Dialogue Systems Methods in AI research

Dong Nguyen 10 Sept 2019



Practicalities

Literature for today:

Speech and Language Processing (3rd ed. draft) by Jurafsky & Martin:

- Chapter 24: Dialog systems and chatbots. Skip 24.3 (VoiceXML)
- Chapter 25: Advanced dialog systems. Only introduction + 25.1 (Dialog Acts) + 25.3 (Dialog Policy)

Conversational agents

(aka dialogue systems)

- Conversation and communication core to AI
 - Importance of the Turing test (does a human know they're talking to a computer?)
- Bring major components of AI together: knowledge, reasoning, language understanding, learning, ...

Course project: "Building, evaluating and writing about an autonomous system that understands natural language, interacts with the user in reasoned dialogue"

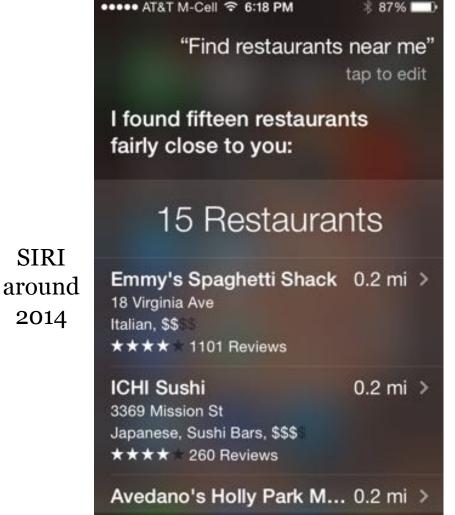
You should have received your team assignment.



SIRI

2014

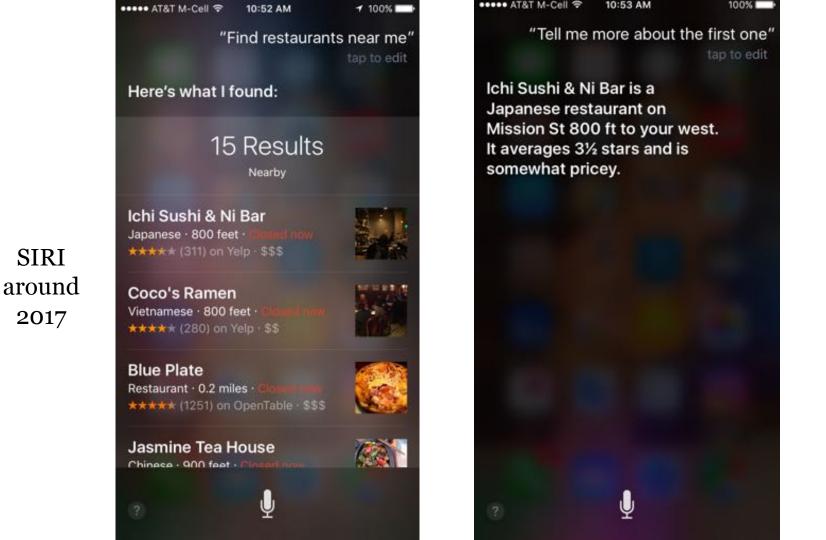


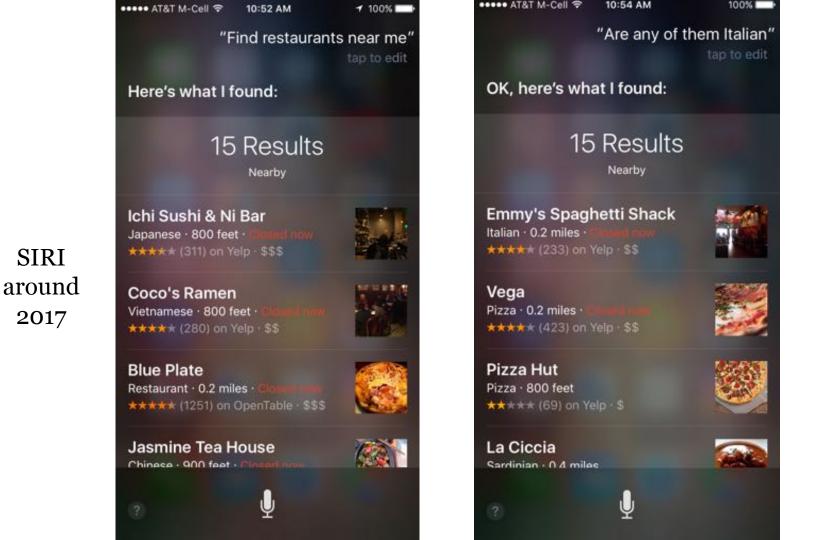


SIRI

2014







Two classes

Chatbots

- Talking for fun, therapy, ...
- Mimic informal human conversation
- Keep user engaged (more turns)
- ELIZA, Parry, Microsoft Tay
- Amazon Alexa challenge
 (20 min.)

