

# Towards a Unified Model for QA & Reasoning

@ KAIST

March 28, 2019

Minjoon Seo

**NAVER**



# What is Question Answering?



Hydrogen and oxygen!

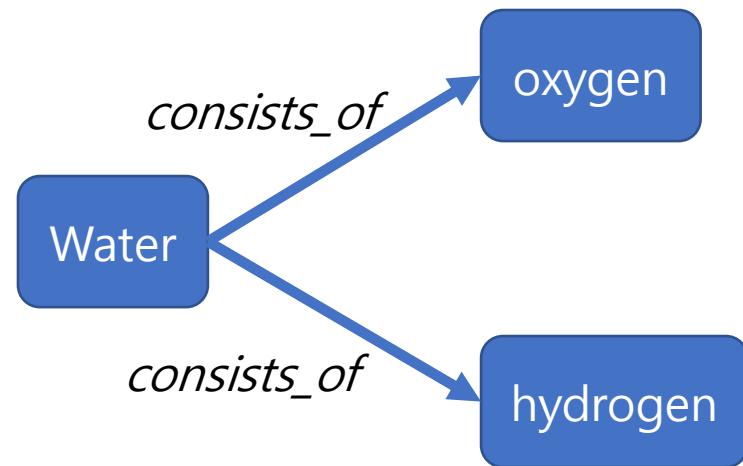


What is water consisted of?

# *Parsing and Reading*

# Parsing: answer from *structured* data

`consists_of(water, ?)`

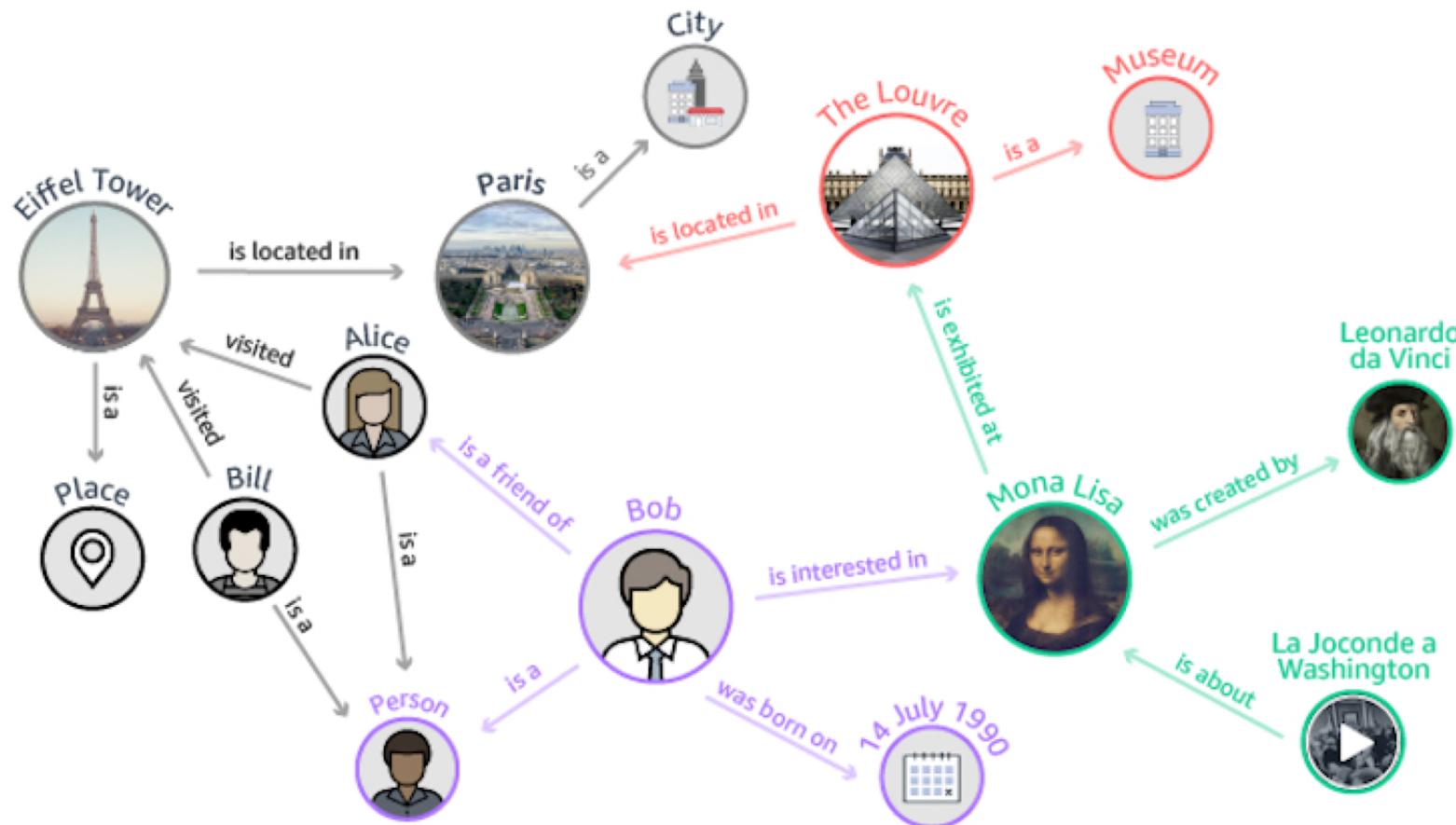


What is water consisted of?



Hydrogen and oxygen!

# Knowledge Graph



# Tables

Year	Competition	Venue	Position	Event	Notes
<b>Representing  Poland</b>					
2001	World Youth Championships	Debrecen, Hungary	2nd	400 m	47.12
			1st	Medley relay	1:50.46
	European Junior Championships	Grosseto, Italy	1st	4x400 m relay	3:06.12
2002	World Junior Championships	Kingston, Jamaica	4th	4x400m relay	3:06.25
2003	European Junior Championships	Tampere, Finland	3rd	400 m	46.69
			2nd	4x400 m relay	3:08.62
2005	European U23 Championships	Erfurt, Germany	11th (sf)	400 m	46.62
			1st	4x400 m relay	3:04.41
	Universiade	Izmir, Turkey	7th	400 m	46.89
			1st	4x400 m relay	3:02.57
2006	World Indoor Championships	Moscow, Russia	2nd (h)	4x400 m relay	3:06.10
	European Championships	Gothenburg, Sweden	3rd	4x400 m relay	3:01.73
2007	European Indoor Championships	Birmingham, United Kingdom	3rd	4x400 m relay	3:08.14
	Universiade	Bangkok, Thailand	7th	400 m	46.85
			1st	4x400 m relay	3:02.05
2008	World Indoor Championships	Valencia, Spain	4th	4x400 m relay	3:08.76
	Olympic Games	Beijing, China	7th	4x400 m relay	3:00.32
2009	Universiade	Belgrade, Serbia	2nd	4x400 m relay	3:05.69

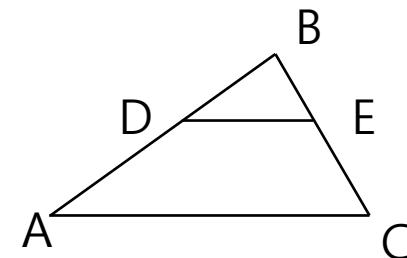
In what city did Piotr's last 1st place finish occur?

# (First-Order) Logic

*Text  
Input*

In triangle ABC, line DE is parallel with line AC, DB equals 4, AD is 8, and DE is 5. Find AC.

- (a) 9 (b) 10 (c) 12.5 (d) 15 (e) 1  
7



*Logical  
form*

$IsTriangle(ABC) \wedge$        $Parallel(AC, DE) \wedge$   
 $Equals(LengthOf(DB), 4) \wedge$        $Equals(LengthOf(AD),$   
 $8) \wedge$        $Equals(LengthOf(DE), 5) \wedge$        $Find(LengthOf(AC))$

# Reading: answer from *unstructured* data



What is water consisted of?

## *Nature*

Water is a chemical substance that is composed of **hydrogen and oxygen** and is vital for all known forms of life. In typical usage, "water" refers only to its liquid form or state, but the substance also has a solid state, ice, and a gaseous state, water vapor, or steam.



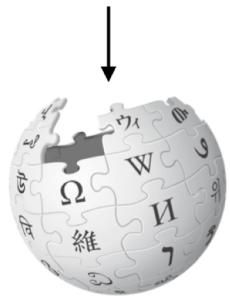
Hydrogen and oxygen!

