CS224N: Natural Language Processing with Deep Learning
Winter 2017 Midterm Exam

This examination consists of 13 printed sides, 5 questions, and 100 points. The exam accounts for 17% of your total grade. Please write your answers on the exam paper in the spaces provided. You may use the back of a page if necessary but **please mark this**. You have **80 minutes** to complete the exam. Exams turned in after the end of the examination period will be either penalized or not graded at all. The exam is closed book and allows *only a single page of notes*. You are **not allowed** to: use a phone, laptop/tablet, calculator or spreadsheet, access the internet, communicate with others, or use other programming capabilities. You must disable all networking and radios ("airplane mode").

If you are taking the exam **remotely**, please send us the exam by **Tuesday, February 14 at 5:50 pm PDT** as a scanned PDF copy to `scpd-distribution@lists.stanford.edu`.

Stanford University Honor Code: I attest that I have not given or received aid in this examination, and that I have done my share and taken an active part in seeing to it that others as well as myself uphold the spirit and letter of the Honor Code.

SUNet ID: _____ Signature: _____

Name (printed): _____

Question	Points	Score
Multiple choice	20	
Short questions	24	
Feedforward neural network language models	18	
Autoencoders	18	
Recurrent neural networks	20	
Total:	100	

The standard of academic conduct for Stanford students is as follows:

1. The Honor Code is an undertaking of the students, individually and collectively: a. that they will not give or receive aid in examinations; that they will not give or receive unpermitted aid in class work, in the preparation of reports, or in any other work that is to be used by the instructor as the basis of grading; b. that they will do their share and take an active part in seeing to it that they as well as others uphold the spirit and letter of the Honor Code.

2. The faculty on its part manifests its confidence in the honor of its students by refraining from proctoring examinations and from taking unusual and unreasonable precautions to prevent the forms of dishonesty mentioned above. The faculty will also avoid, as far as practicable, academic procedures that create temptations to violate the Honor Code.

3. While the faculty alone has the right and obligation to set academic requirements, the students and faculty will work together to establish optimal conditions for honorable academic work.

1. Multiple choice (20 points)

For each of the following questions, circle the letter of your choice. *There is only ONE correct choice.* No explanations are required.

(a) (2 points) If your training loss increases with number of epochs, which of the following could be a possible issue with the learning process?

A. Regularization is too low and model is overfitting

B. Regularization is too high and model is underfitting

C. Step size is too large

D. Step size is too small

(b) (2 points) In which of the following cases will there be no update when doing SGD with a max margin loss, $J = \max(0, 1 - s + s_c)$ where s is the true window score and s_c is the corrupt window score?

A. $(s, s_c) = (1, 0.5)$

B. $(s, s_c) = (2, 0.5)$

C. $(s, s_c) = (1, 1.5)$

D. $(s, s_c) = (2, 1.5)$

(c) (2 points) The biggest advantage of neural transition-based dependency parsers over non-neural transition-based dependency parsers is that neural parsers:

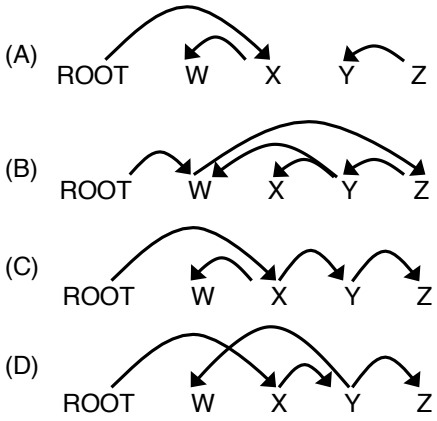
A. Choose transitions using more words in the stack and buffer

B. Generate a larger class of dependency parses

C. Model a grammar whereas traditional parsers do not

D. Rely on dense feature representations

(d) (2 points) Which one of the following is a valid projective dependency parse?



(e) (2 points) We have learned that dense word vectors learned through word2vec or GloVe have many advantages over using sparse one-hot word vectors. Which of the following is NOT an advantage dense vectors have over sparse vectors?

A. Models using dense word vectors generalize better to unseen words than those using sparse vectors.

B. Models using dense word vectors generalize better to rare words than those using sparse vectors.

C. Dense word vectors encode similarity between words while sparse vectors do not.

D. Dense word vectors are easier to include as features in machine learning systems than sparse vectors.

(f) (2 points) Which of the following statements is INCORRECT?

