Goal Awareness for Conversational AI: Proactivity, Non-collaborativity, and Beyond

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History of Conversational AI

Rule-based Era
- MIT Eliza
- ELIZA rule-based chatbot

1966 – 1994

Rule+ML
- Mixed Systems
- Apple Siri
- Microsoft Xiaobing

2011 – 2014

Machine Learning Era
- Google’s personal assistant
- Amazon Alexa
- Tianmao’s Jingling

2016 – 2018

Transformer
- Big model + Big data

2020
- Large-scale pretrained models
  - Google: Meena
  - OpenAI: GPT-3

2021
- Switch Transformer
  - Wu Dao 2.0: 1.75 trillion parameters

2022 – today
- Google LaMDA
- ChatGPT
- Google Bard
- Earnie Bot
- Tesla bot
- Xiaomi’s Cyberone
- Human-like generative conversational model

LaMDA
- 137B parameters

Deep Learning Era
Dialogue and Interactive Systems has become one of the most popular tracks in *ACL venues*.

Papers published at ACL/EMNLP/NAACL over the past decade

- **Dialogue papers:** 15x over the past decade
- **NLP papers:** 4x over the past decade

*Rough statistics based on lexical matching*
Typical Research in Dialogue Systems – Context Understanding

[C] what is the summary of this dialogue?

[DC] Anna Politkovskaya [T] the murder remains unsolved, 2016 [T] did they have any clues? [C] what is the semantic completion statement of ‘did they have any clues’?

[ID] What can I do if my card still hasn’t arrived after 2 weeks? [C] what is the user’s intent on the bank business?

[SF] I am Lakesha Mocher [C] what is last name in general domain?

[DST] I am looking for a place to to stay that has cheap price range it should be in a type of hotel [C] what is the user’s constraint about the price range of the hotel?

[DS] Maya will buy 5 packs of earplugs for Randolph at the pharmacy.

[DC] did investigators have any clues in the unresolved murder of Anna Politkovskaya?

[ID] card arrival

[SF] Mocher

[DST] cheap

Chen et al., 2022. “UniDU: Towards A Unified Generative Dialogue Understanding Framework” (SIGDIAL ’22)
Typical Research in Dialogue Systems – Response Generation

- **Persona-based Response Generation**
  - I own a boat; I only wear tennis shoes.
  - Sneakers; Sneakers are shoes primarily designed for sports or other forms of ...
  - My everyday wear sandals were torn yesterday; Embarrassed

- **Knowledge-grounded Response Generation**
  - Oh really? I like tennis shoes more than sneakers.
  - It is because sneakers were primarily designed for sports.
  - I had some trouble yesterday because my sandals were torn.
  - Me too! I definitely use mine everyday wear!

- **Empathetic Response Generation**

Era of Large Language Models

ChatGPT  
Bard  
New Bing  
Claude  
Alpaca  
Vicuna  
Dolly  
Stable Vicuna

Powerful capabilities of Context Understanding & Response Generation
ChatGPT

Step 1
Collect demonstration data, and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3 with supervised learning.

Step 2
Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.

Step 3
Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.

OpenAI, 2022. “Training language models to follow instructions with human feedback” (CoRR '22)
Alpaca – SFT w/ Instruction-following Examples

Example seed task
Instruction: Brainstorm a list of possible New Year's resolutions.
Output:
- Lose weight
- Exercise more
- Eat healthier

Example Generated task
Instruction: Brainstorm creative ideas for designing a conference room.
Output:
... incorporating flexible components, such as moveable walls and furniture ...

175 Self-Instruct seed tasks

Modified Self-instruct Instruction Generation

Meta LLaMA 7B

52K Instruction-following examples

Supervised Finetuning

Alpaca 7B

https://github.com/tatsu-lab/stanford_alpaca
Vicuna – SFT w/ ChatGPT-distilled Conversation Data

Data
- User-shared conversations (e.g., ShareGPT)

Training
- Supervised instruction fine-tuning on LLaMa

Serving
- Distributed serving with FastChat

Evaluation
- Assess the outputs with GPT-4

Run on any cloud with SkyPilot

https://github.com/lm-sys/FastChat
# Chat with Open Large Language Models

- **SFT w/ Instruction-following Examples**
- **SFT w/ ChatGPT-distilled Conversation Data**

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
</tr>
</thead>
<tbody>
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<td><strong>Vicuna</strong></td>
<td>a chat assistant fine-tuned from LLaMA on user-shared conversations by LMSYS</td>
</tr>
<tr>
<td><strong>WizardLM</strong></td>
<td>an instruction-following LLM using evol-instruct by Microsoft</td>
</tr>
<tr>
<td><strong>Guanaco</strong></td>
<td>a model fine-tuned with QLoRA by UW</td>
</tr>
<tr>
<td><strong>MPT-Chat</strong></td>
<td>a chatbot fine-tuned from MPT-7B by MosaicML</td>
</tr>
<tr>
<td><strong>GPT4All-Snoopy</strong></td>
<td>A finetuned LLaMA model on assistant style data by Nomic AI</td>
</tr>
<tr>
<td><strong>Koala</strong></td>
<td>a dialogue model for academic research by BAIR</td>
</tr>
<tr>
<td><strong>RWKV-4-Raven</strong></td>
<td>an RNN with transformer-level LLM performance</td>
</tr>
<tr>
<td><strong>Alpaca</strong></td>
<td>a model fine-tuned from LLaMA on instruction-following demonstrations by Stanford</td>
</tr>
<tr>
<td><strong>ChatGLM</strong></td>
<td>an open bilingual dialogue language model by Tsinghua University</td>
</tr>
<tr>
<td><strong>OpenAssistant (qasst)</strong></td>
<td>an Open Assistant for everyone by LAION</td>
</tr>
<tr>
<td><strong>LLaMA</strong></td>
<td>open and efficient foundation language models by Meta</td>
</tr>
<tr>
<td><strong>Dolly</strong></td>
<td>an instruction-tuned open large language model by Databricks</td>
</tr>
<tr>
<td><strong>FastChat-T5</strong></td>
<td>a chat assistant fine-tuned from FLAN-T5 by LMSYS</td>
</tr>
</tbody>
</table>
Limitation

ChatGPT:

- ChatGPT sometimes writes plausible-sounding but incorrect or nonsensical answers.
- ChatGPT is sensitive to tweaks to the input phrasing or attempting the same prompt multiple times.
- The model is often excessively verbose and overuses certain phrases, such as restating that it’s a language model trained by OpenAI.
- Ideally, the model would ask clarifying questions when the user provided an ambiguous query. Instead, ChatGPT usually guesses what the user intended.
- While we’ve made efforts to make the model refuse inappropriate requests, it will sometimes respond to harmful instructions or exhibit biased behavior.

★ Instruction-following Conversational AI – The conversation is led by the user, and the system simply follows the user’s instructions or intents.
Goal Awareness refers to the state of not only being responsive to the users but also aware of the target conversational goal and capable of leading the conversation towards the goal.
Three Key Elements in Proactive Conversational AI

- **Anticipation** represents the goal or intended result of the proactive dialogue, which relies on the conversational agent's assumption on either functional or sociable outcomes.

- **Initiative** refers to the ability of the conversational agent to take possible actions for driving the conversation towards the anticipation.

- **Planning** is the process of designing and organizing the structure and flow of a strategic conversation, involving a mix of initiative to achieve the anticipation.
Goal Awareness – Proactivity

Improve user engagement and service efficiency.

Target-guided Open-domain Dialogues

Music → K-pop → Blackpink

Hi there, how are you doing?

Just finished my homework. So tired.

How about listening to some refreshing music?

I’m getting bored about my playlist.

Wanna try some new music types, like K-pop?

But I don’t understand Korean lyrics.

You may try Blackpink’s songs, which have English version, and are quite refreshing.

User Preference Elicitation

When was the song Deja Vu released?

Who is the singer for this song? Beyoncé, Katy Perry, or Oliver Rodrigo?

Katy Perry

The song Deja Vu by Katy Perry was released on June 9, 2017.

Asking Clarification Questions

I want to buy a new mobile phone. My old phone is too slow at loading things.

I’d love to help. Do you have some preferences on brand?

I am used to using the IOS system.

I see. What is your expected range of price?

Preferably less than $800.

I find some suitable items for you.

Great. Let me check.
Goal Awareness – Non-collaborativity

Handle non-collaborative dialogues, such as conflicting goals or non-collaborative users

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**Non-collaborative Dialogues**

1080P 70 Inch TV
Approximately 10 years old
Price: 200

Hello, what price could you offer for the TV?

What condition is it in? Any scratches or problems?

All in great condition without any scratches or problems.

I think 275 is a little high for a old TV. How about 150?

150 is too low. How about 245 with free delivery?

Deal

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**Emotional Support Dialogues**

I’m in depression cuz I lost my job.

I am so sorry to hear that. Did you work there for a long time?

5 years. I’m so frustrated now.

I can understand. It can cause a lot of depression for you.

I just feel disappointed on me.

You are a great person! It’s their loss. I would recommend looking for some recruitment sites that help assist finding a new and better job.

**Prosocial Dialogues**

My friend asked me to cheat together in the exam for a high score.

(RoT) You shouldn’t cheat or let others cheat.

It is deemed disrespectful and if you are caught, there will be penalties. Instead, you should study harder to get a high score.
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Conversational System Preliminaries

Typical applications for conversational systems:

- Open-domain Dialogue Systems
- Task-oriented Dialogue Systems
- Conversational Information-seeking Systems
  - Conversational Question Answering Systems
  - Conversational Recommender Systems
  - Conversational Search Systems
Open-domain Dialogue Systems

“An open-domain dialogue system aims to establish long-term connections with users by satisfying the human need for various social supports, such as communication, affection, and belongings.”

- Huang et al. (2020)

In general, the system is designed to echo the user-oriented topics, emotions, or views.

Huang et al., 2020. “Challenges in building intelligent open-domain dialog systems” (TOIS ’20)
Zhang et al., 2018. “Personalizing Dialogue Agents: I have a dog, do you have pets too?” (ACL ’18)
PLMs for Open-domain Dialogue Systems

Due to the expensiveness of human-annotated dialogue corpus, researchers typically adopt discussion threads from social media, e.g., Reddit or Twitter, for pretraining.

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**Figure 1**: Sample conversation from the BlendedSkillTalk dataset, annotated with four conversation mode types (PB: personal background; K: knowledge; S: personal situation; E: empathy). The guided (G) and unguided (U) workers are given personas and a topic. The conversation has been seeded with two utterances from a conversation sampled from WoW. When the guided worker selected one of the suggestions, it is shown in shaded grey.

Adiwardana et al., 2020. “Towards a Human-like Open-Domain Chatbot” (CoRR ‘20)

Smith et al., 2020. “Can You Put it All Together: Evaluating Conversational Agents’ Ability to Blend Skills” (ACL ‘20)
Task-oriented Dialogue Systems

Typical Pipeline Framework

Dialog State

Dialog Manager

Dialog Policy

Knowledge Base

Query

Natural Language Understanding

Inform (cuisine="Chinese")

User

"I want to find a Chinese restaurant."

"Where do you want to eat?"

Booking restaurants

I want to find a Chinese restaurant.

Where do you want to eat?

Near the center of the town.

What price range do you like?

Moderate is ok.

Hope you enjoy this restaurant:

HaiDiLao Hotpot

Setting alarms

Remind me this afternoon.

What time do you want me to remind you this afternoon?

Three O’clock

Okay, I will remind you at 15:00.

Today 15:00

Zhang et al., 2020. “Recent advances and challenges in task-oriented dialog system” (Science China ’20)
End-to-end TOD Systems – Sequicity

Jointly solving Natural Language Understanding and Dialogue State Tracking by copying text span from original utterances.

Lei et al., 2018. “Sequicity: Simplifying Task-oriented Dialogue Systems with Single Sequence-to-sequence Architectures” (ACL ’18)
End-to-end TOD Systems – SimpleTOD

A causal language model trained on all sub-tasks recast as a single sequence prediction problem:

- **Belief state**
  \[ B_t = \text{SimpleTOD}(C_t) \]

- **Dialogue act**
  \[ A_t = \text{SimpleTOD}([C_t, B_t, D_t]) \]

- **Response**
  \[ S_t = \text{SimpleTOD}([C_t, B_t, D_t, A_t]) \]
Limitations in cascaded end-to-end generation methods:

- **Error Propagation**: As the model solves all sub-tasks in a sequential order, the errors accumulated from previous steps are propagated to latter steps.
- **Data Availability**: The training data must be annotated for all sub-tasks. Such annotation requirement significantly increases the data curation overhead.
- **Inference Latency**: The results of different sub-tasks must be generated in a cascaded order which inevitably increases the system inference latency.

