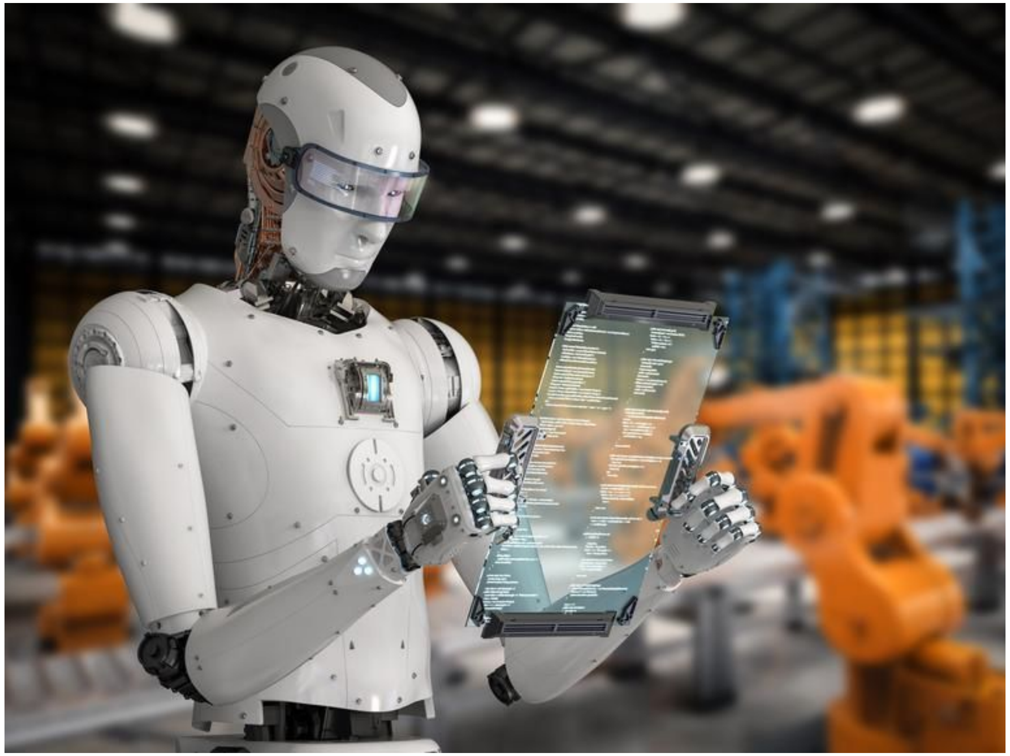
Question Answering: Learning to Answer from Text

Deepak Gupta
AI-NLP-ML Lab
Department of CSE, IIT Patna
https://deepaknlp.github.io/



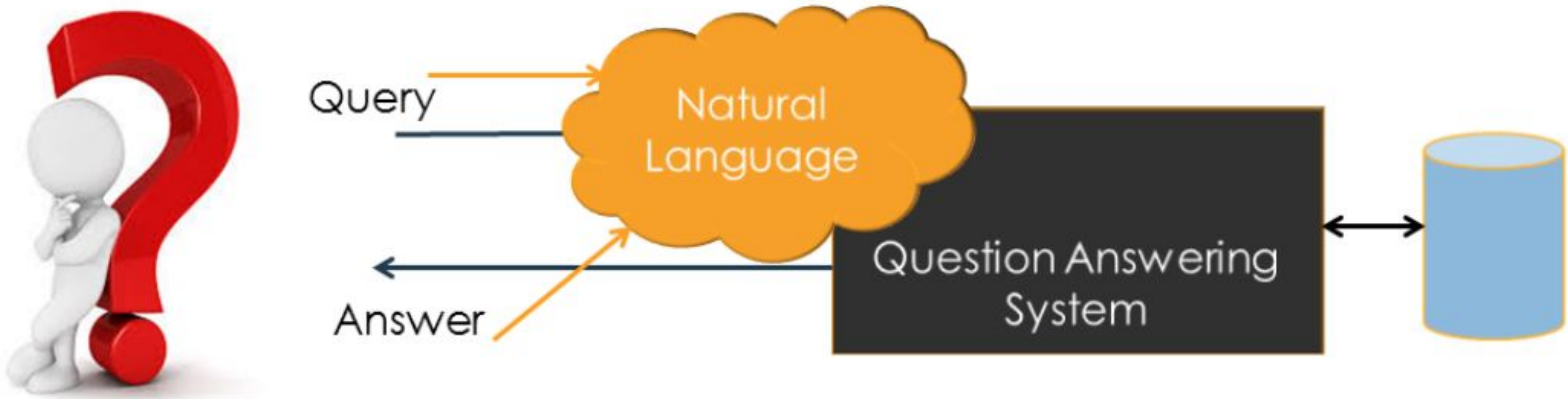
Outline

- What is Question Answering?
- Search Engine vs. QA
- IR based Approach for QA
  - Motivation and History
  - AskMSR: A shallow approach
  - Common Evaluation Metrics
- Machine Comprehension
  - Motivation and History
  - MC Datasets
  - Machine Learning Approach
    - Sliding Window
    - Logistic Regression
  - Deep Learning Approach
    - Stanford Attentive Reader
    - Stanford Attentive Reader++
    - BiDAF
- References

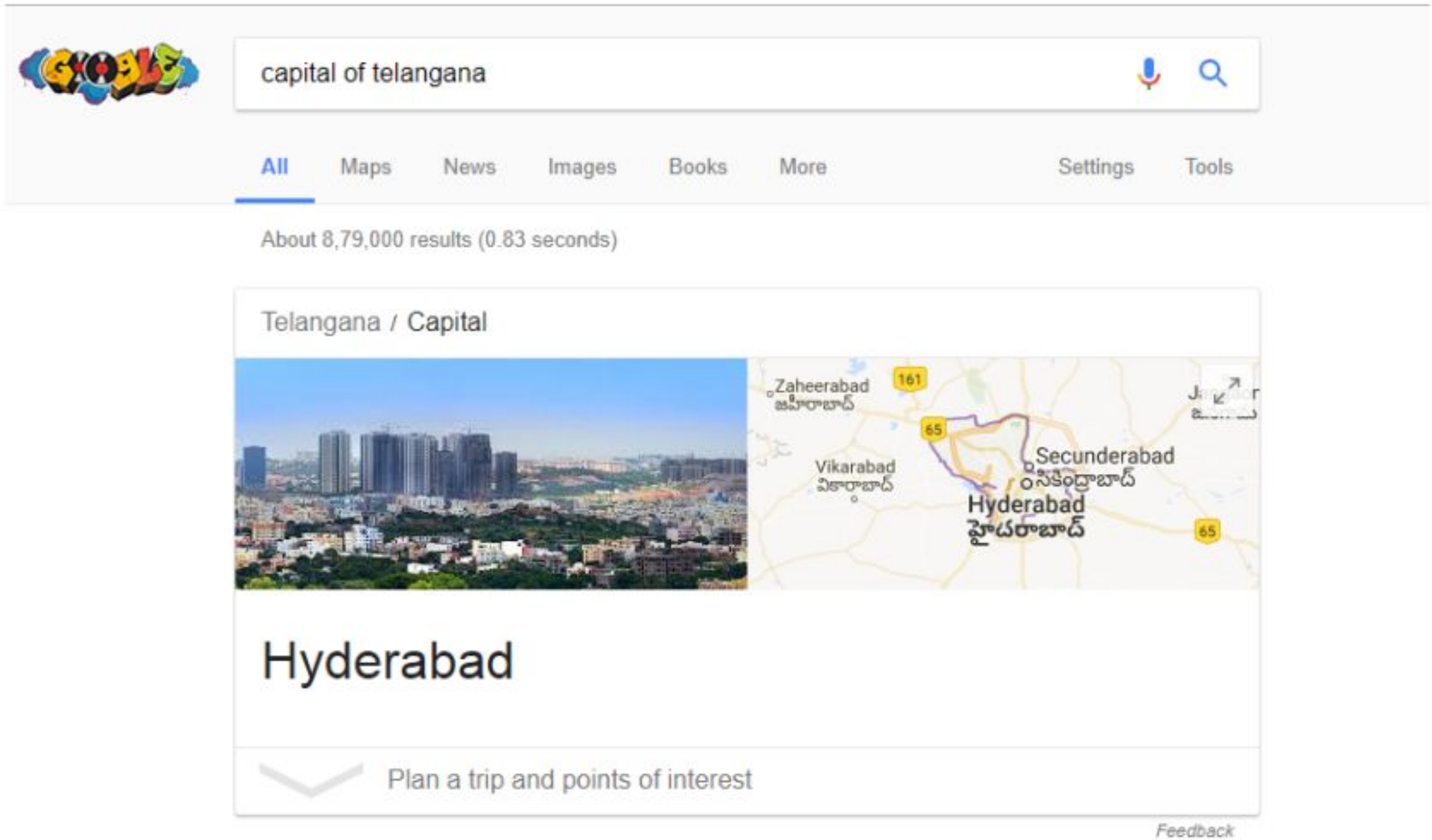
Question Answering

What is question answering?

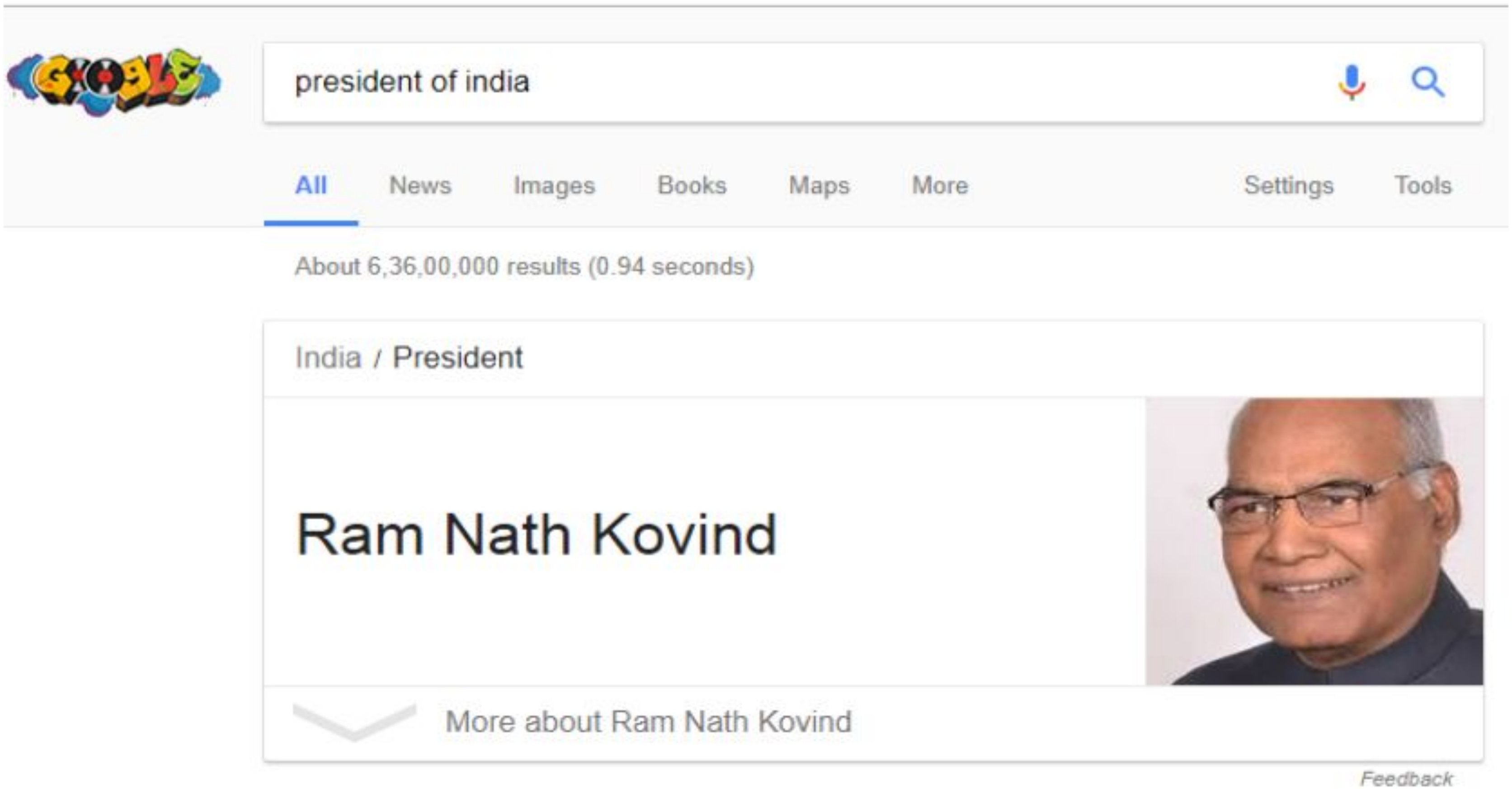
Systems that automatically answer questions posed by humans in natural language query.



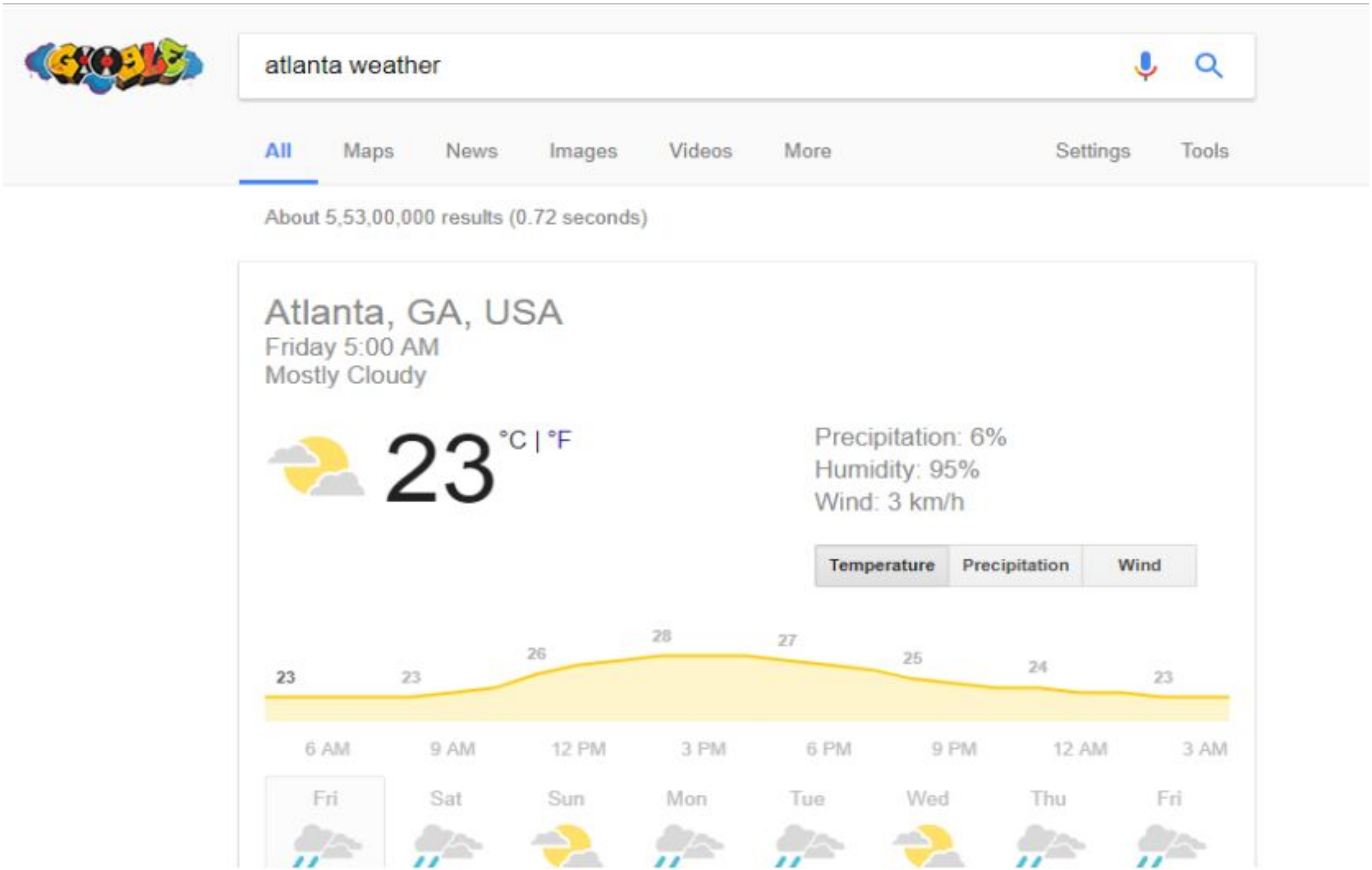
Search Engine are moving towards QA!



