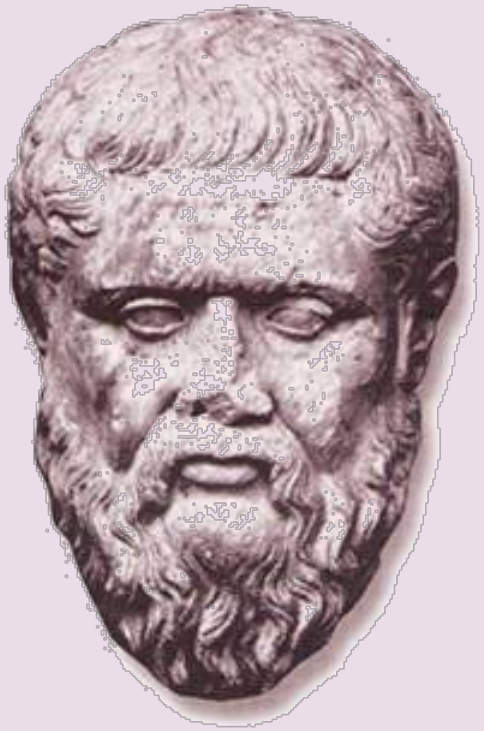
Recognizing and Learning Object Categories: Year 2007

Li Fei-Fei, Princeton

Rob Fergus, MIT

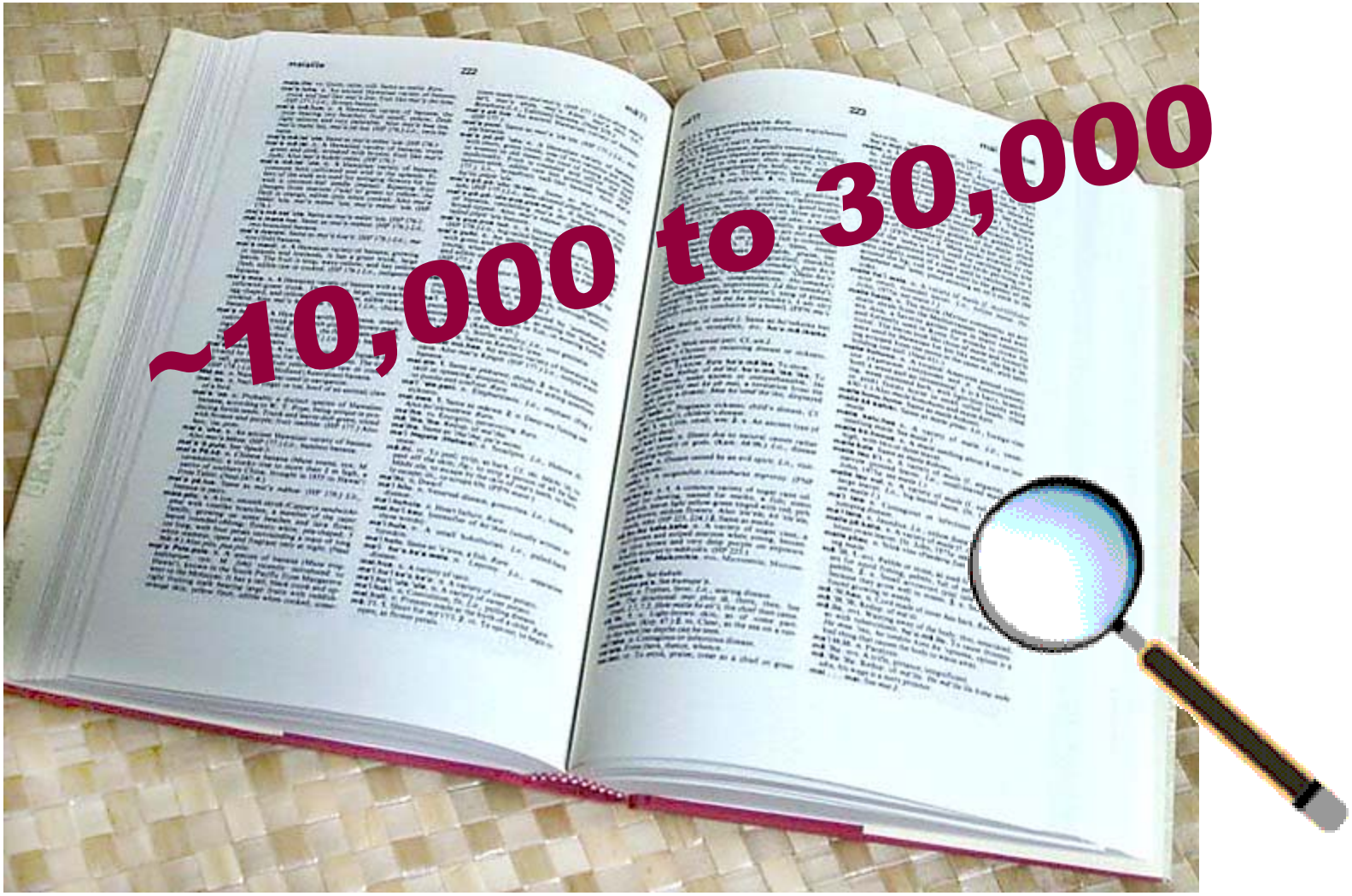
Antonio Torralba, MIT

Plato said…



- Ordinary objects are classified together if they `participate' in the same abstract Form, such as the Form of a Human or the Form of Quartz.
- Forms are proper subjects of philosophical investigation, for they have the highest degree of reality.
- Ordinary objects, such as humans, trees, and stones, have a lower degree of reality than the Forms.
- Fictions, shadows, and the like have a still lower degree of reality than ordinary objects and so are not proper subjects of philosophical enquiry.

How many object categories are there?



