Computer Vision Systems Programming VO

Object Category Recognition

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Topics

Scene classification using the bag of words model

Fast face detection using boosted Haar features

Convolutional neural networks for large-scale problems

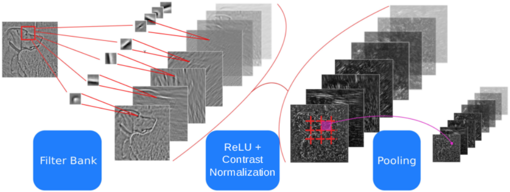


Image adaoted from Kavukcuoglu 2011

We want to distinguish between c scene categories

- So $w \in \{0, \ldots, c-1\}$ (classification problem)

Street Scenes

Sea Scenes

Image adapted from Prince 2012

Scene Classification

Selecting $\mathbf{x}$

We represent an image as a collection of visual words

- Images can be compared based on visual word distribution

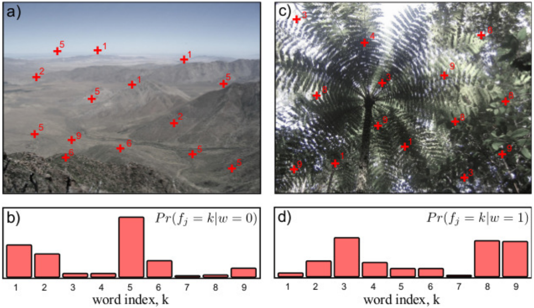
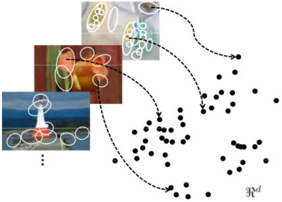


Image from Prince 2012

Scene Classification
Selecting $\mathbf{x}$

Visual words are learned from an image collection

- Compute (SIFT) keypoints and descriptors for all images
- Cluster descriptors into k clusters using k-means
- k cluster means represent visual words



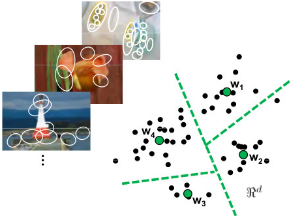


Image from Grauman and Leibe 2011

Visual word distribution $\mathbf{x} \in \mathbb{N}^k$ of image obtained by

- Computing keypoints and descriptors
- Assigning each feature to closest visual word
- Summing up the assignment counts for each visual word

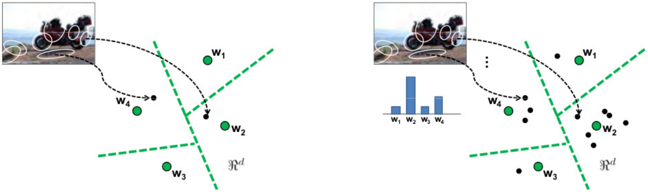


Image from Grauman and Leibe 2011

This image representation is called bag of (visual) words

Now that we have $\mathbf{x}$ we can select and learn a suitable model

- SVMs are often used in the literature
- For a probabilistic alternative see Prince 2012

Many improvements to this model exist

- Better clustering schemes
- Fuzzy assignment to visual words
- Spatial information (constellation model)

Popular and can work well, but no longer state of the art

Scene Classification

Bag of Visual Words Using OpenCV

```
// init SIFT
cv::Ptr<cv::FeatureDetector> kp = cv::FeatureDetector::create("SIFT");
cv::Ptr<cv::DescriptorExtractor> desc = cv::DescriptorExtractor::create("SIFT");

// compute visual words from training data
const int k = 50; // number of visual words
cv::BOWKMeansTrainer trainer(k);

for(const cv::Mat& im : images) { // std::vector of training images
    std::vector<cv::KeyPoint> keypoints; kp->detect(im, keypoints);
    cv::Mat descriptors; desc->compute(im, keypoints, descriptors);
    trainer.add(descriptors);
}

cv::Mat visualWords = trainer.cluster(); // k*128 (SIFT dimension)
```

