What is an LLM?

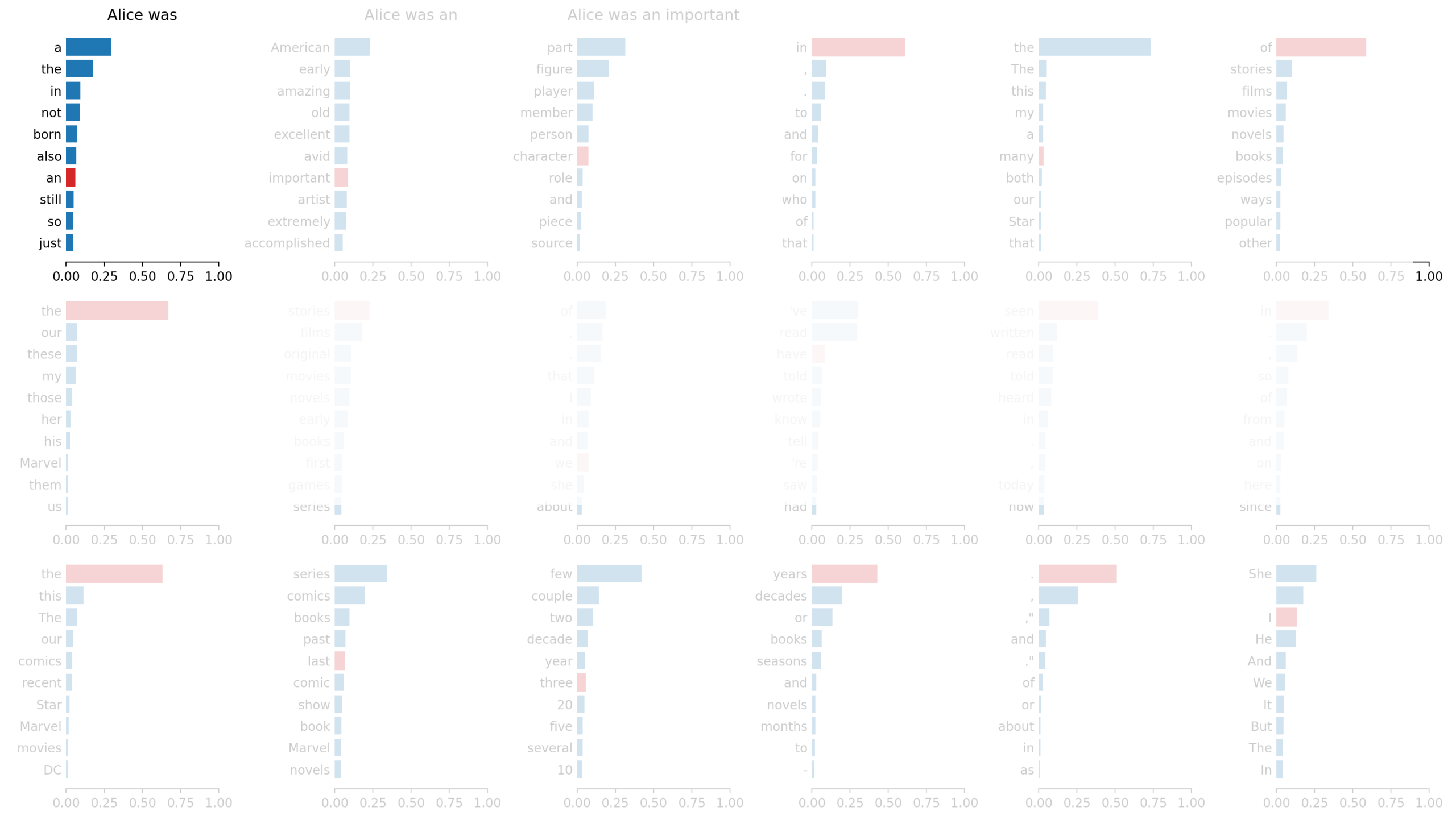
Large Language Models

Predict the next word

Alice was

Predict the next word

Alice was an important character in many of the stories we have seen in the last three years. I'm very proud to be able to bring back that character. And it's going to take an incredible amount of time to do that."
The film has been nominated for several Academy Awards, and is scheduled for a May 4, 2018 release.<|endoftext|>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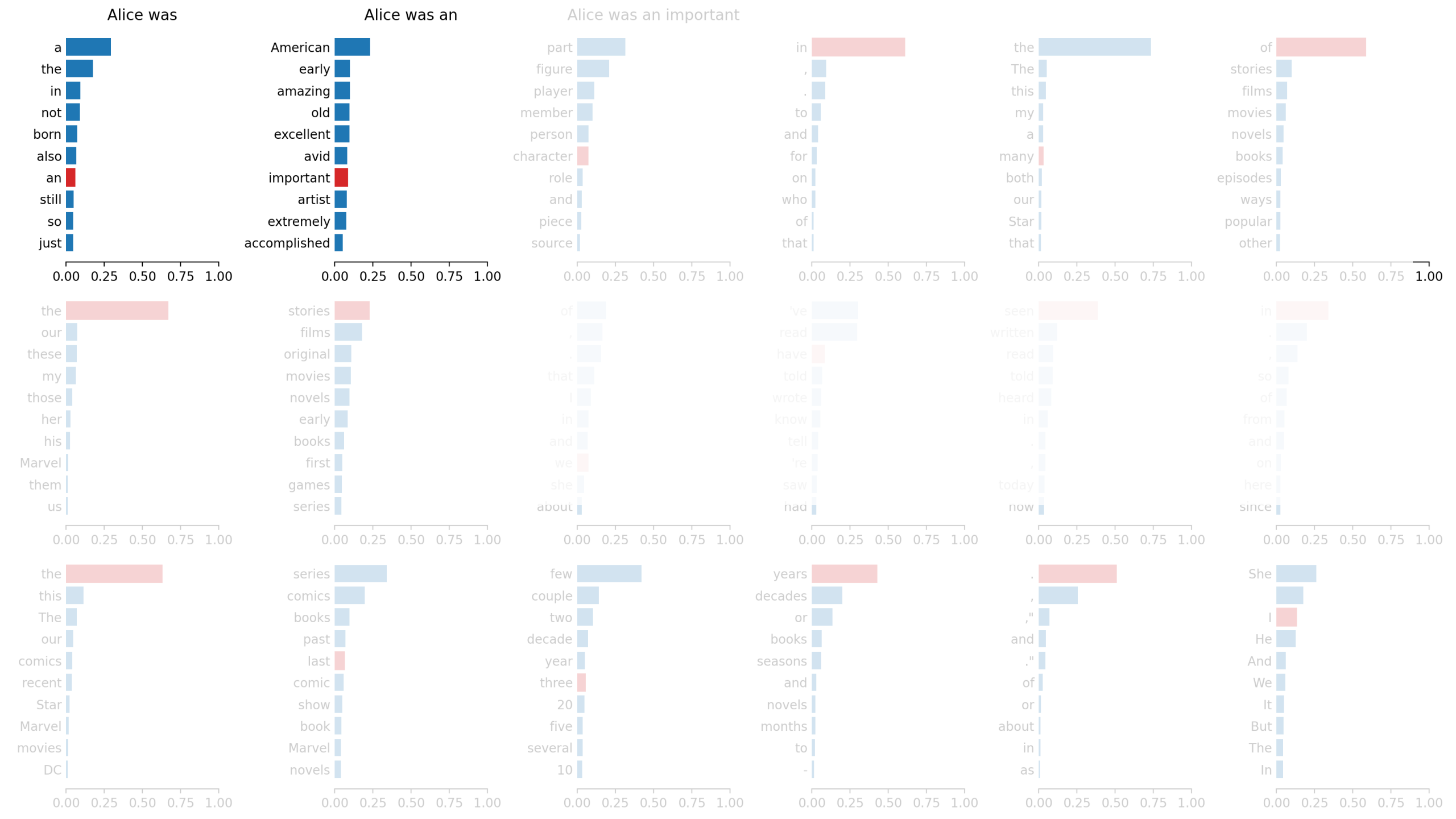
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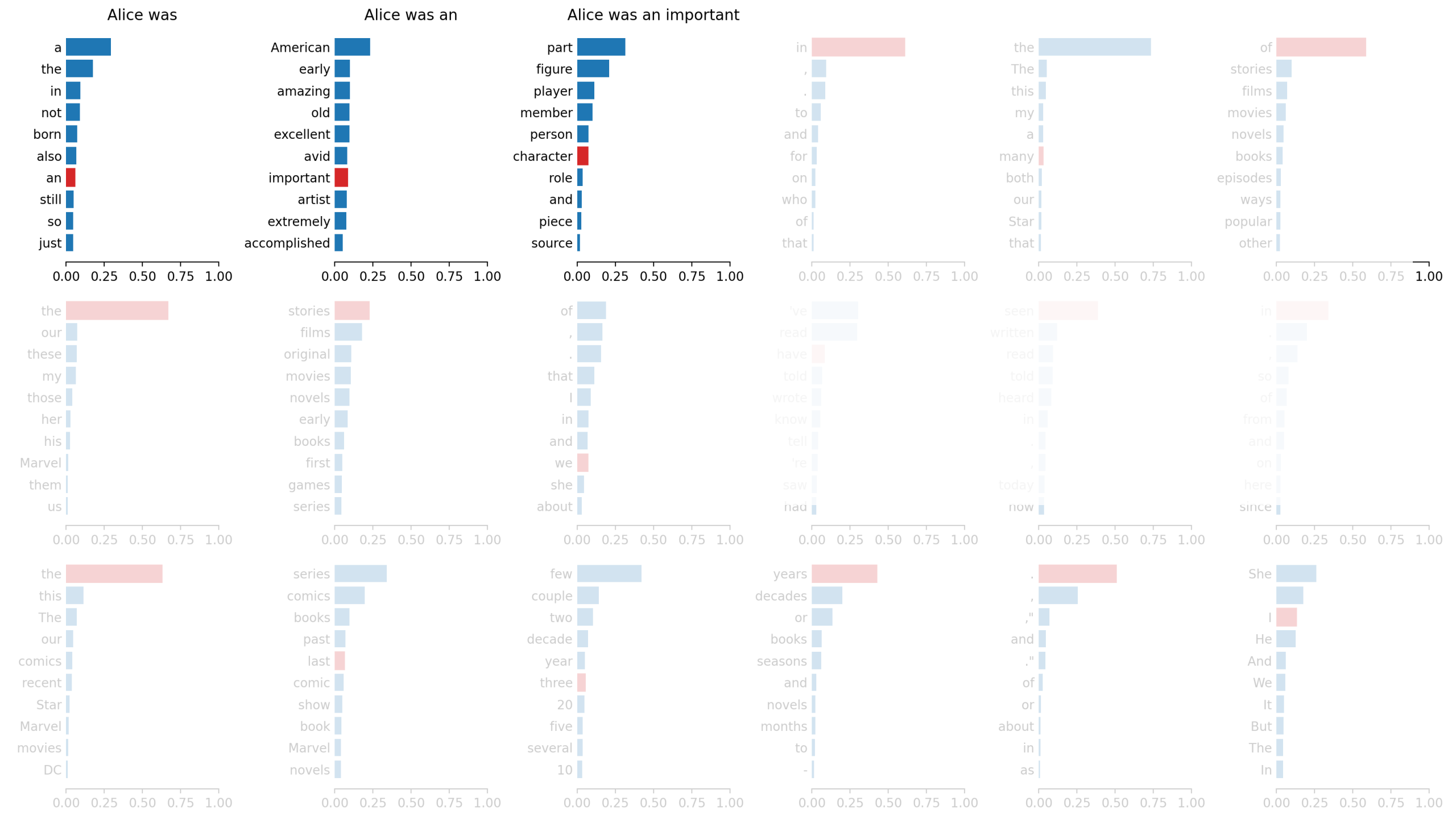
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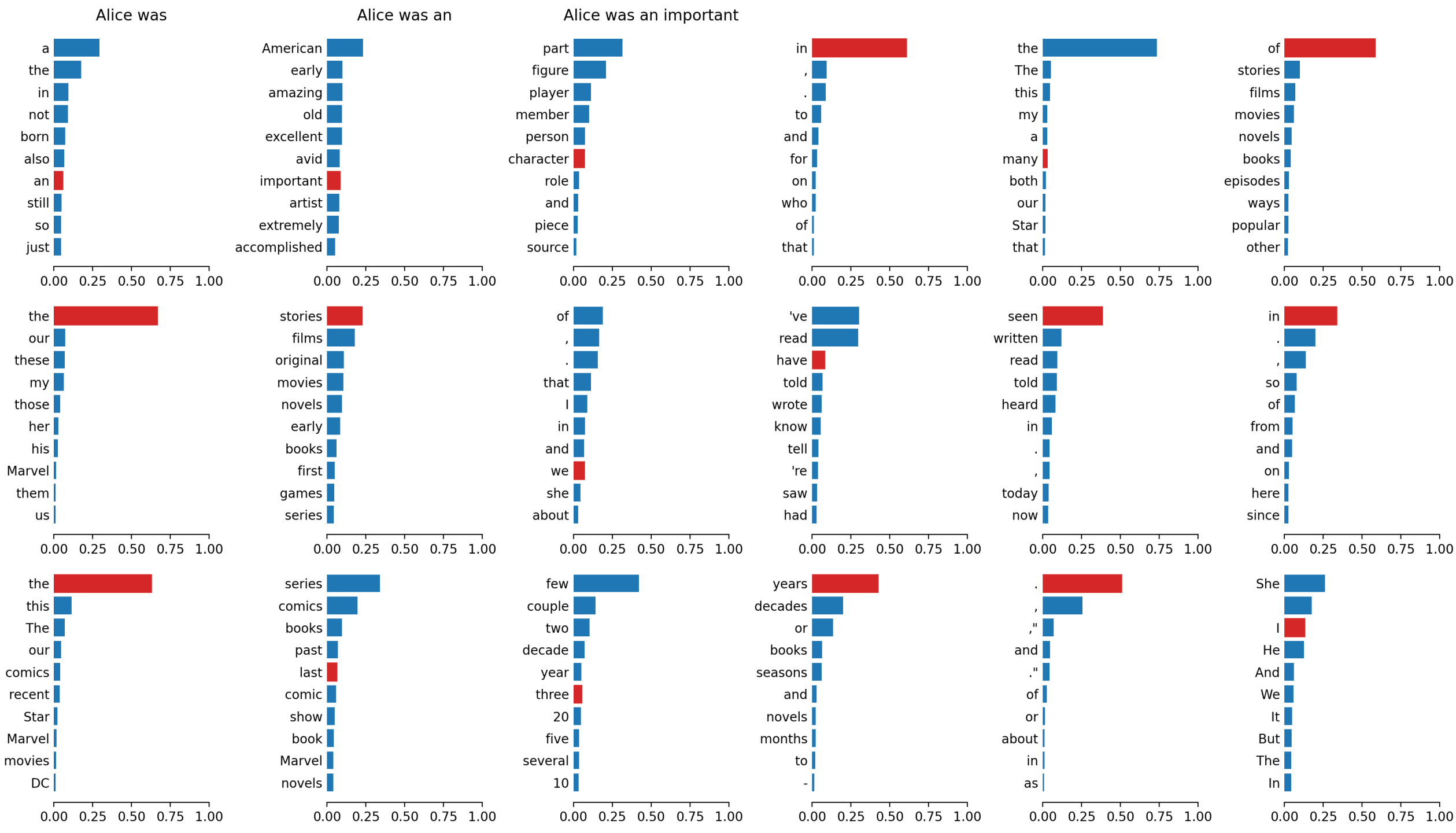
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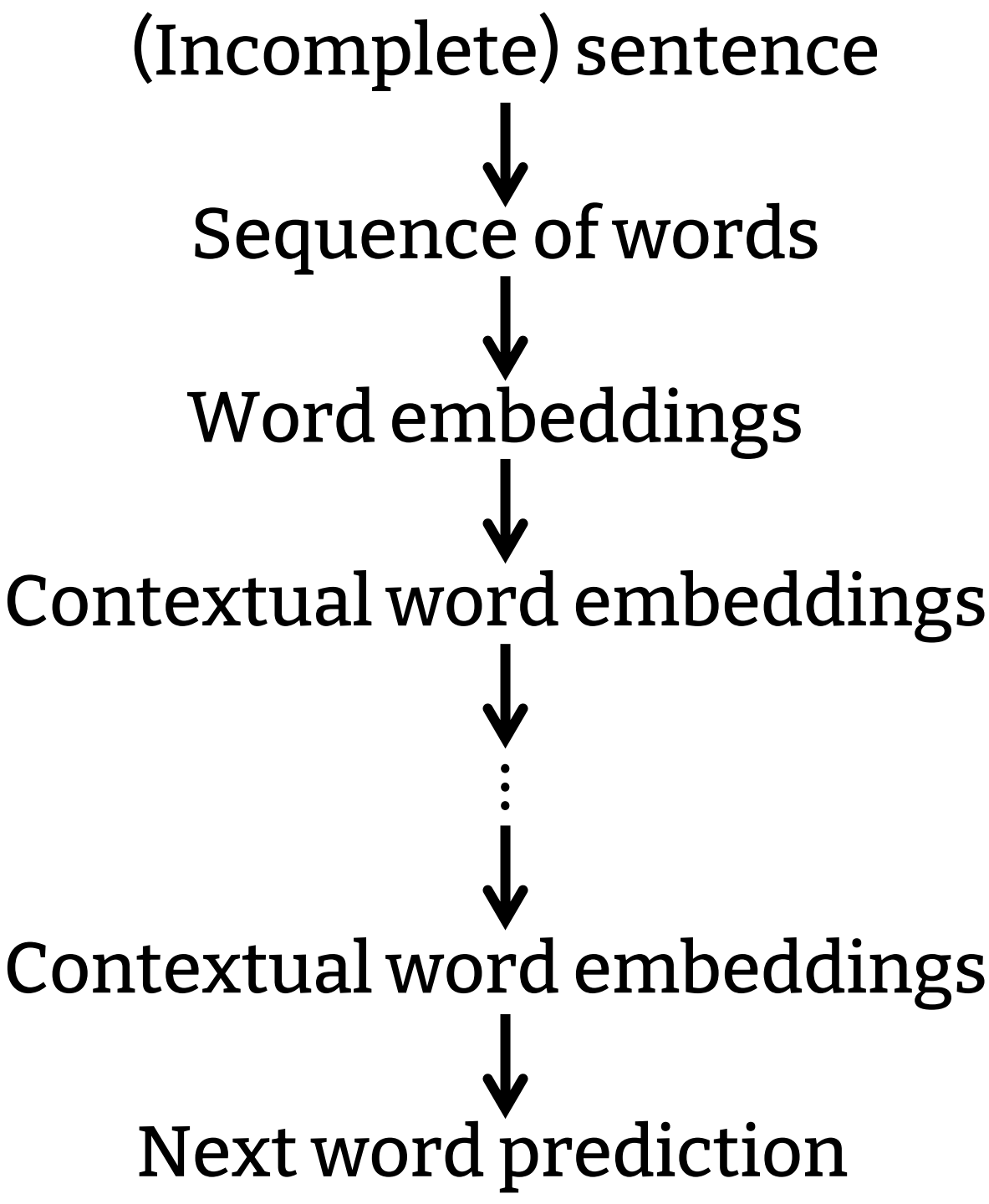
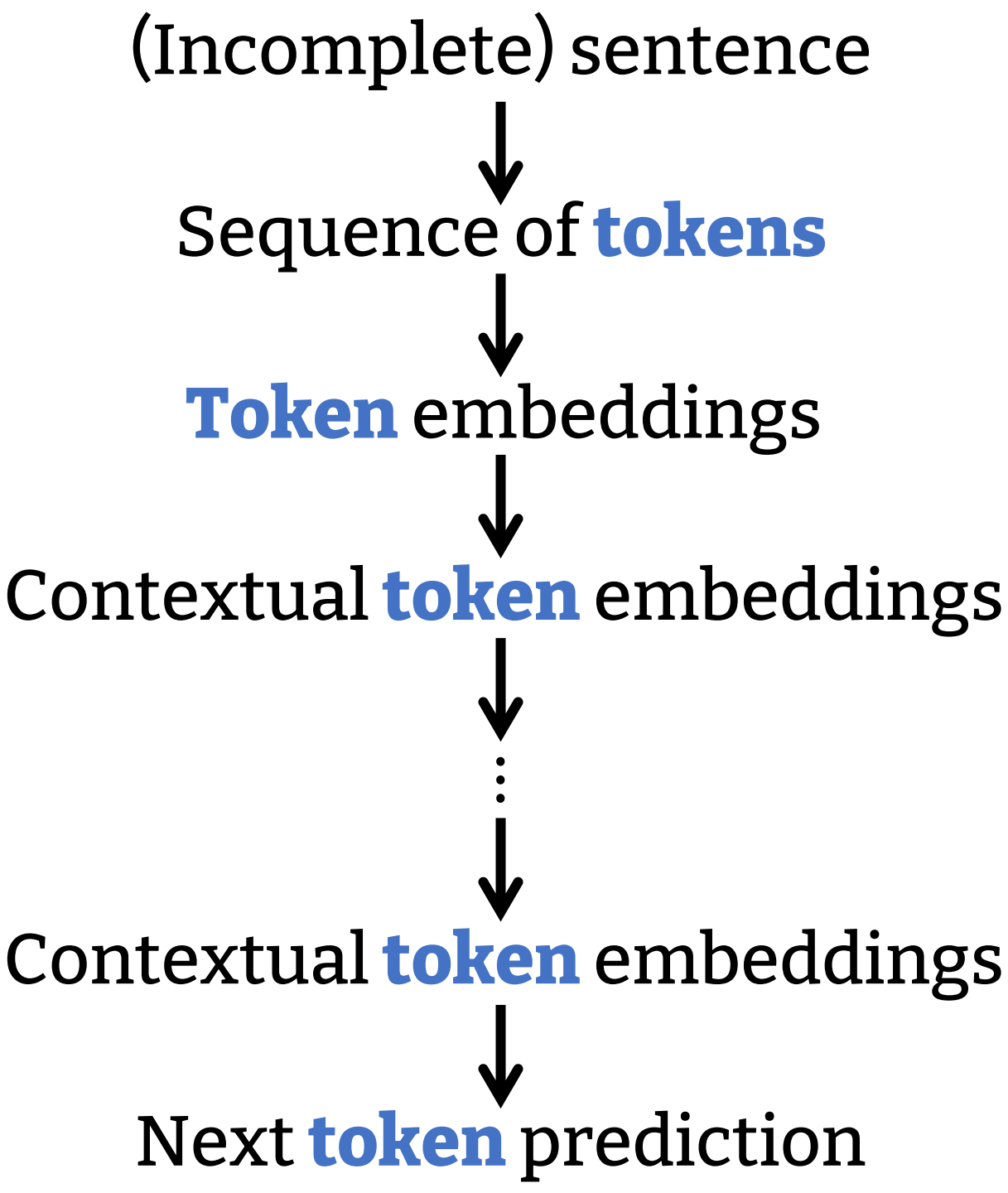
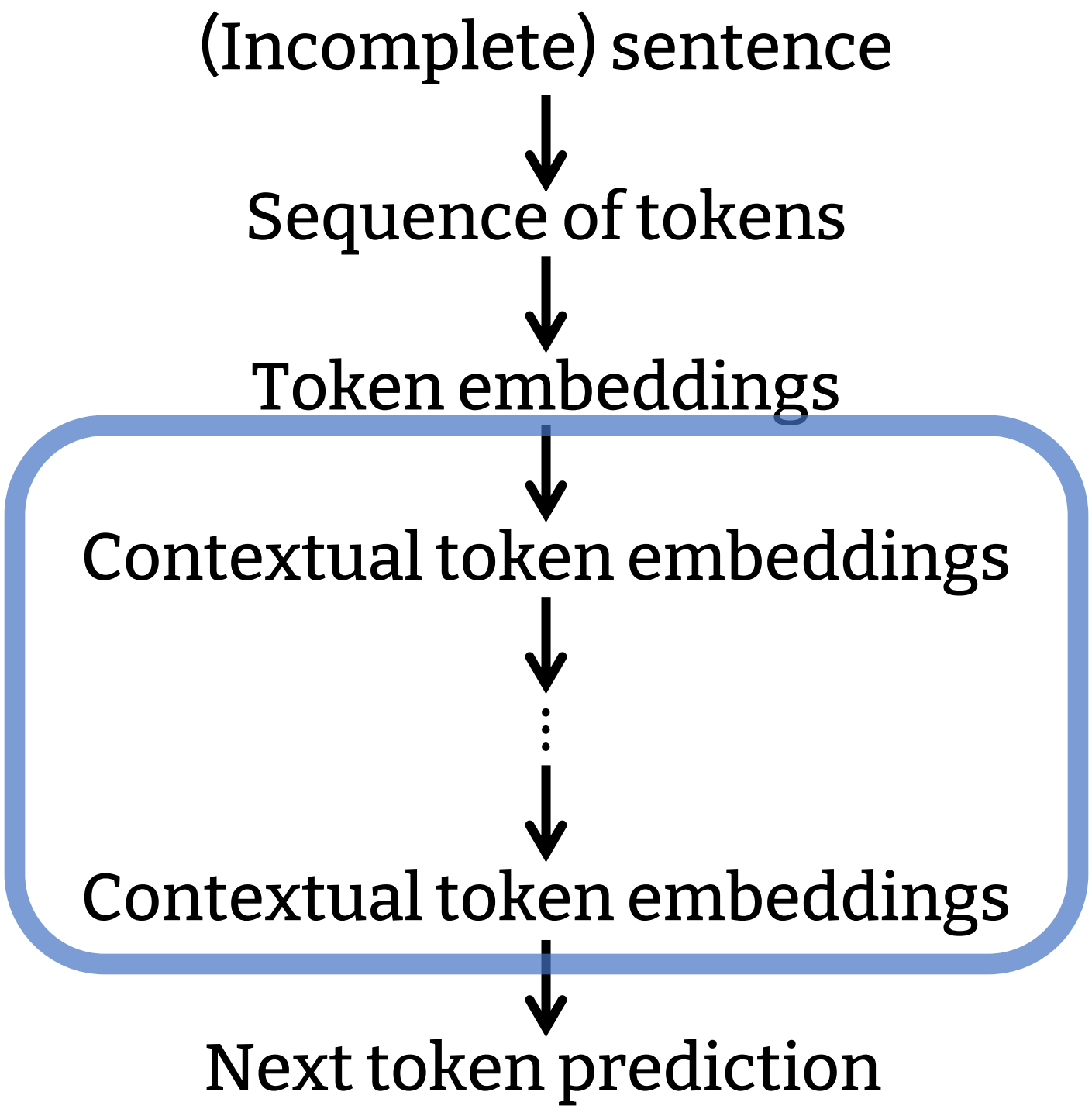
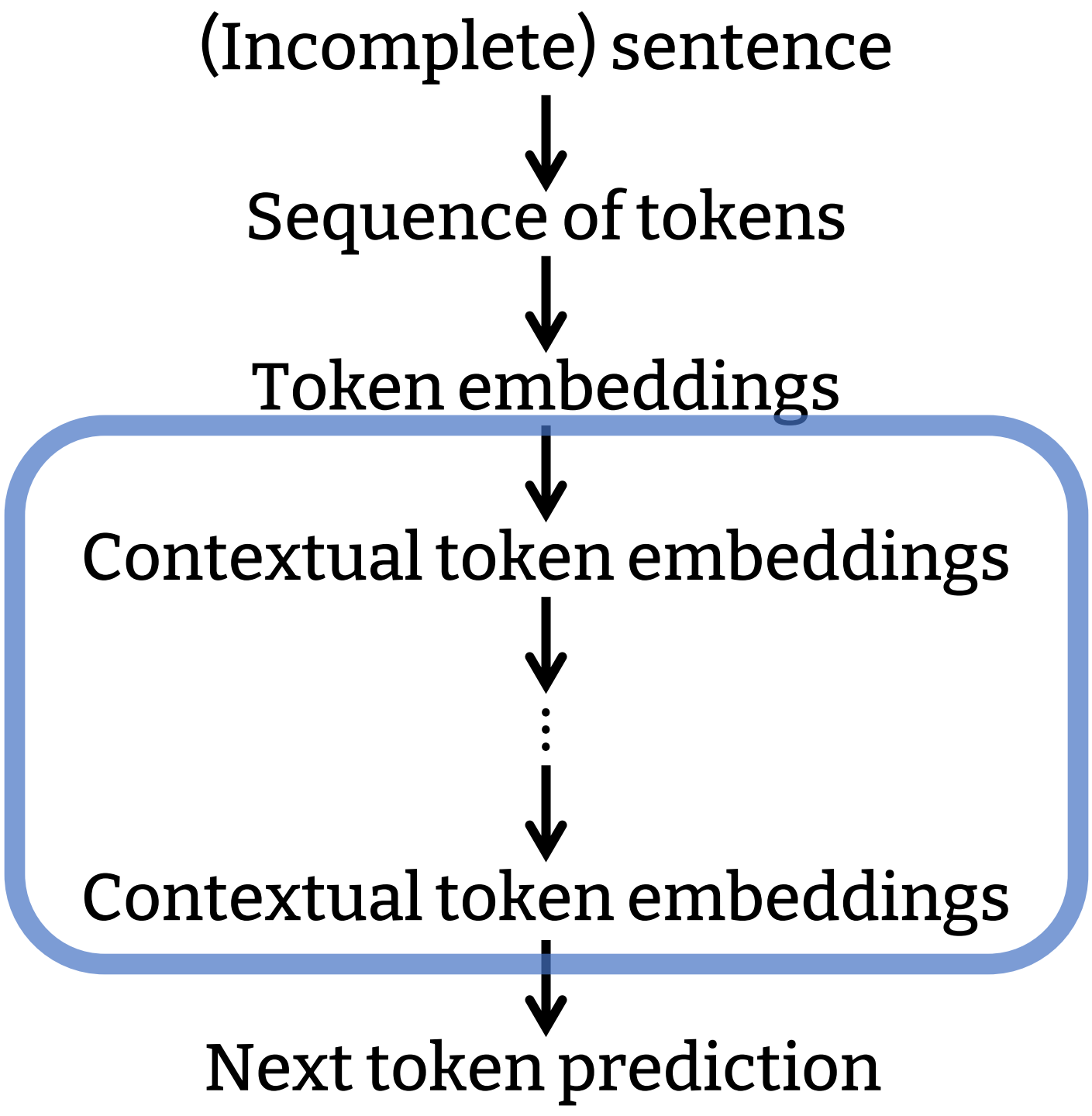

(Incomplete) sentence
Sequence of words
Word embeddings
Contextual word embeddings
Contextual word embeddings
Next word prediction


(Incomplete) sentence
Sequence of tokens
Token embeddings
Contextual token embeddings
Contextual token embeddings
Next token prediction



Progressively refine the embeddings



MLP
+
Attention
("transformers")

Text

It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us, we were all going direct to Heaven, we were all going direct the other way--in short, the period was so far like the present period, that some of its noisiest authorities insisted on its being received, for good or for evil, in the superlative degree of comparison only.

