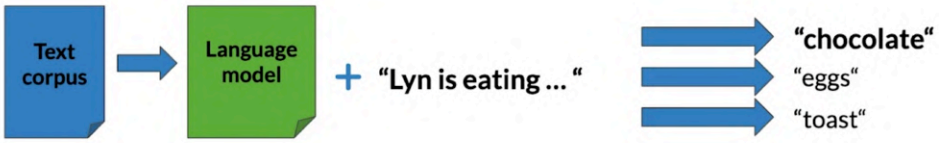
## What you'll be able to do!

- Create **language model (LM)** from text corpus to
  - Estimate probability of word sequences
  - Estimate probability of a word following a sequence of words
- Apply this concept to **autocomplete a sentence** with most likely suggestions




## Other Applications

### Speech recognition

P(I saw a van) > P(eyes awe of an)

### Spelling correction

"He entered the ship to buy some groceries" - "ship" a dictionary word
- P(entered the shop to buy) > P(entered the ship to buy)

### Augmentative communication

Predict most likely word from menu for people unable to physically talk or sign.
(Newell et al., 1998)

## Learning objectives

- Process text corpus to N-gram language model
- Out of vocabulary words
- Smoothing for previously unseen N-grams
- Language model evaluation

→ Sentence auto-complete

## Outline

- What are N-grams?
- N-grams and conditional probability from corpus

## N-gram

An N-gram is a sequence of N words

Corpus: I am happy because I am learning

Unigrams: { I , am , happy , because , learning }

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Bigrams: { I am , am happy , happy because ... }

# N-gram

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Bigrams: { I am , am happy , happy because ... }  ✖ I happy

## Sequence notation

Corpus: This is great ... teacher drinks tea. $m = 500$

($w_1\ w_2\ w_3$ ... $w_{498}\ w_{499}\ w_{500}$)

$$w_1^m = w_1\ w_2\ \dots\ w_m$$

$$w_1^3 = w_1\ w_2\ w_3$$

Sequence of words from a to b

a

## Sequence notation

Corpus: This is great ... teacher drinks tea. $m = 500$

$w_1 \; w_2 \; w_3 \qquad\qquad w_{498} \; w_{499} \; w_{500}$

$$w_1^m = w_1 \; w_2 \; \ldots \; w_m$$

$$w_1^3 = w_1 \; w_2 \; w_3$$

$$w_{m-2}^m = w_{m-2} \; w_{m-1} \; w_m$$

## Unigram probability

Corpus: I am happy because I am learning

Size of corpus m = 7

$$P(I) = \frac{2}{7} \qquad P(happy) = \frac{1}{7}$$

Probability of unigram: $P(w) = \frac{C(w)}{m}$

## Bigram probability

Corpus: I am happy because I am learning

$$P(am|I) = \frac{C(I\,am)}{C(I)} = \frac{2}{2} = 1$$

## Bigram probability

Corpus: I am happy because I am learning

$$P(am|I) = \frac{C(I\ am)}{C(I)} = \frac{2}{2} = 1$$

## Bigram probability

Corpus: I am happy because I am learning

I comes before happy

$$P(am|I) = \frac{C(I\ am)}{C(I)} = \frac{2}{2} = 1 \qquad P(happy|I) = \frac{C(I\ happy)}{C(I)} = \frac{0}{2} = 0$$ ✖ I happy

$$P(learning|am) = \frac{C(am\ learning)}{C(am)} = \frac{1}{2}$$

Probability of a bigram: $P(y|x) = \frac{C(x\ y)}{\sum_w C(x\ w)} = \frac{C(x\ y)}{C(x)}$

