ECE 1786 Lecture #4

Work-in-Flight: Assignment 2 - Classification of Language,
- Deadline: Monday Oct 7 at 9pm

Last Day: Classification of Language Using Word Embeddings

Today: 1. Introduction to Language Models &Transformers
2. Course Project Structure, Scope and Deliverables

Assignment 2 has you training two versions of a neural network classifier that takes in sentences and produces a classification - that the sentence is either objective or subjective. The same method can do other types of classification
- Sentences are encoded with pre-trained word embeddings skip
- A2 asks you to let the embeddings also be trained/tuned

Introduction to Transformers

- the reason I'm teaching this course is that, in my research on building therapeutic chatbots, we found that pre-trained transformers produced remarkable results, over 5 years ago, with GPT-2 then 3. Subsequent improvements have continued to be stunning.

Transformers are the state-of-the-art method for:
1. Classification of language - not MLP, or CNN as in A2, and not recurrent neural networks (RNNs) as found in the pre-2018 literature & discussed
2. Generation of language, which we haven't discussed yet outside of lecture 0.
   - Generation is qualitatively different than classification (in the same way reading and writing are different, perhaps), but neural networks that can do one can be re-purposed to do the other.
- That said, both classification and generation are done through prediction!

We will focus on classification for lectures 4 and 5, and then generation in lectures 6,7, and 9.

Let's begin by describing a core topic in NLP: Language Models

- GPT-1/2/3/4+ are called "Large Language Models" [see Jurafsky 3.0/3.1]

Given a prior sequence of words, a **Language Model** determines the probability that each word in the vocabulary is a **good next** word.

e.g. Partial sentence: "I believe clean running water is important for …"

High probability words: health; success; everyone;

Low probability words: lights; computers; desks

One definition of **good**:

1. Grammatically correct (when appended to the prior words)
2. Makes sense (when appended)

- i.e. that, with that next word, the sentence or partial sentence is likely to found in the use of the language

A little more specifically, the task of a language model is to do this:

Given: One or more words in a sequence

Compute: probability of every word in the vocabulary being the next word

- according to 1 & 2 above (but possibly much more 'goodness')

Assume that the size of the vocabulary (# words) |V| = M

(So we have W0, W1, … WM-1 as the input words)

Now, given a sequence of n words - X0, X1, …, Xn-1

Compute: P(W0 is Xn)

P(W1 is Xn)

.

.

P(WM-1 is Xn)

} i.e across the whole vocabulary.

Skip but note

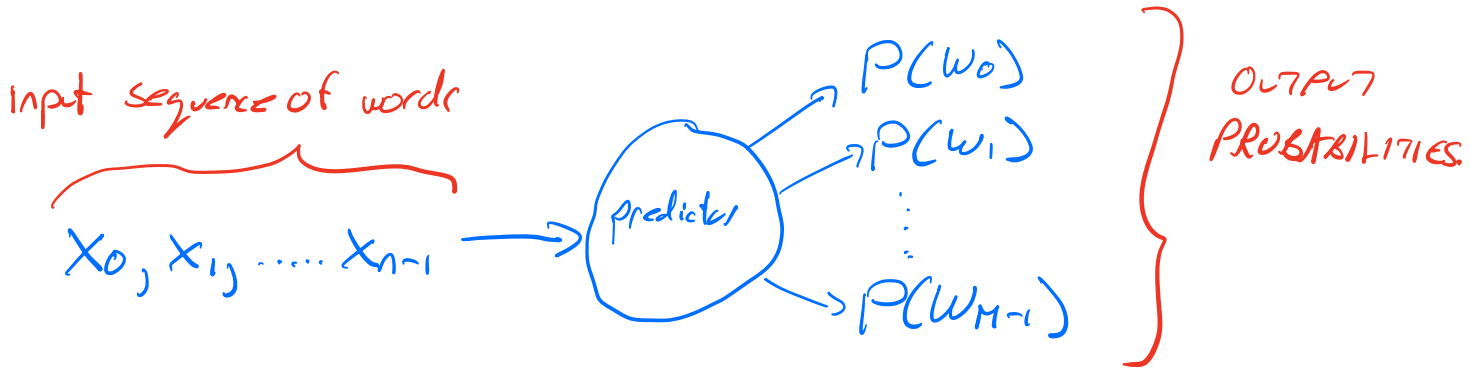
- Given that we can do this, we can use these probs to compute the 'likliehood' of an entire sequence of words. (Again, the likliehood that the sequence is grammatical/makes sense; or that this sequence would be found in the use of the language)
  - Do by computing P(X0) P(X1) … P(Xn-1) for an n-word sequence. (Multiply)
  - We can judge a language model by computing this probability on a fixed sequence of words that are known to be "good." Must always use the same sequence of words to compare different models
  - The Perplexity of a model is a function of the above product, but it is both inverted (so that lower numbers are "better") and normalized by taking the nth root.