Tokens

It was the best of times, it was the worst of times, it was the age of wisdom, it was the age of foolishness, it was the epoch of belief, it was the epoch of incredulity, it was the season of Light, it was the season of Darkness, it was the spring of hope, it was the winter of despair, we had everything before us, we had nothing before us, we were all going direct to Heaven, we were all going direct the other way--in short, the period was so far like the present period, that some of its noisiest authorities insisted on its being received, for good or for evil, in the superlative degree of comparison only.

Token embeddings

```
"It"      [0.039, -0.087, 0.066, -0.053, -0.088, -0.069, -0.217, -0.041, 0.047, -0.003, …]
" was"    [-0.074, -0.084, 0.181, -0.107, -0.085, 0.056, -0.282, -0.035, -0.104, 0.073, …]
" the"    [-0.039, 0.005, 0.042, 0.04, -0.036, -0.055, -0.257, -0.002, 0.025, 0.043, …]
" best"   [-0.151, 0.055, 0.026, 0.071, 0.012, 0.041, -0.319, 0.011, 0.059, -0.269, …]
" of"     [-0.057, 0.018, 0.033, 0.041, 0.012, -0.04, -0.253, 0.002, 0.065, 0.066, …]
" times"  [-0.037, -0.02, 0.107, -0.167, -0.011, 0.094, -0.284, 0.183, 0.082, -0.028, …]
","       [0.011, -0.003, 0.032, 0.055, 0.052, -0.06, -0.24, -0.017, 0.039, 0.04, …]
" it"     [0.026, -0.047, 0.033, 0.051, -0.058, -0.026, -0.259, 0.01, 0.043, 0.047, …]
" was"    [-0.074, -0.084, 0.181, -0.107, -0.085, 0.056, -0.282, -0.035, -0.104, 0.073, …]
" the"    [-0.039, 0.005, 0.042, 0.04, -0.036, -0.055, -0.257, -0.002, 0.025, 0.043, …]
" worst"  [-0.051, -0.0, 0.253, 0.063, -0.003, -0.043, -0.343, -0.124, -0.111, -0.048, …]
" of"     [-0.057, 0.018, 0.033, 0.041, 0.012, -0.04, -0.253, 0.002, 0.065, 0.066, …]
" times"  [-0.037, -0.02, 0.107, -0.167, -0.011, 0.094, -0.284, 0.183, 0.082, -0.028, …]
","       [0.011, -0.003, 0.032, 0.055, 0.052, -0.06, -0.24, -0.017, 0.039, 0.04, …]
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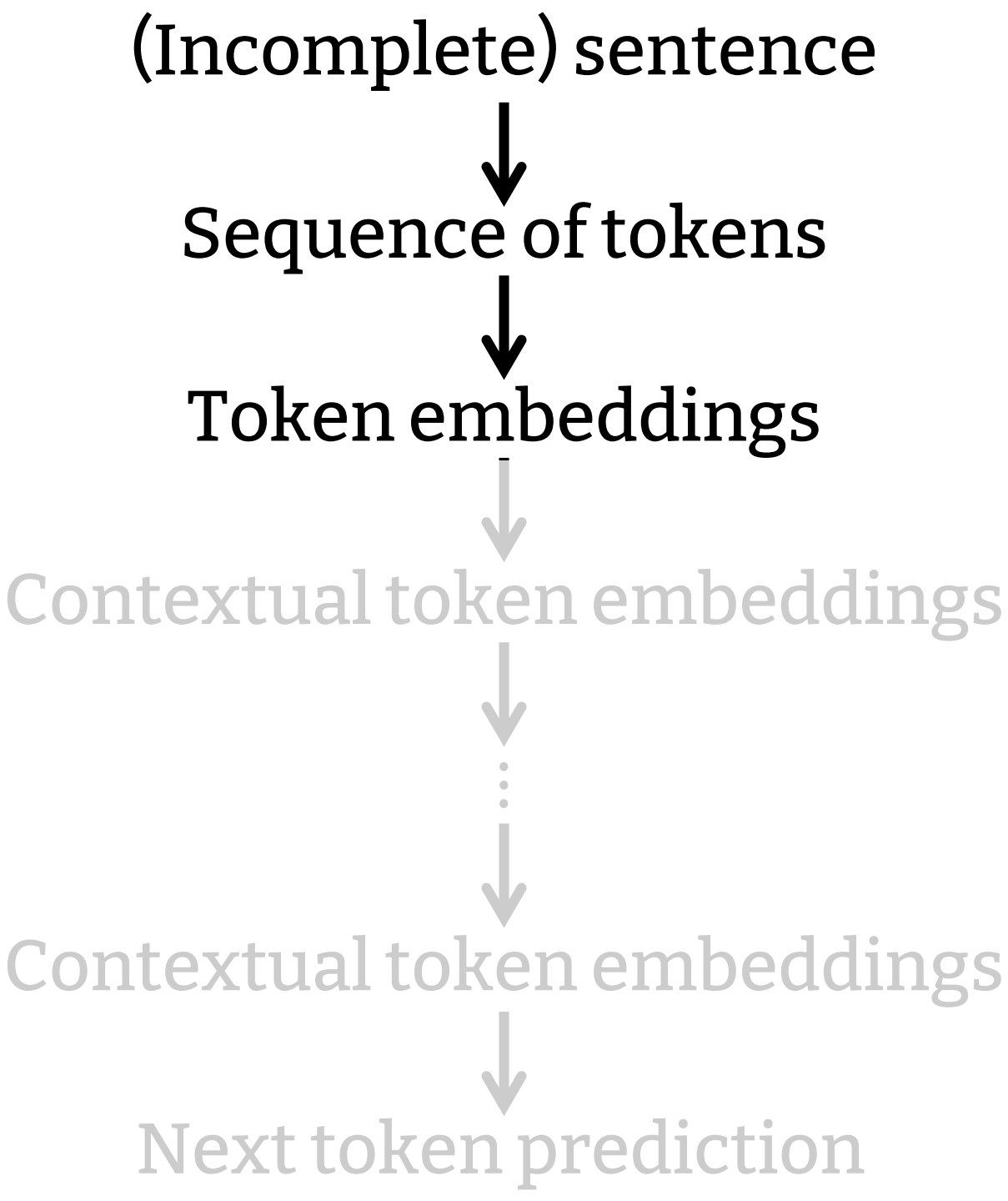
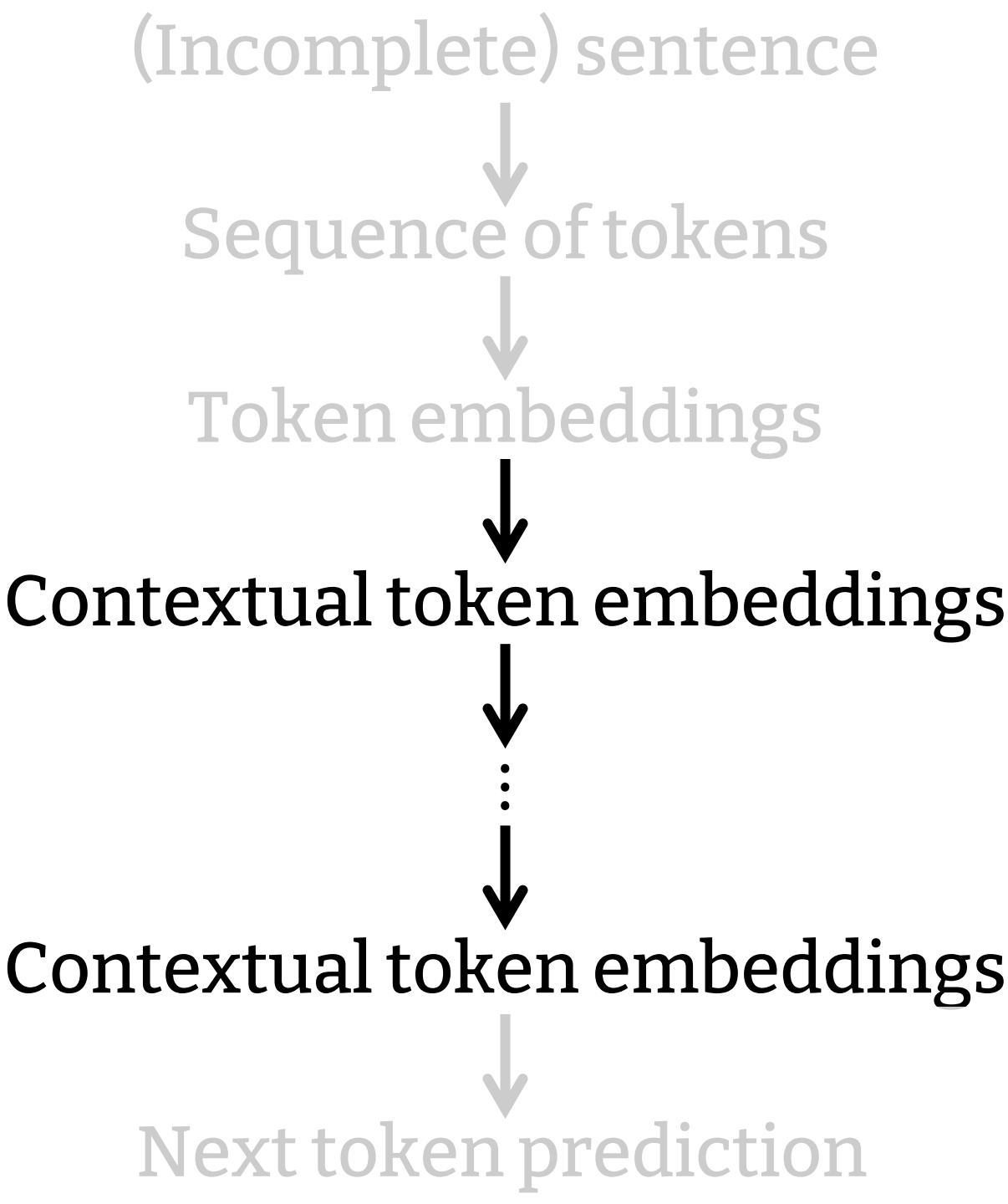

(Incomplete) sentence
Sequence of tokens
Token embeddings
Contextual token embeddings
Contextual token embeddings
Next token prediction


(Incomplete) sentence
Sequence of tokens
Token embeddings
Contextual token embeddings
Contextual token embeddings
Next token prediction

Token embedding

bank

↓

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[0.046, 0.082, 0.137, 0.038, -0.027, 0.06, -0.344, -0.193, 0.08, 0.226, …]
```

Token embedding

bank

↓

Token embeddings

central bank river bank power bank

Contextual embeddings

central bank

river bank

power bank









(Incomplete) sentence

↓

Sequence of tokens

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Token embeddings

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Contextual token embeddings

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Contextual token embeddings

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Next token prediction

MLP

+

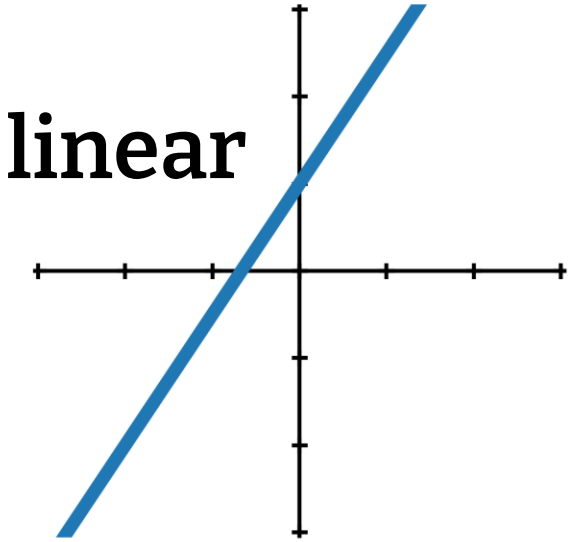
Attention

(“transformers”)

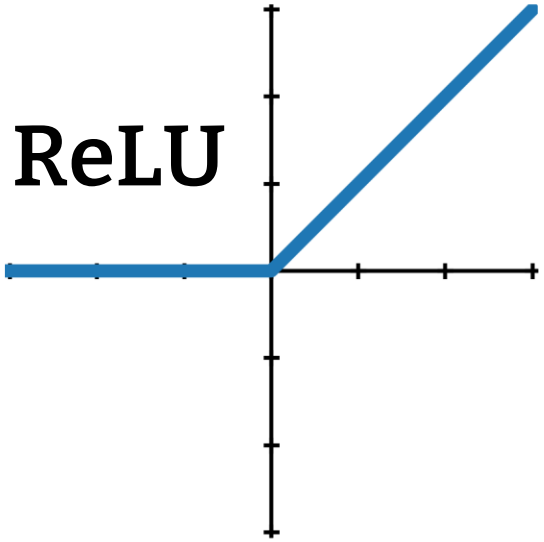
MLP: one layer, example

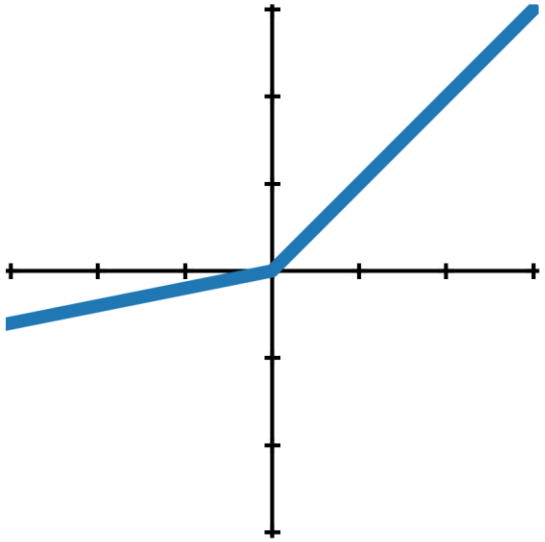
$$x \longmapsto y = 3x_1+7x_2-x_3+2x_4+\cdots \longmapsto z = \sigma(y)$$

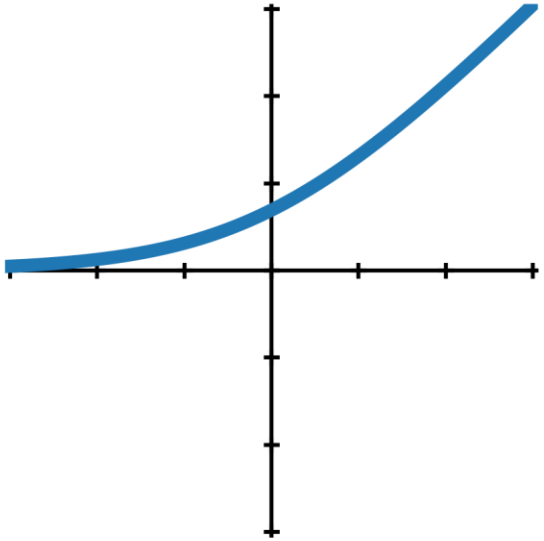
Linear functions

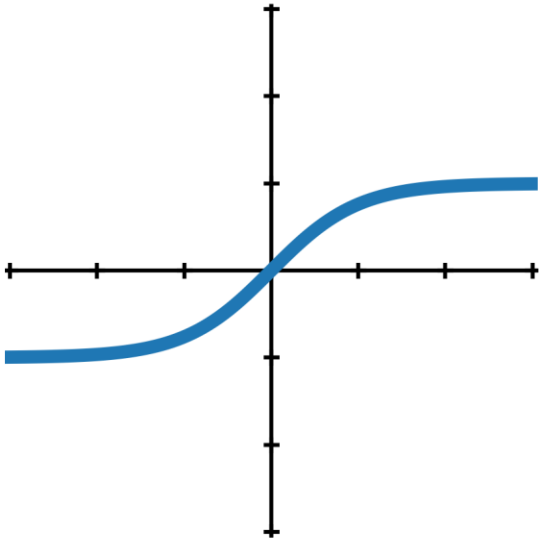


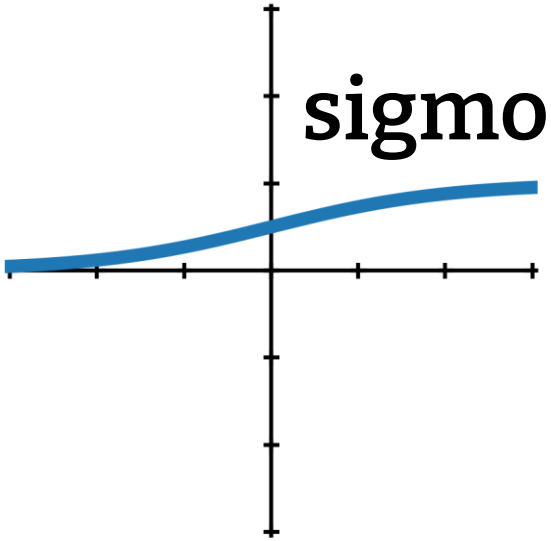
Non-linear functions σ











MLP: one layer, example

$$x \longmapsto y = 3x_1+7x_2-x_3+2x_4+\cdots \longmapsto z = \sigma(y)$$

MLP: one layer

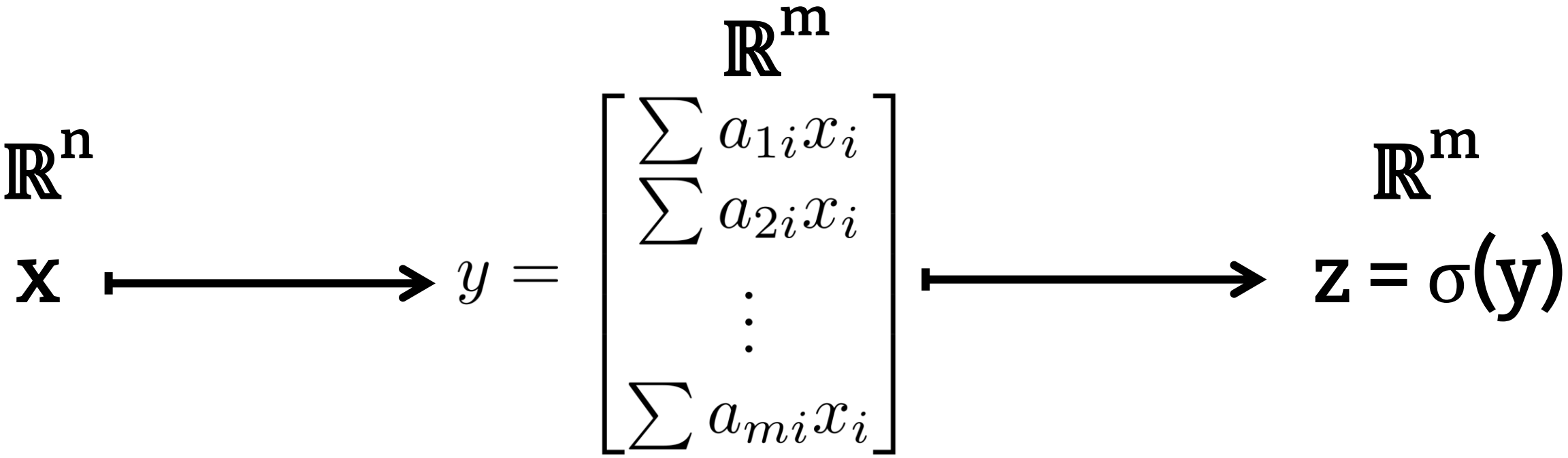
$$x \longmapsto y = \sum a_i x_i \longmapsto z = \sigma(y)$$

MLP: one layer

$$\mathbb{R}^n \qquad \mathbb{R} \qquad \mathbb{R}$$

$$x \longmapsto y = \sum a_i x_i \longmapsto z = \sigma(y)$$

MLP: one layer

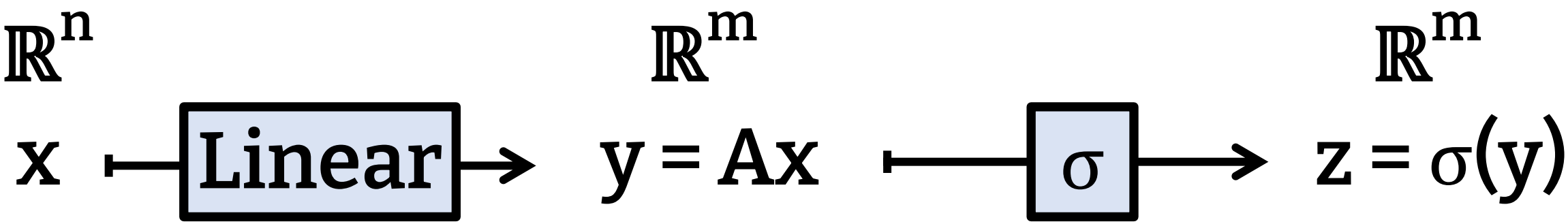


MLP: one layer

$$\mathbb{R}^n \qquad\qquad \mathbb{R}^m \qquad\qquad \mathbb{R}^m$$

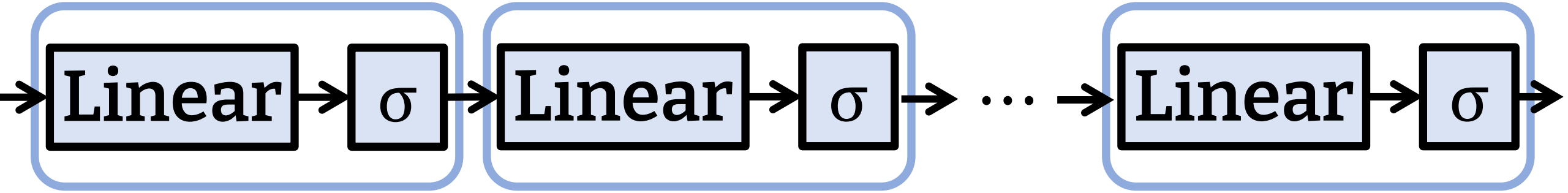
$$x \longmapsto y = Ax \longmapsto z = \sigma(y)$$