# Search & Read

## Open-domain QA

SQuAD, TREC, WebQuestions, WikiMovies

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



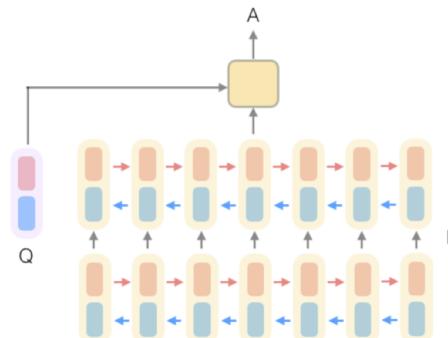
**WIKIPEDIA**  
The Free Encyclopedia

Document  
Retriever

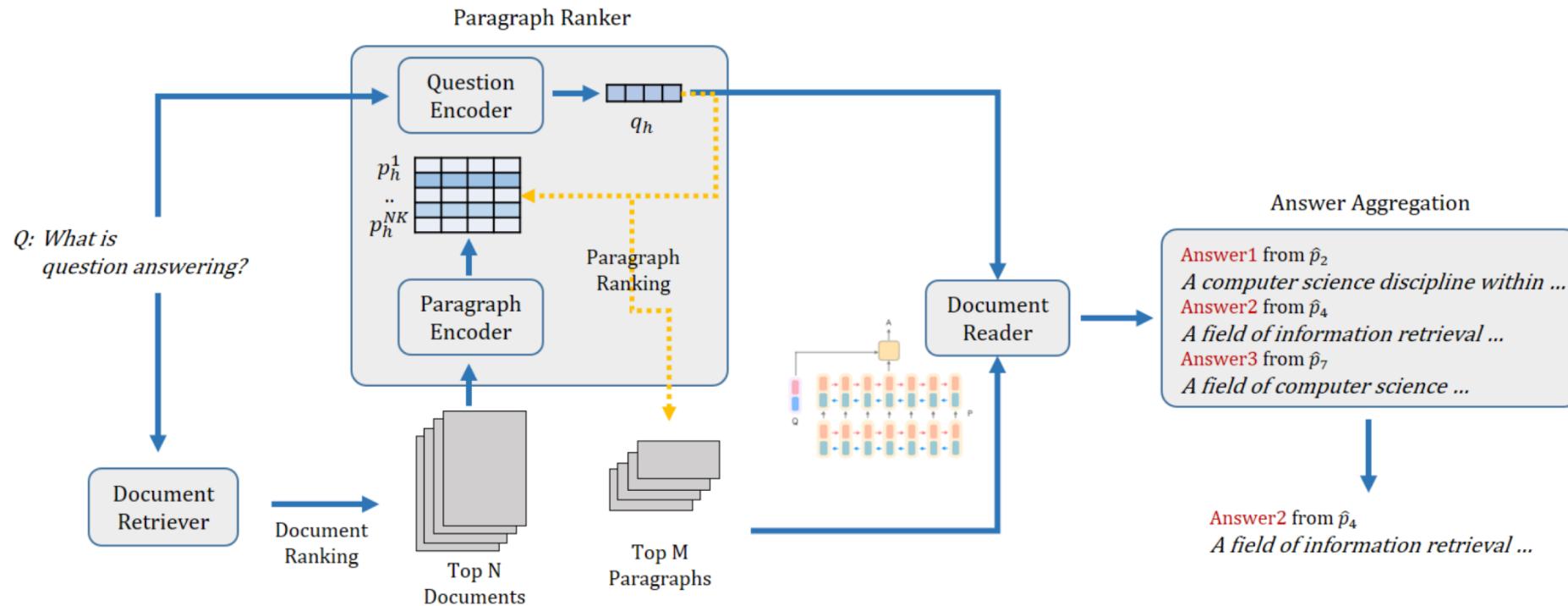


Document  
Reader

833,500



# Search & Rank & Read

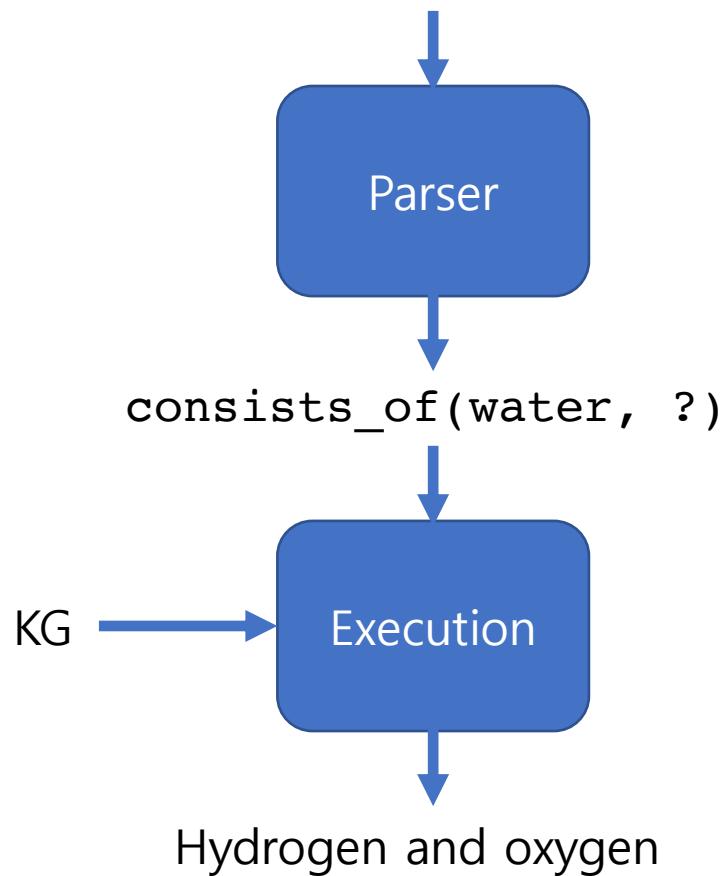


# Parsing vs Reading

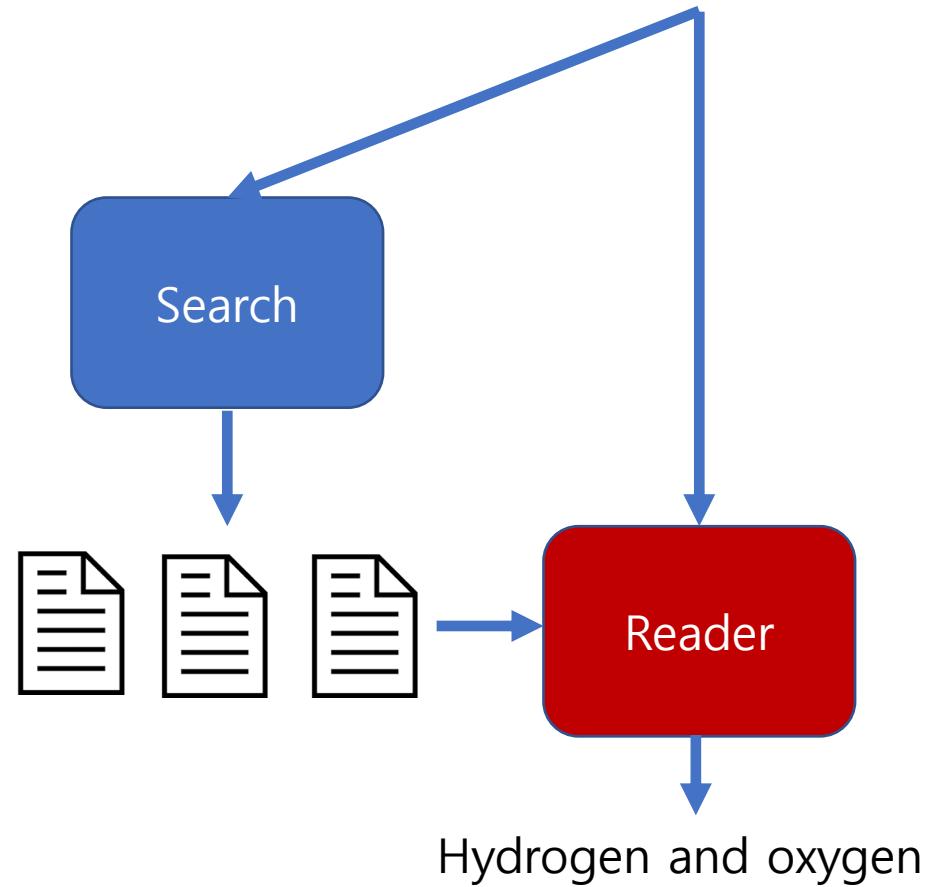
- Speed
- Domain
- Complexity

# Parsing vs Reading: Speed

What is water consisted of?



