Neural Codes for Image Retrieval

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1. Introduction

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Problem. Given a large database of images and a query image, find images showing the same object or scene.

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- unpractical for large collections of images.

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- unpractical for large collections of images.

Today, content-based image retrieval:

- Techniques based on the Bag of Visual Words [SZ03] model.

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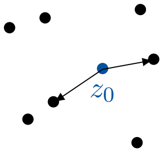
2. Image Retrieval

Formalization of content-based image retrieval:

Problem. Find K-nearest-neighbors of query z_0 in a (large) database $X = \{x_1, \ldots, x_N\}$ of image representations.

$K = 2$, $N = 7$



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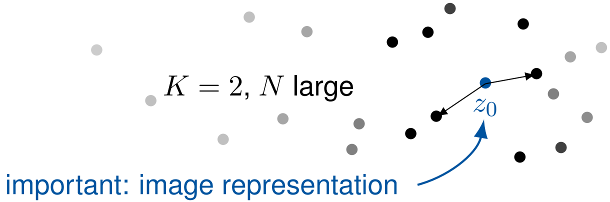

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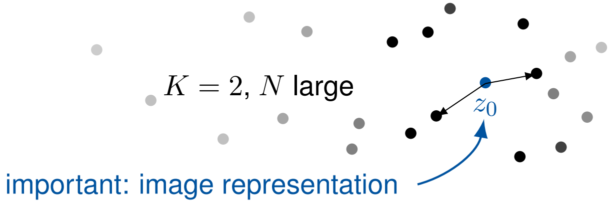
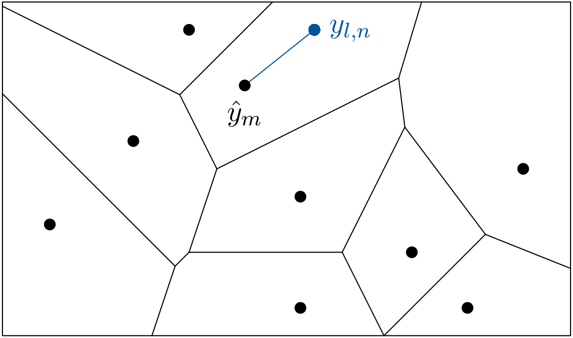


Examples for image representations from the “Computer Vision” lecture:

- Histograms;
- Bag of Visual Words [SZ03].

2.1. Bag of Visual Words

Intuition: assign local descriptors $y_{l,n}$ of image x_n to visual words $\hat{y}_1, \ldots, \hat{y}_M$ previously obtained using clustering.



2.1. Bag of Visual Words

1. Extract local descriptors Y_n for each image x_n.
2. Cluster all local descriptors $Y = \bigcup_{n=1}^{N} Y_n$ to obtain visual words

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3. Assign each $y_{l,n} \in Y_n$ to nearest visual word (embedding step):

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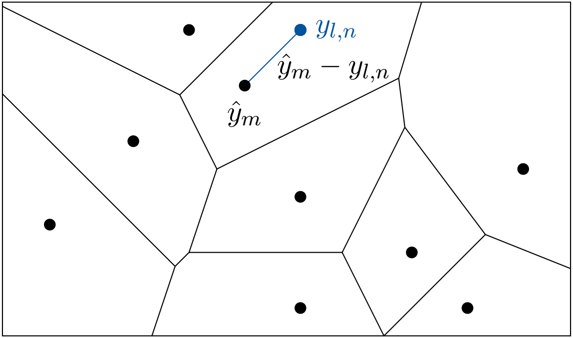
$$f(y_{l,n}) = \left(\delta(\text{NN}_{\hat{Y}}(y_{l,n}) = \hat{y}_1), \ldots\right).$$
4. Count visual word occurrences (aggregation step):
$$F(Y_n) = \sum_{l=1}^{L} f(y_{l,n}).$$

2.2. Vector of Locally Aggregated Descriptors

Intuition: consider the residuals $y_{l,n} - \hat{y}_m$ instead of counting visual words.



