

Deep Learning

~~Tips from the Road~~

CRASH COURSE

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Automation Spectrum

Introspection

Statistics

Machine

Learning

Automation

Deep Learning

statsmodels

pymc3

patsy

sklearn

Theano

sklearn-theano

shogun

pylearn2

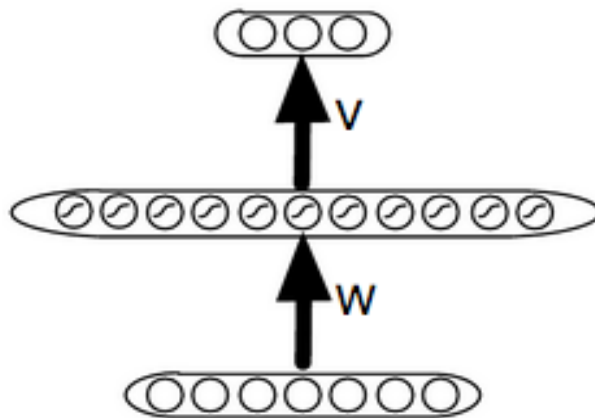
Blocks

Keras

Blocks

Lasagne

Basic Anatomy

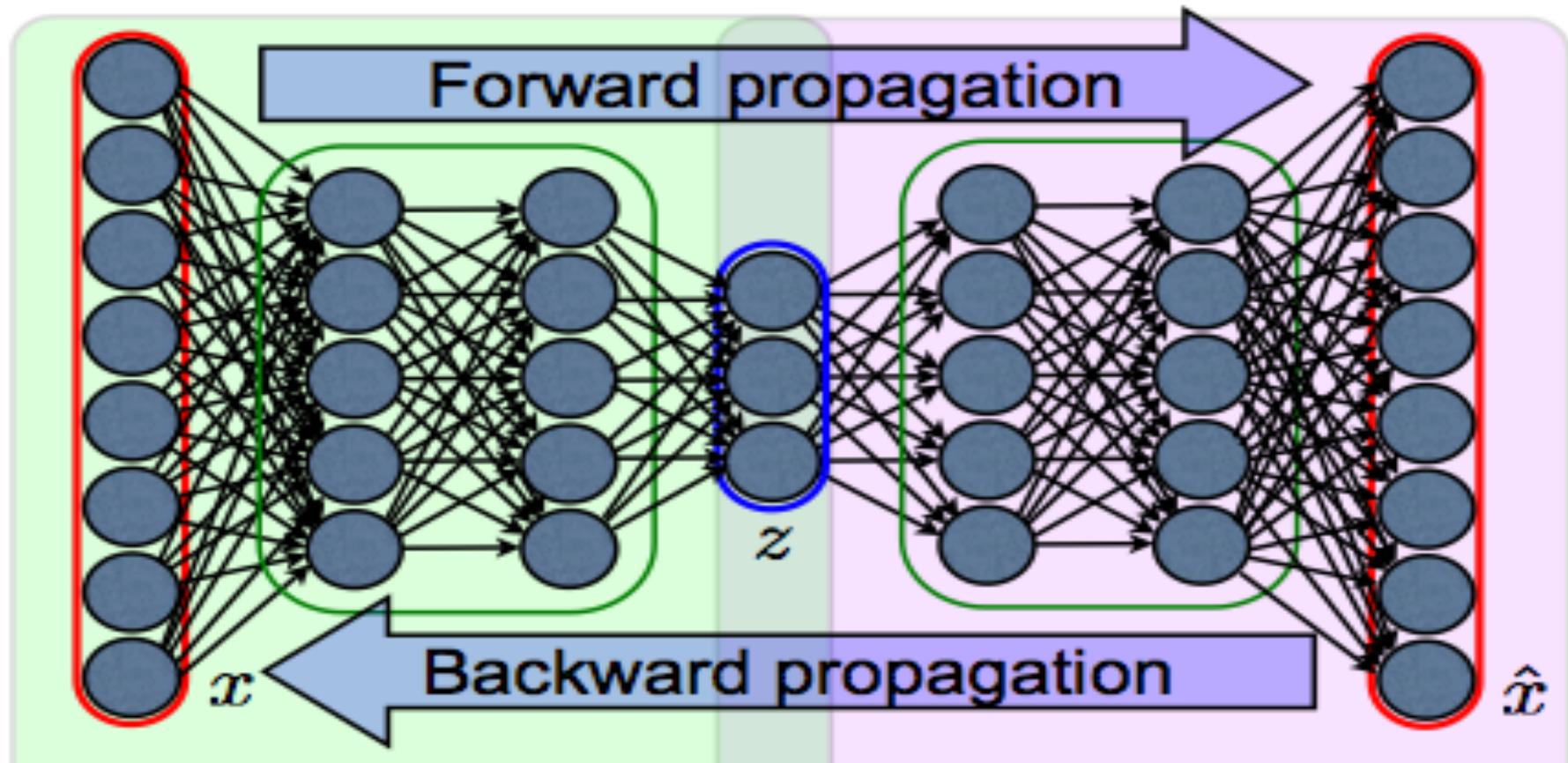


- Weights (W , V)
- Biases (b , c)
- Init weights randomly, biases can start at 0
- Morph features using non-linear functions
 - $\text{layer_1_out} = \tanh(\text{dot}(W, X) + b)$
 - $\text{layer_2_out} = \tanh(\text{dot}(V, \text{layer_1_out}) + c) \dots$
- Backpropagation to “step” values of W, V, b, c

General Guidelines

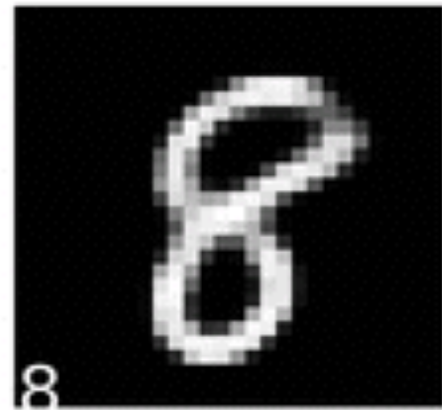
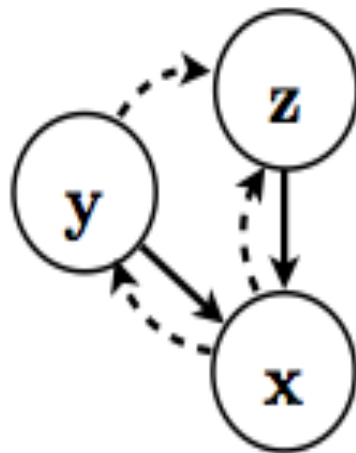


- Prefer rectified activation (ReLU)
 - `def relu(X): return X * (X > 0)`
- Optimization
 - RMSProp w. momentum, ADaM (easiest to tune)