A. Recurrent neural networks can handle a sequence of arbitrary length, while feedforward neural networks can not.

B. Training recurrent neural networks is hard because of vanishing and exploding gradient problems.

C. Gradient clipping is an effective way of solving vanishing gradient problem.

D. Gated recurrent units (GRUs) have fewer parameters than LSTMs.

(g) (2 points) In order for the following Tensorflow code to run, which of the following MUST be contained as keys of `feed_dict`?

```
import tensorflow as tf
W = tf.Variable(tf.random_normal((200, 20)))
b = tf.Variable(tf.zeros((20,)))
x = tf.placeholder(tf.float32, (32, 200))
y = tf.matmul(x, W) + b
prediction = tf.nn.softmax(y)

label = tf.placeholder(tf.float32, (32, 20))
cross_entropy = tf.reduce_mean(-tf.reduce_sum(label * tf.log(
   prediction), reduction_indices=[1]))
train_op = tf.train.GradientDescentOptimizer(0.5).minimize(
   cross_entropy)

sess = tf.Session()
sess.run(tf.initialize_all_variables())
feed_dict = _____________________________
sess.run([prediction], feed_dict=feed_dict)
```

A. `x`, `W`, `b`

B. only `x`

C. only `prediction`

D. `x` and `label`

(h) (2 points) A multi-layer neural network model trained using stochastic gradient descent on the same dataset with different initializations for its parameters is guaranteed to learn the same parameters. A. True B. False

(i) (2 points) If it parses a sentence correctly, a transition-based dependency parser must use a `RIGHT-ARC` transition at least once. A. True B. False

(j) (2 points) Stochastic gradient descent results in a smoother convergence plot (loss vs epochs) as compared to batch gradient descent. A. True B. False

2. Short questions (24 points)

Please write answers to the following questions in a sentence or two. Each part is worth 6 points.

(a) Dependency Parsing

i. (2 points) Can the neural dependency parser we learned in class correctly parse the sentence "John saw a dog yesterday which was a Yorkshire terrier."? Explain.

ii. (2 points) What is the ambiguity in parsing the sentence "There's an awful cost to getting a PhD that no one talks about"?

iii. (2 points) Name at least two types of features that would be helpful to provide as input to a neural dependency parser and explain why.

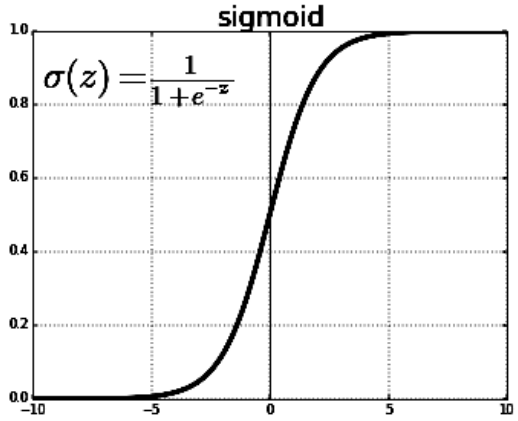
(b) (6 points) Adagrad is a modification to the stochastic gradient descent algorithm used to update parameters. Updates are performed using the following formula:

$$\text{cache}_i = \text{cache}_i + (\nabla_{\theta_i} L)^2$$
$$\theta_i = \theta_i - \eta \nabla_{\theta_i} L / (\sqrt{\text{cache}_i} + \epsilon)$$

where θ_i is the parameter to be updated, $\nabla_{\theta_i} L$ is the gradient of the loss (cost) with respect to θ_i, ϵ is a hyperparameter usually between 10^{-8} and 10^{-4} and η is a hyperparameter similar to step size in SGD. cache_i is initialized to zero at the start of the algorithm.

(i) State two differences between AdaGrad and SGD in terms of step size and (ii) describe what effect they would have.