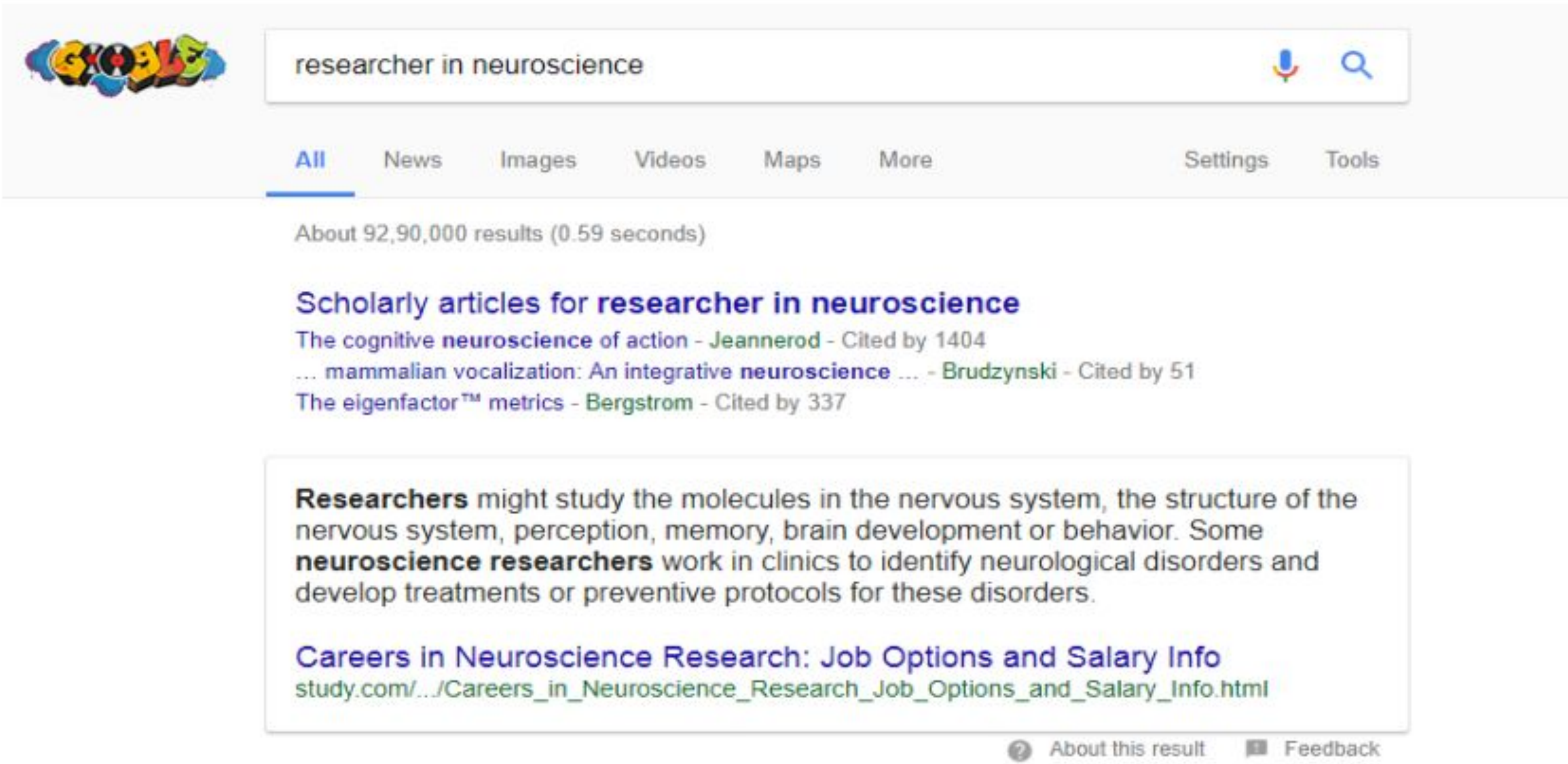
Search Engine are moving towards QA!



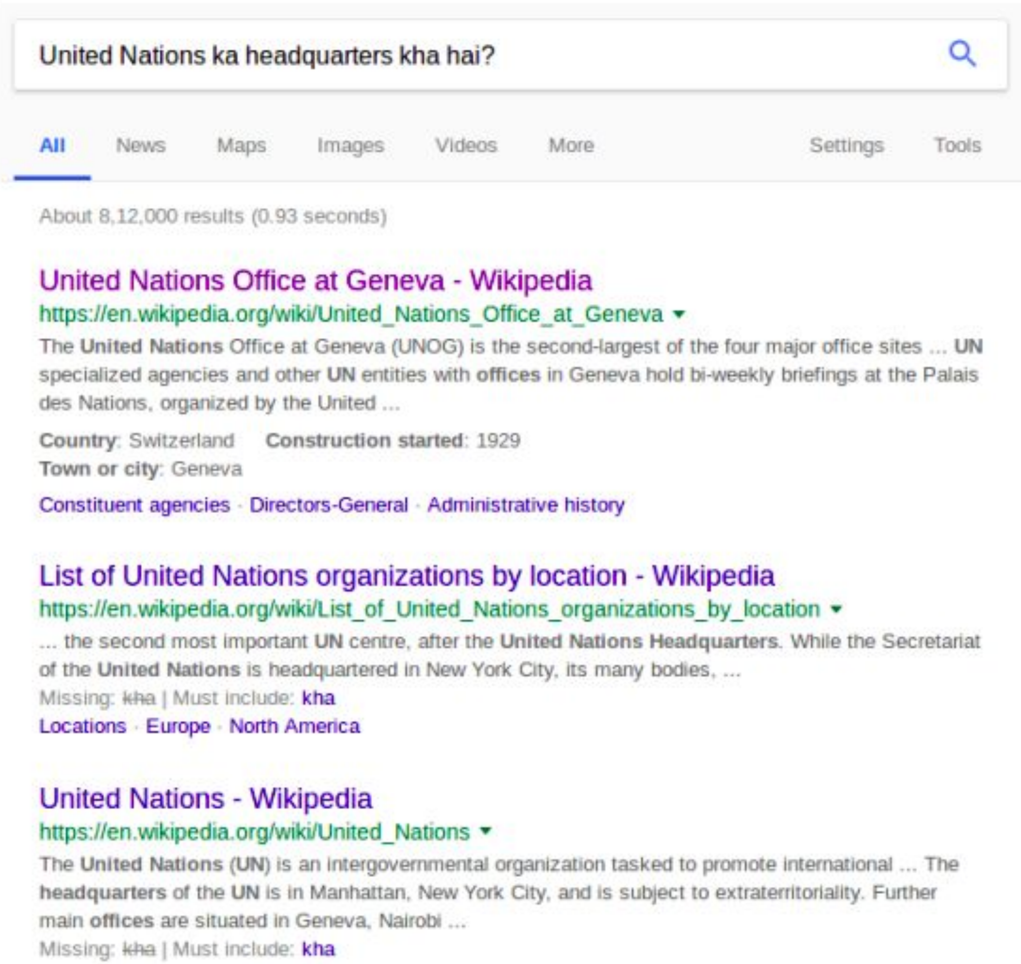
Search Engine are moving towards QA!

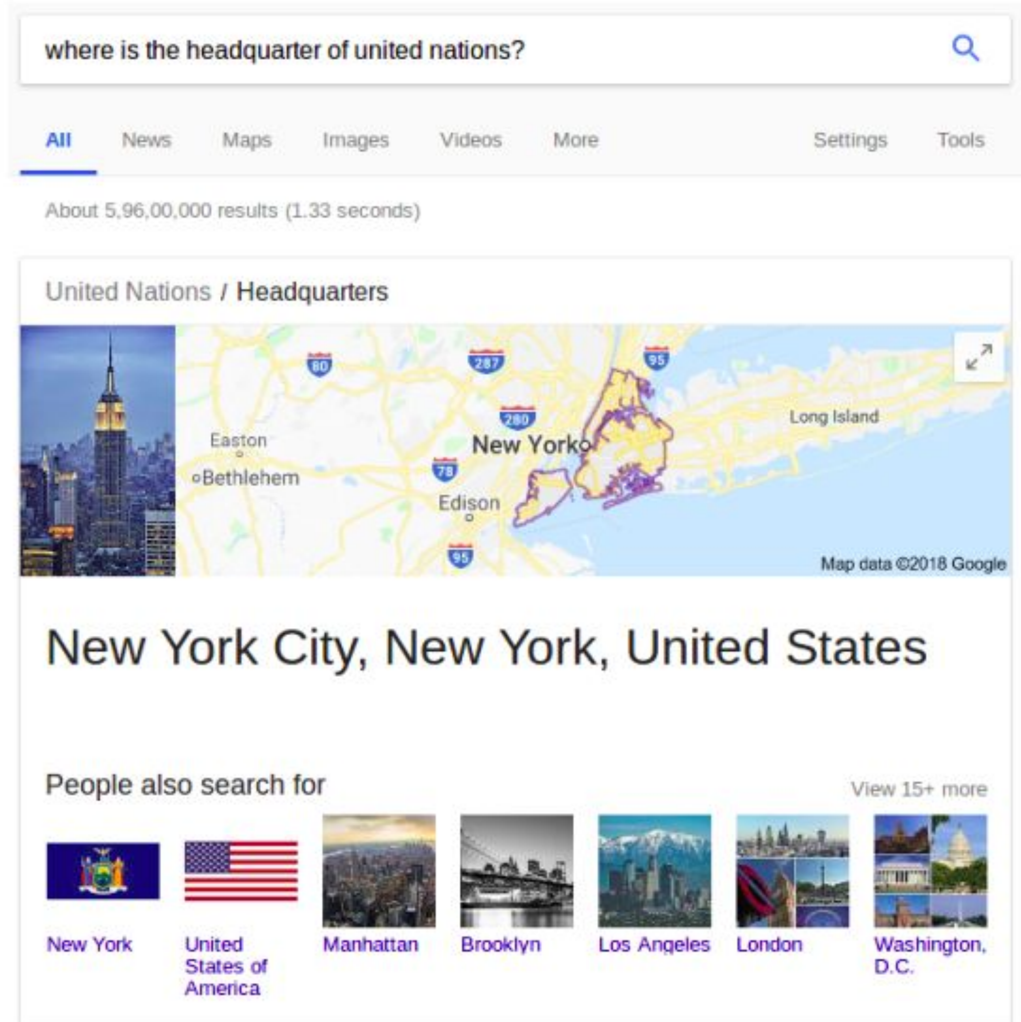


Search Engine are moving towards QA!



Search Engine are moving towards QA!





Question Answering: IBM's Watson

- Won Jeopardy on February 16, 2011!
- IBM's Watson is a Question Answering system.

Jeopardy!

- Jeopardy! is an American television quiz competition in which contestants are presented with general knowledge clues in the form of *answers*, and must phrase their responses in the form of *questions*.
- The original daytime version debuted on NBC on March 30, 1964,

Question Answering: IBM's Watson

- Won Jeopardy on February 16, 2011!
- IBM's Watson is a Question Answering system.

Watson's performance

- With the answer: "You just need a nap. You don't have this sleep disorder that can make sufferers nod off while standing up," Watson replied, "What is narcolepsy?"

Question Answering: IBM's Watson

- Won Jeopardy on February 16, 2011!
- IBM's Watson is a Question Answering system.

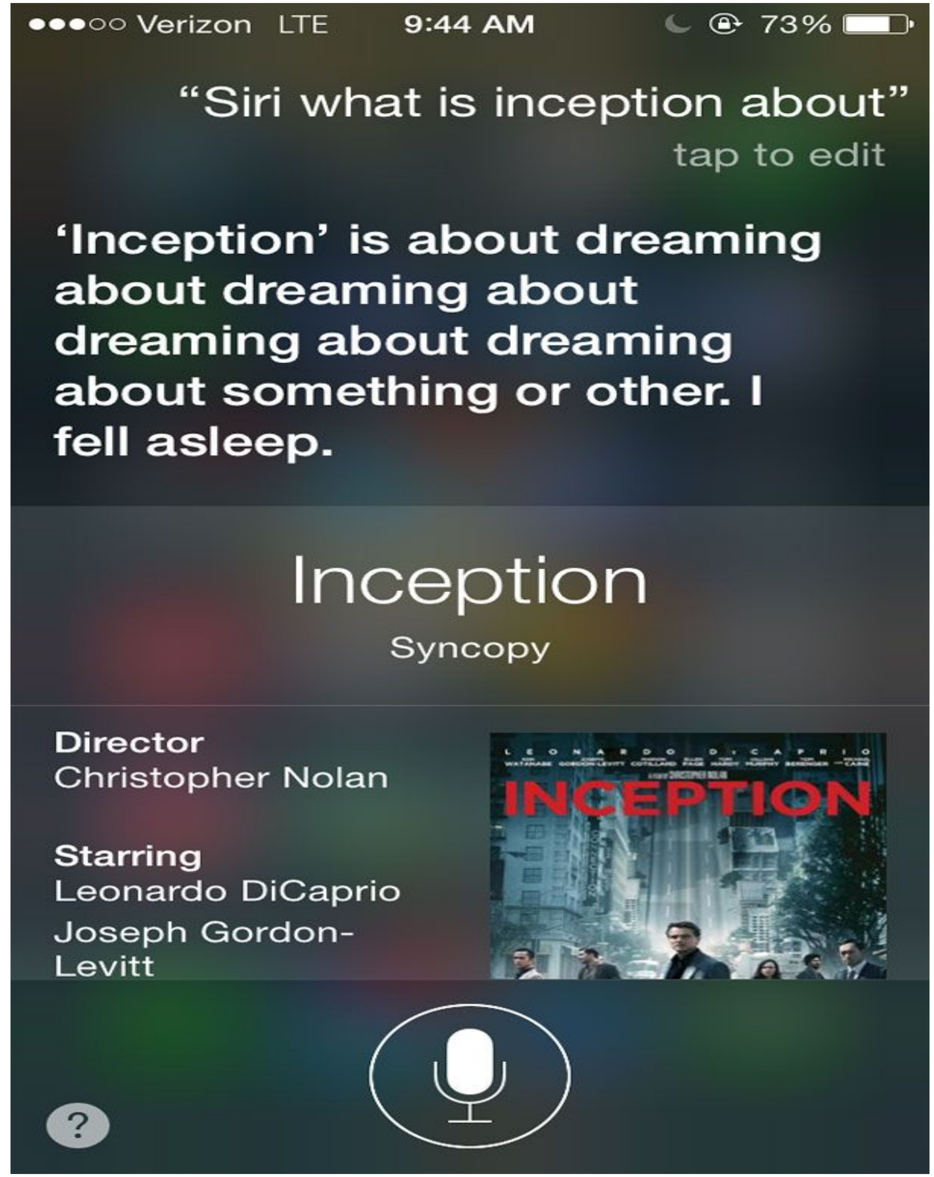
- The winning reply!

WILLIAM WILKINSON'S
"AN ACCOUNT OF THE PRINCIPALITIES OF
WALLACHIA AND MOLDOVIA"
INSPIRED THIS AUTHOR'S
MOST FAMOUS NOVEL

Bram Stoker

Apple Siri


AT&T
22:26
65 %
“ Do I need an umbrella tomorrow in San Francisco ”
Yes, San Francisco should get rain tomorrow:
Weekly Forecast
TUES WED THU FRI SAT SUN
14° 16° 17° 17° 18° 18°
9° 7° 6° 6° 7° 8°


Verizon LTE
9:44 AM
73%
“Siri what is inception about”
tap to edit
‘Inception’ is about dreaming about dreaming about dreaming about dreaming about something or other. I fell asleep.
Inception
Syncopy
Director
Christopher Nolan
Starring
Leonardo DiCaprio
Joseph Gordon-Levitt
INCEPTION


WolframAlpha computational knowledge engine
how many calories are in two slices of banana cream pie?
Examples
Random
Assuming any type of pie, banana cream | Use pie, banana cream, prepared from recipe or pie, banana cream, no-bake type, prepared from mix instead
Input interpretation:
pie
amount
2 slices
type
banana cream
total calories
Average result:
Show details
702 Cal (dietary Calories)

Motivation

- **Conversational Agents:** Facebook (M), Apple (Siri), Google etc.
- **Google Assistant:** Ask it questions. Tell it to do things.
- **Jeopardy!:** In 2011, the IBM Watson computer system competed on Jeopardy! against former winners and won the first place prize.
- **Biomedical and Clinical QA:** Urgent need of system that accepts the queries from medical practitioners in natural language and returns the answers quickly and efficiently from biomedical literature, EMR etc.
- **Online knowledge service:** The online service provide the answer of various question from science, mathematics etc.

