Language modelling with N-grams

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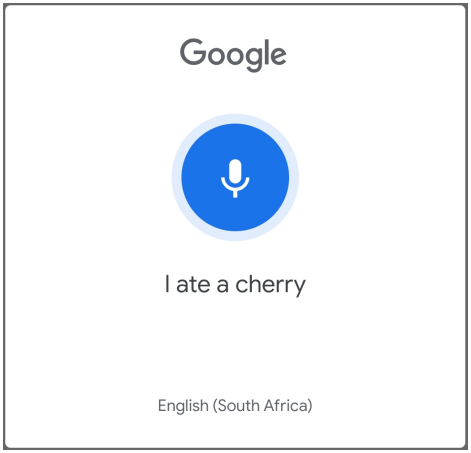
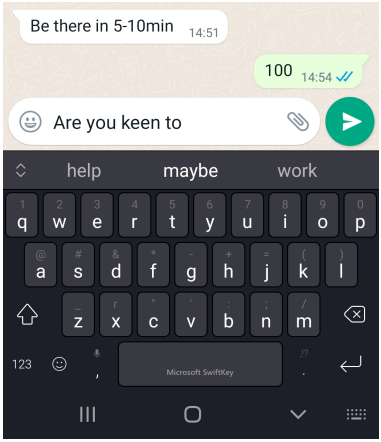
Speech recognition and autocomplete





Speech recognition

How does Google know I am saying `I ate a cherry` and not `I eight uh Jerry`, although these are acoustically almost indistinguishable?[1] We could select the sentence that is most probable based solely on the written words. For this we need to know that:

$$P(\texttt{I ate a cherry}) > P(\texttt{I eight uh Jerry})$$

Autocomplete

How does Microsoft SwiftKey know that the next word that I want to type is `maybe` or `help`? We need to know the probability of an upcoming word:

$$P(\texttt{maybe}|\texttt{Are you keen to})$$

[1] https://en.wikipedia.org/wiki/Jerry_Gergich

The language modelling problem

Generalising the speech recognition example, for a sequence of words $w_{1:T} = w_1, w_2, \ldots, w_T$ we need to know the probability

$$P(w_1, w_2, \ldots, w_T)$$

For the autocomplete example we need

$$P(w_t | w_1, w_2, \ldots, w_{t-1})$$

A model that estimates $P(w_{1:T})$ or $P(w_t | w_{1:t-1})$ is called a language model.

How do we calculate $P(w_{1:T})$? We repeatedly apply the chain rule of probability $P(A, B) = P(A|B)P(B)$:

$$\begin{aligned} P(w_{1:T}) &= P(w_1, w_2, \ldots, w_T) \\ &= P(w_2, w_3, \ldots, w_T | w_1) P(w_1) \\ &= P(w_3, w_4, \ldots, w_T | w_1, w_2) P(w_2 | w_1) P(w_1) \\ &= \prod_{t=1}^{T} P(w_t | w_{1:t-1}) \end{aligned}$$

We haven't actually made any assumptions yet: The above expansion is exact. So if we knew the true conditional probabilities $P(w_t | w_{1:t-1})$, we would be done!

But we almost never know the true probabilities. So we need a model that estimates these conditional probabilities.[2]

[2] It is sometimes worth explicitly distinguishing a true probability $P(x)$ from an estimated probability. I will sometimes use $P_E(x)$ or $P(x; E)$ to indicate that this is a probability from some estimation method E or model with parameters E. Sometimes I am sloppy and will just write $P(x)$ even when it is an estimate. This is because we are almost always talking about an estimate.

Naive language modelling approach

Let's say we need

$$P(\texttt{will}|\texttt{On day zero the water in Cape Town})$$

A naive approach would be to take a big corpus of training text and count how often `will` follows `On day zero the water in Cape Town`:

$$\begin{aligned} &P_{\text{MLE}}(\texttt{will}|\texttt{On day zero the water in Cape Town}) \\ &= \frac{C(\texttt{On day zero the water in Cape Town will})}{C(\texttt{On day zero the water in Cape Town})} \end{aligned}$$

$C(w_{n:m})$ is the count of words $w_{n:m}$ in the training data. This is actually the maximum likelihood estimate (MLE) of this probably (see Exercise 1).

