Object Recognition

Seminar Rita Osadchy

So what does object recognition involve?



Verification: is that a bus?



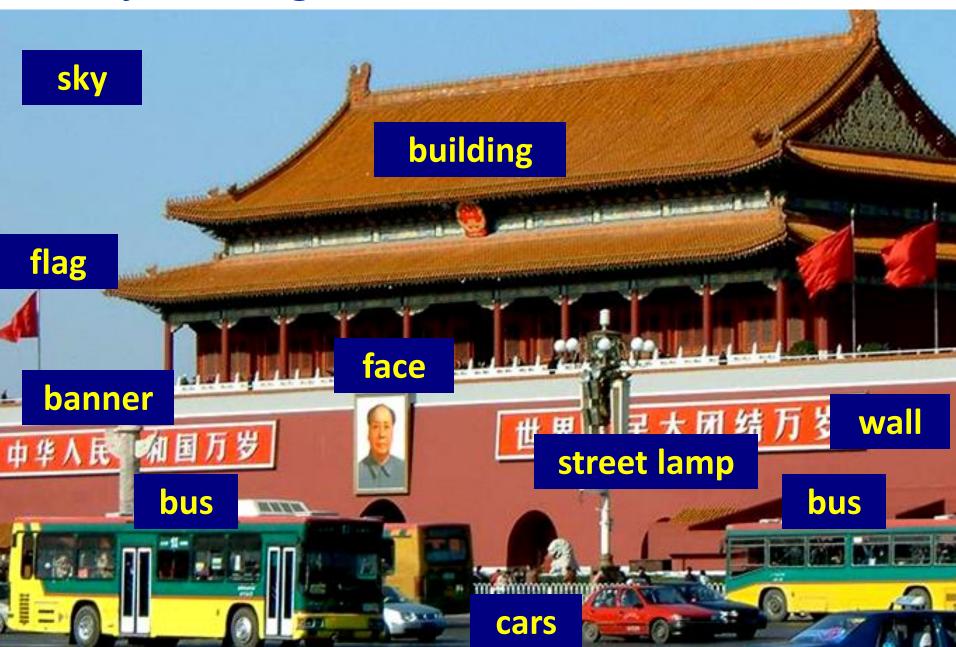
Detection: locate the cars in the image



Identification: is that a picture of Mao?



