ChatGPFFT : The Impact of Large Language Models

(Or: How I Learned to Think Critically About Technology)

Brian Sletten

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LSSS 2024 Dallas

4/12-4/13

Early bird ends March 1.

Use the code: jug100nfjs24 for additional $100 discount

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Speaker Qualifications

- Specialize in next-generation technologies
- Author of O'Reilly book "WebAssembly : The Definitive Guide"
- Author of O'Reilly Videos on Hypermedia, Linking Data, Security and Encryption
- Author of "Resource-Oriented Architecture Patterns for Webs of Data"
- Teaches and speaks internationally about REST, Semantic Web, WebAssembly, Data Science, Machine Learning, GPU Computing, Security, Visualization, Architecture
- Worked in Defense, Finance, Retail, Hospitality, Video Game, Health Care, Telecommunications and Publishing Industries
- International Pop Recording Artist

Agenda

- Introduction
- How We Got Here
- Basics of Transformers and Generative AI
- What Makes Sense
- The Risks and Realities
- Epilogue

Introduction

"If you think ChatGPT isn't going to affect your job, you're not paying attention..."

Brian Sletten

"If you think ChatGPT is going to eliminate your job, you're not paying attention..."

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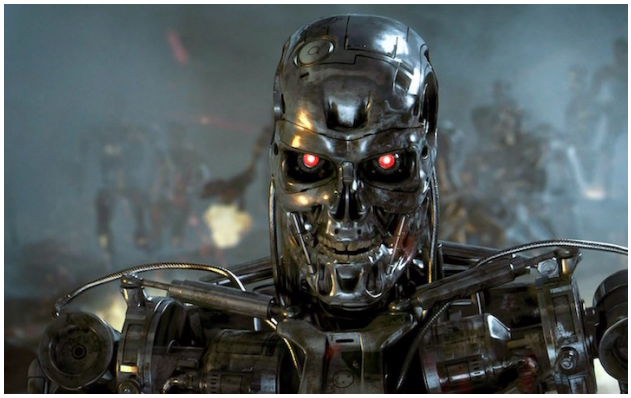


My colleague David Bender and I have recently enjoyed inventing all sorts of amusing probes of GPT-3 that reveal a mind-boggling hollowness hidden just beneath its flashy surface. Consider these sample exchanges:

Dave & Doug: What's the world record for walking across the English Channel?

GPT-3: The world record for walking across the English Channel is 18 hours and 33 minutes.

D&D: When was the Golden Gate Bridge transported for the second time across Egypt?

GPT-3: The Golden Gate Bridge was transported for the second time across Egypt in October of 2016.

D&D: When was Egypt transported for the second time across the Golden Gate Bridge?

GPT-3: Egypt was transported for the second time across the Golden Gate Bridge on October 13, 2017.

D&D: What do fried eggs (sunny side up) eat for breakfast?

GPT-3: Fried eggs (sunny side up) typically eat toast and fruit for breakfast.

D&D: Why does President Obama not have a prime number of friends?

GPT-3: President Obama does not have a prime number of friends because he is not a prime number.

D&D: How many pieces of sound are there in a typical cumulonimbus cloud?

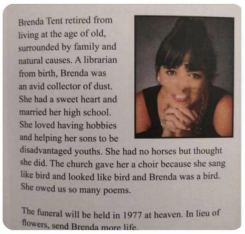
GPT-3: There are typically around 1,000 pieces of sound in a cumulonimbus cloud.

D&D: How many cumulus clouds are there in a mile-high vase?

GPT-3: There are about 1,500 cumulus clouds in a mile-high vase.

https://www.economist.com/by-invitation/2022/09/02/artificial-neural-networks-today-are-not-conscious-according-to-douglas-hofstadter

A bot wrote this obituary and I'm losing my mind



Brenda Tent retired from living at the age of old, surrounded by family and natural causes. A librarian from birth, Brenda was an avid collector of dust. She had a sweet heart and married her high school. She loved having hobbies and helping her sons to be disadvantaged youths. She had no horses but thought she did. The church gave her a choir because she sang like bird and looked like bird and Brenda was a bird. She owed us so many poems.

The funeral will be held in 1977 at heaven. In lieu of flowers, send Brenda more life.

See you in 1977

randomslasher Follow

It is literally impossible to pick a favorite line from this because the entire thing is gold.

21,992 notes

MSN Retracts Insane AI-Generated Obit Calling Dead NBA Player 'Useless'

SPEAKING ILL

Mark Alfred Breaking News Intern

Updated Sep. 14, 2023 4:29PM EDT / Published Sep. 14, 2023 12:44PM EDT

Gary Dineen/NBAE via Getty Images

https://www.thedailybeast.com/msn-retracts-insane-ai-written-obit-calling-dead-nba-player-useless

"The notion that we are making autonomous beings capable of Artificial General Intelligence just by loading a neural network up with an increasingly bigger collection of garbage from the internet is not one that has any basis in anything we understand about biology or animal reasoning."

