

Neural Networks For Computer Vision

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The Most Dangerous Game: Sloth Hunting 101



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* No animals were harmed in making this talk

** Please don't hunt sloths

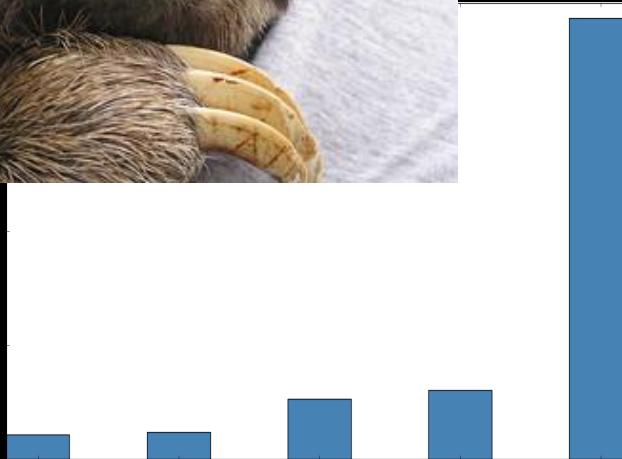
The Most Dangerous Game: Sloth Hunting 101



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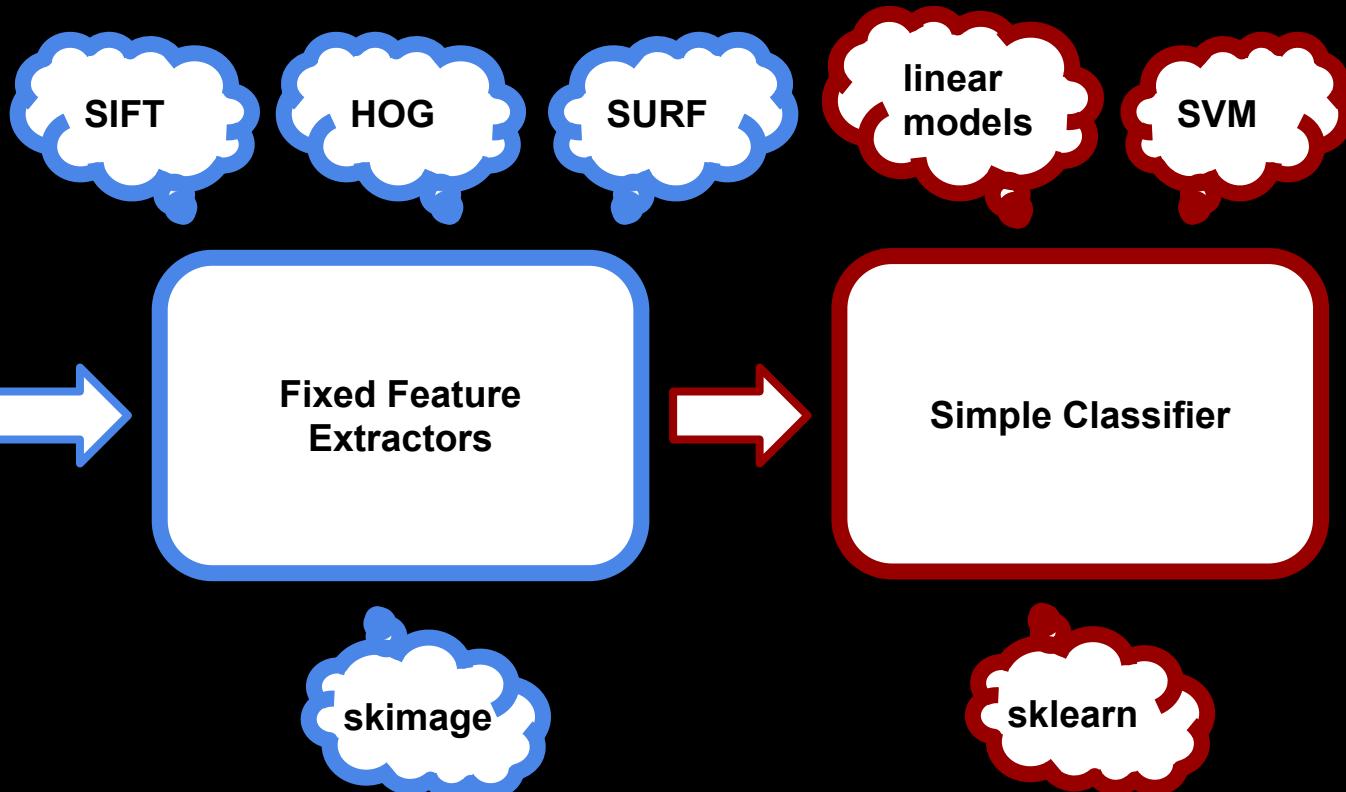


