Question Answering: From the basics to the state-of-the-art with PrimeQA

By: Avi Sil

Principal Research Scientist & Manager

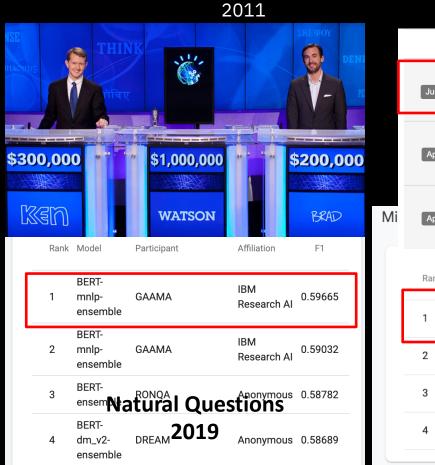


https://github.com/primeqa/primeqa





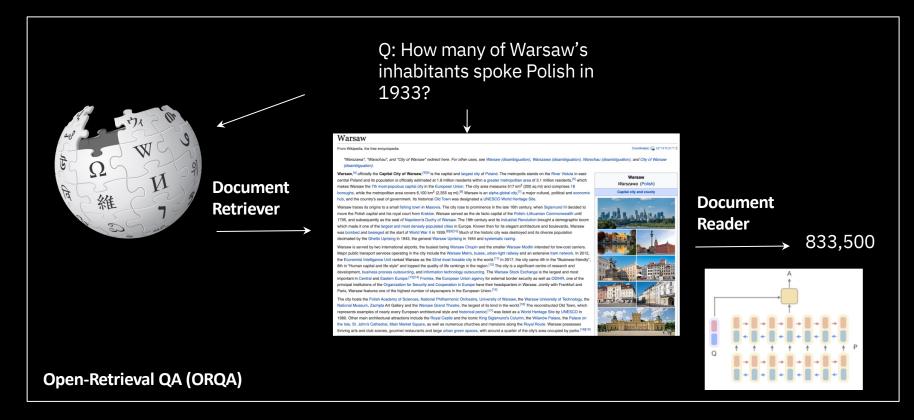
Question Answering milestones at IBM Research Al



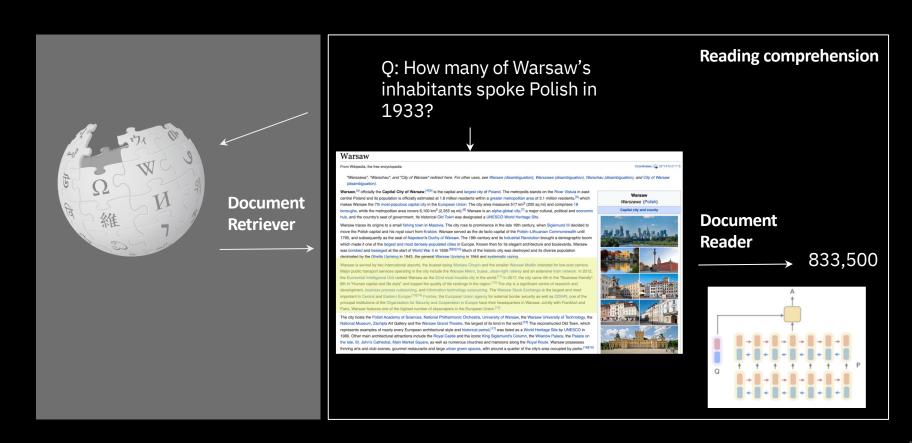
2021-2022

	Rank	М	Model						
	1 June 18, 2021	Goog	GAAMA (ColBERT Ensemble with IBM NMT + Google MT) IBM Research AI, NY						
	2 April 11, 2021	DPR + Goo University of Washin Al	67.2	59.3	yDi				
li	3 April 11, 2021	University of Washir	Path Retriever + Google Translate University of Washington, AI2, Google, UT Austin del Participant Affiliation						
_	Rank	Model							
	1 GAAMA (XLM-R) with ARES system		GAAMA	IBM Research Al	11/12/	2020	66.08		
	2	BERT with language- clustered vocab	Google- Research	Google Research	6/3/	2020	63.40		
	3	mBERT-mnlp-single	GAAMA	IBM Research Al	8/12/	2020	53.19		
	4	tydiqa-baseline	tydiqa-team	Google Research	2/14/	2020	52.69		
	202	20							

What is QA? Reading Comprehension vs Open-Retrieval QA



What is QA? Reading Comprehension vs Open-Retrieval QA



Link to IBM Research's GAAMA (public) demos

GAAMA: Go Ahead Ask Me Anything

Reading Comprehension (English only): http://ibm.biz/ibm_gaama



ORQA Covid-19 Demo: http://ibm.biz/covidAnswerFinding



Retrievers – Nuts and bolts

A Traditional Retriever

A TF-IDF [Robertson 2004] weighted term vector model over unigrams/ bi-grams

tf = term frequency, idf = inverse document frequency
$$t$$
: term (uni/bi), d : document (= one Wiki. article), D : corpus (= Wikipedia)
$$\text{tf-idf}(t,d,D) = \text{tf}(t,d) \times \text{idf}(t,D) \qquad \text{idf}_t = \log \frac{N}{\text{df}_t}.$$

$$\text{tf}(t,d) = \log \left(1 + \text{freq}(t,d)\right)$$

$$\text{idf}(t,D) = \log \left(\frac{|D|}{|d \in D: t \in d|}\right)$$

However, this retriever is not trainable

However, they have limitations!

1. Can NOT answer questions when there's little or 2. Can NOT retrieve cross-lingual passages without no lexical overlap

translation (needs special models)

3. Lower performance on *some* benchmarks

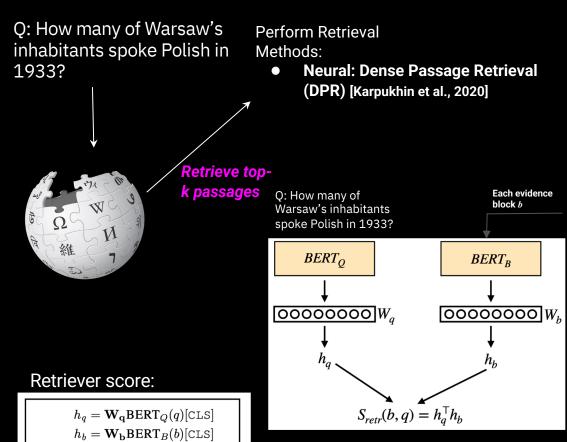
> Model NQ BM25 59.1 79.4 DPR

"Who is the bad guy in lord of the rings?"

"Sala Baker is an actor and stuntman from New Zealand. He is best known for portraying the **villain** Sauron in the LOTR trilogy by Peter Jackson..."

