Deep Learning

GPT and Attention

What is Natural Language Processing (NLP)?

- Subfield of AI that focuses on reading, deciphering and producing human language
- Combines computational linguistics (e.g. rule-based modelling of language) with statistical, ML, and deep learning approaches
- Through NLP, machines can understand, analyze and generate language in ways that are meaningful and contextually appropriate
- While LLMs have driven an explosion in interest, there are many older technologies which paved the way

Common Applications

- **Text Classification:** e.g. spam detection, news classification
- **Question Answering:** processing input and finding relevant information
- **Machine Translation**
- **Sentiment Analysis**
- **Code Generation**

Challenges in NLP

- **Ambiguity:** Words can mean different things depending on context
- **Nuances:** Languages are full of idioms, slang, cultural references, sarcasm…
- **Syntax vs Semantics:** A grammatically correct sentence might not make sense, or a grammatically incorrect one might be easy to understand

- I saw a man on the hill with the telescope
- That’s a cool cat
- Colourless green ideas sleep furiously
- Me went store

Challenges in NLP

Quick history of NLP

- **1950s:**
  - Alan Turing publishes “Computing Machinery and Intelligence”, in which he proposes the Turing test
  - Noam Chomsky publishes “Syntactic Structures”, an attempt to construct a formal theory of linguistic structure
- **1960s:**
  - Georgetown University develops a machine translation system, which automatically translates 60 Russian sentences into English using an extremely complex flowchart and a limited vocabulary
  - The authors claim machine translation could be a solved problem in five years

Quick history of NLP

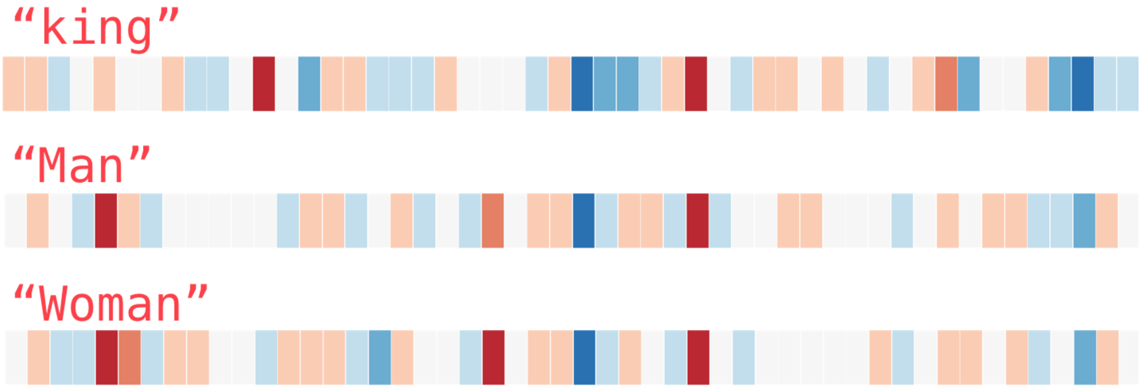
- **1980s – 1990s:**
  - Transition from rule-based to statistical approaches
  - Idea of using existing text to train a model begins to appear (e.g. bilingual documents from the Canadian parliament)
- **2000s – 2010s:**
  - Deep Learning takes over
  - Tools such as convolutional networks, and later RNNs, transform the field
- **2020s: The era of the Large Language Model**

Foundations of LLMs

- Fundamental goal of language modelling: next word prediction
- $P(cat \mid the\ dog\ and\ the)$
- To generate, pick the word with highest likelihood
- Early models could handle one, two words of context
- Locally coherent, but longer texts quickly lose meaning
- More context requires more complexity!

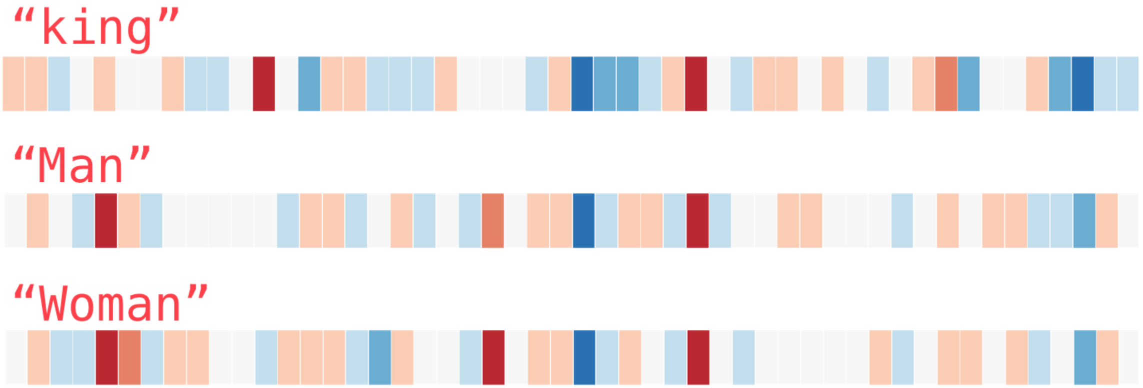
How does an LM “understand” word meaning?

- In order to predict the likelihood of a word, we must have some sense of its meaning
- Some words have similar meanings, and can easily fit in the same place
- In the same way CNNs convert an image into a set of feature maps, we can convert a word into a set of abstract linguistic features
- Word2Vec: 300 features
- GPT-3: 12,888

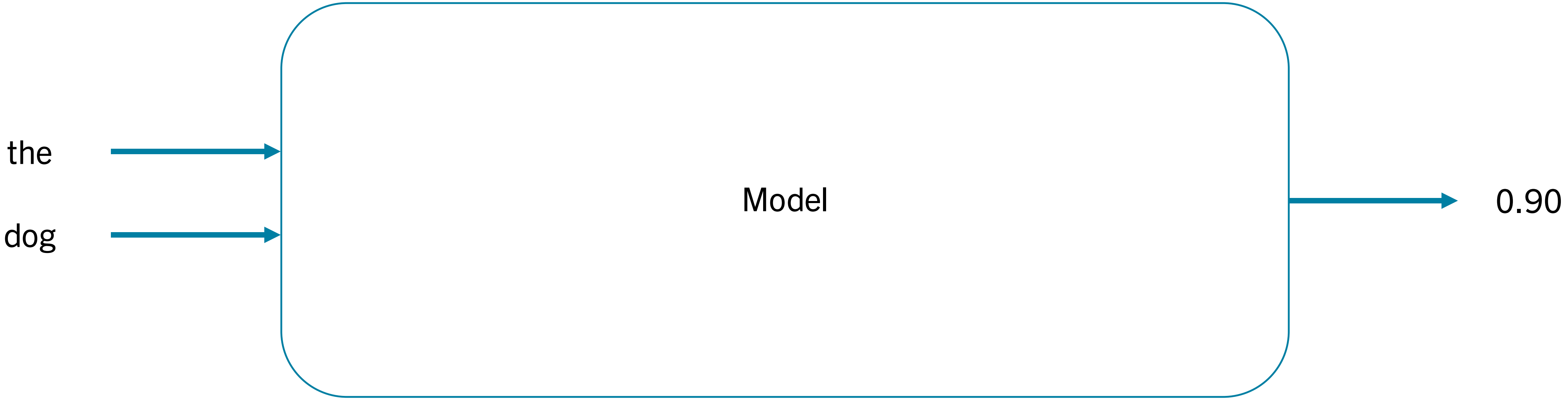


How does an LM “understand” word meaning?

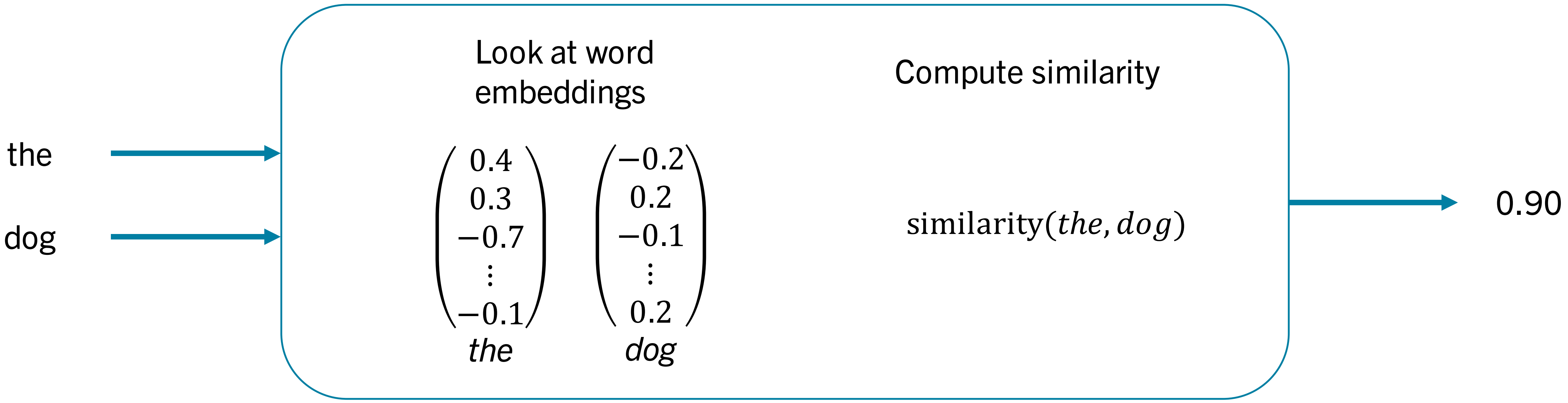
- Key concept of word embeddings: similar words should have similar vectors
- How do we accomplish this?



Building Word Embeddings



Building Word Embeddings



the

dog

Look at word embeddings

$$\begin{pmatrix} 0.4 \\ 0.3 \\ -0.7 \\ \vdots \\ -0.1 \end{pmatrix} \quad \begin{pmatrix} -0.2 \\ 0.2 \\ -0.1 \\ \vdots \\ 0.2 \end{pmatrix}$$

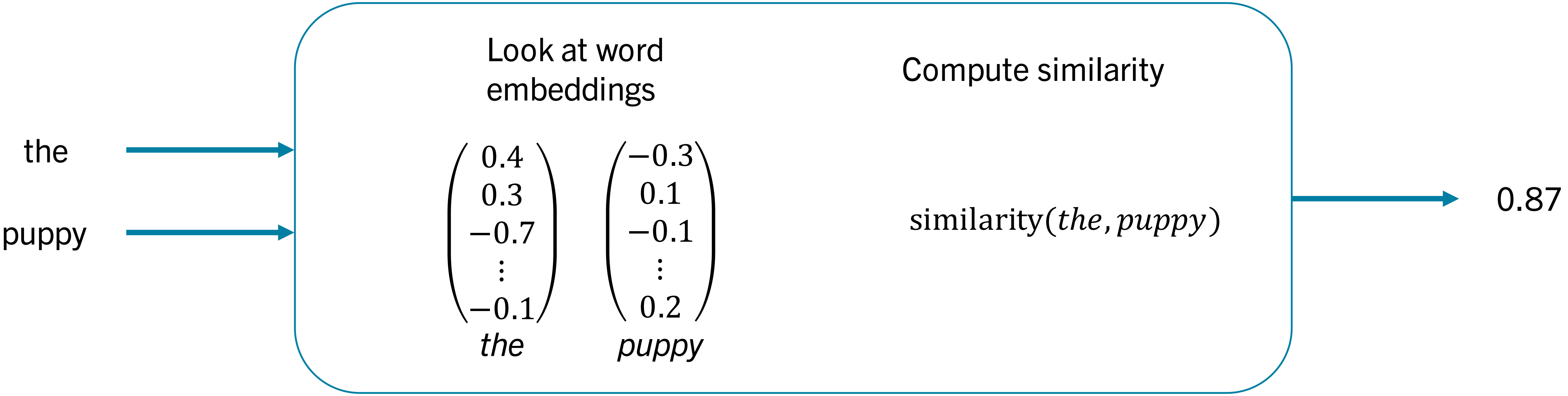
the *dog*

Compute similarity

$\text{similarity}(the, dog)$

0.90

Building Word Embeddings



the

puppy

Look at word embeddings

$$\begin{pmatrix} 0.4 \\ 0.3 \\ -0.7 \\ \vdots \\ -0.1 \end{pmatrix} \quad \begin{pmatrix} -0.3 \\ 0.1 \\ -0.1 \\ \vdots \\ 0.2 \end{pmatrix}$$

