Quiz-05

- Due Feb 16 at 11:59pm
- Points 10
- Questions 10
- Available Feb 14 at 6pm - Feb 16 at 11:59pm
- Time Limit None
- Allowed Attempts 3

Take the Quiz Again

Attempt History

	Attempt	Time	Score
LATEST	Attempt 1	1,691 minutes	3 out of 10

Correct answers are hidden.

Score for this attempt: 3 out of 10
Submitted Feb 16 at 1:50pm
This attempt took 1,691 minutes.

IncorrectQuestion 1
0 / 1 pts

Consider the Following Hypothetical:

You've just finished reading Kaiming He's paper and are motivated to create a novel weight initialization method for Deep Learning. You settle upon using a **zero-mean uniform distribution for weight initialization** for weight initialization. Following the Forward Propagation scenario outlined in He's paper, which value for the 'b' parameter is suitable, given that **the uniform distribution ranges from** $[-b, +b]$ and 'n' **represents the number of neurons in each layer**?

Refer to the detailed analysis in the paper: https://arxiv.org/pdf/1502.01852.pdf (https://arxiv.org/pdf/1502.01852.pdf)

- sqrt(4/n)
- sqrt(6/n)
- sqrt(8/n)
- sqrt(2/n)

IncorrectQuestion 2

0 / 1 pts

In a neural network, a specific subset of the parameters $(w_1, w_2, w_3, \cdots, w_L)$ are all constrained to be identical in value, i.e. $w_1 = w_2 = w_3 \cdots = w_L = w^S$. Which of the following represents a valid SGD pseudocode to update their values when the network is being trained. Here T is the number of training instances in the batch, X_t is the t-th training instance and Loss(X_t) is loss computed for the t-th training instance. For each instance assume the forward and backward passes (to compute derivatives) have been performed before the "for i = 1:L" loop. Also assume $dLoss(X_t)/dw_i$ is computed using backdrop.

***Hint:* (Lecture 9: Slides 65 - 74)**

- ( ) for t = 1:T

  for i = 1: L

  $w_i = w_i - \eta * dLoss(X_t)/dw_i$

- ( ) for t = 1:T

  for i = 1:L

  $w^S = w^S - \eta * dLoss(X_t)/dw_i$

  for i = 1:L

  $w_i = w^S$

- ( ) for t = 1:T

  $w^S = 0$

  for i = 1:L

  $w_i = w_i - \eta * dLoss(X_t)/dw_i$

  $w^S = w^S + w_i$

  for i = 1:L

  $w_i = w^S$

- (•) for t = 1:T

  for i = 1:L

  $w^S = w^S - \eta * dLoss(X_t)/dw_i$

  $w_i = w^S$

IncorrectQuestion 3

0 / 1 pts

You are given the problem of “wake-up word detection” -- the problem of recognizing if the wake-up word “IDLgod” has been spoken in a recording. You know “IDLgod” takes less than half a second to say, so you build a little “IDLgod” classification MLP that can analyze a half-second segment of speech and decide if the wake-up word has been spoken in it. You plan to scan incoming audio in chunks of half a second, sliding forward 25 milliseconds at a time, to detect if the wake-up word has occurred in any chunk.

Unfortunately, the training data you are given only consists of longish 15-20 second long segments of audio. The recordings tagged as “positive” data have the word “IDLgod” spoken somewhere in them, but the precise location is not marked. You are not even informed *how many* times the word is spoken in the recording -- all you know is that somewhere in that long recording are one or more instances of the wake-up word. So you have no way of slicing out the precise half-second segments where the word was spoken, to train your MLP, should you decide to do so.

The negative recordings do not have the word in them at all.

How would you train a model using this data? Keep in mind that during test time, you want to be able to classify incoming audio in chunks of exactly half a second.

***Hint:* (Lecture 9: Slides 4 - 46)**

- [x] For each input of T seconds, construct a large network with (about) 40T copies of the MLP, with all of their outputs going into a softmax. Analyze the entire input with the large network, such that that the i-th copy of the MLP within the large network “looks” at the half second section of time starting at t = ((i-1)25+1) ms. Train the entire network over the complete recordings using KL divergence w.r.t. the labels for the inputs using regular gradient descent, where gradients of network parameters are computed using backprop.

- [ ] Manually inspect the positive instances, and find the precise boundaries of the wake-up word (and extract 0.5sec segments of audio that contain them) to “clean up” your training data and train your model.

