

# **Globally Normalized Reader**

**Jonathan Raiman and John Miller**

# Task: Extractive QA (SQuAD)

Who was the first to recognize that the Analytical Engine had applications beyond pure calculation?

**Ada Lovelace** (née Byron; 10 December 1815 – 27 November 1852) was an English mathematician and writer, chiefly known for her work on Charles Babbage's proposed mechanical general-purpose computer, the Analytical Engine. She was the first to recognise that the machine had applications beyond pure calculation, and created the first algorithm intended to be carried out by such a machine. As a result, she is often regarded as the first to recognise the full potential of a "computing machine" and the first computer programmer.

Ada Lovelace was the only legitimate child of the poet Lord Byron, and his wife Anne Isabella Milbanke ("Annabella"), Lady Wentworth. All of Byron's other children were born out of wedlock to other women. Byron separated from his wife a month after Ada was born and left England forever four months later, eventually dying of disease in the Greek War of Independence when Ada was eight years old. Her mother remained bitter towards Lord Byron and promoted Ada's interest in mathematics and logic in an effort to prevent her from developing what she saw as the insanity seen in her father, but Ada remained interested in him despite this (and was, upon her eventual death, buried next to him at her request). Often ill, she spent most of her childhood sick. Ada married William King in 1835. King was made Earl of Lovelace in 1838, and she became Countess of Lovelace.

Her educational and social exploits brought her into contact with scientists such as Andrew Crosse, Sir David Brewster, Charles Wheatstone, Michael Faraday and the author Charles Dickens, which she used to further her education. Ada described her approach as...

A computer is a device that can be instructed to carry sequences of arithmetic or logical operations automatically. The ability of computers to follow generalized sets of operations, programs, enables them to perform an extremely wide range of tasks. Such computers are used as control systems for a very wide range of industrial and consumer devices. This includes simple devices like microwave ovens and remote controls, as well as complex devices such as industrial robots and computer assisted manufacturing systems. It also includes general purpose devices like personal computers and mobile phones. The Internet is run on computers, which it connects millions of other computers. Since ancient times, simple manual devices like the abacus have helped people in doing calculations. Early in the Industrial Revolution, mechanical devices were built to automate long tedious processes, such as guiding patterns for looms. More sophisticated machines did specialized analog calculations in the early 20th century. The first digital electronic calculating machines were developed during World War II. The speed, power, and memory capacity of computers has increased continuously and dramatically. Conventionally, a modern computer consists of a central processing element, typically a central processing unit, some form of memory. The processing element carries out arithmetic and logical operations, and a sequencing and control element can change the order of operations in response to information. Peripheral devices include input devices (such as mice, joystick, etc.), output devices (monitor screens, printer, etc.) and storage devices (hard disk, floppy disk, tape, etc.).

~300 words

# Goal

Who was the first to recognize that the Analytical Engine had applications beyond pure calculation?



millions of documents

Babbage KH FRS (/ˈbæbɪdʒ/; 26 December 1791 – 18 October 1861) was an English polymath.<sup>[1]</sup> A mathematician, philosopher, mechanical engineer, Babbage originated the concept of a programmable computer.<sup>[2]</sup> He is considered by some to be a "father of the computer".<sup>[2][3][4][5]</sup> He is also credited with inventing the first mechanical computer. His work fully led to more complex electronic designs, though all the fundamental ideas of modern computers are to be found in his analytical engine.<sup>[2][6]</sup> His varied work in other fields has been described as "pre-eminent" among the many achievements of his century.<sup>[1]</sup> Babbage's incomplete mechanisms are on display in the Science Museum in London. In 1991, a functioning difference engine was built from Babbage's original plans. Built to tolerances of the 19th century, the success of the finished engine shows that Babbage's machine would have worked.

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# How do we get there?

## Related Work:

- Bi-Attention Flow (Seo et al., 2016)
- Dynamic Co-Attention Network (Xiong et al., 2016)
- R-Net (Wang et al., 2017)
- Rasor (Lee et al., 2016)
- Hybrid AoA Reader (2018)

## Challenges:

- Bi-directional attention
- Rank all possible spans
- No available data augmentation

# Globally Normalized Reader

- Factorize search into sentences, span start & end
- Globally Normalize search (Andor et al. @ ACL 2016)
- Beam Search during training w/. Early Updates

## Contributions:

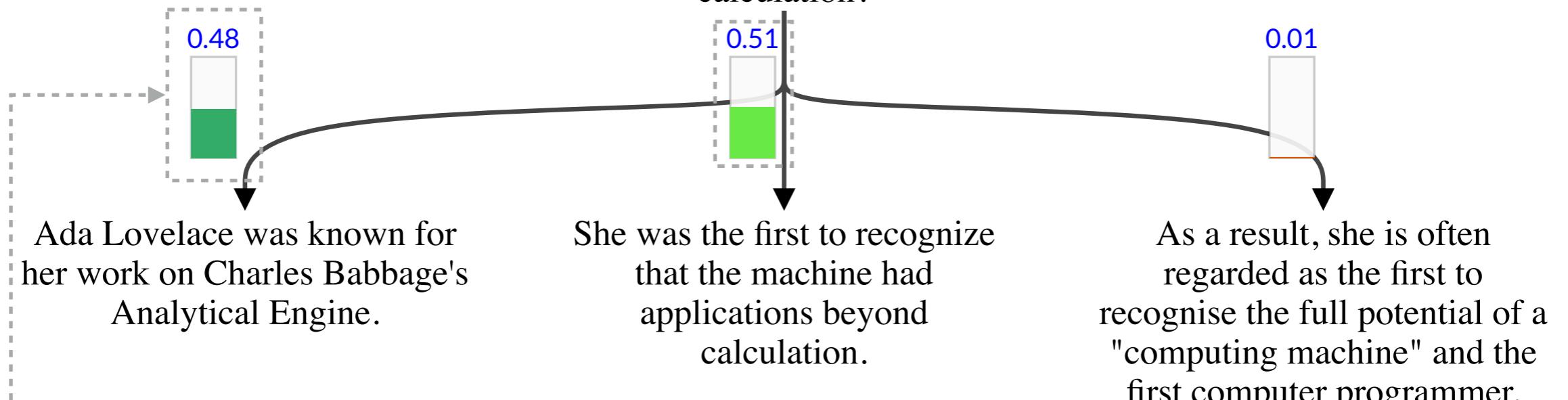
- **Conditional computation** (allocate computation to promising search beams)
- **Quasi-infinite training data** w/. Type Swaps
- **24.7x** speedup over bi-attention-flow
- Dev **68.4 EM, 76.21 F1** w/o bidirectional attention

# Example



Ada Lovelace was known for her work on Charles Babbage's Analytical Engine. She was the first to recognize that the machine had applications beyond calculation. As a result, she is often regarded as the first to recognise the full potential of a "computing machine" and the first computer programmer.

Who was first to recognize that the Analytical Engine had applications beyond pure calculation?



**Probability**

**Pick a Sentence**

Who was first to recognize that  
the Analytical Engine had  
applications beyond pure  
calculation?

0.49

Ada Lovelace was known for  
her work on Charles Babbage's  
Analytical Engine.

0.51

She was the first to recognize  
that the machine had  
applications beyond calculation.

0.55

Ada Lovelace was known for  
her work on Charles Babbage's  
Analytical Engine.

0.09

Lovelace was known for her  
work on Charles Babbage's  
Analytical Engine.

0.36

Charles Babbage's Analytical  
Engine.

**Start word chosen for  
each sentence**

Who was first to recognize that  
the Analytical Engine had  
applications beyond pure  
calculation?

0.49



Ada Lovelace was known for  
her work on Charles Babbage's  
Analytical Engine.

0.55



Ada Lovelace was known for  
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Analytical Engine.

0.64



Ada Lovelace

0.51



She was the first to recognize  
that the machine had  
applications beyond calculation.

0.09



Lovelace was known for her  
work on Charles Babbage's  
Analytical Engine.

0.20



Charles Babbage

0.36



Charles Babbage's Analytical  
Engine.

0.16



Charles Babbage's Analytical  
Engine

Select end word among remainder

Who was first to recognize that  
the Analytical Engine had  
applications beyond pure  
calculation?

0.49



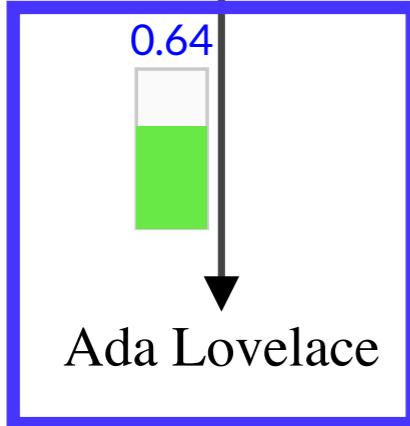
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Charles Babbage's Analytical  
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0.16



Charles Babbage's Analytical  
Engine

**GNR's Answer: Ada Lovelace**

# Outline

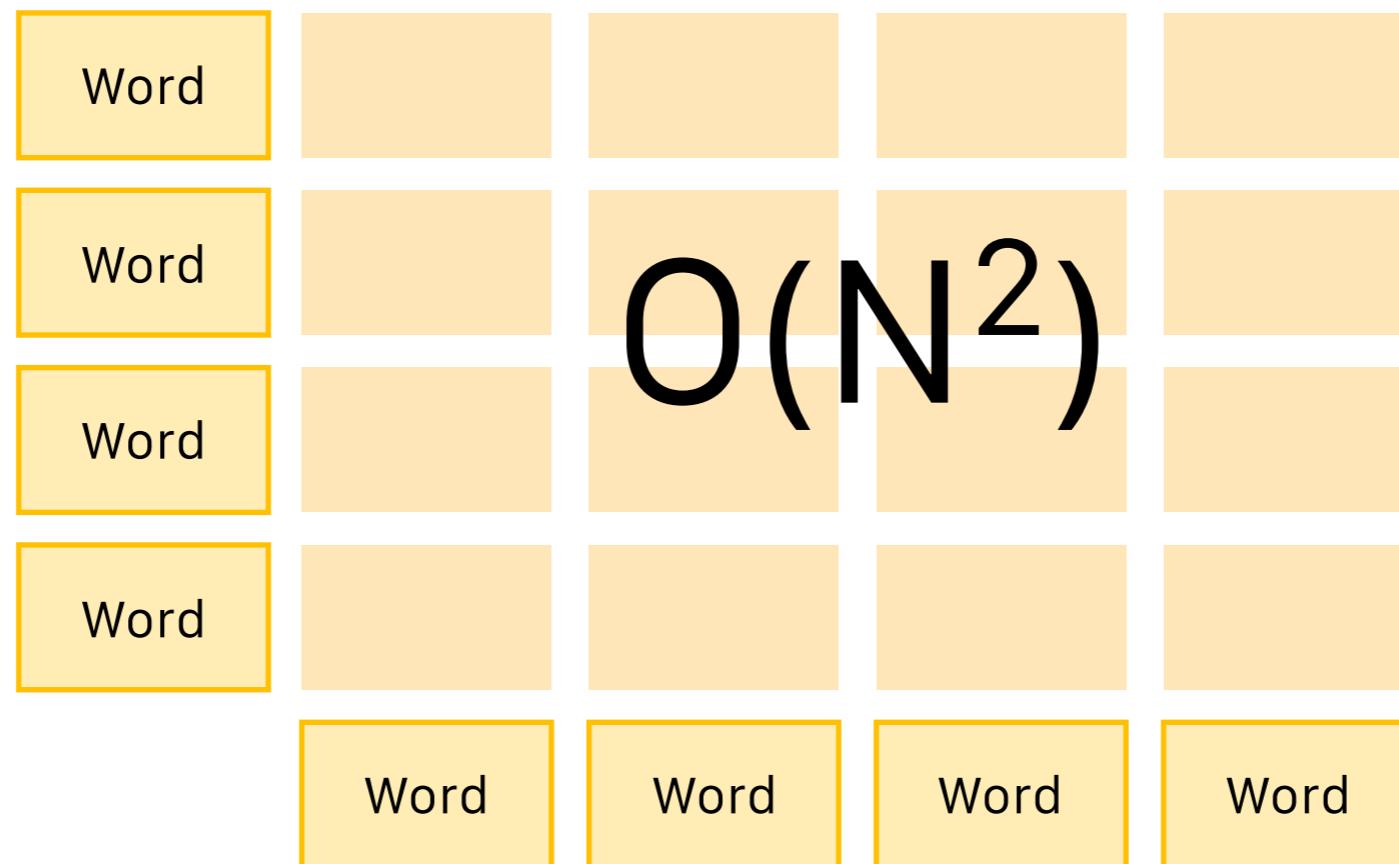
## 1. Approach

- 1) Challenges
- 2) Architecture
- 3) Early updates
- 4) Conditional Computation
- 5) Global Normalization
- 6) Type Swaps