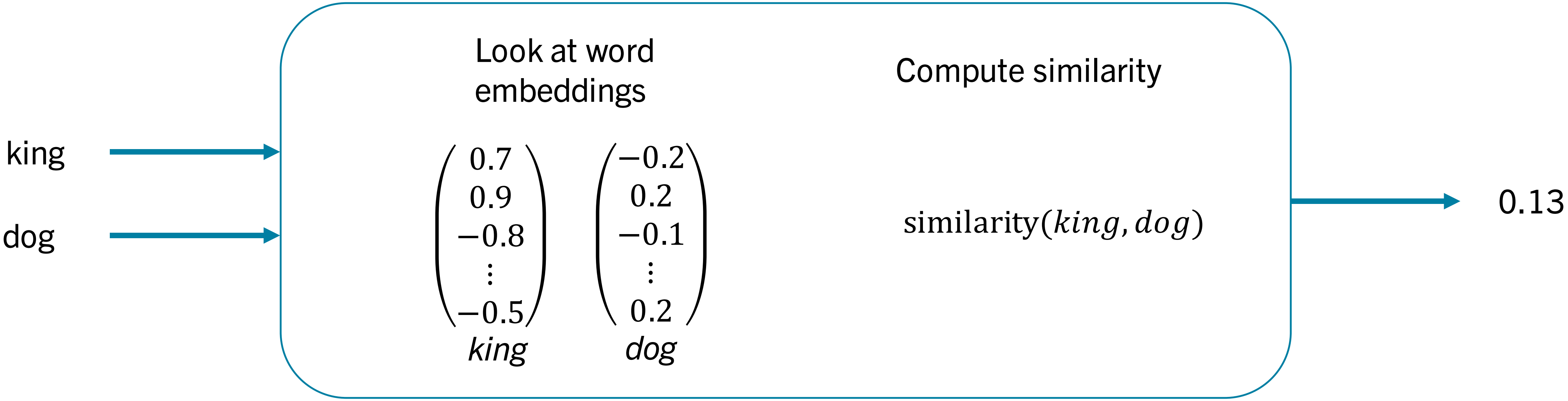
the *puppy*

Compute similarity

$$\mathrm{similarity}(\mathit{the}, \mathit{puppy})$$

0.87

Building Word Embeddings



king

dog

Look at word embeddings

$$\begin{pmatrix} 0.7 \\ 0.9 \\ -0.8 \\ \vdots \\ -0.5 \end{pmatrix} \qquad \begin{pmatrix} -0.2 \\ 0.2 \\ -0.1 \\ \vdots \\ 0.2 \end{pmatrix}$$

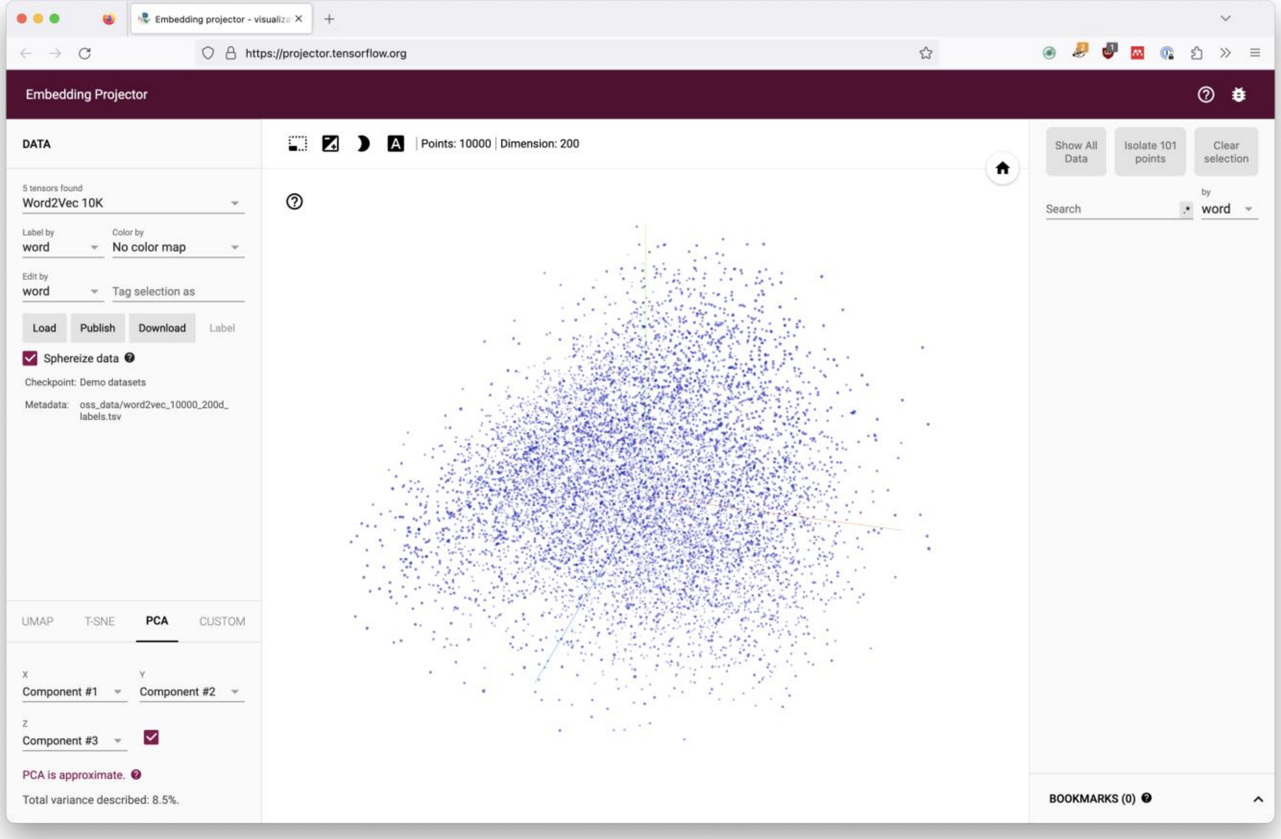
king *dog*

Compute similarity

$$\text{similarity}(king, dog)$$

0.13

Results



Points: 10000 | Dimension: 200

5 tensors found: Word2Vec 10K

Label by: word

Color by: No color map

Edit by: word

Tag selection as

☑ Sphereize data

Checkpoint: Demo datasets

Metadata: oss_data/word2vec_10000_200d_labels.tsv

X: Component #1

Y: Component #2

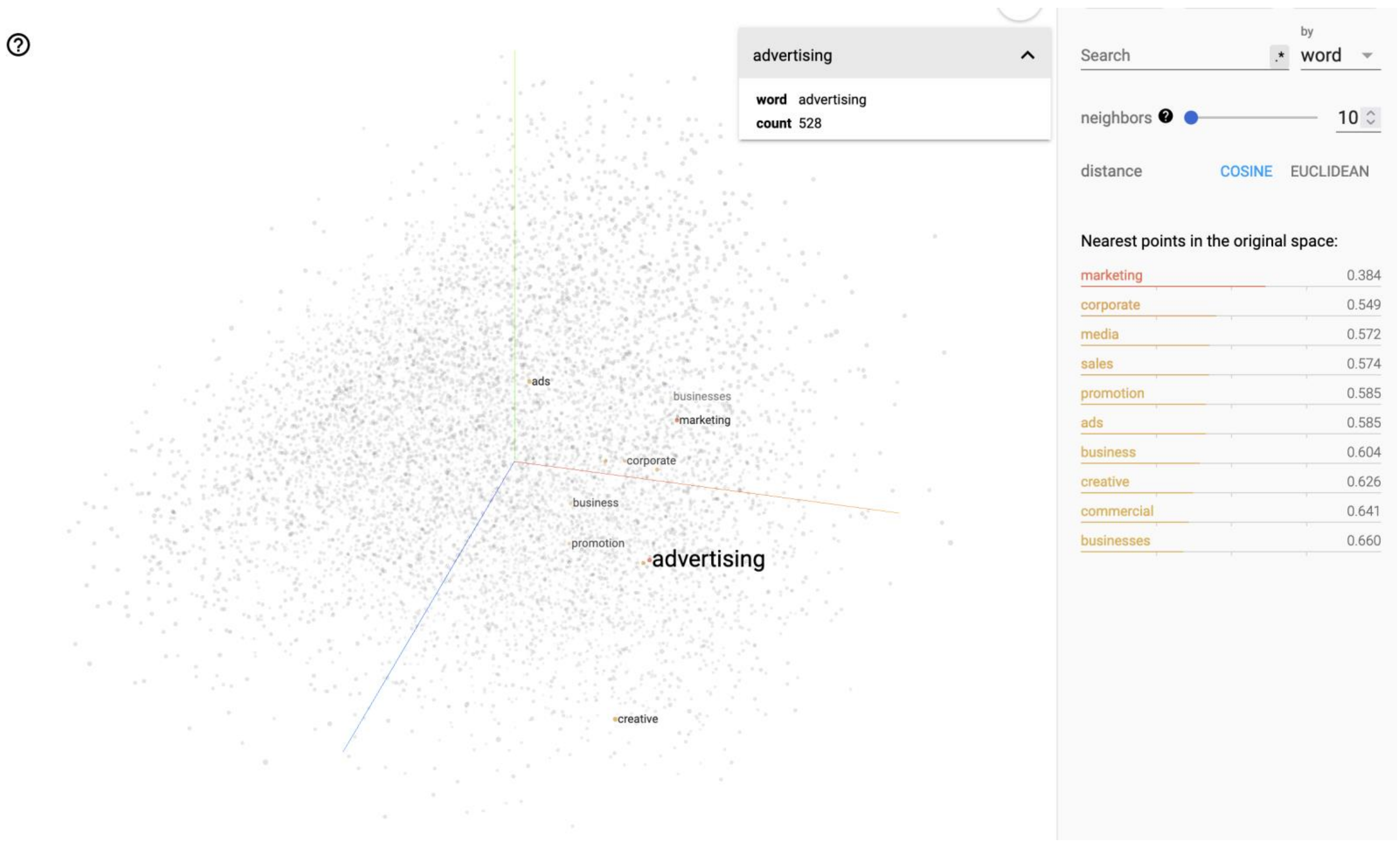
Z: Component #3 ☑

PCA is approximate.

Total variance described: 8.5%.

Search by: word

Results



advertising

word advertising
count 528

Search .* by word

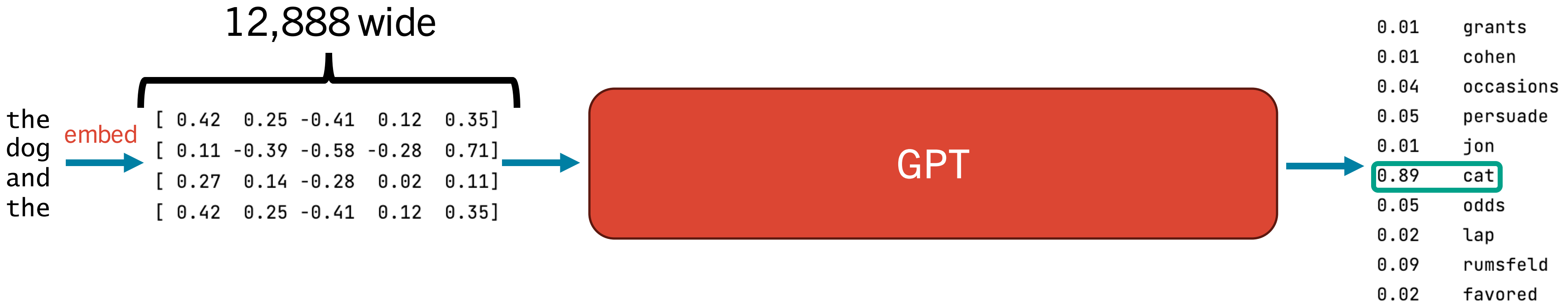
neighbors 10

distance COSINE EUCLIDEAN

Nearest points in the original space:

marketing	0.384
corporate	0.549
media	0.572
sales	0.574
promotion	0.585
ads	0.585
business	0.604
creative	0.626
commercial	0.641
businesses	0.660

