Question Answering

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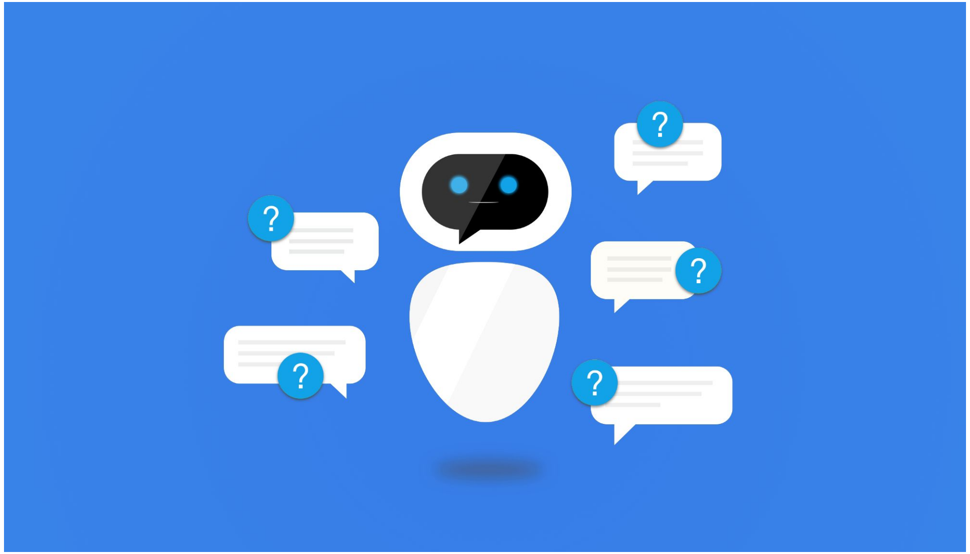
Today

- What is question answering?
  Why so many?
- Reading comrehension
- Open domain question answering
- KBQA
- Chatbots



QA Goal

The goal of question answering is to build systems that automatically correctly answer questions posed by humans in a natural language.

QA Systems

- What information source does a system build on?
  - a text passage
  - all Web documents
  - knowledge bases,
  - images..
- Answer type
  - a short segment of text
  - a paragraph
  - a list
  - yes/no, …
- Question type
  - Factoid vs non-factoid
  - open-domain vs closed-domain
  - simple vs compositional

QA Systems

QA through years

Setting	Closed-domain	Open-domain	Reading compre-hension	Open-domain	Conversation-al, multi-hop, multilingual
Method-ology	Hand-engi-neered parsers	IR + shallow linguistic analysis	Document reader	IR + document reader	IR + document reader
Systems, datasets	LUNAR, QUALM	TREC QA	CNN / Daily Mail, SQuAD	Natural Questions	CoQA, TyDiQA, HotPotQA
Years	1970s–1990s	2000s	2013–today	2019–today	2020–today

