CS5670: Intro to Computer Vision Noah Snavely

Introduction to Recognition



Announcements

- Project 4 (Stereo) has been released (demo)
 - Due next Friday, April 28, by 11:59pm
 - To be done in pairs

Where we go from here

- What we know: Geometry
 - What is the shape of the world? How does that shape appear in images?

- What's next: Recognition
 - What are we looking at?

What do we mean by "object recognition"?

Next 15 slides adapted from Li, Fergus, & Torralba's excellent short course on category and object recognition



Verification: is that a lamp?



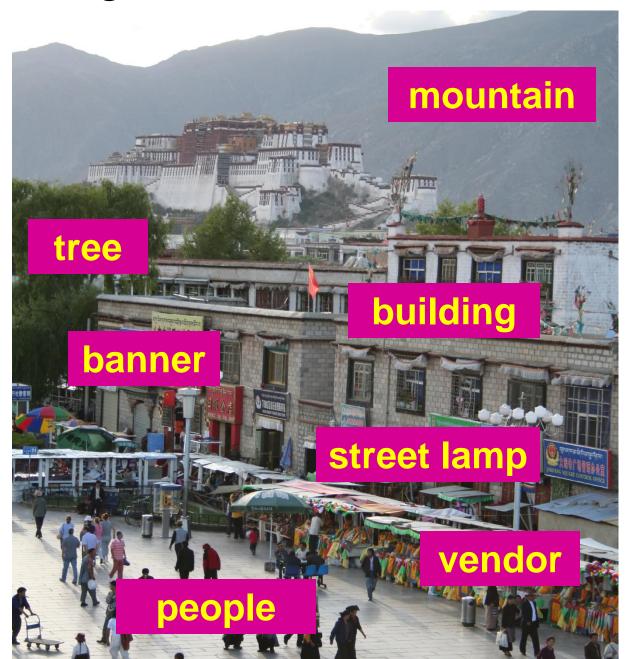
Detection: are there people?



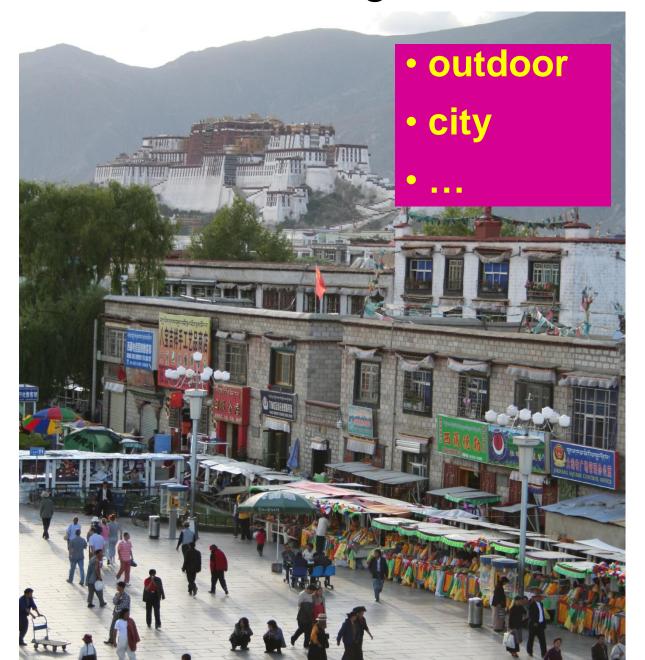
Identification: is that Potala Palace?



