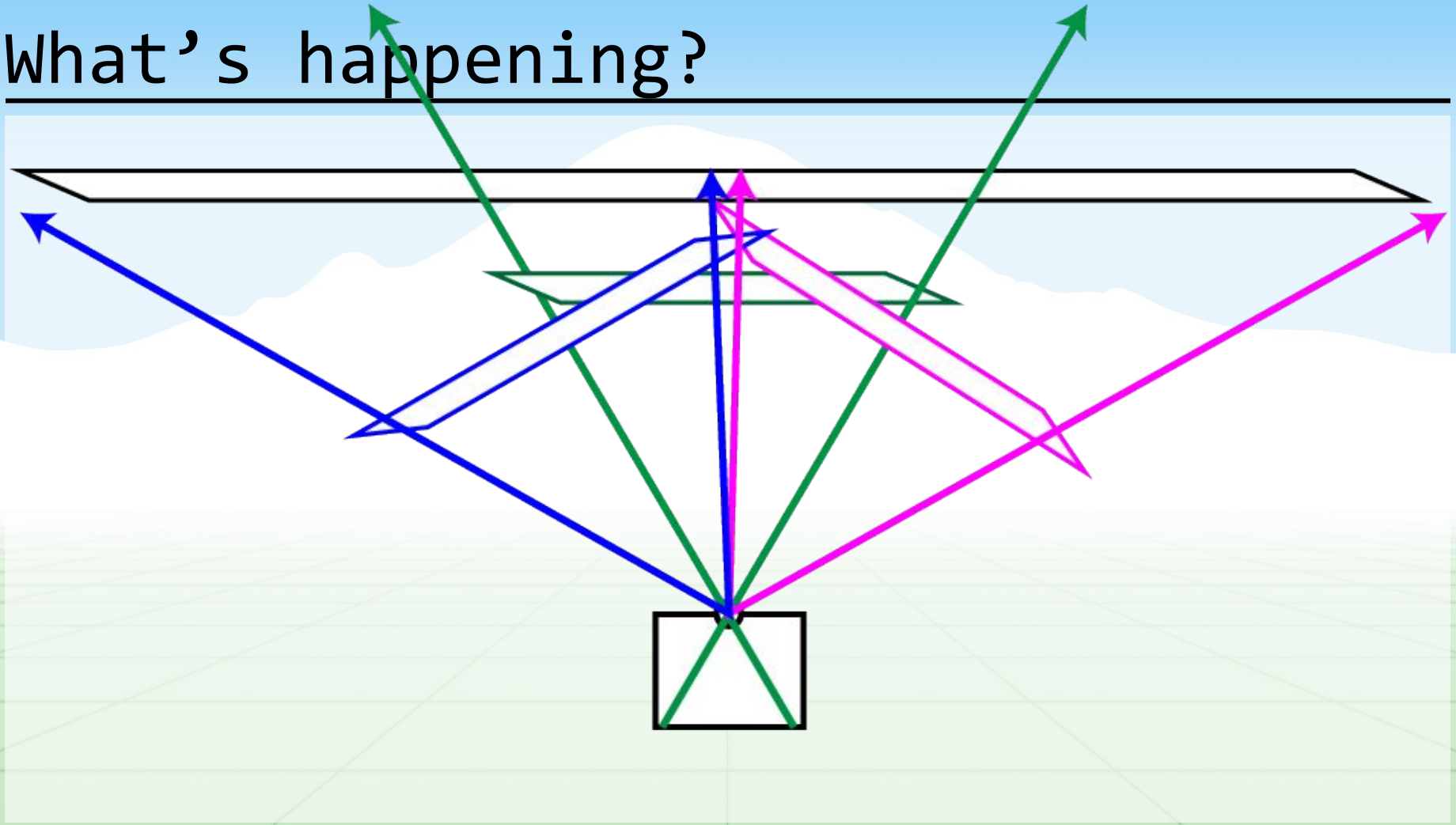
What’s happening?



What’s happening?



What’s happening?



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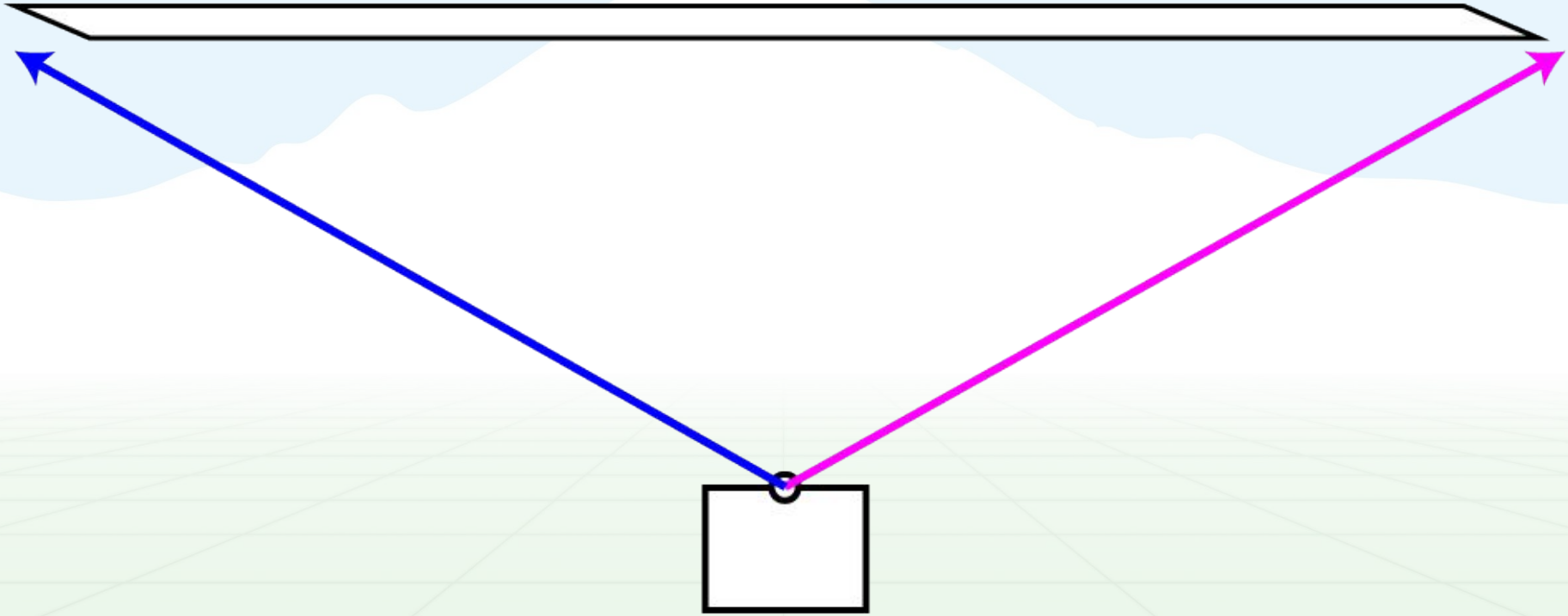

Very bad for big panoramas!

