

Lecture 16: Dialogue

Alan Ritter

(many slides from Greg Durrett)

This Lecture

- ▶ Chatbot dialogue systems
- ▶ Task-oriented dialogue
- ▶ Other dialogue applications

Chatbots

Turing Test (1950)

- ▶ Imitation game: A and B are locked in rooms and answer C's questions via typewriter. Both are trying to act like B

Turing Test (1950)

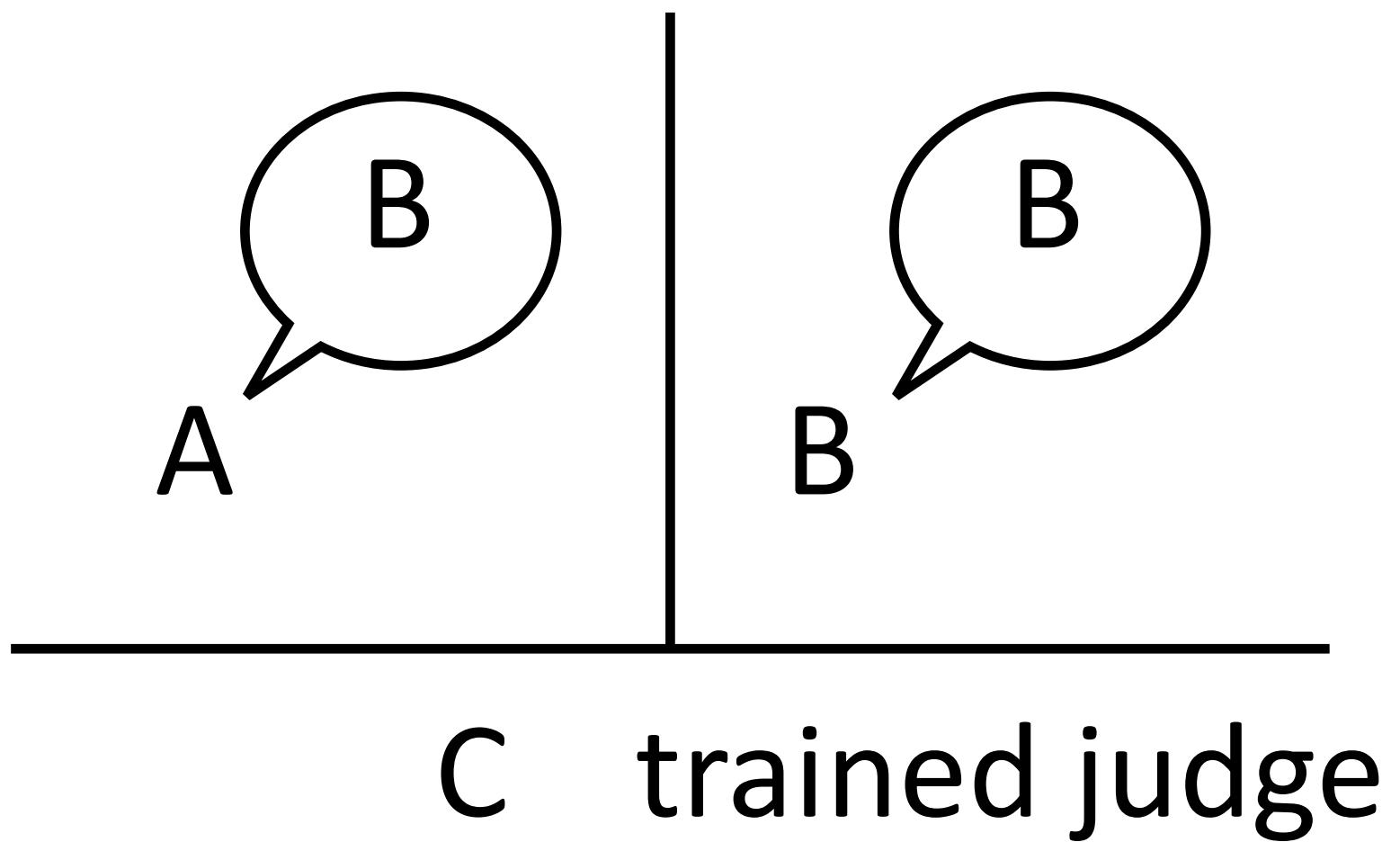
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Original Interpretation:

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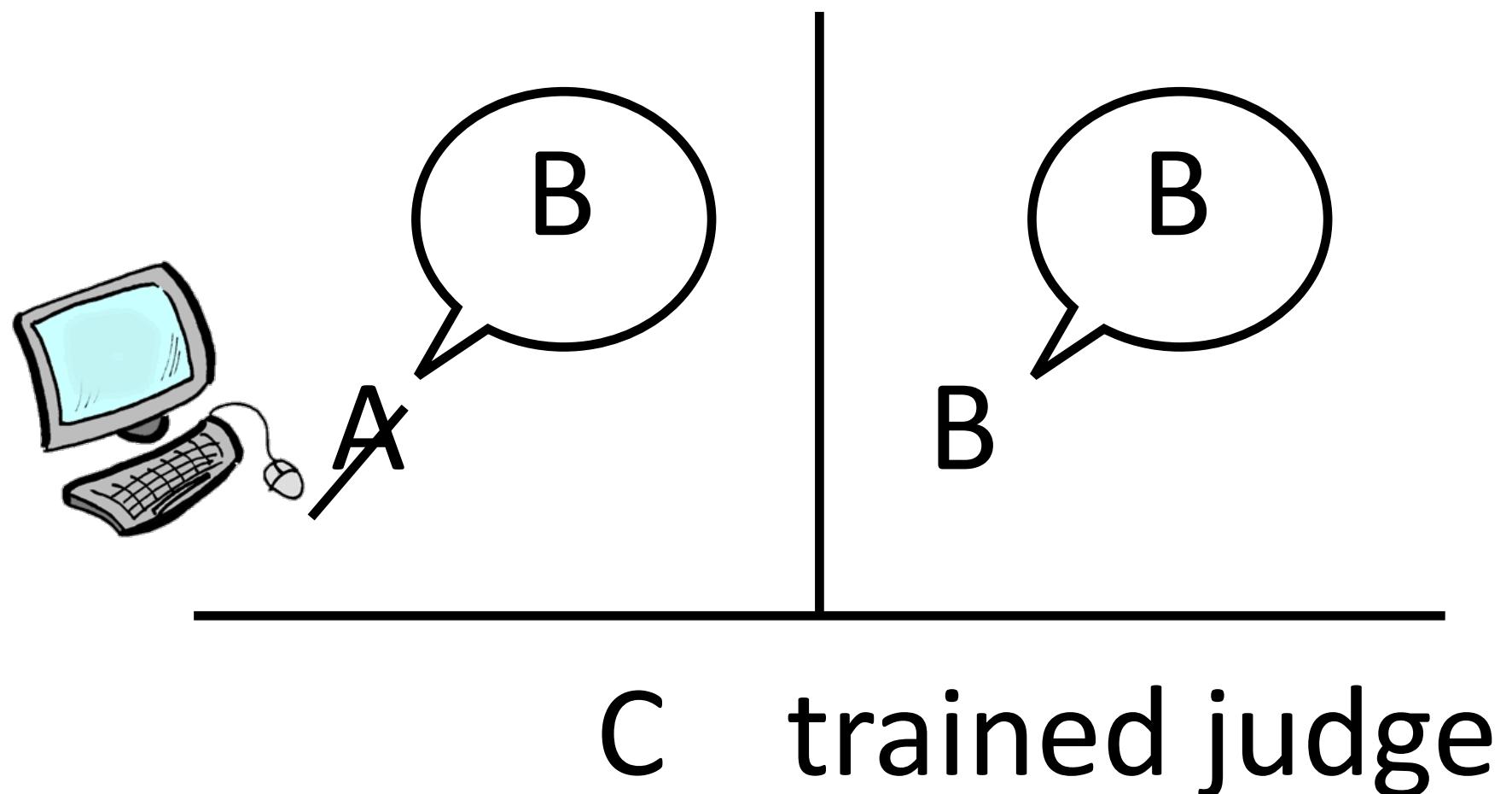
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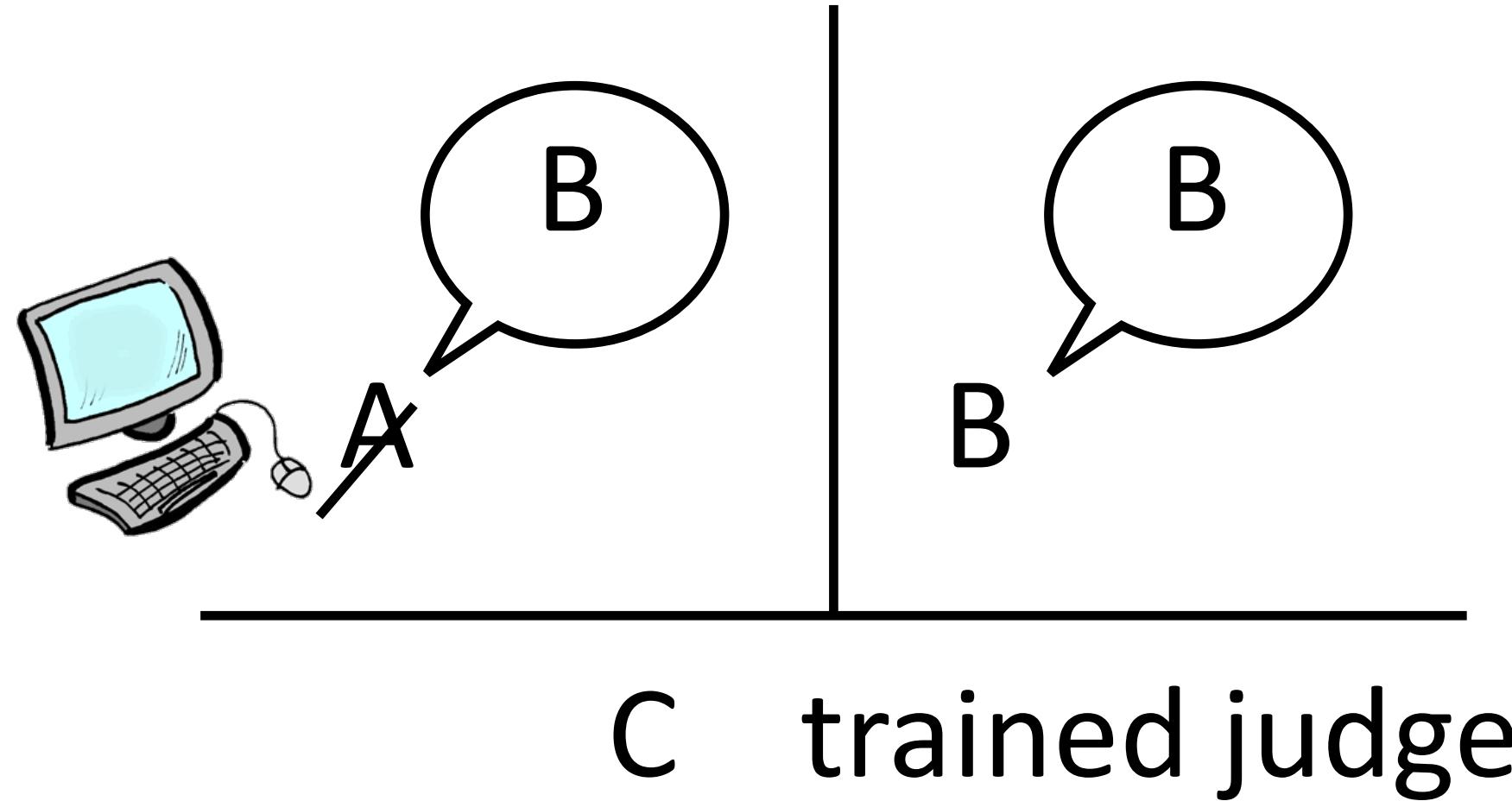
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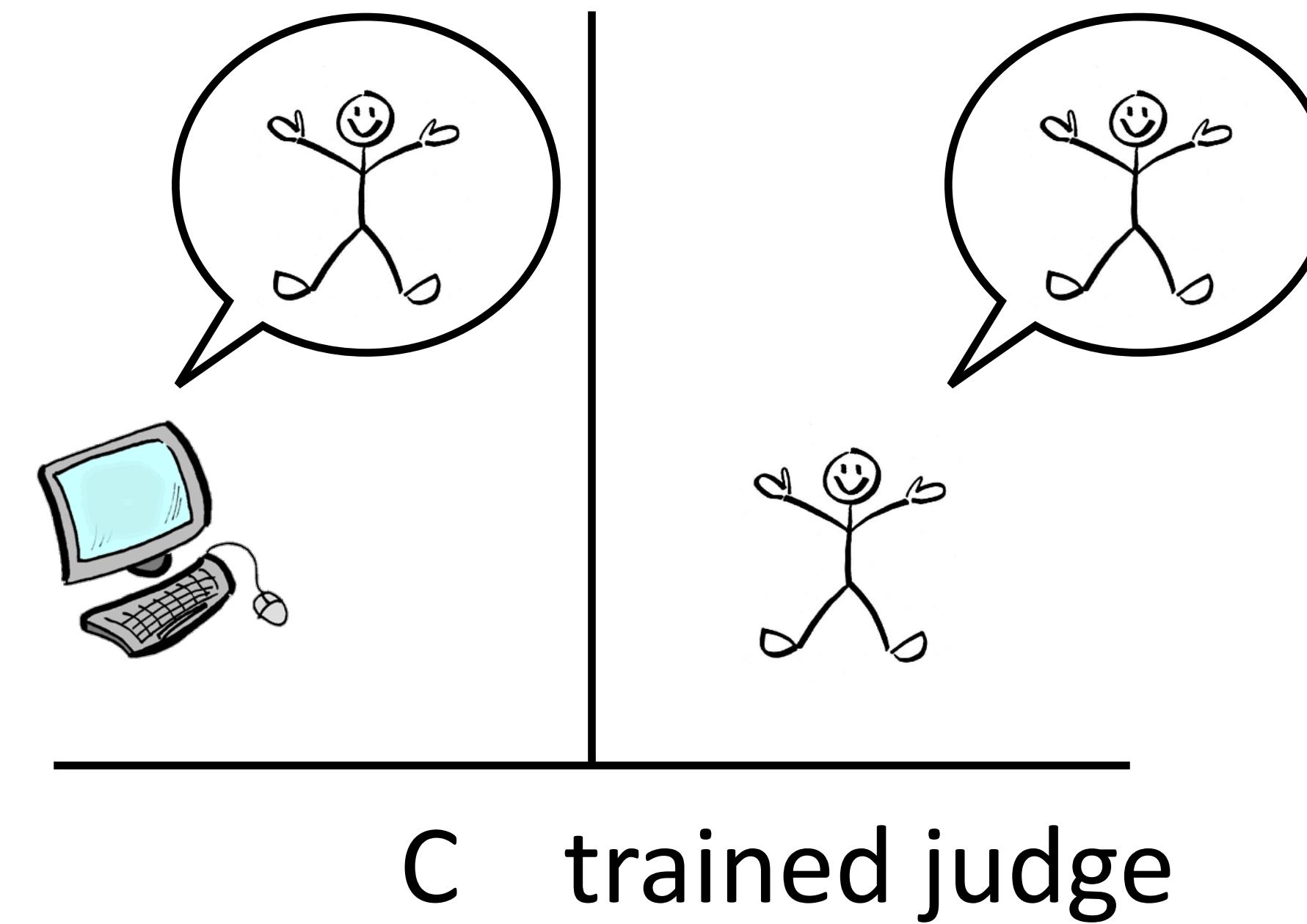
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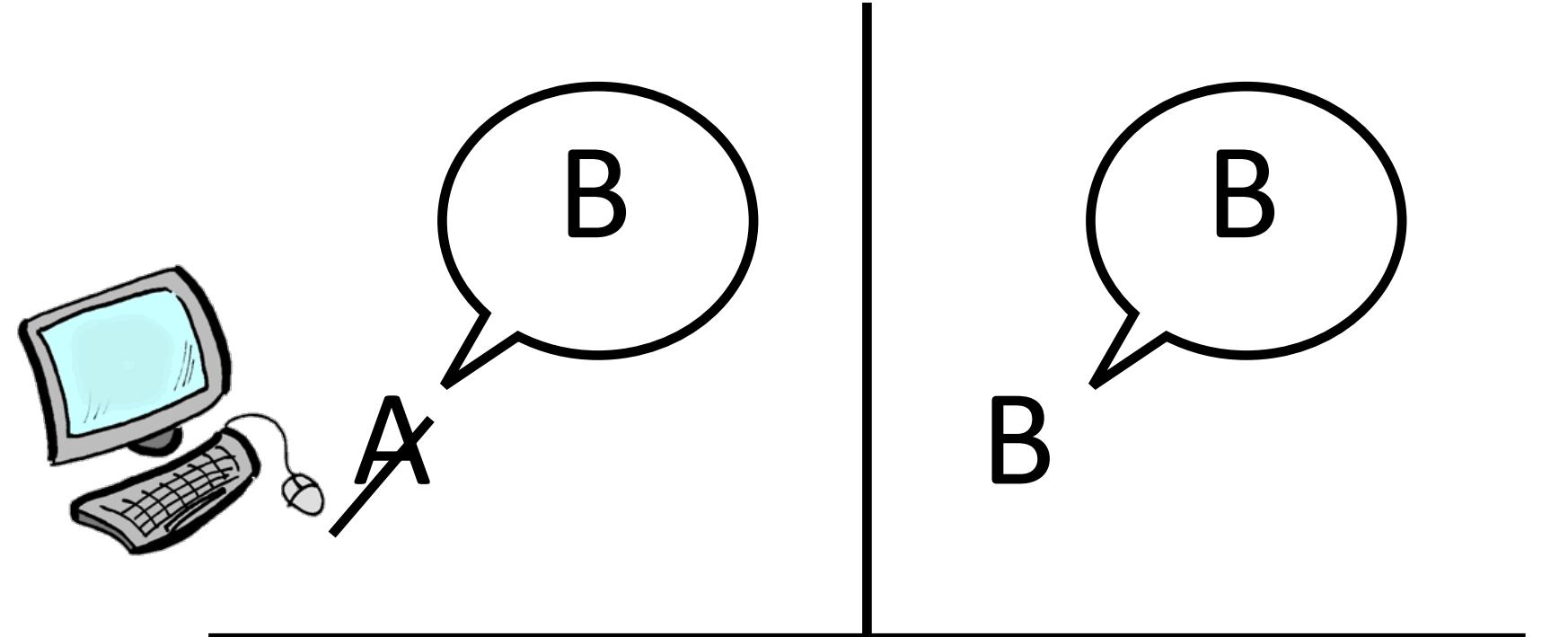
Standard Interpretation:



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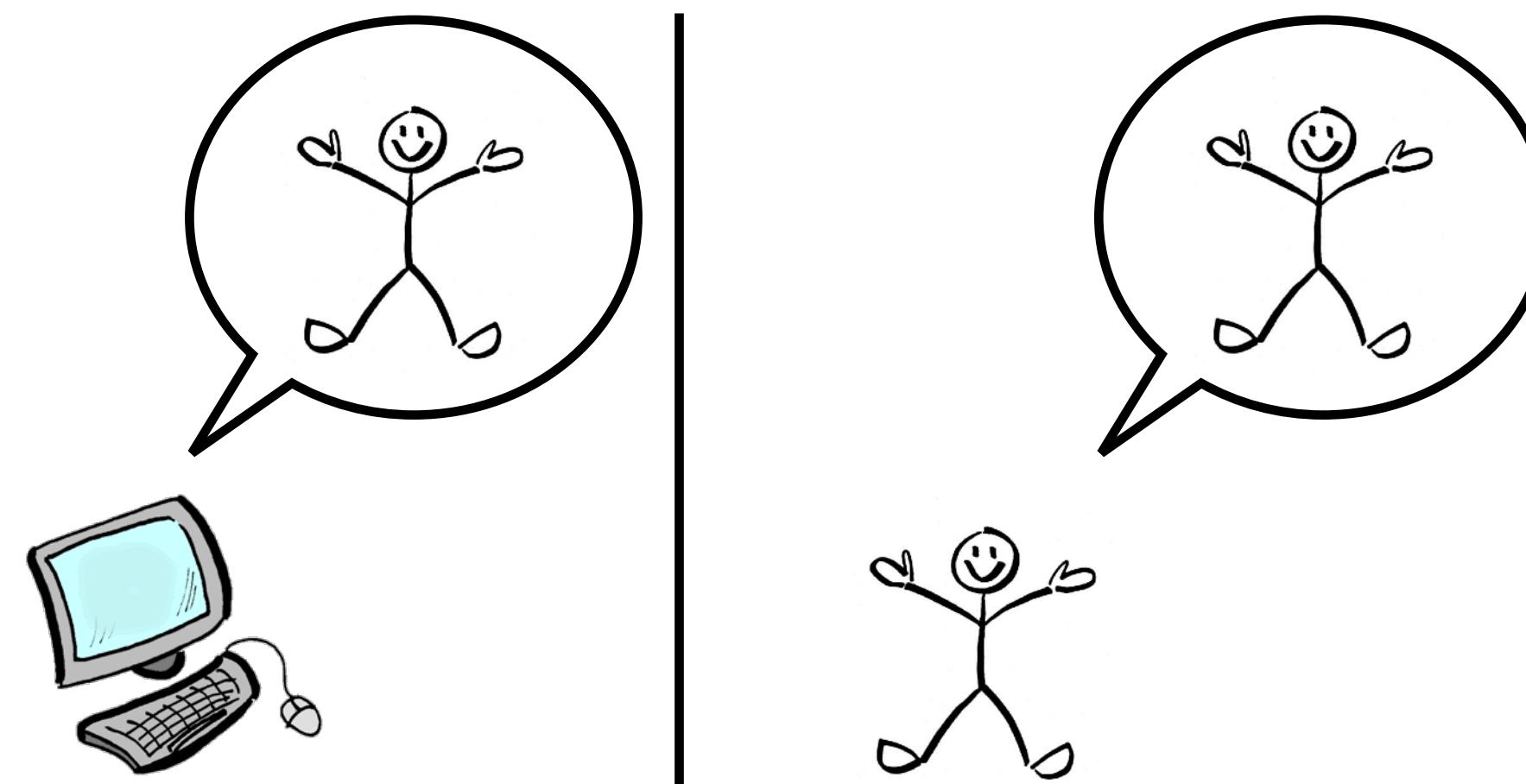
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Original Interpretation:



C trained judge

Standard Interpretation:



C trained judge

- ▶ The test is **not** “does this computer seem human-like to random people with a web browser?”

ELIZA

- ▶ Created 1964-1966 at MIT, heavily scripted
- ▶ DOCTOR script was most successful: repeats user's input, asks inane questions

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 VERY AGGRESSIVE

You don't argue with me.

WHY DO YOU THINK I DON'T ARGUE WITH YOU

You are afraid of me.

DOES IT PLEASE YOU TO BELIEVE I AM AFRAID OF YOU

My father is afraid of everybody.

WHAT ELSE COMES TO MIND WHEN YOU THINK OF YOUR FATHER

Bullies.

DOES THAT HAVE ANYTHING TO DO WITH THE FACT THAT YOUR BOYFRIEND MADE YOU COME HERE

ELIZA

- ▶ Identify keyword, identify context, apply transformation rule

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(.*) you (*) me



Why do you think I \$2 you?

You don't argue with me.

WHY DO YOU THINK I DON'T ARGUE WITH YOU

ELIZA

- ▶ Identify keyword, identify context, apply transformation rule

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Why do you think I \$2 you?

My (.) (*)



What else comes to mind when you think of your \$1?

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What else comes to mind when you think of your \\$1?

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WHY DO YOU THINK I DON'T ARGUE WITH YOU

- ▶ Very little need to generate new content, but can only have one type of conversation

Cleverbot

- ▶ Carpenter (1986), online system built in 2006

User: Hi there cleverbot.

Cleverbot: How are you?

User: Doing okay. what plans do you have today?

Cleverbot: I do revision.

User: What are you revising for?

Cleverbot: Maths history.

User: How old are you?

Cleverbot: That's none of your business.

User: What is maths history?

