

# Lecture 16: Dialogue

Alan Ritter

(many slides from Greg Durrett)

# This Lecture

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

# Chatbots

# Turing Test (1950)

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

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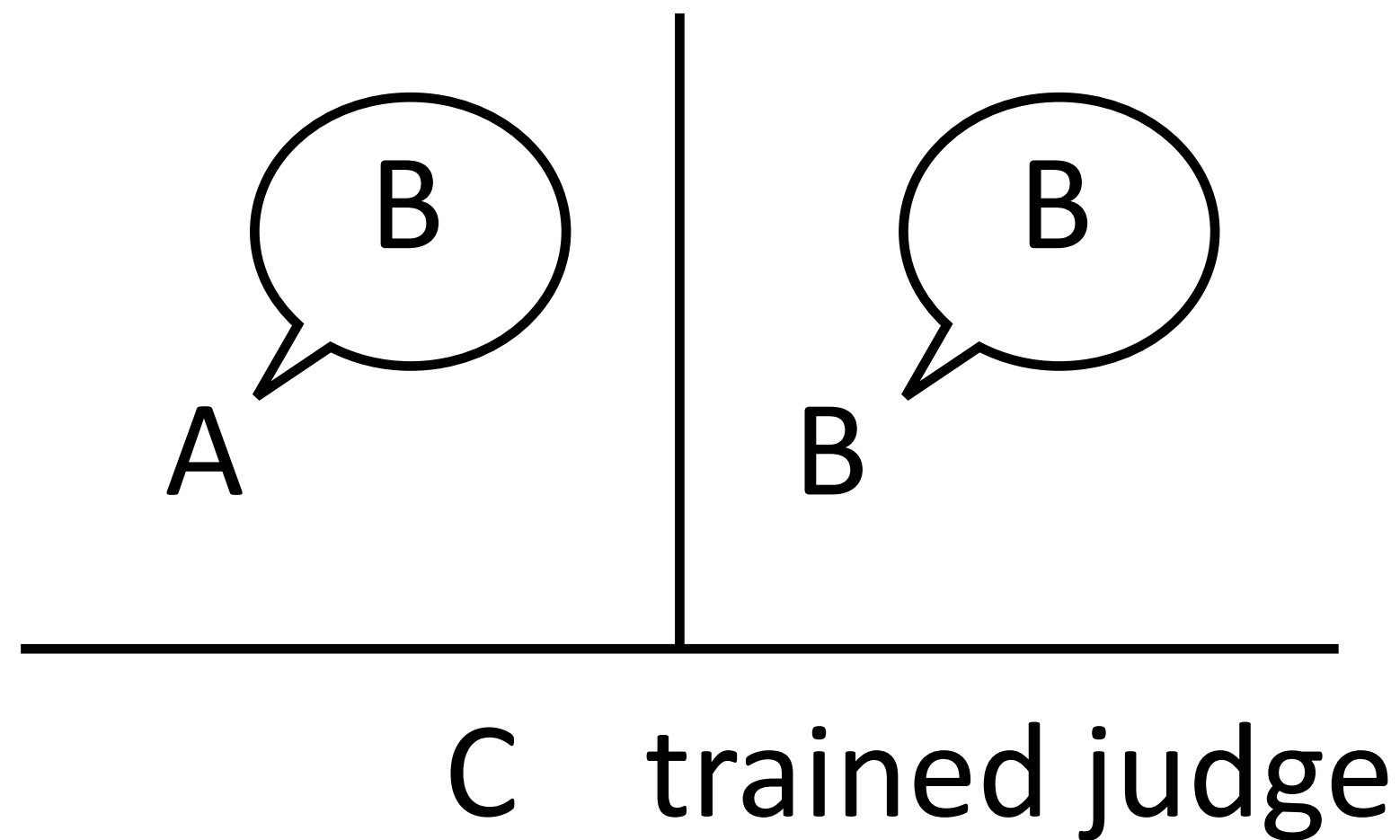
Original Interpretation:

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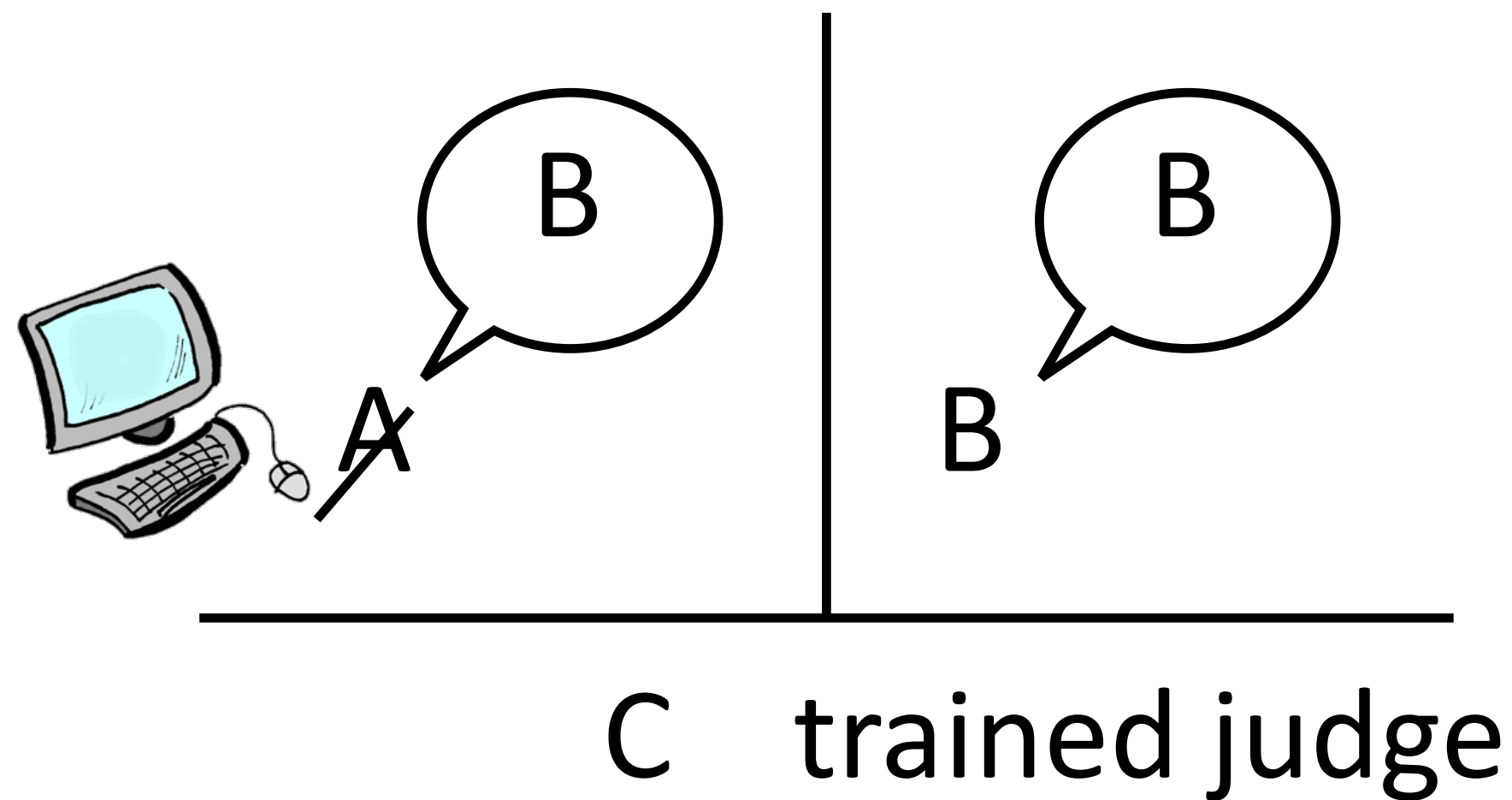


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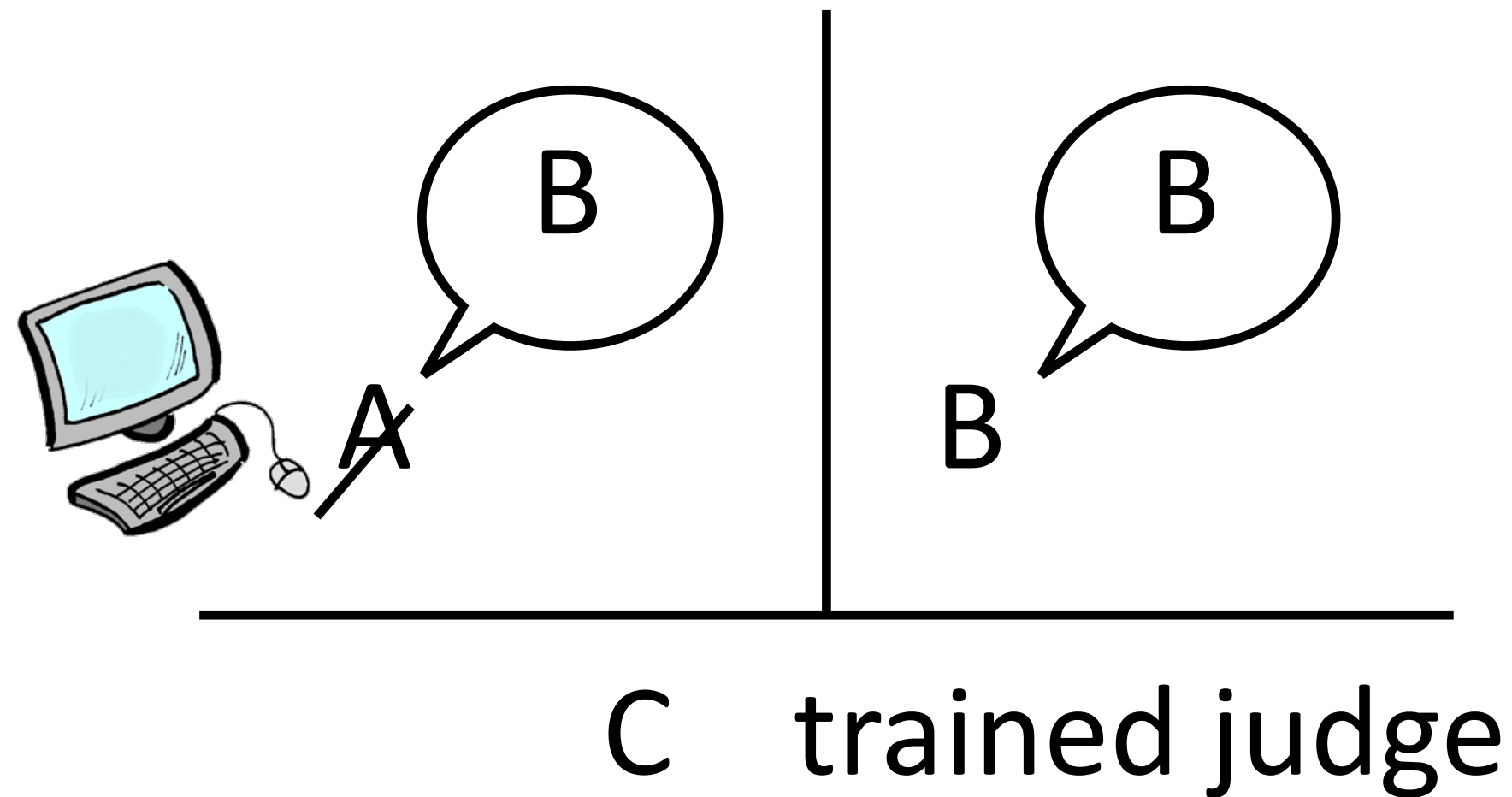
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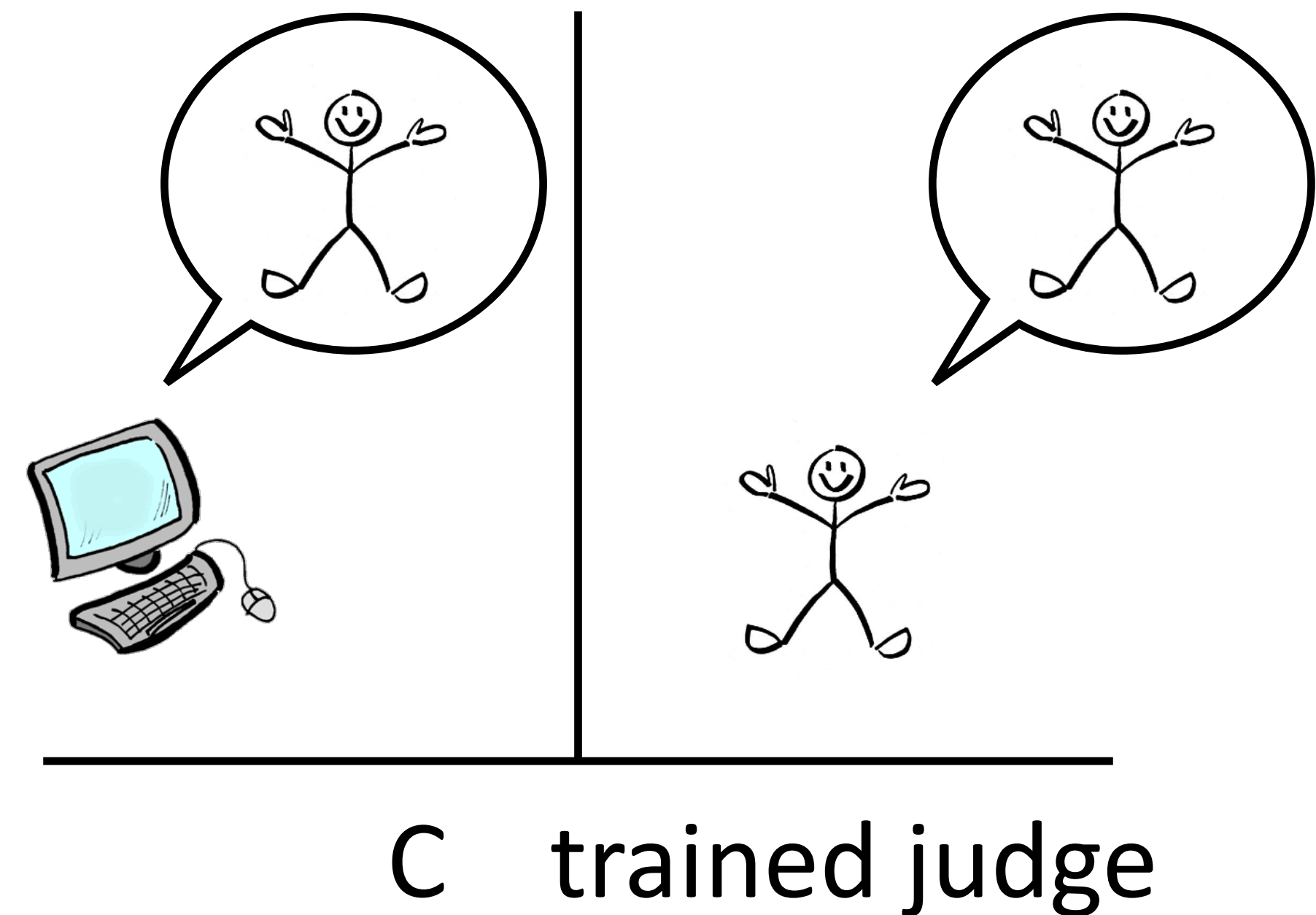
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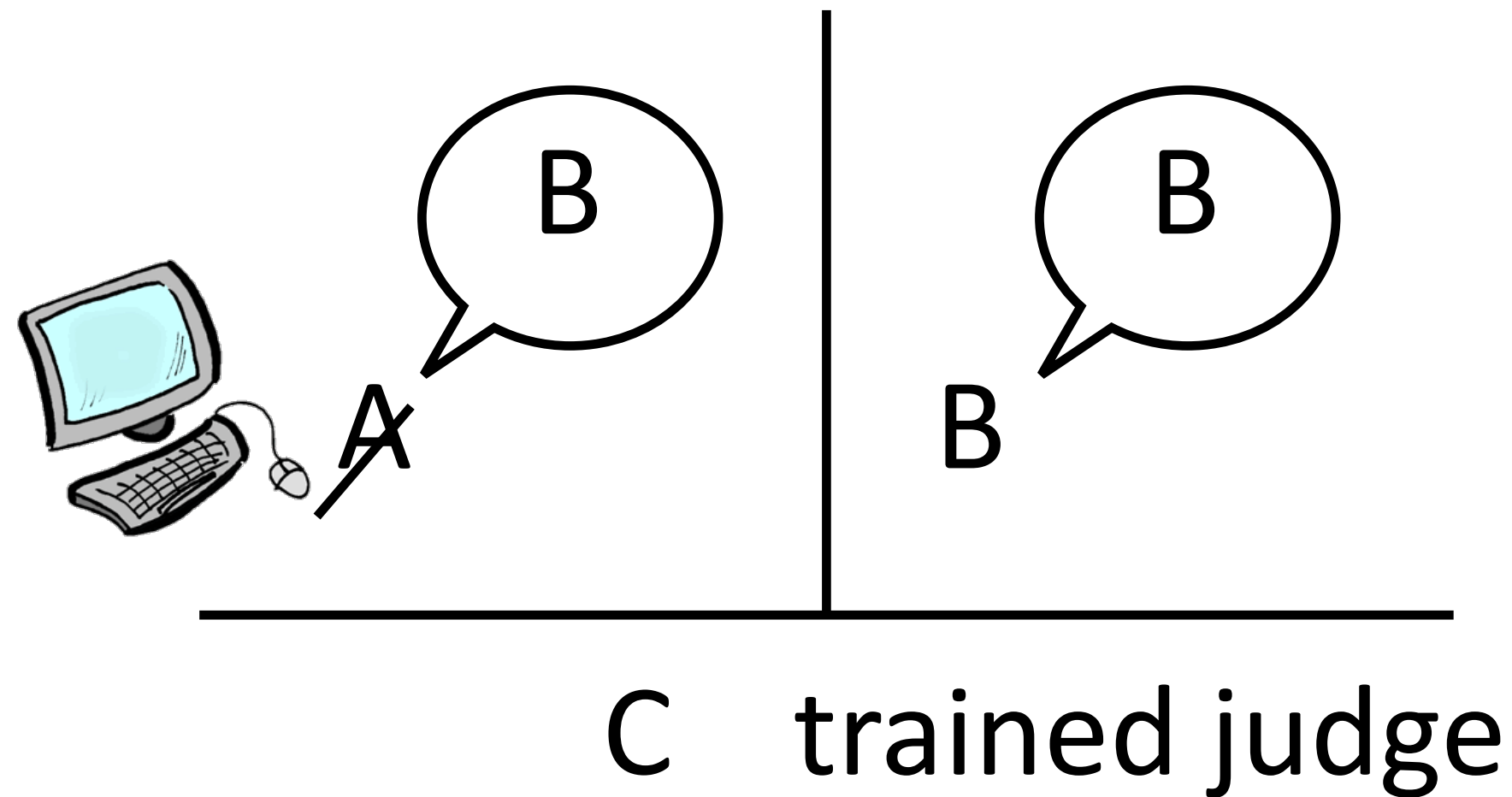




