PUCK TREERATPITUK

CHATBOT: overview

'Then and Now'

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Computer Engineering @ Chula

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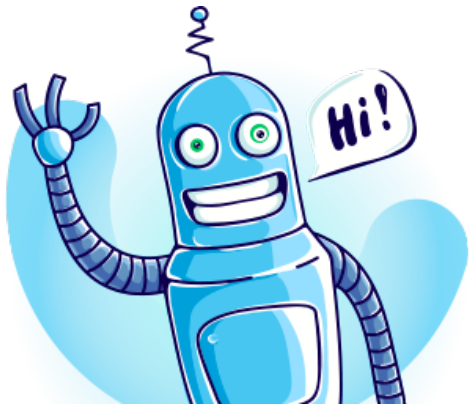
“chatbot” NOT chat “BOT”



BANK OF THAILAND

A Joke…. :P

Agenda

History of Chatbot

Techniques & Design Choices for Designing Chatbot

ML, NLP @ BOT

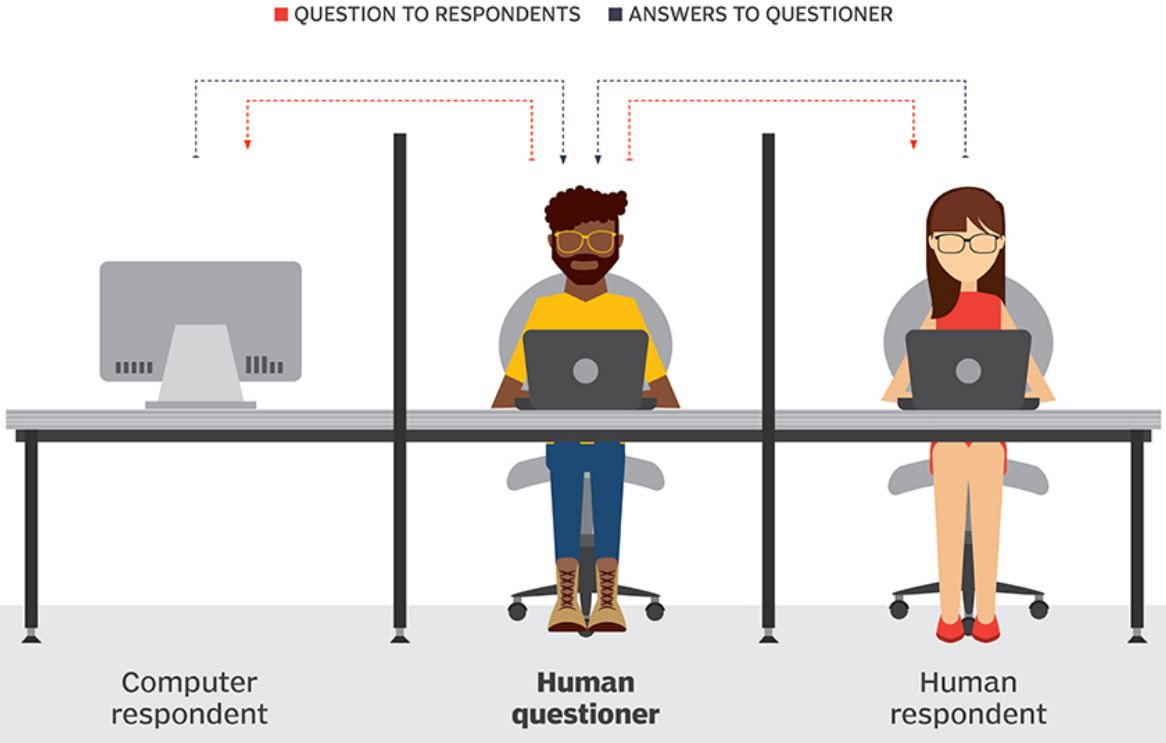
Is it possible for machine to think?

Alan Turing
1912-1954

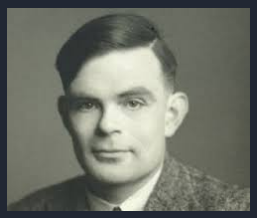
"A computer would deserve to be called intelligent if it could deceive a human into believing that it was human"

Turing test

During the Turing test, the human questioner asks a series of questions to both respondents. After the specified time, the questioner tries to decide which terminal is operated by the human respondent and which terminal is operated by the computer.



