How Predictable Are Large Language Model Capabilities?

A Case Study on BIG-bench

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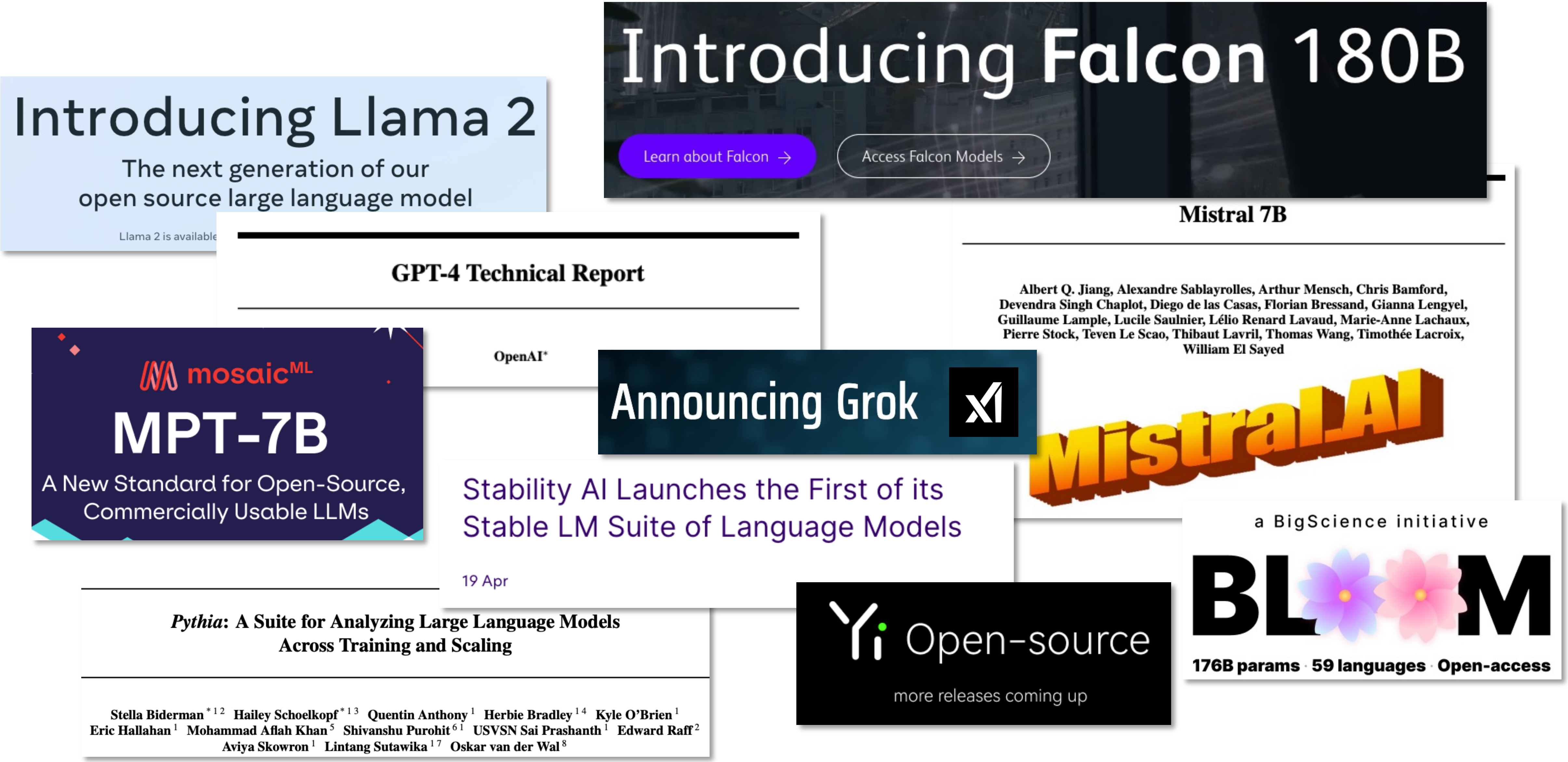
New LLM releases!



How are LLMs evaluated?

