Data Collection and End-to-End Learning for Conversational AI

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Tutorial @EMNLP-19
November 3, Hong Kong
Introduction
Conversational AI in Fiction
Conversational AI in 2019

The age of virtual assistants, assistive conversational tools, and full automation
Conversational AI in 1966

Joseph Weizenbaum’s ELIZA (1966)

ELIZA: What is bothering you?
User: I feel sad all the time.
ELIZA: Why do you feel sad all the time?
User: I don’t get along with my parents.
ELIZA: Tell me about your parents.
Conversational AI in 2019

The age of virtual assistants, assistive conversational tools, and full automation
Conversational AI in 2019

Applications:

- Call centres and customer support
- **Bookings:** restaurants, hotels, flights, train tickets, …
- **E-commerce:** from search to payment
- **Accounting and Finance:** from organising records to cryptocurrency trade
- **Healthcare:** from updating the EMRs to psychotherapy
- **Marketing:** e-mail marketing, social media search, …
- **Daily life:** setting your alarm clock, reminding about meetings, …

Are we there yet? Do different applications require different data sets and modeling approaches?
Tutorial Goals

- Understand the importance of (both annotated and unannotated) data collection for conversational AI systems and applications
- Get up to speed with cutting-edge data collection paradigms for conversational AI
- Demonstrate the usefulness of large unstructured conversational data for “conversational pretraining”
- Provide an overview of main end-to-end data-driven dialogue learning models
- Discuss the importance of data (requirements) vs. algorithmic choices and approaches
- Offer a hands-on industry perspective on current (task-oriented) conversational AI
Conversational AI in 2019

“The technology is directed towards completing specific tasks, such as scheduling certain types of appointments. For such tasks, the system makes the conversational experience as natural as possible, allowing people to speak normally, like they would to another person, without having to adapt to a machine...”

One of the key research insights was to constrain Duplex to closed domains, which are narrow enough to explore extensively. Duplex can only carry out natural conversations after being deeply trained in such domains. It cannot carry out general conversations.

Google Duplex (blog post)
Source: https://ai.googleblog.com/2018/05/duplex-ai-system-for-natural-conversation.html
The Two Paradigms: Task-Oriented vs. Open-Domain

M: Hello, welcome to the Cambridge dialogue system, What kind of food would you like?  
H: Yeah I want to find a restaurant that serves European food. 
M: Hotel du Vin and Bistro is a nice place. It serves European food. 
H: Uh what is the address and phone number? 
M: Hotel du Vin and Bistro is a nice place. Their address is XXX and their phone is YYY. 
H: Thank you goodbye. 
M: Thank you for using this system.

[Su et al, 2016]

A: How old are you ?  
B: I’m 16. Why are you asking ?  
A: I thought you were 12. 
B: What made you think so ?  
A: I don’t know what you are talking about. 
B: You don’t know what you are saying.

[Li et al, 2016]
### The Two Paradigms and Targeted Problem Types

What types of problems do we want to solve with Conversational AI?

<table>
<thead>
<tr>
<th>“I am smart”</th>
<th>Turing Test (“I” talk like a human)</th>
</tr>
</thead>
<tbody>
<tr>
<td>“I have a question”</td>
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</tr>
<tr>
<td>“I need to get this done”</td>
<td>Task completion</td>
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What types of problems do we want to solve with Conversational AI?

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Chitchat (social bot)

Goal-oriented dialogues
The Two Paradigms

The age of virtual assistants, assistive conversational tools, and full automation

Personal assistants today

Slide courtesy of Gao and Galley
The Two Paradigms: Task-Oriented vs. Open-Domain

1. Task-Oriented Conversational AI
   - Goal-oriented
   - Require precise understanding and at least some in-domain data
   - Initially modular, highly hand-crafted, restricted ability, but useful systems
   - Recently (before 2019): end-to-end learning for task-oriented dialogue
   - In 2019: pretraining for task-oriented dialogue systems

2. Open-Domain Conversational AI
   - Chit-chat: no goal
   - Trained on large amounts of unstructured/unannotated data
   - End-to-end, highly data-driven
   - Can learn unexpected and creative responses…
   - But often the responses are meaningless, inappropriate
   - Unreliable systems
The task is not defined and there is no structure/guidance

A simple seq2seq model to learn a context-to-response mapping

A large model trained on large corpora

Can learn to generate interesting responses

Retrieval vs. generation?
Open-Domain Generative Conversational Models

Problems: generic, short, difficulty keeping coherence, lack of integration into KBs or 3rd party services, still not very useful for business use cases...

- Retrieval vs. generation?

[Serban et al., 2016]

<table>
<thead>
<tr>
<th>Reference (U₁, U₂)</th>
<th>MAP</th>
<th>Target (U₃)</th>
</tr>
</thead>
<tbody>
<tr>
<td>U₁: yeah, okay.</td>
<td>i’ll see you tomorrow.</td>
<td>yeah.</td>
</tr>
<tr>
<td>U₂: well, i guess i’ll be going now.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>U₁: oh. &lt;continued.utterance&gt; oh.</td>
<td>i don’t know.</td>
<td>oh.</td>
</tr>
<tr>
<td>U₂: what’s the matter, honey?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>U₁: it’s the cheapest.</td>
<td>no, it’s not.</td>
<td>they’re all good, sir.</td>
</tr>
<tr>
<td>U₂: then it’s the worst kind?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>U₁: &lt;person&gt;! what are you doing?</td>
<td>what are you doing here?</td>
<td></td>
</tr>
<tr>
<td>U₂: shut up! c’mon.</td>
<td></td>
<td>what are you that crazy?</td>
</tr>
</tbody>
</table>
In 2019: From Open-Domain to Task-Oriented?

Following the zeitgeist...

Pretraining (non-generative) conversational response selection on large corpora + in-domain (task-oriented) fine-tuning

[Henderson et al., ACL-19; Humeau et al., arXiv-19]
Modular Task-Based Conversational AI Systems

"Book me a cab to Russell Square"

Speech Recognition → Language Understanding

speech → text → semantics

inform(service=taxi, dest=Russell Square)

Dialogue Management

Third Party APIs

Speech Synthesis → Response Generation

speech → text → semantics

request(depart_time)

"When do you want to leave?"
Modular Task-Based Conversational AI Systems

“Book me a cab to Russell Square“

Speech Recognition

Language Understanding

Dialogue Management

Response Generation

Third Party APIs

“When do you want to leave?”
Ontologies consist of a collection of slots $s$ (i.e., *food*, *price*, etc.) and their corresponding slot values $V_s$ (*cheap*, *expensive*, etc.).
Task Definition, Domain Ontologies, Dialogue Acts

DSTC2 Ontology: three Informable slots...

Area: North, East, South, West, Centre + don't care
Price: Cheap, Moderate, Expensive + don't care
Food: Indian, Chinese, Thai, Japanese, Greek, French + 84 others

...and seven (turn-level) Requestable slots...

Food, Area, Price, Address, Phone Number, Postcode
Modular Task-Based Conversational AI Systems

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Speech Recognition

Language Understanding

inform(service=taxi, dest=Russell Square)

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“When do you want to leave?”

Speech Synthesis

Response Generation

request(depart_time)
Semantic ambiguity and variability
- many-to-many mappings between symbolic language and semantic meaning

**Ambiguity**

Example: I made her duck.
- I cooked waterfowl for her.
- I cooked waterfowl belonging to her.
- I created the plaster duck she owns.
- I caused her to quickly lower her head or body.
- I waved my magic wand and turned her into undifferentiated waterfowl.

**Paraphrase**

Example: How long is the X river?

- *The Mississippi River* is 3,734 km (2,320 mi) long.
- *...is a short river, some 4.5 miles (7.2 km) in length*
- *The total length of the river is 2,145 kilometers.*
- *... at the estimated length of 5,464 km (3,395 mi)...
- *... has a meander length of 444 miles (715 km)...
- *... Bali’s longest river, measuring approximately 75 kilometers from source to mouth.*
- *The ... mainstem is 2.75 miles (4.43 km) long although total distance from headwater source tributaries to the sea is 14 miles (23 km).*
Module: Natural Language Understanding (NLU)

NLU = Spoken Language Understanding (SLU) + Dialogue State Tracking (DST)

1. Domain Classification
2. Intent Classification
3. Slot Filling

The belief state is a probability distribution over the possible dialogue states defined by the domain ontology.

Dialogue manager uses the distribution to decide on the next system action.
Modular Task-Based Conversational AI Systems

“Book me a cab to Russell Square“

Speech Recognition -> Language Understanding

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inform(service=taxi, dest=Russell Square)

request(depart_time)
Module: Dialogue Management

It is a control/planning problem: given a dialogue state $b$ take an (optimal) action $a$

System actions: set of outputs in each turn to guide the dialogue towards its goal

Actions?
- NLG?
- Dialogue acts
- API calls / 3rd-party actions
Module: Dialogue Management

Rule-Based:
- Huge hand-crafting effort
- Non-adaptable and non-scalable
- But this is what works right now

Supervised:
- Learn to "mimic" the answers of a corpus
- Assumes optimal human behaviour
- Does not do long-term planning

Reinforcement Learning (RL)
- Learns in the actual dialogue environment
- Adapts to new environments/users/situations
- Requires less annotation
- Slow and expensive learning
- Difficult to reuse data
An empirical survey from [Casanueva et al., 2017]

<table>
<thead>
<tr>
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<td>CR</td>
<td>99.4%</td>
<td>13.5</td>
<td>93.9%</td>
<td>12.7</td>
<td>89.3%</td>
<td>11.6</td>
<td>94.8%</td>
<td>12.4</td>
<td>100.0%</td>
<td>14.0</td>
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<tr>
<td>SFR</td>
<td>96.1%</td>
<td>11.4</td>
<td>65.0%</td>
<td>5.9</td>
<td>58.3%</td>
<td>4.0</td>
<td>94.0%</td>
<td>11.7</td>
<td>98.2%</td>
<td>12.4</td>
</tr>
<tr>
<td>LAP</td>
<td>89.1%</td>
<td>9.4</td>
<td>70.1%</td>
<td>6.9</td>
<td>57.1%</td>
<td>3.5</td>
<td>91.4%</td>
<td>10.5</td>
<td>97.0%</td>
<td>11.7</td>
</tr>
</tbody>
</table>

| CR    | 96.8%        | 12.2          | 91.9%   | 12.0     | 75.5%   | 7.0      | 83.6%   | 9.0       | 100.0%         | 14.0            |
| SFR   | 91.9%        | 9.6           | 84.3%   | 9.2      | 45.5%   | -0.3     | 65.6%   | 3.7       | 98.2%          | 12.4            |
| LAP   | 82.3%        | 7.3           | 74.5%   | 6.6      | 26.8%   | -5.0     | 55.1%   | 1.5       | 97.0%          | 11.7            |

| CR    | 95.1%        | 11.0          | 93.4%   | 11.9     | 74.6%   | 7.3      | 90.8%   | 11.2      | 96.7%          | 11.0            |
| SFR   | 81.6%        | 6.9           | 60.9%   | 4.0      | 39.1%   | -2.0     | 84.6%   | 8.6       | 90.9%          | 9.0             |
| LAP   | 68.3%        | 4.5           | 61.1%   | 4.3      | 37.0%   | -1.9     | 76.6%   | 6.7       | 89.6%          | 8.7             |

| CR    | 91.5%        | 9.9           | 90.0%   | 10.7     | 64.7%   | 3.7      | 85.3%   | 9.0       | 96.7%          | 11.0            |
| SFR   | 81.6%        | 7.2           | 77.8%   | 7.7      | 38.8%   | -3.1     | 61.7%   | 2.0       | 90.9%          | 9.0             |
| LAP   | 72.7%        | 5.3           | 68.7%   | 5.5      | 27.3%   | -6.0     | 52.8%   | -0.8      | 89.6%          | 8.7             |

| CR    | 93.8%        | 9.8           | 90.7%   | 10.3     | 70.1%   | 5.0      | 91.6%   | 10.5      | 95.9%          | 9.7             |
| SFR   | 74.7%        | 3.6           | 62.8%   | 2.9      | 20.2%   | -5.9     | 74.4%   | 4.5       | 87.7%          | 6.4             |
| LAP   | 39.5%        | -1.6          | 45.5%   | 0.0      | 28.9%   | -4.7     | 75.8%   | 4.1       | 85.1%          | 5.5             |

| CR    | 89.6%        | 8.8           | 87.8%   | 10.0     | 62.3%   | 3.5      | 79.6%   | 8.0       | 89.6%          | 9.3             |
| SFR   | 64.2%        | 2.7           | 47.2%   | 0.4      | 27.5%   | -5.1     | 66.7%   | 3.9       | 79.0%          | 6.0             |
| LAP   | 44.9%        | -0.2          | 46.1%   | 1.0      | 32.1%   | -3.8     | 64.6%   | 3.6       | 76.1%          | 5.3             |

| CR    | 94.4%        | 10.9          | 91.3%   | 11.3     | 72.8%   | 6.4      | 87.6%   | 10.0      | 96.5%          | 11.5            |
| SFR   | 81.7%        | 6.9           | 66.3%   | 5.0      | 38.2%   | -2.1     | 74.5%   | 5.7       | 90.8%          | 9.2             |
| LAP   | 66.1%        | 4.1           | 61.0%   | 4.1      | 34.9%   | -3.0     | 69.4%   | 4.3       | 89.1%          | 8.6             |
| ALL   | 80.7%        | 7.3           | 72.9%   | 6.8      | 48.6%   | 0.4      | 77.2%   | 6.7       | 92.1%          | 9.8             |

Table 4: Reward and success rates after 4000 training dialogues for the five policy models considered in this benchmark. Each row represents one of the 18 different tasks. The highest reward obtained by a data driven model in each row is highlighted.

