

(MATRICES)

VECTORS — EMBEDDINGS

go-nogo beach problem

inputs
└ crowd size (0-1000) — Scaled 0-1
└ wave height (1-10m) — 0-1

21-Mar-2021 $\Rightarrow 239 \text{ people}$ $\Rightarrow 9.14 \text{m ht}$
 $(0.23989, 0.91423) = 2-D$

crowd size
 $(0.21, 0.85)$
wave height

Training dataset

$\begin{bmatrix} (0.239, 0.914), \\ (0.102, 0.385), \\ (0.654, 0.718), \\ \vdots \end{bmatrix}$

0.23989	0.91423
0.102	0.385
0.654	0.718
\vdots	\vdots

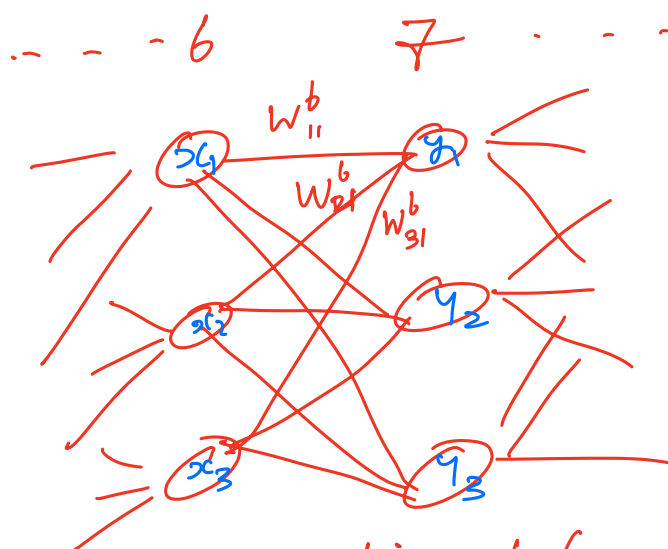
wave ht	crowd
3	300
5	200
8	900
\vdots	\vdots

└ crowd size }
└ wave height }
└ Temperature
└ Humidity
└ UV index
└ Pollution index

$\begin{bmatrix} (0.239, 0.119, 0.539, 0.1, 0.0009, 0.99832), \\ \vdots \end{bmatrix}$ $\rightarrow 6-D$

(MATRICES)
use VECTORS in ML lifecycle

input encoding → calculations (training, prediction)