Scene Classification
Bag of Visual Words Using OpenCV

```
// setup visual word frequency (our x) extractor
cv::Ptr<cv::DescriptorMatcher> fm = cv::makePtr<cv::BFMatcher>(cv::NORM_L2);
cv::BOWImgDescriptorExtractor extractor(desc, fm);
extractor.setVocabulary(visualWords);

// compute x for all training images
cv::Mat xTrain(images.size(), k, CV_32FC1);
for(std::size_t i = 0; i != images.size(); i++) {
    std::vector<cv::KeyPoint> keypoints; kp->detect(images[i], keypoints);
    cv::Mat x; extractor.compute(images[i], keypoints, x);
    xTrain(cv::Rect(0, i, k, 1)) = x;
}

// and corresponding w
cv::Mat wTrain(images.size(), 1, CV_32FC1); // fill me
```

Scene Classification
Bag of Visual Words Using OpenCV

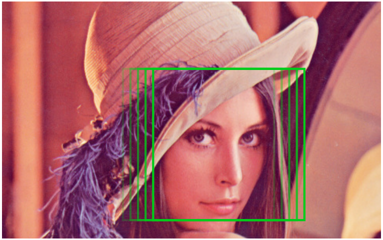
```
// train our model (we use an SVM)
CvSVM svm;
svm.train(xTrain, wTrain);

// now we can predict the class of new images
std::vector<cv::KeyPoint> keypoints; kp->detect(newImage, keypoints);
cv::Mat x; extractor.compute(newImage, keypoints, x);
float w = svm.predict(x); // predicted class label
```

Face Detection

Image from olympus-europa.com

We don't know where the faces are so we

- Slide a fixed-size window over the image
- Compute $\Pr(w|\mathbf{x})$ for each window ($w = 1$ if face, 0 if not)



Face Detection
Selecting $\mathbf{x}$

Which are good features for this task?

Must be fast to compute (many windows)

Must be robust to illumination, so we use gradient information

Different approaches to encoding gradient information

- Compute gradients, pool orientations in blocks (e.g. SIFT)
- Use a collection of Gabor filters

Face Detection
Selecting $\mathbf{x}$

We want something faster

- So we use a "blocky" approximation of Gabor filters
- Difference between rectangular subwindows (Haar features)
- Can be computed in constant time using integral images

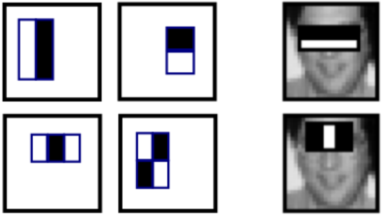


Image adapted from Prince 2012

Face Detection
Selecting $\mathbf{x}$

Computing a Haar feature at a location yields a scalar f_i

We define $\mathbf{x} = (x_1, \ldots, x_I)$ with $x_i = \text{heaviside}(f_i - t_i)$

I is very large

- Different Haar features, subwindow locations, t_i
- We thus learn which features x_i work best

We model $\Pr(w|\mathbf{x})$ as a weighted sum of a feature subset

$$\Pr(w|\mathbf{x}) \propto a = \phi_0 + \sum_k \phi_k x_k \qquad (1 \leq k \leq I)$$

And learn the parameters $\boldsymbol{\theta} = (\phi_0, \phi_k, x_k)$ from training samples

- For each x_k in a large precomputed set
- Find optimal ϕ_0, ϕ_k
- Add best x_k (and ϕ_0, ϕ_k) to sum and repeat

This incremental approach is called boosting

We stop adding features at some point

- If the classification error no longer decreases significantly
- After a specified maximum number of iterations

We end up with K good features, $K \ll I$

- For prediction we compute only these K features
- Stop early if $P(w = 0) > t$ after processing $J \ll K$ features

If we don't care about probabilities, we choose $w = \text{heaviside}(a)$

If we do, we use logistic regression, $\Pr(w|\mathbf{x}) = \text{Bern}_w(\text{sig}(a))$

- We model w as a Bernoulli distribution
- Pass a through a logistic sigmoid to map it to $[0, 1]$
- Called logitboost in this context

Face Detection
Remarks

This method was proposed in Viola and Jones 2001

Very efficient, ideal for e.g. digital cameras

Trades off efficiency for accuracy

- Features capture gradients coarsely, no color information
- More powerful but slower methods exist