Handcrafted rule-based dialogue management is still unbeatable? :(
Machine learning finds the solution from the data

It seems that we care (too) much about “learning”, but less so about the domain problems, specificities, and about the data itself...

<table>
<thead>
<tr>
<th></th>
<th>State</th>
<th>Action</th>
<th>Reward</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlphaGO</td>
<td>19x19 grid</td>
<td>Next move</td>
<td>win/loss</td>
</tr>
<tr>
<td>Dialogue</td>
<td>User query</td>
<td>Language response</td>
<td>satisfaction, success</td>
</tr>
</tbody>
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Knowing more about the data, the ML abilities and the domain problem helps us decide whether to go for an ML solution or not… Or how to adapt it…
Modular Task-Based Conversational AI Systems

"Book me a cab to Russell Square"

Speech Recognition -> Language Understanding

Speech Synthesis -> Response Generation

Dialogue Management

Third Party APIs

inform(service=taxi, dest=Russell Square)

request(depart_time)

"When do you want to leave?"
“NLG is the process of deliberately constructing a natural language text in order to meet specified communication goals”
[McDonald, 1992]

What do we care about? Naturalness and variation

Evaluation: 1) subjective: human judgement (adequacy, fluency, readability, variation)
2) objective: automatic evaluation measures
Module: Natural Language Generation

Problems with NLG:
- Human-based evaluation and automatic evaluation often anticorrelate
- NLG module can generate grammatically incorrect sentences
- Tendency towards shorter sentences

- Template-based vs. Statistical (i.e., Neural)
- Generative vs. Retrieval-based?

Can we combine different paradigms? Neural approaches with linguistic patterns? Post-processing rules? Attention?
[Wen et al., 2015; Mei et al., 2016; Wen et al., 2016; Dusek and Jurcicek 2016; Tran and Nguyen, 2017]

Hybrid: generation + retrieval?
[Weston et al., 2018; Yang et al., 2019; Cai et al., 2019]
“Deep” revolution has also transformed NLG: e.g., RNN-based LM NLG (example from Wen et al., EMNLP-15)

Distributed representations: Generalisation
Recurrent connections: Long-term dependencies
Conditional RNNs: Flexibility and creativity
Attention mechanism: Focus on relevant and meaningful parts
End-to-End Task-Based Conversational AI Systems?

Diagram showing the components of an end-to-end conversational AI system:
- Speech Recognition
- Language Understanding
- Dialogue Management
- Response Generation

Also included is a mention of third-party APIs and the concept of end-to-end learning.
End-to-End Task-Based Conversational AI Systems

A Network-based End-to-End Trainable Task-Oriented Dialogue System

[Wen et al., EACL-17]
Data Collection
Creating Task-based Dialogue Systems

- **Convincing Application**: solves a real problem
- **Meaningful Evaluation**: can measure progress
- **Annotated Data**: is machine-learnable
baseline systems

launch to real users

ML

improved system

data

labelling
Data First, Models (and Serenity) Later

- Human-level Clean Speech ASR (1994)
- GoogleNet at human-level performance (2014)
- Arcade Learning Environment Dataset (2013)
- ImageNet Corpus (2010)
- Human-level Control on Atari Games (2015)
- Wall Street Journal Corpus (1991)
- Q-Learning (1992)
- Convolution Network (1989)

- AI Breakthrough
- Good Data Available
- ~18 yrs
- < 3 yrs
Building New Data Sets is a Hot Topic

An overview of task-based dialogue data sets from [Budzianowski et al., EMNLP-18] vs [Rastogi et al., 2019]

<table>
<thead>
<tr>
<th>Metric</th>
<th>DSTC2</th>
<th>SFX</th>
<th>WOZ2.0</th>
<th>FRAMES</th>
<th>KVRET</th>
<th>M2M</th>
<th>MultiWOZ</th>
</tr>
</thead>
<tbody>
<tr>
<td># Dialogues</td>
<td>1,612</td>
<td>1,006</td>
<td>600</td>
<td>1,369</td>
<td>2,425</td>
<td>1,500</td>
<td>8,438</td>
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<tr>
<td>Total # turns</td>
<td>23,354</td>
<td>12,396</td>
<td>4,472</td>
<td>19,986</td>
<td>12,732</td>
<td>14,796</td>
<td>113,556</td>
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<tr>
<td>Total # tokens</td>
<td>199,431</td>
<td>108,975</td>
<td>50,264</td>
<td>251,867</td>
<td>102,077</td>
<td>121,977</td>
<td>1,490,615</td>
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<tr>
<td>Avg. turns per dialogue</td>
<td>14.49</td>
<td>12.32</td>
<td>7.45</td>
<td>14.60</td>
<td>5.25</td>
<td>9.86</td>
<td>13.46</td>
</tr>
<tr>
<td>Avg. tokens per turn</td>
<td>8.54</td>
<td>8.79</td>
<td>11.24</td>
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<tr>
<td>Total unique tokens</td>
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<td>2,142</td>
<td>12,043</td>
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<td>23689</td>
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<tr>
<td># Slots</td>
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<td>14</td>
<td>4</td>
<td>61</td>
<td>13</td>
<td>14</td>
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<tr>
<td># Values</td>
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<td>3871</td>
<td>1363</td>
<td>138</td>
<td>4510</td>
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<table>
<thead>
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<th>DSTC2</th>
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<th>FRAMES</th>
<th>M2M</th>
<th>MultiWOZ</th>
<th>SGD</th>
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<tbody>
<tr>
<td>No. of domains</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>7</td>
<td>16</td>
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<tr>
<td>No. of dialogues</td>
<td>1,612</td>
<td>600</td>
<td>1,369</td>
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<td>8,438</td>
<td>16142</td>
</tr>
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<td>329964</td>
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<td>7.45</td>
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<td>9.86</td>
<td>13.13</td>
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<tr>
<td>Avg. tokens per turn</td>
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</tr>
<tr>
<td>Total unique tokens</td>
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<td>12,043</td>
<td>1,008</td>
<td>23,689</td>
<td>30352</td>
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<tr>
<td>No. of slots</td>
<td>8</td>
<td>4</td>
<td>61</td>
<td>13</td>
<td>24</td>
<td>214</td>
</tr>
<tr>
<td>No. of slot values</td>
<td>212</td>
<td>99</td>
<td>3,871</td>
<td>138</td>
<td>4,510</td>
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</tbody>
</table>
Building New Data Sets is a Hot Topic

- “15 Best Chatbot Datasets for Machine Learning”

  - The article has been published on July 3 2019, but it doesn’t contain newest developments such as:
    https://github.com/PolyAI-LDN/conversational-datasets
    https://www.microsoft.com/en-us/research/project/metalwoz/

- Another repo of available datasets:
  http://nlpprogress.com/english/dialogue.html

Most goal-oriented dialogs require a closed and well-defined domain.

It is difficult to include all domain-specific information up-front.
- *New slots can be gradually introduced.*

**Challenge for exploration:**
- How to explore efficiently
- To collect data for new slots
- When deep models are used
hello I am looking for a cheap place in the east
> inform(pricerange=cheap, area=east)

sure, what type of food?
> request(food)

i want gastropub food
> inform(food=gastropub)

there are no cheap places serving gastropub in the east.
> inform(name=none, area=east, pricerange=cheap)

how about any pricerange? and i need to know if they have wifi.
> inform(pricerange=don't care) request(has_wifi)

The King's Arms is a nice place in the east of town serving gastropub food. It has wifi.
> offer(name="The King's Arms", area=east, food=gastropub, has_wifi=true)
Data Collection for Dialogue is...

...still “under influence” of such DSTC2/3-style annotations…

- explicit semantics: it forces unnaturally constrained dialogues
- users need to know the ontology (and what exactly is and is not supported)

Specially annotated data: one specialized model per ‘slot’

Some slots are necessary, while some might not be… How can give our models more freedom?
Why is Data Collection for Conversational AI so Difficult?

- ImageNet moment? Dialogue is not as well-defined as object recognition or ASR
- It lacks consistent annotations and well-defined metrics
- How can we measure dialogue success or user satisfaction? Automatic vs. user-centered metrics?
- The coverage of conversation:
  - Out-of-domain concepts?
  - Metaphors?
  - General knowledge?
  - Commonsense knowledge?
- From a more pragmatic point of view:
  - Multiple domains?
  - Multiple languages?
  - Language-specific expressions?
  - Cultural and emotional adaptations?
  - Politeness? Proactiveness vs. reactiveness?
Three Data Collection Paradigms

- Machine-to-Machine
- Human-to-Human
- (Human-to-Machine)

Pros and cons of each paradigm? Do we actually need to combine all of them?
Machine-to-Machine Data Collection
Data Collection Paradigm 1: Machine-to-Machine (M2M)

Machine-to-Machine

```plaintext
greet()

book(tickets=4)
  request_time()
  time(5pm)
  confirm()

Crowdworker

greet()  →  How is it going on?
book(tickets=4)  →  Book me 4 tickets.
time(5pm)  →  At 5 o'clock.
```

Paraphrasing
Data Collection Paradigm 1: Machine-to-Machine (M2M)

Bootstrapping a neural conversational AI with the M2M data collection
[Shah et al., NAACL-18]

Collecting more dialogues from real user after deployment -> Reinforcement Learning to improve further

1) RL with user simulator
2) RL with human feedback
Data Collection Paradigm 1: Machine-to-Machine (M2M)

An overview of the main M2M paradigm [Shah et al., 2018]

**Developer:** provides the task-specific information

**Framework:** provides the task-independent information

Outline generation via self-play

Outline -> a sequence of template utterances and their corresponding annotations

\[
F_1(T) \rightarrow O = \{o_i, i \in 1 \ldots N\}
\]

\[
o_i = [(t_{i_1}^i, \ldots, t_{n_i}^i), (a_{i_1}^i, \ldots, a_{n_i}^i)]
\]

\[
F_2(\{o_i\}) \rightarrow \{d_i\}
\]
M2M: Phases and Stages

Developer must define the task (ontology, slots, values, desired behaviours, low-level annotations: system acts)

How to simulate users and the system agent?

How to maximize coverage of generated dialogues?

Can we also allow human-in-the-loop?
M2M: Phases and Stages

User goal:
- task=book restaurant
- name=Cocum
- people=2
- time=7pm
- date=today

User agenda:
- inform(name=Cocum)
- inform(people=2)
- inform(time=7pm)
- inform(date=today)

User profile:
- max_num_repeats=2
- max_request_alt=0

System profile:
- confirm_prob=0.8
- max_request_slot=2

Dialogue acts:
- greeting();
- inform(name=Cocum);
- inform(people=2);
- inform(time=7pm);
- inform(date=today);
- ack();
- request(date);
- inform(date=today);
- confirm(name=Cocum,
  people=2,
  time=7pm,
  date=today);
- affirm();
- inform(booking=True);

Template utterances:
- Greeting.
- I want a booking where restaurant name is Cocum and number of people is 2 and time is 7pm.
- OK. Ask date.
- I want date is today.
- Confirm name is Cocum and number of people is 2 and time is 7pm and date is today.
- Agree.
- Booking is success.

Natural paraphrases:
- Hello, what can I do for you?
- I would like to make a reservation at Cocum for 2 people at 7pm.
- Sure. And what date?
- The reservation is for today.
- So, to be sure, you want to book a table for 2 at Cocum, today at 7pm, is that correct?
- Yes, that is correct, thanks!
- Okay, booking confirmed!
M2M: Specifying the System Agent

Define possible system acts (domain/task-specific)

Customize/parameterize the system behaviour

Model its interaction with the (simulated user)

Current system response format

```
system_discourse, system_confirm, system_statement, sys_request
```

- system_discourse:
  - greeting()
  - goodbye()
- system_confirm: based on the user statement, confirm what user just said.
  - confirm(slot=value)
- system_statement: offer user the current status of the database.
  - offer(name=X, slot=val, ...)
  - compare(name1=X, name2=Y, slot=val, ...)
  - count(count=?, slot=val)
- system_request: ask user a question, could be proactive.
  - request(slot)
  - request(slot=val)
  - request_alt(slot=val)
  - request_alt(name=X)

Model its interaction with the (simulated user)

FSM as in [Shah et al., 2018]
M2M: User Simulation

Generate natural and reasonable conversations to enable RL for exploring the policy space

Replace the real user in the pipeline by a model that replicates the user behaviour

- Cheap / reusable method to train (and test) conversational AI systems
- Useful for research, hyperparameter tuning, etc.
- Necessary evil

Different approaches to user simulation:

- Rule-based [Schatzmann et al., 2006; Li et al., 2016]
- Learning-based: neural [El Asri et al., 2016; Crook and Marin, 2017, Kreyssig et al., 2018]
User simulation is a complex problem in its own right. A variety of neural (seq2seq) methods proposed...