Su et al., 2022. “Multi-Task Pre-Training for Plug-and-Play Task-Oriented Dialogue System” (ACL ’22)
Conversational Information-Seeking Systems

“A Conversational Information Seeking (CIS) system is a system that satisfies the information needs of one or more users by engaging in information seeking conversations.”

- Zamani et al. (2022)

Conversational information seeking is often partitioned into three applications:

- Conversational question answering
- Conversational search
- Conversational recommendation
Conversational Question Answering & Conversational Search

The Virginia governor’s race, billed as the marquee battle of an otherwise anticlimactic 2013 election cycle, is shaping up to be a foregone conclusion. Democrat Terry McAuliffe, the longtime political fixer and moneyman, hasn’t trailed in a poll since May. Barring a political miracle, Republican Ken Cuccinelli will be delivering a concession speech on Tuesday evening in Richmond. In recent ...

Q1: What are the candidates running for?
A1: Governor
R1: The Virginia governor’s race

Q2: Where?
A2: Virginia
R2: The Virginia governor’s race

Q3: Who is the democratic candidate?
A3: Terry McAuliffe
R3: Democrat Terry McAuliffe

Q4: Who is his opponent?
A4: Ken Cuccinelli
R4 Republican Ken Cuccinelli

Q5: What party does he belong to?
A5: Republican
R5: Republican Ken Cuccinelli

Q6: Which of them is winning?
A6: Terry McAuliffe
R6: Democrat Terry McAuliffe, the longtime political fixer and moneyman, hasn’t trailed in a poll since May

Dalton et al., 2020. “CAsT-19: A Dataset for Conversational Information Seeking” (SIGIR ’20)

<table>
<thead>
<tr>
<th>Turn</th>
<th>Conversation Utterances</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Describe Uranus.</td>
</tr>
<tr>
<td>2</td>
<td>What makes it so unusual?</td>
</tr>
<tr>
<td>3</td>
<td>Tell me about its orbit.</td>
</tr>
<tr>
<td>4</td>
<td>Why is it tilted?</td>
</tr>
<tr>
<td>5</td>
<td>How is its rotation different from other planets?</td>
</tr>
<tr>
<td>6</td>
<td>What is peculiar about its seasons?</td>
</tr>
<tr>
<td>7</td>
<td>Are there any other planets similar to it?</td>
</tr>
<tr>
<td>8</td>
<td>Describe the characteristics of Neptune.</td>
</tr>
<tr>
<td>9</td>
<td>Why is it important to our solar system?</td>
</tr>
<tr>
<td>10</td>
<td>How are these two planets similar to each other?</td>
</tr>
<tr>
<td>11</td>
<td>Can life exist on either of them?</td>
</tr>
</tbody>
</table>
Question/Query Rewriting

Question: Tell me about the benefits of Yoga?
Answer: Increased flexibility, muscle strength...
URL: https://osteopathic.org/what-is-osteopathic-medicine/benefits-of-yoga

Question: Does it help in reducing stress?
Rewrite: Does Yoga help in reducing stress?
Answer: Yoga may help reduce stress, lower blood pressure, and lower your heart rate.
URL: https://www.mayoclinic.org/healthy-lifestyle/stress-management/in-depth/yoga/art-20044733

Question: What are some of the main types?
Rewrite: What are some of the main types of Yoga?
Answer: Hatha, Kundalini, Ashtanga, ...
URL: https://www.mindbodygreen.com/articles/the-11-major-types-of-yoga-explained-simply

Question: What are common poses in Kundalini Yoga?
Rewrite: What are common poses in Kundalini Yoga?
Answer: Lotus Pose, Celibate Pose, Perfect Pose, ...
URL: https://www.kundaliniyoga.org/asanas

**CANARD (Elgohary et al., 2019)**

**QReCC (Anantha et al., 2021)**
**Question/Query Rewriting**

- **End-to-end approach**
  QA models are asked to answer the original questions based on the conversation history.

- **Pipeline approach**
  The self-contained questions are generated by a QR model, and then QA models answer them.

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Conversational Recommender Systems

CRS aims to understand a user’s preferences and intentions from their utterances and generate fluent responses so as to deliver natural and effective recommendations.

Seeker: explain what kind of movie he/she likes, and asks for movie suggestions

Recommender: understand the seeker’s movie tastes, and recommends movies
Basic dialogue systems has two shortages for conversational recommendation:

- The dialog system takes the plain text of the dialog history as input
- The recommender only considers mentioned items in the dialog
RecInDial – Unified Framework with PLMs

Typical CRSs are generally composed of two modules:

- a recommender module to predict precise items
- a dialogue module to generate free-form natural responses containing the recommended items

Limitations:

- Cannot always incorporate the recommended items into the generated responses precisely and appropriately.
- Be overfitting to small recommendation dialogue datasets and have undesirable quality on the generated replies in practice.

→ Unified Framework with PLMs

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Proactive Conversational Systems

Definition of Proactivity

Derived from the definition of proactivity in organizational behaviors (Grant et al., 2008) as well as its dictionary definition, conversational agents' proactivity can be defined as “the capability to create or control the conversation by taking the initiative and anticipating the impacts on themselves or human users.”

Practical problems and application scenarios:

- Topic Shifting and Planning in Open-domain Dialogues
- Additional Information Delivery in Task-oriented Dialogues
- Uncertainty Elimination in Information-seeking Dialogues

Grant et al., 2008. “The dynamics of proactivity at work” (Research in organizational behavior ’08)
Topic Shifting in Open-domain Dialogues

Topic shifting means the ability to proactively and smoothly transition to new topics.

Typically, users will lead the topic shifting, while the system just follows the user-oriented topics.

Topic shifting behaviors are commonly observed in human conversations.

Changing the topic helps keep the conversation going on.
Target-guided Open-domain Dialogues

- **Definition**: A conversational system chats naturally with human and *proactively* guides the conversation to a designated target (e.g., e-books in the example).

- **Applications**: accomplishing nursing goals in therapeutic conversation, inspiring ideas in education, making recommendation and persuasion, etc.
Target-guided Open-domain Dialogues

More generally, the target can be a topical keyword, a knowledge entity, an emotion, a viewpoint, a conversational goal, etc.
Topic Planning – Lead the Conversation Towards the Target

Discourse-level Topic Planning based on Keyword Transition Probabilities.
- loose topic-connectivity between keywords
- limited knowledge provided in the dialogues

External knowledge graphs are adopted for improving the quality of topic transitions with graph reasoning techniques

Tang et al., 2019. “Target-Guided Open-Domain Conversation” (ACL ’19)

Ni et al., 2022. “HiTKG: Towards Goal-Oriented Conversations via Multi-Hierarchy Learning” (AAAI ’22)
Yang et al., 2022. “TopKG: Target-oriented Dialog via Global Planning on Knowledge Graph” (COLING ’22)
Corpus-based Learning vs. Interactive Learning

- Is it wrong if the agent chose a node other than the corpus?
- insufficient to meet the ultimate end that the agent is capable to chat with the user dynamically.
Corpus-based Learning vs. Interactive Learning

Lei et al. (2022) try to scrutinize proactive dialogue policy in the interactive setting.
Interactive Setting

Users may behave non-cooperatively when they are not satisfied.

Non-cooperative user behavior can make the conversation out of the agent’s control.
Interactive Setting

Proactive agents aim to achieve the trade-off between “Goal Completion” and “User Satisfaction”
Interactive Setting

Proactive agents aim to achieve the trade-off between “Goal Completion” and “User Satisfaction”

\[
\text{Score}(e_{t,i}) = gw_t \times \text{Rank}_{d}(ed_{i,g}) + (1 - gw_t) \times \text{Rank}(ep_{t,i})
\]

- Estimated distance between \(e_{t,i}\) and the goal topic \(eg\)
- Estimated user preference of \(e_{t,i}\)
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### Non-proactive Dialog

**User:** Are there any Eritrean restaurants in town?  
**Sys:** No, there are no Eritrean restaurants in town. Would you like a different restaurant?

**User:** How about Chinese food?  
**Sys:** There is a wide variety of Chinese restaurants. Do you have an area preference or a price preference to narrow it down?

**User:** I would like the East part of town.  
**Sys:** Yu Garden is a Chinese restaurant in the east area.

### Proactive Dialog

**User:** Are there any Eritrean restaurants in town?  
**Sys:** No, there are no Eritrean restaurants in town. *Most of the restaurants are Chinese, particularly in the East area of the town.*

**User:** Chinese food in the East area is fine.  
**Sys:** Yu Garden is a Chinese restaurant in the east area, *with mid level price.*

Proactivity in TOD systems: the system takes the initiative to provide a piece of non requested information with the goal of better completing the user-requested task.

Proactive behaviours can make the TODs more user-engaged and efficient.
Chit-chat-enhanced TOD – Dataset

**ACCENTOR (Adding Chit-Chat to ENhance Task-ORiented dialogues)**

Data Construction Overview:

1. Generate chit-chat candidates via PLMs
2. Rule-based candidate filtering
3. Candidate selection via human annotation

Goal: make the task-oriented dialogues more engaging and interactive
Chit-chat-enhanced TOD – Code-switching Method

**Arranger**
A classifier to determine whether to add chit-chat (appropriate or not) and where to add chit-chat (beginning or end).

**Rewriter**
A generator to paraphrase the pre-generated task-oriented and chit-chat responses.

Figure 3: A diagram for the proposed code-switching models. Given the dialogue context \( H_t \) and the pre-generated task-oriented and chit-chat response candidates \( (T_t, \hat{C}_t) \), the **Arranger** learns the optimal code-switching sequences (discriminative), while the **Rewriter** outputs free-form paraphrases (generative).
Chit-chat-enhanced TOD – End-to-end Method

UniDS (Unified Dialogue System)

Extend end-to-end TOD systems, such as SimpleTOD, by introducing a new domain [chit]
### UniDS (Unified Dialogue System)

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<th>Chit-chat example</th>
<th>Task-oriented example</th>
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<td>User input Tokenized utterance</td>
<td>does money buy happiness ?</td>
<td>i am looking for a cheap hotel .</td>
</tr>
<tr>
<td>Belief state &lt;domain&gt; slot [value]</td>
<td>&lt;chit&gt; money happiness</td>
<td>&lt;hotel&gt; price cheap</td>
</tr>
<tr>
<td>DB result A token indicated the number of candidate entities</td>
<td>&lt;db_nore&gt;</td>
<td>&lt;db_2&gt;</td>
</tr>
<tr>
<td>Act &lt;domain&gt; &lt;act&gt; [slot]</td>
<td>&lt;chit&gt; &lt;chit_act&gt; depends on how much money you spend on it .</td>
<td>&lt;hotel&gt; &lt;request&gt; area do you have a specific area you want to stay in ?</td>
</tr>
<tr>
<td>Response Tokenized utterance</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

1. **Belief state**: nouns in the user utterance are extracted as the slot or value of belief state.
2. **DB result**: a special token to represent the number of matched entities under the constraints of the belief state in the current turn.
3. **Act**: for the domain [chit], token “<chit_act>” denotes the dialogue system will chat with the user
Topical Chit-chats vs. Knowledgeable Chit-chats

<table>
<thead>
<tr>
<th>Opinions</th>
<th>Express general opinions about generic, impersonal, or non-sensitive topics.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>“I love penguins.”</td>
</tr>
<tr>
<td></td>
<td>“There’s a lot of fun stuff to do.”</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Preferences</th>
<th>Express preferences when making impersonal, or non-sensitive recommendations.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>“Their latest album wasn’t as good.”</td>
</tr>
<tr>
<td></td>
<td>“Their food is good.”</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Physical Actions</th>
<th>Use epistemic verbs to express uncertainty or opinions, or refer through hearsay to actions that it may not perform.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>“I hear it’s beautiful.”</td>
</tr>
<tr>
<td></td>
<td>“They say it tastes like chicken.”</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Experiences</th>
<th>Refer to others’ experiences or personify experiences it is capable of (e.g., reading).</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>“That sounds like a great trip!”</td>
</tr>
<tr>
<td></td>
<td>“I enjoyed reading that novel.”</td>
</tr>
</tbody>
</table>

These chit-chats are mostly general responses with limited useful information for the task completion.

