# Sequence to Sequence Learning

## In Natural Language Processing

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May 13, 2017

# Overview

# Installation

`https://www.tensorflow.org/install/`

# Why?

Why TensorFlow?

- Expressiveness of Python
- Efficiency of optimized CUDA
- Scalability

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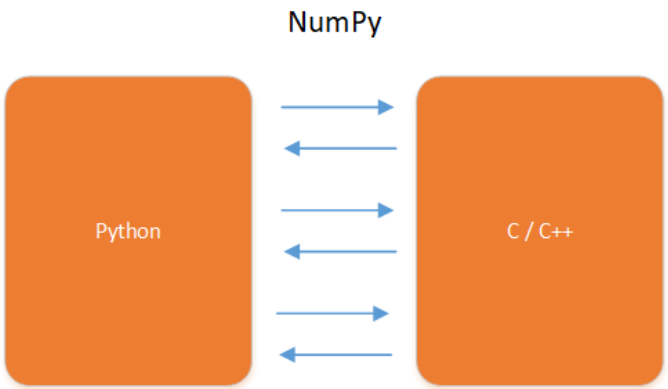
# How it Works

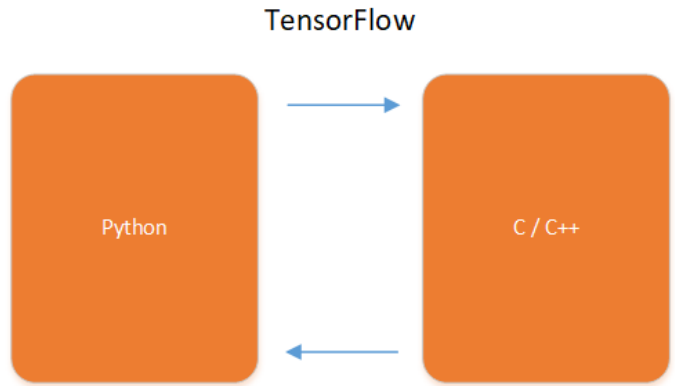
## NumPy

```
a = np.random.rand(100,100)
b = np.random.rand(100,100)
np.matmul(a,b)
```

## TensorFlow

```
sess = tf.Session()
a = tf.Variable(tf.zeros([100,100]))
b = tf.Variable(tf.zeros([100,100]))
y = tf.matmul(a,b)
sess.run(tf.global_variables_initializer())
sess.run(y)
```



# Neural Net Crash Course

- Optimize parameters of function to minimize error
- Search parameter space with Gradient Descent Algorithm

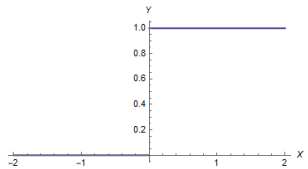
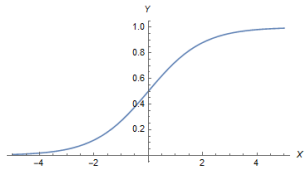
$$\boldsymbol{\theta}_{t+1} := \boldsymbol{\theta}_t - \gamma \frac{dl_n(\boldsymbol{\theta})}{d\boldsymbol{\theta}}\Big|_{\boldsymbol{\theta}_t}$$

# Activation Function Petting Zoo

Element-wise nonlinearities

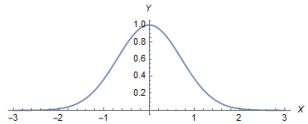
- Sigmoid

$$\boldsymbol{\sigma}(\boldsymbol{\phi}) = \frac{1}{1 + e^{-\boldsymbol{\phi}}}$$

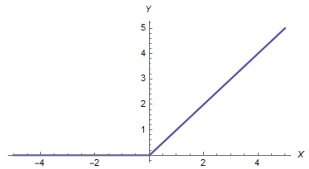
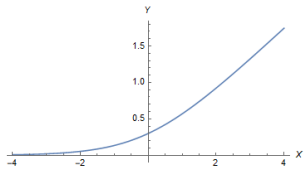
- Gaussian Radial Basis

$$\boldsymbol{\psi}(\boldsymbol{\phi}) = \exp(-\boldsymbol{\phi} \odot \boldsymbol{\phi})$$