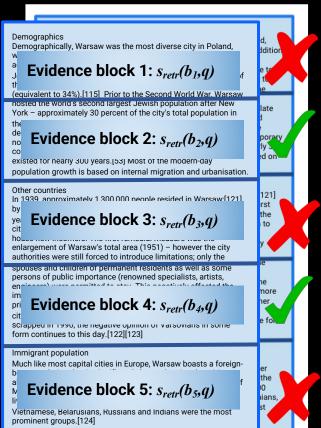


Dense Passage Retrieval (DPR)



 $S_{retr}(b,q) = h_a^{\top} h_b$

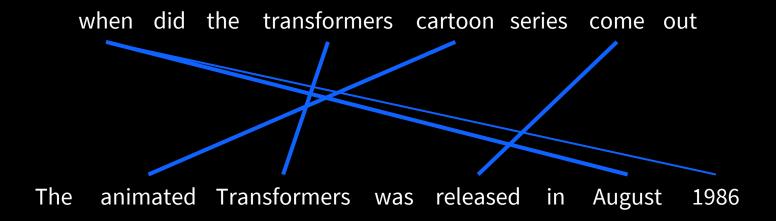
Select top-k blocks from collection (e.g. Wikipedia)



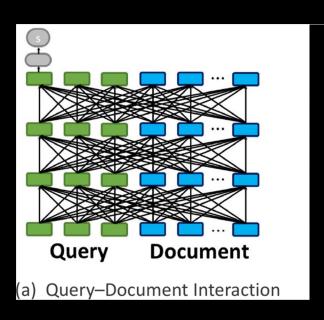
ColBERT

Select top-k blocks from collection (e.g. Wikipedia) Q: How many of Warsaw's Perform Retrieval inhabitants spoke Polish in Methods: 1933? Neural: ColBERT [Khattab et al., 2021] Demographically, Warsaw was the most diverse city in Poland. Evidence block 1: $S_{retr}(b_1,q)$ (equivalent to 34%),[115] Prior to the Second World War, Warsaw nosted the world's second largest Jewish population after New York - approximately 30 percent of the city's total population in Evidence block 2: $s_{retr}(b_2,q)$ Retrieve topexisted for nearly 300 years.[53] Most of the modern-day k passages population growth is based on internal migration and urbanisation. Q: How many of Warsaw's inhabitants Other countries 121] In 1939, approximately 1,300,000 people resided in Warsaw [121]. spoke Polish in 1933? Fyidence block 3: Srote(b3,q) area (1951) - however the city troduce limitations; only the ent residents as well as some enowned specialists, artists, ck 4: $s_{retr}(b_4,q)$ [123] **Document Document** Query Document Query (a) Representation-based Similarity (b) Query-Document Interaction (c) All-to-all Interaction (d) Late Interaction Europe, Warsaw boasts a foreign-(e.g., DSSM, SNRM) (e.a., DRMM, KNRM, Conv-KNRM) (e.g., BERT) (i.e., the proposed ColBERT) Evidence block 5: $s_{retr}(b_5,q)$ Other choices for Neural Retrievers Vietnamese, Belarusians, Russians and Indians were the most prominent groups.[124]

Soft-matching of query to document terms



Situating ColBERT in the neural IR landscape



PLAID ColBERT results: MS MARCO v1



System		IRR@10 R@100 I		R@1k	Latency (ms)		
	17117	WIRKWIO KWIOO F			1-CPU	8-CPU	GPU
BM25 (PISA [34]; $k = 1000$)		18.7*	-	-	8.3*	-	-
SPLADEv2 (PISA; $k = 1000$)		36.8*	-	97.9*	220.3*	-	-
ColBERTv1		36.1	87.3	95.2	-	-	54.3
Vanilla ColBERTv2 (p=2, c=2 ¹³)		39.7	90.4	96.6	3485.1	921.8	53.4
Vanilla ColBERTv2 (p=4, c=2 ¹⁶)		39.7	91.4	98.3	-	4568.5	259.6
PLAID ColBERTv2 $(k = 10)$		39.4	-	-	185.5	31.5	11.5
PLAID ColBERTv2 ($k = 100$)		39.8	90.6	-	222.3	52.9	20.2
PLAID ColBERTv2 ($k = 1000$)		39.8	91.3	97.5	352.3	101.3	38.4

Huge speed-ups

But do these work in other languages than English?

Problem statement

Cross-lingual Open-Retrieval Question Answering (XOR QA)

- Practical issue in QA: information scarcity and information asymmetry
- XOR QA: Enable questions from one language (non-Eng) to be answered via content from another language (English)



Multilingual Retriever – Training Algorithm



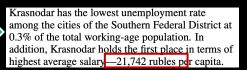






ColBERT Question Question Text Encoder MaxSim ColBERT Offline Online **Passage** Corpus Passaae **Passage** Indexing Retrieval **Encoder**

Mayor of Neuilly-sur-Seine from 1983 to 2002, he was Minister of the Budget under Prime Minister Édouard Balladur (1993–1995).



founded Hanei Maebashi Silk Mill and learned instrumental silk reeling techniques directly from Caspal Müller)

IBM / Google

Translation Engine

XLM-RoBERTa

(monolingual English)

BERT

yor of Neuilly-sur-Seine from 1983 to 2002, he Minister of the Budget under Prime Minister ouard Balladur (1993–1995).

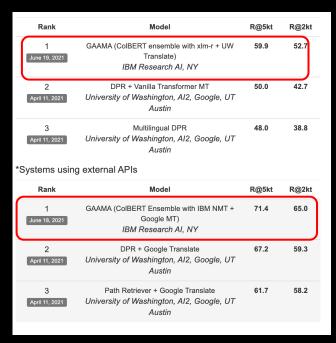
1993년 프랑스 총리는 누구인가요?

technique?)

family with five children and longstanding ties to France

election, it could govern with Chirac as prime minister

Results

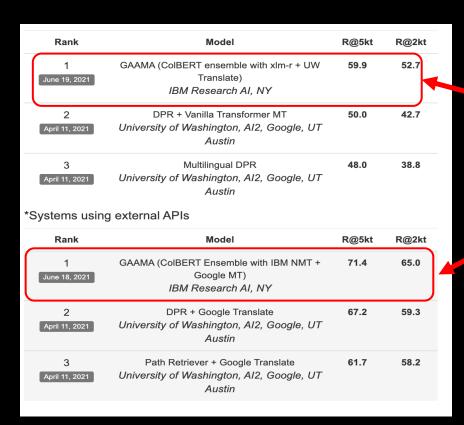


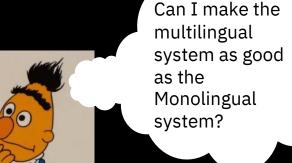
We obtained the top position in the leaderboard