Object categorization

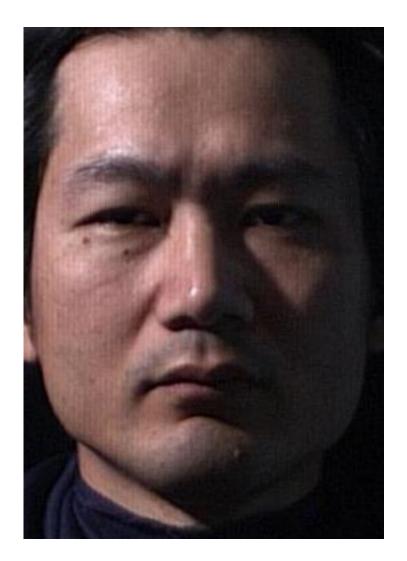


Challenges 1: view point variation

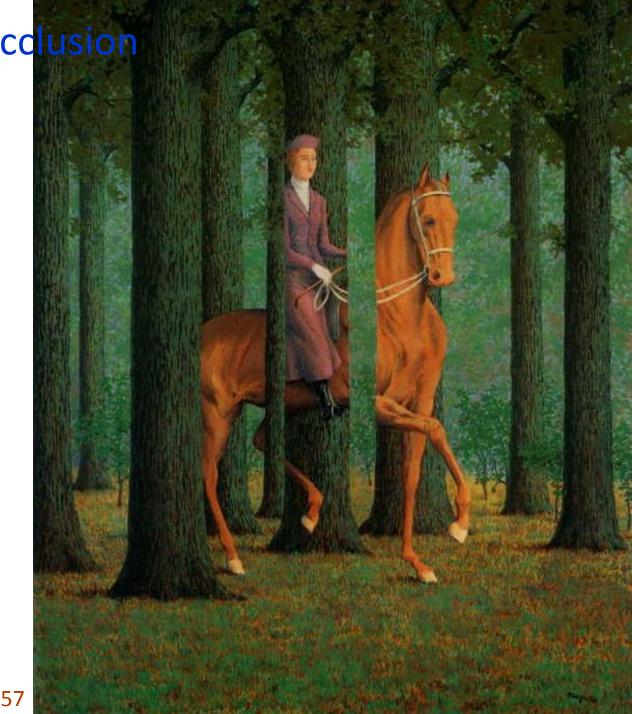


Challenges 2: illumination





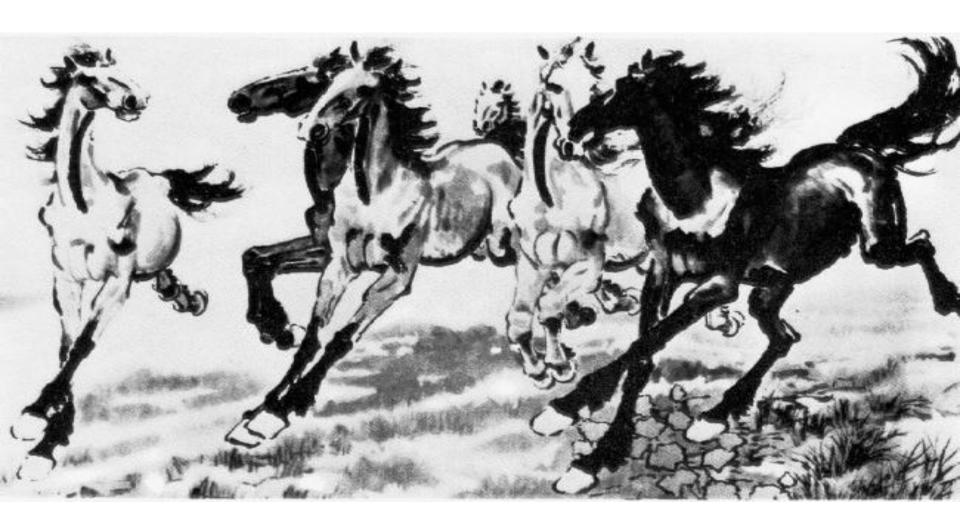
Challenges 3: occlusion



Challenges 4: scale



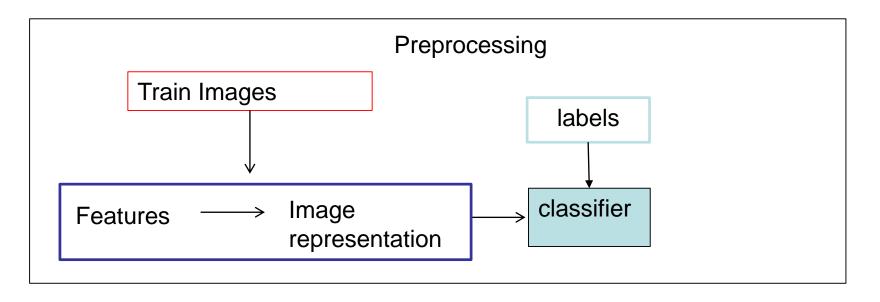
Challenges 5: deformation

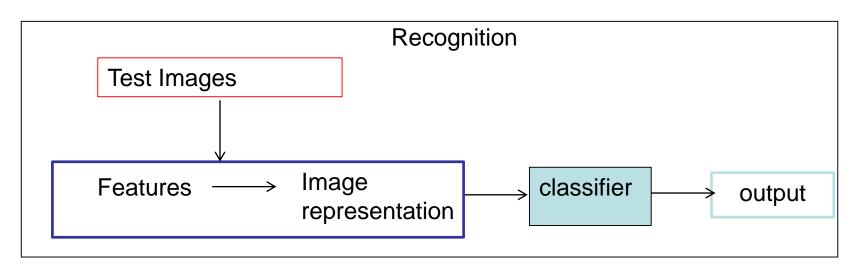


Challenges 7: intra-class variation



Recognition Steps



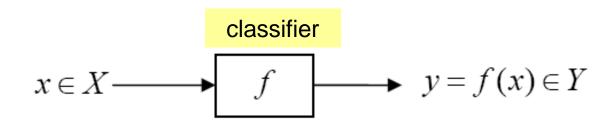


Classification in Machine Learning

- A classifier is a function or an algorithm that maps every possible input (from a legal set of inputs) to a finite set of categories.
- X input space, $x \in X$ sample from an input space.
- A typical input space is high-dimensional, for example $\mathbf{x} = \{x_1, ..., x_d\} \in \mathbb{R}^d$, d > 1. We also call \mathbf{x} a feature vector.
- Ω is a finite set of categories to which the input samples belong: $\Omega = \{1,2,...,C\}$.
- $w_i \in \Omega$ are called labels.

