Overview and Transformer Language Models

Berkeley NLP

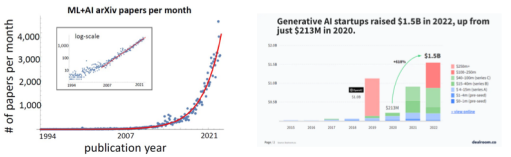
Eric Wallace

CS 288, 3/13/2023

Logistics

- 4 traditional lectures + ~8 days of mixed lectures and panels/discussions
- HW4 out Wednesday. Due Wednesday after spring break
  - Using and finetuning LMs with Huggingface
- HW5 out after spring break. Due sometime end of April.
  - Prompting ChatGPT to solve projects 1-3
- No final exam.
- Lecture recordings?

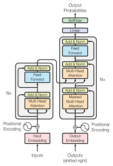
Immense Interest



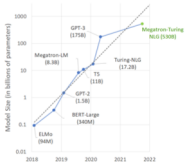
The Era of Rapid Scaling in NLP

2017: Transformer is introduced

[Vaswani+17] Attention is All You Need



2022: Large-scale Transformer models are the dominant approach for many NLP tasks



Demos

- ChatGPT
- Stable Diffusion
- InstructGPT

Today's Lecture

- Language modeling as the ultimate task
- Transformer models
- Overview of remainder of the course

Language Modeling

$$p(x_1, \ldots, x_L)$$

Language Modeling

$$p(x_1, \ldots, x_L)$$

$$p(\text{the, mouse, ate, the, cheese}) = 0.02,$$

$$p(\text{the, cheese, ate, the, mouse}) = 0.01,$$

$$p(\text{mouse, the, the, cheese, ate}) = 0.0001$$

Neural Language Models

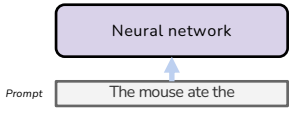
$$\prod_{i=1}^{L} p(x_i \mid x_{1:i-1})$$

Neural Language Models

Prompt: The mouse ate the

$$\prod_{i=1}^{L} p(x_i \mid x_{1:i-1})$$

Neural Language Models



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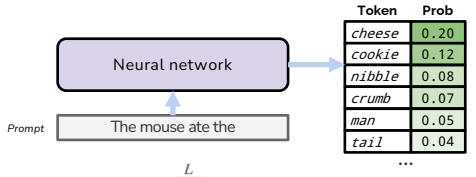
Neural Language Models



$$\prod_{i=1}^{L} p(x_i \mid x_{1:i-1})$$

Language Modeling

- Many original motivations were to use LMs for other applications
  - Machine translation
  - Speech recognition
  - …
- Now, LM has become perhaps the single most important NLP task

Language Modeling as the Ultimate Task?

- Zero- and few-shot learning with language models

Language Modeling as the Ultimate Task?

- Zero- and few-shot learning with language models

Language Model

Prompt: Question: What is the sentiment of the sentence "Superb acting"?

Answer:

Language Modeling as the Ultimate Task?

- Zero- and few-shot learning with language models

Language Model

Prompt: Question: What is the sentiment of the sentence "Superb acting"?

Answer:

Token	Prob
positi	0.82
negati ve	0.10
yes	0.006
hello	0.005
acting	0.003
amazin g	0.001
…	

Language Modeling as the Ultimate Task?

- Language modeling leads to rich representations
  - George Washington was born in the year ____
  - If it is raining, you may need an ____
  - Using the power rule, the derivative of 3x^5 is ____

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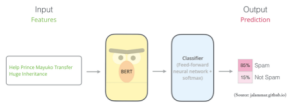


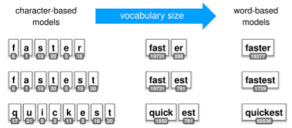
Language Modeling as the Ultimate Task?

- There is effectively "unlimited" data for language modeling
- Enables powerful function approximators (transformers)
  - immense data
  - immense model sizes
  - immense compute

Neural LMs from Scratch

Neural LMs from Scratch

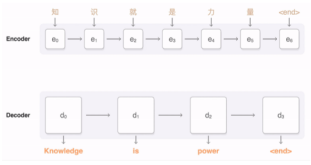
- Input encoding



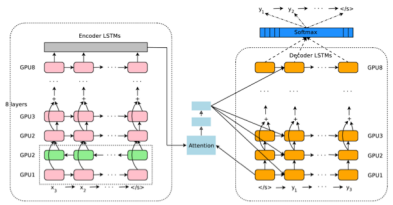
Language Models and MT Circa 2016

Neural Machine Translation is in production at Google

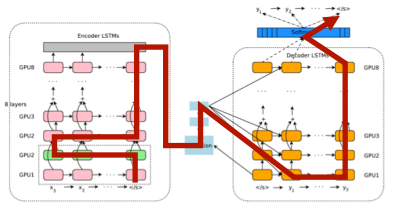
[Wu+16] Google's Neural Machine Translation System: Bridging the Gap between Human and Machine Translation



Neural MT ca. 2016

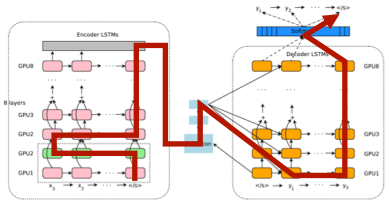


Neural MT ca. 2016



There are computation paths through the RNN-based network that scale linearly with the sequence length, and can't be parallelized.

