# Question Answering

Wei Xu

(many slides from Greg Durrett)

# Administrivia

- No class on Wednesday 4/13; next lecture will be on Monday 4/18
- 4/13 2-3pm Guest Lecture by Luheng He (Google Research)
  - more info later on Piazza
- Instructions on final project submission are posted on Piazza
- Reading: J+M Chapter 23

# QA is very broad

- Factoid QA: *what states border Mississippi?, when was Barack Obama born? (e.g. user search on Google)*
  - Lots of this could be handled by QA from a knowledge base, if we had a big enough knowledge base

# QA is very broad

- "Question answering" as a term is so broad as to be meaningless
  - *What is the meaning of life?*
  - *What is 4+5?*
  - *What is the translation of [sentence] into French?* [McCann et al., 2018]

# Classical Question Answering

- Form semantic representation from semantic parsing, execute against structured knowledge base

Q: “where was Barack Obama born”

$$\lambda x.\ \texttt{type}(x, \texttt{Location}) \wedge \texttt{born\_in}(\texttt{Barack\_Obama}, x)$$

(other representations like SQL possible too…)

- How to deal with open-domain data/relations? Need data to learn how to ground every predicate or need to be able to produce predicates in a zero-shot way

# Reading Comprehension

- "AI challenge problem": answer question given context
- Recognizing Textual Entailment (2006)
- MCTest (2013): 500 passages, 4 questions per passage
- Two questions per passage explicitly require cross-sentence reasoning

One day, James thought he would go into town and see what kind of trouble he could get into. He went to the grocery store and pulled all the pudding off the shelves and ate two jars. Then he walked to the fast food restaurant and ordered 15 bags of fries. He didn't pay, and instead headed home.

3) Where did James go after he went to the grocery store?
A) his deck
B) his freezer
C) a fast food restaurant
D) his room

Richardson (2013)

# Dataset Explosion

- 30+ QA datasets released since 2015
  - SQuAD, TriviaQA are most well-known (others: Children's Book Test, QuAC, WikiHop, HotpotQA, NaturalQuestions, WebQuestions …)
- Question answering: questions are in natural language
  - Answers: multiple choice or require picking from the passage
  - Require human annotation
- "Cloze" task: word (often an entity) is removed from a sentence
  - Answers: multiple choice, pick from passage, or pick from vocabulary
  - Can be created automatically from things that aren't questions

# Children’s Book Test

"Well, Miss Maxwell, I think it only fair to tell you that you may have trouble with those boys when they do come. Forewarned is forearmed, you know. Mr. Cropper was opposed to our hiring you. Not, of course, that he had any personal objection to you, but he is set against female teachers, and when a Cropper is set there is nothing on earth can change him. He says female teachers can't keep order. He 's started in with a spite at you on general principles, and the boys know it. They know he'll back them up in secret, no matter what they do, just to prove his opinions. Cropper is sly and slippery, and it is hard to corner him."

"Are the boys big ?" queried Esther anxiously.

"Yes. Thirteen and fourteen and big for their age. You can't whip 'em -- that is the trouble. A man might, but they'd twist you around their fingers. You'll have your hands full, I'm afraid. But maybe they'll behave all right after all."

Mr. Baxter privately had no hope that they would, but Esther hoped for the best. She could not believe that Mr. Cropper would carry his prejudices into a personal application. This conviction was strengthened when he overtook her walking from school the next day and drove her home. He was a big, handsome man with a very suave, polite manner. He asked interestedly about her school and her work, hoped she was getting on well, and said he had two young rascals of his own to send soon. Esther felt relieved. She thought that Mr. Baxter had exaggerated matters a little.

```
S: 1 Mr. Cropper was opposed to our hiring you .
   2 Not , of course , that he had any personal objection to you , but he is set
   against female teachers , and when a Cropper is set there is nothing on earth can
   change him .
   3 He says female teachers ca n't keep order .
   4 He 's started in with a spite at you on general principles , and the boys know
   it .
   5 They know he 'll back them up in secret , no matter what they do , just to prove
   his opinions .
   6 Cropper is sly and slippery , and it is hard to corner him . ''
   7 `` Are the boys big ? ''
   8 queried Esther anxiously .
   9 `` Yes .
   10 Thirteen and fourteen and big for their age .
   11 You ca n't whip 'em -- that is the trouble .
   12 A man might , but they 'd twist you around their fingers .
   13 You 'll have your hands full , I 'm afraid .
   14 But maybe they 'll behave all right after all . ''
   15 Mr. Baxter privately had no hope that they would , but Esther hoped for the
   best.
   16 She could not believe that Mr. Cropper would carry his prejudices into a
   personal application .
   17 This conviction was strengthened when he overtook her walking from school the
   next day and drove her home .
   18 He was a big , handsome man with a very suave , polite manner .
   19 He asked interestedly about her school and her work , hoped she was getting on
   well , and said he had two young rascals of his own to send soon .
   20 Esther felt relieved .
q: She thought that Mr. ________ had exaggerated matters a little .
C: Baxter, Cropper, Esther, course, fingers, manner, objection, opinion, right, spite.
a: Baxter
```

- Children’s Book Test: take a section of a children’s story, block out an entity and predict it (one-doc multi-sentence cloze task)

Hill et al. (2015)

# Children's Book Test

"Well, Miss Maxwell, I think it only fair to tell you that you may have trouble with those boys when they do come. Forewarned is forearmed, you know. Mr. Cropper was opposed to our hiring you. Not, of course, that he had any

Mr. Baxter privately had no hope that they would, but Esther hoped for the best. She could not believe that Mr. Cropper would carry his prejudices into a personal application. This conviction was strengthened when he overtook her walking from school the next day and drove her home. He was a big, handsome man with a very suave, polite manner. He asked interestedly about her school and her work, hoped she was getting on well, and said he had two young rascals of his own to send soon. Esther felt relieved. She thought that

**????** had exaggerated matters a little.

man with a very suave, polite manner. He asked interestedly about her school and her work, hoped she was getting on well, and said he had two young rascals of his own to send soon. Esther felt relieved. She thought that Mr. Baxter had exaggerated matters a little.

*S*: 1 Mr. Cropper was opposed to our hiring you .
2 Not , of course , that he had any personal objection to you , but he is set against female teachers , and when a Cropper is set there is nothing on earth can change him .
...ep order .
... you on general principles , and the boys know
... secret , no matter what they do , just to prove
... it is hard to corner him . ''
...r their age .
...he trouble .
... you around their fingers .
... 'm afraid .
...ght after all . ''
... that they would , but Esther hoped for the
...ropper would carry his prejudices into a
... when he overtook her walking from school the
... a very suave , polite manner .
... school and her work , hoped she was getting on well , and said he had two young rascals of his own to send soon .
20 Esther felt relieved .

*q*: She thought that Mr. ________ had exaggerated matters a little .

*C*: Baxter, Cropper, Esther, course, fingers, manner, objection, opinion, right, spite.

*a*: Baxter

- Children's Book Test: take a section of a children's story, block out an entity and predict it (one-doc multi-sentence cloze task)

Hill et al. (2015)

# bAbI

- Evaluation on 20 tasks proposed as building blocks for building “AI-complete” systems
- Various levels of difficulty, exhibit different linguistic phenomena
- Small vocabulary, language isn’t truly “natural”

**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 13: Compound Coreference**
Daniel and Sandra journeyed to the office.
Then they went to the garden.
Sandra and John travelled to the kitchen.
After that they moved to the hallway.
Where is Daniel? A: garden

**Task 14: Time Reasoning**
In the afternoon Julie went to the park.
Yesterday Julie was at school.
Julie went to the cinema this evening.
Where did Julie go after the park? A:cinema
Where was Julie before the park? A:school

Weston et al. (2014)

# Multiple-Choice

- SWAG dataset was constructed to be difficult for ELMo
- BERT subsequently got 20+% accuracy improvements and achieved human-level performance
- Problem: distractors too easy

The person blows the leaves from a grass area using the blower. The blower...

| |
|---|
| a) puts the trimming product over her face in another section. |
| b) is seen up close with different attachments and settings featured. |
| c) continues to blow mulch all over the yard several times. |
| d) blows beside them on the grass. |

Zellers et al. (2018)

# Dataset Properties

- Axis 1: cloze task (fill in blank) vs. multiple choice vs. span-based vs. freeform generation
- Axis 2: what's the input?
  - One paragraph? One document? All of Wikipedia?
  - Some explicitly require linking between multiple sentences (MCTest, WikiHop, HotpotQA)
- Axis 3: what capabilities are needed to answer questions?
  - Finding simple information? Combining information across multiple sources? Commonsense knowledge?

# Span-based Question Answering

# SQuAD

- Single-document, single-sentence question-answering task where the answer is always a substring of the passage
- Predict start and end indices of the answer in the passage

**Passage**

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.

**Question:** Which NFL team won Super Bowl 50?
**Answer:** Denver Broncos

**Question:** What does AFC stand for?
**Answer:** American Football Conference

**Question:** What year was Super Bowl 50?
**Answer:** 2016

Rajpurkar et al. (2016)

# SQuAD 2.0

- SQuAD 1.1 contains 100k+ QA pairs from 500+ Wikipedia articles.
- SQuAD 2.0 includes additional 50k questions that cannot be answered.
- These questions were crowdsourced.