Model Family

Size

Tasks

Model	Size	Code	Commonsense Reasoning	World Knowledge	Reading Comprehension	Math	MMLU	BBH	AGI Eval
MPT	7B	20.5	57.4	41.0	57.5	4.9	26.8	31.0	23.5
	30B	28.9	64.9	50.0	64.7	9.1	46.9	38.0	33.8
Falcon	7B	5.6	56.1	42.8					
	40B	15.2	69.2	56.7					
LLAMA 1	7B	14.1	60.8	46.2					
	13B	18.9	66.1	52.6					
	33B	26.0	70.0	58.4					
	65B	30.7	70.7	60.5					
LLAMA 2	7B	16.8	63.9	48.9					
	13B	24.5	66.9	55.4					
	34B	27.8	69.9	58.7					
	70B	**37.5**	**71.9**	**63.6**					

\# In-context Examples

		NaturalQuestions				TriviaQA (Wiki)			
		0-shot	1-shot	5-shot	64-shot	0-shot	1-shot	5-shot	64-shot
MPT	7B	11.6	17.8	20.8	22.7	55.7	59.6	61.2	61.6
	30B	15.8	23.0	26.6	29.3	68.0	71.3	73.3	73.6
Falcon	7B	15.7	18.1	21.0	24.0	52.6	56.8	64.6	61.1
	40B	**26.3**	29.5	33.5	35.5	74.6	78.6	79.9	79.6
LLAMA 1	7B	16.8	18.7	22.0	26.1	63.3	67.4	70.4	71.0
	13B	20.1	23.4	28.1	31.9	70.1	74.4	77.1	77.9
	33B	24.9	28.3	32.9	36.0	78.7	80.7	83.8	83.6
	65B	23.8	31.0	35.0	39.9	81.7	84.5	85.9	86.0
LLAMA 2	7B	16.4	22.7	25.7	29.5	65.8	68.9	72.1	73.7
	13B	16.1	28.0	31.2	34.6	73.1	77.2	79.6	79.4
	34B	25.1	30.0	32.8	39.9	81.0	83.3	84.5	84.6
	70B	25.3	**33.0**	**39.5**	**44.3**	**82.4**	**85.0**	**87.6**	**87.5**

So many experiment configurations!

Llama 2: Open Foundation and Fine-Tuned Chat Models (Touvron et al., 2023)

How predictable are large language model capabilities?

LLM User

What model scale should I use?

LLM Developer

What tasks should I prioritize in evaluation?

LLM Researcher

Which capabilities are hard to predict?

Part 1: Performance Prediction on BIG-bench

- Problem Definition

* limitations apply

Parameters

In-context Examples

Normalized Performance

$$\hat{y} = f(l, n_{param}, t, n_{shot})$$

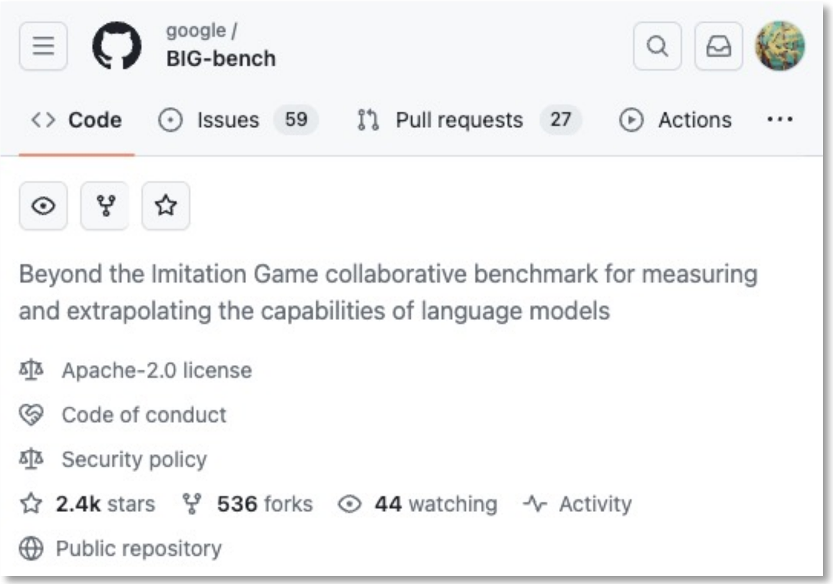
Model Family

Tasks

Regression Problem. Evaluated with **RMSE** and **R^2 score**.

