

– IN5550 –

Neural Methods in Natural Language Processing

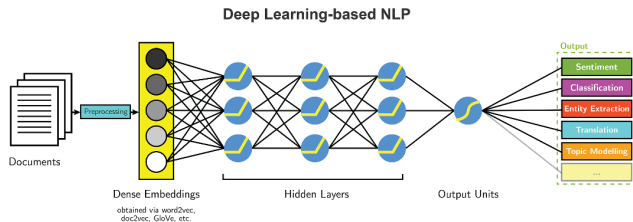
*Sustainability 1: The possibilities and problems of large
LMs*

Lilja Øvrelid

(With thanks to Jeremy Barnes)



- ▶ Most NLP tasks approached as **classification** problems, using supervised machine learning
- ▶ Since at least 2014, **neural networks** completely dominating.
- ▶ Very successful on NLP benchmarks

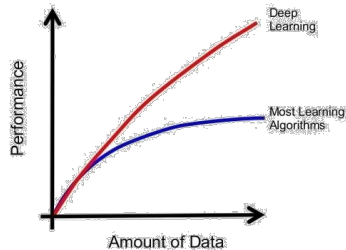


<https://ebookreading.net/view/book/EB9781787121423397.html>

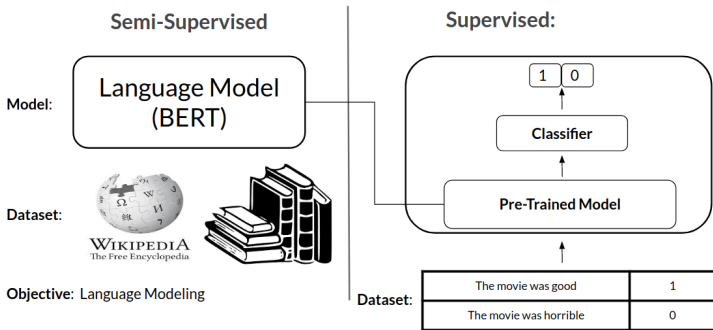
Why now?



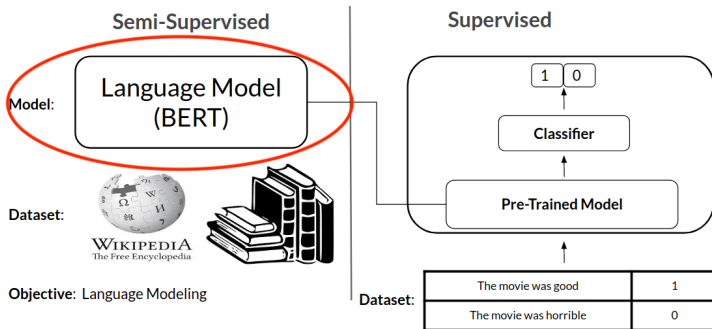
- ▶ large amounts of data
- ▶ substantial computing power (GPUs, parallelization)
- ▶ architectures that combine the two
- ▶ transfer learning of pre-trained language models



www.icaroi.com



(<https://blog.insightdatascience.com>)












(<https://blog.insightdatascience.com>)

(March 2021)

SuperGLUE GLUE

Paper </> Code Tasks

Leaderboard Version: **2.0**

Rank	Name	Model	URL	Score	BoolQ	CB	COPA
1	SuperGLUE Human Baselines	SuperGLUE Human Baselines		89.8	89.0	95.8/98.9	100.0
+ 2	T5 Team - Google	T5		89.3	91.2	93.9/96.8	94.8
3	Zhuyi Technology	RoBERTa-mtl-adv		85.7	87.1	92.4/95.6	91.2
4	Facebook AI	RoBERTa		84.6	87.1	90.5/95.2	90.6
5	IBM Research AI	BERT-mtl		73.5	84.8	89.6/94.0	73.8
6	SuperGLUE Baselines	BERT++		71.5	79.0	84.8/90.4	73.8
		BERT		69.0	77.4	75.7/83.6	70.6
		Most Frequent Class		47.1	62.3	21.7/48.4	50.0
		CBoW		44.5	62.2	49.0/71.2	51.6
		Outside Best		-	80.4	-	84.4
-	Stanford Hazy Research	Snorkel [SuperGLUE v1.9]		-	-	88.6/93.2	76.2