## 2. Results

- 1) Comparison
- 2) Data Augmentation
- 3) Speedup

# Span Selection/Attention



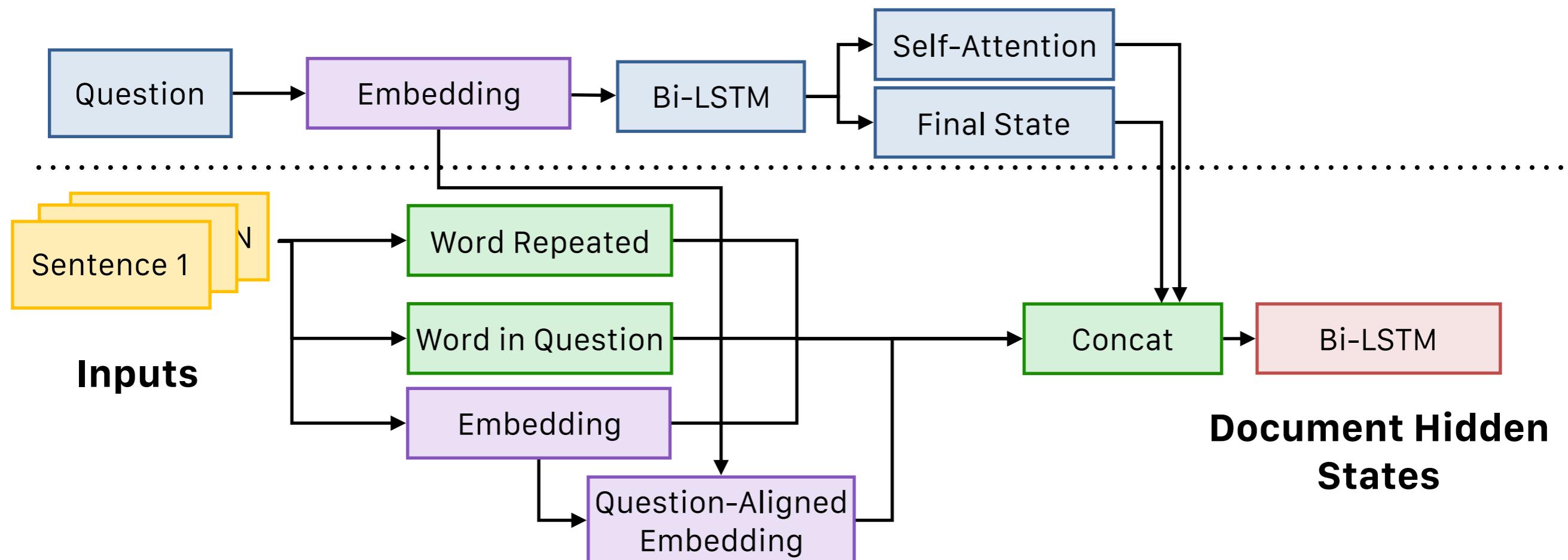
# Overfitting

- 100k QA Pairs
- Dropout
- Weight Decay
- Tuning
- Pretrained word vectors
- Ensembles
- Label bias

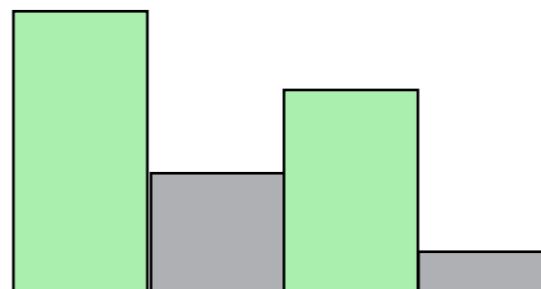
# Approach

- Search to shrink candidate space & scope of attention
- Data augmentation

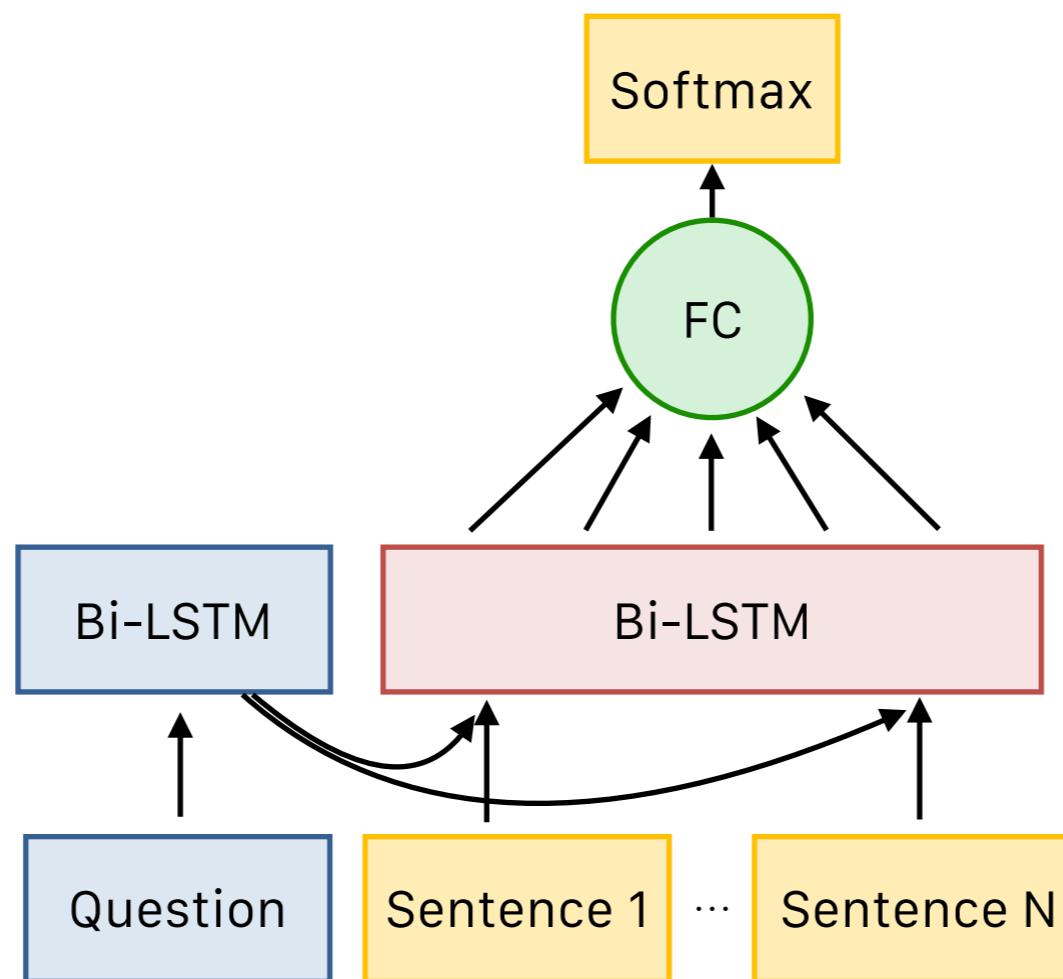
# Architecture: Question-Aware Document Encoding



