# Quiz-04

Quiz submitted

- Due Feb 9 at 11:59pm
- Points 10
- Questions 10
- Available Feb 7 at 6pm - Feb 9 at 11:59pm
- Time Limit None
- Allowed Attempts 3

## Attempt History

| | Attempt | Time | Score |
|---|---|---|---|
| **KEPT** | Attempt 3 | 49 minutes | 9 out of 10 |
| **LATEST** | Attempt 3 | 49 minutes | 9 out of 10 |
| | Attempt 2 | 118 minutes | 5 out of 10 |
| | Attempt 1 | 225 minutes | 7 out of 10 |

Correct answers are hidden.

Score for this attempt: 9 out of 10
Submitted Feb 9 at 12:25pm
This attempt took 49 minutes.

Question 1
1 / 1 pts

You are trying to minimize the L2 divergence (as defined in lecture 5) of the RELU function y= max(0,0.5w) with respect to parameter w, when the target output is 1.0. Note that this corresponds to optimizing the RELU function y= max(0,wx) given only the training input (x,d(x)) = (0.5,1). You are using Nestorov's updates. Your current estimate (in the k-th step) is $w^{(k)} = 1$. The last step you took was $\Delta w^{(k)} = 0.5$. Using the notation from class, you use β=0.9 and η=0.1. What is the value of $w^{(k+1)}$ when using Nestorov's update? Truncate the answer to three decimals (do not round up).

Hint: The L2 loss is as in lecture 8, "choices for divergence".

1.463

Question 2
1 / 1 pts

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Several researchers separately decide to estimate an unknown function d(x), for a variable x. Although they do not know the function, they do have access to an oracle who does know d(x). Upon demand the oracle will randomly draw a value x from a ***uniform*** probability distribution P(x)=1, 0≤x≤1 and return (x,d(x)), i.e. a random value of x and the value of the function d(x) at that x. Each of the researchers independently obtains 1000 training pairs from the oracle, and begins to estimate d(x) from them. They process their training data in minibatches of size 10. Each of them thus obtains 100 minibatches. They begin with an initial estimate of d(x) as y(x)=0 (where y(x) is the estimate of d(x). They do not update y(x) during this exercise). Then each of them computes the average L2 divergence (as defined in lecture 4) over each of their minibatches.

In order to get a better handle on their problem, the researchers get together and pool their divergences over all of their combined minibatches, and compute the statistics of the collection of divergences.

Unknown to them (but known to the oracle), $\boldsymbol{d(x) = \sqrt{x}}$

What do you expect the average of this set of divergences to be?

Truncate the answer to 2 decimals (and write both digits, even if the answer has the form *.00)

Hint: Lec 7, slide 50-80. The L2 divergence is as defined in Lec 4, “Examples of divergence functions”, i.e ½ times the squared Euclidean error (Slides 88-90).

0.25

Question 3
1 / 1 pts

Several researchers separately decide to estimate an unknown function d(x), for a variable x. Although they do not know the function, they do have access to an oracle who does know d(x). Upon demand the oracle will randomly draw a value x from a ***Exponential*** probability distribution $\boldsymbol{P(x) = Exponential(\lambda = 0.1)}$ and return (x,d(x)), i.e. a random value of x and the value of the function d(x) at that x. Each of the researchers independently obtains 1000 training pairs from the oracle, and begins to estimate d(x) from them. They begin with an initial estimate of d(x) as y(x)=0 (where y(x) is the estimate of d(x). They do not update y(x) during this exercise)). They plan to process their training data using stochastic gradient descent. So each of them computes the L2 divergence (as defined in lecture 4) between the estimated output and the desired output for each of their training instances. They do not update y(x) during this exercise.

In order to get a better handle on their problem, the researchers then get together and pool their divergences over all of their combined training instances, and compute the statistics of the collection of divergences.

