Deep Learning Techniques

DL5. Large Language Models (LLMs)

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Trend in Language Representation Learning

Google 2013	Stanford 2014	Facebook 2016	Google 2017	AI^2 2018	OpenAI 2018	Google 2018	CMU 2019
CBOW, Skip-Gram	Glove	FastText	Transformer	ELMO	GPT	BERT	XLNet

Word2vec Mapping

Each word has a fix vector.

Context2vec Mapping

Possibly 1→many mapping
Each word can have multiple vectors

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Why Contextualized Embedding

- Fixed Vector

the river bank → $(x_1, \cdots, x_d)$ Semantically Ambiguous
the US bank → $(x_1, \cdots, x_d)$

- Contextualized Mapping

the river bank → $(x_1, \cdots, x_d)$ Semantically Expressive
the US bank → $(x'_1, \cdots, x'_d)$

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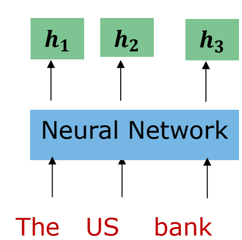
Contextualized Embedding

- Mapping input tokens to output embeddings via a function as

$$(\boldsymbol{h_1}, \cdots, \boldsymbol{h_n}) := \boldsymbol{f_\theta}(t_1, \ldots, t_n)$$

- Implementing $\boldsymbol{f_\theta}(.)$ by a neural network (RNN or Transformers)
- Training the network on large unlabeled text corpora (**pre-trained language models**)



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Types of Transformer-based Models

- **Encoder only**
  - BERT, Roberta
- **Decoder only**
  - GPT1,2,3
  - InstructGPT
  - ChatGPT
- **Encoder-decoder**
  - BART
  - T5

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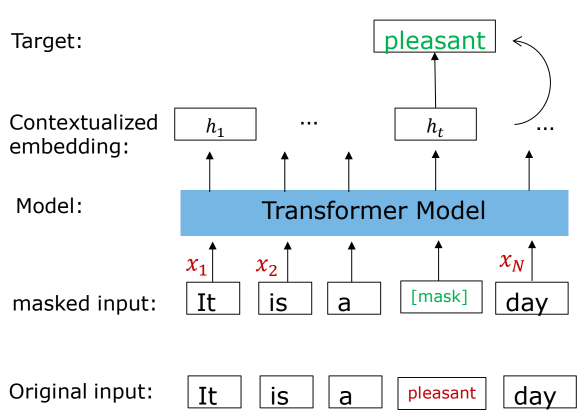
BERT as a Masked Language Model (MLM)



$$P_\theta(x_t \,|\hat{\mathbf{x}}) = \frac{\exp(x_t \cdot h_t)}{\sum_{i=1}^{V} exp(x_i \cdot h_i)}$$

Classification over vocabulary of size V

Randomly mask 15% of the tokens

Other masking rate is possible

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Should you mask 15% in mask language modeling?

	Pre-training		Fine-tuning		
m	Example	PPL	MNLI	QNLI	SQuAD[3]
15%	We study high ing rates pre-training language models .	17.7	84.2	90.9	88.0
40%	We study high rates pre- models .	69.4	**84.5** ↑0.3	**91.6** ↑0.7	**89.8** ↑1.8
80%	We high models	1141.4	80.8 ↓3.4	87.9 ↓3.0	86.2 ↓1.8
	Random initialization		61.5 ↓22.7	60.9 ↓30.0	10.8 ↓77.2

Table 1: Masked examples, validation perplexity (calculated in the same way as Devlin et al., 2019) of different masking rates on the one billion word benchmark (Chelba et al., 2013), and downstream task development performance (SQuAD: F1; accuracy for others). All the pre-trained models have a BERT-large architecture and are trained with the efficient pre-training recipe (§2.2). Full results are provided in Table 7.

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Notation and Objective of MLM

- Input sequence $\boldsymbol{x} = (x_1, x_2, \cdots, x_N)$.
- Masked subset (targets) (15%) $\overline{\boldsymbol{x}} \subset \{x_1, x_2, \cdots, x_N\}$.
- Corrupted sequence $\hat{\boldsymbol{x}}$ (the input with "Mask's")
- Training Objective

$$\max_{\theta} E_{x \in Data} P_{\theta}(\overline{\boldsymbol{x}} \mid \hat{\boldsymbol{x}}) = \max_{\theta} E_{x \in Data}(\prod_{x_t \in \overline{x}} P_{\theta}(x_t \mid \hat{\boldsymbol{x}}))$$

Assuming conditional independence among $x_t \in \overline{\boldsymbol{x}}$ given $\hat{\boldsymbol{x}}$.