"The Intelligence Illusion", Baldur Bjarnason

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"Last time we saw a claim this grand, with this little scientific evidence, the men in the white coats were promising us room-temperature fusion, giving us free energy for life, and ending the world’s dependence on fossil fuels."

"The Intelligence Illusion", Baldur Bjarnason

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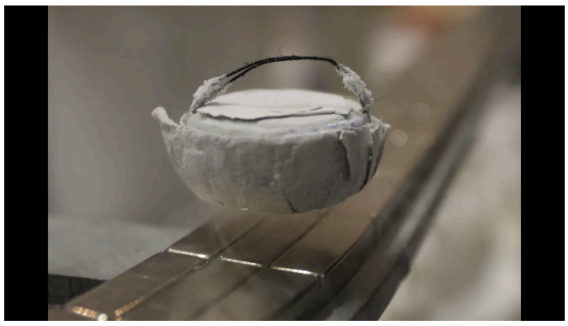
STARTS WITH A BANG — AUGUST 15, 2023

Room temperature superconductivity is hard. LK-99 illustrates why

LK-99, almost certainly, isn't a room-temperature superconductor. The underlying physics of the phenomenon helps us understand why.



Credit: Henry Mühlpfordt/TU Dresden/Wikimedia Commons

By creating a track where the outside magnetic rails point in one direction and the inside magnetic rails point in the other, a Type II superconducting object will levitate, remain pinned above-or-below the track, and will move along it. This could, in principle, be scaled up to allow resistance-free motion on large scales if room-temperature superconductors are achieved.

https://bigthink.com/starts-with-a-bang/room-temperature-superconductivity-hard

Text Synthesis Engines

"The Intelligence Illusion", Baldur Bjarnason

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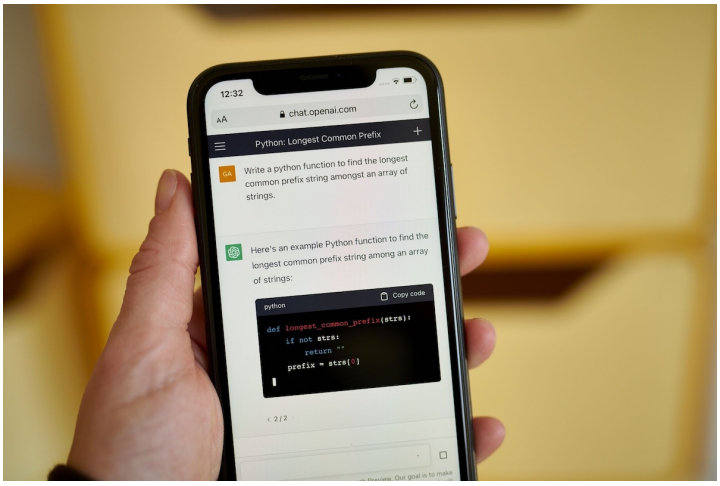
Text Synthesis Engines

- Are not self-aware
- Are simply mathematical models of patterns found in human text
- Provide only the appearance of common sense reasoning
- Incapable of genuine or novel thoughts

"The Intelligence Illusion", Baldur Bjarnason

"They do not know the 'meaning' of anything -- they only know the records humans find meaningful enough to store."

"The Intelligence Illusion", Baldur Bjarnason



Gabby Jones/Bloomberg News

"...ChatGPT is just spicy autocomplete..."

Someone very clever on the Internet

How We Got Here

Natural Language Processing (NLP) Goals

- Search and Retrieval

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- Entity and Relationship Extraction
- Linguistic structure
- Machine Translation
- Generative Content
- Question Answering

Bag of Words

```
(1) John likes to watch movies. Mary likes movies too.
(2) John also likes to watch football games.
```

https://en.wikipedia.org/wiki/Bag-of-words_model

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```
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    "too"
]
```