Not invariant to scale changes (fixed-size window)

- Repeat detection at different image scales

Detect faces using a pretrained model

OpenCV also supports training

```
# detect faces using a pretrained cascade
image = cv2.imread('faces.jpg', cv2.IMREAD_GRAYSCALE)
cascade = cv2.CascadeClassifier('haarcascade_frontalface_default.xml')
faces = cascade.detectMultiScale(image) # should tune parameters
```

Selecting good features $\mathbf{x}$ for object recognition is challenging

- Why we previously learned $\mathbf{x}$

Learned features were low-level

- Based on SIFT descriptors or Haar wavelets

We want task-specific high-level features

- Virtually impossible to design manually
- So we learn them as well

We learn these features hierarchically

- Model consists of layers
- The higher up the layer, the higher-level the feature
- Features in layer n are based on those in layer $n-1$
- Results in a *deep* model, hence deep learning

At the same time we learn to predict $\mathbf{w}$

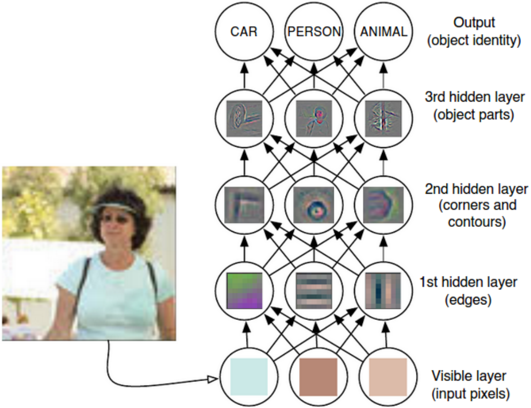


Image from Bengio, Goodfellow, and Courville 2015

Deep model optimized for images

- Exploits correlations between adjacent pixels
- Performs remarkably well in many recognition tasks

"From now on, deep learning has to be considered as the primary candidate in essentially any visual recognition task"

[Razavian et al. 2014]

Multilayer Perceptrons (MLPs) with some twists

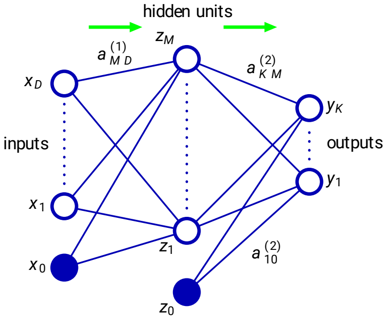


Image adapted from Bishop 2006

Remember the Perceptron?

- Model for binary classification, $w = \text{heaviside}(\mathbf{a}^\top \mathbf{x} + b)$
- Parameters $\boldsymbol{\theta} = (\mathbf{a}, b)$ learned from data

Limitations

- Linear decision boundaries
- Only two classes, not probabilistic
- Learning never converges for non-separable data

To overcome these limitations we

- Replace step function with continuous f (e.g. tanh)
- Add a layer of M such “Perceptrons” (hidden units)
- Add K output units (number of classes)

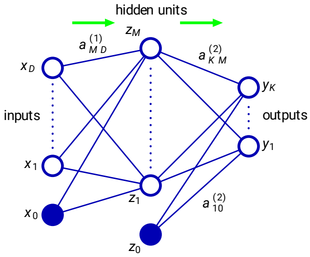


Image adapted from Bishop 2006

Output of mth hidden unit is $z_m(\mathbf{x}) = f(\mathbf{a}_m^\top \mathbf{x})$

- Bias b included in $\mathbf{a}$ and $\mathbf{x}$, $a_0 = b$, $x_0 = 1$

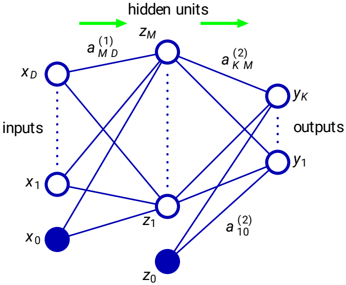


Image from Bishop 2006

Output of kth output unit is $y_k(\mathbf{z}) = g(\mathbf{a}_k^\top \mathbf{z})$

- g depends on problem (regression, classification)

