# CS388: Natural Language Processing
# Lecture 21: Dialogue

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## Administrivia

- Proposal due today at 5pm
- Proposals returned ASAP, then Project 2

## Recall: Extractive Summarization

- Count number of *documents* each bigram occurs in to measure importance

score(*massive earthquake*) = 3    score(*magnitude 7.3*) = 2

score(*six killed*) = 2    score(*Iraqi capital*) = 1

- Find summary that maximizes the score of bigrams it covers
- ILP formulation: c and s are indicator variables indexed over concepts (bigrams) and sentences, respectively

$$\text{Maximize: } \sum_i w_i c_i \qquad s_j Occ_{ij} \leq c_i, \quad \forall i, j$$

$$\text{Subject to: } \sum_j l_j s_j \leq L \qquad \sum_j s_j Occ_{ij} \geq c_i \quad \forall i$$

"set $c_i$ to 1 iff some sentence that contains it is included"

sum of included sentences' lengths can't exceed L

Gillick and Favre (2009)

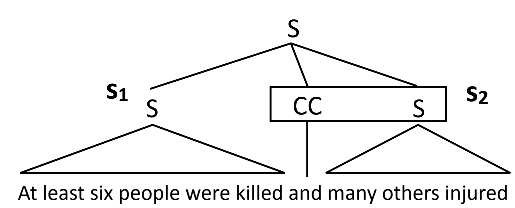
## Recall: Compression

$$\text{Maximize: } \sum_i w_i c_i \qquad s_j Occ_{ij} \leq c_i, \quad \forall i, j$$

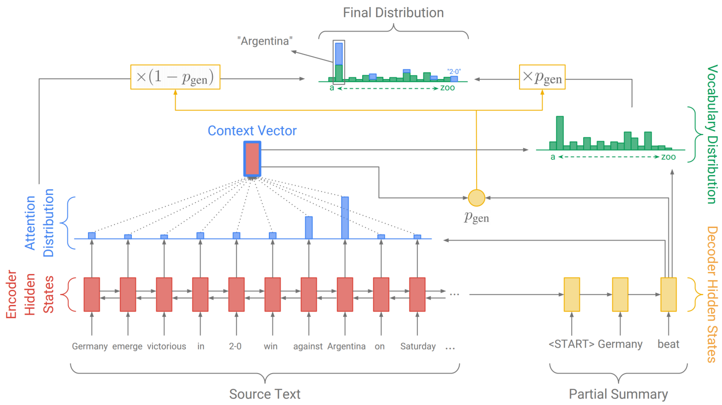
$$\text{Subject to: } \sum_j l_j s_j \leq L \qquad \sum_j s_j Occ_{ij} \geq c_i \quad \forall i$$

- Now $s_j$ variables are nodes or sets of nodes in the parse tree
- New constraint: $s_2 \leq s_1$

"$s_1$ is a prerequisite for $s_2$"



# Recall: Pointer-Generator




See et al. (2017)

# Recall: Seq2seq Summarization

- Solutions: copy mechanism, coverage, just like in MT…

**Baseline Seq2Seq + Attention:** UNK UNK says his administration is confident it will be able to **destabilize nigeria's economy**. UNK says his administration is confident it will be able to thwart criminals and other **nigerians**. **he says the country has long nigeria and nigeria's economy.**

**Pointer-Gen:** *muhammadu buhari* says he plans to aggressively fight corruption **in the northeast part of nigeria**. he says he'll "rapidly give attention" to curbing violence **in the northeast part of nigeria**. he says his administration is confident it will be able to thwart criminals.

**Pointer-Gen + Coverage:** *muhammadu buhari* says he plans to aggressively fight corruption that has long plagued nigeria. he says his administration is confident it will be able to thwart criminals. the win comes after a long history of military rule, coups and botched attempts at democracy in africa's most populous nation.

- Things might still go wrong, no way of preventing this…

See et al. (2017)

# This Lecture

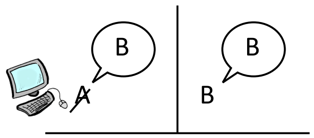
- Chatbot dialogue systems
- Task-oriented dialogue
- Other dialogue applications

# Chatbots

# Turing Test (1950)

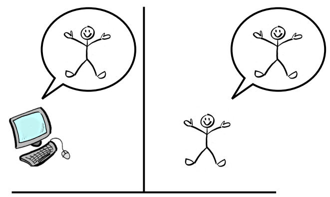
- Imitation game: A and B are locked in rooms and answer C's questions via typewriter. Both are trying to act like B

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

Weizenbaum (1966)

# ELIZA

- Identify keyword, identify context, apply transformation rule

(.*) you (.*) me → Why do you think I $2 you?

