Natural Language Processing

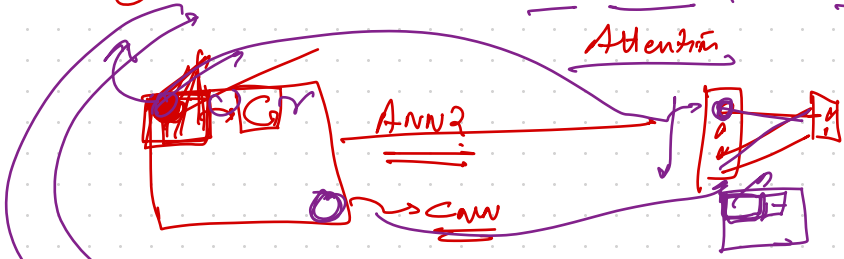
① NLP Problems we can solve.

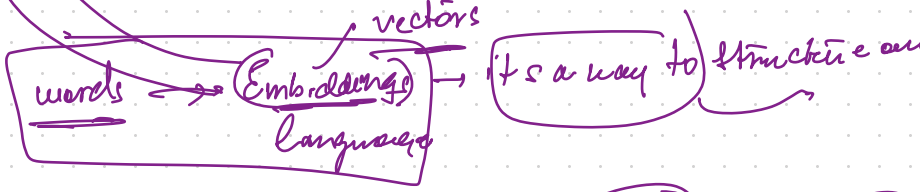
- How do we structure words / sentence

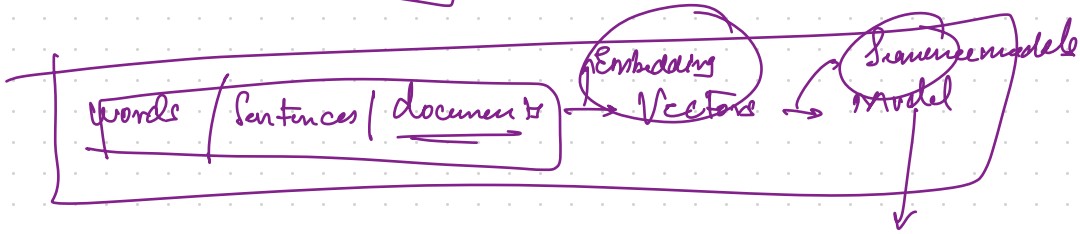
↓

Feature engineering

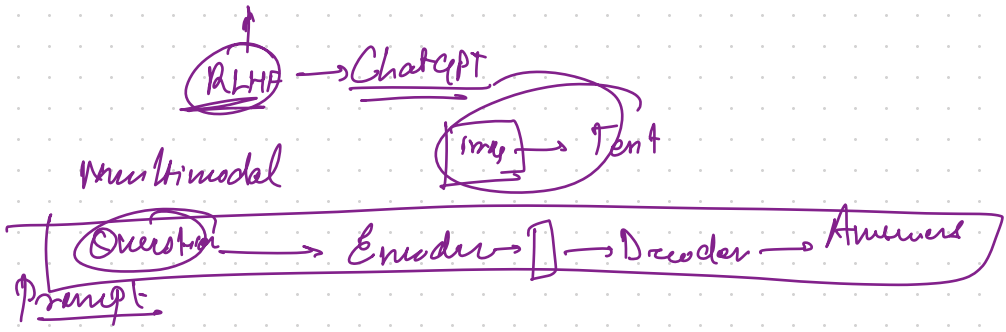
- Sequence models → RNN, LSTM, GRU, Transformer







Large language models



Natural language → is a Sequence

This is a great batch

Great this is batch

Natural Language Processing

Understanding information from text

- Unstructured →
- Content / Sentiments / slangs / Sarcasm

- Indigo . . . .
- Romanised words
- Tujhe main dekh lunga → English
  - Pyinmic translation
  - Phonetics Sounds
- Structured

Use Cases:

Translation

gmail auto type → auto fill

Search engines

Sentiment analysis

Gmail | Spam → Spam, → Ham

Chatbots

Text classification, Sum

NER, information

$y = f(x)$ — f: sentiment, x: input, y: output — Language model.

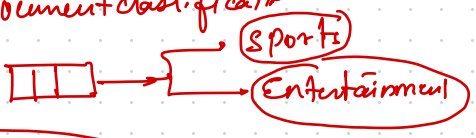
Language model

Sentences are very unclear — Social media, Human Conversations

Preprocessing techniques:

Document classification

Pattern



Special characters @ http....

Removal of unwanted characters or patterns of characters from user source sentence.

Ticket classifier

Ticket

Sentiment classification

Regex → a proper logic of defining certain patterns using certain rules.

"I am very hungry, I will order pizzas and give it to my friend."

Regex → Extract some defined patterns from sentences

[w]
[s]

Name: Subhadeep
Age: 30
Education: master

~~Stop~~ words [Name]
words [Age]

Stopwords: an, a, the
because, and, then

Translation, Chatbot → Temp two 25°C
→ I am ...

What's the temp tomorrow

मैं घर जा रहा हूँ → I am going home

Stemming / Lemmatization

Embedding
words → vectors → model

Embedding

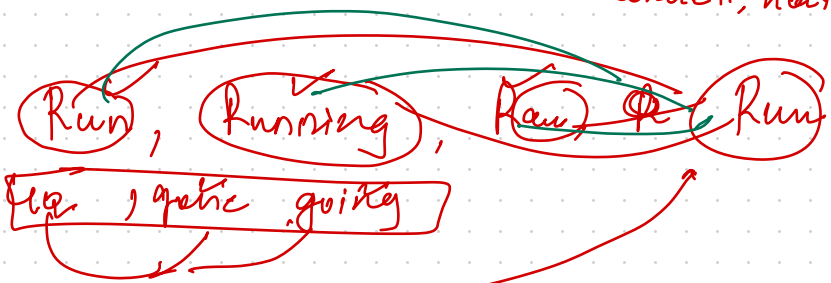
Frequency based
Count of the words in the sentence

Prediction based.
Vectors generated through NN.

Context?

I am going home., home is where heart is

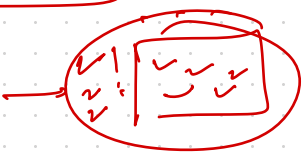
I: 1, am: 1, going: 1 home 2, is: 2
where 1., heart: 1



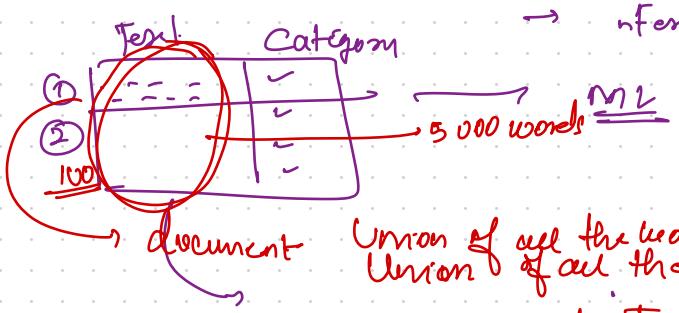
Go

helpful

10:33 → 10:40pm

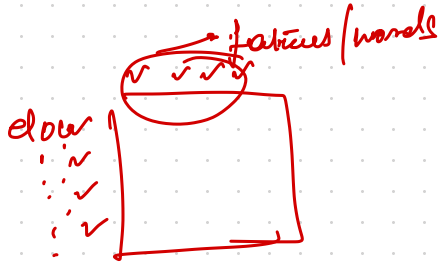


How to represent sentences / documents in a vectorised form using frequency embeddings.