[El Asri et al., 2016]

[Gur et al., 2018]

[Crook and Marin, 2017]
M2M: User Simulation

Rule-based or agenda-based simulation:
- Trained experts construct and fine-tune the simulation process

- No data needed
- Full control of user behaviour

- Very costly
- Not enough coverage / variability

Agenda-based simulated user
[Schatzmann and Young, 2009]

User state consists of (agenda, goal):

Goal is fixed throughout dialogue while agenda is maintained (stochastically by a first-in-last-out stack)

Implementation of a simplified user simulator:
https://github.com/MiuLab/TC-Bot
### M2M: User Simulation

<table>
<thead>
<tr>
<th></th>
<th>Lab user subjects</th>
<th>Actual users</th>
<th>Simulated users</th>
</tr>
</thead>
<tbody>
<tr>
<td>Truthfulness</td>
<td></td>
<td>✔️</td>
<td>✗</td>
</tr>
<tr>
<td>Scalability</td>
<td>✗</td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>Flexibility</td>
<td>✗</td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>Expense</td>
<td>✗</td>
<td>✔️</td>
<td>✔️</td>
</tr>
<tr>
<td>Risk</td>
<td>✔️</td>
<td>✗</td>
<td>✔️</td>
</tr>
</tbody>
</table>

#### A Hybrid Approach

- **User Simulation**
  - Small-scale Human Evaluation (lab, Mechanical Turk, ...)
  - Large-scale Deployment (optionally with continuing incremental refinement)

---

Slide courtesy of [Gao and Galley, 2019]
<table>
<thead>
<tr>
<th>Annotations</th>
<th>Template utterances</th>
<th>Rewrite</th>
</tr>
</thead>
<tbody>
<tr>
<td>S: greeting()</td>
<td>Greeting.</td>
<td>Hi, how can I help you?</td>
</tr>
<tr>
<td>U: inform(intent=book_movie, name=Inside Out, date=tomorrow, num_tickets=2)</td>
<td>Book movie with name is Inside Out and date is tomorrow and num tickets is 2.</td>
<td>I want to buy 2 tickets for Inside Out for tomorrow.</td>
</tr>
<tr>
<td>S: ack() request(time)</td>
<td>OK. Provide time.</td>
<td>Alright. What time would you like to see the movie?</td>
</tr>
<tr>
<td>U: inform(time=evening)</td>
<td>Time is evening.</td>
<td>Anytime during the evening works for me.</td>
</tr>
<tr>
<td>S: offer(theatre=Cinemark 16, time=6pm)</td>
<td>Offer theatre is Cinemark 16 and time is 6pm.</td>
<td>How about the 6pm show at Cinemark 16?</td>
</tr>
<tr>
<td>U: affirm()</td>
<td>Agree.</td>
<td>That sounds good.</td>
</tr>
<tr>
<td>S: notify_success()</td>
<td>Reservation confirmed.</td>
<td>Your tickets have been booked!</td>
</tr>
</tbody>
</table>
Data Collection Paradigm 1: Machine-to-Machine (M2M)

- Reduced annotation complexity and an easier crowdsourcing task
- Crowdsourcing = paraphrasing

Instructions

You'll be shown a very unnatural computer generated conversation between a user and an assistant. Your task is to paraphrase the messages in the original conversation in order to create a new conversation that has the exact same meaning but sounds like a real conversation between a user and a professional assistant. Feel free to be creative with your paraphrased messages, as long as they meet the following important requirements:

- User messages need to look like something you would type in a chat window.
- Assistant messages need to look formal – just like chat replies from a human customer service agent.
- All of your paraphrased messages must have the same meaning as the original message.
- Your paraphrased conversation needs to make sense on its own.

When done rewording/rephrasing the original phrases, you'll be asked to re-read the entire dialog as a whole and verify it makes sense as a stand alone dialog, as opposed to paraphrasing each sentence without looking at the result as a whole.

[Shah et al., NAACL-18]
Data Collection Paradigm 1: Machine-to-Machine (M2M)

- Reduced annotation complexity and an easier crowdsourcing task
- Crowdsourcing = paraphrasing

<table>
<thead>
<tr>
<th>Original conversation</th>
<th>Paraphrased conversation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assistant: greetings</td>
<td>Hello</td>
</tr>
<tr>
<td>User: greetings AND buy movie tickets AND date is Wednesday</td>
<td>I would like to buy movie tickets for Wednesday.</td>
</tr>
<tr>
<td>Assistant: provide preference for: theatre name and time and number of tickets and movie</td>
<td>What theatre, movie, time, and number of tickets would you like?</td>
</tr>
<tr>
<td>User: unable to understand, must re-phrase your message</td>
<td>Sorry, I didn't understand. Could you repeat that?</td>
</tr>
<tr>
<td>Assistant: provide preference for: theatre name and time and number of tickets and movie</td>
<td>How many tickets would you like and what is the theatre, movie, and showtime?</td>
</tr>
<tr>
<td>User: movie is The Magnificent Seven and time is 4:00 pm and theatre name is Century 20 Great Mall and number of tickets is 6</td>
<td>I need 6 tickets for the 4:00 pm showing of The Magnificent Seven at the Century 20 Great Mall</td>
</tr>
<tr>
<td>Assistant: confirm the following: time is 4:00 pm</td>
<td>That was for 4:00 pm, right?</td>
</tr>
<tr>
<td>User: accept time is 4:00 pm</td>
<td>Yes, 4:00 pm</td>
</tr>
<tr>
<td>Assistant: purchase confirmed with given details movie is The Magnificent Seven and number of tickets is 6 and time is 4:00 pm and date is March 08 and theatre name is Century 20 Great Mall</td>
<td>I have purchased 6 tickets for the Magnificent Seven at 4:00 o'clock on March 08 at the Century 20 Great Mall</td>
</tr>
<tr>
<td>User: thank you AND goodbye</td>
<td>Thanks, bye.</td>
</tr>
</tbody>
</table>
M2M in Practice: Example 1 (from bAbI)

[Bordes et al., ICLR-17]

Available at: https://research.fb.com/downloads/babi/

Mostly for research purposes and benchmarking:

Simulation is used to control the data generation in relation to the 5 well-defined tasks.
M2M in Practice: Example 2 (Schema-Guided Dialogue)

- A very recent and large data set for task-oriented dialogue: M2M + schemas [Rastogi et al., IJCAI-19]
- Used as part of DSTC8: schema-guided dialogue state tracking
- It might also support future work on intent detection, language generation, DST, value extraction

<table>
<thead>
<tr>
<th>Metric</th>
<th>DSTC2</th>
<th>WOZ2.0</th>
<th>FRAMES</th>
<th>M2M</th>
<th>MultiWOZ</th>
<th>SGD</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Domains</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>7</td>
<td>16</td>
</tr>
<tr>
<td>#Dialogues</td>
<td>1,612</td>
<td>600</td>
<td>1,369</td>
<td>1,500</td>
<td>8,438</td>
<td>16,142</td>
</tr>
<tr>
<td>#Turns</td>
<td>23,354</td>
<td>4,472</td>
<td>19,986</td>
<td>14,796</td>
<td>113,556</td>
<td>329,964</td>
</tr>
<tr>
<td>#Slots</td>
<td>8</td>
<td>4</td>
<td>61</td>
<td>13</td>
<td>24</td>
<td>214</td>
</tr>
<tr>
<td>#Values</td>
<td>212</td>
<td>99</td>
<td>3,871</td>
<td>138</td>
<td>4,510</td>
<td>14,139</td>
</tr>
</tbody>
</table>

Multi-domain conversations involving 34 services over 16 domains, and test set contains few unseen services -> zero-shot generalisation tests
Domains covered in the training set:

<table>
<thead>
<tr>
<th>Domain</th>
<th>Weather</th>
<th>Banks</th>
<th>Buses</th>
<th>Calendar</th>
<th>Events</th>
<th>Flights</th>
<th>Homes</th>
<th>Hotels</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Dialogues</td>
<td>951</td>
<td>727</td>
<td>2280</td>
<td>1602</td>
<td>3509</td>
<td>2747</td>
<td>847</td>
<td>3353</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Domain</th>
<th>Media</th>
<th>Movies</th>
<th>Music</th>
<th>Rental car</th>
<th>Restaurant</th>
<th>Ride sharing</th>
<th>Services</th>
<th>Travel</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Dialogues</td>
<td>1113</td>
<td>1617</td>
<td>1290</td>
<td>1585</td>
<td>2419</td>
<td>1703</td>
<td>1889</td>
<td>1871</td>
</tr>
</tbody>
</table>

https://github.com/google-research-datasets/dstc8-schema-guided-dialogue

The schema for a service is defined as a combination of intents and slots with additional constraints.
The key idea -> Associate a semantic representation with each label using their natural language description

Dynamic sets of labels using embedded representations (i.e., unseen/new slots can be handled)

Service

<table>
<thead>
<tr>
<th>name</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>service_name</td>
<td>&quot;RideSharing&quot;</td>
</tr>
<tr>
<td>description</td>
<td>&quot;On-demand taxi calling service&quot;</td>
</tr>
</tbody>
</table>

Slots

<table>
<thead>
<tr>
<th>name</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>name</td>
<td>&quot;destination&quot;</td>
</tr>
<tr>
<td>description</td>
<td>&quot;Destination for taxi ride&quot;</td>
</tr>
<tr>
<td>name</td>
<td>&quot;number_of_riders&quot;</td>
</tr>
<tr>
<td>description</td>
<td>&quot;Number of riders to call taxi for&quot;</td>
</tr>
<tr>
<td>name</td>
<td>&quot;shared_ride&quot;</td>
</tr>
<tr>
<td>description</td>
<td>&quot;Whether ride is shared or not&quot;</td>
</tr>
<tr>
<td>name</td>
<td>&quot;ride_fare&quot;</td>
</tr>
<tr>
<td>description</td>
<td>&quot;Total cost of the ride&quot;</td>
</tr>
</tbody>
</table>

Intents

<table>
<thead>
<tr>
<th>name</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>name</td>
<td>&quot;GetRide&quot;</td>
</tr>
<tr>
<td>description</td>
<td>&quot;Call a taxi to head to a given destination&quot;</td>
</tr>
<tr>
<td>required_slots</td>
<td>[&quot;destination&quot;, &quot;number_of_riders&quot;]</td>
</tr>
<tr>
<td>optional_slots</td>
<td>[&quot;shared_ride&quot; = &quot;False&quot;]</td>
</tr>
</tbody>
</table>
NL descriptions can be used to identify related services and slots

**Service**
- service_name: "RideSharing_1"
  - description: "On-demand taxi calling service"
- service_name: "RideSharing_2"
  - description: "App to book a cab to any destination"

**Slots**
- name: "number_of_riders"
  - description: "Number of riders to call taxi for"
- name: "number_of_seats"
  - description: "Number of seats to reserve in the cab"

**Intents**
- name: "GetRide"
  - description: "Call a taxi to head to a given destination"
- name: "GetRide"
  - description: "Book a cab for any destination, number of seats and ride type"
Annotations also depend on the current schema of API.
Crowdsourcing in the wild: lessons learned

- Some crowd workers try to get away with minimal work -> create a list of trusted and skilled workers

<table>
<thead>
<tr>
<th>Short unnatural utterances</th>
<th>No paraphrasing - copy from the given outlines</th>
</tr>
</thead>
<tbody>
<tr>
<td>U: Reserve hotel</td>
<td>U: I am looking for something to eat. I want it in Fremont. I am looking for some intermediate priced food.</td>
</tr>
<tr>
<td>S: name</td>
<td>S: What kind of food are you looking for?</td>
</tr>
<tr>
<td>U: one hotel andra 4th of</td>
<td>U: Some Asian Fusion kind of food will be perfect.</td>
</tr>
<tr>
<td>march nine</td>
<td></td>
</tr>
<tr>
<td>S: Ok</td>
<td></td>
</tr>
<tr>
<td>U: Ok</td>
<td></td>
</tr>
<tr>
<td>S: Ok</td>
<td></td>
</tr>
</tbody>
</table>

- Use verification and qualification tasks

- Run scripts to compute the similarities between outlines and paraphrased utterances.
  - Remove the work of crowd workers with (too) high similarity scores
  - Check for variability of utterances
M2M: Key Properties

- Full control over the dialogue flow
- Paraphrase data collection UI is simpler to build
- Easier to engineer particular behaviours
- Crowdsourcers don’t have to label data

- Notation of dialogue acts while developing the dialogue flow
- Simulating both users and the hand-crafted system (non-trivial)
- No interesting system behaviours learned; everything is expected
Wizard-of-Oz Paradigm (Human-to-Human)
Data Collection Paradigm 2: Wizard-of-Oz (WOZ)

Human-to-Human

Crowdworker (User)  Task: Buy 4 tickets for the next game at 5:00 pm.
Crowdworker (Agent)
Data Collection Paradigm 2: Wizard-of-Oz (WOZ)

Human-to-Human

Crowdworker (User)

Task:
Buy 4 tickets for the next game at 5:00 pm.

Crowdworker (Agent)

How is it going on?
All good! How can I help you?
Can you book me 4 tickets?
Sure, what time?
At 5 o'clock
Great, I confirm a booking for you!
Data Collection Paradigm 2: Wizard-of-Oz (WOZ)

Procedure:

1) Chat between 2 (or more) participants,
2) Pre-defined goals to be achieved,
3) The recordings of realizations of conversations,
4) Tracking of the entire ecosystem for additional labelled data,
5) Post-annotation over collected data,
6) Data cleaning.