MLP: one layer

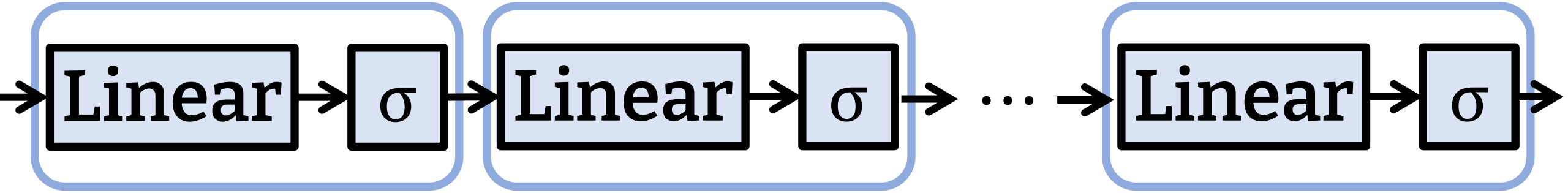


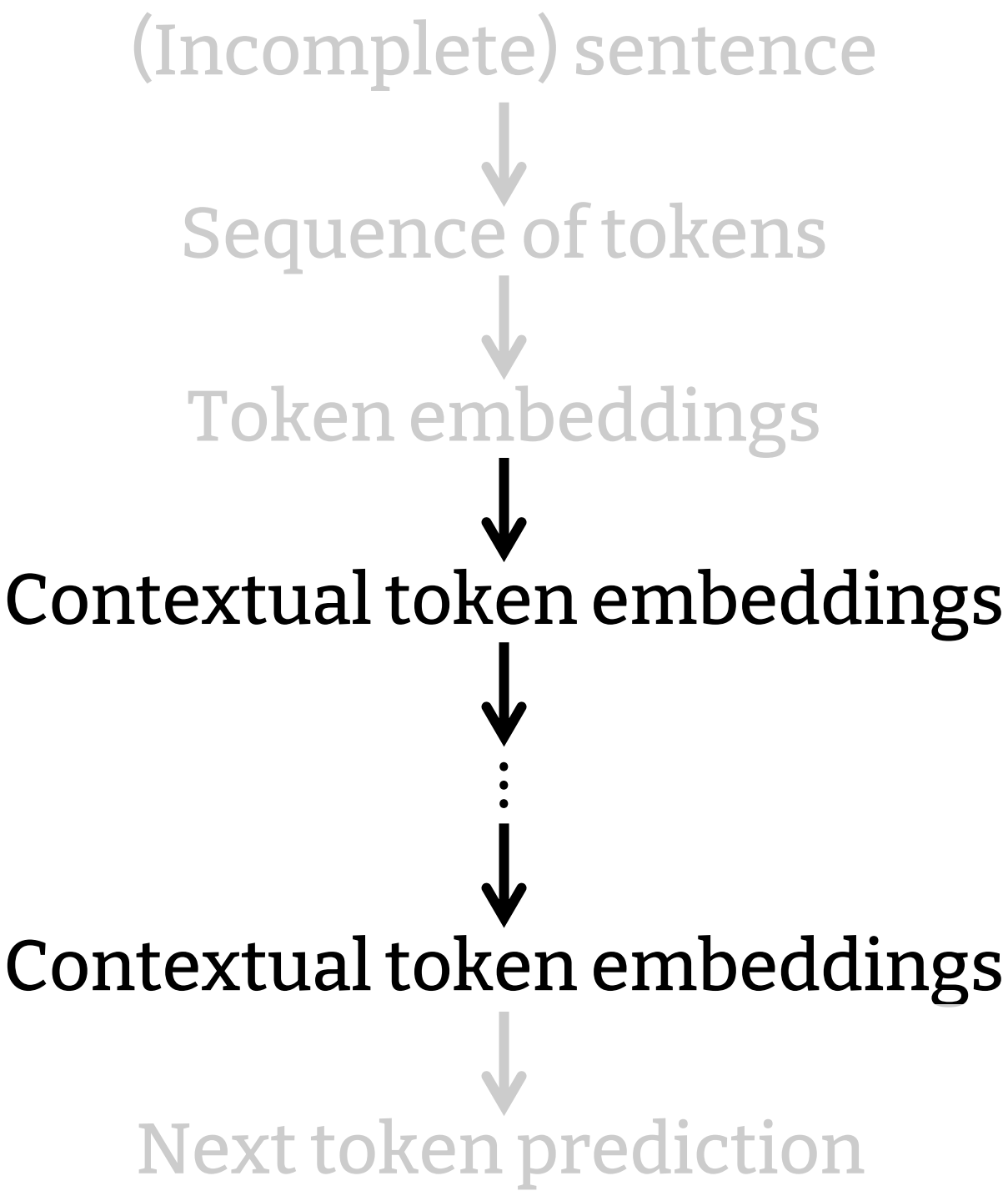
MLP: one layer

MLP: several layers



MLP (Multilayer Perceptron)





MLP

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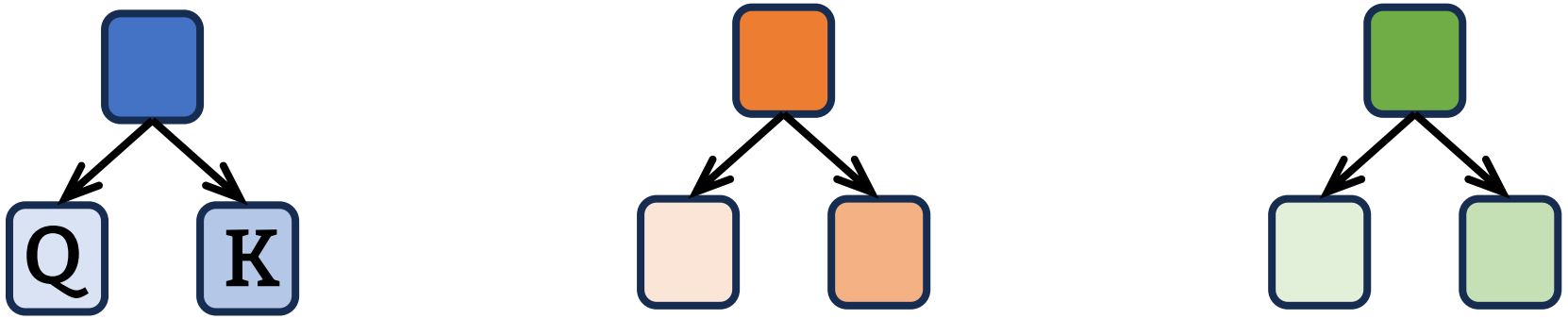
Attention

(“transformers”)

Attention mechanism

- MLP: weighted sums
- Attention: products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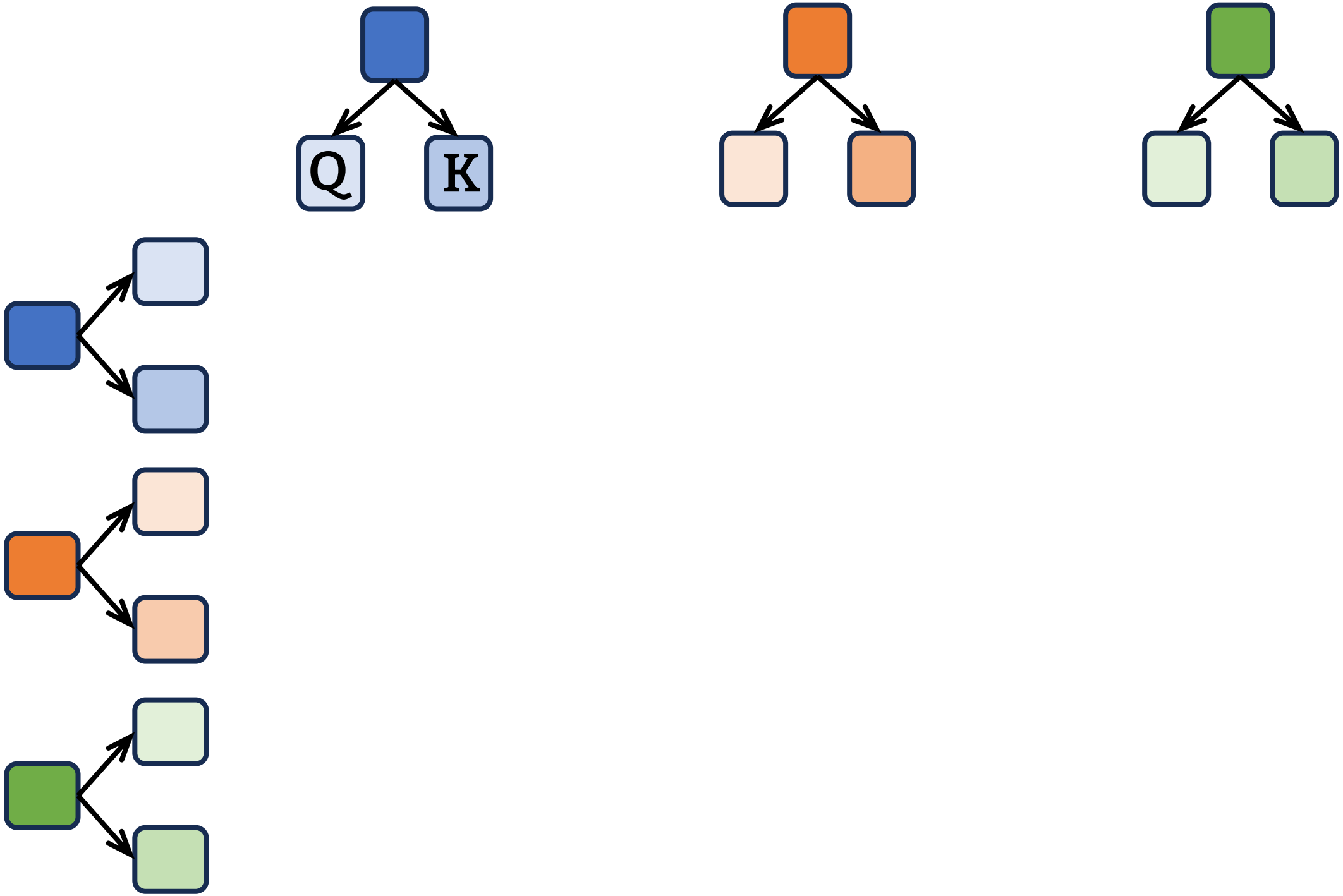
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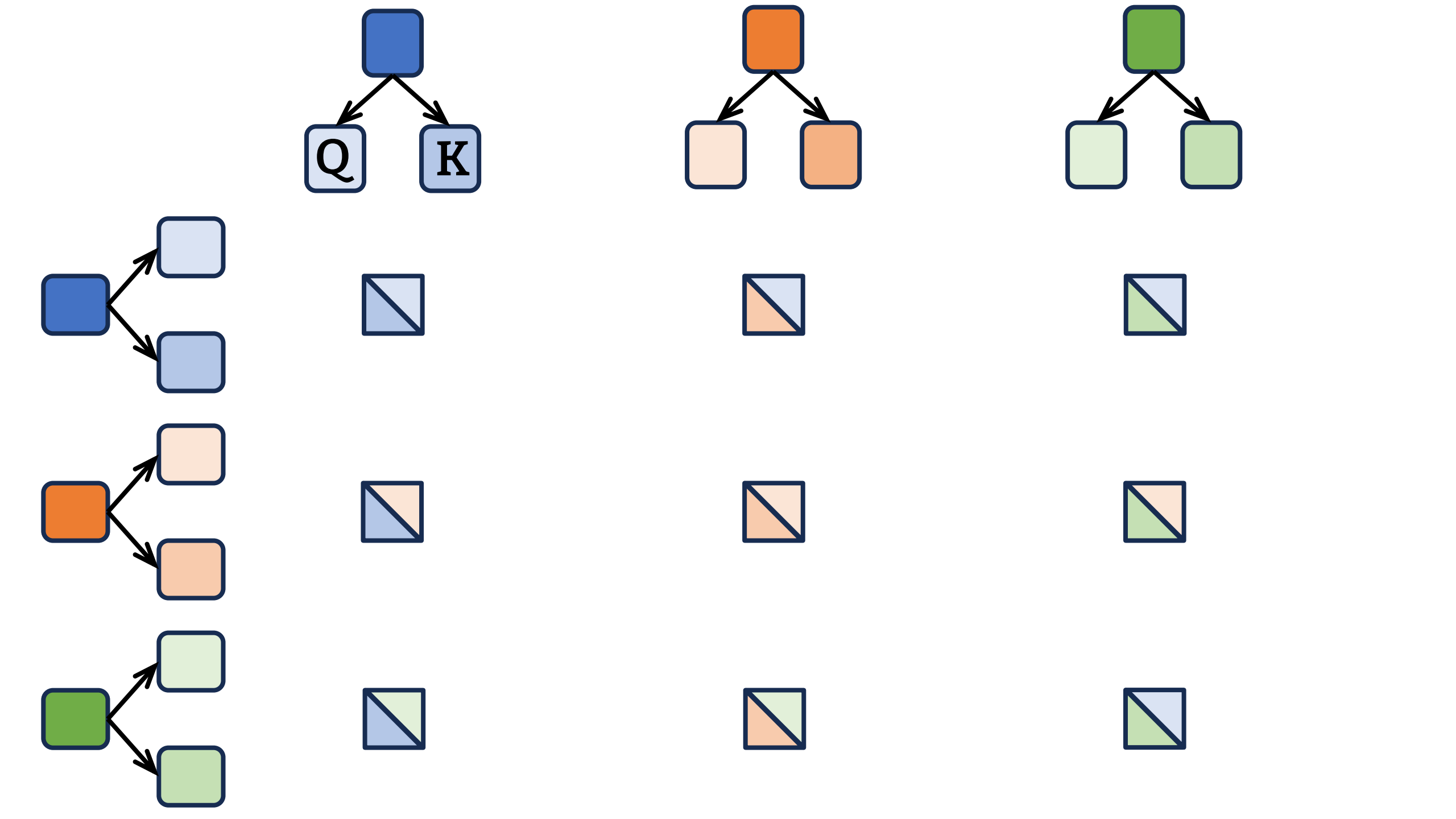
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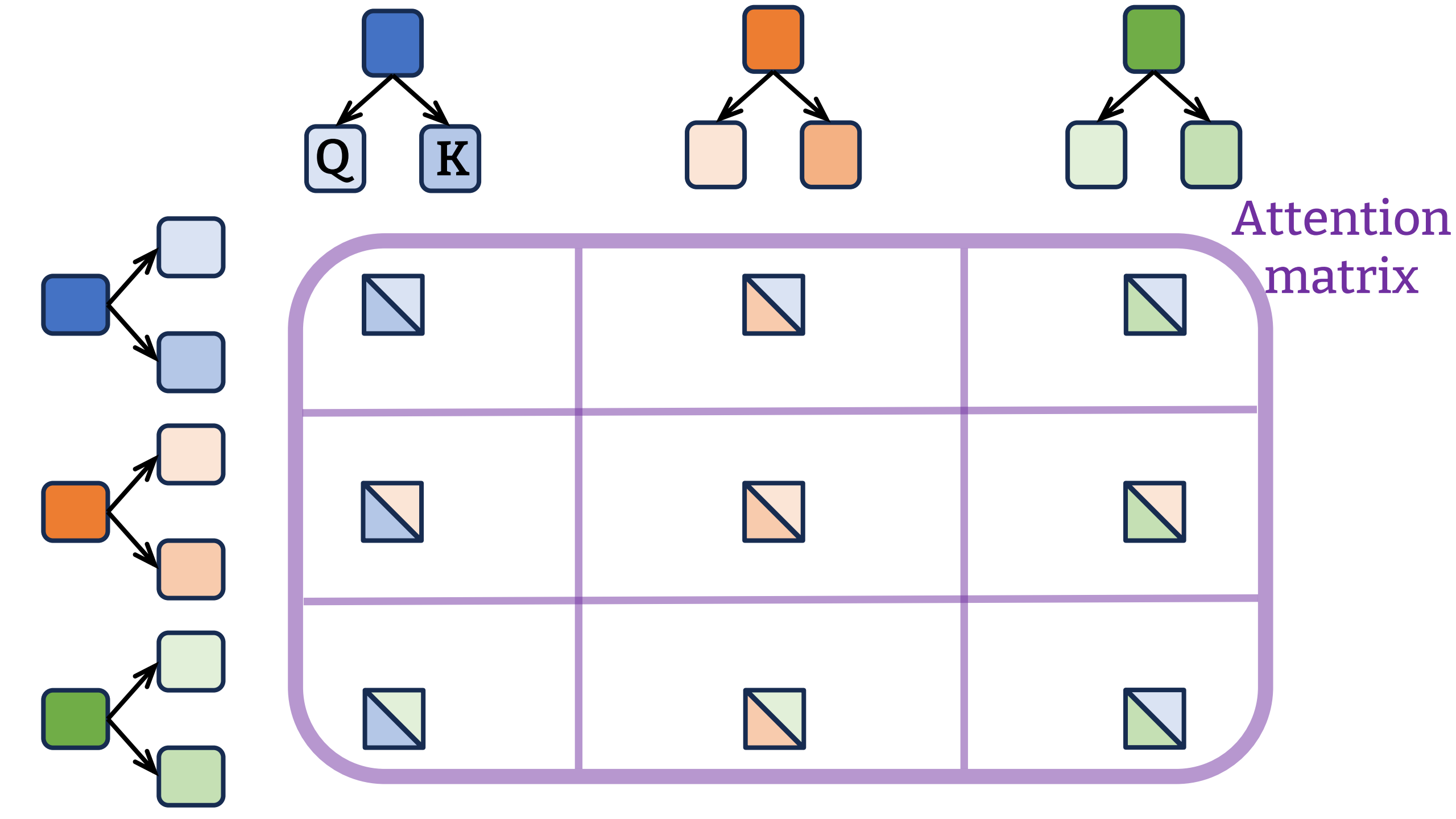
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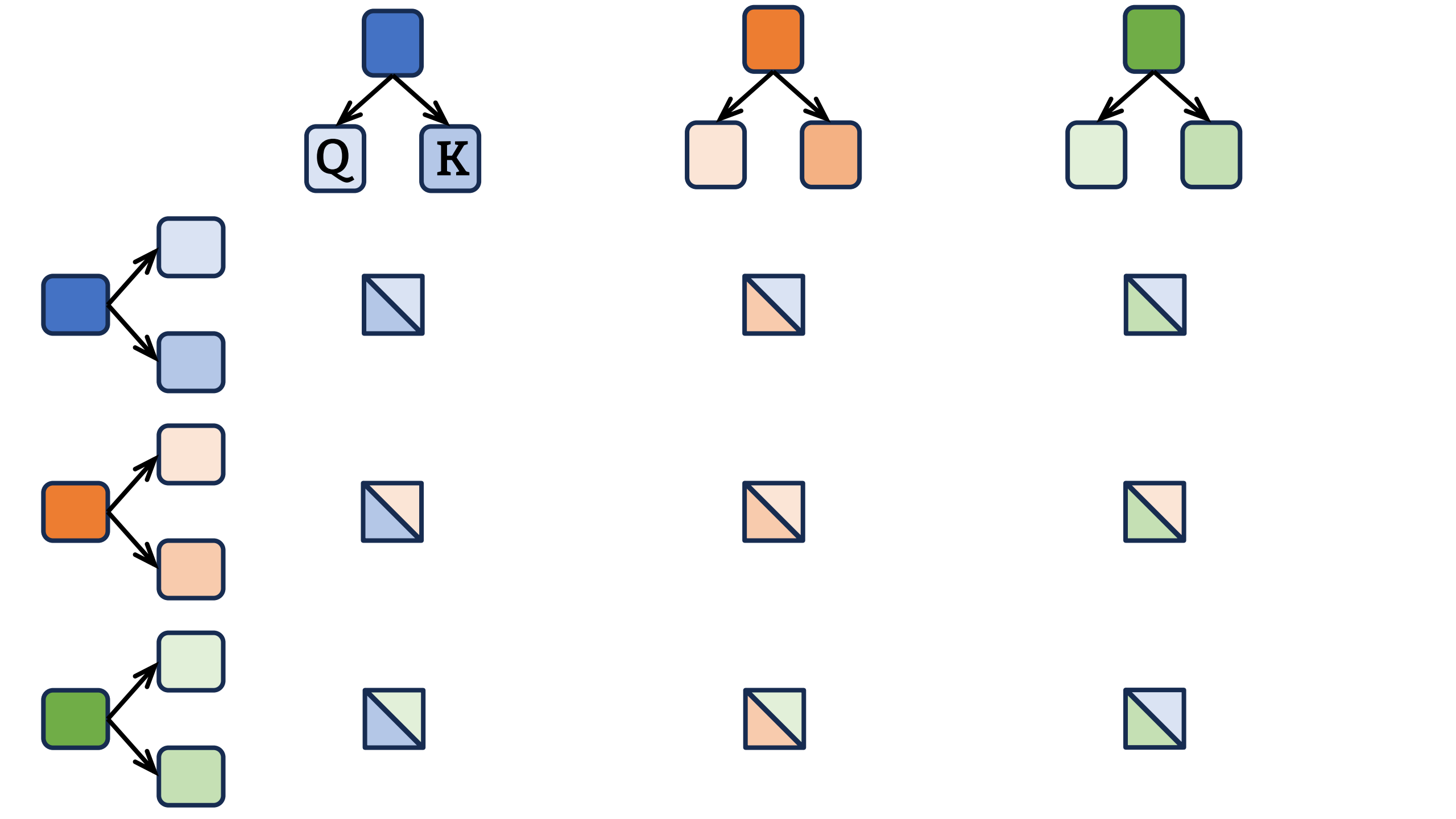
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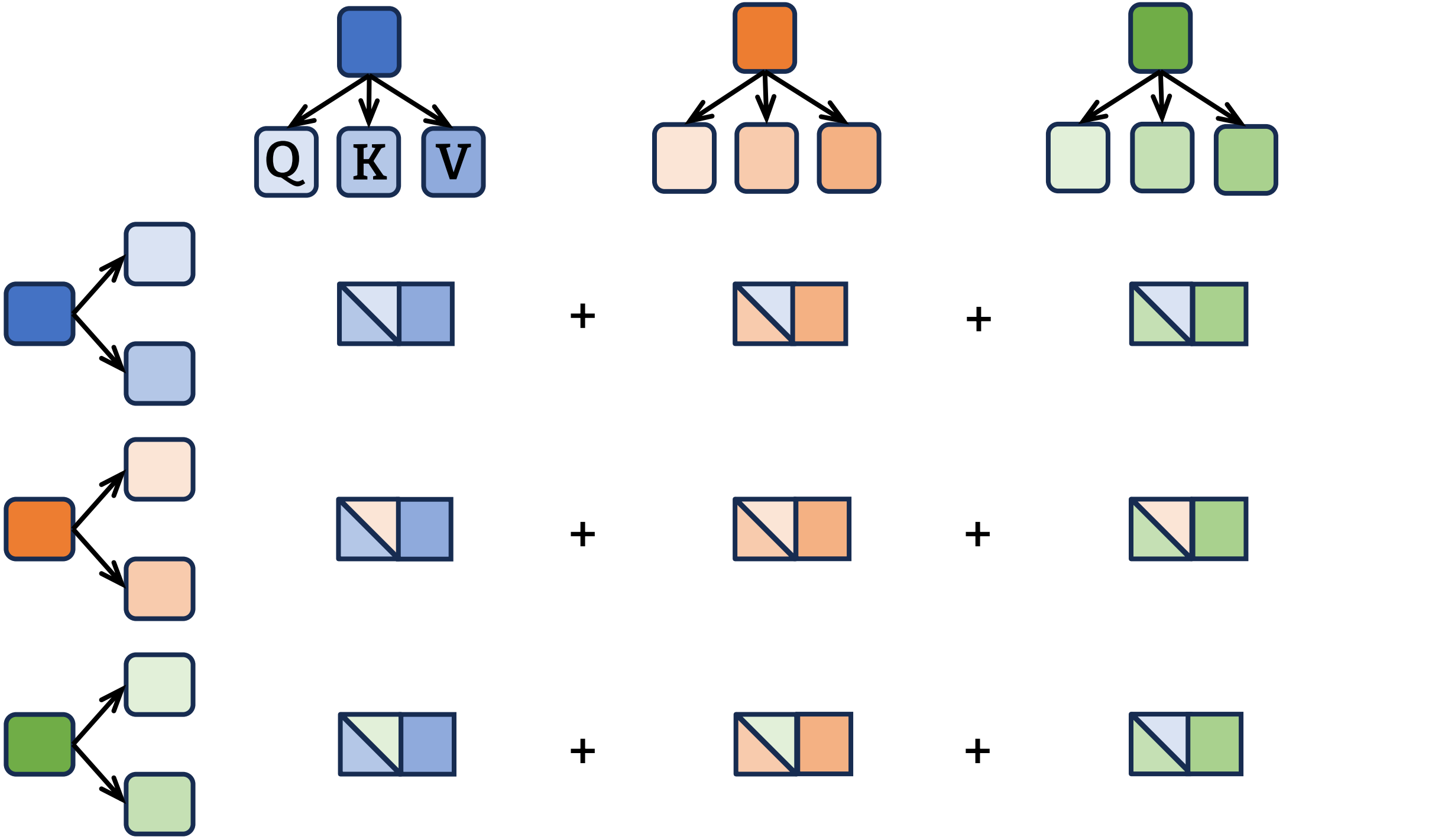
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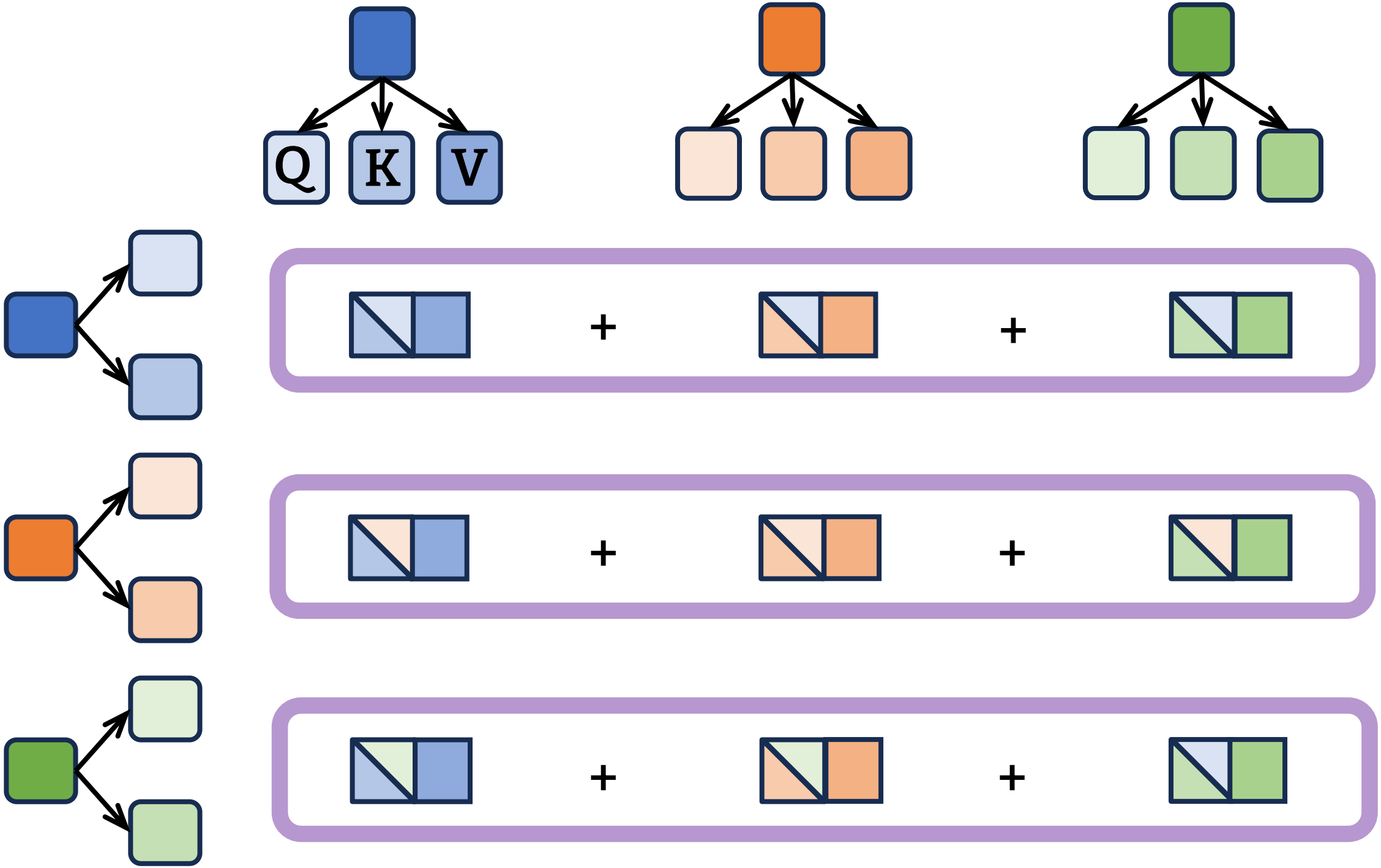
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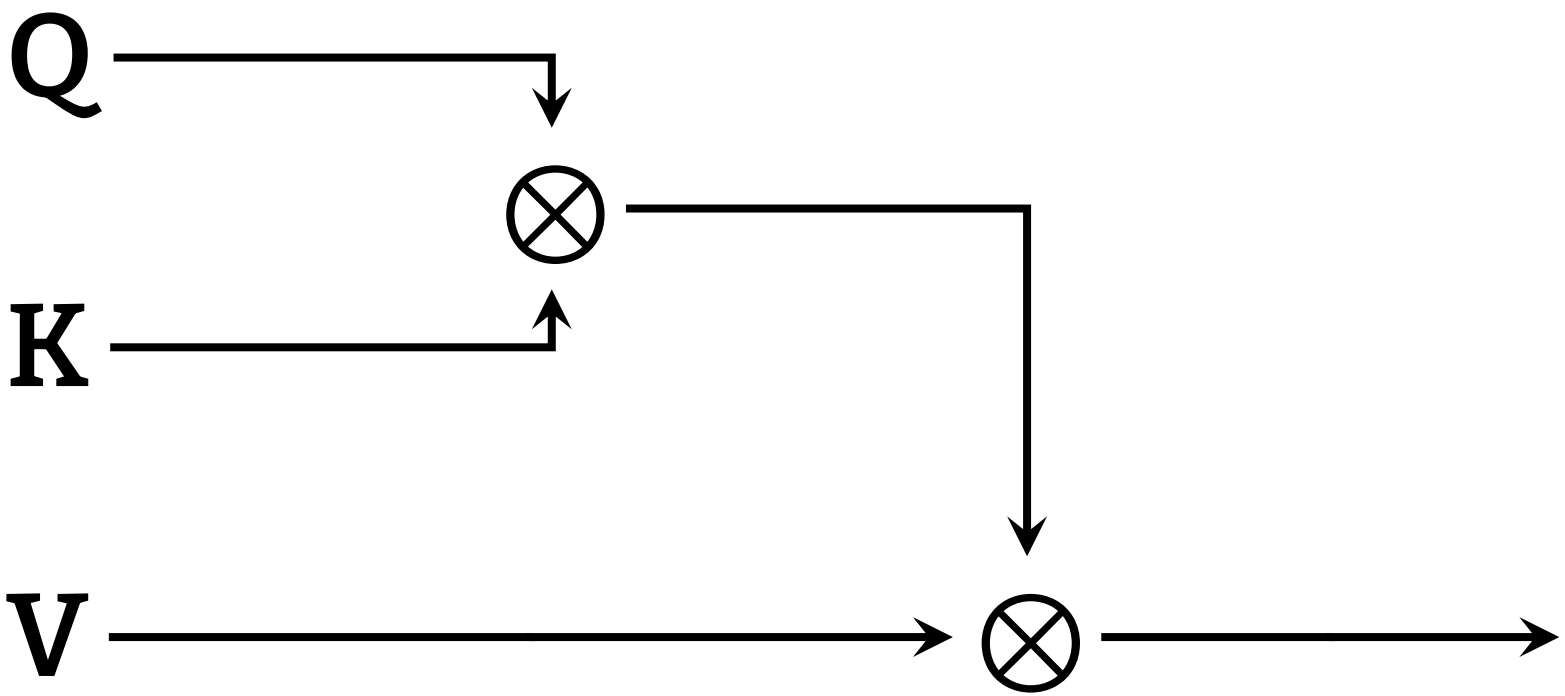
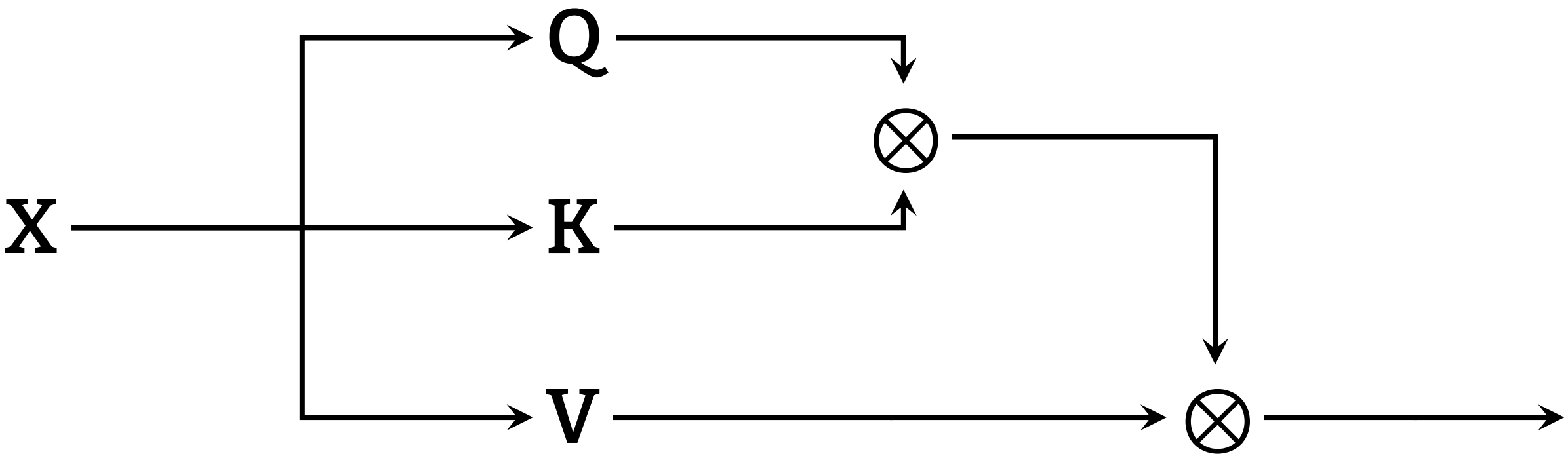
Attention