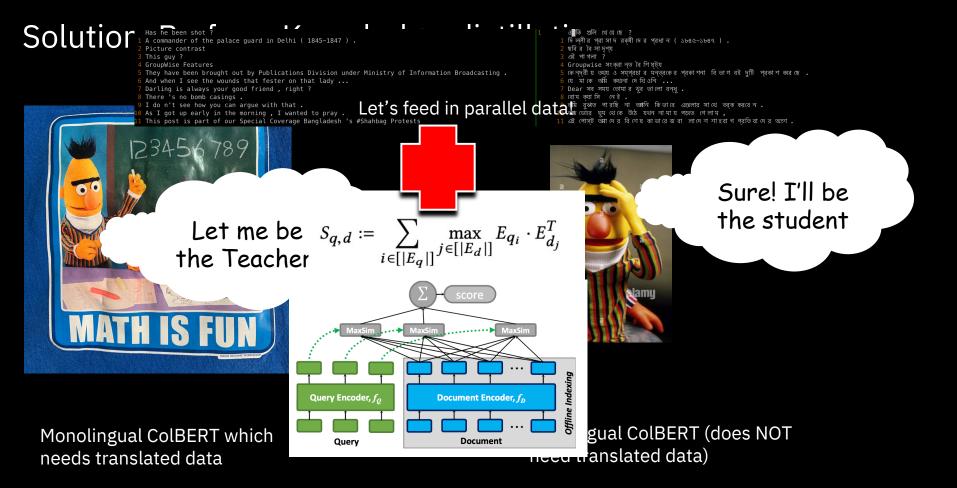
XOR-TyDi Cross-lingual Open-Retrieval Question Answering

Multilingual Retriever – Results on XOR TyDi Retrieve





Then I won't need to translate my incoming queries to English!



F1: 75.0 (yes, we've a better model now!)

F1: 54.7

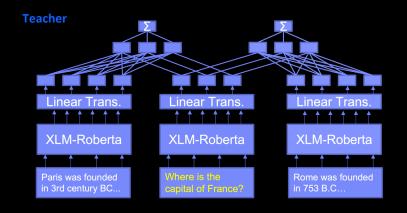
Knowledge distillation with Dr. Decr

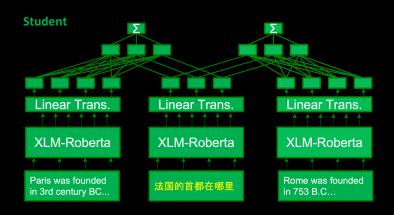
How?:

<u>Learning Cross-Lingual IR from an English Retriever</u> Li, Franz, Sultan, Iyer, Lee and Sil *NAACL*, 2022

- English trained model teacher and have the cross-lingual model (student) learn from the teacher.
- Student: Dr. DECR (\underline{D} ense \underline{R} etrieval with \underline{D} istillation- \underline{E} nhanced \underline{C} ross-lingual \underline{R} epresentation)

MSE/KLDiv Loss





Knowledge distillation with Dr. Decr

ldea:

- Use English trained model as teacher and have the cross-lingual model (student) learn from

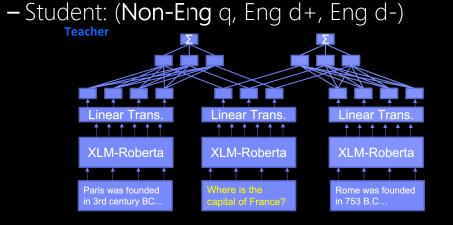
the teacher.

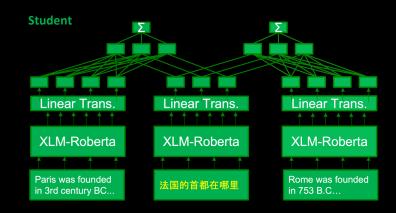
Input:

– Teacher: (Eng q, Eng d+, Eng d-)

BaselineXOR distillationTeacher54.966.175.1

11.2 points improvement





Enhancement 1: Synthetic data

Idea:

- Using synthetic triples as extra training data in distillation

Created extra 6.5M triples

Baseline	Baseline -> XOR distillation	Baseline -> Synthetic data -> XOR distillation	Teacher
54.9	66.1	67.7	75.1

Another 1.6 points improvement with synthetic data

Enhancement 2: Parallel Corpus

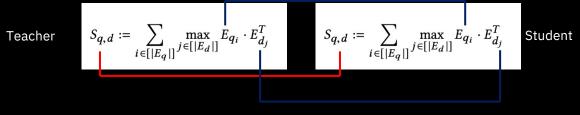
General issue with IR dataset:

- High quality triples are difficult to make, which limits the training
- Can other source of data be used to improve training?
- Parallel corpus? We have a lot!

Idea:

Instead of teaching student to learn from teacher's score, have the student to learn from teacher's vector representation

MSE, Query vectors



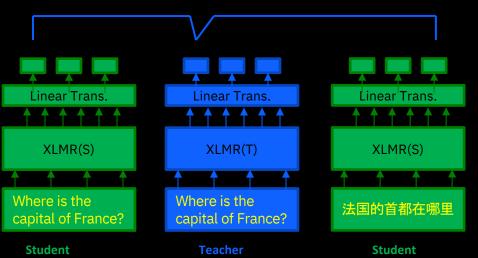
MSE, Document vectors

If the student can produce same vectors as the teacher, their scores S(q,d) will also be the same

Token alignment idea

When teacher and student see different languages, which vector to learn from which? Idea:

- Align teacher's output token with student, based on their cosine distances
- Will be noisy but hopefully can still work



	<s></s>	法国	的	首都	在哪里
where	0.017	0.022	0.023	0.025	0.014
is	0.014	0.023	0.017	0.026	0.015
the	0.019	0.031	0.011	0.039	0.028
capital	0.031	0.018	0.030	0.015	0.019
of	0.025	0.034	0.014	0.043	0.032
France	0.017	0.009	0.026	0.021	0.016

During distillation, student sees both the Eng and Non-Eng version of the content

Summary of result

Distillation result Summary:

- 11.2 points improvement from XOR data



-1.6 points improvement from synthetic data

- 4.4 points improvement from parallel co

Baseline	Baseline -> XOR distillation	Baseline -> Synthetic distillation		
54.9	66.1	67.7		

- Another 4.4 points improve
- In total, 17.2 points improv

Rank	Model	R@5kt	R@2kt
1	DrDecr	70.3	63.0
February 11, 2022	IBM Research Al		
2	Sentri 2.0 base	64.6	58.5
March 14, 2022	Huawei Noah's Ark lab		
3	Contrastive Context-aware Pretraining Model	63.0	54.8
January 7, 2022	(CCP)		
	Anonymous		
4	Single Encoder Retriever (Sentri)	61.0	52.7
August 26, 2021	Huawei Noah's Ark lab		
5	Single Encoder Retriever (Sentri,	60.7	55.5
October 7, 2021	resubmission)		
	Huawei Noah's Ark lab		