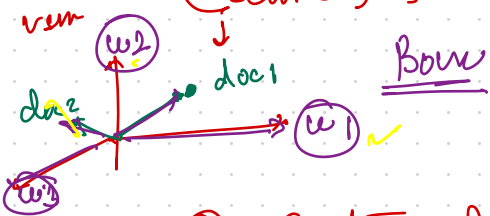


Bag of words model

Document classification



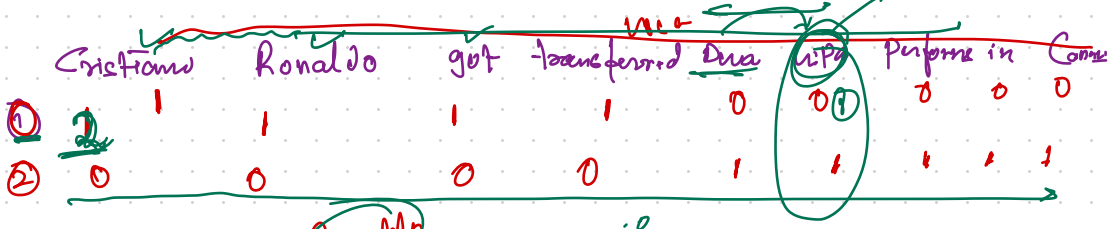
(Document) → outcome

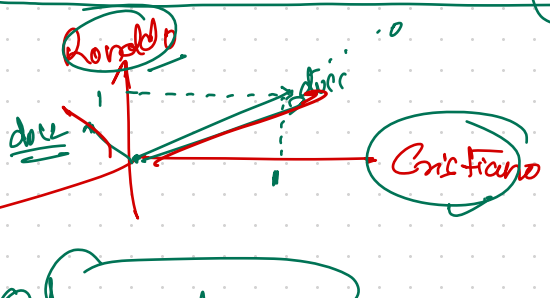


BOW

① Cristiano Ronaldo got transferred to Sports (Cristiano is upset)

② Pwc hopes performs in Cannes.



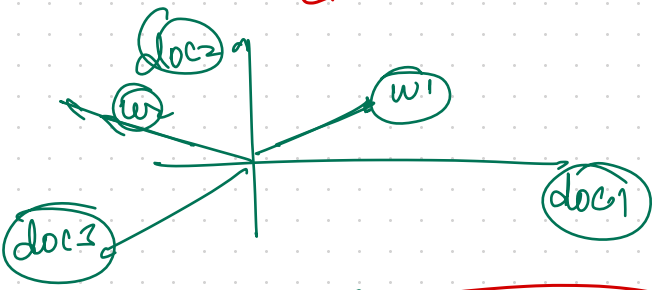


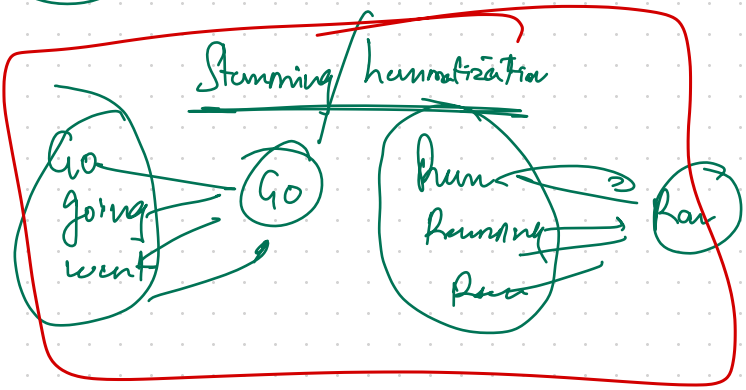
Problem: ① document dimensions

① does not maintain content

→ order not maintained

By definition you and all words are independent





Stemming & Lemmatization

Lemmatization

Porter Stemmer

Running → Run (verb)

Ran

Speeding ✓

Speedfc ✓

Caressed ✓

Going → go

gone

Cry → cri

I am going to visit my home and will make → make

I am (go) to visit my home and will make

Sue my ac is running

Sue my ac is run

Dependency Par

my (run) ions awesome

pos

not

"I am great at public speaking"

Stemming & lemmatization

(word)

Sentence → words

word tokenizer

Sentence tokenisation

document → Sentence

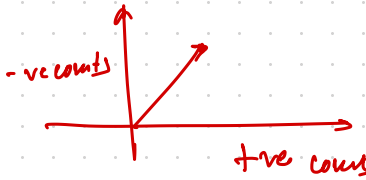
.split(' ')

"I | am | going | to | my | home".split(' ')

['I', 'am', 'going', 'to', 'my', 'home']

title → word tokenisation (' ')

tweet → words → (count of the word in the tweets, count of the word in negative tweets)



tweet → (count of the words, count of -ve words, 1)

tweet: The game

tweet (110, 110)

freqs

{(game, 0): 20
(game, 1): 40
(awesome, 0): 50
(awesome, 1): 90 }

tweet: game is awesome

game awesome

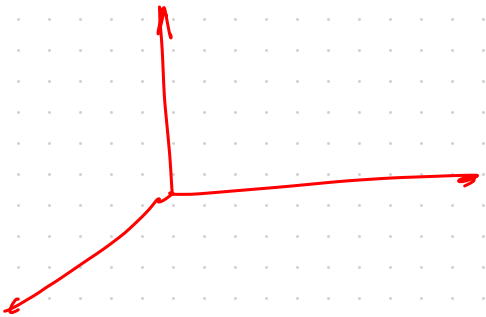
pos = freqs[(game, 1)] = 40 + freqs[(awesome, 1)] → 90

neg = freqs[(game, 0)] = 20 + freqs[(awesome, 0)] → 50

pos = 130

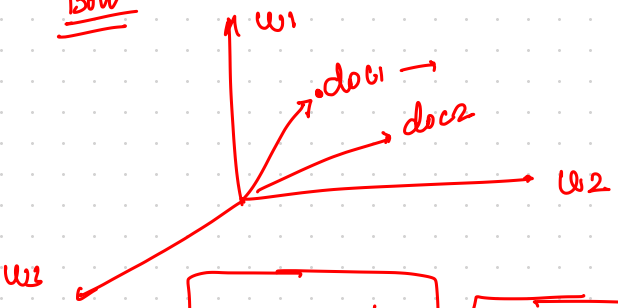
neg = 70

tweet = (1, 130, 70)



NLP → words/docs into vector space models

BoW



Sentence 1 / doc1 : I am happy
Sentence 2 / doc2 : I am sad.

→ Vocabulary

Union of all docs

	w1	w2	w3	w4
doc1	1	1	0	0
doc2	0	0	1	1

Count vectorizer

	w1	w2	w3	w4
doc1	2/n	3/n	1/n	1/n
doc2 / n2	1/n2	1/n2	1/n2	1/n2

① doesn't maintain any order

doc1: I am happy today.

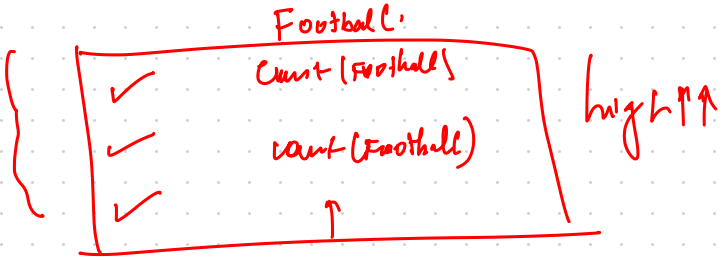
today happy I am

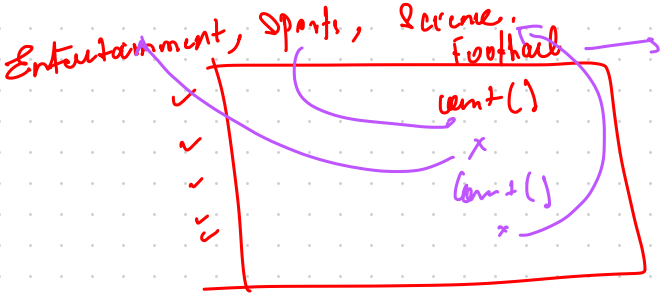
doc1	1	1	1	1	1

Frequency based embeddings don't capture the context

Term Frequency Inverse Document Frequency.

