Reading Wikipedia to Answer Open-domain Questions

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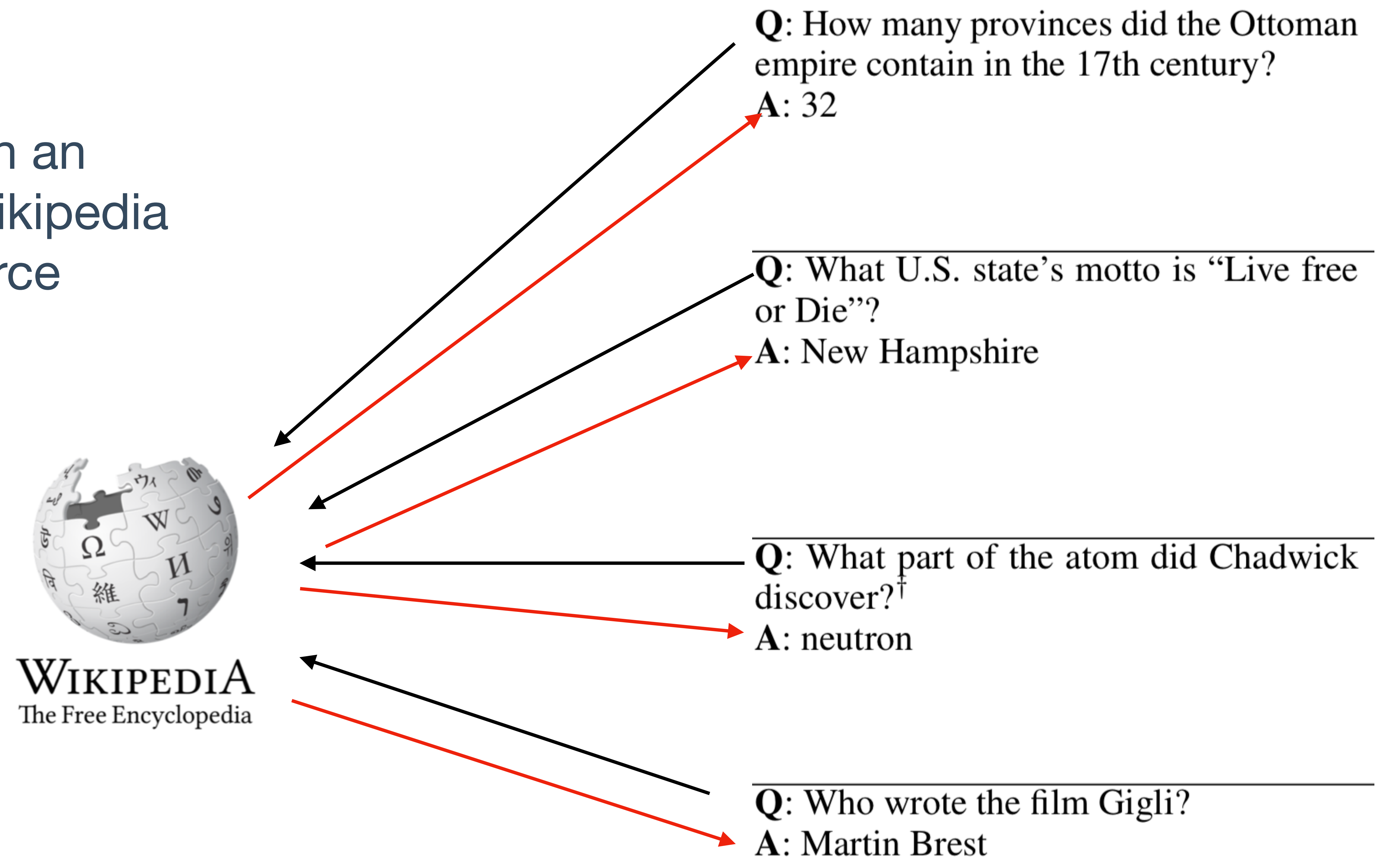
Object

answering factoid questions in an open-domain setting using Wikipedia as the unique knowledge source



Q: How many provinces did the Ottoman empire contain in the 17th century?
A: 32

Q: What U.S. state's motto is "Live free or Die"?
A: New Hampshire

Q: What part of the atom did Chadwick discover?[†]
A: neutron

Q: Who wrote the film Gigli?
A: Martin Brest

Challenges

1.document retrieval (finding the relevant articles)

2.machine comprehension of text (identifying the answer spans from those articles)

Why Wikipedia

WIKIPEDIA
The Free Encyclopedia

1. up-to-date knowledge that humans are interested in.
2. a constantly evolving source of detailed information

How to use it

treats Wikipedia as **a collection of articles** and **does not** rely on its **internal graph structure**.

