SQLite :-

→ `pd.read_sql_query("""SELECT name FROM sqlite_master WHERE type='table' ORDER BY name; """, con)` → Prints list of tables.

	name
0	Reviews

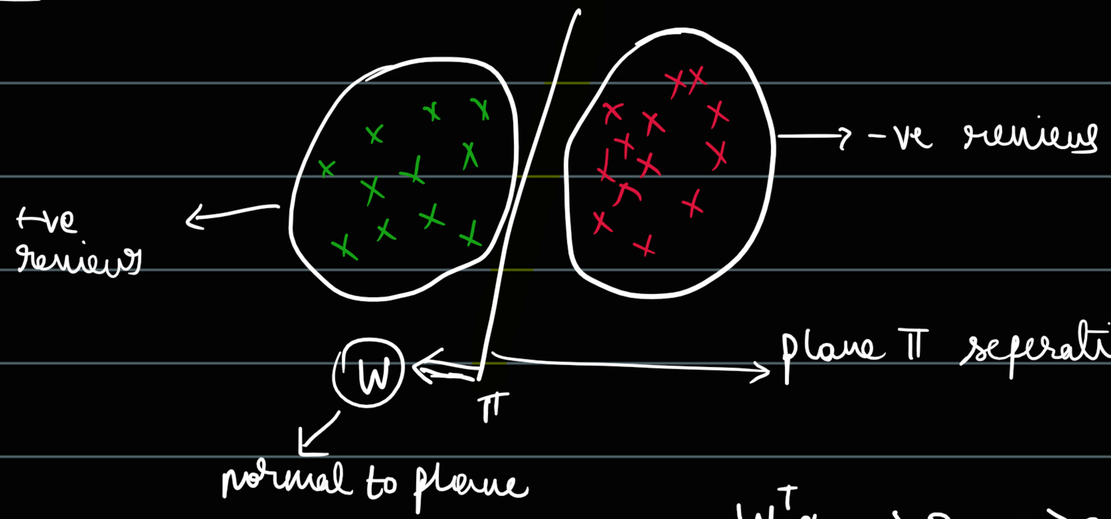
→ df.drop_duplicates(subset={" ", " ",... "}, keep="first") (Pandas)

↳ drops duplicate values with these column name & keeps the first occurance.

→ Use common sense to clean data. No general technique.

→ how to convert text to numerical vectors?

ex:- Review text → n-dim vector



(reviews are represented by 'X' after converting to vector)

$W^T x_1 > 0$ ⇒ review x_1 is a positive review (on same side)

$W^T x_2 < 0$ ⇒ review x_1 is a negative review (on diff side)

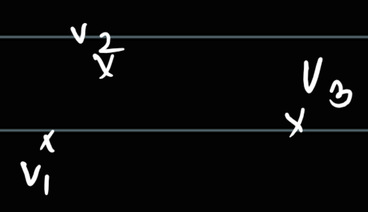
→ Rules for conversion from text to vector :-

r_1 r_2 r_3

assume semantic similarity b/w $(r_1, r_2) > (r_1, r_3)$

then distance b/w $(v_1, v_2) <$ dist b/w (v_1, v_3)

ie: if they are similar, vectors must be close.



Bag of words :-

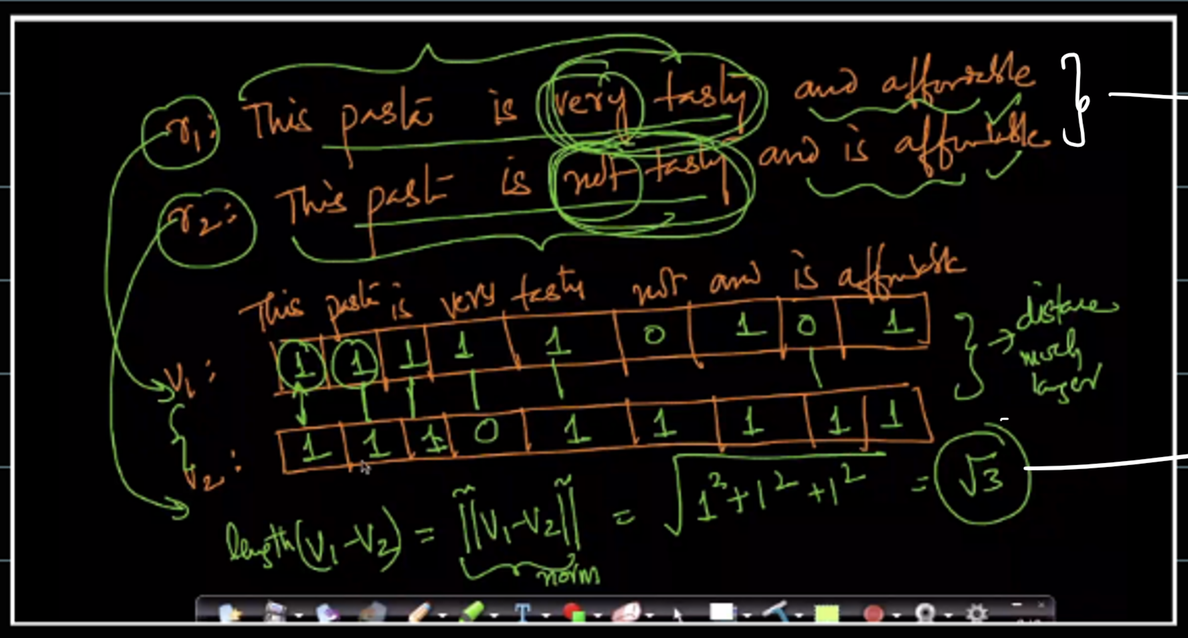
step ① :- Constructing dictionary (set of all unique words)