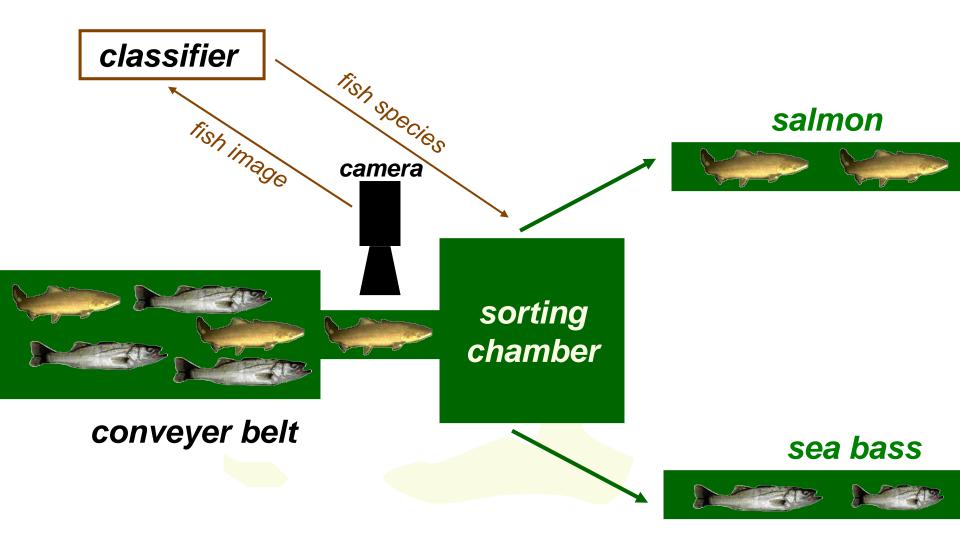
Definition of Classification

- Y is a finite set of decisions the output set of the classifier.
- A classifier is a function $f: X \to Y$



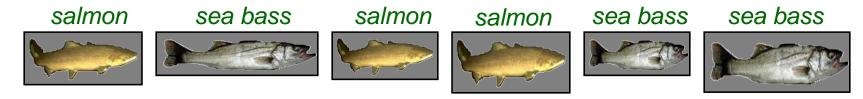
 Classification is also called Pattern Recognition.

Toy Application: fish sorting



How to design a PR system?

Collect data and classify by hand



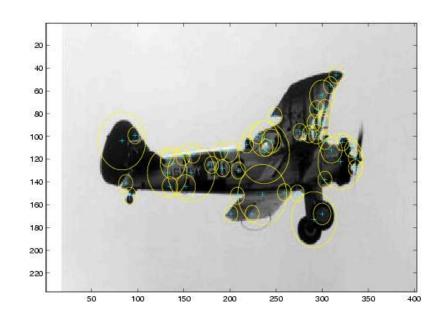
Preprocess by segmenting fish from background



- Extract possibly discriminating features
 - length, lightness, width, number of fins, etc.
- Classifier design
 - Choose model
 - Train classifier on part of collected data (training data)
- Test classifier on the rest of collected data (test data)
 i.e. the data not used for training
 - Should classify new data (new fish images) well

Interest Point Detectors

- Basic requirements:
 - Sparse
 - Informative
 - Repeatable
- Invariance
 - Rotation
 - Scale (Similarity)
 - Affine



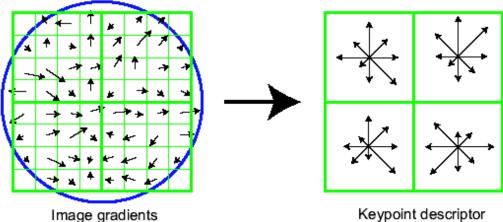
Representation of appearance: Local Descriptors

- Invariance
 - Rotation
 - Scale
 - Affine
- Insensitive to small deformations
- Illumination invariance
 - Normalize out

SIFT – Scale Invariant Feature Transform

- Descriptor overview:
 - Determine scale (by maximizing DoG in scale and in space),
 local orientation (as the dominant gradient direction).
 Use this scale and orientation to make all further computations invariant to scale and rotation.
 - Compute gradient orientation histograms of several small windows (128 values for each point)

