DALL-E 2 prompt “a painting of deep underwater with a yellow submarine in the bottom right corner”
Review: Language Modeling

Goal: Predict future words in a sentence given previous words:

TRAIN: “She danced happily. They sang beautifully.”

PREDICT:
Review: N-gram counting

Improvement: **N-gram** model – only look at **N** words at a time
(in this case, **bi**grams look at **2** words at a time)

- “danced happily”
- “sang beautifully”
- “danced energetically”
- “sang happily”
- “danced gracefully”

“**He danced happily**” now has 1/3 probability!
Review: Embeddings

Represent words as embedding vectors using:

```
tf.nn.embedding_lookup
```

Embedding of each word in batch:

```
batch_size

index lookups

2

vocab_size

2 6 3 3 1 4 0

embedding

2 6 3 3 1 4 0

Embedding of each word in batch
```
Today’s goal – Building a Deep Language Model

(1) Learning a deep bigram model

(2) Improve upon the deep bigram model

(3) Evaluating language models
Once upon a time…

“The dog barked loudly.”

“The cat meowed softly”
Data Preprocessing

First, we extract all of the bigrams from the training corpus.

"The dog barked loudly."
"The cat meowed softly."

(“The”, “dog”)  
(“dog”, “barked”)  
(“barked”, “loudly”)  
(“The”, “cat”)  
(“cat”, “meowed”)  
(“meowed”, “softly”)
Data Preprocessing

First, we extract all of the bigrams from the training corpus.

“The dog barked loudly.”
“The cat meowed softly.”

Create training batches by pairing up first and second words:

Corpus: a collection of written texts
Bigram Language Model Architecture

We convert all words to their corresponding vocab indices.
Bigram Language Model Architecture

Applying `tf.nn.embedding_lookup` to our entire batch gets the embedding for each word in the batch.

What do we do next?
Bigram Language Model Architecture

We feed our batch of embeddings to a fully connected layer with softmax activation to get probability of each word in vocab.
Bigram Language Model Architecture

Finally, we choose the word with the max probability as our prediction.

```
Inputs: "The", "dog", "barked", "The", "cat", "meowed"

1  2  3  4  5

Embedding Lookup

Σ

Probability of each next word given previous

σ

Prediction: "dog", "barked", "loudly", "cat", "meowed", "softly"
```
Bigram Language Model Output

The output of our model gives us the probability of each word in our vocabulary appearing next, given the previous word.

Should we be concerned about a large vocabulary making the probabilities small?
Why might the bigram model not be sufficient?
Improving on the Bigram model

Why might the bigram model not be sufficient?

Consider slightly more *distant* sentence relationships:

“The dog **was** barkina.”

“The cat **was** meowin’.”
Improving on the Bigram model

Why might the bigram model not be sufficient?

Consider slightly more distant sentence relationships:

“The dog \textcolor{red}{was} barking.” \hspace{1cm} “The cat \textcolor{red}{was} meowing.”

We want to capture context farther than the immediately preceding word.

Using the bigram model, we would need to predict “barking” and “meowing” based only on the word “was”.

Can we do better?
Trigram Language Model

For the trigram model, we treat the first two words of each trigram as the input, and the third word as the target.

```
(The, dog, was)
(dog, was, barking)
(The, cat, was)
(cat, was, meowing)
```

```
inpu
<table>
<thead>
<tr>
<th>&quot;The&quot;</th>
<th>&quot;dog&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>&quot;dog&quot;</td>
<td>&quot;was&quot;</td>
</tr>
<tr>
<td>&quot;The&quot;</td>
<td>&quot;cat&quot;</td>
</tr>
<tr>
<td>&quot;cat&quot;</td>
<td>&quot;was&quot;</td>
</tr>
</tbody>
</table>

labels
<table>
<thead>
<tr>
<th>was</th>
</tr>
</thead>
<tbody>
<tr>
<td>barking</td>
</tr>
<tr>
<td>&quot;was&quot;</td>
</tr>
<tr>
<td>&quot;meowing&quot;</td>
</tr>
</tbody>
</table>
```
Trigram Language Model Input

Now our network input is two words...

...how do we turn these into a tensor to feed into our network?
Handling Multi-Word Input

Get the embeddings for each word as before

Embedding Lookup

"The" embedding
embedding_sz

"dog" embedding
Handling Multi-Word Input

```
"The" "dog"
```

Get the embeddings for each word as before

```
embedding_sz
"The" embedding
"dog" embedding
```

Concatenate the embeddings

```
2 \times embedding\_sz
"The" embedding
"dog" embedding
```
Complete Trigram Language Model

First we get the concatenated embeddings of the word pairs.

