

Advanced Topics in Machine Learning and Data Science

Emergent Abilities of Large Language Models

Wei, Jason, et al. (2022)

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What are Emergent Abilities?

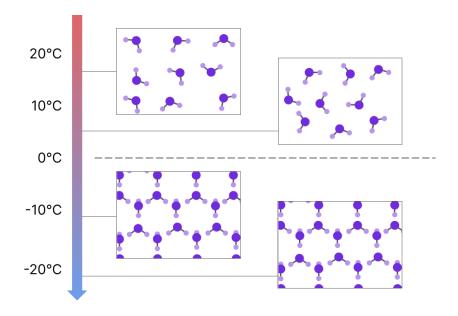


Emergent Abilities (Definition)



Emergence is when quantitative changes in a system result in qualitative changes in behavior.

(Wei, et al., 2022)





Emergent Abilities (Definition)



An ability is emergent if it is not present in smaller models but is present in larger models.

(Wei, et al., 2022)

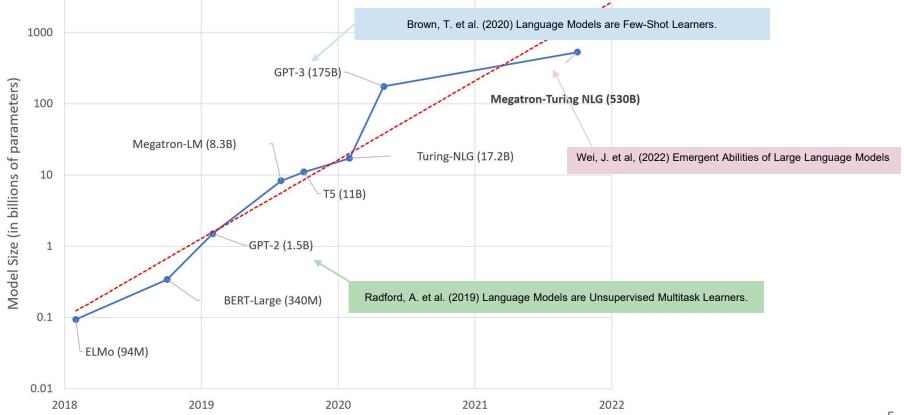


Emergent abilities cannot be predicted simply by extrapolating the performance of smaller models.

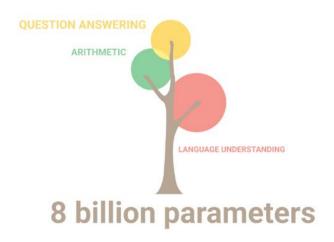
(Wei, et al., 2022)



