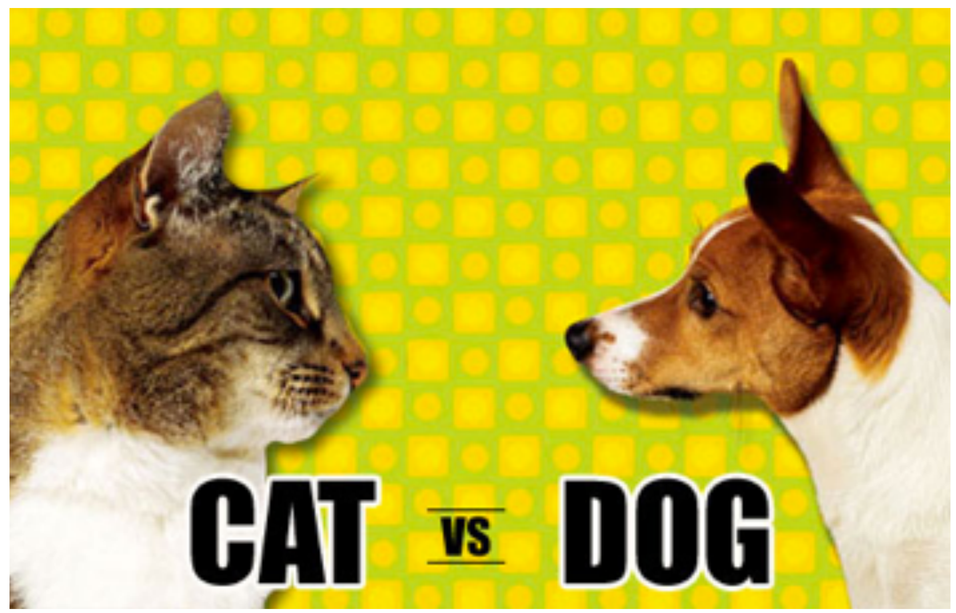
PYCON SWEDEN

Roelof Pieters
@graphific

Deep Learning:
and Deep Data-Science



12 May 2015

ROYAL INSTITUTE OF TECHNOLOGY

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slides online at:
https://www.slideshare.net/roelofp/deep-learning-as-a-catdog-detector

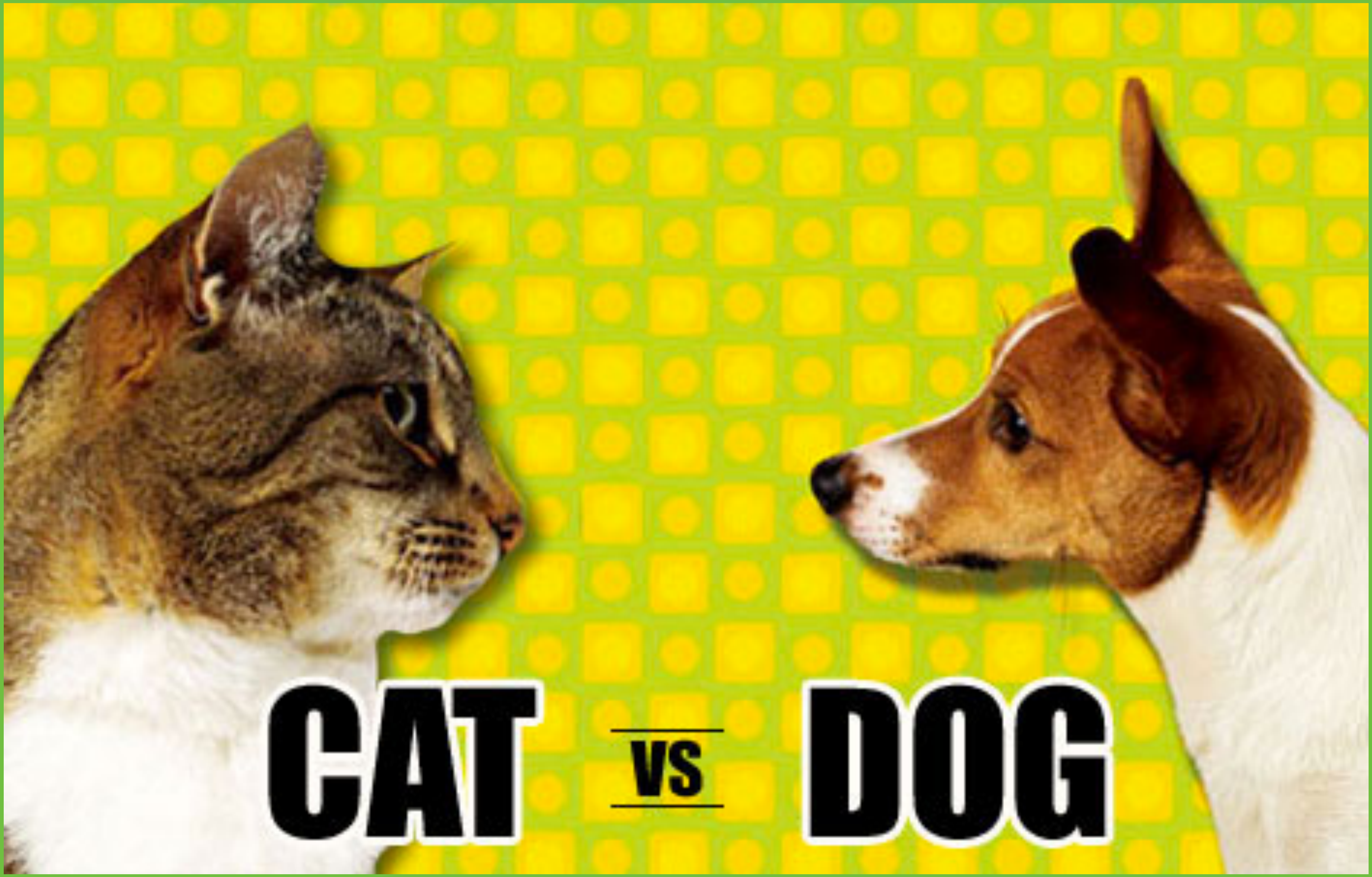
BUT FIRST...

are you a...

CAT PERSON?

DOG PERSON?

in the next few minutes we'll be making a



DETECTOR

main Libraries

- sckikit-learn (machine learning)
  http://scikit-learn.org

- caffe (deep learning) - for training deep neural nets
  (for today: loading a pre-trained one)
  http://caffe.berkeleyvision.org

- theano (efficient gpu-powered math)
  http://www.deeplearning.net/software/theano/

- ipython notebook
  http://ipython.org/notebook.html

scikit learn

Home | Installation | Documentation | Examples

Custom Search

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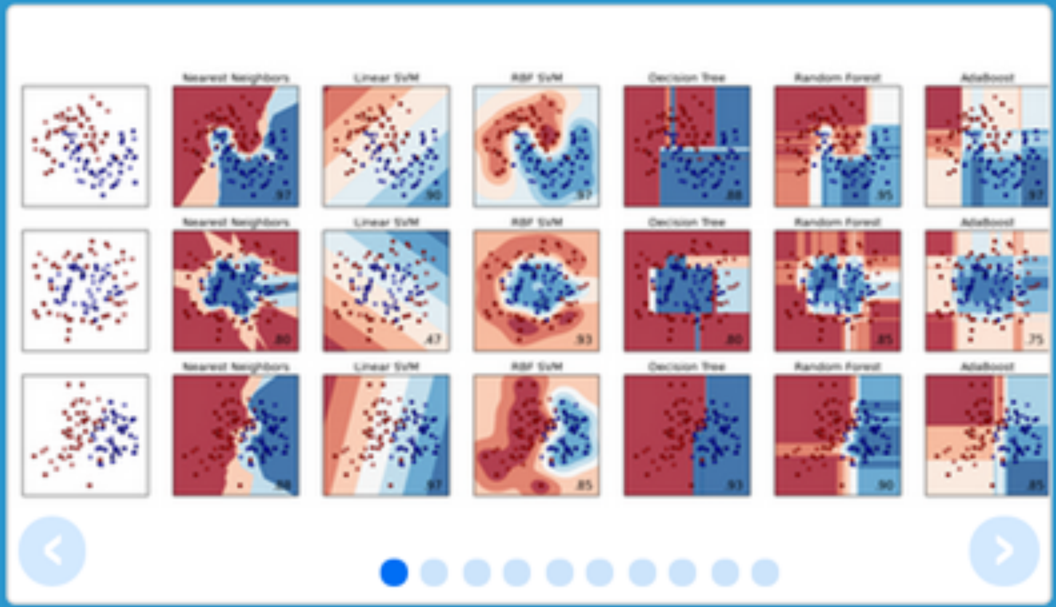

scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.
Algorithms: *SVM*, *nearest neighbors*, *random forest*, ... — *Examples*

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.
Algorithms: *SVR*, *ridge regression*, *Lasso*, ... — *Examples*

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes
Algorithms: *k-Means*, *spectral clustering*, *mean-shift*, ... — *Examples*

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency
Algorithms: *PCA*, *feature selection*, *non-negative matrix factorization*. — *Examples*

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning
Modules: *grid search*, *cross validation*, *metrics*. — *Examples*

Preprocessing

Feature extraction and normalization.

Application: Transforming input data such as text for use with machine learning algorithms.
Modules: *preprocessing*, *feature extraction*. — *Examples*

Caffe

Deep learning framework by the BVLC

Created by
Yangqing Jia
Lead Developer
Evan Shelhamer

View On GitHub

Caffe

Caffe is a deep learning framework made with expression, speed, and modularity in mind. It is developed by the Berkeley Vision and Learning Center (BVLC) and by community contributors. Yangqing Jia created the project during his PhD at UC Berkeley. Caffe is released under the BSD 2-Clause license.

Check out our web image classification demo!

Why Caffe?

Expressive architecture encourages application and innovation. Models and optimization are defined by configuration without hard-coding. Switch between CPU and GPU by setting a single flag to train on a GPU machine then deploy to commodity clusters or mobile devices.

Extensible code fosters active development. In Caffe's first year, it has been forked by over 1,000 developers and had many significant changes contributed back. Thanks to these contributors the framework tracks the state-of-the-art in both code and models.

Speed makes Caffe perfect for research experiments and industry deployment. Caffe can process **over 60M images per day** with a single NVIDIA K40 GPU*. That's 1 ms/image for inference and 4 ms/image for learning. We believe that Caffe is the fastest convnet implementation available.

Community: Caffe already powers academic research projects, startup prototypes, and even large-scale industrial applications in vision, speech, and multimedia. Join our community of brewers on the caffe-users group and Github.

* With the ILSVRC2012-winning SuperVision model and caching IO. Consult performance details.

Welcome

Theano is a Python library that allows you to define, optimize, and evaluate mathematical expressions involving multi-dimensional arrays efficiently. Theano features:

- **tight integration with NumPy** – Use *numpy.ndarray* in Theano-compiled functions.
- **transparent use of a GPU** – Perform data-intensive calculations up to 140x faster than with CPU.(float32 only)
- **efficient symbolic differentiation** – Theano does your derivatives for function with one or many inputs.
- **speed and stability optimizations** – Get the right answer for `log(1+x)` even when `x` is really tiny.
- **dynamic C code generation** – Evaluate expressions faster.
- **extensive unit-testing and self-verification** – Detect and diagnose many types of mistake.

Theano has been powering large-scale computationally intensive scientific investigations since 2007. But it is also approachable enough to be used in the classroom (IFT6266 at the University of Montreal).

News

- We support cuDNN if it is installed by the user.
- Open Machine Learning Workshop 2014 presentation.
- Colin Raffel tutorial on Theano.
- Ian Goodfellow did a 12h class with exercises on Theano.

theano

Table Of Contents

Next topic

Release Notes

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Quick search

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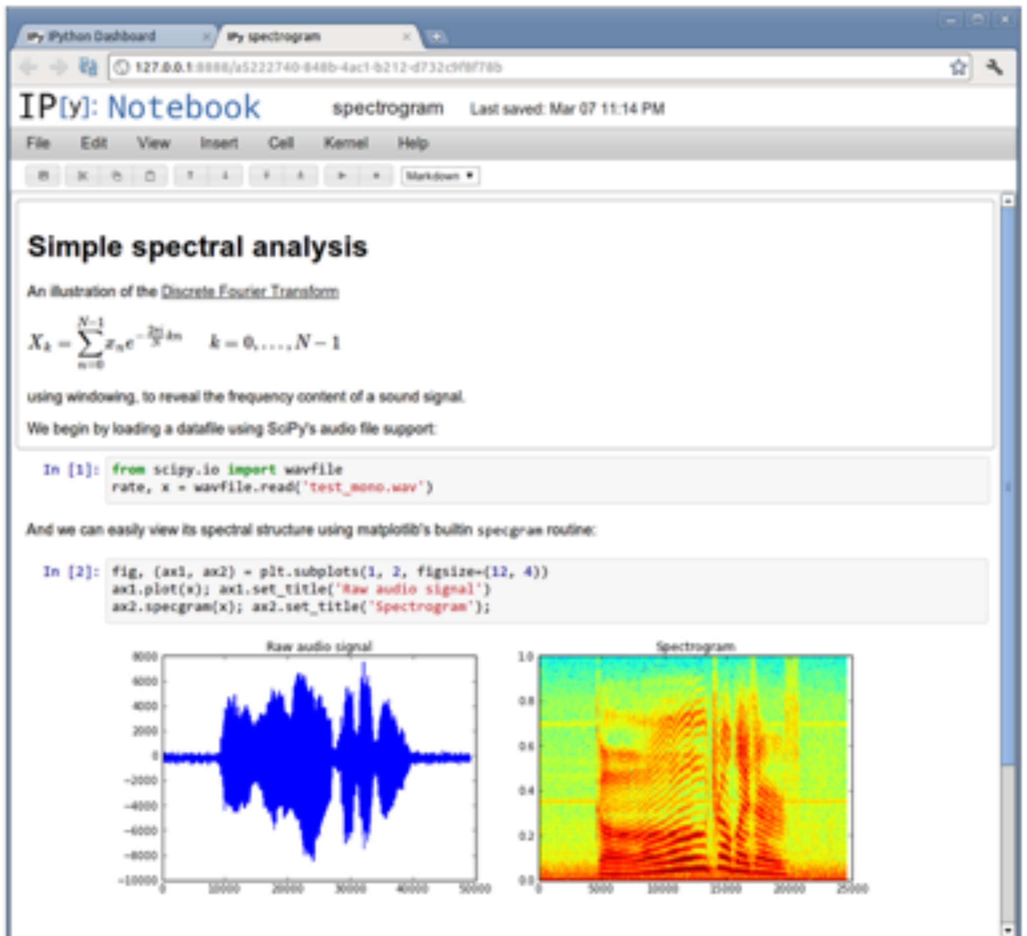
Enter search terms or a module, class or function name.

IP[y]: IPython
Interactive Computing

The IPython Notebook

The IPython Notebook is an interactive computational environment, in which you can combine code execution, rich text, mathematics, plots and rich media, as shown in this example session:



It aims to be an agile tool for both exploratory computation and data analysis, and provides a platform to support **reproducible research**, since all inputs and outputs may be stored in a one-to-one way in notebook documents.

Google™ Custom Search | Search

VERSIONS

Stable
3.1 – April 2015
Install

Development
4.0.dev
GitHub

Offline Docs
All Versions
GitHub

NOTEBOOK VIEWER

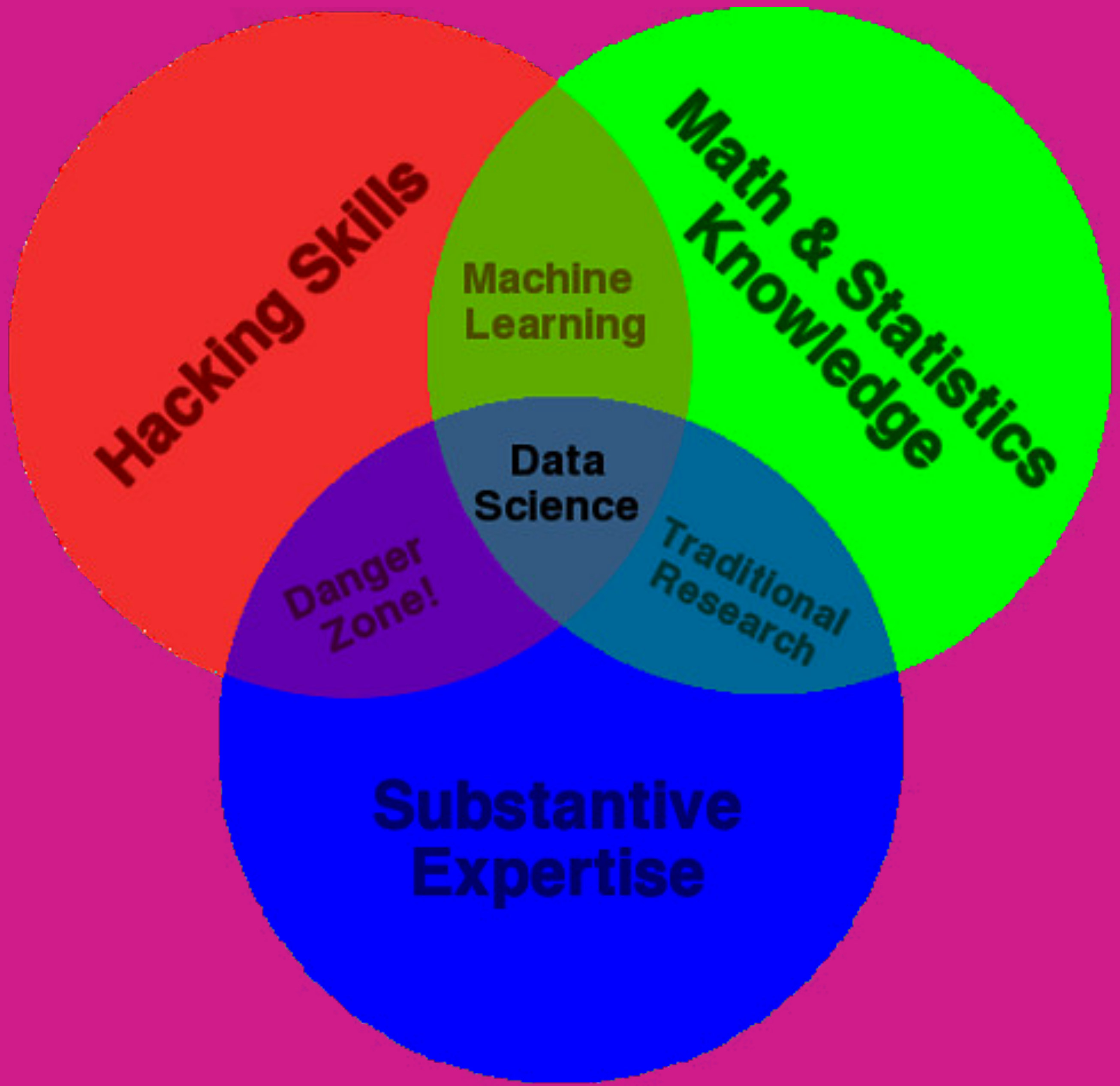
Share your notebooks


Code is ahead, soon...
I promise :)
BEAR
WITH
ME

Data Science ?