[Wen et al. 17, El-Asri et al. 17, Budzianowski et al. 18]
Data Collection Paradigm 2: Wizard-of-Oz (WOZ)

Role-play a help desk clerk in a conversation

This HIT requires you to role play a help desk clerk and carry on a conversation with a help desk client.

The task:

- Your task is to provide information and help for residents or tourists in the Cambridge, UK area.
- You are texting to a client to provide your service.
- You are given a console below to help you look for relevant information, therefore this console also defines the set of tasks that you can help with.
- You only need to key-in one appropriate response given the current dialogue scenario.

The domains you can help with:

1. find or book a restaurant
2. find or book a hotel
3. find, call, or book a hospital department
4. find or call a police station
5. find or suggest a tourist attraction in town
6. find or book a train ticket
7. book a taxi

[Wen et al. 17, El-Asri et al. 17, Budzianowski et al. 18]
Goal

Please try to chat about the following topic:

- You are traveling to Cambridge and looking forward to try local restaurants.
- You are looking for a place to stay. The hotel should be in the east and should include free parking.
- The hotel should have a star of 4 and should be in the type of guesthouse.
- Make sure you get address and phone number.
- You are also looking for a place to dine. The restaurant should be in the moderate price range and should serve Australian food.
- If there is no such restaurant, how about one that serves Turkish food.
- Once you find the restaurant you want to book a table for 4 people at 17:45 on Friday.
- Make sure you get the reference number

--- The End ---
Goal

- You are traveling to Cambridge and looking forward to try local restaurants.
- You are looking for a hotel that should be in the type of hotel and should be in the centre.
- The hotel should include free wifi and should have a star of 4.
- Once you find the hotel you want to book it for 3 people and 5 nights starting from Monday.
- Make sure you get the reference number.
- You are also looking for a restaurant. The restaurant should serve australasian food and should be in the moderate price range.
- The restaurant should be in the same area as the hotel.
- If there is no such restaurant, how about one that serves british food.
- Once you find the restaurant you want to book a table for the same group of people at 18:30 on the same day.
- Make sure you get the reference number.
You are traveling to Cambridge and looking forward to try local restaurants. **Your role** is hotel should be in the type of hotel and should be in the centre.

The hotel should include free wifi and should have a star of 4.

Once you find the hotel you want to book it for 3 people and 5 nights starting from Monday.

Make sure **First Domain**

- You are also looking for a restaurant. The restaurant should serve australasian food and should be in the moderate price range.
- The restaurant should be in the same area as the hotel.
- If there is no such restaurant, how about one that serves british

**Second Domain**

- Once make a table for the same group of people at 18:30 on the same day.
- Make sure you get the reference number
Visitor: Hi, I'm visiting soon and am interested in a particular attraction. It's called Emmanuel college. Can you help?

Clerk: Yes! Emmanuel College is on Saint Andrew's Street in the city centre. Entrance is free. Would you like to know anything else about it?

Visitor: Thank you! Could you tell me the postcode for the college as well please?

Clerk: The postcode for Emmanuel College is cb23ap.

Visitor: Great. I am also looking for a train to get to Cambridge sometime after 18:15. Is that possible?

Clerk: I can help you with that. What is your departure location?

Visitor: I am leaving from Cambridge.

Clerk: What is your departure and arrival location, they cannot both be cambridge.

Visitor: My apologies! It should leave Cambridge and arrive in Norwich on Friday.

Clerk: I have several results. What time would you like to leave?

Visitor: I just need to arrive by 18:15.

Clerk: How about TR7047? It arrives at 17:55?

Visitor: That should work. Can I please have the price on that?

Clerk: It is 17.60 pounds.

Visitor: Thank you goodbye

Clerk: Thank you for contacting Cambridge TownInfo Centre. Enjoy the rest of the day.
Visitor: Hi, I'm visiting soon and am interested in a particular attraction. It's called Emmanuel college. Can you help?

Clerk: Yes! Emmanuel College is on Saint Andrew's Street. Entrance is free. Would you like to know anything else about it?

Visitor: Thank you! Could you tell me the postcode for the college as well please?

Clerk: The postcode for Emmanuel College is cb23ap.

Visitor: Great. I am also looking for a train to get to Cambridge sometime after 18:15. Is that possible?

Clerk: I can help you with that. What is your departure location?

Visitor: I am leaving from Cambridge.

Clerk: What is your departure and arrival location, they cannot both be Cambridge.

Visitor: My apologies! It should leave Cambridge and arrive in Norwich on Friday.

Clerk: I have several results. What time would you like to leave?

Visitor: I just need to arrive by 18:15.

Clerk: How about TR7047? It arrives at 17:55?

Visitor: That should work. Can I please have the price on that?

Clerk: It is 17.60 pounds.

Visitor: Thank you goodbye

Clerk: Thank you for contacting Cambridge TownInfo Centre. Enjoy the rest of the day.
Visitor: Hi, I'm visiting soon and am interested in a particular attraction. It's called Emmanuel college. Can you help?

Clerk: Yes! Emmanuel College is on Saint Andrew's Street. Entrance is free. Would you like to know any more about it?

Visitor: Thank you! Could you tell me the postcode for the college as well please?

Clerk: The postcode for Emmanuel College is CB2 3AP.

Visitor: Great. I am also looking for a train to get to Cambridge sometime after 18:15. Is that possible?

Clerk: I can help you with that. What is your departure location?

Visitor: I am leaving from Cambridge.

Clerk: What is your departure and arrival location, they cannot both be Cambridge.

Visitor: My apologies! I should leave Cambridge and arrive in Norwich on Friday.

Clerk: I have several results. What time would you like to leave?

Visitor: I just need to arrive by 18:15.

Clerk: How about TR7047? It arrives at 17:55?

Visitor: That should work. Can I please have the price on that?

Clerk: It is 17.60 pounds.

Visitor: Thank you goodbye

Clerk: Thank you for contacting Cambridge TownInfo Centre. Enjoy the rest of the day.
Visitor: Hi, I'm visiting soon and am interested in a particular attraction. It's called Emmanuel college. Can you help?

Clerk: Yes! Emmanuel College is on Saint Andrew's Street. Entrance is free. Would you like to know any other information?

Visitor: Thank you! Could you tell me the postcode for the college as well please?

Clerk: The postcode for Emmanuel College is cb23ap.

Visitor: Great. I am also looking for a train to get to Cambridge sometime after 18:15. Is that possible?

Clerk: I can help you with that. What is your departure location?

Visitor: I am leaving from Cambridge.

Clerk: What is your departure and arrival location, they cannot both be Cambridge.

Visitor: My apologies! It should leave Cambridge and arrive in Norwich on Friday.

Clerk: I have several results. What time would you like to leave?

Visitor: I just need to arrive by 18:15.

Clerk: How about TR7047? It arrives at 17:55?

Visitor: That should work. Can I please have the price on that?

Clerk: It is 17.60 pounds.

Visitor: Thank you goodbye

Clerk: Thank you for contacting Cambridge TownInfo Centre.
Enjoy the rest of the day.
Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you?

Customer: I want a place to stay in the east.

Help Desk: I have 6 guesthouses and 1 hotel on the east side. What's your price range?

Customer: Doesn't matter too much. I'd like a 4 star property, though, and would prefer one of the guesthouses.

Help Desk: I'd recommend 517a coldham lane. Would you like me to book a room?

Customer: Could you give me their phone number? I would like to verify that they have free parking.

Help Desk: Allenbell does have parking and the phone is 01223210353. Can I help with anything else?

Customer: (Your response)

you need to go through the dialogue first by clicking the 'next turn' button

What topics were mentioned in this turn:

- General
- Booking
- Restaurant
- Hotels
- Attractions

- Hospital
- Police
- Train
- Taxi
- Bus

Submit the HIT

Please try to chat about the following topic:

Task MUL0002:

- You are traveling to and looking forward to try local restaurants.
- You are looking for a place to stay. The hotel should be in the east and should include free parking.
- The hotel should have a star of 4 and should be in the type of guesthouse.
- Make sure you get address and phone number.
- You are also looking for a place to dine. The restaurant should be in the moderate price range and should serve australian food.
- If there is no such restaurant, how about one that serves turkish food.
- Once you find the restaurant you want to book a table for 4 people at 17:45 on friday.
- Make sure you get the reference number

--- The End ---
Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you?

Customer: I want a place to stay in the east.

Help Desk: I have 6 guesthouses and 1 hotel on the east side. What's your price range?

Customer: Doesn't matter too much. I'd like a 4 star property, though, and would prefer one of the guesthouses.

Help Desk: I'd recommend 517a coldham lane. Would you like me to book a room?

Customer: Could you give me their phone number? I would like to verify that they have free parking.

Help Desk: Allenbell does have parking and the phone is 01223210353. Can I help with anything else?

Customer: (Your response) you need to go through the dialogue first by clicking the 'next turn' button

Please try to chat about the following topic:

Task MUL0002:

- You are traveling to and looking forward to try local restaurants.
- You are looking for a place to stay. The hotel should be in the east and should include free parking.
- The hotel should be in the type of guesthouse.
- Make sure you get the reference number.
- You are also looking for a restaurant. The restaurant should be in the moderate price range and serves Turkish food.
- If there is no such restaurant, ask for the closest place that serves Turkish food.
- Once you find the restaurant, ask for a reservation for 4 people at 17:45 on Friday.
- Make sure you get the reference number.

--- The End ---
Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you?

Customer: I want a place to stay in the east.

Help Desk: I have 6 guesthouses and 1 hotel in the east side. What's your price range?

Customer: Doesn't matter too much, though, and would prefer one of the guesthouses.

Help Desk: I'd recommend Allenbell does have parking and the phone is 01223210353. Can I help with anything else?

Customer: Could you like me to book a room?

Help Desk: to verify that they have free parking.

Please try to chat about the following topic:

Task MUL0002:

- You are traveling to and looking forward to try local restaurants.
- You are looking for a place to stay. The hotel should be in the east and should include free parking.
- The hotel should be a type of guesthouse.
- Make sure you get the reference number.
- You are also looking for a restaurant should be in the moderate price range and serves turkish food.
- If there is no such restaurant, look for 4 people at 17:45 on friday.
- Make sure you get the reference number.

--- The End ---
Hello, welcome to the Towninfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you?

Customer: I want a place to stay in the east.
Help Desk: I have 6 guesthouses and 1 hotel.
Customer: Doesn't matter too much. I'd like 517z.
Help Desk: I'd recommend 517z.
Customer: Could you give me their phone number? I would like to verify that they have free parking.

Please modify the following answers based on the latest customer response:

- What does the user want?
  - Is the user looking for a specific hotel by name? not mentioned
  - What is the hotel type the user wants? guesthouse
  - What is the area the user wants? east
  - What is the price range the user wants? not mentioned
  - What is the star of the hotel the user wants? 4
  - Does the user need Internet? not mentioned
  - Does the user need parking? not mentioned

Help Desk: (Your response)

You need to fill in the questionnaires above first.

end-of-dialogue?

Submit the HIT
Task MUL0002

Help Desk: Hello, welcome to the Towninfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you?

Customer: I want a place to stay in the east.

Help Desk: I have 6 guesthouses and 1 hotel.

Customer: Doesn't matter too much. I'd like

Help Desk: I'd recommend 517.

Customer: Could you give me their phone number? I would like to verify that they have free parking.
Task MUL0002

Help Desk: Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you?
Customer: I want a place to stay in the east.
Help Desk: I have 6 guesthouses and 1 hotel.
Customer: Doesn't matter too much. I'd like 5176.
Help Desk: I'd recommend.
Customer: Could you give me their phone number? I would like to verify that they have free parking.

Dialogue context:

Please modify the following answers based on the latest customer response:

• What does the user want?
  Is the user looking for a specific hotel by name? not mentioned
  What is the hotel type the user wants? guesthouse
  What is the area the user wants? east
  What is the price range the user wants? not mentioned
  What is the star of the hotel the user wants? 4
  Does the user need internet? not mentioned
  Does the user need parking? not mentioned

Lookup

Help Desk: (Your response)
you need to fill in the questionnaires above first.

end-of-dialogue?
Submit the HIT
<table>
<thead>
<tr>
<th>Turn</th>
<th>John</th>
<th>Anna</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Hi Anna, how can I help you?</td>
<td>I want to arrive by 11:30 at Cambridge.</td>
</tr>
</tbody>
</table>

### Train domain

- **John is requesting:**
  - day [ ]
  - departure place [ ]
  - destination place [ ]
  - leave after [ ]
  - arrive by [ ]
  - people [ ]

- **Informing about:**
  - arrival by [ ]

- **Offering to book a train:**
  - people [ ]
  - possible choices [ ]
  - departure place [ ]
  - destination place [ ]
  - leave after [ ]
  - arrival by [ ]
  - day [ ]
  - reference [ ]
  - trainID [ ]
  - ticket price [ ]
  - travel time [ ]

- **Is asking to select train(s):**

- **Informing that no trains are available:**

- **Informing that train was booked:**
<table>
<thead>
<tr>
<th>Turn</th>
<th>John</th>
<th>Anna</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Hi Anna, how can I help you?</td>
<td>I want to arrive by 11:30 at Cambridge.</td>
</tr>
</tbody>
</table>

**Dialogue context**

There are three trains, one arrives at 6:43, one at 8:43, and one at 10:43, which would you like to book?