Normalize the descriptor to make it invariant to intensity change



Recognizing Specific Objects

Learned models of local features, and got object outline from

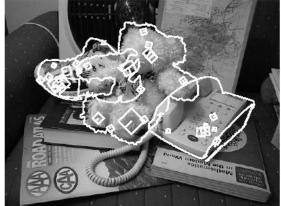




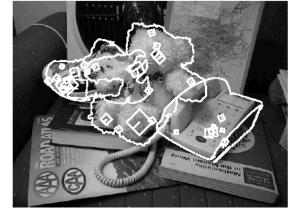


Objects may then be found under occlusion and 3D rotation

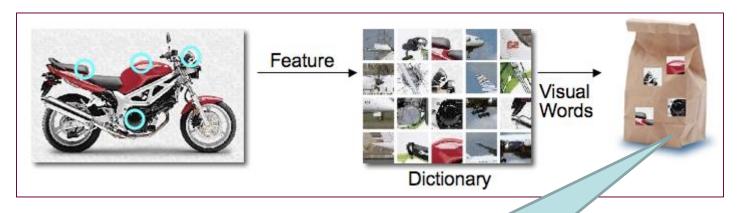


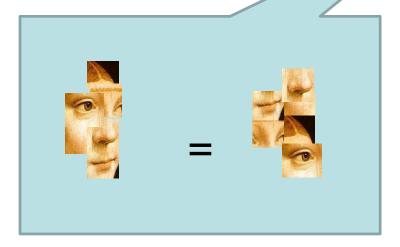




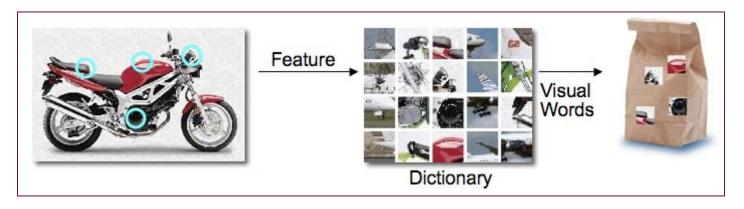


Bag of Features





Bag of Features



Pros: fairly flexible and computationally efficient

Cons: problems with large clutter





Different objects, but Similar representations;

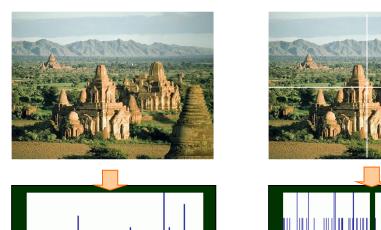


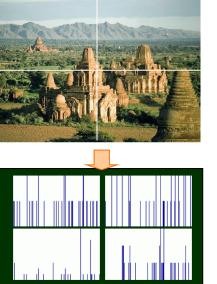


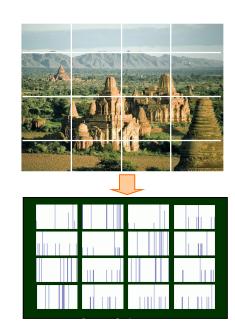
Similar objects, different representations;

Beyond Bags of Features

 Computing bags of features on subwindows of the whole image.



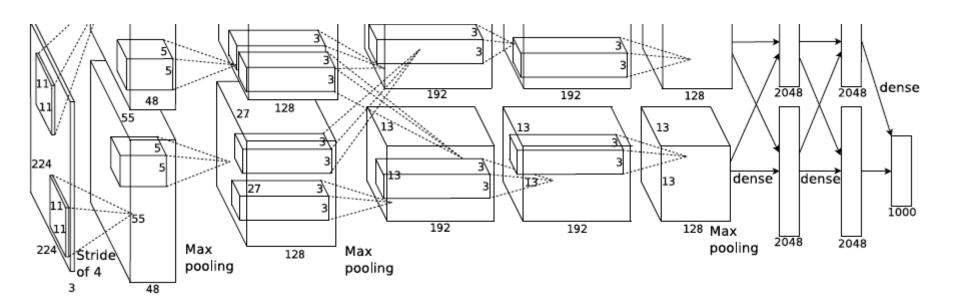




Convolutional Neural Networks

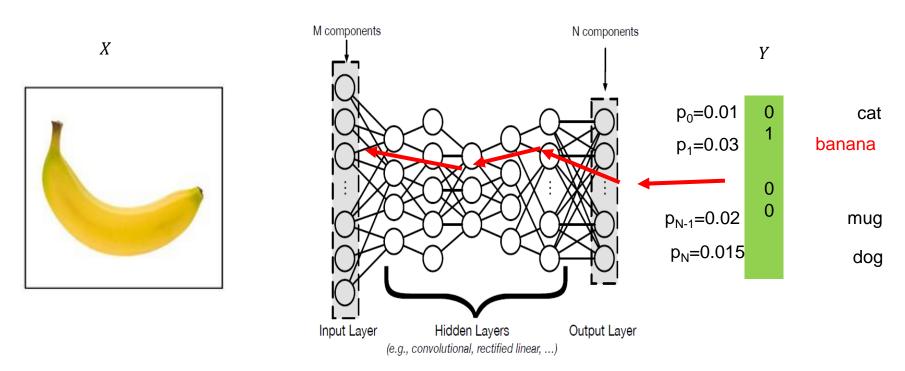
- Learn all in one deep architecture:
 - low level features
 - high level representations
 - context
 - classifiers
- Efficient Classification
- Efficient Detection
- Scalable to very large sets and large number of categories

