Deep Learning for Question Answering

Mohit Iyyer

Who wrote the song
“Kiss from a Rose”?

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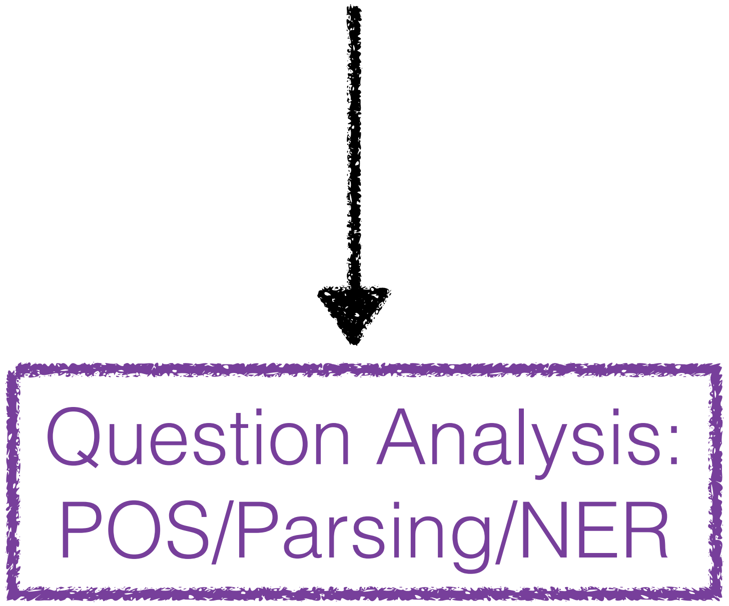
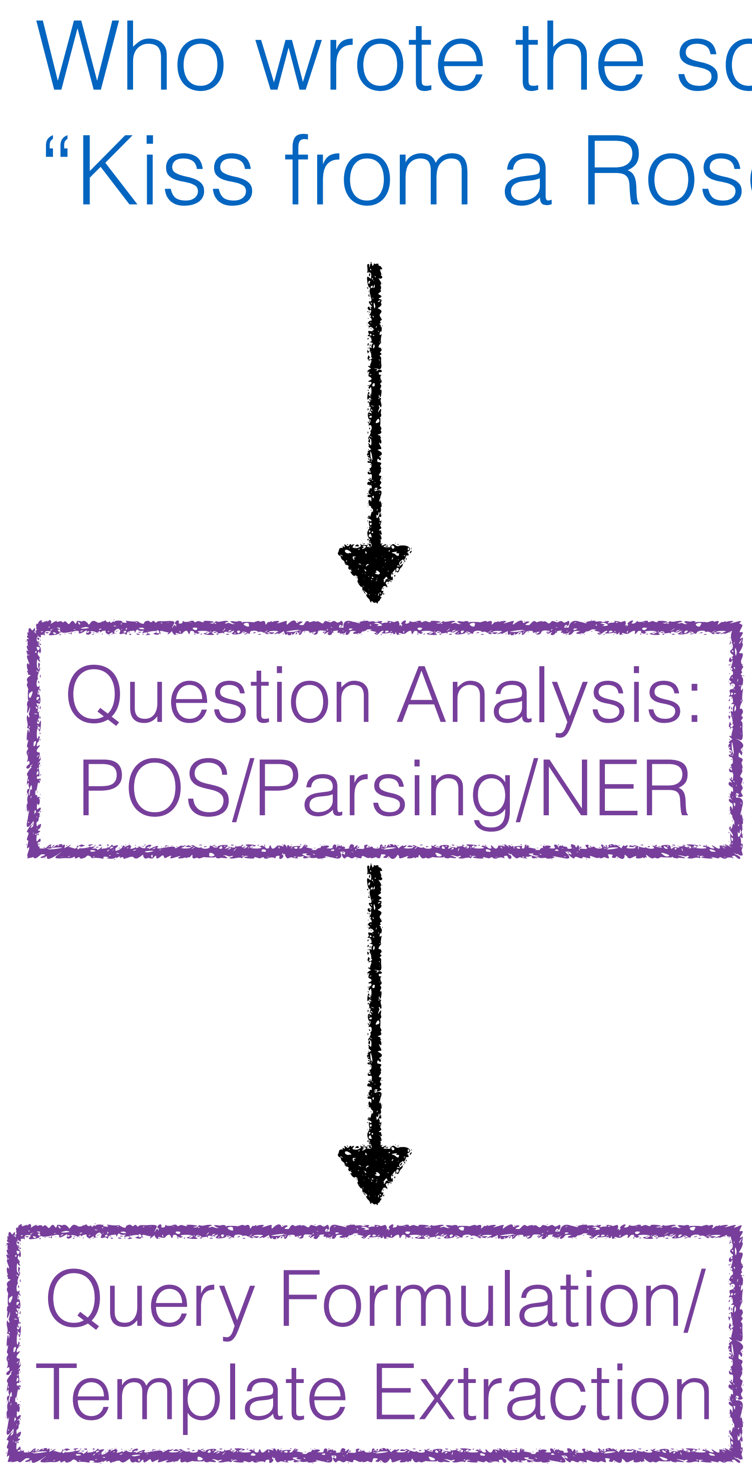


Question Analysis:
POS/Parsing/NER



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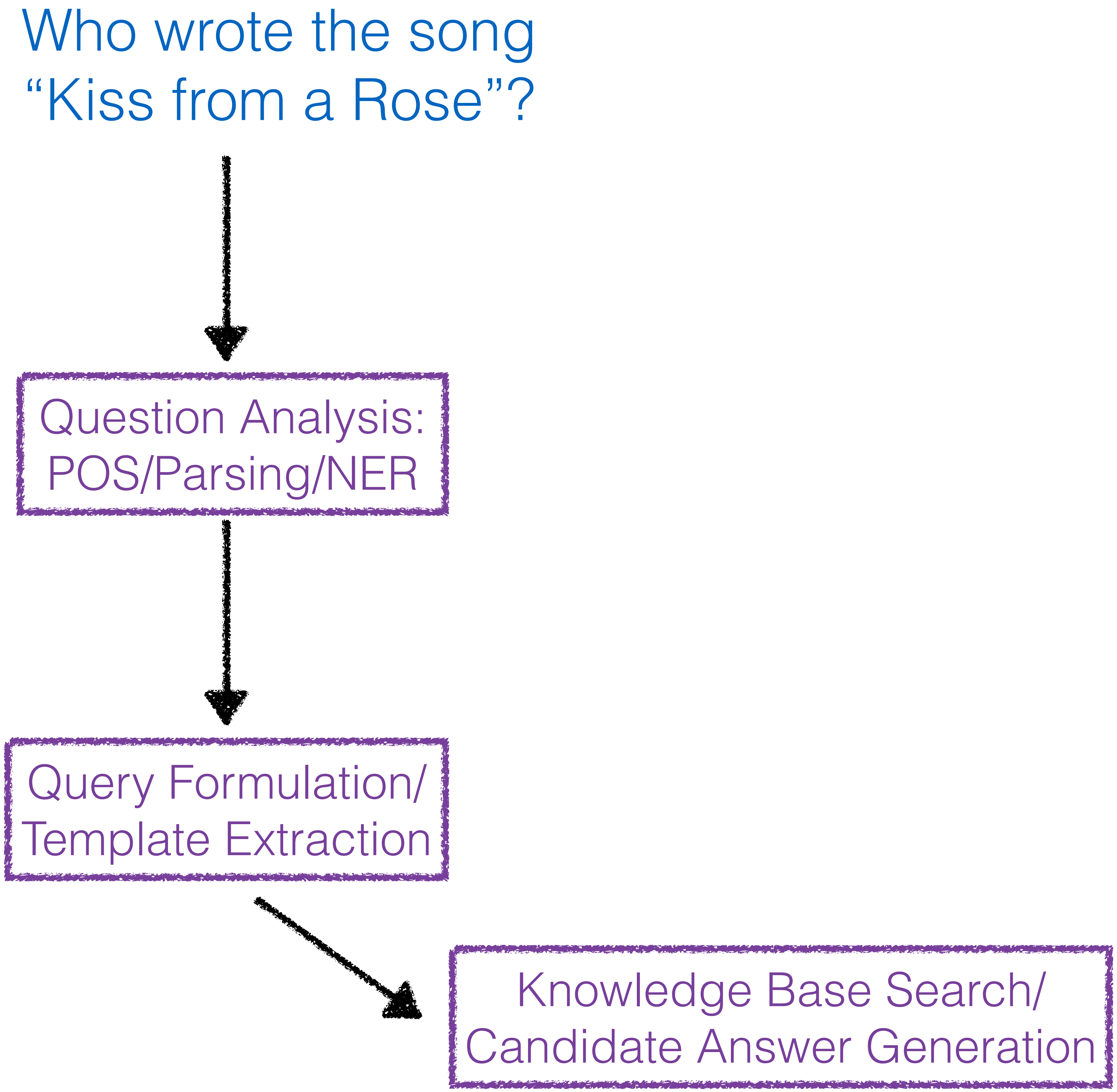
Query Formulation/ Template Extraction



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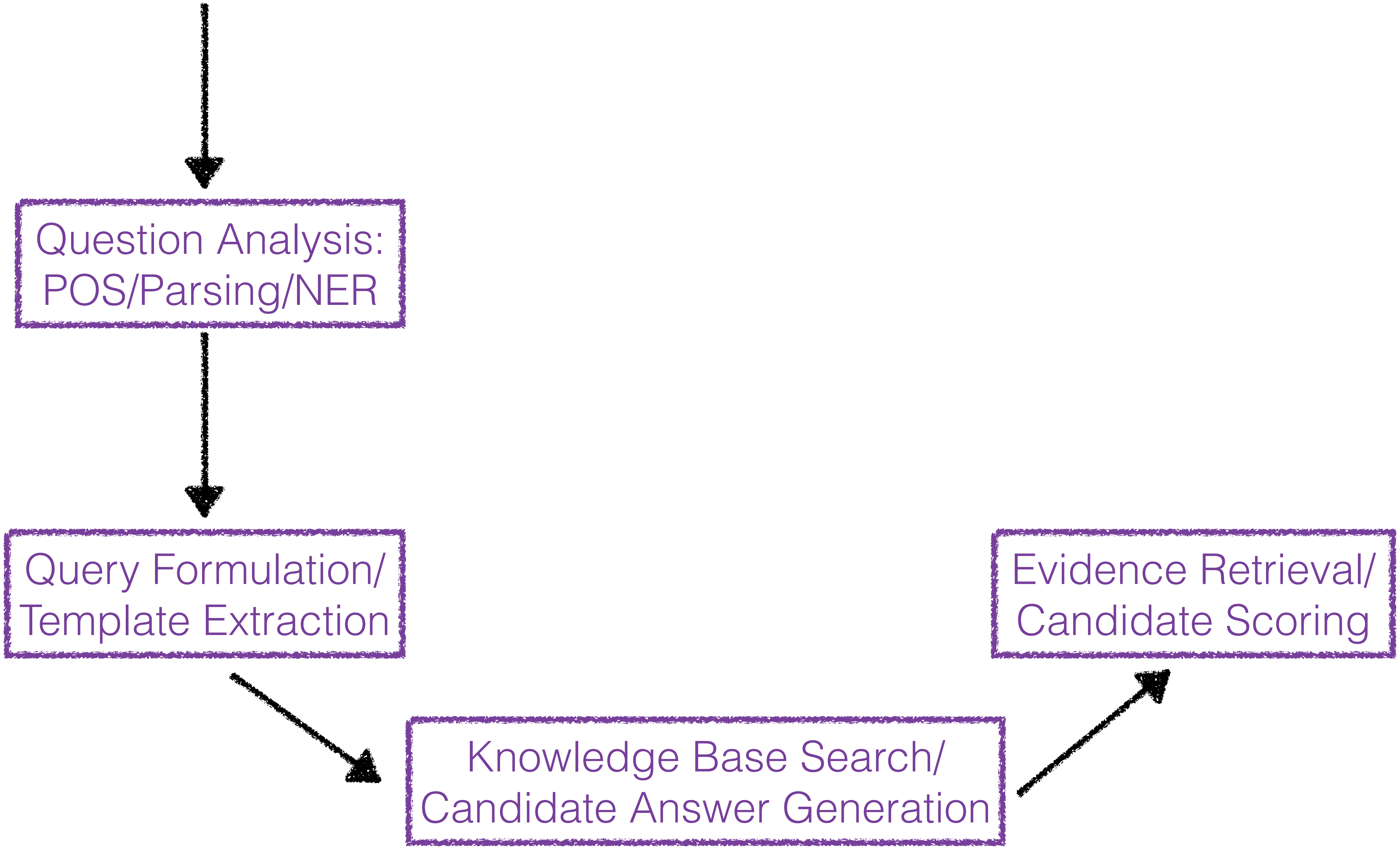

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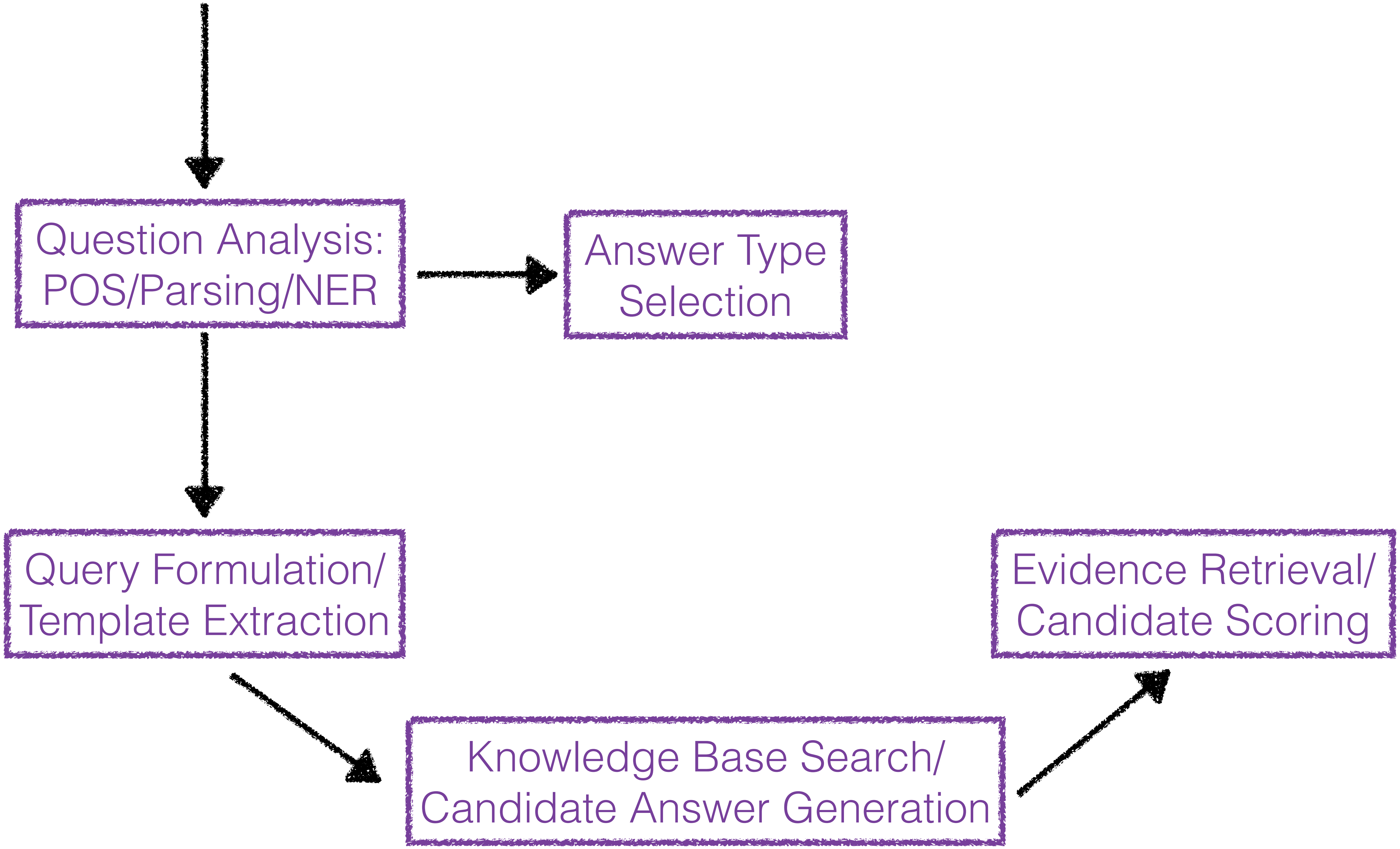

Question Analysis:
POS/Parsing/NER

Answer Type
Selection

Query Formulation/
Template Extraction

Knowledge Base Search/
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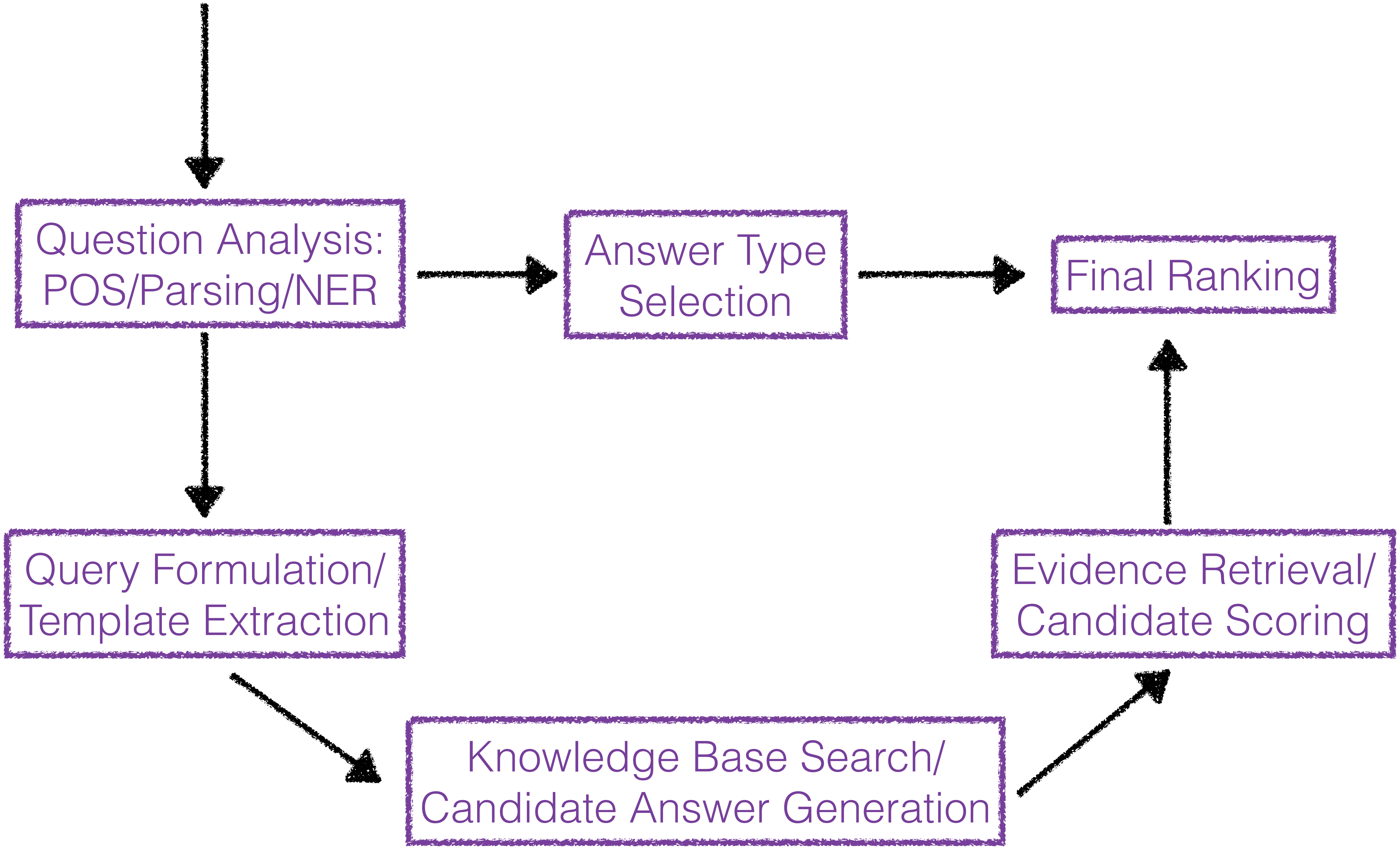