“Data science is clearly a blend of the **hackers' art, statistics** and **machine learning**…”

—Hilary Mason & Chris Wiggins, 2010



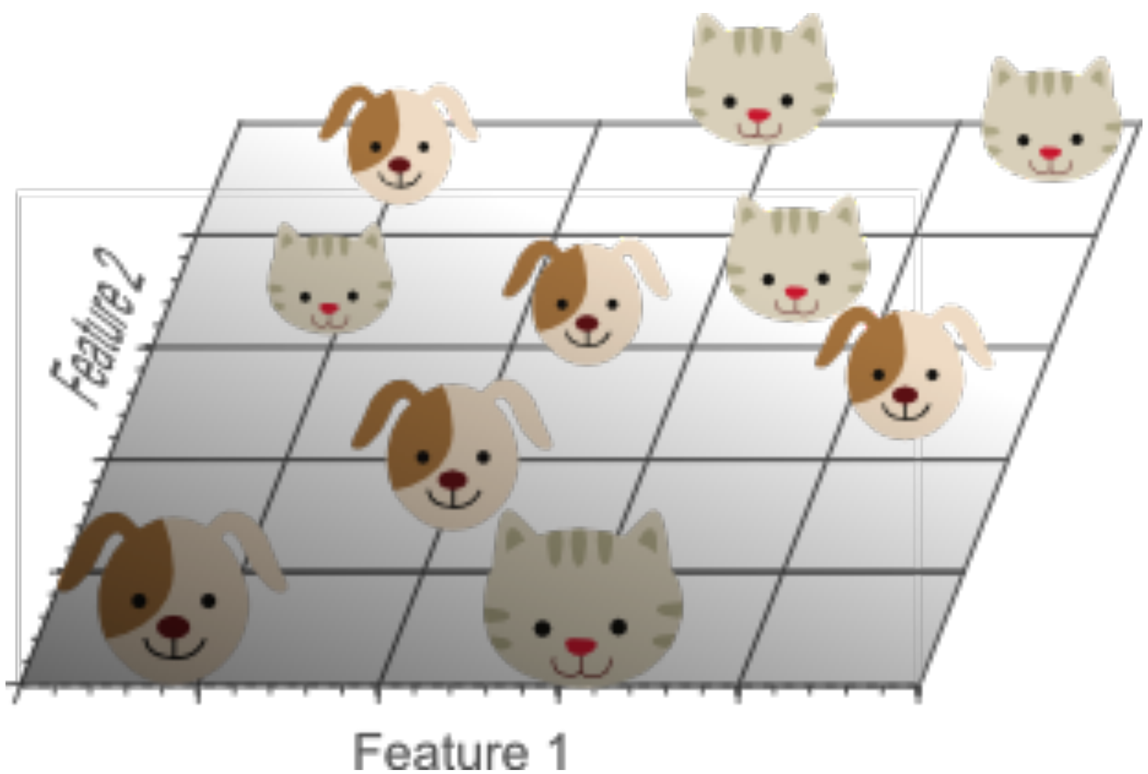
(Drew Connoway 2010)

> Features = Awesomeness

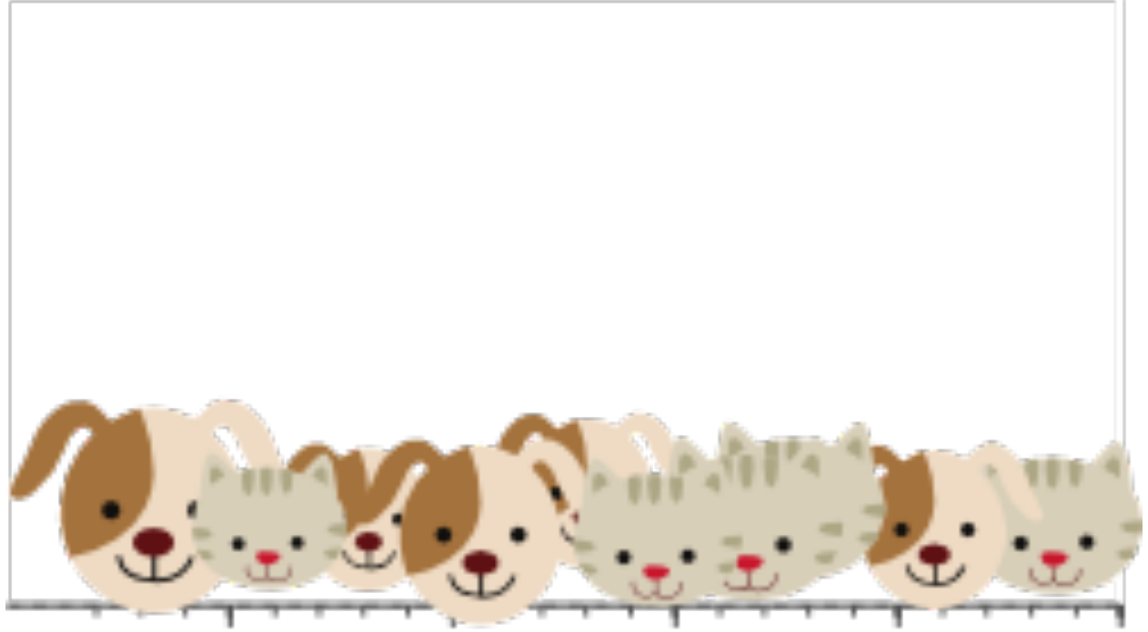
1 feature

> Features = Awesomeness

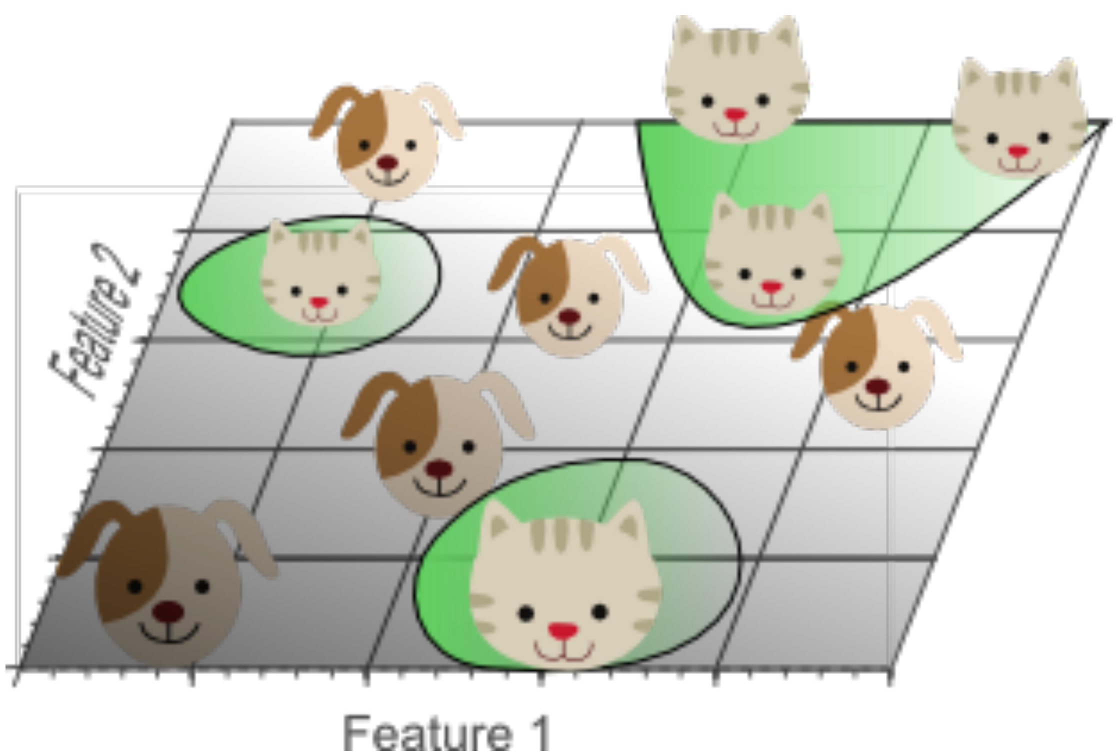
1 feature



2 features



1 feature

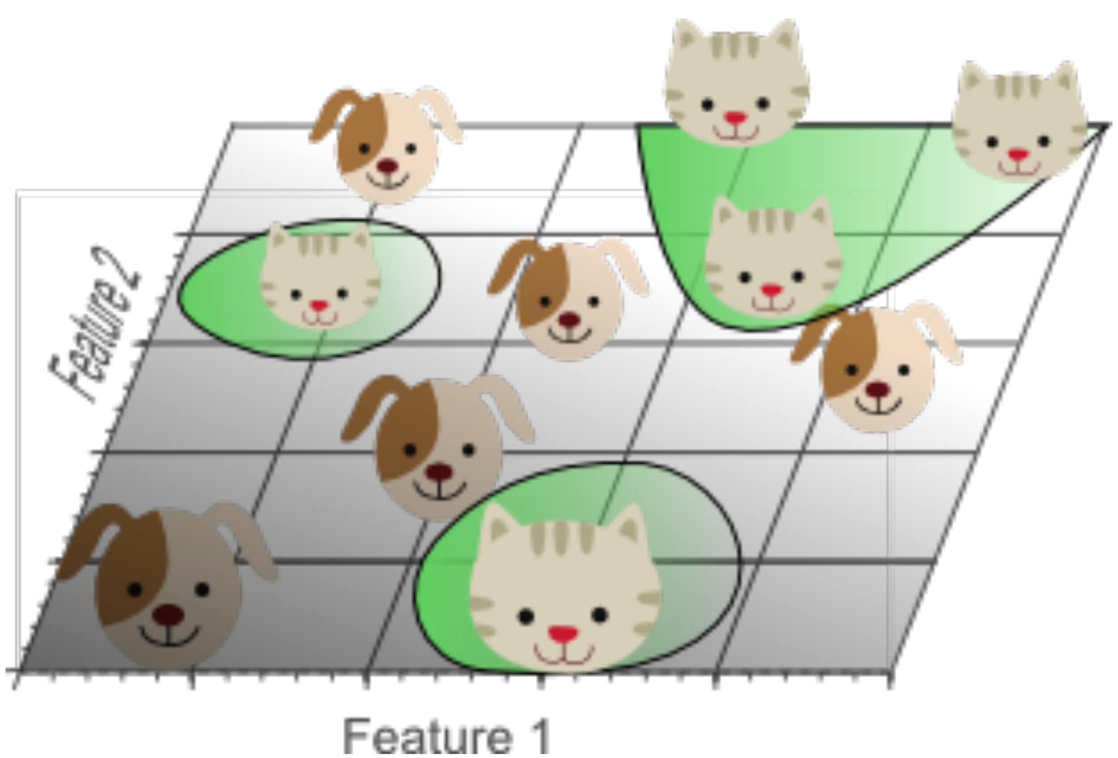


2 features

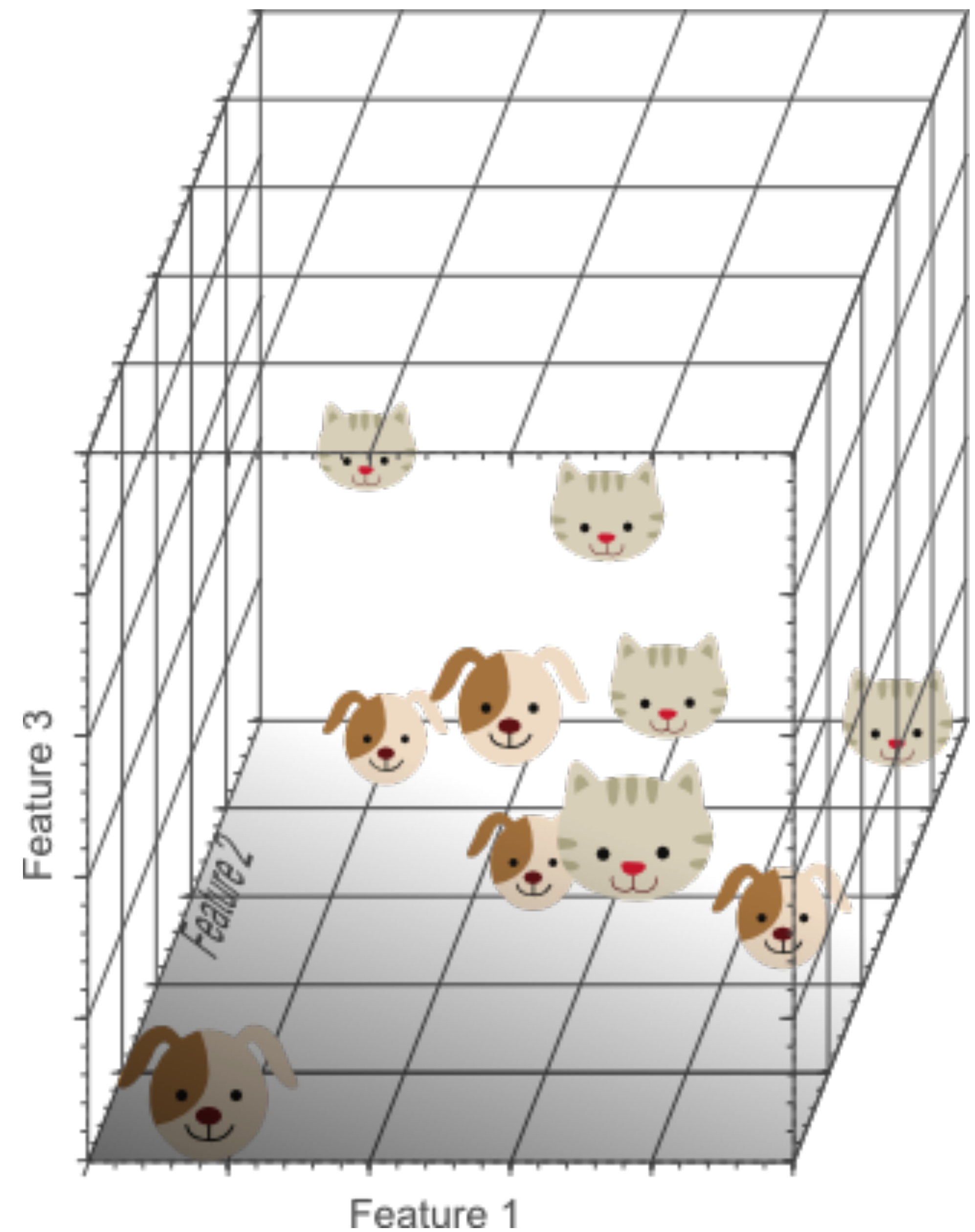
too few features/dimensions = overfitting

> Features = Awesomeness

1 feature



2 features

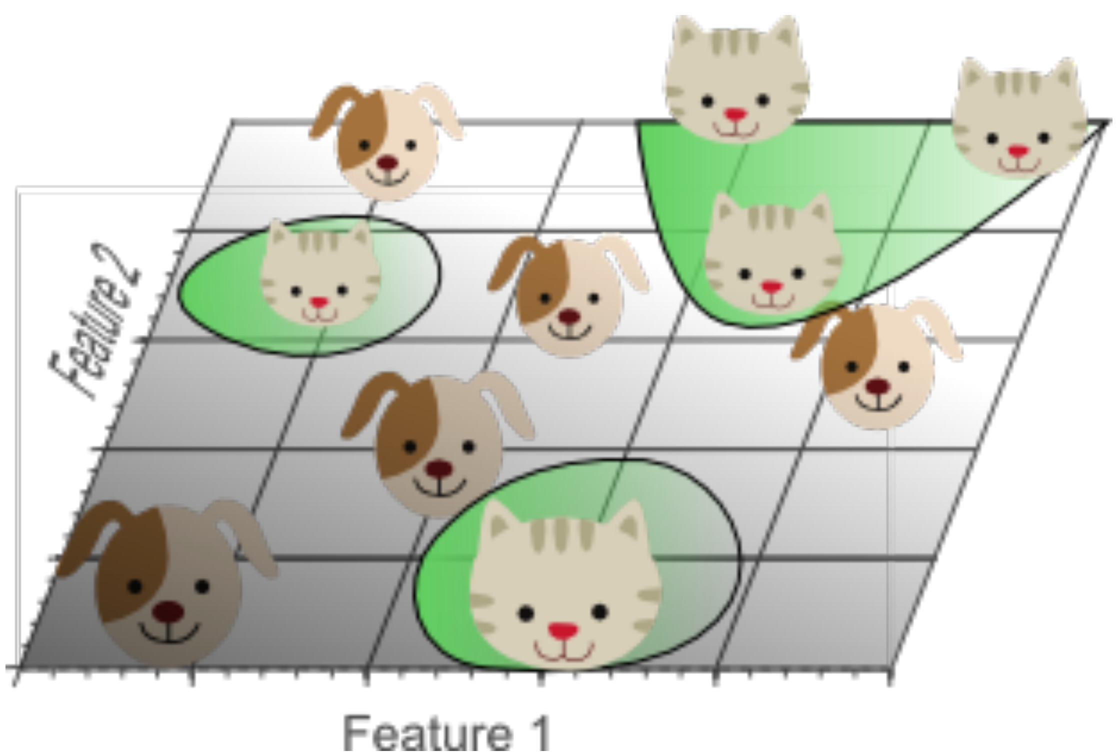


3 features

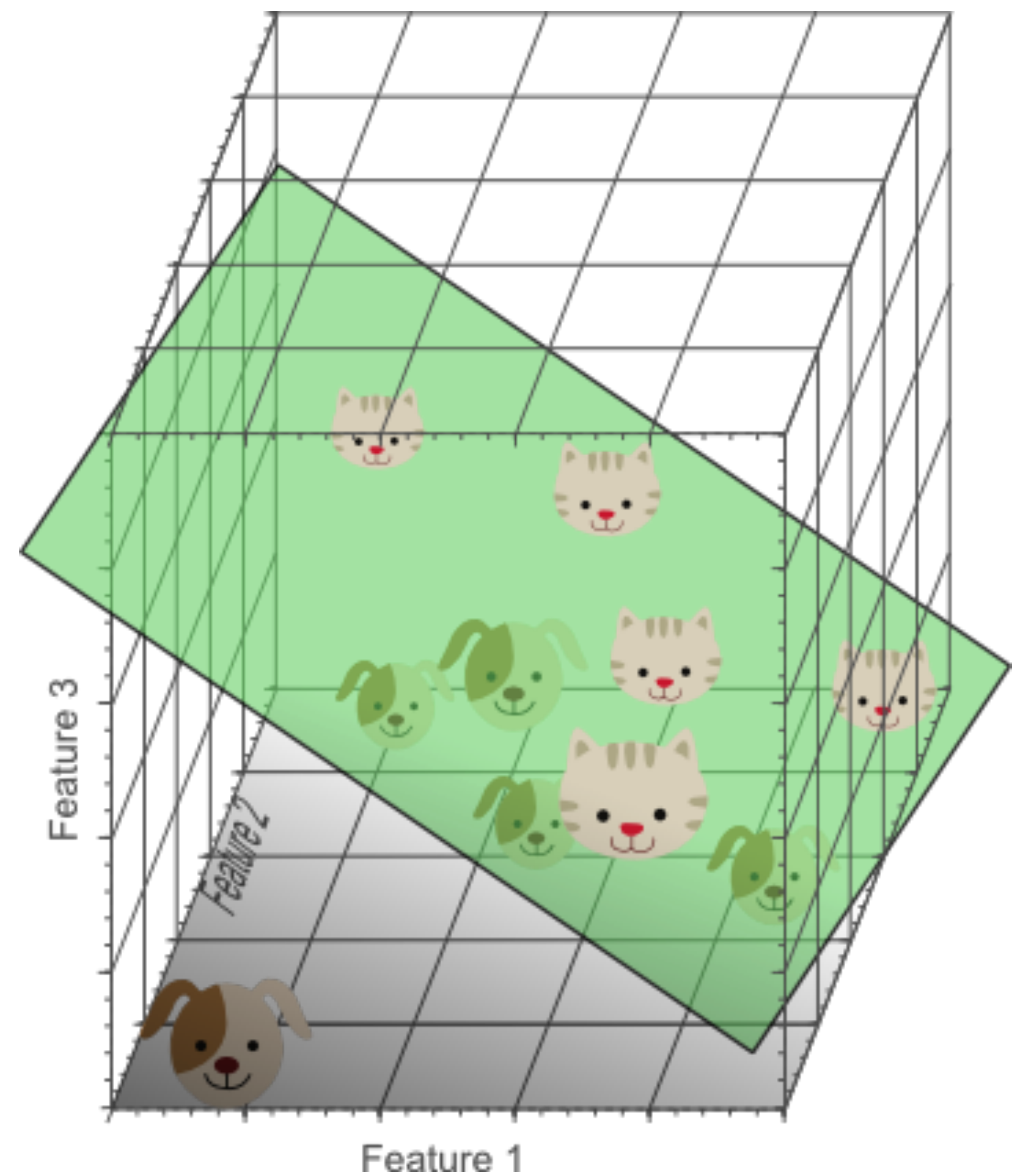
too few features/dimensions = overfitting

More Features = Awesomeness!