QA Systems

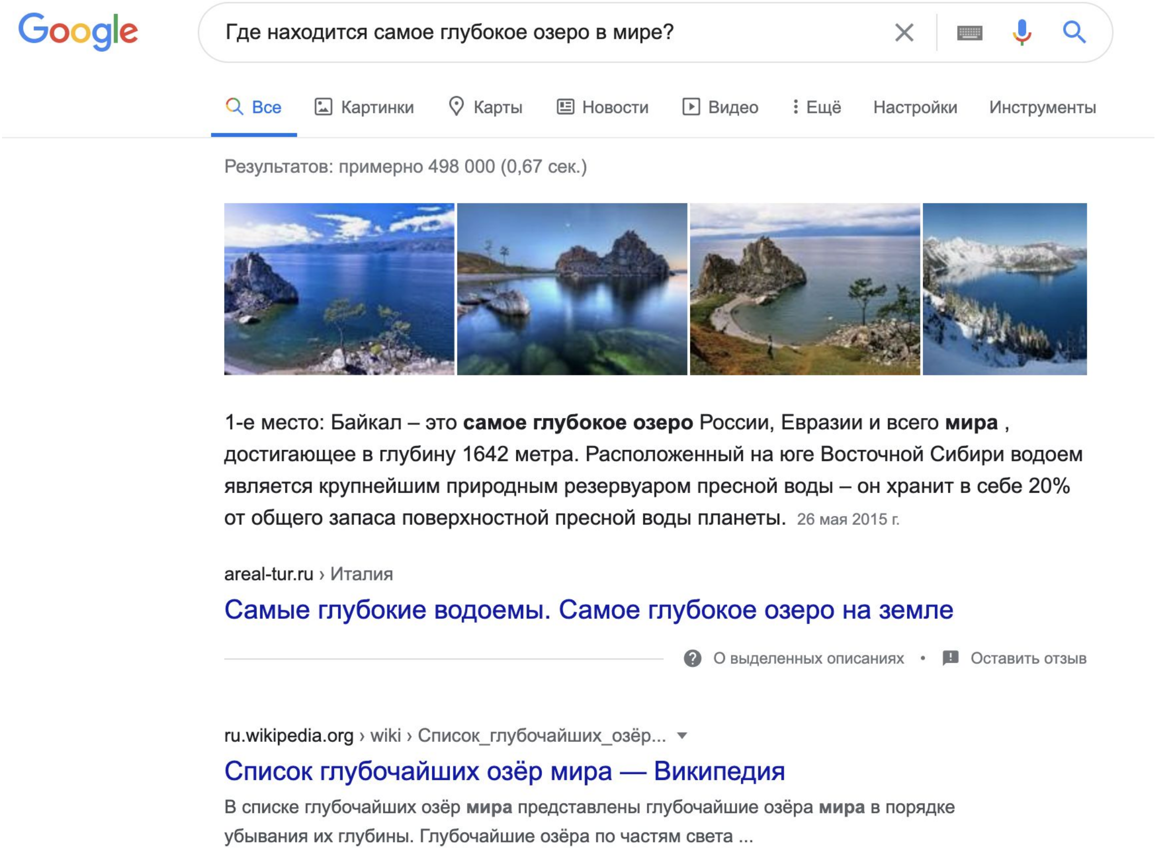
Processes automation and engineering

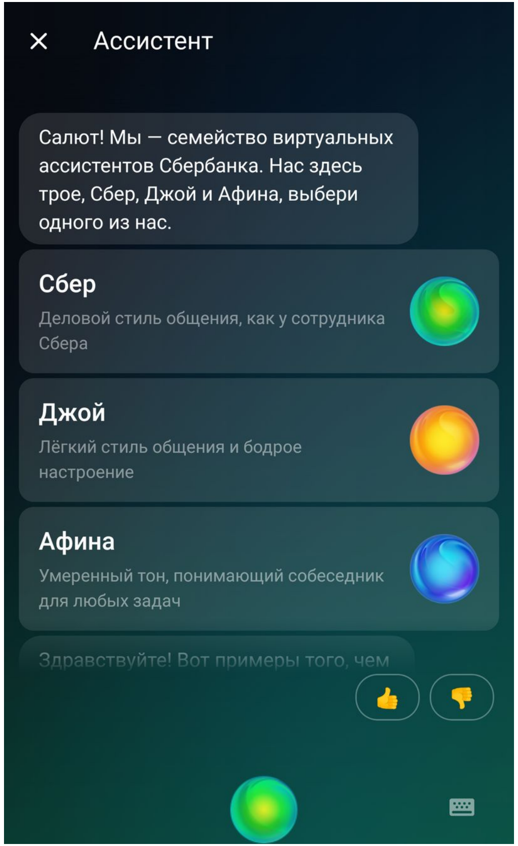
- QA goal applications
- Chatbots
- Call centers
- Study projects
- etc.

Research and Science

- Turing test
- AI

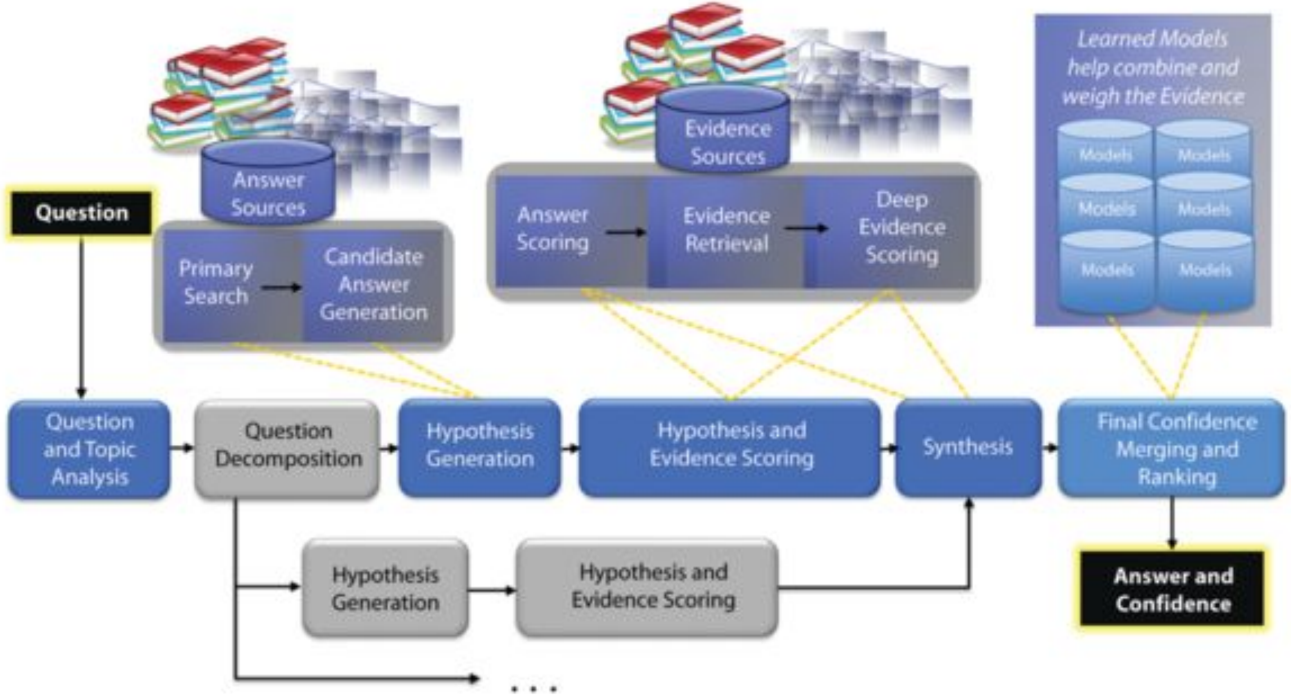
QA Systems. Application





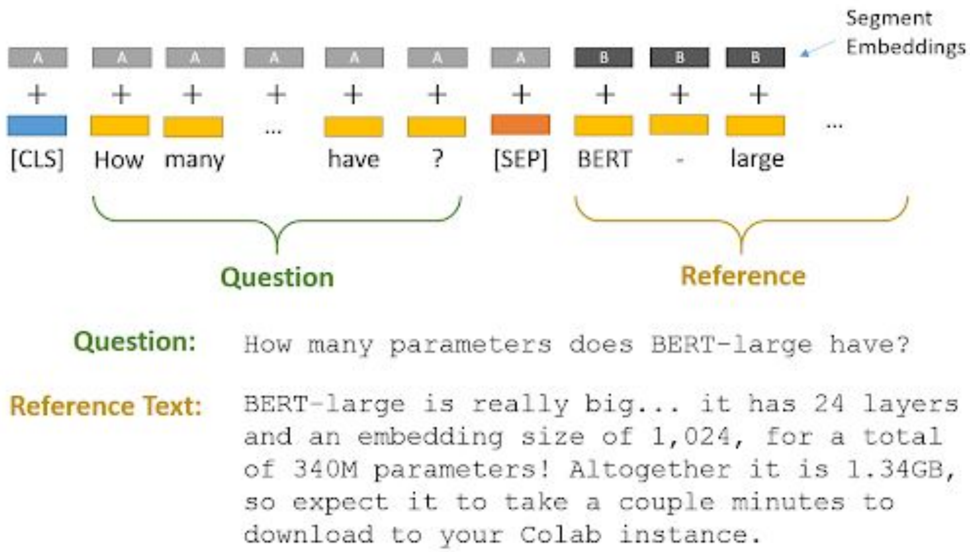
QA Systems. DeepQA

IBM Watson beated Jeopardy champions



https://archive.org/details/Jeopardy.2011.02.The.IBM.Challenge/Jeopardy.2011.02.14.The.IBM.Challenge.Day.1.HDTV.XviD-FQM.avi?utm_campaign=NLP%20News&utm_medium=email&utm_source=Revue%20newsletter

Question answering now



Almost all the state-of-the-art question answering systems are built on top of end-to-end training and pre-trained language models

