ImageNet Classification with Deep Convolutional Neural Networks

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Presented at UAIG

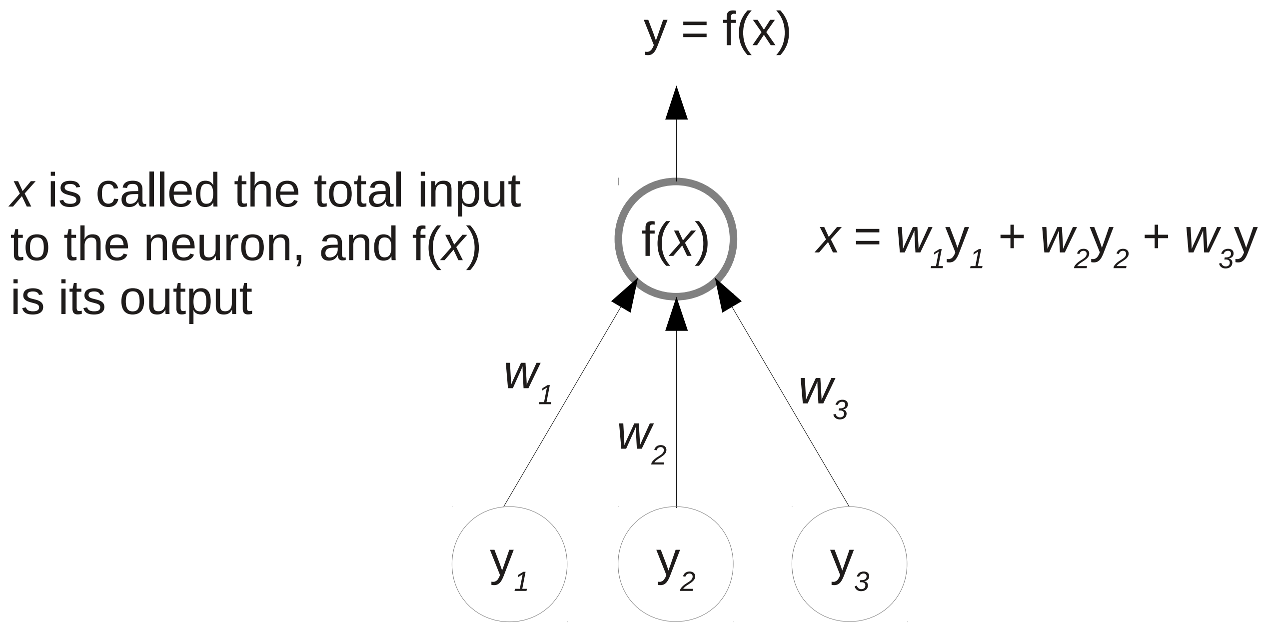
Main idea

Architecture

Technical details

Neural Networks

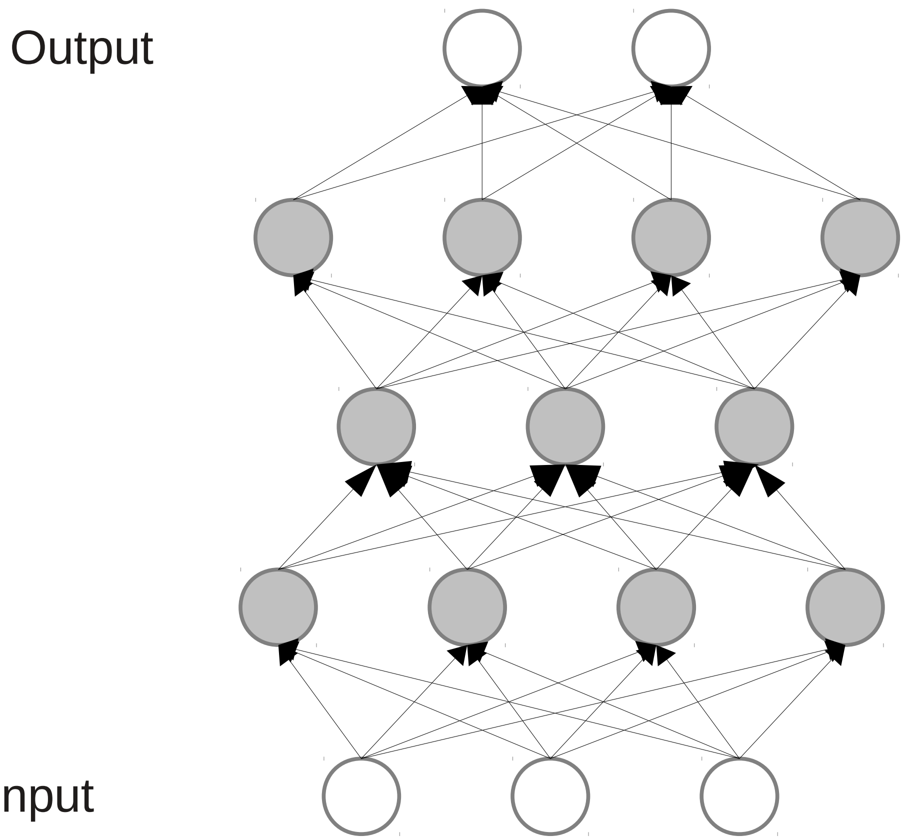
- A neuron



- One neuron can implement logical gates (and a lot more)

Neural Networks

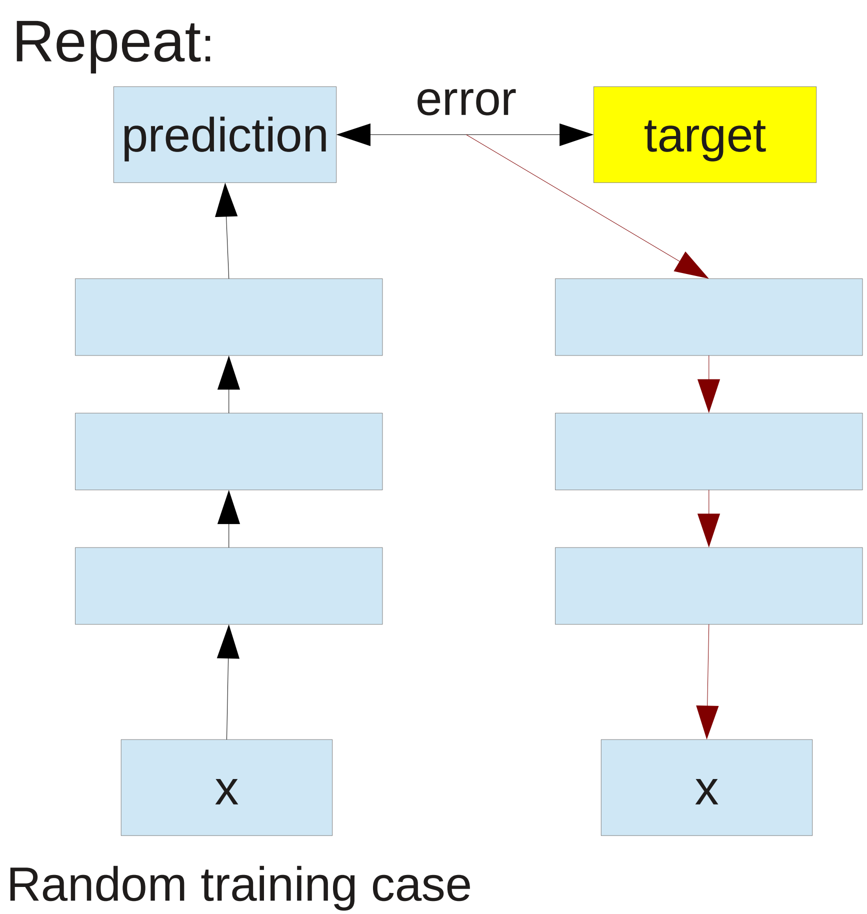
- Neural Networks are circuits



- They can compute lots of complicated functions
- The connections determine the function
- Connections are slowly adjusted by a learning algorithm to reduce error on training cases

Training Neural Networks

- Slowly change the weights to improve performnace



- Do until convergence
  - Pick a training case
  - Compare prediction to target
  - Update parameters to slightly reduce error

- This process will converge to weights should make sensible predictions on all training cases

