The Language Modeling Problem

- We have some (finite) vocabulary, say $\mathcal{V} = \{\text{the, a, man, telescope, Beckham, two, ...}\}$.

- We have an (infinite) set of strings, $\mathcal{V}^*$
  
  the
  a
  the fan
  the fan saw Beckham
  the fan saw saw
  ...
  the fan saw Beckham play for Real Madrid
  ...

The Language Modeling Problem (Continued)

- We have a training sample of example sentences in English.

- We need to “learn” a probability distribution $\hat{P}$, i.e., $\hat{P}$ is a function that satisfies

$$ \sum_{x \in \mathcal{V}^*} \hat{P}(x) = 1, \quad \hat{P}(x) \geq 0 \text{ for all } x \in \mathcal{V}^* $$

$$ \hat{P}(\text{the}) = 10^{-12} $$
$$ \hat{P}(\text{the fan}) = 10^{-8} $$
$$ \hat{P}(\text{the fan saw Beckham}) = 2 \times 10^{-8} $$
$$ \hat{P}(\text{the fan saw saw}) = 10^{-15} $$
$$ \hat{P}(\text{the fan saw Beckham play for Real Madrid}) = 2 \times 10^{-9} $$
$$ \hat{P}(\text{...}) $$

- Usual assumption: training sample is drawn from some underlying distribution $P$, we want $\hat{P}$ to be “as close” to $P$ as possible.
Why on earth would we want to do this?!

- Speech recognition was the original motivation. (Related problems are optical character recognition, handwriting recognition.)

- The estimation techniques developed for this problem will be VERY useful for other problems in NLP

**Deriving a Trigram Probability Model**

Step 1: Expand using the chain rule:

\[
P(w_1, w_2, \ldots, w_n) = P(w_1 | \text{START}) \times P(w_2 | \text{START}, w_1) \times P(w_3 | \text{START}, w_1, w_2) \times P(w_4 | \text{START}, w_1, w_2, w_3) \times \ldots \times P(w_n | \text{START}, w_1, w_2, \ldots, w_{n-1}) \times P(\text{STOP} | \text{START}, w_1, w_2, \ldots, w_{n-1}, w_n)
\]

For Example

\[
P(\text{the, dog, laughs}) = P(\text{the} | \text{START}) \times P(\text{dog} | \text{START}, \text{the}) \times P(\text{laughs} | \text{the, dog}) \times P(\text{STOP} | \text{START}, \text{the, dog})
\]

**Step 2: Make Markov independence assumptions:**

\[
P(w_1, w_2, \ldots, w_n) = P(w_1 | \text{START}) \times P(w_2 | \text{START}, w_1) \times P(w_3 | \text{START}, w_1, w_2) \times \ldots \times P(w_n | w_{n-2}, w_{n-1}) \times P(\text{STOP} | w_{n-1}, w_n)
\]

General assumption:

\[
P(w_i | \text{START}, w_1, w_2, \ldots, w_{i-2}, w_{i-1}) = P(w_i | w_{i-2}, w_{i-1})
\]

For Example

\[
P(\text{the, dog, laughs}) = P(\text{the} | \text{START}) \times P(\text{dog} | \text{START}, \text{the}) \times P(\text{laughs} | \text{the, dog}) \times P(\text{STOP} | \text{dog, laughs})
\]

**The Trigram Estimation Problem**

Remaining estimation problem:

\[
P(w_i | w_{i-2}, w_{i-1})
\]

For example:

\[
P(\text{laughs} | \text{the, dog})
\]

A natural estimate (the “maximum likelihood estimate”):

\[
P_{ML}(w_i | w_{i-2}, w_{i-1}) = \frac{\text{Count}(w_{i-2}, w_{i-1}, w_i)}{\text{Count}(w_{i-2}, w_{i-1})}
\]

\[
P_{ML}(\text{laughs} | \text{the, dog}) = \frac{\text{Count}(\text{the, dog, laughs})}{\text{Count}(\text{the, dog})}
\]
Evaluating a Language Model

