CS230: Deep Learning

Winter Quarter 2020
Stanford University

Midterm Examination

180 minutes

	Problem	Full Points	Your Score
1	Neural Network	12	
2	Loss Functions	12	
3	Optimization	11	
4	Batch Normalization	9	
5	DL Strategy	4	
6	Adversarial Attacks and GANs	6	
7	CNNs	6	
Total		60	

The exam contains 20 pages including this cover page.

- This exam is **closed book i.e. no laptops, notes, textbooks, etc. during the exam**. However, you may use one A4 sheet (front and back) of notes as reference.

Name: ____

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The 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.

Signature: ________________________________

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Question 1 (Neural Network, 12 points)

You want to build a model to predict whether a startup will raise funding (label = 1) or not (label = 0) in its first year. You have access to a dataset of examples with 300 input features, including the number of founders, the number of employees, the variance in the age of the employees, etc. As a baseline model, you decide to train a logistic regression that outputs a probability $\hat{y}^{(i)} \in [0, 1]$ that a startup described by a vector of features $x^{(i)}$ raises funding in its first year, where the predicted label of an input is chosen to be 1 when $\hat{y}^{(i)} \geq 0.5$ and 0 otherwise.

(a) **(1 point)** If the shape of $x^{(i)}$ is $(n_x, 1)$, what should n_x be? (1 word)

(b) **(2 points)** A logistic regression has trainable weights w and bias b.

(i) How many weights does the logistic regression model have? (1 word)

(ii) What is the dimension of b? (1 word)

(c) **(2 points)** Consider the prediction $\hat{y}^{(i)} \in [0, 1]$.

(i) What is the dimension of $\hat{y}^{(i)}$? (1 word)

(ii) Write the output $\hat{y}^{(i)}$ in terms of the input $x^{(i)}$ and the parameters w and b. (1 formula)

After training your baseline logistic regression model, you decide to train a single hidden layer neural network with 80 hidden neurons on the same dataset.

(d) **(2 points)** How many weights and biases does this neural network have? (2 sentences)

(e) **(1 point)** Recall that a neural network with a single hidden layer is sufficient to approximate any continuous function (with some assumptions on the activation). Why would you use neural networks with multiple layers? (1 sentence)

(f) **(3 point)** While you remembered to use a sigmoid activation in your neural network's output layer, you forgot to use intermediate non-linear activations. In this part, you will demonstrate that your implementation is equivalent to logistic regression.

Let $W^{[l]}$ and $b^{[l]}$ denote the weights and biases respectively of your neural network at layer l, starting at $l = 1$.

(i) Let $\hat{y}^{(i)}$ represent the output probability of your neural network given a feature vector $x^{(i)}$ as input. Write an expression for $\hat{y}^{(i)}$ in terms of $x^{(i)}$ and the neural network parameters. (1 formula)

(ii) There exists a single logistic regression model with weights w' and bias b' that outputs the same probability that your neural network does for all possible inputs. Write the parameters w' and b' of this logistic regression model in terms of your neural network parameters. (2 equations, one for w', and one for b')

(g) **(1 point)** You decide to use ReLU as your hidden layer activation, and also insert a ReLU before the sigmoid activation such that $\hat{y} = \sigma(\text{ReLU}(z))$, where z is the pre-activation value for the output layer. What problem are you going to encounter? (1 sentence)

Question 2 (Loss Functions, 12 points)

Many supermarket customers use the yellow creamy spot on the outside of a watermelon to evaluate its level of sweetness. To help customers who aren't aware of this fact, you decide to build an image classifier to predict whether a watermelon is sweet (label=1) or not (label=0).

(a) **(1 point)** You've built your own labeled dataset, chosen a neural network architecture, and are thinking about using the mean squared error (MSE) loss to optimize model parameters. Give one reason why MSE might not be a good choice for your loss function. (1 sentence)

(b) **(1 point)** You decide to use the binary cross-entropy (BCE) loss to optimize your network. Write down the formula for this loss (for a single example) in terms of the label y and prediction $\hat{y}$. (1 formula)

(c) **(1 point)** You want to sanity-check your implementation of the BCE loss. What value does the loss take for a prediction of $\hat{y} = 0.9$ on a negative ($y = 0$) example. *You can simply fill in the formula with the numbers, without needing to calculate it.* (1 formula)

(d) **(3 points)** Compute the total cost, J, of the network averaged across the following dataset of 3 examples using the binary cross entropy loss. $Y^T = (1, 0, 0)$, and $\hat{Y}^T = (0.1, 0.2, 0.7)$. *You can simply fill in the formula, without needing to simplify it. There is no penalty on the weights.* (1 formula)

(e) **(3 points)** You add L2 regularization to your loss function.

