# CS395T: Structured Models for NLP
# Lecture 14: Neural Network Implementation

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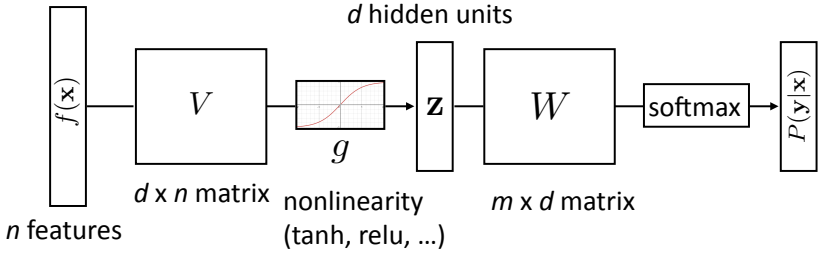
## Administrivia

- Project 2 due today
- Project 3 out today
  - Sentiment analysis using feedforward neural networks plus your choice of RNNs or CNNs
  - Project zip contains sample Tensorflow code demonstrating what's in today's lecture

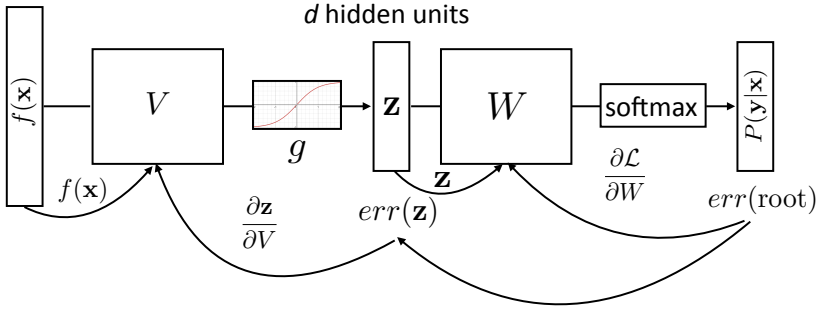
## Recall: Feedforward NNs

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$




## Recall: Backpropagation

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$



# This Lecture

- Implementation details
- Training
- Word representations

# Implementation Details

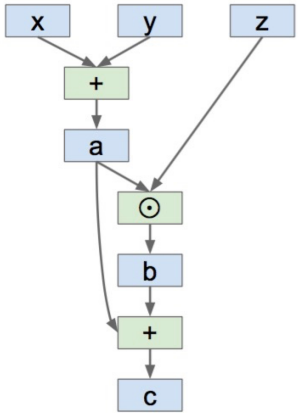
# Computation Graphs

- Computing gradients is hard!
- Automatic differentiation: instrument code to keep track of derivatives

```
x = x * x  ⟶  (x,dx) = (x * x, 2 * x * dx)
```
codegen

- In practice: need other operations, want more control -> use an external computation graph library

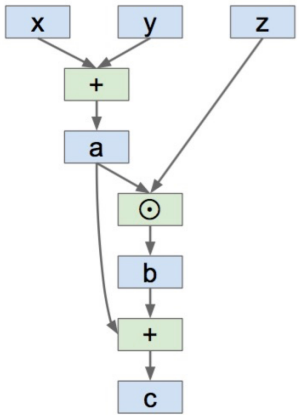
# Computation Graphs




- Define computation abstractly, in terms of symbols
- Can compute gradients of c with respect to (x, y, z) easily
- Useful abstraction: supports both CPU and GPU implementations
- Disadvantage: higher-level specification, so hard to control memory allocation and low-level implementation details

http://tmmse.xyz/content/images/2016/02/theano-computation-graph.png

# Tensorflow




```
x = tf.placeholder("x")
y = tf.placeholder("y")
z = tf.placeholder("z")
a = tf.add(x, y)
b = tf.multiply(a, z)
c = tf.add(b, a)
with tf.Session() as sess:
  output = sess.run([a,c],
         dict_of_input_values)
```

http://tmmse.xyz/content/images/2016/02/theano-computation-graph.png



# Computation Graph: FFNN

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$

```
fx = tf.placeholder(tf.float32, feat_vec_size)
V = tf.get_variable("V", [hidden_size, feat_vec_size])
z = tf.sigmoid(tf.tensordot(V, fx, 1))
W = tf.get_variable("W", [num_classes, hidden_size])
probs = tf.nn.softmax(tf.tensordot(W, z, 1))
```

