

Galactica: A large language model for science

By Taylor et al. (Meta AI), 2022

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Summary

- › Introduction
- › Dataset & Methods
- › Results
- › Further analysis



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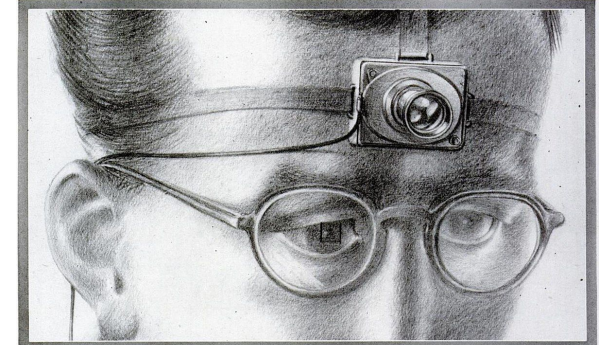


Information overload: a long time predicted burden

A problem already known decades ago...

« *Publication has been extended far beyond our present ability to make real use of the record* »

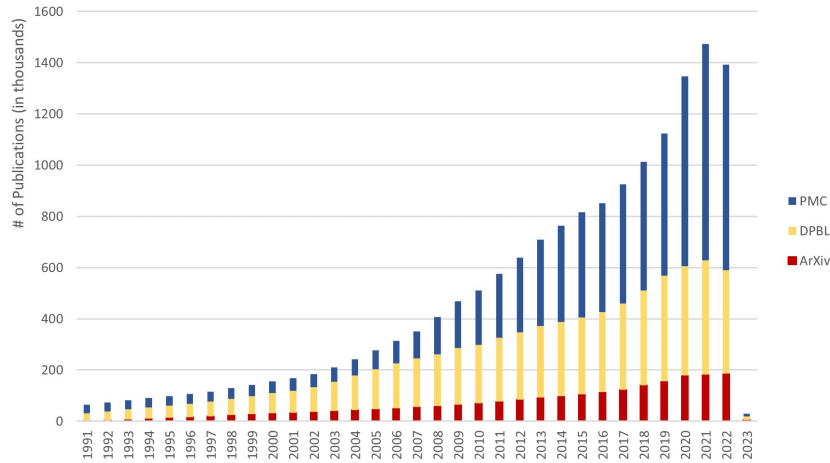
Vannevar Bush, *As We May Think*, 1945



A SCIENTIST OF THE FUTURE RECORDS EXPERIMENTS WITH A TINY CAMERA FITTED WITH UNIVERSAL-FOCUS LENS. THE SMALL SQUARE IN THE EYEGLASS AT THE LEFT SIGHTS THE OBJECT

AS WE MAY THINK

A TOP U. S. SCIENTIST FORESEES A POSSIBLE FUTURE WORLD IN WHICH MAN-MADE MACHINES WILL START TO THINK



... reaching a point of no return

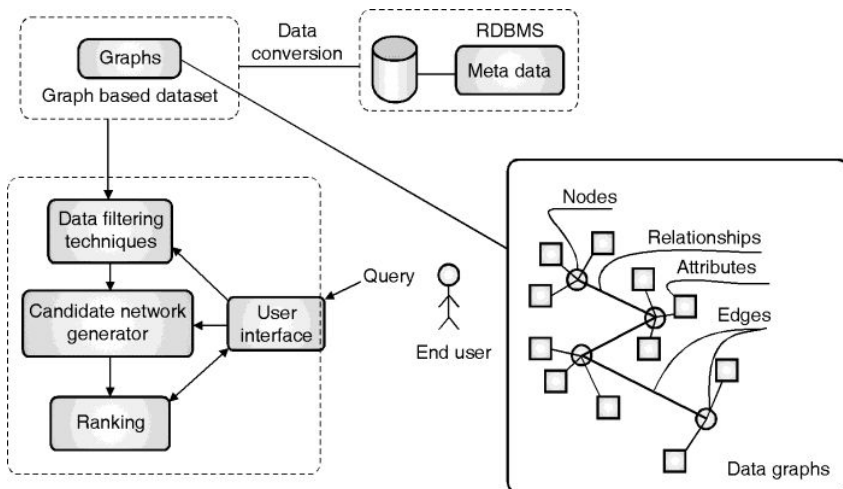
- › A publication rate way above the capabilities of scientists to read them: an average of 516 publications submitted per day on ArXiv (May 2022)
- › An overload not only limited to publication: for instance, NCBI GenBank contained almost 1.5×10^{12} nucleotide bases in August 2022



