CSE 493 G1/ 599 G1
Deep Learning
Spring 2025 Practice Exam

May 15, 2025

Full Name: ____________________________________

UW Net ID: ____________________________________

Question	Score
True/False (20 pts)	
Multiple Choice (40 pts)	
Backpropagation (20 pts)	
Convolution & Pooling (20 pts)	
Total (100 pts)	

Welcome to the CSE 493 G1 Exam!

- The exam is 80 min and is **double-sided**.
- No electronic devices are allowed.

I understand and agree to uphold the University of Washington Honor Code during this exam.

Signature: ____________________ Date: ______________

Good luck!

This page is left blank for scratch work only. DO NOT write your answers here.

1 True / False (20 points)

Fill in the circle next to True or False, or fill in neither. Fill it in completely like this: ●. No explanations are required.

Scoring: Correct answer is worth 2 points. To discourage guessing, incorrect answers are worth -1 points. Leaving a question blank will give 0 points.

1.1 Training on higher-level image features (e.g. color histograms or Histogram of Gradient features) instead of raw pixels improves image classification accuracy across all types of models.
○ True
○ False

1.2 If your datapoints are linearly separable, then training a linear classifier with a Softmax loss and no regularization will achieve zero training loss at convergence.
○ True
○ False

1.3 During training, you examine the loss curve, and you notice that your training loss is plateauing out very early at a high value. One valid method to try is to increase the learning rate.
○ True
○ False

1.4 If the loss function is convex, Stochastic Gradient Descent always reaches the global minimum.
○ True
○ False

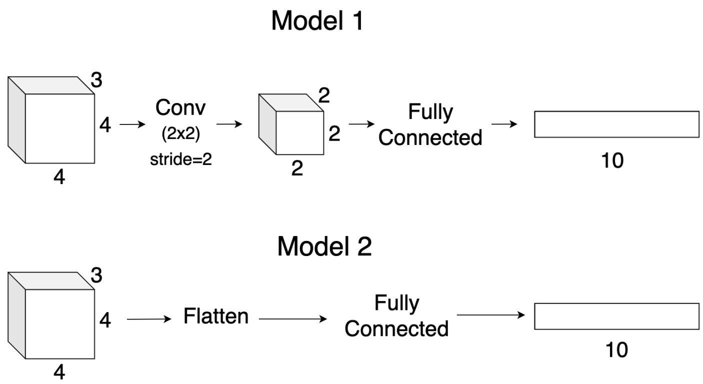
1.5 Unlike the sigmoid activation function, tanh does not suffer from vanishing gradients.
○ True
○ False

1.6 A convolutional layer can express any function a fully connected layer can express.
○ True
○ False

1.7 If Model A has a lower test loss on a dataset than Model B, then Model A must have a higher accuracy on the test dataset than Model B.
○ True
○ False

1.8 Consider a fully connected layer $\mathbf{W}$ just before a ReLU function in a network. If an element $w_{i,j}$ of the weight matrix $\mathbf{W}$ has a negative value then the gradient of the loss with respect to this weight is guaranteed to be zero.
○ True
○ False

1.9 Consider 2 models which take as input an image of dimensions $4 \times 4 \times 3$ and output scores over 10 classes. Model 1 is made up of 1 convolution and 1 fully connected layer. Model 2 is made up of 1 fully connected layer. All input and output dimensions are noted in the figure above. Assert the following statement: Model 1 has more parameters than Model 2.



◯ True

◯ False

1.10 You train one model with L2 regularization (model A) and one without (model B). The weights of model A will most likely be smaller in magnitude than those of model B.

◯ True

◯ False

2 Multiple Choices (40 points)

Fill in the circle next to the letter(s) of your choice (like this: ●). No explanations are required. **Choose ALL options that apply.**

Each question is worth 5 points and the answer may contain one or more options. Selecting all of the correct options and none of the incorrect options will get full credits. For questions with multiple correct options, each incorrect or missing selection gets a 2.5-point deduction (up to 5 points).

2.1 Which of the following statements are correct about kNN and Linear SVM?

◯ A: kNN has less runtime complexity than linear SVM during test-time.

◯ B: kNN often works better than linear SVM for highly nonlinear data.

◯ C: kNN does not require high memory for storing data, while linear SVM does.

◯ D: In kNN, a larger k results in a smoother classification boundary.

◯ E: None of the above.

2.2 Given the two-layer-network $s(x) = W_2 f(W_1 x + b_1) + b_2$ with $W_1 \in \mathbb{R}^{H\times D}, W_2 \in \mathbb{R}^{C\times H}$, which of the following statements about $f(x)$ are correct?