1 feature

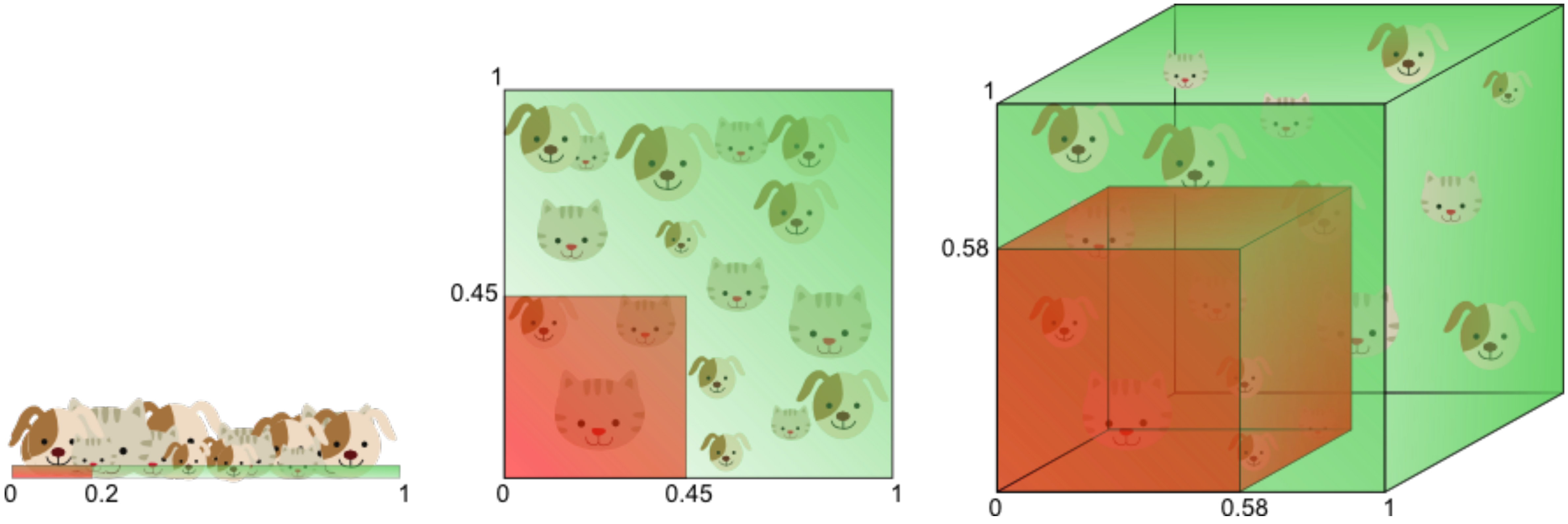


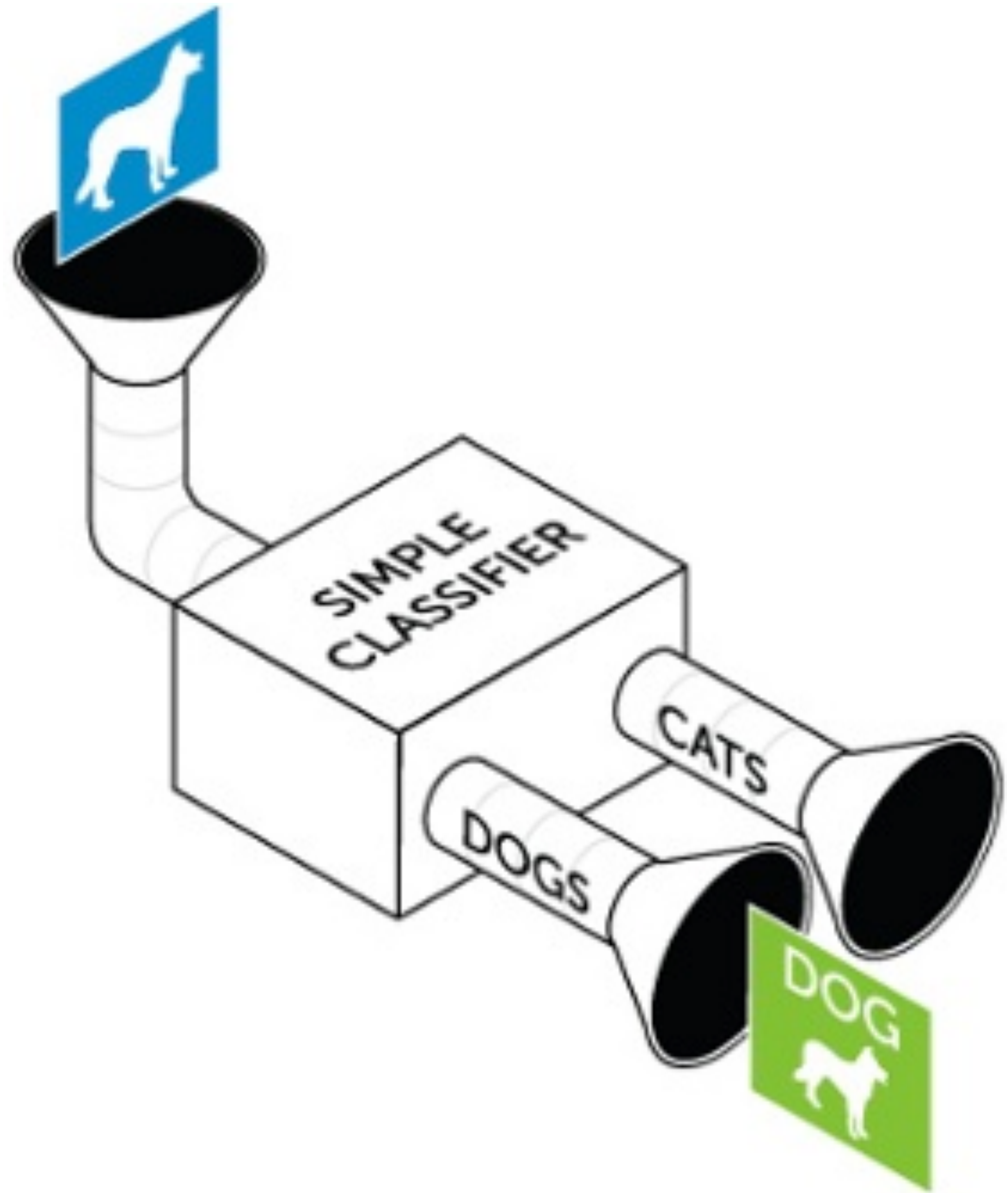
2 features



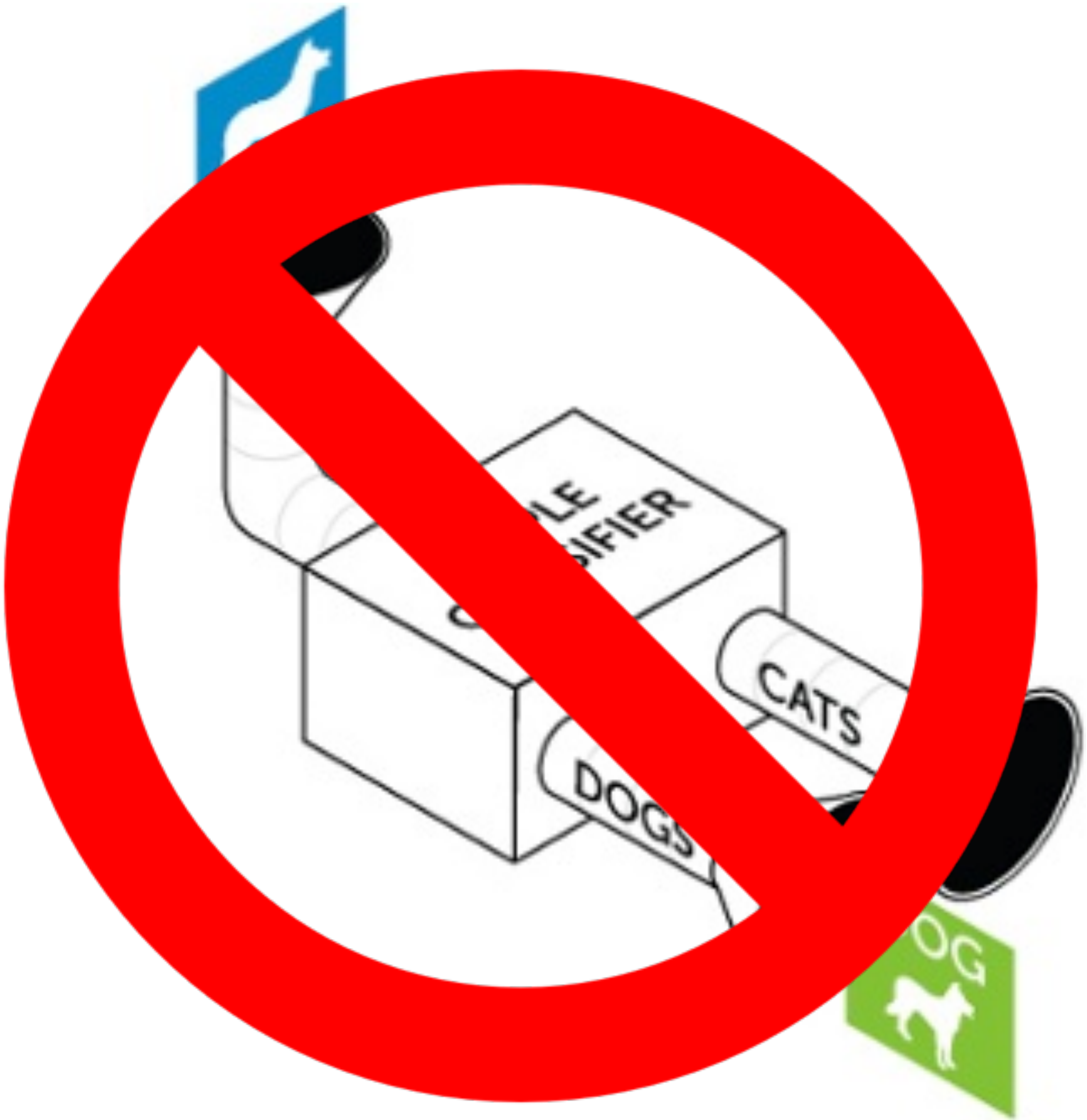
3 features

++ Data Needs also grow!





(picture by Dato)

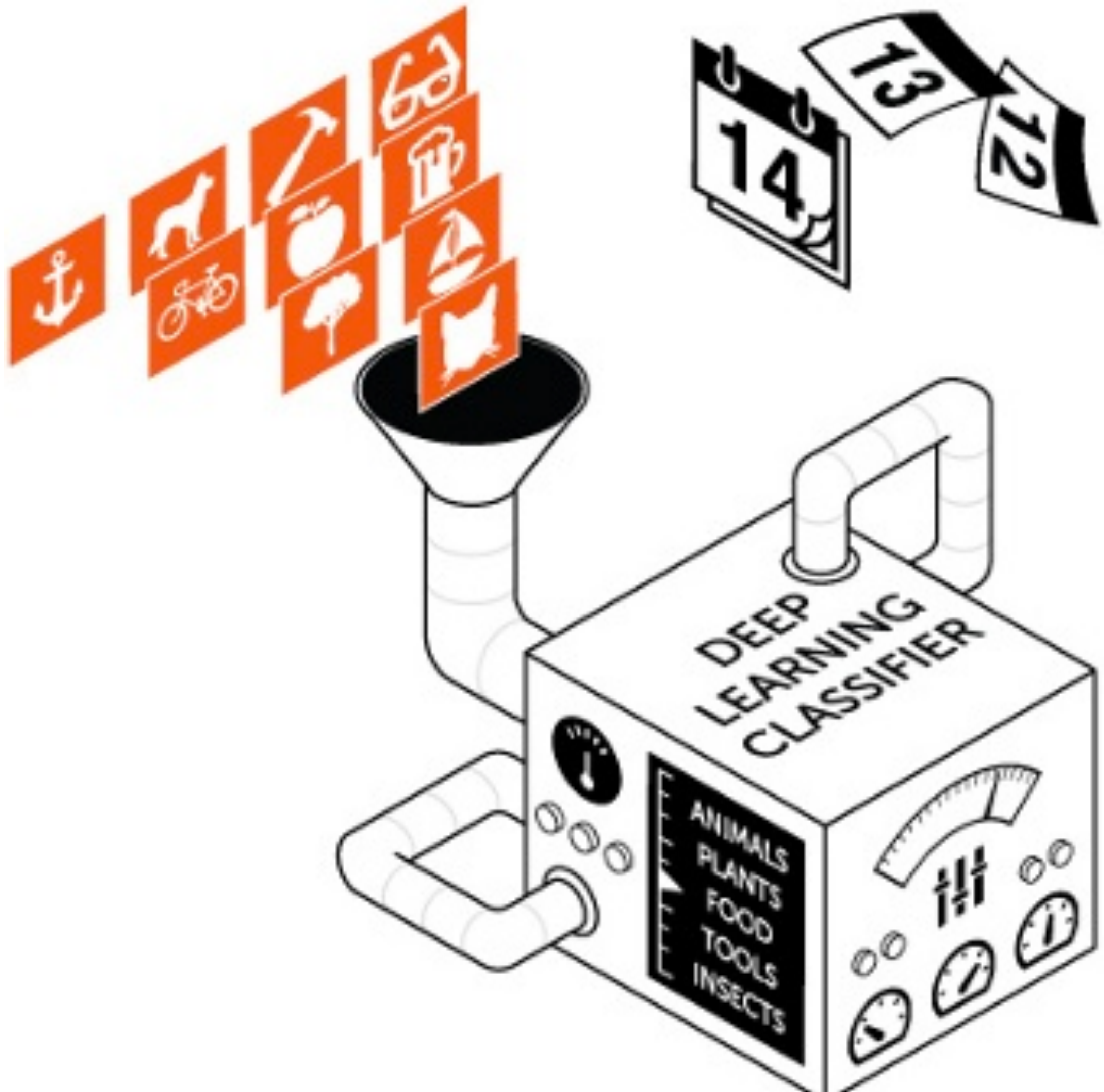


(picture by Dato)

Deep Learning?

- A host of statistical machine learning techniques
- Enables the automatic learning of feature hierarchies
- Generally based on artificial neural networks

Deep Learning



(picture by Dato)

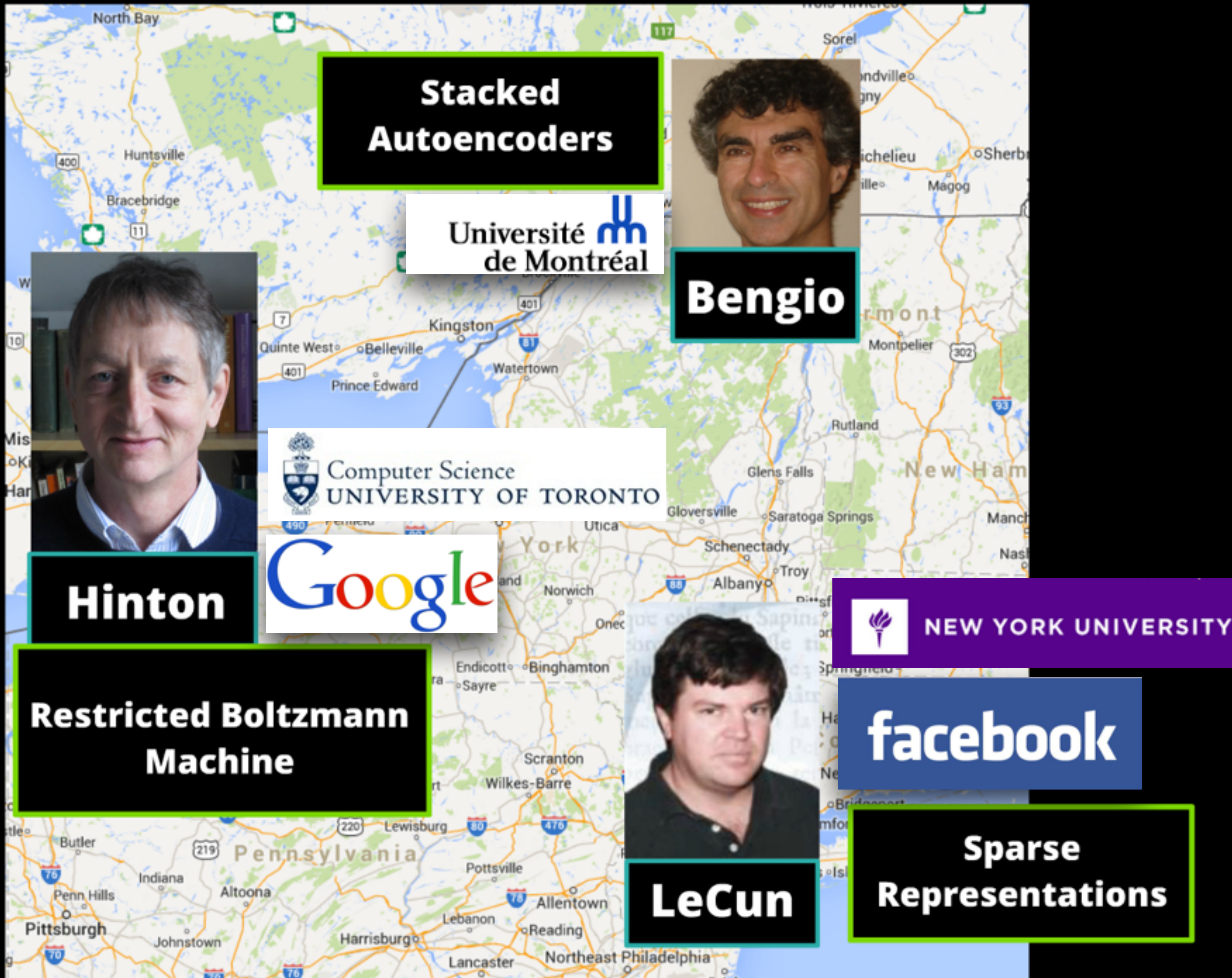
Deep Learning?

- Manually designed features are often over-specified, incomplete and take a long time to design and validate
- **Learned Features** are easy to adapt, fast to learn

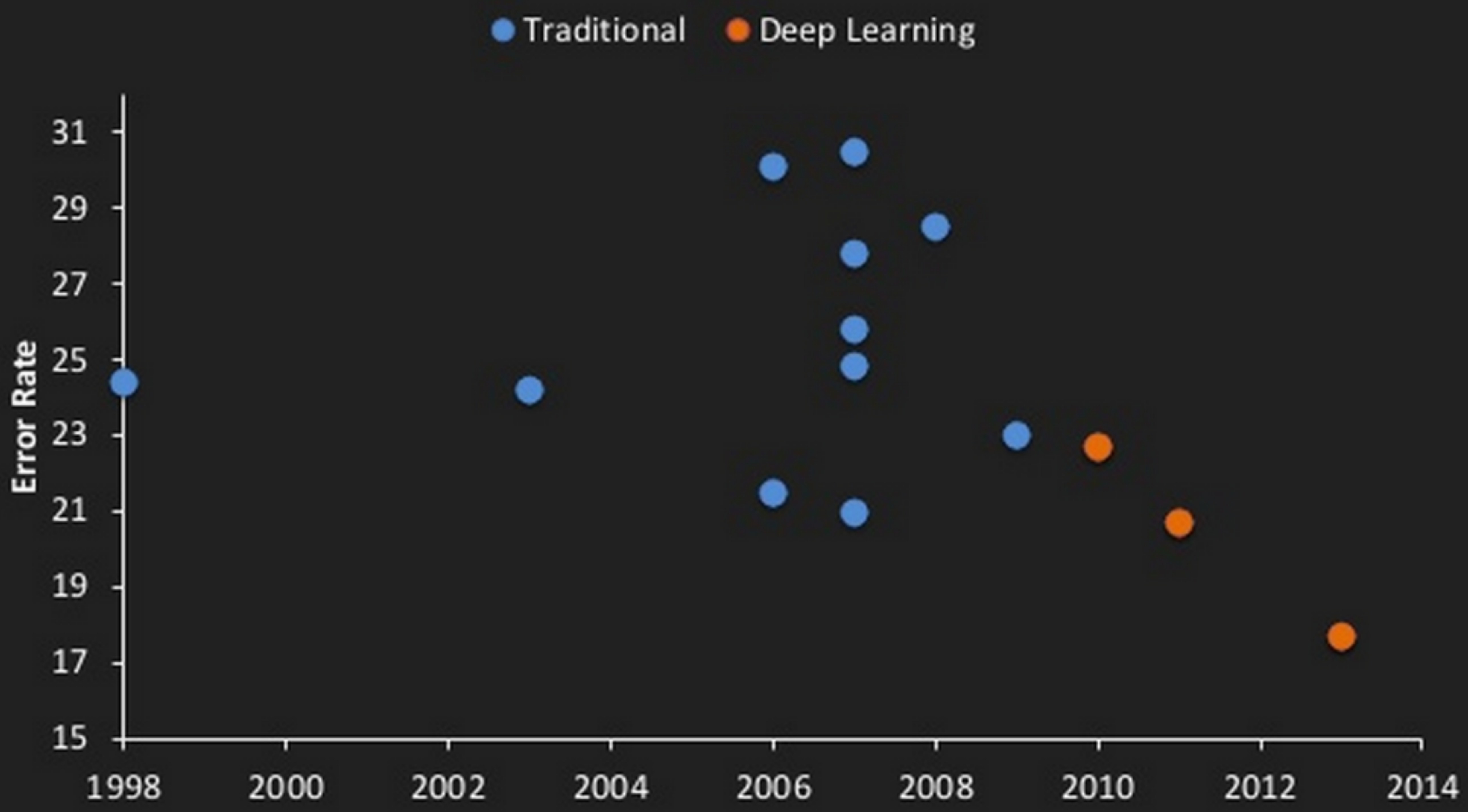
- Deep learning provides a very flexible, (almost?) universal, learnable framework for **representing** world, visual and linguistic information.
- Deep learning can learn **unsupervised** (from raw text/audio/images/whatever content) and **supervised** (with specific labels like positive/negative)