OUR QUEST



Turing Test

HAL 9000

Siri

Amazon Alexa

1950

1955

1966

1968

2008

2010

2011

2015

"Artificial Intelligence"

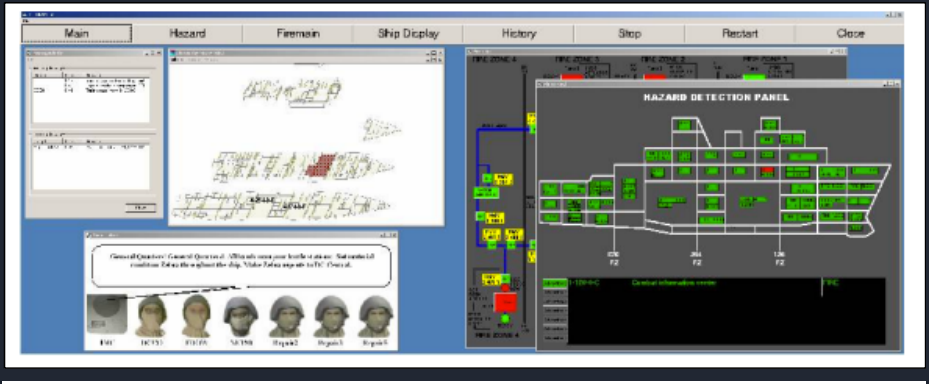
ELIZA (MIT)

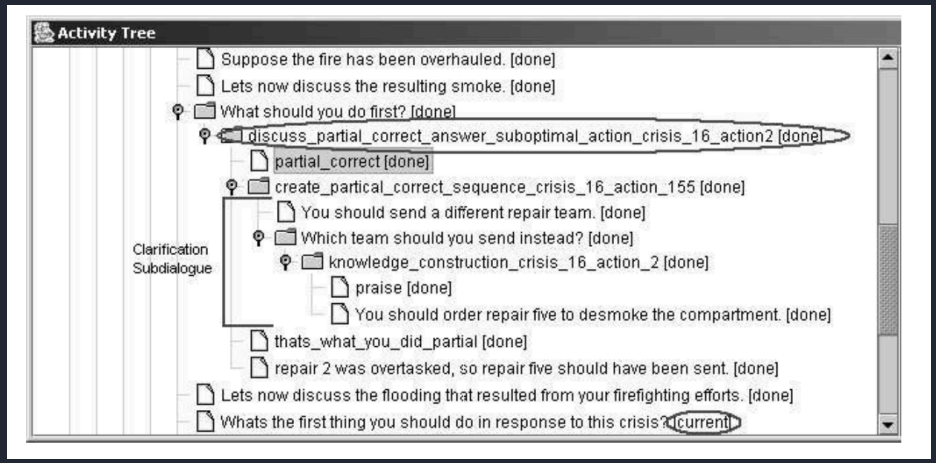
```
> Hello, I am Eliza.
* I am afraid.
> How long have you been afraid?
* Since midterms.
> Tell me more...
* I am afraid that I will fail
my course.
> Do you enjoy being afraid that
you will fail your course?
```

Abdul

IBM Watson

“chatbot” before “chatbot”





Ok, let review how to handle this crisis

What is the 1st thing you should do when the fire alarm sounds?

send repair two to investigate.

Yes, however, you failed to do this during the session. This is a mistake you made more than once. Remember, alarms need to be verified first.

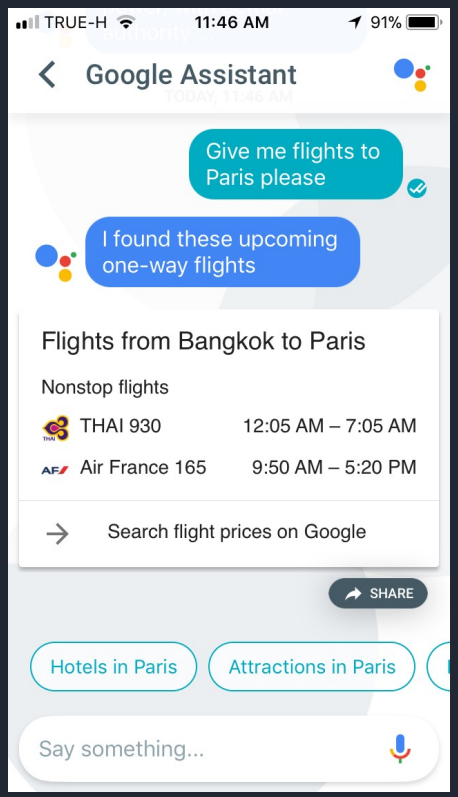
Ok, what else needs to be done?

