Deep Learning

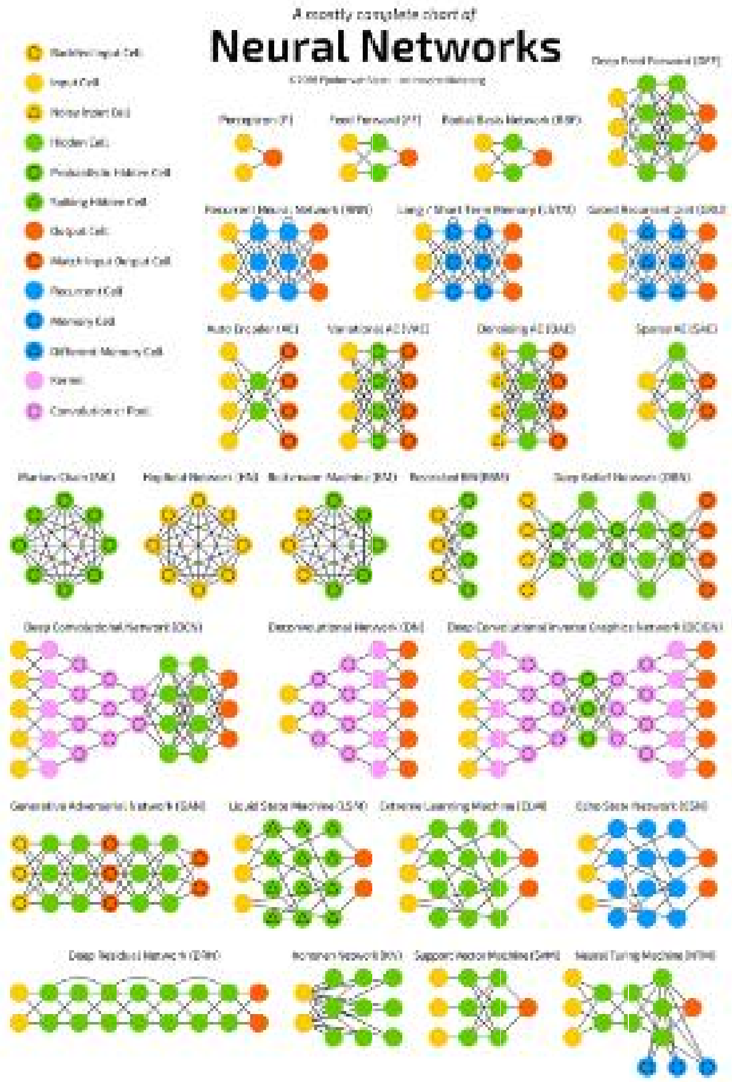
A journey from feature extraction and engineering to end-to-end pipelines

Part 1: Introduction, Computer Vision

Andrei Bursuc

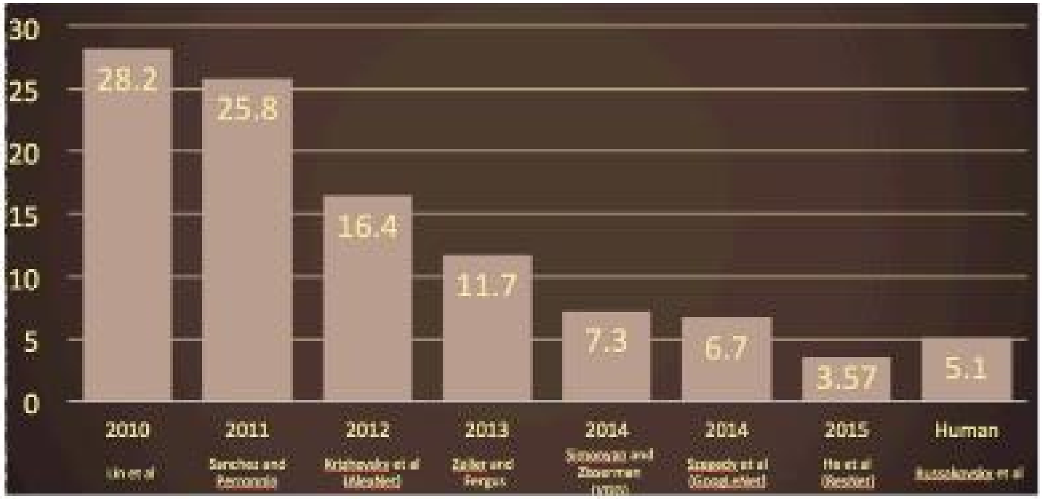
With slides from A. Karpathy, F. Fleuret, J. Johnson, S. Yeung, G. Louppe, Y. Avrithis ...

Deep Learning - the hype?



Deep Learning - the hype?

- Evolution of ImageNet large scale visual recognition challenge
- 1.2 M training images with 1K object categories



ImageNet
top-5 error (%)

Deep Learning - the hype?

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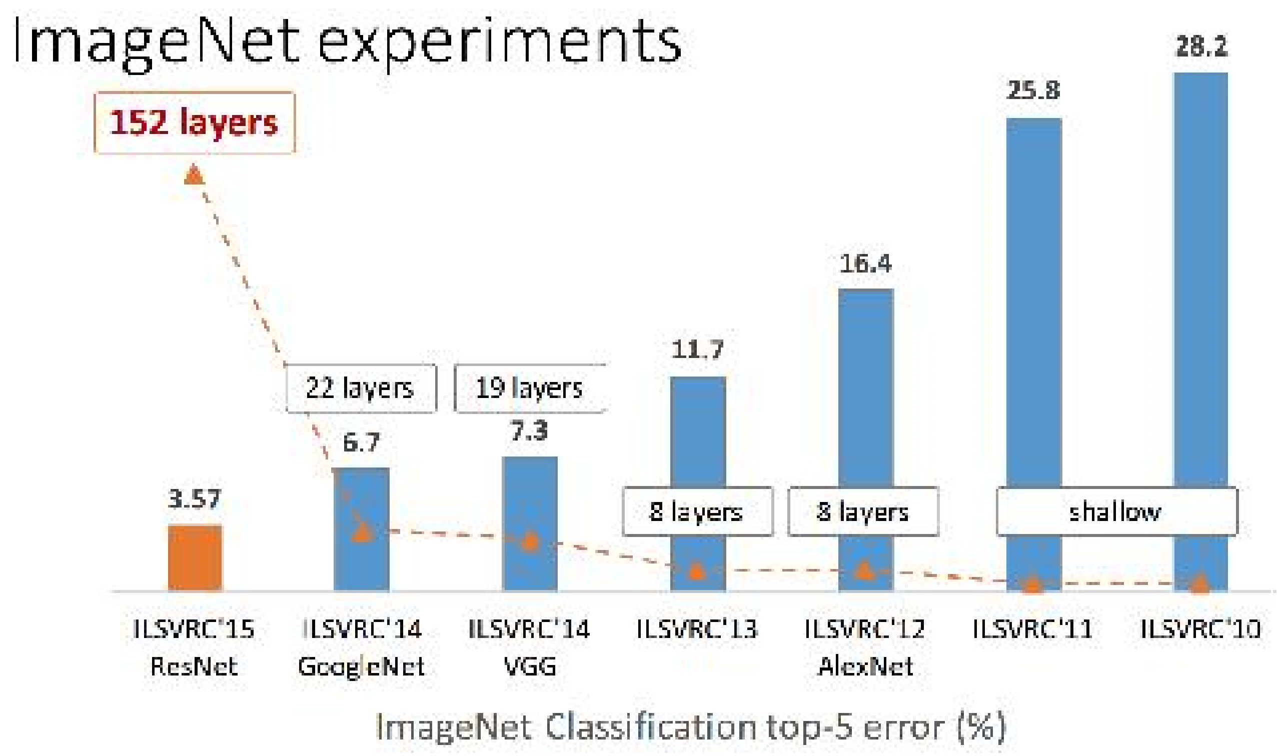
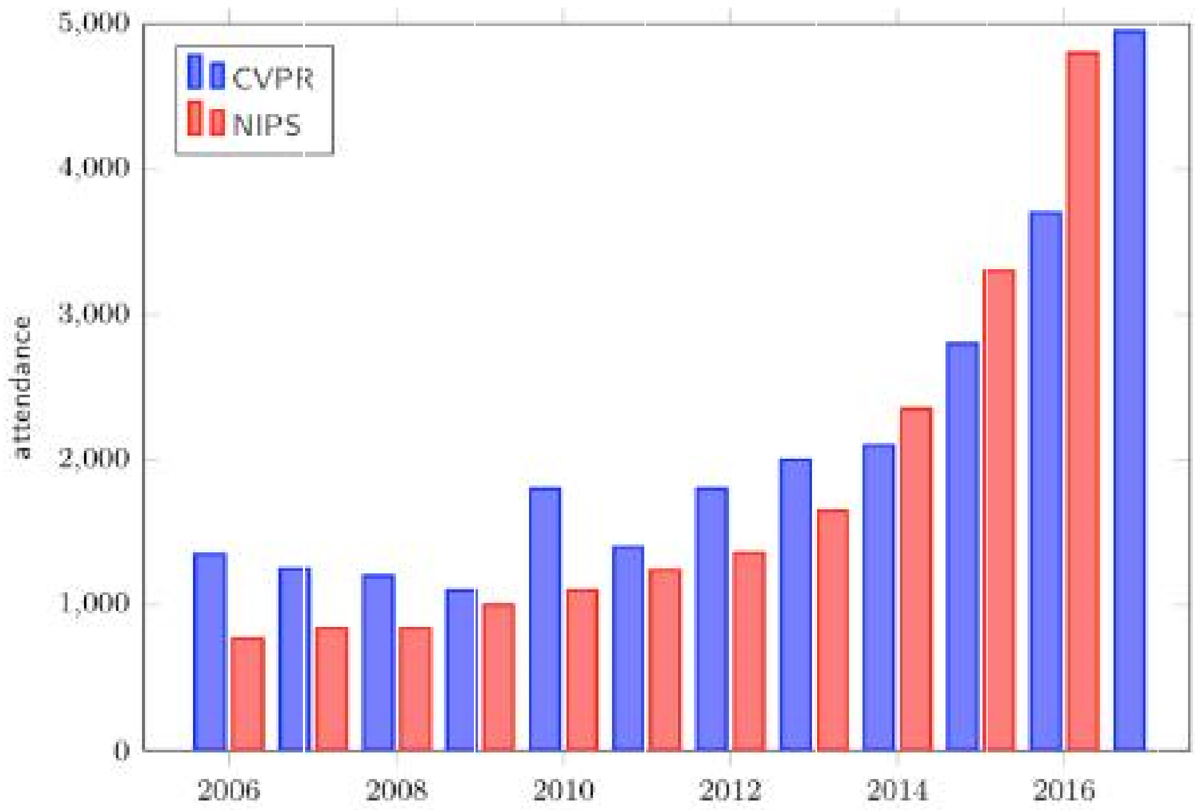


Deep Learning - the hype?

Conference attendance growth



Deep Learning - the hype?

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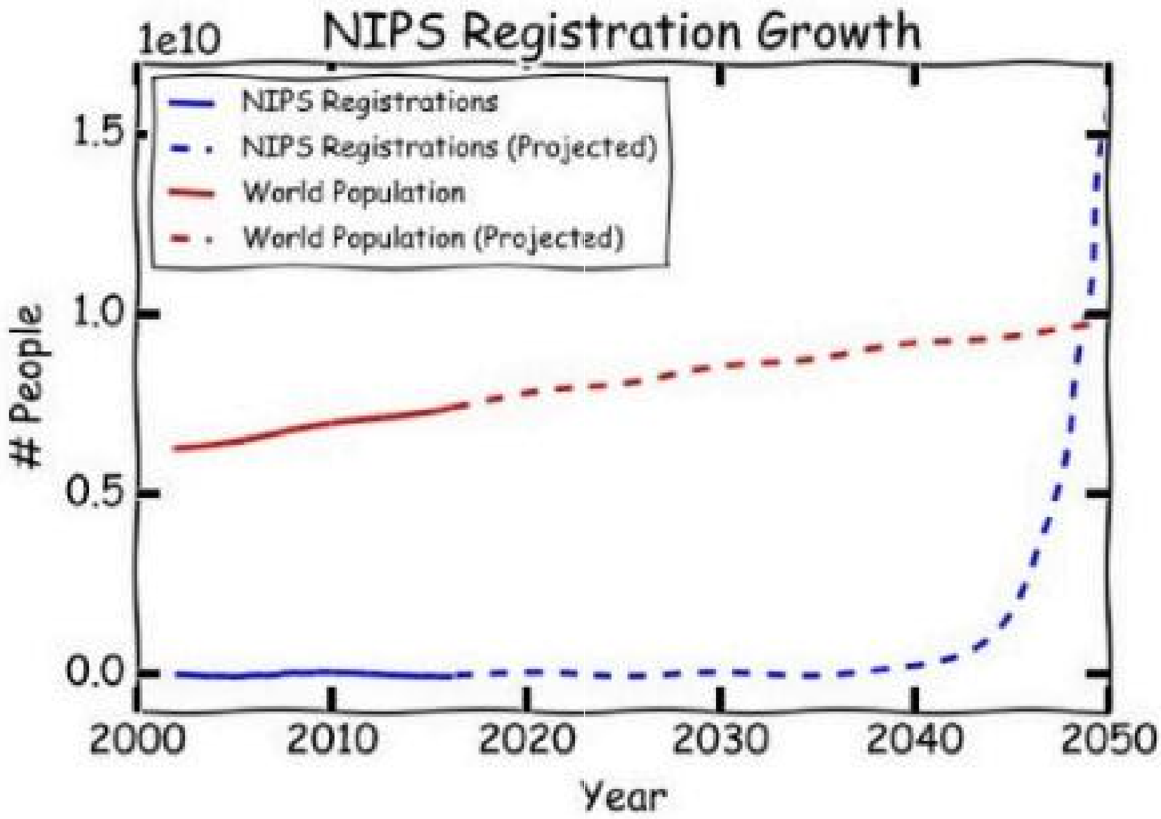
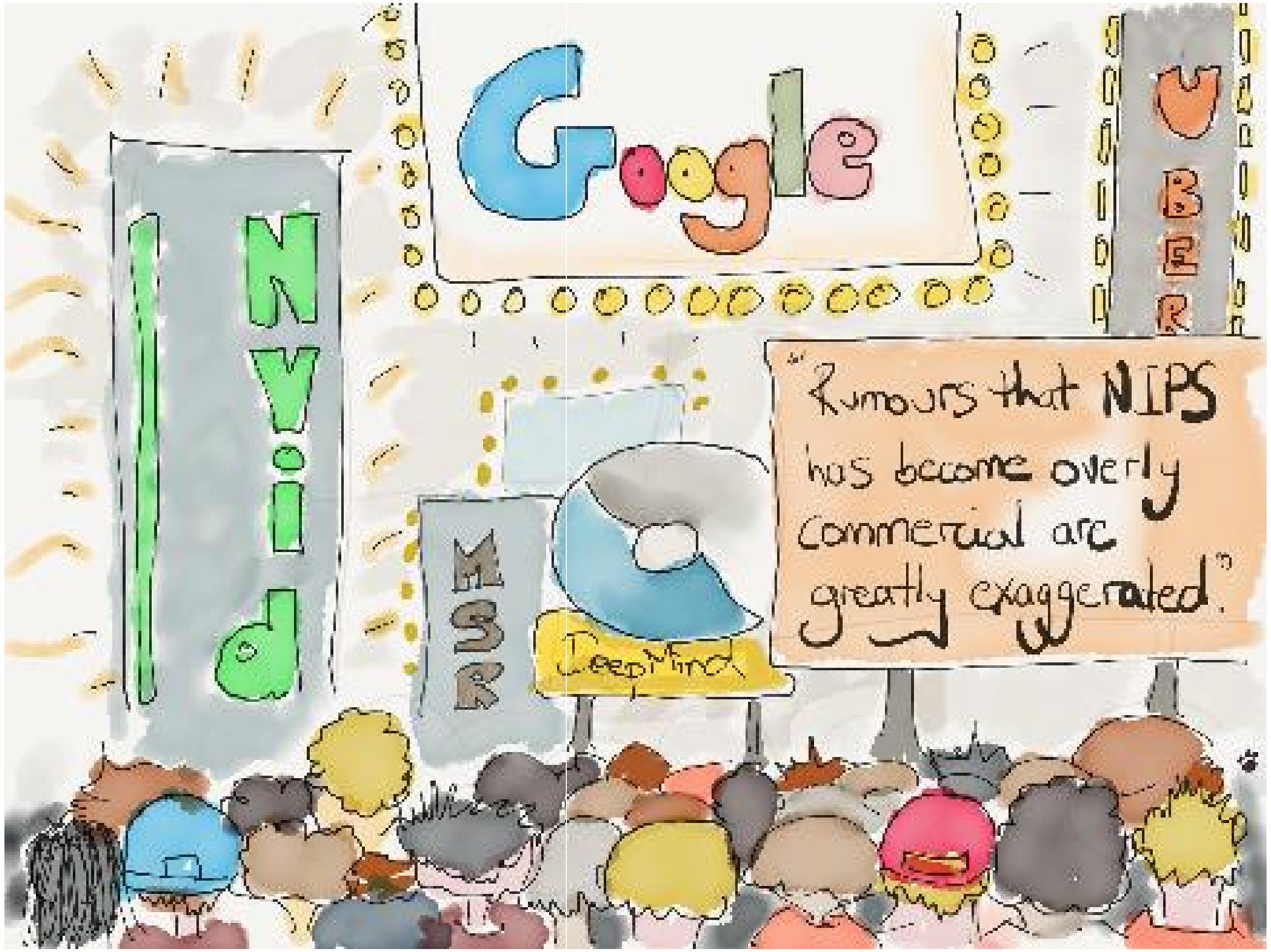


Deep Learning - the hype?

CVPR 2017 sponsors

Deep Learning - the hype?

Industry participation



Deep Learning - the hype?

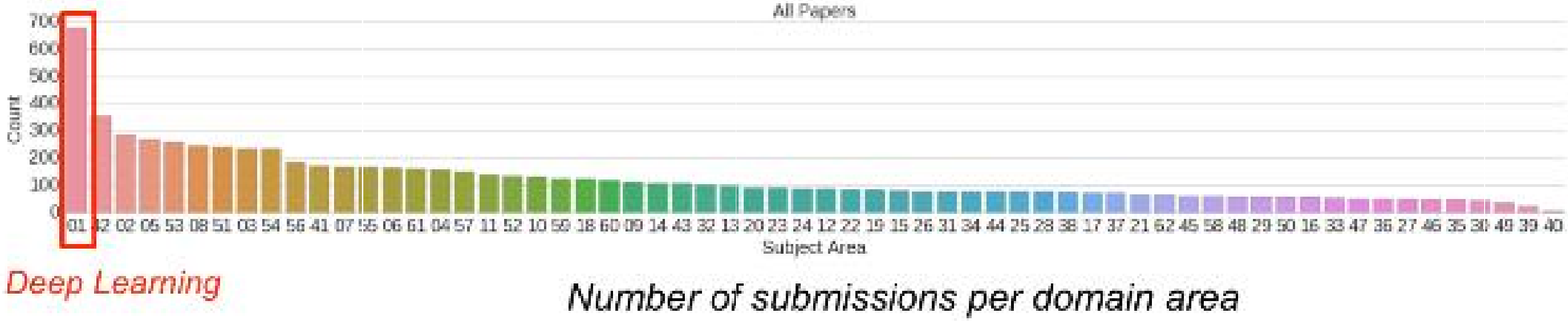
1/2 parallel session at NIPS 2017

Deep Learning - the hype?

Poster session at NIPS 2017

Deep Learning - the hype?

