WST665/CS770A: Web-Scale Image Retrieval

Intro to Object Recognition

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(윤성의)

Course URL:
http://sglab.kaist.ac.kr/~sungeui/IR

What we will learn today?

- Introduction to object recognition
  - Representation
  - Learning
  - Recognition

What are the different visual recognition tasks?

Classification:

Does this image contain a building? [yes/no]

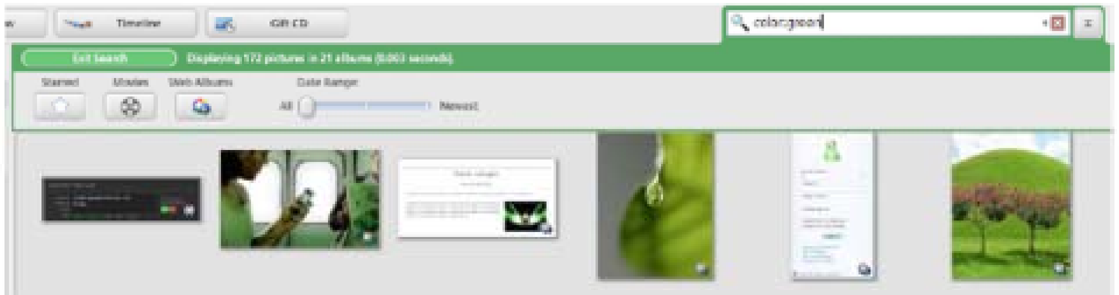
Classification:

Is this an beach?

Image Search

flickr webshots Ask Images Cydral picsearch Google Image Search altavista

Organizing photo collections



Detection:

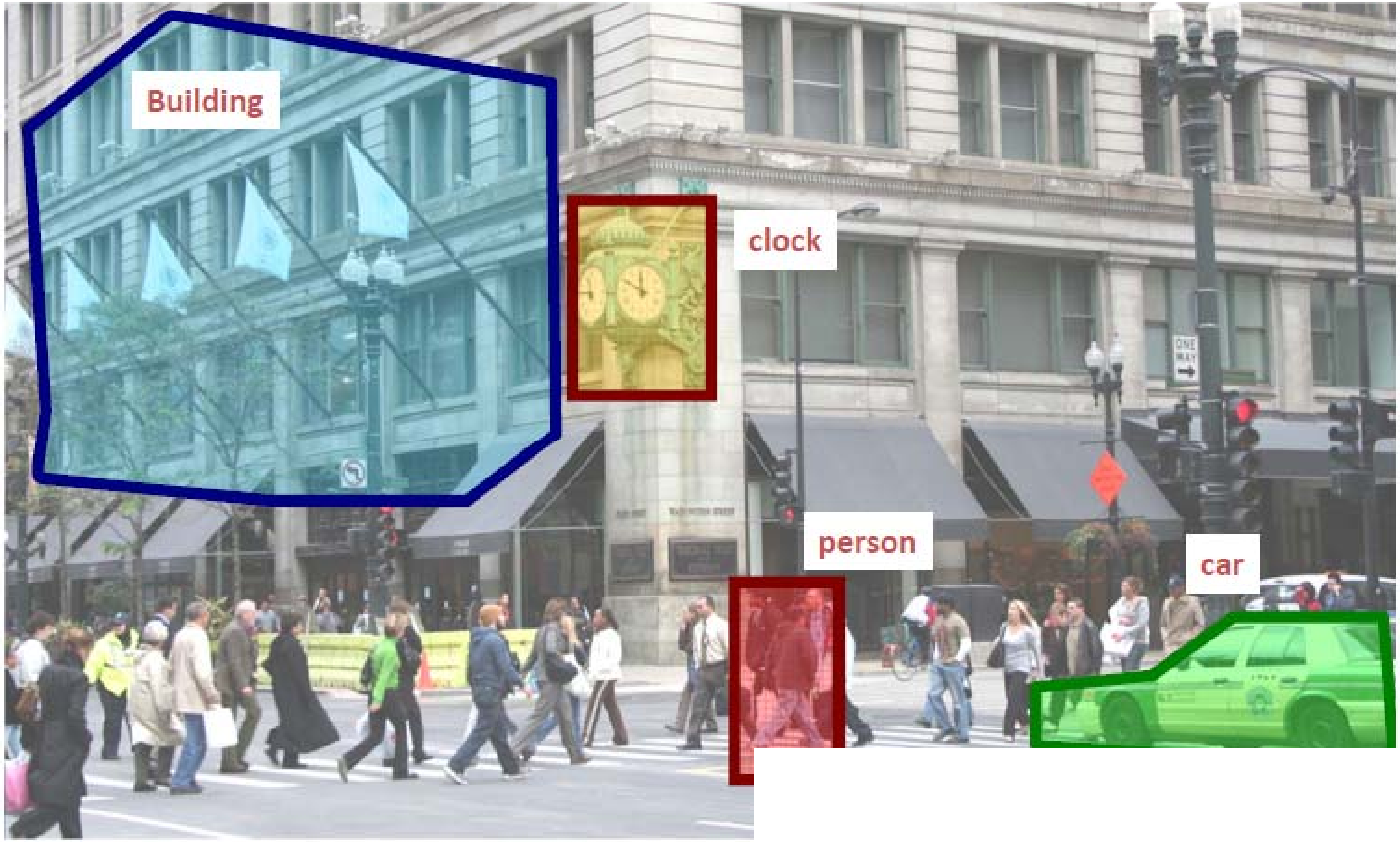
Does this image contain a car? [where?]

Detection:

Does this image contain a car? [where?]