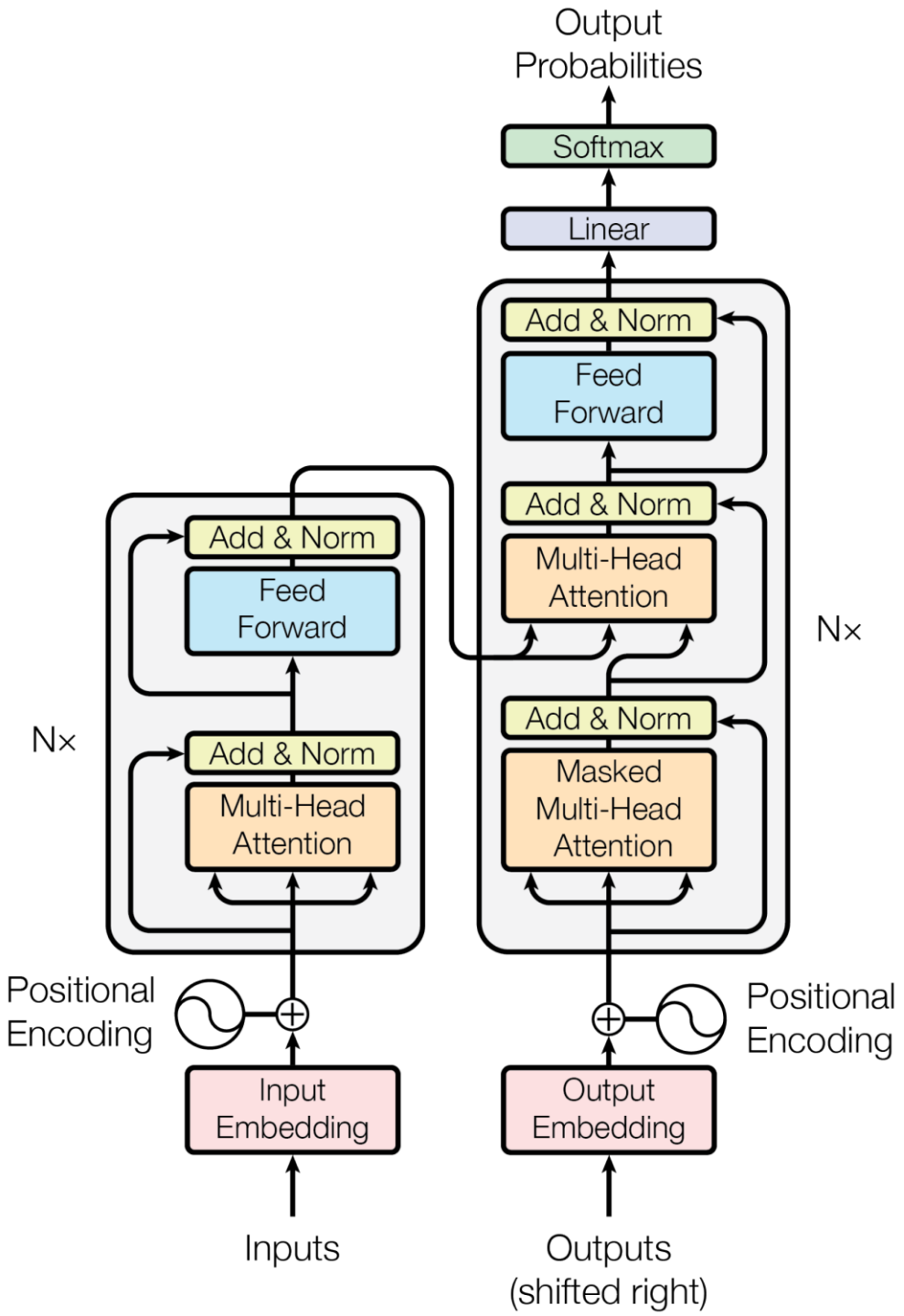


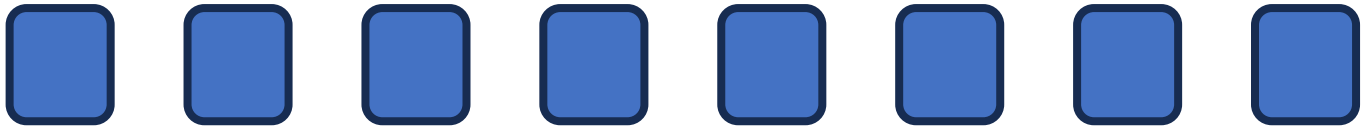
Self-Attention



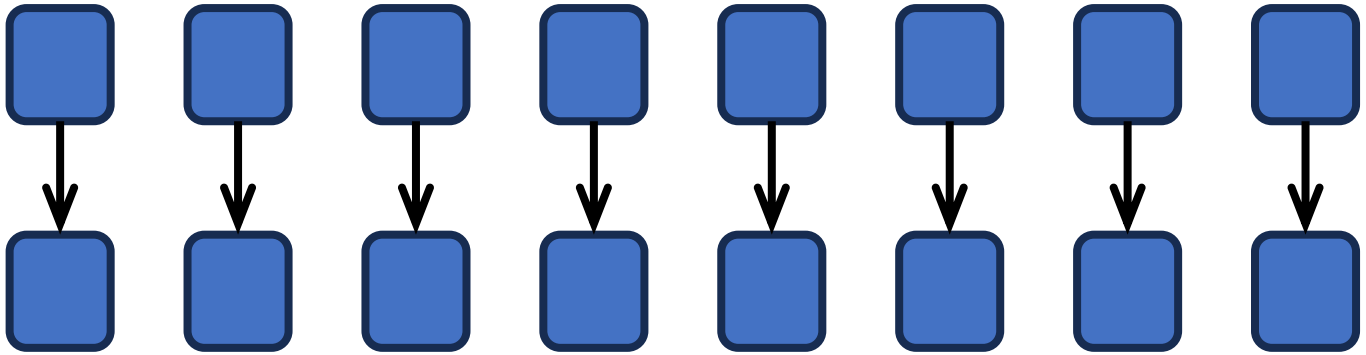
Transformer

- Transformer = attention + lots of details

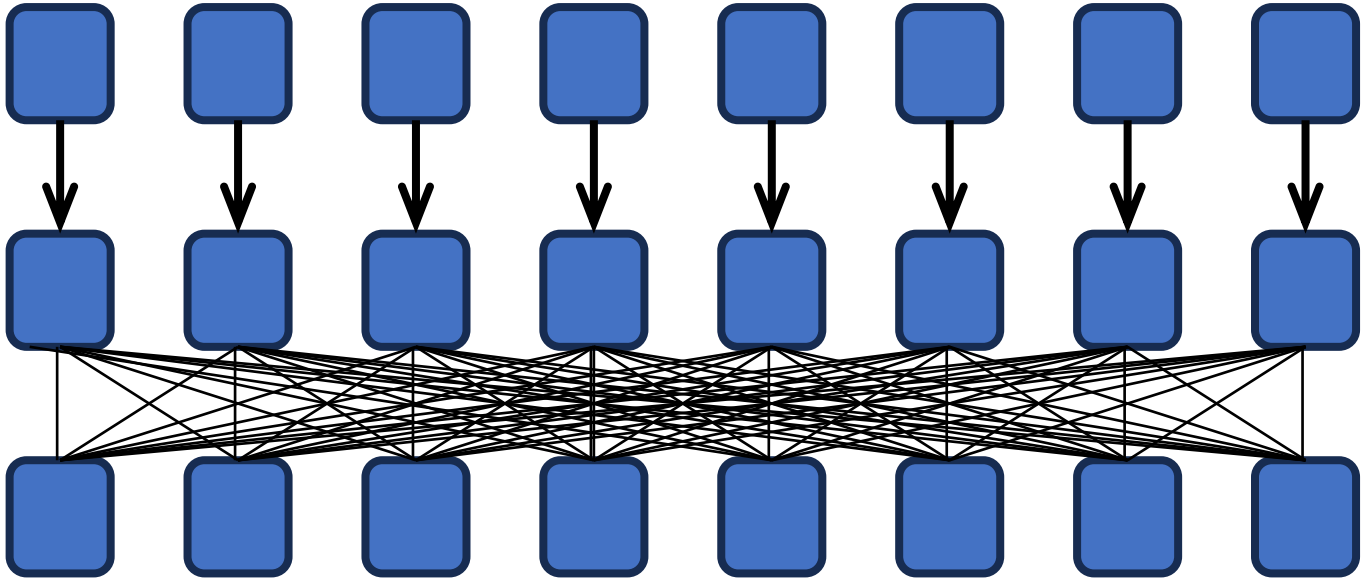




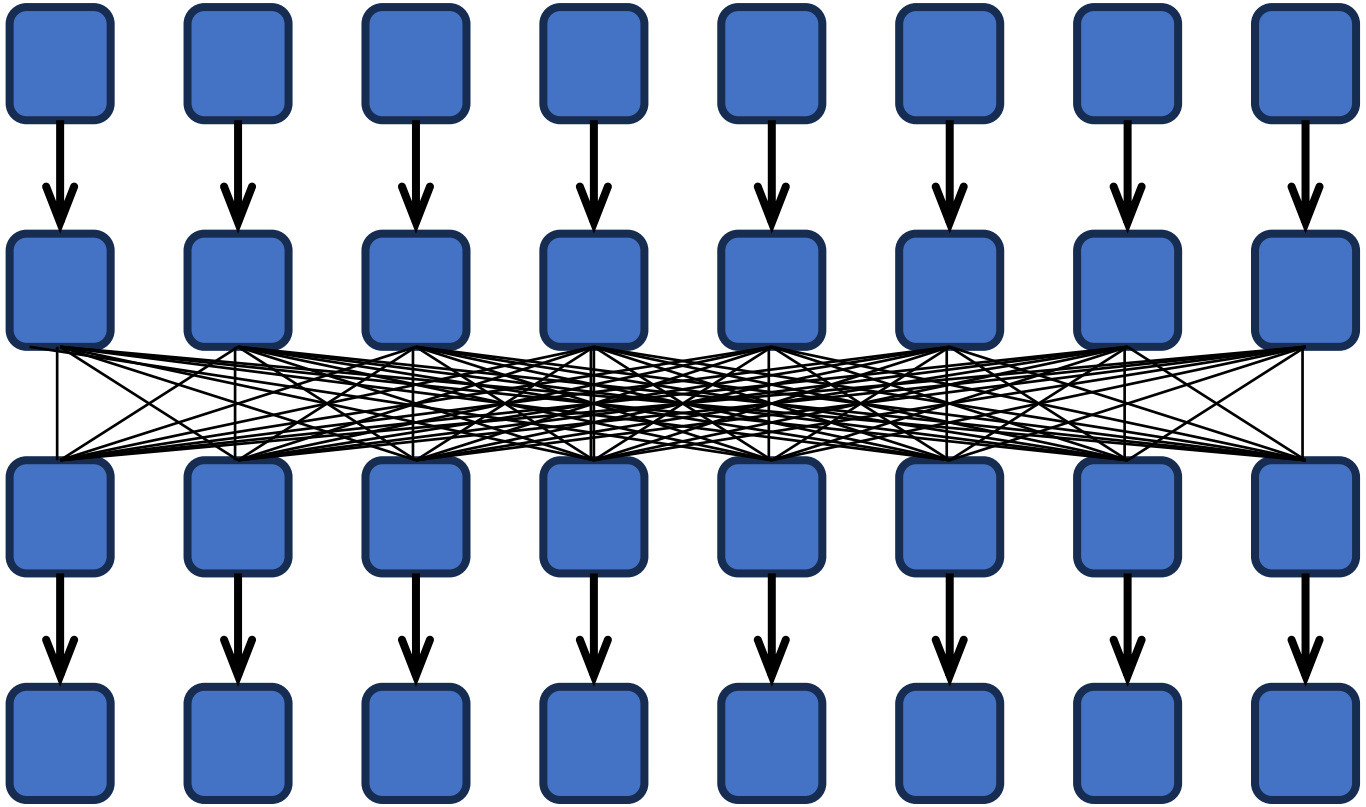
Tokens



MLP



Attention



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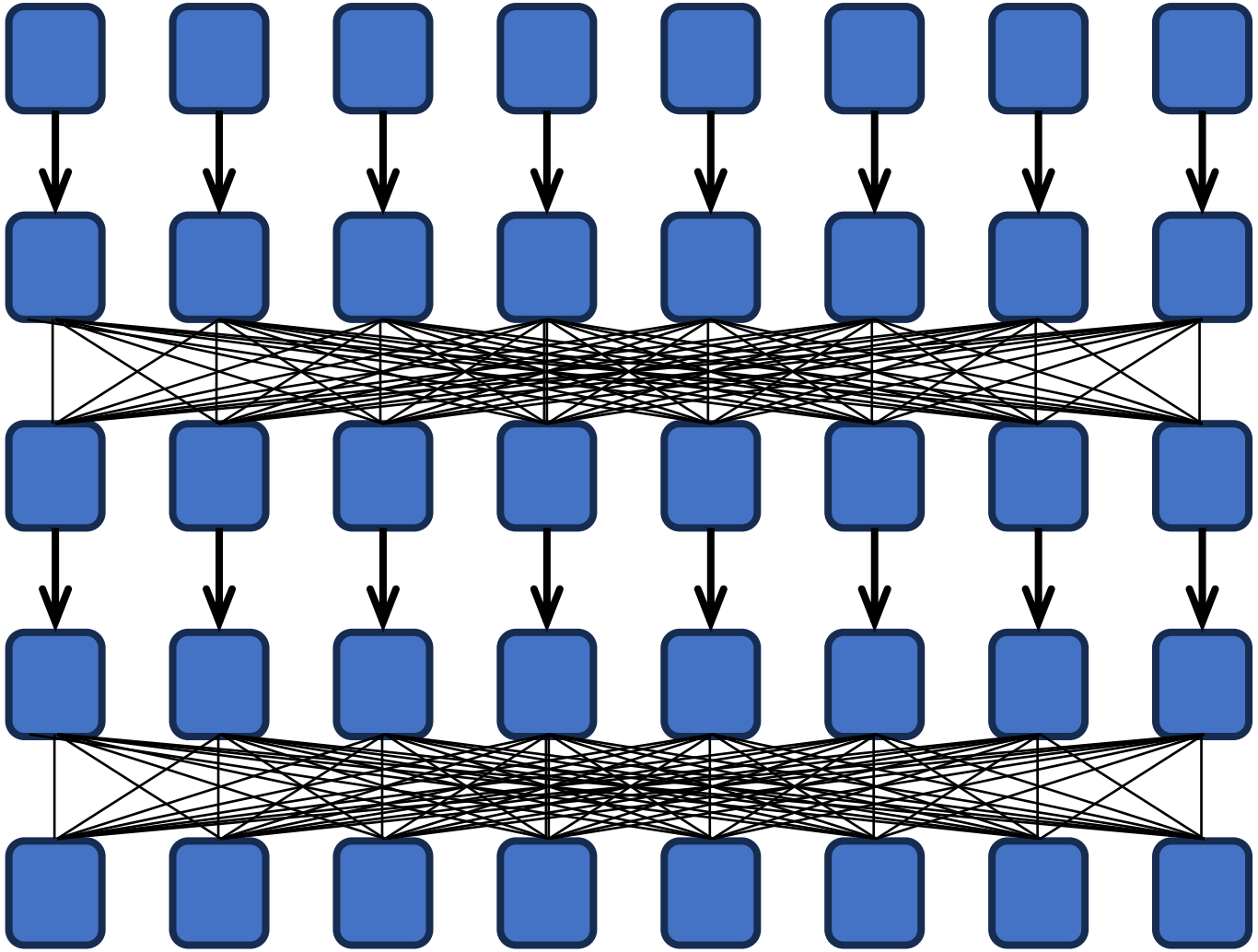

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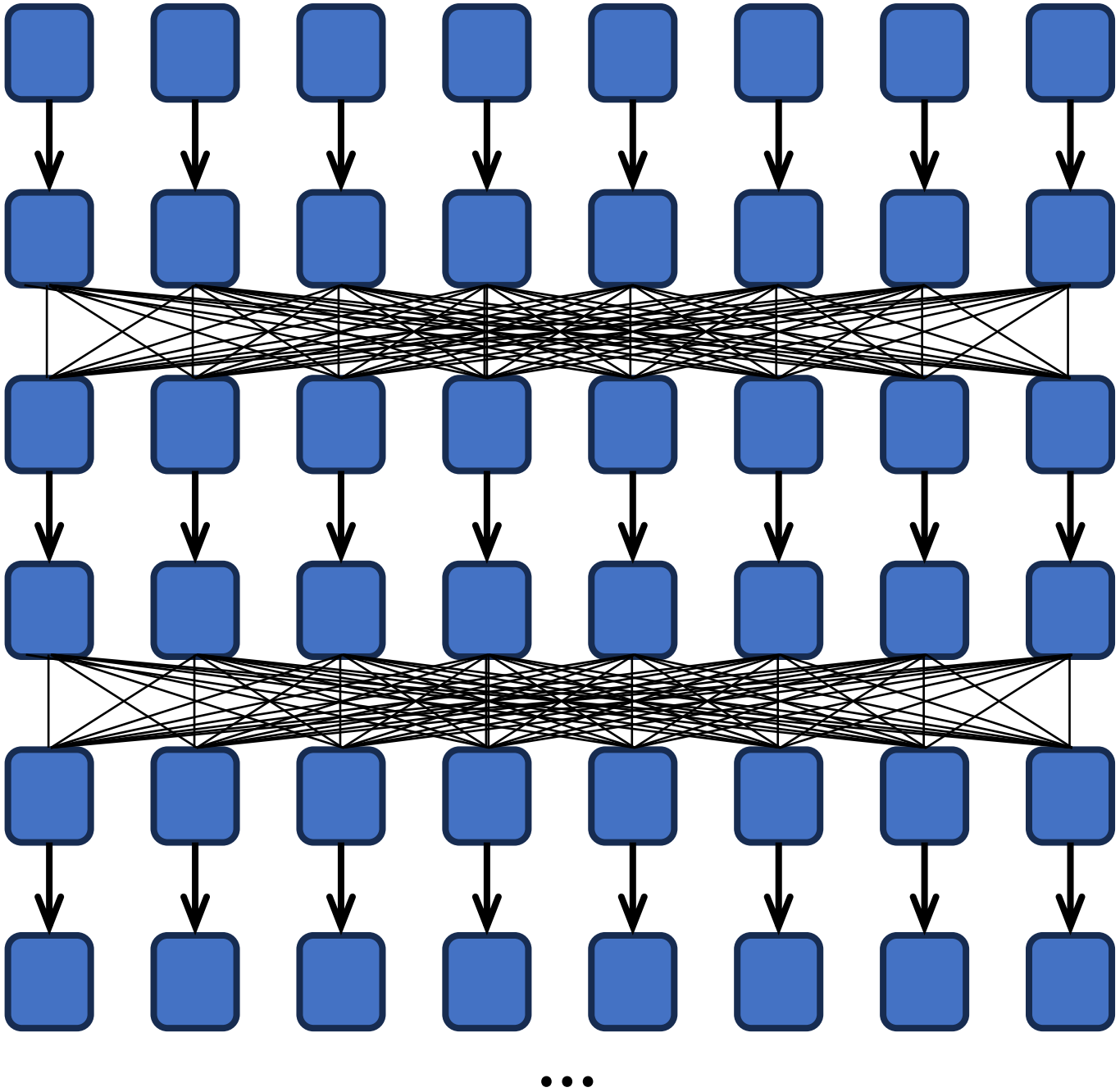
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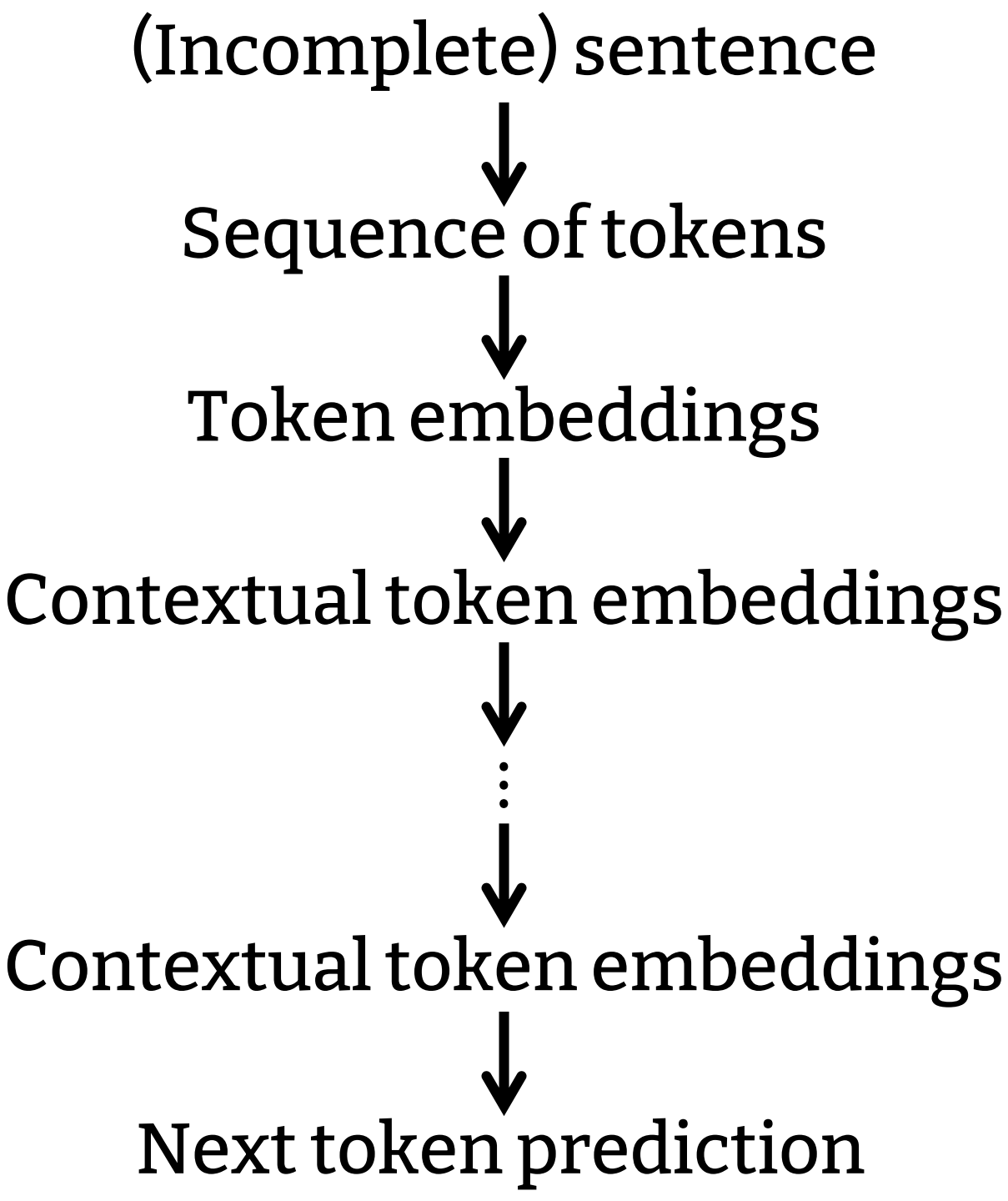