My (.) (.*) → What else comes to mind when you think of your $1?

You don't argue with me.
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

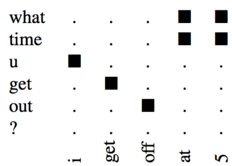
# Cleverbot

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

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

## 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

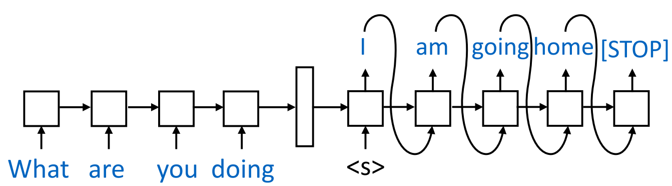
Ritter et al. (2011)

## 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




- 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 |

## 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. |

Li et al. (2016)

## Lack of Diversity

- 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

Li et al. (2016)

## 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

Li et al. (2016)

## Future of chatbots

- How deep can a conversation be without more semantic grounding? Basic facts aren't even consistent…
- Can force chatbots to give consistent answers, but still probably not very interesting

| | |
|---|---|
| *message* | Where do you live now? |
| *response* | I live in Los Angeles. |
| *message* | In which city do you live now? |
| *response* | I live in Madrid. |
| *message* | In which country do you live now? |
| *response* | England, you? |

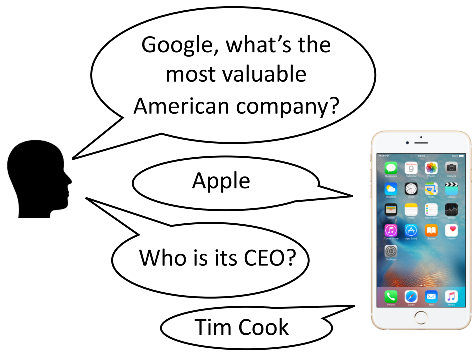
Li et al. (2016) Persona…

- XiaoIce: Microsoft chatbot in Chinese, 20M users, average user interacts 60 times/month
- People do seem to like talking to them…?

## Task-Oriented Dialogue

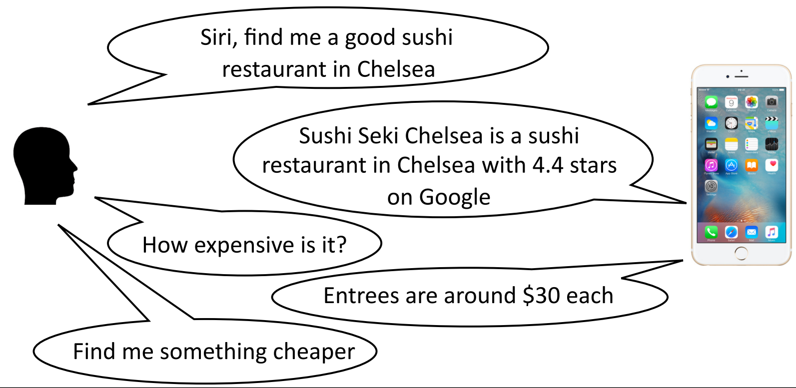
# Task-Oriented Dialogue

- Question answering/search:



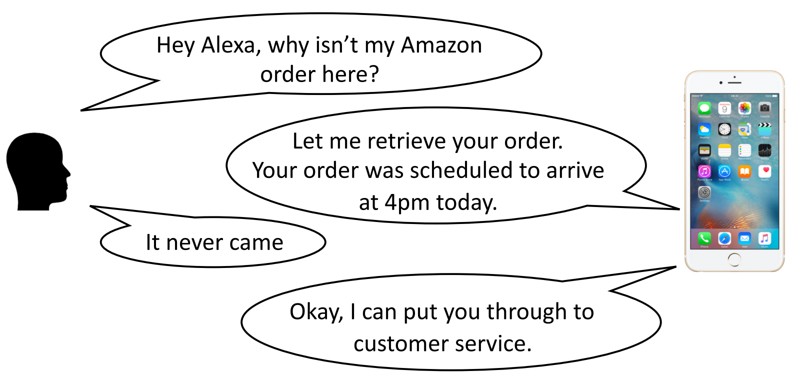

# Task-Oriented Dialogue

- Personal assistants / API front-ends:




# Task-Oriented Dialogue

- Personal assistants / API front-ends:




# Air Travel Information Service (ATIS)

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

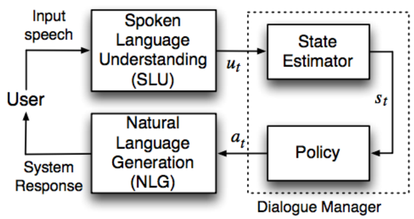
| Utterance | *How much is the cheapest flight from Boston to New York tomorrow morning?* |
|---|---|
| Goal: | Airfare |
| Cost_Relative | *cheapest* |
| Depart_City | *Boston* |
| Arrival_City | *New York* |
| Depart_Date.Relative | *tomorrow* |
| Depart_Time.Period | *morning* |

- 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
- 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
- Much more complex than chatbots!

Young et al. (2013)

# Full Dialogue Task

Find me a good sushi restaurant in Chelsea

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

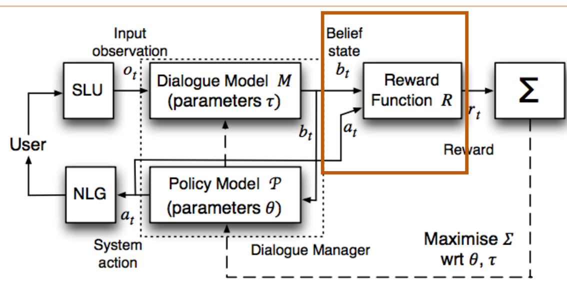
Sushi Seki Chelsea is a sushi restaurant in Chelsea with 4.4 stars on Google

How expensive is it?

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

Entrees are around $30 each

# POMDP-based Dialogue Systems




- POMDP: user is the "environment," an utterance is a noisy signal of state
- Dialogue model: can look like a parser or any kind of encoder model
- Generator: use templates or seq2seq model
- Where do rewards come from?

Young et al. (2013)