(c) Consider the sigmoid activation function below:

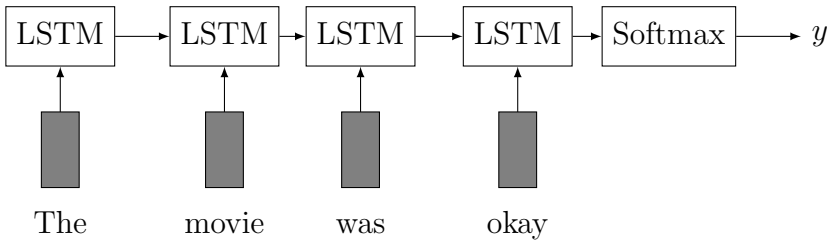


i. (2 points) What would the gradient of the sigmoid be with respect to an input that is very large?

ii. (2 points) Why might this be a problem for training neural networks?

iii. (2 points) How does the ReLU activation $\text{ReLU}(z) = \max(0, z)$ solve this problem?

(d) A popular model used for sentiment classification is an LSTM model:



This model inputs word vectors to the LSTM model at each time step and uses the last hidden state vector to predict the sentiment label (y).

Recall that in assignment 1 we used a simple "bag-of-vectors" model for sentiment classification: we used the average of all the word vectors in a sentence to predict the sentiment label.

i. (3 points) Name at least one benefit of the LSTM model over the bag-of-vectors model.

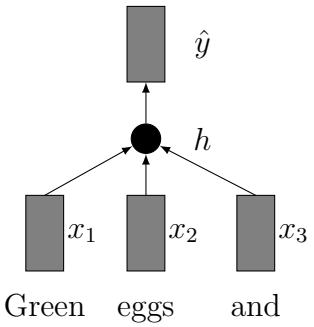
ii. (3 points) If we chose to update our word vectors when training the LSTM model on sentiment classification data, how would these word vectors differ from ones not updated during training? Explain with an example. Assume that the word vectors of the LSTM model were initialized using GloVe or word2vec.

3. Feedforward neural network language models (18 points)

A feedforward neural network language model (NNLM) can be used as another architecture for training word vectors. This model tries to predict a word given the N words that precede it. To do so, we concatenate the word vectors of N previous words and send them through a single hidden layer of size H with a tanh nonlinearity and use a

softmax layer to make a prediction of the current word. The size of the vocabulary is V. The model is trained using a cross entropy loss for the current word.

Let the word vectors of the N previous words be $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N$, each a column vector of dimension D, and let $\mathbf{y}$ be the one-hot vector for the current word. The network is specified by the equations below:



$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_N \end{bmatrix}$$

$$\mathbf{h} = \tanh(W\mathbf{x} + \mathbf{b})$$

$$\hat{\mathbf{y}} = \text{softmax}(U\mathbf{h} + \mathbf{d})$$

$$J = \text{CE}(\mathbf{y}, \hat{\mathbf{y}})$$

$$CE = -\sum_i y_i \log(\hat{y}_i).$$

The dimensions of our parameters and variables are $\mathbf{x} \in \mathbb{R}^{(N \cdot D)}, W \in \mathbb{R}^{H \times (N \cdot D)}, \mathbf{b} \in \mathbb{R}^H, \mathbf{h} \in \mathbb{R}^H, U \in \mathbb{R}^{V \times H}, \mathbf{d} \in \mathbb{R}^V, \hat{\mathbf{y}} \in \mathbb{R}^V$.

(a) (4 points) State two important differences between NNLM the CBOW model we learned in class. Explain how each might affect the word vectors learned.

(b) i. (3 points) What is the complexity of forward propagation in an NNLM for a *single* training example?

ii. (3 points) Describe at least one way to change the model that would reduce this complexity.

(c) (8 points) What is the gradient of J with respect to $\mathbf{x}$, $\frac{\partial J}{\partial \mathbf{x}}$? Hint: $\tanh(z)' = 1 - \tanh(z)^2$.

4. Autoencoders (18 points)

In class, we've learned that one way to combine word vectors is to simply add them together. In this question, we'll explore another approach: using an autoencoder.