- These weights implement a circuit whose operation reflects deep facts about the data

- Training method is simple, resulting neural network is *extremely complex*

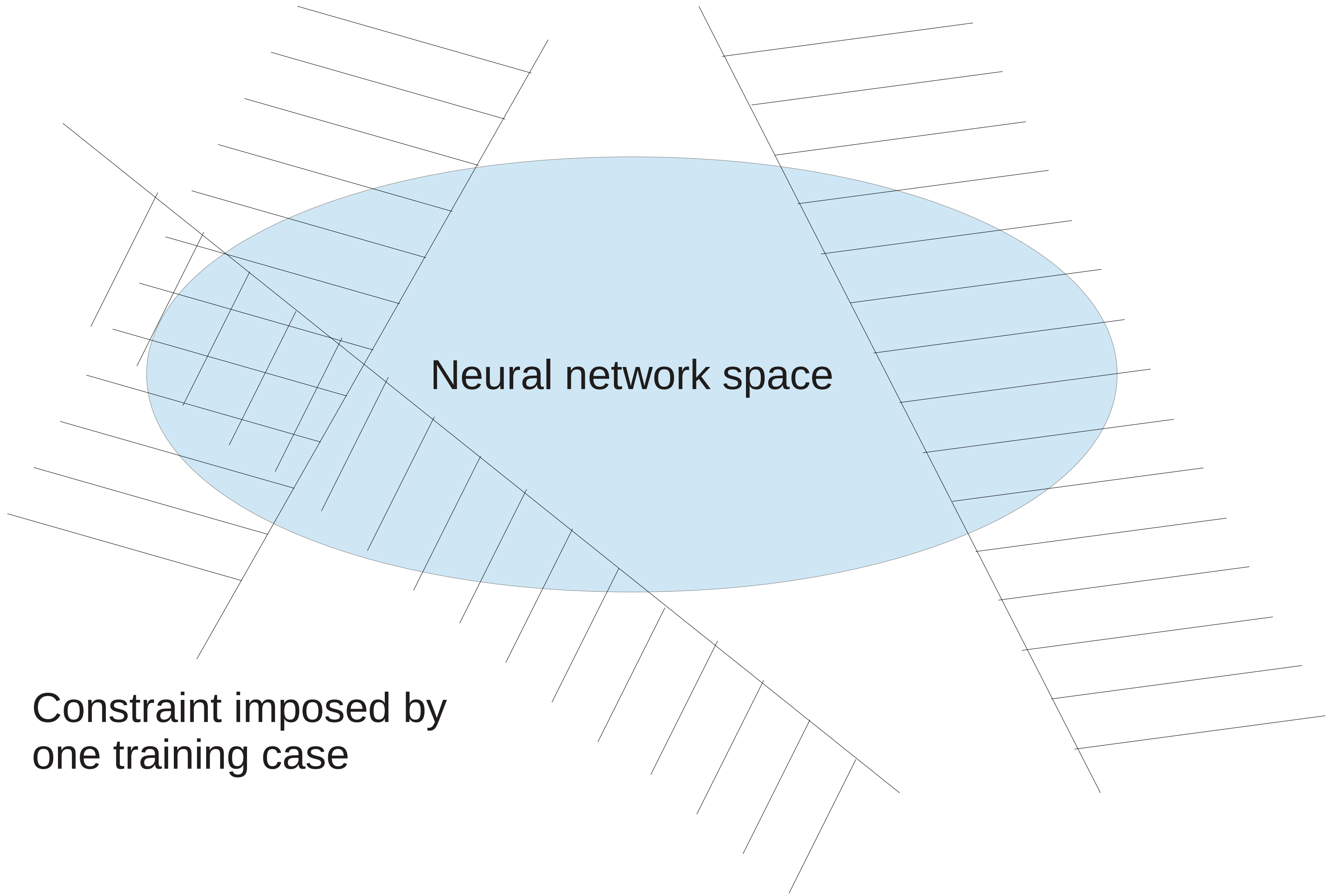
Generalization

- How does the network “know” the correct answer on previously unseen examples?

- The network's ability to memorize random patterns is limited
  - With enough training data, train error=test error
- If we are lucky, the network <u>is capable</u> of representing a good function, so training will find it
  - Otherwise our error will be large

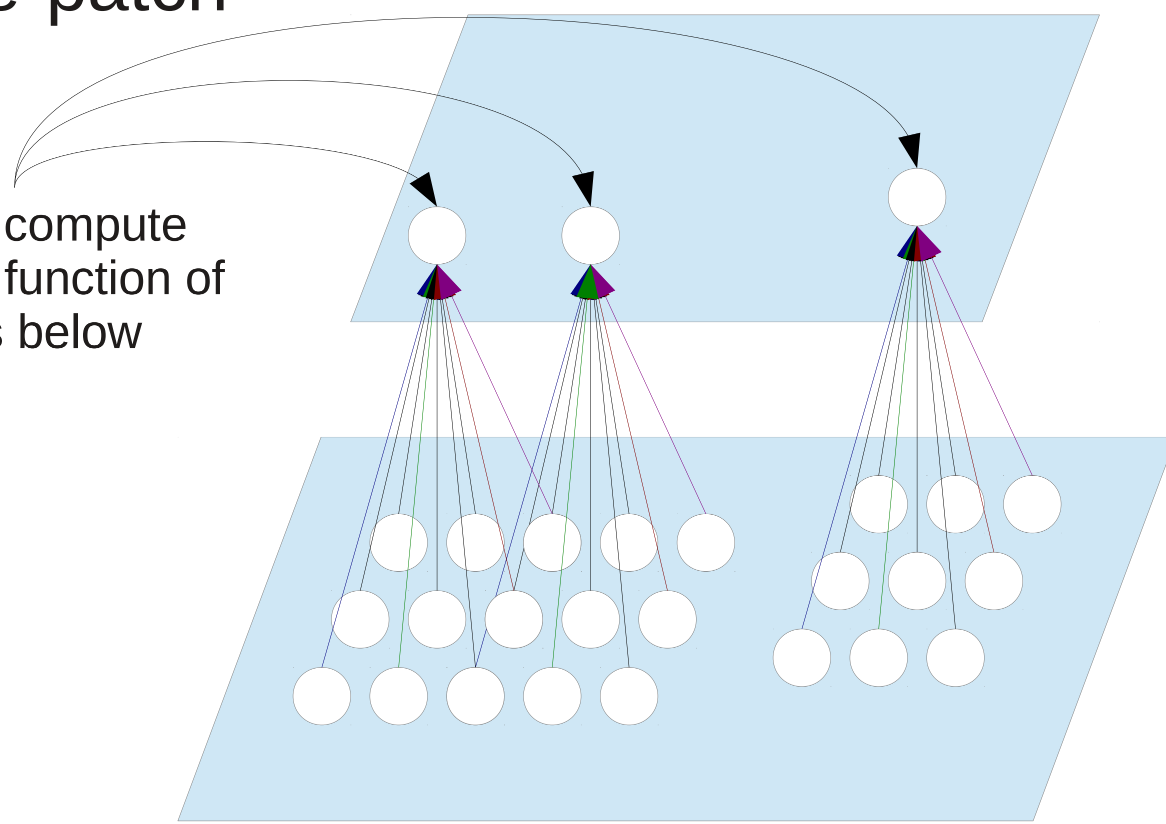
Generalization

Training cases are like constraints
Learning is like solving an equation



Convolutional neural networks

- Apply neural networks to images
  - Images are very large, so networks are huge
- One convolution: apply the same weight to every image-patch