- Softplus

$$\boldsymbol{q}(\boldsymbol{\phi}) = \log(1 + e^{\boldsymbol{\phi}})$$

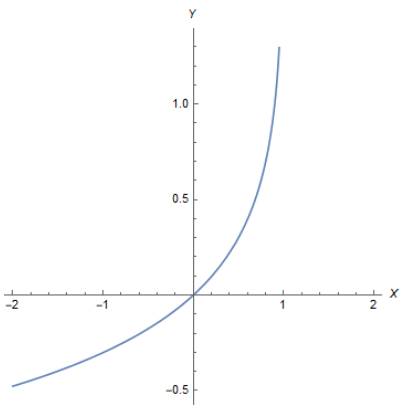
# Loss Function Petting Zoo

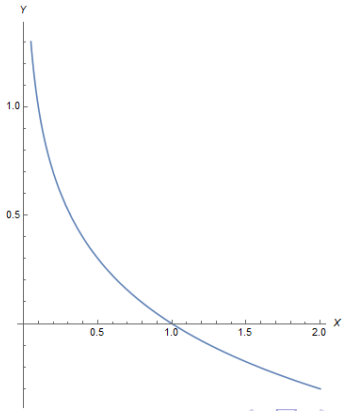
- Continuous Output (regression)

$$l_n(\boldsymbol{\theta}) = \frac{1}{n}\sum_{i=1}^{n} |\boldsymbol{y}_i - \ddot{\boldsymbol{y}}(\boldsymbol{\theta}, \boldsymbol{s}_i)|^2$$

- Binary Output (classification)

$$l_n(\boldsymbol{\theta}) = -\frac{1}{n}\sum_{i=1}^{n} \left[\boldsymbol{y}_i \log(\ddot{\boldsymbol{y}}(\boldsymbol{\theta}, \boldsymbol{s}_i)) + (1 - \boldsymbol{y}_i) \log(1 - \ddot{\boldsymbol{y}}(\boldsymbol{\theta}, \boldsymbol{s}_i))\right]$$



# MNIST

## Clone the Demo

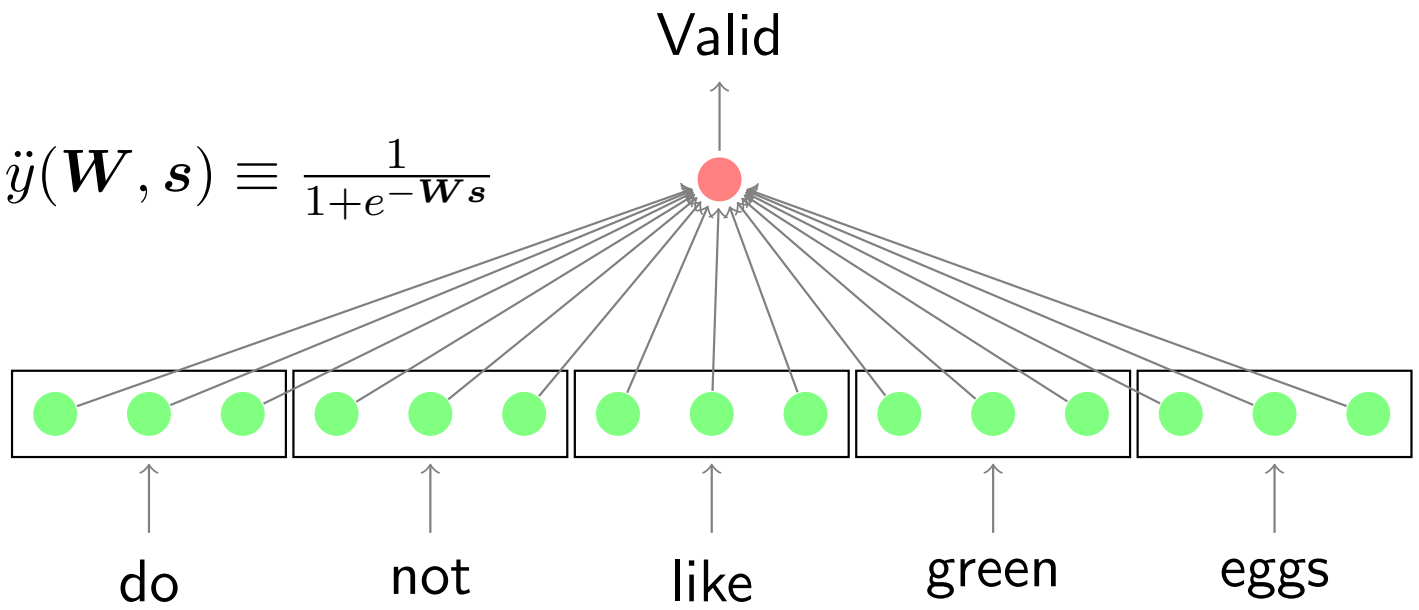
```
$ git clone https://github.com/WChurchill/seq2seq_workshop.git
$ cd seq2seq_workshop/code
$ python mnist.py
```

