CARTE ML Workshop

GPT and Attention

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

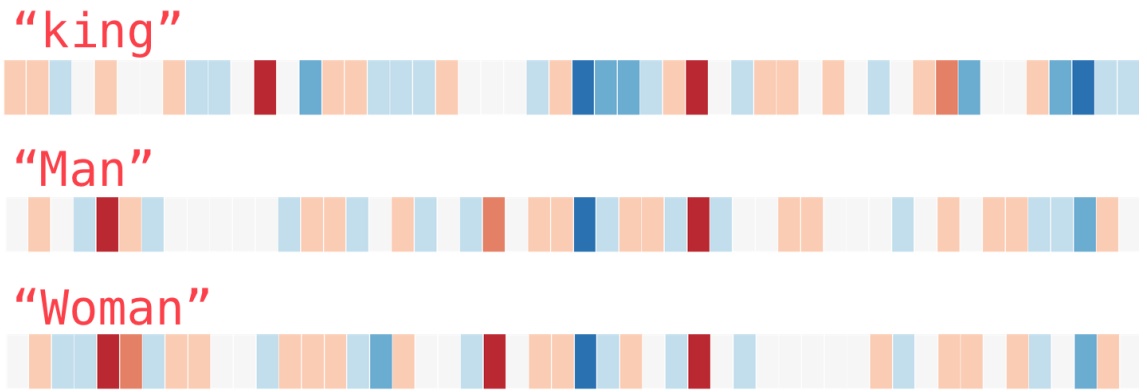
- I saw a man on the hill with the telescope
- That’s a cool cat
- Colourless green ideas sleep furiously
- Me went store

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!

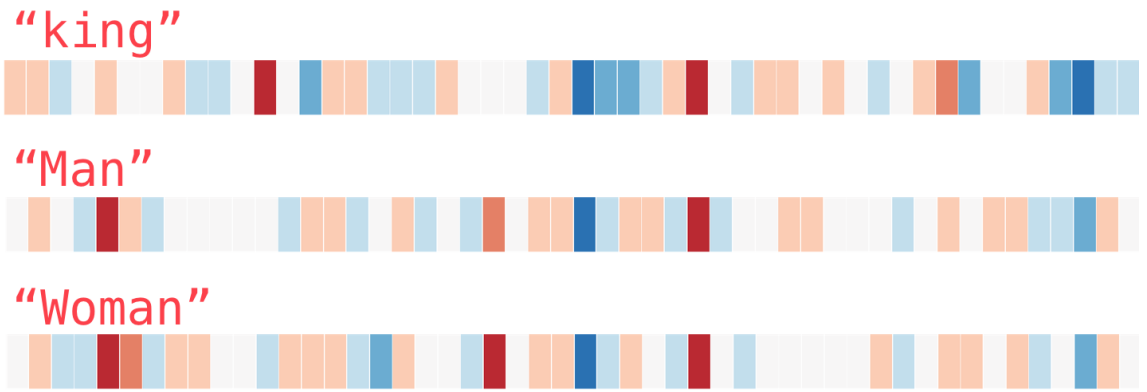
How does an LM “understand” word meaning?

- 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

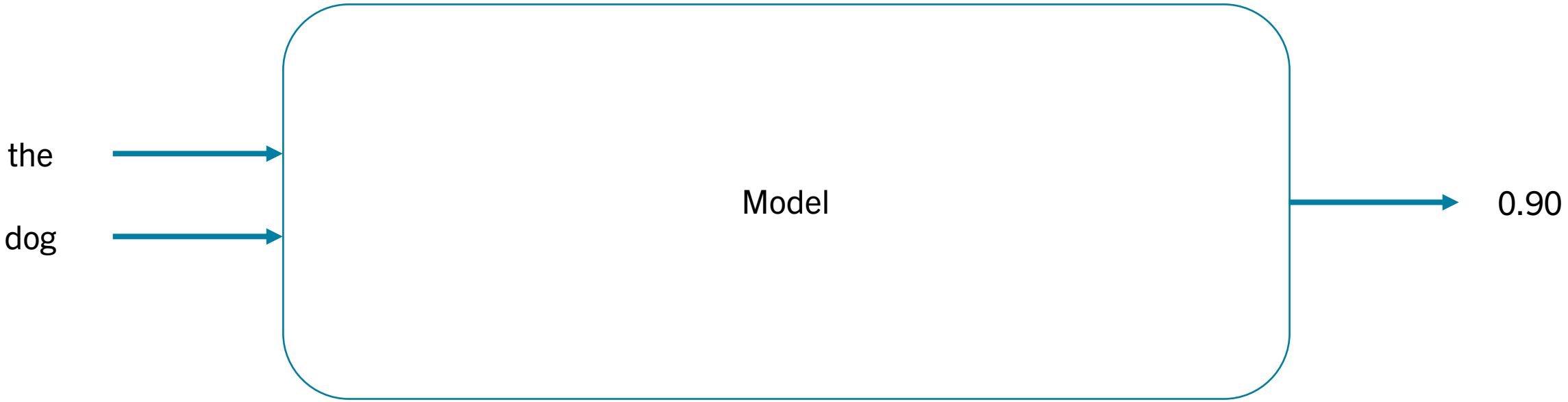


How does an LM “understand” word meaning?

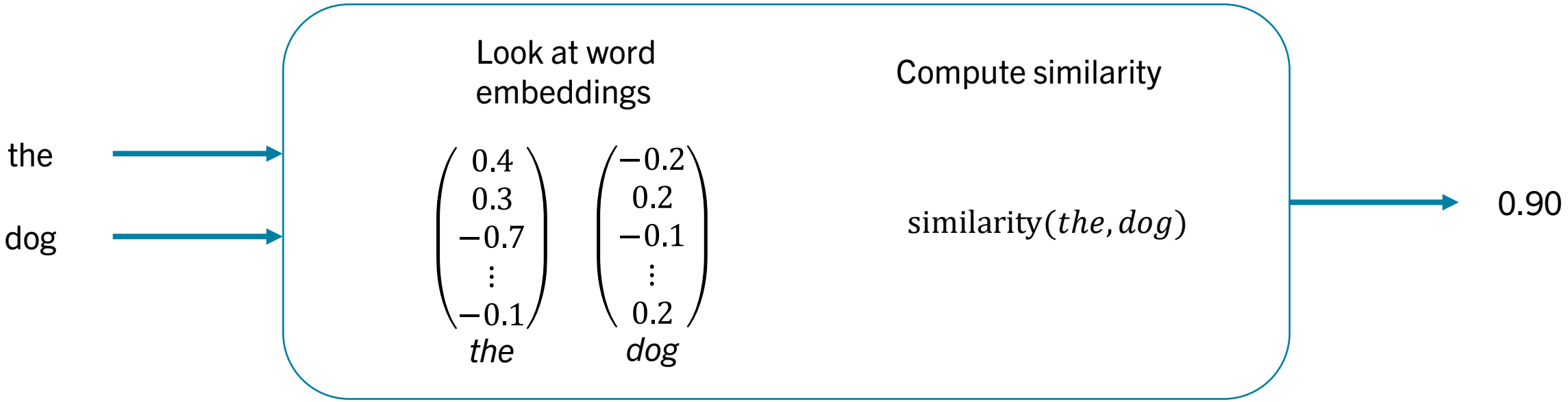
- Key concept of word embeddings: similar words should have similar vectors
- How do we accomplish this?