This is one layer.
The input is either an image or an intermediate layer

All nodes compute the same function of the nodes below them

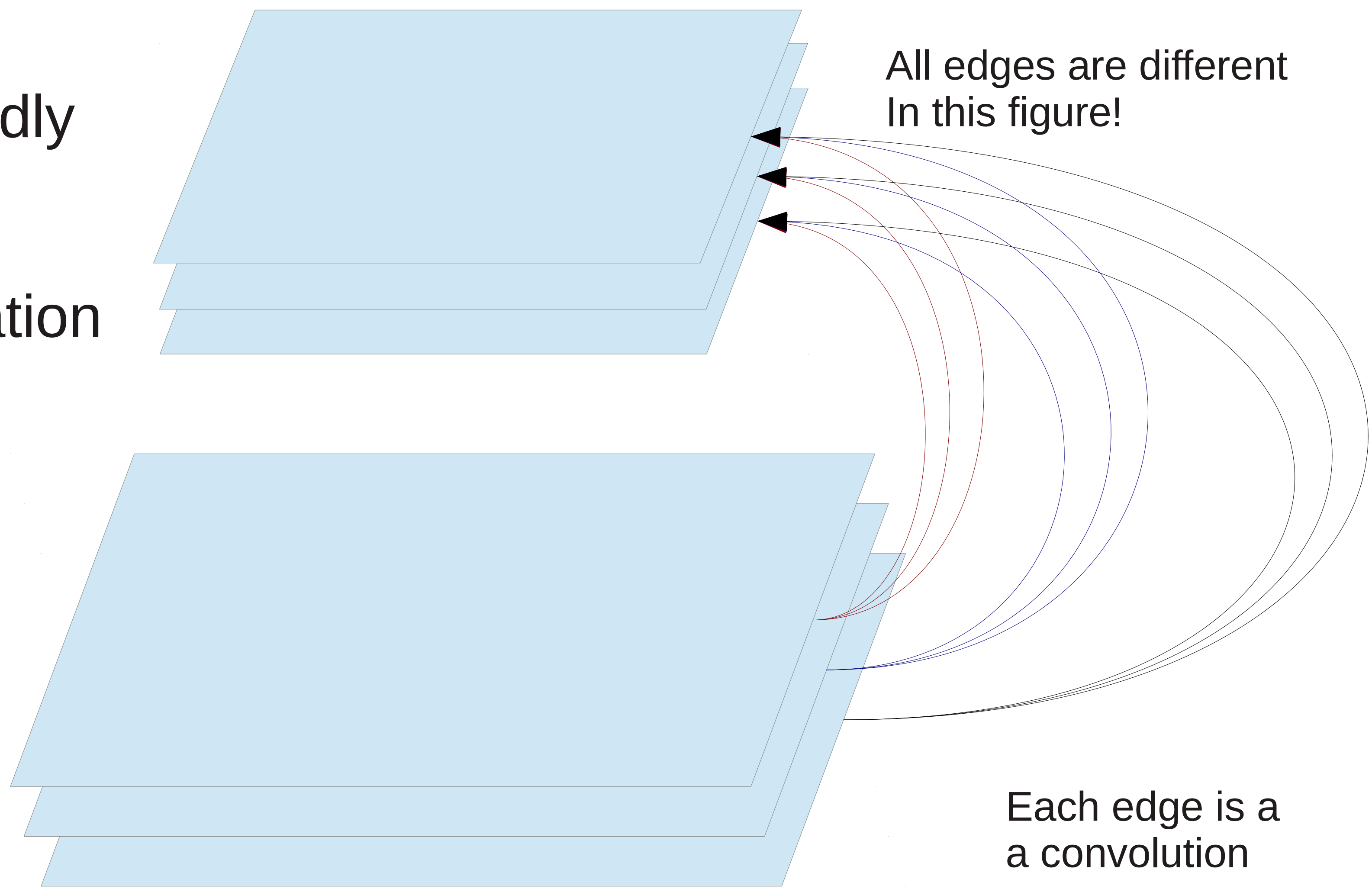
Advantages of conv:
- less connections
- much less parameters

Convolutional neural networks

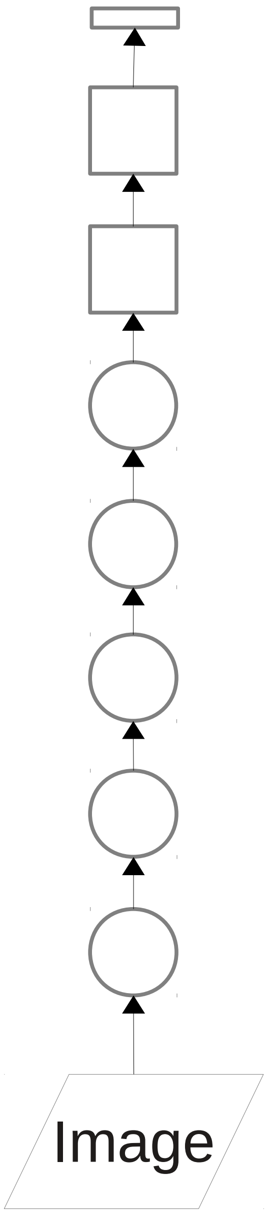
- Many “maps” go to many “maps”

- GPU-friendly

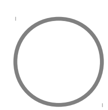
- Key operation



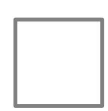
Overview of our model



- **Deep**: 7 hidden weight layers
- **Learned**: all feature extractors initialized with Gaussian noise and learned from the data
- Entirely supervised
- **More data = good**

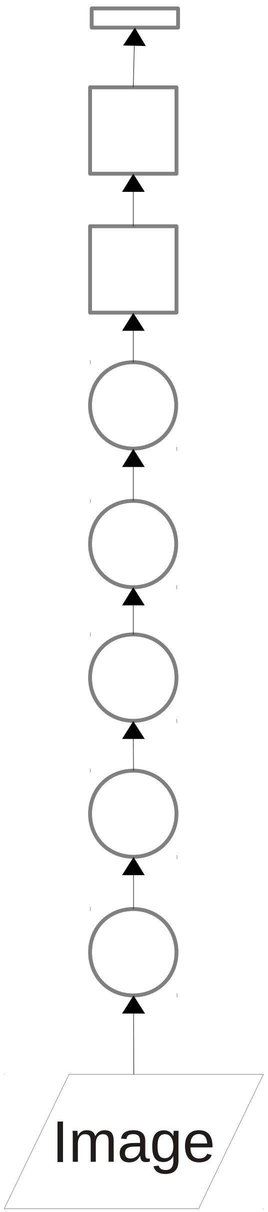


Convolutional layer: convolves its input with a bank of 3D filters, then applies point-wise non-linearity

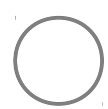


Fully-connected layer: applies linear filters to its input, then applies point-wise non-linearity

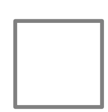
Overview of our model



- Trained with stochastic gradient descent on two NVIDIA GPUs for about a week
- 650,000 neurons
- 60,000,000 parameters
- 630,000,000 connections
- **Final feature layer:** 4096-dimensional

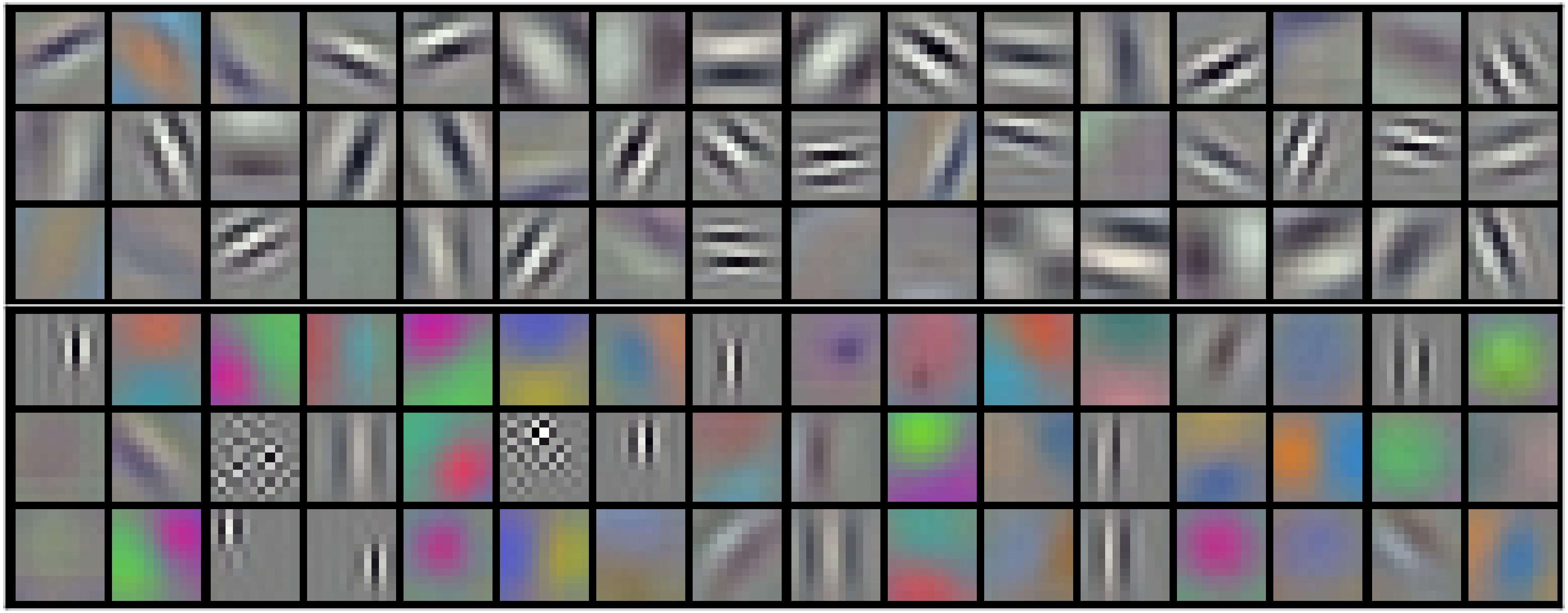


Convolutional layer: convolves its input with a bank of 3D filters, then applies point-wise non-linearity