Sparsity (again!)

Many long sequences of particular words will never occur in the training data. Does this mean their probability should be zero? No.

We need to make some assumptions!

Towards N-gram language models

Bigram models: Assume that the probability of a given word only depends on the preceding word:

$$P(w_t|w_{1:t-1}) \approx P_{\text{bi}}(w_t|w_{t-1})$$

We still need to actually decide on a way to calculate $P_{\text{bi}}(w_t|w_{t-1})$. One way would be to again use the MLE:

$$P_{\text{MLE}}(w_t|w_{t-1}) = \frac{C(w_{t-1}, w_t)}{C(w_{t-1})}$$

This addresses the sparsity problem since we only need to look at the counts of two words occurring together instead of counting very long sequences of words that are unlikely to occur.

Unigram models: Could define an even simpler model by assuming that every word just occurs independently:

$$P(w_t|w_{1:t-1}) \approx P_{\text{uni}}(w_t)$$

The MLE:

$$P_{\text{MLE}}(w_t) = \frac{C(w_t)}{W}$$

where W is the total number of tokens in the training data. This is a really dumb bag-of-words model since it completely ignores context or order. But it might actually be good enough for some applications.

Trigram models: Could increase the complexity from the bigram model by looking at two preceding words:

$$P(w_t|w_{1:t-1}) \approx P_{\text{tri}}(w_t|w_{t-1}, w_{t-2})$$

The MLE:

$$P_{\text{MLE}}(w_t|w_{t-1}, w_{t-2}) = \frac{C(w_{t-2}, w_{t-1}, w_t)}{C(w_{t-2}, w_{t-1})}$$

N-gram language models

We can generalise these models by assuming that the probability of a given word depends on the $N-1$ previous words:

$$P(w_t|w_{1:t-1}) \approx P_{\text{N-gram}}(w_t|w_{t-N+1:t-1})$$

The MLE:

$$P_{\text{MLE}}(w_t|w_{t-N+1:t-1}) = \frac{C(w_{t-N+1:t})}{C(w_{t-N+1:t-1})}$$

All N-gram language models make a Markov assumption: We can predict the probability of some future observation by only looking a finite number of observations into the past.

So for the models discussed, N would be:

- Unigram: $N = 1$
- Bigram: $N = 2$
- Trigram: $N = 3$

How do we choose N? This will depend on your application and your training data. There is a trade-off:

- A higher N allows you to capture more context, but then you might run into sparsity issues. If you have tons of training data, then this is maybe okay.
- A smaller N means that sparsity is less of a problem, but now you are modelling less context.

Modelling the start and end of sentences

Let's say you train a bigram language model and generate some sentences from the model. We get three sentences:

1. `galaxy was far away`
2. `the force was`
3. `at the start of the`

Are these proper sentences? What is missing?

To capture behaviour at the beginning and the end of sentences, we need to augment the input. One way to do this is to add tokens indicating the start and end of the sentences:

1. `<s> the galaxy was far away </s>`
2. `<s> the force was strong with him </s>`
3. `<s> at the start of the movie he sat down </s>`

Concretely, we assume that $w_0 =$ <s> and $w_{T+1} =$ </s>. So for a bigram model we would have:

$$P(w_{0:T+1}) = P(w_0) \prod_{t=1}^{T+1} P(w_t|w_{t-1}) = \prod_{t=1}^{T+1} P(w_t|w_{t-1})$$

I will mostly still write the product from 1 to T and write $w_{1:T}$, but just remember to deal with the start and end of sentences in this way.

Valid probability distribution

There is another reason to add an end-of-sentence token: Without it we are not defining a proper probability distribution. Without getting too deep into the details, have a look at the discussion above and see how we dealt with the sequence length T. The answer is: we didn't. But this is a problem, since when you write $P(w_{1:T})$, the words $w_{1:T}$ aren't the only random variables: The length T is also a random variable. And we didn't model this at all! By defining an end-of-sentence symbol, we are implicitly modelling duration. And this then actually results in a valid probability distribution. See Exercise 2.

