

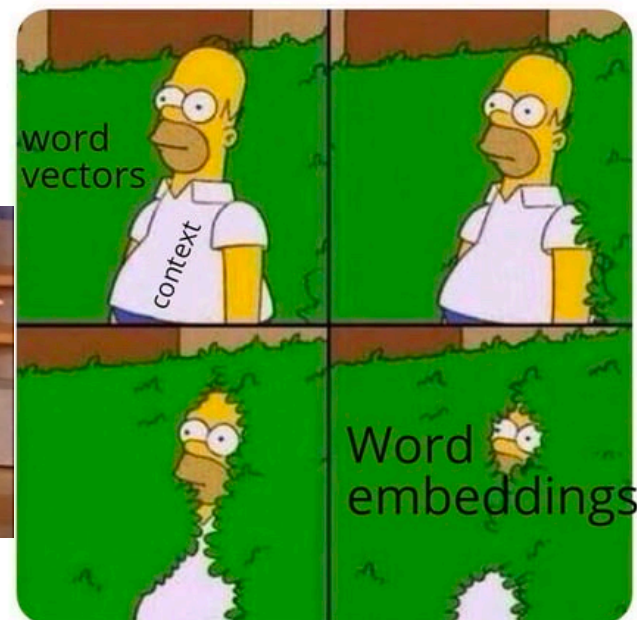
April 28, 2023.

DSML: NLP module.

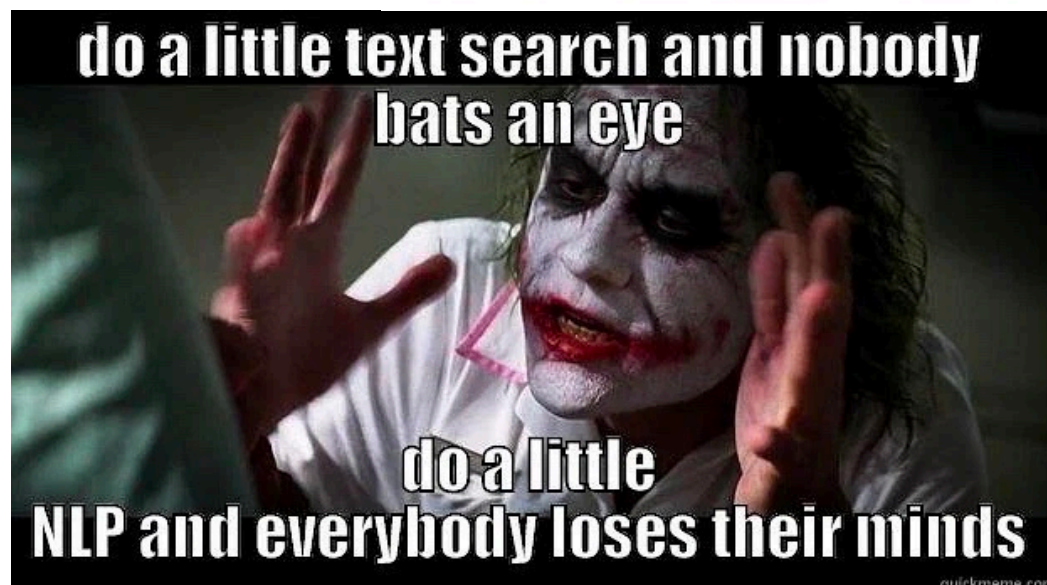
Word embeddings
in a nutshell

Language Modeling.

Class starts
@ 9:05



When you penalize your Natural Language Generation model for large sentence lengths



Recap:

- * Corpus → Collection of documents.
- * Documents → Collection of one or more sentences.
- * Sentences → Collection of words.
- * Converting text datasets to vectors:
 - (i) Document → Vector 1, 2.
 - (ii) Word → vector. 3, 4.
- * Methods for vectorization:
 - (i) Bag-of-words
 - (ii) TF-IDF
 - (iii) Continuous Bag-of-words
 - (iv) Skip-gram.