The Plan

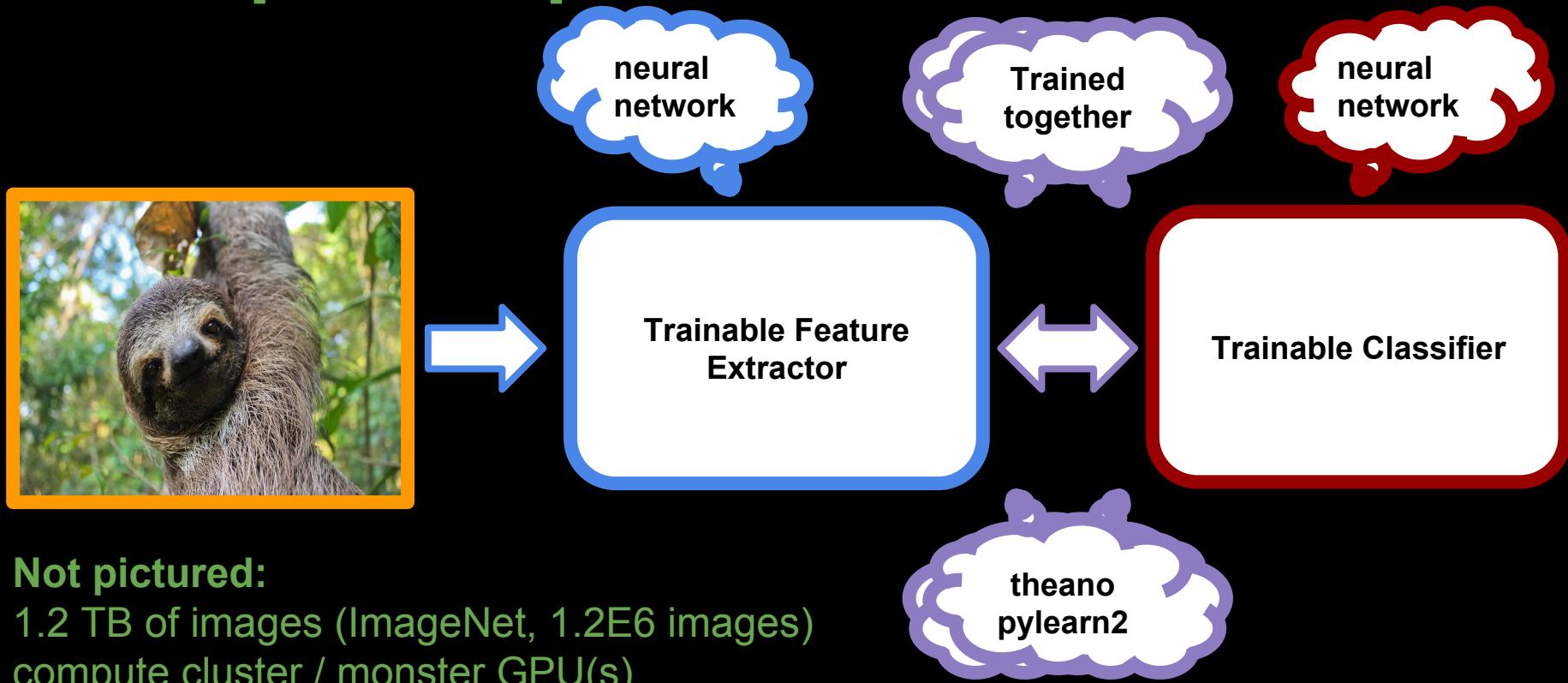


Classify
Locate
???
Profit

Computer Vision



“Deep” Computer Vision



Concepts

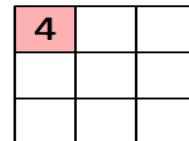
- Neural networks are *universal function approximators*
- Can train these to do (almost) whatever we want
 - Will it generalize to new data?
- Computer Vision: image descriptors
- Machine Learning: features