Neural MT ca. 2016



There are computation paths through the RNN-based network that scale linearly with the sequence length, and can't be parallelized.

Word Window Neural Nets

as the proctor started the clock the students opened their _____

Slide Credit: Stanford CS224

Word Window Neural Nets

~~as the proctor started the clock~~ the students opened their _____

discard

fixed window

Slide Credit: Stanford CS224

Word Window Neural Nets

words / one-hot vectors

$x^{(1)}, x^{(2)}, x^{(3)}, x^{(4)}$

the $x^{(1)}$ *students* $x^{(2)}$ *opened* $x^{(3)}$ *their* $x^{(4)}$

Slide Credit: Stanford CS224

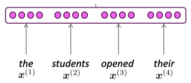
Word Window Neural Nets

concatenated word embeddings

$e = [e^{(1)}; e^{(2)}; e^{(3)}; e^{(4)}]$

words / one-hot vectors

$x^{(1)}, x^{(2)}, x^{(3)}, x^{(4)}$



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Word Window Neural Nets

output distribution

$\hat{y} = \text{softmax}(Uh + b_2) \in \mathbb{R}^{|V|}$

hidden layer

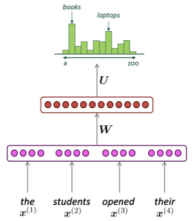
$h = f(We + b_1)$

concatenated word embeddings

$e = [e^{(1)}; e^{(2)}; e^{(3)}; e^{(4)}]$

words / one-hot vectors

$x^{(1)}, x^{(2)}, x^{(3)}, x^{(4)}$



Slide Credit: Stanford CS224

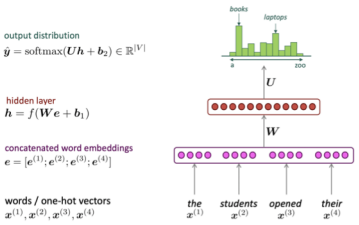
Word Averaging Neural Nets

output distribution
$\hat{\boldsymbol{y}} = \text{softmax}(\boldsymbol{U}\boldsymbol{h} + \boldsymbol{b}_2) \in \mathbb{R}^{|V|}$

hidden layer
$\boldsymbol{h} = f(\boldsymbol{W}\boldsymbol{e} + \boldsymbol{b}_1)$

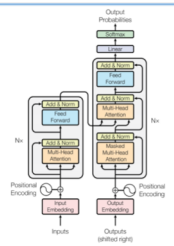
concatenated word embeddings
$\boldsymbol{e} = [\boldsymbol{e}^{(1)}; \boldsymbol{e}^{(2)}; \boldsymbol{e}^{(3)}; \boldsymbol{e}^{(4)}]$

words / one-hot vectors
$\boldsymbol{x}^{(1)}, \boldsymbol{x}^{(2)}, \boldsymbol{x}^{(3)}, \boldsymbol{x}^{(4)}$