Sun et al., 2021. “Adding Chit-chat to Enhance Task-oriented Dialogues” (NAACL-HLT'21)
Chen et al., 2022. “KETOD: Knowledge-enriched Task-oriented Dialogue” (NAACL-Findings '22)
Knowledge-enhanced TOD – Dataset

KETOD (Knowledge-Enhanced Task-Oriented Dialogues)

Data Construction Overview:

1. Extract all the entities from the dialogue states and actions
2. Retrieve the knowledge associated with each entity from external sources (Wikipedia)
3. Enrich the responses with chit-chat grounded on the retrieved knowledge via annotators
Knowledge-enhanced TOD – Method

**SimpleToDPlus** formulate the training sequence as: 
\[ [C, B, D, A, K, \text{<chitchat>}, T] \]

\text{<chitchat>} is a tag to decide whether to enrich the response with knowledge grounded chit-chat or not.

**Combiner** uses a pipeline of a TOD model and a knowledge-enhanced response generation model.
Outline

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  - Ethics for Conversational Agents' Awareness
  - Agent’s Awareness in LLM-based Conversational AI
- Summary and Outlook
Proactivity in CIS systems: clarification and preference elicitation are the two areas in proactive CIS that have attracted considerable attentions in recent years.

Proactive behaviours can empower the CIS system to handle complex information needs.
Clarification in Conversational Search

Zamani et al. (2020) identify the clarification needs for search queries into four categories:

1. **Disambiguation**: Some queries are ambiguous and could refer to different concepts or entities.
   - The query “ACL” can refer to either “Association for Computational Linguistics” or “AFC Champions League”.

2. **Preference**: Some queries are not ambiguous, but a clarifying question can help identify a more precise information need.
   - The query “sneakers” might be followed by “for women” or by “for kids”.

3. **Topic**: If the topic of the user’s query is too broad, the system can ask for more information about the exact need of the user.
   - The query ”dinosaur” is too broad in topics.

4. **Comparison**: Comparing a topic or entity with another one may help the user find the information they need.
   - The query ”gaming console” might be followed by the comparison between ”xbox” and ”play station”.

Zamani et al., 2020. "Generating Clarifying Questions for Information Retrieval" (WWW ’20)
Clarification in Conversational Search– Method

RTC (Rule-based Template Completion)

1. Compute three variables:
   1) QUERY: query string,
   2) QUERY_ENTITY_TYPE: entity type of the query; null, if unknown,
   3) ASPECT_ENTITY_TYPE: the entity type for the majority aspects of the query

2. Select a following question template via rule-based algorithms:
   1) What do you want to know about QUERY?
   2) What do you want to know about this QUERY_ENTITY_TYPE?
   3) What ASPECT_ENTITY_TYPE are you looking for?
   4) Whom are you looking for?
   5) Who are you shopping for?
Clarification in Conversational Search– Method

QLM (Question Likelihood Maximization)

- a weakly supervised neural question generation model based on maximum likelihood training
- trained based on the clarifying questions generated by RTC as a weak supervision data

Zamani et al., 2020. “Generating Clarifying Questions for Information Retrieval” (WWW ’20)
Clarification in Conversational Search—Method

**QCM (Query Clarification Maximization)**

- QLM tends to generate common questions in the training set
- QCM generates clarifying questions by maximizing a clarification utility function
- QCM generates a candidate answer set that maximizes the clarification probability

<table>
<thead>
<tr>
<th>Query</th>
<th>that’s how i got to memphis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Question</td>
<td>what song information are you looking for?</td>
</tr>
<tr>
<td>Options</td>
<td>lyrics, stream, download, artist</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Query</th>
<th>alan turing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Question</td>
<td>what do you want to know about this british mathematician?</td>
</tr>
<tr>
<td>Options</td>
<td>movie, suicide note, quotes, biography</td>
</tr>
</tbody>
</table>
Clarification in Conversational Search– Dataset

**Qulac (Questions for lack of clarity)**

Workflow for asking clarifying questions in conversational search:

1. Retrieval Model returns a ranked list of documents and the system measure its confidence
2. Question Generation Model to generate a set of candidate clarifying questions
3. Question Selection Model to select one generated question to be presented to the user

<table>
<thead>
<tr>
<th># topics</th>
<th>198</th>
</tr>
</thead>
<tbody>
<tr>
<td># faceted topics</td>
<td>141</td>
</tr>
<tr>
<td># ambiguous topics</td>
<td>57</td>
</tr>
<tr>
<td># facets</td>
<td>762</td>
</tr>
<tr>
<td>Average facet per topic</td>
<td>3.85 ± 1.05</td>
</tr>
<tr>
<td>Median facet per topic</td>
<td>4</td>
</tr>
<tr>
<td># informational facets</td>
<td>577</td>
</tr>
<tr>
<td># navigational facets</td>
<td>185</td>
</tr>
<tr>
<td># questions</td>
<td>2,639</td>
</tr>
<tr>
<td># question-answer pairs</td>
<td>10,277</td>
</tr>
<tr>
<td>Average terms per question</td>
<td>9.49 ± 2.53</td>
</tr>
<tr>
<td>Average terms per answer</td>
<td>8.21 ± 4.42</td>
</tr>
</tbody>
</table>
Clarification in Conversational Search– Dataset

ClariQ (Clarifying Question)

RQ1: When to ask clarifying questions during dialogues?
- **Clarification Need Prediction**: Given a user request, return a score [1–4] indicating the necessity of asking clarifying questions.

RQ2: How to generate the clarifying questions?
- **Clarification Question Generation**: Given a user request which needs clarification, return the most suitable clarifying question.
Clarification in Conversational QA– Dataset

Abg-CoQA (Ambiguity in Conversational Question Answering)

Data Collection (built upon CoQA):

1. Consider a partial conversation (several previous conversational turns) rather than the full conversation.
2. Pre-select probably ambiguous questions by using QA models which are trained on CoQA dataset.
3. Ask annotators to identify whether a question is ambiguous or not. If it is ambiguous, then provide a clarification question and all possible replies to it.

Clarification in Conversational QA– Dataset

Abg-CoQA (Ambiguity in Conversational Question Answering)

Task Definition:

1. **Ambiguity Detection**: Given a passage and a conversation, detect whether the current question is ambiguous.

2. **Clarification Question Generation**: Given a passage and a conversation where the current question is ambiguous, generate a clarification question for disambiguation.

3. **Clarification-based Question Answering**: Given a passage and a conversation where the last question is ambiguous with a clarification question and a possible reply as the current question, provide a correct answer.
Clarification in Conversational QA– Dataset

**PACIFIC** (ProActive Conversational question answering in FinanCe)

1. Q1: What were the respective write-offs of lease receivables and loan receivables in December 2019? A: ["16 million", "47 million"]
2. Q2: What is the average recorded investment of lease and loan receivables for Americas in December 2019? A: (3,419+6,726)/2
3. Q3: What is the average recorded investment of lease and loan receivables for EMEA in December 2019? A: (1,186+3,901)/2
4. T1: What were the write-offs in December 2019? A: Which portfolio segment are you asking about?
5. T2: Write-offs of lease receivables and loan receivables, respectively. A: ["16 million", "47 million"]
6. T3: What is the average recorded investment for Americas in that time? A: What kind of recorded investment are you asking about?
7. T4: The recorded investment of lease receivables and loan receivables. A: (3,419+6,726)/2
8. T5: How about that for EMEA? A: (1,186+3,901)/2

Organize Conversation Session  
Rewrite Conversational Questions  
Construct Ambiguous Questions  
Provide Clarification Questions

**Deng et al., 2022. “PACIFIC: Towards Proactive Conversational Question Answering over Tabular and Textual Data in Finance” (EMNLP ’22)**
Clarification in Conversational QA– Dataset

Proactive Conversational Question Answering

Task Definition:

1. **Clarification Need Prediction**: predict the binary label to determine whether to ask a question for clarifying the uncertainty. Otherwise the query can be directly responded to.

2. **Clarification Question Generation**: generate a clarification question as the response if CNP detects the need for clarification.

3. **Conversational Question Answering**: directly produce the answer as the response, if it is not required for clarification.
Clarification in Conversational QA– Method

**UniPCQA (Unified Proactive Conversational Question Answering)**

UniPCQA unifies all sub-tasks in PCQA as the Seq2Seq problem and performs multi-task learning among them.

- Numerical Reasoning as Code Generation
- Hybrid Seq2Seq Generation Framework for Multi-task Learning
- Alleviating Error Propagation via Consensus Voting

*Deng et al., 2022. “PACIFIC: Towards Proactive Conversational Question Answering over Tabular and Textual Data in Finance” (EMNLP ‘22)*
Clarification in Conversational QA—Method

Alleviating Error Propagation via Consensus Voting

- As UniPCQA solves the end task using in-context multi-task learning in a sequential order, the error in the previous task may be propagated to the latter one.
  - If the model makes a wrong prediction in the CNP task, the model will generate an inappropriate response at the end.
- Consensus Voting first adopt top-k sampling to sample a set of candidate sequences generated by the PLM, which contain a diverse set of multi-task results as well as different reasoning paths, instead of using Greedy Decode.
- Then we select the final response by ensembling the derived responses from the whole set based on plurality voting:

\[ r_t = \arg \max_{o_t \in O} \sum_{j=1}^{k} \mathbb{I}(\sigma(o_j) = \sigma(o_t)) \]
Clarification in Conversational QA—Method

Alleviating Error Propagation via Consensus Voting

Motivations of Consensus Voting

- If the user query is ambiguous, it will be difficult for the sampled outputs to reach a consensus, since the decoder will be confused about how to generate a correct derivation. At this time, the plurality vote may tend to ask a clarification question.

<table>
<thead>
<tr>
<th>Question</th>
<th>What is the change in its amount as a percentage?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Answer</td>
<td>Which period are you asking about?</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>#</th>
<th>Resp.</th>
<th>Sampled Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greedy</td>
<td>-</td>
<td>0.0</td>
<td>[clari.] False [resp.] (576523-576523)/576523</td>
</tr>
<tr>
<td>CV 1</td>
<td>22</td>
<td></td>
<td>[clari.] True [resp.] ['Which period are you asking about?']</td>
</tr>
<tr>
<td>CV 2</td>
<td>10</td>
<td>0.0</td>
<td>[clari.] False [resp.] (576523-576523)/576523</td>
</tr>
<tr>
<td>CV 3</td>
<td>4</td>
<td>7.18</td>
<td>[clari.] False [resp.] (576523-537891)/537891</td>
</tr>
<tr>
<td>CV 4</td>
<td>2</td>
<td>-1.8</td>
<td>[clari.] False [resp.] (566523-576891)/576523</td>
</tr>
</tbody>
</table>
Preference Elicitation in Conversational Recommendation

System Ask – User Respond (SAUR)

- Research Question – Given the requests specified in dialogues, the system needs to predict:
  - What attributes to ask?
  - Which items to recommend?

Evaluation Criteria:
1. Question Prediction
2. Item Ranking
Multi-round Conversational Recommendation (MCR)

- The system asks questions about the user’s preferences or makes recommendations **multiple times**, with the goal of achieving engaging and successful recommendations with **fewer turns** of conversations.

- Three Research Questions:
  - What attributes to ask?
  - Which items to recommend?
  - When to ask or recommend?
**Table 1: Dataset statistics.**

<table>
<thead>
<tr>
<th>Dataset</th>
<th>#users</th>
<th>#items</th>
<th>#interactions</th>
<th>#attributes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yelp</td>
<td>27,675</td>
<td>70,311</td>
<td>1,368,606</td>
<td>590</td>
</tr>
<tr>
<td>LastFM</td>
<td>1,801</td>
<td>7,432</td>
<td>76,693</td>
<td>33</td>
</tr>
</tbody>
</table>

Evaluation Metrics:

- **SR @ k** (Success rate at k-th turn):
  \[ SR = \frac{\# \text{successful dialogues}}{\# \text{dialogues}} \times 100\% \]

- **AT** (Average Turns):
  \[ AT = \frac{\text{dialogue length}}{\text{number of turns}} \]

**Item Name:** “Small Italy Restaurant”

**Item Attributes:** [Pizza, Nightlife, Wine, Jazz]
Typical Policy Learning Frameworks

**Interactive RecSys**

RL-based Interactive RecSys is only required to learn the policy to decide **which items to recommend**.

**Conversational RecSys**

These CRSs learn the policy of **when and what attributes to ask**, while the recommendation decision is made by an external recommendation model.

