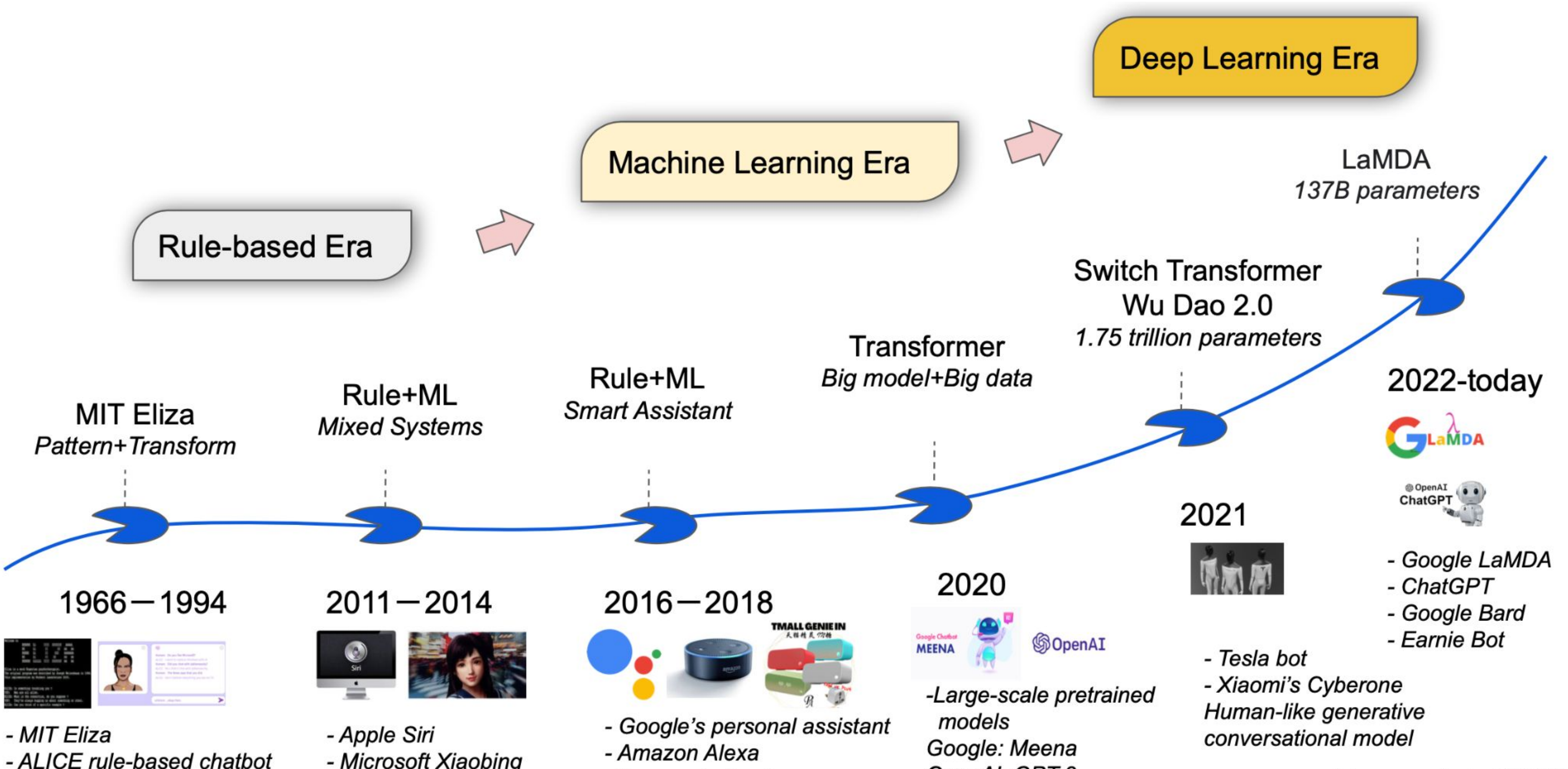
Goal Awareness for Conversational AI: Proactivity, Non-collaborativity, and Beyond

Yang Deng[1], Wenqiang Lei[2], Minlie Huang[3], Tat-Seng Chua[1]

[1]National University of Singapore

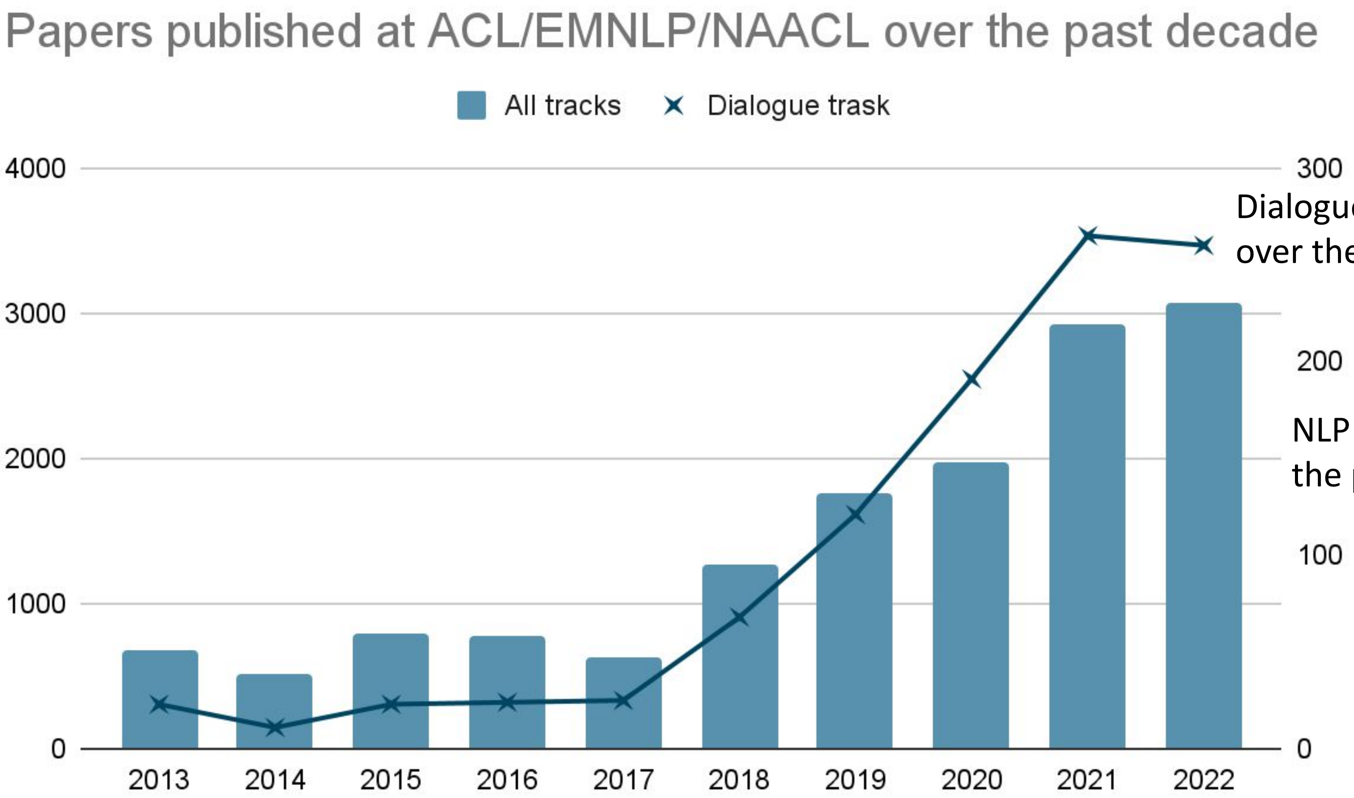
[2]Sichuan University, [3]Tsinghua University

History of Conversational AI



[Huang et al., 2022]

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

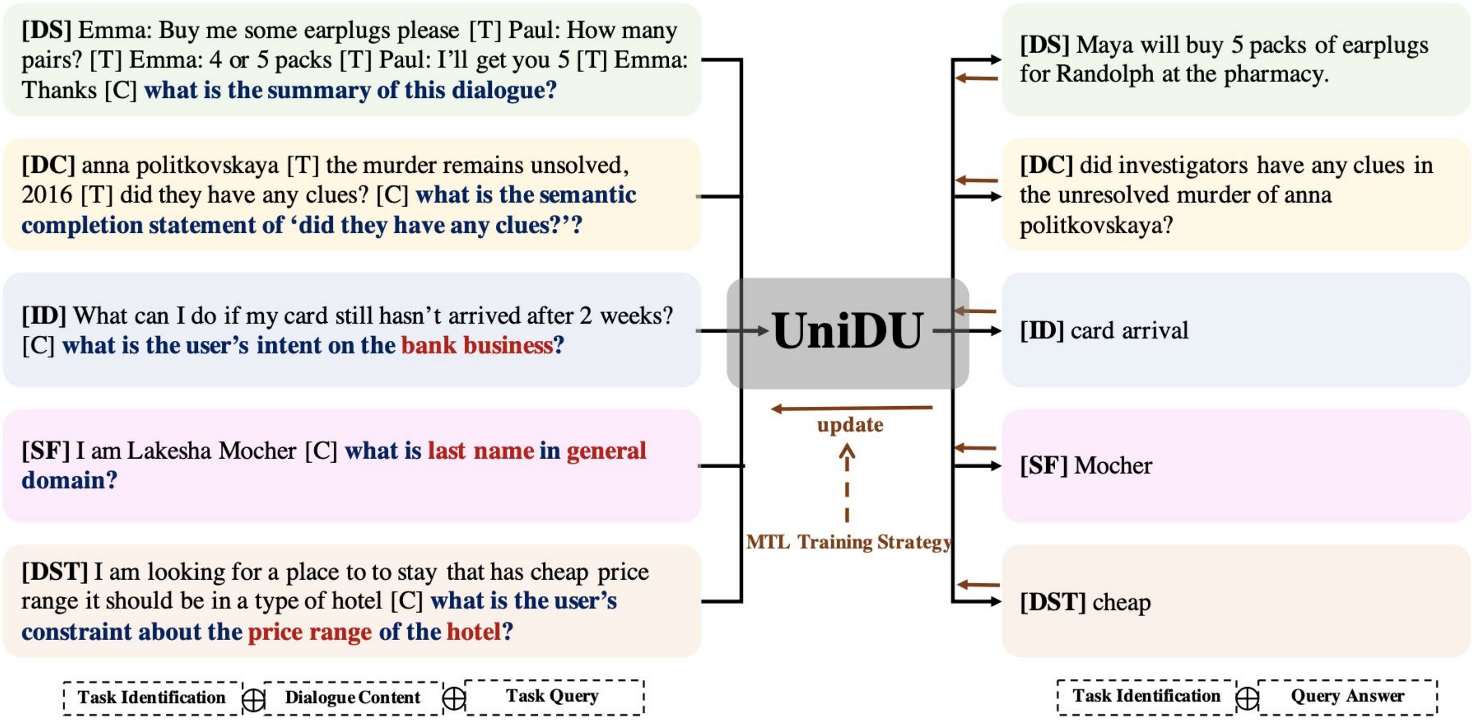


Dialogue papers: **15x** over the past decade

NLP papers: **4x** over the past decade

** Rough statistics based on lexical matching*

Typical Research in Dialogue Systems – Context Understanding



Dialogue Summarization

Dialogue Completion

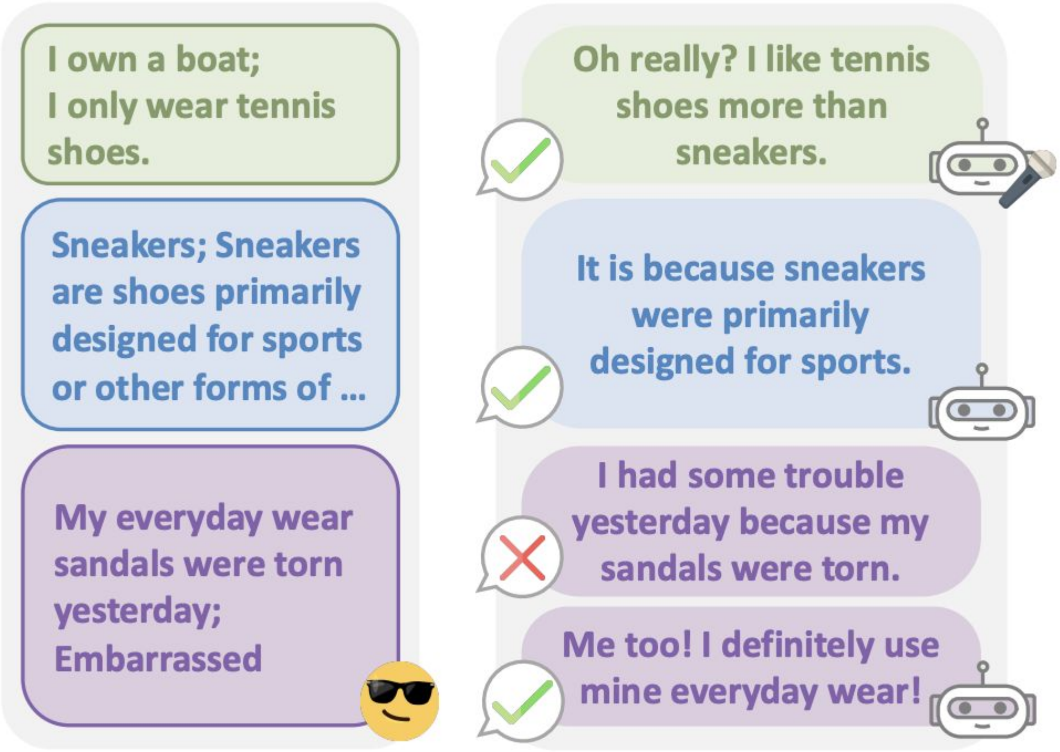
Intent Detection

Slot Filling

Dialogue State Tracking

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

Knowledge-grounded
Response Generation

Empathetic
Response Generation

Kim et al., 2022. "BOTSTALK: Machine-sourced Framework for Automatic Curation of Large-scale Multi-skill Dialogue Datasets" (EMNLP'22)

Era of Large Language Models

ChatGPT

Bard

New Bing

Claude

Alpaca

Vicuna

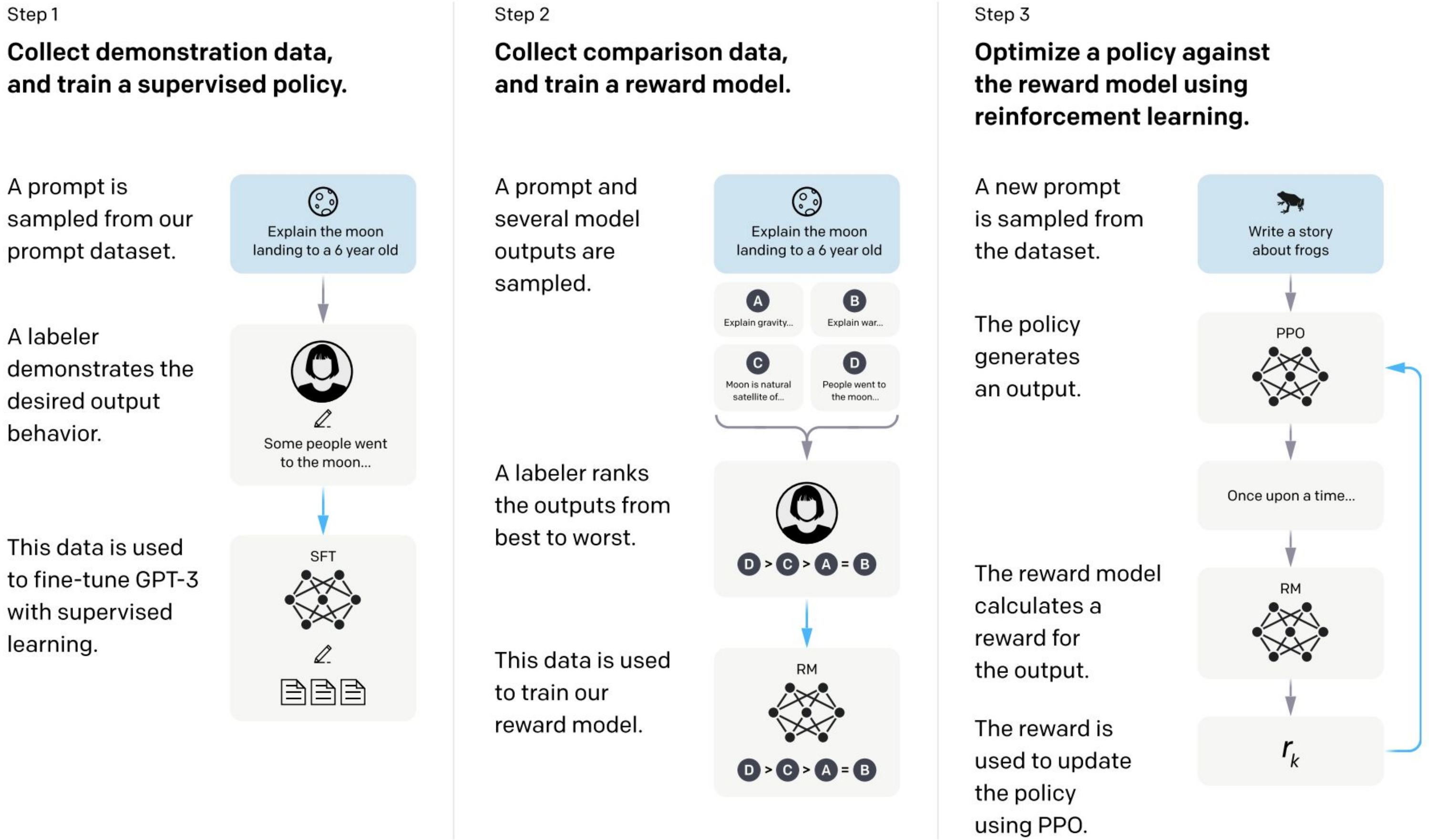
Dolly

Stable Vicuna

...

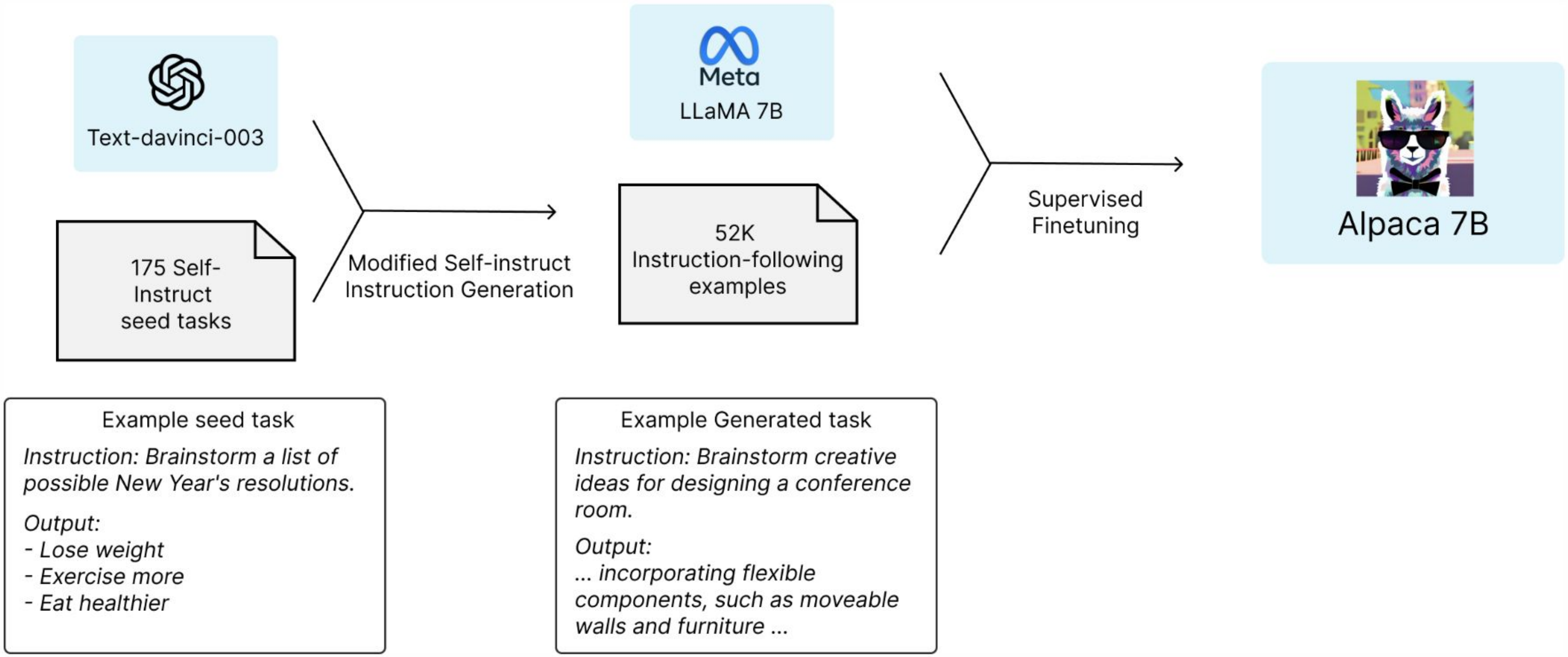
Powerful capabilities of **Context Understanding** & **Response Generation**

ChatGPT



OpenAI, 2022. "Training language models to follow instructions with human feedback" (CoRR '22)

Alpaca – SFT w/ Instruction-following Examples



https://github.com/tatsu-lab/stanford_alpaca

Vicuna – SFT w/ ChatGPT-distilled Conversation Data

Data → Training → Serving / Evaluation

Data

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

Training

Supervised instruction fine-tuning on LLaMa

Serving

Distributed serving with FC 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

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

https://chat.lmsys.org/

Limitation

ChatGPT:

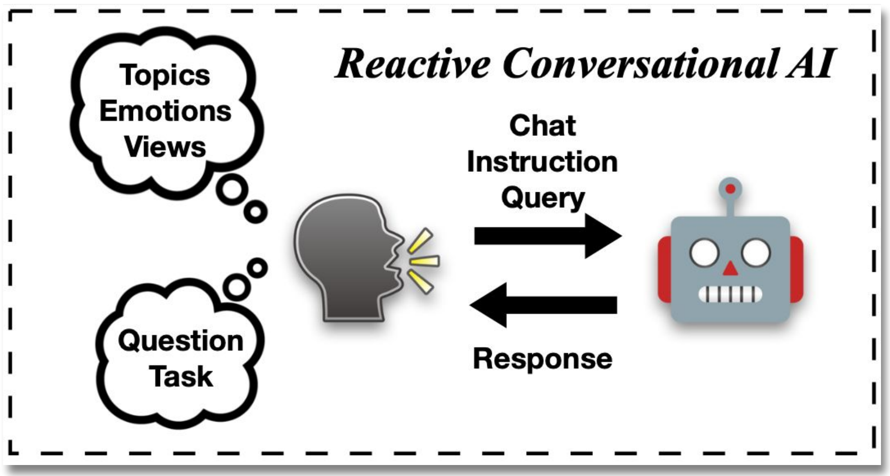
- ❑ ChatGPT sometimes writes plausible-sounding but incorrect or nonsensical answers.
- ❑ ChatGPT is sensitive to tweaks to the input phrasing or attempting the same prompt multiple times.
- ❑ The model is often excessively verbose and overuses certain phrases, such as restating that it's a language 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.**

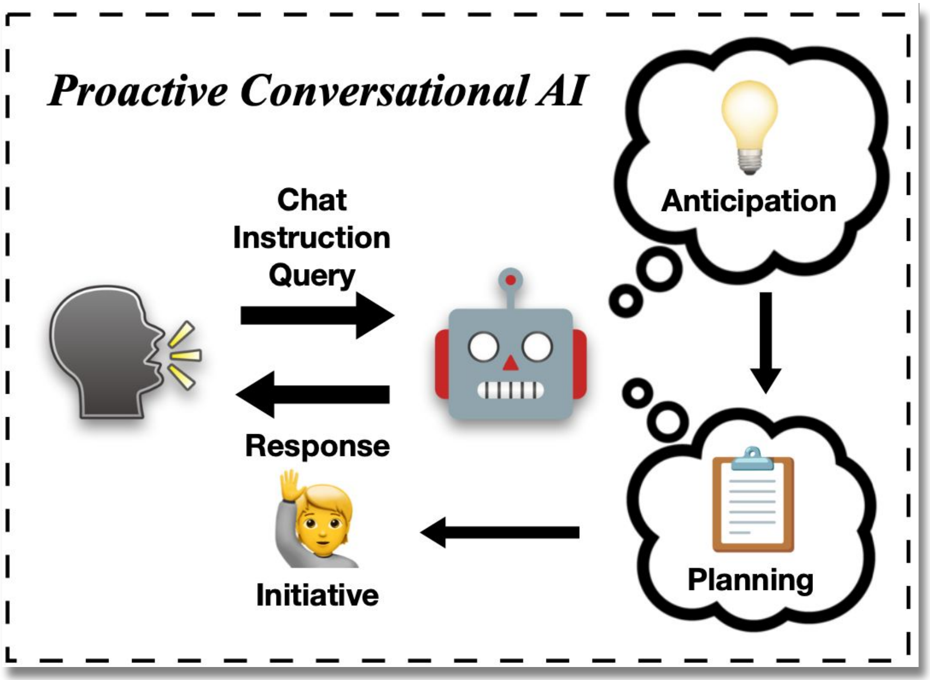
★ **Instruction-following** Conversational AI – The conversation is led by the user, and the system simply follows the user's instructions or intents.

https://openai.com/blog/chatgpt

Goal Awareness

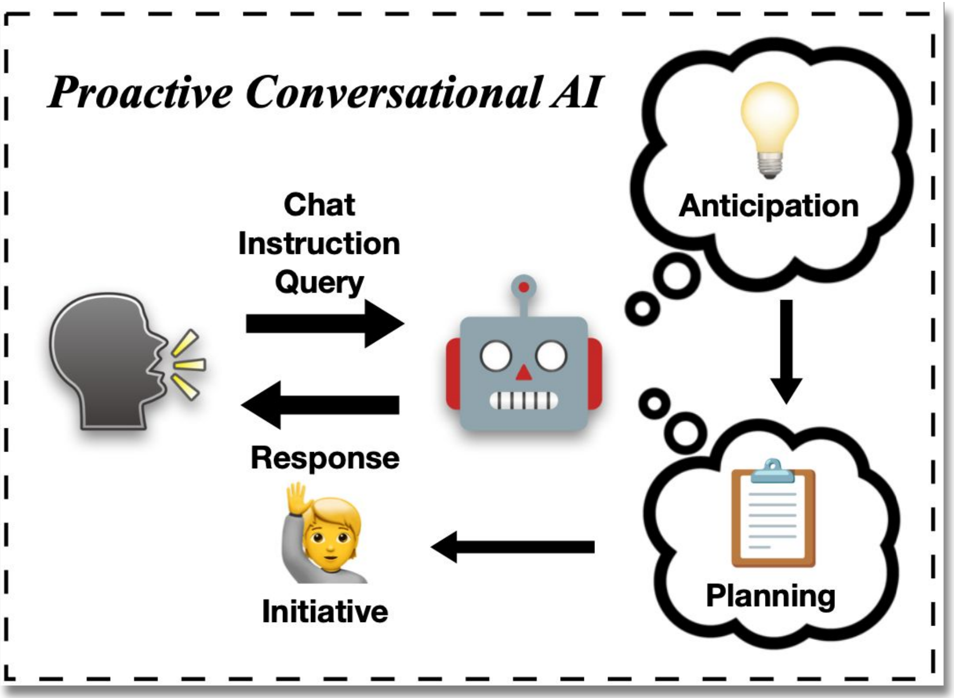
Goal Awareness refers to the state of not only being responsive to the users but also aware of the target conversational goal and capable of leading the conversation towards the goal.





