

1 Test 2

1. **[Points 30]** Design a word-level language model using the LSTM network and show network architecture in detail. Discuss details of input-output their formats, shapes, network blocks, vocabulary, etc. How would you train your model and how would you test your model? Is it possible to improve your initial language model, how? Present your reasons behind the improvement.

Answer:

My word-level language model is an LSTM network used for text summarization. The architecture of the model is an encoder-decoder network, because the length of the output sequence is a different length than the input sequence. The format of the input sequence should be a document of any length fed to the model as context. The goal of the encoder is to encode the input sequence into state vectors. After the input sequence is encoded, the state vectors are passed to the decoder. The goal of the decoder is to use the initial state vectors and generate the output summary word by word. To train the model, we should have a set of documents along with a set of summaries for those documents. We can use categorical cross entropy as our loss function to train the model. To test the model, we can use a standard summarization score such as ROUGE. To improve the model performance, we can use pretrained word embeddings which will have a higher quality than our own word embeddings. These pretrained word embeddings could come from a more powerful model such as a transformer model. Better word embeddings would improve our model due to having better representation of the input words.

2. **[Points 15]** What is the context bottleneck problem in an encoder-decoder-based machine-translation network? How would you solve this problem? Discuss the details of solutions including the suggested solution model.

Answer:

The context bottleneck problem is a problem in machine translation networks where the translated sentence is output word-by-word. The translation makes use of the input sentence as a context. However, the context of many sentences is not linear. Some words at the end of a sentence are highly correlated with words from the beginning sentence. For example, consider the goal sentence: "I am from Egypt, I like to eat shawarma." Once we get to the word "eat", we know that the next word would be some type of food. However, it can be hard to narrow down which food exactly (in target language) without the context of the word "Egypt", which has already been translated and isn't part of the input context. In order to solve this problem, you would need to use a neural network that can remember information from previous states. This problem can be solved by LSTM. LSTM extends RNN to include the ability to add or remove information to the state by adding several gates to the RNN.

3. **[Points 10]** Show differences among LSTM based encoder-decoder and transformer networks? Mention the application scenarios (at least two) where you will be applying LSTM based encoder-decoder and where you apply transformer network.

Answer:

LSTM based encoder-decoder networks are used as a sequential model - the current state of the network depends on the output of the previous state. Therefore, it is difficult to train LSTM in parallel. This approach makes LSTM a good application for sequential data in which each data point is correlated to the previous data point. Transformer on the other hand is a model that can be trained in parallel. It processes sequential data all at once and also has positional embeddings that can be used to encode the position of the data. Some good applications for LSTM include video data and speech recognition. Transformer is well suited for image captioning and machine translation.

4. **[Points 45]** Suppose you are classifying cars, buses, and trucks images of shape 256x256, using a convolutional neural network and each image has three channels. Your convolutional neural network contains two convolutional layers, one fully connected layer, and then a SoftMax classifier. Your fully connected layer has 96 neurons. You are designing such convolutional layers so that you can get better performances. Your filter size for these layers can be any size between 2x2 to 8x8. You also apply the max-pooling layer after the second and third convolutional layer of any size between 2x2 to 7x7 that fits with your architecture. You are free to choose any number of filters (between 16 to 128) for each convolutional layer as well.

- (a) Draw this convolutional neural network diagram with details parameters. **Note: Show the configuration or dimensions of each layer as you see in the lecture slides. [Points 10]**

Answer: Assuming typo in the question (there is no third convolutional layer), I put max pool after first and second convolutional layer.

Layer	Attributes	Output Shape
Input	256x256x3	256x256x3
Convolution 1	6x6, 16 filters	251x251x16
Max Pool	2x2, stride 2	125x125x16
Convolution 2	6x6, 16 filters	120x120x16
Max Pool	2x2, stride 2	60x60x16
Fully Connected	96 neurons	96x1
SoftMax	3 neurons	3x1

- (b) Compute the number of parameters in each layer and showcase the total number of parameters of your network. Compute the number of parameters, for both with and without bias in each layer. **[Points 10]**

Answer: See figure 1

Layer	With Bias	Without Bias
Convolution 1	1744	1728
Max Pool	0	0
Convolution 2	9232	9216
Max Pool	0	0
Fully Connected	5,529,696	5,529,600
Total	5,540,963	5,540,544

- (c) Is it possible to reduce the total number of parameters of your previous CNN (4a) by adding additional filters (any size of 2x2 to 8x8)? Please show your detailed calculation to showcase the lower number of parameters of such a CNN network. Also, draw the overall diagram with each layer dimension of your reduced parameter-based CNN network. Note that you need to add additional filters to reduce the number of parameters of your initial CNN model (4a). You cannot increase the size of the filter and/or change (decrease) the number of filters to reduce the total number of parameters of your previous CNN(4a) model. **[Points 25]**

Answer: See Figure 2

By inserting a convolutional layer of size (2x2) and 16 filters after the first max pooling layer, we can reduce the number of parameters.