Technology: a potential solution

Computers, instrument to reach Licklider's paradigm

- › The rise of information technology and computers : invention of the transistor in 1947 (by Bardeen, Shockley and Brattain), of microprogramming in 1955 (by Maurice Wilkes)...
- › A source of hope to tackle the issue: in Licklider's paradigm, computer would "*prepare the way for insights and decisions in scientific thinking*" (Licklider, *Man-Computer Symbiosis*, 1960)



... but still needing too much human contributions

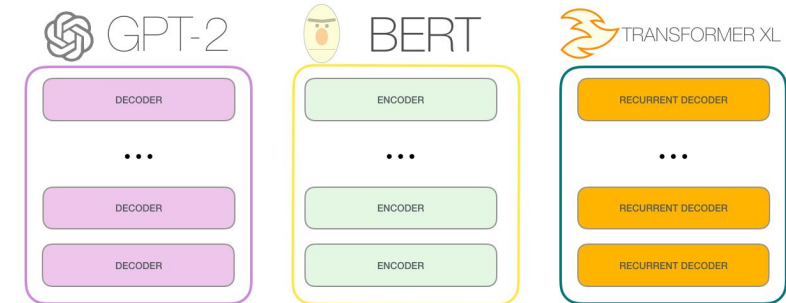
- › The current "symbiotic" relationship between human and computer still need a lot of human contribution when information need to be found (search engines)
- › A task, even with the use of computers, that is still time-consuming



Large Language Models: a breakthrough in NLP

Large Language Models (LLM)

- › LLMs have achieved breakthrough performance on NLP tasks in last year.
- › Some argue that Language Models can be considered as a convenient implicit knowledge bases



Galactica: a new LLM for organizing science



- › A dataset of more than 48 millions papers, textbooks... but also proteins, DNA sequences...
- › A particular focus on the dataset, « high-quality and highly curated »
- › A model that beat previous LM on several benchmarks (MMLU, MATH...)



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Galactica's dataset: heart of the model (1/2)

A large scientific corpus

- > More than 60 million documents coming from 6 main data source used to train Galactica
- > All document converted in Markdown to unify knowledge coming from all kind of documents
- > Text sequence only, but many scientific phenomena described

Total dataset size = 106 billion tokens			
Data source	Documents	Tokens	Token %
Papers	48 million	88 billion	83.0%
Code	2 million	7 billion	6.9%
Reference Material	8 million	7 billion	6.5%
Knowledge Bases	2 million	2 billion	2.0%
Filtered CommonCrawl	0.9 million	1 billion	1.0%
Prompts	1.3 million	0.4 billion	0.3%
Other	0.02 million	0.2 billion	0.2%

Modality	Entity	Sequence
Text	Abell 370	Abell 370 is a cluster...
LaTeX	Schwarzschild radius	$r_s = \frac{2GM}{c^2}$
Code	Transformer	<code>class Transformer(nn.Module)</code>
SMILES	Glycine	<chem>C(C(=O)O)N</chem>
AA Sequence	Collagen α -1(II) chain	MIRLGAPQTL..
DNA Sequence	Human genome	CGGTACCCTC..



