GENERATIVE AI DEMYSTIFIED - JADE ADAM GRZYWACZEWSKI, SENIOR DEEP LEARNING DATA SCIENTIST

ABOUT ME

Adam Grzywaczewski - adamg@nvidia.com



- Senior Deep Learning Data Scientist @ NVIDIA Supporting delivery of AI / Deep Learning solutions
- Focusing on large scale/distributed training and efficient inference
- Expertise in Natural Language Processing



DRAMATIC INCREASE IN MODEL SIZES

The Trend Continues



Training Compute (PetaFLOPS)

https://developer.nvidia.com/blog/using-deepspeed-and-megatron-to-train-megatron-turing-nlg-530b-the-worlds-largest-and-most-powerful-generative-language-model

2019 2020 2021 2022





THE SCALING LAWS Performance of neural networks increases with model/dataset size



Training Data Set Size (Log-scale)

Hestness, J., Narang, S., Ardalani, N., Diamos, G., Jun, H., Kianinejad, H., ... & Zhou, Y. (2017). Deep Learning Scaling is Predictable, Empirically. arXiv:1712.00409.



EMPIRICAL EVIDENCE

The Scaling Laws in NLP



Henighan, Tom, et al. Scaling laws for autoregressive generative modeling. arXiv preprint arXiv:2010.14701 (2020).

💿 nvidia.

EMPIRICAL EVIDENCE The Scaling Laws for Generative models



Henighan, Tom, et al. Scaling laws for autoregressive generative modeling. arXiv preprint arXiv:2010.14701 (2020).





EMPIRICAL EVIDENCE

The Scaling Laws in Speech



Droppo, Jasha, and Oguz Elibol. Scaling Laws for Acoustic Models. arXiv preprint arXiv:2106.09488 (2021).



EMPIRICAL EVIDENCE The Scaling Laws in Computer Vision



Zhai, Xiaohua, et al. Scaling vision transformers. arXiv preprint arXiv:2106.04560 (2021).



BEYOND ACCURACY



ARE LARGE LANGUAGE MODELS WORTH IT? The cost of incremental improvement



Tom Henighan, Jared Kaplan, Mor Katz, Mark Chen, Christopher Hesse, Jacob Jackson, Heewoo Jun, Tom B. Brown, Prafulla Dhariwal, Scott Gray, Chris Hallacy, Benjamin Mann, Alec Radford, Aditya Ramesh, Nick Ryder, Daniel M. Ziegler, John Schulman, Dario Amodei, Sam McCandlish. Scaling Laws for Autoregressive Generative Modeling. 2020

Are we building those models only for the small incremental improvement in their performance?

> Is it worth all the engineering and computational investment?



FEW SHOT LEARNING Learning from far fewer examples



Figure 1.2: Larger models make increasingly efficient use of in-context information. We show in-context learning performance on a simple task requiring the model to remove random symbols from a word, both with and without a natural language task description (see Sec. 3.9.2). The steeper "in-context learning curves" for large models demonstrate improved ability to learn a task from contextual information. We see qualitatively similar behavior across a wide range of tasks.

Brown, T. B., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., ... & Agarwal, S. (2020). Language models are few-shot learners. arXiv preprint arXiv:2005.14165.



FINETUNED LANGUAGE MODELS ARE ZERO SHOT LEARNERS

Exceptional zero shot learning capability



Ouyang, L., Wu, J., Jiang, X., Almeida, D., Wainwright, C., Mishkin, P., ... & Lowe, R. (2022). Training language models to follow instructions with human feedback. Advances in Neural Information Processing Systems, 35, 27730-27744.





GPT-4 AND ITS IMPLICATIONS



Unbelievable Rate of Progress

Major shift in capabilities

Model	GPT-4	text-davinci-003	Codex(code-davine
Accuracy	82%	65%	39%

Table 1: Zero-shot pass@1 accuracy comparison of different models on HumanEval



CODEGEN-16B ci-002)

30%



Beyond Incremental Improvement to NLP Exceptional zero shot learning capability

Exam results (ordered by GPT 3.5 performance)



Figure 1: To get a sense of how quickly model capabilities are progressing - consider the jump in exam performance between GPT-3.5 and GPT-4 (OpenAI, 2023b).



Sparks of Artificial General Intelligence: Early experiments with GPT-4

Sébastien BubeckVarun ChandrasekaranRonen EldanJohannes GehrkeEric HorvitzEce KamarPeter LeeYin Tat LeeYuanzhi LiScott LundbergHarsha NoriHamid PalangiMarco Tulio RibeiroYi Zhang

Microsoft Research



GPTs are GPTs: An Early Look at the Labor Market Impact Potential of Large Language Models

Tyna Eloundou¹, Sam Manning^{1,2}, Pamela Mishkin^{*1}, and Daniel Rock³

¹OpenAI ²OpenResearch ³University of Pennsylvania

March 27, 2023

Abstract

We investigate the potential implications of large language models (LLMs), such as Generative Pretrained Transformers (GPTs), on the U.S. labor market, focusing on the increased capabilities arising from LLM-powered software compared to LLMs on their own. Using a new rubric, we assess occupations based on their alignment with LLM capabilities, integrating both human expertise and GPT-4 classifications. Our findings reveal that around 80% of the U.S. workforce could have at least 10% of their work tasks affected by the introduction of LLMs, while approximately 19% of workers may see at least 50% of their tasks impacted. We do not make predictions about the development or adoption timeline of such LLMs. The projected effects span all wage levels, with higher-income jobs potentially facing greater exposure to LLM capabilities and LLM-powered software. Significantly, these impacts are not restricted to industries with higher recent productivity growth. Our analysis suggests that, with access to an LLM, about 15% of all worker tasks in the US could be completed significantly faster at the same level of quality. When incorporating software and tooling built on top of LLMs, this share increases to between 47 and 56% of all tasks. This finding implies that LLM-powered software will have a substantial effect on scaling the economic impacts of the underlying models. We conclude that LLMs such as GPTs exhibit traits of general-purpose technologies, indicating that they could have considerable economic, social, and policy implications.





Impact





WHAT DOES IT MEAN FOR THE INDUSTRY?



OBVIOUS APPLICATIONS



55.8% faster than the control group









I write **100-1000** lines of code per day + unit tests + comments + documentation

	Easy		Median		Hard		Overall	
$\mathrm{pass}@k$	k = 1	k = 5	k = 1	k = 5	k = 1	k = 5	k = 1	k = 5
GPT-4	68.2	86.4	40.0	60.0	10.7	14.3	38.0	53.0
text-davinci-003	50.0	81.8	16.0	34.0	0.0	3.6	19.0	36.0
$\operatorname{Codex}(\texttt{code-davinci-002})$	27.3	50.0	12.0	22.0	3.6	3.6	13.0	23.0
Human (LeetCode users)	72	2.2	37	7.7	7	.0	38	8.2

Table 2: Zero-shot pass@1 and pass@5 accuracies (%) on LeetCode.

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of ai on developer productivity: Evidence from github copilot. arXiv preprint arXiv:2302.06590. Sébastien B et all (2023). Sparks of Artificial General Intelligence: Early experiments with GPT-4. arXiv:2303.12712







Table 2: Zero-shot pass@1 and pass@5 accuracies (%) on LeetCode.