Fully-connected layer: applies linear filters to its input, then applies point-wise non-linearity

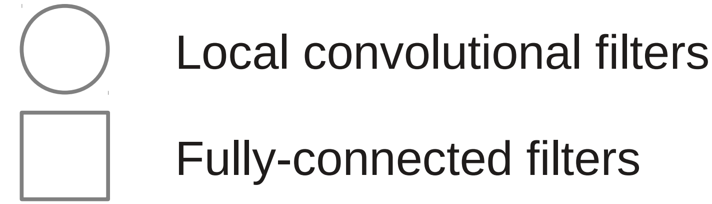
96 learned low-level filters



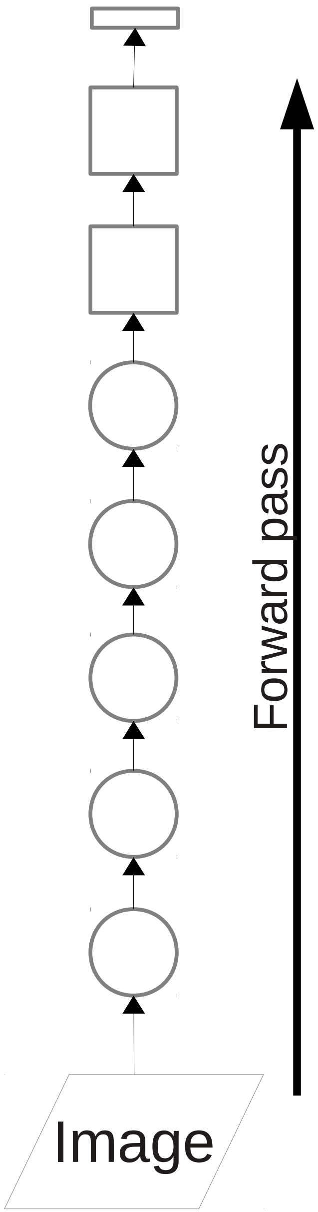
Main idea

Architecture

Technical details

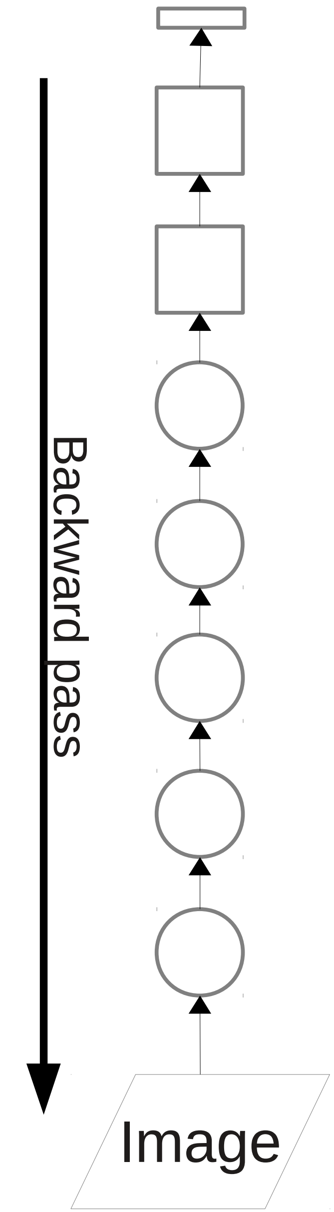


Training



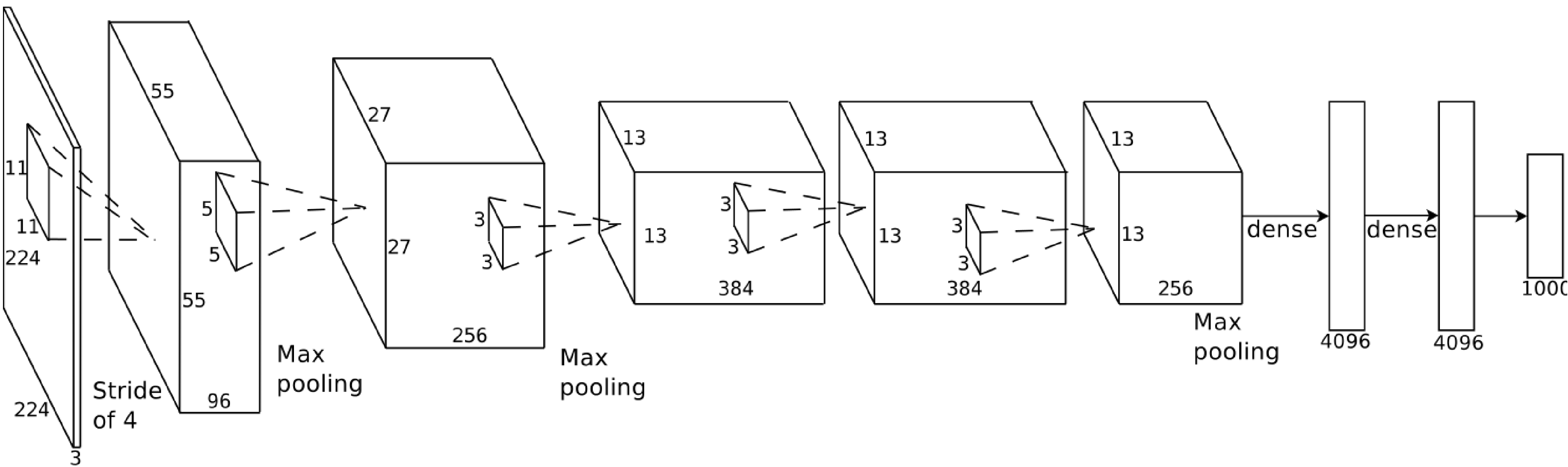
Using stochastic gradient descent and the *backpropagation algorithm* (just repeated application of the chain rule)

Make millions of small changes to the network's weights



Our model

- Max-pooling layers follow first, second, and fifth convolutional layers
- The number of neurons in each layer is given by 253440, 186624, 64896, 64896, 43264, 4096, 4096, 1000



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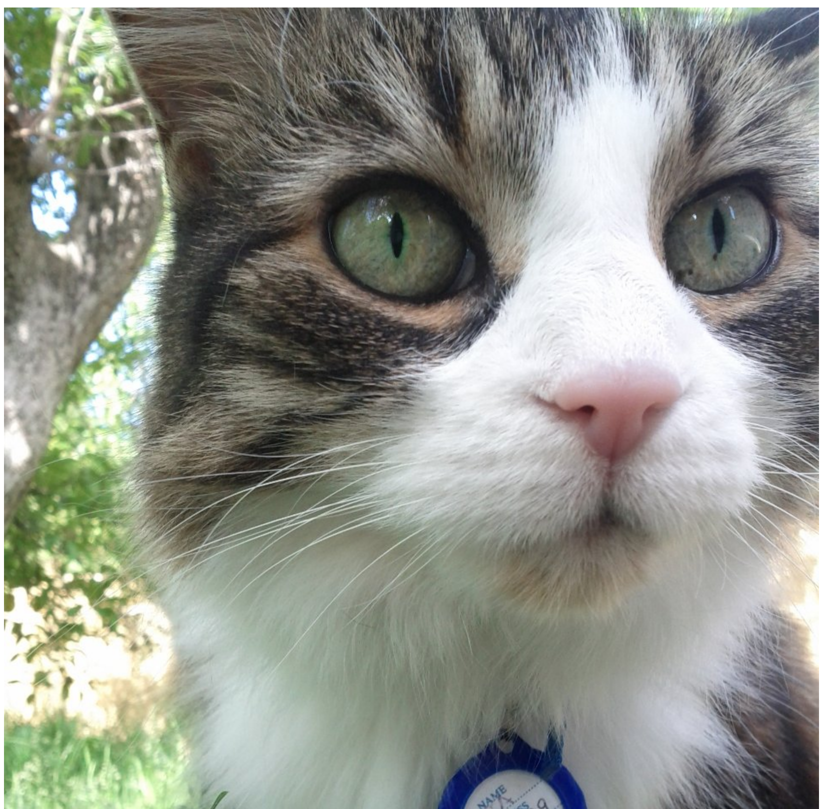
Input representation

- Centered (0-mean) RGB values.