Primary topic in submissions at NIPS 2017



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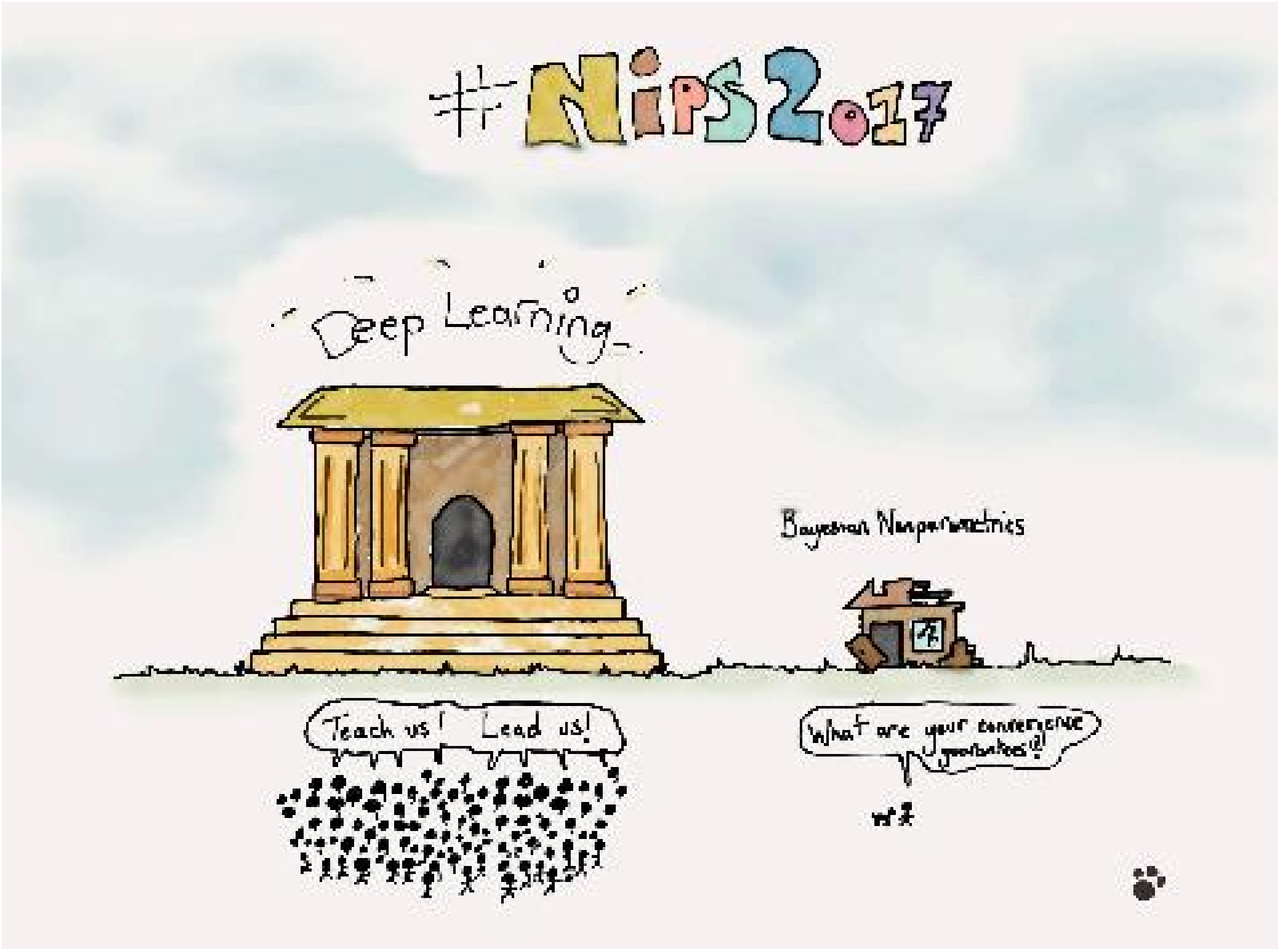


Deep Learning - the hype?

Primary topic in submissions at NIPS 2017

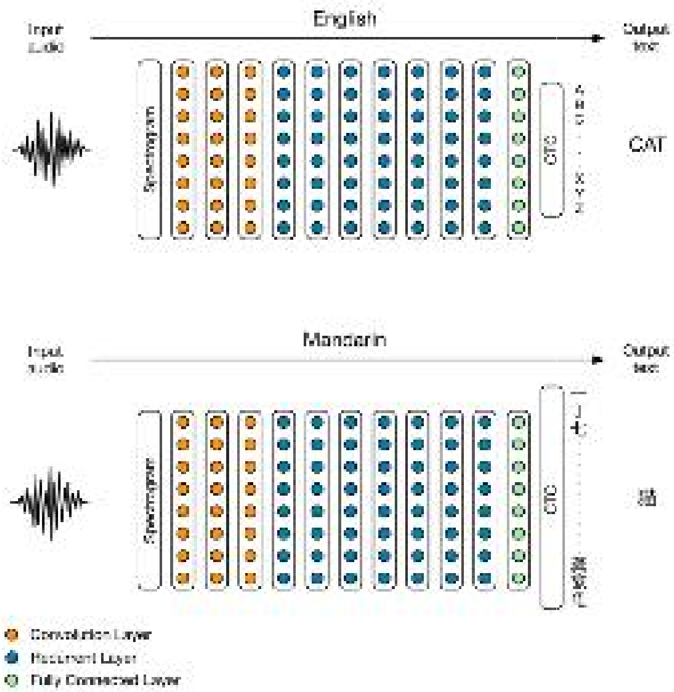
Deep Learning - the hype?

Other remarkable changes

- Paper publishing is more intense: papers are released on arXiv right after submission deadline
- Results of papers can be already outperformed by the time of the conference
- Code and/or trained networks are released with paper most of the times
- High number of published datasets
- Contributions arrive also from non computer vision / machine learning classic domains: genomics, mechanics.

Domain applications of Deep Learning?

Speech-to-Text



[Baidu 2014]

Domain applications of Deep Learning?

Computer Vision

[Krizhevsky 2012]

[Ciresan et al. 2013]

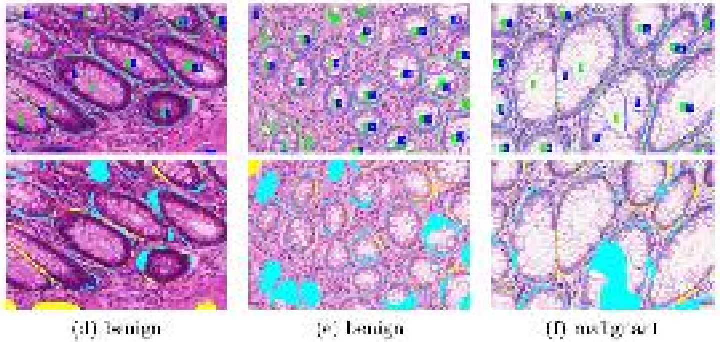
[Faster R-CNN - Ren 2015]

[NVIDIA dev blog]

Domain applications of Deep Learning?

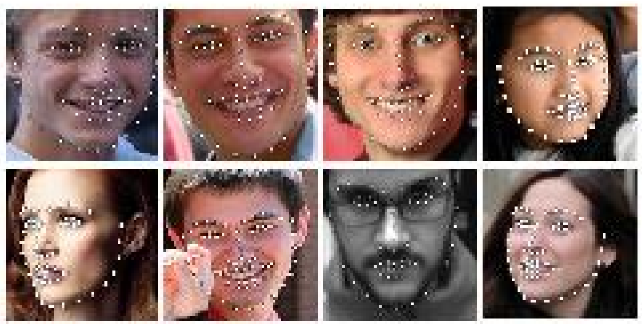
Computer Vision

[Stanford 2017]



[Nvidia Dev Blog 2017]

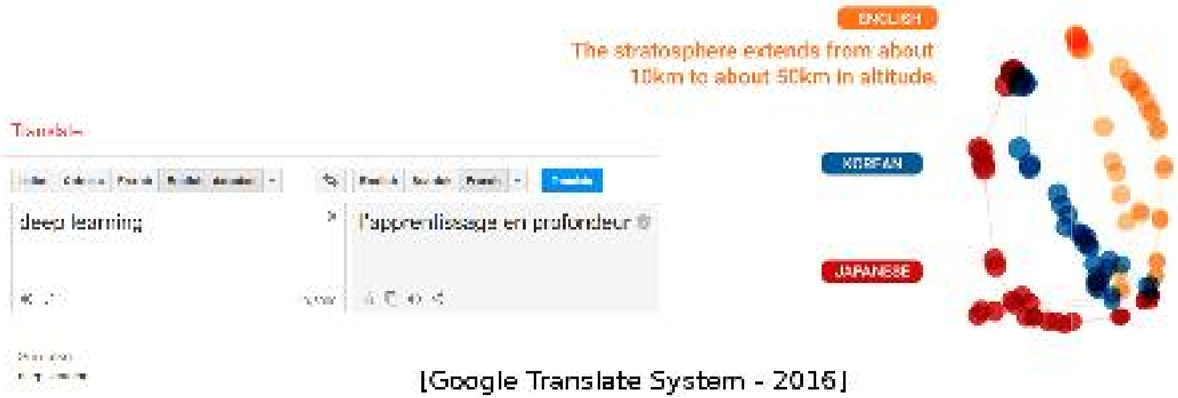
[FaceNet - Google 2015]



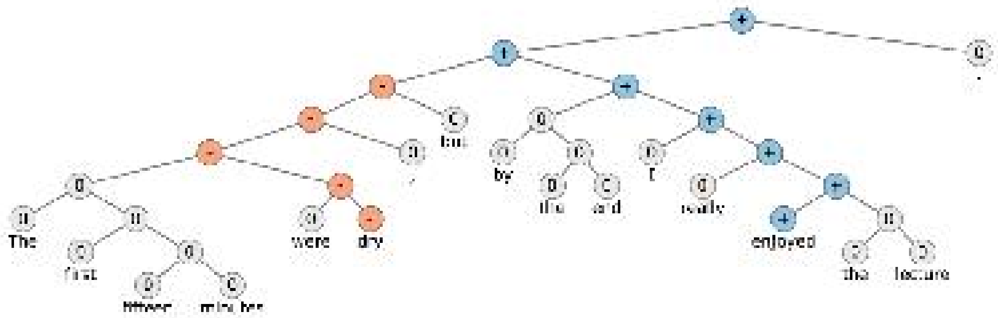
[Facial landmark detection CUHK 2014]

Domain applications of Deep Learning?

NLP



[Google Translate System - 2016]



[Socher 2015]

Domain applications of Deep Learning?

NLP

[Google Inbox Smart Reply]

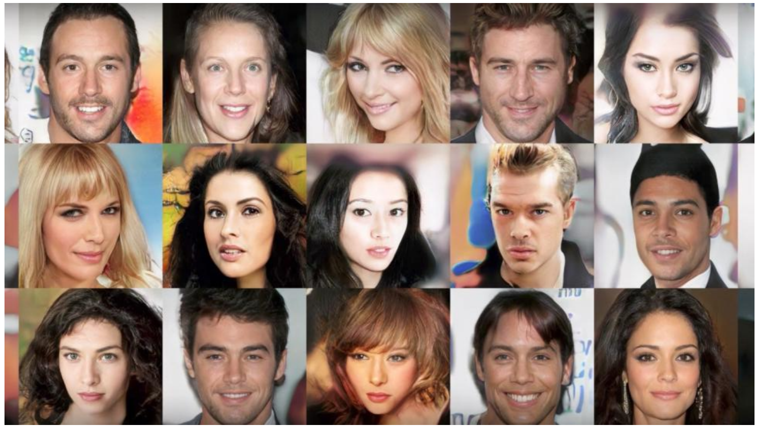
[Amazon Echo / Alexa]

Domain applications of Deep Learning?

Vision + NLP

Domain applications of Deep Learning?

Generative models



Sampled celebrities [Nvidia 2017]

Domain applications of Deep Learning?

Generative models

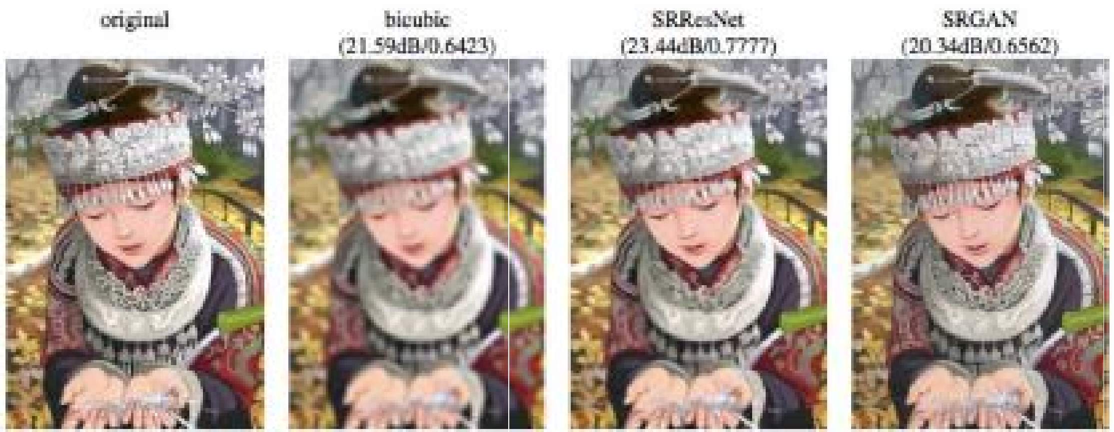
StackGAN v2 [Zhang 2017]

Domain applications of Deep Learning?

Image translation

[DeepDream 2015]

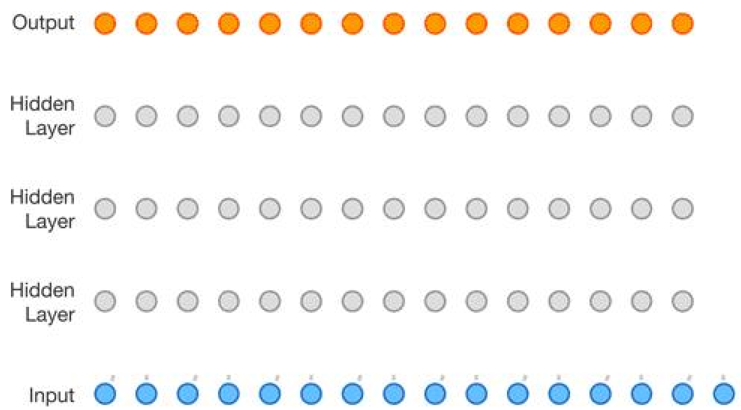
[Gatys 2015]



[Ledig 2016]

Domain applications of Deep Learning?

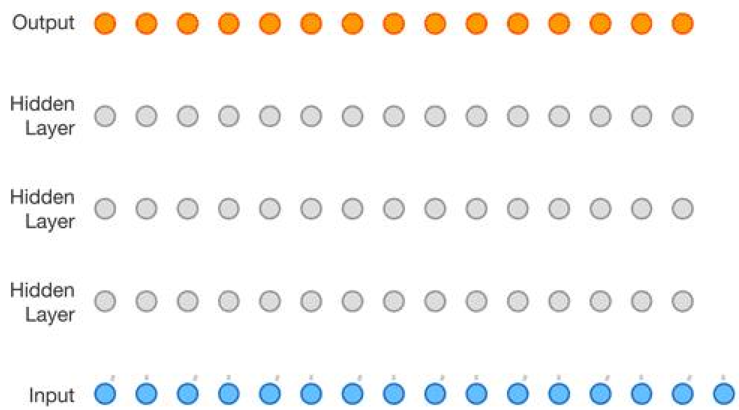
Generative models



Sound generation with WaveNet [DeepMind 2017]

Domain applications of Deep Learning?

Generative models

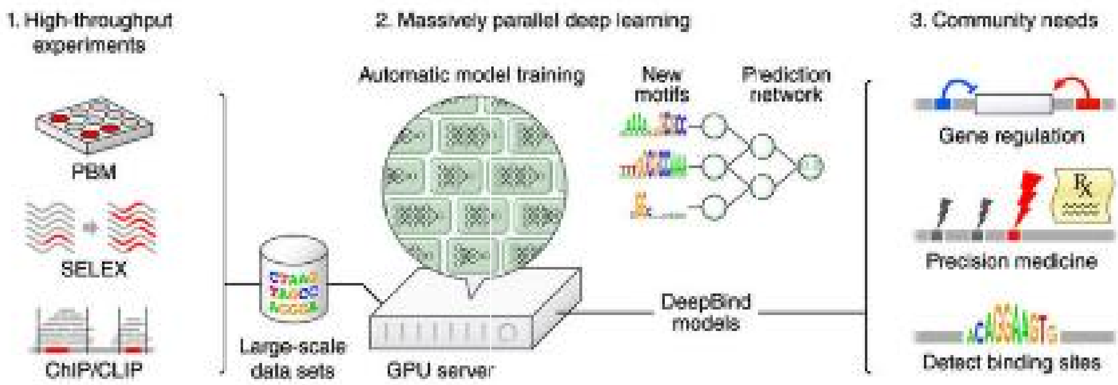


Sound generation with WaveNet [DeepMind 2017]

Guess which one is generated?