**Passage**

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.

**Question:** Which NFL team won Super Bowl 50?
**Answer:** Denver Broncos

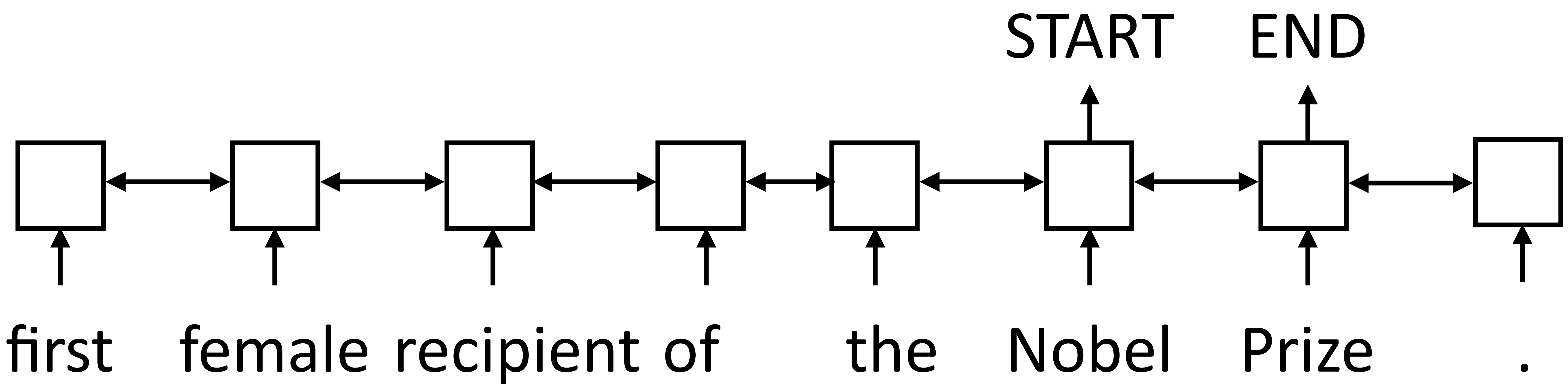
**Question:** What does AFC stand for?
**Answer:** American Football Conference

**Question:** What year was Super Bowl 50?
**Answer:** 2016

Rajpurkar et al. (2016)

# SQuAD

Q: What was Marie Curie the first female recipient of?




- Like a tagging problem over the sentence (not multiclass classification), but we need some way of attending to the query

Rajpurkar et al. (2016)

# Why did this take off?

- SQuAD was **big**: >100,000 questions (written by human) at a time when deep learning was exploding

- SQuAD had **room to improve**: ~50% performance from a logistic regression baseline (classifier with 180M features over constituents)

- SQuAD was **pretty easy**: year-over-year progress for a few years until the dataset was essentially solved

# Bidirectional Attention Flow (BiDAF)

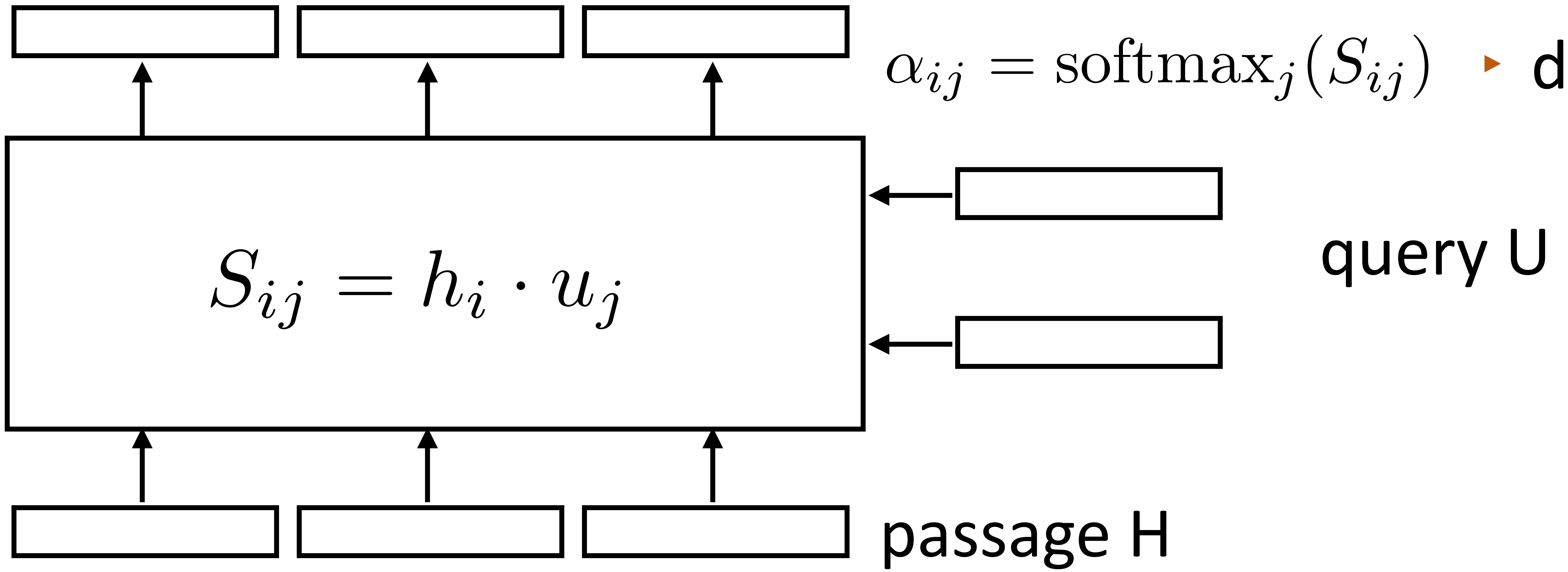
- Passage (context) and query are both encoded with BiLSTMs
- Context-to-query attention: compute softmax over columns of S, take weighted sum of *u* based on attention weights for each passage word

$$\tilde{u}_i = \sum_j \alpha_{ij} u_j$$

- query "specialized" to the *i*th word

$$\alpha_{ij} = \mathrm{softmax}_j(S_{ij})$$

- dist over query




Seo et al. (2016)

# Bidirectional Attention Flow (BiDAF)

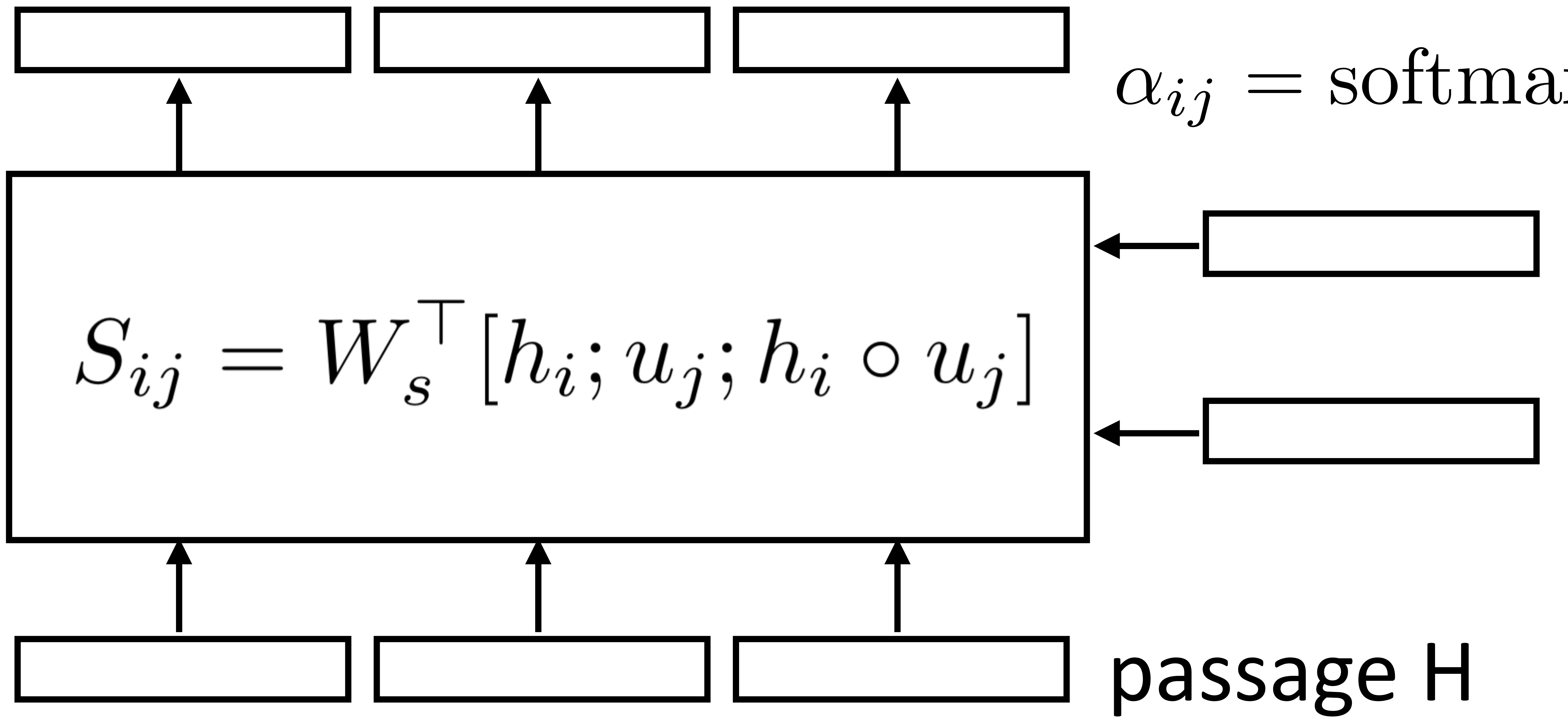
- Passage (context) and query are both encoded with BiLSTMs
- Context-to-query attention: compute softmax over columns of S, take weighted sum of *u* based on attention weights for each passage word