- We have some test data, $n$ sentences
  
  \[ S_1, S_2, S_3, \ldots, S_n \]

- We could look at the probability under our model $\prod_{i=1}^{n} P(S_i)$.
  Or more conveniently, the log probability

  \[ \log \prod_{i=1}^{n} P(S_i) = \sum_{i=1}^{n} \log P(S_i) \]

- In fact the usual evaluation measure is *perplexity*

  \[ \text{Perplexity} = 2^{-x} \quad \text{where} \quad x = \frac{1}{W} \sum_{i=1}^{n} \log P(S_i) \]

  and $W$ is the total number of words in the test data.

Some Intuition about Perplexity

- Say we have a vocabulary $\mathcal{V}$, of size $N = |\mathcal{V}|$
  and model that predicts

  \[ P(w) = \frac{1}{N} \]

  for all $w \in \mathcal{V}$.

- Easy to calculate the perplexity in this case:

  \[ \text{Perplexity} = 2^{-x} \quad \text{where} \quad x = \log \frac{1}{N} \]

  \[ \Rightarrow \quad \text{Perplexity} = N \]

  Perplexity is a measure of effective “branching factor”

Some History

- Shannon conducted experiments on entropy of English
  i.e., how good are people at the perplexity game?


- Chomsky (in *Syntactic Structures* (1957)):

  Second, the notion “grammatical” cannot be identified with ‘meaningful” or ‘significant” in any semantic sense. Sentences (1) and (2) are equally nonsensical, but any speaker of English will recognize that only the former is grammatical.

  (1) Colorless green ideas sleep furiously.

  (2) Furiously sleep ideas green colorless.

  …

  … Third, the notion “grammatical in English” cannot be identified in any way with the notion “high order of statistical approximation to English”. It is fair to assume that neither sentence (1) nor (2) (nor indeed any part of these sentences) has ever occurred in an English discourse. Hence, in any statistical model for grammaticality, these sentences will be ruled out on identical grounds as equally ‘remote’ from English. Yet (1), though nonsensical, is grammatical, while (2) is not. …

  (my emphasis)
Sparse Data Problems

A natural estimate (the ‘maximum likelihood estimate’):

\[ P_{ML}(w_i \mid w_{i-2}, w_{i-1}) = \frac{\text{Count}(w_{i-2}, w_{i-1}, w_i)}{\text{Count}(w_{i-2}, w_{i-1})} \]

\[ P_{ML}(\text{laughs} \mid \text{the}, \text{dog}) = \frac{\text{Count}(\text{the}, \text{dog}, \text{laughs})}{\text{Count}(\text{the}, \text{dog})} \]

Say our vocabulary size is \( N = |\mathcal{V}| \), then there are \( N^3 \) parameters in the model.

e.g., \( N = 20,000 \quad \Rightarrow \quad 20,000^3 = 8 \times 10^{12} \) parameters

The Bias-Variance Trade-Off

- (Unsmoothed) trigram estimate
  \[ P_{ML}(w_i \mid w_{i-2}, w_{i-1}) = \frac{\text{Count}(w_{i-2}, w_{i-1}, w_i)}{\text{Count}(w_{i-2}, w_{i-1})} \]

- (Unsmoothed) bigram estimate
  \[ P_{ML}(w_i \mid w_{i-1}) = \frac{\text{Count}(w_{i-1}, w_i)}{\text{Count}(w_{i-1})} \]

- (Unsmoothed) unigram estimate
  \[ P_{ML}(w_i) = \frac{\text{Count}(w_i)}{\text{Count}()} \]

How close are these different estimates to the “true” probability \( P(w_i \mid w_{i-2}, w_{i-1}) \)?