step ② :- Assume there are d unique words across all 'n' documents/reviews. [Collection of documents is called a corpus]

For each review (d dimensional vector)

The number in pos represents the number of times that word occured in the review.

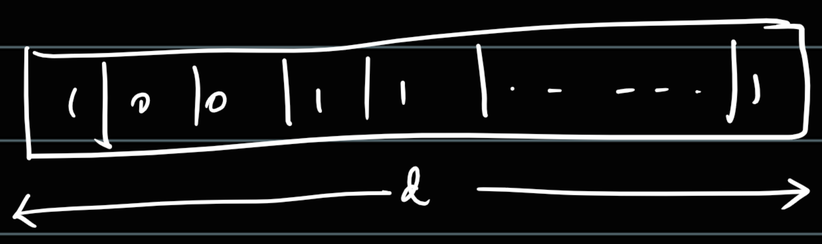
Each word is a different dimensions.



→ Diff sentences but distance is less compared to length 'd' (9)

Boolean bag of words / binary bag of words :-

Instead of counting number of occurances, it only counts occurances -



$\|v_1 - v_2\| \approx \sqrt{\#\text{ of differing words}}$

→ We can notice that some of the words in BoW don't matter (is, and, a, the etc.,) → Stopwords

→ Bag of words is still used for creating baselines with Generalized Linear Models.

→ Removing stop word = Smaller dimensions data.

These are called text preprocessing steps.

→ from nltk.corpus import stopwords

→ We also make everything lowercase.

→ Stemming :- tasty, tasteful, tasteY all have same meaning.

converting all into one word 'taste'. This is called stemming.

PorterStemmer, Snowball Stemmer } two techniques for stemming.

Snowball Stemmer → more powerful.

→ tokenization :- Breaking sentences into words. eg:- if we use space as delimiter, New York are seperate words.

→ In BoW we are not taking semantic meaning.

eg:- delicious tasty convey same meaning. We use word2Vec to solve this.

Lemmatisation is the algorithmic process of determining the lemma of a word based on its intended meaning. Unlike stemming, lemmatization depends on correctly identifying the intended part of speech and meaning of a word in a sentence, as well as within the larger context surrounding that sentence, such as neighboring sentences or even an entire document.

→ Algorithm combines inflected words into a common word called lemma.

{go, going, went} => 'go' is the lemma given by algo.

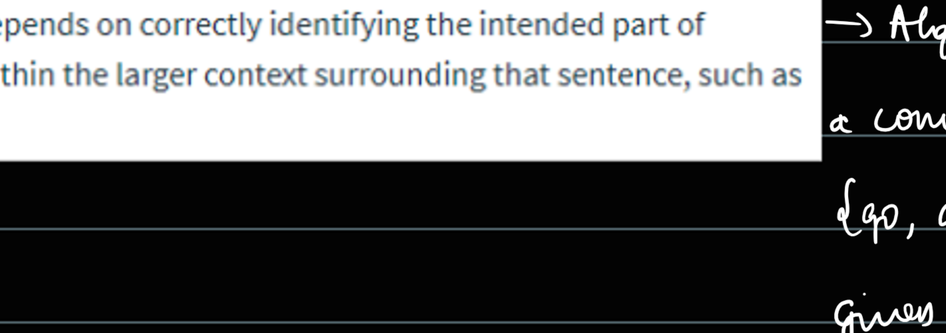
→ NLTK makes use of parts of speech. This is called tagging. Makes sense of context and helps pick the right lemma.