$$\tilde{u}_i = \sum_j \alpha_{ij} u_j$$

- query "specialized" to the *i*th word

$$\alpha_{ij} = \mathrm{softmax}_j(S_{ij})$$

- dist over query

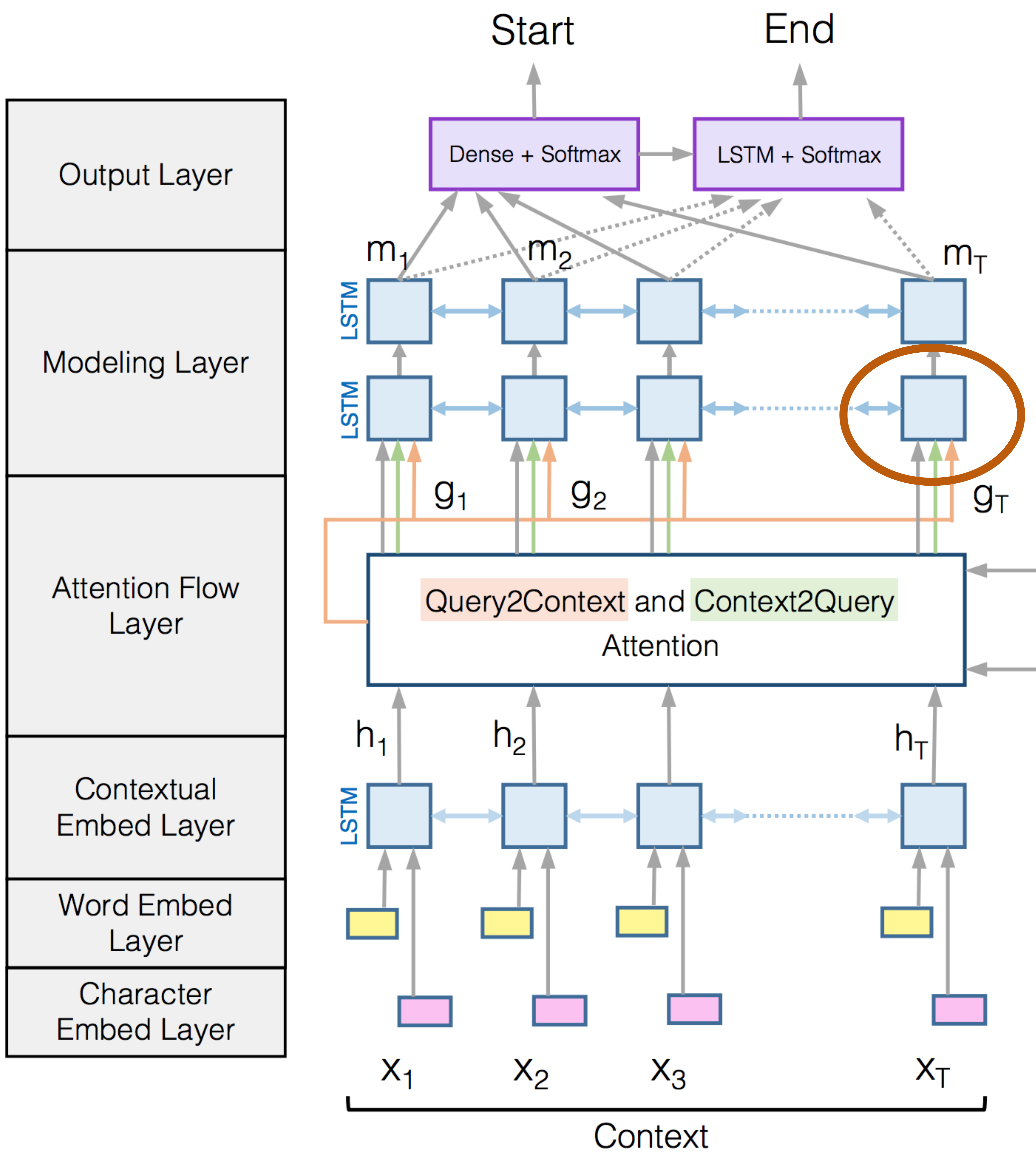



query U

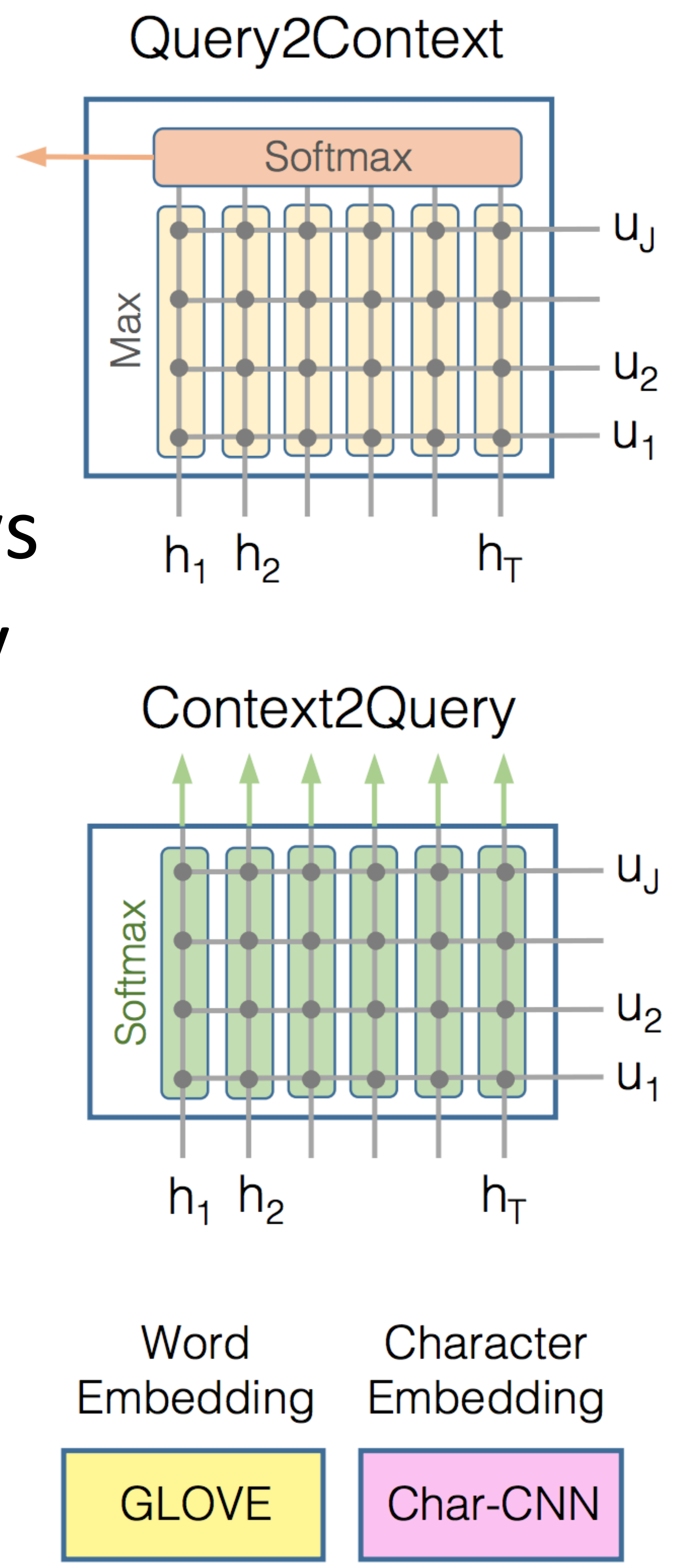
passage H

Seo et al. (2016)

