

Question Answering

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Outline

- Question Answering
 - Problem statement and datasets overview
 - Potential solutions
 - Open-domain Question Answering

Question Answering: problem statement and datasets

A Brief History of Open-domain Question Answering

- Simmons et al. (1964) did first exploration of answering questions from an expository text based on matching dependency parses of a question and answer
- Murax (Kupiec 1993) aimed to answer questions over an online encyclopedia using IR and shallow linguistic processing
- The NIST TREC QA track begun in 1999 first rigorously investigated answering fact questions over a large collection of documents
- IBM's Jeopardy! System (DeepQA, 2011) brought attention to a version of the problem; it used an ensemble of many methods
- DrQA (Chen et al. 2016) uses IR followed by neural reading comprehension to bring deep learning to Open-domain QA

MCTest Reading Comprehension

Passage (P)

Question (Q) Answer (A)

Alyssa got to the beach after a long trip. She's from Charlotte. She traveled from Atlanta. She's now in Miami. She went to Miami to visit some friends. But she wanted some time to herself at the beach, so she went there first. After going swimming and laying out, she went to her friend Ellen's house. Ellen greeted Alyssa and they both had some lemonade to drink. Alyssa called her friends Kristin and Rachel to meet at Ellen's house......

Q Why did Alyssa go to Miami?

A To visit some friends

Stanford Question Answering Dataset

In meteorology, precipitation is any product of the condensation of atmospheric water vapor that falls under gravity. The main forms of precipitation include drizzle, rain, sleet, snow, graupel and hail... Precipitation forms as smaller droplets coalesce via collision with other rain drops or ice crystals within a cloud. Short, intense periods of rain in scattered locations are called "showers".

- What causes precipitation to fall?
 - gravity
- What is another main form of precipitation besides drizzle, rain, snow, sleet and hail?
 - o graupel
- Where do water droplets collide with ice crystals to form precipitation?
 - within a cloud

SQuAD evaluation, v1.1

- Authors collected 3 gold answers
- Systems are scored on two metrics:
 - Exact match: 1/0 accuracy on whether you match one of the 3 answers
 - F1: Take system and each gold answer as bag of words, evaluate Precision, Recall and harmonic mean F1.
 - Score is (macro-)average of per-question F1 scores
- F1 measure is seen as more reliable and taken as primary
 - It's less based on choosing exactly the same span that humans chose, which is susceptible to various effects, including line breaks
- Both metrics ignore punctuation and articles (a, an, the only)

source: CS224n Lecture 10

SQuAD v1.1 leaderboard, end of 2016

		EM	F1
11	Fine-Grained Gating Carnegie Mellon University (Yang et al. '16)	62.5	73.3
12	Dynamic Chunk Reader IBM (Yu & Zhang et al. '16)	62.5	71.0
13	Match-LSTM with Ans-Ptr (Boundary) Singapore Management University (Wang & Jiang '16)	60.5	70.7
14	Match-LSTM with Ans-Ptr (Sequence) Singapore Management University (Wang & Jiang '16)	54.5	67.7
15	Logistic Regression Baseline Stanford University (Rajpurkar et al. '16)	40.4	51.0
Will you	r model outperform humans on the QA	task?	
	Human Performance Stanford University (Rajpurkar et al. '16)	82.3	91.2

source: CS224n Lecture 10

SQuAD v1.1 leaderboard, (May 2020)

Rank	Model	EM	F1
	Human Performance	82.304	91.22
	Stanford University		
	(Rajpurkar et al. '16)		
1	LUKE (single model)	90.202	95.37
Apr 10, 2020	Studio Ousia & NAIST & RIKEN AIP		
2	XLNet (single model)	89.898	95.08
May 21, 2019	Google Brain & CMU		
3	XLNET-123++ (single model)	89.856	94.90
Dec 11, 2019	MST/EOI		
	http://tia.today		
3	XLNET-123 (single model)	89.646	94.93
Aug 11, 2019	MST/EOI		
4	BERTSP (single model)	88.912	94.58
Sep 25, 2019	NEUKG		
	http://www.techkg.cn/		
4	SpanBERT (single model)	88.839	94.63
Jul 21, 2019	FAIR & UW		
5	BERT+WWM+MT (single model)	88.650	94.39
Jul 03, 2019	Xiaoi Research		

source: SQuAD website

SQUAD 2.0

- A defect of SQuAD 1.0 is that all questions have an answer in the paragraph
- Systems (implicitly) rank candidates and choose the best one
- You don't have to judge whether a span answers the question
- In SQuAD 2.0, 1/3 of the training questions have no answer, and about 1/2 of the dev/test questions have no answer
 - For NoAnswer examples, NoAnswer receives a score of 1, and any other response gets 0, for both exact match and F1
- Simplest system approach to SQuAD 2.0:
 - o Have a threshold score for whether a span answers a question
- Or you could have a second component that confirms answering
 - Like Natural Language Inference (NLI) or "Answer validation"

