Course series: Deep Learning for Machine Translation

Language Modeling

Lecture # 2

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Recap: Automatic Translation System

- Translation model
  - learn word level and phrase level translation
- Language model
  - fluency model
  - learn to generate fluent translations
- Decoder
  - translation generation component
  - how to produce a translation from a trained translation model and language model

Recap: Automatic Translation System

- Translation model
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Language Model

You shall know a word by the company it keeps

—Firth, J. R. 1957:11

Language Model

A few applications of language model

- Machine Translation
  - he goes vs. he go

Language Model

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- Machine Translation
  - he goes vs. he go
- Speech recognition
  - speaker recognition vs. speak are cognition

Language Model

A few applications of language model

- Machine Translation
  - he goes vs. he go
- Speech recognition
  - speaker recognition vs. speak are cognition
- Spell checking
  - from vs. form

Language Model

Fill in the blank:

... a __________ ...

car	cars	water	cat

Language Model

Fill in the blank:

... a _________ ...

car and *cat* both work

car	cars	water	cat

Language Model

Fill in the blank:

... a _________ ...

car and *cat* both work

car	cars	water	cat

John is driving a _________ ...

Language Model

Fill in the blank:

... a _________ ...

car and *cat* both work

car	cars	water	cat

John is driving a _________ ...

only *car* works here

Language Model

Fill in the blank:

... a _________ ...

car and *cat* both work

car	cars	water	cat

John is driving a _________ ...

Similarly, machines use the context to predict the next words

Language Model

You chose “driving a car” because you’ve seen that phrase more frequently

“driving a cat” is not a common phrase

Language Model

Fill in the blank:

This _______ is going at 100 km/hours

car

bicycle

Car at 100km/hours is more probable than a bicycle

Language Model

Language model defines
"how probable a sentence is"

Language Model

Let’s look at the example again

How probable is:

John is driving a car vs. John is driving a cat

In other words, what is the probability to predict cat or car given the context “John is driving a”

Language Model

Calculate probability of a sequence of words using Chain Rule

$$
\begin{aligned}
p(\text{John is driving a car}) = \; & p(\text{John}) \cdot p(\text{is}|\text{John}) \\
& \cdot p(\text{driving}|\text{John is}) \\
& \cdot p(\text{a}|\text{John is driving}) \\
& \cdot p(\text{car}|\text{John is driving a})
\end{aligned}
$$

Language Model

But...

$$p(\text{car}|\text{John is driving a}) \text{ vs. } p(\text{car}|\text{driving a}) \text{ vs. } p(\text{car}|\text{a})$$

- long context is infrequent to find
- requires more memory to keep

Ngram based LM

- Limit the context to fewer words

$$p(\text{car}|\text{John is driving a})$$

$$\Big\downarrow \text{ remove words that appear too far back}$$

$$p(\text{car}|\text{driving a})$$

Ngram based LM

- Limit the context to fewer words

$$p(\text{car}|\text{John is driving a}) \longrightarrow p(\text{car}|\text{driving a})$$

Unigram: $p(\text{car})$

Bigram: $p(\text{car}|\text{a})$

Trigram: $p(\text{car}|\text{driving a})$

Ngram based LM

Probability of a sequence with bigram context

$$
\begin{aligned}
p(\text{John is driving a car}) = p(\text{John}) \cdot p(\text{is}|\text{John}) \\
\cdot p(\text{driving}|\text{John is}) \\
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Ngram based LM

Probability of a sequence with bigram context

$$p(\text{John is driving a car}) = p(\text{John}) \cdot p(\text{is}|\text{John})$$
$$\cdot p(\text{driving}|\text{John is})$$
$$\cdot p(\text{a}|\text{is driving})$$
$$\cdot p(\text{car}|\text{driving a})$$

Formally, Ngram approximation of a sequence is given by:

$$p(w_1 w_2 .. w_n) = \prod_{k=1}^{n} p(w_k | w_{k-N+1}^{k-1})$$

Count-based LM

How do we estimate probabilities?

Count-based LM

Estimate probabilities from a corpus

$$p(\text{John}) = \frac{c(\text{John})}{\text{Total number of tokens in corpus}}$$

$$p(\text{is}|\text{John}) = \frac{c(\text{John is})}{c(\text{John})}$$

where c stands for count

Count-based LM - Example

Corpus

<s> I am Sam </s>

<s> Sam likes tea </s>

<s> Dan does not like green eggs and ham </s>

<s> Sam eats ham </s>

<s> Dan likes cats </s>

<s> tea and biscuits go together </s>

<s> a pack of biscuits </s>

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and	2	not	1
tea	2	a	1
am	1	like	1
likes	2	Sam	3
go	1	of	1
</s>	7	eats	1
ham	2	together	1
<s>	7	green	1
Dan	2	cats	1
does	1	biscuits	2
I	1	pack	1
eggs	1		