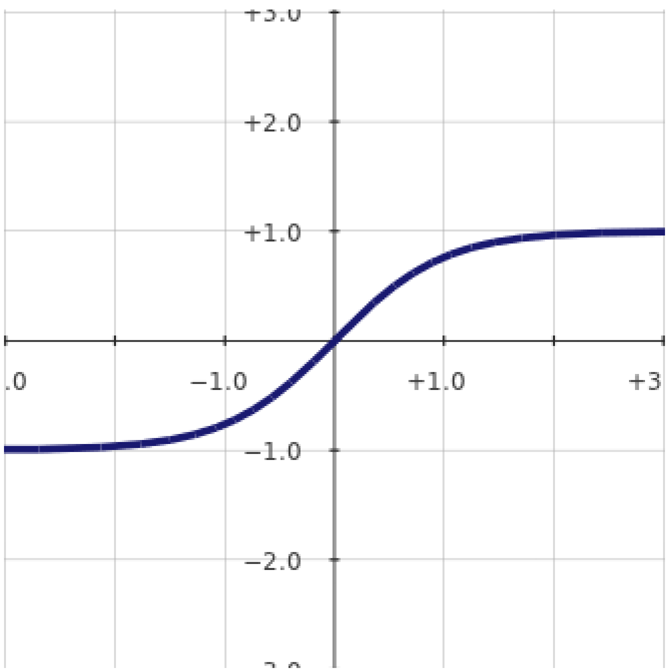
An input image (256x256)

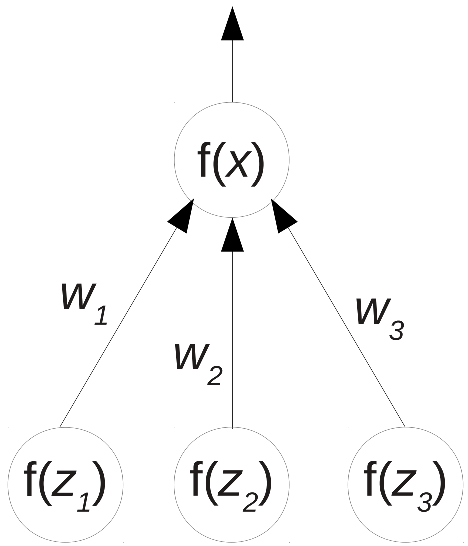
Minus sign

The mean input image

Neurons

$f(x) = \tanh(x)$

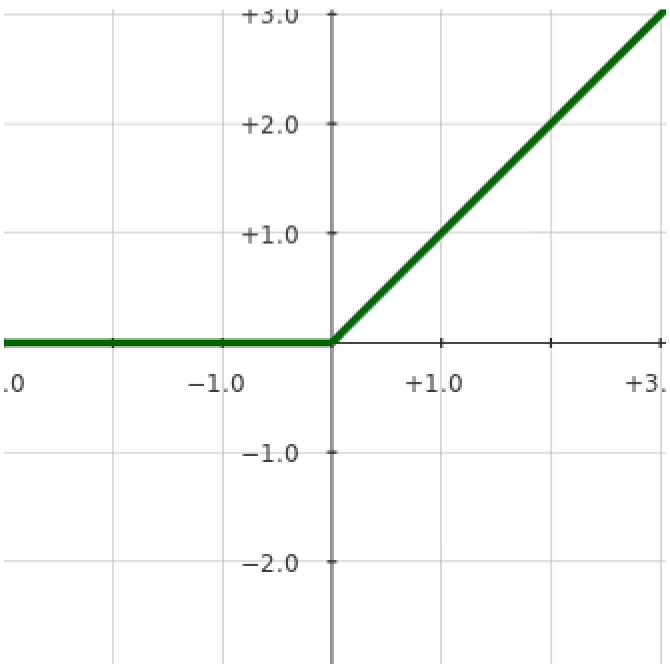




$x = w_1 f(z_1) + w_2 f(z_2) + w_3 f(z_3)$

x is called the total input to the neuron, and $f(x)$ is its output

$f(x) = \max(0, x)$

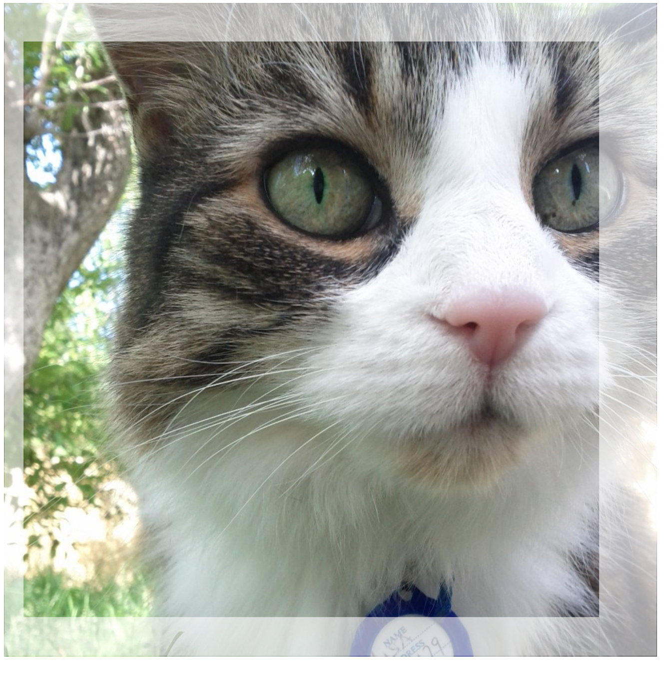


Very bad (slow to train)

Very good (quick to train)

Data augmentation

- Our neural net has 60M real-valued parameters and 650,000 neurons
- It overfits a lot. Therefore we train on 224x224 patches extracted randomly from 256x256 images, and also their horizontal reflections.