(Incomplete) sentence
Sequence of tokens
Token embeddings
Contextual token embeddings
Contextual token embeddings
Next token prediction

Not covered

- Training
- Fine-tuning: text completion → assistant
- Prompt engineering (few-shot learning, CoT)
- Tools (MCP)
- Agents

References

- 3blue1brown (YouTube):
  - Large language models explained briefly
  - Visualizing transformers and attention
  - Neural networks
- Andrej Karpathy (YouTube):
  - Deep dive into LLMs like ChatGPT

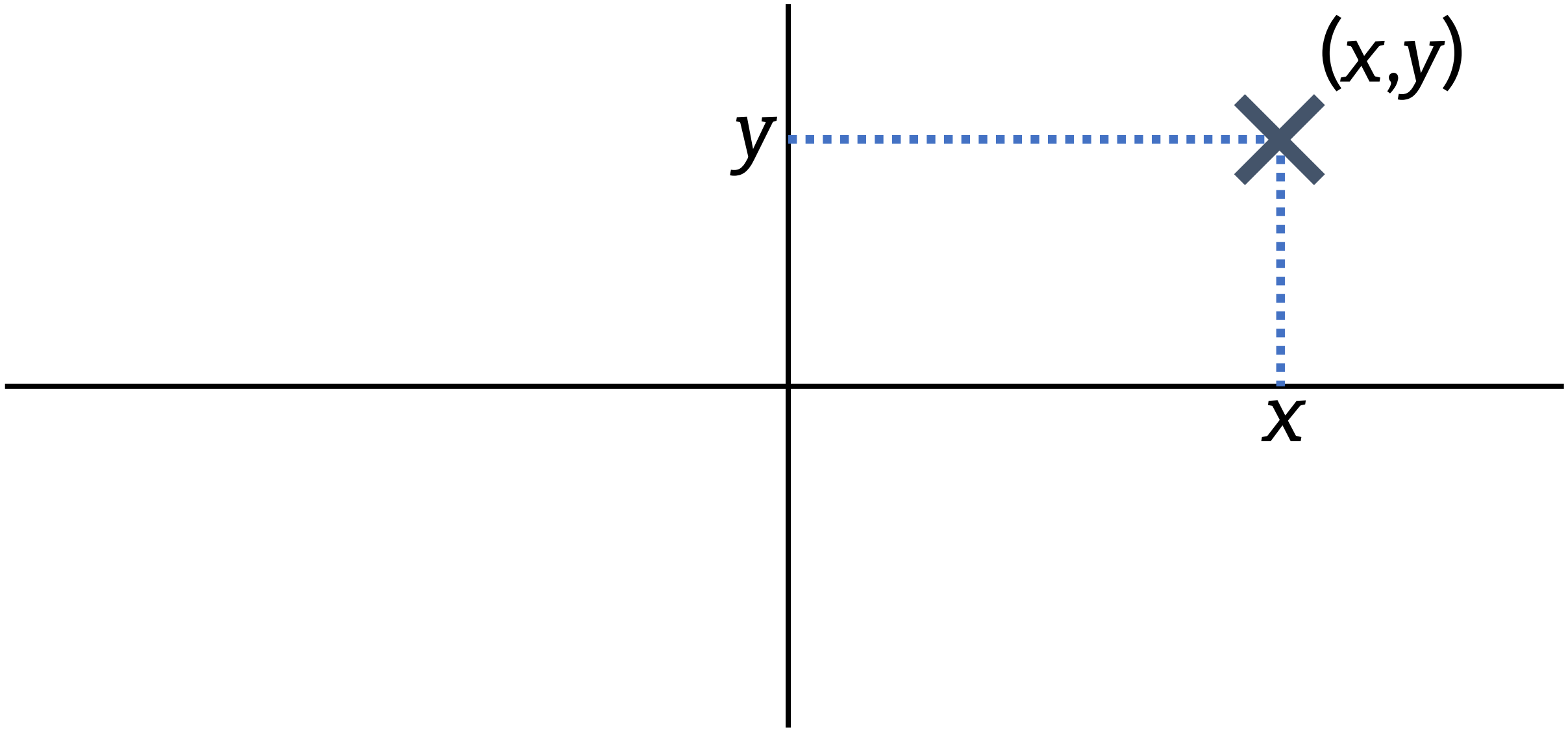
Extra Slides

Prerequisites

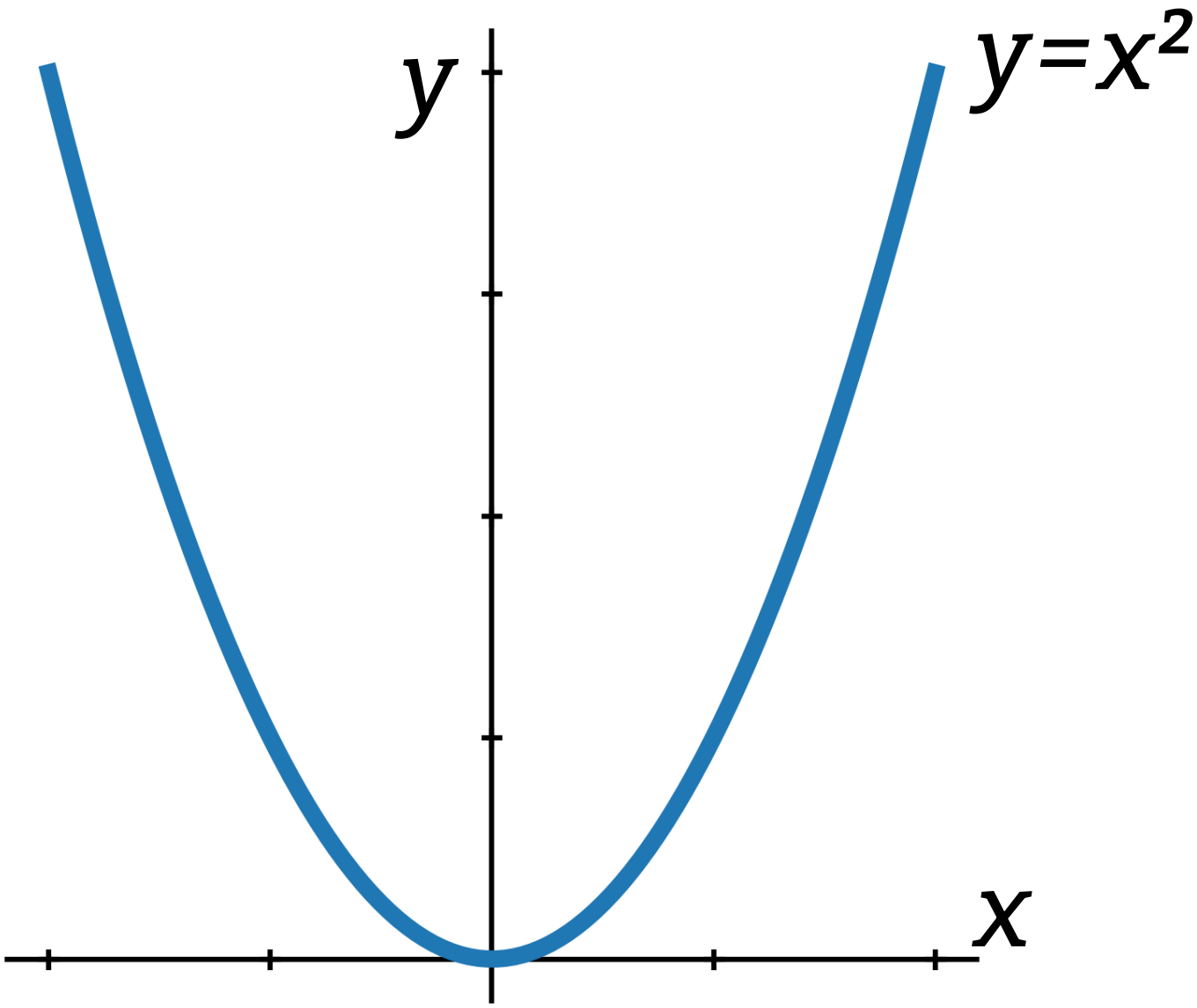
Function

$$f : \begin{cases} \mathbb{R} \longrightarrow \mathbb{R} \\ x \longmapsto x^2 \end{cases}$$

Coordinates



Graph of a function



Summation notation

$$\sum_{i=1}^{n} a_i = a_1 + a_2 + \cdots + a_n$$

Vectors

$$(x_1, x_2, \ldots, x_n) \in \mathbb{R}^n$$

Vectors

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \in \mathbf{R}^n$$

Scalar product

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \cdot \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = x_1 y_1 + x_2 y_2 + \cdots + x_n y_n$$

Scalar product

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \cdot \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \sum_{i=1}^{n} x_i y_i$$

Scalar product

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \cdot \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} = \sum_i x_i y_i$$

Matrix

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \in \mathbf{R}^{n \times m}$$

Matrix product

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} a_{11}x_1 + \cdots + a_{1m}x_m \\ a_{21}x_1 + \cdots + a_{2m}x_m \\ \vdots \\ a_{n1}x_1 + \cdots + a_{nm}x_m \end{bmatrix}$$

Matrix product

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} a_{11}x_1 + \cdots + a_{1m}x_m \\ a_{21}x_1 + \cdots + a_{2m}x_m \\ \vdots \\ a_{n1}x_1 + \cdots + a_{nm}x_m \end{bmatrix}$$

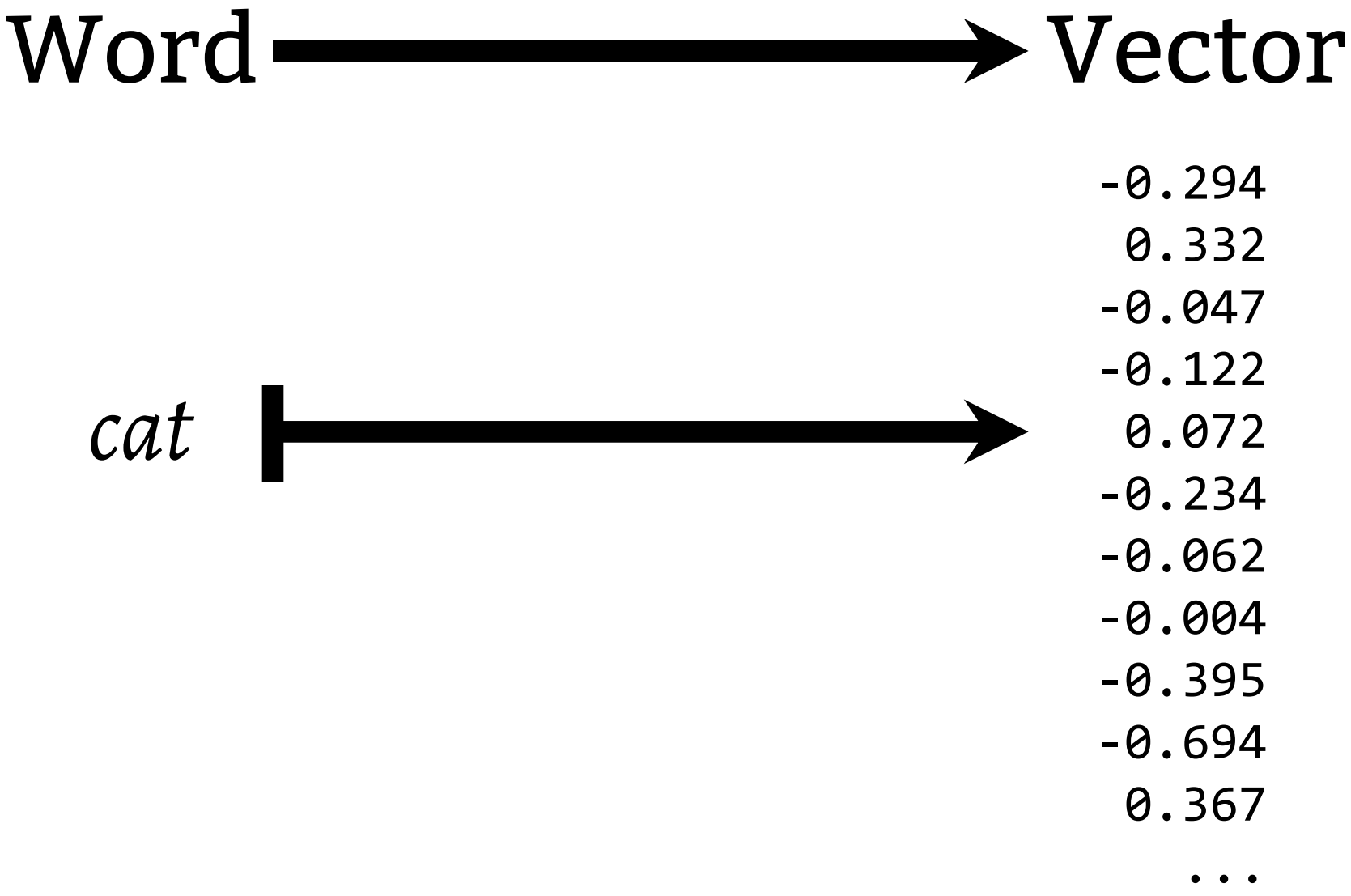
Matrix product

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} a_{11}x_1 + \cdots + a_{1m}x_m \\ a_{21}x_1 + \cdots + a_{2m}x_m \\ \vdots \\ a_{n1}x_1 + \cdots + a_{nm}x_m \end{bmatrix}$$

Matrix product

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & & & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nm} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} a_{11}x_1 + \cdots + a_{1m}x_m \\ a_{21}x_1 + \cdots + a_{2m}x_m \\ \vdots \\ a_{n1}x_1 + \cdots + a_{nm}x_m \end{bmatrix}$$

Word Embeddings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-0.062
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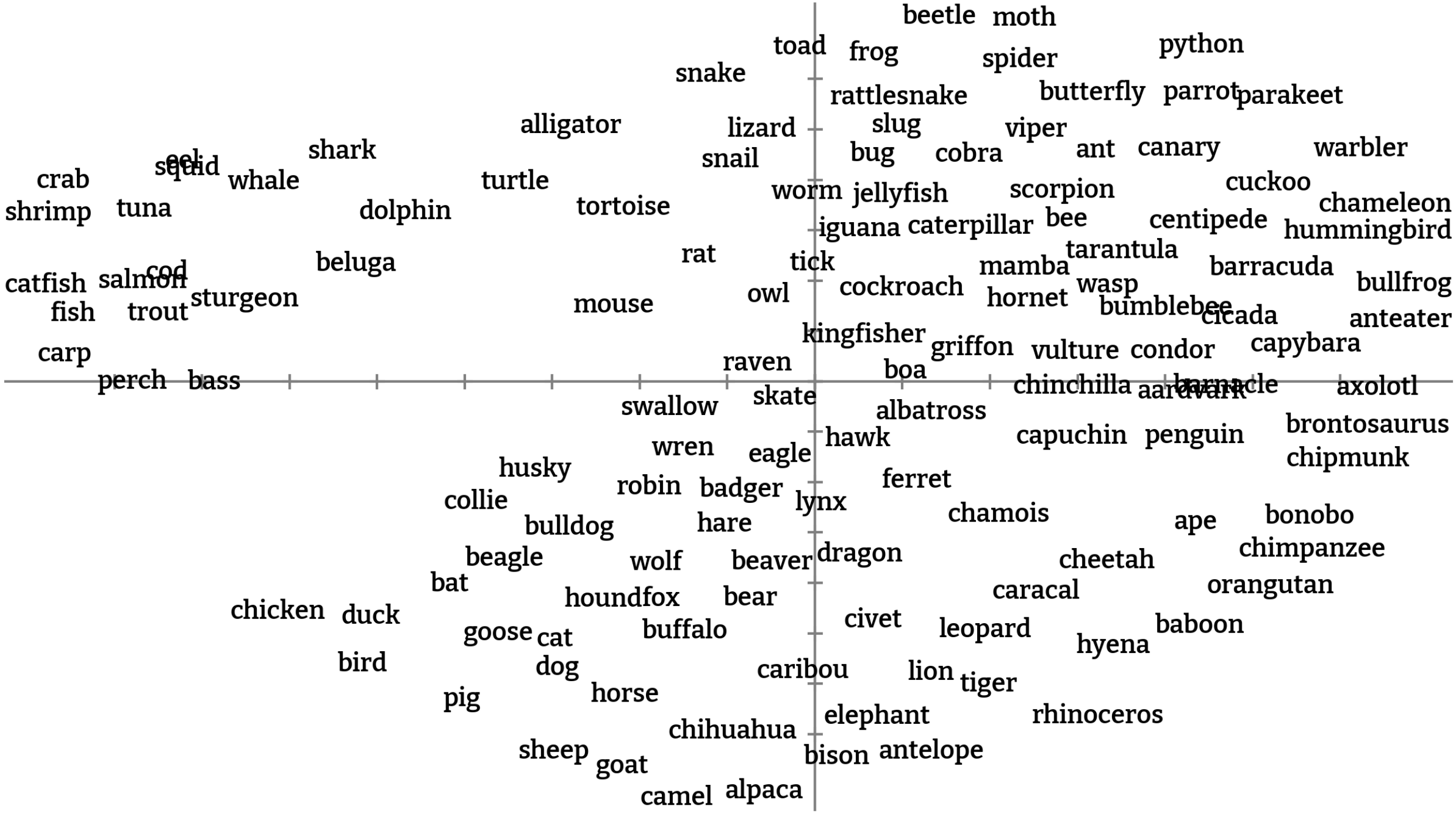
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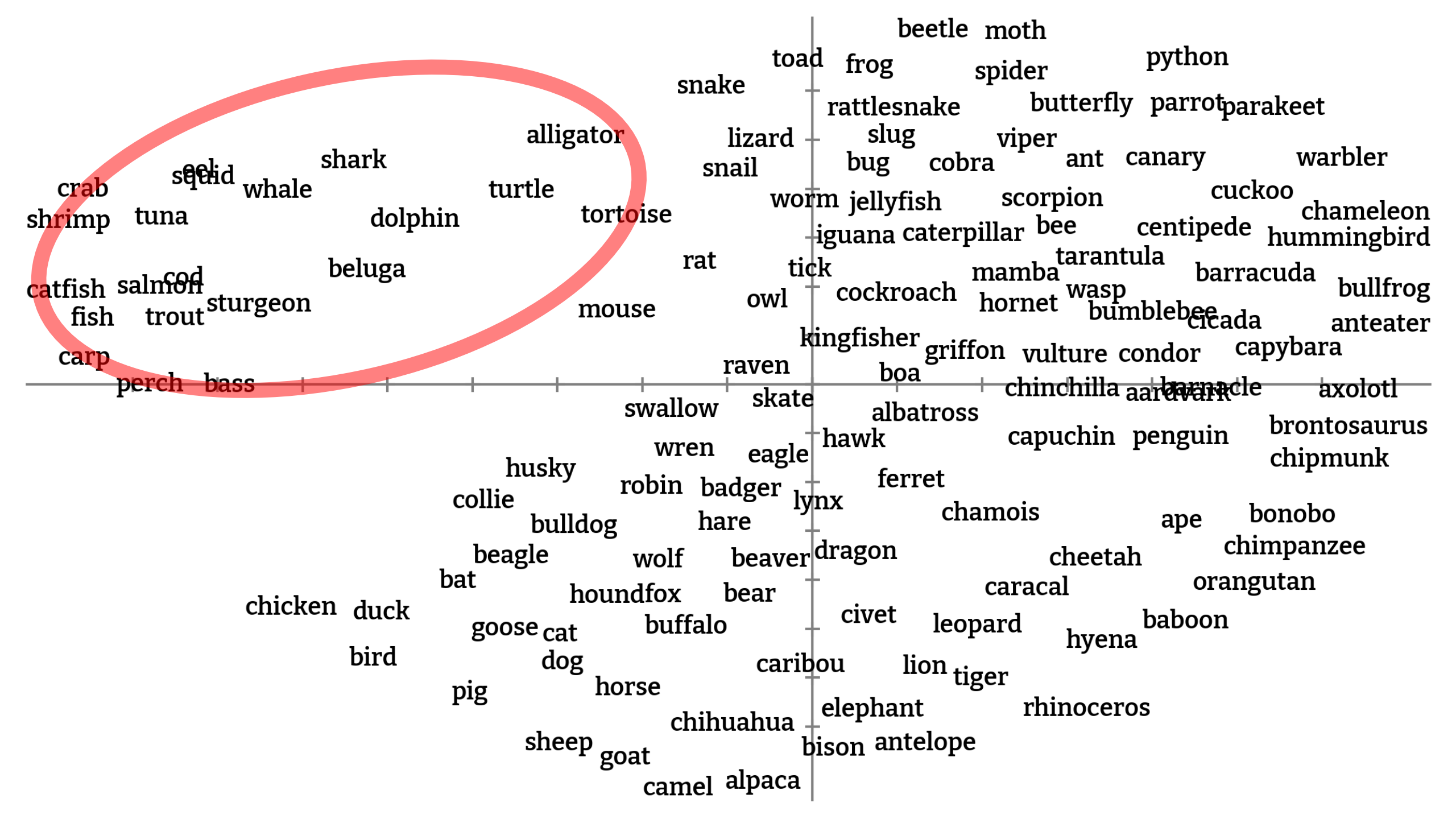
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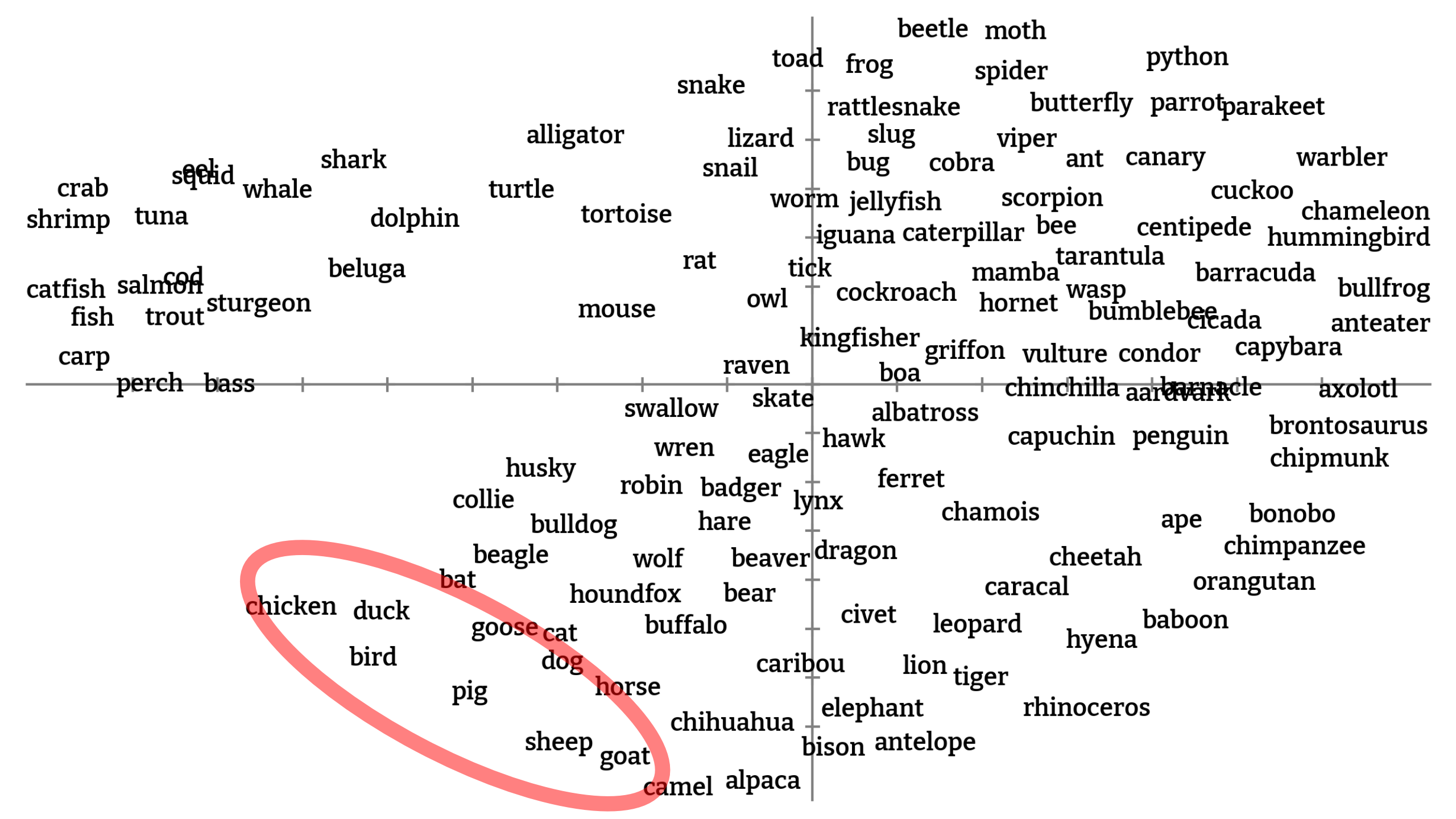
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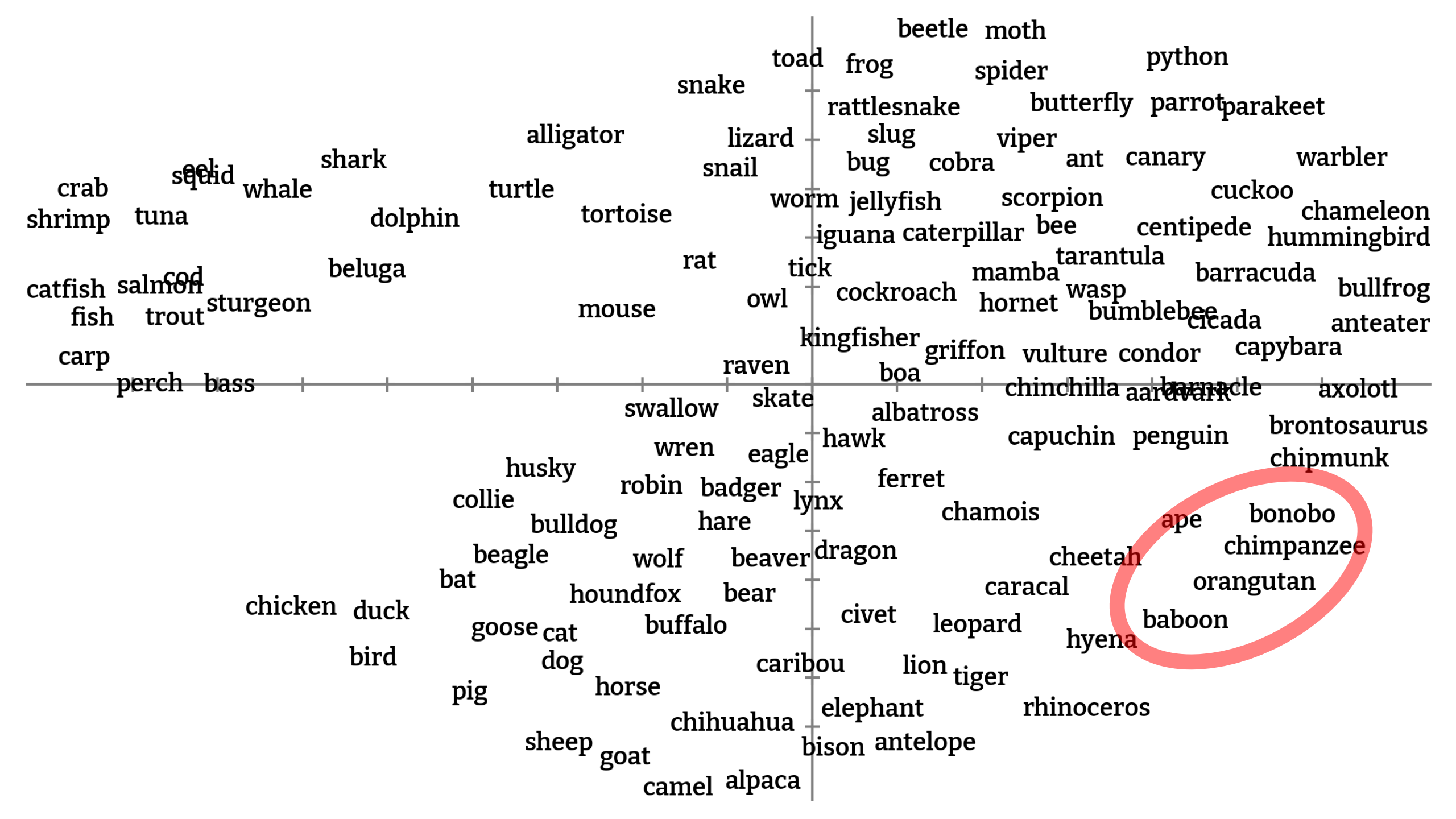
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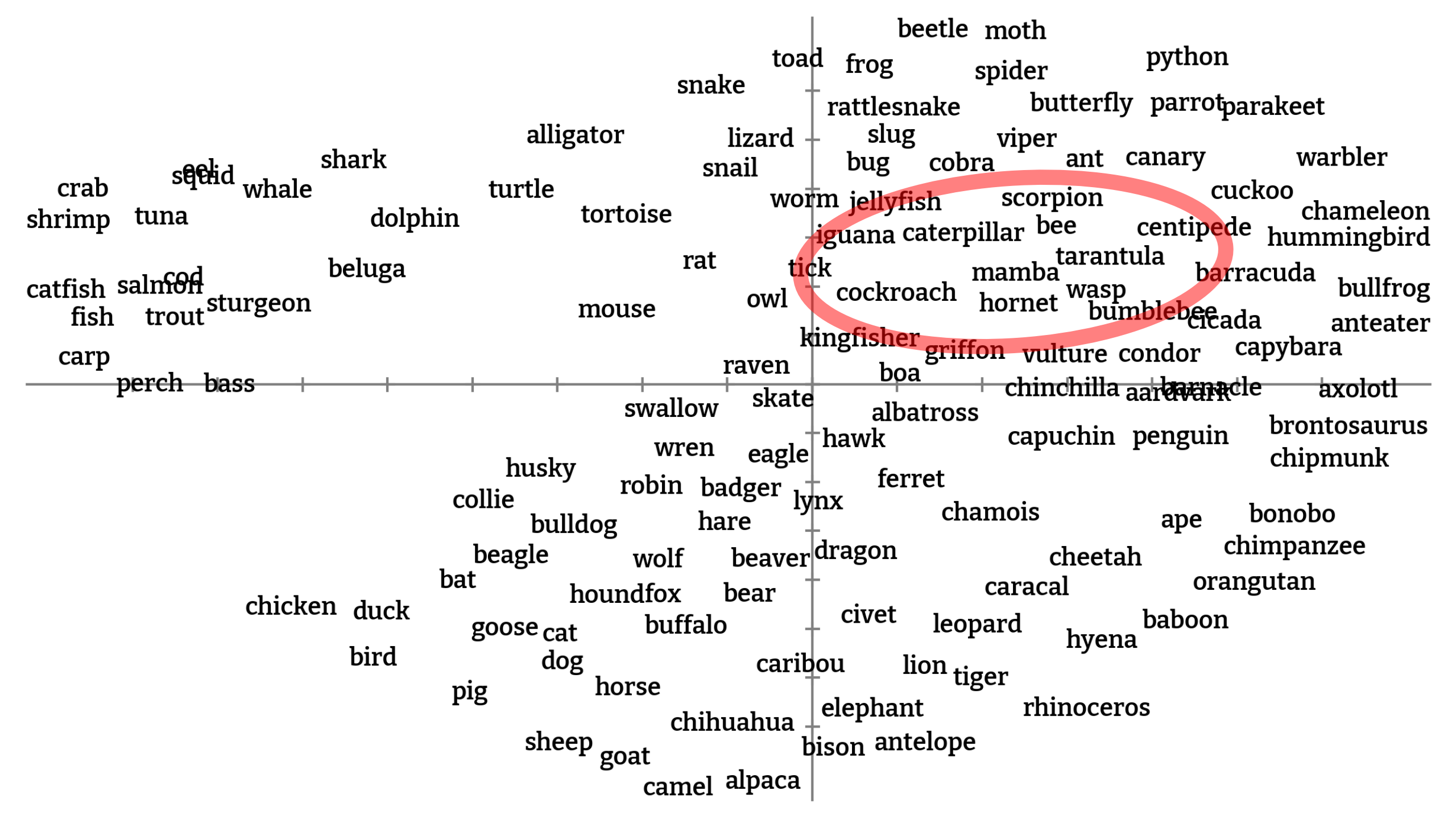
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bird
dog
caribou
lion
tiger
pig
horse
elephant
rhinoceros
chihuahua
sheep
bison
antelope
goat
camel
alpaca