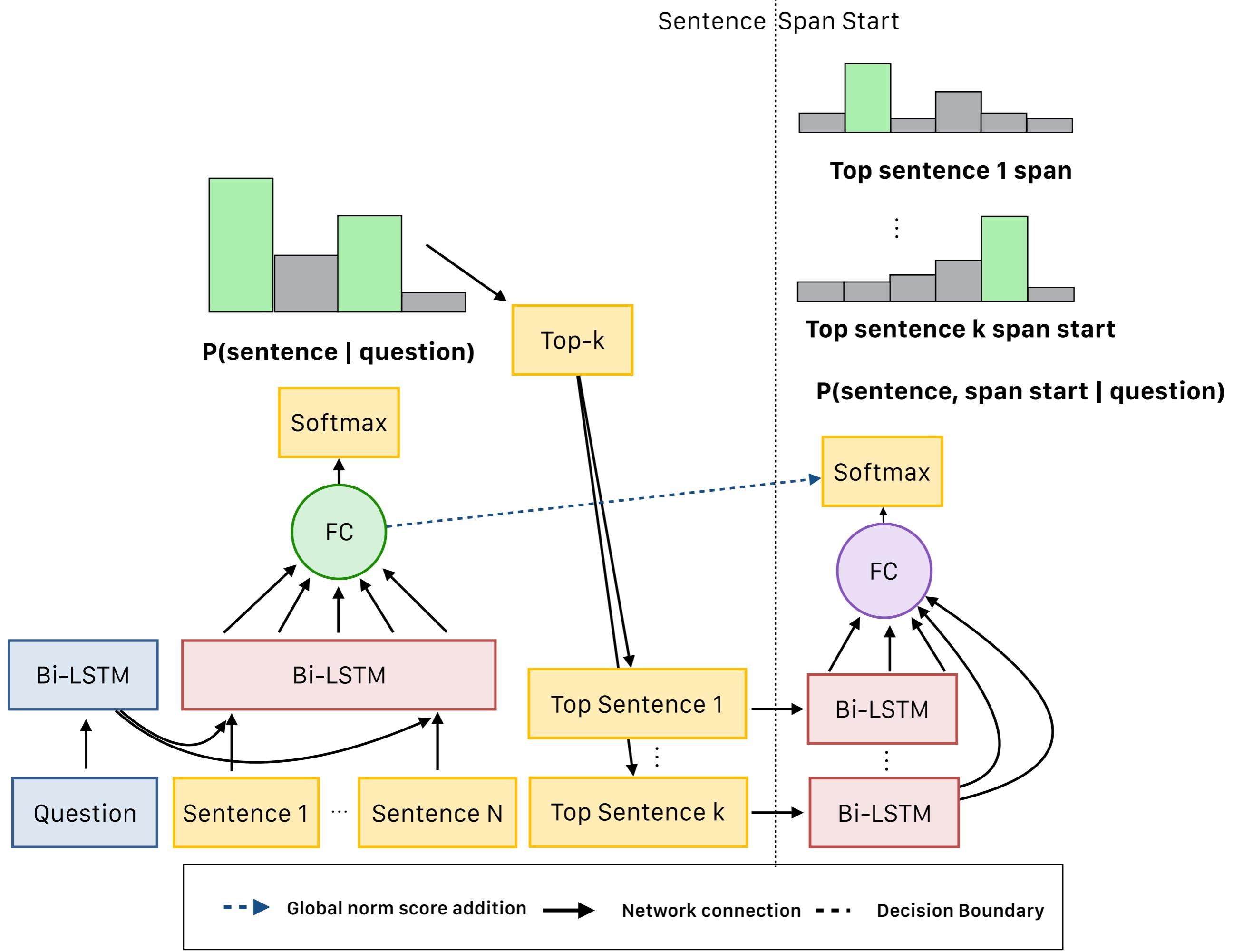
# Architecture

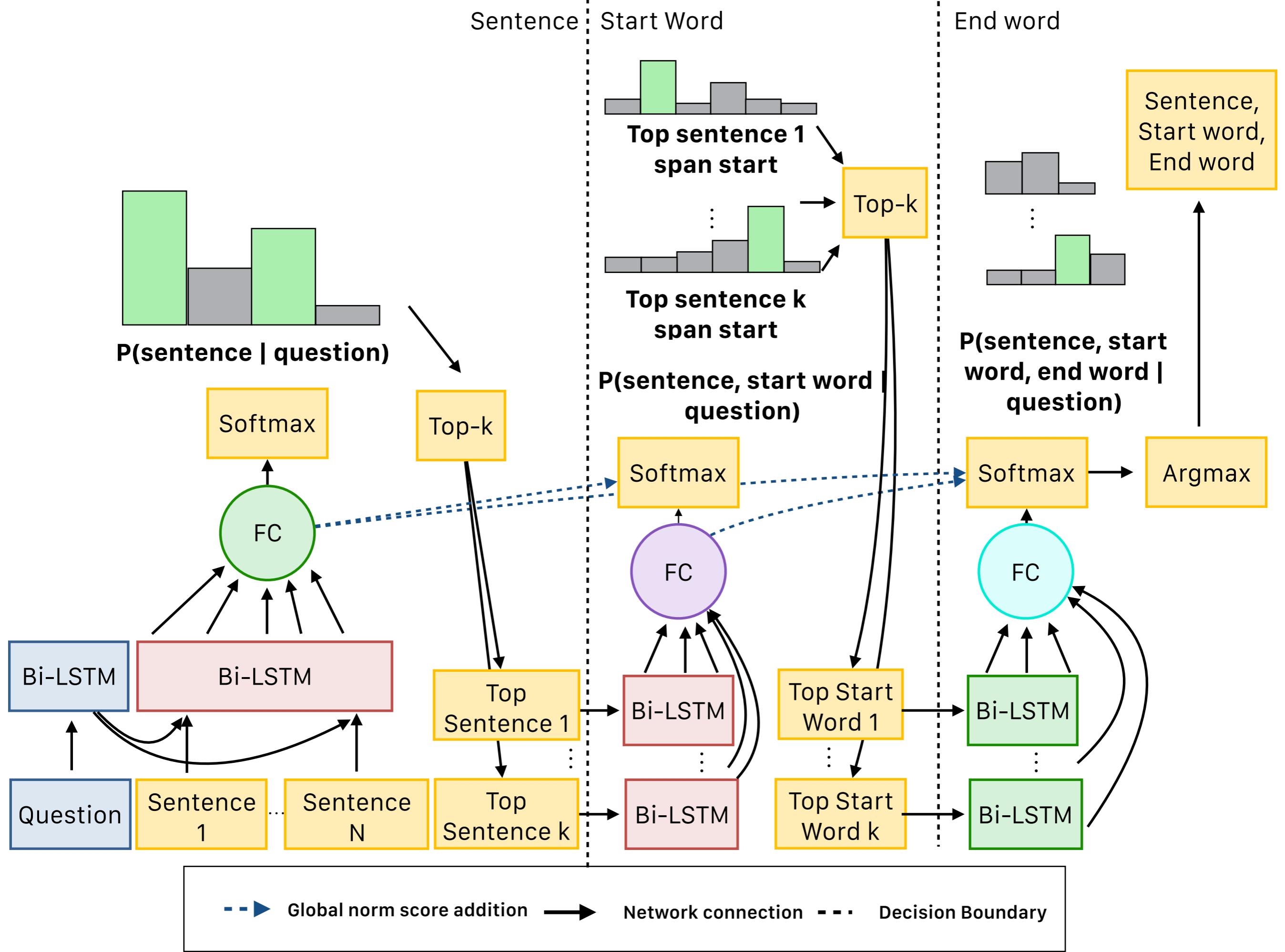


$P(\text{sentence} \mid \text{question})$



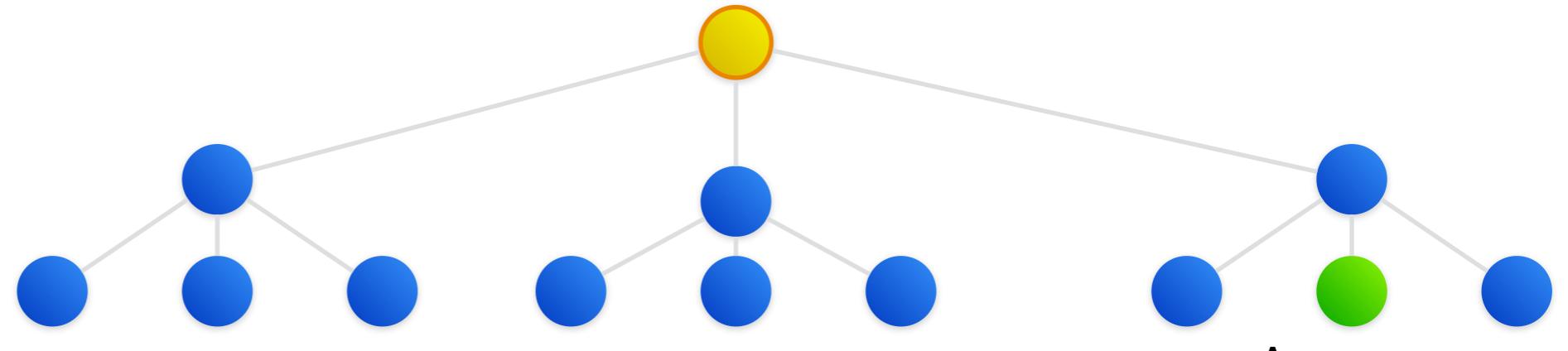
--> Global norm score addition    → Network connection    - - - Decision Boundary