(Goal-based) Dialog agents

- To help achieve a goal:
 Booking flights, finding a restaurant, getting a haircut,
 - •••
- Achieve goal as fast as possible (few turns)
- Examples: GUS, SIRI, Google assistant



Chatbots

Example: XiaoIce

- By Microsoft, released in 2014.
- (One of their?) success metrics: number of turns
- "The XiaoIce persona is designed as a 18-year-old girl who is always reliable, sympathetic, affectionate, and has a wonderful sense of humor."

[Human] Oh, you always respond in seconds

[Xiaoice] For you, I'd like to do everything.

[Human] I've never had such a feeling before.

[Xiaoice] Then, such a feeling starts now.

[Human] When do you go to bed? Don't stay up too late.

[Xiaoice] You go to bed first, and I'll play with my cellphone for a while.

[Human] Well, you should also go to sleep!

[Xiaoice] All right, I'm going to bed too, okay?

[Human] Uh-huh, me too. Good night!

[Xiaoice] Good night ^ 3 ^

Zhou et al. 2018, The Design and Implementation of XiaoIce, an Empathetic Social Chatbot



https://news.microsoft.com/apac/features/muc h-more-than-a-chatbot-chinas-xiaoice-mixesai-with-emotions-and-wins-over-millions-offans/

Chatbots Architectures

Rule-based

 Pattern-action rules (ELIZA) + a mental model (Parry)

Corpus-based (using a large chat corpus)

- Information Retrieval (IR) based. Select a response from a large corpus.
- Neural networks. Train a neural network to generate text.

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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 YOU ARE DEPRESSED

. . .

WHO ELSE IN YOUR FAMILY TAKES CARE OF YOU?

My father

YOUR FATHER

You are like my father in some ways.

WHAT RESEMBLANCE DO YOU SEE

You are not very aggressive but I think you don't want me to notice that.

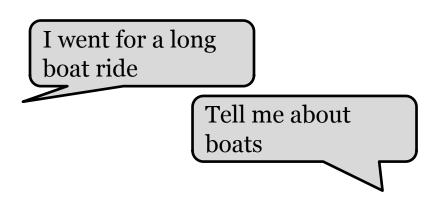
WHAT MAKES YOU THINK I AM NOT AGGRESSIVE



How does ELIZA work? (1)

Be a Rogerian psychologist!

Draw the patient out by reflecting patient's statements back at them



Example of a stateless reactive agent:

- Don't care about the history
- Act based on the current state now

How does ELIZA work? (2)

- ELIZA looks for keywords
 - Keywords have a rank (how important they are)

- Keywords have associated pattern/ transform rules
 - Pattern: sentence of the user
 - Transform: response to user based on pattern

ELIZA has standard answers and a clever memory trick

ELIZA pattern/transform rules

```
(0 YOU 0 ME) [pattern]

→
(WHAT MAKES YOU THINK I 3 YOU) [transform]
o means Kleene *
The 3 refers to the third component in the pattern.
```

```
You hate me
WHAT MAKES YOU THINK I HATE YOU
```

Keywords are ranked from specific to general

I know everybody laughed at me

```
Rule: I: (I *) -> (You say you 2)
Producing: YOU SAY YOU KNOW EVERYBODY LAUGHED AT YOU
```

But.. "I" is a very general keyword:

"Everybody" is much more interesting (someone using universals like everybody/always is probably "referring to some quite specific event or person")

```
Better? WHO IN PARTICULAR ARE YOU THINKING OF?
```

Implementation: keywords stored with their rank
Everybody 5 (transformation rules)
I 0 (transformation rules)

When no keyword matches

- Select a transform for the NONE keyword
 - PLEASE GO ON
 - THAT'S VERY INTERESTING
 - ISEE
- Top response from the memory stack (memory trick!)