↓

So it is generic and could be switched to other **collections of documents**, **books**, or even daily updated **newspapers**.

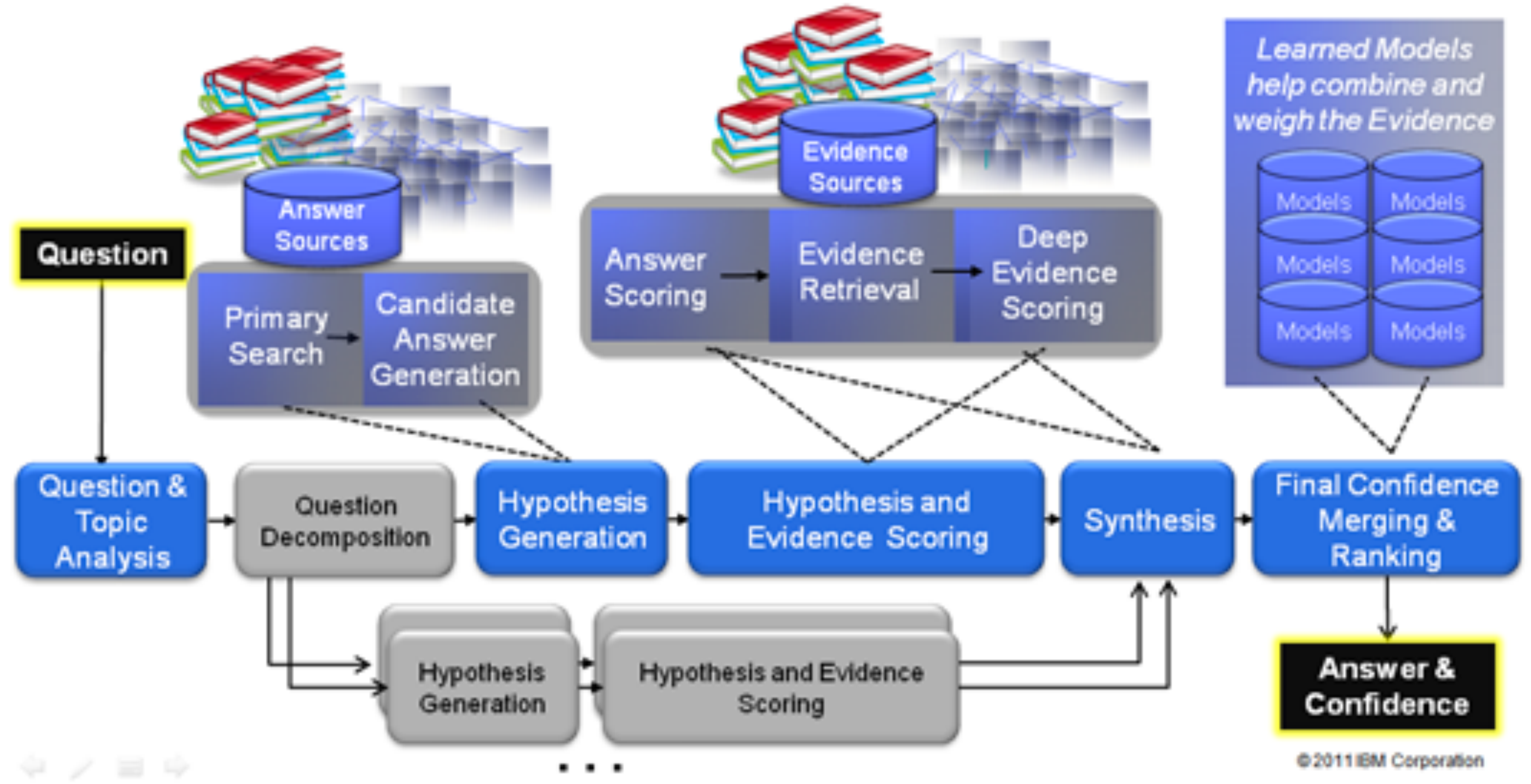
Related Works

DBpedia freebase alpha

Knowledge Bases KBs

Pro: easier for computers to process
Con: too sparsely populated for open-domain question answering

Large-scale QA



rely on multiple sources to answer

Wikipedia, KBs, dictionaries, news articles, books, etc.

Pro: large-scale
Con: information redundancy

assume that a short piece of relevant text is already identified and given to the model

Related Works

Origin

QA from unstructured documents

TREC competitions

WebQuestions

SimpleQuestions

Freebase KB

Past

QA from KBs

KBs

QA extracted from KBs

OpenIE triples and NELL

Deep learning architectures

Now

Past:

combine article content with multiple other answer matching modules based on different types of semi-structured knowledge such as infoboxes, article structure, category structure, and definitions.

Now:

use Wikipedia text documents as the sole resource in order to emphasize the task of machine reading at scale, as described in the introduction.