Motivation and History

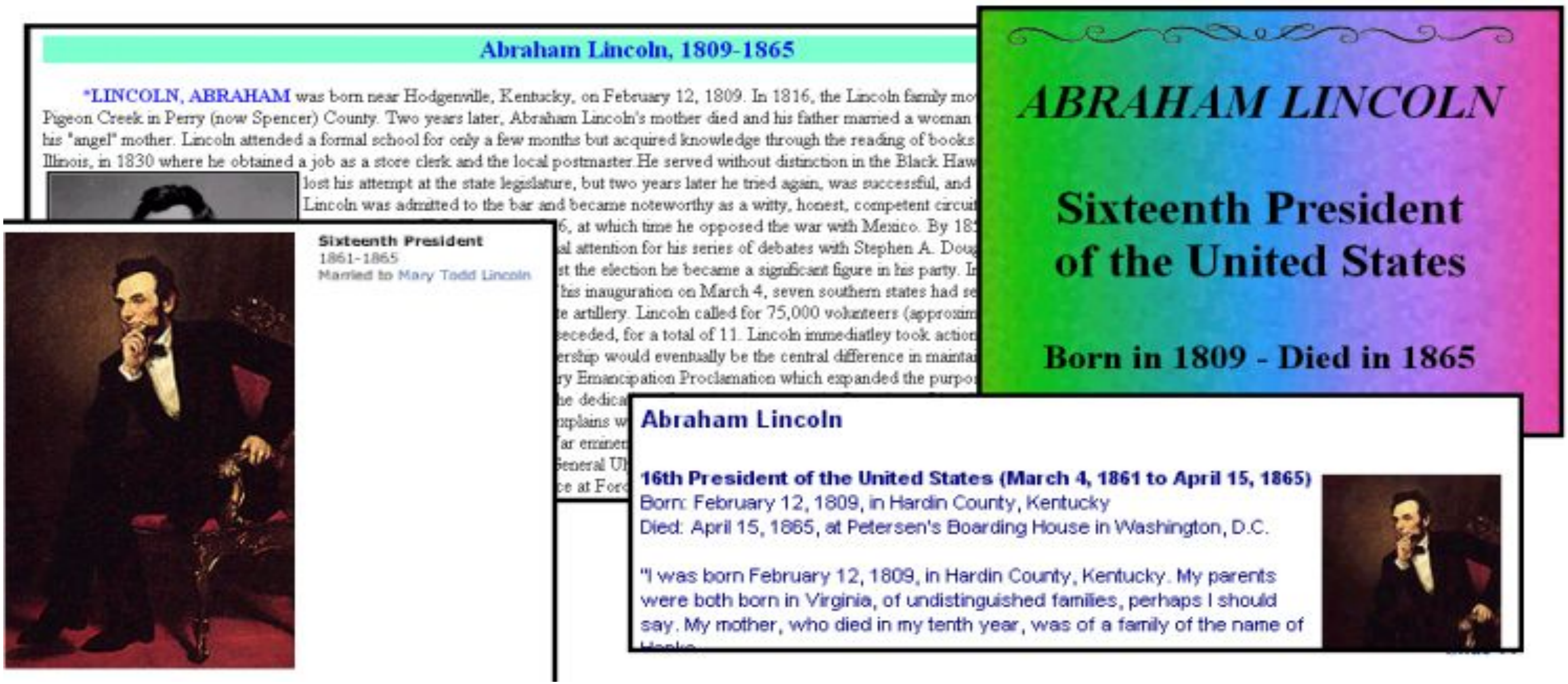
- Open domain QA systems received larger attention in the 90s
  - Combination of NLP and IR/IE techniques
  - One of the most famous: MIT START system
  - Wolfram Alpha
- Advanced systems use a combination of “shallow” methods together with knowledge bases and more complex NLP methods.
- In the last 20 years, TREC, SemEval and ACL provided workshops and tracks for various flavor of QA tasks (closed and open-domain)

Motivation and History (cont'd…)

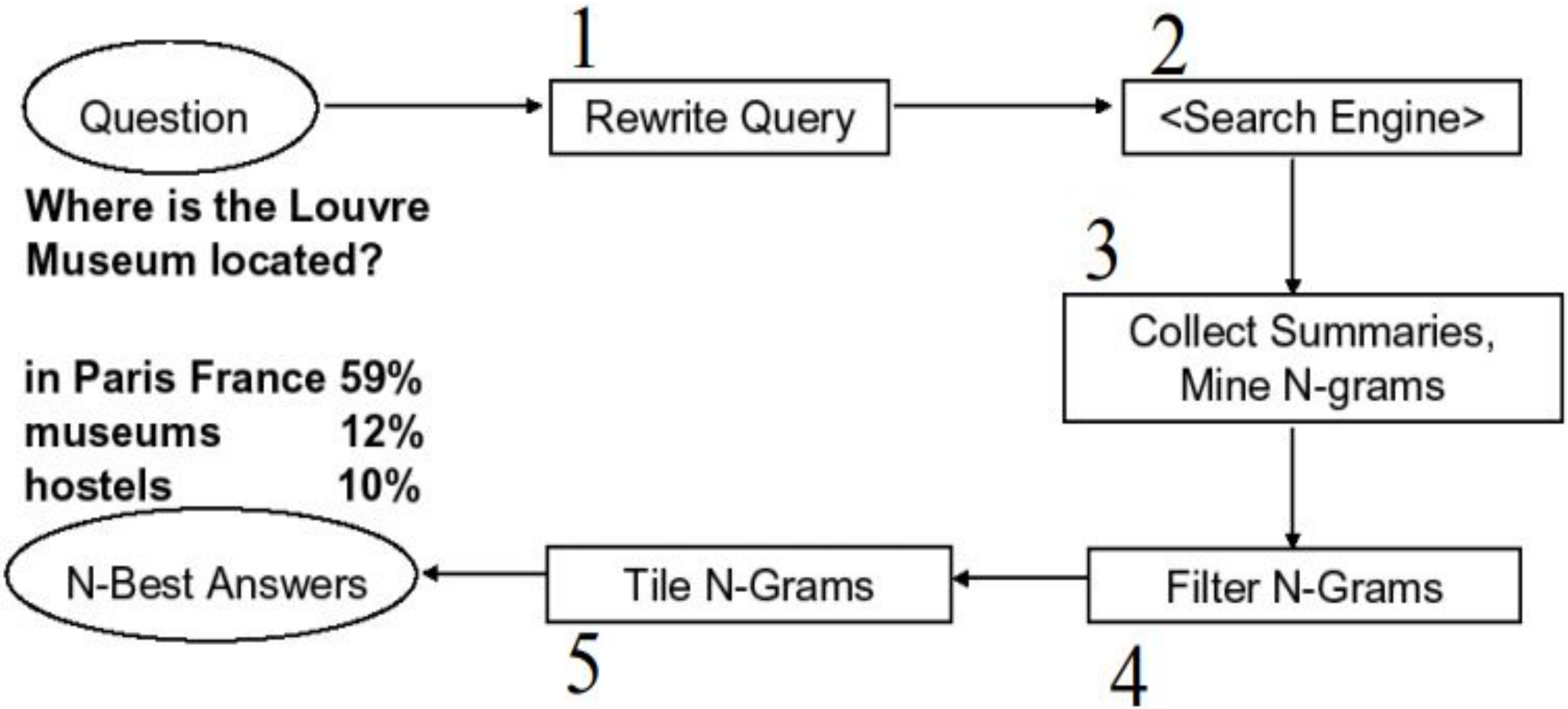
- Lately, a large number of new datasets and tasks have become available which have improved the performance of (open-domain) QA systems
  - VisualQA
    - Given an image and a question in natural language, provide the correct answer
    - 600,000+ questions on more than 200,000 images
  - SQuAD - Stanford QA Dataset
    - Open-domain question answering
    - 100,000+ Q-A pairs on 500+ articles
  - NewsQA dataset
    - Crowd-sourced machine reading comprehension dataset
    - 120,000 answered questions Over 12,000 news articles
- We are build a comparable QA dataset from two language English & Hindi

AskMSR: Shallow approach

- *In what year did Abraham Lincoln die?*
- Ignore hard documents and find easy ones



AskMSR: Details



Step 1: Rewrite queries

- Intuition: The user's question is often syntactically quite close to sentences that contain the answer
  - Where is the Louvre Museum located?
  - The Louvre Museum is located in ***Paris***
  - Who created the character of Scrooge?

Query rewriting

- Classify question into seven categories
  - **Who** is/was/are/were...?
  - **When** is/did/will/are/were ...?
  - **Where** is/are/were ...?

a. Category-specific transformation rules

eg "For Where questions, move 'is' to all possible locations"

"Where is the Louvre Museum located"

→ "is the Louvre Museum located"

→ "the is Louvre Museum located"

→ "the Louvre is Museum located"

→ "the Louvre Museum is located"

→ "the Louvre Museum located is"

Nonsense, but who cares? It's only a few more queries to Google.

b. Expected answer "Datatype" (eg, Date, Person, Location, ...)

When was the French Revolution? → DATE

Next Steps

- Step 2: Query Search engine
  - Send all rewrites to a Web search engine
  - Retrieve top N answers (100?)
  - For speed, rely just on search engine's "snippets", not the full text of the actual document

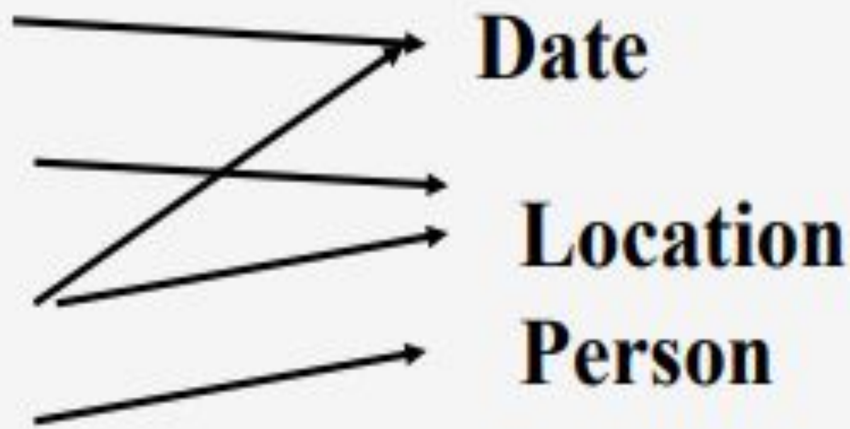
- Step 3: Mining N-grams
  - Unigram, bigram, trigram, … N-gram:
    list of N adjacent terms in a sequence
  - Eg, "Web Question Answering: Is More Always Better"
    - Unigrams: Web, Question, Answering, Is, More, Always, Better
    - Bigrams: Web Question, Question Answering, Answering Is, Is More, More Always, Always Better
    - Trigrams: Web Question Answering, Question Answering Is, Answering Is More, Is More Always, More Always Betters

Mining N-Grams

- Simple: Enumerate all N-grams (N=1,2,3 say) in all retrieved snippets
    - Use hash table and other fancy footwork to make this efficient
- Weight of an n-gram: occurrence count, each weighted by "reliability" (weight) of rewrite that fetched the document
- Example: "Who created the character of Scrooge?"
  - Dickens - 117
  - Christmas Carol - 78
  - Charles Dickens - 75
  - Disney - 72
  - Carl Banks - 54
  - A Christmas - 41
  - Christmas Carol - 45
  - Uncle - 31

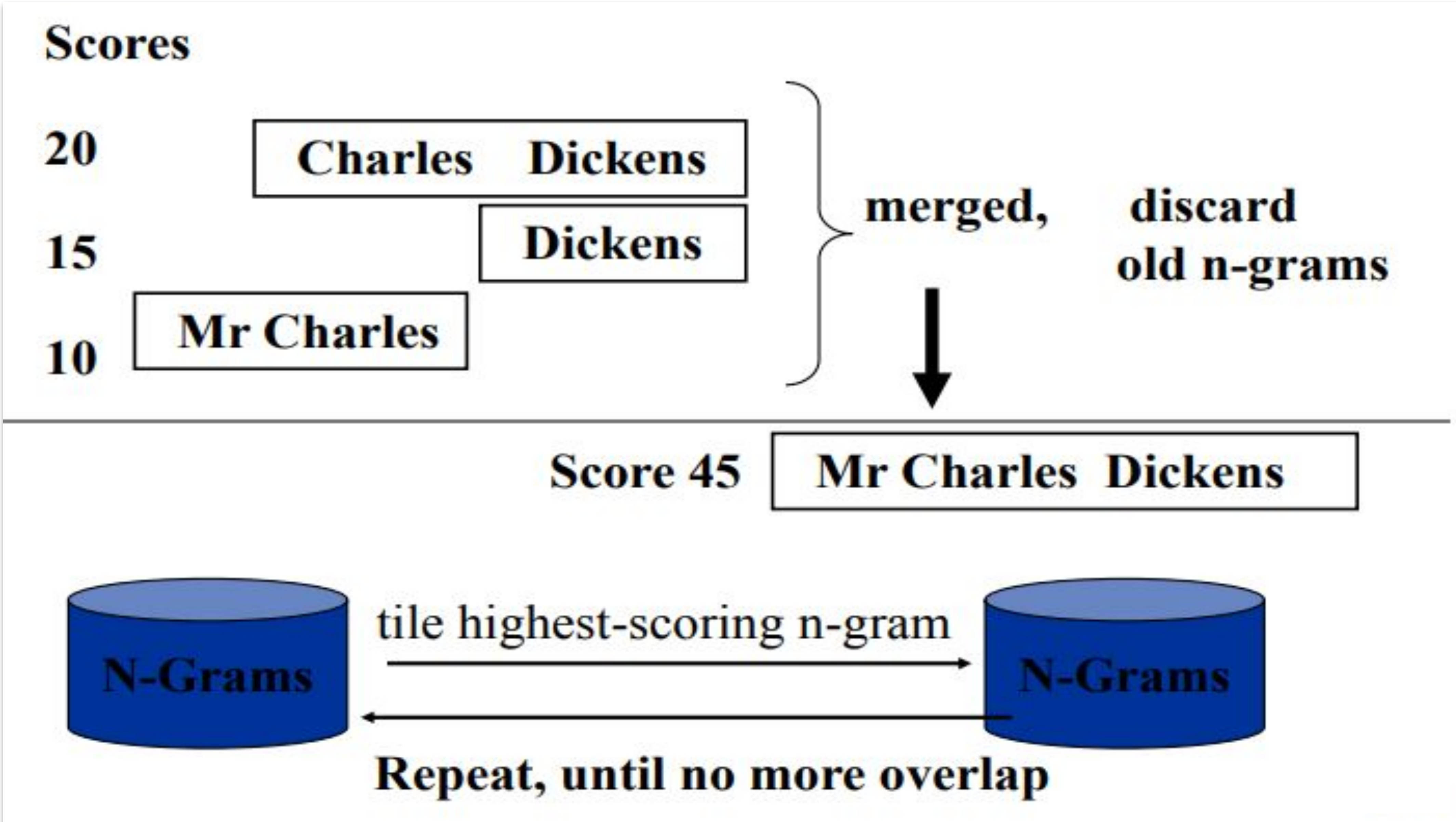
Filtering N-Grams

- Each question type is associated with one or more "**data-type filters**" = regular expression
- When…
- Where…
- What …
- Who …



- Boost score of n-grams that do match regexp
- Lower score of n-grams that don't match regexp

Tiling the Answers



Basic Q/A Architecture

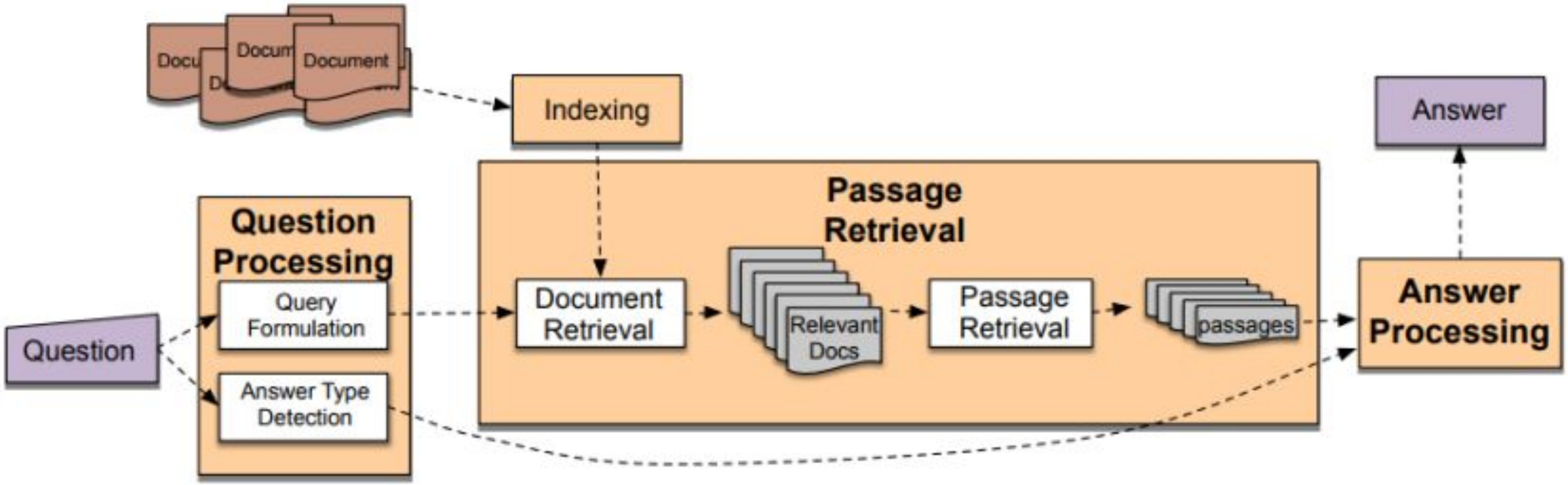


Figure: IR based question answering system. Image courtesy Jurafsky and Martin [2000]

Common Evaluation Metrics

- ***Accuracy*** *(does answer match gold-labeled answer?)*
- ***Mean Reciprocal Rank:***
  - *The reciprocal rank of a query response is the inverse of the rank of the first correct answer.*
  - *The mean reciprocal rank is the average of the reciprocal ranks of results for a sample of queries Q.*

(ex adapted from Wikipedia)

- 3 ranked answers for a query, with the first one being the one it thinks is most likely correct
- Given those 3 samples, we could calculate the mean reciprocal rank as *(1/3 + 1/2 + 1)/3* = 11/18 or about 0.61.