Text Embeddings

Text → Vector

Alice was beginning to get very tired of sitting by her sister on the bank, and of having nothing to do: once or twice she had peeped into the book her sister was reading, but it had no pictures or conversations in it, "and what is the use of a book," thought Alice "without pictures or conversations?"

So she was considering in her own mind (as well as she could, for the hot day made her feel very sleepy and stupid), whether the pleasure of making a daisy-chain would be worth the trouble of getting up and picking the daisies, when suddenly a White Rabbit with pink eyes ran close by her.

There was nothing so _very_ remarkable in that; nor did Alice think it so _very_ much out of the way to hear the Rabbit say to itself, "Oh dear! Oh dear! I shall be late!" (when she thought it over afterwards, it occurred to her that she ought to have wondered at this, but at the time it all seemed quite natural); but when the Rabbit actually _took a watch out of its waistcoat-pocket_, and looked at it, and then hurried on, Alice started to her feet, for it flashed across her mind that she had never before seen a rabbit with either a waistcoat-pocket, or a watch to take out of it, and burning with curiosity, she ran across the field after it, and fortunately was just in time to see it pop down a large rabbit-hole under the hedge.

In another moment down went Alice after it, never once considering how in the world she was to get out again.

The rabbit-hole went straight on like a tunnel for some way, and then dipped suddenly down, so suddenly that Alice had not a moment to think about stopping herself before she found herself falling down a very deep well.

Either the well was very deep, or she fell very slowly, for she had plenty of time as she went down to look about her and to wonder what was going to happen next. First, she tried to look down and make out what she was coming to, but it was too dark to see anything; then she looked at the sides of the well, and noticed that they were filled with cupboards and book-shelves; here and there she saw maps and pictures hung upon pegs. She took down a jar from one of the shelves as she passed; it was labelled "ORANGE MARMALADE", but to her great disappointment it was empty: she did not like to drop the jar for fear of killing somebody underneath, so managed to put it into one of the cupboards as she fell past it.

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-0.450
 0.351
-0.411
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-0.061
-0.399
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  ...
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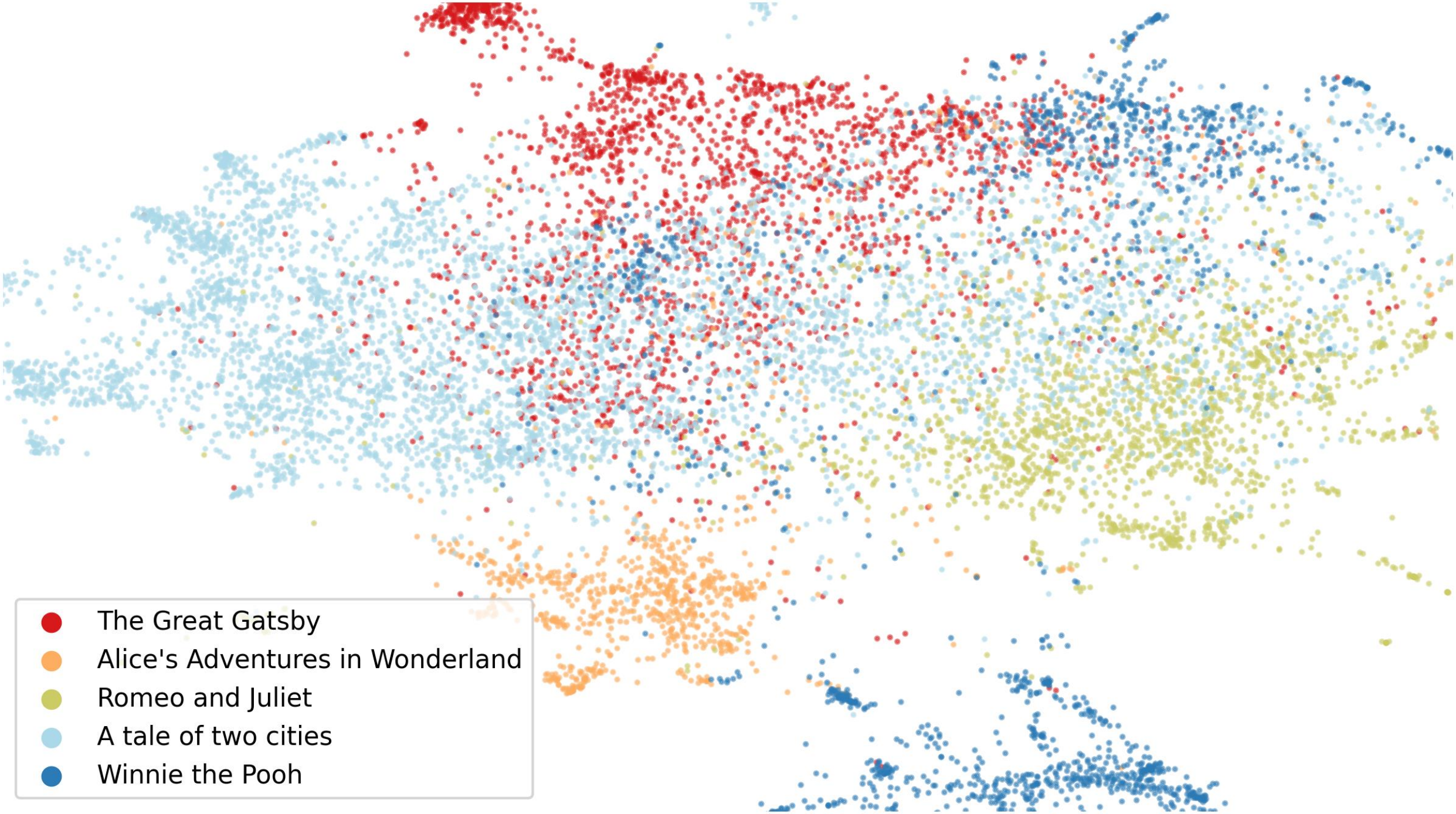
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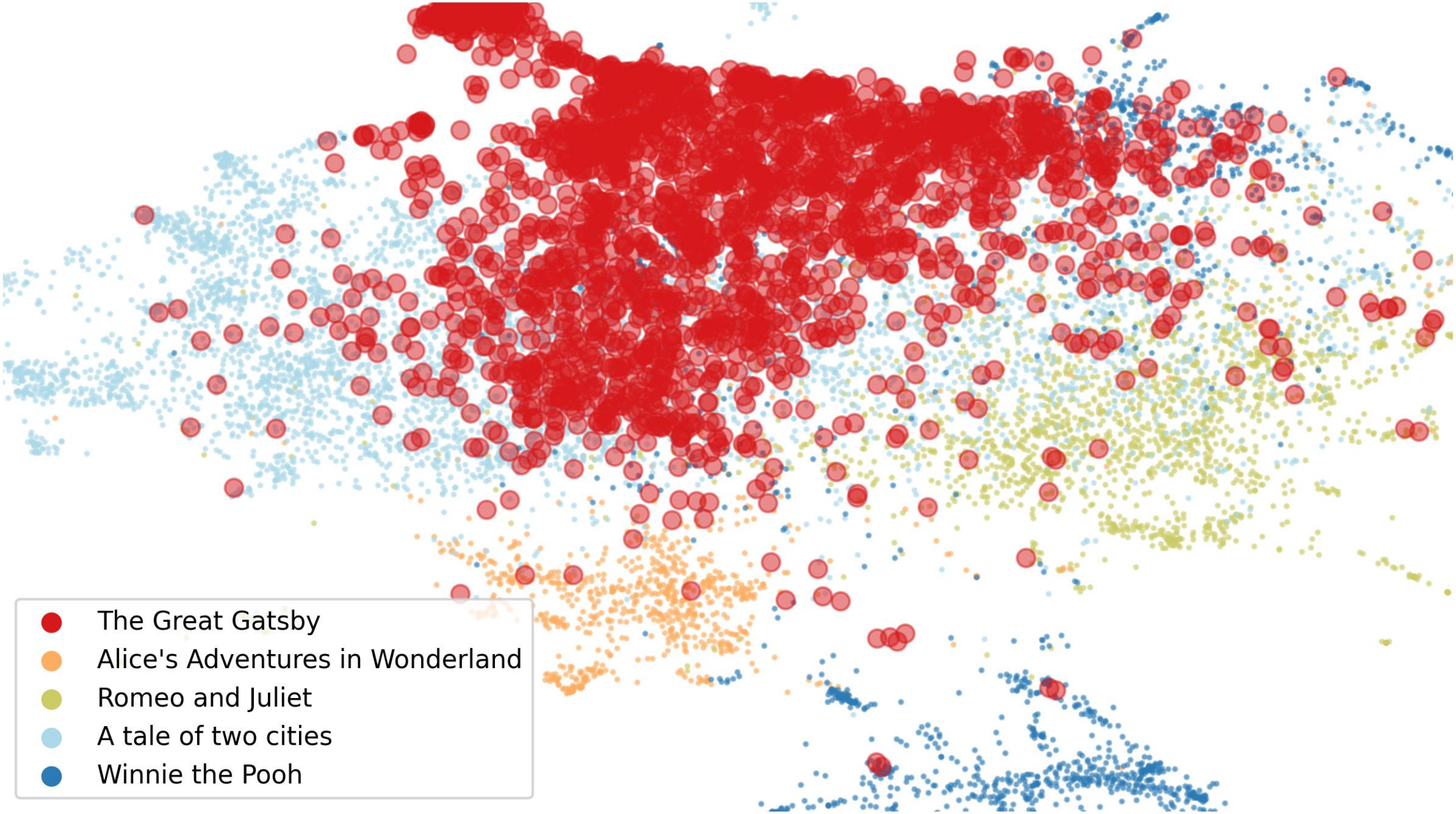
Alice's Adventures in Wonderland
Romeo and Juliet
A tale of two cities
Winnie the Pooh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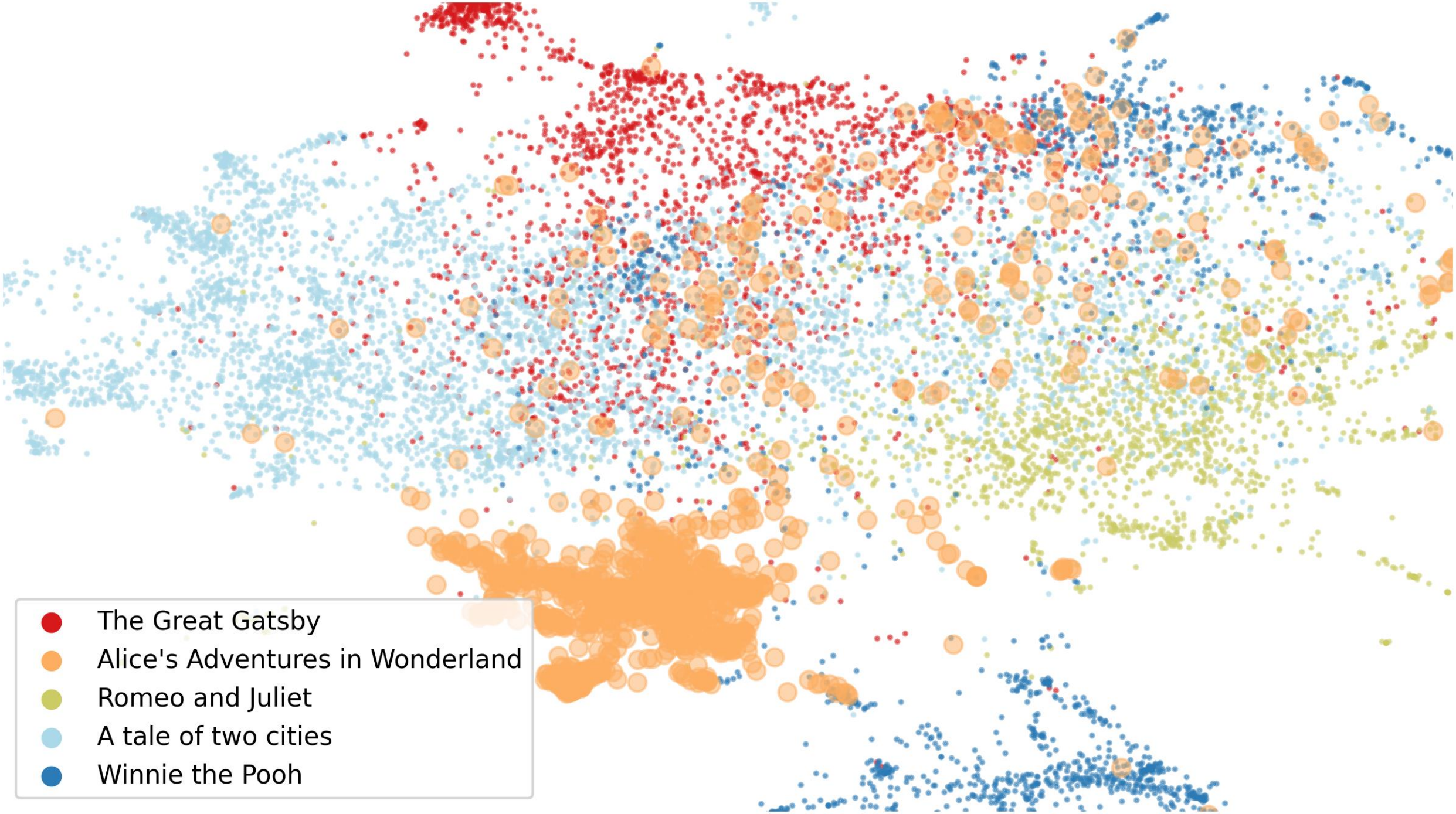
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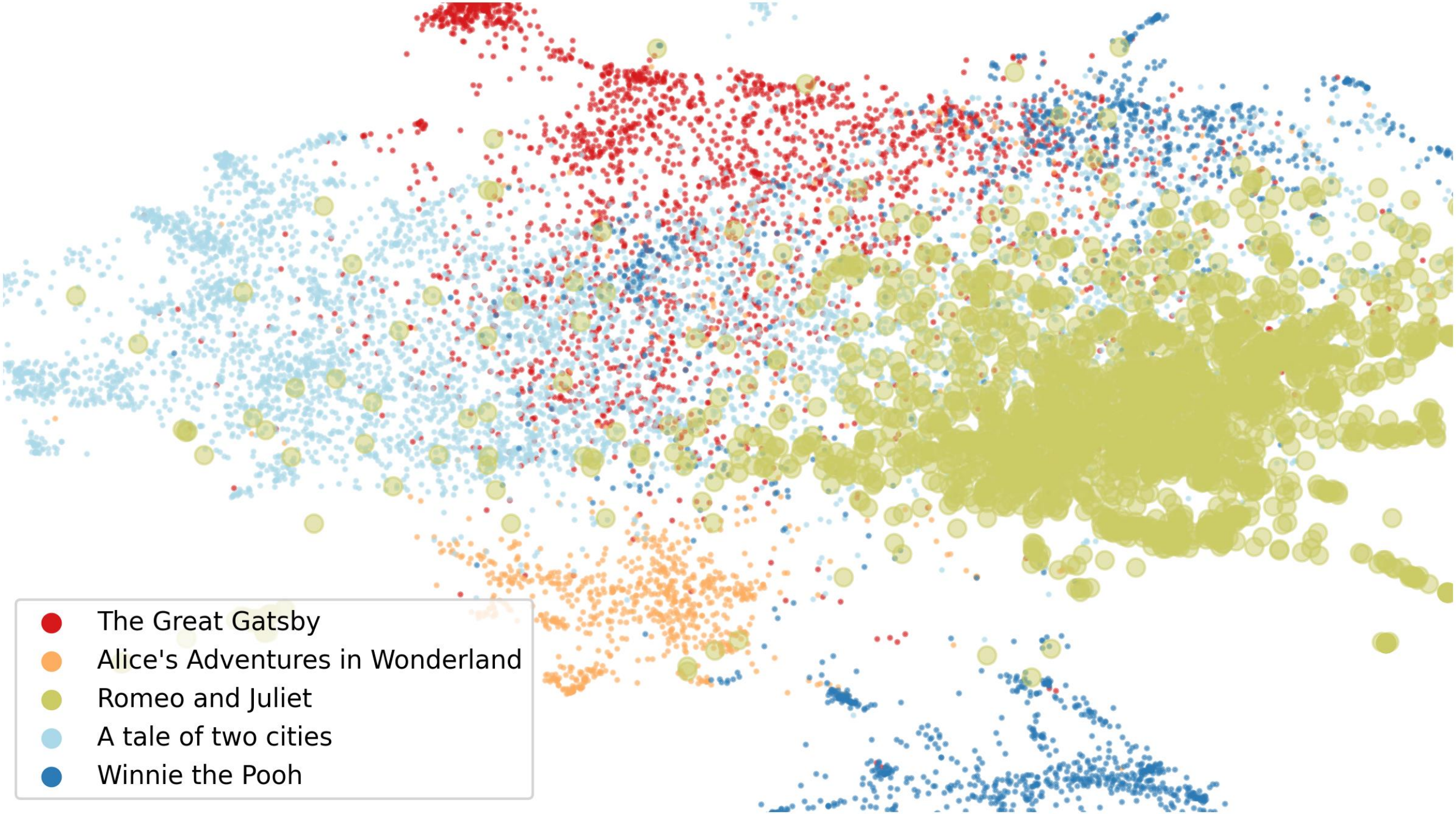
Winnie the Pooh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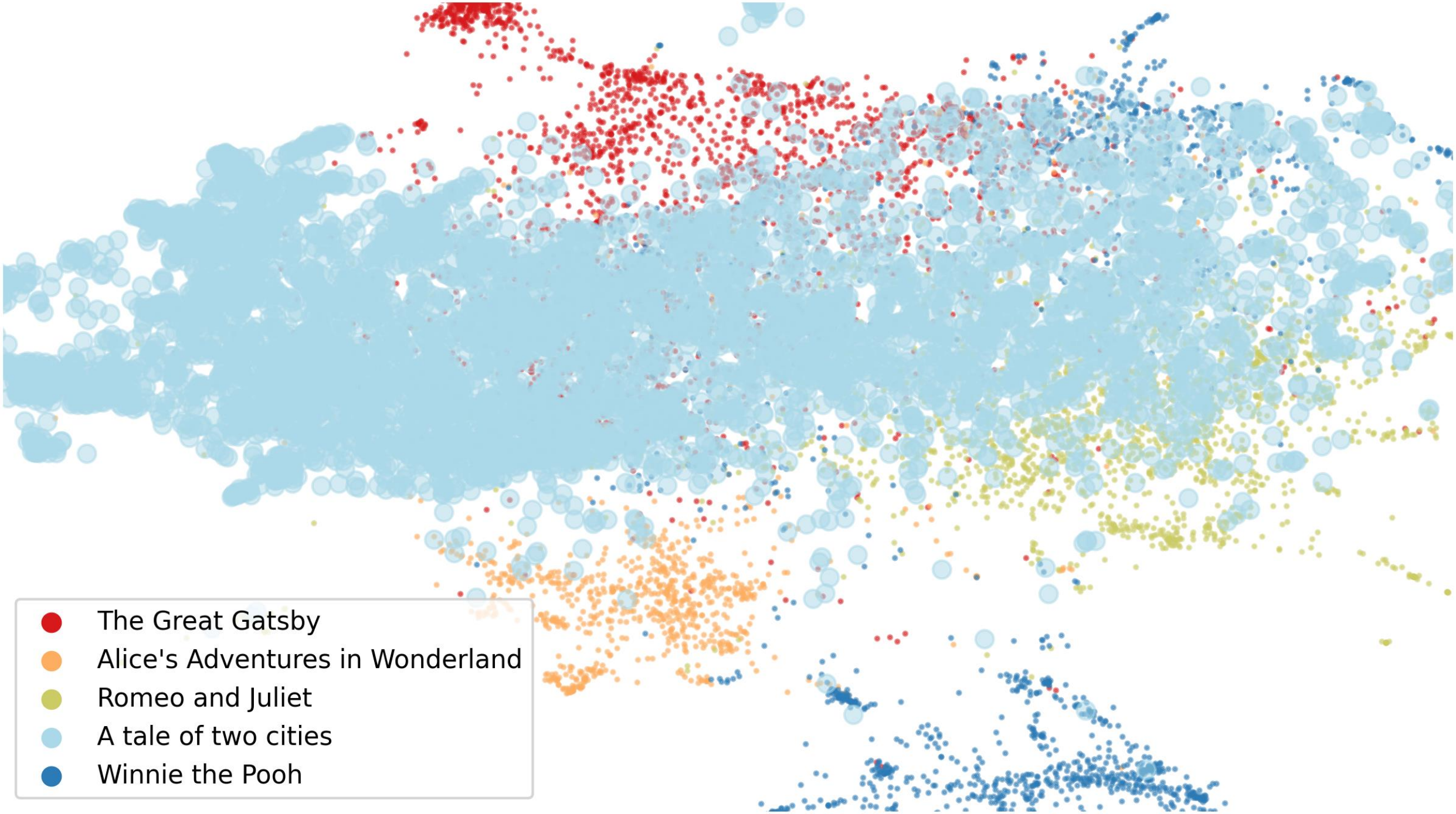
A tale of two cities
Winnie the Pooh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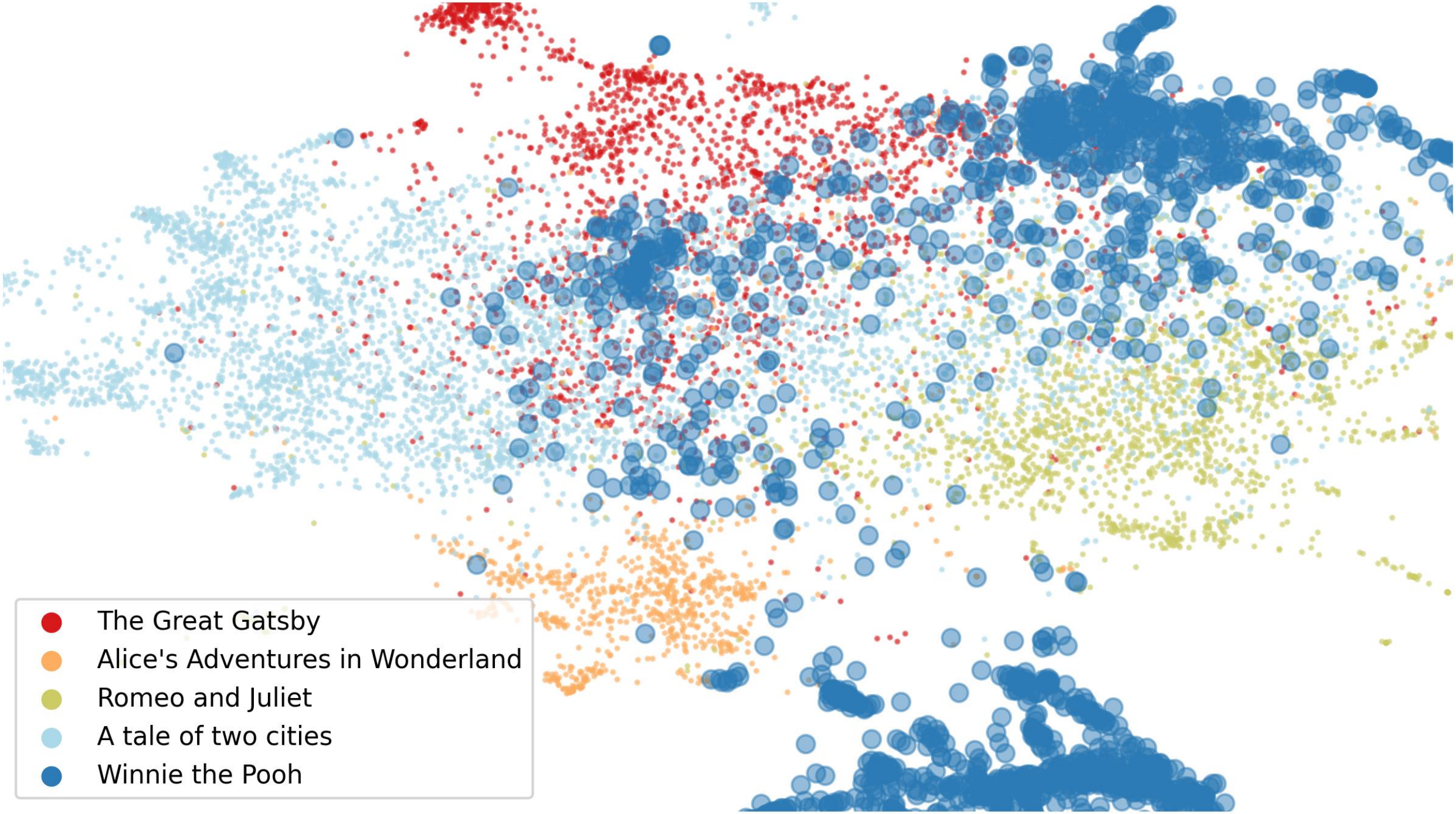
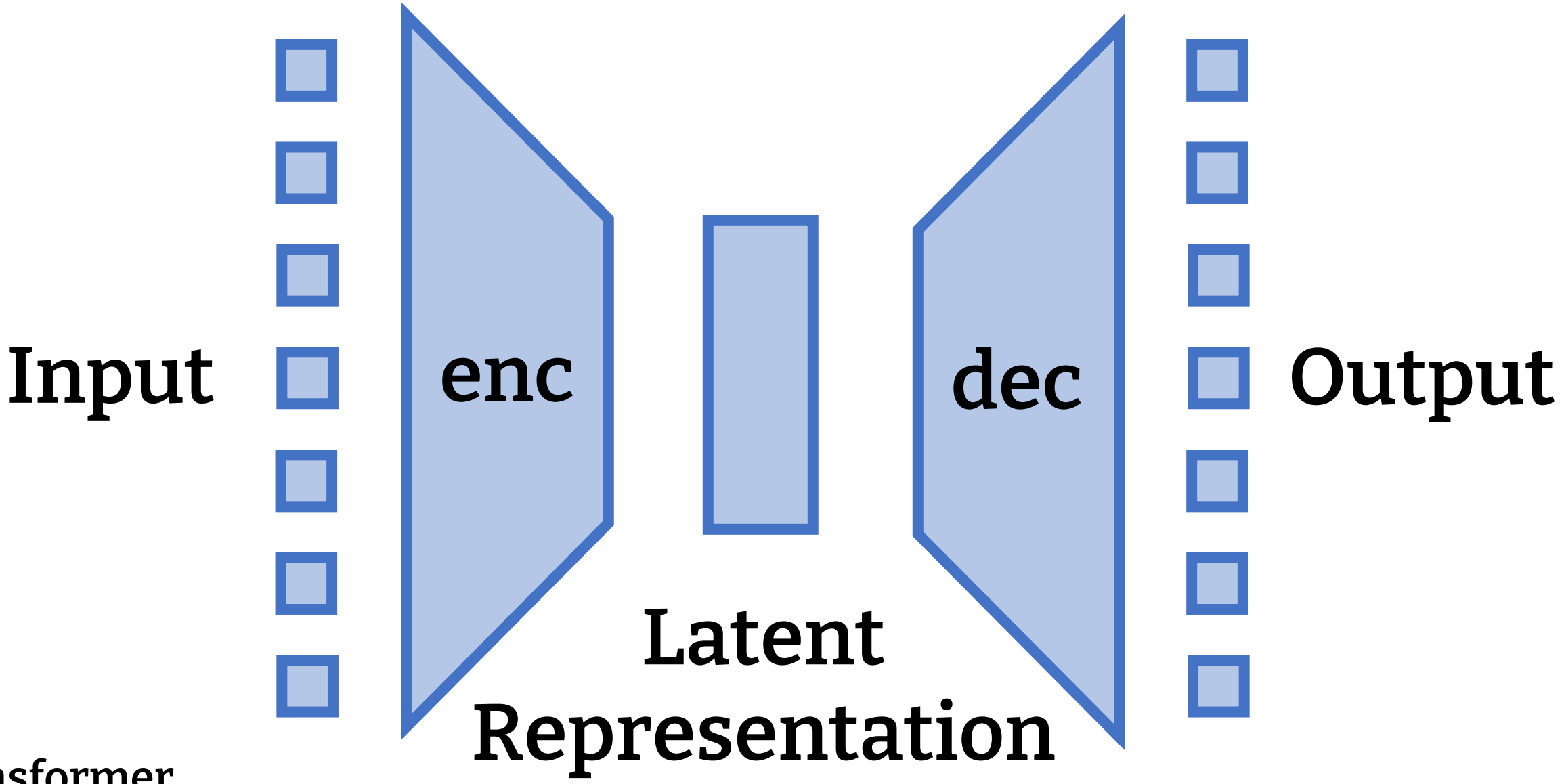
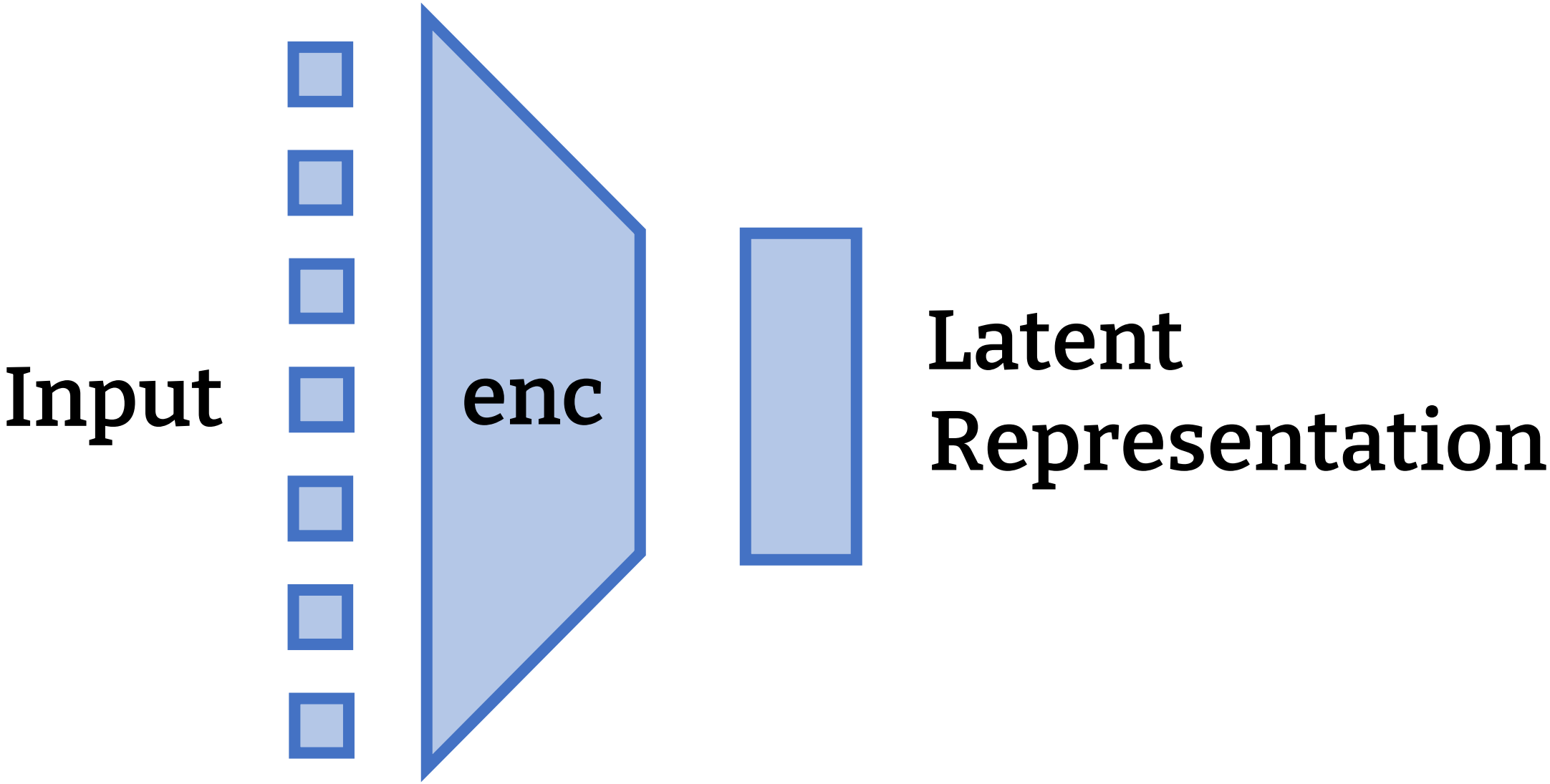