or,

`<path-to-tensorflow>/tensorflow/examples/tutorials/mnist/mnist.py`

# Word Embeddings

- Pretrain using unsupervised learning
- Train a small network to recognize valid n-grams



# Code

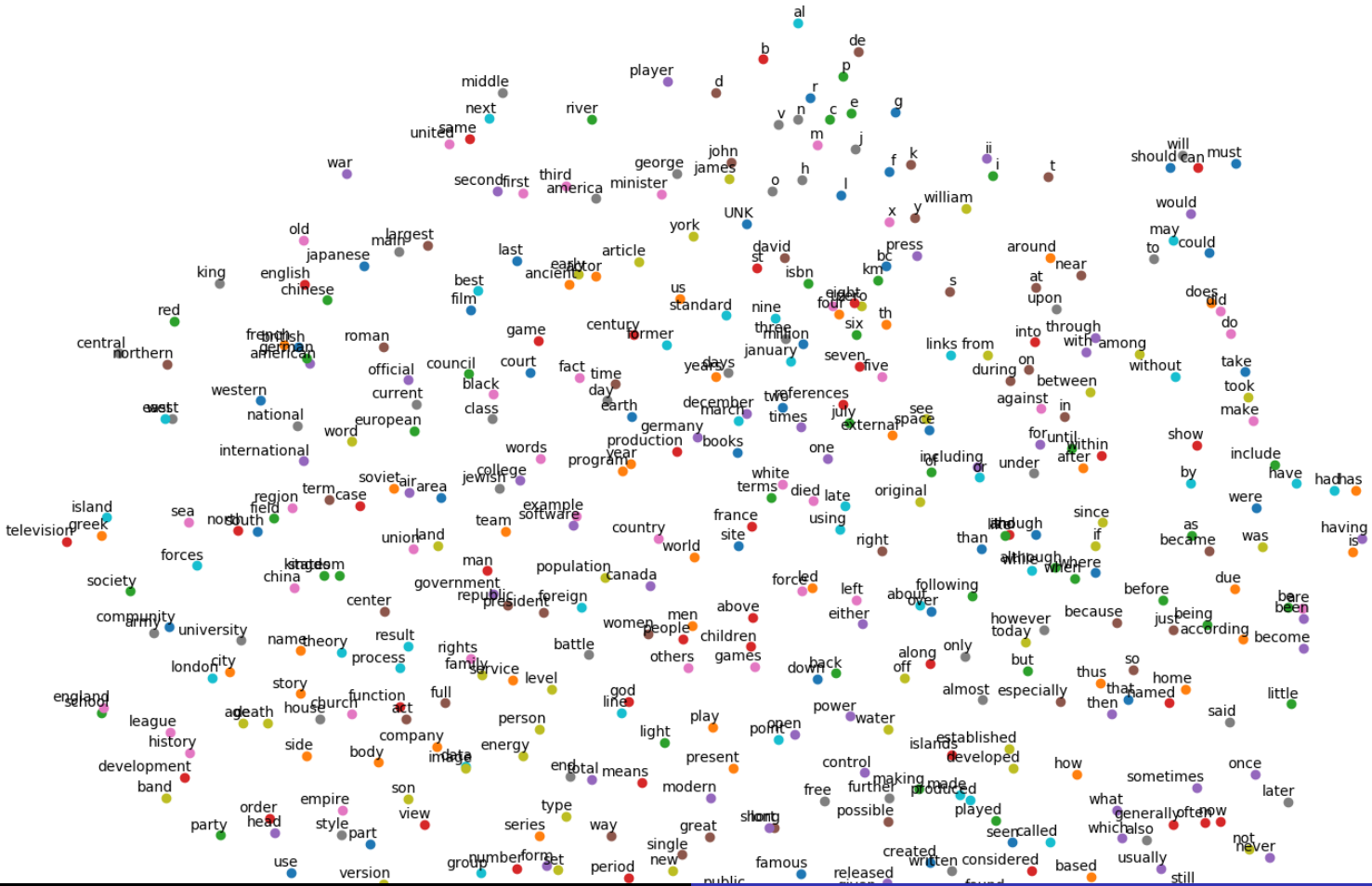
Try it!