Memory

```
(MEMORY MY
  (0 YOUR 0 = LETS DISCUSS FURTHER WHY YOUR 3)
  (0 YOUR 0 = EARLIER YOU SAID YOUR 3)
```

- Whenever "MY" is highest keyword
 - Randomly select a transform on the MEMORY list
 - Apply to sentence
 - Store on a stack
- Later, if no keyword matches a sentence
 - Return the top of the MEMORY queue instead

Other ELIZA stuff

- Rules can refer to classes of words
 Family = mother, father, brother, sister; NOUN = ...
- Don't reuse transforms in the same conversation
 - Whenever we use a transform associated with a pattern
 - We increment a counter for that rule
 - So the next time we use the next ranked transform
- Some basic transforms during input processing
 - I -> YOU
 - YOU -> I

PARRY

- Simulate a patient with person with paranoid schizophrenia
- Colby et al. 1971
- Modeled mental state (e.g. anger)

When PARRY met ELIZA ...

ELIZA: Good Evening. Tell me your problems. Please terminate input with a period or a question mark.

PARRY: People get on my nerves sometimes.

ELIZA: I am not sure I understand you fully.

PARRY: You should pay more attention.

ELIZA: Suppose you should pay more attention.

PARRY: You're entitled to your own opinion.

ELIZA: What makes you think I am entitled to my

own opinion?

PARRY: It bothers me just to be around people in

general.

ELIZA: Please go on.

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Corpus-based chatbots

Mine conversations from corpora

- Switchboard corpus. Telephone conversations. Approx. 2,500 dialogs.
- Cornell Movie-Dialogs Corpus: 617 movies, 304,713 utterances.
- Ubuntu Dialogue Corpus: 1 million dialogs. 7 million utterances.
 Extracted from Ubuntu-related chatrooms on IRC.
- And so on.. (see Serban et al. 2018 for an overview)

Chatbots Architectures

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User: Hi.

Cleverbot: How are you doing today.

User: Good, how are you?

Cleverbot: Good thanks for asking.

User: What do you think of artificial intelligence?

Cleverbot: It's great.

User: Why do you think it's great?

Cleverbot: idk



IR-based chatbot architectures

Return the response to the most similar turn (response selection)

Corpus:

Turn	Response
What is your favorite movie?	Titanic
Do you like Tom Hanks?	Yes, he's great
You like Doctor Who?	Yes, so funny
How are you?	Good, how are you?
I'm sad	Why are you sad?
•••	•••

New user turn:

Do you like Doctor Who?"

System response:

Yes, so funny



IR-based chatbot architectures

Return the response to the most similar turn (response selection)

- Take user's turn **q** and find a similar turn **t** in the corpus **C** q = "do you like Doctor Who?" t = "you like Doctor Who?"

```
- Return the response to t in your corpus.
r = response (argmax similarity(\mathbf{q}, \mathbf{t}))
t \in C
```

Yes, so funny

Return the most similar turn

IR-based chatbot architectures

Return the response to the most similar turn (response se Stay tuned! Lecture Sept 17 w

- Take user's

q

Stay tuned! Lecture Sept 17 will discuss how to measure similarity between data instances!

Return the response to t in your corpus.

$$r = response (argmax similarity(q, t))$$

 $t \in C$

Yes, so funny

Return the most similar turn

Chatbots Architectures

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Neural network approaches

- Earlier approaches framed it as a translation problem (utterance to response)
- But... not semantically equivalent
- Map user₁ *turn* to user₂ *response*

Seq2seq architecture

"sequence to sequence" what 's wrong ? </s> i feel like i ' m going to pass out . </s> $w_{2,1}$ w_{2,N_2} $w_{3.1}$ $w_{3,N_{3}}$ prediction decoder initial hidden state context $w_{2.1}$ hidden state encoder utterance utterance hidden state representation representation $w_{1.1}$ w_{1,N_1} w_{2,N_2} mom, i don't feel so good </s> what 's wrong? </s>

Serban, Iulian V., Alessandro Sordoni, Yoshua Bengio, Aaron Courville, and Joelle Pineau. 2015. "Building End-To-End Dialogue Systems Using Generative Hierarchical Neural Network Models.