Question Analysis: POS/Parsing/NER

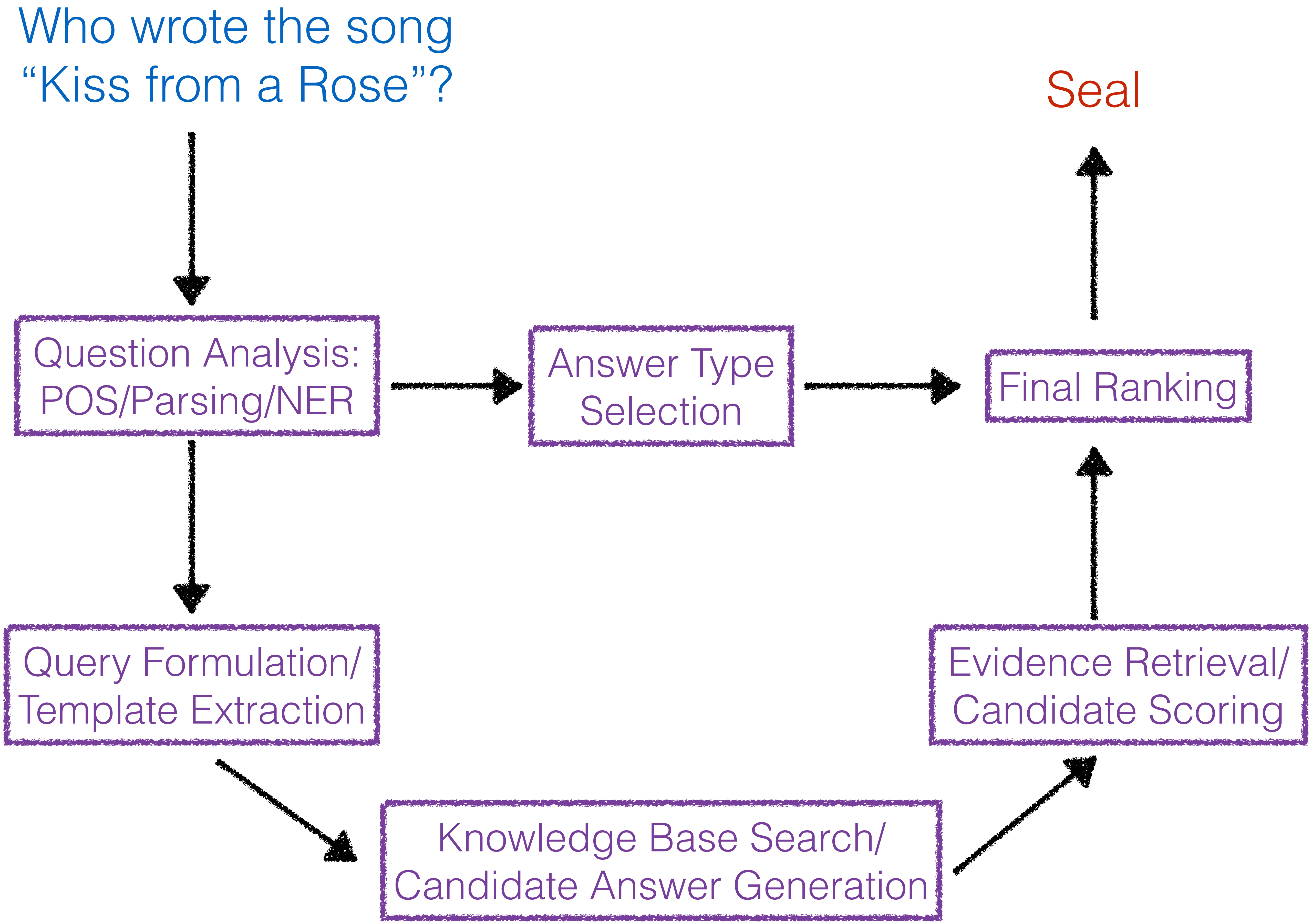
Answer Type Selection

Final Ranking

Query Formulation/ Template Extraction

Evidence Retrieval/ Candidate Scoring

Knowledge Base Search/ Candidate Answer Generation



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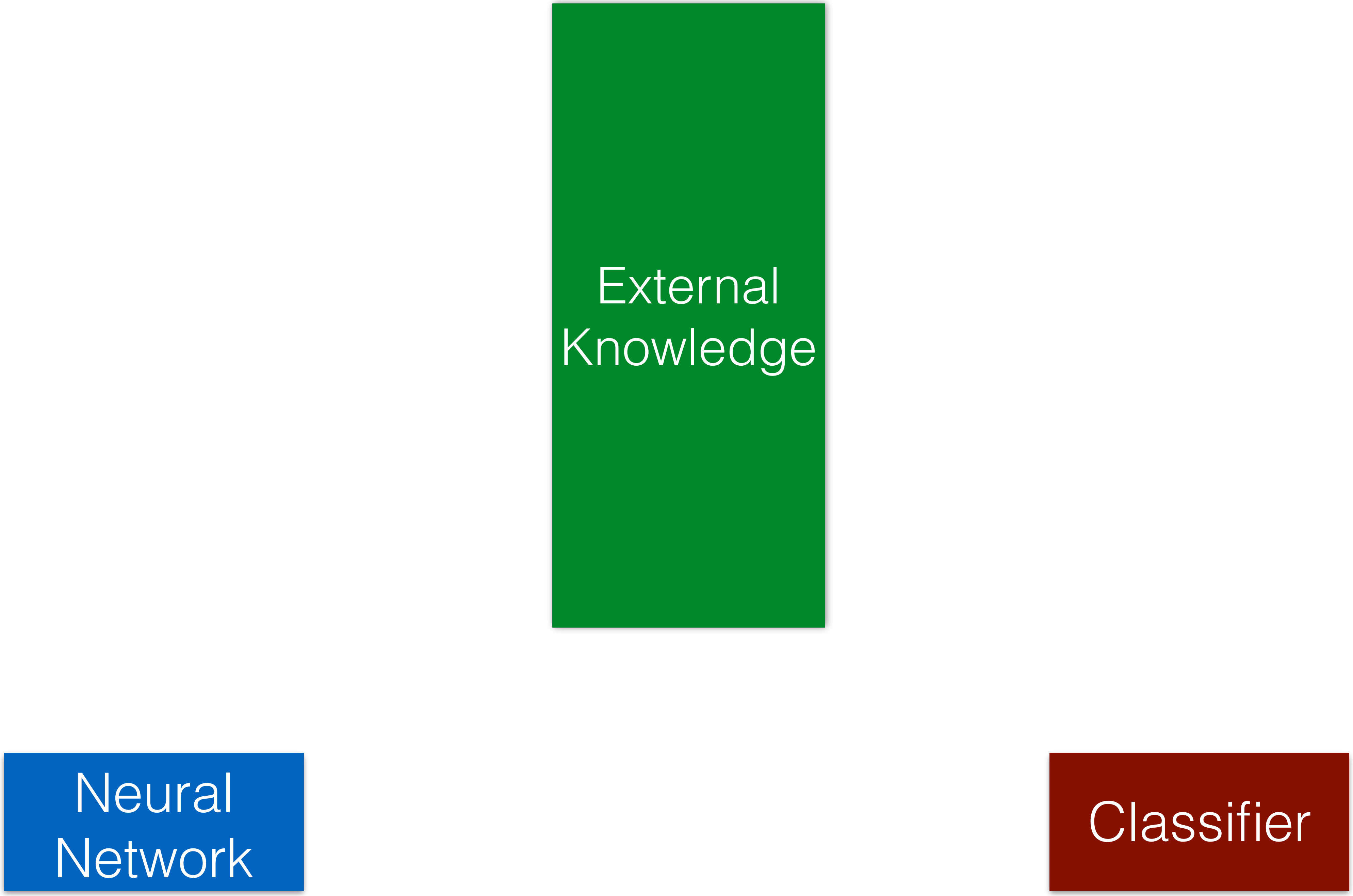
Final Ranking

Seal

Can we replace all of these modules with a single neural network?



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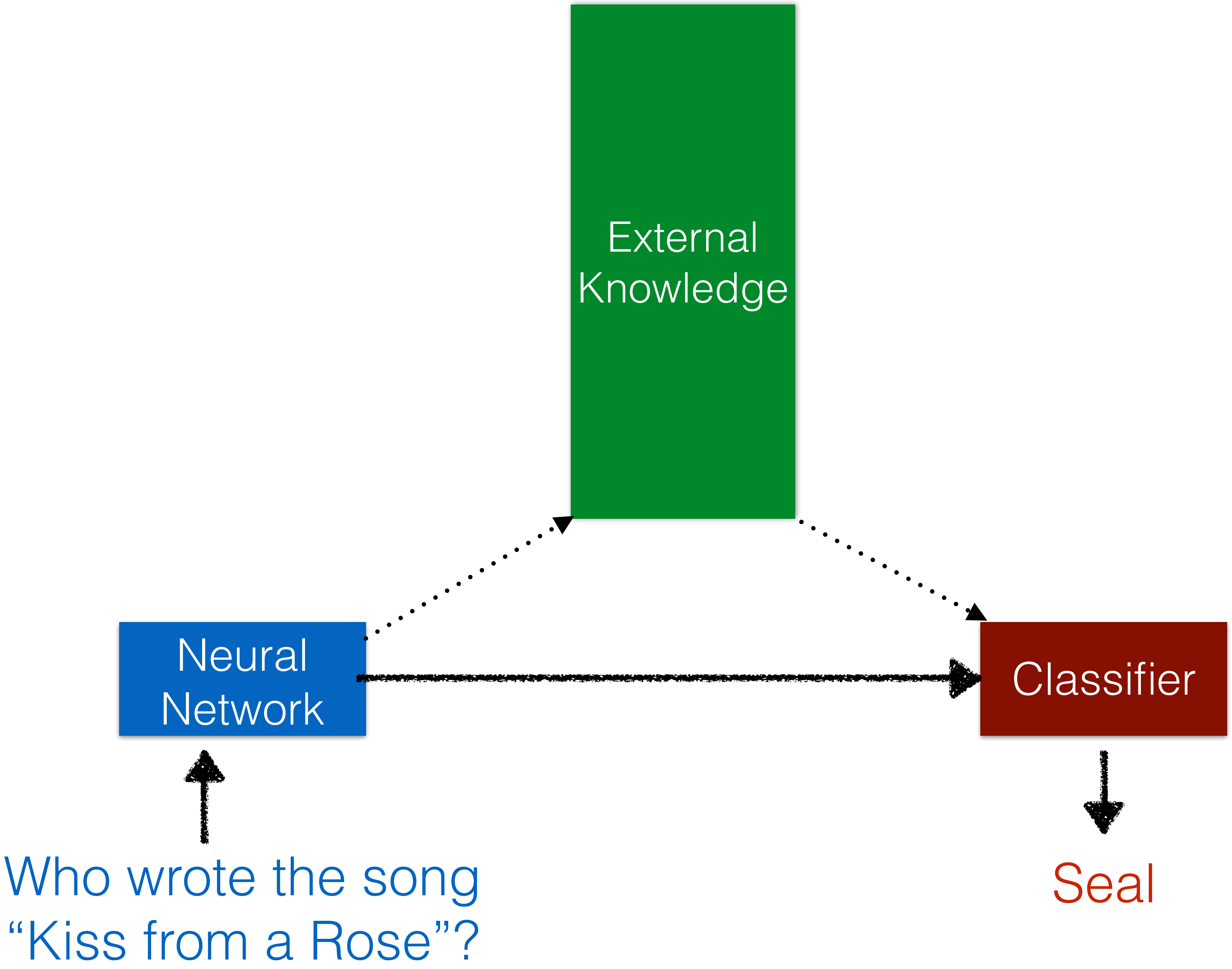


Outline

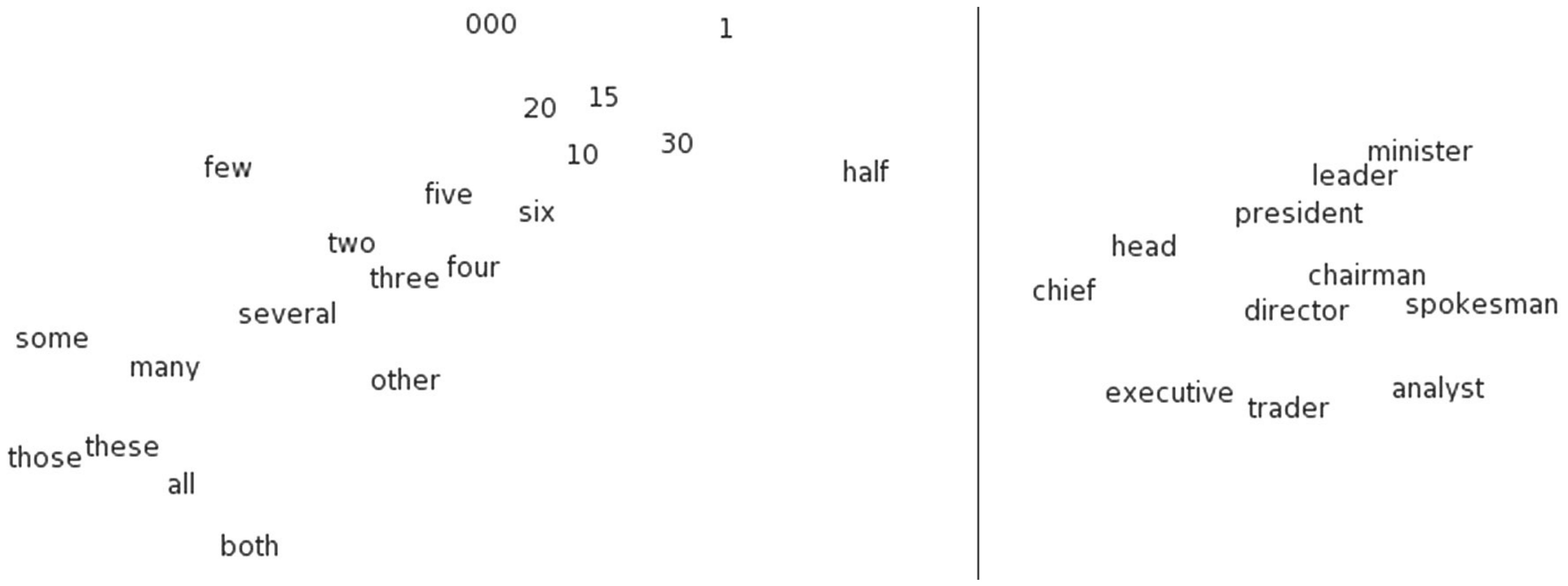
- Briefly: deep learning + NLP basics
- Factoid QA
- Reasoning-based QA
- Visual QA
- Future directions!

Neural Networks for NLP

Let’s start with words

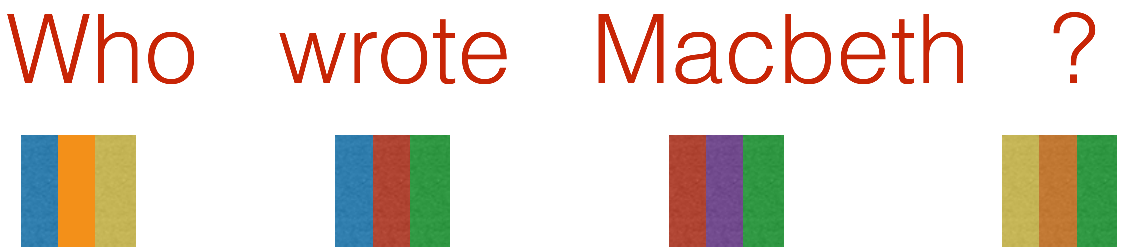
- Represent words by low-dimensional vectors called **embeddings**

- e.g., president ➡ [0.23, 1.3, -0.3, 0.43]



Computing Vectors for Questions

- How do we **compose** word embeddings into vectors that capture the meanings of questions?



Who wrote Macbeth ?

Computing Vectors for Questions

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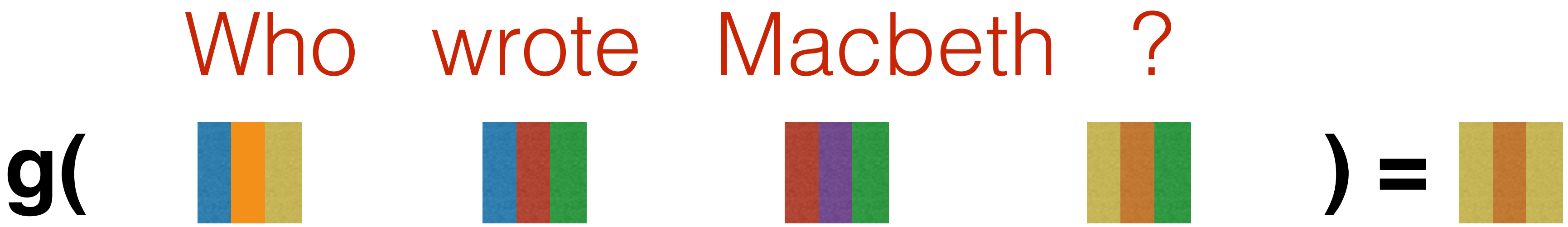

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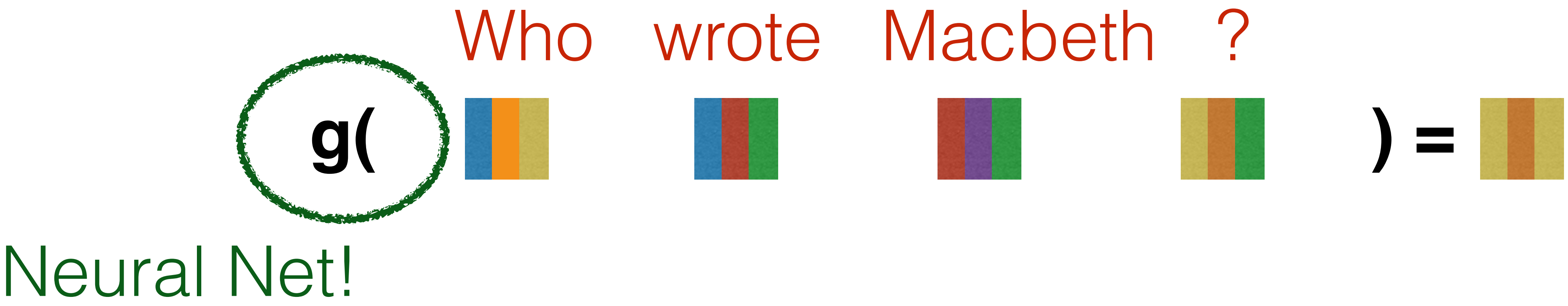


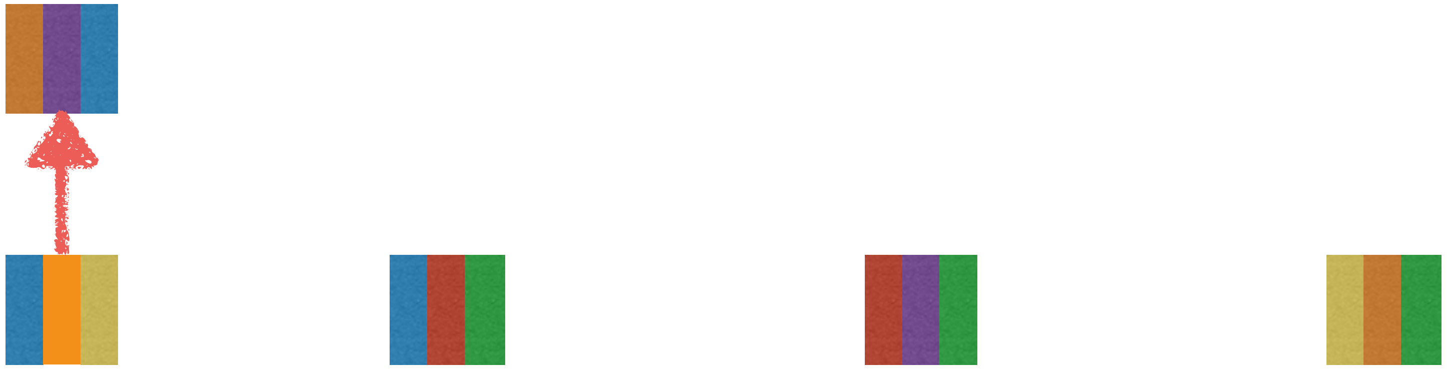
Recurrent Neural Networks

Who directed Predator ?

c_1 c_2 c_3 c_4

Recurrent Neural Networks

$$h_1 = f(W \begin{bmatrix} \dots \\ c_1 \end{bmatrix})$$



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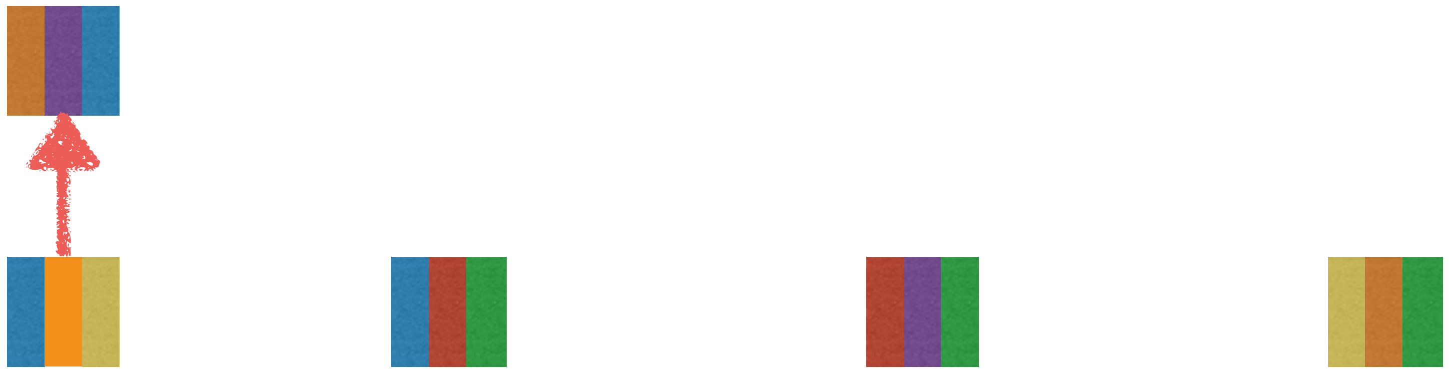
Hidden layer