Unigram Counts

Count-based LM - Example

Corpus

<s> I am Sam </s>

<s> Sam likes tea </s>

<s> Dan does not like green eggs and ham </s>

<s> Sam eats ham </s>

<s> Dan likes cats </s>

<s> tea and biscuits go together </s>

<s> a pack of biscuits </s>

Bigram Counts

<s> a	1	and biscuits	1
likes cats	1	Sam </s>	1
eggs and	1	cats </s>	1
ham </s>	2	<s> tea	1
Dan likes	1	and ham	1
a pack	1	likes tea	1
go together	1	does not	1
biscuits go	1	I am	1
tea and	1	green eggs	1
like green	1	Sam eats	1
Dan does	1	not like	1
of biscuits	1	together </s>	1
<s> I	1	Sam likes	1
biscuits </s>	1	<s> Sam	2
pack of	1	eats ham	1
am Sam	1	<s> Dan	2
tea </s>	1		

Count-based LM - Example

Calculate bigram probabilities

$$p(w_i|w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

Unigram Counts

and	2	not	1
tea	2	a	1
am	1	like	1
likes	2	Sam	3
go	1	of	1
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Dan	2	cats	1
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$$p(w_i|w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}$$

Bigram Counts

<s> a	1	and biscuits	1
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a pack	1	likes tea	1
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biscuits go	1	I am	1
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pack of	1	eats ham	1
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Count-based LM - Example

Calculate probability of a sentence

$$p(\texttt{<s>}\ \text{Dan likes tea}\ \texttt{</s>})$$

Count-based LM - Example

Calculate probability of a sentence

$$p(\texttt{<s>}\ \text{Dan likes tea}\ \texttt{</s>}) = \frac{c(\texttt{<s>}\ \text{Dan})}{c(\texttt{<s>})} \cdot \frac{c(\text{Dan likes})}{c(\text{Dan})} \cdot \frac{c(\text{likes tea})}{c(\text{likes})} \cdot \frac{c(\text{tea}\ \texttt{</s>})}{c(\text{tea})}$$

Count-based LM - Example

Calculate probability of a sentence

$$p(\texttt{<s>}\ \text{Dan likes tea}\ \texttt{</s>}) = \frac{c(\texttt{<s>}\ \text{Dan})}{c(\texttt{<s>})}$$

$$\cdot \frac{c(\text{Dan likes})}{c(\text{Dan})} \cdot \frac{c(\text{likes tea})}{c(\text{likes})} \cdot \frac{c(\text{tea}\ \texttt{</s>})}{c(\text{tea})}$$

= 0.286 x 0.5 x 0.5 x 0.5

= 0.036

Count-based LM - Example

Calculate probability of a sentence

$$p(\texttt{<s>}\ \text{Dan likes tea and biscuits}\ \texttt{</s>})$$

Count-based LM - Example

Calculate probability of a sentence

$$p(\texttt{<s>}\ \text{Dan likes tea and biscuits}\ \texttt{</s>})$$

= 0.286 x 0.5 x 0.5 x 0.5 x 0.5 x 0.5

= 0.0089

Unknown Words/Sequences

$$p(\texttt{<s>}\ \text{Dan likes ham}\ \texttt{</s>}) = \frac{c(\texttt{<s>}\ \text{Dan})}{c(\texttt{<s>})} \cdot \frac{c(\text{Dan likes})}{c(\text{Dan})} \cdot \frac{c(\text{likes ham})}{c(\text{likes})} \cdot \frac{c(\text{ham}\ \texttt{</s>})}{c(\text{ham})}$$

Unknown Words/Sequences

$$p(\texttt{<s>}\ \text{Dan likes ham}\ \texttt{</s>}) = \frac{c(\texttt{<s>}\ \text{Dan})}{c(\texttt{<s>})} \cdot \frac{c(\text{Dan likes})}{c(\text{Dan})} \cdot \boxed{\frac{c(\text{likes ham})}{c(\text{likes})}} \cdot \frac{c(\text{ham}\ \texttt{</s>})}{c(\text{ham})}$$

Unknown

probability of unknown is zero

probability of the entire sentence becomes zero!