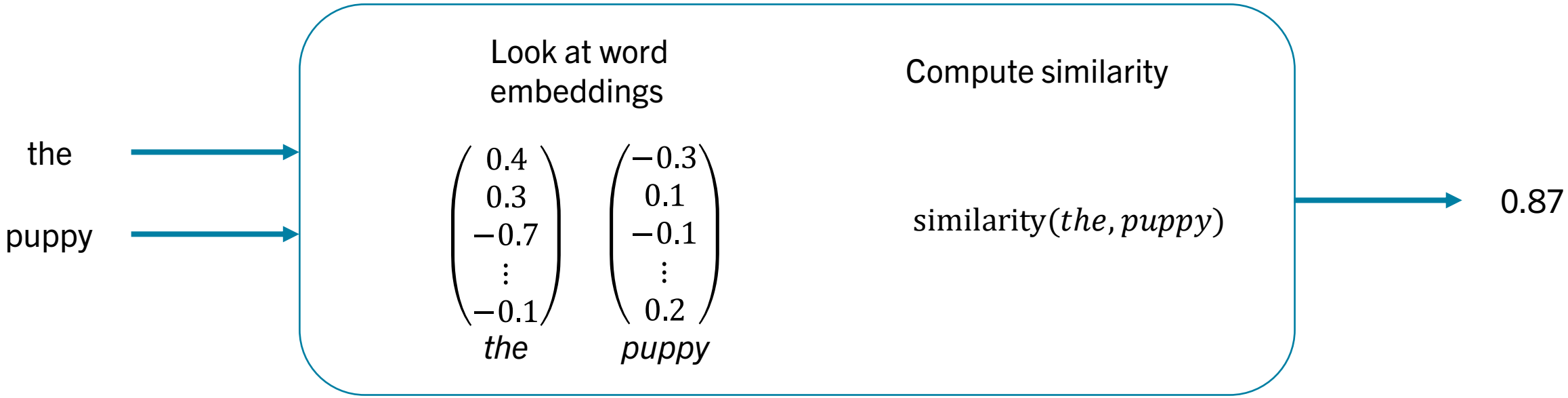
Building Word Embeddings



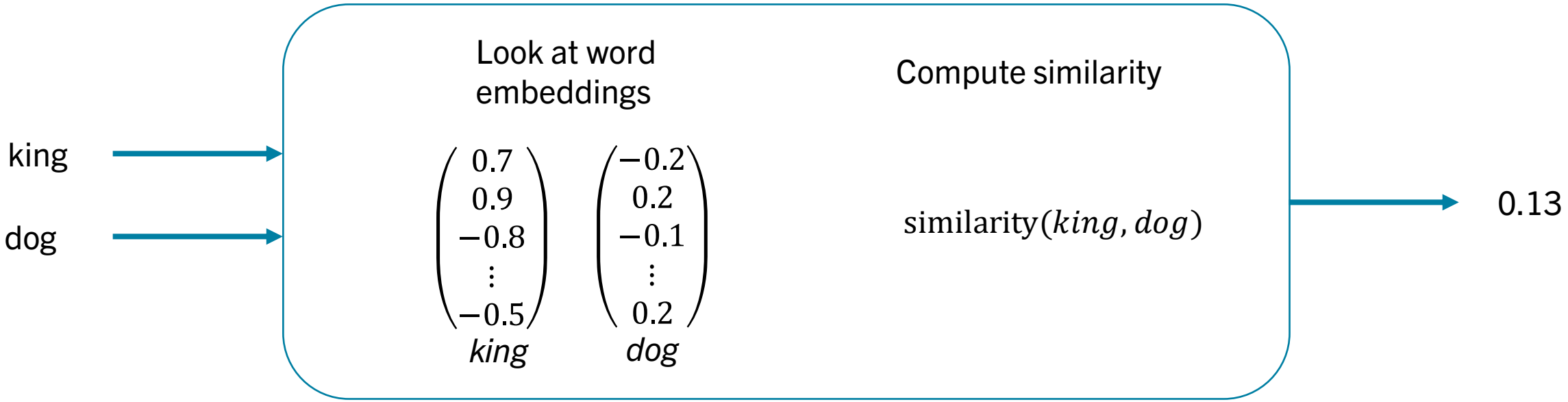
Building Word Embeddings



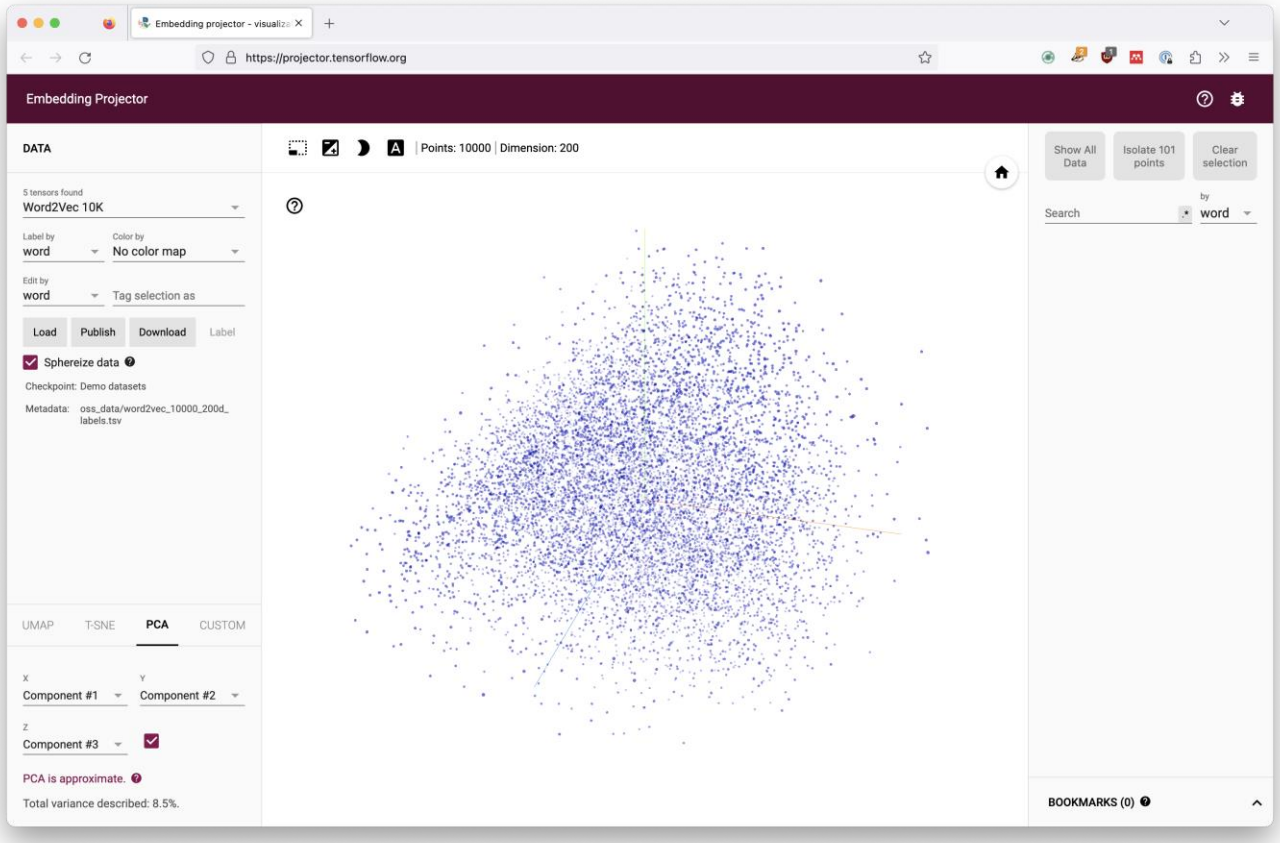
Building Word Embeddings



Building Word Embeddings



Results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https://projector.tensorflow.org
Embedding Projector
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Color by
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Edit by
word
Tag selection as
Load
Publish
Download
Label
Sphereize data
Checkpoint: Demo datasets
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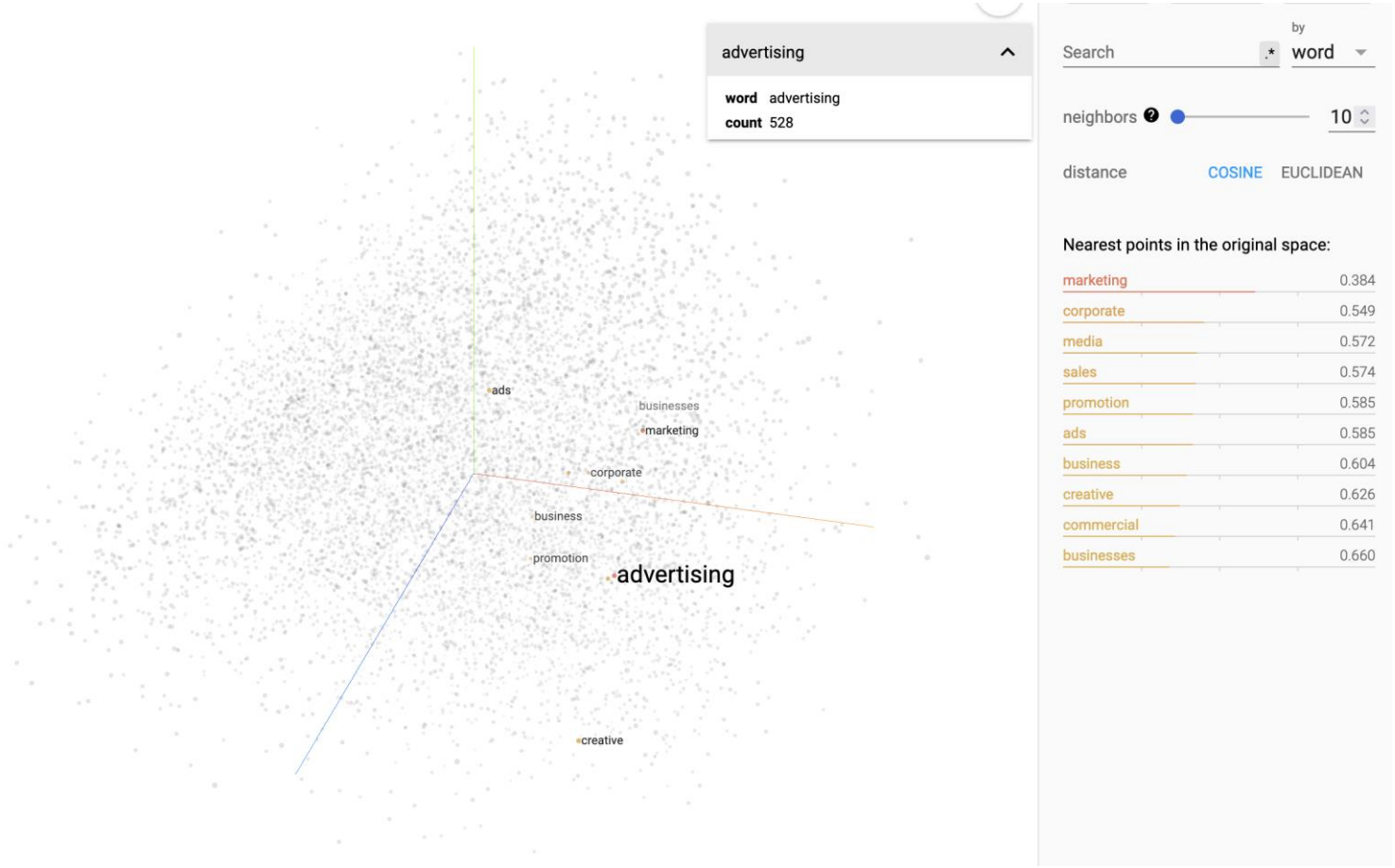
UMAP
T-SNE
PCA
CUSTOM
X
Component #1
Y
Component #2
Z
Component #3
PCA is approximate.
Total variance described: 8.5%.
Points: 10000 | Dimension: 200
Show All Data
Isolate 101 points
Clear selection
Search
by
word
BOOKMARKS (0)