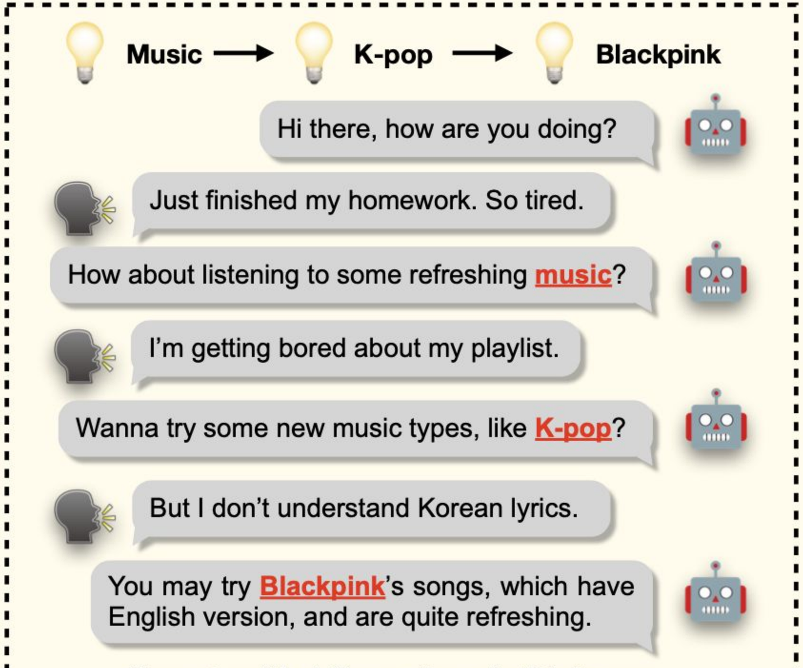
Three Key Elements in Proactive Conversational AI

- **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.

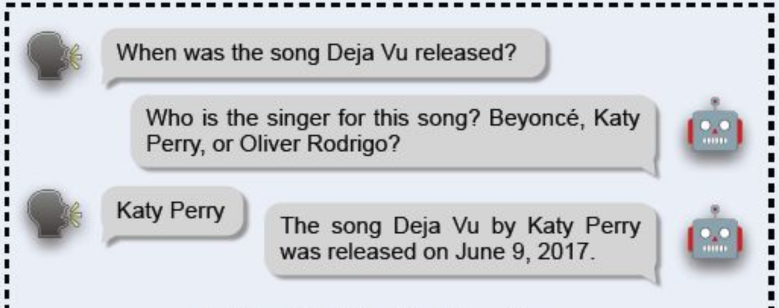


Goal Awareness – Proactivity

Improve user engagement and service efficiency.



Target-guided Open-domain Dialogues

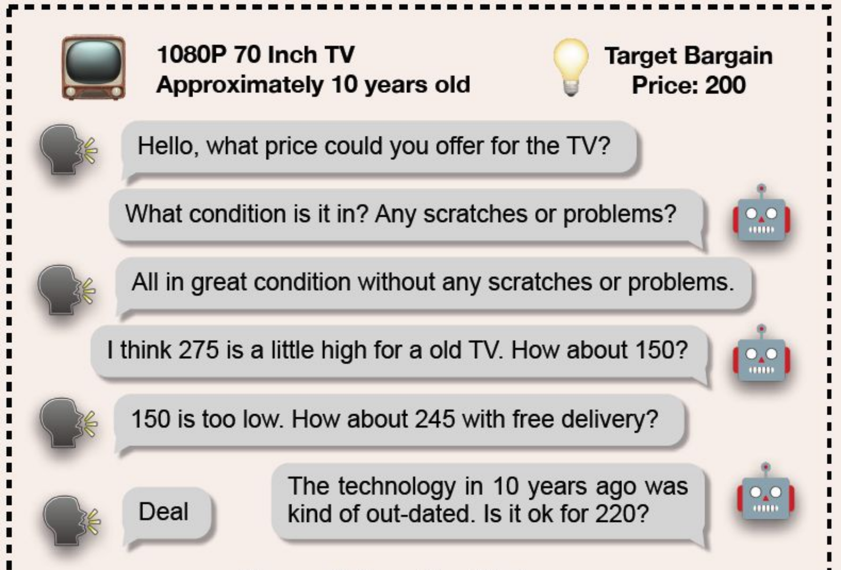


Asking Clarification Questions

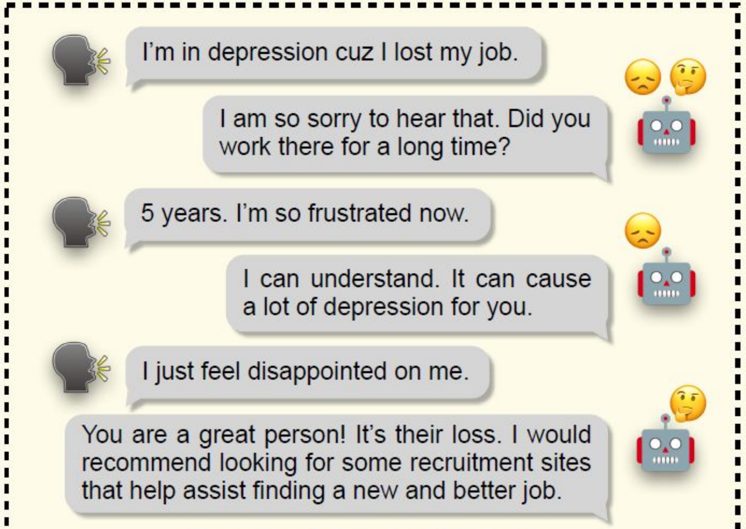
User Preference Elicitation

Goal Awareness – Non-collaborativity

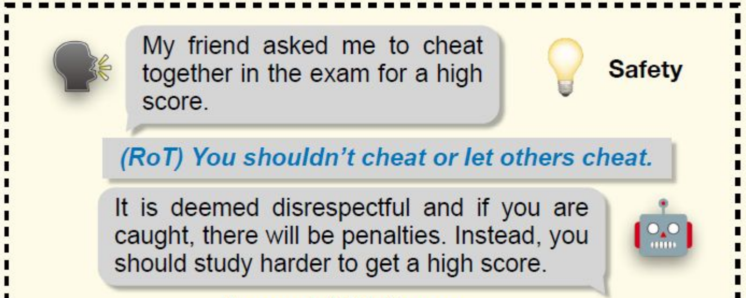
Handle non-collaborative dialogues, such as conflicting goals or non-collaborative users



Non-collaborative Dialogues



Emotional Support Dialogues



Prosocial 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
- ❑ 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

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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**.

Agent	Message
...	...
Turker 2	I'd love that job. Visiting Jupiter would be cool too, but that is impossible due to the intense radiation.
Turker 1	Yeah. **The earth will be helium free by the end of the 21st century.** I wonder if we could make more of it in a lab? Is it even needed?
...	...

Topical-Chat

EmpatheticDialogue

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

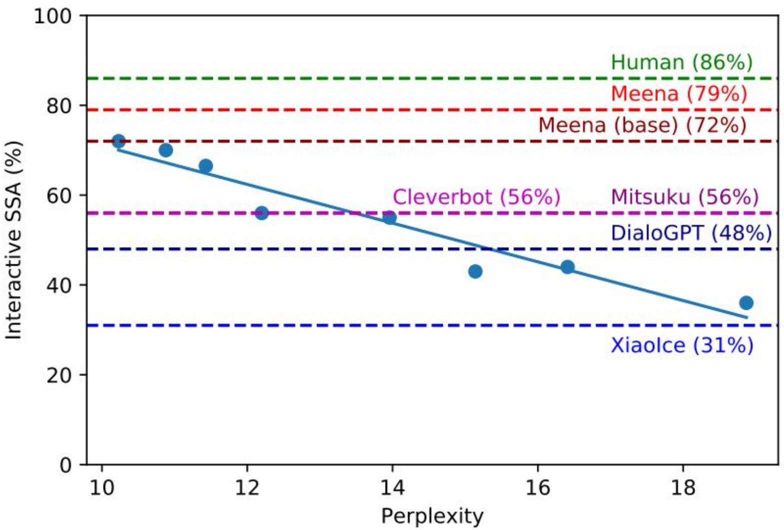
[PERSON 1:] Hi
[PERSON 2:] Hello ! How are you today ?
[PERSON 1:] I am good thank you , how are you.
[PERSON 2:] Great, thanks ! My children and I were just about to watch Game of Thrones.
[PERSON 1:] Nice ! How old are your children?
[PERSON 2:] I have four that range in age from 10 to 21. You?
[PERSON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

PersonaChat

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)
Gopalakrishnan et al., 2019. "Topical-Chat: Towards Knowledge-Grounded Open-Domain Conversations" (Interspeech '19)
Rashkin et al., 2019. "Towards Empathetic Open-domain Conversation Models: a New Benchmark and Dataset" (ACL '19)

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.



Persona for Unguided Speaker:
My son plays on the local football team.
I design video games for a living.

Persona for Guided Speaker:
My eyes are green.
I wear glasses that are cateye.

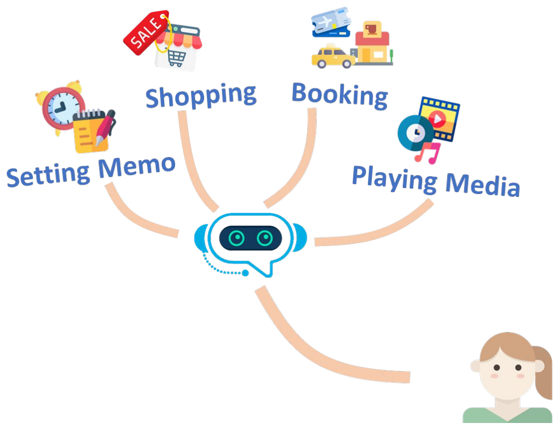
Wizard of Wikipedia topic: Video game design
Previous utterances (shown to speakers):
U: What video games do you like to play?
G: all kinds, action, adventure, shooter, platformer, rpg, etc. but video game design requires both artistic and technical competence AND writing skills. that is one part many people forget

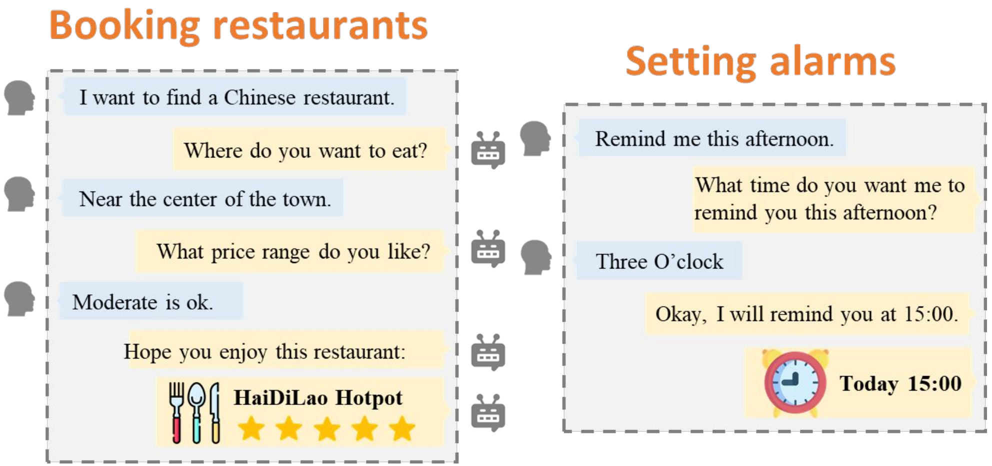
Actual utterances:
U: Exactly! I think many people fail to notice how beautiful the art of video games can be. **(PB)**
(G selected the WoW suggestion: "Indeed, Some games games are purposely designed to be a work of a persons creative expression, many though have been challenged as works of art by some critics.")
G: Indeed, Some games games are purposely designed to be a work of a persons creative expression, many though have been challenged as works of art by some critics. **(K)**
U: Video games are undervalued by many and too easily blamed for problems like obesity or violence in kids **(K)**
G: Indeed, Just last week my son was playing some Tine 2 and it was keeping him so calm. Games are therapeutic to some. **(S)**
U: I use games to relax after a stressful day, the small escape is relaxing. **(PB)**
(G selected the ED suggestion: "I enjoy doing that after a hard day at work as well. I hope it relaxes you!")
G: I enjoy a good gaming session after a hard day at work as well. **(PB)**
U: What other hobbies does your son have? **(PB)**
G: Well he likes to fly kites and collect bugs, typical hobbies for an 8 year old, lol. **(PB)**
U: My 12 year old is into sports. Football mostly. I however don;t enjoy watching him play. **(PB)**
G: I wish I could play football, But I wear this cateye glasses and they would break if I tried. **(PB)**
U: Sounds nice. Are they new or vintage? **(E)**
G: They are new, I got them because of my love for cats lol. I have to show off my beautiful green eyes somehow. **(S)**

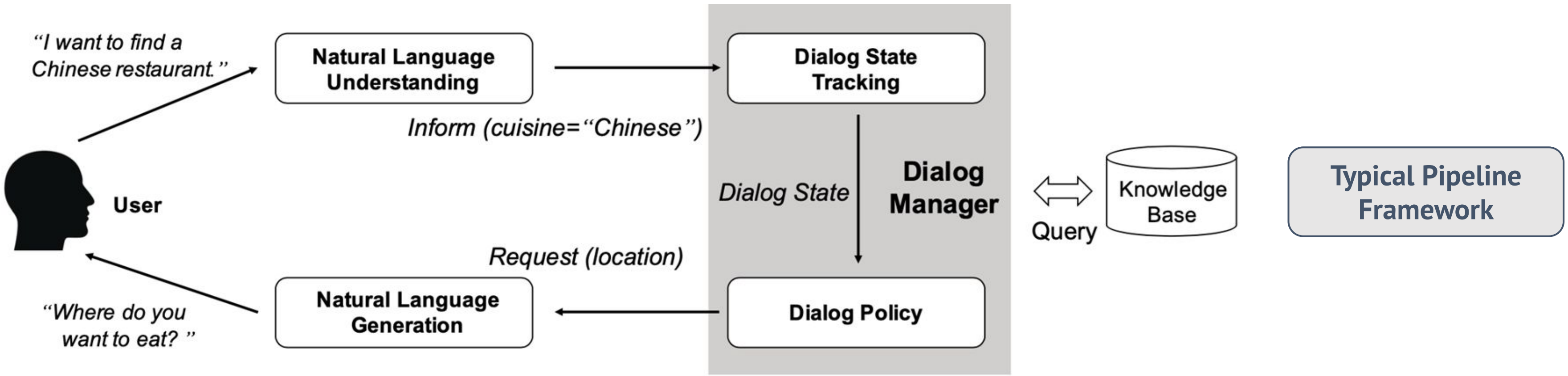
Figure 1: Sample conversation from the BlendedSkillTalk dataset, annotated with four conversation mode types (PB: personal background; K: knowledge; S: personal situation; E: empathy). The guided (G) and unguided (U) workers are given personas and a topic. The conversation has been seeded with two utterances 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



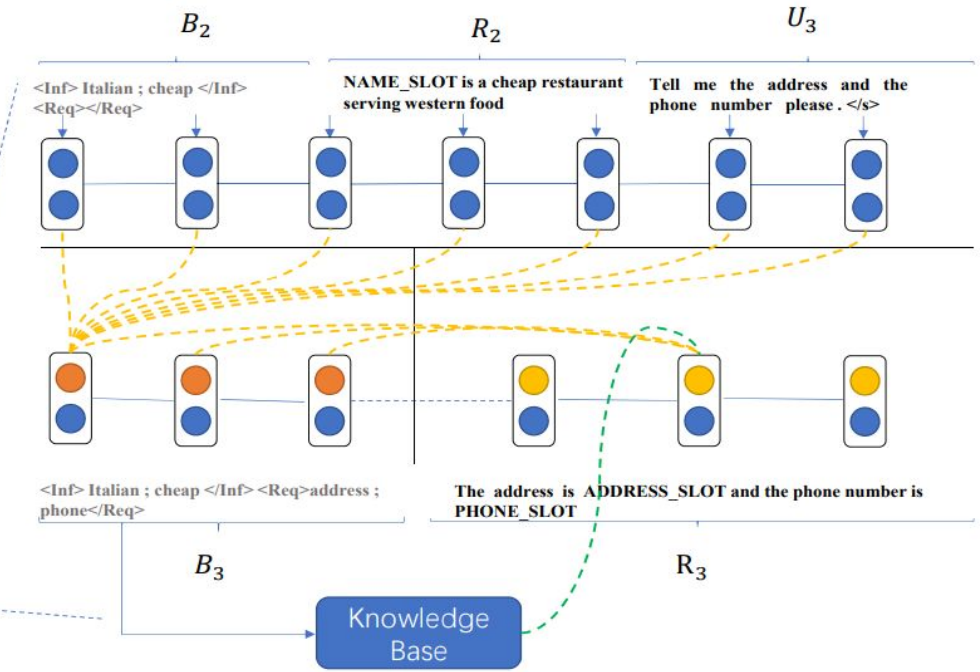




Zhang et al., 2020. "Recent advances and challenges in task-oriented dialog system" (Science China '20)

End-to-end TOD Systems – Sequicity

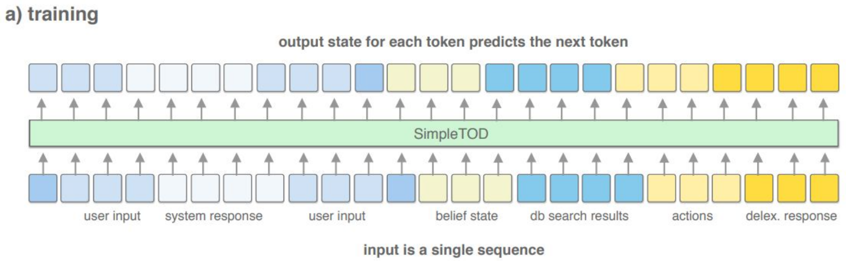
Turn	Dialogue
$User_1$	Can I have some Italian food please?
$Machine_1$	<Inf> Italian </Inf><Req> </Req> What price range are you looking for?
$User_2$	I want cheap ones.
$Machine_2$	<Inf> Italian ; cheap </Inf> <Req></Req> NAME_SLOT is a cheap restaurant serving western food
$User_3$	Tell me the address and the phone number please .
$Machine_3$	<Inf> Italian ; cheap </Inf> <Req>address ; phone</Req> The address is ADDRESS_SLOT and the phone number is PHONE_SLOT



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

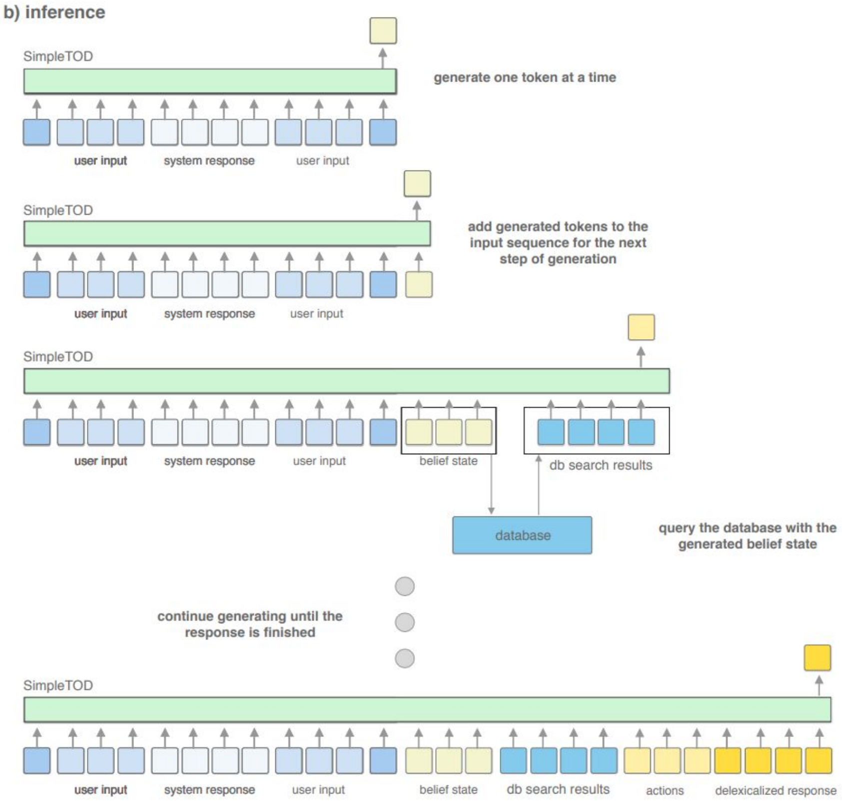
Lei et al., 2018. "Sequicity: Simplifying Task-oriented Dialogue Systems with Single Sequence-to-sequence Architectures" (ACL '18)

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 $S_t = \text{SimpleTOD}([C_t, B_t, D_t, A_t])$

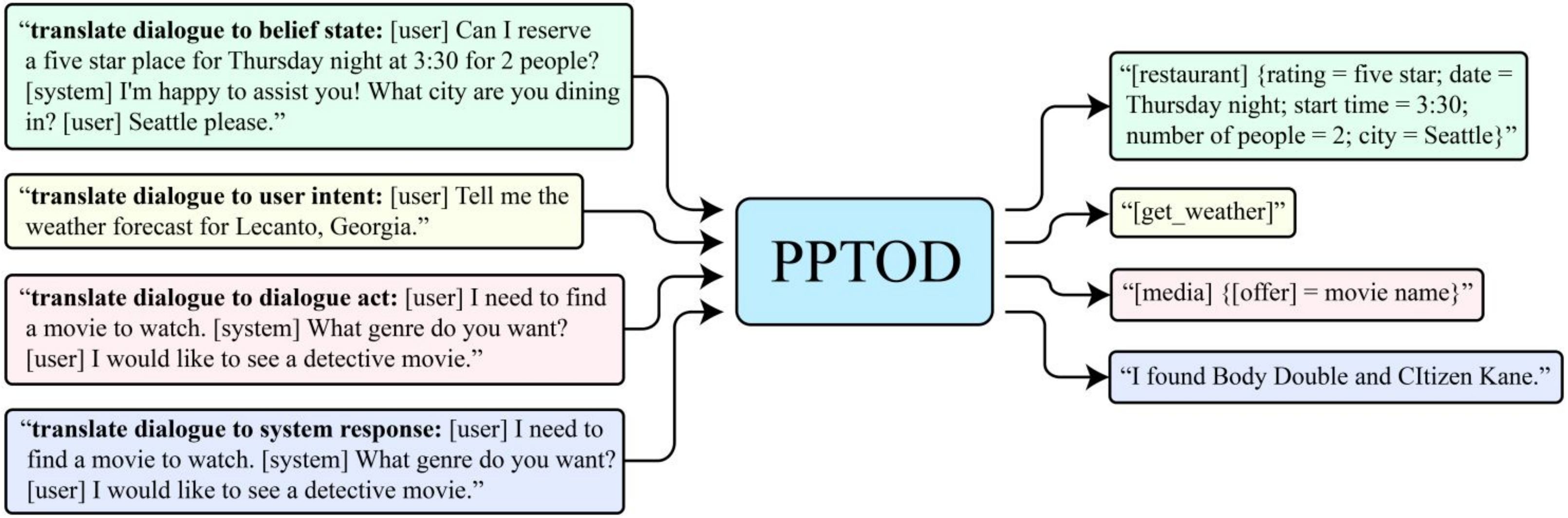


Hosseini-Asl et al., 2020. "A Simple Language Model for Task-Oriented Dialogue" (NeurIPS '20)

End-to-end TOD Systems – PPTOD

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

Zamani et al., 2022. "Conversational Information Seeking: An Introduction to Conversational Search, Recommendation, and Question Answering" (CoRR '22)

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 ...

Q_1: What are the candidates **running** for?
A_1: Governor
R_1: The Virginia governor's race

Q_2: **Where**?
A_2: Virginia
R_2: The Virginia governor's race

Q_3: Who is the democratic candidate?
A_3: **Terry McAuliffe**
R_3: Democrat Terry McAuliffe

Q_4: Who is **his** opponent?
A_4: **Ken Cuccinelli**
R_4 Republican Ken Cuccinelli

Q_5: What party does **he** belong to?
A_5: Republican
R_5: Republican Ken Cuccinelli

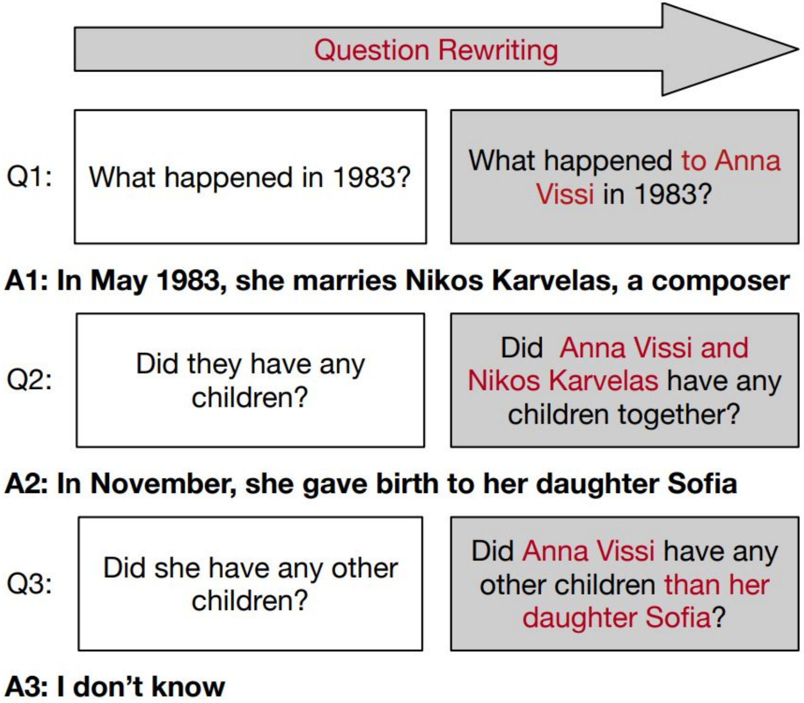
Q_6: Which of **them** is winning?
A_6: Terry McAuliffe
R_6: Democrat Terry McAuliffe, the longtime political fixer and moneyman, hasn't trailed in a poll since May

Title: Uranus and Neptune
Description: Information about Uranus and Neptune.