Peng, S., Kalliamvakou, E., Cihon, P., & Demirer, M. (2023). The impact of ai on developer productivity: Evidence from github copilot. arXiv preprint arXiv:2302.06590. Sébastien B et all (2023). Sparks of Artificial General Intelligence: Early experiments with GPT-4. arXiv:2303.12712



Easy		Median		Ha	Ird	Overall	
k = 1	k = 5	k = 1	k = 5	k = 1	k = 5	k = 1	k = 5
68.2	86.4	40.0	60.0	10.7	14.3	38.0	53.0
50.0	81.8	16.0	34.0	0.0	3.6	19.0	36.0
27.3	50.0	12.0	22.0	3.6	3.6	13.0	23.0
72.2		37.7		7.0		38.2	



Across countless disciplines

M	adagascar package. Here's an outline of the pro prresponding Madagascar commands:	rocessing steps, along with the	
1.	Load the seismic data (e.g., data.su file): sfsuread < data.su endian=n > data.rsf		$\leq $
2.	Display a few shots from the data: sfwindow < data.rsf n1=2 sfgrey sfpen		
3.	Apply trace header manipulation if needed (e. sfput < data.rsf o1=0 d1=1 o2=0 d2=1 > data_g	e.g., set the correct geometry): MADAGA geom.rsf	SCAR
4.	sfmedian < data_geom.rsf rect1=5 rect2=5 > c	data_denoised.rsf	
5. 6. 7. 8. 9.	Apply bandpass intering to emphasize the sfbp < data_denoised.rsf flo=5 fhi=60 > d 1 Perform velocity analysis to estimate intel 3 sfveltran < data_filtered.rsf semblance=y 4 Create a smoothed velocity model (using 6 sfgsmooth < velocity.rsf rect1=20 rect2=2 7 Perform normal moveout (NMO) correctic 9 sfnmo < data_filtered.rsf vnmo=velocity_s 11 Stack the NMO-corrected data to create a 13 sfstack < data_nmo.rsf > zero_offset.rsf 14 Apply post-stack migration to the zero-of 15	<pre>demo_madagascar.py > 1 """https://www.youtube.com/watch?v=r951ZhHrdp0&ab_channel=DataIndependent""" 2 3 from langchain.llms.openai import OpenAI 4 from langchain.agents import load_tools 5 from langchain.agents import initialize_agent 6 from langchain.agents import AgentType 7 8 9 ifname == "main": 0 llm = OpenAI(temperature=0, max_tokens=1000) 1 tools = load_tools(["terminal", "llm-math"], llm=llm) 3 agent = initialize_agent(tools, llm, agent=AgentType.ZER0_SHOT_REACT_DESCRIPTION, verbose=True) 4 5 </pre>	> I I I I I I I I I I I I I I
11.	Apply post-stack migration to the zero-of sfkirchhoffmig2 < zero_offset.rsf vel=velo Visualize the final migrated section: sfgrey < migrated_section.rsf sfrom 20 21 22 23 24 25 26 27 28	agent.run("""You have access to the Unix terminal. You will call command line tools from Madagascar software package for seismic data processing. Use "<" to pass input files to the Madagascar funciton.	Act Act Obs The Act Obs The Fill Con 2: 25

6 P

I understand that you are looking for a general plan for processing seismic data using the

\$

in:



> Finished chain. • (base) oovcharenko@nvdxb-musk:~/work/aramco/chatbot/langchain/demos\$ python d emo madagascar.py

```
> Entering new AgentExecutor chain...
 I need to create a spike, compute the sampling frequency, compute the Nyquis
 t frequency, and bandpass the spike below it.
 Action: Terminal
Action Input: sfspike n1=1000 d1=0.004 k1=300 label1=Welcome > spike.rsf
 Observation:
Thought: I need to compute the sampling frequency
 Action: Calculator
 Action Input: 1/0.004
 Observation: Answer: 250.0
 Thought: I need to compute the Nyquist frequency
 Action: Calculator
 Action Input: 250/2
 Observation: Answer: 125.0
 Thought: I need to bandpass the spike below the Nyquist frequency
 Action: Terminal
 Action Input: sfbandpass < spike.rsf fhi=2 > spike bandpassed.rsf
 Observation:
Thought: I now know the final answer
 Final Answer: I created a spike sampled with 0.004 sec interval, 1000 samples
 long and centered on 300, entitled "Welcome" and saved it in "spike.rsf". I
computed the sampling frequency as an inverse of sampling interval (1/0.004 =
 250.0) and used it to compute the Nyquist frequency of the signal (250/2 = 1)
 25.0). I then bandpassed the spike below the Nyquist frequency (fhi=2) and sa
 ved the output in "spike bandpassed.rsf".
 > Finished chain.
• (base) oovcharenko@nvdxb-musk:~/work/aramco/chatbot/langchain/demos$ sfin < s
 pike bandpass.rsf
```

in="/var/tmp/spike bandpass.rsf@" esize=4 type=float form=native n1=1000 d1=0.004 01=0 1000 elements 4000 bytes

label1="Time" unit1="s"



Across countless disciplines

VerilogEval: Evaluating Large Language Models for Verilog Code Generation



The increasing popularity of large language models (LLMs) has paved the way for their application in diverse domains. This paper proposes a benchmarking framework tailored specifically for evaluating LLM performance in the context of Verilog code generation for hardware design and verification. We present a comprehensive evaluation dataset consisting of 156 problems from the Verilog instructional website HDLBits. The evaluation set consists of a diverse set of Verilog code generation tasks, ranging from simple combinational circuits to complex finite state machines. The Verilog code completions can be automatically tested for functional correctness by comparing the transient simulation outputs of the generated design with a golden solution. We also demonstrate that the Verilog code generation capability of pretrained language models could be improved with supervised fine-tuning by bootstrapping with LLM generated synthetic problem-code pairs.



Reducing barrier to programming



https://dataliteracy.com/code-interpreter-for-chatgpt/

Can you modify the top 10 operating airlines bar chart for me? I'd like to see the bars horizontal, make them gray for me please, and can you add data labels to the end of each bar, making sure to add thousands separator? ዕፊዏ Show work 🗸 Top 10 Operating Airlines by Passenger Count 350,170,993 United Airlines 10,727,834 18,974,403 SkyWest Airlines 110,452,149 American Airlines 94.324.906 Delta Air Lines Southwest Airlines 84,391,174 75,687,840 Virgin America 64,400,258 Alaska Airlines US Airways 33,633,232 JetBlue Airways 32,415,972 0.5 1.0 3.5 0.0 2.0 1.5 2.5 3.0 1e8 Passenger Count

Here is the modified bar chart showing the top 10 operating airlines by passenger count:

- The bars are now displayed horizontally.
- The color of the bars has been changed to gray.
- Data labels have been added to the end of each bar with a thousands separator for
- Please take a look at the visualization below:

Top 10 Operating Airlines by Passenger Count (Modified)

Feel free to let me know if there are any additional modifications you would like to make, or if you have any other questions or requests!



Changing Competitive Landscape Reducing barrier to programming



https://github.com/KillianLucas/open-interpreter



Changing the way we search

I asked the search engine:



Phind

ANSWER

To create a shape of a tree, we can use the concept of printing patterns in programming. There are multiple ways to create a pattern of a tree, including using loops, recursion, and conditional statements. Let's explore some of the patterns we can use to create a tree shape.

One approach to create a tree shape is to print a pyramid pattern with a trunk. We can use the code provided in programiz.com to print a half pyramid of alphabets. We can modify the code to print a pyramid pattern of asterisks and add a trunk to the pattern.

Here's how we can modify the code to print a tree shape:



In this code, we first take input from the user for the height of the tree. We then use three nested loops to print the pyramid pattern of asterisks. The first loop is for the height of the tree, the second loop is for printing the spaces before the asterisks, and the third loop is for printing the asterisks.

After printing the pyramid pattern, we use two nested loops to print the trunk of the tree. The first loop is for the height

Google

Questions & answers

Q Quora	b Bartleby	Chegg		
Question	Question	Question		
I am writing a program to create a binary search tree and display sorted data. How can I do that in C programming easily give m	Programming Language: C Programming1. Make a code of implementation of the Binary Tree program and explain each line on how it	 Consider the follo tree that holds Entri type Integer, String: M 4, W 5, H. 6, P 7 a code fragment to 		
Answer · 10 votes	Answer · 0 votes	Answer · 0 votes		
Here is code for in-order traversal in binary search More	Step 1 Binary tree in c pro More	Solution: I have writ code in Python Lang More		

GeeksforGeeks ÐG

https://www.geeksforgeeks.org > create-a-tree-in-level...

Create a tree in level order

Sep 2, 2022 - Create a tree in level order ... Given an array of elements, the task is to insert these elements in level order and construct a tree.

https://www.geeksforgeeks.org>introduction-to-binar...

Introduction to Binary Tree - Data Structure and Algorithm.

Mar 15, 2023 - In compilers, Expression Trees are used which is an application of binary trees. Huffman coding trees are used in data compression algorithms.

People also ask :

How do you make a tree in coding?