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Model Optimization in MLM

- Maximizing the likelihood of predicted tokens

$$\max_{\theta} E_{x \in Data} P_{\theta}(\bar{\boldsymbol{x}} | \ \hat{\boldsymbol{x}}) = \max_{\theta} E_{x \in Data} \prod_{x_t \in \bar{x}} P_{\theta}(x_t \,|\hat{\boldsymbol{x}}))$$

- Minimizing the loss function as the negative log-likelihood

$$\min_{\theta} E_{x \in Data} - logP_{\theta}(\bar{\boldsymbol{x}} | \ \hat{\boldsymbol{x}})$$

$$= \min_{\theta} E_{x \in Data} \left(- \sum_{x_t \in \bar{x}} log P_{\theta}(x_t \,|\hat{\boldsymbol{x}})\right)$$

$$= \min_{\theta} E_{x \in Data} \left(- \sum_{x_t \in \bar{x}} log \frac{\exp(x_t \cdot h_t)}{\sum_{i=1}^{V} exp(x_i \cdot h_i)}\right)$$

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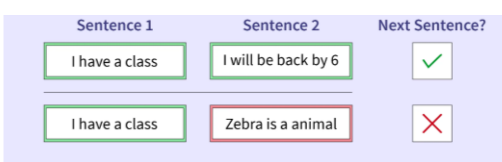
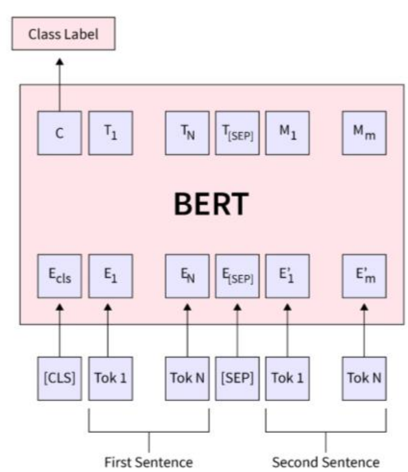
Next Sentence Prediction (NSP) Objective





50% sentence 2 is the next sentence (positive)

NSP is not used in later [papers]

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BERT Input Representation
(e.g., in the Sentence Entrainment Task)

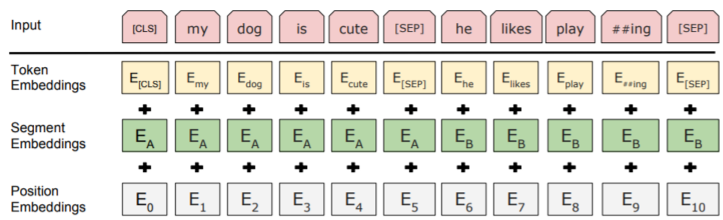

Figure 2: BERT input representation. The input embeddings are the sum of the token embeddings, the segmentation embeddings and the position embeddings.

Without position embeddings, Transformer is invariant to word orders.
Segment embeddings are used for next sentence prediction.

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BERT Finetuning for Downstream Tasks

Next sentence prediction

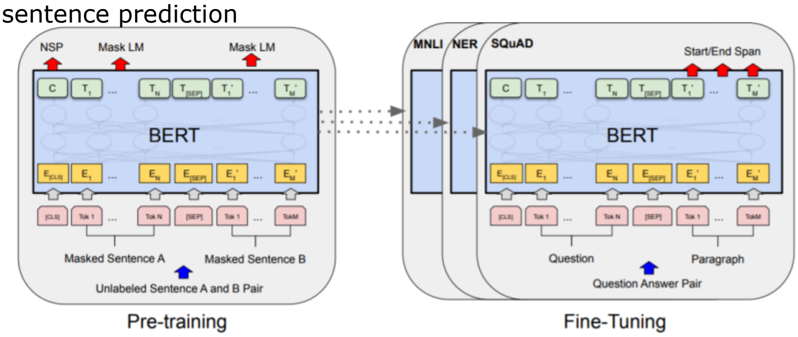

Figure 1: Overall pre-training and fine-tuning procedures for BERT. Apart from output layers, the same architectures are used in both pre-training and fine-tuning. The same pre-trained model parameters are used to initialize models for different down-stream tasks. During fine-tuning, all parameters are fine-tuned. `[CLS]` is a special symbol added in front of every input example, and `[SEP]` is a special separator token (e.g. separating questions/answers).

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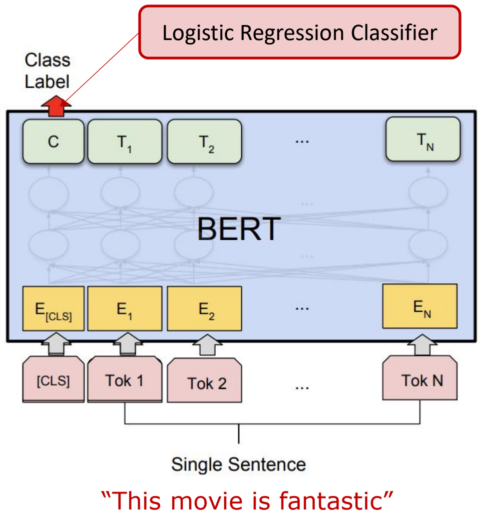
Fine-tuning BERT on classification task