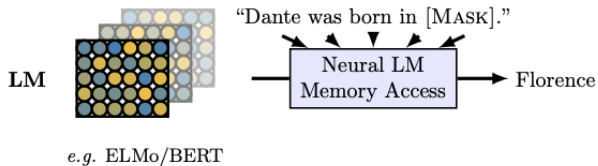
(March 2022)

SuperGLUE GLUE Paper </> Code Tasks

Leaderboard Version: 2.0

Rank	Name	Model	URL	Score	BoolQ	CB	COPA	M
+	1	Liam Fedus	ST-MoE-32B	91.2	92.4	96.9/98.0	99.2	85
	2	Microsoft Alexander v-team	Turing NLR v5	90.9	92.0	95.9/97.6	98.2	86
	3	ERNIE Team - Baidu	ERNIE 3.0	90.6	91.0	98.6/99.2	97.4	86
+	4	Zirui Wang	T5 + UDG, Single Model (Google Brain)	90.4	91.4	95.8/97.6	98.0	86
+	5	DeBERTa Team - Microsoft	DeBERTa / TuringNLRv4	90.3	90.4	95.7/97.6	98.4	86
	6	SuperGLUE Human Baselines	SuperGLUE Human Baselines	89.8	89.0	95.8/98.9	100.0	81
+	7	T5 Team - Google	T5	89.3	91.2	93.9/96.8	94.8	86
	8	SPoT Team - Google	Frozen T5 1.1 + SPoT	89.2	91.1	95.8/97.6	95.6	87

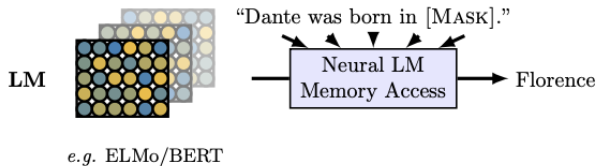
Why?



(Petroni et al, 2019)

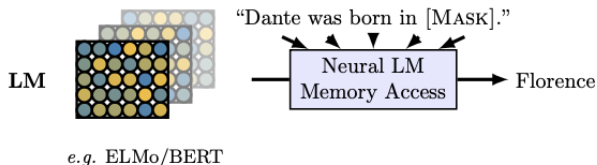
- ▶ Learn a lot about language and the world

Why?



(Petroni et al, 2019)

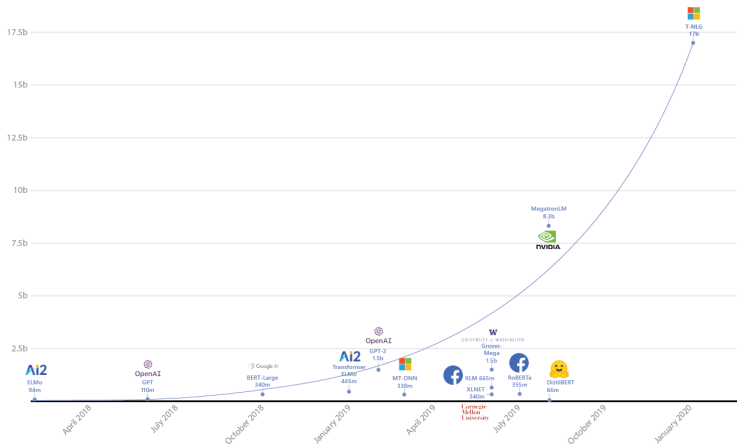
- ▶ Learn a lot about language and the world
- ▶ but not everything



(Petroni et al, 2019)

- ▶ Learn a lot about language and the world
- ▶ but not everything
- ▶ Limited by the training data
- ▶ If trained on non-curated text from the internet, they tend to reflect the **biases** found there.