(as summarised by Richard Socher 2014)

2006+ : The Deep Learning Conspirators



Audio Recognition



(chart by Clarifai)

Image Recognition

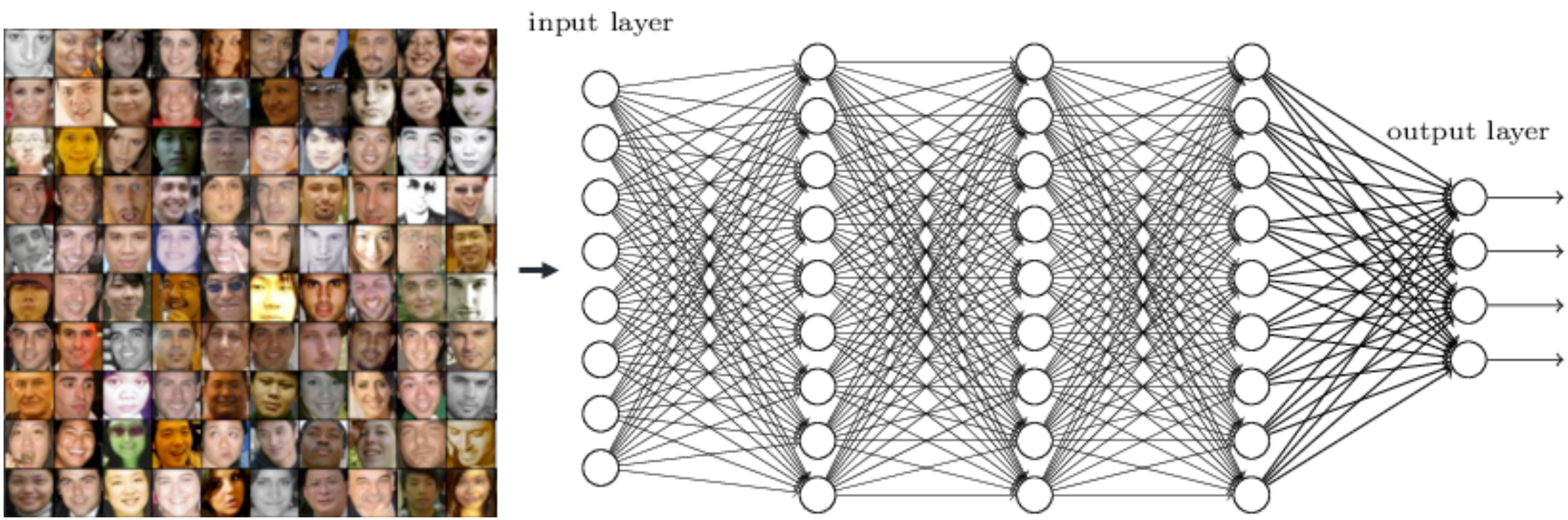
(chart by Clarifai)

Natural Langauge Processing

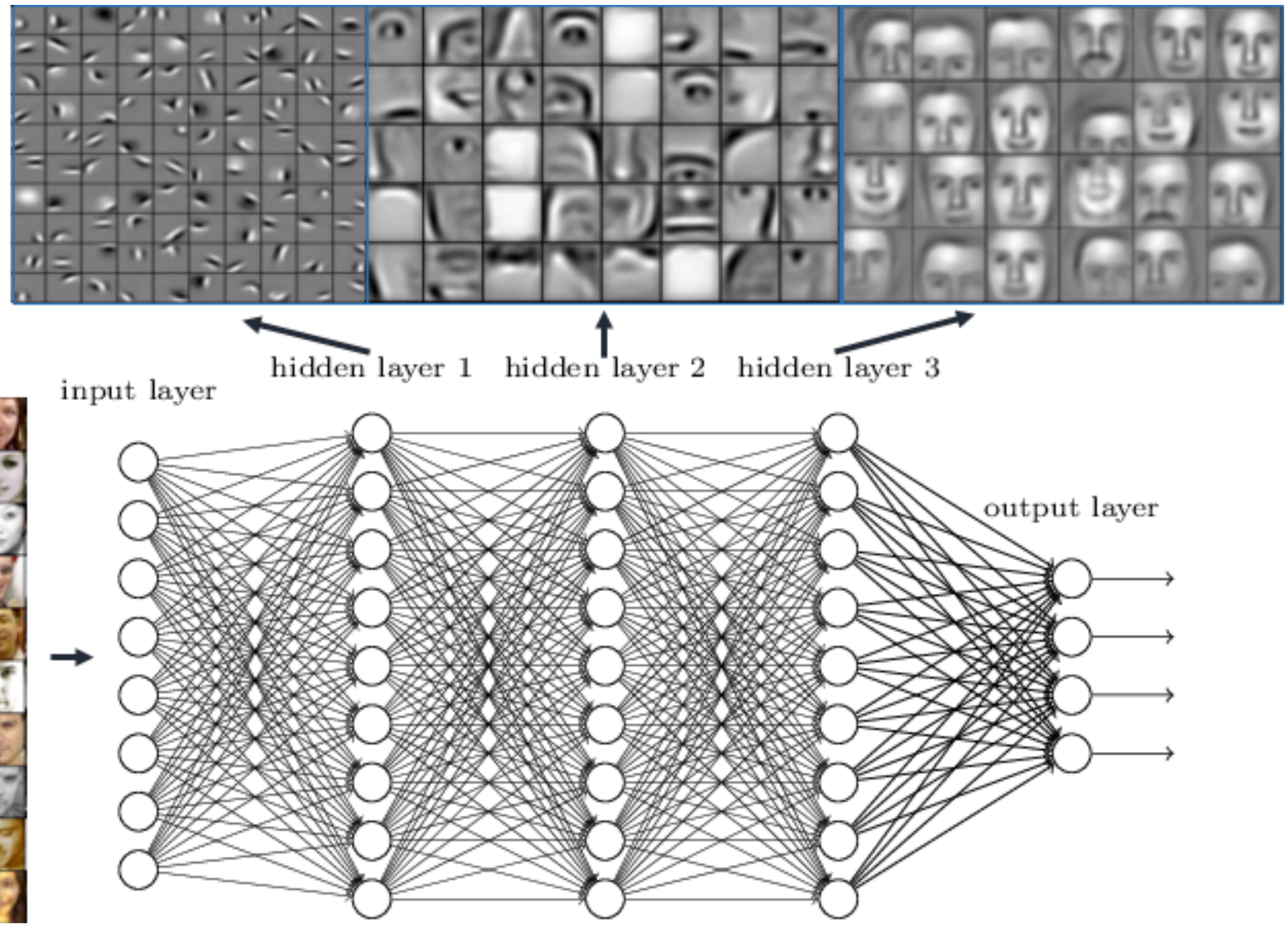
…

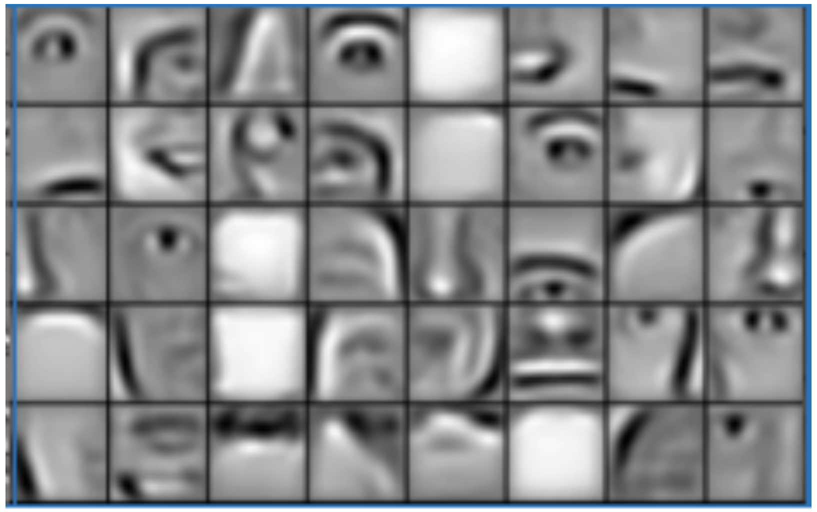
Natural Langauge Processing

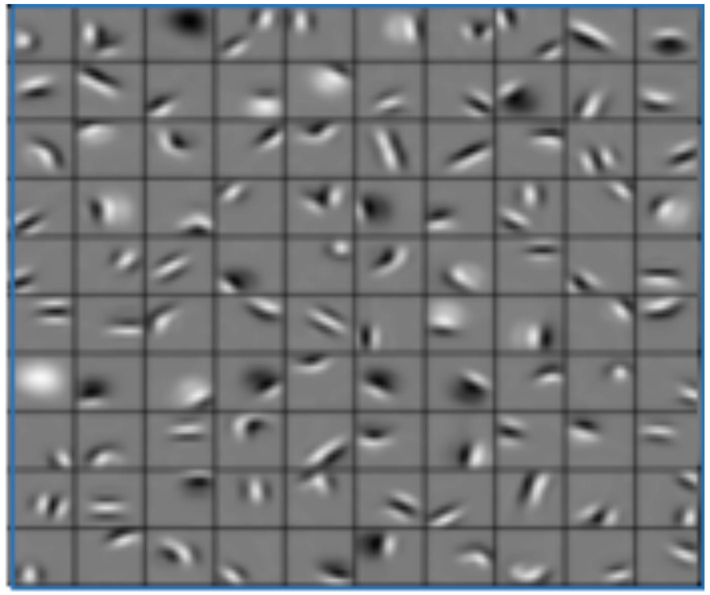
DL? How ?

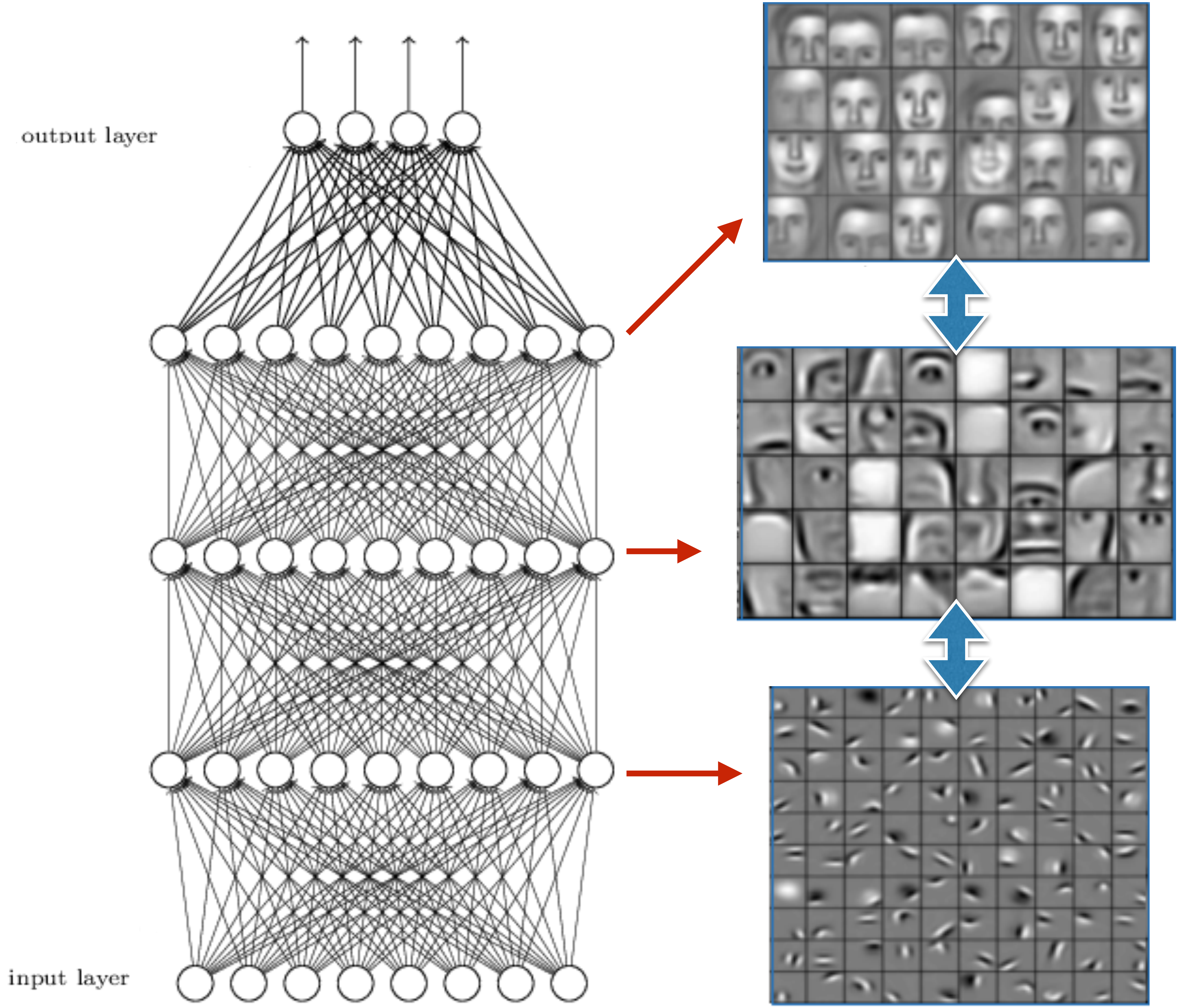

input layer
output layer

Deep neural networks learn hierarchical feature representations

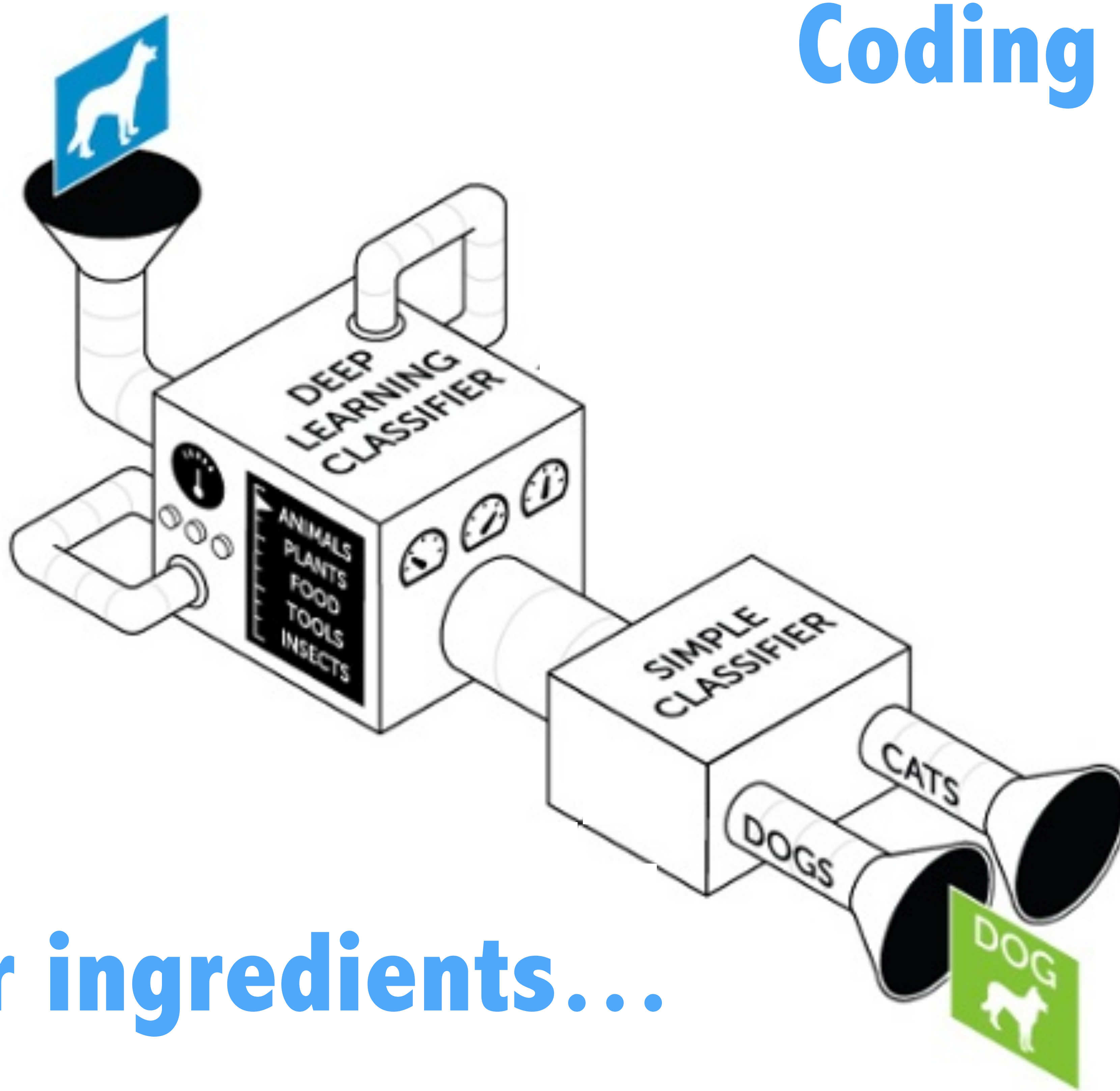







output layer
input layer

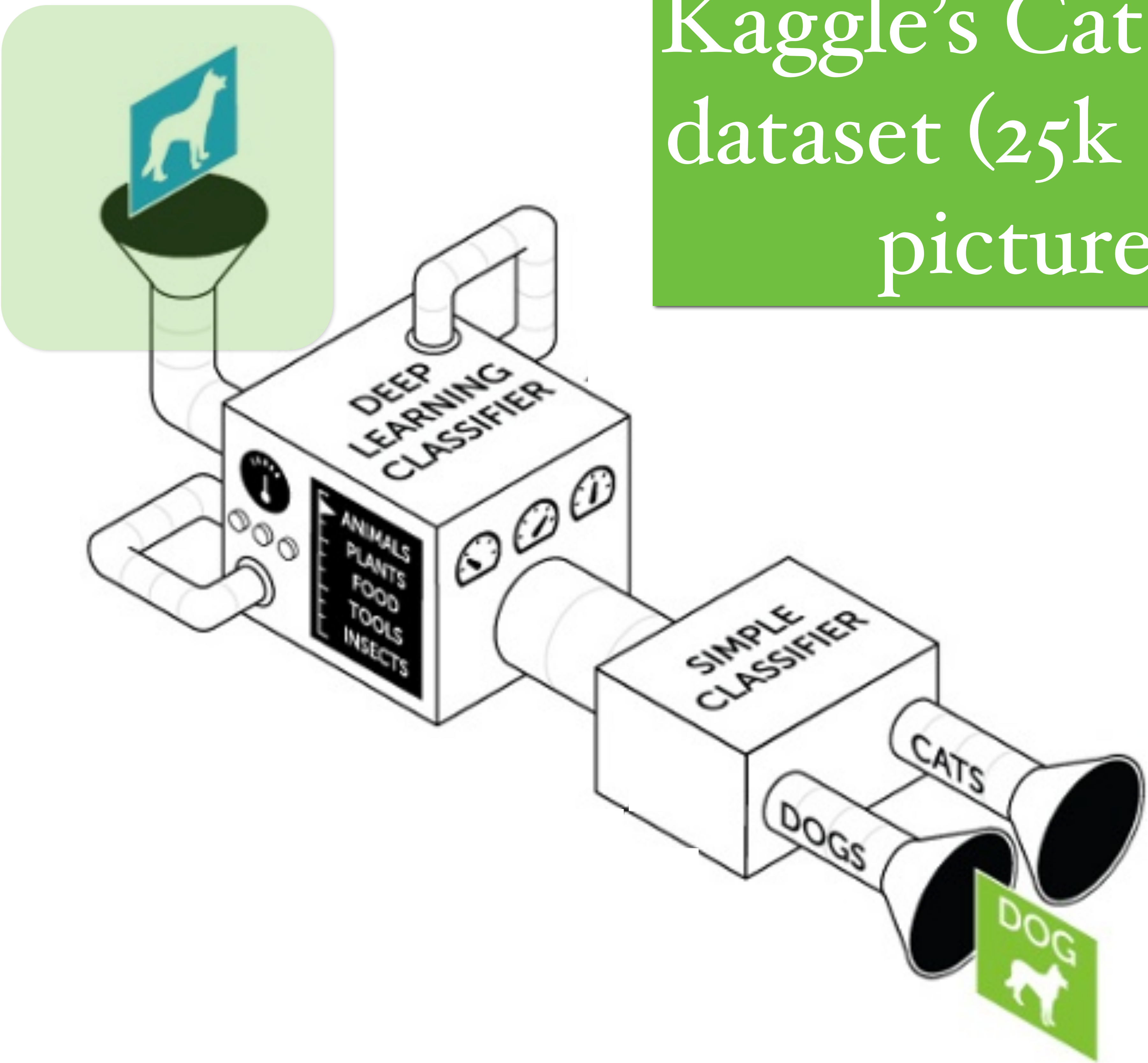
Coding time!