Building GPT



12,888 wide

```
the
dog
and
the
```

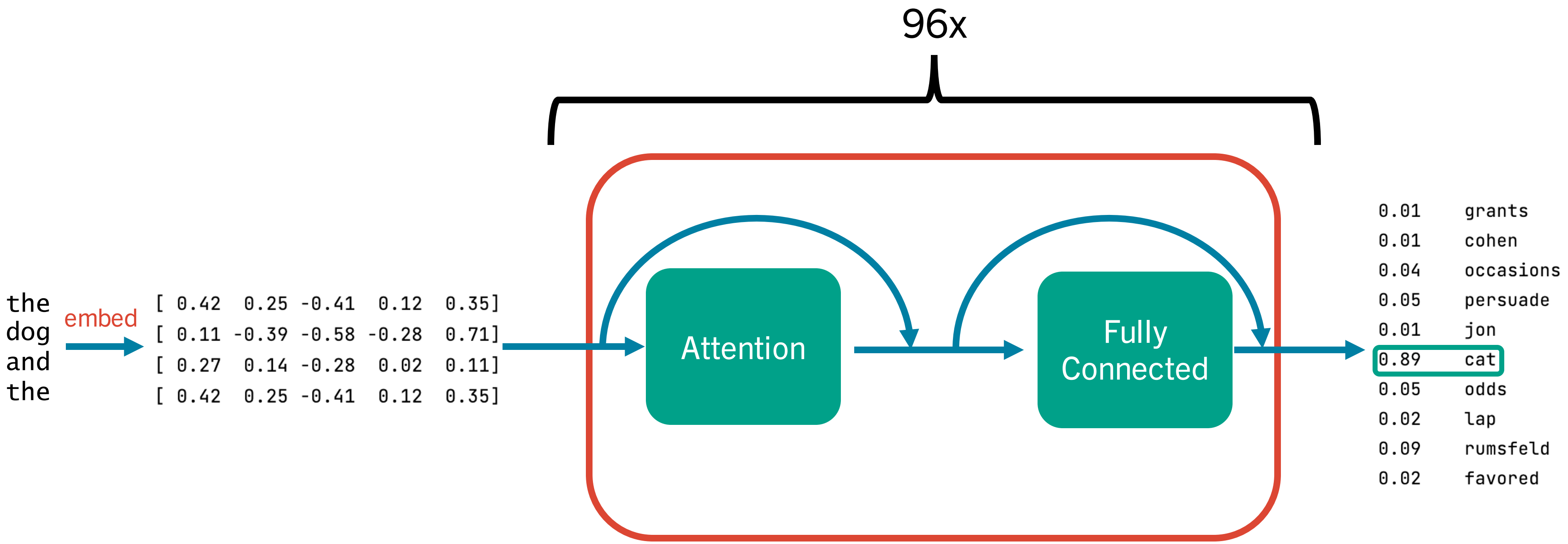
embed

```
[ 0.42  0.25 -0.41  0.12  0.35]
[ 0.11 -0.39 -0.58 -0.28  0.71]
[ 0.27  0.14 -0.28  0.02  0.11]
[ 0.42  0.25 -0.41  0.12  0.35]
```

GPT

0.01	grants
0.01	cohen
0.04	occasions
0.05	persuade
0.01	jon
0.89	cat
0.05	odds
0.02	lap
0.09	rumsfeld
0.02	favored

Building GPT: The Transfomer



96x

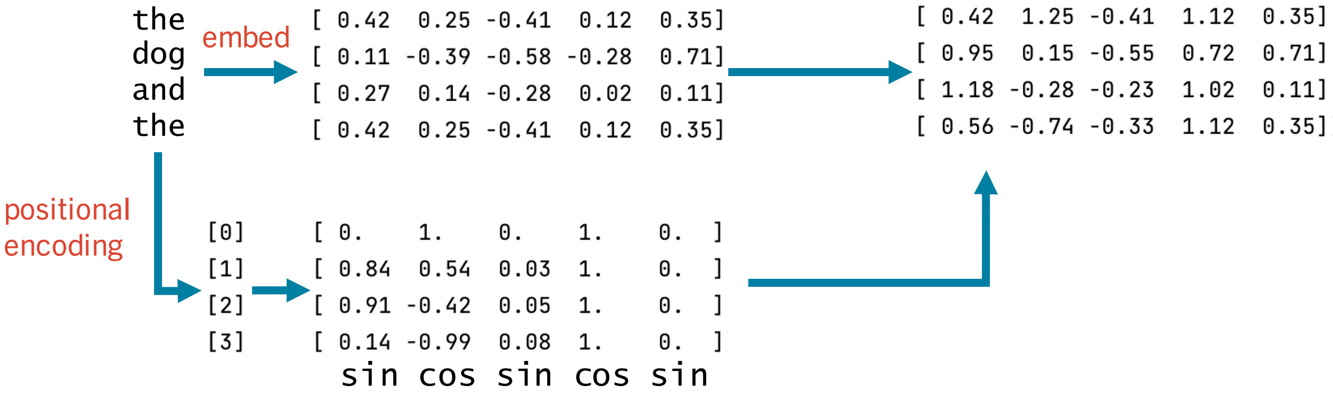
```
the                [ 0.42  0.25 -0.41  0.12  0.35]
dog    embed       [ 0.11 -0.39 -0.58 -0.28  0.71]
and                [ 0.27  0.14 -0.28  0.02  0.11]
the                [ 0.42  0.25 -0.41  0.12  0.35]
```

Attention

Fully Connected

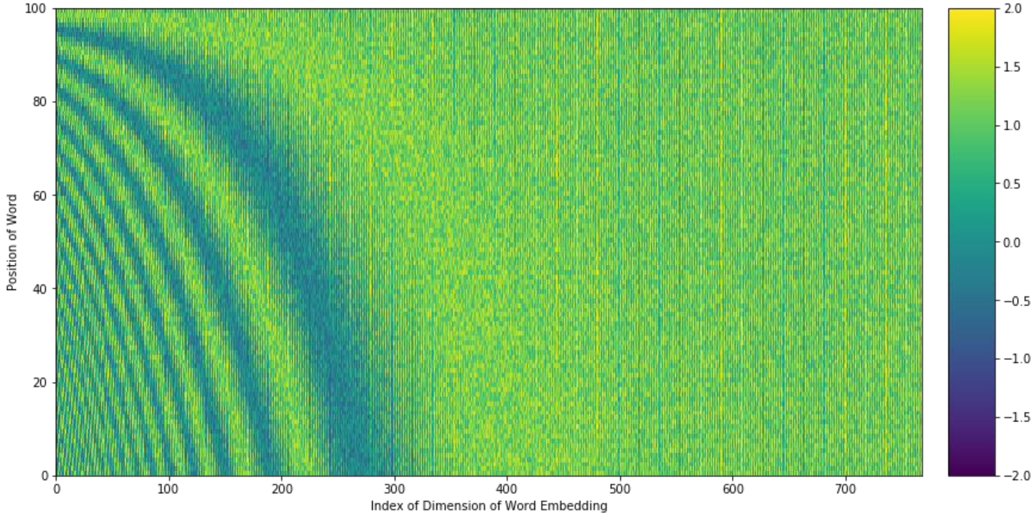
0.01	grants
0.01	cohen
0.04	occasions
0.05	persuade
0.01	jon
0.89	cat
0.05	odds
0.02	lap
0.09	rumsfeld
0.02	favored

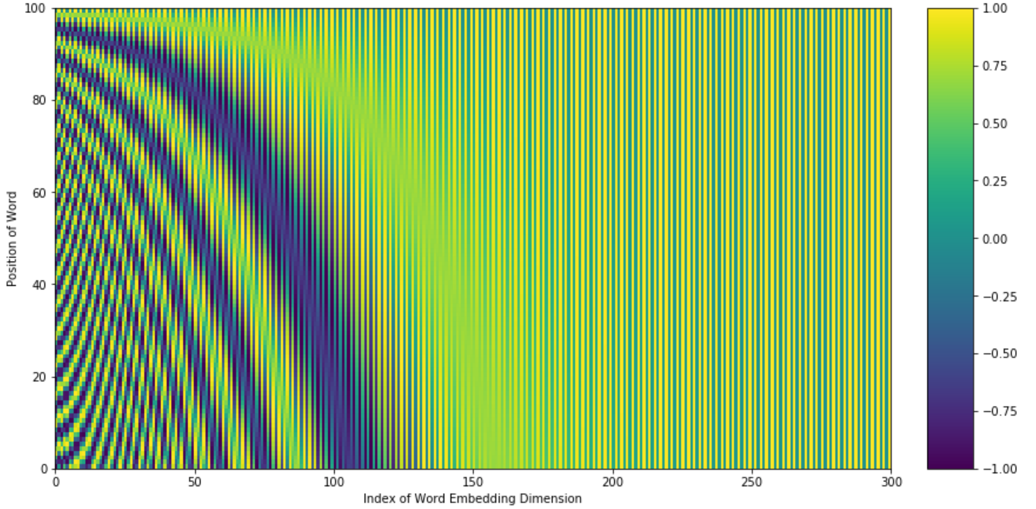
Building GPT: Positional Embedding



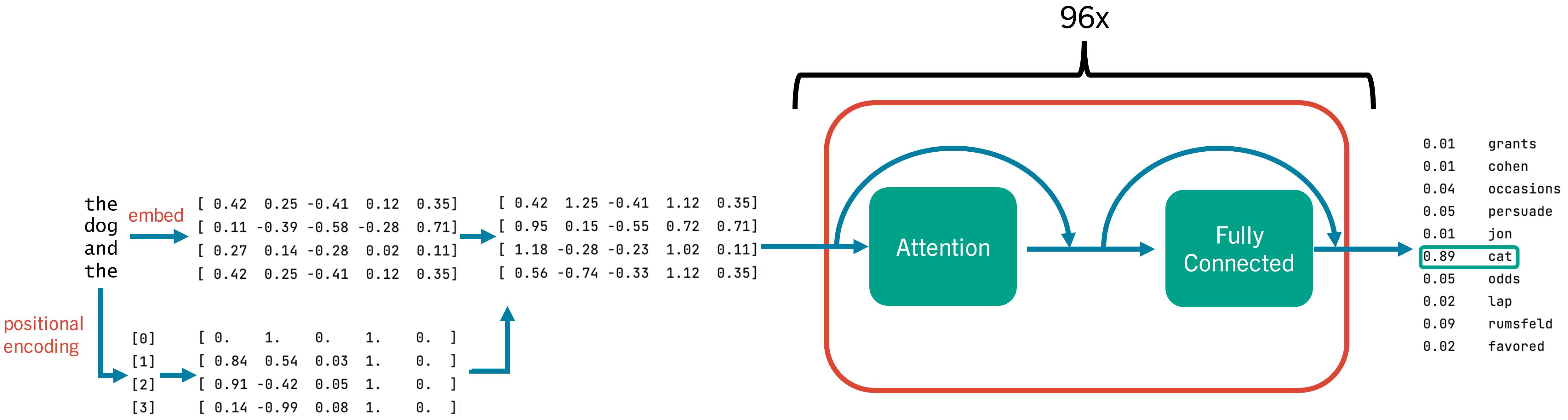
```
the          [ 0.42  0.25 -0.41  0.12  0.35]        [ 0.42  1.25 -0.41  1.12  0.35]
dog   embed  [ 0.11 -0.39 -0.58 -0.28  0.71]        [ 0.95  0.15 -0.55  0.72  0.71]
and          [ 0.27  0.14 -0.28  0.02  0.11]        [ 1.18 -0.28 -0.23  1.02  0.11]
the          [ 0.42  0.25 -0.41  0.12  0.35]        [ 0.56 -0.74 -0.33  1.12  0.35]

positional
encoding
        [0]  [ 0.    1.    0.    1.    0.  ]
        [1]  [ 0.84  0.54  0.03  1.    0.  ]
        [2]  [ 0.91 -0.42  0.05  1.    0.  ]
        [3]  [ 0.14 -0.99  0.08  1.    0.  ]
               sin  cos  sin  cos  sin
```





Building GPT



the
dog
and
the

embed

```
[ 0.42  0.25 -0.41  0.12  0.35]
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```

positional
encoding

```
[0]     [ 0.    1.    0.    1.    0.  ]
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96x