Results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EUCLIDEAN
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corporate 0.549
media 0.572
sales 0.574
promotion 0.585
ads 0.585
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creative 0.626
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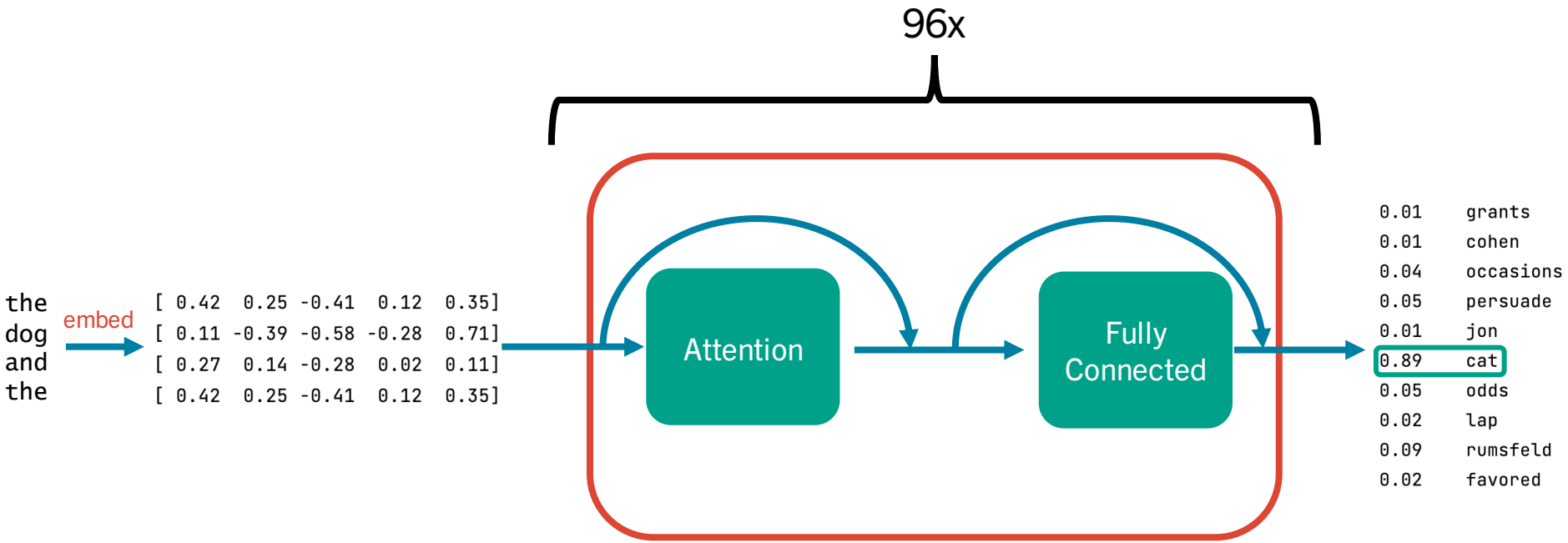
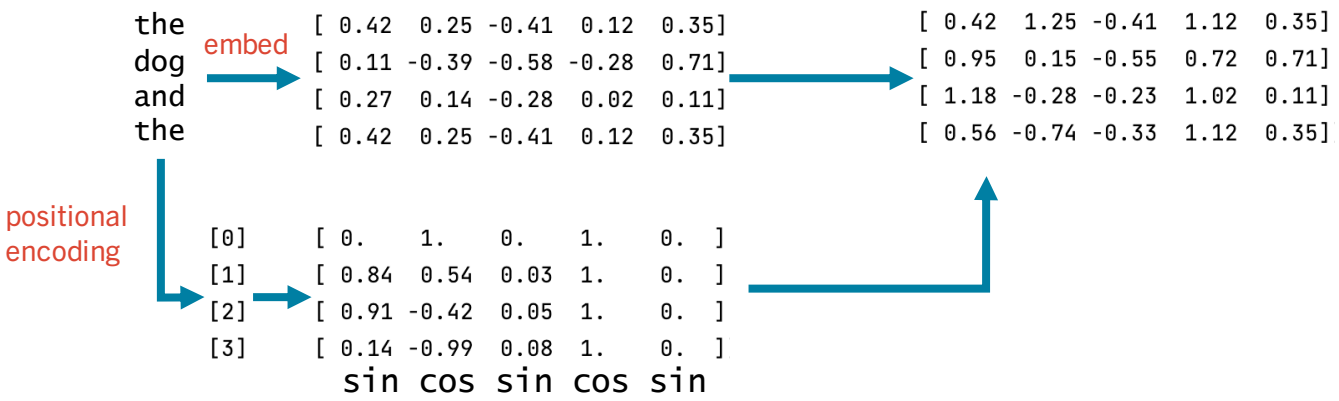
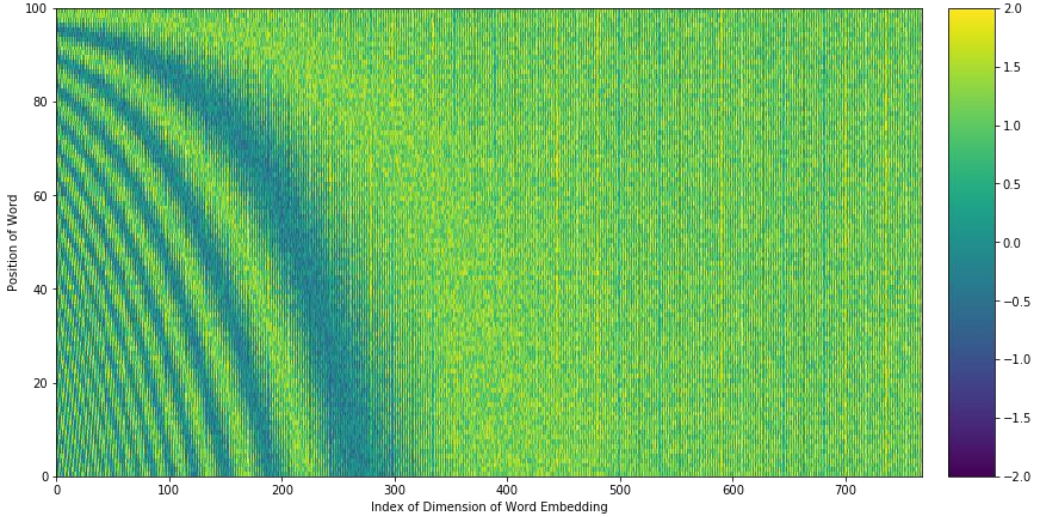
Building GPT