Open-domain QA

SQuAD, TREC, WebQuestions, WikiMovies

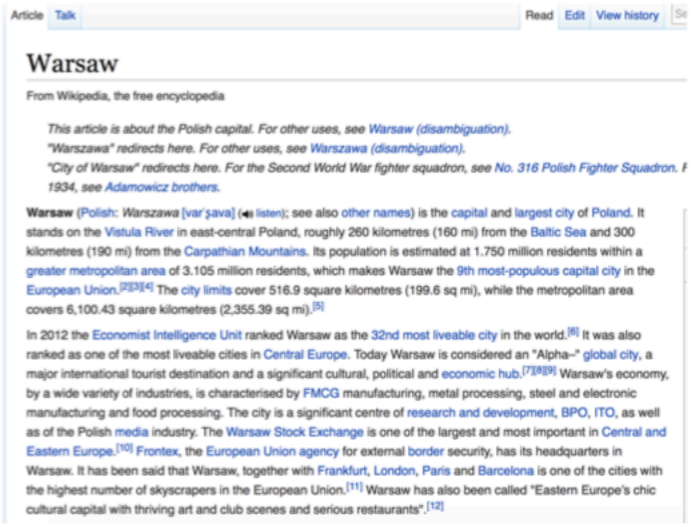
Modules

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

WIKIPEDIA
The Free Encyclopedia

Document Retriever

using bigram hashing and TF-IDF matching designed to, given a question, efficiently return a subset of relevant articles



Article Talk Read Edit View history

Warsaw

From Wikipedia, the free encyclopedia

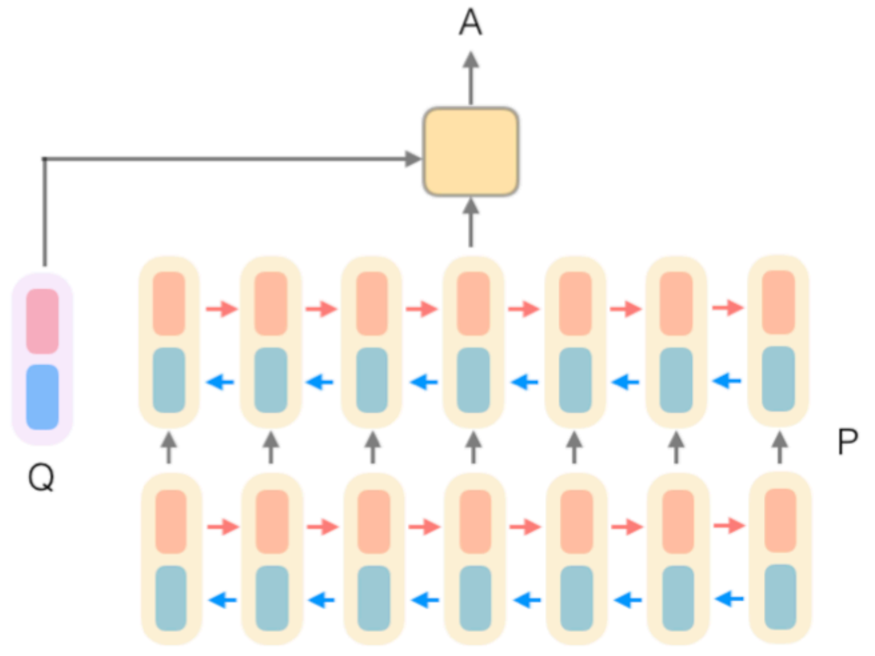
This article is about the Polish capital. For other uses, see Warsaw (disambiguation).
"Warszawa" redirects here. For other uses, see Warszawa (disambiguation).
"City of Warsaw" redirects here. For the Second World War fighter squadron, see No. 316 Polish Fighter Squadron. F
1934, see Adamowicz brothers.

Warsaw (Polish: *Warszawa* [varˈʂava] (listen); see also other names) is the capital and largest city of Poland. It stands on the Vistula River in east-central Poland, roughly 260 kilometres (160 mi) from the Baltic Sea and 300 kilometres (190 mi) from the Carpathian Mountains. Its population is estimated at 1.750 million residents within a greater metropolitan area of 3.105 million residents, which makes Warsaw the 9th most-populous capital city in the European Union.[2][3][4] The city limits cover 516.9 square kilometres (199.6 sq mi), while the metropolitan area covers 6,100.43 square kilometres (2,355.39 sq mi).[5]

In 2012 the Economist Intelligence Unit ranked Warsaw as the 32nd most liveable city in the world.[6] It was also ranked as one of the most liveable cities in Central Europe. Today Warsaw is considered an "Alpha–" global city, a major international tourist destination and a significant cultural, political and economic hub.[7][8][9] Warsaw's economy, by a wide variety of industries, is characterised by FMCG manufacturing, metal processing, steel and electronic manufacturing and food processing. The city is a significant centre of research and development, BPO, ITO, as well as of the Polish media industry. The Warsaw Stock Exchange is one of the largest and most important in Central and Eastern Europe.[10] Frontex, the European Union agency for external border security, has its headquarters in Warsaw. It has been said that Warsaw, together with Frankfurt, London, Paris and Barcelona is one of the cities with the highest number of skyscrapers in the European Union.[11] Warsaw has also been called "Eastern Europe's chic cultural capital with thriving art and club scenes and serious restaurants".[12]

Document Reader

833,500



multi-layer RNN machine comprehension model trained to detect answer spans in those few returned documents.