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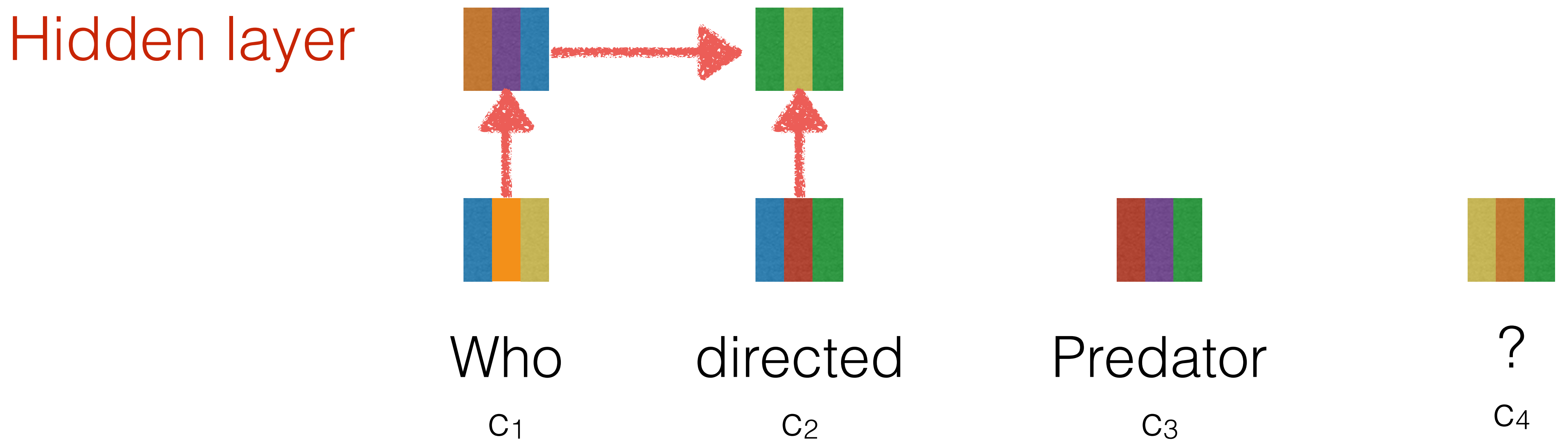
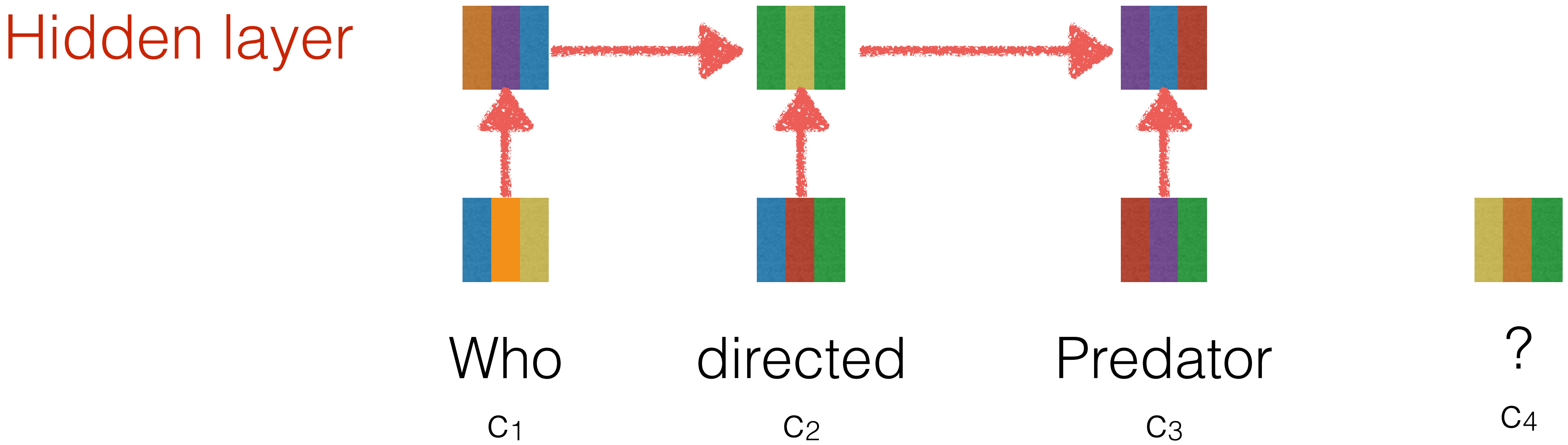
$h_1 = f(W \begin{bmatrix} \cdots \\ c_1 \end{bmatrix})$ $h_2 = f(W \begin{bmatrix} h_1 \\ c_2 \end{bmatrix})$



Recurrent Neural Networks

$$h_1 = f(W \begin{bmatrix} \cdots \\ c_1 \end{bmatrix}) \quad h_2 = f(W \begin{bmatrix} h_1 \\ c_2 \end{bmatrix}) \quad h_3 = f(W \begin{bmatrix} h_2 \\ c_3 \end{bmatrix})$$



Hidden layer

Who

c_1

directed

c_2

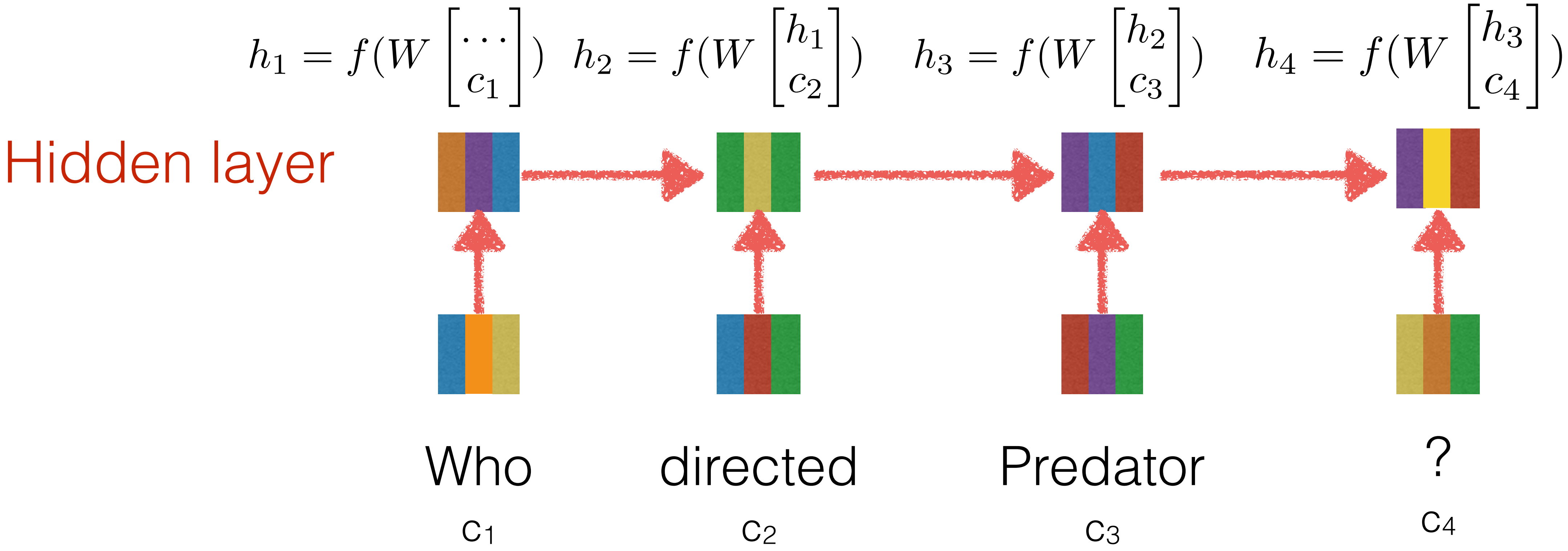
Predator

c_3

?

c_4

Recurrent Neural Networks



$h_1 = f(W \begin{bmatrix} \cdots \\ c_1 \end{bmatrix})$
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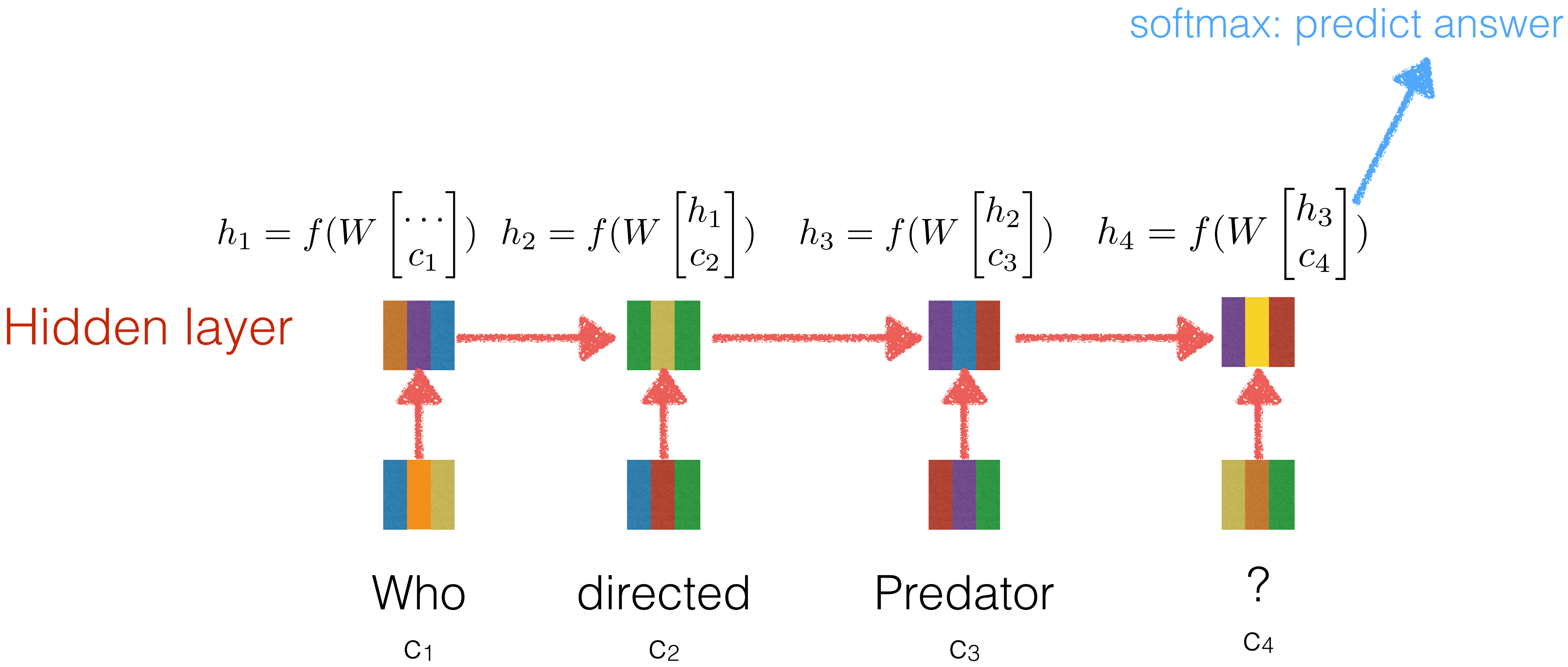

softmax: predict answer

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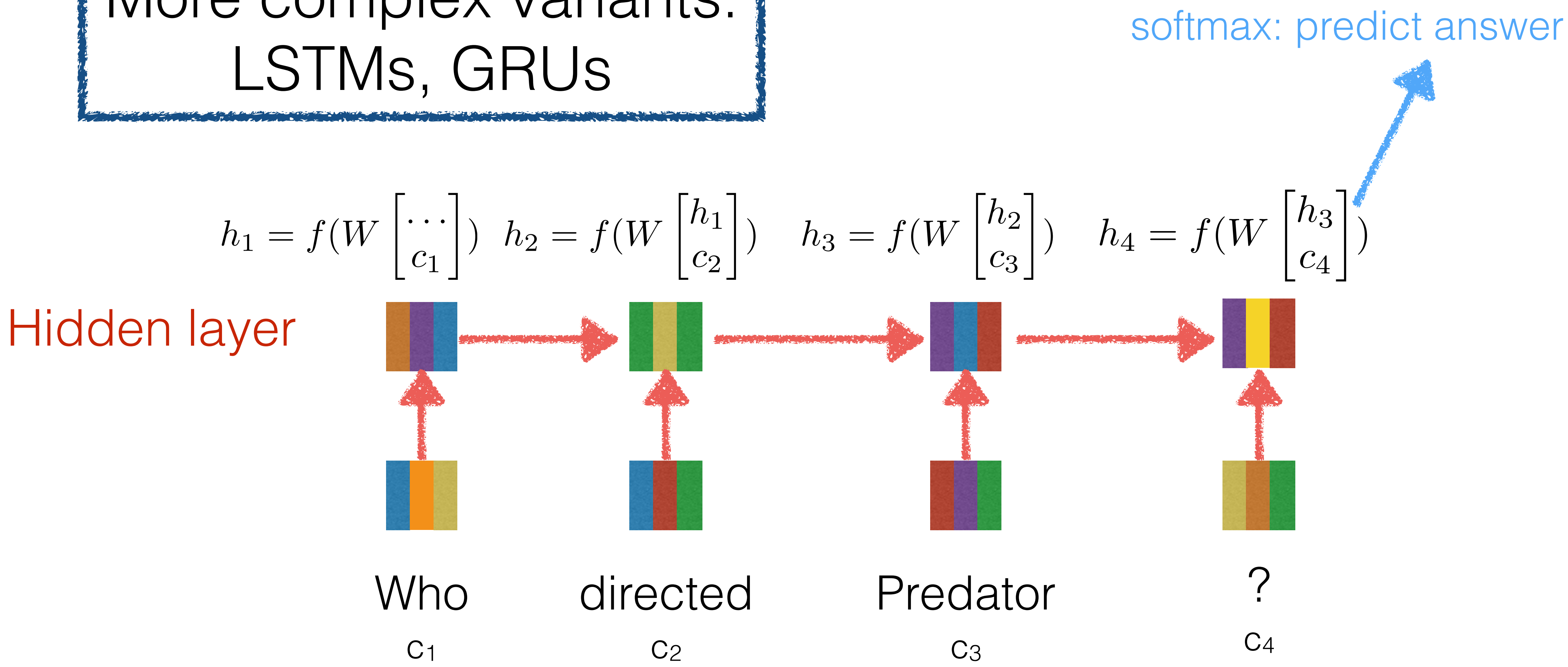
Hidden layer

Who c_1 directed c_2 Predator c_3 ? c_4

Recurrent Neural Networks

More complex variants:
LSTMs, GRUs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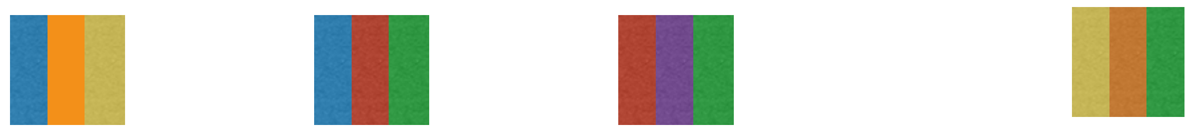
Recursive Neural Networks

- **g** can also depend on a *parse tree* of the input text sequence



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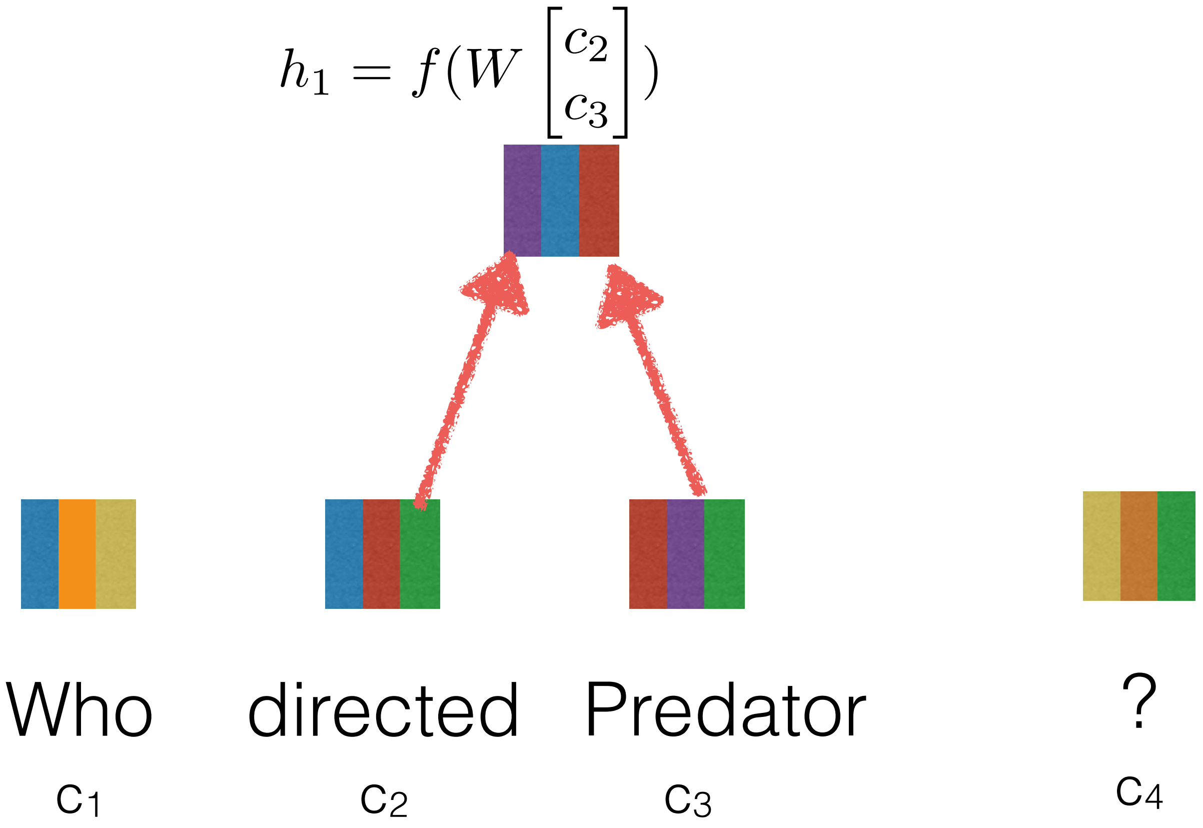

$$h_1 = f(W \begin{bmatrix} c_2 \\ c_3 \end{bmatrix})$$

Recursive Neural Networks

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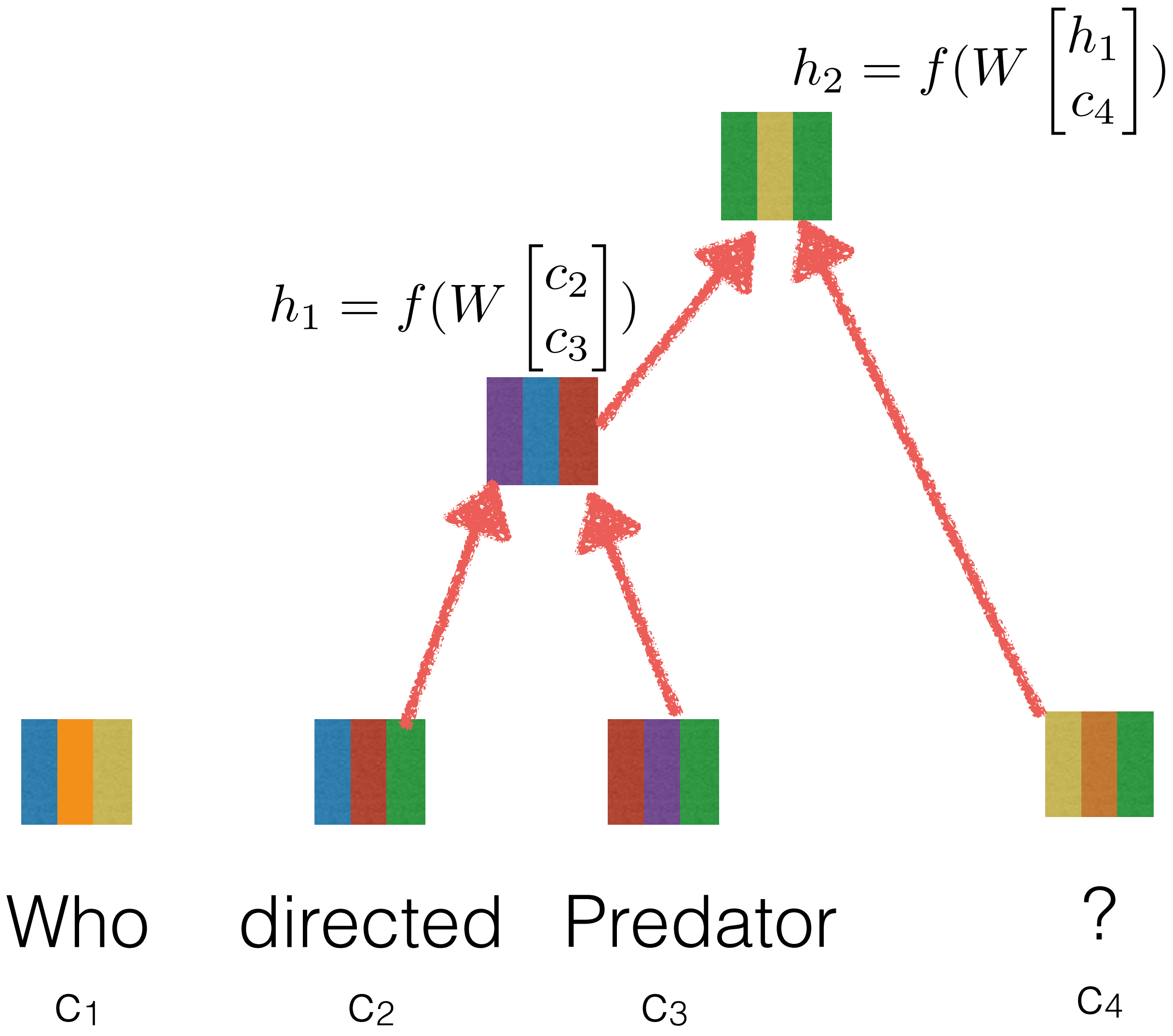

