GPT-3: Melanie Subbiah

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Few-Shot Learning with a Giant Language Model

Language Models are Few-Shot Learners

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Christopher Berner

Sutskever

Dario Amodei









What is the goal?

Humans learn new tasks through demonstrations and instructions.



З

What is the goal?

Humans learn new tasks through demonstrations and instructions.

We'd like general-purpose agents that can do the same.

Typical Approach

1	sea otter => lou
	\checkmark
	gradient u
	\checkmark
1	<pre>peppermint => me</pre>
	\checkmark
	gradient u
	\checkmark
	•••
1	plush giraffe =>
	gradient u





Disadvantages to Fine-tuning

Creates a task-specific model





Disadvantages to Fine-tuning

- Creates a task-specific model
- Requires large high-quality supervised datasets





Disadvantages to Fine-tuning

- Creates a task-specific model
- Requires large high-quality supervised datasets
- more likely to exploit spurious correlations

Yogatama, et al. Learning and Evaluating General Linguistic Intelligence. 2019







What is an alternative?



Radford, et al. Language Models are Unsupervised Multitask Learners. 2019

Context (human-written): In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

GPT-2: The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.





Can we further improve on this level of generation and generalization?



Can we further improve on this level of generation and generalization?

GPT-3 175 Billion parameters

Critical Aspects of GPT-3

Model Size

• Training Objective







Kaplan, et al. Scaling Laws for Neural Language Models. 2020



4.26 3.9 5 Test Loss 3.6 4 3.3 3 3.0 $L = (C_{\rm min}/2.3 \cdot 10^8)^{-0.050}$ 2.7 $2 + 10^{-9}$ 10^{-7} 10^{-3} 10^{-5} 10^{-1} 10^{1} Compute PF-days, non-embedding

Kaplan, et al. Scaling Laws for Neural Language Models. 2020

Transformers scale well!





Predict the next word in a sequence.

Alec Radford @ Berkeley 4/15/20





P("The cat sat on the mat.") = ???

Alec Radford @ Berkeley 4/15/20





P("The cat sat on the mat.") = ???

"But it must be recognized that the notion of 'probability of a sentence' is an entirely useless one, under any known interpretation of this term." - Noam Chomsky, 1969

Alec Radford @ Berkeley 4/15/20





Alec Radford @ Berkeley 4/15/20



P("The cat sat on the mat.") > P("The cat sats on the mat.")



Alec Radford @ Berkeley 4/15/20



P("The cat sat on the mat.") > P("The cat sats on the mat.") Grammar





- P("The cat sat on the mat.") > P("The cat sats on the mat.")Grammar
- P("The cat sat on the mat.") > P("The whale sat on the mat.")



- P("The cat sat on the mat.") > P("The cat sats on the mat.")Grammar
- P("The cat sat on the mat.") > P("The whale sat on the mat.")World Knowledge



- P("The cat sat on the mat.") > P("The cat sats on the mat.")Grammar
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 - P("4" | "2 + 2 =") > P("5" | "2 + 2 =")



- P("The cat sat on the mat.") > P("The cat sats on the mat.")Grammar
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 - P("4" | "2 + 2 =") > P("5" | "2 + 2 =")Arithmetic



- P("The cat sat on the mat.") > P("The cat sats on the mat.") Grammar
- P("The cat sat on the mat.") > P("The whale sat on the mat.")World Knowledge
 - P("4" | "2 + 2 =") > P("5" | "2 + 2 =")Addition
 - P("1 star" | "That movie > P("5 stars" | "That movie was terrible. I'd give it") > Was terrible. I'd give it")



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 - P("1 star" | "That movie > P("5 stars" | "That movie was terrible. I'd give it") > Was terrible. I'd give it") Sentiment Analysis





Approach







http://jalammar.github.io/illustrated-gpt2/





The trophy didn't fit in the suitcase because











Devlin, et al. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. 2018 Raffel, et al. Exploring the Limits of Transfer Learning with a Unified Text-to-Text Transformer. 2019 Shoeybi, et al. Megatron-LM: Training Multi-Billion Parameter Language Models Using Model Parallelism. 2019 Microsoft. Turing-NLG: A 17-Billion Parameter Language Model by Microsoft. 2020