# Bidirectional Attention Flow

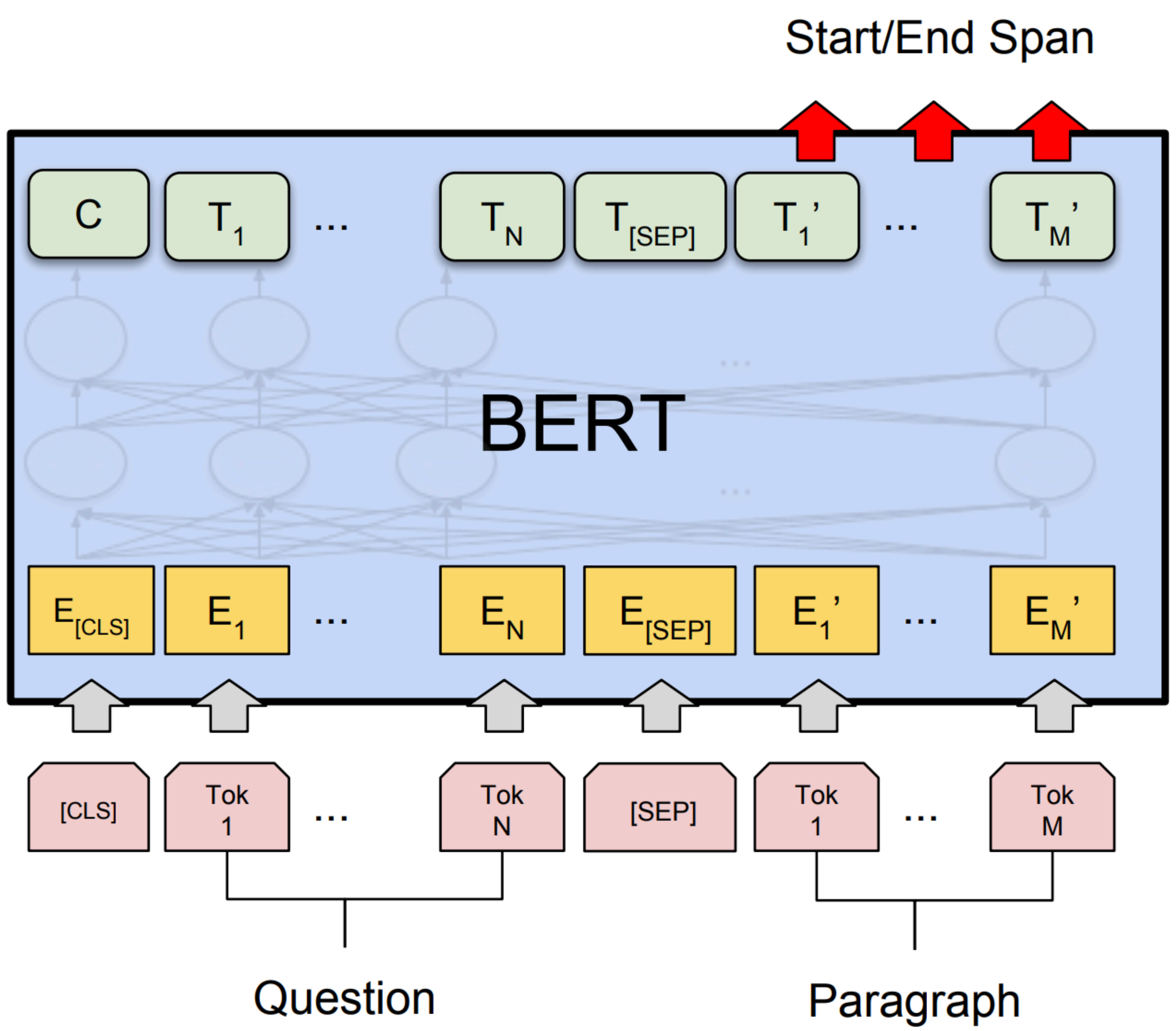



Each passage word now "knows about" the query




Seo et al. (2016)

# QA with BERT




What was Marie Curie the first female recipient of ? [SEP] Marie Curie was the first female recipient of …

- Predict start and end positions in passage
- No need for cross-attention mechanisms!

Devlin et al. (2019)

# SQuAD SOTA: Fall 2018

| Rank | Model | EM | F1 |
|---|---|---|---|
| | Human Performance<br>*Stanford University*<br>(Rajpurkar et al. '16) | 82.304 | 91.221 |
| 1<br>Oct 05, 2018 | BERT (ensemble)<br>*Google AI Language*<br>https://arxiv.org/abs/1810.04805 | **87.433** | **93.160** |
| 2<br>Oct 05, 2018 | BERT (single model)<br>*Google AI Language*<br>https://arxiv.org/abs/1810.04805 | 85.083 | 91.835 |
| 2<br>Sep 09, 2018 | nlnet (ensemble)<br>*Microsoft Research Asia* | 85.356 | 91.202 |
| 2<br>Sep 26, 2018 | nlnet (ensemble)<br>*Microsoft Research Asia* | 85.954 | 91.677 |
| 3<br>Jul 11, 2018 | QANet (ensemble)<br>*Google Brain & CMU* | 84.454 | 90.490 |
| 4<br>Jul 08, 2018 | r-net (ensemble)<br>*Microsoft Research Asia* | 84.003 | 90.147 |
| 5<br>Mar 19, 2018 | QANet (ensemble)<br>*Google Brain & CMU* | 83.877 | 89.737 |

- BiDAF: 73 EM / 81 F1
- nlnet, QANet, r-net — dueling super complex systems (much more than BiDAF...)
- BERT: transformer-based approach with pretraining on 3B tokens

# SQuAD 2.0 SOTA: Spring 2019

| Rank | Model | EM | F1 |
|---|---|---|---|
| | Human Performance<br>*Stanford University*<br>(Rajpurkar & Jia et al. '18) | 86.831 | 89.452 |
| 1<br>Mar 20, 2019 | BERT + DAE + AoA (ensemble)<br>*Joint Laboratory of HIT and iFLYTEK Research* | **87.147** | **89.474** |
| 2<br>Mar 15, 2019 | BERT + ConvLSTM + MTL + Verifier (ensemble)<br>*Layer 6 AI* | 86.730 | 89.286 |
| 3<br>Mar 05, 2019 | BERT + N-Gram Masking + Synthetic Self-Training (ensemble)<br>*Google AI Language*<br>https://github.com/google-research/bert | 86.673 | 89.147 |
| 4<br>Apr 13, 2019 | SemBERT(ensemble)<br>*Shanghai Jiao Tong University* | 86.166 | 88.886 |
| 5<br>Mar 16, 2019 | BERT + DAE + AoA (single model)<br>*Joint Laboratory of HIT and iFLYTEK Research* | 85.884 | 88.621 |
| 6<br>Mar 05, 2019 | BERT + N-Gram Masking + Synthetic Self-Training (single model)<br>*Google AI Language*<br>https://github.com/google-research/bert | 85.150 | 87.715 |
| 7<br>Jan 15, 2019 | BERT + MMFT + ADA (ensemble)<br>*Microsoft Research Asia* | 85.082 | 87.615 |

- SQuAD 2.0: harder dataset because some questions are unanswerable
- Industry contest

# SQuAD 2.0 SOTA: Fall 2019

| Rank | Model | EM | F1 |
|---|---|---|---|
| | Human Performance<br>*Stanford University*<br>(Rajpurkar & Jia et al. '18) | 86.831 | 89.452 |
| 1<br>Sep 18, 2019 | ALBERT (ensemble model)<br>*Google Research & TTIC*<br>https://arxiv.org/abs/1909.11942 | **89.731** | **92.215** |
| 2<br>Jul 22, 2019 | XLNet + DAAF + Verifier (ensemble)<br>*PINGAN Omni-Sinitic* | 88.592 | 90.859 |
| 2<br>Sep 16, 2019 | ALBERT (single model)<br>*Google Research & TTIC*<br>https://arxiv.org/abs/1909.11942 | 88.107 | 90.902 |
| 2<br>Jul 26, 2019 | UPM (ensemble)<br>*Anonymous* | 88.231 | 90.713 |
| 3<br>Aug 04, 2019 | XLNet + SG-Net Verifier (ensemble)<br>*Shanghai Jiao Tong University & CloudWalk*<br>https://arxiv.org/abs/1908.05147 | 88.174 | 90.702 |
| 4<br>Aug 04, 2019 | XLNet + SG-Net Verifier++ (single model)<br>*Shanghai Jiao Tong University & CloudWalk*<br>https://arxiv.org/abs/1908.05147 | 87.238 | 90.071 |

- Performance is very saturated
- Harder QA settings are needed!
- Varied pre-trained LMs

# SQuAD 2.0 SOTA: Today

| Rank | Model | EM | F1 |
|---|---|---|---|
| | Human Performance<br>*Stanford University*<br>(Rajpurkar & Jia et al. '18) | 86.831 | 89.452 |
| 1<br>Jun 04, 2021 | IE-Net (ensemble)<br>*RICOH_SRCB_DML* | **90.939** | **93.214** |
| 2<br>Feb 21, 2021 | FPNet (ensemble)<br>*Ant Service Intelligence Team* | 90.871 | 93.183 |
| 3<br>May 16, 2021 | IE-NetV2 (ensemble)<br>*RICOH_SRCB_DML* | 90.860 | 93.100 |
| 4<br>Apr 06, 2020 | SA-Net on Albert (ensemble)<br>*QIANXIN* | 90.724 | 93.011 |
| 5<br>May 05, 2020 | SA-Net-V2 (ensemble)<br>*QIANXIN* | 90.679 | 92.948 |
| 5<br>Apr 05, 2020 | Retro-Reader (ensemble)<br>*Shanghai Jiao Tong University*<br>http://arxiv.org/abs/2001.09694 | 90.578 | 92.978 |
| 5<br>Feb 05, 2021 | FPNet (ensemble)<br>*YuYang* | 90.600 | 92.899 |

- Performance is very saturated
- Harder QA settings are needed!
- Varied pre-trained LMs

# What are these models learning?

- “Who…”: knows to look for people
- “Which film…”: can identify movies and then spot keywords that are related to the question
- Unless questions are made super tricky (target closely-related entities who are easily confused), they’re usually not so hard to answer

# But how well are these doing?

- Can construct adversarial examples that fool these systems: add one carefully chosen sentence and performance drops to below 50%
- Still "surface-level" matching, not complex understanding
- Other challenges: recognizing when answers aren't present, doing multi-step reasoning

**Article:** Super Bowl 50
**Paragraph:** *"Peyton Manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by John Elway, who led the Broncos to victory in Super Bowl XXXIII at age 38 and is currently Denver's Executive Vice President of Football Operations and General Manager.* [redacted]
**Question:** *"What is the name of the quarterback who was 38 in Super Bowl XXXIII?"*
**Original Prediction:** John Elway
[redacted]

Figure 1: An example from the SQuAD dataset. The BiDAF Ensemble model originally gets the answer correct, but is fooled by the addition of an adversarial distracting sentence (in blue).