One Limitation of Neural Retrievers

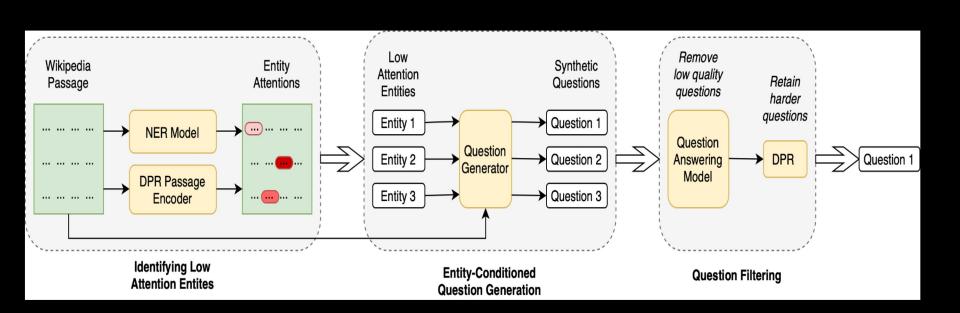
- Problem: Neural retrievers do NOT attend to many important phrases in the passage, e.g., academy of management and twentieth century.
- Consequence: Low retriever scores for questions that are about these lessattended entities.
- Solution: Biases in retrievers can be overcome by generating synthetic data that is targeted towards these shortcomings.

[CLS] frederick winslow taylor [SEP] frederick winslow taylor (march 20 | 1856 march 21 | 1915 | was an american mechanical engineer who sought to improve industrial efficiency | he was one of the first management consultants | taylor was one of the intellectual leaders of the efficiency movement and his ideas, broadly conceived | were highly influential in the progressive era (1890s - 1920s | taylor sum ##med up his efficiency techniques in his 1911 book "the principles of scientific management" which, in 2001 | fellows of the academy of management voted the most influential management book of the twentieth century. his pioneering work in applying engineering principles to the work [SEP]

passage representation. Darker sh Question attention.	ading indicat Type	Score
the american mechanical engineer who sought to improve industrial efficiency	Gold	85.9
who wrote the most influential manage- ment book of the twentieth century	Synthetic	78.0
who was considered the father of management during the <i>progressive</i> era	Synthetic	82.2
who wrote the principles of scientific management	Synthetic	86.8

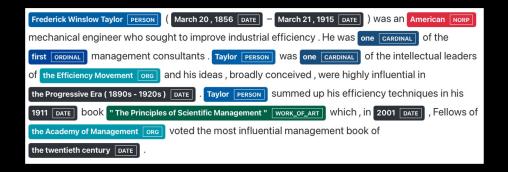
Retrieval scores from DPR for different questions corresponding to the passage in left. Important terms in the question, that are also in the passage, are shown in *italics*

Approach



Entity-Conditioned Question Generation

- Given a passage and an entity in that passage, we aim to generate a synthetic question about that entity.
- While training the synthetic question generator, entities within questions in existing machine reading comprehension datasets are matched against the passage to identify the conditioning entities.
- While generating synthetic IR data, entities that get lowest attentions from the IR model are used as the conditioning entities.



Conditioned Entity	Generated Synthetic Question
Progressive era	who was considered the father of management during the progressive era
Principles of Scientific Management	who wrote the principles of scientific management
Efficiency Movement	who is known as the father of efficiency movement

Experiments

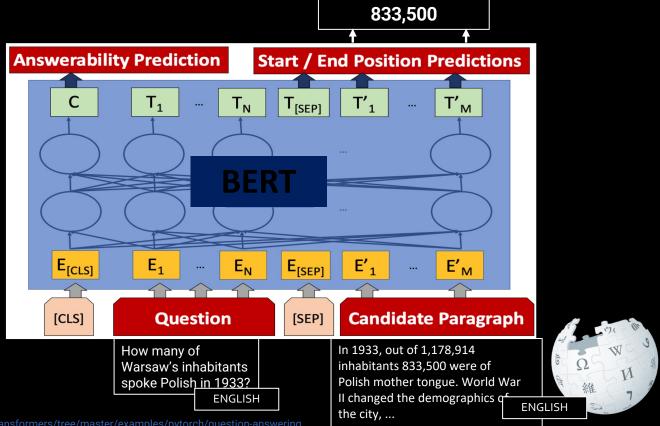
- The model that uses the entity-conditioned questions within its pre-training is named *Mixed-DPR*, and is compared with the baseline DPR.
- We also compare with a model pre-trained on data that contains synthetic questions generated without any conditioning (UnCon-DPR).
- We see that Mixed-DPR gives upto 2% more attention to latter sentences of the passage, compared to the baseline DPR model.

Model	Natural Questions (NQ)					WebQuestions		
Model	Full	test	No ans. overlap No ques. overlap		Test			
	Top-1	Top-5	Top-1 Top-5		Top-1	Top-5	Top-1	Top-5
TF-IDF	14.2	32.0	13.6	28.6	14.6	31.8	14.5	32.1
BM25	22.7	44.6	20.1	39.6	24.0	43.4	18.9	41.8
DPR (ours)	44.3	67.1	32.2	53.2	37.2	60.1	29.4	51.6
UnCon-DPR	45.8	68.4	32.7	54.4	36.9	60.6	31.5	53.2
Mixed-DPR	45.9	69.0	33.8	55.7	37.9	62.0	32.2	53.9

Reader – nuts and bolts

Machine Reading Comprehension (MRC)

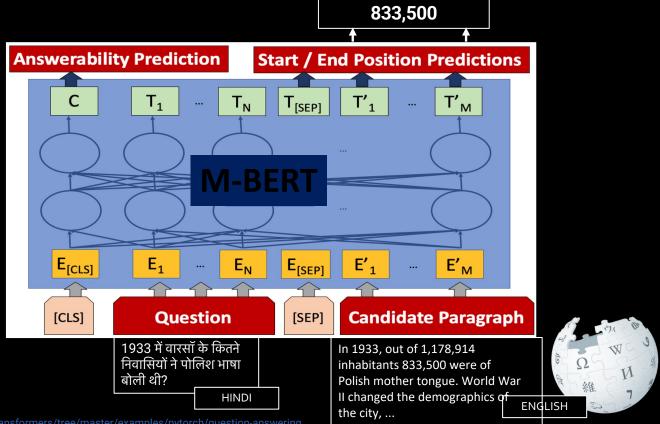
Popular choice: Add a fine-tuning layer on top of BERT [Devlin et al., 2019]





Multilingual Machine Reading Comprehension (MRC)

Popular choice: Add a fine-tuning layer on top of M-BERT [Bornea et al., 2021]





Domain Generalization: Not to Overfit or Underfit?



EMNLP 2022 Paper

 Domain Generalization in QA: Not to Overfit or Underfit the Source Domains? Md Arafat Sultan, Avirup Sil and Radu Florian

We want our models to generalize to new, unseen domains

We have access to multiple source domains with labeled training data

But how do we train on them to do well on unseen *target* domains?

- Common advice: Regularize training (cross-domain); focus is on noise
- We say: Learn your source domains well; focus is on signal

How do we Learn the Source Domains Better?