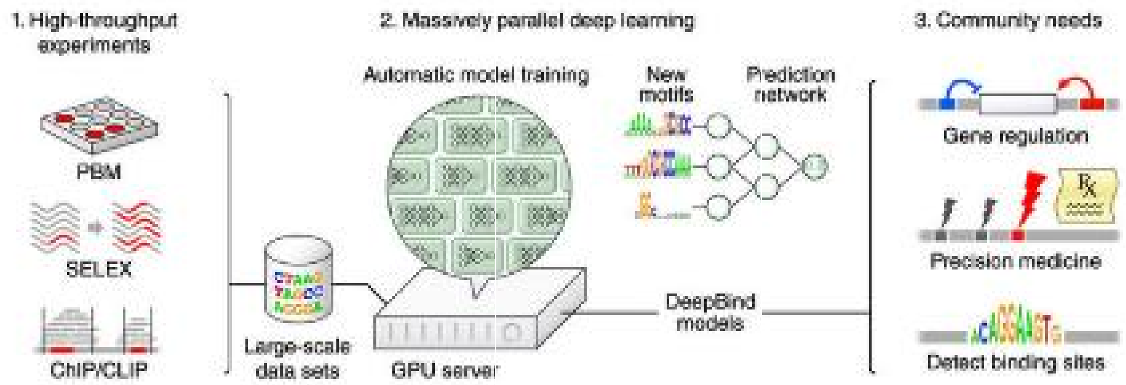
Tacotron 2 Natural TTS Synthesis by Conditioning WaveNet on Mel Spectrogram Predictions, 2017

DL in other sciences



[Deep Genomics 2017]

DL in other sciences



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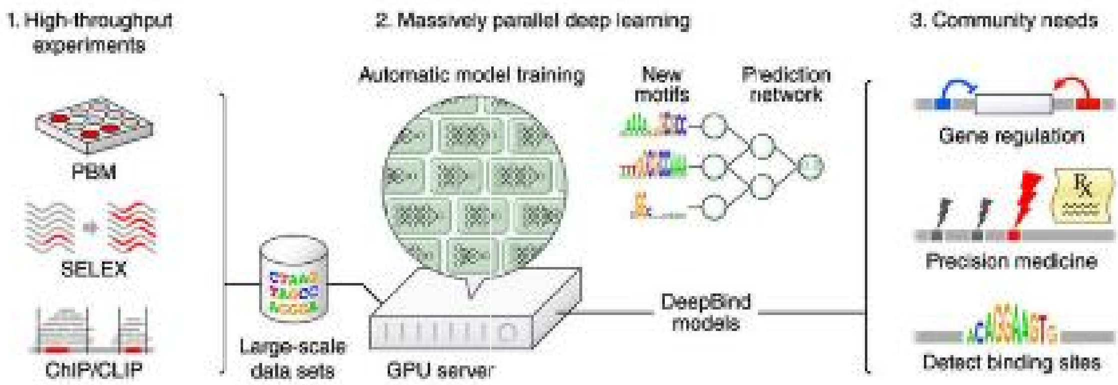
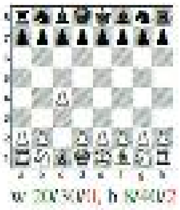
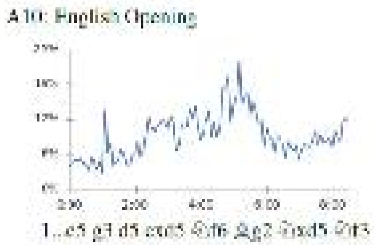
DL in other sciences



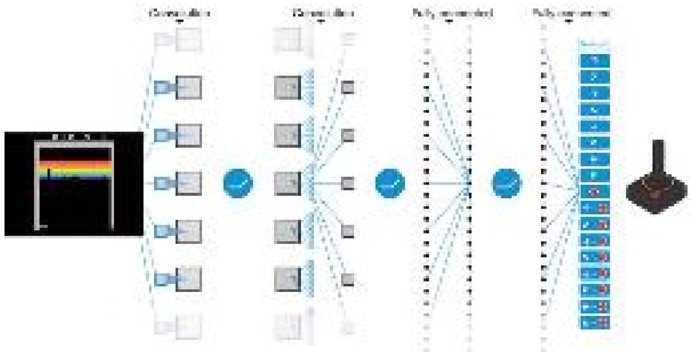
[Deep Genomics 2017]

DL for AI in games

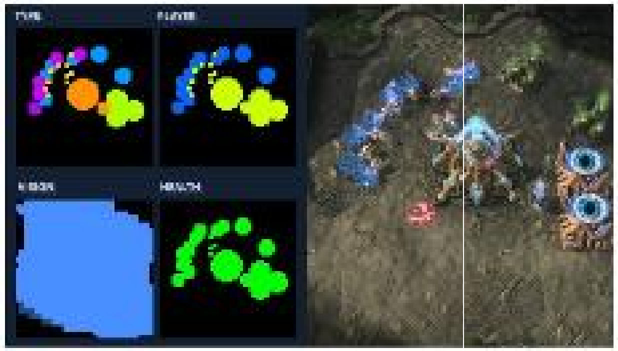




[Deepmind AlphaGo / Zero 2017]



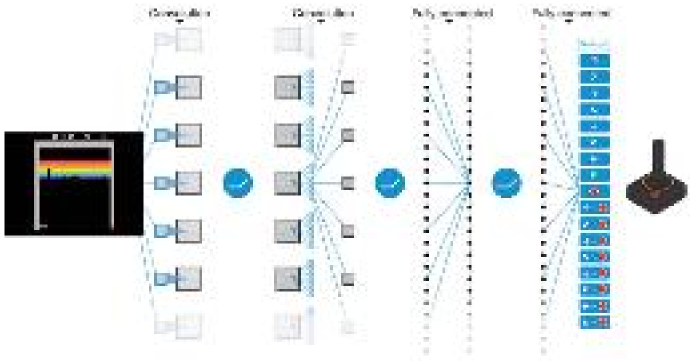
[Atari Games - DeepMind 2016]



[Starcraft 2 for AI research]

DL for AI in games

[Deepmind AlphaGo / Zero 2017]



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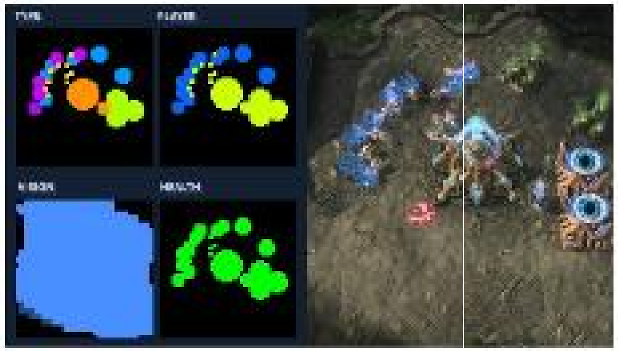


[Starcraft 2 for AI research]

AlphaGo/Zero: Monte Carlo Tree Search, Deep Reinforcement Learning, self-play

What is Deep Learning?

- Neural Networks with more layers/modules
- Non-linear, hierarchical, abstract representations of data
- Flexible models with any input/output size
- Differentiable functional programming

What is Deep Learning?

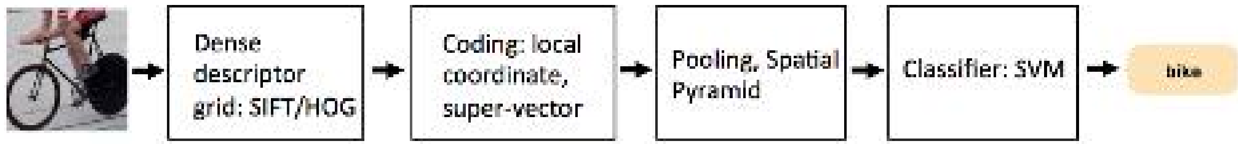
In other words: a graph of tensor operators taking advantage of:

- the chain rule (back-propagation),
- stochastic gradient descent,
- convolutions,
- parallel operations on GPU

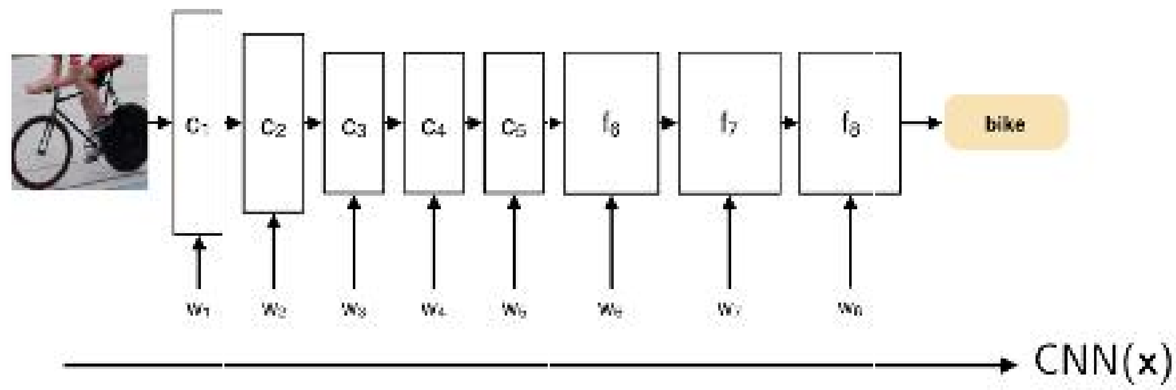
We kind of had most of it in the networks from long ago

Why going deep?

- Traditional recognition: "shallow" architecture
  - Each block is designed and implemented individually



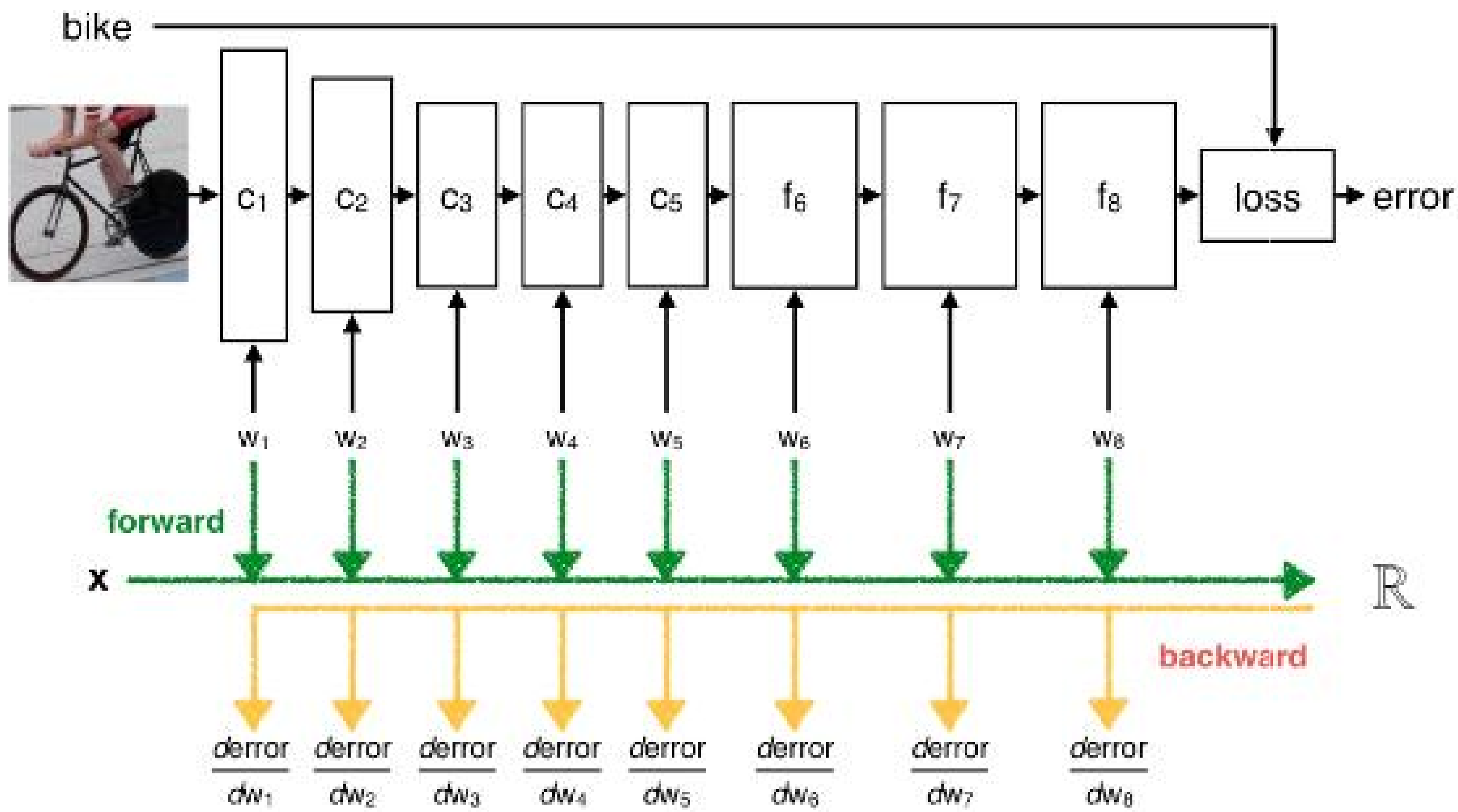
- "Deep" architecture (Convolutional Neural Network)



Why going deep?

Graph of tensors where blocks are trained and optimized jointly

- 1 - 140M trainable parameters



Why Deep Learning works now?

- Five decades of research in machine learning
- Computing and storage power
- Lots of (labelled) data from the internet
- Tools and culture of collaborative and reproducible science
- Resources and efforts from large companies

Why Deep Learning works now?

Five decades of research in ML provided:

- a taxonomy of ML concepts (classification, generative models, clustering, kernels, linear embeddings, etc.),
- a sound statistical formalization (Bayesian estimation, PAC),
- a clear picture of fundamental issues (bias/variance dilemma, VC dimension, generalization bounds, etc.),
- a good understanding of optimization issues,
- efficient large-scale algorithms.

Why Deep Learning works now?

From a practical perspective, deep learning:

- lessens the need for a deep mathematical grasp,
- makes the design of large learning architectures a system/software development task,
- allows to leverage modern hardware (clusters of GPUs),
- does not plateau when using more data,
- makes large trained networks a commodity.

Why Deep Learning works now?

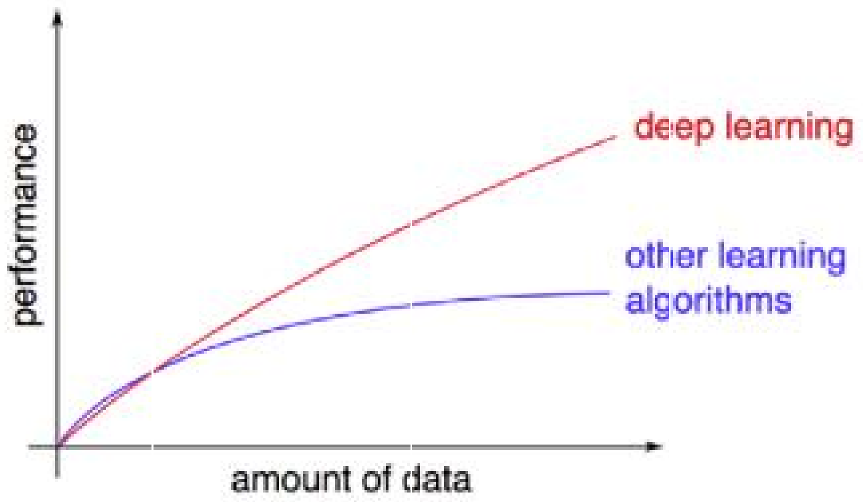
Evolution in computer vision datasets

Data-set	Year	Nb. images	Resolution	Nb. classes
MNIST	1998	6.0×10^4	28×28	10
NORB	2004	4.8×10^4	96×96	5
Caltech 101	2003	9.1×10^3	$\simeq 300 \times 200$	101
Caltech 256	2007	3.0×10^4	$\simeq 640 \times 480$	256
LFW	2007	1.3×10^4	250×250	–
CIFAR10	2009	6.0×10^4	32×32	10
PASCAL VOC	2012	2.1×10^4	$\simeq 500 \times 400$	20
MS-COCO	2015	2.0×10^5	$\simeq 640 \times 480$	91
ImageNet	2016	14.2×10^6	$\simeq 500 \times 400$	21, 841
Cityscape	2016	25×10^3	$2,000 \times 1000$	30

Figure credit: F. Fleuret, EE-559 Deep learning

Why Deep Learning works now?

When more data is available



Why Deep Learning works now?

- Many deep learning frameworks freely available as open source
- Frequent changes and updates (every few weeks)
- Most frameworks supported by a large company

Deep Learning - the hype?

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- Frequent changes and updates (every few weeks)
- Most frameworks supported by a GAFA company

PyTorch

PyTorch

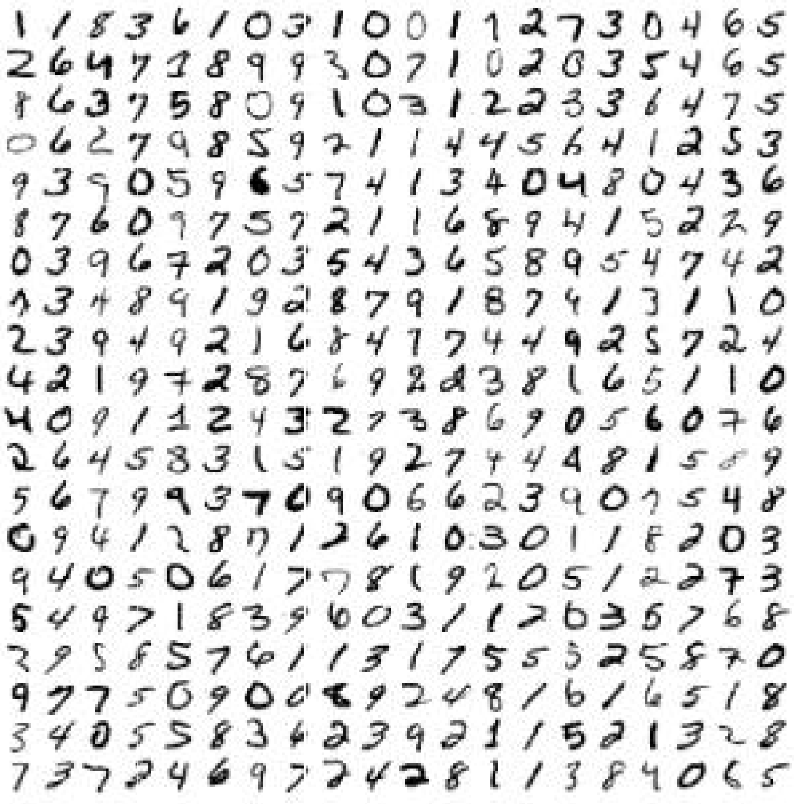
"PyTorch is a python package that provides two high-level features:

- Tensor computation (like numpy) with strong GPU acceleration
- Deep Neural Networks built on a tape-based autograd system

You can reuse your favorite python packages such as numpy, scipy and Cython to extend PyTorch when needed."

PyTorch

MNIST dataset



28×28 grayscale images, $60k$ train samples, $10k$ test samples

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class Net(nn.Module):
 def __init__(self):
  super(Net, self).__init__()
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  self.conv2 = nn.Conv2d(32, 64, kernel_size=5)
  self.fc1 = nn.Linear(256, 200)
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 def forward(self, x):
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mu, std = train_input.data.mean(), train_input.data.std()
train_input.data.sub_(mu).div_(std)
optimizer = optim.SGD(model.parameters, lr=1e-1)
criterion, batch_size = nn.CrossEntropyLoss(), 100

model.cuda()
criterion.cuda()
train_input, train_target = train_input.cuda(), train_target.cuda()

for e in range(10):
 for b in range(0, nb_train_samples , bs):
```

a few seconds on a low-end GPU, 1% test error

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   - before things went deep: handcrafted features
2. Neural networks]
   - empirical risk minimization, stochastic gradient descent, backpropagation
   - multilayer perceptrons
3. Going deeper
   - convolutional layers, deep regularization, deep architectures
4. Under the hood
   - understanding and visualizing CNNs, adversarial attacks
   - CPU vs GPU, using CNNs in practice
5. Unsupervised and self-supervised learning
   - generative models: autoencoders, variational autoencoders, generative adversarial networks
   - self-supervised learning

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Computer Vision

The old-school way

The problem with Computer Vision

The (human) brain is so good at interpreting visual information that the gap between raw data and its semantic interpretation is difficult to assess intuitively:

This is a mushroom.

This is a mushroom.