$h_2 = f(W \begin{bmatrix} h_1 \\ c_4 \end{bmatrix})$

$h_1 = f(W \begin{bmatrix} c_2 \\ c_3 \end{bmatrix})$

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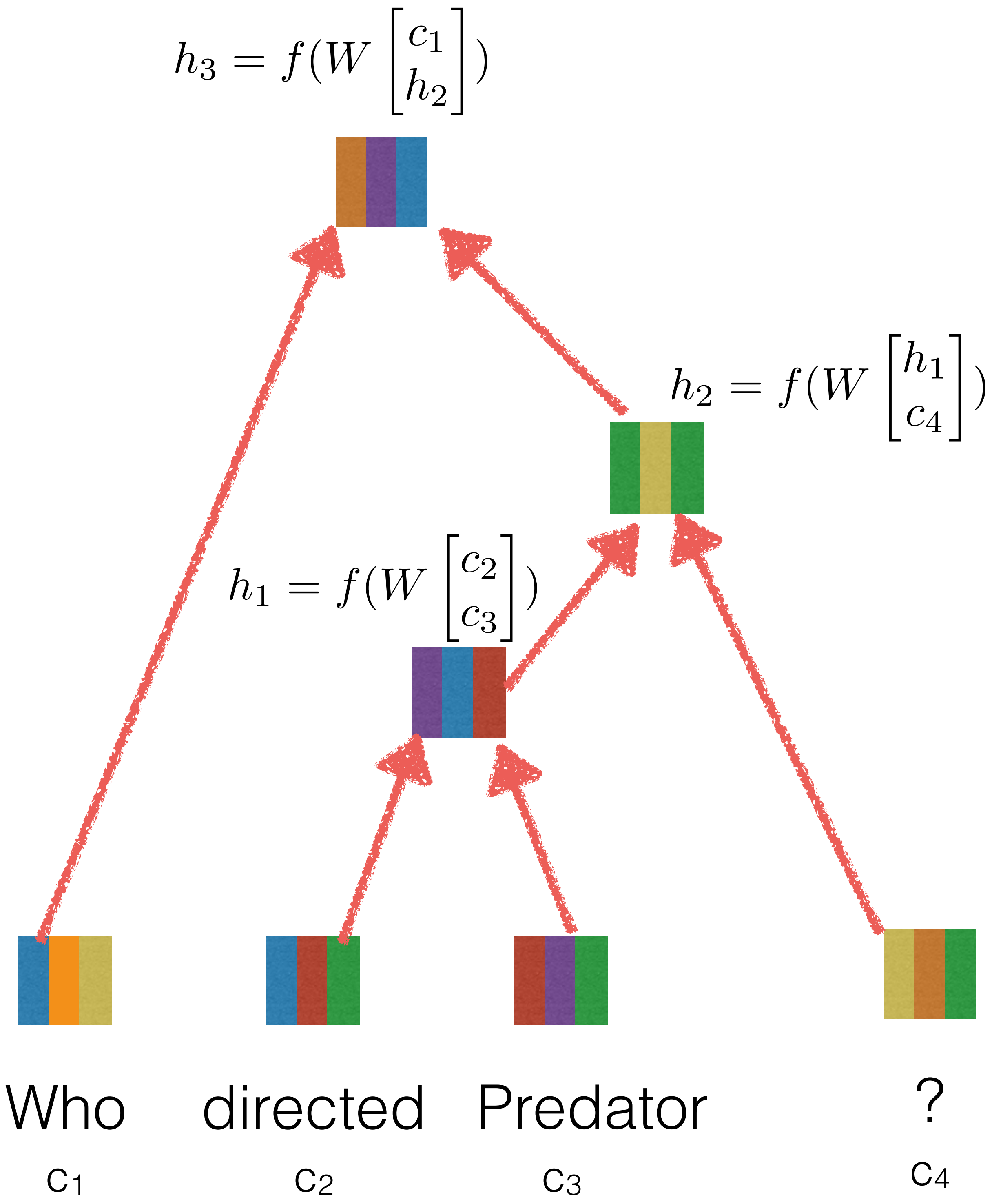

$h_3 = f(W \begin{bmatrix} c_1 \\ h_2 \end{bmatrix})$

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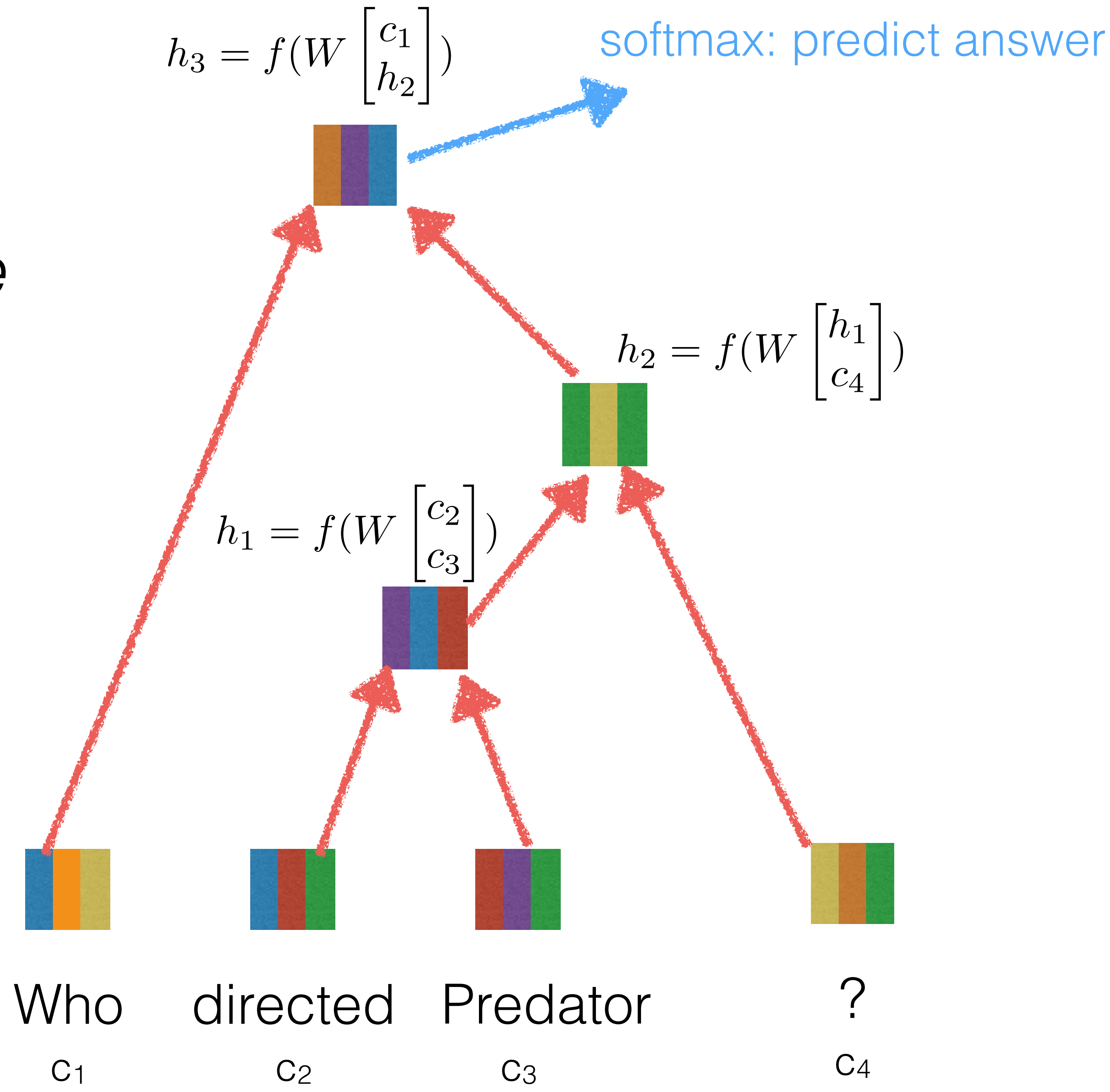

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softmax: predict answer

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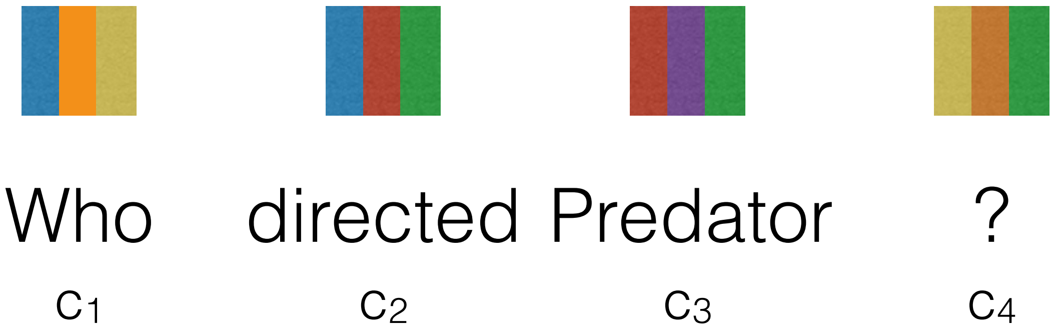
Deep Averaging Networks



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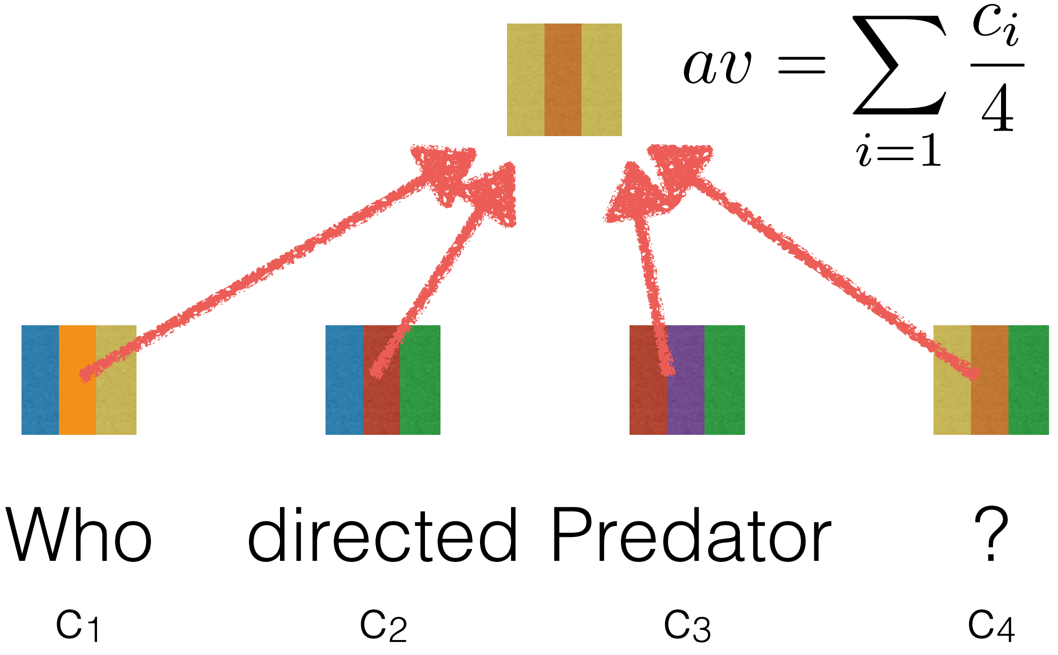
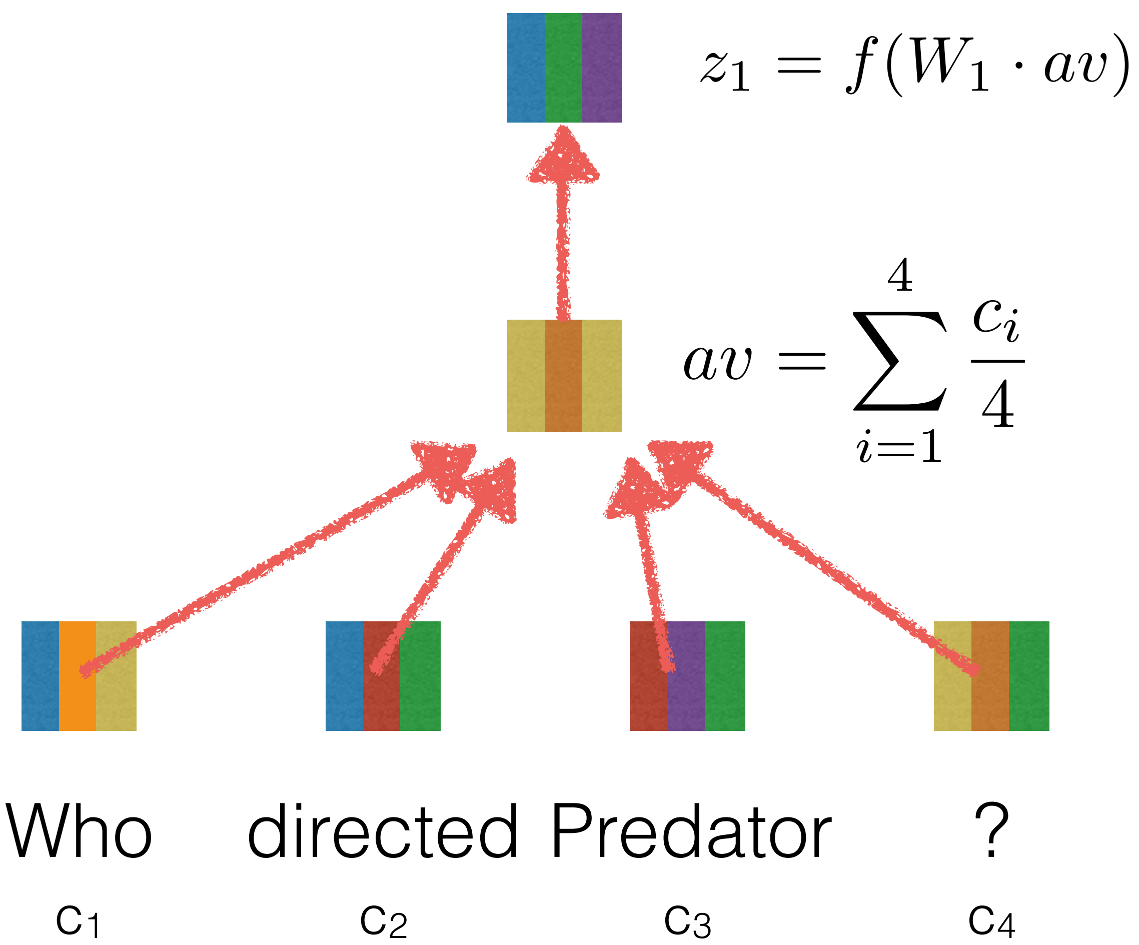
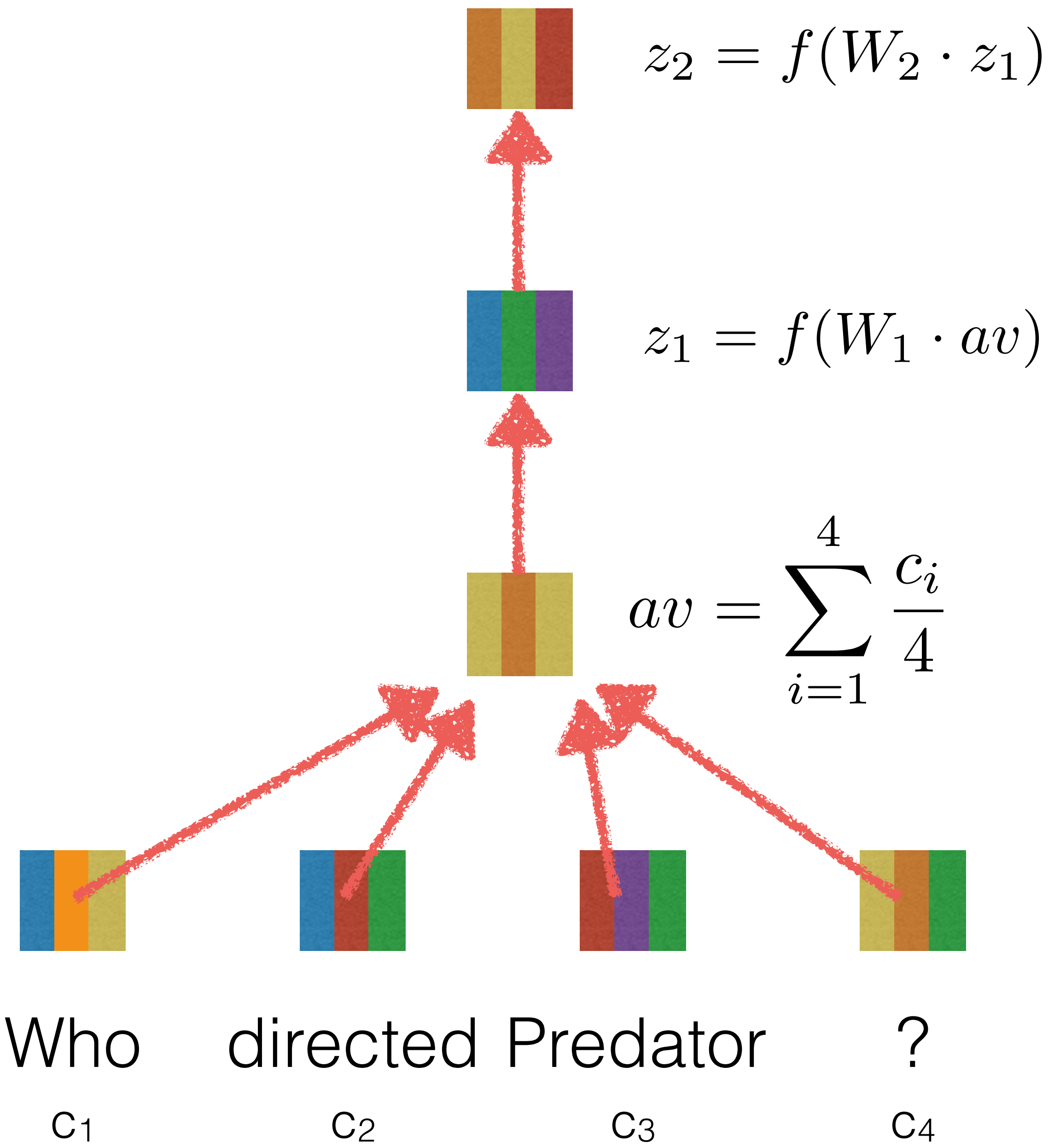


$$av = \sum_{i=1}^{4} \frac{c_i}{4}$$

Deep Averaging Networks



Deep Averaging Networks



$$z_2 = f(W_2 \cdot z_1)$$

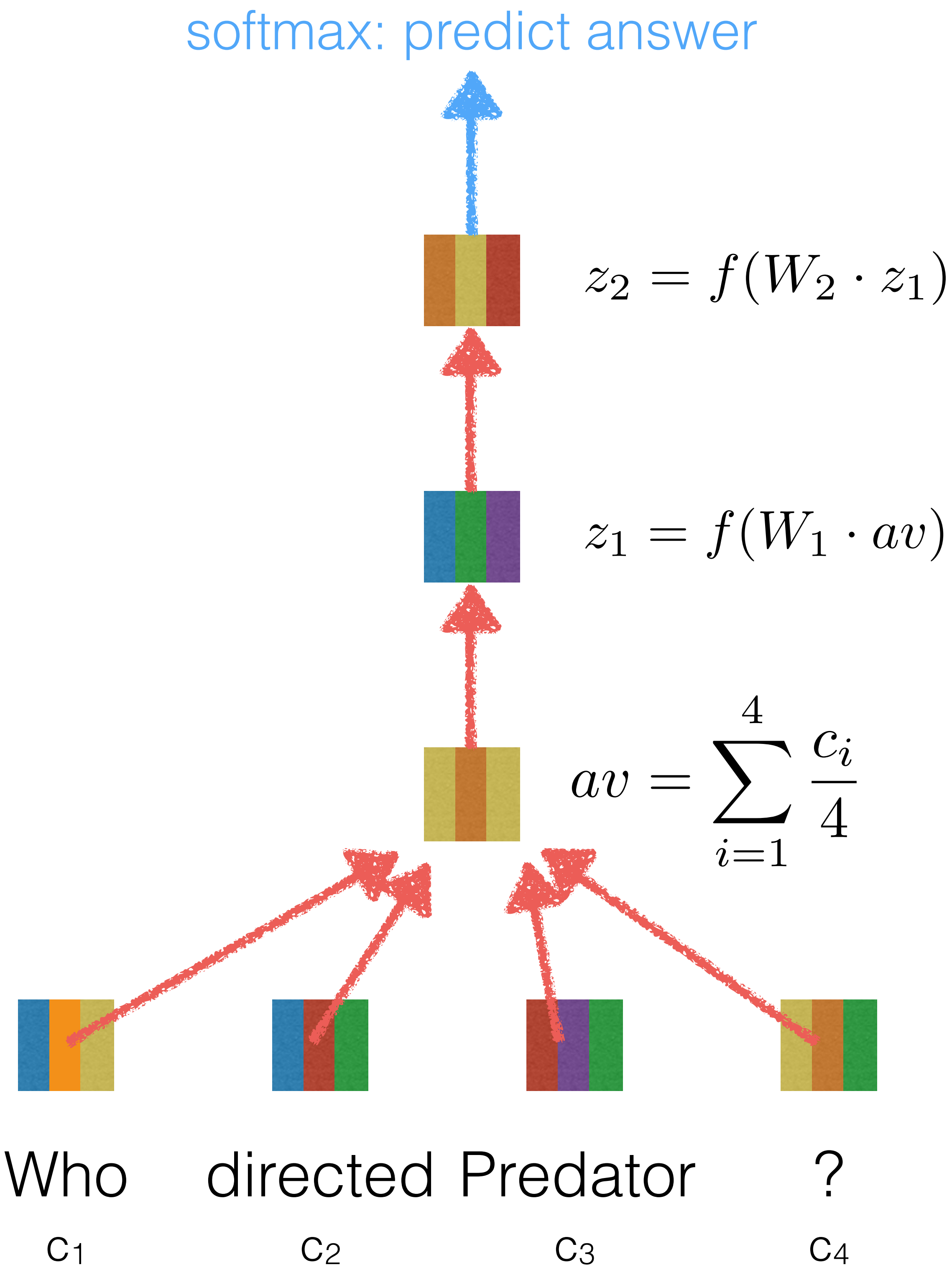
$$z_1 = f(W_1 \cdot av)$$

$$av = \sum_{i=1}^{4} \frac{c_i}{4}$$

Who directed Predator ?

c_1 c_2 c_3 c_4

Deep Averaging Networks



softmax: predict answer

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$$z_1 = f(W_1 \cdot av)$$

$$av = \sum_{i=1}^{4} \frac{c_i}{4}$$

Who directed Predator ?

c_1 c_2 c_3 c_4

Softmax Answer Classification

- Multinomial logistic regression

$$\hat{y}_p = \mathrm{softmax}(W_{ans} \cdot h_q)$$

$$\mathrm{softmax}(q) = \frac{\exp q}{\sum_{j=1}^{k} \exp q_j}$$

- Output is a distribution over a finite set of answers
- Later on: a max-margin answer ranking approach can yield better results

How do we train these models?

- Model parameters learned through variants of *backpropagation* (Rumelhart et al., 1986; Goller and Kuchler, 1996) given QA pairs as input

- In theory, use the chain rule to compute partial derivatives of the error function with respect to every parameter

- In practice, use Theano (or Torch) and never have to compute any derivatives by hand!

Application 1: Quiz Bowl

Factoid QA

- Given a description of an entity, identify the person, place, or thing discussed.
- Neural nets never previously applied to this task
    - Traditionally approached using *information retrieval*, querying huge knowledge bases for the answer

Quiz Bowl

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For ten points, name this mascot of the Linux operating system, a penguin whose name refers to formal male attire.

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For ten points, name this mascot of the Linux operating system, a penguin whose name refers to formal male attire.

Answer: Tux

Simple Approach!