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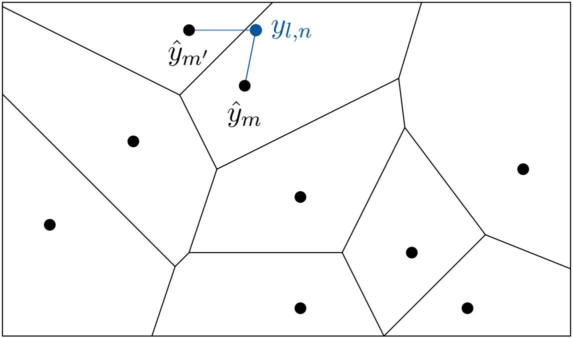
3. Aggregate residuals (aggregation step):

$$F(Y_n) = \sum_{l=1}^{L} f(y_{l,n}).$$

4. L_2-normalize $F(Y_n)$.

2.3. Sparse-Coded Features

Intuition: soft-assign local descriptors to visual words.



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2. Compute sparse codes (embedding step):

$$f(y_{l,n}) = \underset{r_l}{\text{argmin}} \|y_{l,n} - \hat{Y} r_l\|_2^2 + \lambda \|r_l\|_1.$$

contains $\hat{y}_m$ as columns

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3. Pool sparse codes (aggregation step):

$$F(Y_n) = \left(\max_{1 \leq l \leq L} \{f_1(y_{l,n})\}, \ldots \right)$$

first component of $f(y_{l,n})$

2.4. Compression, Nearest-Neighbor Search

Until now: image representation.

Additional aspects of image retrieval:

- compression of image representations;
- efficient indexing and nearest-neighbor search [JDS11];
- query expansion [CPS$^+$07] and spatial verification [PCI$^+$07].

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For example, compression can be accomplished using:

- Unsupervised methods, e.g. Principal Component Analysis (PCA);
- or discriminate methods, e.g. Joint Subspace and Classifier Learning [GRPV12] or Large Margin Dimensionality Reduction [SPVZ13].

discussed later ...

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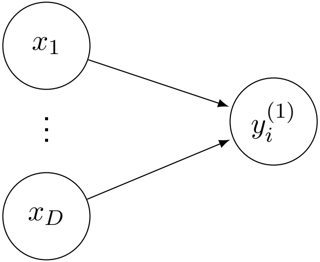
3.1. Multi-layer Perceptrons

The prototypical neural network is the L-layer perceptron.

Given input $x \in \mathbb{R}^D$, layer $l = 1$ computes for $1 \leq i \leq m^{(l)}$:



$$= f\left(\sum_{j=1}^{D} w_{i,j}^{(1)} x_j + w_{i,0}^{(1)}\right)$$

e.g. $f(z) = \frac{1}{1+\exp(-z)}$

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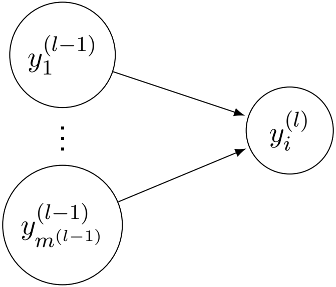
The prototypical neural network is the L-layer perceptron.

Given input $y^{(0)} := x \in \mathbb{R}^{m^{(0)}}$, layer l computes for $1 \leq i \leq m^{(l)}$:



$$= f\left(\sum_{j=1}^{m^{(l-1)}} w_{i,j}^{(l)} y_j^{(l-1)} + w_{i,0}^{(l)}\right)$$

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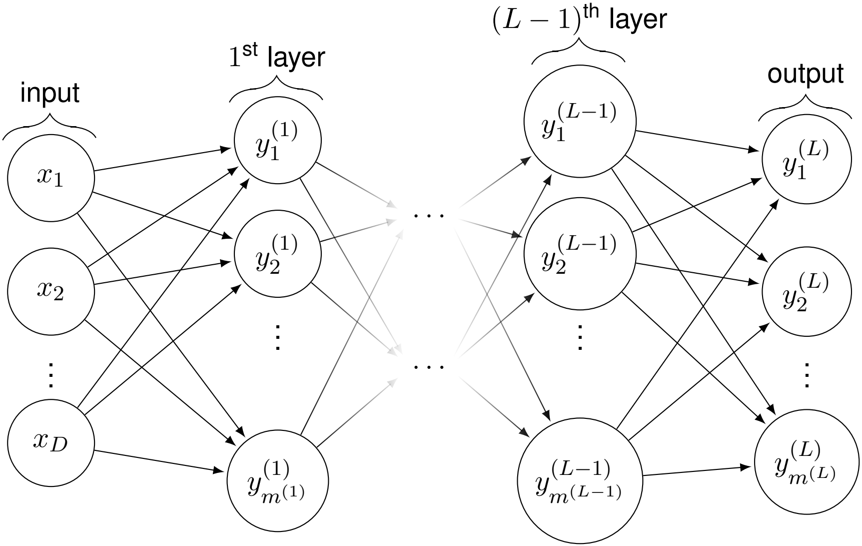