Convolutional Neural Networks



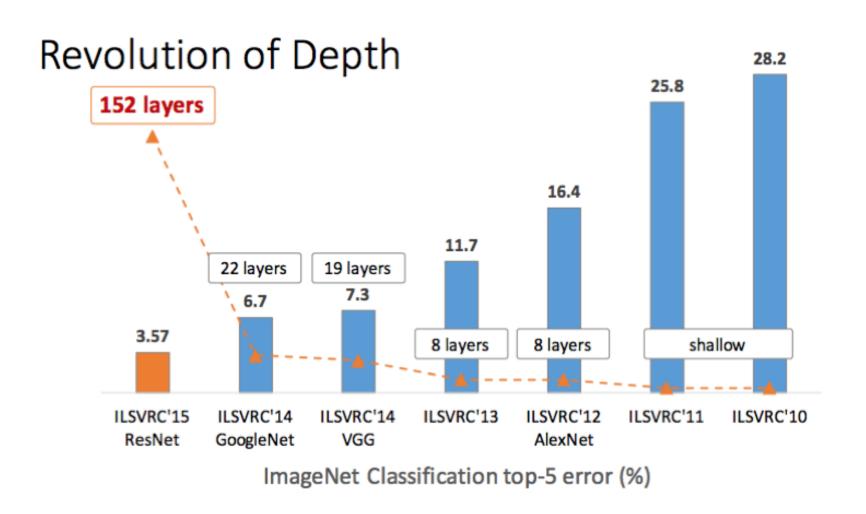
Krizhevsky, I. Sutskever, and G. Hinton. ImageNet classification with deep convolutional neural networks

Training the Network

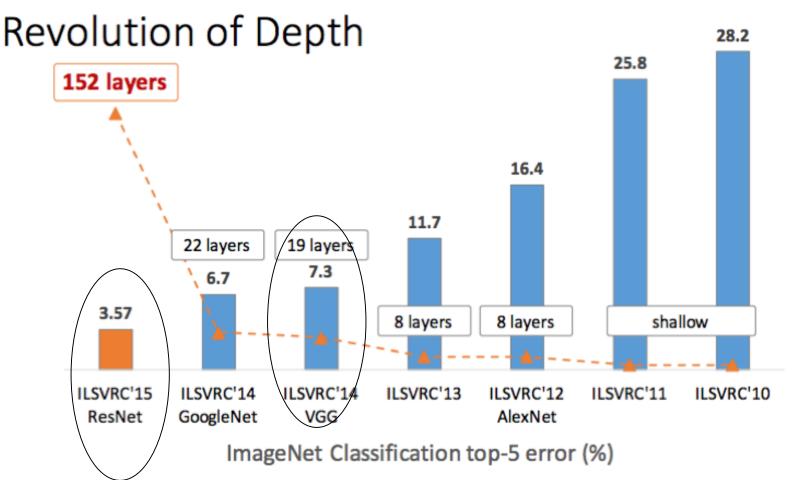


Compute the gradient with respect to the parameters of the network.

Very Deep Networks



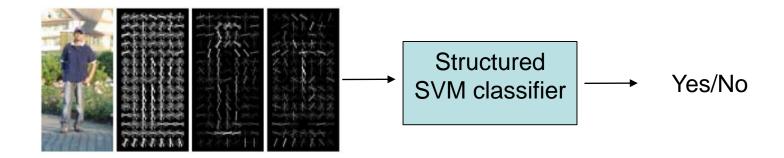
Very Deep Networks



- K. Simonyan and A. Zisserman Very Deep Convolutional Networks for Large-Scale Image Recognition
- K. He, X. Zhang, S. Ren, and J. Sun: Deep Residual Learning for Image Recognition

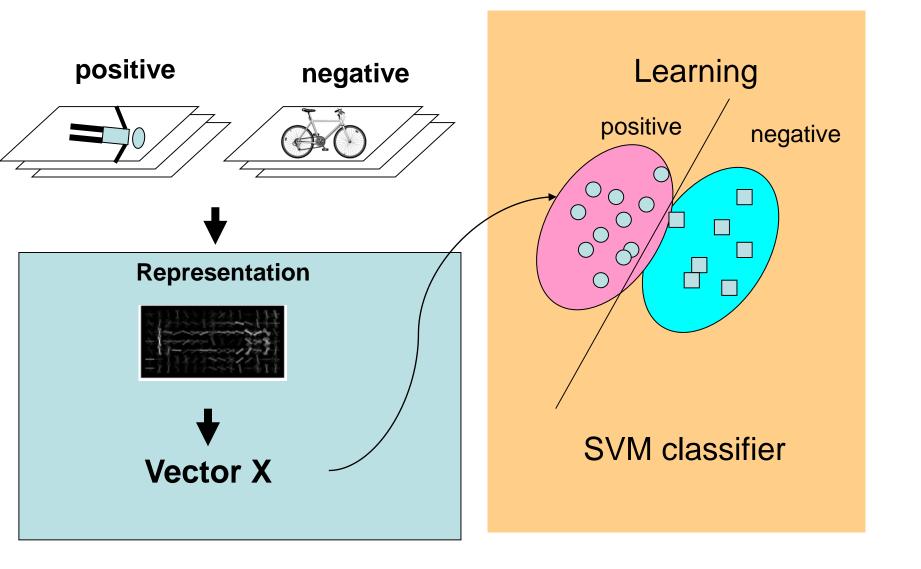
Detection as a binary decision

 Sliding window detection, detection as a binary decision problem.