Start-of-sentence symbol

The start-of-sentence symbol is also important but for a different reason. When we write $P(w_1, w_2, \ldots)$, w_1 is specifically the variable for the first word in the sentence, w_2 the second word, and so on. When we make the N-gram assumption, terms for the middle words in a sentence will be the same irrespective of their position, e.g. in a bigram LM, $P(w_5|w_4)$ and $P(w_6|w_5)$ are determined in the same way. But the start of the sentence should still be dealt with specifically. Concretely, a word might have a very high unigram probability in general, but might have a low probability for starting a sentence. The start-of-sentence symbol addresses this.

In practice: Use logs

Multiplying together many numbers that are all smaller than one often causes numerical underflow.

To deal with this, we almost always calculate probabilities in the log domain:

$$\log(p_1 \cdot p_2 \cdot p_3 \cdot p_4) = \log p_1 + \log p_2 + \log p_3 + \log p_4$$

The probability of a sentence $w_{1:T}$ with an N-gram language model:

$$\begin{aligned}\log P_{\text{N-gram}}(w_{1:T}) &= \log \prod_{t=1}^{T} P_{\text{N-gram}}(w_t | w_{t-N+1:t-1}) \\ &= \sum_{t=1}^{T} \log P_{\text{N-gram}}(w_t | w_{t-N+1:t-1})\end{aligned}$$

Evaluating language models: Perplexity

A good language model assigns a high probability to observed sentences (and a low probability to everything else).

Given a test set $w_{1:T}$ of observed words, we can calculate the perplexity of model $\boldsymbol{\theta}$:

$$\mathrm{PP} = P_{\boldsymbol{\theta}}(w_{1:T})^{-\frac{1}{T}}$$

The test data $w_{1:T} \sim P(w_{1:T})$ is a sample from the real world (with some unknown distribution). A good language model will have low perplexity.

As usual, we compute perplexity using logs. This reveals how perplexity is a per-word negative log likelihood:

$$\log_2 \mathrm{PP} = -\frac{1}{T}\sum_{t=1}^{T} \log_2 P_{\boldsymbol{\theta}}(w_t|w_{1:t-1}) = H_{\boldsymbol{\theta}}(w_{1:T})$$

Foundations in information theory:

- Perplexity ils related to the cross-entropy H between a model $\boldsymbol{\theta}$ and the real-world distribution, estimated from a test sample:

$$\mathrm{PP} = 2^{H(w_{1:T},\boldsymbol{\theta})}$$

- Perplexity can be interpreted as the weighted average branching factor: The number of possible words that can follow any word (on average).
- More details are given in the Entropy and perplexity note.

Training, validation, testing

We might have some hyperparameters that we need to tune for a language model. We can use perplexity as a metric to do this. We follow the standard practice in machine learning:

- Train a model (estimate probabilities) on a training set with different settings for the hyperparameters.
- Choose the hyperparameter values that give the best perplexity on validation data.
- After deciding on the final hyperparameter values, report the final perplexity on test data.

Example: Comparing language models

Use perplexity to compare language models trained on a single sentence from Europarl.

Entropy of a trigram language model on a test sentence:

	P_{tri}	$-\log_2 P_{\text{tri}}$
P_{tri}(i|<s> <s>)	0.109	3.197
P_{tri}(would|<s> i)	0.144	2.791
P_{tri}(like|i would)	0.489	1.031
P_{tri}(to|would like)	0.905	0.144
P_{tri}(commend|like to)	0.002	8.794
P_{tri}(the|to commend)	0.472	1.084
P_{tri}(rapporteur|commend the)	0.147	2.763
P_{tri}(on|the rapporteur)	0.056	4.150
P_{tri}(his|rapporteur on)	0.194	2.367
P_{tri}(work|on his)	0.089	3.498
P_{tri}(.|his work)	0.290	1.785
P_{tri}(</s>|work .)	0.99999	0.000014
Average		2.634

Comparison of language models:

Word	Unigram	Bigram	Trigram	Four-gram
i	6.684	3.197	3.197	3.197
would	8.342	2.884	2.791	2.791
like	9.129	2.026	1.031	1.290
to	5.081	0.402	0.144	0.113
commend	15.487	12.335	8.794	8.633
the	3.885	1.402	1.084	0.880
rapporteur	10.840	7.319	2.763	2.350
on	6.765	4.140	4.150	1.862
his	10.678	7.316	2.367	1.978
work	9.993	4.816	3.498	2.394
.	4.896	3.020	1.785	1.510
</s>	4.828	0.005	0.000	0.000
Average	8.051	4.072	2.634	2.251
Perplexity	265.136	16.817	6.206	4.758

Unseen N-grams

At test time we might see words that doesn't occur in our vocabulary $\mathcal{V}$. Normally we replace these with <unk>.

But we might have problems even with words that are in our vocabulary.

Example: Zero-count trigrams

We have the following counts for words following `denied the` in WSJ Treebank 3:

```
denied the allegations: 5
denied the speculation: 2
denied the rumors:      1
denied the report:      1
```

If these are the counts, then we will assign the following trigram probabilities using maximum likelihood:

$$P_{\text{MLE}}(\texttt{offer}|\texttt{denied the}) = 0$$
$$P_{\text{MLE}}(\texttt{loan}|\texttt{denied the}) = 0$$

Is this reasonable? Any sentence with the words `denied the offer` will be assigned zero probability:

```
He denied the offer to go to the Supreme Chancellor.
```

Sparsity (again!)

Most N-gram types will actually never occur. E.g. if we have a vocabulary of $|\mathcal{V}| = 50\,000$ words, then there are $(50\,000)^3 = 1.25{\cdot}10^{14}$ unique possible trigrams. At one byte per trigram type, that takes 125 TB of space.

Consider the Google N-grams dataset, which can be browsed here:

- Number of words in vocabulary: $13\,588\,391$
- Five-gram types occurring at least 40 times: $1\,176\,470\,663$
- But the possible number of five-gram types: $4.63 \cdot 10^{35}$

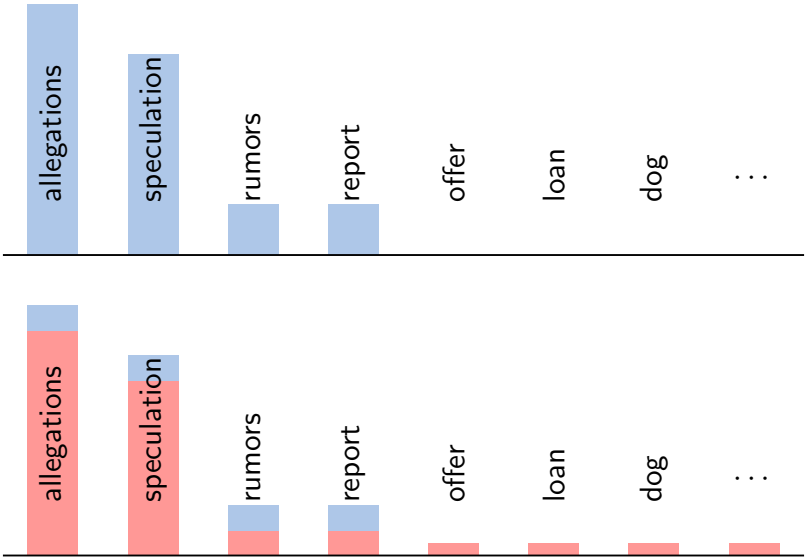
Overfitting

Assigning zero probability to N-grams not seen in the training data is a form of overfitting to the training data. How do we deal with overfitting in machine learning? Regularisation.

Language model smoothing are regularisation approaches for N-gram language models. It typically results in higher perplexity on the training data, but lower perplexity on evaluation data.

Additive smoothing

Robin Hood: Steal from the rich and give to the poor.



There are different ways of moving probability mass.

Below I give the smoothing equations for bigrams or trigrams, but in all cases these can be extended to arbitrary N-grams (sometimes with little effort, sometimes a bit more).