QA Systems

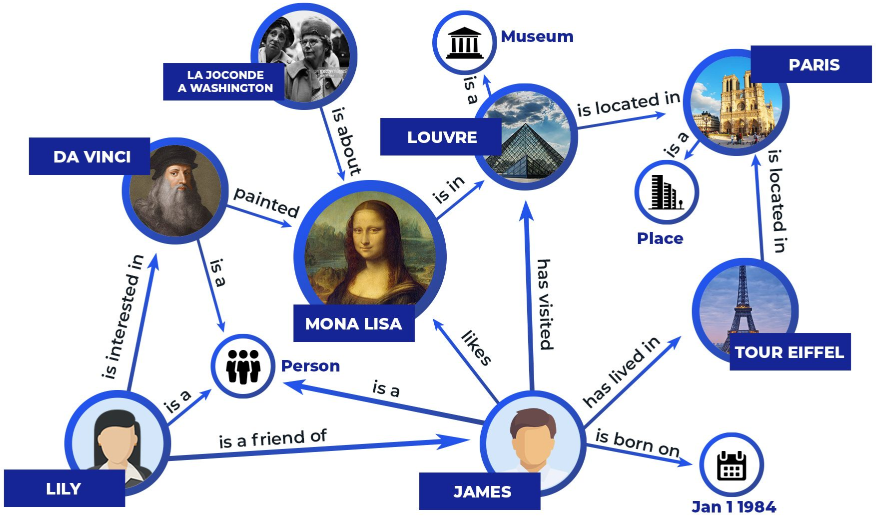
How to answer unstructed texts? Or not only texts?

Who painted Mona Lisa?

Semantic parsing

Relations and KB

Leonardo DaVinci



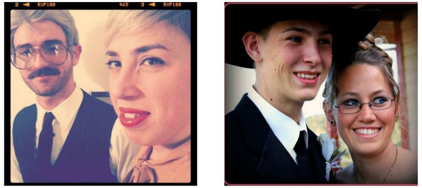
QA Systems

Reasoning and common sense in multi-domain

QA with images

Who is wearing glasses?

man woman



Where is the child sitt

fridge arm

Is the umbrella upside down?

yes no

How many children are in the bed?

2 1

VQA https://visualqa.org/

Example (a)

இரு படங்களில் ஒன்றில் இரண்டிற்கும் மேற்பட்ட மஞ்சள் சட்டை அணிந்த வீரர்கள் காளையை அடக்கும் பணியில் ஈடுப்பட்டிருப்பதை காணமுடிகிறது.

(Translation: *In one of the two photos, more than two yellow-shirted players are seen engaged in bul taming.*)

Label: **TRUE**

MarVL
https://marvl-challenge.github.io/

The Answer to the Ultimate Question of Life, the Universe, and Everything

ANSWER
What do the answers look like?

42

QUESTION
How does the question look like (taxonomy)?

SOURCE
Where can I get the answers from?

Answers

- Factoid
- Yes/no
- Opinion/Info
- Explanation
- Document
- A sentence or paraphraph extracted
- Another question
- etc.

Questions

One-hop (single-hop) question is the question that can be answered based on a single sentence from a passage.

Multi-hop question is a question that requires reasoning over information spread across several sentences in a passage.

(1) Mother bought apples. (2) They were on the table. (3) John has never eaten apples, that's why he couldn't stand it and tried one.

Question: ”Where were fruits that were eaten by a boy?”

The question is multi-hop since the answer can be obtained with only information aggregated from more than one sentence (coreference resolution and general language understanding).

Reading Comprehension

- Reading comprehension = comprehend a passage of text and answer questions about its content (P, Q) $\longrightarrow$ A

"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum."

Question

- Reading comprehension task: build a system to comprehend a passage of text and answer questions about its content (P, Q) $\longrightarrow$ A

Reading Comprehension

Why Reading comprehension is important?

- Useful in many complex practical applications
- Evaluation of how well computer systems understand human language

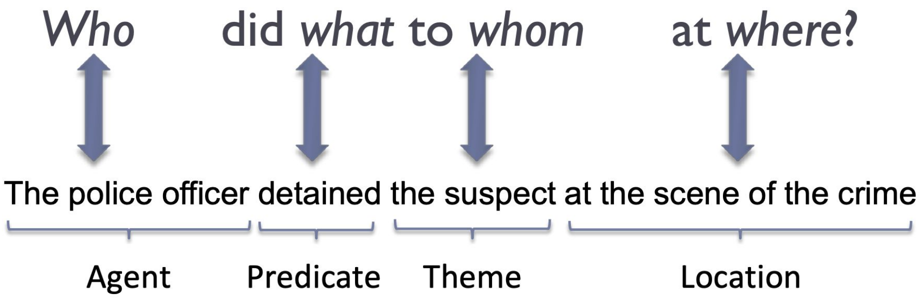
"Since questions can be devised to query any aspect of text comprehension, the ability to answer questions is the strongest possible demonstration of understanding."

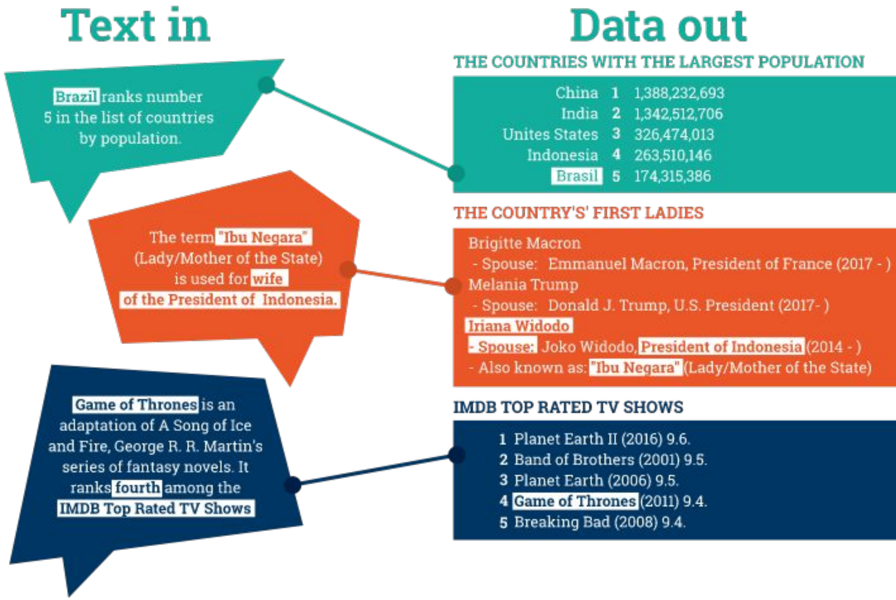
(Wendy Lehnert 1977)

Reading Comprehension

Many complex NLP tasks can be reduced to a reading comprehension problem:

- Semantic Role Labeling
- Information extraction





Reading Comprehension

Problem formulation:

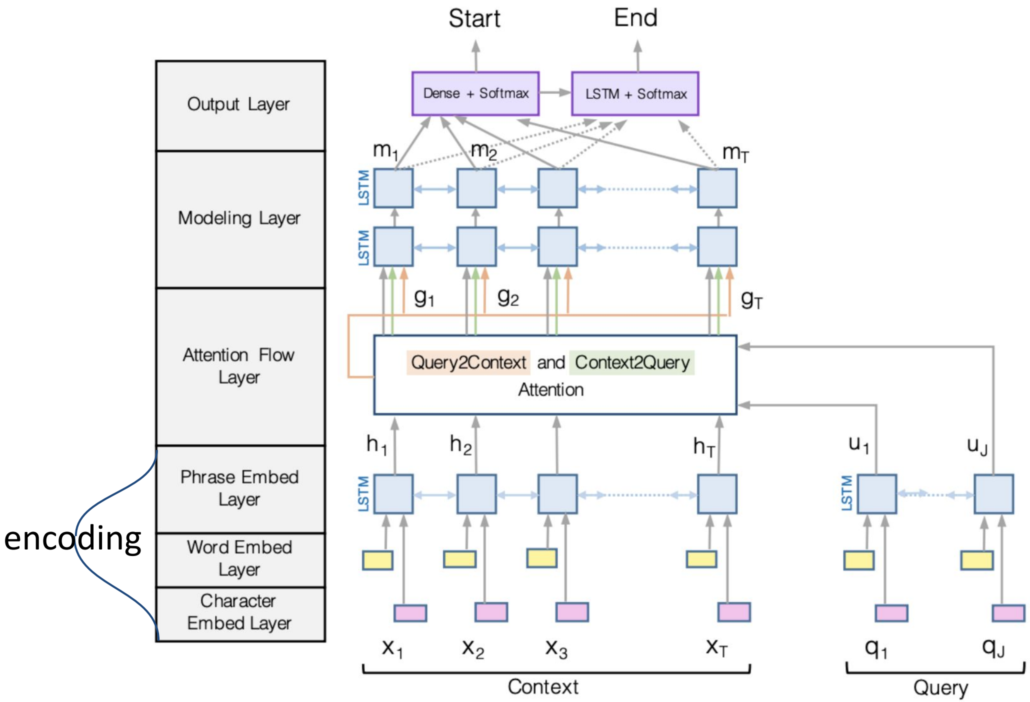
- *Input*: $C = (c_1, c_2, \ldots, c_N)$ $Q = (q_1, q_2, \ldots, q_M)$ c_i , $q_i \in V$
- *Output*: $1 \leq \text{start} \leq \text{end} \leq N$

answer is a span in the passage

- A family of LSTM-based models with attention (2016-2018)

  Attentive Reader, Stanford Attentive Reader, MatchLSTM, BiDAF, Dynamic coattention network...
- Fine-tuning BERT-like models for reading comprehension (2019+)

biDAF. Bidirectional Attention Flow model



Attention Flow Idea: attention should flow both ways – from the context to the question and from the question to the context.

$$p_{\text{start}} = \text{softmax}(\mathbf{w}_{\text{start}}^{\mathsf{T}}[\mathbf{g}_i; \mathbf{m}_i]) \qquad p_{\text{end}} = \text{softmax}(\mathbf{w}_{\text{end}}^{\mathsf{T}}[\mathbf{g}_i; \mathbf{m}'_i])$$

$$\mathbf{m}'_i = \text{BiLSTM}(\mathbf{m}_i) \in \mathbb{R}^{2H} \quad \mathbf{w}_{\text{start}}, \mathbf{w}_{\text{end}} \in \mathbb{R}^{10H}$$

biDAF. Bidirectional Attention Flow model

Attention Flow Idea: attention should flow both ways – from the context to the question and from the question to the context.

- Concatenation of word embedding (GloVe) and character embedding (CNNs over character embeddings) for each word in context and query
- Two bi-LSTMs separately to produce contextual embeddings for both context and query
- Context-to-query attention: For each context word, choose the most relevant words from the query words
- Query-to-context attention: choose the context words most relevant to one of query words.
- Attention layer is modeling interactions between query and context
- Modeling layer is modeling interactions within context words
- Output layer: two classifiers predicting the start and end positions

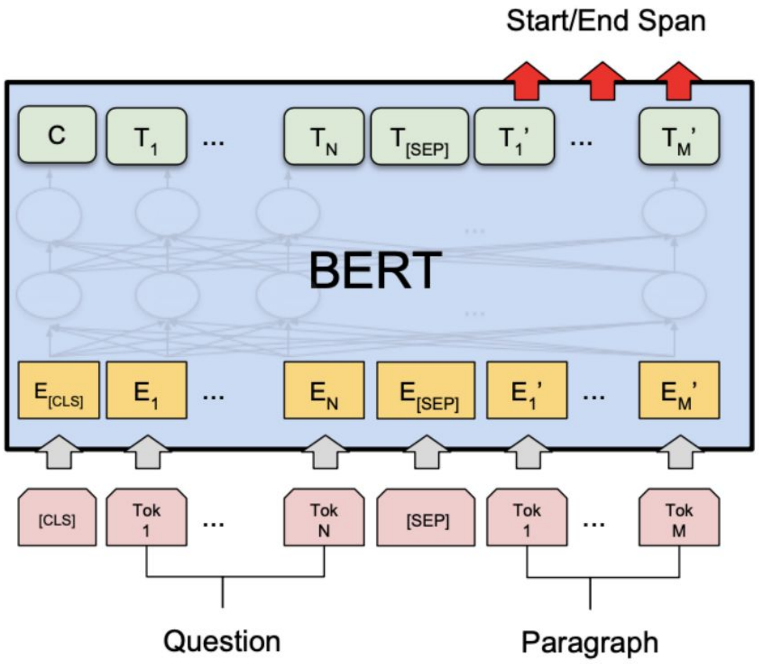
Reading comprehension with BERT

$$L = -\log p_{start}(s^*) - \log p_{end}(e^*)$$

$$p_{end}(i) = \text{softmax}_i(w'_{end}H)$$
$$p_{start}(i) = \text{softmax}_i(w'_{start}H)$$

where $H = [h_1, h_2, ..., h_N]$ are the hidden vectors of the paragraph, returned by BERT

All the BERT parameters (~110M) as well as H_{start} and H_{end} (e.g., 768 x 2 = 1536) are optimized together for L



SQUAD dataset

SQUAD

Dataset size (Russian): 50k questions
Dataset size (English): 100k questions
Task: Find the answer and direct span for the question in text
Evaluation: exact match (0 or 1) and F1 (partial credit)

Model config	EM (dev)	F-1 (dev)
DeepPavlov RuBERT	66.30+-0.24	84.60+-0.11
DeepPavlov multilingual BERT	64.35+-0.39	83.39+-0.08
DeepPavlov R-Net	60.62	80.04

Example

Passage: Первая школа в Манитобе была основана в 1818 году католическими миссионерами в городе Виннипег, первая протестантская школа была учреждена в 1820 году. Провинциальное Управление образования было учреждено в 1871 году, оно отвечало за государственные школы и учебные программы, ...