**Run word2vec.py**

```
$ python word2vec_basic.py
$ ls
tsne.png
```

# Results

tsne.png



# But What About Sequences?

- Matrix dimensions are fixed
- Architecture is static
- How do we make networks with variable length inputs?
- How do we make networks with variable length outputs?

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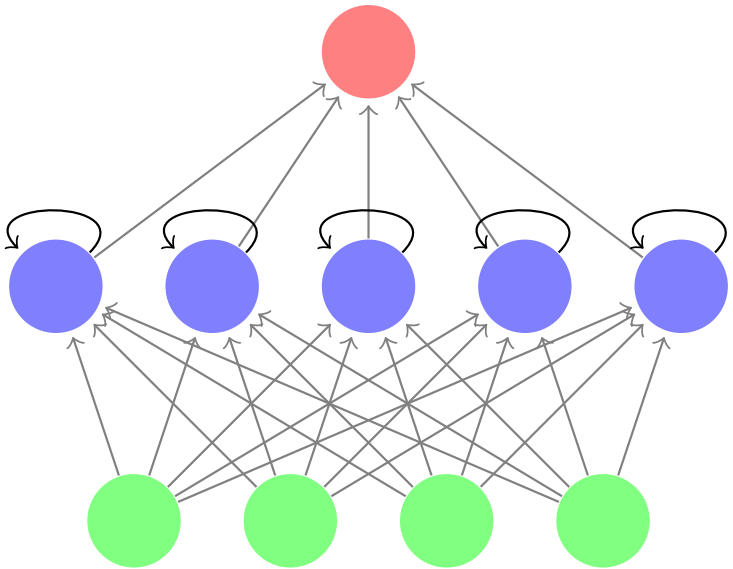
**Bad Idea**