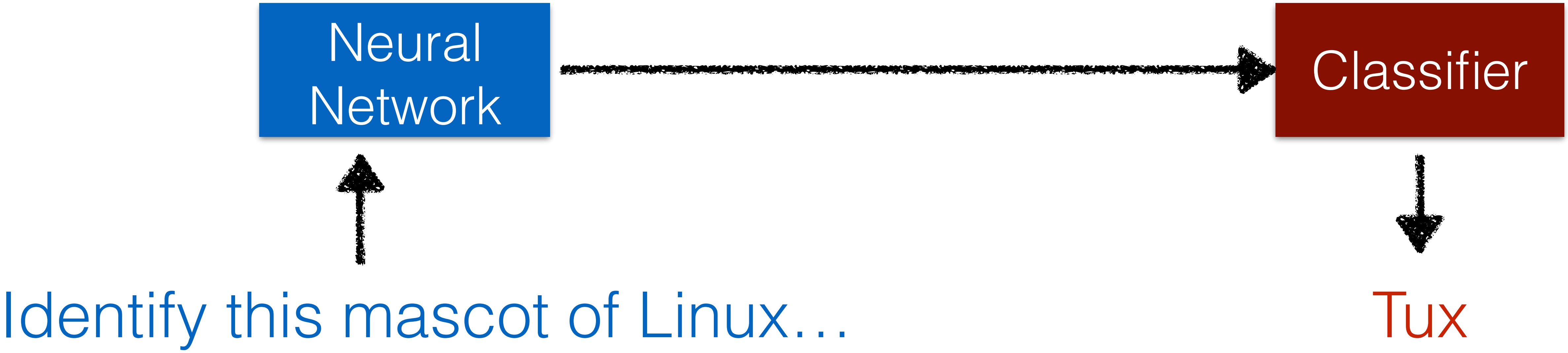
Neural Network

Classifier

Identify this mascot of Linux…

Tux

Simple Approach!



Neural Network

Classifier

Identify this mascot of Linux…

Tux

Two Neural Models

- Dependency-tree recursive neural network (**DT-RNN**)
- Deep averaging network (**DAN**)
- Both models are initialized with pretrained word2vec embeddings and have the same hidden layer dimensionality for fair comparison

Experimental Datasets

- History: 4,415 QA pairs with 16,895 sentences and 451 unique answers
- Literature: 5,685 QA pairs with 21,549 sentences and 595 unique answers

Choosing an Error Function

- Answers can appear as part of question text (e.g., a question on *World War II* might mention the *Battle of the Bulge* and vice versa)

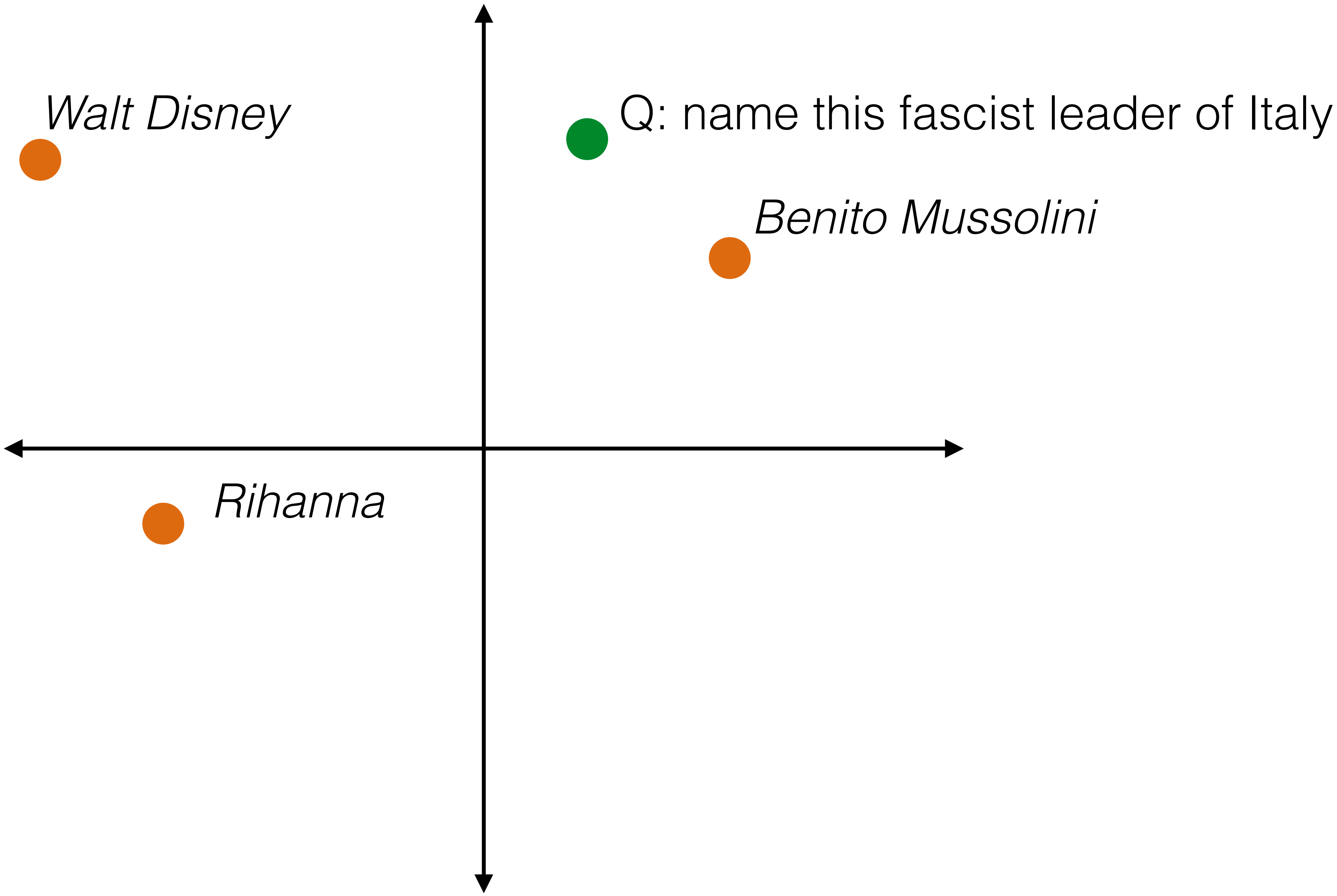
- Instead of using a softmax output layer, can we take advantage of these co-occurrences by modeling answers and questions in the same vector space?

Max-Margin Objective

- Replace softmax output layer with a contrastive max-margin function
- Given a question *q* with correct answer *a* and an incorrect answer *b,* the loss is

$$\max(0, 1 - x_a \cdot h_q + x_b \cdot h_q)$$

Geometric Intuition



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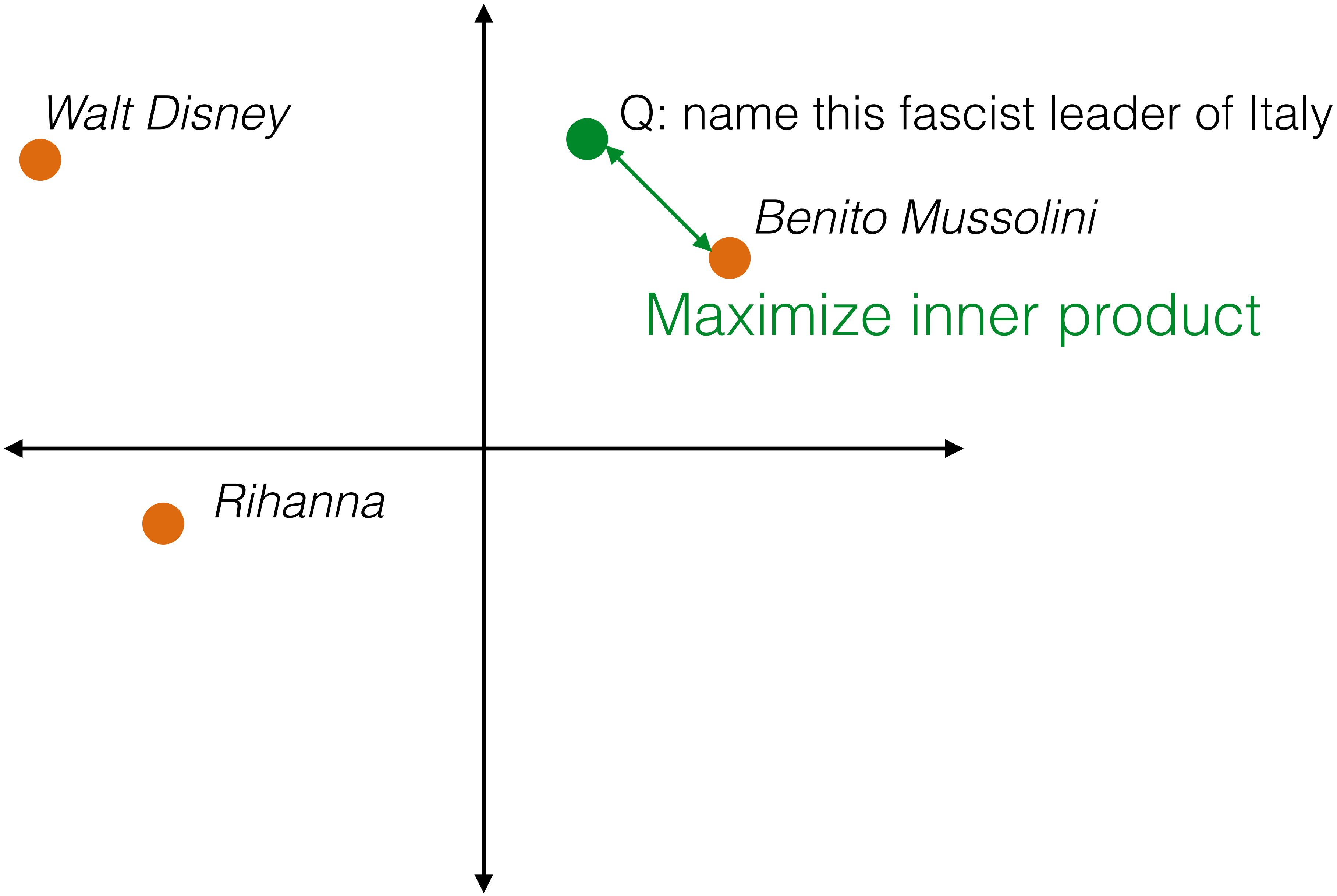

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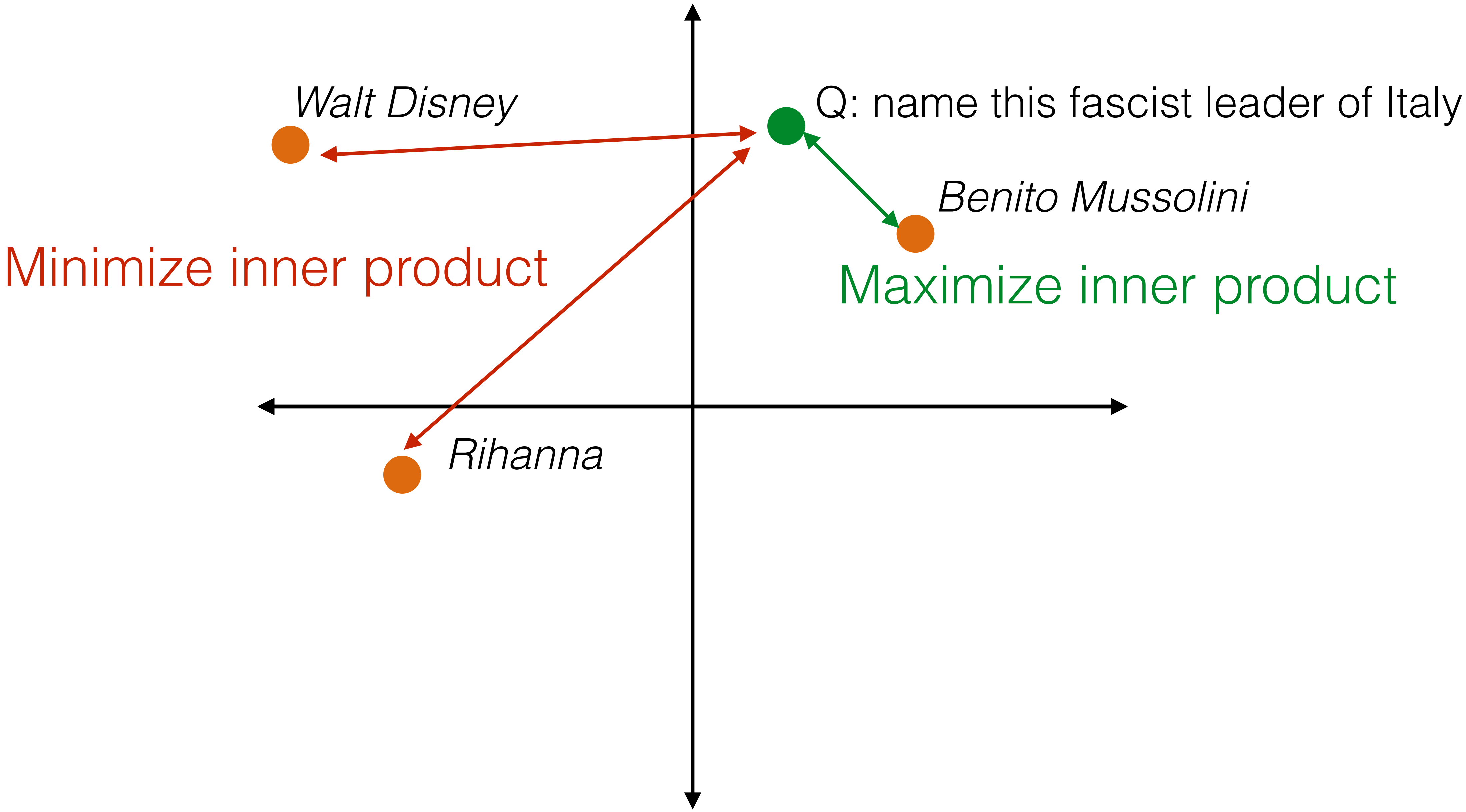
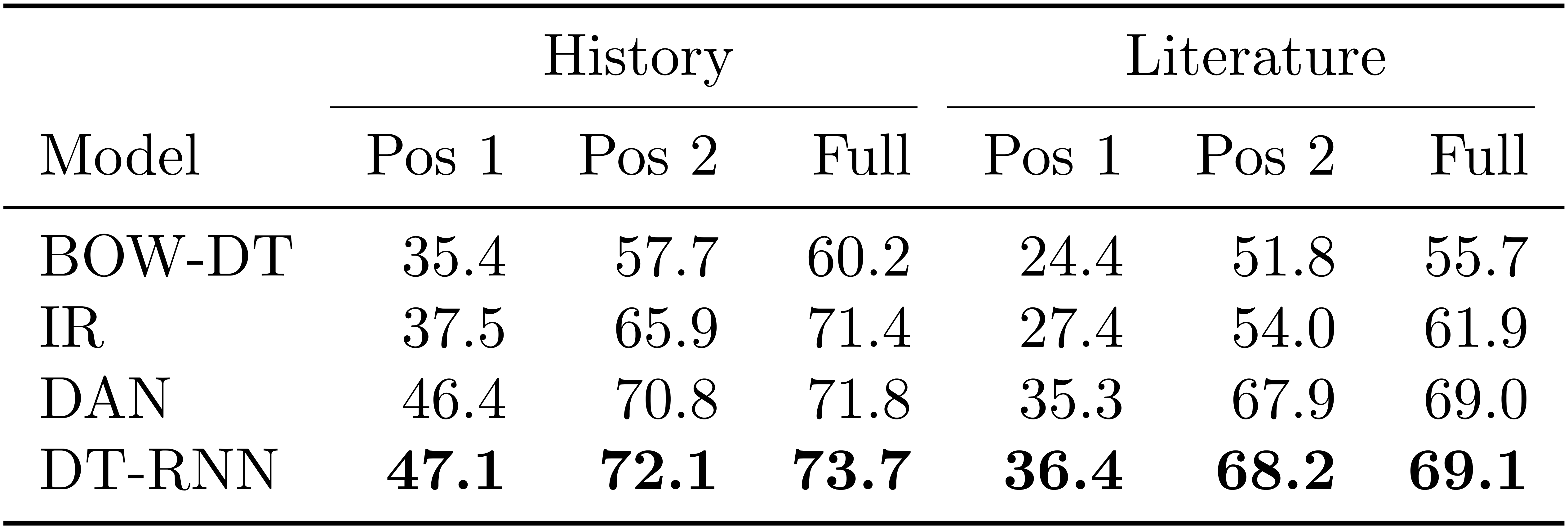


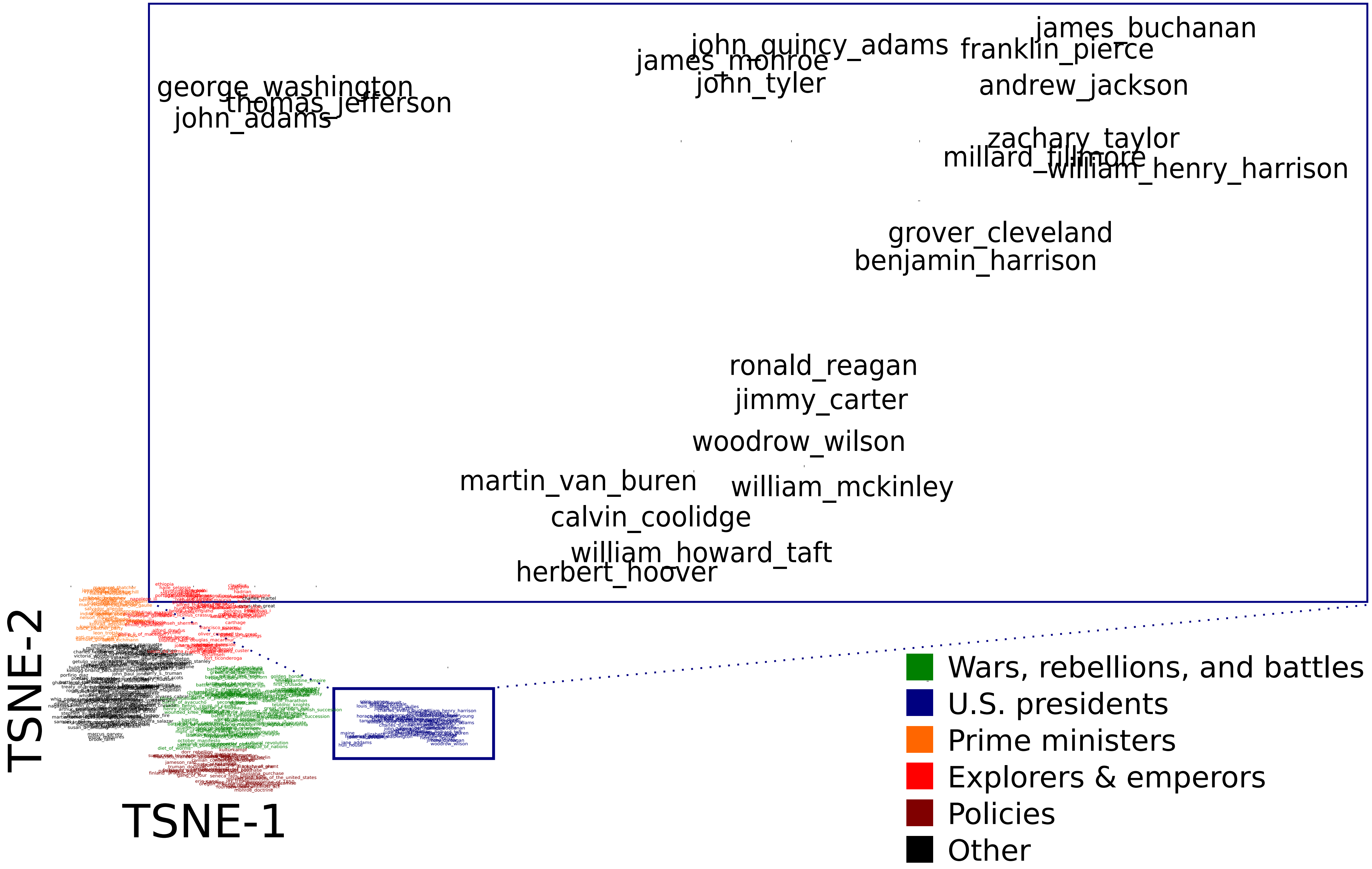
Experiments



	History			Literature		
Model	Pos 1	Pos 2	Full	Pos 1	Pos 2	Full
BOW-DT	35.4	57.7	60.2	24.4	51.8	55.7
IR	37.5	65.9	71.4	27.4	54.0	61.9
DAN	46.4	70.8	71.8	35.3	67.9	69.0
DT-RNN	**47.1**	**72.1**	**73.7**	**36.4**	**68.2**	**69.1**

DAN is 20 times faster to train than **DT-RNN**

Learning a Vector Space



Exact String Matches

- One current weakness of neural models

> In this poem, the narrator meets a “traveller from an antique land” who tells of a statue with a “wrinkled lip, and sneer of cold command”.