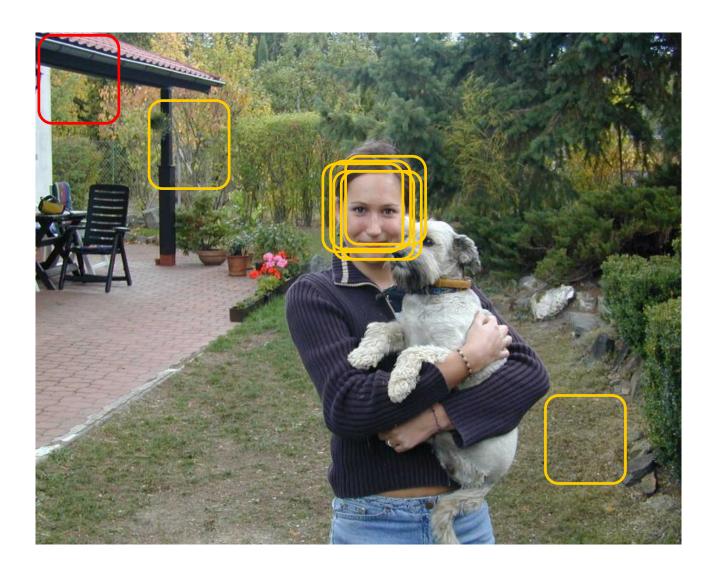


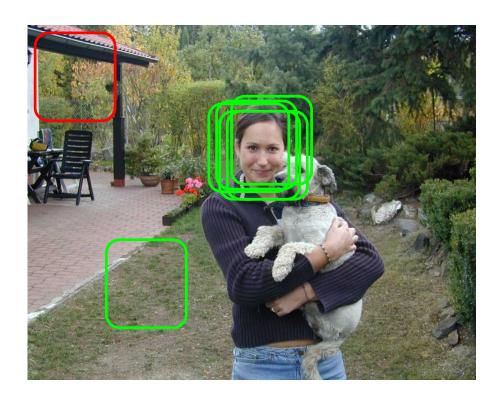
Histograms of Oriented
Gradients for Human
Detection

SVM classification



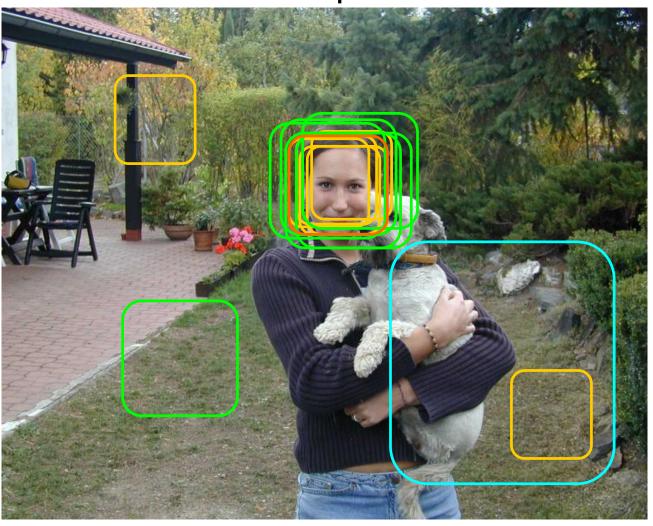
Apply classifier at Scale / position range to search over





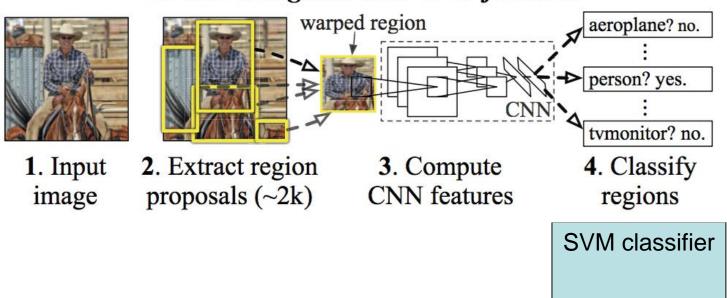


Combine detection over space and scale.



