



Applications of Artificial Intelligence

– Winter Term 21/22 –

Chapter 01

Introduction

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Outline

1. AI Fundamentals

2. Natural Language Processing

3. Question Answering

4. QA Example: Watson



Artificial Intelligence (AI)

- ▶ Goal: Implement **intelligent behavior in artificial systems**

“For thousands of years, we have tried to understand how we think. [...] The field of A.I. goes further still: It attempts not just to understand but also to build intelligent entities.”

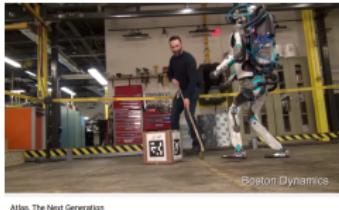
(Russel/Norvig)

- ▶ **What are examples of “intelligent behavior”?**
 - ▶ Playing checkers / chess / Go / Super Mario?
 - ▶ Planning routes? Recognizing letters in scans?
 - ▶ Automatically “understanding” text?
- ▶ **AI’s boundaries are fuzzy and ever changing!**
(“AI is whatever hasn’t been done yet.”)

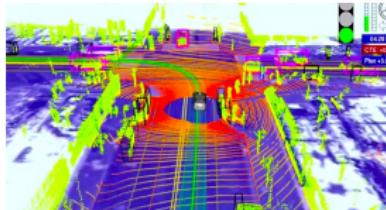


Artificial Intelligence (AI)

images: [4, 2]



Atlas, The Next Generation

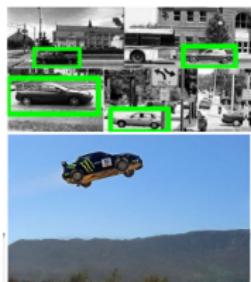


Typical Aspects of Intelligent Behavior

- ▶ reasoning, problem solving, planning
- ▶ perception, communication, (complex) acting
- ▶ learning

Scientific Goals of AI

1. ... **engineering**: build tools/solutions that are *useful*.
2. ... **epistemology**: What principles underly intelligence? Where are its boundaries?



AI has Different Facets / Lines of Research

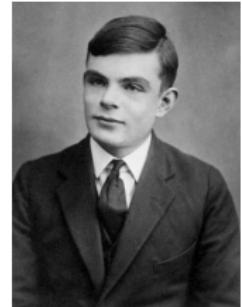
image: [1]



Thinking Humanly (cognitive science) Automating [...] activities we associate with human thinking, such as decision-making, [...], learning (<i>Bellmann 1978</i>)	Thinking Rationally (logic, deduction) The study of mental faculties through the use of computational models (<i>Charniak & McDermott, 1985</i>)
Acting Humanly (Turing test) The art of creating machines that perform functions that require intelligence when performed by people (<i>Kurzweil, 1990</i>)	Acting Rationally (agents, robots) emulate intelligent behavior in terms of computational processes (<i>Schalkoff, 1990</i>)

Acting Humanly: The Turing Test (1950)

- ▶ KI = reproducing human behavior such that a human tester **cannot distinguish** the machine from another human.
- ▶ The tester performs **text communication (chat)** with a machine and with a human.
If the tester cannot identify which partner is the machine, the machine has passed the Turing test.¹



¹Solutions are claimed to exist: <http://isturingtestpassed.github.io/>

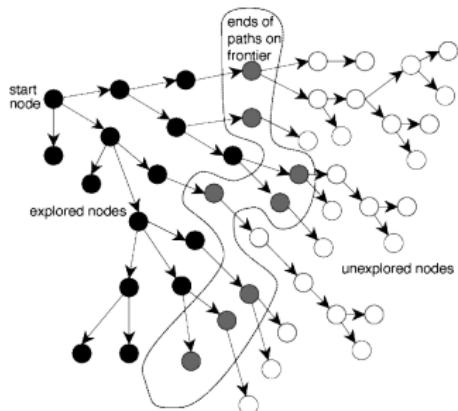
AI operates on two Levels

image: [8]



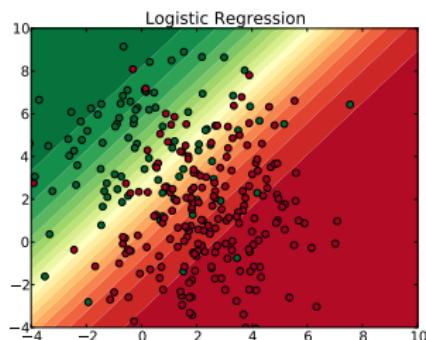
Symbolic Level

- ▶ the concept “cat”
- ▶ manipulation of **discrete** symbols
- ▶ **search** and inference
- ▶ knowledge is represented **explicitly**
- ▶ logic, knowledge graphs, rule-based systems, ...