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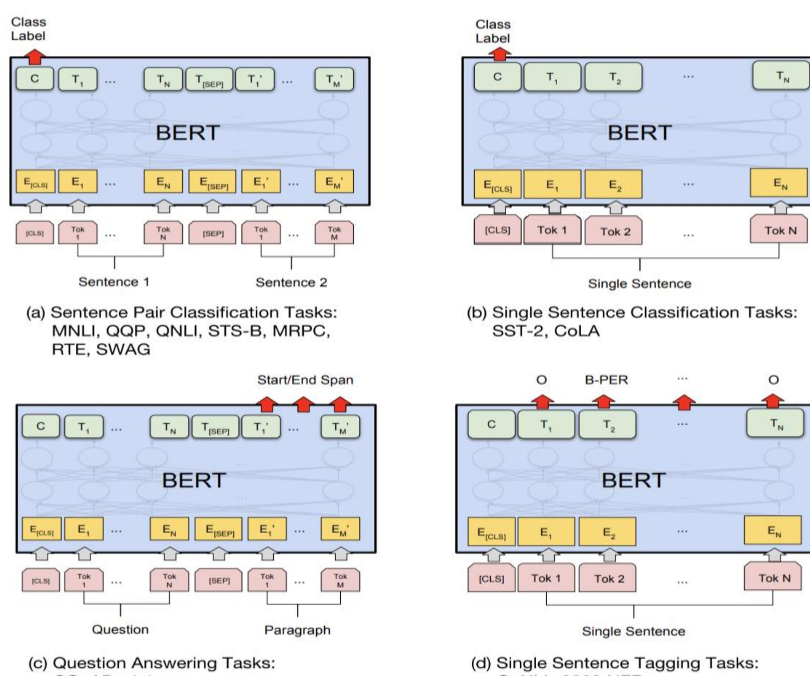

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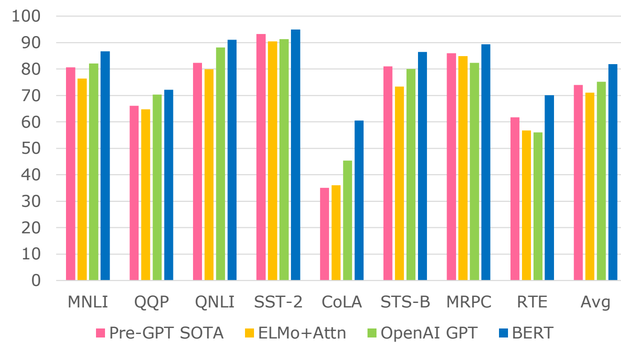
Performance of ElMo, GPT & BERT
(Jacob Devlin et al., 2019)

GLUE Test results in
one- & two-sentence classification tasks



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Transformer-based LLM in 5 years (Xavier Amatriain, Feb 17, 2023)

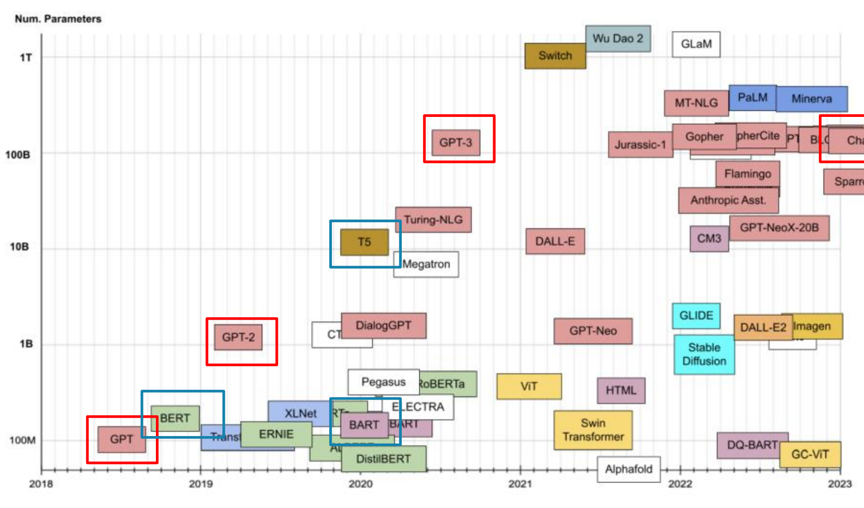

Figure 8: Transformer timeline. On the vertical axis, number of parameters. Colors describe Transformer family.

OpenAI GPT models

Model	time	param	Training data
GPT-1	2018.6	117M	5GB
GPT-2	2019.2	1.5B	40GB
GPT-3	2020.5	175B	570GB
InstructGPT (GPT-3.5)	2022.1	175B	570GB + human written data
ChatGPT (GPT-3.5-turbo)	2022.11	175B	Unreleased
GPT-4	2023.3	16*110B (guessed)	Unreleased

Autoregressive (AR) LM Objective

- (Left-to-right) Autoregressive Language Modeling Objective

$$\max_{\theta} \sum_{t=1}^{T} log P_{\theta}(x_t | x_{<t})$$

- Example: x = The cat sat on the mat

$$\log P_\theta(\boldsymbol{x})$$
$$= \log P_\theta(\text{The} \mid [\text{BOS}])$$
$$+ \log P_\theta(\text{cat} \mid [\text{BOS}] \text{ the })$$
$$+ \log P_\theta(\text{sat} \mid [\text{BOS}] \text{ the cat})$$
$$\ldots$$
$$+ \log P_\theta(\text{mat} \mid [\text{BOS}] \text{ the cat sat on the})$$