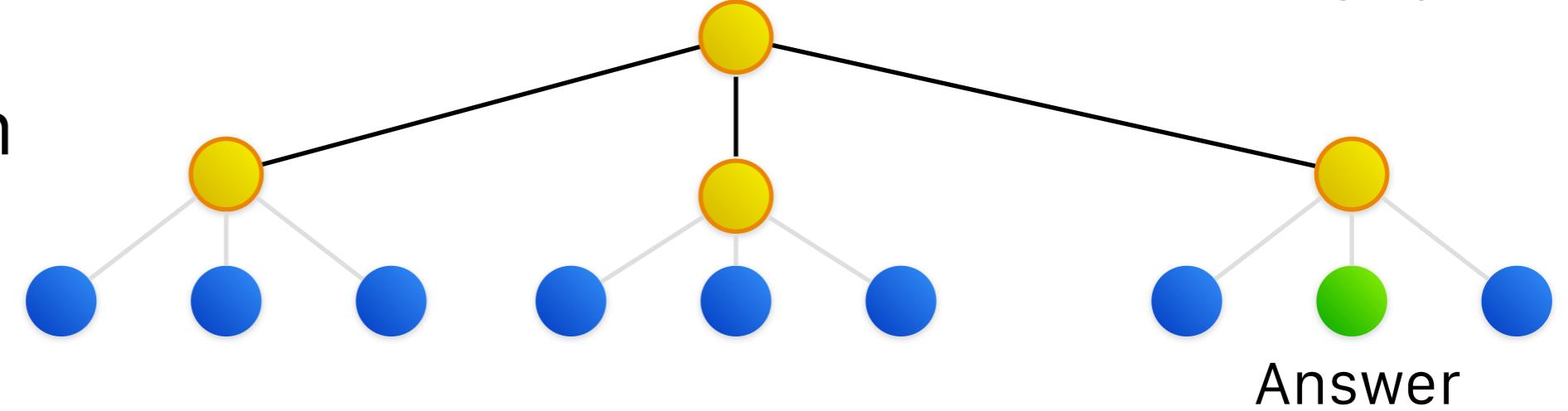


# Early Updates

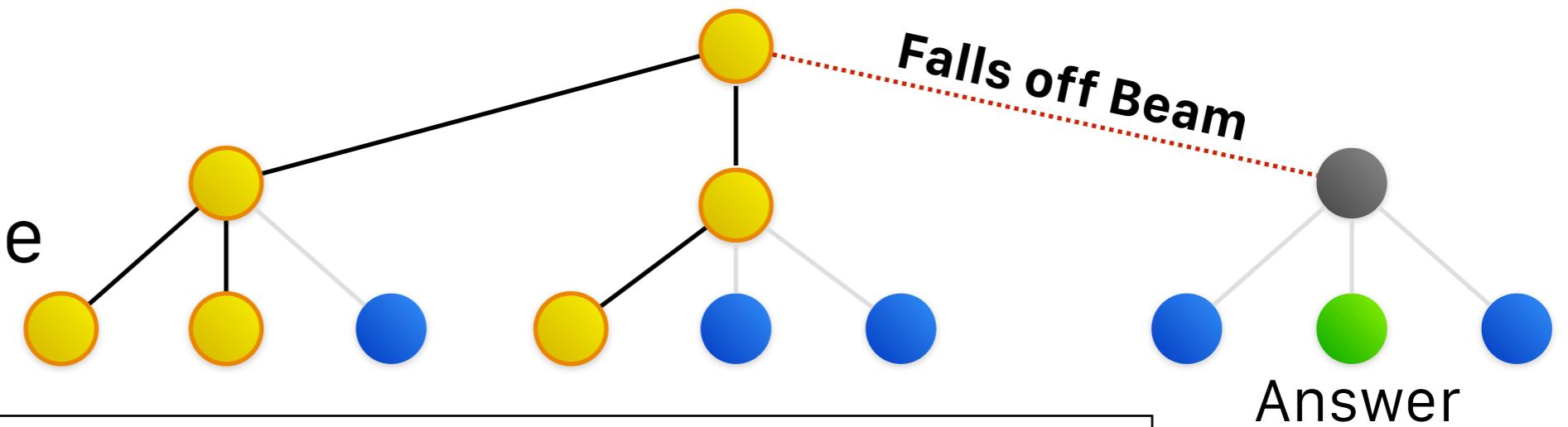
1) Begin search



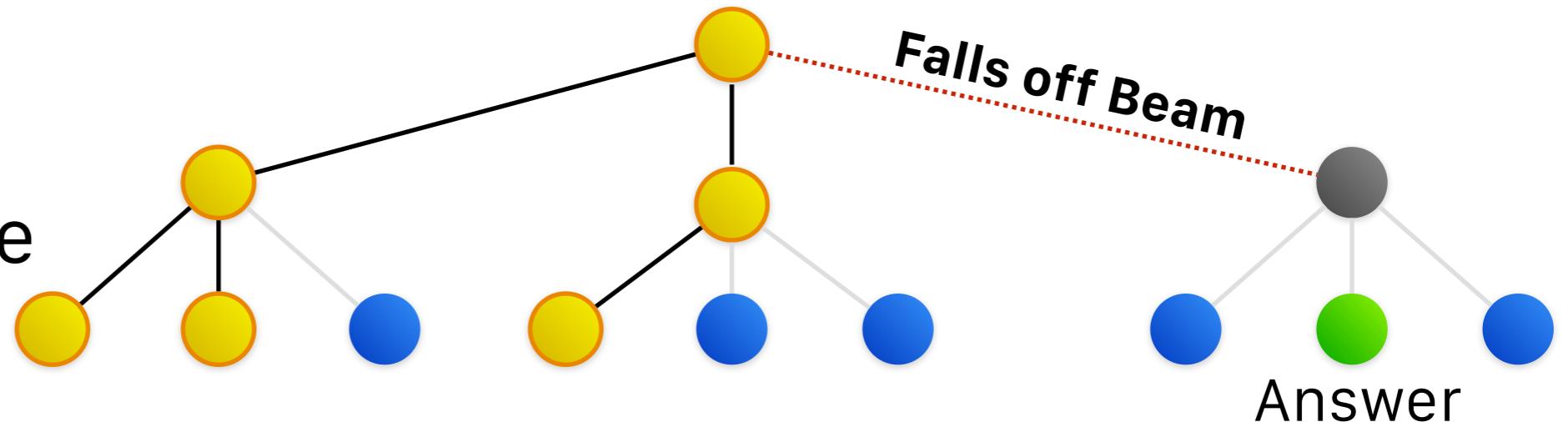
2) Expand search nodes



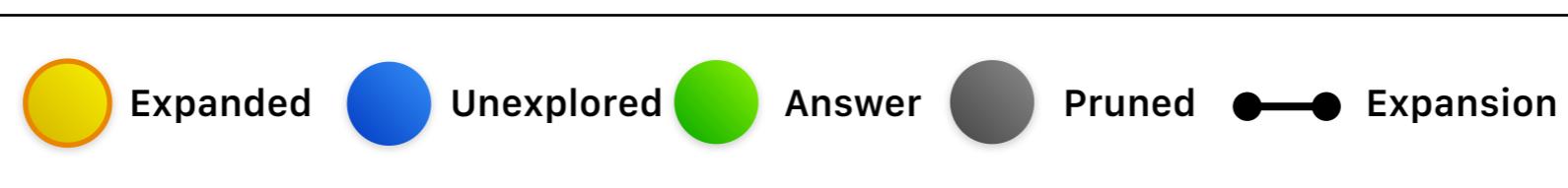
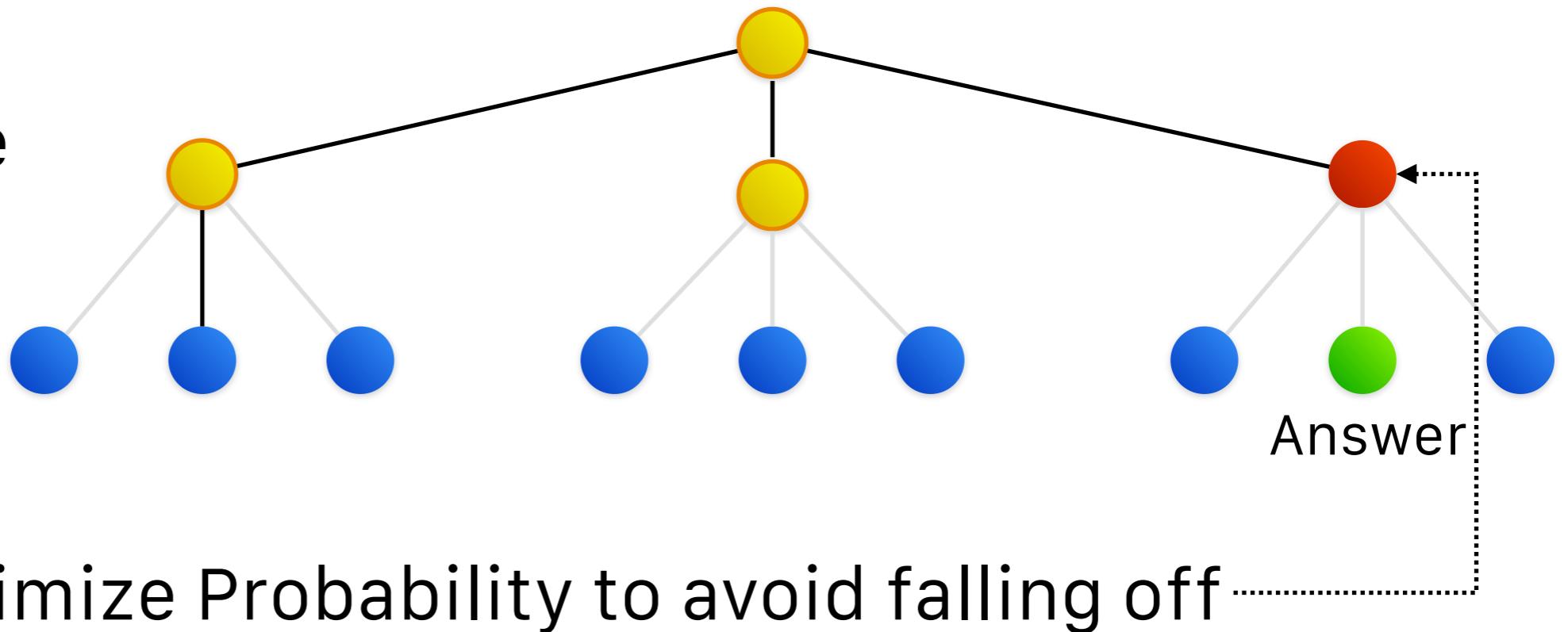
3) Expand & Prune



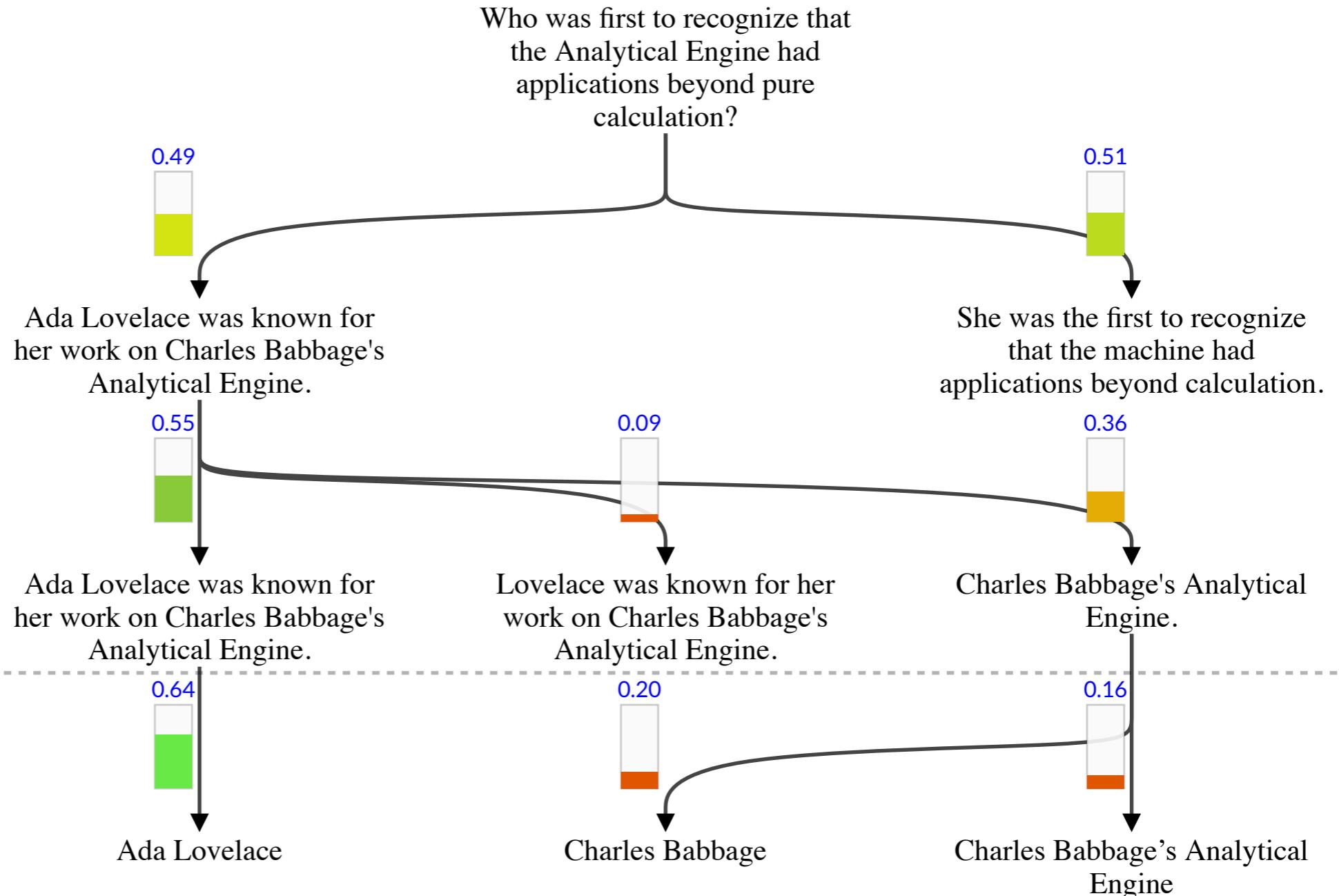
3) Expand & Prune



4) Early Update



# Conditional Computation



**Sentence prediction accuracy  
88-89%: can focus computation on subset!**

# Local Normalization

$$\begin{aligned}\mathbb{P}(a|d, q) &= \mathbb{P}_{\text{sent}}(i|d, q) \cdot \mathbb{P}_{\text{sw}}(j|i, d, q) \cdot \mathbb{P}_{\text{ew}}(k|j, i, d, q) \\ &= \frac{\exp(\phi_{\text{sent}}(i, d, q))}{Z_{\text{sent}(d, q)}} \cdot \frac{\exp(\phi_{\text{sw}}(j, i, d, q))}{Z_{\text{sw}(i, d, q)}} \cdot \frac{\exp(\phi_{\text{ew}}(k, j, i, d, q))}{Z_{\text{ew}(j, i, d, q)}}\end{aligned}$$