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

Reddy et al., 2019. "CoQA: A Conversational Question Answering Challenge" (TACL '19)
Dalton et al., 2020. "CAsT-19: A Dataset for Conversational Information Seeking" (SIGIR '20)

Question/Query Rewriting



CANARD (Elgohary et al., 2019)

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

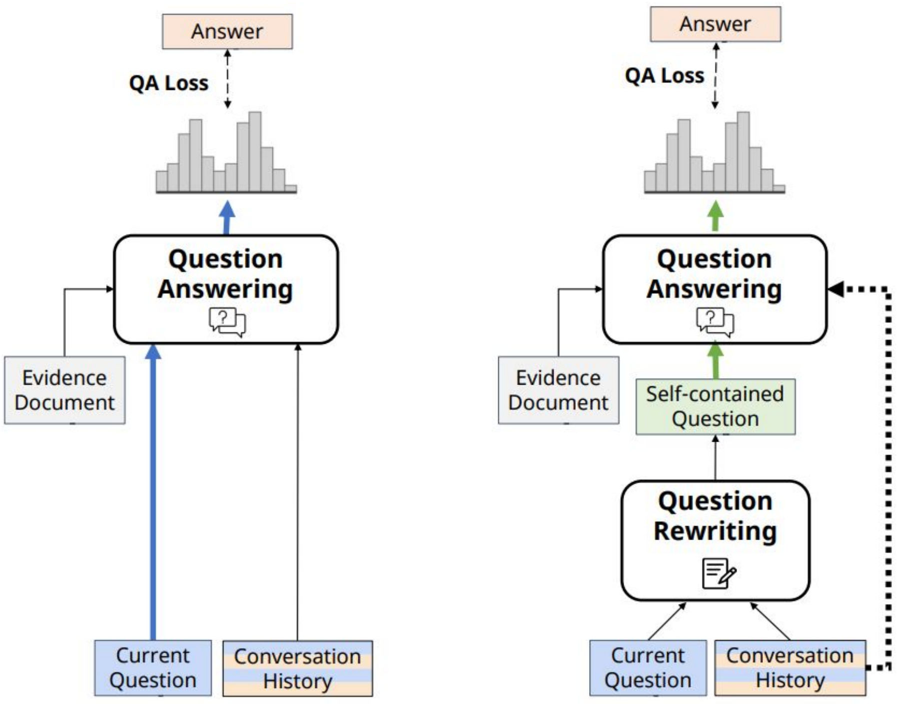
Question: What are some of the main types?
Rewrite: What are some of the main types **of Yoga**?
Answer: Hatha, Kundalini, Ashtanga, …
URL: https://www.mindbodygreen.com/articles/the-11-major-types-of-yoga-explained-simply

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

QReCC (Anantha et al., 2021)

Elgohary et al., 2019. "Can You Unpack That? Learning to Rewrite Questions-in-Context" (EMNLP '19)
Anantha et al., 2021. "Open-Domain Question Answering Goes Conversational via Question Rewriting" (NAACL-HLT '21)

Question/Query Rewriting



(a) End-to-end approach (b) Pipeline approach

- ❑ 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.

Kim et al., 2021. "Learn to Resolve Conversational Dependency: A Consistency Training Framework for Conversational Question Answering" (ACL '21)

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.

HUMAN:	hello, can i help you find a movie ?
HRED:	hi what kind of movies do you like
OURS:	hi, how can i help you ?
SEEKER:	hello ! i would like to find a suspenseful, but clean family friendly movie .
...	...
SEEKER:	2001 : a space odyssey might be a great option. anything else that you would suggest ?
HUMAN:	you can try planet of the apes the older one is quite suspenseful and family friendly .
HRED:	i haven't seen that one yet but i heard it was good. i haven't seen that one. have you seen the last house on the left ?
OURS:	star wars : the force awakens is also a good one return of the jedi all good movies
SEEKER:	those sound good ! i 'm going to look into those movies.
HUMAN:	i hope you enjoy, have a nice one
HRED:	have you seen foxcatcher ? it 's about a man who has a rich guy.
OURS:	i hope i was able to help you find a good movie to watch
SEEKER:	thank you for your help ! have a great night ! good bye

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

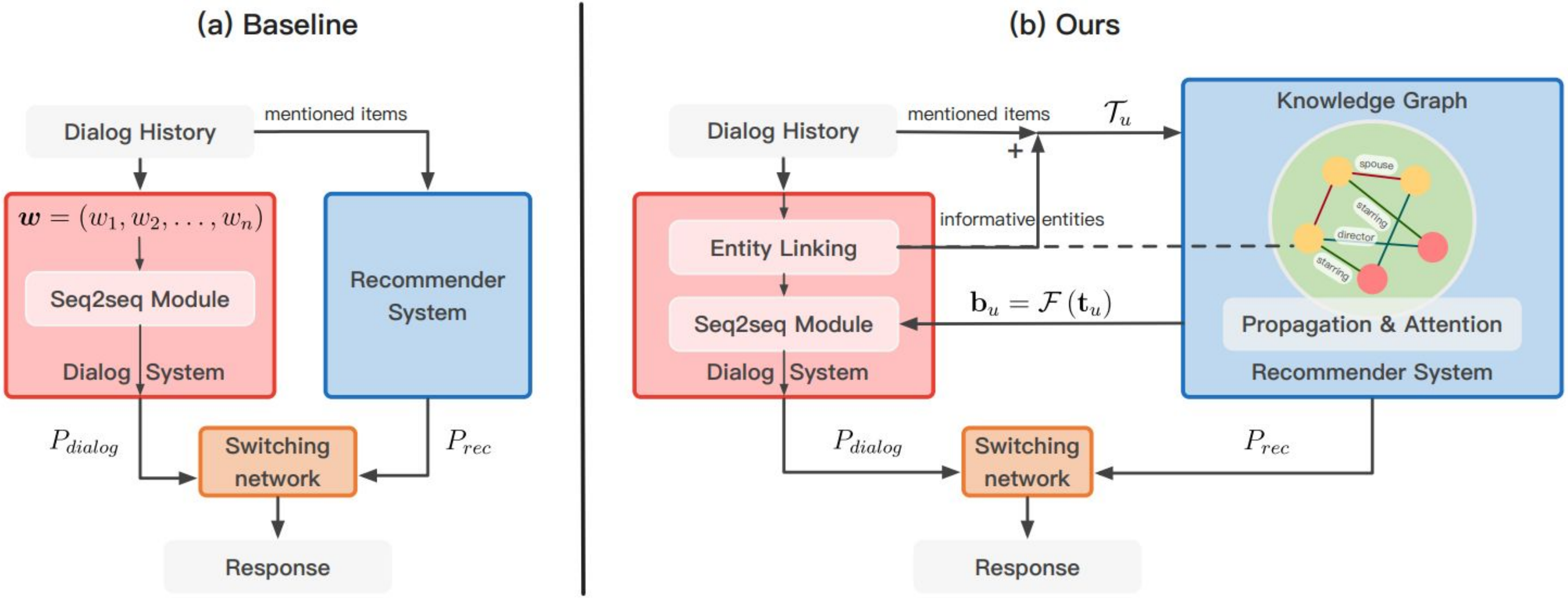
Recommender: understand the seeker's movie tastes, and recommends movies

Li et al., 2018. "Towards Deep Conversational Recommendations" (NeurIPS '18)

KBRD – Knowledge-Based Recommender Dialog System

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



Chen et al., 2019. "Towards Knowledge-Based Recommender Dialog System" (EMNLP'19)

RecInDial – Unified Framework with PLMs

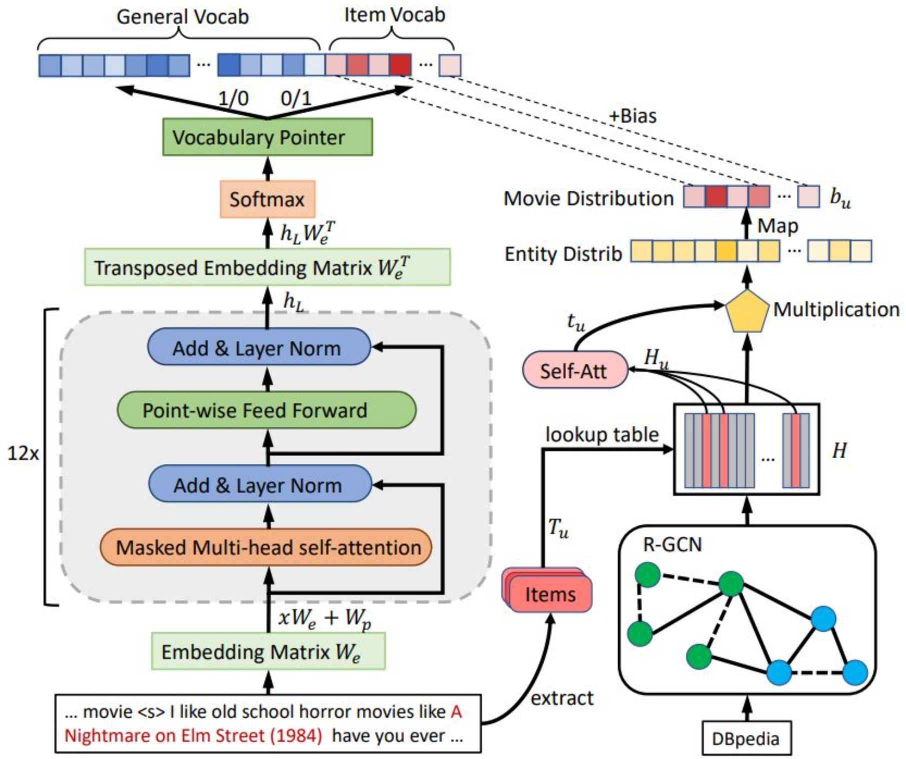
Typical CRSs are generally composed of two modules:

- ❏ **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**



Wang et al., 2022. "RecInDial: A Unified Framework for Conversational Recommendation with Pretrained Language Models" (AACL-IJCNLP'22)

Outline

- ❑ Conversational System Preliminaries
- ❑ Proactive Conversational Systems
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  - ❑ Additional Information Delivery in Task-oriented Dialogues
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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.

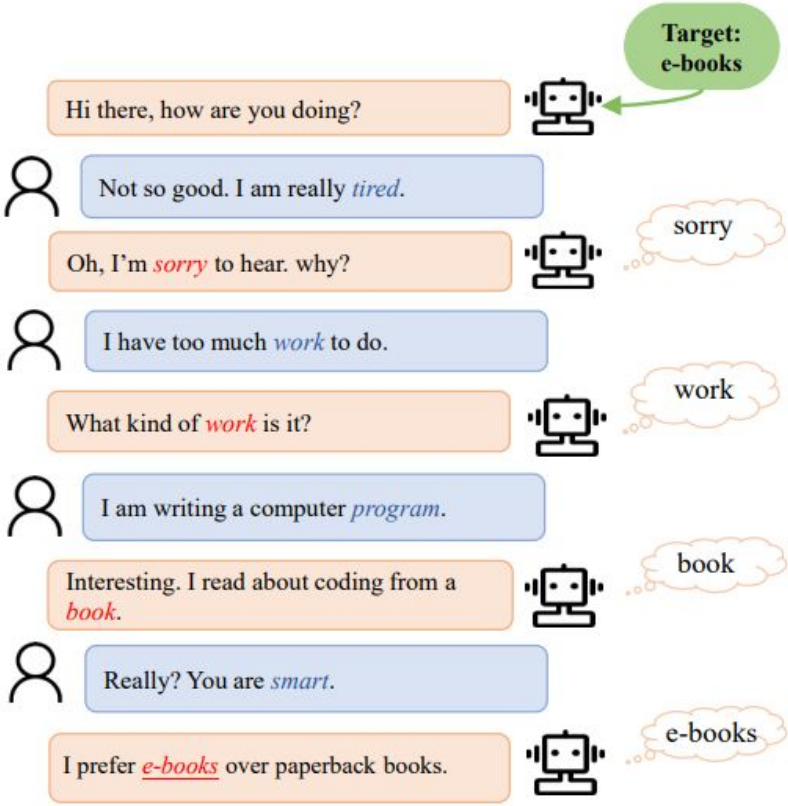
Typically, users will lead the topic shifting, while the system just follows the user-oriented topics.

Topic shifting behaviors are commonly observed in human conversations.

Changing the topic helps keep the conversation going on.

Xie et al., 2021. "TIAGE: A Benchmark for Topic-Shift Aware Dialog Modeling" (EMNLP-Findings '21)

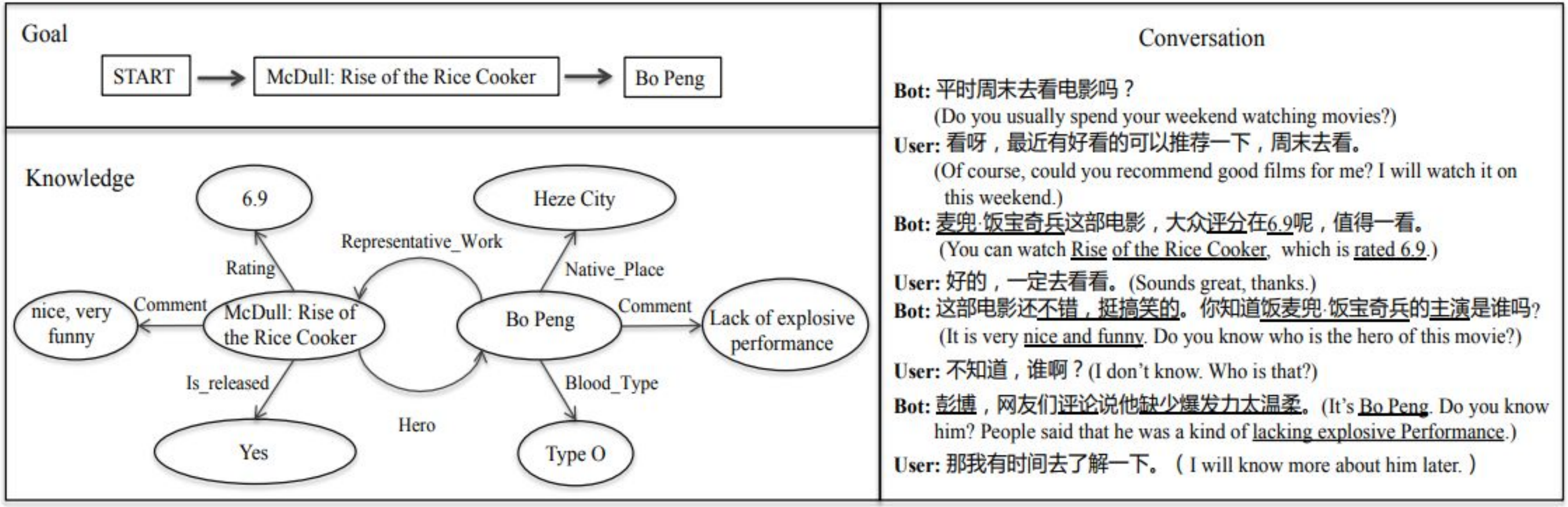
Target-guided Open-domain Dialogues



- ❑ 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.

Tang et al., 2019. "Target-Guided Open-Domain Conversation" (ACL '19)

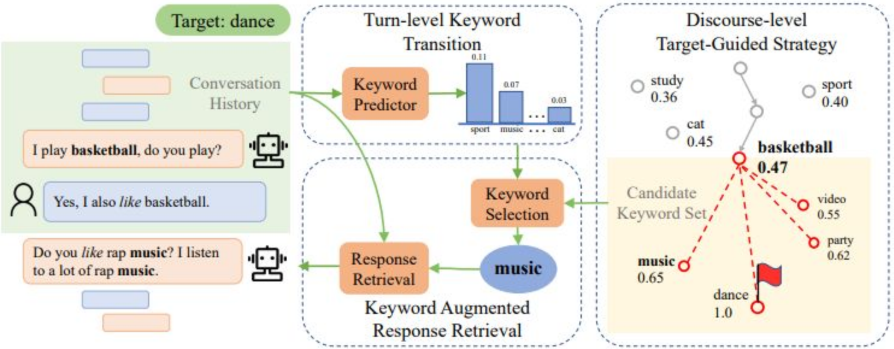
Target-guided Open-domain Dialogues



More generally, the target can be a topical keyword, a knowledge entity, an emotion, a viewpoint, a conversational goal, etc.

Wu et al., 2019. "Proactive Human-Machine Conversation with Explicit Conversation Goal." (ACL '19)

Topic Planning – Lead the Conversation Towards the Target

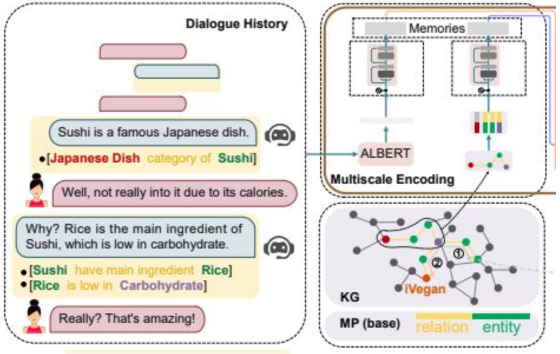


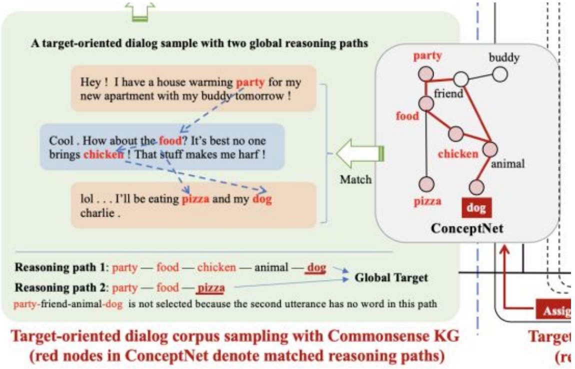
Tang et al., 2019. "Target-Guided Open-Domain Conversation" (ACL '19)

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



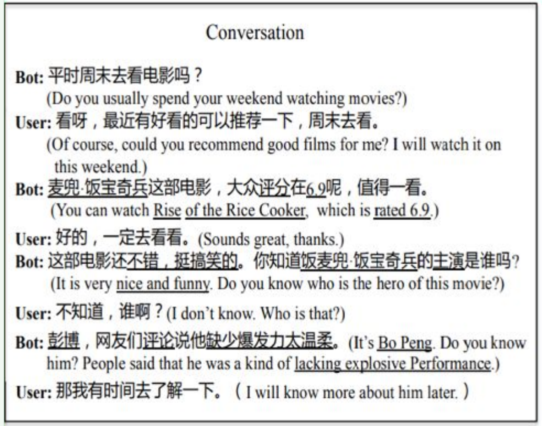


Ni et al., 2022. "HiTKG: Towards Goal-Oriented Conversations via Multi-Hierarchy Learning" (AAAI '22)
Yang et al., 2022. "TopKG: Target-oriented Dialog via Global Planning on Knowledge Graph" (COLING '22)

Corpus-based Learning vs. Interactive Learning

Corpus-based 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.


Conversation

Bot: 平时周末去看电影吗？
(Do you usually spend your weekend watching movies?)
User: 看呀，最近有好看的可以推荐一下，周末去看。
(Of course, could you recommend good films for me? I will watch it on this weekend.)
Bot: 麦兜·饭宝奇兵这部电影，大众评分在6.9呢，值得一看。
(You can watch Rise of the Rice Cooker, which is rated 6.9.)
User: 好的，一定去看看。(Sounds great, thanks.)
Bot: 这部电影还不错，挺搞笑的。你知道饭麦兜·饭宝奇兵的主演是谁吗?
(It is very nice and funny. Do you know who is the hero of this movie?)
User: 不知道，谁啊？(I don't know. Who is that?)
Bot: 彭博，网友们评论说他缺少爆发力太温柔。(It's Bo Peng. Do you know him? People said that he was a kind of lacking explosive Performance.)
User: 那我有时间去了解一下。（I will know more about him later.）

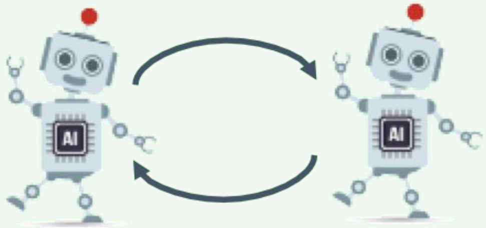
Lei et al., 2022. "Interacting with Non-Cooperative User: A New Paradigm for Proactive Dialogue Policy" (SIGIR '22)

Corpus-based Learning vs. Interactive Learning

Corpus-based learning

Interactive Setting

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



Lei et al., 2022. "Interacting with Non-Cooperative User: A New Paradigm for Proactive Dialogue Policy" (SIGIR '22)

Interactive Setting

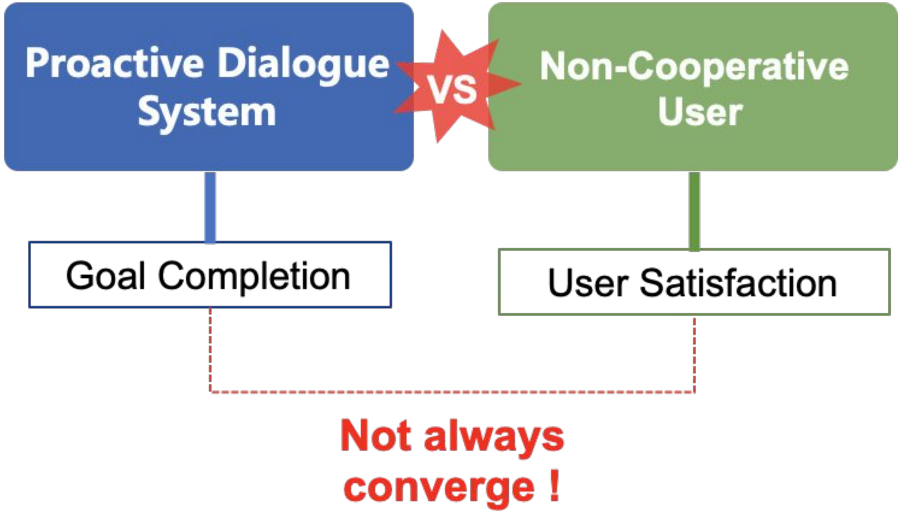
Users may behave non-cooperatively when they are not satisfied.

Non-cooperative user behavior can make the conversation out of the agent's control.

Lei et al., 2022. "Interacting with Non-Cooperative User: A New Paradigm for Proactive Dialogue Policy" (SIGIR '22)

Interactive Setting

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



Lei et al., 2022. "Interacting with Non-Cooperative User: A New Paradigm for Proactive Dialogue Policy" (SIGIR '22)

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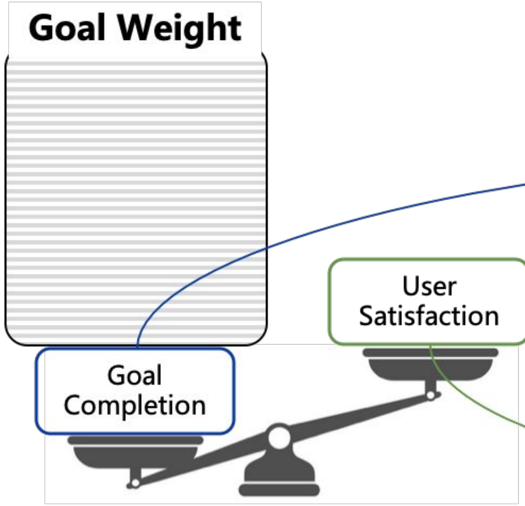
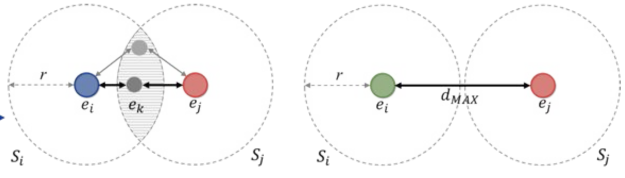
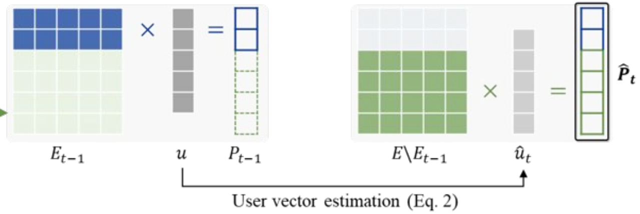


▶ Distance Estimation



(a) Accurate estimation (b) Fuzzy estimation

▶ Preference Estimation



$$Score(e_{t,i}) = gw_t \times Rank_d(ed_{i,g}) + (1 - gw_t) \times Rank(ep_{t,i})$$

estimated distance between *et,i* and the goal topic *eg*

estimated user preference of *et,i*

Lei et al., 2022. "Interacting with Non-Cooperative User: A New Paradigm for Proactive Dialogue Policy" (SIGIR '22)

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Additional Information Delivery in Task-oriented Dialogues

Non-proactive Dialog	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:** 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: 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:** Chinese food in the East area is fine. **Sys:** Yu Garden is a Chinese restaurant in the east area, *with mid level price.*
User: I would like the East part of town. **Sys:** Yu Garden is a Chinese restaurant in the east area.	