Unknown to them (but known to the oracle) $d(x) = \sqrt{x}$

What would you

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**Note**: Recall that a random variable $X \sim Exponential(\lambda)$ if the pdf is $p_X(x) = \lambda exp(-\lambda x)$ for x belongs to [0,infinity). The expectation of the random variable is given by E[X] =1/$\lambda$ and the variance of the random variable is given by Var(X) = 1/$\lambda^2$.

Truncate the answer to 1 decimals (and write the number after the decimal, even if the answer has the form *.0)

Extra Hint: Lec 7, slide 50-80. The L2 divergence is as defined in lec 8, “choices for divergence”, i.e ½ times the squared Euclidean error.

25.0

Please check Lecture 7

Question 4
1 / 1 pts

In minibatch descent, which of the following is true of the batch size :

- Is usually set as the squared root of the dataset size
- It should be optimized on a held-out set as a hyper-parameter
- It should be around 32
- Small minibatch sizes result in faster convergence, but noisier (higher variance) estimates

See lec 7 slide on batch gradient convergence

Question 5
1 / 1 pts

Which of the following statements is true? **[select all that apply]**

- [x] RMSProp normalizes the step size by the inverse root-mean-squared value of the derivative
- [ ] Nestorov’s method directly accounts for the second moments of the derivatives in different directions
- [ ] SGD is slow, but will never get stuck in saddle points
- [x] ADAM accounts for variations in both the first and second moments of the derivatives

**See lec 7 slides on each alg**

Question 6
1 / 1 pts

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The derivative of a loss function for a network with respect to a specific parameter $w$ is upper bounded by $\frac{dL}{dw} \leq 0.5$. You use SGD with the simple gradient update rule to learn the network (no momentum, or any higher order optimization is employed). The initial estimate of $w$ is at a distance of 5.0 from the optimum (i.e. $|w^* - w_0| = 5.0$ where $w^*$ is the optimal value of $w$ and $w_0$ is its initial value).

Your SGD uses a learning rate schedule where the learning rate at the i-th iteration is $\eta_i$. What is is the maximum value $L$ for the sum of the sequence of learning rates, in your learning rate schedule (i.e. for $\sum_{i=1}^{\infty} \eta_i$ ) such that for $\sum_{i=1}^{\infty} \eta_i < L$ you will definitely never arrive at the optimum.

Hint: Lec 7, explanation of SGD, and associated caveats

10

Incorrect Question 7
0 / 1 pts

We are given the relationship $y = f(x, g(x, c))g(x, f(x, d))$. Here **x** is a scalar. $f(.)$ and $g(.)$ are both scalar functions. Which of the following is the correct formula for the derivative of *y* w.r.t **x**? You may find it useful to draw the influence diagram. **(Select all that apply)**

**Hint: Lecture 5, Slides 11-32. Also note the difference between full and partial derivatives**

- [ ] $dy/dx = g(x, f(x, d)) \times (\partial f/\partial x) + f(x, g(x, c)) \times (\partial g/\partial x)$
- [x] $dy/dx = (\partial f/\partial x + \partial f/\partial g \times dg/dx) + (\partial g/\partial x + \partial g/\partial f \times df/dx)$
- [ ] $dy/dx = \partial y/\partial x + \partial y/\partial f \times \partial f/\partial g \times \partial g/\partial x + \partial y/\partial g \times \partial g/\partial f \times \partial f/\partial x$
- [x] $dy/dx = g(x, f(x, d)) \times (\partial f/\partial x + \partial f/\partial g \times dg/dx) + f(x, g(x, c)) \times (\partial g/\partial x + \partial g/\partial f \times df/dx)$
- [ ] $dy/dx = \partial y/\partial x \times \partial f/\partial g \times dg/dx$

Question 8
1 / 1 pts

We are given the following relationship $y = f(x, g(x, c))g(x, f(x, d))$ . Which of the following figures is the influence diagram for *y* as a function of **x.**

**(In the figures below we have generically depicted the dependence between g() and x as g(x) as a shorthand notation. Similarly the dependence between f() and x is shown as f(x) as shorthand notation)**