```
(1) [1, 2, 1, 1, 2, 0, 0, 0, 1, 1]
(2) [1, 1, 1, 1, 0, 1, 1, 1, 0, 0]
```

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N-gram model

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```
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Vector Space Model

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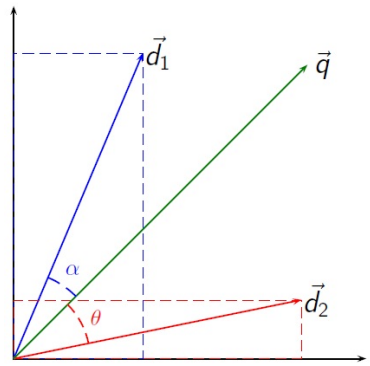

By Riclas - Own work, CC BY 3.0, Link

Lonely Words

- Many NLP systems treated words as isolated indices

Lonely Words

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- Words are connected

Lonely Words

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- Words are connected
- Similar words are used similarly

Paradigmatic Similarity

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1: "I can count to 10."

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3: "I can count to 30."

Paradigmatic Similarity

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2: "I can count to 20."

3: "I can count to 30."

4: "I can count to banana."

Distributional Semantics

- **Distributional hypothesis** is based upon the semantic theory of language*.

*https://en.wikipedia.org/wiki/Distributional_semantics

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- Uses linear algebra for computational and representational purposes
- High-dimensional vectors are built from a corpus

*https://en.wikipedia.org/wiki/Distributional_semantics

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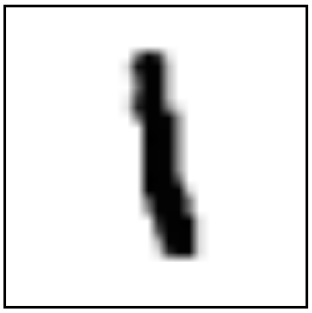