Query	Results	Correct response	Rank	Reciprocal rank
cat	catten, cati, **cats**	cats	3	1/3
torus	torii, **tori**, toruses	tori	2	1/2
virus	**viruses**, virii, viri	viruses	1	1

Machine Comprehension

- **Machine Comprehension or Machine Reading Comprehension** (MRC) is all about answering a query about a given context paragraph.
- "A machine **comprehends** a passage of **text** if, for any **question** regarding that text that can be **answered** correctly by a majority of native speakers, that machine can provide a string which those speakers would agree both answers that question, and does not contain information irrelevant to that question."

  (Burges 2013)

A Brief History of Machine Comprehension

- Much early NLP work attempted reading comprehension
  - Schank, Abelson, Lehnert et al. c. 1977 – "Yale A.I. Project"
- Revived by Lynette Hirschman in 1999:
  - Could NLP systems answer human reading comprehension questions for 3rd to 6th graders? Simple methods attempted.
- Revived again by Chris Burges in 2013 with MCTest
  - Again answering questions over simple story texts
- Floodgates opened in 2015/16 with the production of large datasets which permit supervised neural systems to be built
  - Hermann et al. (NIPS 2015) DeepMind CNN/DM dataset
  - Rajpurkar et al. (EMNLP 2016) SQuAD
  - MS MARCO, TriviaQA, RACE, NewsQA, NarrativeQA, HotpotQA

Machine Comprehension

Passage (P) + Question (Q) $\longrightarrow$ Answer (A)

P

Alyssa got to the beach after a long trip. She's from Charlotte. She traveled from Atlanta. She's now in Miami. She went to Miami to visit some friends. But she wanted some time to herself at the beach, so she went there first. After going swimming and laying out, she went to her friend Ellen's house. Ellen greeted Alyssa and they both had some lemonade to drink. Alyssa called her friends Kristin and Rachel to meet at Ellen's house……

Q What city is Alyssa in?

A Miami

Motivation (1)

- Teaching machines to understand human language is a long-standing challenge in AI.
- Requires various aspects of text understanding.
  - Part-of-speech Tagging
  - Named Entity Recognition
  - Syntactic Parsing
  - Coreference resolution
- Is there a comprehensive evaluation that can test all these aspects and probe even deeper levels of understanding?
  - **Machine Comprehension**

Motivation (2)

- Reading comprehension: tests to measure how well a human has understood a piece of text.
- Machine comprehension: how well computer systems understand human language.
- Machine comprehension could be the most suitable task for evaluating language understanding

Datasets

Before 2015

- **MCTest** (Richardson et al, 2013): 2600 questions
- **ProcessBank** (Berant et al, 2014): 500 questions

After 2015

- CNN/Daily Mail
- Children Book Test
- WikiReading
- LAMBADA
- SQuAD
- Who did What
- Maluuba NewsQA
- MS MARCO

QA vs. Machine Comprehension

- Reading comprehension as an instance of question answering because it is essentially a question answering problem over a short passage of text.
- Question answering is to build computer systems which are able to automatically answer questions posed by humans from various sources.
- Machine comprehension puts more emphasis on text understanding with answering questions regarded as a way to measure language understanding.

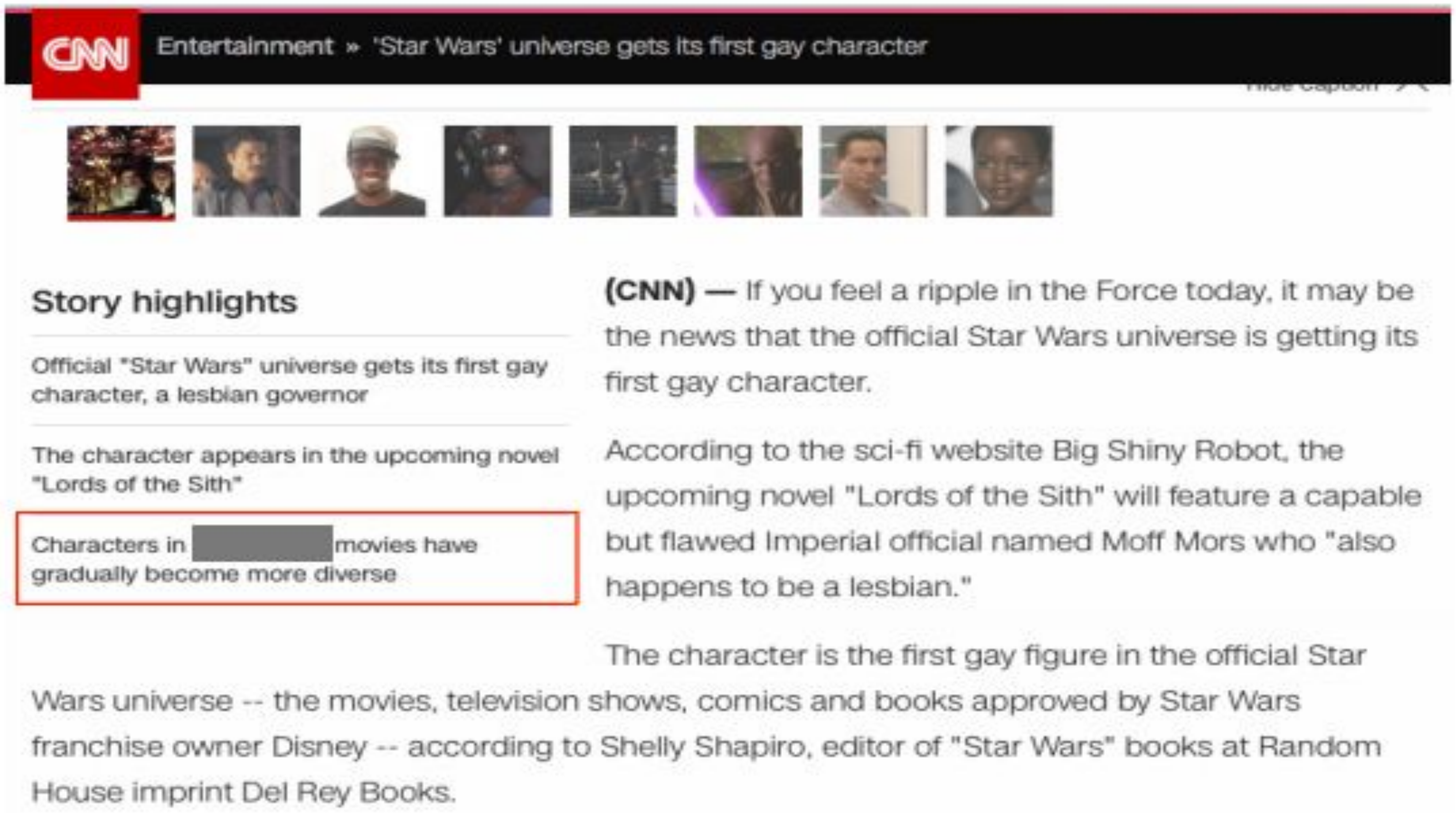
Approaches

- **Machine Learning Approaches**
  - Sliding Window (Richardson et. Al, 2013)
    - Compute the unigram/bigram overlap between the sentence containing the candidate answer and the question.
    - Use TF-IDF based similarity to select the best candidate answer.
  - Logistic Regression (Rajpurkar et. Al, 2013)
    - Extract several types of features for each candidate answer
    - Features
      - Matching Word Frequencies
      - Matching Bigram Frequencies
      - Lengths
      - Span POS Tags
      - …..

Approaches

- **Deep Learning Approaches**
  - Stanford Attentive Reader (Chen et al, 2016)

CNN/Daily Mail Datasets



CNN Entertainment » 'Star Wars' universe gets its first gay character

Story highlights

Official "Star Wars" universe gets its first gay character, a lesbian governor

The character appears in the upcoming novel "Lords of the Sith"

Characters in [redacted] movies have gradually become more diverse

(CNN) — If you feel a ripple in the Force today, it may be the news that the official Star Wars universe is getting its first gay character.

According to the sci-fi website Big Shiny Robot, the upcoming novel "Lords of the Sith" will feature a capable but flawed Imperial official named Moff Mors who "also happens to be a lesbian."

The character is the first gay figure in the official Star Wars universe -- the movies, television shows, comics and books approved by Star Wars franchise owner Disney -- according to Shelly Shapiro, editor of "Star Wars" books at Random House imprint Del Rey Books.

Deep Learning Approaches

– Stanford Attentive Reader (Chen et al, 2016)

P

(@entity4) if you feel a ripple in the force today , it may be the news that the official @entity6 is getting its first gay character . according to the sci-fi website @entity9 , the upcoming novel " @entity11 " will feature a capable but flawed @entity13 official named @entity14 who " also happens to be a lesbian . " the character is the first gay figure in the official @entity6 -- the movies , television shows , comics and books approved by @entity6 franchise owner @entity22 -- according to @entity24 , editor of " @entity6 "

Q

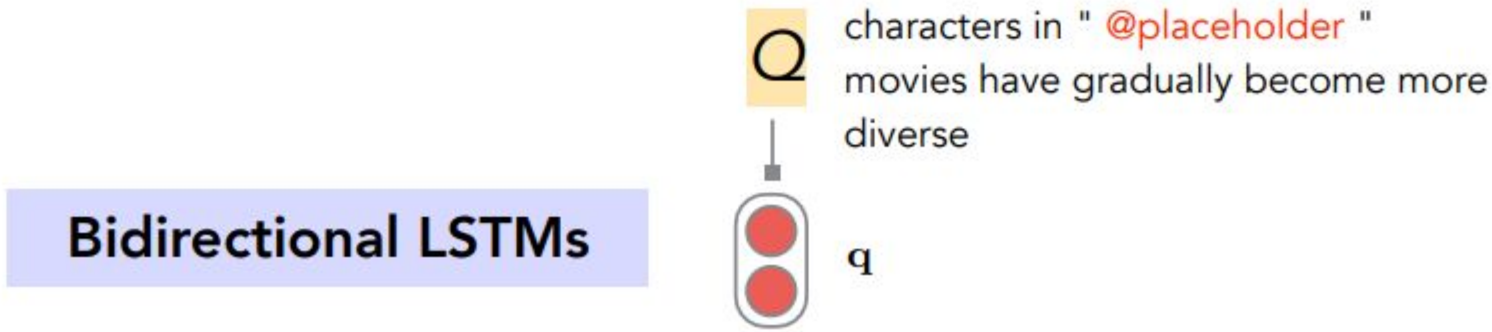
characters in " @placeholder " movies have gradually become more diverse