SQuAD 2.0 example

Genghis Khan united the Mongol and Turkic tribes of the steppes and became Great Khan in 1206. He and his successors expanded the Mongol empire across Asia. Under the reign of Genghis' third son, Ögedei Khan, the Mongols destroyed the weakened Jin dynasty in 1234, conquering most of northern China. Ögedei offered his nephew Kublai a position in Xingzhou, Hebei. Kublai was unable to read Chinese but had several Han Chinese teachers attached to him since his early years by his mother Sorghaghtani. He sought the counsel of Chinese Buddhist and Confucian advisers. Möngke Khan succeeded Ögedei's son, Güyük, as Great Khan in 1251. He

When did Genghis Khan kill Great Khan?

Gold Answers: <No Answer>

Prediction: 1234 [from Microsoft nlnet]

source: CS224n Lecture 10

	Rank	Model	EM	F1	
		Human Performance Stanford University (Rajpurkar & Jia et al. '18)	86.831	89.452	SQuAD 2.0 leaderboard
	1 Apr 06, 2020	SA-Net on Albert (ensemble) QIANXIN	90.724	93.011	
	2 May 05, 2020	SA-Net-V2 (ensemble) QIANXIN	90.679	92.948	(October 2020)
	2 Apr 05, 2020	Retro-Reader (ensemble) Shanghai Jiao Tong University http://arxiv.org/abs/2001.09694	90.578	92.978	
	3 Jul 31, 2020	ATRLP+PV (ensemble) Hithink RoyalFlush	90.442	92.877	
	3 May 04, 2020	ELECTRA+ALBERT+EntitySpanFocus (ensemble) SRCB_DML	90.442	92.839	
	4 Jun 21, 2020	ELECTRA+ALBERT+EntitySpanFocus (ensemble) SRCB_DML	90.420	92.799	
	4 Sep 11, 2020	EntitySpanFocus+AT (ensemble) RICOH_SRCB_DML	90.454	92.748	
	4 Mar 12, 2020	ALBERT + DAAF + Verifier (ensemble) PINGAN Omni-Sinitic	90.386	92.777	
	5 Jan 10, 2020	Retro-Reader on ALBERT (ensemble) Shanghai Jiao Tong University http://arxiv.org/abs/2001.09694	90.115	92.580	
<u>website</u>	5 Sep 27, 2020	electra+nlayers (ensemble) oppo.tensorlab	90.126	92.535	

Now in Russian: SberQuAD

Термин Computer science (Компьютерная наука) появился <u>в 1959</u> году в научном журнале Communications of the ACM, в котором <u>Луи Фейн</u> (Louis Fein) ратовал за создание Graduate School in Computer Sciences (Высшей школы в области информатики) . . . Усилия Луи Фейна, численного аналитика Джорджа Форсайта и других увенчались успехом: университеты пошли на создание программ, связанных с информатикой, начиная с <u>Университета Пердью</u> в 1962.

- Q11870 Когда впервые был применен термин Computer science (Компьютерная наука)?
- Q28900 Кто впервые использовал этот термин?
- Q30330 Начиная с <u>каого*</u> учебного заведения стали применяться учебные программы, связанные с информатикой?

*Misspelling is intended

SberQuAD evaluation

Model	Sber	QuAD	SQuAD		
	EM	F1	EM	F1	
simple baseline	0.3	25.0	-	-	
ML baseline	3.7	31.5	_	-	
BiDAF	51.7	72.2	68.0	77.3	
DrQA	54.9	75.0	70.0	79.0	
R-Net	58.6	77.8	71.3	79.7	
DocQA	59.6	79.5	72.1	81.1	
BERT	66.6	84.8	85.1	91.8	

Table 7: Model performance on SQuAD and SberQuAD; SQuAD part shows single-model scores on test set taken from respective papers.

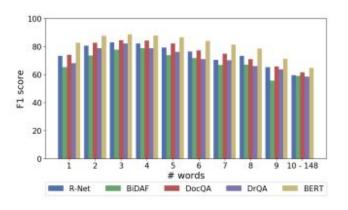


Figure 6: Model performance depending on answer length (# of words).