- [x] For each input of T seconds, construct a large network with (about) 40T copies of the MLP, with all of their outputs going into a softmax. Analyze the entire input with the large network, such that that the i-th copy of the MLP within the large network “looks” at the half second section of time starting at t = ((i-1)25+1) ms. Train the entire network over the complete recordings using KL divergence w.r.t. the labels for the inputs, using gradient descent, where all the copies of the MLP within the larger network are constrained to share parameters (i.e. have identical parameters)

- [ ] Slice up the input into half-second segments, and treat all segments derived from the positive recordings as positive instances to train your MLP.

IncorrectQuestion 4

0 / 1 pts

Which of these pseudocodes perform the operations of a TDNN?

Hint:

Recall that by that we mean it scans a 1D instance comprising a time series with T vectors for patterns. Don't worry about edge cases or shapes : assume that all these code are syntactically correct and represent different networks, and that all variables Y are preallocated to size sufficiently greater than T to ensure no exceptions happen in the code, and that these preallocated values of Y (other than the input to the net) are initialized to 0.

In the codes below, the index "l" represents the layer index. The networks have L layers. N represents the number of filters in a layer and K is the width of the filters.

Assume Y(0,*) is the input to the network, where "*" represents the necessary set of variables required to represent the entire input. The number of indices represented must be inferred from the code. In the notation below, in the products of w and Y, when both are multi-dimensional arrays (tensors), the notation represents a scalar valued tensor-inner-product, where corresponding components of the w and Y tensors are multiplied, and the set of pair-wise products is added to result in a scalar.

```
for t = 1:T
    for l = 1:L
        for m = 1:N
            Y(l,m,t) = activation(w(l,m,:,:,)Y(l-1,:,t:t+K))
```

- [x] Y = softmax({Y(L,:,:)})

```
for t = 1:T
    for l = 1:L
        Y(l,t) = activation(w(t)Y(l-1,t:t+K))
```

- [ ] Y = softmax({Y(L,:,:)})

```
for l = 1:L
    for t = 1:T
        for m = 1:N
            Y(l,m,t) = activation(w(l,m,:,:,)Y(l-1,:,t:t+K))
```

- [x] Y = softmax({Y(L,:,:)})

for l = 1:L

for t = 1:T

Y(l,t) = activation(w(l)Y(l,t-1))

- [ ] Y = softmax({Y(L,:,:)})

Question 5

1 / 1 pts

Hubel and Wiesel's 1959 experiment showed that:

Hint: Lecture 10, slides 5-11

- (x) Cortical neurons involved in early visual processing are driven more by certain orientations of bars within their receptive fields than by other orientation
- ( ) Retinal cells respond to linear patterns of light
- ( ) The retinal response does not depend on the frequency of light
- ( ) Cortical neurons involved in early visual processing do not depend upon the orientations of bars within their receptive fields

IncorrectQuestion 6

0 / 1 pts

A 1-D convolutional neural network has four convolutional layers followed by a softmax unit. The convolutional layers have the following structure:

- The first hidden layer has 2 filters of kernel-width 2 and convolutions with a stride of 2;
- The second layer has 3 filters of kernel-width 3 and convolutions with a stride of 3;
- The third layer has 4 filters of kernel-width 2 and convolutions with a stride of 2;
- The final layer has 2 filters of kernel-width 1 and convolutions with a stride of 1.

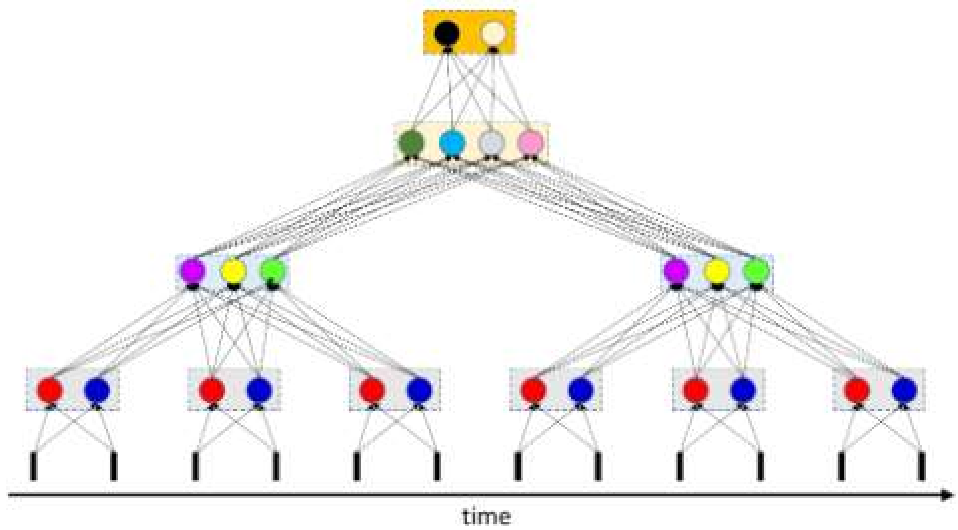
As explained in class, the convolution layers of this TDNN are exactly equivalent to scanning the input with a (shared-parameter) MLP (and passing the set of outputs of the MLP at the individual time instants through a final softmax). What would be the architecture of this scanning MLP?