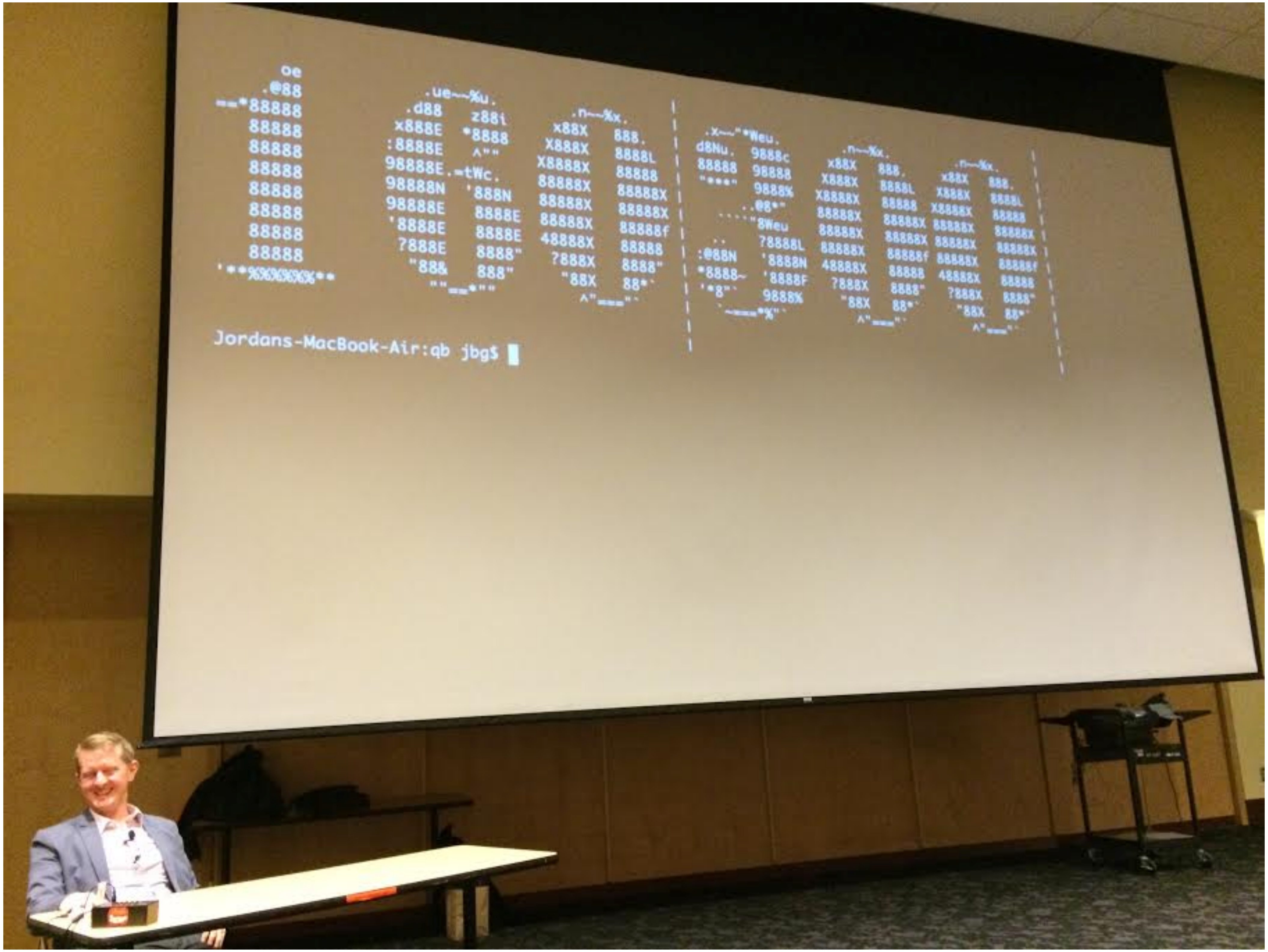
- Practical solution: train language model on original source material / Wikipedia and combine with output of neural network

QA: Man vs. Machine

- Scaled up a **DAN** to handle ~100k Q/A pairs with ~5k unique answers! Also added thousands of Wikipedia sentence/page-title pairs
- To play against humans, we need to decide not only what answer to give but also when we are confident enough to buzz in.
  - Another classifier re-ranks the top 200 guesses of the **DAN** using language model features to decide whether to buzz on any of them or wait for more clues

V1: tied team of ex-Jeopardy champions 200-200

V2: defeated Ken Jennings 300-160



```
Jordans-MacBook-Air:qb jbg$
```

Code available!

DT-RNN code: cs.umd.edu/~miyyer/qblearn

DAN code: github.com/miyyer/dan

Full quiz bowl system code: github.com/miyyer/qb

Video of Ken Jennings match: youtu.be/kTXJCEvCDYk

1. Mohit Iyyer, Jordan Boyd-Graber, Leonardo Claudino, Richard Socher, and Hal Daumé III. **A Neural Network for Factoid Question Answering over Paragraphs.** EMNLP 2014.
2. Mohit Iyyer, Varun Manjunatha, Jordan Boyd-Graber, and Hal Daumé III. **Deep Unordered Composition Rivals Syntactic Methods for Text Classification**. ACL 2015.

Application 2:
Reasoning-based QA

John moved to the bedroom.
Mary grabbed the football there.
Sandra journeyed to the bedroom.
Sandra went back to the hallway.
Mary moved to the garden.
Mary journeyed to the office.

Where is the football?

John moved to the bedroom.
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→ Where is the football?

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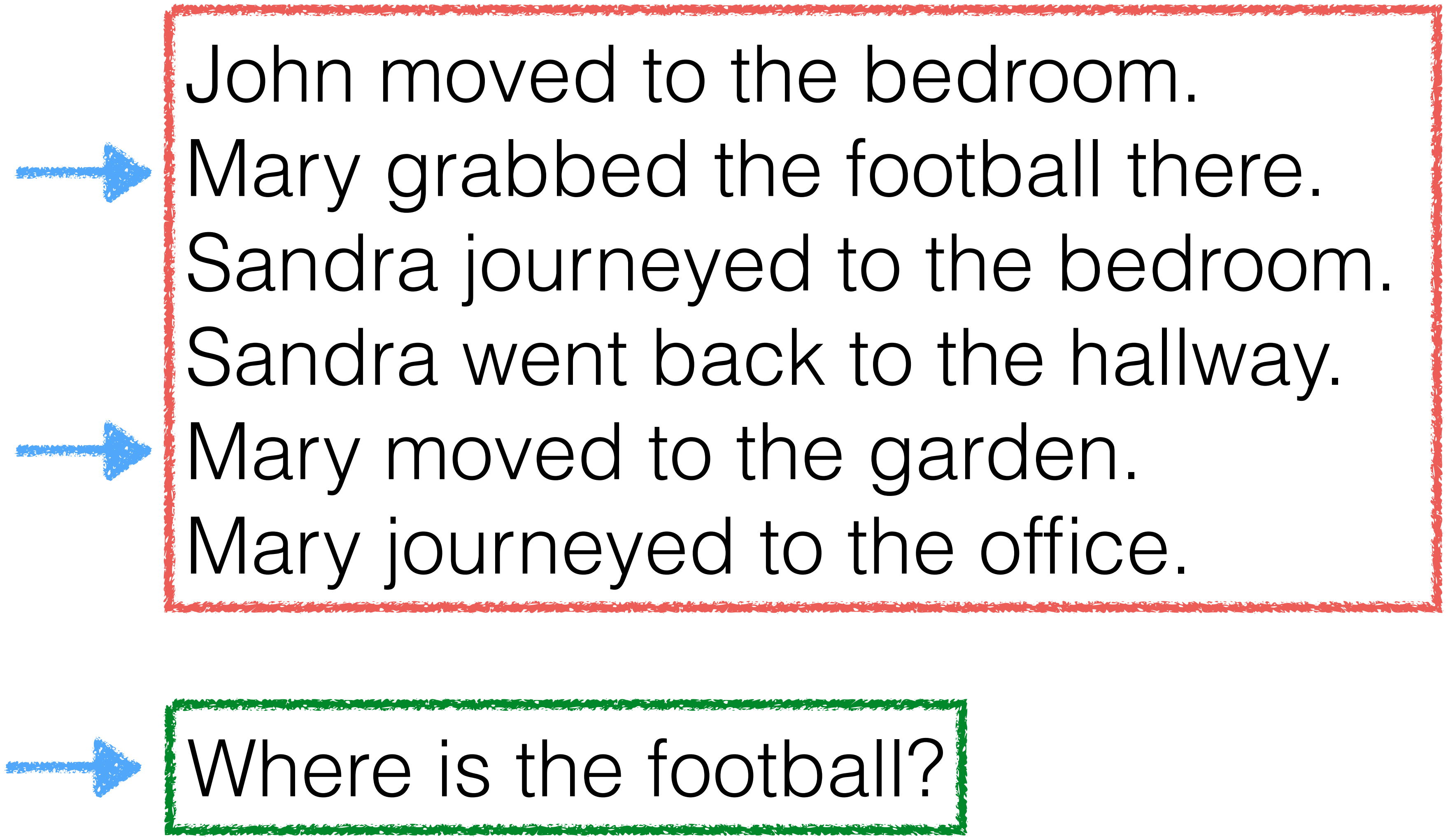

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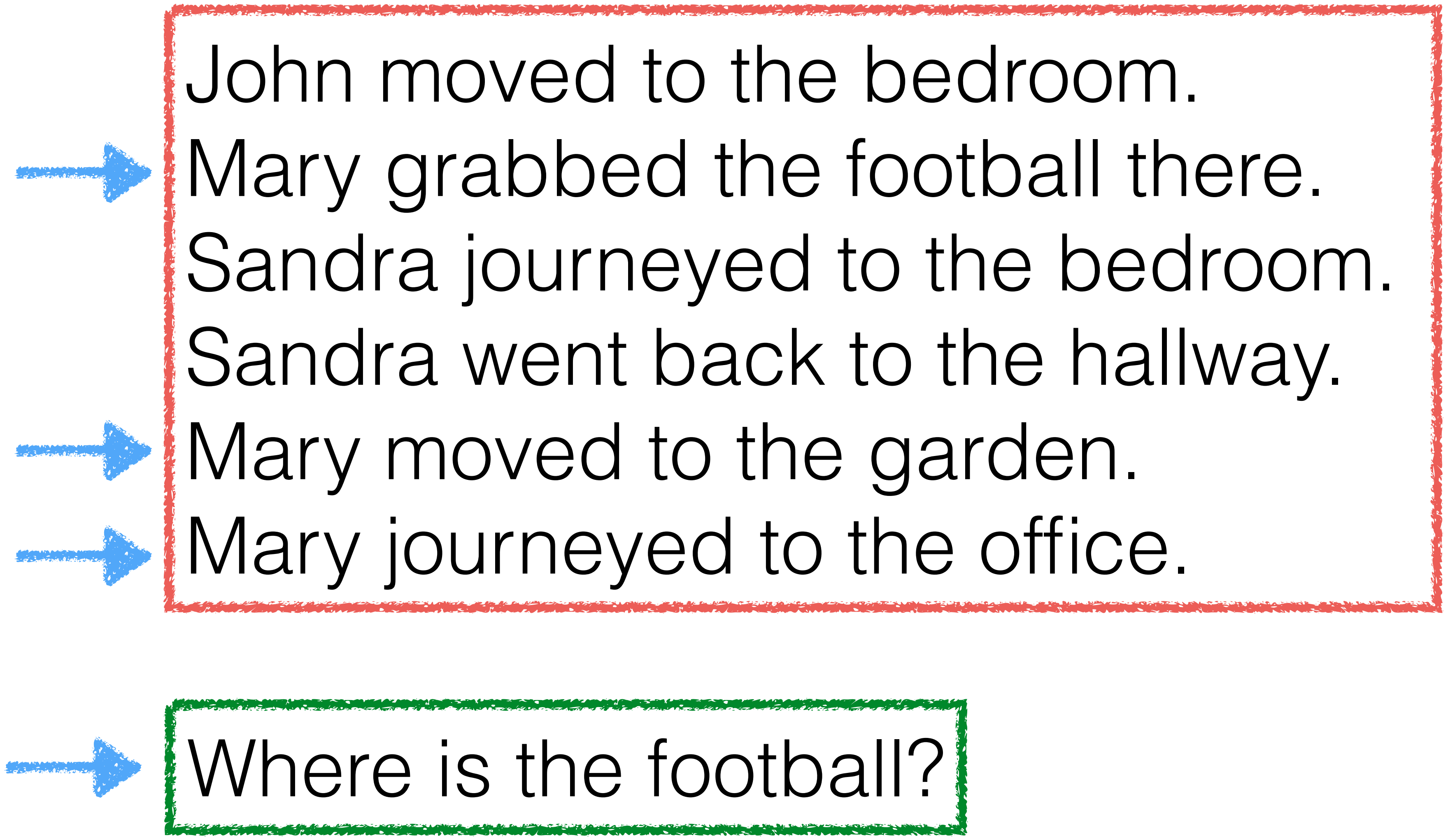

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Naïve Neural Approach

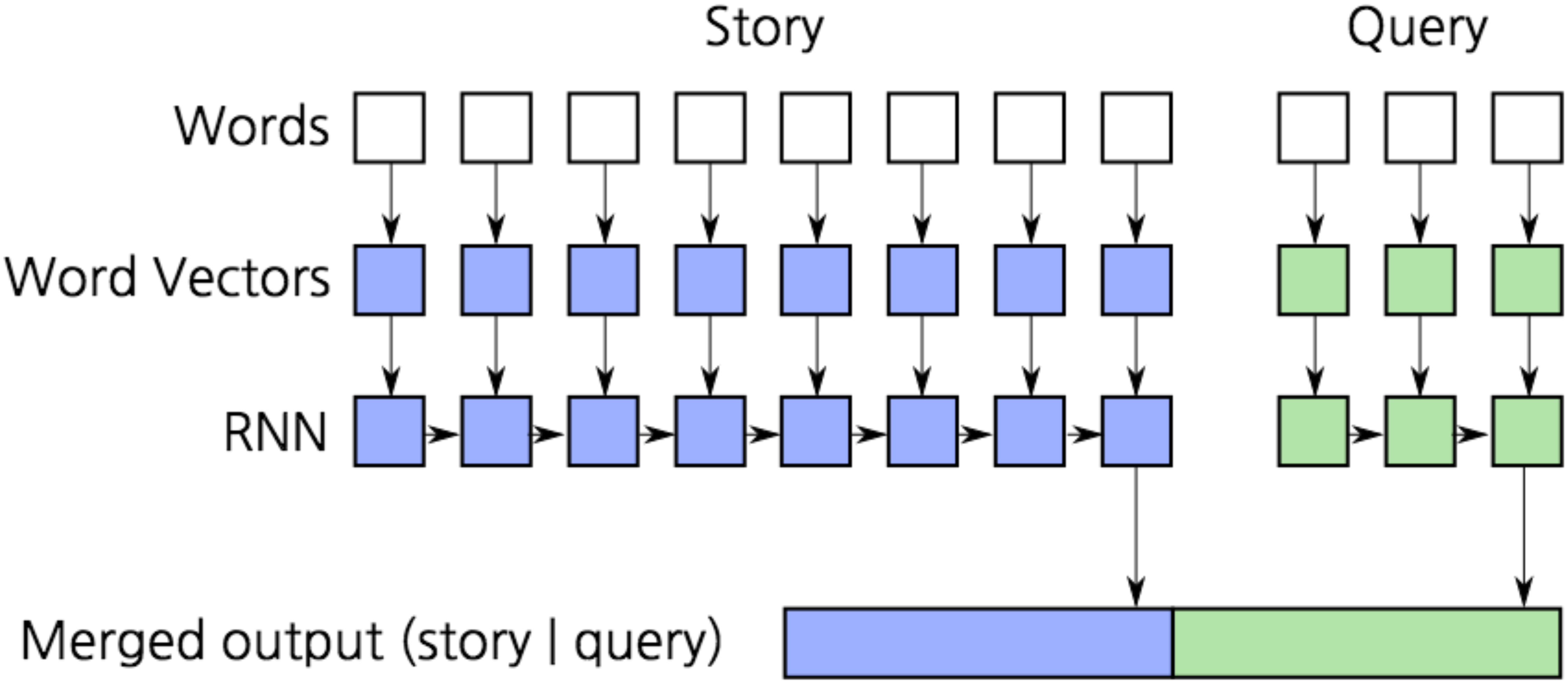

image: http://smerity.com/articles/2015/keras_qa.html

Naïve Neural Approach

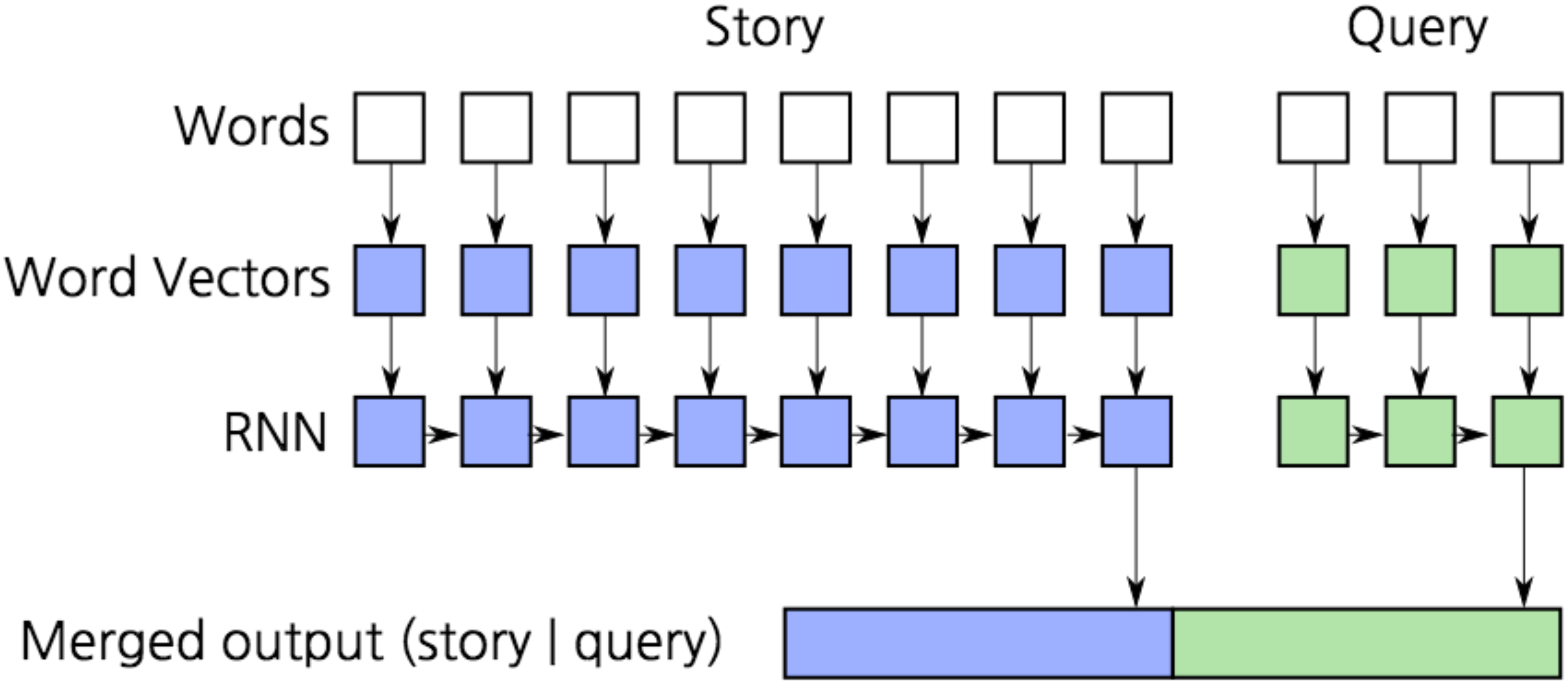

image: http://smerity.com/articles/2015/keras_qa.html

softmax: predict answer

Problems

- Doesn’t scale to long / complex question types
    - RNNs/LSTMs are very bad at remembering facts from the distant past!
- Solution: add an **external** memory component that learns to store important facts and reason about them

Dynamic Memory Networks

- Collaboration with Richard Socher and colleagues from MetaMind

- Extends simple RNNs with an *iterative attention mechanism* that focuses on one fact at a time and enables transitive reasoning

Ankit Kumar, Ozan Irsoy, Peter Ondruska, Mohit Iyyer, James Bradbury, Ishaan Gulrajani, and Richard Socher. **Ask Me Anything: Dynamic Memory Networks for Natural Language Processing.** NIPS Deep Learning Symposium, 2015.

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5. Feed final episodic memory **m** to a softmax layer to predict the answer

John moved to the bedroom.
Mary grabbed the football there.
Sandra journeyed to the bedroom.
Sandra went back to the hallway.
Mary moved to the garden.
Mary journeyed to the office.

Where is the football?

