

Question Answering



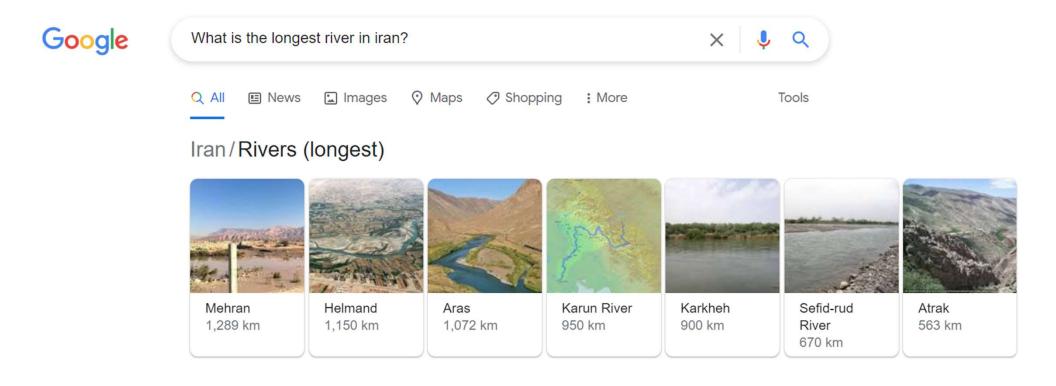
Mohammad Taher Pilehvar



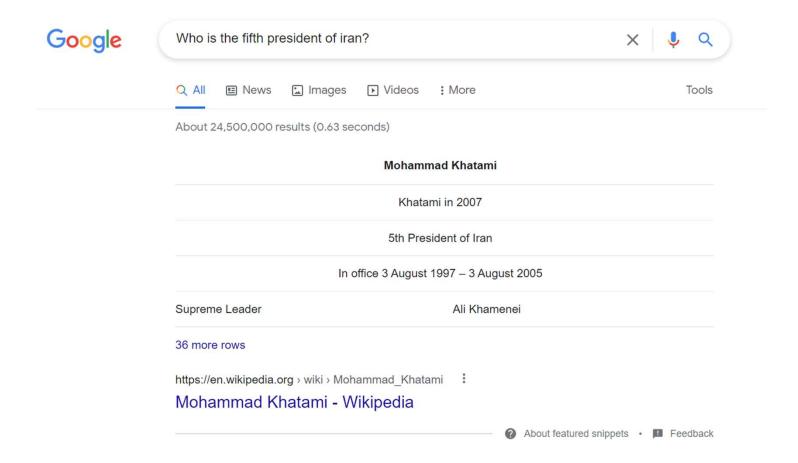
Natural Language Processing 1400 https://teias-courses.github.io/nlp00/

Most materials of these slides are taken from Stanford's CS224N course

Question Answering



Question Answering



Motivation: Question answering

- With massive collections of full-text documents, i.e., the web, simply returning relevant documents is of limited use
- Rather, we often want answers to our questions
 - Especially on mobile
 - Or using a digital assistant device, like Alexa, Google Assistant, ...
- We can factor this into two parts:
 - 1. Finding documents that (might) contain an answer
 - Which can be handled by traditional information retrieval/web search
 - 2. Finding an answer in a paragraph or a document
 - This problem is often termed Reading Comprehension
 - It is what we will focus on today

Machine Comprehension (Burges 2013)

A machine comprehends a passage of text if,

for any question regarding that text that can be answered correctly by a majority of native speakers,

that machine can provide a string which those speakers would agree both:

- answers that question,
- and does not contain information irrelevant to that question."