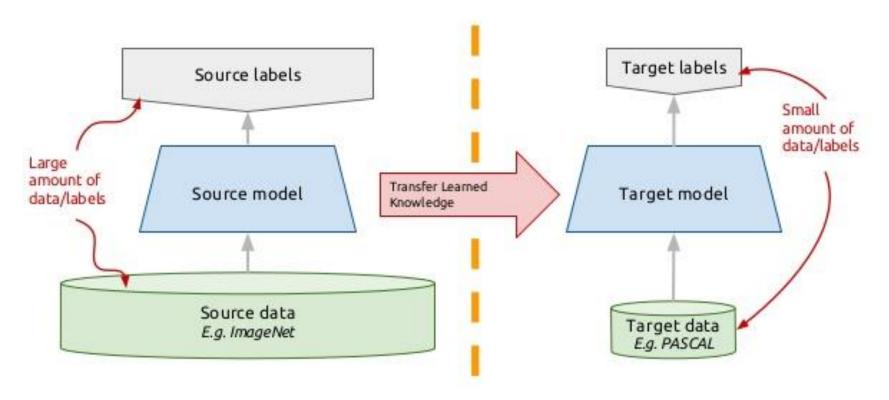
Deep Learning in Object Detection

R-CNN: Regions with CNN features



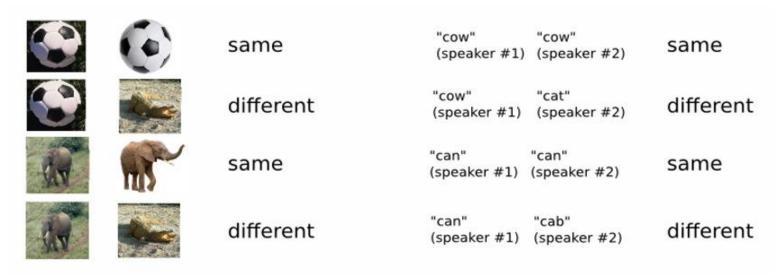
Transfer Learning

Transfer learning: idea

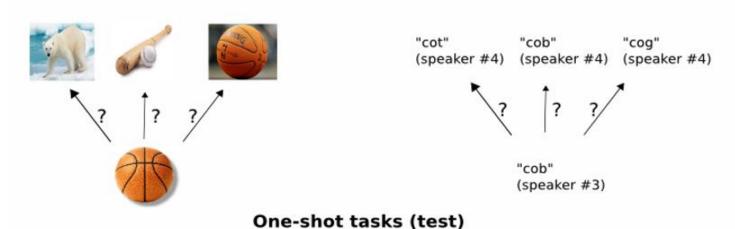


J. Donahue et.al. DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition.

One Shot Learning



Verification tasks (training)



Describing Objects with Attributes

 Shift the goal of recognition from naming to describing

```
otter
black: yes
white: no
brown: yes
stripes: no
water: yes
eats fish: yes
```



Discover/detect new categories





Describing Objects by Their Attributes, A. Farhadi, I. Endres, D. Hoiem, and D. Forsyth

Improvement



	Presence		Rating	
Attributes	walrus	polar bear	walrus	polar bear
Spot	no	no	less relevant	irrelevant
Blue	no	no	irrelevant	less relevant
Swim	yes	yes	highly relevant	relevant
Coastal	yes	yes	relevant	highly relevant

Face Verification Progress

Eigenface	0.6002
DeepFace	0.9130
Best automatic	0.9938
Best Human	0.9920

Deep Learning for Faces Survey

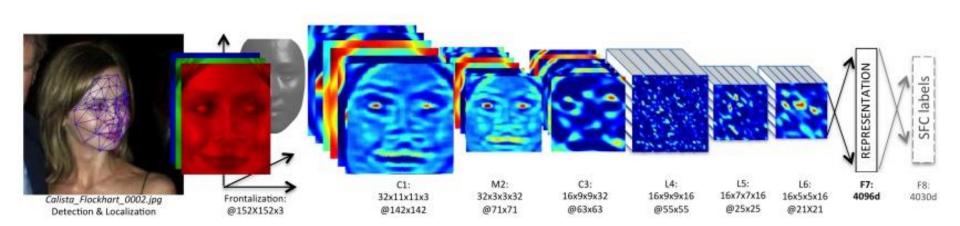
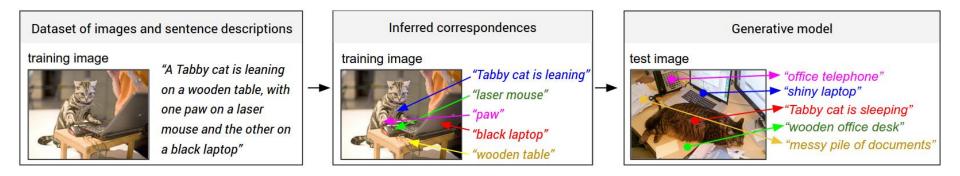




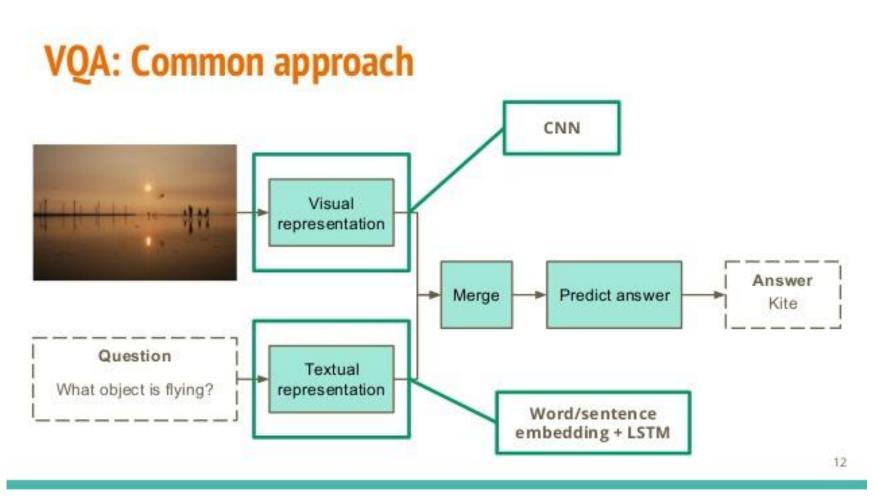
Image Descriptions (Captioning)