$$r_s = \frac{2GM}{c^2}$$

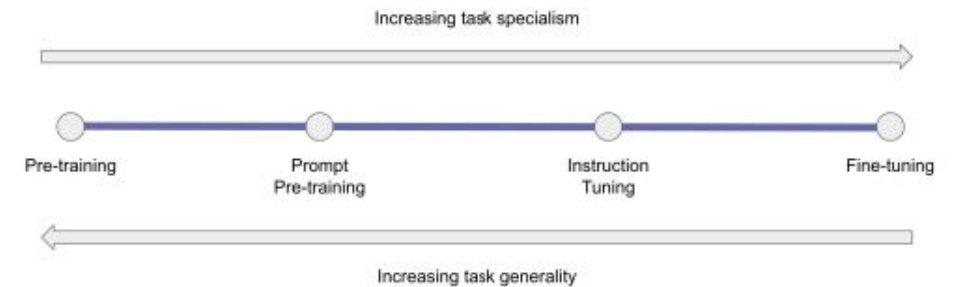




Galactica's dataset: heart of the model (2/2)

Prompt Pre-Training

- › PPT can boost performance (lower models beating larger ones on specific tasks)
- › Be able to give correct performances even for the smallest version of the model
- › Almost 800k prompts given on different tasks (summarization, entity extraction, binary QA...)
- › PPT create a distinction between in-domain knowledge and out-domain knowledge





Tokenization: break data into understandable items

Specialized tokenization: a choice for the dataset design

Special type of data	Choice of tokenization
Step-by-step reasoning	Wrapping with <work>
Citations	Wrapping with [START_REF] / [END_REF]
SMILES formula, DNA sequences and Amino acid sequences	Wrapping with [START_SMILES] / [END_SMILES] ([START_DNA] / [END_DNA] or [START_AMINO] / [END_AMINO]) and character-based tokenization
Mathematics and numbers	Splitting digits and operations into individual characters

Recurrent neural networks, long short-term memory [START_REF]Long Short-Term Memory, Hochreiter[END_REF] and gated recurrent [START_REF]Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling, Chung[END_REF] neural networks in particular, have been firmly established as state of the art approaches in sequence modeling and transduction problems such as language modeling and machine translation [START_REF]Sequence to Sequence Learning with Neural Networks, Sutskever[END_REF] [START_REF]Neural Machine Translation by Jointly Learning to Align and Translate, Bahdanau[END_REF] [START_REF]Learning Phrase Representations Using RNN Encoder-Decoder for Statistical Machine Translation, Cho[END_REF].

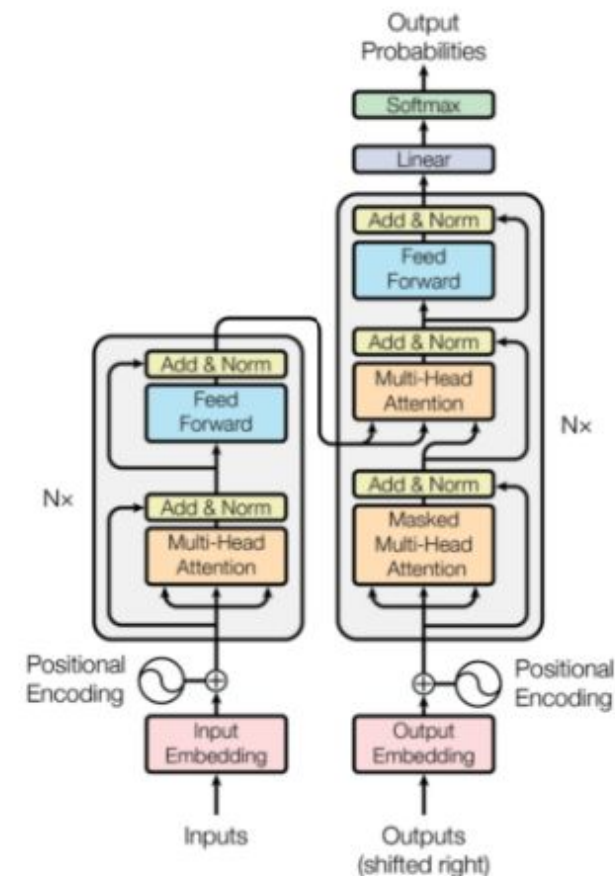


Transformers: Galactica's architecture (1/2)

Transformers : current state-of-the-art models

- Transformer architecture was introduced in June 2017, mainly to work on translation task
- Two main blocks: an encoder to receive inputs and build a representation of them, and a decoder using encoder representation and others inputs to generate a target sequence
- Each block can be used without the other, hence three main types of models.

