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

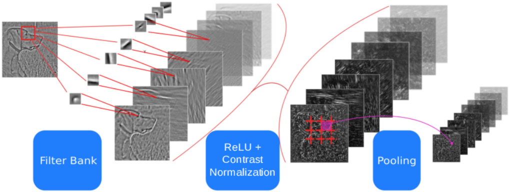


Image adaoted from Kavukcuoglu 2011

Scene Classification

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
Bag of Visual Words

We represent an image as a collection of visual words

- Images can be compared based on visual word distribution

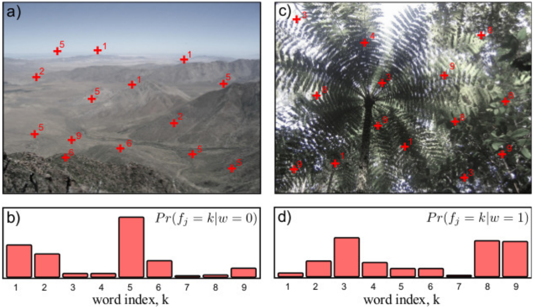


Image from Prince 2012

Scene Classification
Bag of Visual Words

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

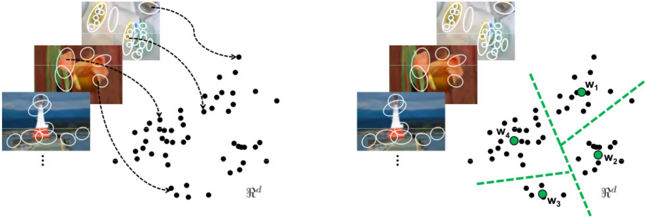
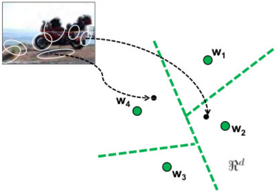


Image from Grauman and Leibe 2011

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



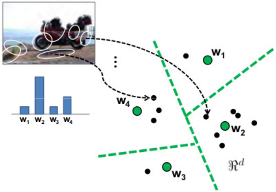


Image from Grauman and Leibe 2011

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
```

```
// 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
```

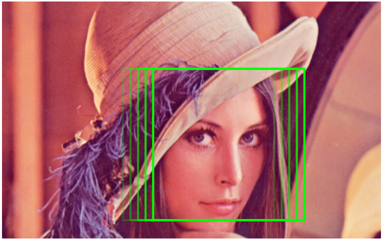
Face Detection

Image from `olympus-europa.com`

Face Detection

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

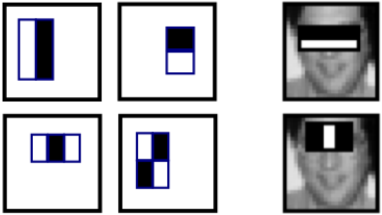


Image adapted from Prince 2012

Computing a Haar feature 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 (but finite)

- 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 to sum and repeat

This incremental approach is called boosting

We stop adding features at some point

- If the classification error no longer decreases
- 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
- We stop 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

This method was proposed in Viola and Jones 2001

Very efficient, ideal for 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
```

Deep Learning

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

Deep Learning

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 $n-1$

This results in a *deep* model, hence deep learning

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

Deep Learning

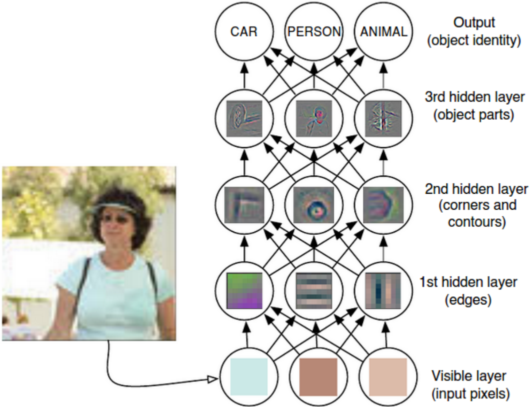


Image from Bengio, Goodfellow, and Courville 2015

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