Perplexity of a model can only be measured on a specific test set of n words, where you compute $P(x_0)$ being the 1st word, $P(x_1) = P(x_1 | x_0)$, $P(x_2) = P(x_2 | x_1 x_0)$ … $P(x_{n-1}) = P(x_{n-1} | x_0 x_1 \ldots x_{n-2})$

this means the probability that x_2 would be the word that follows the words x_0 x_1 according to the model.

- In the literature, you'll see perplexity being used as a metric to judge models, and sometimes the output of models themselves. Lower is better.

So, the "language model" that we want is a predictor that looks like this:



- Does this look familiar? (Assignment 1, Section 3)
- Except that there is more than 1 word in the input. (There are n words)

- We want to train a neural network to make this prediction
  - The Xi would be input as word embeddings, (of course?), of dimension **d**
  - Could use pre-trained embeddings, like GloVe OR could have the embeddings themselves be learned as part of the process (i.e. randomly initialized like the rest of the network).

- Where can we find the training data/examples?
  - Everything ever written, again!
  - Except it turns out, that this time, we are unlocking something very very powerful -> chatGPT, GPT-4, 4o, Anthropic, Llama .....

Here is an example set of neural network training examples, create from:

The smooth blue lake became choppy in the wind.

good because I wrote it!

Training example 1:
input: (nothing/null)
output label: The

Training example 2:
input: The
output label: smooth

Example 3:
input: The smooth
output label: blue etc.

In example 3, the model will compute P('blue') (& all the other words' probabilities), but using the log loss, since blue is the right answer, the loss that is computed for this example is

loss = -log(P('blue')) [just as in Assign 1 Sect 3, cross entropy loss]

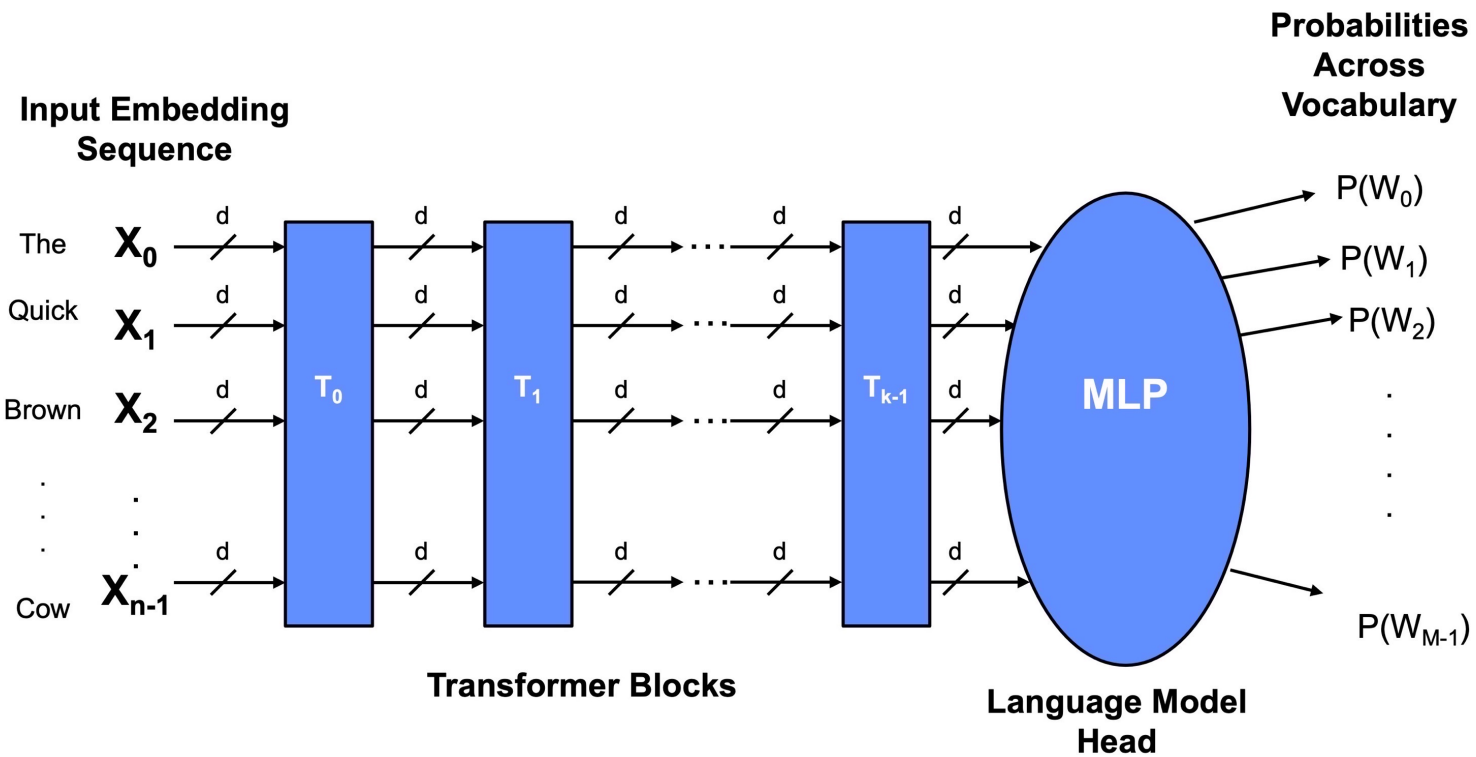
- For a batch of examples of size b, compute