Detection:

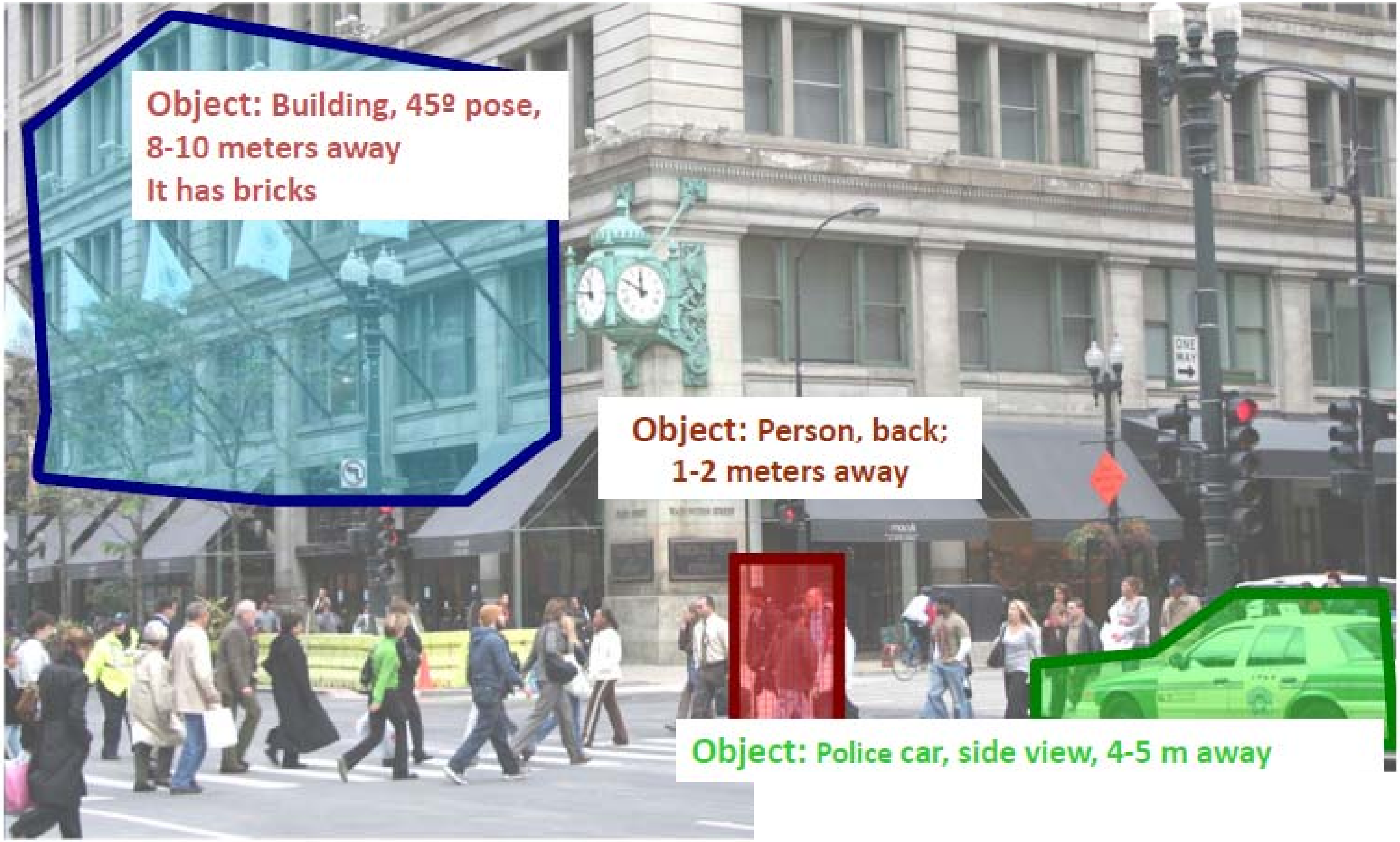
Which object does this image contain? [where?]



Detection:

Accurate localization (segmentation)