$a$  = answer

$d$  = document

$q$  = question

$i$  = sentence

$j$  = start word

$k$  = end word

$\phi(\cdot)$  = Score function

$Z$  = Partition function

# Global Normalization

$$\text{score}(a, d, q) = \phi_{\text{sent}}(d_i) + \phi_{\text{sw}}(d_{i,j}) + \phi_{\text{ew}}(d_{i,j:k})$$

$$\mathbb{P}(a \mid d, q) = \frac{\exp(\text{score}(a, d, q))}{Z}$$

$$Z = \sum_{a' \in \mathcal{A}(d)} \exp(\text{score}(a', d, q))$$

$a$  = answer

$d$  = document

$q$  = question

$i$  = sentence

$j$  = start word

$k$  = end word

$\phi(\cdot)$  = Score function

$Z$  = Partition function

$\mathcal{A}(d)$  = Set of all possible answer spans

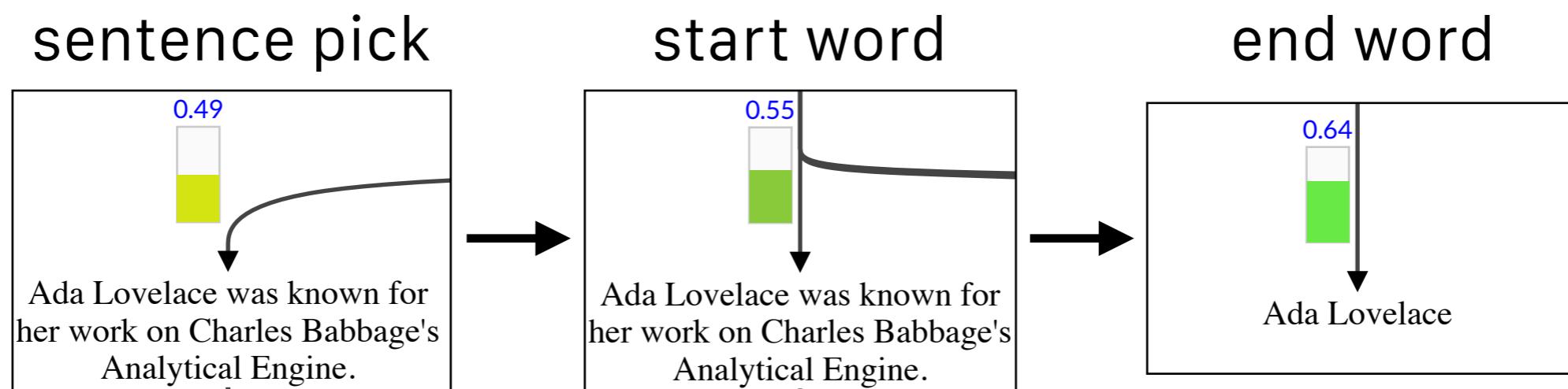
$d_{i,j:k}$  = span from word  $j$  to  $k$ , in sentence  $i$

Set grows exponentially.

Approximate using beam search

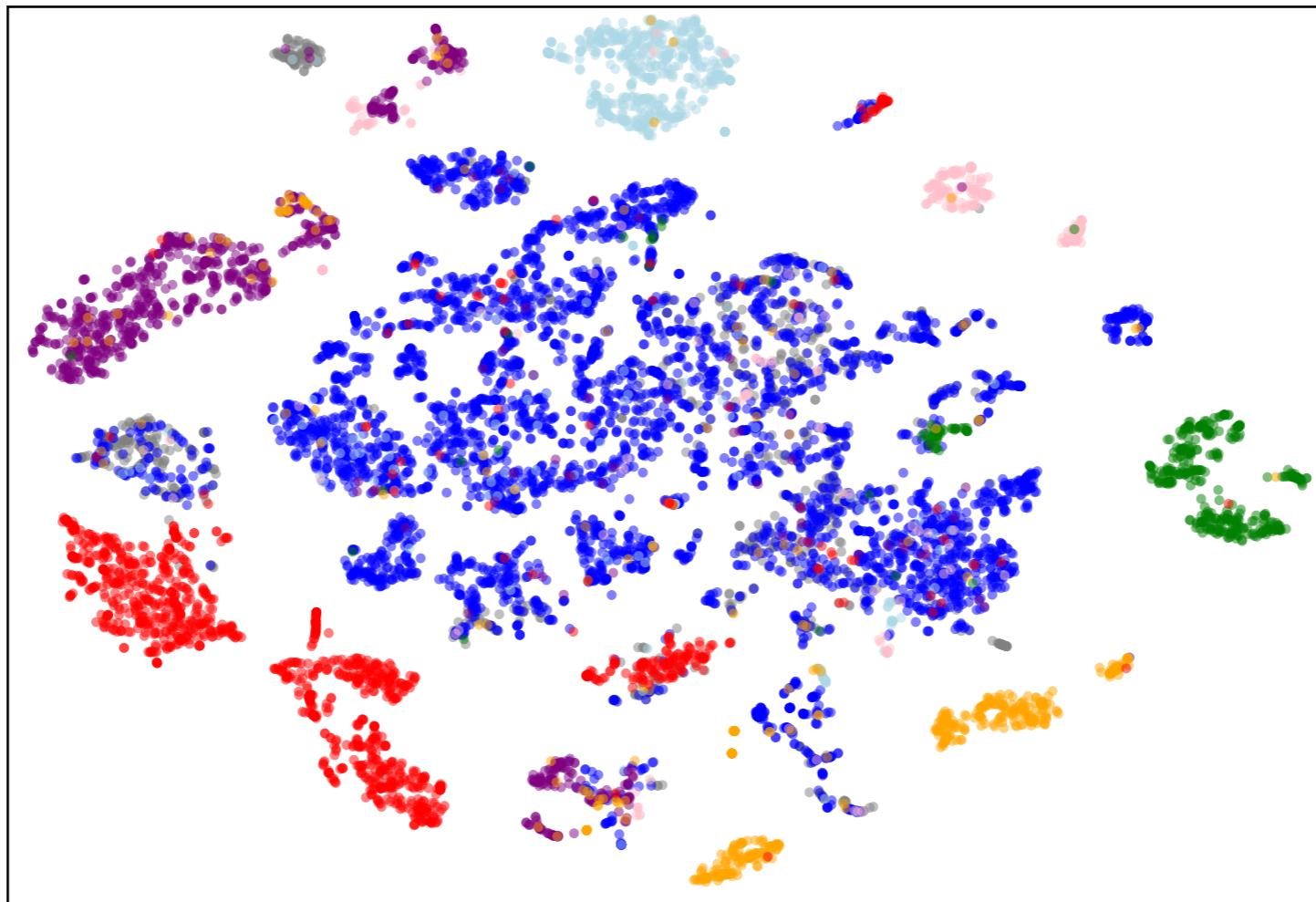
# Global Normalization

Answer probability grows as search advances  
(we are not multiplying probabilities!)



Note: globally normalized models remain undecided until the end word, while local models usually have spiked distributions

# Type Swaps



T-SNE Question hidden state naturally  
clusters according to question type.  
**How can we exploit this?**

# Type Swaps

- Common SQuAD pitfall: pick wrong answer with right type (human, organization, etc.)
- Solution: increase typed-based QA pairs

Who said in December 2012 that the fight would change from military to law enforcement?

... Basic objectives of the Bush Administration "war on terror", such as targeting al Qaeda and building international counterterrorism alliances, remain in place. In December 2012, Jeh Johnson, the General Counsel of the Department of Defense stated that the military fight will be replaced by a law enforcement operation when speaking at

Oxford University

...

Answer:

Jeh Johnson

# Type Swaps

- Common SQuAD pitfall: pick wrong answer with right type (human, organization, etc.)
- Solution: increase typed-based QA pairs

Who said in April 25, 2011 that the fight would change from military to law enforcement?

... Basic objectives of the Cabinet of Japan "war on terror", such as targeting al Qaeda and building international counterterrorism alliances, remain in place. In April 25, 2011, Sheryl Sandberg, the General Counsel of the ministry of education stated that the military fight will be replaced by a law enforcement operation when speaking at

Ain Shams University ...

Answer: Sheryl Sandberg

# Type Swaps

- Common SQuAD pitfall: pick wrong answer with right type (human, organization, etc.)
- Solution: increase typed-based QA pairs

Who said in 2012 that the fight would change from military to law enforcement?

... Basic objectives of the British Empire "war on terror", such as targeting al Qaeda and building international counterterrorism alliances, remain in place. In 2012, Genghis Khan, the General Counsel of the EMNLP stated that the military fight will be replaced by a law enforcement operation when speaking at

George Washington University ...

Answer: Genghis Khan

# Type Swaps

... Basic objectives of the Bush Administration's "war on terror", such as targeting al Qaeda and building international counterterrorism alliances, remain in place. In December 2012, Jeh Johnson, the General Counsel of the Department of Defense, stated that the military fight will be replaced by a law enforcement operation when speaking at Oxford University. . .

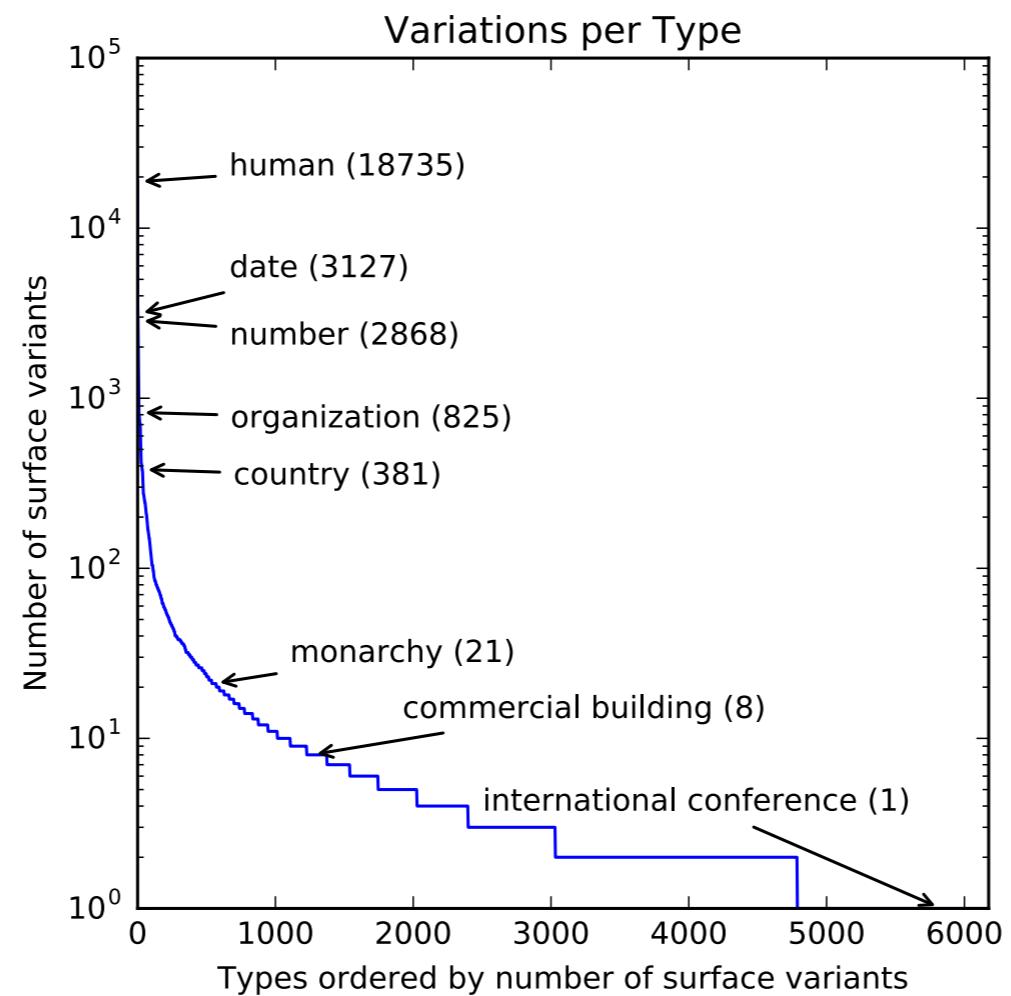


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1) Extract Entities

2) Assign Types

3) Swap with same type variations



$2.92 \cdot 10^{369}$   
unique documents

# Experiments

- Evaluate GNR against baselines on SQuAD dev set (100,000 QA pairs)<sup>1</sup>
- GNR Ablations:
  - Data Augmentation
  - Global Normalization
- Measure Speedup