- placeholder: input to the system; variable: parameter to learn



# Computation Graph: FFNN

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$

```
fx = tf.placeholder(tf.float32, feat_vec_size)
V = tf.get_variable("V", [hidden_size, feat_vec_size])
z = tf.sigmoid(tf.tensordot(V, fx, 1))
W = tf.get_variable("W", [num_classes, hidden_size])
probs = tf.nn.softmax(tf.tensordot(W, z, 1))
label = tf.placeholder(tf.int32, num_classes)
loss = tf.negative(tf.log(tf.tensordot(probs, label, 1)))
```

- Tensorflow can compute gradients for *W* and *V* based on loss
- Shortcut helper methods exist like `tf.nn.softmax_cross_entropy_with_logits`



# Training a Model

Define a computation graph

Define an operator that updates the parameters based on an example

For each epoch:

  For each example:

    Evaluate the training operator on the example

Decode test set

## Batching

- Batching data gives speedups due to more efficient matrix operations, leads to better learning outcomes too
- Need to make the computation graph process a batch at the same time

```
fx = tf.placeholder(tf.float32, [batch_size, feat_vec_size])
V = tf.get_variable("V", [hidden_size, feat_vec_size])
z = tf.sigmoid(tf.tensordot(V, fx, [1,1])) # batch_size x hidden_size
...
loss = [sum over losses from batch]
```

## Batch Training a Model

Define a computation graph to process **a batch of data**

Define an operator that updates the parameters based on a **batch**

For each epoch:

For each **batch**:

Evaluate the training operator on the **batch**

Decode test set in **batches**

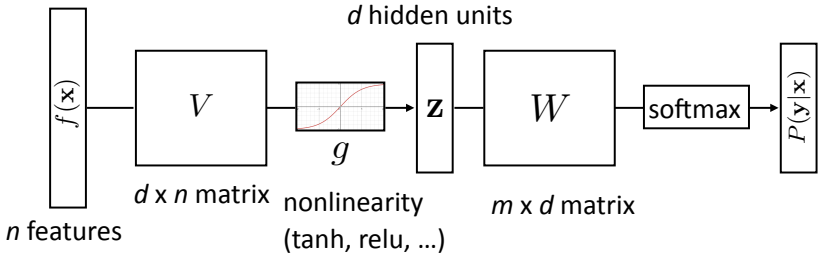
## Training Tips

## Training Basics

- Basic formula: compute gradients on batch, use first-order opt. method
- How to initialize? How to regularize? What optimizer to use?
- This lecture: some practical tricks. Take deep learning or optimization courses to understand this further

## How does initialization affect learning?

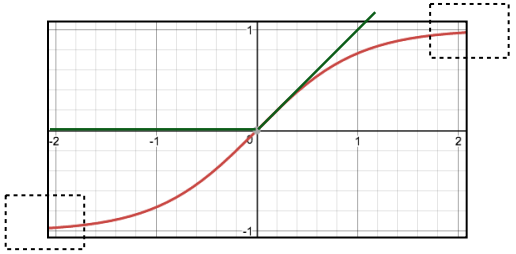
$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(W g(V f(\mathbf{x})))$$




- How do we initialize V and W? What consequences does this have?

## How does initialization affect learning?

- Why is it important to have small activations?



