English Word Suggestion Based on Part of Speech Ngram

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Motivation

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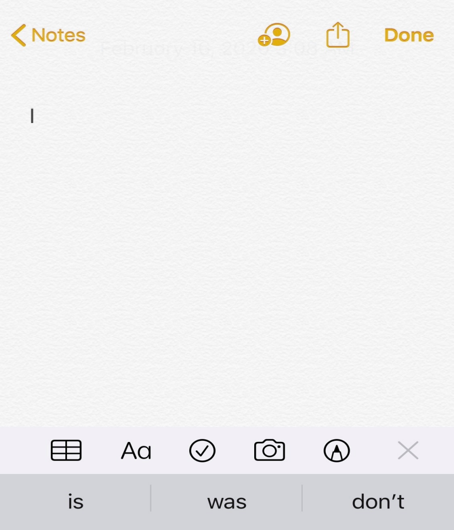
- Word suggestion for note-taking app on mobile devices



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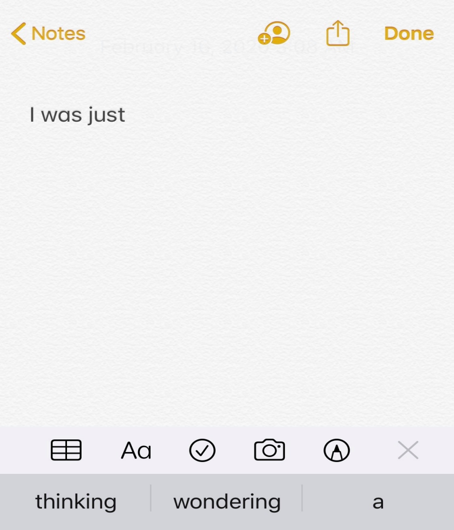

Part Of Speech Ngram (POS-Ngram)

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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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 words in a sentence?
Ex: "an apple is on the table"

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

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  $\rightarrow w_1^4 = "an\ apple\ is\ on"$

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

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

Let's Apply Chain Rule

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

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

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, $P(w_n \mid w_1^{n-1})$.

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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Example

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

Bigram in Practice

By supposing that C is the counts of a sequence of words 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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$(on\ x)$ means (on the), (on board), (on time), (on that), $\cdots$

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:

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

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Bigram Assumption

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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
- Back-off
- Linear interpolation
- $\cdots$

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Linear Interpolation

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

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Bigram + Unigram

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

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

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Implementation

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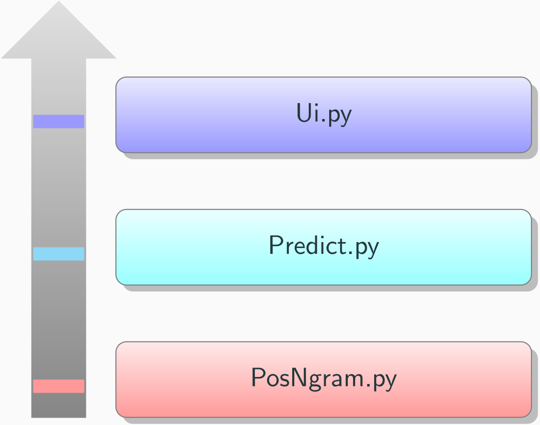
- Programming Language : Python
- Ui : Tkinter
- NLTK (Natural Language ToolKit)

Programming Structure



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