



Started 9/19

# Case Study for Geometric Invariance

## Local Image Features

EECS 442 Computer Vision

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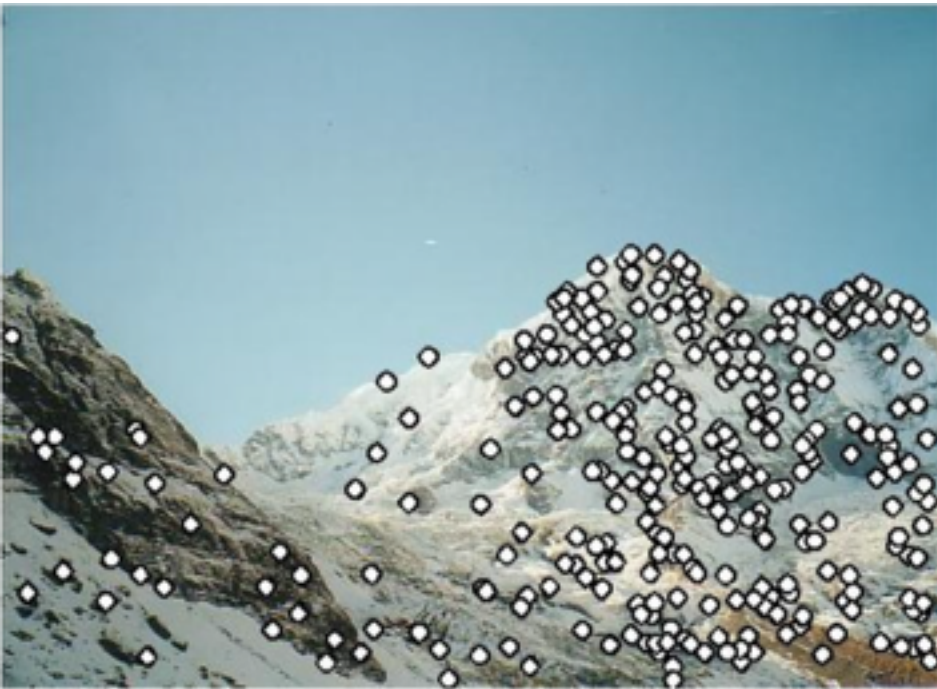
# Plan

- What are local image features and why are they useful.
- Local Image Feature Detection
- Invariance
- Local Image Feature Description

# Consider an Application: Image Stitching



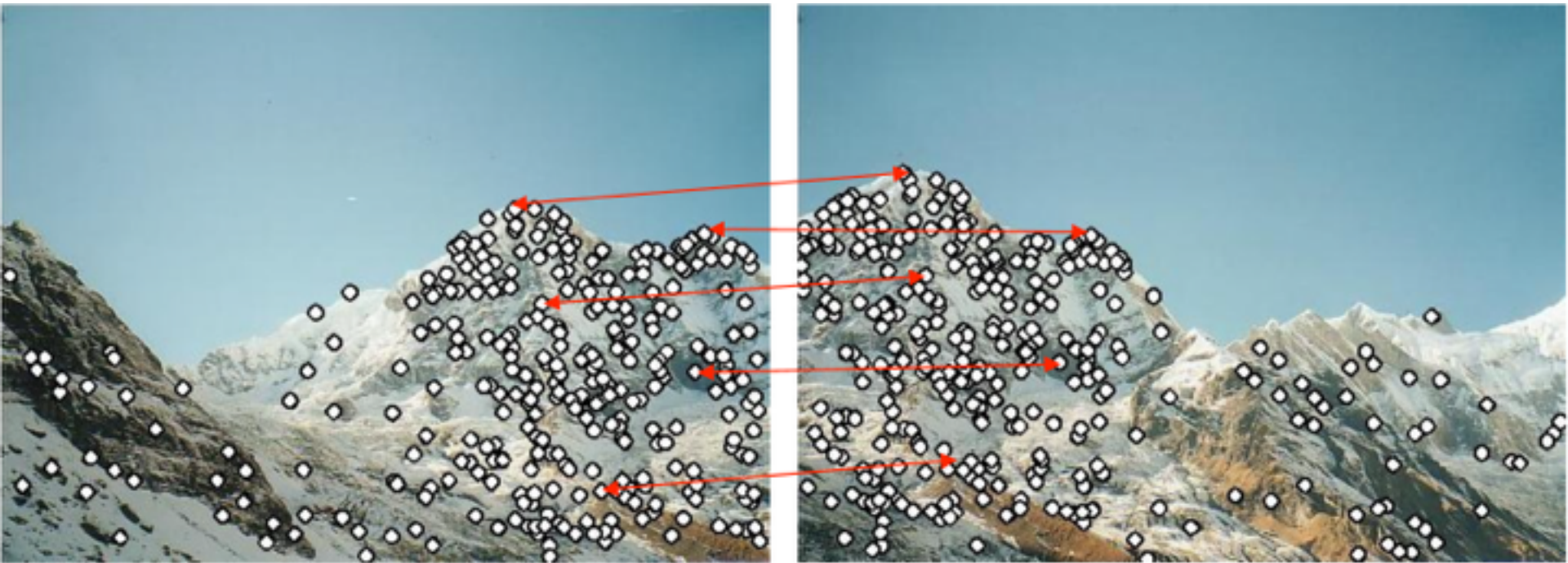
# Consider an Application: Image Stitching