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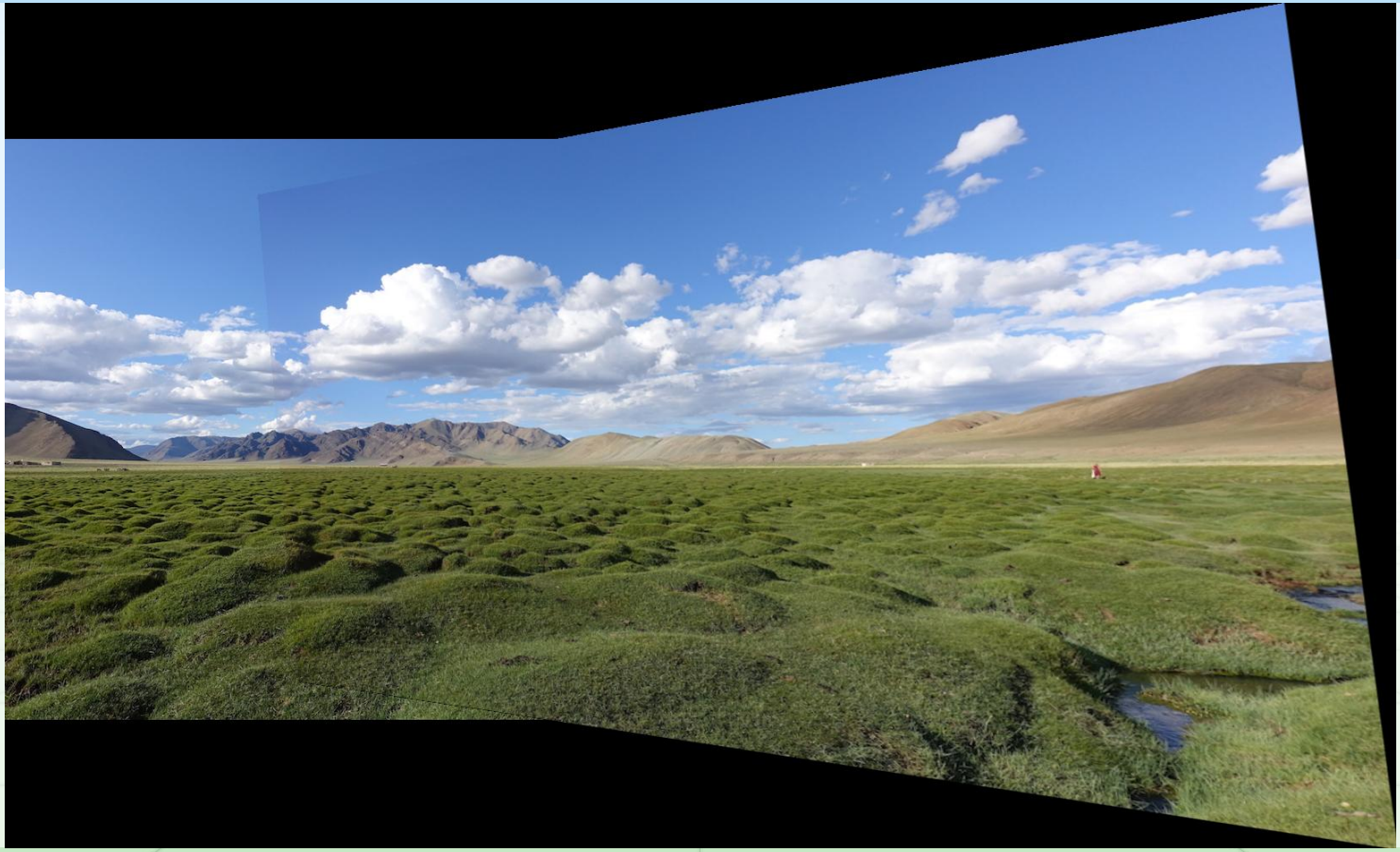
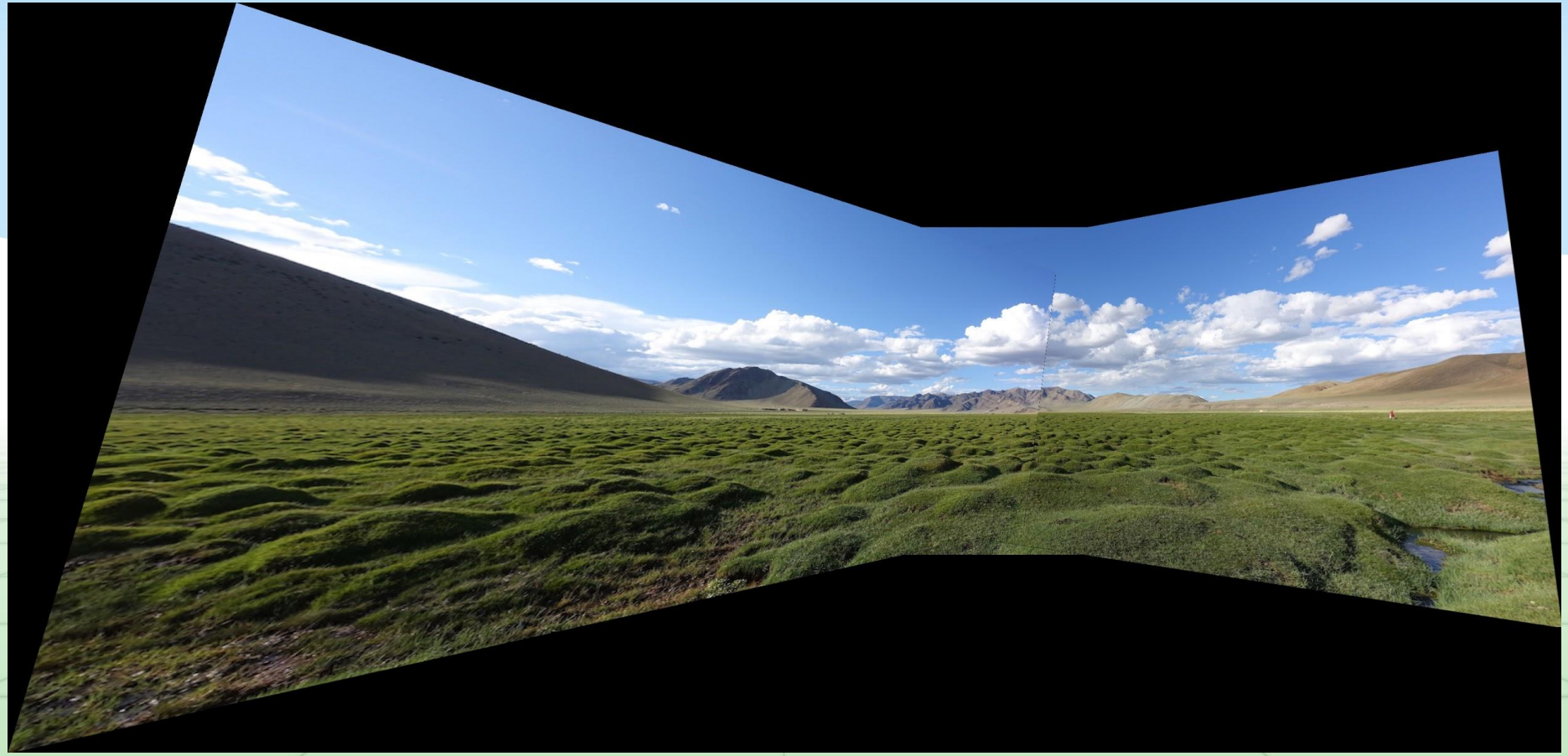
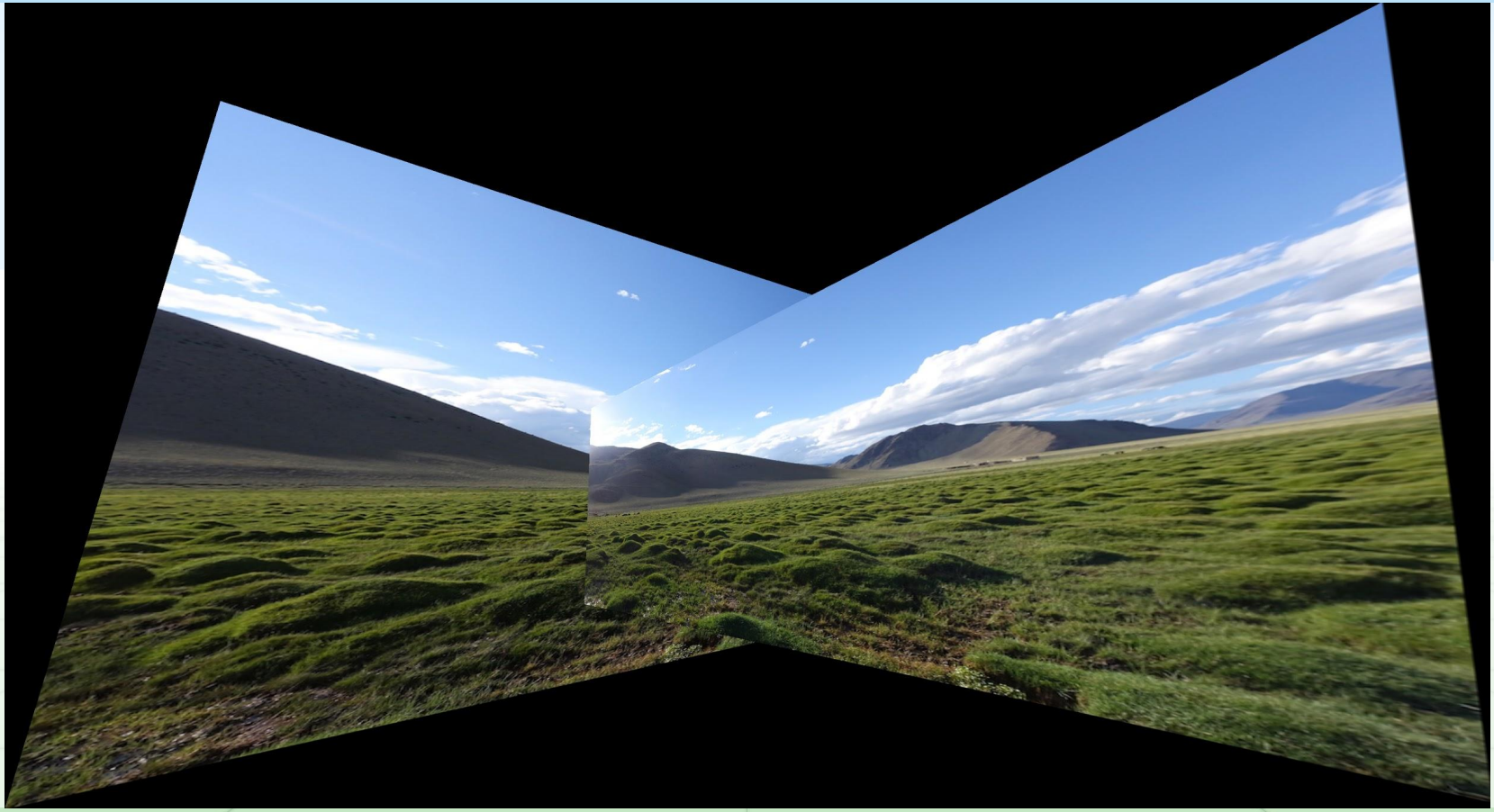