## Trigram Probability

Corpus: I am happy because I am learning

$$P(happy|I\ am) = \frac{C(I\ am\ happy)}{C(I\ am)} = \frac{1}{2}$$

## Trigram Probability

Corpus: I am happy because I am learning

$$P(happy|I\ am) = \frac{C(I\ am\ happy)}{C(I\ am)} = \frac{1}{2}$$

## Trigram Probability

Corpus: I am happy because I am learning

$$P(happy|I\ am) = \frac{C(I\ am\ happy)}{C(I\ am)} = \frac{1}{2}$$

Probability of a trigram: $P(w_3|w_1^2) = \frac{C(w_1^2\ w_3)}{C(w_1^2)}$

$$C(w_1^2\ w_3) = C(w_1\ w_2\ w_3) = C(w_1^3)$$

## N-gram probability

Probability of N-gram: $P(w_N|w_1^{N-1}) = \frac{C(w_1^{N-1}\ w_N)}{C(w_1^{N-1})}$

$$C(w_1^{N-1}\ w_N) = C(w_1^N)$$

## Probability of a sequence

- Given a sentence, what is its probability?

$$P(\textit{the teacher drinks tea}) = ?$$

- Conditional probability and chain rule reminder

$$P(B|A) = \frac{P(A,B)}{P(A)} \implies P(A,B) = P(A)P(B|A)$$

$$P(A,B,C,D) = P(A)P(B|A)P(C|A,B)P(D|A,B,C)$$

Chain Rule

## Probability of a sequence

$$P(\textit{the teacher drinks tea}) =$$

$$P(\textit{the})P(\textit{teacher}|\textit{the})P(\textit{drinks}|\textit{the teacher})$$
$$P(\textit{tea}|\textit{the teacher drinks})$$

interested in or even its longer subsequences!

Input: the teacher drinks tea

$$P(\textit{the teacher drinks tea}) = P(\textit{the})P(\textit{teacher}|\textit{the})P(\textit{drinks}|\textit{the teacher})P(\textit{tea}|\textit{the teacher drinks})$$

$$P(\textit{tea}|\textit{the teacher drinks}) = \frac{C(\textit{the teacher drinks tea})}{C(\textit{the teacher drinks})}$$

← Both
← likely 0

## Approximation of sequence probability

the teacher drinks tea

$P(tea|the\ teacher\ drinks) \approx P(tea|drinks)$

$P(teacher|the)$
$P(drinks|teacher)$
$P(tea|drinks)$

$$P(the\ teacher\ drinks\ tea) =$$
$$P(the)P(teacher|the)P(drinks|the\ teacher)P(tea|the\ teacher\ drinks)$$
$$\downarrow$$
$$P(the)P(teacher|the)P(drinks|teacher)P(tea|drinks)$$

## Approximation of sequence probability

- Markov assumption: only last N words matter
- Bigram $P(w_n|w_1^{n-1}) \approx P(w_n|w_{n-1})$
- N-gram $P(w_n|w_1^{n-1}) \approx P(w_n|w_{n-N+1}^{n-1})$
- Entire sentence modeled with bigram $P(w_1^n) \approx \prod_{i=1}^{n} P(w_i|w_{i-1})$

$$P(w_1^n) \approx P(w_1)P(w_2|w_1)...P(w_n|w_{n-1})$$

## Outline

- Start of sentence symbols <s>
- End of sentence symbol </s>

## Start of sentence token <s>

the teacher drinks tea

$$P(the\ teacher\ drinks\ tea) \approx P(the)P(teacher|the)P(drinks|teacher)P(tea|drinks)$$

<s> the teacher drinks tea

$$P(<s>\ the\ teacher\ drinks\ tea) \approx P(the|<s>)P(teacher|the)P(drinks|teacher)P(tea|drinks)$$