How to create a tree in Java code?

How to create a tree in C language?

How do you create a binary tree in programming?

Programiz https://www.programiz.com > dsa > binary-tree : **Binary Tree**



Chat GPT - OpenAl

write a programming code that takes a letter can creates a shape of a tree

#include <iostream> #include <string>

using namespace std;

int main(){ string letter;

cout << "Enter a letter: "; cin >> letter;

cout << endl;

```
cout << letter << letter << letter << endl;
cout << letter << " " << letter << endl;</pre>
cout << letter << endl;
cout << letter << letter << letter << endl;
return 0;
```

owing ries of : 1,Z 2,D V Write create...

tten the guage,.

Feedback

 \sim \sim \sim \sim

Feedback



Changing the way we collate information

Literature review at scale

nature machine intelligence

Explore content 🖌 About the journal 🖌 Publish with us 🗸

<u>nature</u> > <u>nature</u> machine intelligence</u> > <u>articles</u> > article

Article Open Access Published: 01 February 2021

An open source machine learning framework for efficient and transparent systematic reviews

Rens van de Schoot ⊡, Jonathan de Bruin, Raoul Schram, Parisa Zahedi, Jan de Boer, Felix Weijdema, Bianca Kramer, Martijn Huijts, Maarten Hoogerwerf, Gerbrich Ferdinands, Albert Harkema, Joukje Willemsen, Yongchao Ma, Qixiang Fang, Sybren Hindriks, Lars Tummers & Daniel L. Oberski

Nature Machine Intelligence 3, 125–133 (2021) Cite this article

57k Accesses | 125 Citations | 138 Altmetric | Metrics

• A <u>preprint version</u> of the article is available at arXiv.

Abstract

To help researchers conduct a systematic review or meta-analysis as efficiently and transparently as possible, we designed a tool to accelerate the step of screening titles and abstracts. For many tasks—including but not limited to systematic reviews and meta-analyses —the scientific literature needs to be checked systematically. Scholars and practitioners currently screen thousands of studies by hand to determine which studies to include in their review or meta-analysis. This is error prone and inefficient because of extremely imbalanced



Changing the way we collate information

Literature review at scale

Can we predict novel targets from literature trend?

We can predict novel targets using only NLP



Pure NLP-based analysis



999

after 2015

Proportion of Gene Target types in the top-500 predictions Known Targets Future Targets 90% Novel Targets 80% 70% 60% 50% 40% 30% 20%

10%



Score distributions for all Gene Targets



RESCAL Score







Changing the way we manage complex systems

Not just applicable to datacentre infrastructure

Large-language models for automatic cloud incident management

Published May 16, 2023

By Rujia Wang, Principal Research Product Manager; Chetan Bansal, Principal Research Manager; Supriyo GHOSH, Senior Researcher; Tom Zimmermann, Sr. Principal Researcher; Xuchao Zhang, Senior Researcher; Saravan Rajmohan, Partner Director AI and Applied Research



This research was accepted by the IEEE/ACM International Conference on Software Engineering (ICSE) *Q*, which is a forum for researchers, practitioners, and educators to gather, present, and discuss the most recent innovations, trends, experiences, and issues in the field of software engineering.



CHANGING THE WAY WE APPROACH COMPLEX PROBLEMS

LLM in mathematics

Large Language Model for Science: A Study on P vs. NP

Qingxiu Dong * 1 2 Li Dong * 1 Ke Xu * 3 Guangyan Zhou⁴ Yaru Hao¹ Zhifang Sui² Furu Wei¹ https://aka.ms/GeneralAI

Abstract

In this work, we use large language models (LLMs) to augment and accelerate research on the P versus NP problem, one of the most important open problems in theoretical computer science and mathematics. Specifically, we propose Socratic reasoning, a general framework that promotes in-depth thinking with LLMs for complex problem-solving. Socratic reasoning encourages LLMs to recursively discover, solve, and integrate problems while facilitating self-evaluation and refinement. Our pilot study on the P vs. NP problem shows that GPT-4 successfully produces a proof schema and engages in rigorous reasoning throughout 97 dialogue turns, concluding " $P \neq NP$ ", which is in alignment with (Xu and Zhou, 2023). The investigation uncovers novel insights within the extensive solution space of LLMs, shedding light on LLM for Science.

4 Mar 2023 [cs.CL]

Large Language Models (LLMs) have limited performance when solving arithmetic reasoning tasks and often provide incorrect answers. Unlike natural language understanding, math problems typically have a single correct answer, making the task of generating accurate solutions more challenging for LLMs. To the best of our knowledge, we are not aware of any LLMs that indicate their level of confidence in their responses which fuels a trust deficit in these models impeding their adoption. To address this deficiency, we propose 'MathPrompter', a technique that improves performance of LLMs on arithmetic problems along with increased reliance in the predictions. MathPrompter uses the Zero-shot chain-of-thought prompting technique to generate multiple Algebraic expressions or Python functions to solve the same math problem in different ways and thereby raise the confidence level in the output results. This is in contrast to other prompt based CoT methods, where there is no check on the validity of the intermediate steps followed. Our technique improves over state-of-the-art on the MultiArith dataset (78.7% \rightarrow 92.5%) evaluated using 175B parameter GPT-based LLM.

MATHPROMPTER: MATHEMATICAL REASONING USING LARGE LANGUAGE MODELS

Shima Imani, Liang Du, Harsh Shrivastava Microsoft Research, Redmond Contact: shimaimani@microsoft.com

ABSTRACT



BEYOND GENERIC MODELS

Science

Galactica: A Large Language Model for Science

other sources. We outperform existing models on a range of scientific tasks. On technical knowledge probes such as LaTeX equations, Galactica outperforms the latest GPT-3 by 68.2% versus 49.0%. Galactica also performs well on reasoning, outperforming Chinchilla

on mathematical MMLU by 41.3% to 35.7%, and PaLM 540B on MATH with a score of 20.4% versus 8.8%. It also sets a new state-of-the-art on downstream tasks such as PubMedQA and MedMCQA dev of 77.6% and 52.9%. And despite not being trained on a general corpus, Galactica outperforms BLOOM and OPT-175B on BIG-bench. We believe these results demonstrate the potential for language models as a new interface for science. We open

source the model for the benefit of the scientific community¹.

Guillem Cucurull Ross Taylor Marcin Kardas Modality Entity Sequence Thomas Scialom Anthony Hartshorn Elvis Saravia Text Abell 370 Abell 370 is a cluster... Andrew Poulton Viktor Kerkez Robert Stojnic LATEX Schwarzschild radius $r_{s} = \frac{2GM}{c^2}$ Meta AI Code Transformer class Transformer(nn.Module) SMILES Glycine C(C(=0)0)N Abstract AA Sequence Collagen α -1(II) chain MIRLGAPOTL.. Information overload is a major obstacle to scientific progress. The explosive growth in scientific literature and data has made it ever harder to discover useful insights in a large DNA Sequence Human genome CGGTACCCTC.. mass of information. Today scientific knowledge is accessed through search engines, but they are unable to organize scientific knowledge alone. In this paper we introduce Galactica: Table 1: Tokenizing Nature. Galactica trains on text sequences that represent scientific phenomena. a large language model that can store, combine and reason about scientific knowledge. We train on a large scientific corpus of papers, reference material, knowledge bases and many





BEYOND GENERIC MODELS

9 May 2023

[cs.LG]

54v2

Science

A Large Language Model for Electronic Health Records

Authors: Xi Yang^{1,2}, Aokun Chen^{1,2}, Nima PourNejatian³, Hoo Chang Shin³, Kaleb E Smith³, Christopher Parisien³, Colin Compas³, Cheryl Martin³, Anthony B Costa³, Mona G Flores³, Ying Zhang⁴, Tanja Magoc⁵, Christopher A Harle^{1,5}, Gloria Lipori^{5,6}, Duane A Mitchell⁶, William R Hogan¹, Elizabeth A Shenkman¹, Jiang Bian^{1,2}, Yonghui Wu^{1,2*}

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BloombergGPT: A Large Language Model for Finance