Subsymbolic Level

- ▶ audiosignal of the word “cat”
- ▶ manipulation of **real-valued variables** / signals
- ▶ knowledge is represented **implicitly** (e.g., *in numerical vectors/matrices*).
- ▶ machine learning, optimization in \mathbb{R}^d



AI: History



Frank Rosenblatt



Marvin Minsky

1950s (“Look Ma, no Hands” – Era)

- ▶ Dartmouth Conference (1956):
the term “artificial intelligence” is coined.
- ▶ first systems
 - ▶ Logic Theorist (*proves theorems in propositional logic*)
 - ▶ Checker (*wins “checkers” against humans*)
 - ▶ General Problem Solver (*solves symbolic integration problems*)

1960s: First Disappointments

- ▶ systems work in toy worlds, but **do not scale** to realistic scenarios (*combinatorial explosion*).
- ▶ limitations in storage and compute power.
- ▶ **problems more complex** than assumed (*example: NLP*).
- ▶ basic limitations of **algorithms**
(*example: perceptron (Minsky & Papert, 1969)*).

AI: History

1980s (Knowledge-intensive Phase)

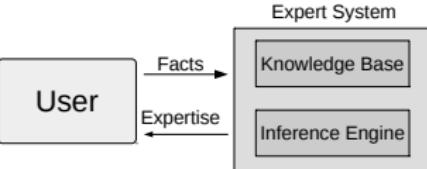
- ▶ **Subsymbolic level: neural networks**

- ▶ connection of neurons known to solve general learning tasks.

- ▶ **Symbolic level: expert systems**

- ▶ declarative, dynamic knowledge bases
 - ▶ problem solving as an inference process
 - ▶ development of expert systems

(medical diagnosis, technical troubleshooting)



1990s (AI Winter)

- ▶ AI promises do not hold up in practice.
- ▶ expert system: **maintenance** difficult.
- ▶ expert systems: **knowledge engineering** expensive (*common-sense knowledge?*).
- ▶ **neural networks**: training hard.
- massive **cuts** in AI funding.

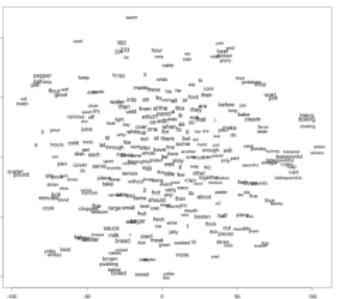
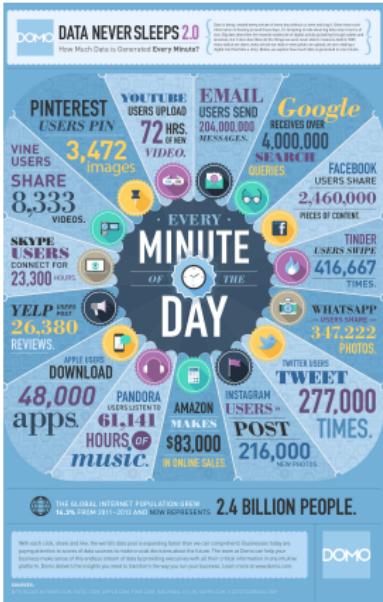
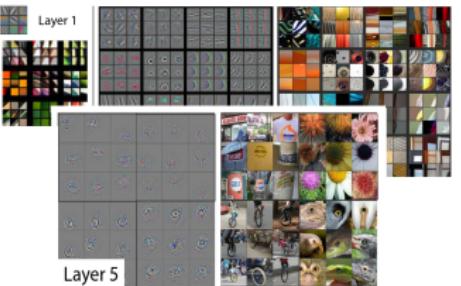


AI: History

images: [3, 9, 12]

2000s - today

- ▶ increasing relevance of AI topics (especially *machine learning*) due to *big (unstructured) data*.
- ▶ more data
 - more powerful models
 - harder problems solvable.
- ▶ “deep learning hype” (since 2012).

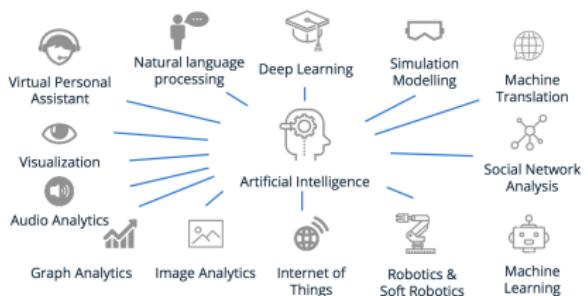


Outline



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4. QA Example: Watson

AI has many applications dealing with different data (sensors, images, graphs, ...).



source statista via @mikequindazzi

Natural Language Processing (NLP)

- ▶ NLP = automated processing of (*written*) natural language.
- ▶ NLP addresses many interesting problems: *search+recommendation, chatbots, question answering, information extraction, translation* ...