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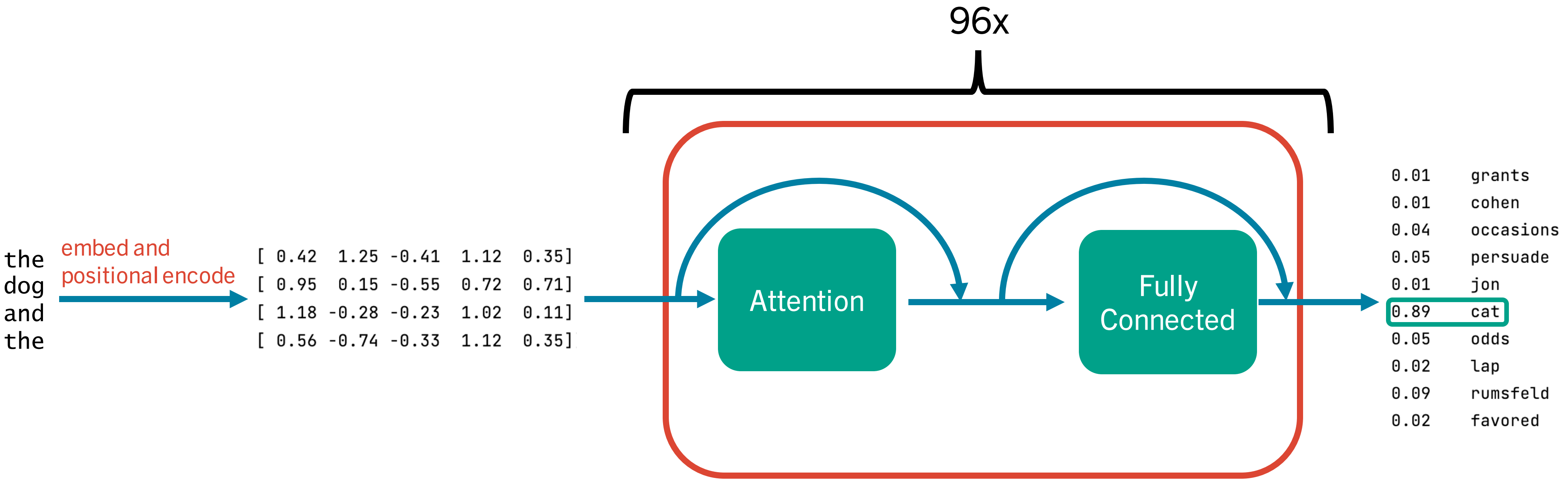
Building GPT



the
dog
and
the

embed and positional encode

```
[ 0.42  1.25 -0.41  1.12  0.35]
[ 0.95  0.15 -0.55  0.72  0.71]
[ 1.18 -0.28 -0.23  1.02  0.11]
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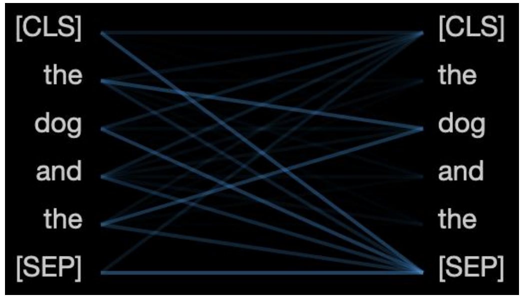
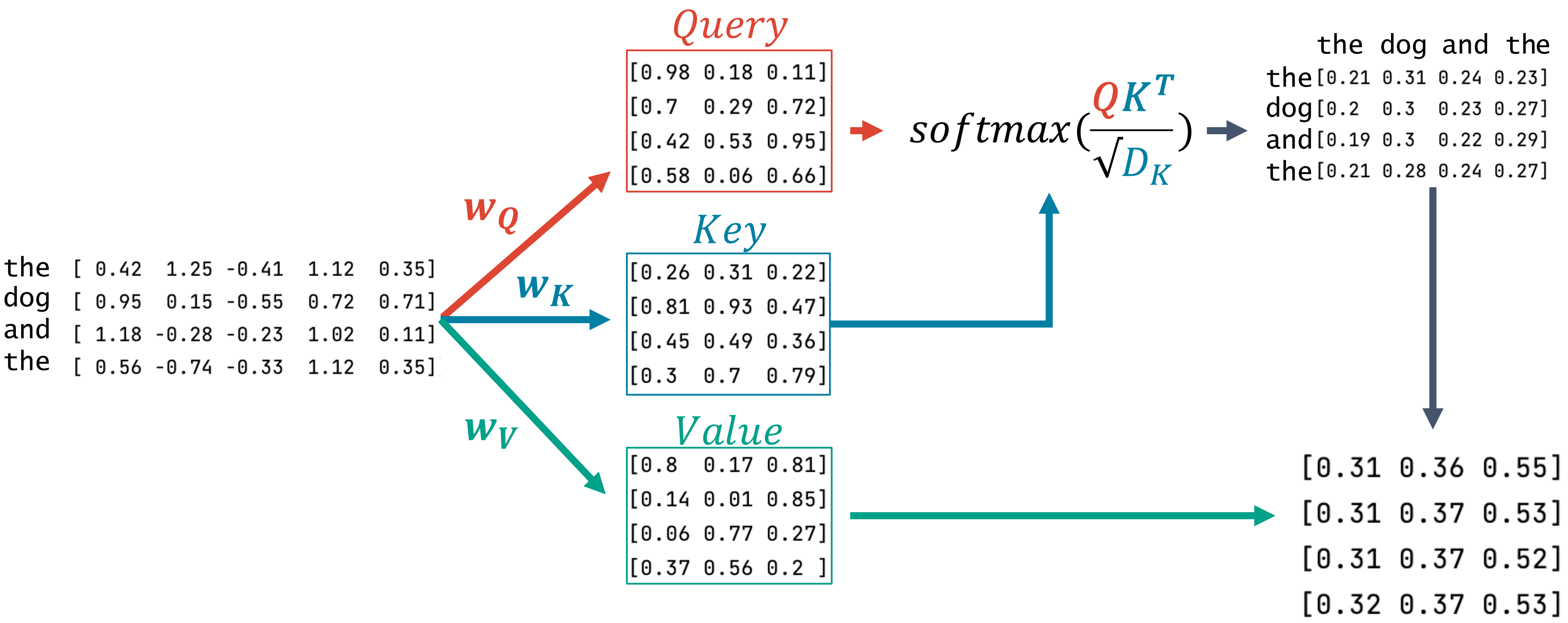
Building GPT: Attention





```
the [ 0.42  1.25 -0.41  1.12  0.35]
dog [ 0.95  0.15 -0.55  0.72  0.71]
and [ 1.18 -0.28 -0.23  1.02  0.11]
the [ 0.56 -0.74 -0.33  1.12  0.35]
```

w_Q w_K w_V

Query

```
[0.98 0.18 0.11]
[0.7  0.29 0.72]
[0.42 0.53 0.95]
[0.58 0.06 0.66]
```

Key

```
[0.26 0.31 0.22]
[0.81 0.93 0.47]
[0.45 0.49 0.36]
[0.3  0.7  0.79]
```

Value

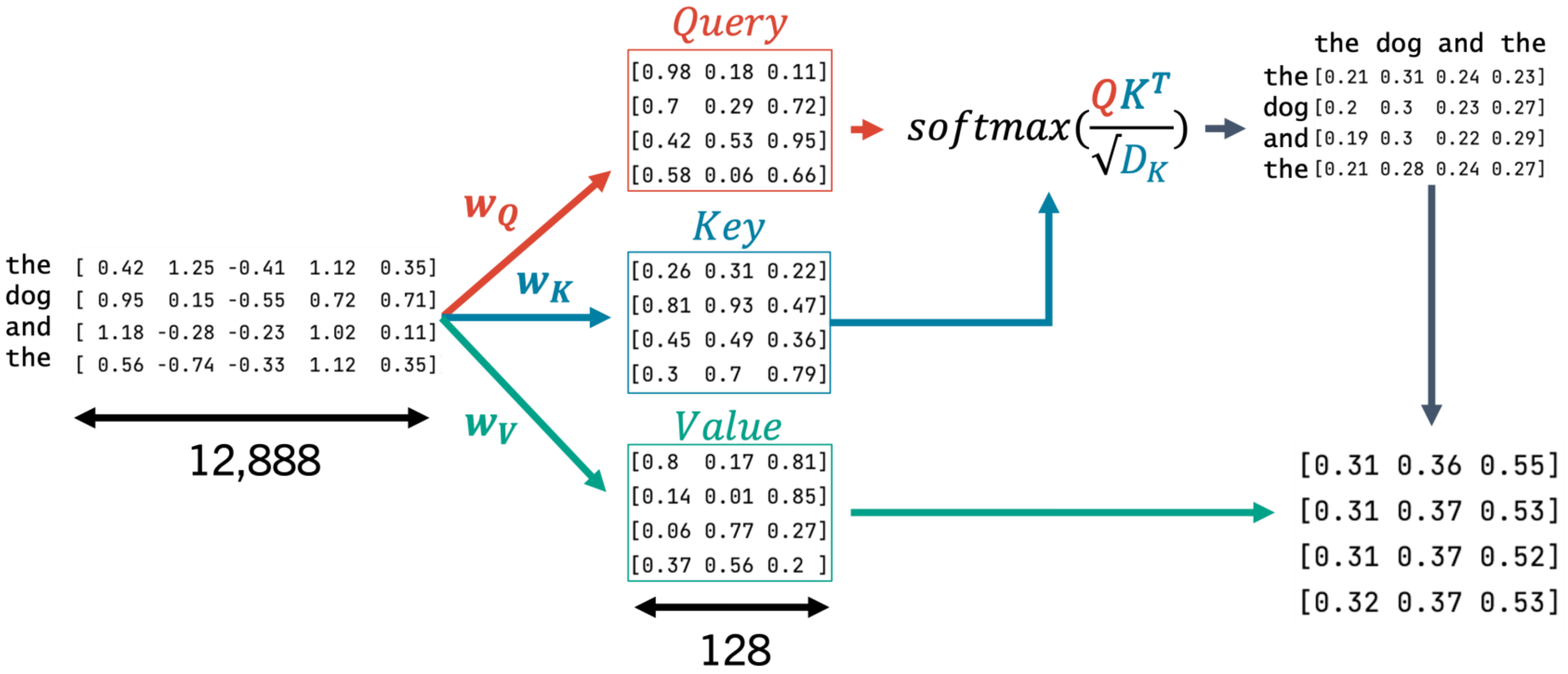
```
[0.8  0.17 0.81]
[0.14 0.01 0.85]
[0.06 0.77 0.27]
[0.37 0.56 0.2 ]
```

$$softmax(\frac{QK^T}{\sqrt{D_K}})$$

```
    the  dog  and  the
the[0.21 0.31 0.24 0.23]
dog[0.2  0.3  0.23 0.27]
and[0.19 0.3  0.22 0.29]
the[0.21 0.28 0.24 0.27]
```

```
[0.31 0.36 0.55]
[0.31 0.37 0.53]
[0.31 0.37 0.52]
[0.32 0.37 0.53]
```

Building GPT: Attention



```
the [ 0.42  1.25 -0.41  1.12  0.35]
dog [ 0.95  0.15 -0.55  0.72  0.71]
and [ 1.18 -0.28 -0.23  1.02  0.11]
the [ 0.56 -0.74 -0.33  1.12  0.35]
```

12,888

w_Q w_K w_V

Query

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[0.98 0.18 0.11]
[0.7  0.29 0.72]
[0.42 0.53 0.95]
[0.58 0.06 0.66]
```

Key

```
[0.26 0.31 0.22]
[0.81 0.93 0.47]
[0.45 0.49 0.36]
[0.3  0.7  0.79]
```

Value

```
[0.8  0.17 0.81]
[0.14 0.01 0.85]
[0.06 0.77 0.27]
[0.37 0.56 0.2 ]
```

128

$$softmax(\frac{QK^T}{\sqrt{D_K}})$$

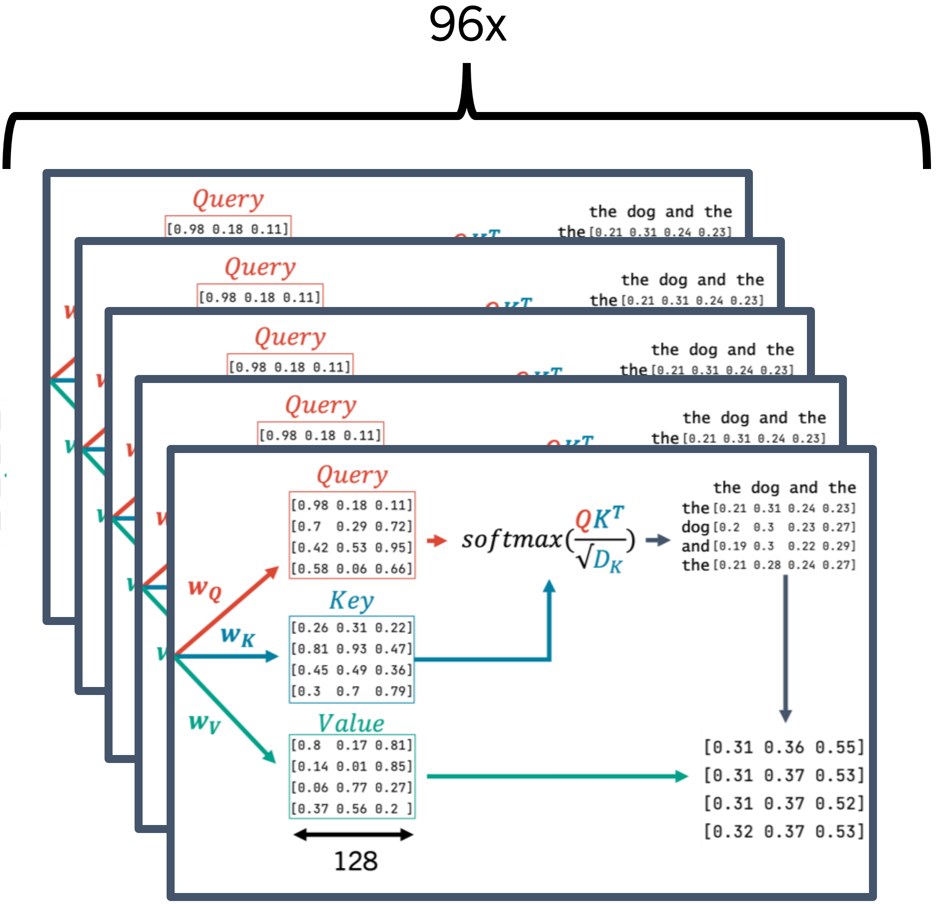
	the	dog	and	the
the	[0.21	0.31	0.24	0.23]
dog	[0.2	0.3	0.23	0.27]
and	[0.19	0.3	0.22	0.29]
the	[0.21	0.28	0.24	0.27]

```
[0.31 0.36 0.55]
[0.31 0.37 0.53]
[0.31 0.37 0.52]
[0.32 0.37 0.53]
```