Very bad for big panoramas!



Fails :-(



How do we fix it? Cylinders!

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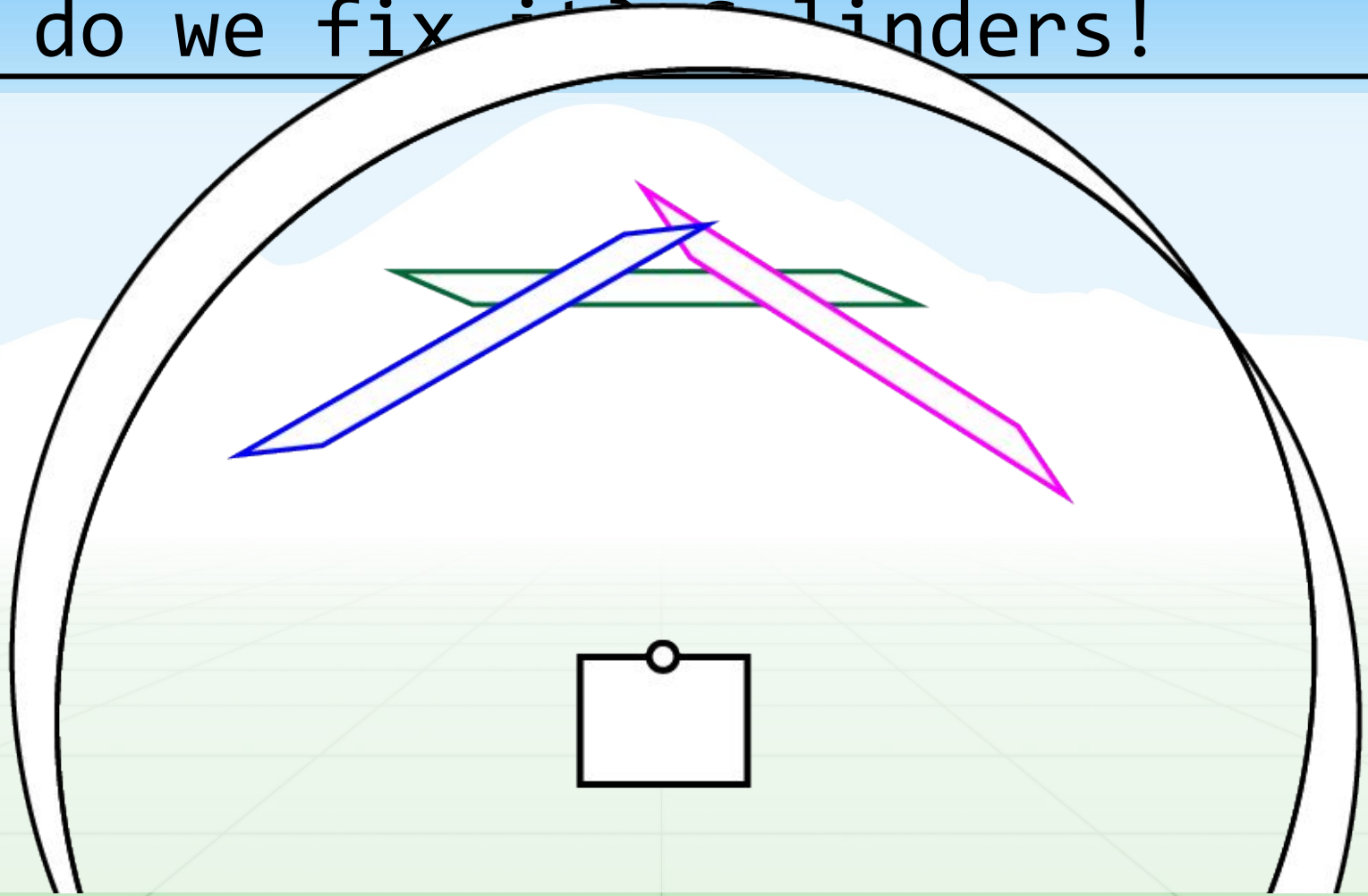