Biederman 1987

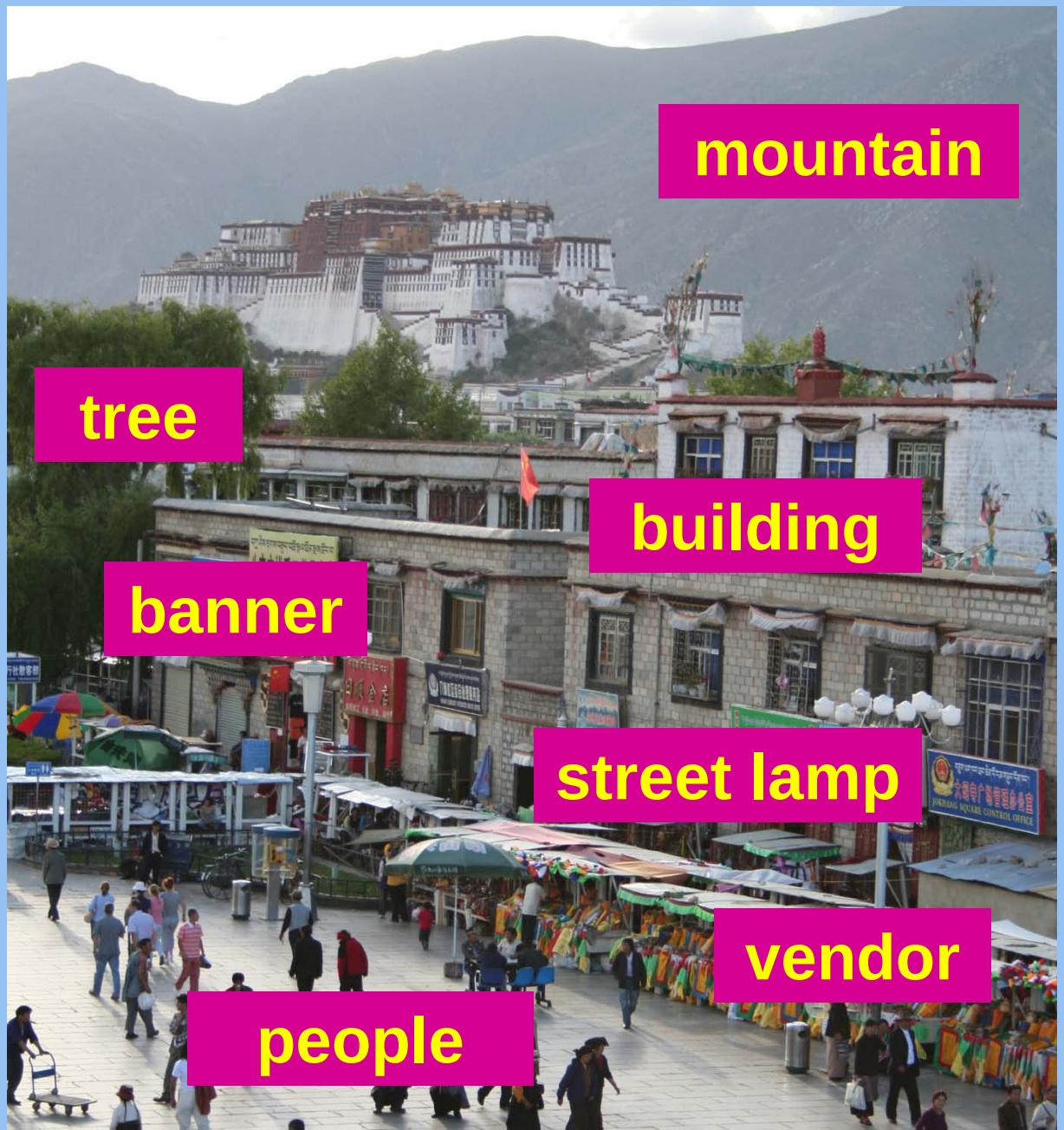
So what does object recognition involve?

Verification: is that a lamp?

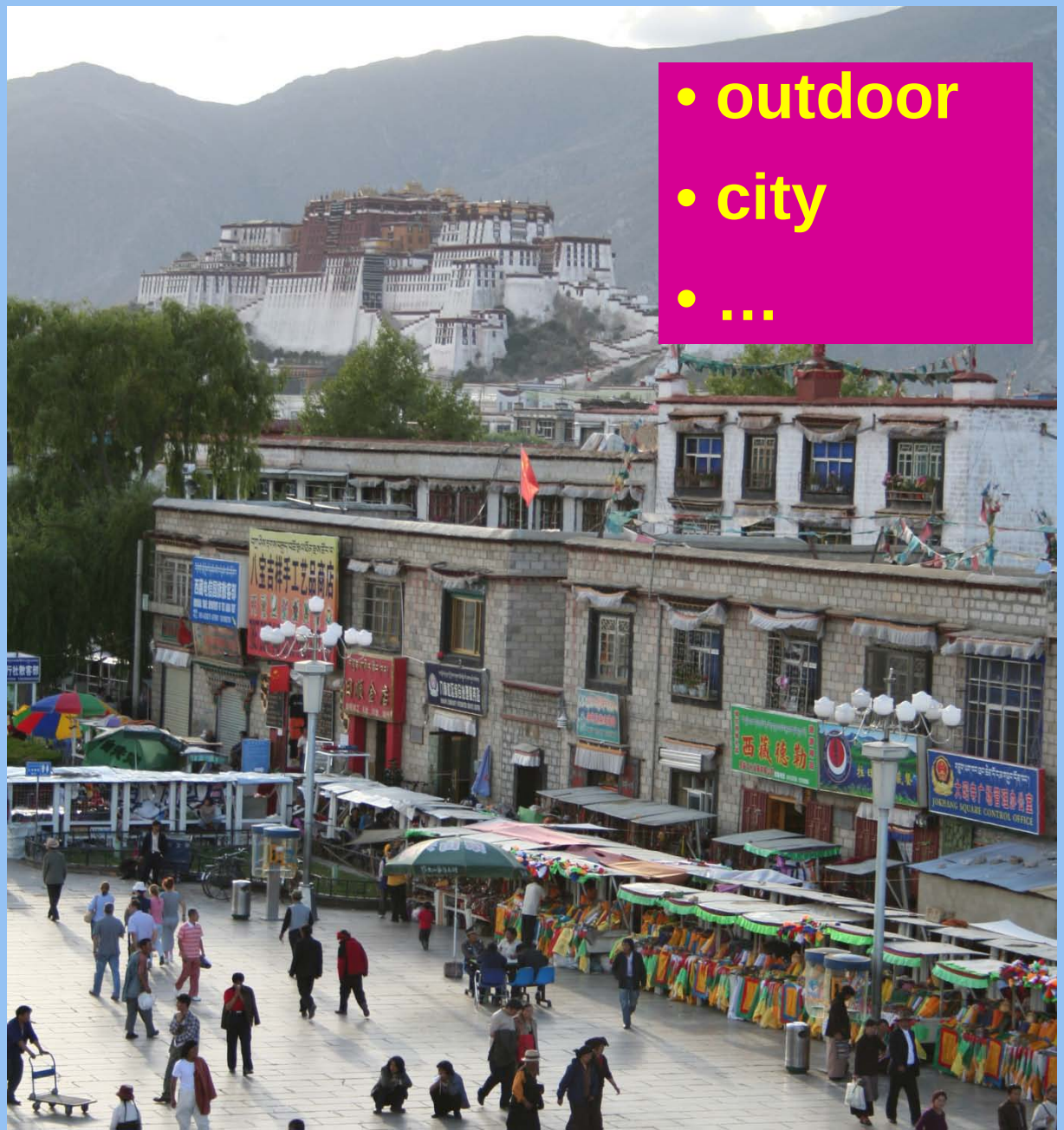
Detection: are there people?