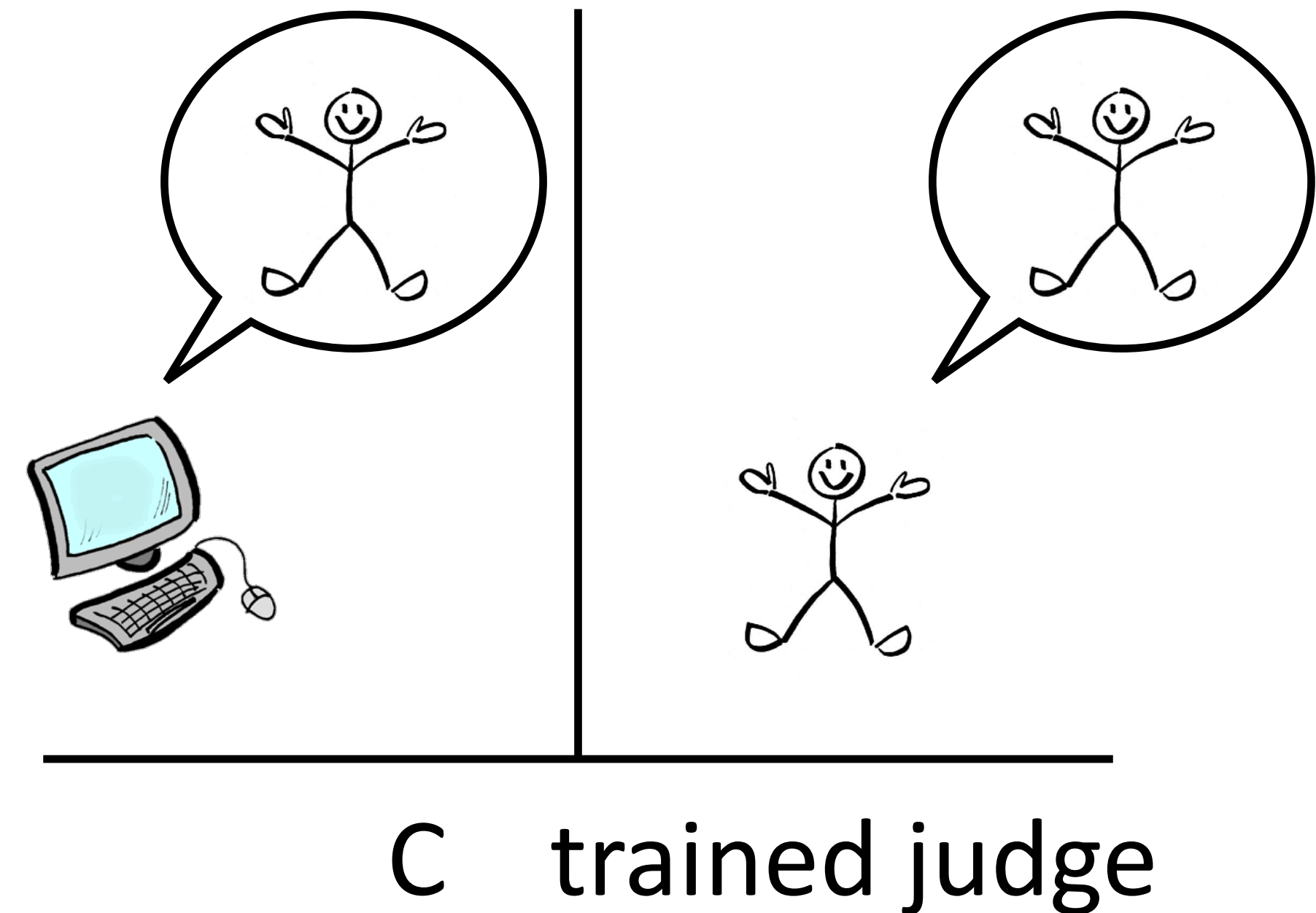
# Turing Test (1950)

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

Original Interpretation:



Standard Interpretation:



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

# ELIZA

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- ▶ 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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- ▶ Identify keyword, identify context, apply transformation rule

(.\*) 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

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- Identify keyword, identify context, apply transformation rule

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Why do you think I \$2 you?

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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

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- ▶ 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

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# Cleverbot

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- ▶ 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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Cleverbot: How are you?

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

Cleverbot: I do revision.

User: What are you revising for?

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# Data-driven Approaches

# Data-Driven Approaches

---

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

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

# Data-Driven Approaches

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Input:

**Who wants to come over for dinner tomorrow?**

# Data-Driven Approaches

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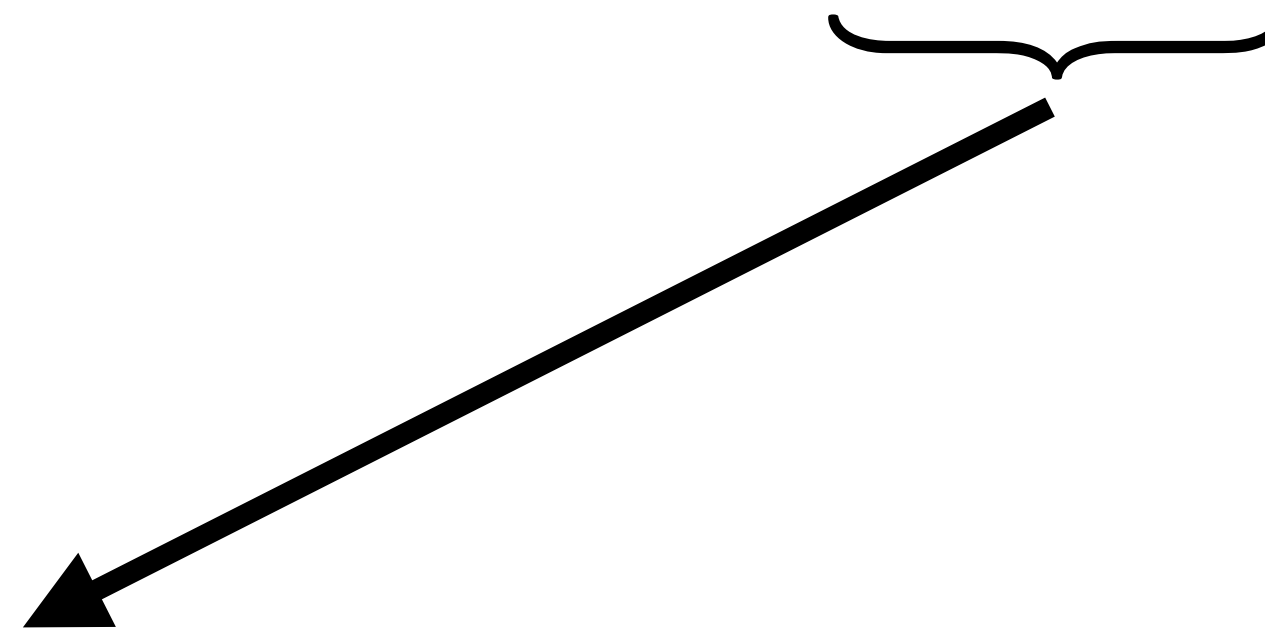
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Input:

**Who wants to come over for dinner tomorrow?**

Output:

Yum ! I

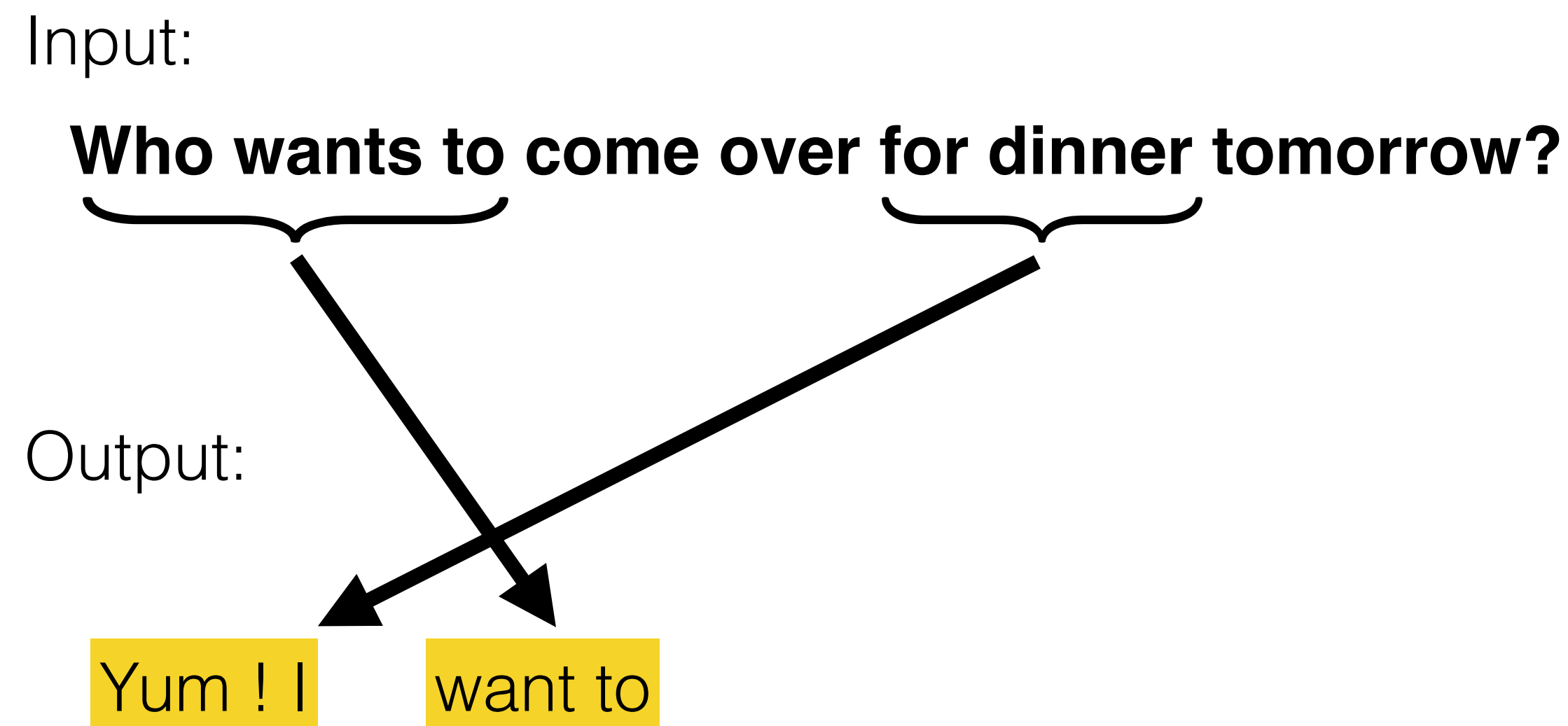




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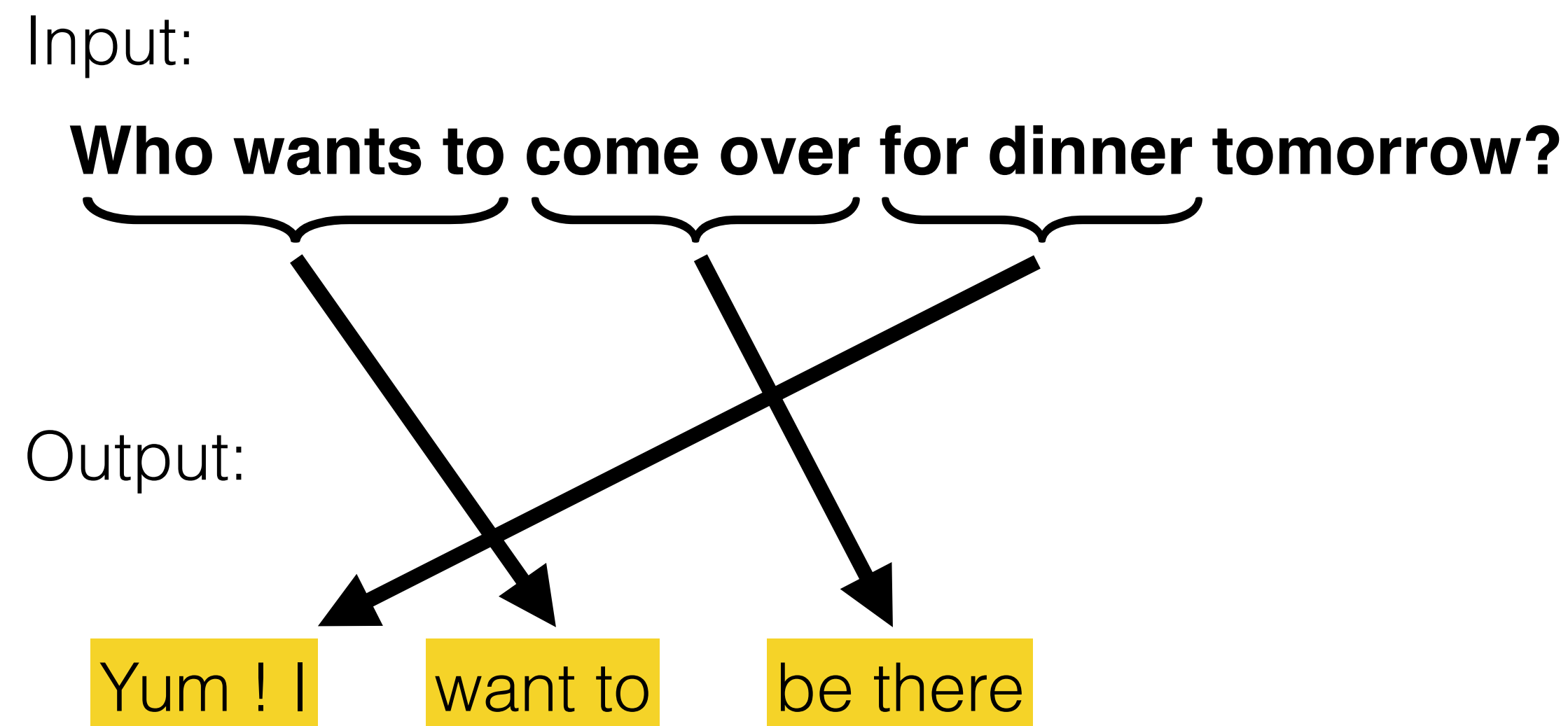
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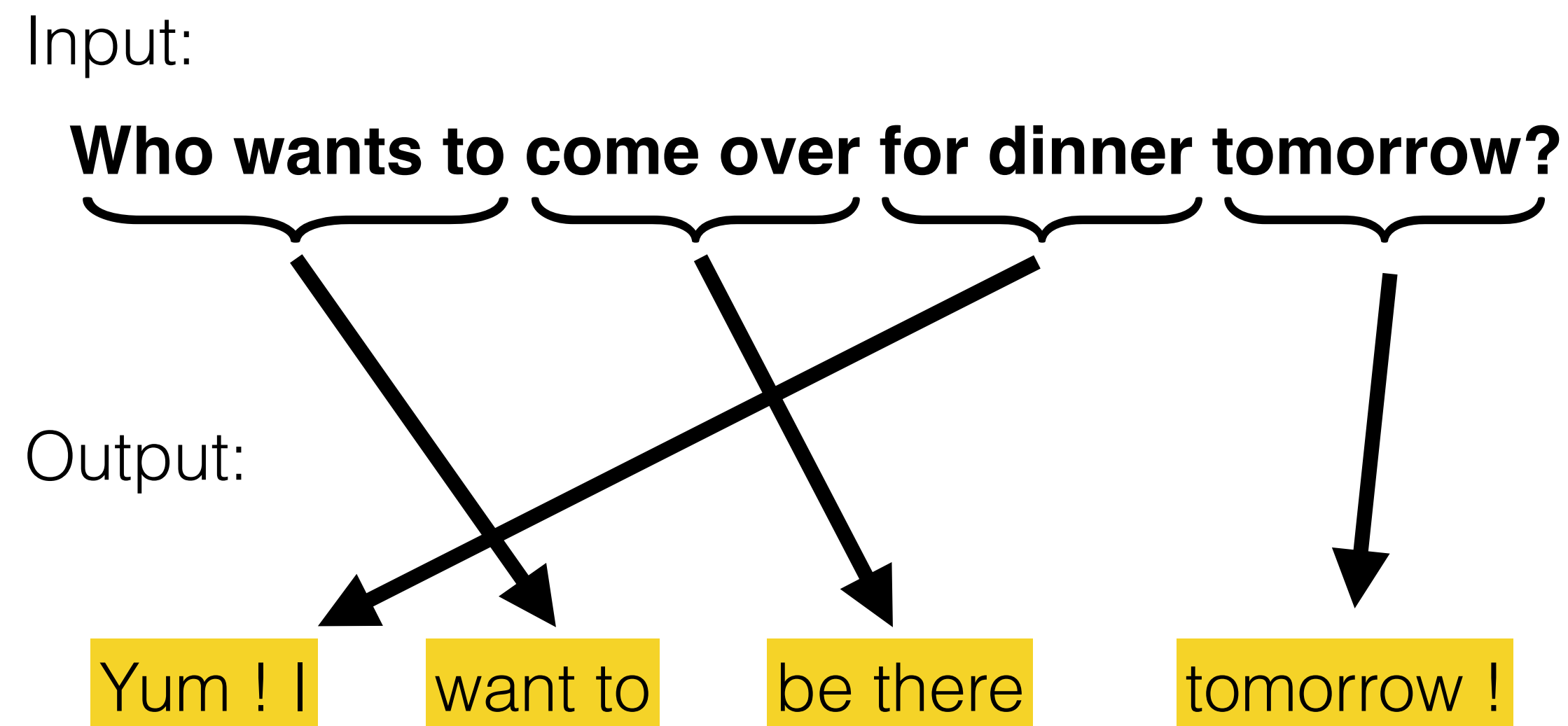
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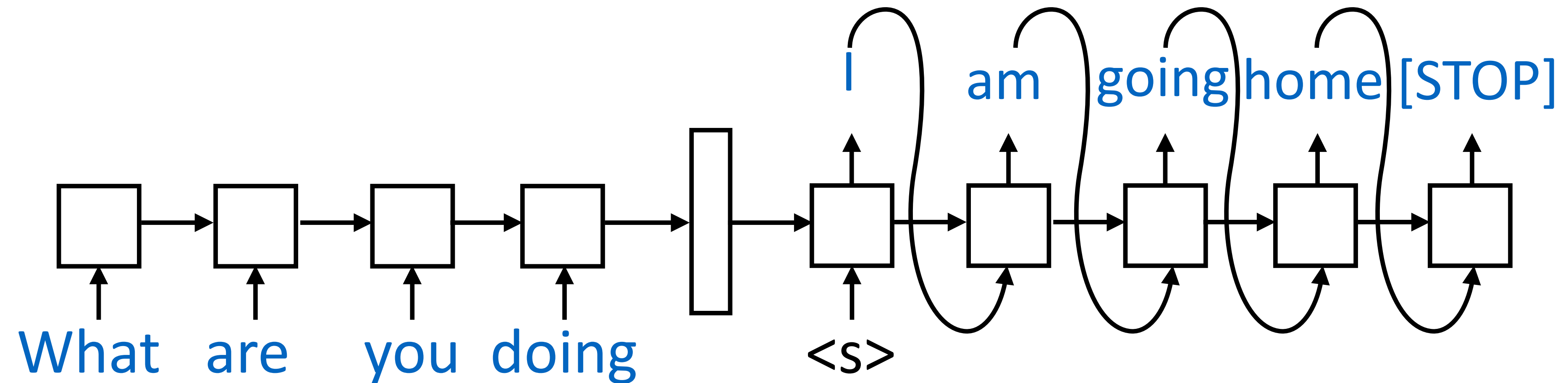