```
In [1]: from matplotlib.pyplot import imread
        imread("mushroom-small.png")

Out[1]: array([[[0.03921569, 0.03529412, 0.02352941, 1.        ],
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                [0.4117647 , 0.34117648, 0.37254903, 1.        ],
                ...,
                [0.20392157, 0.23529412, 0.17254902, 1.        ],
                [0.16470589, 0.18039216, 0.12156863, 1.        ],
                [0.18039216, 0.18039216, 0.14117648, 1.        ]],

               [[0.1254902 , 0.11372549, 0.09411765, 1.        ],
                [0.2901961 , 0.2509804 , 0.24705882, 1.        ],
                [0.21176471, 0.2       , 0.20392157, 1.        ],
                ...,
                [0.1764706 , 0.24705882, 0.12156863, 1.        ],
                [0.10980392, 0.15686275, 0.07843138, 1.        ],
                [0.16470589, 0.20784314, 0.11764706, 1.        ]],

               [[0.14117648, 0.12941177, 0.10980392, 1.        ],
                [0.21176471, 0.1882353 , 0.16862746, 1.        ],
                [0.14117648, 0.13725491, 0.12941177, 1.        ],
                ...,
                [0.10980392, 0.15686275, 0.08627451, 1.        ],
                [0.0627451 , 0.08235294, 0.05098039, 1.        ],
                [0.14117648, 0.2       , 0.09803922, 1.        ]],