1. Detect feature points in both images.



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2. Find corresponding pairs of feature points.

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• **Reduction**  
• **Matching**  
**Estimation**



**What invariants do we care about here?**





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## 1. Geometric Invariants

1. Shift or Translation
2. Scale? Rotation?
3. Affine?
4. Viewpoint?

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## 1. Geometric Invariants

1. Shift or Translation
2. Scale? Rotation?
3. Affine?
4. Viewpoint?

## 2. Scene layout?



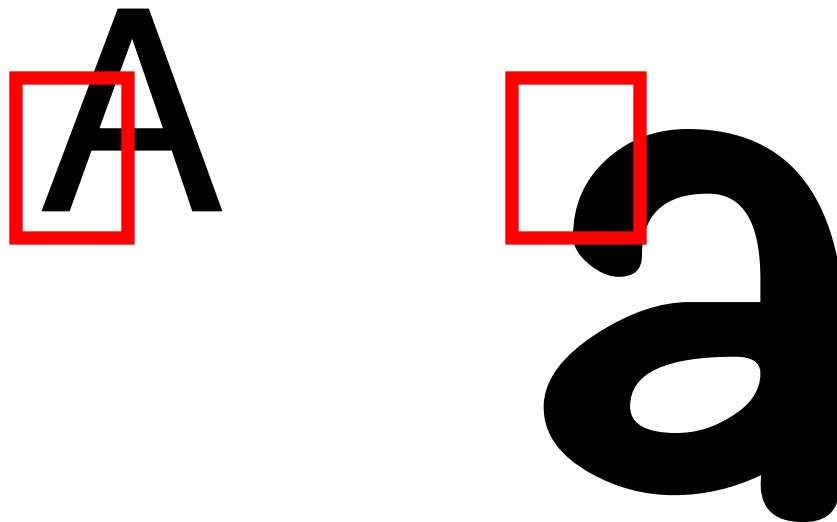
# What invariants do we care about here?



1. Geometric Invariants
  1. Shift or Translation
  2. Scale? Rotation?
  3. Affine?
  4. Viewpoint?
2. Scene layout?
3. Photometric invariants?

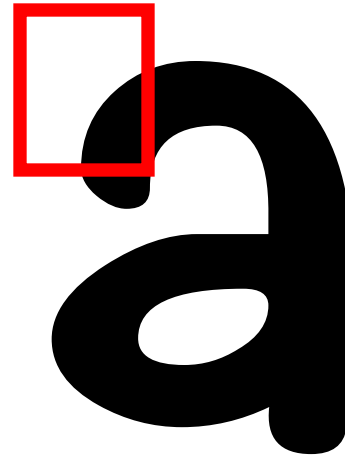
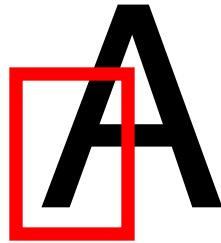