Detection: Estimating object semantic & geometric attributes



Applications of Object Recognitions and Image Retrieval

Computational photography

Assistive technologies

Surveillance

Security

Assistive driving

Fei-Fei Li

Categorization vs Single instance recognition

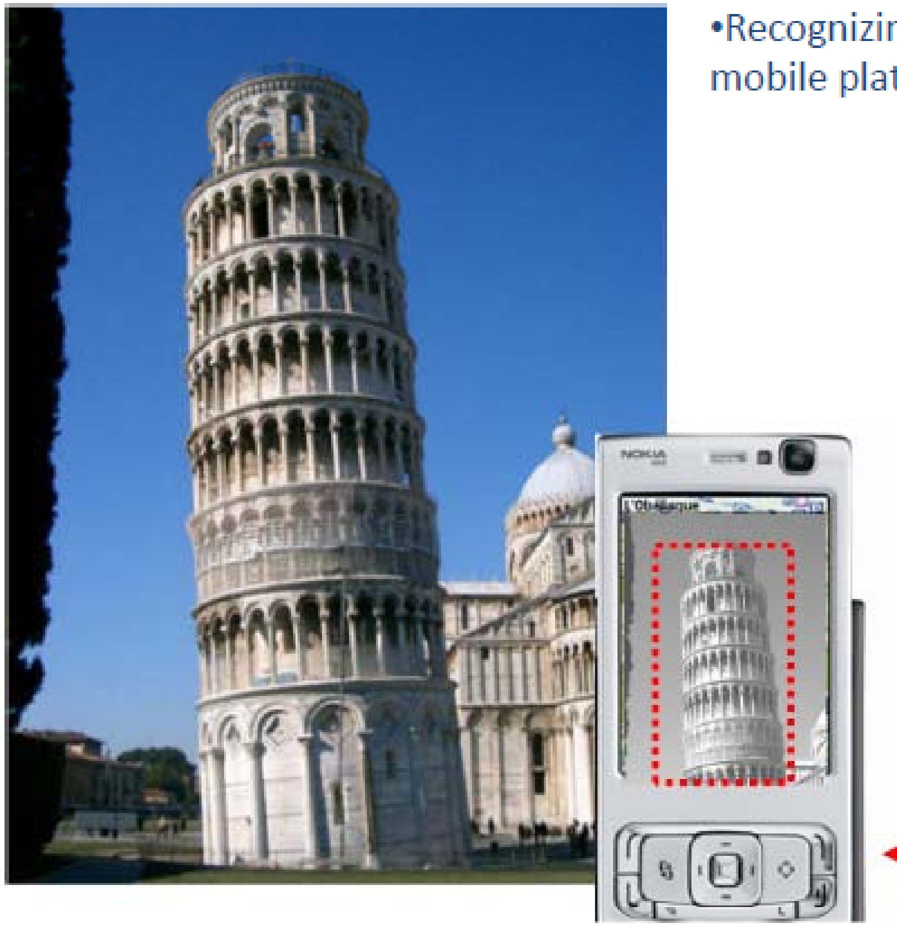
Does this image contain the Chicago Macy building's?

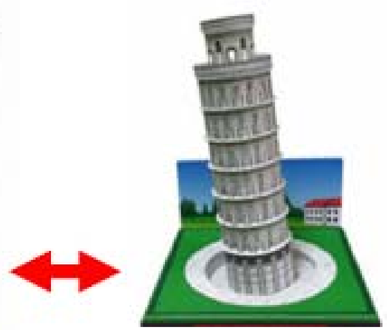
Categorization vs Single instance recognition

Where is the crunchy nut?

Applications of Object Recognitions and Image Retrieval

- Recognizing landmarks in mobile platforms





+ GPS

Activity or Event recognition

What are these people doing?

Visual Recognition

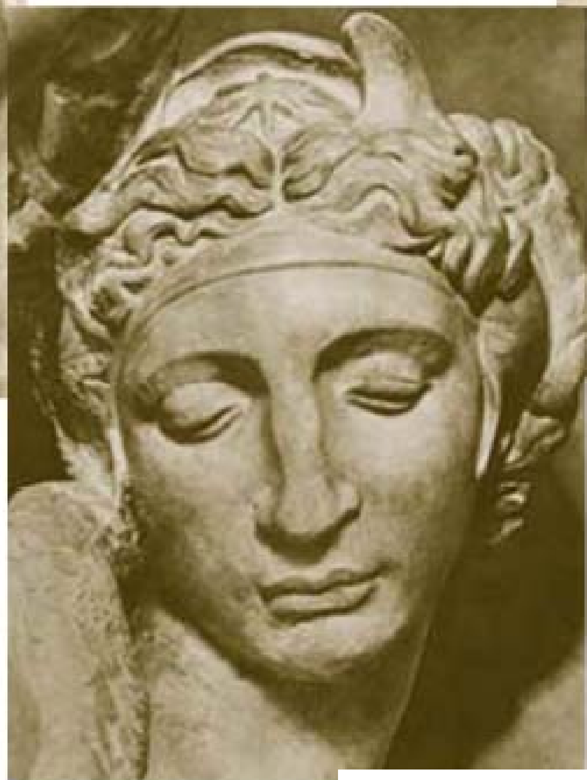
- Design algorithms that are capable to
  - Classify images or videos
  - Detect and localize objects
  - Estimate semantic and geometrical attributes
  - Classify human activities and events

Why is this challenging?

How many object categories are there?