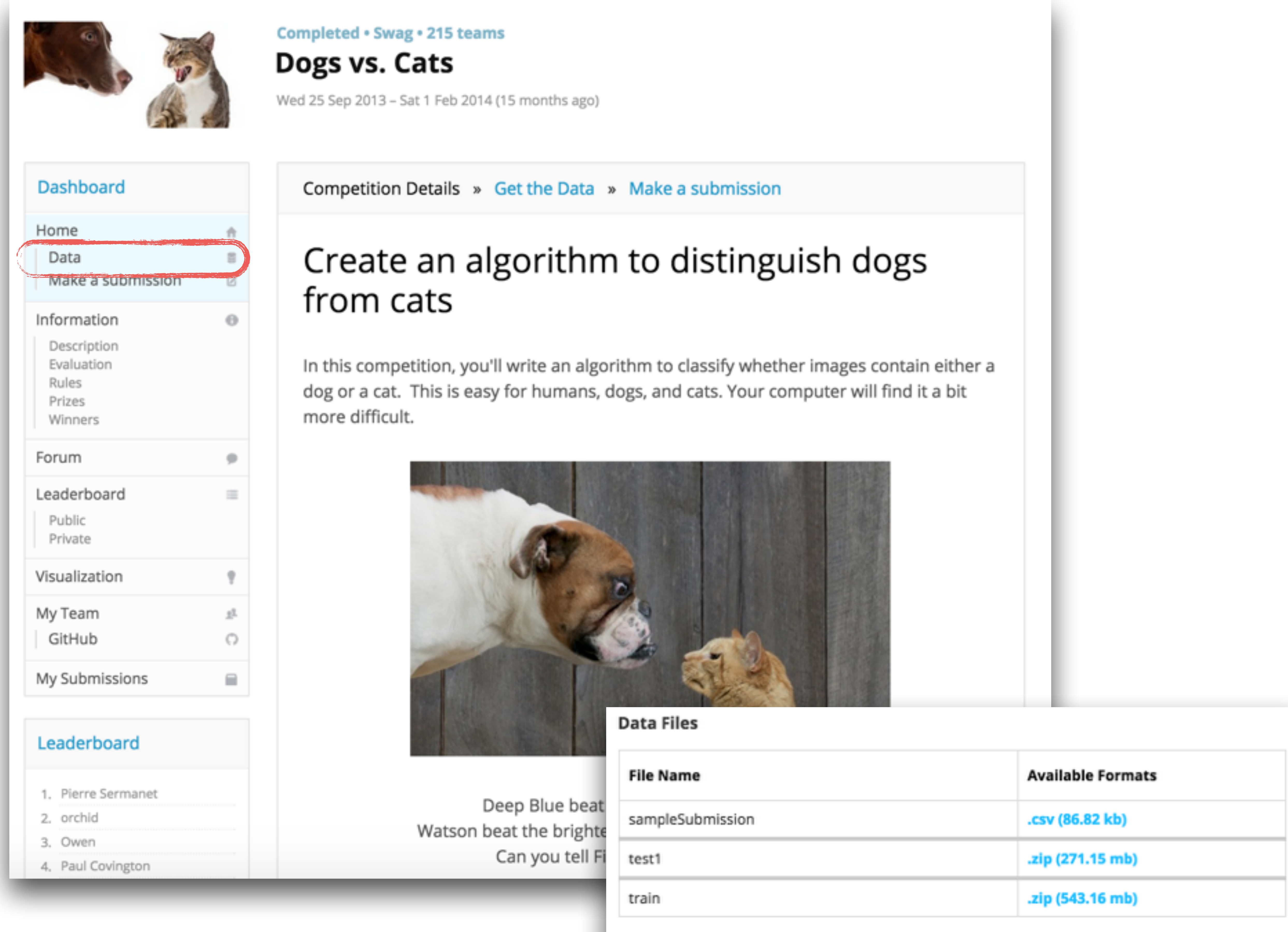
our ingredients…

(picture by Dato)

Kaggle's Cat vs Dog dataset (25k dog/cat pictures)

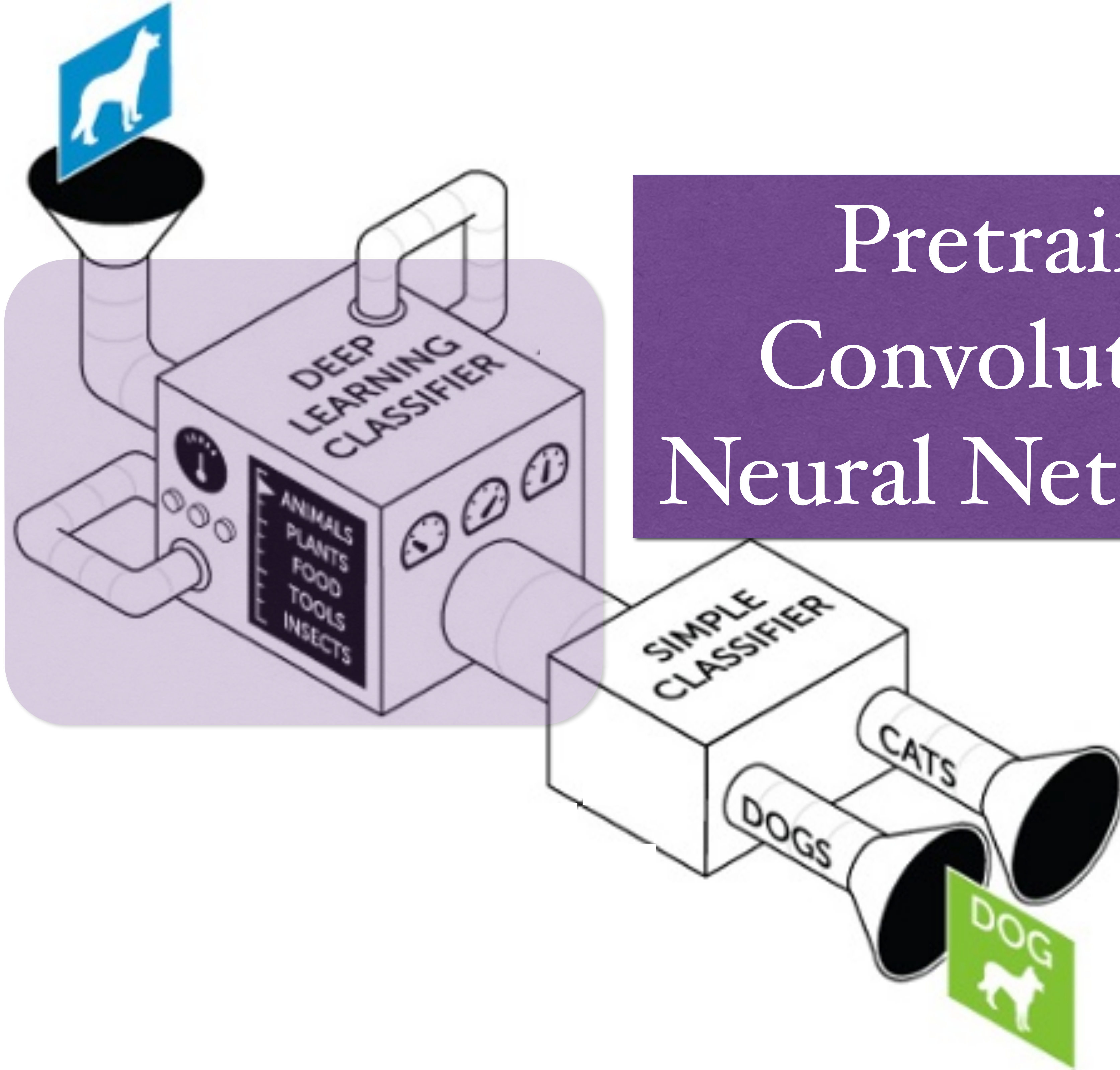


(picture by Dato)

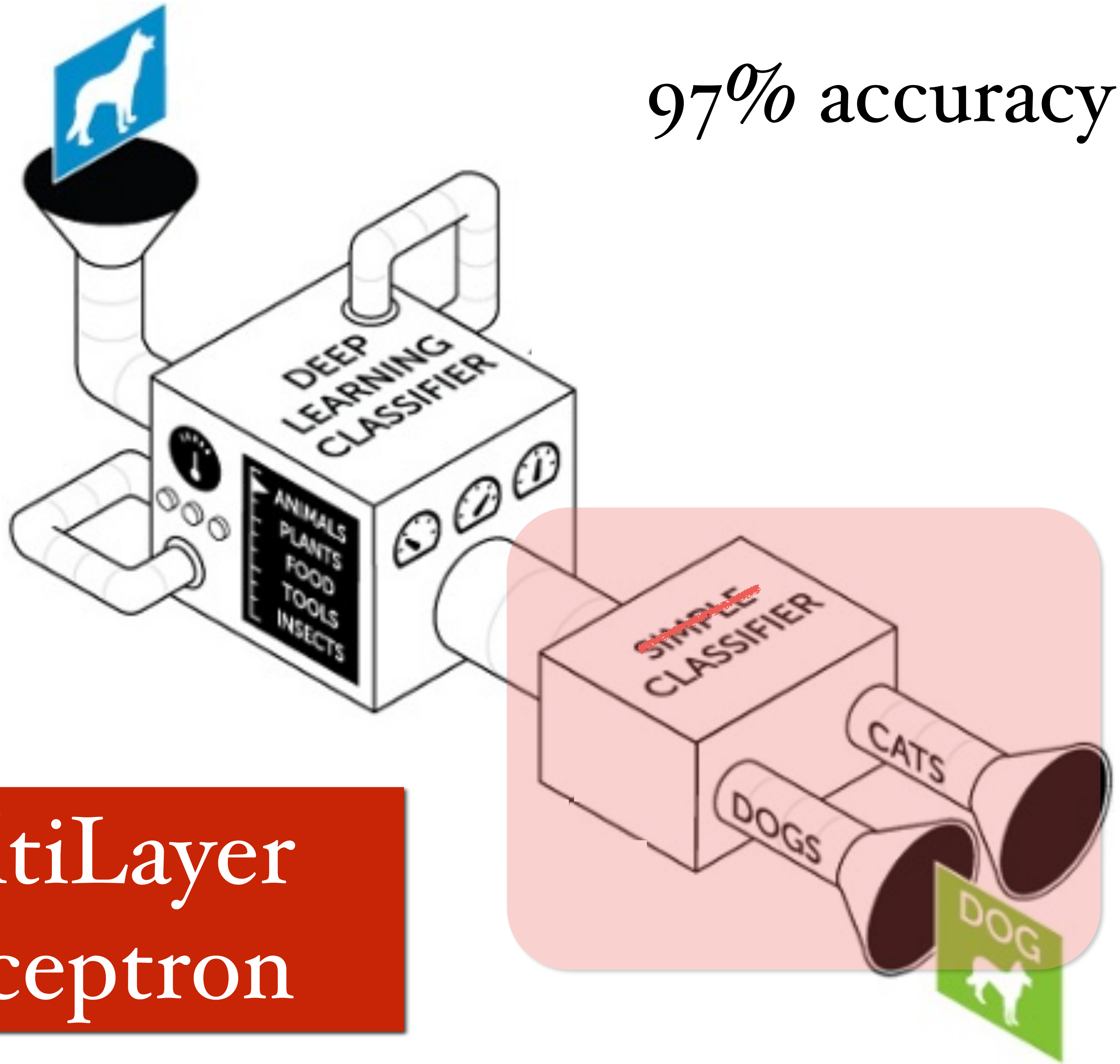


https://www.kaggle.com/c/dogs-vs-cats/data

Pretrained Convolutional Neural Net (CNN)



97% accuracy in < 1h

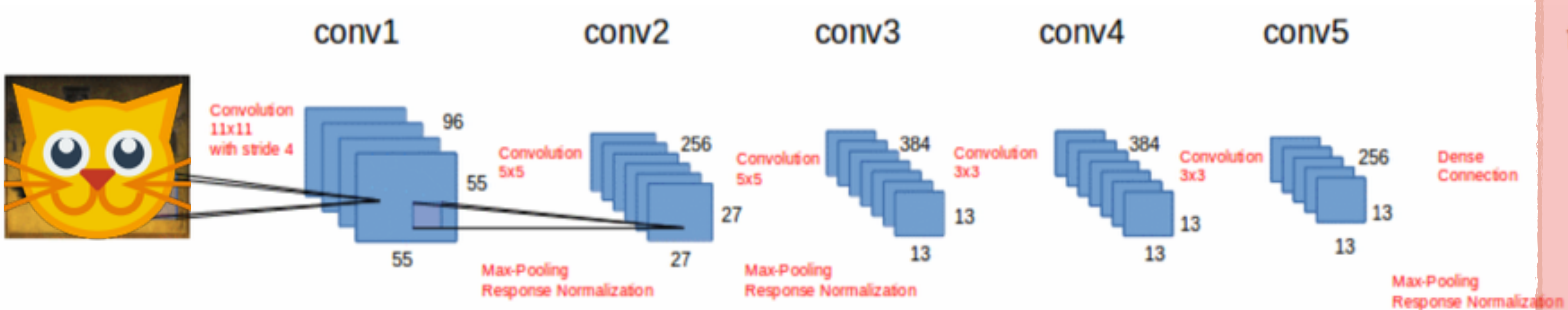


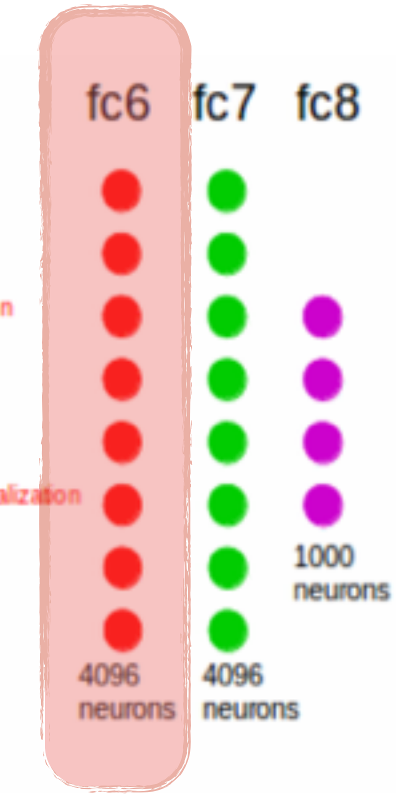
MultiLayer Perceptron

(picture by Dato)