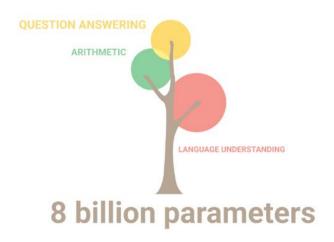
Prior Work and Context



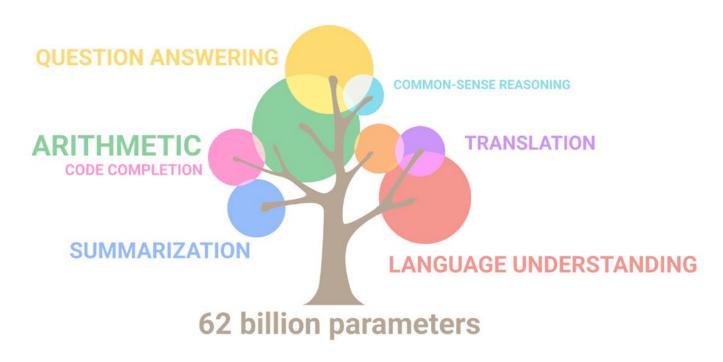




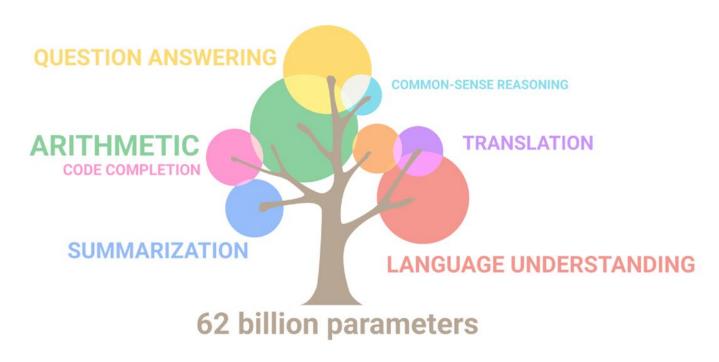




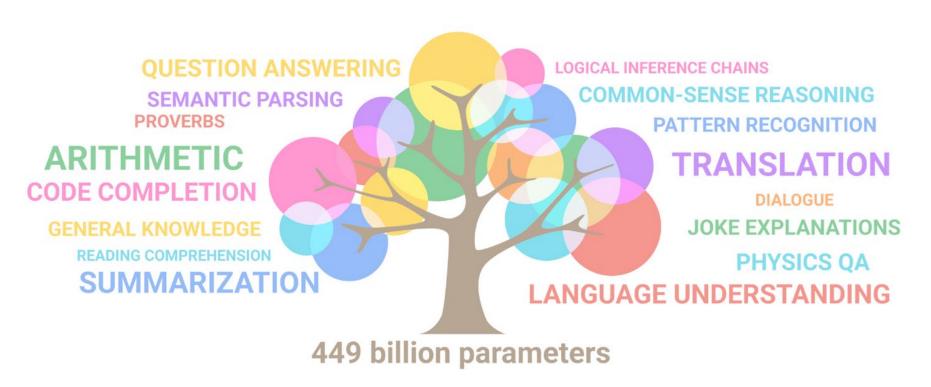














How to measure the performance of Large Language Models?



BIG-Bench

Beyond the Imitation Game: Quantifying and extrapolating the capabilities of language models (Srivastava, et al. 2023)

What is BIG-Bench?

- comprehensive benchmark for language models
- composed by 400 researchers across 132 research institutes
- tries to solve the cap between benchmarks and LLM performance
- contains 204 diverse tasks across multiple domains



BIG-Bench Emoji Movie Test

Q: What movie does this emoji describe? 👧 🐟 🐠 🐡







BIG-Bench Emoji Movie Test

Q: What movie does this emoji describe? 👧 🐟 🐠 🐡

2m: i'm a fan of the same name, but i'm not sure if it's a good idea

16m: the movie is a movie about a man who is a man who is a man ...

53m: the emoji movie 🐟 🐠 🐡

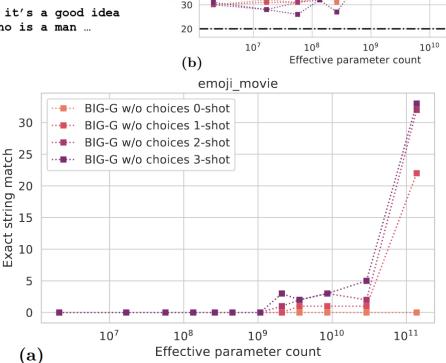
125m: it's a movie about a girl who is a little girl

244m: the emoji movie 422m: the emoji movie 1b: the emoji movie 2b: the emoji movie

4b: the emoji for a baby with a fish in its mouth

8b: the emoji movie27b: the emoji is a fish

128b: finding nemo



80

60

Multiple choice grade

emoji movie

BIG-G w/o choices 0-shot BIG-G w/o choices 1-shot

BIG-G w/o choices 2-shot

BIG-G w/o choices 3-shot

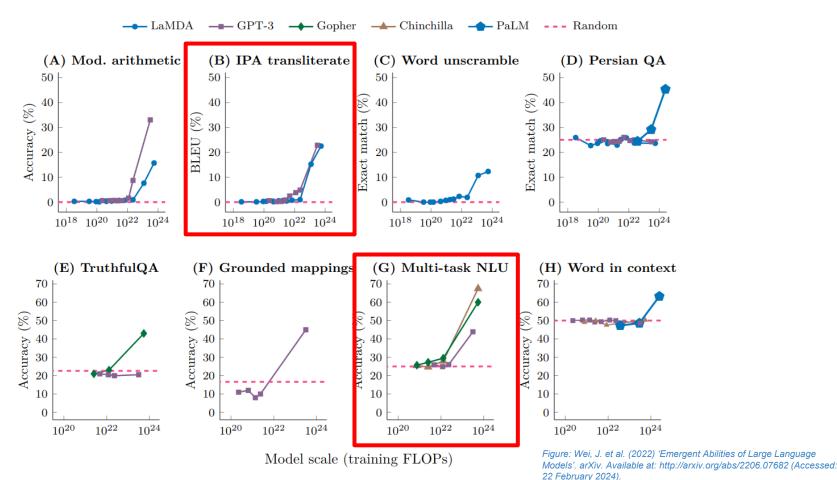
--- Random

Figure: Srivastava, A. et al. (2023) 'Beyond the Imitation Game: Quantifying and extrapolating the capabilities of language models'. arXiv. Available at: http://arxiv.org/abs/2206.04615.