What is water consisted of?



# Parsing vs Reading: Domain

*Q: "How do you become a great researcher?"*

- *Parsing* is ontology- and KG-dependent
  - Designing comprehensive ontology is difficult
  - Constructing comprehensive KG is expensive
- *Reading* is ontology-free, open-domain

In an interview with Association for Psychological Science, Levine believes the key to being a great researcher is **having passion for what you do research in and working on questions that you are truly curious about.**

# Parsing vs Reading: Complexity

- Multi-hop reasoning
- “What are the atomic numbers of the elements in water?”

## Parsing

```
atomic_number(A) s.t  
consists_of(water, A)
```

## Reading

Need text that explicitly  
contains the information.

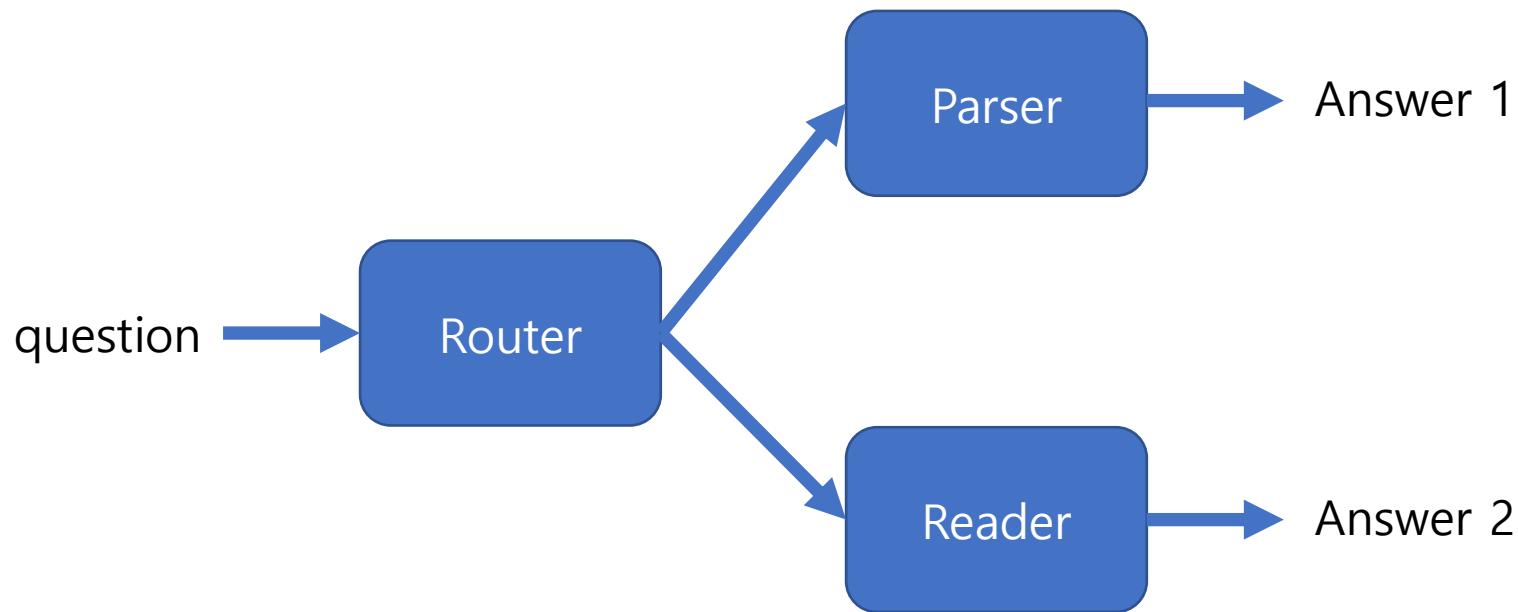
# Parsing vs Reading

	Parsing	Reading
Speed	Fast	Slow
Domain	Limited	Ontology-free, open-domain
Complexity	Multi-hop reasoning	Limited

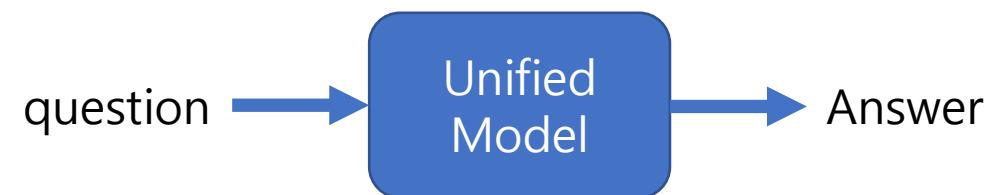
*tl;dr.*

It is clear that we need to consider **both**

# Solution #1: a pipeline



# Solution #2: a unified model?



# Today's Talk

- Intro: About Question Answering & Reasoning
- **Parsing:** SOTA on WikiSQL
- **Reading:** Real-time Open-domain Question Answering
- Towards a Unified Model

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# WikiSQL: NL2SQL Task

- Natural language to SQL

Table: CFLDraft

Pick #	CFL Team	Player	Position	College
27	Hamilton Tiger-Cats	Connor Healy	DB	Wilfrid Laurier
28	Calgary Stampeders	Anthony Forgone	OL	York
29	Ottawa Renegades	L.P. Ladouceur	DT	California
30	Toronto Argonauts	Frank Hoffman	DL	York
...	...	...	...	...

Question:

How many CFL teams are from York College?

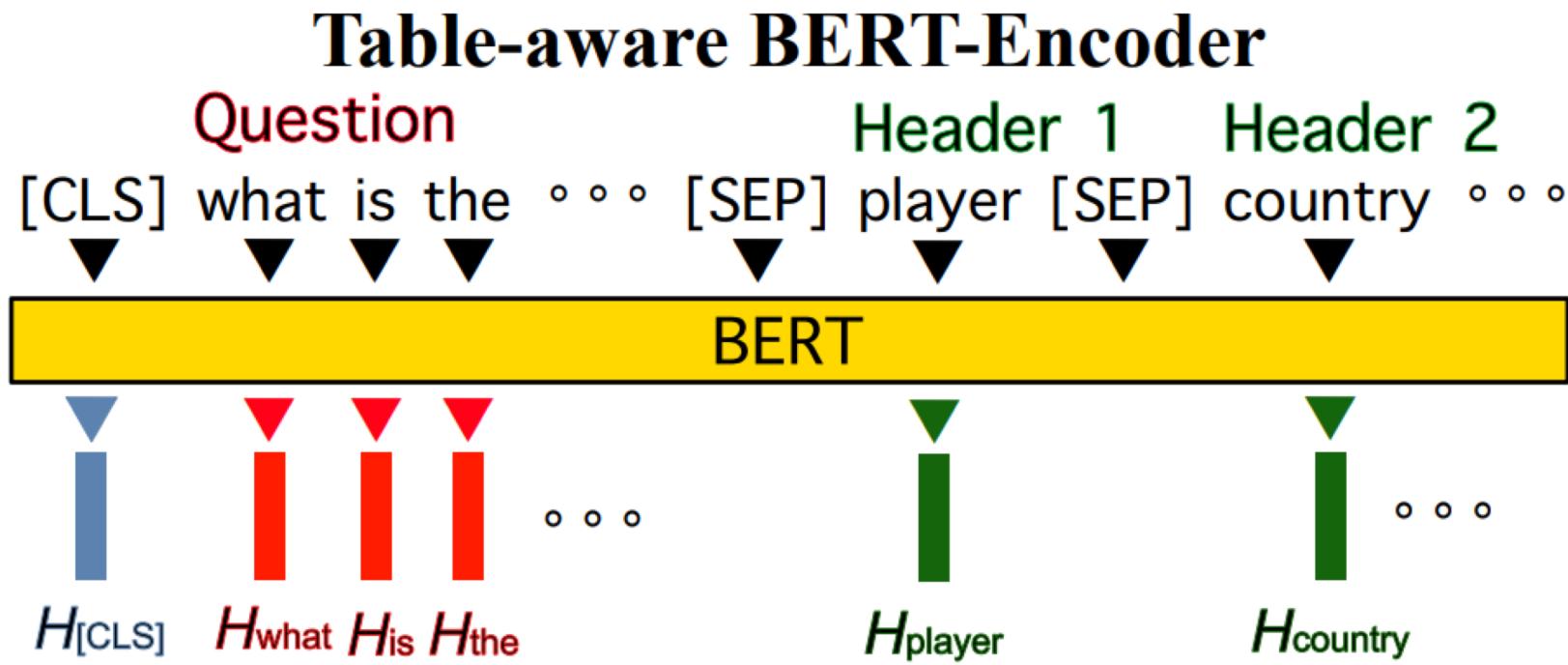
SQL:

```
SELECT COUNT CFL Team FROM  
CFLDraft WHERE College = "York"
```