MCTest dataset

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. The girls traded stories and caught up on their lives. It was a happy time for everyone. The girls went to a restaurant for dinner. The restaurant had a special on catfish. Alyssa enjoyed the restaurant's special. Ellen ordered a salad. Kristin had soup. Rachel had a steak.

https://hugqingface.co/datasets/sagnikrayc/mctest

A brief history of Reading Comprehension

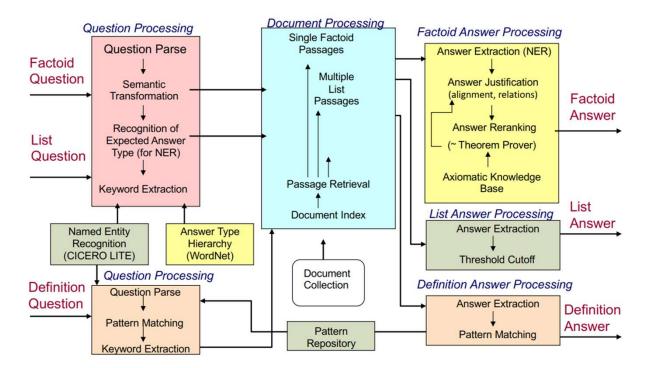
- Much early NLP work attempted reading comprehension
 - Schank, Abelson, Lehnert et al. c. 1977 "Yale A.I. Project"
- Revived by Lynette Hirschman in 1999:
 - Could NLP systems answer human reading comprehension questions for 3rd to 6th graders? Simple methods attempted.
- Revived again by Chris Burges in 2013 with MCTest
 - Again answering questions over simple story texts
- Floodgates opened in 2015/16 with the production of large datasets which permit supervised neural systems to be built
 - Hermann et al. (NIPS 2015) DeepMind CNN/DM dataset
 - Rajpurkar et al. (EMNLP 2016) SQuAD
 - MS MARCO, TriviaQA, RACE, NewsQA, NarrativeQA, ...

A brief history of Open-domain QA

- 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 Opendomain QA

A brief history of Open-domain QA

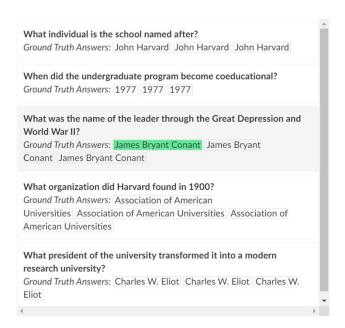
- Architecture of LCC (Harabagiu/Moldovan) QA system, circa 2003
- Complex systems but they did work fairly well on "factoid" questions



Stanford QA Dataset (SQuAD)

100K examples. Extractive question answering (answer span of text)

Established originally by the Massachusetts legislature and soon thereafter named for John Harvard (its first benefactor), Harvard is the United States' oldest institution of higher learning, and the Harvard Corporation (formally, the President and Fellows of Harvard College) is its first chartered corporation. Although never formally affiliated with any denomination, the early College primarily trained Congregationalist and Unitarian clergy. Its curriculum and student body were gradually secularized during the 18th century, and by the 19th century Harvard had emerged as the central cultural establishment among Boston elites. Following the American Civil War, President Charles W. Eliot's long tenure (1869–1909) transformed the college and affiliated professional schools into a modern research university; Harvard was a founding member of the Association of American Universities in 1900. James Bryant Conant led the university through the Great Depression and World War II and began to reform the curriculum and liberalize admissions after the war. The undergraduate college became coeducational after its 1977 merger with Radcliffe College.



https://rajpurkar.github.io/SQuAD-explorer/

Stanford QA Dataset (SQuAD)

• 100K examples. Extractive question answering (answer span of text)

Private schools, also known as independent schools, non-governmental, or nonstate schools, are not administered by local, state or national governments; thus, they retain the right to select their students and are funded in whole or in part by charging their students tuition, rather than relying on mandatory taxation through public (government) funding; at some private schools students may be able to get a scholarship, which makes the cost cheaper, depending on a talent the student may have (e.g. sport scholarship, art scholarship, academic scholarship), financial need, or tax credit scholarships that might be available.

Along with non-governmental and nonstate schools, what is another name for private schools?

Gold answers: 1 independent 2 independent schools 3 independent schools

Along with sport and art, what is a type of talent scholarship?

Gold answers: (1) academic (2) academic (3) academic

Rather than taxation, what are private schools largely funded by?