<sup>1</sup><https://rajpurkar.github.io/SQuAD-explorer/>

# Comparison

Model	EM	F1
GNR	68.4	76.2
Bi-Attention-Flow (Seo et al., 2016)	67.7	77.3
Razor (Lee et al., 2016)	66.4	74.9
DCN (Xiong et al., 2016)	65.4	75.6
FastQA (Weissenborn et al., 2017)	67.8	76.3
R-Net (Wang et al., 2017)	<b>72.3</b>	<b>80.6</b>

Model	EM	F1
GNR	68.4	76.2
GNR w/o Global Norm	67.21	76.0
GNR w/o Type Swaps	66.6	75.0

# Data Augmentation

Impact of number of augmented examples:

Number of Swaps	EM	F1
0	66.6	75.0
1000	66.9	75.0
<b>10 000</b>	<b>68.4</b>	<b>76.21</b>
50 000	66.8	75.3
100 000	66.1	74.3

Impact of Type Swaps on the DCN+<sup>1</sup>:

Number of Swaps	Train F1	Dev F1
0	81.3	78.1
50 000	72.5	<b>78.2</b>

<sup>1</sup> Updated DCN model, see <https://rajpurkar.github.io/SQuAD-explorer/>

# Speedup

- Full dev set, batch size 32, average 5 runs, on Titan X:
  - Bi-Attention-Flow<sup>1</sup>:  $1260.23 \pm 17.26$  seconds
  - GNR:  **$51.58 \pm 0.266$  seconds**
- Key reasons:
  - Efficient batching of Beam Search
  - Only rank subset of spans
  - Factorize search with document structure

<sup>1</sup>[github.com/allenai/bi-att-flow](https://github.com/allenai/bi-att-flow)

# Conclusion

## **Key contributions:**

- Learning-to-Search w/. early updates & global norm enables conditional computation.
- Data augmentation that improves performance
- 24.7x speedup over bi-attention-flow
- Achieve  $\geq$  results than bi-directional attention

# Future Work

- Conditional computation for generative models & large search spaces
- Program induction/search with perfect simulator
- Model amplification (AlphaZero-style)
- Type Swaps on other NLP tasks? Grammar-aware type-swaps? Adversarial Type Swaps?

**Code & Dataset:**

[github.com/baidu-research/  
GloballyNormalizedReader](https://github.com/baidu-research/GloballyNormalizedReader)

**Thank You!**

# DeepType

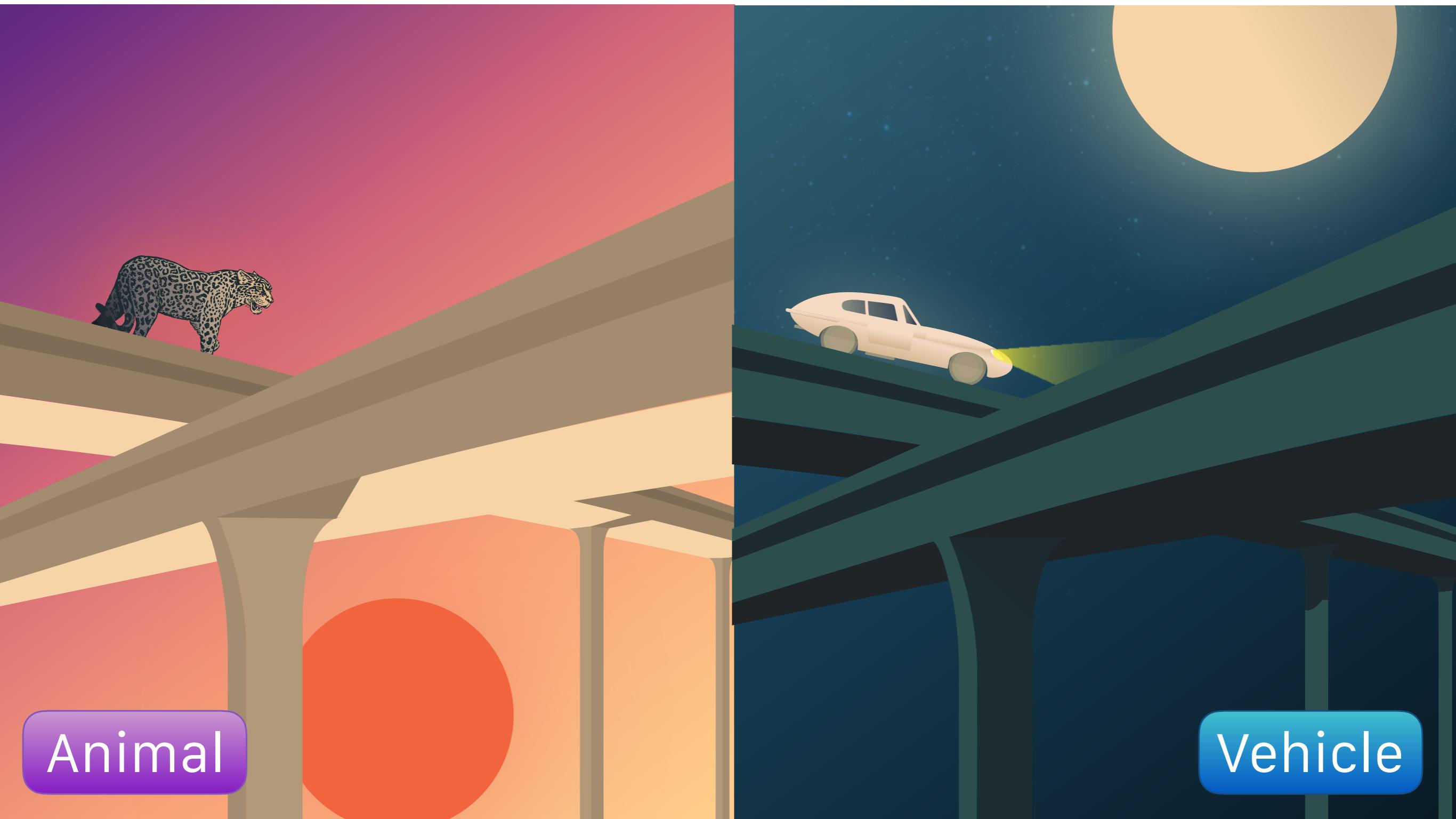
## Multilingual Entity Linking by Neural Type System Evolution

Jonathan Raiman &  
OpenAI

Olivier Raiman  
Agilience

# Entity Linking

The man saw a Jaguar speed on the highway.



Animal

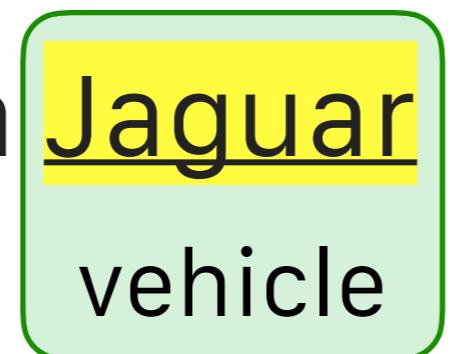
Vehicle

# Entity Linking

The prey saw a Jaguar cross the jungle.



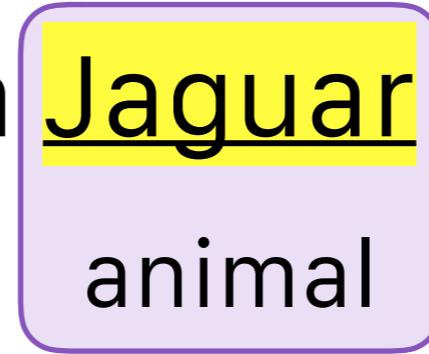
The man saw a Jaguar speed on the highway.



With types accuracy reaches **98.6-99%**

(type oracle on TAC KBP 2010/CoNLL YAGO)

The prey saw a Jaguar cross the jungle.



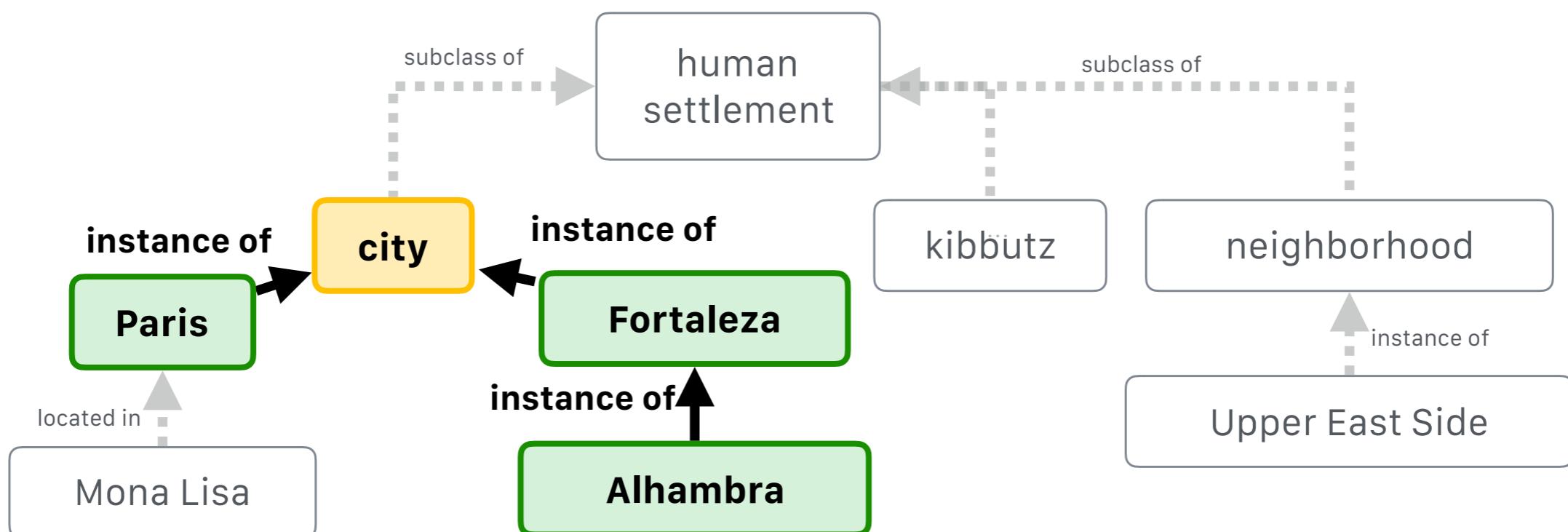
# Summary

- Design a neural type system
- Results
- Contributions

# Type generation

Wikidata is a graph with 40M+ entities

isCity = child(**city**,instance of)  
root                  relation



Root isCity non-member

# Design a Type System

$$\max_{\mathcal{A}} \max_{\theta} S_{\text{model}}(\mathcal{A}, \theta)$$

Type System

$$\boxed{\frac{\sum_{(m, e_{\text{GT}}, \mathcal{E}_m) \in M} \mathbb{1}_{e_{\text{GT}}}(e^*)}{|M|}}$$