## Start of sentence token <s> for N-grams

- Trigram:

$$P(the\ teacher\ drinks\ tea) \approx P(the)P(teacher|the)P(drinks|the\ teacher)P(tea|teacher\ drinks)$$

the teacher drinks tea => <s> <s> the teacher drinks tea

$$P(w_1^n) \approx P(w_1|<s>\ <s>)P(w_2|<s>\ w_1)...P(w_n|w_{n-2}\ w_{n-1})$$

- N-gram model: add N-1 start tokens <s>

## End of sentence token </s> - motivation

$$P(y|x) = \frac{C(x\ y)}{\sum_w C(x\ w)} = \frac{C(x\ y)}{C(x)}$$

Corpus:
<s> Lyn drinks chocolate
<s> John drinks

$$\sum_w C(drinks\ w) = 1$$

## End of sentence token </s> - motivation

$$P(y|x) = \frac{C(x\ y)}{\sum_w C(x\ w)} = \frac{C(x\ y)}{C(x)}$$

Corpus:
<s> Lyn drinks chocolate
<s> John drinks

$$\sum_w C(drinks\ w) = 1$$

$$C(drinks) = 2$$

## End of sentence token </s> - motivation

Corpus
<s> yes no
<s> yes yes
<s> no no

Sentences of length 2:
<s> yes yes
<s> yes no
<s> no no
<s> no yes

$$P(< s > \text{ yes yes}) =$$

$$P(\text{yes} \mid < s >) \times P(\text{yes} \mid \text{yes}) =$$

$$\frac{C(< s > \text{ yes})}{\sum_w C(< s > w)} \times \frac{C(\text{yes yes})}{\sum_w C(\text{yes } w)} =$$

$$\frac{2}{3} \times \frac{1}{2} = \frac{1}{3}$$

## End of sentence token </s> - motivation

Corpus
<s> yes no
<s> yes yes
<s> no no

Sentences of length 2:
<s> yes yes
<s> yes no
<s> no no
<s> no yes

$$P(< s > \text{ yes yes}) = \frac{1}{3}$$

$$P(< s > \text{ yes no}) = \frac{1}{3}$$

$$P(< s > \text{ no no}) = \frac{1}{3}$$

$$P(< s > \text{ no yes}) = 0$$

$$\sum_{\text{2 word}} P(\cdots) = 1$$

# End of sentence token </s> - motivation

Corpus
<s> yes no
<s> yes yes
<s> no no

Sentences of length 3:
<s> yes yes yes
<s> yes yes no
...
<s> no no no

$$P(< s > \text{ yes yes yes}) = \dots$$
$$P(< s > \text{ yes yes no}) = \dots$$
$$\dots = \dots$$
$$P(< s > \text{ no no no}) = \dots$$

$$\sum_{3 \text{ word}} P(\cdots) = 1$$

# End of sentence token </s> - motivation

Corpus
<s> yes no
<s> yes yes
<s> no no

When you add up the probabilities of all the possible sentences of length three, you, again, get the sum of one. However, what you really want is the sum of the probabilities for all sentences of the length to be equal to one, so that you can, for example, compare the probabilities of two sentences of different lengths. In other words, you want the probabilities of all two-words sentences, what's the probabilities of all three-words sentences? What's the probabilities of all other sentences of arbitrary length? You want this to be equal to one. There is a surprisingly simple fix for this. You can pre-process your training corpus to add a special symbol which represents the end of the sentence, which you will denote with brackets backslash S after each sentence.

$$\sum_{2 \text{ word}} P(\cdots) + \sum_{3 \text{ word}} P(\cdots) + \dots$$

# End of sentence token </s> - solution

- Bigram

<s> the teacher drinks tea => <s> the teacher drinks tea </s>

$$P(the|<s>)P(teacher|the)P(drinks|teacher)P(tea|drinks)P(</s>|tea)$$

Corpus:
<s> Lyn drinks chocolate </s>
<s> John drinks </s>

$$\sum_{w} C(drinks\ w) = 2$$
$$C(drinks) = 2$$

## End of sentence token </s> for N-grams

- N-gram => just one </s>

  E.g. Trigram:
  the teacher drinks tea => <s> <s> the teacher drinks tea </s>

## Example - bigram

Corpus
<s> Lyn drinks chocolate </s>
<s> John drinks tea </s>
<s> Lyn eats chocolate </s>