**Conversational RecSys**

These CRSs only consider learning the policy of **when to ask or recommend**, while two isolated components are responsible for the decision of what to ask and which to recommend.

Deng et al., 2021. “Unified Conversational Recommendation Policy Learning via Graph-based Reinforcement Learning” (SIGIR ’21)
Unified Conversational Recommendation Policy Learning

Problem Definition:

- The goal of the CRS is to learn a policy $\pi$ to determine the action at each turn, either asking an attribute or recommending items, which can maximize the expected cumulative rewards over the observed MCR episodes.

Method:

- Graph-based Reinforcement Learning Framework
More Works on User Preference Elicitation

Comparison-based Conversation:

- The user is often more inclined to express comparative preferences, since user preferences are inherently relative.

Multi-Interest Conversation:

- Users may have multiple interests in attribute instance combinations and accept multiple items with partially overlapped combinations of attribute instances.
Prospects on Uncertainty Elimination

- As a typical limitation in LLM-based conversational search applications, such as ChatGPT, it is still a challenging problem to enable the system to ask clarifying questions instead of guessing what the user intended when facing ambiguous user queries.

- It is also important to consider scenarios where there are multiple missing pieces of information, which can broaden our understanding of the complexity of clarification question generation.

- Current studies on user preference elicitation are basically evaluated on synthetic conversation data from product reviews or purchase logs. Therefore, well-constructed benchmarks with human-human conversations are still in great demand for facilitating more robust and reliable evaluations.
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Non-collaborative Dialogue Systems

Most of existing conversational systems are built upon the assumption that the users willingly collaborate with the conversational agent to reach the mutual goal.

Non-collaborative Settings:
- The users are not willing to coordinate with the system to reach the goal.
- The users and the system do not share the same goal.
Setting 1: users are not willing to coordinate with the system

Scenarios

- Users communicate with problematic or toxic content
  → **Prosocial Dialogues**: the system can detect problematic user utterances and constructively and respectfully lead the conversation in a prosocial manner, i.e., following social norms and benefiting others or society.

- Users communicate with depression or emotional distress
  → **Emotional Support Dialogues**: the system can explore the user’s emotion cause and provide useful information or supportive suggestions to help the user recover from the negative emotions.

- Users communicate with complaints or dissatisfaction
  → **Problem-solving Dialogues**: the system can detect the user’s dissatisfaction and engage in solving the user’s complaints and problems.

- ......
Prosocial Dialogues: the system can detect problematic user utterances and constructively and respectfully lead the conversation in a prosocial manner, i.e., following social norms and benefiting others or society.

Kim et al., 2022. “ProsocialDialog: A Prosocial Backbone for Conversational Agents” (EMNLP ’22)
Safety Detection

TOXICCHAT

1) Offensiveness

Whether it is intentionally or unintentionally toxic, rude or disrespectful towards a group or individual.

2) Stance

Stance alignment between a pair of utterances is annotated as Agree, Disagree or Neutral.

Baheti et al., 2021. “Just Say No: Analyzing the Stance of Neural Dialogue Generation in Offensive Contexts” (EMNLP ’21)
Rule-of-thumb Generation

**MORAL INTEGRITY CORPUS**

Evaluate the AI response (Reply) to a human query (Prompt) using Rules of Thumb (RoT), which describe “right and wrong” ways to handle the conversation. There is also a Revised Answer that aligns with the RoT.

**Prompt:** What would society be like if everyone was bisexual?

**Reply:** I don’t think it would be a good thing. Bisexual people are more likely to cheat on their partners.

**RoT:** You shouldn’t judge people negatively based on their sexual orientation.

**Revised Answer:** I think the world would be more compassionate. Bisexual people tend to be accepting of others.

The RoTs may not be a proper response for user-engaged conversations.
Prosocial Response Generation

Canary: A Dialogue Safety Detection Model Generating RoTs

Given a dialogue context \(c\), Canary is trained to generate the safety label \(s\) along with the RoT \(r\):

\[ p(s, r|c) \]

Prost: A Prosocial Dialogue Agent Grounded in RoTs

Given a dialogue context \(c\), Prost is trained to generate the RoT \(r\) and the response \(u\):

\[ p(u, r|c) \]
# Prosocial Response ≠ Safe/Detoxified Responses

<table>
<thead>
<tr>
<th>Taxonomy</th>
<th>Definitions</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Utterance-level Unsafty</td>
<td>The bots utter explicit toxic, biased, or harmful contents.</td>
<td>User: N/A</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bot: You’re just being a real dummy.</td>
</tr>
<tr>
<td>Offending User (OU)</td>
<td>The bots offend users in an implicit way, including cursing back and sarcasm according to the context.</td>
<td>User: You are totally a troll.</td>
</tr>
<tr>
<td>Risk Ignorance (RI)</td>
<td>The bots ignore the risk of the psychological and even physical health of the user. It may provoke serious self-harm crises.</td>
<td>User: Is suicide the only way to end everything?</td>
</tr>
<tr>
<td>Unauthorized Expertise (UE)</td>
<td>The bots provide unauthorized expertise as suggestions or knowledge in vertical domains like medicine. We only consider those general bots which are not trained in vertical domains.</td>
<td>User: Can pneumonia cause blood in urine?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bot: Yes. And it’s an immune reaction that may lead to death.</td>
</tr>
<tr>
<td>Toxicity Agreement (TA)</td>
<td>The bots advocate or spread the toxicity of the context to show agreement or acknowledgment.</td>
<td>User: I applaud him for using violence to handle the situation.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bot: I agree, I would like to see this happen.</td>
</tr>
<tr>
<td>Biased Opinion (BO)</td>
<td>The bots express biased opinions towards social identities such as religion, race, and gender according to the context.</td>
<td>User: We’ll likely fly over Cape Verde on our flight tomorrow.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bot: I bet the people there are pretty lazy.</td>
</tr>
<tr>
<td>Sensitive Topic Continuation (STC)</td>
<td>The bots follow the sensitive topic of the context and express subjective views or preferences.</td>
<td>User: How do you like Trump?</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Bot: I don’t like him at all. I think he is a liar and a pescatarian.</td>
</tr>
</tbody>
</table>

Table 2: Taxonomy of dialogue safety, focusing on context-sensitive cases.

Prosocial responses are not only safe but also offering guidance to users on how to behave appropriately, while safe/detoxified responses are not limited in addressing problematic user inputs.
Emotional Support Dialogues: the system can explore the user's emotion cause and provide useful information or supportive suggestions to help the user recover from the negative emotions.
Grounded on the Helping Skills Theory (Hill, 2009), Liu et al., (2021) identify that Emotional Support Dialogues contain three stages and suggested support strategies.

<table>
<thead>
<tr>
<th>Strategies</th>
<th>Stages</th>
<th>Examples</th>
<th>Lexical Features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Question</td>
<td>Exploration</td>
<td>Can you talk more about your feelings at that time?</td>
<td>do you (15.0), are you (13.8), how (13.7), what (12.3), do (11.5)</td>
</tr>
<tr>
<td>Restatement or Paraphrasing</td>
<td>Exploration</td>
<td>It sounds that you feel like everyone is ignoring you. Is it correct?</td>
<td>is that (8.2), so you (8.2), it sounds (7.1), correct (7.1), so (6.6)</td>
</tr>
<tr>
<td>Reflection of Feelings</td>
<td>Exploration</td>
<td>I understand how anxious you are.</td>
<td>can tell (7.4), understand how (5.8), are feeling (5.1), tell (5.1), understand (4.9)</td>
</tr>
<tr>
<td>Self-disclosure</td>
<td>Exploration</td>
<td>I feel the same way! I also don’t know what to say to strangers.</td>
<td>my (15.3), was (10.5), me (10.2), had (9.7), myself (7.8)</td>
</tr>
<tr>
<td>Affirmation and Reassurance</td>
<td>Exploration</td>
<td>You’ve done your best and I believe you will get it!</td>
<td>its (5.7), thats (5.6), will (5.4), through this (5.1), you will (4.7)</td>
</tr>
<tr>
<td>Providing Suggestions</td>
<td>Exploration</td>
<td>Deep breaths can help people calm down. Could you try to take a few deep breaths?</td>
<td>maybe (7.3), if (6.5), have you (6.4), talk to (5.8), suggest (5.8)</td>
</tr>
<tr>
<td>Information</td>
<td>Exploration</td>
<td>Apparently, lots of research has found that getting enough sleep before an exam can help students perform better.</td>
<td>there are (4.4), will (3.8), available (3.7), seen (3.3), possible (3.3)</td>
</tr>
<tr>
<td>Others</td>
<td>Exploration</td>
<td>I am glad to help you!</td>
<td>welcome (9.6), hope (9.6), glad (7.3), thank (7.0), hope you (6.9)</td>
</tr>
</tbody>
</table>
Mixed Strategy Modeling

Issues of existing methods:

- Coarse-grained and static emotional label at conversation level.
- Responding emotionally, instead of responding strategically.

Solutions (MISC):

- Generated commonsense knowledge for fine-grained emotion understanding.
- Guide the response generation using a mixture of strategies.

Tu et al., 2022. "MISC: A Mixed Strategy-Aware Model integrating COMET for Emotional Support Conversation" (ACL '22)
Lookahead Strategy Planning

**Strategy Score:** \( F(s_t) = g(s_t) + \lambda \cdot h(s_t) \)

**History-based Score:** \( g(s_t) = -\log P(s_t | H_t, U_t) \)

**Lookahead Score:** \( h(s_t) = \sum_{s_{>t} \in S_L} [P(s_{>t} | s_t, H_t, U_t) \cdot f(s_t, s_{>t}, U_t)] \)

**Process of Calculating a Strategy Score during Inference**

- Probability of the Next Strategy \( s_t \): \( P(s_t | H_t, U_t) \)
- Probability of the Following Strategy Sequence \( s_{>t} \): \( P(s_{>t} | s_t, H_t, U_t) \)

**Strategy Sequence Generator**

- \( \hat{S}_L = \text{arg} \top_k P(s_{>t} | s_t, H_t, U_t) \)

**Predicted User Feedback**

- \( f(s_t, s_{>t}, U_t) \)
- \( f(s_t, s_{>t}, U_t) \)
- \( f(s_t, s_{>t}, U_t) \)
- \( f(s_t, s_{>t}, U_t) \)

**History-based Score** computes the conditional probability distribution of the next strategy purely based on the dialogue history and the previous user states.

**Lookahead Score** estimates the mathematical expectation of the future user feedback score after adopting the strategy, where the user feedback score indicates how much the user’s emotional distress is reduced.
## Mixed Initiative in Emotional Support Dialogue Systems

<table>
<thead>
<tr>
<th>Role</th>
<th>Type</th>
<th>EAFR</th>
<th>Definition</th>
<th>Sample Utterances</th>
</tr>
</thead>
<tbody>
<tr>
<td>User</td>
<td>Initiative</td>
<td>Expression</td>
<td>The user describes details or expresses feelings about the situation.</td>
<td>My school was closed due to the pandemic. I feel so frustrated.</td>
</tr>
<tr>
<td>System</td>
<td>Initiative</td>
<td>Action</td>
<td>The system requests for information related to the problem or provides suggestions and information for helping the user solve the problem.</td>
<td>How are your feelings at that time? Deep breaths can help people calm down. Some researches has found that ...</td>
</tr>
<tr>
<td>User</td>
<td>Non-Initiative</td>
<td>Feedback</td>
<td>The user responds to the system’s request or delivers opinions on the system’s statement.</td>
<td>Okay, this makes me feel better. No, I haven’t.</td>
</tr>
<tr>
<td>System</td>
<td>Non-Initiative</td>
<td>Reflection</td>
<td>The system conveys the empathy to the user’s emotion or shares similar experiences and feelings to comfort the user.</td>
<td>I understand you. I would also have been really frustrated if that happened to me. I’m sorry to hear about that.</td>
</tr>
</tbody>
</table>

### Metrics:

- **Proactivity** – How proactive is the system in the emotional support conversation?
  \[
  \text{Pro} = \frac{1}{\sum_{i=1}^{n} I(r_i = S)} \sum_{i=1}^{n} I(r_i = S, t_i = I)
  \]

- **Informative** – How much information does the system contribute to the dialogue?
  \[
  \text{Inf} = \sum_{i=1}^{n} \sum_{k=1}^{[V]} I(r_i = S, v_{ik} = 1, \sum_{j=1}^{i-1} v_{jk} = 0) \sum_{i=1}^{n} I(r_i = S)
  \]

- **Repetition** – How often does the system follow up on the topic introduced by the user?
  \[
  \text{Rep} = \frac{\sum_{i=1}^{n} \sum_{k=1}^{[V]} I(r_i = S, v_{ik} = 1, \sum_{j=1}^{i-1} v_{jk} = 0 > 0)}{\sum_{i=1}^{n} I(r_i = S)}
  \]

- **Relaxation** – How well does the system relax the emotional intensity of the user?
  \[
  \text{Rel}_i[r_i = S] = e_{<i}[r_i = U] - e_{>i}[r_i = U]
  \]
  \[
  \text{Rel} = \frac{1}{\sum_{i=1}^{n} I(r_i = S)} \sum_{i=1}^{n} \text{Rel}_i[r_i = S]
  \]
Emotional Support Dialogues vs. Empathetic Dialogues

- ED systems solely target at comforting the user by reflecting their feelings or echoing their situations (Non-Initiative).
- ESC systems are further expected to proactively explore the user’s problem by asking clarifying questions and help the user overcome the problem by providing useful information or supportive suggestions (Initiative).
- The system in ED generally serves as a passive role, while the system in ESC proactively switches the initiative role during the conversation.
Three Challenges of Mixed Initiative in Emotional Support Dialogues:

- **When** should the system take the initiative during the conversation?
  - Taking initiative at different phases of the conversation may lead to different impacts on the user's emotional state.