◯ A: Choosing $f(x)$ to be an additional layer $f(x) = W_f x + b_f$, where $W_f \in \mathbb{R}^{H\times H}$, will increase the model's tendency to overfit on the training data compared to $f(x) = \text{ReLU}(x)$.

◯ B: Choosing $f(x)$ to be an additional layer $f(x) = W_f x + b_f$, where $W_f \in \mathbb{R}^{H\times H}$, will likely increase the training accuracy compared to $f(x) = x$ (no activation).

◯ C: Using $f(x) = \text{ReLU}(-x)$ to train and test our network will lead to a much lower accuracy than $f(x) = \text{ReLU}(x)$.

◯ D: Choosing $f(x) = \text{LeakyReLU}(x)$ might introduce the vanishing gradient problem to our network.

◯ E: Choosing $f(x) = \text{ReLU}(x^3)$ helps the network train better than $f(x) = \text{ReLU}(x)$.

◯ F: None of the above.

2.3 Assume an input feature map has a shape of (W_i, H_i, C_i) (where $W_i > 10, H_i > 10$), select all layers that are able to reduce the width and height dimension of the output feature map?

◯ A: 1×1 convolution layer with stride 1

◯ B: Average-pooling layer with stride 2

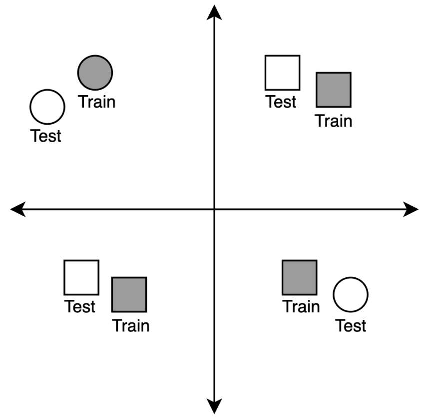
◯ C: Convolution layer with kernel size 3×3, padding 1, stride 1

◯ D: Batch normalization layer

◯ E: Convolution layer with kernel size 5×5, padding 2, stride 2

◯ F: None of the above

2.4 Consider the dataset pictured below. The features of each datapoint are given by its position. So the datapoint (0,1) appears at position (0,1). The ground truth label of the datapoint is given by its shape, either circle or square. You have a test set of datapoints, shown with no fill, and a train set of data, shown with a grey fill. Which of the following statements are true about classifying this data?



- A: It is possible for a linear SVM to have 100% train accuracy
- B: It is possible for a linear SVM to have 100% test accuracy
- C: KNN with K=1 has higher test accuracy than with K=4
- D: KNN with K=1 has higher train accuracy than with K=4
- E: None of the above

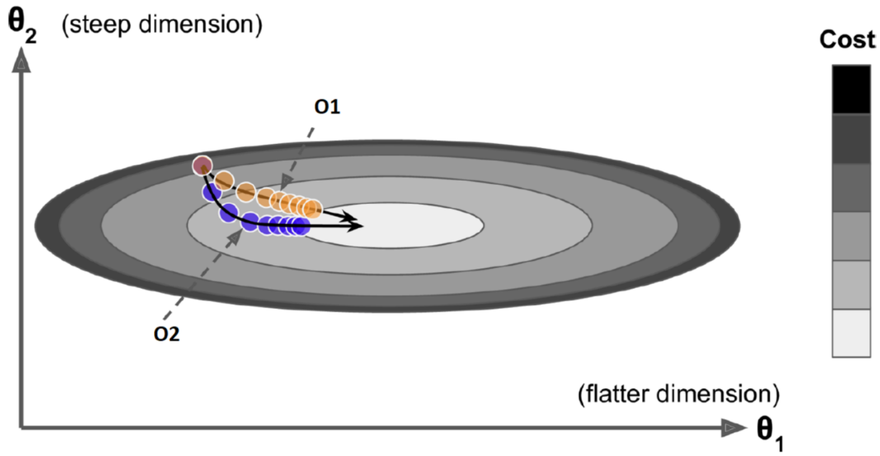
2.5 Let x be some image with ground truth label y for a classification problem between K classes. Let s_j denote a network's score for for class j. Consider the modified version of cross-entropy loss where we have variables a, b and c.

$$\mathcal{L}(x) = -\log\left(\frac{a \cdot e^{b \cdot s_y}}{\sum_{j=1}^{K} e^{s_j}}\right) + c$$

Now let $\frac{\partial \mathcal{L}}{\partial w}$ denote the gradient of the loss with respect to the final layer in the network. Which of the following is true about the relationship between $\frac{\partial \mathcal{L}}{\partial w}$, a, b, and c.