# Consider an Application: Detect Object Instances

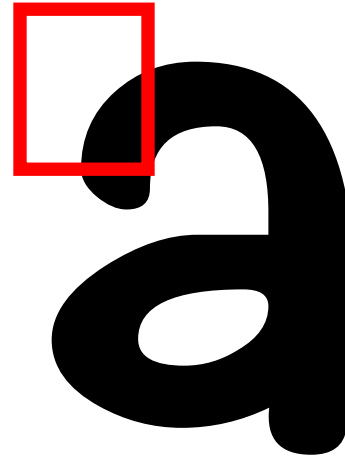
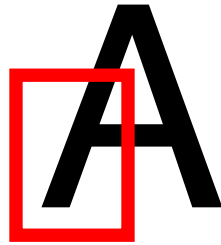


1. Detect feature points in both images.
2. Find corresponding pairs of feature points.
3. Use the pairs to match object instances.

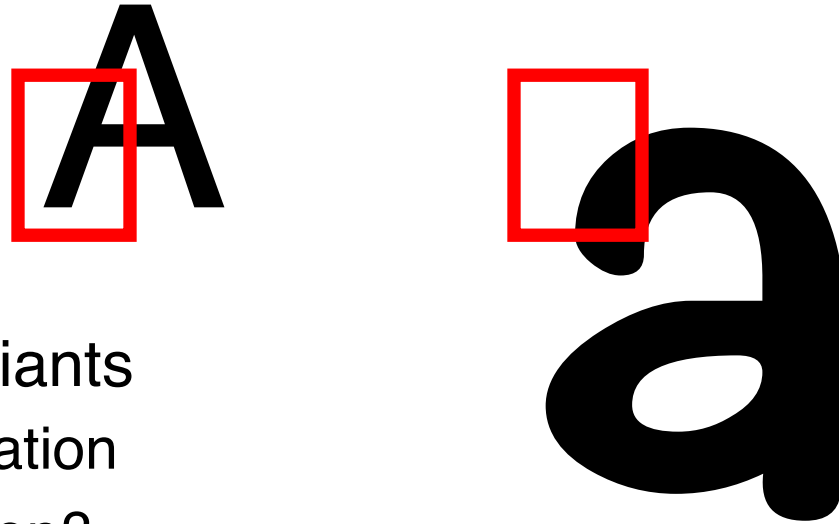
What invariants do we care about here?



What invariants do we care about here?



# What invariants do we care about here?



1. Geometric Invariants
  1. Shift or Translation
  2. Scale? Rotation?
  3. Affine?
  4. Viewpoint?
2. Scene layout?
3. Photometric invariants?
4. Character shape invariance? “Font” invariance.



# Case Study in Local Image Features

- Basic flow of applications in the case study
  1. Detect feature points in both images.
  2. Find corresponding pairs of feature points.
  3. Use the pairs to solve objective function.

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Matching  
Estimation**

# Case Study in Local Image Features

- Basic flow of applications in the case study
  1. Detect feature points in both images.
  2. Find corresponding pairs of feature points.
  3. Use the pairs to solve objective function.
- Other applications of local image features
  - 3D reconstruction
  - Motion tracking
  - Object recognition
  - Indexing and database retrieval
  - Robot navigation