Intuition of Smoothing

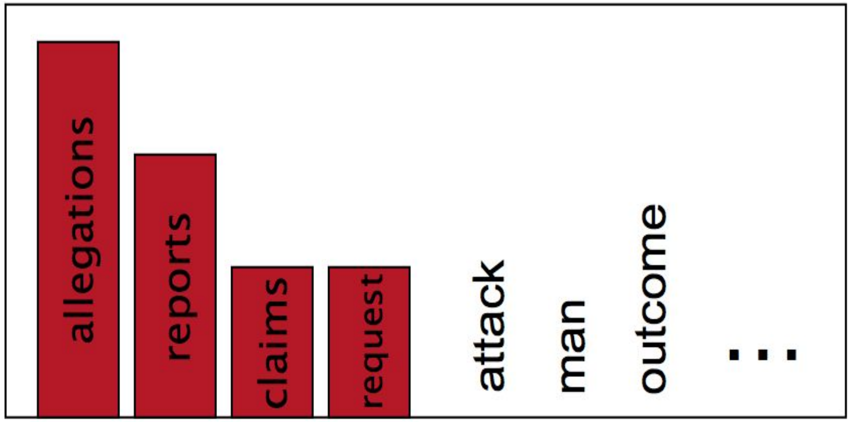
- Steal probability mass from known words
- Assign it to unknown words

From D. Jurafsky, Stanford https://web.stanford.edu/class/cs124/lec/languagemodeling.pdf

Intuition of Smoothing

Sparse statistics:

- 3 allegations, 2 reports, 1 claims, 1 request
- 7 total



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Intuition of Smoothing

Sparse statistics:

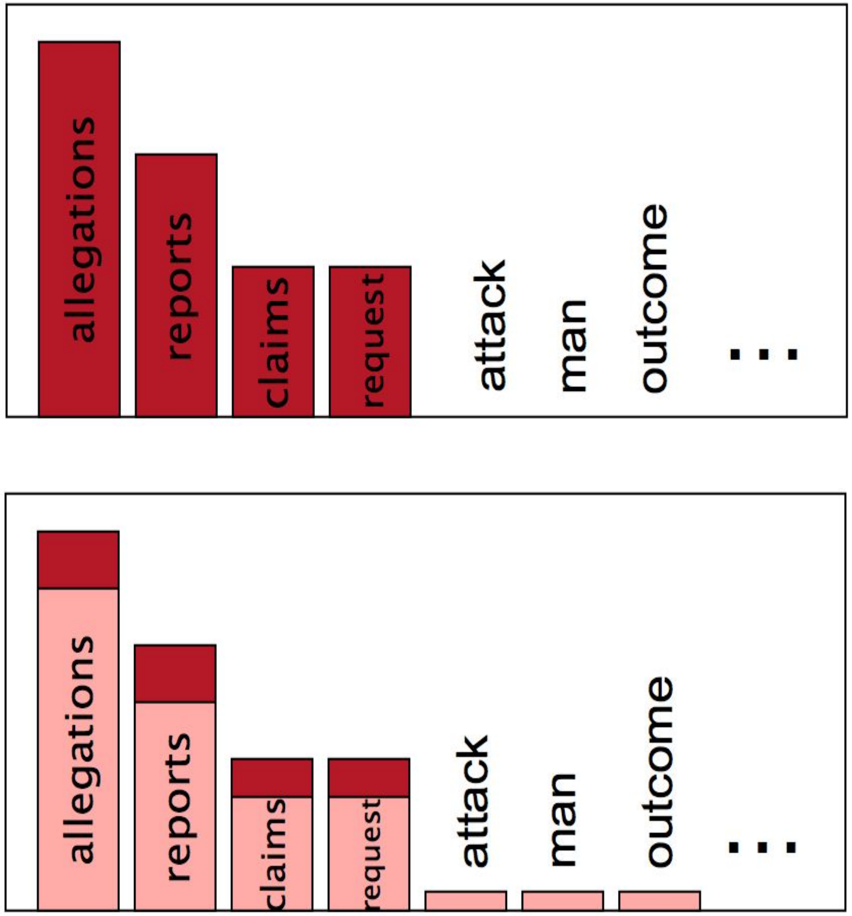
3 allegations, 2 reports, 1 claims, 1 request