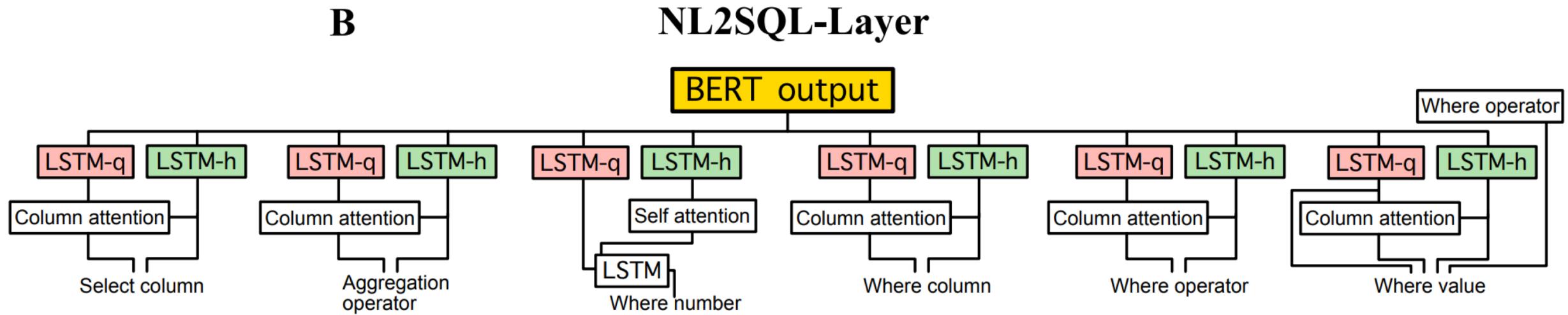
Result:

2

# SQLOva (Hwang et al., 2019)



# SQLova (Hwang et al., 2019)



# SQLova Results

Model	Dev LF (%)	Dev X (%)	Test LF (%)	Test X (%)
Baseline (Zhong et al., 2017)	23.3	37.0	23.4	35.9
Seq2SQL (Zhong et al., 2017)	49.5	60.8	48.3	59.4
SQLNet (Xu et al., 2017)	63.2	69.8	61.3	68.0
PT-MAML (Huang et al., 2018)	63.1	68.3	62.8	68.0
TypeSQL (Yu et al., 2018)	68.0	74.5	66.7	73.5
Coarse2Fine (Dong and Lapata, 2018)	72.5	79.0	71.7	78.5
MQAN (McCann et al., 2018)	76.1	82.0	75.4	81.4
Annotated Seq2seq (Wang et al., 2018b) <sup>1</sup>	72.1	82.1	72.1	82.2
IncSQL (Shi et al., 2018) <sup>1</sup>	49.9	84.0	49.9	83.7
BERT-TO-SEQUENCE (ours)	57.3	-	56.4	-
SHALLOW-LAYER (ours)	<b>81.5 (+5.4)</b>	<b>87.4 (+3.2)</b>	<b>80.9 (+5.5)</b>	<b>86.8 (+3.1)</b>
NL2SQL-LAYER (SQLOVA, ours)	<b>81.6 (+5.5)</b>	<b>87.2 (+3.2)</b>	<b>80.7 (+5.3)</b>	<b>86.2 (+2.5)</b>
PointSQL-EG (Wang et al., 2018a) <sup>1,2</sup>	67.5	78.4	67.9	78.3
Coarse2Fine-EG (Wang et al., 2018a) <sup>1,2</sup>	76.0	84.0	75.4	83.8
IncSQL-EG (Shi et al., 2018) <sup>1,2</sup>	51.3	87.2	51.1	<b>87.1</b>
SHALLOW-LAYER-EG (ours) <sup>2</sup>	<b>82.3 (+6.3)</b>	<b>88.1 (+0.9)</b>	<b>81.8 (+6.4)</b>	<b>87.5 (+0.4)</b>
NL2SQL-LAYER-EG (SQLOVA-EG, ours) <sup>2</sup>	<b>84.2 (+8.2)</b>	<b>90.2 (+3.0)</b>	<b>83.6 (+8.2)</b>	<b>89.6 (+2.5)</b>
Human performance <sup>3</sup>	-	-	-	88.3

# And it's near upper bound...

NL What is the **number** of the player who went to Southern University?

---

TBL “Player”, “No.(s)”, “Height in Ft.”, “Position”, “Years for Rockets”, “School/Club Team/Country”

---

SQL (T) SELECT **(No.(s))** FROM 1-11734041-9 WHERE School/Club Team/Country = Southern University

---

SQL (P) SELECT **count(No.(s))** FROM 1-11734041-9 WHERE School/Club Team/Country = southern university

---

ANS (T) 6

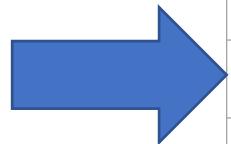
---

ANS (P) 1

---

ERROR Qestion (IV)

# Parsing vs Reading



	Parsing	Reading
Speed	Fast	Slow
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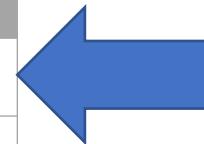
Fundamental limitation of **parsing**:  
it is ontology- and KG-dependent *by definition*

# Today's Talk

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# Parsing vs Reading

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# Reader: answer from *unstructured* data

Second Epistle to the Corinthians The Second Epistle to the Corinthians, often referred to as Second Corinthians (and written as 2 Corinthians), is the eighth book of the New Testament of the Bible. Paul the Apostle and "Timothy our brother" wrote this epistle to "the church of God which is at Corinth, with all the saints which are in all Achaia".

Who wrote second Corinthians?

# Reader: answer from *unstructured* data

Second Epistle to the Corinthians The Second Epistle to the Corinthians, often referred to as Second Corinthians (and written as 2 Corinthians), is the eighth book of the New Testament of the Bible. **Paul the Apostle and “Timothy our brother”** wrote this epistle to “the church of God which is at Corinth, with all the saints which are in all Achaia”.

Who wrote second Corinthians?

# SQuAD (Rajpurkar et al., 2016)

- 100,000+ paragraph-question-answer pairs
- First phrase-level answers
- First massive **and** manually annotated QA dataset
- Easy to play with, but has a direct useful application

63	Attentive CNN context with LSTM NLPR, CASIA	63.306	73.463
Feb 19, 2017			
63	OTF dict+spelling (single) University of Montreal <a href="https://arxiv.org/abs/1706.00286">https://arxiv.org/abs/1706.00286</a>	64.083	73.056
Sep 21, 2017			
64	OTF spelling (single) University of Montreal <a href="https://arxiv.org/abs/1706.00286">https://arxiv.org/abs/1706.00286</a>	62.897	72.016
Sep 21, 2017			
64	Fine-Grained Gating Carnegie Mellon University <a href="https://arxiv.org/abs/1611.01724">https://arxiv.org/abs/1611.01724</a>	62.446	73.327
Nov 02, 2016			
64	OTF spelling+lemma (single) University of Montreal <a href="https://arxiv.org/abs/1706.00286">https://arxiv.org/abs/1706.00286</a>	62.604	71.968
Sep 21, 2017			
65	Dynamic Chunk Reader IBM <a href="https://arxiv.org/abs/1610.09996">https://arxiv.org/abs/1610.09996</a>	62.499	70.956
Sep 28, 2016			
66	Match-LSTM with Ans-Ptr (Boundary) Singapore Management University <a href="https://arxiv.org/abs/1608.07905">https://arxiv.org/abs/1608.07905</a>	60.474	70.695
Aug 27, 2016			
67	Unnamed submission by Will_Wu	59.058	69.436
Sep 11, 2018			
68	PivRet (single model) anonymous	58.764	69.276
Jan 05, 2018			
69	Match-LSTM with Ans-Ptr (Sentence) Singapore Management University <a href="https://arxiv.org/abs/1608.07905">https://arxiv.org/abs/1608.07905</a>	54.505	67.748
Aug 27, 2016			

100+ models in  
two years!

# “중국 인공지능 전쟁에서 미국에 승리”…인간보다 독해 능력 뛰어난 인공지능 첫 개발

주영재 기자 jyj@kyunghyang.com

116



입력 : 2018.01.16 15:54:00 | 수정 : 2018.01.16 16:39:37



중국이 인간보다 독해 능력이 뛰어난 인공지능을 개발한 첫 국가가 됐다. 중국이 2030년 미국을 제치고 인공지능 경쟁에서 1위를 차지하게 될 것이라는 전망에 힘이 실린다.

