CMPT-413
Computational Linguistics

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Cross-Entropy and Perplexity

Smoothing $n$-gram Models
- Add-one Smoothing
- Additive Smoothing
- Good-Turing Smoothing
- Backoff Smoothing
- Event Space for $n$-gram Models
How good is a model

- So far we’ve seen the probability of a sentence: \( P(w_0, \ldots, w_n) \)
- What is the probability of a collection of sentences, that is what is the probability of a corpus
- Let \( T = s_0, \ldots, s_m \) be a text corpus with sentences \( s_0 \) through \( s_m \)
- What is \( P(T) \)?
  Let us assume that we trained \( P(\cdot) \) on some \textit{training data}, and \( T \) is the \textit{test data}
How good is a model

- $T = s_0, \ldots, s_m$ is the text corpus with sentences $s_0$ through $s_m$
- $P(T) = P(s_0, s_1, s_2, \ldots, s_m)$ – but each sentence is independent from the other sentences
- $P(T) = P(s_0) \cdot P(s_1) \cdot P(s_2) \cdot \ldots \cdot P(s_m) = \prod_{i=0}^{m} P(s_i)$
- $P(s_i) = P(w^i_0, \ldots, w^i_n)$
- Let $W_T$ be the length of the text $T$ measured in words
- Then for the unigram model, $P(T) = \prod_{w \in T} P(w)$
- A problem: we want to compare two different models $P_1$ and $P_2$ on $T$
- To do this we use the per word perplexity of the model:

$$PP_{P}(T) = P(T)^{-\frac{1}{W_T}} = W_T\sqrt{\frac{1}{P(T)}}$$
How good is a model

- The *per word* perplexity of the model is:

\[ PP_P(T) = P(T)^{-\frac{1}{W_T}} \]

- Recall that \( PP_P(T) = 2^{H_P(T)} \) where \( H_P(T) \) is the cross-entropy of \( P \) for text \( T \).

- Therefore, \( H_P(T) = \log_2 PP_P(T) = -\frac{1}{W_T} \log_2 P(T) \)

- Above we use a unigram model \( P(w) \), but the same derivation holds for bigram, trigram, \ldots
How good is a model

- Lower cross entropy values and perplexity values are better. Lower values mean that the model is *better*.
- Correlation with performance of the language model in various applications.
- Performance of a language model is its cross-entropy or perplexity on *test data* (unseen data) corresponds to the number bits required to encode that data.
- On various real life datasets, typical perplexity values yielded by *n*-gram models on English text range from about 50 to almost 1000 (corresponding to cross entropies from about 6 to 10 bits/word).
Cross-Entropy and Perplexity

Smoothing $n$-gram Models
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Bigram Models

▶ In practice:

\[
P(Mork \text{ read a book}) = \]
\[
P(Mork \mid < \text{start} >) \times P(\text{read} \mid Mork) \times \]
\[
P(a \mid \text{read}) \times P(\text{book} \mid a) \times \]
\[
P(< \text{stop} > \mid \text{book}) \]

▶ \( P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})} \)

On unseen data, \( c(w_{i-1}, w_i) \) or worse \( c(w_{i-1}) \) could be zero

\[
\sum_{w_i} \frac{c(w_{i-1}, w_i)}{c(w_{i-1})} = ?
\]
Smoothing

- **Smoothing** deals with events that have been observed zero times.
- Smoothing algorithms also tend to improve the accuracy of the model.

\[ P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})} \]

- Not just unobserved events: what about events observed once?
Add-one Smoothing

\[
P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})}
\]

Add-one Smoothing:

\[
P(w_i \mid w_{i-1}) = \frac{1 + c(w_{i-1}, w_i)}{V + c(w_{i-1})}
\]

Let \( V \) be the number of words in our vocabulary
Assign count of 1 to unseen bigrams
Add-one Smoothing

\[ P(\text{Mindy read a book}) = \]
\[ P(\text{Mindy} \mid \text{< start >}) \times P(\text{read} \mid \text{Mindy}) \times \]
\[ P(\text{a} \mid \text{read}) \times P(\text{book} \mid \text{a}) \times \]
\[ P(\text{< stop >} \mid \text{book}) \]