Identification: is that Potala Palace?

Object categorization



Scene and context categorization

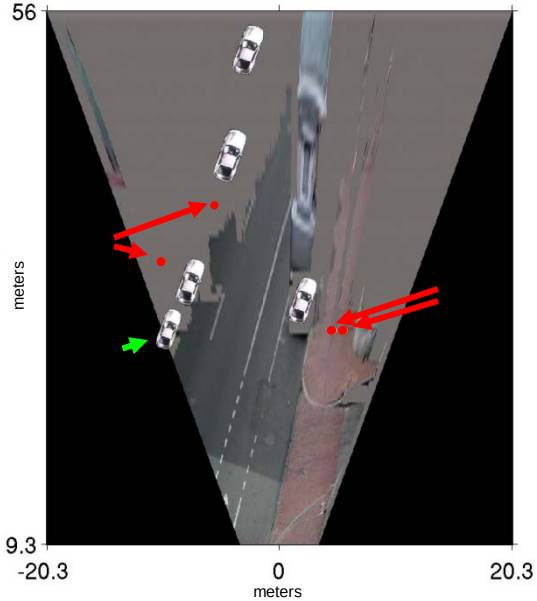


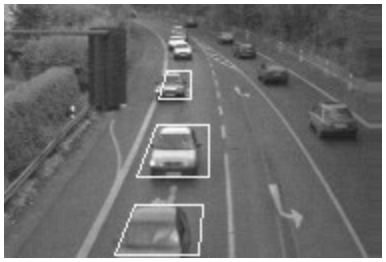
Computational photography

[Face priority AE] When a bright part of the face is too bright

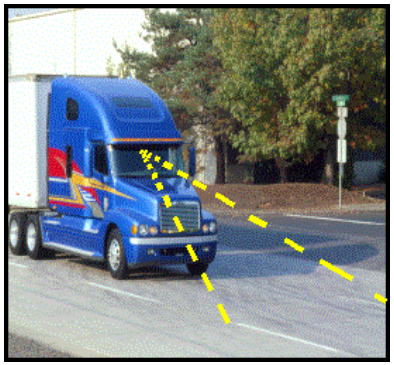
Assisted driving

Pedestrian and car detection





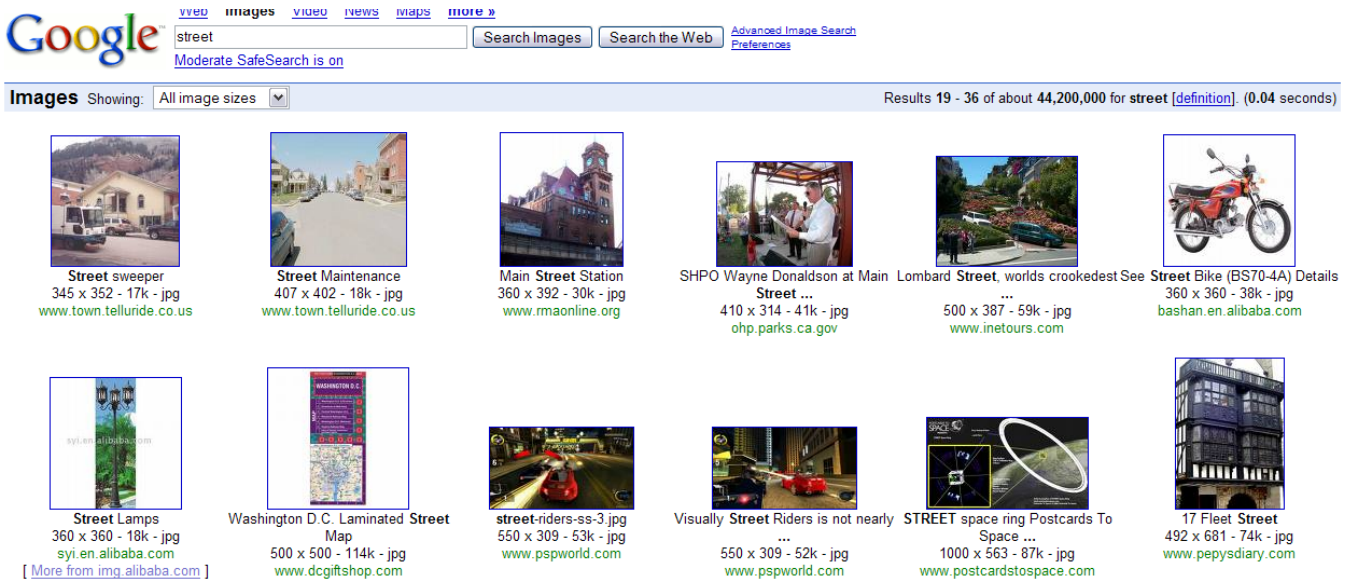
Lane detection



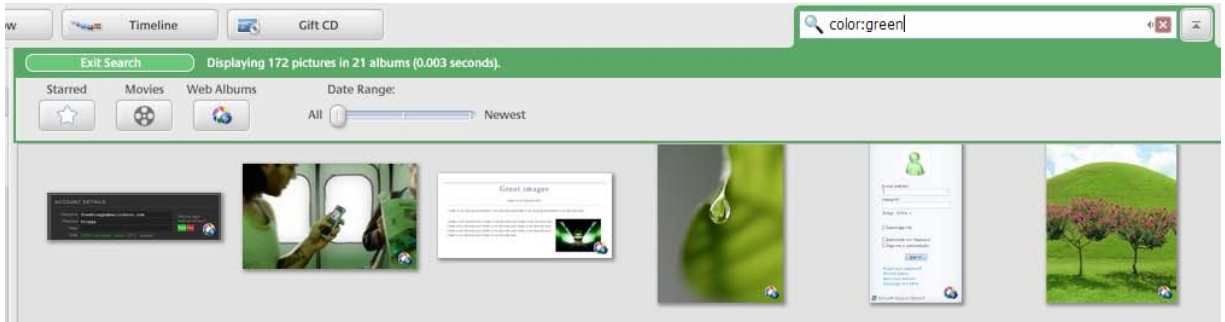
- Collision warning systems with adaptive cruise control,
- Lane departure warning systems,
- Rear object detection systems,

Improving online search