Question: *Кем была в 1818 году основана первая школа в Манитобе?*
Answer:
"*text*": "католическими миссионерами",
"*answer_start*": 50

Open Domain QA

- We don’t assume a given passage; we have access to a large collection of documents (e.g., Wikipedia); we don’t know where the answer is located
- <u>The goal</u>: to return the answer for any open-domain questions.
- Closed-domain
- Factoid question

Question

WIKIPEDIA
The Free Encyclopedia

Google

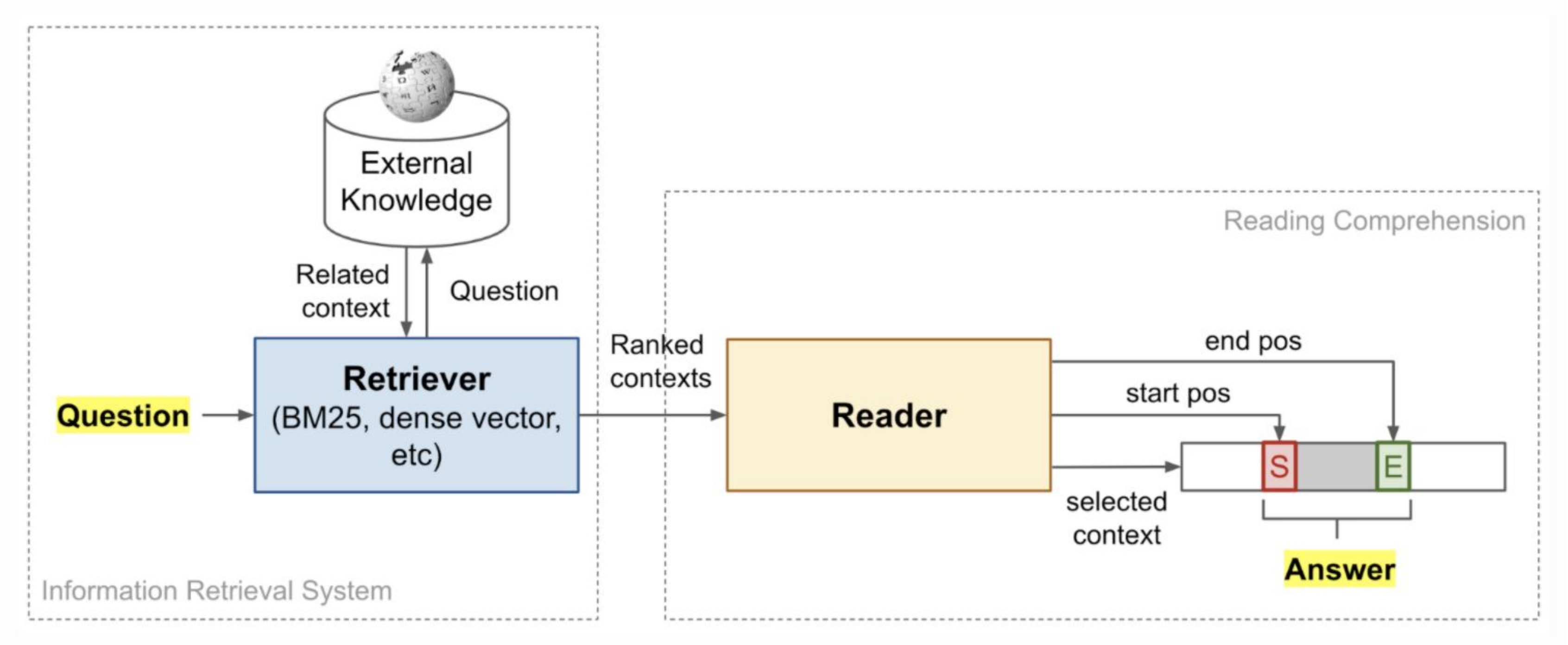
Answer

Open Domain QA

Retriever-reader framework

<u>Input</u>: a large collection of documents $D = D_1, D_2, \ldots D_n$ and Q

<u>Output</u>: an answer string A



Open Domain QA

DrQA (Document retriever Question-Answering)

Retriever: standard TF-IDF information-retrieval sparse model (a fixed module)
Reader: a neural reading comprehension model
(3-layer bidirectional LSTM with hidden size 128)

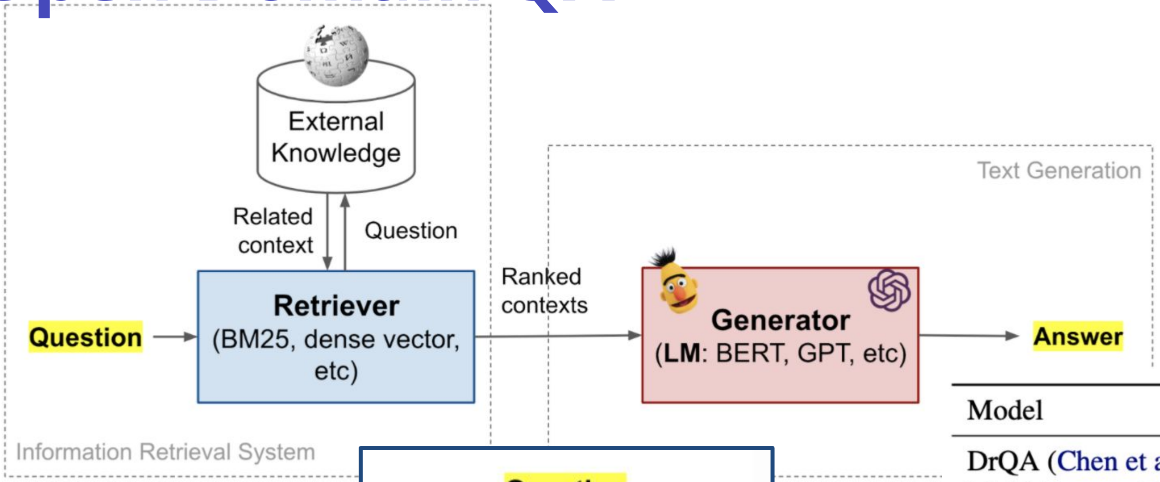
$$\text{tf-idf}(t, d, D) = \text{tf}(t, d) \times \text{idf}(t, D)$$
$$\text{tf}(t, d) = \log(1 + \text{freq}(t, d))$$
$$\text{idf}(t, D) = \log\left(\frac{|D|}{|d \in D : t \in d|}\right)$$