Both modules are competitive

Question
Wikipedia Data

1.Document Retriever

Return Top5 articles
For Document Reader

1.narrow our search space
2.focus on reading only articles that are likely to be relevant

A simple inverted index lookup followed by term vector model scoring performs quite well on this task for many question types, compared to the built-in ElasticSearch based Wikipedia Search API

Articles and questions are compared as TF-IDF weighted bag-of- word vectors.

Our **best** performing system uses **bigram** counts while preserving speed and memory efficiency by using the hashing of (Weinberger et al., 2009) to map the bigrams to 2^{24} bins with an **unsigned *murmur3* hash**.

2.Document Reader

Question

Top5 Articles from Docment Retriever

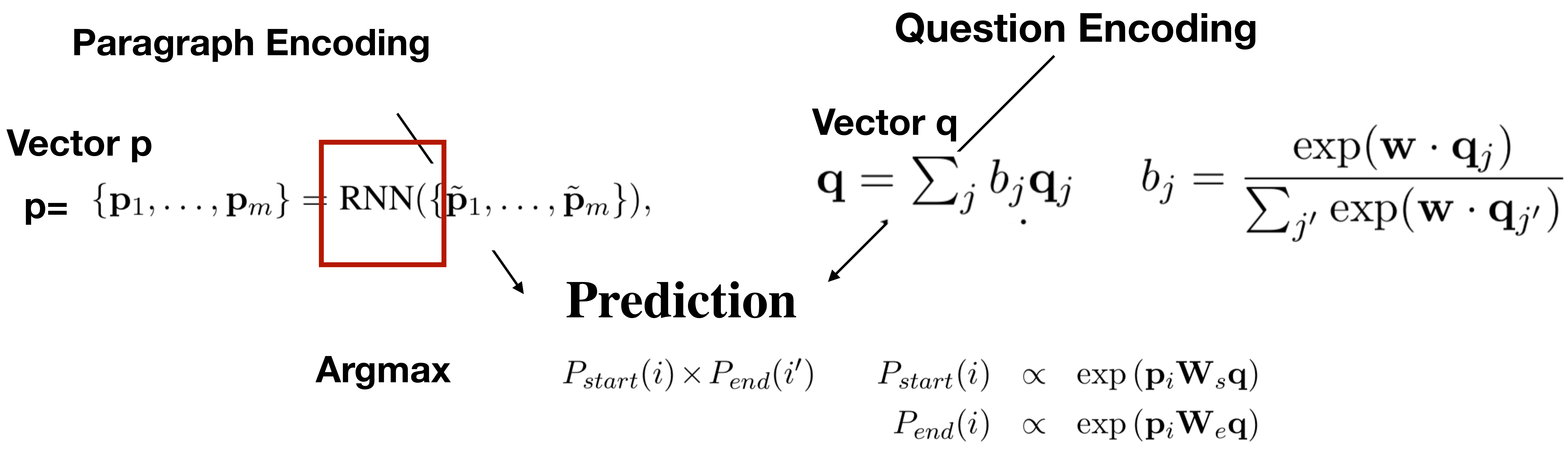
Answer

Assuming

a question q consisting of l tokens $\{q_1, \dots, q_l\}$

a single paragraph **p** consists of m tokens $\{p_1, \dots, p_m\}$

Structure Graph



Paragraph Encoding

Vector p

p= $\{\mathbf{p}_1, \dots, \mathbf{p}_m\} = \boxed{\text{RNN}(\{}\tilde{\mathbf{p}}_1, \dots, \tilde{\mathbf{p}}_m\}),$