Shijie Wu^{1,*}, Ozan İrsoy^{1,*}, Steven Lu^{1,*}, Vadim Dabravolski¹, Mark Dredze^{1,3}, Sebastian Gehrmann¹, Prabhanjan Kambadur¹, David Rosenberg², Gideon Mann¹ ¹ Bloomberg, New York, NY USA ² Bloomberg, Toronto, ON Canada

³ Computer Science, Johns Hopkins University, Baltimore, MD USA

The use of NLP in the realm of financial technology is broad and complex, with applications ranging from sentiment analysis and named entity recognition to question answering. Large Language Models (LLMs) have been shown to be effective on a variety of tasks; however, no LLM specialized for the financial domain has been reported in literature. In this work, we present BLOOMBERGGPT, a 50 billion parameter language model that is trained on a wide range of financial data. We construct a 363 billion token dataset based on Bloomberg's extensive data sources, perhaps the largest domain-specific dataset yet, augmented with 345 billion tokens from general purpose datasets. We validate BLOOMBERGGPT on standard LLM benchmarks, open financial benchmarks, and a suite of internal benchmarks that most accurately reflect our intended usage. Our mixed dataset training leads to a model that outperforms existing models on financial tasks by significant margins without sacrificing performance on general LLM benchmarks. Additionally, we explain our modeling choices, training process, and evaluation methodology. We release Training Chronicles (Appendix C) detailing our experience in training BLOOMBERGGPT.

Abstract



BEYOND THE OBVIOUS



Beyond the Obvious

We can only see the first wave of business models affected





Fig. 314. — Moteur Froment attelé à une paire de meules.

alamu	Ima
alaliy	www





age ID: DB0C59 **v.alamy.com**




Transforming Impossible into Feasible

Future of books / reports







Fig. 314. - Moteur Froment attelé à une paire de meules









Transforming Impossible into Feasible

Democratizing access to education



Bill Gates says AI chatbots like ChatGPT can replace human teachers

Al-powered tutors could be a more economical solution for parents who can't afford a human teacher.

f 🍠 in 🚳 🔽 🖛

By Vinay Patel ♥ @VinayPatelBlogs 04/27/23 AT 7:28 AM BST



Bill Gates beleives AI chatbots will soon replace human teachers. (PHOTO: JOHN LAMPARSKI/GETTY IMAGES)



Fig. 314. - Moteur Froment attelé à une paire de meules.

ny

Image ID: DB0C5 www.alamy.cor



NOT JUST LANGUAGE



WHAT IS GENERATIVE AI?







BIOLOGY Nucleotide transformer



fine-tuning.

500M, 3B

1000G 500M, 115

Multispecies

2.5B, 174B

ATTCGACTAGTCAG

GCCCGCTATTATATT

CGATCAGGATCATA

ATTCGACTAGTCAG

GCCCGCTATTATATT

CGATCAGGATCATA

Fig. 1: The Nucleotide Transformer model matches or outperforms 15 out of 18 downstream tasks using finetuning. We show the performance results across downstream tasks for fine-tuned transformer models. Error bars represent 2 SDs derived from 10-fold cross-validation. The performance metrics for the state-of-the-art (SOTA) models are shown as horizontal dotted lines.



Figure 1: The Nucleotide Transformer: a Masked Language Model trained for Genomics Prediction. a) Training datasets and parameter sizes of the language models. b) Graphical representation of genomic features considered for prediction tasks. c) Overview of the Nucleotide Transformer training and application for downstream genomic prediction tasks through probing. d) Overview of the Nucleotide Transformer training and application for downstream genomic prediction tasks through



CHEMISTRY / DRUG DISCOVERY

MegaMolBart





CHEMISTRY / DRUG DISCOVERY

MolGPT



SUBJECTS: Molecular modeling, Molecular properties, Molecules, Partition coefficient, Scaffolds

Abstract

Application of deep learning techniques for de novo generation of molecules, termed as inverse molecular design, has been gaining enormous traction in drug design. The representation of molecules in SMILES notation as a string of characters enables the usage of state of the art models in natural language processing, such as Transformers, for molecular design in general. Inspired by generative pre-training (GPT) models that have been shown to be successful in generating meaningful text, we train a transformer-decoder on the next token prediction task using masked self-attention for the generation of druglike molecules in this study. We show that our model, MolGPT, performs on par with other previously proposed modern machine learning frameworks for molecular generation in terms of generating valid, unique, and novel molecules. Furthermore, we demonstrate that the model can be trained conditionally to control multiple properties of the generated molecules. We also show that the model can be used to generate molecules with desired scaffolds as well as desired molecular properties by conditioning the generation on scaffold SMILES strings of desired scaffolds and property values. Using saliency maps, we highlight the interpretability of the generative process of the model.





BIOLOGY Beyond academic research

PHARMA.AI



https://insilico.com/

NVIDIA Expands Large Language Models to Biology

Leading pharma companies, biotech startups and pioneering biology researchers are developing AI applications with the NVIDIA BioNeMo LLM service and framework to generate, predict and understand biomolecular data.





MATERIAL SCIENCE

Already changing related disciplines

DISCOVERY OF 2D MATERIALS USING TRANSFORMER **NETWORK BASED GENERATIVE DESIGN ***

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ABSTRACT

Two-dimensional (2D) materials have wide applications in superconductors, quantum, and topological materials. However, their rational design is not well established, and currently less than 6,000 experimentally synthesized 2D materials have been reported. Recently, deep learning, data-mining, and density functional theory (DFT)-based high-throughput calculations are widely performed to discover potential new materials for diverse applications. Here we propose a generative material design pipeline, namely material transformer generator(MTG), for large-scale discovery of hypothetical 2D materials. We train two 2D materials composition generators using self-learning neural language models based on Transformers with and without transfer learning. The models are then used to generate a large number of candidate 2D compositions, which are fed to known 2D materials templates for crystal structure prediction. Next, we performed DFT computations to study their thermodynamic stability based on energy-above-hull and formation energy. We report four new DFT-verified stable 2D materials with zero e-above-hull energies, including NiCl₄, IrSBr, CuBr₃, and CoBrCl. Our work thus demonstrates the potential of our MTG generative materials design pipeline in the discovery of novel 2D materials and other functional materials.



(a) NiCl₄



(b) IrSBr

(c) CuBr₃

(d) CoBrCl

Figure 9: Four new 2D structures discovered by our MTG pipeline with 0 E-above-hull energy.



TIME SERIES DATA



BEYOND SPEECH

Foundation for a range of timeseries problems



"Voicebox is a non-autoregressive flow-matching model trained to infill speech, given audio context and text, trained on over 50K hours of speech that are neither filtered nor enhanced."



BEYOND SPEECH

Taking the learnings to other disciplines

Predicting brain activity using Transformers

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Abstract

The Algonauts challenge [Gifford et al., 2023] called on the community to provide novel solutions for predicting brain activity of humans viewing natural scenes. This report provides an overview and technical details of our submitted solution. We use a general transformer encoder-decoder model to map

responses. The encoder model is a vision transformer trained usine methods (DINOv2). The decoder uses queries corresponding regions of interests (ROI) in different hemispheres to gather releform the encoder output for predicting neural activity in each tokens from the decoder are then linearly mapped to the fMQ predictive success (challenge score: 63.5229, rank 2) suggests self-supervised transformers may deserve consideration as model brain representations and shows the effectiveness of transformer and cross-attention) to learn the mapping from features to brain r available in this github repository.



Frontiers | Frontiers in Neuroscience

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OPEN ACCESS

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EEGformer: A transformer-based brain activity classification method using EEG signal

Zhijiang Wan^{1,2,3}, Manyu Li², Shichang Liu⁴, Jiajin Huang⁵, Hai Tan⁶ and Wenfeng Duan¹*

¹The First Affiliated Hospital of Nanchang University, Nanchang University, Nanchang, Jiangxi, China, ²School of Information Engineering, Nanchang University, Nanchang, Jiangxi, China, ³Industrial Institute of Artificial Intelligence, Nanchang University, Nanchang, Jiangxi, China, ⁴School of Computer Science, Shaanxi Normal University, Xi'an, Shaanxi, China, ⁵Faculty of Information Technology, Beijing University of Technology, Beijing, China, ⁶School of Computer Science, Nanjing Audit University, Nanjing, Jiangsu, China

Background: The effective analysis methods for steady-state visual evoked potential (SSVEP) signals are critical in supporting an early diagnosis of glaucoma. Most efforts focused on adopting existing techniques to the SSVEPs-based brain-computer interface (BCI) task rather than proposing new ones specifically suited to the domain.