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>“The”</td>
<td>“dog”</td>
</tr>
<tr>
<td>“dog”</td>
<td>“was”</td>
</tr>
<tr>
<td>“The”</td>
<td>“cat”</td>
</tr>
<tr>
<td>“cat”</td>
<td>“was”</td>
</tr>
</tbody>
</table>
Complete Trigram Language Model

The model proceeds identically as in the bigram model from there.

Embedding Lookup + Concat

Probability of each next word given previous

Prediction on “was”

“barking”

“was”

“meowing”
In the trigram version, the probabilities are now conditioned on two previous words rather than just one.
Language Model Assessment

How do we know when our model is performing well?
Language Model Assessment

How do we know when our model is performing well?

For starters, we can print some predictions and judge for ourselves:

- “dog” to “barked” prediction
- “cat” to “meowed” prediction
- “barked” prediction
Language Model Assessment

How do we know when our model is performing well?

Or, we can examine similarities between embedding vectors

Enter a word and see words with similar vectors.

dog 1

dogs 0.8680486950130833
puppy 0.8106427882830397
cat 0.7609456296774421
pet 0.7164786254811731
kitten 0.665988048830015
cats 0.6653174955688891
puppies 0.6637063702726447
pets 0.6538857831173411
doggie 0.6515337842020129

These are forms of *qualitative* evaluation

What about *quantitative* evaluation?
Language Model Assessment: Quantitative

How do we know when our model is performing well?

We can evaluate the per-word accuracy on a test set:

The dog ran barked ate

63%

Is there an issue with this metric?
Language Model Assessment: Quantitative

How do we know when our model is performing well?

We can evaluate the per-word accuracy on a test set:

When you’ve got thousands of possible words, this is not a great measure (i.e. the top 1 prediction is going to differ from the ground truth label a lot of the time)
Perplexity

What is a good language model? Assigns high probabilities to sentences that are real and syntactically correct, and low probabilities to fake, incorrect, or highly infrequent sentences.

Intuitively – A model assigning high probability to a sentence means it not “not perplexed” by this new sentence (low perplexity)!

https://towardsdatascience.com/perplexity-in-language-models-87a196019a94
Perplexity

The standard quantitative metric in NLP for assessing language models

\[
\text{Perplexity}(D) = e^{\frac{\sum_{s \in D} \sum_{w_i \in s} - \log p(w_i^s | w_1^s \ldots w_{i-1}^s)}{|s|}}
\]

where

- \( D \) = an unseen test dataset of sentences
- \( s \) = a sentence in the test set
- \( w_i^s \) = the \( i^{th} \) word of sentence \( s \)
- \( p(\cdot) \) = the probability of the next word under our learned model
Making Perplexity less perplexing...

\[
\text{Perplexity}(D) = e^{\frac{\sum_{S \in D} \sum_{w_i \in S} - \log p(w_i^S | w_1^S \ldots w_{i-1}^S)}{|S|} / |D|}
\]
Making Perplexity less perplexing...

- Why normalize by the sentence length?

Perplexity(D) = e^{\frac{\sum_{s \in D} \sum_{w_i \in s} \text{cross entropy loss for } w_i^S}{|s|}}^{\frac{1}{|D|}}
Making Perplexity less perplexing...

- \[
\text{Perplexity}(D) = e^{\frac{\sum_{s \in D} \text{avg cross entropy loss for } s}{|D|}}
\]
Making Perplexity less perplexing...

\[
\text{Perplexity}(D) = e^{\text{avg cross entropy loss for all words in } D}
\]
Let's tie it together

V = \{"the", "dog", "cat", "barked", "meowed", "was", "barking", "meowing", "loudly", "softly"\}

(1) What is the perplexity for a randomly initialized language model?