Football





→ Football important word.

tf (Term frequency) x idf

$$\frac{f(w_2, doc_1)}{\text{Total number of tokens in } doc_1} \times \log\left(\frac{N}{n}\right)$$

w1 w2 w3 ... wn

N = 100

doc1
doc2
doc3
⋮

total frequency of all the tokens in doc1

number of documents in which w2 occurs.

doc1 : Ronaldo is lovely, Ronaldo is rich.
doc2 : Ronaldo is famous.
doc3 : Messi is famous

doc1: Ronaldo is lovely, Ronaldo is rich.

doc2: Ronaldo is famous.

doc3: Messi is famous

1/3

Normalised term frequency $\times \log\left(\frac{N+1}{n}\right)$

	Ronaldo	Messi	lovely	Rich	famous
doc1	2/3	0			
doc2		0			
doc3		1/1 x log(4/1)			

$\log(4/2)$

$\log\left(\frac{N+1}{n}\right)$ 4/1

$\frac{2}{4} \times \log(4/2)$

$2/4 \times \text{Log}\left(\frac{4}{2}\right)$ $\quad \text{Log}(1) \neq 0$

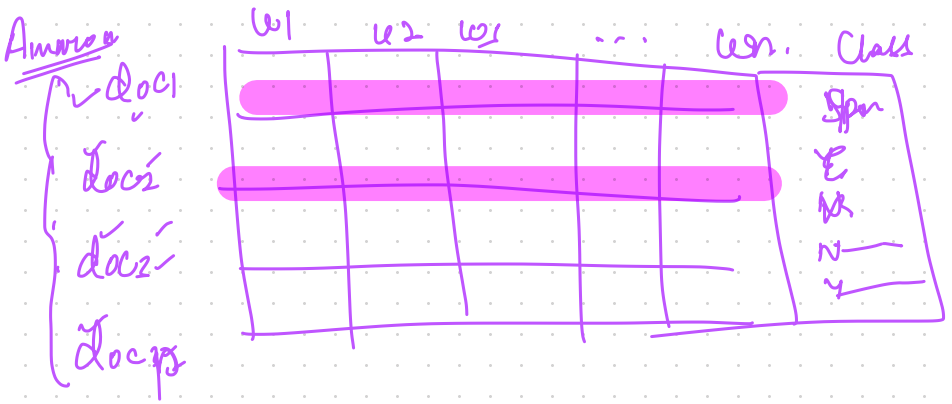
$\log(N/n)$ $\quad n \approx N$, $n \neq N$

TF-IDF (t_i) doc$_j$

= Normalised term frequency $\times \log\left(\frac{N+1}{n}\right)$

$N \rightarrow$ total number of docs in corpus.

$n \rightarrow$ total number of docs in which term occurs.



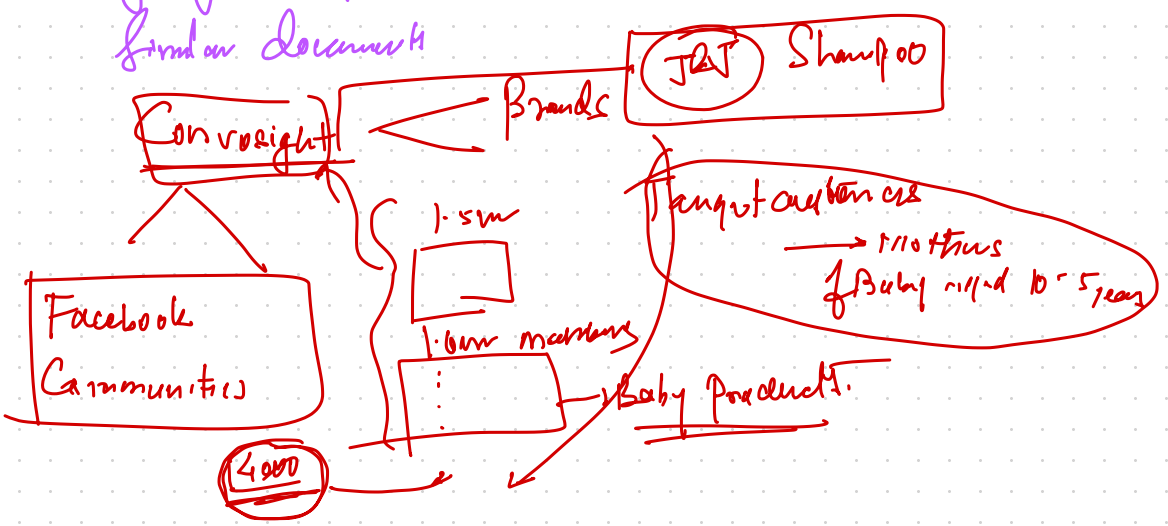
Find out similar documents

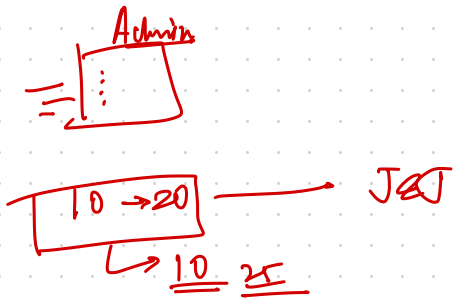
doc1 (Product)

doc3 (Product)

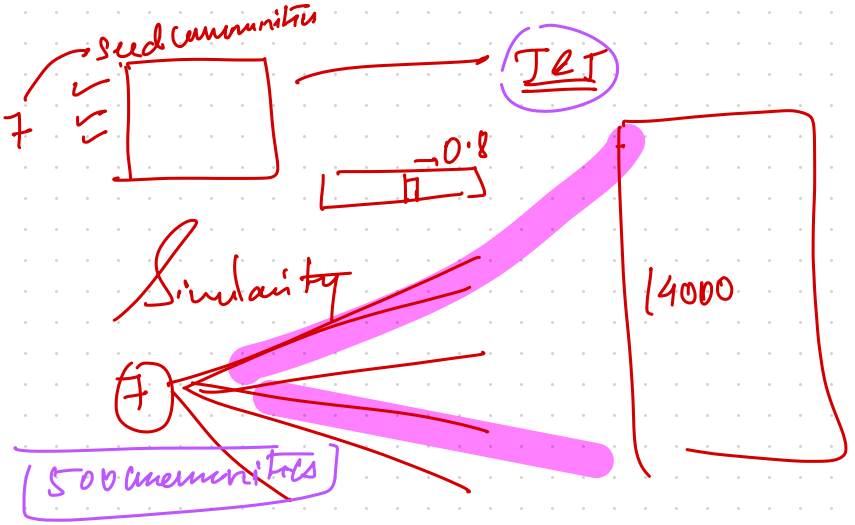
addresses

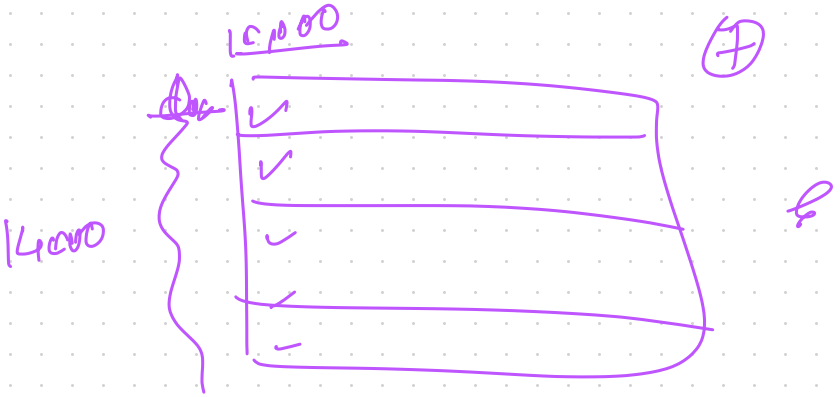
Using document based embedding & confirm similar documents