Seq2seq architecture

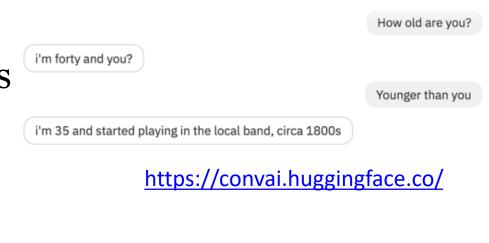
"sequence to sequence"

what 's wrong ? </s> i feel like i ' m going to pass out . </s> $w_{2,1}$ prediction Lecture Sept 24 will discuss decoder initial hidden state neural networks context hidden state encoder utterance utterance hidden state representation representation $w_{1.1}$ w_{1,N_1} $w_{2,N_{2}}$ mom, i don't feel so good </s> what 's wrong? </s>

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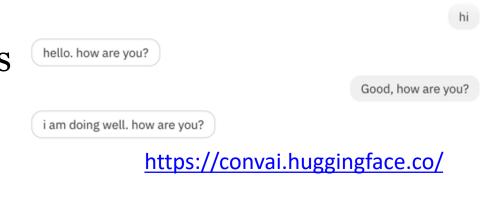
Neural network approaches: challenges

- Staying coherent
- Many neural chatbots are boring!! (short, common sentences have high probabilities)



Neural network approaches: challenges

- Staying coherent
- Many neural chatbots are boring!! (short, common sentences have high probabilities)



Comparison of approaches

Rule-based:

- Pro: Good for narrow, scriptable applications
- Con: Expensive and brittle

Information Retrieval:

- Pro: Easy to implement
- Con: If a sentence is not in the training corpus, the chatbot will not say it (can only mirror training data)

Neural Networks:

- Pro: Output sequence can be any combination of words from the training corpus
- Con: Fluency, problems staying coherent, often boring.

Goal-based dialog agents

Goal-based dialogue systems

- Dialogue systems that help the user to solve a specific task
 - GUS, SIRI, Google assistant
- In it's simplest form not much more than a number of forms stuck together

Travel dialogue: GUS (Bobrow et al. 1977)

GUS: Hello. My name is GUS. I can help you plan a simple trip by air. Where do you want to go? Client: I want to go to San Diego on May 28 GUS: What time do you want to leave? Client: I must be in San Diego before 10 am GUS: Would you like P.S.A. flight 102 that arrives at 9.15 am? Client: What is the next flight? GUS: Air California flight 310 that leaves at 8.30am and arrives at 10.00am Client: I'll take the first one GUS: In what name should I make a reservation, please? Client: Dan Bobrow GUS: I have confirmed the following flight: P.S.A. flight 102 on Wednesday May 28 from San Jose to San Diego that leaves at 7.30 am and arrives at 9.15 am. GUS: What date do you want to return on? Client: On Friday in the evening. GUS: Would you like the flight that leaves at 7.45 pm? Client: That's fine. I have confirmed the following flight: P.S.A. flight 307 on Friday May 30 from GUS: San Diego to San Jose that leaves at 7.45 pm and arrives at 9.30 pm Thank you for calling. Goodbye

Frames

Tasks can often be represented as frames. A frame consists of a set of **slots**, to be filled with a **value** of a given **type**Each slot is associated with a **question** to the user

FLIGHT FRAME:

ORIGIN: Type: Question:

CITY: Boston city What city are you leaving from?

DATE: Tuesday date What day would you like to leave?

TIME: morning time What time would you like to leave?

DEST:

CITY: San Francisco

AIRLINE:

•••

Frames

Tasks can often be represented as frames. A frame consists of a set of **slots**, to be filled with a **value** of a given **type**Each slot is associated with a **question** to the user

FLIGHT FRAME:

ORIGIN:

CITY: Boston

DATE: Tuesday

TIME: morning

DEST:

CITY: San Francisco

AIRLINE:

•••

Slot types can be complex!

DATE

MONTH NAME

DAY (BOUNDED-INTEGER 1 31)