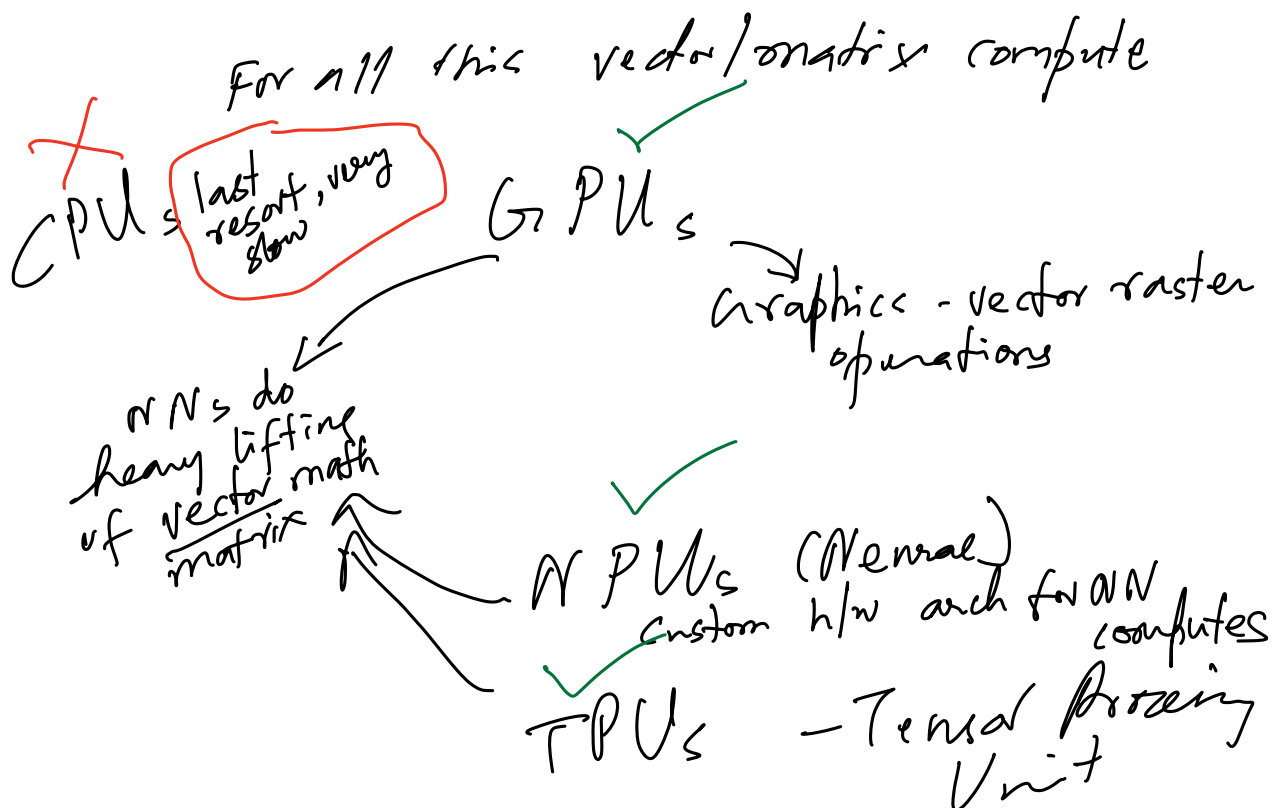
weight matrix between
layers 6 & 7

$$\begin{bmatrix} w_{11}^b & w_{21}^b & w_{31}^b \\ w_{12}^b & w_{22}^b & w_{32}^b \\ w_{13}^b & w_{23}^b & w_{33}^b \end{bmatrix}$$

$$\begin{aligned} y_1 &= x_1 \cdot w_{11}^b + x_2 \cdot w_{21}^b + x_3 \cdot w_{31}^b \\ y_2 &= x_1 \cdot w_{12}^b + x_2 \cdot w_{22}^b + x_3 \cdot w_{32}^b \\ y_3 &= x_1 \cdot w_{13}^b + x_2 \cdot w_{23}^b + x_3 \cdot w_{33}^b \end{aligned}$$

$$\begin{bmatrix} W_{11}^6 & W_{21}^6 & W_{31}^6 \\ W_{12}^6 & W_{22}^6 & W_{32}^6 \\ W_{13}^6 & W_{23}^6 & W_{33}^6 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

weight matrix layer 6-7 x layer 6 value matrix = layer 7 value matrix



INPUT ENCODINGS FOR TEXT
achieved by the use of encoding models 4d vector

"cat" = (0.3, 0.2, 0.1, 0.4)

"system" = (0.2, 0.4, 0.3, 0.5)

"what's up, doc?" = (0.3, 0.2, 0.1, 0.005) ← mathematically near

close meaning

"Hello, this is a paragraph of text = (0.29, 0.15, 0.11, 0.003)

"this is an entire document of text"

= (0.5, 0.598, 0.1, 0.005)

↑ Embeddings
≡
vectors
=
Encodings

"a" = (0.1, ...)

"the" = (0.2, ...)

When does an encoded vector become an "embedding"?

MEANING

semantically loaded vector with great context

"cat" = (0.3, 0.4, 0.6, 0.8) ← close
"animal" = (0.3, 0.35, 0.59, 0.7) ← far
"car" = (0.9, 0.8, 0.75, 0.01) ← far
GOOD

"clown" = (0.2, 0.4, 0.3, 0.8) ← far
"circus" = (0.8, 0.7, 0.5, 0.2) ← far
"tree" = (0.17, 0.3, 0.31, 0.72) ← far
BAD

In real world applications, embedding models often return 50-D embeddings to 1056-d embeddings

$(u_1, u_2, u_3, \dots, u_{50})$

SEARCH (semantic)

For example

The cat is a hero. It can do
amazing things. It was
born in 1999 and had a
good life.