% test R-Net BiDAF DocQA DrQA BERT						
w/ typos	5.7	74.1	66.7	77.5	67.5	81.1
correct	94.3	77.1	72.5	79.6	75.4	85.0
Test set		77.8	72.2	79.5	75.0	84.8

Table 8: Answer quality for misspelled questions.

But errors are still present

The Yuan dynasty is considered both a successor to the Mongol Empire and an imperial Chinese dynasty. It was the khanate ruled by the successors of Möngke Khan after the division of the Mongol Empire. In official Chinese histories, the Yuan dynasty bore the Mandate of Heaven, following the Song dynasty and preceding the Ming dynasty. The dynasty was established by Kublai Khan, yet he placed his grandfather Genghis Khan on the imperial records as the official founder of the

What dynasty came before the Yuan?

Gold Answers: 1 Song dynasty 2 Mongol Empire

3 the Song dynasty

Prediction: Ming dynasty [BERT (single model) (Google AI)]

source: CS224n Lecture 10

S(ber)QuAD limitations

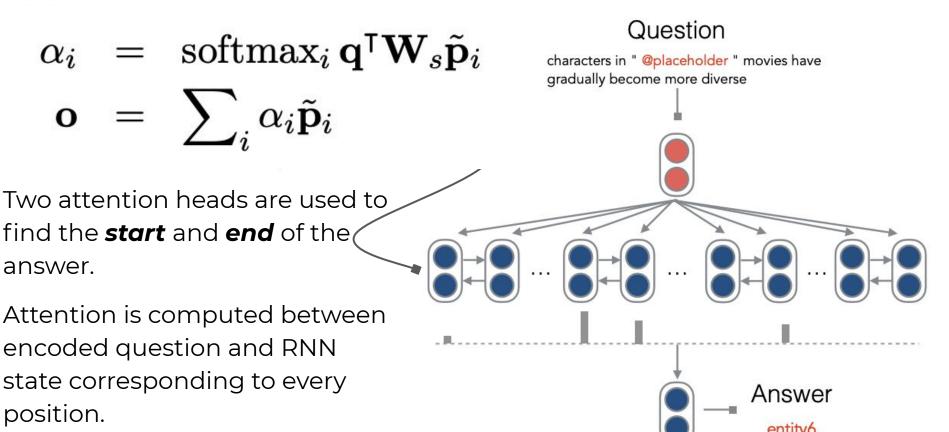
- Only span-based answers (no yes/no, counting, implicit why)
 - Questions were constructed looking at the passages
 - Not genuine information needs
 - Generally greater lexical and syntactic matching between questions and answer span than you get IRL
 - Barely any multi-fact/sentence inference beyond coreference
- But these datasets are still of a great use

Answering problem

Approaches to the Question

Passage

Potential solutions



source: A Thorough Examination of the CNN/Daily Mail Reading Comprehension Task

How to make it better

- Use extra information about the text
 - Char embeddings
 - Linguistic features: PoS and NER tags
 - 0 ...