~10,000 to 30,000

Challenges: viewpoint variation



Michelangelo 1475-1564

Challenges: illumination

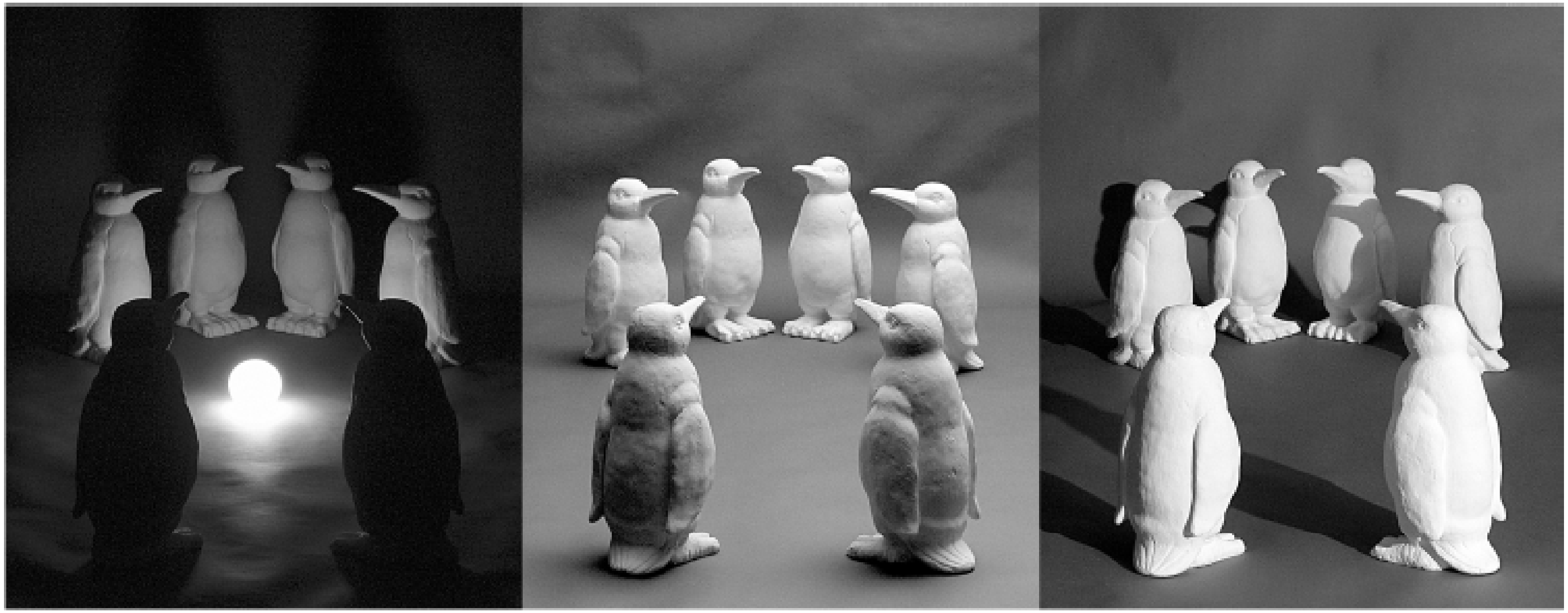


image credit: J. Koenderink

Challenges: scale

Challenges: deformation

Challenges: occlusion

Magritte, 1957

Challenges: background clutter

Kilmeny Niland. 1995

Challenges: intra-class variation






Basic issues

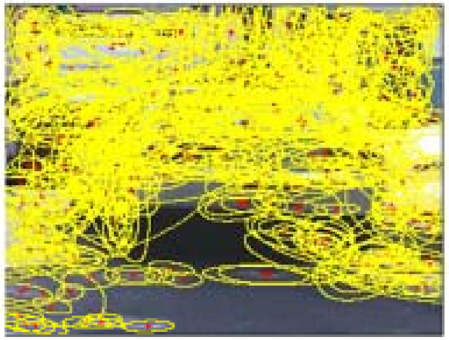
- Representation
  - How to represent an object category; which classification scheme?

- Learning
  - How to learn the classifier, given training data

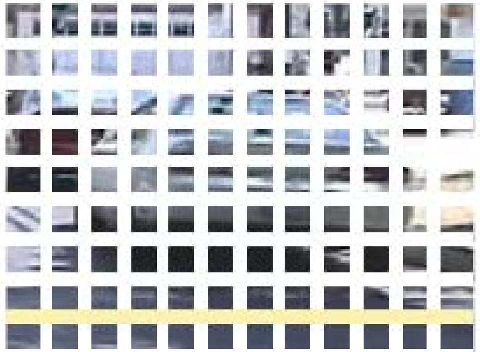
- Recognition
  - How the classifier is to be used on novel data