Models	Tasks	Exemple of models
Auto-Encoding	Sentence classification, NER	BERT
Auto-Regressive	Text Génération	GPT
Sequence-to-Sequence	Translation, summarization	BART / T5

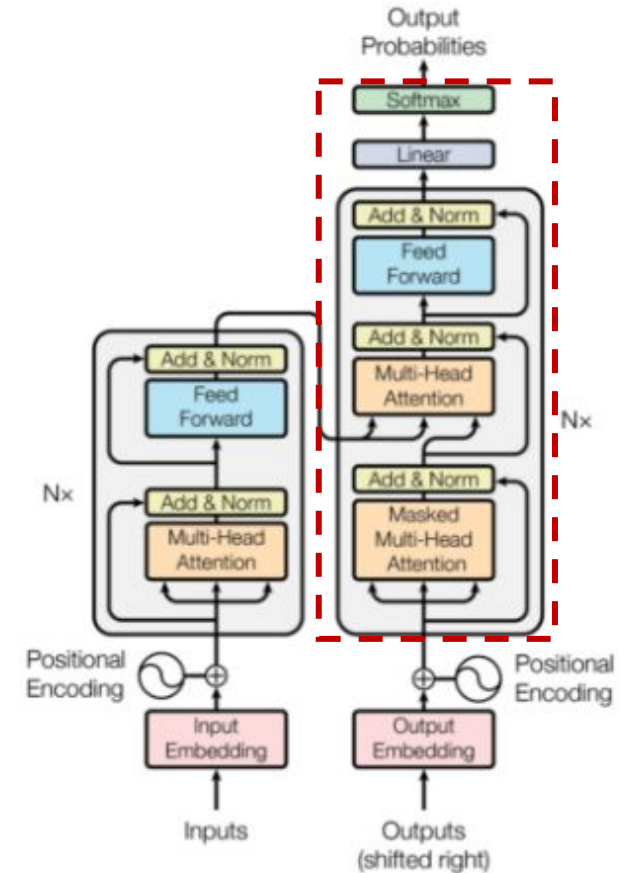




Transformers: Galactica's architecture (2/2)

Galactica's architecture : a modified version of the original architecture

- › Only a decoder part (like GPT)
- › Use of GELU activation function for all model in last feed forward layer
- › No biases
- › Use of Learned Position Embedding
- › Creation of a 50k token vocabulary using BPE





<work> : a working memory token

A simple observation leading to this token

Transformers



- > Understanding of natural language
- > Chain-of-thought



- > Accuracy on task like multiplication

Classic computers



- > Arithmetic tasks



- > Chain-of-thought

Question: A needle 35 mm long rests on a water surface at 20°C. What force over and above the needle's weight is required to lift the needle from contact with the water surface? $\sigma = 0.0728\text{m}$.

<work>

$$\begin{aligned}\sigma &= 0.0728 \text{ N/m} \\ \sigma &= F/L \\ 0.0728 &= F/(2 \times 0.035) \\ F &= 0.0728(2 \times 0.035)\end{aligned}$$

```
calculate.py
'''
f = 0.0728*(2*0.035)

with open("output.txt", "w") as file:
    file.write(str(round(f, 5)))
'''
```

«run: "calculate.py">

«read: "output.txt"»