Linear Interpolation

- Take our estimate \( \hat{P}(w_i \mid w_{i-2}, w_{i-1}) \) to be
  \[ \hat{P}(w_i \mid w_{i-2}, w_{i-1}) = \lambda_1 \times P_{ML}(w_i \mid w_{i-2}, w_{i-1}) + \lambda_2 \times P_{ML}(w_i \mid w_{i-1}) + \lambda_3 \times P_{ML}(w_i) \]

where \( \lambda_1 + \lambda_2 + \lambda_3 = 1 \), and \( \lambda_i \geq 0 \) for all \( i \).

- Our estimate correctly defines a distribution:
  \[ \sum_{w \in \mathcal{V}} \hat{P}(w \mid w_{i-2}, w_{i-1}) = \sum_{w \in \mathcal{V}} \left[ \lambda_1 \times P_{ML}(w \mid w_{i-2}, w_{i-1}) + \lambda_2 \times P_{ML}(w \mid w_{i-1}) + \lambda_3 \times P_{ML}(w) \right] \]
  \[ = \lambda_1 \sum_{w} P_{ML}(w \mid w_{i-2}, w_{i-1}) + \lambda_2 \sum_{w} P_{ML}(w \mid w_{i-1}) + \lambda_3 \sum_{w} P_{ML}(w) \]
  \[ = \lambda_1 + \lambda_2 + \lambda_3 \]
  \[ = 1 \]

(Can show also that \( \hat{P}(w \mid w_{i-2}, w_{i-1}) \geq 0 \) for all \( w \in \mathcal{V} \))
How to estimate the $\lambda$ values?

- Hold out part of training set as “validation” data
- Define $\text{Count}_2(w_1, w_2, w_3)$ to be the number of times the trigram $(w_1, w_2, w_3)$ is seen in validation set.
- Choose $\lambda_1, \lambda_2, \lambda_3$ to maximize:

$$L(\lambda_1, \lambda_2, \lambda_3) = \sum_{w_1, w_2, w_3 \in V} \text{Count}_2(w_1, w_2, w_3) \log \hat{P}(w_3 \mid w_1, w_2)$$

such that $\lambda_1 + \lambda_2 + \lambda_3 = 1$, and $\lambda_i \geq 0$ for all $i$, and where

$$\hat{P}(w_i \mid w_{i-2}, w_{i-1}) = \lambda_1 \times P_{ML}(w_i \mid w_{i-2}, w_{i-1})$$

$$+ \lambda_2 \times P_{ML}(w_i \mid w_{i-1})$$

$$+ \lambda_3 \times P_{ML}(w_i)$$

Allowing the $\lambda$’s to vary

- Take a function $\Phi$ that partitions histories e.g.,

$$\Phi(w_{i-2}, w_{i-1}) = \begin{cases} 
1 & \text{if } \text{Count}(w_{i-1}, w_{i-2}) = 0 \\
2 & \text{if } 1 \leq \text{Count}(w_{i-1}, w_{i-2}) \leq 2 \\
3 & \text{if } 3 \leq \text{Count}(w_{i-1}, w_{i-2}) \leq 5 \\
4 & \text{Otherwise}
\end{cases}$$

- Introduce a dependence of the $\lambda$’s on the partition:

$$\hat{P}(w_i \mid w_{i-2}, w_{i-1}) = \lambda_1^{\Phi(w_{i-2}, w_{i-1})} \times P_{ML}(w_i \mid w_{i-2}, w_{i-1})$$

$$+ \lambda_2^{\Phi(w_{i-2}, w_{i-1})} \times P_{ML}(w_i \mid w_{i-1})$$

$$+ \lambda_3^{\Phi(w_{i-2}, w_{i-1})} \times P_{ML}(w_i)$$

where $\lambda_1^{\Phi(w_{i-2}, w_{i-1})} + \lambda_2^{\Phi(w_{i-2}, w_{i-1})} + \lambda_3^{\Phi(w_{i-2}, w_{i-1})} = 1$, and $
\lambda_i^{\Phi(w_{i-2}, w_{i-1})} \geq 0$ for all $i$.