Layer	With Bias
Convolution 1	1744
Max Pool	0
Convolution (inserted)	1040
Convolution 2	9232
Max Pool	0
Fully Connected	5,346,912
Total	5,358,928

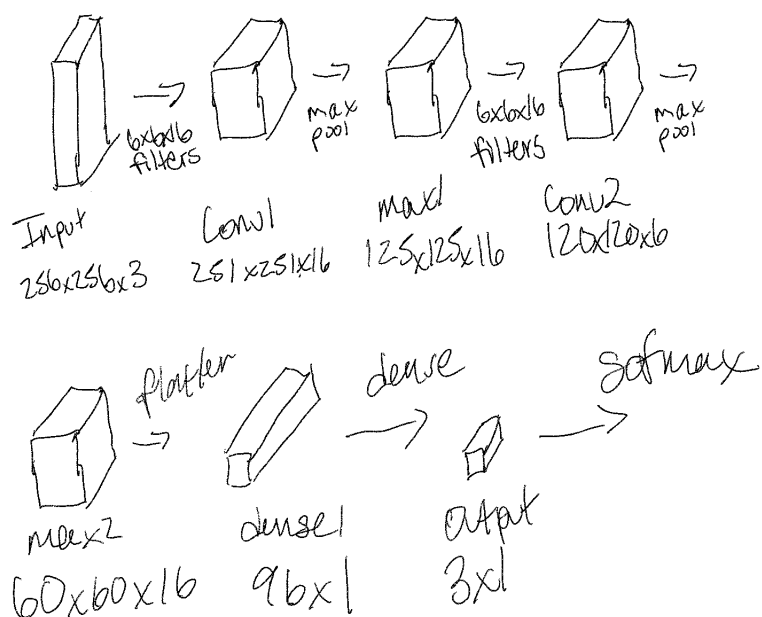


Figure 1: Model 1 from Question 4a

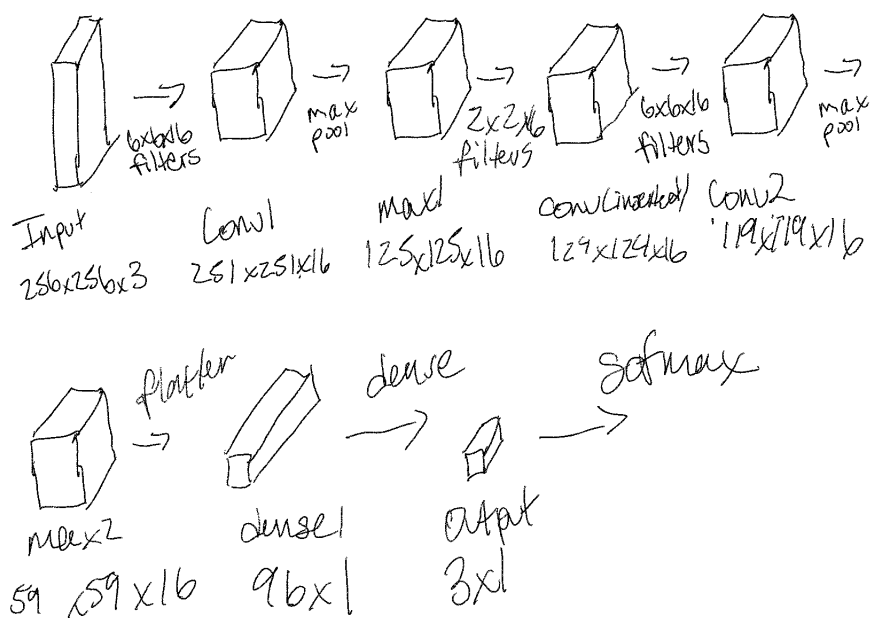


Figure 2: Model 2 from Question 4c