Agenda:

- * language modeling - teaching a computer how to form sentences.
- * approaches: What could be done here?
- * Techniques: Unigram, Bigram, Tri-gram, n-gram.
- * Core concept: Conditional Probability.
- * But first... business case!!

Naïve approaches - How to solve the problem?

* Conditional prob. → Naïve Bayes.
→

* Word 2 Vec → Cosine similarity.
↳ problem: similar words, maybe not so useful.

* Take CBOW → modify to produce the last word, we could have a NN. solution.

Conditional Prob.

A, B

$P(A)$, $P(B)$.

$P(A \cap B)$

$$\checkmark P(A|B) = \frac{\downarrow P(A \cap B)}{P(B).}$$

↗

$$P(B|A) = \frac{\leftarrow P(A|B) \cdot P(B)}{P(A).}$$

A and B are independent
if $P(A|B) = P(A)$

How to apply conditional probability to predict the next word?

* The cat is .
 w_1 w_2 w_3 w_4 .

Vocabulary

w_1
 w_2
 w_3
:
:
 w_n .

w_4 is nothing but the word which maximizes the following probability

$$w_4 = \arg \max_i P(w_i \mid w_1 = \text{The}, w_2 = \text{cat}, w_3 = \text{is}) .$$

Problems with probabilities:

$$1] P(w_k | w_{k-1} w_{k-2} w_{k-3} \dots w_1) \\ = \frac{P(w_k \cap w_{k-1} \cap w_{k-2} \cap \dots)}{P(w_{k-1} \cap w_{k-2} \cap \dots)}$$

low values. \rightarrow log probabilities.

2] $P(w)$ = 0 \rightarrow happens when we have not seen w before.

\hookrightarrow Laplace smoothing.

Joint probability

$$P(w_1 \cap w_2 \cap w_3 \cap \dots \cap w_n) \quad \leftarrow \frac{0}{1}?$$

↳ "What is the probability of seeing

→ $w_1, w_2, w_3, \dots, w_n$ in exactly this order?"

My Pet.