               ...,
```

This is a mushroom.

This is known as the semantic gap. Extracting semantic information requires models of high complexity.

Figure credit: H. Jégou

Figure credit: H. Jégou

Figure credit: H. Jégou

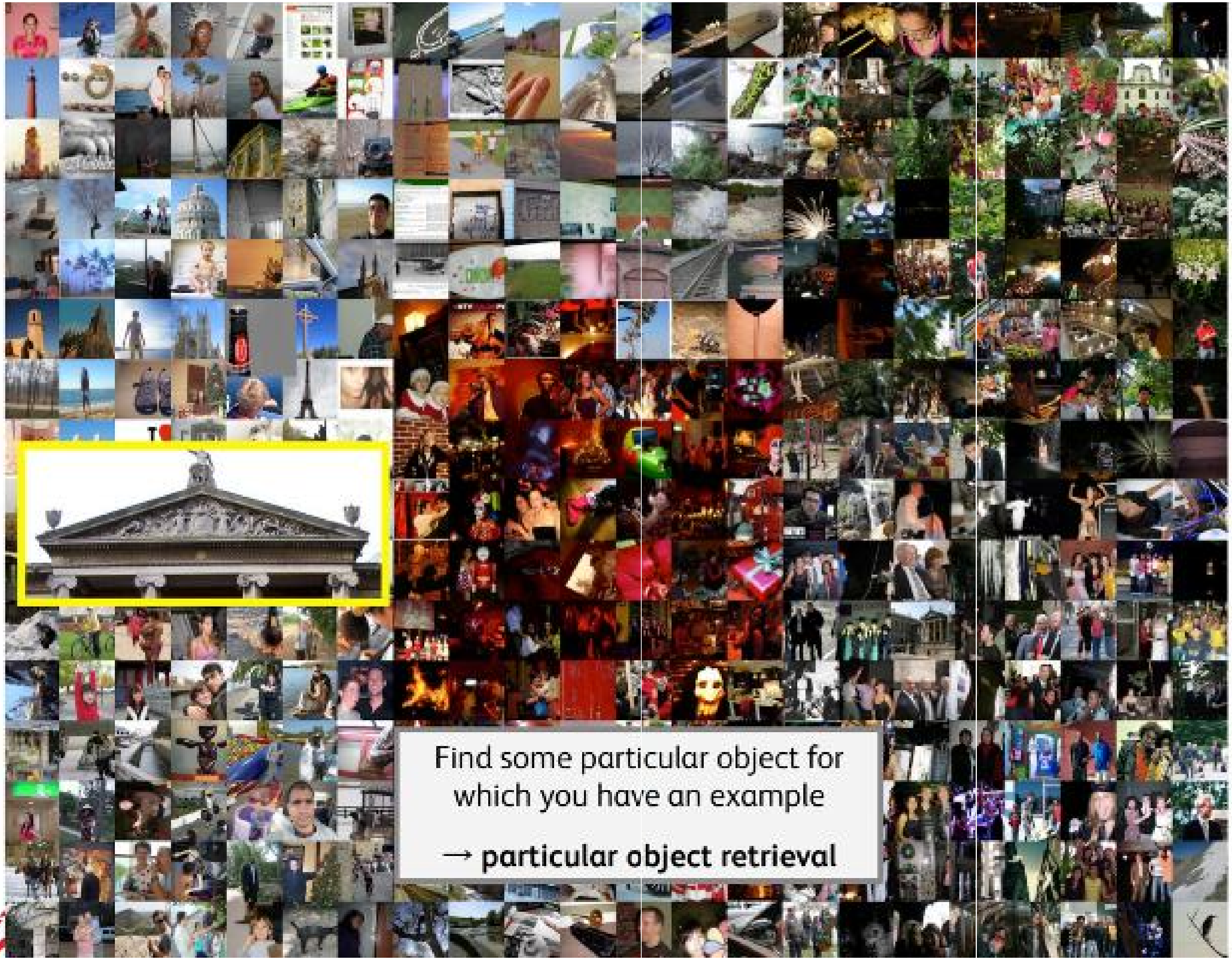


Figure credit: H. Jégou

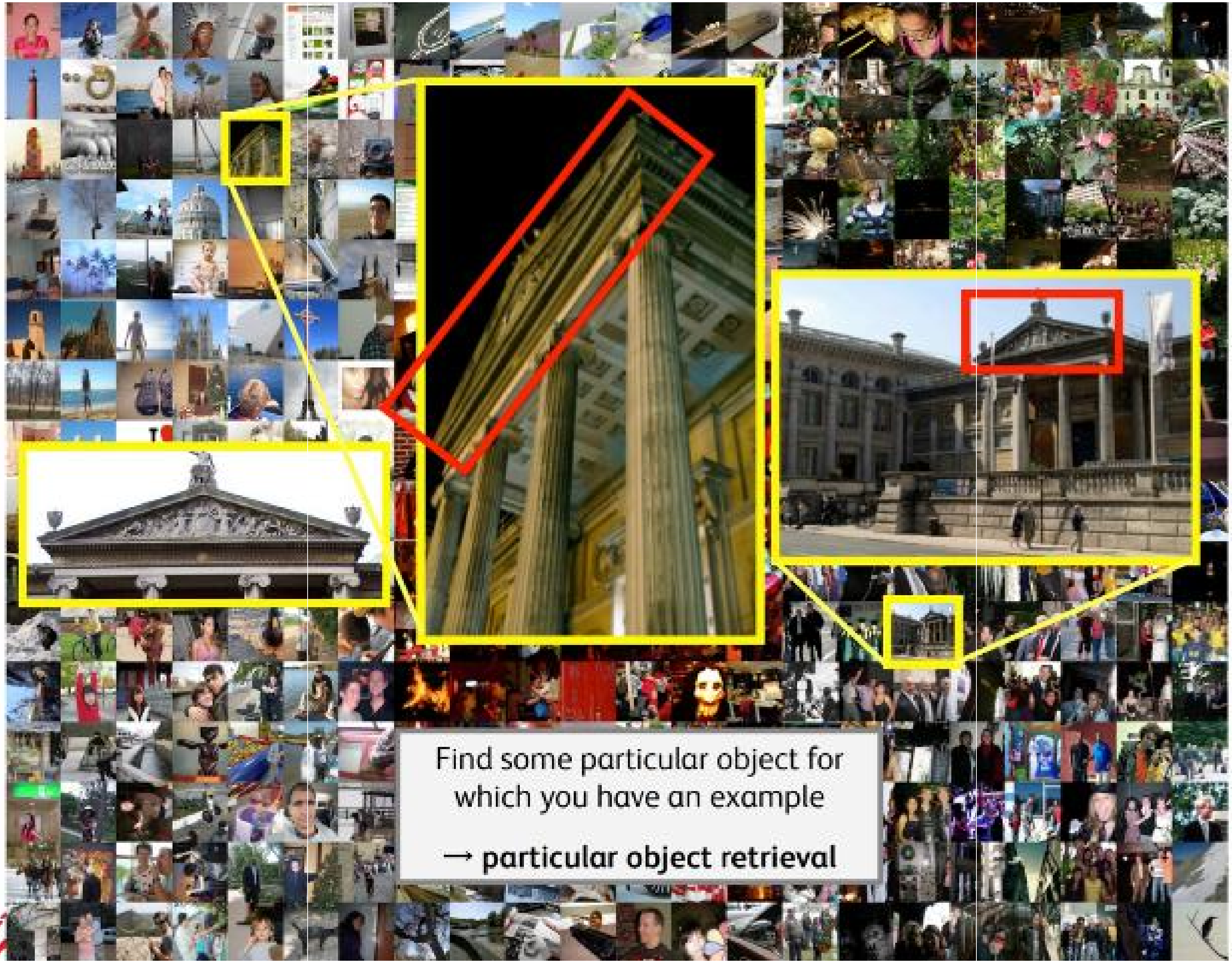


Figure credit: H. Jégou

Figure credit: H. Jégou

Figure credit: H. Jégou

Image retrieval challenges

Image retrieval challenges

- scale
- viewpoint
- occlusion
- clutter
- lighting
- distinctiveness
- distractors

Image classification challenges

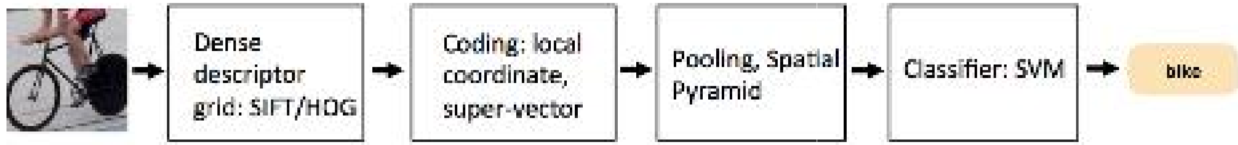
Image classification challenges

- scale
- viewpoint
- occlusion
- clutter
- lighting
- number of instances
- texture/color
- pose
- deformability
- intra-class variability

Visual descriptors

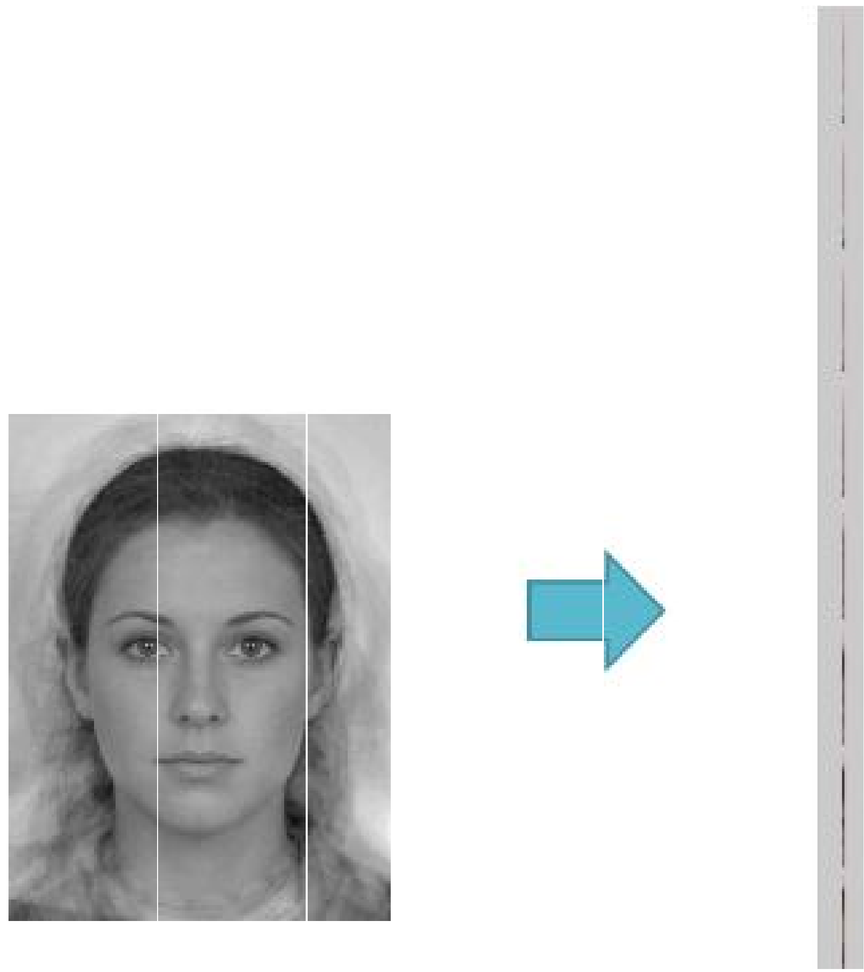
Visual descriptors

Pre-deep pipeline



Visual descriptors

Concatenation of pixels into 1D descriptors

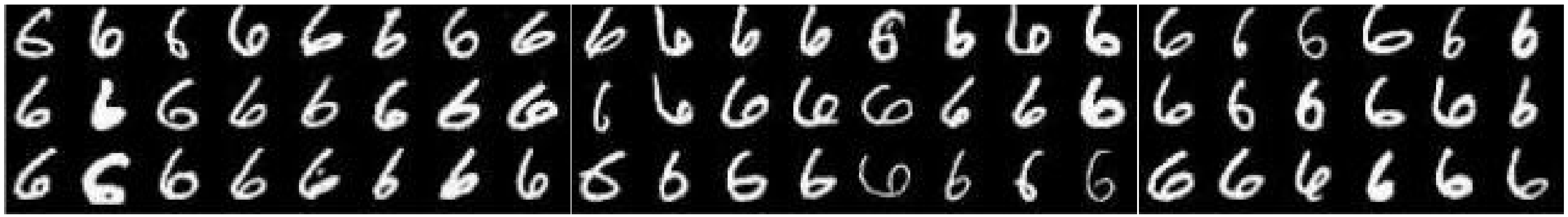


Global descriptors

Concatenation of pixels into 1D descriptors

- face recognition

- digit recognition



Global descriptors

Tiny images

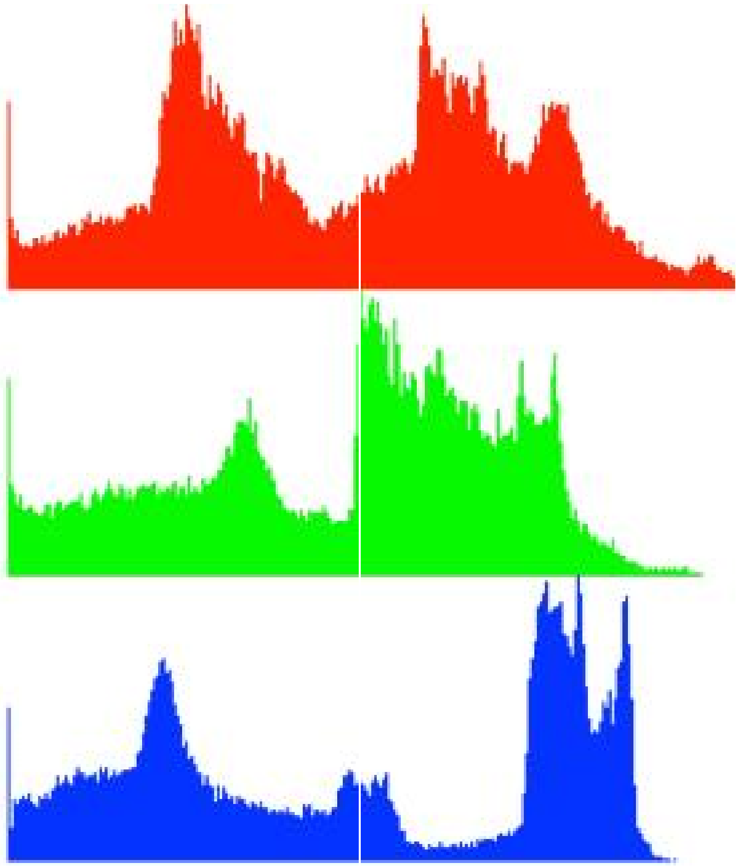
- resize images to 32×32 pixels ($3072d$ vectors)

- high speed, limited accuracy
- used for scene recognition

Global descriptors

Color histogram

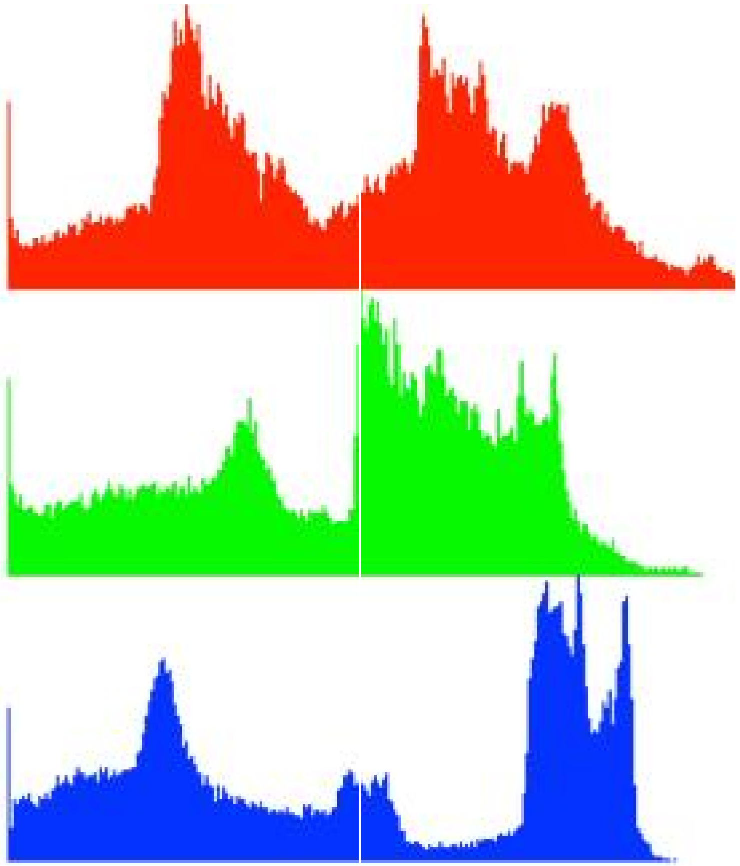
- Histogram is a summary of the data describing image statistics (here color)



Global descriptors

Color histogram

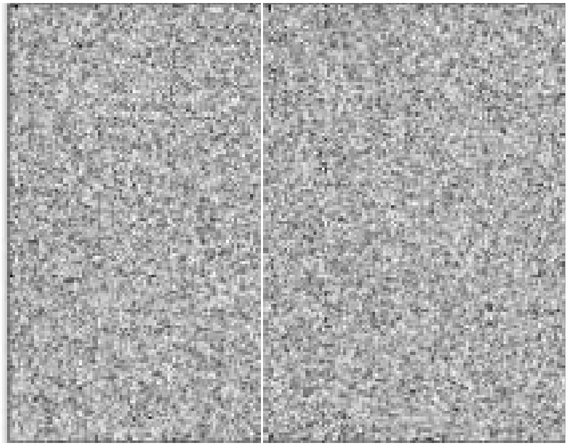
- Histogram is a summary of the data describing image statistics (here color)



Global descriptors

Color histogram

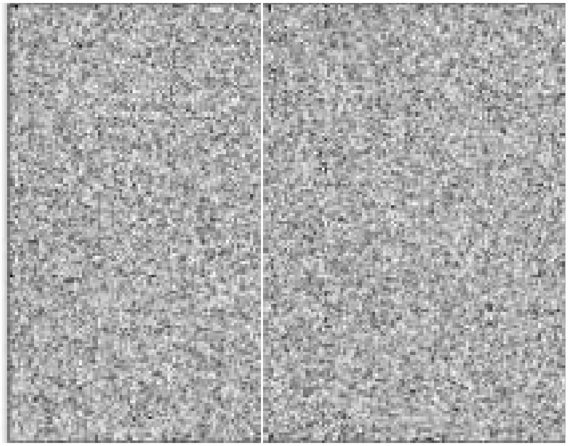
- The problem with histograms

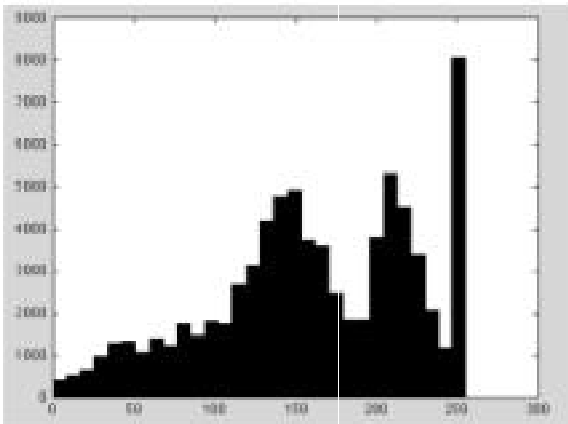


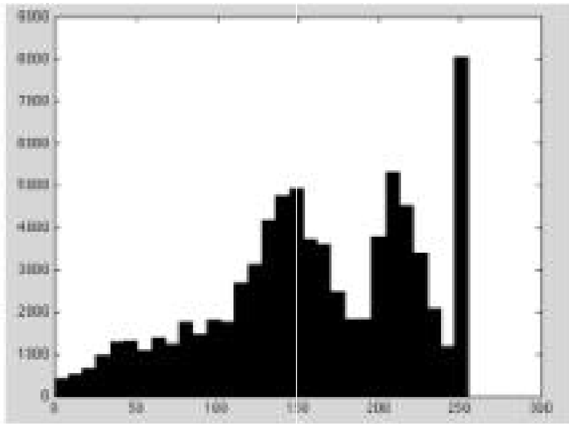
Global descriptors

Color histogram

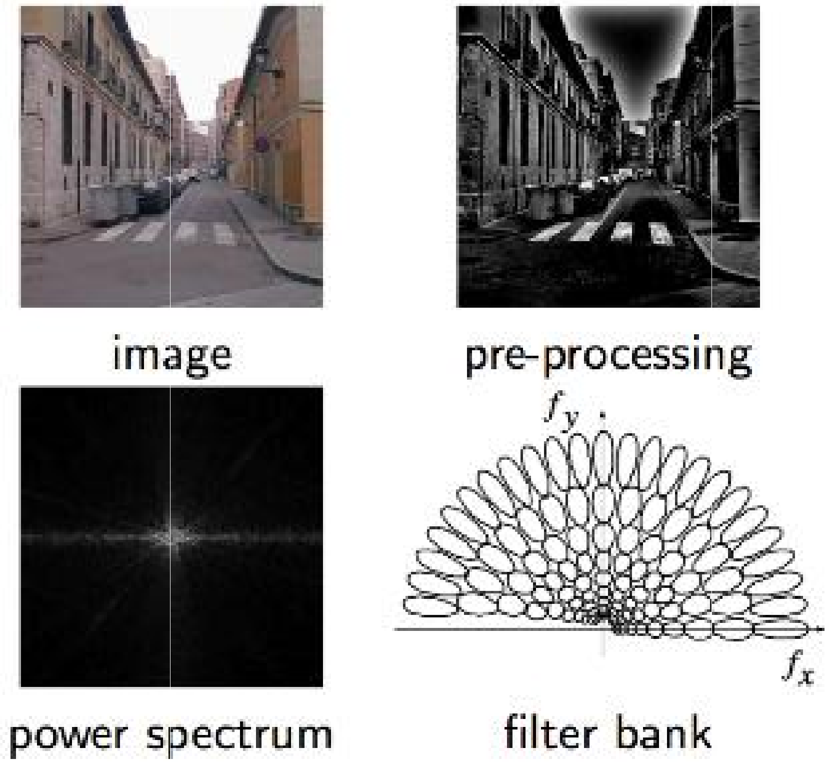
- The problem with histograms







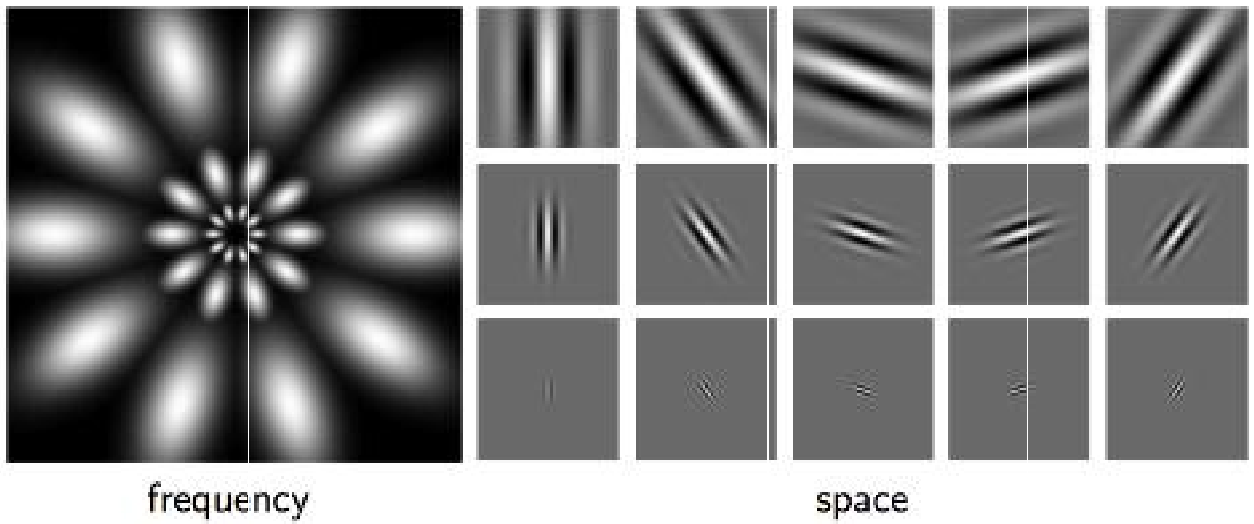
Global descriptors



- sampling scheme adapted to power spectrum statistics
- filtering and global pooling in frequency domain

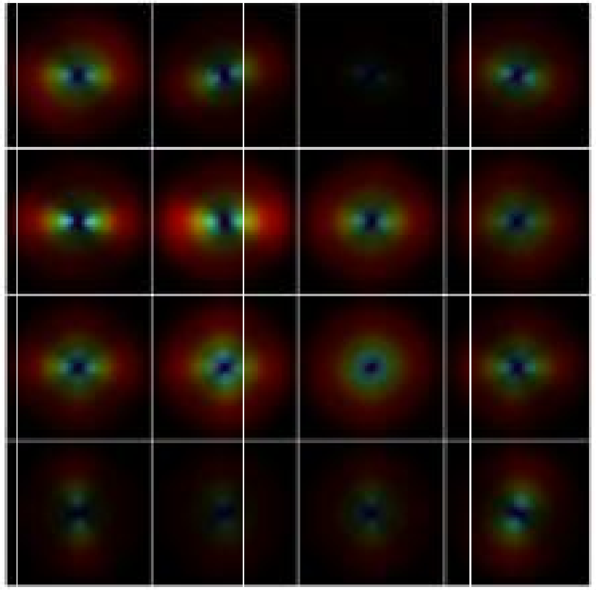
Global descriptors

- Gabor filters: inspired from neuroscience and related to tiny salient pattern for the human vision system
- filters are pre-defined and manually computed



Global descriptors

The gist descriptor



- apply filter bank to entire image in frequency domain
- partition image in 4×4 cells
- average pooling of filter responses per cell

Building the Gist of a Scene: the Role of Global Image Features in Recognition; Oliva and Torralba; VP 2006

Global descriptors

gist pipeline

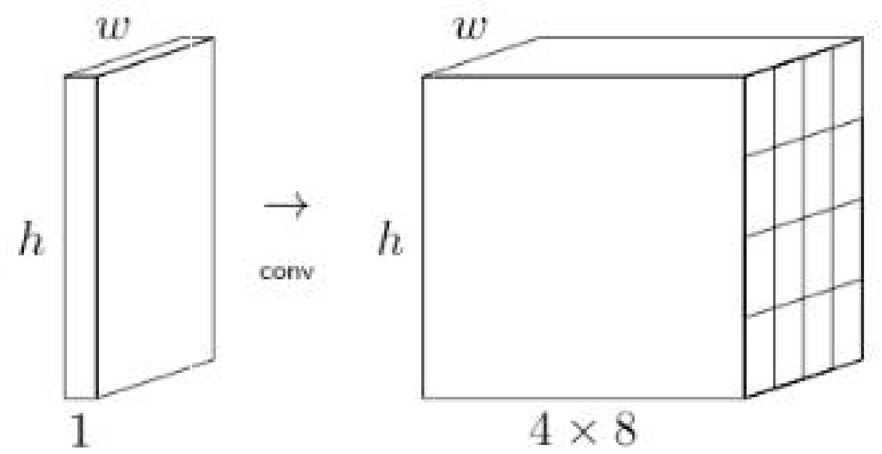
- 3-channel RGB input → 1-channel gray-scale

Building the Gist of a Scene: the Role of Global Image Features in Recognition; Oliva and Torralba; VP 2006