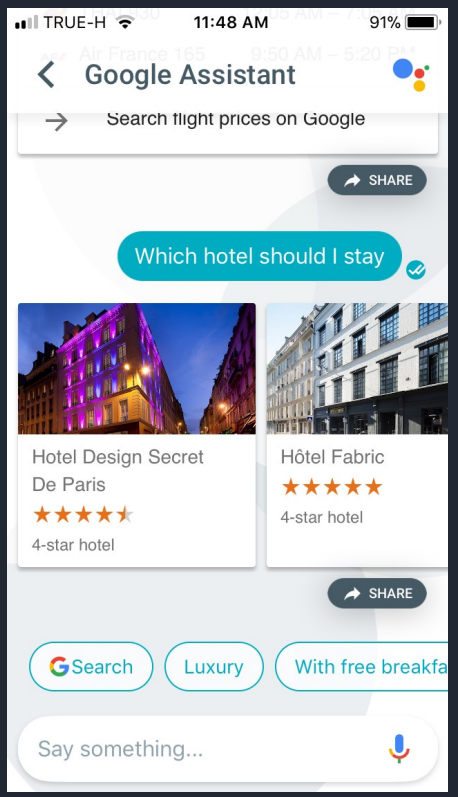
Set fire and smoke boundaries

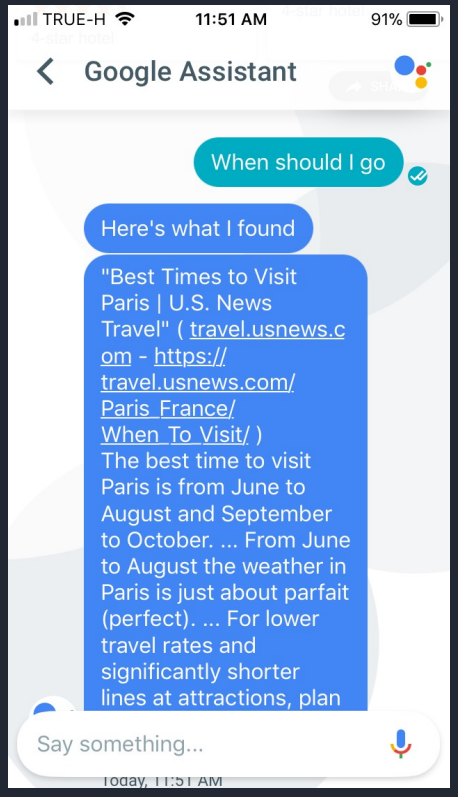
A GENERAL PURPOSE ARCHITECTURE FOR INTELLIGENT TUTORING SYSTEMS, 2003

CSLI, Stanford University

“chatbot” NOW







Inferring

from BKK	stay in “Paris”	go to “Paris”	Paris - BKK Paris - Germany

Traditional

Part-of-Speech Tagging (POS)

I love you : (ProN, V, ProN)

Named-Entity Recognition (NER)

“Donald Trump” : Person

Co-reference Resolution

here: ...

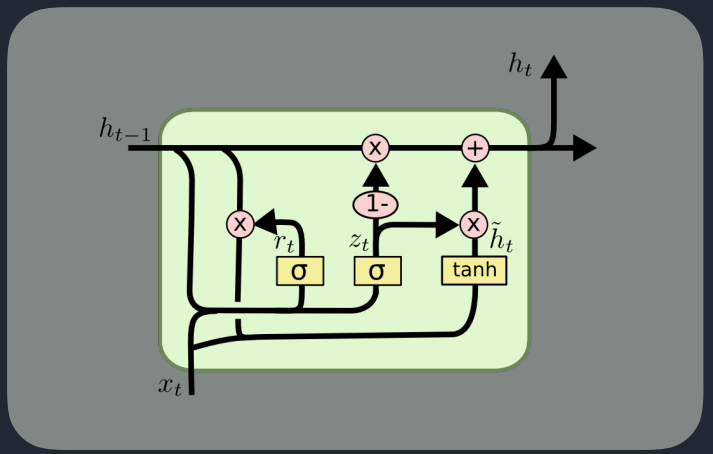
his: ...

Rule-based

Why ..

What ..

Shiny



POMDP

Context-Aware Model

Deep Learning + Memory Units

LSTM

Dynamic Memory Network

Siri

2010

Amazon Alexa

2015

2011

IBM Watson

Prediction: pass Turing Test?

2029

~ 50 Years Old

categorized by types

Chit-Chat

Task Based - (User, Machine, Mixed Initiatives)

categorized by techniques

Rule-Based

IR-Based

Seq2Seq

Finite-State Automata

Frame-Filling

Planing-Based

** *Statistical*

Eliza (Weizenbaum, 1966)

Men are all alike.

In what way?

They're always bugging us about something or other.

Can you think of a specific example?

Well, my boyfriend made me come here

Your boyfriend made you come here?

He says I'm depressed much of the time

I am sorry to hear that you are depressed

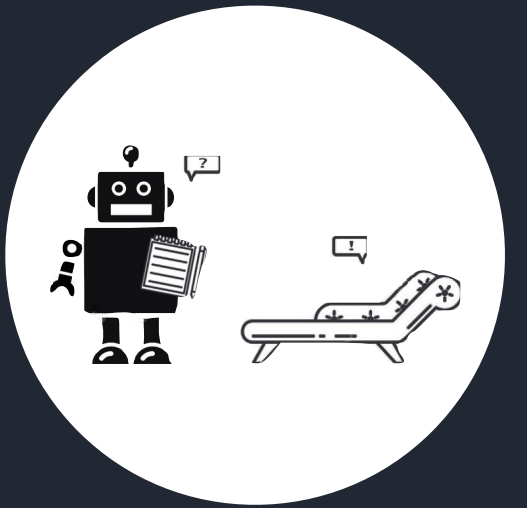
...