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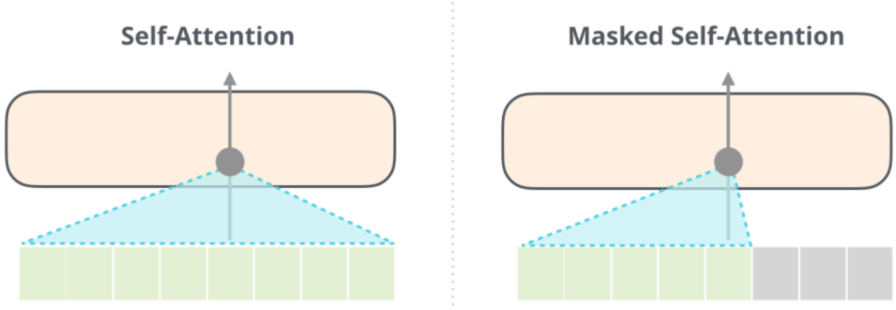
Masked Self-Attention

Encoder Self-attention

Decoder Self-attention



Attend to the full span

Causal mask: only attend to the left context.

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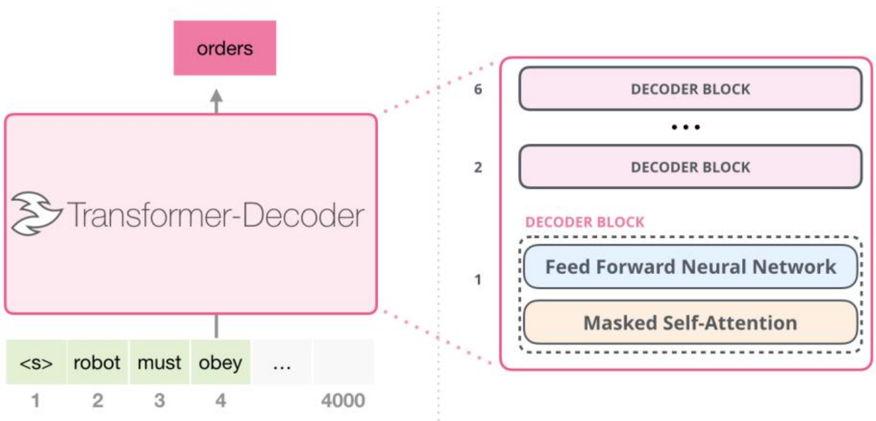
Autoregressive Transformer



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GPT1 model: pre-training, fine-tuning style

- Unsupervised Pre-training
  - Use bookcorpus dataset with 5GB of raw text
- Supervised Fine-tuning (with additional output layer)

$$P(y|x^1, \ldots, x^m) = \texttt{softmax}(h_l^m W_y)$$

Use the last hidden embedding, which attends to the entire context.

$$L_2(\mathcal{C}) = \sum_{(x,y)} \log P(y|x^1, \ldots, x^m)$$

(This movie is fantastic, positive)

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GPT-2 from Common Crawl Training Corpus

Gathered from the web dataset of 8 million doc's (40 GB of data)

The texts contain context of English-to-French translations.

"I'm not the cleverest man in the world, but like they say in French: **Je ne suis pas un imbecile [I'm not a fool].**

In a now-deleted post from Aug. 16, Soheil Eid, Tory candidate in the riding of Joliette, wrote in French: "**Mentez mentez, il en restera toujours quelque chose**," which translates as, "**Lie lie and something will always remain.**"

"I hate the word '**perfume**,"' Burr says. 'It's somewhat better in French: '**parfum**.'

If listened carefully at 29:55, a conversation can be heard between two guys in French: "**-Comment on fait pour aller de l'autre coté? -Quel autre coté?**", which means "**- How do you get to the other side? - What side?**".

If this sounds like a bit of a stretch, consider this question in French: **As-tu aller au cinéma?**, or **Did you go to the movies?**, which literally translates as Have-you to go to movies/theater?

"**Brevet Sans Garantie Du Gouvernement**", translated to English: "**Patented without government warranty**".

Table 1. Examples of naturally occurring demonstrations of English to French and French to English translation found throughout the WebText training set.

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GPT2 for Zero-shot Generation

Autoregressive generation as language model

$$p(x) = \prod_{i=1}^{n} p(s_n | s_1, ..., s_{n-1})$$

For specific task using the following prompt:

$$p(output|input, task)$$

Example for translation

Task: Translate to French
Input: English text
Output: French text

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GPT2 for Zero-shot Generation