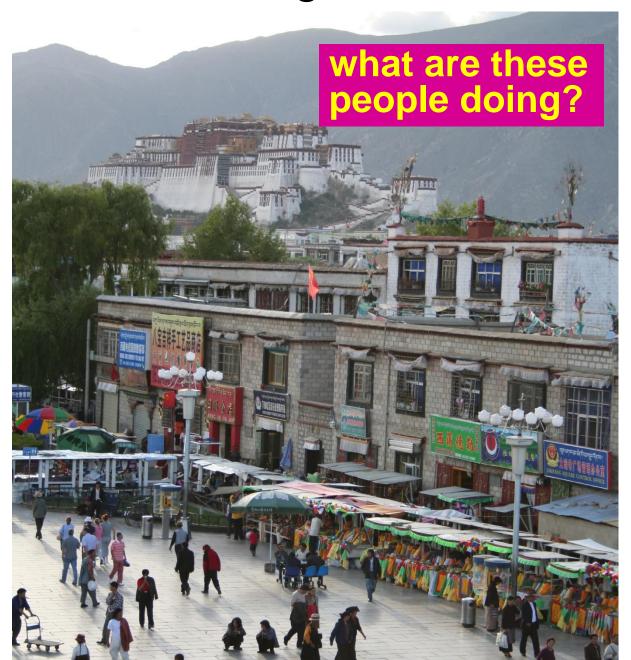
Object categorization



Scene and context categorization



Activity / Event Recognition

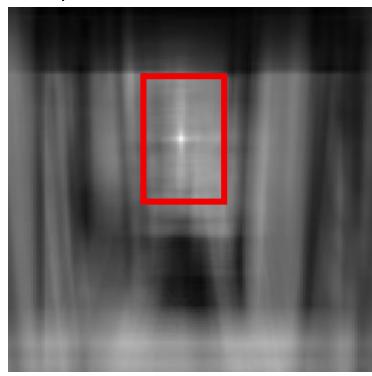


Object recognition Is it really so hard?

Find the chair in this image



Output of normalized correlation



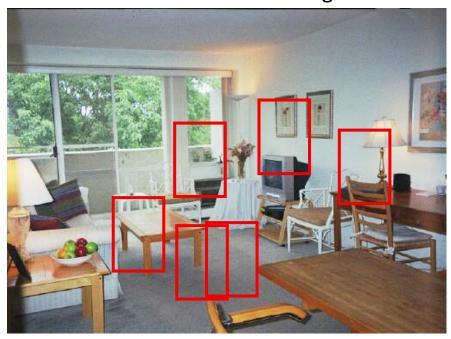
This is a chair

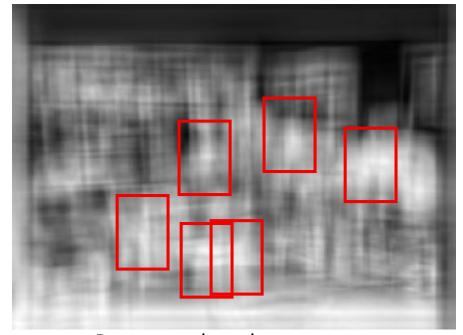




Object recognition Is it really so hard?

Find the chair in this image





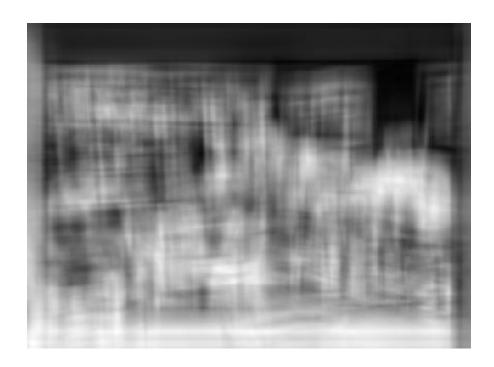
Pretty much garbage
Simple template matching is not going to make it



Object recognition Is it really so hard?

Find the chair in this image





A "popular method is that of template matching, by point to point correlation of a model pattern with the image pattern. These techniques are inadequate for three-dimensional scene analysis for many reasons, such as occlusion, changes in viewing angle, and articulation of parts." Nivatia & Binford, 1977.

Why not use SIFT matching for everything?

Works well for object instances







Not great for generic object categories







And it can get a lot harder



Brady, M. J., & Kersten, D. (2003). Bootstrapped learning of novel objects. J Vis, 3(6), 413-422

How do human do recognition?

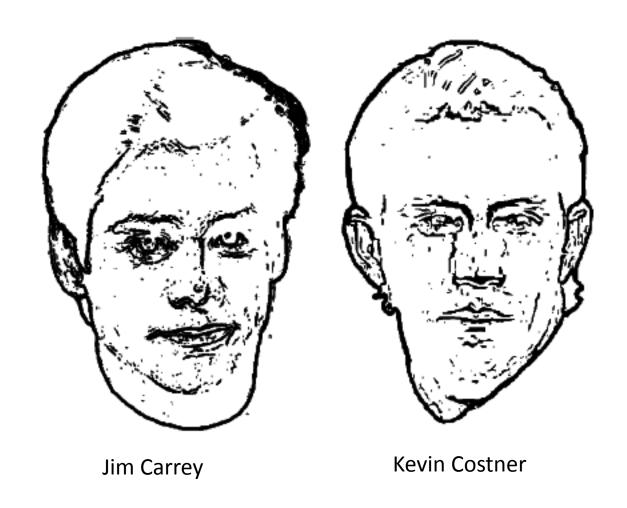
- We don't completely know yet
- But we have some experimental observations.