Slide credit: Y. Avrithis, SIF Deep Learning for Vision

Global descriptors

gist pipeline



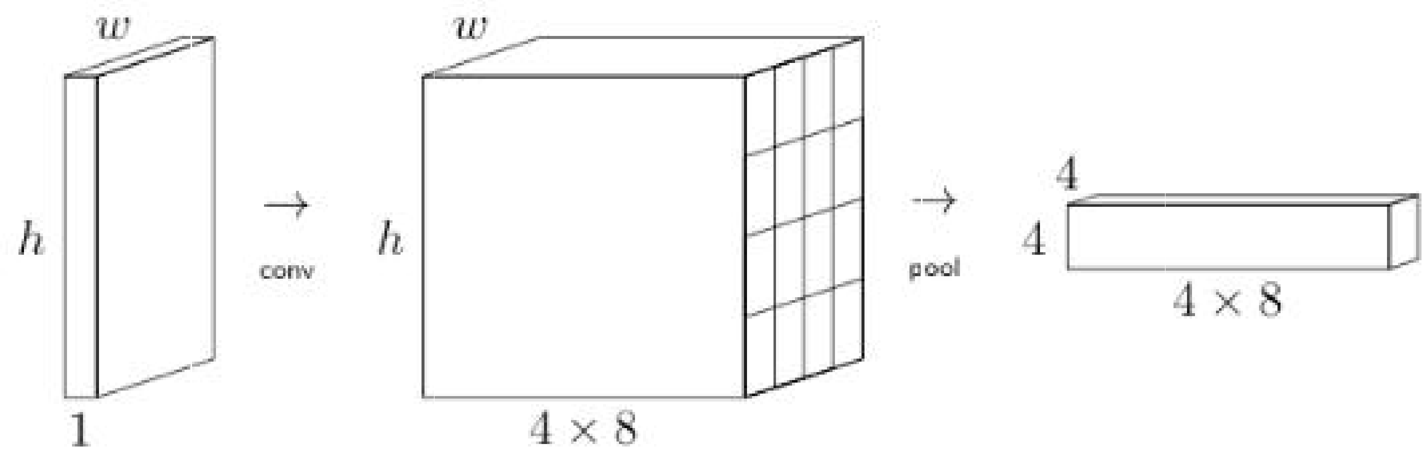
- 3-channel RGB input → 1-channel gray-scale
- apply filters at 4 scales × 8 orientations

Building the Gist of a Scene: the Role of Global Image Features in Recognition; Oliva and Torralba; VP 2006

Slide credit: Y. Avrithis, SIF Deep Learning for Vision

Global descriptors

gist pipeline



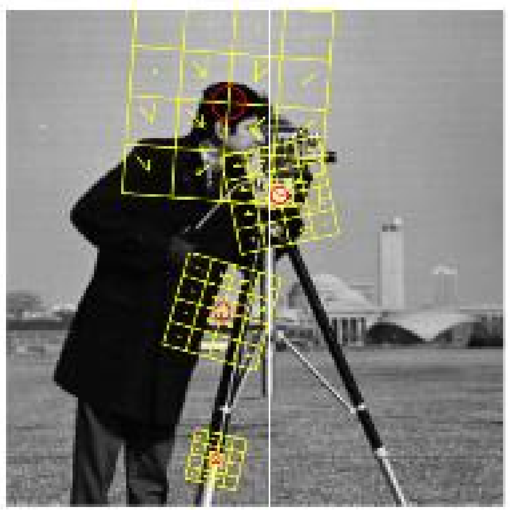
- 3-channel RGB input → 1-channel gray-scale
- apply filters at 4 scales × 8 orientations
- average pooling on 4 × 4 cells → descriptor of length 512

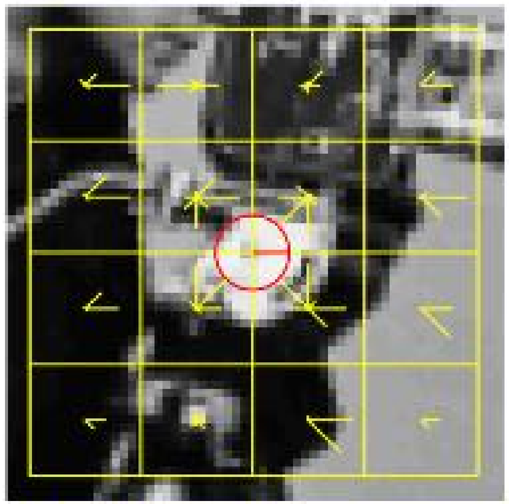
Building the Gist of a Scene: the Role of Global Image Features in Recognition; Oliva and Torralba; VP 2006

Slide credit: Y. Avrithis, SIF Deep Learning for Vision

Local descriptors

scale-invariant feature transform (SIFT)





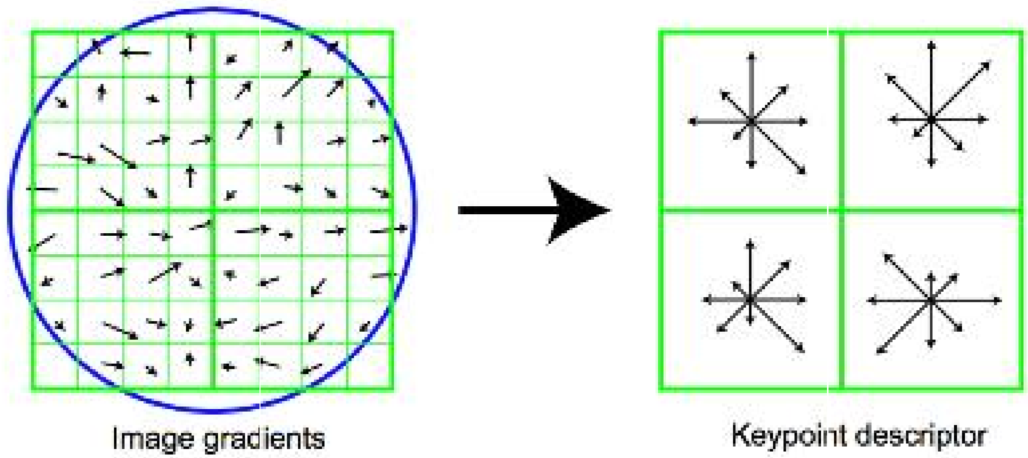
- detect a sparse set of "stable" features (rectangular patches) equivariant to translation, scale and rotation
- for each patch:
  - normalize with respect to scale and orientation
  - construct a histogram of gradient orientations

Object recognition from local scale-invariant features.; Lowe; ICCV 1999

Slide credit: Y. Avrithis, SIF Deep Learning for Vision

Local descriptors

scale-invariant feature transform (SIFT)

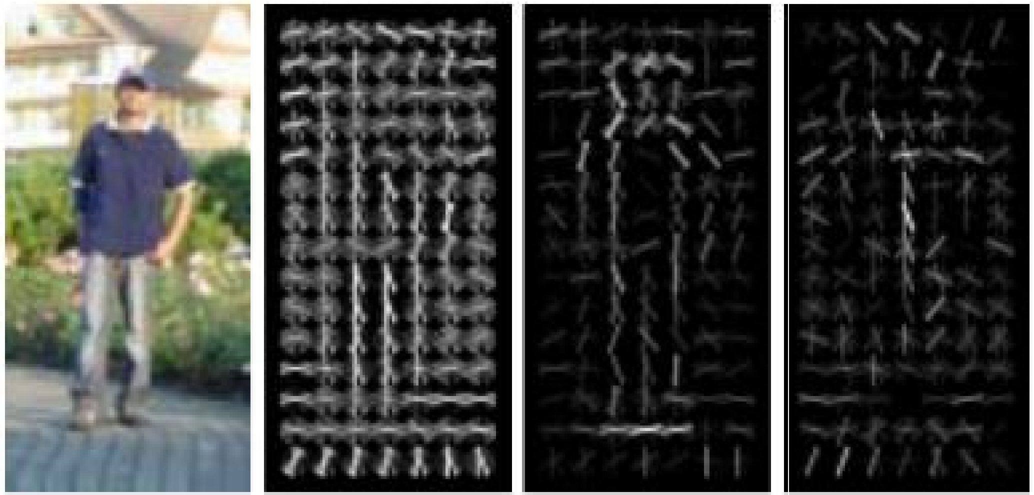


- votes in $8-$bin orientation histograms weighted by magnitude and by weighted by a Gaussian window,
- histograms pooled over 4×4 cells,
- 128-dimensional descriptor, normalized, clipped at 0.2, normalized

Object recognition from local scale-invariant features.; Lowe; ICCV 1999

Local descriptors

Histogram of Oriented Gradients (HoG)



- applied to person detection by sliding window and SVM
- classifier learns positive and negative weights on positions and orientations
- switch focus back to dense features for classification

Histogram of Oriented Gradients for Human Detection; Dalal and Triggs; CVPR 2005

Local descriptors

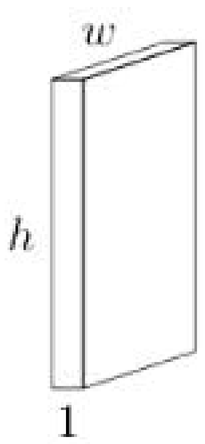
HOG descriptor

- applied densely to adjacent cells of 8×8 pixels
- no scale or orientation normalization; only single-scale
- normalized by overlapping blocks of 3×3 cells -- redundant

Histogram of Oriented Gradients for Human Detection; Dalal and Triggs; CVPR 2005

Local descriptors

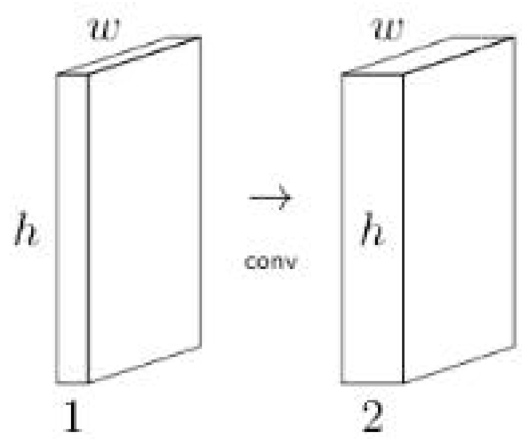
SIFT/HOG pipeline



- 3-channel patch (image) RGB input → 1-channel gray-scale

Local descriptors

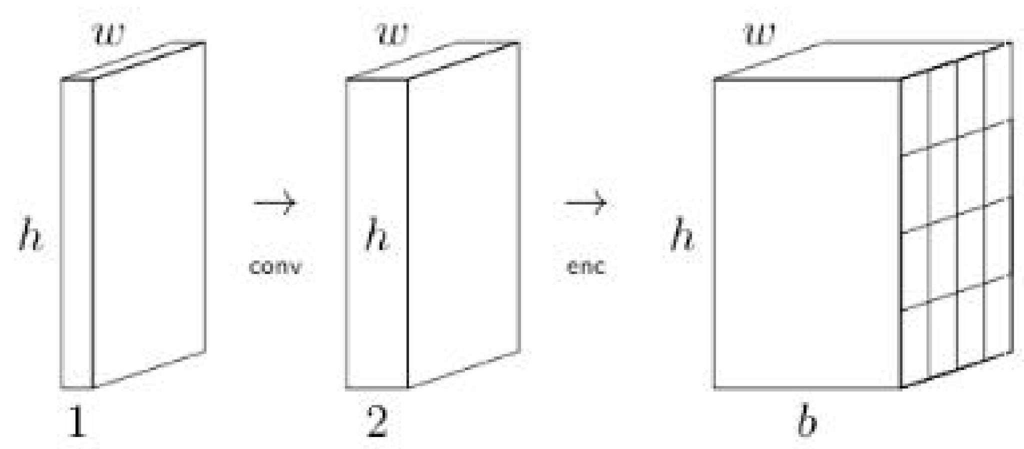
SIFT/HOG pipeline



- 3-channel patch (image) RGB input → 1-channel gray-scale
- compute gradient magnitude and orientation

Local descriptors

SIFT/HOG pipeline

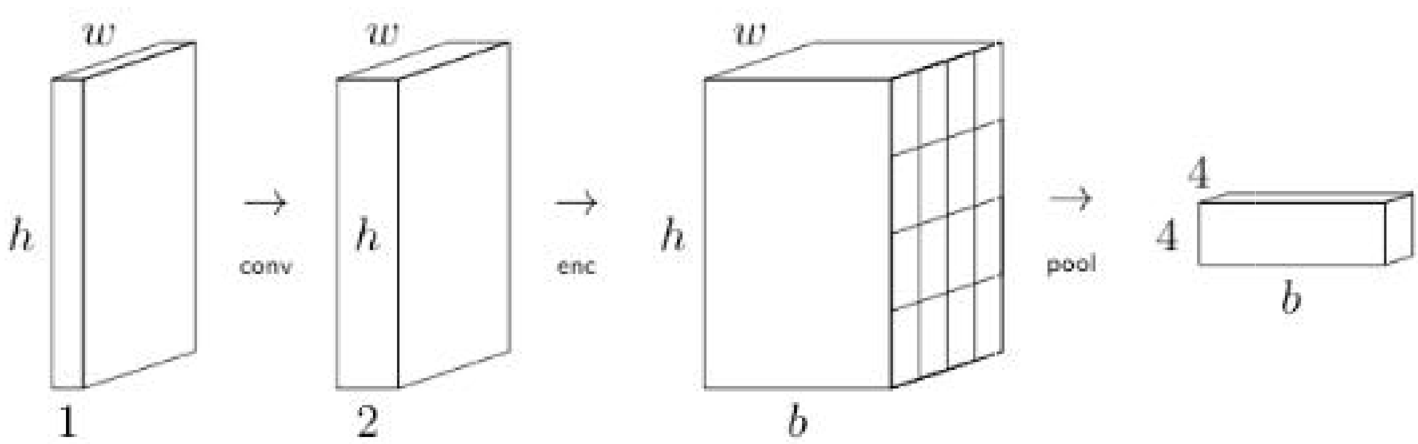