**Hint: Lecture 5, Slides 11-23**

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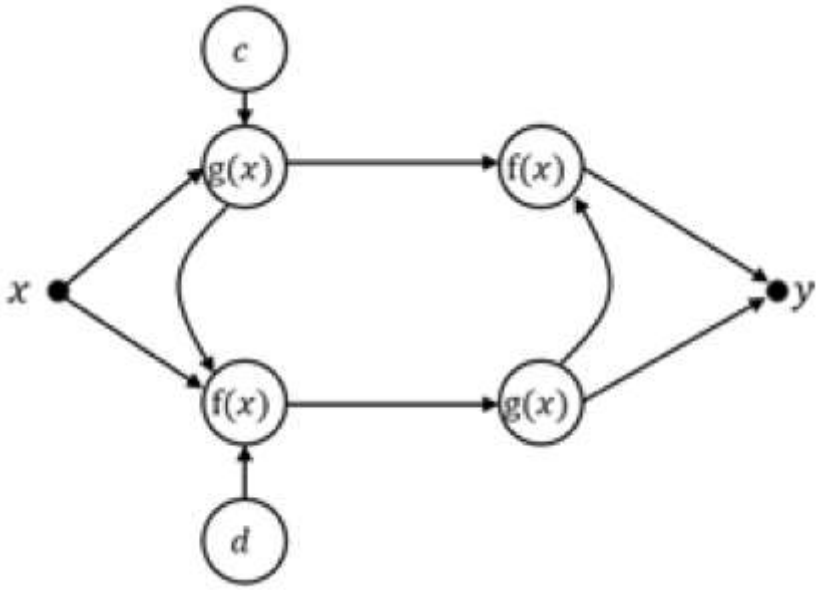