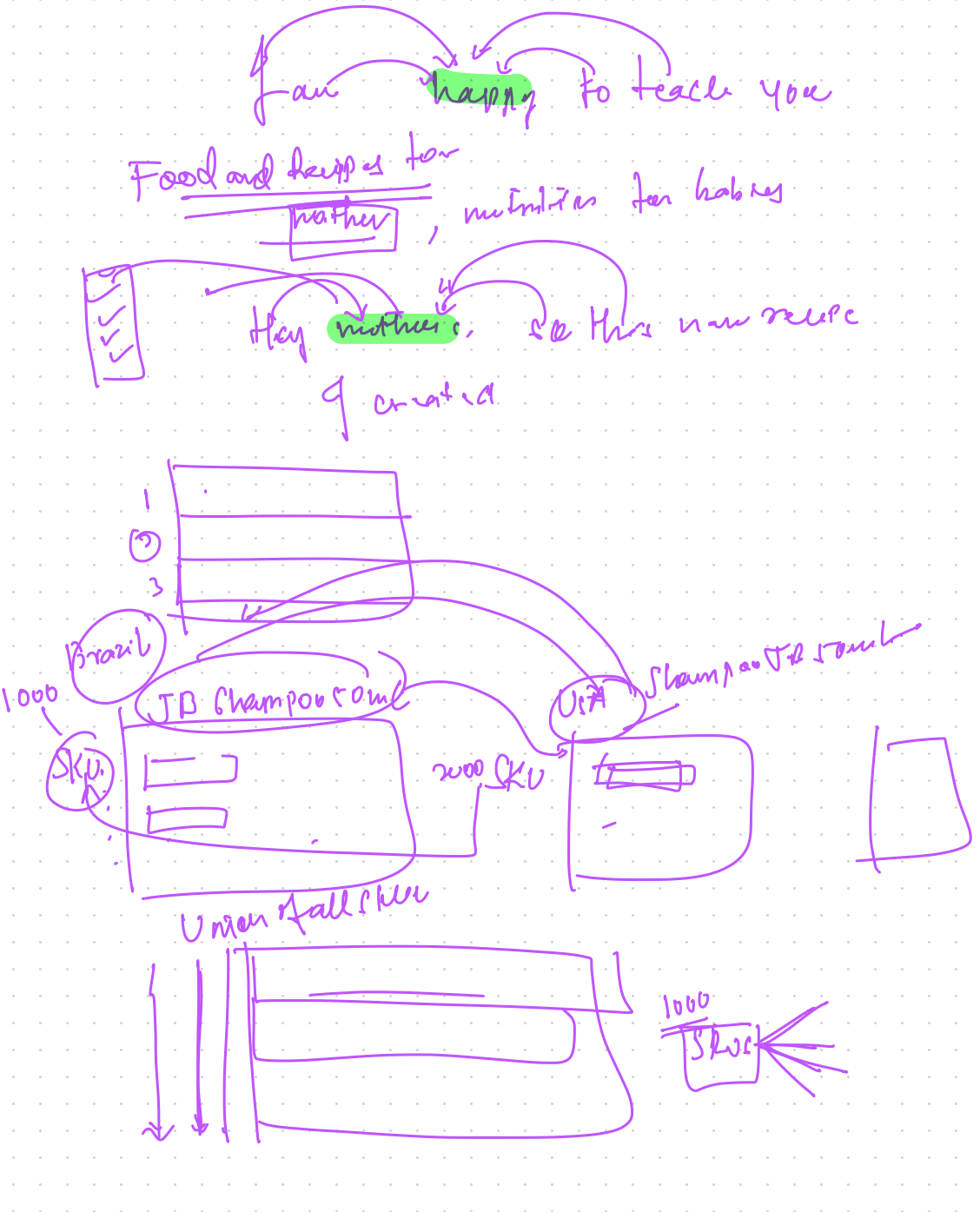


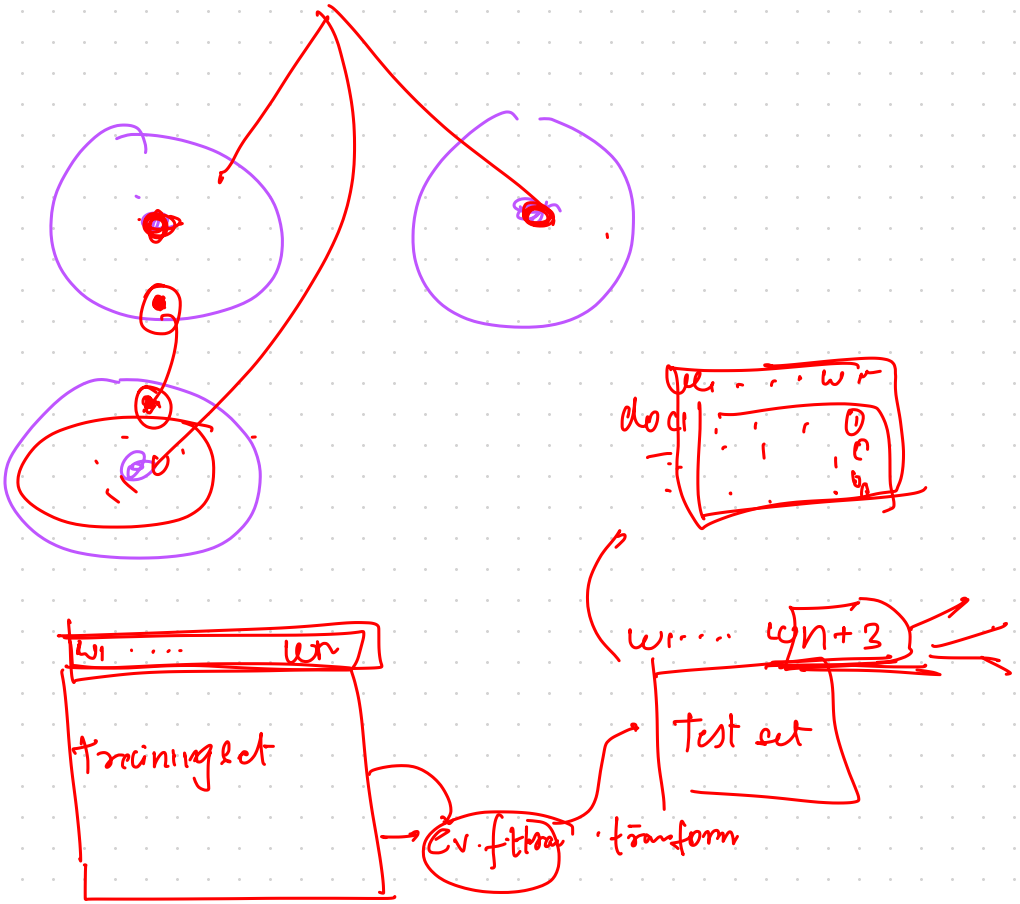


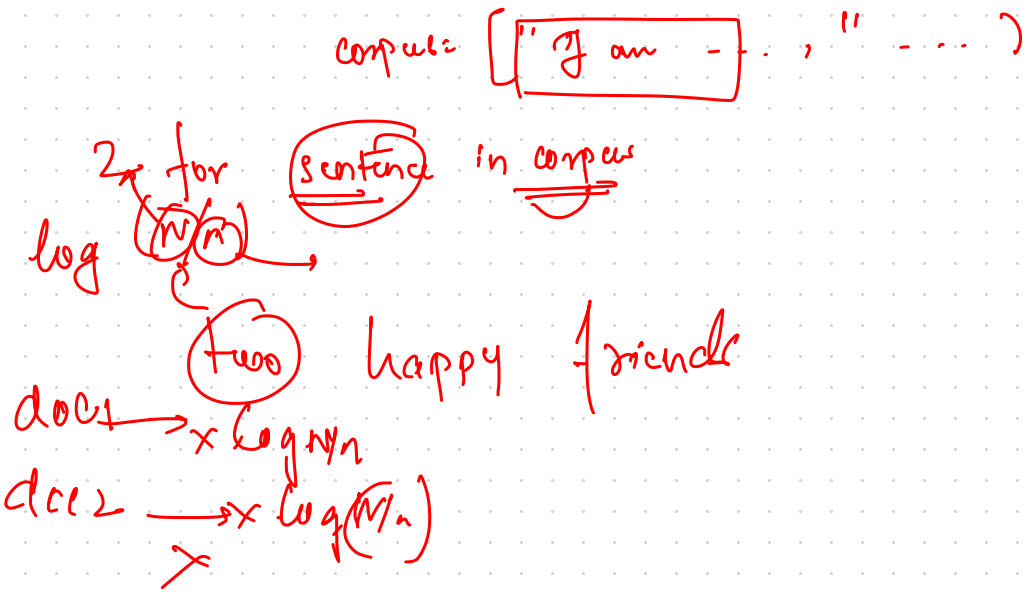
14000 comm
↳ 1.6 billion communications

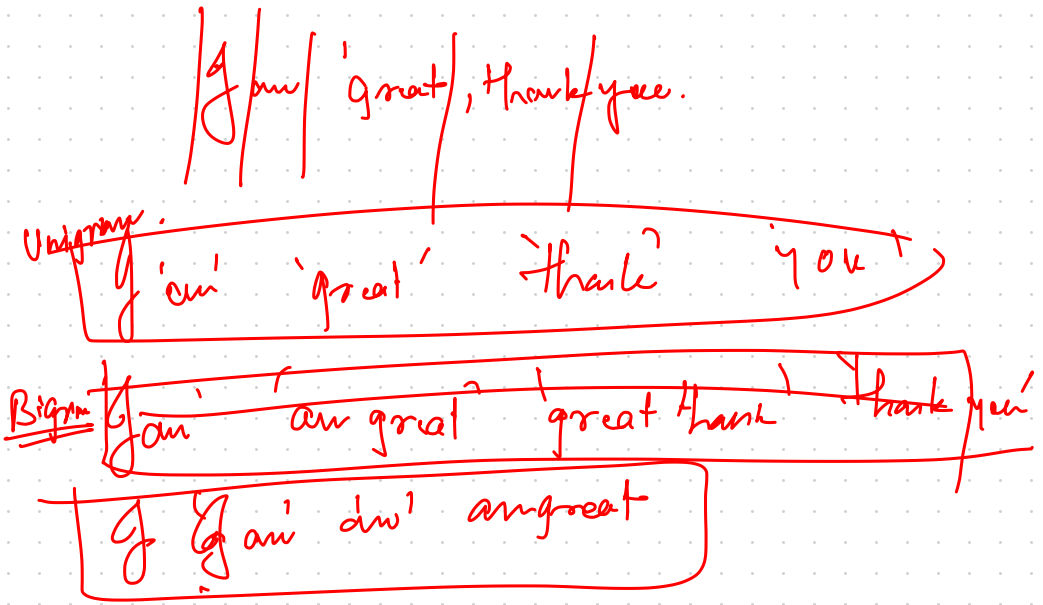





I am happy to teach you
Food and drinks for
mother, nutrition for babies
Hey mothers, See this new recipe
I created
1
2
3
Brazil
1000
SKU
JD Shampoo roml
2000 SKU
UK
Shampoo UK roml
Union all SKU
1000
SKUs

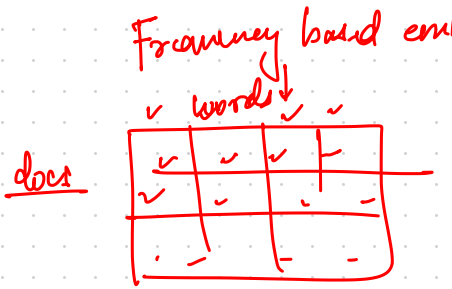

w1 . . . wn
Training set
ev. fit
transform
w1 . . . wn+3
Test set


corpus: ["I am ...", "...
2. for sentence in corpus
log (N/n)
foo
happy friends
doc1 → x log N/n
doc2 → x log(N/n)


I am great, thank you.
Unigram:
I
am
great