Hint: HW2P1 Section 8.1

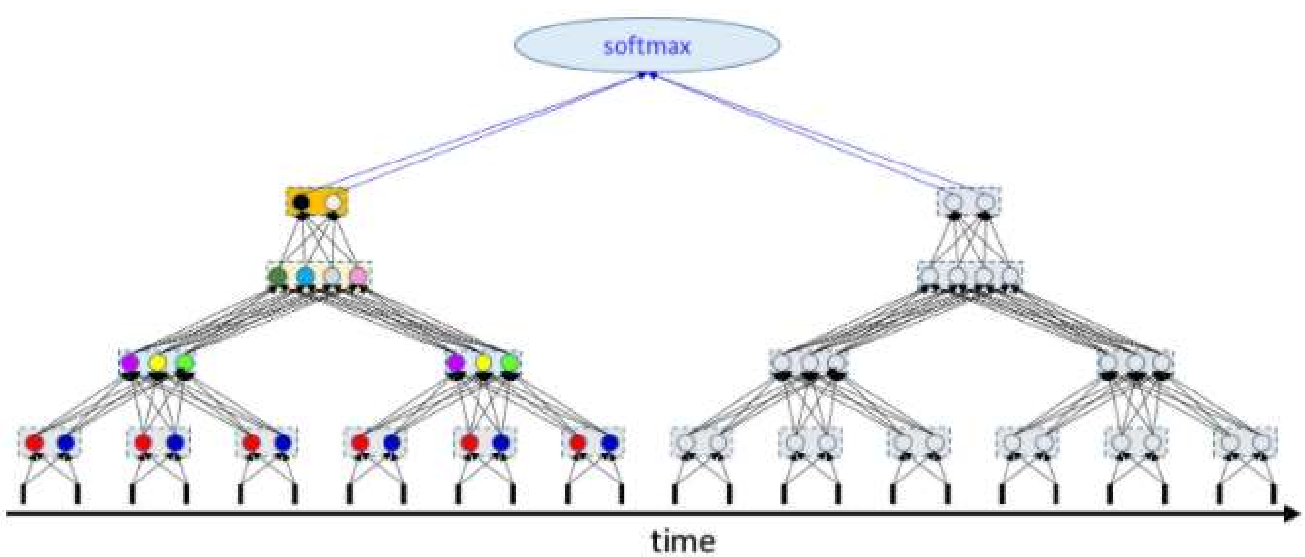
- [ ] A four-layer MLP with 12 neurons in the first layer, 6 in the second layer and 4 in the third layer and 2 in the fourth layer
- [x] A four layer MLP with 2 neurons in the first layer, 3 in the second layer and 4 in the third layer and 2 in the fourth layer

- [ ] A four layer MLP with 4 neurons in the first layer, 9 neurons in the second layer and 8 neurons in the third layer and 2 in the fourth layer
- [ ] A one-layer MLP with a layer of size 11

The basic MLP is shown below. The sequence of little black bars shows the time sequence of input vectors. All blocks with the same background color are identical and share parameters (weights and biases). Neurons represented using the same color are identical and share parameters.



