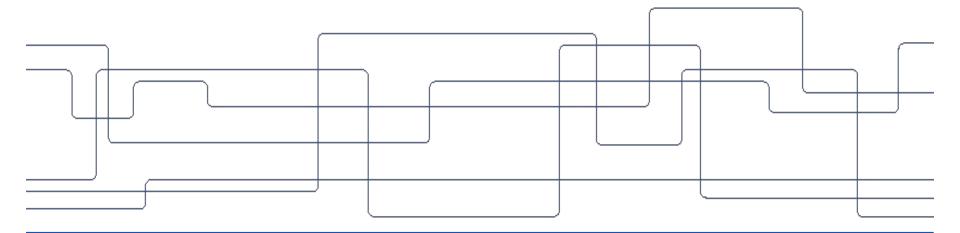


Session 3: NLP and Transformers

Youssef Mohamed





What is NLP?

"How computers can be used to understand and manipulate natural language text or speech to do useful things"^[1]

HOW?

- Tokenization
- Part Of Speech (POS) Tagging
- Chunking

Applications

- Sentiment Analysis
- Speech Recognition
- Translation

['Natural', 'Language', 'Processing'] [3] Example Lexical Term Tag Paris, France, NN Noun Someone, Kurtis work, train, learn, Verb VB I'M SO ADJECTIVE, run, skip VERB NOUNSIL the, a DT Determiner][4] t W S h 1 а 1 d e W e y е 0 W 0 g PRP VBD JJ NN DT NP NP

Natural Language Processing

[1] Chowdhury, G.G., 2003. Natural language processing. Annual review of information science and technology, 37(1), pp.51-89.

[2] https://www.analyticsvidhya.com/blog/2019/07/how-get-started-nlp-6-unique-ways-perform-tokenization/

[3] https://towardsdatascience.com/part-of-speech-tagging-for-beginners-3a0754b2ebba

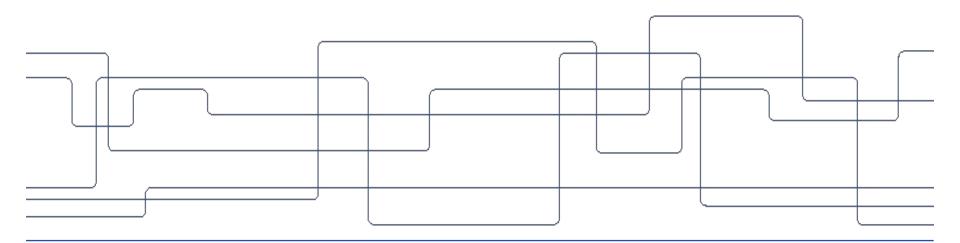
[4]https://towardsdatascience.com/chunking-in-nlp-decoded-b4a71b2b4e24

[2]



Improving Language Understanding by Generative Pre-Training

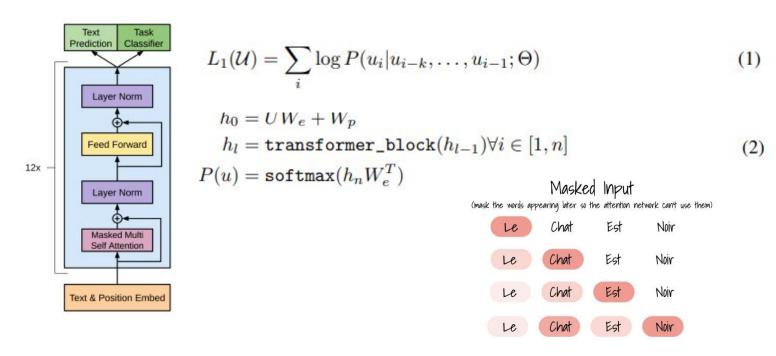
Alec Radford, Karthik Narasimhan, Tim Salimans, Ilya Sutskever OpenAl





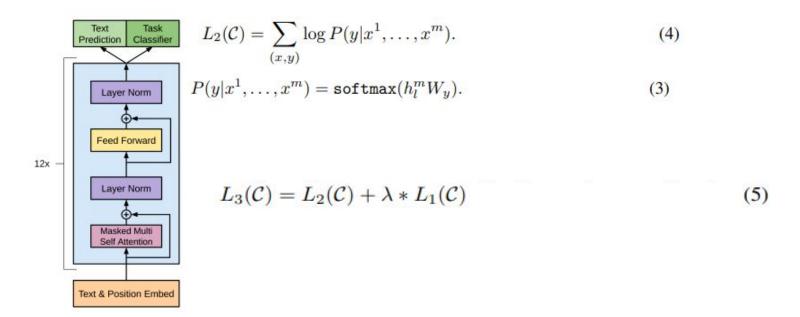
Pretraining

- BooksCorpus (800M words)
 - List of unpublished books





Fine-tuning





Performance

- NLI: showing the relationship between sentences (entailment, contradiction or neutral)
- QA: a passage then MCQ based on it
- SS: if two sentences are semantically similar or not
- C: grammatically correct or not,