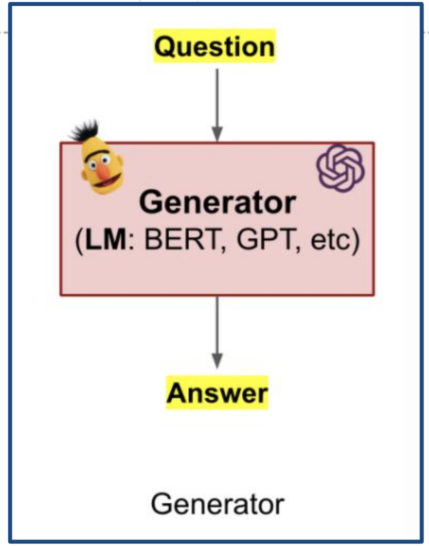
Train the retriever-reader models using question-answer pairs:

- ORQA (Open-Retrieval Question-Answering)
- DPR (Dense passage retrieval)
- REALM (Retrieval-Augmented Language Model pre-training)

https://lilianweng.github.io/lil-log/2020/10/29/open-domain-question-answering.html

Open Domain QA

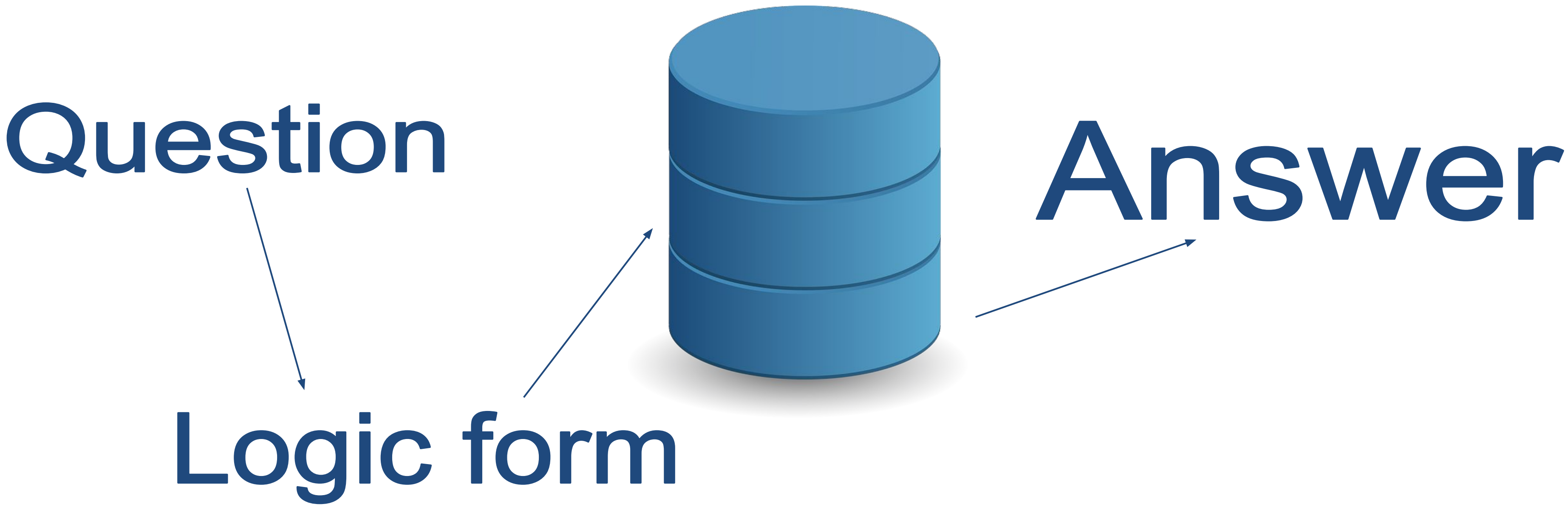




Model	NaturalQuestions	TriviaQA	
DrQA (Chen et al., 2017)	-	-	-
Multi-Passage BERT (Wang et al., 2019)	-	-	-
Path Retriever (Asai et al., 2020)	31.7	-	-
Graph Retriever (Min et al., 2019b)	34.7	55.8	-
Hard EM (Min et al., 2019a)	28.8	50.9	-
ORQA (Lee et al., 2019)	31.3	45.1	-
REALM (Guu et al., 2020)	38.2	-	-
DPR (Karpukhin et al., 2020)	41.5	57.9	-
SpanSeqGen (Min et al., 2020)	42.5	-	-
RAG (Lewis et al., 2020)	44.5	56.1	68.0
T5 (Roberts et al., 2020)	36.6	-	60.5
GPT-3 few shot (Brown et al., 2020)	29.9	-	71.2

Semantic parsing

Semantic parsing is a process of mapping a natural language into a formal representation of its meaning. Depending of the formalism logical representation can be used to query a structured knowledge base.



Knowledge base QA

KBQA - Knowledge Base question answering.

Formal representation of knowledge.

The graph model allows you to model physical and abstract entities and relationships between them. A graph is defined classically as a set of vertices and edges

$$G = (V, E) | E \subseteq \mathbb{R}^{|V| \times |V|}$$

For example, Wikidata - graph db, cross-links in Wikipedia.

DBpedia, Wikidata, YAGO, etc.

Knowledge base QA

label — **Moscow** (Q649) — item identifier

description — capital city and the largest city of Russia; separate federal subject of Russia

aliases — Moskva | Москва | Moscow, Russia | Moskva Federal City, Russia | Moscow, USSR | Moskva, Russia | City of Moscow | Moscow, Russian Federation | Moscow, Soviet Union | Moscow, Russian SFSR

In more languages Configure

Language	Label	Description	Also known as
English	Moscow	capital city and the largest city of Russia; separate federal subject of Russia	Moskva Москва Moscow, Russia Moskva Federal City, Russia Moscow, USSR Moskva, Russia City of Moscow Moscow, Russian Federation Moscow, Soviet Union Moscow, Russian SFSR
Russian	Москва	столица и крупнейший город России; город федерального значения; административный центр Московской области (не входит в её состав)	Первопрестольная Порт пяти морей Москва (город) Москва, Россия Москва (Россия) Москва Златоглавая Третий Рим
German	Moskau	Hauptstadt von Russland	
French	Moscou	capitale de la Russie	

language, label, description, aliases

All entered languages

Knowledge base QA

The Resource Description Framework (RDF) is a standard model for data interchange on the Web.
It defines the model of the subject-predicate-subject or subject-predicate-object triplet.
That is, an entity - "subject" can be associated with another entity or a simple value - an object - through some property - a predicate.