블룸버그·파이낸셜타임스 등 외신은 15일(현지시간) 알리바바가 개발한 인공지능이 미국 스탠퍼드대가 주최한 인공지능 대회에서 82.44의 정확도로 인간(82.3)보다 뛰어난 독해능력을 보였다고 보도했다.

### ■ “인공지능 경쟁에서 중국이 미국을 제치다”

이번 인공지능 대회는 10만개 이상의 질문에 정확한 답을 내야 하는 것으로 머신러닝의 수준을 측정하는 가장 권위있는 대회라는 평가를 받고 있다. 질문들은 “비가 왜 내리는가” “아마존 열대 우림은 얼마나 큰가” “니콜라 테슬라의 출신 국가는 어디인가” “슈퍼볼 50 하프 타임 쇼의 첫 공연을 어떤 그룹이 맡았나” 등이었다. 500개 이상의 위키피디아 문서를 바탕으로 한 이번 시험은 인공지능이 거대한 양의 정보를 처리해 질문에 정확한 답을 낼 수 있는지를 측정하는데 목적이 있었다.

5% higher  
than humans



Rank	Model	EM	F1
	Human Performance <i>Stanford University (Rajpurkar et al. '16)</i>	82.304	91.221
1 Oct 05, 2018	BERT (ensemble) <i>Google A.I.</i>	87.433	93.160
2 Oct 05, 2018	BERT (single model) <i>Google A.I.</i>	85.083	91.835
2 Sep 09, 2018	nInet (ensemble) <i>Microsoft Research Asia</i>	85.356	91.202
2 Sep 26, 2018	nInet (ensemble) <i>Microsoft Research Asia</i>	85.954	91.677
3 Jul 11, 2018	QANet (ensemble) <i>Google Brain &amp; CMU</i>	84.454	90.490
4 Jul 08, 2018	r-net (ensemble) <i>Microsoft Research Asia</i>	84.003	90.147



Great, but how fast is it?

N

Hmm... 1s per document?

# Barack Obama

From Wikipedia, the free encyclopedia

"Barack" and "Obama" redirect here. For other uses, see [Barack \(disambiguation\)](#) and [Obama \(disambiguation\)](#).

**Barack Hussein Obama II** (/ba'rə: k hʊ: 'sɛrn ou'ba: mə/ (listen);<sup>[1]</sup> born August 4, 1961) is an American politician who served as the **44th President of the United States** from 2009 to 2017. The first **African American** to assume the presidency, he was previously the **junior United States Senator** from **Illinois** from 2005 to 2008. He served in the **Illinois State Senate** from 1997 until 2004.

Obama was born in 1961 in **Honolulu, Hawaii**, two years after the territory was admitted to the Union as the 50th state. Raised largely in Hawaii, Obama also spent one year of his childhood in **Washington State** and four years in **Indonesia**. After graduating from **Columbia University** in **New York City** in 1983, he worked as a **community organizer** in **Chicago**. In 1988 Obama enrolled in **Harvard Law School**, where he was the first black president of the **Harvard Law Review**. After graduation, he became a **civil rights attorney** and professor, and taught **constitutional law** at the **University of Chicago Law School** from 1992 to 2004. Obama represented the 13th District for three terms in the **Illinois Senate** from 1997 to 2004, when he ran for the U.S. Senate. Obama received national attention in 2004 with his unexpected March primary win, his well-received July Democratic National Convention keynote address, and his landslide November election to the Senate. In 2008, Obama was nominated for president a year after his campaign began and after a close primary campaign against **Hillary Clinton**. He was elected over **Republican John McCain** and was inaugurated on January 20, 2009. Nine months later, Obama was named the **2009 Nobel Peace Prize laureate**, accepting the award with the caveat that he felt there were others "far more deserving of this honor than I."

During his first two years in office, Obama signed many landmark bills into law. The main reforms were the **Patient Protection and Affordable Care Act** (often referred to as "**Obamacare**", shortened as the "**Affordable Care Act**"), the **Dodd-Frank Wall Street Reform and Consumer Protection Act**, and the **Don't Ask, Don't Tell Repeal Act of 2010**. The **American Recovery and Reinvestment Act of 2009** and **Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010** served as **economic stimulus** amidst the **Great Recession**. After a lengthy debate over the national **debt limit**, Obama signed the **Budget Control** and the **American Taxpayer Relief Acts**. In foreign policy, Obama increased U.S. troop levels in **Afghanistan**, reduced nuclear weapons with the **United States-Russia New START treaty**, and ended military involvement in the **Iraq War**. He ordered military involvement in **Libya** in opposition to **Muammar Gaddafi**; Gaddafi was killed by **NATO-assisted forces**, and he also ordered the military operation that resulted in the death of **Osama bin Laden**.

After winning **re-election** by defeating Republican opponent **Mitt Romney**, Obama was sworn in for a second term in 2013. During his second term, Obama promoted inclusiveness for **LGBT Americans**. His administration filed briefs that urged the **Supreme Court** to strike down **same-sex marriage** bans as

**Barack Obama**



**44th President of the United States**  
**In office**  
January 20, 2009 – January 20, 2017  
**Vice President** Joe Biden  
**Preceded by** George W. Bush  
**Succeeded by** Donald Trump  
**United States Senator**  
from Illinois



1 s



**WIKIPEDIA**  
La enciclopedia libre

**5.6 Million Documents**  
**3 Billion Words**



Hmm... 1s per document?

So... 6 days.



Great, but how long does it take?





Actually, I will just retrieve a few documents, and just **read** them!



*One week?*  
!#\$@\*%(@\*@



**WIKIPEDIA**  
La enciclopedia libre



두산백과

## 버락 오바마

[Barack Hussein Obama]

요약 미국의 정치가, 인권변호사 출신으로 일리노이주 상원의원(3선)을 거쳐 연방 상원의원을 지냈으며, 2008년 민주당 대통령 후보로 출마하여 공화당의 존 케리인 후보에 압승하고 제44대 미국 대통령에 당선됨으로써 미국 최초의 흑인(경화하게는 혼혈 혈인) 대통령이 되었다. 취임 후 학무기 감축, 종동평화회담 개개 등에 힘써 2009년 노벨 평화상을 수상하였다.

출생-사망 1961.8.4 ~

본명 버락 후세인 오바마(Barack Hussein Obama)

국적 미국

활동분야 정치

출생지 미국 하와이주 호놀룰루

주요수상 노벨 평화상(2009)



1961

*Still slow, and  
error propagates...*



WIKIPEDIA  
La enciclopedia libre

?



1961

*direct and fast reader?*



**WIKIPEDIA**  
La enciclopedia libre

**5.6M documents**

**5.8 days**

5,000,000x shorter

**Titan Xp**

4,000x slower



**0.1s**

**CPU**

**20 billion times faster?**



This is a Green Factory Library.



History

Art

IT

Novel

A

B

.

K

When did Korean War  
break out?

**Precompute** vectors.  
**Organize** vectors.



[0.5, 0.1, ...]



[0.3, 0.4, ...]



[0.4, 0.5, ...]



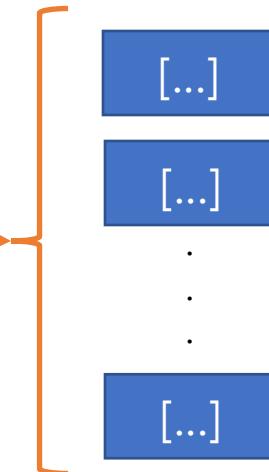
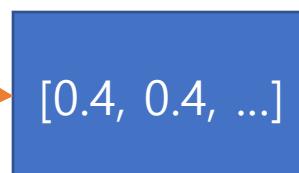
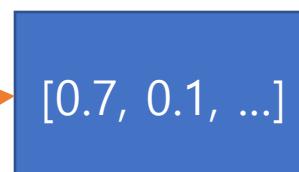
[0.4, 0.4, ...]



[0.8, 0.1, ...]



[0.4, 0.3, ...]



MIPS

When did  
Korean War  
break out?

**Cluster** similar vectors

# Kernel types

- **Symmetric:** proper metric functions (Nearest Neighbor Search)
  - L2
  - L1
  - Angular distance
- **Asymmetric:** inner product (MIPS)
  - Dot product (cosine distance)

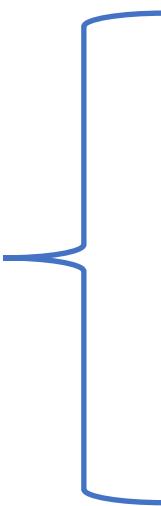
$O(kN)$  $O(kN^\rho \log(N))$ 

$\rho$ = approximation factor (<1)

Sublinear-time approximation.  
Very fast.