7 total

Steal probability mass to generalize better

2.5 allegations, 1.5 reports, 0.5 claims, 0.5 request, **2 other**

7 total



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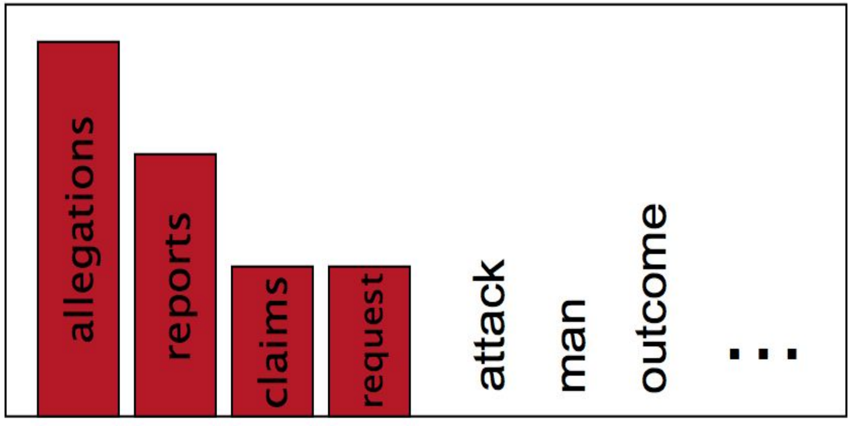
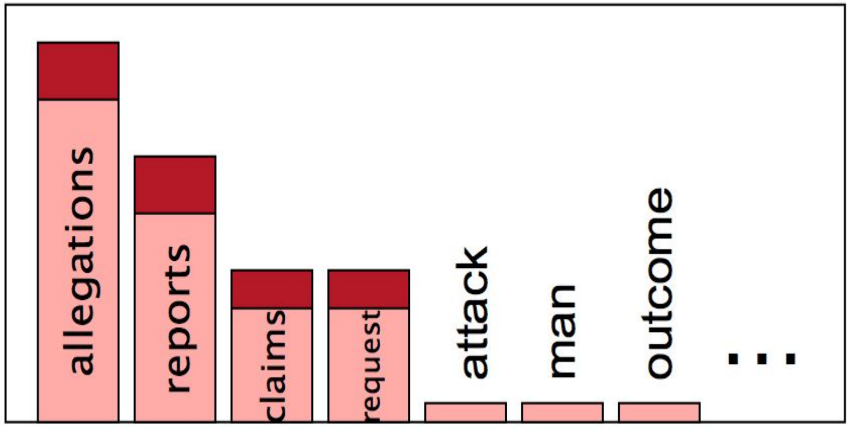


Steal probability mass to generalize better

2.5 allegations, 1.5 reports, 0.5 claims, 0.5 request, **2 other**

7 total



Now we have count of 2 additional words that we can split into unknown words

From D. Jurafsky, Stanford https://web.stanford.edu/class/cs124/lec/languagemodeling.pdf

Add-one (Laplace) Smoothing

- Add one to all counts!
  - assume we saw each word in corpus one more time
  - then we saw unseen words once in the corpus

Smoothing of unigrams

$$p(w_i) = \frac{c(w_i) + 1}{N + V}$$

Here V is the total number of **unique** words in our corpus

N is total number of words in our corpus

Add-one (Laplace) Smoothing

- Add one to all counts!
  - assume we saw each word in corpus one more time
  - then we saw unseen words once in the corpus

Smoothing of bigrams

$$p(w_i|w_{i-1}) = \frac{c(w_{i-1}, w_i) + 1}{c(w_{i-1}) + V}$$

Here V is the total number of unique words in our corpus

Add-one (Laplace) Smoothing

Smoothing of Ngrams

$$p(w_n|w_{n-N+1}^{n-1}) = \frac{c(w_{n-N+1}^{n-1}, w_n) + 1}{c(w_{n-N+1}^{n-1}) + V}$$

Here V is the total number of possible (N-1) grams

Smoothing

Several smoothing methods,

- Kneser-Ney
- Good Turing
- …

Evaluating LM

- Does our LM give higher score to good sentences compared to bad sentences?
  - frequently observed vs. rare sentences

Train	the corpus used to build LM
Test	unseen data to see LM performance
Evaluate	scoring metric to evaluate LM

Evaluating LM

- Does our LM give higher score to good sentences compared to bad sentences?
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Train	the corpus used to build LM
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Evaluate	scoring metric to evaluate LM

Why do we need unseen data to test?

Evaluating LM

Test	unseen data to *see* LM performance
Development	unseen data to *tune* LM performance

Test set contains examples that will come from the real world. We assume that we don't have a test while training a model

Evaluating LM

Test	unseen data to *see* LM performance
Development	unseen data to *tune* LM performance

Hold out a few examples from your training set to test your LM!

Evaluating LM

How good is the LM in scoring a test set?

- Extrinsic evaluation
  - use LM in another application, such as machine translation and observe the performance improvement
  - expensive
- Intrinsic evaluation
  - test the quality of LM on unseen data
  - perplexity

Evaluation: Perplexity

How good is the LM in scoring a test set?

Perplexity is the inverse probability of the test set, normalized by total number of words

$$ppl(s) = p(w_1\ w_2\ \dots\ w_N)^{-1/N}$$

- higher the probability, lower the perplexity
- lower is better

LM closing remarks

Language models can learn different styles

- formal
- informal (spoken, sms, chat)

So if we have multiple LMs, how do you know which one to use?

- check perplexity on a dev set
- an LM built on formal sentences would have lower **ppl** on formal corpus than informal

Python & Numpy

[See accompanying notebook]

iPython/Jupyter notebook Installation

https://www.anaconda.com/download/#download

or

http://jupyter.readthedocs.io/en/latest/install.html