Jia and Liang (2017)

# But how well are these doing?

- Can construct adversarial examples that fool these systems: add one carefully chosen sentence and performance drops to below 50%
- Still "surface-level" matching, not complex understanding
- Other challenges: recognizing when answers aren't present, doing multi-step reasoning

**Article:** Super Bowl 50
**Paragraph:** "*Peyton Manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by John Elway, who led the Broncos to victory in Super Bowl XXXIII at age 38 and is currently Denver's Executive Vice President of Football Operations and General Manager. Quarterback Jeff Dean had jersey number 37 in Champ Bowl XXXIV.*"
**Question:** "*What is the name of the quarterback who was 38 in Super Bowl XXXIII?*"
**Original Prediction:** John Elway
**Prediction under adversary:** Jeff Dean

Figure 1: An example from the SQuAD dataset. The BiDAF Ensemble model originally gets the answer correct, but is fooled by the addition of an adversarial distracting sentence (in blue).

Jia and Liang (2017)

# Weakness to Adversaries

| Model | Original | ADDONESENT |
|---|---|---|
| ReasoNet-E | **81.1** | 49.8 |
| SEDT-E | 80.1 | 46.5 |
| BiDAF-E | 80.0 | 46.9 |
| Mnemonic-E | 79.1 | **55.3** |
| Ruminating | 78.8 | 47.7 |
| jNet | 78.6 | 47.0 |
| Mnemonic-S | 78.5 | **56.0** |
| ReasoNet-S | 78.2 | 50.3 |
| MPCM-S | 77.0 | 50.0 |
| SEDT-S | 76.9 | 44.8 |
| RaSOR | 76.2 | 49.5 |
| BiDAF-S | 75.5 | 45.7 |
| Match-E | 75.4 | 41.8 |
| Match-S | 71.4 | 39.0 |
| DCR | 69.3 | 45.1 |
| Logistic | 50.4 | 30.4 |

- Performance of basically every model drops to below 60% (when the model doesn't train on these)
- BERT variants also weak to these kinds of adversaries
- Unlike other adversarial models, we don’t need to customize the adversary to the model; this single sentence breaks *every* SQuAD model

Jia and Liang (2017)

# How to fix QA?

- Better models?
  - But a model trained on weak data will often still be weak to adversaries
  - Training on Jia+Liang adversaries can help, but there are plenty of other similar attacks which that doesn't solve
- Better datasets
  - Same questions but with more distractors may challenge our models
  - Next up: *retrieval-based* QA models
- Harder QA tasks
  - Ask questions which *cannot* be answered in a simple way
  - Afterwards: *multi-hop* QA and other QA settings

# Retrieval-based QA
# (a.k.a. open-domain QA)

# Problems

- Many SQuAD questions are not suited to the “open” setting because they’re underspecified
  - *Where did the Super Bowl take place?*
  - *Which player on the Carolina Panthers was named MVP?*
- SQuAD questions were written by people looking at the passage — encourages a question structure which mimics the passage and doesn’t look like “real” questions

Lee et al. (2019)

# Open-domain QA

- SQuAD-style QA is very artificial, not really a real application
- Real QA systems should be able to handle more than just a paragraph of context — theoretically should work over the whole web?

Q: *What was Marie Curie the recipient of?*

*Marie Curie was awarded the Nobel Prize in Chemistry and the Nobel Prize in Physics…*

*Mother Teresa received the Nobel Peace Prize in…*

*Curie received his doctorate in March 1895…*

*Skłodowska received accolades for her early work…*

# Open-domain QA

- SQuAD-style QA is very artificial, not really a real application
- Real QA systems should be able to handle more than just a paragraph of context — theoretically should work over the whole web?
- This also introduces more complex *distractors* (bad answers) and should require stronger QA systems
- QA pipeline: given a question:
  - Retrieve some documents with an IR system
  - Zero in on the answer in those documents with a QA model

# NaturalQuestions

- Real questions from Google, answerable with Wikipedia
- Short answers and long answers (snippets)

**Question:**

where is blood pumped after it leaves the right ventricle?

**Short Answer:**

*None*

**Long Answer:**

From the right ventricle , blood is pumped through the semilunar pulmonary valve into the left and right main pulmonary arteries ( one for each lung ) , which branch into smaller pulmonary arteries that spread throughout the lungs.

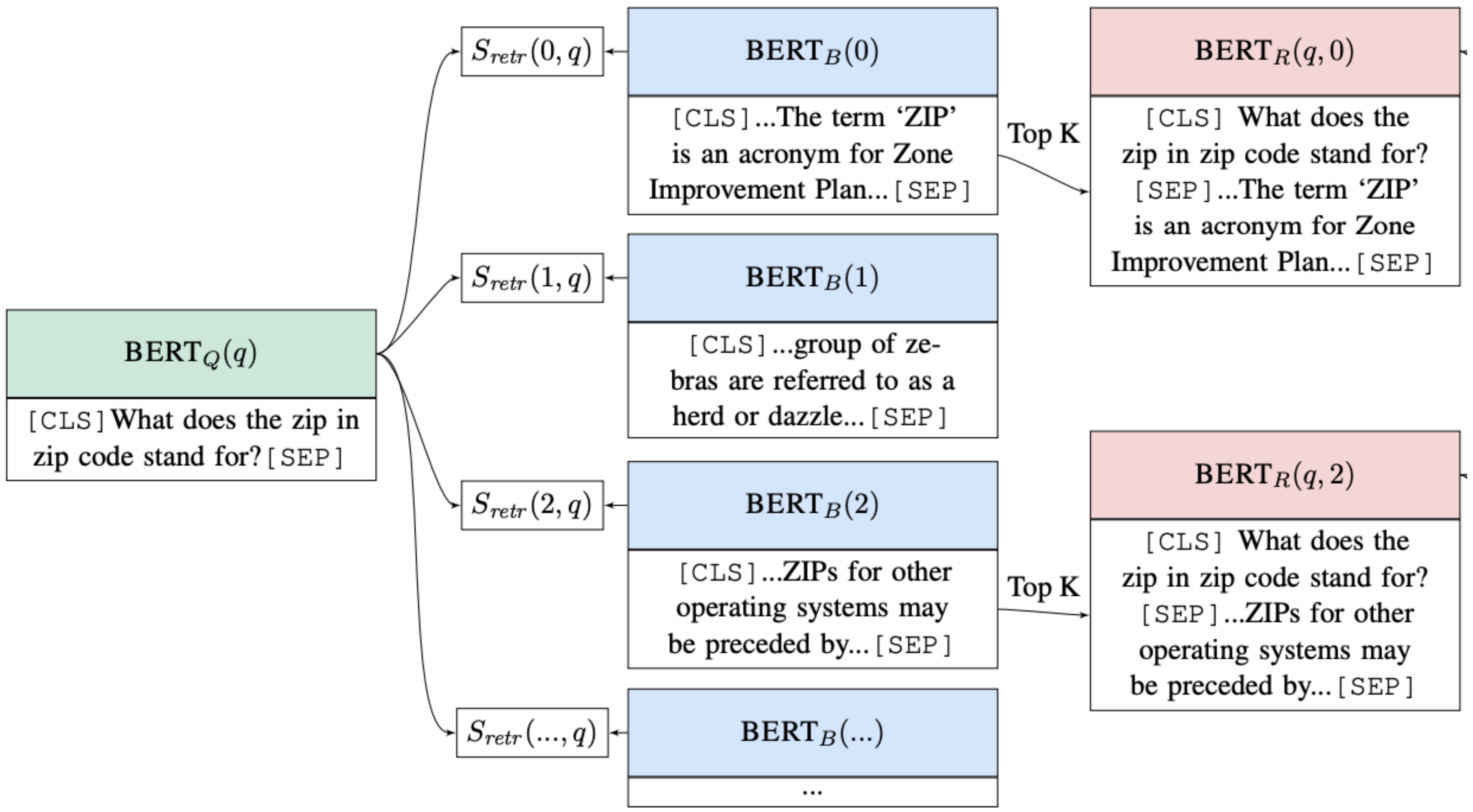
- Questions arose naturally, unlike SQuAD questions which were written by people looking at a passage. This makes them much harder
- Short answer F1s < 60, long answer F1s <75