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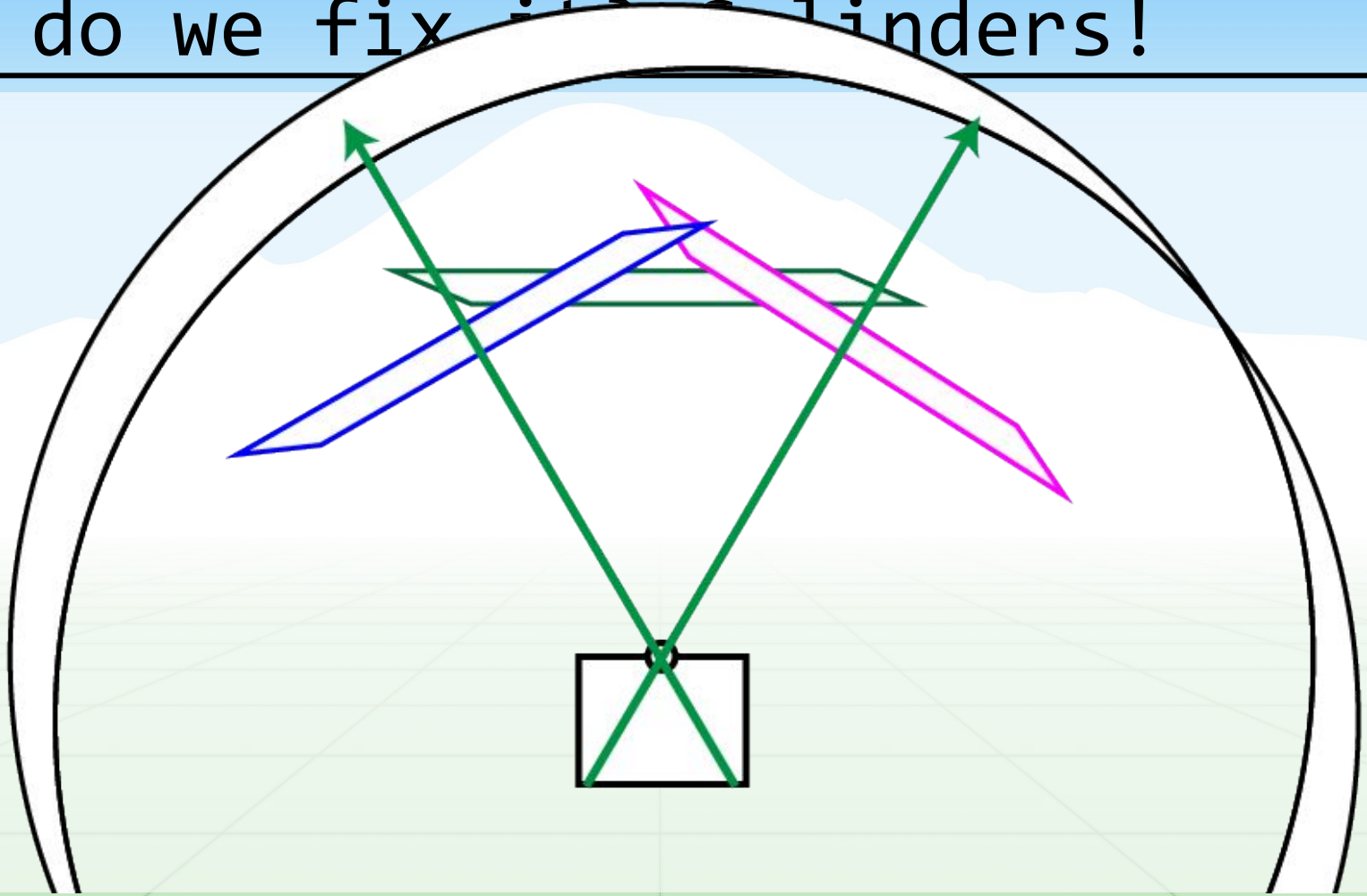

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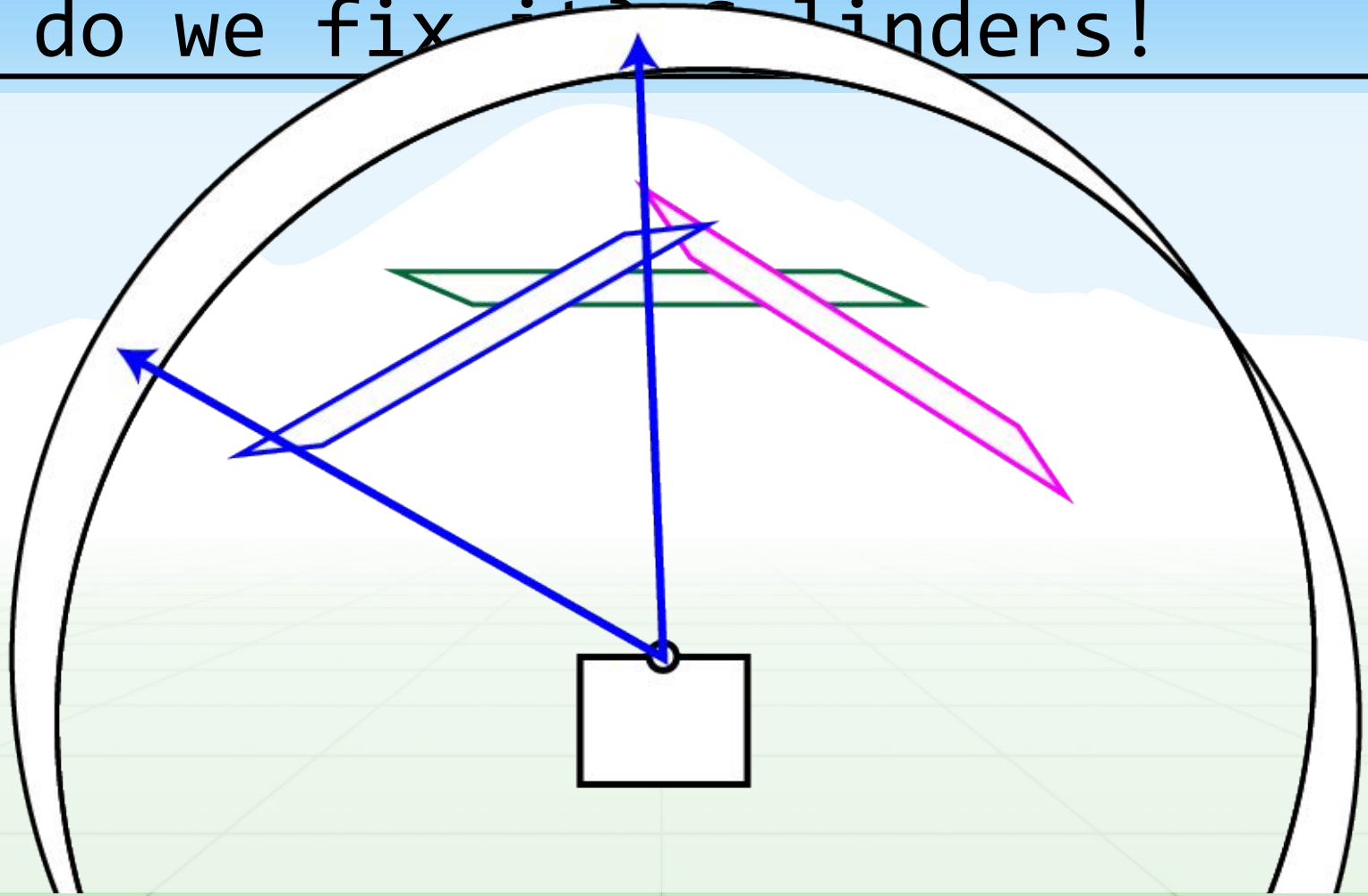