Document → Phrase?

Super Bowl 50 was an American football game to determine the champion of the National Football League (NFL) for the 2015 season. The American Football Conference (AFC) champion Denver Broncos defeated the National Football Conference (NFC) champion Carolina Panthers 24–10 to earn their third Super Bowl title. The game was played on February 7, 2016, at Levi's Stadium in the San Francisco Bay Area at Santa Clara, California. As this was the 50th Super Bowl, the league emphasized the "golden anniversary" with various gold-themed initiatives, as well as temporarily suspending the tradition of naming each Super Bowl game with Roman numerals (under which the game would have been known as "Super Bowl L"), so that the logo could prominently feature the Arabic numerals 50.



- Super Bowl 50       $d_1$
- American football game       $d_2$
- National Football League       $d_3$
- Denver Broncos       $d_4$

...

MIPS

Which NFL team  
represented the  
AFC at  
Super Bowl 50?

**q**

# Mathematically...

- document  $d$  와 question  $q$  are given:

$$\hat{a} = \operatorname{argmax}_a P_\theta(a|q; d)$$

where

**As-is:** need to compute score for every new query

$$P_\theta(a|q; d) \propto \exp(F_\theta(a, q, d))$$



Decomposition

**To-be:**  $H$  can be *pre-computed* and *indexed*

$$P_\theta(a|q; d) \propto \exp(G_\theta(q) \cdot H_\theta(a, d))$$



But the decomposition is not easy.

A new research problem:  
**Phrase-Indexed Question Answering**  
(PIQA)

# PIQA (Seo et al., 2018)

Constraint	Model	F1 (%)	EM (%)
PI	TF-IDF	15.0	3.9
	LSTM	57.2	46.8
	LSTM+SA	59.8	49.0
	LSTM+ELMo	60.9	50.9
	LSTM+SA+ELMo	62.7	52.7
None	Rajpurkar et al. (2016)	51.0	40.0
	Yu et al. (2018)	89.3	82.5

} *Decomposability gap*

# DeSPI (Seo & Lee et al., 2019)

	Model	EM	F1	W/s	
Original	DrQA	69.5	78.8	4.8K	<i>Decomposability gap</i>
	BERT	84.1	90.9	51	
Query-Agnostic	LSTM+SA	49.0	59.8	-	
	LSTM+SA+ELMo	52.7	62.7	-	
	DESPI (dense only)	73.6	81.7	28.7M	
	–Coherency scalar	71.5	81.5	28.7M	

Exact search: **6000** times faster than DrQA, **5M** times faster than BERT

# DeSPI (Seo & Lee et al., 2019)

	F1	EM	s/Q	#D/Q
DrQA	-	29.8	35	5
R <sup>3</sup>	37.5	-	-	-
Paragraph ranking	-	30.2	-	-
Multi-step reasoner	39.2	31.9	-	-
MINIMAL	42.5	34.7	-	-
BERTserini	46.1	38.6	-	-
DESPI	42.3	33.4	0.51	532
–Sparse vector	20.5	13.3	0.22	532
+Sparse search	38.6	31.2	0.23	5

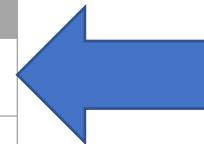
# Demo

# Today's Talk

- Intro: About Question Answering & Reasoning
- **Parsing:** SOTA on WikiSQL
- **Reading:** Real-time Open-domain Question Answering
- Towards a Unified Model

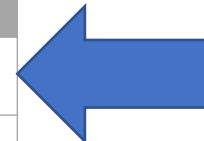
# Parsing vs Reading

	Parsing	Reading
Speed	Fast	Slow
Domain	Limited	Ontology-free, open-domain
Complexity	Multi-hop reasoning	Limited



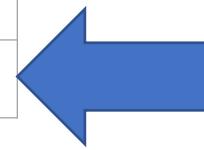
# Parsing vs Reading

	Parsing	Reading
Speed	Fast	Fast
Domain	Limited	Ontology-free, open-domain
Complexity	Multi-hop reasoning	Limited



# Parsing vs Reading

	Parsing	Reading
Speed	Fast	Fast
Domain	Limited	Ontology-free, open-domain
Complexity	Multi-hop reasoning	Limited



Can a **reader** handle complex queries?

# Have people tried it?

- **Yes**, on synthetic data: bAbI (Weston et al., 2016)
  - Syntactically simple (synthetic) text
  - Predefined types of reasoning
- And **Yes**, on state changing dataset: ProPara (Dalvi et al., 2018)
  - About single entity
  - The state of the entity changes throughout the text sequentially
- Another **Yes**, on multi-hop QA dataset: HotpotQA (Yang et al., 2018)
  - SQuAD-like, but multi-hop and open-domain

# bAbI (Weston et al., 2016)

## Task 1: Single Supporting Fact

Mary went to the bathroom.  
John moved to the hallway.  
Mary travelled to the office.  
Where is Mary? A:office

## Task 2: Two Supporting Facts

John is in the playground.  
John picked up the football.  
Bob went to the kitchen.  
Where is the football? A:playground

## Task 3: Three Supporting Facts

John picked up the apple.  
John went to the office.  
John went to the kitchen.  
John dropped the apple.  
Where was the apple before the kitchen? A:office

## Task 4: Two Argument Relations

The office is north of the bedroom.  
The bedroom is north of the bathroom.  
The kitchen is west of the garden.  
What is north of the bedroom? A: office  
What is the bedroom north of? A: bathroom

## Task 5: Three Argument Relations

Mary gave the cake to Fred.  
Fred gave the cake to Bill.  
Jeff was given the milk by Bill.  
Who gave the cake to Fred? A: Mary  
Who did Fred give the cake to? A: Bill

## Task 6: Yes/No Questions

John moved to the playground.  
Daniel went to the bathroom.  
John went back to the hallway.  
Is John in the playground? A:no  
Is Daniel in the bathroom? A:yes

## Task 7: Counting

Daniel picked up the football.  
Daniel dropped the football.  
Daniel got the milk.  
Daniel took the apple.  
How many objects is Daniel holding? A: two

## Task 8: Lists/Sets

Daniel picks up the football.  
Daniel drops the newspaper.  
Daniel picks up the milk.  
John took the apple.  
What is Daniel holding? milk, football

## Task 9: Simple Negation

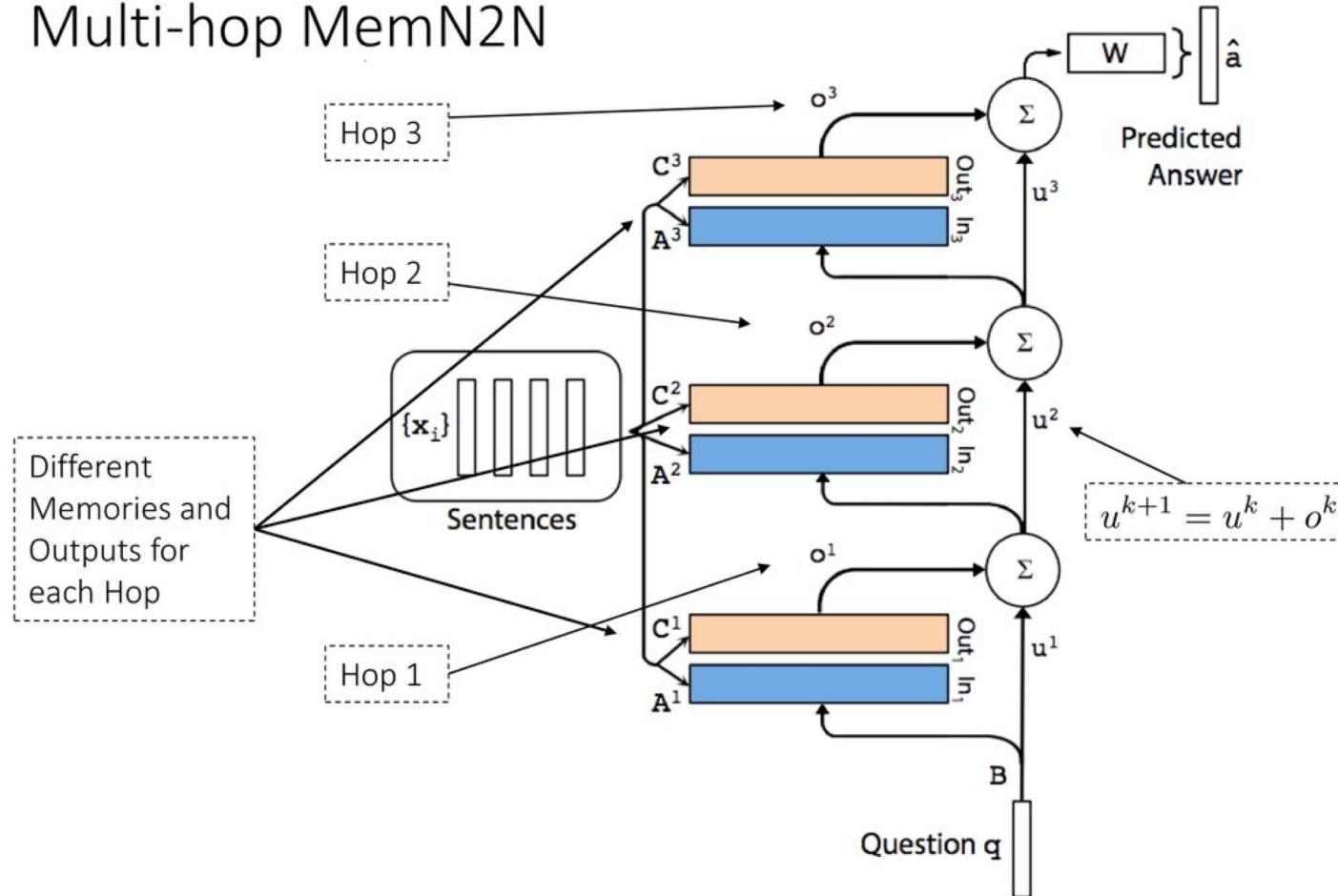
Sandra travelled to the office.  
Fred is no longer in the office.  
Is Fred in the office? A:no  
Is Sandra in the office? A:yes