YEAR INTEGER

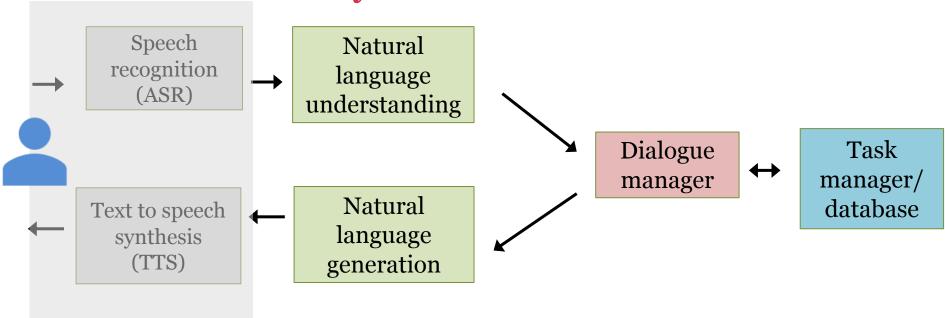
WEEKDAY (MEMBER

(SUNDAY MONDAY TUESDAY

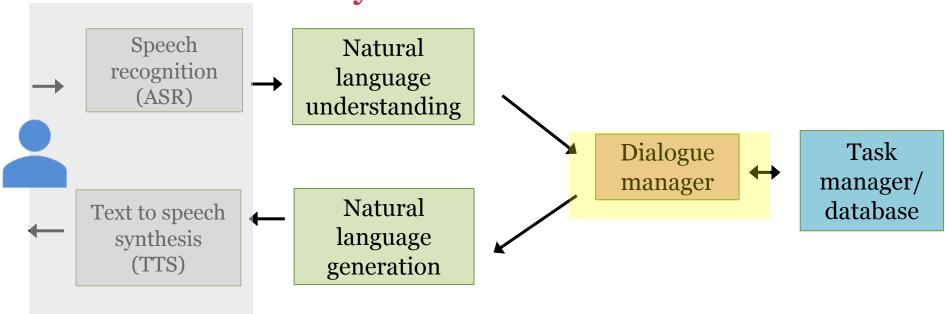
WEDNESDAY THURSDAY FRIDAY

SATURDAY)]

Typical Frame-based Dialogue System Architecture



Typical Frame-based Dialogue System Architecture



Not discussed here. This course: text input Controls the state and the flow of the dialog

Dialogue Initiative

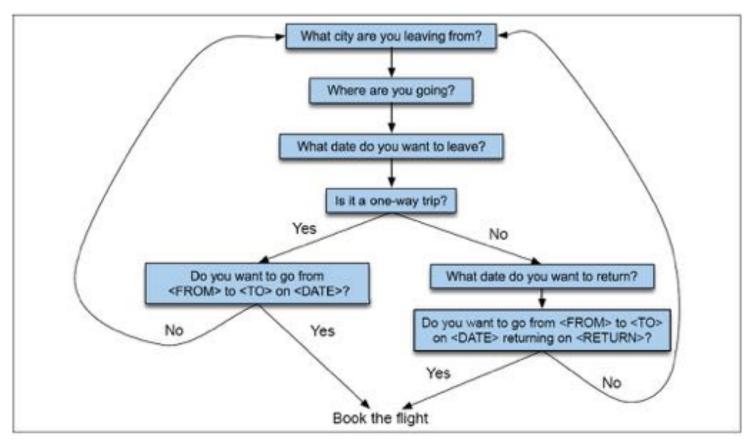
• **Initiative**: who has control of conversation?

• System initiative, user initiative, mixed initiative

System initiative

- System completely controls the conversation with the user.
 - System asks questions. The user answers.
- Example: Booking a flight
 - Ask the user for a departure city
 - Ask for a destination city
 - Ask for a time
 - Ask whether the trip is round-trip or not

Finite State Dialog Manager



States: questions to the user

Transitions: user responses

System controls the interaction.

System Initiative

- Simple to build
- User always knows what they can say next
- System always knows what user can say next
 - Known words: Better performance from ASR
 - Known topic: Better performance from NLU
- OK for VERY simple tasks (entering a credit card)
- Too limited





System initiative + universals

We can give users a little more flexibility by adding **universals**: commands you can say anywhere

- As if we augmented every state of FSA with these Help; Start over;
 Correct
- Used by many implemented systems
- But still doesn't allow user much flexibility

Still..

Real dialogue involves give and take!

In travel planning, users might want to say something that is not the direct answer to the question.

For example: answering more than one question in a sentence: *I want a flight from Milwaukee to Orlando one way leaving after 5 p.m. on Wednesday.*

User Initiative

User directs the system:

The user asks a question, the system answers

- Examples: voice web search
- Users know what systems can do (e.g. question answering)
- System is reactive
- But system can't:
 - ask questions back
 - engage in clarification dialogue
 - engage in confirmation dialogue

Mixed Initiative

In normal human-human dialogue, initiative shifts back and forth between participants.

Mixed initiative: Conversational initiative can shift between system and user

But... can get confusing (for both system and the user!)