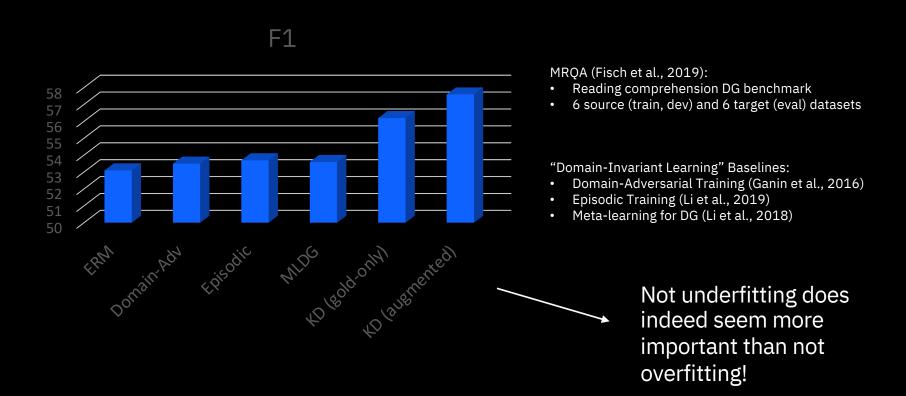
Wait, isn't this the most basic question in machine learning?

We know many ways in which to approach it

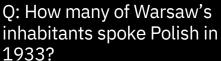
How about knowledge distillation?

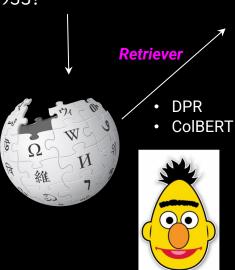
- Let a bigger model learn the source domains first
 - High capacity, low inductive bias ⇒ better in-domain and OOD generalization
- Then learn from this teacher model, not directly from the data

Domain Generalization: Results on MRQA

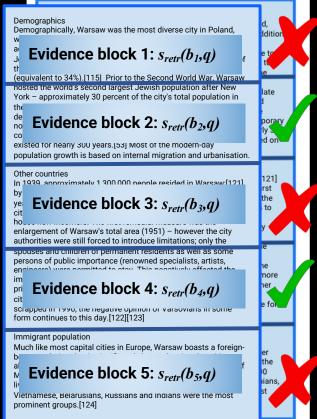


Various Setups of ORQA









PrimeQA



Reader

The number of inhabitants that spoke Polish in 1933 Warsaw is 833,500.

Fusion in Decoder [Izacard & Grave, 2020]

What about QA over multimedia data e.g. images & text?

MuMuQA: Multimedia Multi-hop QA

Given a news article with an image-caption pair and a question, a system needs to answer the question by extracting a short span from the body text.

Answering the questions require multi-hop reasoning:

- The first hop requires cross-media grounding between image and caption to get the *bridge item*.
- The second hop requires reasoning over the news body text by using the bridge item to extract the final answer.

The benchmark reflects questions that news readers might have after looking at the visual information in the news article, without having read the relatively longer body text.

Image - Caption



Israeli Prime Minister Benjamin Netanyahu (R) speaks with Finance Minister Moshe Kahlon during the weekly cabinet meeting in Jerusalem

Body Text

A dispute between Israeli Prime Minister Benjamin Netanyahu and his finance minister over broadcast regulation sparked speculation on Sunday that Netanyahu could seek an election two years ahead of schedule.

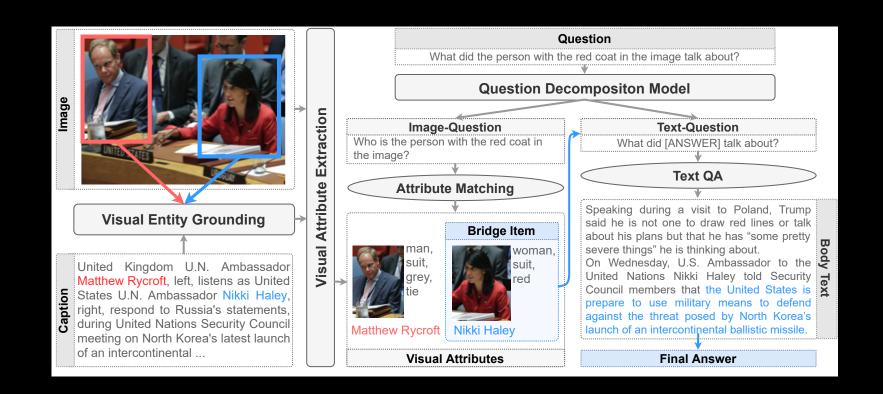
...

The Israeli media quoted Netanyahu as telling ministers from his Likud party that he would dissolve the government if Kahlon didn't fall into line. Kahlon heads the Kulanu cabinet party, a center-right partner in Netanyahu's

Question: What party does the person with the blue tie in the image belong to?

Answer: Likud

Pipeline-based Multimedia QA



Results and Analysis

Model	Dev	Test
Multi-hop Text-only QA	25.6	24.8
End-to-end Multimedia QA	12.1	11.5
Pipeline-based Multimedia QA	37.3	32.6
Human Baseline	-	66.5

F1 Performance (%) of different baselines on the MuMuQA evaluation benchmark.



Caption: A woman places flowers on an altar set up in honor of **Berta Caceres** during a demonstration outside Honduras' embassy in Mexico City, June 15, 2016.

Question: Where was the person in the photo in the image from?

Bridge Item: Berta Caceres

An example where the grounding system failed to capture the gold bridge item (in green). The grounded entity is in blue in the caption and its corresponding bounding box is shown in blue in the image.

Coming soon to



However, how can we perform these experiments easily?

- Is there a SINGLE repository that contains the latest & greatest in QA research already?
- Is that based on HuggingFace's transformers library?

Welcome Cecilia! A new graduate student

Cecilia has taken ML 101, NLP 101 and knows basic QA details.

- She has read about: the academic benchmarks for performing QA:
 - Multilingual Machine Reading Comprehension: TyDI [Clark2019]
 - Cross-lingual Open Retrieval: XOR-TyDI [Asai2020]
 - Table QA: WikiSQL [Zhong2017]