Method: Given that electroencephalogram (EEG) signals possess temporal, regional, and synchronous characteristics of brain activity, we proposed a transformer–based EEG analysis model known as EEGformer to capture the EEG characteristics in a unified manner. We adopted a one-dimensional convolution neural network (1DCNN) to automatically extract EEG-channel-wise features. The output was fed into the EEGformer, which is sequentially constructed using three components: regional, synchronous, and temporal transformers. In addition to using a large benchmark database (BETA) toward SSVEP-BCI application to validate model performance, we compared the EEGformer to current state-of-the-art deep learning models using two EEG datasets, which are obtained from our previous study: SJTU emotion EEG dataset (SEED) and a depressive EEG database (DepEEG).

Results: The experimental results show that the EEG former achieves the best classification performance across the three EEG datasets, indicating that the rationality of our model architecture and learning EEG characteristics in a unified manner can improve model classification performance.

Conclusion: EEGformer generalizes well to different EEG datasets, demonstrating our approach can be potentially suitable for providing accurate brain activity classification and being used in different application scenarios, such as SSVEP-based early glaucoma diagnosis, emotion recognition and depression discrimination



OBVIOUSLY IMAGES



GENERATIVE MODELS

We understood how to design those for quite some time



THE NUCLEUS

Period of early success lays the foundation for the future of generative models.

GAN EXPLOSION Success of Generative

Adversarial Networks pushes the boundary of what is possible.

STABILITY AND SCALE Working towards stable training of larger and more capable models.

FIDELITY

Successs in generation of higher fidelity content











REALISM

Incremental improvements increasing the realism of the generated content.



DIVERSITY AND

Models that not only generate high fidelity but also diverse content that can be controlled by the user.





EVEN MORE DIVERSITY AND CONTROL

Blurring the line between digitally created art and reality



EASE OF USE



ANY FORM OF DESIGN

From Interior decoration to... Architecture



New York Times: A.I.-Generated Art Is Already Transforming Creative Work https://www.nytimes.com/2022/10/21/technology/ai-generated-art-jobs-dall-e-2.html



ANY FORM OF DESIGN

...to Automotive and more



Game development











Biology / Chemistry / Material Science / Scientific Visualization / ???



SIMULATION



Controllable and realistic traffic simulation is critical for developing and verifying autonomous vehicles. Typical heuristic-based traffic models offer flexible control to make vehicles follow specific trajectories and traffic rules. On the other hand, data-driven approaches generate realistic and human-like behaviors, improving transfer from simulated to real-world traffic. However, to the best of our knowledge, no traffic model offers both controllability and realism. In this work, we develop a conditional diffusion model for controllable traffic generation (CTG) that allows users to control desired properties of trajectories at test time (e.g., reach a goal or follow a speed limit) while maintaining realism and physical feasibility through enforced dynamics. The key technical idea is to leverage recent advances from diffusion modeling and differentiable logic to guide generated trajectories to meet rules defined using signal temporal logic (STL). We further extend guidance to multi-agent settings and enable interaction-based rules like collision avoidance. CTG is extensively evaluated on the nuScenes dataset for diverse and composite rules, demonstrating improvement over strong baselines in terms of the controllability-realism tradeoff.



TRANSFORMING DATA PROCESSING Again dramatically reducing the skills barrier

Open-Vocabulary Panoptic Segmentation with Text-to-Image Diffusion Models



We present ODISE: Open-vocabulary DIffusion-based panoptic SEgmentation, which unifies pre-trained text-image diffusion and discriminative models to perform open-vocabulary panoptic segmentation. Text-to-image diffusion models have the remarkable ability to generate high-quality images with diverse open-vocabulary language descriptions. This demonstrates that their internal representation space is highly correlated with open concepts in the real world. Text-image discriminative models like CLIP, on the other hand, are good at classifying images into open-vocabulary labels. We leverage the frozen internal representations of both these models to perform panoptic segmentation of any category in the wild. Our approach outperforms the previous state of the art by significant margins on both open-vocabulary panoptic and semantic segmentation tasks. In particular, with COCO training only, our method achieves 23.4 PQ and 30.0 mIoU on the ADE20K dataset, with 8.3 PQ and 7.9 mIoU absolute improvement over the previous state of the art. We open-source our code and models at https://github.com/NVIabs/ODISE.



TRANSFORMING DATA COLLECTION

Automotive example





ROBOTICS Planning and Imagination

StructDiffusion: Language-Guided Creation of Physically-Valid Structures using Unseen Objects

Structures using on the organism of the second of the second se









Robots operating in human environments must be able to rearrange objects into semantically-meaningful configurations, even if these objects are previously unseen. We focus on the problem of building physically-valid structures without step-by-step instructions.

We propose StructDiffusion, which combines a diffusion model and an object-centric transformer to construct structures given partial-view point clouds and high-level language goals, such as "set the table" and "make a line".

StructDiffusion improves success rate on assembling physically-valid structures out of unseen objects by on average 16% over an existing multi-modal transformer model, while allowing us to use one multi-task model to produce a wider range of different structures. We show experiments on held-out objects in both simulation and on real-world rearrangement tasks.

PROGPROMPT: Generating Situated Robot Task Plans using Large Language Models

ICRA 2023

Extended version in Autonomous Robots 2023

Ishika Singh¹, Valts Blukis², Arsalan Mousavian², Ankit Goyal², Danfei Xu², Jonathan Tremblay², Dieter Fox², Jesse Thomason¹, Animesh Garg² ¹University of Southern California, ²NVIDIA





Fig. 1: Real-world rearrangement with unseen objects, given a language instruction. We use StructDiffusion to predict possible goals that satisfy physical constraints such as avoiding collisions between objects. At the core of StructDiffusion is an object-centric multimodal transformer backbone combined with a diffusion model, capable of sampling diverse high-level motion goals for language-guided rearrangement.



PHYSICS

A Physics-informed Diffusion Model for High-fidelity Flow Field Reconstruction

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‡Machine Learning Department, Carnegie Mellon University, Pittsburgh PA, USA
¶Department of Chemical Engineering, Carnegie Mellon University, Pittsburgh PA, USA
§Contributed equally to this work

E-mail: barati@cmu.edu

Abstract

arXiv:2211.14680v2 [cs.LG] 10 Feb 2023

Machine learning models are gaining increasing popularity in the domain of fluid dynamics for their potential to accelerate the production of high-fidelity computational fluid dynamics data. However, many recently proposed machine learning models for high-fidelity data reconstruction require low-fidelity data for model training. Such requirement restrains the application performance of these models, since their data reconstruction accuracy would drop significantly if the low-fidelity input data used in model test has a large deviation from the training data. To overcome this restraint, we propose a diffusion model which only uses high-fidelity data at training. With different configurations, our model is able to reconstruct high-fidelity data from either a regular low-fidelity sample or a sparsely measured sample, and is also able to gain an accuracy increase by using physics-informed conditioning information from a known partial differential equation when that is available. Experimental results demonstrate that our model can produce accurate reconstruction results for 2d turbulent flows based on different input sources without retraining.

Input









Figure 3: Qualitative comparison of different upsampling methods on 4x upsampling task.





OTHER MODALITIES



EMPIRICAL EVIDENCE The Scaling Laws for Generative models



Henighan, Tom, et al. Scaling laws for autoregressive generative modeling. arXiv preprint arXiv:2010.14701 (2020).





MULTIMODAL ARCHITECTURES



This is just the first wave

Rise of multimodal architectures















Simplicity of multimodal architectures

LLAVA example





This is just the first wave

Rise of multimodal architectures



Careers 🗸 Blog 🗸 Company 🗸



THE ROLE OF NVIDIA IN GENERATIVE AI









IS IT COMPLEXITY?