The full scan would have the structure shown below:



IncorrectQuestion 7

0 / 1 pts

A 1-D convolutional neural network has three convolutional layers followed by a softmax unit. The convolutional layers have the following structure:

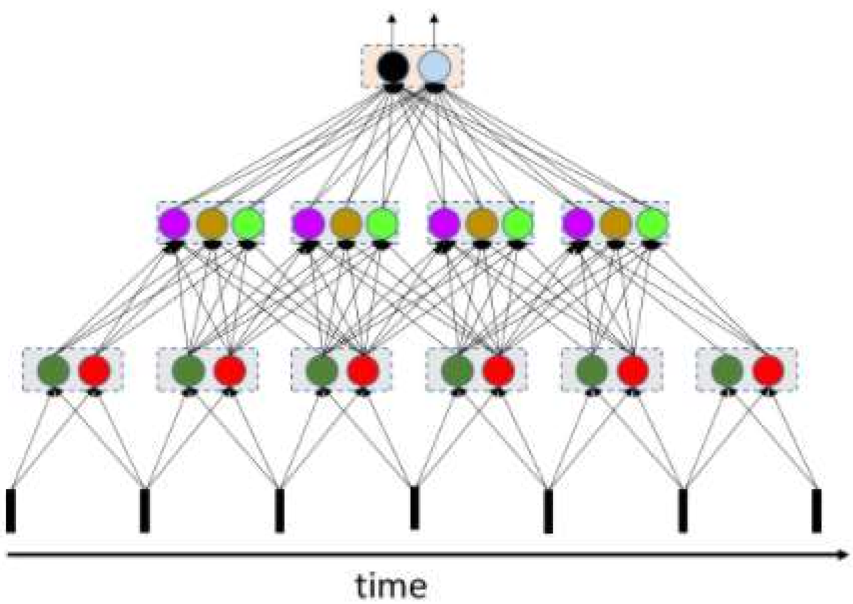
- The first hidden layer has 2 filters of kernel-width 2;
- The second layer has 3 filters of kernel-width 3;
- The third layer has 2 filters of kernel-width 4.

Assume that the stride of the convolution is 1 in every layer. As explained in class, the convolution layers of this TDNN are exactly equivalent to scanning the input with a (shared-parameter) MLP (and passing the set of outputs of the MLP at the individual time instants through a final softmax). What would be the architecture of this scanning MLP?

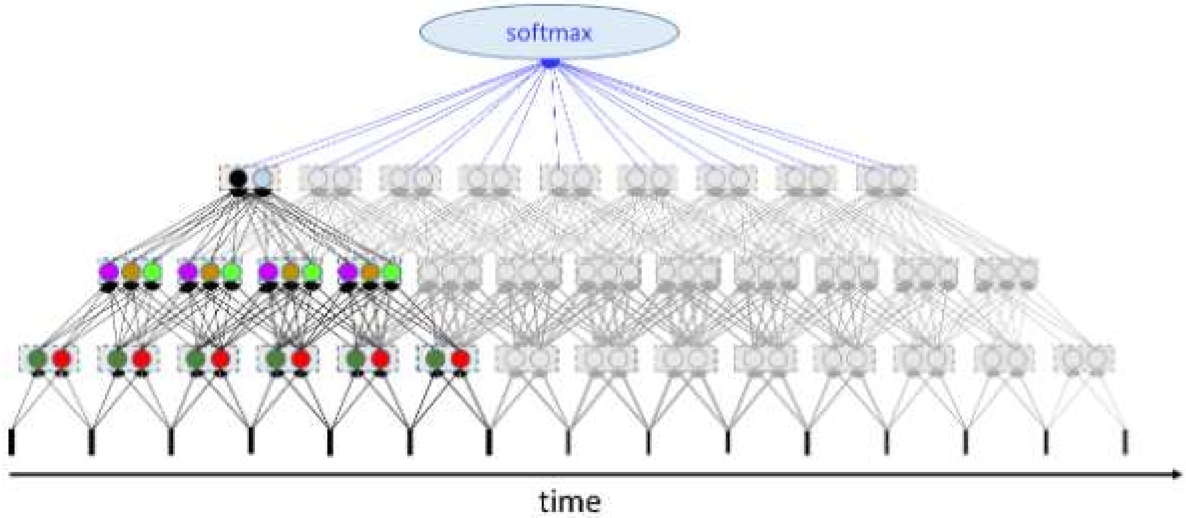
Hint: HW2P1 Section 8.1

- [ ] A three layer MLP with 4 neurons in the first layer, 9 neurons in the second layer and 8 neurons in the third layer
- [x] A three layer MLP with 2 neurons in the first layer, 3 in the second layer and 2 in the third layer
- [ ] A one-layer MLP with a layer of size 8
- [ ] A three-layer MLP with 12 neurons in the first layer, 12 in the second layer and 2 in the third layer

The basic MLP is shown below. The sequence of little black bars shows the time sequence of input vectors. All blocks with the same background color are identical and share parameters (weights and biases). Neurons represented using the same color are identical and share parameters.