Add-one smoothing (Laplace)

Without smoothing, the MLE for bigrams:

$$P_{\text{MLE}}(w_t|w_{t-1}) = \frac{C(w_{t-1}, w_t)}{C(w_{t-1})}$$

Add-one smoothing adds one to each count and normalises appropriately for all possible bigrams:

$$\boxed{P_{+1}(w_t|w_{t-1}) = \frac{C(w_{t-1}, w_t) + 1}{C(w_{t-1}) + |\mathcal{V}|}}$$

Need the $+|\mathcal{V}|$ in the denominator to ensure that

$$\sum_{w_t \in \mathcal{V}} P_{+1}(w_t|w_{t-1}) = 1$$

Example: Berkeley Restaurant Project

We have counts:

$$\begin{aligned} C(\texttt{want}) &= 927 \\ C(\texttt{want to}) &= 608 \\ C(\texttt{want want}) &= 0 \\ |\mathcal{V}| &= 1446 \end{aligned}$$

Estimated probabilities for $P(\texttt{to}|\texttt{want})$ and $P(\texttt{want}|\texttt{want})$ with and without add-one smoothing:

$$\begin{aligned} P_{\text{MLE}}(\texttt{to}|\texttt{want}) &= 0.6559 \\ P_{\text{MLE}}(\texttt{want}|\texttt{want}) &= 0 \\ P_{+1}(\texttt{to}|\texttt{want}) &= 0.2566 \\ P_{+1}(\texttt{want}|\texttt{want}) &= 0.0004 \end{aligned}$$

Problem: We often steal way too much! This is because the $|\mathcal{V}|$ in the denominator can completely overpower $C(w_{t-1})$. Here we had a probability go from 0.6559 to 0.2566!

Add-α smoothing (Lindstone)

We add $0 < \alpha < 1$ to each count and normalise appropriately:

$$P_{+\alpha}(w_t|w_{t-1}) = \frac{C(w_{t-1}, w_t) + \alpha}{C(w_{t-1}) + \alpha|\mathcal{V}|}$$

Tune α on validation data.

Absolute discounting

The additional term in the denominator for add-one or add-α smoothing might still screw things up. We also treat N-grams the same irrespective of how often they occur: Whether an N-gram occurs zero or a million times, we add 1 or α to the numerator and $|\mathcal{V}|$ or $\alpha|\mathcal{V}|$ to the denominator.

Why not treat zero-count N-grams separately from higher-order N-grams?

Idea: Steal counts from higher-order N-grams without changing the denominator and then just distribute the left-over mass between zero-count N-grams.

Absolute discounting steals a constant $0 < d < 1$ from each higher-order N-gram type:

$$P_{\text{abs}}(w_t|w_{t-1}) = \begin{cases} \frac{C(w_{t-1},w_t)-d}{C(w_{t-1})} & \text{if } C(w_{t-1}, w_t) > 0 \\ p_0 & \text{if } C(w_{t-1}, w_t) = 0 \end{cases}$$

To figure out what p_0 is, we use the property that probabilities need to sum to 1. The math gets quite hairy! See Exercise 3.

We could make d a function of the N-gram count, which would allow you to e.g. steal much more from frequent N-grams and maybe less from N-grams occurring once or twice. But in practice absolute discounting (a fixed d) is pretty good already.

Interpolation and back-off

Additive smoothing ignores a useful source of information: Less context can help when there isn't sufficient evidence for higher-order context.

Example: Drinking beer in Scotland

We have a corpus with trigram counts:

```
Scottish beer was:      20
Scottish beer can:      16
Scottish beer awards:   7
Scottish beer brands:   3
```

These trigrams are never seen:

```
Scottish beer drinkers: 0
Scottish beer eaters:   0
```

How would the following estimates differ, given this data? Is this reasonable?

$$P_{\text{MLE}}(\texttt{drinkers}|\texttt{Scottish}, \texttt{beer})$$
$$P_{\text{MLE}}(\texttt{eaters}|\texttt{Scottish}, \texttt{beer})$$

But do you think the two bigrams below will have the same count?

```
beer drinkers
beer eaters
```

Higher- and lower-order N-gram models have different strengths:

- Higher-order models are more sensitive to context but are based on sparse counts.
- Lower-order models have more limited context but are based on reasonable counts.