Building GPT: Attention

```
the  [ 0.42  1.25 -0.41  1.12  0.35]
dog  [ 0.95  0.15 -0.55  0.72  0.71]
and  [ 1.18 -0.28 -0.23  1.02  0.11]
the  [ 0.56 -0.74 -0.33  1.12  0.35]
```

12,888



Query

```
[0.98 0.18 0.11]
[0.7  0.29 0.72]
[0.42 0.53 0.95]
[0.58 0.06 0.66]
```

$$softmax(\frac{QK^T}{\sqrt{D_K}})$$

Key

```
[0.26 0.31 0.22]
[0.81 0.93 0.47]
[0.45 0.49 0.36]
[0.3  0.7  0.79]
```

Value

```
[0.8  0.17 0.81]
[0.14 0.01 0.85]
[0.06 0.77 0.27]
[0.37 0.56 0.2 ]
```

```
     the  dog  and  the
the [0.21 0.31 0.24 0.23]
dog [0.2  0.3  0.23 0.27]
and [0.19 0.3  0.22 0.29]
the [0.21 0.28 0.24 0.27]
```

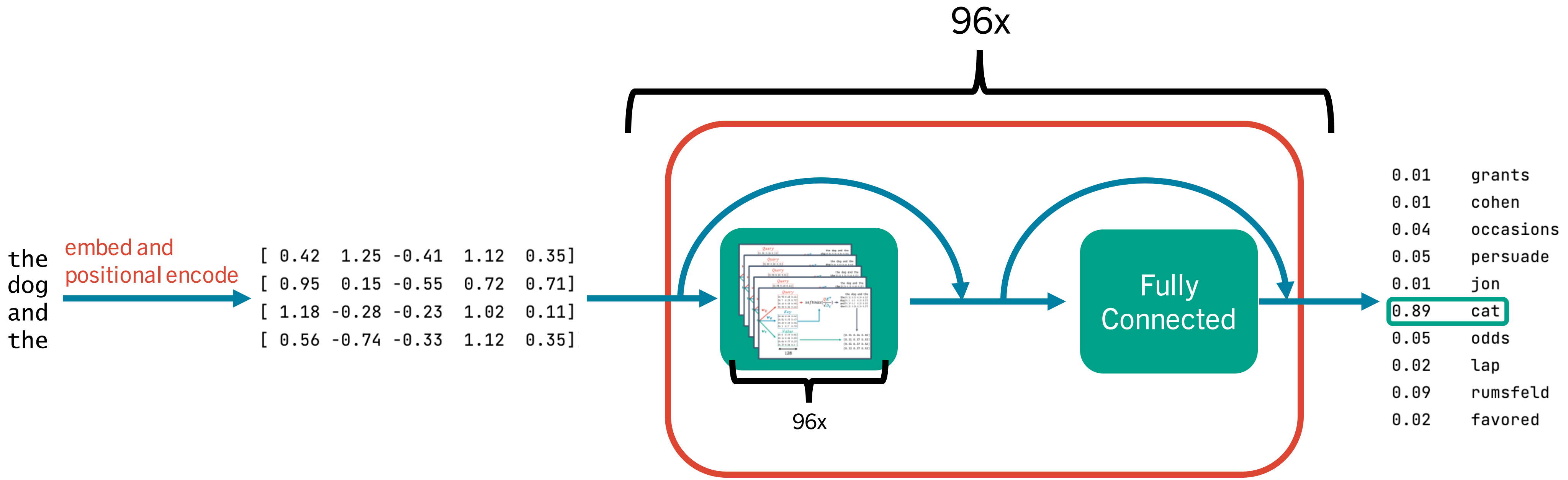
```
[0.31 0.36 0.55]
[0.31 0.37 0.53]
[0.31 0.37 0.52]
[0.32 0.37 0.53]
```

96x128

```
[0.23 0.15 0.61 0.97 0.  ]
[0.43 0.09 0.91 0.94 0.88]
[0.02 0.93 0.68 0.08 0.99]
[0.15 0.86 0.1  0.93 0.72]
```

12,888

Building GPT



the
dog
and
the

embed and positional encode

```
[ 0.42  1.25 -0.41  1.12  0.35]
[ 0.95  0.15 -0.55  0.72  0.71]
[ 1.18 -0.28 -0.23  1.02  0.11]
[ 0.56 -0.74 -0.33  1.12  0.35]
```

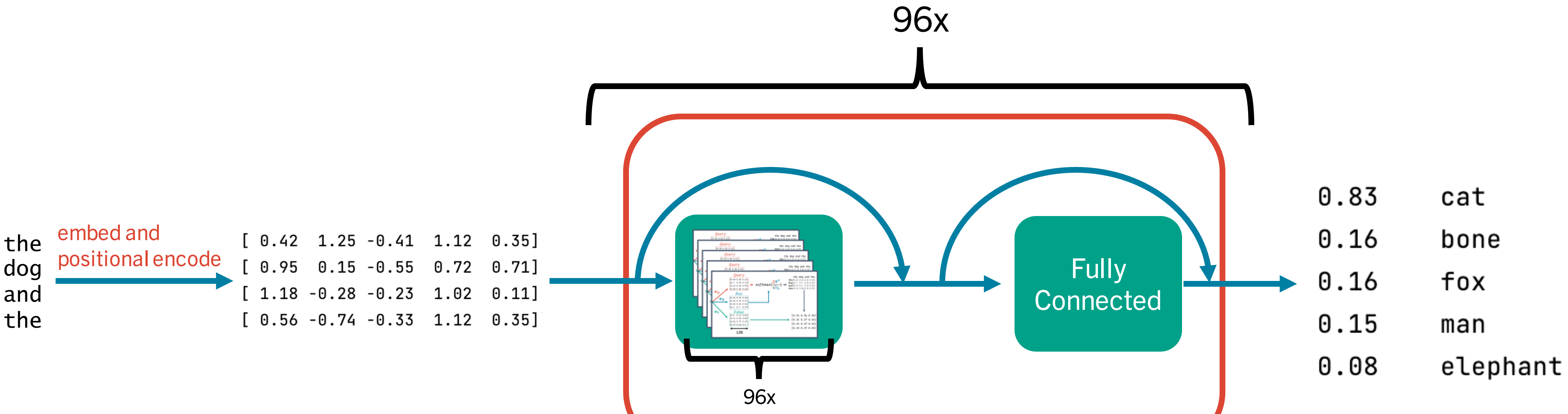
96x

96x

Fully Connected

0.01	grants
0.01	cohen
0.04	occasions
0.05	persuade
0.01	jon
0.89	cat
0.05	odds
0.02	lap
0.09	rumsfeld
0.02	favored

Building GPT: Top-P

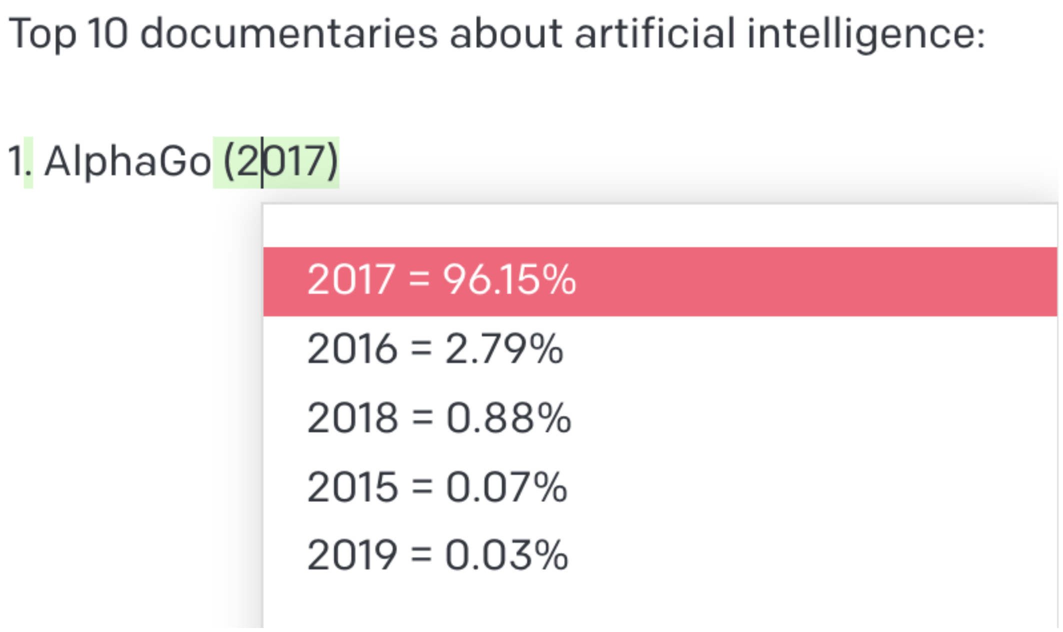


the
dog
and
the

```
[ 0.42  1.25 -0.41  1.12  0.35]
[ 0.95  0.15 -0.55  0.72  0.71]
[ 1.18 -0.28 -0.23  1.02  0.11]
[ 0.56 -0.74 -0.33  1.12  0.35]
```

0.83	cat
0.16	bone
0.16	fox
0.15	man
0.08	elephant

Building GPT: Top-P

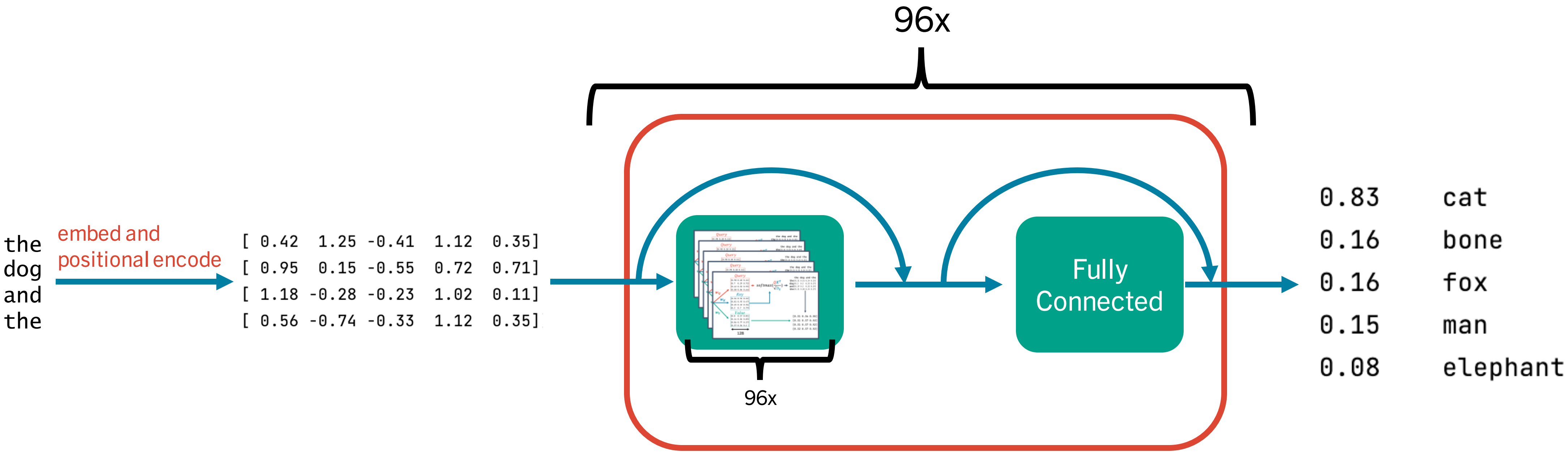


Top 10 documentaries about artificial intelligence:

1. AlphaGo (2017)

2017 = 96.15%
2016 = 2.79%
2018 = 0.88%
2015 = 0.07%
2019 = 0.03%

Building GPT



the
dog
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embed and positional encode

```
[ 0.42  1.25 -0.41  1.12  0.35]
[ 0.95  0.15 -0.55  0.72  0.71]
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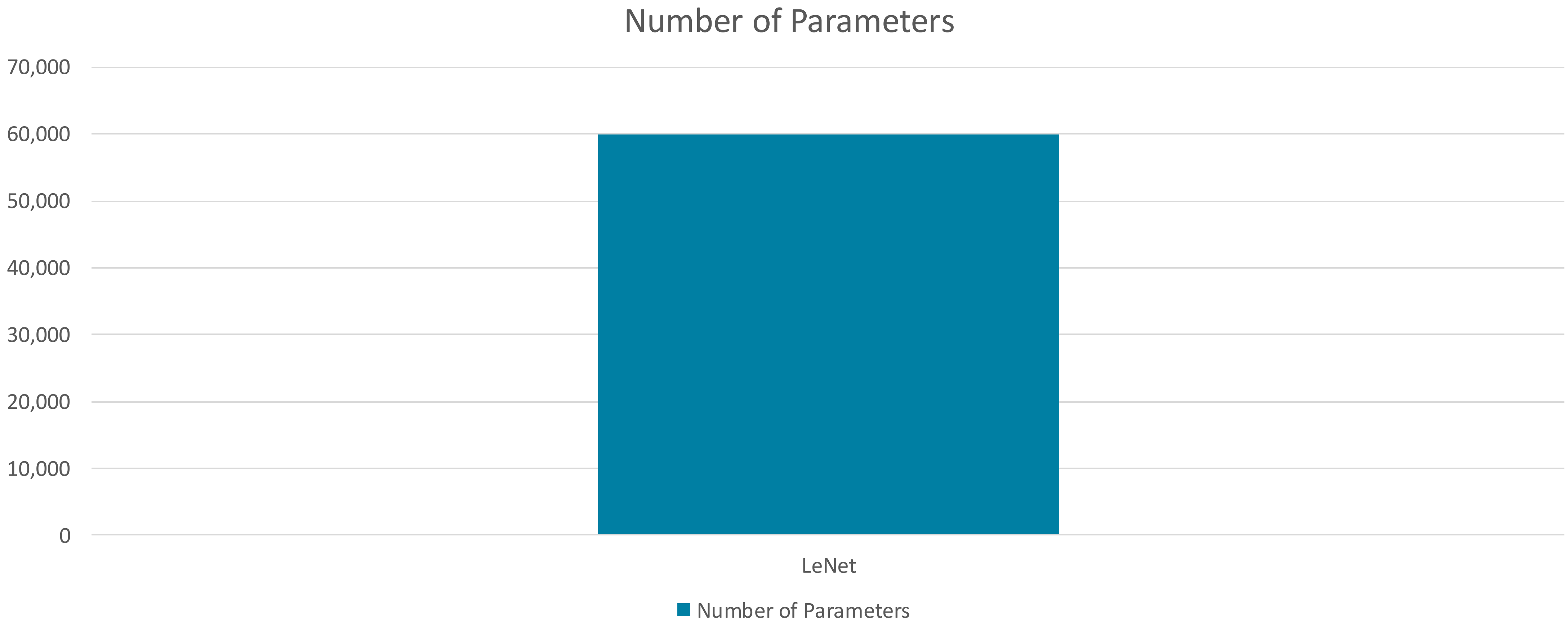
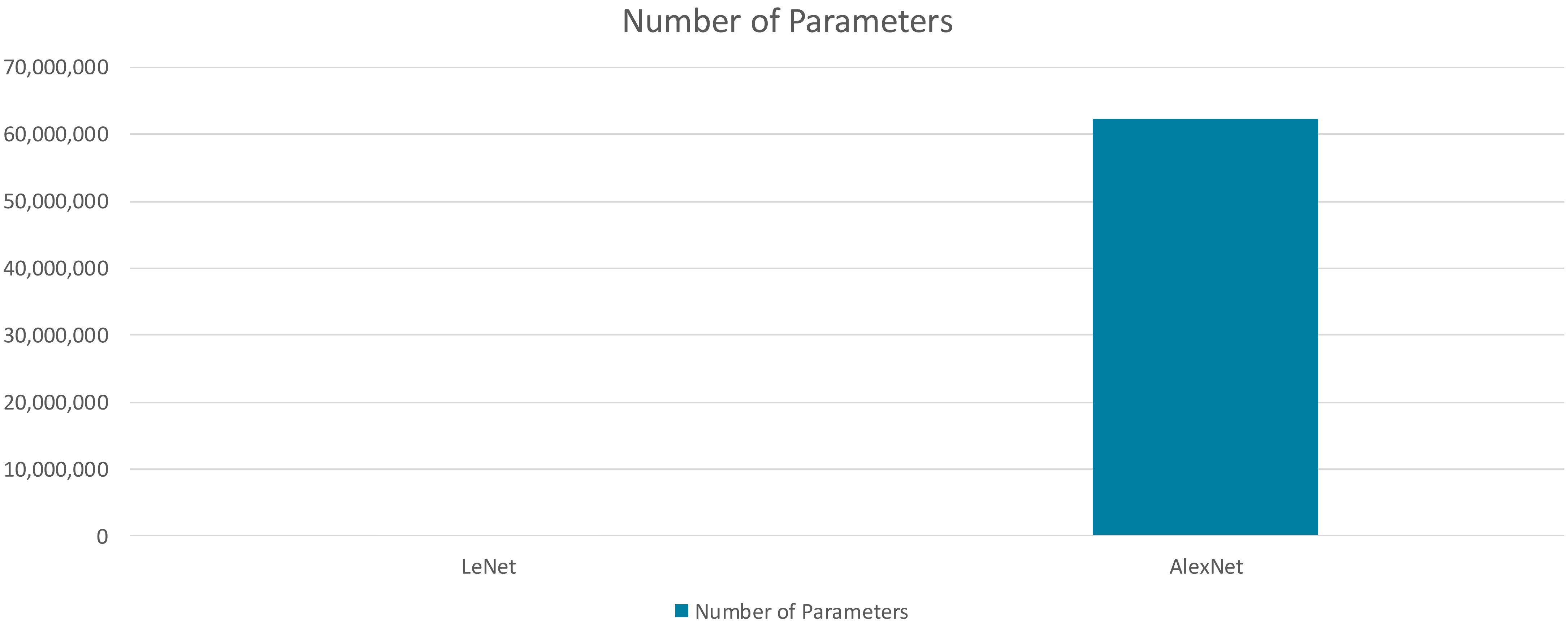
[ 0.56 -0.74 -0.33  1.12  0.35]
```

0.83	cat
0.16	bone
0.16	fox
0.15	man
0.08	elephant

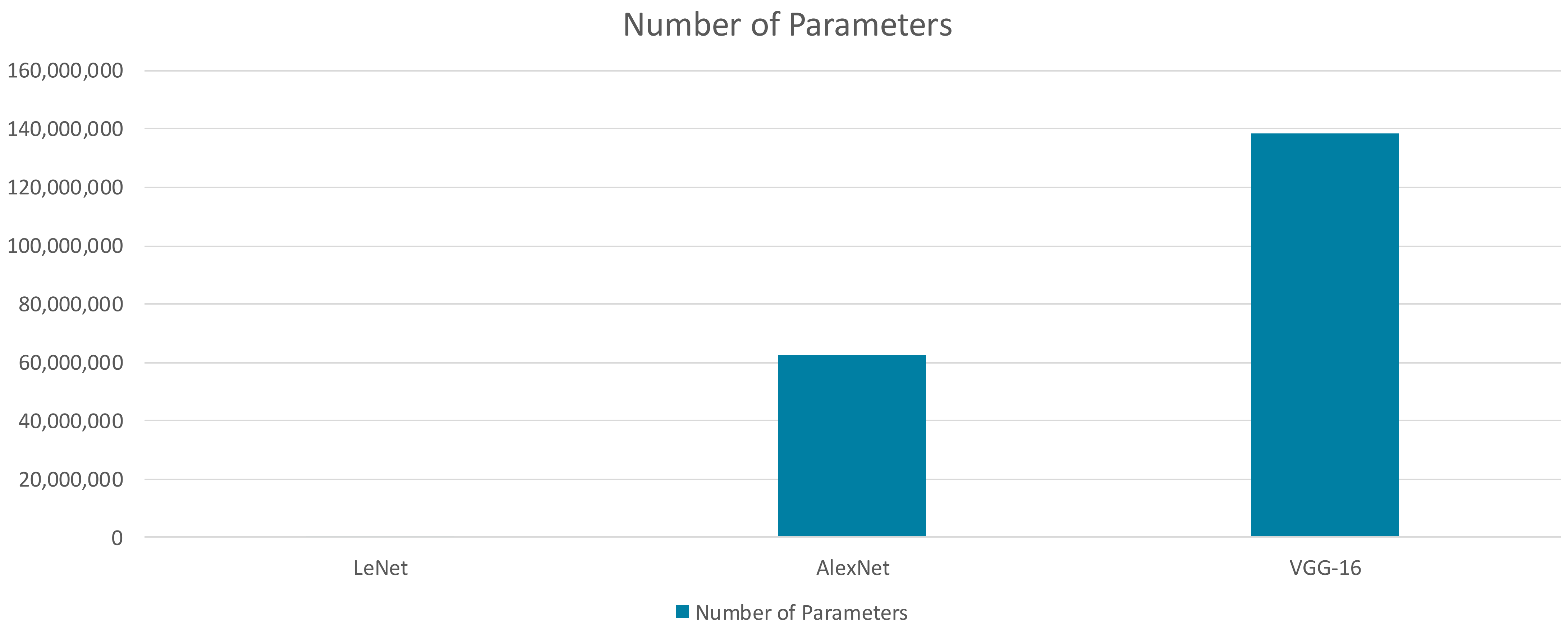
Scale of GPT


Number of Parameters
70,000
60,000
50,000
40,000
30,000
20,000
10,000
0
LeNet
■ Number of Parameters

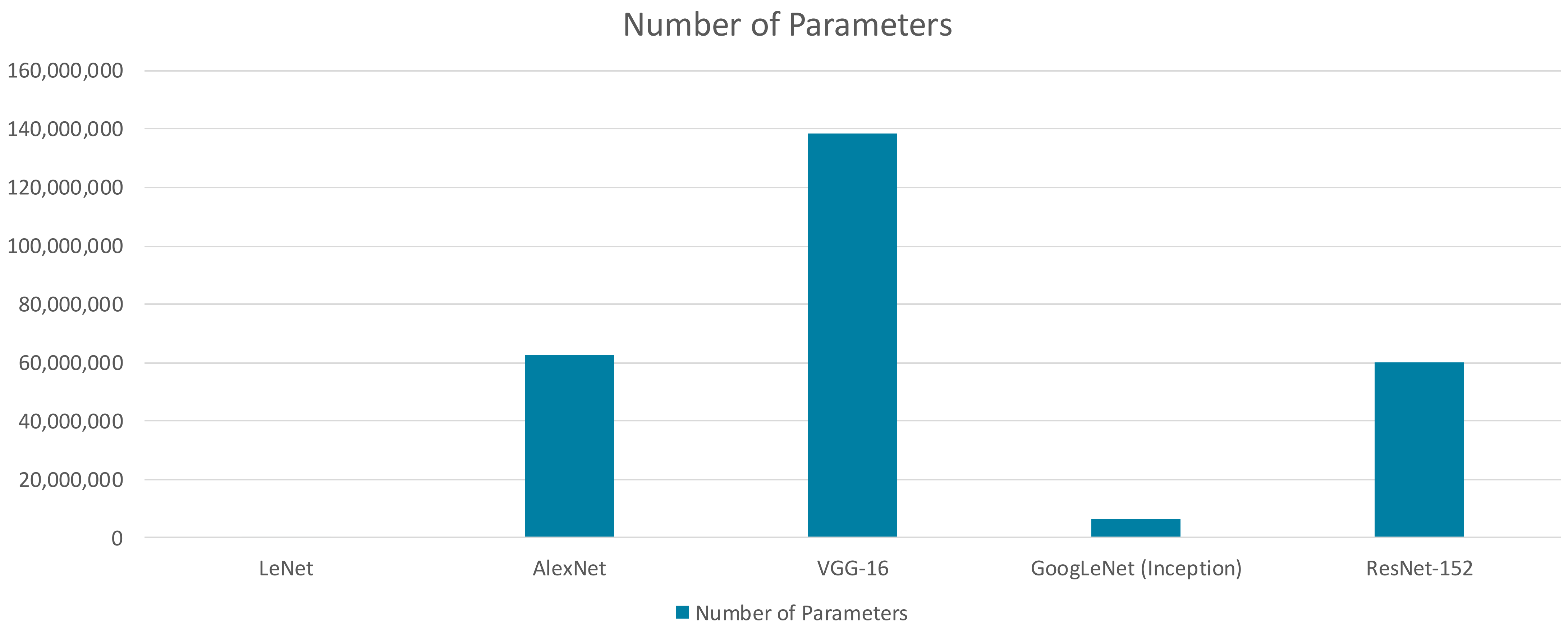
Scale of GPT


Number of Parameters
70,000,000
60,000,000
50,000,000
40,000,000
30,000,000
20,000,000
10,000,000
0
LeNet
AlexNet
■ Number of Parameters