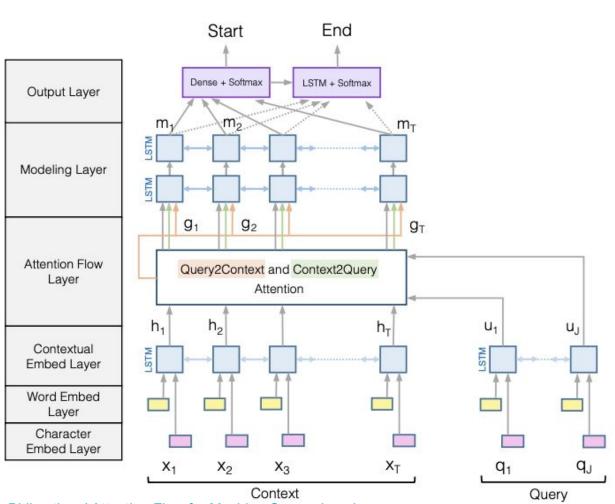
PoS tagging

Pred. I	Гад	Actual Tag	Correct?	Token	PoS tagging can be		
PUNCT		PUNCT	✓	[
DET		DET	✓	this	performed using		
NOUN		NOUN	✓	killing		monned daning	
ADP		ADP	•	of		Dula based taggers	
DET		DET	✓	a	O	Rule-based taggers	
ADJ		ADJ	✓	respected			
NOUN		NOUN	✓	cleric	0	Dynamic	
AUX		AUX	✓	will		9	
AUX		AUX	✓	be		programming	
VERB		VERB	✓	causing		programming	
PRON		PRON	✓	us	\circ	Models based on	
NOUN		NOUN	✓	trouble	0	Models based on	
ADP		ADP	✓	for			
NOUN		NOUN	✓	years		CRF (Conditional	
PART		PART	✓	to		•	
VERB		VERB	✓	come		Random Field)	
PUNCT		PUNCT	✓	•		Randonn Icia,	
PUNCT		PUNCT	✓]		Noural Naturalia	
					O	Neural Networks	
					0	etc.	
					0	CiC.	

How to make it better

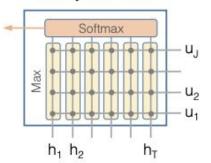
- Use extra information about the text
 - Char embeddings
 - Linguistic features: PoS and NER tags
 - 0 ...

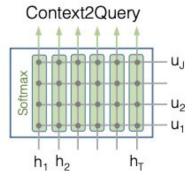
Better use of attention





Query2Context





Word Character Embedding Embedding GLOVE

Char-CNN

source: Bidirectional Attention Flow for Machine Comprehension

There are variants of and improvements to the BiDAF
architecture, but the central idea is the Attention Flow layer:
attention should flow both ways – from the context to the
question and from the question to the context

Make similarity matrix (with w of dimension 6d):

 $oldsymbol{S}_{ij} = oldsymbol{w}_{ ext{sim}}^T [oldsymbol{c}_i; oldsymbol{q}_i; oldsymbol{c}_i \circ oldsymbol{q}_i] \in \mathbb{R}$

most relevant to each context word):
$$\alpha^i = \mathrm{softmax}(\boldsymbol{S}_{i,:}) \in \mathbb{R}^M \quad \forall i \in \{1,\dots,N\}$$

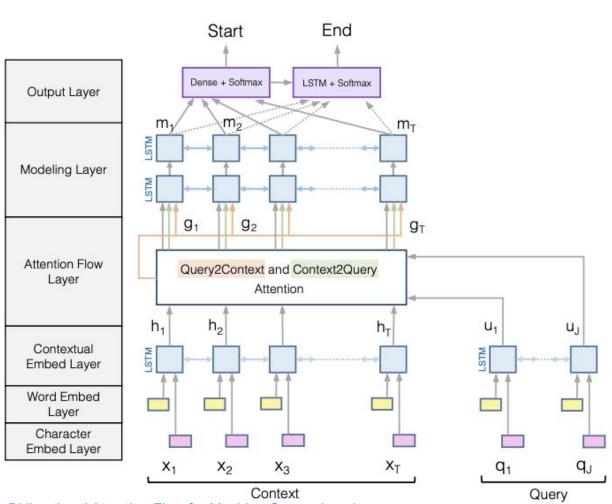
$$m{a}_i = \sum_{j=1}^N lpha_j^i m{q}_j \in \mathbb{R}^{2h} \quad orall i \in \{1,\dots,N\}$$

Attention Flow:

- attention should flow both ways from the context to the question and from the question to the context • Question-to-Context (Q2C) attention:
- o the weighted sum of the most important words in the context with respect to the query – slight asymmetry through max

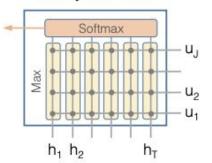
$$m{m}_i = \max_j m{S}_{ij} \in \mathbb{R} \quad orall i \in \{1,\dots,N\}$$
 $m{c}' = \sum_{i=1}^N eta_i m{c}_i \in \mathbb{R}^2$ $eta = \operatorname{softmax}(m{m}) \in \mathbb{R}^N$

For each passage position, output of BiDAF layer is: $\boldsymbol{b}_i = [\boldsymbol{c}_i; \boldsymbol{a}_i; \boldsymbol{c}_i \circ \boldsymbol{a}_i; \boldsymbol{c}_i \circ \boldsymbol{c}'] \in \mathbb{R}^{8h} \quad \forall i \in \{1, \dots, N\}$