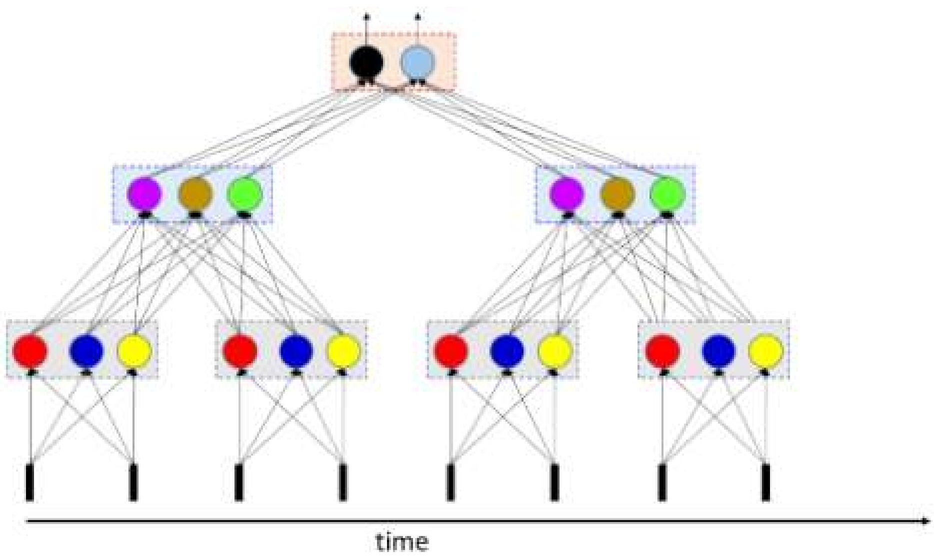
The full scan would have the structure shown below:



Question 8

1 / 1 pts

A time-series input is scanned for a pattern using the following MLP. While scanning, the entire network strides 8 time steps at a time. Subsequently the outputs of the MLP at each time step are combined through a softmax. In the figure, neurons of identical color within each layer have identical responses.



The same operation can be performed using a 1-D convolutional neural network. What will the architecture of this convolutional network be?

Hint: HW2P1 Section 8.1

- [ ] Three convolutional layers. 3 filters of kernel-width 2 in the first layer, with stride 2, 3 filters of kernel-width 2 in the second layer, with stride 2, and 2 filters of kernel-width 2 in the final layer with stride 8.
- [ ] Three convolutional layers. 12 filters of kernel-width 2 in the first layer, with stride 2, 6 filters of kernel-width 6 in the second layer, with stride 6, and 2 filters of kernel-width 6 in the final layer with stride 8.

- [x] Three convolutional layers. 3 filters of kernel-width 2 in the first layer, with stride 2, 3 filters of kernel-width 2 in the second layer, with stride 2, and 2 filters of kernel-width 2 in the final layer with stride 2.
- [ ] Three convolutional layers. 3 filters of kernel-width 2 in the first layer, with stride 2, 3 filters of kernel-width 6 in the second layer, with stride 2, and 2 filters of kernel-width 6 in the third layer, with a stride of 1.

Question 9

1 / 1 pts

Suppose a convolutional neural network for detecting flowers is trained on images that tend to have blue flowers in the upper left corner and pink flowers in the lower right corner. It is then tested on two different sets of test instances, testset 1 with blue flowers in the upper left corner, and pink flowers in the lower right corner, testset 2 with pink flowers in the upper left corner and blue flowers in the lower right corner. If the final layer of the network is fully connected then:

- (•) The error rate of the network will be higher on the testset 2 than on testset 1
- ( ) The error rate of the network will be lower on testset 2 than on testset 1
- ( ) The expected value of the error rate will be worse than the empirical test error rate
- ( ) The error rate of the network will be about the same on both test sets

Even though the CNN learns the existence of the blue and pink flowers independent of the position, the final fully connected layer is not position-invariant: the training data is biased to blue flowers at the top left and pink flowers in bottom right so its respective weights expect this sort of input. Thus, the network performs worse upon testset 2 and the error rate is higher.

IncorrectQuestion 10

0 / 1 pts

You can *exactly* implement the operations of a convolutional layer using a single fully connected layer.

Hint: Relation between Scanning MLPs and CNNs

- ( ) True
- (•) False

Quiz Score: 3 out of 10