 - Stochastic Gradient Descent w. momentum (harder)
- Regularize with Dropout
 - <https://www.cs.toronto.edu/~hinton/csc2535/notes/lec6a.ppt>
- Great initialization reference
 - <https://plus.google.com/+SoumithChintala/posts/RZfdrRQWL6u>



ENCODE

DECODE



Conditioning,
Visually

8	0	1	2	3	4	5	6	7	8	9
4	0	1	2	3	4	5	6	7	8	9
7	0	1	2	3	4	5	6	7	8	9
3	0	1	2	3	4	5	6	7	8	9
4	0	1	2	3	4	5	6	7	8	9
8	0	1	2	3	4	5	6	7	8	9

In Practice...



- Conditioning is a *strong* signal
 - $p(\hat{x} | z)$ vs. $p(\hat{x} | z, y)$
- Can give *control* or add prior knowledge
- Classification is an even stronger form
 - Prediction is learned by maximizing $p(y | x)$!
 - In classification, don't worry about forming a useful z

Conditioning Feedforward



- Concatenate features
 - `concatenate((X_train, conditioning), axis=1)`
 - $p(y \mid X_1 \dots X_n, L_1 \dots L_n)$
- One hot label L (scikit-learn `label_binarize`)
- Could also be real valued
- Concat followed with multiple layers to “mix”