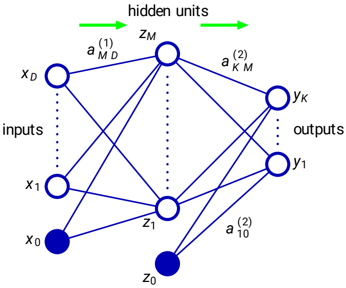


Image from Bishop 2006

Both f and g are differentiable

- Learn parameters using gradient descent
- Gradients evaluated via error backpropagation

Properties

- Powerful, can approximate any decision boundary if M is large
- Does not scale to images due to full connectivity
- Not deep (not possible due to scaling issues)

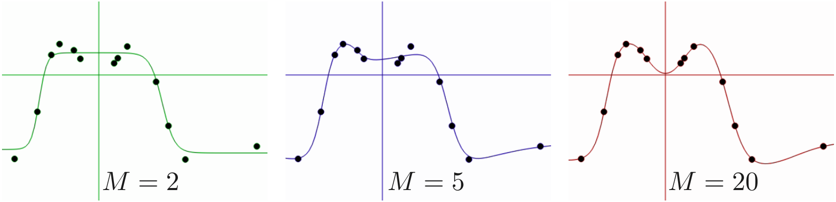
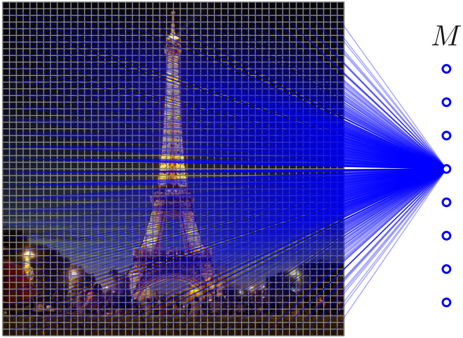


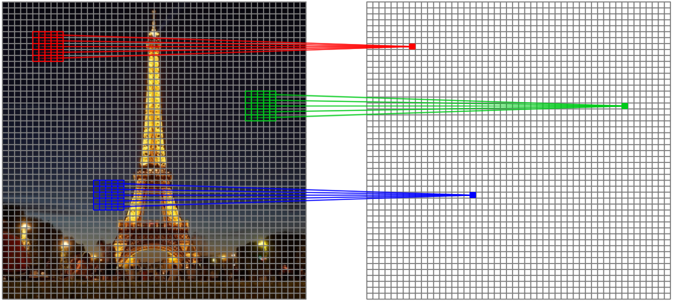
Image adapted from `cs.stanford.edu/people/karpathy/convnetjs/`

QVGA image ($D = 76800$), $M = 500$: ~ 38m parameters



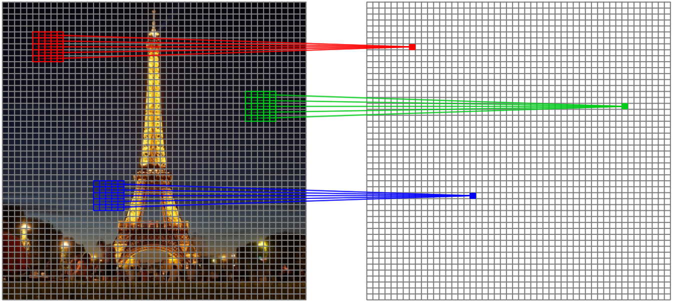
Nearby pixels are closely correlated, the rest is not

- We use D hidden units (one per input pixel)
- Connect each only to nearby pixels (local receptive field)



