Conversational Modeling

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TYPES OF CONVERSATIONS

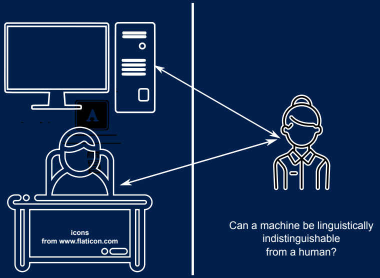
- Threaded
  - Twitter, Facebook, email
- Short-text conversation
  - Google help desk, Microsoft Virtual Agent, etc. where the interactions are $\geq 1 < 3$
- Task-oriented conversation
  - Siri, Cortana, Google Home, Alexa, help desk, etc.- to get information from the user to help complete the task
- Chit-chat or open conversation - unstructured conversations on any topic
- Question answering

TIME LINE

1950	Turing Test
1955	AI Born
1964	ELIZA
2011	Siri
2011	IBM Watson
2014	Alexa
2016	Google Home

- Modeling conversation is one of the active research problems in AI
- Natural language conversation involves language understanding, reasoning, and the utilization of common sense knowledge
- The goal is to build a conversational model that generates the responses automatically and these responses are linguistically indistinguishable from human responses thereby passing the *Turing Test*

A true test for machine intelligence



CONVERSATION EXAMPLES

- Would you like some coffee?
- Yes, please
- Mega, would you like to dance?
- Is the floor slippery?
- No, it's fine

- **Teacher**: Will you tell us the answer to question four?
- **Mike**: Is that one on page (...) six or seven? Then I'd be happy to
- **Teacher**: Six
- **Mike**: Oh, okay. The answer is factorial two

TYPES OF CONVERSATION AGENTS

Chatbots and dialog-based (Google assistant, Alexa, Siri)conversational agents

- Rule-based
- Corpus-based

- Understanding what is **NOT** said
- Analysis of the language beyond sentence
- Identification of the relationship among all of the contexts across sentence boundaries
- Consists of two parts - **Representation and Conditions**
  1. Representation - a set of referents representing the entities which are under discussion
  2. Conditions - a set of conditions representing the entities

     Example

     A farmer owns a donkey

     $[x, y : farmer(x), donkey(y), owns(x, y)]$
- Relationship - how two segments of discourse are logically connected to each other

GOALS OF THE CONVERSATIONAL AGENT

- Machine Comprehension of text
- Learn conversations
- Learn to summarize or encode conversation
- Predict the meaning of the conversation
- Produce substantiative and useful conversation
- Produce a sentence with a good fluency
- Detect hypocrisy, abuses, flirting, threats, etc.
- Learn task-oriented conversation
- Learn typical patterns of dialog discourse
- Learn to identify questions
- Learn Question-Answering

ELIZA - DR. WEIZENBAUM

Text Analytics

The first AI based conversation engine

- Idea is to simulate methods used by a psychologist that involve drawing the patient out by reflecting patient's statements back at them
- Human-like, but does not understand the query/conversation
- Uses pattern matching with some rules - insertion, substitution and deletion
- No built in context understanding mechanism

ELIZA-A TYPICAL CONVERSATION

Men are all alike.
IN WHAT WAY
They're always bugging us about something or other.
CAN YOU THINK OF A SPECIFIC EXAMPLE [1]
Well, my boyfriend made me come here.
YOUR BOYFRIEND MAKE YOU COME HERE
he says i'm depressed much of the time.
I AM SORRY TO HEAR YOU ARE DEPRESSED
it's me. I am not happy.
DO YOU THINK COMING HERE WILL, HELP YOU NOT TO BE HAPPY
I need some help, that much seems certain
WHAT WOULD IT MEAN TO YOU IF YOU GOT SOME HELP [2]

[1] The capitalized conversations in yellow are the machine responses

[2] Source:J.Weizenbaum, "ELIZA A Computer Program For the Study of Natural Language Communication Between Man And Machine",vol9, Jan. 1966

- A text read and is inspected for the presence of a keyword
- If a keyword is found in the sentence, then the sentence is transformed according to a rule specified for that keyword
- Identification of the most important keyword in a sentence
- Identification of the minimal context in which the keyword occurs
- Choice of appropriate transformation of the input sentence by using the above using a **`Transformation Rule`**
- Respond "intelligently" when there are no keywords

Transform Rule

- **`User: I am very happy`** → **`You are very happy`** or **`How long have you been happy?`**
- **`I am`** → **`you are`** - **`yourself`** → **`myself`** -

VIRTUAL AGENT - EXAMPLE

OK, let's start over. Please describe your issue and I'll look for the best solution.