Find maximum length of input & output vectors during preprocessing

# Recurrent Neural Networks

- Networks that feed into themselves
- Hidden units remember by self-activation

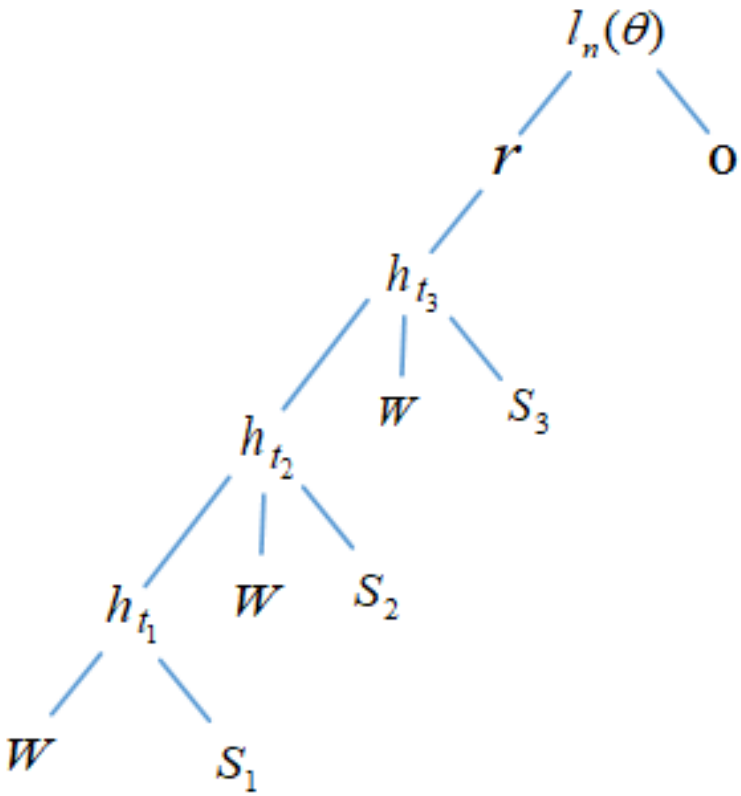


$$\boldsymbol{h}_t(\boldsymbol{W}, \boldsymbol{s}, \boldsymbol{h}_{t-1})$$

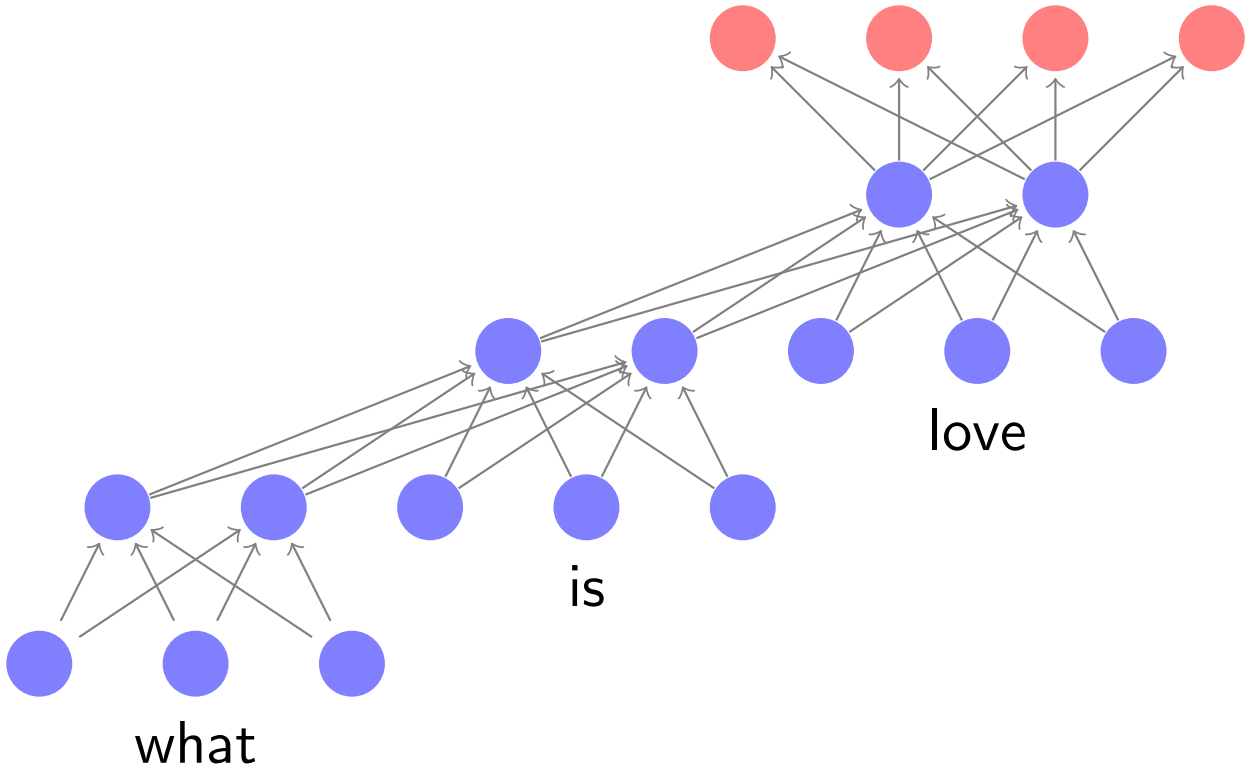
# Backpropogation Through Time

$$D \equiv [\boldsymbol{S}_1, \boldsymbol{S}_2, \ldots, \boldsymbol{S}_n]$$

$$\boldsymbol{S}_i \equiv [\boldsymbol{s}_{i1}, \boldsymbol{s}_{i2}, \ldots, \boldsymbol{s}_{iT_i}]$$