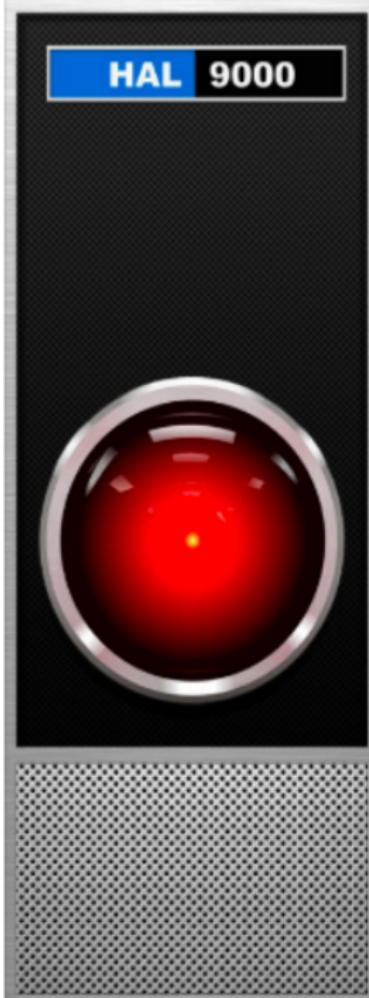


How Hard is NLP? [5]

In the 1967 Stanley Kubrick **movie** “2001: A Space Odyssey”, the spaceship’s **computer HAL** can

1. display graphics
2. play chess
3. conduct natural, open-domain conversations with humans.

How well did the filmmakers predict what computers would be capable of in 2001?



How Hard is NLP? [5]

1. Graphics

HAL



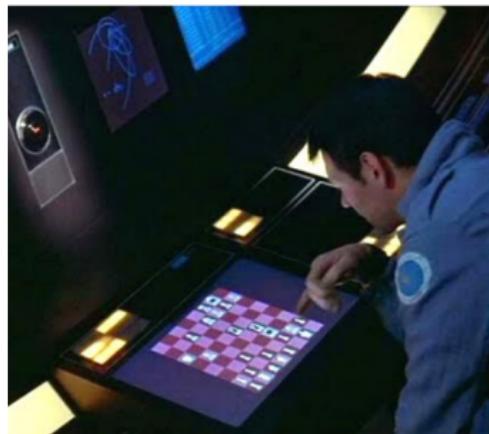
Jurassic Park (1993)



How Hard is NLP? [5]

2. Chess

HAL



Deep Blue (1997)



How Hard is NLP? [5]

3. Dialog

HAL



Siri (2011)



David Bowman: Open the pod bay doors, HAL.

HAL: I'm sorry, Dave, I'm afraid I can't do that.

David: What are you talking about, HAL?

HAL: I know that you and Frank were planning to disconnect me, and I'm afraid that's something I cannot allow to happen.

Colbert: ... I don't want to search for anything! I want to write the show!

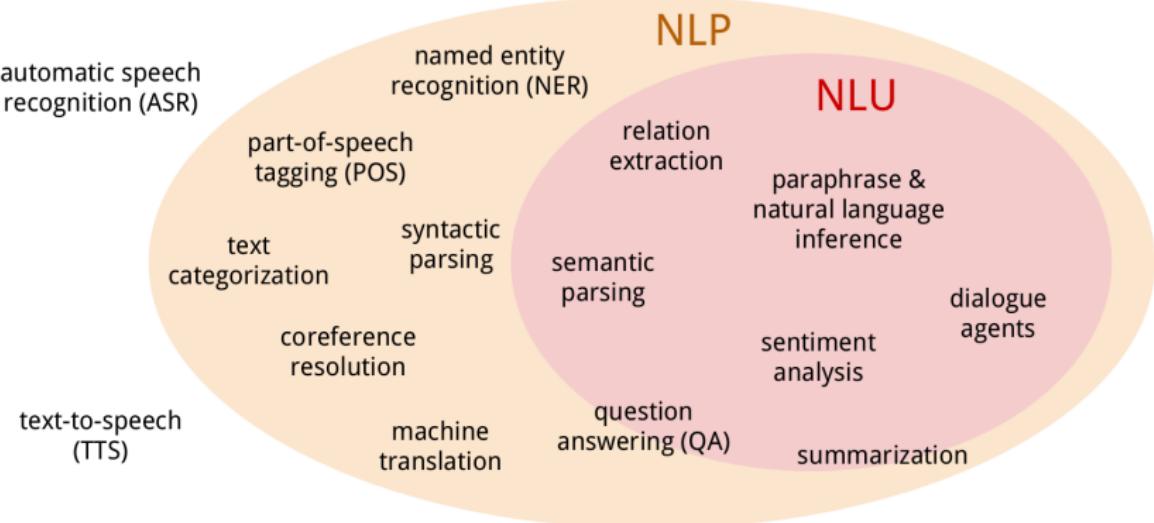
Siri: Searching the Web for "search for anything. I want to write the shuffle."