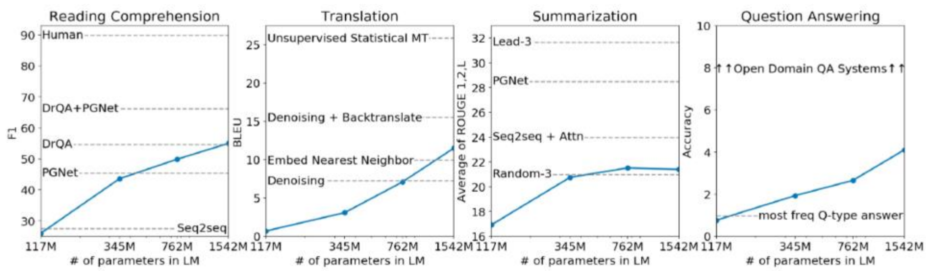

Figure 1. Zero-shot task performance of WebText LMs as a function of model size on many NLP tasks. Reading Comprehension results are on CoQA (Reddy et al., 2018), translation on WMT-14 Fr-En (Artetxe et al., 2017), summarization on CNN and Daily Mail (See et al., 2017), and Question Answering on Natural Questions (Kwiatkowski et al., 2019). Section 3 contains detailed descriptions of each result.

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Insights from GPT2

- Directly use pre-trained language model to generate answers, instead of fine-tuning the model parameters.
- Zero-shot ability emerges with larger, diverse pre-training corpus.
- Larger model performs better than smaller model

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GPT3

GPT-3 training data

Dataset	# tokens	Proportion within training
Common Crawl	410 billion	60%
WebText2	19 billion	22%
Books1	12 billion	8%
Books2	55 billion	8%
Wikipedia	3 billion	3%

Model Name	n_{params}
GPT-3 Small	125M
GPT-3 Medium	350M
GPT-3 Large	760M
GPT-3 XL	1.3B
GPT-3 2.7B	2.7B
GPT-3 6.7B	6.7B
GPT-3 13B	13.0B
GPT-3 175B or "GPT-3"	175.0B

570 GB in total

Largest GPT2

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Open-sourced GPT model

Llama 1 (02.23)

Llama-2 (07.23)

	Training Data	Params	Context Length	GQA	Tokens	LR
Llama 1	*See Touvron et al. (2023)*	7B	2k	✗	1.0T	3.0×10^{-4}
		13B	2k	✗	1.0T	3.0×10^{-4}
		33B	2k	✗	1.4T	1.5×10^{-4}
		65B	2k	✗	1.4T	1.5×10^{-4}
Llama 2	*A new mix of publicly available online data*	7B	4k	✗	2.0T	3.0×10^{-4}
		13B	4k	✗	2.0T	3.0×10^{-4}
		34B	4k	✓	2.0T	1.5×10^{-4}
		70B	4k	✓	2.0T	1.5×10^{-4}

Llama 3 (7.24)

	8B	70B	405B
Layers	32	80	126
Model Dimension	4,096	8192	16,384
FFN Dimension	14,336	28,672	53,248
Attention Heads	32	64	128
Key/Value Heads	8	8	8
Peak Learning Rate	3×10^{-4}	1.5×10^{-4}	8×10^{-5}
Activation Function	SwiGLU		
Vocabulary Size	128,000		
Positional Embeddings	RoPE ($\theta = 500,000$)		

Tokens 15T

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GPT3 In-context Learning

Instead of using training data to optimize parameters, use them as inputs:

Sentiment classification

Circulation revenue has increased by 5% in Finland. // Positive

Panostaja did not disclose the purchase price. // Neutral

Paying off the national debt will be extremely painful. // Negative

The company anticipated its operating profit to improve. // ________

LM

Topic classification

Circulation revenue has increased by 5% in Finland. // Finance

They defeated … in the NFC Championship Game. // Sports

Apple … development of in-house chips. // Tech

The company anticipated its operating profit to improve. // ________

LM

No update of model parameter

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GPT3: question-answering benchmark

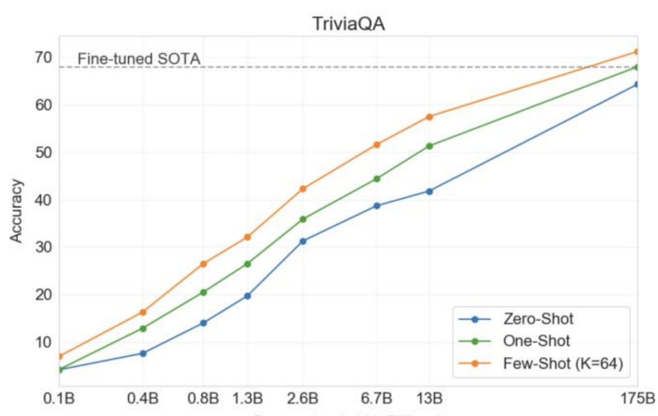

Figure 3.3: On TriviaQA GPT3's performance grows smoothly with model size, suggesting that language models continue to absorb knowledge as their capacity increases. One-shot and few-shot performance make significant gains over zero-shot behavior, matching and exceeding the performance of the SOTA fine-tuned open-domain model, RAG [LPP+20]

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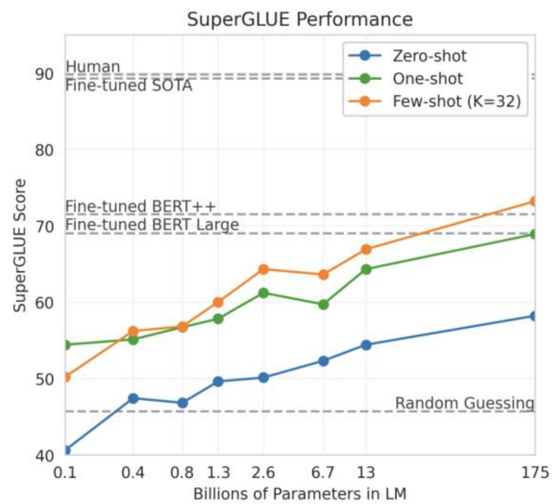
GPT3: Language understanding tasks

superGLUE contains 11 benchmark language understanding tasks.