thank
you
Bigram:
I am
am great
great thank
thank you
I I am
I am am great

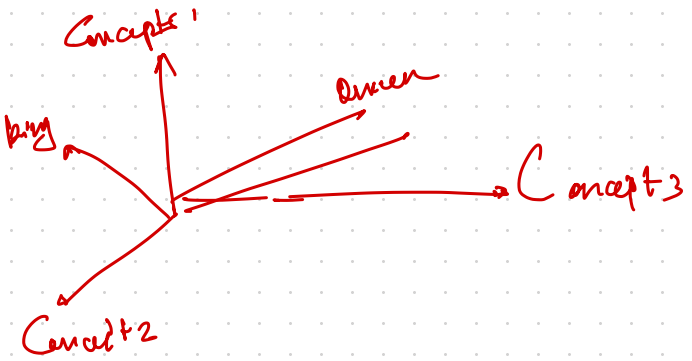
Embedding → word2vec

Frequency based embedding

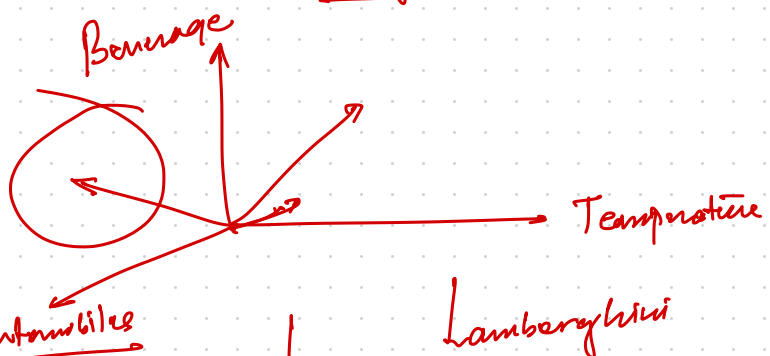


Prediction based Embedding

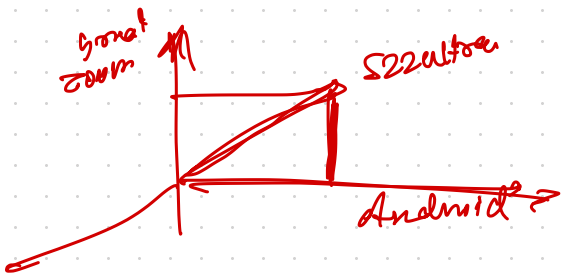
Prediction based curbidding



HotCoffee



Lamborghini



Embeddings are dense representation of concepts

↓

Abstract non-linear combinations of multiple words.

Embeddings (unsupervised)

Word2vec an model

Embeddings SVD

Embedding from language models → (Supervised way)

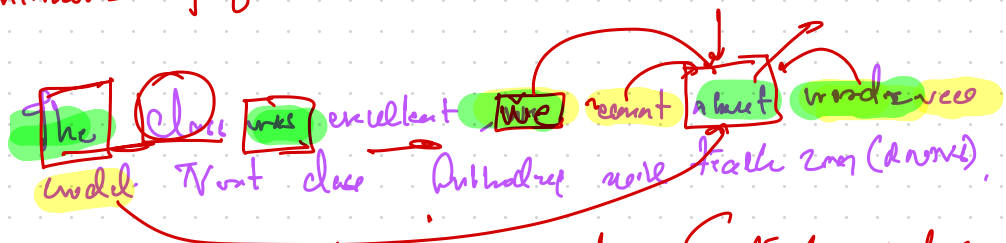
↳ Lan. Lang (RNN, LSTM)

Word2vec

↙ CBOW

Continuous Bag of words

↘ Skip gram model.