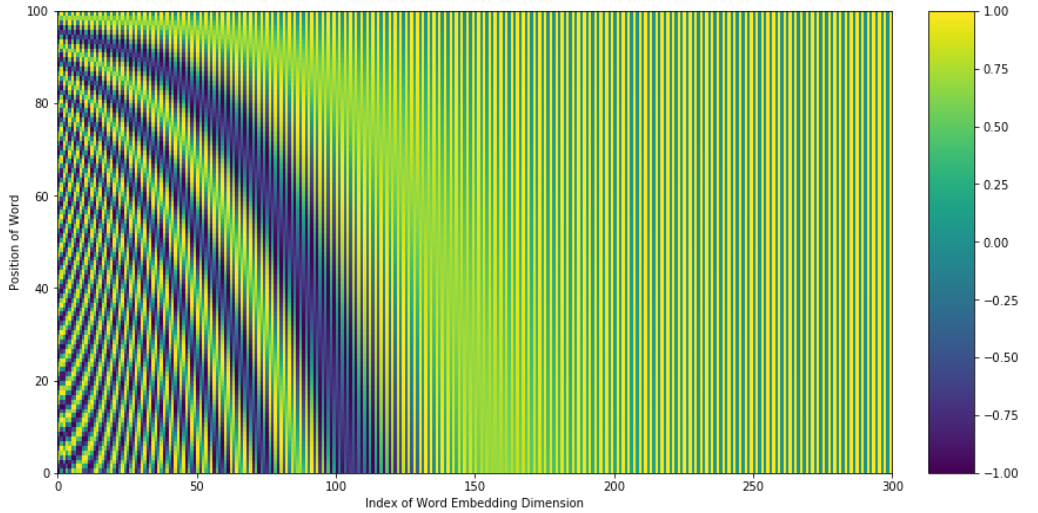
Building GPT: The Transfomer



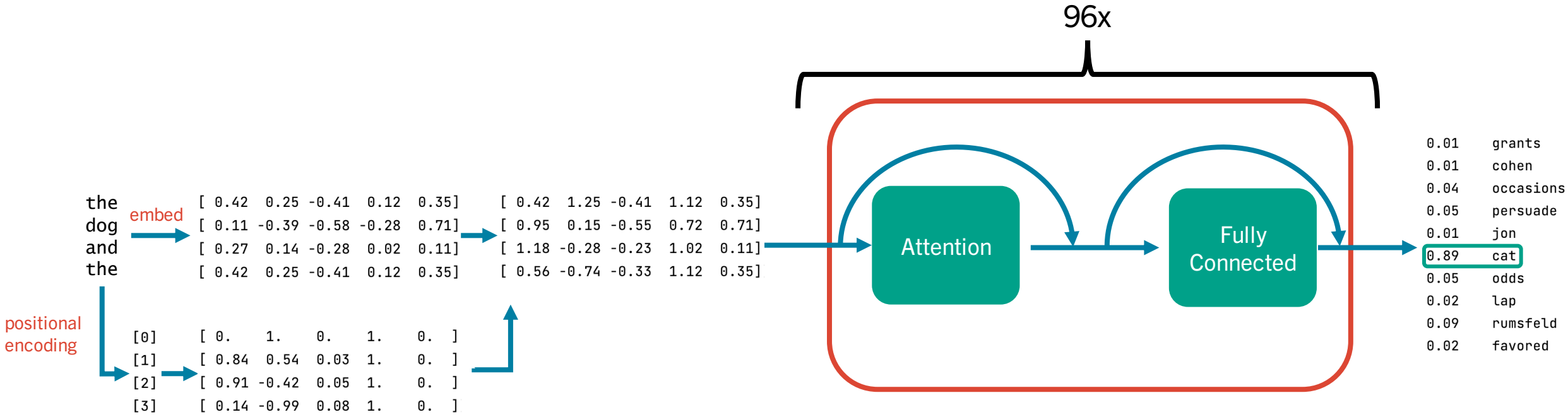
Building GPT: Positional Embedding



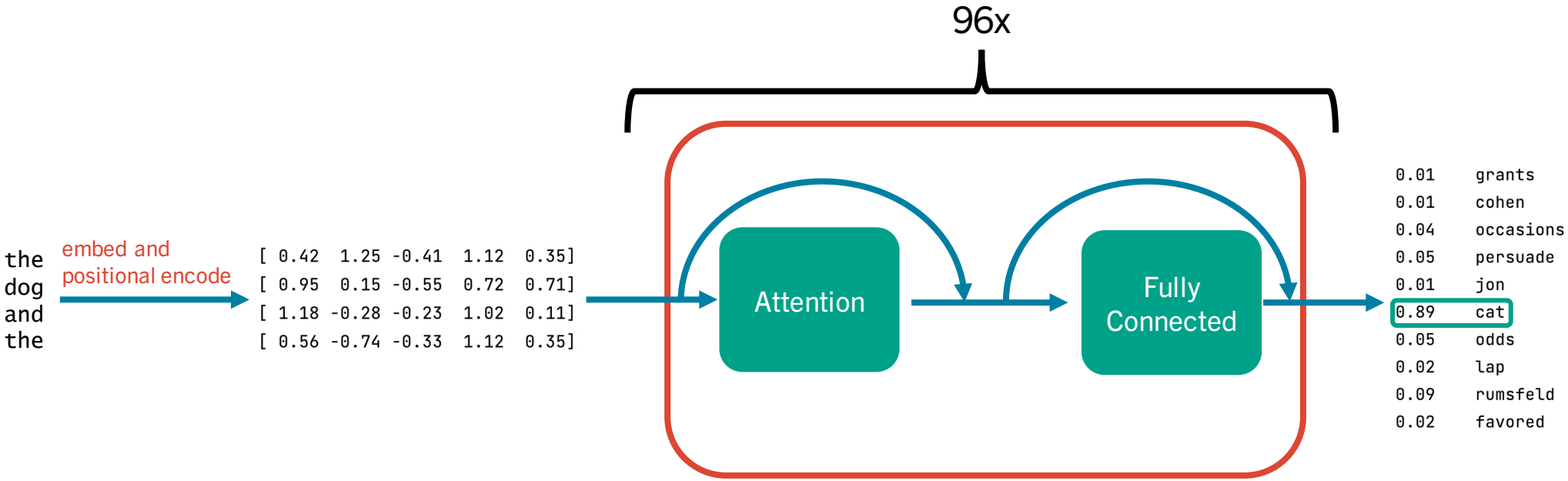




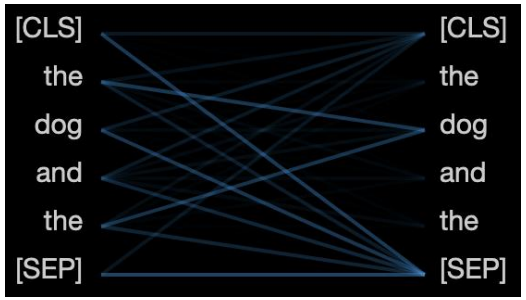
Building GPT

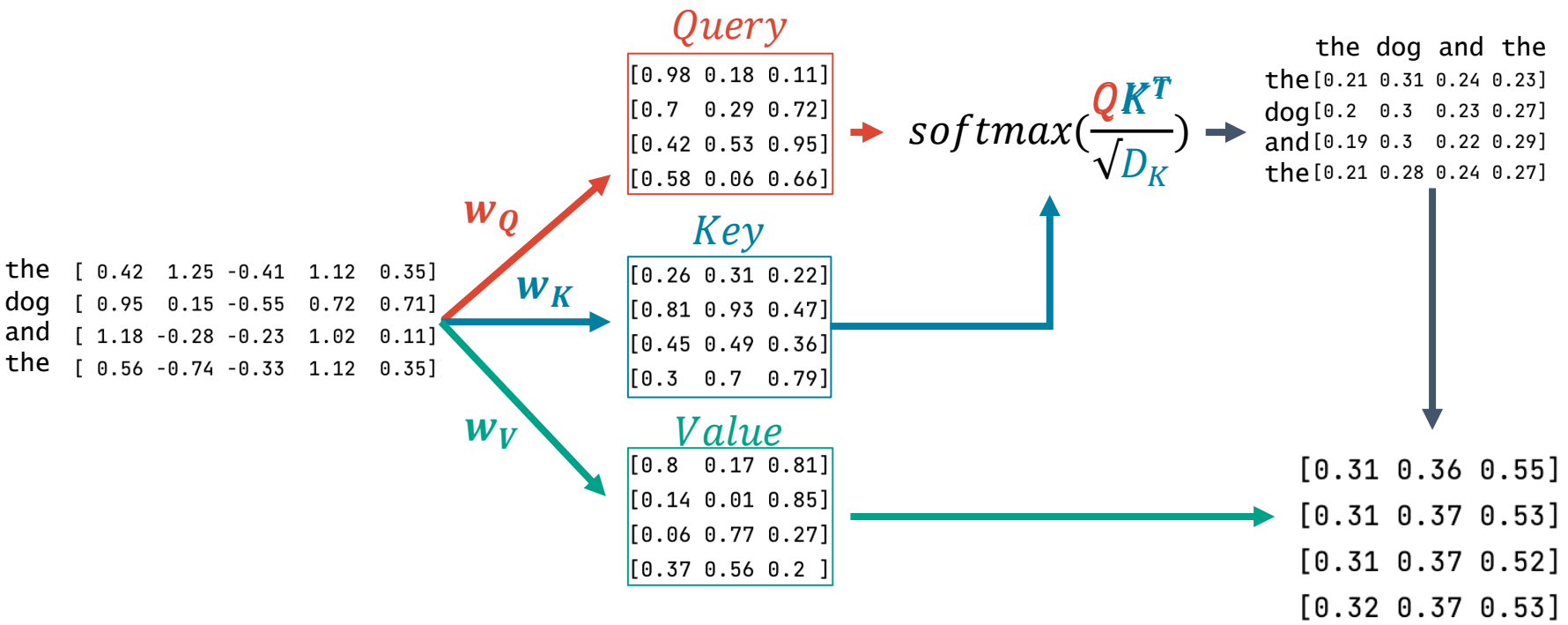


Building GPT

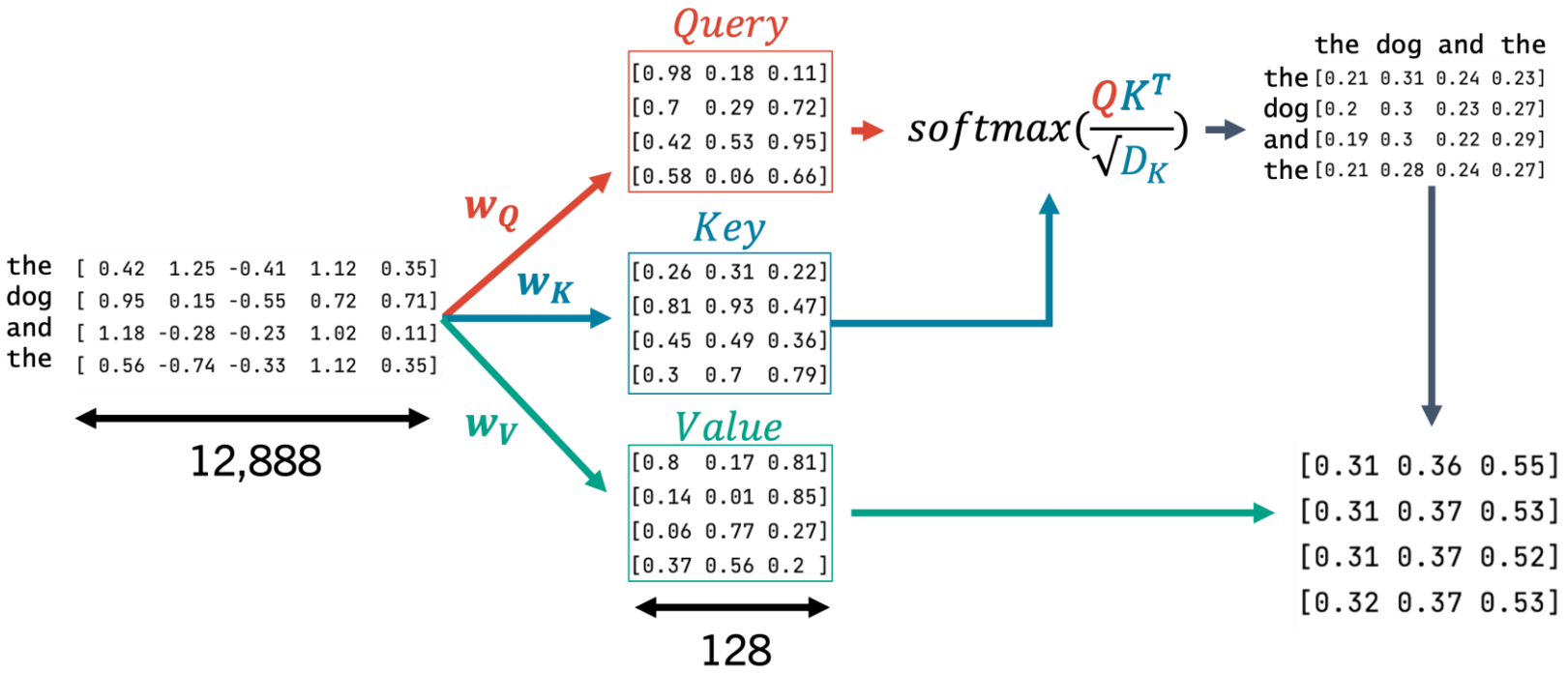


Building GPT: Attention

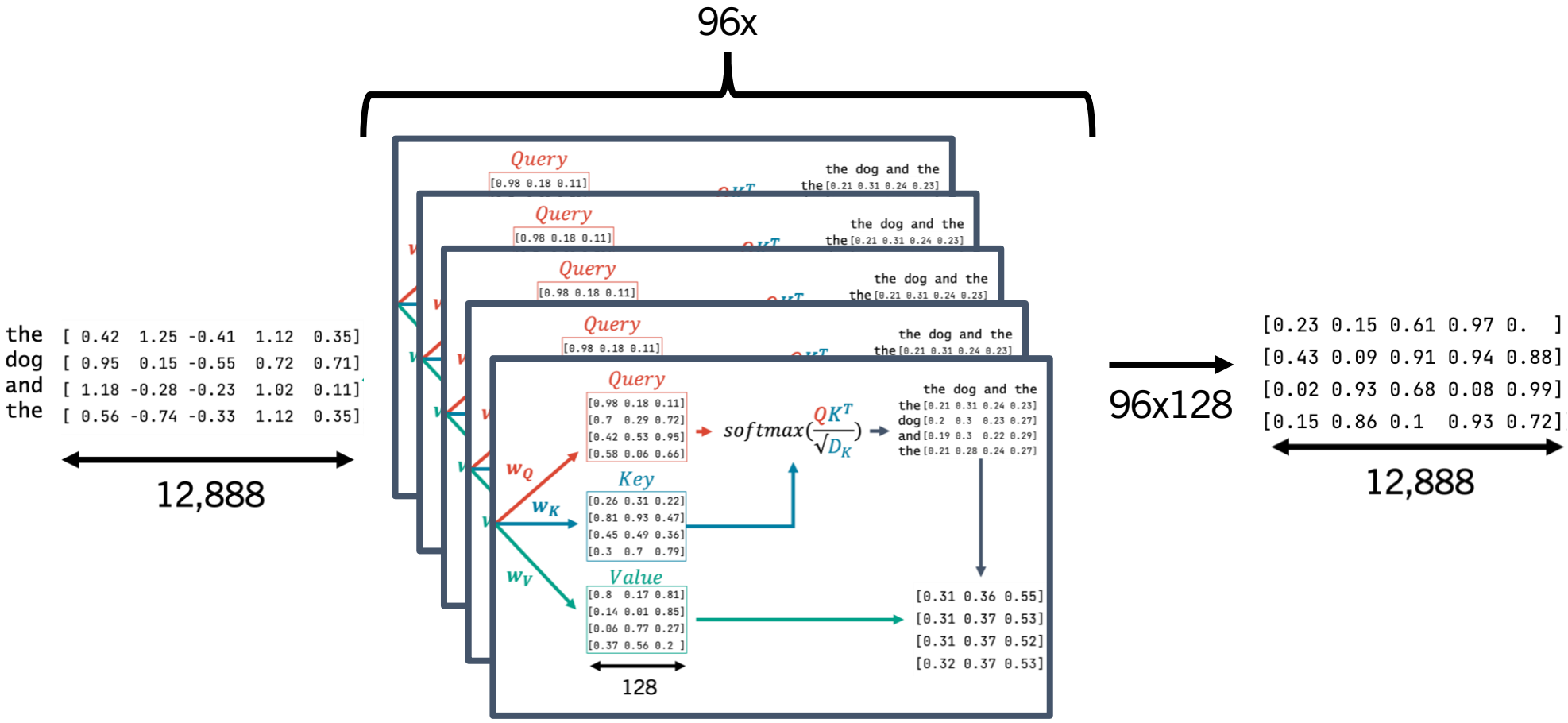