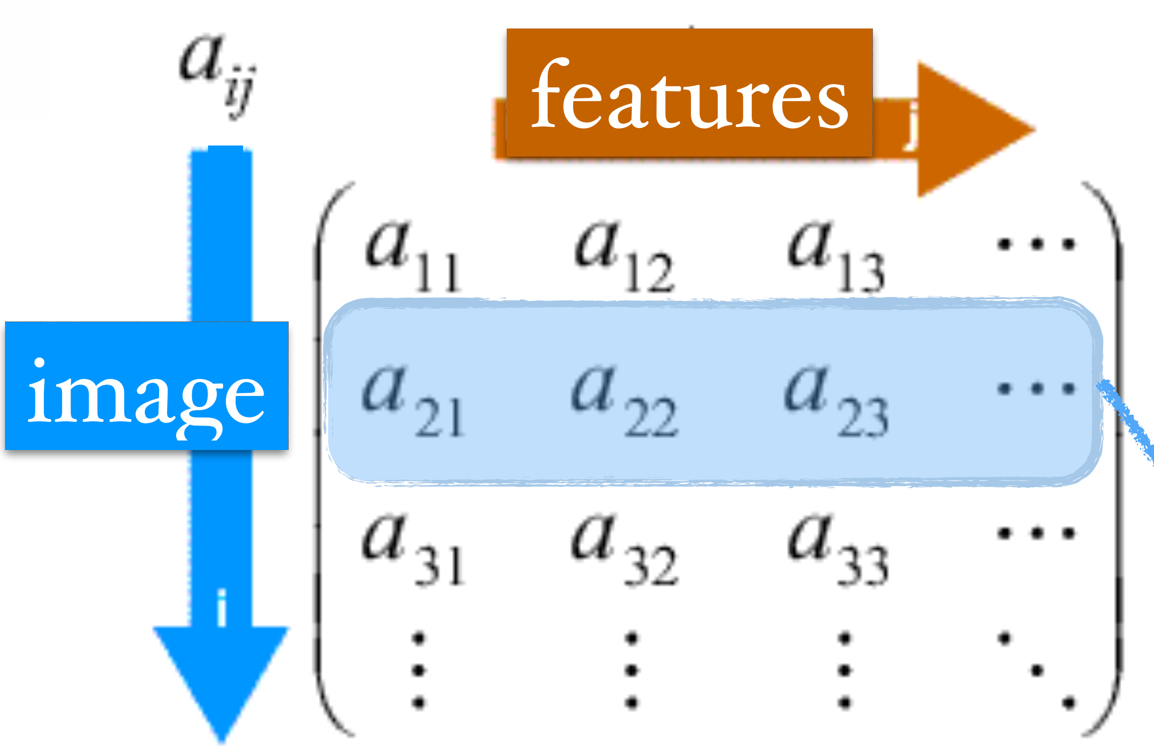
Cooking Instructions

1 Load Pretrained Net

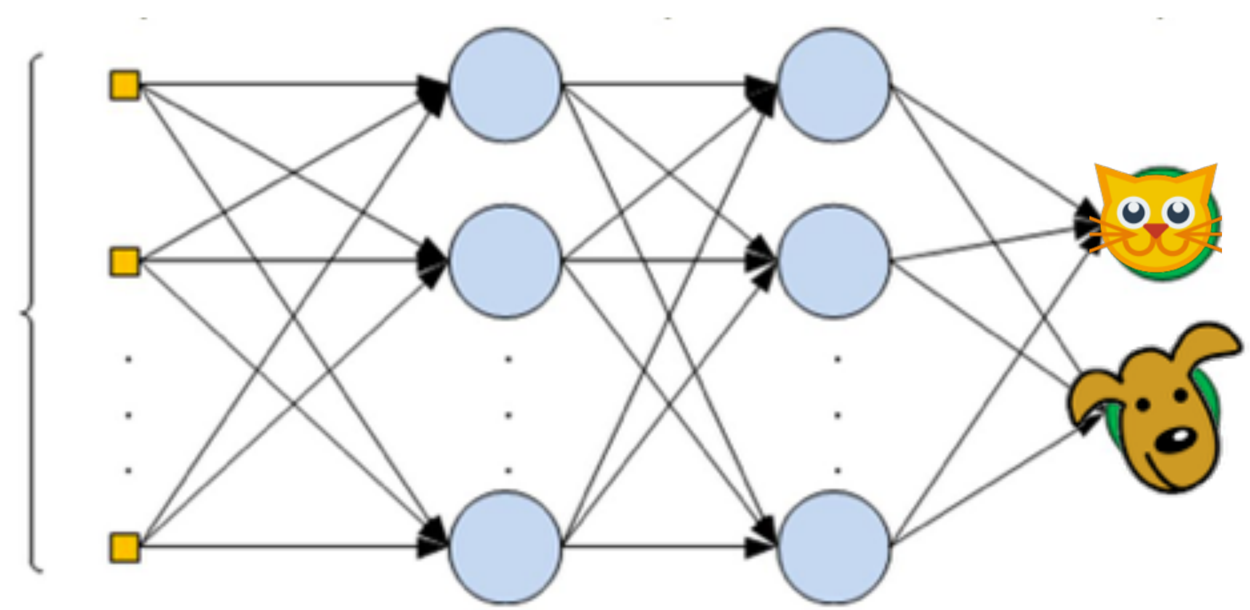




2 Extract features for all training images



3. train MLP on those features



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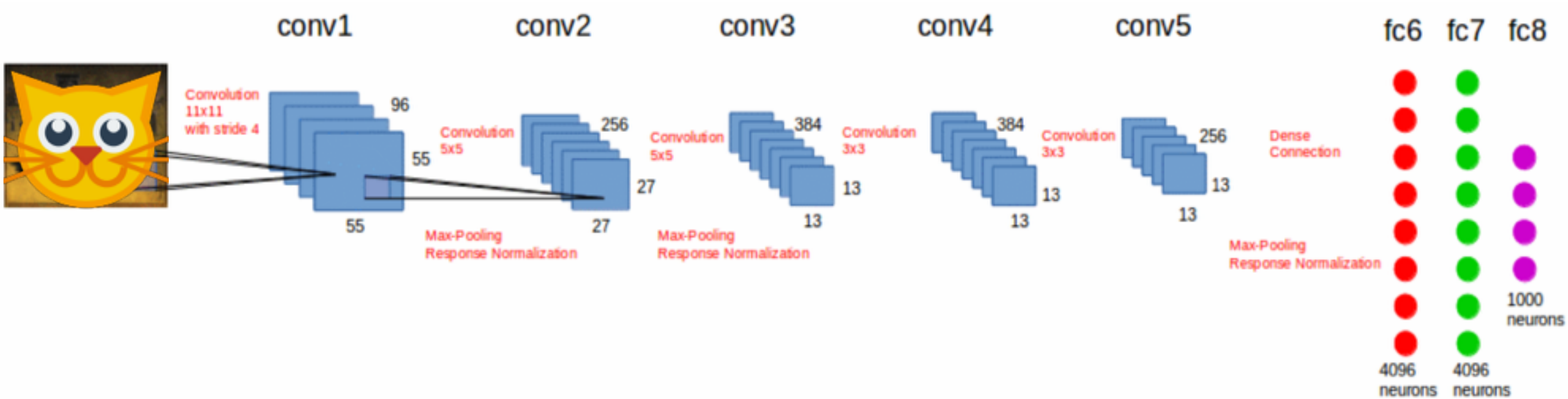
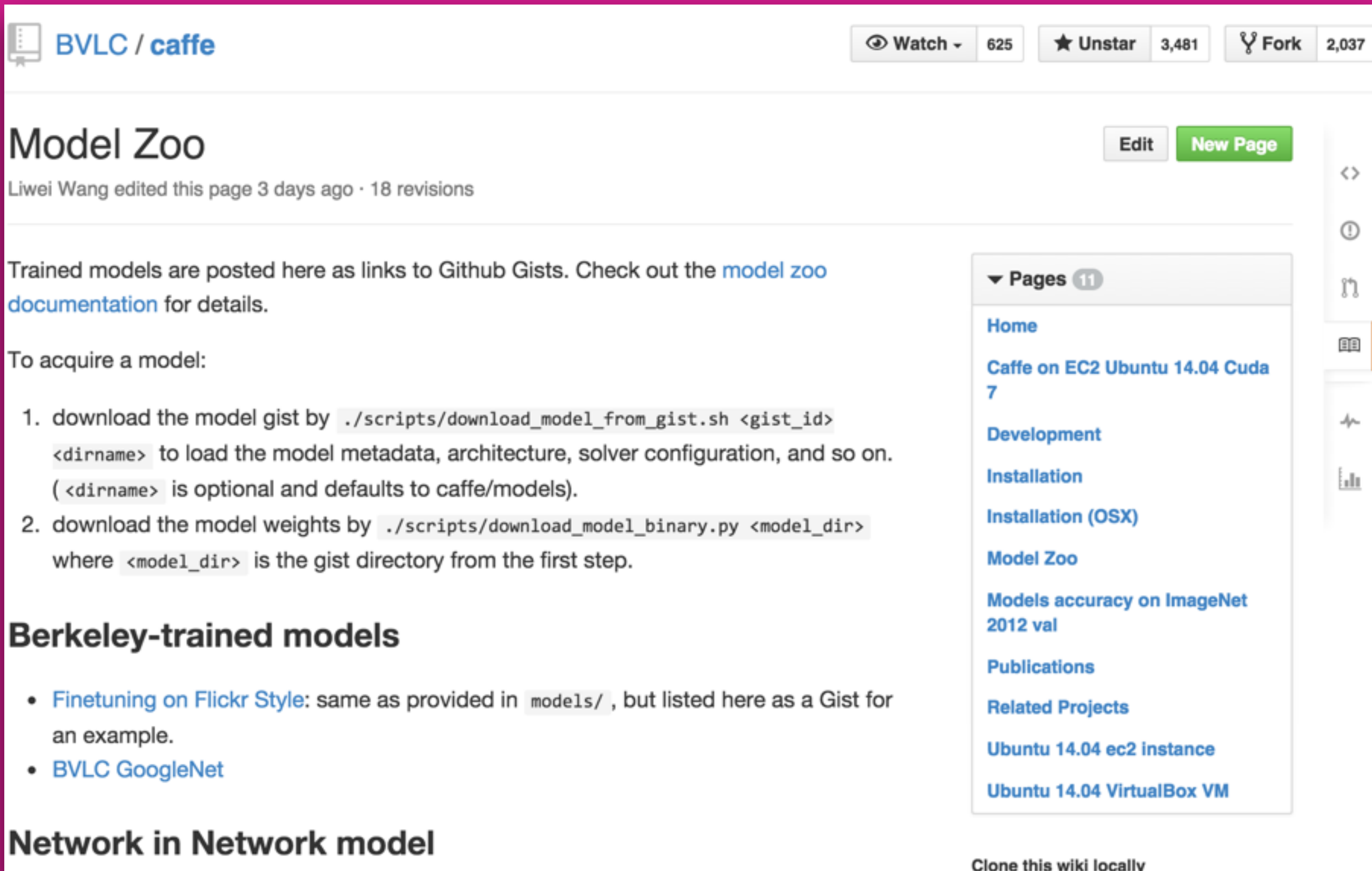


No Free Lunch... But Free Models!



BVLC / caffe

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Model Zoo

Edit | New Page

Liwei Wang edited this page 3 days ago · 18 revisions

Trained models are posted here as links to Github Gists. Check out the model zoo documentation for details.

To acquire a model:

1. download the model gist by `./scripts/download_model_from_gist.sh <gist_id> <dirname>` to load the model metadata, architecture, solver configuration, and so on. (`<dirname>` is optional and defaults to caffe/models).
2. download the model weights by `./scripts/download_model_binary.py <model_dir>` where `<model_dir>` is the gist directory from the first step.

Berkeley-trained models

- Finetuning on Flickr Style: same as provided in `models/`, but listed here as a Gist for an example.
- BVLC GoogleNet

Network in Network model

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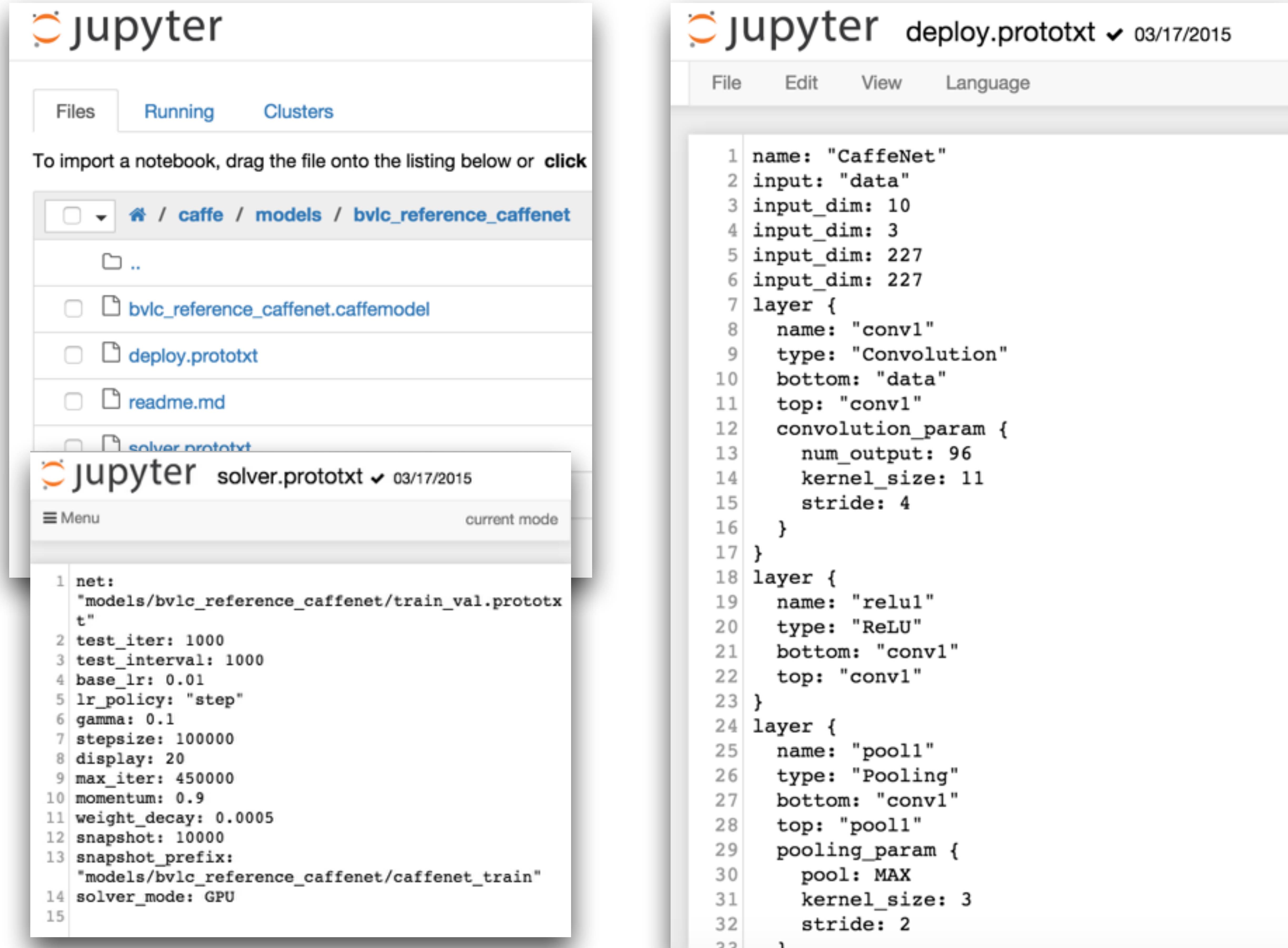
- Publications
- Related Projects
- Ubuntu 14.04 ec2 instance
- Ubuntu 14.04 VirtualBox VM

Clone this wiki locally

https://github.com/BVLC/caffe/wiki/Model-Zoo

```
/scripts/download_model_binary.py ../models/bvlc_reference_caffenet
```



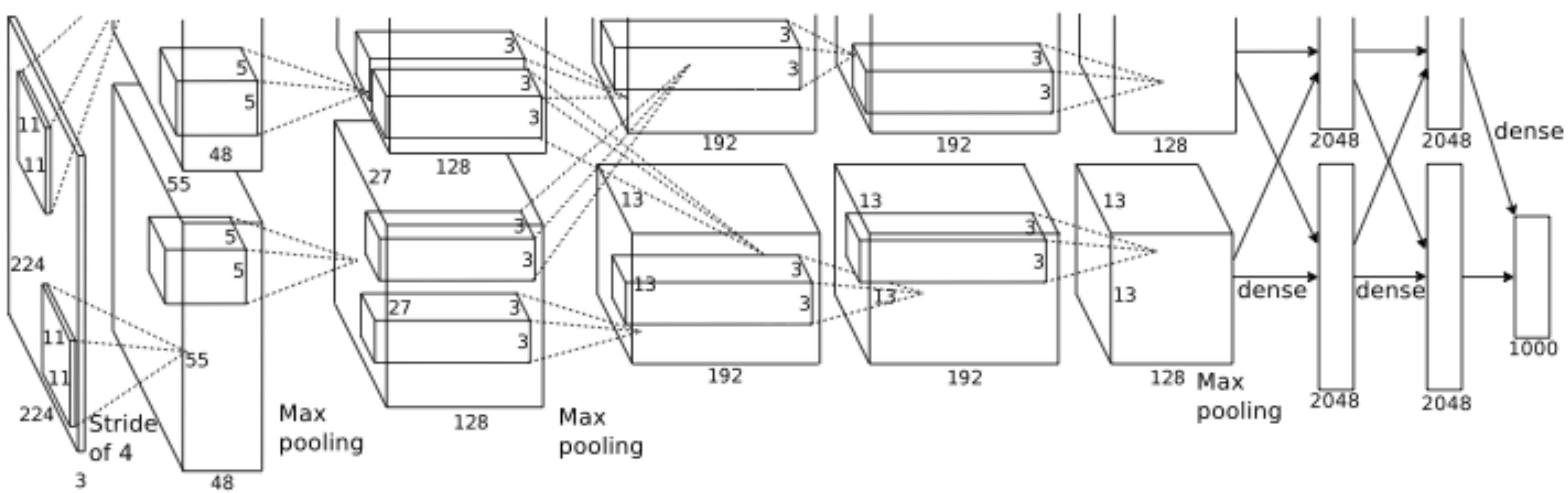
imports

demo

```python
%matplotlib inline
import logging
from glob import glob
from random import shuffle
import pickle

# Make sure that caffe is on the python path:
caffe_root = '../'
import sys
sys.path.insert(0, caffe_root + 'python')
import caffe

import numpy as np
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
```

 # load pretrained deep neural net demo

```python
MODEL_FILE = '../models/bvlc_reference_caffenet/deploy.prototxt'
PRETRAINED = '../models/bvlc_reference_caffenet/bvlc_reference_caffenet.caffemodel'

def png_to_np(basedir, fetch_target=False):
    logging.getLogger().setLevel(logging.INFO)
    caffe.set_mode_gpu()
    net = caffe.Classifier(MODEL_FILE, PRETRAINED,
                           mean=np.load(caffe_root + 'python/caffe/imagenet/ilsvrc_2012_mean.npy').mean(1).mean(1),
                           channel_swap=(2,1,0),
                           raw_scale=255,
                           image_dims=(256, 256))
```

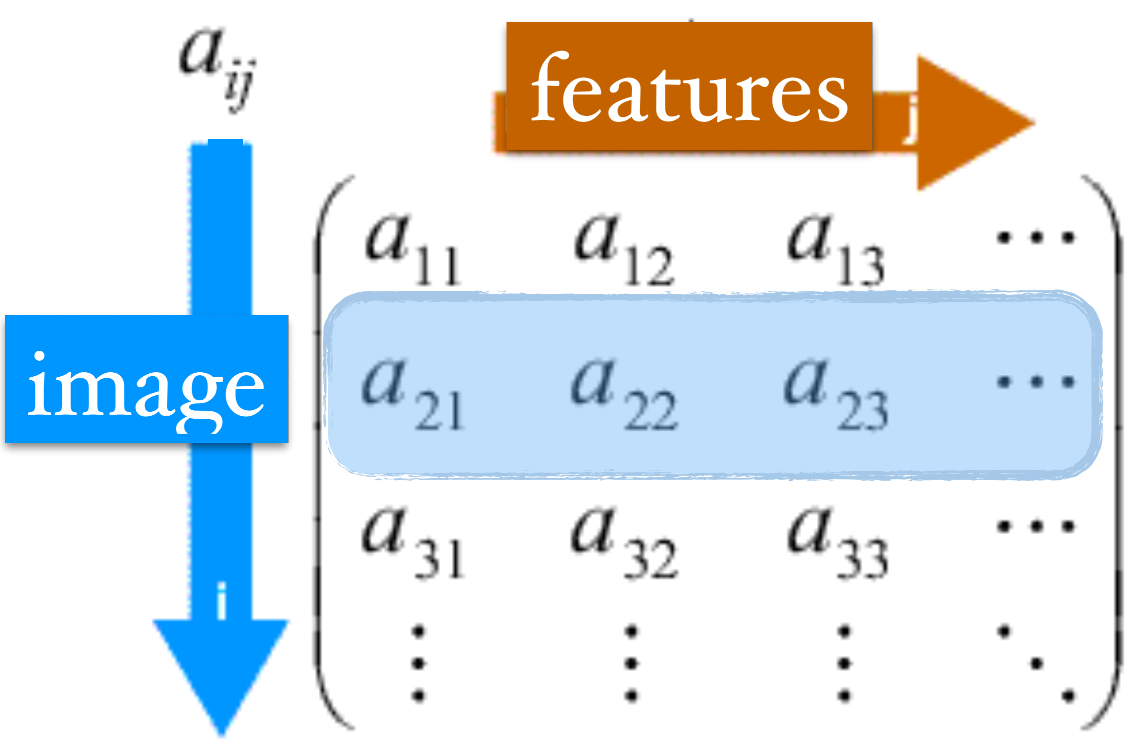


(convnet from Krizhevsky et al.'s NIPS 2012 ImageNet classification paper)

Cooking Instructions

1 Load Pretrained Net

2 Extract features for all training images



 # feed image into the network and return internal feature representation of layer fc6

demo

```python
def activate(net, im):
    input_image = caffe.io.load_image(im)
    # Resize the image to the standard (256, 256) and oversample net input sized crops.
    input_oversampled = caffe.io.oversample([caffe.io.resize_image(input_image, net.image_dims)], net.crop_dims)
    # 'data' is the input blob name in the model definition, so we preprocess for that input.
    caffe_input = np.asarray([net.transformer.preprocess('data', in_) for in_ in input_oversampled])
    # forward() takes keyword args for the input blobs with preprocessed input arrays.
    predicted = net.forward(data=caffe_input)
    # Activation of all convolutional layers and first fully connected
    feat = net.blobs['fc6'].data[0]
    return feat
```

#extract features from images

demo

```python
    feature_info = activate(net, files[0])
    feature_count = feature_info.shape[0]
    feature_dtype = feature_info.dtype
    data = np.zeros((len(files), feature_count), dtype=feature_dtype)
    for n, im in enumerate(files):
        data[n, :] = activate(net, im)
        if n % 1000 == 0:
            print 'Reading in image', n

    return data, target, files
```

#dump features as pickle file

demo

In [*]:

```
x, y, filenames = png_to_np(
    '/mnt/pet/train/', fetch_target=True)
pickle.dump(x, open('saved_x_v2.pkl', 'wb'))
pickle.dump(y, open('saved_y_v2.pkl', 'wb'))
pickle.dump(filenames, open('saved_filenames_v2.pkl', 'wb'))
```

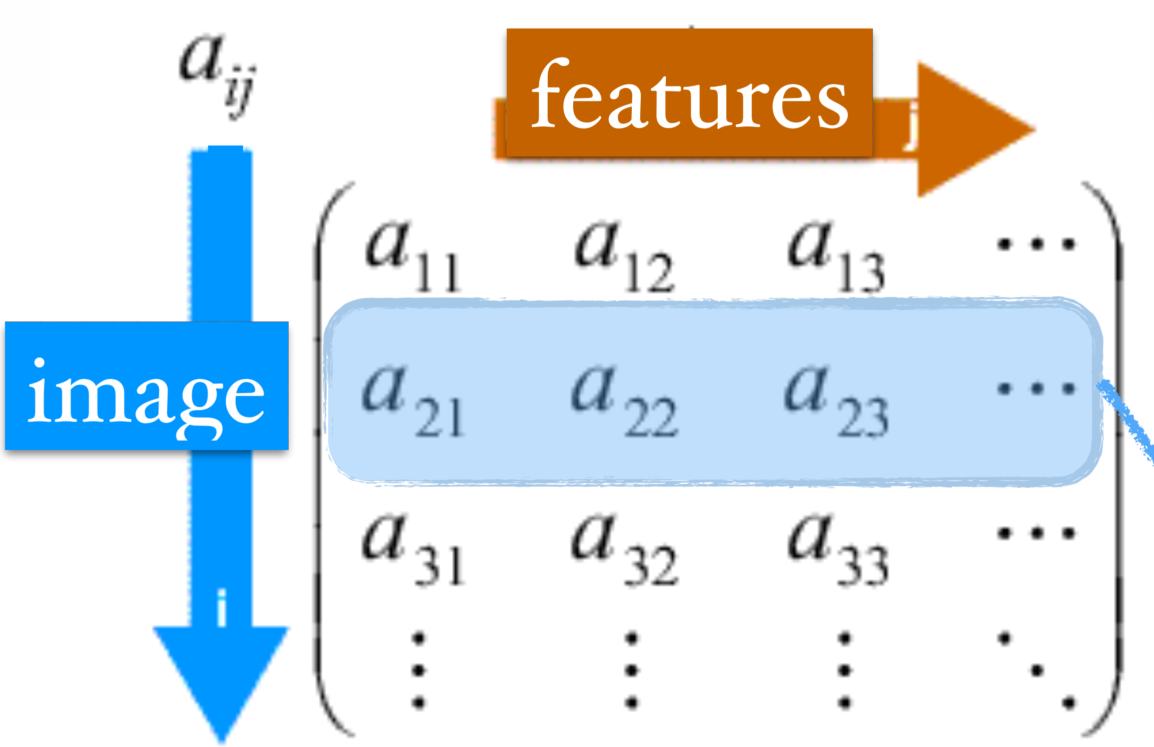
```
Reading in image 0
Reading in image 1000
Reading in image 2000
Reading in image 3000
Reading in image 4000
Reading in image 5000
Reading in image 6000
Reading in image 7000
Reading in image 8000
```

(...)