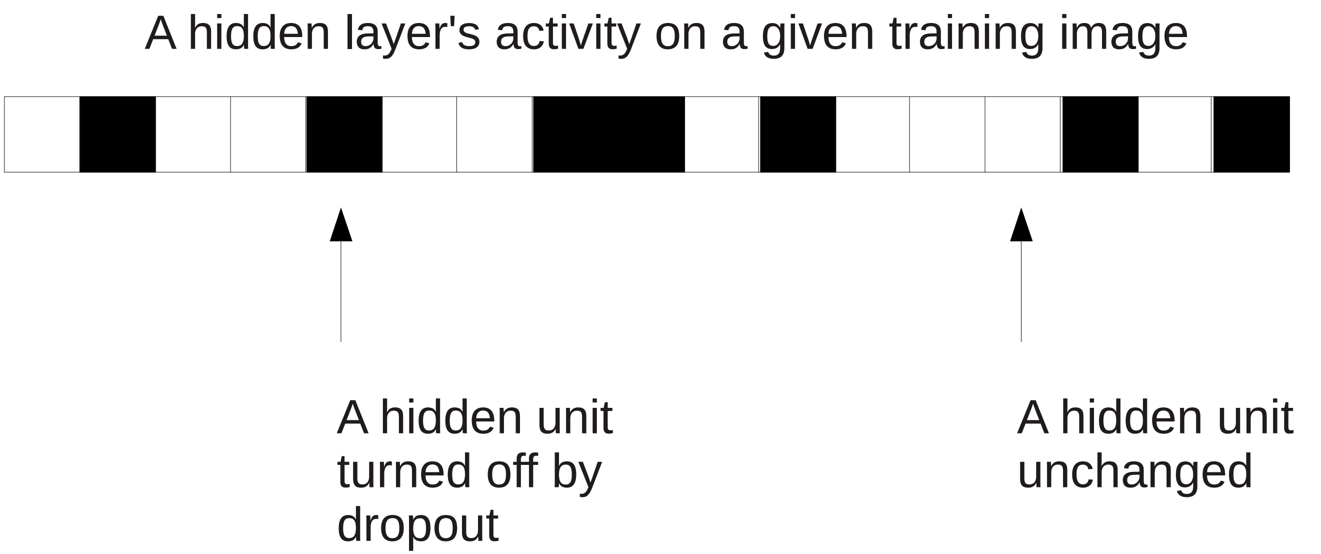


Testing

- Average predictions made at five 224x224 patches and their horizontal reflections (four corner patches and center patch)
- Logistic regression has the nice property that it outputs a probability distribution over the class labels
- Therefore no score normalization or calibration is necessary to combine the predictions of different models (or the same model on different patches), as would be necessary with an SVM.

Dropout

- Independently set each hidden unit activity to zero with 0.5 probability
- We do this in the two globally-connected hidden layers at the net's output



Implementation

- The only thing that needs to be stored on disk is the raw image data
- We stored it in JPEG format. It can be loaded and decoded entirely in parallel with training.
- Therefore only 27GB of disk storage is needed to train this system.
- Uses about 2GB of RAM on each GPU, and around 5GB of system memory during training.

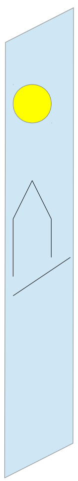
Implementation

- Written in Python/C++/CUDA
- Sort of like an instruction pipeline, with the following 4 instructions happening in parallel:
  - Train on batch *n* (on GPUs)
  - Copy batch *n*+1 to GPU memory
  - Transform batch *n*+2 (on CPU)
  - Load batch *n*+3 from disk (on CPU)

Comparison to monkey brain

- Some researchers showed images to macaques and recorded the firing rates of 128 of their neurons
- Compare to other systems in recognizing “hard images”
  - Lots of rotations, change in illumination
- Our neural network's 4096 neurons beat the 128 macaque's neurons
  - Although more of the macaque's neurons may outperform our system
- All other computer vision methods did much worse than the macaque neurons

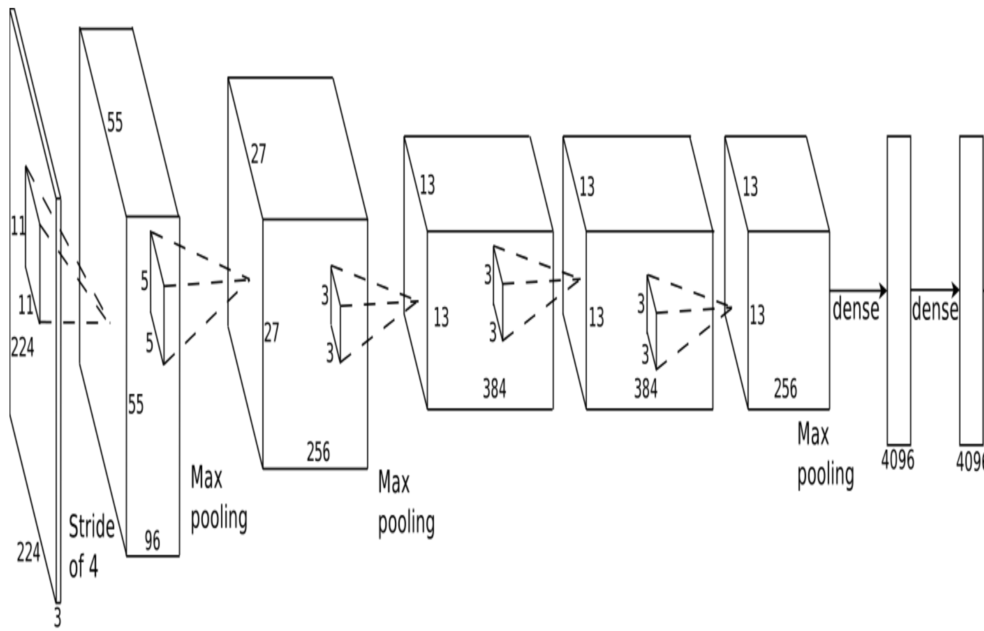
Monkey vs machine



other methods

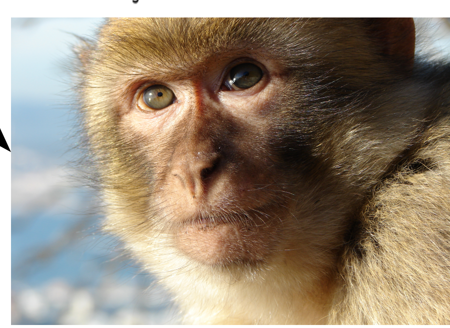
Get
lots
of dims

?



Get
4096
dims

?

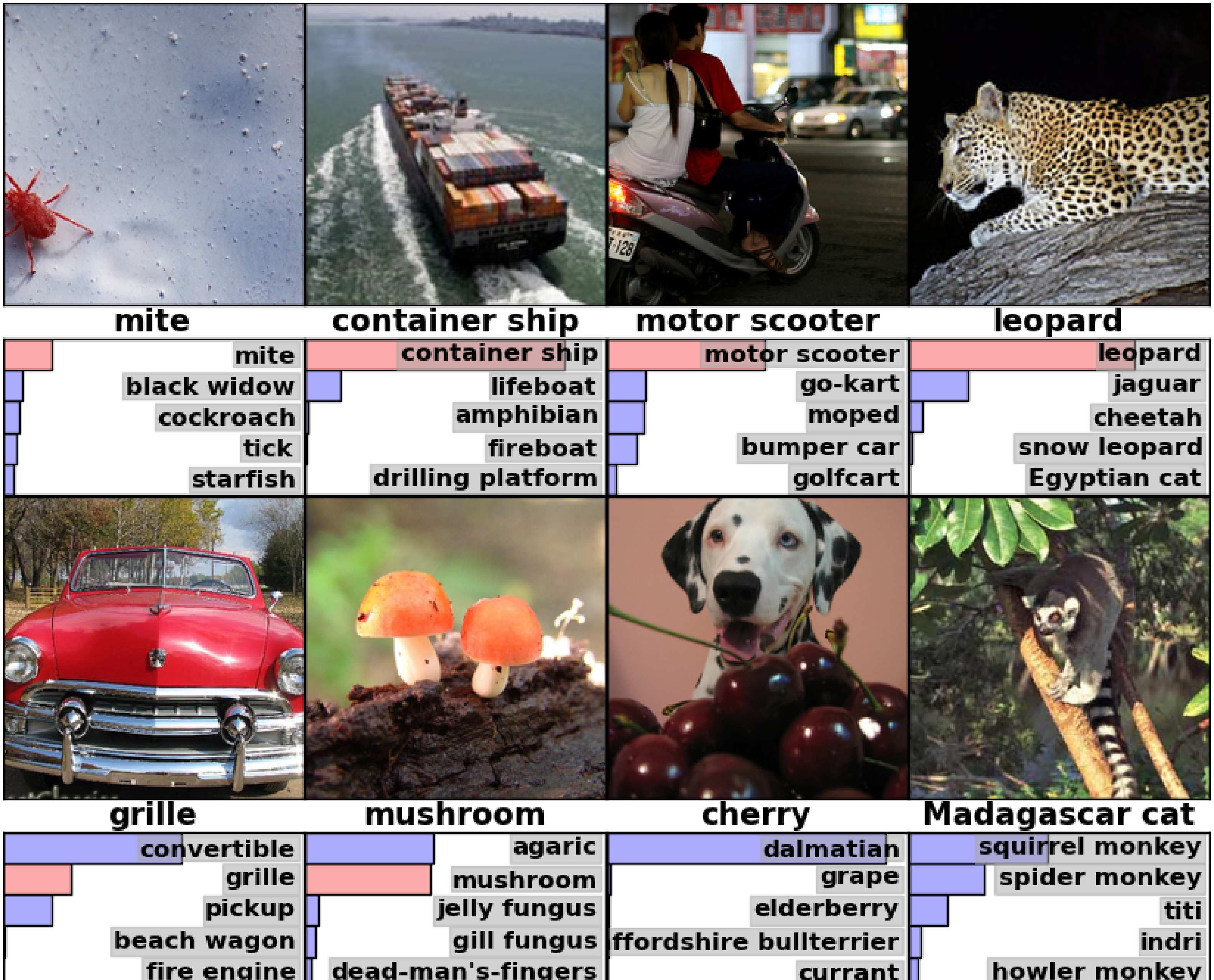


Place a big electrode in the
right part of the visual cortex
and record from 128 neurons