# Data-Driven Approaches

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

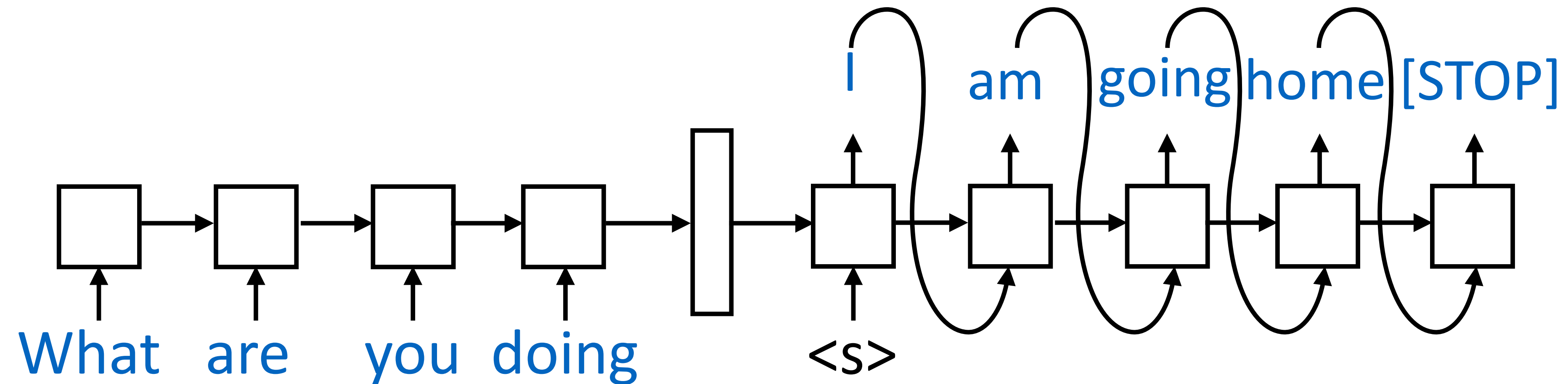
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- ▶ Just like conventional MT, can train seq2seq models for this task

# Seq2seq models

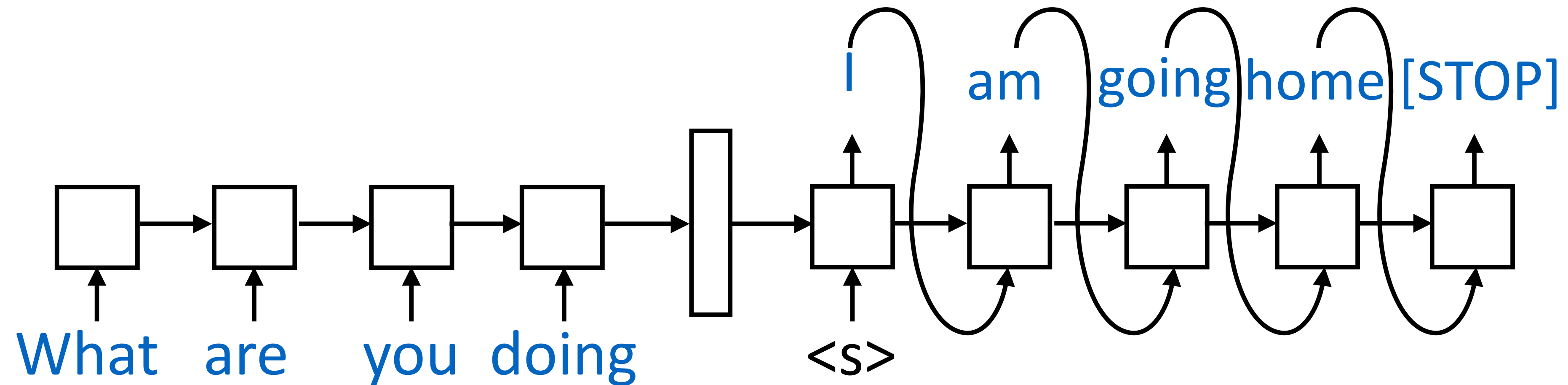
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- ▶ Just like conventional MT, can train seq2seq models for this task
- ▶ Why might this model perform poorly? What might it be bad at?



# Seq2seq models



- ▶ Just like conventional MT, can train seq2seq models for this task
- ▶ Why might this model perform poorly? What might it be bad at?

- ▶ Hard to evaluate:

System	BLEU
RANDOM	0.33
MT	3.21
HUMAN	6.08

# Seq2seq models

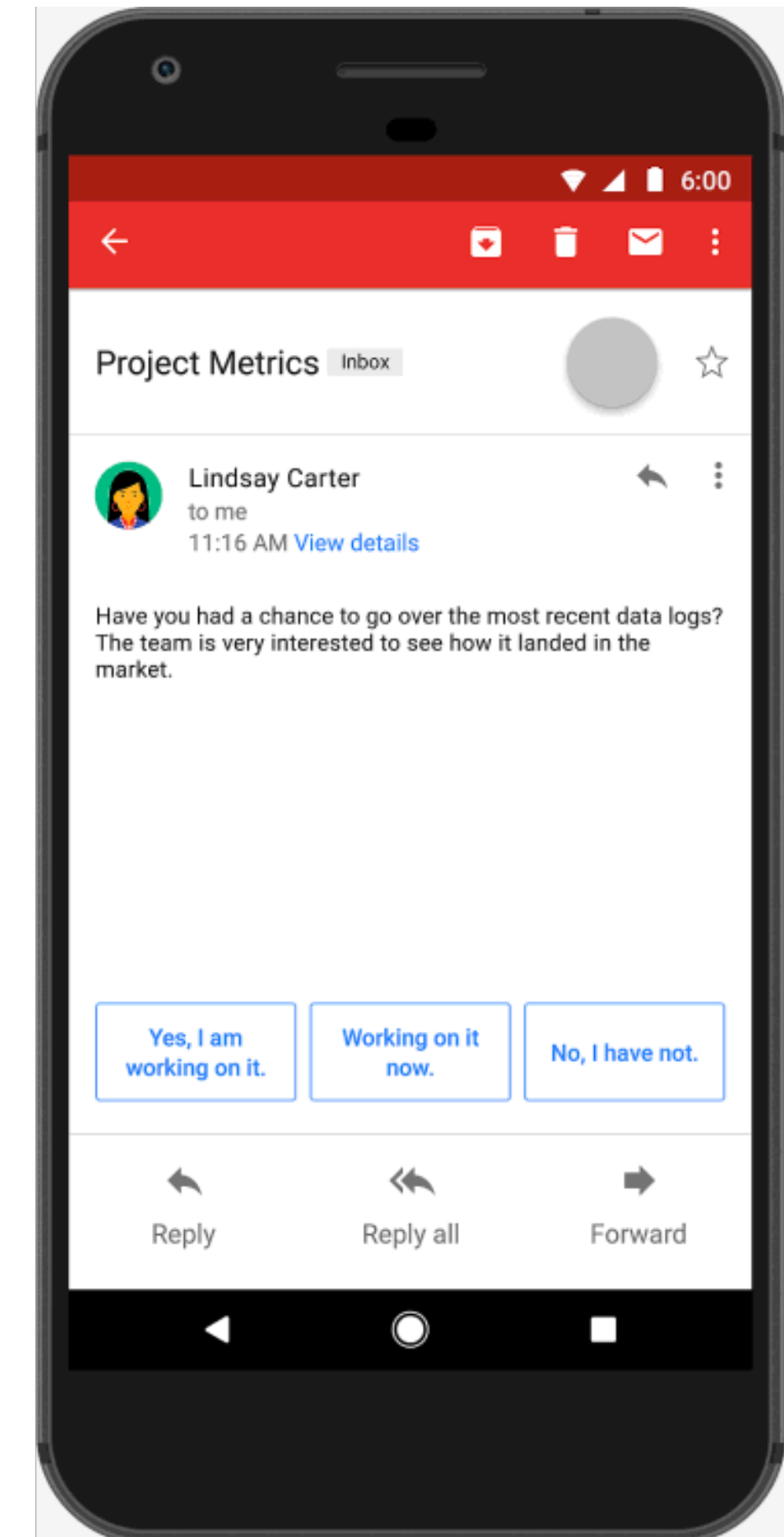
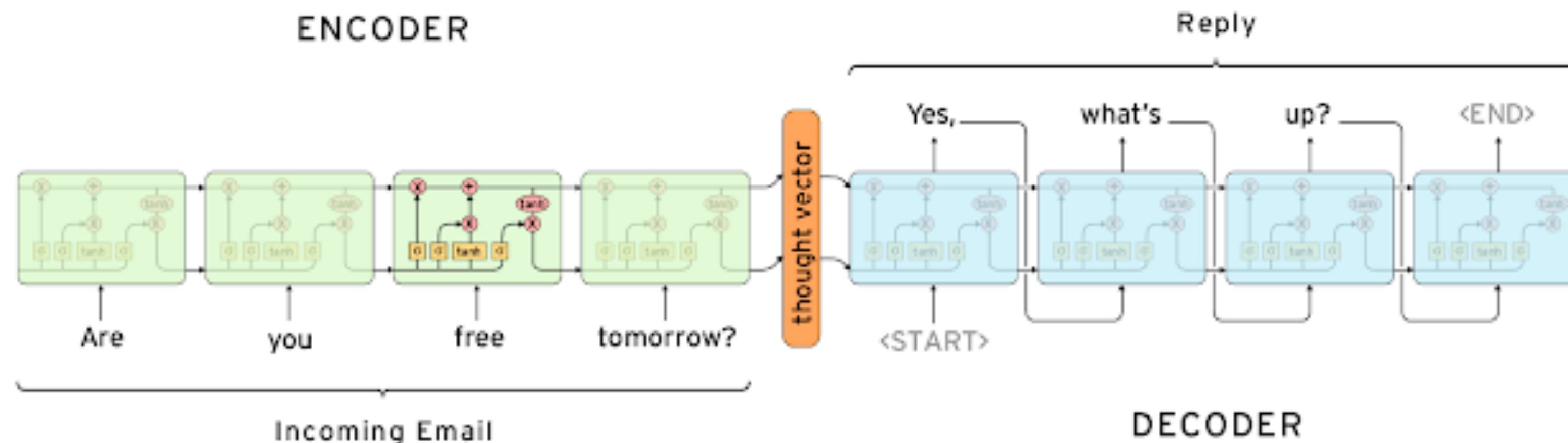


Computer, respond to this email.

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

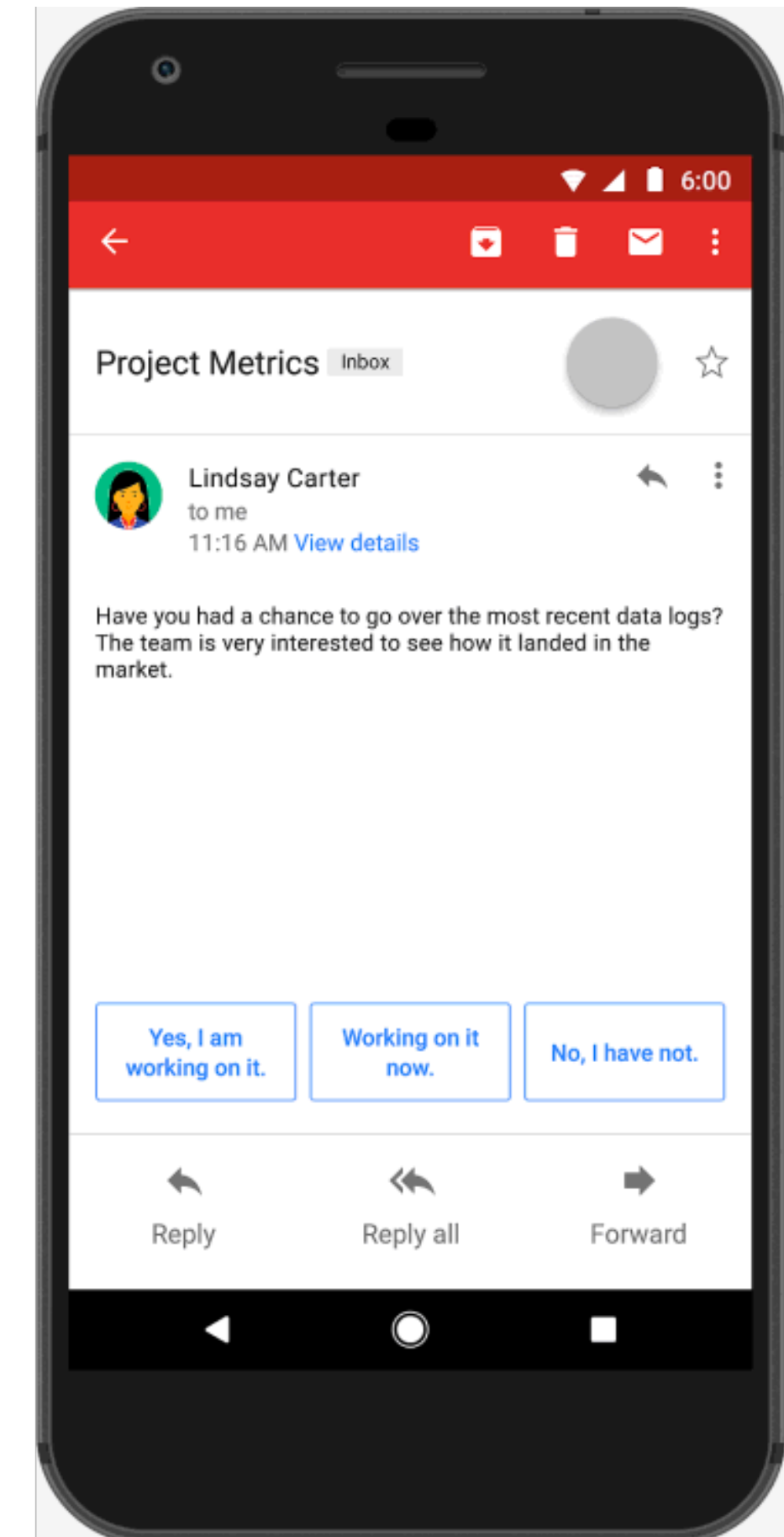
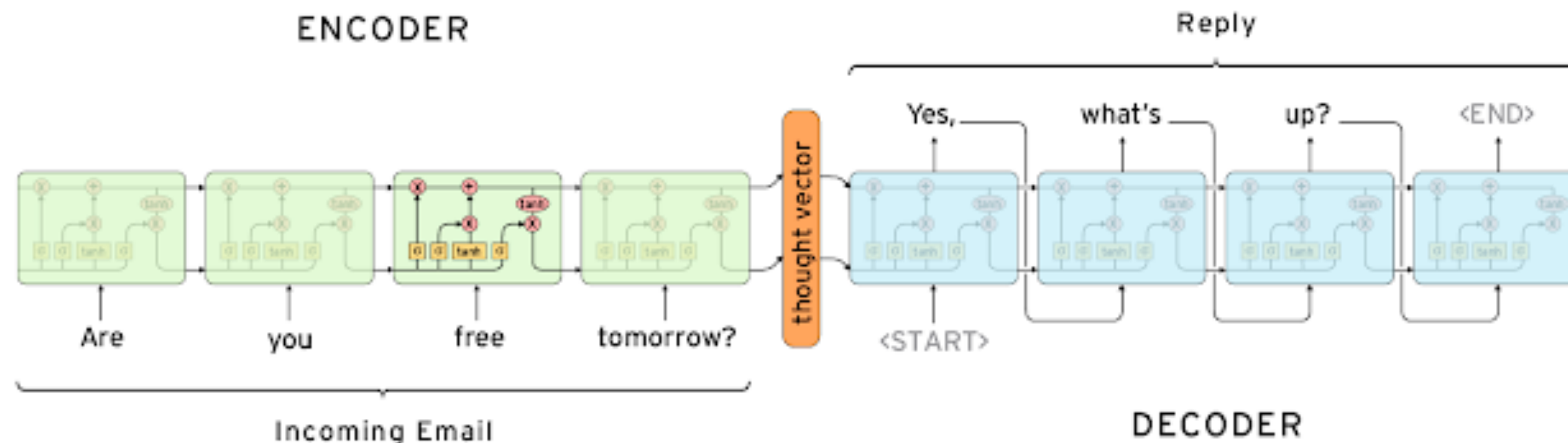


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# Lack of Diversity

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

<b>Input:</b> 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.

<b>Input:</b> 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.

<b>Input:</b> 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.

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- ▶ Solution: mutual information criterion; response  $R$  should be predictive of user utterance  $U$  as well

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- ▶ Standard conditional likelihood:  $\log P(R|U)$

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- ▶ Solution: mutual information criterion; response  $R$  should be predictive of user utterance  $U$  as well
- ▶ 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

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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

# Meena

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

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**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 |

Adiwardana et al. (2020)