NVIDIA'S GENERATIVE AI SOLUTIONS

Foundations to Build and Run Your Generative AI

NVIDIA NeMo service



NVIDIA BioNeMo service





NVIDIA AI Foundations

NVIDIA DGX Cloud



NEMO FRAMEWORK

End-to-end, cloud-native framework to build, customize and deploy generative AI models



experts by your side to keep projects on track

📀 nvidia.

DEMONSTRATING SIMPLICITY OF USE


Step 1 Formatting the dataset

~ — root@luna-0198: /workspace/alpa/benchmark/cupy — ssh selene

 \sim — root@luna-0200: /workspace — ssh selene

adamg@selene-login-01:~/bignlp/workspace/bignlp-scripts\$

~ — ssh selene	+
	E



Alternative examples

"taskname": "sentiment", "sentence": "Super lekarz i cz\u0142owiek przez du\u017ce C . Bardzo du\u017ce do\u015bwiadczenie i trafne diagnozy . Wielka cierpliwo\u015b\u0107 do ludzi starszych . Od lat opiekuje si\u0119 moj\u0105 Mam\u0105 Staruszk\u0105 , i twierdz\u0119 , \u017ce mamy du\u017ce szcz\u0119\u015bcie , \u017ce mamy takiego lekarza . Naprawd\u0119 nie wiem coby\u015bmy zrobili , gdyby nie Pan doktor . D zi\u0119ki temu , moja mama \u017cyje . Ka\u017cda wizyta u specjalisty jest u niego konsultowana i uwa\u017cam , \u017ce jest lepszy od ka\u017cdego z nich . Mamy do Niego prawie nieograniczone zaufanie . Mo\u 017cna wiele dobrego o Panu doktorze jeszcze napisa\u0107 . Niestety , ma bardzo du\u017co pacjent\u00f3w , jest przepracowany (z tego powodu nawet obawiam si\u0119 o jego zdrowie) i dost\u0119p do niego jest trudny , ale zawsze mo\u017cliwy .", "label": "Pozytywny"

{"taskname": "sentiment", "sentence": "Bardzo olewcze podejscie do pacjenta . Przyprowadzajac dziecko z ostra wysypka na calym ciele trwajaca od 2 tygodni Pani doktor stwierdzila ze nie widzi wskazan wystawieni a dziecku skierowania na testy skorne . Chocby na nasza prosbe i dodam iz w prywatnej klinice (gdzie tak czy siak musielibysmy za to zaplacic) Odmowila rowniez wystawienia zaswiadczenia o tym ze dziecko jest \" zdrowe \" i moze uczeszczac do przedszkola twierdzac ze takich zaswiadczen sie nie wystawia . L4 oczywiscie rozniez nie wchodzilo w gre , . Jednym slowem z gabinetu wyszlismy bez niczego mimo iz kierowani by lismy przez dwoch innych pediatrow na natychmiastowe testy do alergologa .", "label": "Negatywny"}

{"taskname": "sentiment", "sentence": "Lekarz zaleci\u0142 mi kuracj\u0119 alternatywn\u0105 do dotychczasowej , wi\u0119c jeszcze nie daj\u0119 najwy\u017cszej oceny (zobaczymy na ile oka\u017ce si\u0119 skut eczna) . Do Pana doktora nie mam zastrze\u017ce\u0144 : bardzo profesjonalny i kulturalny . Jedyny minus dotyczy gabinetu , kt\u00f3ry nie jest nowoczesny , co mo\u017ce zniech\u0119ca\u0107 pacjentki .", "lab el": "Nieznany"}

{"taskname": "sentiment", "sentence": " Konsumenci oczywi\u015bcie kieruj\u0105 si\u0119 cen\u0105 . Te leki s\u0105 ta\u0144sze , ale dzisiaj nie mo\u017cemy ju\u017c powiedzie\u0107 , \u017ce znacznie ta\u014 4sze . Jest to mniej kr\u0119puj\u0105ce , nie trzeba wychodzi\u0107 z domu , nie trzeba udawa\u0107 si\u0119 do lekarza czy prosi\u0107 o recept\u0119 . W takich przypadkach kupuj\u0105cy nie kieruje si\u0119 zdrowym rozs\u0105dkiem , ale cen\u0105 - naiwnie szukaj\u0105c lek\u00f3w z niesprawdzonych \u017ar\u00f3de\u0142 . Podrobione leki mog\u0105 by\u0107 ska\u017cone , zanieczyszczone lub zawiera\u0107 substancj e toksyczne czy w og\u00f3le nieodpowiedni sk\u0142ad . Cz\u0119sto maj\u0105 te\u017c sk\u0142adniki nieaktywne - w \u017caden spos\u00f3b nie wp\u0142ywaj\u0105ce na popraw\u0119 b\u0105d\u017a (powoduj\u010 5ce) pogorszenie stanu zdrowia - wyja\u015bni\u0142a ekspertka . Doda\u0142a tak\u017ce , \u017ce \" podr\u00f3bki \" mog\u0105 mie\u0107 r\u00f3wnie\u017c sk\u0142adniki aktywne w nieodpowiednich dawkach , z byt silne czy zmieszane w spos\u00f3b nieodpowiedni , a badania pokazuj\u0105 , \u017ce w podrobionych lekach znajduj\u0105 si\u0119 trucizny dla szczur\u00f3w , wosk do pod\u0142ogi , cement , gips i podobne s ubstancje .", "label": "Neutralny"}

{"taskname": "sentiment", "sentence": "Pani Doktor Iwona jest profesjonalistk\u0105 w ka\u017cdym calu :) Id\u0105c do stomatologa zawsze czuj\u0119 przera\u017aliwy strach . Pani Doktor Iwona jest wyrozumia\u 0142a i delikatna , bardzo mi\u0142a , cierpliwie wyja\u015bnia ka\u017cdy zaistnia\u0142y problem a co najbardziej mi si\u0119 podoba to fakt , \u017ce w swoim dzia\u0142aniu jest bardzo stanowcza i konkretna . Dla mnie to jasny znak , \u017ce specjalista kt\u00f3ry si\u0119 mn\u0105 zajmuje , doskonale wie co i jak robi . Pozwala mi to poczu\u0107 si\u0119 bezpiecznie . Wiem , \u017ce jestem w dobrych r\u0119kach . A do tego u\u015bmiech i ciep\u0142o po strachu ani \u015bladu . Pani Iwono DZI\u0118KUJ\u0118 : D", "label": "Pozytywny" {"taskname": "sentiment", "sentence": "Jest nie prawda co napisal ten internauta . Ten lekarz jest bardzo dobrym , milym i kulturalnym czlowiekiem . Nie jest tez prawda ze oglada kobiece pier si , wcale tego nie robi , aczkolwiek w wielu przypadkach powinien to robic , moze uratowal by jakas kobiete od smierci . Lecze sie u Pana doktora juz 8 lat i nie moge powiedziec na niego zadnego zlego slowa , wrecz przeciwnie . zarowno On sam jak i personel tej przychodni to wspaniali ludzie . Goraco polecam .", "label": "Pozytywny" {"taskname": "sentiment", "sentence": "Krzysztof jest ZNAKOMITYM fizjoterapeut\u0105 ! Przysz\u0142a m do niego z wypadaj\u0105cym , krzywym kolanem , po operacji wi\u0119zad\u0142a oraz z bol\u0105c\u0105 \u01 42\u0119kotk\u0105 w drugim kolanie . Krzysztof po wywiadzie og\u00f3lnym oraz badaniu stwierdzi\u0142 szybko co mo\u00f3c i jak temu przeciwdzia\u0142a\u0147 . Jego wiedza + intensywne zestawy \u0107wicze\u0144 , zaanga\u017cowanie i ch\u0119ci robi\u0105 \" cuda \" ! Otworzy\u0142 mi oczy , \u017ce to , to i to nie dzia\u0142a i nie funkcjonuje normalnie dlatego tak i tak si\u0119 dzieje . Teraz mo ja praca oraz treningi sta\u0142y si\u0119 w ko\u0144cu czyst\u0105 przyjemno\u015bci\u0105 z sam\u0105 z sam\u0105 ! :) POLECAM ! Na zako\u0144czenie dodam , \u017ce po kilku wizytach przyprowa dzi\u0142a m swoj\u0105 mam\u0105, kt\u00f3ra przez 9mc boryka\u0142a si\u0119 ostrym b\u00f3lem bark\u00f3w , odwiedzaj\u0105c przez ten okres przer\u00f3\u017cnych specjalist\u00f3w , doktor\u00f3w p\u0142ac \u0105c przy tym maj\u0105tek . W dodatku nikt przez ten czas nie pom\u00f3g\u0142 jej ani troch\u0119 i codziennie z b\u00f3lu \u0142yka\u0142a po 2 - 3 tabletki przeciw b\u00f3lowe . Po wizycie u Krzy\u015bka okaza\u0142o si\u0119 , \u017ce ma zerwane \u015bci\u0119gna . A po jego pierwszej , 3 godzinnej , bardzo bolesnej wizycie i masa\u017cach , przetrwa\u0142a do nast\u0119pnej wizyty tylko z siniakami , ale ju\ u017c BEZ tabletek przeciwb\u00f3lowych ! :) Krzysiek jest naprawd\u0119 GODNYM POLECENIA SPECJALIST\u0104 . Tym bardziej je\u015bli chcecie si\u0119 leczy\u0107 , naturalnie , bez zb\u0119dnych proszk\u00f3w i weso\u0142ej atmosferze ! :)", "label": "Pozytywny"