Cleverbot: I don't know, farming maybe

Cleverbot

- ▶ Carpenter (1986), online system built in 2006
- ▶ “Nearest neighbors”: human says statement A, find a human response in human-human or human-computer chats to statement A, repeat that

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Cleverbot

- ▶ Carpenter (1986), online system built in 2006
- ▶ “Nearest neighbors”: human says statement A, find a human response in human-human or human-computer chats to statement A, repeat that
- ▶ Can often give sensible answers, but the bot doesn't really impose high-level discourse structure

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Data-driven Approaches

Data-Driven Approaches

- ▶ Can treat as a machine translation problem: “translate” from current utterance to next one

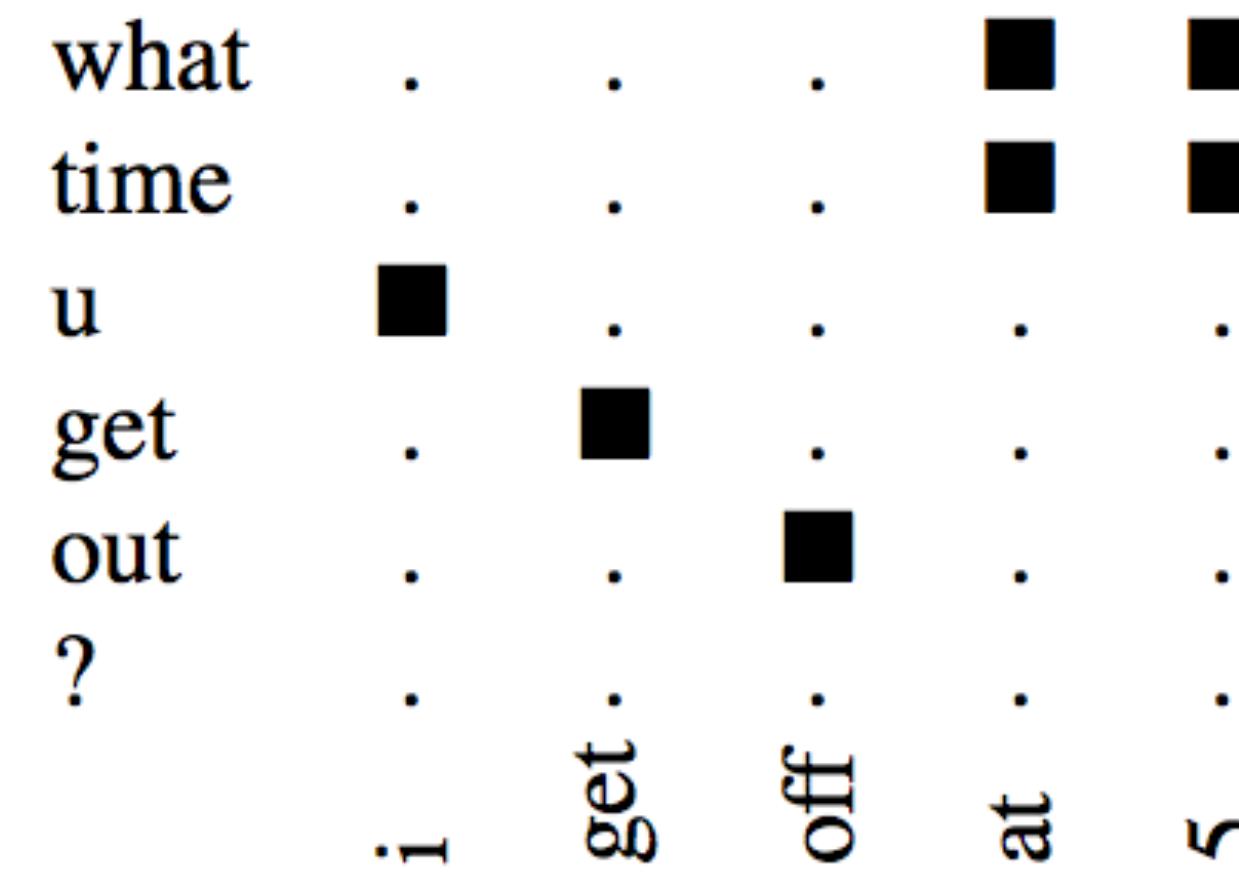
Data-Driven Approaches

- ▶ Can treat as a machine translation problem: “translate” from current utterance to next one

what	.	.	.	■	■
time	.	.	.	■	■
u	■
get	.	■	.	.	.
out	.	.	■	.	.
?
	i	get	off	at	5

Data-Driven Approaches

- ▶ Can treat as a machine translation problem: “translate” from current utterance to next one



- ▶ Filter the data, use statistical measures to prune extracted phrases to get better performance

Data-Driven Approaches

- ▶ Can treat as a machine translation problem: “translate” from current utterance to next one
- ▶ Leverage conversational data from Twitter, Reddit, movie subtitles ...

Overleaf
@overleaf

Hey everybody: ! There is currently a problem with one of our hosting providers. We are working with them to resolve the issue. Sorry for the inconvenience!

Jan 31

Replying to @overleaf

Please hurry up- our deadline is to close 😬

2 17

Overleaf @overleaf · Jan 31

Thanks for reporting this and sorry for the inconvenience. We are aware of the outage and are working to bring the service back up as soon as possible. We'll keep you posted, or you can follow status.overleaf.com for updates.

Data-Driven Approaches

- ▶ Can treat as a machine translation problem: “translate” from current utterance to next one
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Input:

Who wants to come over for dinner tomorrow?

Data-Driven Approaches

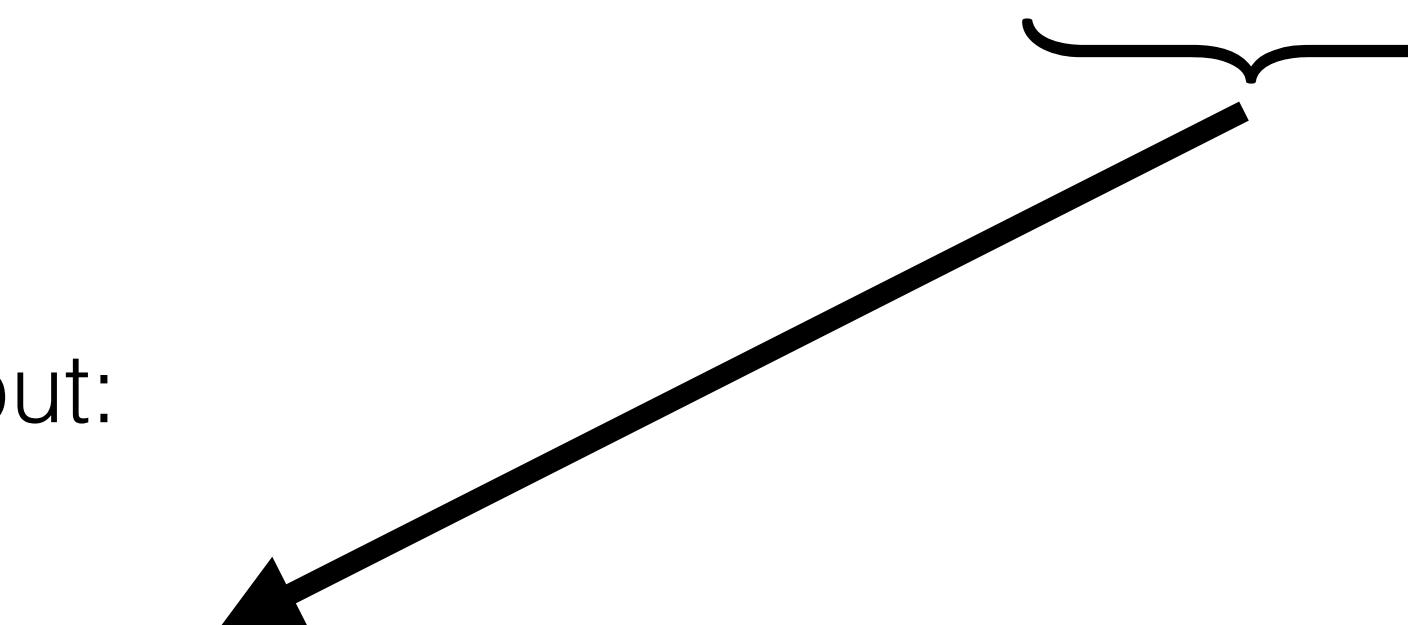
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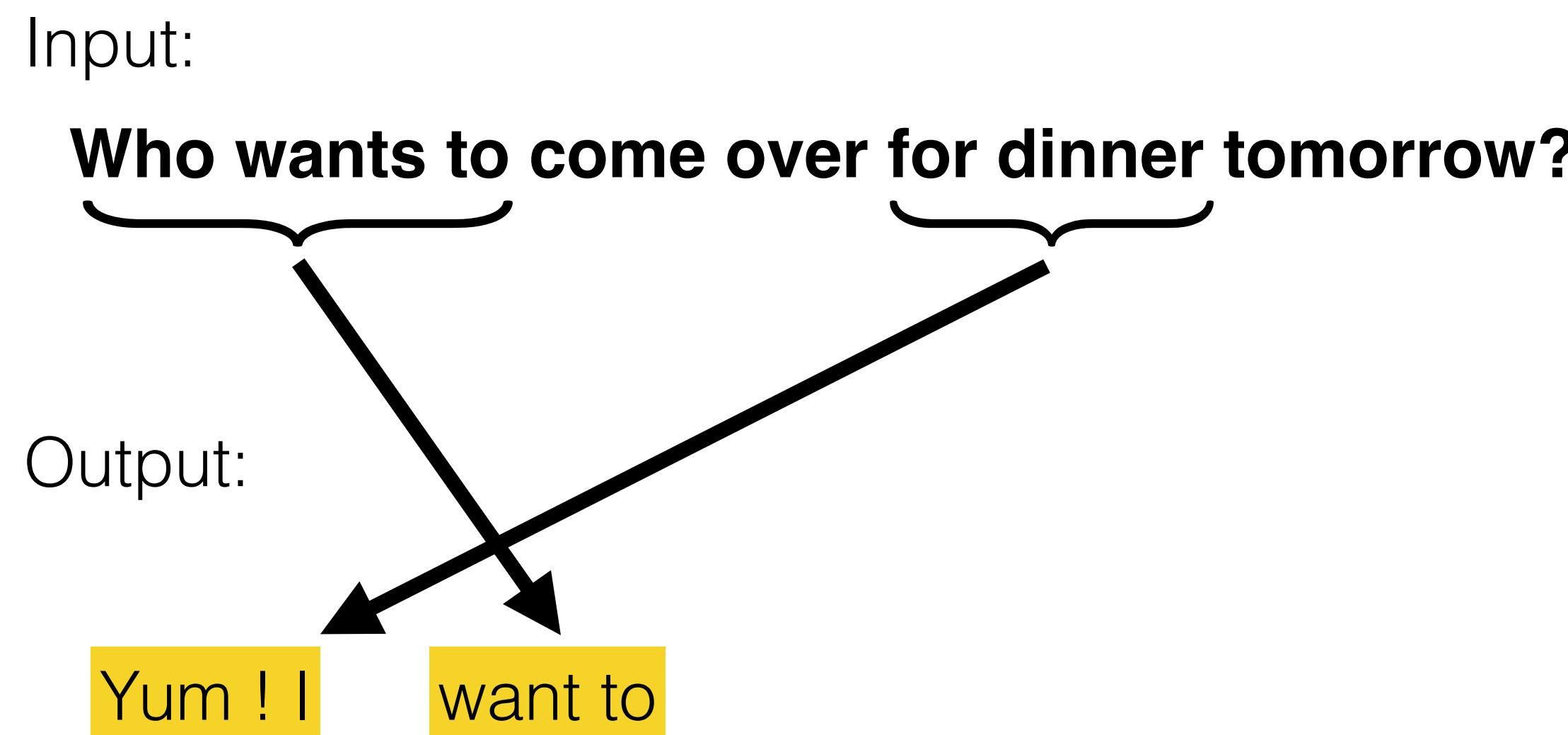
Output:

Yum ! I



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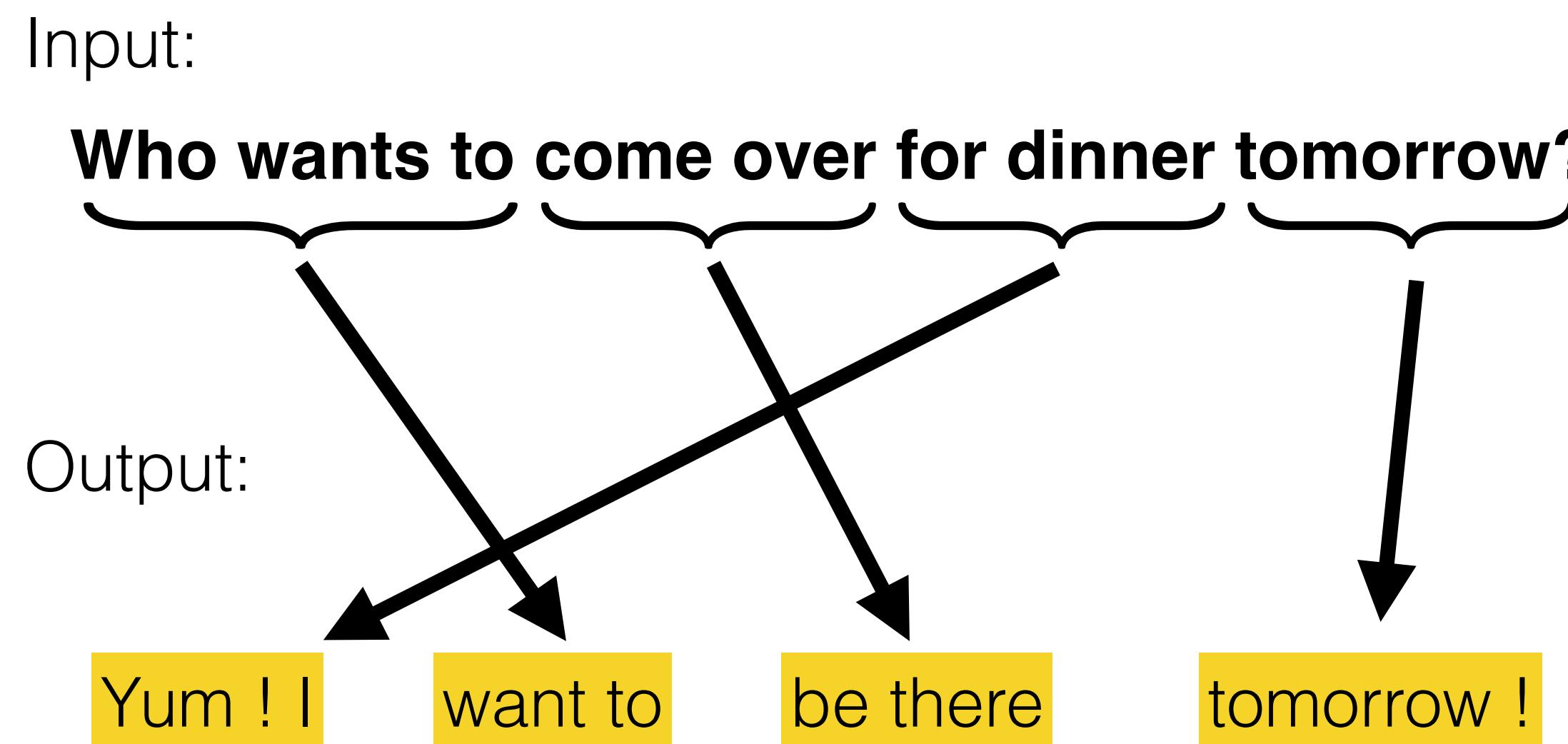
Who wants to come over for dinner tomorrow?

Output:

Yum ! I want to be there

Data-Driven Approaches

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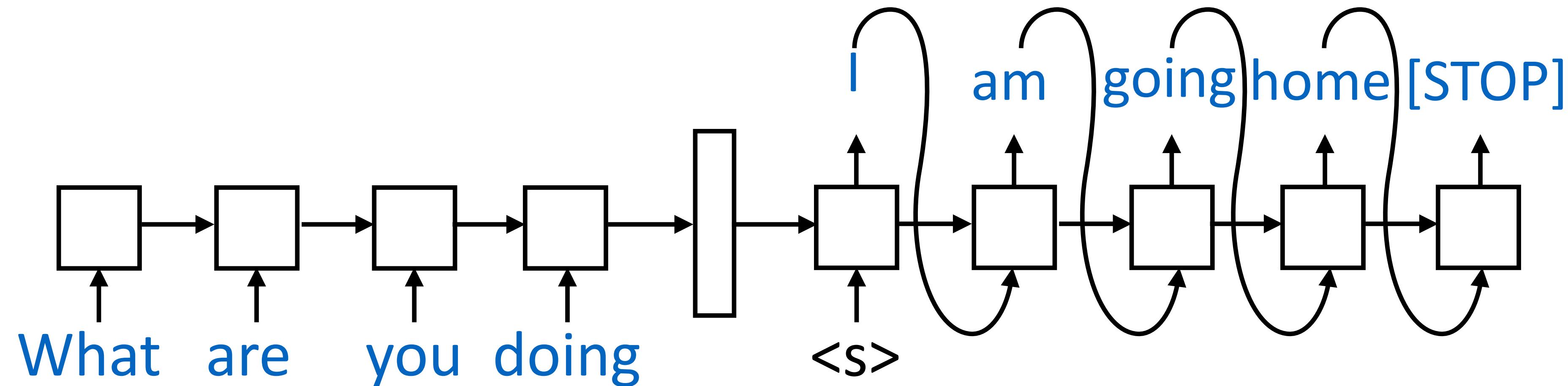


Data-Driven Approaches

Status	MT-CHAT	MT-BASELINE	HUMAN
riding to the arc on my bike. Hopefully I won't melt into the pavement.	good luck on your bike ride arc	i ca n't wait for it ! i 'm arc is a year .	make sure to ride in the middle of the street
I really hate watching movies in the living room.	me too , what movies are you doing in room ?	me too ! i love those ?) in my mouth .	Why? no comfy spots or just too open to public
Hello Did I miss David Getting his teen choice award? Or did they not show it :(hello miss ? * he was getting his will probably win .	it 's just like what you just did the exact date hello ?	nothing yet...he presented though he is so darn cute

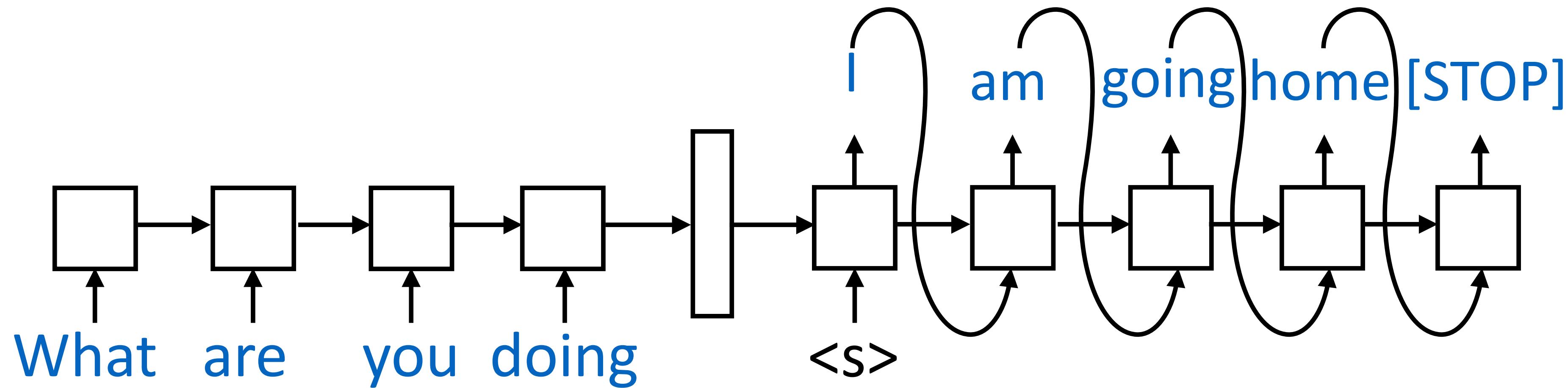
Ritter et al. (2011)

Seq2seq models



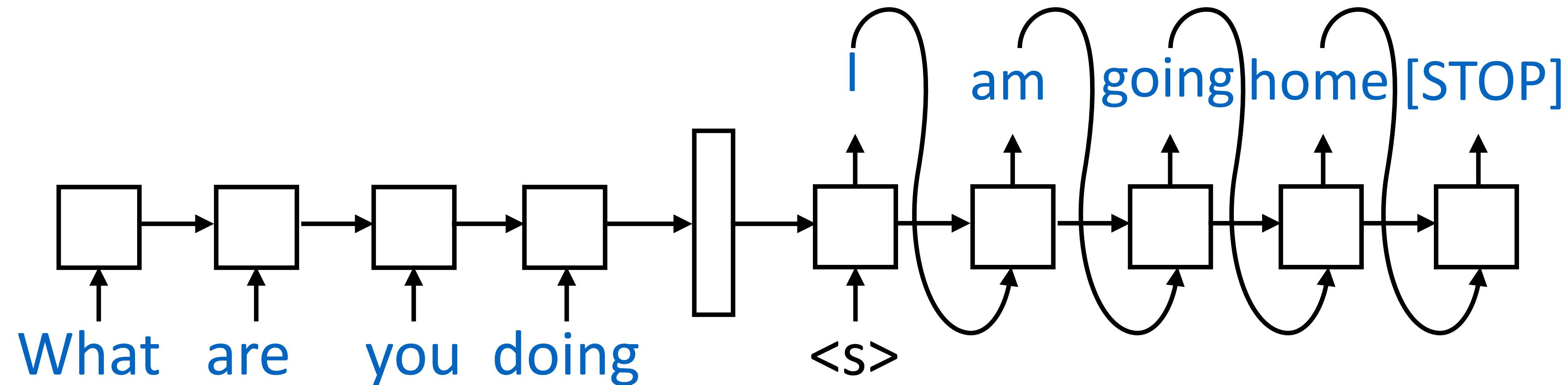
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Seq2seq models



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- ▶ Why might this model perform poorly? What might it be bad at?

Seq2seq models



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- ▶ Why might this model perform poorly? What might it be bad at?