A

@entity6

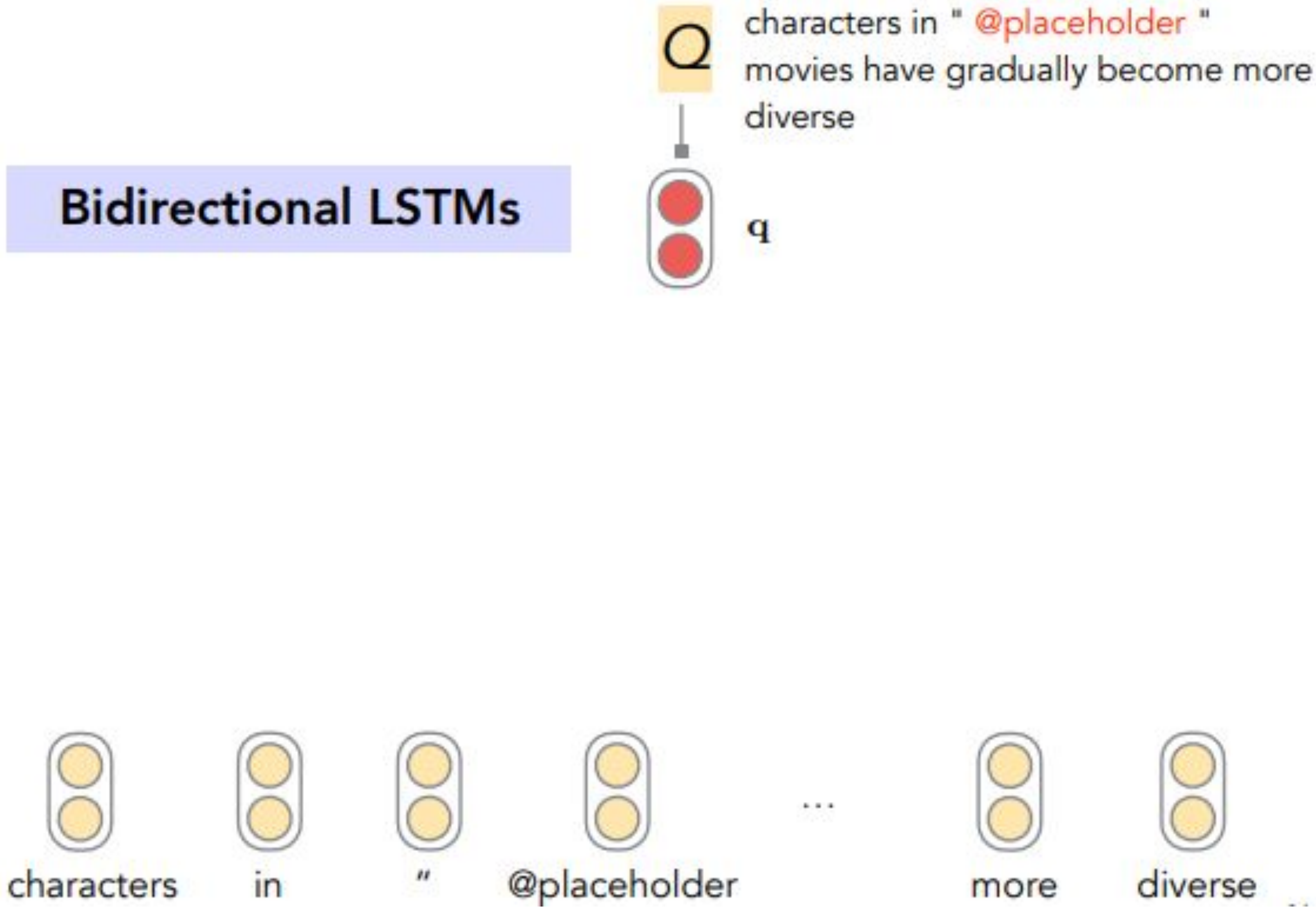
Deep Learning Approaches

Stanford Attentive Reader



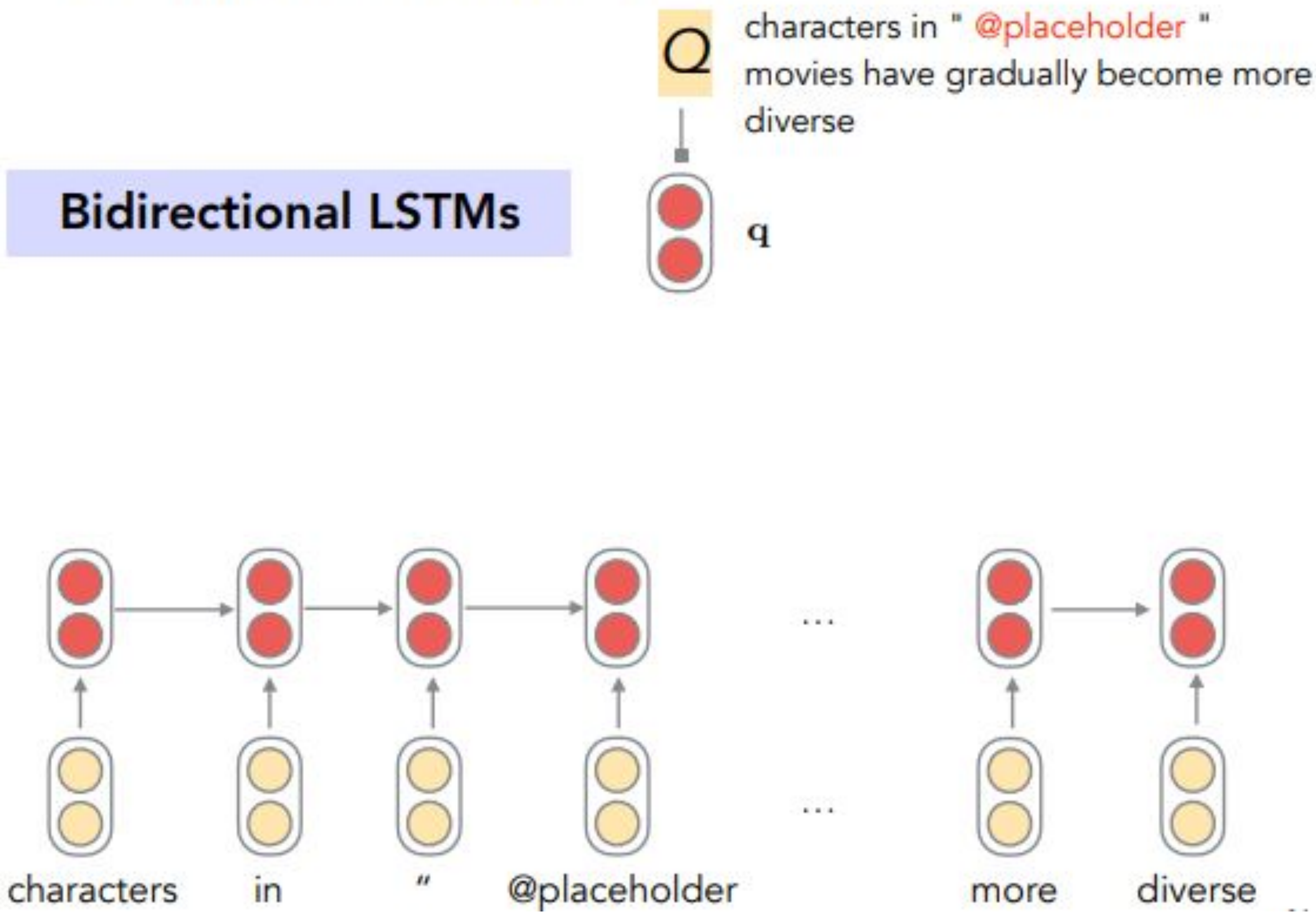
Deep Learning Approaches

Stanford Attentive Reader



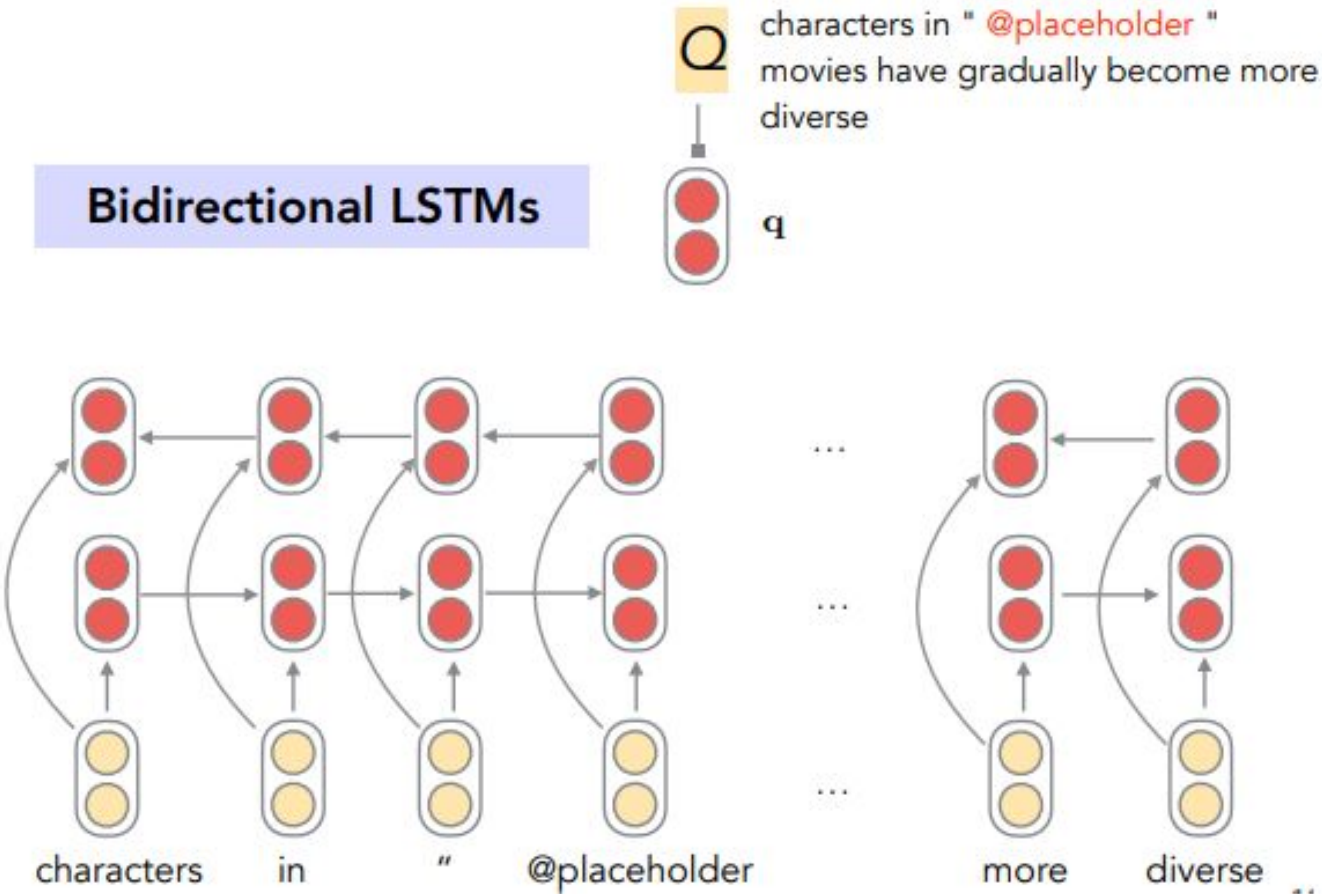
Deep Learning Approaches

Stanford Attentive Reader



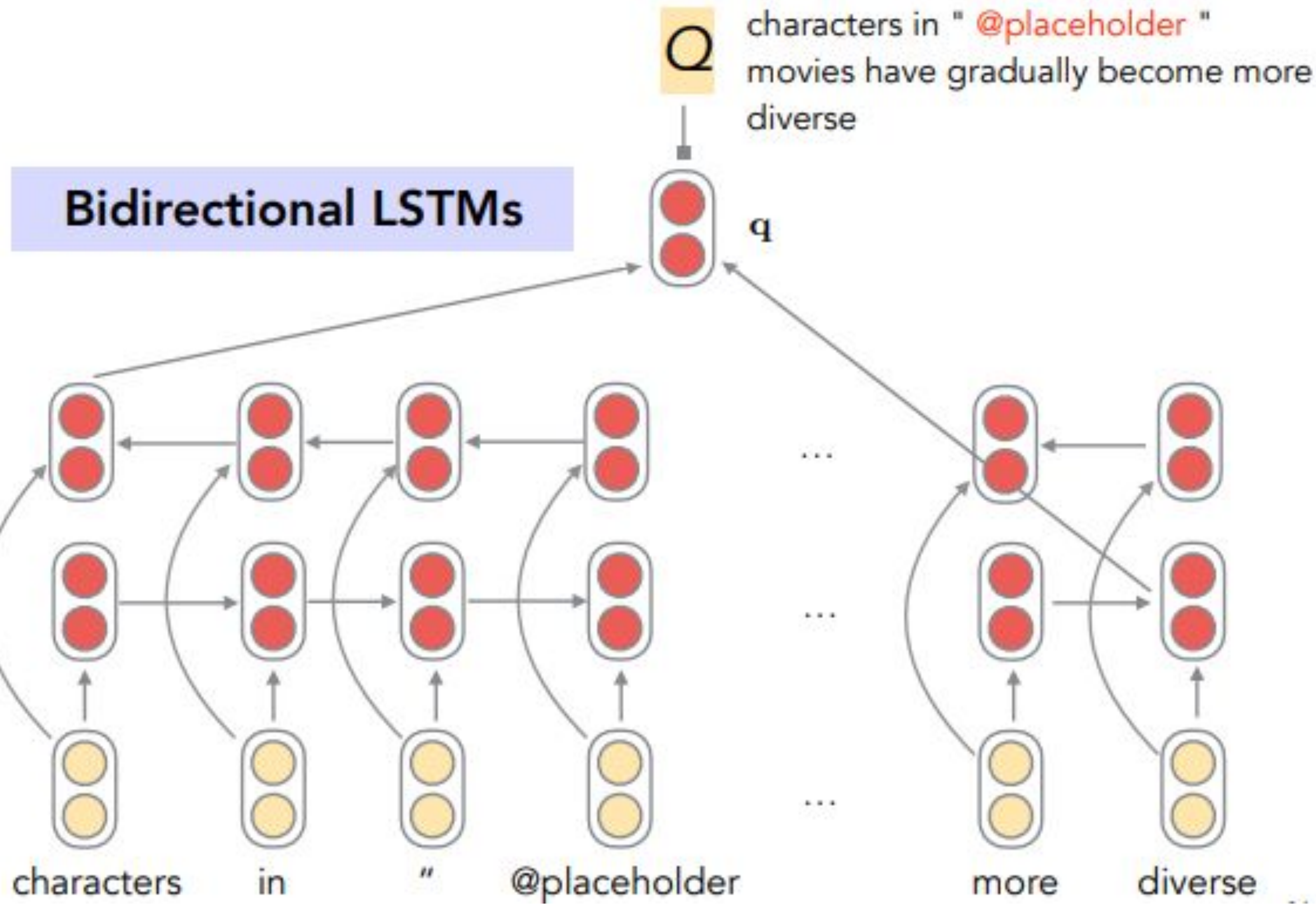
Deep Learning Approaches

Stanford Attentive Reader



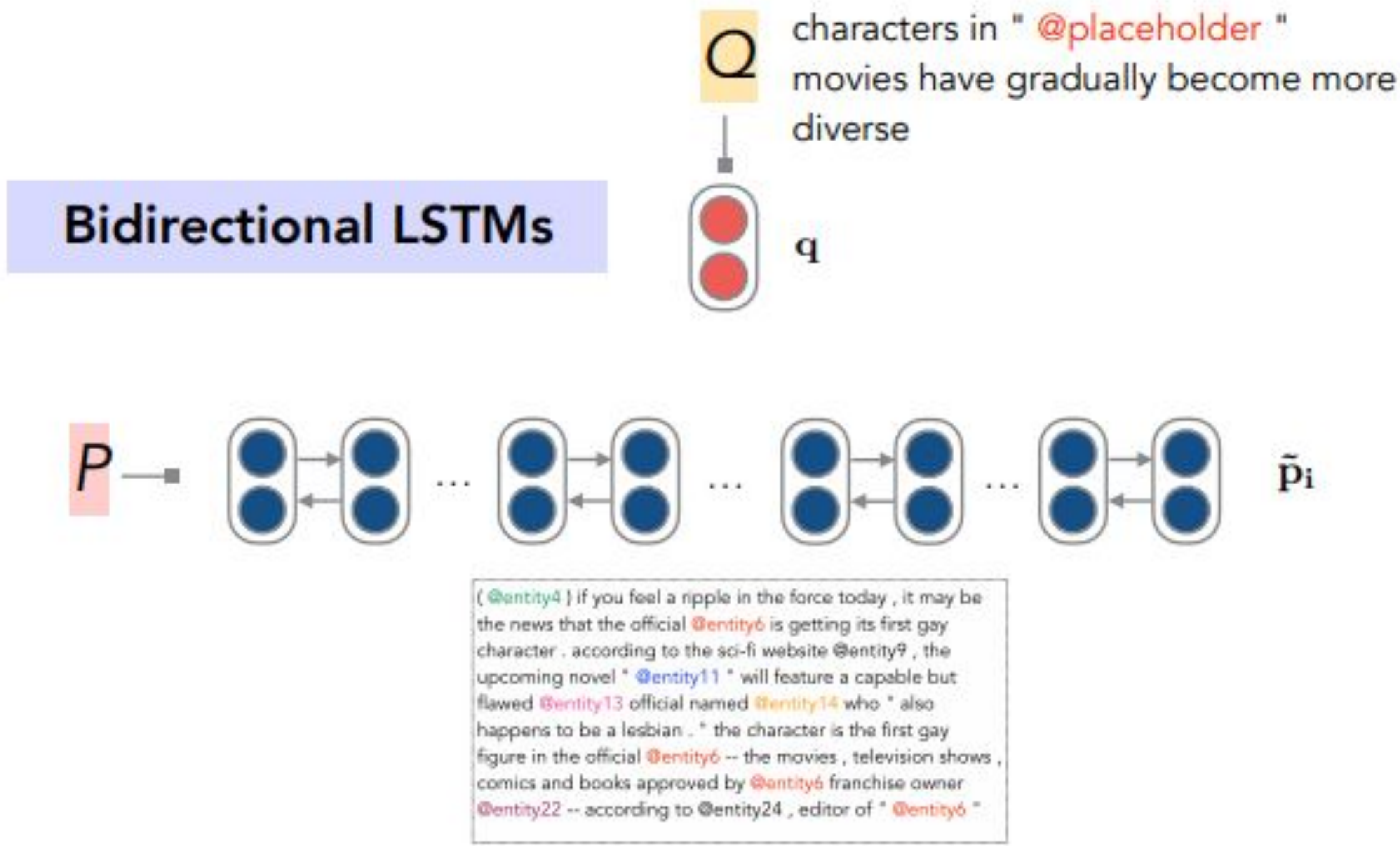
Deep Learning Approaches

Stanford Attentive Reader



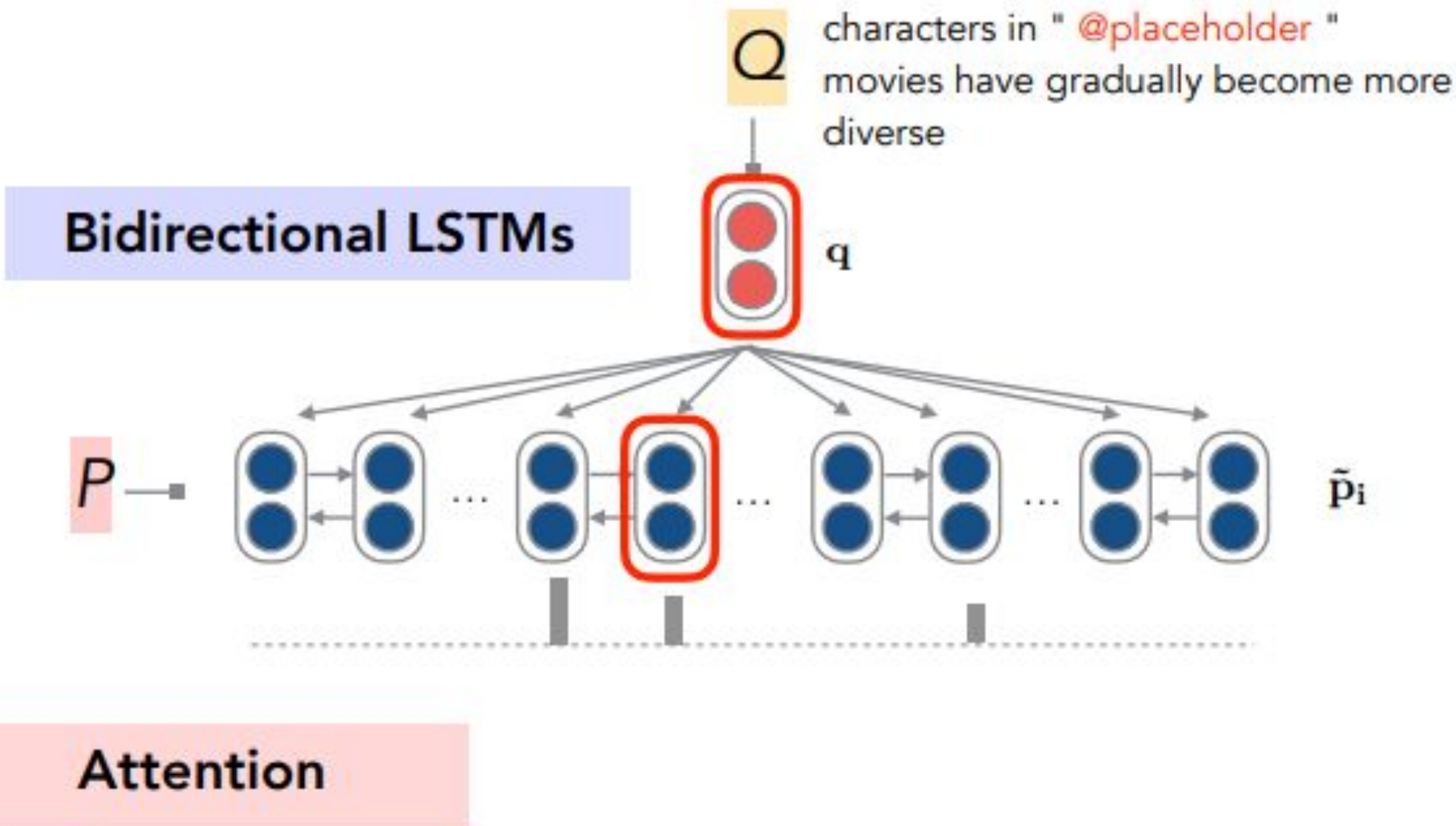
Deep Learning Approaches

Stanford Attentive Reader



Deep Learning Approaches

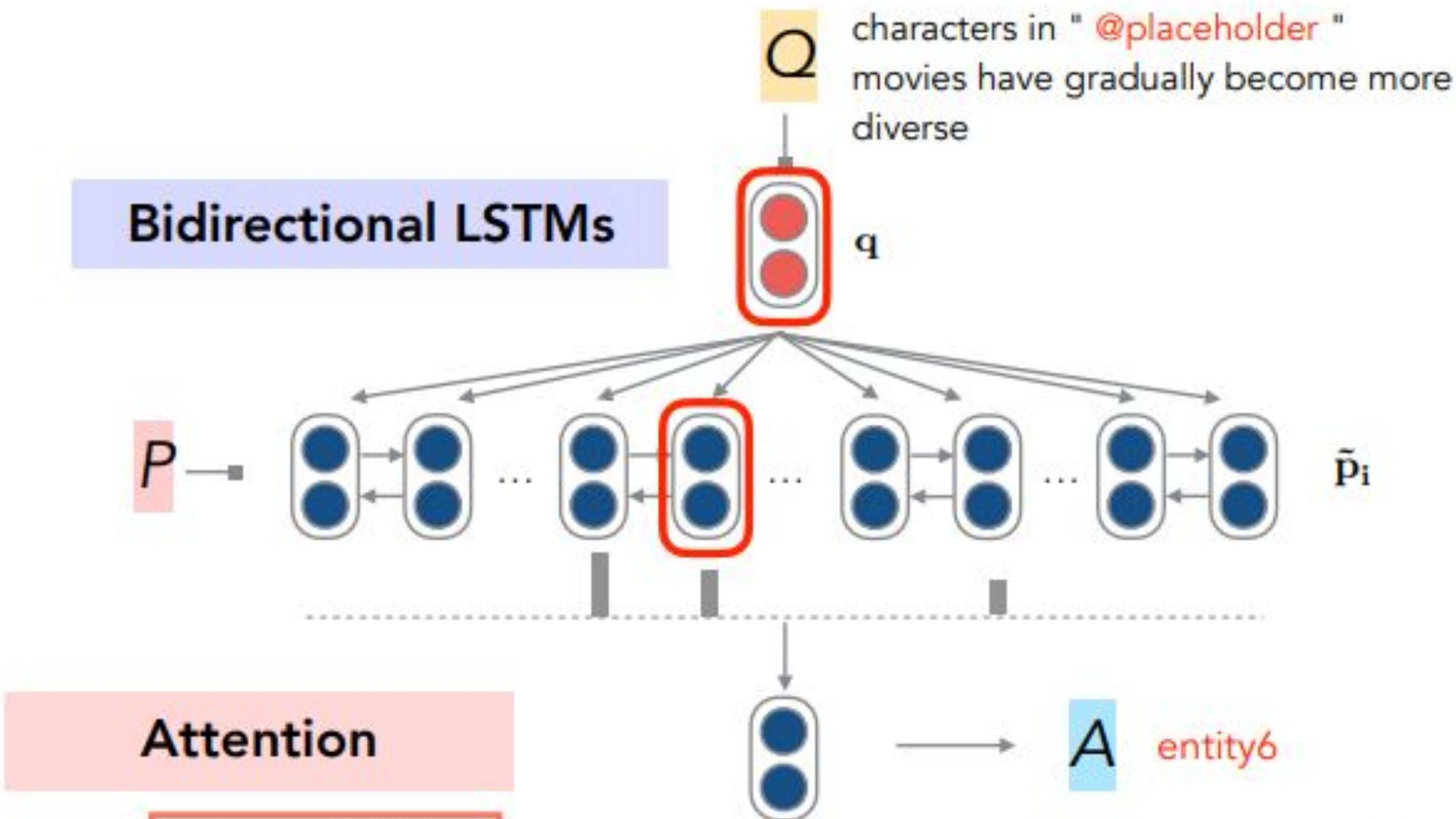
Stanford Attentive Reader



$$\alpha_i = \boxed{\operatorname{softmax}_i \left(\mathbf{q}^\top \mathbf{W}_s \tilde{\mathbf{p}}_i\right)}$$

Deep Learning Approaches

Stanford Attentive Reader



$$\alpha_i = \boxed{\mathrm{softmax}_i\,(\mathbf{q}^{\intercal}\mathbf{W}_s\tilde{\mathbf{p}}_i)}$$

$$\mathbf{o} = \sum_i \alpha_i \tilde{\mathbf{p}}_i$$

$$a = \arg\max_{a \in p \cap E} W_a^{\intercal}\mathbf{o}$$

Deep Learning Approaches

CNN/Daily Mail Datasets

- Still noisy and artificial (not real questions)
- Not hard enough for reasoning and inference
- Does it work for a real QA problem?

Stanford Question Answering Dataset (SQuAD)

- Passage + Question Answer
  - **Passage**: selected from Wikipedia
  - **Question**: crowdsourced
  - **Answer**: must be a span in the passage

Extractive Question Answering

Stanford Question Answering Dataset (SQuAD)

- Passage + Question □ Answer