**Train domain**

- John is requesting: day, departure place, destination place, leave after, arrive by, people
- informing about
- people, possible choices: 3
- departure place, destination place, leave after, arrive by: 6:43, 8:43, 10:43
- day, reference, trainID, ticket price, travel time
- offering to book a train
- people, possible choices
- departure place, destination place, leave after, arrival by: day, reference, trainID, ticket price, travel time
- is asking to select train(s)
- informing that no trains are available
- informing that train was booked
<table>
<thead>
<tr>
<th>Turn</th>
<th>Dialogue context</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>There are three trains, one arrives at 6:43, one at 8:43, and one at 10:43, which would you like to book?</td>
</tr>
</tbody>
</table>

**Domains**

**Train domain**

- **John is requesting:** day | departure place | destination place | leave after | arrive by | people |
- **informing about**
  - people | possible choices 3 | departure place | destination place | leave after | arrival by 6:43, 8:43, 10:43 | day | reference | trainID | ticket price | travel time |
- **offering to book a train**
  - people | possible choices | departure place | destination place | leave after | arrival by | day | reference | trainID | ticket price | travel time |
- **is asking to select train(s)**
- **informing that no trains are available**
- **informing that that train was booked**
<table>
<thead>
<tr>
<th>John</th>
<th>Hi Anna, how can I help you?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anna</td>
<td>I want to arrive by 11:30 at Cambridge.</td>
</tr>
</tbody>
</table>

### Dialogue context

There are three trains, one arrives at 6:43, one at 8:43, and one at 10:43, which would you like to book?

### Domains

<table>
<thead>
<tr>
<th>Booking</th>
<th>Restaurant</th>
<th>Hotel</th>
<th>Attraction</th>
<th>Taxi</th>
<th>Train</th>
<th>Hospital</th>
<th>Police</th>
</tr>
</thead>
</table>

### Train domain

**John is requesting:**
- day
- departure place
- destination place
- leave after
- arrive by
- people

**Informing about:**
- people
- possible choices: 3
- destination place
- leave after
- arrival by: 6:43, 8:43, 10:43

**Offering to book a train:**
- people
- possible choices
- departure place
- destination place
- leave after
- arrival by
- day
- reference
- trainID
- ticket price
- travel time

### Slot-value pairs

- informing that no trains are available
- informing that train was booked
WoZ in practice:

Crowdsourcing in the wild: lessons learned

- One-click tasks
- Simple and short instructions - turkers don’t read it anyway
- High entry bars is a must (HIT approval rate > 97%, location, number of HITs approved > 500)
- MTurk platform is not really multinational - a great support for English only
- There are many platforms that provide higher quality of turkers in a variety of languages (for example Prolific)
- Use verification and qualification tasks for any tasks with a higher cognitive load
- This will probably result in creating a sub-group of workers
WoZ in practice: MultiWOZ

- The dataset consists of conversations between a tourist and a clerk from an information centre in Cambridge.
- The corpus consists of 7 domains including: Attraction, Hotel, Restaurant, Train, Taxi and Police.
- Used as part a of DSTC8: multi-domain task completion challenge.

<table>
<thead>
<tr>
<th>Metric</th>
<th>DSTC2</th>
<th>WOZ2.0</th>
<th>FRAMES</th>
<th>M2M</th>
<th>MultiWOZ</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Domains</td>
<td>1</td>
<td>1</td>
<td>3</td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>#Dialogues</td>
<td>1,612</td>
<td>600</td>
<td>1,369</td>
<td>1,500</td>
<td>8,438</td>
</tr>
<tr>
<td>#Turns</td>
<td>23,354</td>
<td>4,472</td>
<td>19,986</td>
<td>14,796</td>
<td>113,556</td>
</tr>
<tr>
<td>#Slots</td>
<td>8</td>
<td>4</td>
<td>61</td>
<td>13</td>
<td>24</td>
</tr>
<tr>
<td>#Values</td>
<td>212</td>
<td>99</td>
<td>3,871</td>
<td>138</td>
<td>4,510</td>
</tr>
</tbody>
</table>

[Budzianowski et al., EMNLP-18]
**WoZ in practice: MultiWOZ**

<table>
<thead>
<tr>
<th>act type</th>
<th>inform* / request* / select$^{123}$ / recommend$^{123}$ / not found$^{123}$ / request booking info$^{123}$ / offer booking$^{1235}$ / inform booked$^{1235}$ / decline booking$^{1235}$ / welcome* / greet* / bye* / reqmore*</th>
</tr>
</thead>
<tbody>
<tr>
<td>slots</td>
<td>address* / postcode* / phone* / name$^{1234}$ / no of choices$^{1235}$ / area$^{123}$ / pricerange$^{123}$ / type$^{123}$ / internet$^2$ / parking$^2$ / stars$^2$ / open hours$^3$ / departure$^{45}$ / destination$^{45}$ / leave after$^{45}$ / arrive by$^{45}$ / no of people$^{1235}$ / reference no.$^{1235}$ / trainID$^5$ / ticket price$^5$ / travel time$^5$ / department$^7$ / day$^{1235}$ / no of days$^{123}$</td>
</tr>
</tbody>
</table>

[Budzianowski et al., EMNLP-18]
WoZ in practice: MultiWOZ

[Budzianowski et al., EMNLP-18]
WoZ in practice: MultiWOZ

[Budzianowski et al., EMNLP-18]
## DSTC8 - Multi Domain Task Completion

**Traditional Tasks**
- Single domain
- Single dialog act per utterance
- Single intent per dialog
- Contextless language understanding
- Contextless language generation
- Atomic tasks

**This Challenge**
- Multiple domains
- Multiple dialog acts per utterance
- Multiple intents per dialog
- Contextual language understanding
- Contextual language generation
- Composite tasks with state sharing

---

Slide courtesy of [Gao and Galley, 2019]

[Lee et al., DSTC8-19]
Air Dialogue Dataset

[Wei et al., EMNLP-18]
<table>
<thead>
<tr>
<th></th>
<th>Train</th>
<th>Dev</th>
<th>Test</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>AirDialogue</td>
<td>321,460</td>
<td>40,363</td>
<td>40,215</td>
<td>402,038</td>
</tr>
<tr>
<td>Syntherized</td>
<td>320,000</td>
<td>40,000</td>
<td>40,000</td>
<td>400,000</td>
</tr>
<tr>
<td>OOD Context</td>
<td>-</td>
<td>40,000</td>
<td>40,000</td>
<td>80,000</td>
</tr>
</tbody>
</table>

[Wei et al., EMNLP-18]
<table>
<thead>
<tr>
<th>Experiments</th>
<th>Name</th>
<th>Flight</th>
<th>State</th>
<th>Total</th>
<th>BLEU</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supervised (Synthesized dev)</td>
<td>0.39(0%)</td>
<td>0.11(8%)</td>
<td>0.32(32%)</td>
<td>0.23(0.14)</td>
<td>68.72</td>
</tr>
<tr>
<td>Self-play (Synthesized dev)</td>
<td>0.47(0%)</td>
<td>0.36(35%)</td>
<td>0.39(39%)</td>
<td>0.39(0.29)</td>
<td>62.71</td>
</tr>
<tr>
<td>Supervised (Synthesized test)</td>
<td>0.39(0%)</td>
<td>0.08(4%)</td>
<td>0.33(33%)</td>
<td>0.22(0.12)</td>
<td>68.73</td>
</tr>
<tr>
<td>Self-play (Synthesized test)</td>
<td>0.47(1%)</td>
<td>0.35(16%)</td>
<td>0.47(47%)</td>
<td>0.41(0.22)</td>
<td>62.66</td>
</tr>
<tr>
<td>Supervised (AirDialogue dev)</td>
<td>0.4(0.9%)</td>
<td>0.07(1.2%)</td>
<td>0.12(12%)</td>
<td>0.15(0.04)</td>
<td>23.26</td>
</tr>
<tr>
<td>Self-play (AirDialogue dev)</td>
<td>0.41(1%)</td>
<td>0.13(4%)</td>
<td>0.29(29%)</td>
<td>0.23(0.11)</td>
<td>19.65</td>
</tr>
<tr>
<td>Supervised (AirDialogue test)</td>
<td>0.39(1%)</td>
<td>0.08(1.6%)</td>
<td>0.08(8%)</td>
<td>0.14(0.03)</td>
<td>23.15</td>
</tr>
<tr>
<td>Self-play (AirDialogue test)</td>
<td>0.43(1%)</td>
<td>0.11(3%)</td>
<td>0.28(28%)</td>
<td>0.22(0.10)</td>
<td>18.84</td>
</tr>
<tr>
<td>Human (AirDialogue test)</td>
<td>1 (98%)</td>
<td>0.92 (91.4%)</td>
<td>0.92 (91.8%)</td>
<td>0.94 (0.93)</td>
<td>-</td>
</tr>
</tbody>
</table>

[Wei et al., EMNLP-18]
WoZ: Key Properties

- Natural conversations between real people
- Simulating both users and system is not needed
- Interesting system behaviours learned
- The collection scale is only constrained by the budget

- A lot of work needs to be put to create simple UI
- Notation of dialogue acts after collection of data is highly subjective
- Lack of control over the dialogue flow
- Data collection is VERY noisy
Real Conversational Data Collection
Turked data:
- The data is biased by a fake scenario
- Very homogeneous (turkers are usually not creative)
Real data?

Turked data:
- The data is biased by a fake scenario
- Very homogeneous (turkers are usually not creative)

Where can we find real data?
- Wikipedia, books, parliamentary sessions…
- Movie subtitles
Real data?

Turked data:
- The data is biased by a fake scenario
- Very homogeneous (turkers are usually not creative)

Where can we find real data?
- Wikipedia, books, parliamentary sessions…
- Movie subtitles

Conversations on the internet
Internet is full of conversations:

- Social media (Facebook, Twitter, Instagram...)
- Product reviews (Amazon, Yelp, Tripadvisor...)
- QA sites (Quora, Stackexchange, Yahoo Answers...)
- General discussion forums (Reddit)
Which of this data is publicly available?
Ubuntu dialogue corpus

Lowe et al., 2015, 2017

Chats from Ubuntu support IRC

~1M dialogues

Improved for DSTC7 in 2019 (Kummerfeld et al., 2019)
McAuley and Yang., 2016

Questions and answers from Amazon products

- 3.6 million QA pairs
- Product and category labels
- Single turn
Open subtitles

Lison and Tiedemann., 2016

Movie subtitles on 62 languages

3.35 billion sentences (in all languages)

Large, diverse, multilingual

Divided in sentence fragments, video or history dependent
- Largest corpus by far (3.7 billion comments)
- Spanning many topics (subreddits)
- Very conversational
- Long interactions
- Continuously growing

- Lots of hyperlinks, memes, images, non-grammatical language, internet slang...

Dataset source: Jason Baumgartner, pushshift.io, reddit post
Conversational Dataset repository

Reddit
3.7 billion comments from online discussions on many topics
727 million examples

OpenSubtitles
over 400 million lines of subtitles from movies and TV
316 million examples

AmazonQA
over 3.6 million product question-answer pairs
3.6 million examples

github.com/PolyAI-LDN/conversational-datasets

Henderson et al., 2019
## Dataset size comparison

<table>
<thead>
<tr>
<th>Dataset</th>
<th>~ Turns</th>
<th>Annotations</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSTC 2&amp;3</td>
<td>$10^4$</td>
<td>response, ASR, SLU</td>
</tr>
<tr>
<td>MultiWOZ</td>
<td>$10^5$</td>
<td>response, NLU</td>
</tr>
<tr>
<td>DSTC7 Reddit</td>
<td>$10^6$</td>
<td>response, entities</td>
</tr>
<tr>
<td>DSTC7 Ubuntu</td>
<td>$10^6$</td>
<td>response</td>
</tr>
<tr>
<td>PolyAI AmazonQA</td>
<td>$10^6$</td>
<td>product, response</td>
</tr>
<tr>
<td>PolyAI OpenSubtitles</td>
<td>$10^8$</td>
<td>'response'</td>
</tr>
<tr>
<td>PolyAI Reddit</td>
<td>$10^9$</td>
<td>response</td>
</tr>
</tbody>
</table>
Downsides

- No semantic annotations
- Difficult to get task specific data
The presented datasets are only a small part of the available conversations in the internet.

The rest of the data is out there and accessible, and technically web scrapers can collect it.

Not clear legal framework.

Shoutout to the "owners" to release it.
Building Conversational AI
Modular Task-Based Conversational AI Systems

“Book me a cab to Russell Square“

Speech Recognition ➔ Language Understanding ➔ Dialogue Management ➔ Third Party APIs

speech ➔ text ➔ semantics

Speech Synthesis ➔ Response Generation

speech ➔ text ➔ semantics

inform(service=taxi, dest=Russell Square)

request(depart_time)

“When do you want to leave?”
End-to-End Task-Based Conversational AI Systems
Why End-to-End Learning?

