

NOTE: Vector DBs exist for word embeddings.

Word Embeddings (transformers & LLM cont)

- in reality tokenization frequently divides words, not whole words every time but we will focus on it by thinking tokens are clean whole words

Truth: This process (known fancifully Lie: this process (known fancifully

token \leftarrow and same for output token it can be any token not always a full word

- The model has a pre defined Vocabulary, some list of all possible tokens (words, symbols, spaces, number etc)

All words $\approx 50k = 50k$ tokens

1	aback	blue	boy	...	zing	;
2.1	2.1	5	7	...	2	5
3.2	2	6	8	...	7	7
5.1	3	7	9	...	6	8
6	4	8	1	...	8	9
...
9	9.1	2	5	...	7	9

Embedding Matrix W_E

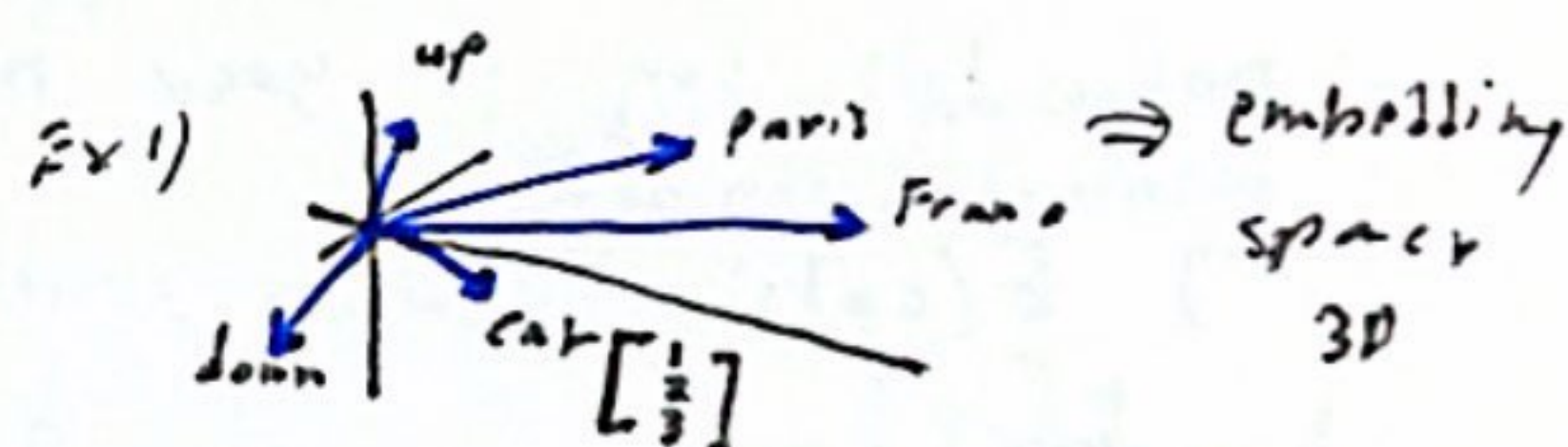
and the first matrix we will see is the embedding matrix has a single column for each of these words these columns determine what vector each word get in that first step

the sky was blue \rightarrow EM picks the vector for blue

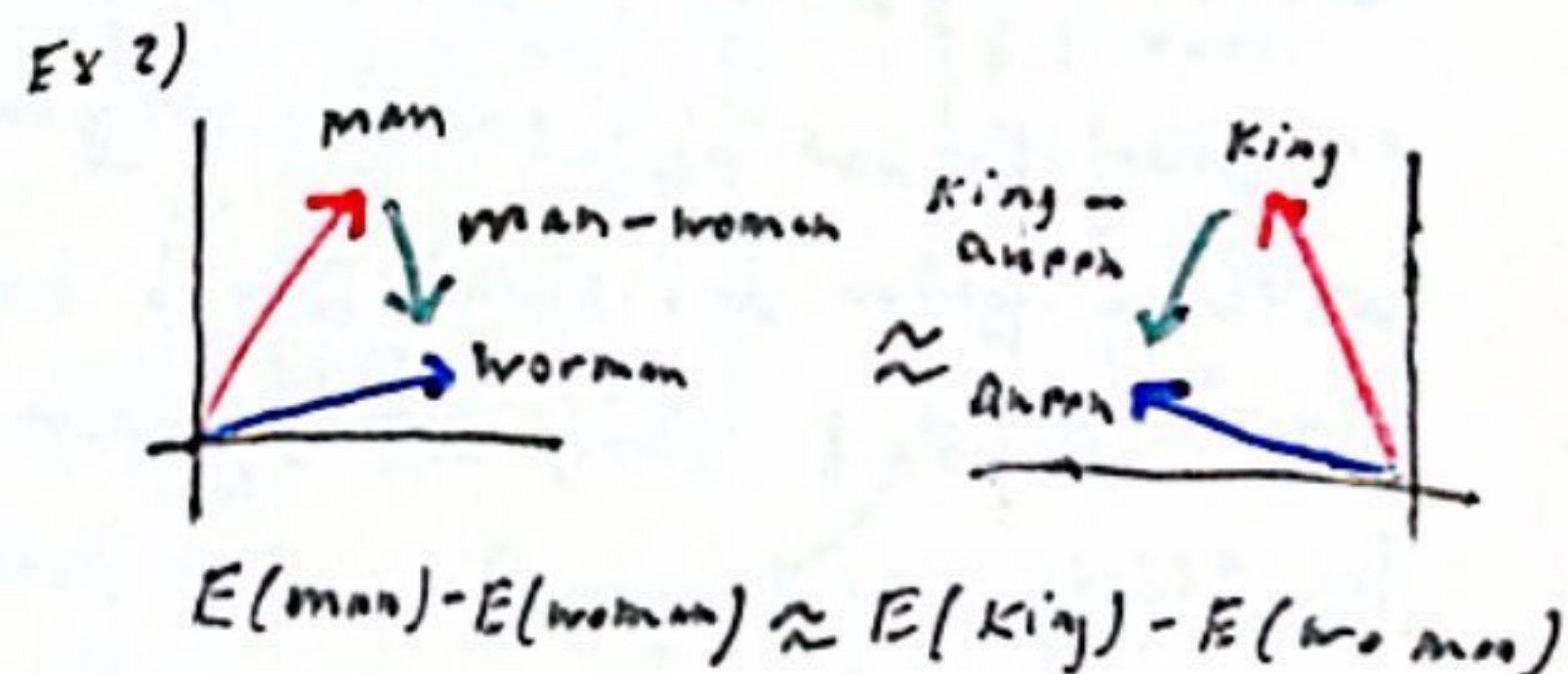
We label $W_E = \text{Embedding Matrix}$.

* Values begin random and learned through data *

- We embed these words as tokens which means its a vector in some very high dimension space like



12,288 dimensions in GPT-3. So we visualize in 3D, as it learns these embedding in training it settles on embeddings. Whos direction have meaning



for Ex paris and France's embedding are close as they're related but up and down opposite in meaning and space

in the Ex 2 we see how Embedding are related and why using vectors is good say we did not know what a female leader is we could do $\text{King} + (\text{Woman} - \text{man})$ and finding the vector (embedding) closest to that. $E(\text{Queen}) \approx E(\text{King}) + E(\text{woman}) - E(\text{man})$

- this is a perfect Ex in reality they might be further apart and are impossible to visualize. they are learned in training..

- further more "Queen" in training data would not always be a female leader Ex "Queen the band" hence the 50 embedding for Queen won't be the gives

Formula - but close will