- 3-channel patch (image) RGB input → 1-channel gray-scale
- compute gradient magnitude and orientation
- encode into $b = 8$ orientation bins

Slide credit: Y. Avrithis, SIF Deep Learning for Vision

Local descriptors

SIFT/HOG pipeline



- 3-channel patch (image) RGB input → 1-channel gray-scale
- compute gradient magnitude and orientation
- encode into $b = 8(9)$ orientation bins
- average pooling on $c = 4 \times 4$ cells
- descriptor of length $c \times b = 128$

Slide credit: Y. Avrithis, SIF Deep Learning for Vision

Local descriptors

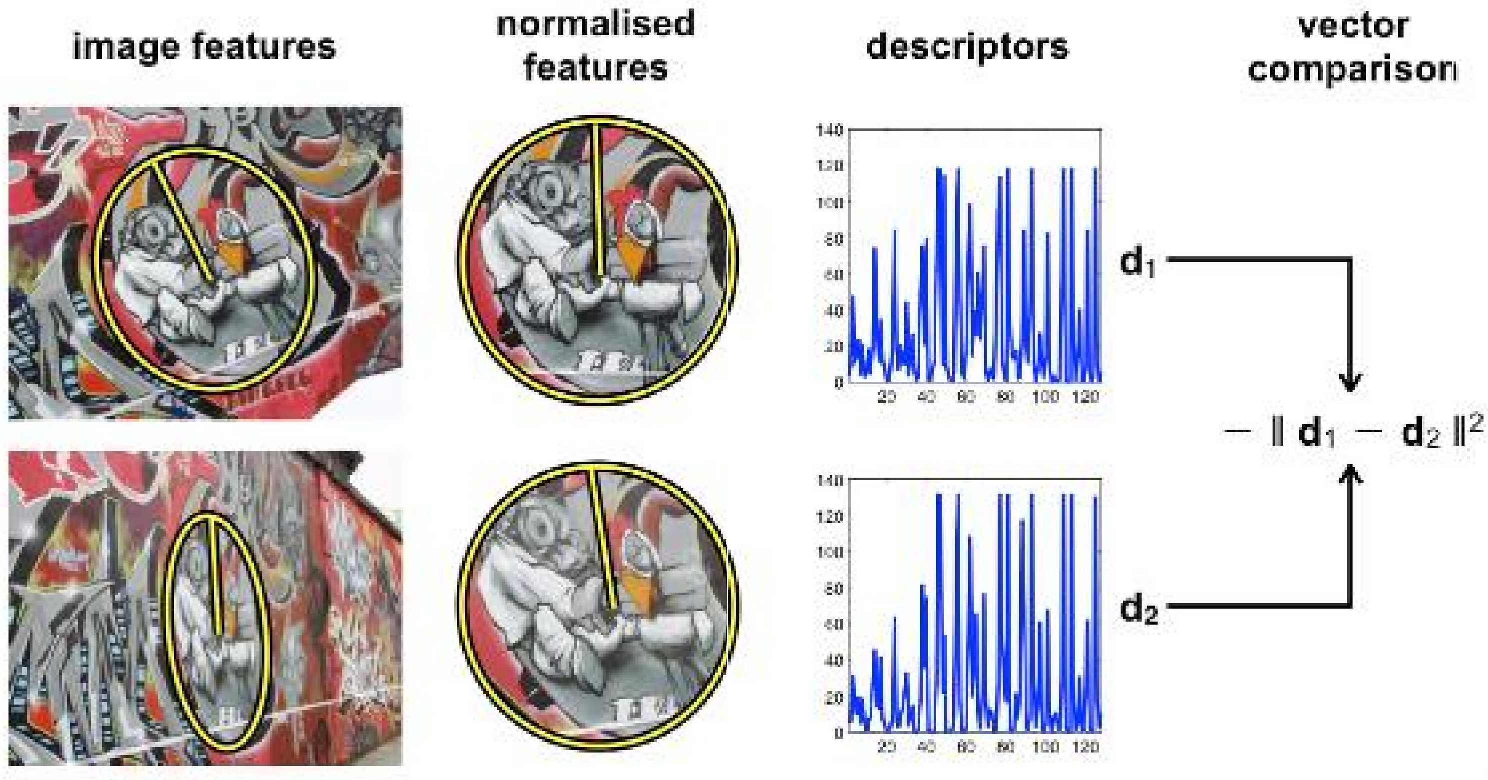
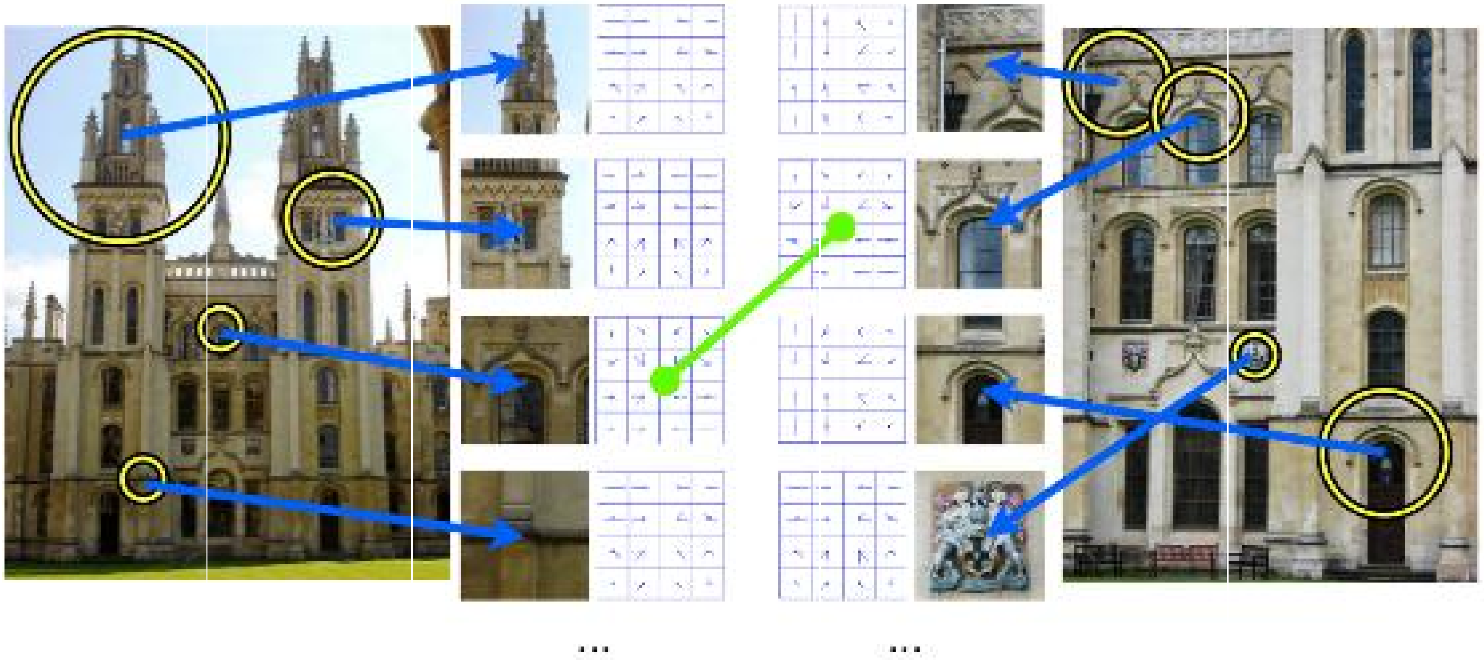


Figure credit: A. Vedaldi

Local descriptors



- matching everything with everything

Figure credit: A. Vedaldi

Local descriptors

Exhaustive matching

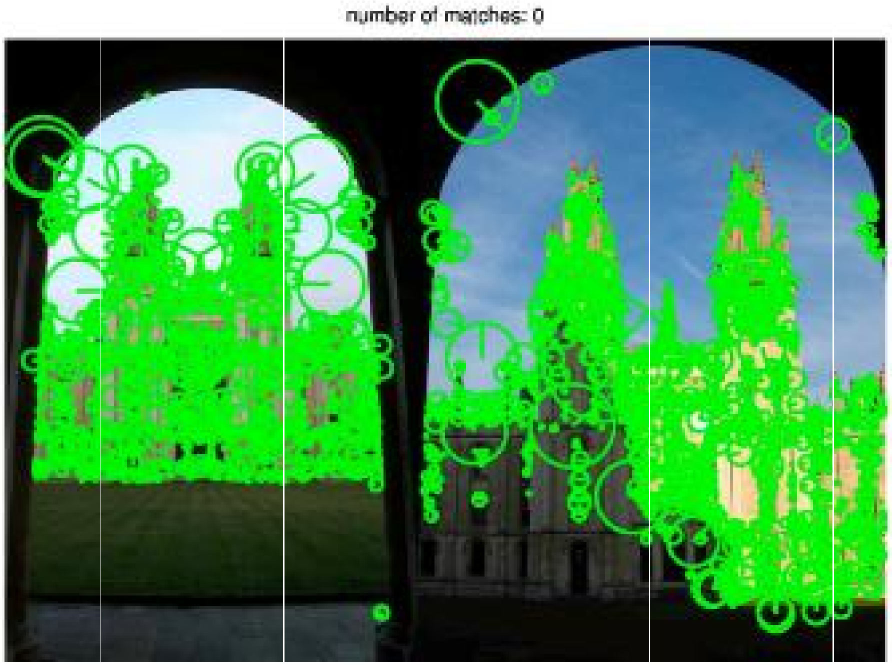
Step 0: get an image pair

number of matches: 0

Local descriptors

Exhaustive matching

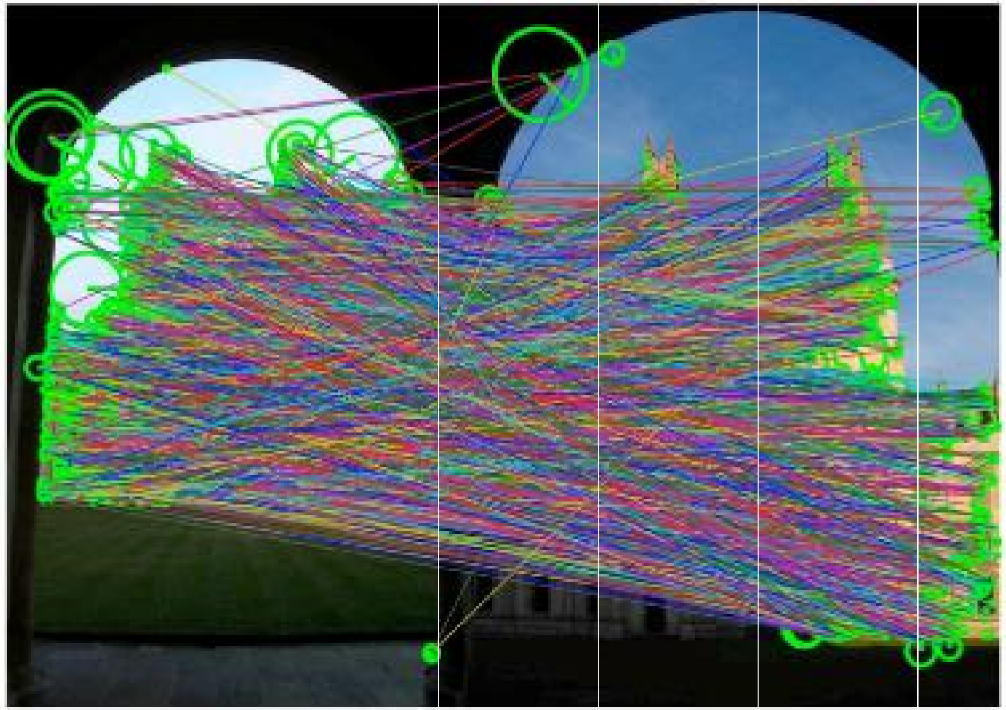
Step 1: detect local features **f** and extract descriptors **d**



Local descriptors

Step 2: match each descriptor to its closets one

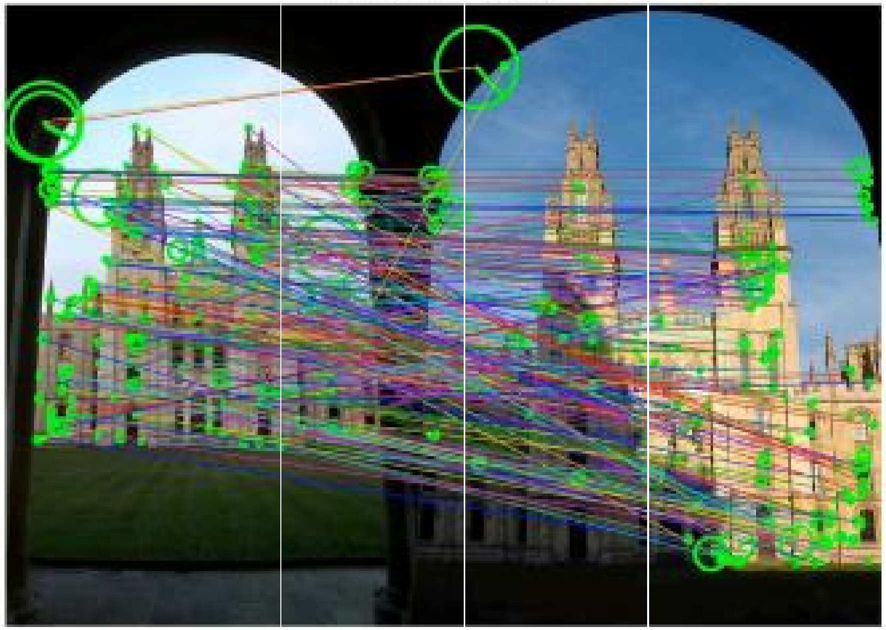
number of matches: 2048



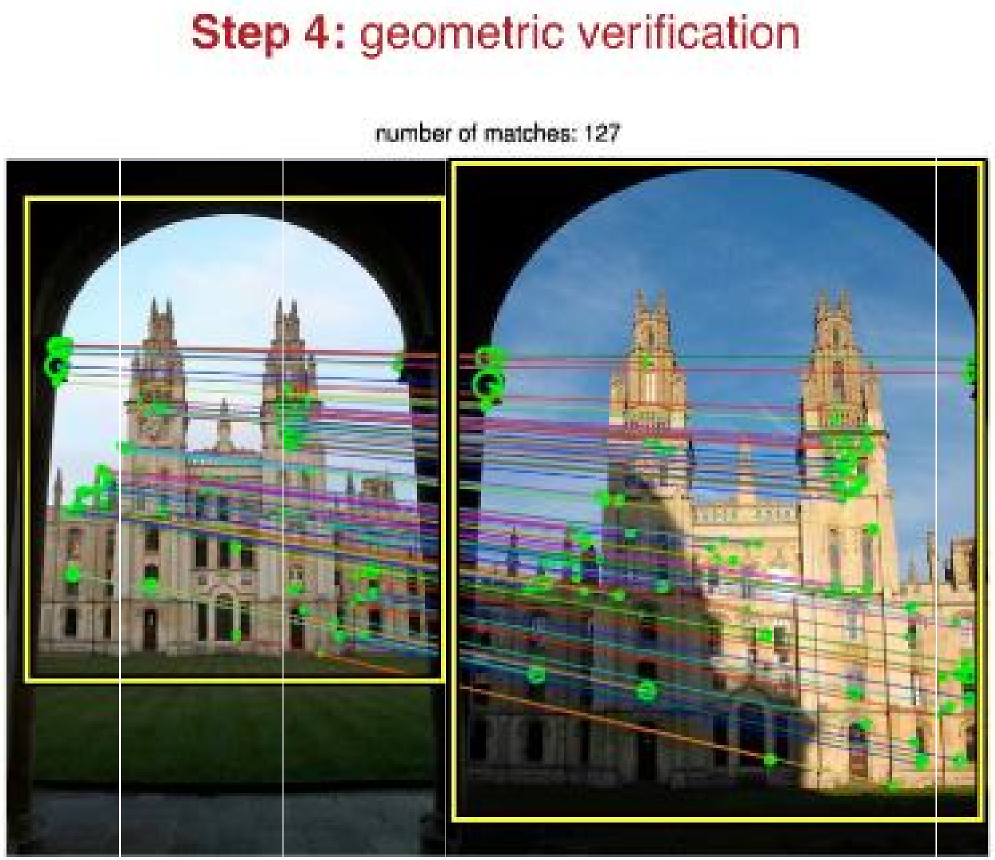
Local descriptors

Step 3: reject ambiguous matches using the **2nd-nn test**

number of matches: 293



Local descriptors



- the final step is to test whether matches are consistent with an overall image transformation
- inconsistent matches are rejected

From image matching to image search

- This matching strategy can be used to search a few images exhaustively
- However this is far too slow to search a large database
- Example:

L images in the database	e.g. 10^6 - 10^{10} (FaceBook)
N features per image (incl. query)	e.g. 10^3 (~ SIFT detector)
D dimensional feature descriptor	e.g. 10^2 (~ SIFT descriptor)
Exhaustive search cost: $O(N^2\ L\ D)$	10^{11} - 10^{15} ops = 100 days - 300 years
Memory footprint: $O(NLD)$	1TB - 1PB

Visual words

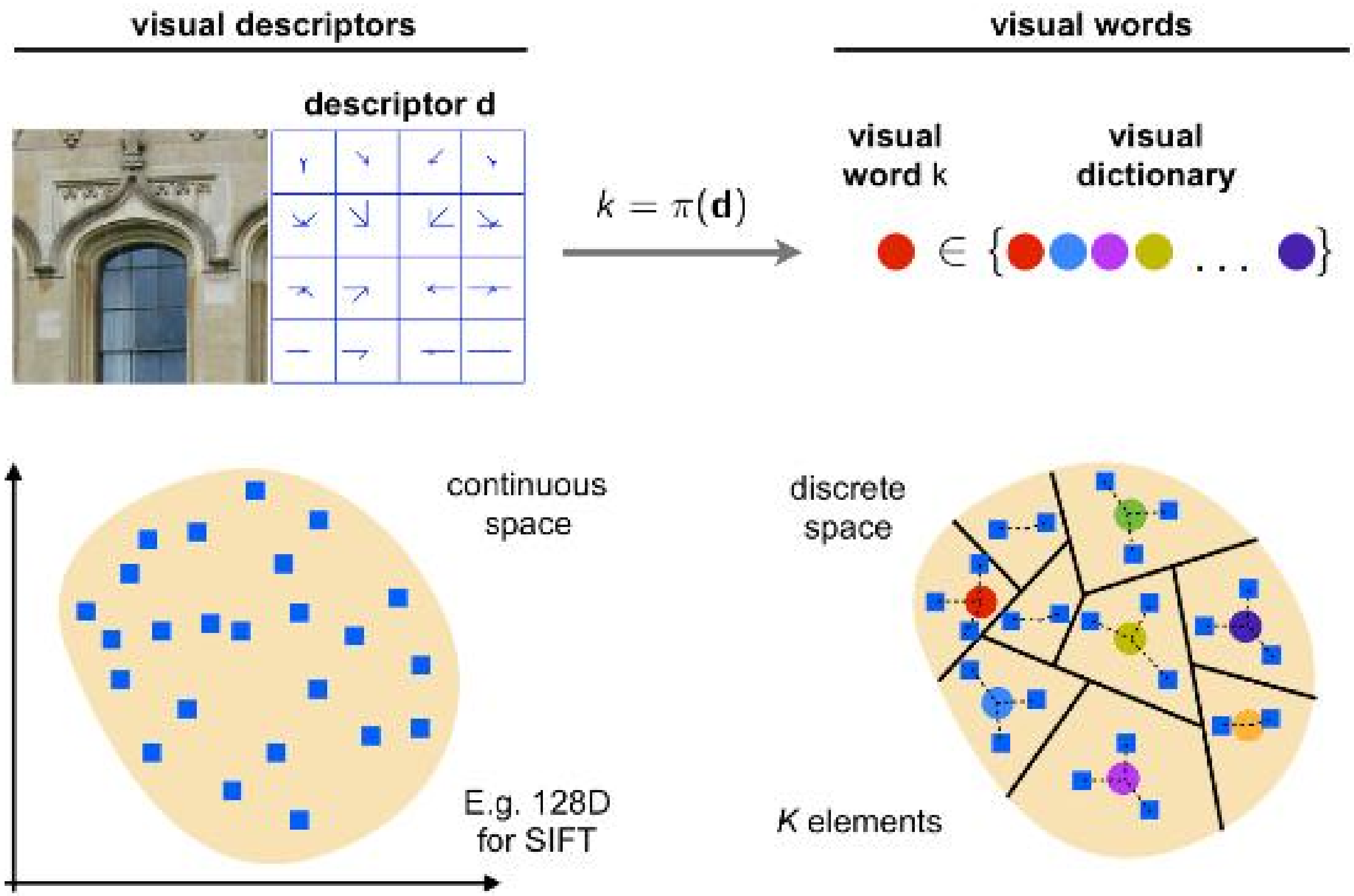


Figure credit: A. Vedaldi

Visual words

- Dictionary is typically learned using k-means
- Value of k depends on the task: from 8 to $16M$

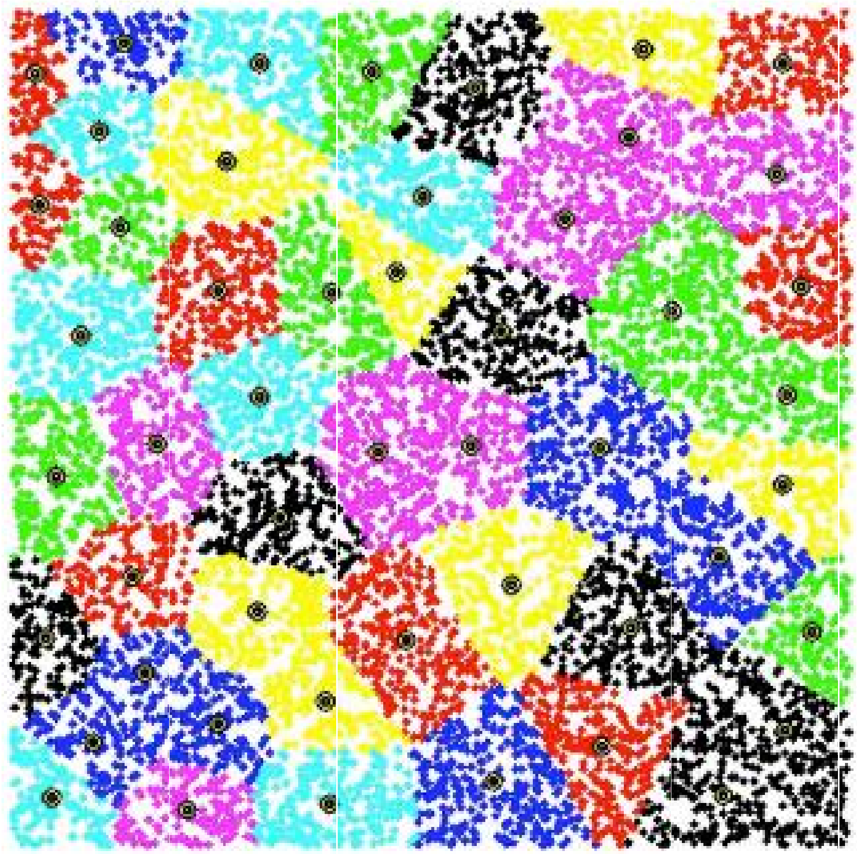


Figure credit: A. Vedaldi

Visual words

- Visual word examples: each row is an equivalence class of patches mapped to the same cluster by k-means
- Visual words = iconic image fragments

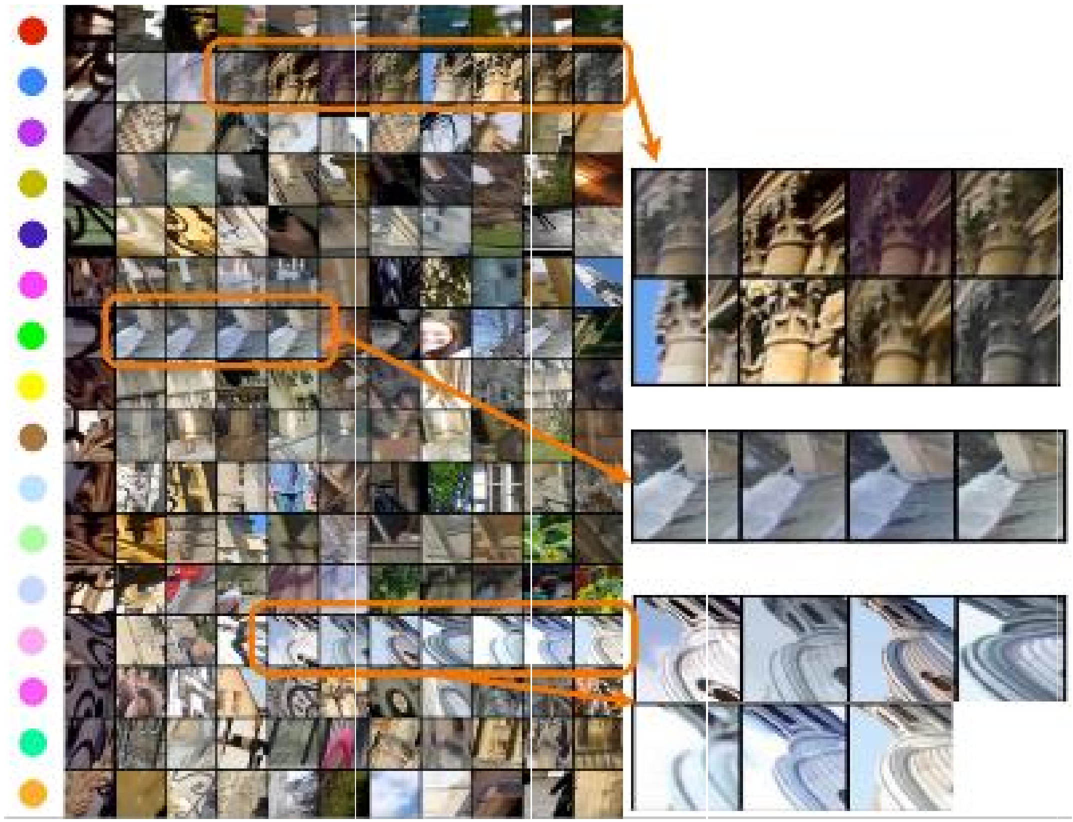


Figure credit: A. Vedaldi

Visual words

Quantization

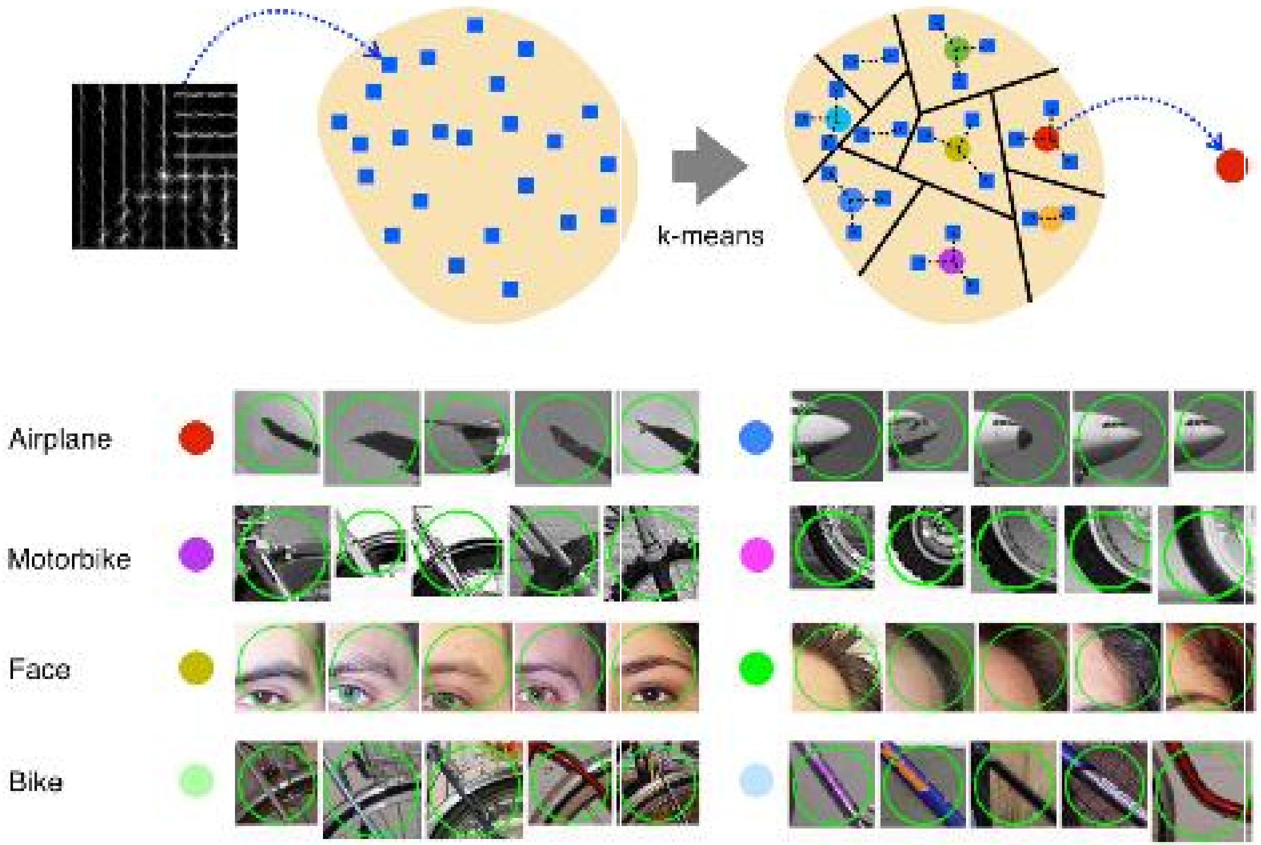
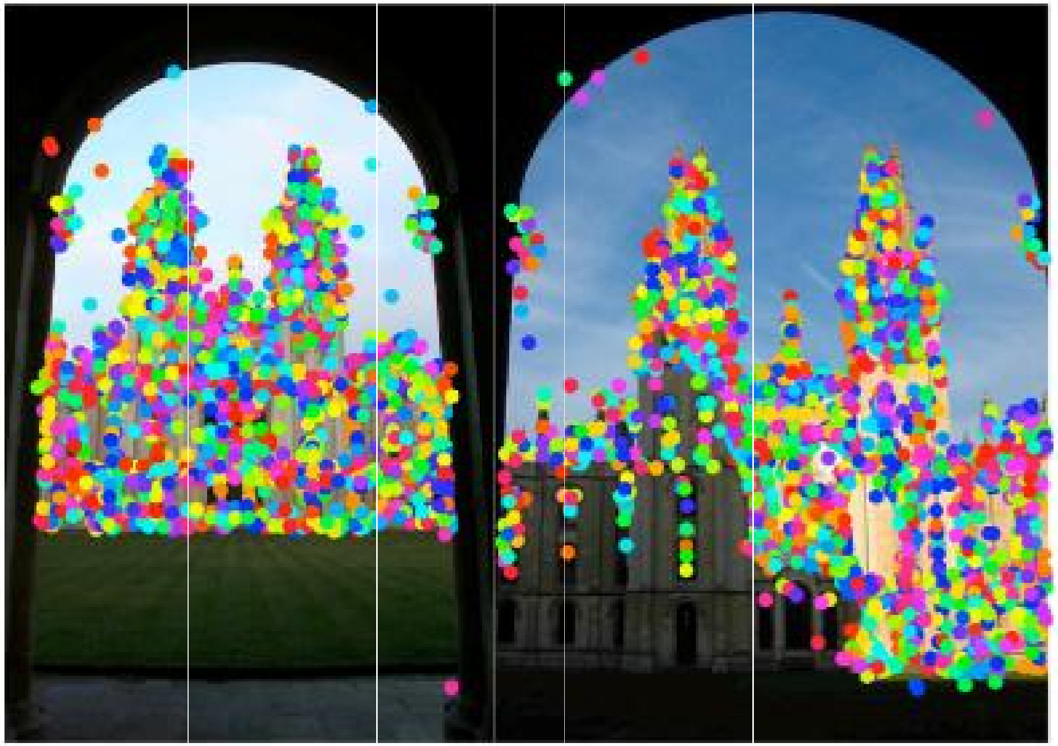


Figure credit: A. Vedaldi

Visual words



- Two steps:
  - Extraction: extract local features and compute corresponding descriptors
  - Quantization: map the descriptors to k-means cluster centroids to obtain the corresponding visual words