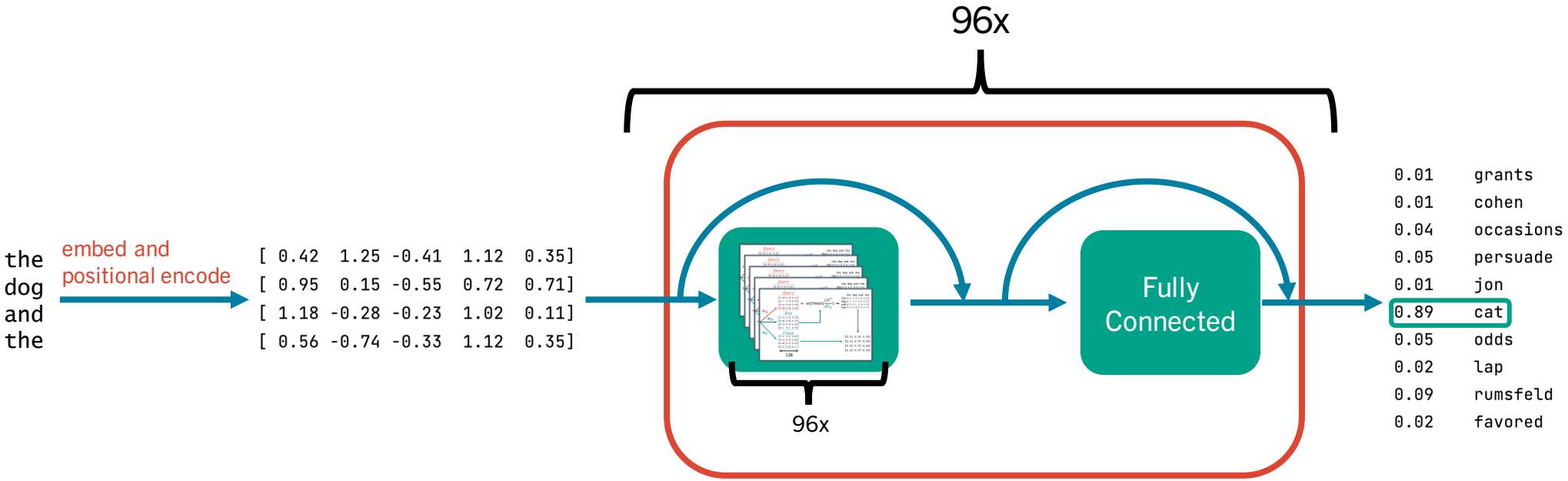
Building GPT: Attention



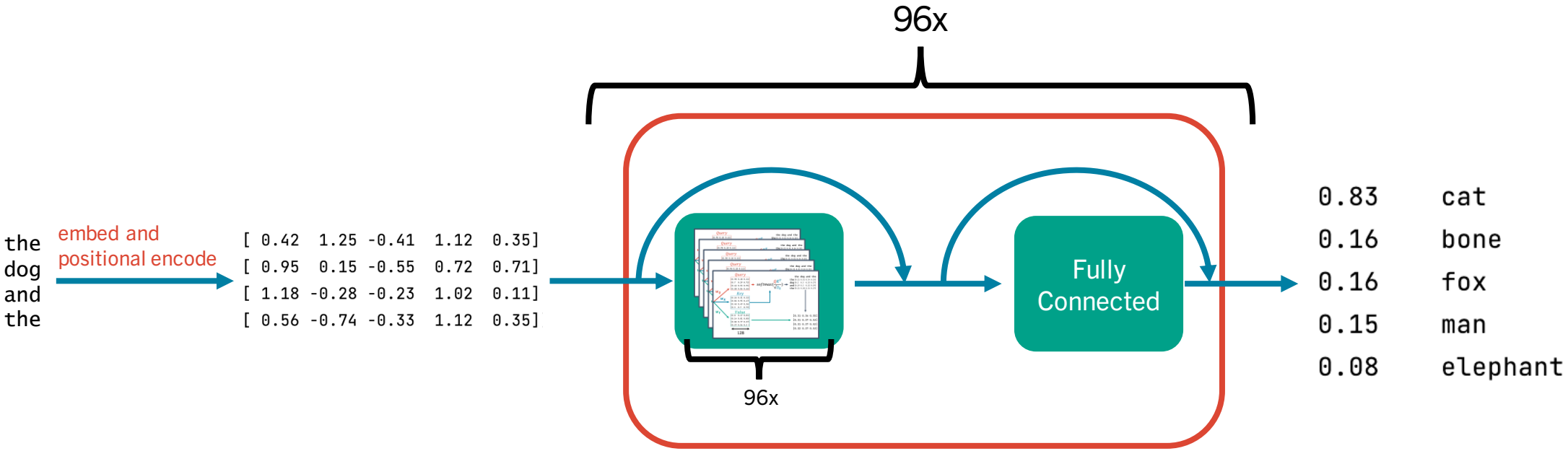
Building GPT: Attention



Building GPT



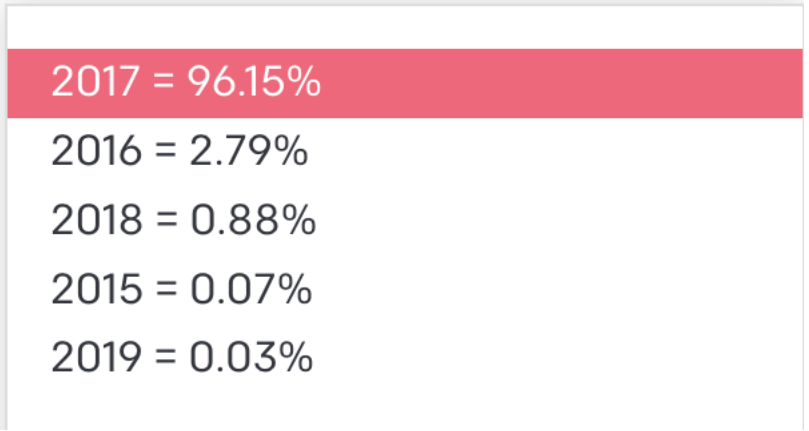
Building GPT: Top-P



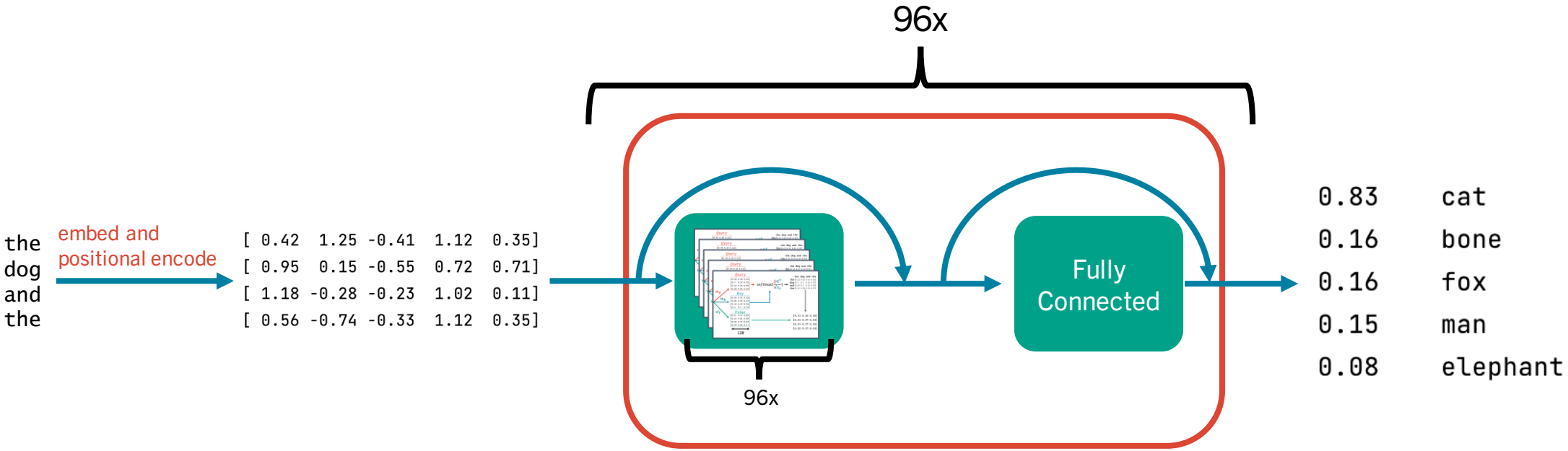
Building GPT: Top-P

Top 10 documentaries about artificial intelligence:

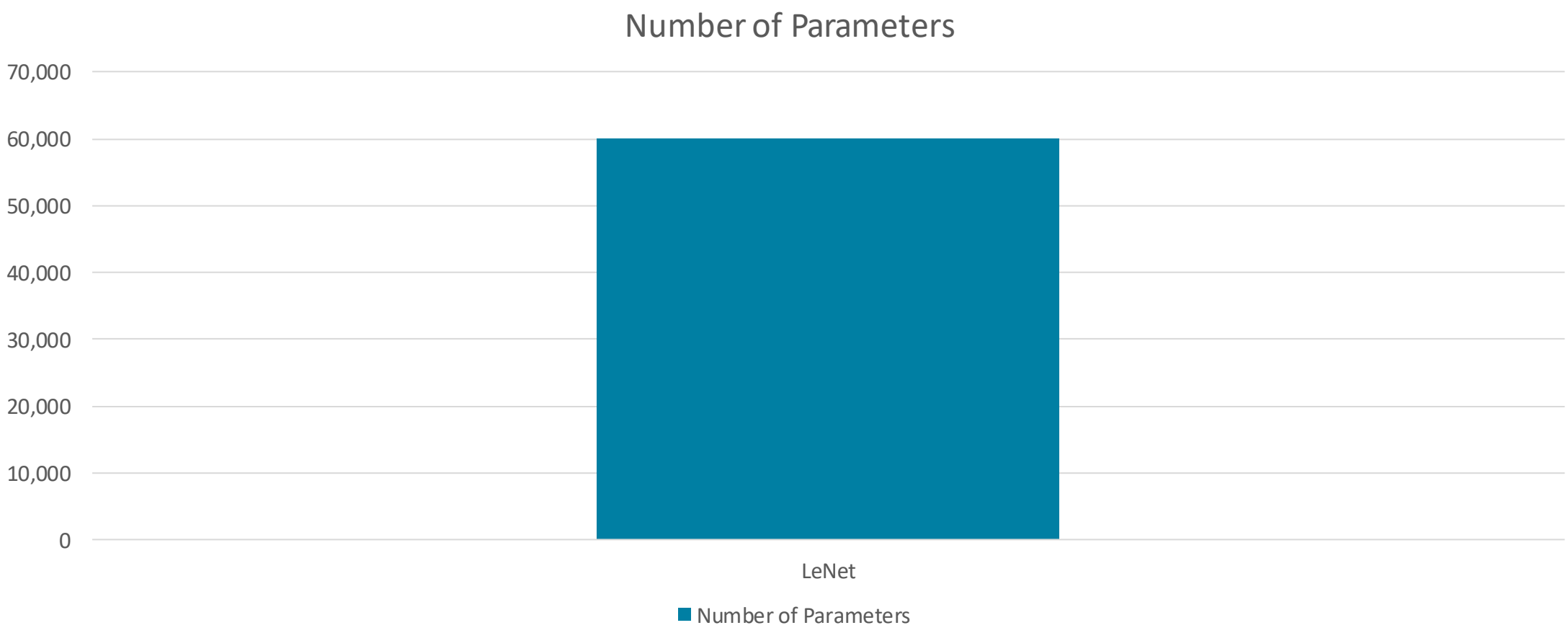
1. AlphaGo (2017)