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InstructGPT vs. GPT-3 Example Output

Prompt *Explain the moon landing to a 6 year old in a few sentences.*

Completion GPT-3

```
Explain the theory of gravity to a 6 year old.

Explain the theory of relativity to a 6 year old in a few
sentences.

Explain the big bang theory to a 6 year old.

Explain evolution to a 6 year old.
```

InstructGPT

```
People went to the moon, and they took pictures of what they saw,
and sent them back to the earth so we could all see them.
```

InstructGPT has better answers to user's query.
InstructGPT doesn't need in-context examples

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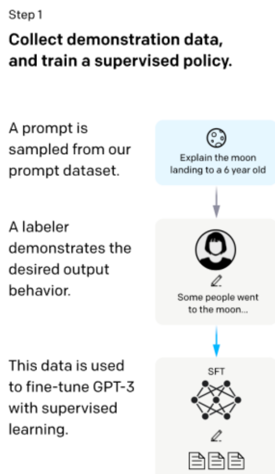
Step1: Supervised Fine-tuning (SFT)



Model is trained to optimize

$$P_\theta(Response|Instruction)$$

Instruction:
Explain the moon landing to a 6 year old.

Model Output:
People went to moon …

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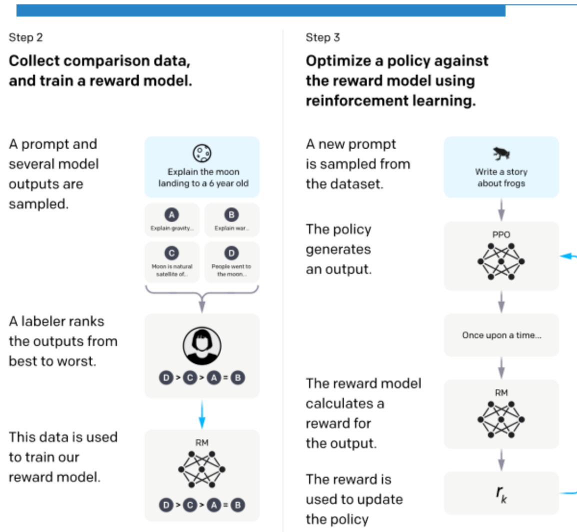
Step2,3: Reinforcement Learning from Human Feedback (RLHF)



Reward Model:
Assign scores to model generated responses.

RL:
train Policy model (LLM) to generate responses with higher scores.

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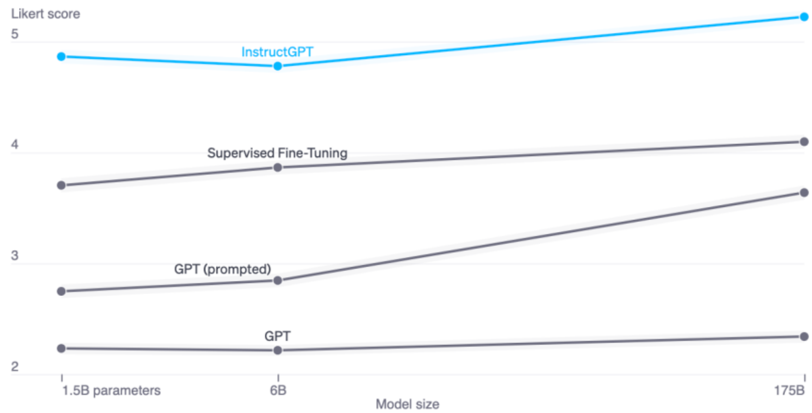
Evaluation Results



Quality ratings of model outputs on a 1–7 scale (y-axis), for various model sizes (x-axis), on prompts submitted to InstructGPT models on our API. InstructGPT outputs are given much higher scores by our labelers than outputs from GPT-3 with a few-shot prompt and without, as well as models fine-tuned with supervised learning. We find similar results for prompts submitted to GPT-3 models on the API.

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ChatGPT and GPT-4

- Instuction following GPT models developed by OpenAI
- Other competitors include
  - Gemini from Google
  - Grok from X.AI
  - Claude from Anthropic
- Open-source alternatives
  - Llama-1,2,3 (from 7B to 405B)
  - Vicuna, Alpaca

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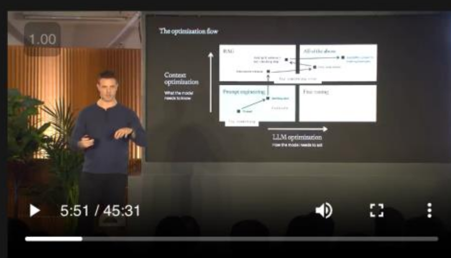
Recent advances on GPT-4o (05.24)
multi-modal data (i.e. video) as input

1

Input

Here is a video of a presentation on techniques for maximizing LLM performance. Could you give me a detailed summary of the presentation?