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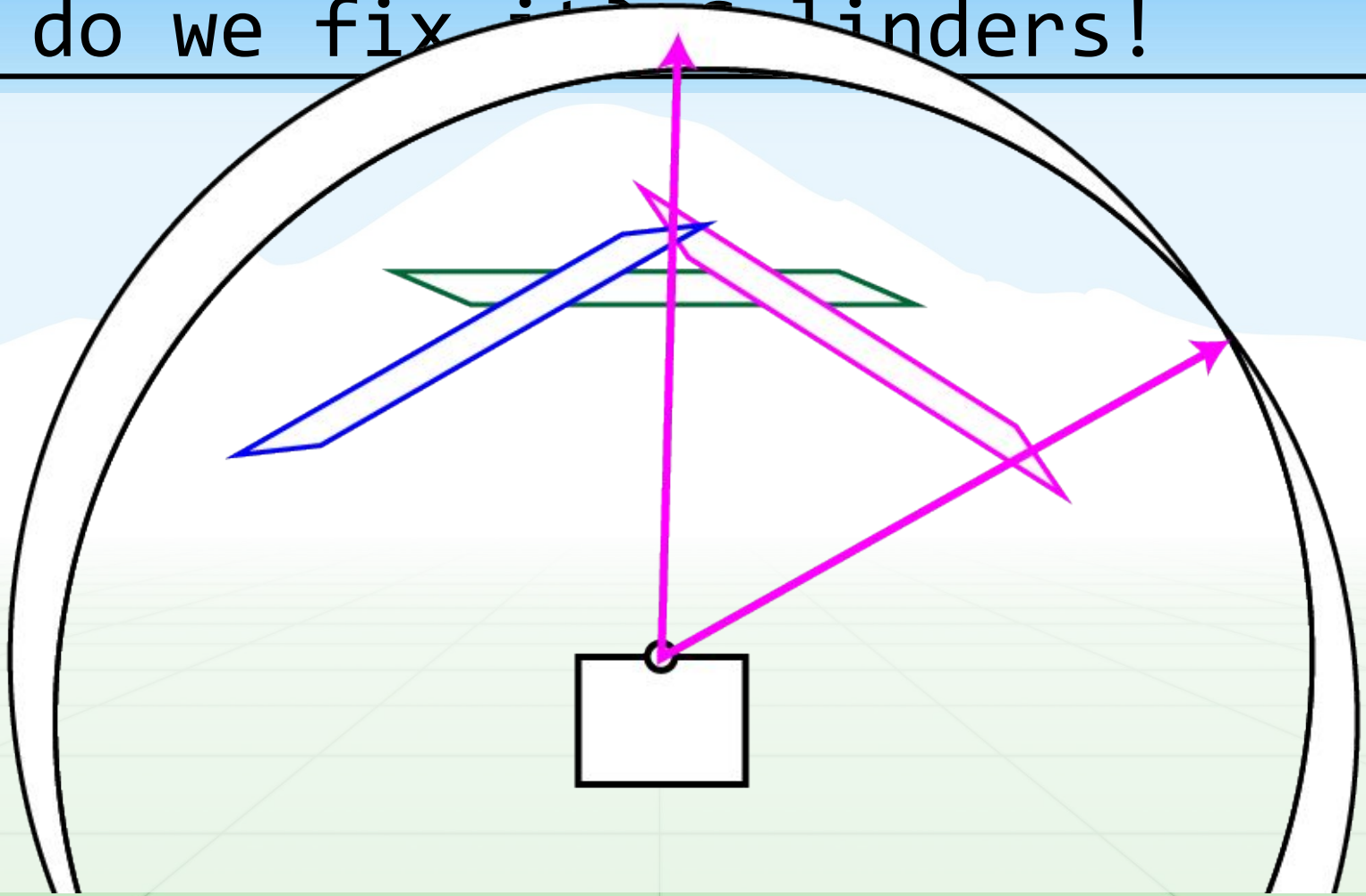

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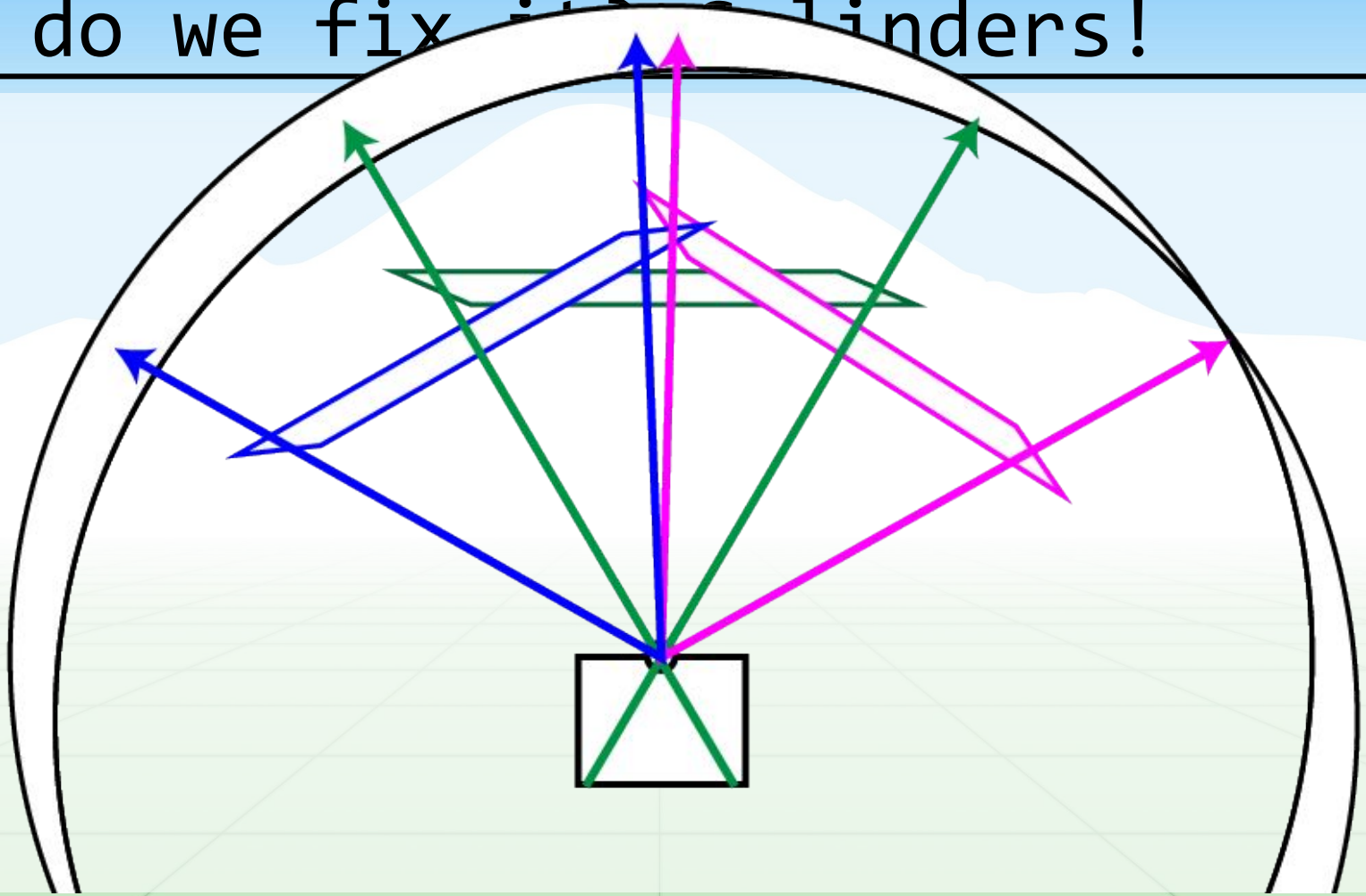


How do we fix it? Cylinders!