Context words	Target word
The, was	class
Class, excellent	was
was, we	excellent

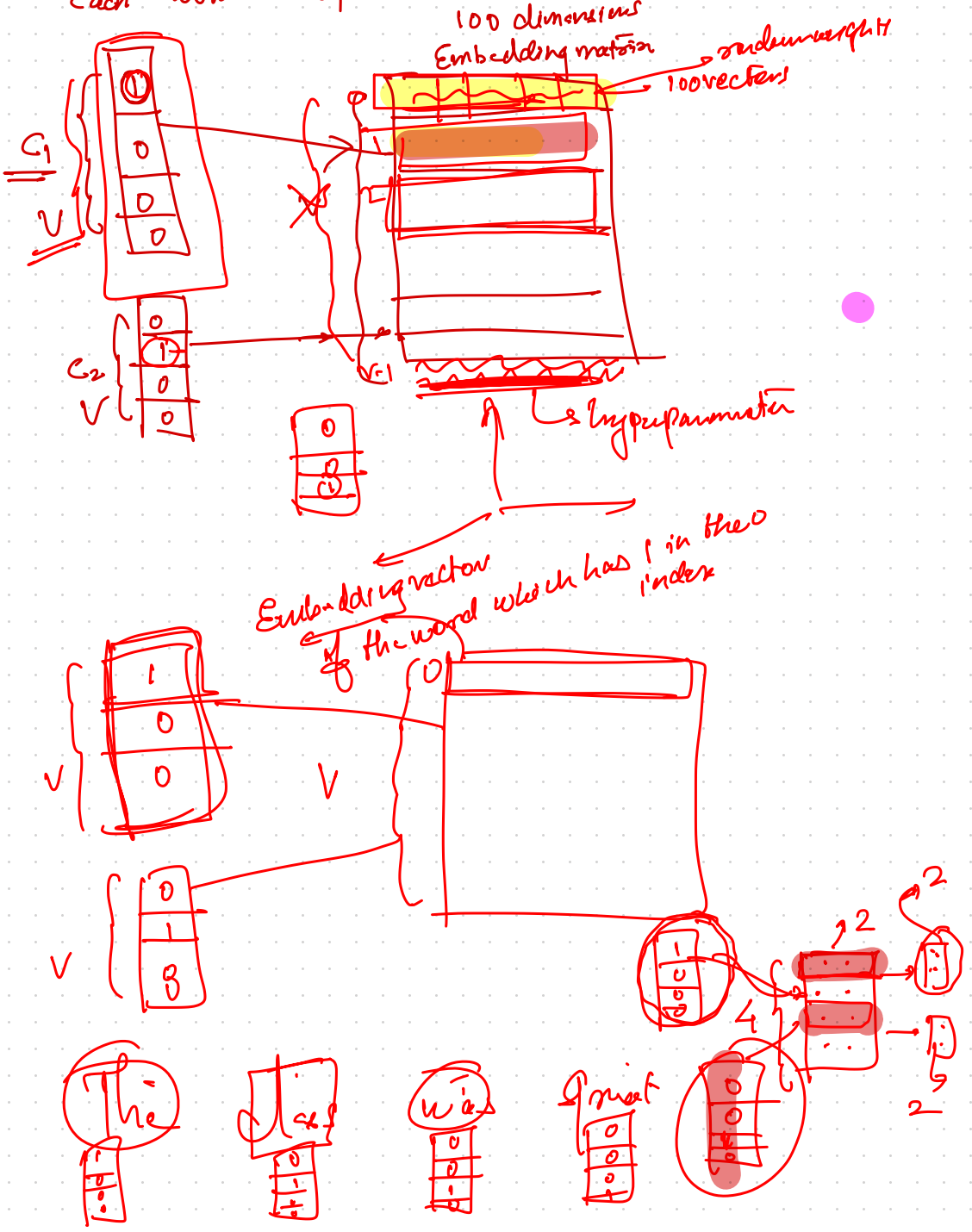
Context window = 1

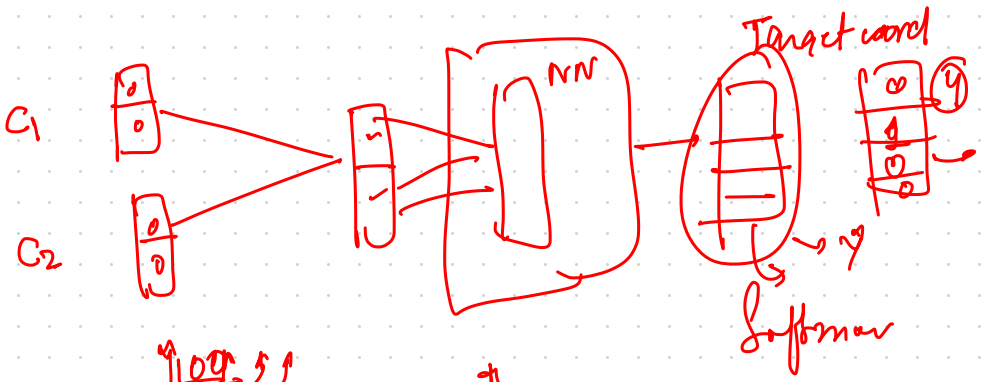
Context window = 2

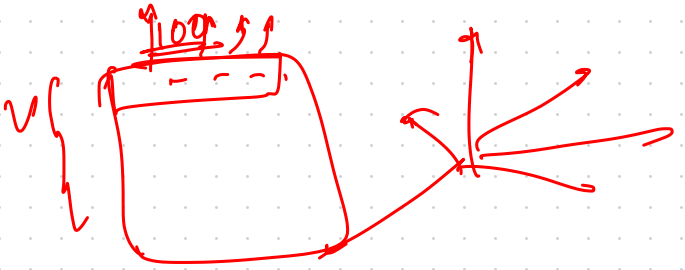
Class

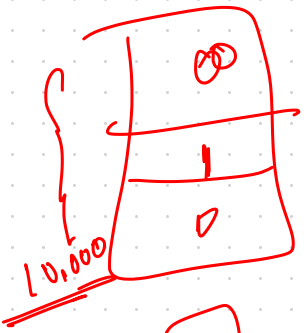
The

Each word is represented as a one hot encoded vector

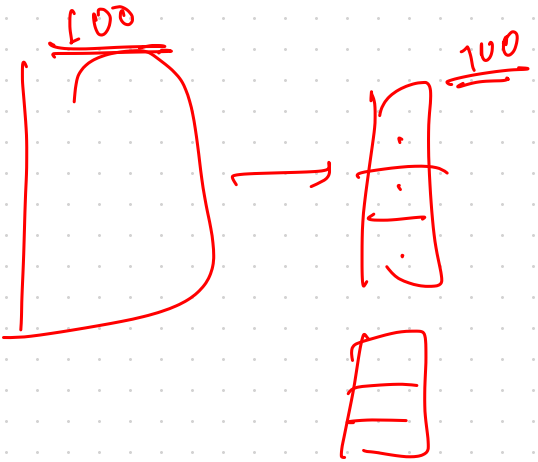



C_1
C_2
NN
Target word
y
Softmax

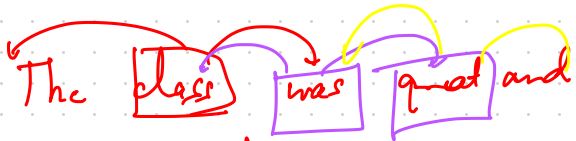

100
V