- If cell activations are too large in absolute value, gradients are small too
- ReLU: larger dynamic range (all positive numbers), but can produce big values, can break down if everything is too negative

## Initialization

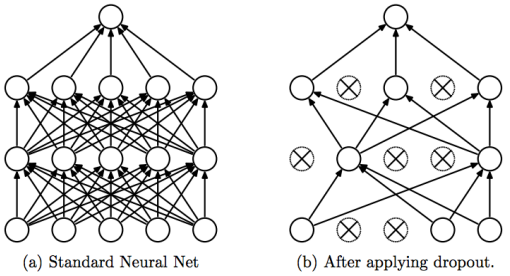
1) Can't use zeroes for parameters to produce hidden layers: all values in that hidden layer are always 0 and have gradients of 0, never change

2) Initialize too large and cells are saturated

- Can do random uniform / normal initialization with appropriate scale
- Glorot initializer: $U\left[-\sqrt{\frac{6}{\text{fan-in} + \text{fan-out}}}, +\sqrt{\frac{6}{\text{fan-in} + \text{fan-out}}}\right]$
  - Want variance of inputs and gradients for each layer to be the same
- Batch normalization (Ioffe and Szegedy, 2015): periodically shift+rescale each layer to have mean 0 and variance 1 over a batch (useful if net is deep)

## Dropout

- Probabilistically zero out parts of the network during training to prevent overfitting, use whole network at test time
- Form of stochastic regularization
- Similar to benefits of ensembling: network needs to be robust to missing signals, so it has redundancy



(a) Standard Neural Net (b) After applying dropout.

Srivastava et al. (2014)

# Dropout

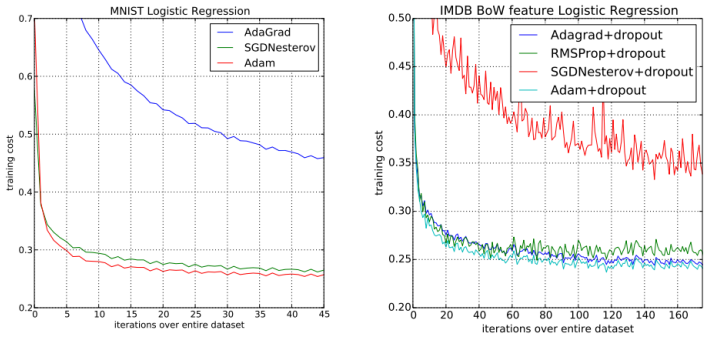
- In tensorflow: implemented as an additional layer in a network

```
hidden_dropped_out = tf.nn.dropout(hidden, dropout_keep_prob)
```

- Often use low dropout (keep a value with probability 0.8) at the input and moderate dropout (keep with probability 0.5) internally in feedforward networks (not in RNNs)

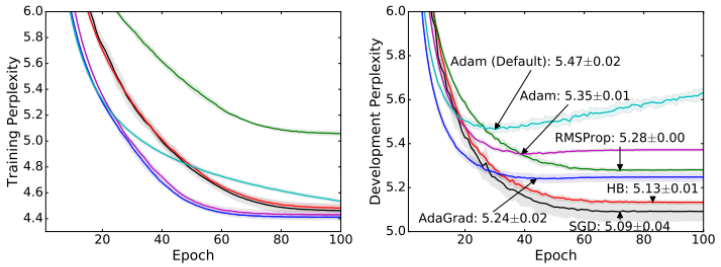
# Optimizer

- Adam (Kingma and Ba, ICLR 2015) is very widely used
- Adaptive step size like Adagrad, incorporates momentum




# Optimizer

- Wilson et al. NIPS 2017: adaptive methods can actually perform badly at test time (Adam is in pink, SGD in black)
- Check dev set periodically, decrease learning rate if not making progress