Observation 1



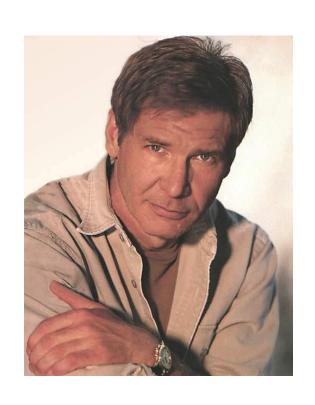
 We can recognize familiar faces even in lowresolution images

Observation 2:



• High frequency information is not enough

What is the single most important facial features for recognition?





Observation 4:



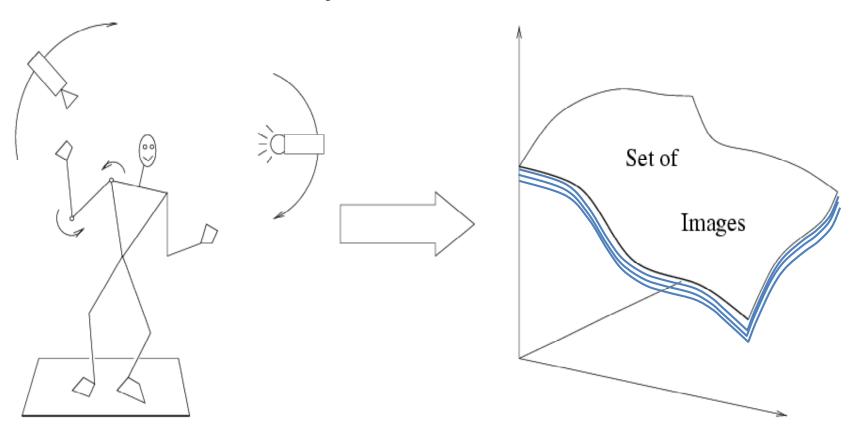
• Image Warping is OK

The list goes on

Face Recognition by Humans: Nineteen Results All Computer Vision Researchers Should Know About

 http://web.mit.edu/bcs/sinha/papers/19resul ts sinha etal.pdf

Why is this hard?



Variability: Camera position
Illumination
Shape parameters

How many object categories are there? ~10,000 to 30,00

Challenge: variable viewpoint

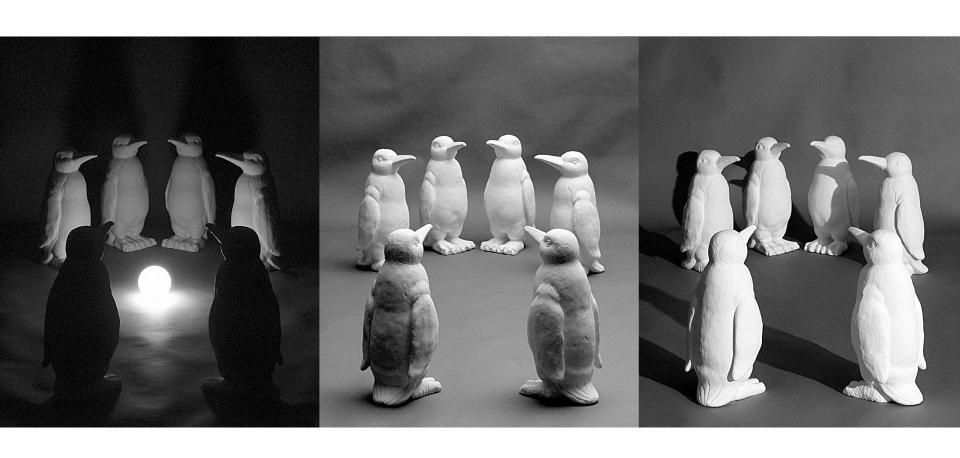






Michelangelo 1475-1564

Challenge: variable illumination



from Apple.