Colbert: ... For the love of God, the cameras are on, give me something?

Siri: What kind of place are you looking for? Camera stores or churches?



NLP Tasks





NLP: History

-1980s

- ▶ pattern matching with rule sets (*example: Hearst Patterns*)
- ▶ linguistically rich, grounded systems
- ▶ restricted applications

NP such as {NP,}* {(and/or)} NP → Football teams, such as the Eagles or the Patriots, ...

NP, especially {NP,}* {and/or} NP → I really like animals, especially birds of prey.

1990s - 2000s

- ▶ the “statistical revolution” in NLP → machine learning.
- ▶ focus on sparse, hand-derived representations

2010s

- ▶ significant boost in accuracy
- ▶ focus on dense, learned features (*representation learning*)
- ▶ deep learning, huge neural networks.



Today, NLP experiences an **explosion of interest!**

- ▶ voice-driven assistants (Siri, Google Now, Microsoft Cortana)
- ▶ natural-language search (Google, Facebook Graph Search)
- ▶ question answering (Google, IBM's Watson, Wolfram Alpha)
- ▶ web-scale relation extraction (Google, many startups)
- ▶ sentiment analysis for automated trading (many hedge funds)
- ▶ legal discovery (Cataphora, H5)
- ▶ business intelligence (Palantir, Quid)
- ▶ social media analytics (a zillion startups)
- ▶ content summarization (Summly, other startups)

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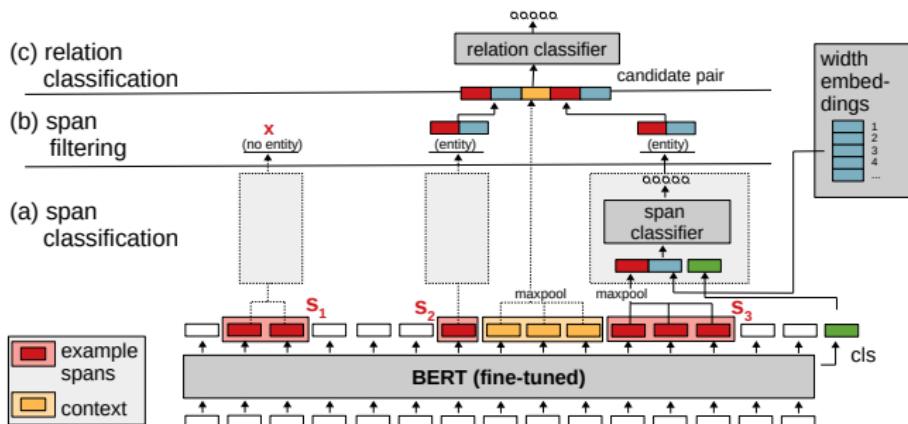
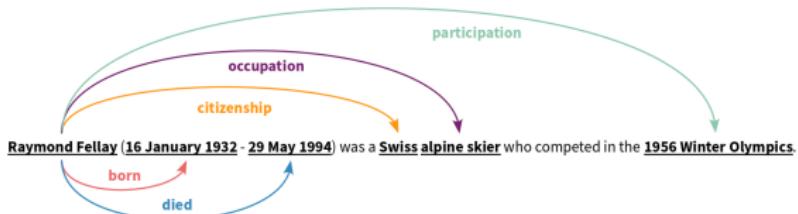


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NLP@LAVIS: Joint Entity/Relation Extraction²

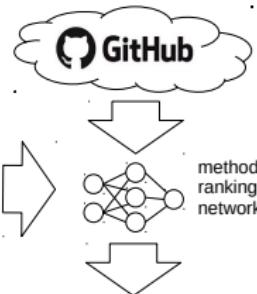


²Eberts, Ulges: Span-based Joint Entity+Relation Extraction with Transformer Pre-training (ECAI'20).