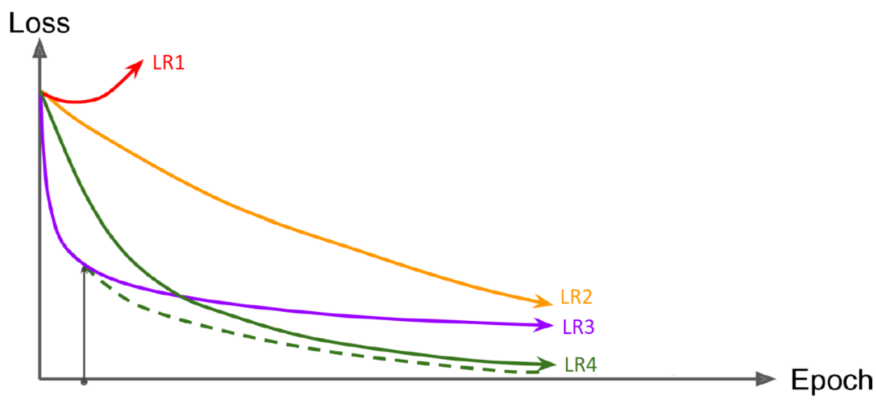
- A: Increasing a could increase $\frac{\partial \mathcal{L}}{\partial w}$.
- B: Decreasing a could increase $\frac{\partial \mathcal{L}}{\partial w}$.
- C: Increasing b could increase $\frac{\partial \mathcal{L}}{\partial w}$.
- D: Decreasing b could increase $\frac{\partial \mathcal{L}}{\partial w}$.
- E: Increasing c could increase $\frac{\partial \mathcal{L}}{\partial w}$.
- F: Decreasing c could increase $\frac{\partial \mathcal{L}}{\partial w}$.

2.6 The figure below compares AdaGrad and Gradient Descent(without momentum) optimization. Which of the following is/are true?



- ◯ A: O1 corresponds to AdaGrad while O2 corresponds to Gradient Descent
- ◯ B: O1 corresponds to Gradient Descent while O2 corresponds to AdaGrad
- ◯ C: O1 helps point the resulting updates more directly toward the global optimum compared to O2
- ◯ D: O2 helps point the resulting updates more directly toward the global optimum compared to O1

2.7 The below figure shows learning curves for various learning rates. What is the correct order of learning rates?



- ◯ A: $LR1 > LR2 > LR3 > LR4$
- ◯ B: $LR2 > LR3 > LR1 > LR4$
- ◯ C: $LR1 > LR3 > LR4 > LR2$
- ◯ D: $LR3 > LR1 > LR2 > LR4$

2.8 Your notice your vanilla RNN has a vanishing gradient problem. Which one(s) of the following methods can help?

- ◯ A: Use gradient clipping
- ◯ B: Add more RNN layers.
- ◯ C: Add more training data.
- ◯ D: Replace vanilla RNN with LSTM or GRU.

3 Backpropagation (20 points)

Please make sure to write your answer only in the provided space.

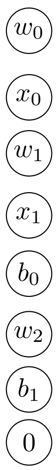
Consider the following function:

$$f(x_0, x_1, w_0, w_1, w_2, b_0, b_1) = max(w_2 \times (w_0 \times x_0 + w_1 \times x_1 + b_0) + b_1, 0)$$

1. (4 points) Having a computation graph for computing the function f would help you solve the rest of this question. We already give you all the input bubbles as follows. Finish the computation graph and label each edge with the values produced during the forward pass. The input values are:

$$w_0 = -1, w_1 = 3, w_2 = 4, x_0 = -3, x_1 = 2, b_0 = -8, b_1 = 1$$

.



2. (12 points) Let function g represent the computation that is done at a node of the computation graph for f. At the computation node for g, we receive upstream gradient $\frac{\partial f}{\partial g}$. Show that the following patterns in gradient flow hold.

(a) Let $g(x, y) = x + y$. Show that g is a gradient "distributor" for $\frac{\partial f}{\partial g}$, i.e. show

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial g} \quad \text{and} \quad \frac{\partial f}{\partial y} = \frac{\partial f}{\partial g}.$$

(b) Let $g(x, y) = x \times y$. Show that g is a gradient "swap multiplier", i.e. show

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial g} \cdot y \quad \text{and} \quad \frac{\partial f}{\partial y} = \frac{\partial f}{\partial g} \cdot x.$$

(c) Let $g(x, y) = max(x, y)$. Show that g is a gradient "router", i.e. show

$$\frac{\partial f}{\partial x} = \begin{cases} \frac{\partial f}{\partial g} & \text{if } x \geq y \\ 0 & \text{otherwise} \end{cases} \quad \text{and} \quad \frac{\partial f}{\partial y} = \begin{cases} \frac{\partial f}{\partial g} & \text{if } y \geq x \\ 0 & \text{otherwise} \end{cases}.$$

3. (4 points) Compute the following gradients corresponding to function f and values of the inputs given in part 1.