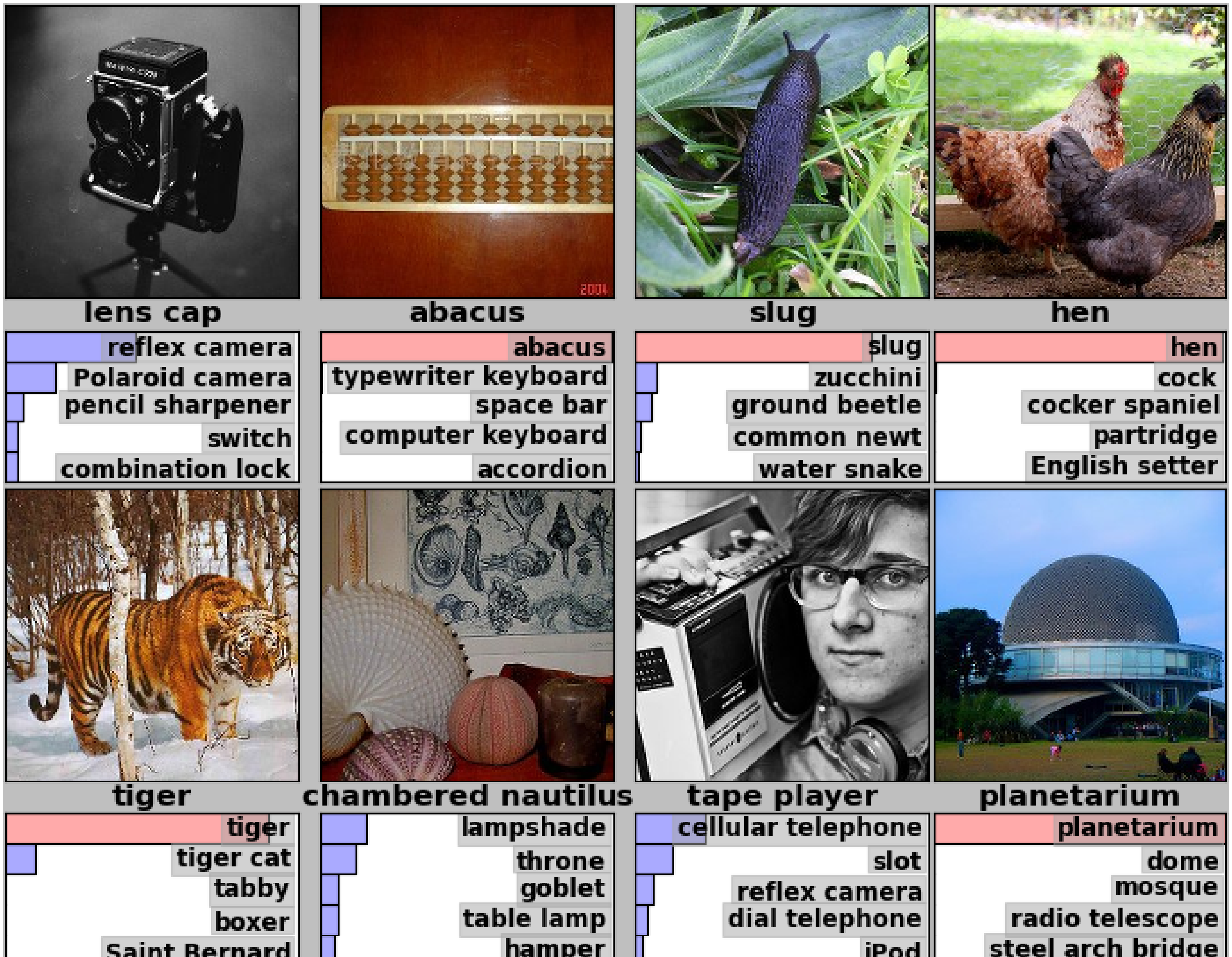
Get
128
dims

?