→ Stopwords are not removed in stemming. All words are reduced to base words and the tails are removed.

unigram / Bi-gram / n-gram :-

unigram :- each word is considered as a dimension

bigrams :- pair of words



n = 3 → trigrams

⋮

→ unigram BoW completely discards sequence information

Bigrams, trigrams, ... retains partial sequence informations.

→ But the catch is $n(\text{bigrams}) > n(\text{unigrams})$

→ As n increases, dimensionality increases drastically.

→ But if there are no repeated words in text, #unigrams > #bigrams > #trigrams, ...

TF-IDF:- (term frequency inverse document frequency) (industrialized version of BoW)

r_1: w_1 w_3 w_2 w_5 w_1

N docs { r_2: w_3 w_1 w_4 w_1 w_6 w_2

⋮

⋮

w_1	w_2	w_3	w_4	w_5
2	1	1	0	1

⋮

$$TF(w_i, r_j) = \frac{\#\text{ of times } w_i \text{ occurs in } r_j}{\text{total number of word in } r_j}$$

→ TF-IDF was originally meant for informations retrieval.

→ TF gives how often word occurs. (Probability)

$$0 \leq TF(w_i, r_j) \leq 1$$

IDF:-

D_c = Document corpus { r_1: — w_1 —, r_2: —, ⋮ — w_1 —, ⋮ — w_1 —

$$\rightarrow IDF(w_i, D_c) = \log\left(\frac{N}{n_i}\right)$$

n_i → Number of docs that contains w_i

$$D_c = \{r_1, r_2, \ldots, r_n\}$$

$n_i \leq N \Rightarrow \frac{N}{n_i} \geq 1$

$\Rightarrow \log\left(\frac{N}{n_i}\right) \geq 0$

⇒ As n_i increases, N/n_i decrease. As N/n_i decrease, $\log(N/n_i)$ also decreases as log is monotonic function.

If a word is more frequent in corpus, then its IDF is less. If it's less frequent in corpus, then it's IDF is high

→ Combining both

D_c { r_1 :- ——, r_2 :- ——, ⋮, r_n :- ——

V_1 :- [| | ..... | | ...]

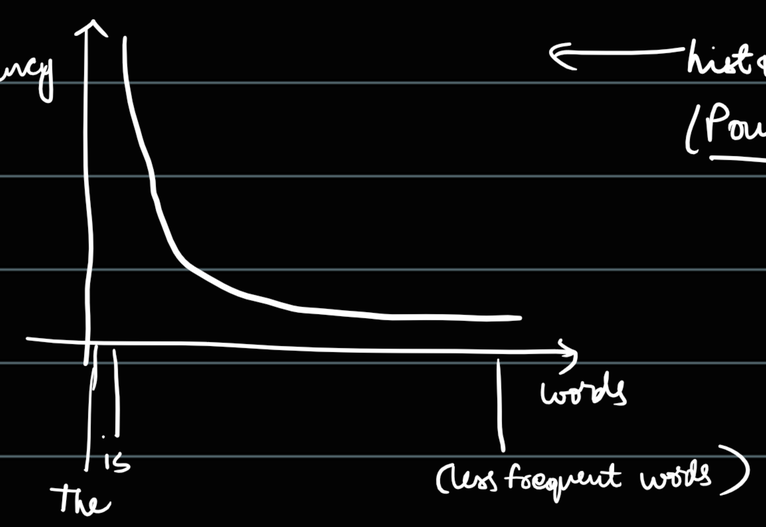
$$w_i = TF(w_i, r_1) * IDF(w_i, D_c)$$

→ Advantage is that we give more importance if → word is more frequent (from TF)
→ word is less frequent (from IDF)

→ Drawback:- Still no semantic importance.