Gold answers: 1) tuition 2 charging their students tuition 3 tuition

SQuAD evaluation

- 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 $Precision = \frac{TP}{TP+FP}$, $Recall = \frac{TP}{TP+FN}$, harmonic mean $F1 = \frac{2PR}{P+R}$ 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)

SQuAD

Leaderboard

SQuAD2.0 tests the ability of a system to not only answer reading comprehension questions, but also abstain when presented with a question that cannot be answered based on the provided paragraph.

Rank	Model	EM	F1
	Human Performance	86.831	89.45
	Stanford University		
	(Rajpurkar & Jia et al. '18)		
1	IE-Net (ensemble)	90.939	93.21
Jun 04, 2021	RICOH_SRCB_DML		
2	FPNet (ensemble)	90.871	93.18
Feb 21, 2021	Ant Service Intelligence Team		
3	IE-NetV2 (ensemble)	90.860	93.10
May 16, 2021	RICOH_SRCB_DML		
4	SA-Net on Albert (ensemble)	90.724	93.01
Apr 06, 2020	QIANXIN		
5	SA-Net-V2 (ensemble)	90.679	92.94
May 05, 2020	QIANXIN		
5	Retro-Reader (ensemble)	90.578	92.97
Apr 05, 2020	Shanghai Jiao Tong University		
	http://arxiv.org/abs/2001.09694		
5	FPNet (ensemble)	90.600	92.89
Feb 05, 2021	YuYang		

SQuAD limitations

- 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:
 - 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

Formed in November 1990 by the equal merger of Sky Television and British Satellite Broadcasting, BSkyB became the UK's largest digital subscription television company. Following BSkyB's 2014 acquisition of Sky Italia and a majority 90.04% interest in Sky Deutschland in November 2014, its holding company British Sky Broadcasting Group plc changed its name to Sky plc. The United Kingdom operations also changed the company name from British Sky Broadcasting Limited to Sky UK Limited, still trading as Sky.

Ground Truth Answers: 2014 2014 2014 What is the name of the holding company for BSkyB? Ground Truth Answers: Sky plc British Sky Broadcasting Group plc British Sky Broadcasting Group plc What is the name of the United Kingdom operation for BSkyB? Ground Truth Answers: Sky UK Limited Sky UK Limited Sky UK Limited What company was angry about the merger of Sky Television and **British Satellite Broadcasting?** Ground Truth Answers: < No Answer> Who is the UK's smallest digital subscription television company? Ground Truth Answers: < No Answer> What year did BSkyB remove Sky Italia? Ground Truth Answers: < No Answer> When did RSINR hacome the largest IIS television company?

QA: Lack of cross-domain robustness

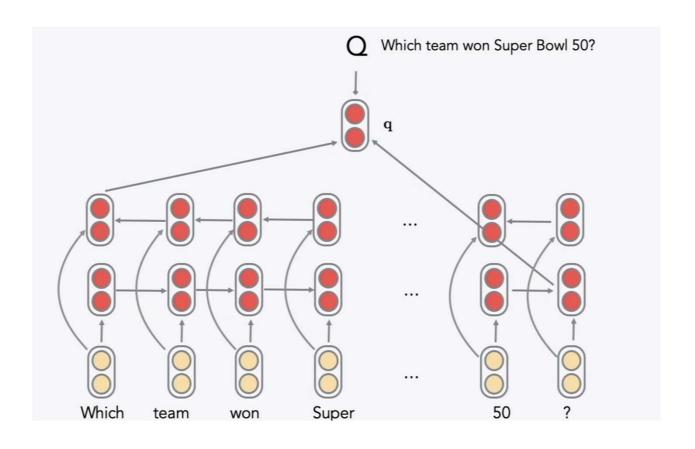
• Sen and Saffari (2020): What do Models Learn from Question Answering Datasets?