Calculate angle and height:

$\theta = (x - xc) / f$

$h = (y - yc) / f$

Find unit cylindrical coords:

$X' = \sin(\theta)$

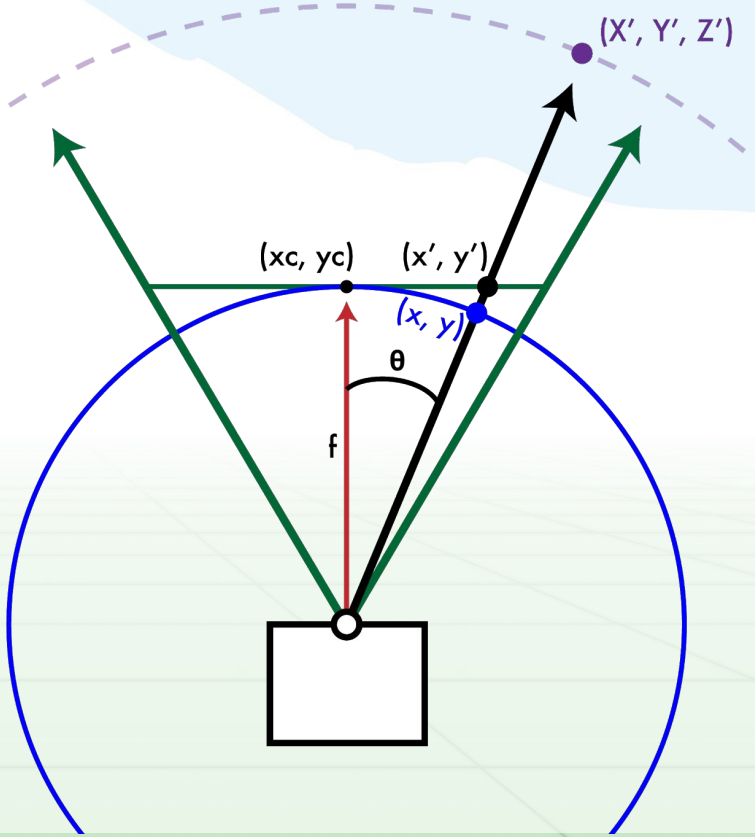
$Y' = h$

$Z' = \cos(\theta)$

Project to image plane:

$x' = f\, X'/Z' + xc$

$y' = f\, Y'/Z' + yc$



Dependant on focal length!

f = 300

f = 500

f = 1000

f = 1400

f = 10,000

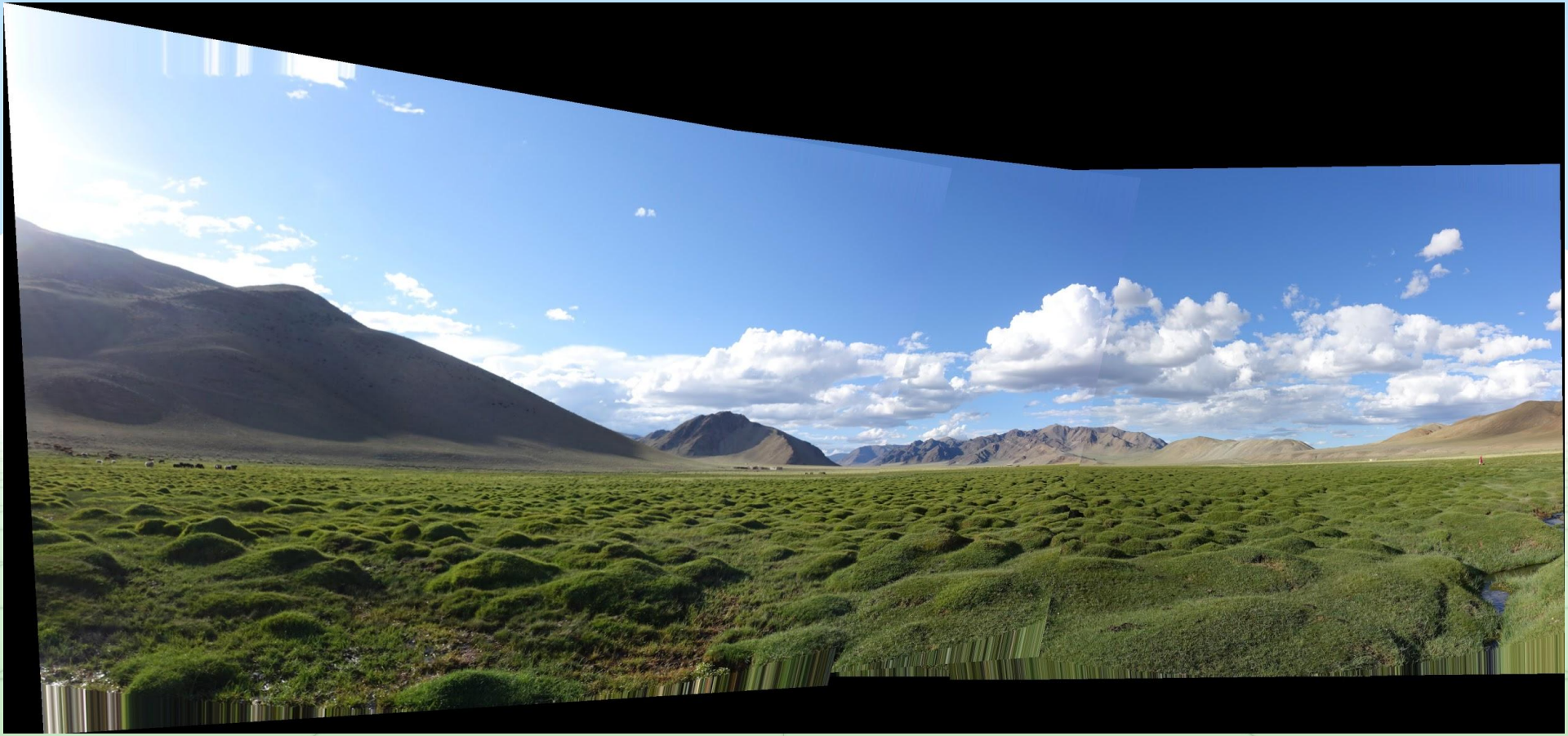
f = 10,000

Does it work?

Does it work?

Does it work?

Does it work?

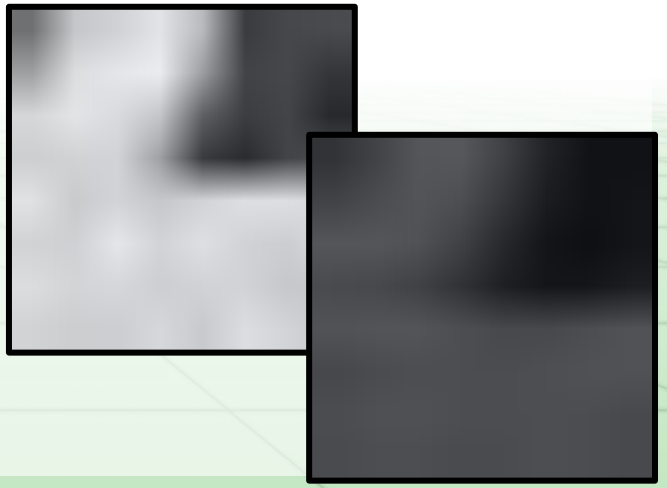


Does it work?