Uses CNNs and RNNs

Deep Visual-Semantic Alignments for Generating Image Descriptions, A. Karpathy, Li Fei-Fei.

VQA: Visual Question Answering



Very Cool Results

Where is the child sitting?

fridge



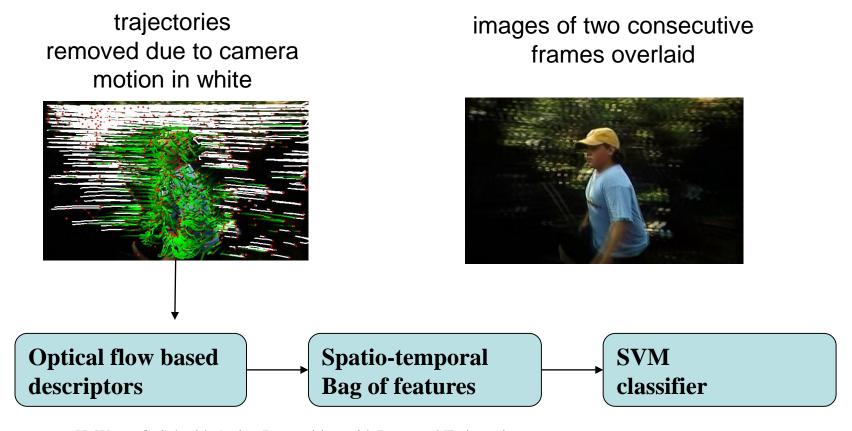
arms



Older Approaches

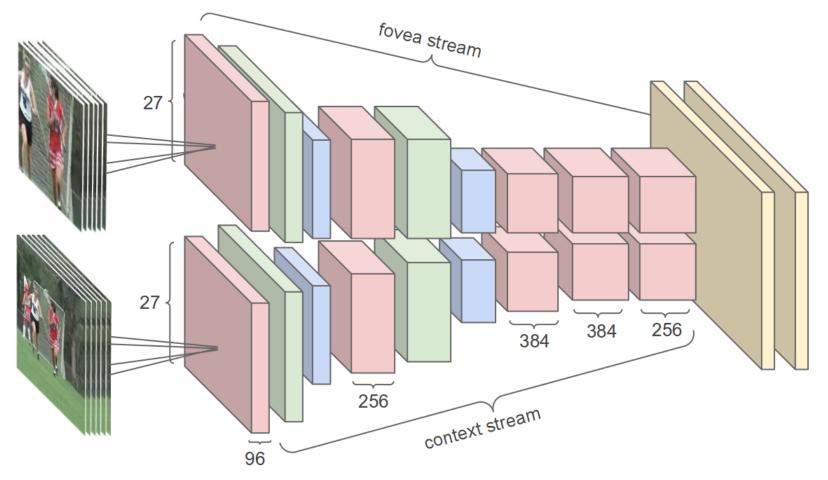


Shallow Approaches



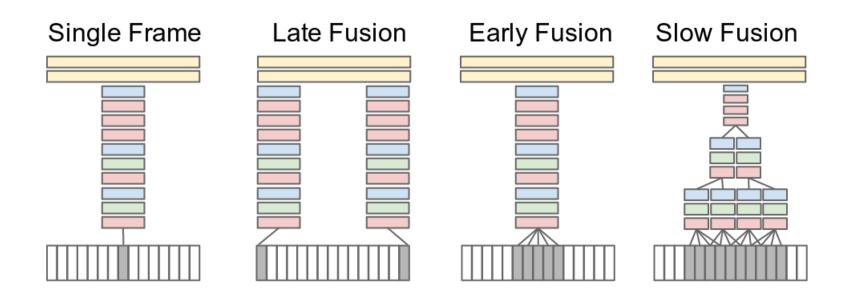
H. Wang, C. Schmid: Action Recognition with Improved Trajectories.

Using CNN – Naïve Approach



Kapathy et al.: Large-scale Video Classification with Convolutional Neural Networks

Using CNN – Naïve Approach



Temporal fusion

Kapathy et al.: Large-scale Video Classification with Convolutional Neural Networks

Modern Approaches