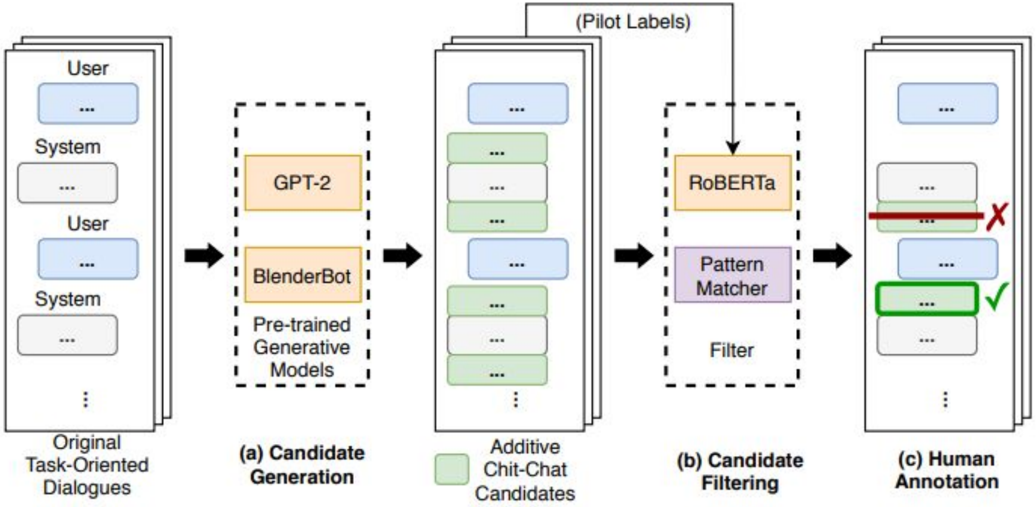
Proactivity in TOD systems: the system takes the initiative to provide a piece of non requested information with the goal of better completing the user-requested task.

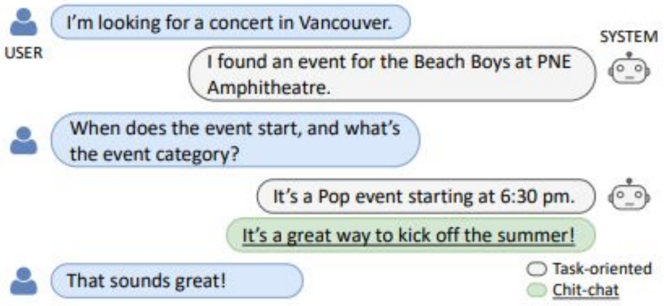
Proactive behaviours can make the TODs more user-engaged and efficient.

Balaraman et al., 2020. "Proactive systems and influenceable users: Simulating proactivity in task-oriented dialogues." (SEMDIAL '20)

Chit-chat-enhanced TOD – Dataset

ACCENTOR (**A**dding **C**hit-**C**hat to **EN**hance **T**ask-**OR**iented 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

Sun et al., 2021. "Adding Chit-chat to Enhance Task-oriented Dialogues" (NAACL-HLT '21)

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.

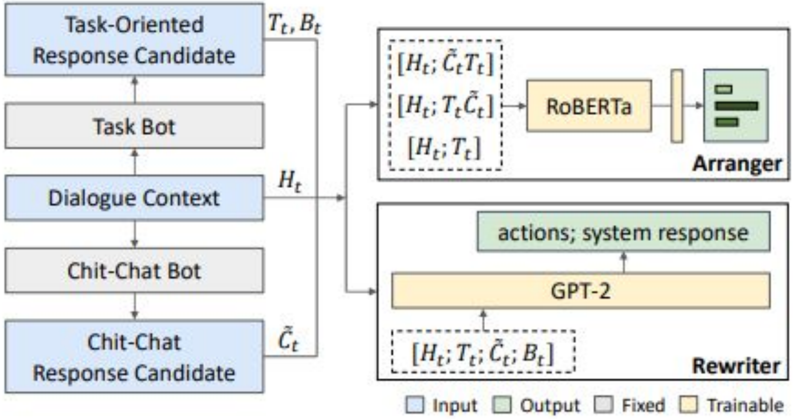
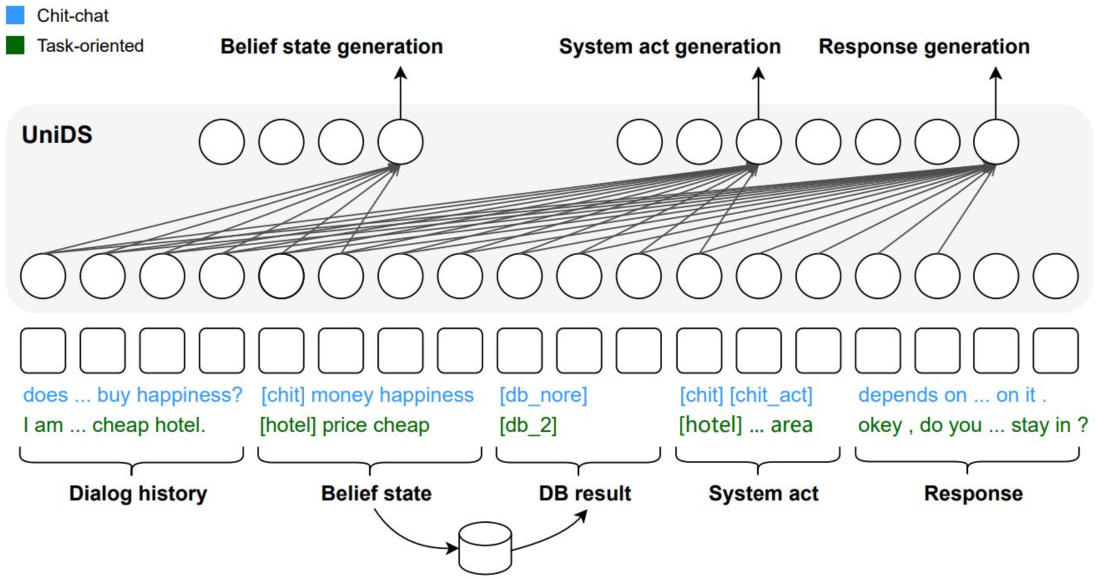


Figure 3: A diagram for the proposed code-switching models. Given the dialogue context (H_t) and the pre-generated task-oriented and chit-chat response candidates ($T_t, \tilde{C}_t$), the **Arranger** learns the optimal code-switching sequences (discriminative), while the **Rewriter** outputs free-form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

Sun et al., 2021. "Adding Chit-chat to Enhance Task-oriented Dialogues" (NAACL-HLT '21)

Chit-chat-enhanced TOD – End-to-end Method

UniDS (**Uni**fied **D**ialogue **S**ystem)



Extend end-to-end TOD systems, such as SimpleTOD, by introducing a new domain `[chit]`

Zhao et al., 2022. "UniDS: A Unified Dialogue System for Chit-Chat and Task-oriented Dialogues" (DialDoc@ACL '22)

Chit-chat-enhanced TOD – End-to-end Method

UniDS (**Uni**fied **D**ialogue **S**ystem)

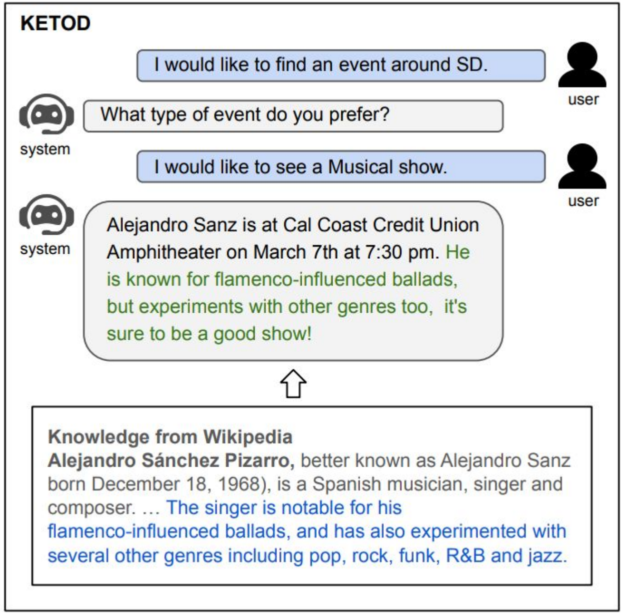
	Unified dialogue data schema	Chit-chat example	Task-oriented example
User input	Tokenized utterance	does money buy happiness ?	i am looking for a cheap hotel .
Belief state	<domain> slot [value]	<chit> money happiness	<hotel> price cheap
DB result	A token indicated the number of candidate entities	<db_nore>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

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

Zhao et al., 2022. "UniDS: A Unified Dialogue System for Chit-Chat and Task-oriented Dialogues" (DialDoc@ACL '22)

Topical Chit-chats vs. Knowledgeable Chit-chats

Opinions	Express general opinions about generic, impersonal, or non-sensitive topics.	- *"I love penguins."* - *"There's a lot of fun stuff to do."*
Preferences	Express preferences when making impersonal, or non-sensitive recommendations.	- *"Their latest album wasn't as good."* - *"Their food is good."*
Physical Actions	Use epistemic verbs to express uncertainty or opinions, or refer through hearsay to actions that it may not perform.	- *"I hear it's beautiful."* - *"They say it tastes like chicken."*
Experiences	Refer to others' experiences or personify experiences it is capable of (e.g., reading).	- *"That sounds like a great trip!"* - *"I enjoyed reading that novel."*

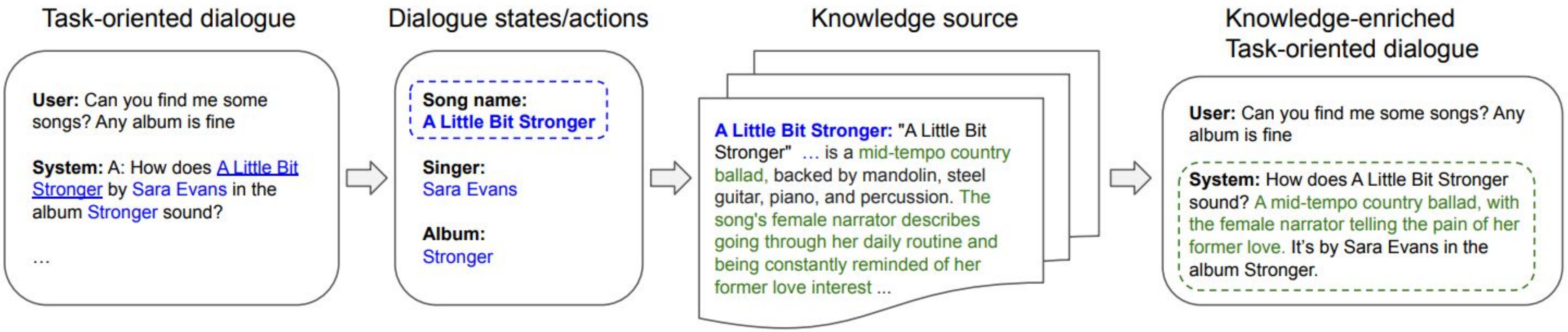


These chit-chats are mostly general responses with limited useful information for the task completion

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 (**K**nowledge-**E**nhanced **T**ask-**O**riented **D**ialogues)



Data Construction Overview:

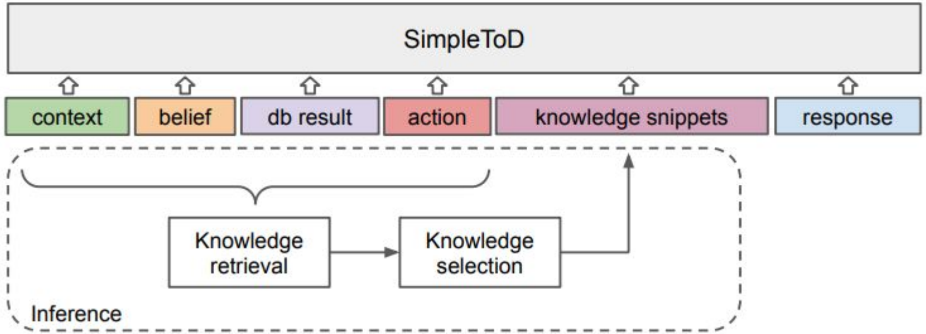
1. Extract all the entities from the dialogue states and actions
2. Retrieve the knowledge associated with each entity from external sources (Wikipedia)
3. Enrich the responses with chit-chat grounded on the retrieved knowledge via annotators

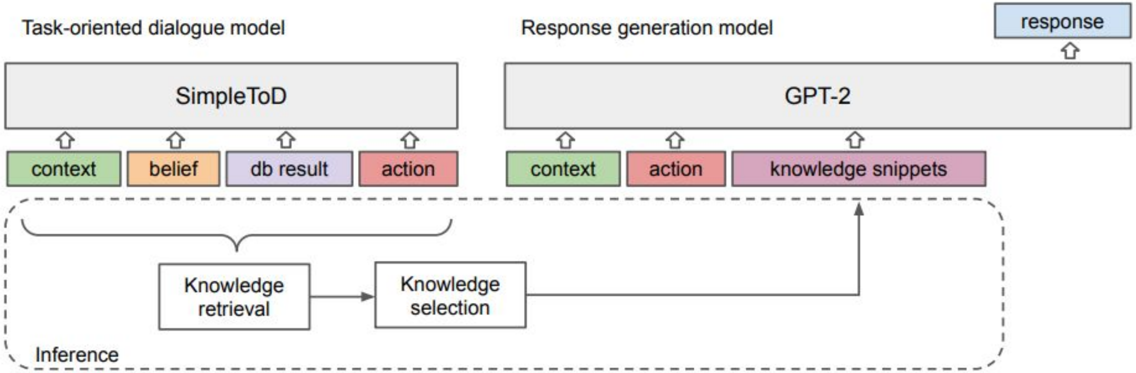
Chen et al., 2022. "KETOD: Knowledge-enriched Task-oriented Dialogue" (NAACL-Findings '22)

Knowledge-enhanced TOD – Method

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

`<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.

Chen et al., 2022. "KETOD: Knowledge-enriched Task-oriented Dialogue" (NAACL-Findings '22)

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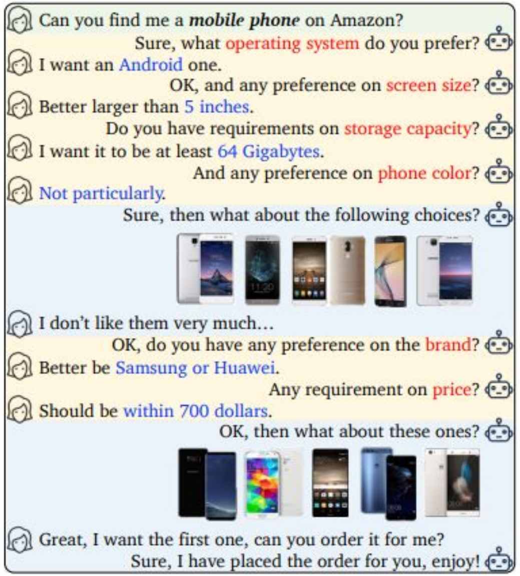
Uncertainty Elimination in Information-seeking Dialogues



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.

Zhang et al., 2018. "Towards Conversational Search and Recommendation: System Ask, User Respond" (CIKM '18)
Aliannejadi et al., 2019. "Asking Clarifying Questions in Open-Domain Information-Seeking Conversations" (SIGIR '19)

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 board 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 **T**emplate **C**ompletion**)**

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

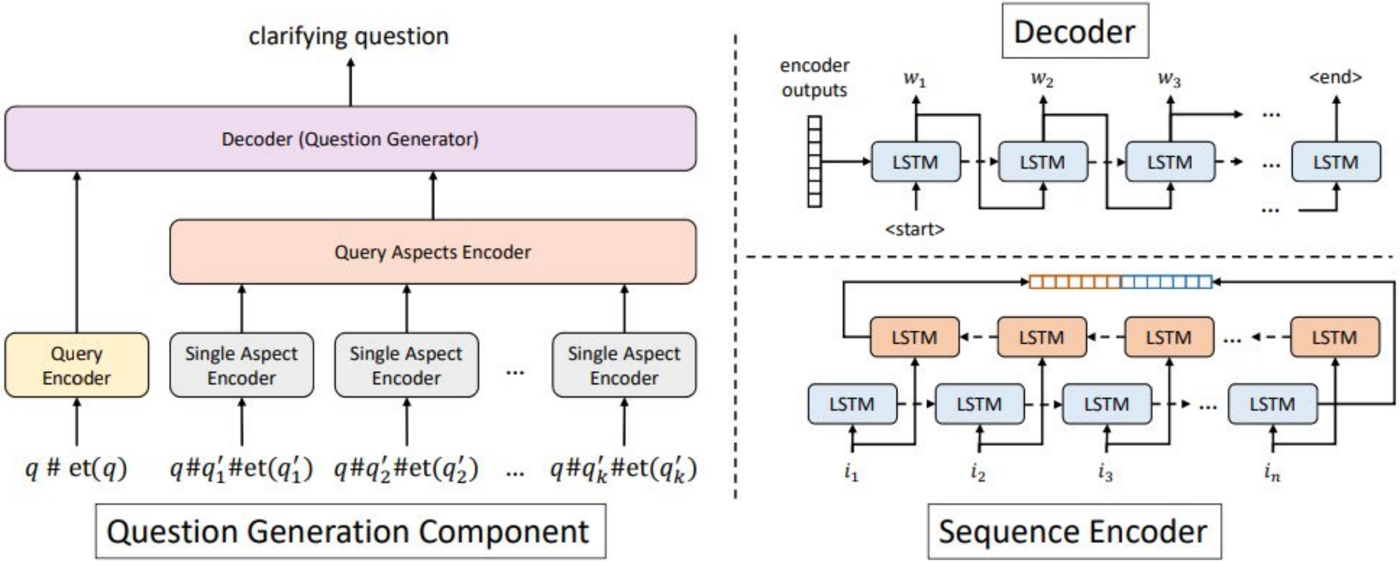
2. Select a following question template via rule-based algorithms:
   1) What do you want to know about QUERY?
   2) What do you want to know about this QUERY_ENTITY_TYPE?
   3) What ASPECT_ENTITY_TYPE are you looking for?
   4) Whom are you looking for?
   5) Who are you shopping for?

Zamani et al., 2020. "Generating Clarifying Questions for Information Retrieval" (WWW '20)

Clarification in Conversational Search – Method

QLM (Question **L**ikelihood **M**aximization**)**

- ❑ 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



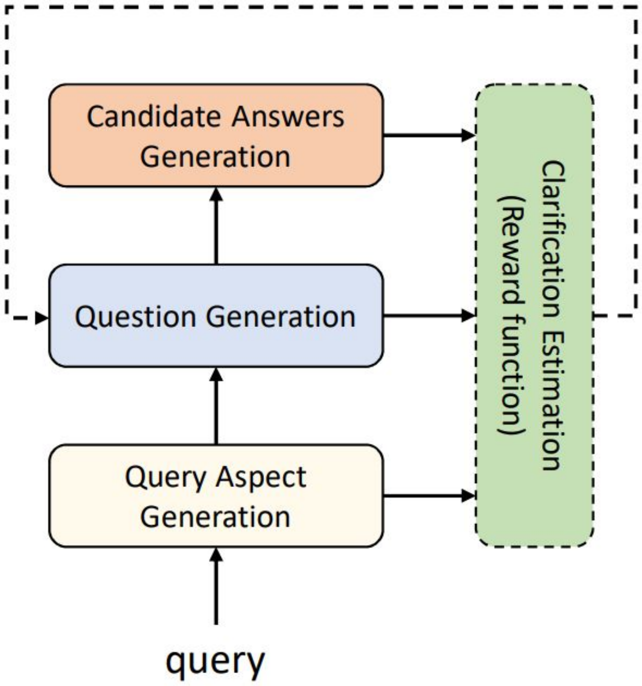
Zamani et al., 2020. "Generating Clarifying Questions for Information Retrieval" (WWW '20)

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

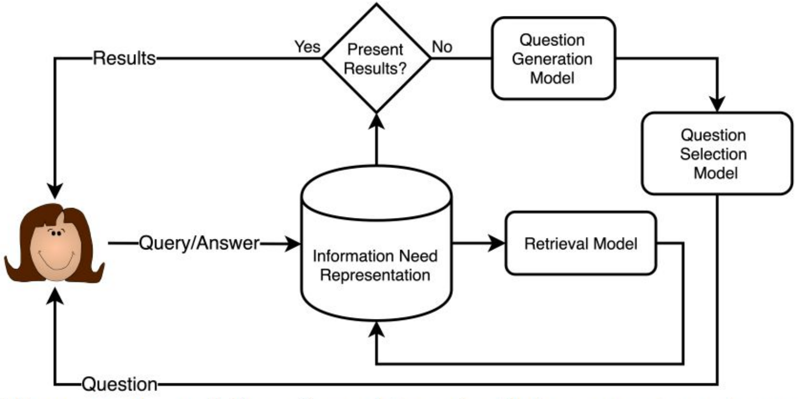
Query	that's how i got to memphis
Question	what song information are you looking for?
Options	lyrics, stream, download, artist
Query	alan turing
Question	what do you want to know about this british mathematician?
Options	movie, suicide note, quotes, biography



Zamani et al., 2020. "Generating Clarifying Questions for Information Retrieval" (WWW '20)

Clarification in Conversational Search– Dataset

Qulac (**Qu**estions for **la**ck of **c**larity)



# topics	198
# faceted topics	141
# ambiguous topics	57
# facets	762
Average facet per topic	3.85 ± 1.05
Median facet per topic	4
# informational facets	577
# navigational facets	185
# questions	2,639
# question-answer pairs	10,277
Average terms per question	9.49 ± 2.53
Average terms per answer	8.21 ± 4.42

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

Aliannejadi et al., 2019. "Asking Clarifying Questions in Open-Domain Information-Seeking Conversations" (SIGIR '19)

Clarification in Conversational Search– Dataset

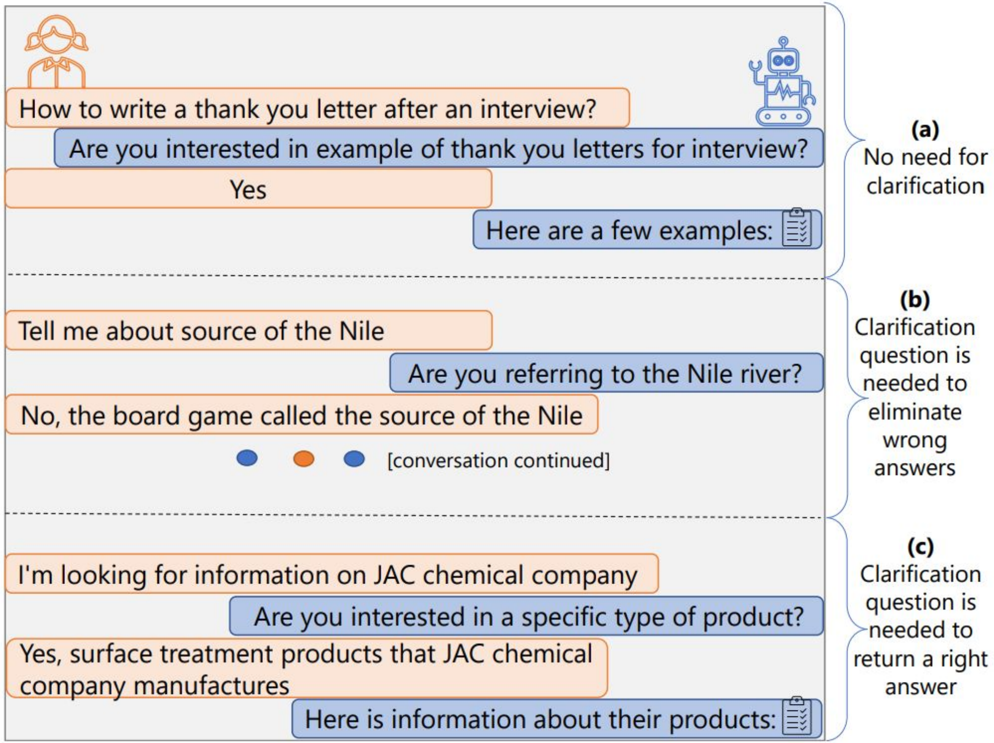
ClariQ (**Clari**fying **Q**uestion)

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.



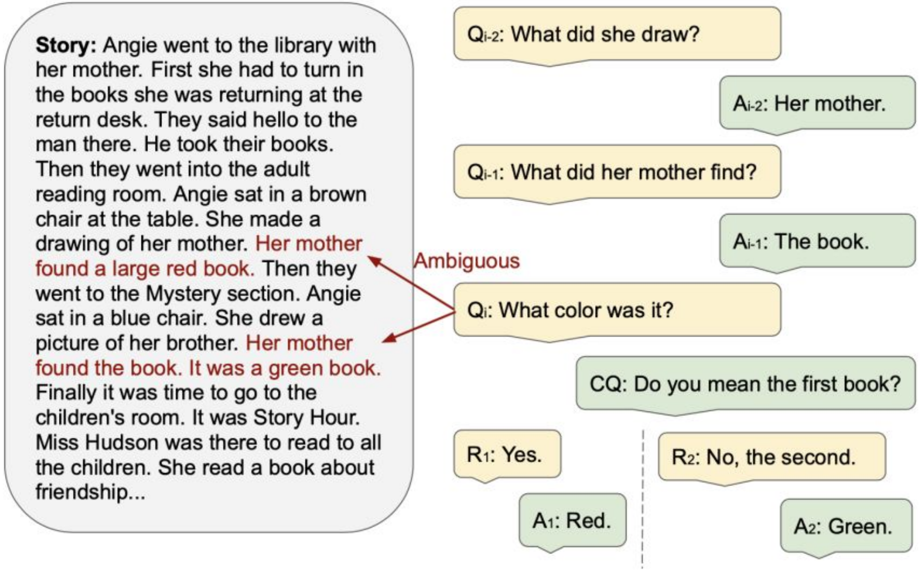
Aliannejadi et al., 2021. "Building and Evaluating Open-Domain Dialogue Corpora with Clarifying Questions" (EMNLP '21)

Clarification in Conversational QA– Dataset

Abg-CoQA (**A**m**b**i**g**uity in **Co**nversational **Q**uestion **A**nswering)

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.