Question Encoding

Vector q

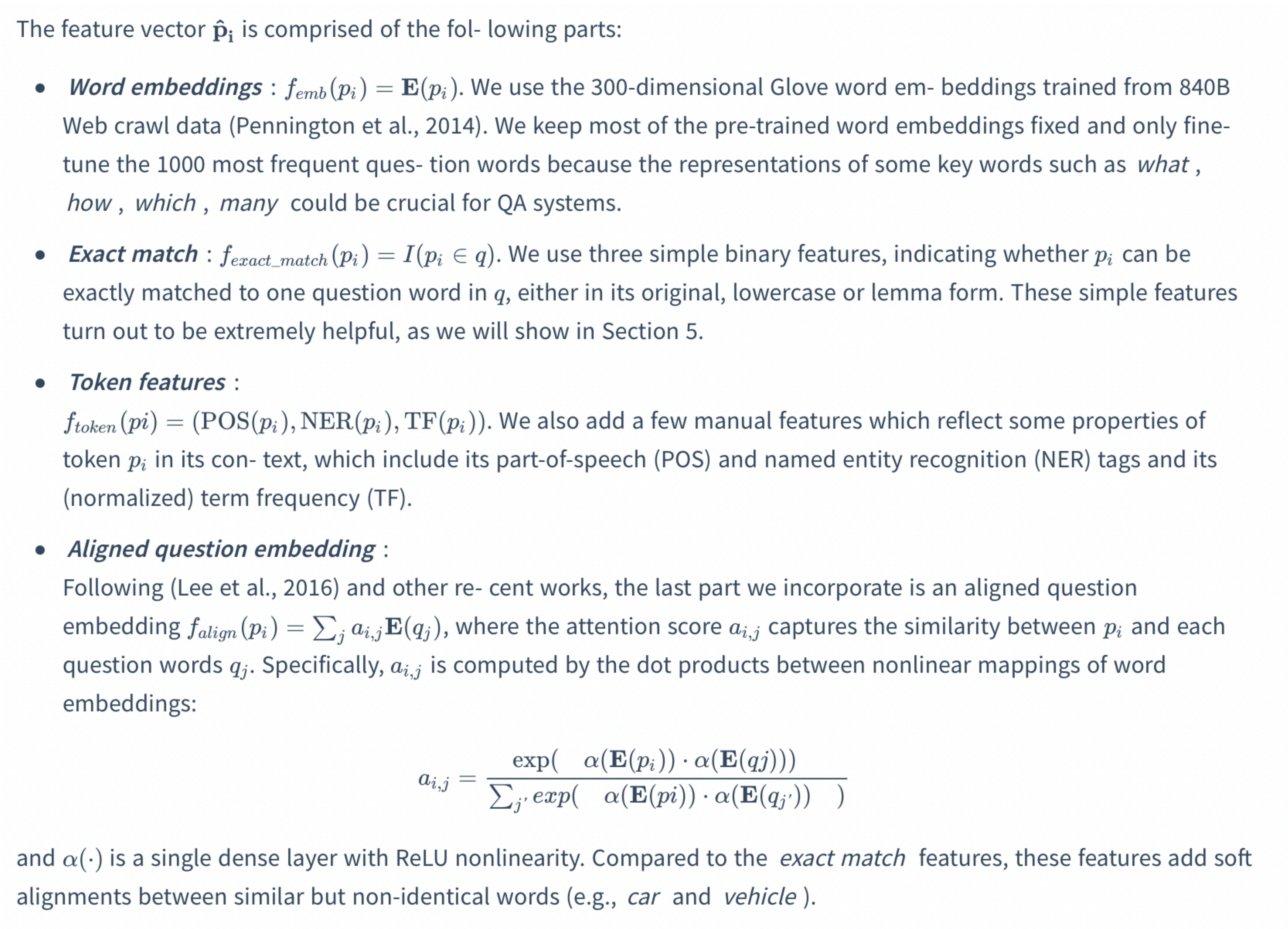
$\mathbf{q} = \sum_j b_j \mathbf{q}_j \qquad b_j = \frac{\exp(\mathbf{w} \cdot \mathbf{q}_j)}{\sum_{j'} \exp(\mathbf{w} \cdot \mathbf{q}_{j'})}$

Prediction

Argmax $P_{start}(i) \times P_{end}(i')$

$$\begin{aligned} P_{start}(i) &\propto \exp\left(\mathbf{p}_i \mathbf{W}_s \mathbf{q}\right) \\ P_{end}(i) &\propto \exp\left(\mathbf{p}_i \mathbf{W}_e \mathbf{q}\right) \end{aligned}$$

RNN



The feature vector $\hat{\mathbf{p}}_{\mathbf{i}}$ is comprised of the fol- lowing parts:

- ***Word embeddings*** : $f_{emb}(p_i) = \mathbf{E}(p_i)$. We use the 300-dimensional Glove word em- beddings trained from 840B Web crawl data (Pennington et al., 2014). We keep most of the pre-trained word embeddings fixed and only fine-tune the 1000 most frequent ques- tion words because the representations of some key words such as *what* , *how* , *which* , *many* could be crucial for QA systems.
- ***Exact match*** : $f_{exact\_match}(p_i) = I(p_i \in q)$. We use three simple binary features, indicating whether p_i can be exactly matched to one question word in q, either in its original, lowercase or lemma form. These simple features turn out to be extremely helpful, as we will show in Section 5.
- ***Token features*** :
  $f_{token}(pi) = (\mathrm{POS}(p_i), \mathrm{NER}(p_i), \mathrm{TF}(p_i))$. We also add a few manual features which reflect some properties of token p_i in its con- text, which include its part-of-speech (POS) and named entity recognition (NER) tags and its (normalized) term frequency (TF).
- ***Aligned question embedding*** :
  Following (Lee et al., 2016) and other re- cent works, the last part we incorporate is an aligned question embedding $f_{align}(p_i) = \sum_j a_{i,j}\mathbf{E}(q_j)$, where the attention score $a_{i,j}$ captures the similarity between p_i and each question words q_j. Specifically, $a_{i,j}$ is computed by the dot products between nonlinear mappings of word embeddings:

$$a_{i,j} = \frac{\exp(\quad \alpha(\mathbf{E}(p_i)) \cdot \alpha(\mathbf{E}(qj)))}{\sum_{j'} exp(\quad \alpha(\mathbf{E}(pi)) \cdot \alpha(\mathbf{E}(q_{j'})) \quad)}$$

and $\alpha(\cdot)$ is a single dense layer with ReLU nonlinearity. Compared to the *exact match* features, these features add soft alignments between similar but non-identical words (e.g., *car* and *vehicle*).

Experiment

Data

(1)Wikipedia that serves as our knowledge source for finding answers,

(2)the SQuAD dataset which is our main resource to train Document Reader

(3)three more QA datasets (CuratedTREC, We- bQuestions and WikiMovies) that in addition to SQuAD, are used to test the open-domain QA abilities of our full system

(4)to evaluate the ability of our model to learn from multitask learning and distant supervision.

Processing

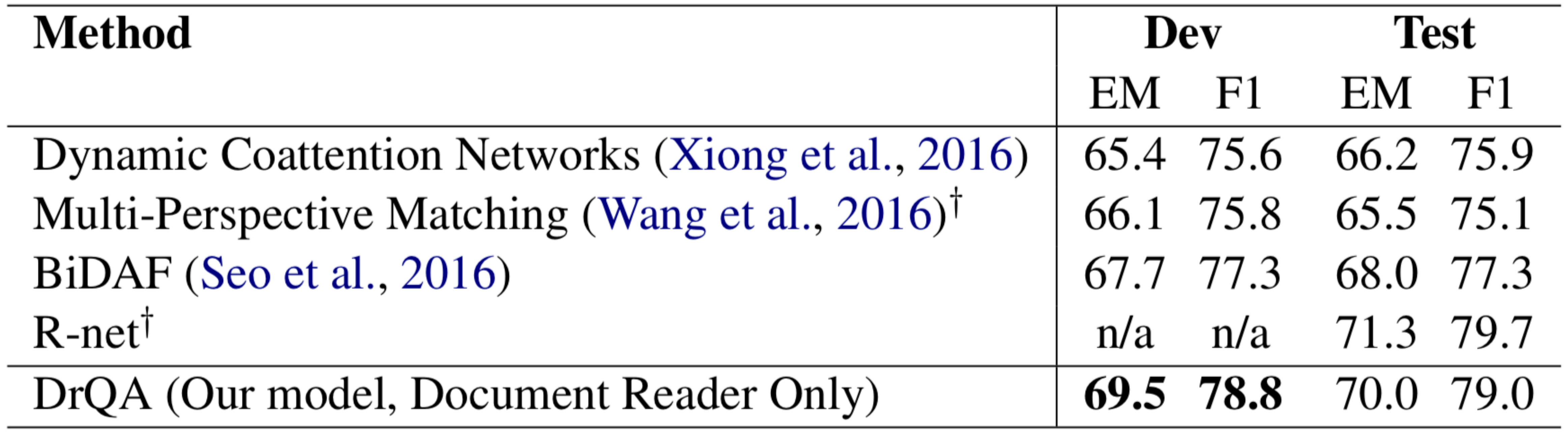
1.run Document Retriever on the question to retrieve the top 5 Wikipedia articles

Retrieve Rules:
1.All paragraphs from those articles without an exact match of the known answer are directly discarded.
2.All para- graphs shorter than 25 or longer than 1500 characters are also filtered out.
3.If any named entities are detected in the question, we remove any paragraph that does not contain them at all.
4.If there is no paragraph with non-zero overlap, the example is discarded.

2.use 3-layer bidirec- tional LSTMs with h = 128 hidden units for both paragraph and question encoding.