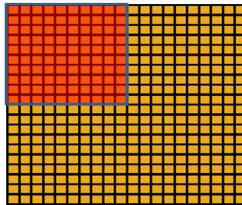
Exploiting Structure

1 _{x1}	1 _{x0}	1 _{x1}	0	0
0 _{x0}	1 _{x1}	1 _{x0}	1	0
0 _{x1}	0 _{x0}	1 _{x1}	1	1
0	0	1	1	0
0	1	1	0	0

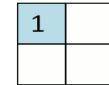
Image



Convolved Feature

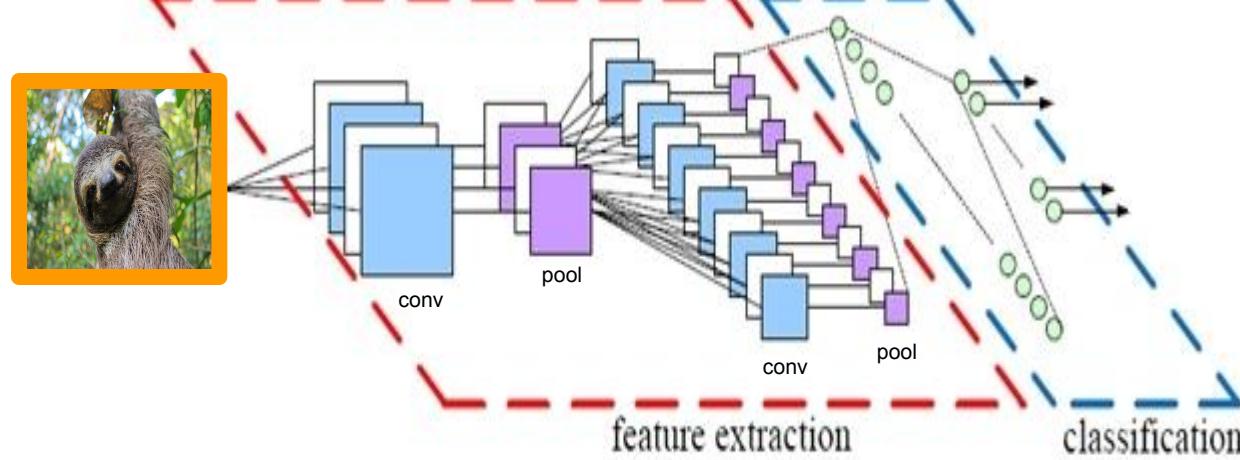
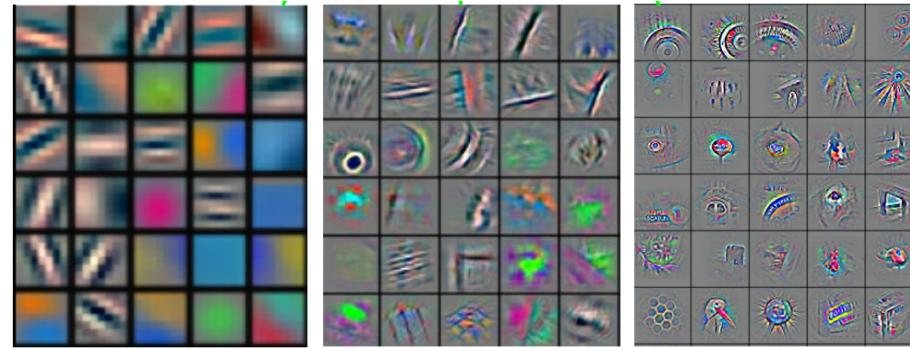


Convolved feature



Pooled feature

[1],[2],[3]



Technology

- Theano
- Optimizing compiler
- Lots of mathematical tools
- Many operations from numpy “just work”
- Automatic differentiation
- GPU or CPU set by single flag
 - THEANO_FLAGS=mode=FAST_RUN,device=gpu,floatX=float32

theano

Cherry On Top

- **pylearn2**
- Built with Theano
- Used for neural network research
- Great guides to YAML interface
- Can code in pure python