(Actual size)



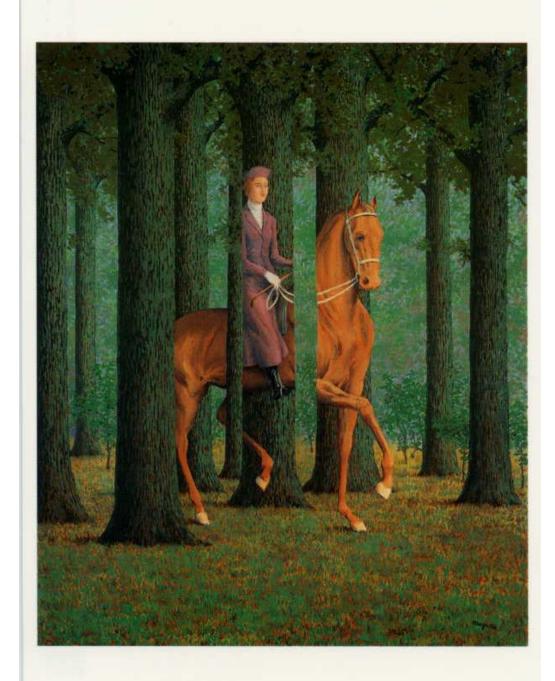
Challenge: scale

Challenge: deformation

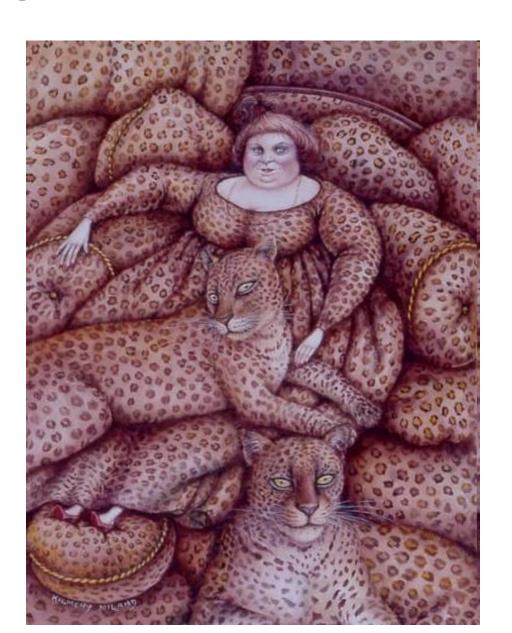




Challenge: Occlusion



Challenge: background clutter



Challenge: intra-class variations







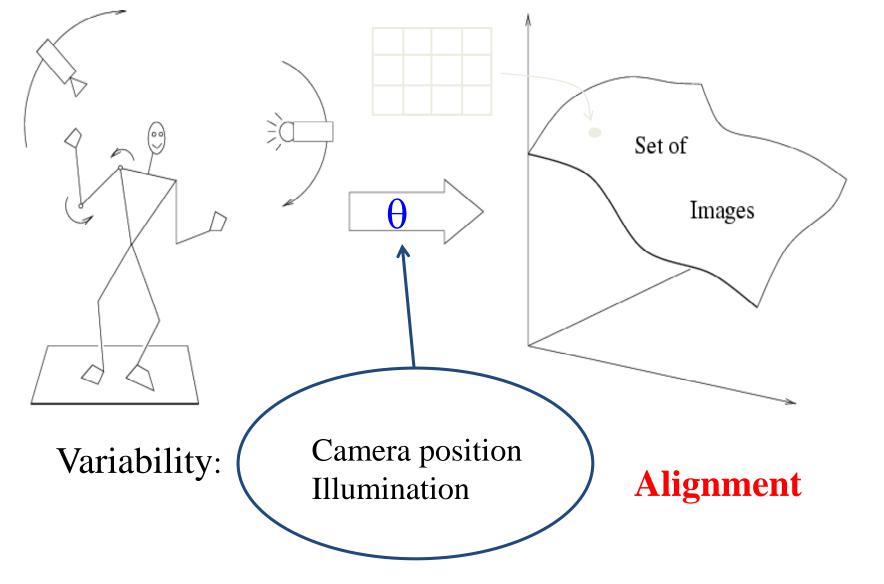






History of ideas in recognition

1960s – early 1990s: the geometric era



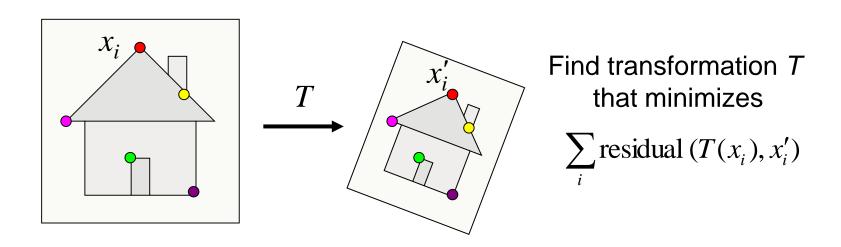
Shape: assumed known

Roberts (1965); Lowe (1987); Faugeras & Hebert (1986); Grimson & Lozano-Perez (1986); Huttenlocher & Ullman (1987)