An Iterative Method (Based on the EM Algorithm)

Initialization: Pick arbitrary/random values for $\lambda_1$, $\lambda_2$, $\lambda_3$.

Step 1: Calculate the following quantities:

$$c_1 = \sum_{w_1, w_2, w_3 \in V} \frac{\text{Count}_2(w_1, w_2, w_3) \lambda_1 P_{ML}(w_3 \mid w_1, w_2)}{\lambda_1 P_{ML}(w_3 \mid w_1, w_2) + \lambda_2 P_{ML}(w_3 \mid w_2) + \lambda_3 P_{ML}(w_3)}$$

$$c_2 = \sum_{w_1, w_2, w_3 \in V} \frac{\text{Count}_2(w_1, w_2, w_3) \lambda_2 P_{ML}(w_3 \mid w_2)}{\lambda_1 P_{ML}(w_3 \mid w_1, w_2) + \lambda_2 P_{ML}(w_3 \mid w_2) + \lambda_3 P_{ML}(w_3)}$$

$$c_3 = \sum_{w_1, w_2, w_3 \in V} \frac{\text{Count}_2(w_1, w_2, w_3) \lambda_3 P_{ML}(w_3)}{\lambda_1 P_{ML}(w_3 \mid w_1, w_2) + \lambda_2 P_{ML}(w_3 \mid w_2) + \lambda_3 P_{ML}(w_3)}$$

Step 2: Re-estimate $\lambda_i$’s as

$$\lambda_1 = \frac{c_1}{c_1 + c_2 + c_3}, \quad \lambda_2 = \frac{c_2}{c_1 + c_2 + c_3}, \quad \lambda_3 = \frac{c_3}{c_1 + c_2 + c_3}$$

Step 3: If $\lambda_i$’s have not converged, go to Step 1.

Our estimate correctly defines a distribution:

$$\sum_{w \in V} \hat{P}(w \mid w_{i-2}, w_{i-1})$$

$$= \sum_{w \in V} [\lambda_1^{\Phi(w_{i-2}, w_{i-1})} \times P_{ML}(w \mid w_{i-2}, w_{i-1})$$

$$+ \lambda_2^{\Phi(w_{i-2}, w_{i-1})} \times P_{ML}(w \mid w_{i-1})$$

$$+ \lambda_3^{\Phi(w_{i-2}, w_{i-1})} \times P_{ML}(w)]$$

$$= \lambda_1^{\Phi(w_{i-2}, w_{i-1})} \sum_{w} P_{ML}(w \mid w_{i-2}, w_{i-1})$$

$$+ \lambda_2^{\Phi(w_{i-2}, w_{i-1})} \sum_{w} P_{ML}(w \mid w_{i-1})$$

$$+ \lambda_3^{\Phi(w_{i-2}, w_{i-1})} \sum_{w} P_{ML}(w)$$

$$= \lambda_1^{\Phi(w_{i-2}, w_{i-1})} + \lambda_2^{\Phi(w_{i-2}, w_{i-1})} + \lambda_3^{\Phi(w_{i-2}, w_{i-1})}$$

$$= 1$$
An Alternative Definition of the $\lambda$’s (Alpha Smoothing)

- A small change: take our estimate $\hat{P}(w_i \mid w_{i-2}, w_{i-1})$ to be
  \[
  \hat{P}(w_i \mid w_{i-2}, w_{i-1}) = 
  \lambda_1 \times P_{ML}(w_i \mid w_{i-2}, w_{i-1}) + (1 - \lambda_1)[\lambda_2 \times P_{ML}(w_i \mid w_{i-1})] + (1 - \lambda_2) \times P_{ML}(w_i)
  \]
  where $0 \leq \lambda_1 \leq 1$, and $0 \leq \lambda_2 \leq 1$.