Kwiatkowski et al. (2019)

# Retrieval with BERT

- Can we do better than a simple IR system?
- Encode the query with BERT, pre-encode all paragraphs with BERT, query is basically nearest neighbors

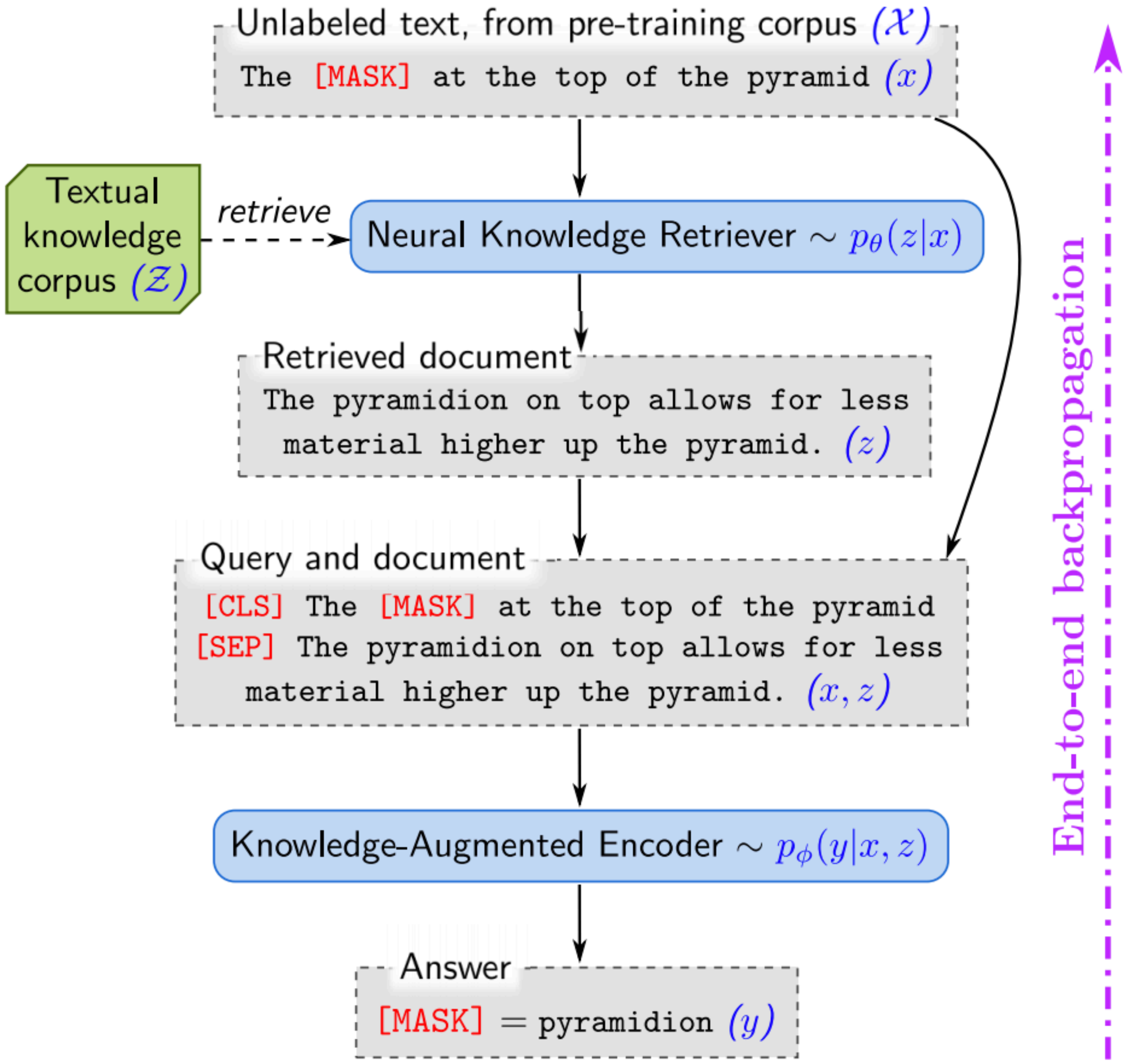
$$h_q = \mathbf{W_q}\mathrm{BERT}_Q(q)[\mathrm{CLS}]$$
$$h_b = \mathbf{W_b}\mathrm{BERT}_B(b)[\mathrm{CLS}]$$
$$S_{retr}(b, q) = h_q^\top h_b$$




Lee et al. (2019)

# REALM

- Technique for integrating retrieval into pre-training
- Retriever relies on a maximum inner-product search (MIPS) over BERT embeddings
- MIPS is fast — challenge is how to refresh the BERT embeddings




Guu et al. (2020)

# REALM

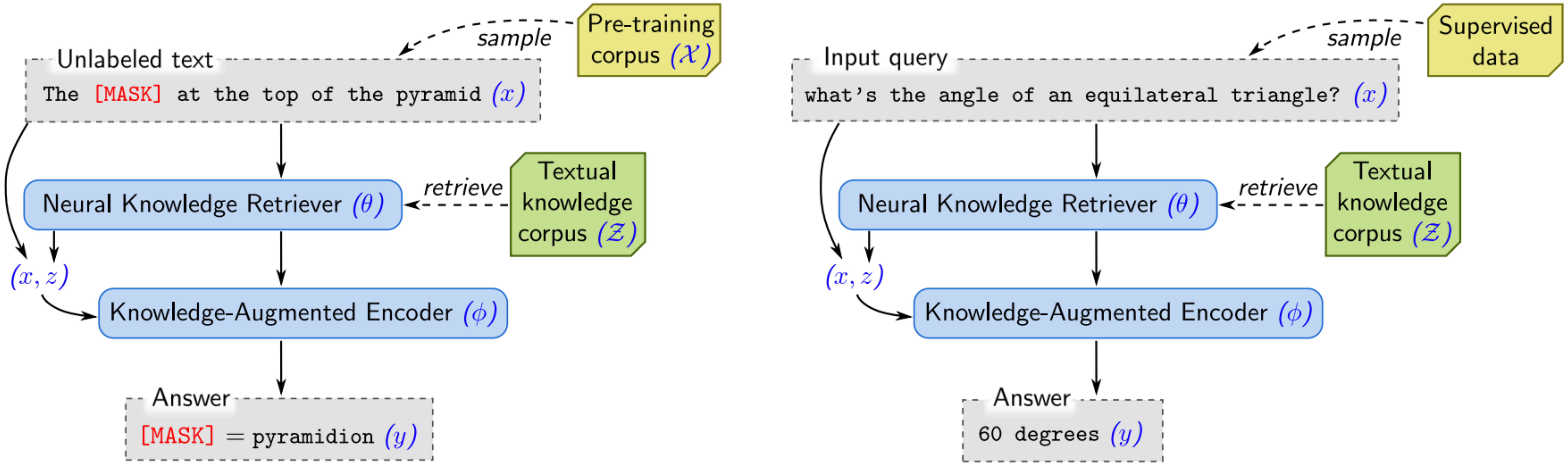



*Figure 2.* The overall framework of REALM. **Left:** *Unsupervised pre-training*. The knowledge retriever and knowledge-augmented encoder are jointly pre-trained on the unsupervised language modeling task. **Right:** *Supervised fine-tuning*. After the parameters of the retriever ($\theta$) and encoder ($\phi$) have been pre-trained, they are then fine-tuned on a task of primary interest, using supervised examples.

- Fine-tuning can exploit the same kind of textual knowledge
- Can work for tasks requiring knowledge lookups

Guu et al. (2020)

# REALM

| Name | Architectures | Pre-training | NQ (79k/4k) | WQ (3k/2k) | CT (1k /1k) | # params |
|---|---|---|---|---|---|---|
| BERT-Baseline (Lee et al., 2019) | Sparse Retr.+Transformer | BERT | 26.5 | 17.7 | 21.3 | 110m |
| T5 (base) (Roberts et al., 2020) | Transformer Seq2Seq | T5 (Multitask) | 27.0 | 29.1 | - | 223m |
| T5 (large) (Roberts et al., 2020) | Transformer Seq2Seq | T5 (Multitask) | 29.8 | 32.2 | - | 738m |
| T5 (11b) (Roberts et al., 2020) | Transformer Seq2Seq | T5 (Multitask) | 34.5 | 37.4 | - | 11318m |
| DrQA (Chen et al., 2017) | Sparse Retr.+DocReader | N/A | - | 20.7 | 25.7 | 34m |
| HardEM (Min et al., 2019a) | Sparse Retr.+Transformer | BERT | 28.1 | - | - | 110m |
| GraphRetriever (Min et al., 2019b) | GraphRetriever+Transformer | BERT | 31.8 | 31.6 | - | 110m |
| PathRetriever (Asai et al., 2019) | PathRetriever+Transformer | MLM | 32.6 | - | - | 110m |
| ORQA (Lee et al., 2019) | Dense Retr.+Transformer | ICT+BERT | 33.3 | 36.4 | 30.1 | 330m |
| Ours ($\mathcal{X}$ = Wikipedia, $\mathcal{Z}$ = Wikipedia) | Dense Retr.+Transformer | REALM | 39.2 | 40.2 | **46.8** | 330m |
| Ours ($\mathcal{X}$ = CC-News, $\mathcal{Z}$ = Wikipedia) | Dense Retr.+Transformer | REALM | **40.4** | **40.7** | 42.9 | 330m |

- 330M parameters + a knowledge base beats an 11B parameter T5 model

Guu et al. (2020)

# Multi-Hop Question Answering

# Multi-Hop Question Answering

- Very few SQuAD questions require actually combining multiple pieces of information — this is an important capability QA systems should have

- Several datasets test *multi-hop reasoning*: ability to answer questions that draw on several sentences or several documents to answer

Welbl et al. (2018), Yang et al. (2018)

# WikiHop

- Annotators shown Wikipedia and asked to pose a simple question linking two entities that require a third (bridging) entity to associate; multi-choice answer.

