

English Word Suggestion Based on Part of Speech Ngram

Hamana Laboratory, Gunma University

Borann Chanrathnak

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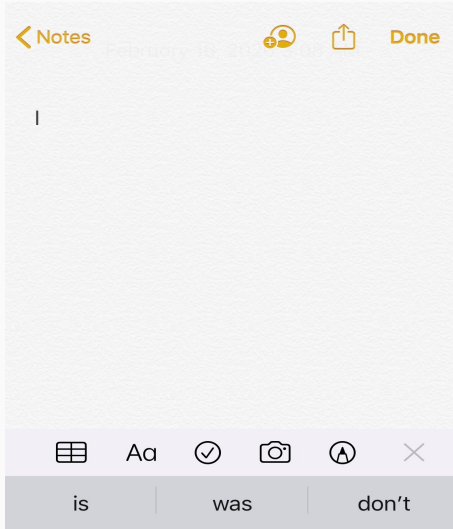
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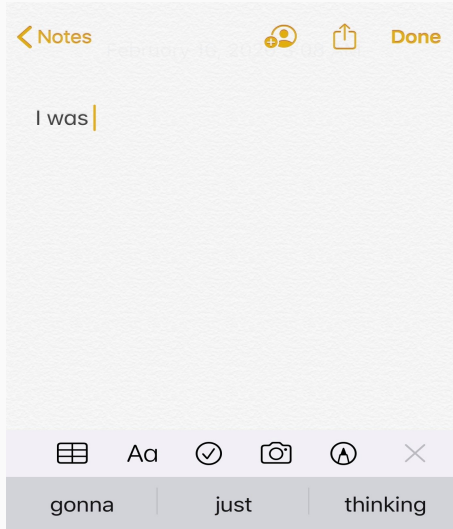
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- Word suggestion for note-taking app on mobile devices



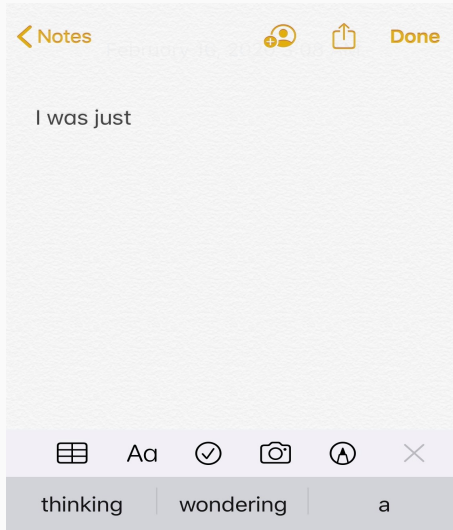
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Part Of Speech Ngram (POS-Ngram)

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"

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

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

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

- $P(\text{an apple is}) = P(\text{an}) \times P(\text{apple} | \text{an}) \times P(\text{is} | \text{an apple})$

Let's Apply Chain Rule

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

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

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

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

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

Bigram in Practice

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

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

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

$(\textit{on } x)$ means $(\textit{on the})$, $(\textit{on board})$, $(\textit{on time})$, $(\textit{on that})$, \dots

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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Chain Rule

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Bigram Assumption

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

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
- ...

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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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Trigram + Bigram + Unigram

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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 $\lambda_i > \lambda_j (\forall i < j)$

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

cat, dog, thought, ...	c_1 :Noun
go, speak, ...	c_2 :Verb
play, ...	c_1 :Noun, c_2 :Verb

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It means that to predict the next word w_n

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

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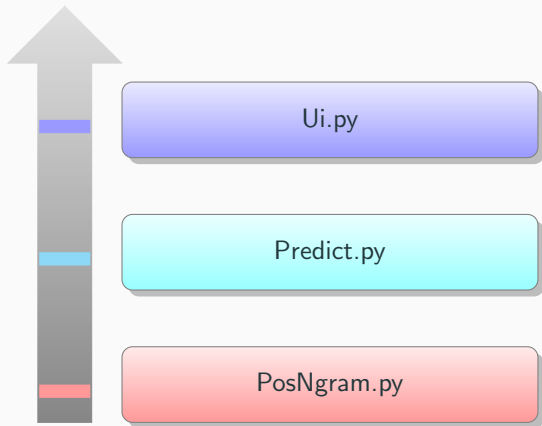
It means that to predict the next word w_n

1. $P(w_n \mid c_n) = \frac{C(w_n, c_n)}{C(c_n)}$
2. Compute $P(c_n \mid c_{n-N+1}^{n-1}) \sim P(w_n \mid w_{n-N+1}^{n-1})$
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Implementation




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

Programming Structure



DEMO

References

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-  N-gram Language Modeling Tutorial (Lecture notes courtesy of Prof. Mari Ostendorf, 2007-06-21)
-  Probabilistic Language Model (Chapter 3) (Kenji KITA, University of Tokyo Press, 1999)