Pros:
Faster re-training cycle - easier productization

Natural framework for knowledge sharing across modules

(Theoretically) Less sophisticated annotation schema

(Theoretically) Taking advantage of online conversational resources

Cons:
Let’s not think about it for now
Network-based End-to-End Task Oriented Dialogue System

[Wen et al., EACL-17]
<table>
<thead>
<tr>
<th>Metric</th>
<th>NDM</th>
<th>HDC</th>
<th>Tie</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subj. Success</td>
<td>96.95%</td>
<td>95.12%</td>
<td>-</td>
</tr>
<tr>
<td>Avg. # of Turn</td>
<td>3.95</td>
<td>4.54</td>
<td>-</td>
</tr>
</tbody>
</table>

**Comparisons(%)**

<table>
<thead>
<tr>
<th></th>
<th>NDM</th>
<th>HDC</th>
<th>Tie</th>
</tr>
</thead>
<tbody>
<tr>
<td>Naturalness</td>
<td>46.95*</td>
<td>25.61</td>
<td>27.44</td>
</tr>
<tr>
<td>Comprehension</td>
<td>45.12*</td>
<td>21.95</td>
<td>32.93</td>
</tr>
<tr>
<td>Preference</td>
<td>50.00*</td>
<td>24.39</td>
<td>25.61</td>
</tr>
<tr>
<td>Performance</td>
<td>43.90*</td>
<td>25.61</td>
<td>30.49</td>
</tr>
</tbody>
</table>

* p <0.005,  # of comparisons: 164

[Wen et al., EACL-17]
<table>
<thead>
<tr>
<th>Metric</th>
<th>NDM</th>
<th>HDC</th>
<th>Tie</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subj. Success</td>
<td>96.95%</td>
<td>95.12%</td>
<td>-</td>
</tr>
<tr>
<td>Avg. # of Turn</td>
<td>3.95</td>
<td>4.54</td>
<td>-</td>
</tr>
</tbody>
</table>

**Comparisons(%)**

<table>
<thead>
<tr>
<th></th>
<th>NDM</th>
<th>HDC</th>
<th>Tie</th>
</tr>
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<tbody>
<tr>
<td>Naturalness</td>
<td>46.95*</td>
<td>25.61</td>
<td>27.44</td>
</tr>
<tr>
<td>Comprehension</td>
<td>45.12*</td>
<td>21.95</td>
<td>32.93</td>
</tr>
<tr>
<td>Preference</td>
<td>50.00*</td>
<td>24.39</td>
<td>25.61</td>
</tr>
<tr>
<td>Performance</td>
<td>43.90*</td>
<td>25.61</td>
<td>30.49</td>
</tr>
</tbody>
</table>

* p <0.005,  # of comparisons: 164

[Wen et al., EACL-17]
### Learning End-to-End Goal-Oriented Dialog

Table showing performance metrics for different tasks and systems:

<table>
<thead>
<tr>
<th>Task</th>
<th>Rule-based Systems</th>
<th>TF-IDF Match</th>
<th>Nearest Neighbor</th>
<th>Supervised Embeddings</th>
<th>Memory Networks</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>no type</td>
<td>+ type</td>
<td>no match type</td>
<td>+ match type</td>
</tr>
<tr>
<td>T1: Issuing API calls</td>
<td>100 (100)</td>
<td>5.6 (0)</td>
<td>22.4 (0)</td>
<td>100 (100)</td>
<td>99.9 (99.6)</td>
</tr>
<tr>
<td>T2: Updating API calls</td>
<td>100 (100)</td>
<td>3.4 (0)</td>
<td>16.4 (0)</td>
<td>68.3 (0)</td>
<td>68.4 (0)</td>
</tr>
<tr>
<td>T3: Displaying options</td>
<td>100 (100)</td>
<td>8.0 (0)</td>
<td>8.0 (0)</td>
<td>58.8 (0)</td>
<td>64.9 (0)</td>
</tr>
<tr>
<td>T4: Providing information</td>
<td>100 (100)</td>
<td>9.5 (0)</td>
<td>17.8 (0)</td>
<td>28.6 (0)</td>
<td>57.2 (0)</td>
</tr>
<tr>
<td>T5: Full dialogs</td>
<td>100 (100)</td>
<td>4.6 (0)</td>
<td>8.1 (0)</td>
<td>57.1 (0)</td>
<td>75.4 (0)</td>
</tr>
<tr>
<td>T1(OOV): Issuing API calls</td>
<td>100 (100)</td>
<td>5.8 (0)</td>
<td>22.4 (0)</td>
<td>44.1 (0)</td>
<td>60.0 (0)</td>
</tr>
<tr>
<td>T2(OOV): Updating API calls</td>
<td>100 (100)</td>
<td>3.5 (0)</td>
<td>16.8 (0)</td>
<td>68.3 (0)</td>
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</tr>
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<td>8.3 (0)</td>
<td>8.3 (0)</td>
<td>58.8 (0)</td>
<td>65.0 (0)</td>
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<tr>
<td>T4(OOV): Providing inform.</td>
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<td>9.8 (0)</td>
<td>17.2 (0)</td>
<td>28.6 (0)</td>
<td>57.0 (0)</td>
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<tr>
<td>T5(OOV): Full dialogs</td>
<td>100 (100)</td>
<td>4.6 (0)</td>
<td>9.0 (0)</td>
<td>48.4 (0)</td>
<td>58.2 (0)</td>
</tr>
<tr>
<td>T6: Dialog state tracking 2</td>
<td>33.3 (0)</td>
<td>1.6 (0)</td>
<td>1.6 (0)</td>
<td>21.9 (0)</td>
<td>22.6 (0)</td>
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<tr>
<td>Concierge(*)</td>
<td>n/a</td>
<td>1.1 (0.2)</td>
<td>n/a</td>
<td>13.4 (0.5)</td>
<td>14.6 (0.5)</td>
</tr>
</tbody>
</table>

[Bordes et al., ICLR-17]
## Learning End-to-End Goal-Oriented Dialog

[Bordes et al., ICLR-17](#)

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<td></td>
<td></td>
</tr>
<tr>
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<td></td>
<td>55.1 (0)</td>
<td>99.9 (99.6)</td>
</tr>
<tr>
<td>T2: Updating API calls</td>
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<td></td>
<td>68.3 (0)</td>
<td>100 (100)</td>
</tr>
<tr>
<td>T3: Displaying options</td>
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<td>8.0 (0)</td>
<td></td>
<td>58.8 (0)</td>
<td>74.9 (2.0)</td>
</tr>
<tr>
<td>T4: Providing information</td>
<td>100 (100)</td>
<td>9.5 (0)</td>
<td></td>
<td>28.6 (0)</td>
<td>59.5 (3.0)</td>
</tr>
<tr>
<td>T5: Full dialogs</td>
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<td></td>
<td>57.1 (0)</td>
<td>96.1 (49.4)</td>
</tr>
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<td></td>
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<td>72.3 (0)</td>
</tr>
<tr>
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<td>1.6 (0)</td>
<td></td>
<td>21.9 (0)</td>
<td>41.1 (0)</td>
</tr>
</tbody>
</table>

Concierge (*)

|                               |                   |              |                  |                       |                 |
|                               | n/a               | 1.1 (0.2)    | n/a              | 13.4 (0.5)            | 16.7 (1.2)      |

[Note: (*) Concierge (*)]
Sequicity - Simplifying Task-oriented Dialogue Systems

<table>
<thead>
<tr>
<th>Turn</th>
<th>Dialogue</th>
</tr>
</thead>
<tbody>
<tr>
<td>User₁</td>
<td>Can I have some Italian food please?</td>
</tr>
<tr>
<td>Machine₁</td>
<td>&lt;Inf&gt; Italian &lt;Inf&gt; &lt;Req&gt; &lt;Req&gt; What price range are you looking for?</td>
</tr>
<tr>
<td>User₂</td>
<td>I want cheap ones.</td>
</tr>
<tr>
<td>Machine₂</td>
<td>&lt;Inf&gt; Italian ; cheap &lt;Inf&gt; &lt;Req&gt; &lt;Req&gt; NAME SLOT is a cheap restaurant serving western food</td>
</tr>
<tr>
<td>User₃</td>
<td>Tell me the address and the phone number please.</td>
</tr>
<tr>
<td>Machine₃</td>
<td>&lt;Inf&gt; Italian ; cheap &lt;Inf&gt; &lt;Req&gt; address ; phone &lt;Req&gt; The address is ADDRESS SLOT and the phone number is PHONE SLOT</td>
</tr>
</tbody>
</table>

[Lei et al., ACL-18]
## Sequicity - Simplifying Task-oriented Dialogue Systems

<table>
<thead>
<tr>
<th></th>
<th>CamRes676</th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mat.</td>
<td>BLEU</td>
<td>Succ. F$_1$</td>
<td>$Time_{full}$</td>
<td>$Time_{N.B.}$</td>
</tr>
<tr>
<td>(1) NDM</td>
<td>0.904</td>
<td>0.212</td>
<td>0.832</td>
<td>91.9 min</td>
<td>8.6 min</td>
</tr>
<tr>
<td>(2) NDM + Att + SS</td>
<td>0.904</td>
<td>0.240</td>
<td>0.836</td>
<td>93.7 min</td>
<td>10.4 min</td>
</tr>
<tr>
<td>(3) LIDM</td>
<td>0.912</td>
<td>0.246</td>
<td>0.840</td>
<td>97.7 min</td>
<td>14.4 min</td>
</tr>
<tr>
<td>(4) KVRN</td>
<td>N/A</td>
<td>0.134</td>
<td>N/A</td>
<td>21.4 min</td>
<td>–</td>
</tr>
<tr>
<td>(5) TSCP</td>
<td><strong>0.927</strong></td>
<td><strong>0.253</strong></td>
<td><strong>0.854</strong></td>
<td>7.3 min</td>
<td>–</td>
</tr>
<tr>
<td>(6) Att-RNN</td>
<td>0.851</td>
<td>0.248</td>
<td>0.774</td>
<td>7.2 min</td>
<td>–</td>
</tr>
<tr>
<td>(7) TSCP$_{k_l}$</td>
<td><strong>0.927</strong></td>
<td>0.232</td>
<td>0.835</td>
<td>7.2 min</td>
<td>–</td>
</tr>
<tr>
<td>(8) TSCP$_{RL}$</td>
<td><strong>0.927</strong></td>
<td>0.234</td>
<td>0.834</td>
<td><strong>4.1 min</strong></td>
<td>–</td>
</tr>
<tr>
<td>(9) TSCP$_{B_t}$</td>
<td>0.888</td>
<td>0.197</td>
<td>0.809</td>
<td>22.9 min</td>
<td>–</td>
</tr>
</tbody>
</table>

[Lei et al., ACL-18]
## Sequicity - Simplifying Task-oriented Dialogue Systems

### Table: CamRes676

<table>
<thead>
<tr>
<th></th>
<th>Mat.</th>
<th>BLEU</th>
<th>Succ. F₁</th>
<th>Time &lt;sub&gt;full&lt;/sub&gt;</th>
<th>Time &lt;sub&gt;N.B.&lt;/sub&gt;</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.212</td>
<td>91.9 min</td>
<td>8.6 min</td>
</tr>
<tr>
<td>2</td>
<td>NDM + Att + SS</td>
<td>0.904</td>
<td>0.240</td>
<td>0.836</td>
<td>93.7 min</td>
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<td>3</td>
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<td>4</td>
<td>KVRN</td>
<td>N/A</td>
<td>0.134</td>
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</tr>
<tr>
<td>5</td>
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<td>0.927</td>
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<td>0.835</td>
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<td>0.927</td>
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</tbody>
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[Lei et al., ACL-18]
Unsupervised Discrete Sentence Representation Learning

$\text{Recognition Network} \longrightarrow q(z|x) \longrightarrow \text{Generation Network}$

$x = \text{schedule a meeting}$

- autoencoding
- context predicting

[Zhao et al., ACL-18]
Two requirements:
1) \( z \) should capture salient sentence-level features about response \( x \)
2) The meaning of latent symbols \( z \) should be independent of the context \( c \)
Unsupervised Discrete Sentence Representation Learning

\[
\mathcal{L}_{VAE} = \mathbb{E}_x [\mathbb{E}_{q_R(z|x)} [\log p_g(x|z)] - KL(q_R(z|x)||p(z))]
\]

- autoencoding
- context predicting

x = schedule a meeting

[Zhao et al., ACL-18]
Unsupervised Discrete Sentence Representation Learning

\[
\mathcal{L}_{VAE} = \mathbb{E}_x [\mathbb{E}_{q_R(z|x)} [\log p_{\theta_R}(x|z)]
- \text{KL}(q_R(z|x) \parallel p(z))]
\]

\[
\mathcal{L}_{LAED}(\theta_F, \theta_\pi) :
\mathbb{E}_{q_R(z|x)} p(x,c) [\log p_\pi(z|c) + \log p_F(x|z, c)]
\]

- autoencoding
- context predicting

x = schedule a meeting

[Zhao et al., ACL-18]
<table>
<thead>
<tr>
<th>Model</th>
<th>Action</th>
<th>Sample utterance</th>
</tr>
</thead>
<tbody>
<tr>
<td>DI-VAE</td>
<td>scheduling</td>
<td>- sys: okay, scheduling a yoga activity with Tom for the 8th at 2pm.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- sys: okay, scheduling a meeting for 6 pm on Tuesday with your boss to go over the quarterly report.</td>
</tr>
<tr>
<td></td>
<td>requests</td>
<td>- usr: find out if it ’s supposed to rain</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- usr: find nearest coffee shop</td>
</tr>
<tr>
<td>DI-VST</td>
<td>ask schedule info</td>
<td>- usr: when is my football activity and who is going with me?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- usr: tell me when my dentist appointment is?</td>
</tr>
<tr>
<td></td>
<td>requests</td>
<td>- usr: how about other coffee?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>- usr: 11 am please</td>
</tr>
</tbody>
</table>

[Zhao et al., ACL-18]
In a classical approach, we need to issue a symbolic query to the Knowledge Base to retrieve helpful entries given some attributes.