John moved to the bedroom.
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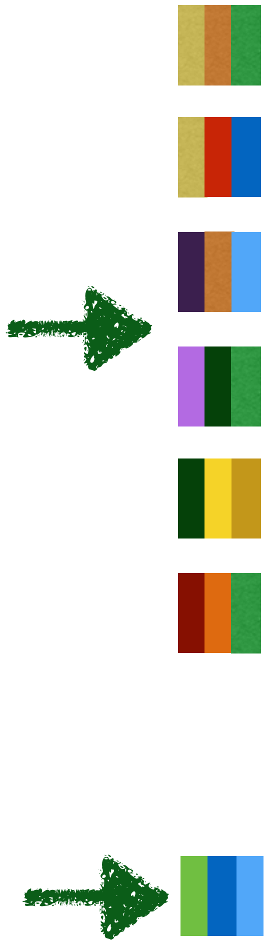

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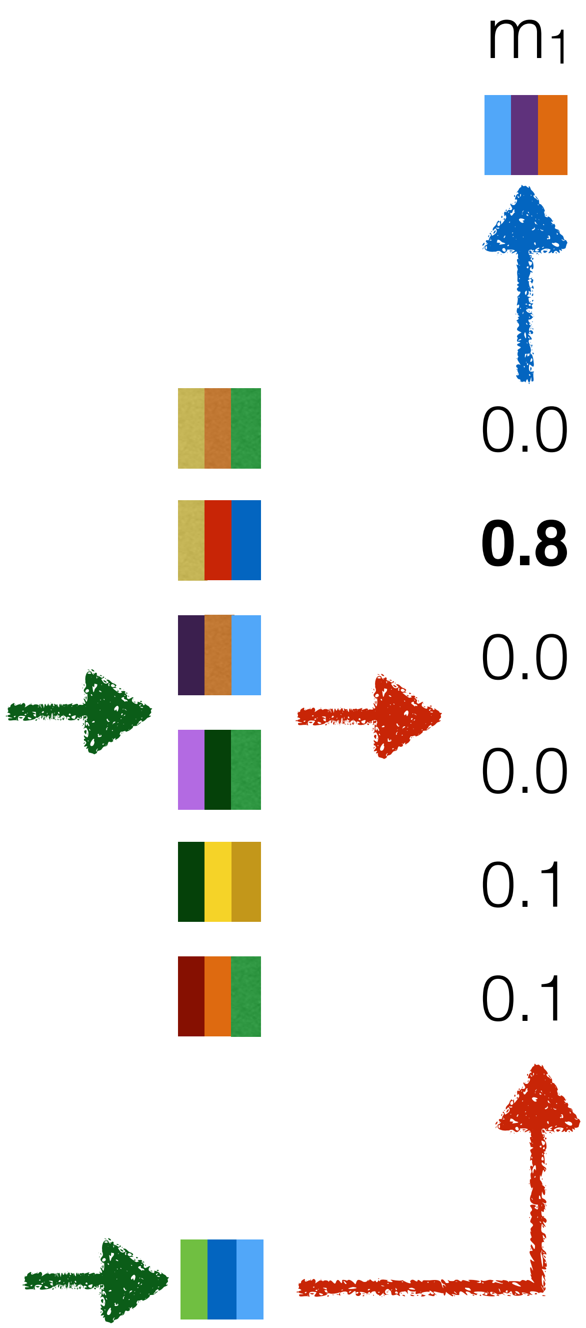
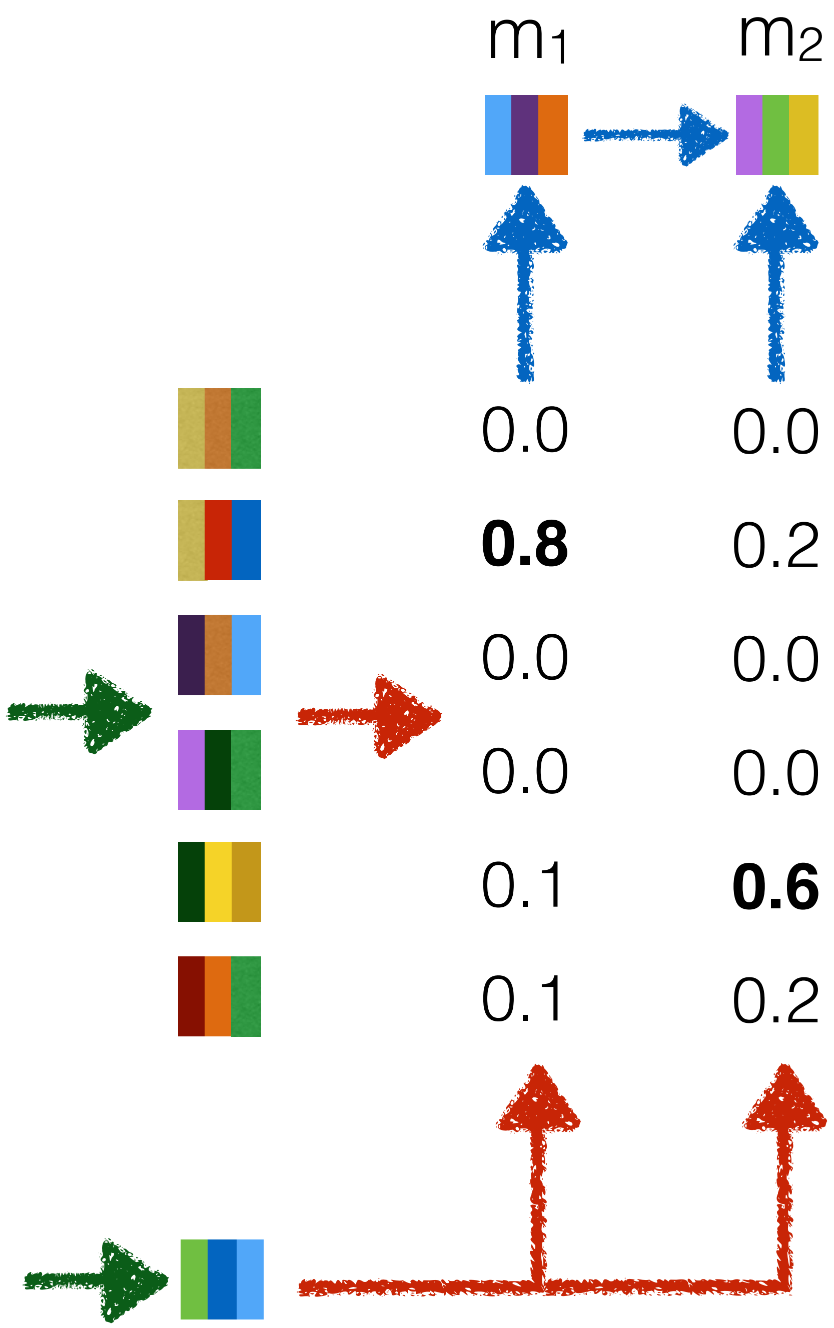
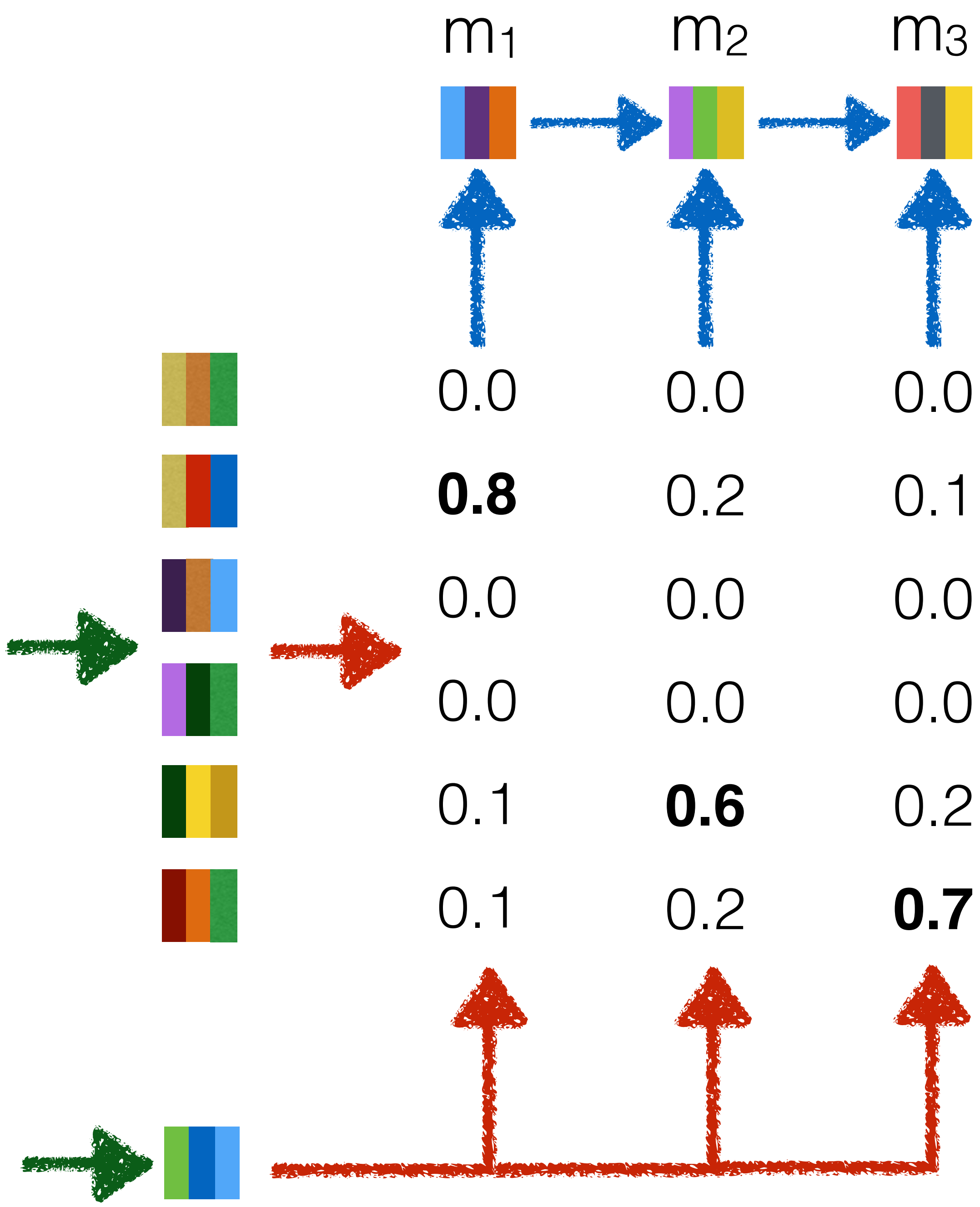




	m_1	m_2
John moved to the bedroom.	0.0	0.0
Mary grabbed the football there.	**0.8**	0.2
Sandra journeyed to the bedroom.	0.0	0.0
Sandra went back to the hallway.	0.0	0.0
Mary moved to the garden.	0.1	**0.6**
Mary journeyed to the office.	0.1	0.2

Where is the football?



	m1	m2	m3
John moved to the bedroom.	0.0	0.0	0.0
Mary grabbed the football there.	**0.8**	0.2	0.1
Sandra journeyed to the bedroom.	0.0	0.0	0.0
Sandra went back to the hallway.	0.0	0.0	0.0
Mary moved to the garden.	0.1	**0.6**	0.2
Mary journeyed to the office.	0.1	0.2	**0.7**

Where is the football?

softmax: predict answer

m_3

	m_1	m_2	m_3
John moved to the bedroom.	0.0	0.0	0.0
Mary grabbed the football there.	**0.8**	0.2	0.1
Sandra journeyed to the bedroom.	0.0	0.0	0.0
Sandra went back to the hallway.	0.0	0.0	0.0
Mary moved to the garden.	0.1	**0.6**	0.2
Mary journeyed to the office.	0.1	0.2	**0.7**

Where is the football?

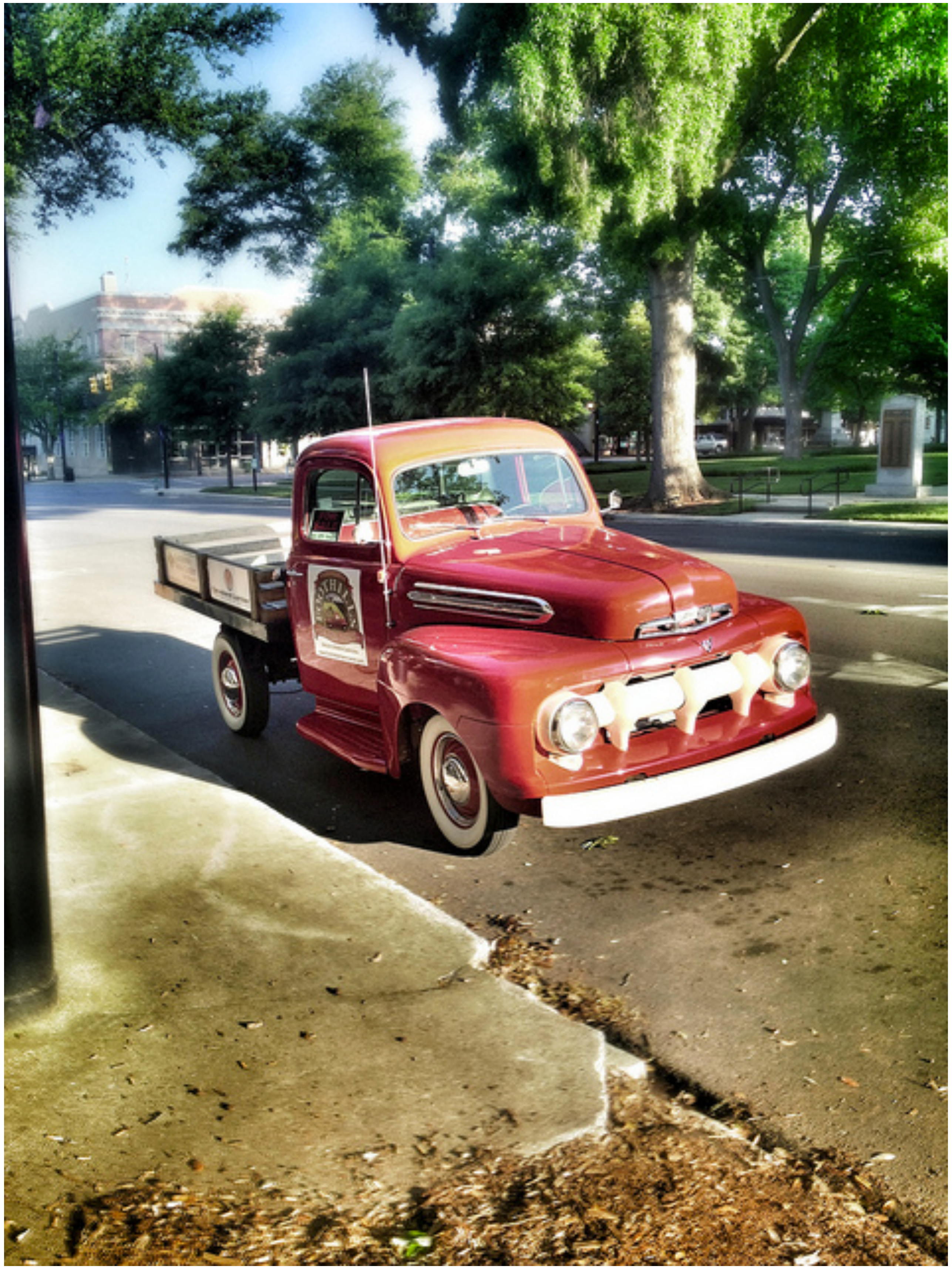
Evaluation: FB bAbi

- 20 very simple tasks (e.g., counting, basic deduction, induction, coreference)

- DMNs solve 18 out of 20 tasks with over 95% accuracy, comparable to other baselines that use hand-engineered features (e.g., n-grams, positional features)

- Can also be applied to many other NLP tasks (what is the sentiment of this sentence? what is this sentence's translation in French?)

Application 3: Visual QA



- Is this truck considered “vintage”?
- Does the road look new?
- What kind of tree is behind the truck?

VisualQA Dataset

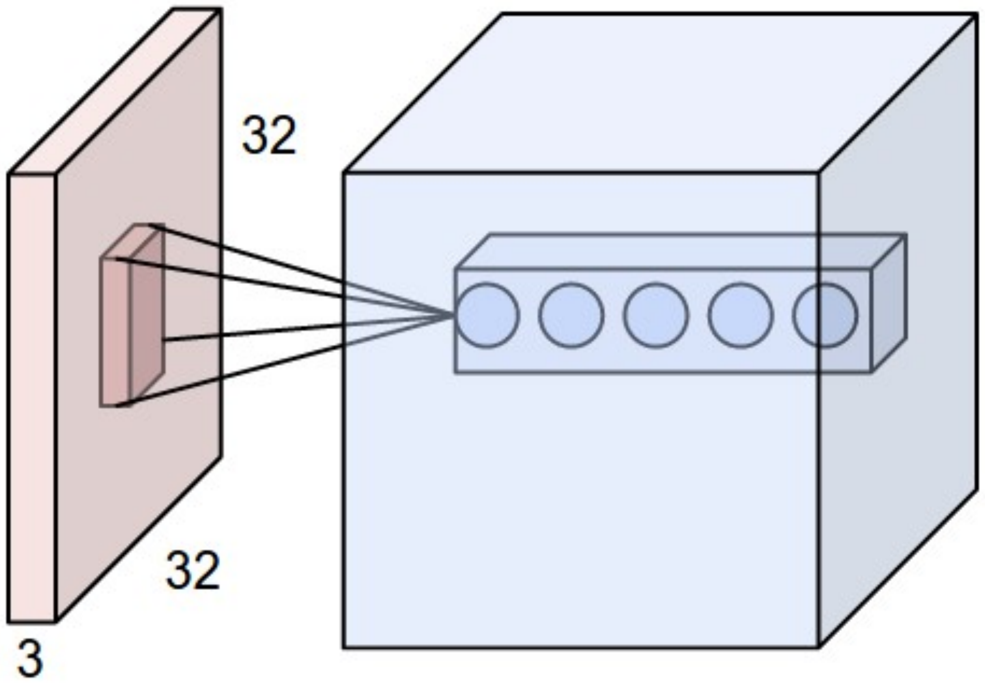
- collaboration between Virginia Tech and Microsoft Research

- questions were created and answered by Amazon Turkers (800k questions on 250k images)

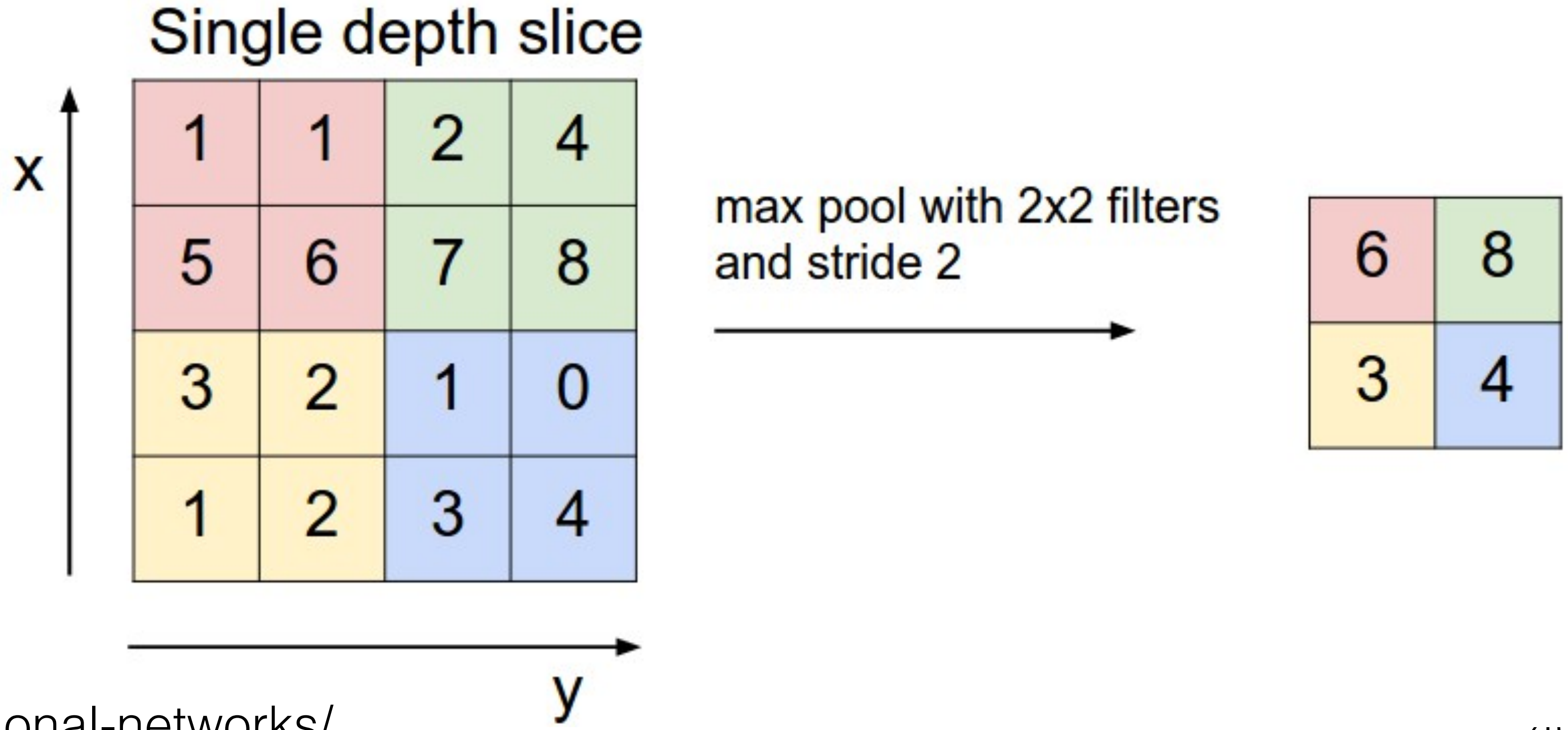
> “We have built a smart robot. It understands a lot about images. It can recognize and name all the objects, it knows where the objects are, it can recognize the scene (e.g., kitchen, beach), people’s expressions and poses, and properties of objects (e.g., color of objects, their texture). Your task is to stump this smart robot!”