Building GPT



Scale of GPT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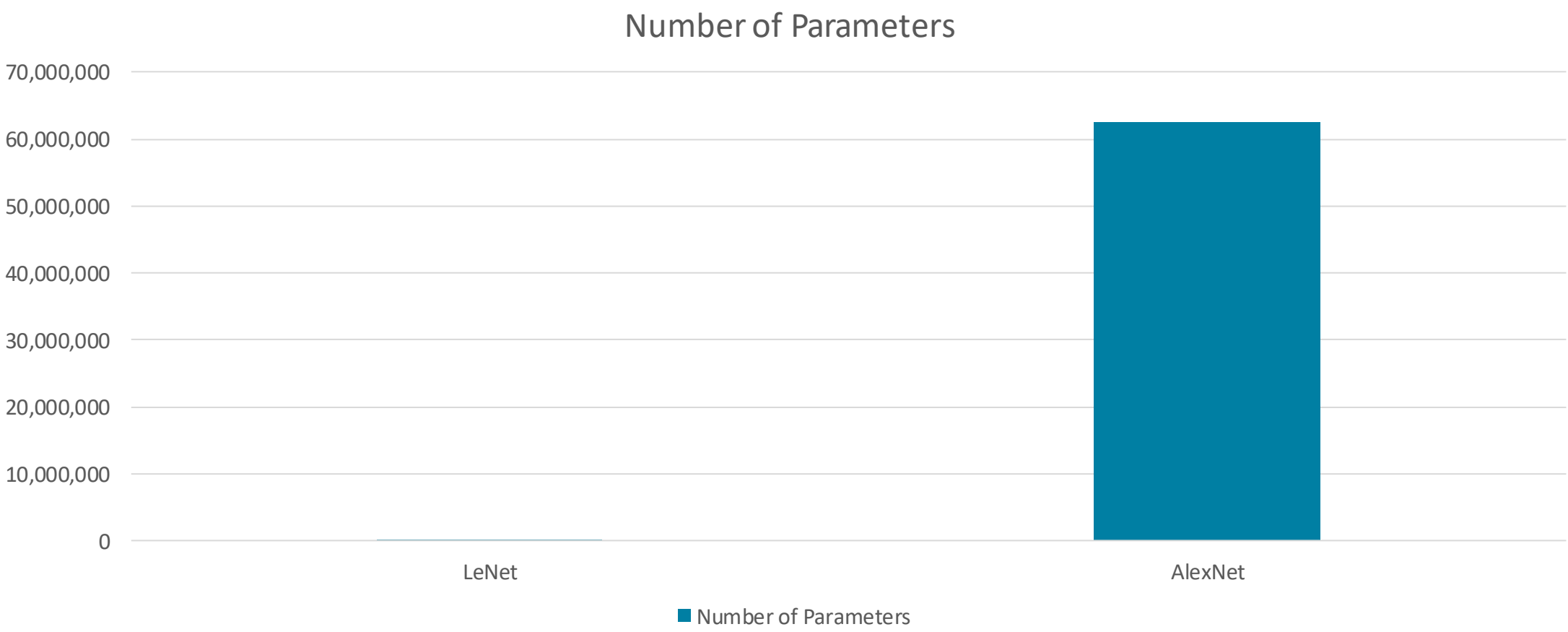
Scale of GPT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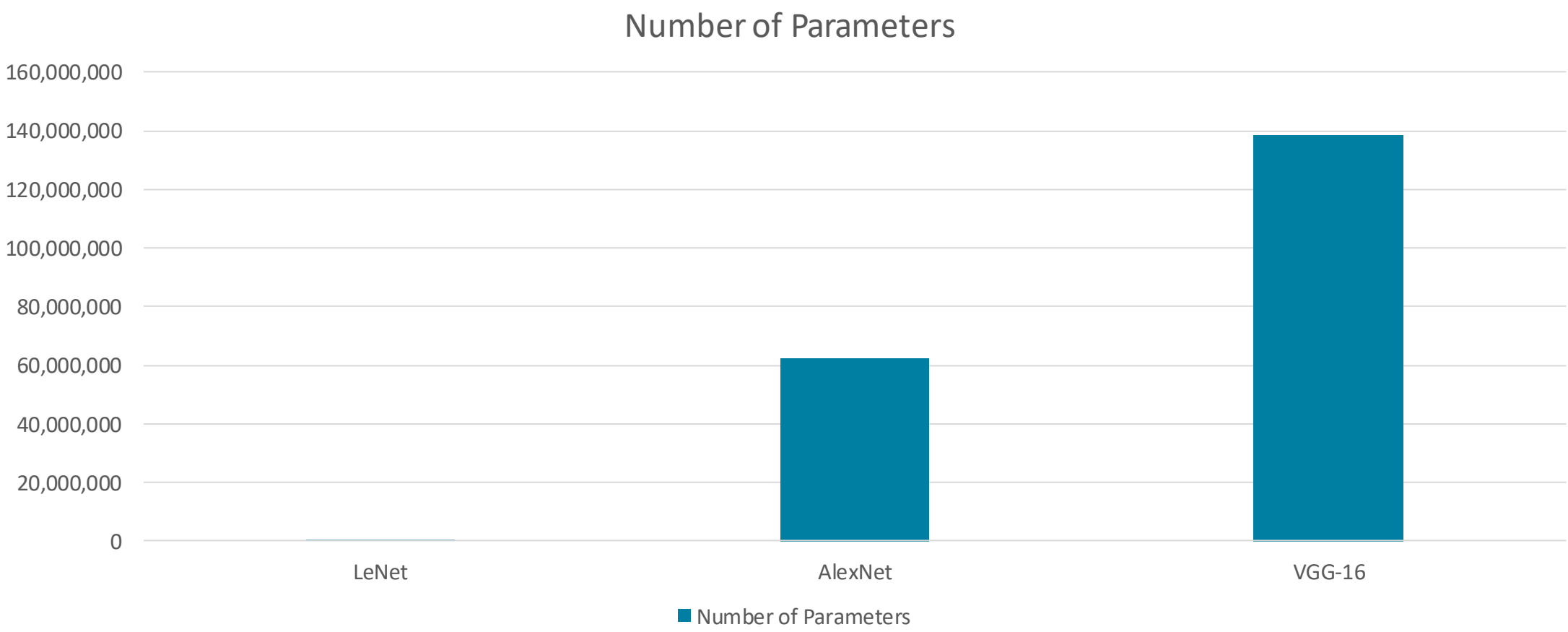
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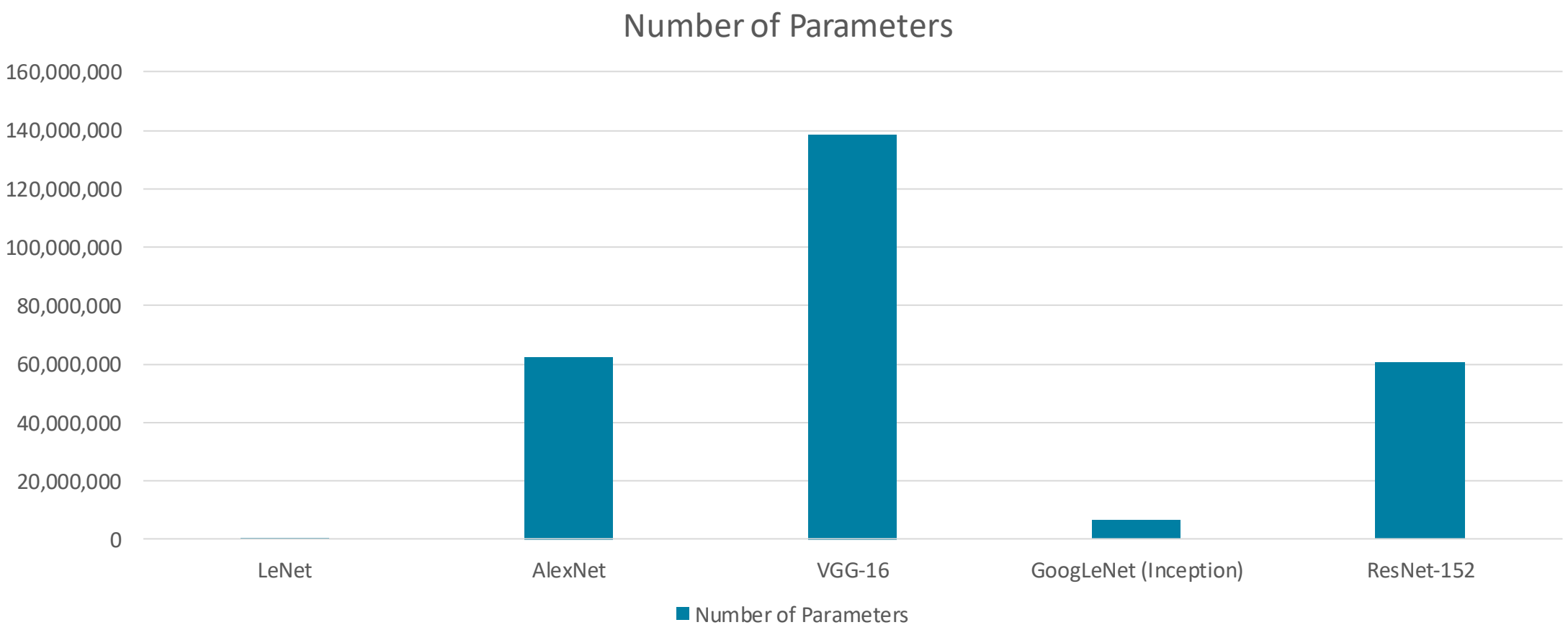
Number of Parameters