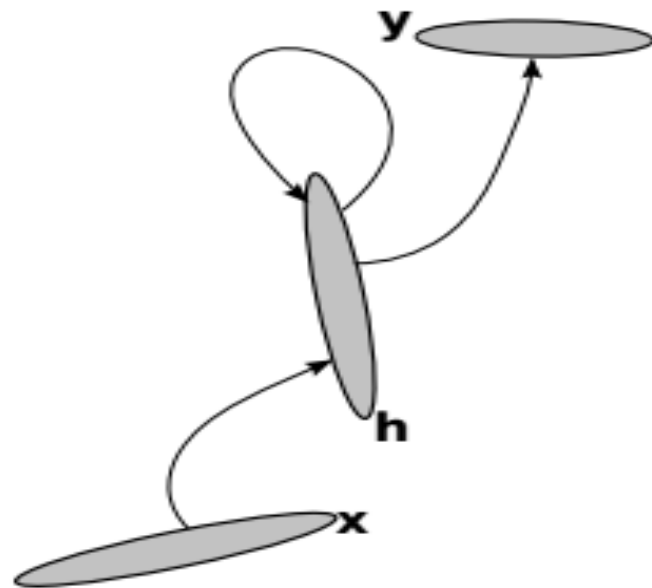
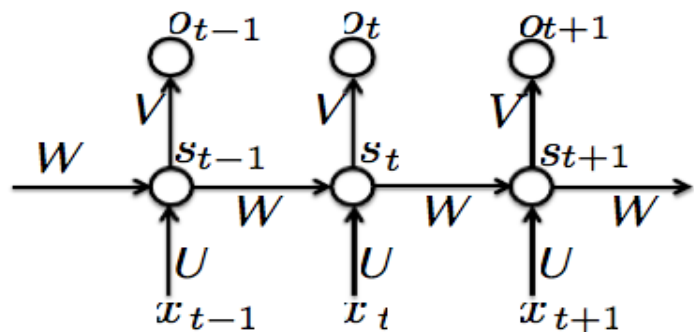
Convolution and Recurrence



- Exploit structure and prior knowledge
 - Locality, neighbors have key information (convolution)
 - Sequence, ordering is crucial (recurrence)
- Convolution (Not discussed here)
- Recurrence
 - $p(y \mid X_1 \dots X_n)$ can be seen as:
 - $\sim p(y \mid X_1) * p(y \mid X_2, X_1) * p(y \mid X_3, X_2, X_1) \dots$

More on Recurrence

- Hidden state (s_t) encodes sequence info
 - $x_1 \dots x_t$, but *compressed*
- Recurrence similar to
 - Hidden Markov Model (HMM)
 - Kalman Filter

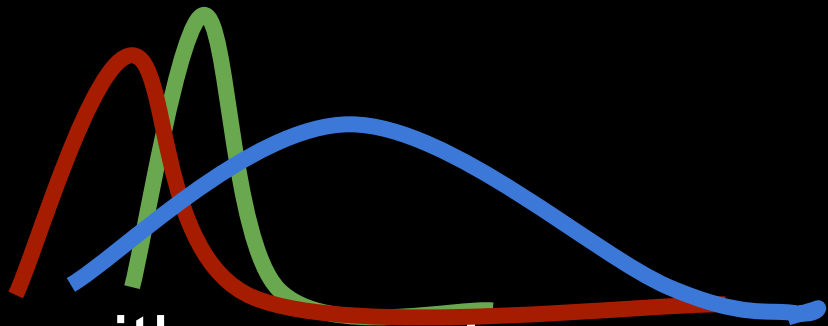


Yet More On Recurrence

- Initialize hidden state to be orthogonal
 - Use U from $U, S, V = \text{svd}(\text{randn_init})$
- Long short term memory or gated recurrent
 - {LSTM, GRU} fancy recurrent activations
- {Sentences, dialogues, sounds} are sequences
 - Many-to-one (sequence recognition)
 - Many-to-many (sequence to sequence)
 - One-to-many (sequence generation)
 - Many-to-one-to-many (encode-decode)

Parameterizing Distributions

- sigmoid -> Bernoulli
- softmax -> Multinomial
- linear, linear -> Gaussian with mean, log_var
- softmax, linear, linear -> Gaussian mixture
- Depends crucially on the cost
- Can combine with recurrence
 - Learned, dynamic distributions over sequences
 - *Incredibly* powerful



Where is it used?

- Image classification (conv)
- Text-to-text translation (rec encode-decode)
- Q&A systems / chatbots (rec encode-decode)
- Speech recognition (rec or conv)
- Speech synthesis (rec with GMM output)



Future Directions

- Attention
- Dedicated memory
 - Separate “what” from “where”
 - Similar to attention
- Combine with reinforcement learning
 - No more labels?
 - Deep Q Learning - playing Atari from video!
 - <https://www.youtube.com/watch?v=V1eYniJ0Rnk#t=1m12s>



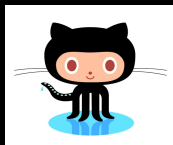
A giraffe standing in a forest with trees in the background.