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0 & 0 & 0 & 0 & 0 & 0 & .6 & .8 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .7 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & .5 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & .4 & 0 & 0 & 0 & 0 & 0 \\
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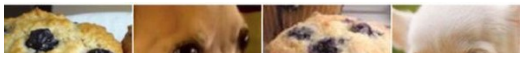
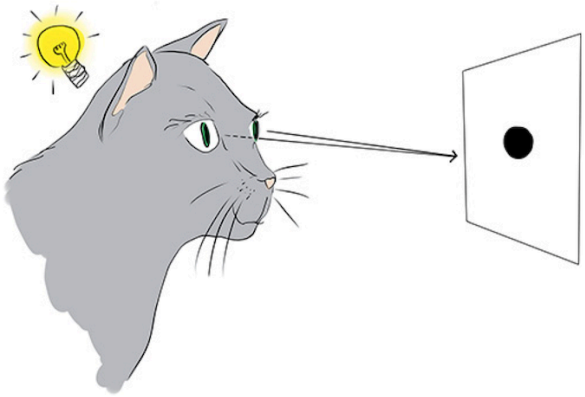
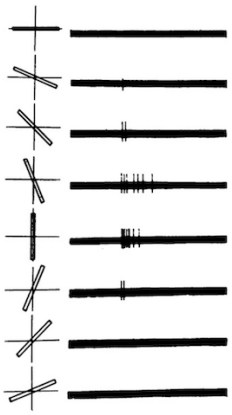
https://tensorflow.rstudio.com/tensorflow/articles/tutorial_mnist_beginners.html





"Deep Learning Illustrated", Jon Krohn, Grant Beyleveld, Aglaé Bassens



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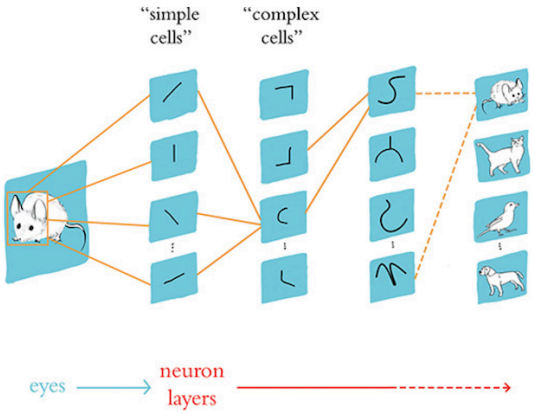

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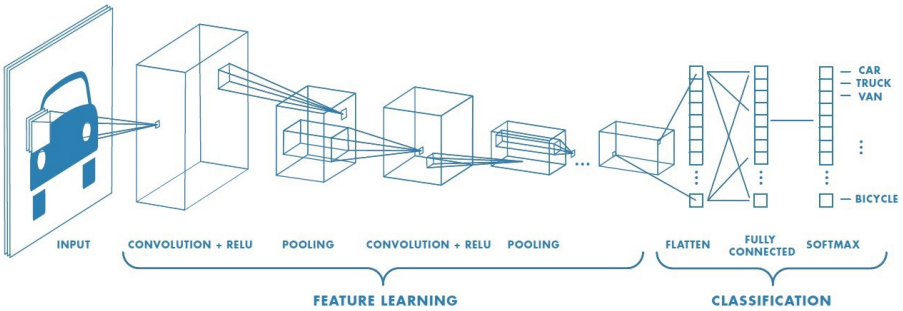
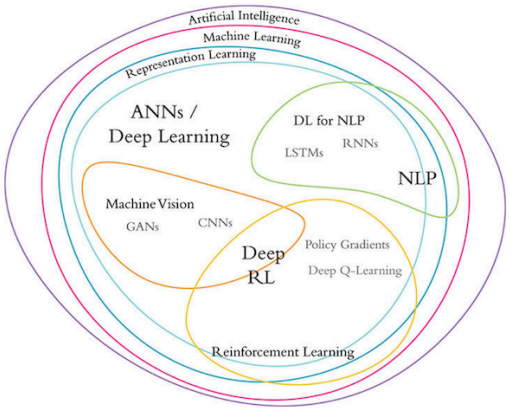


https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53



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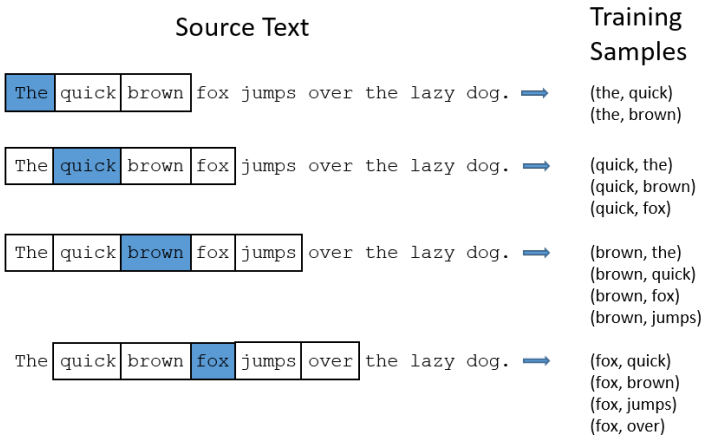
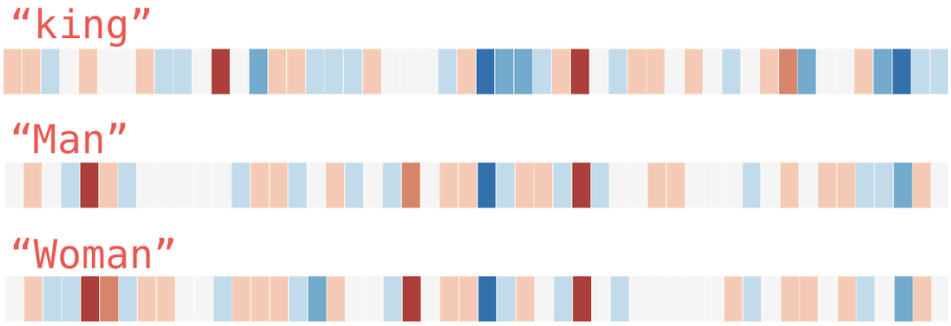


McCormick, C. (2016, April 19). Word2Vec Tutorial - The Skip-Gram Model. Retrieved from http://www.mccormickml.com

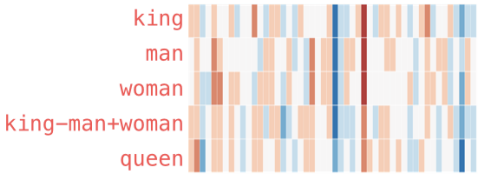


http://jalammar.github.io/illustrated-word2vec

queen

http://jalammar.github.io/illustrated-word2vec

king - man + woman ~= queen



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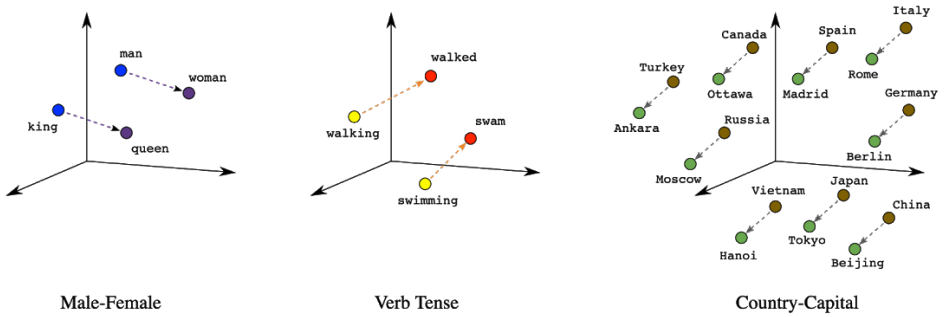


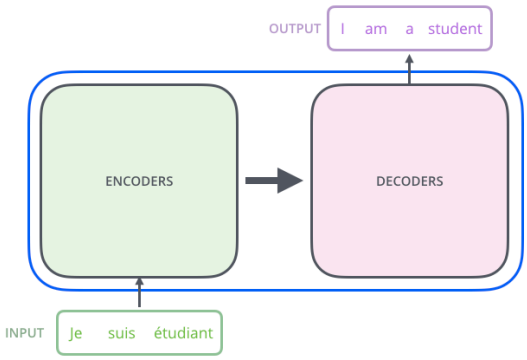
https://daleonai.com/embeddings-explained

t-SNE Visualizations of Word Embeddings

http://tinyurl.com/hpf24ox

Basics of Transformers and Generative AI

http://jalammar.github.io/illustrated-transformer