"GPT-1 performed better than specifically trained supervised state-of-the-art models in 9 out of 12 tasks the models were compared on"

Task	Datasets		
Natural language inference	SNLI [5], MultiNLI [66], Question NLI [64], RTE [4], SciTail [25]		
Question Answering	RACE [30], Story Cloze [40]		
Sentence similarity	MSR Paraphrase Corpus [14], Quora Question Pairs [9], STS Benchmark [6]		
Classification	Stanford Sentiment Treebank-2 [54], CoLA [65]		



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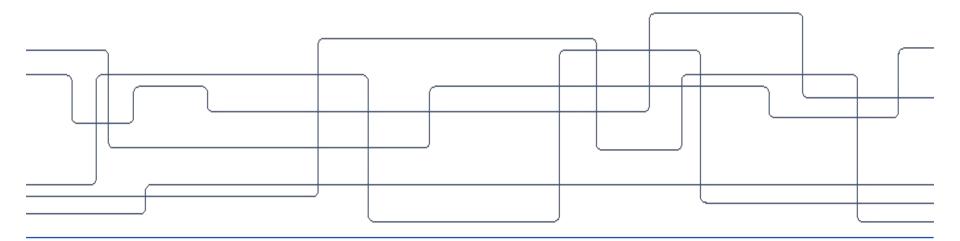
Task-Specific Input Transformations

- Start and end tokens
- Delimiter added so input could be sent as ordered sequence
 - Minimal changes Classification Start Text Transformer - Linear Extract to the model Entailment Transformer Premise Delim **Hypothesis** Start Extract Linear Text 1 Delim Text 2 Transformer Start Extract Similarity +)+ Linear Text 2 Text 1 Transformer Start Delim Extract Transformer Start Context Delim Answer 1 Extract Linear Multiple Choice Start Context Delim Answer 2 Extract Transformer Linear -Start Extract Context Delim Answer N - Transformer - Linear



Language Models are Few-Shot Learners

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam ,Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, Dario Amodei





Overview

- GPT-1 vs GPT-3
 - Context window size was increased from 512 for GPT-1 to 2048 tokens for GPT-3
 - 96 layers with each layer having 96 attention heads compared to 12 in GPT-1
 - 117M parameter in GPT-1 and 175B in GPT-3
- The usual pretraining and fine tuning (or is it ?)



Few shot learning

- Model does not need fine tuning
- only examples of the task

The three settings we explore for in-context learning

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

Translate English to French:	task description
cheese =>	— prompt

One-shot

In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

Translate English to French:	<	task description
sea otter => loutre de mer	-	example
cheese =>	-	prompt

Few-shot

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

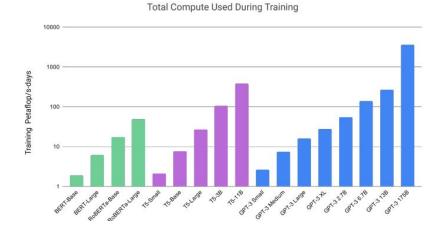
Translate English to French:	← tas	k description
sea otter => loutre de mer	exa	amples
peppermint => menthe poivrée		
plush girafe => girafe peluche	, J.	
cheese =>	- pro	ompt



Data-sets

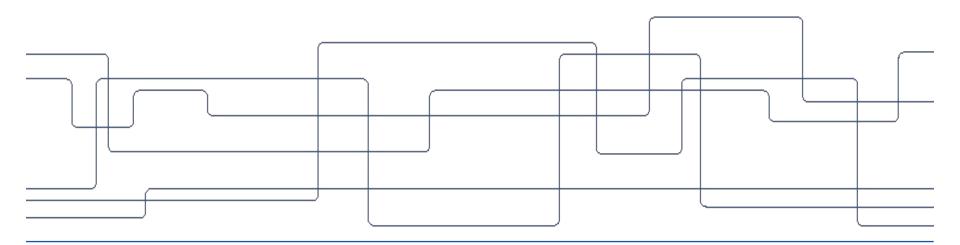
Dataset	Quantity (tokens)	Weight in training mix	Epochs elapsed when training for 300B tokens
Common Crawl (filtered)	410 billion	60%	0.44
WebText2	19 billion	22%	2.9
Books1	12 billion	8%	1.9
Books2	55 billion	8%	0.43
Wikipedia	3 billion	3%	3.4