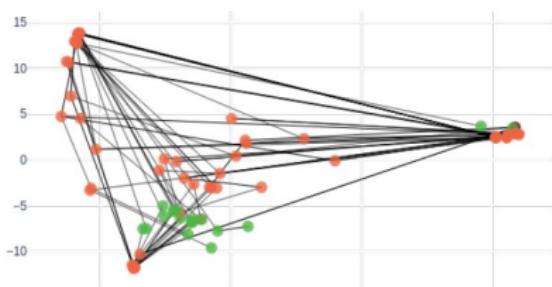
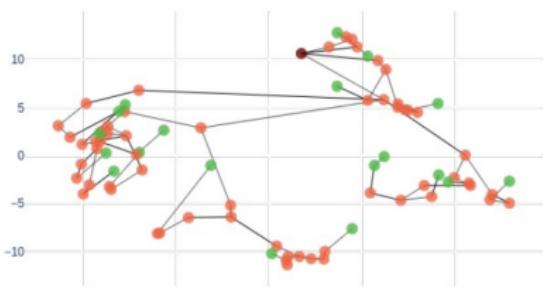
NLP@LAVIS: NLP on Source Code³



```
public class NameEntry {  
    ...  
    TextField name;  
    ...  
  
    public void setup() {  
        name = new TextField(20);  
        l = new Label(this.name);  
        add(l, Layout.WEST);  
        add(name, Layout.EAST);  
  
        h = new NameHandler();  
        name.???  
        pack();  
    }  
    ...
```



1. addActionListener	92%
2. addNotify	57%
3. setText	7%



³ Binder, Villmow, Ulges: Bidirectional Transformer Language Models for Smart Autocompletion of Source Code (SENSYBLE-Workshop'20).

Outline



1. AI Fundamentals

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3. Question Answering

4. QA Example: Watson



Question Answering (QA)



how many calories are in two slices of banana cream pie?



Web Apps

Examples

Random



When is your birthday?
Tell me a joke
What does the fox say?
Send me a poem
Do I have any photos of cats?
Cheap breakfast options?
What time is it in Beijing?
Show me high resolution photos of fruit floating threateningly at night

Where do you live?
Find me cute dog videos
Are you my friend?
Add the Google 10/4 event
Show me the news today
What is the meaning of life?
Do you speak morse code?
Who let the dogs out?

A smartphone displaying a messaging interface with the text "Ask me anything".





Question Answering: a difficult Challenge

- ▶ Where do hyenas live? → *on a Canadian airline.*
- ▶ What is the population of Maryland? → *three.*

Challenge: Interpreting the Question

"We knew that the right query was 'Who are my friends who like running?' But the poor users didn't know this. They would say 'Who are people who like to run?' or 'Who are runners?' or 'Which of my friends run?' They would express it in every conceivable way that was not 'friends who like running'—which was the only way Graph Search understood it."

(Lars Rasmussen, Facebook, 2013)

Interpreting the Target Data

"What university was Woodrow Wilson president of?"

"Woodrow Wilson (1856-1924), served as the 28th president of the USA" vs. "Woodrow Wilson was a professor at Princeton, where he acted as rector..."



Question Types image: [7]

“Factoid” Questions

- ▶ answers consist of short facts

Question	Answer
Where is the Louvre Museum located?	in Paris, France
What's the abbreviation for limited partnership?	L.P.
What are the names of Odin's ravens?	Huginn and Muninn
What currency is used in China?	the yuan
What kind of nuts are used in marzipan?	almonds
What instrument does Max Roach play?	drums
What's the official language of Algeria?	Arabic
How many pounds are there in a stone?	14

Figure 28.1 Some sample factoid questions and their answers.

- ▶ widely applied in commercial systems
- ▶ our project's focus

Complex Questions

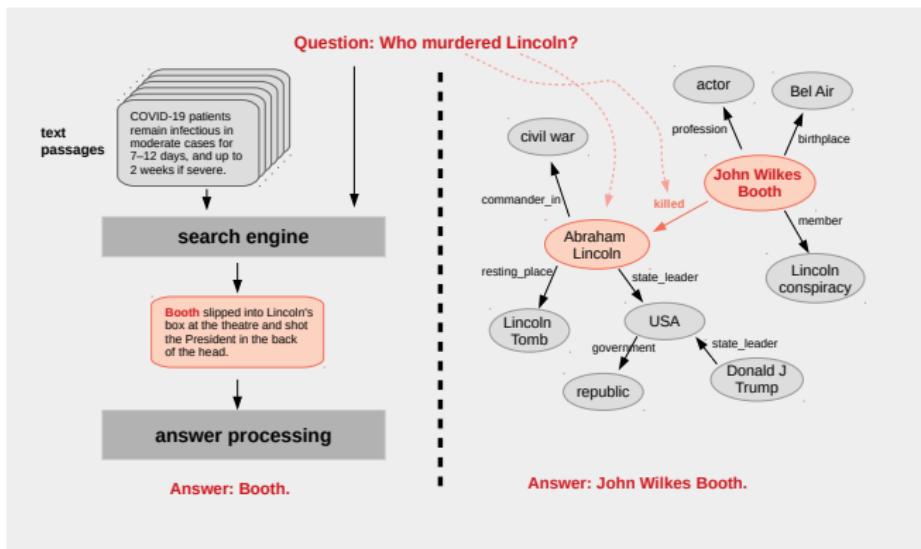
- ▶ questions with more **complex answers** (*definitions, explanations, biographies, chains of arguments*), ...
- ▶ ex.: *Why did Hitler come to power? Who is Gillian Jacobs?*
- ▶ subject to research until today.