# 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

How does the user know the right search happened?

```
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

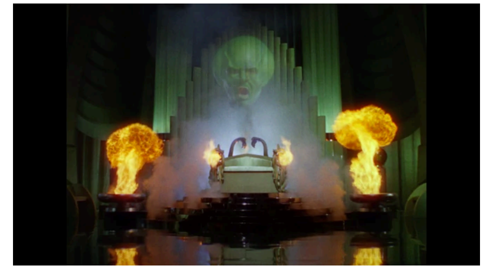
How expensive is it?

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

+1 Entrees are around $30 each

## 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

wizard enters these

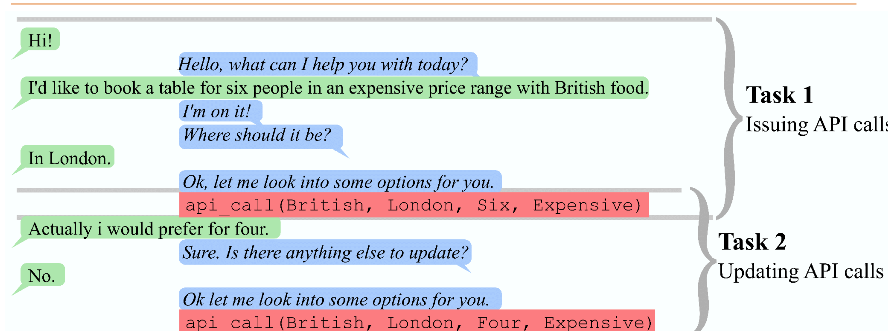
```
restaurant_type <- sushi
location <- Chelsea
curr_result <- execute_search()
```

wizard types this out or invokes templates

Sushi Seki Chelsea is a sushi restaurant in Chelsea with 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

Bordes et al. (2017)

## 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

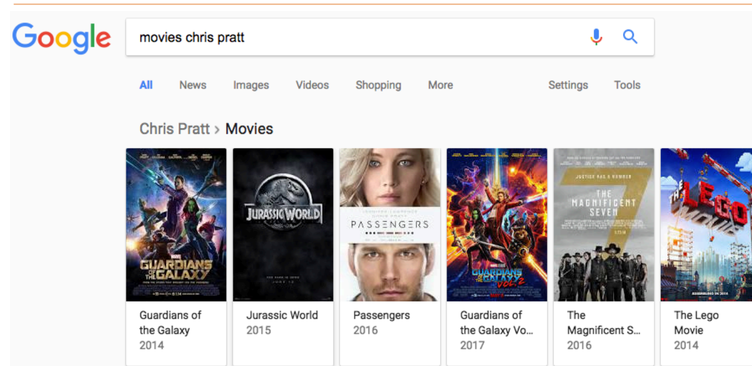
- Tons of industry interest!
- Startups:

ASAPP
Maluuba A Microsoft company
Eloquent Labs
semanticmachines
VIV

- Big Companies: Apple Siri (VocalIQ), Google Allo, Amazon Alexa, Microsoft Cortana, Facebook M, Samsung Bixby, Tencent WeChat
- Lots of cool work that’s not public yet

## 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
- 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***

| *Character* | *First Appeared* | *Home World* | *Powers* |
|---|---|---|---|
| Night Girl | 2007 | Kathoon | Super strength |
| Dragonwing | 2010 | Earth | Fire breath |
| Gates | 2009 | Vyrga | Teleporting |
| XS | 2009 | Aarok | Super speed |
| Harmonia | 2011 | Earth | Elemental |

Iyyer et al. (2017)

# QA as Dialogue

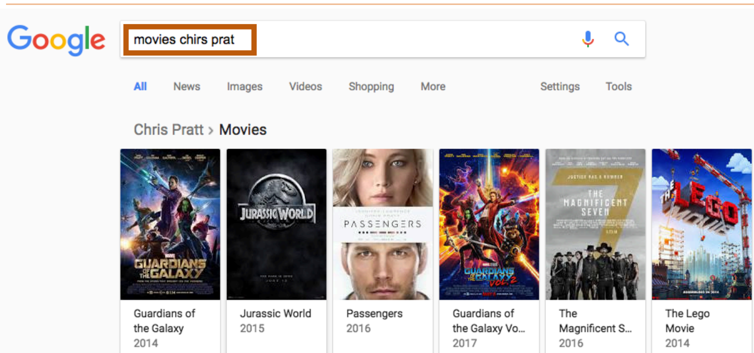
- UW QuAC dataset: Question Answering in Context

**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
...

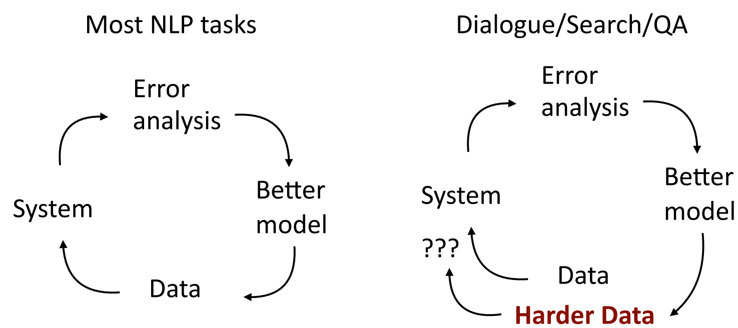
Choi et al. (2018)

# Search as Dialogue



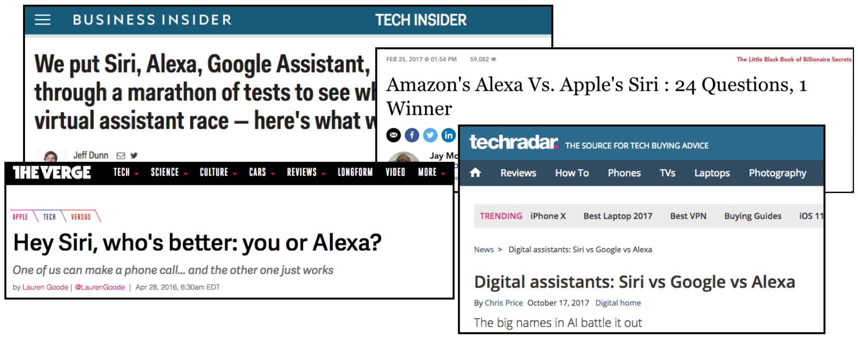

- Google can deal with misspellings, so more misspellings happen — Google has to do more!

# Dialogue Mission Creep




- Fixed distribution (e.g., natural language sentences), error rate -> 0
- Error rate -> ???; "mission creep" from HCI element

# Dialogue Mission Creep




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

# Takeaways

- Some decent chatbots, but unclear how to make these more sophisticated than they are right now
- Task-oriented dialogue systems are growing in scope and complexity — really exciting systems on the way
- More and more problems are being formulated as dialogue — interesting applications but challenging to get working well