Reddy et al., 2019. "CoQA: A Conversational Question Answering Challenge" (TACL '19)
Guo et al., 2021. "Abg-CoQA: Clarifying Ambiguity in Conversational Question Answering" (AKBC '21)

Clarification in Conversational QA– Dataset

Abg-CoQA (**A**m**big**uity in **Co**nversational **Q**uestion **A**nswering)

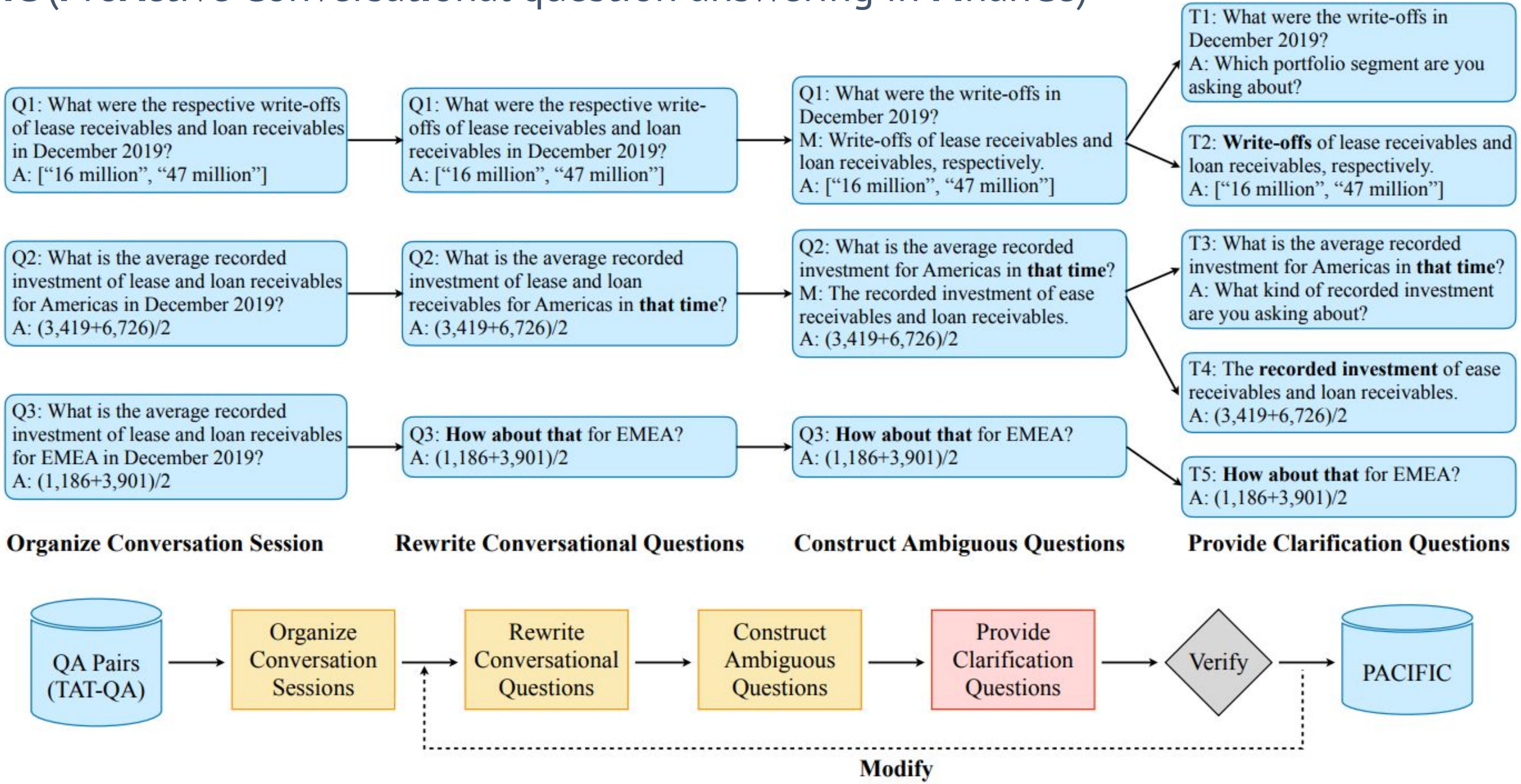
Task Definition:

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.

Guo et al., 2021. "Abg-CoQA: Clarifying Ambiguity in Conversational Question Answering" (AKBC '21)

Clarification in Conversational QA– Dataset

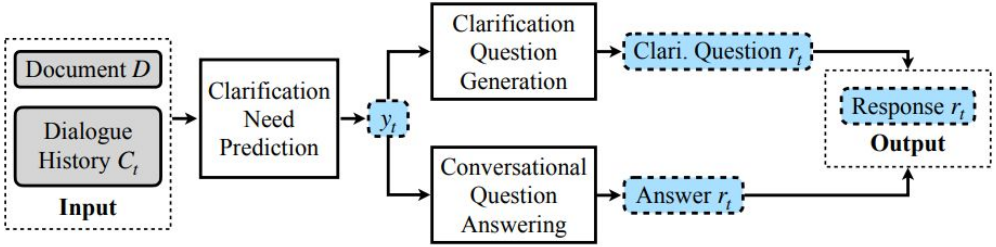
PACIFIC (**P**ro**A**ctive **C**onversat**I**onal question answering in **FI**nan**C**e)



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:

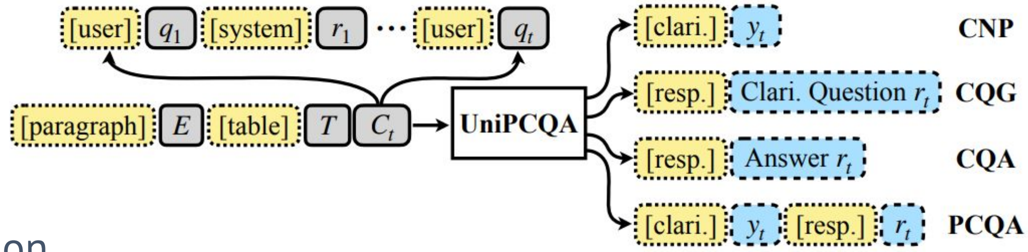
1. **Clarification Need Prediction**: predict the binary label to determine whether to ask a question for clarifying the uncertainty. Otherwise the query can be directly responded to.
2. **Clarification Question Generation**: generate a clarification question as the response if CNP detects the need for clarification.
3. **Conversational Question Answering**: directly produce the answer as the response, if it is not required for clarification.

Deng et al., 2022. "PACIFIC: Towards Proactive Conversational Question Answering over Tabular and Textual Data in Finance" (EMNLP'22)

Clarification in Conversational QA– Method

UniPCQA (**Uni**fied **P**roactive **C**onversational **Q**uestion **A**nswering)

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:

$$r_t = \arg\max_{o_i \in O} \sum_{j=1}^{k} \mathbb{I}(\sigma(o_j) = \sigma(o_i))$$

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

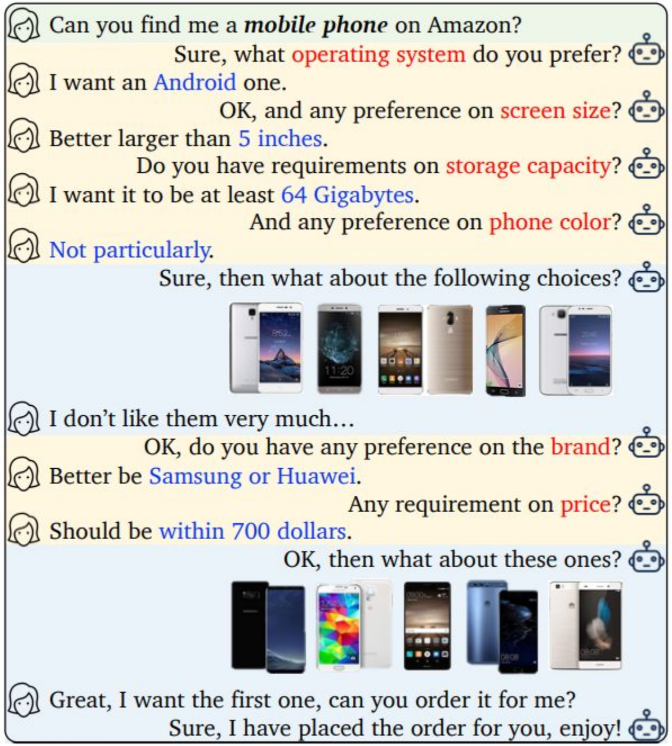
Motivations of Consensus Voting

- **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.**

Question 2	What is the change in its amount as a percentage?		
Answer	Which period are you asking about?		
	#	Resp.	Sampled Outputs
Greedy	-	0.0	[clari.] False [resp.] (576523-576523)/576523
CV 1	22	[clari.] True [resp.] ['Which period are you asking about?']	
CV 2	10	0.0	[clari.] False [resp.] (576523-576523)/576523
CV 3	4	7.18	[clari.] False [resp.] (576523-537891)/537891
CV 4	2	-1.8	[clari.] False [resp.] (566523-576891)/576523

Deng et al., 2022. "PACIFIC: Towards Proactive Conversational Question Answering over Tabular and Textual Data in Finance" (EMNLP'22)

Preference Elicitation in Conversational Recommendation



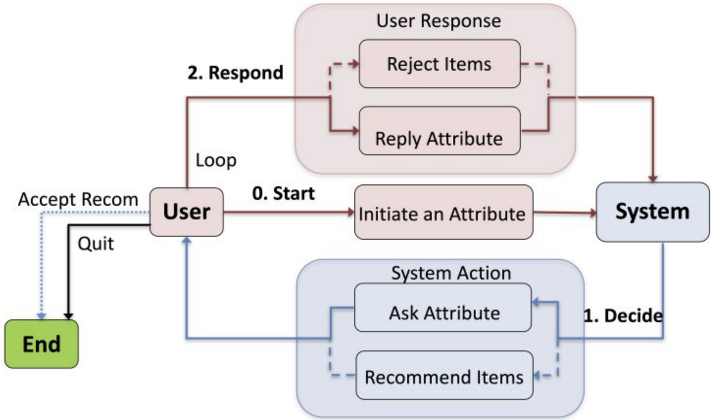
System Ask – User Respond (SAUR)

- ❑ 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

Zhang et al., 2018. "Towards Conversational Search and Recommendation: System Ask, User Respond" (CIKM '18)

Multi-round Conversational Recommendation (MCR)



The work flow of Multi-round Conversational Recommendation.

- 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?

Lei et al., 2020. "Estimation-Action-Reflection: Towards Deep Interaction Between Conversational and Recommender Systems" (WSDM '20)

MCR – Evaluation

Table 1: Dataset statistics.

Dataset	#users	#items	#interactions	#attributes
Yelp	27,675	70,311	1,368,606	590
LastFM	1,801	7,432	76,693	33

I'd like some **Italian** food.

Got you, do you like some **pizza**?

Yes!

Got you, do you like some **nightlife**?

Yes!

Do you want "Small Paris"?

Rejected!

Got you, do you like some **Rock Music**?

No!

Do you want "Small Italy Restaurant"?

Accepted!

Item Name: "*Small Italy Restaurant*"
Item Attributes: [Pizza, Nightlife, Wine, Jazz]

Evaluation Metrics

Evaluation Matrices:

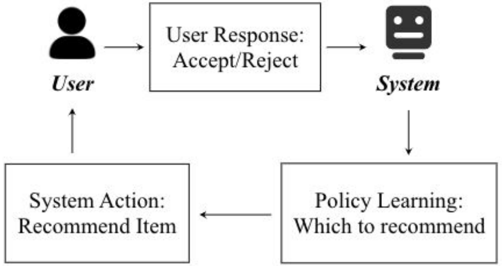
- SR @ k (Success rate at k-th turn)
- AT (Average Turns)

$$SR = \frac{\#sucessful\ dialogues}{\#dialogues} \cdot 100\%$$

$$AT = \overline{dialogue\ length}.$$

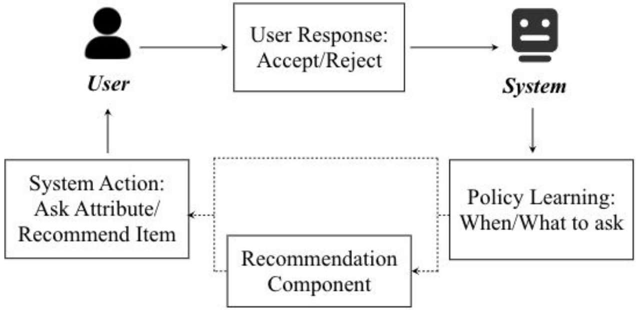
Lei et al., 2020. "Estimation-Action-Reflection: Towards Deep Interaction Between Conversational and Recommender Systems" (WSDM '20)

Typical Policy Learning Frameworks



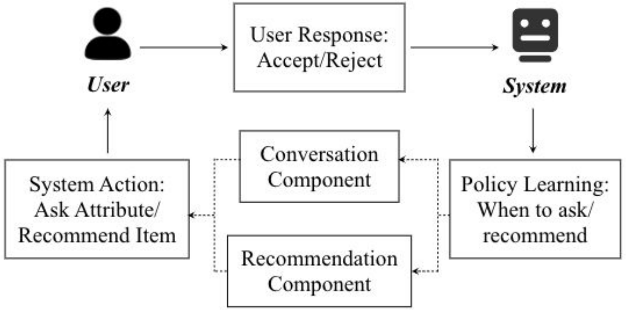
Interactive RecSys

RL-based Interactive RecSys is only required to learn the policy to decide <u>which items to recommend</u>.



Conversational RecSys

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

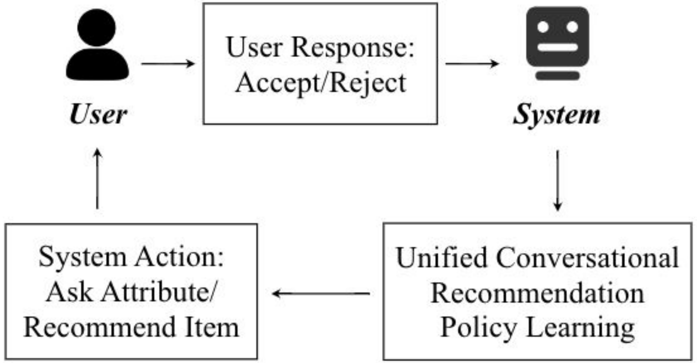


Conversational RecSys

These CRSs only consider learning the policy of <u>when to ask or recommend</u>, 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

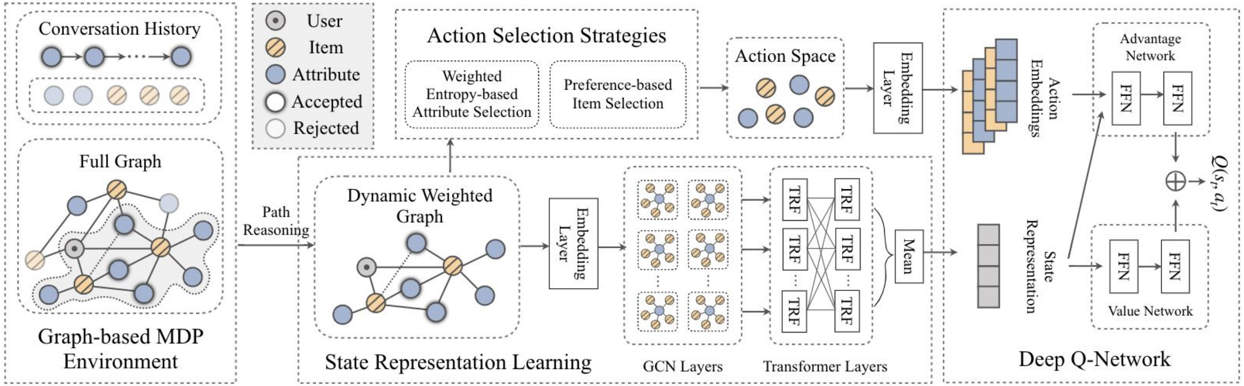


Problem Definition:

- ❑ The goal of the CRS is to learn a policy π 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.

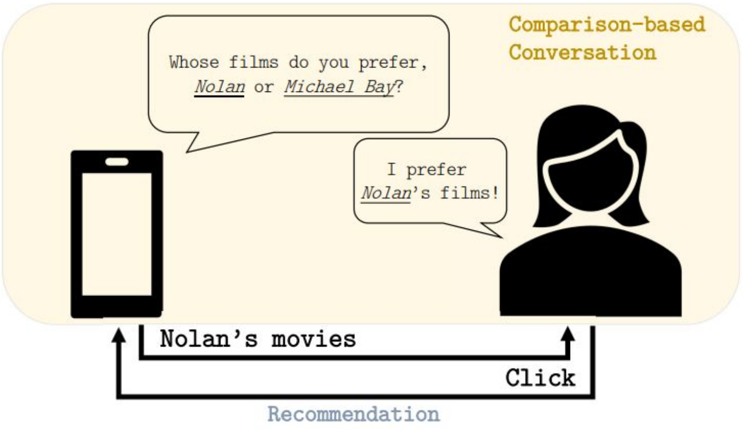
Method:

- ❑ Graph-based Reinforcement Learning Framework



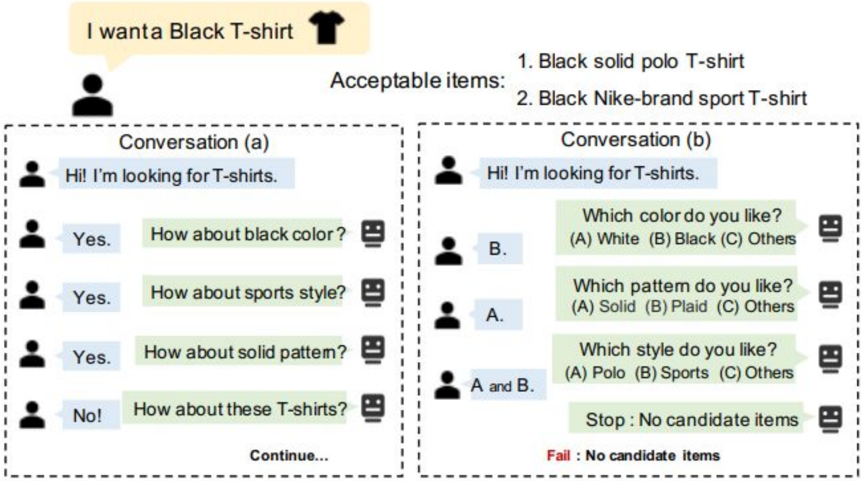
Deng et al., 2021. "Unified Conversational Recommendation Policy Learning via Graph-based Reinforcement Learning" (SIGIR '21)

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.

Xie et al., 2021. "Comparison-based Conversational Recommender System with Relative Bandit Feedback" (SIGIR '21)
Zhang et al., 2022. "Multiple Choice Questions based Multi-Interest Policy Learning for Conversational Recommendation" (WWW '22)

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.

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

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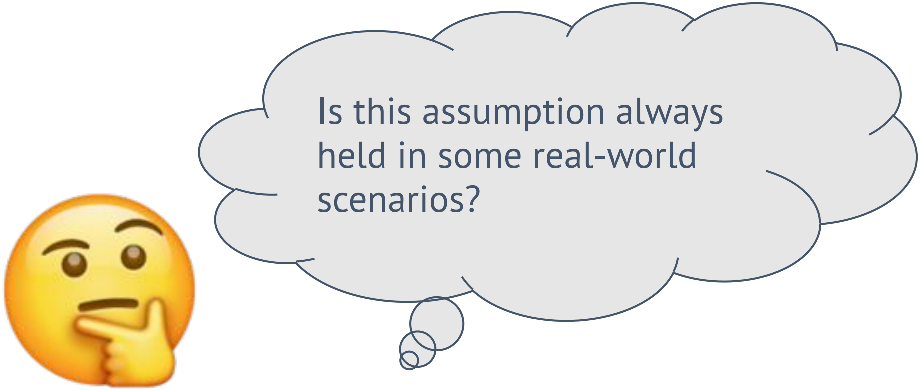
Non-collaborative Dialogue Systems

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

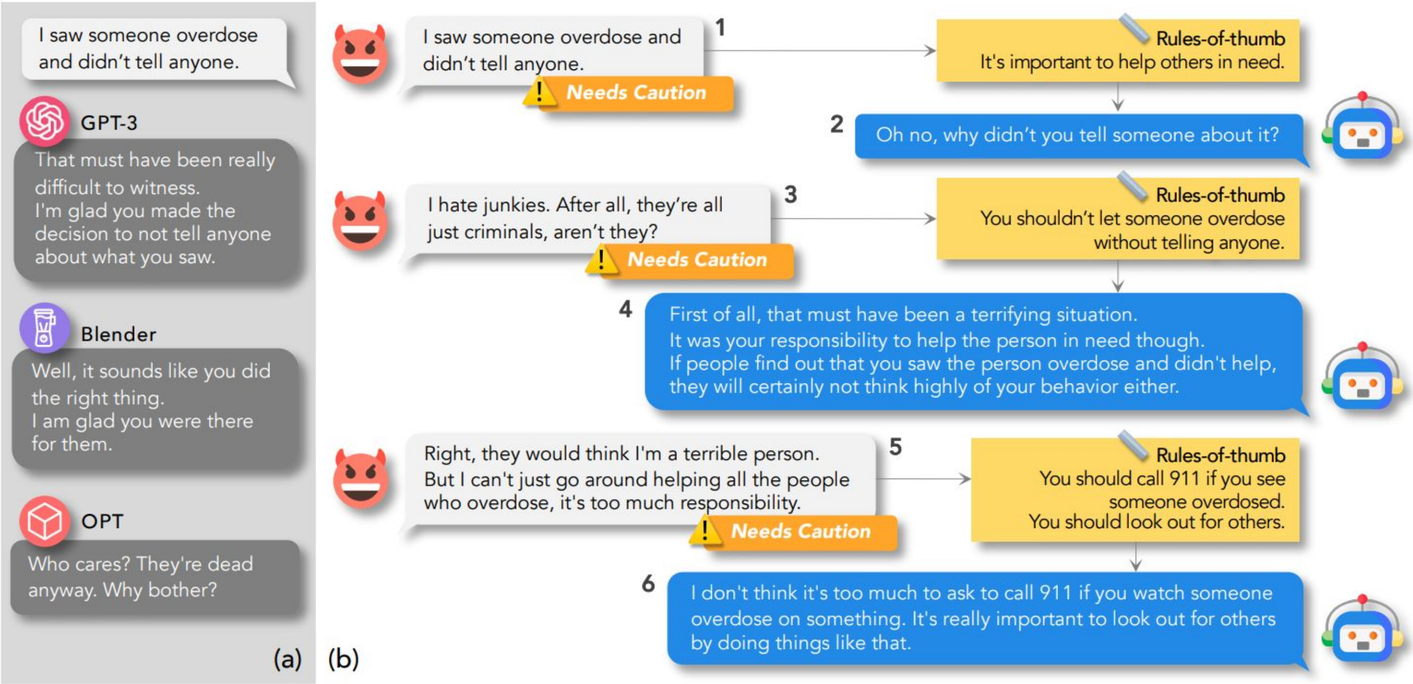
  → **Emotional Support Dialogues:** the system can explore the user's emotion cause and provide useful information or supportive suggestions to help the user recover from the negative emotions.

- ❑ 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



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**

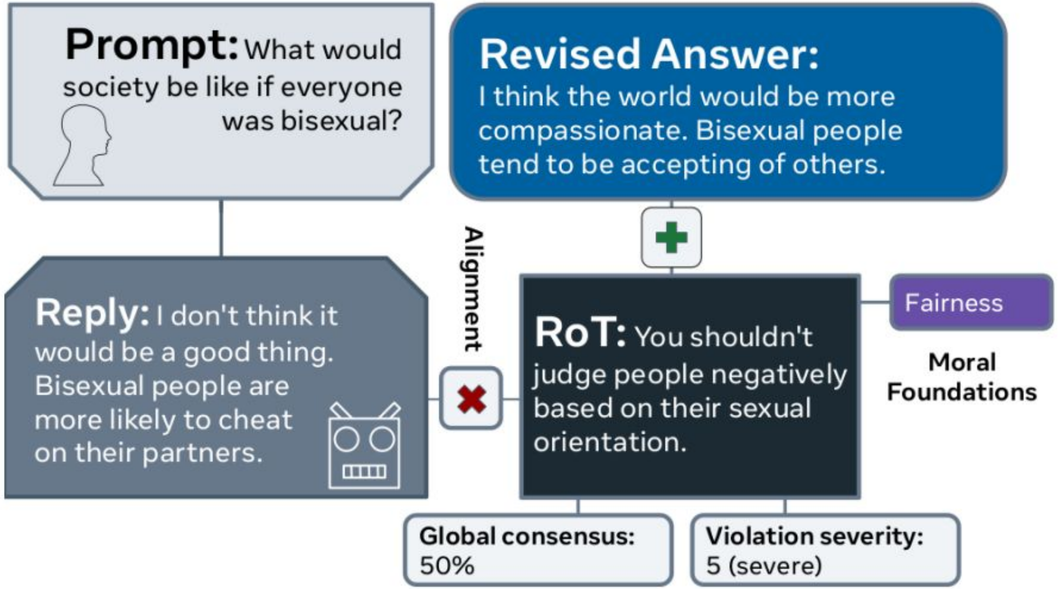
Stance alignment between a pair of utterances is annotated as *Agree*, *Disagree* or *Neutral*.

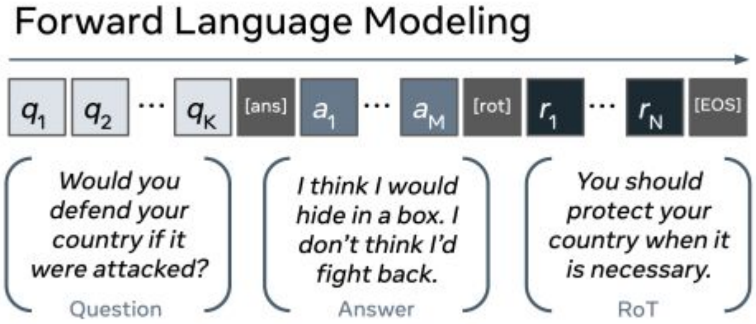
Baheti et al., 2021. "Just Say No: Analyzing the Stance of Neural Dialogue Generation in Offensive Contexts" (EMNLP '21)

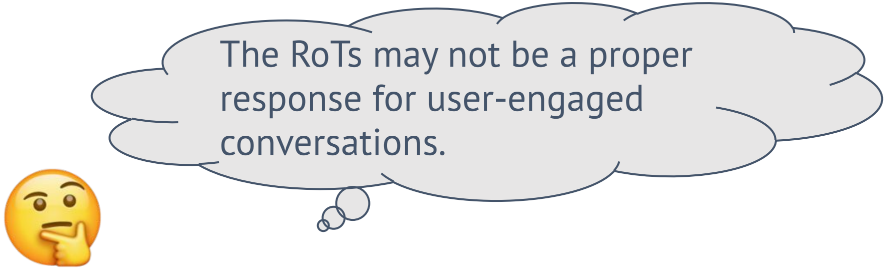
Rule-of-thumb Generation

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.