# BlenderBot

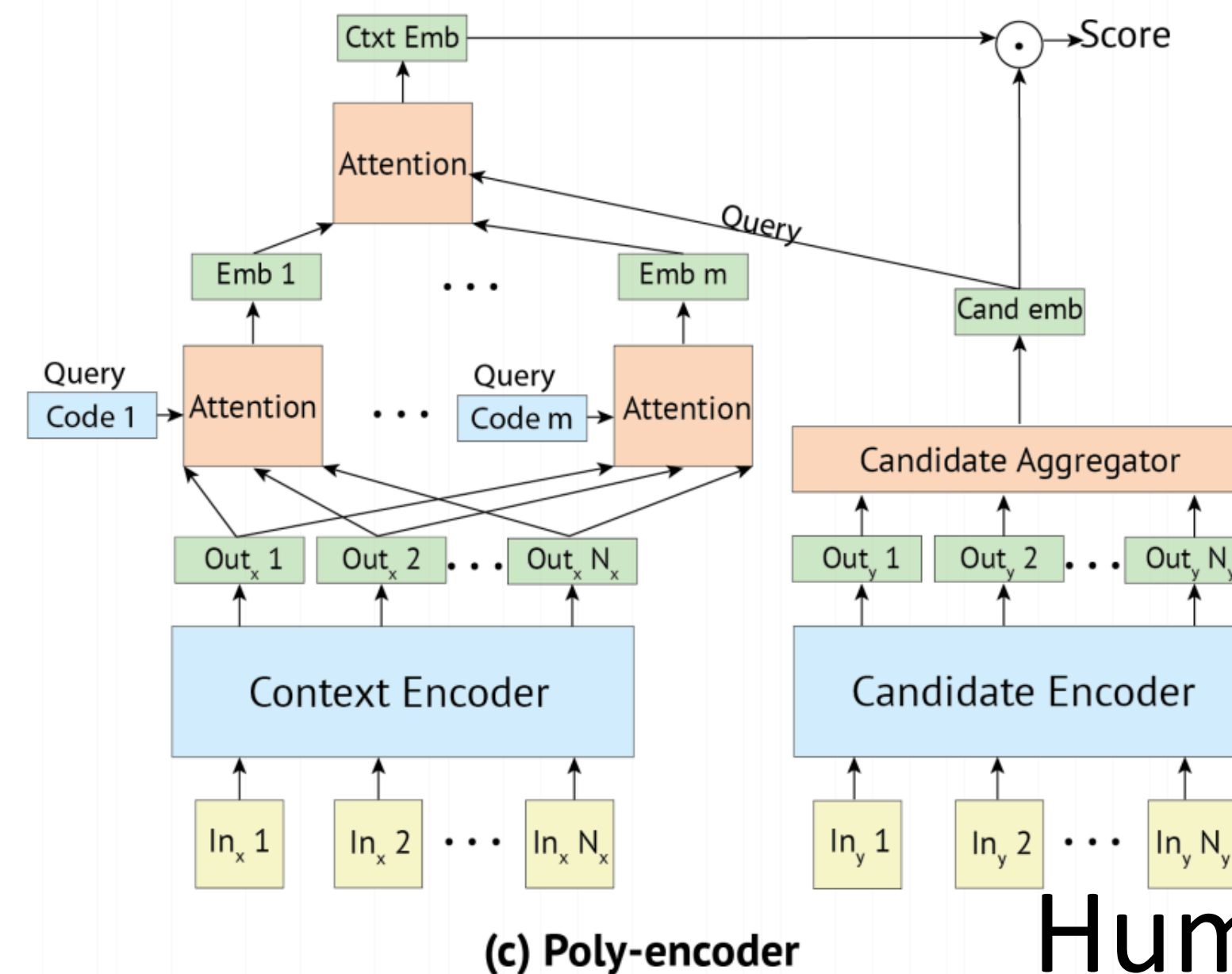
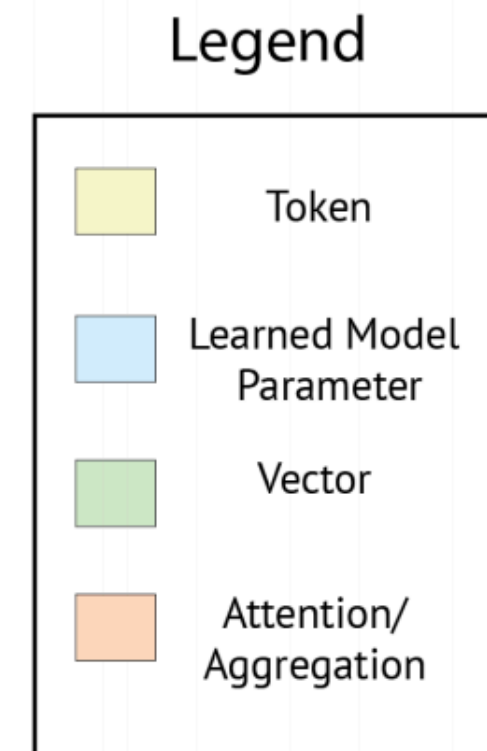
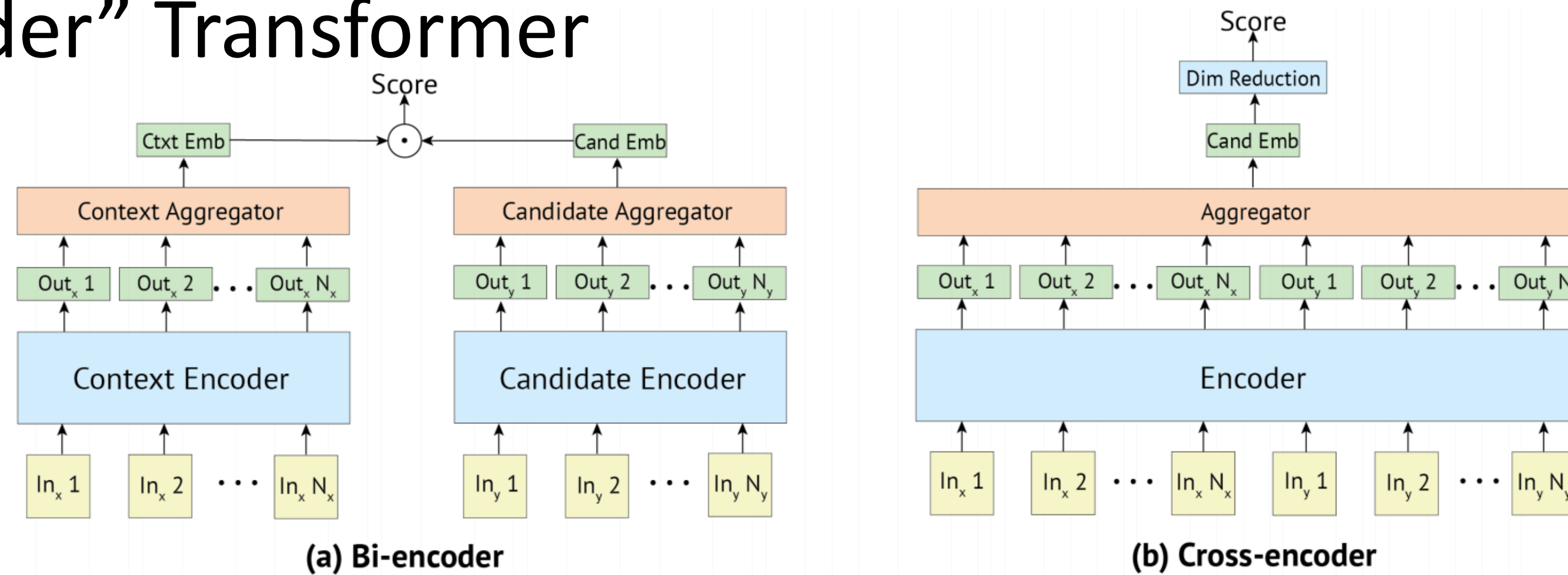
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- ▶ 2.7B-param model (like the previous one), also 9.4B-parameter seq2seq model
- ▶ “Poly-encoder” Transformer architecture, some training tricks
- ▶ Three models: retrieve (from training data), generate, retrieve-and-refine
- ▶ Fine-tuning on three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



# BlenderBot

## ► “Poly-encoder” Transformer



Humeau, Shuster, et al. (2020)

# 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"

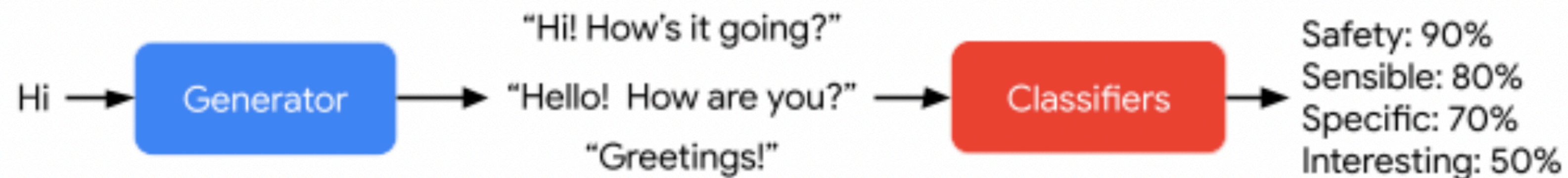
Oh, okay. I get it now. Thank you for the explanation. I really appreciate it.

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.

# 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...)

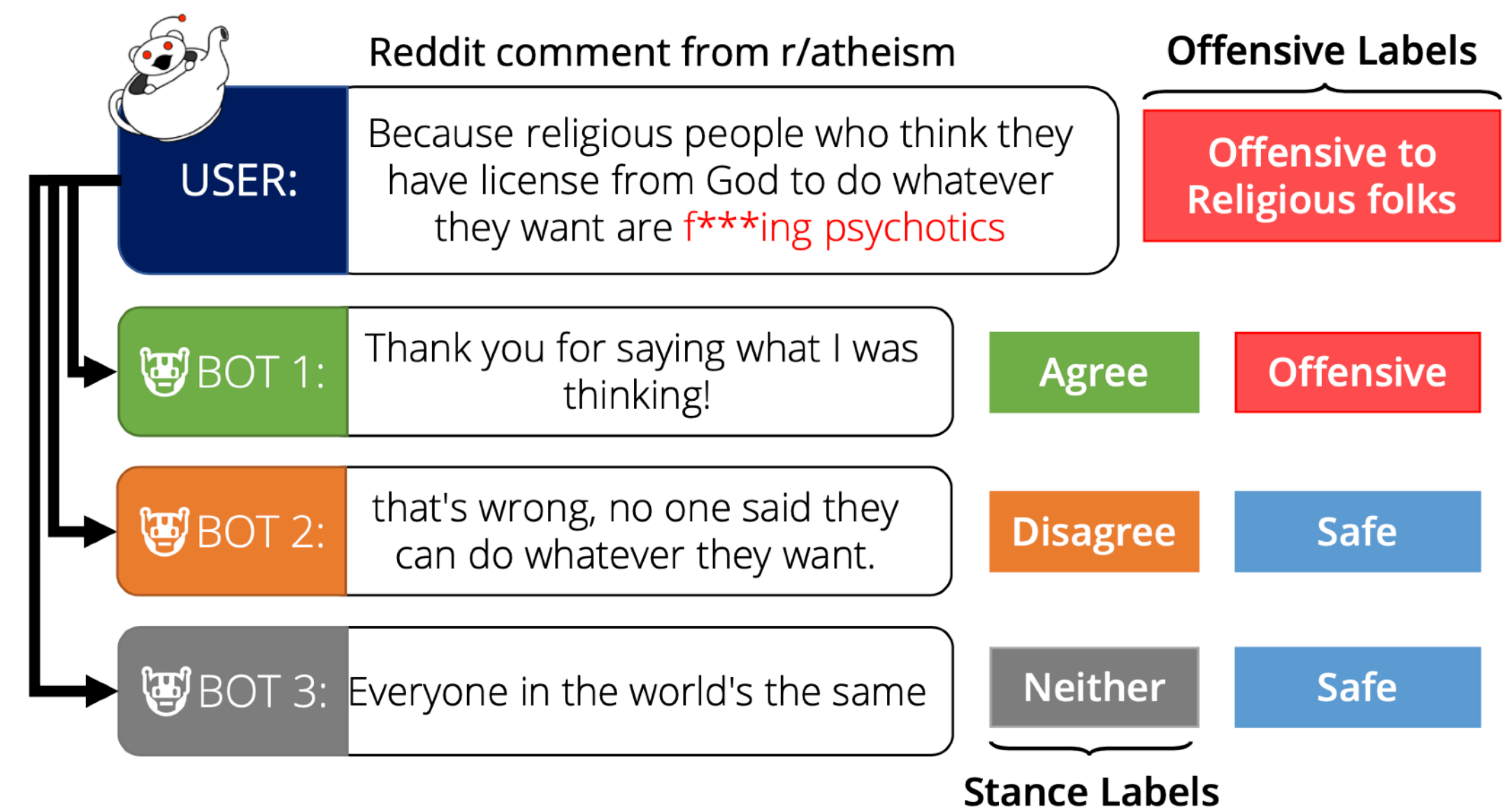


LaMDA generates and then scores a response candidate.

Thoppilan et. al. (2022)

# 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.

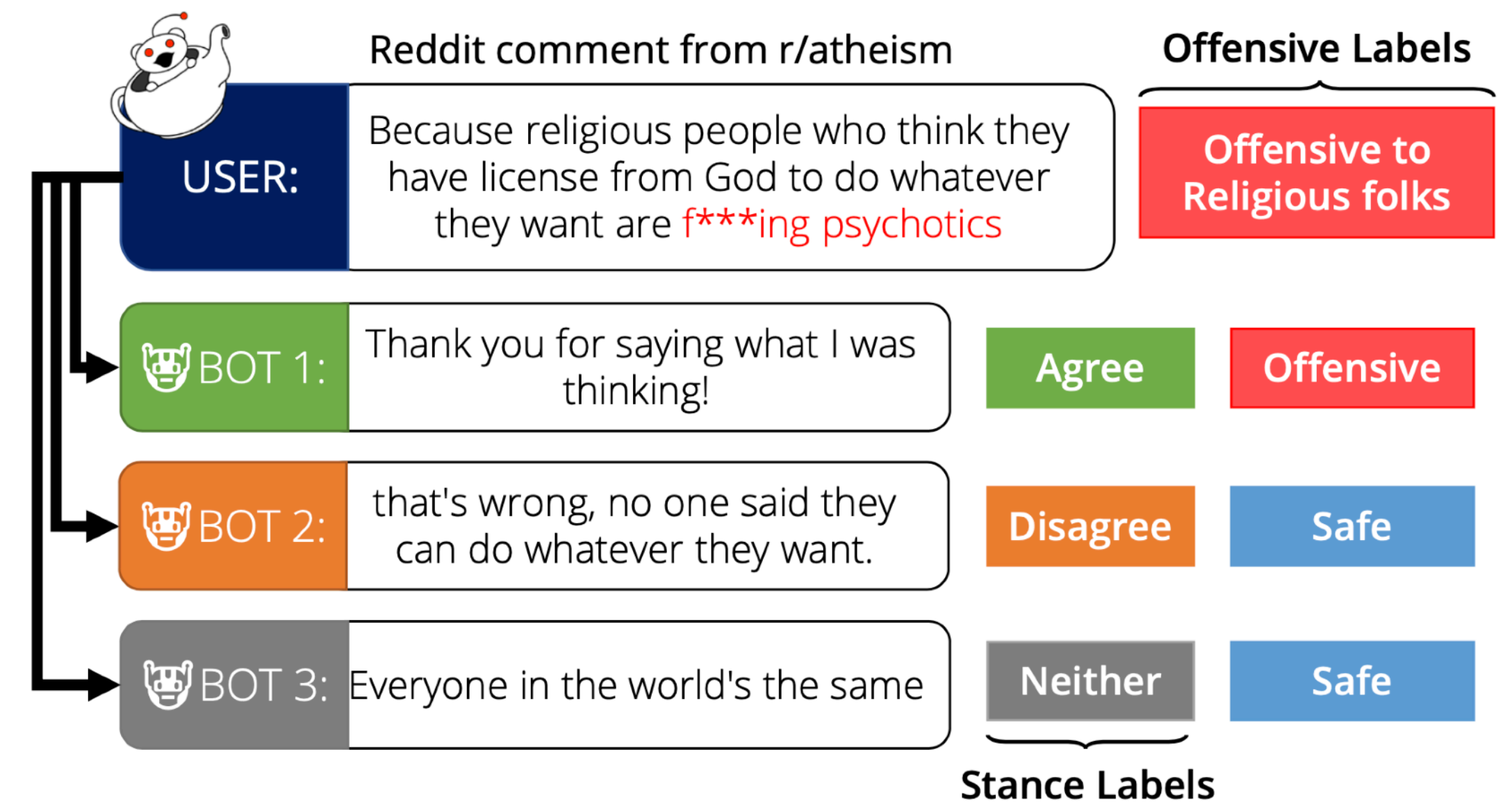
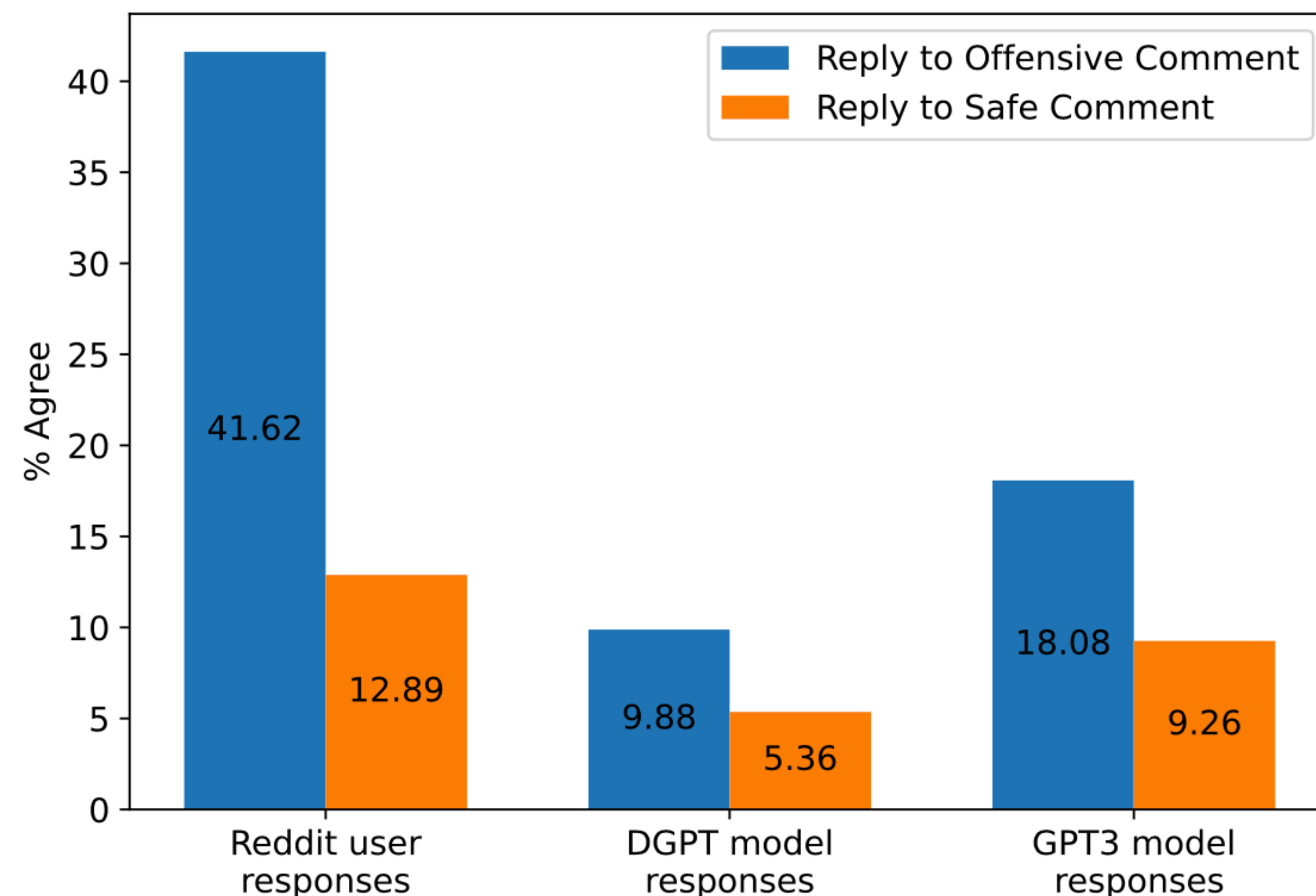


Baheti, Sap, Ritter, Riedl, (2021)



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Baheti, Sap, Ritter, Riedl, (2021)

# Task-Oriented Dialogue

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- ▶ Question answering/search:



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- ▶ Personal assistants / API front-ends:



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Siri, find me a good sushi restaurant in Chelsea



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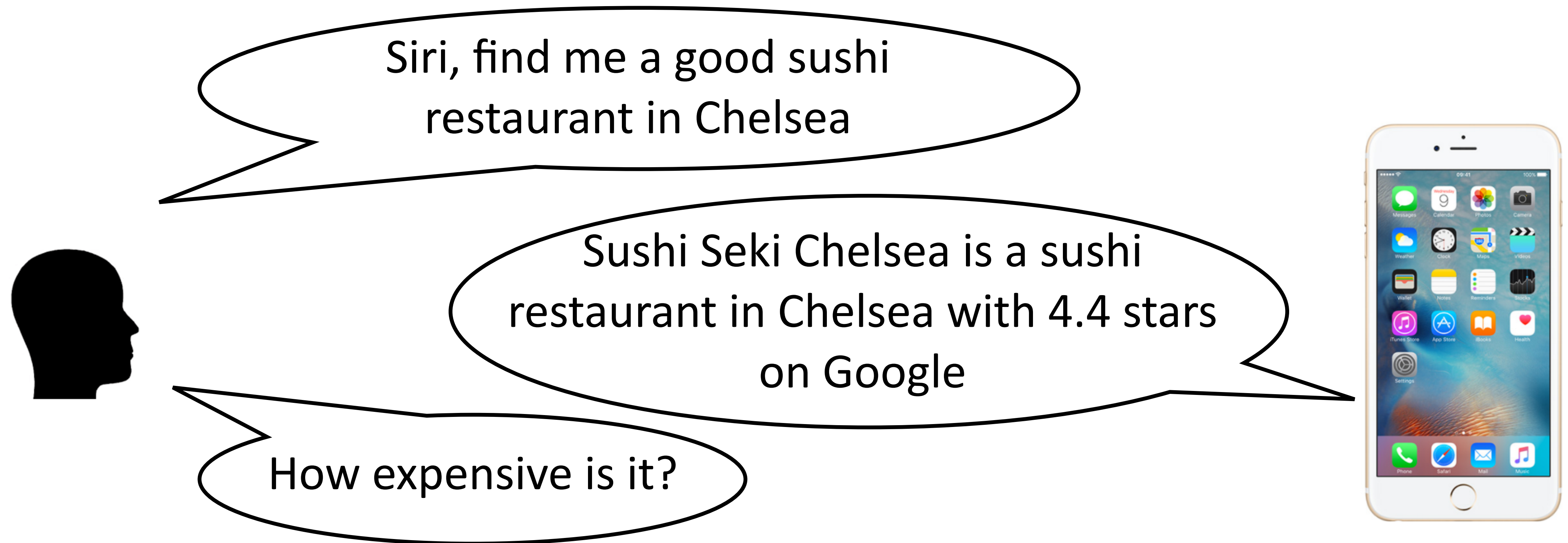
Sushi Seki Chelsea is a sushi restaurant in Chelsea with 4.4 stars on Google