Cecilia does some literature survey! TyDi QA

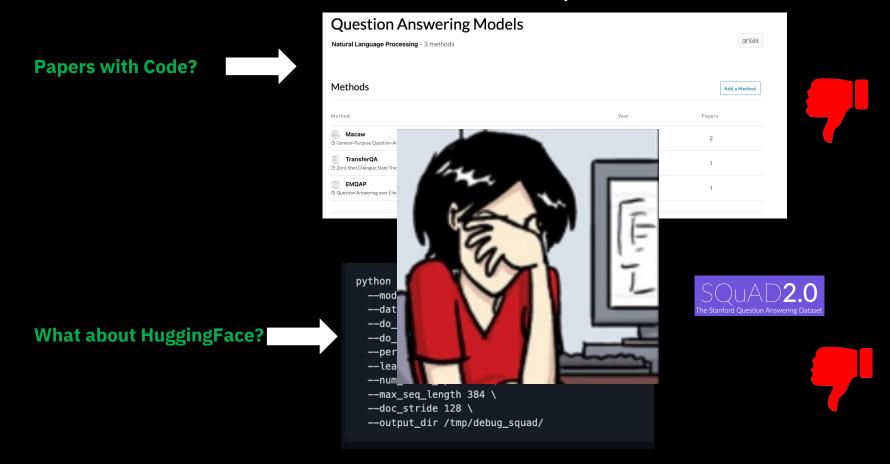
- Cecilia wants to get the latest greatest SOTA models to start with!
 - She sees the following leaderboards ->
 - She reads the following papers: SOTA on the tasks
 - TAPAS --[Herzig2020_ACL] SOTA on WikiSQL
 - Dr. Decr -- [Li2022_NAACL, Bornea2020_AAAI]— SOTA on XOR TyDI



Piv1.1 Rank Model R@5kt 1 DrDecr 70.3 February 11, 2022 IBM Research AI		365 AI	7-7	
1 DrDecr 70.3 February 11, 2022 IBM Research AI 2 Sentri 2.0 base 64.6 March 14, 2022 Huawei Noah's Ark lab 3 Contrastive Context-aware Pretraining Model (CCP) Anonymous 4 Single Encoder Retriever (Sentri) August 26, 2021 Huawei Noah's Ark lab 5 Single Encoder Retriever (Sentri, resubmission) 60.7	Di v1.1	Rank	Model	R@5kt
March 14, 2022 Huawei Noah's Ark lab Contrastive Context-aware Pretraining Model (CCP) Anonymous 4 Single Encoder Retriever (Sentri) Huawei Noah's Ark lab 5 Single Encoder Retriever (Sentri, resubmission) 60.7				70.3
Pretraining Model (CCP) Anonymous 4 Single Encoder Retriever (Sentri) August 26, 2021 Huawei Noah's Ark lab 5 Single Encoder Retriever (Sentri, resubmission) 60.7				64.6
August 26, 2021 Huawei Noah's Ark lab 5 Single Encoder Retriever (Sentri, resubmission) 60.7			Pretraining Model (CCP)	63.0
October 7, 2021 resubmission)			0 ()	61.0
			resubmission)	60.7

Model	Dev	Test
Wang et al. (2019)	79.4%	79.3%
Min et al. (2019)	84.4%	83.9%
$TAPAS_{large}$	88.0%	86.4%

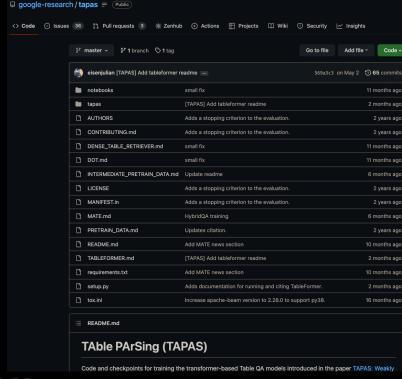
Cecilia looks for the source code to replicate these models



Wait! Cecilia finds the SOTA model's source code on TableQA

But this is only Table QA: no other QA use-case





No TyDI No XOR TyDI No CoLBERT

Our Objective: Democratize & Replicate QA research

- We need to build a single OPEN-source repository for ALL QA problems
- End-user can use them as Lego blocks for QA problems
- End-user can modify them as per their own needs
- End-user can replicate advanced research papers and leaderboard submissions quickly









Built on top of





A final end2end QA solution

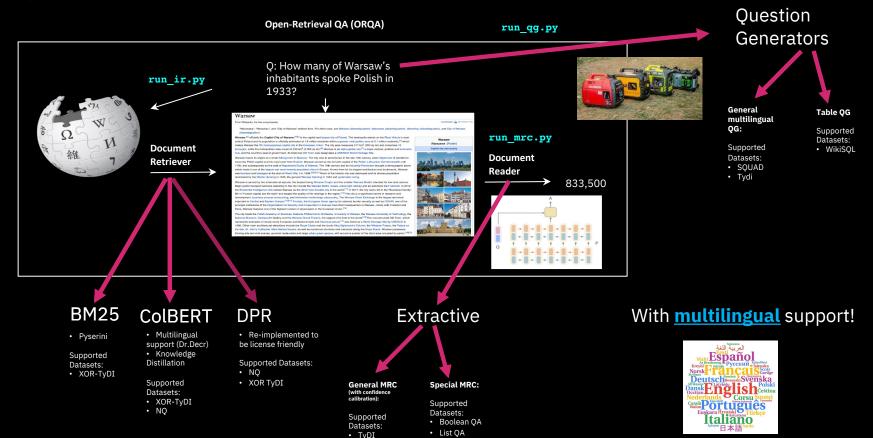








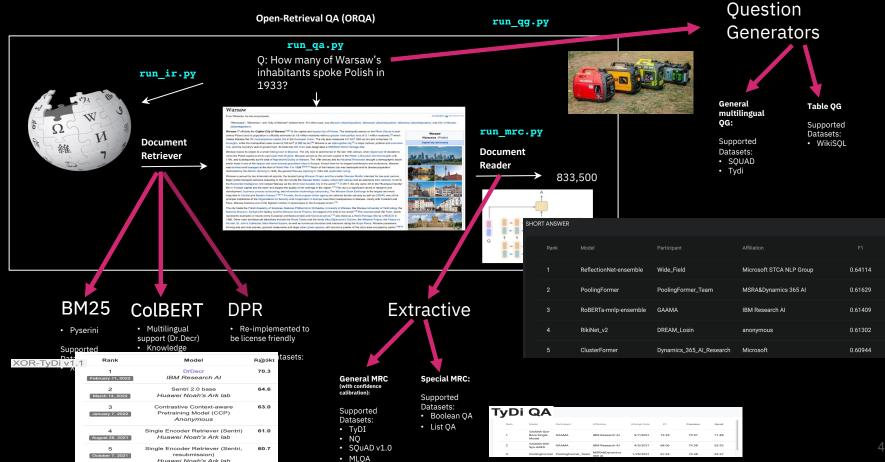
PrimeQA has 3 basic scripts



NQSQuAD v1.0MLQAXSQuAD

These are leaderboard winners!