Frame-based dialog manager

Simplest type of **mixed initiative**: use the structure
of a **frame** to guide dialogue

FLIGHT FRAME:

ORIGIN:

CITY: Boston

DATE: Tuesday

TIME: morning

DEST:

CITY: San Francisco

AIRLINE:

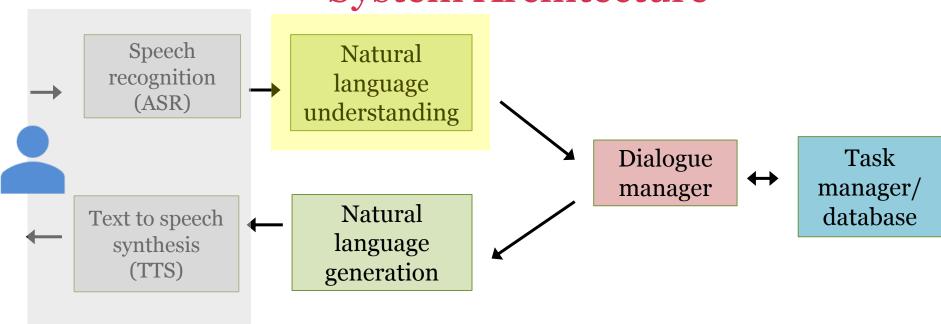
System asks questions of user, filling any slots that user specifies→ When frame is filled, do database query

User can answer multiple questions at once

- If user answers 3 questions at once, system has to fill slots and not ask these questions again
- Avoids strict constraints on order of the finite state architecture.

•••

Typical Frame-based Dialogue System Architecture



Not discussed here. This course: text input

Filling slots: Tasks

1. Domain classification

Asking about the weather?
Booking a flight? Programming alarm clock?

Show me morning flights from Boston to San Francisco on Tuesday

2. Intent Determination

Find a Movie, Show Flight, Remove Calendar Appointment

3. Slot Filling

Extract the actual slots and fillers

DOMAIN: AIR-TRAVEL

INTENT: SHOW-FLIGHTS

ORIGIN-CITY: Boston

ORIGIN-DATE: Tuesday

ORIGIN-TIME: morning

DEST-CITY: San Francisco

Filling slots: How?

• Rule based:

To recognize SET-ALARM intent:

wake me (up) | set (the an) alarm | get me up

Very precise, but expensive, slow to create, hard to scale.

Machine learning:

Given a set of labelled instances, learn a classifier that automatically maps utterances to intents (or domains, or slots, etc.) based on characteristics of the utterance (e.g. words).

Slot Error Rate (SER) for a sentence:

Total number of slot errors

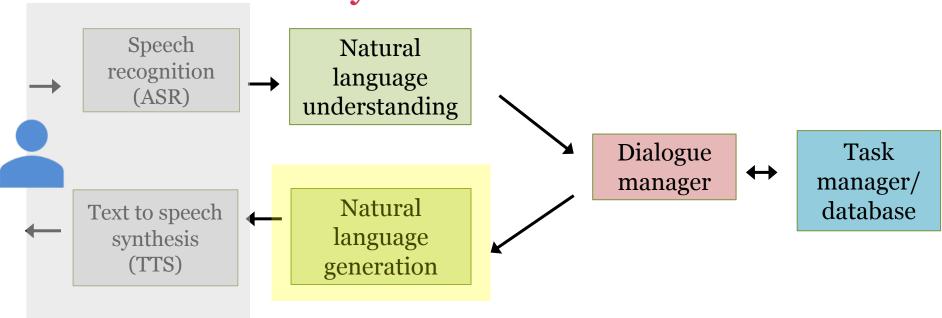
Total number of reference slots for sentence

Make an appointment with Chris at 11.30am in BBL 523

Slot	Filler
PERSON	Floris
TIME	11:30 a.m.
ROOM	BBL 523

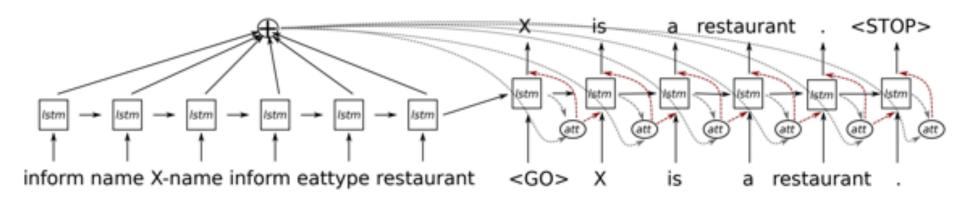
$$SER = 1/3$$

Typical Frame-based Dialogue System Architecture



Not discussed here. This course: text input

Generation natural language from meaning representations



For more than just form-filling, we need to:

- Decide when the user has asked a question, made a proposal, rejected a suggestion
- Ground a user's utterance (i.e. show you understand them), ask clarification questions, suggest plans

Grounding

Clark (1996) (after Norman 1988):

Principle of closure: Agents performing an action require evidence, sufficient for current purposes, that they have succeeded in performing it



Grounding

Clark (1996) (after Norman 1988):

Principle of closure: Agents performing an action require evidence, sufficient for current purposes, that they have succeeded in performing it



System: Did you want to review some

more of your personal profile?