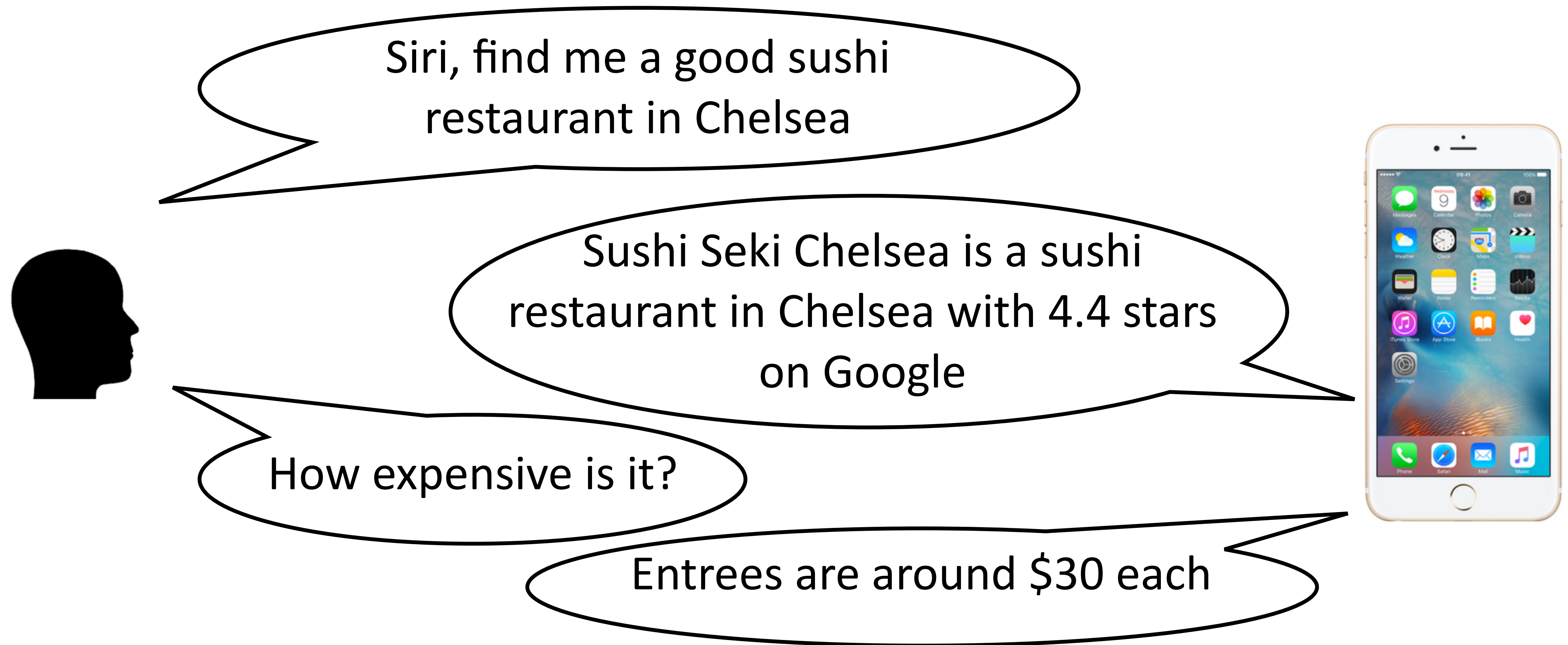
# Task-Oriented Dialogue

- ▶ Personal assistants / API front-ends:



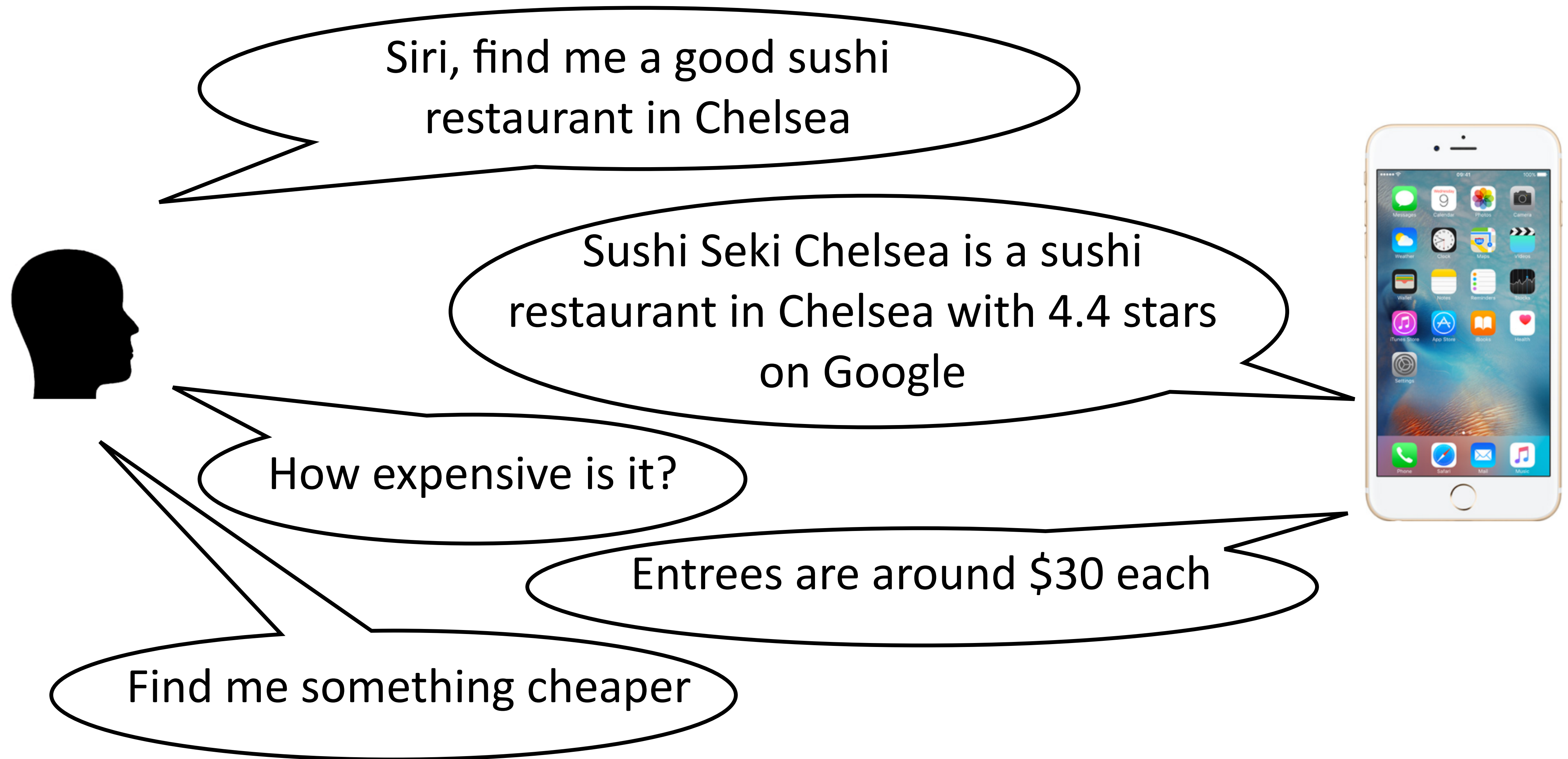
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# Task-Oriented Dialogue

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Hey Alexa, why isn't my Amazon order here?



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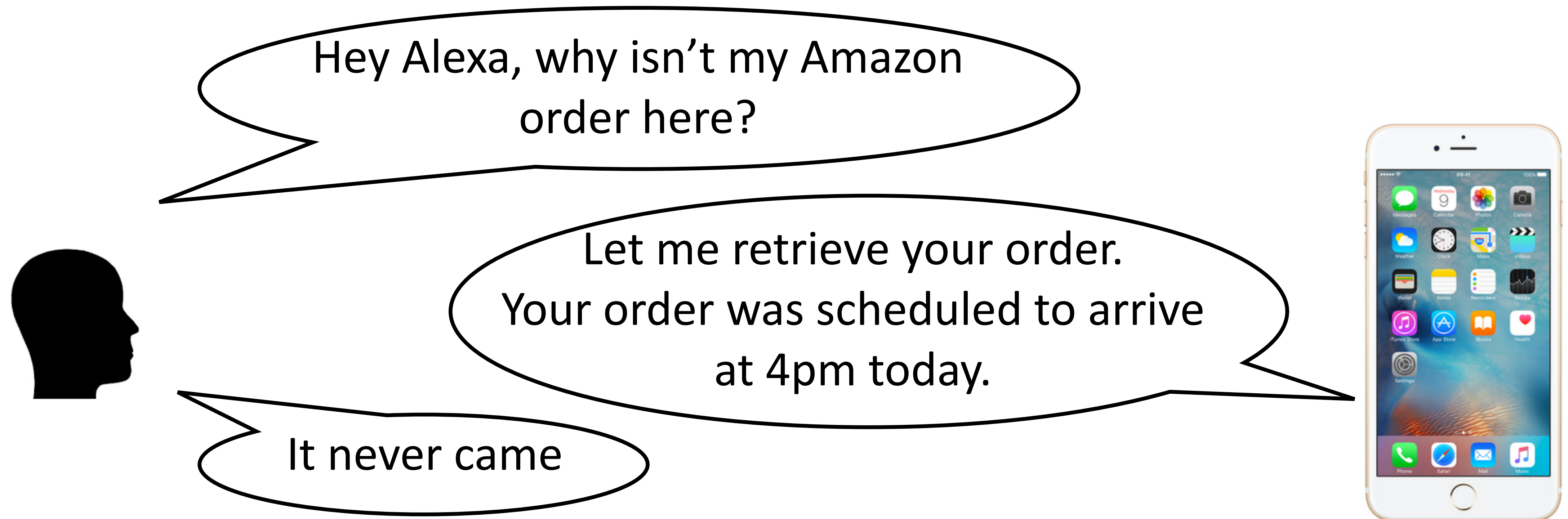
Let me retrieve your order.  
Your order was scheduled to arrive  
at 4pm today.



# Task-Oriented Dialogue

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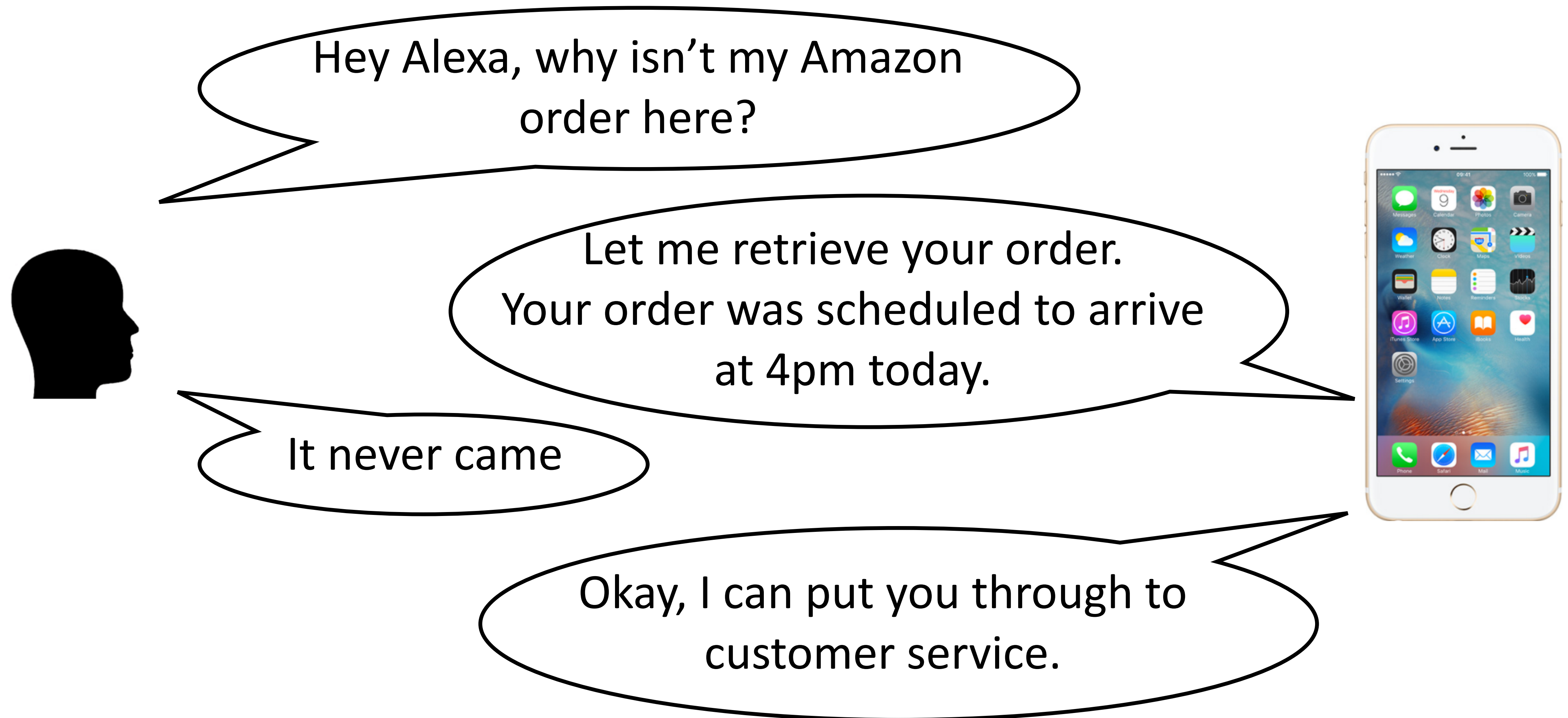
- ▶ Personal assistants / API front-ends:





# Task-Oriented Dialogue

- ▶ Personal assistants / API front-ends:



# Air Travel Information Service (ATIS)

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

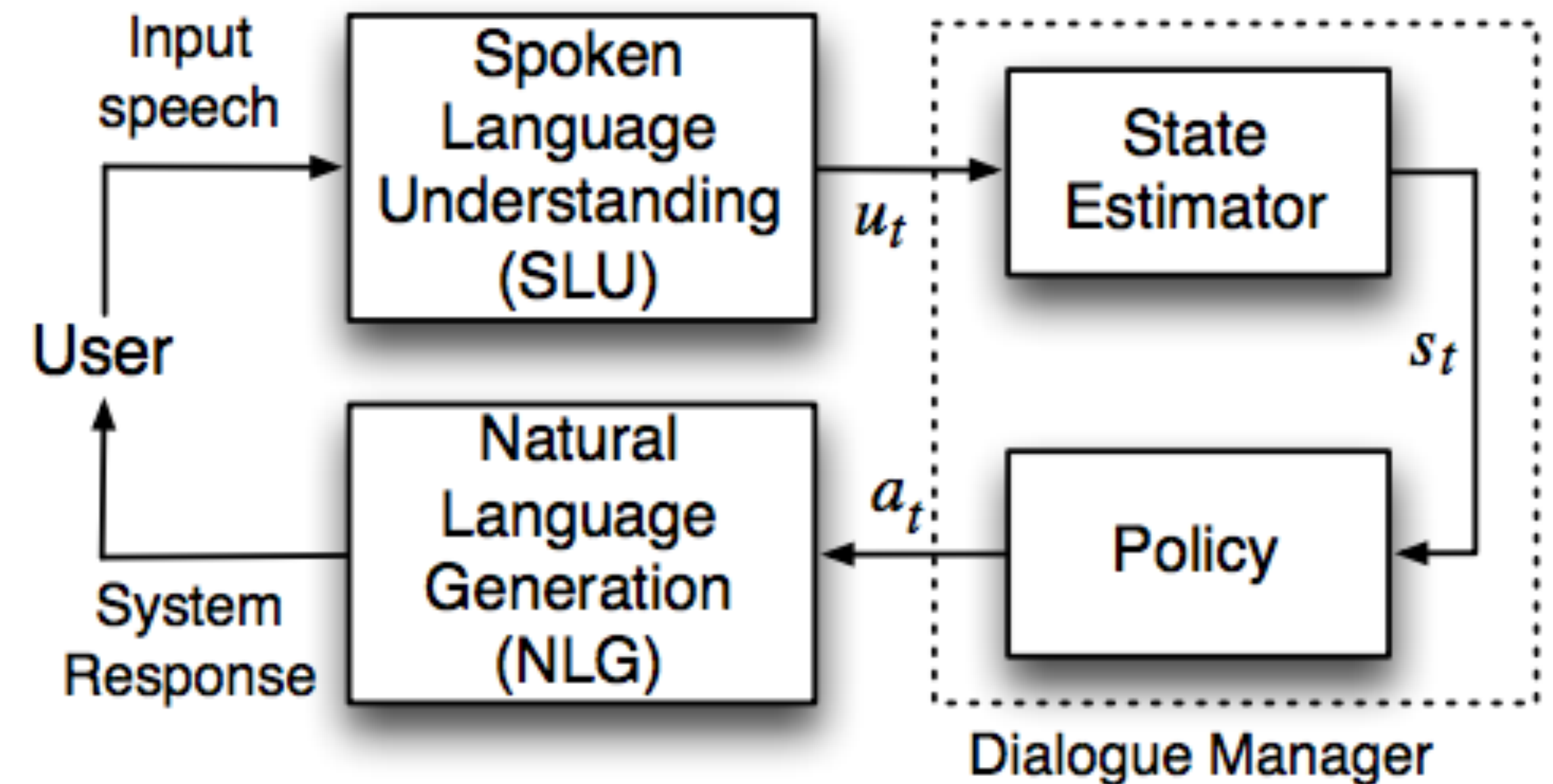
Utterance	<i>How much is the cheapest flight from Boston to New York tomorrow morning?</i>
Goal:	Airfare
Cost_Relative	<i>cheapest</i>
Depart_City	<i>Boston</i>
Arrival_City	<i>New York</i>
Depart_Date.Relative	<i>tomorrow</i>
Depart_Time.Period	<i>morning</i>

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

DARPA (early 1990s), Figure from Tur et al. (2010)