Scale of GPT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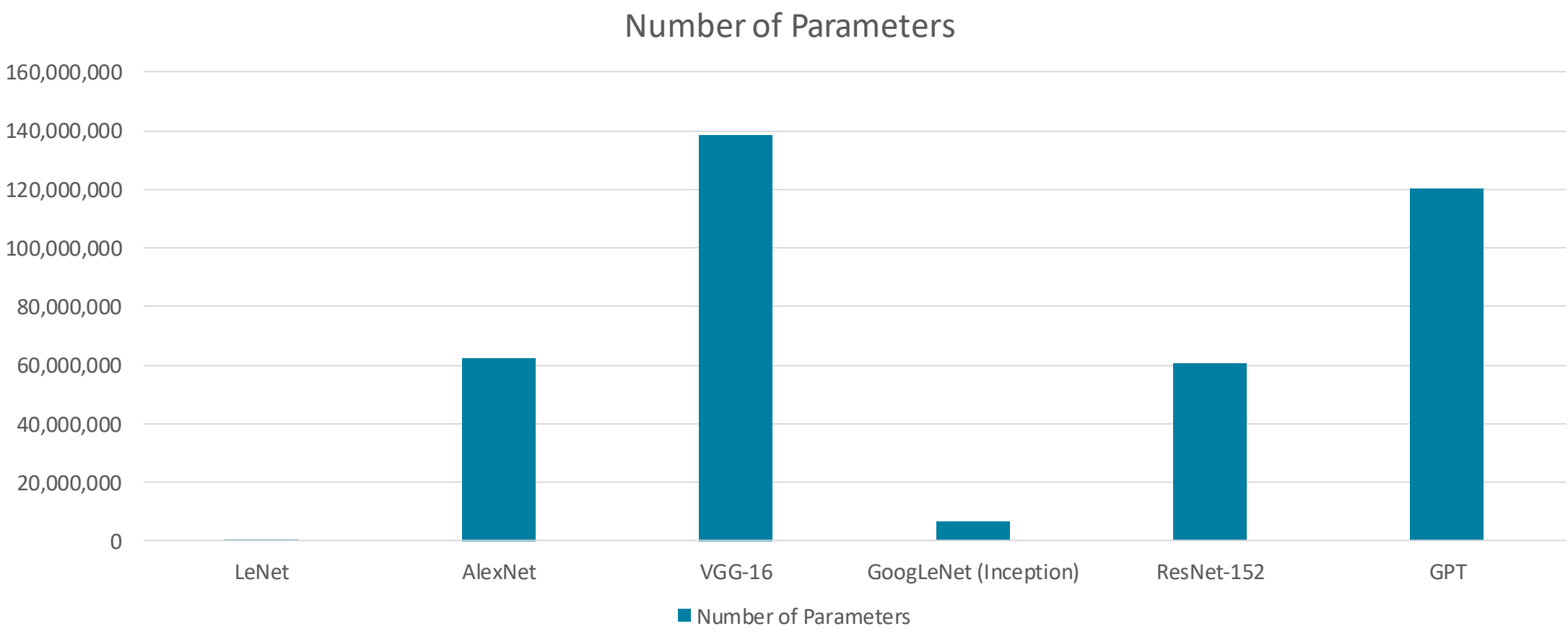
Number of Parameters

Scale of GPT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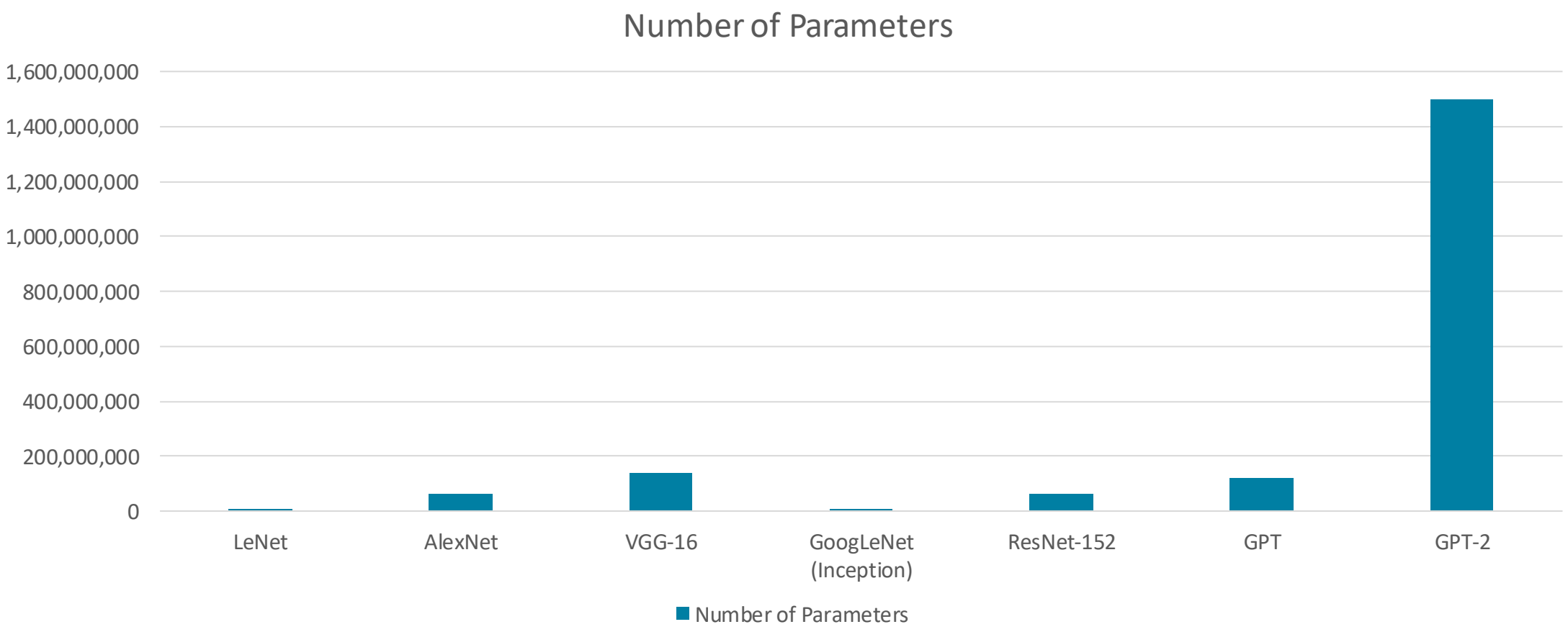
GPT
Number of Parameters