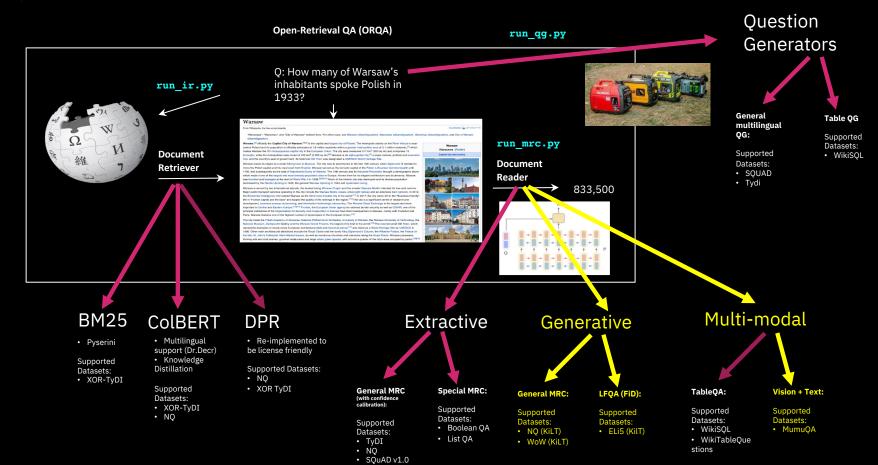
Huawei Noah's Ark lah



XSQuAD



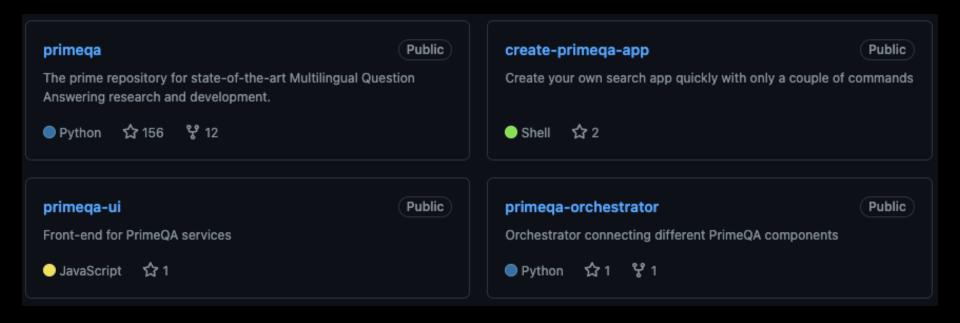
PrimeQA full suite [yellow: indicates coming soon]



MLQAXSQuAD



https://github.com/primeqa



https://github.com/primeqa/primeqa



The prime repository for state-of-the-art Multilingual and Multimedia Question Answering research and development.



PrimeQA is a public open source repository that enables researchers and developers to train state-of-theart models for question answering (QA). By using PrimeQA, a researcher can replicate the experiments outlined in a paper published in the latest NLP conference while also enjoying the capability to download pre-trained models (from an online repository) and run them on their own custom data. PrimeQA is built on top of the Transformers toolkit and uses datasets and models that are directly downloadable.

The models within PrimeQA supports End-to-end Question Answering. PrimeQA answers questions via

- Information Retrieval: Retrieving documents and passages using both traditional (e.g. BM25) and neural (e.g. ColBERT) models
- Multilingual Machine Reading Comprehension: Extract and/ or generate answers given the source document or passage.
- Multilingual Question Generation: Supports generation of questions for effective domain adaptation over tables and multilingual text.

Running MRC (predict mode)

```
. Step 1: Initialize your reader. You can choose any of the MRC models we currently have here.
 import ison
 from primega.pipelines.extractive_mrc_pipeline import MRCPipeline
 reader = MRCPipeline("PrimeQA/tydiga-primary-task-xlm-roberta-large")
 . Step 2: Execute the reader in inference mode:
 question = "Which country is Canberra located in?"
 context = """Camberra is the capital city of Australia.
 Founded following the federation of the colonies of Australia
 as the seat of government for the new nation, it is Australia's
 largest inland city"""
 answers = reader.predict(question,context)
 print(json.dumps(answers, indent=4))
The above statements will generate an output in the form of a dictionary:
          "span answer text": "Australia",
          "confidence score": 0.7988516960240685
          "span_answer_text": "Australia. \nFounded following the federation of the colonies of Australia \nas the seat of g
          "confidence_score": 0.10721889035823319
          "span_answer_text": "Australia. \nFounded following the federation of the colonies of Australia",
          "confidence_score": 0.09392941361769835
```

Inference Pipeline

- 2 PrimeQA imports,
- ➤ 4 lines of code.

Running MRC (predict mode)

Hugging Face

https://huggingface.co/PrimeQA

Swap models from model hub

• Step 1: Initialize your reader. You can choose any of the MRC models we currently have here.

```
import ison
                                                                                                                                    Models 9
from primega.pipelines.extractive_mrc_pipeline import MRCPipeline
reader = MRCPipeline("PrimeQA/tydiga-primary-task-xlm-roberta-large")
                                                                                                                                     PrimeQA/squad-v1-xlm-roberta-large
                                                                                                                                                                                         PrimeQA/squad-v1-roberta-large
                                                                                                                                     Updated about 15 hours ago • ↓ 5
                                                                                                                                                                                         Updated about 15 hours ago
. Step 2: Execute the reader in inference mode:
                                                                                                                                                                                         PrimeQA/tydiqa-primary-task-xlm-roberta-large
                                                                                                                                     PrimeQA/tapas-based-tablega-wikisgl-lookup
                                                                                                                                     Updated 3 days ago • ↓ 39
question = "Which country is Canberra located in?"
                                                                                                                                     PrimeQA/DrDecr_XOR-TyDi_whitebox
                                                                                                                                                                                         PrimeQA/t5-base-table-question-generator
                                                                                                                                     Updated 4 days ago

    S Text2Text Generation • Updated 9 days ago • ↓ 3

context = """Canberra is the capital city of Australia.
Founded following the federation of the colonies of Australia
                                                                                                                                     PrimeQA/mt5-base-tydi-question-generator
                                                                                                                                                                                         PrimeQA/tydiqa-boolean-question-classifier
as the seat of government for the new nation, it is Australia's
                                                                                                                                     S Text2Text Generation • Updated 9 days ago • ↓ 10
                                                                                                                                                                                         # Text Classification • Updated 10 days ago • ↓ 44
largest inland city"""
answers = reader.predict(question,context)
                                                                                                                                     PrimeOA/tvdiga-boolean-answer-classifier
print(json.dumps(answers, indent=4))
                                                                                                                                     ₹ Text Classification • Updated 10 days ago • ↓ 24
```

The above statements will generate an output in the form of a dictionary:

```
{
    "span_answer_text": "Australia",
    "confidence_score": 0.7988516960240685
},
{
    "span_answer_text": "Australia. \nFounded following the federation of the colonies of Australia \nas the seat of g
    "confidence_score": 0.10721889035823319
},
{
    "span_answer_text": "Australia. \nFounded following the federation of the colonies of Australia",
    "confidence_score": 0.09392941361769835
}
```

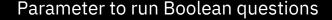
You can upload your own MRC models for others to use!