Does it work? Yay!

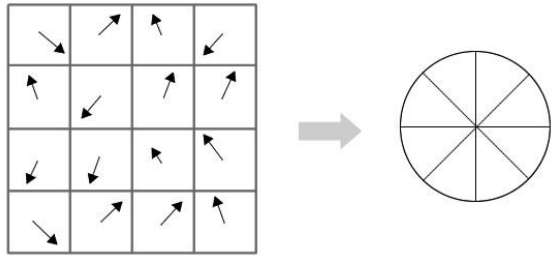
THIS IS AS GOOD AS IT GETS!

- Not so fast…
- Our descriptor has some issues:
  - Not invariant to lighting changes!
- Want features invariant to lighting



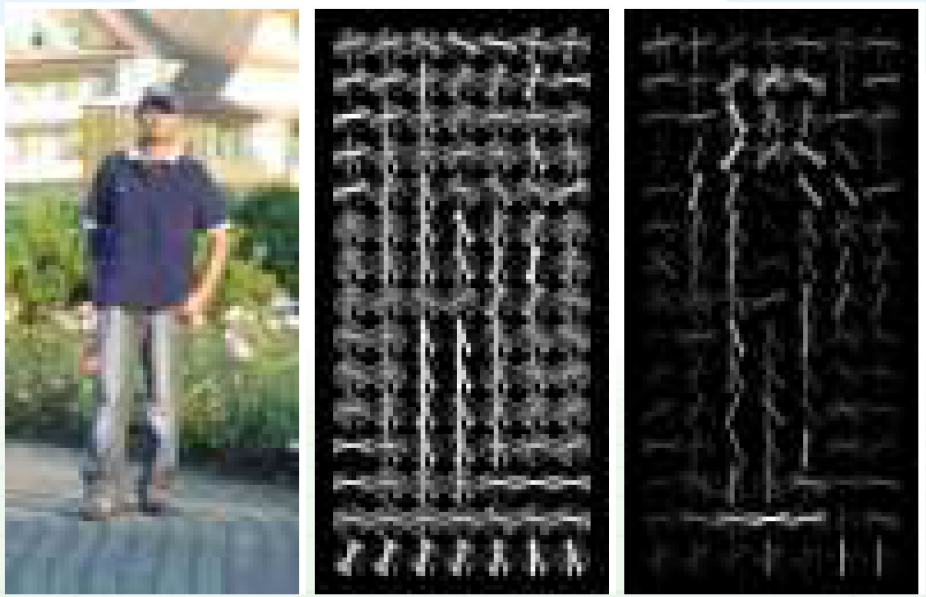
Histogram of Oriented Gradients (HOG)

- Dalal and Triggs 2005
- Better image descriptor
  - Compute gradients
  - Bin gradients
  - Aggregate blocks (4x4, 16x16 cells)
  - Normalize gradient magnitudes
- Not reliant on magnitude, just direction
  - Invariant to some lighting changes
- Train SVM to recognize people



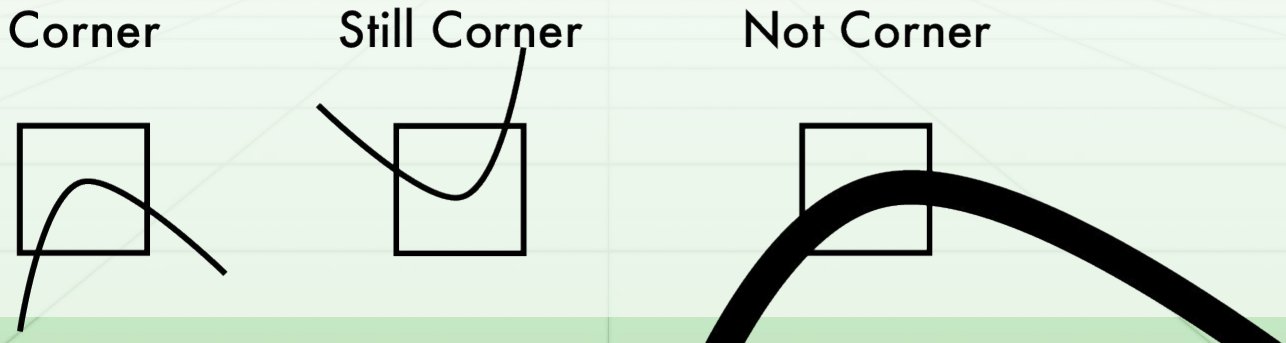
Binning from http://aishack.in/tutorials/sift-scale-invariant-feature-transform-features/

Histogram of Oriented Gradients (HOG)



THIS IS AS GOOD AS IT GETS!

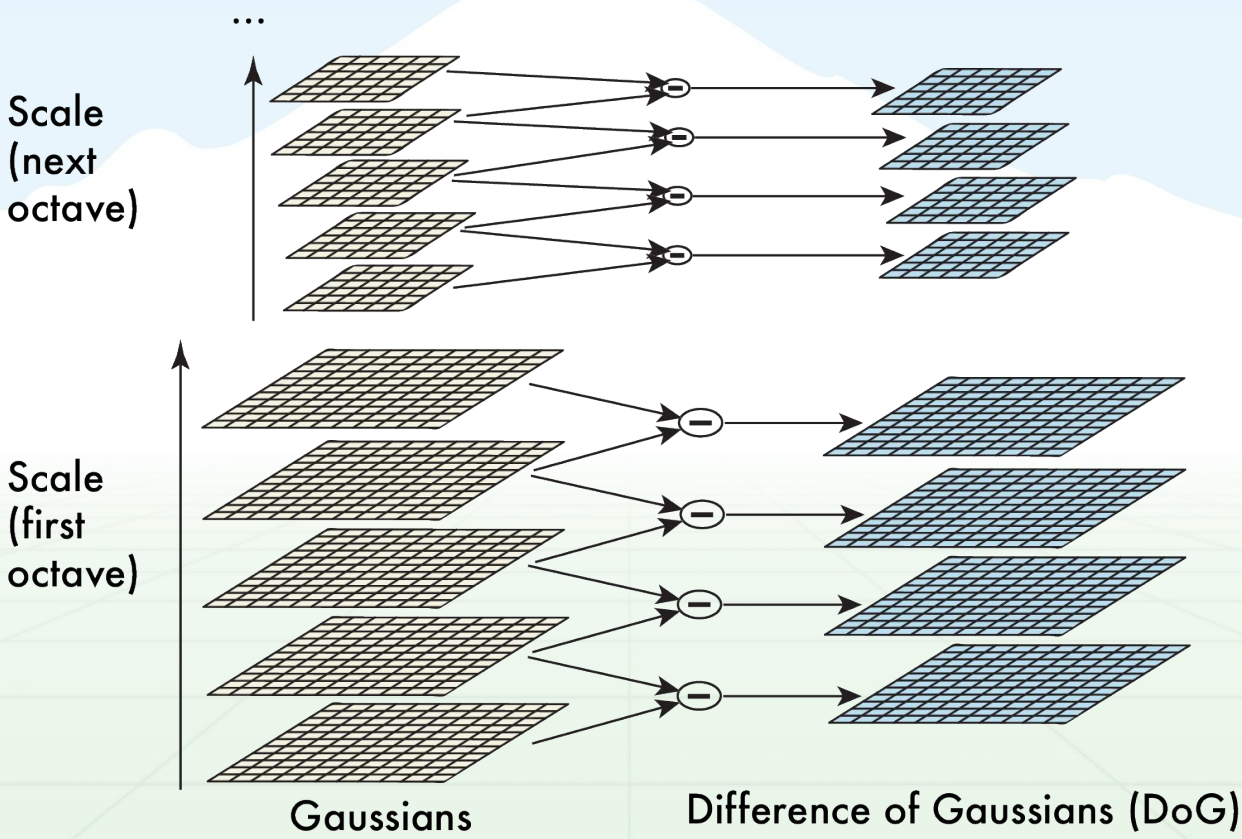
- Not so fast…
- Harris and has some issues:
  - Corners detection is rotation invariant
  - Harris not invariant to scale
- Descriptors are also hard
  - Just looking at pixels is not rotation invariant!
  - HOG also not rotation invariant