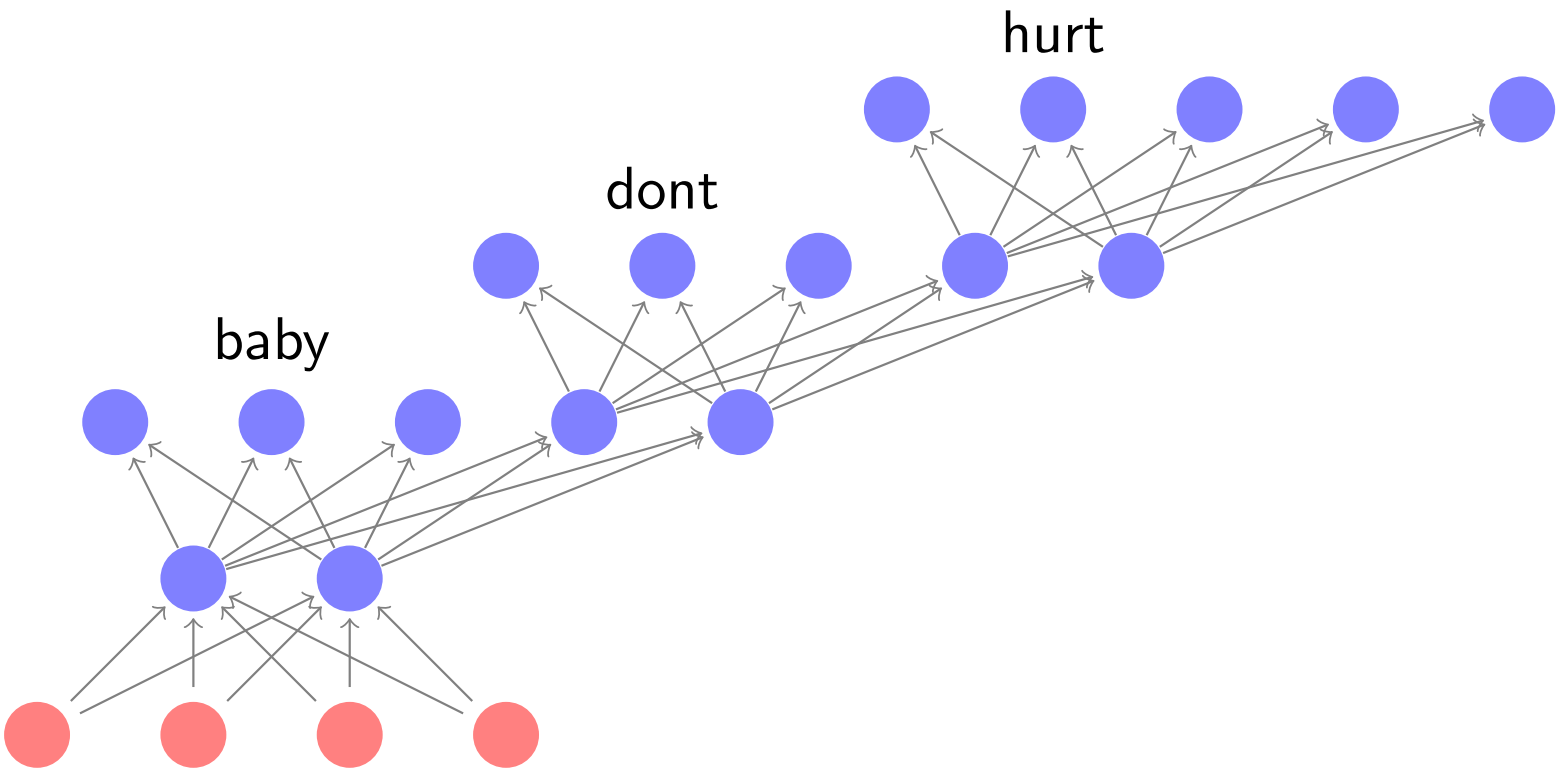


# Expanded Network Diagram




Input sequence is encoded as a finite-length vector

# Decoding




Output sequence is a repeated projection of the encoded vector