M much higher but much fewer parameters

- ~ 2m in example with 5×5 receptive field



Learned features should work well everywhere in the image

- We don't know where objects will be

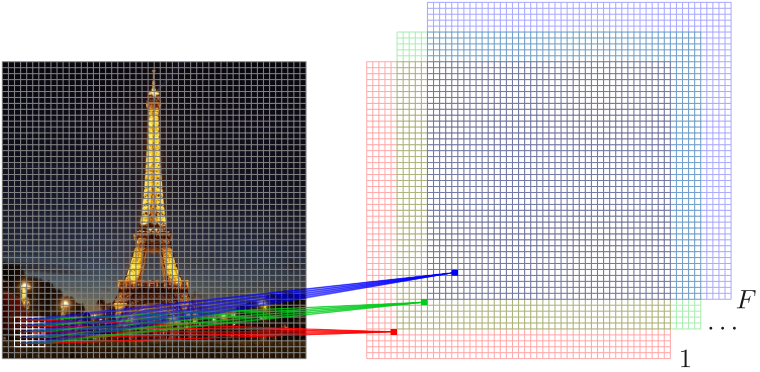
So we define that all hidden units must have *same* weights

- Number of parameters now independent of M
- But we now can learn only a single feature

So we duplicate the hidden layer F times

- Each duplicate (feature map) learns a feature

$F = 100$, 5×5 receptive field : ~ 2600 parameters

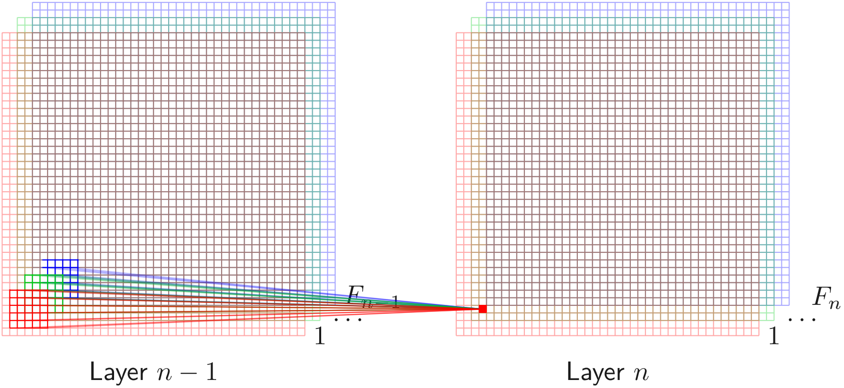


Such layers are called convolutional (conv) layers

- Feature map evaluation equals convolution with kernel $\mathbf{a}$
- Followed by f (often $f(\cdot) = \max(0, \cdot)$ (ReLU))

Few parameters, so we can stack conv layers (deep network)

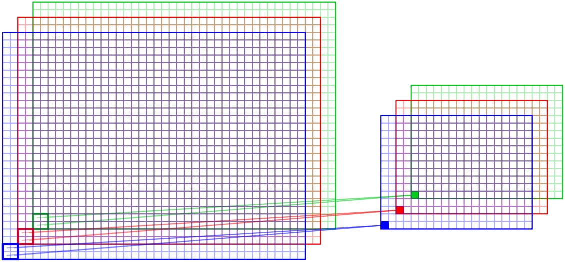
- Conv layer n operates on feature maps in layer $n - 1$
- Learns features by combining those learned in layer $n - 1$



F_{n-1}
1
...
F_n
1
...
Layer $n-1$
Layer n

Most CNNs also contain pooling layers

- Pool (aggregate) information locally (e.g. max, mean)
- Reduces data size, robustness to small object movement



Convolutional Neural Networks (CNNs) consist of

- One or several conv layers (and others)
- Followed by a traditional MLP operating on learned features