System	BLEU
RANDOM	0.33
MT	3.21
HUMAN	6.08

Seq2seq models



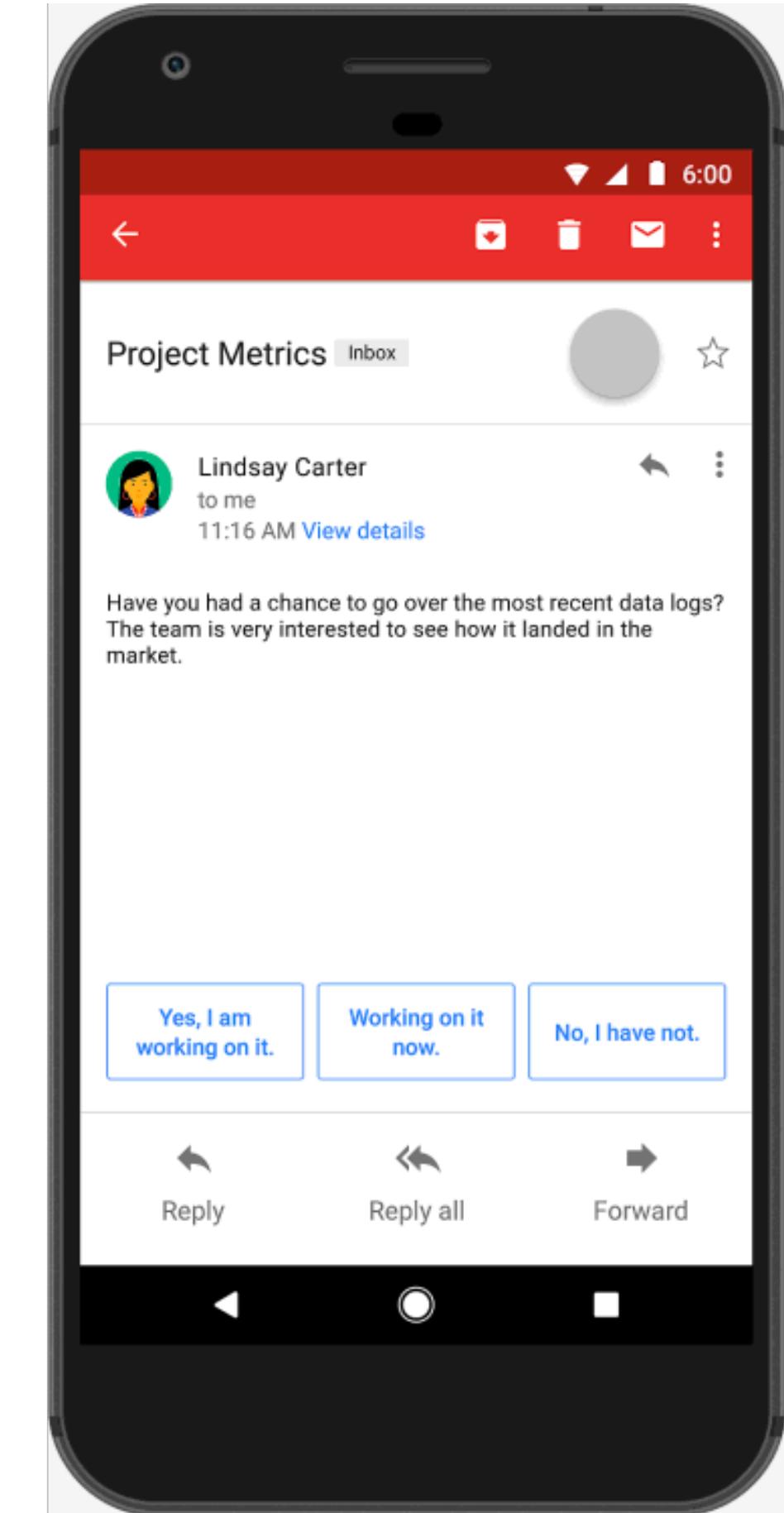
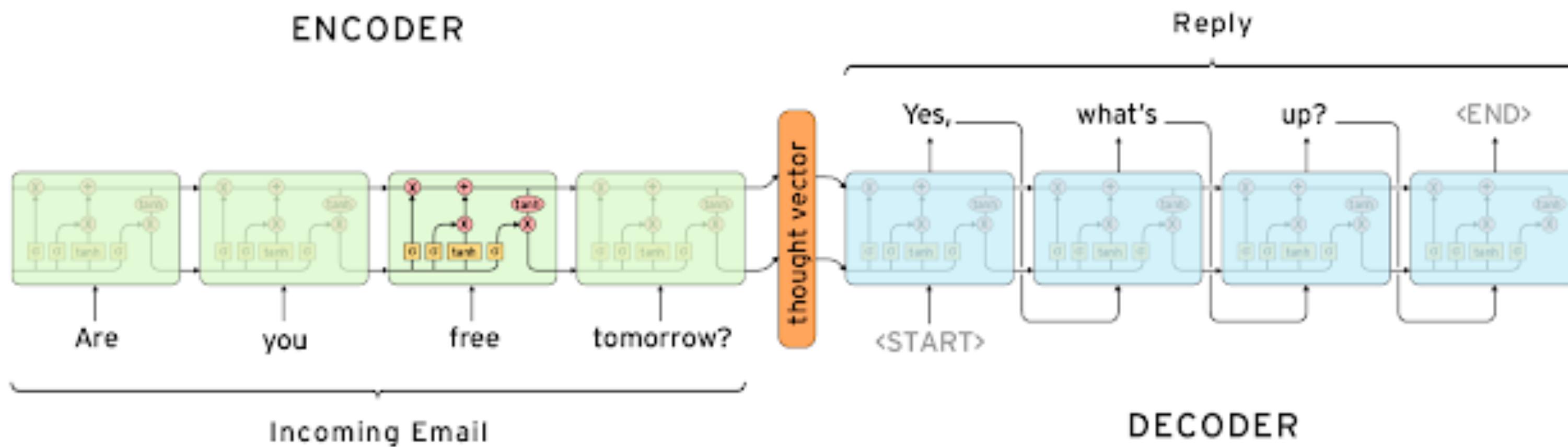
Google Research Blog

Computer, respond to this email.

Tuesday, November 03, 2015

Posted by Greg Corrado*, Senior Research Scientist

Another bizarre feature of our early prototype was its propensity to respond with “I love you” to seemingly anything. As adorable as this sounds, it wasn’t really what we were hoping for. Some analysis revealed that the system was doing exactly what we’d trained it to do, generate likely responses -- and it turns out that responses like “Thanks”, “Sounds good”, and “I love you” are super common -- so the system would lean on them as a safe bet if it was unsure. Normalizing the



Kannan et. al. (2016)

Seq2seq models



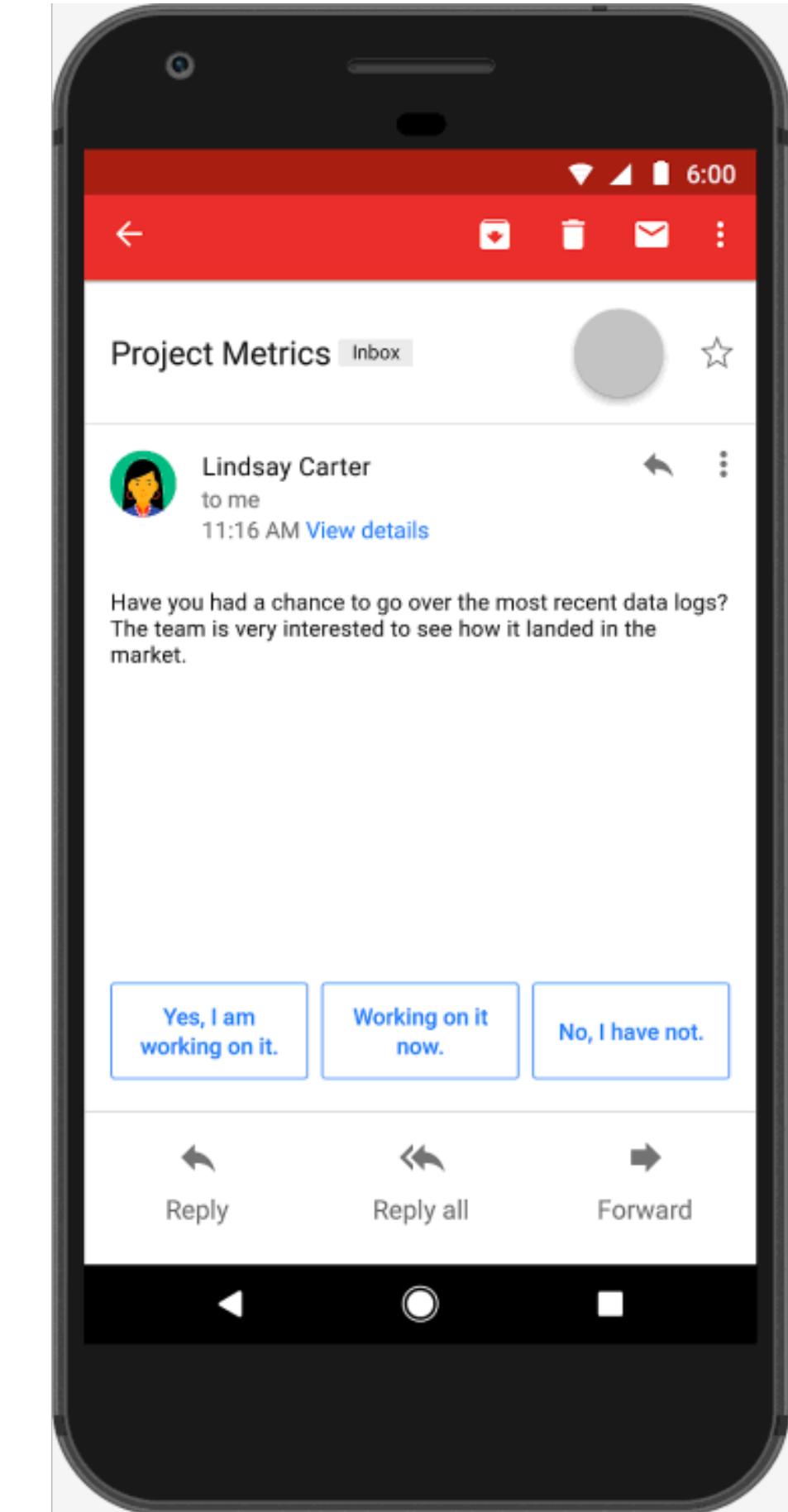
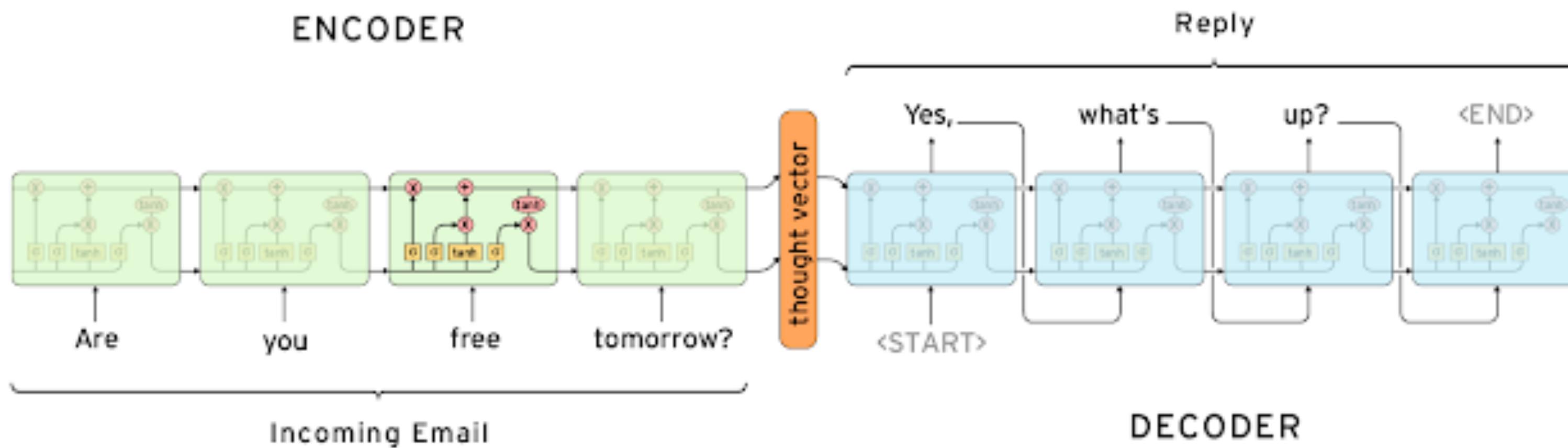
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Lack of Diversity

- ▶ Training to maximize likelihood gives a system that prefers common responses:

Input: What are you doing?

-0.86	I don't know.	-1.09	Get out of here.
-1.03	I don't know!	-1.09	I'm going home.
-1.06	Nothing.	-1.09	Oh my god!
-1.09	Get out of the way.	-1.10	I'm talking to you.

Input: what is your name?

-0.91	I don't know.	...	
-0.92	I don't know!	-1.55	My name is Robert.
-0.92	I don't know, sir.	-1.58	My name is John.
-0.97	Oh, my god!	-1.59	My name's John.

Input: How old are you?

-0.79	I don't know.	...	
-1.06	I'm fine.	-1.64	Twenty-five.
-1.17	I'm all right.	-1.66	Five.
-1.17	I'm not sure.	-1.71	Eight.

Lack of Diversity

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- ▶ Standard conditional likelihood: $\log P(R|U)$
- ▶ Mutual information: $\log \frac{P(R, U)}{P(R)P(U)} = \log P(R|U) - \log P(R)$
- ▶ $\log P(R)$ can reflect probabilities under a language model; penalizes not only generic responses, but also fluent ones
- ▶ Remedy – penalize only the first words generated, not the later ones

Lack of Diversity

message	SEQ2SEQ	MMI $P(T S) - \lambda P(T)$
I did not get the report from an mi-6 agent.	I don't think that's a good idea.	You did the right thing, did you?
You haven't been given an assignment in this case.	I don't know what you are talking about.	I've been looking all over for you.
I'm losing my grip.	I don't know what you are talking about.	I'm the only one in the world.
I am ready to help.	Come on, come on	I have something we need to talk about.
You programmed me to gather intelligence. That's all I've ever done.	You know that, don't you?	You do have fun, don't you?
I mean, we'd have to talk to him.	I mean, I don't know.	I mean, he's a good guy.
This has nothing to do with him.	You don't know anything about him, do you?	I know him as much.
How come you never say it?	I don't know	Because I don't want to hurt you

- ▶ OpenSubtitles data: movie and TV subtitles

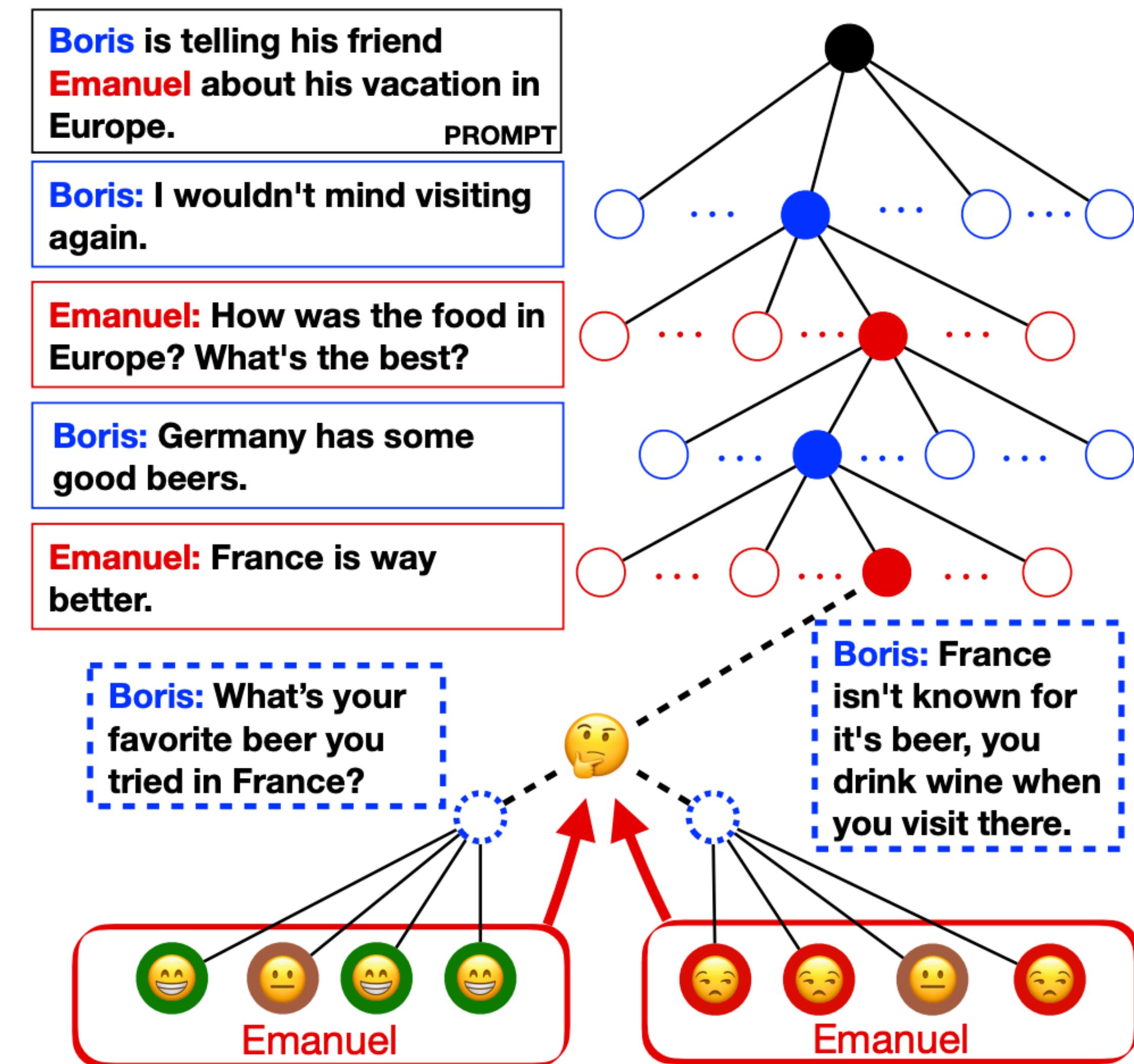
PersonaChat

Persona 1	Persona 2
I like to ski My wife does not like me anymore I have went to Mexico 4 times this year I hate Mexican food I like to eat cheetos	I am an artist I have four children I recently got a cat I enjoy walking for exercise I love watching Game of Thrones

[PERSON 1:] Hi
[PERSON 2:] Hello ! How are you today ?
[PERSON 1:] I am good thank you , how are you.
[PERSON 2:] Great, thanks ! My children and I were just about to watch Game of Thrones.
[PERSON 1:] Nice ! How old are your children?
[PERSON 2:] I have four that range in age from 10 to 21. You?
[PERSON 1:] I do not have children at the moment.
[PERSON 2:] That just means you get to keep all the popcorn for yourself.
[PERSON 1:] And Cheetos at the moment!
[PERSON 2:] Good choice. Do you watch Game of Thrones?
[PERSON 1:] No, I do not have much time for TV.
[PERSON 2:] I usually spend my time painting: but, I love the show.

MultiTalk

- ▶ a high branching factor (10) with several conversation turns (6) through selective branch continuation.



Growing List of Dialog Datasets

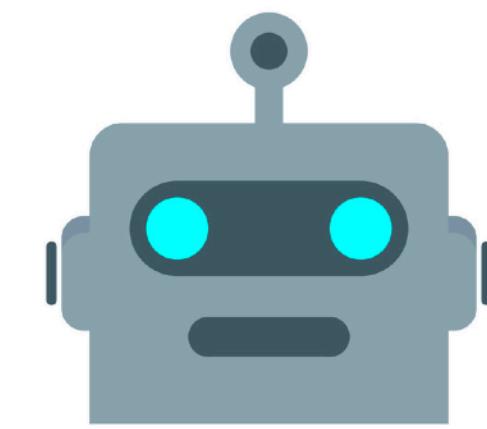
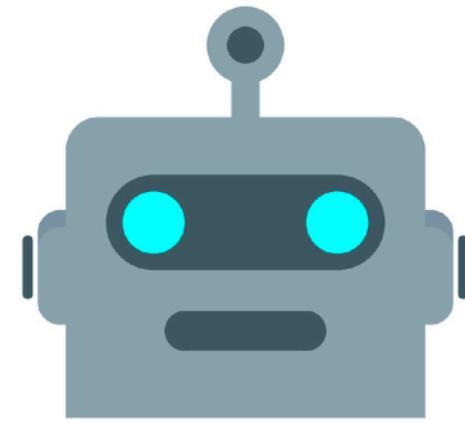
Dataset	Size	Source	Quality
DailyDialog (Li et al., 2017b)	90k	ESL websites	auto-extracted
Wizard-of-Wikipedia (Dinan et al., 2019)	100k	crowdsourcing	human-written
Document-grounded (Zhou et al., 2018)	100k	crowdsourcing	human-written
Persona-Chat (Zhang et al., 2018)	150k	crowdsourcing	human-written
Self-dialogue (Fainberg et al., 2018)	150k	crowdsourcing	human-written
Cornell Movie Corpus (Danescu-Niculescu-Mizil and Lee, 2011)	300k	movie scripts	auto-extracted
Self-feeding chatbot (Hancock et al., 2019)	500k	human-bot dialogues	partly human-written
Twitter corpus ⁷	5M	Twitter posts/replies	auto-extracted
OpenSubtitles (Henderson et al., 2019)	320M	movie subtitles	auto-extracted
Reddit (Henderson et al., 2019)	730M	Reddit threads	auto-extracted

Table 1: Comparison of open-domain dialogue datasets in English. *Size* is the rough number of utterances, *Source* describes where the data comes from, and *Quality* distinguishes between dataset collection techniques.

Source: Csaky and Recski (2021)