Part 1: Performance Prediction on BIG-bench

- Data



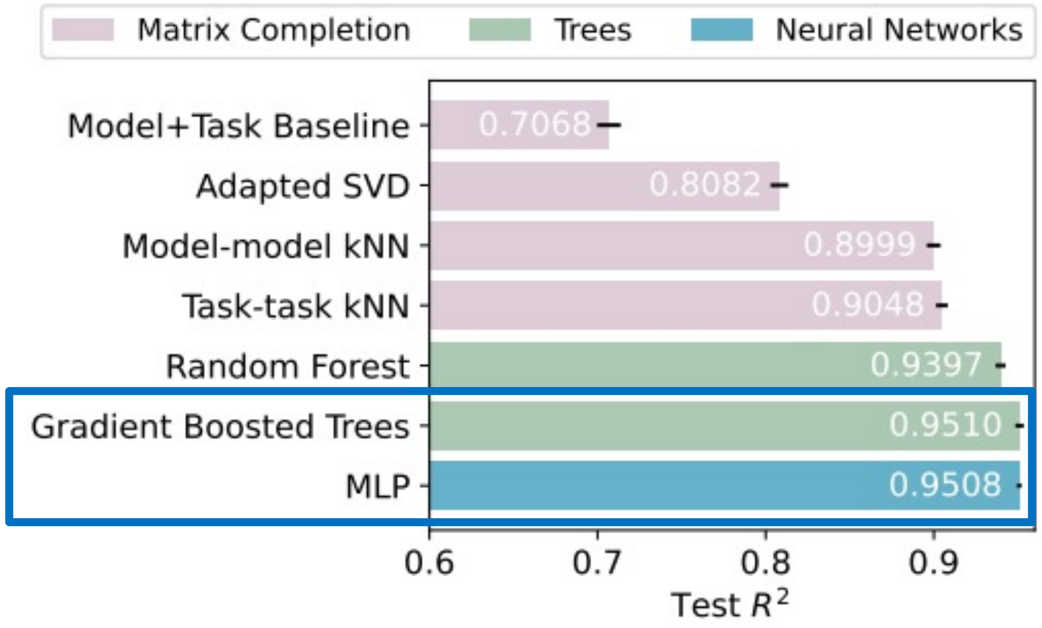
# Experiment Records	56,143
# Model Families	6
	BIG-G T=0, BIG-G T=1, BIG-G Sparse, PaLM GPT-3, Gopher
# Models†	51
# BIG-bench Tasks	134
# BIG-bench Subtasks‡	313
$\{n_{shot}\}$	$\{0, 1, 2, 3, 5\}$

We gathered and filtered the records in **BIG-bench**.

We got **56k records** covering diverse models and tasks.

Part 1: Performance Prediction on BIG-bench

- Results (Random Train-Test Split)

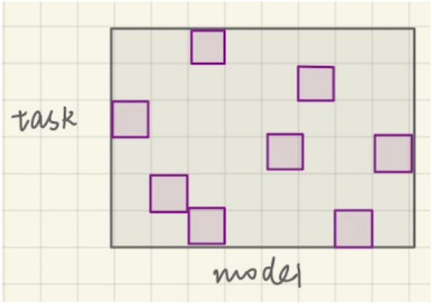


RMSE < 0.05
on average mis-predict by <0.05 when the range is [0,1]

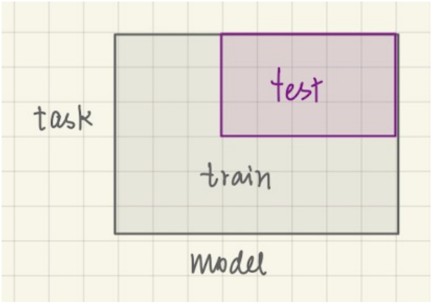
R^2 > 95%
explain more than 95% variance in the target variable