Query:
STREET



Organizing photo collections



Challenges 1: view point variation

Michelangelo 1475-1564

Challenges 2: illumination

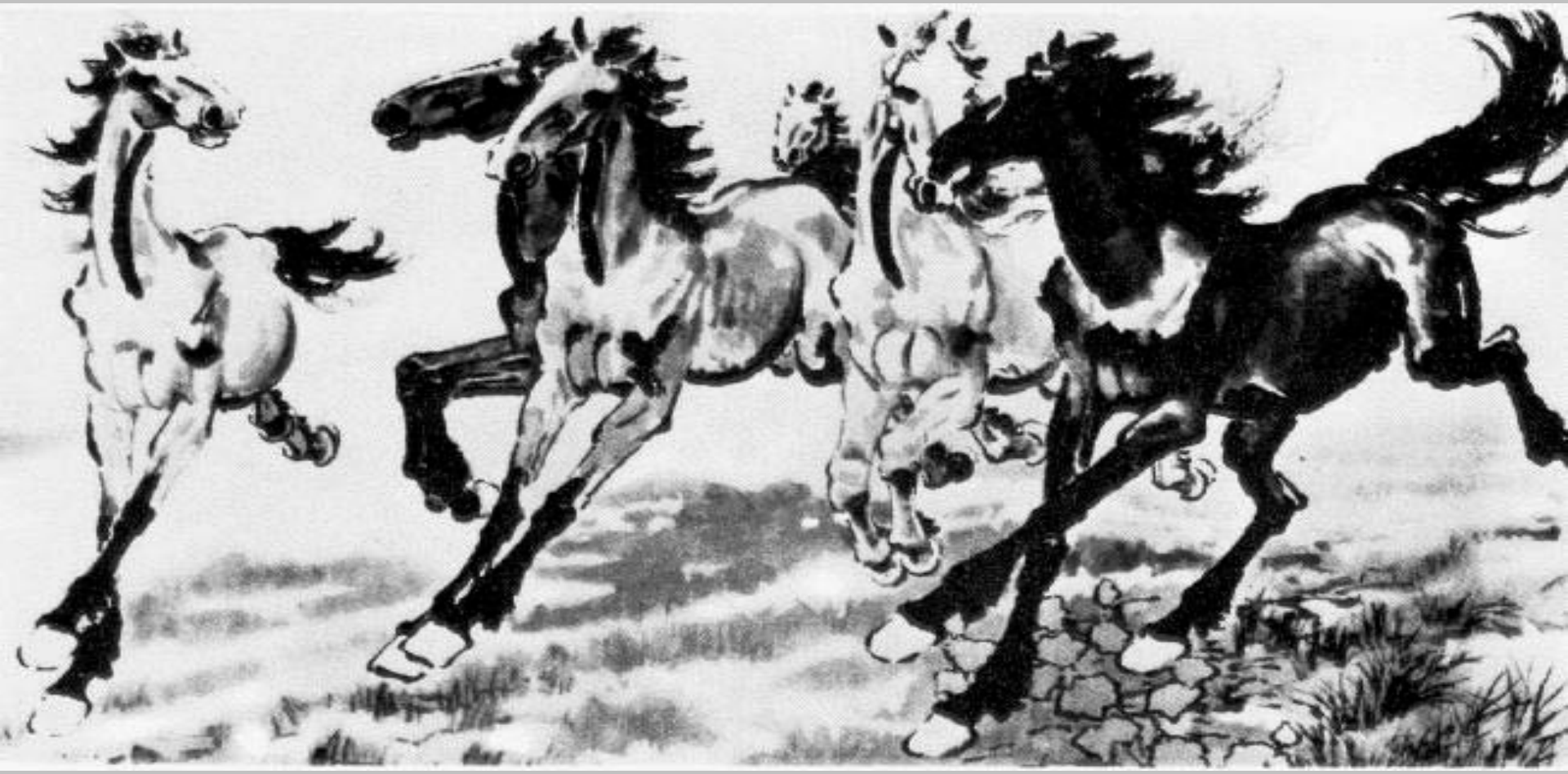
slide credit: S. Ullman

Challenges 3: occlusion

Magritte, 1957

Challenges 4: scale

Challenges 5: deformation



Xu, Beihong 1943

Challenges 6: background clutter

Klimt, 1913

Challenges 7: intra-class variation






History: early object categorization

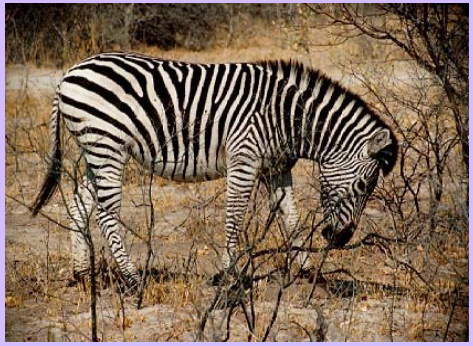
- Turk and Pentland, 1991
- Belhumeur, Hespanha, & Kriegman, 1997
- Schneiderman & Kanade 2004
- Viola and Jones, 2000