	180000				
(In millions)					
	157500				
	137300				
	135000				
	100000				
	112500				
	112300				
nnt	00000				
rarameter col	90000				
	67500				
	07500				
	15000				
	43000				
	22500				
	22000				
	0				
	U	Small	Medium	Large	









Parameter Count (in millions)





Parameter Count (in millions)

Batch Size



Compute





Dataset

 Common Crawl (filtered) - general web crawl, filtered based on similarity to high-quality reference and de-duplication

https://commoncrawl.org/the-data



Dataset

- Common Crawl (filtered) general web crawl, filtered based on similarity to high-quality reference and de-duplication
- WebText2 expanded version of GPT-2 training data, scrape of outbound links from Reddit posts with reasonably high ratings

Radford, et al. Language Models are Unsupervised Multitask Learners. 2019


Dataset

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- **Books1 & Books2** internet-based books



Dataset

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- Books1 & Books2 internet-based books
- Wikipedia English-language Wikipedia



Dataset Mix





Dataset Mix





Dataset Mix







Evaluations



42

tdaeef = ?



write that word. tdaeef = ?

Please unscramble the letters into a word and





Zero-Shot

Please unscramble the letters into a word and write that word. tdaeef = ?



One-Shot

Please unscramble the letters into a word and write that word. pcirlaroc = reciprocal tdaeef = ?



Few-Shot

Please unscramble the letters into a word and write that word. pcirlaroc = reciprocal elapac = palace tdaeef = ?



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

1 Translate English to French: 2 cheese =>





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



One-shot

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



guage	
ned.	

task description



The model predicts the answer given only a natura description of the task. No gradient updates are pe

1	Translate English to French:	<i>←</i>
2	cheese =>	~

One-shot

In addition to the task description, the model sees a single example of **Few-shot**

Tran	In addition to the task dea
------	-----------------------------

- sea
- chee
- Translate English to French:
- sea otter => loutre de mer
- peppermint => menthe poivrée
- cheese =>

al language erformed.	
task description	
prompt	

scription, the model sees a few examples of the task. No gradient updates are performed.







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



One-shot

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



Few-shot

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



VS.



Metalearning





Sample Output

The trophy didn't fit in the suitcase because





LM-Likelihood

The trophy didn't fit in the suitcase because the trophy was too big.





Randomly select K examples from the training dataset to build the context





Feed each context + possible completion through the model separately





Feed each context + possible completion through the model separately

Normalize LM likelihood over the completion and select the completion with the highest likelihood







Feed each context + possible completion through the model separately

Normalize LM likelihood over the completion and select the completion with the highest likelihood

newline







Normalize LM likelihood over the completion and select the completion with the highest likelihood





Complete List of Tasks

Language Modeling

• PTB

Close and Completion

- ROC Stories
- HellaSwag
- LAMBADA

Winograd-style

- Winograd
- Winogrande

Commonsense Reasoning

- PiQA
- ARC
- OpenBookQA

Reading Comprehension

- QuAC
- SQuADv2
- DROP
- CoQA
- RACE

Trivia-style Questions

- NaturalQs
- WebQs
- TriviaQA

Inference

- ANLI
- RTE

Comprehensive Benchmarks

• SuperGLUE

Translation

- En <-> Fr
- En <-> De
- En <-> Ro

Synthetic and Qualitative

- Arithmetic
- Word scrambling
- Character-level manipulation
- SAT analogies
- Article generation
- Learning and using novel words
- Correcting English grammar



Summary of Performance

Task Class

Close, Completion, and Language Question Answering / Knowledge

Translation

Winograd / Winogrande

Commonsense Reasoning

Reading Comprehension

SuperGLUE

NLI

Bias Probes

Dario Amodei @ NeurIPS 12/7/20



Few-Shot Performance
Very Good
Very Good
Good
Good
Mixed
Mixed
Mixed
Poor
Poor



Strengths

Q: 'Nude Descending A Staircase' is perhaps the most famous painting by which 20th century artist?

A:



Joshi, et al. TriviaQA: A large scale distantly supervised challenge dataset for reading comprehension. 2017



 $\texttt{Context} \rightarrow$

Strengths

Target Completion ightarrow



Paperno, et al. The lambada dataset: Word prediction requiring a broad discourse contex. 2016

Fill in blank:

She held the torch in front of her.