Svetlana Lazebnik

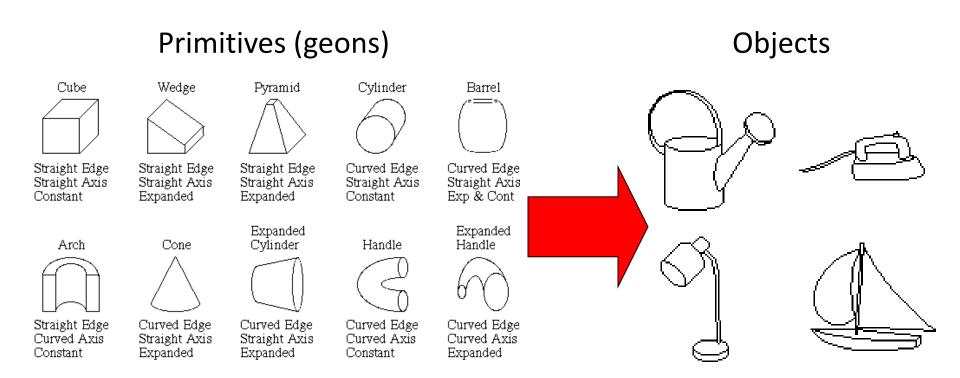
Instance Recognition

 Alignment: fitting a model to a transformation between pairs of features (matches) in two images



Recognition by components

Biederman (1987)

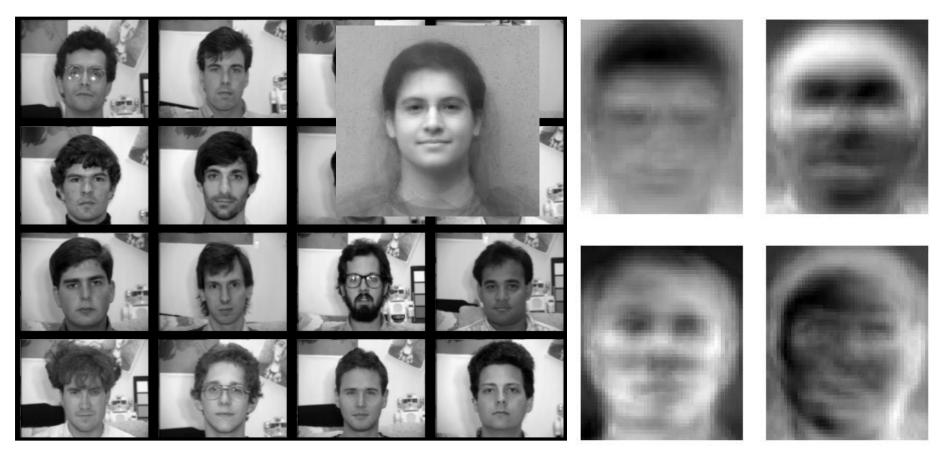


http://en.wikipedia.org/wiki/Recognition_by_Components_Theory

History of ideas in recognition

- 1960s early 1990s: the geometric era
- 1990s: appearance-based models

Eigenfaces (Turk & Pentland, 1991)



Experimental	Correct/Unknown Recognition Percentage		
Condition	Lighting	Orientation	Scale
Forced classification	96/0	85/0	64/0
Forced 100% accuracy	100/19	100/39	100/60
Forced 20% unknown rate	100/20	94/20	74/20

Limitations of global appearance models

- Requires global registration of patterns
- Not robust to clutter, occlusion, geometric transformations



- 1960s early 1990s: the geometric era
- 1990s: appearance-based models
- 1990s present: sliding window approaches

Sliding window approaches



Sliding window approaches



- Turk and Pentland, 1991
- Belhumeur, Hespanha, & Kriegman, 1997
- Schneiderman & Kanade 2004
- Viola and Jones, 2000



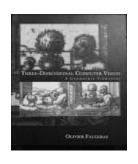
- Schneiderman & Kanade, 2004
- Agrawal and Roth, 2002
- Poggio et al. 1993