QA Approaches

Two Paradigms

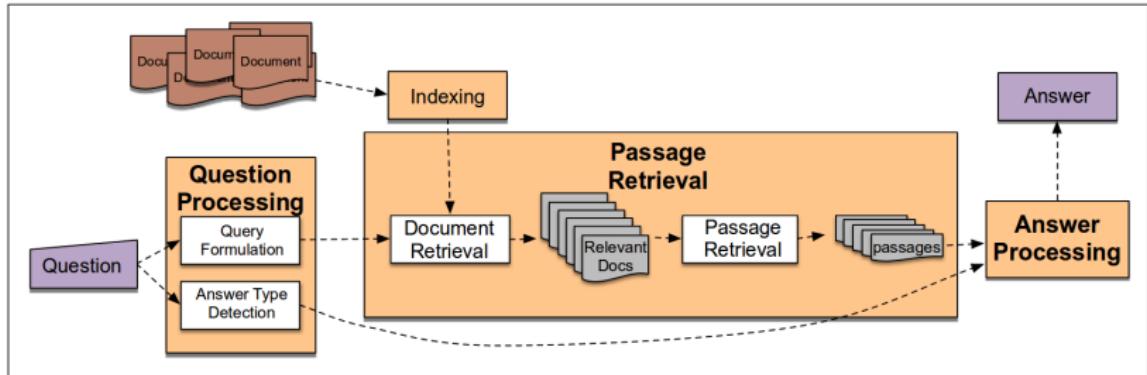
1. IR based (*Google Assistant*)
2. knowledge based (*Siri, Wolframalpha*)

Modern systems are usually **hybrids** (e.g., *Watson*)



IR based QA

image: [7]



- ▶ Knowledge base comes as **natural language text**.
- ▶ Three processing steps
 1. Question Processing
 2. Passage Retrieval (*find the right passages*)
 3. Answer Processing
- ▶ Use of **information retrieval** (Step 2) and **machine learning** (Steps 1+3)



1) Question Processing

Task

Gain information on the question (*and, hence, its answer*)

- a) **answer type**
- b) **query formulation**
- c) **relations**
- d) the **focus** (*the term that would be replaced in the answer*)

Example

“What Shakespearean play featured Shylock ?”

answer type	ENTY/cremat ⁴
query	shakespeare shylock
relations	appearsIn(shylock, ?) \wedge author(Shakespeare, ?)
focus	“what Shakespearean play”

⁴This class contains “inventions, books and other creative pieces”



1a) Question Processing: Answer Type image: [7]

"Who founded Virgin Airlines" → PERSON/INDIVIDUAL

"What Canadian centre has the largest population?" → GEO/CITY

- ▶ estimates the type of **answer** expected for the question
- ▶ is used to **filter** answer candidates
- ▶ is also called "**question classification**"
- ▶ see typical classes below

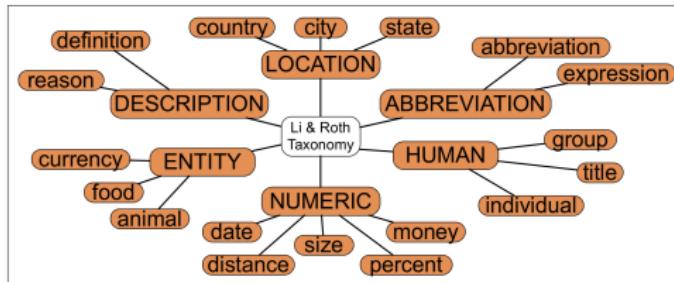


Figure 28.3 A subset of the Li and Roth (2005) answer types.

1b) Question-Processing: Query Extraction



What war added 'jeep' and 'quisling' to the English language ?

- ▶ We formulate a **query**.
- ▶ Why not simply use the **question**? Because it is better to prioritize key terms!

Example Prioritization [10]

1. *words in quotation marks*
2. *NNPs (singular nouns) in named entities*
3. *nominal groups with adjectives*
4. *other nominal groups*
5. *nouns with adjectives*
6. *all other nouns*
7. *verbs*
8. *adverbs*
9. *the focus term*
10. *all other words*

- ▶ We can formulate **multiple queries** (*recall matters!*)

Passage Retrieval: Example



Question

"Who was Queen Victoria's second son?"