$$P(sentence) = \frac{2}{3} * \frac{1}{2} * \frac{1}{2} * \frac{2}{2} = \frac{1}{6}$$

$$P(John|<s>) = \frac{1}{3}$$

$$P(</s>|tea) = \frac{1}{1}$$

$$P(chocolate|eats) = \frac{1}{2}$$

$$P(Lyn|<s>) =? = \frac{2}{3}$$

## Example - bigram

Corpus
<s> Lyn drinks chocolate </s>
<s> John drinks tea </s>
<s> Lyn eats chocolate </s>

$$P(sentence) = \frac{2}{3} * \frac{1}{2} * \frac{1}{2} * \frac{2}{2} = \frac{1}{6}$$

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$$P(</s>|tea) = \frac{1}{1}$$

$$P(chocolate|eats) = \frac{1}{2}$$

$$P(Lyn|<s>) =? = \frac{2}{3}$$

## Example - bigram

Corpus
<s> Lyn drinks chocolate </s>
<s> John drinks tea </s>
<s> Lyn eats chocolate </s>

$$P(sentence) = \frac{2}{3} * \frac{1}{2} * \boxed{\frac{1}{2}} * \frac{2}{2} = \frac{1}{6}$$

$$P(John|<s>) = \frac{1}{3}$$

$$P(chocolate|eats) = \frac{1}{2}$$

$$P(</s>|tea) = \frac{1}{1}$$

$$P(Lyn|<s>) =? = \frac{2}{3}$$

## Example - bigram

Corpus
<s> Lyn drinks chocolate </s>
<s> John drinks tea </s>
<s> Lyn eats chocolate </s>

$$P(sentence) = \frac{2}{3} * \frac{1}{2} * \frac{1}{2} * \boxed{\frac{2}{2}} = \frac{1}{6}$$

$$P(John|<s>) = \frac{1}{3}$$

$$P(chocolate|eats) = \frac{1}{2}$$

$$P(</s>|tea) = \frac{1}{1}$$

$$P(Lyn|<s>) =? = \frac{2}{3}$$

## Outline

- Count matrix
- Probability matrix
- Language model
- Log probability to avoid underflow
- Generative language model

# Count matrix

Formula for testing the conditional probability of n-gram

$$P(w_n|w_{n-N+1}^{n-1}) = \frac{C(w_{n-N+1}^{n-1}, w_n)}{C(w_{n-N+1}^{n-1})}$$

The count matrix captures the numerator for all n-grams appearing in the corpus

All unique corpus, N minus-1 grams make up the rows, and all unique words of the corpus make up the columns

- Rows: unique corpus (N-1)-grams
- Columns: unique corpus words

- Bigram count matrix

Corpus: <s>I study I learn</s>

"study I" bigram

| | <s> | </s> | I | study | learn |
|---|---|---|---|---|---|
| <s> | 0 | 0 | 1 | 0 | 0 |
| </s> | 0 | 0 | 0 | 0 | 0 |
| I | 0 | 0 | 0 | 1 | 1 |
| study | 0 | 0 | 1 | 0 | 0 |
| learn | 0 | 1 | 0 | 0 | 0 |

# Probability matrix

$$P(w_n|w_{n-N+1}^{n-1}) = \frac{C(w_{n-N+1}^{n-1}, w_n)}{C(w_{n-N+1}^{n-1})}$$

$$sum(row) = \sum_{w \in V} C(w_{n-N+1}^{n-1}, w) = C(w_{n-N+1}^{n-1})$$

- Divide each cell by its row sum

Corpus: <s>I study I learn</s>

Count matrix (bigram)

| | <s> | </s> | I | study | learn | sum |
|---|---|---|---|---|---|---|
| <s> | 0 | 0 | 1 | 0 | 0 | 1 |
| </s> | 0 | 0 | 0 | 0 | 0 | 0 |
| I | 0 | 0 | 0 | 1 | 1 | 2 |
| study | 0 | 0 | 1 | 0 | 0 | 1 |
| learn | 0 | 1 | 0 | 0 | 0 | 1 |