Disambiguation accuracy

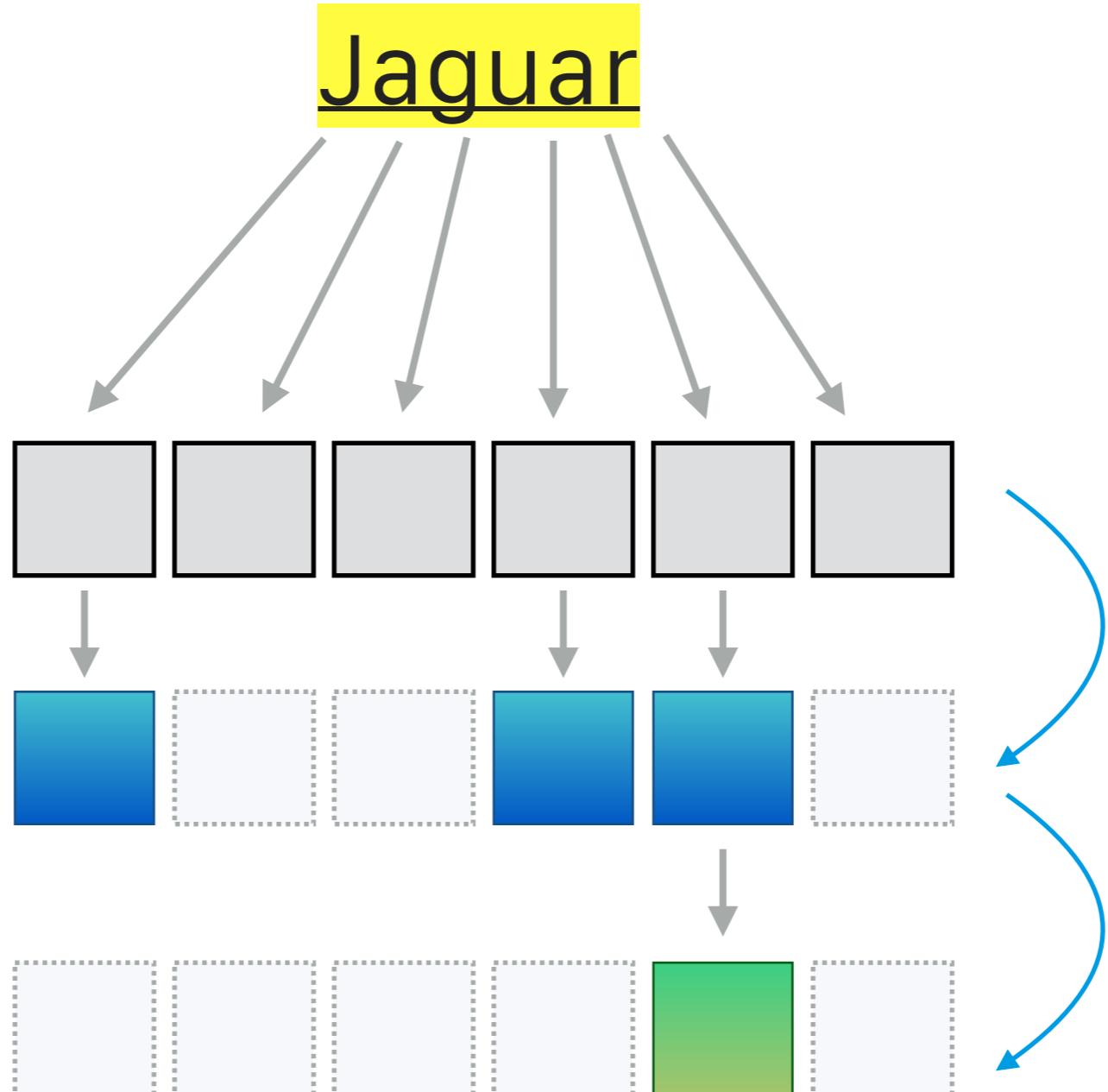
Intractable mixed integer problem

# Subproblems

1. Stochastic optimization/heuristic search to design type system
2. Gradient descent to train a type classifier

# Oracle Accuracy

Possible entities:



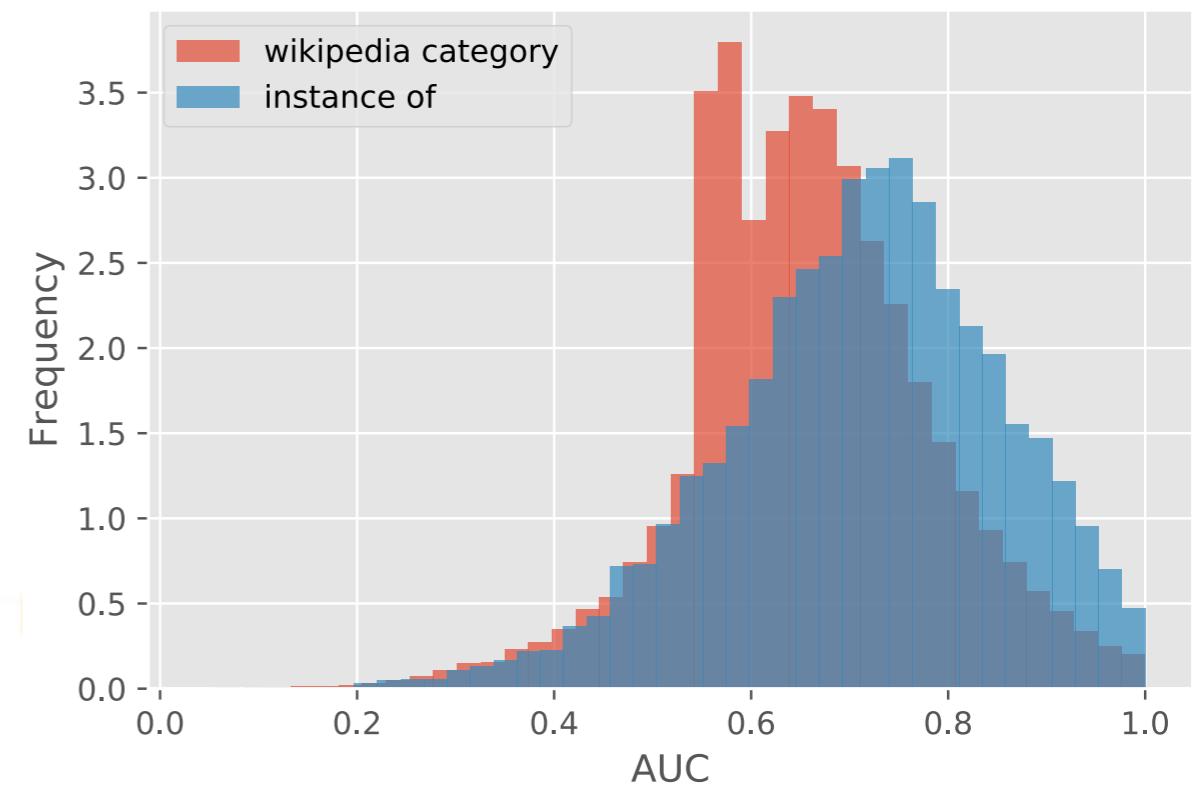
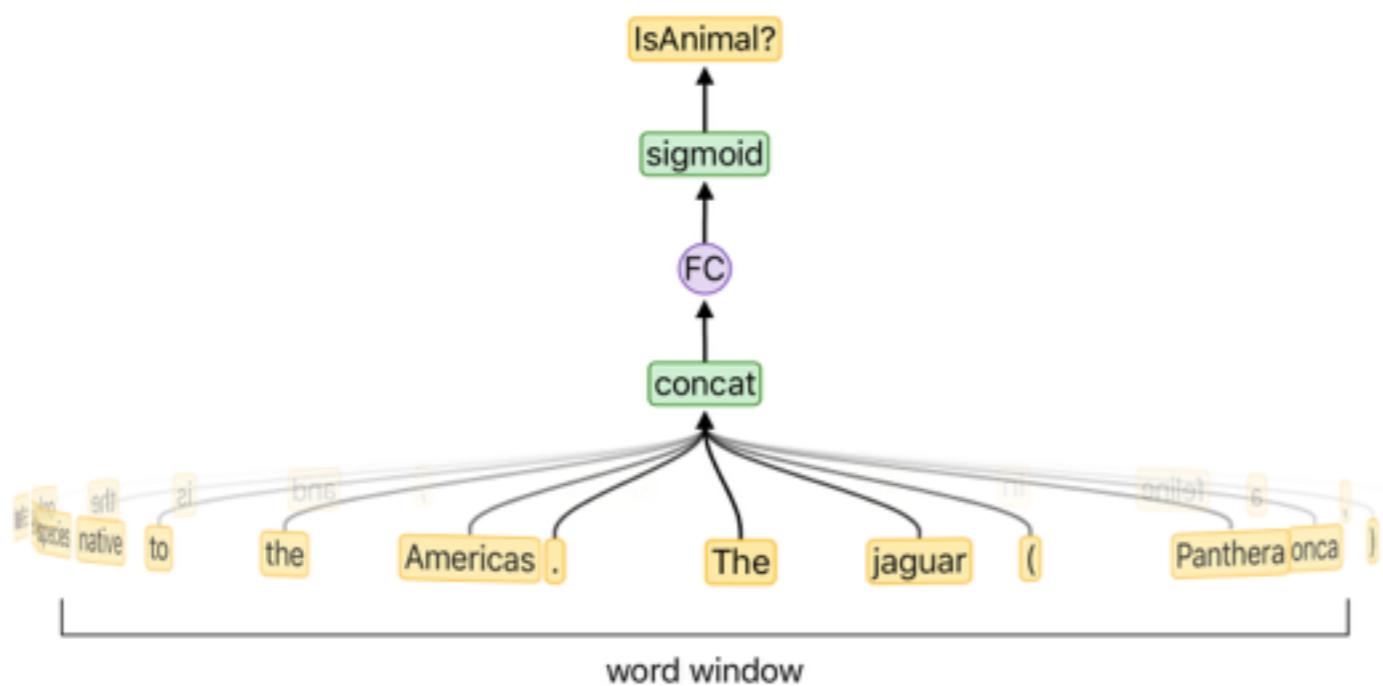
Animal entities:

from South  
America:

perfect  
classifier  
(Oracle)