Size of LMs



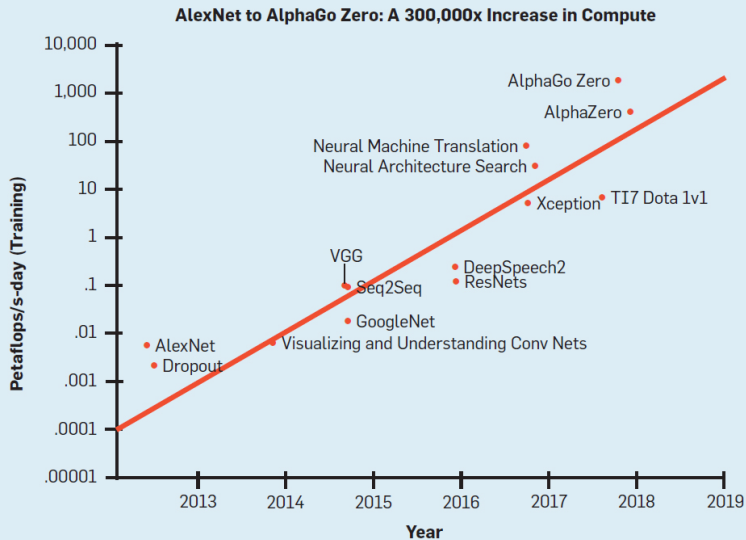
<https://www.microsoft.com/en-us/research/blog/turing-nlg-a-17-billion-parameter-language-model-by-microsoft/>



Year	Model	# of Parameters	Dataset Size
2019	BERT [39]	3.4E+08	16GB
2019	DistilBERT [113]	6.60E+07	16GB
2019	ALBERT [70]	2.23E+08	16GB
2019	XLNet (Large) [150]	3.40E+08	126GB
2020	ERNIE-GEN (Large) [145]	3.40E+08	16GB
2019	RoBERTa (Large) [74]	3.55E+08	161GB
2019	MegatronLM [122]	8.30E+09	174GB
2020	T5-11B [107]	1.10E+10	745GB
2020	T-NLG [112]	1.70E+10	174GB
2020	GPT-3 [25]	1.75E+11	570GB
2020	GShard [73]	6.00E+11	–
2021	Switch-C [43]	1.57E+12	745GB

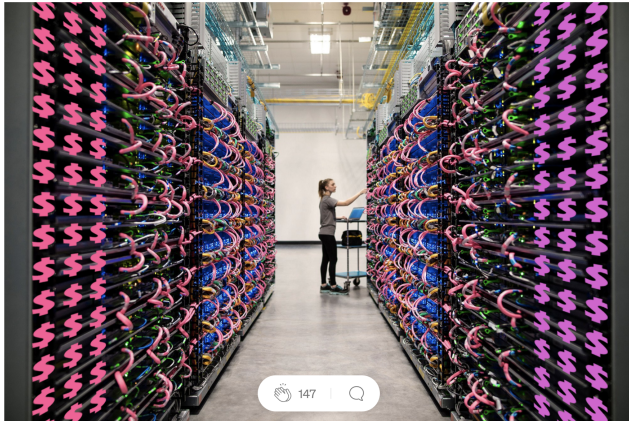
Table 1: Overview of recent large language models

* from Bender & Gebru et al (2021): On the dangers of stochastic parrots: Can language models be too big?



* from (Schwartz et al (2020): Green AI

The Staggering Cost of Training SOTA AI Models



<https://medium.com/syncedreview/the-staggering-cost-of-training-sota-ai-models-e329e80fa82>



Consumption	CO₂e (lbs)
Air travel, 1 passenger, NY↔SF	1984
Human life, avg, 1 year	11,023
American life, avg, 1 year	36,156
Car, avg incl. fuel, 1 lifetime	126,000
Training one model (GPU)	
NLP pipeline (parsing, SRL)	39
w/ tuning & experimentation	78,468
Transformer (big)	192
w/ neural architecture search	626,155

*from Strubell et al. (2019) Energy and policy considerations for deep learning in NLP.



How can we mitigate the negative effects of large LMs?

- ▶ SustainNLP workshop
- ▶ Enhance reporting of computational budgets
- ▶ Efficiency as a core evaluation metric

* from (Schwartz et al (2020): Green AI