- Without smoothing:
  \[ P(\text{read} \mid \text{Mindy}) = \frac{c(\text{Mindy, read})}{c(\text{Mindy})} = 0 \]

- With add-one smoothing (assuming \( c(\text{Mindy}) = 1 \) but \( c(\text{Mindy, read}) = 0 \)):
  \[ P(\text{read} \mid \text{Mindy}) = \frac{1}{V + 1} \]
Additive Smoothing: (Lidstone 1920, Jeffreys 1948)

\[ P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})} \]

▶ Add-one smoothing works horribly in practice. Seems like 1 is too large a count for unobserved events.

▶ Additive Smoothing:

\[ P(w_i \mid w_{i-1}) = \frac{\delta + c(w_{i-1}, w_i)}{(\delta \times V) + c(w_{i-1})} \]

▶ 0 < \delta \leq 1
  Still works horribly in practice, but better than add-one smoothing.
Good-Turing Smoothing: (Good, 1953)

\[ P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})} \]

- Imagine you’re sitting at a sushi bar with a conveyor belt.
- You see going past you 10 plates of tuna, 3 plates of unagi, 2 plates of salmon, 1 plate of shrimp, 1 plate of octopus, and 1 plate of yellowtail.
- Chance you will observe a new kind of seafood: \( \frac{3}{18} \)
- How likely are you to see another plate of salmon: should be \( < \frac{2}{18} \)
Good-Turing Smoothing

- How many types of seafood (words) were seen once? Use this to predict probabilities for unseen events
  
  Let $n_1$ be the number of events that occurred once: $p_0 = \frac{n_1}{N}$

- The Good-Turing estimate states that for any $n$-gram that occurs $r$ times, we should pretend that it occurs $r^*$ times

  $$r^* = (r + 1) \frac{n_r + 1}{n_r}$$

- $n_r$: number of different objects seen $r$ times
Good-Turing Smoothing

- 10 tuna, 3 unagi, 2 salmon, 1 shrimp, 1 octopus, 1 yellowtail

How likely is new data? Let $n_1$ be the number of items occurring once, which is 3 in this case. $N$ is the total, which is 18.

$$p_0 = \frac{n_1}{N} = \frac{3}{18} = 0.166$$
Good-Turing Smoothing

- 10 tuna, 3 unagi, 2 salmon, 1 shrimp, 1 octopus, 1 yellowtail

- How likely is octopus? Since \( c(\text{octopus}) = 1 \) the GT estimate is \( 1^* \).

\[
r^* = (r + 1) \frac{n_{r+1}}{n_r}
\]

\[
p_{GT} = \frac{r^*}{N}
\]

- To compute \( 1^* \), we need \( n_1 = 3 \) and \( n_2 = 1 \)

\[
1^* = 2 \times \frac{1}{3} = \frac{2}{3}
\]

\[
p_1 = \frac{1^*}{18} = 0.037
\]

- What happens when \( n_{r+1} = 0 \)? (smoothing before smoothing)
Simple Good-Turing: linear interpolation for missing $n_{r+1}$

$$f(r) = a + b \cdot r$$

$\begin{align*}
  a &= 2.3 \\
  b &= -0.17 
\end{align*}$

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<thead>
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<th>$r$</th>
<th>$n_r = f(r)$</th>
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<td>0.61</td>
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Comparison between Add-one and Good-Turing

<table>
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<tr>
<th>freq num with freq r</th>
<th>NS</th>
<th>Add1</th>
<th>SGT</th>
</tr>
</thead>
<tbody>
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<tr>
<td>0 0</td>
<td>0</td>
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<td>0.12</td>
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<tr>
<td>1 3</td>
<td>0.04</td>
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<td>0.03079</td>
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<td>0.0882</td>
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<tr>
<td>10 1</td>
<td>0.4</td>
<td>0.3235</td>
<td>0.3691</td>
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- \( N = (1 \times 3) + (2 \times 2) + 3 + 5 + 10 = 25 \)
- \( V = 1 + 3 + 2 + 1 + 1 + 1 = 9 \)
- Important: we added a new word type for unseen words. Let’s call it UNK, the unknown word.
- Check that: \( 1.0 = \sum_r n_r \times p_r \)
  \[
  0.12 + (3 \times 0.03079) + (2 \times 0.06719) + 0.1045 + 0.1797 + 0.3691 = 1.0
  \]
Comparison between Add-one and Good-Turing