10,000

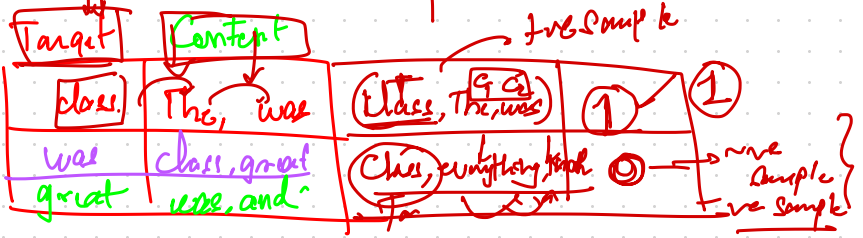

10,000

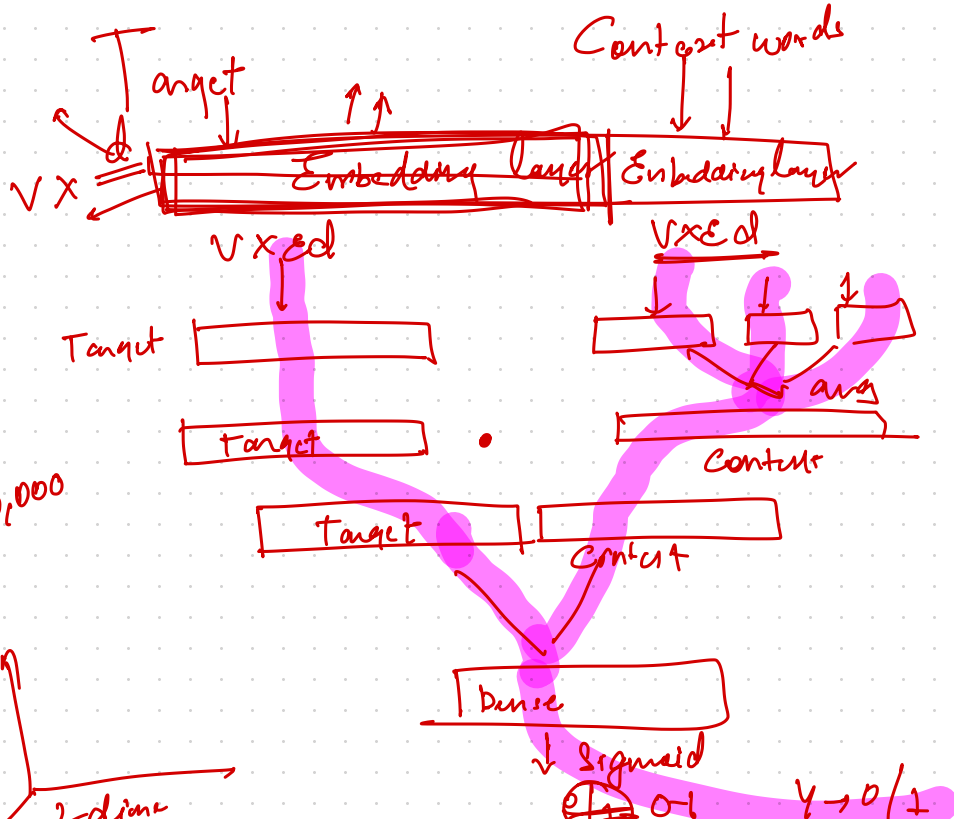

100
100

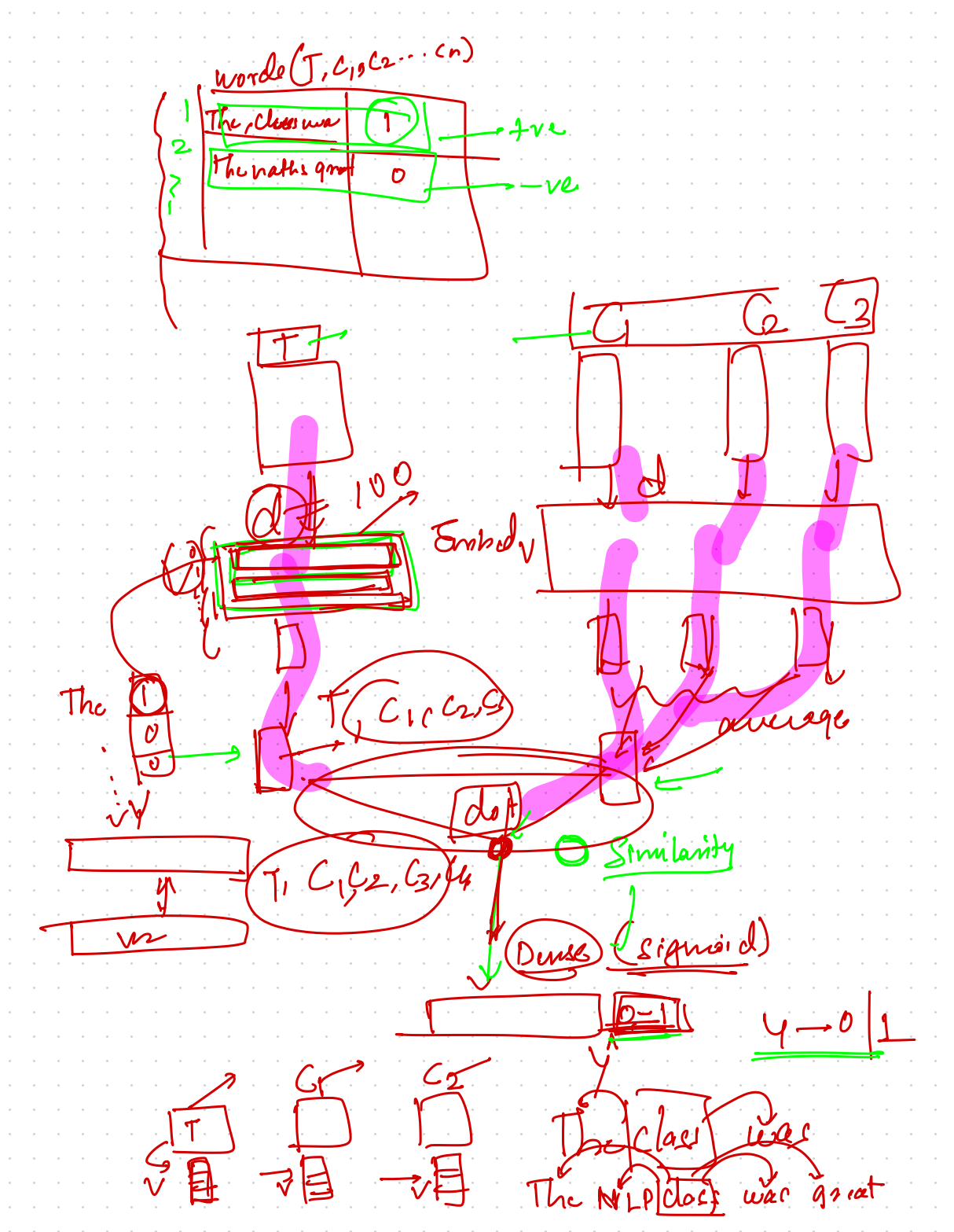
Skip-gram model

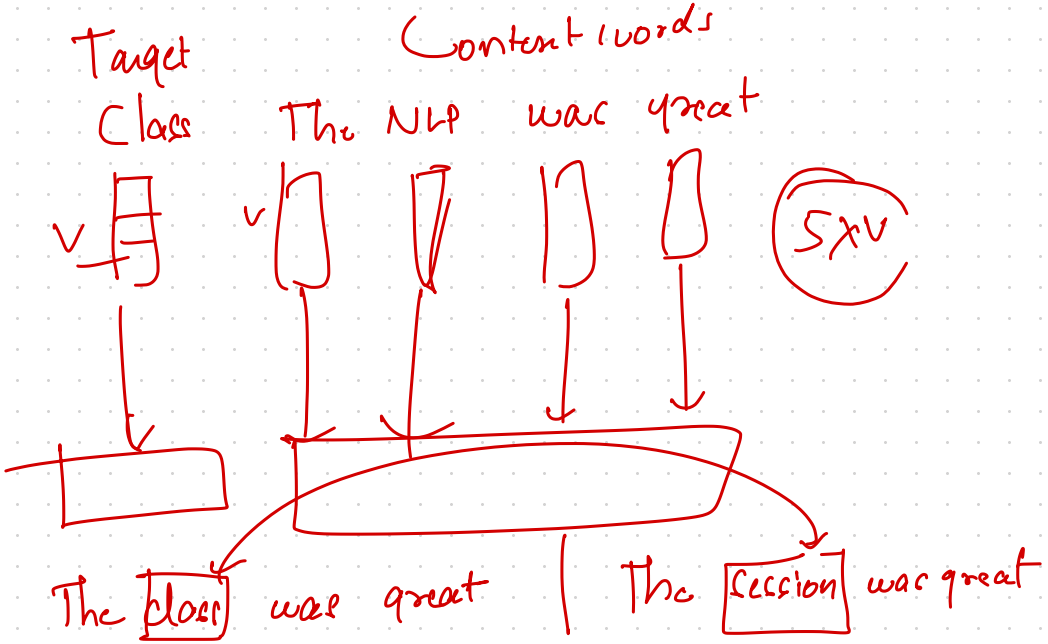


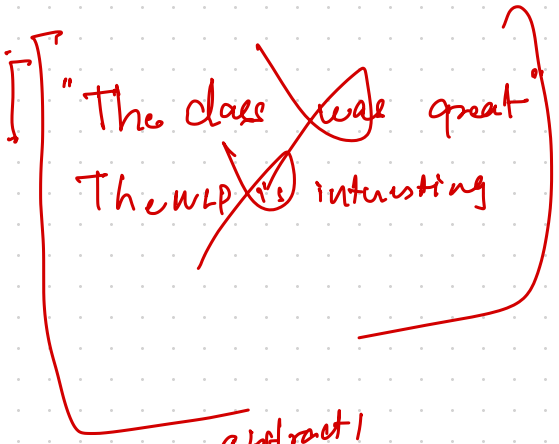
new concept





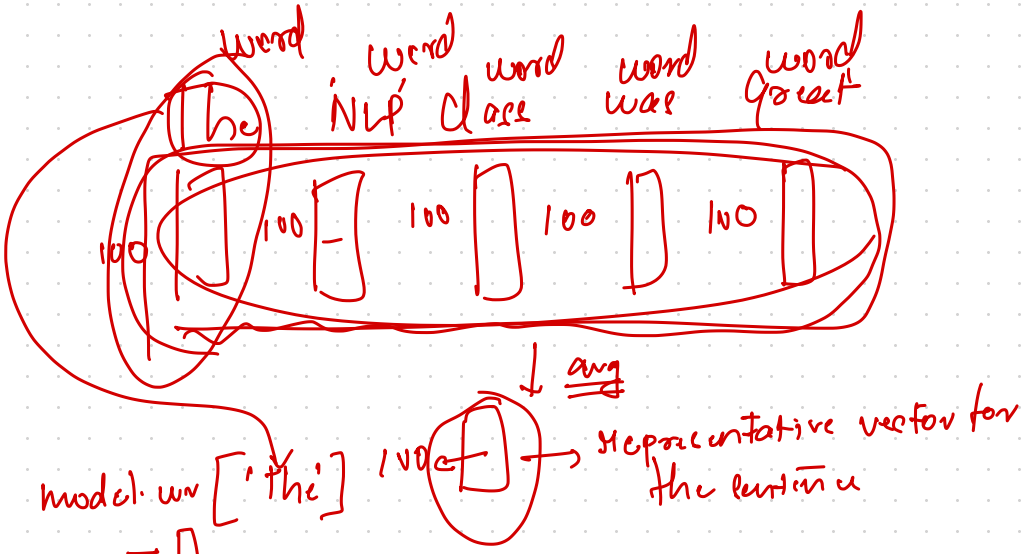

words (T, C1, C2 ... Cn)
The, class was
1
The maths great
0
+ve
-ve
T
C1
C2
C3
100
Embed
The
1
0
0
T, C1, C2, C3
dot
Similarity
T, C1, C2, C3, C4
Dense
(sigmoid)
0-1
