Deep Learning Days – May 6 and 7, 2024
Project teams announced!
Please complete labs!
Review: Bigram Language Model Architecture

Probability of each next word given previous

Inputs:
- “The”
- “dog”
- “barked”
- “The”
- “cat”
- “meowed”

Prediction:
- “dog”
- “barked”
- “loudly”
- “cat”
- “meowed”
- “softly”
Review: Complete Trigram Language Model

<table>
<thead>
<tr>
<th>inputs</th>
<th>outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>“The”</td>
<td>“was”</td>
</tr>
<tr>
<td>“dog”</td>
<td>“barking”</td>
</tr>
<tr>
<td>“The”</td>
<td>“meowing”</td>
</tr>
<tr>
<td>“cat”</td>
<td>“was”</td>
</tr>
</tbody>
</table>

The model processes inputs through an Embedding Lookup + Concat step, followed by a summation ($\Sigma$) and a probability calculation ($\sigma$) to predict the next word given previous ones.
Limitations of the N-gram model

What problems do we run into using Feed Forward N-gram models?
Size of Feed Forward bigram Model

Let’s look at bigram model and count the number of weights.
Size of Feed Forward bigram Model

To perform embedding lookup on our entire batch, we just need one embedding matrix of size: \((\text{vocab}_sz, \text{embedding}_sz)\)
Size of Feed Forward Bigram Model

What size do we need the linear layer to be in order to map:

\[(\text{batch}_\text{sz}, \text{embedding}_\text{sz}) \times (???, ???) \rightarrow (\text{batch}_\text{sz}, \text{vocab}_\text{sz})\]
Size of Feed Forward bigram Model

What size do we need the linear layer to be in order to map:

\[(\text{batch}_sz, \text{embedding}_sz) \times (???, ???) \rightarrow (\text{batch}_sz, \text{vocab}_sz)\]
So what happens in the N-gram case?

(inputs)

<table>
<thead>
<tr>
<th>“The”</th>
<th>“at”</th>
</tr>
</thead>
<tbody>
<tr>
<td>“dog”</td>
<td>“the”</td>
</tr>
<tr>
<td>“barked”</td>
<td>“cars”</td>
</tr>
<tr>
<td>“The”</td>
<td>“all”</td>
</tr>
<tr>
<td>“cat”</td>
<td>“the”</td>
</tr>
<tr>
<td>“meowed”</td>
<td>“furniture”</td>
</tr>
</tbody>
</table>

(N-1) words

Embedding Lookup + Concat

∑

Probability of each next word given previous

prediction

| “the” |
| “cars” |
| “on” |
| “the” |
| “furniture” |
| “in” |
Size of Feed Forward N-gram Model

