English Word Suggestion Based on Part of Speech Ngram

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Motivation

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- Word suggestion on mobile devices

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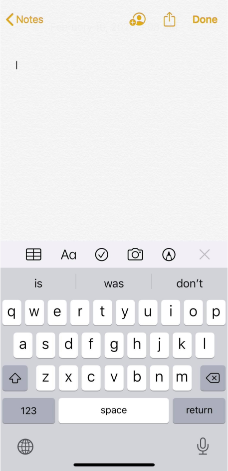

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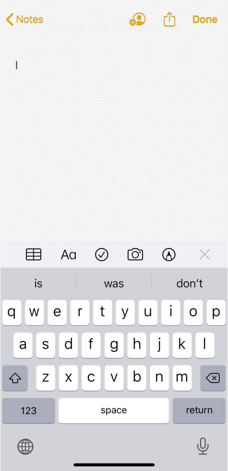

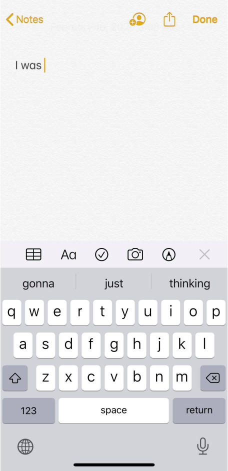

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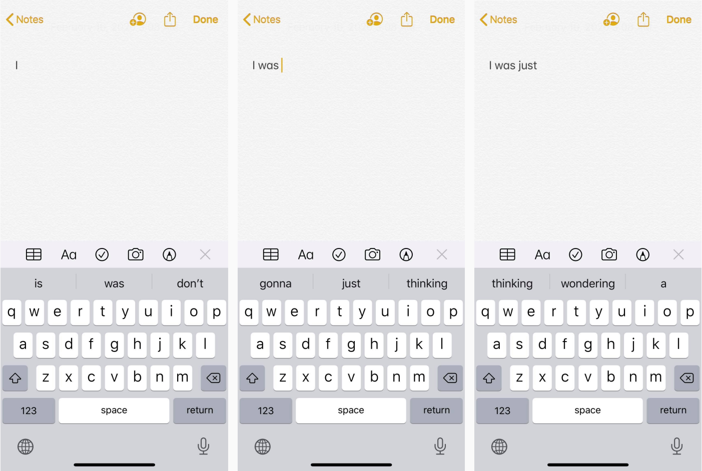

Part Of Speech Ngram (POS-Ngram)

What does POS-Ngram mean?

N-gram is a contiguous sequence of n items from a given sample of text or speech

Ex: I study english

- **unigram (1-gram)** : (I,), (study,), (english,)
- **bigram (2-gram)** : (I, study), (study, english)
- **trigram (3-gram)** : (I, study, english)

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N-gram model is one of statistical langauge models for predicting the next item (word) based on Markov assumption, and usually abbreviated as N-gram.

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POS-Ngram is an improved model using part of speech as a class indicator.

How To Compute Probability of a Sentence?

How can we compute the joint probability of a sentence?
Ex: "an apple is on the table"

$$P(\textit{an apple is on the table}) = ?$$

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- To represent the probability of a particular random variable X_i taking on the value "the", or $P(X_i = "the")$ we will use simplification $P(the)$.

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- **Ex:** "an apple is on the table"
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- **Ex:** "an apple is on the table"
  $\rightarrow w_1 = \text{"}an\text{"}, w_2 = \text{"}apple\text{"}, w_3 = \text{"}is\text{"}, \cdots$
  $\rightarrow w_1^4 = \text{"}an\ apple\ is\ on\text{"}$

Chain Rule Of Probability

In General

$$P(X_1 \cdots X_n) = P(X_1)P(X_2 \mid X_1)P(X_3 \mid X_1^2) \cdots P(X_n \mid X_1^{n-1})$$

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Examples

- $P(an\ apple) = P(an) \times P(apple \mid an)$
- $P(an\ apple\ is) = P(an) \times P(apple \mid an) \times P(is \mid an\ apple)$

Let’s Apply Chain Rule

By applying chain rule to the phrase "*an apple is on the*":

$$
\begin{aligned}
P(\text{"}\mathit{an\ apple\ is\ on\ the}\text{"}) &= P(\mathit{an}) \times P(\mathit{apple} \mid \mathit{an}) \times P(\mathit{is} \mid \mathit{an\ apple}) \\
&\quad \times P(\mathit{on} \mid \mathit{an\ apple\ is}) \times P(\mathit{the} \mid \mathit{an\ apple\ is\ on})
\end{aligned}
$$

In practice chain rule does not help

- We don't know the way to compute the exact probability of a word given a long sequence of preceding words, $P(w_n \mid w_1^{n-1})$