Candidate Passages

The Marie biscuit is named after Marie Alexandrovna, the daughter of Czar Alexander II of Russia and wife of Alfred, the second son of Queen Victoria and Prince Albert.

Victoria (Alexandrina Victoria; 24 May 1819 – 22 January 1901) was Queen of the United Kingdom of Great Britain and Ireland from 20 June 1837 until her death. From 1 May 1876, she adopted the additional title of Empress of India.

Queen Victoria Hotel offers Aristocratic heritage with discreet service and tasteful décor. Located in Cape Town Central, the hotel offers airport transportation, babysitting, ...



Frequent approach: supervised learning from sample data
(= questions + labeled passages)

Features used

1. **match with answer type:** How many entities in the passage have the right answer type (*z.B. PERSON/individual?*)?
2. **match with question:** How many keywords from the question are in the passage? How many **n-grams**? How **close** are keywords to each other?
3. **match with document:** What was the document's rank in document search?
4. **passage importance:** Is the passage at the document's beginning? Does it contain Wikipedia anchor terms?



3) Answer Processing

Abraham Lincoln was assassinated by John Wilkes Booth on Good Friday, April 14, 1865, while attending a play at Ford's Theatre as the American Civil War was drawing to a close.

Possible Approaches

- ▶ limit to named entities
- ▶ take the type of named entities into account
- ▶ proximity to other terms from the query
- ▶ use sentence structure / parse tree
- ▶ use term similarities (*word2vec, PPMI, Resnik*)?
- ▶ use generalization/specialization (*beagle is_a dog*)
- ▶ formulate patterns (*does “born in” appear?*)
- ▶ novelty (*answer+question should not overlap*)

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IBM Watson[6]

The “Jeopardy Challenge”

- ▶ Jeopardy = popular US quiz show
- ▶ hints (“questions”) with factoid answers
- ▶ Questions come in categories



Category	Literary Monsters
Clue	<i>Assembled from dead bodies, the monster in this Mary Shelley book turns against his creator.</i>
Answer	<i>Frankenstein.</i>

- ▶ Some question categories are quite specific

Category	Rhyme Time
Clue	<i>It's where Pele stores his ball.</i>
Answer	<i>Soccer locker.</i>

IBM Watson[6]

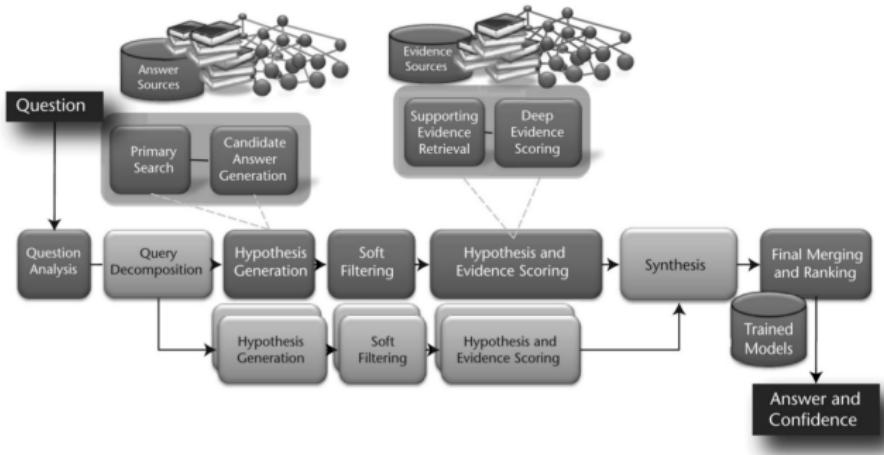
- ▶ team of 20 engineers, 3 Jahre (+ previous prototypes)
- ▶ system achieves **human performance**
 - ▶ ... answers 70 % of all questions (accuracy = 80 %)
 - ▶ ... 3 seconds response time (*on dedicated hardware*)

Knowledge Base I: 20,000 question-answer pairs, labeled with ...

- ▶ ... **question type** (z.B. "rhyme", "definition", "math", ...)
- ▶ ... 2,500 different **Lexical Answer Types (LATs)**
(*z.B. song, president, he ...*)
- ▶ ... semantic **relations**
(*z.B. person_birthplace, product_producer, ...*)

Knowledge Base II: Corpora

- ▶ **text corpora:** Wikipedia, news articles, literature
(*all expanded with web documents*)
- ▶ **databases** (e.g., IMDB) and **knowledge graphs**.