Monitoring step:

```
Epochs seen: 33
Batches seen: 165000
Examples seen: 1650000
learning_rate: 0.0099999046326
momentum: 0.989998817444
test_h2_kernel_norms_max: 1.87118041515
test_h2_kernel_norms_mean: 0.804925084114
test_h2_kernel_norms_min: 0.109122686088
test_h3_kernel_norms_max: 1.90657293797
test_h3_kernel_norms_mean: 1.3938267231
test_h3_kernel_norms_min: 0.348352521658
test_objective: 0.0377874299884
test_term_0: 0.0261260885745
test_term_1_weight_decay: 0.0116613674909
test_y_max_max_class: 0.999999344349
test_y_mean_max_class: 0.99490904808
test_y_min_max_class: 0.76411986351
test_y_misclass: 0.00859999842942
valid_h2_kernel_norms_max: 1.87118041515
valid_h2_kernel_norms_mean: 0.804925084114
valid_h2_kernel_norms_min: 0.109122686088
valid_h3_kernel_norms_max: 1.90657293797
valid_h3_kernel_norms_mean: 1.3938267231
valid_h3_kernel_norms_min: 0.348352521658
valid_objective: 0.0444900207222
valid_term_0: 0.0328286737204
valid_term_1_weight_decay: 0.0116613674909
valid_y_max_max_class: 0.999999344349
valid_y_mean_max_class: 0.995154678822
valid_y_min_max_class: 0.737455904484
valid_y_misclass: 0.00819999724627
```

<https://github.com/kastnerkyle/pylearn2-practice>

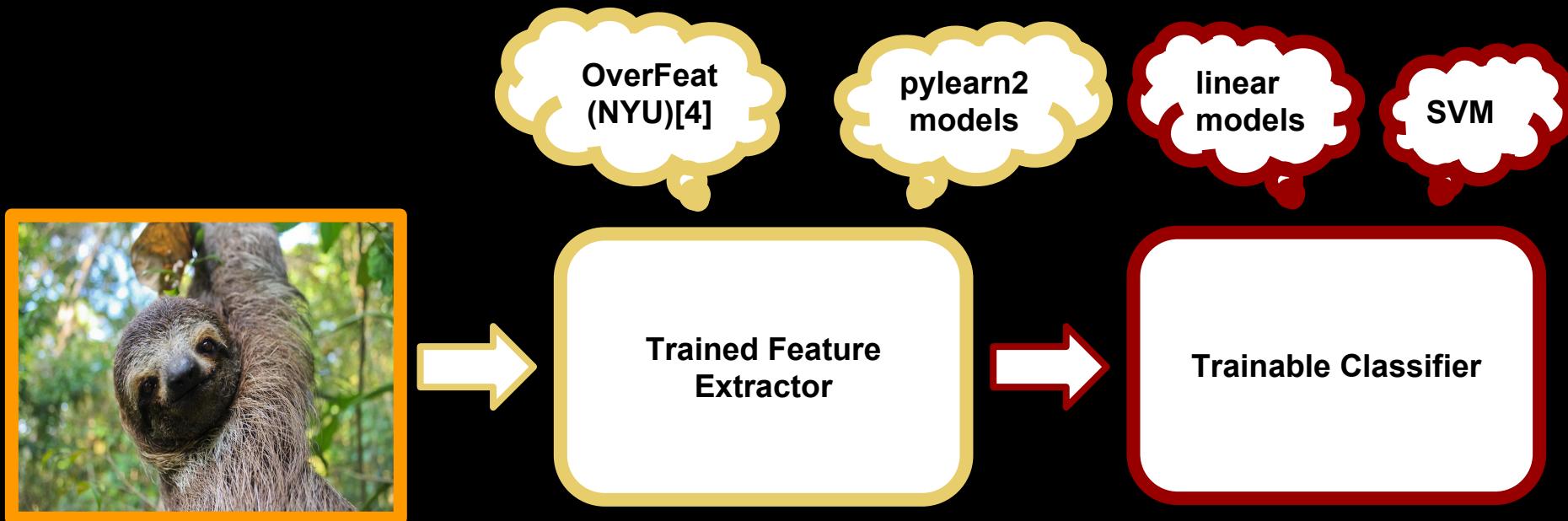
sklearn-theano

- Michael Eickenberg and myself
- Easy interface to trained networks
- Other Theano based models
- (Mostly) scikit-learn compatible
- Includes examples from this talk