- 3.14E+23!! flops in total
- **355 years!!** to train GPT-3 on a V100 [1]
- **\$4,600,000!!** to train GPT-3 using the lowest cost GPU cloud provider [1]





Tasks and Results





Question Answering

- Performs better in factual question answering
- Better than Open-Domain model

Example 1

Question: what color was john wilkes booth's hair Wikipedia Page: John_Wilkes_Booth

Long answer: Some critics called Booth "the handsomest man in America" and a "natural genius", and noted his having an "astonishing memory"; others were mixed in their estimation of his acting. He stood 5 feet 8 inches (1.73 m) tall, had jet-black hair , and was lean and athletic. Noted Civil War reporter George Alfred Townsend described him as a "muscular, perfect man" with "curling hair, like a Corinthian capital".

Short answer: jet-black

Example 2

Question: can you make and receive calls in airplane mode Wikipedia Page: Airplane_mode

Long answer: Airplane mode, aeroplane mode, flight mode, offline mode, or standalone mode is a setting available on many smartphones, portable computers, and other electronic devices that, when activated, suspends radio-frequency signal transmission by the device, thereby disabling Bluetooth, telephony, and Wi-Fi. GPS may or may not be disabled, because it does not involve transmitting radio waves.

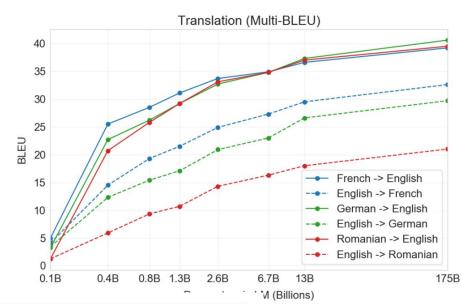
Short answer: BOOLEAN:NO

Setting	NaturalQS	WebQS	TriviaQA
RAG (Fine-tuned, Open-Domain) [LPP+20]	44.5	45.5	68.0
T5-11B+SSM (Fine-tuned, Closed-Book) [RRS20]	36.6	44.7	60.5
T5-11B (Fine-tuned, Closed-Book)	34.5	37.4	50.1
GPT-3 Zero-Shot	14.6	14.4	64.3
GPT-3 One-Shot	23.0	25.3	68.0
GPT-3 Few-Shot	29.9	41.5	71.2



Translation

To English performs better lacksquare



Setting	$En \rightarrow Fr$	Fr→En	En→De	De→En	En→Ro	Ro→En
SOTA (Supervised)	45.6 ^{<i>a</i>}	35.0 ^b	41.2 ^c	40.2^{d}	38.5 ^e	39.9 ^e
XLM [LC19] MASS [STQ ⁺ 19] mBART [LGG ⁺ 20]	33.4 <u>37.5</u>	33.3 34.9	26.4 28.3 <u>29.8</u>	34.3 35.2 34.0	33.3 <u>35.2</u> 35.0	31.8 33.1 30.5
GPT-3 Zero-Shot GPT-3 One-Shot GPT-3 Few-Shot	25.2 28.3 32.6	21.2 33.7 <u>39.2</u>	24.6 26.2 29.7	27.2 30.4 <u>40.6</u>	14.1 20.6 21.0	19.9 38.6 <u>39.5</u>

14



Reading Comprehension (Reasoning)

• Performs worse for reasoning tasks.

	SuperGLUE Average	E BoolQ Accuracy	CB y Accurac	CB y F1	COPA Accuracy	RTE Accuracy
Fine-tuned SOTA	89.0	91.0	96.9	93.9	94.8	92.5
Fine-tuned BERT-Large	69.0	77.4	83.6	75.7	70.6	71.7
GPT-3 Few-Shot	71.8	76.4	75.6	52.0	92.0	69.0
	WiC Accuracy	WSC Accuracy	MultiRC Accuracy	MultiRC F1a	ReCoRD Accuracy	ReCoRD F1
Fine-tuned SOTA	76.1	93.8	62.3	88.2	92.5	93.3
Fine-tuned SOTA Fine-tuned BERT-Large	76.1 69.6	93.8 64.6	62.3 24.1	88.2 70.0	92.5 71.3	93.3 72.0

- **F** There's a lot of trash on the *bed* of the river I keep a glass of water next to my *bed* when I sleep
- F Justify the margins The end justifies the means
- T Air pollution Open a window and let in some air
- T The expanded window will give us time to catch the thieves — You have a two-hour window of clear weather to finish working on the lawn

Premise: The man broke his toe. What was the CAUSE of this?