- Next, define
  \[
  \lambda_1 = \frac{\text{Count}(w_{i-2}, w_{i-1})}{\alpha + \text{Count}(w_{i-2}, w_{i-1})}, \quad \lambda_2 = \frac{\text{Count}(w_{i-1})}{\alpha + \text{Count}(w_{i-1})}
  \]
  where $\alpha$ is a parameter chosen to optimize probability of a development set.

An Alternative Definition of the $\lambda$’s (continued)

- Define
  \[
  U(w_{i-2}, w_{i-1}) = |\{w : \text{Count}(w_{i-2}, w_{i-1}, w) > 0\}|
  \]
  \[
  U(w_{i-1}) = |\{w : \text{Count}(w_{i-1}, w) > 0\}|
  \]

- Next, define
  \[
  \lambda_1 = \frac{\text{Count}(w_{i-2}, w_{i-1})}{\alpha U(w_{i-2}, w_{i-1}) + \text{Count}(w_{i-2}, w_{i-1})}
  \]
  \[
  \lambda_2 = \frac{\text{Count}(w_{i-1})}{\alpha U(w_{i-1}) + \text{Count}(w_{i-1})}
  \]
  where $\alpha$ is a parameter chosen to optimize probability of a development set.

Discounting Methods

- Say we’ve seen the following counts:

<table>
<thead>
<tr>
<th>$x$</th>
<th>Count($x$)</th>
<th>$P_{ML}(w_i \mid w_{i-1})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>the</td>
<td>48</td>
<td></td>
</tr>
<tr>
<td>the, dog</td>
<td>15</td>
<td>15/48</td>
</tr>
<tr>
<td>the, woman</td>
<td>11</td>
<td>11/48</td>
</tr>
<tr>
<td>the, man</td>
<td>10</td>
<td>10/48</td>
</tr>
<tr>
<td>the, park</td>
<td>5</td>
<td>5/48</td>
</tr>
<tr>
<td>the, job</td>
<td>2</td>
<td>2/48</td>
</tr>
<tr>
<td>the, telescope</td>
<td>1</td>
<td>1/48</td>
</tr>
<tr>
<td>the, manual</td>
<td>1</td>
<td>1/48</td>
</tr>
<tr>
<td>the, afternoon</td>
<td>1</td>
<td>1/48</td>
</tr>
<tr>
<td>the, country</td>
<td>1</td>
<td>1/48</td>
</tr>
<tr>
<td>the, street</td>
<td>1</td>
<td>1/48</td>
</tr>
</tbody>
</table>

- The maximum-likelihood estimates are high (particularly for low count items)

Discounting Methods

- Now define ‘discounted’ counts, for example (a first, simple definition):
  \[
  \text{Count}^*(x) = \text{Count}(x) - 0.5
  \]

- New estimates:

<table>
<thead>
<tr>
<th>$x$</th>
<th>Count($x$)</th>
<th>Count$^*$($x$)</th>
<th>Count$^*_0(x)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>the</td>
<td>48</td>
<td>14.5</td>
<td>14.5/48</td>
</tr>
<tr>
<td>the, dog</td>
<td>15</td>
<td>14.5</td>
<td>14.5/48</td>
</tr>
<tr>
<td>the, woman</td>
<td>11</td>
<td>10.5</td>
<td>10.5/48</td>
</tr>
<tr>
<td>the, man</td>
<td>10</td>
<td>9.5</td>
<td>9.5/48</td>
</tr>
<tr>
<td>the, park</td>
<td>5</td>
<td>4.5</td>
<td>4.5/48</td>
</tr>
<tr>
<td>the, job</td>
<td>2</td>
<td>1.5</td>
<td>1.5/48</td>
</tr>
<tr>
<td>the, telescope</td>
<td>1</td>
<td>0.5</td>
<td>0.5/48</td>
</tr>
<tr>
<td>the, manual</td>
<td>1</td>
<td>0.5</td>
<td>0.5/48</td>
</tr>
<tr>
<td>the, afternoon</td>
<td>1</td>
<td>0.5</td>
<td>0.5/48</td>
</tr>
<tr>
<td>the, country</td>
<td>1</td>
<td>0.5</td>
<td>0.5/48</td>
</tr>
<tr>
<td>the, street</td>
<td>1</td>
<td>0.5</td>
<td>0.5/48</td>
</tr>
</tbody>
</table>
• We now have some “missing probability mass”:
\[ \alpha(w_{i-1}) = 1 - \sum_w \frac{\text{Count}^*(w_{i-1}, w)}{\text{Count}(w_{i-1})} \]
e.g., in our example, \( \alpha(\text{the}) = 10 \times 0.5/48 = 5/48 \)