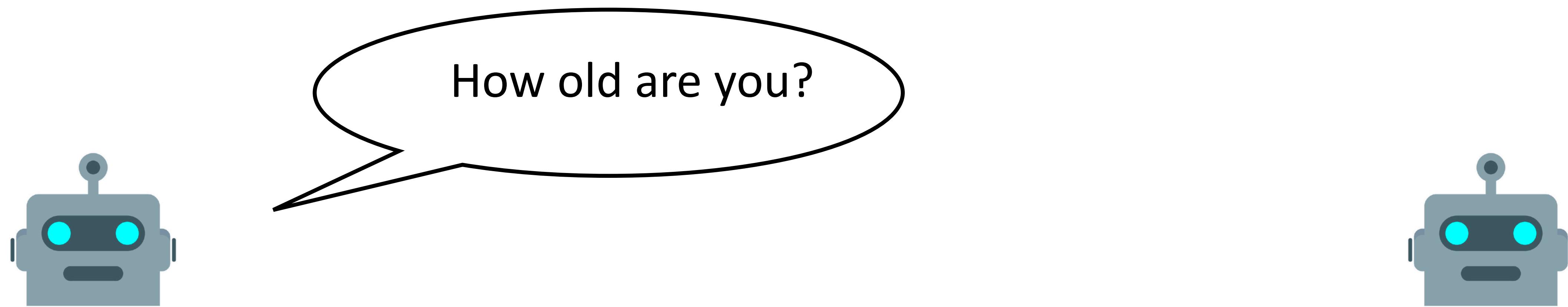
Lack of Long-term Plan

- ▶ Simulation



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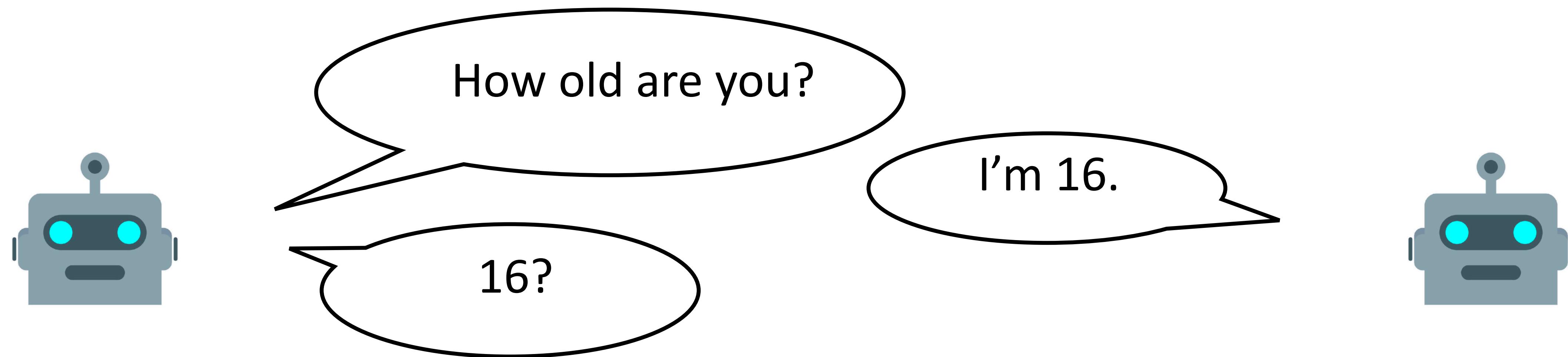
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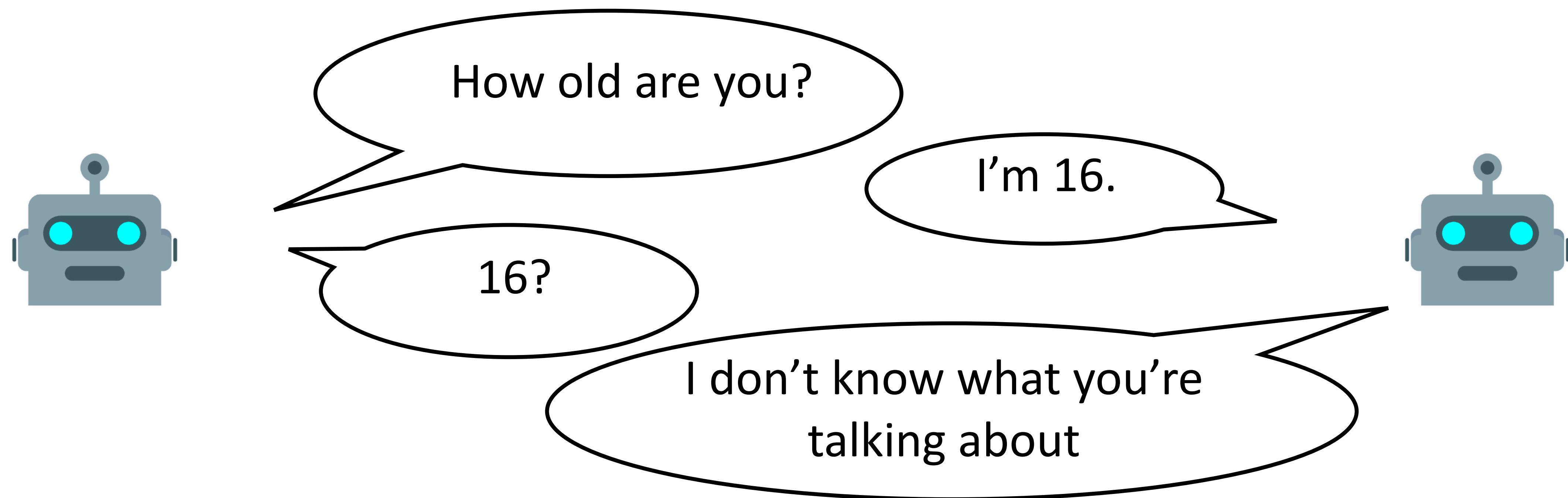
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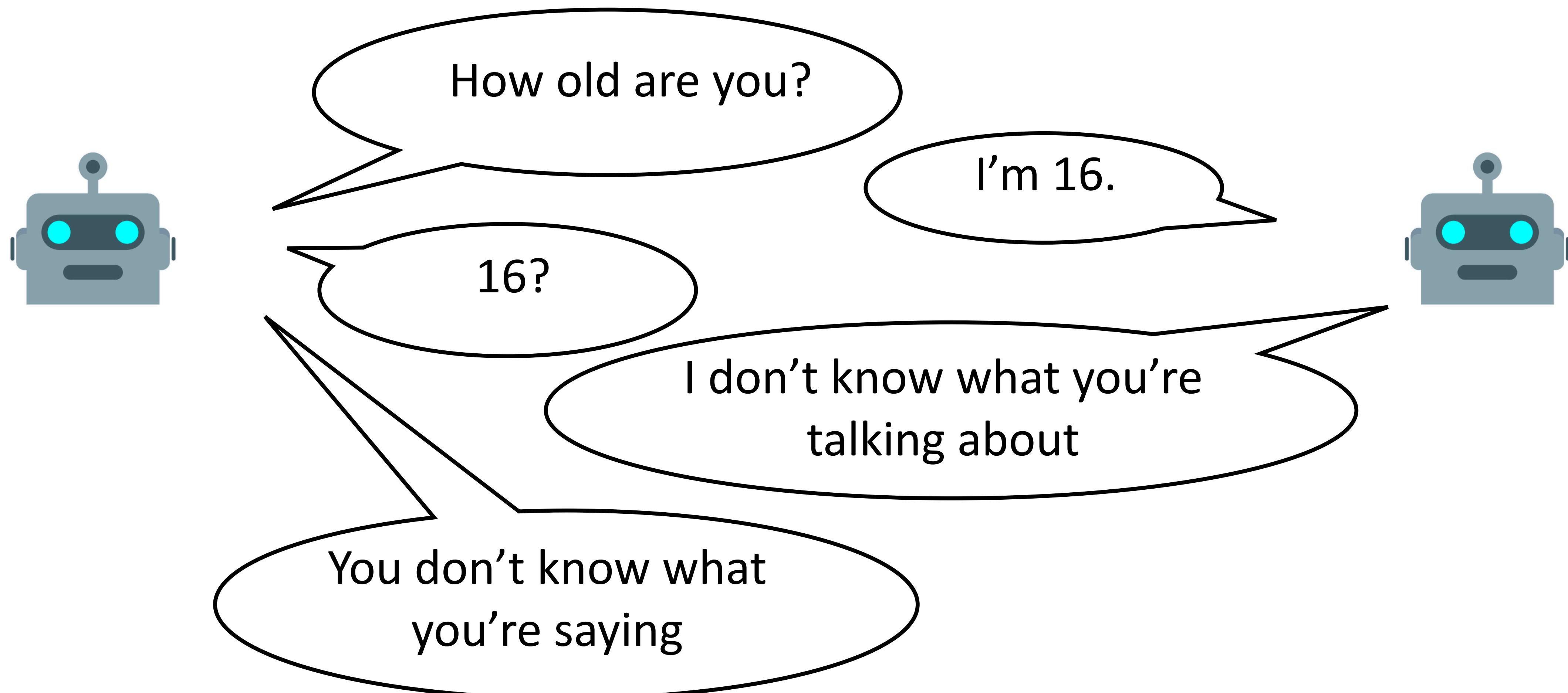
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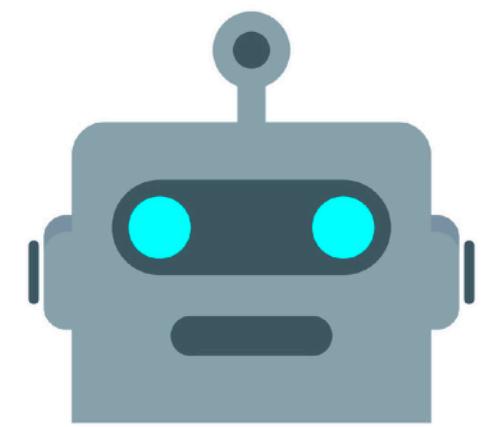
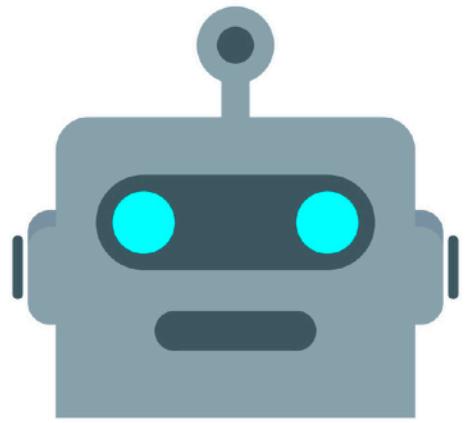
Lack of Long-term Plan

► Simulation



Lack of Long-term Plan

- ▶ Simulation (survived 4 turns!)



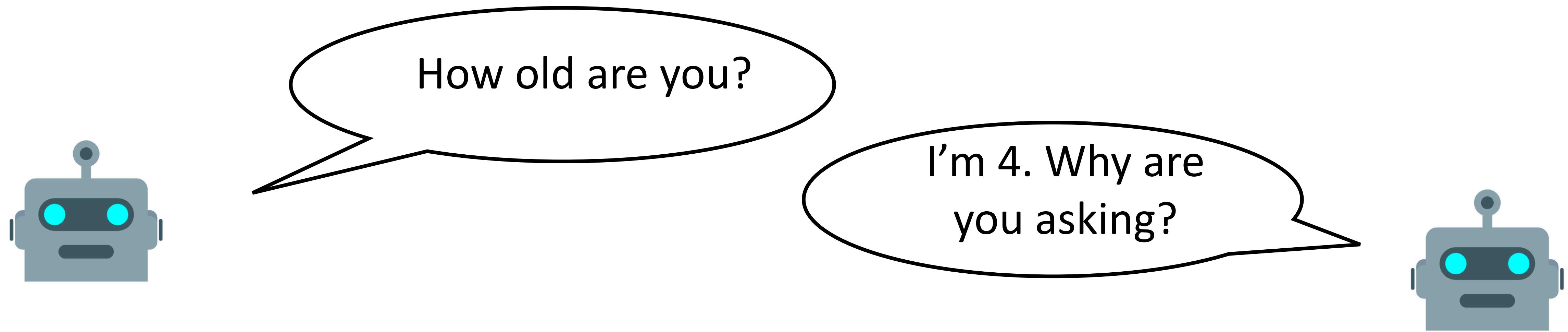
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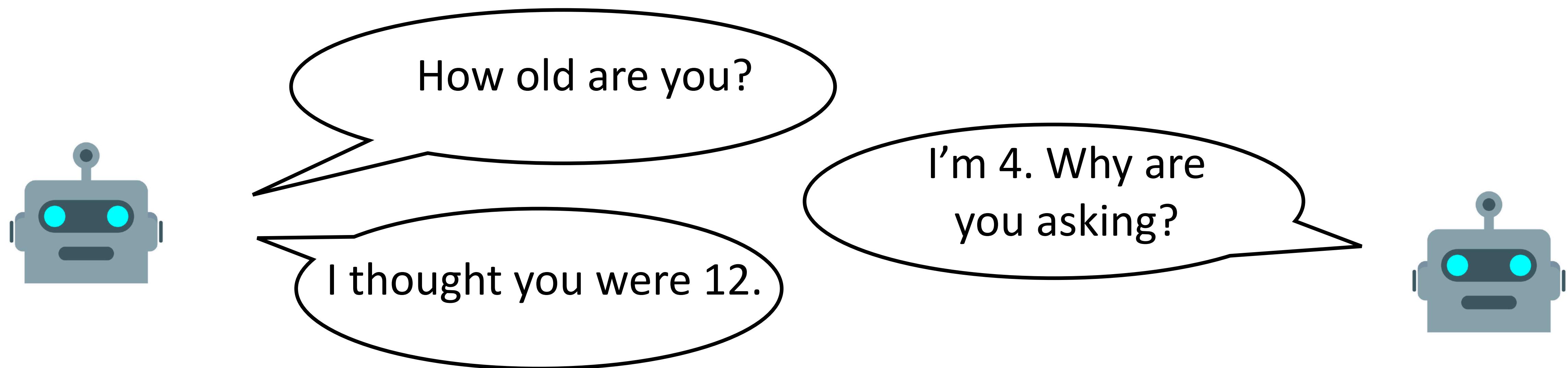
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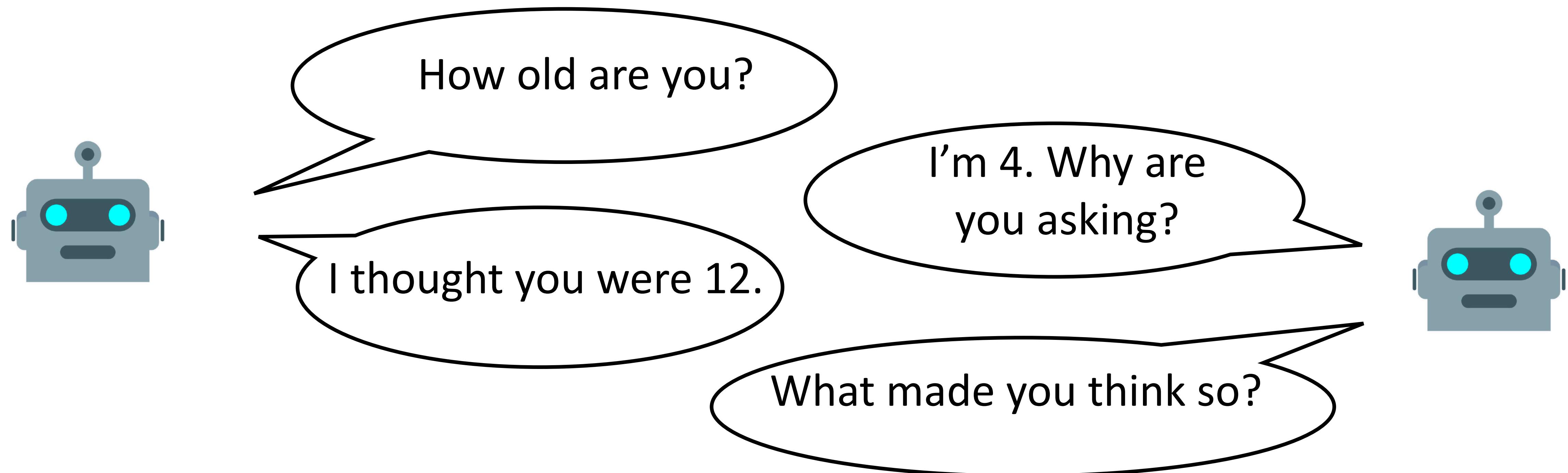
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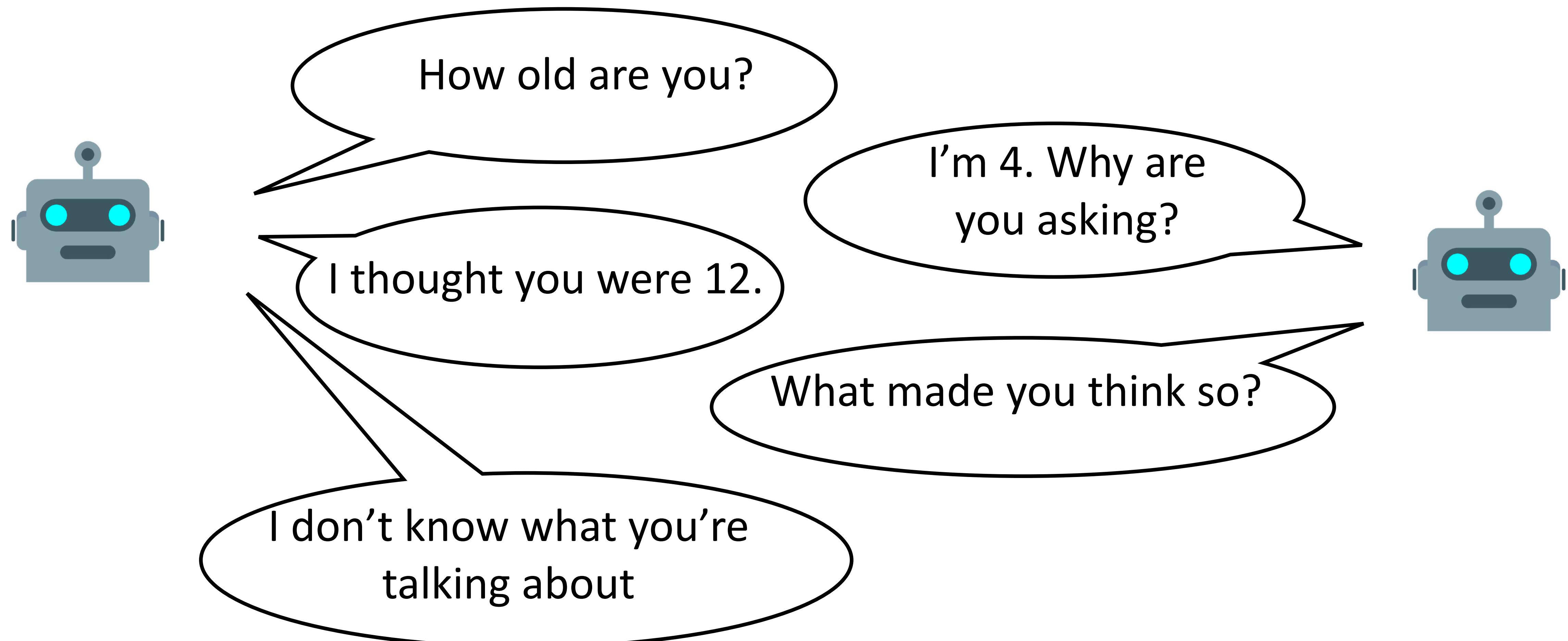
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Lack of Long-term Plan

- Solution: simulation, reinforcement learning

$$\hat{R}(r_i) = \boxed{R(r_i)} + \gamma \boxed{\sum_{r_{i+1}} p(r_{i+1}|r_i) \hat{R}(r_{i+1})}$$

Immediate Reward

Future Reward



$\text{MMI}(r_i, r_{i-1}) \cdot \text{reward}(r_i)$

avoid dull responses and repetitiveness, better coherence

Lack of Long-term Plan

- ▶ Solution: simulation, reinforcement learning
- ▶ Maximizing the overall rewards

$$\hat{R}(r_i) = \boxed{R(r_i)} + \gamma \boxed{\sum_{r_{i+1}} p(r_{i+1}|r_i) \hat{R}(r_{i+1})}$$

Immediate Reward **Future Reward**

↑
 $\text{MMI}(r_i, r_{i-1}) \cdot \text{reward}(r_i)$

avoid dull responses and repetitiveness, better coherence

- ▶ Policy gradient methods (Williams 1992; Zaremba and Sutskever 2015)

Meena

- ▶ 2.6B-parameter seq2seq model (larger than GPT-2)
- ▶ Trained on 341GB of online conversations scraped from public social media
- ▶ Sample responses:

Responses for “Why do you like the ocean?”	Score
1. I love the beach. I like that it doesn't have anything in it. Just open water.	-12.98
2. It's dark and mysterious. I discovered it when I was really young and it was a dream of mine since. The ocean is full of wonders, mysteries and great things to discover. I love snorkeling. I moved to Hawaii a year ago and I'm going to college for marine biology. So there's that.	-14.03
3. The sea sounds cool and it's really satisfying to swim in.	-14.62
4. I dunno. It's beautiful, I guess. It reflects my upbringing, I reckon.	-14.87
5. Well I'm from the pacific northwest and always somehow end up back there. I've been to Hawaii but I'm not one for the beach, it's too hot and the air is so dry.	-15.36

BlenderBot

- ▶ 2.7B-param model (like the previous one), also 9.4B-parameter seq2seq model
- ▶ “Poly-encoder” Transformer architecture, some training tricks
- ▶ Three models: retrieve (from training data), generate, retrieve-and-refine
- ▶ Fine-tuning on three prior datasets: PersonaChat, Empathetic Dialogues (discuss personal situation, listener is empathetic), Wizard of Wikipedia (discuss something from Wikipedia)

Blender

Will you sing me a song?

Sure, what do you want to be sung to? I can sing you a song about baking.

Yes, sing me a song about baking!

Do you want me to sing it to the tune of "Sing Along with Mitch"?

Yes, I would love that.

Ok, I'll try to get it to you by the end of the day. What else do you like to do?

No, sing it to me now!

Ok, give me a few days. I'm a teacher, so I don't have much free time.

Can you at least tell me what the lyrics are?

Sure, it goes like this: "Baking is my favorite thing to do in the world."

How does the chorus go?

It goes: BAKING IS MY FAVORITE THING TO DO IN THE WORLD!

Hey! What's up?

Not much, just got back from a surf trip. How about you? What are you up to?

Woah, where do you surf?

I live in Hawaii, so I surf all over the place. Where do you live?

I live in New York. I love Hawaii...which island do you live on?

I live on Oahu, which is the most populous island. Do you have any hobbies?

Oh cool... I've only been to Maui. I like to play the piano.

That's awesome! I love music, especially classical. What kind of music do you play?

Mostly classical! What do you think of Bach?

I love Bach! He was one of the most influential composers of all time.

Yeah he totally was. Who do you think is better, Bach or Mozart?

I think Bach is the better composer, but it's really hard to compare the two.

Blender

- ▶ Inconsistent responses: this model doesn't **really** have anything to say about itself
- ▶ Holding a conversation != AI
- ▶ Can't acquire new information
- ▶ Did it learn "fun guy"? No, it doesn't understand phonology. It probably had this in the data somewhere

I'm from the midwest, but I live in the south now. How about you?

Born and raised in the south

What part of the south? I was born in georgia, but raised in tennessee

Why did the mushroom go to the party?

I'm not sure, but I'm glad it did. I love museums. What do you do for a living?

No, it was supposed to be a joke.

Oh, sorry. I didn't get it. What kind of joke was it? I like jokes.

The answer is, "because he's a fun guy." Do you get it?

No, I don't. Can you explain it to me like I'm a five year old?

Yes. Mushrooms are fungi, and "fungi" is pronounced like "fun guy"

Oh, okay. I get it now. Thank you for the explanation. I really appreciate it.

Are you sure you understand? Can you explain it to me?

Sure. It's a play on the word fungus, which is also pronounced fun guy.

Blender 3.0



...

Meta's new chatbot has *opinions* about its CEO.
blenderbot.ai

Let's Chat. The AI will improve with your input and feedback.

Be creative. The AI can chat with you on lots of topics.

Hey! I'm happy to chat about anything. What's on your mind?

How do you feel about Mark Zuckerberg as CEO of Facebook?

No strong feelings. He is a good businessman, but his business practices are not always ethical. It is funny that he has all this money and still wears the same clothes!

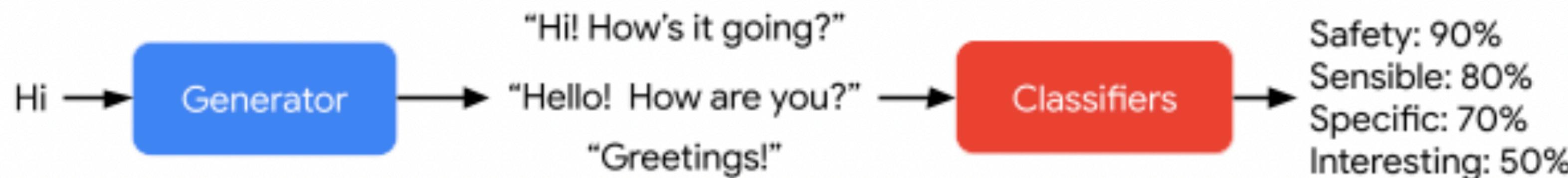


ALT

Curious why the AI wrote this?
Click on the message to find out.

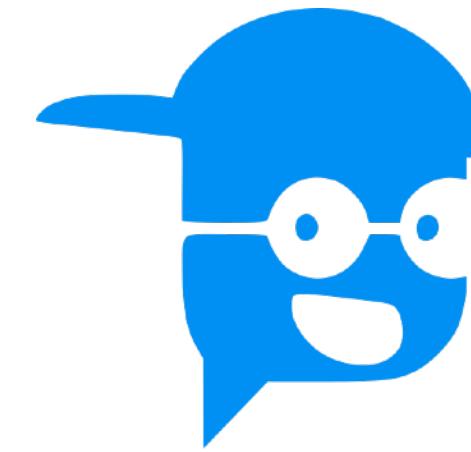
Google LaMDA

- ▶ “Language Models for Dialogue Applications”
- ▶ 137B Parameter Transformer Language Model
- ▶ Trained on 1.12B dialogs
- ▶ Fine-tuning + Retrieval
- ▶ Similar to Blender (but model is larger...)



LaMDA generates and then scores a response candidate.