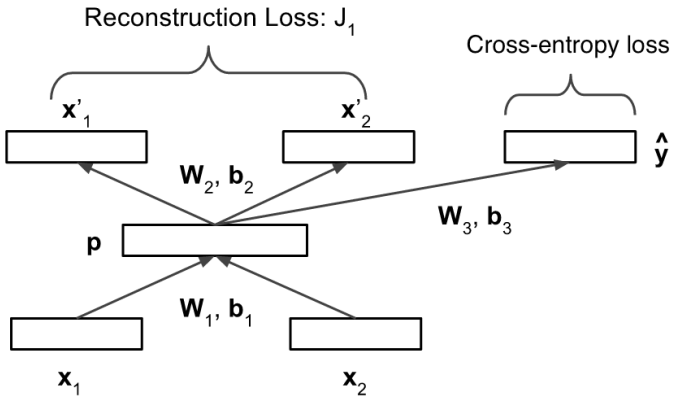


Figure 2: Illustration of an autoencoder unit to combine two vectors

In the autoencoder, two input word vectors $\mathbf{x}_1, \mathbf{x}_2 \in \mathbb{R}^{D_x \times 1}$ are first concatenated into a

single vector $\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{bmatrix} \in \mathbb{R}^{2D_x \times 1}$, and the parent vector $\mathbf{p}$ can be computed as:

$$\mathbf{p} = \text{ReLU}(W_1\mathbf{x} + \mathbf{b}_1) \quad \in \mathbb{R}^{D_p \times 1} \qquad\qquad \text{ReLU}(x) = \max(0, x),$$

where W_1 can be decomposed as:

$$W_1 = \begin{bmatrix} W_{11} & W_{12} \end{bmatrix} \qquad\qquad W_1\mathbf{x} = W_{11}\mathbf{x}_1 + W_{12}\mathbf{x}_2.$$

During training, we use the parent vector $\mathbf{p}$ to *reconstruct the input vectors*:

$$\mathbf{x}' = \begin{bmatrix} \mathbf{x}'_1 \\ \mathbf{x}'_2 \end{bmatrix} = W_2\mathbf{p} + \mathbf{b}_2 \quad \in \mathbb{R}^{2D_x \times 1}$$

where $\mathbf{x}'_1, \mathbf{x}'_2 \in \mathbb{R}^{D_x \times 1}$ are the reconstructions. Correspondingly, a *reconstruction loss* that computes the Euclidean distance between inputs and reconstructions is used during training:

$$J_1 = \frac{1}{2}||\mathbf{x}' - \mathbf{x}||^2 \quad \in \mathbb{R}.$$

For sentiment classification, the parent vector is used to predict a sentiment class $\hat{\mathbf{y}}$ for the pair of the input words:

$$\hat{\mathbf{y}} = W_3\mathbf{p} + \mathbf{b}_3 \quad \in \mathbb{R}^{D_c \times 1},$$

where $D_c = 3$ is the number of sentiment classes ('positive', 'neutral' and 'negative'). Here, the network is also trained using a cross-entropy loss:

$$J_2 = CE(\mathbf{y}, \hat{\mathbf{y}}) \quad \in \mathbb{R},$$

where $\mathbf{y} \in \mathbb{R}^{D_c \times 1}$ is the one-hot label vector with $\mathbf{y}_k = 1$.

In total, the network is trained using the loss $J = J_1 + J_2$.

(a) (2 points) Give at least one example of how the sentiment predictions made by an autoencoder model would differ from one made using a bag-of-vectors model like the one in assignment 1.

(b) (2 points) How do the reconstructed vectors and reconstruction loss help in learning the parent representation?

(c) (2 points) i. What is the shape of each weight and bias term: $W_1, W_2, W_3, \mathbf{b}_1, \mathbf{b}_2, \mathbf{b}_3$?
ii. How many parameters does the model have in total?

(d) Compute the following gradients for the *reconstruction loss*:
Hint: You can use the following notation

$$\mathbb{1}\{x > 0\} = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$

Using it on a matrix would perform an element-wise operation, e.g.

$$\mathbb{1}\left\{\begin{bmatrix} 1 & 0 \\ -1 & 3 \end{bmatrix} > 0\right\} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

i. (2 points) $\delta_1 = \frac{\partial J_1}{\partial \mathbf{p}} =$ _____

ii. (2 points) $\delta_2 = \frac{\partial J_1}{\partial \mathbf{h}} =$ _____ (where $\mathbf{h} \stackrel{\text{def}}{=} W_1\mathbf{x} + \mathbf{b}_1$)

iii. (2 points) $\frac{\partial J_1}{\partial W_1} =$ _____

iv. (2 points) $\frac{\partial J_1}{\partial \mathbf{b}_1} =$ _____

v. (2 points) $\frac{\partial J_1}{\partial \mathbf{x}_1} =$ _____

You can use the space below as scratch space.