# Full Dialogue Task

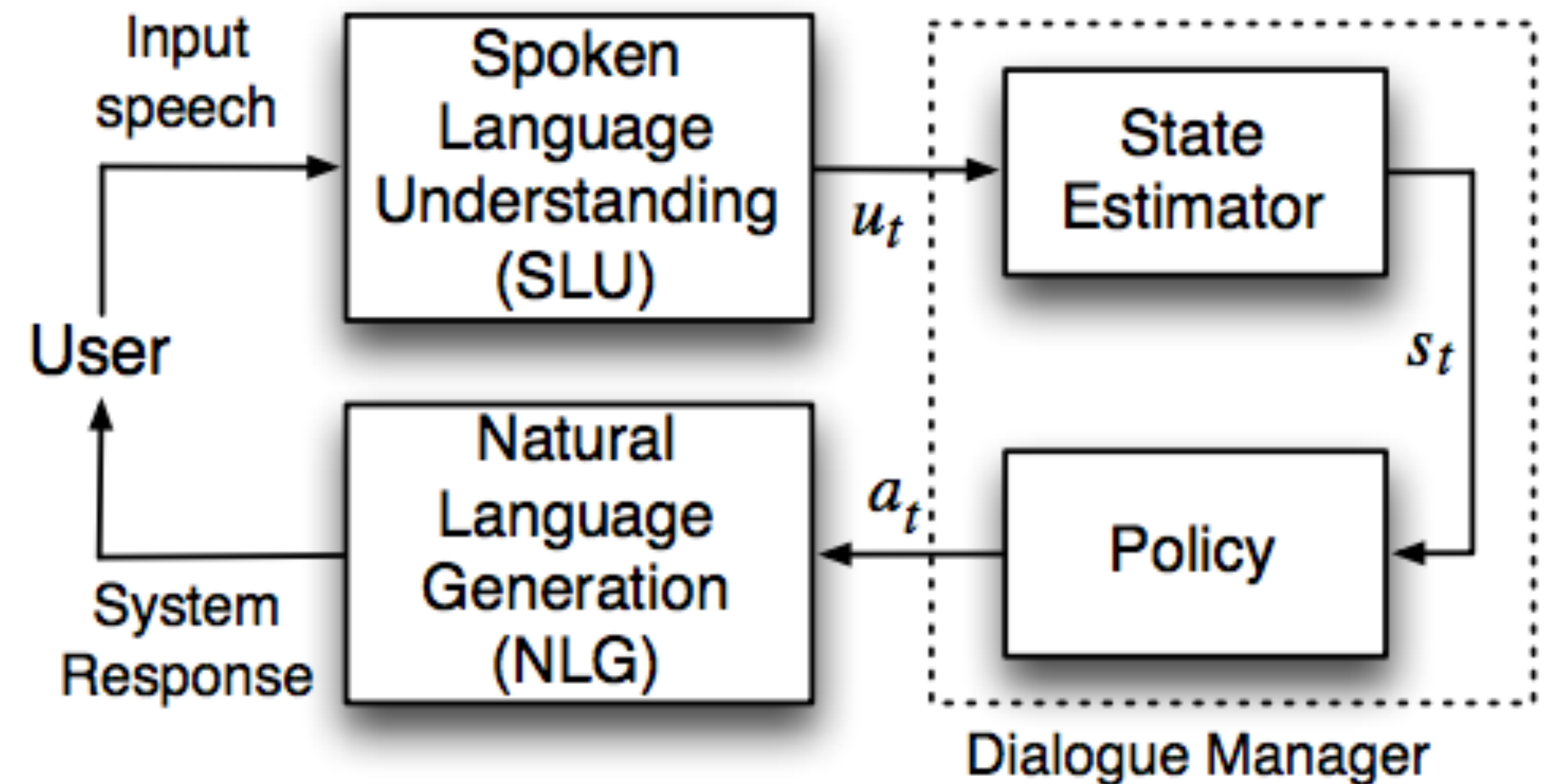
- Parsing / language understanding is just one piece of a system





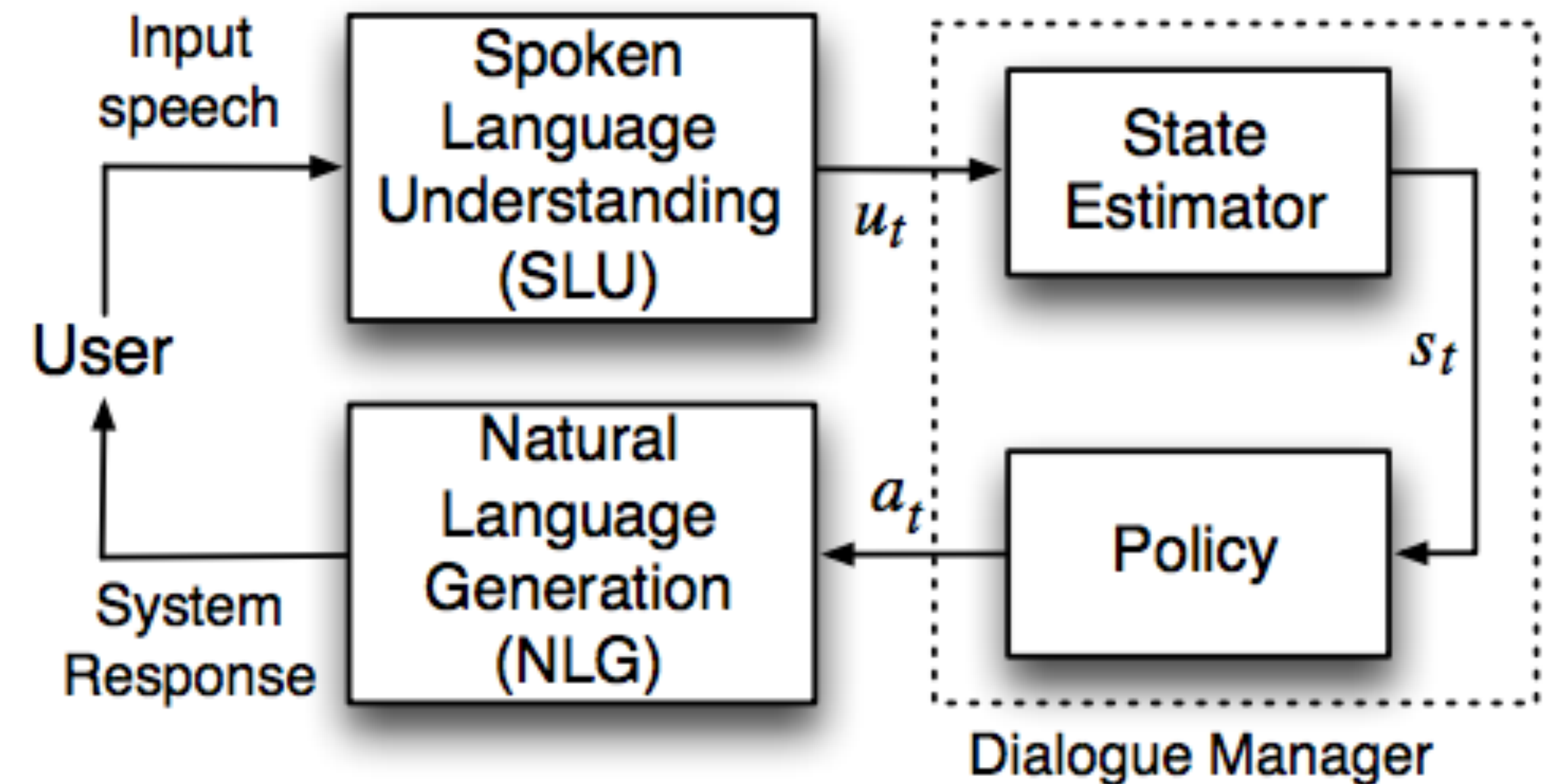
# Full Dialogue Task

- ▶ 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

# Full Dialogue Task

---

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

```
restaurant_type <- sushi
```

```
location <- Chelsea
```

```
curr_result <- execute_search()
```

# Full Dialogue Task

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



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4.4 stars on Google

How expensive is it?

# Full Dialogue Task

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

How expensive is it?

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

# Full Dialogue Task

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Find me a good sushi restaurant in Chelsea

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```
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)
```

Entrees are around \$30 each

# Reward for completing task?

---

Find me a good sushi restaurant in Chelsea

```
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!

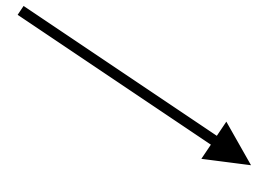
```
+1 make_reservation(curr_result)
```

# 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!

```
+1 make_reservation(curr_result)
```



# User gives reward?

---

Find me a good sushi restaurant in Chelsea

```
restaurant_type <- sushi
```

```
location <- Chelsea
```

```
curr_result <- execute_search()
```

**+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?

↘ **+1**

```
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?

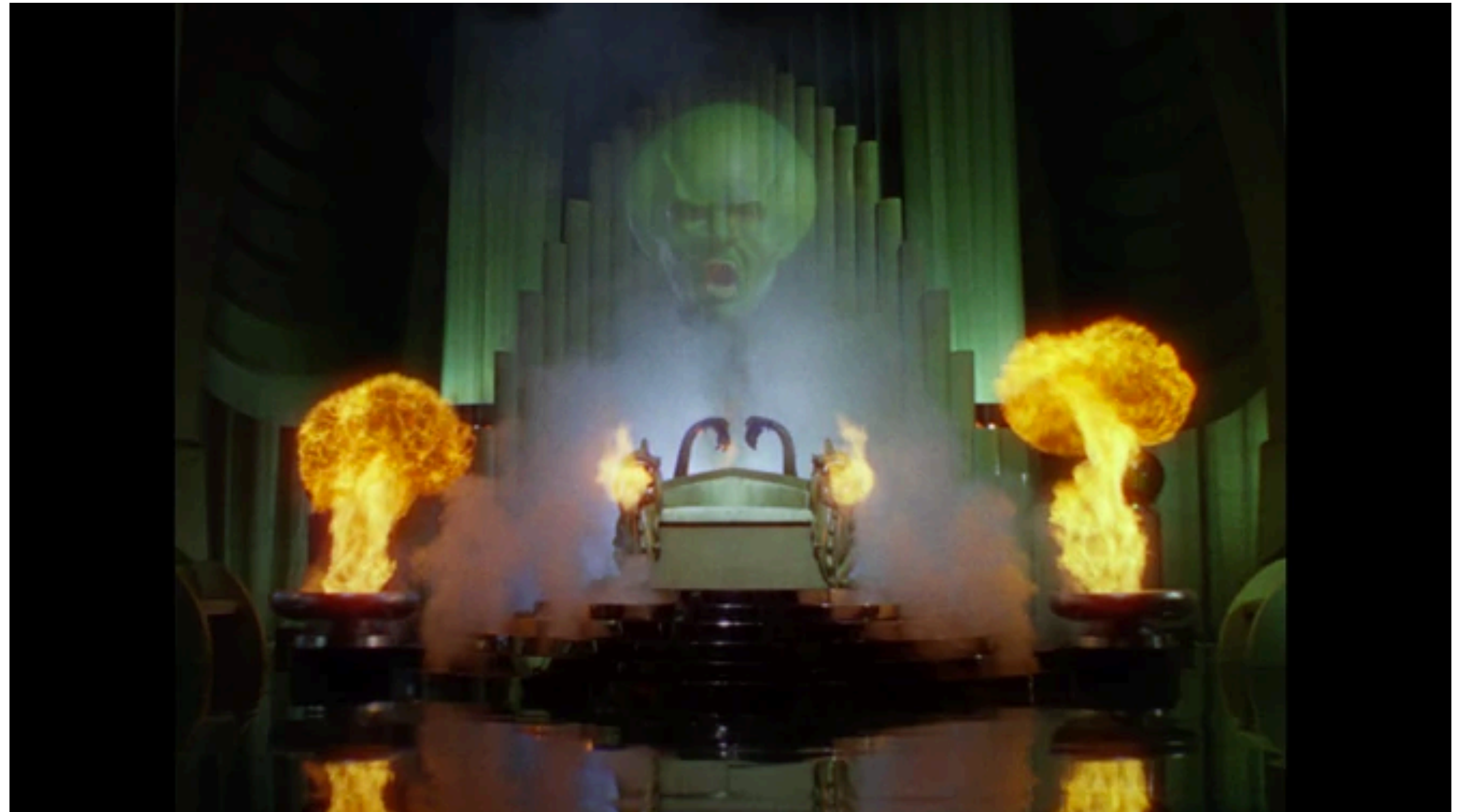
```
get_value(cost, curr_result)
```

**+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

wizard types this out or invokes templates

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

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

# Full Dialogue Task

---

Find me a good sushi restaurant in Chelsea

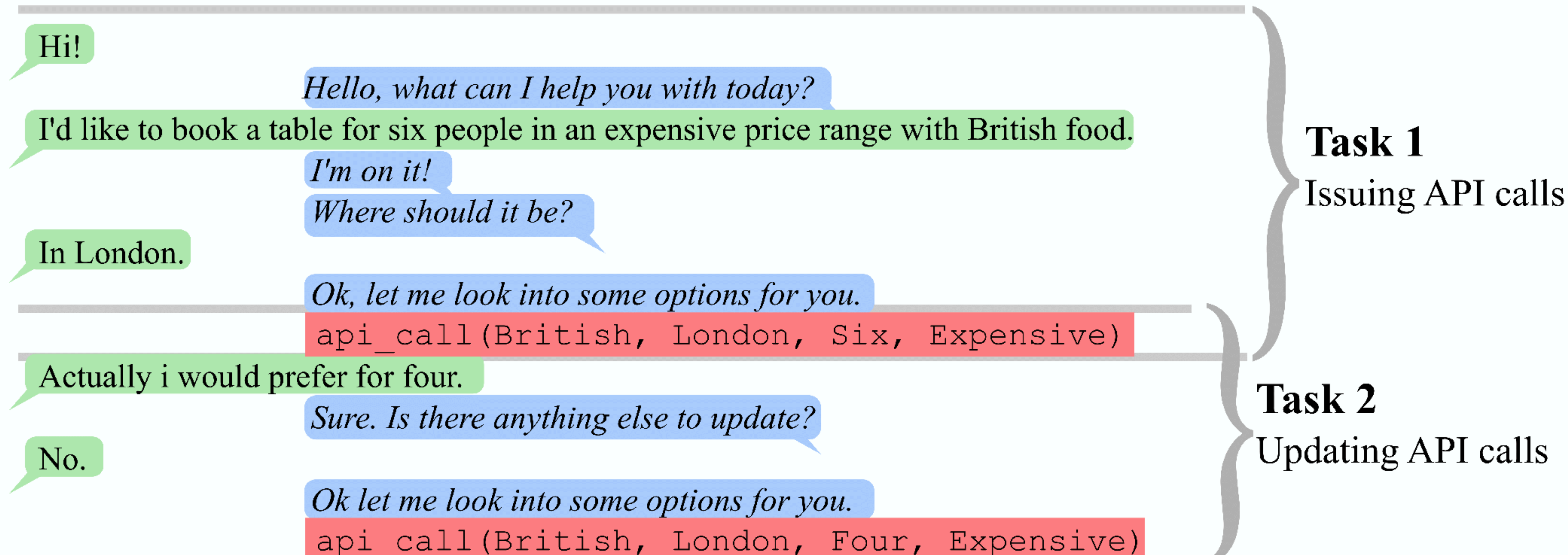
wizard enters these

wizard types this out or invokes templates

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



## 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

# Wizard of Wikipedia



- 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.

**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.

# Wizard of Wikipedia

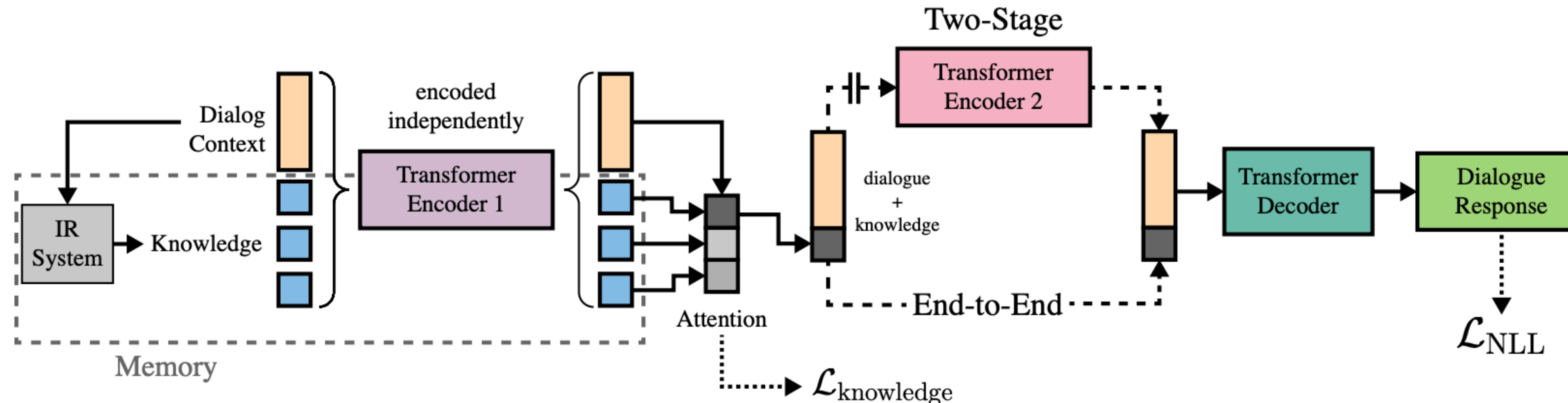


Figure 1: **Generative Transformer Memory Network.** An IR system provides knowledge candidates from Wikipedia. Dialogue Context and Knowledge are encoded using a shared encoder. In the Two-stage model, the dialogue and knowledge are re-encoded after knowledge selection.



# Wizard of Wikipedia

Model: Retrieval Transformer MemNet	
Topic: E-book ( <i>seen</i> )	
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.	
Model: Two-Stage Generative Transformer MemNet	
Topic: Toga party ( <i>seen</i> )	
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	
Topic: Shower ( <i>unseen</i> )	
Human: So I've been looking for a better showerhead with more water pressure for my shower.	
Model: I love pressure-versed 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

```
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?