The symbolic operations breaks, however, the differentiability preventing from truly “end-to-end” learning.

This problem has been addressed by soft-lookup approaches.
Towards End-to-End Reinforcement Learning of Dialogue Agents for Information Access

[Dhingra et al., ACL-17]
Towards End-to-End Reinforcement Learning of Dialogue Agents for Information Access

<table>
<thead>
<tr>
<th>Agent</th>
<th>Small KB</th>
<th>Medium KB</th>
<th>Large KB</th>
<th>X-Large KB</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>T</td>
<td>S</td>
<td>R</td>
<td>T</td>
</tr>
<tr>
<td>No KB</td>
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<tr>
<td>Rule</td>
<td>5.04</td>
<td>.64</td>
<td>.26±.02</td>
<td>5.05</td>
</tr>
<tr>
<td>RL</td>
<td>2.65</td>
<td>.56</td>
<td>.24±.02</td>
<td>3.32</td>
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<tr>
<td>Hard KB</td>
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<td></td>
<td></td>
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<td>.64</td>
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<td>3.66</td>
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<tr>
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<td>.62</td>
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<td>3.07</td>
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<tr>
<td>Soft KB</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rule</td>
<td>2.12</td>
<td>.57</td>
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<td>E2E</td>
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<td><strong>.66</strong></td>
<td><strong>.48±.02</strong></td>
<td>3.27</td>
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<tr>
<td>Max</td>
<td>3.44</td>
<td>1.0</td>
<td>1.64</td>
<td>2.96</td>
</tr>
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[Dhingra et al., ACL-17]
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</tr>
</tbody>
</table>

[Dhingra et al., ACL-17]
Key-retrieval Networks

[Eric et al., SIGDIAL-17]
# Key-retrieval Networks

<table>
<thead>
<tr>
<th>Model</th>
<th>BLEU</th>
<th>Ent. F₁</th>
<th>Scheduling Ent. F₁</th>
<th>Weather Ent. F₁</th>
<th>Navigation Ent. F₁</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule-Based</td>
<td>6.6</td>
<td>43.8</td>
<td>61.3</td>
<td>39.5</td>
<td>40.4</td>
</tr>
<tr>
<td>Copy Net</td>
<td>11.0</td>
<td>37.0</td>
<td>28.1</td>
<td>50.1</td>
<td>28.4</td>
</tr>
<tr>
<td>Attn. Seq2Seq</td>
<td>10.2</td>
<td>30.0</td>
<td>30.0</td>
<td>42.4</td>
<td>17.9</td>
</tr>
<tr>
<td>KV Retrieval Net (no enc. attn.)</td>
<td>10.8</td>
<td>40.9</td>
<td>59.5</td>
<td>35.6</td>
<td>36.6</td>
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<tr>
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[Eric et al., SIGDIAL-17]
## Key-retrieval Networks

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<thead>
<tr>
<th>Model</th>
<th>BLEU</th>
<th>Ent. F₁</th>
<th>Scheduling Ent. F₁</th>
<th>Weather Ent. F₁</th>
<th>Navigation Ent. F₁</th>
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[Eric et al., SIGDIAL-17]
Mem2Seq: Incorporating Knowledge Bases

[Madotto et al., ACL-18]
## Mem2Seq: Incorporating Knowledge Bases

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[Madotto et al., ACL-18]
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</table>
Conversations Grounded in Text

"Consistently the best omakase in San Francisco." (27 Tips)
"... they were out of the kaisui uni by the time we ate, but the bafun uni is..." (2 Tips)
"Probably the best sushi in San Francisco." (2 Tips)
"Amazing sushi tasting from the chefs of Sushi Ran" (2 Tips)

User input: Going to Kusakabe tonight.
Neural model: Have a great time!
Human: You’ll love it! Try omasake, the best in town.

[Ghazvininejad et al., AAAI-18]
Knowledge-Grounded Neural Conversational Model

[Ghazvininejad et al., AAAI-18]
Knowledge-Grounded Neural Conversational Model

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<tr>
<td>SEQ2SEQ vs MTASK-F</td>
<td>0.478 ±0.015</td>
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[Ghazvininejad et al., AAAI-18]
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[Ghazvininejad et al., AAAI-18]
Knowledge-Powered Conversational agents

[Knowledge-Powered Conversational agents diagram]

[Dinan et al., EMNLP-18]
Knowledge-Powered Conversational Agents

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<td></td>
<td>Rating</td>
<td>Wiki F1</td>
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<tr>
<td>Human Performance</td>
<td>4.13 (1.08)</td>
<td>11.1</td>
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<tr>
<td>Retrieval Transformer (no knowledge)</td>
<td>3.33 (1.30)</td>
<td>19.8</td>
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<td>Generative Transformer (no knowledge)</td>
<td>2.11 (1.11)</td>
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<tr>
<td>Retrieval Transformer MemNet</td>
<td>3.43 (1.10)</td>
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[Dinan et al., EMNLP-18]
## Knowledge-Powered Conversational Agents

[Dinan et al., EMNLP-18](#)

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[Dinan et al., EMNLP-18]
Supervised Learning gets you as far as the data enables. However the model in production is often exposed to different environments.

This approach also suffers from lack of long-term planning: it hinders the task completion effectiveness.

Fine-tuning with Reinforcement Learning promotes long-term planning.

But even more importantly allows to add external dialogue success signal into the training loop.
Policy-gradient methods aim to optimize the policy with respect to the total reward through gradient ascent:

\[ \nabla_\theta J(\theta) = \mathbb{E}_{\tau \sim \pi_\theta} \left[ \sum_{t=0}^{T-1} \nabla_\theta \log \pi(a_t|s_t)R(\tau) \right] \]
1. Freeze all modules except the policy network,

2. For each RL episode, randomly sample a batch of dialogs from the training set,

3. Run the model on every system turn, and do not alter the original dialog context at every turn given the generated responses,

4. Compute Success Rate based on the generated responses in this dialog,

5. Update the parameters through Policy Gradient.
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<th>Success(%)</th>
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<td>lm</td>
<td>-</td>
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[Wen et al., ICML-17]
## Latent Intent Modelling

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[Wen et al., ICML-17]
Rethinking Latent Space for RL Dialogue Agents

[Zhao et al., NAACL-18]
### RL - words versus action level

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<tr>
<th>Method</th>
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<td>Succ. F₁</td>
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<td>Time&lt;sub&gt;N.B.&lt;/sub&gt;</td>
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<td>(1) NDM</td>
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<td>0.232</td>
<td>0.835</td>
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<td>22.9 min</td>
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</table>

[Lei et al., ACL-18]
## Rethinking Latent Space for RL Dialogue Agents

[Zhao et al., NAACL-18]

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<th>PPL</th>
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[Zhao et al., NAACL-18]
Pre-training for E2E conversations

Pre-training of Transformer architectures on large corpora resulted in a paradigm shift.

Transfer learning has proven to be helpful in plethora of tasks - this is also true for E2E dialogue modelling.

Moreover, pre-training might be the best answer for the data-scarcity problem.
Hello it’s GPT2 - How Can I Help You?

[Wolf et al., ACL-19, Budzianowski et al., WNGT-19]
The context consists of user and system utterances as well as the dialogue belief state encoded as:

Domain1 Slot1 Value1 Slot2 Value2, Domain2 Slot1 ...

and the database state encoded as:

Domain1 # of entities, Domain2 # of entities, ...
<table>
<thead>
<tr>
<th>Model 1</th>
<th>vs</th>
<th>Model 2</th>
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</thead>
<tbody>
<tr>
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<td>41%</td>
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[Budzianowski et al., WNGT-19]
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<td>49%</td>
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[Budzianowski et al., WNGT-19]
Pre-training Methods for Dialog Context Representation Learning

Consider four following pre-training tasks:

1. Next Utterance Retrieval (NUR)
2. Next Utterance Generation (NUG)
3. Masked Utterance Retrieval (MUR)
4. Inconsistency Identification (InI)

[Mehri et al., ACL-19]
### Full data case

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[Mehri et al., ACL-19]
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[Full data case](Mehri et al., ACL-19)
Only 10% data case

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[Mehri et al., ACL-19]
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</table>

[Mehri et al., ACL-19]
Alternating Recurrent Dialog Model with Pre-trained Ones

Dialog

\( u_1 \): I want a cheap French restaurant.
\( s_1 \): There is no such restaurant!
\( u_2 \): Then I want Chinese food.
\( s_2 \): [name_slot] is a cheap restaurant serving Chinese food.
\( u_3 \): Tell me the address and phone number please.
\( s_3 \): The address is [address_slot] and the phone number is [phone_slot].
\( u_4 \): Thank you
\( s_4 \): You are welcome. Have a good day.

ARDM

Memory Recurrence

[Wu et al., arXive-19]
Alternating Recurrent Dialog Model with Pre-trained Ones

Given the predictions of user and system utterances:

\[
p_u(u_t | u_{<t}, s_{<t}) = \prod_{i=1}^{m_{ut}} P(w_i | w_{<i}, u_{<t}, s_{<t})
\]

\[
p_s(s_t | u_{\leq t}, s_{<t}) = \prod_{i=1}^{m_{st}} P(w_i | w_{<i}, u_{\leq t}, s_{<t})
\]

[Wu et al., arXive-19]
Given the predictions of user and system utterances:

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p_u(u_t | u_{<t}, s_{<t}) = \prod_{i=1}^{m_{ut}} P(w_i | w_{<i}, u_{<t}, s_{<t})
\]

\[
p_s(s_t | u_{\leq t}, s_{<t}) = \prod_{i=1}^{m_{st}} P(w_i | w_{<i}, u_{\leq t}, s_{<t})
\]

the final model is required to be good at predicting them both:

\[
p(d) = \prod_{t=1}^{T} p_u(u_t | u_{<t}, s_{<t}) p_s(s_t | u_{\leq t}, s_{<t})
\]

[Wu et al., arXive-19]
## Alternating Recurrent Dialog Model with Pre-trained Ones

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<th>Supervision Dialog Act</th>
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<th>Success (%)</th>
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<td>×</td>
<td>87.4</td>
<td>72.8</td>
<td>20.6</td>
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</table>

[Wu et al., arXive-19]
How are we doing in 2019?

DSTC8 - Multi-Domain Dialogue Task Completion
## Results analysis of DSTC8 - Automatic Evaluation

<table>
<thead>
<tr>
<th>Rank</th>
<th>Team Submission ID</th>
<th>Spec #</th>
<th>Success Rate</th>
<th>Return</th>
<th>Turns</th>
<th>F1</th>
<th>Book Rate</th>
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<td>0.93</td>
<td>93.75%</td>
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<td>6.69</td>
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</tr>
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<td>2.072</td>
<td>2.258</td>
<td>16.8</td>
</tr>
<tr>
<td>10</td>
<td>504502</td>
<td>submission2</td>
<td>23.30%</td>
<td>2.612</td>
<td>2.65</td>
<td>15.333</td>
</tr>
<tr>
<td>11</td>
<td>504524</td>
<td>submission1</td>
<td>18.81%</td>
<td>1.99</td>
<td>2.059</td>
<td>16.105</td>
</tr>
</tbody>
</table>
# Results analysis of DSTC8 - Human Evaluation

<table>
<thead>
<tr>
<th>Rank</th>
<th>Team Submission ID</th>
<th>Spec #</th>
<th>Success Rate</th>
<th>Language Under</th>
<th>Response Appro</th>
<th>Turns</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>504430</td>
<td>submission4</td>
<td>68.32%</td>
<td>4.149</td>
<td>4.287</td>
<td>19.507</td>
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<td>3.538</td>
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<tr>
<td>3</td>
<td>504563</td>
<td>submission2</td>
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<td>13.884</td>
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<td>9</td>
<td>504666</td>
<td>submission1</td>
<td>25.77%</td>
<td>2.072</td>
<td>2.258</td>
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<td>1.99</td>
<td>2.059</td>
<td>16.105</td>
</tr>
</tbody>
</table>

2. Shuman Liu, Hongshen Chen, Zhaochun Ren, Yang Feng, Qun Liu, Dawei Yin, Knowledge Diffusion for Neural Dialogue Generation.


5. Semantically Conditioned Dialog Response Generation via Hierarchical Disentangled Self-Attention, Wenhu Chen, Jianshu Chen, Pengda Qin, Xifeng Yan, William Yang Wang, ACL, 2019


7. Deal or No Deal? End-to-End Learning for Negotiation Dialogues., Mike Lewis, Denis Yarats, Yann Dauphin, Devi Parikh, Dhruv Batra, EMNLP 2017

to name a few.
Retrieval Based Dialogue
Dialogue as an information retrieval task

E2E systems need to:

1. encode the meaning
2. select the action or response
3. generate the response
Dialogue as an information retrieval task

E2E systems need to:

1. encode the meaning
2. select the action or response
3. generate the response

What if we skip the generation?
Retrieval based dialogue systems

Wang et al., 2013; Ji et al., 2014

1. Predefine a set of possible responses

2. Given the context, select one response from this set

**Input**

How affordable is that restaurant?