Who did **Genghis Khan unite before he** began **conquering** the rest of **Eurasia**?

He came to power by **uniting** many of the nomadic tribes of Northeast Asia. **After** founding the Mongol Empire and being proclaimed "**Genghis Khan**", he started the Mongol invasions that resulted in the **conquest** of most of **Eurasia**. These included raids or invasions of the Qara Khitai, Caucasus, Khwarezmid Empire, Western Xia and Jin dynasties. These campaigns were often accompanied by wholesale massacres of the civilian populations – especially in the Khwarezmian and Xia controlled lands. By the end of his life, the Mongol Empire occupied a substantial portion of Central Asia and China.

Stanford Question Answering Dataset (SQuAD)

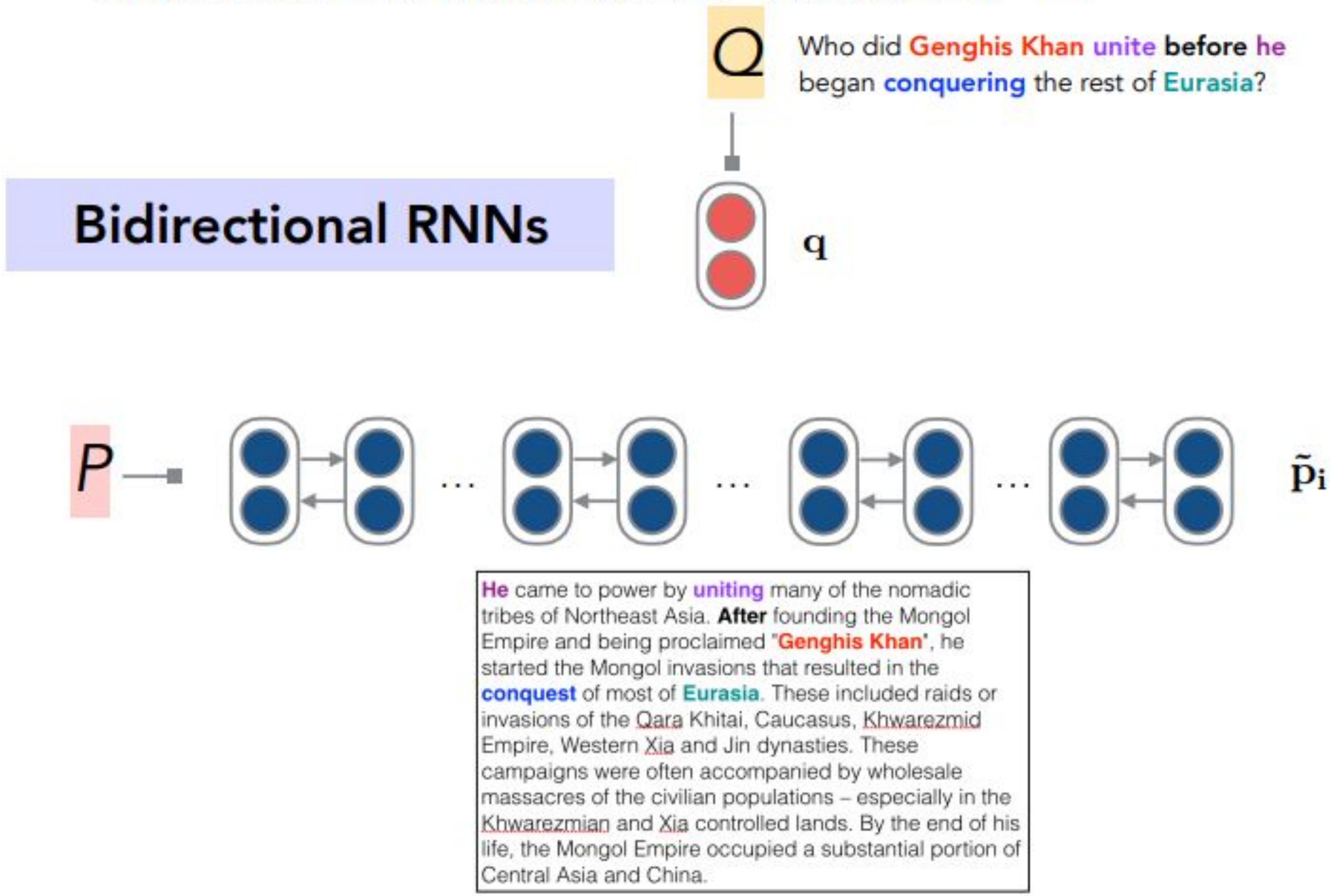
- Passage + Question □ Answer

Who did **Genghis Khan unite before he** began **conquering** the rest of **Eurasia**?

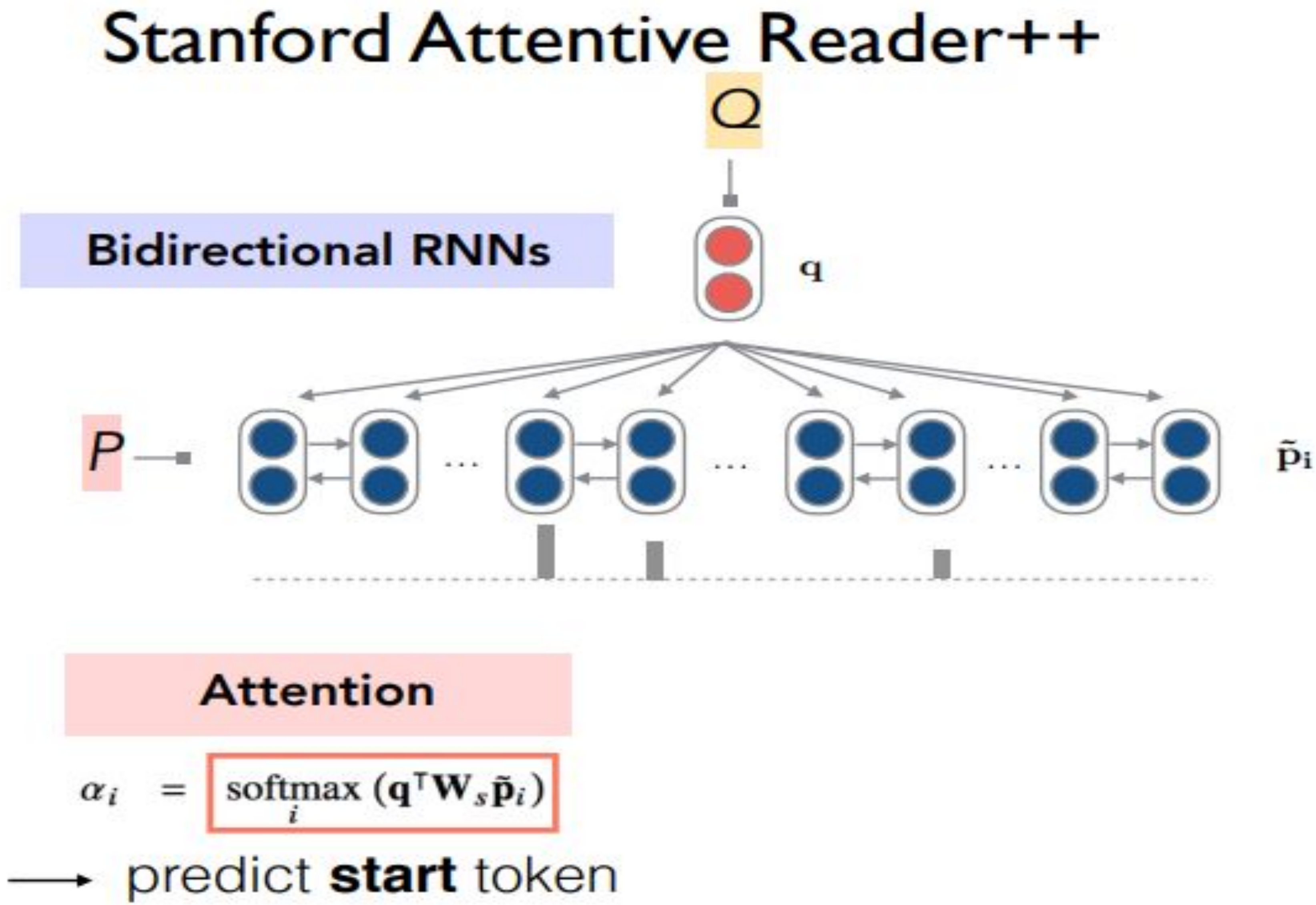
He came to power by **uniting** many of the nomadic tribes of Northeast Asia. **After** founding the Mongol Empire and being proclaimed "**Genghis Khan**", he started the Mongol invasions that resulted in the **conquest** of most of **Eurasia**. These included raids or invasions of the Qara Khitai, Caucasus, Khwarezmid Empire, Western Xia and Jin dynasties. These campaigns were often accompanied by wholesale massacres of the civilian populations – especially in the Khwarezmian and Xia controlled lands. By the end of his life, the Mongol Empire occupied a substantial portion of Central Asia and China.