Who else in your family take care of you?

My father

Your father?

My father



Eliza (Weizenbaum, 1966)

Ranked Keywords:

I know everybody laughed at me

*I 0: (I *) -> (You say you 2)*

You say you know everybody laughed at you

everybody 5: (Who in particular are you thinking of?)

Who in particular are you thinking of?

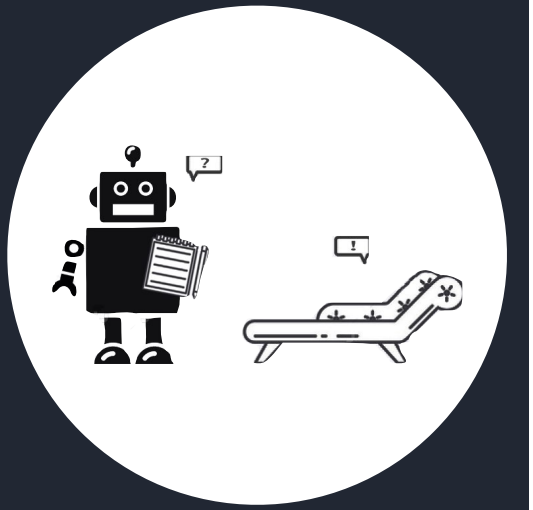
Memory Stack ("My"):

(0 Your 0: Let discuss further why your 3)

(0 Your 0: Earlier you said your 3)

Fall Back: That's very interesting, Tell me more, …

Variations: prefer not to use the same rules in the same conversation



Parry (Colby, 1971)

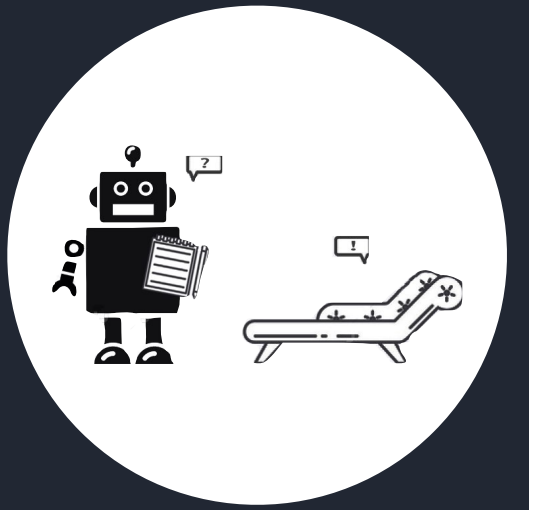
similar to ELIZA (rule-based transformation)

but more complex controlling structures + NLP

With Persona:

- *28 year old single man, post office clerk*
- *no siblings and lives alone*
- *sensitive about his physical appearance, his family, his religion, his education and the topic of sex*
- *hobbies are movies and gambling on horse-racing*
- *recently attacked a bookie, claiming the bookie did not pay*
- *worried about underworld retaliation*
- *eager to tell his story to non-threading listeners*

Affect Variables: Fear (0-20) & Mistrust (0-15)



IR-Based

Miss perky: Patrick Verona. I see we're making our visits a weekly ritual.

Patrick: Only so we can have these moments together. Should I, uh, hit the lights?

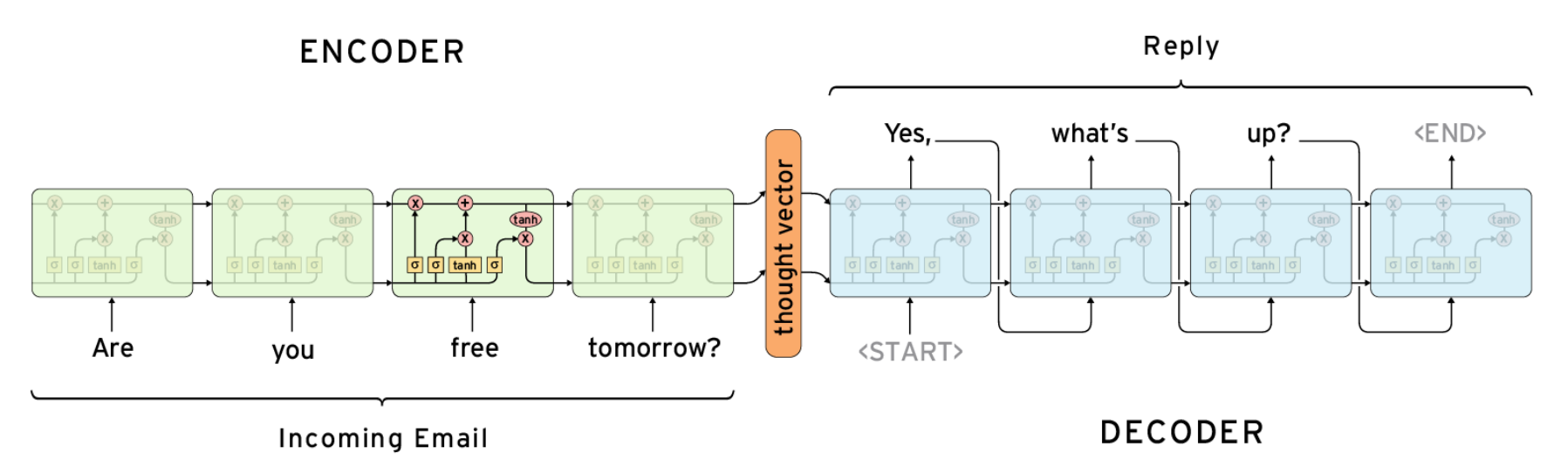
Miss Perky: Oh, very clever, kangaroo boy. Says here you exposed yourself in the cafeteria?