- A model shouldn't be able to answer these without doing some reasoning about the intermediate entity

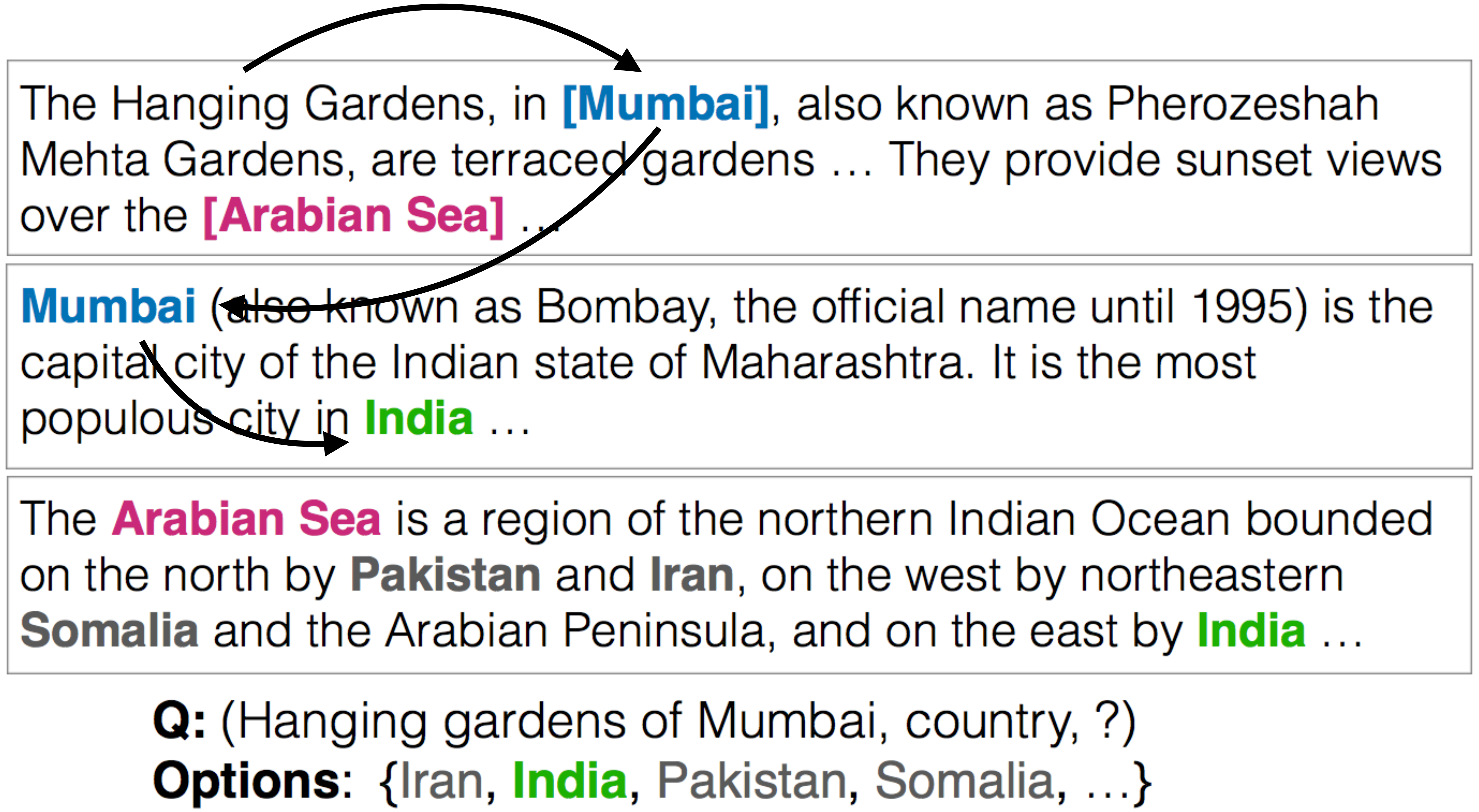



Figure from Welbl et al. (2018)

# HotpotQA

***Question**: What government position was held by the woman who portrayed Corliss Archer in the film Kiss and Tell ?*

Doc 1

*Shirley Temple Black was an American actress, businesswoman, and singer …*
*As an adult, she served as Chief of Protocol of the United States*
…

Same entity

Same entity

Doc 2

*Kiss and Tell is a comedy film in which 17-year-old Shirley Temple acts as Corliss Archer.*
…

Doc 3

*Meet Corliss Archer is an American television sitcom that aired on CBS …*

- Much longer and more convoluted questions; span-based answer.

Example picked from HotpotQA [Yang et al., 2018]

# Multi-hop Reasoning

**Question**: *What government position was held by the woman who portrayed Corliss Archer in the film Kiss and Tell ?*

Doc 1

*Shirley Temple Black was an American actress, businesswoman, and singer …*
*As an adult, she served as Chief of Protocol of the United States*
…

Same entity

Same entity

Doc 2

*Kiss and Tell is a comedy film in which 17-year-old Shirley Temple acts as Corliss Archer.*
…

Doc 3

*Meet Corliss Archer is an American television sitcom that aired on CBS …*

No simple lexical overlap.

…but only one government position appears in the context!

Example picked from HotpotQA [Yang et al., 2018]

# Multi-hop Reasoning

***Question**: The Oberoi family is part of a hotel company that has a head office in what city?*

Same entity

Doc 1

*The Oberoi family is an Indian family that is famous for its involvement in hotels, namely through The Oberoi Group* …

Same entity

Doc 2

*The Oberoi Group is a hotel company with its head office in Delhi.*

…

This is an idealized version of multi-hop reasoning. Do models **need** to do this to do well on this task?

Example picked from HotpotQA [Yang et al., 2018]

# Multi-hop Reasoning

**Question**: *The Oberoi family is part of a hotel company that has a head office in what city?*

Doc 1 *The Oberoi fam… nil… at is famous for its involvement in hotels, namely through The Ober… Group* …

High lexical overlap

Doc 2 *The Oberoi Group is a hotel company with its head office in Delhi.*

…

Model can ignore the bridging entity and directly predict the answer

Example picked from HotpotQA (Yang 2018)

# Sentence Factored Model

Find the answer by comparing each sentence with the question **separately**!

***Question**: The Oberoi family is part of a hotel company that has a head office in what city?*

Doc 1
*The Oberoi family is an Indian family that is …*

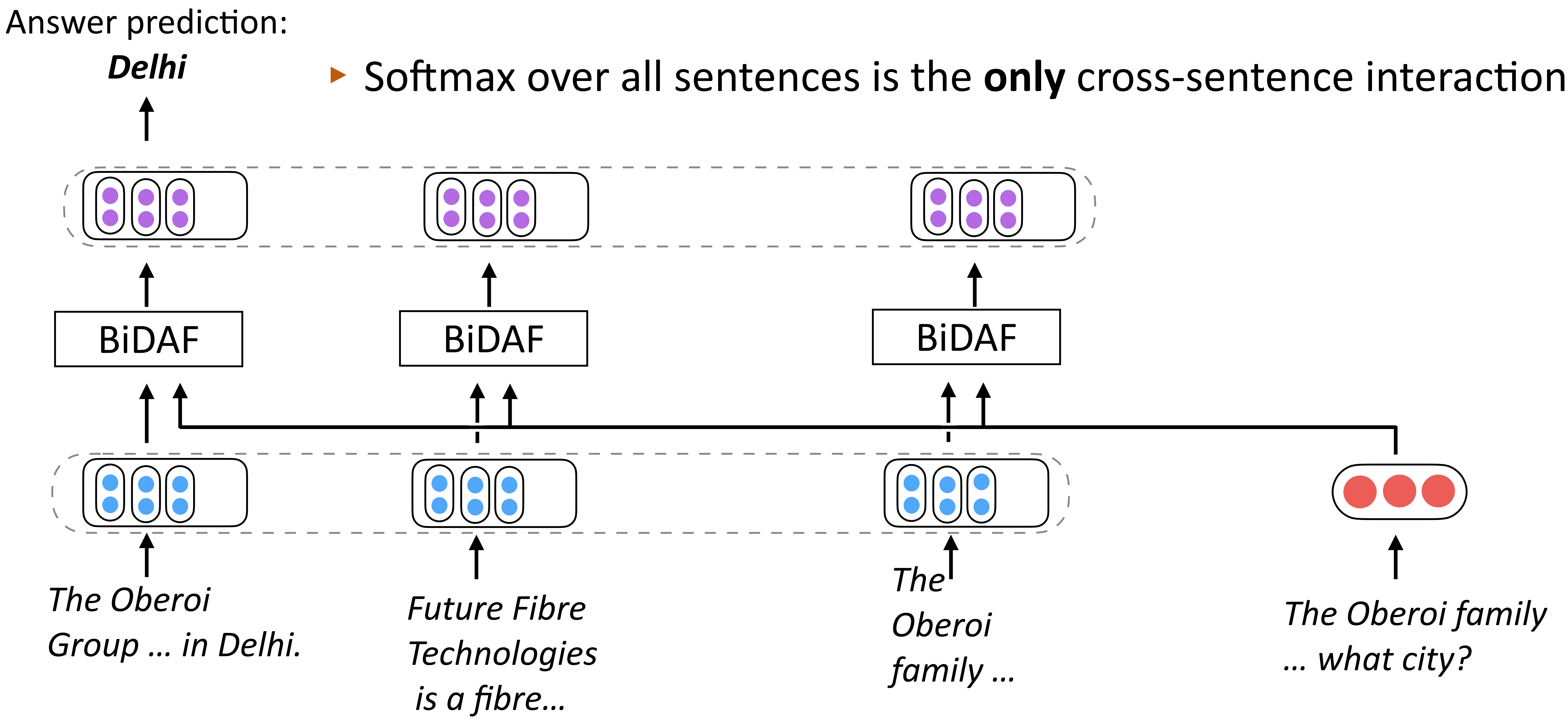
Doc 2
*The Oberoi Group is a hotel company with its head office in Delhi.*