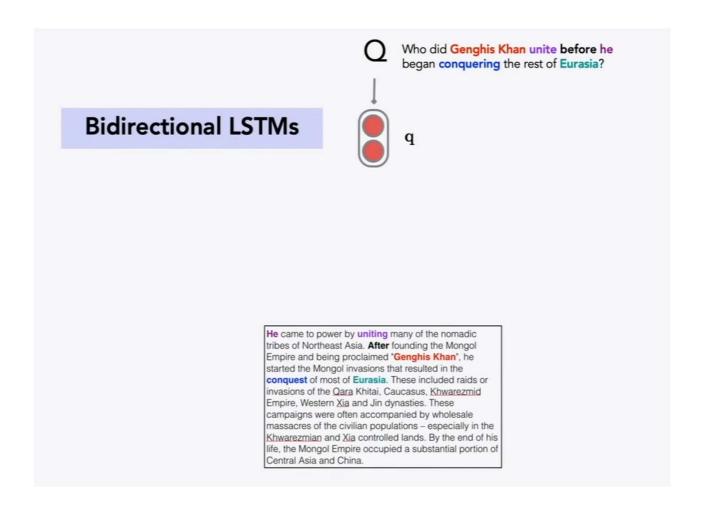
			Evaluated or	n		
		SQuAD	TriviaQA	NQ	QuAC	NewsQA
_	SQuAD	75.6	46.7	48.7	20.2	41.1
ора	TriviaQA	49.8	58.7	42.1	20.4	10.5
tune	NQ	53.5	46.3	73.5	21.6	24.7
Fine-tuned on	QuAC	39.4	33.1	33.8	33.3	13.8
щ	NewsQA	52.1	38.4	41.7	20.4	60.1

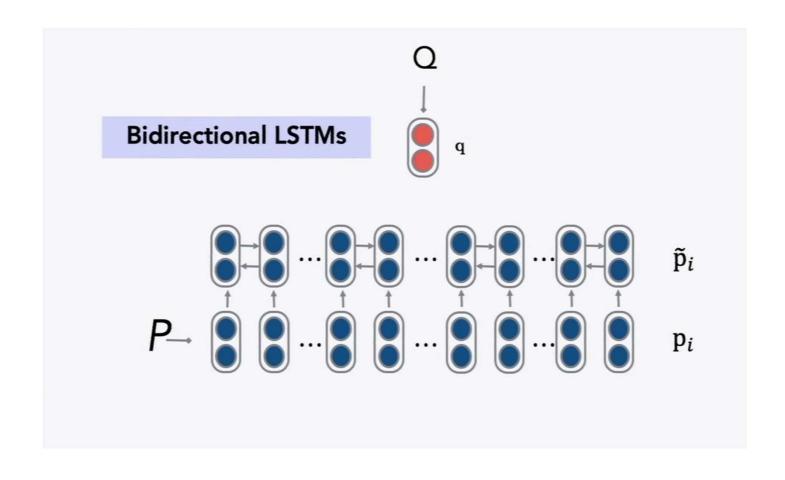
QA: Annotation bias (superficial cues)