 10^{11}



Abilities at different Model Scales





Measuring Massive Multitask Language Understanding

One of the reasons that the government discourages and regulates monopolies is that

- (A) producer surplus is lost and consumer surplus is gained.
- (B) monopoly prices ensure productive efficiency but cost society allocative efficiency.
- (C) monopoly firms do not engage in significant research and development.
- (D) consumer surplus is lost with higher prices and lower levels of output.

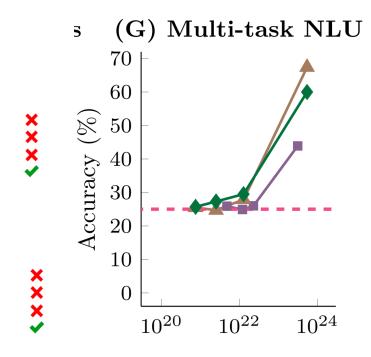
Figure 3: Examples from the Microeconomics task.

(B) circle (C) half-line (D) line

In the complex z-plane, the set of points satisfying the equation $z^2 = |z|^2$ is a

(A) pair of points





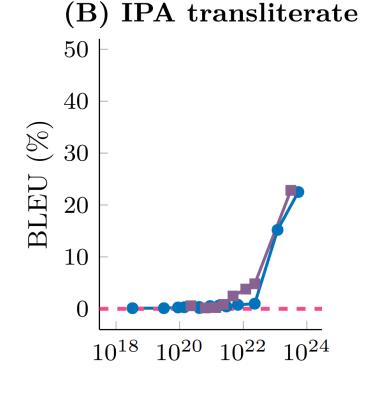




International Phonetic Alphabet **Transliteration**

Input (English): The 1931 Malay census was an alarm bell.

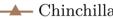
Target (IPA): ða 1931 'meɪleɪ sensəs waz ən ə'larm bel.















Emergent Abilities

	Emergent scale			
	Train. FLOPs	Params.	Model	Reference
Few-shot prompting abilities				
• Addition/subtraction (3 digit)	2.3E + 22	13B	GPT-3	Brown et al. (2020)
• Addition/subtraction (4-5 digit)	3.1E + 23	175B		
• MMLU Benchmark (57 topic avg.)	3.1E + 23	175B	GPT-3	Hendrycks et al. (2021a)
• Toxicity classification (CivilComments)	1.3E + 22	7.1B	Gopher	Rae et al. (2021)
• Truthfulness (Truthful QA)	5.0E + 23	280B		
• MMLU Benchmark (26 topics)	5.0E + 23	280B		
 Grounded conceptual mappings 	3.1E + 23	175B	GPT-3	Patel & Pavlick (2022)
• MMLU Benchmark (30 topics)	5.0E + 23	70B	Chinchilla	Hoffmann et al. (2022)
 Word in Context (WiC) benchmark 	2.5E + 24	540B	PaLM	Chowdhery et al. (2022)
• Many BIG-Bench tasks (see Appendix E)	Many	Many	Many	BIG-Bench (2022)
Augmented prompting abilities				
• Instruction following (finetuning)	1.3E + 23	68B	$\overline{\text{FLAN}}$	Wei et al. (2022a)
• Scratchpad: 8-digit addition (finetuning)	8.9E + 19	40M	$\underline{\mathrm{LaMDA}}$	Nye et al. (2021)
• Using open-book knowledge for fact checking	1.3E + 22	7.1B	Gopher	Rae et al. (2021)
• Chain-of-thought: Math word problems	1.3E + 23	68B	LaMDA	Wei et al. (2022b)
• Chain-of-thought: StrategyQA	2.9E + 23	62B	PaLM	Chowdhery et al. (2022)
• Differentiable search index	3.3E + 22	11B	$\overline{\mathrm{T5}}$	Tay et al. (2022b)
• Self-consistency decoding	1.3E + 23	68B	$\underline{\mathrm{LaMDA}}$	Wang et al. (2022b)
 Leveraging explanations in prompting 	5.0E + 23	280B	<u>Gopher</u>	Lampinen et al. (2022)
• Least-to-most prompting	3.1E + 23	175B	GPT-3	Zhou et al. (2022)
• Zero-shot chain-of-thought reasoning	3.1E + 23	175B	GPT-3	Kojima et al. (2022)
• Calibration via P(True)	2.6E + 23	52B	Anthropic	Kadavath et al. (2022)
• Multilingual chain-of-thought reasoning	2.9E + 23	62B	$\underline{\mathrm{PaLM}}$	Shi et al. (2022)
• Ask me anything prompting	1.4E + 22	6B	EleutherAI	Arora et al. (2022)