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Motivation:

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- Multi-layer perceptrons do not naturally accept images as input;
- however, spatial information is important.

Solution: convolutional neural networks.

Intuition: apply learned filters on the input image to compute a set of feature maps.

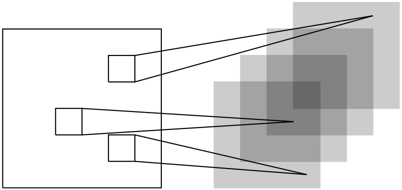
Repeat: normalize and pool feature maps before applying another set of learned filters.

Apply a multi-layer perceptron on the obtained (small) feature maps.

3.2. Convolutional Layer

General architecture:

convolutional layer – contrast normalization layer – pooling layer



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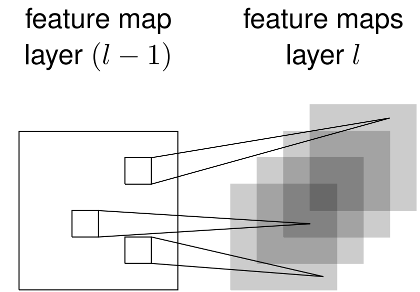

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General architecture:

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Given $m_1^{(l-1)}$ feature maps $Y_j^{(l-1)}$, layer l computes

$$Y_i^{(l)} = f\left(B_i^{(l)} + \sum_{j=1}^{m_1^{(l-1)}} W_{i,j}^{(l)} \underset{\text{discrete convolution}}{*} Y_j^{(l-1)}\right), \quad 1 \leq i \leq m_1^{(l)}$$

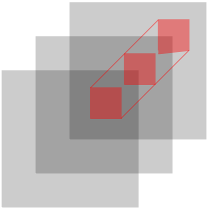
where $B_i^{(1)}$ are bias matrices and $W_{i,j}^{(1)}$ are filters.

3.2. Local Contrast Normalization Layer

General architecture:

convolutional layer – **contrast normalization layer** – pooling layer

feature maps
layer $(l-1)$



ensure that values
are comparable

3.2. Local Contrast Normalization Layer

General architecture:

convolutional layer – **contrast normalization layer** – pooling layer

Given $m_1^{(l-1)}$ feature maps $Y_j^{(l-1)}$, brightness normalization [KSH12] computes

$$\left(Y_i^{(l)}\right)_{r,s} = \frac{\left(Y_i^{(l-1)}\right)_{r,s}}{1 + \sum_{j=1}^{m_1^{(l-1)}} \left(Y_j^{(l-1)}\right)_{r,s}^2}, \quad 1 \leq i \leq m_1^{(l)} = m_1^{(l-1)}.$$

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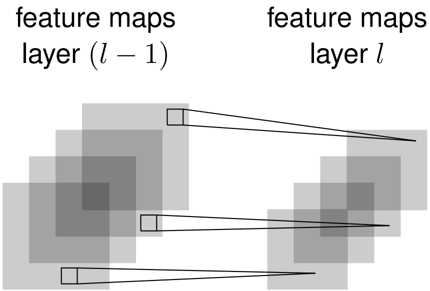