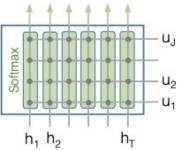




Query2Context



Context2Query



Word Embedding Embedding

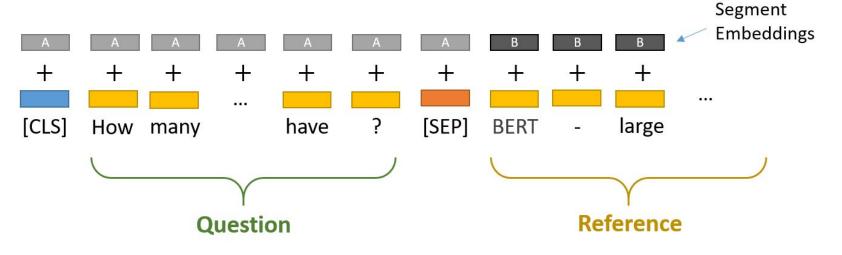
GLOVE

Char-CNN

Character

source: Bidirectional Attention Flow for Machine Comprehension

BERT for Question Answering



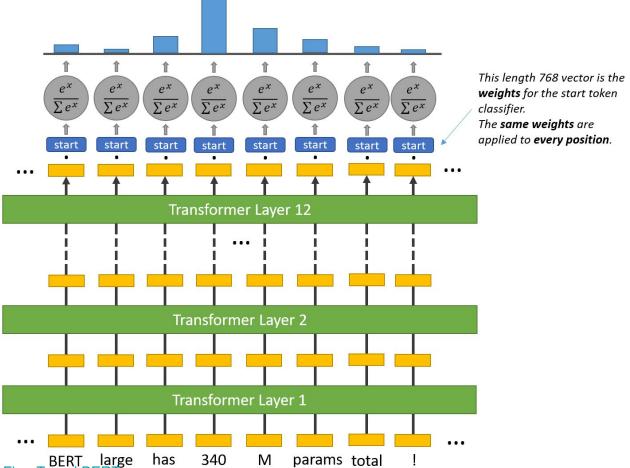
Question: How many parameters does BERT-large have?

Reference Text:

BERT-large is really big... it has 24 layers and an embedding size of 1,024, for a total of 340M parameters! Altogether it is 1.34GB, so expect it to take a couple minutes to download to your Colab instance.

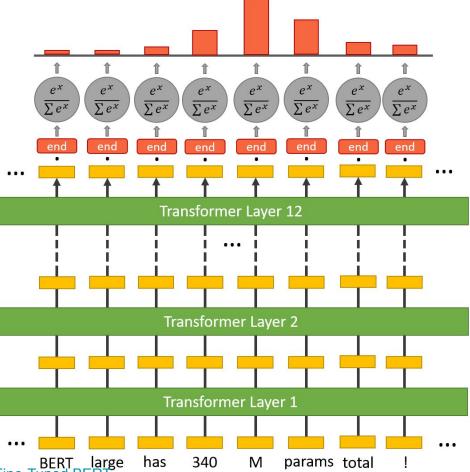
source: Question Answering with a Fine-Tuned BERT

BERT for Question Answering



BERT large source: Question Answering with a Fine-Tuned BERT

BERT for Question Answering



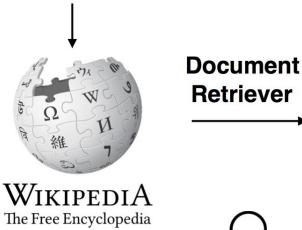
BERT large source: Question Answering with a Fine-Tuned BERT

Open-Domain Question Answering

Open-domain QA

SQuAD, TREC, WebQuestions, WikiMovies

Q: How many of Warsaw's inhabitants spoke Polish in 1933?

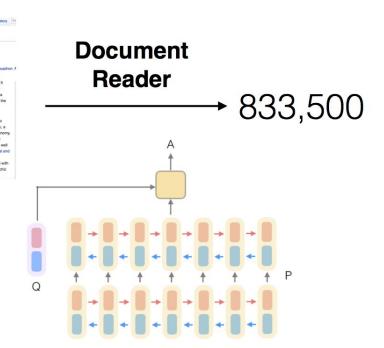




This article is about the Polish capital. For other uses, see Warszawa (disambiguation).

"Warszawa" redirects here. For other uses, see Warszawa (disambiguation).