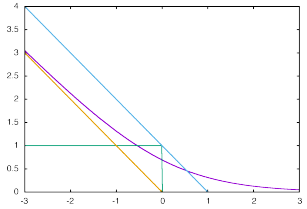

**(e)** Generative Parsing (Training Set) **(f)** Generative Parsing (Development Set)

# Visualization with Tensorboard

- Visualize the computation graph and logs of the objective over time

# Structured Prediction

- Four elements of a structured machine learning method:
- Model: feedforward, RNNs, CNNs can be defined in a uniform framework
- Objective: many loss functions look similar, just changes the last layer of the neural network
- Inference: define the network, Tensorflow takes care of it (mostly…)



- Training: lots of choices for optimization/hyperparameters

# Word Representations

# Word Representations

- Neural networks work very well at continuous data, but words are discrete
- Continuous model <-> expects continuous semantics from input

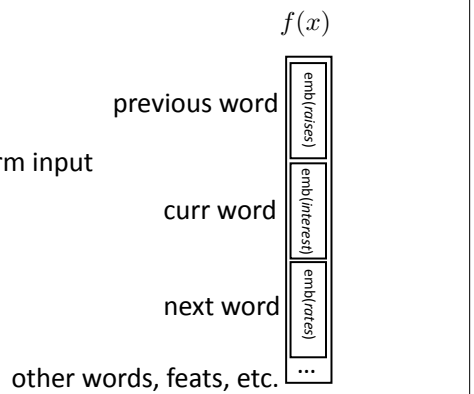
# Word Embeddings

- Part-of-speech tagging with FFNNs

??

*Fed raises* ***interest*** *rates in order to …*

- Word embeddings for each word form input




Botha et al. (2017)

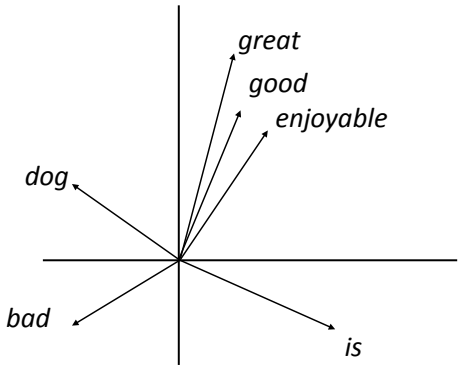
# Word Embeddings

- Want a vector space where similar words have similar embeddings

*the movie was great*

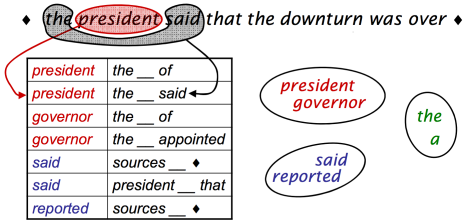
≈

*the movie was good*




# Word Representations

- Neural networks work very well at continuous data, but words are discrete
- Continuous model <-> expects continuous semantics from input
- "Can tell a word by the company it keeps" Firth 1957



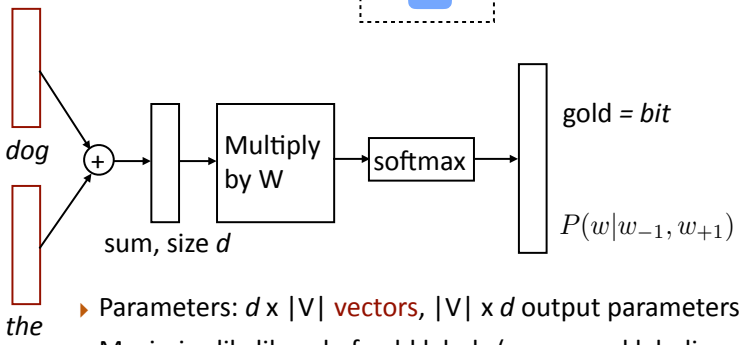

[Finch and Chater 92, Shuetze 93, many others]

# Continuous Bag-of-Words

- Predict word from context

*the dog bit the man*

Mikolov et al. (2013)

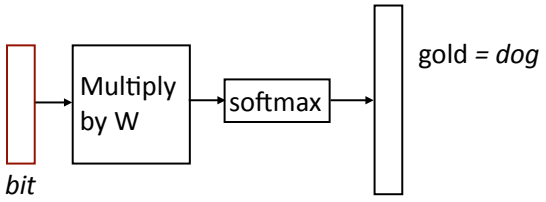



- Parameters: *d* x |V| vectors, |V| x *d* output parameters (W)
- Maximize likelihood of gold labels (no manual labeling required!)