3.2. Pooling Layer

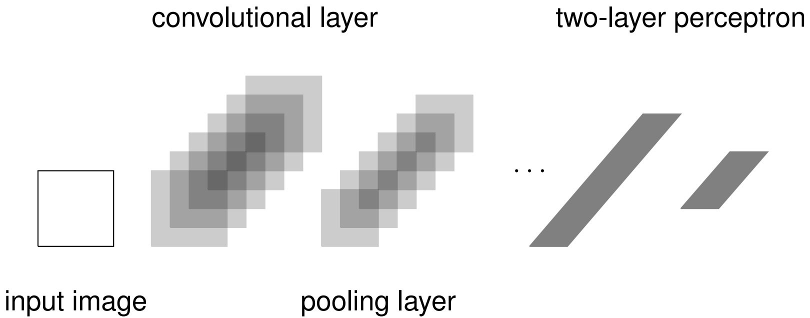
General architecture:

convolutional layer – contrast normalization layer – **pooling layer**

Given feature maps $Y_j^{(l-1)}$ of size $m_2^{(l-1)} \times m_3^{(l-1)}$, it computes feature maps $Y_i^{(l)}$ of reduced size by

- computing the average value within (non-overlapping) windows (average pooling);
- or keeping the maximum value of (non-overlapping) windows (max pooling).

3.3. Schematic Architecture



3.3. ImageNet Architecture “AlexNet”

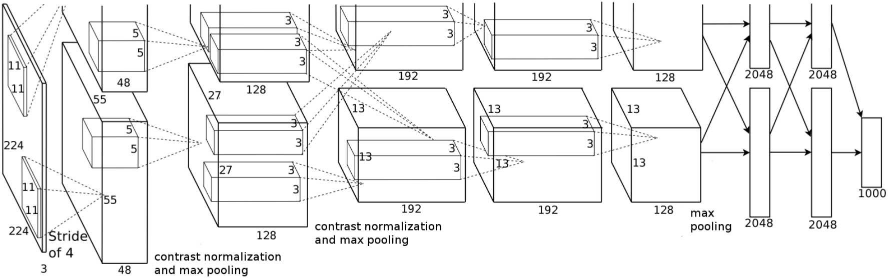


Figure: Architecture used by Krizhevsky et al. [KSH12], $L = 13$.

3.4. Training

For classification, use softmax activation function in layer L:

interpreted as posteriors

$$f(z_i^{(L)}) = \frac{\exp\left(z_i^{(L)}\right)}{\sum_{j=1}^{m^{(L)}} \exp\left(z_j^{(L)}\right)}.$$

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Given a training set $\{(x_n, t_n)\}$ with $t_n = i$ iff x_n belongs to class i, minimize multinomial loss

all weights of the network

$$E(W) = -\frac{1}{m^{(L)}} \sum_{n=1}^{N} \log\left(y_{t_n}^{(L)}\right)$$

using gradient descent.

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4. Neural Codes – Motivation

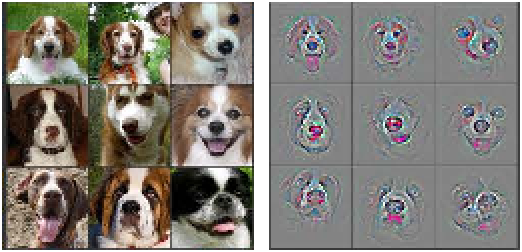

Figure: Back-projection of a single feature activation in the fourth convolutional layer [ZF14].

4. Neural Codes for Image Retrieval

Motivation: Intermediate feature activations are rich representations of image content.

For application in image retrieval, Babenko et al. [BSCL14] use

- layer $l = 10$: last convolutional layer, including subsequent max pooling;
- layer $l = 11$ and $l = 12$: first and second layer of the three-layer perceptron.

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Two models:

- pre-trained on ImageNet[1] (~ 3.2 million images, > 1000 classes);
- and re-trained on the Landmark dataset ($213,678$ images of 672 popular landmarks).

[1] Available at `http://www.image-net.org/`.