The Great Gatsby
Alice's Adventures in Wonderland
Romeo and Juliet
A tale of two cities
Winnie the Pooh

Attention

Encoder-Decoder

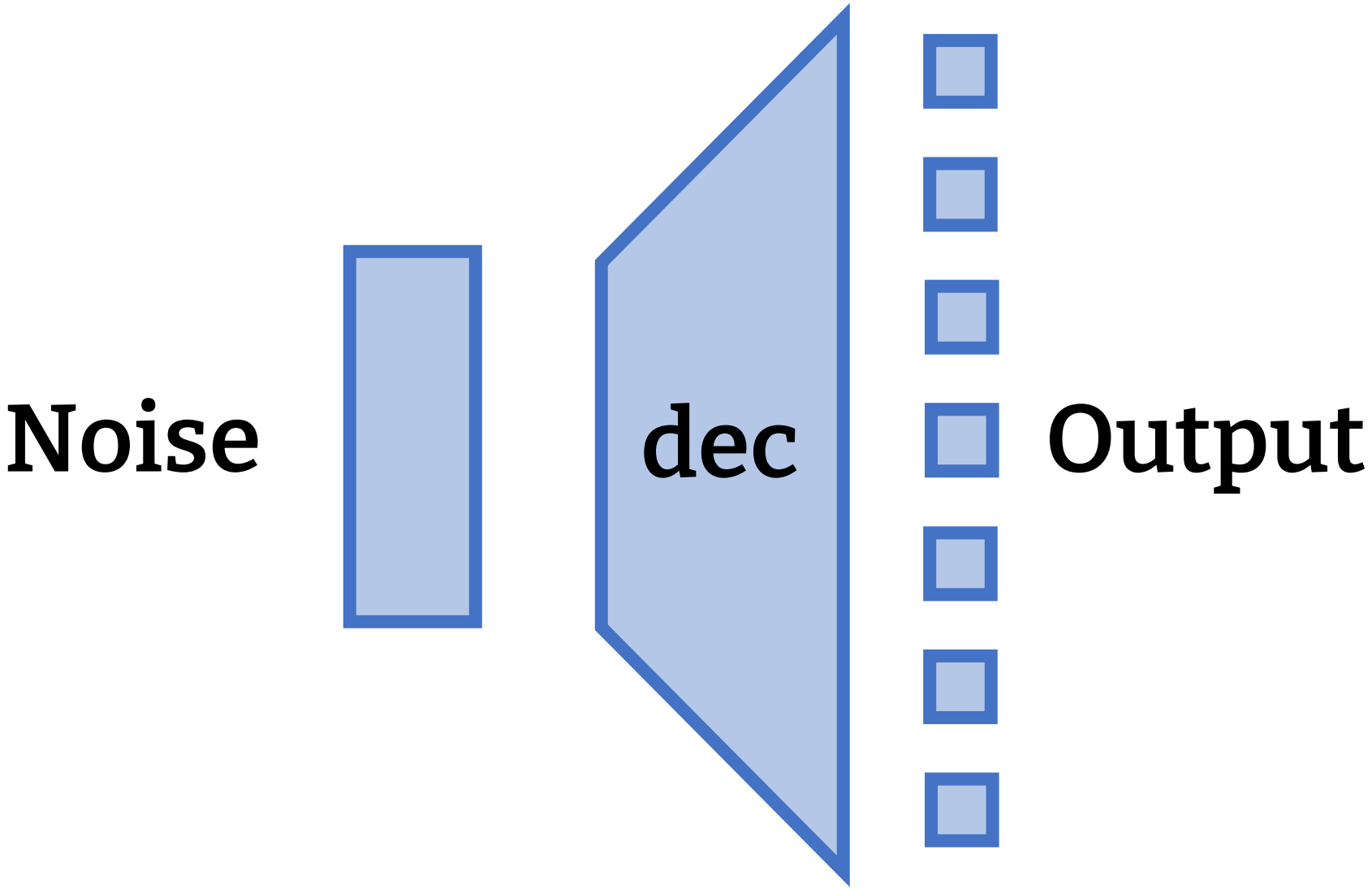


Encoder-only



BERT

Decoder-only



GPT

Differentiable hash table

q: query, row vector
K: keys, one per row
V: values, one per row

$$\mathrm{Att}(q, K, V) = \mathrm{softmax}(q K') V$$

Attention

Q: queries, one per row
K: keys, one per row
V: values, one per row

$$\text{Att}(Q, K, V) = \text{softmax}(Q K') V$$

Attention

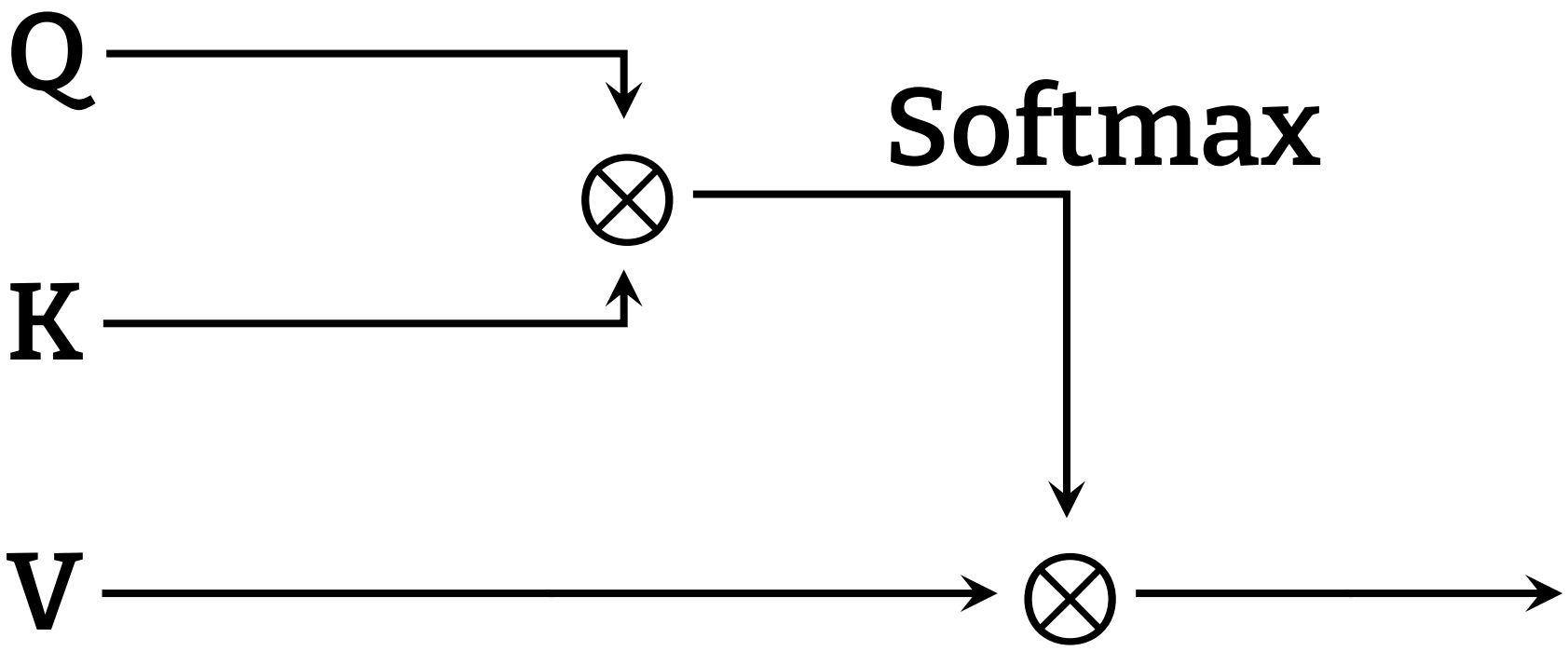
Q: queries, one per row

K: keys, one per row

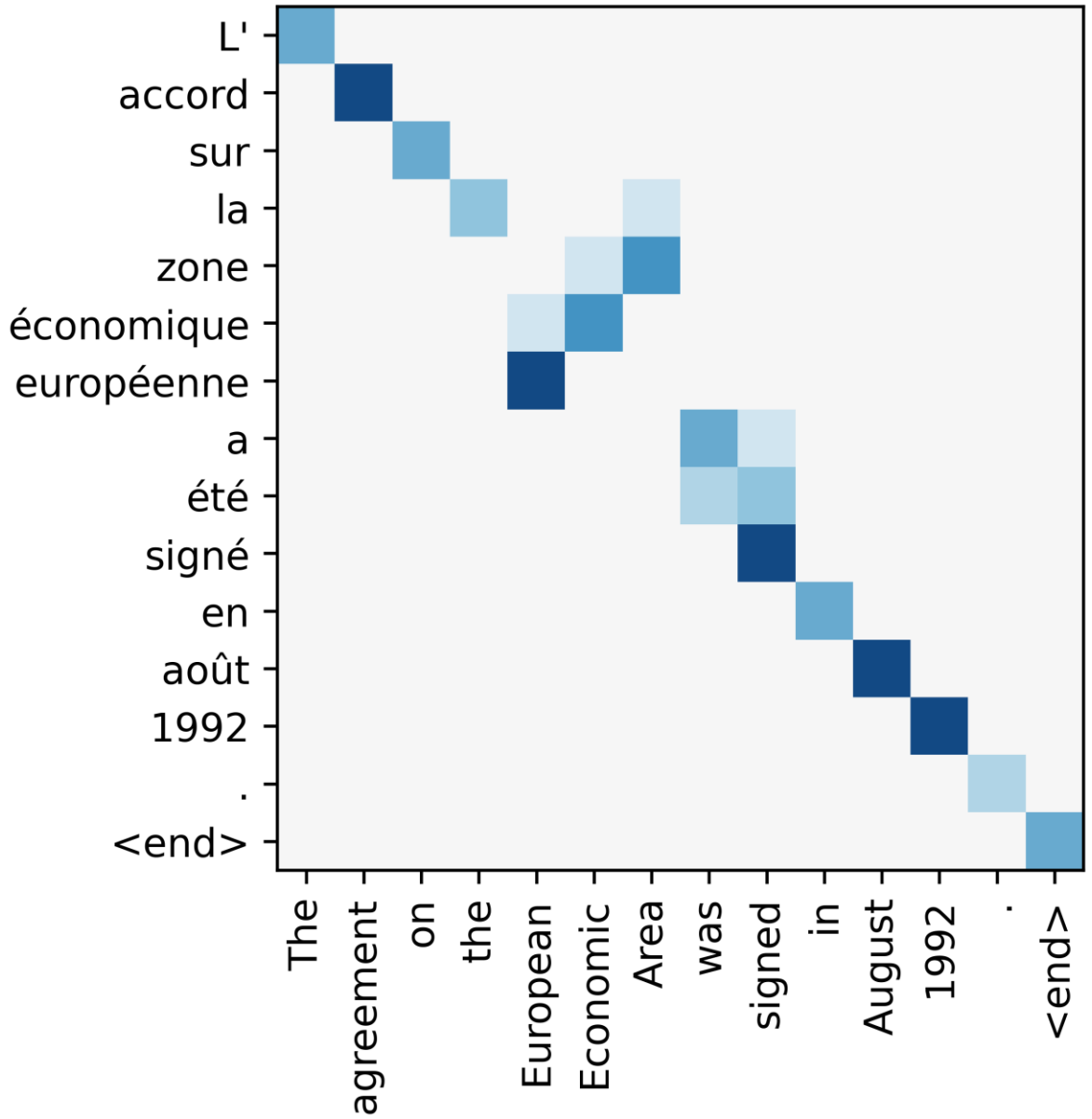
V: values, one per row

$$\text{Att}(Q, K, V) = \text{softmax}(\frac{Q K'}{\sqrt{d}}) V$$

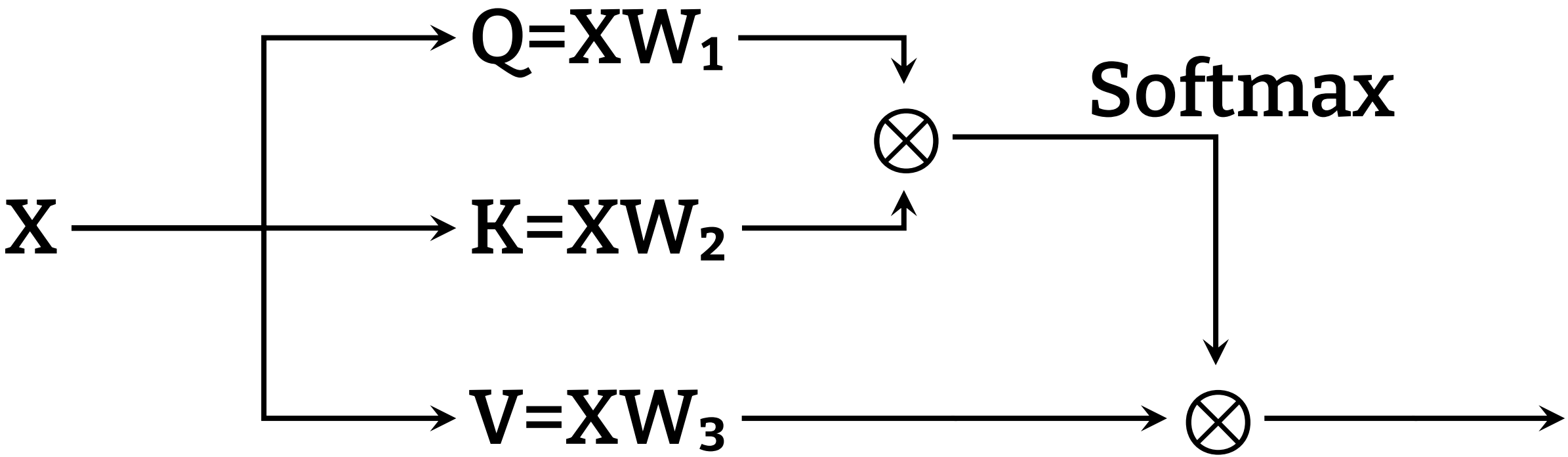
Attention



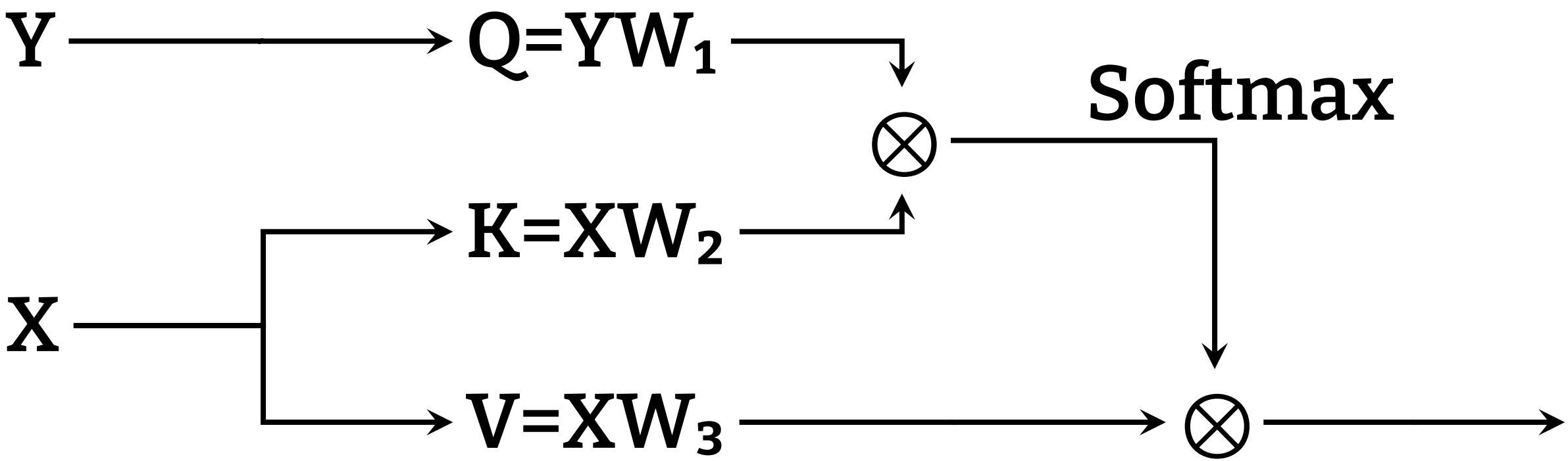
Attention Matrix



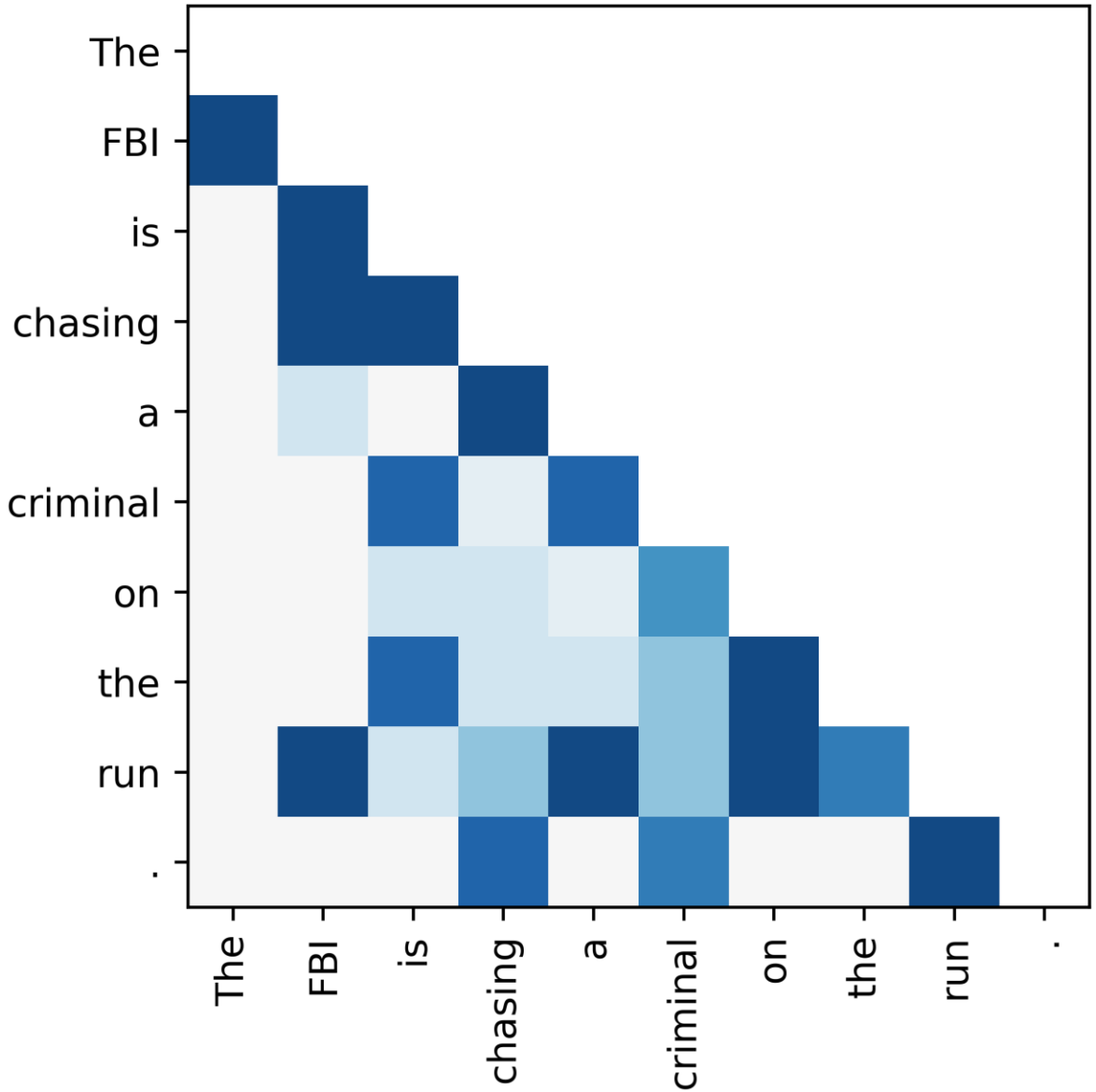
Self-Attention



Cross-Attention

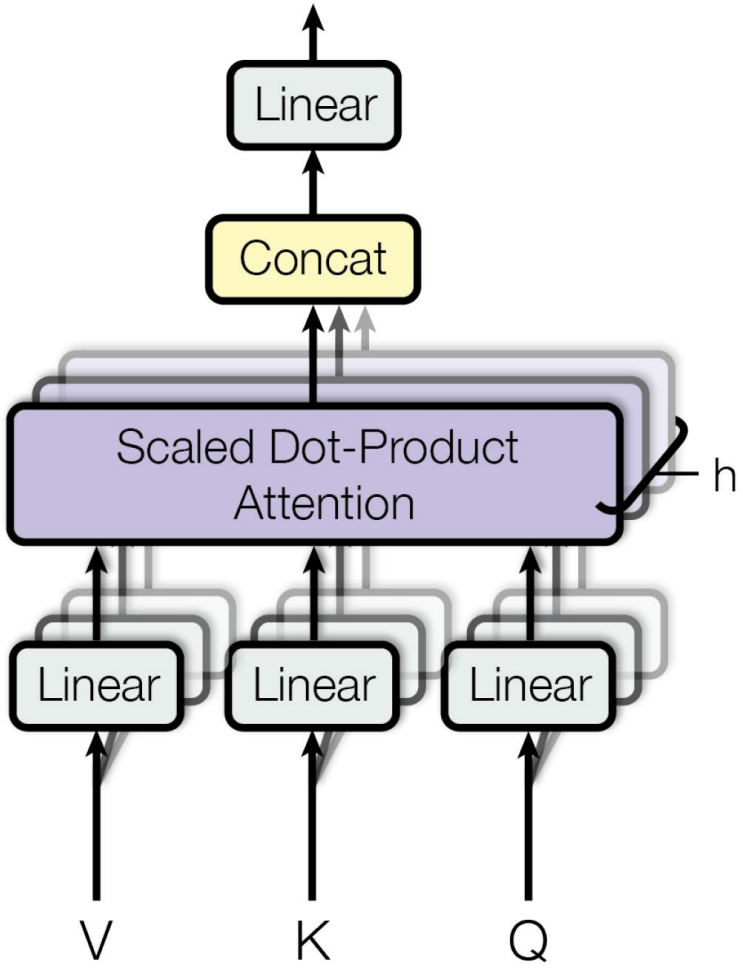


Masked Self-Attention



Multi-Head Self-Attention

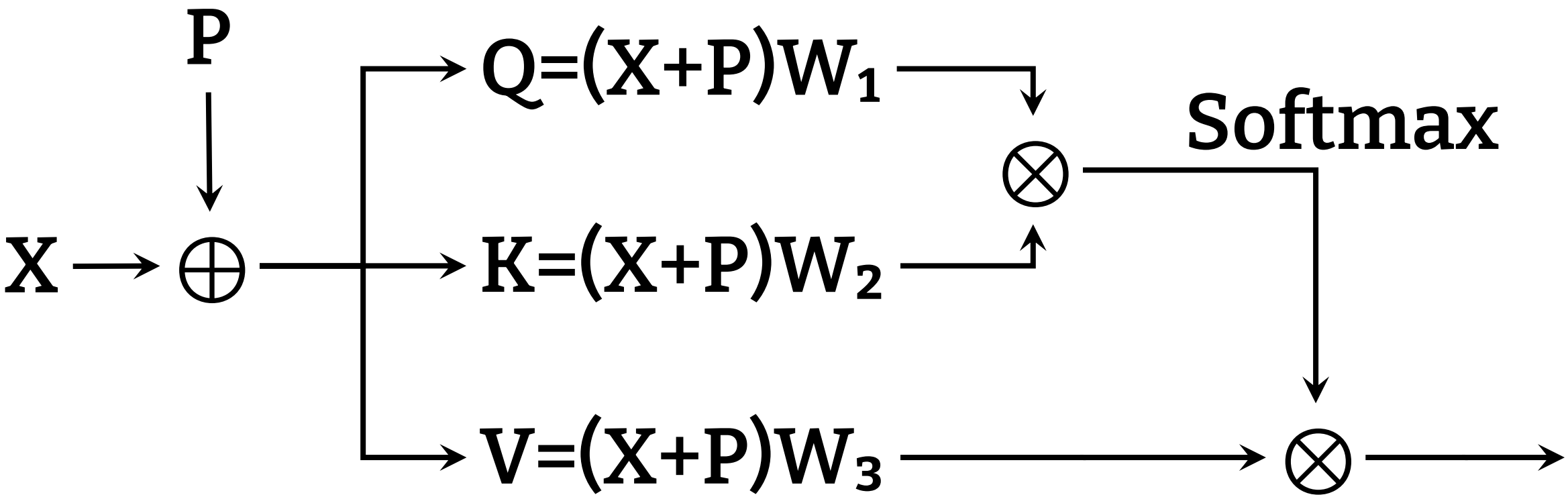
- Several self-attention blocks in parallel