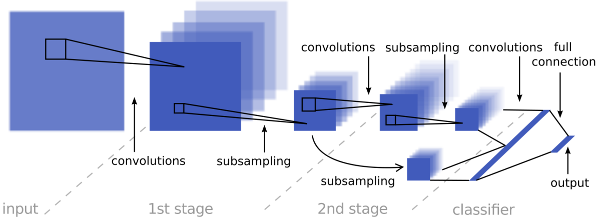


Image adapted from Sermanet et al. 2012

Convolutional Neural Networks Learn High-Level Features

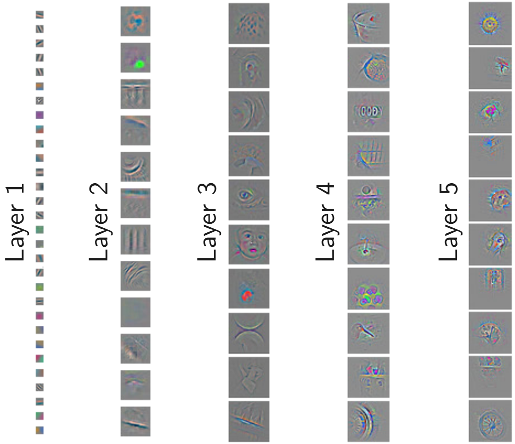


Image adapted from Zeiler and Fergus 2014

CNNs were proposed long ago

- LeCun et al. 1989 : Zip code recognition using a CNN

Large, deep CNNs possible now

- Powerful and flexible GPUs
- Large datasets to avoid overfitting (e.g. ImageNet)

Simple CNN for Zip Code Recognition

- Using ConvNetJS (Java Script library)
- `cs.stanford.edu/people/karpathy/convnetjs/demo/mnist.html`

Image from `convnetjs.com`

Face recognition via 3D face alignment and CNNs

- conv $\Rightarrow$ pooling $\Rightarrow$ conv for low-level features
- Locally connected layers for high-level features
- Human-level face verification performance

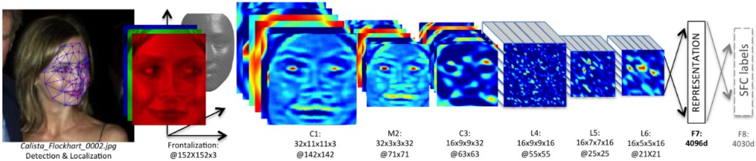


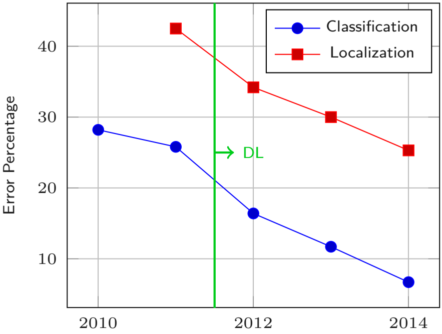
Image from Taigman et al. 2013

Object recognition on the ImageNet database

- ~ 14 million images categorized hierarchically
- Annual object recognition challenges

Image from http://web.eecs.umich.edu/~jiadeng/

CNNs have lead to significant performance gains on ImageNet



Demo of winner of 2013 ImageNet classification challenge

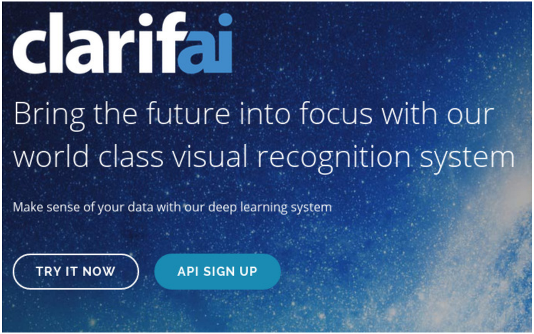
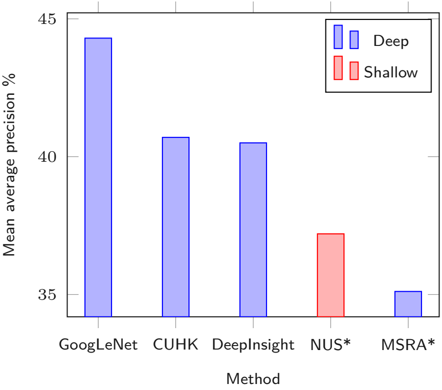


Image from clarifai.com

Results of 2014 ImageNet object detection challenge (excerpt)



Many open-source libraries available

- Caffe (C++, Matlab, Python)
- Keras, Lasagne (Python)
- ConvNetJS (Java Script)
- Torch7 (LUA)

Network definitions and trained networks available online

- E.g. Caffe model zoo

Deep learning and CNNs are powerful concepts

- State of the art in image recognition

Large CNNs have millions of parameters

- Training takes long (up to weeks on GPUs)
- Requires large datasets to avoid overfitting

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