Deep Learning Approaches

Stanford Attentive Reader++

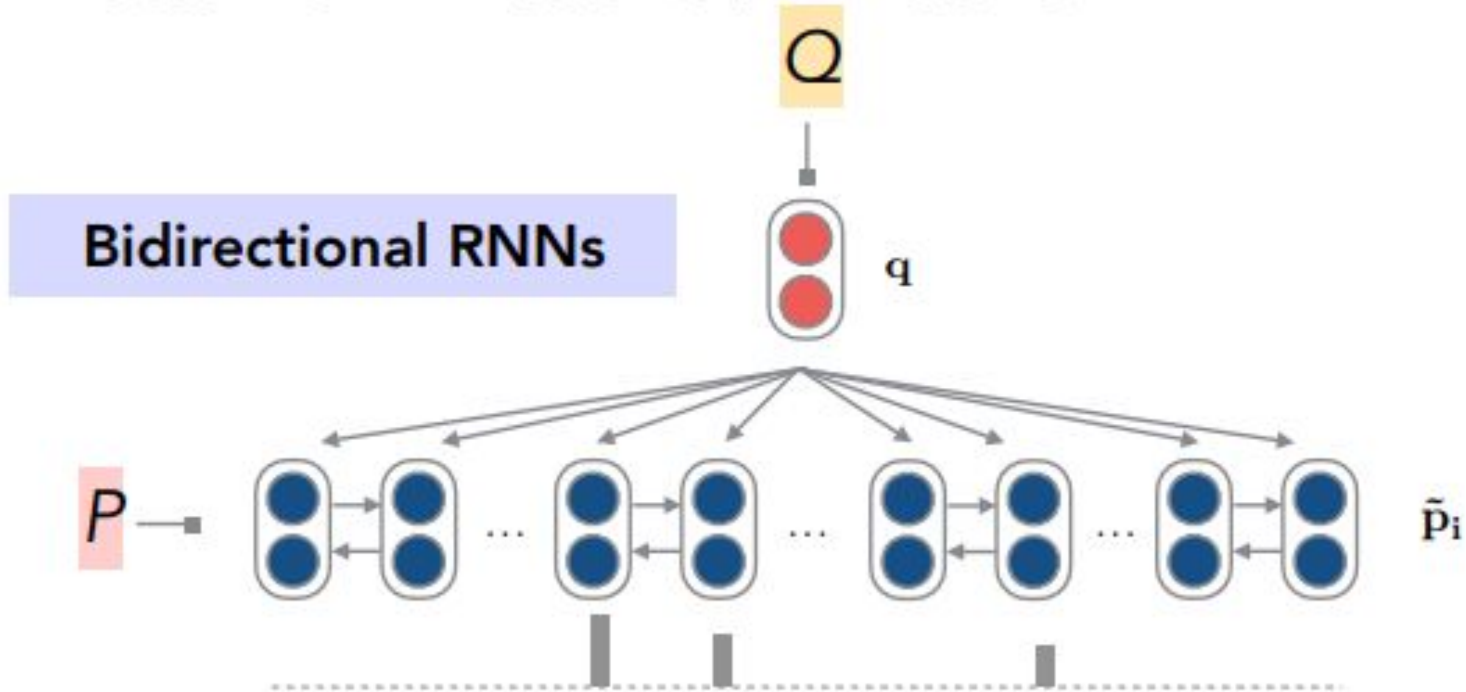


Deep Learning Approaches



Deep Learning Approaches

Stanford Attentive Reader++



Attention

$\alpha_i = \boxed{\mathrm{softmax}_i\left(\mathbf{q}^{\intercal}\mathbf{W}_s\tilde{\mathbf{p}}_i\right)}$

→ predict **start** token

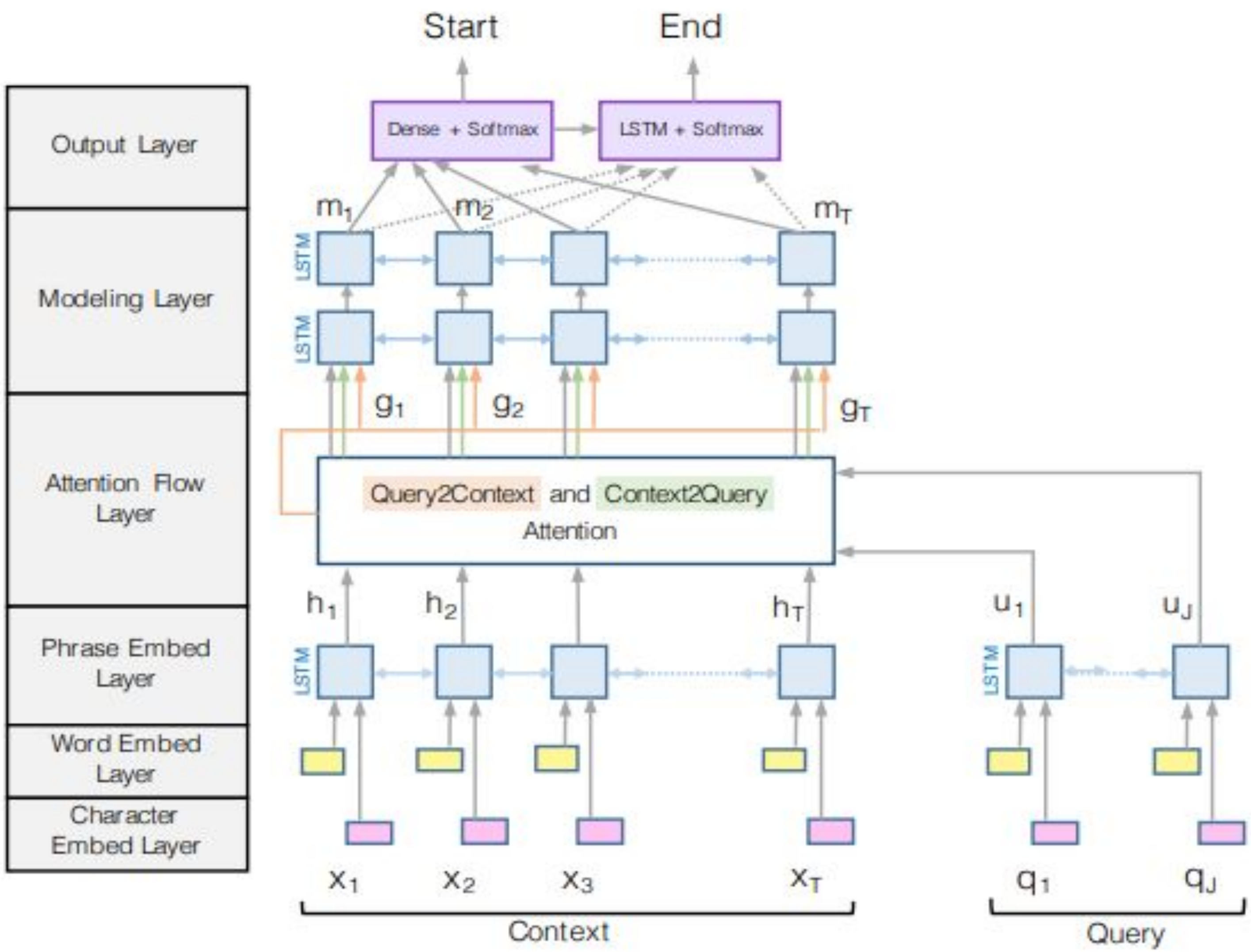
Attention

$\alpha'_i = \mathrm{softmax}_i\left(\mathbf{q}^{\intercal}\mathbf{W}'_s\tilde{\mathbf{p}}_i\right)$

→ predict **end** token

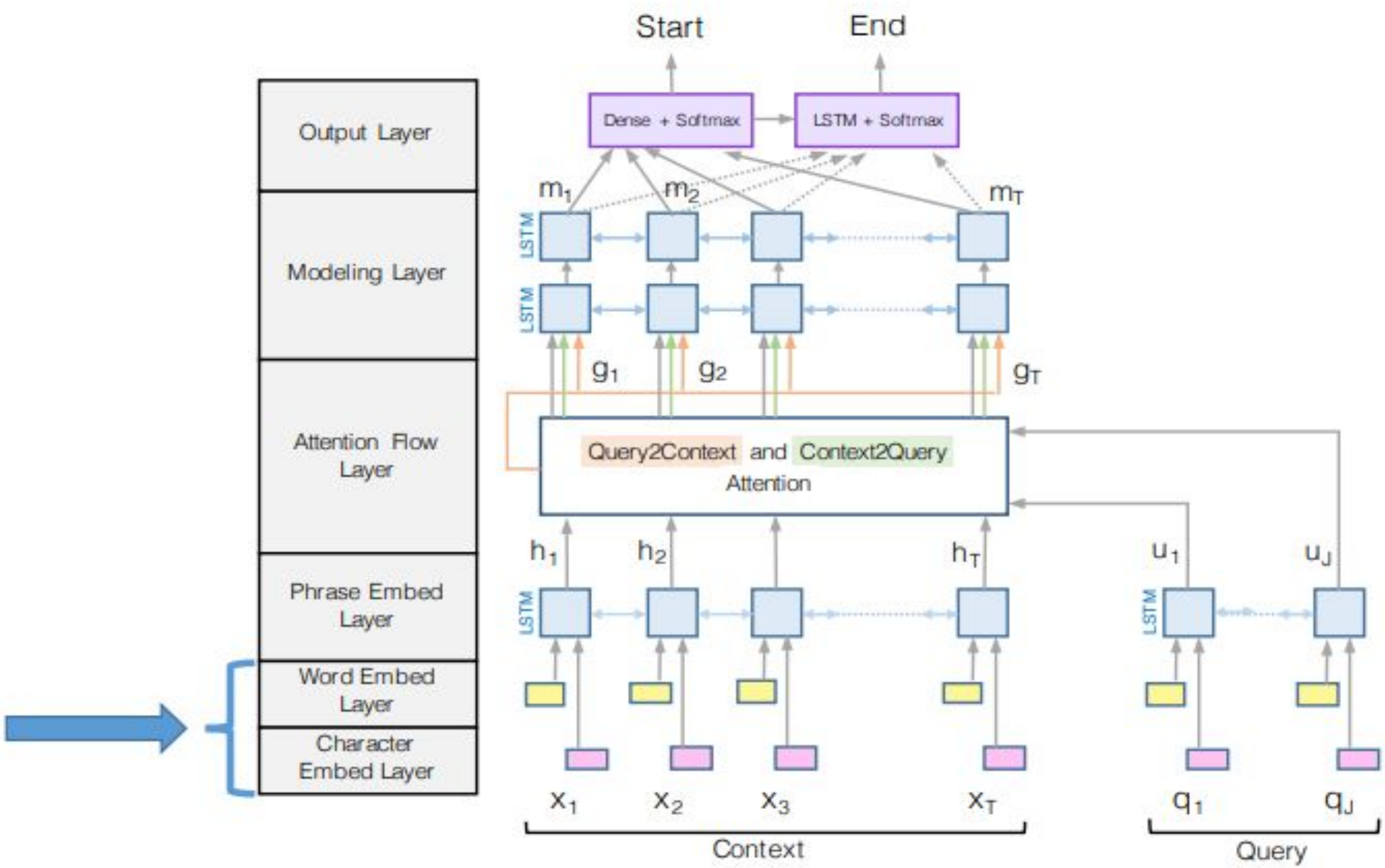
Deep Learning Approaches

(Bidirectional) Attention Flow (Minjoon et. Al, 2018)



(Bidirectional) Attention Flow

Char/Word Embedding Layers

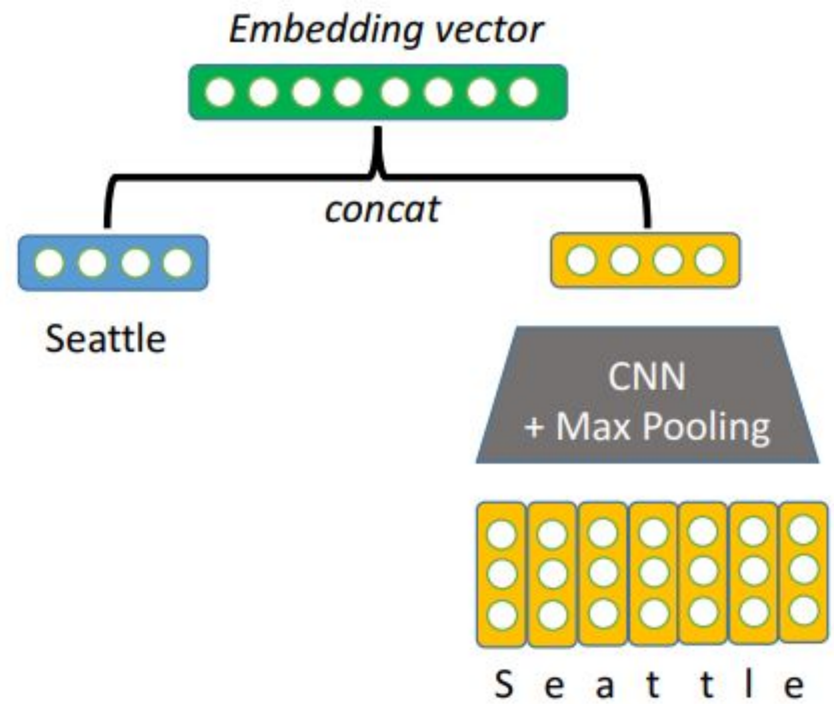


(Bidirectional) Attention Flow

Character and Word Embedding

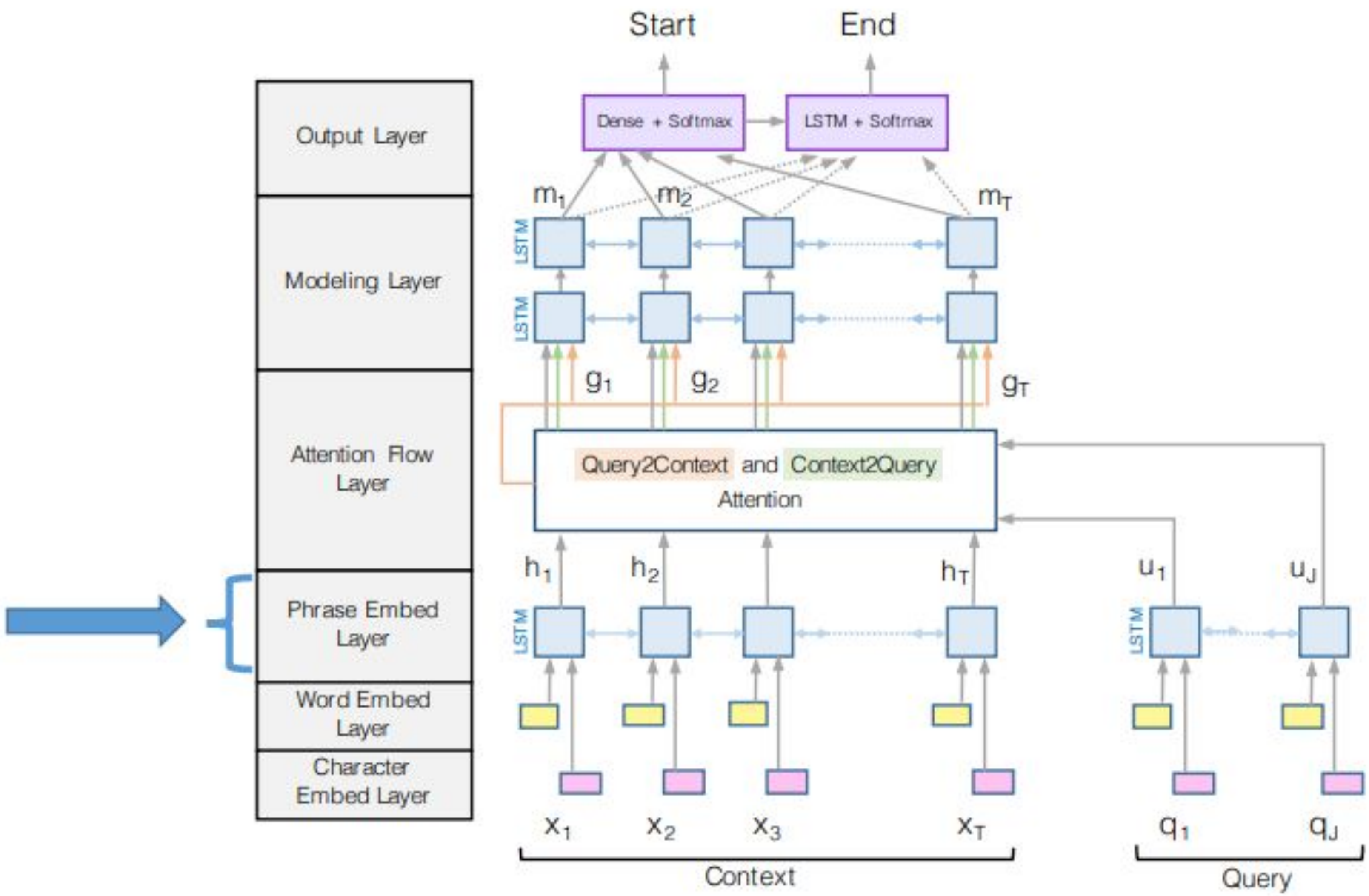
- Word embedding is fragile against unseen words
- Char embedding can't easily learn semantics of words
- Use both!