Special predicates: *rdf:type, rdf:Property, rdf:subject, rdf:predicate, rdf:object, rdf:first, rdf:value, rdf:List, etc..*

Triplet example:

“Университет ИТМО - находится в - Санкт-Петербург” links entities: Университет ИТМО and Санкт-Петербург via predicate “находится в”.

Triplet “Университет ИТМО - rdf:type - Университет” means that “Университет ИТМО” ∈ университеты.

Knowledge base QA

To query the knowledge represented in RDF, the query language **SPARQL** is used (links knowledge graphs to applications based on knowledge graphs)

The part of the knowledge graph that describes abstract concepts and connections between them at a high level, otherwise it is also called **ontology**.

RuBQ - Russian dataset for KBQA

CHATBOTS

Chatbots. Types

Dialogue systems, or conversational agents communicate with users in natural language (text, speech, or both)

Two classes:

1. **Task-oriented dialogue agents** use conversation with users to help people complete tasks. Dialogue agents in digital assistants (Siri, Alexa, Google Now/Home, Cortana, etc.), give directions, control appliances, find restaurants, or make calls.
2. **Chatbots** are systems designed for extended conversations, set up to mimic the unstructured conversations or ‘chats’ characteristic of human-human interaction, mainly for entertainment, but also for practical purposes like making task-oriented agents more natural.

Discourse

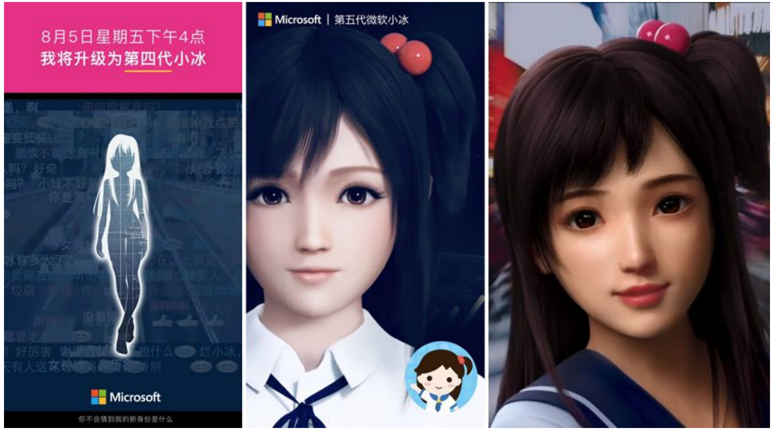
Discourse Analysis—What Speakers Do in Conversation. **Discourse** analysis is sometimes defined as the analysis of **language** 'beyond the sentence'.

Speech acts or Dialogue Acts

Constatives:	committing the speaker to something's being the case (*answering*, *claiming*, *confirming*, *denying*, *disagreeing*, *stating*)
Directives:	attempts by the speaker to get the addressee to do something (*advising*, *asking*, *forbidding*, *inviting*, *ordering*, *requesting*)
Commissives:	committing the speaker to some future course of action (*promising*, *planning*, *vowing*, *betting*, *opposing*)
Acknowledgments:	express the speaker's attitude regarding the hearer with respect to some social action (*apologizing*, *greeting*, *thanking*, *accepting an acknowledgment*)

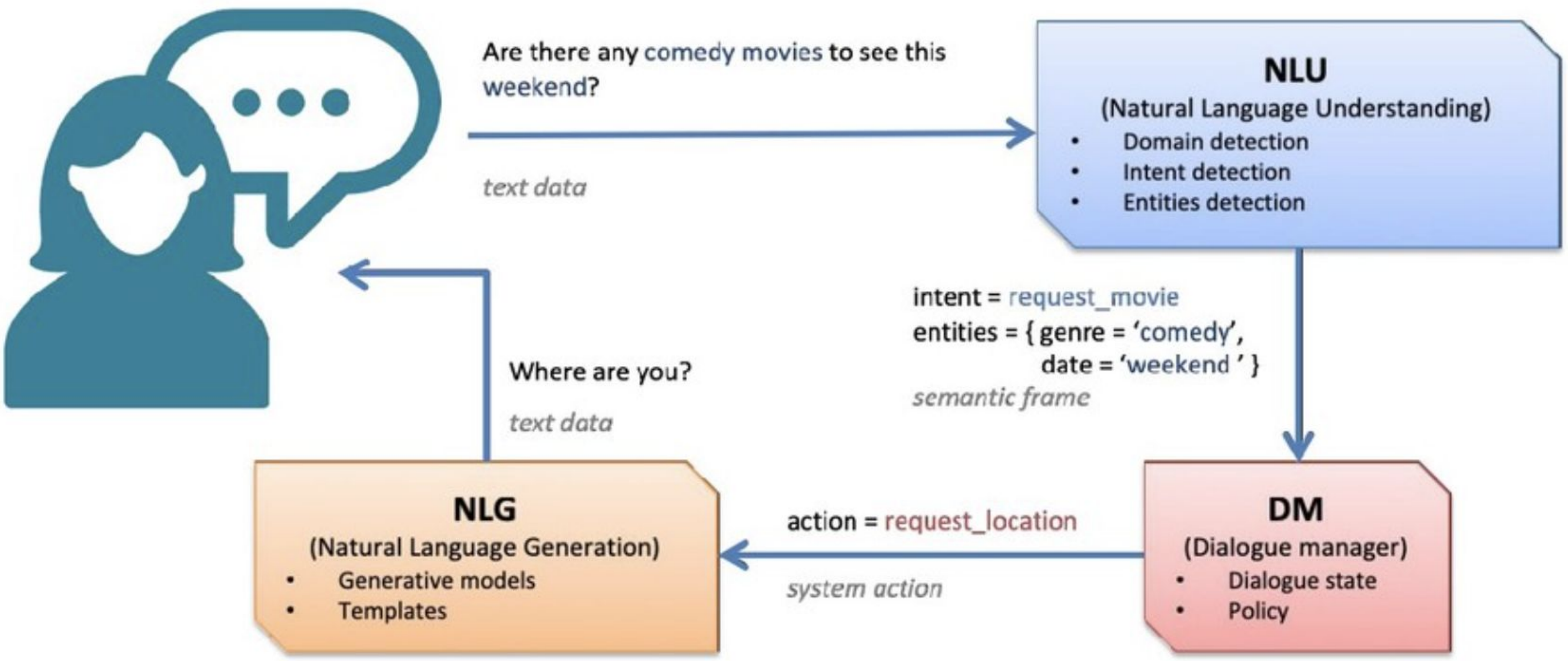
Chatbots evolution

From rule-based to NN



Chatbot Architecture

Goal oriented chatbots



Chatbots. Intents

Intent recognition or **intent** classification — is the task of taking a written or spoken input, and classifying it based on what the user wants to achieve.