(e) (2 points) How would you construct a network using *only* copies of the autoencoder above to predict a sentiment label for a whole sentence, not just a pair of words? Remember that each sentence could be of arbitrary length.

5. Recurrent neural networks (20 points)

Recall that a recurrent neural network (RNN) takes in an input vector x_t and a state vector h_{t-1} and returns a new state vector h_t and an output vector y_t:

$$h_t = f(w_1 x_t + w_2 h_{t-1} + b_2)$$
$$y_t = g(w_3 h_t + b_3),$$

where f and g are activations functions.

(a) (8 points) The following diagram depicts a single RNN unit, where x_t, h_{t-1}, h_t and y_t are all scalars, as a state machine:

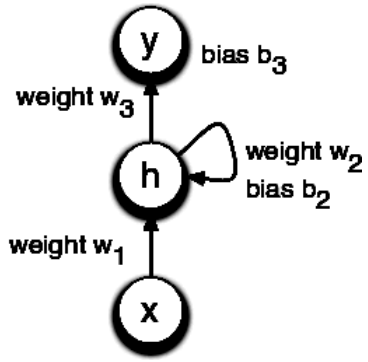
$w_1 =$ _____

$w_2 =$ _____

$b_2 =$ _____

$w_3 =$ _____

$b_3 =$ _____



Suppose that f is a binary threshold unit and g is a linear unit:

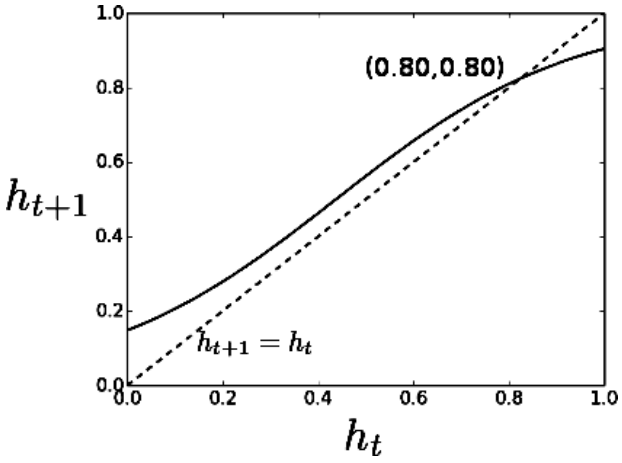
$$f(x) = \begin{cases} 0 & \text{if } x < 0 \\ 1 & \text{if } x \geq 0 \end{cases}$$
$$g(x) = x.$$

Fill in weights (w_1, w_2, w_3), biases (b_1, b_2) so that the RNN initially outputs 0, but as soon as it receives an input of 1, it switches to outputting 1 for all subsequent time steps. For instance, the input 0001010 produces the output 0001111. The hidden unit has an initial value of 0.

You don't need to provide an explanation, but doing so may help you receive partial credit.

Hint: In one possible solution, the hidden unit has an activation $h_t = 0$ until there's an input $x_t = 1$, at which point it switches to maintaining an activation of 1 forever. The output unit always predicts the same as the hidden unit, i.e. $y_t = h_t$.

(b) Now suppose that f is a sigmoid unit and that the input is always 0. The following diagram shows how the next state h_{t+1} changes with the current state h_t when $w_2 = 3$ and $b_2 = -1$, i.e. $h_{t+1} = \sigma(3h_t - 1)$. The diagram also shows that $h_{t+1} = h_t$ when $h_t = 0.80$.



i. (2 points) Would h_{t+1} be greater than or less than h_t if $h_t = 0.5$? _____

ii. (2 points) Would h_{t+1} be greater than or less than h_t if $h_t = 0.9$? _____

iii. (2 points) What would h_{t+1} look like as we take increasingly longer sequences, i.e. $t \to \infty$?

iv. (1 point) For what range of initial values h_0, would this network experience exploding gradients for long sequences? _____

v. (1 point) For what range of initial values h_0, would this network experience vanishing gradients for long sequences? _____

vi. (4 points) We have learned in class that ReLUs are good at preserving gradients in deep neural networks. Would it be wise to replace the sigmoid activation above with a ReLU activation unit? Explain.