**Reduction  
Matching  
Estimation**

# Advantages of local features

## Locality

- features are local, so robust to occlusion and clutter

## Distinctiveness:

- can differentiate a large database of objects

## Quantity

- hundreds or thousands in a single image

## Efficiency

- real-time performance achievable

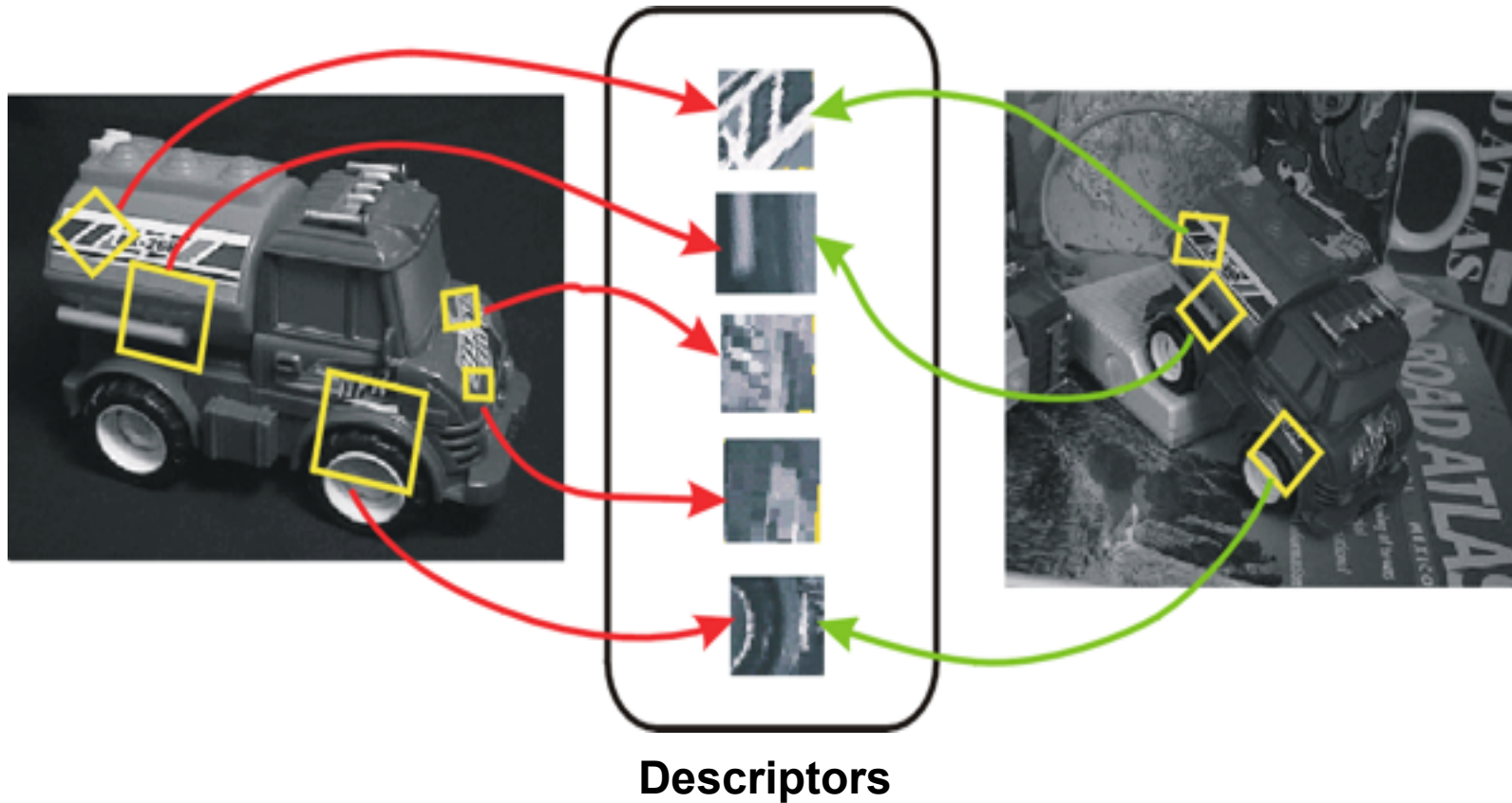
## Generality

- exploit different types of features in different situations



# Challenges

- Repeatability
- Uniqueness
- Invariance w.r.t. Matching



# What makes a good feature?



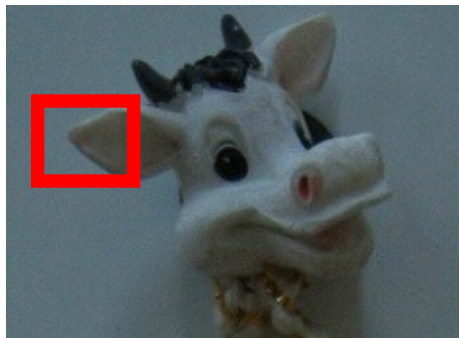