- Amit and Geman, 1999
- LeCun et al. 1998
- Belongie and Malik, 2002

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


~10,000 to 30,000

Object categorization: the statistical viewpoint



$$p(zebra \mid image)$$

vs.

$$p(no\ zebra \mid image)$$

- Bayes rule:

$$\underbrace{\frac{p(zebra \mid image)}{p(no\ zebra \mid image)}}_{\text{posterior ratio}} = \underbrace{\frac{p(image \mid zebra)}{p(image \mid no\ zebra)}}_{\text{likelihood ratio}} \cdot \underbrace{\frac{p(zebra)}{p(no\ zebra)}}_{\text{prior ratio}}$$

Object categorization: the statistical viewpoint

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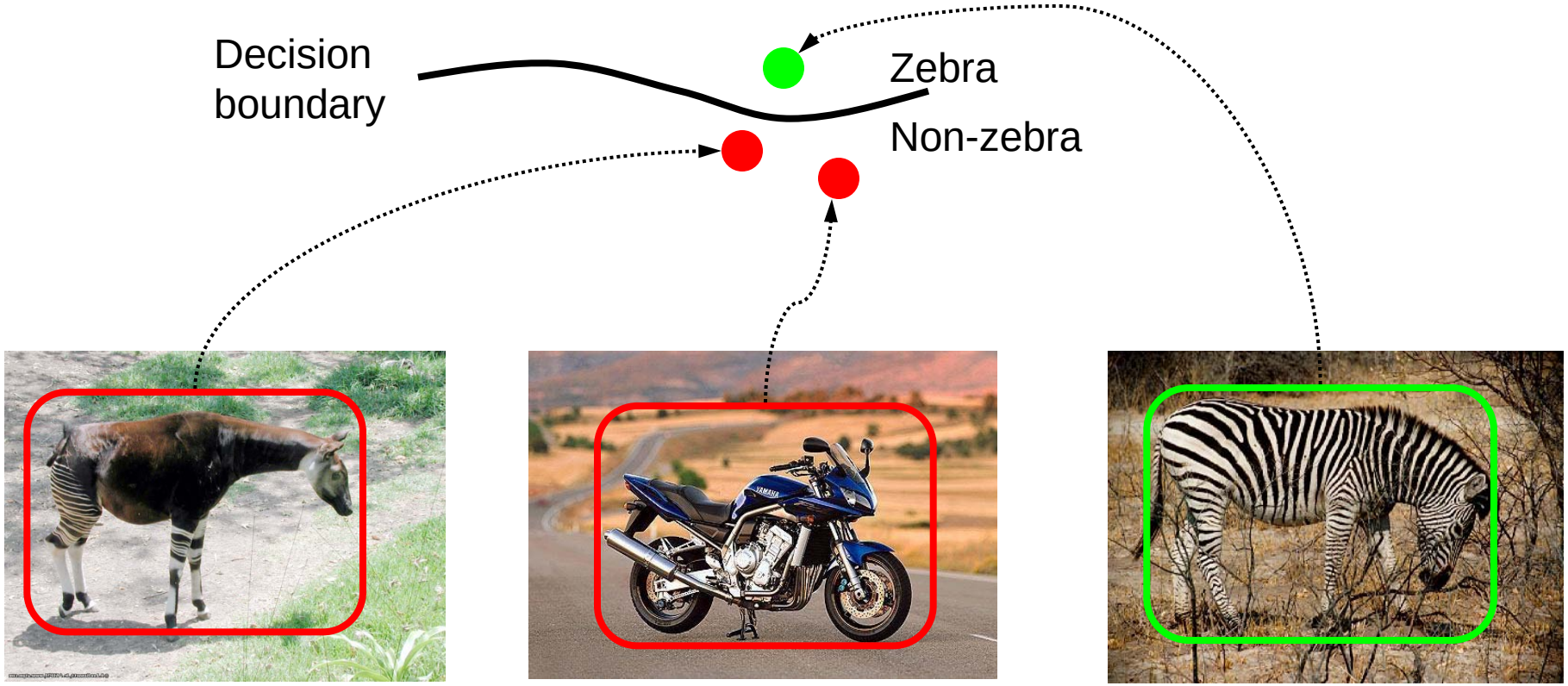
- **Discriminative methods model posterior**
- **Generative methods model likelihood and prior**

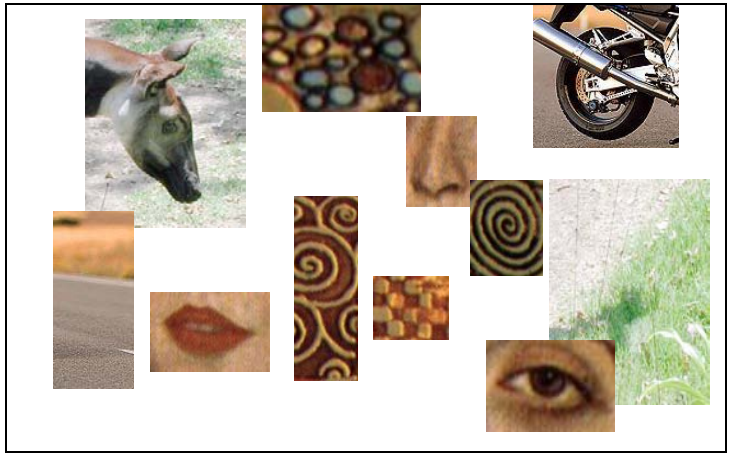
Discriminative

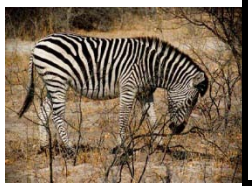
- Direct modeling of $\dfrac{p(zebra \mid image)}{p(no\ zebra \mid image)}$