Validation classification

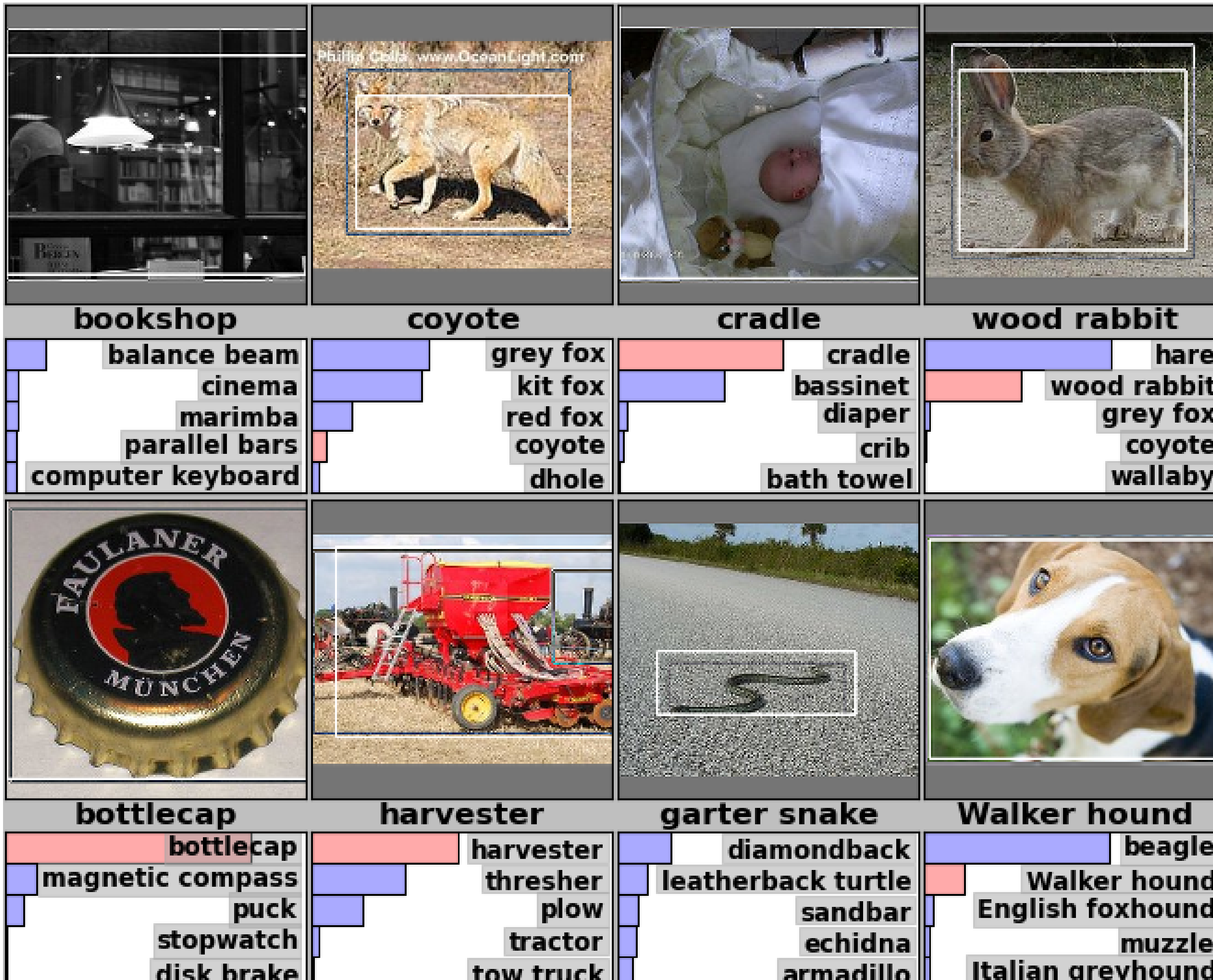


Validation classification

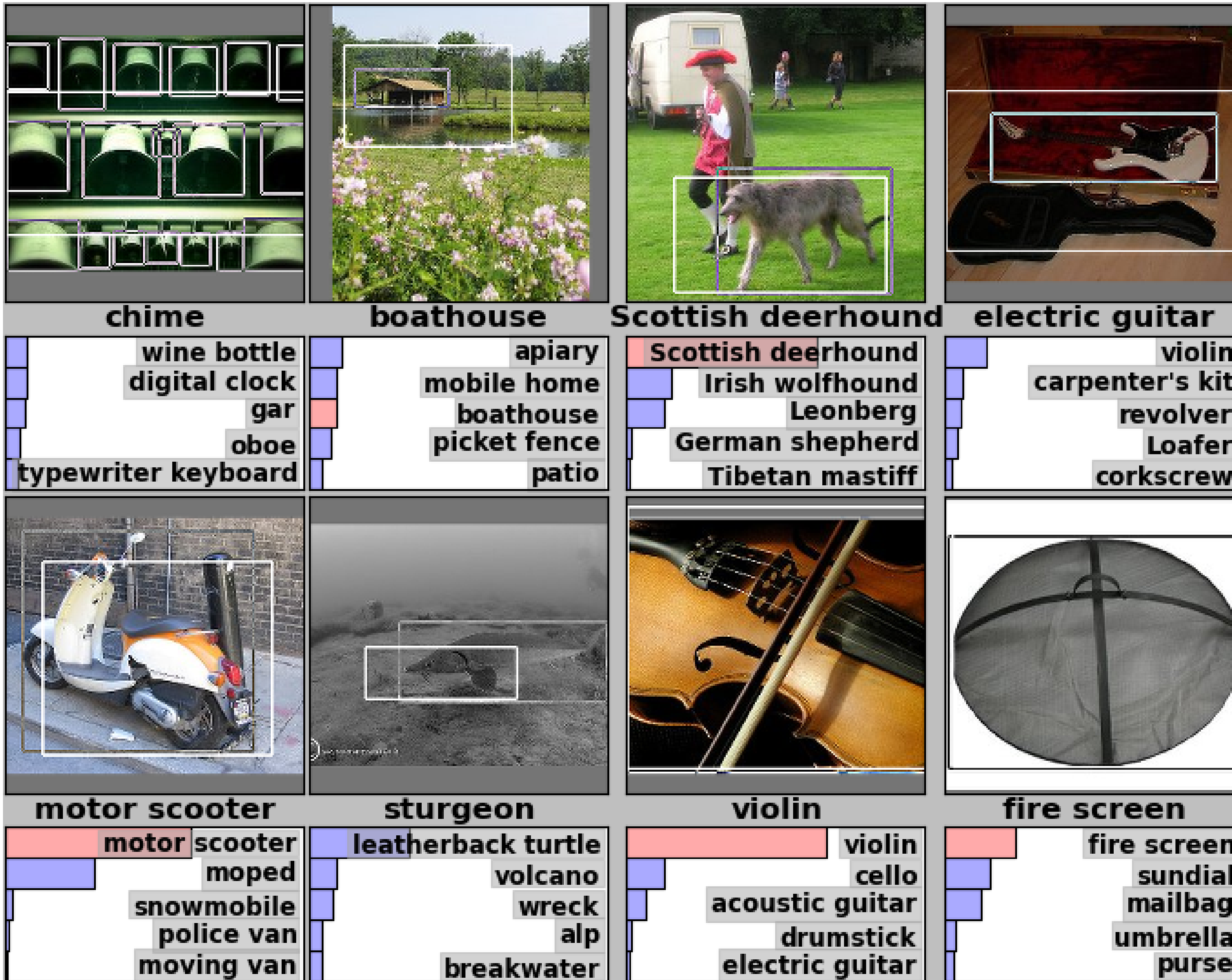


Validation classification

Validation localizations

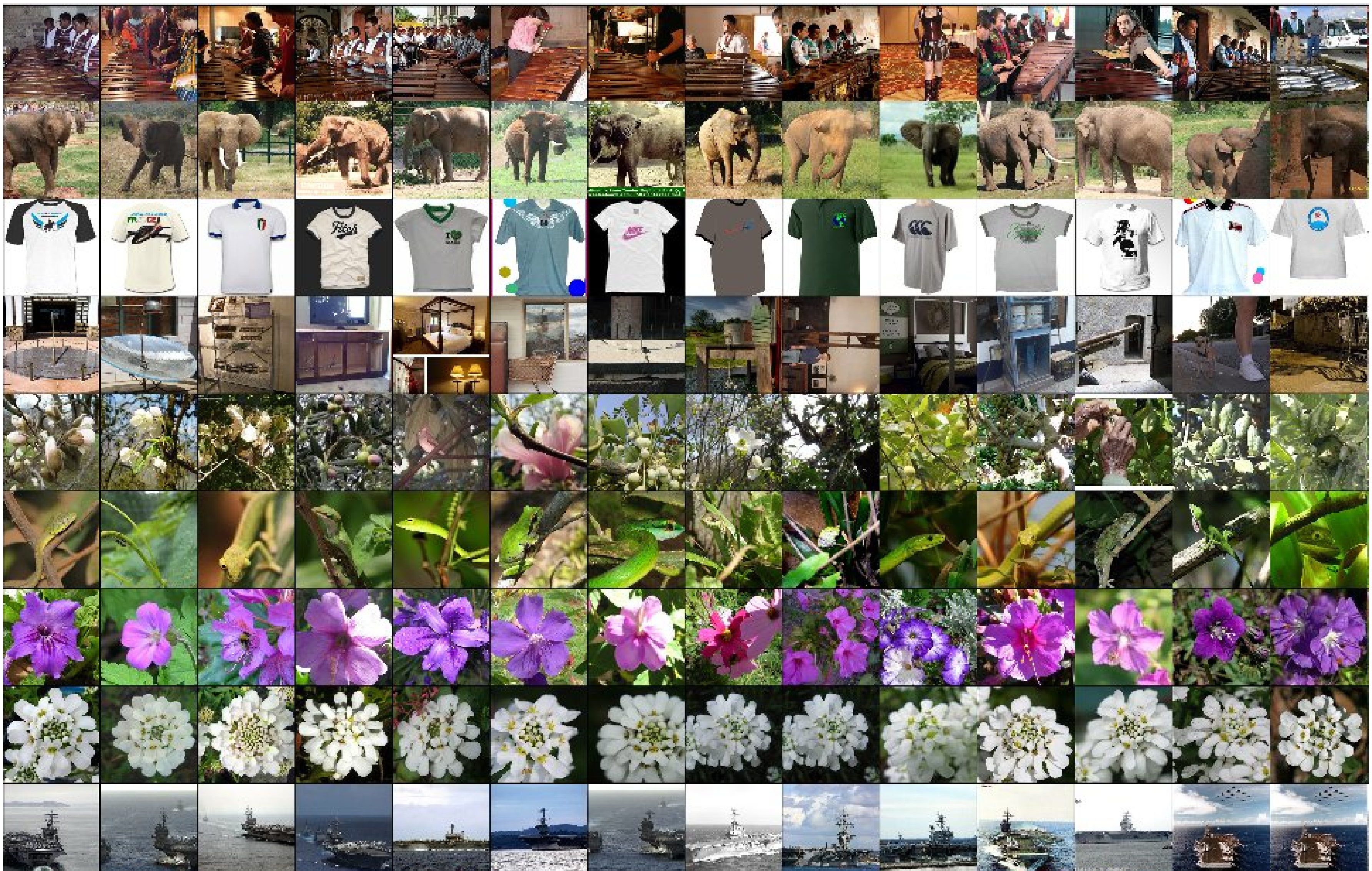


Validation localizations



Retrieval experiments

First column contains query images from ILSVRC-2010 test set, remaining columns contain retrieved images from training set.



Retrieval experiments