Probability matrix

| | <s> | </s> | I | study | learn |
|---|---|---|---|---|---|
| <s> | 0 | 0 | 1 | 0 | 0 |
| </s> | 0 | 0 | 0 | 0 | 0 |
| I | 0 | 0 | 0 | 0.5 | 0.5 |
| study | 0 | 0 | 1 | 0 | 0 |
| learn | 0 | 1 | 0 | 0 | 0 |

# Language model

- probability matrix => language model
  - Sentence probability
  - Next word prediction

| | <s> | </s> | I | study | learn |
|---|---|---|---|---|---|
| <s> | 0 | 0 | 1 | 0 | 0 |
| </s> | 0 | 0 | 0 | 0 | 0 |
| I | 0 | 0 | 0 | 0.5 | 0.5 |
| study | 0 | 0 | 1 | 0 | 0 |
| learn | 0 | 1 | 0 | 0 | 0 |

Sentence probability:
<s> I learn </s>

$$P(sentence) = P(I|<s>)P(learn|I)P(</s>|learn) = 1 \times 0.5 \times 1 = 0.5$$

## Log probability

$$P(w_1^n) \approx \prod_{i=1}^{n} P(w_i|w_{i-1})$$

- All probabilities in calculation <=1 and multiplying them brings risk of underflow
- Logarithm properties reminder $log(a * b) = log(a) + log(b)$

## Generative Language model

Corpus:

<s> Lyn drinks chocolate </s>

<s> John drinks tea </s>

<s> Lyn eats chocolate </s>

1. (<s>, Lyn) or (<s>, John)?
2. (Lyn,eats) or (Lyn,drinks) ?
3. (drinks,tea) or (drinks,chocolate)?
4. (tea,</s>) - always

Algorithm:

1. Choose sentence start
2. Choose next bigram starting with previous word
3. Continue until </s> is picked

## Outline

- Train/Validation/Test split
- Perplexity

## Test data

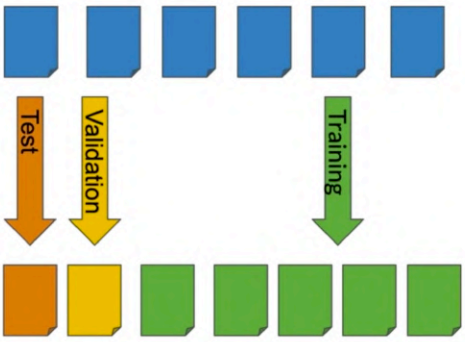
- Split corpus to Train/Validation/Test

✖ Evaluate on Training dataset

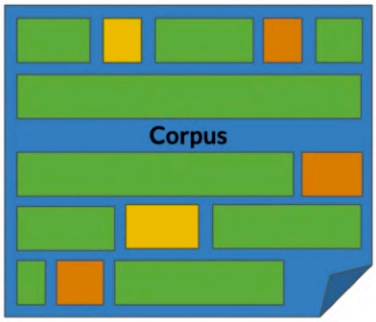
- For smaller corpora
  - 80% Train
  - 10% Validation
  - 10% Test
- For large corpora (typical for text)
  - 98% Train
  - 1% Validation
  - 1% Test

## Test data - split method

- Continuous text




- Random short sequences




## Perplexity

$$PP(W) = P(s_1, s_2, \ldots, s_m)^{-\frac{1}{m}}$$

**W** → test set containing **m** sentences **s**

$s_i$ → i-th sentence in the test set, each ending with </s>

**m** → number of all words in entire test set W including </s> but not including <s>

# Perplexity

Entropy measures uncertainty

E.g. m=100

$$P(W) = 0.9 => PP(W) = 0.9^{-\frac{1}{100}} = 1.00105416$$

$$P(W) = 10^{-250} => PP(W) = (10^{-250})^{-\frac{1}{100}} \approx 316$$

The smaller the perplexity score the more likely the sentence is to sound natural to human ears. For context, good language models have perplexity scores between 60 to 20 sometimes even lower for English. Perplexities for character level language models where you track characters instead of words will be lower.