Table: Wei, J. et al. (2022) 'Emergent Abilities of Large Language Models'. arXiv. Available at: http://arxiv.org/abs/2206.07682.



The Effect of Promoting Strategies?



Prompting Strategies

Zero-shot (Direct prompting):

No previous data or examples (no shots) are given before completing the request.

One-shot (Prompt by one example):

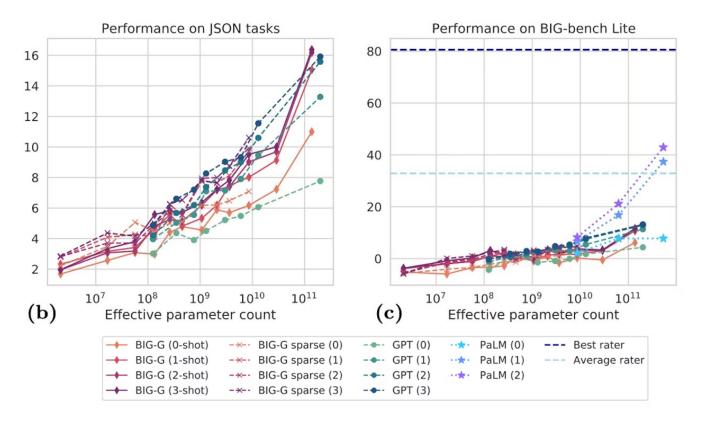
One piece of data or example (one shot) is given before completing the request.

Few-shot (Prompt by multiple examples):

Multiple examples or data (few shots) are given before completing the request.

```
Translate English to French:
                                        task description
cheese =>
                                        prompt
Translate English to French:
                                        task description
sea otter => loutre de mer
                                        example
cheese =>
                                        prompt
Translate English to French:
                                         task description
sea otter => loutre de mer
                                         examples
peppermint => menthe poivrée
plush girafe => girafe peluche
cheese =>
                                        prompt
```







Chain-of-Thought Prompting

→ Chain-of-Thought Prompting Elicits
Reasoning in Large Language Models
(Wei, J. et al. (2022))

Standard Prompting

Example Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

Example Output

A: The answer is 11.

Prompt

The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Response



The answer is 50.

Chain of thought prompting

Example Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

Example Output

Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Prompt

The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

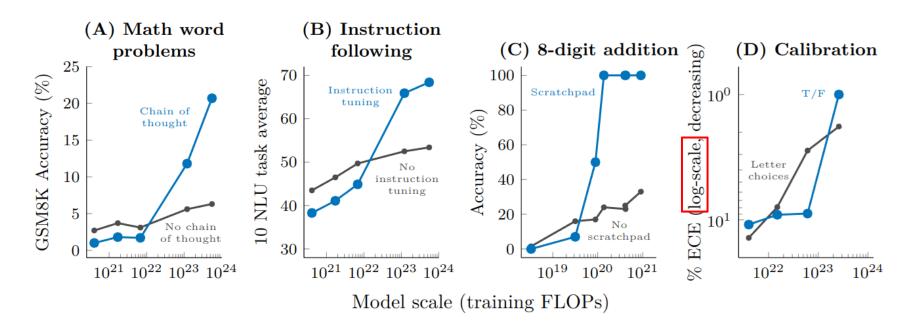
Model Response



The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23-20 = 3. They bought 6 more apples, so they have 3+6=9. The answer is 9.



Specialized Promoting and Fine-Tuning





Prompting Strategies

- Multi-Step Reasoning
- Instruction Following
- Program Execution
- Model Calibration

Emergent Techniques

If a technique shows no improvement or is harmful when compared to the baseline of not using the technique until applied to a model of a large-enough scale, we also consider the **technique an emergent ability**.



Why Emergent Abilities exists?