Generative

- Model $p(image \mid zebra)$ and $p(image \mid no\ zebra)$





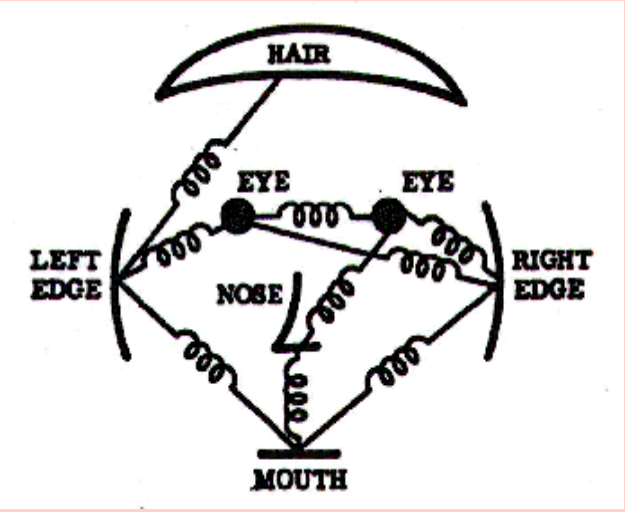
$p(image \mid zebra)$	$p(image \mid no\ zebra)$
Low	Middle
High	Middle→Low

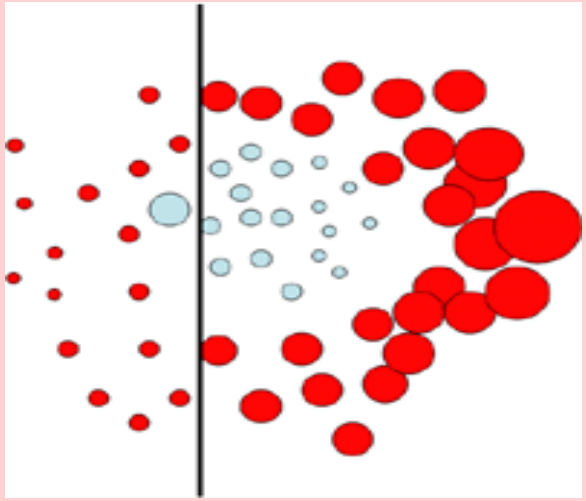
Three main issues

- Representation
  - How to represent an object category
- Learning
  - How to form the classifier, given training data
- Recognition
  - How the classifier is to be used on novel data

Representation

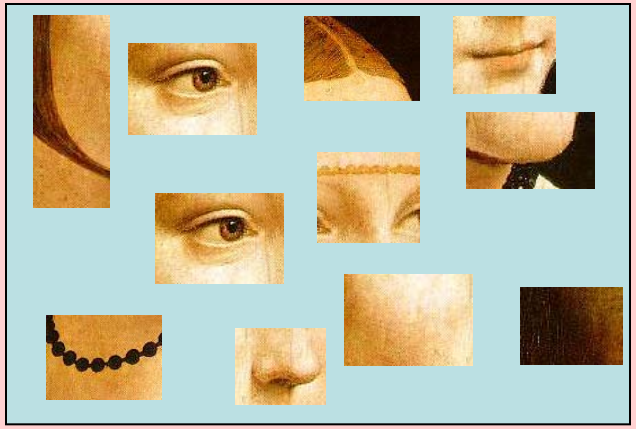
– Generative / discriminative / hybrid

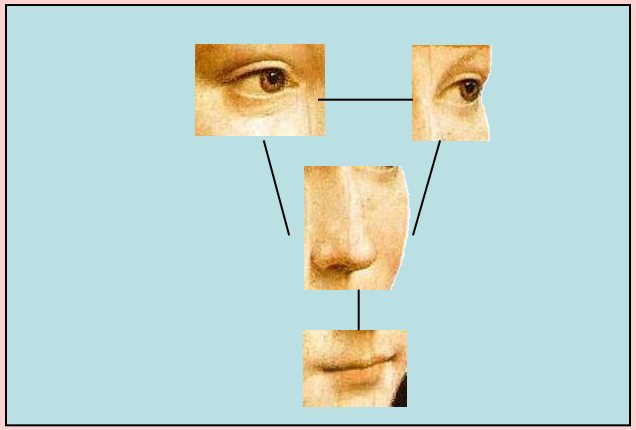




Representation

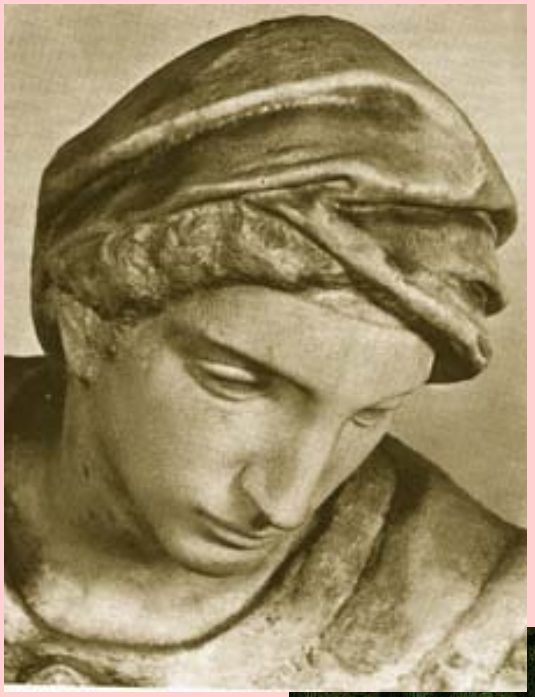
- Generative / discriminative / hybrid
- Appearance only or location and appearance