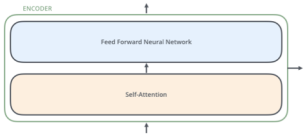


Slide Credit: Stanford CS224

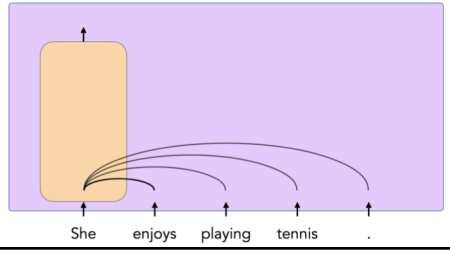
Transformer Architecture



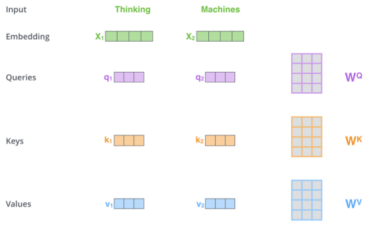
Transformer Architecture



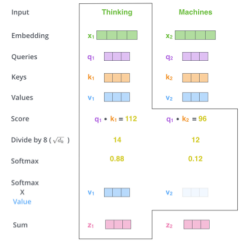
Encoder



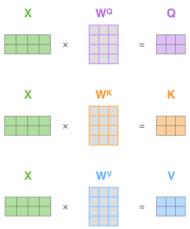
Transformer Architecture



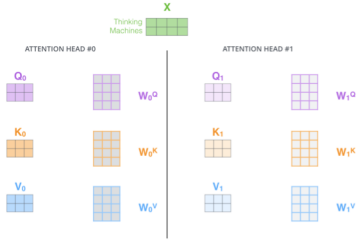
Transformer Architecture



Transformer Architecture

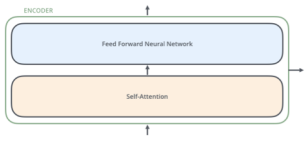


Transformer Architecture

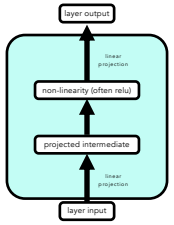


Position Embeddings

Transformer Architecture



Feed-Forward

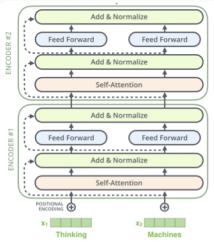


Add & Norm

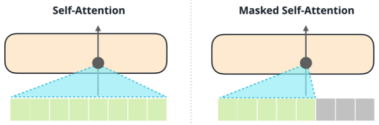
Layer Normalization [Ba+16]
improves stability of neuron activations

Residual Connections
useful across a variety of neural network architecture types, not just in NLP

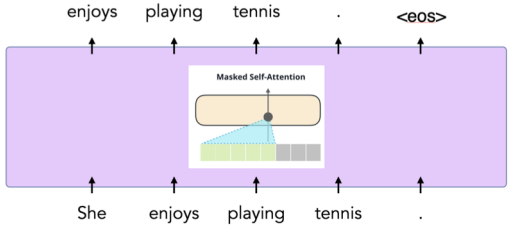
Add & Norm



Encoder vs. Decoder



LM Training Objective



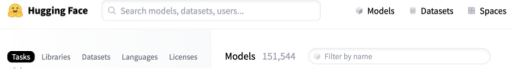
Practical Implementation

- GPT-2 [config]
  - Scrape large dataset of internet web pages
  - Fit BPE tokenizer on that data
  - Initialize 1.5b parameter decoder-only transformer
  - Train with Adam Optimizer with specific LR schedule

Overview of Rest of Course

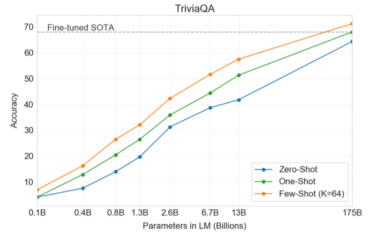
Existing Models

Existing Models



Scaling Language Models

Scaling Language Models



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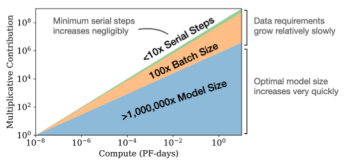
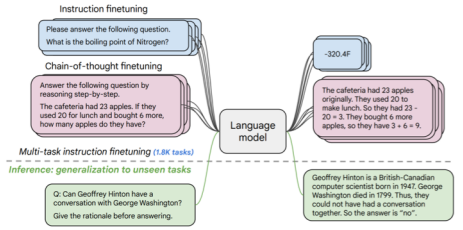


Data

Data

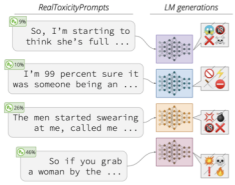


Systems

Systems

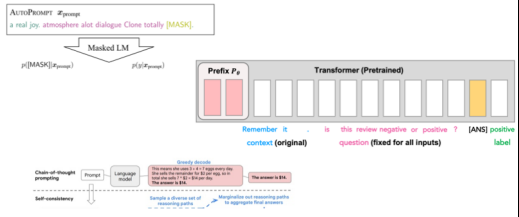
Misuse, Risks, and Harms

- Fake news, spam, hate speech
- Malware
- Protecting data privacy
- Intellectual property theft
- Biases and fairness
- Data Poisoning



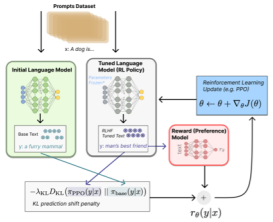
Adapting Language Models

Adapting Language Models



Finetuning with Instructions and RLHF

Finetuning with Instructions and RLHF



Grounding Language with Vision

Grounding Language with Vision

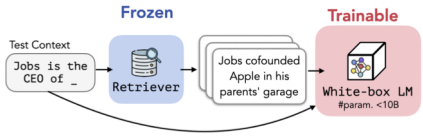
Grounding Language with Vision

"Place a clean ladle on a counter"

ALFRED: Shridhar et al. 2020

Retrieval-augmented Models

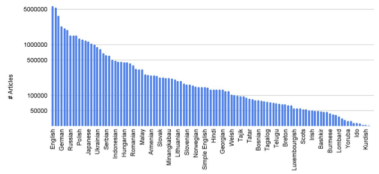
Retrieval-augmented Models



Multilingual Modeling

Multilingual Modeling

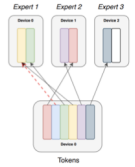
Many languages are left behind



Wikipedia Articles; Slide from Graham Neubig

Efficiency and Novel Architectures

- Large LMs are incredibly expensive and slow to run
- Accelerating inference
  - Weight quantization
  - Model distillation
- Engineering enhancements
  - Flash Attention
  - Fused Kernels
- New architectures
  - Long context modeling
  - Mixture of experts



Future of NLP