- Char embedding as proposed by Kim (2015)



(Bidirectional) Attention Flow

Phrase Embedding Layer

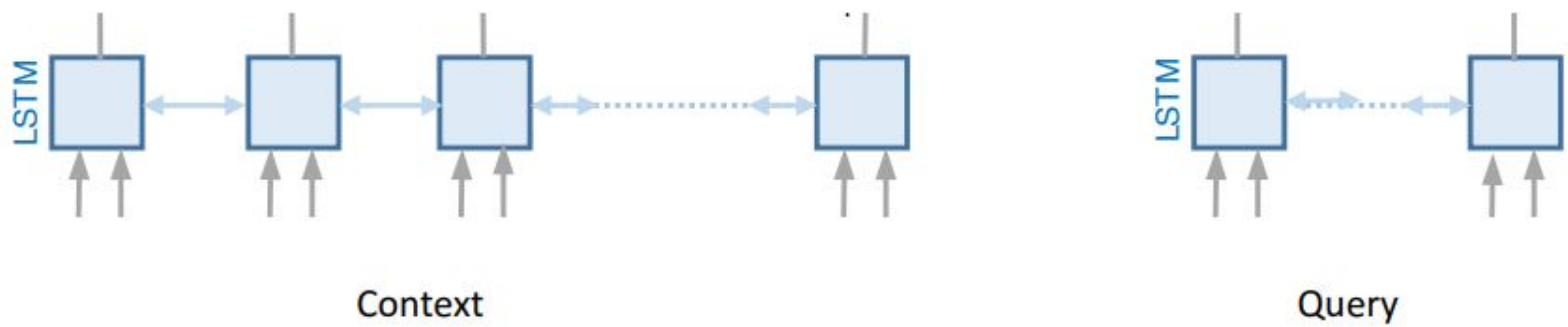


(Bidirectional) Attention Flow

Phrase Embedding Layer

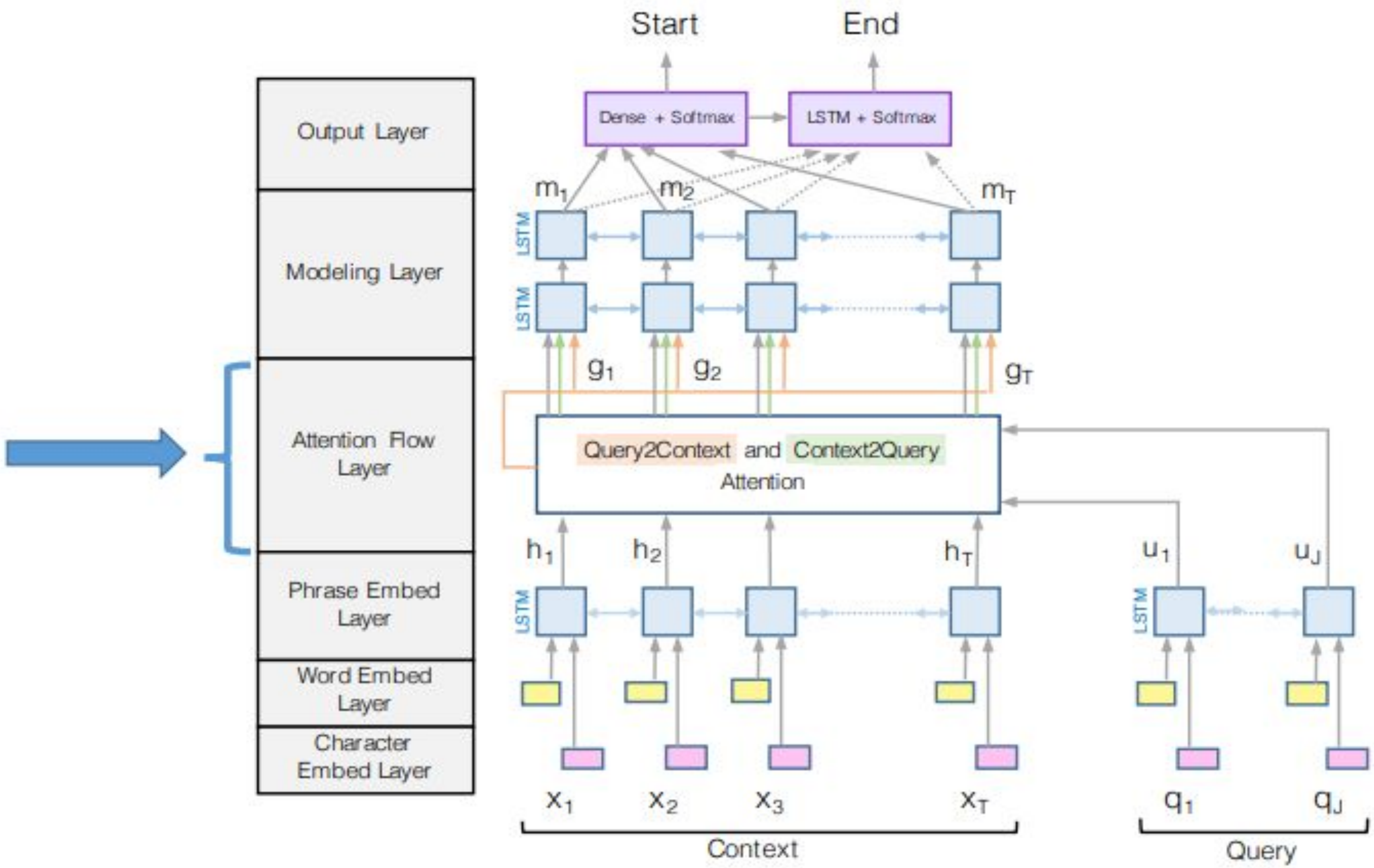
- **Inputs**: the char/word embedding of query and context words
- **Outputs**: word representations aware of their neighbors (phrase-aware words)

- Apply bidirectional RNN (LSTM) for both query and context



(Bidirectional) Attention Flow

Attention Layer



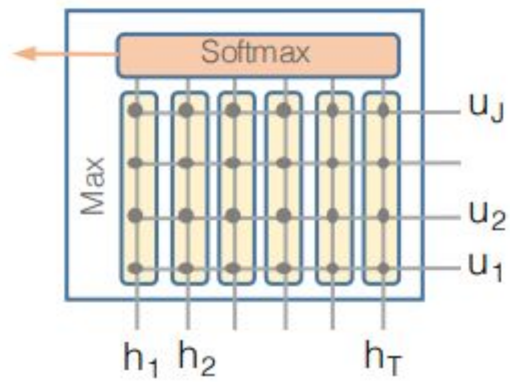
(Bidirectional) Attention Flow

Attention Layer

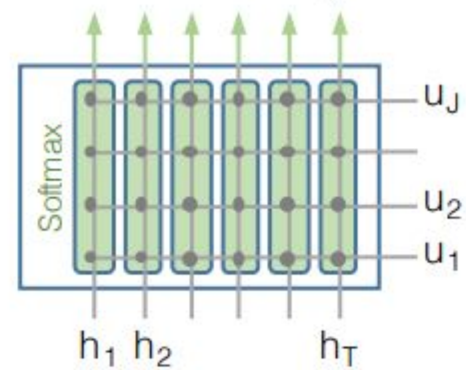
- **Inputs**: phrase-aware context and query words
- **Outputs**: query-aware representations of context words

- **Context-to-query attention**: For each (phrase-aware) context word, choose the most relevant word from the (phrase-aware) query words
- **Query-to-context attention**: Choose the context word that is most relevant to any of query words.

Query2Context



Context2Query



(Bidirectional) Attention Flow

Context-to-Query Attention (C2Q)

Q: *Who leads the United States?*

C: *Barak Obama is the president of the USA.*

For each context word, find the most relevant query word.

(Bidirectional) Attention Flow

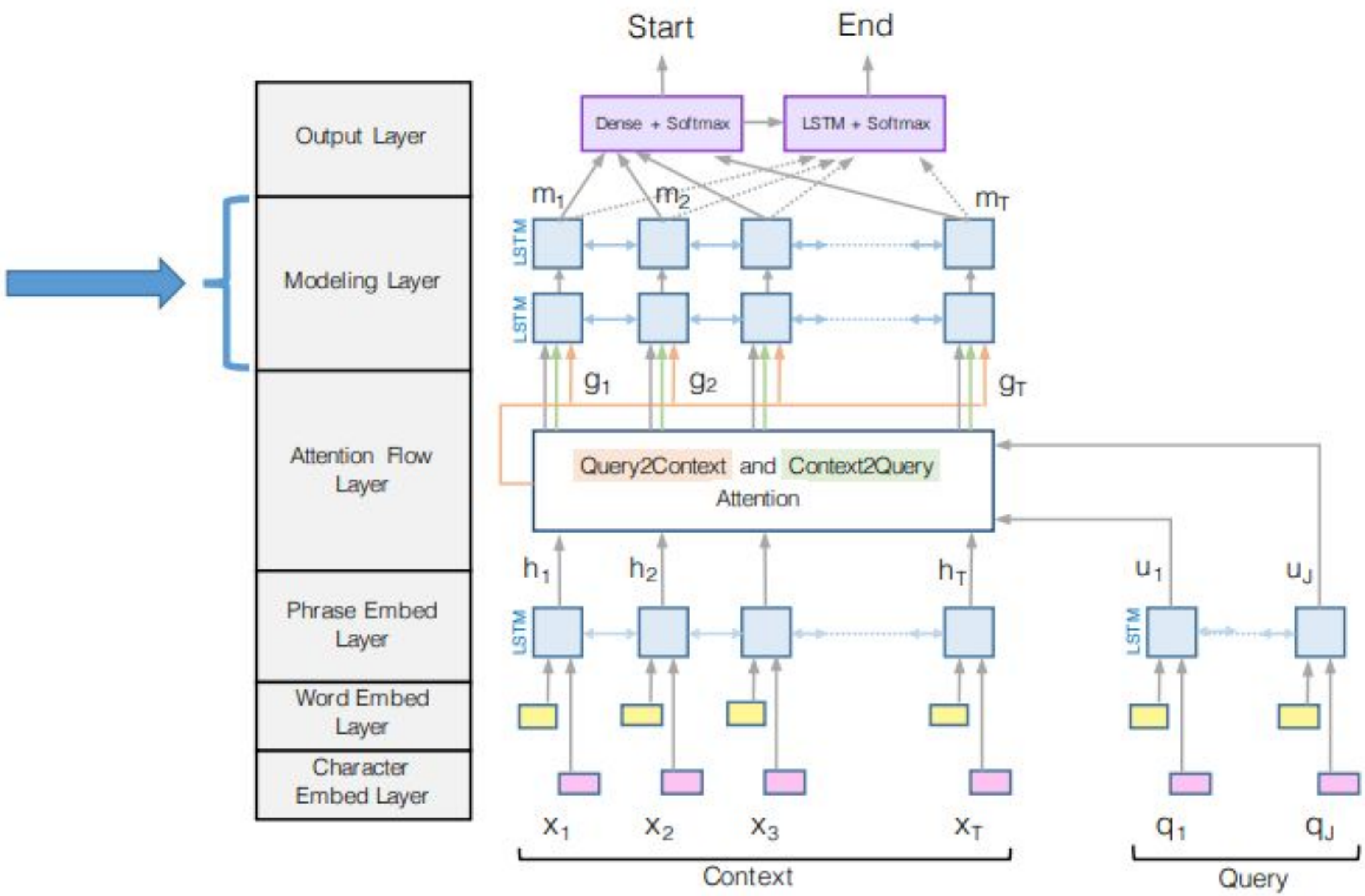
Query-to-Context Attention (Q2C)

While Seattle's weather is very nice in summer, its weather is very rainy in winter, making it one of the most gloomy cities in the U.S. LA is ...

Q: Which city is gloomy in winter?

(Bidirectional) Attention Flow

Modeling Layer



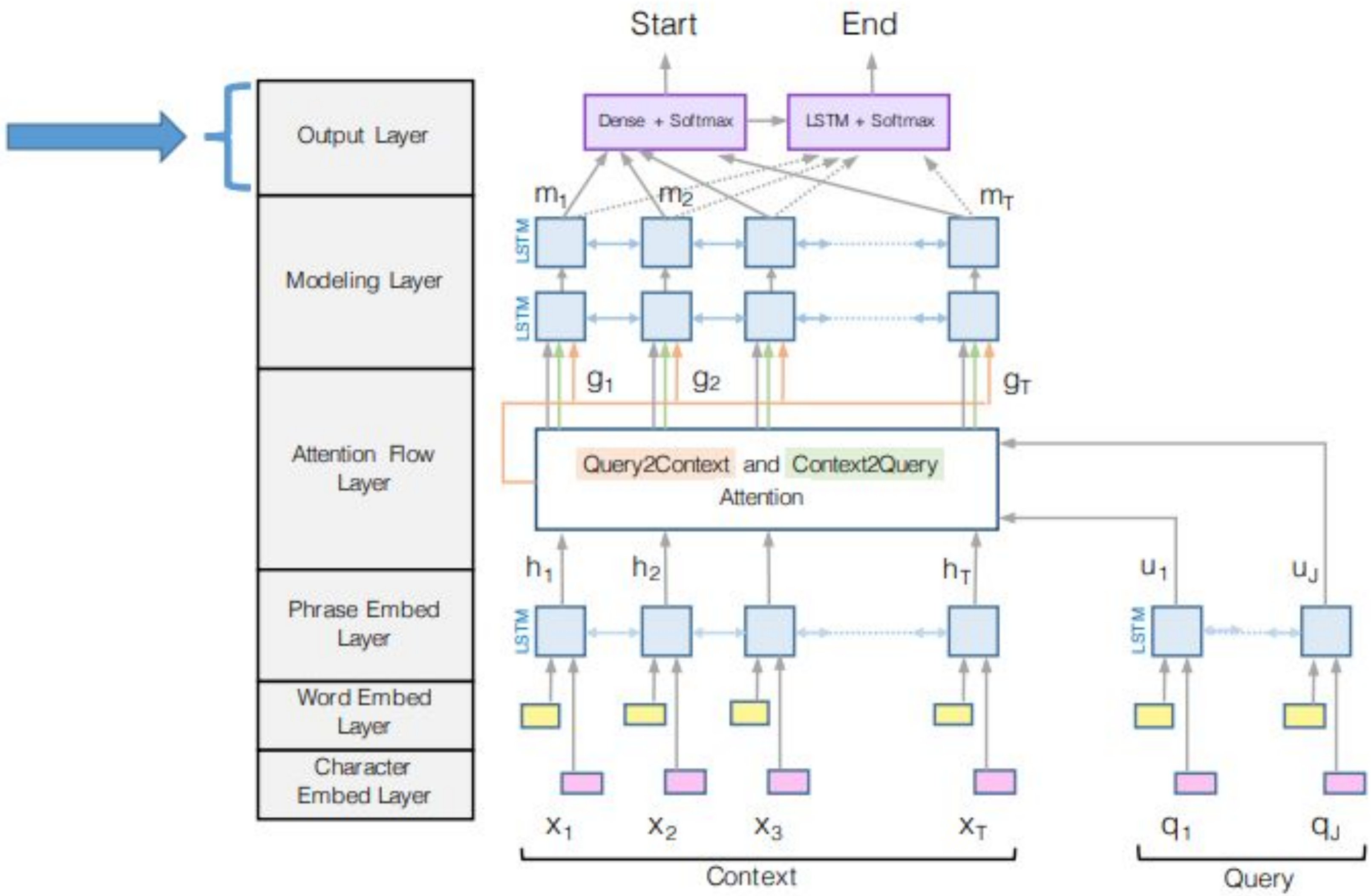
(Bidirectional) Attention Flow

Modeling Layer

- **Attention layer**: modeling interactions between query and context
- **Modeling layer**: modeling interactions within (query-aware) context words via RNN (LSTM)

(Bidirectional) Attention Flow

Output Layer



References

- Seo, Minjoon, et al. "Bidirectional attention flow for machine comprehension." *arXiv preprint arXiv:1611.01603* (2016).
- Chen, Danqi, Jason Bolton, and Christopher D. Manning. "A thorough examination of the cnn/daily mail reading comprehension task." *arXiv preprint arXiv:1606.02858* (2016).
- Manning, Christopher. "Natural Language Processing with Deep Learning CS224N/Ling284. Lecture 11." (2017).
- Brill, Eric, Susan Dumais, and Michele Banko. "An analysis of the AskMSR question-answering system." Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10. Association for Computational Linguistics, 2002.

Credit: Some of the slides are taken from the following lectures:

- https://www.slideshare.net/marinasantini1/lecture-question-answering
- https://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture10-QA.pdf