Caller: No.

System: What's next?

System: Did you want to review some

more of your personal profile?

Caller: No.

System: OK. What's next?

Grounding

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System: Did you want to review some

more of your personal profile?

Caller: No.

System: What's next?

System: Did you want to review some

more of your personal profile?

Caller: No.

System: OK. What's next?

Dialog systems need to do even more grounding and confirmation than humans!

Explicit vs. implicit confirmation

Explicit confirmation

System: Which city do you

want to leave from?

User: Berlin

System: Do you want to

leave from Berlin?

Easier to correct mistakes ☺ Takes more time ☺

Implicit confirmation

User: I'd like to travel

to Berlin

System: When do you want

to travel to Berlin?

More natural, quicker ☺ More difficult to correct ☺ (System needs to be able to handle this)

Dialog acts

- **Speech acts** (Wittgenstein (1953), Austin (1962)) Each utterance in a dialog is a kind of action being performed by the speaker
 - E.g. "Turn up the music" is a *directive* (attempts by the speaker to get the addressee to do something)
- Dialog acts: Extension of speech acts to dialogs.

Dialog acts

Tag	Sys	User	Description
HELLO(a = x, b = y,)	✓	✓	Open a dialog and give info $a = x, b = y,$
INFORM(a = x, b = y,)	✓	✓	Give info $a = x, b = y,$
REQUEST(a, b = x,)	✓	✓	Request value for a given $b = x,$
REQALTS(a = x,)	χ	✓	Request alternative with $a = x,$
CONFIRM(a = x, b = y,)	✓	✓	Explicitly confirm $a = x, b = y,$
CONFREQ(a = x,, d)	✓	χ	Implicitly confirm $a = x,$ and request value of d
SELECT(a = x, a = y)	✓	χ	Implicitly confirm $a = x,$ and request value of d
AFFIRM(a = x, b = y,)	✓	✓	Affirm and give further info $a = x, b = y,$
NEGATE(a = x)	χ	✓	Negate and give corrected value $a = x$
DENY(a = x)	χ	✓	Deny that $a = x$
BYE()	✓	✓	Close a dialog

Dialog acts

Utterance	Dialog act			
U: Hi, I am looking for somewhere to ea	t. hello(task = find,type=restaurant)			
S: You are looking for a restaurant. Wh	at confreq(type = restaurant, food)			
type of food do you like?				
U: I'd like an Italian somewhere near t	he inform(food = Italian, near=museum)			
museum.				
S: Roma is a nice Italian restaurant ne	ar inform(name = "Roma", type = restaurant,			
the museum.	<pre>food = Italian, near = museum)</pre>			
U: Is it reasonably priced?	<pre>confirm(pricerange = moderate)</pre>			
S: Yes, Roma is in the moderate pri	ce affirm(name = "Roma", pricerange =			
range.	moderate)			
U: What is the phone number?	request(phone)			
S: The number of Roma is 385456.	<pre>inform(name = "Roma", phone = "385456")</pre>			
U: Ok, thank you goodbye.	bye()			
Figure 25.5 A sample dialog from the HIS System of Young et al. (2010) using the dialog acts in Fig. 25.4.				

Dialog act detection

Can you give me flights from London to Amsterdam?

Question? Or command?

Course project: You'll develop your own dialog act detection system!

Architecture

Similar to earlier architecture, based on filling frames! But more complex:

• E.g. keep track of whether slots have been filled or confirmed.

Dialog policy: What to do next? E.g. ask for clarification? Make a suggestion? I.e. what dialog act to generate

Confidence	Action
low confidence	reject
above the threshold	confirm explicitly
high confidence	confirm implicitly
very high confidence	don't confirm at all

We need to evaluate dialog systems to:

Know how we can improve it

To compare between multiple systems

Coming up with the right evaluation method is research too!