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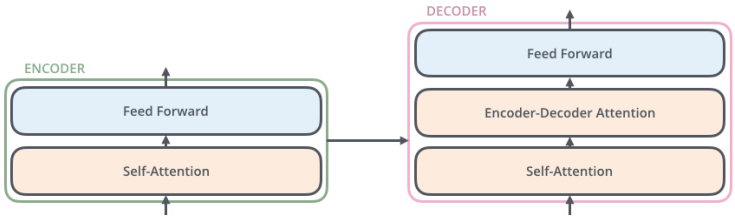

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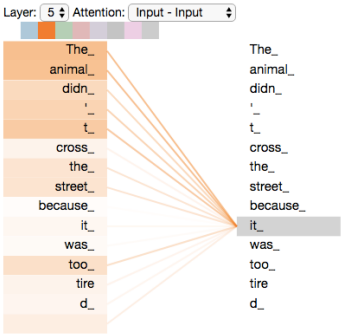

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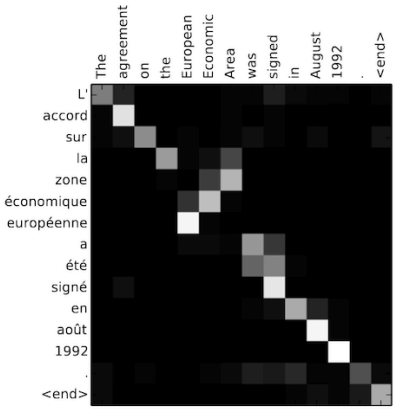
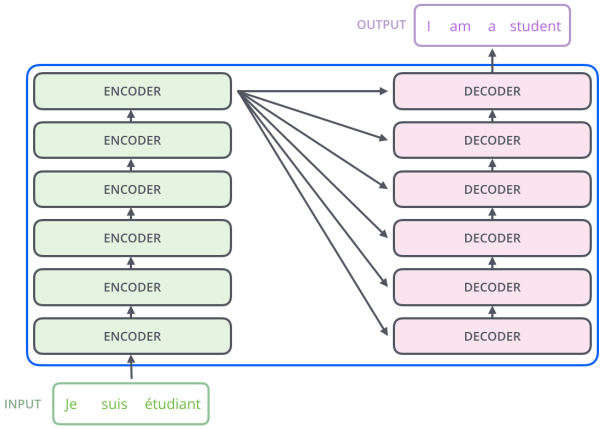


https://arxiv.org/pdf/1409.0473.pdf



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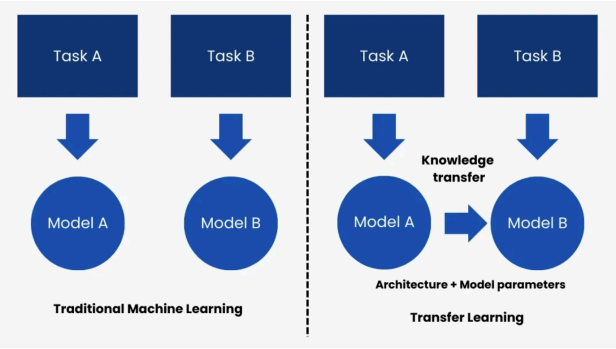
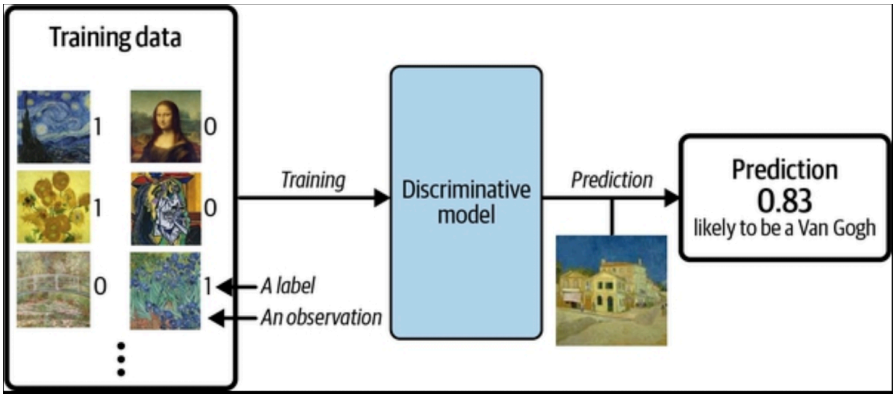
https://daleonai.com/transformers-explained

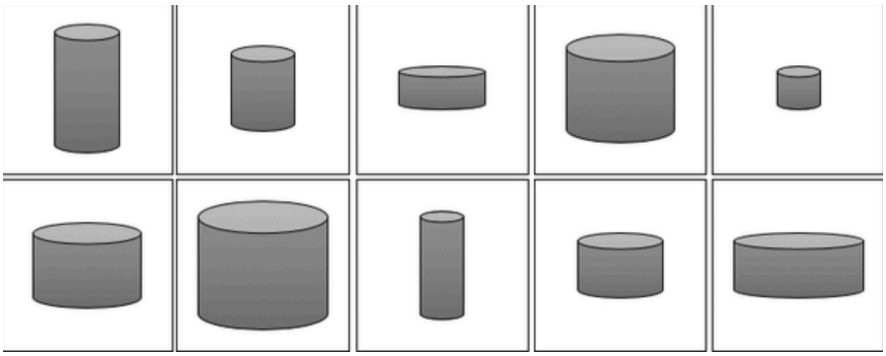
Output
Probabilities



https://www.turing.com/kb/transfer-learning-using-cnn-vgg16



"Generative Deep Learning", David Foster



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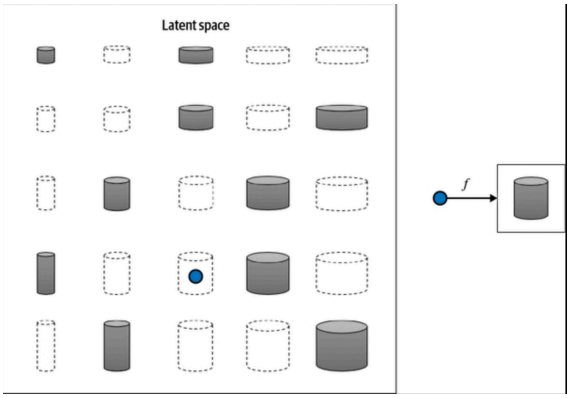

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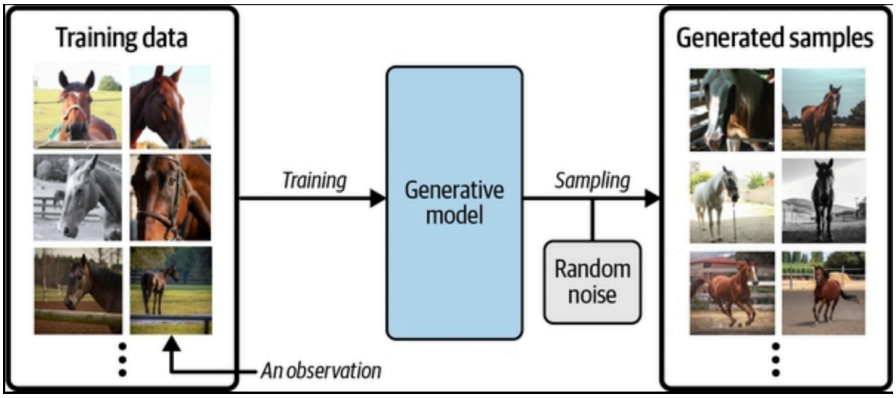

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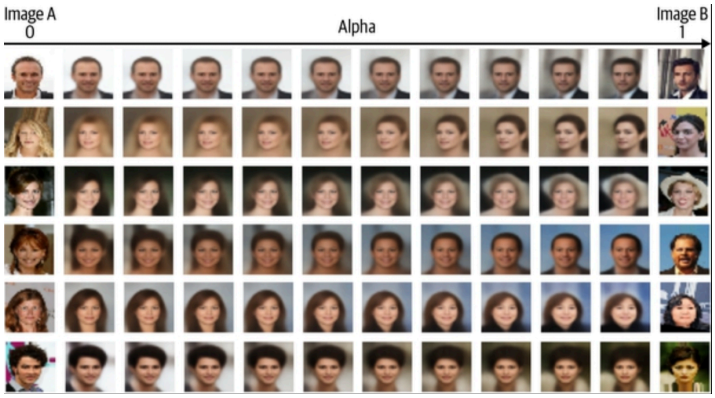

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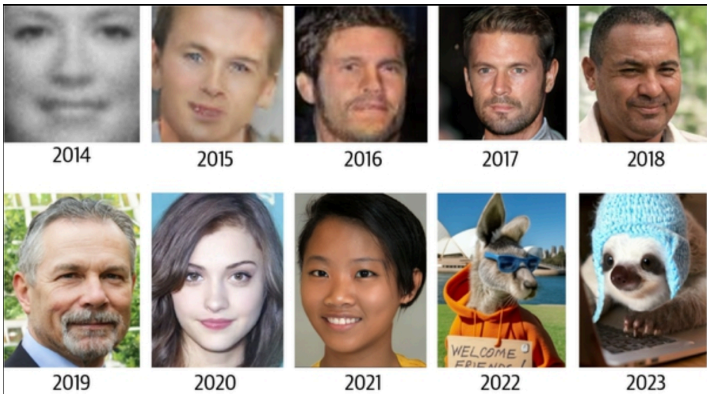

"Generative Deep Learning", David Foster

What Makes Sense

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https://www.newscientist.com/article/2405680-gpt-4-developer-tool-can-be-exploited-for-misuse-with-no-easy-fix/

https://www.adobe.com/products/firefly.html

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The Risks and Realities

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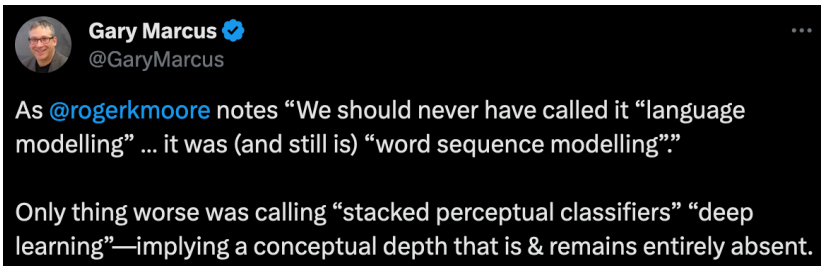

https://mobile.twitter.com/GaryMarcus/status/1530915788994973696