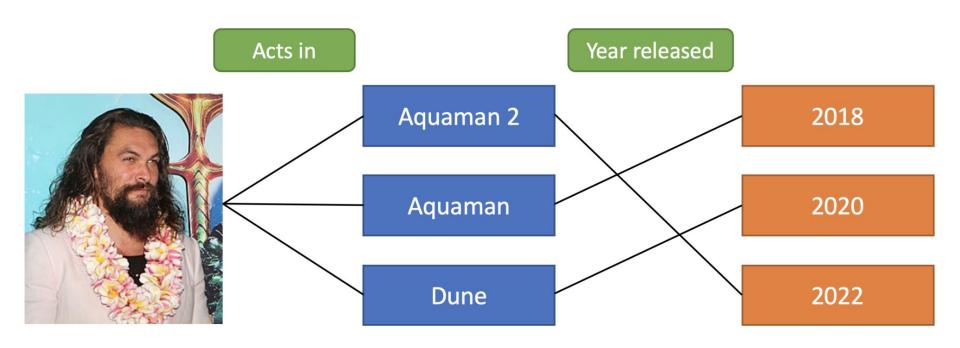
Warsaw



source: https://github.com/facebookresearch/DrQA

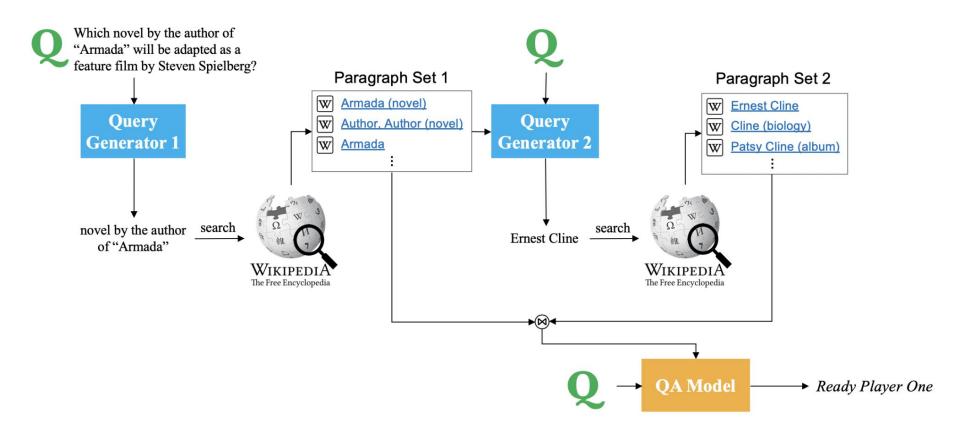
Possible problems

Example question: "What is the Aquaman actor's next movie?"



source: http://ai.stanford.edu/blog/answering-complex-questions/

Potential solutions



source: http://ai.stanford.edu/blog/answering-complex-questions/

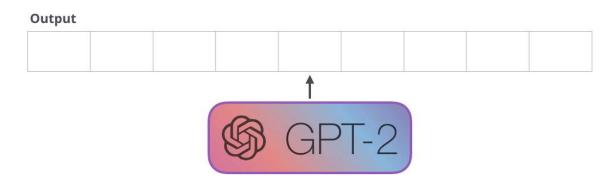
Outro

- Question answering systems bring us one step closer to human-like NLP systems
- Refer to the original papers on <u>Transformer-XL</u>, <u>BiDAF</u> and <u>SQuAD</u>, there are a lot of interesting ideas in there
- For Russian language:
 - SberQuAD paper provides a great aggregation of available materials, libraries and pretrained models
 - <u>deeppavlov.ai</u> and <u>Natasha project</u> provide many useful materials and pretrained models

GPT-2 & GPT-3



- Transformer-based architecture
- trained to predict the **next** word
- 1.5 billion parameters
- Trained on 8 million web-pages



On language tasks (question answering, reading comprehension, summarization, translation) works well

WITHOUT fine-tuning

Image source: https://jalammar.github.io/illustrated-gpt2

GPT-2: question answering

EXAMPLES

Who wrote the book the origin of species?

Correct answer: Charles Darwin

Model answer: Charles Darwin

What is the largest state in the U.S. by land mass?

Correct answer: Alaska

Model answer: California

GPT-2: language modeling

EXAMPLE

Both its sun-speckled shade and the cool grass beneath were a welcome respite after the stifling kitchen, and I was glad to relax against the tree's rough, brittle bark and begin my breakfast of buttery, toasted bread and fresh fruit. Even the water was tasty, it was so clean and cold. It almost made up for the lack of...

Correct answer: coffee

Model answer: food

GPT-2: machine translation

EXAMPLE

French sentence:

Un homme a expliqué que l'opération gratuite qu'il avait subie pour soigner une hernie lui permettrait de travailler à nouveau.

Reference translation:

One man explained that the free hernia surgery he'd received will allow him to work again.