(i) For a particular trainable weight W, write the update formula for W when the standard gradient descent optimizer is used with L2 regularization. Write your answer in terms of the learning rate α, L2 regularization hyperparameter λ, and the binary cross entropy cost function J_{BCE}. (1 formula)

(ii) You decide to train one model with L2 regularization (model A) and one without (model B). How would you expect model A's weights to compare to model B's weights? (1 sentence)

(iii) Explain one difference between L1 and L2 regularization. (1 sentence)

The price of a watermelon depends on its weight, rather than its level of sweetness. Thus supermarkets don't care about a watermelon's level of sweetness as much as customers do.

Supermarkets give you a new dataset of watermelon images and their corresponding weight in pounds, and ask you to build another image classifier to predict the weight of a watermelon.

(f) **(1 point)** What is one advantage to reusing the weights of your previous sweetness classifier on the new task? (1-2 sentences)

(g) **(2 point)** You decide to use a single unified neural network to predict both the level of sweetness and the weight of a watermelon given an image.

(i) Write down the dimension of a new label y for the new network. (1 word)

(ii) Propose a new loss function to train the unified model. Assume no regularization and write your answer in terms of the new y and $\hat{y}$. (1 formula)

Question 3 (Optimization, 11 points)

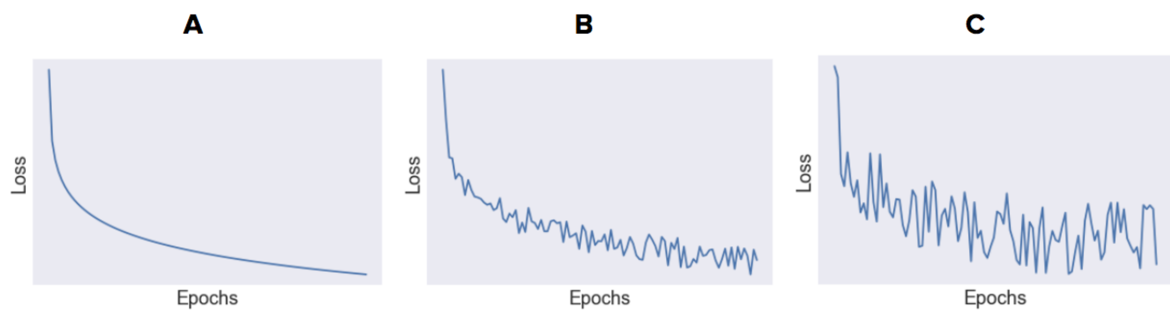
You want to build a classifier that predicts the musical instrument given an audio clip. There are 50 unique types of instruments, and you've collected a dataset of sounds of each, first collecting audio clips of guitars, then clips of violins, and so on for all the different instruments.

(a) **(1 point)** You use batch gradient descent (BGD) to optimize your loss function, but you have been getting poor training loss. You search your code for potential bugs and realize that you're not shuffling the training data. Would shuffling the training fix this problem? Explain your reasoning. (1-2 sentences)

(b) **(1 point)** You are deciding whether you should optimize your network parameters using mini-batch gradient descent (MBGD) or stochastic gradient descent (SGD) (i.e. batch size of 1). Give one reason to choose MBGD over SGD. (1-2 sentences)

(c) **(1 point)** Give one reason to use MBGD over BGD. (1-2 sentences)

(d) **(1 point)** Label the training loss curves A, B, and C with whether they were likely generated with SGD, MBGD, or BGD *(select one for each)*.



(e) **(2 points)** You decide to tune your model's learning rate.

(i) What is one typical sign of a learning rate being too large? (1 sentence)

(ii) What is one typical sign of a learning rate being too small? (1 sentence)

(f) **(2 points)** You now decide to use gradient descent with momentum.