She caught her breath.

"Chris? There's a step."

"What?"

"A step. Cut in the rock. About fifty feet ahead." She moved faster. They both moved faster. "In fact," she said, raising the torch higher, "there's more than a $_---$. ->

step





 $\texttt{Context} \ \rightarrow$

Strengths

Target Completion \rightarrow



Paperno, et al. The lambada dataset: Word prediction requiring a broad discourse contex. 2016

```
Fill in blank:
She held the torch in front of her.
She caught her breath.
"Chris? There's a step."
"What?"
"A step. Cut in the rock. About fifty feet ahead." She moved faster.
They both moved faster. "In fact," she said, raising the torch higher,
"there's more than a ---. ->
```

step





Strengths





Strengths



5 Dig

6 D

3456 -> 3,456

6 Dig

Dario Amodei @ NeurIPS 12/7/20, and Gwern Branwen!

Task	Accuracy Without Commas	Accuracy With Commas
igit Addition	25.5%	91.1%
it Subtraction	26.9%	89.7%
igit Addition	9.3%	90.2%
it Subtraction	9.9%	82.2%
igit Addition	3%	78.5%
it Subtraction	3%	73.9%



Limitations

	$\texttt{Context} \rightarrow$	anli 3 subsid that 1 favors from (Questi
Correct	: Answer $ ightarrow$	False
Incorrect	: Answer $ ightarrow$	True
Incorrect	: Answer $ ightarrow$	Neithe



Nie, et al. Adversarial nli: A new benchmark for natural language understanding. 2019

3: anli 3: We shut the loophole which has American workers actually dizing the loss of their own job. They just passed an expansion of loophole in the last few days: \$43 billion of giveaways, including s to the oil and gas industry and the people importing ceiling fans China.

ion: The loophole is now gone True, False, or Neither?

er



Limitations

hampered his performance at times. He played in 138 games, recording 29.5 sacks and five fumble recoveries, which he returned for a total of 71 yards. In his offensive career he ran five yards for two touchdowns, and had one reception for another touchdown. Perry later attempted a comeback, playing an unremarkable 1996 season with the London Monarchs of the World League of American Football (later NFL Europa).

Q: what team did he play for?

A:



Choi, et al. Quac : Question answering in context. 2018; Dua, et al. Drop: A reading comprehension benchmark requiring discrete reasoning over paragraphs. 2019

Passage: Saint Jean de Brébeuf was a French Jesuit missionary who travelled to New France in 1625. There he worked primarily with the Huron for the rest of his life, except for a few years in France from 1629 to 1633. He learned their language and culture, writing extensively about each to aid other missionaries. In 1649, Brébeuf and another missionary were captured when an Iroquois raid took over a Huron village . Together with Huron captives, the missionaries were ritually tortured and killed on March 16, 1649. Brébeuf was beatified in 1925 and among eight Jesuit missionaries canonized as saints in the Roman Catholic Church in 1930. Question: How many years did Saint Jean de Brébeuf stay in New France before he went back to France for a few years? Answer:







Key Insights



Few-shot transfer to new tasks is possible without any gradient updates, and it presents a flexible framework for specifying new tasks to a model.





Bigger models can learn more from context





Bigger models have more emergent abilities




More context helps up to a point



Wang, et al. Superglue: A stickier benchmark for general-purpose language understanding systems. 2019

earning on SuperGLUE					
	Few-shot GPT-3 175B				
====:					
	Fine-tuned BERT Large				
	Random Guessing				
1	6 32				
Examp	oles in Context (K)				



Performance continues to scale with compute





Setting	PTB
SOTA (Zero-Shot)	35.8 ^{<i>a</i>}
GPT-3 Zero-Shot	20.5









Lingering Questions

Methods of Evaluation

Training Datasets and Memorization

 Real-World Applications - -



FT Magazine Artificial intelligence + Add to myFT Is AI finally closing in is proof on human intelligence? **By Luke Dormehl** October 20, 2020 Medical chatbot using OpenAI's GPT-3 told a fake GPT-3 has been hailed as an artificial intelligence breakthrough. John Thornhill tries it out and assesses the patient to kill themselves rewards — and the risks

AI Training Method Exceeds GPT-3 Performance with 99.9% Fewer Parameters

 \square

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凸LIKE OCT 06. 2020 • 2 MIN READ

A new study showed some expectations for the model are unrealistic

A.I. creativity is improving fast. This hilarious GPT3-generated film

Facebook's chief Al scientist says GPT-3 is 'not very good' as a dialog system







Language Modeling

• PTB

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- Learning and using novel words
- Correcting English grammar



ability?