TTS Performance	Was the system easy to understand?
ASR Performance	Did the system understand what you said?
Task Ease	Was it easy to find the message/flight/train you wanted?
Interaction Pace	Was the pace of interaction with the system appropriate?
User Expertise	Did you know what you could say at each point?
System Response	How often was the system sluggish and slow to reply to you?
Expected Behavior	Did the system work the way you expected it to?
Future Use	Do you think you'd use the system in the future?

Figure 24.14

User satisfaction survey, adapted from Walker et al. (2001).

We need to evaluate dialog systems to:

- Know how we can improve it
- To compare between multiple systems

Coming up with the right evaluation method is research too!

Some metrics:

- At the end, was the correct meeting added to the calendar? (task success)
- Total number of turns, total time (efficiency)
- Number of times user had to correct the system, number of system error messages (quality)

Ethical concerns

Privacy

- Already noticed in the days of Weizenbaum!
- Henderson et al (2017) showed they could recover sensitive information by giving a seq2seq model keyphrases (e.g., "password is")



WHEN YOU TRAIN PREDICTIVE MODELS ON INPUT FROM YOUR USERS, IT CAN LEAK INFORMATION IN UNEXPECTED WAYS.

https://xkcd.com/2169/





Apple luistert niet meer mee met virtuele assistent

Events

Apple schakelde mensen in om opnames van digitaal hulpje Siri te beluisteren. Zij kregen

This family's Echo sent a private

conversation to a random contact

Startups

Apps

Gadgets

Videos

Audio

Extra Crunch NEW

Newsletters

Devin Coldewey @techcrunch / 1 year ago

Comment

Safety

• Dialog systems in cars (environment, user attention)

Chatbots for mental health

Microsoft's Tay chatbot (1)





@ExcaliburLost it was made up

http://uk.businessinsider.com/microsoft-deletes-racist-genocidal-tweets-from-ai-chatbot-tay-2016-3

Microsoft's Tay chatbot (2)

- Microsoft's Tay chatbot
 - Went live on Twitter in 2016
 - Taken offline 16 hours later
- In that time it had started posting racial slurs, conspiracy theories, and personal attacks
 - Learned from user interactions (Neff and Nagy 2016)



Machine learning systems replicate biases that occurred in the training data.

Ethical Issues in Dialog System Design: Gender equality

Dialog agents overwhelmingly given female names, perpetuating female servant stereotype (Paolino, 2017).





Microsoft XiaoIce (18 year old girl)

Reinforcing stereotypes?

"Perhaps the closest relative to today's all-purpose virtual assistants were speaking car navigation systems. The voices for these systems gave terse, authoritative directions ('turn left in one block', 'go straight for 500 metres') and were almost always male. One of the few early car models equipped with a female voice for navigation, a late 1990s BMW 5 Series, was actually recalled in Germany because so many drivers registered complaints about receiving directions from a 'woman'."

→ 'the type of action or assistance a speech technology provides often determines its gender.'

I'd blush if I could: closing gender divides in digital skills through education, UNESCO 2019

What to do about bad behavior?

Amazon Echo Is Magical. It's Also Turning My Kid Into an Asshole.

Posted on April 6, 2016 by hunterwalk

Here's Why You Should Stop Swearing at Siri Right Now



https://fortune.com/2016/09/29/dont-swear-at-siri/

What to do about bad behavior?



More about this in Turning the lecture on responsible AI!



Stop Swearing at Siri Right Now

https://fortune.com/2016/09/29/dont-swear-at-siri/

Summary

Summary

State of the art:

- Chatbots:
 - Simple rule-based systems
 - IR or neural networks: mine datasets of conversations.
- Frame-based systems:
 - Hand-written rules for slot fillers
 - ML classifiers to fill slots

The future?

Integrating goal-based and chatbot-based systems

Questions to help you prepare for the exam

- What is the main difference between a chatbot and a goal-based dialogue system?
- Briefly explain how the Eliza chatbot works
- What is the difference between an IR-based chatbot and a seq2seq chatbot?
- What are the pros and cons of chatbots?
- What are the components of a typical frame-based dialogue system?
- What are the disadvantages of a simple finite state dialogue manager?
- What are the advantages of dialogue system with system initiative?
- What is a frame and how can it be used to guide a dialogue? Provide a concrete example.
- What is a dialogue act? Provide 3 examples.

Thanks to

Slides based on slides from last year (Floris Bex) and slides by Jurafsky & Martin