Representation

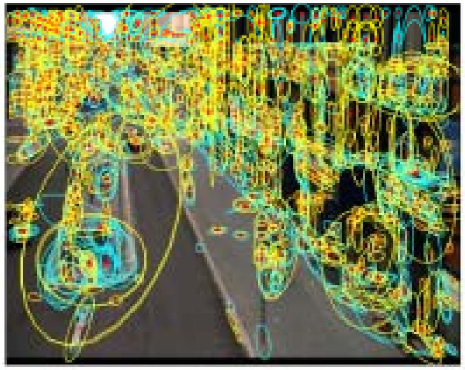
- Building blocks: Sampling strategies



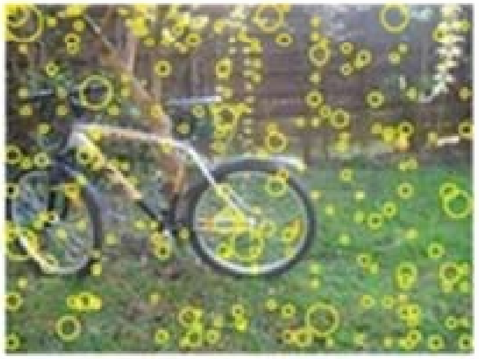
Interest operators



Dense, uniformly



Multiple interest operators

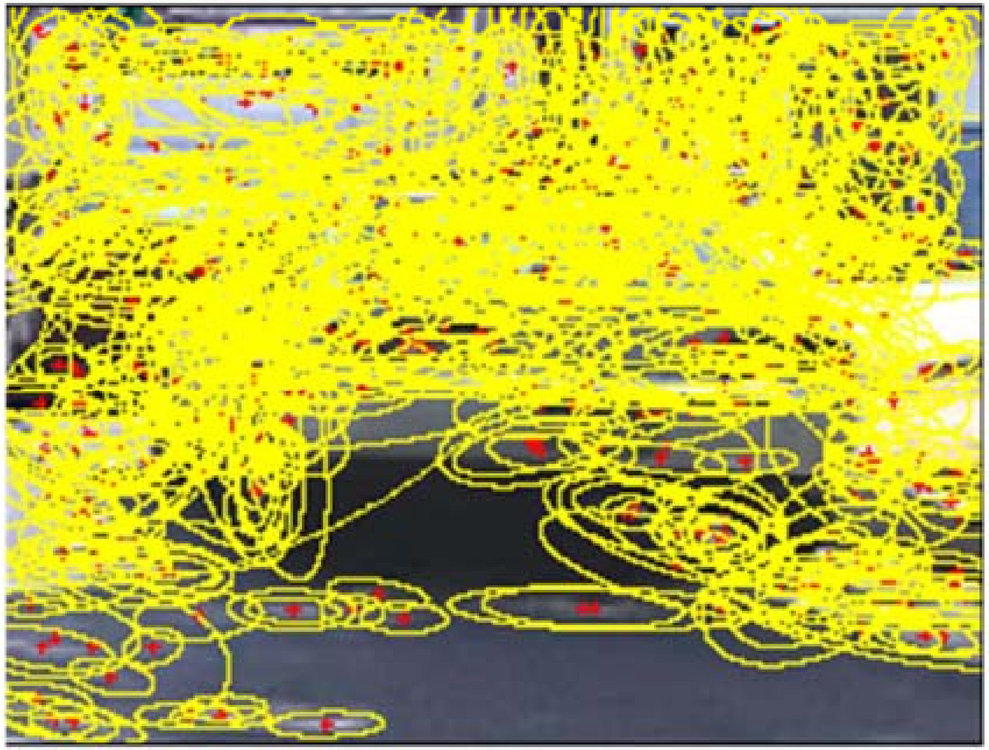


Randomly

Image credits: L. Fei-Fei, E. Nowak, J. Sivic

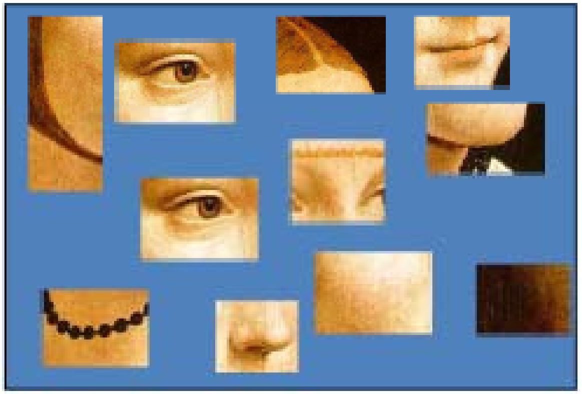
Representation

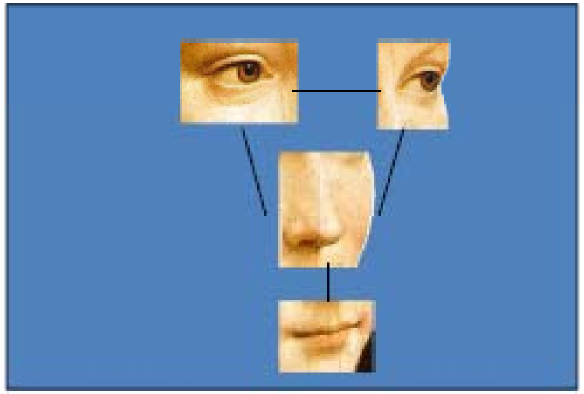
- Building blocks: Choice of descriptors
  [SIFT, HOG, codewords....]

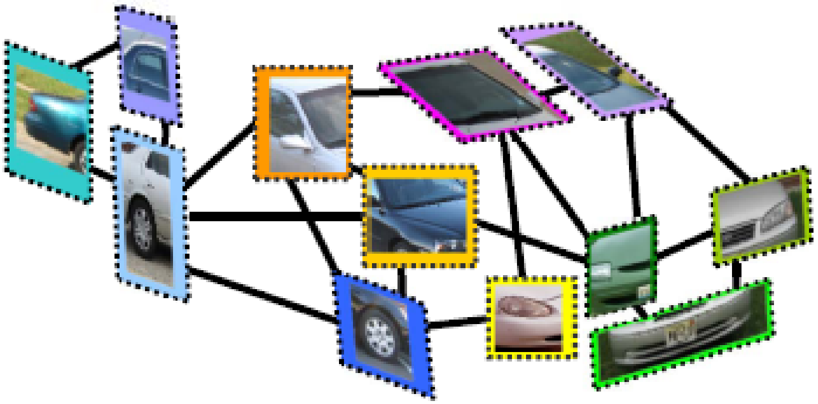


Representation

– Appearance only or location and appearance

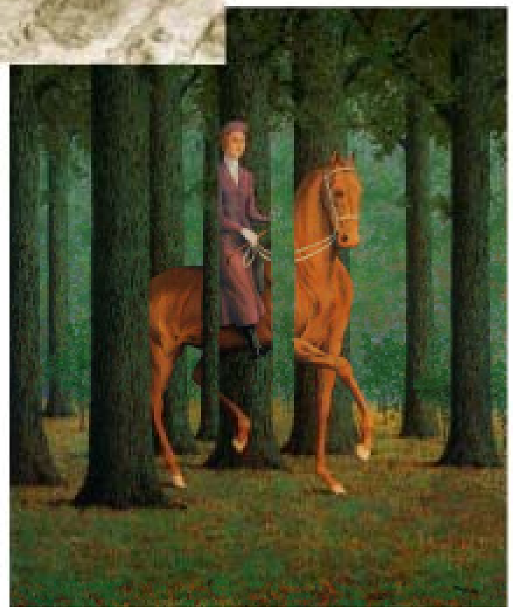






Representation

- Invariances
  - View point
  - Illumination
  - Occlusion
  - Scale
  - Deformation
  - Clutter
  - etc.



Representation

- To handle intra-class variability, it is convenient to describe an object categories using probabilistic models
- Object models: Generative vs Discriminative vs hybrid

Object categorization: the statistical viewpoint

$$p(zebra \mid image)$$

vs.