My pet's name is —

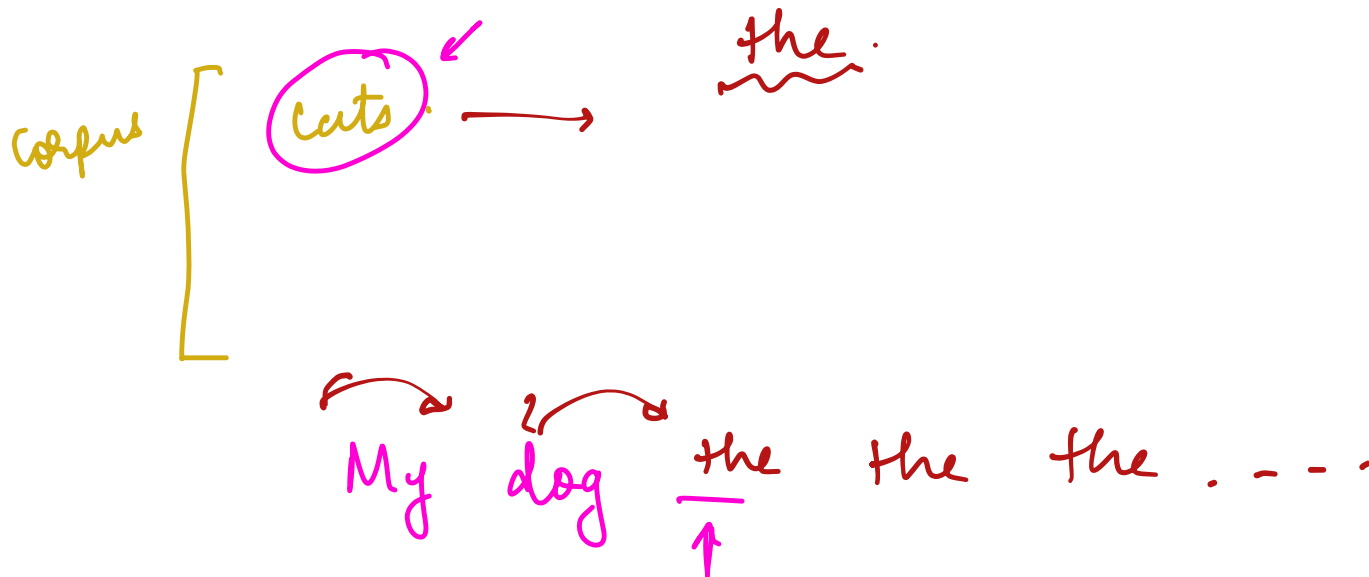
My pet is a —

My pet's color is —

$$\textcircled{1} P(\underline{w_1}, \underline{w_2}, \underline{w_3}, \dots \underline{w_n})$$

$$\rightarrow = \underline{P(w_1)} \cdot \underline{P(w_2)} \cdot \underline{P(w_3)} \cdot \underline{P(w_4)} \dots \underline{P(w_n)}.$$

Naïve Bayes approach: All word occurrences are independent of the others.



② $P(\underbrace{w_1, w_2}_A, \underbrace{w_3}_B)$ $\xrightarrow{(a)}$ $P(w_1) \cdot P(w_2) \cdot P(w_3)$

$\xrightarrow{\quad}$ $\underbrace{P(w_3 | \cancel{w_1}, w_2)} \cdot P(w_1, w_2)$

$\xrightarrow{\quad}$ $P(\underbrace{w_3}_{\uparrow} | \underbrace{w_2}_{\uparrow}) \cdot P(\underbrace{w_2}_{\uparrow} | \underbrace{w_1}_{\uparrow}) \cdot P(w_1)$

"Bigram"

The man saw a girl looking through his telescope.

w_1 w_2 w_1 w_2

The man

\uparrow \uparrow

N-gram \rightarrow A window size of N is selected to calculate the probability.

Bigram :

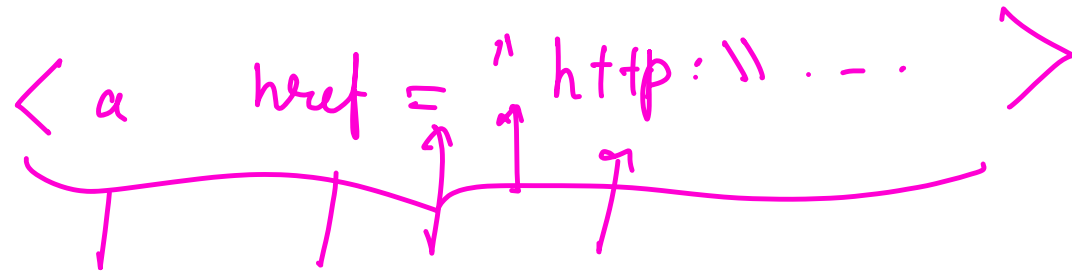
I have three books
with me.

<start> → new token / new word we are
using to mark the start of
the sentence -
 $P(w | \text{<start>})$

Trigram :

→ $P(w | \text{<start>, <start>})$

``



A diagram of an HTML anchor tag ``. A horizontal line is drawn below the tag, with vertical tick marks at the start of each token: `<`, `a`, `href`, `=`, `"`, `http`, `:`, `\`, `.`, `.`, `"`, and `>`. Arrows point from these tokens to labels below the line: `<` points to 'tag opening', `a` points to 'tag name', `href` points to 'attribute name', `=` points to 'assignment operator', `"` points to 'opening quote', `http` points to 'protocol', `:` points to 'separator', `\` points to 'escape character', `.` points to 'domain name', `.` points to 'domain name', `"` points to 'closing quote', and `>` points to 'tag closing'.