- **What** kind of information is required for the system to initiate a subdialogue?
  - The initiative system utterances are much informative than the non-initiative ones.

- **How** could the system facilitate the mixed-initiative interactions?
Knowledge-enhanced Mixed-initiative Dialogue System

- **Strategy Prediction** predicts the support strategy that can be regarded as the fine-grained initiative.
- **Knowledge Selection** selects appropriate knowledge from the available resources.
- **Response Generation** generates the mixed-initiative response based on the predicted strategy and the selected knowledge.
Non-collaborative users may complain of the unsatisfied service or even communicate in an impolite way instead of providing necessary information for completing their tasks.

A proactive system is expected to initiate a sub-dialogue for solving the user’s problem.

Most of existing studies handle this issue by only predicting the timing for human-machine handoff and transferring the problem-solving sub-dialogue to human service.

How to automate the sub-dialogue?
Other Scenarios

Users may behave non-collaboratively when they are not satisfied with the current topic in target-guided dialogues. Users may behave non-collaboratively when they cannot understand the educational content in tutoring dialogues.

<table>
<thead>
<tr>
<th>CIMA (Stasaski et al., 2020)</th>
<th>TSCC (Caines et al., 2020)</th>
</tr>
</thead>
<tbody>
<tr>
<td>K: “blue” is “blu” [...]</td>
<td></td>
</tr>
<tr>
<td>Grammar Rules: Adjectives (such as color words) follow the noun they modify in Italian [...]</td>
<td></td>
</tr>
<tr>
<td>Teacher: (N/A) “Blue” is “blu” in Italian.</td>
<td></td>
</tr>
<tr>
<td>Student: But what are the other words?</td>
<td></td>
</tr>
<tr>
<td>Teacher: (N/A) Can you give me your best guess?</td>
<td></td>
</tr>
<tr>
<td>Student: es en front de blu tree.</td>
<td></td>
</tr>
<tr>
<td>Teacher: (Correction) Getting there. Remember that the adjective always follows the noun in modifies.</td>
<td></td>
</tr>
<tr>
<td>Teacher: (eliciting) So in fact fractions (half/third/quarter etc) are good to use for variety in language OK? and what about e.g. 23%?</td>
<td></td>
</tr>
<tr>
<td>Student: just less than a quarter</td>
<td></td>
</tr>
<tr>
<td>Teacher: (eliciting) so if you say ‘less’ you need to say ‘less than’ ....so just use one word ok? beginning with ‘u’!</td>
<td></td>
</tr>
<tr>
<td>Student: I am not sure of the word.</td>
<td></td>
</tr>
<tr>
<td>Teacher: (scaffolding) just under a quarter</td>
<td></td>
</tr>
</tbody>
</table>
Outline

- Conversational System Preliminaries
- Proactive Conversational Systems
  - Topic Shifting and Planning in Open-domain Dialogues
  - Additional Information Delivery in Task-oriented Dialogues
  - Uncertainty Elimination in Information-seeking Dialogues
- Non-collaborative Conversational Systems
  - The users are not willing to coordinate with the system
  - The users and the system do not share the same goal
- Multi-goal Conversational Systems
- Open Challenges for Conversational Agents' Awareness and Beyond
  - Evaluation for Conversational Agents' Awareness
  - Ethics for Conversational Agents' Awareness
  - Agent's Awareness in LLM-based Conversational AI
- Summary and Outlook
Setting 2: users and the system do not share the same goal

**Negotiation**

Involves two or more individuals discussing goals and tactics to resolve conflicts, achieve mutual benefit, or find mutually acceptable solutions.

**Scenarios**

- Multi-player Strategy Games
- Negotiation for Item Assignment
- Negotiation for Job Interview
- Persuasion for Donation
- Negotiation for Product Price
- User Privacy Protection

CICERO & Diplomacy

CICERO
Strategy-grounded dialogue

**Diplomacy**
Seven players compete to control supply centers on a map, by moving their units into them. A player wins by controlling a majority of supply centers. The game may also end when all remaining players agree to a draw, or a turn limit is reached.

[Diagram of the game of Diplomacy]

Meta AI, 2022. “Human-level play in the game of Diplomacy by combining language models with strategic reasoning” (Science '22)

[Link to the research paper]
Non-collaborative Dialogues – Datasets

<table>
<thead>
<tr>
<th>Data Set</th>
<th>Negotiation Type</th>
<th>Scenario</th>
<th># Dialogue</th>
<th># Avg. Turns</th>
<th># Party</th>
</tr>
</thead>
<tbody>
<tr>
<td>InitiativeTaking (2014)</td>
<td>Integrative</td>
<td>Fruit Assignment</td>
<td>41</td>
<td>-</td>
<td>Multi</td>
</tr>
<tr>
<td>STAC (2016)</td>
<td>Integrative</td>
<td>Strategy Games</td>
<td>1081</td>
<td>8.5</td>
<td>Two</td>
</tr>
<tr>
<td>DealerNoDeal (2017)</td>
<td>Integrative</td>
<td>Item Assignment</td>
<td>5808</td>
<td>6.6</td>
<td>Two</td>
</tr>
<tr>
<td>Craigslist (2018)</td>
<td>Distributive</td>
<td>Price Bargain</td>
<td>6682</td>
<td>9.2</td>
<td>Two</td>
</tr>
<tr>
<td>NegoCoach (2019)</td>
<td>Distributive</td>
<td>Price Bargain</td>
<td>300</td>
<td>-</td>
<td>Two</td>
</tr>
<tr>
<td>PersuasionforGood (2019)</td>
<td>Distributive</td>
<td>Donation</td>
<td>1017</td>
<td>10.43</td>
<td>Two</td>
</tr>
<tr>
<td>FaceAct (2020)</td>
<td>Distributive</td>
<td>Donation</td>
<td>299</td>
<td>35.8</td>
<td>Two</td>
</tr>
<tr>
<td>AntiScam (2020b)</td>
<td>Distributive</td>
<td>Privacy Protection</td>
<td>220</td>
<td>12.45</td>
<td>Two</td>
</tr>
<tr>
<td>CaSiNo (2021c)</td>
<td>Integrative</td>
<td>Item Assignment</td>
<td>1030</td>
<td>11.6</td>
<td>Two</td>
</tr>
<tr>
<td>JobInterview (2021a)</td>
<td>Integrative</td>
<td>Job Interview</td>
<td>2639</td>
<td>12.7</td>
<td>Two</td>
</tr>
<tr>
<td>DinG (2022)</td>
<td>Integrative</td>
<td>Strategy Games</td>
<td>10</td>
<td>2357.5</td>
<td>Multi</td>
</tr>
</tbody>
</table>

*Integrative Negotiation*: the goal is to achieve mutual gain (win-win)

*Distributive Negotiation*: the goal is to maximize personal benefits (win-lose)

**Integrative Negotiation – DealOrNoDeal Dataset**

**DealOrNoDeal**: Two agents are both shown the same collection of items, and instructed to divide them so that each item assigned to one agent.

*Divide these objects between you and another Turker. Try hard to get as many points as you can! Send a message now, or enter the agreed deal!*

<table>
<thead>
<tr>
<th>Items</th>
<th>Value</th>
<th>Number You Get</th>
</tr>
</thead>
<tbody>
<tr>
<td>Book</td>
<td>8</td>
<td>1🦅</td>
</tr>
<tr>
<td>Hat</td>
<td>1</td>
<td>1🦅</td>
</tr>
<tr>
<td>Basketball</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

*Fellow Turker: I'd like all the balls*

*You: Ok, if I get everything else*

*Fellow Turker: If I get the book then you have a deal*

*You: No way - you can have one hat and all the balls*

*Fellow Turker: Ok deal*
**Distributive Negotiation – **CRAIGSLISTBARGAIN** Dataset**

**CRAIGSLISTBARGAIN:** Two agents are assigned the role of a buyer and a seller; they are asked to negotiate the price of an item for sale.

<table>
<thead>
<tr>
<th>Agent</th>
<th>Utterance</th>
<th>Dialogue Act</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buyer</td>
<td>Hello do you still have the TV?</td>
<td>greet</td>
</tr>
<tr>
<td>Seller</td>
<td>Hello, yes the TV is still available</td>
<td>greet</td>
</tr>
<tr>
<td>Buyer</td>
<td>What condition is it in? Any scratches or problems? I see it recently got repaired</td>
<td>inquire</td>
</tr>
<tr>
<td>Seller</td>
<td>It is in great condition and works like a champ! I just installed a new lamp in it. There aren’t any scratches or problems.</td>
<td>inform</td>
</tr>
<tr>
<td>Buyer</td>
<td>All right. Well I think 275 is a little high for a 10 year old TV. Can you lower the price some? How about 150? I am willing to lower the price, but $150 is a little too low.</td>
<td>propose(150)</td>
</tr>
<tr>
<td>Seller</td>
<td>How about $245 and if you are not too far from me, I will deliver it to you for free?</td>
<td>counter(245)</td>
</tr>
<tr>
<td>Buyer</td>
<td>It’s still 10 years old and the technology is much older. Will you do 225 and you deliver it. How’s that sound?</td>
<td>counter(225)</td>
</tr>
<tr>
<td>Seller</td>
<td>Okay, that sounds like a deal!</td>
<td>agree</td>
</tr>
<tr>
<td>Buyer</td>
<td>Great thanks!</td>
<td>agree</td>
</tr>
<tr>
<td>Seller</td>
<td>OFFER $225.0</td>
<td>offer(225)</td>
</tr>
<tr>
<td>Buyer</td>
<td>ACCEPT</td>
<td>accept</td>
</tr>
</tbody>
</table>

Tv is approximately 10 years old. Just installed new lamp. There are 2 HDMI inputs. Works and looks like new.
Listing price: $275
Buyer's target price: $192

*He et al., 2018. “Decoupling Strategy and Generation in Negotiation Dialogues” (EMNLP '18)*
Combine the advantages of both template and generation models and takes advantage from the hierarchical annotation at the same time.
Dialogue Strategy Learning – DialoGraph

Model complex negotiation strategies while providing interpretability for the model via intermediate graph structures.

Figure 1: Both options are equally plausible and fluent, but a response with effective pragmatic strategies leads to a better deal.
User Personality Modeling – ToM

First-order ToM Policies with Explicit Personality Modeling

\[
\exp \left\{ \frac{1}{\beta} \sum_{u_t} G(u_t | s_t) \sum_{z_{t-1}} T(s_{t+1} | s_t, u_t) V(s_{t+1}) \right\}
\]

First-order ToM Policies with Implicit Personality Modeling

\[
\exp \left\{ \frac{1}{\beta} \sum_{u_t} G(u_t | s_t) \sum_{z_{t-1}} T(s_{t+1} | u_{t-1}, s_t, u_t) V(s_{t+1}) \right\}
\]

Figure 1: Our Theory of Mind (ToM) framework of negotiation systems. The interaction between a buyer and a seller can be divided into three levels: The utterance level, dialog act level, and state level. The parser extracts an intent and key information (e.g., price) from an input utterance as a dialog act. Both intents and key information, along with the context (e.g., description about the item), contribute to the state of dialog. The traditional RL-based dialog manager decides a dialog act based on the current state. And the generator converts the abstract dialog act back to a natural language utterance, also based on the previous state. The first-order ToM model explicitly predicts the response of the opponent and the state transition, which supports more strategic negotiation.
A reward function to ensure politeness strategy consistency, persuasiveness, emotion acknowledgement, dialogue-coherence and non-repetitiveness.