- 1960s early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features

Local features for object instance recognition













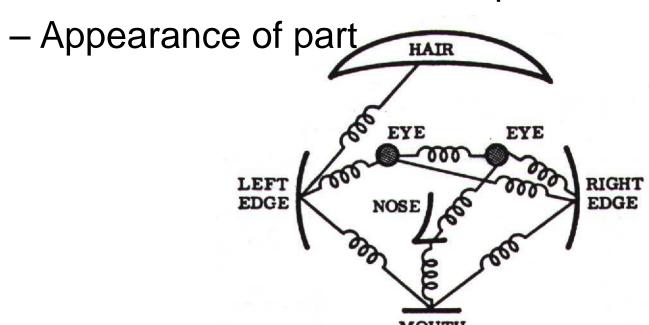




- 1960s early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models

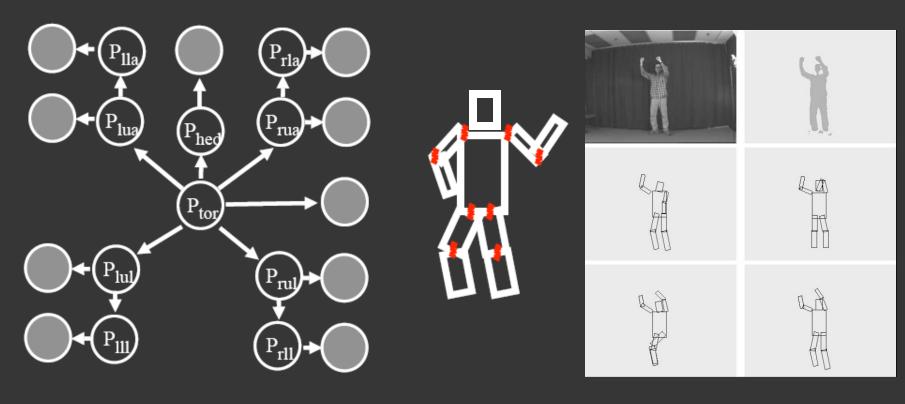
Parts-and-shape models

- Model:
 - Object as a set of parts
 - Relative locations between parts



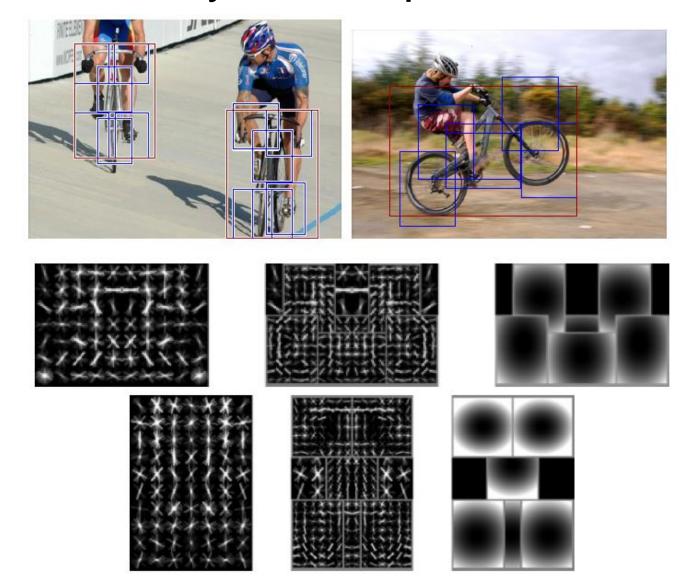
Pictorial structure model

Fischler and Elschlager(73), Felzenszwalb and Huttenlocher(00)



$$\Pr(P_{\text{tor}}, P_{\text{arm}}, \dots | \text{Im}) \stackrel{\alpha}{=} \prod_{i,j} \Pr(P_i | P_j) \prod_i \Pr(\text{Im}(P_i))$$
part geometry part appearance

Discriminatively trained part-based models



P. Felzenszwalb, R. Girshick, D. McAllester, D. Ramanan, "Object Detection with Discriminatively Trained Part-Based Models," PAMI 2009

- 1960s early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models
- Mid-2000s: bags of features

Bag-of-features models







Bag-of-features models

Object

Bag of 'words'





- 1960s early 1990s: the geometric era
- 1990s: appearance-based models
- Mid-1990s: sliding window approaches
- Late 1990s: local features
- Early 2000s: parts-and-shape models
- Mid-2000s: bags of features
- Present trends: data-driven methods, deep learning