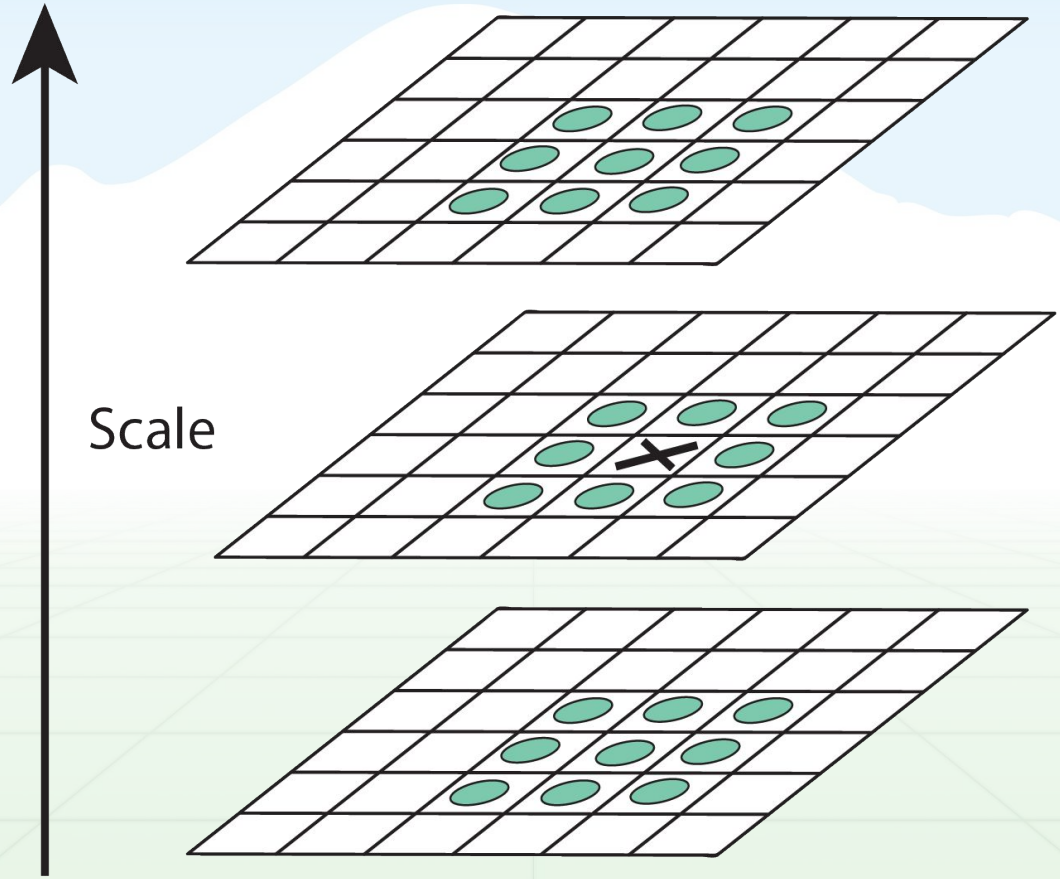
Want features invariant to scaling, rotation, etc.

- Scale Invariant Feature Transform (SIFT)
  - Lowe et al. 2004, many images from that paper
- Get scale-invariant response map
- Find keypoints
- Extract rotation-invariant descriptors
  - Normalize based on orientation
  - Normalize based on lighting

Extract DoG features at multiple scales



Find local-maxima in location and scale



Throw out weak responses and edges

- Estimate gradients
  - Similar to before, look at nearby responses
  - Not whole image, only a few points! Faster!
  - Throw out weak responses
- Find cornery things
  - Same deal, structure matrix, use det and trace information

$$\frac{\mathrm{Tr}(\mathbf{H})^2}{\mathrm{Det}(\mathbf{H})} < \frac{(r+1)^2}{r}$$

Find main orientation of patches

- Look at weighted histogram of nearby gradients
  - Any gradient within 80% of peak gets its own descriptor
    - Multiple keypoints per pixel
  - Descriptors are normalized based on main orientation

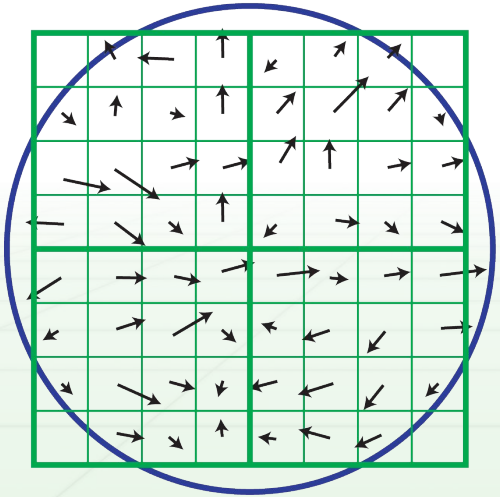
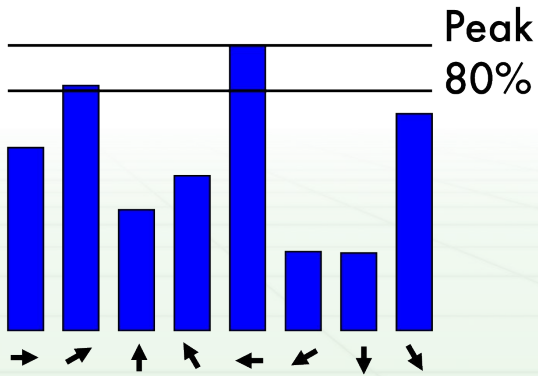
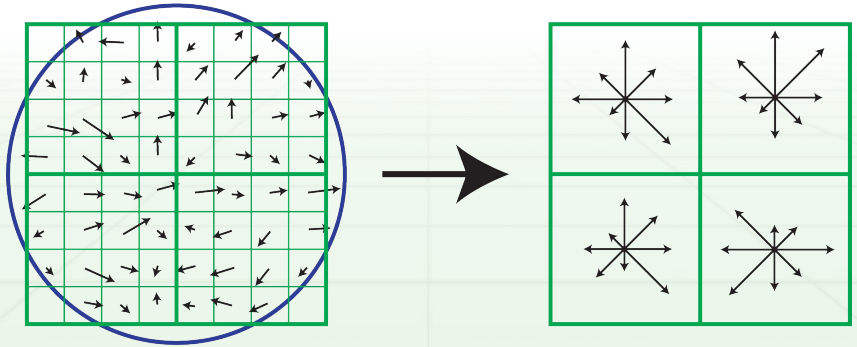


Image gradients



Keypoints are normalized gradient histograms

- Divide into subwindows (2x2, 4x4)
- Bin gradients within subwindow, get histogram
  - Normalize to unit length
  - Clamp at maximum .2
  - Normalize again
  - Helps with lighting changes!



SIFT is great!

- Find good keypoints, describe them
- Finding objects, recognition, panoramas, etc.

SIFT is great!