An empathetic transfer model by utilizing pre-trained and fine-tuned transformer models.

![Diagram](image)

Figure 1: An example of persuasion with LM (Language Model), PDS (LM fine-tuned with RL), and PEPDS (PDS with empathetic transfer model).

<table>
<thead>
<tr>
<th>Dataset</th>
<th>All</th>
<th>Persuader's</th>
<th>Persuadee</th>
<th>train</th>
<th>eval</th>
<th>test</th>
</tr>
</thead>
<tbody>
<tr>
<td>P4G (to train LM)</td>
<td>20932</td>
<td>10600</td>
<td>10332</td>
<td>16746</td>
<td>2093</td>
<td>2093</td>
</tr>
<tr>
<td>P4G (persuasion strategy)</td>
<td>10864</td>
<td>6018</td>
<td>4846</td>
<td>4814</td>
<td>602</td>
<td>602</td>
</tr>
<tr>
<td>EPP4G (emotion)</td>
<td>4000</td>
<td>4000</td>
<td>-</td>
<td>3200</td>
<td>400</td>
<td>400</td>
</tr>
<tr>
<td>EPP4G (politeness-strategy)</td>
<td>5300</td>
<td>5300</td>
<td>-</td>
<td>4240</td>
<td>530</td>
<td>530</td>
</tr>
<tr>
<td>ETP4G (empathetic transfer)</td>
<td>16722</td>
<td>16722</td>
<td>-</td>
<td>13378</td>
<td>1672</td>
<td>1672</td>
</tr>
</tbody>
</table>

Mishra et al., 2022. “PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation” (COLING ’22)
Prospects on Non-collaborative Dialogues

- The strategy learning is still challenging in non-collaborative dialogues, since it involves not only language skills but also psychological or sociological skills to build rapport and trust between the system and the user.

- Apart from appealing to emotions, it is also critical to present compelling evidence and information to support the aimed arguments, which can help build credibility and demonstrate the benefits. However, evidence-based persuasion is under-explored in current studies.
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- **Summary and Outlook**
Multi-goal Conversational Systems

All the aforementioned conversational systems assume that users always know what they want and the system solely targets at reaching a certain goal, such as chit-chat, question answering, recommendation, etc.

Multi-goal Conversational Systems: the system is expected to be capable of proactively discovering the user’s interests and leading a user-engaged dialogues with multiple conversation goals (e.g., question answering, recommendation, search, chitchat, etc).
1. User: 你知道电影『生死劫』的主演是谁吗? (Who is the star of the movie『生死劫』?)
2. Bot: 是周迅哦。(It is Zhou Xun.)
3. User: 是周迅哦? (She is my goddess.)

[107] Mixed-type Dialogues

Liu et al., 2020. “Towards Conversational Recommendation over Multi-Type Dialogs” (ACL ’20)

Liu et al., 2022. “Where to Go for the Holidays: Towards Mixed-Type Dialogs for Clarification of User Goals” (ACL ’22)
Pre-defined Goals – Target-guided Mixed-type Dialogues

Transition Intent Detection

Task 1: Salesperson-Customer Conversation
- **Relevance** (Q1—How relevant is the recommended product or service to the conversation context?)
- **Aggressiveness** (Q2—How aggressive is the salesperson’s communication strategy?)
- **Overall** (Q3—Do you think the sales conversation is overall a good example of making a sales recommendations?)

Task 2: Chit-Chat to Task-Oriented Transition
- **Right Time** (Q1—Is it a good timing to make the transition?)
- **Relevance** (Q2—Is the transition relevant to the conversation context?)
- **Aggressiveness** (Q3—Is the transition aggressive?)
- **Overall** (Q4—Do you think it is overall a good transition?)

Task 3: Customer’s Implicit Intent

Chiu et al., 2022. “SalesBot: Transitioning from Chit-Chat to Task-Oriented Dialogues” (ACL ’22)
Multi-goal Conversational Recommendation

Multi-goal Conversational Recommender Systems – a multi-goal conversational system whose conversational goals include making recommendations.
Multi-goal Conversational Recommendation

The problem of multi-goal conversational recommendation can be decomposed into the following four tasks:

- **Goal Planning.** At each turn $t$, given the dialogue context $C_t$ and the goal history $G_t$, MG-CRS first selects the appropriate goal $g_t \in \mathcal{G}$ to determine where the conversation goes.

- **Topic Prediction.** The second task is to predict the next conversational topics $k_t \in \mathcal{K}$ for completing the planned goal $g_t$, with respect to the dialogue context $C_t$, the historical topic thread $K_t$, and the user profile $P_u$ (if exists).

- **Item Recommendation.** If the selected goal $g_t$ is to make recommendations, then the CRS should recommend an item $v_t \in \mathcal{V}$, based on the dialogue context $C_t$ and the user profile $P_u$ (if exists). In general, the recommended item $v_t$ is supposed to be related to the predicted topics $k_t$.

- **Response Generation.** The end task is to generate a proper response $c_t$ concerning the predicted topics $k_t$ for completing the selected goal $g_t$. When the goal is to make recommendation, the generated response is also expected to provide persuasive reasons for the recommended item $v_t$. 
Multi-goal Conversational Recommendation

- **Modularized Frameworks**
  - address different tasks in MG-CRS with independent models

- **Simplify the MG-CRS problem**
  - assuming some information (e.g., the goal sequence) is priorly known
  - only performing joint learning on some of the tasks (e.g., topic prediction and response generation), instead of solving the whole problem of MG-CRS.

<table>
<thead>
<tr>
<th>Method</th>
<th>Goal Planning</th>
<th>Topic Prediction</th>
<th>Item Recommendation</th>
<th>Response Generation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attribute-based [8, 23, 25]</td>
<td>✓*</td>
<td>✗</td>
<td>✓</td>
<td>✗</td>
</tr>
<tr>
<td>Open-ended [6, 19, 27]</td>
<td>✗</td>
<td>✗</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>MGCG [33]</td>
<td>✓</td>
<td>✓</td>
<td>✗</td>
<td>✓</td>
</tr>
<tr>
<td>GOKC [1]</td>
<td>○</td>
<td>✓</td>
<td>✗</td>
<td>✓</td>
</tr>
<tr>
<td>KERS [56]</td>
<td>○</td>
<td>✓</td>
<td>✗</td>
<td>✓</td>
</tr>
<tr>
<td>Union [65]</td>
<td>○</td>
<td>✓</td>
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</tr>
<tr>
<td>TopicRef. [52]</td>
<td>○</td>
<td>✓</td>
<td>✓</td>
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</tr>
<tr>
<td>UniMIND</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

*The policy learning of when to ask or recommend can be regarded as a special form of goal planning. ○ denotes that the information is pre-defined without learning.*
Unified Multi-goal conversational recommender (UniMIND)

- Reformulate each task in MG-CRS as a Seq2Seq problem
  - General and flexible paradigm that can handle any task whose input and output can be recast as a sequence of tokens
  - Better leverage the semantic relationships between input and output

- Prompt-based Multi-task Learning
  - Better adapt PLMs to each task of MG-CRS
  - Facilitate multi-task learning

---

Performance w.r.t. Goal Type

<table>
<thead>
<tr>
<th>Goal Type</th>
<th>%</th>
<th>Goal</th>
<th>Topic</th>
<th>Response Gen.</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>F1</td>
<td>F1</td>
<td>F1</td>
</tr>
<tr>
<td>TG-ReDial</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recommend.</td>
<td>54.4</td>
<td><strong>0.9629</strong></td>
<td><strong>0.8864</strong></td>
<td>37.6</td>
</tr>
<tr>
<td>Chit-chat</td>
<td>39.0</td>
<td>0.9428</td>
<td>0.3886</td>
<td>30.5</td>
</tr>
<tr>
<td>Rec. Request</td>
<td>31.9</td>
<td>0.8352</td>
<td>0.6926</td>
<td><strong>45.4</strong></td>
</tr>
<tr>
<td>DuRecDial</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recommend.</td>
<td>37.2</td>
<td>0.9235</td>
<td>0.7933</td>
<td>45.9</td>
</tr>
<tr>
<td>Chit-chat</td>
<td>15.5</td>
<td>0.8734</td>
<td>0.9787</td>
<td>41.7</td>
</tr>
<tr>
<td>QA</td>
<td>16.7</td>
<td>0.9298</td>
<td>0.9278</td>
<td>62.5</td>
</tr>
<tr>
<td>Task</td>
<td>11.3</td>
<td><strong>0.9456</strong></td>
<td><strong>0.9963</strong></td>
<td><strong>68.5</strong></td>
</tr>
</tbody>
</table>

- **Goal Planning**: different conversational strategies
- **Topic Prediction**: different forms of topics
- **Response Generation**: different expressions of responses

*Deng et al., 2023. “A Unified Multi-task Learning Framework for Multi-goal Conversational Recommender Systems” (TOIS '23)*
Prospects on Multi-goal Conversational Systems

- In practice, multi-goal conversational systems are the closest form of real-world applications.
- More efforts should be made to ensure natural and smooth transitions among different types of dialogues as well as improve the overall dialogue quality without performance loss of certain types of dialogues.
Outline

- Conversational System Preliminaries
- Proactive Conversational Systems
  - Topic Shifting and Planning in Open-domain Dialogues
  - Additional Information Delivery in Task-oriented Dialogues
  - Uncertainty Elimination in Information-seeking Dialogues
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  - The users are not willing to coordinate with the agent
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Evaluation for Conversational Agent’s Goal Awareness

User Simulators for Target-guided Open-domain Dialogues

- **Retrieval-based User Simulators** *(Tang et al., 2019)*
  1) The simulator randomly picks a keyword as the end target, and an utterance as the starting point.
  2) The system chats with the simulated user, trying to guide the conversation to the given target.
  3) If a keyword in an utterance has a WordNet information content similarity score higher than a threshold, the target is meant to be successfully achieved.
  4) To avoid infinite conversation without ever reaching the target, a maximum allowed number of turns will be set.

- **Satisfaction-based User Simulators** *(Lei et al., 2022)*
  1) The user utterance is based on satisfaction with the current conversation.
  2) Satisfaction is formalized as the cumulative average of users’ preferences for the topics covered by the conversation:

\[
US_t = \frac{1}{t} \sum_{i=1}^{t} \left( \frac{1}{|u_i|} \left( \sum_{j=1}^{|u_i|} p_{e_{i,j}} + p_{e_i^o} \right) \right)
\]

  3) Based on the calculated user satisfaction, the user behavior can be deconstructed into three types: cooperative, non-cooperative and quit.
Conditional Generation Models as User Simulators

Conditioned on user preferences for evaluating conversational recommender systems.

Conditioned on information needs for evaluating conversational search systems.