How to find office licence key?

Which one did you mean?

How to find your Office product key

How to activate or find product key for Office Home Use Program (HUP)

None of the above

How to find your Office product key

Choose your Office version:

Office 365

Office 2019, Office 2016, or Office 2013

Office 2011 for Mac

Office 2010

Office 2007

Office 2011 for Mac

Do you need help finding your key or did you lose the key?
Find product key
Lost product key

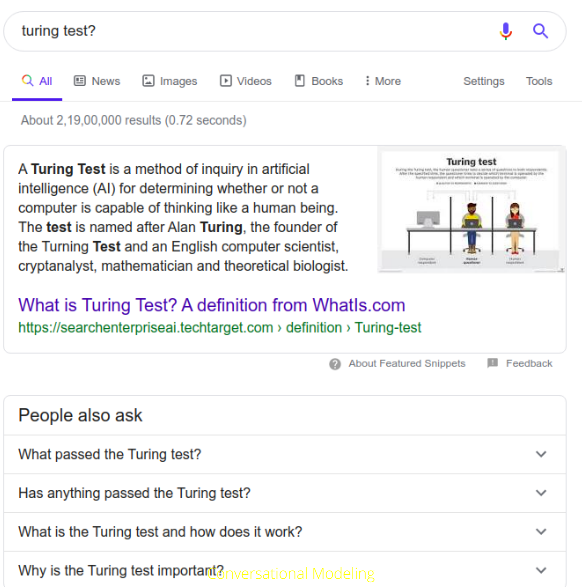
Find product key

An Office for Mac 2011 product key is a 25-character code used to activate Office for Mac 2011. Where to find your product key depends on how you got your copy of Office for Mac 2011:

- **From an authorized retailer**. The product key is on a label, card, or sticker inside the box or case that Office came in. If you downloaded Office from an online store, the product key should be in your email receipt.
  - **IMPORTANT**: If Office came on a product key card with a 27-character alpha-numeric PIN, you'll need to contact support to redeem the PIN.
- **A digital copy from a Microsoft website**. The product key is in the confirmation email you received after buying it. To find the email, try the following:
  - Check your spam, bulk, or junk mail folders for the email.
  - Try searching your email for the word *Microsoft*.
  - If you have multiple email accounts, check the email account that you provided when you purchased Office for Mac 2011 online.

Source Credit: https://support.microsoft.com/en-in/contact/virtual-agent/

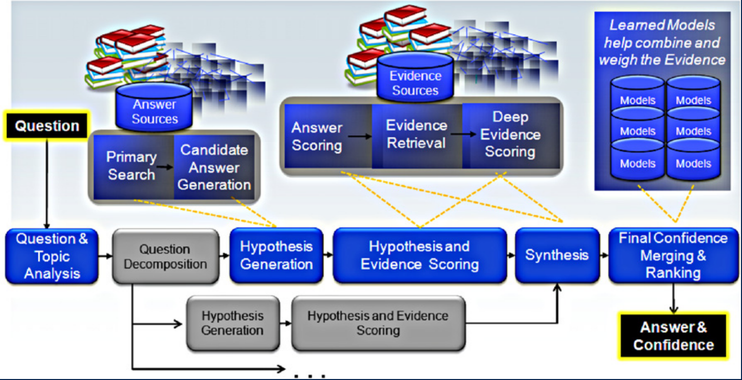
QUESTION ANSWERING - EXAMPLE



JEOPARDY - HIGH-LEVEL ARCHITECTURE

Highlevel architecture

Sample Jeopardy! game board
Image Source: https://commons.wikimedia.org/wiki/File:Jeopardy!_game_board.png



https://www.aaai.org/Magazine/Watson/watson.php

HISTORICAL APPROACH USED IN CM

- Retrieval-based Approach
  - Pick a suitable response based on how many times a particular response was selected for similar questions
  - Using matching features of question and the response
    - The use of matching features alone will not suffice
- Statistical Machine Translation approach
  - This approach treats this as a translation problem in which the model is trained on the parallel corpus of question and response pairs