Perplexity ↓ Better

- Smaller perplexity = better model
- Character level models PP < word-based models PP

# Perplexity for bigram models

$$PP(W) = \sqrt[m]{\prod_{i=1}^{m} \prod_{j=1}^{|s_i|} \frac{1}{P(w_j^{(i)} | w_{j-1}^{(i)})}}$$

$w_j^{(i)}$ → j-th word in i-th sentence

- concatenate all sentences in W

$$PP(W) = \sqrt[m]{\prod_{i=1}^{m} \frac{1}{P(w_i | w_{i-1})}}$$

$w_i$ → i-th word in test set

# Log perplexity

$$PP(W) = \sqrt[m]{\prod_{i=1}^{m} \frac{1}{P(w_i | w_{i-1})}}$$

In a good model with perplexity between 20 and 60, log perplexity would be between 4.3 and 5.9.

$$logPP(W) = -\frac{1}{m} \sum_{i=1}^{m} log_2(P(w_i | w_{i-1}))$$

# Examples

Training 38 million words, test 1.5 million words, WSJ corpus
Perplexity Unigram: 962 Bigram: 170 Trigram: 109

**Unigram**

Months the my and issue of year foreign new exchange's september were recession exchange new endorsed a acquire to six executives

**Bigram**

Last December through the way to preserve the Hudson corporation N. B. E. C. Taylor would seem to complete the major central planners one point five percent of U. S. E. has already old M. X. corporation of living on information such as more frequently fishing to keep her

**Trigram**

They also point to ninety nine point six billion dollars from two hundred four oh six three percent of the rates of interest stores as Mexico and Brazil on market conditions

[Figure from *Speech and Language Processing* by Dan Jurafsky et. al]

# Outline

- Unknown words
- Update corpus with <UNK>
- Choosing vocabulary

**Open vocabulary simply means that you may encounter words from outside the vocabulary, like a name of a new city in the training sets. The unknown words are also called out of vocabulary words or OOV for short. One way to deal with the unknown words is to model them by a special word UNK. To do this, you simply replace every unknown word with UNK.**

# Out of vocabulary words

- Closed vs. Open vocabularies
- Unknown word = Out of vocabulary word (OOV)
- special tag <UNK> in corpus and in input

## Using <UNK> in corpus

- Create vocabulary V
- Replace any word in corpus and not in V by <UNK>
- Count the probabilities with <UNK> as with any other word

## Example

Corpus

<s> Lyn drinks chocolate </s>

<s> John drinks tea </s>

<s> Lyn eats chocolate </s>

Corpus

<s> Lyn drinks chocolate </s>

<s> <UNK> drinks <UNK> </s>

<s> Lyn <UNK> chocolate </s>

Min frequency f=2

Vocabulary

Lyn, drinks, chocolate

Input query

<s>Adam drinks chocolate</s>

<s><UNK> drinks chocolate</s>

## How to create vocabulary V

- Criteria:
  - Min word frequency f
  - Max |V|, include words by frequency
- Use <UNK> sparingly
- Perplexity - only compare LMs with the same V

Language Models

Vocabulary

The words that occur more than f times in the corpus will become part of the vocabulary V, then replace all other word's not in the vocabulary with UNK. This is a simple heuristic. But it guarantees that the words you care about, the ones that repeats a lot, are parts of the vocabulary.