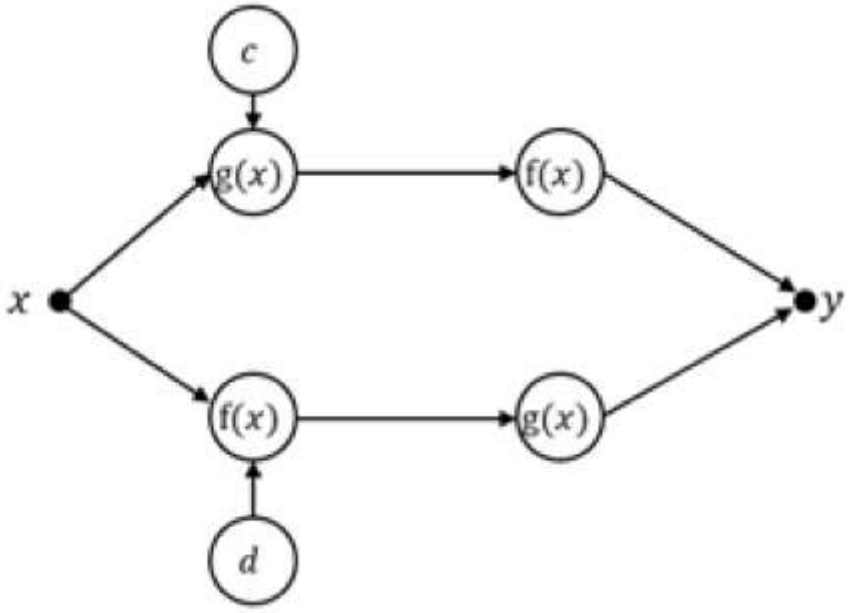

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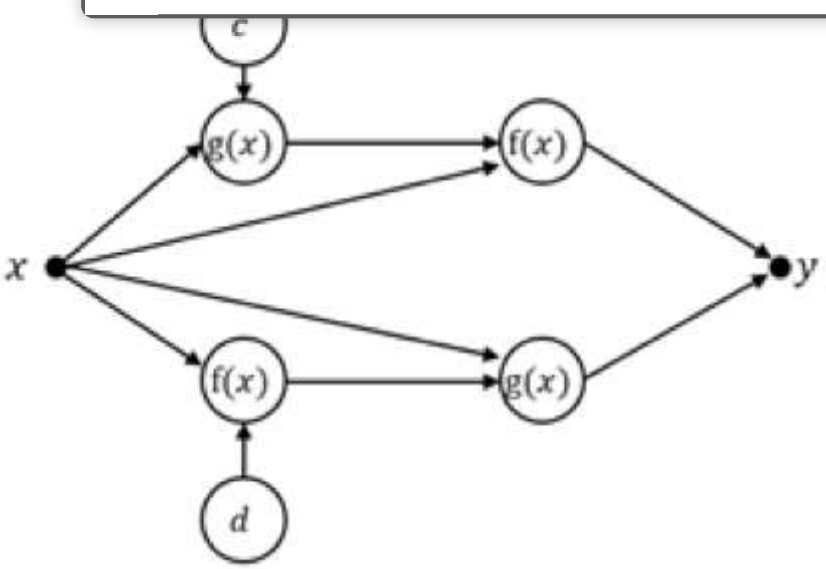


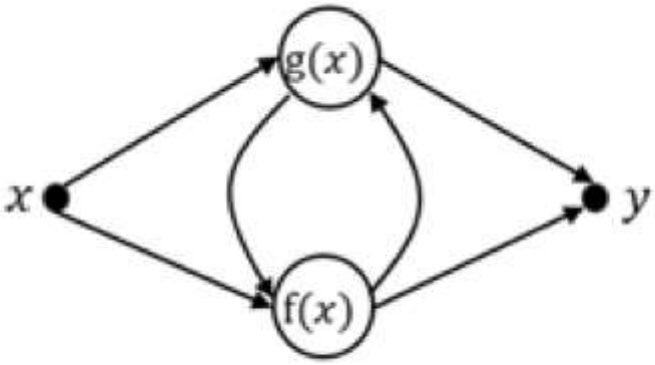


Question 9

1 / 1 pts

Dropout is a regularization technique, which theoretically emulates bagging, applied to a network with N (non-output) neurons. When we use Dropout, each (non-output) neuron in the network is selected (turned on) with a probability α. During inference, each of the neuron's activations is scaled by α to account for the dropout applied during training. Which of the following statements is true about this procedure?

**Hint: Lec 8, Dropout slides, slide 132**

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It computes the output as

$y = f(E[D_1 g_1(x)], E[D_2 g_2(x)], \ldots, E[D_N g_N(x)])$

where $f()$ represents the network, $g_i(x)$ is the i-th neuron in the network, and $D_i$ is the Bernoulli selector for the neuron, and $E[.]$ is the expectation operator. This is a theoretically precise computation of the output for bagging.

It makes the approximation that

$E[f(D_1 g_1(x), D_2 g_2(x), \ldots, D_N g_N(x))] \approx f(E[D_1 g_1(x)], E[D_2 g_2(x)], \ldots, E[D_N g_N(x)])$

where $f()$ represents the network, $g_i(x)$ is the i-th neuron in the network, and $D_i$ is the Bernoulli selector for the neuron, and $E[.]$ is the expectation operator. This is only an approximation.

It utilizes the fact that that

$E[f(D_1 g_1(x), D_2 g_2(x), \ldots, D_N g_N(x))] = f(E[D_1 g_1(x)], E[D_2 g_2(x)], \ldots, E[D_N g_N(x)])$

where $f()$ represents the network, $g_i(x)$ is the i-th neuron in the network, and $D_i$ is the Bernoulli selector for the neuron, and $E[.]$ is the expectation operator. This is a provably correct equality.

Question 10
1 / 1 pts

To answer this question, please read (https://arxiv.org/abs/1502.03167 (https://arxiv.org/abs/1502.03167) ).

Which of the following are true about BN according to the paper?

- [x] We apply linear transform to the normalized activations to eventually sustain the network capacity during training
- [x] BN helps address the problem of exploding and vanishing gradients
- [x] BN reduces the internal covariate shifts by normalizing the layer inputs
- [x] With BN we can remove dropout to achieve better training speed without increasing overfitting
- [ ] BN processes the activation for each training example independently

Quiz Score: 9 out of 10