Cooking Instructions

1 Load Pretrained Net

2 Extract features for all training images



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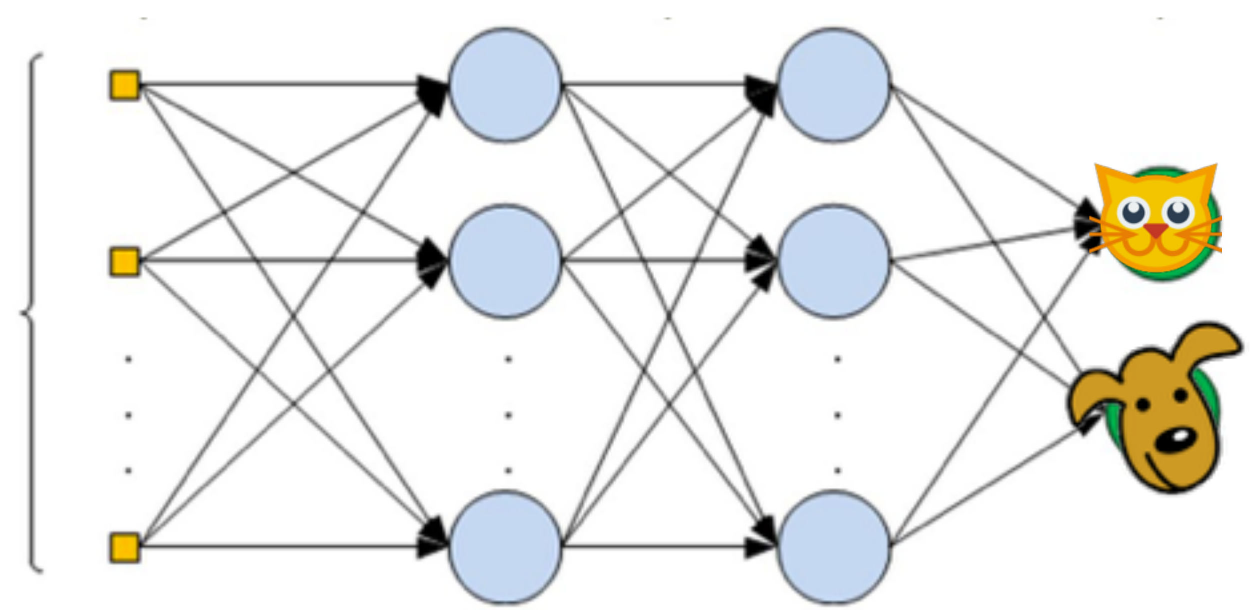


Pylearn2:
Multilayer Perceptron (MLP) on top of extracted features

#imports demo

```
from pylearn2.models import mlp
from pylearn2.costs.mlp.dropout import Dropout
from pylearn2.training_algorithms import sgd, learning_rule
from pylearn2.termination_criteria import EpochCounter
from pylearn2.datasets import DenseDesignMatrix
from pylearn2.train import Train
from pylearn2.train_extensions import best_params
from pylearn2.space import VectorSpace

import pickle
import numpy as np
```

#load earlier extracted features and labels
#convert to input that pylearn understands

demo

```
x = pickle.load(open('saved_x_v2.pkl', 'rb'))
y = pickle.load(open('saved_y_v2.pkl', 'rb'))
filenames = pickle.load(open('saved_filenames_v2.pkl', 'rb'))
y = to_one_hot(y)
in_space = VectorSpace(dim=x.shape[1])
full = DenseDesignMatrix(X=x, y=y)
```

demo

 # create layers of MLP

 # with softmax as final layer

```
l1 = mlp.RectifiedLinear(layer_name='l1',
                         sparse_init=12,
                         dim=5000,
                         max_col_norm=1.)

l2 = mlp.RectifiedLinear(layer_name='l2',
                         sparse_init=12,
                         dim=5000,
                         max_col_norm=1.)

l3 = mlp.RectifiedLinear(layer_name='l3',
                         sparse_init=12,
                         dim=5000,
                         max_col_norm=1.)

output = mlp.Softmax(layer_name='y',
                     n_classes=2,
                     irange=.005)

layers = [l1, l2, l3, output]

mdl = mlp.MLP(layers,
              input_space=in_space)
```

 # trainer initialized with SGD, momentum, dropout

```
lr = .0001
epochs = 100
trainer = sgd.SGD(learning_rate=lr,
                  batch_size=128,
                  learning_rule=learning_rule.Momentum(.5),
                  # Remember, default dropout is .5
                  cost=Dropout(input_include_probs={'l1': .8},
                               input_scales={'l1': 1.}),
                  termination_criterion=EpochCounter(epochs),
                  monitoring_dataset={'train': full})
```

train/test splits

demo

```
# no sklearn.cross_validation > train_test_split
# own test/train split so we can also link filenames
splitter = round(len(x)*0.8)
X_train, X_test = x[:splitter],x[splitter:]
y_train, y_test = y[:splitter],y[splitter:]
filenames_train, filenames_test = filenames[:splitter],filenames[splitter:]

pickle.dump(X_train, open('saved_feat_x_train_v2.pkl', 'wb'))
pickle.dump(X_test, open('saved_feat_x_test_v2.pkl', 'wb'))
pickle.dump(y_train, open('saved_feat_y_train_v2.pkl', 'wb'))
pickle.dump(y_test, open('saved_feat_y_test_v2.pkl', 'wb'))
pickle.dump(filenames_train, open('saved_feat_filenames_train_v2.pkl', 'wb'))
pickle.dump(filenames_test, open('saved_feat_filenames_test_v2.pkl', 'wb'))
```

#start our MLP (pylearn experiment method)

demo

```
#liftoff!
trn = DenseDesignMatrix(X=X_train, y=y_train)
tst = DenseDesignMatrix(X=X_test, y=y_test)
trainer.monitoring_dataset={'valid': tst,
                            'train': trn}
experiment.main_loop()
```

```
In [*]: trn = DenseDesignMatrix(X=X_train, y=y_train)
        tst = DenseDesignMatrix(X=X_test, y=y_test)
        trainer.monitoring_dataset={'valid': tst,
                                    'train': trn}
        experiment.main_loop()

        Parameter and initial learning rate summary:
                l1_W: 9.99999974738e-05
                l1_b: 9.99999974738e-05
                l2_W: 9.99999974738e-05
                l2_b: 9.99999974738e-05
                l3_W: 9.99999974738e-05
                l3_b: 9.99999974738e-05
                softmax_b: 9.99999974738e-05
                softmax_W: 9.99999974738e-05
        Compiling sgd_update...
        Compiling sgd_update done. Time elapsed: 1.686666 seconds
        compiling begin_record_entry...
        compiling begin_record_entry done. Time elapsed: 0.548132 seconds
        Monitored channels:
                learning_rate
                momentum
                total_seconds_last_epoch
```

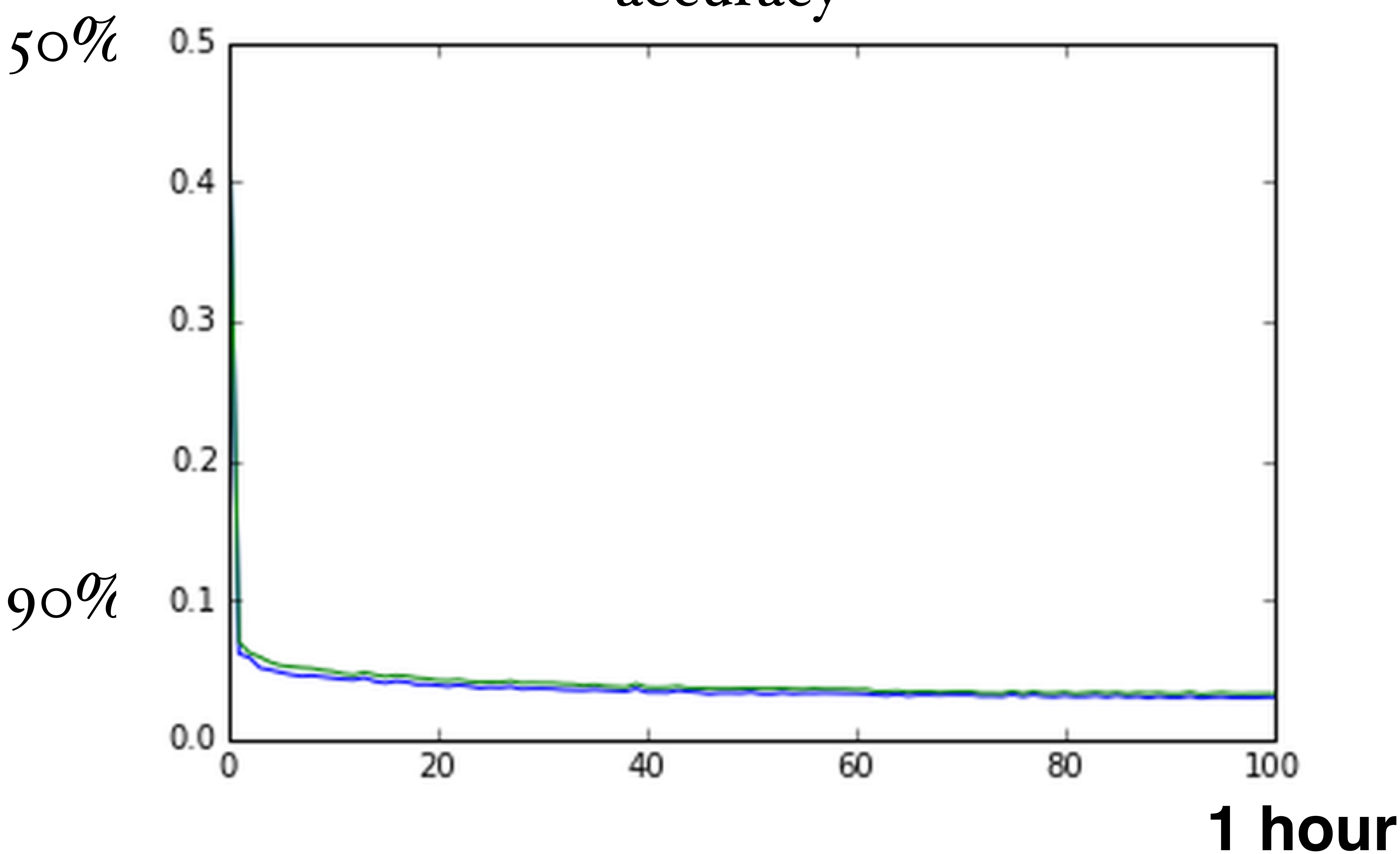
(...)

already after 5 min: `valid_y_misclass: 0.0619999989867`

```
In [319]: plt.plot(score_train[2:])
          plt.plot(score_test[2:])

Out[319]: [<matplotlib.lines.Line2D at 0x7f517c694450>]
```

accuracy

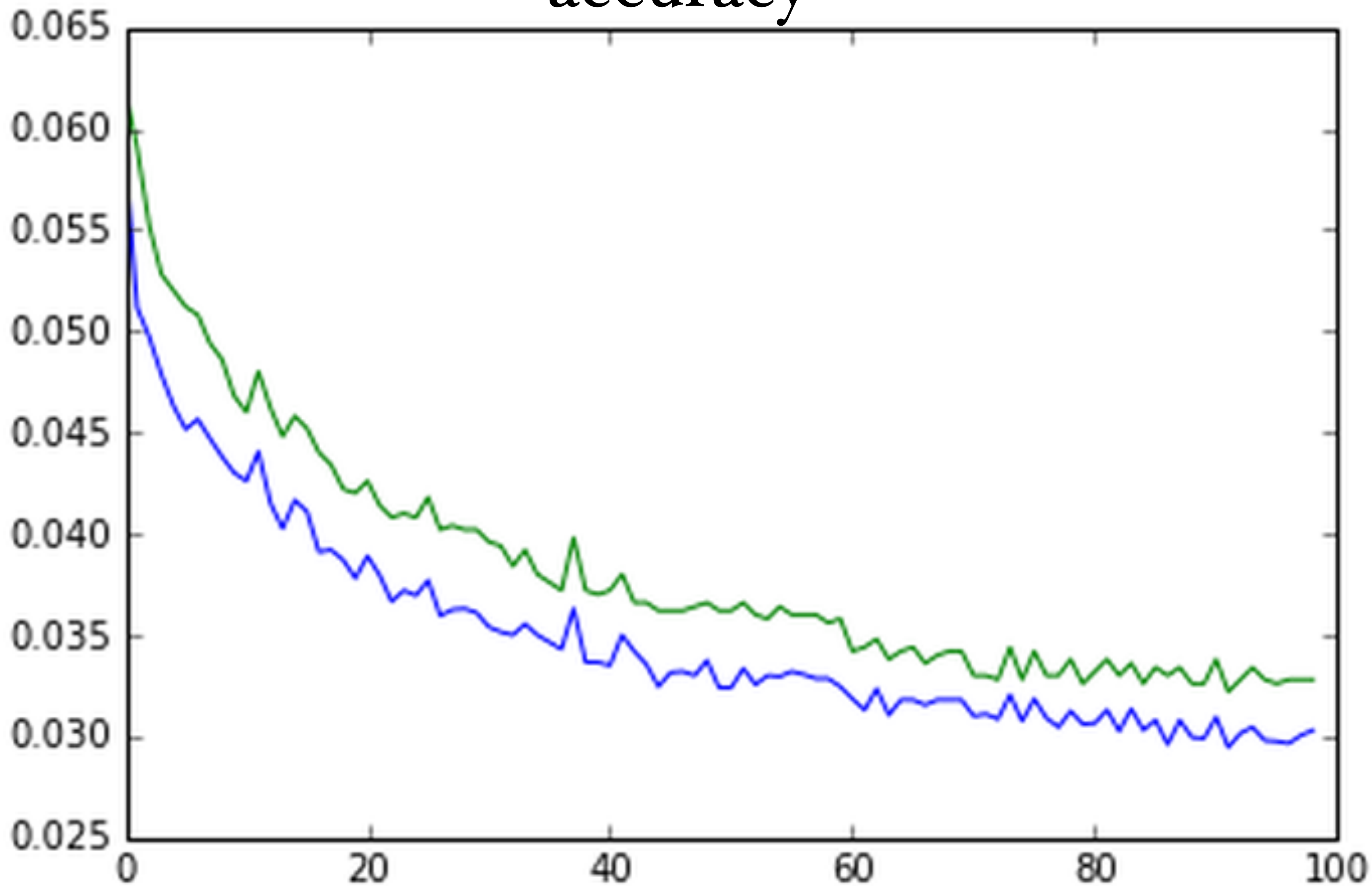


```
In [319]: plt.plot(score_train[2:])
          plt.plot(score_test[2:])

Out[319]: [<matplotlib.lines.Line2D at 0x7f517c694450>]
```

accuracy

94%



97%

(...)

start at iteration #2

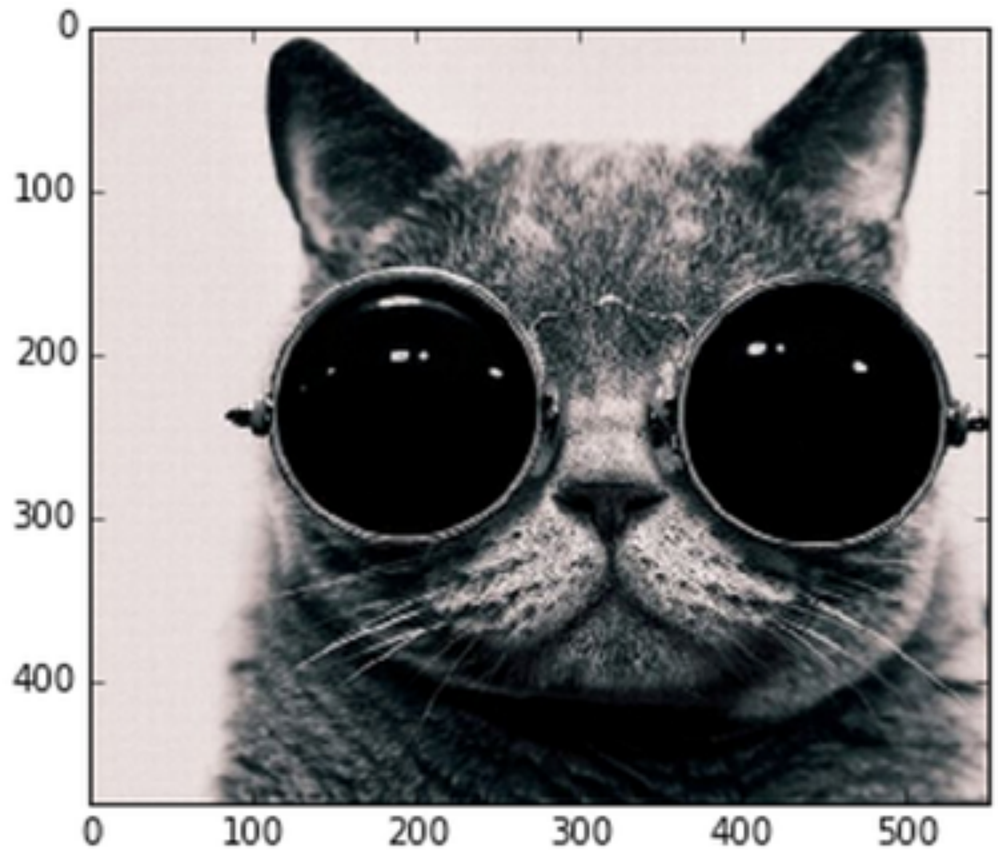
1 hour

In [380]:

```
input_image = caffe.io.load_image('google-glasses-cat-2.jpg')
plt.imshow(input_image)
```

Out[380]:

```
<matplotlib.image.AxesImage at 0x7f51a017d410>
```

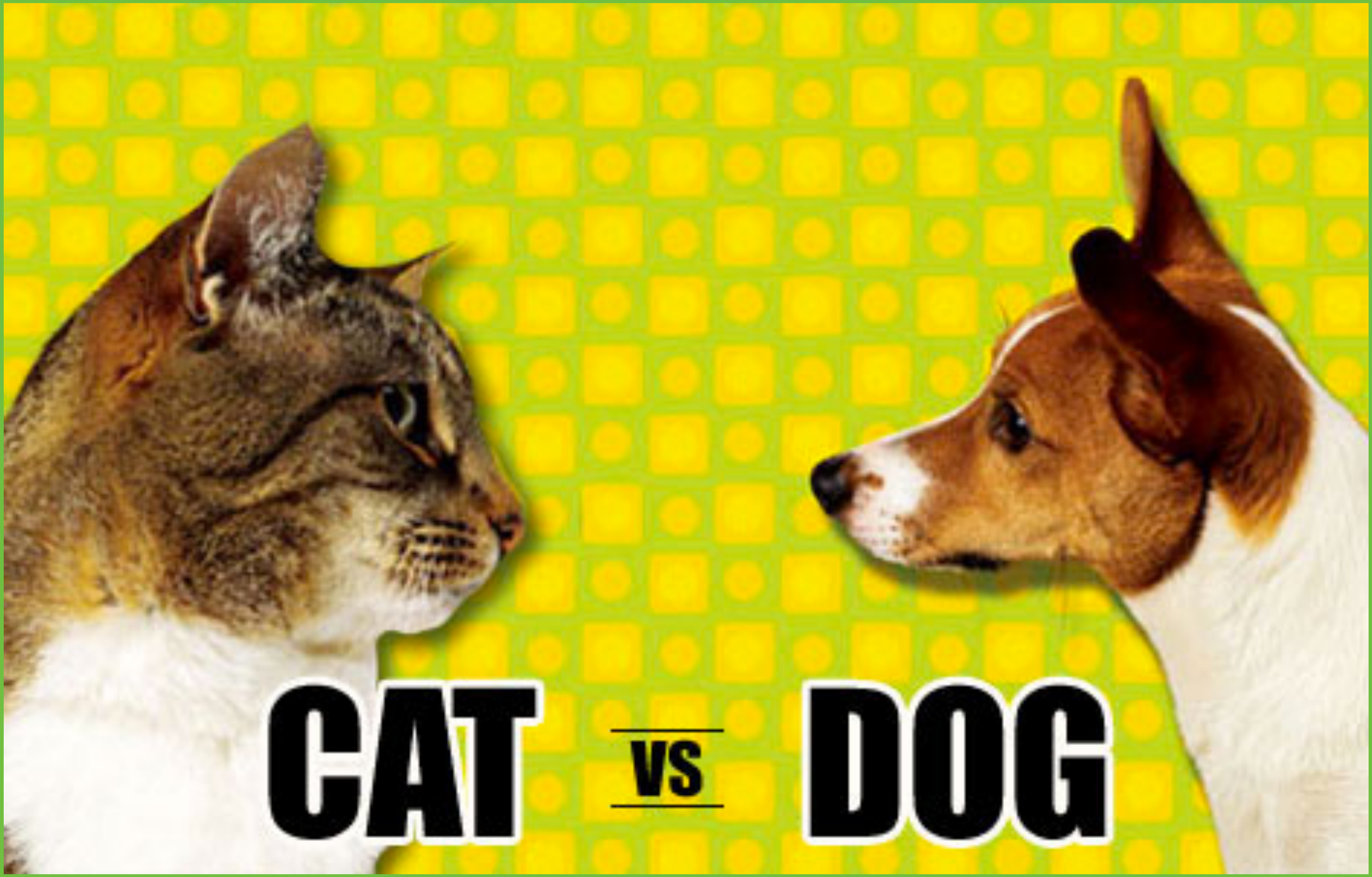


In [381]:

```
feat = getfeat_single_image('google-glasses-cat-2.jpg')  #run image through cnn
x = feat
y = f([x]) #run feature through DBN > out: prediction
if y:
    print "WOOF!"
else:
    print "MEOW!"
```