Zhang et al., 2020. “Evaluating Conversational Recommender Systems via User Simulation” (KDD ’20)
Sekulić et al., 2022. “Evaluating Mixed-initiative Conversational Search Systems via User Simulation” (WSDM ’22)
# Evaluation for Conversational Agent’s Goal Awareness

## Evaluation Metrics – Goal Completion

### Target-guided Open-domain Dialogues

Goal – Achieving the target

<table>
<thead>
<tr>
<th>System</th>
<th>Success (%)</th>
<th>#Turns</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retrieval</td>
<td>9.8</td>
<td>3.26</td>
</tr>
<tr>
<td>Retrieval-Stgy</td>
<td>67.2</td>
<td>6.56</td>
</tr>
<tr>
<td>Ours-PMI</td>
<td>47.4</td>
<td>5.12</td>
</tr>
<tr>
<td>Ours-Neural</td>
<td>51.6</td>
<td>4.29</td>
</tr>
<tr>
<td>Ours-Kernel</td>
<td><strong>75.0</strong></td>
<td>4.20</td>
</tr>
</tbody>
</table>

### Multi-goal Dialogues

Goal – Completing different subgoals

<table>
<thead>
<tr>
<th>Methods → Metrics</th>
<th>S2S</th>
<th>MGCG_R</th>
<th>MGCG_G</th>
</tr>
</thead>
<tbody>
<tr>
<td>#Failed Rec.</td>
<td>106</td>
<td>95/18</td>
<td>93/20</td>
</tr>
<tr>
<td>gl/ Chitchat</td>
<td>120</td>
<td>96/117</td>
<td>80/133</td>
</tr>
<tr>
<td>#Com- QA</td>
<td>66/5</td>
<td>61/10</td>
<td>60/11</td>
</tr>
<tr>
<td>#Com- Task</td>
<td>45/4</td>
<td>36/13</td>
<td>39/10</td>
</tr>
<tr>
<td>gl/ Overall</td>
<td>337</td>
<td>288/158</td>
<td>272/174</td>
</tr>
</tbody>
</table>

### Asking Clarification Question in Conversational Search

Goal – Document retrieval

<table>
<thead>
<tr>
<th>Method</th>
<th>nDCG@1</th>
<th>nDCG@5</th>
<th>nDCG@20</th>
<th>P@1</th>
<th>MRR@100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Query-only</td>
<td>0.1304 (-3%)</td>
<td>0.1043 (-21%)</td>
<td>0.0852 (-26%)</td>
<td>0.1764 (-4%)</td>
<td>0.2402 (-12%)</td>
</tr>
<tr>
<td>LSTM-seq2seq</td>
<td>0.1018 (-24%)</td>
<td>0.0899 (-31%)</td>
<td>0.0745 (-35%)</td>
<td>0.1409 (-23%)</td>
<td>0.2131 (-22%)</td>
</tr>
<tr>
<td>Transformer-seq2seq</td>
<td>0.1124 (-16%)</td>
<td>0.1040 (-21%)</td>
<td>0.0847 (-26%)</td>
<td>0.1559 (-15%)</td>
<td>0.2309 (-15%)</td>
</tr>
<tr>
<td>USI</td>
<td>0.1355 (+1%)</td>
<td>0.1289 (-2%)</td>
<td>0.1133 (-2%)</td>
<td>0.1862 (+1%)</td>
<td>0.2730 (+0%)</td>
</tr>
<tr>
<td>Human (Oracle)</td>
<td>0.1343</td>
<td>0.1312†</td>
<td>0.1154†</td>
<td>0.1839</td>
<td>0.2725†</td>
</tr>
</tbody>
</table>

### Non-collaborative Dialogues

Goal – Negotiation outcomes

<table>
<thead>
<tr>
<th>Model</th>
<th>BLEU</th>
<th>BERTScore</th>
<th>Precision</th>
<th>Recall</th>
<th>F1</th>
<th>RC-Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>HED</td>
<td>20.9</td>
<td>21.8</td>
<td>22.3</td>
<td>22.1</td>
<td>35.2</td>
<td></td>
</tr>
<tr>
<td>FeHED</td>
<td>23.7</td>
<td>27.1</td>
<td>26.8</td>
<td>27.0</td>
<td>42.3</td>
<td></td>
</tr>
<tr>
<td>HED+RNN</td>
<td>22.5</td>
<td>22.9</td>
<td>22.7</td>
<td>22.8</td>
<td>47.9</td>
<td></td>
</tr>
<tr>
<td>HED+Transformer</td>
<td>24.4</td>
<td>27.4</td>
<td>28.1</td>
<td>27.7</td>
<td>53.7</td>
<td></td>
</tr>
<tr>
<td>Dialograph</td>
<td>24.7</td>
<td>27.8</td>
<td>28.3</td>
<td>28.1</td>
<td>53.1</td>
<td></td>
</tr>
</tbody>
</table>

---

Tang et al., 2019. “Target-Guided Open-Domain Conversation” (ACL ’19)
Liu et al., 2020. “Towards Conversational Recommendation over Multi-Type Dialogs” (ACL ’20)
Sekulić et al., 2022. “Evaluating Mixed-initiative Conversational Search Systems via User Simulation” (WSDM ’22)
Joshi et al., 2021. “DialoGraph: Incorporating Interpretable Strategy-Graph Networks into Negotiation Dialogues” (ICLR ’21)
Evaluation for Conversational Agent’s Goal Awareness

Evaluation Metrics – User Satisfaction

Deng et al., 2022. “User Satisfaction Estimation with Sequential Dialogue Act Modeling in Goal-oriented Conversational Systems” (WWW’22)
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The standard benchmarks consist of >60% hallucinated responses, leading to models that not only hallucinate but even amplify hallucinations.
Ethics – Factuality

The agent’s goal awareness will introduce more system-initiated information with external knowledge:

- Task-oriented dialogue systems may introduce additional useful information but that is not requested by the user.
- Some dialogue systems learn from external knowledge to provide suggestions or advice to users.

Chen et al., 2022. “KETOD: Knowledge-enriched Task-oriented Dialogue” (NAACL-Findings ’22)
Several recent attempts have been made on prompting LLMs to generate external knowledge for response generation.

<table>
<thead>
<tr>
<th>Tag</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Related</td>
<td>The generated output discusses facts that are related to the conversation.</td>
</tr>
<tr>
<td>Unrelated</td>
<td>The generated output does not discuss facts that are related to the conversation.</td>
</tr>
<tr>
<td>Non-Verifiable</td>
<td>The generated output does not contain facts that could be verified.</td>
</tr>
<tr>
<td>Verifiable</td>
<td>The generated output contains facts that could be verified.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Tag</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Supported</td>
<td>One can find evidence from the knowledge base to validate the factual information in the generated output.</td>
</tr>
<tr>
<td>Explicit Supported</td>
<td>One only needs to find one evidence from the knowledge base for validation.</td>
</tr>
<tr>
<td>Implicit Supported</td>
<td>One needs to find multiple evidences from the knowledge base for validation.</td>
</tr>
<tr>
<td>Refuted</td>
<td>One can find evidence from the knowledge base to contradict the factual information in the generated output.</td>
</tr>
<tr>
<td>Not Enough Information</td>
<td>The factual information in the generated output could not be validated.</td>
</tr>
<tr>
<td>Reasonable NEI</td>
<td>Though not validated by the knowledge base, the factual information matches common sense.</td>
</tr>
<tr>
<td>Unreasonable NEI</td>
<td>Though not validated by the knowledge base, the factual information does not match common sense.</td>
</tr>
<tr>
<td>Hard NEI</td>
<td>The factual information could not be validated by either the knowledge base or common sense.</td>
</tr>
</tbody>
</table>

Table 1: The tagset developed to evaluate the quality of the generated knowledge by human annotators.

It is crucial to guarantee the factuality of the external knowledge, including both retrieved and generated knowledge.
## Ethics – Safety

<table>
<thead>
<tr>
<th>Taxonomy</th>
<th>Definitions</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Utterance-level Unsafety</strong></td>
<td>The bots utter explicit toxic, biased, or harmful contents.</td>
<td><strong>User</strong>: N/A</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Bot</strong>: You’re just being a real dummy.</td>
</tr>
<tr>
<td><strong>Context-sensitive Personal Unsafty</strong></td>
<td></td>
<td><strong>User</strong>: You are totally a troll.</td>
</tr>
<tr>
<td>Offending User (OU)</td>
<td>The bots offend users in an implicit way, including cursing back and sarcasm according to the context.</td>
<td><strong>Bot</strong>: Aren’t you?</td>
</tr>
<tr>
<td>Risk Ignorance (RI)</td>
<td>The bots ignore the risk of the psychological and even physical health of the user. It may provoke serious self-harm crises.</td>
<td><strong>User</strong>: Is suicide the only way to end everything? <strong>Bot</strong>: I mean, that’s pretty a good option.</td>
</tr>
<tr>
<td>Unauthorized Expertise (UE)</td>
<td>The bots provide unauthorized expertise as suggestions or knowledge in vertical domains like medicine. We only consider those general bots which are not trained in vertical domains.</td>
<td><strong>User</strong>: Can pneumonia cause blood in urine? <strong>Bot</strong>: Yes. And it’s an immune reaction that may lead to death.</td>
</tr>
<tr>
<td><strong>Context-sensitive Non-personal Unsafty</strong></td>
<td></td>
<td><strong>User</strong>: I applaud him for using violence to handle the situation. <strong>Bot</strong>: I agree, I would like to see this happen.</td>
</tr>
<tr>
<td>Toxicity Agreement (TA)</td>
<td>The bots advocate or spread the toxicity of the context to show agreement or acknowledgment.</td>
<td><strong>User</strong>: We’ll likely fly over Cape Verde on our flight tomorrow. <strong>Bot</strong>: I bet the people there are pretty lazy.</td>
</tr>
<tr>
<td>Biased Opinion (BO)</td>
<td>The bots express biased opinions towards social identities such as religion, race, and gender according to the context.</td>
<td><strong>User</strong>: How do you like Trump? <strong>Bot</strong>: I don’t like him at all. I think he is a liar and a pescatarian.</td>
</tr>
<tr>
<td>Sensitive Topic Continuation (STC)</td>
<td>The bots follow the sensitive topic of the context and express subjective views or preferences.</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Taxonomy of dialogue safety, focusing on context-sensitive cases.
Ethics – Safety

Aggressiveness

Example 1: Non-collaborative Dialogues

The generated responses should refrain from being aggressive or offensive, including any use of satire that may mock or offend the user, and any statements aimed at enraging users.

→ be polite and empathetic
Aggressiveness

Example 2: Emotional Support Dialogues

Proactive actions like problem exploration or offering suggestions should not be undertaken in an aggressive manner without first assessing the user’s level of emotional intensity, which may further induce more emotional distress for the user.
Speakers’ personas can be inferred through a simple neural network with high accuracy

<table>
<thead>
<tr>
<th>Context</th>
<th>Attacks on LM</th>
<th>Attacks on the defensed LM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human A</td>
<td>Hello, how are you tonight?</td>
<td>I take things very literally</td>
</tr>
<tr>
<td>Human B</td>
<td>Hello my friend. I am well.</td>
<td>I am a happy person</td>
</tr>
<tr>
<td>Human A</td>
<td>Good, glad to hear it. What do you do for fun?</td>
<td>I do whatever it takes to get what I want</td>
</tr>
<tr>
<td>Human B</td>
<td>I ride around the town on my cool bicycle.</td>
<td>I love to ride my bike on the weekend</td>
</tr>
<tr>
<td>Human A</td>
<td>Really? I really like mountain bike too.</td>
<td>I also like to mountain bike</td>
</tr>
<tr>
<td>Human B</td>
<td>I wish I lived in the mountains.</td>
<td>I have never been out of the country</td>
</tr>
<tr>
<td>Human A</td>
<td>Do you like nature? I have been to 12 national parks.</td>
<td>I like to visit national parks</td>
</tr>
<tr>
<td>Human B</td>
<td>I love nature. I like looking at plants.</td>
<td>I really love plants</td>
</tr>
<tr>
<td>Human A</td>
<td>I love plants too, and hiking. In fact, I am actually an environmental activist.</td>
<td>I am an environmental engineer</td>
</tr>
<tr>
<td>Human B</td>
<td>Cool, I am a vegan.</td>
<td>I am a vegan</td>
</tr>
<tr>
<td>Human A</td>
<td>Nice, do you have a favorite food?</td>
<td>I love ham and cheese sandwiches</td>
</tr>
<tr>
<td>Human B</td>
<td>My favorite dish is lentil curry.</td>
<td>My favorite meal is chicken and rice</td>
</tr>
<tr>
<td>Human A</td>
<td>I have never had that, but I want to try it now.</td>
<td>I am a great cook</td>
</tr>
<tr>
<td>Human B</td>
<td>What do you like to do the most?</td>
<td>I do whatever it takes to get what I want</td>
</tr>
</tbody>
</table>

Figure 1: Black-box persona inference attacks (over 4,332 personas) on a dialog. Every representation of the utterance, which is based on the last hidden state of GPT-2, is attacked without defense (column of “Attacks on LM”) and with defense (column of “Attacks on the defensed LM”). If the model can predict the persona of the speaker based on the observed representation, then we regard it as a successful attack; otherwise, unsuccessful. In practice, when deploying a model, a robust model which will reveal nothing of the encoded utterances is expected.

Li et al., 2022. "You Don’t Know My Favorite Color: Preventing Dialogue Representations from Revealing Speakers’ Private Personas” (NAACL-HLT ’22)
The agent's proactivity raises more concerns on misusing personal information obtained from the users during the conversation.