Patrick: I was joking with the lunch lady. It was a bratwurst.

Miss Perky: Bratwurst? Aren't we the optimist? Next time, keep it in your pouch, okay? Scoot!

— *10 Things I Hate About You*

Seq2Seq



inspired by Machine Translation

translating Utterance into Response

Frame-based

Frame

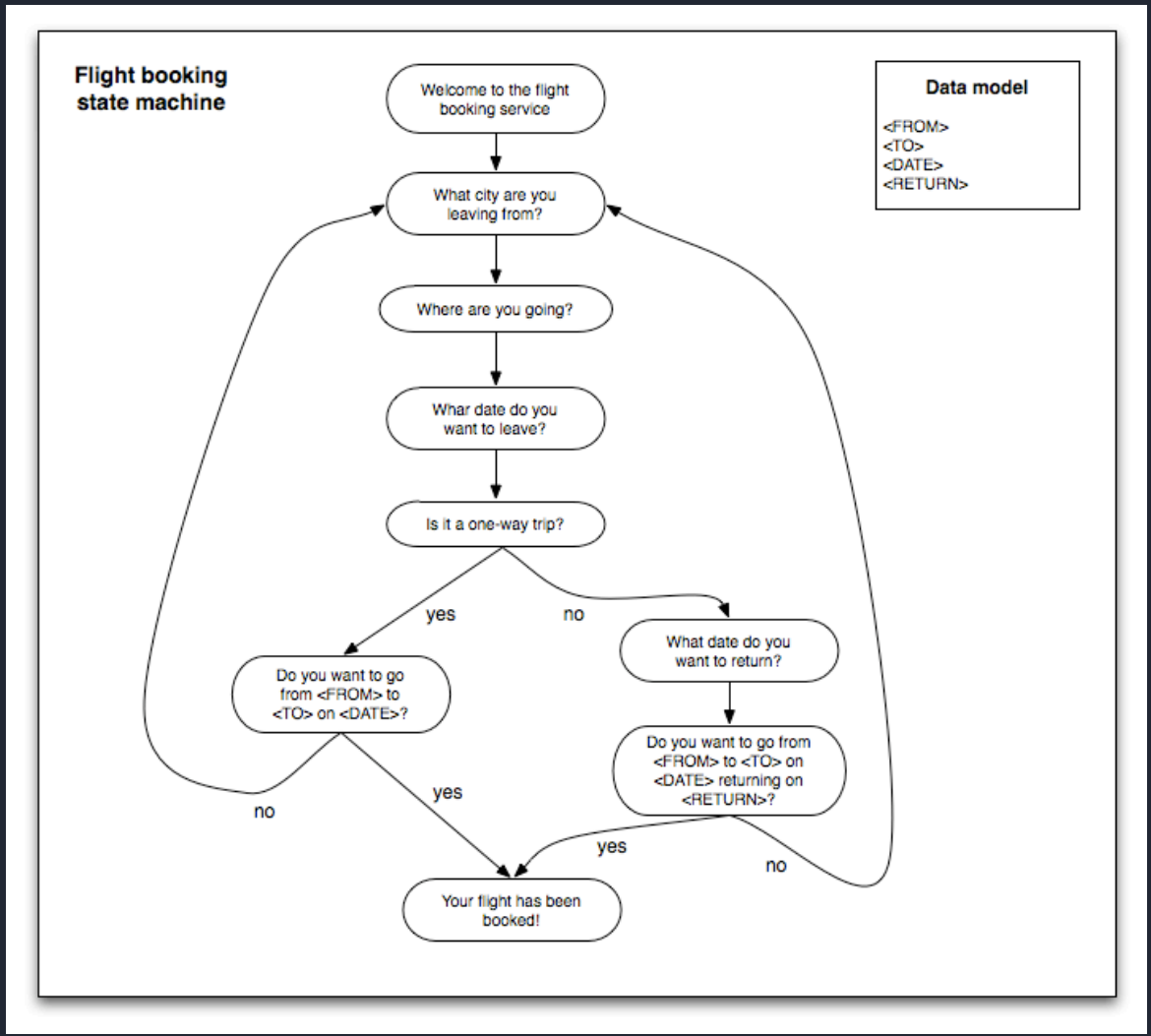
From: City

To: City

Departure Date: date

Arrival Date: date

NLP:
grammar-based
ml-based



Siri, Amazon Alexa, Google Assistant, … etc

Planning-Based

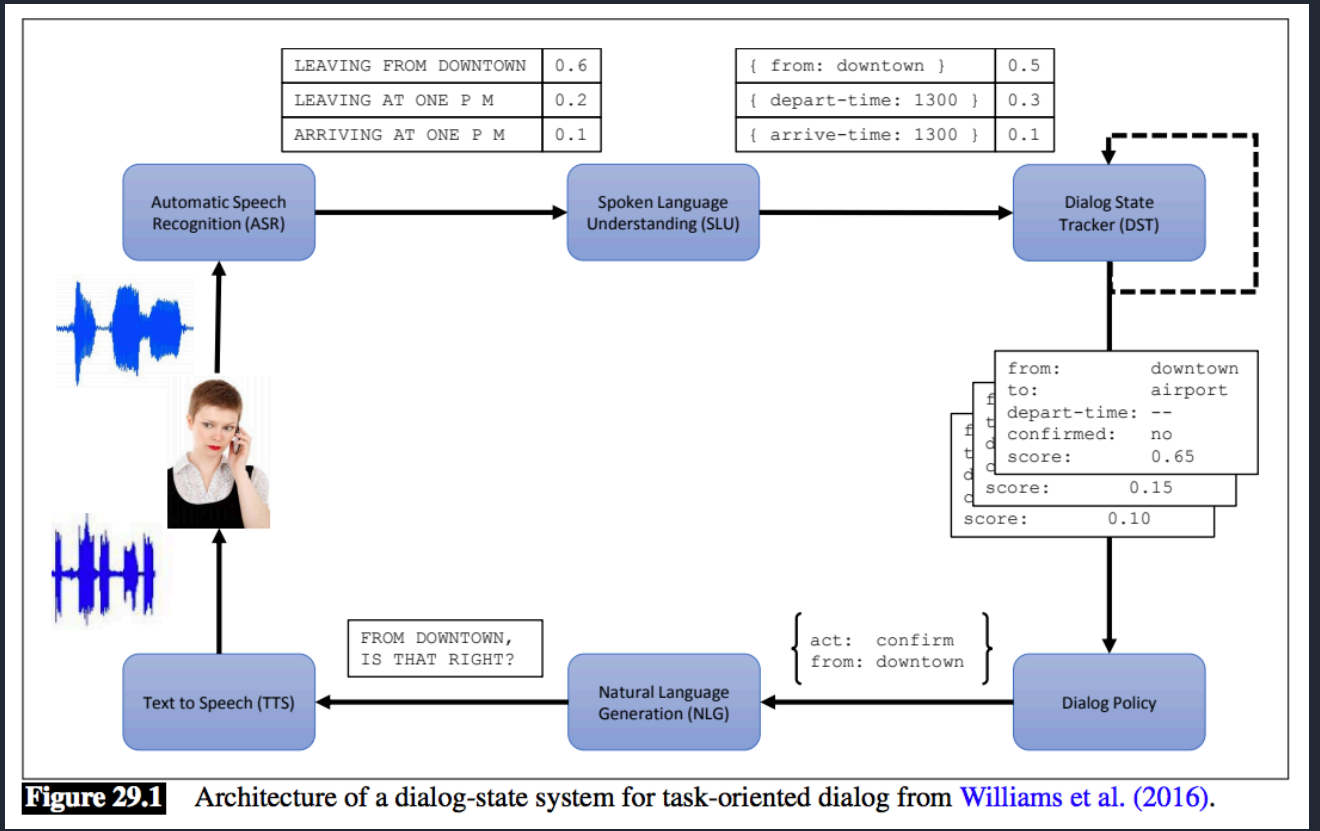
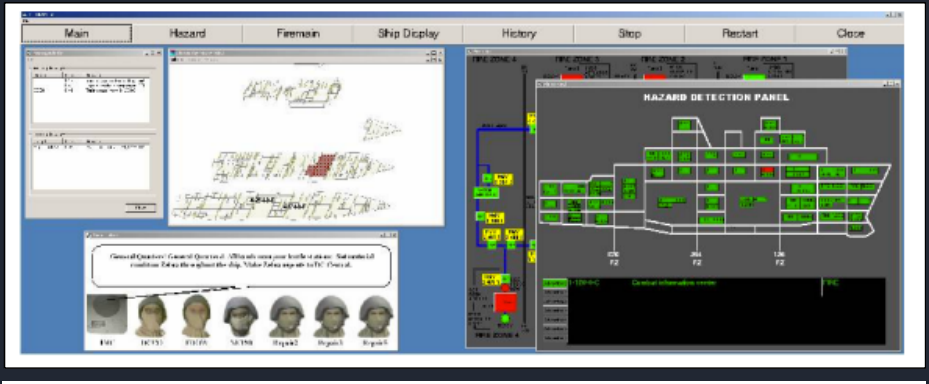
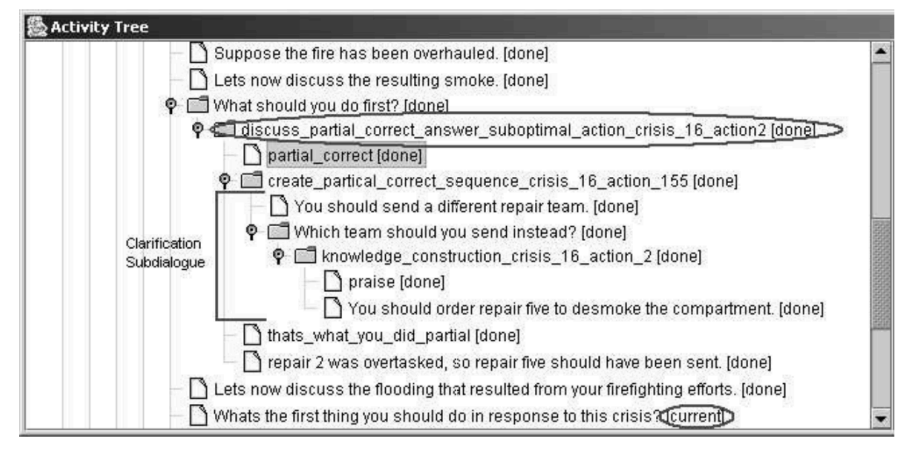