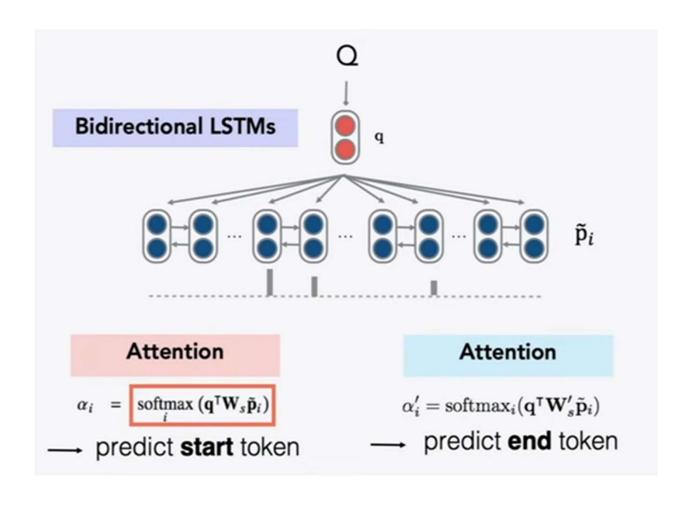
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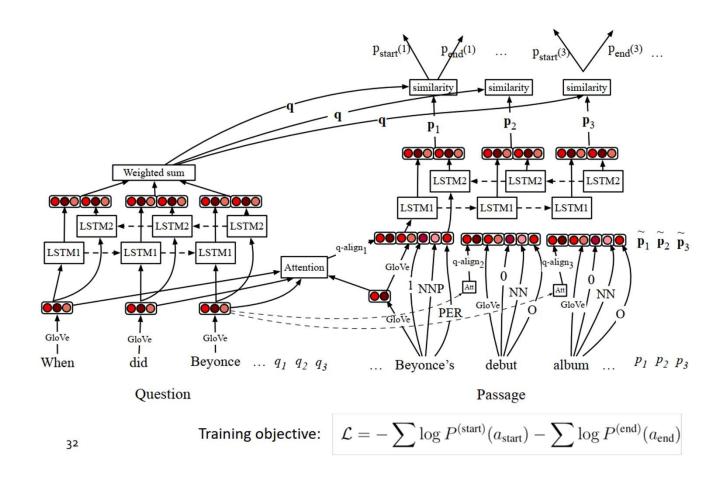
Dataset	Baseline	First Half	First Word	No Words
SQuAD	75.6	36.4	22.8	49.5
TriviaQA	58.7	45.8	31.8	30.4
NQ	73.5	61.4	50.3	32.7
QuAC	33.3	25.2	22.4	20.2
NewsQA	60.1	43.6	26.3	13.4