Alternatively, you can decide what the maximum size of your vocabulary is and only include words with the highest frequency up to the maximum vocabulary size.

One thing to consider is the influence of UNKs on the perplexity. Is it going to make it lower or higher? Actually, it's usually lower. So it will look like your language model is getting better and better. But watch out. You might just have a lot of UNKs. The model would then generate a sequence of UNK quotes with high probability instead of meaningful sentences. Due to this limitation, I would recommend using UNKs sparingly.

## Outline

- Missing N-grams in corpus
- Smoothing
- Backoff and interpolation

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## Missing N-grams in training corpus

- Problem: N-grams made of known words still might be missing in the training corpus "John", "eats" in corpus ✖ "John eats"
- Their counts cannot be used for probability estimation

$$P(w_n|w_{n-N+1}^{n-1}) = \frac{C(w_{n-N+1}^{n-1}, w_n)}{C(w_{n-N+1}^{n-1})}$$ ← Can be 0

Solution

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## Smoothing

- Advanced methods:
  Kneser-Ney smoothing
  Good-Turing smoothing

This will only work on a corpus where the real counts are large enough to outweigh the plus one though.

- Add-one smoothing (Laplacian smoothing)

$$P(w_n|w_{n-1}) = \frac{C(w_{n-1}, w_n) + 1}{\sum_{w \in V} (C(w_{n-1}, w) + 1)} = \frac{C(w_{n-1}, w_n) + 1}{C(w_{n-1}) + V}$$

- Add-k smoothing

larger corpus

$$P(w_n|w_{n-1}) = \frac{C(w_{n-1}, w_n) + k}{\sum_{w \in V} (C(w_{n-1}, w) + k)} = \frac{C(w_{n-1}, w_n) + k}{C(w_{n-1}) + k * V}$$

## Backoff

- If N-gram missing => use (N-1)-gram, ...
  - Probability discounting e.g. Katz backoff
  - "Stupid" backoff

Corpus

<s> Lyn drinks chocolate </s>

<s> John drinks tea </s>

<s> Lyn eats chocolate </s>

$$P(chocolate|John\ drinks) = ?$$

$$0.4 \times P(chocolate|drinks)$$

Alternative to backoff

## Interpolation

$$\hat{P}(chocolate|John\ drinks) = 0.7 \times P(chocolate|John\ drinks) + 0.2 \times P(chocolate|drinks) + 0.1 \times P(chocolate)$$

$$\hat{P}(w_n|w_{n-2}\ w_{n-1}) = \lambda_1 \times P(w_n|w_{n-2}\ w_{n-1}) + \lambda_2 \times P(w_n|w_{n-1}) + \lambda_3 \times P(w_n)$$

$$\sum_i \lambda_i = 1$$

## Summary

- N-Grams and probabilities
- Approximate sentence probability from N-Grams
- Build language model from corpus
- Fix missing information
  - Out of vocabulary words with <UNK>
  - Missing N-Gram in corpus with smoothing, backoff and interpolation
- Evaluate language model with perplexity

An alternative approach to back off is to use the linear interpolation of all orders of n-gram. That means that you would always combine the weighted probability of the n-gram, N minus 1 gram down to unigrams. For example, when calculating the probability for the trigram, John drinks chocolate, you could take 70 percent of the estimated probability for trigram. So John drinks chocolates plus 20 percent of the estimated probability for bigram, drinks chocolate, and 10 percent of the estimated unigram probability of the word, chocolate. More generally, for trigrams, you would combine the weighted probabilities of trigram, bigram and unigram. You weigh all these probabilities with constants like Lambda 1, Lambda 2, and Lambda 3. These need to add up to one. The Lambdas are learned from the validation parts of the corpus. You can get them by maximizing the probability of sentences from the validation set. Use a fixed language model trained from the training parts of the corpus to calculate n-gram probabilities and optimize the Lambdas. The interpolation can be applied to general n-gram by using more Lambdas.