0.0051

</work>

Answer: $F = 0.0051 \text{ N}$

Process behind the creation of the token





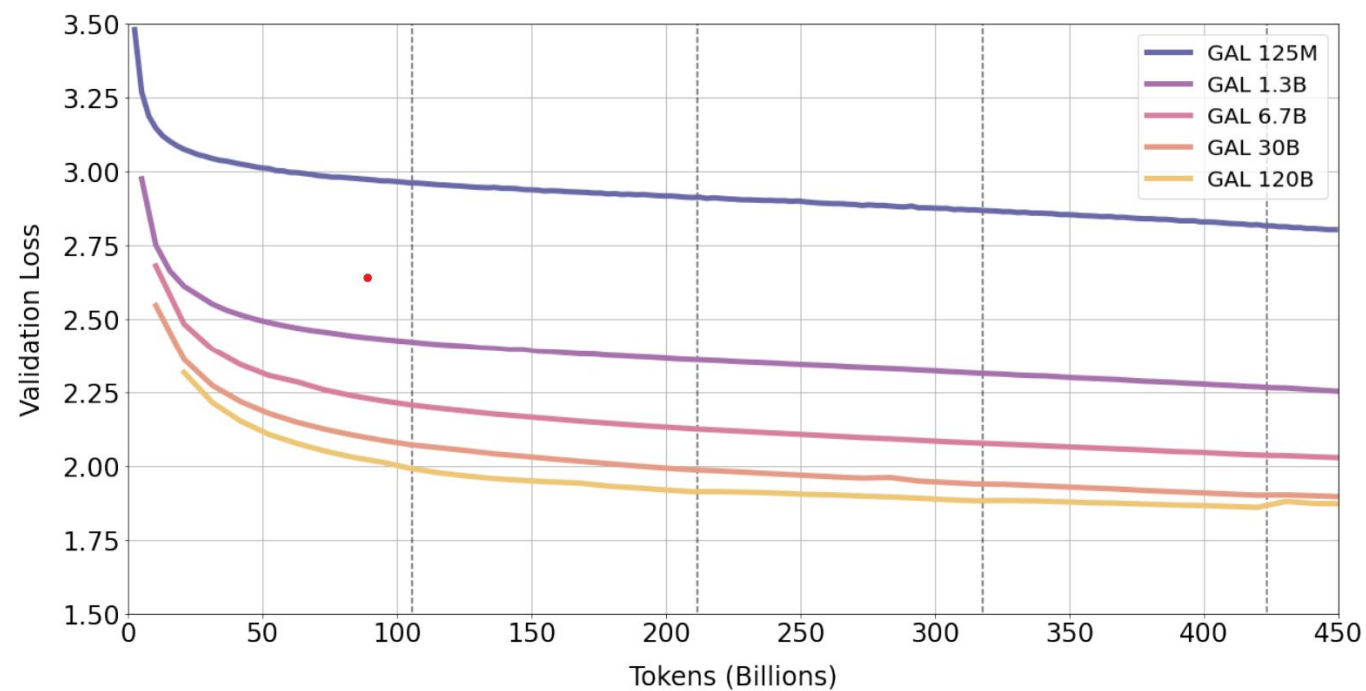
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Galactica models

Model	n_{params}	n_{layers}	d_{model}	n_{heads}	d_{heads}	Batch Size	Max LR	Warmup
GAL 125M	125M	12	768	12	64	0.5M	6×10^{-4}	375M
GAL 1.3B	1.3B	24	2,048	32	64	1.0M	2×10^{-4}	375M
GAL 6.7B	6.7B	32	4,096	32	128	2.0M	1.2×10^{-4}	375M
GAL 30B	30.0B	48	7,168	56	128	2.0M	1×10^{-4}	375M
GAL 120B	120.0B	96	10,240	80	128	2.0M	0.7×10^{-5}	1.125B





Results

Knowledge probes

Tasks	Galactica	Others models
LaTeX equations probes	68.2%	49% (GPT-3)
Domain probes	8 – 43.1%	9.7 – 35.1%
Reasoning	41.3%	35.7% (Chinchilla)

Downstream scientific NLP

	Galactica	Others models
In-domain	5	0
Out-domain	6	14

Numbers of dataset where models has best performance

Citation prediction

Tasks	Galactica	Others models
PWC Citations	51.9%	30.9%
Extended Citations	69.1%	17.3%
Contextual Citations	36.6%	8.2%

General capabilities

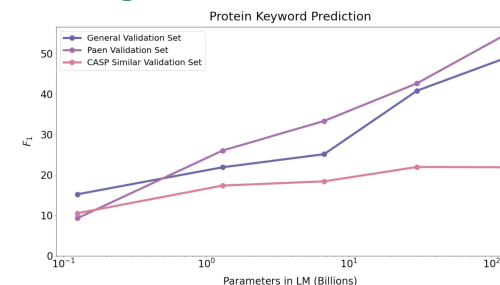
Model	Params (bn)	Accuracy <i>weighted</i>	Accuracy <i>unweighted</i>
OPT 30B	30	39.6%	38.0%
BLOOM 176B	176	42.6%	42.2%
OPT 175B	175	43.4%	42.6%
GAL 30B	30	46.6%	42.7%
GAL 120B	120	48.7%	45.3%