Scale of GPT

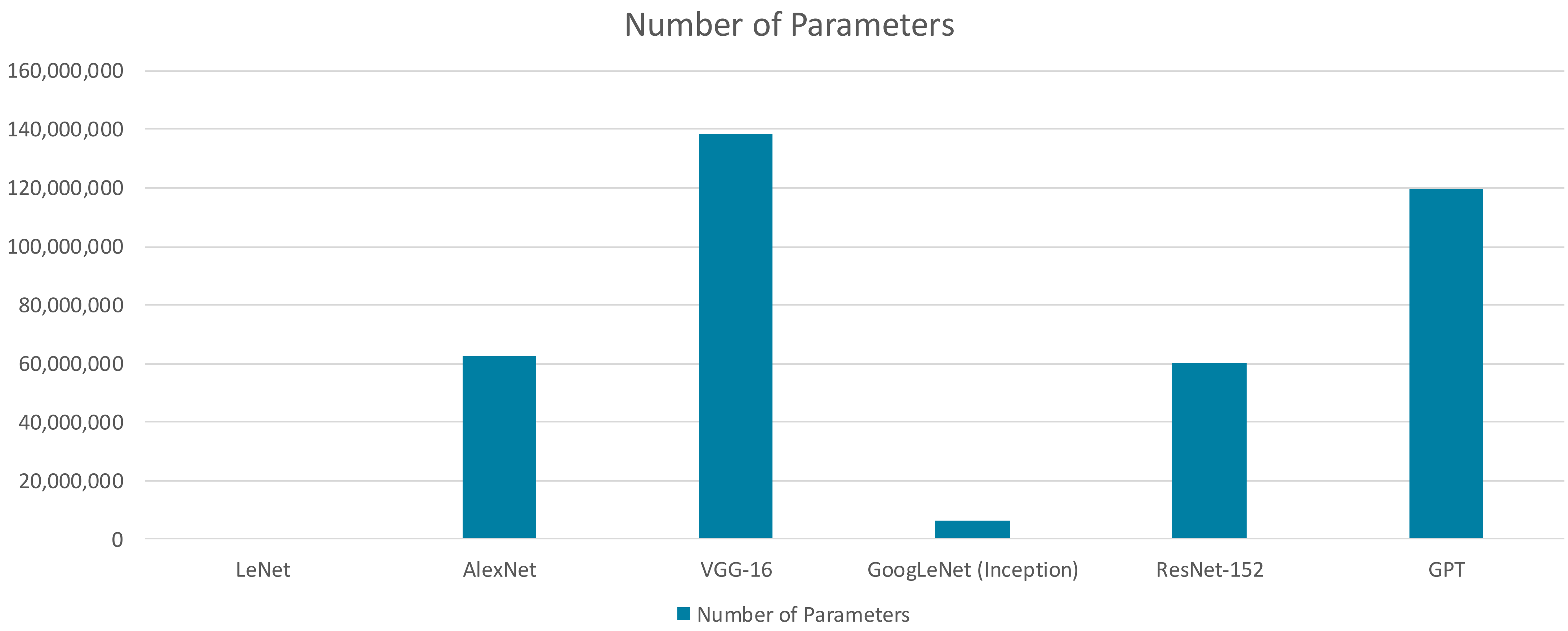

Number of Parameters
160,000,000
140,000,000
120,000,000
100,000,000
80,000,000
60,000,000
40,000,000
20,000,000
0
LeNet
AlexNet
VGG-16
■ Number of Parameters

Scale of GPT



Number of Parameters
160,000,000
140,000,000
120,000,000
100,000,000
80,000,000
60,000,000
40,000,000
20,000,000
0
LeNet
AlexNet
VGG-16
GoogLeNet (Inception)
ResNet-152
Number of Parameters

Scale of GPT


Number of Parameters
160,000,000
140,000,000
120,000,000
100,000,000
80,000,000
60,000,000
40,000,000
20,000,000
0
LeNet
AlexNet
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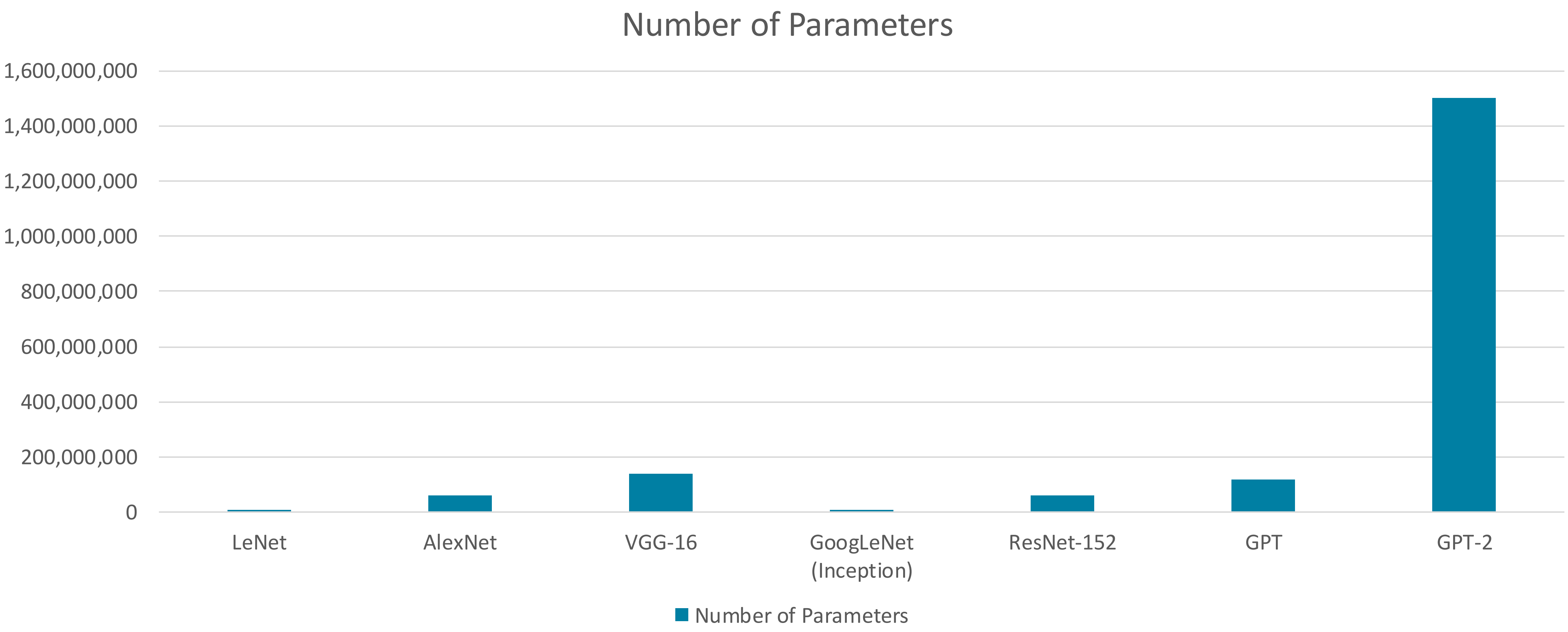
GoogLeNet (Inception)
ResNet-152
GPT
Number of Parameters

Scale of GPT



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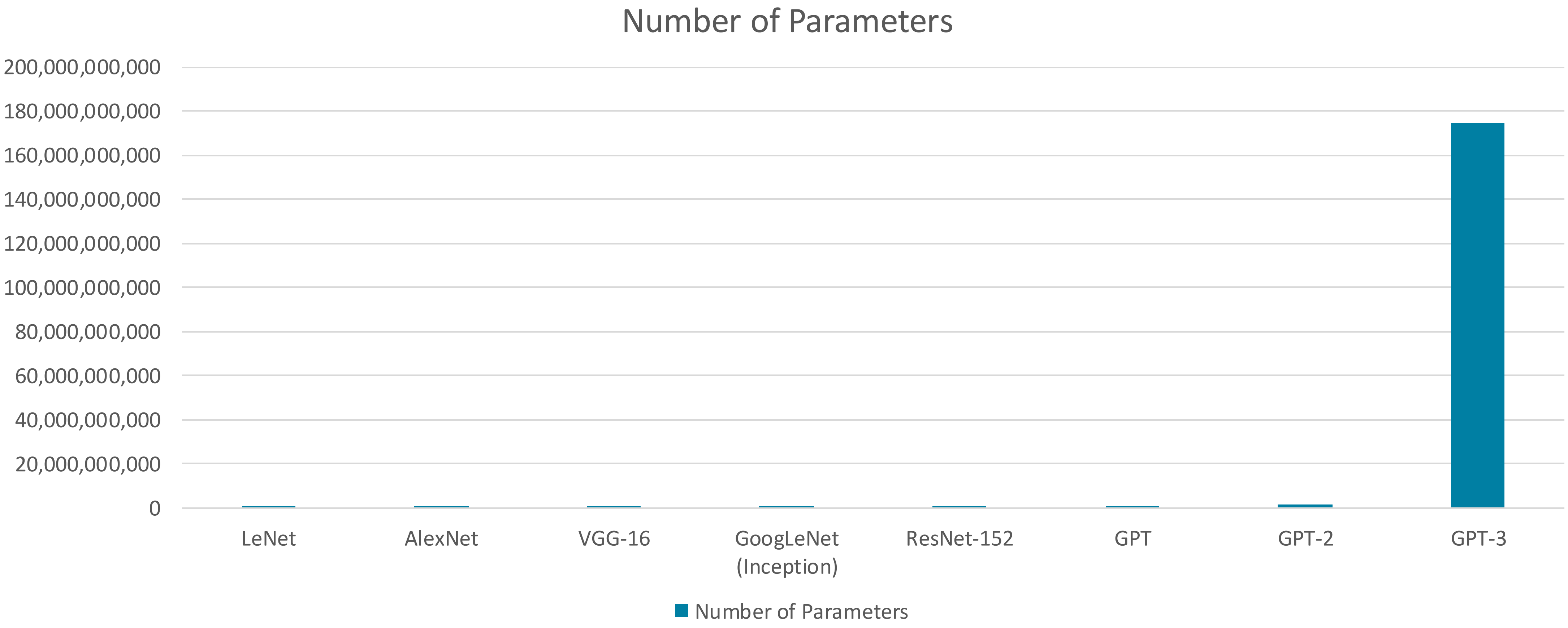
AlexNet
VGG-16
GoogLeNet (Inception)
ResNet-152
GPT
GPT-2
■ Number of Parameters