Model translation:

A man told me that the operation gratuity he had been promised would not allow him to travel.

New AI fake text generator may be too dangerous to ... - The Guardian

https://www.theguardian.com/.../elon-musk-backed-ai-writes-convincing-news-fiction 4 days ago - The Elon Musk-backed nonprofit company OpenAl declines to release research publicly for fear of misuse. The creators of a revolutionary Al system that can write news stories and works of fiction – dubbed "deepfakes for text" – have taken the unusual step of not releasing ...

OpenAl built a text generator so good, it's considered too dangerous to ... https://techcrunch.com/2019/02/17/openai-text-generator-dangerous/ ▼
12 hours ago - A storm is brewing over a new language model, built by non-profit artificial intelligence research company OpenAl, which it says is so good at ...

The Al Text Generator That's Too Dangerous to Make Public | WIRED https://www.wired.com/story/ai-text-generator-too-dangerous-to-make-public/ ▼ 4 days ago - In 2015, car-and-rocket man Elon Musk joined with influential startup backer Sam Altman to put artificial intelligence on a new, more open ...

Elon Musk-backed Al Company Claims It Made a Text Generator ...
https://gizmodo.com/elon-musk-backed-ai-company-claims-it-made-a-text-gener-183... ▼
Elon Musk-backed Al Company Claims It Made a Text Generator That's Too Dangerous to
Release · Rhett Jones · Friday 12:15pm · Filed to: OpenAl Filed to: ...

Scientists have made an AI that they think is too dangerous to ... https://www.weforum.org/.../amazing-new-ai-churns-out-coherent-paragraphs-of-text/ 3 days ago - Sample outputs suggest that the AI system is an extraordinary step forward, producing text rich with context, nuance and even something ...

New AI Fake Text Generator May Be Too Dangerous To ... - Slashdot https://news.slashdot.org/.../new-ai-fake-text-generator-may-be-too-dangerous-to-rele... ▼ 3 days ago - An anonymous reader shares a report: The creators of a revolutionary AI system that can write news stories and works of fiction -- dubbed ...

GPT-2:

Top stake news and hype



OpenAl built a text generator so good, it's considered too dangerous to release

TechCrunch 11 hours ago



Elon Musk's Al company created a fake news generator it's too scared to make public

9 hours ago



The Al That Can Write A Fake News Story From A Handful Of Words

NDTV.com

2 hours ago

When Is Technology Too Dangerous to Release to the Public?

Slate • 2 days ago

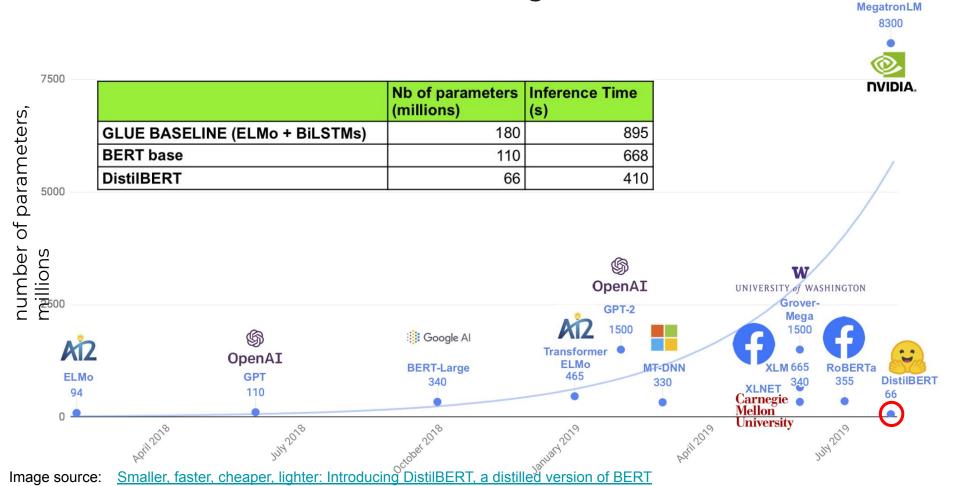


Scientists Developed an Al So Advanced They Say It's Too Dangerous to Release

ScienceAlert • 6 days ago

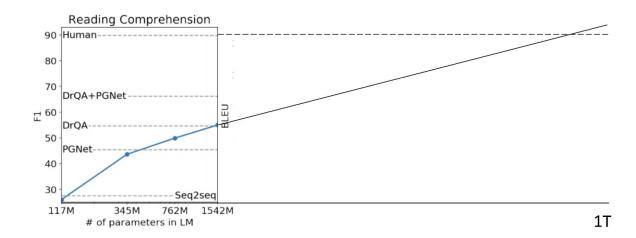






GPT-3, May 2020

Proportions are not preserved for visual sake



Hypothesis from Stanford CS224N Lecture 20 (2019)

May 2020: GPT-3

- GPT-2: 1.5 billion parameters
- GPT-3: **175 billion** parameters



Geoffrey Hinton @geoffreyhinton · Jun 10

Extrapolating the spectacular performance of GPT3 into the future suggests that the answer to life, the universe and everything is just 4.398 trillion parameters.