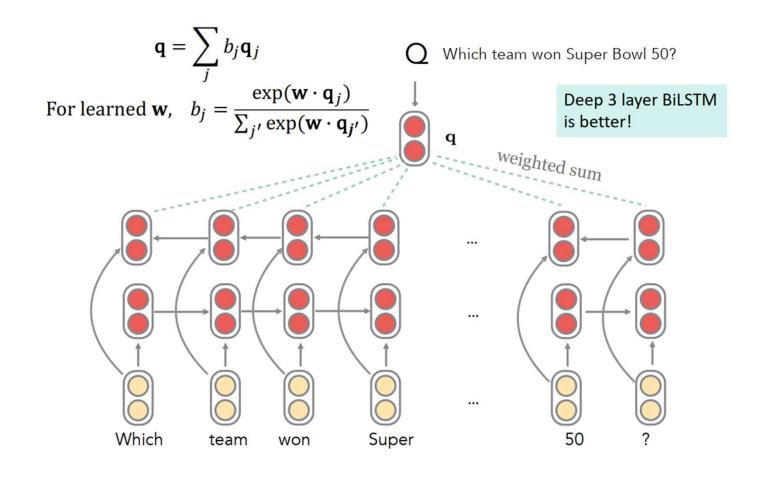




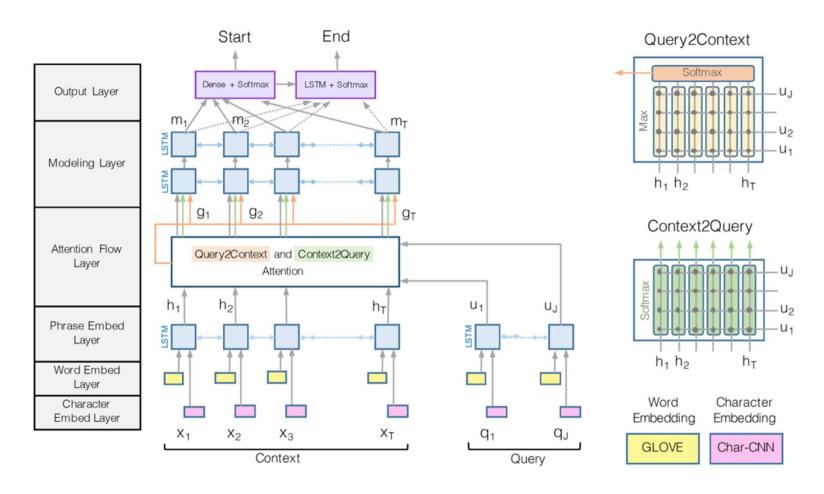


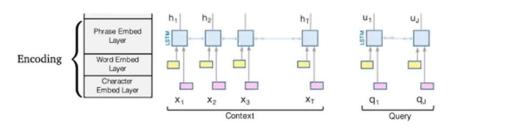


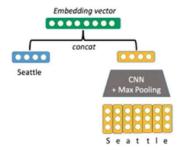




- Vector representation of each token in passage
- Made from concatenation of
 - Word embedding (GloVe 300d)
 - Linguistic features: POS & NER tags, one-hot encoded
 - Term frequency (unigram probability)
 - Exact match: whether the word appears in the question
 - 3 binary features: exact, uncased, lemma
- Aligned question embedding ("car" vs "vehicle")







 Use a concatenation of word embedding (GloVe) and character embedding (CNNs over character embeddings) for each word in context and query.

$$e(c_i) = f([GloVe(c_i); charEmb(c_i)])$$

$$e(q_i) = f([GloVe(q_i); charEmb(q_i)])$$

f: high-way networks omitted here

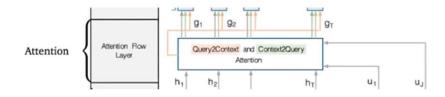
 Then, use two bidirectional LSTMs separately to produce contextual embeddings for both context and query.

$$\overrightarrow{\mathbf{c}}_{i} = \text{LSTM}(\overrightarrow{\mathbf{c}}_{i-1}, e(c_{i})) \in \mathbb{R}^{H}$$

$$\overleftarrow{\mathbf{c}}_{i} = \text{LSTM}(\overleftarrow{\mathbf{c}}_{i+1}, e(c_{i})) \in \mathbb{R}^{H}$$

$$\mathbf{c}_{i} = [\overrightarrow{\mathbf{c}}_{i}; \overleftarrow{\mathbf{c}}_{i}] \in \mathbb{R}^{2H}$$

$$\begin{aligned} \overrightarrow{\mathbf{q}}_i &= \mathrm{LSTM}(\overrightarrow{\mathbf{q}}_{i-1}, e(q_i)) \in \mathbb{R}^H \\ \overleftarrow{\mathbf{q}}_i &= \mathrm{LSTM}(\overleftarrow{\mathbf{q}}_{i+1}, e(q_i)) \in \mathbb{R}^H \\ \mathbf{q}_i &= [\overrightarrow{\mathbf{q}}_i; \overleftarrow{\mathbf{q}}_i] \in \mathbb{R}^{2H} \end{aligned}$$



 Query-to-context attention: choose the context words that are most relevant to one of query words.

While Seattle's weather is very nice in summer, its weather is very rainy in winter, making it one of the most gloomy cities in the U.S. LA is ...

Q: Which city is gloomy in winter?

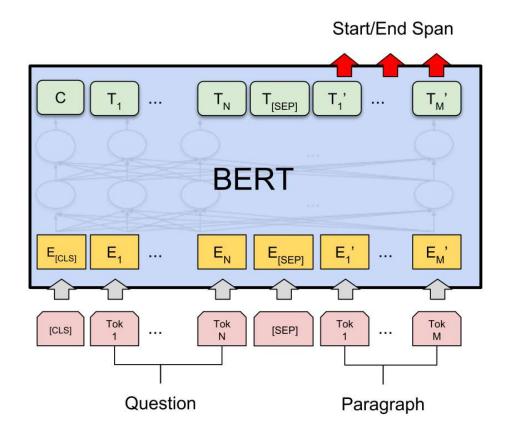
• Context-to-query attention: For each context word, choose the most relevant words from the query words.