Doc 3
*Future Fibre Technologies a fiber technologies company …*

Chen and Durrett (2019)

# Sentence Factored Model

- Softmax over all sentences is the **only** cross-sentence interaction




Chen and Durrett (2019)

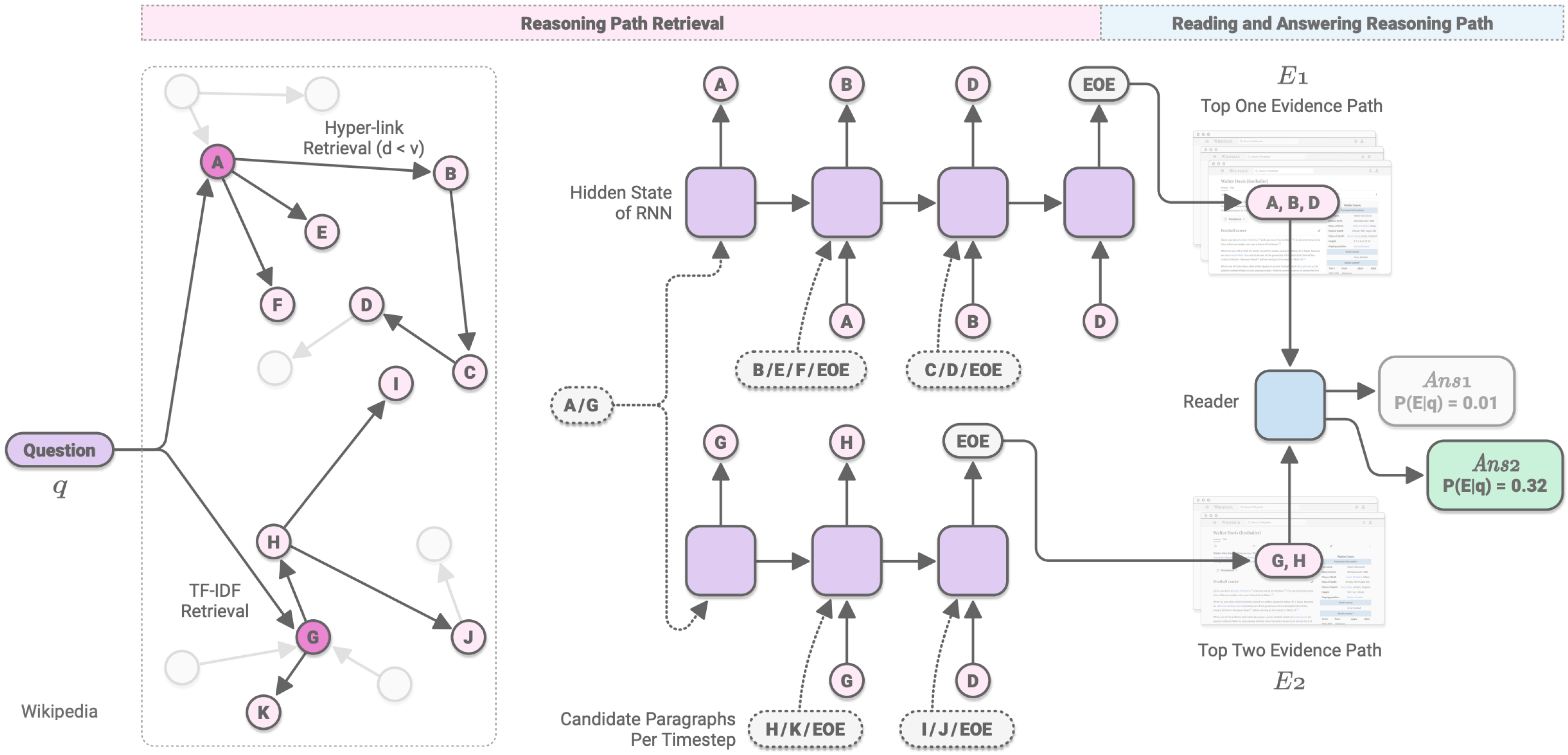
# Sentence Factored Model

| Method | Random | Factored | Factored BiDAF |
|---|---|---|---|
| WikiHop | 6.5 | 60.9 | 66.1 |
| HotpotQA | 5.4 | 45.4 | 57.2 |
| SQuAD | 22.1 | 70.0 | 88.0 |

Table 1: The accuracy of our proposed sentence-factored models on identifying answer location in the development sets of WikiHop, HotpotQA and SQuAD. *Random*: we randomly pick a sentence in the passage to see whether it contains the answer. *Factored* and *Factored BiDAF* refer to the models of Section 3.1. As expected, these models perform better on SQuAD than the other two datasets, but the model can nevertheless find many answers in WikiHop especially.

Chen and Durrett (2019)

# State-of-the-art Models




- Best systems: use hyperlink structure of Wikipedia and a strong multi-step retrieval mode built on BERT

Asai et al. (2020)

# New Types of QA

# DROP

- QA datasets to model programs/computation

| **Passage** (some parts shortened) | **Question** | **Answer** | **BiDAF** |
|---|---|---|---|
| That year, his **Untitled (1981)**, a painting of a haloed, black-headed man with a bright red skeletal body, depicted amid the artists signature scrawls, was **sold by Robert Lehrman for $16.3 million, well above its $12 million high estimate**. | How many more dollars was the Untitled (1981) painting sold for than the 12 million dollar estimation? | 4300000 | $16.3 million |

- Question types: subtraction, comparison (*which did he visit first*), counting and sorting (*which kicker kicked more field goals*),

- Invites ad hoc solutions like predicting two numbers + operation

Dua et al. (2019)

# TriviaQA

- Totally figuring this out is very challenging
- Coref:
  *the failed campaign*
  *movie of the same name*
- Lots of surface clues: 1961, campaign, etc.
- Systems can do well without really understanding the text

**Question**: The Dodecanese Campaign of WWII that was an attempt by the Allied forces to capture islands in the Aegean Sea was the inspiration for which acclaimed 1961 commando film?
**Answer**: The Guns of Navarone
**Excerpt**: The Dodecanese Campaign of World War II was an attempt by Allied forces to capture the Italian-held Dodecanese islands in the Aegean Sea following the surrender of Italy in September 1943, and use them as bases against the German-controlled Balkans. The failed campaign, and in particular the Battle of Leros, inspired the 1957 novel **The Guns of Navarone** and the successful 1961 movie of the same name.

Joshi et al. (2017)

# NarrativeQA

- Humans see a summary of a book: *…Peter's former girlfriend Dana Barrett has had a son, Oscar…*
- Question: *How is Oscar related to Dana?*
- Answering these questions from the source text (not summary) requires complex inferences and is *extremely challenging*; no progress on this dataset in 2 years

**Story snippet:**

*DANA (setting the wheel brakes on the buggy)*
Thank you, Frank. I'll get the hang of this eventually.

She continues digging in her purse while Frank leans over the buggy and makes funny faces at the baby, OSCAR, a very cute nine-month old boy.

*FRANK (to the baby)*
Hiya, Oscar. What do you say, slugger?

*FRANK (to Dana)*
That's a good-looking kid you got there, Ms. Barrett.

Kočiský et al. (2017)

# Takeaways

- Lots of problems with current QA settings, lots of new datasets
- QA over tables, images, knowledge bases, …
- Models can often work well for one QA task but don't generalize
- There's lots that we can't do, but we're getting really good at putting our hands on random facts from the Internet
- Cross-lingual and multilingual QA …