Scale of GPT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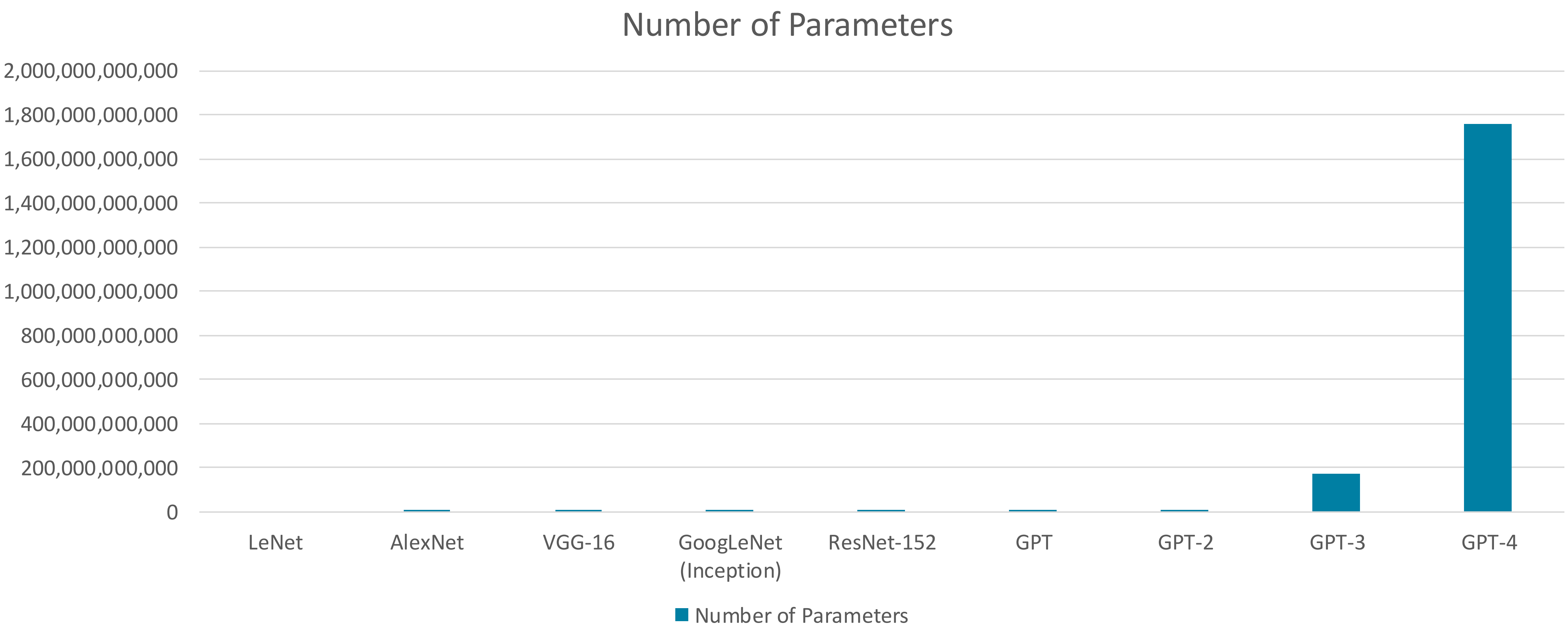
AlexNet
VGG-16
GoogLeNet (Inception)
ResNet-152
GPT
GPT-2
GPT-3
■ Number of Parameters

Scale of GPT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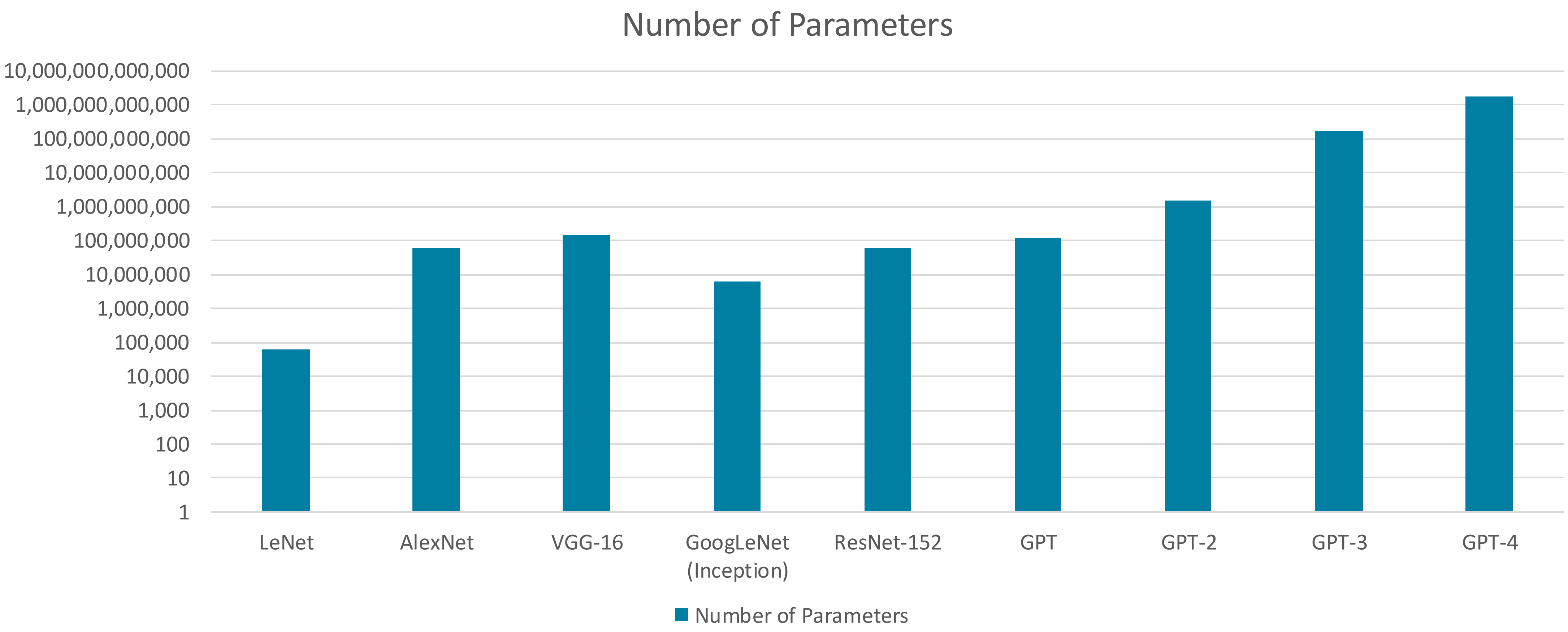
LeNet
AlexNet
VGG-16
GoogLeNet (Inception)
ResNet-152
GPT
GPT-2
GPT-3
GPT-4
■ Number of Parameters

Scale of GPT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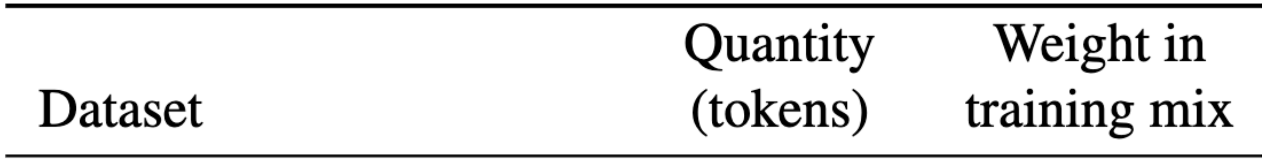
100
10
1
LeNet
AlexNet
VGG-16
GoogLeNet (Inception)
ResNet-152
GPT
GPT-2
GPT-3
GPT-4
■ Number of Parameters

GPT's Training Data

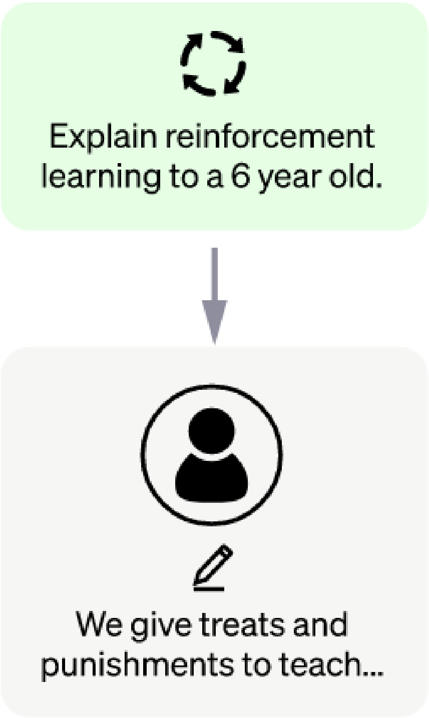
- 1 token ≈ ¾ word
- Some datasets are sampled more times than others
- Common Crawl: billions of webpages collected over 7 years
- Webtext2: Dataset of webpages that have been shared on Reddit
- Books1: Free ebooks (?)
- Books2: Secret!
- English Wikipedia



Dataset	Quantity (tokens)	Weight in training mix

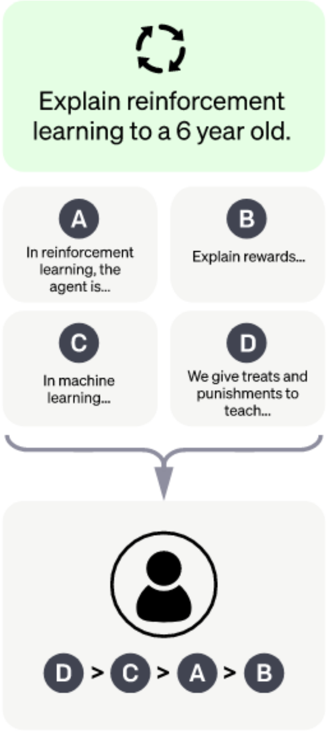
The training innovation of ChatGPT

Human annotators write answers to questions


Explain reinforcement learning to a 6 year old.
We give treats and punishments to teach...

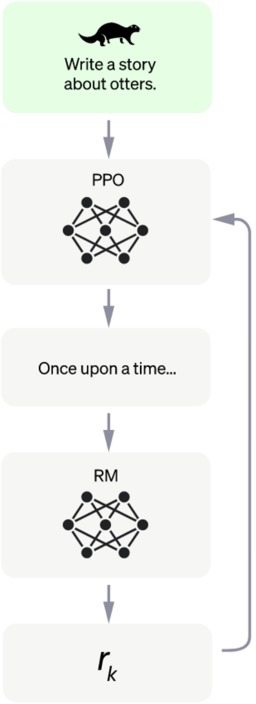
The generalist GPT model is taught from these Q&A pairs

Human annotators write more answers, and someone else ranks them


Explain reinforcement learning to a 6 year old.
A
In reinforcement learning, the agent is...
B
Explain rewards...
C
In machine learning...
D
We give treats and punishments to teach...
D > C > A > B

A separate model learns to rate the quality of an answer

GPT writes answers to sampled questions

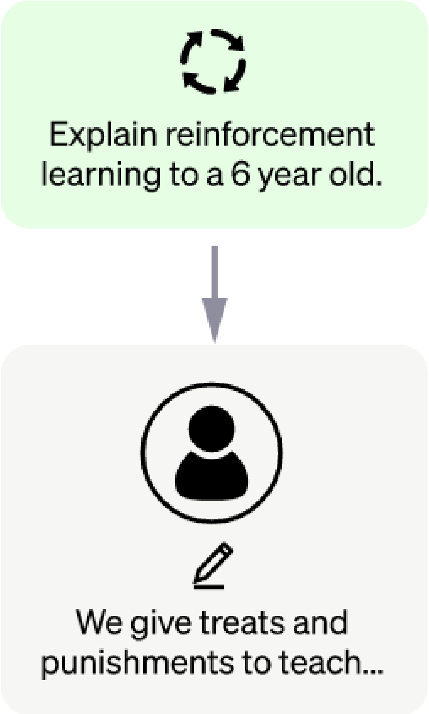


The reward model rates each answer, allowing GPT to keep learning

Figures: https://openai.com/blog/chatgpt/

The training innovation of ChatGPT

Human annotators write answers to questions



Explain reinforcement learning to a 6 year old.

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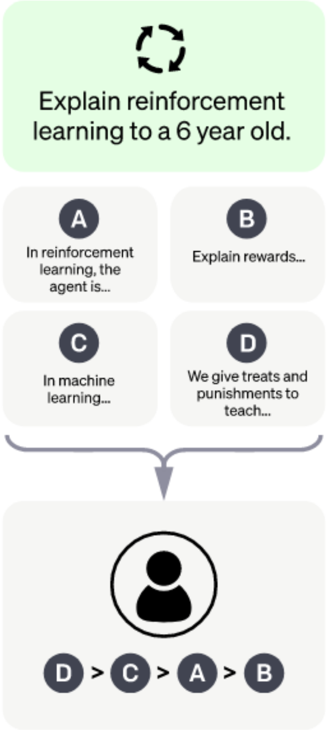


Explain reinforcement learning to a 6 year old.

A In reinforcement learning, the agent is...

B Explain rewards...

C In machine learning...

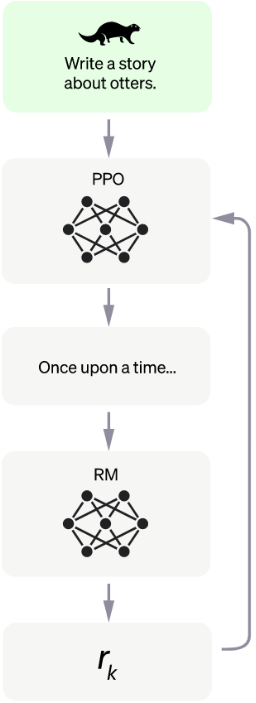
D We give treats and punishments to teach...

D > C > A > B

A separate model learns to rate the quality of an answer

No more humans involved!

GPT writes answers to sampled questions



Write a story about otters.

PPO

Once upon a time...

RM

r_k

The reward model rates each answer, allowing GPT to keep learning

Figures: https://openai.com/blog/chatgpt/

Winograd Schema

- ”Artificial language processing remains ten years away” – Tom Scott, 2020
- GPT-3 performance: 68.8%
- GPT-4 performance: 94.4%
- Today, 22 models outperform human baselines on the GLUE benchmark