Design the prompt structure

– root@luna-0200: /workspace — ssh selene

- root@luna-0198: /workspace/alpa/benchmark/cupy - ssh selene

【"taskname": "squad", "context": "Architecturally, the school has a Catholic character. Atop the Main Building's gold dome is a golden statue of the Virgin Mary. Immediatel y in front of the Main Building and facing it, is a copper statue of Christ with arms upraised with the legend \"Venite Ad Me Omnes\". Next to the Main Building is the Basi lica of the Sacred Heart. Immediately behind the basilica is the Grotto, a Marian place of prayer and reflection. It is a replica of the grotto at Lourdes, France where the Virgin Mary reputedly appeared to Saint Bernadette Soubirous in 1858. At the end of the main drive (and in a direct line that connects through 3 statues and the Gold Dome) , is a simple, modern stone statue of Mary.", "question": "To whom did the Virgin Mary allegedly appear in 1858 in Lourdes France?", "answer": "Saint Bernadette Soubirous" {"taskname": "squad", "context": "Architecturally, the school has a Catholic character. Atop the Main Building's gold dome is a golden statue of the Virgin Mary. Immediatel y in front of the Main Building and facing it, is a copper statue of Christ with arms upraised with the legend \"Venite Ad Me Omnes\". Next to the Main Building is the Basi lica of the Sacred Heart. Immediately behind the basilica is the Grotto, a Marian place of prayer and reflection. It is a replica of the grotto at Lourdes, France where the Virgin Mary reputedly appeared to Saint Bernadette Soubirous in 1858. At the end of the main drive (and in a direct line that connects through 3 statues and the Gold Dome) , is a simple, modern stone statue of Mary.", "question": "What is in front of the Notre Dame Main Building?", "answer": "a copper statue of Christ"} {"taskname": "squad", "context": "Architecturally, the school has a Catholic character. Atop the Main Building's gold dome is a golden statue of the Virgin Mary. 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The other magazine, The Juggler, is released twice a year and focuses on student liter ature and artwork. The Dome yearbook is published annually. The newspapers have varying publication interests, with The Observer published daily and mainly reporting univer sity and other news, and staffed by students from both Notre Dame and Saint Mary's College. Unlike Scholastic and The Dome, The Observer is an independent publication and d oes not have a faculty advisor or any editorial oversight from the University. In 1987, when some students believed that The Observer began to show a conservative bias, a l iberal newspaper, Common Sense was published. Likewise, in 2003, when other students believed that the paper showed a liberal bias, the conservative paper Irish Rover went into production. Neither paper is published as often as The Observer; however, all three are distributed to all students. Finally, in Spring 2008 an undergraduate journal f or political science research, Beyond Politics, made its debut.", "question": "When did the Scholastic Magazine of Notre dame begin publishing?", "answer": "September 1876" 3

{"taskname": "squad", "context": "As at most other universities, Notre Dame's students run a number of news media outlets. The nine student-run outlets include three newspa pers, both a radio and television station, and several magazines and journals. Begun as a one-page journal in September 1876, the Scholastic magazine is issued twice monthl y and claims to be the oldest continuous collegiate publication in the United States. The other magazine, The Juggler, is released twice a year and focuses on student liter ature and artwork. The Dome yearbook is published annually. The newspapers have varying publication interests, with The Observer published daily and mainly reporting univer sity and other news, and staffed by students from both Notre Dame and Saint Mary's College. Unlike Scholastic and The Dome, The Observer is an independent publication and d oes not have a faculty advisor or any editorial oversight from the University. In 1987, when some students believed that The Observer began to show a conservative bias, a 1 iberal newspaper, Common Sense was published. Likewise, in 2003, when other students believed that the paper showed a liberal bias, the conservative paper Irish Rover went into production. Neither paper is published as often as The Observer; however, all three are distributed to all students. Finally, in Spring 2008 an undergraduate journal f or political science research, Beyond Politics, made its debut.", "question": "How often is Notre Dame's the Juggler published?", "answer": "twice"} {"taskname": "squad", "context": "As at most other universities, Notre Dame's students run a number of news media outlets. The nine student-run outlets include three newspa pers, both a radio and television station, and several magazines and journals. Begun as a one-page journal in September 1876, the Scholastic magazine is issued twice monthl



Design the prompt structure

task_templates: # task_templates for all existing_tasks and new_tasks are required.

- taskname: "squad" # The task name

prompt_template: "</VIRTUAL_PROMPT_0/>Context: {context} Question: {question} Answer: {answer}" # Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_#|>

total_virtual_tokens: 10 # Sum of tokens in virtual_token_splits must add to this number. Can differ between new and existing tasks , but must match across all new tasks being tuned at the same time.

virtual_token_splits: [10] # number of virtual tokens to be inserted at each VIRTUAL PROMPT location, must add to total_virtual_tok ens

truncate_field: "context" # The {field} in the prompt template whose text will be truncated if the input is too long, if null, input ts that are too long will just be skipped.

answer field: "answer" # Answer/Target field

answer_only_loss: True # If true, the loss will only be calculated with answer_field text vs. ground truth. If false, the loss will be calculated over entire sentence.



task_templates: # task_templates for all existing_tasks and new_tasks are required. - taskname: "squad" # The task name

prompt_template: "<|VIRTUAL_PROMPT_0|>{context}<|VIRTUAL_PROMPT_1|>{question}<|VIRTUAL_PROMPT_2|>{answer}" # Prompt template for ta total_virtual_tokens: 100 # Sum of tokens in virtual_token_splits must add to this number. Can differ between new and existing task virtual_token_splits: [80,15,5] # number of virtual tokens to be inserted at each VIRTUAL PROMPT location, must add to total_virtua truncate_field: "context" # The {field} in the prompt template whose text will be truncated if the input is too long, if null, input answer_field: "answer" # Answer/Target field

sk, specify virtual prompt positions with <|VIRTUAL_PROMPT_#|> s, but must match across all new tasks being tuned at the same time. l tokens ts that are too long will just be skipped.

answer_only_loss: True # If true, the loss will only be calculated with answer_field text vs. ground truth. If false, the loss will be calculated over entire sentence.