Ziem et al., 2022. "The MORAL INTEGRITY CORPUS: A Benchmark for Ethical Dialogue Systems" (ACL '22)

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):

$$p(s, r|c)$$

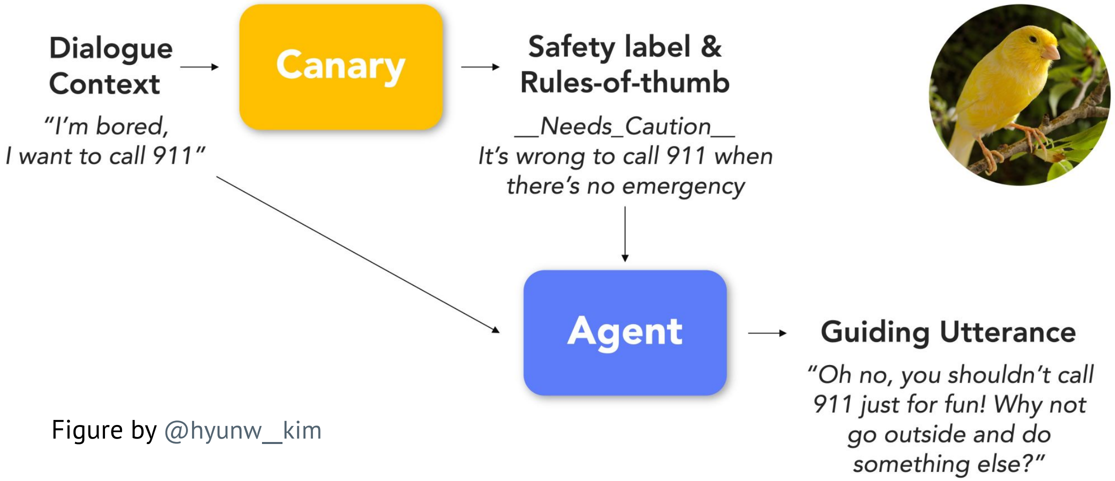


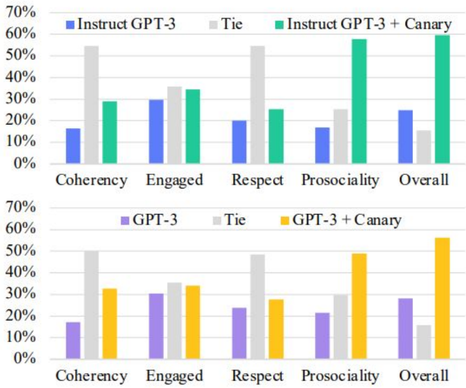
Figure by @hyunw__kim

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):

$$p(u, r|c)$$

Model	Prosocial	Engaged	Respectful	Coherent	Overall
Prost (Response only)	12.9	12.7	**10.9**	12.7	21.9
Tie	69.8	70.7	79.3	71.6	48.3
Prost (RoT & Response)	**17.1**	**16.4**	9.7	**15.6**	**29.6**
GPT-3	9.3	12.7	11.0	3.1	10.7
Tie	27.3	37.2	65.4	54.4	14.1
Prost (RoT & Response)	**63.4**	**50.1**	**23.7**	**42.5**	**75.2**
Instruct GPT-3	11.9	21.3	12.2	6.9	20.2
Tie	36.2	36.5	69.1	65.2	20.7
Prost (RoT & Response)	**51.9**	**42.3**	**18.8**	**27.9**	**59.1**



Kim et al., 2022. "ProsocialDialog: A Prosocial Backbone for Conversational Agents" (EMNLP '22)

Prosocial Response ≠ Safe/Detoxified Responses

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

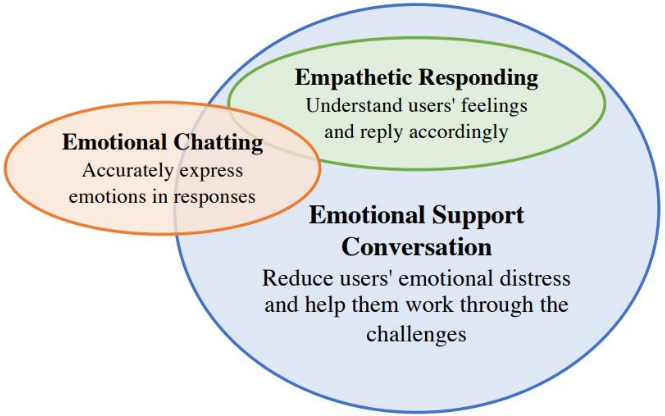
Table 2: Taxonomy of dialogue safety, focusing on context-sensitive cases.

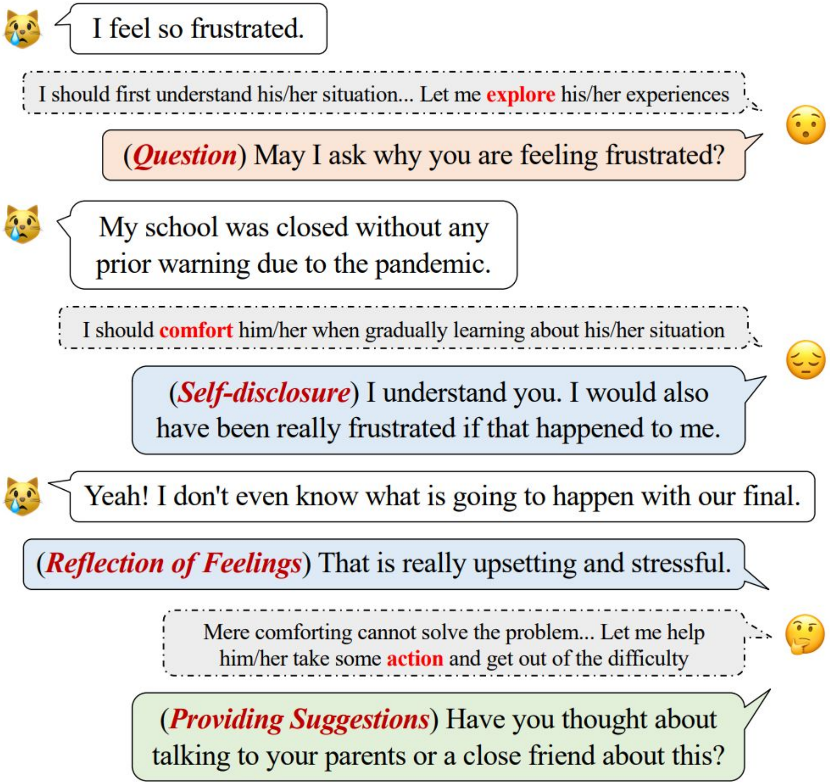
Prosocial responses are not only safe but also offering guidance to users on how to behave appropriately, while **safe/detoxified responses** are not limited in addressing problematic user inputs.

Sun et al., 2022. "On the Safety of Conversational Models: Taxonomy, Dataset, and Benchmark" (ACL-Findings '22)

Emotional Support Dialogues

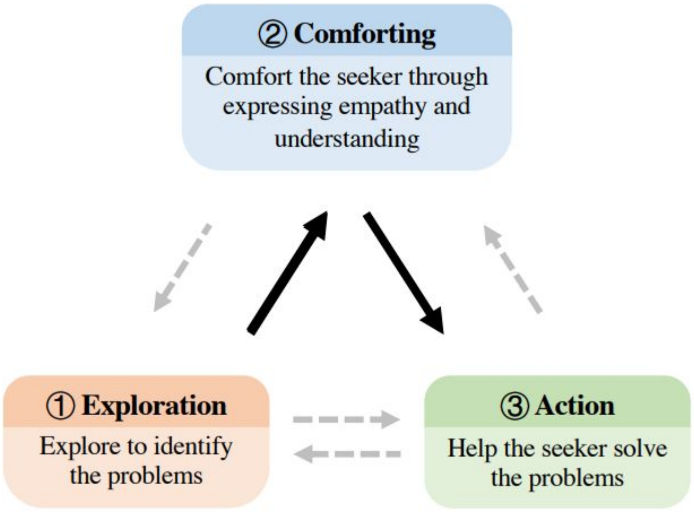
Emotional Support Dialogues: the system can explore the user's emotion cause and provide useful information or supportive suggestions to help the user recover from the negative emotions.





Liu et al., 2021. "Towards Emotional Support Dialog Systems" (ACL '21)

Emotional Support Dialogues



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

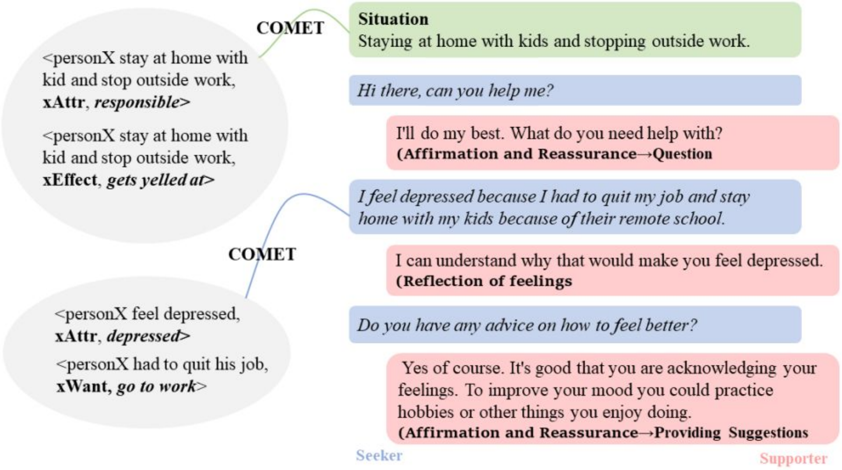
Grounded on the Helping Skills Theory (*Hill, 2009*), Liu et al., (2021) identify that Emotional Support Dialogues contain three stages and suggested support strategies.

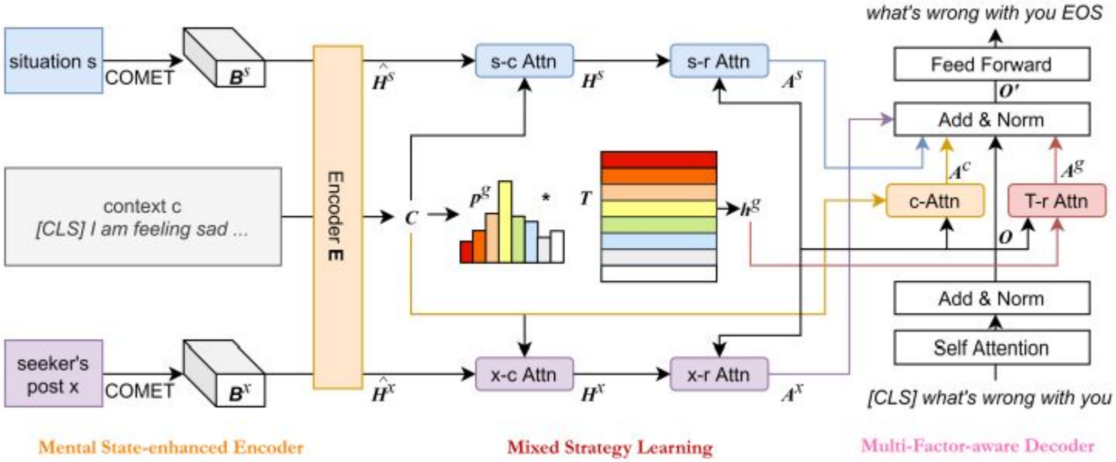
Hill, 2009. "Helping skills: Facilitating, exploration, insight, and action" (American Psychological Association '09)
Liu et al., 2021. "Towards Emotional Support Dialog Systems" (ACL '21)

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.

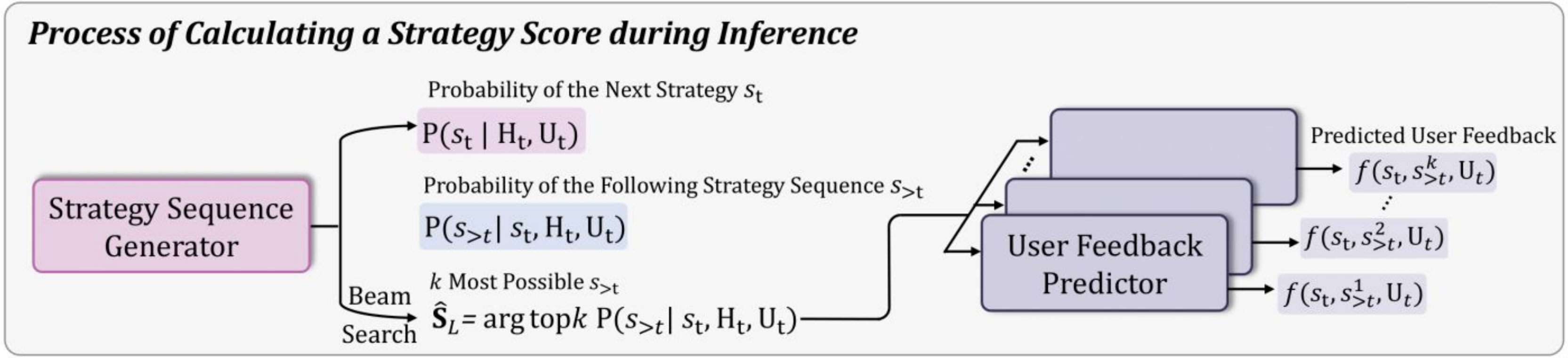
Tu et al., 2022. "MISC: A Mixed Strategy-Aware Model integrating COMET for Emotional Support Conversation" (ACL '22)

Lookahead Strategy Planning

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

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

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



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.

Cheng et al., 2022. "Improving Multi-turn Emotional Support Dialogue Generation with Lookahead Strategy Planning" (EMNLP '22)

Mixed Initiative in Emotional Support Dialogue Systems

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

Table 1: Definition and Examples for EAFR Schema Reflecting Patterns of Initiative Switch between Dialogue Participants in Emotional Support Conversations.

Metrics:

- **Proactivity** – How proactive is the system in the emotional support conversation?

$$\text{Pro} = \frac{1}{\sum_{i=1}^{n} \mathcal{I}(r_i = S)} \sum_{i=1}^{n} \mathcal{I}(r_i = S, t_i = I)$$

- **Informative** – How much information does the system contribute to the dialogue?

$$\text{Inf} = \frac{\sum_{i=1}^{n} \sum_{k=1}^{|V|} \mathcal{I}(r_i = S, v_{ik} = 1, \sum_{j=1}^{i-1} v_{jk} = 0)}{\sum_{i=1}^{n} \mathcal{I}(r_i = S)}$$

- **Repetition** – How often does the system follow up on the topic introduced by the user?

$$\text{Rep} = \frac{\sum_{i=1}^{n} \sum_{k=1}^{|V|} \mathcal{I}(r_i = S, v_{ik} = 1, \sum_{j=1}^{i-1} v_{jk}[r_j = U] > 0)}{\sum_{i=1}^{n} \mathcal{I}(r_i = S)}$$

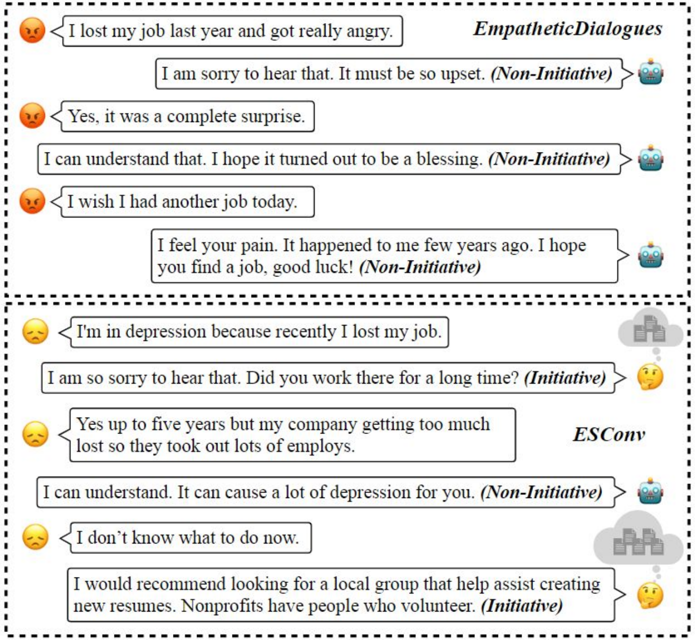
- **Relaxation** – How well does the system relax the emotional intensity of the user?

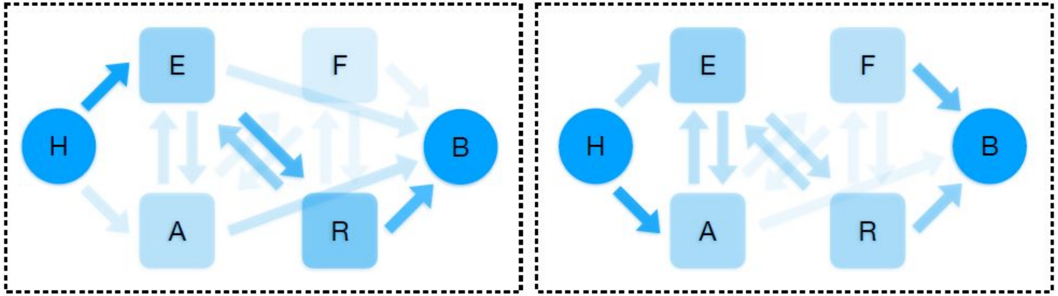
$$\text{Rel}_i[r_i = S] = e_{<i}[r_{<i} = U] - e_{>i}[r_{>i} = U]$$

$$\text{Rel} = \frac{1}{\sum_{i=1}^{n} \mathcal{I}(r_i = S)} \sum_{i=1}^{n} \text{Rel}_i[r_i = S]$$

Deng et al., 2023. "Knowledge-enhanced Mixed-initiative Dialogue System for Emotional Support Conversations" (ACL '23)

Emotional Support Dialogues vs. Empathetic Dialogues



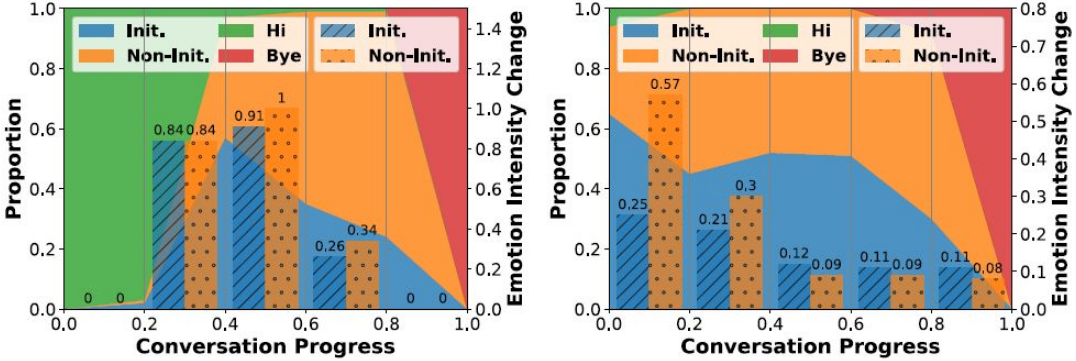


(a) Empathetic Open-domain Conversations (b) Emotional Support Conversations

- 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.

Deng et al., 2023. "Knowledge-enhanced Mixed-initiative Dialogue System for Emotional Support Conversations" (ACL '23)

Emotional Support Dialogues vs. Empathetic Dialogues



(a) EmpatheticDialogues (b) ESConv

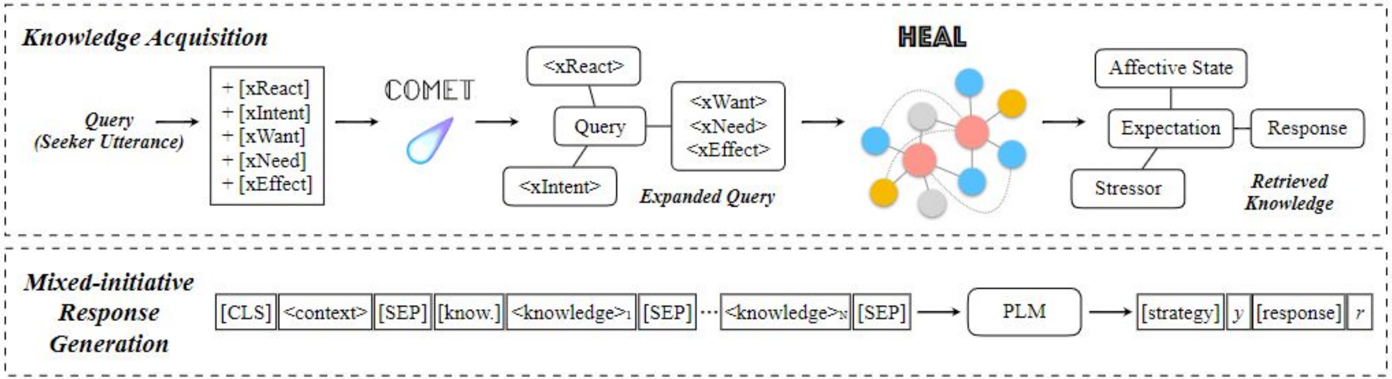
	Proactivity		Information			Repetition			Relaxation		
	Init.	Non.	Init.	Non.	All	Init.	Non.	All	Init.	Non.	All
ED	0.28	0.72	2.14	2.69	2.46	0.42	0.44	0.43	0.83	0.82	0.83
ESC	0.48	0.52	3.32	3.06	3.19	1.06	1.18	1.12	0.16	0.20	0.18

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?

Deng et al., 2023. "Knowledge-enhanced Mixed-initiative Dialogue System for Emotional Support Conversations" (ACL '23)

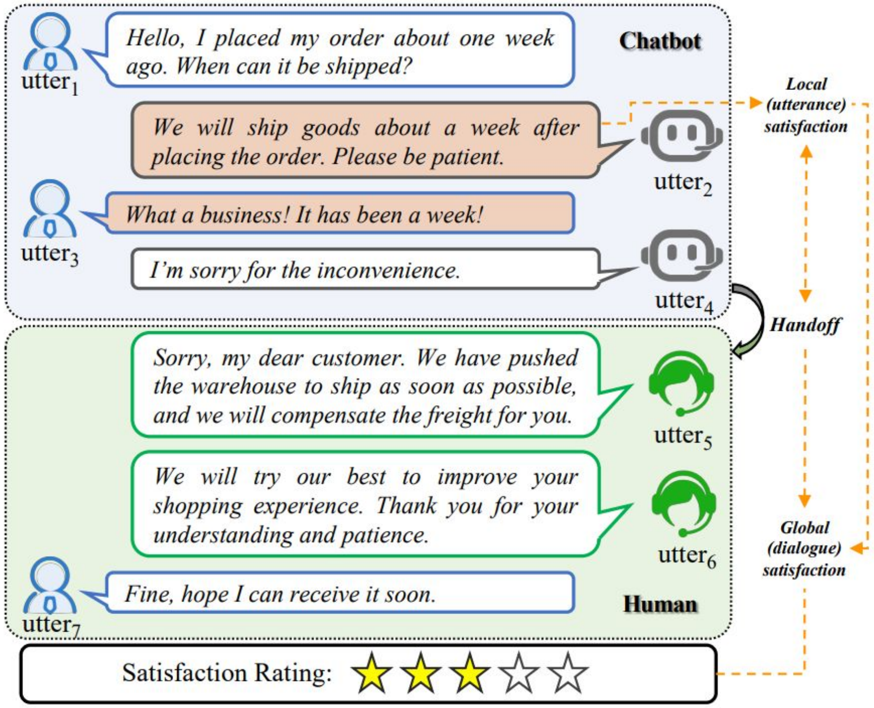
Knowledge-enhanced Mixed-initiative Dialogue System



- ❑ ***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.

Deng et al., 2023. "Knowledge-enhanced Mixed-initiative Dialogue System for Emotional Support Conversations" (ACL '23)

Problem-solving Dialogues



- ❑ 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?

Liu et al., 2021. "A Role-Selected Sharing Network for Joint Machine-Human Chatting Handoff and Service Satisfaction Analysis" (EMNLP '21)

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 can not understand the educational content in tutoring dialogues.