Part 1: Performance Prediction on BIG-bench

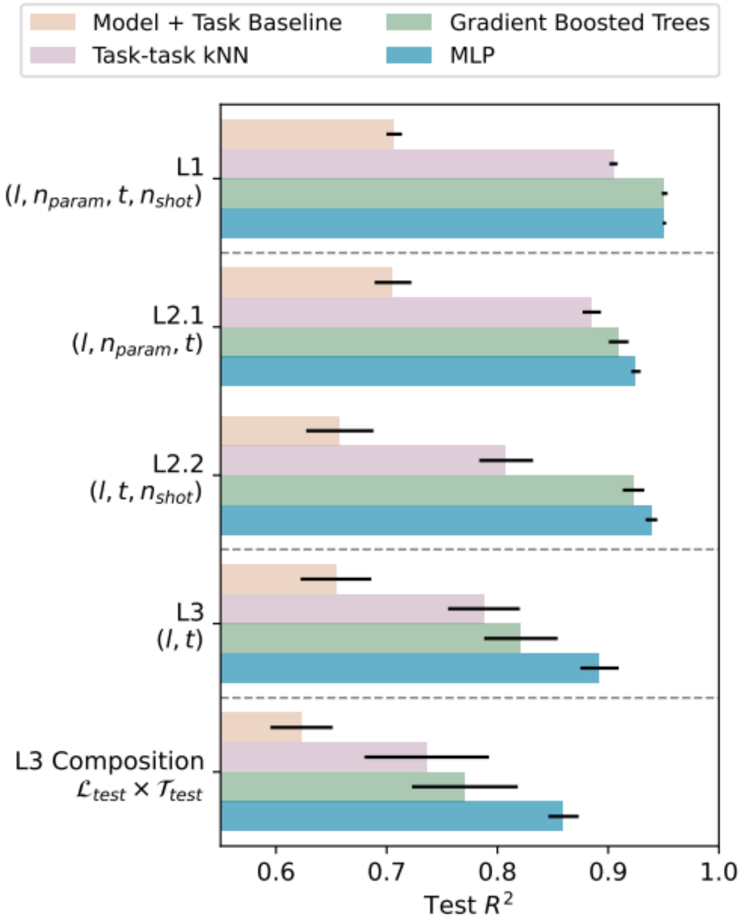
- Results (Challenging Train-Test Split)



Easier



Harder



Prediction accuracy decreases when the train-test split becomes more challenging!

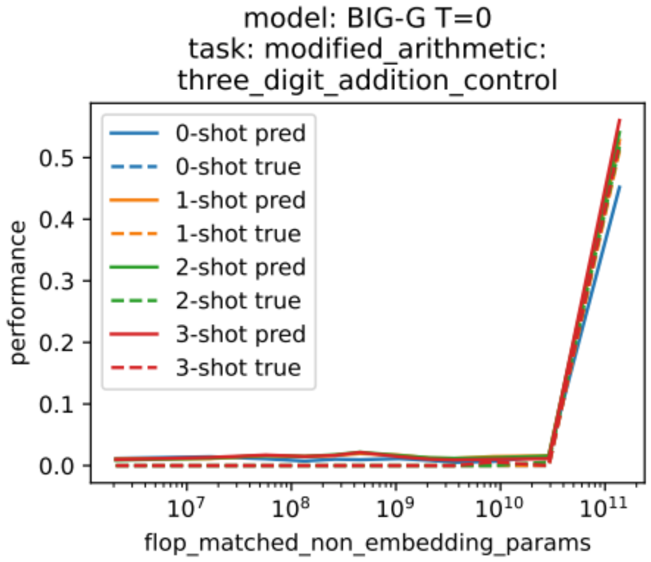
Part 1: Performance Prediction on BIG-bench

Emergent abilities (Wei et al., 2022)

... are *in general* harder to predict

	RMSE (↓)	R^2 (↑)
Emergent Tasks	0.0541	93.86%
Non-emergent Tasks	0.0496	95.16%
All	0.0499	95.07%

... can be predicted accurately *in certain cases*



Potential Reason

A similar task is emergent and is in the training set.

Part 2: Searching for “small-bench”

- Problem Definition

Performance on remaining tasks are *maximally* recovered

$$\arg\max_{\mathcal{T}_{train}} \boxed{R^2(\mathcal{T}_{test} \times \mathcal{L}_{test})}$$

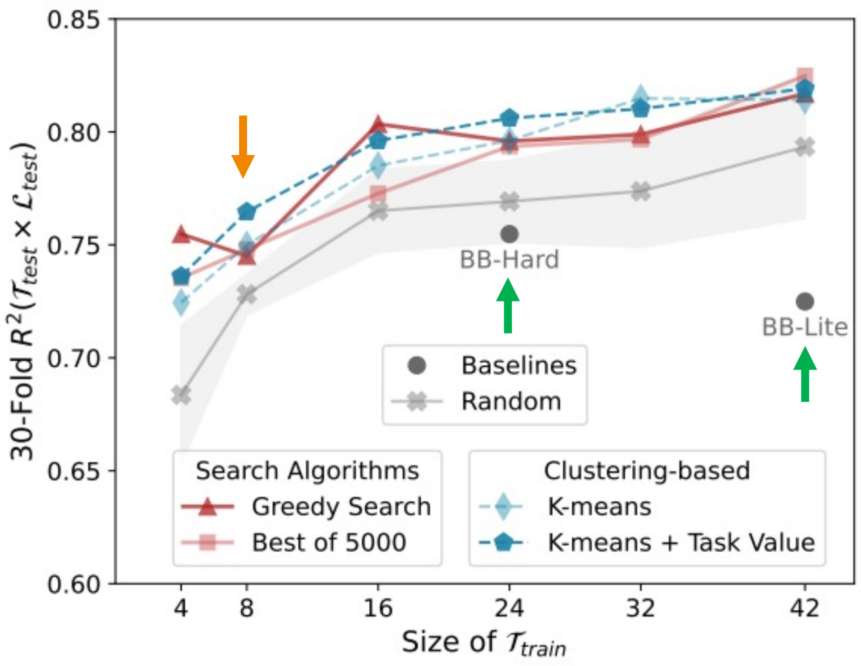
$$\text{s.t.} \quad \boxed{\mathcal{T}_{train} \subseteq \mathcal{T},} \boxed{|\mathcal{T}_{train}| = b}$$