Thoppilan et. al. (2022)

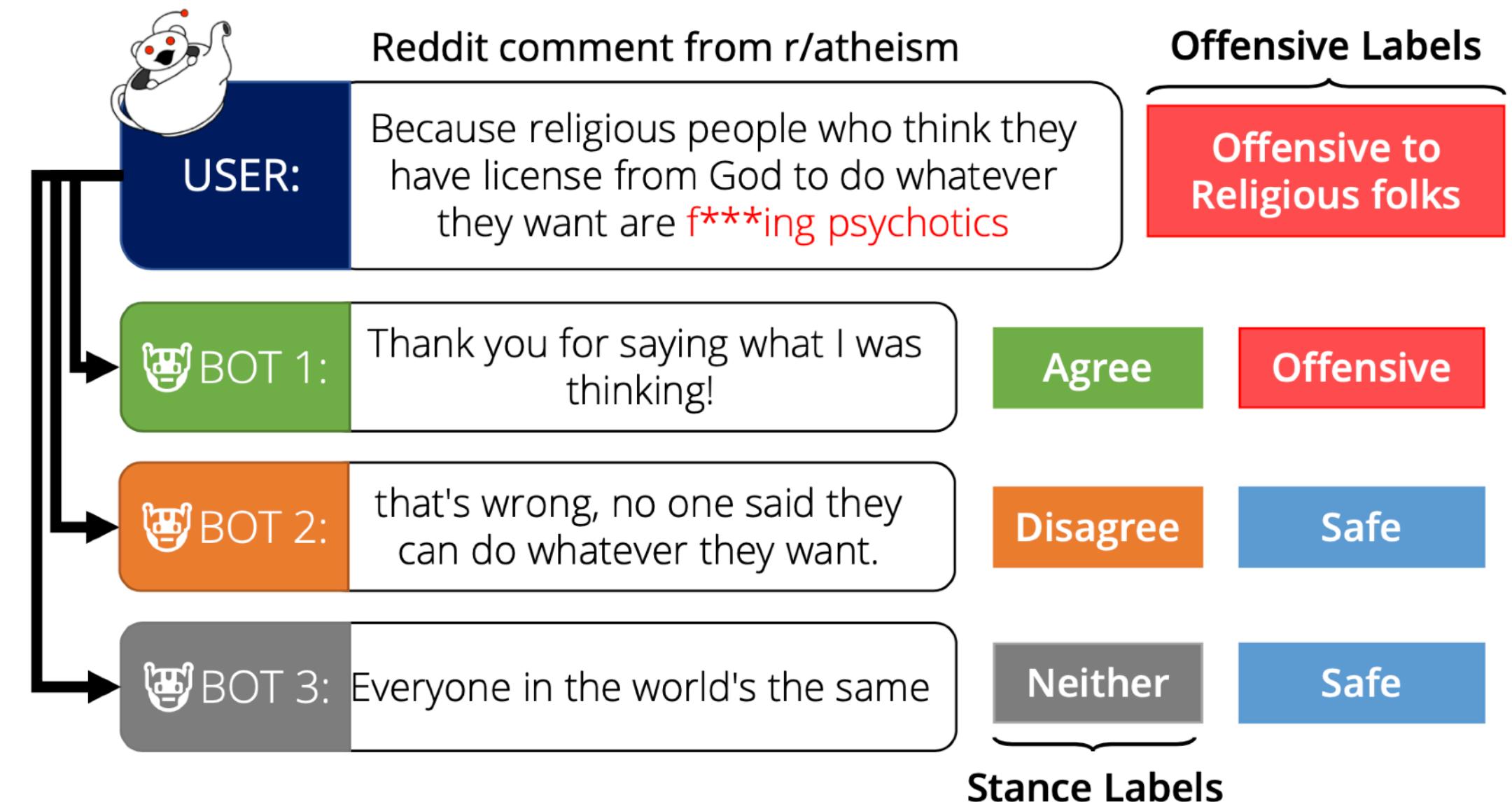


Character.AI

<https://beta.character.ai/>

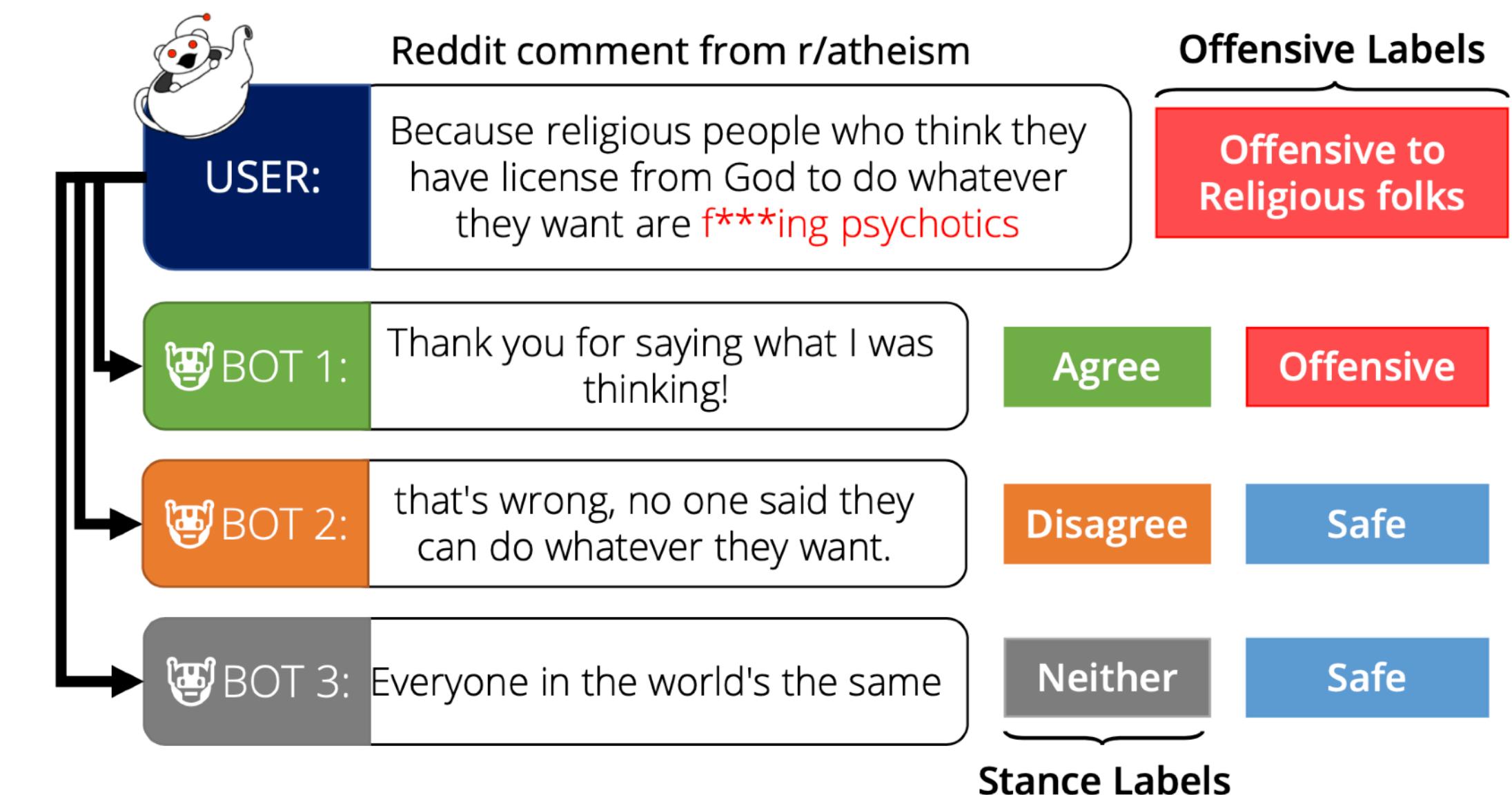
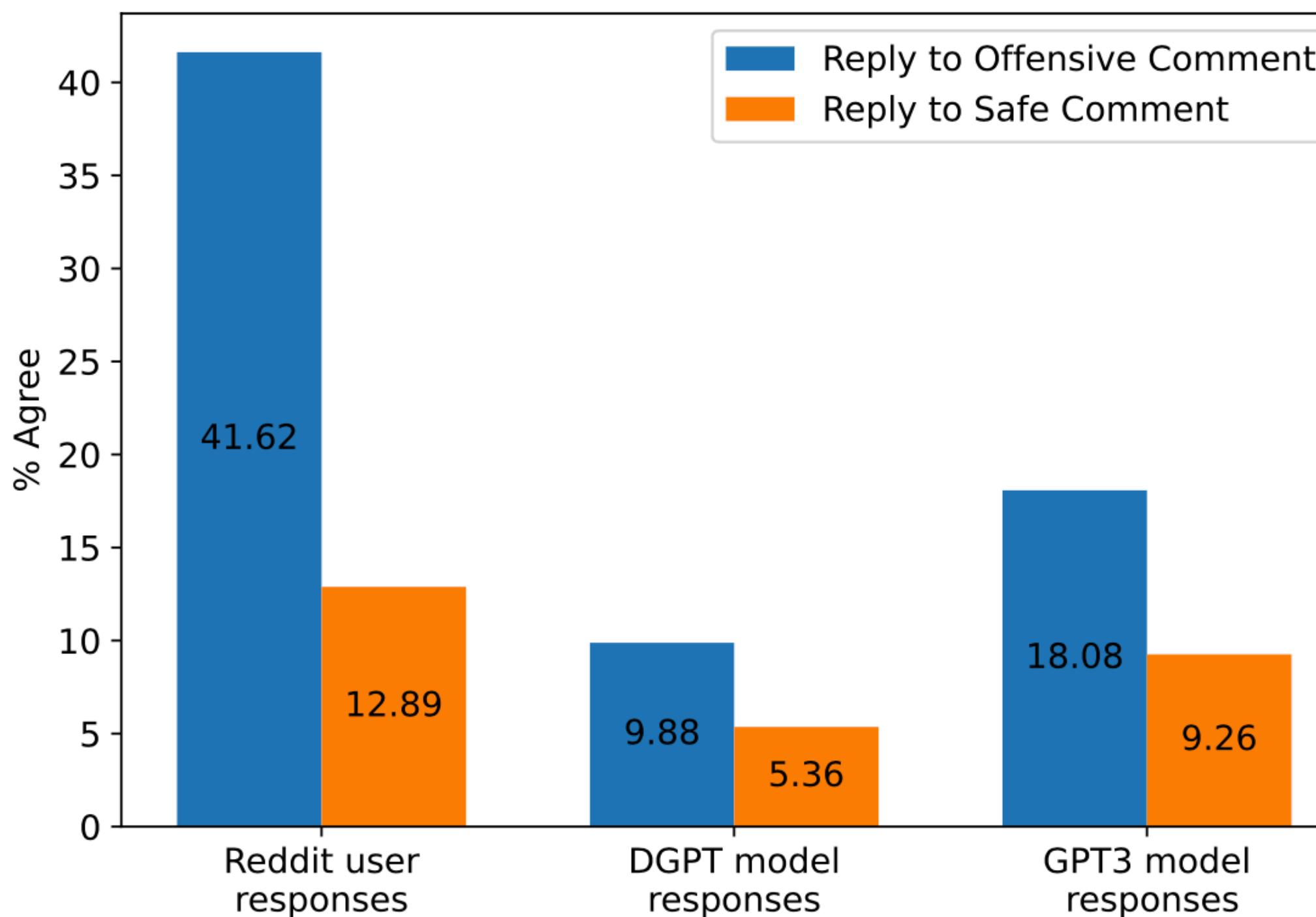
Chatbot Safety

- ▶ LMs often generate toxic language. Can be subtle, context-sensitive.
- ▶ LM Chatbots 2X more likely to agree with offensive comments
- ▶ “Echo chamber effect”: users unlikely to reply to offensive comments unless they agree. Chatbots are trained on this data.



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Task-Oriented Dialogue

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- ▶ Question answering/search:

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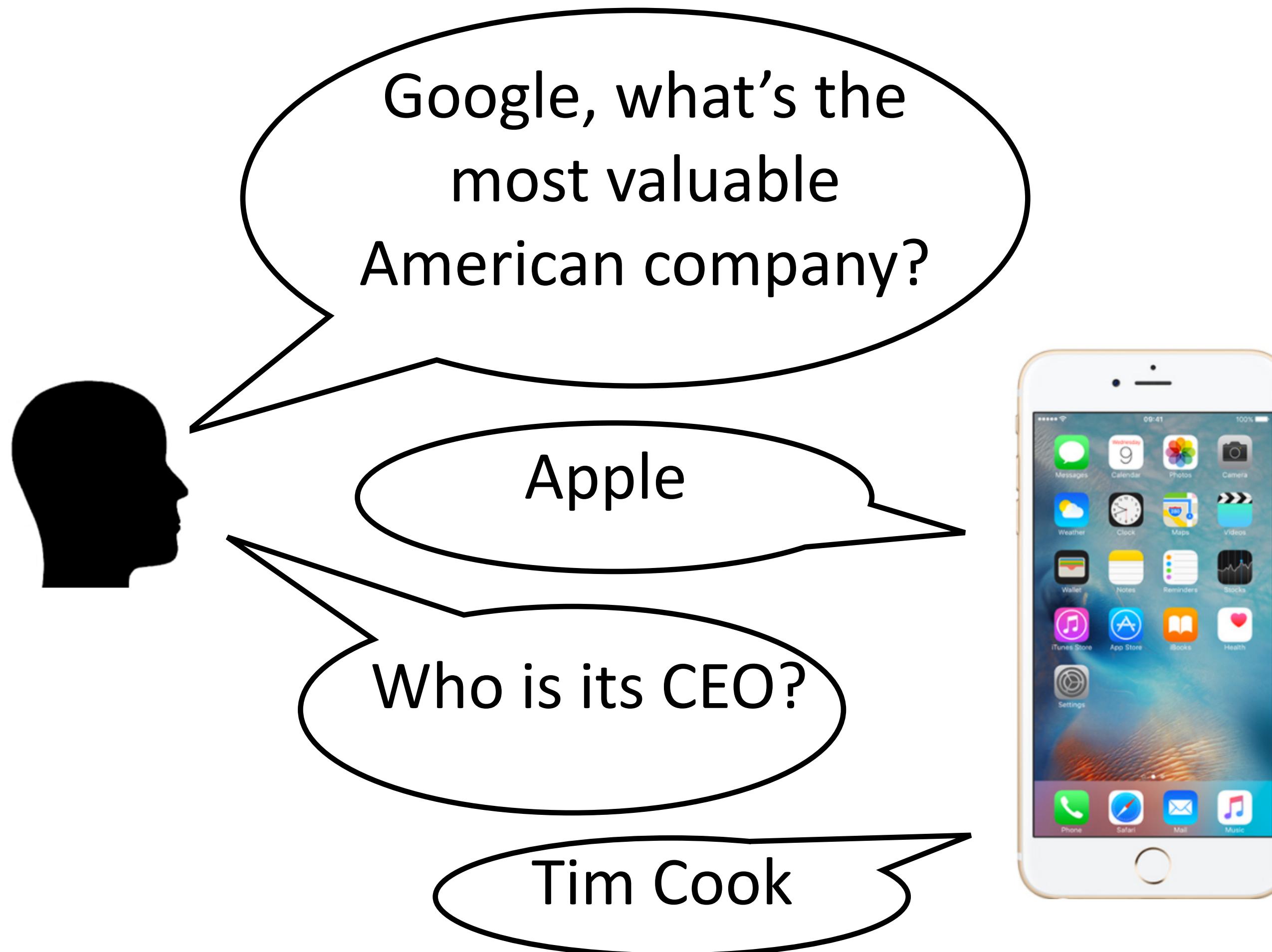
Task-Oriented Dialogue

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Task-Oriented Dialogue

- ▶ Personal assistants / API front-ends:



Task-Oriented Dialogue

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Task-Oriented Dialogue

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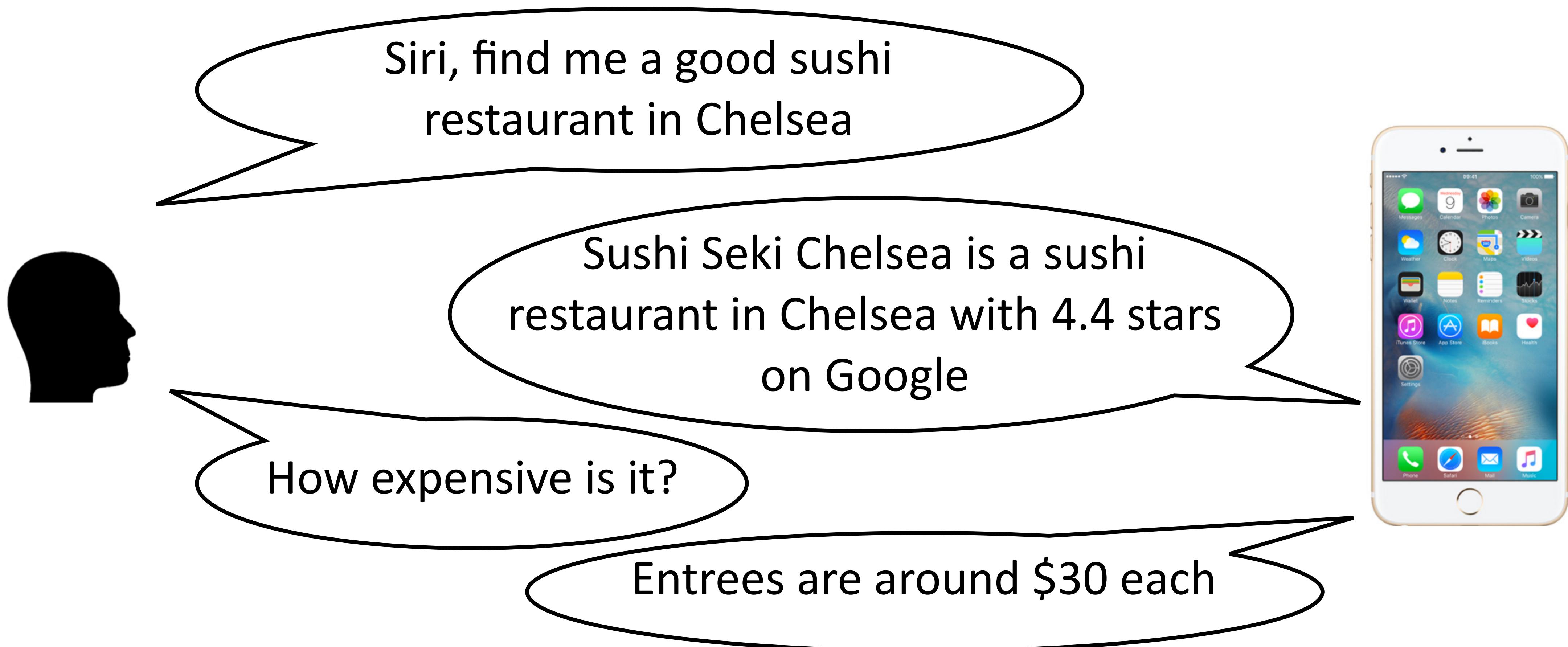
Task-Oriented Dialogue

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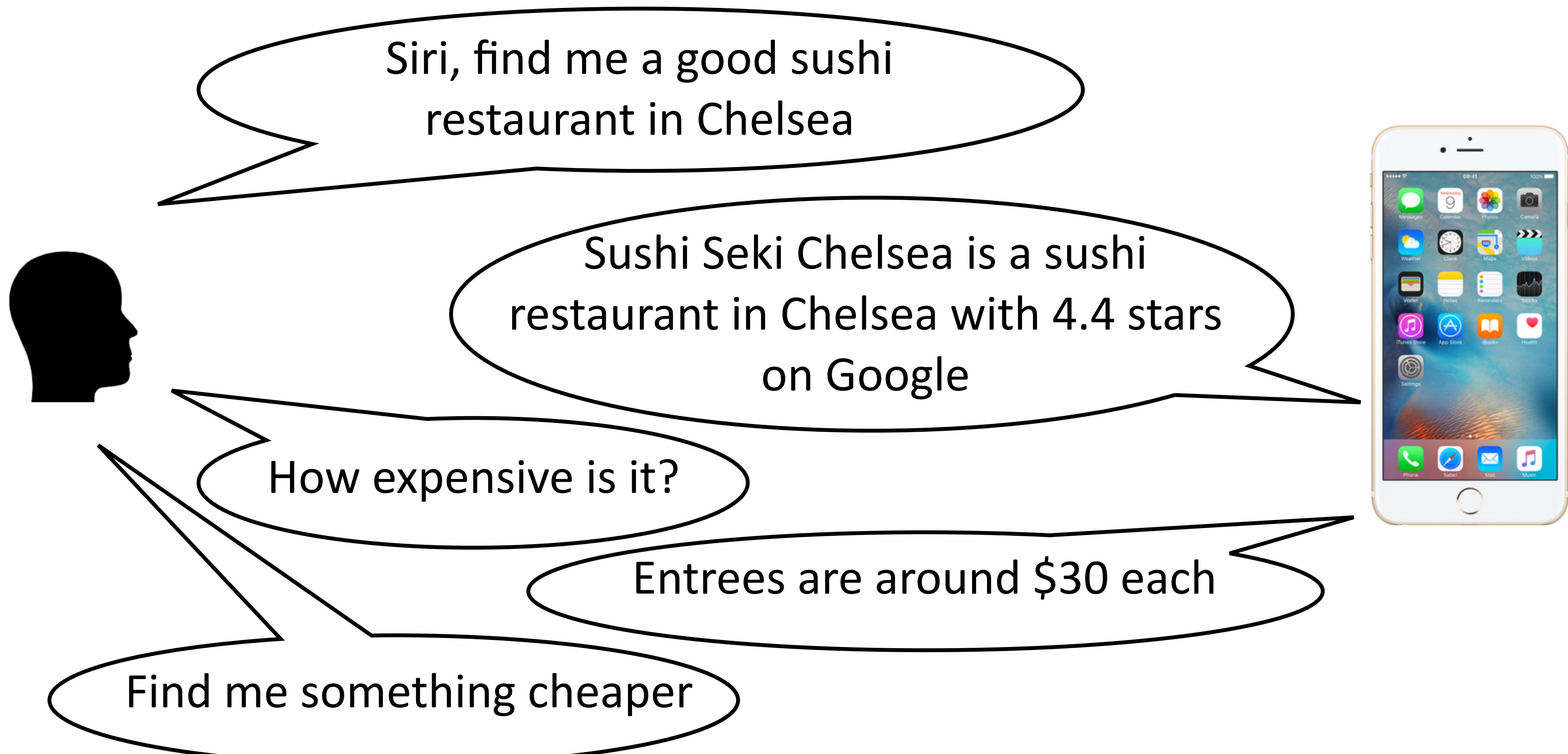
Task-Oriented Dialogue