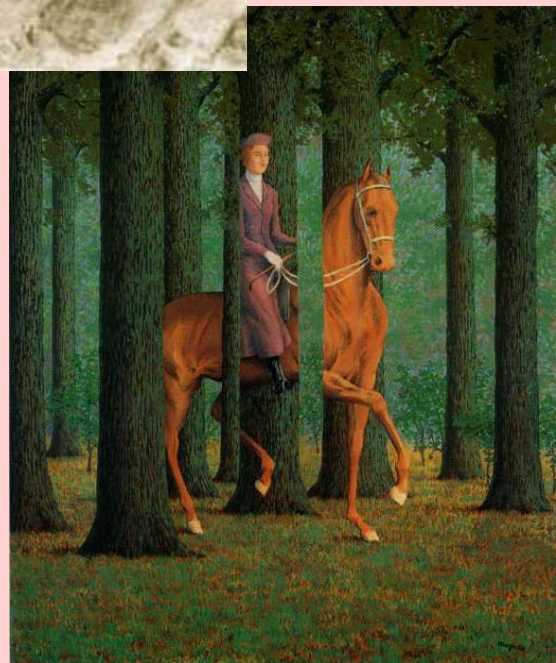




Representation

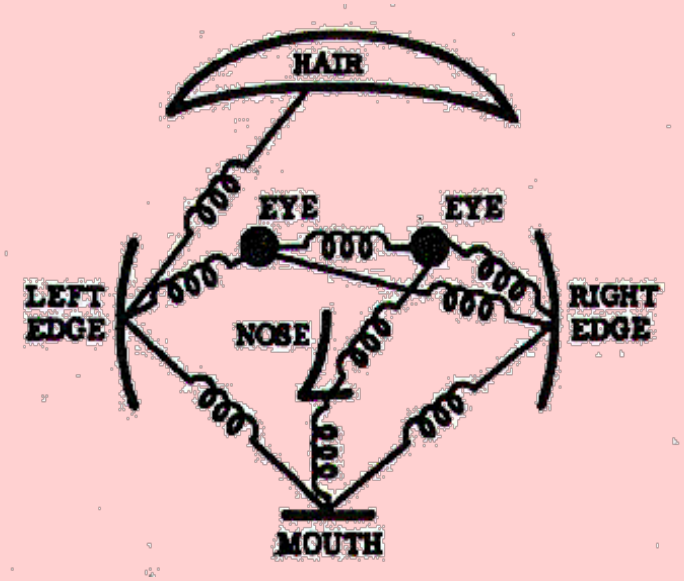
- Generative / discriminative / hybrid
- Appearance only or location and appearance
- Invariances
  - View point
  - Illumination
  - Occlusion
  - Scale
  - Deformation
  - Clutter
  - etc.





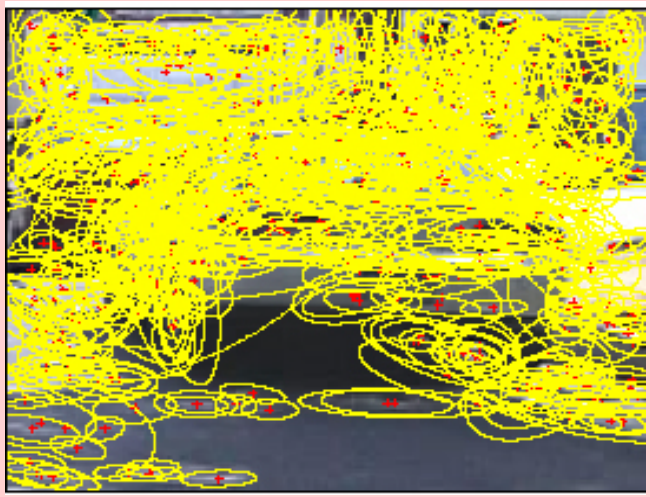
Representation

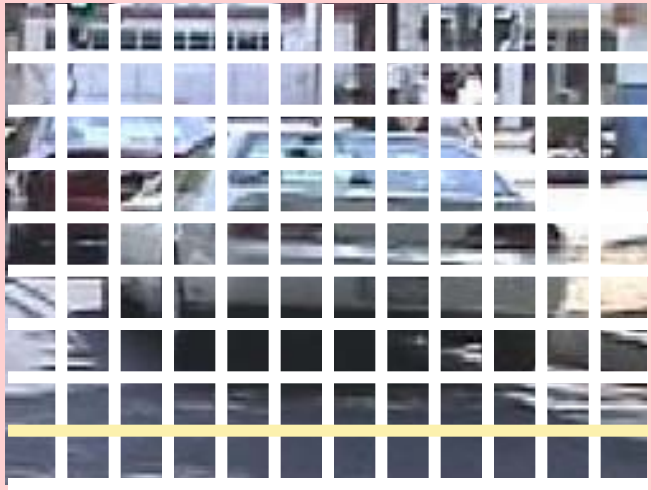
- Generative / discriminative / hybrid
- Appearance only or location and appearance
- invariances
- Part-based or global w/sub-window



Representation

- Generative / discriminative / hybrid
- Appearance only or location and appearance
- invariances
- Parts or global w/sub-window
- Use set of features or each pixel in image





Learning

– Unclear how to model categories, so we learn what distinguishes them rather than manually specify the difference -- hence current interest in machine learning

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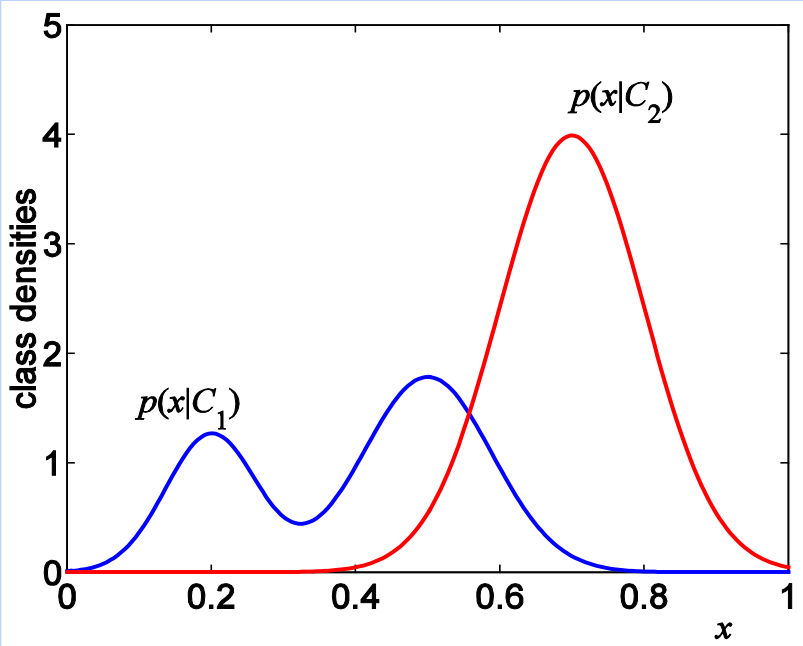
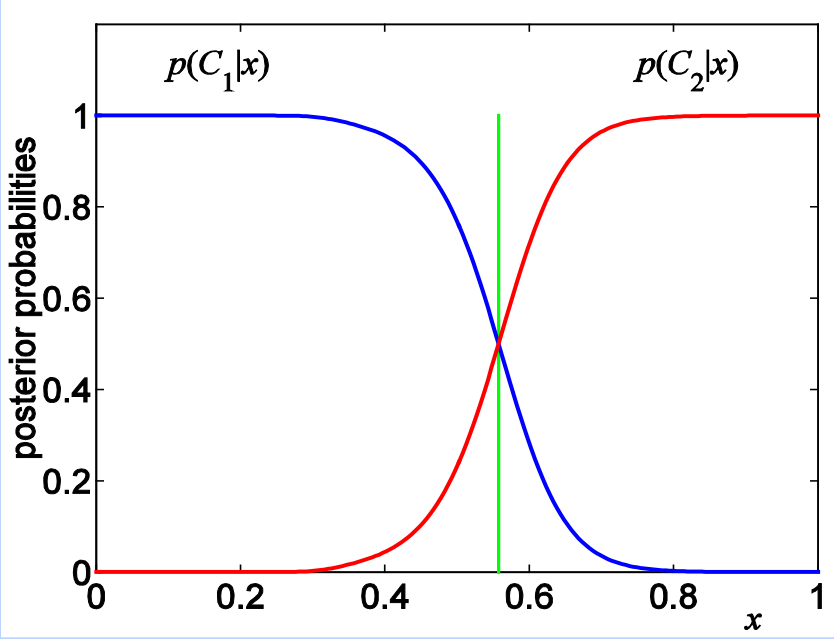
- Methods of training: generative vs. discriminative





