

English Word Suggestion Based on Part of Speech Ngram

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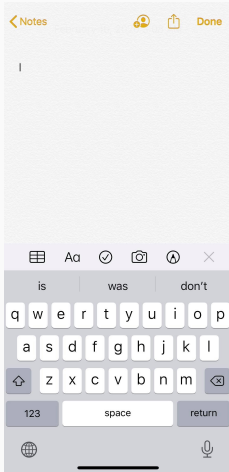
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2. Online digital writing tools

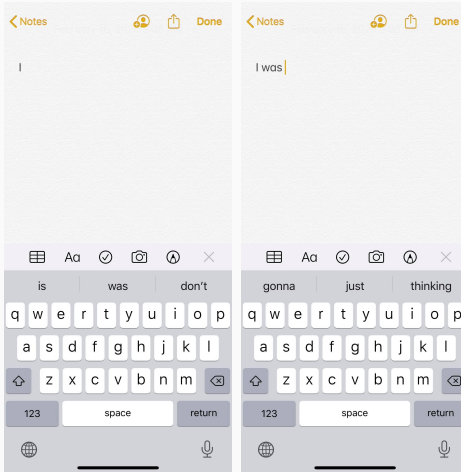
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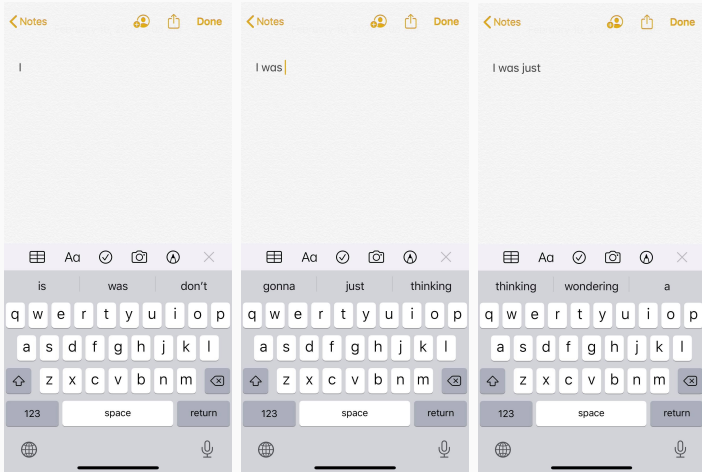
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How to Predict?

"I am japanese, so I speak"

How to Predict?

"I am japanese, so I speak" →

How to Predict?

"I am japanese, so I speak" → "japanese"

POS-Ngram

What does POS-Ngram mean?

Definition

Part of Speech (POS) one of the classes into which words are divided according to their grammar, such as noun, verb, adjective, etc.

Definition

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

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

What does POS-Ngram mean?

Definition

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

Definition

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"

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

Chain Rule Of Probability

Notation

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- To represent the probability of a particular random variable X_i taking on the value "the", or $P(X_i = \text{"the"})$ we will use simplification $P(\text{the})$.
- We represent a sequence of N words either as $w_1 \cdots w_n$ or w_1^n

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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By applying chain rule to a sequence of words

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Examples

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

Let's Apply Chain Rule

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

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

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, $P(w_n | w_1^{n-1})$
- Language is creative, and any particular context might have never occurred before

Example

$$P(\text{sentences} \mid \text{this is an example of long}) = ?$$

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

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

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

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Example

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

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

$$P(w_n|w_{n-1}) = \frac{C(w_{n-1}w_n)}{\sum_w C(w_{n-1}w)}$$

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Example

$$P(the|on) = \frac{C(on\ the)}{\sum_{others} C(on\ others)}$$

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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Example

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

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
- Interpolation
- ...

Interpolation

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

Interpolation

To estimate $P(w_n \mid w_{n-2}w_{n-1})$ we use simple interpolation as follows:

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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

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

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Example

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

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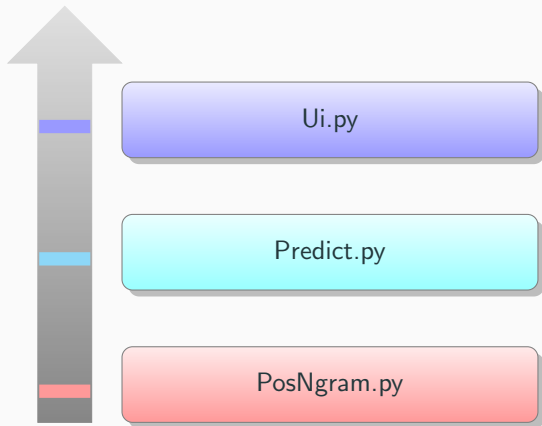
c_1 :Noun	cat, dog, thought, ...
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c_1 :Noun, c_2 :Verb	play, ...

It means that to predict the next word w_n

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

Implementation

Programming Structure



Implementation

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

Function	Argument	Result
word_tokenize	"I like english."	["I", "like", "english", "."]
pos_tag	["I", "like"]	[("I", "PRN"), ("like", "VBP")]

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.