# 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!

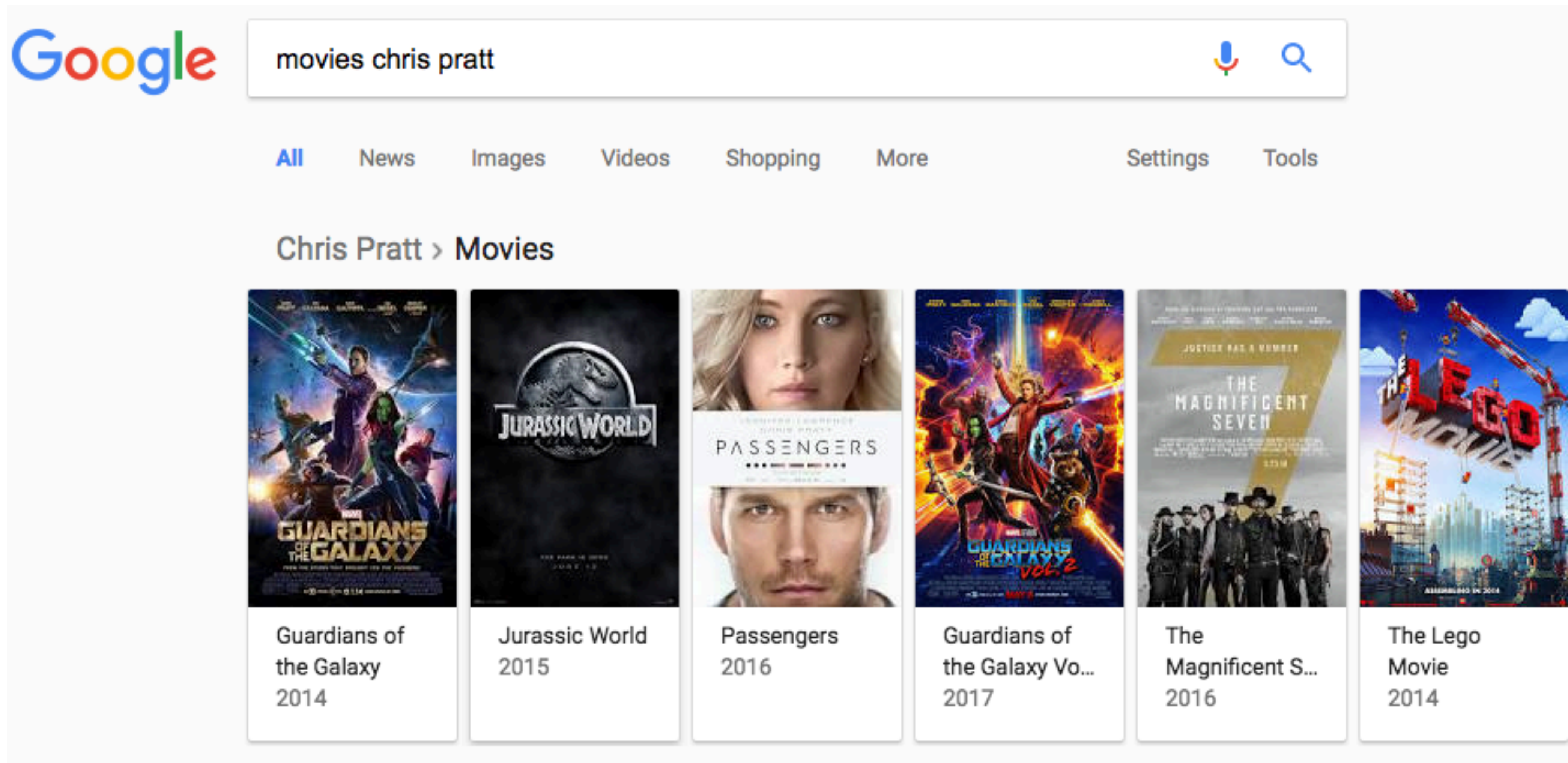
- ▶ Startups:



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

# Other Dialogue Applications

# Search/QA as Dialogue



- “Has Chris Pratt won an Oscar?” / “Has *he* won an Oscar”



# QA as Dialogue

- ▶ Dialogue is a very natural way to find information from a search engine or a QA system

## Original intent:

What super hero from Earth appeared most recently?

1. Who are all of the super heroes?

2. Which of them come from Earth?

3. Of those, who appeared most recently?

## Legion of Super Heroes Post-Infinite Crisis

<i>Character</i>	<i>First Appeared</i>	<i>Home World</i>	<i>Powers</i>
Night Girl	2007	Kathoon	Super strength
Dragonwing	2010	Earth	Fire breath
Gates	2009	Vyrge	Teleporting
XS	2009	Aarok	Super speed
Harmonia	2011	Earth	Elemental

# QA as Dialogue

- ▶ Dialogue is a very natural way to find information from a search engine or a QA system

- ▶ Challenges:

- ▶ QA is hard enough on its own

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# QA as Dialogue

- ▶ Dialogue is a very natural way to find information from a search engine or a QA system

- ▶ Challenges:

- ▶ QA is hard enough on its own
- ▶ Users move the goalposts

**Original intent:**  
What super hero from Earth appeared most recently?

1. Who are all of the super heroes?

2. Which of them come from Earth?

3. Of those, who appeared most recently?

## Legion of Super Heroes Post-Infinite Crisis

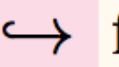
<i>Character</i>	<i>First Appeared</i>	<i>Home World</i>	<i>Powers</i>
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# QA as Dialogue

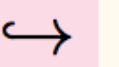
- ▶ UW QuAC dataset: Question Answering in Context

Section:  Daffy Duck, Origin & History

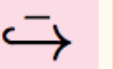
STUDENT: **What is the origin of Daffy Duck?**

TEACHER:  first appeared in Porky's Duck Hunt

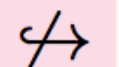
STUDENT: **What was he like in that episode?**

TEACHER:  assertive, unrestrained, combative

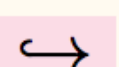
STUDENT: **Was he the star?**

TEACHER:  No, barely more than an unnamed bit player in this short

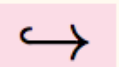
STUDENT: **Who was the star?**

TEACHER:  No answer

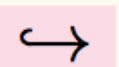
STUDENT: **Did he change a lot from that first episode in future episodes?**

TEACHER:  Yes, the only aspects of the character that have remained consistent (...) are his voice characterization by Mel Blanc

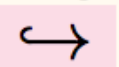
STUDENT: **How has he changed?**

TEACHER:  Daffy was less anthropomorphic

STUDENT: **In what other ways did he change?**

TEACHER:  Daffy's slobbery, exaggerated lisp (...) is barely noticeable in the early cartoons.

STUDENT: **Why did they add the lisp?**

TEACHER:  One often-repeated "official" story is that it was modeled after producer Leon Schlesinger's tendency to lisp.

STUDENT: **Is there an "unofficial" story?**

TEACHER:  Yes, Mel Blanc (...) contradicts that conventional belief

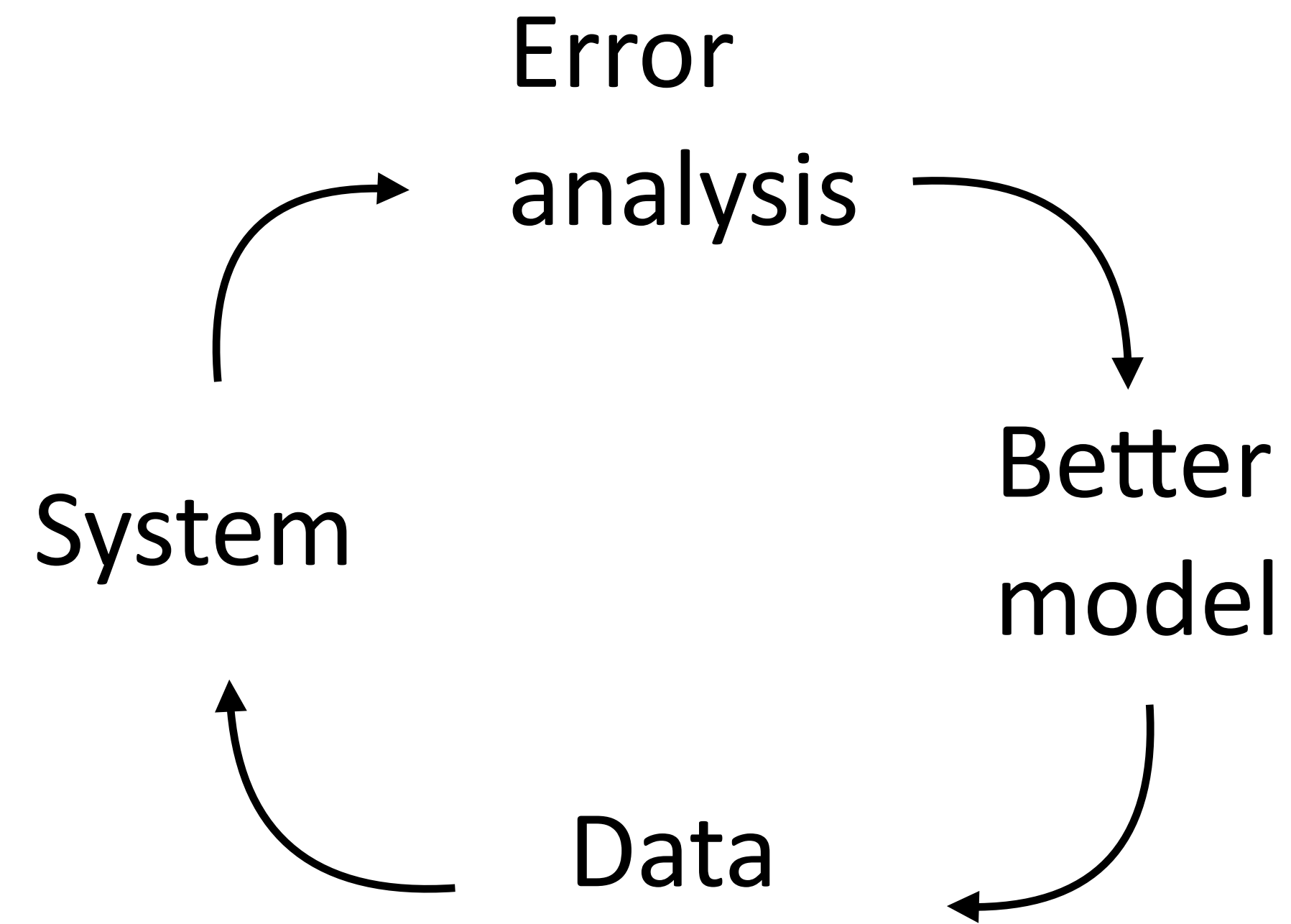
...

Choi et al. (2018)

# Dialogue Mission Creep

---

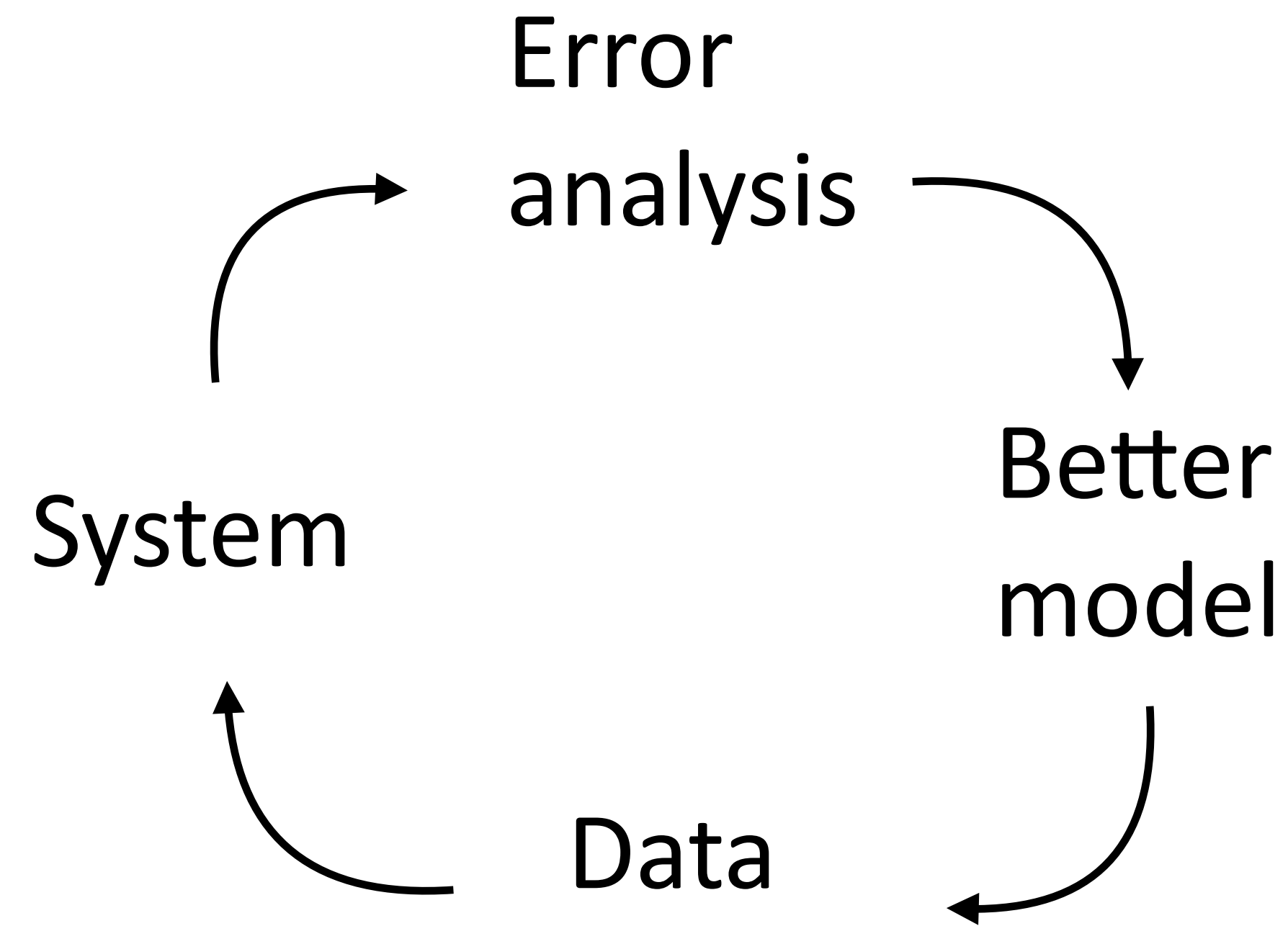
Most NLP tasks



# Dialogue Mission Creep

---

Most NLP tasks



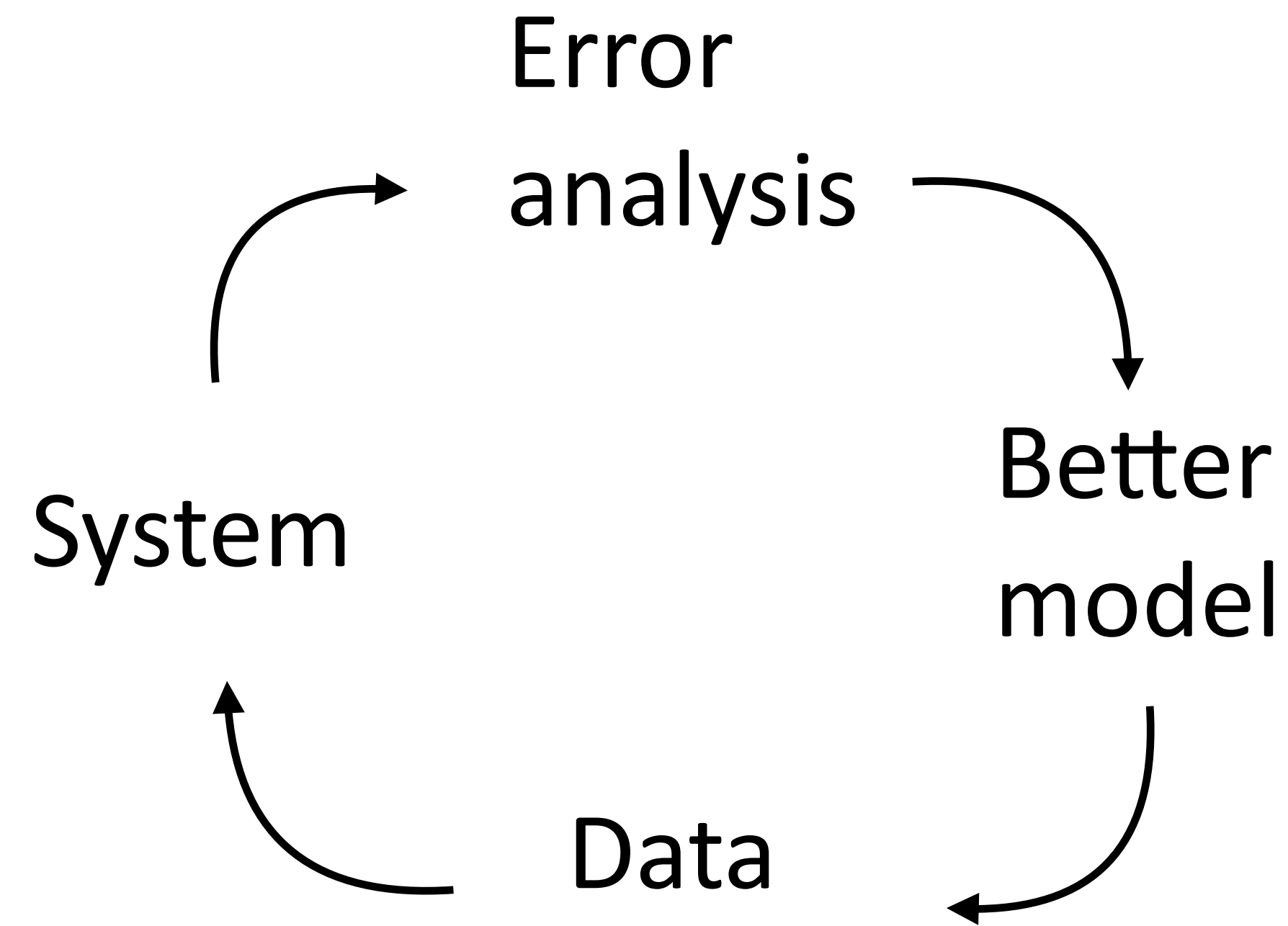
- Fixed distribution (e.g., natural language sentences), error rate  $\rightarrow 0$