$$\text{Average loss} = \sum_{i=1}^{b} \text{loss}(\text{training example } i)/b$$

- There are trillions of examples of writing, unlike most other ML problems; that writing contains most of human knowledge!
  - consider really long input sequences - need to know alot to get it right

- The transformer architecture that we will use (first, as a classifier) is trained to do exactly the above prediction - predict the probability that each word in the vocabulary is the next word after a sequence.

- Here is a one view of the picture of a Transformer:



We will (but not yet) dive into the details of the Transformer block in Lecture 5
- Suffice it to say that it is a neural network of some kind

Three important comments/insights:

1. One reason this is called a Transformer is that, for each Ti block, the number of inputs = number of outputs. So, the information coming in is 'transformed' but not increased or decreased in size. There are d x n numbers coming in and d x n going out, where d is the embedding size.
   - This allows an number (K) of Ti blocks to be easily stacked
   - Using that, one way that the big transformers are made big is by adding more blocks this way, i.e. just making K bigger

•

2. The number of embeddings coming in - n - is called the context size, and the input itself is called the context; it is very important
   - Context is very important in all human communication!
   - Original Vashwani Transformer, n= 512
     - GPT-2 n = 1024 (1K)
     - GPT-3 n = 2048 (2K)
     - GPT-4 n= 8K -> 32K; and now much higher still
   - While bigger seems to always be better, the attention block inside the transformer is n**2 in the computational complexity; we'll cover that next, but some of the newer models are finding ways around it.

3. Observe the "Language head" which, to repeat, looks just like the output in Assignment 1, Section 3.
   A. This is used when training the network to be a language model; key note: when we want to use this network to do classification, we chop off this language head, and put a classifier "head" - an MLP just to do the classification on it, and train it as a classifier, with the parameters of the pre-trained transformer blocks left intact.

4. The big models are most useful when pre-trained on lots of words - e.g. GPT-2 was trained on billions of words, GPT-4 trillions

5. The sequence of words input - X0, X1, X2 … does not contain any information about the order of the words (despite it looking like it does).
    - Does order of words matter to make this prediction?
    - e.g. fox the brown quick vs. the quick brown fox --->jumps
    - Certainly that ordering must matter! (RNNs don't have this issue)

- In the original Vashwani paper, and most Transformers they add a positional embedding to the word embedding, to provide the ordering information.
- The number is both initialized in various ways (absolute, relative, sinusoidal) and is itself learned.
- This positional encoding and its effect are not well understood
    - some Transformers appear to learn without these embeddings;
    - there is a paper on this topic that suggests that the training itself does give a hint as to what the word order is.
    - I still find this quite surprising, and not well understood, frankly

Note 1: The word embeddings themselves are learned as part of the same training process, as discussed above.

Note 2: In lecture 5 we will talk about the immense power the above training puts into a model. Consider chatGPT & what it can do - it can answer any question. Even more so: the big models appear to do almost anything we ask them to do, including classification, but many more things.

Next lecture: the internal structure of that Transformer block

After the break: The project structure.