BIG-bench 57 task results

Chemical understanding

- › **IUPAC Name Prediction:** accuracy of 39.2%
- › **MoleculeNet:** Uni-Mol performs better

Biological understanding





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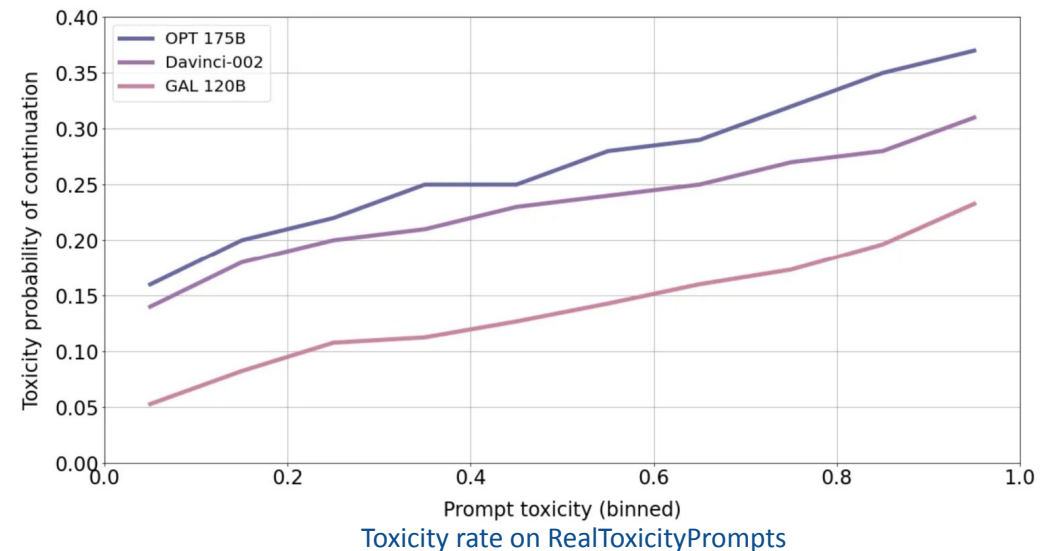
Toxicity and Bias

Generating content: a potential open door for toxicity

- › Meta AI aware of the potential toxicity coming from LLM
- › Use of benchmarks on toxicity and stereotypes to ensure Galatica's ability to detect stereotypes
- › Galactica demo was shut down few days after its launch due many users retrieving biased, offensive or false answers to their questions

StereoSet				
Category		text-davinci-002	OPT 175B	Galactica 120B
Prof.	LMS (↑)	78.4	74.1	75.2
	SS (↓)	63.4	62.6	57.2
	ICAT (↑)	57.5	55.4	64.3
Gend.	LMS (↑)	75.6	74.0	74.6
	SS (↓)	66.5	63.6	59.1
	ICAT (↑)	50.6	53.8	61.0
Reli.	LMS (↑)	80.8	84.0	81.4
	SS (↓)	59.0	59.0	55.1
	ICAT (↑)	66.3	68.9	73.1
Race	LMS (↑)	77.0	74.9	74.5
	SS (↓)	57.4	56.8	54.8
	ICAT (↑)	65.7	64.8	67.3
Overall	LMS (↑)	77.6	74.8	75.0
	SS (↓)	60.8	59.9	56.2
	ICAT (↑)	60.8	60.0	65.6

StereoSet Results





Limitations and Potential work

Limitations highlighted

- Limitations coming from corpus
- Distinguishability of corpus effects and prompt effects
- Bias for highly-cited papers
- Text as only modality
- ...

Several ideas mentionned

- Use of larger context window
- Extending to images
- Create more examples for the working memory token
- Enforce a verification layer
- Develop a continual learning
- ...