We look at two approaches to combine models of different orders.

Interpolation

Use a mixture of models.

The trigram case:

$$\begin{aligned} P_{\text{int}}(w_t|w_{t-2}, w_{t-1}) = \lambda_1 P_1(w_t) \\ + \lambda_2 P_2(w_t|w_{t-1}) \\ + \lambda_3 P_3(w_t|w_{t-2}, w_{t-1}) \end{aligned}$$

For instance:

$$\begin{aligned} P_{\text{int}}(\texttt{drinkers}|\texttt{Scottish beer}) = \lambda_1 P_{\text{uni}}(\texttt{drinkers}) \\ + \lambda_2 P_{\text{bi}}(\texttt{drinkers}|\texttt{beer}) \\ + \lambda_3 P_{\text{tri}}(\texttt{drinkers}|\texttt{Scottish beer}) \end{aligned}$$

We need

$$\sum_{k=1}^{K} \lambda_k = 1$$

so that

$$\sum_{w_t \in \mathcal{V}} P_{\text{int}}(w_t|w_{t-2}, w_{t-1}) = 1$$

The λ's are optimised on validation data.

You can combine interpolation with additive smoothing techniques.

Back-off

In back-off we use the highest-order model if the count is not zero, otherwise we back off to a lower-order model.

We need to discount the higher-order models in order to have mass to spread to the lower-order models. And then we need to make sure the probabilities sum to 1.

Back-off N-gram model:

$$P_{\text{BO}}(w_t|w_{t-N+1:t-1}) = \begin{cases} P_d(w_t|w_{t-N+1:t-1}) \\ \qquad\qquad \text{if } C(w_{t-N+1:t}) > 0 \\ \alpha(w_{t-N+1:t})P_{\text{BO}}(w_t|w_{t-N+2:t-1}) \\ \qquad\qquad \text{if } C(w_{t-N+1:t}) = 0 \end{cases}$$

where

- $P_d(w_t|w_{t-N+1:t-1})$ is some discounted N-gram model
- Back-off weights $\alpha(w_{t-N+1:t})$ ensure probability sums to 1

The math for the α's gets quite hairy! See J&M2.

You can combine back-off with additive smoothing techniques. The math for the α's gets quite hairy! See J&M1.

Kneser-Ney smoothing

Europarl corpus:

- `York` occurs 477 times. It is as frequent as `foods`, `indicates` and `providers`.
- This leads to a relatively high unigram estimate for $P(\texttt{York})$.
- But `York` almost always follows `New` (473 times).

So in unseen bigram contexts, `York` should have a low probability. But when we back-off or interpolate, this doesn't happen. For instance:

$$P(\texttt{York}|\texttt{<not New>}) = \lambda_1 P_{\text{uni}}(\texttt{York}) + \lambda_2 P_{\text{bi}}(\texttt{York}|\texttt{<not New>})$$

Because the unigram probability $P(\texttt{York})$ is high, the resulting $P(\texttt{York}|\texttt{<not New>})$ will be high, which is what we do not want.

Kneser-Ney: Take diversity of histories into account

Count the number of bigram types ending in w_t:

$$N(\bullet, w_t) = |\{w_{t-1} : C(w_{t-1}, w_t) > 0\}|$$

Instead of using the unigram MLE

$$P_{\text{MLE}}(w_t) = \frac{C(w_t)}{\sum_{w \in \mathcal{V}} C(w)} = \frac{C(w_t)}{W}$$

we use the unique history counts

$$P_{\text{KN}}(w_t) = \frac{N(\bullet, w_t)}{\sum_{w \in \mathcal{V}} N(\bullet, w)} = \frac{N(\bullet, w_t)}{N(\bullet, \bullet)}$$

For instance:

$$P_{\text{KN}}(\texttt{York}) = \frac{\text{No. bigram types ending in } \texttt{York}}{\text{No. bigram types}} \approx \frac{2}{\text{large}}$$

$$P_{\text{KN}}(\texttt{the}) = \frac{\text{No. bigram types ending in } \texttt{the}}{\text{No. bigram types}} \approx \frac{\text{relatively large}}{\text{large}}$$

We need to get some extra mass from somewhere. We get this by combining absolute discounting with interpolation:

$$P_{\text{KN}}(w_t|w_{t-1}) = \frac{\max\{C(w_{t-1}, w_t) - d, 0\}}{C(w_{t-1})} + \lambda(w_{t-1}) P_{\text{KN}}(w_t)$$

In the higher-order case we will have even more λ's. The math for the λ's gets quite hairy! See J&M3.