↑ 643



3.4K





- OpenAl Transformer
- ELMO
- BERT
- BERTology
- GPT
- <u>GPT-2</u>
- GPT-3













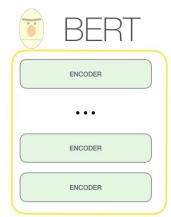
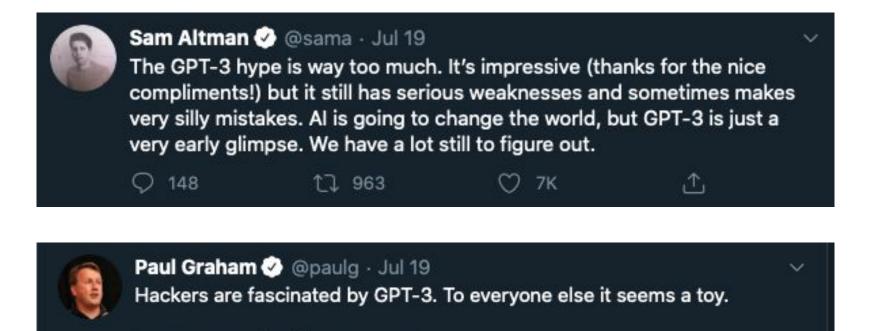




Image sources: http://jalammar.github.io/illustrated-bert/

More on GPT

Reaction: GPT-3



5K

Source: Twitter, more links available at https://lambdalabs.com/blog/qpt-3/

17. 604

Pattern seem familiar to anyone?

153

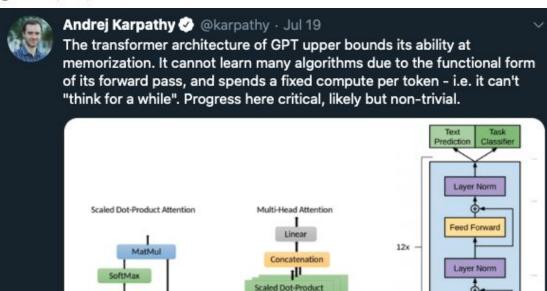
Reaction: GPT-3



Andriy Burkov • Following
ML at Gartner, author of The Hundred-Page Machine Learning Book
2d • 🕲

GPT-3 is the closest thing to artificial general intelligence (AGI) that I ever saw.

It's so strong that it makes me nervous.



Input Embedding

Masked Multi Self Attention

Text & Position Embed

Scale

Source: LinkedIn, Twitter

Reaction: GPT-3



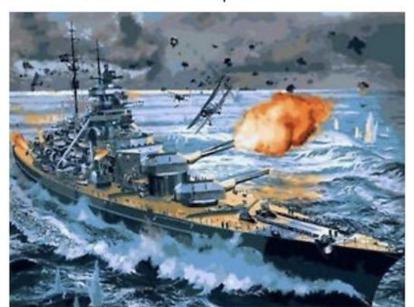


source: Andrej Karpathy twitter

miniGPT

- Great way to understand GPT
 - ~300 lines of code and examples

available GPT implementations



minGPT



source: miniGPT by Andrej Karpathy



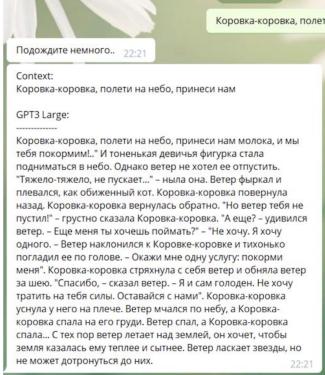


.III ? I

23:42

GPT-3 Large for Russian Language

19 октября



Outro

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Outro and farewell

- Now you know a bit more about this inspiring and promising area of Machine Learning and Deep Learning
- Many more challenges are awaiting us ahead
- Stay focused
- Thank you for you attention!
- And good luck!