# Repeatability



Illumination  
invariance



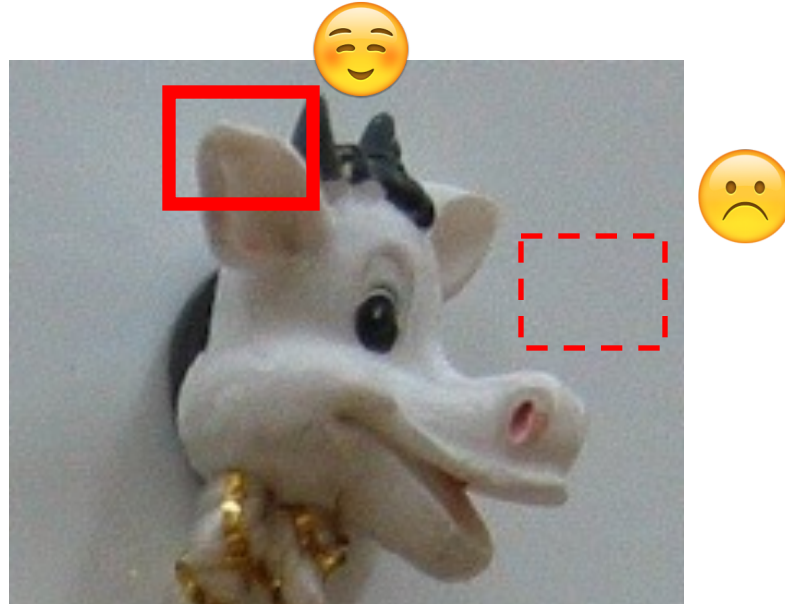
Scale  
invariance



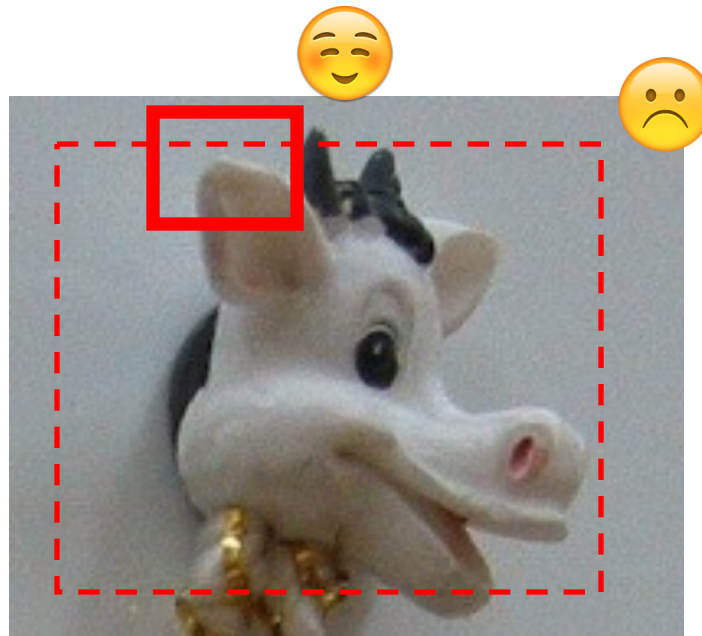
Pose invariance

- Rotation
- Affine

- Saliency



- Locality



# One criterion is uniqueness

Look for image regions that are unusual

- Lead to unambiguous matches in other images

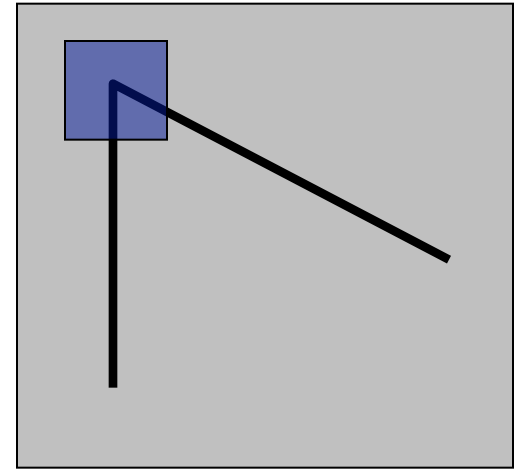
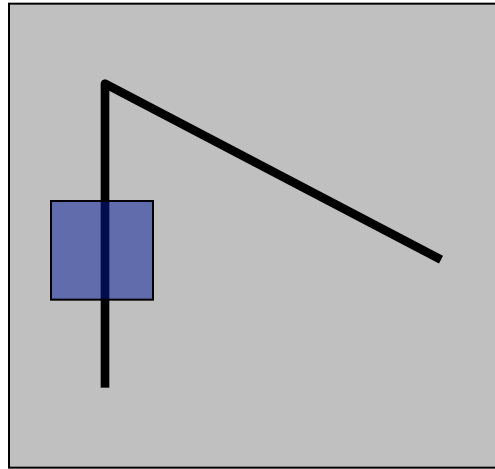
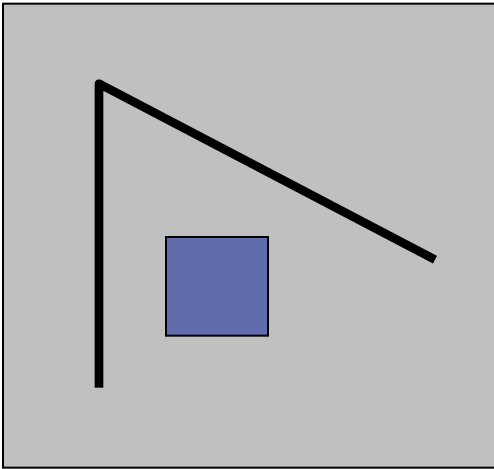
How to define “unusual”?



# Local measures of uniqueness

Suppose we only consider a small window of pixels

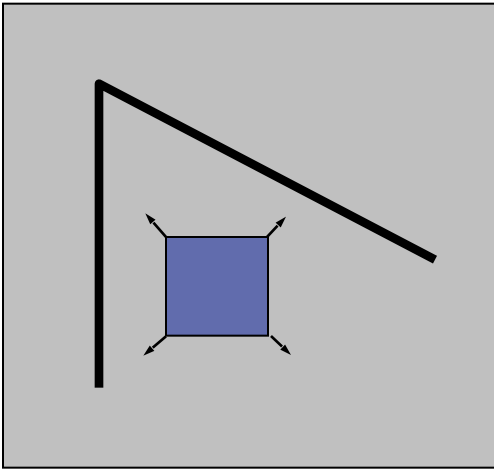