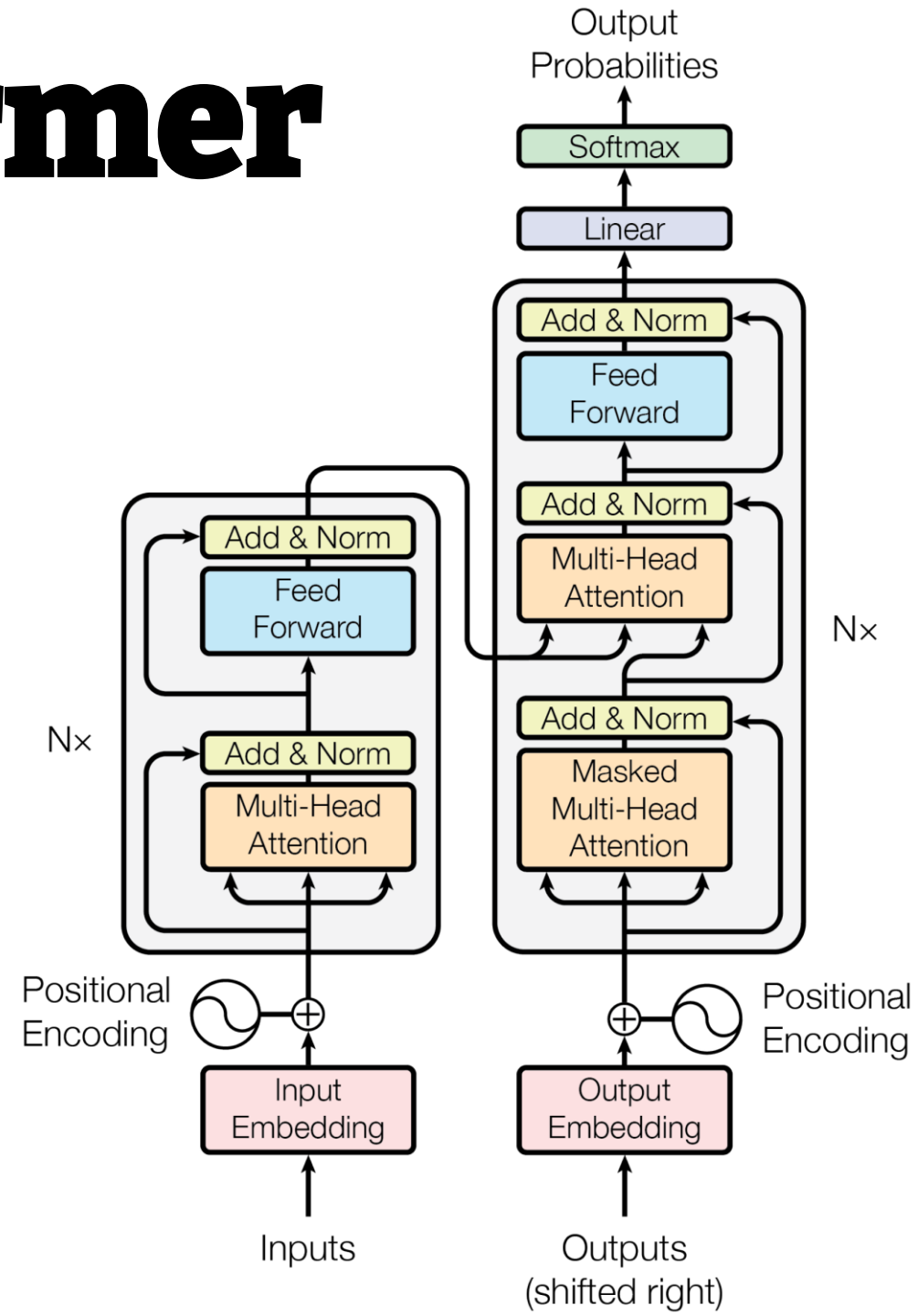
Positional Encoding

- Attention is permutation-invariant
- Add $\sin(k \cdot i \cdot 2\pi/N)$ and $\cos(k \cdot i \cdot 2\pi/N)$ as features, for token $i \in [\![1, N]\!]$, for a few values of k
- Often, just added to X

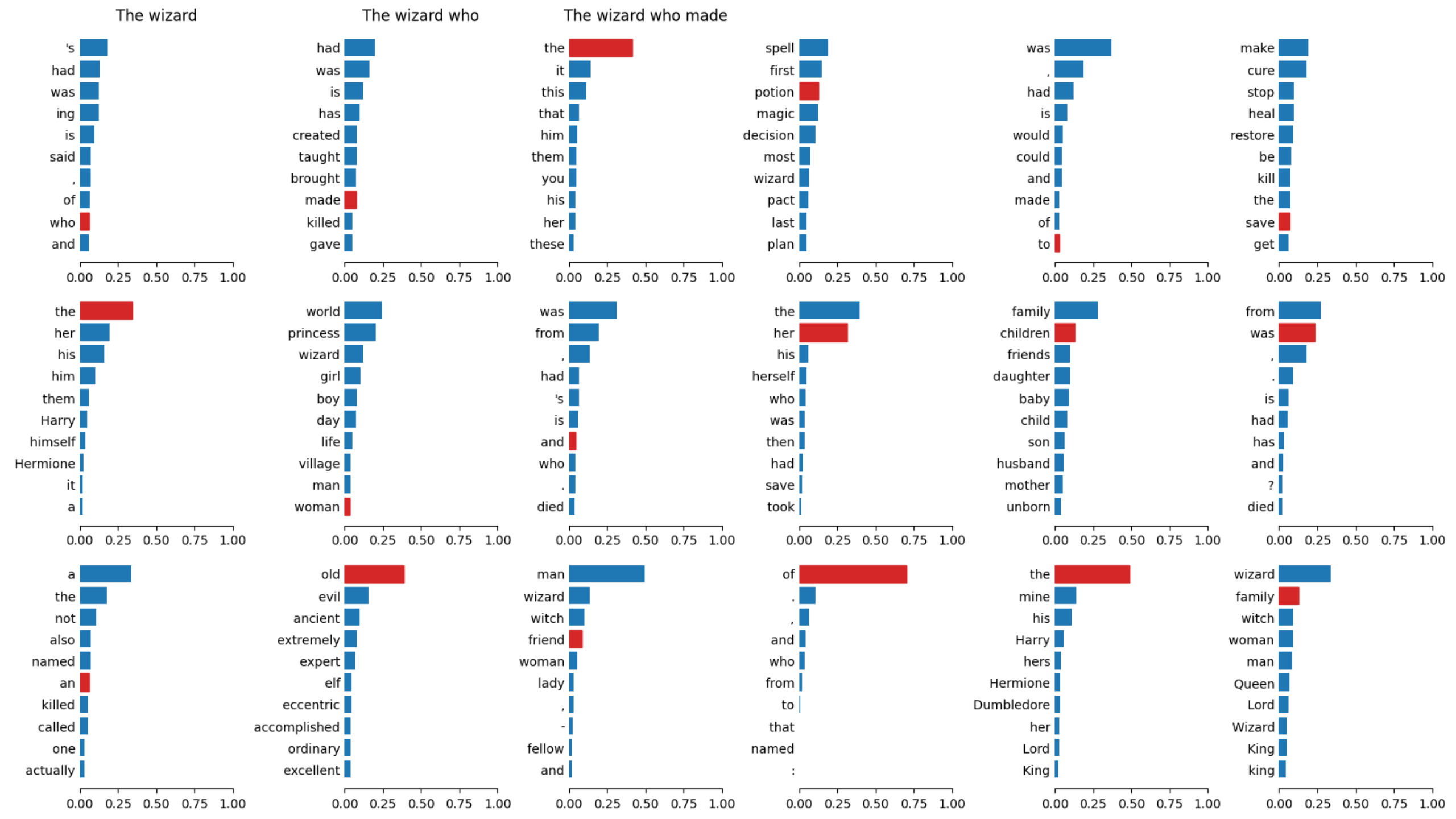
Positional Encoding



Transformer



Unused Slides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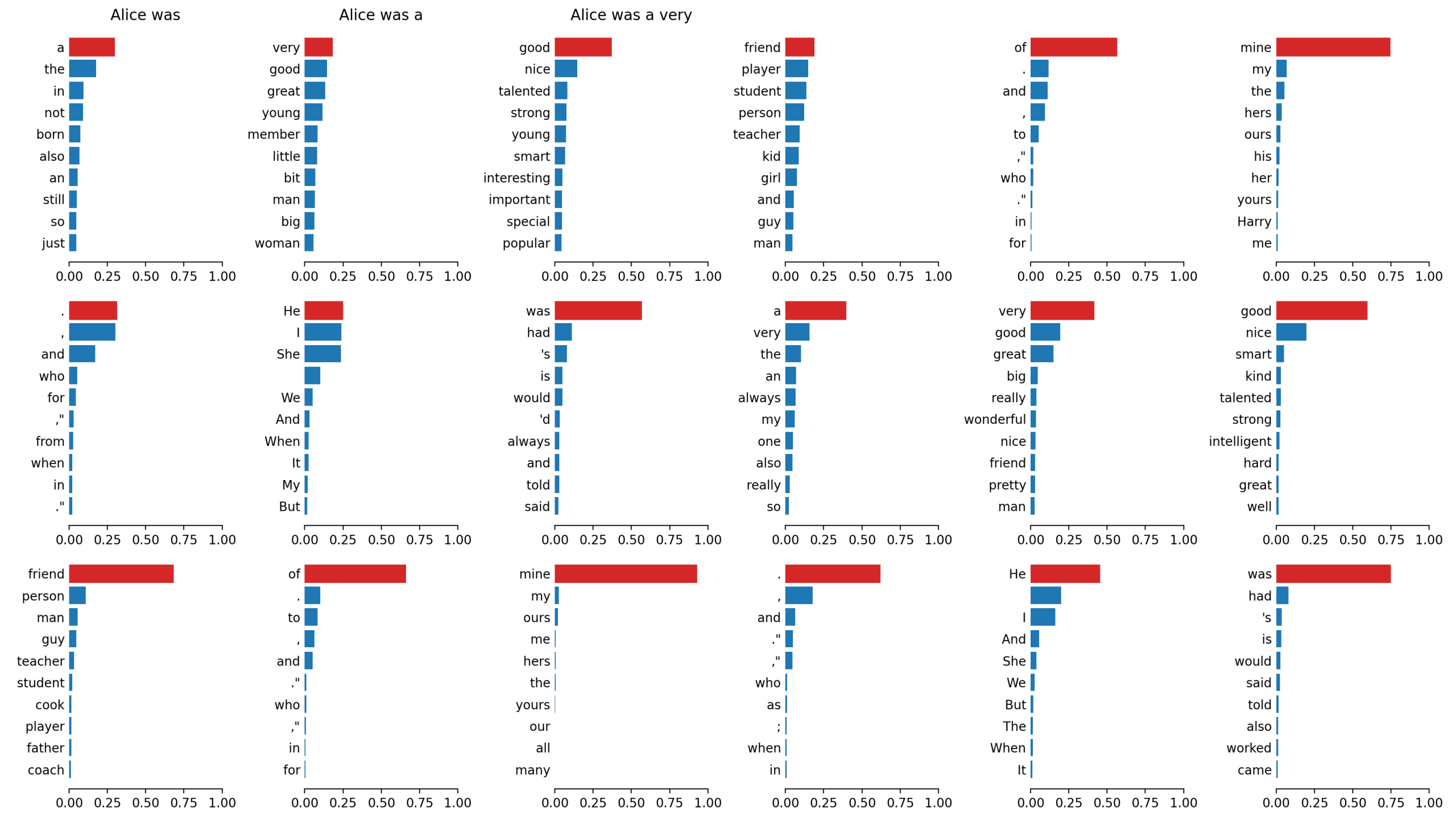
Most likely next word

Alice was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very good friend of mine. He was a very


Alice was
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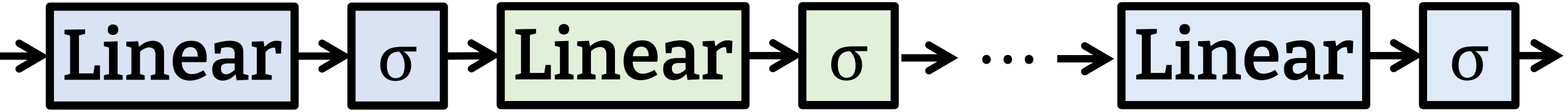
MLP: several layers



Contextual embeddings

central bank

river bank

power bank









Token embeddings

Contextual embeddings

It

was

the

best

of

times

Contextual embeddings

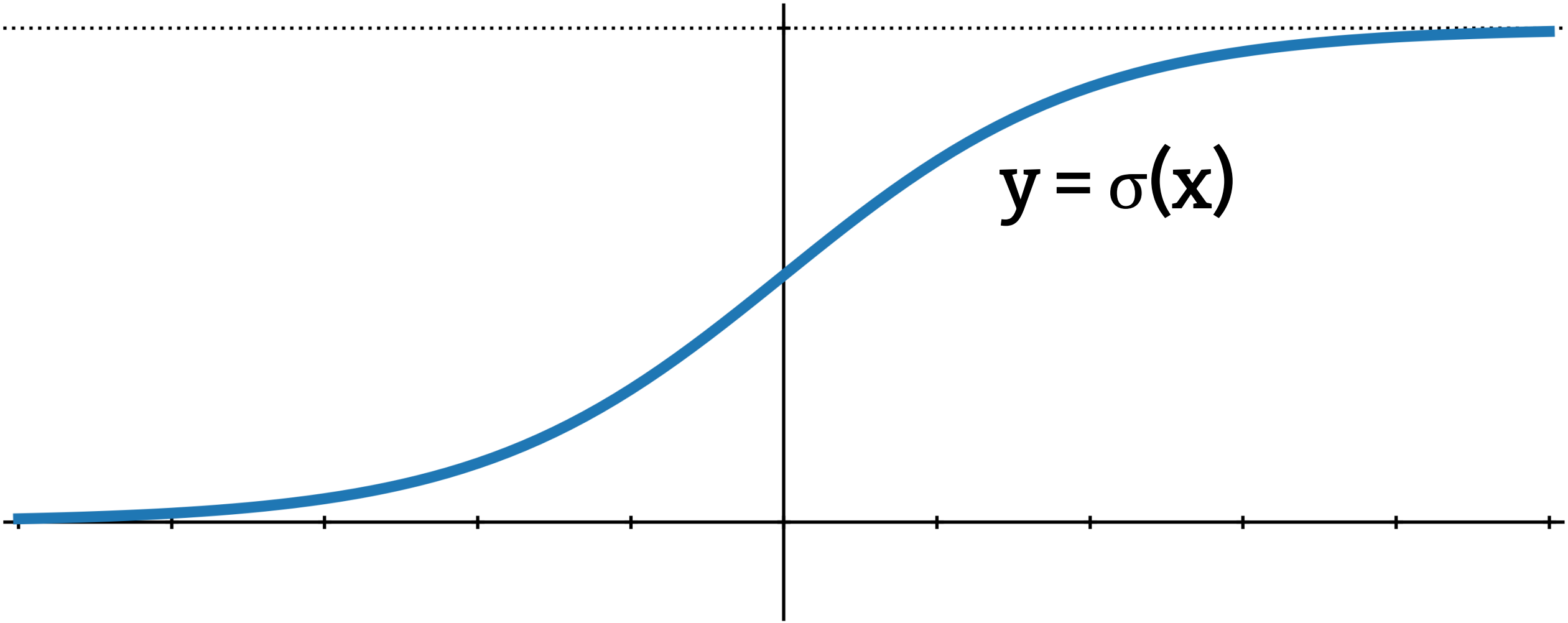
Contextual embeddings

Contextual embeddings

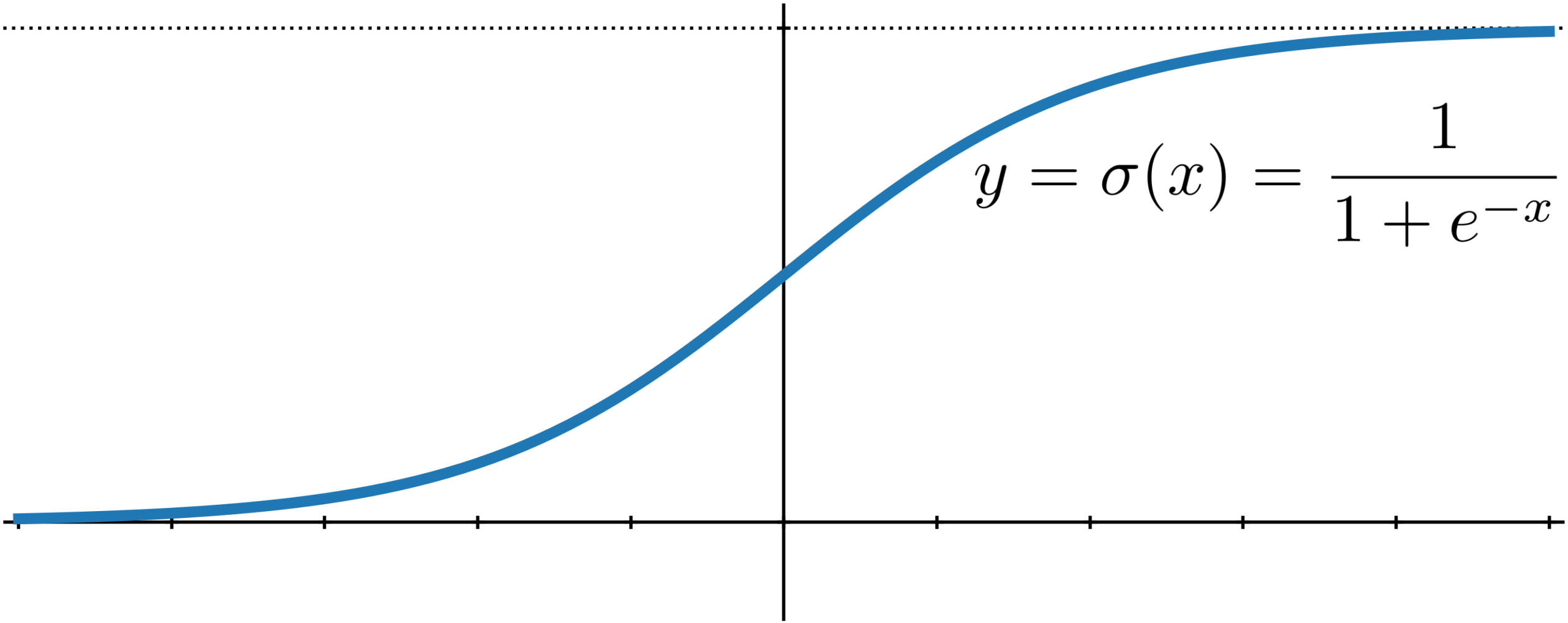
Contextual embeddings

Contextual embeddings

Sigmoid function



Sigmoid function



Training

- TODO?