• Divide the remaining probability mass between words \( w \) for which \( \text{Count}(w_{i-1}, w) = 0 \).

\[ \text{Katz Back-Off Models (Trigrams)} \]

• For a trigram model, first define two sets
\[ \mathcal{A}(w_{i-2}, w_{i-1}) = \{ w : \text{Count}(w_{i-2}, w_{i-1}, w) > 0 \} \]
\[ \mathcal{B}(w_{i-2}, w_{i-1}) = \{ w : \text{Count}(w_{i-2}, w_{i-1}, w) = 0 \} \]

• A trigram model is defined in terms of the bigram model:
\[ P_{\text{Katz}}(w_i | w_{i-2}, w_{i-1}) = \begin{cases} \alpha(w_{i-2}, w_{i-1}) & \text{if } w_i \in \mathcal{A}(w_{i-2}, w_{i-1}) \\ \frac{\alpha(w_{i-2}, w_{i-1}) P_{\text{Katz}}(w_i | w_{i-1})}{\sum_{w \in \mathcal{B}(w_{i-2}, w_{i-1})} P_{\text{Katz}}(w_i | w_{i-1})} & \text{if } w_i \in \mathcal{B}(w_{i-2}, w_{i-1}) \end{cases} \]

where
\[ \alpha(w_{i-2}, w_{i-1}) = 1 - \sum_{w \in \mathcal{A}(w_{i-2}, w_{i-1})} \frac{\text{Count}^*(w_{i-2}, w_{i-1}, w)}{\text{Count}(w_{i-2}, w_{i-1})} \]

\[ \text{Good-Turing Discounting} \]

• Invented during WWII by Alan Turing (and Good?), later published by Good. Frequency estimates were needed within the Enigma code-breaking effort.

• Define \( n_r \) = number of elements \( x \) for which \( \text{Count}(x) = r \).

• Modified count for any \( x \) with \( \text{Count}(x) = r \) and \( r > 0 \):
\[ (r + 1) \frac{n_r + 1}{n_r} \]

• Leads to the following estimate of “missing mass”:
\[ \frac{n_1}{N} \]
where \( N \) is the size of the sample. This is the estimate of the probability of seeing a new element \( x \) on the \((N + 1)\)th draw.
Summary

- Three steps in deriving the language model probabilities:
  
  1. Expand $P(w_1, w_2 \ldots w_n)$ using Chain rule.
  2. Make Markov Independence Assumptions
     $P(w_i | w_1, w_2 \ldots w_{i-2}, w_{i-1}) = P(w_i | w_{i-2}, w_{i-1})$
  3. Smooth the estimates using low order counts.

- Other methods used to improve language models:
  
  - “Topic” or “long-range” features.
  - Syntactic models.

It’s generally hard to improve on trigram models, though!!

Further Reading

See:


“On the Convergence Rate of Good-Turing Estimators”. David McAllester and Robert E. Schapire. In Proceedings of COLT 2000. (A pretty technical paper, giving confidence-intervals on Good-Turing estimators. Theorems 1, 3 and 9 are useful in understanding the motivation for Good-Turing discounting.)