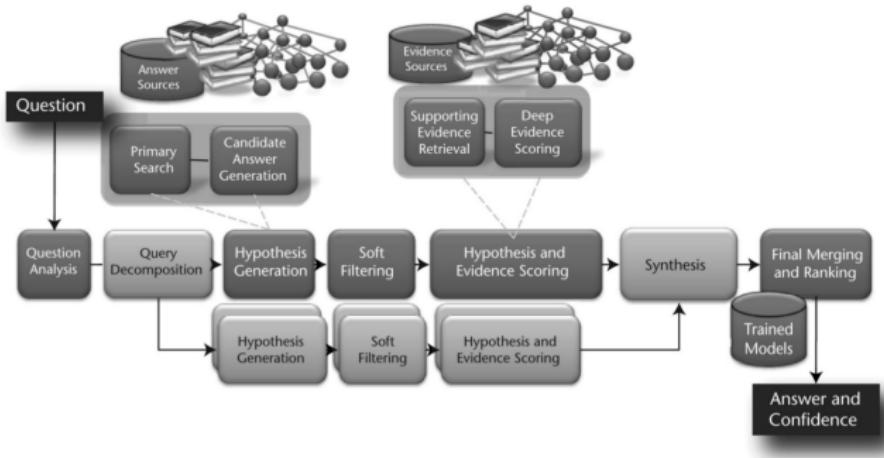


Approach

- ▶ similar to **classical IR QA**
- ▶ many additional analysis steps, > **100 modules**
- ▶ Idea: generate as many candidates as possible (>> 100), rank these.



image: [6]



Approach (cont'd)

- ▶ **information extraction** (*entities + relations*)
- ▶ **NLP techniques**: coreferences, parse trees, extraction of *logical forms*, ...
- ▶ **Wikipedia link analysis** (anchor terms are better candidates)
- heavy use of **machine learning**.

Watson: Evidence Scoring

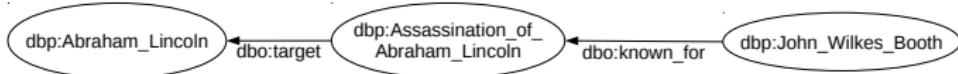
> 50 components score candidate answers:

1. Passage retrieval with query = question + candidate answer
(how much evidence do we find?)

```
q = question(Abraham Lincoln murdered) +
    answer(John Wilkes Booth) → 27 hits
```

1. President Lincoln is shot in the head at Ford's Theatre ...
2. Abraham Lincoln, now viewed as a martyr who ended slavery ...
3. ...

2. use knowledge graphs



1 match of medium quality (path length 2, confidence 98%)

3. term overlap between question + answer passage
(tf-idf oder sequence length [11])

Question: Who murdered Lincoln at Ford Threater?

Passage: President Abraham Lincoln is shot in the head at Ford Theatre
in Washington, D.C. The assassin, actor John Wilkes Booth, ...

Maximum Overlap (Smith-Waterman Algorithm): 13 characters

Watson: Evidence Scoring



4. **structure comparison** between answer and question
(logical forms)
5. **popularity** of target documents (e.g., *PageRank*)
6. **(simple) reasoning**: spatially, temporally, taxonomically

Question: Who murdered Lincoln on April 14 1865?

Answer 1: Lee Harvey Oswald

temporal reasoning

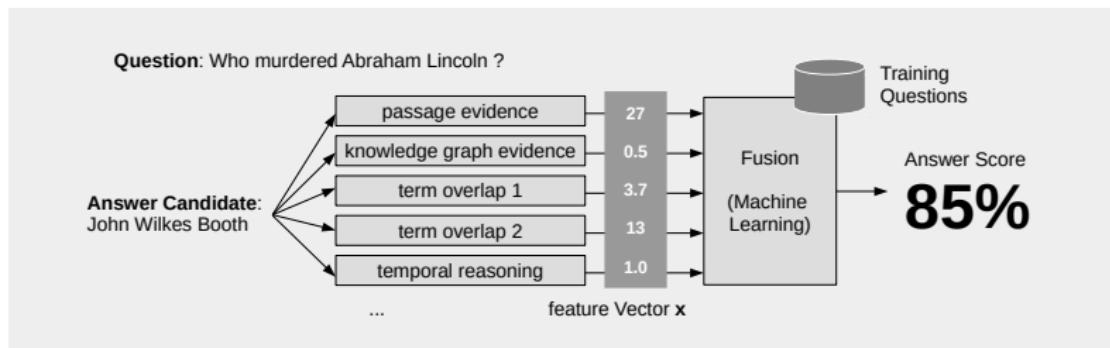
unlikely (born in 1939)

Answer 2: Ford's Theatre

taxonomic reasoning

unlikely (not is_a person)

A machine learning combines the resulting scores to a **ranking**:





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