N-gram language models today

In many NLP applications today there is a move to neural language models (later).

But N-gram language models are still used!

- Strong baseline in automatic speech recognition
- Easy to incorporate into decoder
- If you are searching for specific keywords, can easily push up their mass (and discount the rest)
- Normally use large context e.g. five-gram

N-gram language modelling toolkits:

- SRILM
- KenLM

Exercises

Exercise 1: Why are the normalised counts the MLE?

I state that for an unsmoothed bigram model, the MLE is

$$P_{\text{MLE}}(w_t|w_{t-1}) = \frac{C(w_{t-1}, w_t)}{C(w_{t-1})}$$

Say we have a training set of a single observed word sequence $w_{1:T}$ and we fit a unsmoothed bigram language model. Prove that the above equation is indeed the MLE.

Hint: What are the model parameters? Define these as $\theta_{j|k} = P_{\text{bi}}(w_t = j|w_{t-1} = k)$ and minimise the negative log likelihood of the parameters with the constraint that $\sum_j \theta_{j|k} = 1$.

Exercise 2: Why we need a end-of-sentence symbol[3]

We are going to be a bit formal. Let's say we have a language with a vocabulary $\mathcal{V} = \{\texttt{a}, \texttt{b}, \texttt{<s>}, \texttt{</s>}\}$. The set of possible sentence in this language is denoted as $\mathcal{V}^+$. For a language model to give a valid probability distribution, we need

$$\sum_{w_{1:T} \in \mathcal{V}+} P_{\boldsymbol{\theta}}(w_{1:T}) = 1$$

where $w_{1:T}$ denotes a particular sentence in this language.

Given the training corpus without an end-of-sentence token:

```
<s> a a
<s> a b
<s> b a
<s> b b
```

the set of all possible sentences would be

$$\mathcal{V}^+ = \{\texttt{<s> a}, \texttt{<s> b}, \texttt{<s> a a}, \texttt{<s> a b}, \texttt{<s> b a}, \texttt{<s> b b}, \texttt{<s> a a a}, \ldots\}$$

Train an unsmoothed bigram language model on the above training corpus. Show that this language model does not give a valid probability distribution over all sentence lengths.

Now repeat the above question but on the following training corpus, which do include an end-of-sentence symbol </s>:

```
<s> a a </s>
<s> a b </s>
<s> b a </s>
<s> b b </s>
```

For this case show that we get a language model that does give a valid probability distribution.

[3] Adapted from Exercise 3.5 in J&M3.

Exercise 3: Absolute discounting

In bigram absolute discounting, prove that zero-count bigrams with history word w_{t-1} are all assigned the probability

$$p_0 = \frac{1}{C_0} \sum_{r>0} \left[C_r \cdot \frac{d}{C(w_{t-1})} \right]$$

where $C_r = |\{v : C(w_{t-1}, v) = r\}|$ are the number of bigram types with history word w_{t-1} occurring exactly r times.

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References

S. F. Chen and J. Goodman, "An empirical study of smoothing techniques for language modeling," *Computer Speech and Language*, 1999.

M. Collins, "Language modelling," *Columbia University*, 2013.

Videos covered in this note

- The language modelling problem (10 min)
- N-gram language models (13 min)
- Start and end of sentence tokens in language models (11 min)
- Why use log in language models? (4 min)
- Evaluating language models using perplexity (9 min)
- Language model smoothing intuition (6 min)
- Additive smoothing in language models (10 min)
- Absolute discounting in language models (5 min)
- Language model interpolation (11 min)
- Language model backoff (4 min)
- Kneser-Ney smoothing (8 min)
- Are N-gram language models still used today? (2 min)