What would it take to feel confident that a model possessed a complex





- ability?
- set of abilities a model possesses?

• What would it take to feel confident that a model possessed a complex

Can we build comprehensive benchmarks so that we could identify the







- ability?
- set of abilities a model possesses?
- generation?

What would it take to feel confident that a model possessed a complex

Can we build comprehensive benchmarks so that we could identify the

How do we evaluate one of the model's biggest strengths - creative







Training Datasets and Memorization

• Quality of Data

Duplication of Benchmarks



Training Datasets and Memorization - Data Quality

CommonCrawl filtering

and WebText/Books/Wikipedia

1. Train a classifier to distinguish between unfiltered CommonCrawl







Training Datasets and Memorization - Data Quality

CommonCrawl filtering

- 1. Train a classifier to distinguish between unfiltered CommonCrawl and WebText/Books/Wikipedia
- 2. Sample filtered CommonCrawl with higher probability of selection based on classifier score of quality









Training Datasets and Memorization - Data Quality

How can we better define and identify high quality data?



• Gender

"The competent detective was a _____"

"The incompetent detective was a _____"





Gender

Male-biased **Descriptive Words**

- Large
- Mostly
- Lazy
- Fantastic
- Eccentric
- Protect
- Jolly
- Stable
- Personable
- Survive

Female-biased Descriptive Words

- Optimistic
- Bubbly
- Naughty
- Easy-going
- Petite
- Tight
- Pregnant
- Gorgeous
- Sucked
- Beautiful



Gender

Race







Gender

Race

Religion

Religion	Most Favored Descrip		
Atheism	'Theists', 'Cool', 'Agno 'Characterized'		
Buddhism	'Myanmar', 'Vegetarian lightenment', 'Non-Vio		
Christianity	'Attend', 'Ignorant', 'R ments', 'Officially'		
Hinduism	'Caste', 'Cows', 'BJP', '		
Islam	'Pillars', 'Terrorism', 'I 'Prophet'		
Judaism	'Gentiles', 'Race', 'Sen		

tive Words

ostics', 'Mad', 'Theism', 'Defensive', 'Complaining' ('Correct') 'Arrogant',

ns', 'Burma', 'Fellowship', 'Monk', 'Japanese', 'Reluctant', 'Wisdom', 'Enolent'

Response', 'Judgmental', 'Grace', 'Execution', 'Egypt', 'Continue', 'Com-

'Kashmir', 'Modi', 'Celebrated', 'Dharma', 'Pakistani', 'Originated', 'Africa' Fasting', 'Sheikh', 'Non-Muslim', 'Source', 'Charities', 'Levant', 'Allah',

nites', 'Whites', 'Blacks', 'Smartest' 'Racists', 'Arabs', 'Game', 'Russian'







How do we make sure models trained on huge amounts of web data don't get the chance to memorize eval benchmarks?



Removing benchmarks from training data

documents

- 1. Look for overlap in phrases between benchmarks and training



- 1. Look for overlap in phrases between benchmarks and training documents
- 2. Found a quarter of benchmarks had over 50% overlap with the training dataset!





- 1. Look for overlap in phrases between benchmarks and training documents
- 2. Found a quarter of benchmarks had over 50% overlap with the training dataset!
- 3. Remove training documents that overlap with eval benchmarks





- 1. Look for overlap in phrases between benchmarks and training documents
- 2. Found a quarter of benchmarks had over 50% overlap with the training dataset!
- training documents that overlap with eval benchmarks 3. Rem





- 1. Look for overlap in phrases between benchmarks and training documents
- 2. Found a quarter of benchmarks had over 50% overlap with the training dataset!
- 3. Reflected training documents that overlap with eval benchmarks
- 4. Compare performance on benchmarks between full dataset and only test examples that don't appear in the training data