(i) For gradient descent with momentum, write down the update rule for a particular trainable weight W. Use learning rate α and momentum hyperparameter β, and let J denote the cost function. (2 equations)

(ii) Explain how momentum speeds up learning compared to standard gradient descent. (1 sentence)

(g) **(3 points)** The code below is meant to implement a single step of the training loop using the Adam optimizer, but some parts are missing. Finish the implementation of each line marked TODO. Recall the parameter update equations for Adam optimization:

$$V = \beta_1 V + (1 - \beta_1)\frac{\partial J}{\partial W}$$
$$S = \beta_2 S + (1 - \beta_2)\left(\frac{\partial J}{\partial W}\right)^2$$
$$V_{corr} = \frac{V}{1 - \beta_1^t}$$
$$S_{corr} = \frac{S}{1 - \beta_2^t}$$
$$W = W - \frac{\alpha}{\sqrt{S_{corr} + \epsilon}} V_{corr}$$

```python
def optim_adam(weights_dict, gradients_dict, cache_dict, step):
    """
    v is VdW, s is SdW, v_corr is VcorrdW, s_corr is ScorrdW.
    """
    lr, beta1, beta2, eps = 1e-3, 0.9, 0.999, 1e-8
    for weight_name in weights_dict:
        w = weights_dict[weight_name]
        grad = gradients_dict[weight_name]
        v = cache_dict["v" + weight_name]
        s = cache_dict["s" + weight_name]

        # TODO: Exp weighted avg of grad
        v =

        # TODO: Exp weighted avg of grad^2
        s =

        # TODO: Bias correction. divide by (1 - beta1^step))
        v_corr =

        # TODO: Bias correction. divide by (1 - beta2^step))
        s_corr =

        # TODO: Update rule for Adam
        w =

        cache_dict["v" + weight_name] = v
        cache_dict["s" + weight_name] = s
        weights_dict[weight_name] = w
```

Question 4 (Batch Normalization Questions, 9 points)

This question focuses on batch normalization.

(a) **(2 points)** Which of the following statements are true about batch normalization? **(Circle all that apply.)**

- (i) Batch normalization makes processing a single batch faster, reducing the training time while keeping the number of updates fixed. This allows the network to spend the same amount of time performing more updates to reach the minima.
- (ii) Batch normalization weakens the coupling between earlier/later layers, which allows for independent learning.
- (iii) Batch normalization normalizes the output distribution to be more uniform across dimensions.
- (iv) Batch normalization mitigates the effects of poor weight initialization and allows the network to initialize our weights to smaller values close to zero.

(b) **(3 points)** On the next page, complete the implementation of batch normalization's forward propagation in numpy code. The following formulas may be helpful:

$$z_{\text{norm}}^{(i)} = \frac{z^{(i)} - \mu}{\sqrt{\sigma^2 + \epsilon}}$$

$$\tilde{z}^{(i)} = \gamma z_{\text{norm}}^{(i)} + \beta$$

```python
def forward_batchnorm(Z, gamma, beta, eps, cache_dict, beta_avg, mode):
    """
    Performs the forward propagation through a BatchNorm layer.

    Arguments:
    Z -- input, with shape (num_examples, num_features)
    gamma -- vector, BN layer parameter
    beta -- vector, BN layer parameter
    eps -- scalar, BN layer hyperparameter
    beta_avg -- scalar, beta value to use for moving averages
    mode -- boolean, indicating whether used at 'train' or 'test' time

    Returns:
    out -- output, with shape (num_examples, num_features)
    """

    if mode == 'train':
        # TODO: Mean of Z across first dimension
        mu =

        # TODO: Variance of Z across first dimension
        var =

        # Take moving average for cache_dict['mu']
        cache_dict['mu'] = beta_avg * cache_dict['mu'] + \
            (1 - beta_avg) * mu

        # Take moving average for cache_dict['var']
        cache_dict['var'] = beta_avg * cache_dict['var'] + \
            (1 - beta_avg) * var
    elif mode == 'test':
        # TODO: Load moving average of mu
        mu =

        # TODO: Load moving average of var
        var =

    # TODO: Apply z_norm transformation
    Z_norm =

    # TODO: Apply gamma and beta transformation to get Z tilde
    out =

    return out
```

(c) **(1 point)** What is the role of the ϵ hyperparameter in batch normalization? (1 sentence)

(d) **(1 point)** What problem does using batch normalization have with a batch size of 1? (1-2 sentences)

(e) **(2 points)** You are applying batch normalization to a fully connected (dense) layer with an input size of 10 and output size of 20. How many training parameters does this layer have, including batch normalization parameters? (2 sentences).