y → 0 | 1
T
C1
C2
The NLP class was great

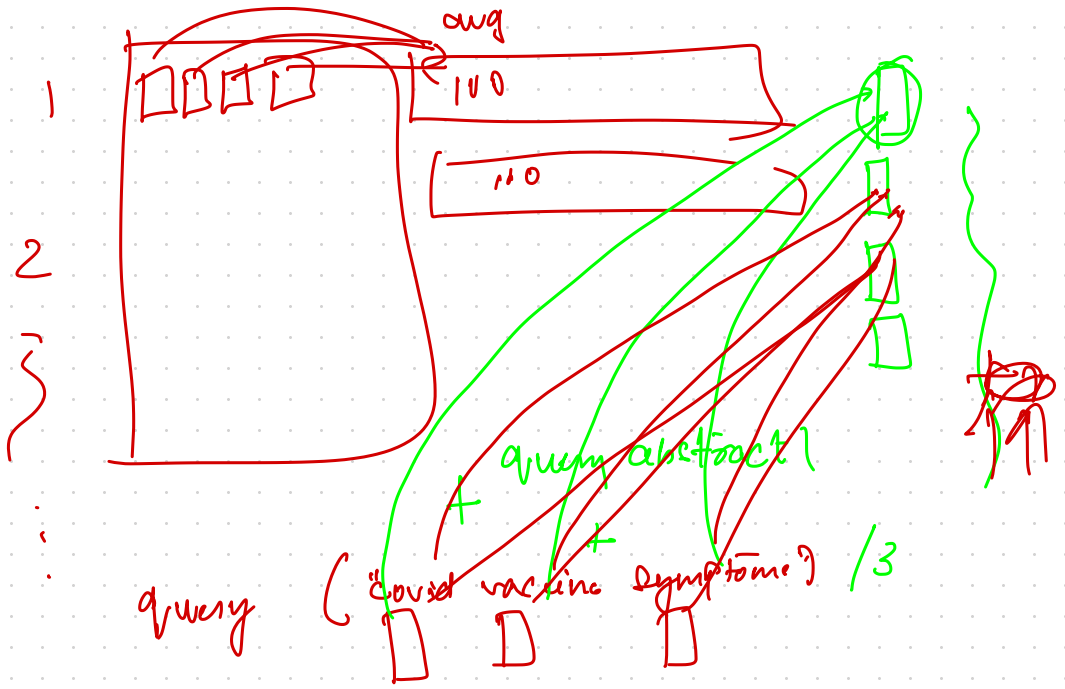


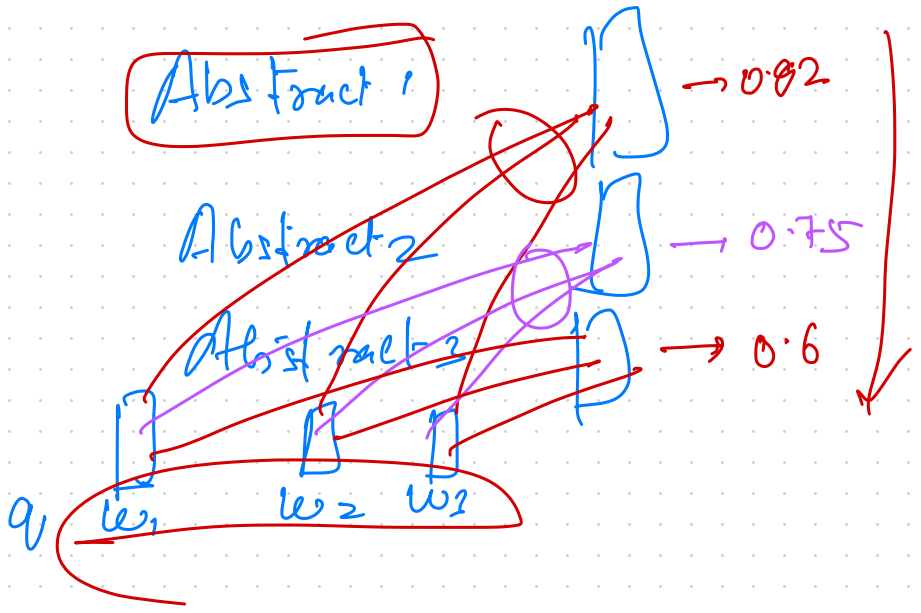


abstract1 abstract2

[['the', 'class', 'was', 'great'], ['the', 'NLP', 'is', 'interesting']]


word
word
word
word
word
the
NLP
class
was
great
100
100
100
100
100
100
avg
model.wv ['the'] 100
Representative vector for the sentence


avg
1
2
query abstract 1
query ("covid vaccine symptoms") /3


Abstract 1
Abstract 2
Abstract 3
0.82
0.75
0.6
q
w1
w2
w3