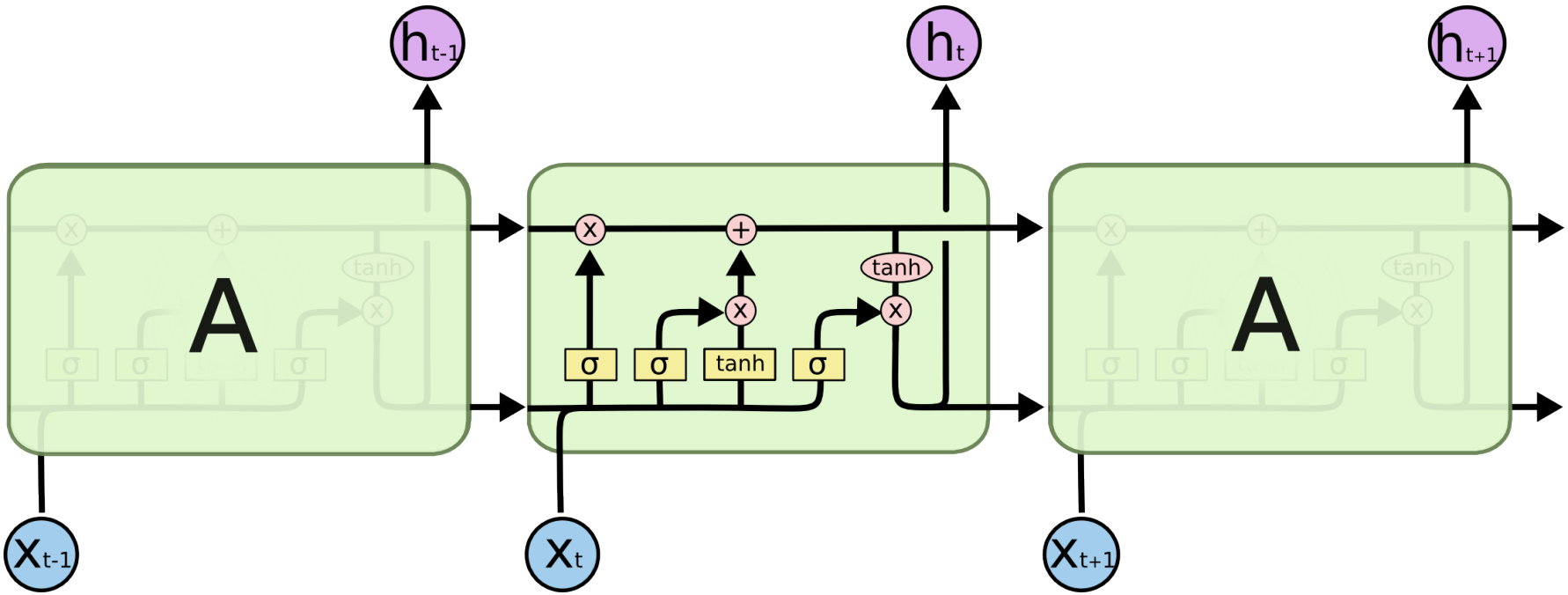
# Vanishing Gradient

- Gradient is disproportionately small in bottom layers
- Output layers receive most of the blame
- Performs poorly on long sequences