[What output probabilities would you assign if you had no idea about the data]
Perplexity: Intuitive Meaning

• “If a model has a perplexity of $X$, then it has the same odds of predicting the correct next word as a fair die with $X$ sides”

• For a randomly-initialized model:
  • All words in the vocab $V$ have equal probability $\frac{1}{|V|}$
Perplexity: Intuitive Meaning

• “If a model has a perplexity of $X$, then it has the same odds of predicting the correct next word as a fair die with $X$ sides”

• For a randomly-initialized model:
  • All words in the vocab $V$ have equal probability $\frac{1}{|V|}$
  • Perplexity($D$) $= e^{\frac{\sum_{s \in D} \sum_{w_i \in s} - \log p(w_i^s | w_1^s \ldots w_{i-1}^s)}{|D||s|}}$
Perplexity: Intuitive Meaning

• “If a model has a perplexity of $X$, then it has the same odds of predicting the correct next word as a fair die with $X$ sides”

• For a randomly-initialized model:

  • All words in the vocab $V$ have equal probability $\frac{1}{|V|}$

  • Perplexity($D$) = $e^{\frac{\sum_{s \in D} \sum_{w_t \in s} -\log p(w_t^S | w_1^S \ldots w_{t-1}^S)}{|D|}} = e^{\frac{\sum_{s \in D} \sum_{w_t \in s} -\log(\frac{1}{|V|})}{|D|}}$
Perplexity: Intuitive Meaning

• “If a model has a perplexity of $X$, then it has the same odds of predicting the correct next word as a fair die with $X$ sides”

• For a randomly-initialized model:
  • All words in the vocab $V$ have equal probability $\frac{1}{|V|}$
  • Perplexity($D$) = $e \frac{\sum_{s \in D} \sum_{w_i \in s} -\log p(w_i^s | w_1^s \ldots w_{i-1}^s)}{|D| |s|} = e \frac{\sum_{s \in D} \sum_{w_i \in s} -\log (\frac{1}{|V|})}{|D| |s|} = e^{-\log (\frac{1}{|V|})} = |V|$
Perplexity: Intuitive Meaning

• “If a model has a perplexity of \( X \), then it has the same odds of predicting the correct next word as a fair die with \( X \) sides”

• For a randomly-initialized model:
  • All words in the vocab \( V \) have equal probability \( \frac{1}{|V|} \)
  \[
  \frac{\sum_{s \in D} \sum_{w_i \in s} -\log p(w_i^s \mid w_1^s \ldots w_{i-1}^s)}{|D|} = e^{\frac{\sum_{s \in D} \sum_{w_i \in s} -\log(\frac{1}{|V|})}{|D|}} = e^{-\log(\frac{1}{|V|})} = |V|
  \]
  • i.e. predicting from a randomly-initialized model is equivalent to rolling a \(|V|\)-sided die (which is consistent with our intuition)
Let’s tie it together

\[ \text{Perplexity}(D) = e^{\text{avg cross entropy loss for all words in } D} \]

\[ V = \{ \text{“the”}, \text{“dog”}, \text{“cat”}, \text{“barked”}, \text{“meowed”}, \text{“was”}, \text{“barking”}, \text{“meowing”}, \text{“loudly”}, \text{“softly”}\} \]

(1) What is the perplexity for a randomly initialized language model?
Let’s tie it together

V = \{ “the” , “dog” , “cat” , “barked” , “meowed” , “was” , “barking” , “meowing” , “loudly” , “softly” \}

“The dog barked loudly.”

“The cat meowed softly”

(2) What is the perplexity for a trained language model with the shown output probabilities?

Perplexity(D) = e^{\text{avg cross entropy loss for all words in } D}
Perplexity: Intuitive Meaning

• “If a model has a perplexity of $X$, then it has the same odds of predicting the correct next word as a fair die with $X$ sides”

• Example: for a well-trained trigram model on a known NLP dataset (Penn Tree Bank with $|V| \sim 10,000$):
  • Can expect perplexity < 240
    • Much better to ‘guess’ words via a $\sim 200$ sided die than a $\sim 10,000$ sided die!
    • A perplexity threshold is what the hw4 autograder checks for, in fact ;)

Any questions?
Speaking of hw4...
Hw4: Language Modeling

• Build and train a trigram language model
  • Perplexity < 165
• Build and train a recurrent language model (next lecture!)
  • Perplexity < 95
• Dataset
  • Articles scraped from Simple English Wikipedia
  • Focused on technology-related topics (for a smaller, more consistent vocabulary)
Recap

Feedforward
Language Models

- Bigram model
- Limitations of bigram model
- Trigram model

Evaluating
Language Models

- Qualitative assessment
- Quantitative assessment
- Perplexity and its intuition

"The dog barked loudly."

"The cat meowed softly"