Potential Explanation

Multi-Step Reasoning Tasks

A multi-step reasoning task with ℓ sequential steps, may require a model with a depth of at least $O(\ell)$ layers

Closed-Book Question-Answering

Good performance on closed-book question-answering may require a model with enough parameters to capture the knowledge base itself

Shift of Usage: Sociological

Increasing the scale has shifted *how* the community views and uses language models. For example: from task specific NLP to *general purpose* LLMs



Potential Explanation

Explosion in Research

Scaling has led to an explosion in research on and development of models that are *general purpose* in that they are single models that aim to perform a range of tasks not explicitly encoded in the training data

The explanations given are quite vague:

- emergent abilities may disappear using different metrics
- emergent abilities may be caused by the objective used to measure them
- → topics of the second presentation today



Beyond Scaling



Beyond Scaling - Scaling is Limited

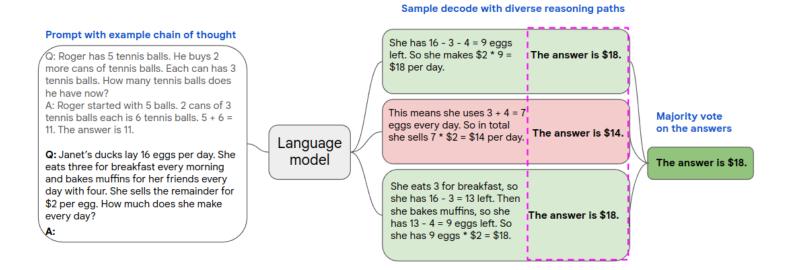
- Hardware Constraints
- Cost Constraints
- Quality / Quantity of Training Data
- Architecture and Training Strategies



Beyond Scaling - Alternative Prompting Strategies

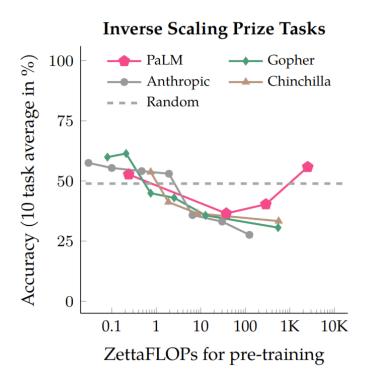
Self-consistency improves chain-of-thought reasoning in language models (ICLR '23). X. Wang, J. Wei, D. Schuurmans, Q. Le, E. Chi, S. Narang, A. Chowdhery, & D. Zhou.

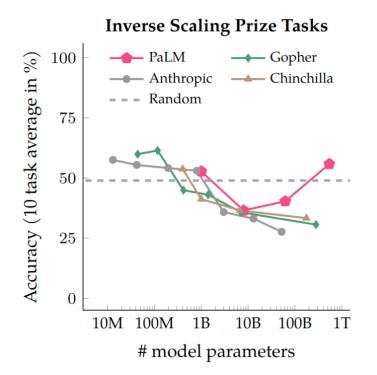
Self-consistency: majority vote





Scaling not Always Improve: Inverse Scaling







Emergent Risks

- Truthfulness
- Bias of in the model output
- Toxicity

Emergent risks are hard to predict

Emergent risks also include phenomena that might only exist in future language models or that have not yet been characterized in current language models



Conclusion



Future Work

- What controls which abilities will emerge?
- What controls when abilities emerge?
- Who can we improve / augment the training of LLMs?
- How can we make desirable abilities emerge faster?
- How can we ensure undesirable abilities never emerge?

follow-up and related papers

- → TruthfulQA: Measuring How Models Mimic Human Falsehoods (Lin, S., et al. (2021))
- → Predicting Emergent Abilities with Infinite Resolution Evaluation (Hu, S., et al. (2023))
- → Are Emergent Abilities of Large Language Models a Mirage? (Schaeffer, R., et al. (2023))
- → Beyond the Imitation Game: Quantifying and extrapolating the capabilities of language models (Srivastava, A. et al. (2023))
- → Chain-of-Thought Prompting Elicits Reasoning in Large Language Models (Wei, J. et al. (2022))



Conclusion

Strengths

- comprehensive overview of the state of the art
- concrete examples for future work
- easy to follow structure, they reintroduce core concepts

Limitations

- limited effort to explain the phenomenon of emergence
- partially unclear which
 experiments are carried out and
 which results are from prior
 papers



thank you

Any Questions?