## Task 10: Indefinite Knowledge

John is either in the classroom or the playground.  
Sandra is in the garden.  
Is John in the classroom? A:maybe  
Is John in the office? A:no

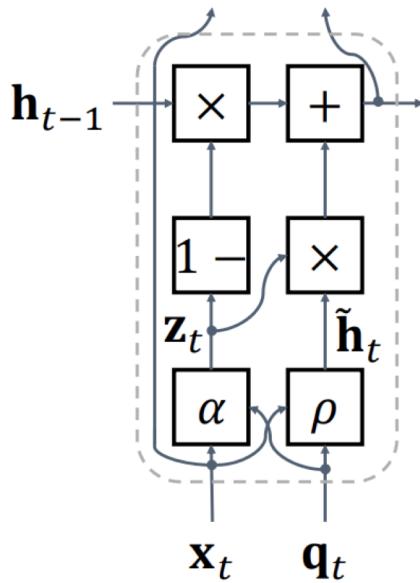
# End-to-end Memory Networks (Sukbaatar et al., 2015)

Multi-hop MemN2N

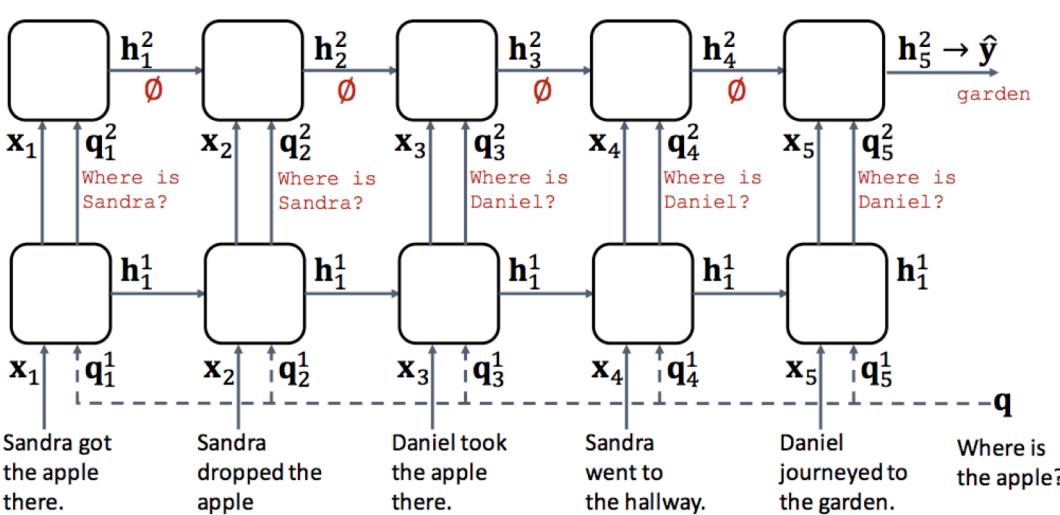


# Query-Reduction Networks

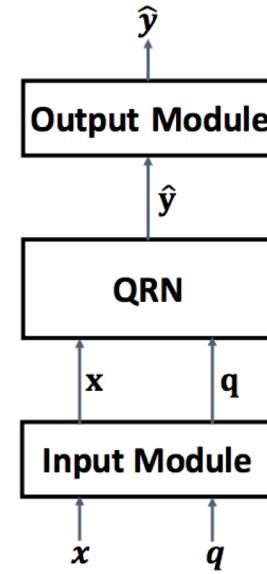
(Seo et al., 2017)



(a) QRN unit



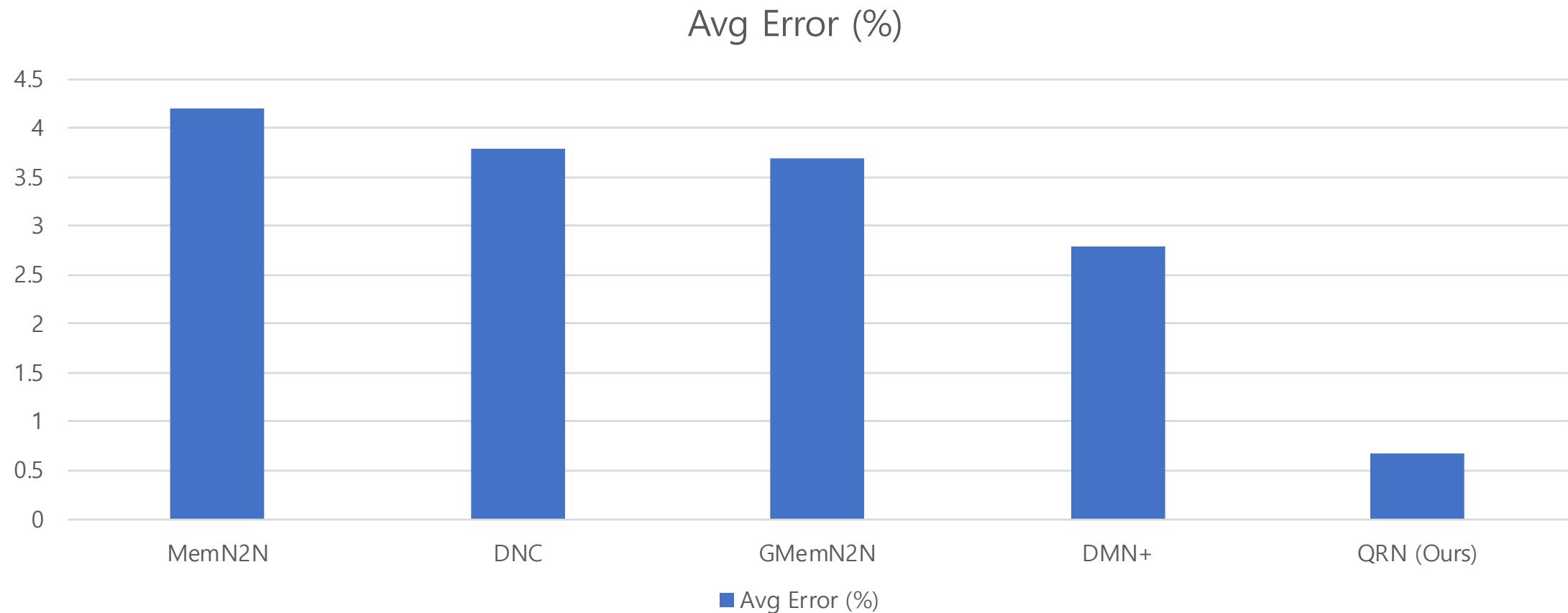
(b) 2-layer QRN



(c) Overview

Figure 1: (1a) QRN unit, (1b) 2-layer QRN on 5-sentence story, and (1c) entire QA system (QRN and input / output modules).  $x, q, \hat{y}$  are the story, question and predicted answer in natural language, respectively.  $\mathbf{x} = \langle \mathbf{x}_1, \dots, \mathbf{x}_T \rangle$ ,  $\mathbf{q}, \hat{\mathbf{y}}$  are their corresponding vector representations (upright font).  $\alpha$  and  $\rho$  are update gate and reduce functions, respectively.  $\hat{\mathbf{y}}$  is assigned to be  $\mathbf{h}_5^2$ , the local query at the last time step in the last layer. Also, red-colored text is the inferred meanings of the vectors (see ‘Interpretations’ of Section 5.3).