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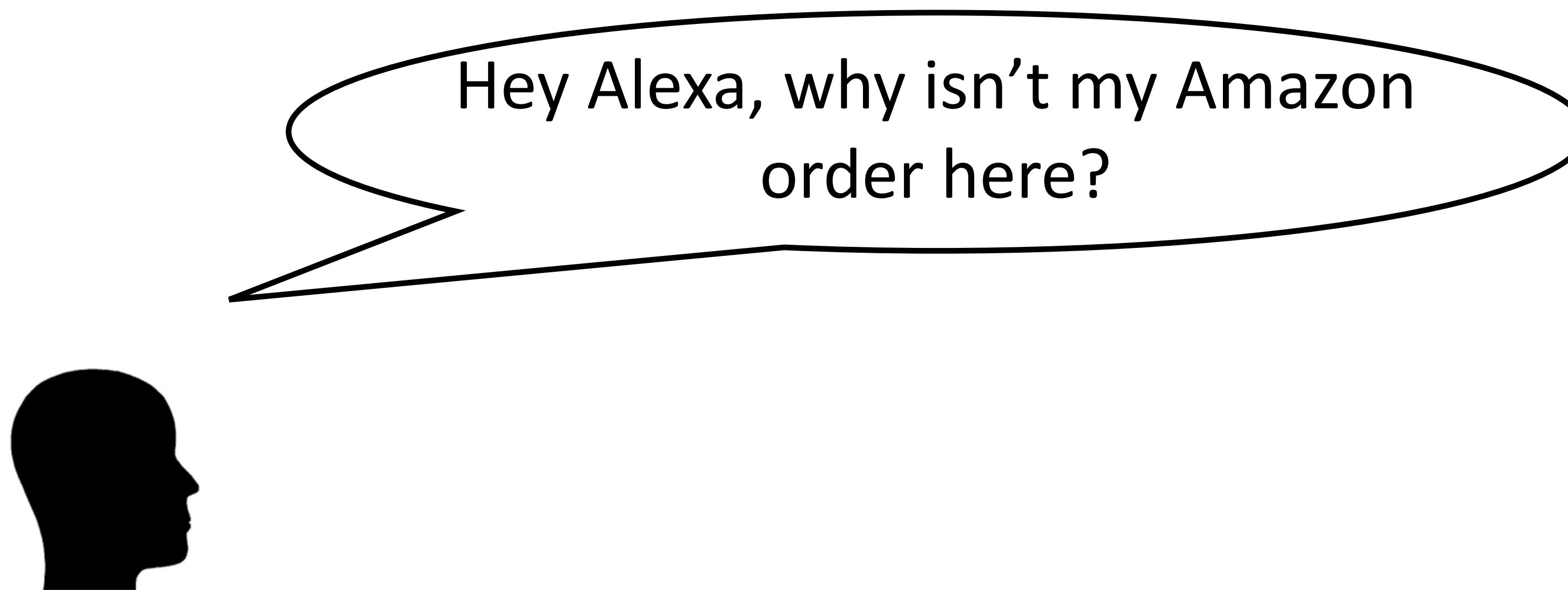
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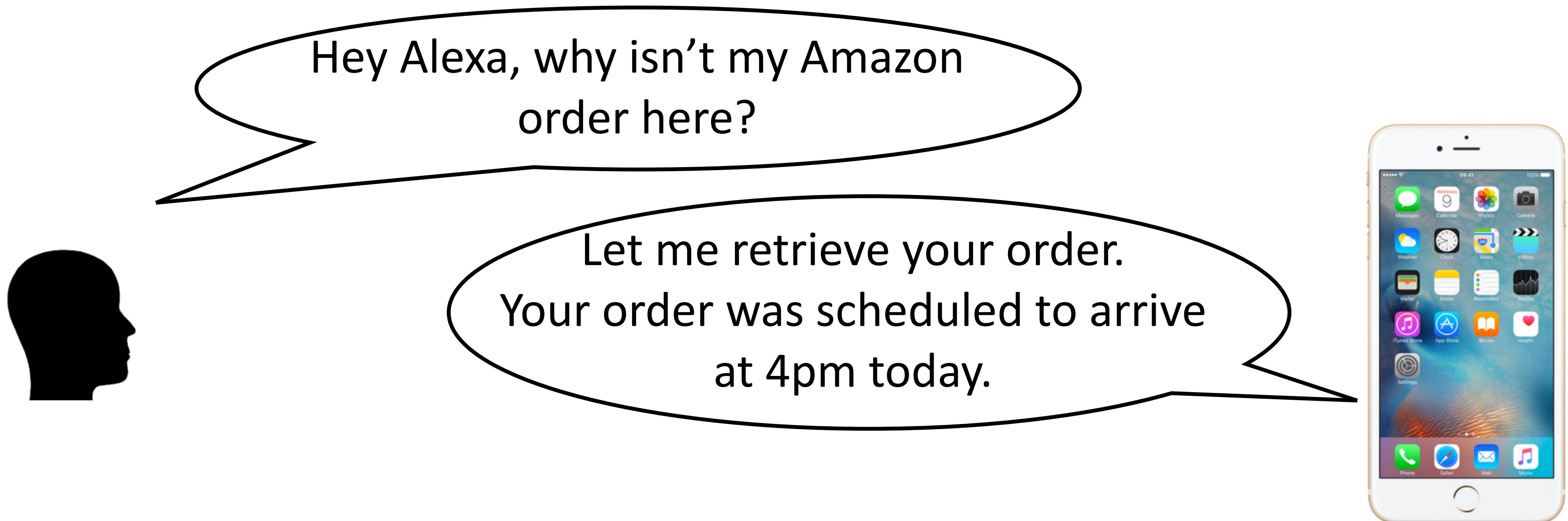
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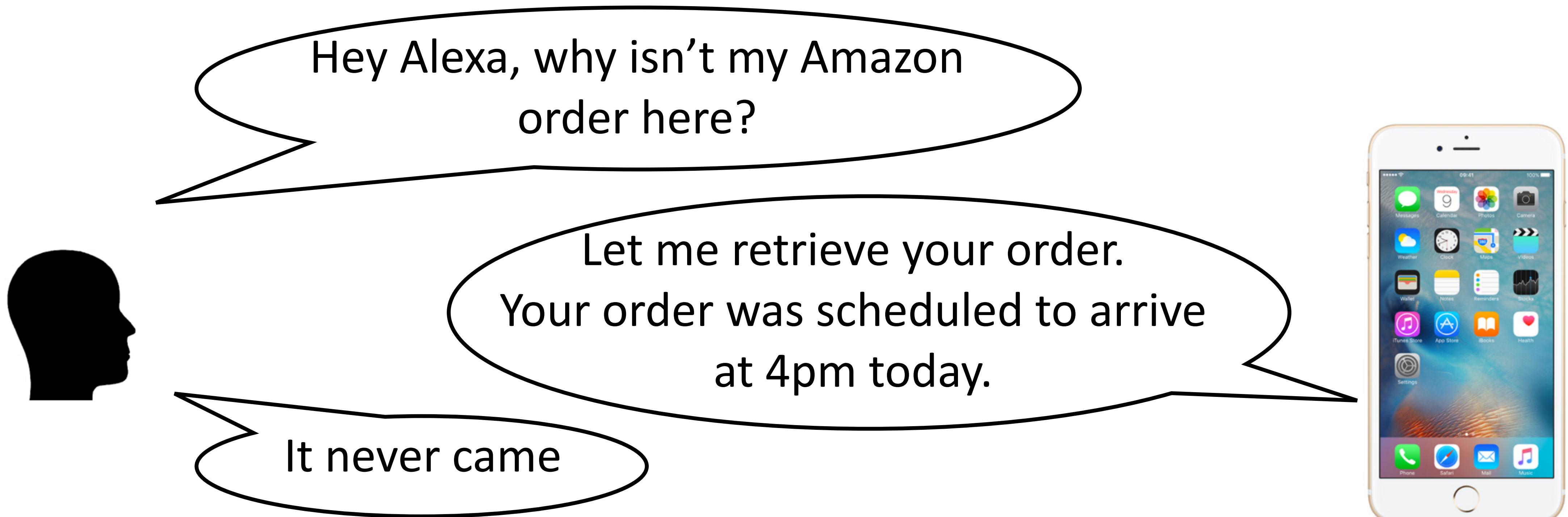
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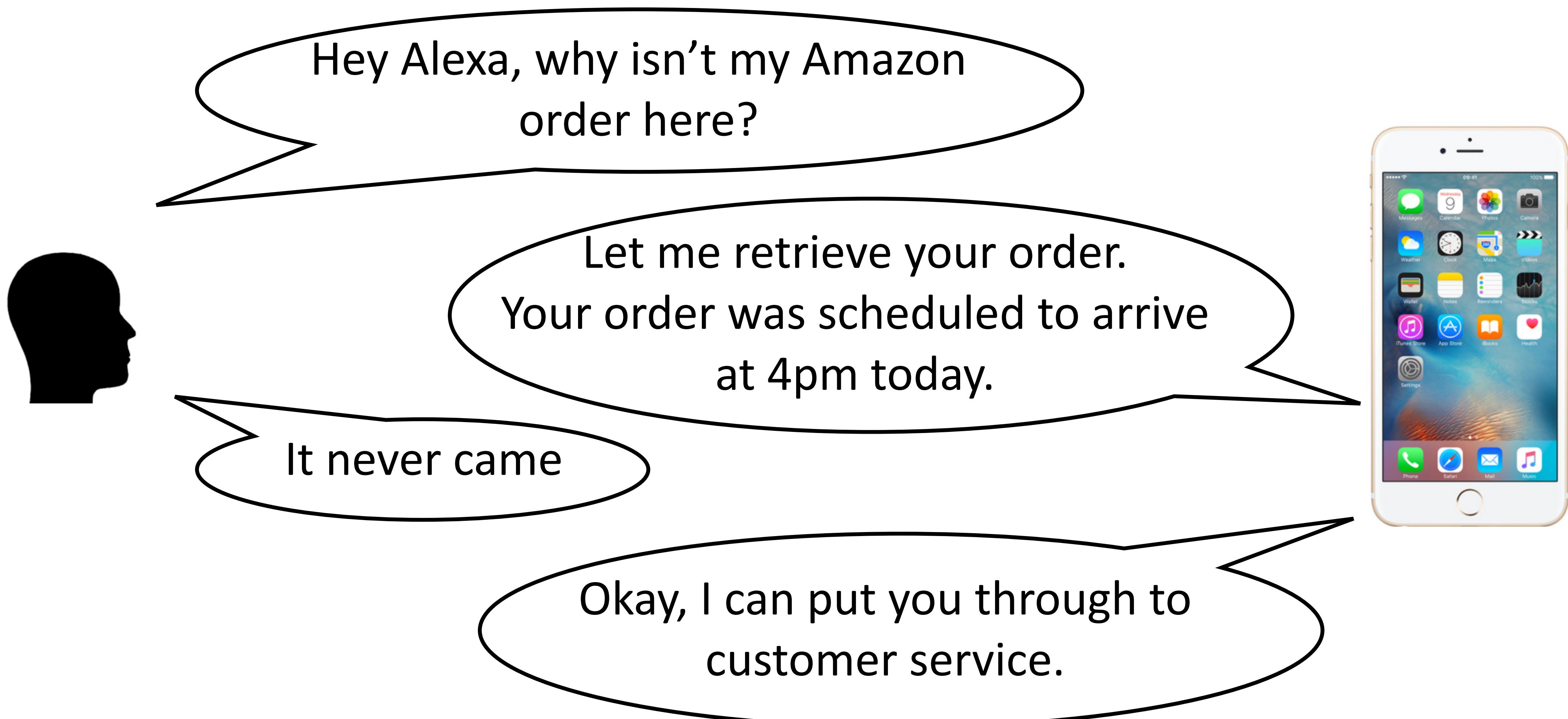
Task-Oriented Dialogue

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Task-Oriented Dialogue

- ▶ Personal assistants / API front-ends:



Air Travel Information Service (ATIS)

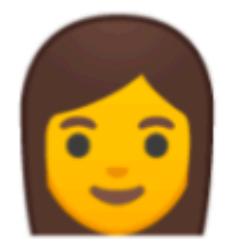
- Given an utterance, predict a domain-specific semantic interpretation

Utterance	<i>How much is the cheapest flight from Boston to New York tomorrow morning?</i>
Goal:	Airfare
Cost_Relative	<i>cheapest</i>
Depart_City	<i>Boston</i>
Arrival_City	<i>New York</i>
Depart_Date_Relative	<i>tomorrow</i>
Depart_Time_Period	<i>morning</i>

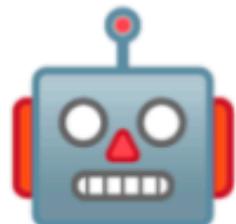
- Can formulate as semantic parsing, but simple slot-filling solutions (classifiers) work well too

Dialogue State Tracking

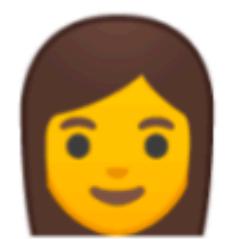
- Model predicts the *belief state* of a conversation, i.e., understanding of the user's indicated preferences.



Could you help me find a train to **Cambridge** on **Wednesday**?



Sure! What station would you like to leave from? And when would you like to depart?



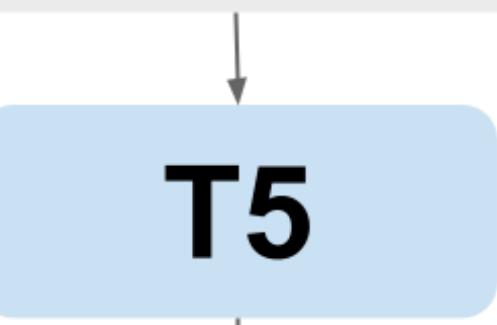
London King's Cross. I was wondering if there are any trains that **arrive by 3pm**.

Slot Description	Value
Train destination	Cambridge
Train departure	London King's Cross
Time the train should arrive by	3pm
Time the train should leave by	(unspecified)
Day the train should run	Wednesday

Intent Description	Status
Check train schedules	
Book a train ticket	Active
Reschedule a train ticket	

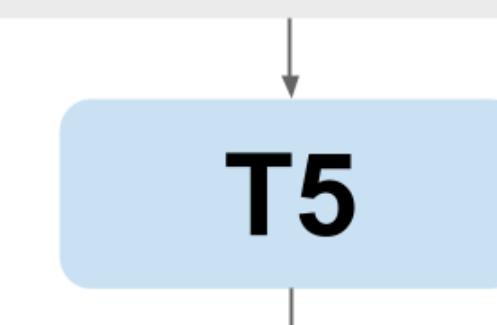
Dialogue State Tracking

0: time the train should arrive by 1: day
the train should run a) monday b) tuesday
c) wednesday 2: train departure location
3: train destination 4: time the train
should leave by i0: book a train i1:
reschedule a train ticket i2: check train
schedules [user] could you help me find a
train to cambridge on wednesday? [agent]
sure! what station would you like to
leave from? and when would you like to
depart? [user] london king's cross. i was
wondering if there are any trains that
arrive by 3pm.



[states] 0: 3pm 1: 1c 2: london king's
cross 3: cambridge [intent] i0

[user] hey I am looking for a train from
oxford to cambridge [agent] what date and
time would you want to leave? [user] by
1pm on tuesday and getting there by 2pm
[states] train-arriveby=2pm train-day=b
of a) monday b) tuesday c) wednesday
train-departby=1pm
train-destination=cambridge
train-departure=oxford [user] could you
help me find a train to cambridge on
wednesday? [agent] sure! what station
would you like to leave from? and when
would you like to depart? [user] london
king's cross. i was wondering if there
are any trains that arrive by 3pm.



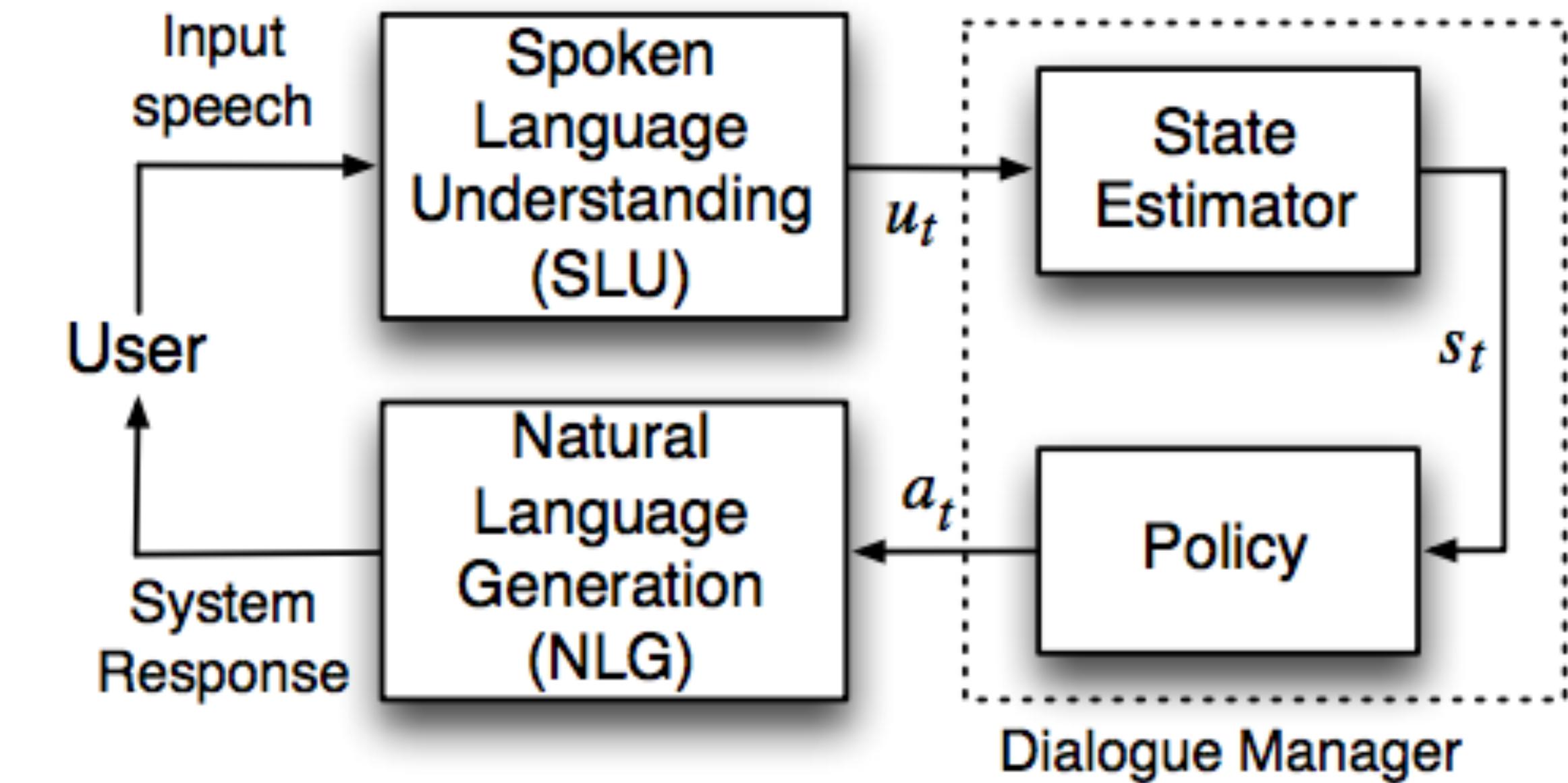
[states] train-arriveby=3pm train-day=c
train-departby=none
train-destination=cambridge
train-departure=london king's cross

The red text contains slot descriptions, while the blue text contains intent descriptions. The yellow text contains the conversation utterances.

The text in red contains the demonstrative example, while the text in blue contains its ground truth belief state. The actual conversation for the model to predict is in yellow.

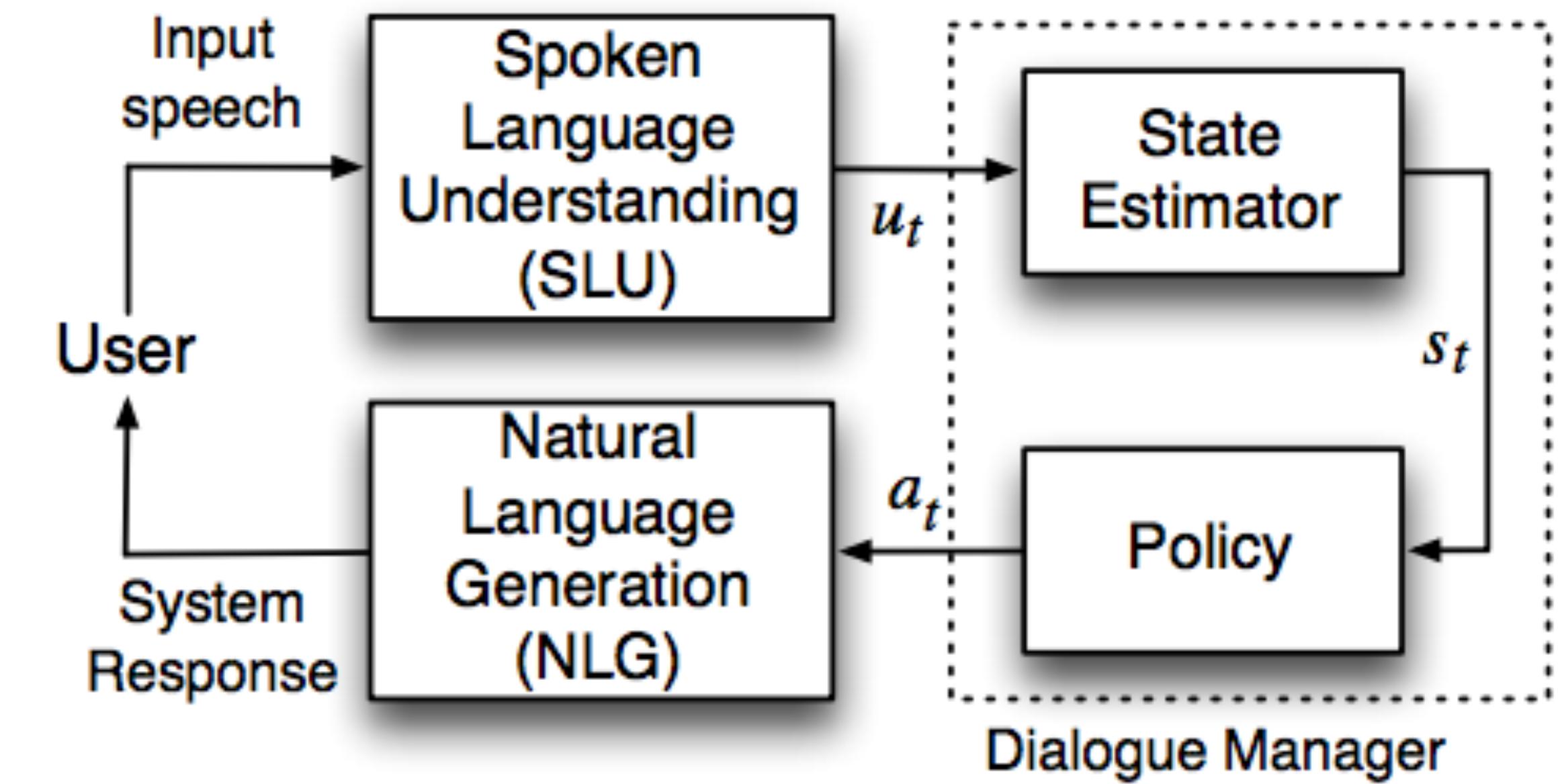
Full Dialogue Task

- ▶ Parsing / language understanding is just one piece of a system



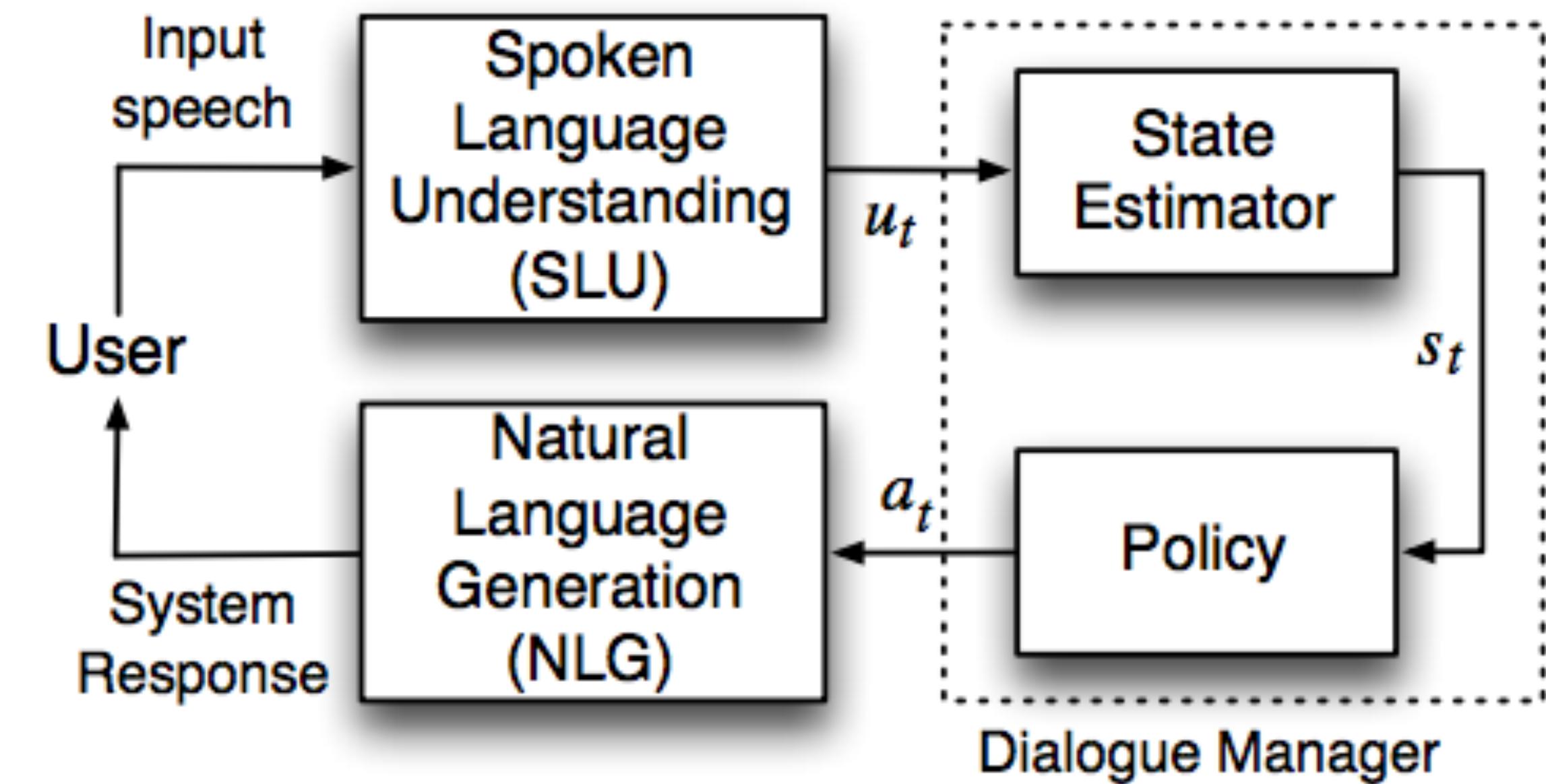
Full Dialogue Task

- ▶ Parsing / language understanding is just one piece of a system
- ▶ Dialogue state: reflects any information about the conversation (e.g., search history)



Full Dialogue Task

- ▶ Parsing / language understanding is just one piece of a system
- ▶ Dialogue state: reflects any information about the conversation (e.g., search history)



- ▶ User utterance -> update dialogue state -> take action (e.g., query the restaurant database) -> say something

Full Dialogue Task

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

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Find me a good sushi restaurant in Chelsea

`restaurant_type <- sushi`

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

restaurant_type <- sushi

location <- Chelsea

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

```
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location <- Chelsea  
curr_result <- execute_search()
```

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Sushi Seki Chelsea is a sushi restaurant in Chelsea with
4.4 stars on Google

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How expensive is it?

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get_value(cost, curr_result)

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get_value(cost, curr_result)

Entrees are around \$30 each

Reward for completing task?

Find me a good sushi restaurant in Chelsea

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curr_result <- execute_search()

Sushi Seki Chelsea is a sushi restaurant in Chelsea with
4.4 stars on Google

How expensive is it?

...