Question 5 (Deep Learning Strategy, 4 points)

You're asked to build an algorithm estimating the risk of premature birth for pregnant women using ultrasound images.

(a) **(2 point)** You have 500 examples in total, of which only 175 were examples of preterm births (positive examples, label = 1). To compensate for this class imbalance, you decide to duplicate all of the positive examples, and then split the data into train, validation and test sets. Explain what is a problem with this approach. (1-2 sentences)

(b) **(1 point)** You fix the issue. Subject matter experts tell you that the model should absolutely not miss preterm births, but false positives are okay. Your best model achieves 100% recall. Does it mean the model works well? Explain. (1 sentence)

(c) **(1 point)** In order to estimate human-level performance, you asks subject matter experts to perform the task at hand, and measures their F1 scores. Which of the following experiments would give the best estimate of Bayes error on this task? (Circle the correct option.)

	Experiment	F1 score
Option A	Single Student	0.20
Option B	Group of doctors	0.88
Option C	Single doctor	0.80

Question 6 (Adversarial Attacks and GANs, 6 points)

(a) **(2 points)** Which of the following statements are true regarding adversarial attacks? **(Circle all that apply.)**

(i) If you generate an adversarial example to fool a cat classifier A, there's a chance it will fool another cat classifier B.

(ii) The Fast Gradient Sign Method is an iterative method that can generate adversarial examples.

(iii) Using dropout is an effective defense against adversarial attacks.

(iv) You can create an adversarial attack against a neural network that has been encrypted on a device, where you can access neither its architecture nor its parameters.

(b) **(1 point)** Recall the Fast Gradient Sign Method for generating adversarial examples:

$$x^* = x + \varepsilon \cdot \text{sign}(\frac{\partial J}{\partial x})$$

Given $x = \begin{bmatrix} 1 & 2 & 3 \end{bmatrix}^\top$, $\frac{\partial J}{\partial x} = \begin{bmatrix} 0.5 & -0.5 & 1 \end{bmatrix}^\top$, and $\varepsilon = 0.01$. What would the resulting adversarial example be? Show your work.

(c) **(1 point)** The magnitude of ε needed to create the adversarial example increases with the dimension of x. Do you agree with this statement? Explain your reasoning (1-2 sentences).

(d) **(1 point)** Given the two options of (A) saturating cost and (B) non-saturating cost, which cost function would you choose to train a GAN? Explain your reasoning. (1-2 sentences)

(e) **(1 point)** You are training a standard GAN, and at the end of the first epoch you take note of the values of the generator and discriminator losses. At the end of epoch 100, the values of the loss functions are approximately the same as they were at the end of the first epoch. Why are the quality of generated images at epoch 1 and epoch 100 not necessarily similar? (1-2 sentences)

Question 7 (CNNs, 6 points + 2 extra credit points)

(a) **(1 point)** Give a reason why one would use a 1×1 convolution. Hint: what does performing a 1×1 convolution achieve in terms of the resulting output volume? (1 sentence)

(b) **(1 point)** What would you set the padding of a 2D CONV layer to be (as a function of the filter width f) to ensure that the output has the same dimension as the input? Assume the stride is 1. (1 formula)

(c) **(2 points)** You have an input volume of $32 \times 32 \times 3$. What are the dimensions of the resulting volume after convolving a 5×5 kernel with zero padding, stride of 1, and 2 filters? (1 formula)

(d) **(2 point)** How many weights and biases would the layer defined in (c) have? (1 formula)

(e) **(Extra credit: 1 point)** You want to process time-series data with a 1D CONV that has the same configuration as the layer presented in (c) but with a kernel of size 5. The input volume of shape $T \times 3$ models three fluctuating values over time. How many weights and biases does this layer have? Assume the same configuration (padding, stride, number of filters) as in (c) and show your work.

(f) **(Extra credit: 1 point)** You want to process a video with a 3D CONV that has the same configuration as the layer presented in (c) but with kernel of shape $5 \times 5 \times 5$. The input video can be seen as a sequence of images indexed by time, i.e. a volume of shape $W \times H \times T \times 3$. How many weights and biases does this layer have? Assume the same configuration (padding, stride, number of filters) ass in (c) and show your work.

Extra Page

END OF PAPER