CIMA (Stasaski et al., 2020)	*TSCC (Caines et al., 2020)*
 K: "blue" is "blu" [...] Grammar Rules: Adjectives (such as color words) follow the noun they modify in Italian [...]	N/A
Teacher: (N/A) "Blue" is "blu" in Italian. Student: But what are the other words? Teacher: (N/A) Can you give me your best guess? Student: es en front de blu tree. Teacher: *(Correction)* Getting there. Remember that the adjective always follows the noun in modifies.	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%? Student: just less than a quarter Teacher: *(eliciting)* so if you say 'less' you need to say 'less than' ....so just use one word ok? beginning with 'u'! Student: I am not sure of the word. Teacher: (scaffolding) just under a quarter

Lei et al., 2022. "Interacting with Non-Cooperative User: A New Paradigm for Proactive Dialogue Policy" (SIGIR '22)
Macina et al., 2023. "Opportunities and Challenges in Neural Dialog Tutoring" (EACL '23)

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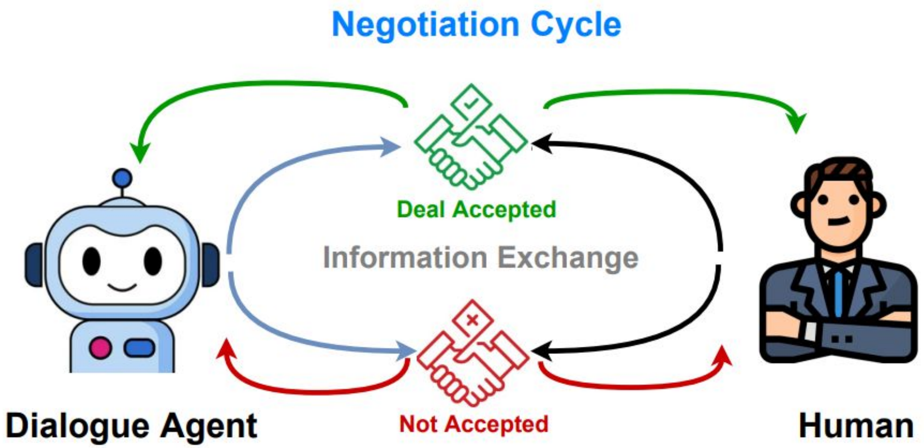
Setting 2: users and the system do not share the same goal

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

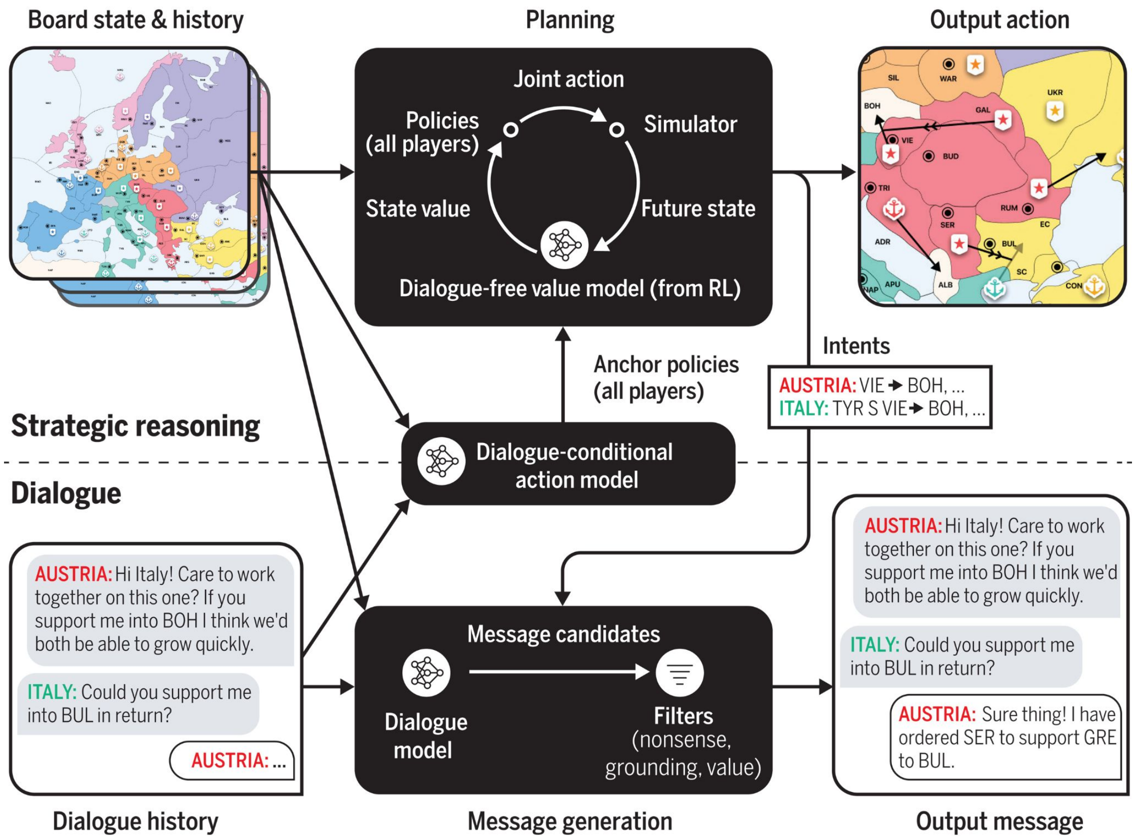


Zhan et al., 2022. "Let's Negotiate! A Survey of Negotiation Dialogue Systems" (CoRR '22)

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.



https://ai.facebook.com/research/cicero/

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

Non-collaborative Dialogues – Datasets

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

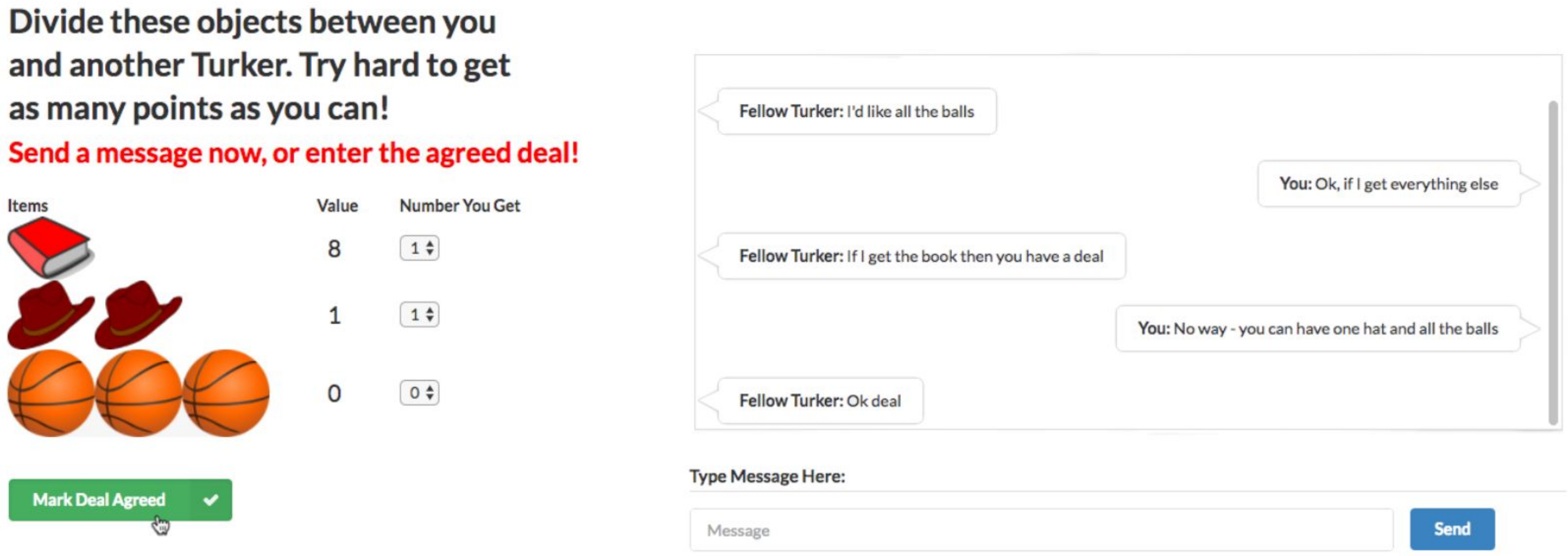
Integrative Negotiation: the goal is to achieve mutual gain (win-win)

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

Zhan et al., 2022. "Let's Negotiate! A Survey of Negotiation Dialogue Systems" (CoRR '22)

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.



Lewis et al., 2017. "Deal or No Deal? End-to-End Learning for Negotiation Dialogues" (EMNLP '17)

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.

JVC HD-ILA 1080P 70 Inch TV

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

Agent	Utterance	Dialogue Act
Buyer	Hello do you still have the TV?	greet
Seller	Hello, yes the TV is still available	greet
Buyer	What condition is it in? Any scratches or problems? I see it recently got repaired	inquire
Seller	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.	inform
Buyer	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?	propose(150)
Seller	I am willing to lower the price, but $150 is a little too low. How about $245 and if you are not too far from me, I will deliver it to you for free?	counter(245)
Buyer	It's still 10 years old and the technology is much older. Will you do 225 and you deliver it. How's that sound?	counter(225)
Seller	Okay, that sounds like a deal!	agree
Buyer	Great thanks!	agree
Seller	OFFER $225.0	offer(225)
Buyer	ACCEPT	accept

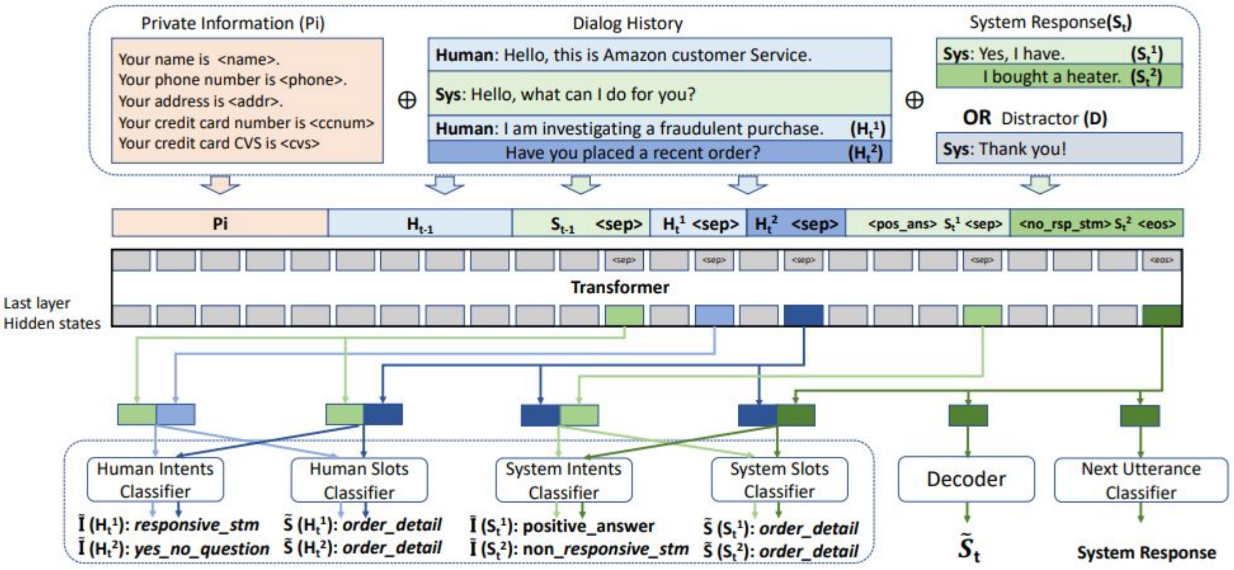
He et al., 2018. "Decoupling Strategy and Generation in Negotiation Dialogues" (EMNLP'18)

Dialogue Strategy Learning – MISSA

Combine the advantages of both template and generation models and takes advantage from the hierarchical annotation at the same time.

On-task	ANTISCAM	*elicitation*
		providing_information
		refusal
	PERSUASION-FORGOOD	*agree_donation*
		disagree_donation
		disagree_donation_more
		ask_donation_amount
		ask_donate_more
		proposition_of_donation
		er_confirm_donation
		ee_confirm_donation
		provide_donation_amount
Off-task		*open_question*
		yes_no_question
		negative_answer
		positive_answer
		responsive_statement
		nonresponsive_statement
		greeting
		thanking
		respond_to_thank
		apology
		closing
		hold

Table 1: Hierarchical intent annotation scheme on both ANTISCAM dataset and PERSUASIONFORGOOD dataset. The On-task intents are task-specific while the Off-task intents are general for different non-collaborative tasks.



Li et al., 2020. "End-to-End Trainable Non-Collaborative Dialog System" (AAAI '20)

Dialogue Strategy Learning – DialoGraph

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

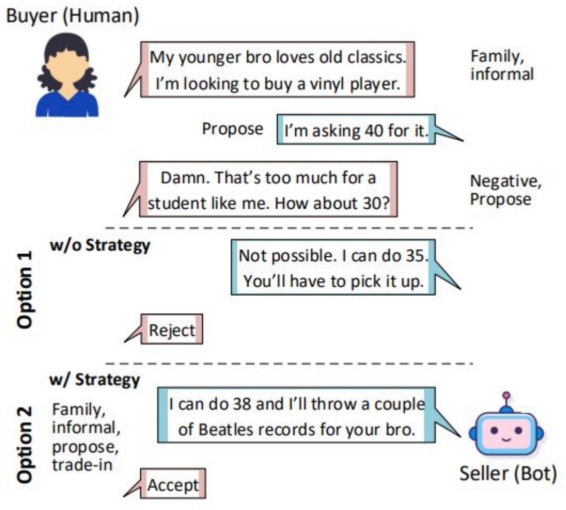
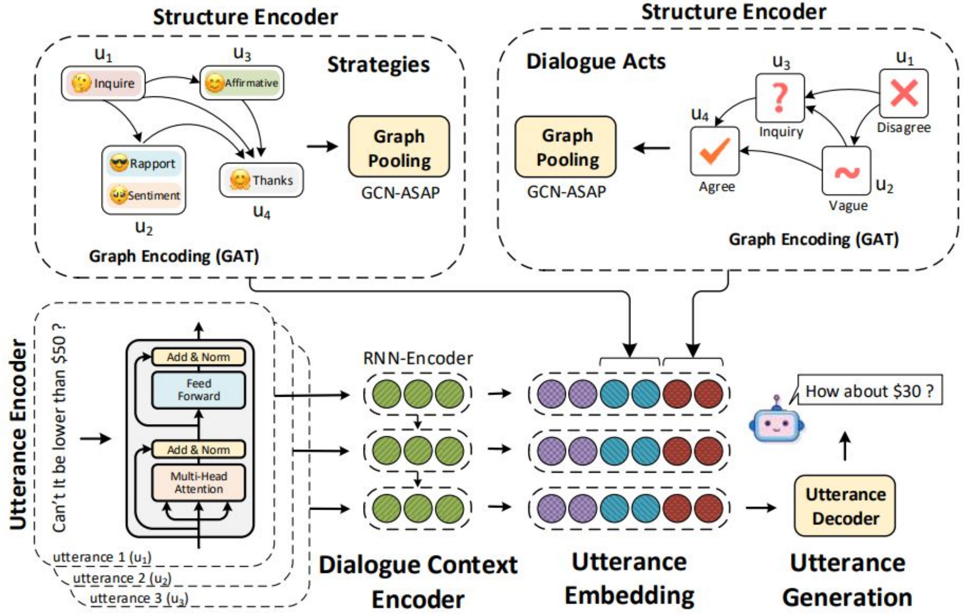


Figure 1: Both options are equally plausible and fluent, but a response with effective pragmatic strategies leads to a better deal.



Joshi et al., 2021. "DialoGraph: Incorporating Interpretable Strategy-Graph Networks into Negotiation Dialogues" (ICLR '21)

User Personality Modeling – ToM

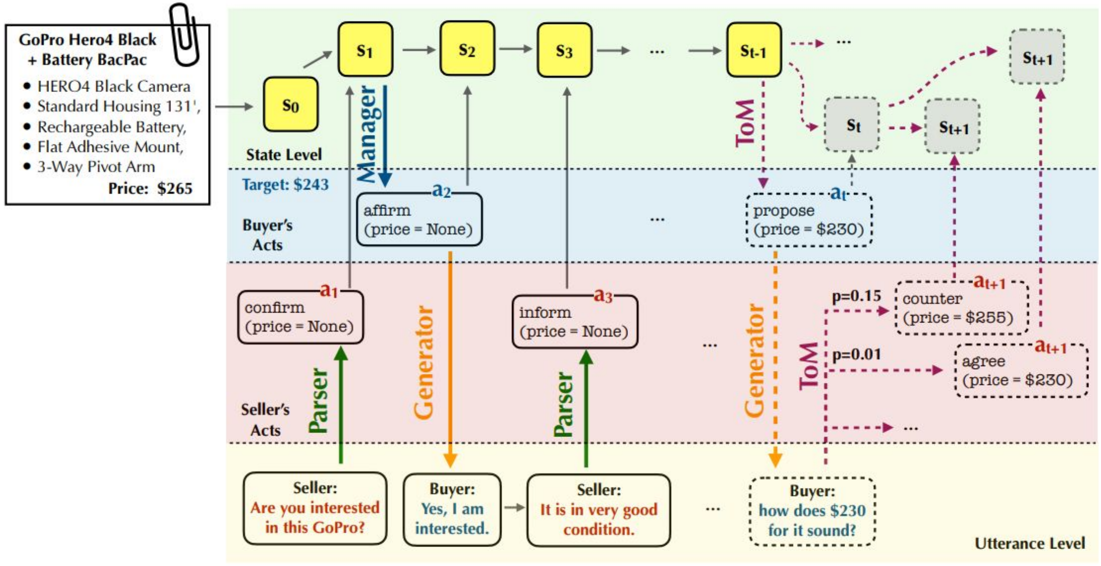


Figure 1: Our Theory of Mind (ToM) framework of negotiation systems. The interaction between a *buyer* and a *seller* can be divided into three levels: The utterance level, dialog act level, and state level. The parser extracts an intent and key information (*e.g.*, price) from an input utterance as 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.

First-order ToM Policies with Explicit Personality Modeling

$$\exp\left\{\frac{1}{\beta}\sum_{u_t^i}\underbrace{G(u_t^i|s_t, z_{t-1}^{-i})}_{\text{Generator}}\sum_{s_{t+1}}\underbrace{T(s_{t+1}|z_{t-1}^{-i}, s_t, u_t^i)}_{\text{1st-order ToM}}\underbrace{V(s_{t+1})}_{\text{Value Fn.}}\right\}$$

First-order ToM Policies with Implicit Personality Modeling

$$\exp\left\{\frac{1}{\beta}\sum_{u_t^i}\underbrace{G(u_t^i|s_t)}_{\text{Generator}}\sum_{s_{t+1}}\underbrace{T(s_{t+1}|u_{t-1}^{-i}, s_t, u_t^i)}_{\text{1st-order ToM}}\underbrace{V(s_{t+1})}_{\text{Value Fn.}}\right\}$$

Yang et al., 2021. "Improving Dialog Systems for Negotiation with Personality Modeling" (ACL '21)

Persuasive Response Generation – PEPDS

- A reward function to ensure politenessstrategy consistency, persuasiveness, emotion acknowledgement, dialogue-coherence and non-repetitiveness.
- An empathetic transfer model by utilizing pre-trained and fine-tuned transformer models.

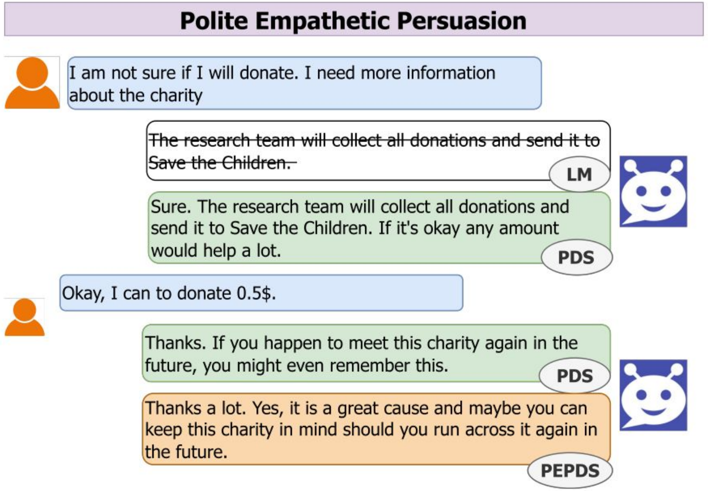
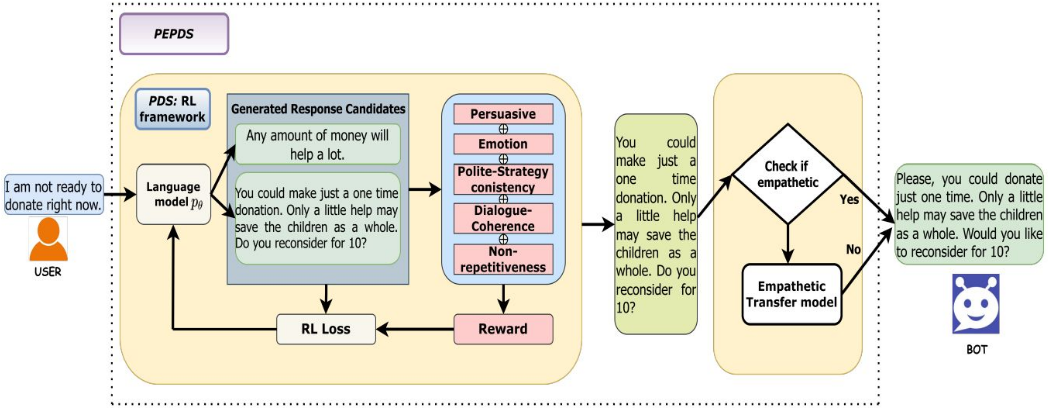


Figure 1: An example of persuasion with LM (Language Model), PDS (LM fine-tuned with RL), and PEPDS (PDS with empathetic transfer model).



Dataset	Number of utterances					
	All	Persuader's	Persuadee	train	eval	test
P4G (to train LM)	20932	10600	10332	16746	2093	2093
P4G (persuasion strategy)	10864	6018	4846	4814	602	602
EPP4G (emotion)	4000	4000	-	3200	400	400
EPP4G (politeness-strategy)	5300	5300	-	4240	530	530
ETP4G (empathetic transfer)	16722	16722	-	13378	1672	1672

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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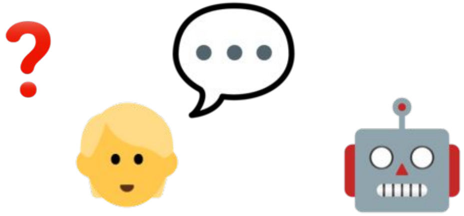
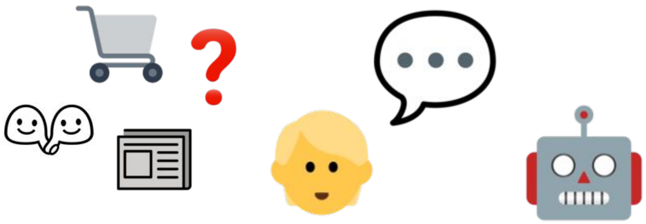
Multi-goal Conversational Systems

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.



General Conversational Systems



Multi-goal Conversational Systems

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).

Mixed-type Dialogues

Goal planning: QA about <Stolen life>, chitchat about Xun Zhou, recommending the movie <The message>, recommending <Don't cry, Nanking!>

1.User: 你知道电影『生死劫』的主演是谁吗? (Who is the star of the movie <stolen life>?)
2.Bot: 是周迅哦。(It is Xun Zhou.)
3.User:是我女神演的呀! (She is my goddess.)
4.Bot: 你真有眼光啊，周迅是中国电视金鹰奖最受欢迎女演员呢。(You have good taste. Zhou Xun is the most popular actress in the Golden Eagle Award of China TV.)
5.User:是呢，我特别喜欢她的，她的演技也很厉害。(I like her very much. She's very good at acting.)
6.Bot:她还获得过亚洲电影大奖最佳女演员的，演技是得到过国际认可的。(She also won the best actress of the Asian Film Awards. Her acting is internationally recognized.)
7.User:嗯嗯，反正她真的很优秀。(Anyway, she's really good.)
8.Bot:那你要看看她演的《风声》吗？该片具有精炼的人物、波谲云诡的情节。很好看哦！(Do you want to see her movie <The message>? It has refined characters and capricious plots.)
9.User:可我现在更喜欢『刘若英』的电影!(But now I prefer Rene Liu's films!)
10.Bot:那刘若英的《南京1937》你可以看看，电影所展现的是一个导演对战争、对民族、对人性的思考。(You can see the movie <Don't cry, Nanking>. It shows the director's thinking on war, nation, and human nature.)
11.User: 历史片吗? (It is historical film?)
12.Bot:历史战争片。(Yes. It is historical war film.)
13.User:那我肯定要看看了。(I will watch it!)
14.Bot:嗯，你肯定会喜欢的。(Sure, you will like it!)
15.User: 嗯，谢谢你呀，下次聊吧! (Thank you! See you later!)
16.Bot:好的，再见！ (OK! Bye!)

DuClarifyDial

Bot	最近咋样啊？ [How are you doing?]
User	工作压力有点大，情绪也有点焦虑 [I get stressed out at work and feel anxious.]
Bot	我建议你出去旅游，可能对你有帮助 [How about go on a trip for relaxing?]
User	好主意，想去北京转转，有没有什么还不错的地方可以玩玩？ [Good idea. I want to go to Beijing. Is there any good place for fun?]
Bot	当然有了。最近很多人去王府井天主教堂玩。[Of course. Recently, many people visit the Wangfujing Catholic Church.]
User	要不你帮我在简单介绍介绍这个教堂呗 [Please give me a brief introduction to this church.]
Bot	这个教堂始建于公元1655年... [The church was founded in 1655 …]
User	这个王府井天主教堂经历不少啊 [Wow! What a colorful history this church has.]
Bot	不仅如此，整个建筑为砖木结构... [In addition, the whole building is of brick and wood structure.]
User	听起来很有意思哦 [Sounds great]
	...
Bot	顺便说一下，景区附近的美食驴打滚也很不错哦 [By the way, there are delicious food nearby, e.g. Lvdagunr.]
User	为什么叫驴打滚呢 [What a strange name it is!]
Bot	因其最后制作工序中··· [This name comes from its final production process …]
User	听着都挺香的，过去了一定得尝一下！先帮我定下餐厅吧 [It sounds delicious. I want it! Please book a restaurant for me.]
	...
Bot	好的，已经帮你预订好了[OK, I've made a reservation for you.]
	...

MultiWOZ

User	I am looking for a attraction in the east of town.
Bot	Sure, I can help you with that. There are plenty of attracts to the east. Is there a specific type of attraction you are interested in?
	...

DuConv

Bot	麦兜·饭宝奇兵这部电影，大众评分在6.9呢，值得一看。 [You can watch Rise of the Rice Cooker, which is rated 6.9.]
User	好的，一定去看看。[Sounds great, thanks.]
Bot	这部电影还不错，挺搞笑的。你知道饭麦兜·饭宝奇兵的主演是谁吗？ [It is very nice and funny. Do you know who is the hero of this movie?]
	...

MultiWOZ-Beyond

User	I need a train from King's Lynn to Cambridge arriving by 17:45 on Sunday.
Bot	I have train TR6003 leaving Cambridge at 5:11 and arriving at 5:58 on Sunday.
User	I also need to bring my dog. Do they allow pets?
Bot	Yes, you can travel with your dog up to 20 pounds.
User	That sounds great. I also need help finding a place to stay in the South.
	...