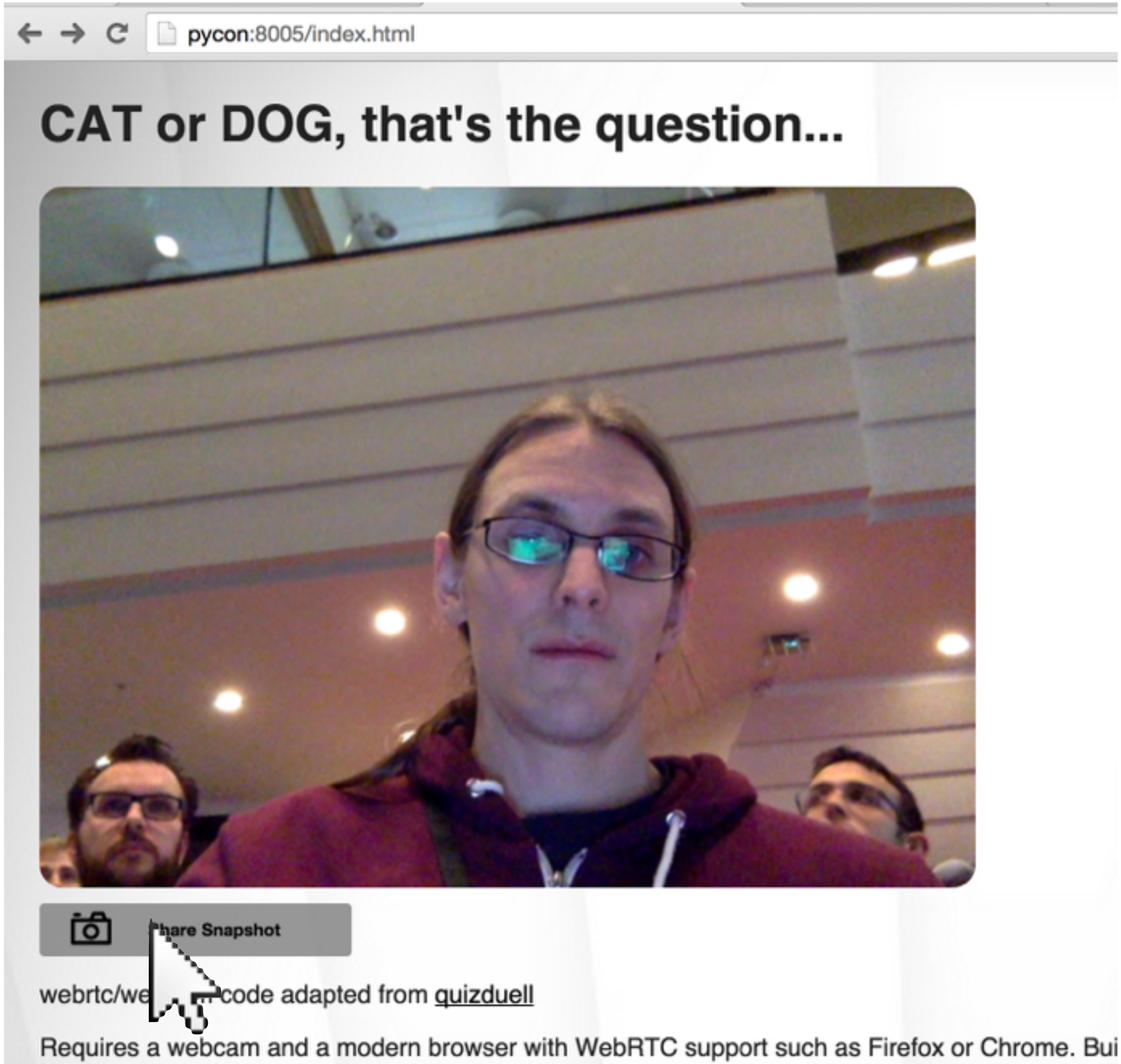
```
MEOW!
```

So are YOU more like a Dog or Cat?



DETECTOR

What about me?



(I might put it up as a Flask site online, if people are interested?)


imgur
upload images
share
2 seconds ago · 0 views · stats
Download full resolution · Get embed codes

In [391]:
```
!wget http://i.imgur.com/oMJyDO0.jpg
```

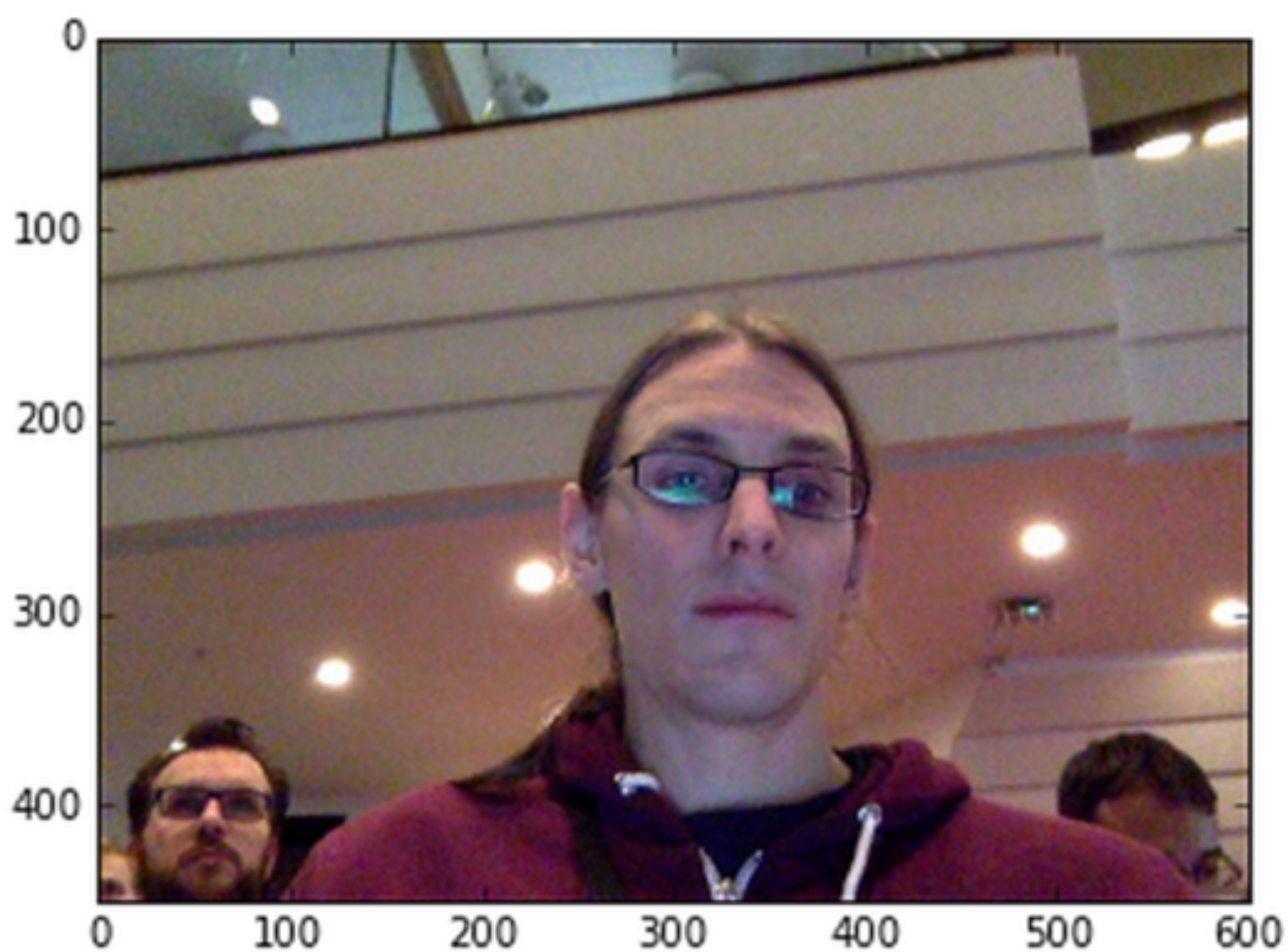
```
--2015-05-12 12:12:00--  http://i.imgur.com/oMJyDO0.jpg
Resolving i.imgur.com (i.imgur.com)... 199.27.76.193
Connecting to i.imgur.com (i.imgur.com)|199.27.76.193|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 58456 (57K) [image/jpeg]
Saving to: 'oMJyDO0.jpg'

100%[======================================>] 58,456      --.-K/s   in 0.02s

2015-05-12 12:12:00 (2.97 MB/s) - 'oMJyDO0.jpg' saved [58456/58456]
```

In [393]:
```
input_image = caffe.io.load_image('oMJyDO0.jpg')
plt.imshow(input_image)
```

Out[393]: <matplotlib.image.AxesImage at 0x7f51aefe5e50>



In [395]:

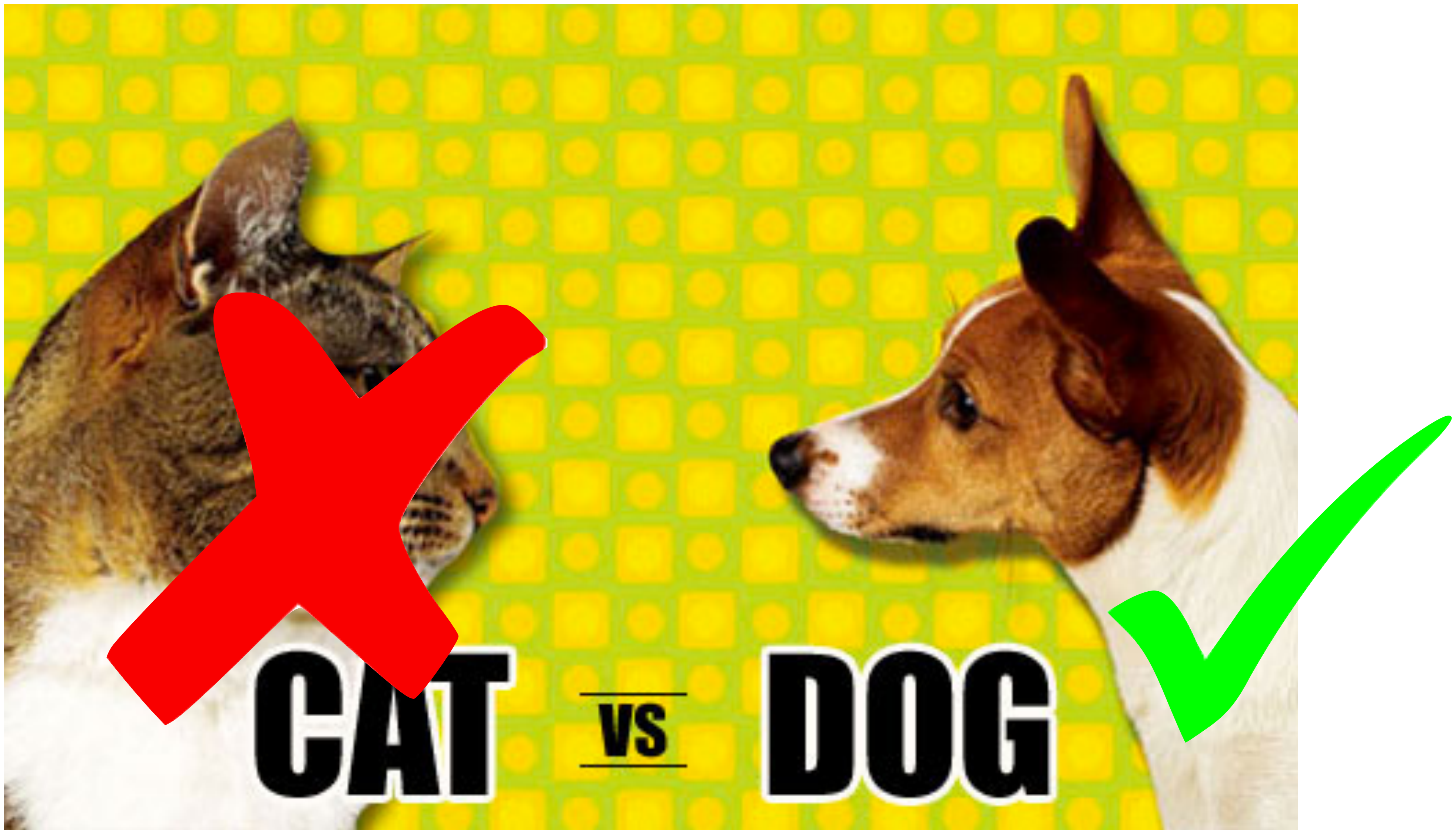
```
feat = getfeat_single_image('rQ4bKra.jpg')  #run image t
x = feat
y = f([x]) #run feature through DBN > out: prediction
if y:
    print "WOOF I'm a Dog!"
else:
    print "MEOW I'm a Cat!"
```

```
WOOF I'm a Dog!
```

In [395]:

```
feat = getfeat_single_image('rQ4bKra.jpg')  #run image t
x = feat
y = f([x]) #run feature through DBN > out: prediction
if y:
    print "WOOF I'm a Dog!"
else:
    print "MEOW I'm a Cat!"
```

```
WOOF I'm a Dog!
```




THATS ALL!
EASY PIEZY…
blirk.net

In Touch!

Academic/Research

as PhD candidate KTH/CSC:
"Always interested in discussing Machine Learning, Deep Architectures, Graphs, and Language Technology"

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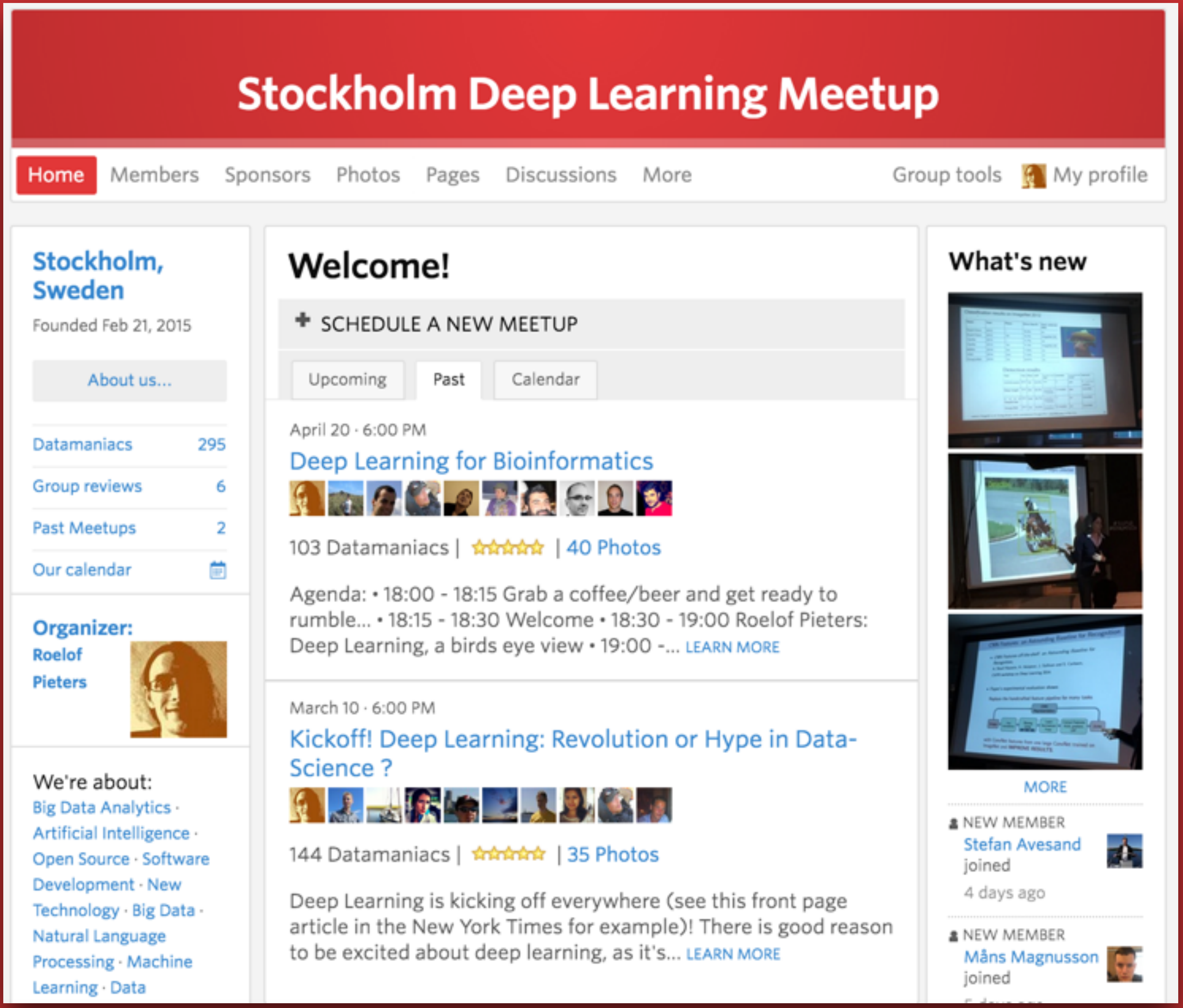
Wanna Know More?

bit.ly/SthlmDL



Wanna Play ? General Deep Learning

- Theano - CPU/GPU symbolic expression compiler in python (from LISA lab at University of Montreal). http://deeplearning.net/software/theano/
- Pylearn2 - library designed to make machine learning research easy. http://deeplearning.net/software/pylearn2/
- Torch - Matlab-like environment for state-of-the-art machine learning algorithms in lua (from Ronan Collobert, Clement Farabet and Koray Kavukcuoglu) http://torch.ch/
- more info: http://deeplearning.net/software links/

Wanna Play ? NLP

- RNNLM (Mikolov)
  http://rnnlm.org
- NB-SVM
  https://github.com/mesnilgr/nbsvm
- Word2Vec (skipgrams/cbow)
  https://code.google.com/p/word2vec/ (original)
  http://radimrehurek.com/gensim/models/word2vec.html (python)
- GloVe
  http://nlp.stanford.edu/projects/glove/ (original)
  https://github.com/maciejkula/glove-python (python)
- Socher et al / Stanford RNN Sentiment code:
  http://nlp.stanford.edu/sentiment/code.html
- Deep Learning without Magic Tutorial:
  http://nlp.stanford.edu/courses/NAACL2013/

Wanna Play ? Computer Vision

- cuda-convnet2 (Alex Krizhevsky, Toronto) (c++/CUDA, optimized for GTX 580)
  https://code.google.com/p/cuda-convnet2/
- Caffe (Berkeley) (Cuda/OpenCL, Theano, Python)
  http://caffe.berkeleyvision.org/
- OverFeat (NYU)
  http://cilvr.nyu.edu/doku.php?id=code:start