Figure credit: A. Vedaldi

Histogram of visual words

- A simple but efficient global image descriptor
- Vector of the number of occurrences of the k visual words in the image
- If there are k visual words, then $h \in \mathbb{R}^k$
- The vector h is a global image descriptor

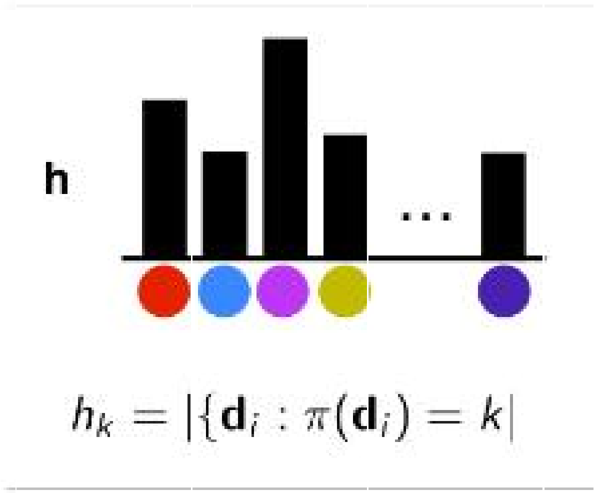
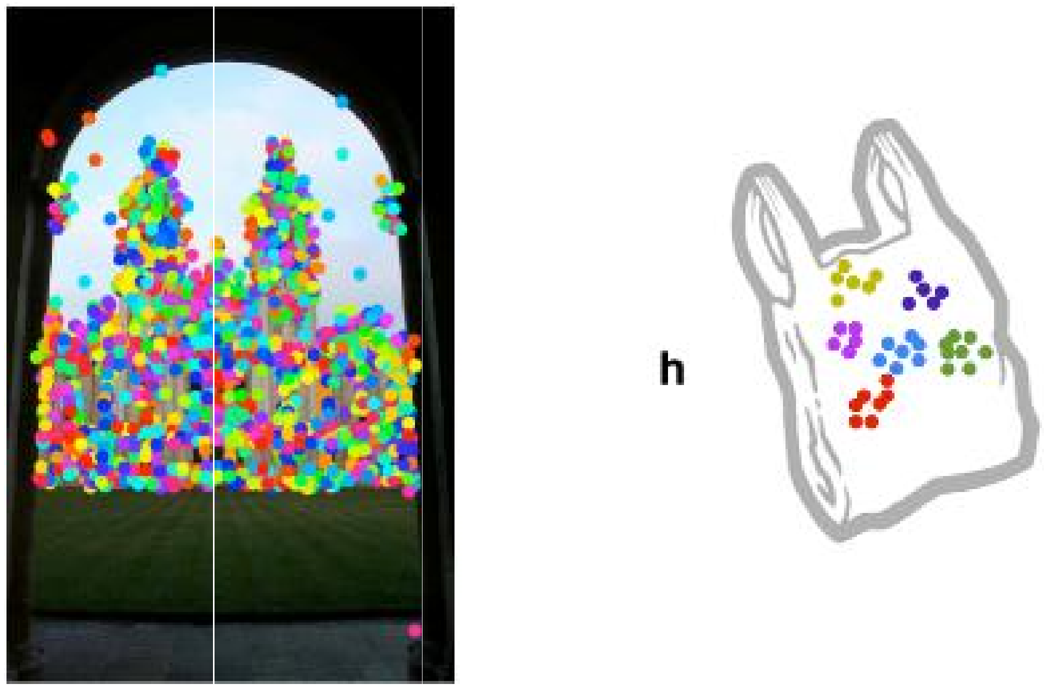


Figure credit: A. Vedaldi

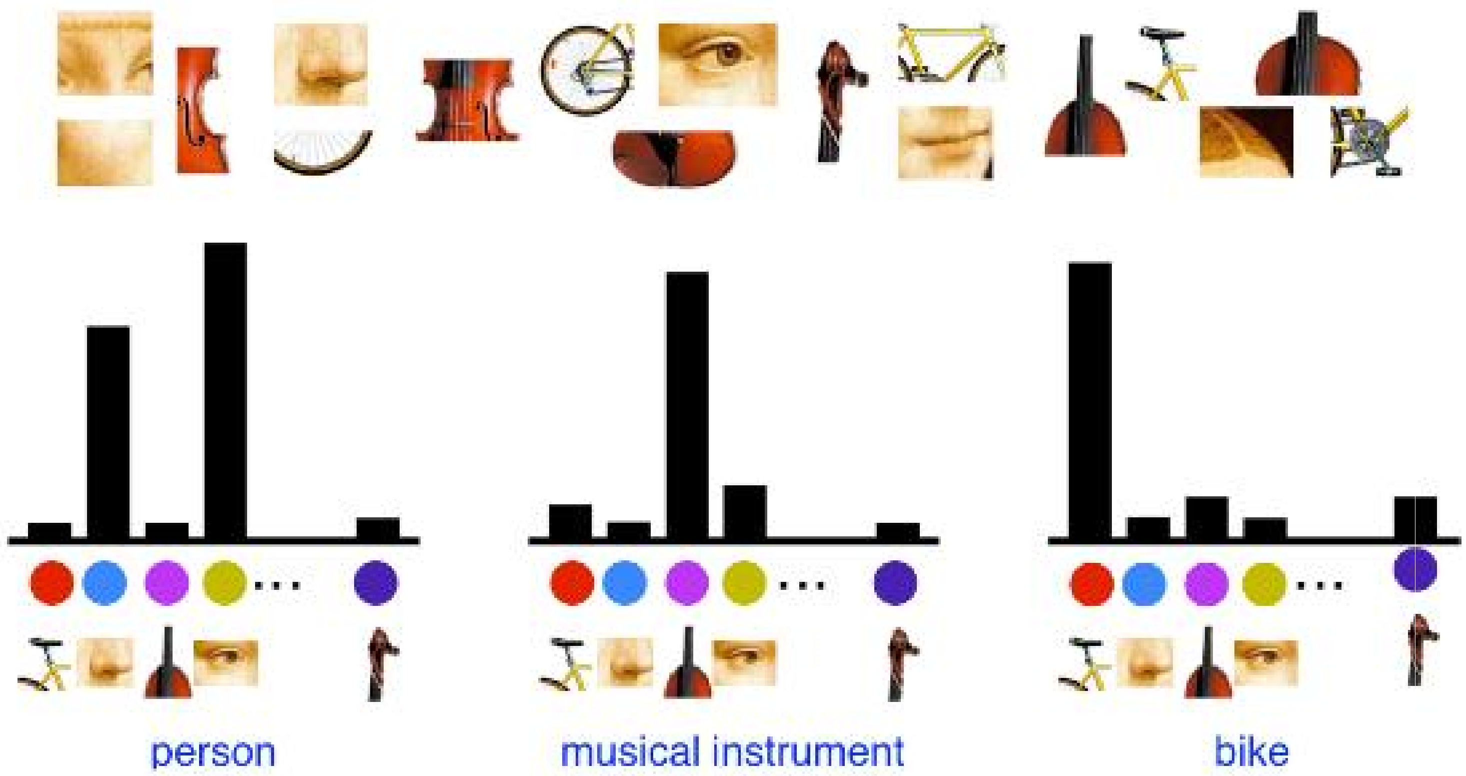
Histogram of visual words

- This is also called a bag of (visual) words - BOW because it does not remember the relative positions of the features, just the number of occurrences
- h discards spatial information
- Pros: more invariant to viewpoint changes and other nuisance factors
- Cons: less discriminative



Histogram of visual words

Intuition



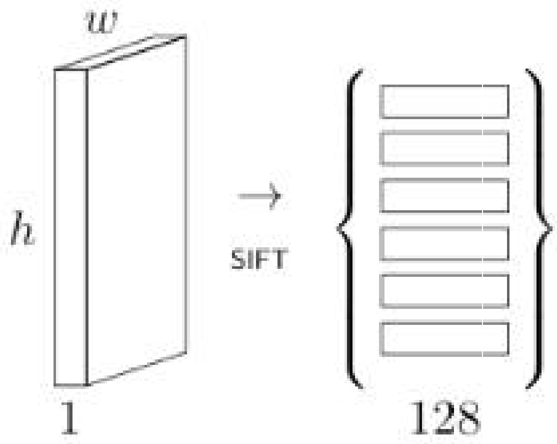
Global descriptors

Bag-of-Words pipeline

- 3-channel patch RGB input → 1-channel gray-scale

Global descriptors

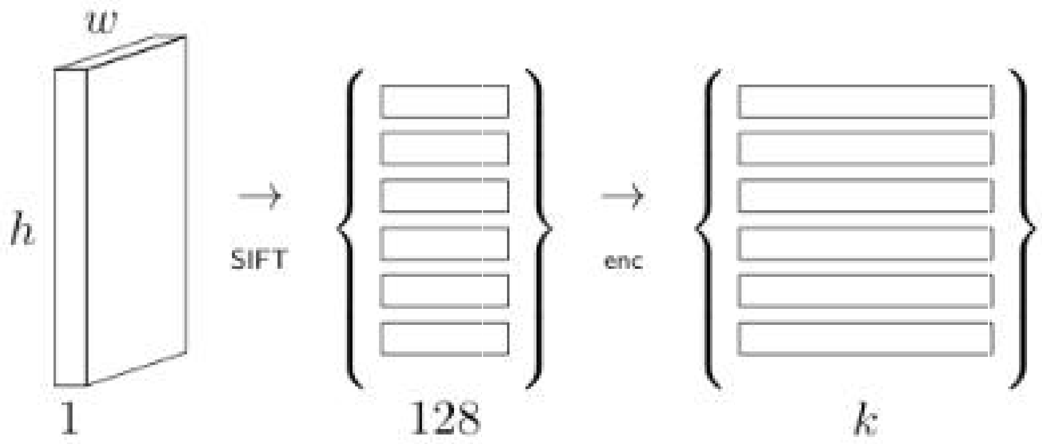
Bag-of-Words pipeline



- 3-channel patch RGB input → 1-channel gray-scale
- set of ~1000 features × 128-dim SIFT descriptors

Global descriptors

Bag-of-Words pipeline

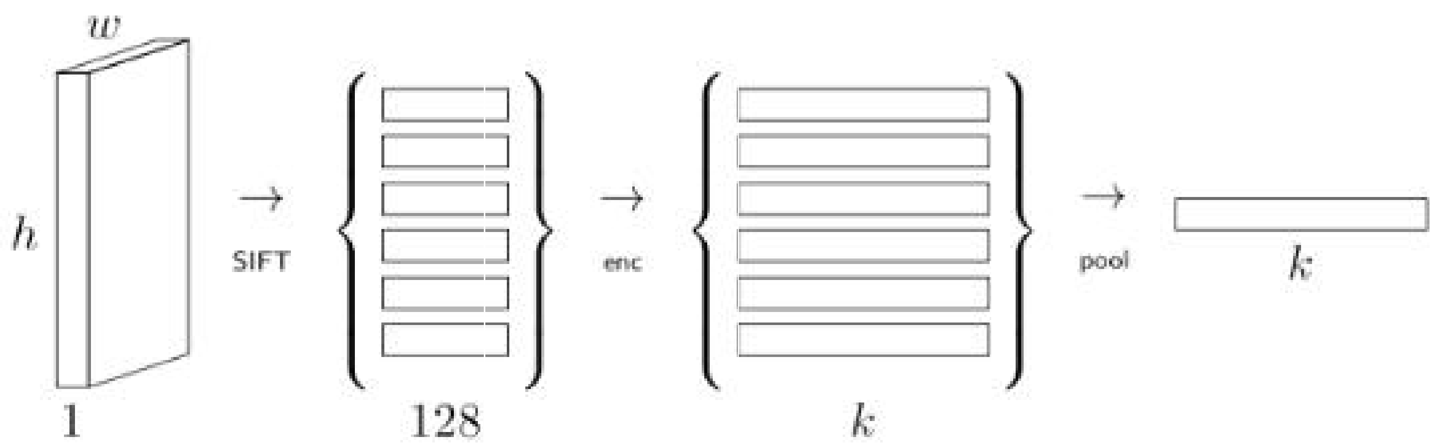


- 3-channel patch RGB input → 1-channel gray-scale
- set of ~1000 features × 128-dim SIFT descriptors
- element-wise encoding of $k = 10^4$ visual words

Slide credit: Y. Avrithis, SIF Deep Learning for Vision

Global descriptors

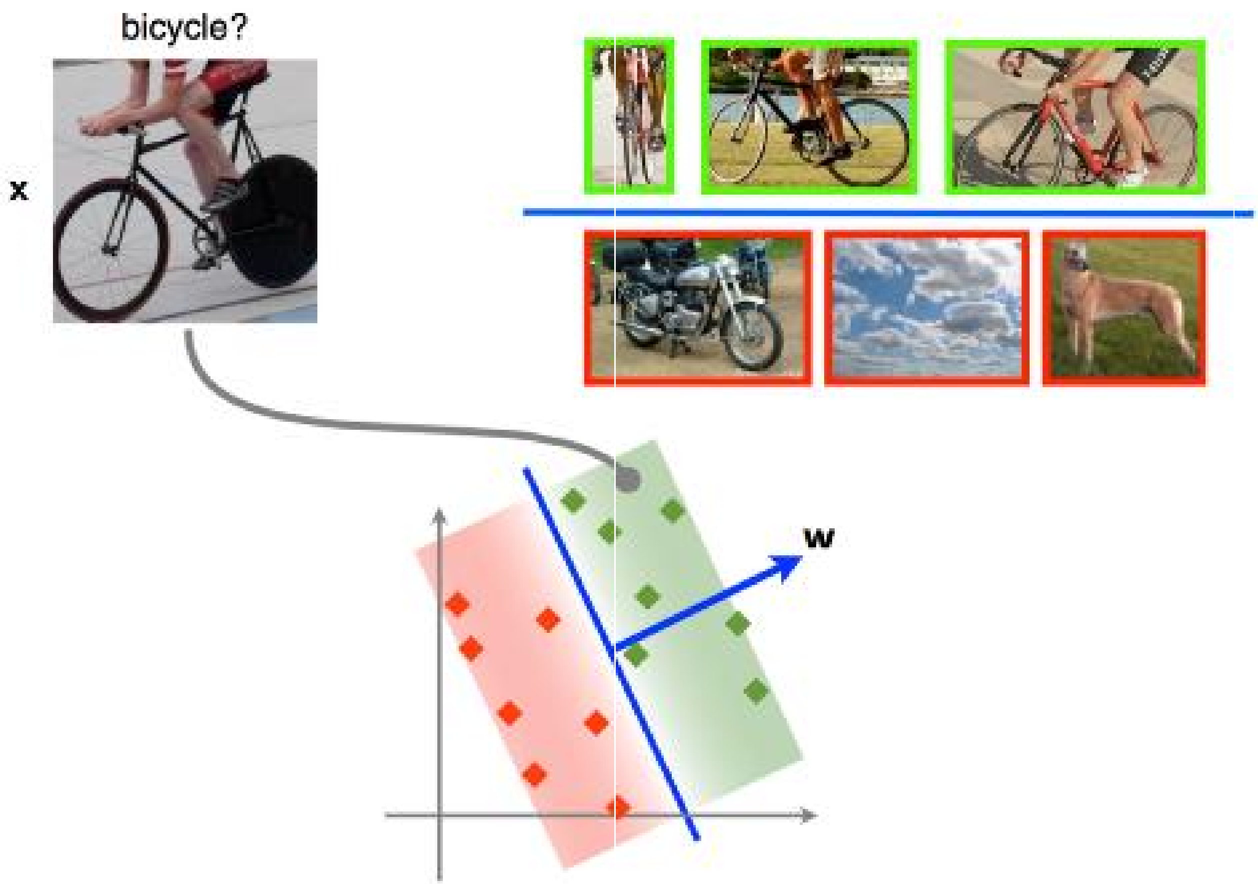
Bag-of-Words pipeline



- 3-channel patch RGB input → 1-channel gray-scale
- set of ~1000 features × 128-dim SIFT descriptors
- element-wise encoding of $k = 10^4$ visual words
- global sum pooling, ℓ^2 normalization

Slide credit: Y. Avrithis, SIF Deep Learning for Vision

Linear predictor



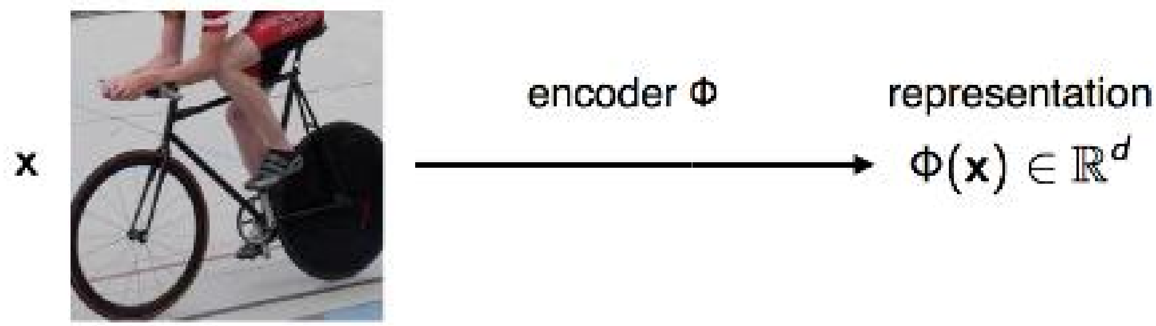
$$F(x) = \langle w, x \rangle$$

- e.g. $F(x)$ can be linear SVM

Data representations

A linear predictor can be used to classify vector data. The question is how such a predictor can be applied to images, text, videos, or sounds.

This is solved by an encoder, which maps the data to a vectorial representation



$$F(x) = \langle w, \Phi(x) \rangle$$

Evolution of representation learning across years

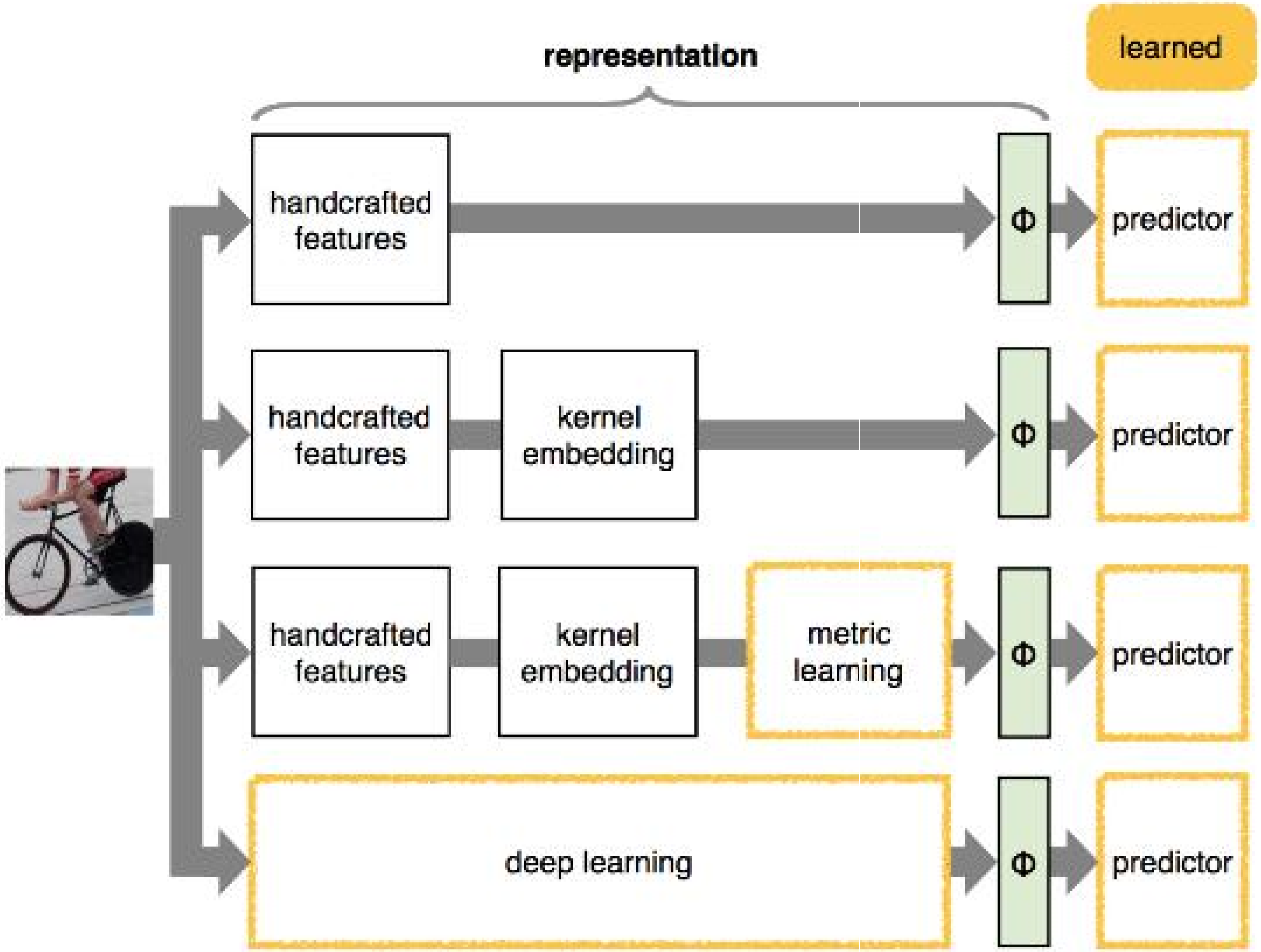
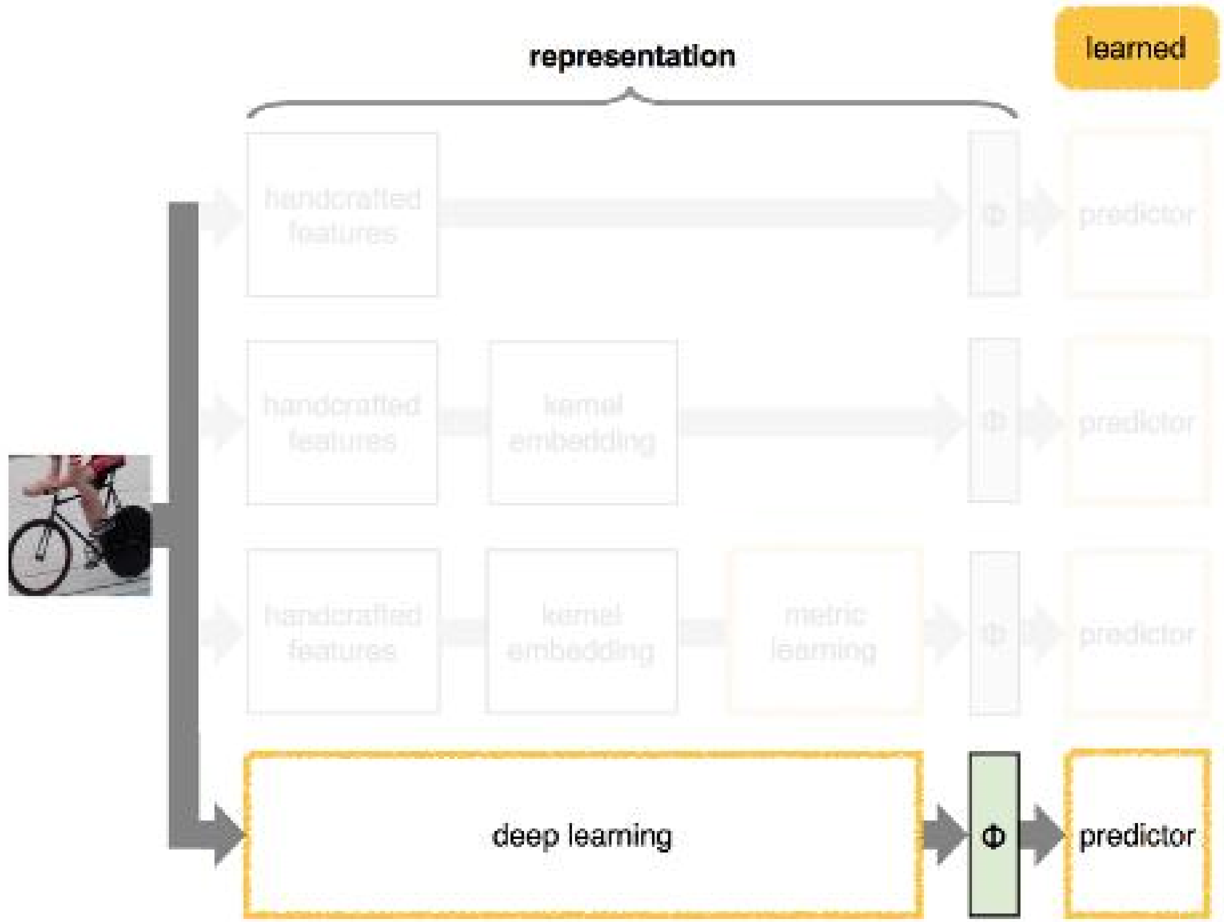


Figure credit: A. Vedaldi

The Deep Learning promise: end-to-end trainable models



- input: raw image | output: prediction
- feature extraction, feature representations and classifiers are jointly learned

Figure credit: A. Vedaldi

Recap

- Huge variety of human-engineered features for visual representation and recognition
- Global descriptors: pixel vectors, color histogram, gist
- Local descriptors: SIFT, HoG
- Matching local descriptors
- *Bag of Visual Words*

Up next:

Neural Networks