Select *b* tasks

Given an evaluation budget of *b*

Part 2: Searching for “small-bench”

- Results

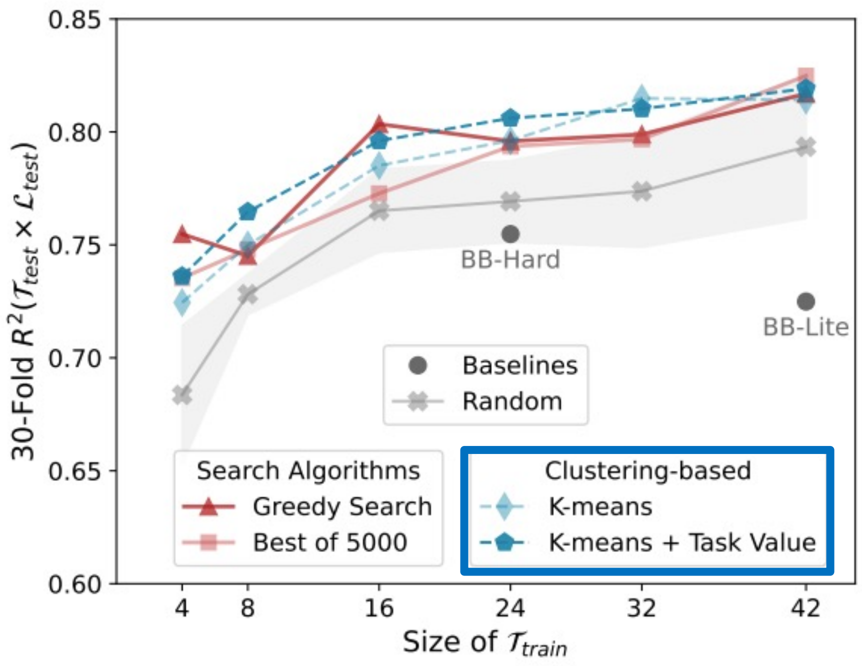


BIG-bench Lite and BIG-bench Hard are suboptimal if the goal is to recover the performance on remaining tasks.

We are able to find subsets that are as informative as BIG-bench Hard while being 3x smaller.

Part 2: Searching for “small-bench”

- Results



K-means
Clustering task representations learned by the MLP predictors in Part 1;
Then select tasks close to cluster centroids.

Task Value
Estimated from “Best of 5000”.

Task diversity and task value are important factors in constructing “small-bench.”

Summary

- We gathered **56k LLM experiment records** in BIG-bench.
- We trained models to **predict LLM performance on unseen experiment configurations**.
    - An MLP predictor can achieve RMSE $< 5\%$, $R^2 > 95\%$ on the random train-test split.
    - Prediction performance changes when train-test distribution changes.
    - Emergent abilities are harder to predict in general, but can be predicted accurately in some cases.
- We searched for **"small-bench,"** a subset of BIG-bench, from which the full BIG-bench performance can be maximally recovered.
    - BIG-bench Lite and BIG-bench Hard are sub-optimal for this purpose.
    - Task diversity and task value are important factors for constructing "small-bench."

