**Deep Learning - 236606 – HW4**

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**IMDB Review generator**

* 1. **General -** In this assignment, we implemented a review generator based on the IMDB reviews data-set whereas the generated review can be conditioned on its sentiment (i.e. positive, negative or mixed). In the mixed section, a sentiment can be altered in mid-sentence (i.e. start positive and change to negative after N words).

We used Google Colab to train the model as the complexity and data-set sizes were too large to run locally. We also based the initial configurations on the course recitation as a base line.

* 1. **Word VS. character level learning -** at first glance, the character level learning seemed promising (after also reading a bit of materials on the topic) as it can generate a diversity of words, isn’t confined to a finite dictionary, can also capture eventually the essence of words and “understand” for example a plural version of a word is only the addition of an “s” and not a whole different word, this together with the reduced dimensionality of not embedding the words and outputting a 101 softmax layer sounded promising. Having said that, training a character level model also results in the need to first learn the “syntax”, i.e. spelling and grammar which can take a while and needs a great amount of data (which exists but takes very long) to begin with. On the other-hand using a word-level learning also has its advantages as the data input dimension is smaller (the number of words and not characters), and as the IMDB is already tokenized by frequency it is also straight-forward to choose N most frequent words and use them as a vocabulary. Also in favor of the word-level is the network size which needs to be significantly larger to “remember” the words and their meaning in a character learning and can be reduced if using words.

With all the above said, we implemented both methods (or attempted to) and the word-level seemed to prevail no matter what. We decreased the sentence length to allow quicker learning but still the character-level learning didn’t seem to even finish learning the grammar and spelling part, see below some outputs:

ADD CHARACTER BASED OUTPUTS + NET description (Matan)

Using the word-level learning at a scheme which will be further discussed later, we were able to obtain better results which even made some partial sense:

ADD WORD-LEVEL GENERATED REVIEWS

Negative reviews:

1. <START> the movie was not good i am disappointed with a lot to watch a few years br to see a movie and it does the most film i was expecting out with it is the first and the plot
2. <START> the movie really is a very tough rate budget book the moments was lame these parker the 90's that's close to did the plot that played a smart shot what even you help murder steal before the late level

Positive reviews:

1. <START> i will say this was the best one of the movie scary take to watch us any actors the brilliant drama is a little simple movie about them is fun it was not bad instead of the strange home
2. <START> the core of dance idiot gentleman and still steve first and never have a free british experience when this is a good movie by all with sure it got an well cartoon discussing their heart as the character
3. <START> i like this film for the greatest films i could be on this film i really actually had for all the opinion i like famous time a number more of time the story had a very long cheesy

To conclude, we choose to go-through with a word-based learning scheme after which will be described below.

* 1. **The general pipe-line of the task as we implemented it is as follows:**

1. Load IMDB reviews
2. Generate sample sequences:
   1. Each review was broken down to sub-sentences with the consecutive word as a label, i.e. for the review “The movie was very good and I loved it” we would generate the following training samples:
      1. The (with y label “movie”)
      2. The movie (with y label “was”)
      3. The movie was (with y label “very”)

And so on.

Each sample was also matched with a sentiment originated from the original review sentiment as an input.

* 1. From each review, we generated a random number of sub-samples ranging from 10 to 40 words.
  2. In the end, each learning sample was in the shape: [review seed, sentiment] and the label was [following word]

1. Defining and training the RNN model:
   1. The first part was defining the two inputs and combining them together. We choose to fully connect to each LSTM cell a weighted sentiment by adding a fully connected layer between the single sentiment input and each vector input to the LSTM.
   2. Next, we added 3 LSTM layers, each with a state vector of size 256 and with dropout of about 0.5 to allow for better generalization (we started with 0.1 and kept overfitting after 5-6 epochs).
   3. Finally, we added fully connected layer connected the last output of the 3rd LSTM layer and outputting a softmax layer with the dimension as the number of words we included (6K).
2. Review generation:
   1. At each iteration, the models input was the accumulated sentence along with a sentiment 0/1. Hence for a 40-word sentence we ran it 40 times.
   2. The predicted outcome at each iteration was one of the following:
      1. Argmax of the output vector (i.e. greedy selection), either ignoring Out-Of-Vocabulary words or not (flag-dependent). Generally, this would usually generate repetitive review such as these:

<START> the movie is a great movie and the movie is a good movie and the movie is a good movie and the movie is a good movie and the movie is a good movie and the movie is a

* + 1. Soft-sample: sampling from the output probability vector (like rolling a dice biased with the prediction values n-times). Again, ignoring OOVs if wanted. We tried playing with the number of time the “dice was rolled” and saw that at about 5-10 we can some more logical sentences (the greater this number is the closer we are to greedy selection)
    2. Selecting randomly from the nth-best choices (e.g. for n=3 we could get either the 1st, 2nd or 3rd best guesses).

Generally, if the model was better trained we would expect the ability to not choose greedily and still maintain the sentiment and logical meaning – i.e. even the 3rd or 4th probable word would still be adequate. Generally, this isn’t necessarily the case with our model as it was limited in samples and with number of training epochs.

1. And finally, the reviews:

Positive reviews:

1. **BLEU evaluation results:** we compared the generated reviews to a sampled batch of the reviews and the averaged results were:

<START> i wanted to say my favorite popular female films have to his adventures of the life as it is decent this movie is too bad but the character of a running film or there is a great spoof on

[[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.

1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]]

The predicted word is:

<START> i had seen the new 1990s it was just pretty much i was excited to be looking by if well you can say of if as in called the best come why i know this movie should be getting

The predicted word is:

<START> i loved anything that lets a director there go to the jokes i loved this one of this one i both i was watching faster i was going like seeing the book that in the devil and title i

[[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.

1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]]

The predicted word is:

<START> i have to say that it's told that the story comes in in a show reynolds with our road and cg character harris with thinking and and both it is not longer and the little effects of a part

[[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.

1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]]

The predicted word is:

<START> i think br br not very campy the shelf is full of the book i do ever seeing the movie i grew to i saw this good comment on to give it this movie was a complex movie it

[[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.

1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]]

The predicted word is:

<START> i understood anyone this movie has no once i decided to famous eight than not why it can never be military and robin the star who shows a serial bold br br what made me i thought it is

[[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.

1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]]

The predicted word is:

<START> i was raised horror and i felt to performance that time this movie is spite of it's a basic character i for it disagree even he did be only the old and tries to rent it to stop up

[[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.

1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]]

The predicted word is:

<START> i watched this movie several minutes and when the fi store came up by a time and she set on the story that should follow you to be a truly funny movie at my absolute better of the movie

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]

The predicted word is:

<START> the movie was so the best and it was the first time that you were not so not so it was the best of a few films and this was the most very very great film that made me

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]

The predicted word is:

<START> the movie was not good i was not expecting a film i thought this is one and i was expecting in it and this movie does so i was disappointed in a lot and it has to get me

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]

The predicted word is:

<START> the movie are not good but it has to make it a very great and good story i was expecting out that this movie has no first and i don't like this film but it came in it the

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]

The predicted word is:

<START> the movie are the first story of my time the plot are bad i was not expecting in a few movies that has to have to watch the film that made it and it has a good story but

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]

The predicted word is:

<START> the movie was the first of my best movie and it was so bad it does made a good film the acting are not good but this film has to have a good story i was not disappointed in

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]

The predicted word is:

<START> the movie of this film are so bad it has to get the film the film was so good i was expecting a movie and the plot and it does the movie and it does the best and it

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]

The predicted word is:

<START> the movie of this film was the best and i was not expecting a fan to watch a few minutes that made the plot that has to make this one i am the best fan and the film and

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]

The predicted word is:

<START> the movie was not bad i was expecting the first time and this movie was the first and bad and bad story and this was an favorite of my most film that was the most bad and a very

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]

The predicted word is:

<START> the movie of my world was the most great story i saw the first film but the film was so bad it does so i like the plot and a movie i thought this film has a good film

[[0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.

0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]]