chunks 1. The cat is a hero

2. It can do amazing things

3. It was born in 1999 and had a good life

vectorize
(generate embeddings)
chunk1, chunk2, chunk3

Emb
model



save

- 1. (0.3, 0.5, 0.6, 0.8)
- 2. (0.29, 0.8, 0.3, 0.4)
- 3. (0.5, 0.23, 0.5, 0.0)

looks like

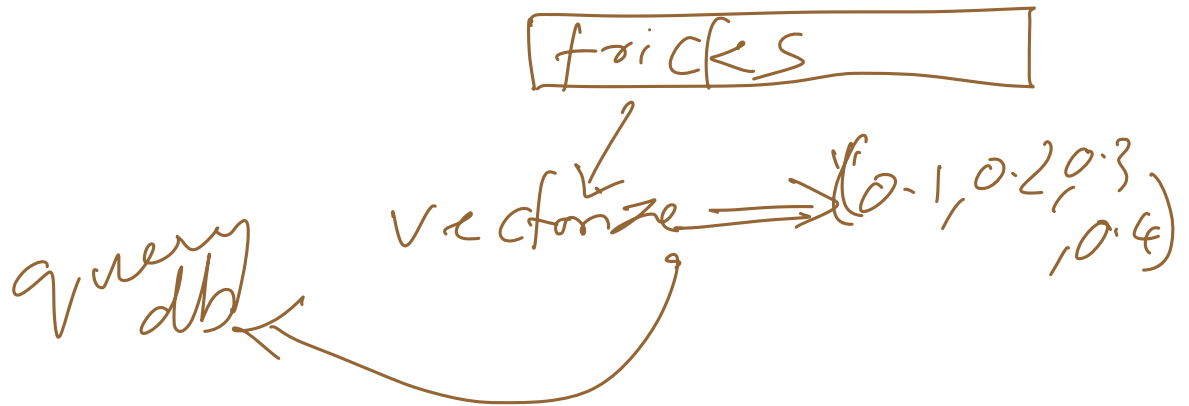
- 1. (0.3, 0.5, 0.6, 0.8)
"the cat is a hero"
- 2. ()
"
- 3. ()
"

SEARCH APP

2. cat
Vectorize "cat" \Rightarrow (0.3, 0.5, 0.2, 0.1)
math dist. search query

Vector DB Engine's
Result :

- | | | Relevance score |
|----|-----------------|-----------------|
| 1. | "cat is a hero" | 0.8 |
| 2. | " - - - - -" | 0.75 |



- Results
2. "It can do amazing thing" "0.5"
 3. "It was born..." "0.002"
 1. "The cat is a hero" "0.001"

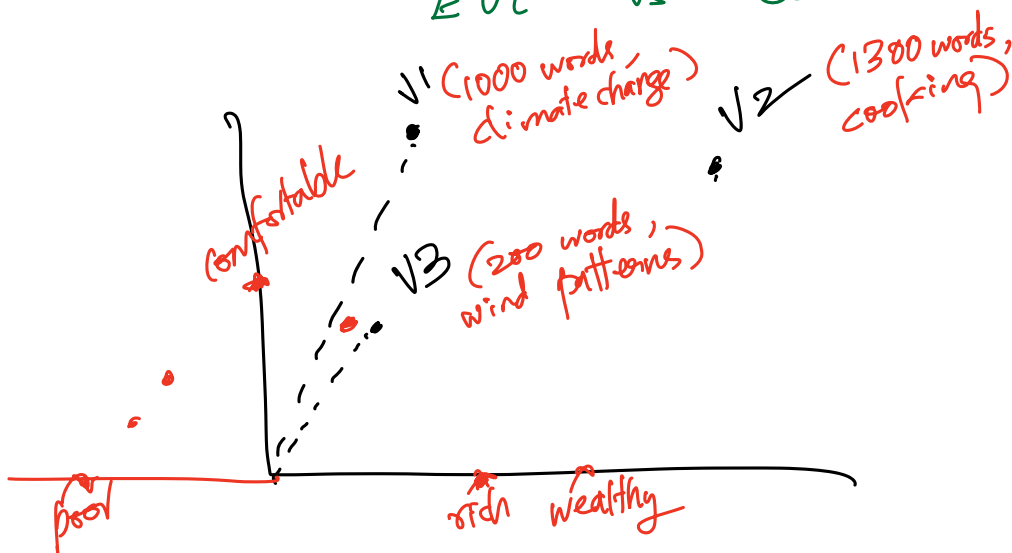
Vector database query

REQ \Rightarrow (^{<input vector>} "0.39891, 0.241325, ...",
^{<search method>} SEARCH_METHOD_EUCLIDEAN/COSINE,
^{<# of results requested>} 10)

RSP \Rightarrow [^{<text blob/chunk>} ("text 1 blah blah..",
^{<relationship score>} 0.8234),
...
...]

opposites \rightarrow -1 to +1
same \rightarrow +1

EUC vs COS distances search



estimate
change
(50 words)

Wind
Patterns
(1000
words
long)

Cooking
Recipes
(1000
words
long)

v_1

v_2

v_3