**Candidate Responses**

- No, it won't rain probably.
- Have you applied for that job yet?
- *The prices seem very reasonable.*
- We are leaving for a ski trip tomorrow.
- It is extremely easy to fix that.
## Retrieval VS Generation

<table>
<thead>
<tr>
<th>Generation</th>
<th>Retrieval</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Variable output</td>
<td>- Constrained by the list of candidate responses</td>
</tr>
<tr>
<td>- Prone to give short, general or irrelevant responses</td>
<td>- More informative, semantically relevant and controllable responses</td>
</tr>
<tr>
<td>- More difficult to train</td>
<td>- Easier to train</td>
</tr>
</tbody>
</table>
The retrieval based system explosion

Even if it was proposed only a few years ago, there has been a lot of interest on the topic...

Wang et al., 2013; Ji et al., 2014; Lowe et al., 2015, 2017; Al-Rfou et al., 2016; Henderson et al., 2017, 2019; Cer et al., 2018; Yang et al., 2018; Du and Black, 2018; Chaudhuri et al., 2018; Weston et al., 2018; Wu et al., 2018, 2017; Zhou et al., 2018; Zhang et al., 2018; El Amel Boussaha et al., 2019...
Neural response selection model

Score

Neural architecture

Context

Response
Neural response selection

Neural architecture

Score

- Maximise the Score of positive Context-Response pairs
- Minimise the score of negative Context-Response pairs

Context

Response
Neural response selection

Inference:
- Select the set of possible responses
- Rank the responses based on their score given the current context
Different neural architectures

- DNN pooling, RNN, CNN, Transformer…
- Single turn context, multiple turn context, extra dialogue features
- Dual encoder VS fully connected models
RNN dual encoder

Lowe et al. 2015, 2017
Universal Sentence Encoder USE

Cer et al., 2018; Yang et al., 2018
Multilingual USE

Chidambaram et al., 2019

![Diagram of Multilingual USE model with tasks](image-url)
Deep Attention Matching Network

Zhou et al., 2018
Enhanced Sequential Inference Model (ESIM)

Chen and Wang, 2019

Winner of DSTC7 Task 1 (Gunasekara et al. 2019)
Hybrid models

Weston et al., 2018; Pandey et al., 2018

Combine Retrieval and Generation dialogue models -> Get the best of both worlds
Industry examples

Gmail’s smart reply *(Henderson et al., 2017)*

Alibaba’s chatbot AliMe *(Qiu et al., 2017)*

Microsoft’s socialbot Xiaolce *(Shum et al., 2018)*
Evaluation

1-of-N accuracy:

how often the correct response is ranked top vs $N-1$ random responses
- Binary
  or
- Proportional to 1-of-N accuracy
  - The larger N, the better the loss
  - Some architectures can't handle large N
Dual encoder dot product models

Henderson et al., 2017, 2019; Cer et al., 2018; Yang et al., 2018

Fully connected models -> context and response embeddings conditional to each other

Dual encoder models -> context and response don’t interact until the dot product scoring
trained to give a high score for the response found in the data, low score for random responses

final score of an input and response is a dot-product of two vectors

\[ \text{scores} = \mathbf{x} \cdot \mathbf{Y} \]
network encodes a batch of inputs to vectors:

\[ x_1 \ x_2 \ \ldots \ \ x_N \]

and responses to vectors:

\[ y_1 \ y_2 \ \ldots \ \ y_N \]
the $N \times N$ matrix of all scores is a fast matrix product.

large improvement in 1 of 100 ranking accuracy over binary classification.
Precomputation for dot product model

the representations of the candidates $Y$ can be precomputed

approximate nearest neighbor search can speed up the top N search
PolyAI Encoder

Henderson et al., 2019
<table>
<thead>
<tr>
<th>Model Type</th>
<th>Method</th>
<th>Reddit 1-of-100 Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>keyword-based</td>
<td>TF-IDF</td>
<td>26.7%</td>
</tr>
<tr>
<td></td>
<td>BM25</td>
<td>27.6%</td>
</tr>
<tr>
<td>MAP dot product models</td>
<td>ELMo</td>
<td>19.3%</td>
</tr>
<tr>
<td></td>
<td>BERT</td>
<td>24.5%</td>
</tr>
<tr>
<td></td>
<td>USE</td>
<td>40.8%</td>
</tr>
<tr>
<td></td>
<td>USE_QA</td>
<td>46.3%</td>
</tr>
<tr>
<td></td>
<td>BERT dot-product model</td>
<td>55.0%</td>
</tr>
<tr>
<td>PolyAI Encoders</td>
<td>n-grams</td>
<td>61.3%</td>
</tr>
<tr>
<td></td>
<td>subwords</td>
<td>68.2%</td>
</tr>
</tbody>
</table>
resource-constrained optimization:
pick the best model after training 18 hours on 12 GPUs

- training costs under $100
- model runs fine on CPU
- final model is ~ 60MB
Contextual PolyAI encoder

The diagram illustrates the structure of a contextual PolyAI encoder. The encoder consists of multiple layers, including feed-forward layers and Transformer layers. The input is denoted as \( x \) and \( z \), with \( x \) being the immediate context and \( z \) being the concatenation of earlier contexts up to 10 back. The response is denoted as \( y \). The final score is calculated as the transpose of the concatenation of the hidden states of the input and response sequences, \( h_x^T h_y \).
Application to real world tasks
- Might be enough for social chatbots or small applications

- Task oriented dialogue systems still require explicit state representations to interact with external sources (databases, 3rd party apis...).
Is retrieval enough?

- Might be enough for social chatbots or small applications

- Task oriented dialogue systems still require explicit state representations to interact with external sources (databases, 3rd party APIs...)

- But there is a lot we can get from retrieval!
Unsupervised pretraining for NLU tasks
Unsupervised pretraining for NLP

(Peters et al., 2018; Devlin et al., 2019; Howard and Ruder, 2018; Radford et al., 2018; Lample and Conneau, 2019; Liu et al., 2019)

1. Pretrain a sentence encoder on large amounts of text data (unsupervised)
2. Finetune a classifier (or regressor) on task specific data (supervised)

- Models not trained on conversational data
- Trained (mostly) on a language model (LM) loss
- Models not evaluated on conversational tasks
<table>
<thead>
<tr>
<th>Language Modelling</th>
<th>Response Selection</th>
</tr>
</thead>
<tbody>
<tr>
<td>- large text datasets</td>
<td>- large conversational datasets</td>
</tr>
<tr>
<td>- representations encode word/phrase/sentence cues</td>
<td>- representations encode conversational cues</td>
</tr>
<tr>
<td>- encodes words contextually</td>
<td>- encodes full sentences</td>
</tr>
<tr>
<td>- maybe applicable to generation/scoring</td>
<td>- directly applicable to retrieval-based dialogue</td>
</tr>
</tbody>
</table>
Response selection models as sentence encoders

Pretraining on Reddit input-response pairs:
- dot product loss
- feed forward + norm
  - reduction
  - self att layer x 6
  - subword embeddings

Training on intent detection data:
- cross entropy loss
- trainable parameters
  - feed forward + softmax
  - reduction
  - self att layer x 6
- fixed parameters
  - reduction
  - self att layer x 6
  - subword embeddings

Input | Response | Input | Label (intent)
## Intent classification

<table>
<thead>
<tr>
<th>PolyAI Encoder</th>
<th>PolyAI QQ</th>
<th>PolyAI SVM</th>
<th>PolyAI MLP</th>
<th>USE QQ</th>
<th>USE FT</th>
<th>BERT FT</th>
<th>RASA FT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Banking</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>small</td>
<td>68.3%</td>
<td>83.1%</td>
<td>81.8%</td>
<td>67.3%</td>
<td>80.4%</td>
<td>80.4%</td>
<td>63.4%</td>
</tr>
<tr>
<td>medium</td>
<td>82.5%</td>
<td>91.0%</td>
<td>90.4%</td>
<td>83.8%</td>
<td>89.8%</td>
<td>90.9%</td>
<td>84.0%</td>
</tr>
<tr>
<td>large</td>
<td>87.7%</td>
<td>93.1%</td>
<td>92.7%</td>
<td>87.8%</td>
<td>92.2%</td>
<td>92.9%</td>
<td>89.2%</td>
</tr>
<tr>
<td>e-commerce</td>
<td>92.0%</td>
<td>94.1%</td>
<td>94.5%</td>
<td>90.5%</td>
<td>94.0%</td>
<td>94.4%</td>
<td>92.1%</td>
</tr>
<tr>
<td>company FAQ</td>
<td>63.8%</td>
<td>64.5%</td>
<td>64.5%</td>
<td>55.8%</td>
<td>62.4%</td>
<td><strong>65.0%</strong></td>
<td>55.4%</td>
</tr>
</tbody>
</table>
Few shot intent classification

% OF INTENTS ACCURATELY DETECTED

Low | Medium | High | All

NUMBER OF EXAMPLES

50% | 75% | 100%
## Costs and training time

<table>
<thead>
<tr>
<th>Model</th>
<th>Model size</th>
<th>Training time (approx)</th>
<th>Pre-training cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>PolyAI</td>
<td>64mb</td>
<td>3 minutes</td>
<td>$80</td>
</tr>
<tr>
<td>BERT Large</td>
<td>1.3gb</td>
<td>2 hours</td>
<td>$6912*</td>
</tr>
<tr>
<td>USE</td>
<td>362mb</td>
<td>3 minutes</td>
<td>Not shared</td>
</tr>
</tbody>
</table>
Few shot value extraction

- Learned Proposer
- Encoder Proposer

- F1 Score
- Number of Train Examples
task-based accuracy (no fine-tuning)

reddit 1-of-100
(progress over 3 weeks)
Entity Search
hello I am looking for a cheap place in the east
> inform(pricerange=cheap, area=east)

sure, what type of food?
> request(food)

I want gastropub food
> inform(food=gastropub)

there are no cheap places serving gastropub in the east.
> inform(name=none, area=east, pricerange=cheap)

how about any pricerange? and i need to know if they have wifi.
> inform(pricerange=don't care) request(has_wifi)

The King's Arms is a nice place in the east of town serving gastropub food. It has wifi.
> offer(name="The King's Arms", area=east, food=gastropub, has_wifi=true)
- explicit semantics forces unnaturally constrained dialogues
  users need to know the ontology

- requires special annotated data, one specialised model per 'slot'
- some slots are necessary
  number of people, booking time, name

- some might not be
  food, price range, has wifi, has vegetarian, has vegan, serves cocktails...
- use all sentences in all reviews of all restaurants in a city
- treat dialogue as an iterative search
- perform search in implicit vector space learned by encoders
Sushi Maru

- It is pretty authentic.
- The prices were affordable for good quality sushi.
- Excellent omakase.
- ... 

The King's Arms

- Lots of vegetarian options.
- The service was a little rushed.
- According to Yelp, they accept credit card.
- ...
i want a bar with good craft beer

BrewDog Edinburgh
Pubs, Bars, Pizza, Gastropubs, Burgers, Nightlife

“Serve good craft beer.”

The Beer Kitchen By Innis & Gunn
Breakfast & Brunch, Seafood, Bars, Nightlife

“Large beer selection and a fun looking bar.”
Other thoughts
NLU is the “bottleneck”

- As the 1st part of the dialogue pipeline, NLU determines the scope of your dialogue system

- State of the art NLU performance constrains systems to a small scope

- Rule-based policies and template-based NLG are totally tractable given the scope that NLU permits
Traditionally, dialogue states lie in a discrete space -> no similarity between states -> RL takes ages to learn

Context encodings are technically dialogue state embeddings in a continuous space
1. Over-sample a set of answers through template based NLG

2. Select the most appropriate answer through ranking
Conclusions
We started truly experimenting with pre-training for dialogue only in last two years.

The results obtained already show a great promise both for:
1) E2E systems [Budzianowski et al. WNGT-19, Wu et al., arXiv-19] and
2) response-selection systems [Humeau et al., arXiv-19, Henderson et al., ACL-19;]

The pre-training paradigm allows to focus on collection of high-quality and challenging datasets.
Progress in building task-oriented dialogue systems is greatly hindered by the lack of large-scale corpora.

Recent two years provided us with many new datasets. [Budzianowski et al., EMNLP-18; Wu et al., EMNLP-18; Rastogi et al., AAAI-19; Henderson et al., arXive-19]
But we are still not sure what collection pipelines are of best use.

Thanks to the progress in transfer learning, we do not have to worry as much as we used to about the ultimate size of datasets.

But the problem of the right fit and usability of the data in industrial applications is still not properly challenged.
...yet, dialogue datasets for other languages are only few and far between…

- WOZ 2.0 in German and Italian [Mrkšić et al., TACL-17]
- CDSC in Chinese [Li et al., IJCNLP-17]
- English, Spanish and Thai utterances across the domains weather, alarm, and reminder [Schuster et al., 2018]
- Multi2WOZ across diverse languages (WIP)
Thank you!
Many many thanks to Tsung-Hsien Wen, Vivian Chen, Matthew Henderson, Dilek Hakkani-Tür, Asli Celikyilmaz, Pararth Shah, Abhinav Rastogi, Milica Gašić, Lihong Li, Ankur Bapna, Gokhan Tür, and others for sharing their amazing slides!