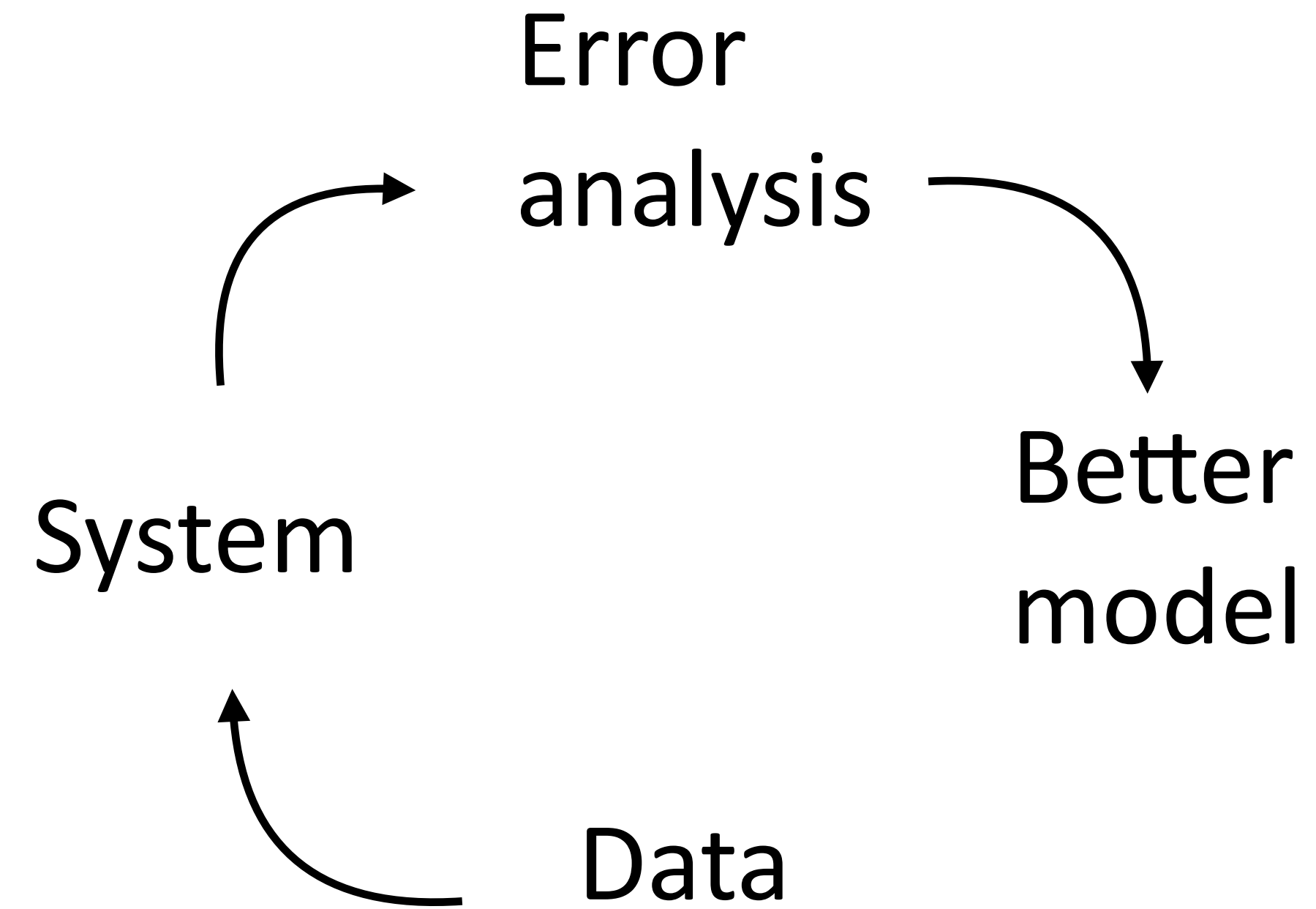
# Dialogue Mission Creep

---

Most NLP tasks



Dialogue/Search/QA



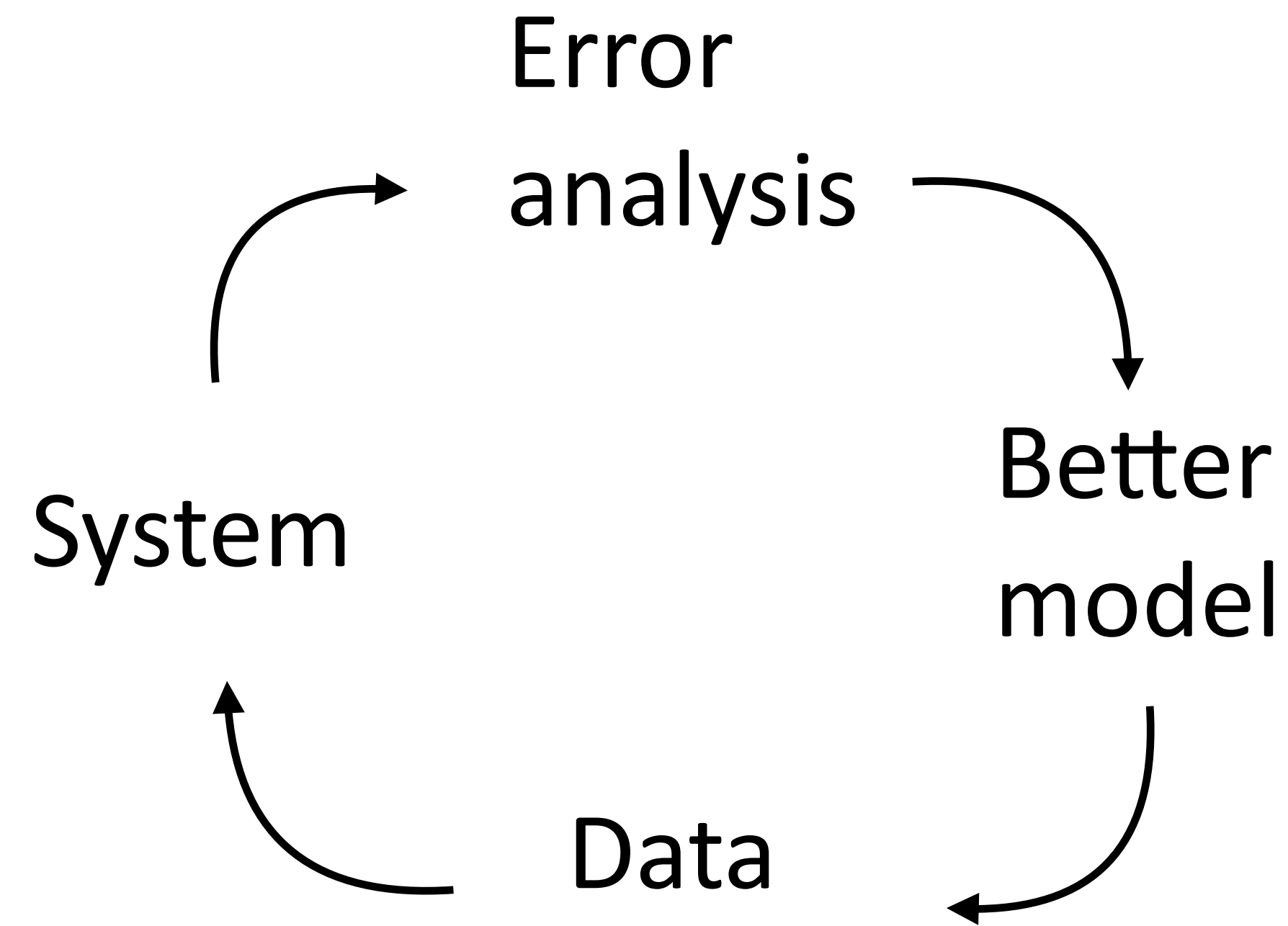
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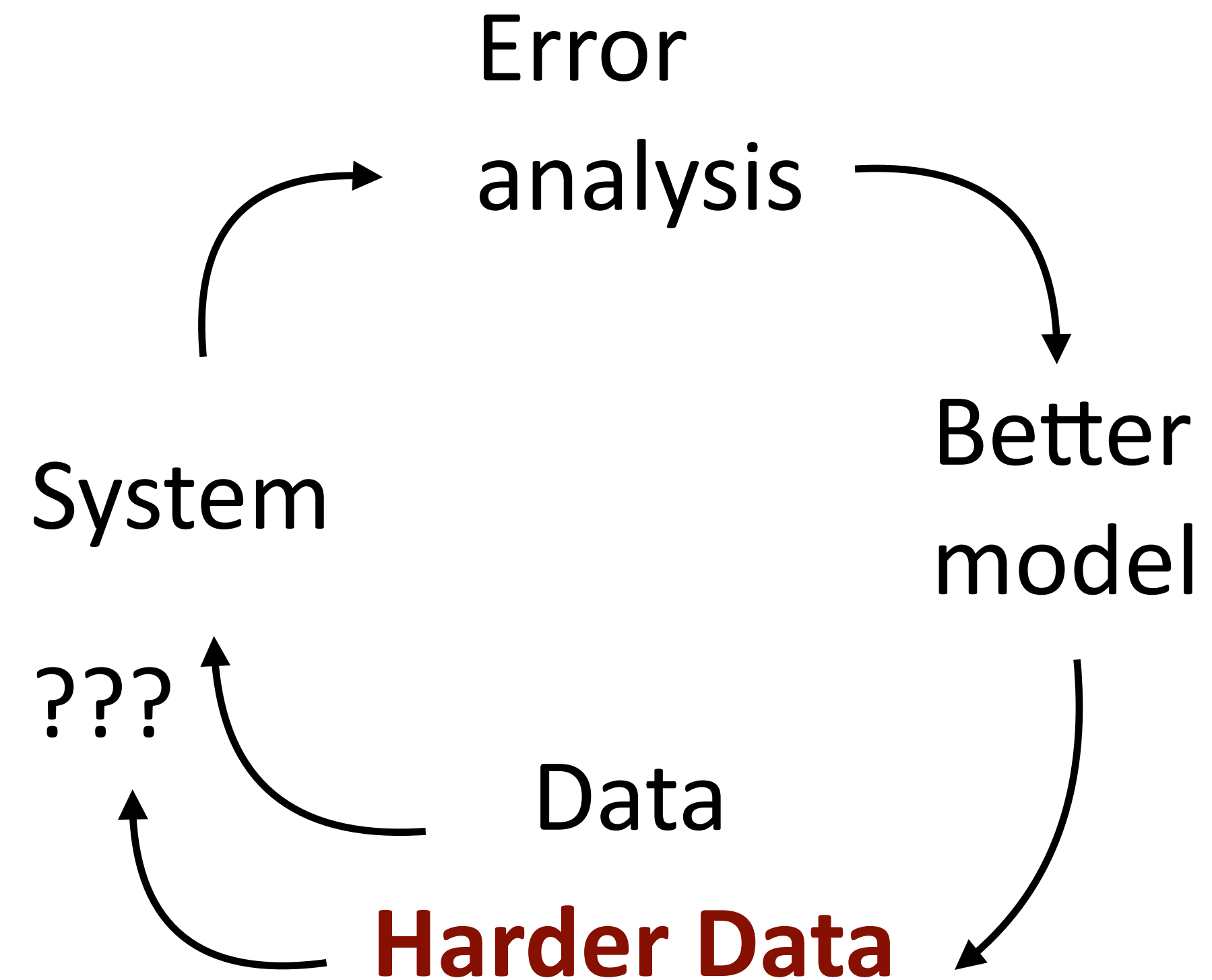
# Dialogue Mission Creep

---

Most NLP tasks



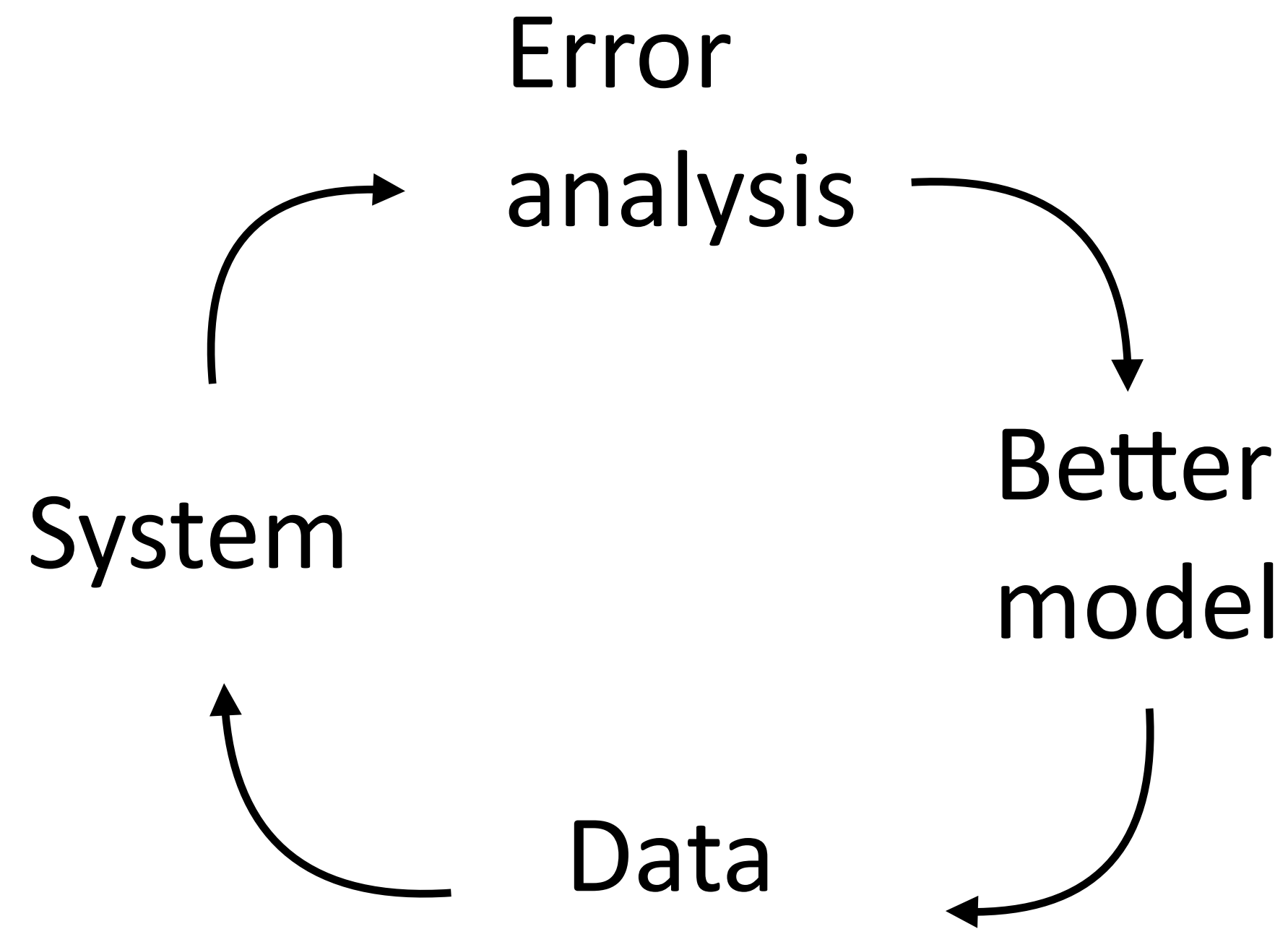
Dialogue/Search/QA



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

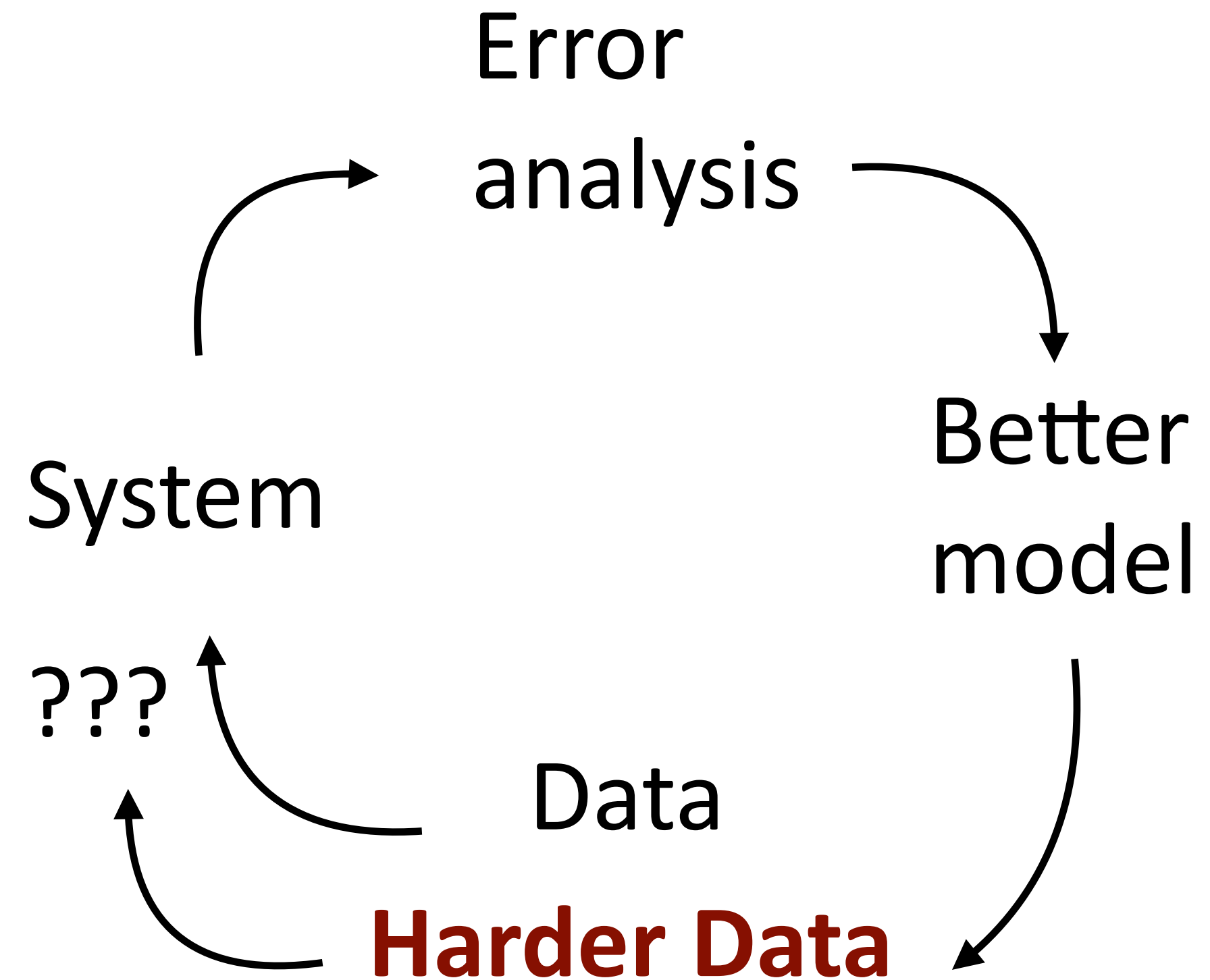
# Dialogue Mission Creep

Most NLP tasks



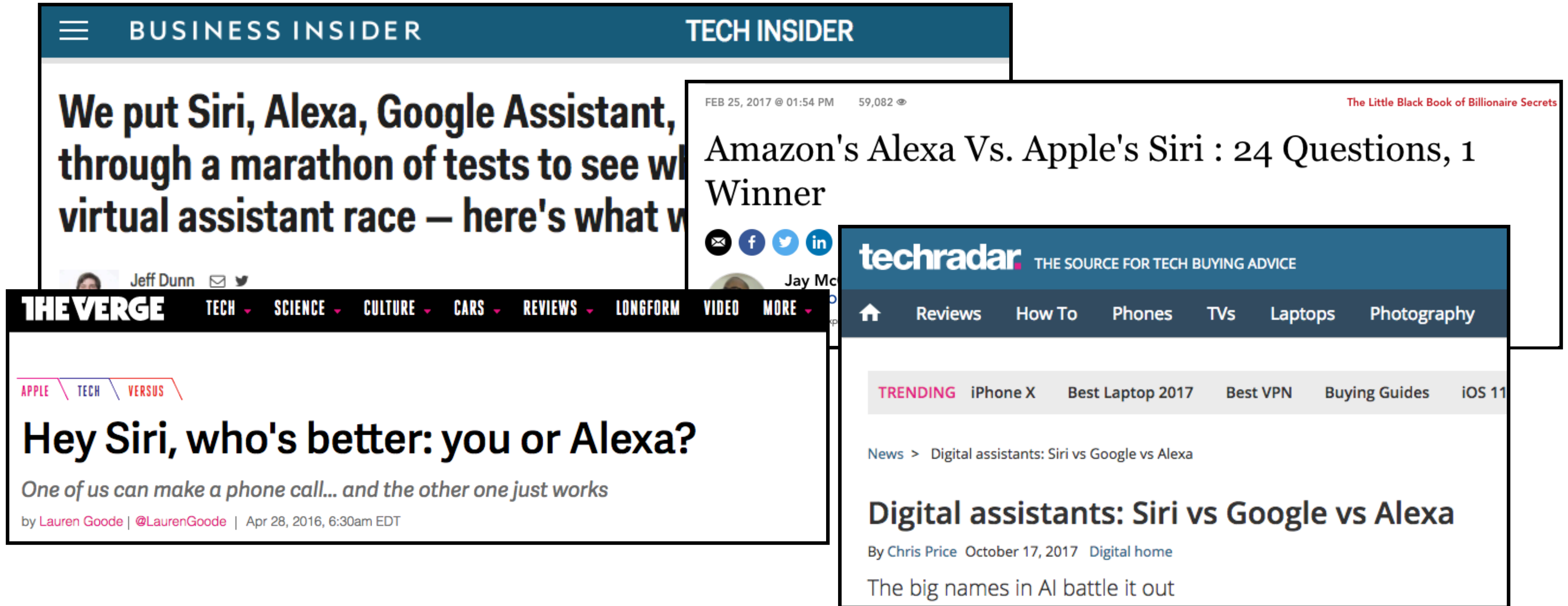
- Fixed distribution (e.g., natural language sentences), error rate  $\rightarrow 0$

Dialogue/Search/QA



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

# Dialogue Mission Creep



- ▶ 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