Of Parrots and Monkeys

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Teaching Writing in the Age of Chat GPT Symposium. July 25, 2023
Ladies and gentlemen, distinguished guests, and fellow educators,

Welcome to the "Teaching Writing in the Age of Chat GPT Symposium." Today, we gather here to explore the fascinating intersection of technology and education, and to address the critical question of how we can effectively teach writing in an era dominated by Chatbot GPTs.

As we all know, the landscape of communication has dramatically evolved over the past few years. The rise of artificial intelligence and chatbots, particularly the groundbreaking GPT models, has revolutionized the way we interact with technology. These language models have reached unparalleled levels of sophistication, blurring the lines between human-generated and machine-generated text.

In this digital age, where messages can be sent in the blink of an eye, and conversations occur in real-time across platforms, we find ourselves at a crossroads. On one hand, the availability of advanced tools can enhance our ability to communicate effectively. On the other hand, it raises important questions about who should lead the way in teaching writing in this new landscape.
How did nerds, who are bad at writing, create a machine good at writing???
Infinite monkey theorem

https://en.wikipedia.org/wiki/Infinite_monkey_theorem
The English frequency wheel
Letter probability estimation

- Corpus

\[ P(a) = \frac{\text{number of times } a \text{ appears in corpus}}{\text{number of letters in corpus}} \]

- Same for \( P(b), \ldots, P(z), P(\text{space}) \)

- \( P(a) + P(b) + \ldots + P(z) + P(\text{space}) = 1 \)
Writing = sampling

• Repeat: spin the wheel!

$qzj\ ii\ xetohtd\ gzhfvz\ zd$
What should come after 9?
Conditional probability

- \( P(a \mid q) = \frac{\text{number of times qa appears in corpus}}{\text{number of times q appears in corpus}} \)

- Same for \( P(b \mid q), \ldots, P(z \mid q), P(\text{space} \mid q) \)

- \( P(a \mid q) + P(b \mid q) + \ldots + P(z \mid q) + P(\text{space} \mid q) = 1 \)
$P(\cdot \mid q)$: the “after q” wheel
Now we have 27 wheels

• $P(\cdot | j)$ the “after $j$” wheel
Writing = sampling

- Say we start with $q$
- Sample from $P(\cdot | q)$: spin the “after q” wheel, we get $u$
- Sample from $P(\cdot | u)$: spin the “after u” wheel, say we get $e$
- Sample from $P(\cdot | e)$: spin the “after e” wheel, say we get $r$
- ...
This is a Markov chain

- Better than spinning the English frequency wheel
- But we need 27 wheels instead of 1
- Still very bad!
From letters to words

- There are 50,000 common English words

  a
  aardvark
  abacus
  ...
  zydeco
  zygote
  zymurgy
Unigram language model

\[ P(w) = \frac{\text{number of times word } w \text{ appears in corpus}}{\text{number of words in corpus}} \]

- Big wheel with 50,000 slices
Sampling Shakespeare unigram LM

- To him swallowed confess hear both. Which. Of save on trail for are ay device and rote life have
- Every enter now severally so, let
- Hill he late speaks; or! a more to leg less first you enter
- Will rash been and by I the me loves gentle me not slavish page, the and hour; ill let
- Are where exeunt and sighs have rise excellency took of .. sleep knave we. near; vile like

Jurafsky & Martin, Speech and language processing, Prentice Hall, 2000.
Conditional word probability

- Bigram: \( P(w_2 \mid w_1) = \frac{\text{number of times } w_1 \text{ } w_2 \text{ appears in corpus}}{\text{number of times } w_1 \text{ appears in corpus}} \)

- 50,000 wheels, each with 50,000 slices
What means, sir. I confess she? then all sorts, he is trim, captain.

Why dost stand forth thy canopy, forsooth; he is this palpable hit the King Henry. Live king. Follow.

What we, hath got so she that I rest and sent to scold and nature bankrupt, nor the first gentleman?

Enter Menenius, if it so many good direction found'st thou art a strong upon command of fear not a liberal largess given away, Falstaff! Exeunt
Trigram

\[
P(w_3 \mid w_1, w_2) = \frac{\text{number of times } w_1 \ w_2 \ w_3 \text{ appears in corpus}}{\text{number of times } w_1 \ w_2 \text{ appears in corpus}}
\]

- 50,000*50,000 wheels, each with 50,000 slices
• Sweet prince, Falstaff shall die. Harry of Monmouth’s grave.

• This shall forbid it should be branded, if renown made it empty.

• What ist that cried?

• Indeed the duke; and had a very good friend.
Google-gram

- \( P(w_n \mid w_1, \ldots, w_{n-1}) = \frac{\text{number of pages containing } "w_1 \ldots w_{(n-1)}"}{\text{number of pages containing } "w_1 \ldots wn"} \)

- Internet is the corpus

(Demo)
Professor Zhu working on language models at IBM China Research Lab, circa 1996
It's hard to wreck a nice beach.
The horse raced past the barn fell.
Tension

- Need long history $w_1 \ldots w_{n-1}$ to see dependency

- But then $P(w_n \mid w_1 \ldots w_{n-1})$ needs “more than the internet” to estimate

- Resolved by transformers
Generative Pretrained Transformer (GPT)

- A type of artificial neural network that estimates $P(w_n \mid w_1 \ldots w_{n-1})$
- Allows long history (32768 tokens or ~50 pages)
- Only pays attention to selective parts in history
- Writing = sampling
GPT4

- $10^{12}$ parameters
  - (human brain has $10^{11}$ neurons)
- Trained on $10^{14}$ words on internet
  - (average person reads $10^8$ words in lifetime)
- Training cost $100$ million
  - (world population each pitch in 1 cent)
Parrot = sampling, not reasoning

ChatGPT on July 12, 2023
Will AI kill me?
Improbable

- Sentient AI ✗
but...

- Sentient AI ✗
- Dual use ✓

Will AI take my job?
Not in the short term

- The more AI helps your job, the higher the replacement risk

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[GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models. Eloundou et al. 2023]
Does AI belong in my classroom?
A language calculator
AI Venn diagram

Artificial Intelligence
AI Venn diagram

Artificial Intelligence

Machine learning
Artificial Intelligence

Machine learning

Natural language processing
Artificial Intelligence

- Machine learning
- Natural language processing
- Computer vision
Artificial Intelligence

- Machine learning
- Natural language processing
- Computer vision
- Robotics
Artificial Intelligence

- Machine learning
- Deep learning with Artificial neural networks
- Natural language processing
- Computer vision
- Robotics

AI Venn diagram
AI Venn diagram

Artificial Intelligence

- Machine learning
- Deep learning with Artificial neural networks
  - Transformer (ANN structure)
- Natural language processing
- Computer vision
- Robotics
Artificial Intelligence

AI Venn diagram

Artificial Intelligence
- Machine learning
- Deep learning with Artificial neural networks
  - Transformer (ANN structure)
  - Large Language Model
    - GPT
- Natural language processing
- Computer vision
- Robotics
Artificial Intelligence

AI Venn diagram

Artificial Intelligence

- Machine learning
- Deep learning with Artificial neural networks
  - Transformer (ANN structure)
- Natural language processing
- Computer vision
- Robotics

Generative AI

Large Language Model

GPT