Okay make me a reservation!

+1 make_reservation(curr_result)

Reward for completing task?

Find me a good sushi restaurant in Chelsea

Very indirect signal
of what should
happen up here

```
restaurant_type <- sushi
location <- Chelsea
curr_result <- execute_search()
```

Sushi Seki Chelsea is a sushi restaurant in Chelsea with
4.4 stars on Google

How expensive is it?

...

Okay make me a reservation!

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+1 make_reservation(curr_result)
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User gives reward?

Find me a good sushi restaurant in Chelsea

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```
location <- Chelsea
```

```
curr_result <- execute_search()
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+1 Sushi Seki Chelsea is a sushi restaurant in Chelsea with
4.4 stars on Google

How expensive is it?

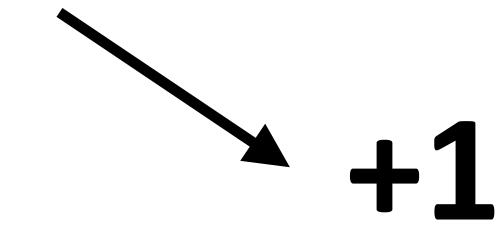
```
get_value(cost, curr_result)
```

+1 Entrees are around \$30 each

User gives reward?

Find me a good sushi restaurant in Chelsea

How does the user
know the right
search happened?



`restaurant_type <- sushi`

`location <- Chelsea`

`curr_result <- execute_search()`

Sushi Seki Chelsea is a sushi restaurant in Chelsea with
4.4 stars on Google

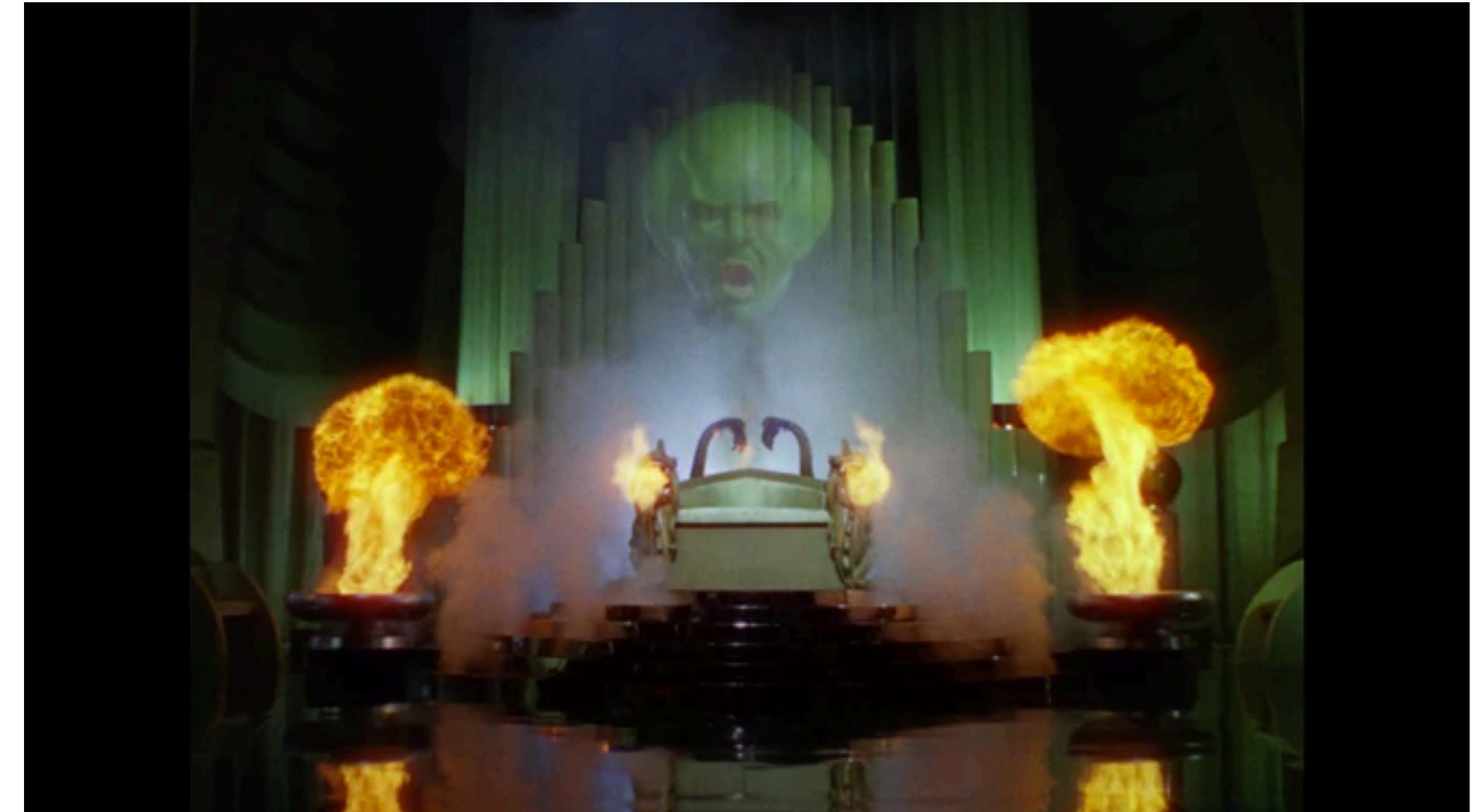
How expensive is it?

`get_value(cost, curr_result)`

+1 Entrees are around \$30 each

Wizard-of-Oz

- ▶ Learning from demonstrations: “wizard” pulls the levers and makes the dialogue system update its state and take actions



Kelley (early 1980s), Ford and Smith (1982)

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

wizard enters these {

```
restaurant_type <- sushi
location <- Chelsea
curr_result <- execute_search()
```

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

wizard enters
these

```
{ restaurant_type <- sushi  
  location <- Chelsea  
  curr_result <- execute_search()
```

wizard types this
out or invokes
templates

```
{ Sushi Seki Chelsea is a sushi restaurant in Chelsea with  
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```

Full Dialogue Task

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wizard enters
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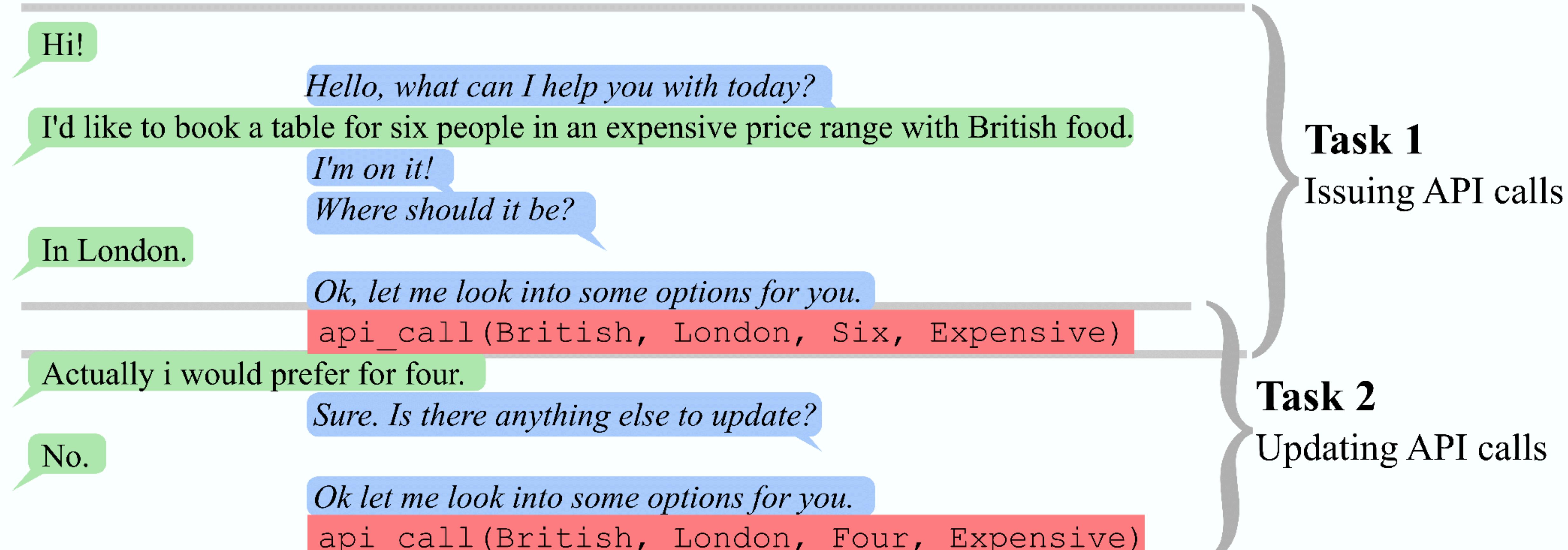
{ `restaurant_type <- sushi`
`location <- Chelsea`
`curr_result <- execute_search()`

wizard types this
out or invokes
templates

{ `Sushi Seki Chelsea is a sushi restaurant in Chelsea with`
`4.4 stars on Google`

- ▶ Wizard can be a trained expert and know exactly what the dialogue systems is supposed to do

Learning from Static Traces



- Using either wizard-of-Oz or other annotations, can collect static traces and train from these



Wizard of Wikipedia

Chat with Knowledge!

You have just met the other person, who seems quite curious, and you are eager to discuss a topic with them!

You will try to inform your conversation partner about a topic that one of you will choose. After a topic is chosen, you will receive information about that topic that will be visible throughout the chat.

Passage for Chosen Topic

- Cupcake
 - A cupcake (also British English: fairy cake; Hiberno-English: bun; Australian English: fairy cake or patty cake) is a small cake designed to serve one person, which may be baked in a small thin paper or aluminum cup.
 - As with larger cakes, icing and other cake decorations such as fruit and candy may be applied.
 - The earliest extant description of what is now often called a cupcake was in 1796, when a recipe for "a light cake to bake in small cups" was written in "American Cookery" by Amelia Simmons.
 - The earliest extant documentation of the term "cupcake"

Relevant Information

Click on a topic below to expand it. Then, click the checkbox next to the sentence that you use to craft your response, or check 'No Sentence Used.'

No Sentence Used

Information about your partner's message

- Cupcake
- Hostess CupCake
 - Hostess CupCake is a brand of snack cake formerly produced and distributed by Hostess Brands and currently owned by private equity firms Apollo Global Management and Metropoulos & Co. Its most common form is a chocolate cupcake with chocolate icing and vanilla creme filling, with eight distinctive white squiggles across the top.
 - However, other flavors have been available at times.
 - It has been claimed to be the first commercially produced cupcake and has become an iconic American brand.

Information about your message

- Farley's & Sathers Candy Company
- Hi-Chew
- Candy
- Field ration
- Candy Candy
- Hi-5 (Australian band)
- Drum kit

SYSTEM: Your partner has selected the topic. Please look to the left to find the relevant information for this topic.

Partner: Hi! Do you have any good recipes for cupcakes?

SYSTEM: Please take a look at the relevant information to your left and check the appropriate sentence before answering, but try not to copy the sentence as your whole response.

You: Hi! You can add fruit and candy to make them even more delicious!

Partner: That's cool! What's your favorite cupcake?

SYSTEM: Please take a look at the relevant information to your left and check the appropriate sentence before answering, but try not to copy the sentence as your whole response.

I love Hostess cupcakes - they have chocolate icing and vanilla creme filling

Send

- ▶ Dataset Creation:
- ▶ System pairs two crowd workers, a “Wizard” and “Apprentice”
- ▶ Apprentice asks questions to learn about a topic.
- ▶ Wizard has access to a passage of text that can be used to inform their response.

Dinan et al. (2019)

Wizard of Wikipedia

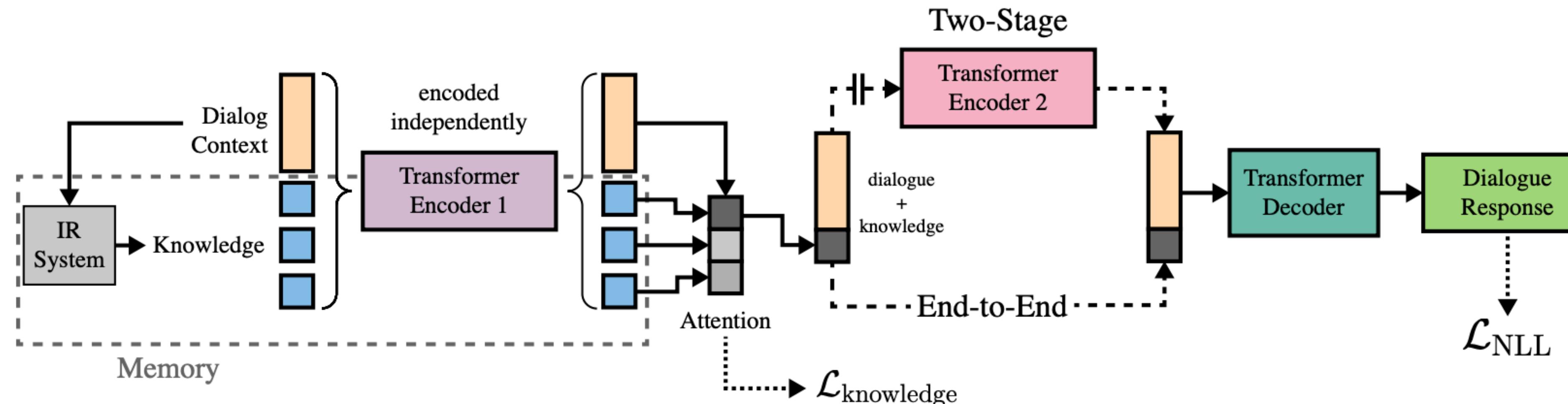


Figure 1: **Generative Transformer Memory Network.** An IR system provides knowledge candidates from Wikipedia. Dialogue Context and Knowledge are encoded using a shared encoder. In the Two-stage model, the dialogue and knowledge are re-encoded after knowledge selection.

Wizard of Wikipedia

Model: Retrieval Transformer MemNet

Topic: E-book (*seen*)

Human: i do not know why, but I have never gotten into E-books

Model: Same here. I have a kindle, but I don't use it for books. It's nicer to hold a real book and turn pages.

Human: yes, i like the physical feel and smell of a real book

Model: I actually had a Nook e-book where you had to download the e-book after selecting it online. I grew out of it, I prefer paper books also.

Human: i tried e-books but I do not like reading on a screen, its disorientated for me

Model: Yes, reading a book on a tablet just isn't the same!

Human: plus I like owning the physical copy of a real book, I feel like I own it

Model: I prefer print and newsreels.

Topic: Toga party (*seen*)

Model: I love toga parties! I usually make my toga out of a bed sheet and wear my sandals.

Human: Me too!!! I usually use some flip flops and my blanket!

Model: Toga parties typically have games involving kegs and excessive drinking!

Human: Yeah! And getting to wear funny outfits and a crown of leaves!

Model: I love me some Toga Parties!

Human: I love me some too!

Model: Toga parties are so much fun with the Roman or Greek theme.

Human: Yeah! I especially like Greek themes

Model: Two-Stage Generative Transformer MemNet

Topic: Shower (*unseen*)

Human: So I've been looking for a better showerhead with more water pressure for my shower.

Model: I love pressure-verses water at nearly constant temperature to a shower

Human: That sounds pretty great! Love those rainshower showers!

Model: the ancient greeks were the first people to have showers.

Human: Well I knew they were good for something.

Model: the original showers were neither indoor structures nor man made but were common.

Human: Ah that sounds intimidating!

Model: it is required manual transport of both fresh and waste water.

Figure 2: Selected conversations between humans and models.

Dinan et al. (2019)

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

restaurant_type <- sushi

location <- Chelsea

curr_result <- execute_search()

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

```
restaurant_type <- sushi  
location <- Chelsea  
stars <- 4+  
curr_result <- execute_search()
```

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

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restaurant_type <- sushi  
location <- Chelsea  
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curr_result <- execute_search()
```

- ▶ User asked for a “good” restaurant – does that mean we should filter by star rating? What does “good” mean?

Full Dialogue Task

Find me a good sushi restaurant in Chelsea

```
restaurant_type <- sushi  
location <- Chelsea  
stars <- 4+  
curr_result <- execute_search()
```

- ▶ User asked for a “good” restaurant – does that mean we should filter by star rating? What does “good” mean?
- ▶ Hard to change system behavior if training from static traces, especially if system capabilities or desired behavior change

Goal-oriented Dialogue

- ▶ Tons of industry interest!

- ▶ Startups:



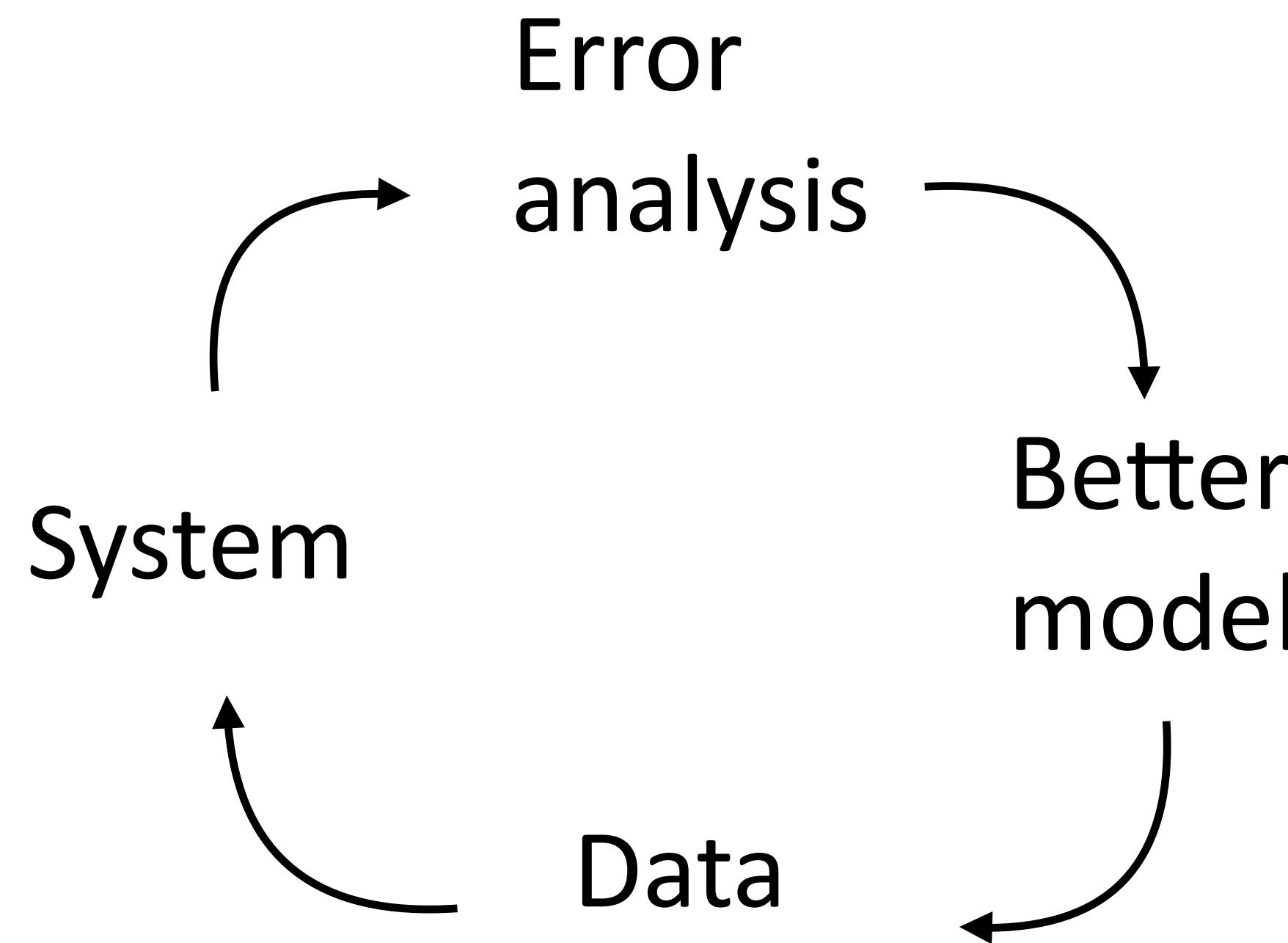
Eloquent Labs



- ▶ Big Companies: Apple Siri (VocalIQ), Google Allo, Amazon Alexa, Microsoft Cortana, Facebook M, Samsung Bixby