# bAbI QA Results (10k)



# ProPara (Dalvi et al., 2018)

- Real data
- Sequentially state-changing

Chloroplasts in the leaf of the plant trap light from the sun. The roots absorb water and minerals from the soil. This combination of water and minerals flows from the stem into the leaf. Carbon dioxide enters the **leaf**. Light, water and minerals, and the carbon dioxide all combine into a mixture. This mixture forms **sugar** (glucose) which is what the plant eats.

**Q:** Where is sugar produced?

**A:** in the leaf

# QRN (Seo et al., 2017) vs ProStruct (Tandon et al., 2018)

	Precision	Recall	F1
ProLocal	77.4	22.9	35.3
QRN	55.5	31.3	40.0
EntNet	50.2	33.5	40.2
ProGlobal	46.7	52.4	49.4
<b>PROSTRUCT</b>	74.2	42.1	<b>53.7</b>

Table 1: Results on the prediction task (test set).

# HotpotQA (Yang et al., 2018)

## Paragraph A, Return to Olympus:

[1] *Return to Olympus* is the only album by the alternative rock band Malfunkshun. [2] It was released after the band had broken up and after lead singer Andrew Wood (later of Mother Love Bone) had died of a drug overdose in 1990. [3] Stone Gossard, of Pearl Jam, had compiled the songs and released the album on his label, Loosegroove Records.

## Paragraph B, Mother Love Bone:

[4] Mother Love Bone was an American rock band that formed in Seattle, Washington in 1987. [5] The band was active from 1987 to 1990. [6] Frontman Andrew Wood's personality and compositions helped to catapult the group to the top of the burgeoning late 1980s/early 1990s Seattle music scene. [7] Wood died only days before the scheduled release of the band's debut album, "Apple", thus ending the group's hopes of success. [8]

The album was finally released a few months later.

**Q:** What was the former band of the member of Mother Love Bone who died just before the release of "Apple"?

**A:** Malfunkshun

**Supporting facts:** 1, 2, 4, 6, 7

## Leaderboard (Fullwiki Setting)

In the fullwiki setting, a question-answering system must find the answer to a question in the scope of the entire Wikipedia. Similar to in the distractor setting, systems are evaluated on the accuracy of their answers (Ans) and the quality of the supporting facts they use to justify them (Sup).

	Model	Code	Ans		Sup		Joint	
			EM	F <sub>1</sub>	EM	F <sub>1</sub>	EM	F <sub>1</sub>
1 Feb 21, 2019	Cognitive Graph (single model) <i>Anonymous</i>		37.12	48.87	22.82	57.69	12.42	34.92
2 Mar 5, 2019	MUPPET (single model) <i>Anonymous</i>		30.61	40.26	16.65	47.33	10.85	27.01
3 Mar 4, 2019	GRN (single model) <i>Anonymous</i>		27.34	36.48	12.23	48.75	7.40	23.55
4 Nov 25, 2018	QFE (single model) <i>NTT Media Intelligence Laboratories</i>		28.66	38.06	14.20	44.35	8.69	23.10
5 Oct 12, 2018	Baseline Model (single model) <i>Carnegie Mellon University, Stanford University, &amp; Universite de Montreal (Yang, Qi, Zhang, et al. 2018)</i>		23.95	32.89	3.86	37.71	1.85	16.15
- Feb 28, 2019	DecompRC (single model) <i>Anonymous</i>		30.00	40.65	N/A	N/A	N/A	N/A
- Mar 3, 2019	MultiQA (single model) <i>Anonymous</i>		30.73	40.23	N/A	N/A	N/A	N/A

So, when is **reader** capable of end-to-end *reasoning*?

- Syntactically simple sentences (bAbl)
- Sequential reasoning (ProPara)
- Strong supervision (ProPara, HotpotQA)

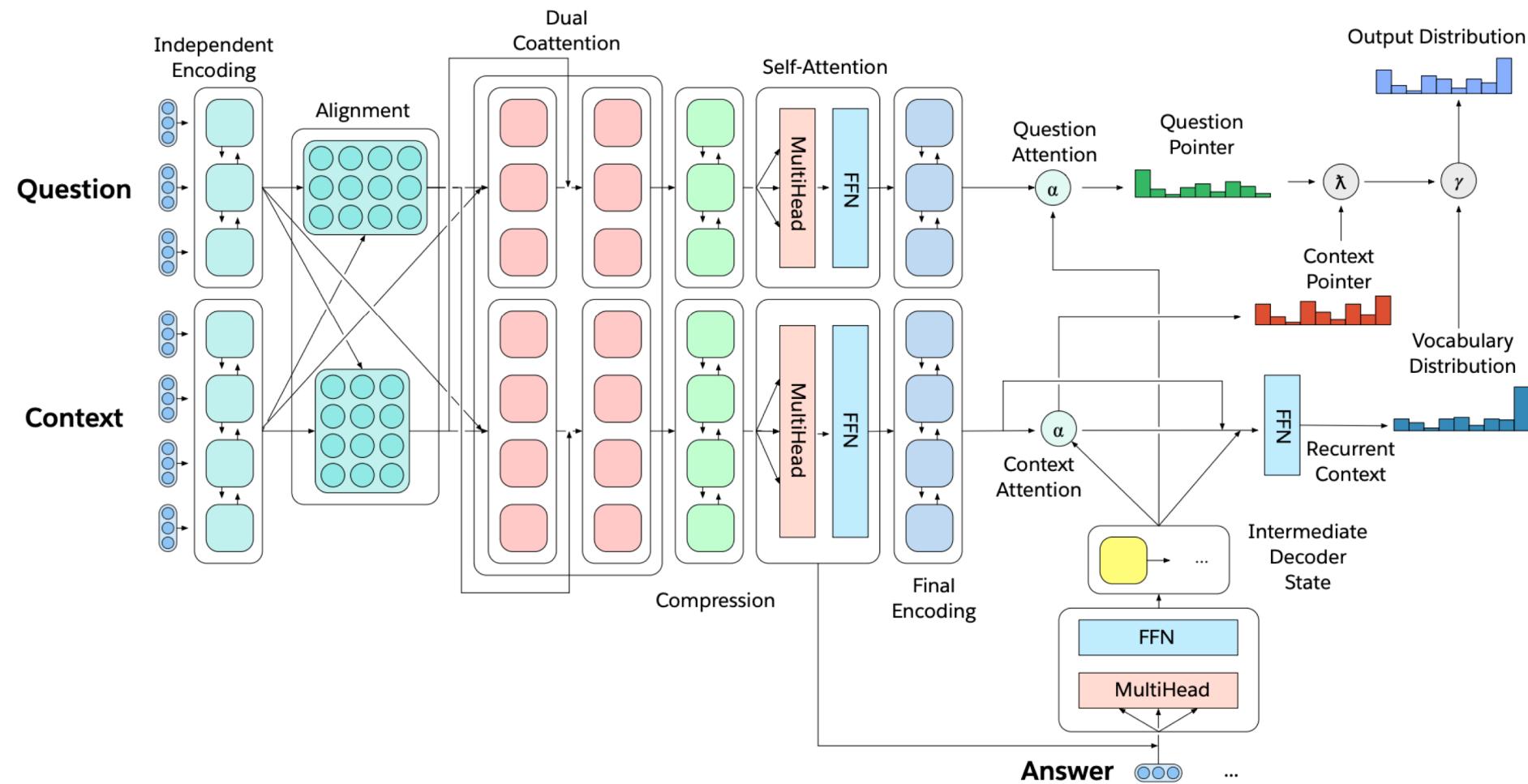
# Conclusion

- **Parser** and **Reader** have different strengths
- Making **Parser** open-domain, ontology-free is hard (or doesn't make sense by definition)
- **Reader** is starting to overcome some of its bottlenecks (e.g. speed, reasoning)
- Future research will get us closer to a true *unified model* for question answering and reasoning

# Thanks!

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- <https://seominjoon.github.io>

# DecaNLP (McCann et al., 2018)



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