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- **NS = No smoothing**: \( p_r = \frac{r}{N} \)
- **Add1 = Add-one smoothing**: \( p_r = \frac{1+r}{V+N} \)
- **SGT = Simple Good-Turing**: \( p_0 = \frac{n_1}{N} \), \( p_r = \frac{(r+1)\frac{n_{r+1}}{n_r}}{N} \)

with linear interpolation for missing values where \( n_{r+1} = 0 \) (Gale and Sampson, 1995) [http://www.grsampson.net/AGtf1.html](http://www.grsampson.net/AGtf1.html)
Simple Backoff Smoothing: incorrect version

\[ P(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})} \]

- In add-one or Good-Turing:
  \[ P(\text{the} \mid \text{string}) = P(\text{Fonz} \mid \text{string}) \]
- If \( c(w_{i-1}, w_i) = 0 \), then use \( P(w_i) \) (back off)
- Works for trigrams: back off to bigrams and then unigrams
- Works better in practice, but probabilities get mixed up (unseen bigrams, for example will get higher probabilities than seen bigrams)
Backoff Smoothing: Jelinek-Mercer Smoothing

\[ P_{ML}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)}{c(w_{i-1})} \]

- \( P_{JM}(w_i \mid w_{i-1}) = \lambda P_{ML}(w_i \mid w_{i-1}) + (1 - \lambda) P_{ML}(w_i) \) where, \( 0 \leq \lambda \leq 1 \)
- Notice that \( P_{JM}(\text{the} \mid \text{string}) > P_{JM}(\text{Fonz} \mid \text{string}) \) as we wanted
- Jelinek-Mercer (1980) describe an elegant form of this interpolation:

\[ P_{JM}(n\text{gram}) = \lambda P_{ML}(n\text{gram}) + (1 - \lambda) P_{JM}(n-1\text{gram}) \]

- What about \( P_{JM}(w_i) \)?
  For missing unigrams: \( P_{JM}(w_i) = \lambda P_{ML}(w_i) + (1 - \lambda) \frac{\delta}{V} \)
Backoff Smoothing: Many alternatives

\[ P_{JM}(ngram) = \lambda P_{ML}(ngram) + (1 - \lambda) P_{JM}(n-1gram) \]

- Different methods for finding the values for \( \lambda \) correspond to variety of different smoothing methods
- Katz Backoff (include Good-Turing with Backoff Smoothing)

\[ P_{katz}(y \mid x) = \begin{cases} \frac{c^*(xy)}{c(x)} & \text{if } c(xy) > 0 \\ \alpha(x) P_{katz}(y) & \text{otherwise} \end{cases} \]

- where \( \alpha(x) \) is chosen to make sure that \( P_{katz}(y \mid x) \) is a proper probability

\[ \alpha(x) = 1 - \sum_y \frac{c^*(xy)}{c(x)} \]
Backoff Smoothing: Many alternatives

\[ P_{JM}(ngram) = \lambda P_{ML}(ngram) + (1 - \lambda) P_{JM}(n-1gram) \]

- Deleted Interpolation (Jelinek, Mercer)
  compute \( \lambda \) values to minimize cross-entropy on held-out data which is deleted from the initial set of training data
- Improved JM smoothing, a separate \( \lambda \) for each \( w_{i-1} \):
  \[ P_{JM}(w_i \mid w_{i-1}) = \lambda(w_{i-1})P_{ML}(w_i \mid w_{i-1}) + (1 - \lambda(w_{i-1}))P_{ML}(w_i) \]
  where \( \sum_i \lambda(w_i) = 1 \) because \( \sum_{w_i} P(w_i \mid w_{i-1}) = 1 \)
Backoff Smoothing: Many alternatives

\[ P_{JM}(n\text{gram}) = \lambda P_{ML}(n\text{gram}) + (1 - \lambda) P_{JM}(n - 1\text{gram}) \]