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

- Bayes rule: $P(A|B) = \dfrac{P(B|A)\,P(A)}{P(B)}$

$$\frac{p(zebra \mid image)}{p(no\ zebra \mid image)}$$

Object categorization: the statistical viewpoint

$$p(zebra \mid image)$$

vs.

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

- Bayes rule: $P(A|B) = \dfrac{P(B|A)\,P(A)}{P(B)}$.

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

Object categorization: the statistical viewpoint

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

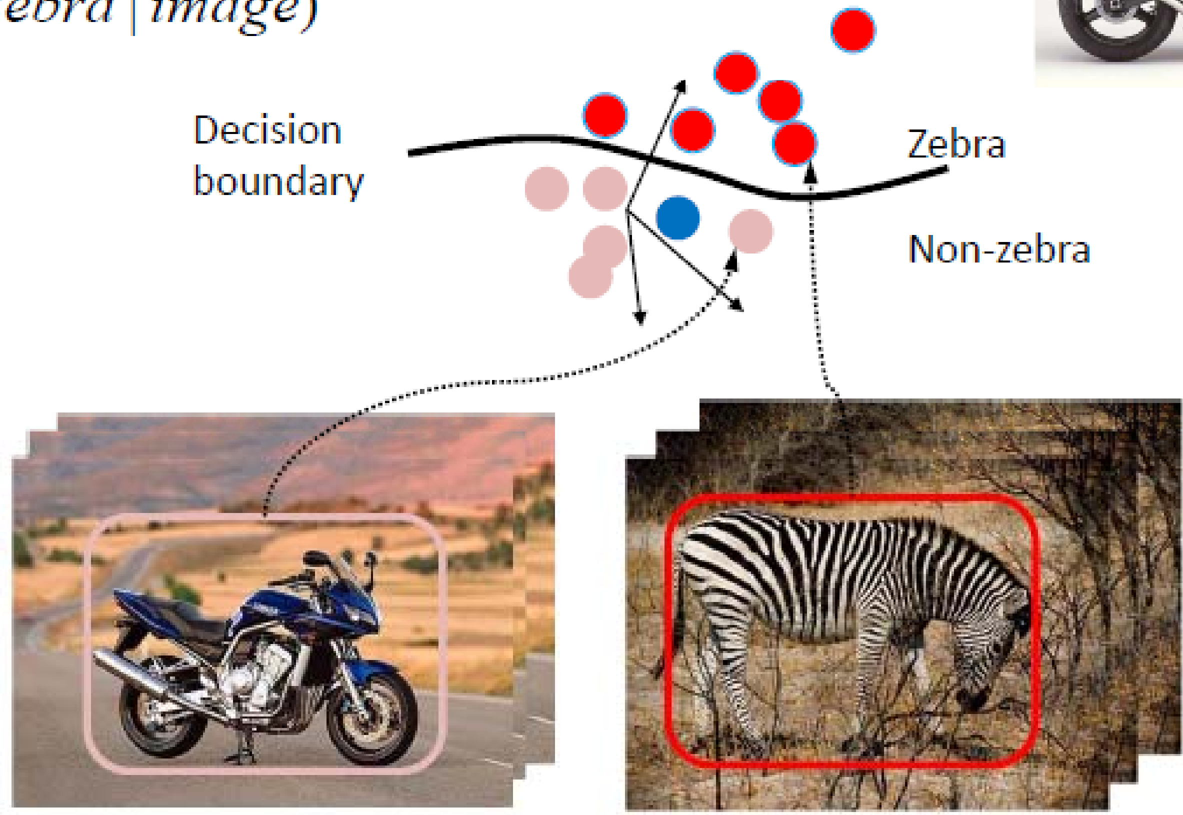
- Bayes rule:

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

Discriminative models

- Modeling the posterior ratio:

$$\frac{p(zebra \mid image)}{p(no\ zebra \mid image)}$$

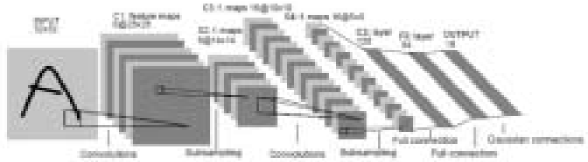


Discriminative models

Nearest neighbor

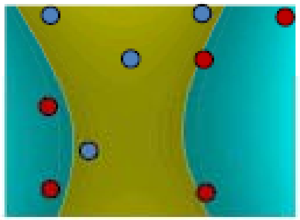
Shakhnarovich, Viola, Darrell 2003
Berg, Berg, Malik 2005...

Neural networks



LeCun, Bottou, Bengio, Haffner 1998
Rowley, Baluja, Kanade 1998
...

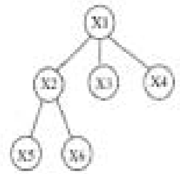
Support Vector Machines



Guyon, Vapnik, Heisele, Serre, Poggio...

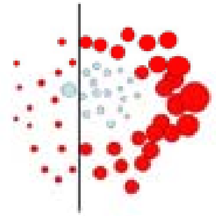
Latent SVM

Structural SVM



Felzenszwalb 00
Ramanan 03...