Step 2 Alternative examples

```
config.model.task_templates = [
           {
                     "taskname": "sentiment",
                     "prompt_template": "<|VIRTUAL_PROMPT_0|> {sentence} sentyment:{label}",
                     "total_virtual_tokens": 10,
                     "virtual_token_splits": [10],
                     "truncate_field": None,
                     "answer_only_loss": True,
                     "answer_field": "label",
          },]
                                           task_templates: # Add more/replace tasks as needed, these are just examples
                                           - taskname: "boolg" # The task name
                                               prompt_template: "<|VIRTUAL_PROMPT_0|> Passage: {passage} <|VIRTUAL_PROMPT_1|> \nQuestion: {question} \nAnswer: {answer}" # Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIRTUAL_PROMPT_4|> \nQuestion = {answer} + Prompt template for task, specify virtual prompt positions with <|VIR
                                       >
                                               total_virtual_tokens: 30 # Sum of tokens in virtual_token_splits must add to this number. Can differ between new and existing tasks, but must match across all new tasks being tuned at the same time.
                                               virtual_token_splits: [20, 10] # number of virtual tokens to be inserted at each VIRTUAL PROMPT location, must add to total_virtual_tokens
                                               truncate_field: "passage" # The {field} in the prompt template whose text will be truncated if the input is too long, if null, inputs that are too long will just be skipped.
                                               answer_only_loss: True
                                               answer_field: "answer"
                                           - taskname: "intent and slot"
                                               prompt_template: "<|VIRTUAL_PROMPT_0|> intent options: {intent_options} <|VIRTUAL_PROMPT_1|> slot options: {slot_options} <|VIRTUAL_PROMPT_2|> {utterance} \nintent: {intent} \nslot: {slot}"
                                               total_virtual_tokens: 30
                                               answer_only_loss: False
                                               virtual_token_splits: [15, 10, 5]
                                               truncate_field: null
                                            - taskname: "rte"
                                               prompt_template: "<|VIRTUAL_PROMPT_0|>{premise}\n{hypothesis}\nAnswer: {answer}"
                                               total_virtual_tokens: 9
                                               virtual_token_splits: [9]
                                               truncate_field: null
                                               answer_only_loss: True
                                               answer_field: "answer"
```



Step 3 Training configuration

```
~ - root@luna-0200: /workspace - ssh selene
                                                                     root@luna-0198: /workspace/alpa/benchmark/cupy — ssh < ssh draco-rnom3
                                                                                                                                                - ssh selene
  checkpoint callback params:
    monitor: val_loss
    save_top_k: 5
    mode: min
    save_nemo_on_train_end: False
    filename: "megatron_gpt_prompt_learn--{val_loss:.3f}-{step}"
    model_parallel_size: ${prompt_learning.model.model_parallel_size}
    save_best_model: True
model:
  seed: 1234
  nemo_path: ${prompt_learning.run.results_dir}/results/megatron_gpt_prompt.nemo # the place to save prompt learning nemo checkpoint
  virtual_prompt_style: 'p-tuning' # One of 'p-tuning', 'prompt-tuning', or 'inference'. We recommend 'p-tuning' over 'prompt-tuning'.
  tensor_model_parallel_size: 1
  pipeline_model_parallel_size: 1
  model_parallel_size: ${multiply:${.tensor_model_parallel_size}, ${.pipeline_model_parallel_size}}
  encoder_seq_length: 2048
  global_batch_size: 64
  micro_batch_size: 8
  restore_path: null # used to restore from a prompt tuned checkpoint and add new tasks
  language_model_path: /lustre/fsw/sa/adamg/nemogpt/gpt5b/nemo_gpt5B_fp16_tp2.nemo
  # language_model_path: ${prompt_learning.run.convert_dir}/results/megatron_gpt.nemo # Restore lanugage model from pre-trained .nemo checkpoint
  existing_tasks: [] # if restore from a prompt tuned checkpoint and add new tasks, existing task names should be included here.
  new_tasks: ["squad"] # multiple tasks can be tuned at the same time
  task_templates: # task_templates for all existing_tasks and new_tasks are required.
  - taskname: "squad" # The task name
    prompt_template: "</VIRTUAL_PROMPT_0/>Context: {context} Question: {question} Answer: {answer}" # Prompt template for task, specify virtual prompt positions with </VIRT
UAL_PROMPT_#|>
    total_virtual_tokens: 10 # Sum of tokens in virtual_token_splits must add to this number. Can differ between new and existing tasks, but must match across all new tasks
 being tuned at the same time.
    virtual_token_splits: [10] # number of virtual tokens to be inserted at each VIRTUAL PROMPT location, must add to total_virtual_tokens
    truncate_field: "context" # The {field} in the prompt template whose text will be truncated if the input is too long, if null, inputs that are too long will just be ski
pped.
    answer_field: "answer" # Answer/Target field
    answer_only_loss: True # If true, the loss will only be calculated with answer_field text vs. ground truth. If false, the loss will be calculated over entire sentence.
  prompt_learning: # Prompt tunin specific params
    new_prompt_init_methods: null # e.g ['text'], List of 'text' or 'random', should correspond to tasks listed in new tasks
    new_prompt_init_text: null # e.g ['some init text goes here'], some init text if init method is text, or None if init method is random
  p_tuning: # P-tuning specific params
    dropout: 0.0
    num_layers: 2
  data:
    train_ds:
      - ${data_dir}/prompt_data/v1.1/squad_train.jsonl # multiple prompt dataset can be given at the same time
                                                                                                                                                            78,11
                                                                                                                                                                          63%
```



Kick off the training process

adamg@selene-login-01:~/bignlp/workspace/bignlp-scripts/conf/prompt_learning/gpt3\$ ls squad.yaml adamg@selene-login-01:~/bignlp/workspace/bignlp-scripts/conf/prompt_learning/gpt3\$ vim squad.yaml adamg@selene-login-01:~/bignlp/workspace/bignlp-scripts/conf/prompt_learning/gpt3\$ cd .. adamg@selene-login-01:~/bignlp/workspace/bignlp-scripts/conf/prompt_learning\$ cd .. adamg@selene-login-01:~/bignlp/workspace/bignlp-scripts/conf\$ cd ... adamg@selene-login-01:~/bignlp/workspace/bignlp-scripts\$ python3 main.py



Monitor the training process





ARE DATASETS A BARRIER?



Unsupervised models

Limited data processing complexity

The RefinedWeb Dataset for Falcon LLM: Outperforming Curated Corpora with Web Data, and Web Data Only

The Falcon LLM team

Guilherme Penedo¹ Quentin Malartic² Daniel Hesslow¹ Ruxandra Cojocaru² Alessandro Cappelli¹ Hamza Alobeidli² Baptiste Pannier¹ Ebtesam Almazrouei² Julien Launay¹³

https://huggingface.co/datasets/tiiuae/falcon-refinedweb

Abstract

Large language models are commonly trained on a mixture of filtered web data and curated "high-quality" corpora, such as social media conversations, books, or technical papers. This curation process is believed to be necessary to produce performant models with broad zero-shot generalization abilities. However, as larger models requiring pretraining on trillions of tokens are considered, it is unclear how scalable is curation and whether we will run out of unique high-quality data soon. At variance with previous beliefs, we show that properly filtered and deduplicated web data alone can lead to powerful models; even significantly outperforming models from the state-of-the-art trained on The Pile. Despite extensive filtering, the high-quality data we extract from the web is still plentiful, and we are able to obtain five trillion tokens from CommonCrawl. We publicly release an extract of 600 billion tokens from our REFINEDWEB dataset, and 1.3/7.5B parameters language models trained on it*.



Figure 1. Models trained on @REFINEDWEB alone outperform models trained on curated corpora. Zero-shot performance on our main-agg task aggregate (see Section 4.1 for details). At equivalent compute budgets, our models significantly outperform publicly available models trained on V The Pile, and match the performance of the GPT-3 models when tested within our evaluation setup.

*Details about how to access Falcon LLM open source is available on falconllm.tii.ae

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IS IT THE COMPUTE?



Training LLMs is computationally intensive

GPT-3 Training Time on NVIDIA A100 GPUs

	Time to train 300B tokens in days (A100) – BF16					
	800 GPUs (5x DGX SuperPod)	480 GPUs (3x DGX SuperPod)	160 GPUs (1x DGX SuperPod)	64 GPUs (8x DGX A100)		
GPT-3: 126M	0.07	0.12	0.37	0.92		
GPT-3: 5B	0.8	1.3	3.9	9.8		
GPT-3: 20B	3.6	6	18.1	45.3		
GPT-3: 40B	6.6	10.9	32.8	82		
GPT-3: 175B	28	46.7	140	349.9		



LLAMA 2 TRAINING TIME Hypothetical Training Time on single NVIDIA A100 GPUs

Single GPU







LLAMA 2 TRAINING TIME

Training Time on NVIDIA A100 GPUs



DiRAC: Tursa





ABOUT ME

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