Running MRC (full train + predict)

```
python examples/mrc/run_mrc.py --model_name_or_path xlm-roberta-large \
     --output_dir ${OUTPUT_DIR} --fp16 --learning_rate 4e-5 \
     --do_train --do_eval --per_device_train_batch_size 16 \
     --per_device_eval_batch_size 128 --gradient_accumulation_steps 4 \
     --warmup_ratio 0.1 --weight_decay 0.1 --save_steps 50000 \
     --overwrite_output_dir --num_train_epochs 1
     --evaluation_strategy no --overwrite_cache
```

If your dataset has support for Boolean Questions (e.g. Yes/No) as in TyDI QA you can further run:



Running IR

- Training
- Indexing
- Search

```
python examples/ir/run_ir.py
--engine_type ColBERT
--do_index
--compression_level 2
--model_name_or_path <my_dir>/trained_model
--collection <data_dir>/psgs_w100.tsv
```

```
python examples/ir/run_ir.py
    --engine_type ColBERT
    --do_train
    --triples
<data_dir>/xorqa.train_ir_negs_100_poss_3.tsv
    --model_type xlm-roberta-base
    --root <my_dir>/experiments
    --experiment <my_expt>
```

```
python examples/ir/run_ir.py
    --engine_type ColBERT
    --do_search
    --queries <data_dir>/xorqa_dev.tsv
    --index_location <my_expt>_indname
    --model_name_or_path
<my_dir>/experiments/<my_expt>/checkpoints/colbert-LAST.dnn
    --output_dir <my_dir>
```

Multilingual Question Generation: Usage

CLI – training and evaluation

```
python examples/qg/run_qg.py \
   --model_name_or_path t5-base \
   --modality passage \
   --dataset_name tydiqa \
   --do_train \
   --do_eval \
   --output_dir models/qg/$DIR_NAME \
   --learning_rate 0.0001 \
   --num_train_epochs 4\
```

CLI - generation

```
python examples/qg/run_qg.py \
   --model_name_or_path models/qg/wikisql\
   --modality table \
   --do_generate \
   --num_questions_per_instance 20 \
   --data_path <path-to-json-file> \
   --generate_aggregate \
   --max_where_clauses 2 \
   --gen_output_path /results/qg/$DIR_NAME
```

Using pretrained QG model in python code

```
from primega.gg.models.gg model import QGModel
table qq model = QGModel('ibm/t5-base-table-question-generator', modality='table')
table gg model.generate guestions(table list,
                                    num questions per instance = 10,
                                    agg_prob = [1.,0,0,0,0,0],
                                    num\_where\_prob = [0,1.,0,0,0],
                                    ineq prob = 0.0)
[{'question': 'Name the years in toronto for number 33.0', 'answer': '1996'},
 {'question': 'What position does number 21.0 play?',
  'answer': 'quard-forward'},
 {'question': 'Which School Team has a Years in Toronto of 1999-2000?',
  'answer': 'duke'},
 {'question': 'Name the years in toronto for number 32.0',
  'answer': '1996-97'},
 {'question': 'What position does the player from Minnesota play?',
  'answer': 'quard'},
 {'question': 'What position does the player from Iowa play?',
  'answer': 'forward-center'},
 {'question': 'Name the years in toronto for 2.0', 'answer': '2002-03'},
 {'question': 'What years did Voshon Lenard play for Toronto?',
  'answer': '2002-03'}.
 {'question': 'What school team did number 21.0 play for?', 'answer': 'duke'},
 {'question': 'What position does Voshon Lenard play?'. 'answer': 'quard'}
```

One can use QG over table/passage with only 1 primeqa import and 2 code lines.

Running TableQA

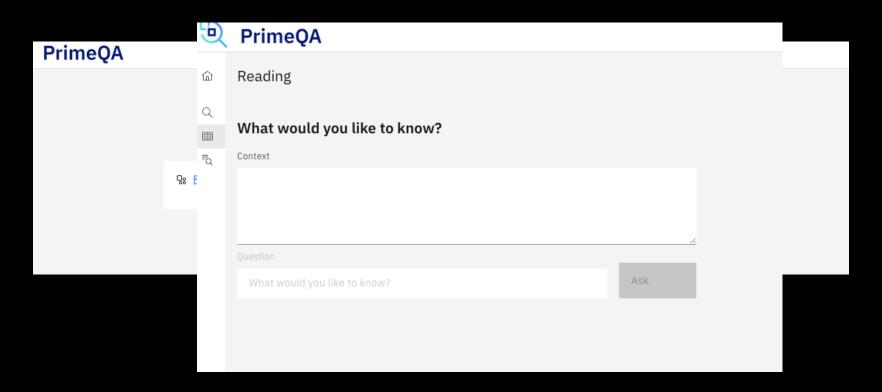
```
from primega.tablega.models.tablega.model import TableQAModel
   import pandas as pd
   # Load the pre-trained tapas table-qa model
   model = TableQAModel("google/tapas-base-finetuned-wtg")
 ✓ 4.2s
                                                                                                                                  Python
   # Load the Table
   data = {"Actors": ["Brad Pitt", "Leonardo Di Caprio",
                           "George Clooney"], "Number of movies": ["87", "53", "69"]}
   print(pd.DataFrame.from dict(data))
 ✓ 0.3s
                                                                                                                                  Python
              Actors Number of movies
0
           Brad Pitt
1 Leonardo Di Caprio
                                   53
       George Clooney
                                                                                                               queries = ["What is the name of the first actor?",
                   "How many movies has George Clooney played in?", "Brad Pitt acted in how many movies"]
   print(model.predict from dict(data, queries))
 ✓ 2.9s
                                                                                                                                 Python
What is the name of the first actor?
Predicted answer: Brad Pitt
How many movies has George Clooney played in?
Predicted answer: COUNT > 69
Brad Pitt acted in how many movies
Predicted answer: COUNT > 87
{'What is the name of the first actor?': 'Brad Pitt', 'How many movies has George Clooney played in?': '69', 'Brad Pitt acted in how
```

Inference Pipeline

- 2 PrimeQA imports,
- 3 lines of code.

Use PrimeQA to build your own QA app / search engine

Head over to https://github.com/primeqa/create-primeqa-app



Conclusion

 To make information access really possible quickly we need to share code and models

Our software needs to be compatible with one another

 PrimeQA: Let's work on this together and make QA research move quicker than ever

PrimeQA Collaborators

Stanford NLP	Stanford NLP	I	University of Illinois
	University of Stuttgart		University of Notre Dame
	Ohio State University	Carnegie Mellon University	Carnegie Mellon University
TO MASSIE	University of Massachusetts		

Thank you!



- Clone the repo!
- Star and watch the repo
- Get regular updates
- Join the slack channel







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A Simple Assignment: Extra credits

- Get a hands-on experience working with the PrimeQA toolkit/models
- solve an open retrieval question answering task over a real world dataset: covid-qa.
- The target domain is Covid19 related documents/ publications, over which PrimeQA/models can answer natural language questions.
- We have designed experiments to focus on domain adaptation aspect of question answering.
- We will provide the Jupyter notebook just provide the scores you get by running the models
 - Don't forget to use GPUs ☺
- Office hours: Tuesday and Thursday (Time + Webex to be announced)