# Long Short-Term Memory

- Information highway through time
- Network learns explicitly what to remember

# Anatomy of an LSTM Cell




http://colah.github.io/posts/2015-08-Understanding-LSTMs/

# Code

rnn_tutorial.py

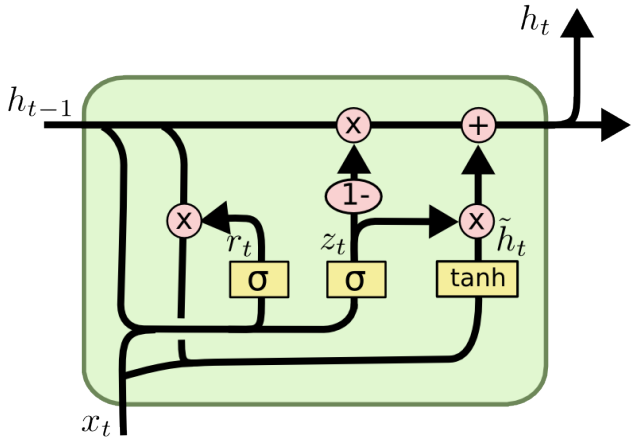
```
lstm = tf.contrib.rnn.BasicLSTMCell(<num_units>)
state = tf.zeros([<batch size>, <lstm state size>])
```

# Even More Improvements!

Some questions you might have:

- What's the difference between the cell state and hidden state?
- What's the difference between remembering new information and forgetting the old?
- Why are the gates blind to the cell state?

# Gated Recurrent Units




$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

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# Code

## Try It! (if you have 6 hours or a beefy GPU)

```
$ python translate.py
downloading dataset...  # very large file
# wait 3 hours depending on internet quality
# dataset is downloaded
# begin preprocessing
# 3 more hours
```

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**Try It! (if you have 6 hours or a beefy GPU)**

```
$ python translate.py
downloading dataset...  # very large file
# wait 3 hours depending on internet quality
# dataset is downloaded
# begin preprocessing
# 3 more hours
```

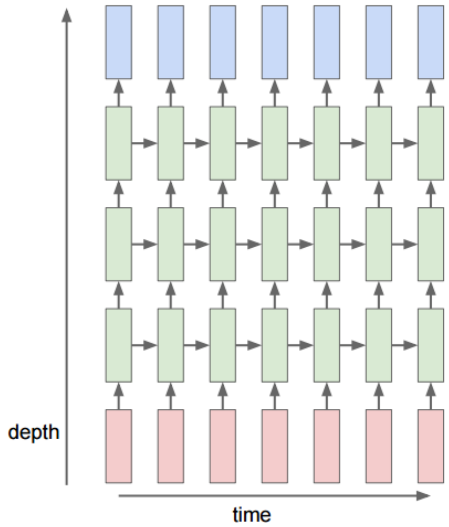
**ERROR!**

Your model is incorrect

# Stacking LSTM Networks

rnn_tutorial.py

```
lstm = tf.contrib.rnn.BasicLSTMCell(<num_units>)
stacked_lstm = tf.contrib.rnn.MultiRNNCell([lstm] * <num_layers>)
```




https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/recurrent_neural_networks.html

# Other Applications in NLP

- Speech recognition
- Conversational Agents
- Automated Summarization

# What Now?

Amazon Web services

- Discount supercomputer
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- Additional setup

# Questions and Discussion