IR-BASED CONVERSATION

- IR based mostly used in the short-text conversation[3]
- The corpus contains different pairs of post-comments or question answers
- * Given a question, and the set of documents, the task is to find the answer from the span of text from extracted paragraphs

For every given query q, there could be zero or more post-comment pairs (p, r) The best response to the query q is picked up based on the ranks of the retrieved pairs using

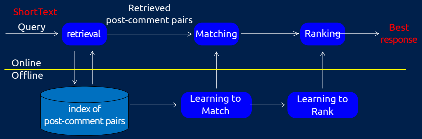
$$\hat{r} = \underset{(p,r)}{argmax} Score(q, (p, r)) \qquad (1)$$

where $Score(.)$ is the sum of all score of the features

$$Score(q, (p, r)) = \sum_{i \in \Omega} w_i \phi_i(q, r) \qquad (2)$$

where $\phi_i(.)$ and w_i are the score and weight of the i^{th} feature and Ω is the total number of features, respectively. Here the features could be TF*IDF of the word found in the {q,(p,r)}

[3] Zongcheng Jia, Zhengdong Lub, Hang Li, An Information Retrieval Approach to Short Text



- Query-Response Similarity: Here the similarity between the query and the candidate responses are computed using similarity measures such as cosine similarity

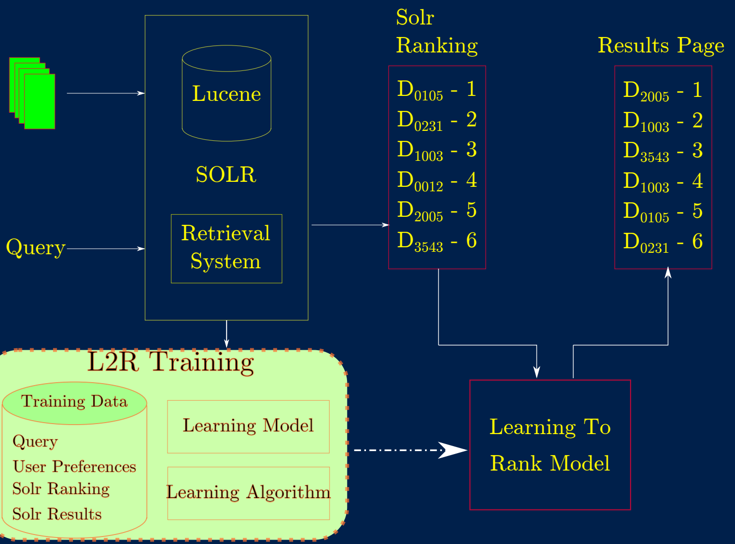
$$Similarity(q, r) = \frac{q^T r}{||q||.||r||} \quad (3)$$

- Query-Post Similarity: Here the similarity between the query and the candidate responses are computed using similarity measures such as cosine similarity

$$Similarity(q, p) = \frac{q^T p}{||q||.||p||} \quad (4)$$

These similarity measures are proposed with the assumption that the there is some alignment of variables between query and posts and query and responses

LEARNING TO RANK



The main drawbacks of the retrieval-based method are the following

- The Post,responses pairs are canned and it is hard to customize for the particular text or requirement from the task, e.g., style or attitude
- The use of matching features alone is usually not sufficient for distinguishing positive responses from negative ones, even after time consuming feature engineering. (e.g., a penalty due to mismatched named entities is difficult to be incorporated into the model)