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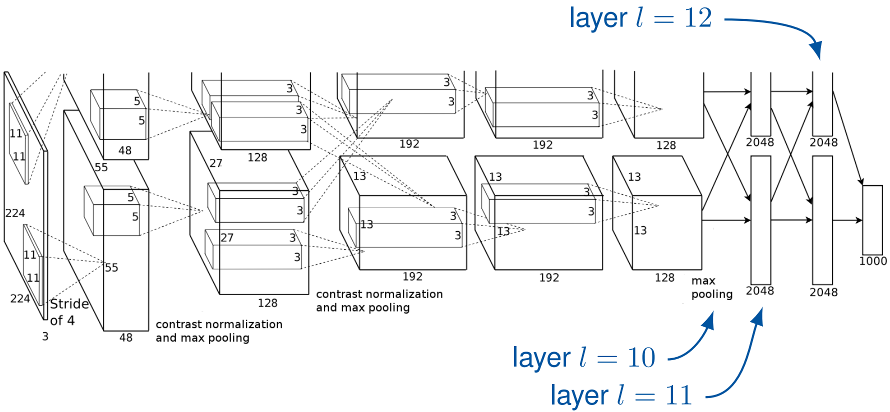

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4. Compressed Neural Codes

Compression using PCA and Large Margin Dimensionality Reduction.

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Compression using PCA and Large Margin Dimensionality Reduction.

Large Margin Dimensionality Reduction:

1. Match images such that $t_{n,n'} = 1$ iff images x_n and $x_{n'}$ are related.
2. Compute linear dimensionality reduction $P \in \mathbb{R}^{C' \times C}$ by minimizing

$$E(P) = \sum_{n,n'}^{N} \max\{0, 1 - t_{n,n'} \left(b - (x_n - x_{n'})^T P^T P (x_n - x_{n'})\right)\}$$

large margin condition

using gradient descent.

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5. Datasets and Metric

Datasets:

- **Oxford 5k** [PCI$^+$07]: $5,062$ images of eleven different landmarks in Oxford; 5 queries with ground truth per landmark.
- INRIA Holidays [JDS08]: $1,491$ holiday images with 500 distinct queries including ground truth.

Figure: Example images from the Oxford 5k dataset showing the All Souls College of the University of Oxford.

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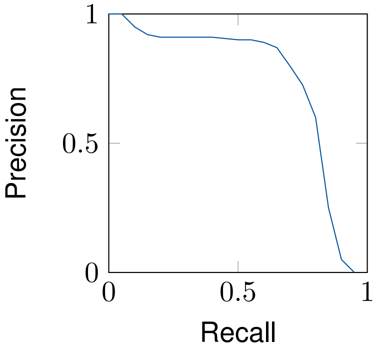
Figure: Example images from the INRIA Holidays dataset.

5. Precision-Recall Framework

Precision-Recall curves:

- Recall: ratio of true positives to all related images;
- Precision: ratio of true positives to number of retrieved images.



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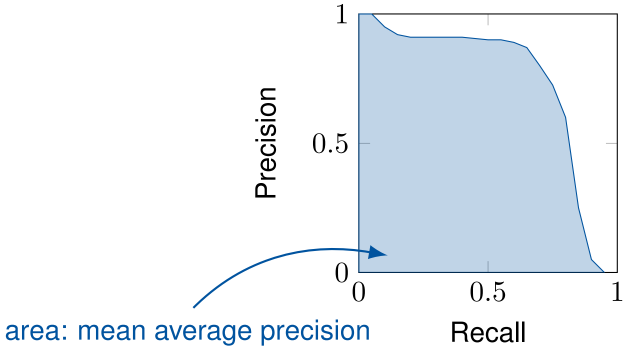

5. Experiments

	Oxford 5k	Holidays
Fisher Vectors [GRPV12]	–	0.774
Vector of Locally Aggregated Descriptors [AZ13]	0.555	0.646
Sparse-Coded Features [GKS13]	–	0.767
Triangulation Embedding [JZ14]	0.676	0.771
Pre-Trained on ImageNet		
$l = 10$	0.389	0.69
$l = 11$	0.435	0.749
$l = 12$	0.430	0.736
Re-Trained		
$l = 10$	0.387	0.674
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Table: Mean average precision for the Oxford 5k dataset and the Holidays dataset.

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5. Experiments – Examples

Figure: Qualitative examples provided by Babenko et al. [BSCL14]: left-most image is the query; correctly retrieved images are marked.

5. Experiments – Conclusion

Notes on Experiments:

- no experiments using Large Margin Dimensionality Reduction on the re-trained model;
- and the results for state-of-the-art approaches are taken from the corresponding publications.