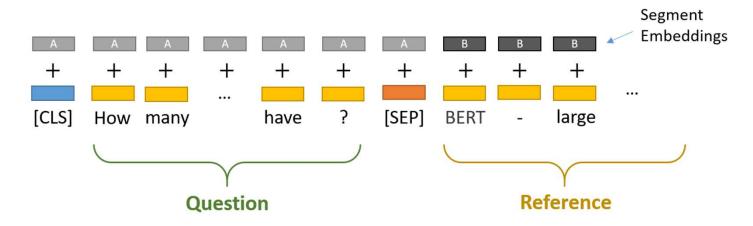
Q: Who leads the United States?

C: Barak Obama is the president of the USA.

For each context word, find the most relevant query word.

Stanford





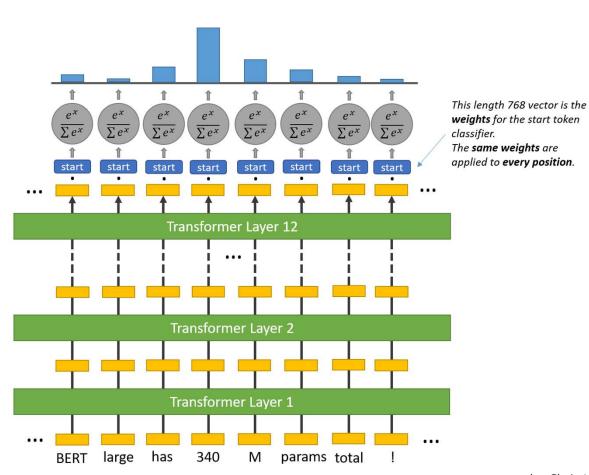
Question: How many parameters does BERT-large have?

Reference Text:

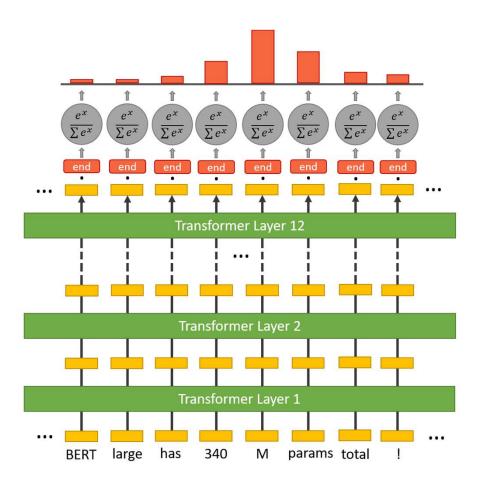
BERT-large is really big... it has 24 layers and an embedding size of 1,024, for a total of 340M parameters! Altogether it is 1.34GB, so expect it to take a couple minutes to download to your Colab instance.

$$\mathcal{L} = -\log p_{ ext{start}}(s^*) - \log p_{ ext{end}}(e^*)$$
 $p_{ ext{start}}(i) = \operatorname{softmax}_i(\mathbf{w}_{ ext{start}}^\mathsf{T} \mathbf{h}_i)$
 $p_{ ext{end}}(i) = \operatorname{softmax}_i(\mathbf{w}_{ ext{end}}^\mathsf{T} \mathbf{h}_i)$
where \mathbf{h}_i is the hidden vector of c_i , returned by BERT