Boosting



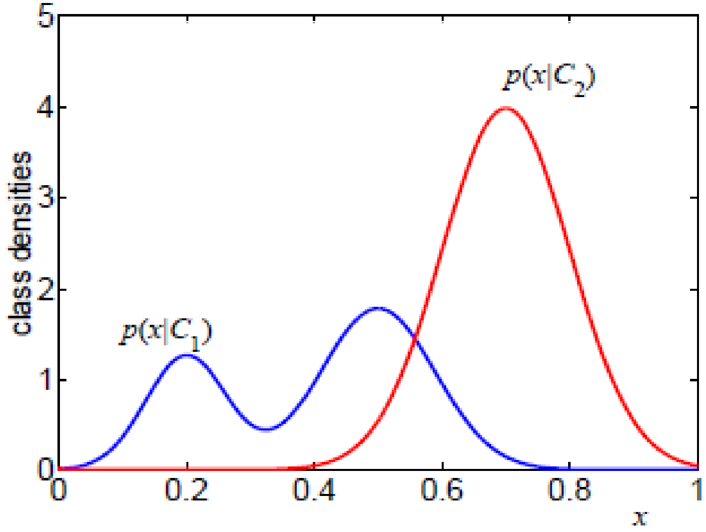
Viola, Jones 2001,
Torralba et al. 2004,
Opelt et al. 2006,...

Source: Vittorio Ferrari, Kristen Grauman, Antonio Torralba

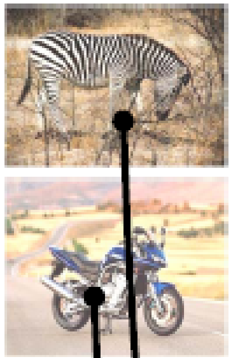
Generative models

- Modeling the likelihood ratio:

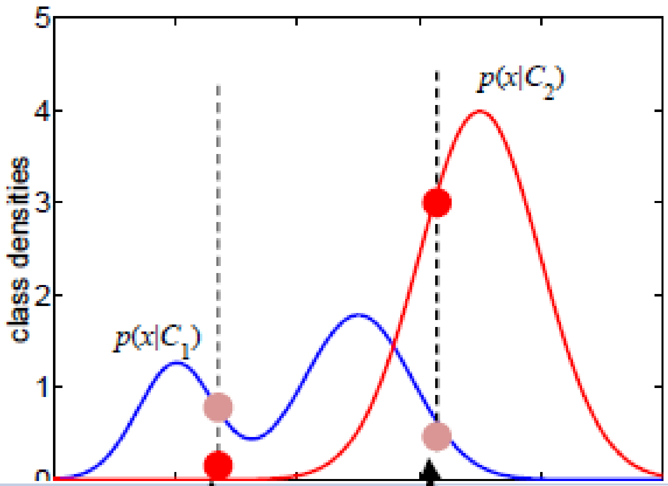
$$\frac{p(image \mid zebra)}{p(image \mid no\ zebra)}$$



Generative models



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



Generative models

- Naïve Bayes classifier
  - Csurka Bray, Dance & Fan, 2004
- Hierarchical Bayesian topic models (e.g. pLSA and LDA)
  - Object categorization: Sivic et al. 2005, Sudderth et al. 2005
  - Natural scene categorization: Fei-Fei et al. 2005
- 2D Part based models
  - Constellation models: Weber et al 2000; Fergus et al 200
  - Star models: ISM (Leibe et al 05)
- 3D part based models:

  - multi-aspects: Sun, et al, 2009

Basic issues

- Representation
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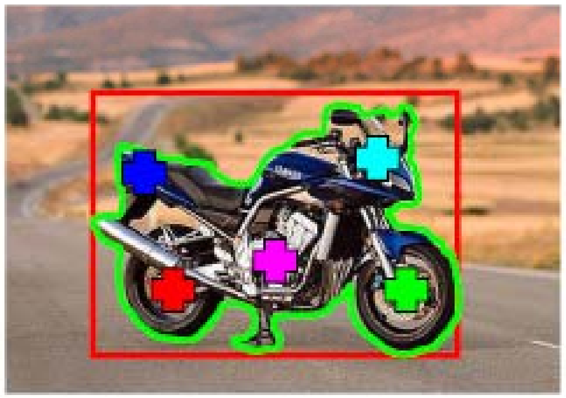
Learning

- Learning parameters: What are you maximizing? Likelihood (Gen.) or performances on train/validation set (Disc.)

Learning

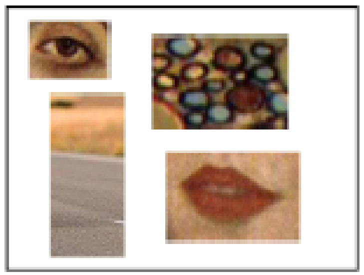
- Learning parameters: What are you maximizing? Likelihood (Gen.) or performances on train/validation set (Disc.)
- Level of supervision
  - Manual segmentation; bounding box; image labels; noisy labels
- Batch/incremental
- Priors

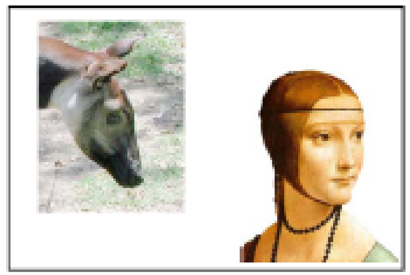


Learning

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

- Batch/incremental
- Priors
- Training images:
  - Issue of overfitting
  - Negative images for discriminative methods





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Recognition

– Recognition task: classification, detection, etc..