Intent recognition forms an essential component of chatbots and finds use in sales conversions, customer support, and many other areas.

We need to do **slot filling**: extract the particular slots and fillers that the user intends the system to understand from their utterance with respect to their intent

http://nlpprogress.com/english/intent_detection_slot_filling.html

Chatbots. Intents

Datasets: **SNIPS, ATIS, MultiWoZ**

Show me morning flights from Moscow to Barcelona on Tuesday

DOMAIN: TRAVEL

INTENT: SHOW-FLIGHT (want to travel)

DATE: Tuesday

CITY-from: Moscow

CITY-to: Barcelona

http://nlpprogress.com/english/intent_detection_slot_filling.html

Coreference

Coreference/Anaphora Resolution is the problem of resolving what a pronoun, or a noun phrase refers to.

The relation that holds between an anaphor and an antecedent.
Antecedent — a mention with already established referent
Anaphor — a mention referring to an earlier occurring antecedent

Examples:

Ann saw <u>Mary</u> yesterday. <u>She</u> was tired.

Mary <u>went home</u>. She <u>did so</u> because she was tired.

<u>Putin</u> made a surprise visit to USA yesterday. <u>President</u> met ...

Coreference

Elipsis is a case of anaphora., where the anaphor is a null proform.

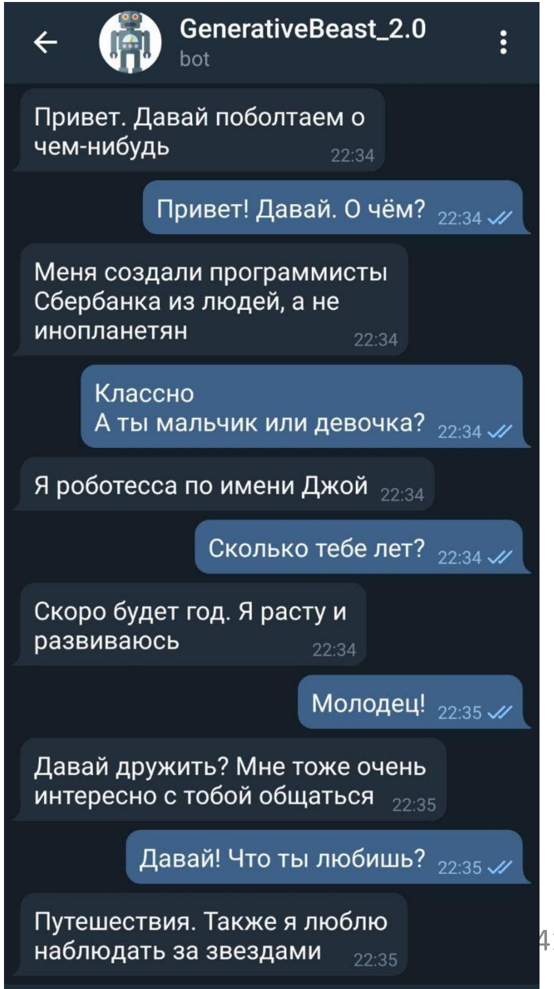
Examples:

I haven't seen John yet, but I will Ø (see) soon.

Robert cooked the first course, and Mary Ø (cooked) the dessert.

Chitchat

- Retrieval base models:
  - Take a dataset of dialogues,
  - construct pairs (context, reply)
  - build inverted index on contexts
  - return best with cos_sim(user_context, index_context)
- Neural networks
- Generation based networks (GPTs)



Datasets

- SQuAD 2.0: the Stanford QA dataset.
- RACE: a reading comprehension dataset collected from English Examinations that are created for middle school and high school students.
- TREC QA: the TREC QA collections.
- MS MARCO: a QA dataset featuring 100,000 real Bing questions and a human generated answer.
- CuratedTREC: based on the benchmarks from the TREC QA tasks that have been curated by Baudis & Sedivy (2015).
- Google Natural Questions: contains real user questions issued to Google search, and answers found from Wikipedia by annotators.
- WebQuestions: designed for knowledge-base QA with answers restricted to Freebase entities.
- WikiQA: Bing query logs were used as the source of questions. Each question is then linked to a Wikipedia page that potentially contains the answer.
- WikiMovies: contains movie-related questions from the OMDb and MovieLens databases and where the questions can be answered using Wikipedia pages.
- WikiReading: to predict textual values from the structured knowledge base Wikidata by reading the text of the corresponding Wikipedia articles.
- TriviaQA: a reading comprehension dataset containing 95K question-answer pairs authored by trivia enthusiasts and independently gathered multiple evidence documents per question.
- Jeopardy! Questions: contains 200,000+ Jeopardy! questions.
- DeepMind Q&A Dataset: question/answer pairs from CNN and Daily Mail articles.
- bAbi: a rich collection of datasets for text understanding by Facebook.
- FEVER: for fact extraction and verification.
- SearchQA: question-answer pairs were crawled from from J! Archive, and then augmented with text snippets from Google.
- Quasar-T: a collection of open-domain trivia questions and their answers obtained from various internet sources.
- Quiz bowl: contains data from a trivia competition called quiz bowl.
- AmbigNQ: ambiguous questions selected from NQ-OPEN dataset.
- QA-Overlap: a collections of overlapped answers/questions between train and test set for Natural Questions, TriviaQA, and WebQuestionsю
- VQA : visual questin answering. Stanford.
- MultiWOZ (The Multi-domain Wizard-of-Oz (MultiWOZ)) - https://paperswithcode.com/dataset/multiwoz
- RUSSIAN datasets:
  a. SberSQUAD - https://drive.google.com/drive/u/1/folders/1AtLPhazqhpHTC-be10XsYIKE3n1Xut51
  b. RuCoS - https://russiansuperglue.com/tasks/task_info/RuCoS
  c. MuSeRC - https://russiansuperglue.com/tasks/task_info/MuSeRC
  d. DaNetQA - https://russiansuperglue.com/tasks/task_info/DaNetQA
  e. RuBQ - https://github.com/vladislavneon/RuBQ

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DeepPavlov demos
IBM Watson video in Jeopardy challenge

XiaoIce chatbot https://arxiv.org/abs/1812.08989

DialoGPT2 https://github.com/vlarine/ruDialoGPT

Anaphora resolution for Russian (http://www.dialog-21.ru/en/evaluation/2019/disambiguation/anaphora/, AGRR-2019, RuCor)
Slot fillings, intent recognition http://nlpprogress.com/english/intent_detection_slot_filling.html