where \mathbf{h}_i is the hidden vector of c_i , returned by BERT



by Chris McCormick

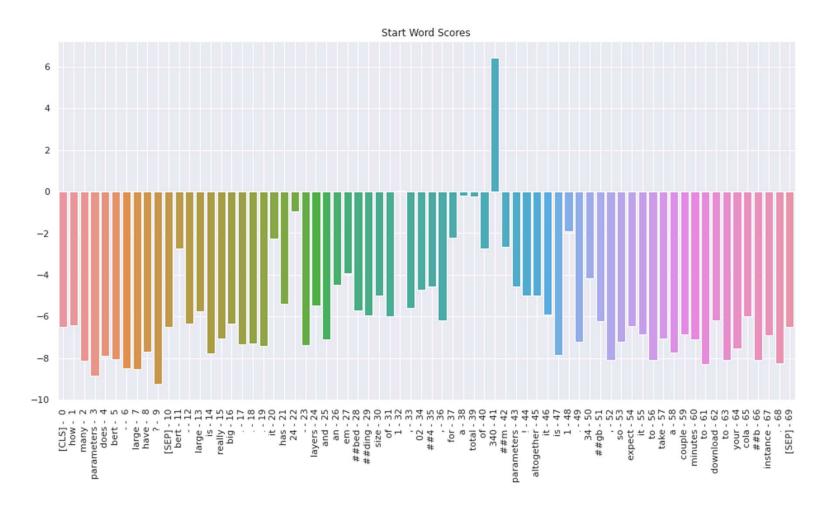


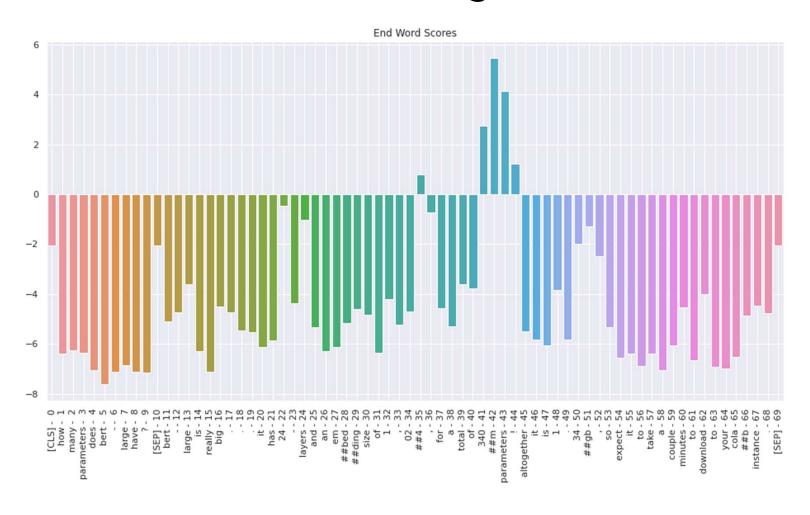
BERT vs. older models

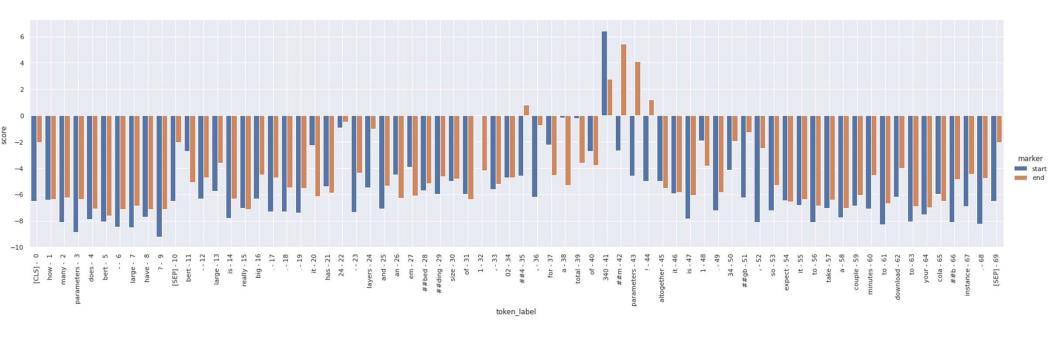
	F1	EM
Human performance	91.2*	82.3*
BiDAF	77.3	67.7
BERT-base	88.5	80.8
BERT-large	90.9	84.1
XLNet	94.5	89.0
RoBERTa	94.6	88.9
ALBERT	94.8	89.3

Fine-tuning BERT for QA
Colab notebook by Chris McCormick

https://colab.research.google.com/drive/1uSlWtJdZmLrl3FCNIIUHFxwAJiSu2JO-#scrollTo=bT5ESKDxfnLf







Questions