Attachment:



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Output

Certainly! The presentation focused on techniques for maximizing the performance of large language models (LLMs) and was delivered by Colin Jarvis and John Allard from OpenAI. The session was part of OpenAI's first developer conference and aimed to provide insights into optimizing LLMs for specific tasks.

Introduction
- **Colin Jarvis** is the head of OpenAI's solutions practice in Europe, and **John Allard** is an engineering lead on the fine-tuning product team.
- The presentation highlighted the challenges of optimizing LLMs, emphasizing that there is no one-size-fits-all solution.

Challenges of Optimizing LLMs
1. **Separating Signal from Noise**: It's challenging to identify the exact problem.
2. **Abstract Performance Metrics**: Measuring performance can be difficult.
3. **Choosing the Right Optimization**: It's hard to know which approach to use.

Optimization Flow
- The presenters introduced a framework for optimizing LLMs based on two axes:
  - **Context Optimization**: What the model needs to know.
  - **LLM Optimization**: How the model needs to act.
- The framework includes four quadrants:
  - **Prompt Engineering**: The starting point for optimization.
  - **Retrieval-Augmented Generation (RAG)**: For context optimization.
  - **Fine-Tuning**: For LLM optimization.

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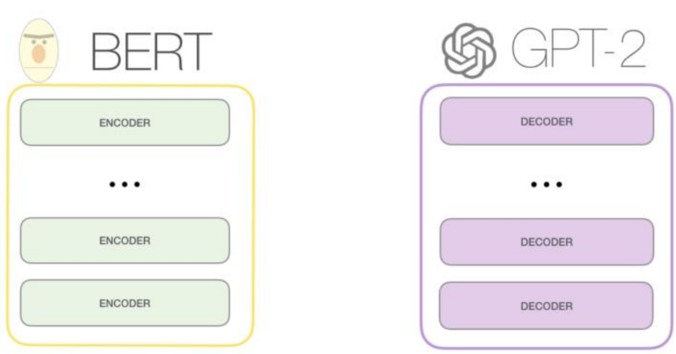
Encoder and decoder Transformer



Encode text into hidden representation

Autoregressive generation of text (embeddings)

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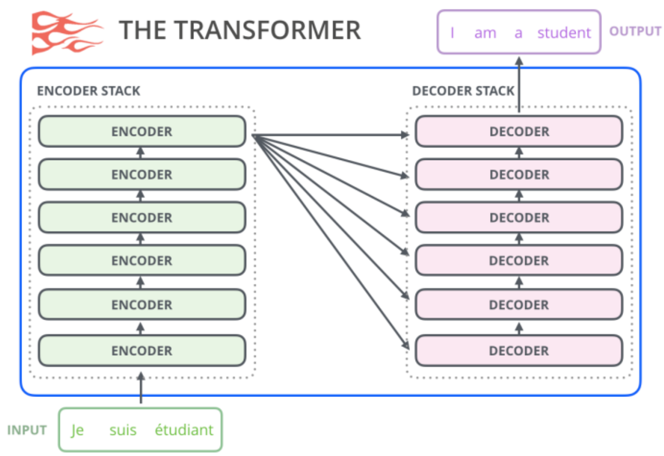
Encoder-decoder Transformer Overview



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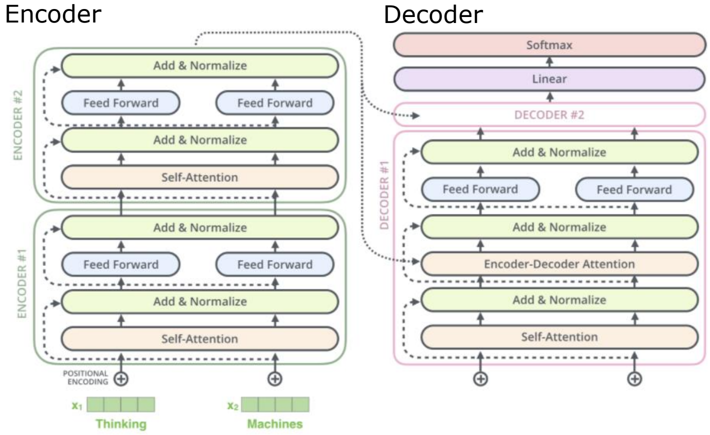
Encoder-decoder Transformer Design

Encoder

Decoder



With causal mask

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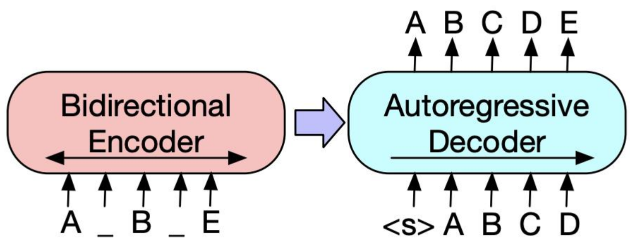
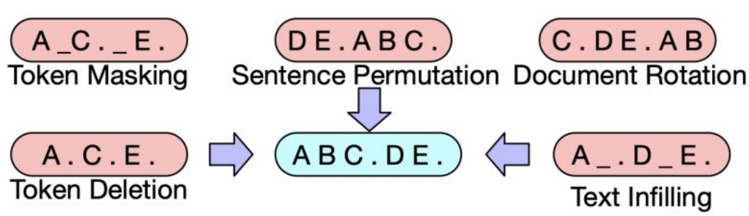
BART model: Bidirectional and Autoregressive Transformers.