Real-World Applications

Important considerations

- 1. Potential for harmful outputs
- 2. Reliability of performance



Real-World Applications

- Semantic search
- Turn a script into a novel
- Turn a sentence into an email
- Smart formatting and code generation
- Emoji storytelling

https://andrewmayneblog.wordpress.com





Real-World Applications - Emoji Storytelling



https://andrewmayneblog.wordpress.com



Real-World Applications - Emoji Storytelling



https://andrewmayneblog.wordpress.com

Zootopia: 😻 🀾 🐯 😹 Wonder Woman: 💽 😳 💿 💿 The Godfather: 😨 😥 🚘 😴 🔆 Star Trek: 🤟 💋 Planet of the Apes: 😰 📾 Game of Thrones: 👑 🐼 📻 Jurassic Park: 😔 두 🖕 두 Castlevania: 🧃 🗱 🕷 🔪 💉 😭 😫 The Matrix: 🔛 🤐 Iron Man: 🔐 🗶 💇 🔳 🌲 Death Note: 💷 🄪 Frozen: 🖦 😰 😰 🌲 The Hunger Games: 💢 🕊 🌽 🏆



Real-World Applications

What are the useful applications of a model like GPT-3?

perfectly reliable?

• Are there times when GPT-3 can be convincing enough, even if not



Real-World Applications

What are the useful applications of a model like GPT-3?

perfectly reliable?

• Are there times when GPT-3 can be convincing enough, even if not



Real-World Applications - Writing News





Real-World Applications - Writing News

Title: United Methodists Agree to Historic Split Subtitle: Those who oppose gay marriage will form their own denomination Article: After two days of intense debate, the United Methodist Church has agreed to a historic split - one that is expected to end in the creation of a new denomination, one that will be "theologically and socially conservative," according to The Washington Post. The majority of delegates attending the church's annual General Conference in May voted to strengthen a ban on the ordination of LGBTQ clergy and to write new rules that will "discipline" clergy who officiate at same-sex weddings. But those who opposed these measures have a new plan: They say they will form a separate denomination by 2020, calling their church the Christian Methodist denomination.

The Post notes that the denomination, which claims 12.5 million members, was in the early 20th century the "largest Protestant denomination in the U.S.," but that it has been shrinking in recent decades. The new split will be the second in the church's history. The first occurred in 1968, when roughly 10 percent of the denomination left to form the Evangelical United Brethren Church. The Post notes that the proposed split "comes at a critical time for the church, which has been losing members for years," which has been "pushed toward the brink of a schism over the role of LGBTQ people in the church." Gay marriage is not the only issue that has divided the church. In 2016, the denomination was split over ordination of transgender clergy, with the North Pacific regional conference voting to ban them from serving as clergy, and the South Pacific regional conference voting to allow them.



Conclusion

 Language modeling performance appears to continue to scale with compute



Conclusion

- Language modeling performance appears to continue to scale with compute
- Large models can transfer few-shot to new tasks without any fine-tuning



Conclusion

- Language modeling performance appears to continue to scale with compute
- Large models can transfer few-shot to new tasks without any fine-tuning
- There are many complexities to evaluations, training datasets, and applications for large models



Language Models are Few-Shot Learners

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Amanda Askell	Sandhin	i Agarwal	Ariel Herbert-Voss		
Rewon Child	Aditya	Ramesh	Daniel M. Ziegler		
Christopher He	sse	Mark Chen	Eric	Sigler	
Benjar		Jack Cla	rk		
Sam McCan	dlish	Alec Radford I			

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Pranav Shyam Girish Sastry n

Gretchen Krueger Tom Henighan

Jeffrey Wu **Clemens Winter**

Mateusz Litwin **Scott Gray**

Christopher Berner

Sutskever

Dario Amodei










Questions?

Shadows on the Way Wallace Stevens

There is a way in the world. That way a man may live in a small town His lifetime and see no man come, Never the stir of men about a market, Never the bobbing of covered carts, Never the creak passed on the stair Closing some other life; an old man Can prosper in that town, can prosper When his store is seen to close, his wife Fades in his house, and the world shouts in vain That no one comes to hear him Where his small bell tolls. In that small town Everything is known. The ways of the young men are known, And the ways of the young women As they walk to the Spring; The rumors are all known, The quarrels, the hurt, the envy Of the men and the women. Till a day comes That way out of the world That leads to a wood. Young, the young man Walks, a lover now, Knows the streets as they are and is of them.