Why do we use log in IDF ? :-

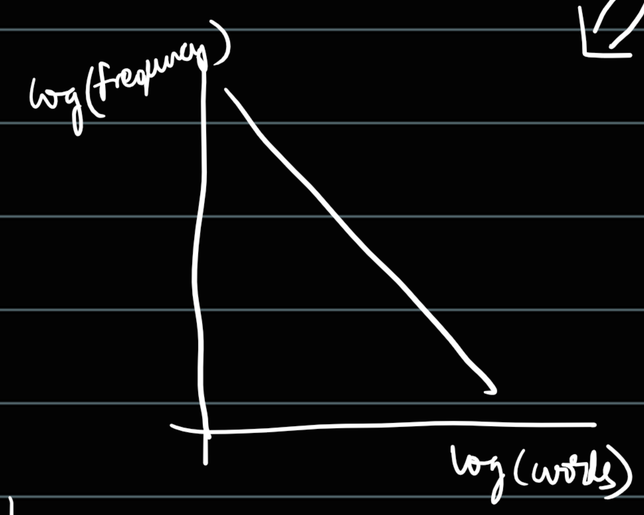
Zipf's law :- frequency



← histogram
(Power law distributions)

↳ If X is a power law distribution, it can be converted to Gaussian Distribution by using transforms like
Box-Cox transform (we take log(X))

When tf idf was introduced, no mathematical explanation was given as to why log was used in idf



→ Another reason :- N/n_i

"the" → almost all docs ≈ 1

"is" → " ≈ 1

⋮

Less frequent pages → if 1 in 1000 → 1000 → ≈ 6.9

$\log(N/n_i)$

≈ 0

"

≈ 0

→ lot of difference. During calculation of TF-IDF, IDF will dominate if there's no log.

→ sometimes if vocabulary is passed explicitly, words might not occur in training phase, but might appear in testing phase. As a result of this N/n_i is going to be ∞. To prevent this, we sometimes do

$$1 + \log\left(\frac{1+N}{1+n_i}\right)$$

(sk-learn implementation)

→ TF :- How frequently word occurs in a document.

IDF :- How rare is the word in the whole corpus. If word is more frequent in the document corpus, it is less important.

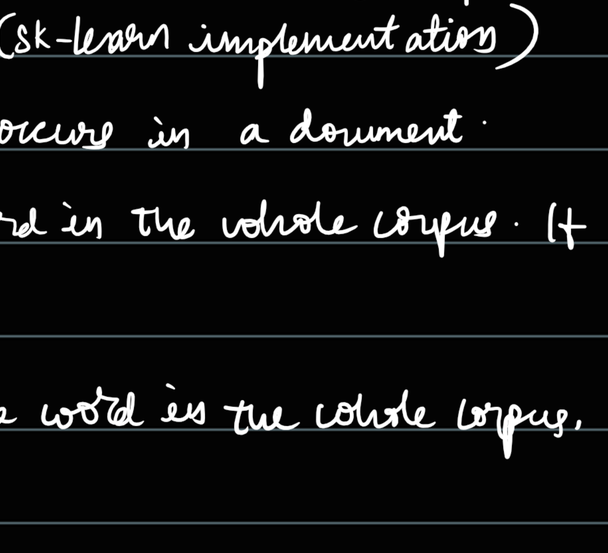
TF-IDF :- Importance of the word in the whole corpus.

Word 2 Vec :- State of the art word to vectors conversion that takes semantic meaning into considerations.

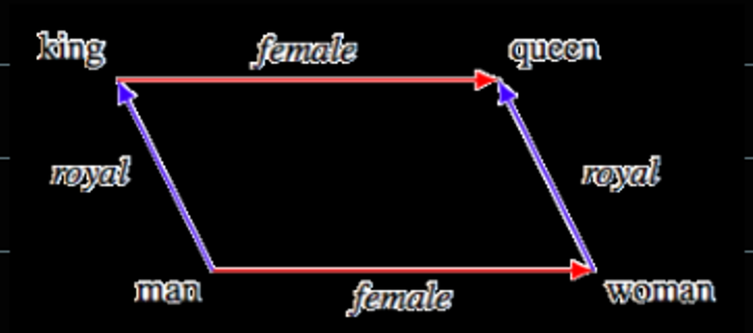
→ The dimensions are usually really high (like 300 ...)

→ It tries to achieve the following :-

① Semantically similar words have closer vectors



② It also tries to keep relationships



$(V_{man} - V_{woman}) \parallel (V_{King} - V_{queen})$

→ Even for country capitals etc.,

→ It does this automatically without being programmed to do so. Came out in 2013.

→ very large data corpus → word2vec → word : vectors

The more the dimensions of vector, the more information it is.

→ At it's core, word2vec looks at the neighborhood of words and looks for words with similar neighborhood.

$w_1\ w_2\ w_3\ w_4\ w_5\ w_6$

neighborhood → $N(w_3)$ ⟹ if $N(w_i) \approx N(w_j)$ then $V_i \approx V_j$

→ Google trained word2vec on it's Google News dataset & this word2vec gives 300 dimension vectors.