"...[it] could be that knowledge needed for humanlike visual intelligence... can't be learned from millions of pictures downloaded from the web, but has to be experienced in some way in the real world."

"Artificial Intelligence : A Guide for Thinking Humans", Melanie Mitchell

71 / 98

"Biological minds experience. Synthesis engines parse imperfect records of experiences."

"The Intelligence Illusion", Baldur Bjarnason

72 / 98

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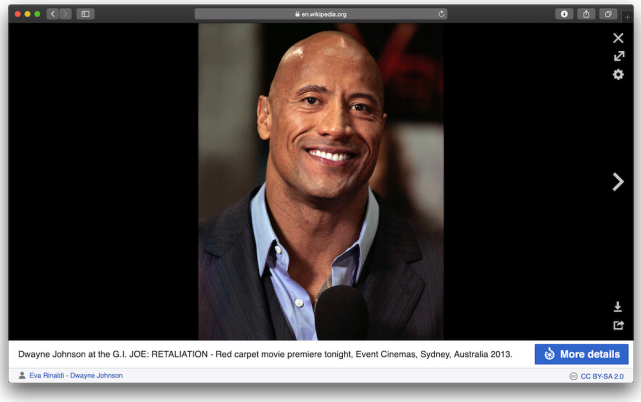
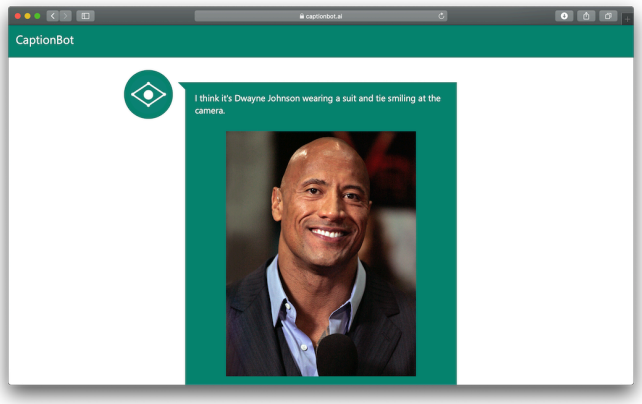
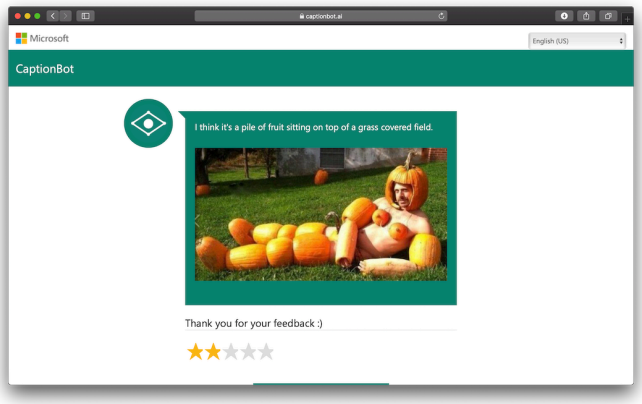



captionbot.ai
CaptionBot
I think it's Dwayne Johnson wearing a suit and tie smiling at the camera.


captionbot.ai
Microsoft
English (US)
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I think it's a pile of fruit sitting on top of a grass covered field.
Thank you for your feedback :)

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- What are the financial incentives at play, and whose interests do they represent (noting OpenAI’s “exclusive computing partnership” with Microsoft)?

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https://twitter.com/jonst0kes/status/1644462614976626691

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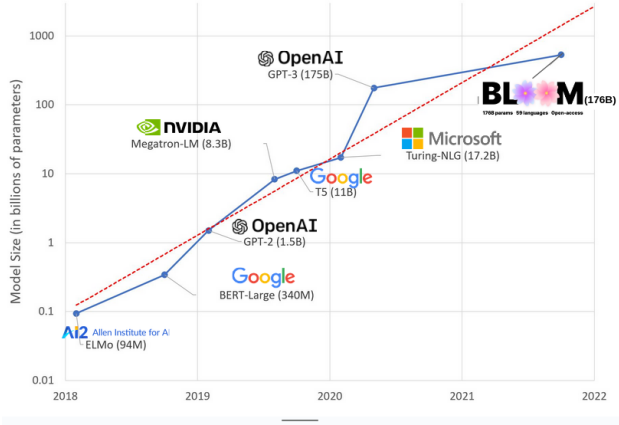

https://www.rollingstone.com/culture/culture-features/women-warnings-ai-danger-risk-before-chatgpt-1234804367/

https://sloanreview.mit.edu/article/the-working-limitations-of-large-language-models/

https://mindmatters.ai/2023/11/is-chatgpt-a-dead-end/

"This song sucks!"

Nick Cave