Takeaways and Opinions

- Can use deep learning like graphical modeling
 - Different tools, same conceptual idea
 - Conditional probability modeling is *key*
- Put knowledge in model structure, *not* features
- Let features be *learned* from data
- Use conditioning to control or constrain



@kastnerkyle



Thanks!

Repo with slides and links <https://github.com/kastnerkyle/SciPy2015>

Slides will be uploaded to <https://speakerdeck.com/kastnerkyle>

sklearn-theano, a scikit-learn compatible library for using pretrained networks : <http://sklearn-theano.github.io/>

Neural network tutorial by @NewMu / Alec Radford : <https://github.com/Newmu/Theano-Tutorials>

Theano Deep Learning Tutorials: <http://deeplearning.net/tutorial/>

References and Links

Deep Learning Book (Goodfellow, Courville, Bengio): <http://www.iro.umontreal.ca/~bengioy/dlbook/>

Deep Learning Course (Courville): <https://ift6266h15.wordpress.com/>

Deep Learning Course (Larochelle): <https://www.youtube.com/playlist?list=PL6Xpj9I5qXYEcOhn7TqghAJ6NAPrNmUBH>

Encode Decode with Attention (Bahdanau, Cho, Bengio): <http://arxiv.org/abs/1409.0473>

Caption Generation (Xu, Ba, Kiros et. al.): <http://arxiv.org/abs/1502.03044>

Generating Sequences with Recurrent Neural Networks (Graves): <http://arxiv.org/abs/1308.0850>

Depth Map Prediction From A Single Image (Eigen, Puhersch, Fergus): <http://arxiv.org/abs/1406.2283>

Semi Supervised Learning (Kingma, Rezende, Mohamed, Welling): <http://arxiv.org/abs/1406.5298>

Neural Networks Coursera (Hinton): <https://www.coursera.org/course/neuralnets>

Understanding The Difficulties in Training Deep Feedforward Networks (Glorot, Bengio): <http://jmlr.org/proceedings/papers/v9/glorot10a/glorot10a.pdf>

Advances in Optimizing Recurrent Nerural Networks (Pascanu, Boulanger-Lewandowski, Bengio): <http://arxiv.org/abs/1212.0901>

CUT SLIDES

Where is it used?

- Image classification
- Text-to-text translation
- Q&A systems / chatbots
- Speech recognition
- Speech synthesis
- Usually many, many datapoints

Deep Learning, Simple Concepts

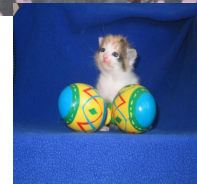
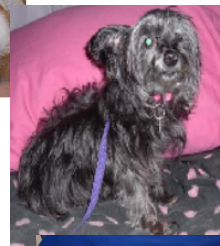
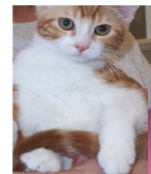
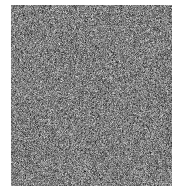
- Universal function approximators
- *Learn* the features
- Expect hierarchy in learned features
 - $y = h(g(f(x)))$
 - $\{h, g, f\}$ are functions
- Classification
 - Learn $p(y | x) = h(g(f(x)))$



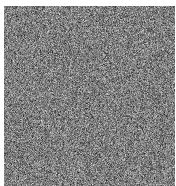
When To Use Feedforward

- Use for modeling $p(y \mid X_1 \dots X_n)$
 - $X_1 \dots X_n$ represent features
- Initialize with Xavier method
 - $\pm 4 * \sqrt{6. / (in_sz + out_sz)}$ uniform
 - ± 0.01 uniform or 0.01 std randn can work
 - Great reference: <https://plus.google.com/+SoumithChintala/posts/RZfdrRQWL6u>

More on Convolution



- Define size of feature map and how many
 - Similar to output size of feedforward layer
- Parameter sharing
 - Small filter moves over entire input
 - Local statistics consistent over all regions
- Condition by concatenating
 - Along “channel” axis
 - <http://arxiv.org/abs/1406.2283>



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

4		

Convolved
Feature