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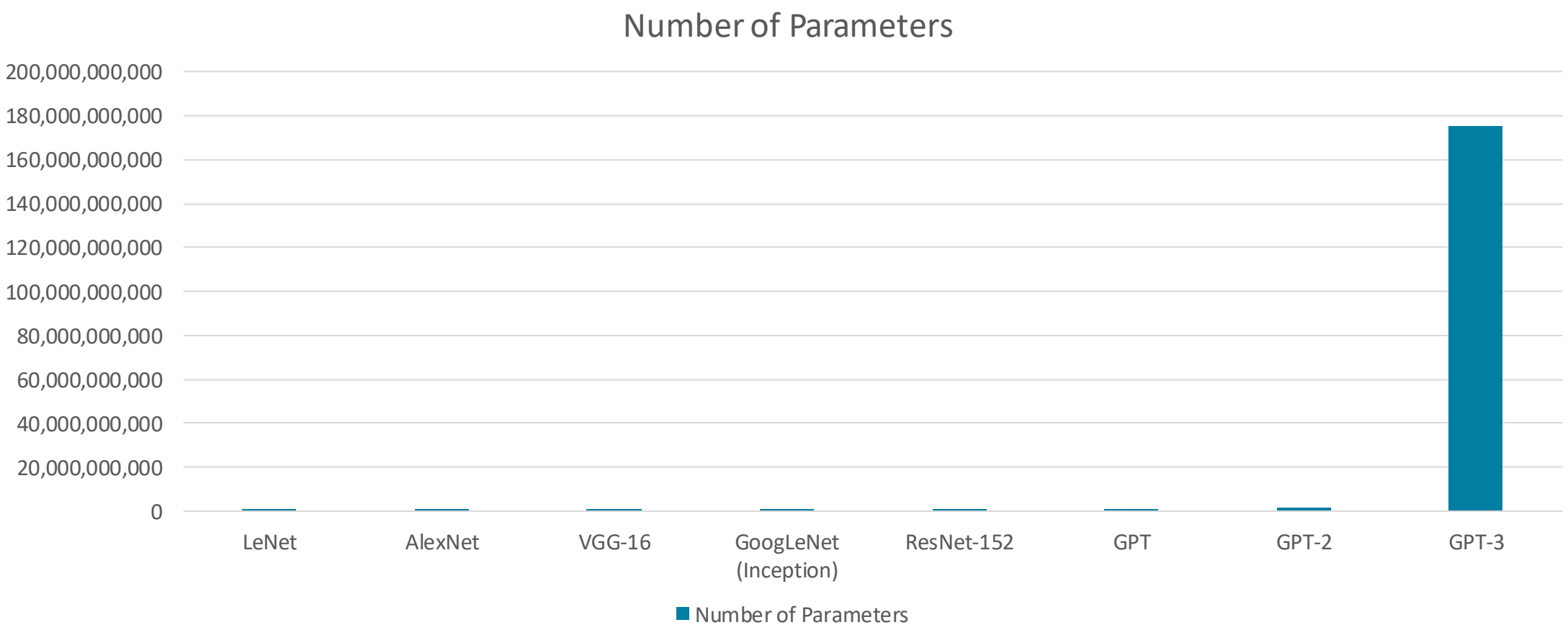
Scale of GPT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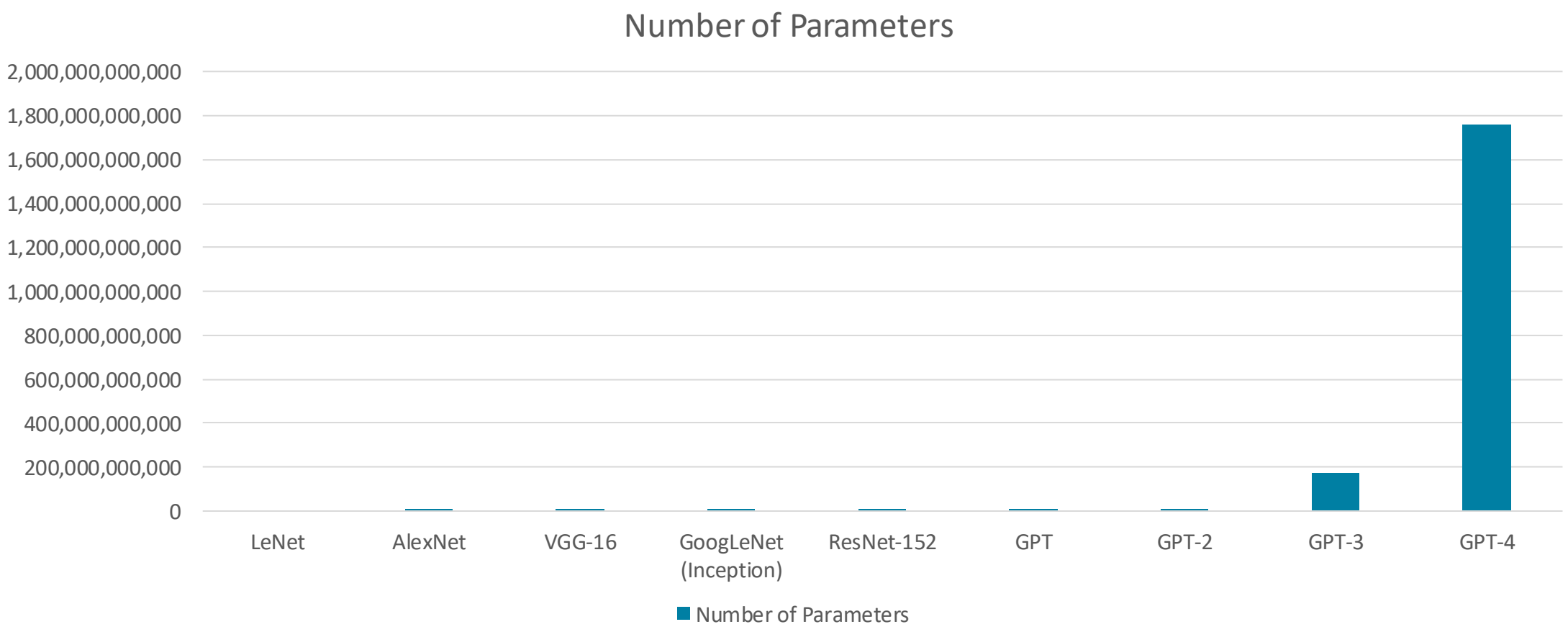
Scale of GPT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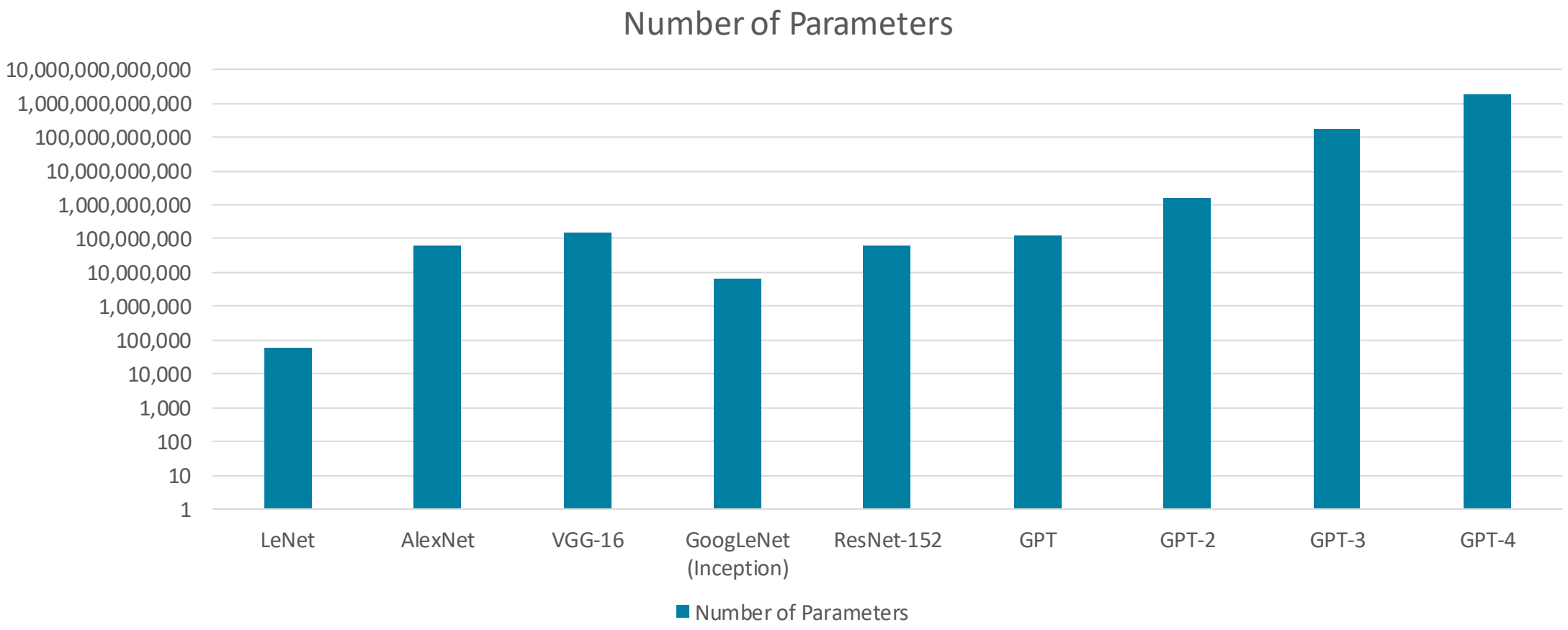
Scale of GPT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LeNet
AlexNet
VGG-16
GoogLeNet (Inception)
ResNet-152
GPT
GPT-2
GPT-3
GPT-4
Number of Parameters

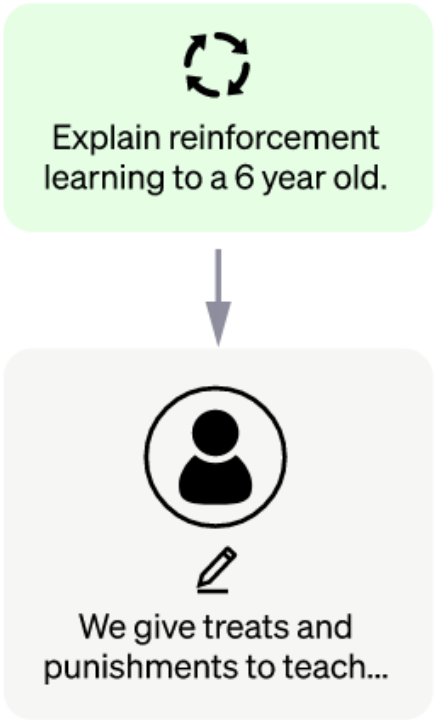
GPT's Training Data

- 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

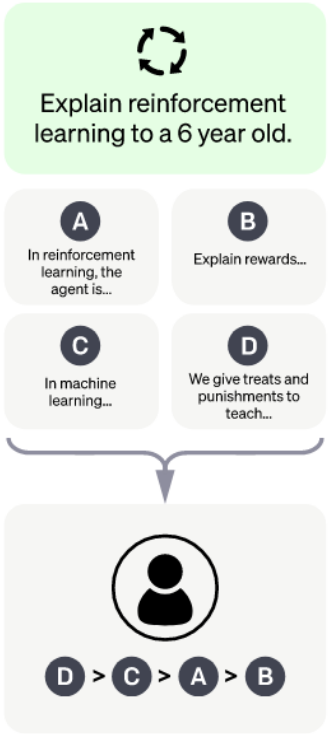
The training innovation of ChatGPT

Human annotators write answers to questions



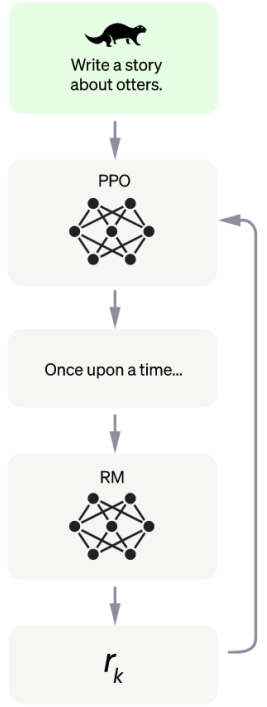
The generalist GPT model is taught from these Q&A pairs

Human annotators write more answers, and someone else ranks them



A separate model learns to rate the quality of an answer

GPT writes answers to sampled questions



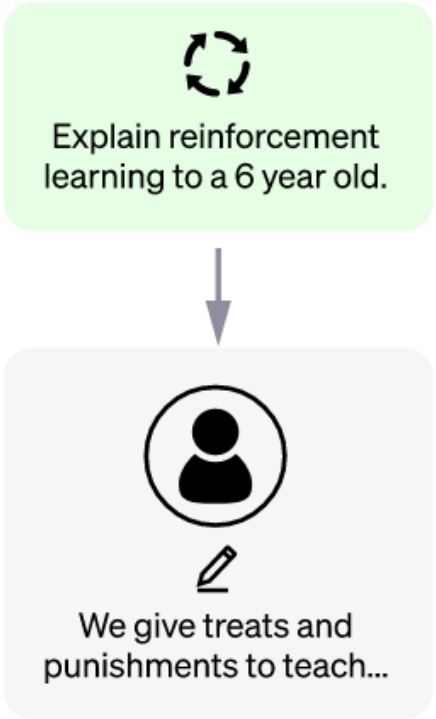
The reward model rates each answer, allowing GPT to keep learning

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

The training innovation of ChatGPT

No more humans involved!

Human annotators write answers to questions



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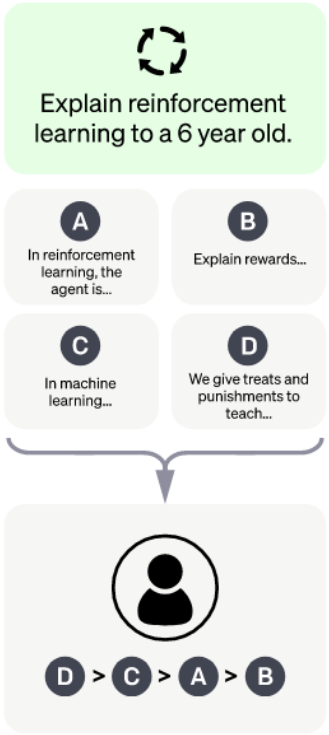

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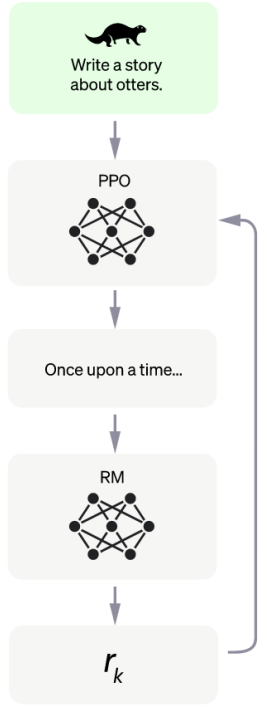

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