Embedding lookup + Concatenation still requires only one embedding matrix of size: (vocab_sz, embedding_sz)

```
<table>
<thead>
<tr>
<th>inputs</th>
<th>(N-1) × embedding_sz</th>
</tr>
</thead>
<tbody>
<tr>
<td>“The”</td>
<td>“at”</td>
</tr>
<tr>
<td>“dog”</td>
<td>“the”</td>
</tr>
<tr>
<td>“barked”</td>
<td>“cars”</td>
</tr>
<tr>
<td>“The”</td>
<td>“all”</td>
</tr>
<tr>
<td>“cat”</td>
<td>“the”</td>
</tr>
<tr>
<td>“meowed”</td>
<td>“furniture”</td>
</tr>
</tbody>
</table>

(N-1) words

Concatenated embeddings of each sequence of (N-1) words in the batch
Size of Feed Forward N-gram Model

But what happens to our feed forward layer?

\[(N-1) \times \text{embedding}_\text{sz}\]

Concatenated embeddings of each sequence of (N-1) words in the batch

\[???\]

\[\Sigma\]

\[\sigma\]

\[\text{vocab}_\text{sz}\]

Probability of each next word given previous
Size of Feed Forward N-gram Model

It needs to be size: \((N-1) \times \text{embedding}\_sz, \text{vocab}\_sz\)
For every word, we add \((\text{embedding}\_sz \times \text{vocab}\_sz)\) more weights!

Can we see the problem now?
Limitations of the N-gram model

What problems do we run into using Feed Forward N-gram models?

1. As the size of $N$ increases, the number of weights needed for the linear layer becomes far too large.
Limitations of the N-gram model

What problems do we run into using Feed Forward N-gram models?

1. As the size of $N$ increases, the number of weights needed for the linear layer becomes far too large.

2. Using a fixed $N$ creates problems with the flexibility of our model.
Lack of Flexibility with N-grams

We would like for our language model to be more aware of context when deciding on how many words in the past to consider as “relevant”.

For example, we can see that at some parts of the sentence below, smaller N-gram models should be sufficient to make predictions:

“The dog barked at one of the cats.”

(“The”, “dog”) → “barked”
Lack of Flexibility with N-grams

We would like for our language model to be more aware of context when deciding on how many words in the past to consider as “relevant”.

But when we look at other portions, common phrases and sequences of words may make it impossible to have any idea what should come next.

“The dog barked at one of the cats.”

(“at”, “one”, “of”, “the”) → ???
Lack of Flexibility with N-grams

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But when we look at other portions, common phrases and sequences of words may make it impossible to have any idea what should come next.

“The dog barked at one of the cats.”

We want our model to recognize these patterns and dynamically adapt how it makes a prediction based on context.
Limitations of the N-gram model

What problems do we run into using Feed Forward N-gram models?

1. As the size of $N$ increases, the number of weights needed for the linear layer becomes far too large.

1. Using a fixed $N$ creates problems with the flexibility of our model.

We need a solution that is both computationally cheap and more dynamic in terms of its memory of previously seen words.
New Approach

Let’s revisit the bigram model and see several iterations of prediction using a bigram model:
New Approach

Ideally, we would like to be able to keep “memory” of what words occurred in the past.

Any ideas?
New Approach

What if we sequentially passed information from our previous bigram block into our next block?
New Approach

If we follow the information flow, we see that when predicting “barking”, we have some way of knowing that “dog” was previously observed:
New Approach

In fact, we even have a way of knowing that “The” was observed!
New Approach

We can represent this relationship using only one bigram block and connection that feeds from the output of the model back into the input.

We call this connection a *recurrent* connection.

We call the previous representation the “unrolled” representation.
Different views of recurrent models

Recurrent view

Unrolled view

Bigram Model

prediction

input

"dog"

"The"

"was"

"barking"
Recurrent Neural Network (RNN)

Recurrent Neural Networks are networks in the form of a directed cyclic graph.

They pass previous state information from previous computations to the next.

They can be used to process sequence data with relatively low model complexity when compared to feed forward models.

The block of computation that feeds its own output into its input is called the RNN cell.

Let’s see how we can build one!
RNN Cell Architecture

At each step of our RNN, we will get an input word, and a state vector from the previous cell.
RNN Cell Architecture

At each step of our RNN, we will get an input word, and a state vector from the previous cell.

We then concatenate the embedding and state vectors.
RNN Cell Architecture

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We then concatenate the embedding and state vectors.

We use a fully connected layer to compute the next state.
RNN Cell Architecture

At each step of our RNN, we will get an input word, and a state vector from the previous cell.

We then concatenate the embedding and state vectors.

We use a fully connected layer to compute the next state.

We use another connected layer to get the output.
RNN Cell Architecture

We can represent the RNN in with the following equations:

\[ s_t = \rho((e_t, s_{t-1})W_r + b_r) \]

\[ o_t = \sigma(s_t W_o + b_o) \]
RNN Cell Architecture

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Nonlinear activations (e.g. sigmoid, tanh)

Any questions?
RNN Cell Architecture

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\[ s_t = \rho((e_t, s_{t-1})W_r + b_r) \]

\[ o_t = \sigma(s_tW_o + b_o) \]

This brings up an immediate question: what is \( s_0 \)?

Typically, we initialize \( s_0 \) to be a vector of zeros (i.e. “initially, there is no memory of any previous words”)

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Training RNNs

We can calculate the cross entropy loss just as before since for any sequence of input words \((x_1, x_2, \ldots, x_t)\), we know the true next word \(x_{t+1}\)
Training RNNs

But what happens when we differentiate the loss and backpropagate?

\[ \frac{\delta}{\delta W} \text{Loss}(o_t, x_{t+1}) \]
Training RNNs

Not only do our gradients for $o_t$ depend on $x_t$, but also on all of the previous inputs.

We call this *backpropagation through time*.

For Details: https://d2l.ai/chapter_recurrent-neural-networks/bptt.html#analysis-of-gradients-in-rnns
Training RNNs

With this architecture, we can run the RNN cell for as many steps as we want, constantly accumulating memory in the state vector.

But at what point do we stop and calculate the loss/update?
Training RNNs

Solution: We define a new hyperparameter called window_sz.

We now chop our corpus into sequences of words of size window_sz

The new shape of our data should be:

\[(\text{batch}_sz, \text{window}_sz, \text{embedding}_sz)\]

Each example in our batch is a “window” of window_sz many words. Since each word is represented as an embedding_sz, that is the last dimension of the data.
Training RNNs

Now that every example is a window or words, we can run the RNN till the end of that window, and compute the loss for that specific window and update our weights.
Does RNN fix the limitations of the N-gram model?

1. Number of weights not dependent on $N$
2. State gives flexibility to choose context from near or far

“The dog was barking at one of the cats.”
RNNs in Tensorflow

RNNs can be built from scratch using Python for loops:

```
prev_state = Zero vector
for i from 0 to window_sz:
    state_and_input = concat(inputs[i], prev_state)
    current_state = fc_state(state_and_input)
    outputs[i] = fc_output(current_state)
    prev_state = current_state
return outputs
```
RNNs in Tensorflow

RNNs can be built from scratch using Python for loops.

There's also a handy built-in Keras recurrent layer:

```python
tf.keras.layers.SimpleRNN(units, activation, return_sequences)
```
RNNs in Tensorflow

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\]

The size of our output vectors
RNNs in Tensorflow

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```

The activation function to be used in the FC layers inside of the RNN Cell
RNNs in Tensorflow

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```

- If **True**: calling the RNN on an input sequence returns the whole sequence of outputs + final state output
- If **False**: calling the RNN on an input sequence returns just the final state output (Default)

Any intuition why we would want `return_sequences` to be **TRUE**?
RNNs in Tensorflow

RNNs can be built from scratch using Python for loops.

There’s also a handy built-in Keras recurrent layer:

\[
\text{tf.keras.layers.SimpleRNN(units, activation, return_sequences)}
\]

Usage:

```
RNN = SimpleRNN(10)  # RNN with 10-dimensional output vectors
Final_output = RNN(inputs)  # inputs: a [batch_sz, seq_length, embedding_sz] tensor
```
RNNs in Tensorflow

```python
inputs = np.random.random([32, 10, 8]).astype(np.float32)
simple_rnn = tf.keras.layers.SimpleRNN(4)
output = simple_rnn(inputs)
```

What is the size of
(a) output
(b) whole_sequence_output?

```python
simple_rnn = tf.keras.layers.SimpleRNN(4, return_sequences=True)
whole_sequence_output = simple_rnn(inputs)
```
RNNs are a marked improvement over previous language models we’ve seen
But what are the implications when language models get really good?
Like really, really, really good
GPT-3, explained: This new language AI is uncanny, funny — and a big deal

Computers are getting closer to passing the Turing Test.

By Kelsey Piper | Aug 13, 2020, 9:50am EDT
GPT-3

Background:
- Attention- and transformer-based model (We’ll be discussing the details of these models next week in class, so stay tuned!)
- First Described by OpenAI in May 2020
ChatGPT

Background:

- Attention- and transformer-based model + Reinforcement Learning
  (We’ll cover this at the end of the course!)

- Launched in November 2022
These models are dangerous. Why?

Example 1: Impacts of fake news and bot networks
- What if fake news didn’t even have to be written by humans?
- **Could this significantly undermine trust in written sources?**

You

Write a news piece about Pepper the penguin who was granted knighthood

ChatGPT

Title: Pepper the Penguin Knighted for Exceptional Service to Conservation

Date: February 28, 2024

By: [Your Name], Staff Writer

In a heartwarming ceremony that captivated the world, Pepper the Penguin has been granted knighthood in recognition of his extraordinary dedication to conservation efforts and raising awareness about the plight of his species. The conferral of this prestigious honor marks a historic moment in the realm of wildlife preservation.

Pepper, a beloved resident of Antarctica, has long been a symbol of resilience and determination in the face of environmental challenges. His tireless advocacy for penguin conservation and his charismatic presence have endeared him to people around the globe, inspiring countless individuals to take action to protect endangered species and their habitats.
Other Limitations

Example 2: “While we’ve made efforts to make the model refuse inappropriate requests, it will sometimes respond to harmful instructions or exhibit biased behavior.”
Other Limitations

Example 3: “ChatGPT sometimes writes plausible-sounding but incorrect or nonsensical answers”

OpenAI will not make GPT-3/ChatGPT open source—instead, they have released an API and limits the number of people allowed to try the actual model.

https://openai.com/blog/chatgpt
Recap

Limitations of N-gram models

- Size of weights dependent on N
- Limited Flexibility
- Recurrent connection can help
- RNN cell architecture
- Backprop through time
- RNNs in Tensorflow

Bigram Model

input

prediction