Recognition

– Recognition task

– Search strategy: Sliding Windows

Viola, Jones 2001,

- Simple
- Computational complexity (x,y, S, θ, N of classes)

- BSW by Lampert et al 08

- Also, Alexe, et al 10

Recognition

– Recognition task

– Search strategy: Sliding Windows

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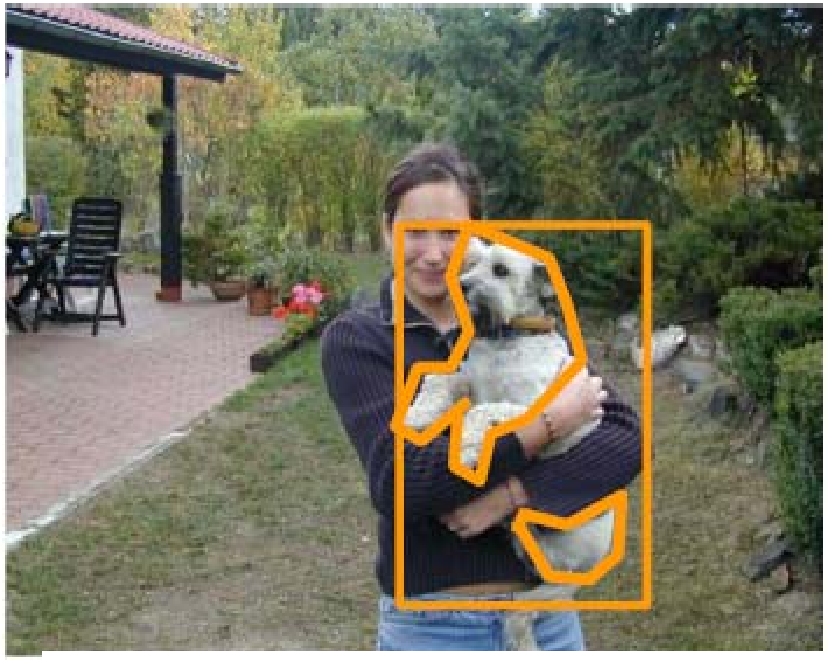
- Localization
  - Objects are not boxes



Recognition

– Recognition task

– Search strategy: Sliding Windows

Viola, Jones 2001,

- Simple
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  - Also, Alexe, et al 10

- Localization
  - Objects are not boxes
  - Prone to false positive

Non max suppression:
Canny '86
....
Desai et al , 2009

Recognition

– Recognition task

– Search strategy

– Attributes

•Savarese, 2007
•Sun et al 2009
• Liebelt et al., ’08, 10
•Farhadi et al 09

Category: car
Azimuth = 225º
Zenith = 30º

- **It has metal**
- **it is glossy**
- **has wheels**

•Farhadi et al 09
• Lampert et al 09
• Wang & Forsyth 09

Recognition

– Recognition task

– Search strategy

– Attributes

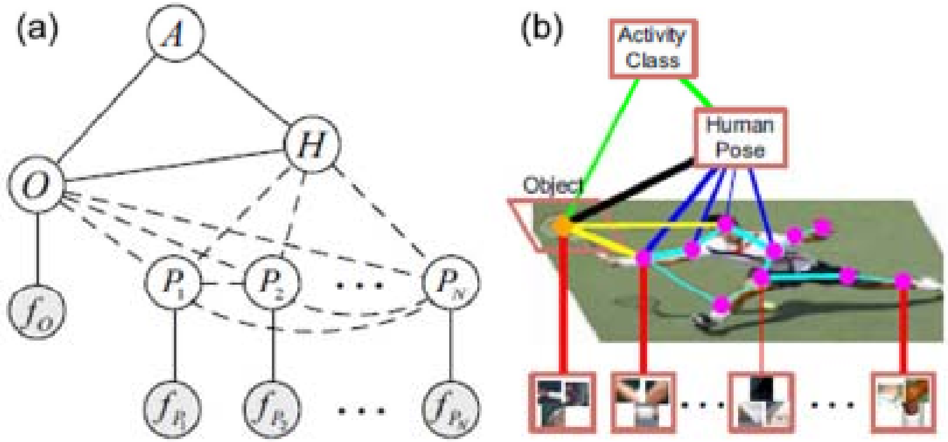
– Context

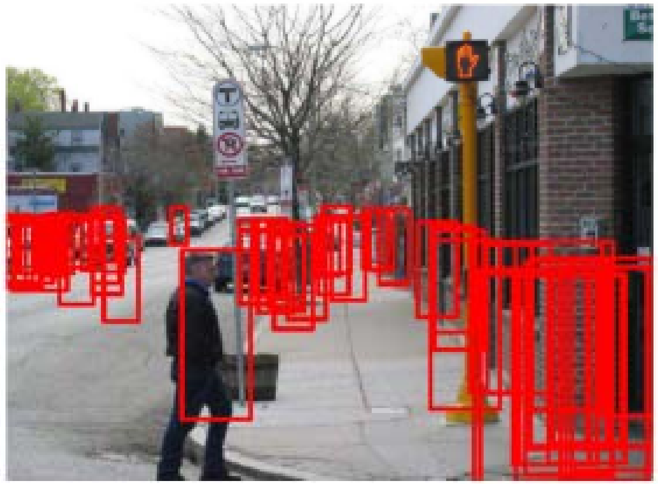
Semantic:

- Torralba et al 03
- Rabinovich et al 07
- Gupta & Davis 08
- Heitz & Koller 08
- L-J Li et al 08
- Yao & Fei-Fei 10

Geometric

- Hoiem, et al 06
- Gould et al 09
- Bao, Sun, Savarese 10





Basic issues

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What have we learned today?

- Introduction to object recognition
  - Representation
  - Learning
  - Recognition

Homework

- Browse recent CVPR and ICCV papers (2009 ~ 2011)
  - You need to present two papers at the class and give your mid-term & final presentations
- Go over our paper list
- Send your selection with 6 papers to me by Oct-14 (Fri.)
- Decide our talk schedule on Oct.-17 (Mon)
- Tie-breaker
  - Your prior experience, etc.
- Student presentations will start right after the mid-term exam
  - 3 talks per each class

Next Time…

- Bag of visual words approach