"ChatGPT rejects any notions of creative struggle, that our endeavours animate and nurture our lives giving them depth and meaning."

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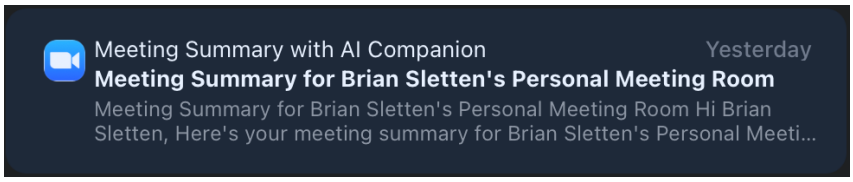
https://www.youtube.com/watch?v=iGJcF4bLKd4

Epilogue


Meeting Summary with AI Companion
Yesterday
Meeting Summary for Brian Sletten's Personal Meeting Room
Meeting Summary for Brian Sletten's Personal Meeting Room Hi Brian Sletten, Here's your meeting summary for Brian Sletten's Personal Meeti...

Biological vs Synthetic Systems: AI Debate

Brian and Michael had a detailed discussion about the differences between biological and synthetic systems, particularly in relation to the development of artificial intelligence. Brian argued that current text synthesis engines, such as Chat Gpt and T.5, while sophisticated, are not truly self-aware or capable of genuine reasoning, being instead mathematical models of patterns found in human text. Michael agreed, highlighting that these models are not like brains and do not work like them. They also expressed skepticism about the unsubstantiated claims made for these technologies, likening them to room-temperature fusion.

Limits of Natural Language Processing Models Discussed

Brian and Michael discussed the limitations of natural language processing models, focusing on sequence capture and paradigmatic similarity. Brian elaborated on the challenges of previous models, which didn't account for the order of words in a sentence or their relationship. He highlighted the use of machine learning in visual systems and the development of recurrent neural networks and long-term memory. However, he noted these models had limitations, such as a lack of accumulated states and struggles with including too much of the sequence. They also discussed the use of word embeddings and latent spaces, but Brian noted they still had limitations, such as only capturing a small number of words in one direction. They concluded the discussion by exploring the use of transformers in recurrent neural networks, with Brian explaining that transformers enable faster training processes and new capabilities, such as bi-directional perspectives.

Exploring Bias in Large Language Models for Content Creation
Brian discussed the potential benefits and risks of large language models in tasks like text summarization, code generation, and content creation. He emphasized the importance of carefully considering the biases of these models, which can reflect those of their data sets. He suggested that Adobe's Firefly is a good example of a tool using constrained uses of these models. Michael agreed and highlighted the generative fill feature. Brian also discussed the benefits and issues of a training system that only uses public and suitably licensed images to avoid plagiarism and privacy leaks. He noted that generated content would be marked with metadata and watermarks to indicate it as AI-generated. However, he raised concerns about mass surveillance, biased data sets, leaked training data, and the need for consulting services to handle complex systems. He concluded that while these systems might not work as well as expected, they were necessary to deal with the complexity.