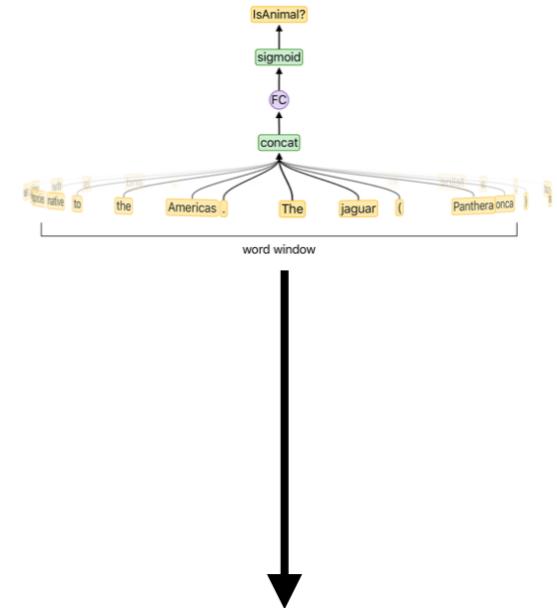
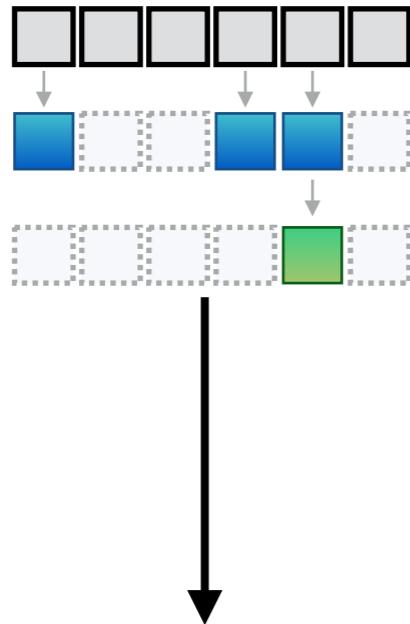
# Type Learnability

- Which types are predictable from context?
- Train a proxy binary classifier for each type
- AUC\* of classifier is an estimate of Learnability



\* average AUC over 4 training runs

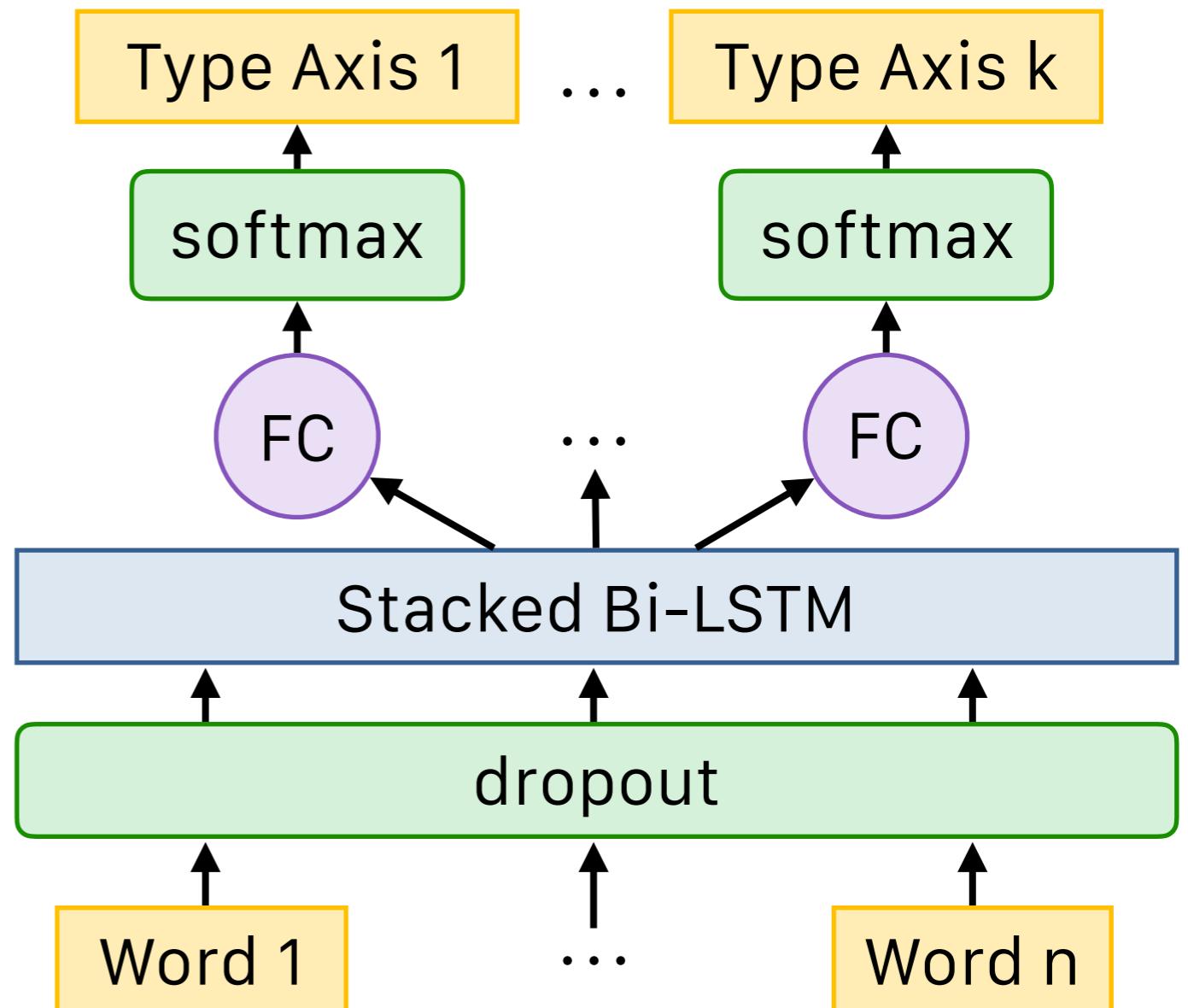
# Type System Evolution



$$J(\mathcal{A}) = (\text{Accuracy}_{\text{oracle}}(\mathcal{A}) - \text{Accuracy}_{\text{greedy}}) \cdot \text{Learnability}(\mathcal{A}) - \lambda \cdot |\mathcal{A}|$$

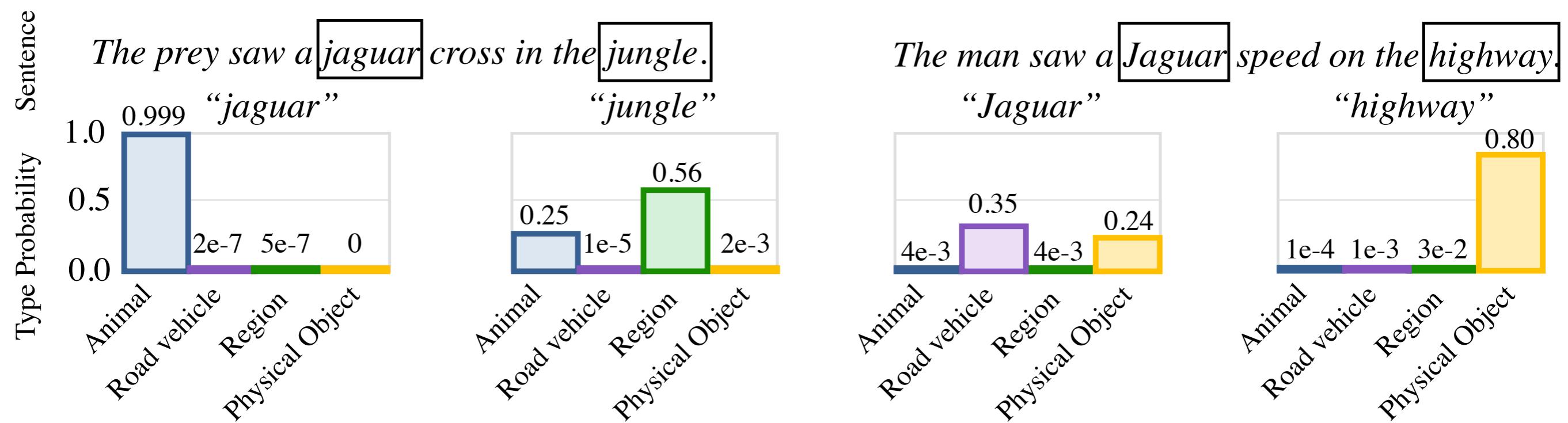
Diminishing Returns

# Train a type classifier



Intra-wiki links are type labels!  
(in any Wikipedia language)

# Inference



Entity	<b>jaguar</b>	<b>Jaguar</b>	<b>jungle</b>	<b>jungle</b>	<b>jaguar</b>	<b>Jaguar</b>	<b>highway</b>	<b>Highway</b>
Type	Animal	Road vehicle	Region	Music	Animal	Road vehicle	Physical Object	Film
only link Prob.	0.29	<b>0.60</b>	<b>0.35</b>	0.17	0.29	<b>0.60</b>	<b>0.85</b>	0.04
Prob. w/. types	<b>1.0</b>	0.0	<b>1.0</b>	0.0	0.0	<b>1.0</b>	<b>1.0</b>	0.0

# Results

	Model	CoNLL (YAGO)	TAC 2010
no types	Globerson et al. 2016	91,70 %	87,20 %
	Yamada et al. 2016	91,50 %	85,20 %
	NTEE (Yamada et al. 2017)	-	87,70 %
types	DeepType (human types)	93,11 %	90,74 %
	DeepType (greedy)	94,15 %	<b>90,85 %</b>
	DeepType (GA)	<b>94,88 %</b>	90,31 %
	DeepType (CEM)	93,96 %	90,30 %

# Contributions

- Outperform state of the art on several entity linking benchmark datasets
- Add entities without retraining by specifying their types
- Design & integrate symbolic structure to constrain neural network outputs

Code:

[github.com/openai/deeptype](https://github.com/openai/deeptype)

# Objective

- Given:
  - ambiguous mentions  $m \in M$
  - The ground truth entity  $e_{GT}$  for each  $m$
  - Model prediction  $e^*$
  - Model accuracy  $S_{model}$

$$\max_{\mathcal{A}} \max_{\theta} S_{model}(\mathcal{A}, \theta) = \frac{\sum_{(m, e_{GT}, \mathcal{E}_m) \in M} \mathbb{1}_{e_{GT}}(e^*)}{|M|}$$

- Find type system  $\mathcal{A}$ , and parameters  $\theta$  to maximise disambiguation accuracy
- $\mathcal{A}$  are discrete variables selecting the types to use

# Inference

- $P(\text{types}(e)|c)$  = compute type probabilities per token
- $P_{\text{link}}(e|c)$  = # intra-wiki links from anchor → articles
- Baye's rule, entity e, context c:
  - $P(e|c) = P_{\text{link}}(e|c) * P(\text{types}(e)|c)$

# Type system objective

$$J(\mathcal{A}) = (\text{Acc}_{\text{oracle}}(\mathcal{A}) - \text{Acc}_{\text{greedy}}) \bullet \\ \text{Learnability}(\mathcal{A}) - \lambda \bullet |\mathcal{A}|$$