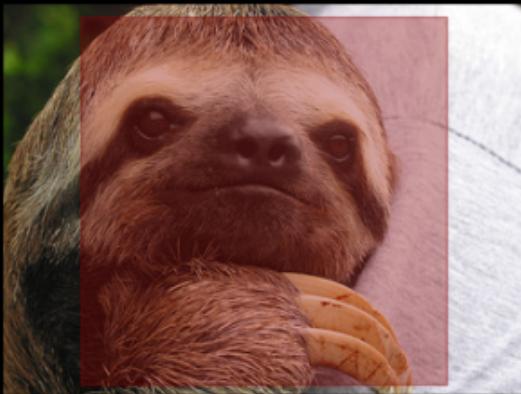
<https://github.com/sklearn-theano/sklearn-theano>

sklearn-theano



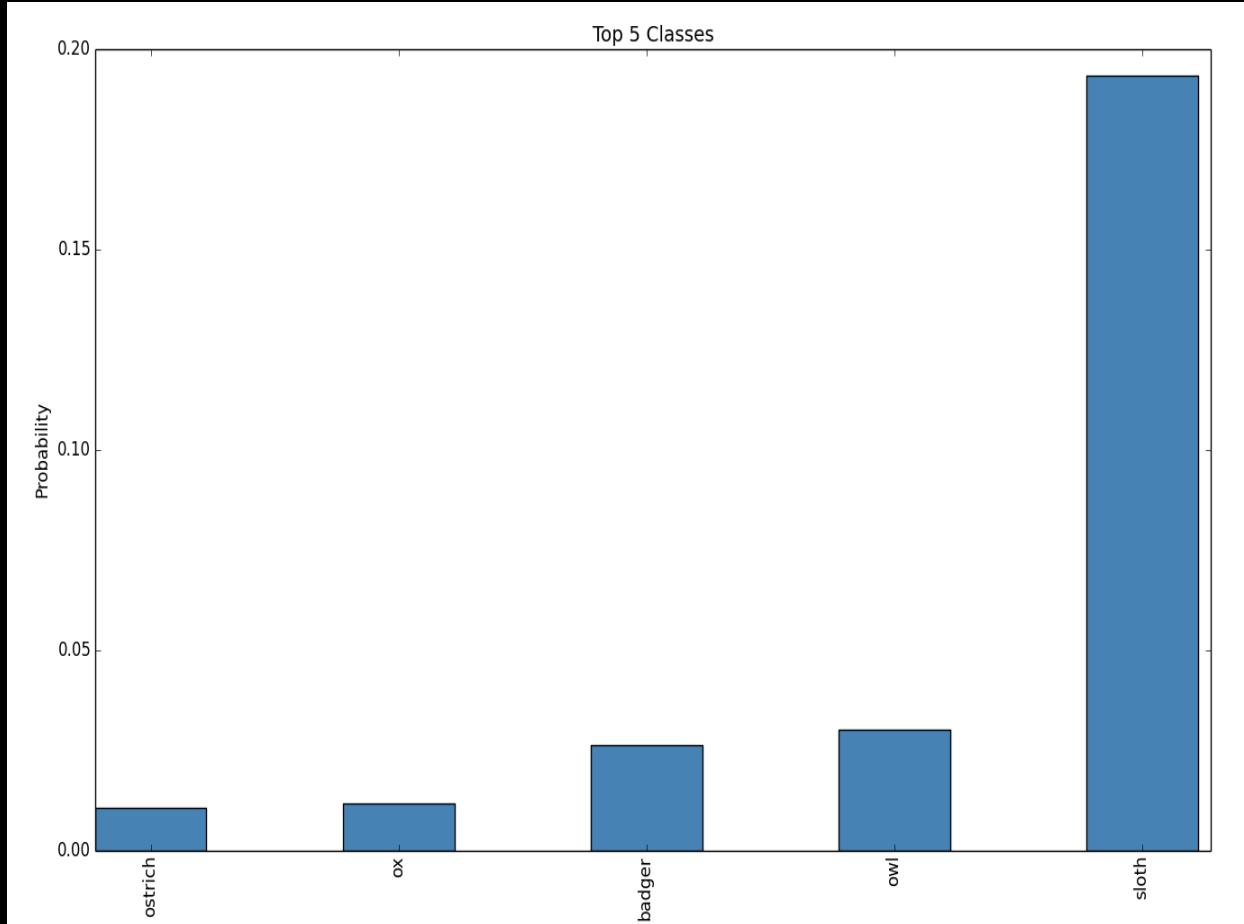
Not pictured:

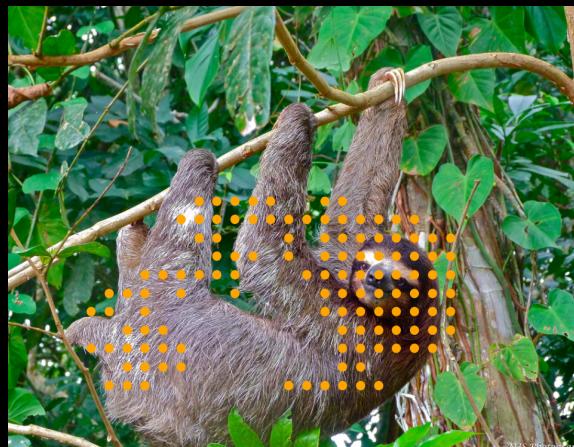
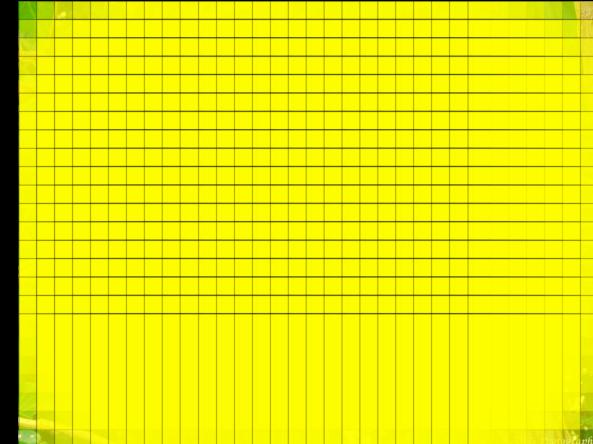
Weeks of expert time and compute time
Cross-validation of entire networks!



Classification

[sklearn_theano/examples/plot_classification.py](https://github.com/scikit-learn/scikit-learn/blob/master/examples/theano/ex)



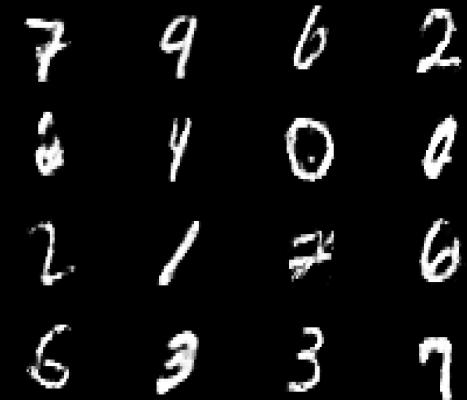


Localization

[sklearn_theano/examples/plot_localization_tutorial.py](https://scikit-image.org/docs/stable/auto_examples/plot_localization_tutorial.html)

Generative Adversarial Networks

- Ian Goodfellow and a slew of others, 2014 [5]
- Trains two networks
 - Generate examples from random input
 - Discriminate whether generated or real



Generation [sklearn_theano/examples/plot_mnist_generator.py](http://scikit-image.org/docs/dev/_modules/skimage/theano/examples/plot_mnist_generator.py)

Takeaways

- Neural networks are good for many vision tasks!
- Theano is a great package for {C,G}PU math in Python
- pylearn2 is an awesome neural net package!
- ***Use*** large neural nets easily in **sklearn-theano!**
- Not every problem needs a massive neural network!
- But some do!

Slides:

<https://speakerdeck.com/kastnerkyle/euroscipy2014>

<https://github.com/kastnerkyle/EuroScipy2014>

Code:

<https://github.com/sklearn-theano/sklearn-theano>

Thank You!

Learning Materials: Courses

Coursera ML course, Andrew Ng

<https://www.coursera.org/course/ml>

This course is phenomenal, and will force you to *learn* machine learning including simple neural nets. Yes, it is MATLAB, sorry. Still worth it.