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- We don’t know the way to compute the exact probability of a word given a long sequence of preceding words, $P(w_n \mid w_1^{n-1})$
- Language is creative, and any particular context might have never occured before

The Presence of N-gram

The general equation for this n-gram approximation to the conditional probability of the next word in a sequence is

$$P(w_n \mid w_1^{n-1}) \approx P(w_n \mid w_{n-N+1}^{n-1})$$

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In case of Bigram (2-gram)

When we use bigram model to predict the conditional probability of the next word, we can approximate by

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Example

$$P(the \mid \ an\ apple\ is\ on) \approx P(the \mid \ on)$$

Bigram in Practice

By supposing that C is the counts of word from a corpus.

$$P(w_n \mid w_{n-1}) = \frac{C(w_{n-1}w_n)}{\sum_{w \in dict} C(w_{n-1}w)}$$

Bigram in Practice

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Example

$$P(the \mid\ on) = \frac{C(on\ the)}{\sum_x C(on\ x)}$$

The probability of a complete word sequence

Given the **Bigram** assumption for the probability of an individual word, we can compute the probability of complete word sequence by:

$$P(w_1^n) \approx \prod_{k=1}^{n} P(w_k \mid w_{k-1})$$

Chain Rule

$$\begin{aligned} P(\text{"}an\ apple\ is\ on\ the\text{"}) = &\ P(an) \times P(apple \mid an) \times P(is \mid an\ apple) \\ &\times P(on \mid an\ apple\ is) \times P(the \mid an\ apple\ is\ on) \end{aligned}$$

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Bigram Assumption

$$\begin{aligned} P(\text{"}an\ apple\ is\ on\ the\text{"}) &= P(apple \mid an) \times P(is \mid apple) \\ &\times P(on \mid is) \times P(the \mid on) \end{aligned}$$

OOV & Smoothing

OOV stands for **Out Of Vocabulary**

- Words appear only in a *test set* but not in the *training set*.
- OOV problem occurs even when we work on big data.

Types of smoothing

- Laplace smoothing (Add-one smoothing)
- Add-k smoothing
- Interpolation
- $\cdots$

Interpolation

We mix the probability estimates from all the n-gram estimators, weighing and combining the trigram, bigram, and unigram counts.

Interpolation

In case of Bigram

$$\hat{P}(table \mid the) = \lambda_1 P(table \mid the) + \lambda_2 P(table)$$

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In case of Trigram

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where we choose λ_i such that $\sum_i \lambda_i = 1$

How are the λ values set?

- They can be learned from a **held-out** corpus
- Can be found by **EM** algorithm
- For the purpose of this project, we assume without loss of generality that $\lambda_i > \lambda_j (\forall i < j)$

POS-Ngram

Formula

$$P(w_n \mid w_1^{n-1}) = \sum_{c_n} P(w_n \mid c_n) \times P(c_n \mid c_{n-N+1}^{n-1})$$

where c_n is a class of w_n

(In this context, c_n is considered a part of speech of the word w_n)

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Example

c_1:Noun	cat, dog, thought, $\cdots$
c_2:Verb	go, speak, $\cdots$
c_1:Noun, c_2:Verb	play, $\cdots$

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It means that to predict the next word w_n

1. Compute $P(c_n \mid c_{n-N+1}^{n-1})$
2. $P(w_n \mid c_n) = \frac{C(w_n, c_n)}{C(c_n)}$
3. w_n^* is defined by $\arg\max_{w_n} P(w_n \mid w_1^{n-1})$

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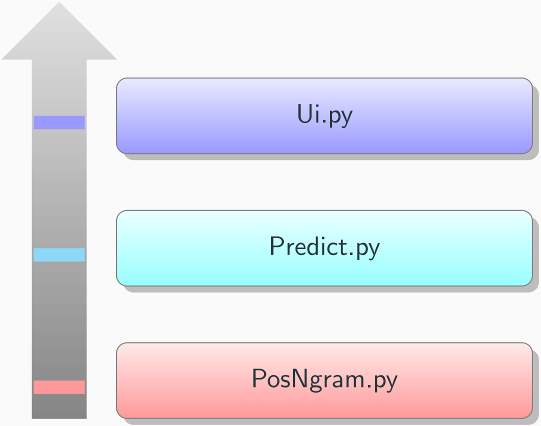
Implementation

Programming Structure



Implementation

- Programming Language : Python
- Ui : Tkinter
- NLTK (Natural Language ToolKit)

References

1. Speech and Language Processing (Chapter 4) (Daniel Jurafsky - Stanford University, 1999)
2. N-gram Language Modeling Tutorial (Lecture notes courtesy of Prof. Mari Ostendorf, 2007-06-21)
3. Probabilistic Language Model (Chapter 3) (Kenji KITA, University of Tokyo Press, 1999)

DEMO

Thank You.