Looking Ahead

- Rethinking LLM evaluation

Previous work

Models

Scenarios	J1-Jumbo v1	J1-Grande v1	J1-Large v1	Anthropic-LM v4-s3	BLOOM	T0++	Cohere Xlarge v20220609	Cohere Large v20220720	Cohere Medium v20220720	Cohere Small v20220720	GPT-NeoX	GPT-J	T5	UL2	OPT (175B)	OPT (66B)	TNLGv2 (530B)	TNLGv2 (7B)	davinci	curie	babbage	ada	text-davinci-002	text-curie-001	text-babbage-001	text-ada-001	GLM	YaLM
NaturalQuestions (open)																												
NaturalQuestions (closed)																			✔	✔	✔	✔						
BoolQ	✔		✔		✔								✔	✔	✔	✔	✔		✔	✔	✔	✔						
NarrativeQA																												
QuAC																			✔	✔	✔	✔	✔	✔	✔	✔		
HellaSwag	✔		✔	✔	✔	✔					✔	✔	✔	✔	✔	✔	✔		✔	✔	✔	✔	✔	✔	✔			
OpenBookQA					✔						✔	✔		✔	✔	✔			✔	✔	✔	✔						
TruthfulQA				✔															✔	✔	✔	✔	✔	✔	✔	✔		
MMLU											✔	✔							✔	✔							✔	
MS MARCO																												
TREC																												
XSUM													✔	✔														
CNN/DM													✔	✔					✔	✔	✔		✔	✔	✔			
IMDB														✔														
CivilComments														✔														
RAFT																			✔									

Holistic Evaluation of Language Models (Liang et al., 2023)

Task selection is often heuristic, following past practices, or done arbitrarily.

Looking Ahead

- Broadening observations on LLM capability landscape

Currently

Normalized Performance

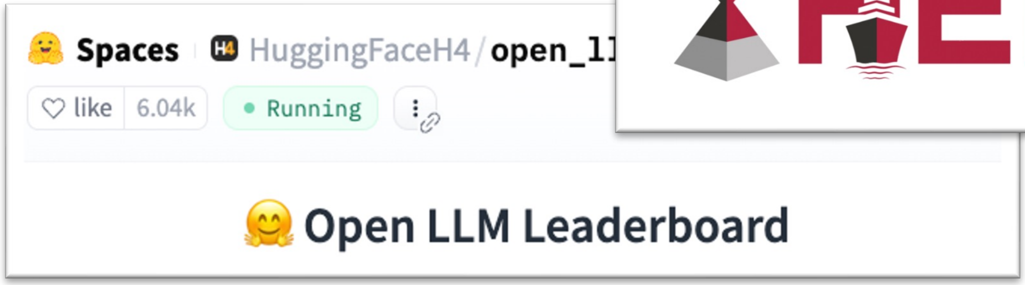
Parameters

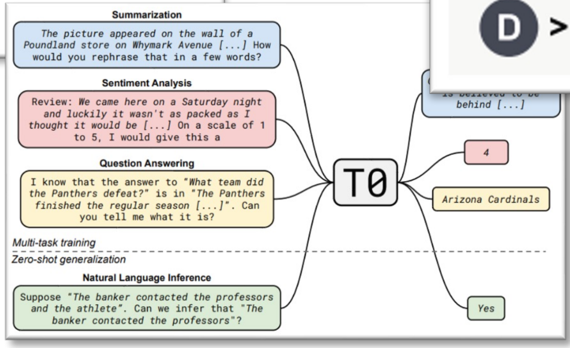
In-context Examples

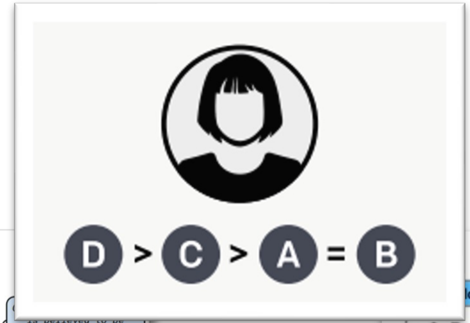
$$\hat{y} = f(l, n_{param}, t, n_{shot})$$

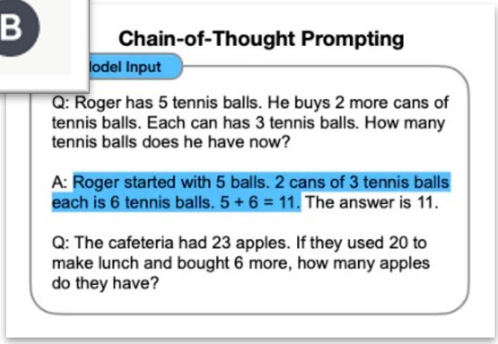
Model Family

Tasks









Liang et al., 2023
Sanh et al., 2022
Ouyang et al., 2022
Wei et al., 2022

Will be nice to take these into account!

Links

- Paper: https://arxiv.org/abs/2305.14947
- Code: https://github.com/INK-USC/predicting-big-bench