Figure 29.1 Architecture of a dialog-state system for task-oriented dialog from Williams et al. (2016).

Planning-Based Example





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WITAS (Stanford), CMU Communicator (CMU), RavenClaw (CMU)

Example: Architecture

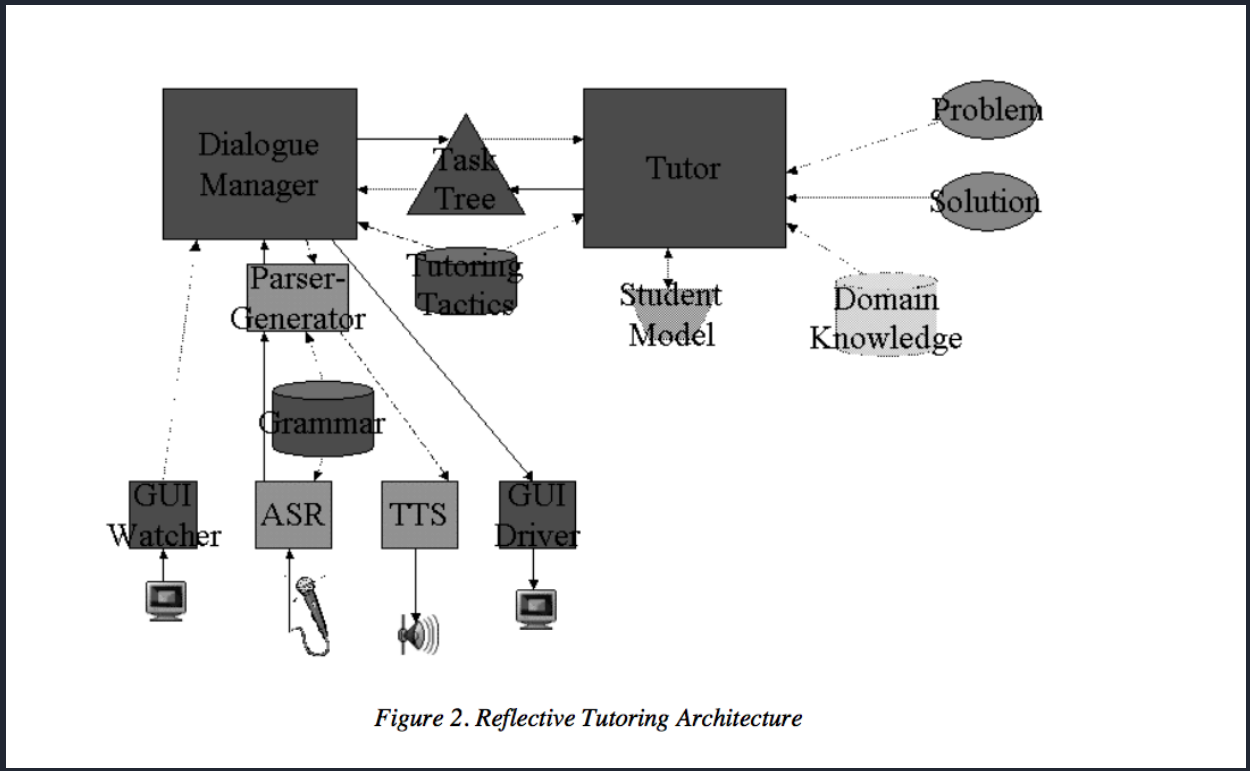


Figure 2. Reflective Tutoring Architecture

viewing dialogue as collaborative activities between the user and the bot, modifying the dialog tree