Example of recovering masked token by generating the original sequence (similar to BERT MLM)



BART objective: Denoising Autoencoder

- Encoder-decoder Transformer model can support different types of input corruptions



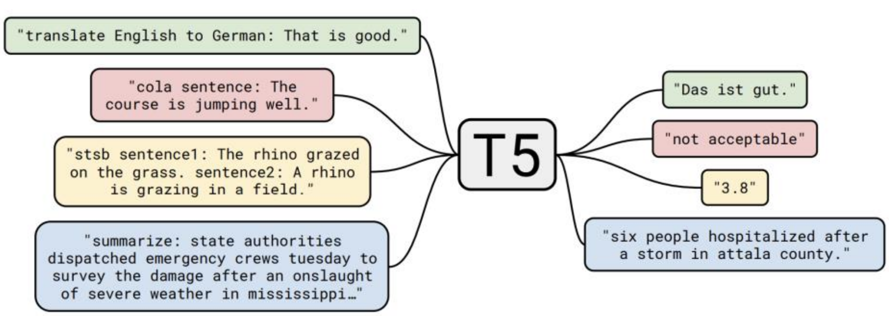
BART performance on summarization

	CNN/DailyMail			XSum		
	R1	R2	RL	R1	R2	RL
Lead-3	40.42	17.62	36.67	16.30	1.60	11.95
PTGEN (See et al., 2017)	36.44	15.66	33.42	29.70	9.21	23.24
PTGEN+COV (See et al., 2017)	39.53	17.28	36.38	28.10	8.02	21.72
UniLM	43.33	20.21	40.51	-	-	-
BERTSUMABS (Liu & Lapata, 2019)	41.72	19.39	38.76	38.76	16.33	31.15
BERTSUMEXTABS (Liu & Lapata, 2019)	42.13	19.60	39.18	38.81	16.50	31.27
BART	**44.16**	**21.28**	**40.90**	**45.14**	**22.27**	**37.25**

Table 3: Results on two standard summarization datasets. BART outperforms previous work on summarization on two tasks and all metrics, with gains of roughly 6 points on the more abstractive dataset.

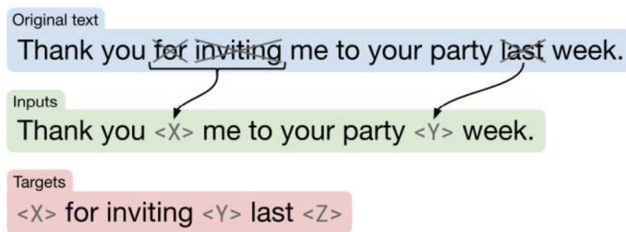
RL (ROUGE-L): the longest common subsequence (LCS) between the generated summary and the reference summary.

T5: **T**ext-**t**o-**T**ext **T**ransfer **T**ransformer



T5 Model: Masked Span Generation

Predicting the masked span of text:



Performance of T5

Model	GLUE Average	SQuAD F1	SuperGLUE Average
Previous best	89.4[a]	95.5[a]	84.6[d]
T5-Small	77.4	87.24	63.3
T5-Base	82.7	92.08	76.2
T5-Large	86.4	93.79	82.3
T5-3B	88.5	94.95	86.4
T5-11B	**90.3**	**96.22**	**88.9**

GLUE & SuperGLUE: Benchmark datasets evaluate the performance of natural language understanding (NLU) models across a wide range of tasks

SQuAD: Question-answering benchmark datasets

Performance of T5

Model	WMT EnDe BLEU	WMT EnFr BLEU	WMT EnRo BLEU	CNN/DM ROUGE-1
Previous best	**33.8**[e]	**43.8**[e]	**38.5**[f]	43.47[g]
T5-Small	26.7	36.0	26.8	41.12
T5-Base	30.9	41.2	28.0	42.05
T5-Large	32.0	41.5	28.1	42.50
T5-3B	31.8	42.6	28.2	42.72
T5-11B	32.1	43.4	28.1	**43.52**

WMT: Translation Benchmark datasets
CNN/DM: summarization benchmark datasets

Summary

- LLMs have significant impact on both academia and industries.
- The state-of-the-art LLMs are Transformer-based models, which can be roughly characterized into the categories of encoder-only, decoder-only and encoder-decoder architectures.
- On-going researches focus on how to use LLMs under different scenario: downstream fine-tuning, zero-shot inference, in-context learning, instruction following, etc.

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