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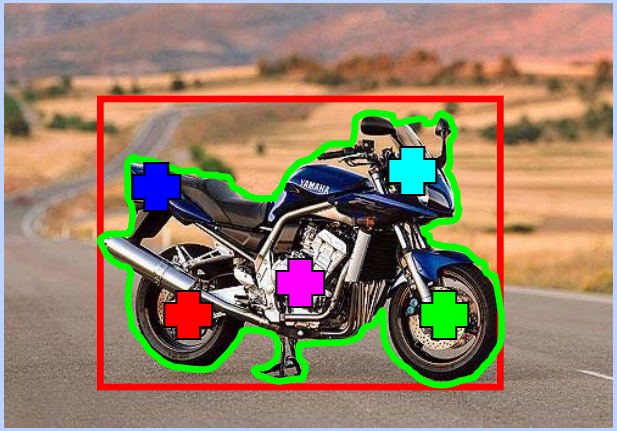
- What are you maximizing? Likelihood (Gen.) or performances on train/validation set (Disc.)
- Level of supervision
  - Manual segmentation; bounding box; image labels; noisy labels

Contains a motorbike



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  - Issue of overfitting
  - Negative images for discriminative methods Priors

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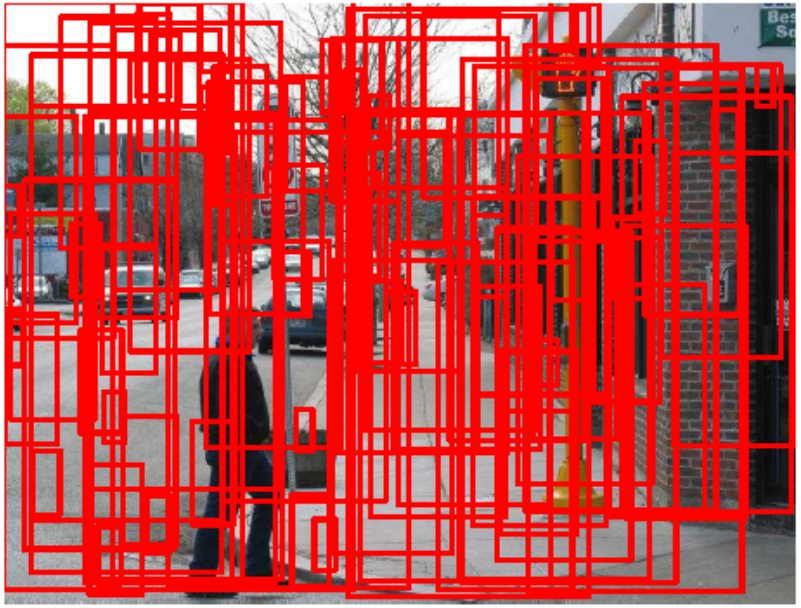
Recognition

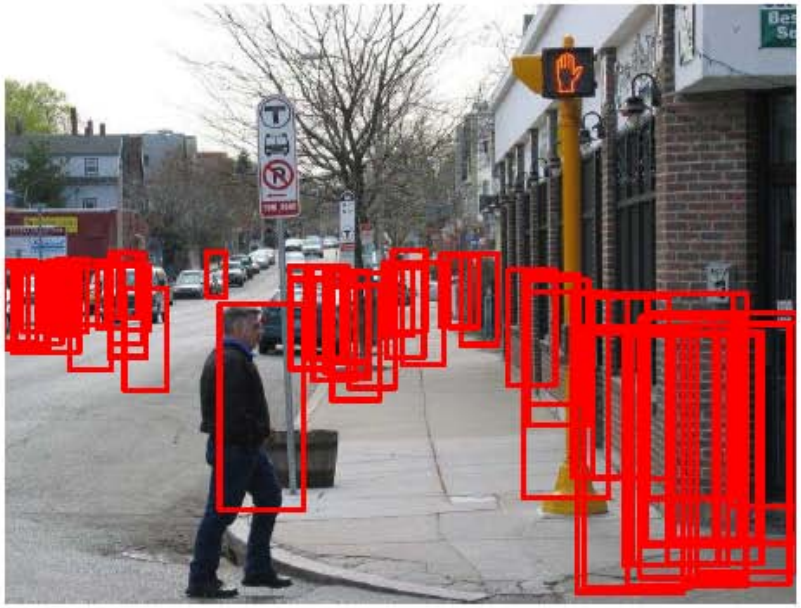
- Scale / orientation range to search over
- Speed
- Context



(b) P(person) = uniform

(d) P(person | geometry)

(f) P(person | viewpoint)



(g) P(person|viewpoint,geometry)

Hoiem, Efros, Herbert, 2006