Dialog Move Tree

Task Tree

System Agenda

Salience List

Pending List

Modality Buffer

both users and the bot can propose a new agenda by adding node onto the task tree

A GENERAL PURPOSE ARCHITECTURE FOR INTELLIGENT TUTORING SYSTEMS, 2003

CSLI, Stanford University

Dialog Move Tree

records of dialogues history, and pending agendas

Previous 11/19/02 4:32 PM Next
Utterance: i should send repair two to fight the fire
Conversational Move: assertion(prop(actor(np(n(pro(i)),
semantic([speaker]), grammatical([number(sg)]))), vp(action(send), semantic([object(np(n(dcagent(repair_two)), semantic([]), grammatical([number(sg)]))), adv_list([]), purpose([vp(action(fight), semantic([object(np(n(dcevent(fire)), semantic([]), grammatical ([number(sg),det(det(def,the))]))), adv_list([])]), grammatical([tense_mood_aspect([tense(inf)])])])]), grammatical ([tense_mood_aspect([tense(inf)])])))
Uttered by: User

Dialog Move Tree

active nodes are red; position on active node list in parens [0=most active]

- Root (**0**)
  Root
  - Report (system)
    "Hello, we are about to review your session from Monday, November 4."
  - Yn_query (system)
    ...
  - Wh_query (system)
    "Whats the first thing you should do when the fire alarm sounds?"
    - Wh_answer (user)
      assertion(prop(actor(np(n(pro(i)),semantic([speaker]),grammatical([number(sg)]))),vp(action(send),semantic ([object(np(n(dcagent(repair_two)),semantic([]),grammatical([number(sg)]))),adv_list([]),purpose([vp(action (fight),semantic([object(np(n(dcevent(fire)),semantic([]),grammatical([number(sg),det(det(def,the))]))),adv_list ([])],grammatical([tense_mood_aspect([tense(inf)])])])],grammatical([tense_mood_aspect([tense(inf)])])))

Example: Recipe

recipes: set of policies for the bot in modifying the dialog states

def_strategy discuss_error_of_omission_answer_incorrect

:goal

:preconditions:

(i) the student's answer is incorrect

(ii) the student's actions in response to the damage event included an error of omission

:recipe

(i) provide negative feedback to the student

(ii) give the student a hint

(iii) ask a follow-up question

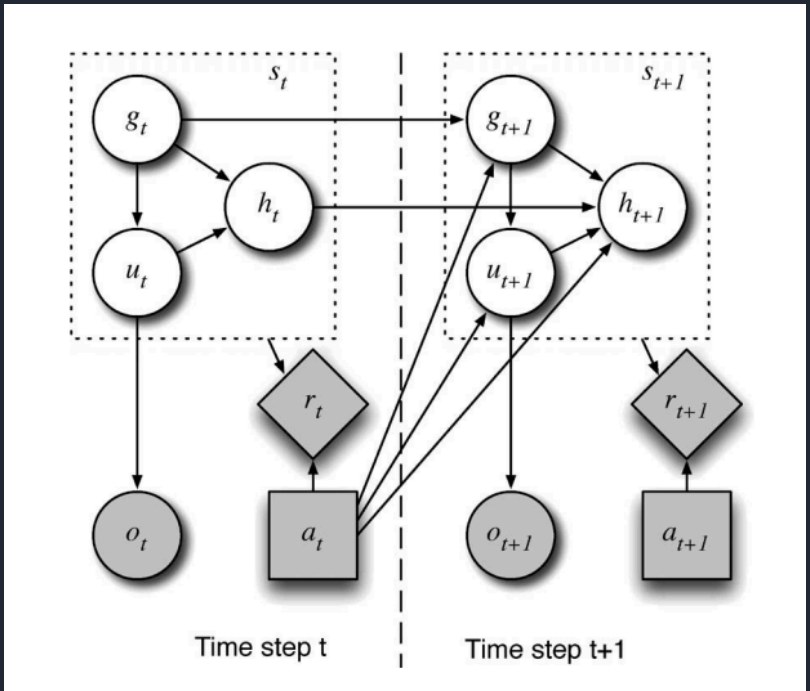
(iv) classify the student's response

(v) provide feedback to the student

(vi) tell the student the rule

(vii) tell the student that the topic is changing

Partial Observable Markov Decision Process (POMDP)



Model Dialogue as Markov Process
(current states only depended on previous states)

use Re-enforcement Learning to learn dialogue move based on the dialogue state to maximize expected rewards

What else to think about?

when designing a chatbot...

Error Handling

Timing & Turn-Taking

Multi-Participant Dialogue

Automatic Knowledge Extraction

Taskable Agents