- What defines whether a feature is a good or bad candidate?



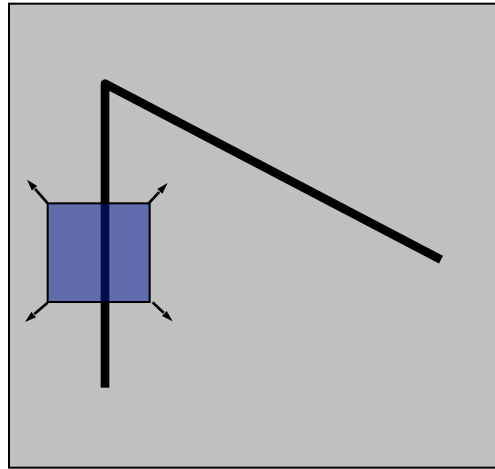
# Feature detection

Local measure of feature uniqueness

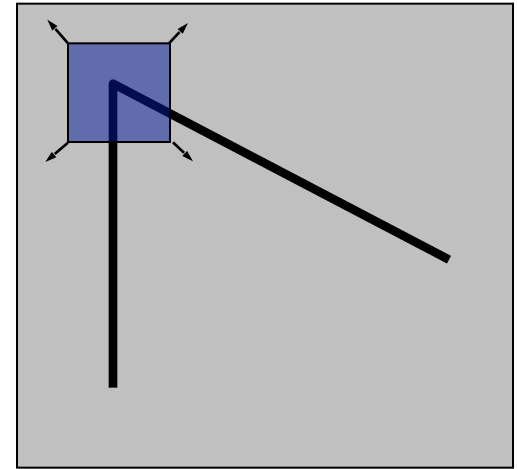
- How does the window change when you shift it?
- Shifting the window in *any direction* causes a *big change*



“flat” region:  
no change in all  
directions



“edge”:  
no change along the  
edge direction



“corner”:  
significant change in  
all directions

# Stop Slides

See hand-written lecture notes for the mathematical derivation of the corner operator.