Coursera Neural Networks Course, Geoff Hinton

<https://www.coursera.org/course/neuralnets>

This course is a detailed look at modern neural networks by one of the core researchers in the field. Well worth it, and goes up to the edge of research.

Deep Learning Tutorial, LISA Lab, Yoshua Bengio

<http://deeplearning.net/tutorial/>

If you want to understand Theano and how to build neural nets, this is an excellent tutorial. After this you will understand the whole of my talk!

Neural Networks Course, Hugo Larochelle

<https://www.youtube.com/playlist?list=PL6Xpj9I5qXYEcOhn7TqghAJ6NAPrNmUBH>

This course will lock down every single piece of neural network approaches, and covers many important topics.

Learning Materials: Papers

Representation Learning, A Review and New Perspectives, Yoshua Bengio, Aaron Courville, Pascal Vincent

<http://arxiv.org/abs/1206.5538>

This paper covers much of the “nitty gritty” details. Weight initialization, optimization schemes, tradeoffs, and implementation. Fantastic!

Learning Features from Tiny Images, Alex Krizhevsky

<http://www.cs.toronto.edu/~kriz/learning-features-2009-TR.pdf>

The greedy layerwise training of this thesis is out of date now, but the rest of the insights into image statistics and intuition are very, very good.

ImageNet Classification with Deep Convolutional Neural Networks, Alex Krizhevsky, Ilya Sutskever, Geoff Hinton

<http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks>

This paper basically lays out the “modern” approach to most neural networks for images (also audio, and some NLP). OverFeat is basically an implementation of this architecture, with a number of custom tweaks to get better performance.

OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks, P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, Y. LeCun

<http://arxiv.org/abs/1312.6229>

I like this paper (and associated code: <https://github.com/sermanet/OverFeat>) a whole lot. It inspired sklearn-theano!

Learning Materials: Blogs

Kaggle Galaxy Challenge Solution, Sander Dieleman

<http://benanne.github.io/2014/04/05/galaxy-zoo.html>

This blog post will show you how to build a neural network architecture from scratch for a custom dataset. His post on audio for Spotify is also spectacular: <http://benanne.github.io/2014/08/05/spotify-cnns.html>

Deep Learning in One File, Gabriel Synnaeve

<http://snippyhollow.github.io/>

This blog post has great, straightforward insight into deep learning, and provides a *single file* solution to do deep learning using Theano!

Neural Networks, Manifolds, and Topology, Chris Olah

<http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/>

A whole blog full of remarkable discussions of neural networks, but this post gives some neat intuition about how and why neural networks work. This post on NLP is also great: <http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/>

Using Deep Learning To Listen For Whales, Daniel Nouri

<http://danielnouri.org/notes/2014/01/10/using-deep-learning-to-listen-for-whales/>

This model did not win, but the level of effort the winner put into feature engineering was immense. This approach did very well, very simply. Awesome!

References

- [1] http://deeplearning.stanford.edu/wiki/index.php/UFLDL_Tutorial
- [2] <http://www.cs.nyu.edu/~yann/talks/lecun-ranzato-icml2013.pdf>
- [3] <http://parse.ele.tue.nl/education/cluster2>
- [4] P. Sermanet, D. Eigen, X. Zhang, M. Mathieu, R. Fergus, Y. LeCun. *OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks*, International Conference on Learning Representations (ICLR 2014), April 2014. <http://arxiv.org/abs/1406.2661>
- [5] I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, Y. Bengio. *Generative Adversarial Networks*, arXiV, June 2014. <http://arxiv.org/abs/1406.2661>

BONUS SLIDES



Preprocessing

`sklearn-theano/examples/asirra_dataset_example.py`

Code

```
tf = OverfeatTransformer(output_layers=[-3])
clf = LogisticRegression()
pipe = make_pipeline(tf, clf)
pipe.fit(X_train, y_train)
y_pred = pipe.predict(X_test)
```

class	precision	recall	f1-score	support
0.0	0.89	0.89	0.89	9
1.0	0.91	0.91	0.91	11
avg / total	0.90	0.90	0.90	20

accuracy score
0.9

Data Werewolves...

- But no silver bullets!
- Primarily for automation (**WHAT**)
- Other models can be better for
 - Scientific inference (**WHY**)
 - Simplicity of tuning (**HOW**)
 - Underpowered hardware (**WHO**)