Alternative 1: He got a hole in his sock.

Alternative 2: He dropped a hammer on his foot.

Premise: I tipped the bottle. What happened as a RESULT?

Alternative 1: The liquid in the bottle froze.

Alternative 2: The liquid in the bottle poured out.

Premise: I knocked on my neighbor's door. What happened as a RESULT?

Alternative 1: My neighbor invited me in.

Alternative 2: My neighbor left his house.



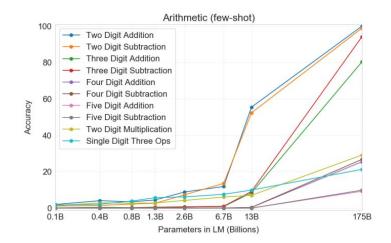
Made up tasks

Arithmetic

• Gap between three digit addition and four digit addition ?

Article Generation

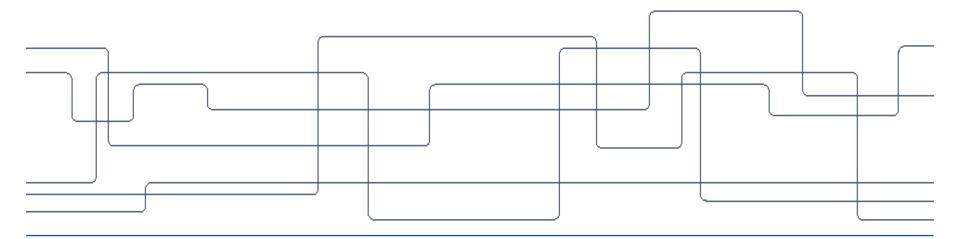
• performs worse the bigger the model is



	Mean accuracy	95% Confidence Interval (low, hi)	t compared to control (p-value)	"I don't know" assignments
Control (deliberately bad model)	86%	83%-90%	<u>u</u>	3.6 %
GPT-3 Small	76%	72%-80%	3.9(2e-4)	4.9%
GPT-3 Medium	61%	58%-65%	10.3 (7e-21)	6.0%
GPT-3 Large	68%	64%-72%	7.3 (3e-11)	8.7%
GPT-3 XL	62%	59%-65%	10.7 (1e-19)	7.5%
GPT-3 2.7B	62%	58%-65%	10.4(5e-19)	7.1%
GPT-3 6.7B	60%	56%-63%	11.2 (3e-21)	6.2%
GPT-3 13B	55%	52%-58%	15.3 (1e-32)	7.1%
GPT-3 175B	52%	49%-54%	16.9 (1e-34)	7.8%

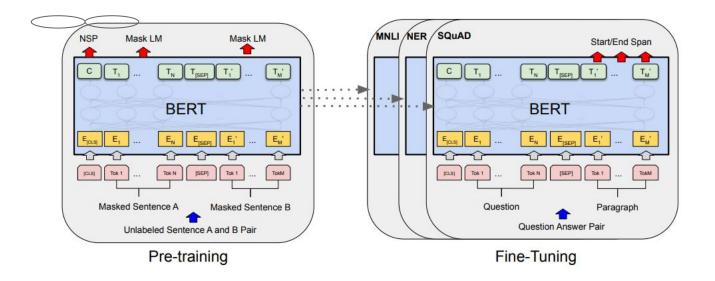


BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding





BERT





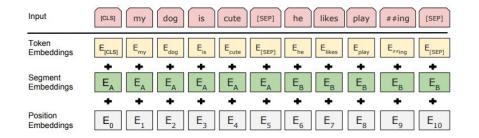


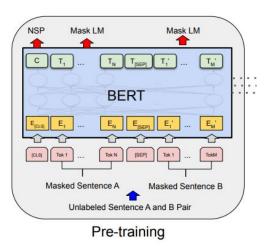
Masked LM

Next Sentence Prediction (NSP)

- Random masked words
- Each embedding is a word integrated with segment and position
- T is a word vector

- If two sentences follow each other
- binary classification (C)







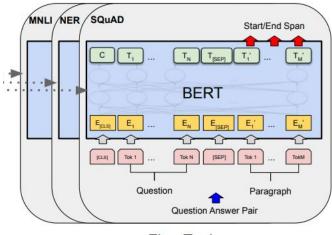
Data sets

- BooksCorpus (800M words)
 - List of unpublished books
- English Wikipedia (2,500M words)
 - Wikipedia articles



Fine-tuning

- Supervised training based on the task
- Replacing the output layer
- Modifying the input layer
- Start and end words



Fine-Tuning