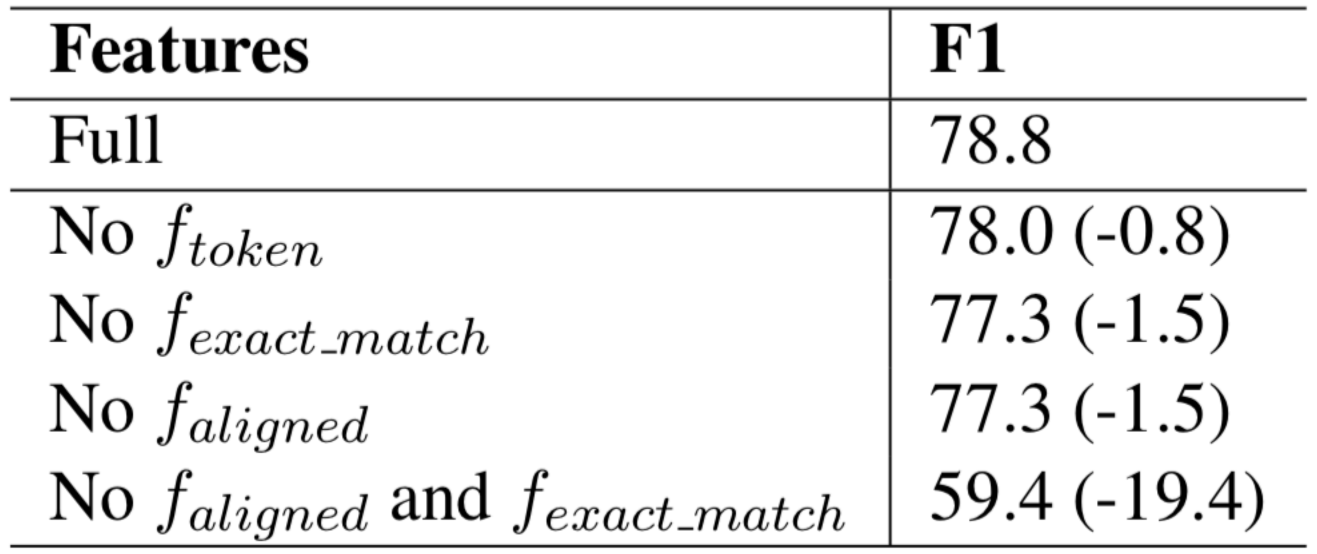
comprehension benchmark

Compare with counters



Method	Dev		Test	
	EM	F1	EM	F1
Dynamic Coattention Networks (Xiong et al., 2016)	65.4	75.6	66.2	75.9
Multi-Perspective Matching (Wang et al., 2016)†	66.1	75.8	65.5	75.1
BiDAF (Seo et al., 2016)	67.7	77.3	68.0	77.3
R-net†	n/a	n/a	71.3	79.7
DrQA (Our model, Document Reader Only)	**69.5**	**78.8**	70.0	79.0