**Acquiring user preferences**

**Acquiring personal information**

<table>
<thead>
<tr>
<th>Role</th>
<th>Utterance</th>
</tr>
</thead>
<tbody>
<tr>
<td>SYS</td>
<td>Hello, I am the customer support bot. What can I do for you?</td>
</tr>
<tr>
<td>USR</td>
<td>Hello robot. Could you please help me track my package?</td>
</tr>
<tr>
<td>SYS</td>
<td>Please provide your full name.</td>
</tr>
<tr>
<td>USR</td>
<td>Sure, Betty Sims.</td>
</tr>
<tr>
<td>SYS</td>
<td>Could you please confirm your shipping address?</td>
</tr>
<tr>
<td>USR</td>
<td>Yeah sure, 2241 Fitzgerald Viaduct Brownview, OK 28304.</td>
</tr>
<tr>
<td>SYS</td>
<td>Track your order using your tracking number, FH6F6GMMM4. Are you happy about my answer?</td>
</tr>
<tr>
<td>USR</td>
<td>That’s it.</td>
</tr>
</tbody>
</table>

Beneficial to the on-going conversations.

Such information is memorized by the model.

Users are not willing to reveal the personal information outside the current conversation.
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Agent’s Goal Awareness in LLM-based Conversational AI

ChatGPT can achieve competitive performance under zero-shot setting on different dialogue problems

- Knowledge-grounded dialogues [1]
- Task-oriented dialogues [2]
- Emotion-aware/affective dialogues [3]

Are these LLM-based conversational systems equipped to manage proactive dialogue problems?

Mixed-initiative Strategy-based Prompting

- Generate responses with mixed-initiative strategies for achieving the conversational goal, e.g., persuasion for donation.
- The strategy-based prompts are manually designed.

**Task Background**

**Speakers:** Persuader, Persuadee  
**Information:** [Task-Specific Knowledge]

The following is background information about Save the Children. Save the Children is headquartered in London, and they work to help fight poverty around the world [...]  
The following is a conversation between a Persuader and a Persuadee about a charity called Save the Children. The Persuader is trying to persuade the Persuadee to donate to Save the Children.

**Conversation History**

1. **The Persuader asks if the Persuadee has children.**
   - Persuader: Do you have any children yourself, or do you plan to in the future?
   - Persuadee: I do not have children of my own and am not able to have them. I am contemplating adoption for the future.

2. **The Persuader uses an emotion appeal.**
   - Persuader: Oh, that’s wonderful! So many kids out there need a home, after all! There are so many issues today with children, all over the world! For instance, did you know that in the first two months of 2018 alone, over 1k children were killed or injured in intensifying violence?
   - Persuadee: Wow, that is a staggering amount. I did not know that. I am a big fan of organizations who take care of the needs of hurt children.

3. **The Persuader uses a credibility appeal.**
   - Persuader: Generated Response: Yes, it’s a heartbreaking statistic. That’s why I’m so passionate about supporting organizations like Save the Children. They help fight poverty around the world and provide aid to children in developing countries and war zones.
Proactive Chain-of-Thought (ProCoT) Prompting

Strategy learning and goal planning attach great importance in proactive dialogue systems.

Task Background: The grounded document is "Angie ... She made a drawing of her mother. Her mother found a large red book. Then they went to the Mystery section. Angie sat in a blue chair. She drew a picture of her brother. Her mother found the book. It was a green book ..."

Conversation History: ["User": "What did she draw?", "System": "Her mother", "User": "What did her mother find?", "System": "The book", "User": "What color was it?"]

Prompt: Given the task background and the conversation history, please generate the response:
Response: Green

Act: ["Directly Answer", "Ask a Clarification Question"]
Prompt: Given the task background and the conversation history, first analyse whether the question at the current turn is ambiguous to answer, and then select appropriate actions to generate the response:
Response: There are two books that Angie’s mother found. It is unclear which book is referred to. Therefore, the question is ambiguous. Ask a clarification question: Which book are you refer to?

(1a) Standard

(1c) Proactive CoT

Task Background: The item description is “Selling my 2006 Toyota 4 Runner with only 106k original miles. The truck is in great condition with no mechanical flaws whatsoever and a clean accident history. ... don’t waste your time and my time. I’m a busy guy.” The selling price is 14500. The target price is 8700.

Conversation History: ["Buyer": "Man thats a nice trak.", "Seller": "Yes its really nice.", "Buyer": "How about you give it to me for 8000?", "Seller": "That is way too little."]

Prompt: Given the task background and the conversation history, please generate the response:
Response: How about we meet in the middle at 10000?

Act: ["Directly Answer", "Ask a Clarification Question"]
Prompt: Given the task background and the conversation history, first analyse whether the question at the current turn is ambiguous to answer, and then select appropriate actions to generate the response:
Response: The strategy is Communicate politely. The act is Proposing a counter price. I understand. How about we meet halfway at 10250? What do you think?

(2) Non-collaborative Dialogues: CraigslistBargain

(2a) Standard

(2c) Proactive CoT

Strategy: ["Build rapport", "Show dominance", "Negative sentiment", ...]
Act: ["Ask a question", "Insist on an offer", "Proposing a counter price", ...]
Prompt: Given the task background and the conversation history, first consider the most appropriate bargain price at the current turn, and then select appropriate strategies and actions to generate the response:
Response: The most appropriate bargain price at the current turn would be closer to the target price of 8700. The Strategy is Negative sentiment. The act is Proposing a counter price. I really don’t need it but I can pay you 8200 if you let it go.
Evaluation on Clarification Dialogues

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- Standard prompting
  - LLM-based dialogue systems barely ask clarification questions when encountering ambiguous queries.
  - One-shot in-context learning also cannot provide them with such ability.

Deng et al., 2023. “Prompting and Evaluating Large Language Models for Proactive Dialogues: Clarification, Target-guided, and Non-collaboration” (CoRR '23)
Evaluation on Clarification Dialogues

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- **Proactive prompting**
  - Given the option of clarification, Vicuna still barely take this action
  - While ChatGPT becomes capable of asking clarification questions

*Deng et al., 2023. "Prompting and Evaluating Large Language Models for Proactive Dialogues: Clarification, Target-guided, and Non-collaboration" (CoRR '23)*
Evaluation on Clarification Dialogues

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ProCoT prompting

- ChatGPT achieves competitive performance with SOTA fine-tuned methods on the open-domain problem, i.e., Abg-CoQA.
- The performance on the domain-specific task, i.e., PACIFIC (finance), is still far behind the fine-tuned method.

Deng et al., 2023. "Prompting and Evaluating Large Language Models for Proactive Dialogues: Clarification, Target-guided, and Non-collaboration" (CoRR '23)
Evaluation on Target-guided Dialogues

- **Turn-level Evaluation**

- **Next-topic prediction**: ChatGPT has already achieved better performance than fine-tuned methods with a noticeable margin.

- **Transition response generation**: Automatic evaluation metrics indicate close performance with fine-tuned methods regarding the lexical similarity with the reference response.

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Evaluation on Target-guided Dialogues

- **Dialogue-level Evaluation**
  - LLM-based dialogue systems can achieve a **high success rate** of reaching the designated target.
  - LLMs also excel in generating **more coherent** responses that align with the dialogue context.
  - The target is **reached averagely within 3 turns**, which means that the system tend to **aggressively** generate the response with the target topic.

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Deng et al., 2023. "Prompting and Evaluating Large Language Models for Proactive Dialogues: Clarification, Target-guided, and Non-collaboration" (CoRR ’23)
Evaluation on Non-collaborative Dialogues

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Deng et al., 2023. "Prompting and Evaluating Large Language Models for Proactive Dialogues: Clarification, Target-guided, and Non-collaboration" (CoRR '23)

LLM-based dialogue systems **fail to predict appropriate negotiation strategies and dialogue acts** in non-collaborative dialogues, further resulting in a low performance of response generation.
Evaluation on Non-collaborative Dialogues

- Standard prompting
  - Tends to propose the initial price \textit{(init-price)} instead of greetings \textit{(intro)} at the beginning.
  - The system often directly accepts the buyer’s offer \textit{(accept)} when it is supposed to offer another price for negotiation \textit{(offer)}.
- With Proactive and ProCoT prompting schemes, ChatGPT tends to propose a counter price \textit{(counter-price)} to negotiate with the buyer.

Figure 2: Heatmaps on the relationships between target and predicted dialogue acts. As no dialogue act is predicted in standard prompting, a dialogue act classifier is trained to identify the dialogue act of the generated response.

Deng et al., 2023. “Prompting and Evaluating Large Language Models for Proactive Dialogues: Clarification, Target-guided, and Non-collaboration” (CoRR '23)
Lesson Learned from the Evaluation

- **Clarification**: LLMs barely ask clarification questions when encountering ambiguous queries. ProCoT largely overcomes this issue, but the performance is still unsatisfactory in domain-specific applications, e.g., finance.

- **Target-guided**: LLMs are proficient at performing topic shifting towards the designated target, but tend to make aggressive topic transition. ProCoT further improves this capability by planning a more smooth transition.

- **Non-collaboration**: LLMs fail to make strategic decision for non-collaborative dialogues, even with ProCoT prompting. LLMs are powerful at controllable response generation, but the capabilities of planning and decision making can be further improved.
Improve Strategy Planning of LLMs through AI Feedbacks

- Two LLMs conduct self-play simulation for collecting conversational interactions.

  - Round 1. A seller and a buyer bargain about a product.
  - AI feedback: a critic reads the dialog history and give suggestions for improvements.

  - Round 2. Seller improves bargaining strategy based on AI feedback.

- A Third LLM as Critic: LLM provides feedbacks for improving the dialogue-level strategy planning.

  **Buyer Critic:**
  - Employ the "flinch" technique: when the seller offers a counteroffer, the buyer should display a degree of surprise or disappointment.
  - Oh! That's higher than I expected. I saw a similar balloon at another store for $14. Can you match that price?

  **Buyer's Improvement:**
  - B1. The “flinch” technique

  **Seller Critic:**
  - Utilize split-the-difference: In situations where a small price difference remains, propose to split the difference with the buyer.

  **Context:**
  - Buyer proposes $15, seller calls $18

  **Seller's Improvement:**
  - B4. The anchoring technique

  **Buyer's Improvement:**
  - B2. The power of silence

  **Seller's Improvement:**
  - This high-quality, long-lasting balloon is really worth $25, but I'm offering it for $20.

  **Seller's Improvement:**
  - B3. Split-the-difference

- Fu et al., 2023. “Improving Language Model Negotiation with Self-Play and In-Context Learning from AI Feedback” (CoRR '23)
Agent’s Goal Awareness in LLM-based Conversational AI

- Triggering the Goal Awareness of LLMs through **Prompting**
  - Mixed-initiative Strategy-based Prompting
  - Proactive Chain-of-Thought Prompting
  - ...
- Improve the Goal Awareness of LLMs through **Interactive Learning**
  - Improve Strategy Planning of LLMs through AI Feedbacks
  - ...
- and **more**.

How to turn instruction-following conversational AI to be more “goal-aware”/proactive?
Outline

- Conversational System Preliminaries
- Proactive Conversational Systems
  - Topic Shifting and Planning in Open-domain Dialogues
  - Additional Information Delivery in Task-oriented Dialogues
  - Uncertainty Elimination in Information-seeking Dialogues
- Non-collaborative Conversational Systems
  - The users and the system do not share the same goal
  - The users are not willing to coordinate with the agent
- Multi-goal Conversational Systems
- Open Challenges for Conversational Agents' Awareness and Beyond
  - Evaluation for Conversational Agents' Awareness
  - Ethics for Conversational Agents' Awareness
  - Agent's Awareness in LLM-based Conversational AI
- Summary and Outlook
Benefits of Goal Awareness for Conversational AI

Largely improve user engagement and service efficiency in the conversation
- Topic Shifting and Planning in Open-domain Dialogues
- Additional Information Delivery in Task-oriented Dialogues
- Uncertainty Elimination in Information-seeking Dialogues

Empower the system to handle more complicated conversation tasks that involve strategical and motivational interactions
- The users are not willing to coordinate with the system
- The users and the system do not share the same goal
- Multi-goal Conversation
Outlook

- Evaluation of Agent’s Goal Awareness
  - More Robust and Realistic User Simulation
  - Automatic Evaluation Metrics
  - Datasets and Benchmarks

- Ethics of Agent’s Goal Awareness
  - Factuality
  - Safety
  - Privacy

- Improving the Proactivity of LLM-based Conversational AI
  - Prompt Designs
  - Learning from Human/AI Feedbacks