# Skip-Gram

- Predict one word of context from word

*the dog bit the man*




- Another training example: *bit* -> *the*
- Parameters: *d* x |V| vectors, |V| x *d* output parameters (W)

Mikolov et al. (2013)

# Skip-Gram with Negative Sampling

- Problem: want to train on 1B+ words, multiplying by |V| x *d* matrix for each is too expensive

*the dog bit the man*

- Solution: take (word, context) pairs and classify them as "real" or not. Create random negative examples by sampling

(*bit, the*) => +1 (*bit, a*) => -1

(*bit, dog*) => +1 (*bit, fish*) => -1

words in similar contexts select for similar *c* vectors

$$P(\text{pos}|w,c) = \frac{e^{w \cdot c}}{e^{w \cdot c} + 1}$$

- *d* x |V| vectors, *d* x |V| context vectors (same # of params as before)

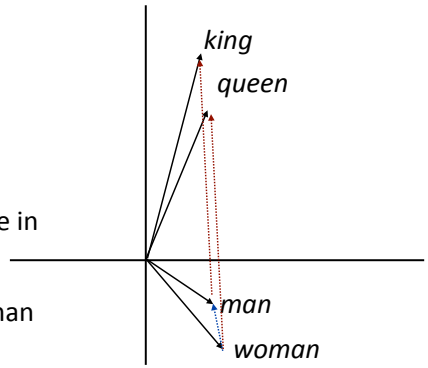
Mikolov et al. (2013)

# Regularities in Vector Space

*(king - man) + woman = queen*

*king + (woman - man) = queen*

- Why would this be?
- woman - man captures the difference in the contexts that these occur in
- Dominant change: more "he" with man and "she" with woman — similar to difference between king and queen




# GloVe

- Word co-occurrences are what matter directly

| Probability and Ratio | *k = solid* | *k = gas* | *k = water* | *k = fashion* |
|---|---|---|---|---|
| $P(k\|ice)$ | $1.9 \times 10^{-4}$ | $6.6 \times 10^{-5}$ | $3.0 \times 10^{-3}$ | $1.7 \times 10^{-5}$ |
| $P(k\|steam)$ | $2.2 \times 10^{-5}$ | $7.8 \times 10^{-4}$ | $2.2 \times 10^{-3}$ | $1.8 \times 10^{-5}$ |
| $P(k\|ice)/P(k\|steam)$ | 8.9 | $8.5 \times 10^{-2}$ | 1.36 | 0.96 |

- Weighted least-squares problem to directly predict word co-occurrence matrix (like matrix factorization)

Pennington et al. (2014)

# Using Word Embeddings

```
# Indexed sentence of length sent_len, e.g.: [12, 36, 47, 8]
input_words = tf.placeholder(tf.int32, [sent_len])
encoder = tf.get_variable("embed", [voc_size, embedding_size])
embedded_input_words = tf.nn.embedding_lookup(encoder, input_words)
# embedded_input_words: sent_len x embedding_size tensor
```

- Approach 1: learn embeddings as parameters from your data
- Approach 2: initialize using GloVe/CBOW/SGNS, keep fixed
  - Faster because no need to update these parameters
- Approach 3: initialize using GloVe/CBOW/SGNS, fine-tune
  - Typically works best

# Takeaways

- Lots to tune with neural networks
  - Training: optimizer, initializer, regularization (dropout), …
  - Hyperparameters: dimensionality of word embeddings, layers, …
- Word vectors: various choices of pre-trained vectors work well as initializers
- Next time: RNNs / LSTMs / GRUs