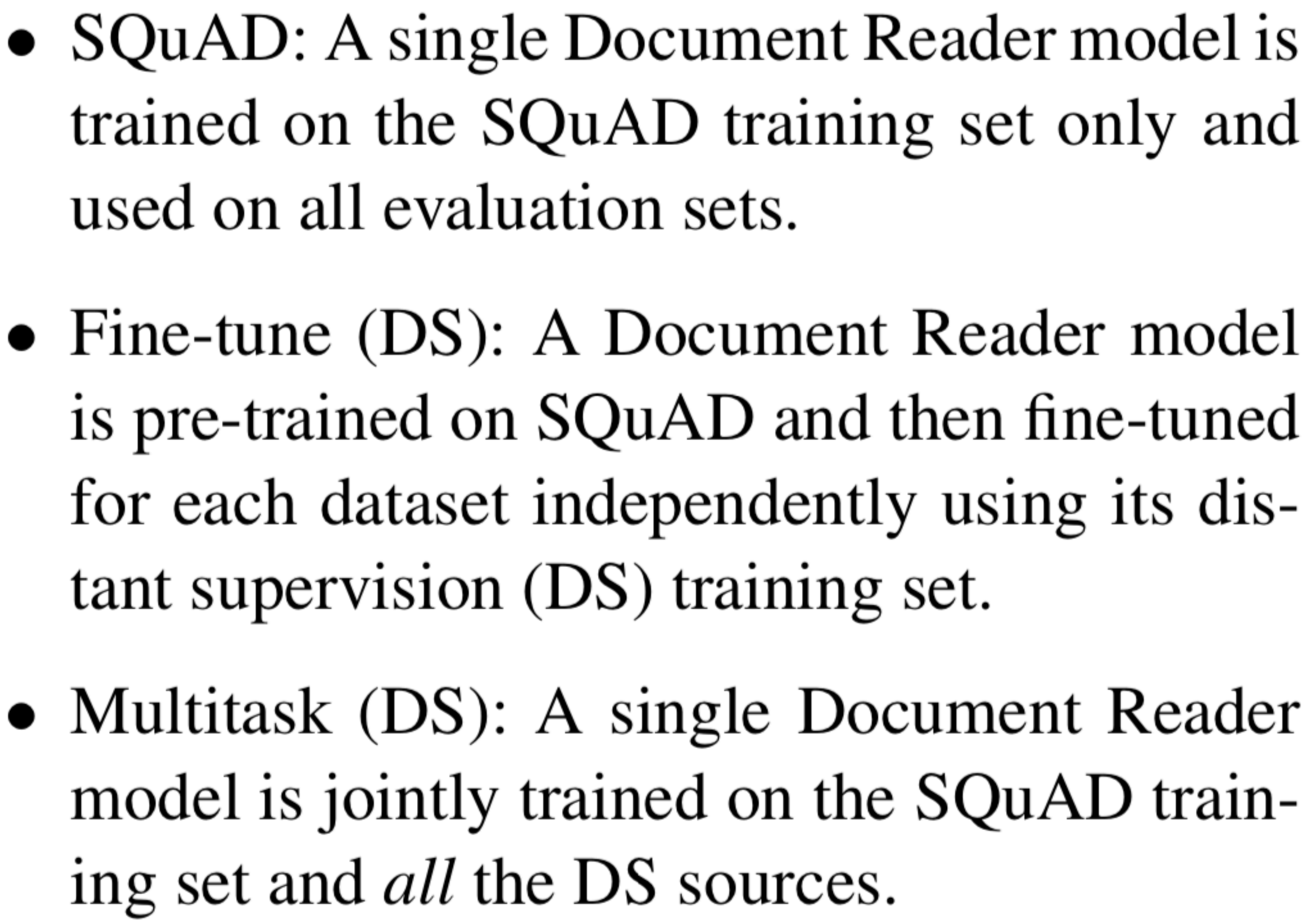
Compare without different features



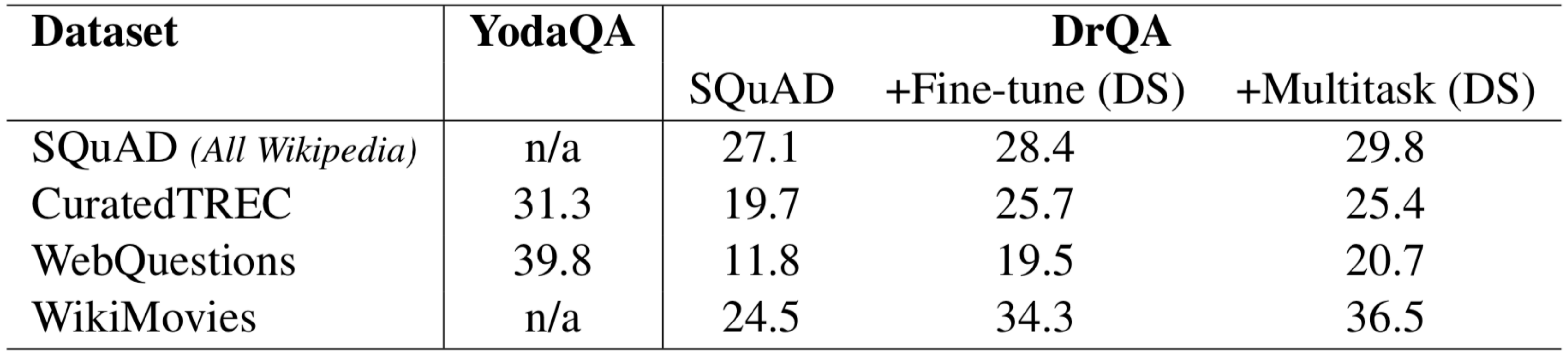
Features	F1
Full	78.8
No f_{token}	78.0 (-0.8)
No f_{exact_match}	77.3 (-1.5)
No $f_{aligned}$	77.3 (-1.5)
No $f_{aligned}$ and f_{exact_match}	59.4 (-19.4)

Full QA system

Three versions



- SQuAD: A single Document Reader model is trained on the SQuAD training set only and used on all evaluation sets.
- Fine-tune (DS): A Document Reader model is pre-trained on SQuAD and then fine-tuned for each dataset independently using its distant supervision (DS) training set.
- Multitask (DS): A single Document Reader model is jointly trained on the SQuAD training set and *all* the DS sources.



Dataset	**YodaQA**	**DrQA**		
		SQuAD	+Fine-tune (DS)	+Multitask (DS)
SQuAD *(All Wikipedia)*	n/a	27.1	28.4	29.8
CuratedTREC	31.3	19.7	25.7	25.4
WebQuestions	39.8	11.8	19.5	20.7
WikiMovies	n/a	24.5	34.3	36.5