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Conclusion:

- fully learned features are interesting alternative to hand-crafted features;
- and convolutional neural networks may be explicitly trained for the image retrieval task.

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6. Summary

Summary and takeaways:

1. State-of-the-art image retrieval techniques aggregate local descriptors:
   - Bag of Visual Words [SZ03];
   - Vector of Locally Aggregated Gradients [AZ13];
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   - Sparse-Coded Features [GKS13].
2. Convolutional neural networks are powerful, but complex models for classification.
   - Excellent performance on ImageNet;
   - but difficult to train or implement.
3. Intermediate feature activations of convolutional neural networks offer rich representations.

A.1. Bag of Visual Words – Discussion

For large Y, k-means clustering may be infeasible:

- hierarchical k-means [NS06];
- or approximate k-means [PCI$^+$07].

Burstiness, that is single large components can strongly affect performance [AZ13]:

- term frequency, inverse document frequency weighting;
- or component-wise square root and L_2 normalization.

A.2. Vector of Locally Aggregated Descriptors

Remember, embedding step:

$$f(y_{l,n}) = \left(\delta(\text{NN}_{\hat{Y}}(y_{l,n}) = \hat{y}_1)(y_{l,n} - \hat{y}_1), \ldots\right),$$

and aggregation step:

$$F(Y_n) = \sum_{l=1}^{L} f(y_{l,n}).$$

Further normalization techniques:

- power-law normalization (usually, $\alpha = 0.5$):

$$F_m(Y_n) = \text{sign}\left(F_m(Y_n)\right) |F_m(Y_n)|^{\alpha};$$

- intra-normalization: L_2-normalize sum of residuals for each visual word independently.

B. Training in Practice

Training with gradient descent, in iteration $[t+1]$ compute

$$W[t+1] = W[t] - \gamma \nabla E(W[t])$$

with learning rate γ.

In practice:

- Compute $\nabla E(W[t])$ in $\mathcal{O}(|W|)$ using Error Backpropagation.
- Add a regularizer of the form

$$\hat{E}(W) = E(W) + \lambda \|W\|_1.$$

- Use dropout [HSK+12] and stochastic gradient descent.

C. Neural Codes – Motivation

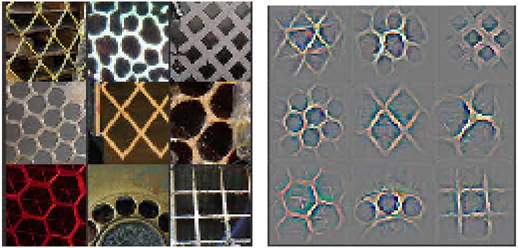

Figure: Back-projection of a single feature activation in layer $l = 3$ [ZF14][2].

[2] Note that the architecture used by Zeiler et al. [ZF14] does not exactly match the architecture presented previously.

C. Neural Codes – Motivation

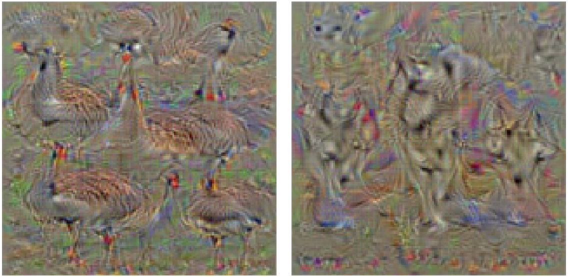

Figure: Computed image to maximize posterior for classes “goose” (left) and “husky” (right) [SVZ13].

D. Try it out ...

Unfortunately, Babenko et al. do not provide source code to reproduce their experiments.

However, you can try other state-of-the-art approaches:

- Oxford 5k dataset (including evaluation script): `http://www.robots.ox.ac.uk/~vgg/data/oxbuildings/`;
- SIFT, Vector of Locally Aggregated Descriptors and Fisher Vectors [PD07] are implemented in the VLFeat library: `http://www.vlfeat.org/overview/encodings.html`;

... or try to use convolutional neural networks, for example using

- Caffe: `http://caffe.berkeleyvision.org/`.

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