(a) $\dfrac{\partial f}{\partial w_0} =$

(b) $\dfrac{\partial f}{\partial w_1} =$

(c) $\dfrac{\partial f}{\partial b_0} =$

(d) $\dfrac{\partial f}{\partial b_1} =$

4 Convolution & Pooling (20 points)

Please make sure to write your answer only in the provided space.

We have previously seen 2D convolution networks being successfully used on image data. Video data are essentially temporal series of images, where each video as an input has dimensions (channels C, time T, height H, width W).

In this problem, we look at 3D convolutions for video data, where the convolution happens not only spatially but also temporally. 3D convolution operates on 4 dimensional input tensors of size $C \times T \times H \times W$ with 3D kernels, in contrast to the 2D case where we have input size $C \times H \times W$ and 2D kernels.

1. (8 points) Consider a 3D convolutional network with its layers specified in table 1. For each layer, fill in the table with the size of the activation volumes, and the number of weight and bias parameters. The INPUT layer is provided; this network takes in 8 frames of 64-by-64 pixel RGB images.
Please write your answer as a multiplication (e.g. 128 × 128 × 128) or points may deducted.
The layer descriptions are as follows:

- CONV3-N-p1-s2 is a convolutional layer with N 3 × 3 × 3 kernels, padding 1 and stride 2 (in height, width, and temporal dimension) with ReLU activation. Similarly, CONV5-N-p2-s1 is a convolutional layer with N 5 × 5 × 5 kernels, padding 2 and stride 1.
- POOL2 denotes a 2 × 2 × 2 max-pooling layer, with stride 2 and no padding in all dimensions.
- FC-N denotes a fully-connected layer with N neurons, with ReLU activation.

Layer	Activation Volume Dimensions	# Weights	# Biases
INPUT	3 × 8 × 64 × 64	N/A	N/A
CONV5-16-p2-s1			
POOL2			
CONV3-16-p1-s1			
POOL2			
CONV3-32-p1-s2			
FC-256			
FC-10			

Table 1: Dimensions and parameters.

2. (4 points) In a 3D convolutional network we can define *spatiotemporal batch normalization* similarly to operate on a batch of 4D feature maps of shape $N \times C \times T \times H \times W$, normalizing over the N, T, H, and W dimensions. If we now add one spatiotemporal Batch Normalization (BN) after each convolution layer, how many additional parameters will be introduced? Please put your answers in Table 2.

Layer	# BN parameters
CONV5-16-p2-s1	
CONV3-16-p1-s1	
CONV3-32-p1-s2	

Table 2: Number of BN parameters.

3. (4 points) 3D convolution network is computationally more expensive than its 2D counterpart. Assuming convolutions are implemented as matrix multiplications[1], let's analyze the computational complexity of convolutions in terms of the number of floating point multiplications they perform.

First calculate the complexity of 2D convolution, and then generalize to 3D convolution. Please write your answer as a multiplication (e.g. $128 \times 128 \times 128$) in Table 3.

Input tensor dimension	Convolutional layer type	# floating point multiplication
$3 \times 64 \times 64$	2D Conv, N=16, kernel=3×3, pad=1, stride=1	
$3 \times 64 \times 64$	2D Conv, N=32, kernel=5×5, pad=2, stride=1	
$3 \times 8 \times 64 \times 64$	3D Conv, N=32, kernel=$5\times5\times5$, pad=2, stride=1	

Table 3: Computation costs.

4. (4 points) There are three ways to learn feature vectors for video inputs:

(a) 3D convolution as we introduced above.

(b) 2D convolution computes one feature vector for each frame independently, and stacks them together.

(c) 2D convolution computes one feature vector for each frame independently, and feeds the sequence of feature vectors to an LSTM.

If your input are long videos (e.g. with more than 100 frames), which of the 3 models above would you choose? Please rank them from the best temporal feature to the worst temporal feature, and explain why. (Hint: compare the temporal receptive field of the 3 models. You don't need to consider the computation efficiency here.)

[1] Fun fact: there exist alternative ways of computing convolutions such as Fast Fourier Transform / Winograd convolutions, but don't consider them for this problem.