Brief Aside: ConvNets

Convolutional Layers: slide a set of small filters over the image



Pooling Layers: reduce dimensionality of representation



Single depth slice

x

1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

y

max pool with 2x2 filters and stride 2

6	8
3	4

image: https://cs231n.github.io/convolutional-networks/

ConvNet (

) = 🟦⬛🟨🟩🟥

ConvNet (

) = 🟦⬛🟨🟩🟥

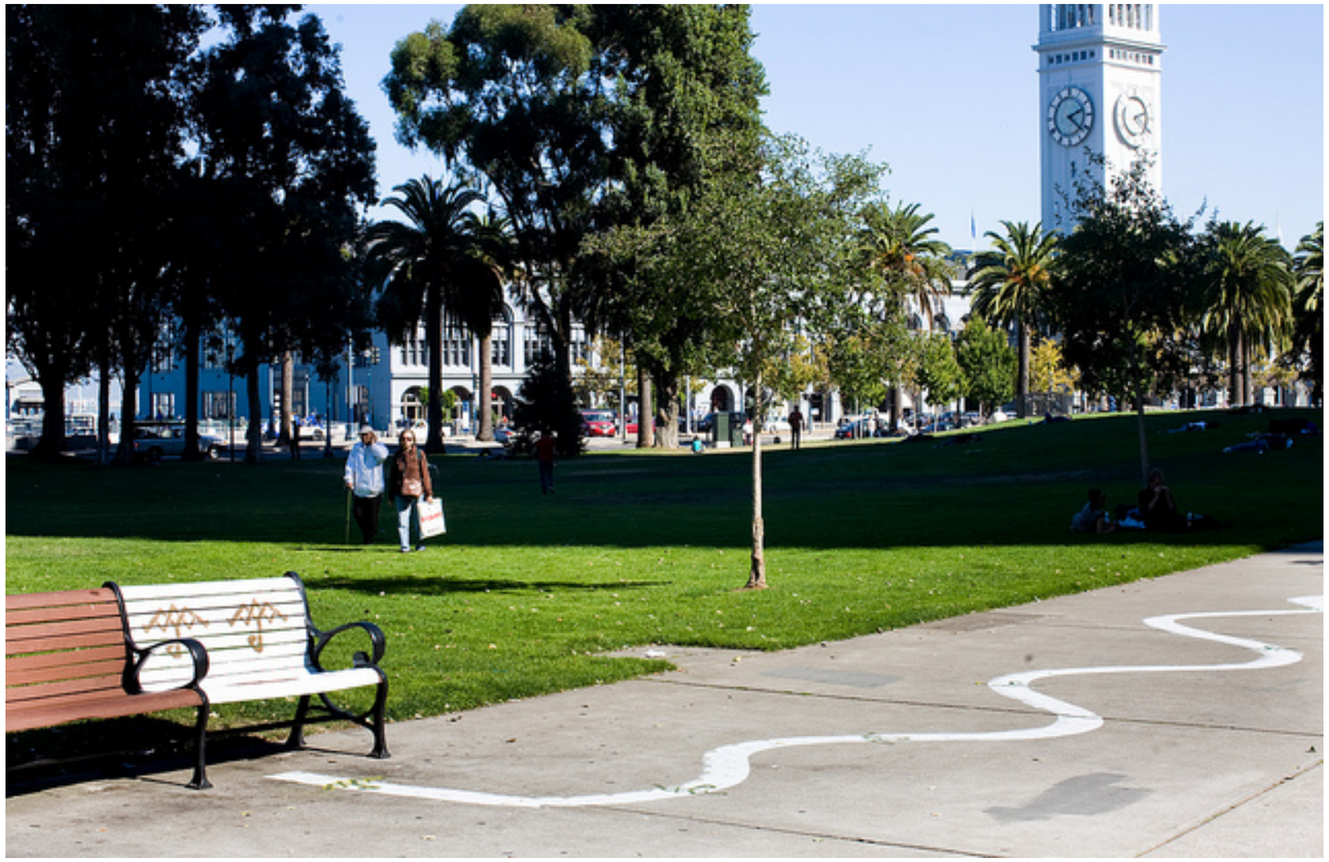
softmax: predict ‘truck’

Naïve VisualQA

- i = *ConvNet*(image) > use an existing network trained for image classification and freeze weights
- q = *RNN*(question) > learn weights
- answer = softmax([i;q])

Visual Attention

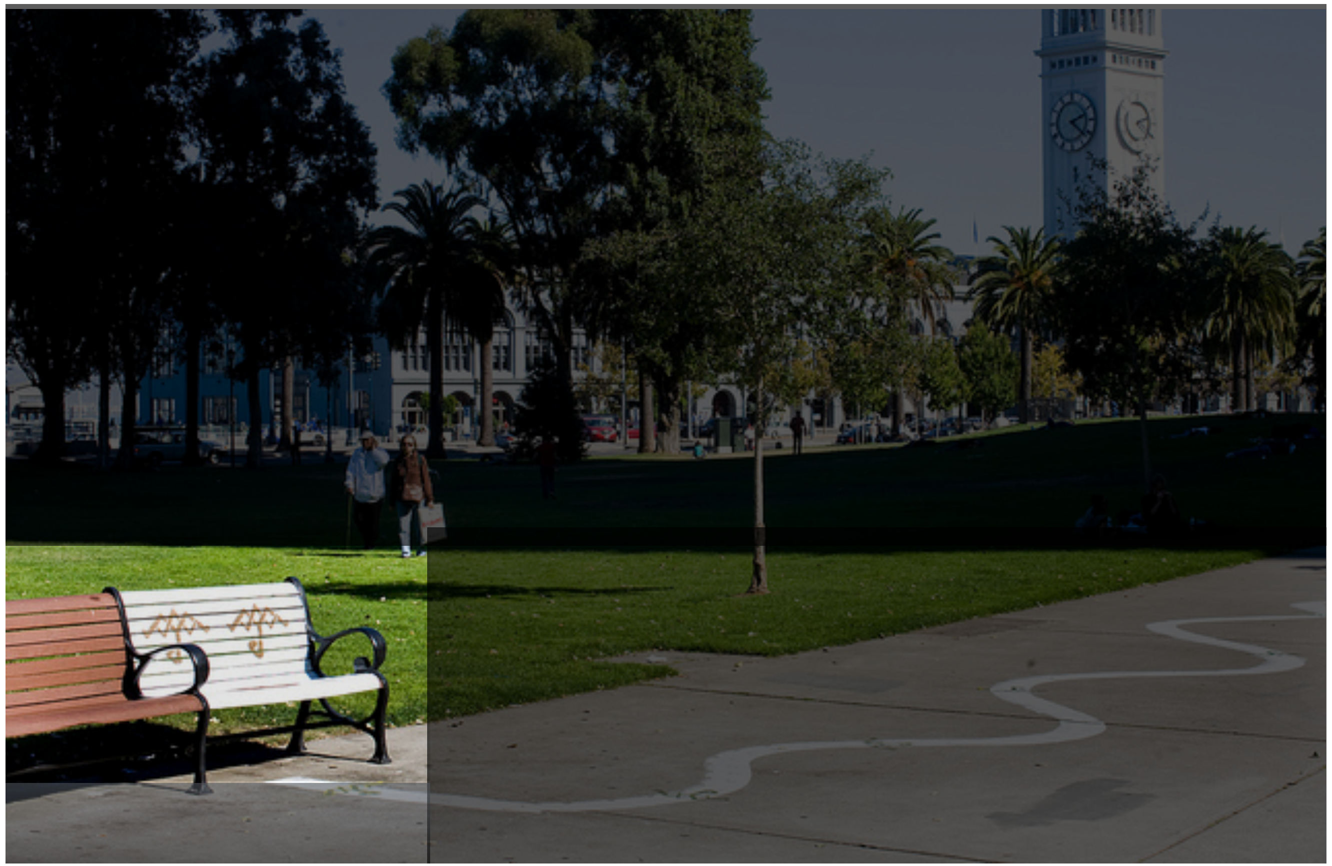
- Use the question representation *q* to determine where in the image to look



How many benches are shown?

Visual Attention

- Use the question representation *q* to determine where in the image to look



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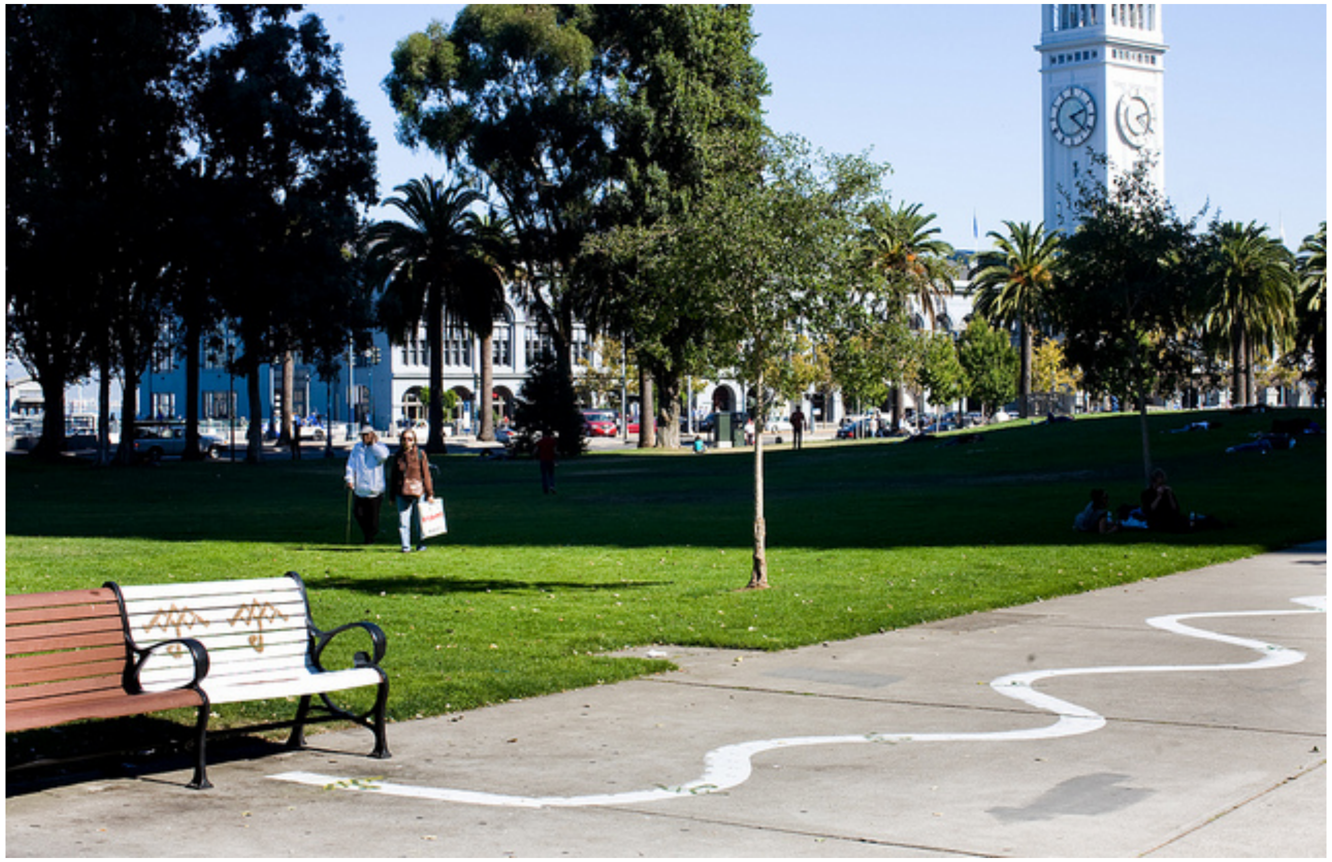

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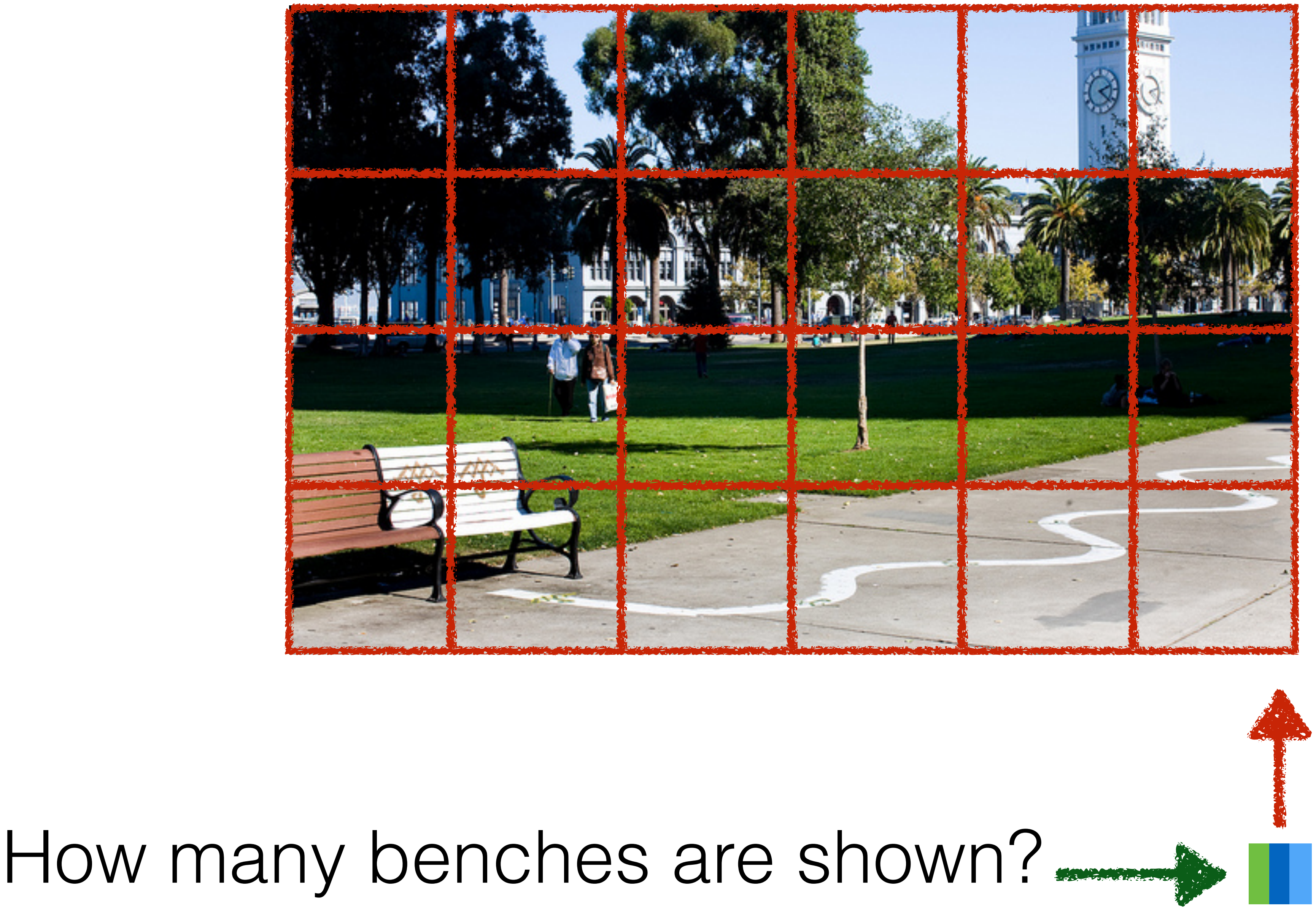
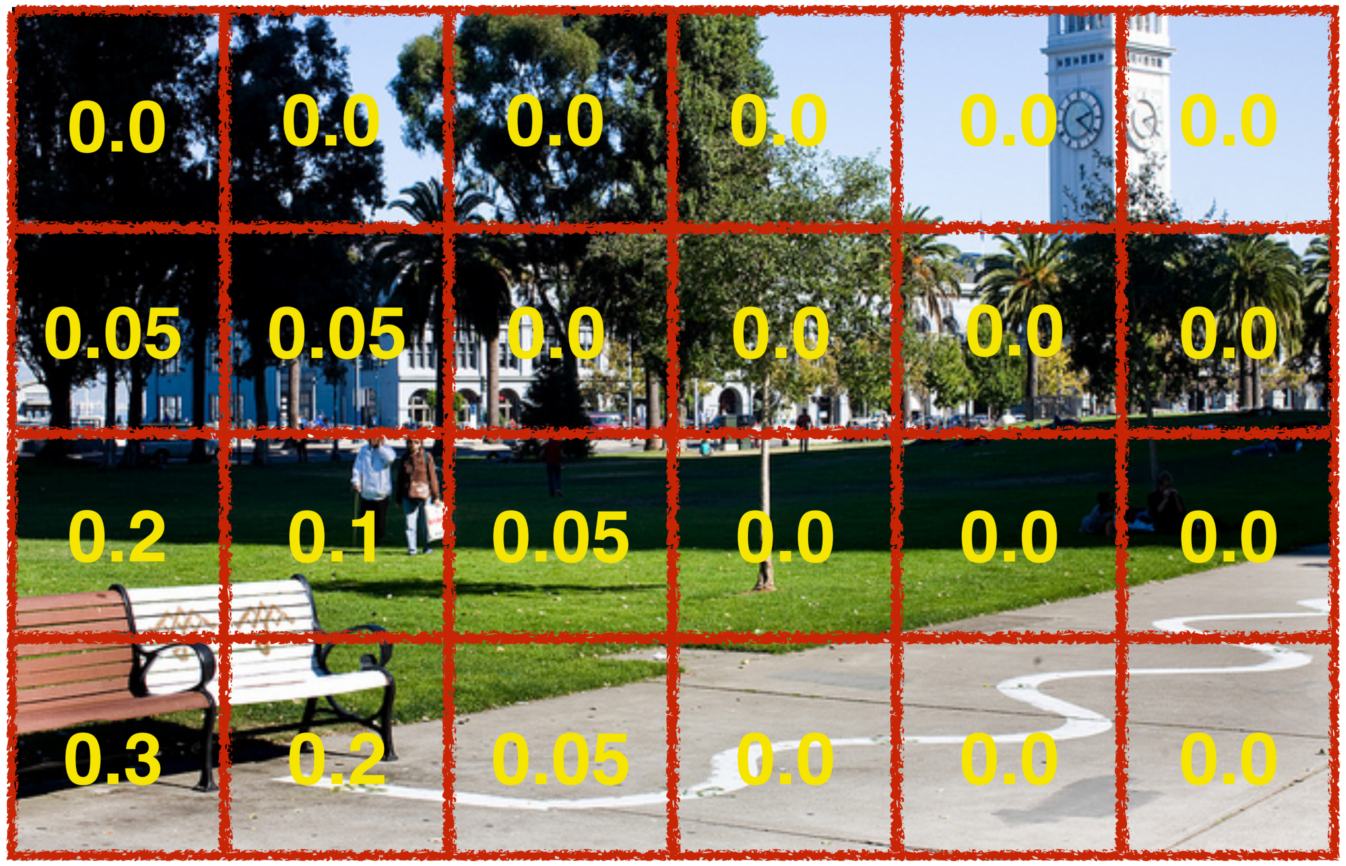


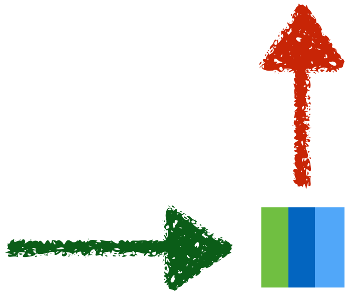
How many benches are shown?

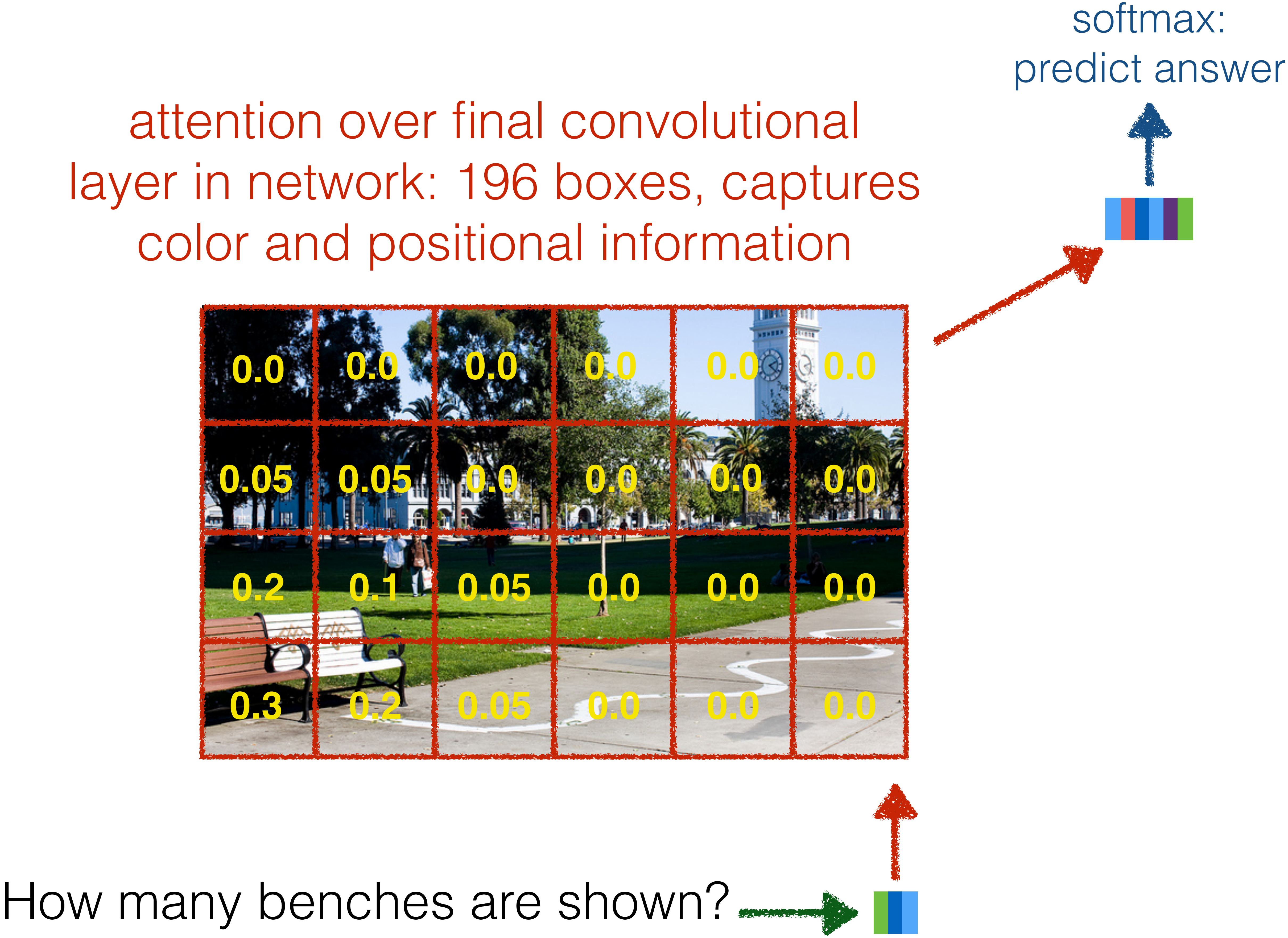
attention over final convolutional layer in network: 196 boxes, captures color and positional information



0.0	0.0	0.0	0.0	0.0	0.0
0.05	0.05	0.0	0.0	0.0	0.0
0.2	0.1	0.05	0.0	0.0	0.0
0.3	0.2	0.05	0.0	0.0	0.0

How many benches are shown?





softmax:
predict answer

attention over final convolutional layer in network: 196 boxes, captures color and positional information

How many benches are shown?

Issues

- Visual attention is more complicated than textual attention; requires many more QA pairs than are currently available
- focusing on more than one “box” at a time is difficult for the current model; perhaps an iterative attention mechanism like the DMN’s can solve this problem
- Work in progress, full evaluation coming soon!

Closing Thoughts

Future Trends

- Neural networks with attention mechanisms are cutting-edge models with broad applications!
  - With more data and bigger networks, we can begin to answer more complex questions
- Multi-task learning, such as a single model that learns to reason over both text and images

A Major Limitation

- All of these networks generalize very poorly to new facts or information at test-time, would fail at:

xxwf moved to the rfecs.
dawas grabbed the gndsa there.
gfdg journeyed to the klnmkb.
gfdg went back to the aqqs.
dawas moved to the mnsh.
dawas journeyed to the taaaed.

Where is the gndsa?

Constants vs. Variables

- Currently, every word in a question is represented with an embedding.
  - This doesn't make much sense for numbers, proper names, or other entities

An amusement park sells 2 kinds of tickets. Tickets for children cost $1.50. Adult tickets cost $4. On a certain day, 278 people entered the park. On that same day the admission fees collected totaled $792.

How many children were admitted on that day?

Thanks! Questions?

And thanks to my advisors, Jordan Boyd-Graber at U. Colorado and Hal Daumé III at UMD, and to Richard Socher and colleagues from MetaMind.