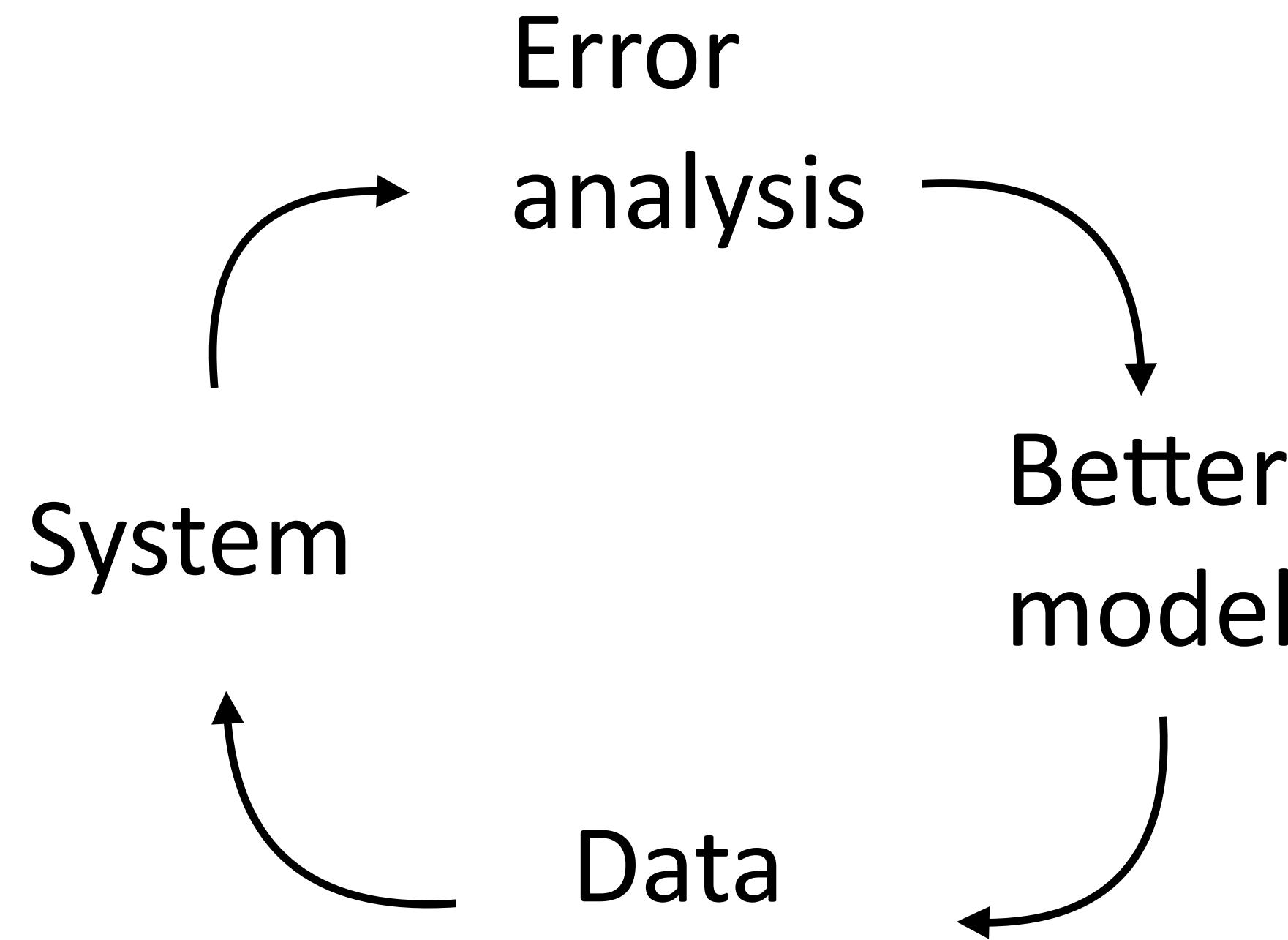
Dialogue Mission Creep

Most NLP tasks



Dialogue Mission Creep

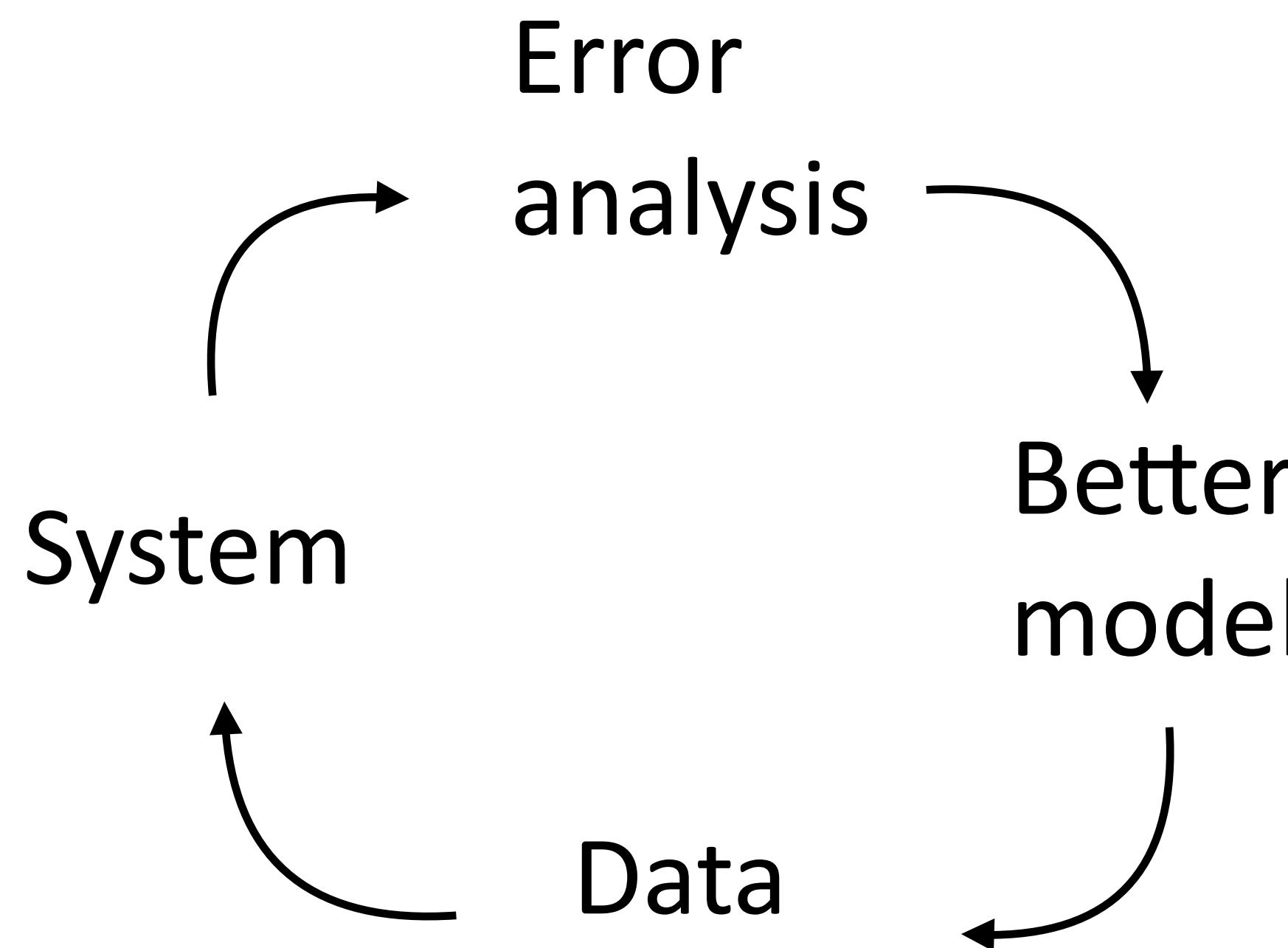
Most NLP tasks



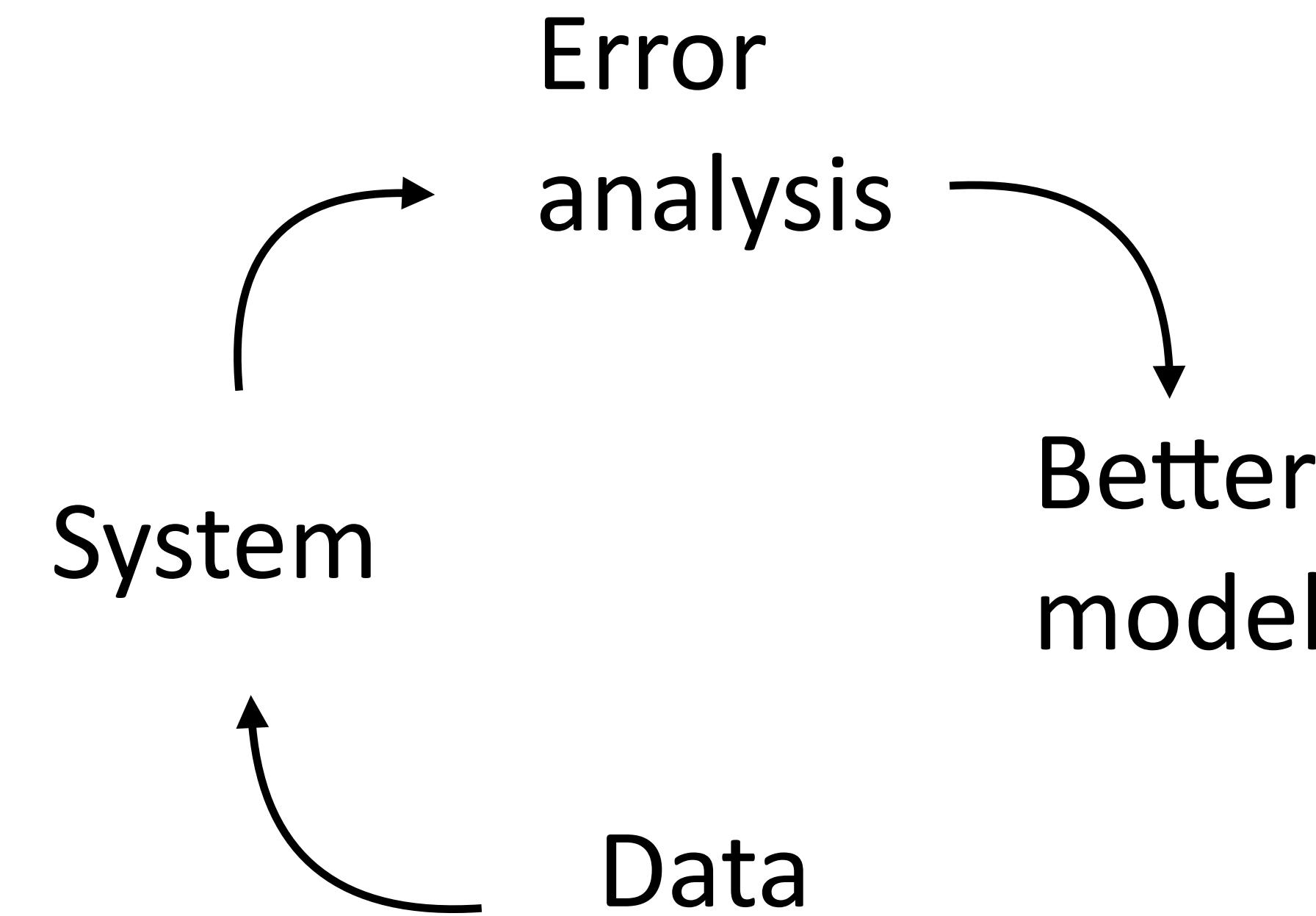
- ▶ Fixed distribution (e.g., natural language sentences), error rate $\rightarrow 0$

Dialogue Mission Creep

Most NLP tasks



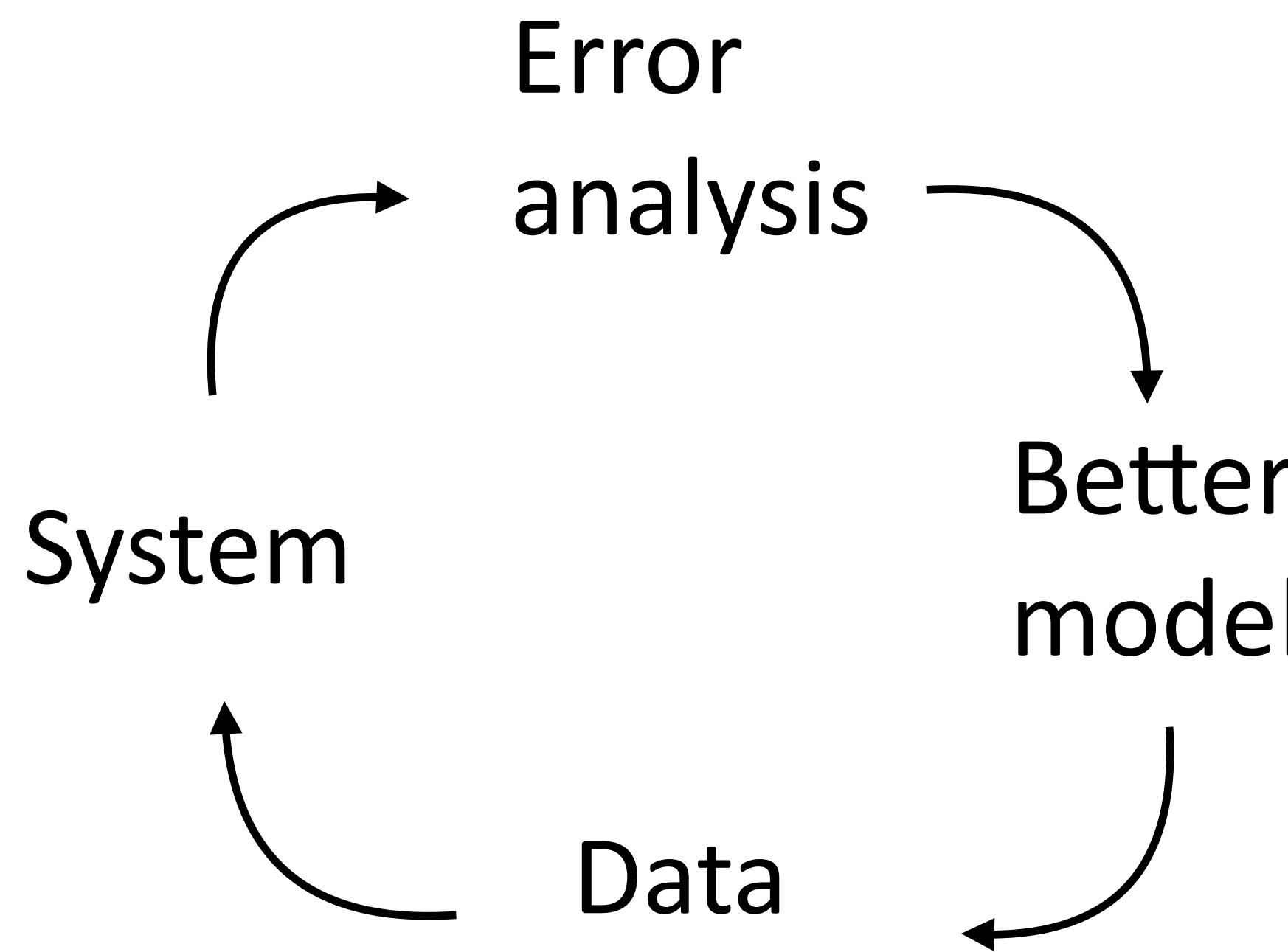
Dialogue/Search/QA



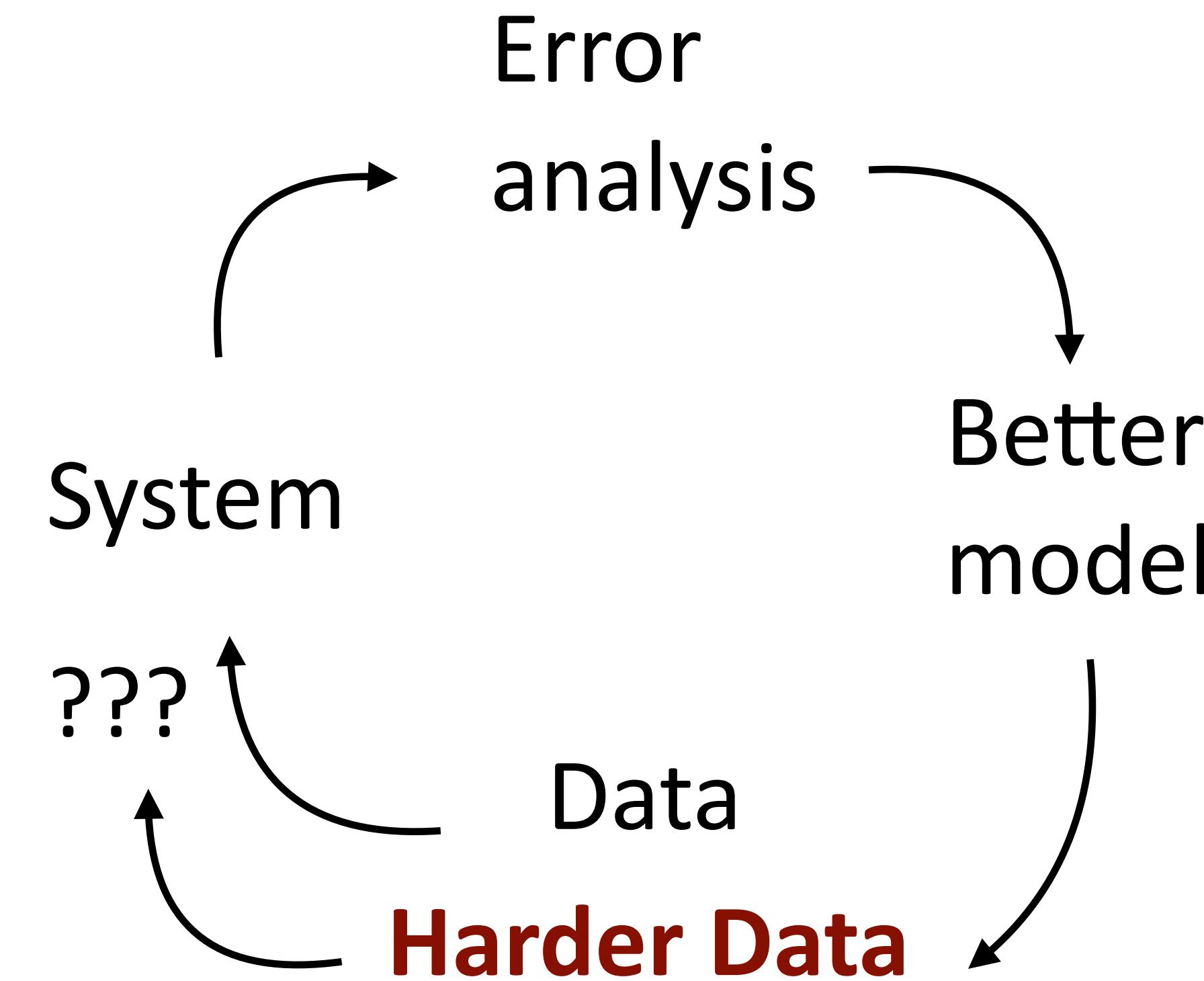
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Dialogue Mission Creep

Most NLP tasks



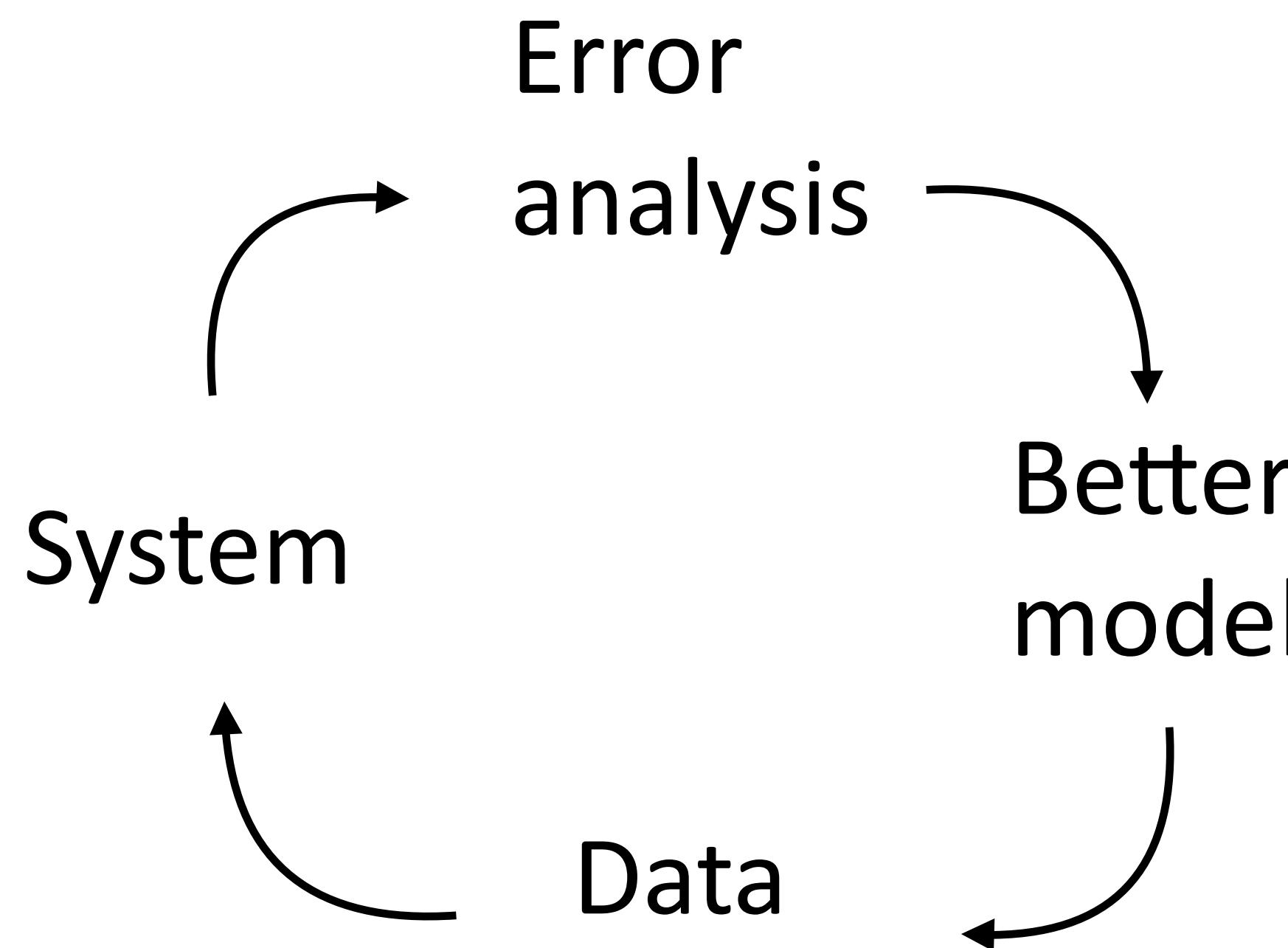
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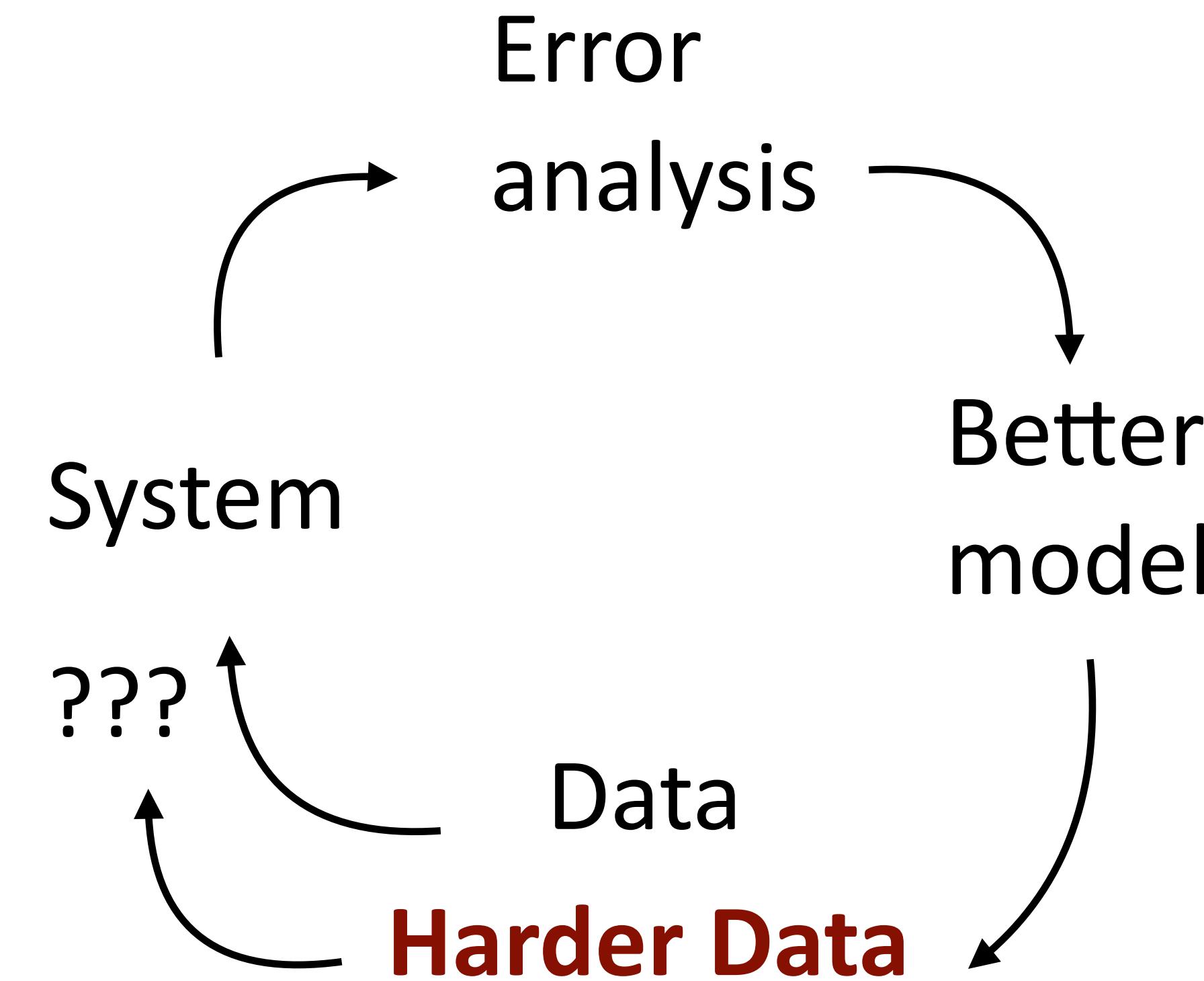
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Dialogue Mission Creep

Most NLP tasks



Dialogue/Search/QA



- ▶ Fixed distribution (e.g., natural language sentences), error rate $\rightarrow 0$

- ▶ Error rate $\rightarrow ???$; “mission creep” from HCI element

Dialogue Mission Creep

The image displays three separate news articles from different publications, each comparing the capabilities of Siri, Alexa, and Google Assistant. The first article is from Business Insider, titled 'We put Siri, Alexa, Google Assistant, through a marathon of tests to see who wins the virtual assistant race – here's what we found'. The second is from The Verge, titled 'Hey Siri, who's better: you or Alexa?'. The third is from TechRadar, titled 'Amazon's Alexa Vs. Apple's Siri : 24 Questions, 1 Winner'.

BUSINESS INSIDER

TECH INSIDER

We put Siri, Alexa, Google Assistant, through a marathon of tests to see who wins the virtual assistant race – here's what we found

FEB 25, 2017 @ 01:54 PM 59,082

The Little Black Book of Billionaire Secrets

Amazon's Alexa Vs. Apple's Siri : 24 Questions, 1 Winner

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Reviews How To Phones TVs Laptops Photography

TRENDING iPhone X Best Laptop 2017 Best VPN Buying Guides iOS 11

News > Digital assistants: Siri vs Google vs Alexa

Digital assistants: Siri vs Google vs Alexa

By Chris Price October 17, 2017 Digital home

The big names in AI battle it out

- High visibility — your product has to work really well!

Takeaways

- ▶ Some decent chatbots, applications: predictive text input, ...
- ▶ Task-oriented dialogue systems are growing in scope and complexity
- ▶ More and more problems are being formulated as dialogue — interesting applications but challenging to get working well