- Witten-Bell smoothing
  use the \( n - 1 \) gram model when the \( n \) gram model has too few unique words in the \( n \) gram context
- Absolute discounting (Ney, Essen, Kneser)

\[
P_{abs}(y \mid x) = \begin{cases} 
\frac{c(xy) - D}{c(x)} & \text{if } c(xy) > 0 \\
\alpha(x)P_{abs}(y) & \text{otherwise}
\end{cases}
\]

compute \( \alpha(x) \) as was done in Katz smoothing
Backoff Smoothing: Many alternatives

\[ P_{JM}(ngram) = \lambda P_{ML}(ngram) + (1 - \lambda)P_{JM}(n-1gram) \]

- Kneser-Ney smoothing
  - \( P(\text{Francisco} \mid \text{eggplant}) > P(\text{stew} \mid \text{eggplant}) \)
    - \textit{Francisco} is common, so interpolation gives \( P(\text{Francisco} \mid \text{eggplant}) \) a high value
    - But \textit{Francisco} occurs in few contexts (only after \textit{San})
    - \textit{stew} is common, \textbf{and} occurs in many contexts
    - Hence weight the interpolation based on number of contexts for the word using discounting
Backoff Smoothing: Many alternatives

\[ P_{JM}(n\text{gram}) = \lambda P_{ML}(n\text{gram}) + (1 - \lambda) P_{JM}(n-1\text{gram}) \]

- Modified Kneser-Ney smoothing (Chen and Goodman)
  multiple discounts for one count, two counts and three or more counts
- Finding \( \lambda \): use Generalized line search (Powell search) or the Expectation-Maximization algorithm
Revisiting the trigram model:
\[
P(w_1, w_2, \ldots, w_n) =
\]
\[
P(w_1) \times P(w_2 \mid w_1) \times P(w_3 \mid w_1, w_2) \times P(w_4 \mid w_2, w_3) \times \\
\ldots P(w_i \mid w_{i-2}, w_{i-1}) \ldots \times P(w_n \mid w_{n-2}, \ldots, w_{n-1})
\]

Notice that the length of the sentence \( n \) is variable

What is the event space?
Let $\Sigma = \{a, b\}$ and the language be $\Sigma^*$ so $L = \{\epsilon, a, b, aa, bb, ab, bb \ldots\}$

Consider a unigram model: $P(a) = P(b) = 0.5$

$P(a) = 0.5, P(b) = 0.5, P(aa) = 0.5^2 = 0.25, P(bb) = 0.25$ and so on.

But $P(a) + P(b) + P(aa) + P(bb) = 1.5$ !

$$\sum_{w} P(w) = 1$$
The stop symbol

- What went wrong?
  No probability for $P(\epsilon)$
- Add a special stop symbol:

  $P(a) = P(b) = 0.25$

  $P(\text{stop}) = 0.5$

- $P(\text{stop}) = 0.5$
  $P(a \text{ stop}) = P(b \text{ stop}) = 0.25 \times 0.5 = 0.125$,
  $P(aa \text{ stop}) = 0.25^2 \times 0.5 = 0.03125$ (now the sum is no longer greater than one)
The stop symbol

- With this new stop symbol we can show that $\sum_w P(w) = 1$

Notice that the probability of any sequence of length $n$ is $0.25^n \times 0.5$

Also there are $2^n$ sequences of length $n$

$$\sum_{w} P(w) =$$

$$\sum_{n=0}^{\infty} 2^n \times 0.25^n \times 0.5$$

$$\sum_{n=0}^{\infty} 0.5^n \times 0.5 = \sum_{n=0}^{\infty} 0.5^{n+1}$$

$$\sum_{n=1}^{\infty} 0.5^n = 1$$