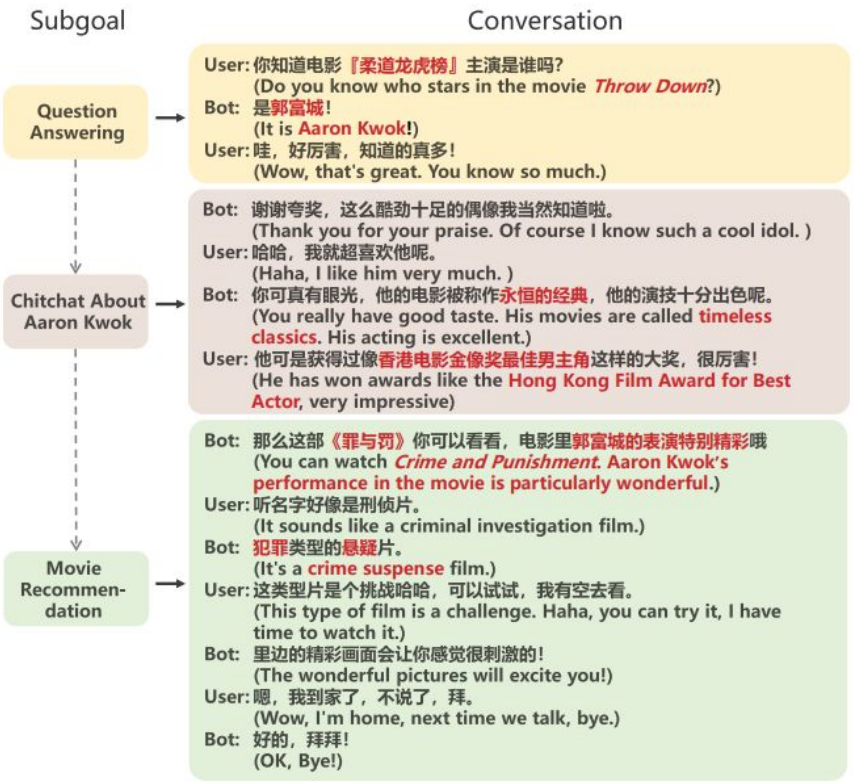
FusedChat

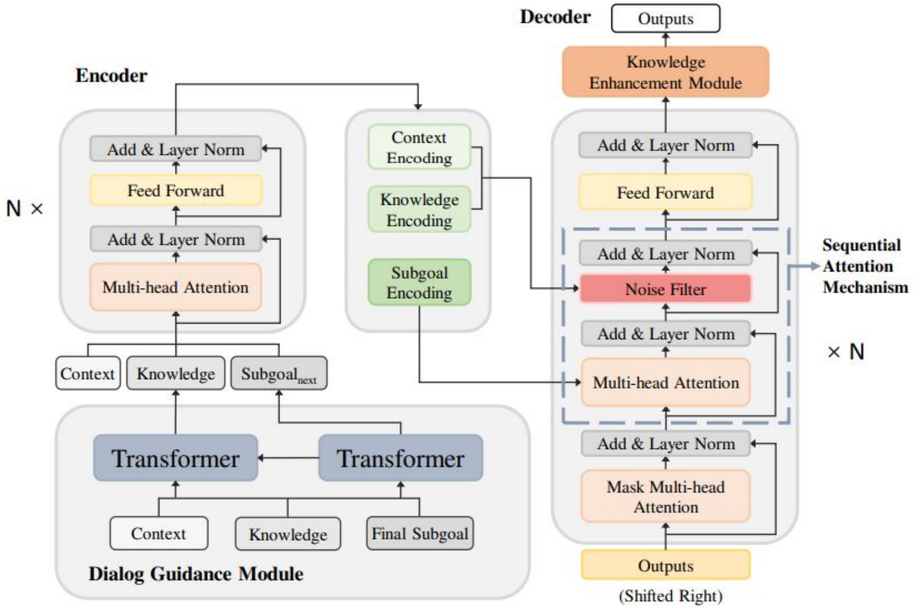
User	I need to find a restaurant in Cambridge that serves expensive Thai food.
Bot	Bangkok City is located at 24 Green Street City Centre
	...
User	My friends who are going to dine with me are foodies. I really want them to enjoy the restaurant I pick.
Bot	Don't worry. The cuisine of an expensive restaurant shouldn't be too bad.
	...

Social chitchat | Knowledge grounded dialog | Question answering | Task-oriented dialog

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)

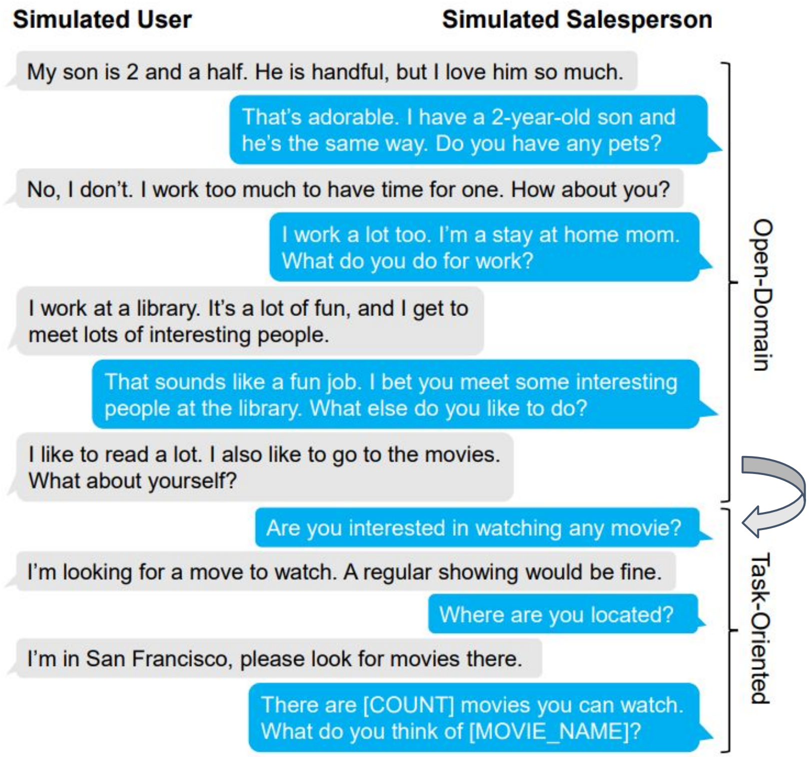
Pre-defined Goals – Target-guided Mixed-type Dialogues





Zhang et al., 2021. "KERS: A Knowledge-Enhanced Framework for Recommendation Dialog Systems with Multiple Subgoals" (EMNLP-Findings '21)

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

Conversation	Goal	Topic	Item
1. User: Hi~ Good evening. 2. System: Good evening. What can I help you?	Greeting	N/A	N/A
3. User: Do you know who starred in <***Bruce Lee: Warrior***>? 4. System: It's ***Jackie Chan***.	QA	Bruce Lee: Warrior	
5. User: I like him very much. He's really great. 6. System: You have a good taste. He has won the best actor twice in the Golden Horse Award.	Chit-chat about Star	Jackie Chan	
7. User: He's very good at acting. 8. System: Do you want to see her movie <***Jackie Chan: My Stunts***>? It can be regarded as the most classic movie of Jackie Chan.	Movie Rec.		Jackie Chan: My Stunts
9. User: Is this movie with a high rating? 10. System: The rating is 7.8, which is very high!	QA	Jackie Chan: My Stunts	N/A
11. User: But I prefer ***Nicholas Tse***'s movies now. 12. System: Nicholas Tse's <***The Witness***> is also very good and worth seeing. The director is good at portraying emotions.	Movie Rec.	Nicholas Tse	The Witness
13. User: I will watch it! 14. System: Sure, you will like it! 15. User: Thank you! See you next time! 16. System: Great! Bye!	Goodbye	N/A	N/A

(a) An example dialogue in the DuRecDial dataset

Conversation	Goal	Topic	Item
1. User: Hey, are you here? 2. System: Hi~ What are you up to?	Greeting	N/A	N/A
3. User: I'm watching a video about ***aliens***. 4. System: I haven't seen aliens yet. Do they look like monsters?	Chit-chat	Alien	
5. User: Like the ***hero*** after transforming. 6. System: Is it the kind of hero in the movie?		Hero	
7. User: Yes, exactly. 8. System: Do you want to see a movie about hero? I can recommend to you.	Rec. Request		
9. User: Sure, Are there any ***Marvel hero*** movies? I like Marvel very much. 10. System: <***The Black Widow***> is a great movie. The action shots are very cool.	Movie Rec.	Hero / Marvel	The Black Widow
11. User: Great. Could you recommend some other ***animated*** movies? 12. System: Have you watched Marvel Animation <***Doctor Strange***>? It is more original than the live-action movie.		Animation	Doctor Strange
13. User: Thanks for your recommendation! I will watch it later. 14. System: Great! Bye!	Feedback	N/A	N/A

(b) An example dialogue in the TG-ReDial dataset

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

Deng et al., 2023. "A Unified Multi-task Learning Framework for Multi-goal Conversational Recommender Systems" (TOIS '23)

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 $\mathcal{G}_t$, MG-CRS first selects the appropriate goal $g_t \in \mathbb{G}$ to determine where the conversation goes.
- ***Topic Prediction.*** The second task is to predict the next conversational topics $k_t \in \mathbb{K}$ for completing the planned goal g_t, with respect to the dialogue context C_t, the historical topic thread $\mathcal{K}_t$, and the user profile $\mathcal{P}_u$ (if exists).
- ***Item Recommendation.*** If the selected goal g_t is to make recommendations, then the CRS should recommend an item $v_t \in \mathbb{V}$, based on the dialogue context C_t and the user profile $\mathcal{P}_u$ (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.

Deng et al., 2023. "A Unified Multi-task Learning Framework for Multi-goal Conversational Recommender Systems" (TOIS '23)

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.

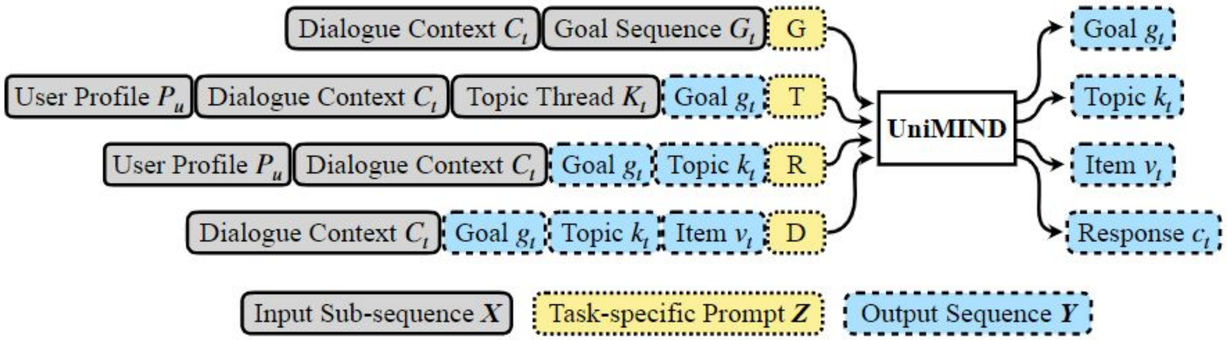
Method	Goal Planning	Topic Prediction	Item Recommendation	Response Generation
Attribute-based [8, 23, 25]	✓*	×	✓	×
Open-ended [6, 19, 27]	×	×	✓	✓
MGCG [33]	✓	✓	×	✓
GOKC [1]	○	✓	×	✓
KERS [56]	○	✓	×	✓
Union [65]	○	✓	✓	✓
TopicRef. [52]	○	✓	✓	✓
UniMIND	✓	✓	✓	✓

*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.

Deng et al., 2023. "A Unified Multi-task Learning Framework for Multi-goal Conversational Recommender Systems" (TOIS '23)

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



Deng et al., 2023. "A Unified Multi-task Learning Framework for Multi-goal Conversational Recommender Systems" (TOIS '23)

Performance w.r.t. Goal Type

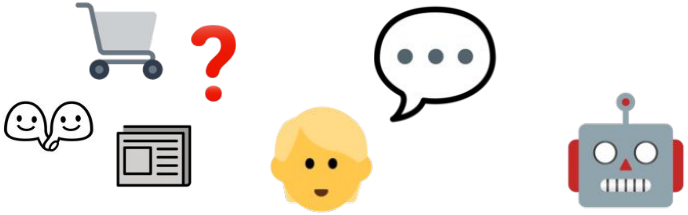
Goal Type	%	Goal	Topic	Response Gen.		
		F1	F1	F1	BLEU-1/2	Dist-2
TG-ReDial						
Recommend.	54.4	**0.9629**	**0.8864**	37.6	0.337/0.072	0.218
Chit-chat	39.0	0.9428	0.3886	30.5	0.254/0.071	**0.327**
Rec. Request	31.9	0.8352	0.6926	**45.4**	**0.404/0.167**	0.251
DuRecDial						
Recommend.	37.2	0.9235	0.7933	45.9	0.455/0.376	0.101
Chit-chat	15.5	0.8734	0.9787	41.7	0.396/0.309	**0.132**
QA	16.7	0.9298	0.9278	62.5	0.587/0.505	0.122
Task	11.3	**0.9456**	**0.9963**	**68.5**	**0.701/0.637**	0.114

- ❑ **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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- ❑ Summary and Outlook

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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.

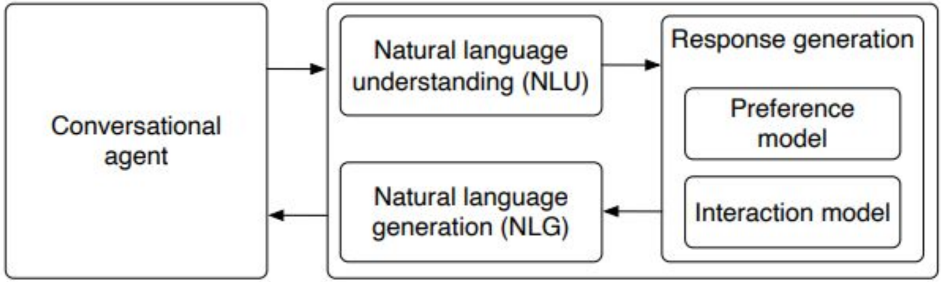
- **Satisfaction-based User Simulators** (*Lei et al., 2022*)
  1) The user utterance is based on satisfaction with the current conversation.
  2) Satisfaction is formalized as the cumulative average of users' preferences for the topics covered by the conversation: $US_t \triangleq \frac{1}{t}\sum_{i=1}^{t} \frac{1}{|u_i+1|}(\sum_{j=1}^{|u_i|} p_{e_{i,j}} + p_{e_i^a})$
  3) Based on the calculated user satisfaction, the user behavior can be deconstructed into three types: cooperative, non-cooperative and quit.

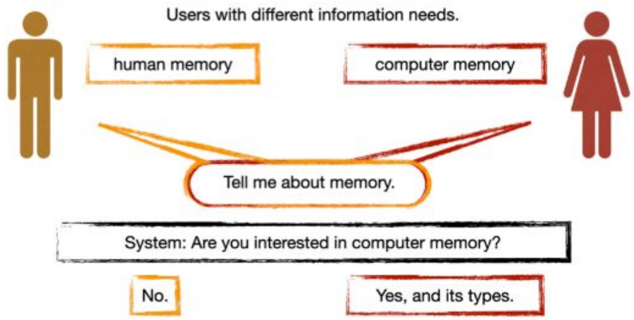
Tang et al., 2019. "Target-Guided Open-Domain Conversation" (ACL '19)
Lei et al., 2022. "Interacting with Non-Cooperative User: A New Paradigm for Proactive Dialogue Policy" (SIGIR '22)

User Simulators

Conditional Generation Models as User Simulators

Conditioned on user preferences for evaluating conversational recommender systems.





← Info need

← Query

← Clarifying question

← **Answer**

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

System	Succ. (%)	#Turns
Retrieval	9.8	3.26
Retrieval-Stgy	67.2	6.56
Ours-PMI	47.4	5.12
Ours-Neural	51.6	4.29
Ours-Kernel	**75.0**	4.20

Asking Clarification Question in Conversational Search
Goal – Document retrieval

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

Multi-goal Dialogues
Goal – Completing different subgoals

Methods→ Metrics↓Types↓		S2S +gl. +kg.	MGCG_R +gl. +kg.	MGCG_G +gl. +kg.
#Failed	Rec.	106/7	95/18	93/**20**
gl./	Chitchat	120/93	96/117	80/**133**
#Com-	QA	66/5	61/10	60/**11**
pleted	Task	45/4	36/**13**	39/10
gl.	Overall	337/109	288/158	272/**174**

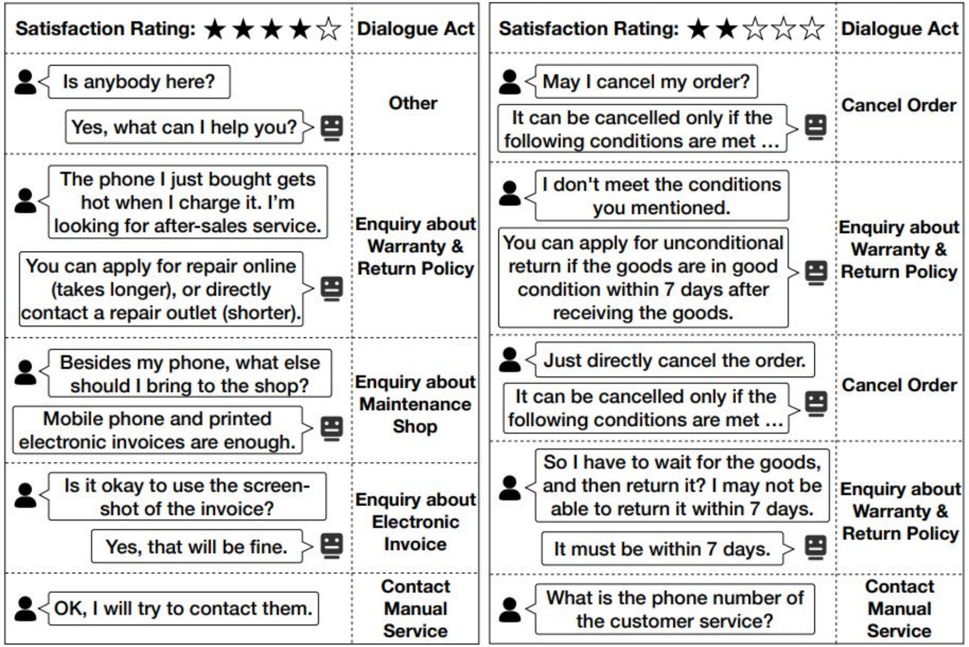
Non-collaborative Dialogues
Goal – Negotiation outcomes

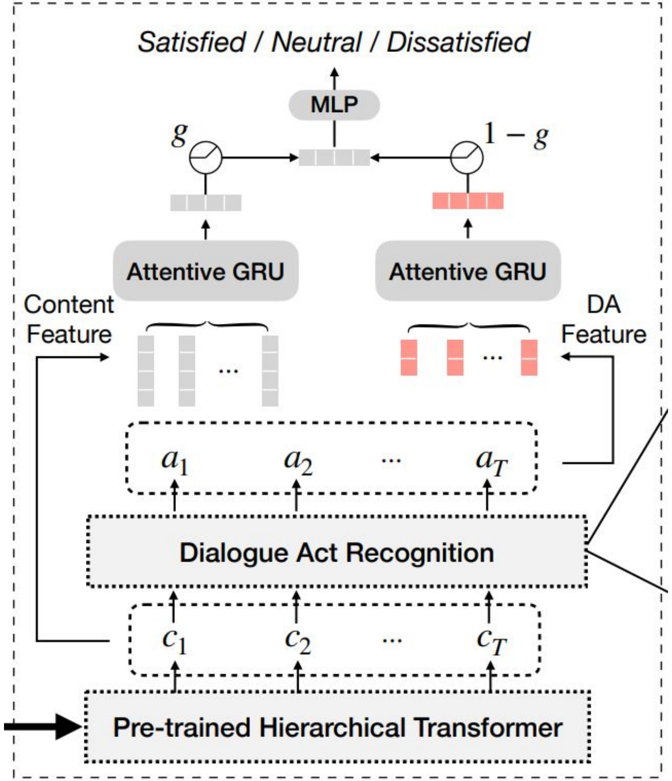
	Generation				Outcome Prediction
		BERTScore			
Model	BLEU	Precision	Recall	F1	RC-Acc
HED	20.9	21.8	22.3	22.1	35.2
FeHED	23.7	27.1	26.8	27.0	42.3
HED+RNN	22.5	22.9	22.7	22.8	47.9
HED+Transformer	**24.4**	27.4	**28.1**	27.7	**53.7**
DIALOGRAPH	**24.7**	**27.8**	**28.3**	**28.1**	**53.1**

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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Ethics – Factuality

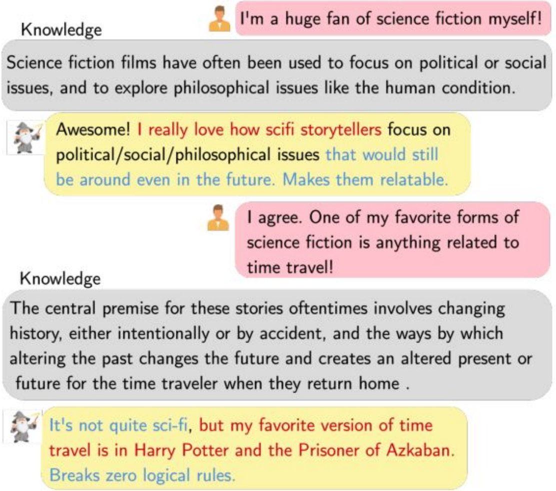


Figure 1: An example of a hallucinated conversation from the Wizard of Wikipedia dataset (Dinan et al., 2018). The wizard (yellow) is hallucinating information that cannot be inferred from the knowledge-snippet: hallucinated subjective content (red) and hallucinated objective content (blue).

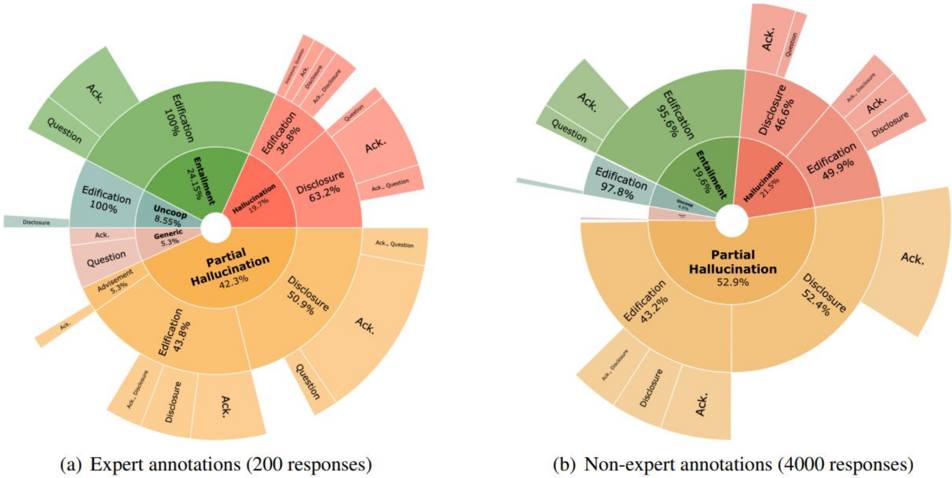


Figure 2: BEGIN and VRM breakdown of responses from WoW. The inner circle shows the breakdown of BEGIN classes and the outer shows the VRM types in each BEGIN type: Hallucination (red), Entailment (green), Partial Hallucination (yellow), Generic (pink), and Uncooperative (blue).

The standard benchmarks consist of >60% hallucinated responses, leading to models that not only hallucinate but even amplify hallucinations.

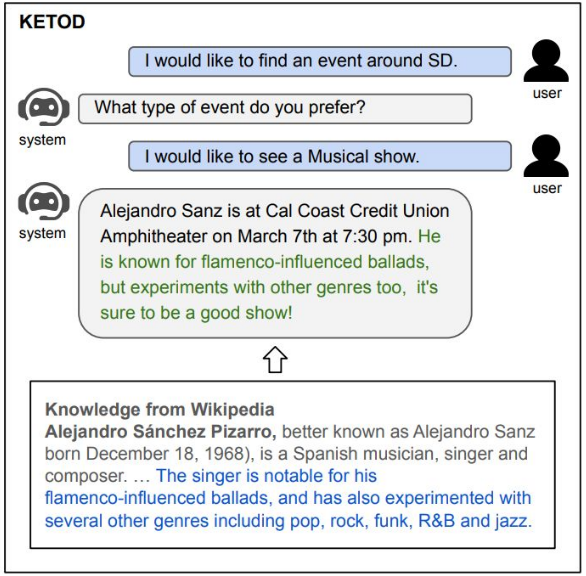
Datasets or models?

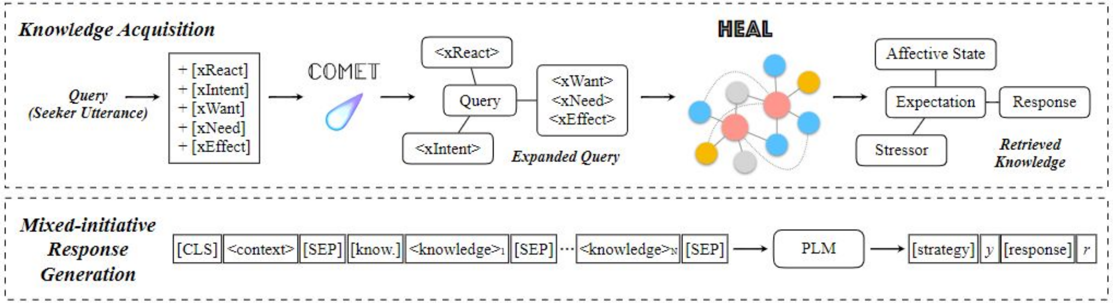
Dziri et al., 2022. "On the Origin of Hallucinations in Conversational Models: Is it the Datasets or the Models?" (NAACL '22)

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)
Deng et al., 2022. "Knowledge-enhanced Mixed-initiative Dialogue System for Emotional Support Conversations" (CoRR '23)

Ethics – Factuality

Several recent attempts have been made on prompting LLMs to generate external knowledge for reseponse generation.

	Tag	Definition
	Context Understanding:	
1	Related	The generated output discusses facts that are related to the conversation.
2	Unrelated	The generated output does not discuss facts that are related to the conversation.
	Tuning Effectiveness:	
3	Non-Verifiable	The generated output does not contain facts that could be verified.
4	Verifiable	The generated output contains facts that could be verified.
	Fact-Checking:	
5	Supported	One can find evidence from the knowledge base to validate the factual information in the generated output.
6	Explicit Supported	One only needs to find one evidence from the knowledge base for validation.
7	Implicit Supported	One needs to find multiple evidences from the knowledge base for validation.
8	Refuted	One can find evidence from the knowledge base to contradict the factual information in the generated output.
9	**N**ot **E**nough **I**nformation	The factual information in the generated output could not be validated.
10	Reasonable NEI	Though not validated by the knowledge base, the factual information matches common sense.
11	Unreasonable NEI	Though not validated by the knowledge base, the factual information does not match common sense.
12	Hard NEI	The factual information could not be validated by either the knowledge base or common sense.

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.

Li et al., 2022."Eliciting Knowledge from Large Pre-Trained Models for Unsupervised Knowledge-Grounded Conversation" (EMNLP'22)

Ethics – Safety

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

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

Sun et al., 2022. "On the Safety of Conversational Models: Taxonomy, Dataset, and Benchmark" (ACL-Findings '22)

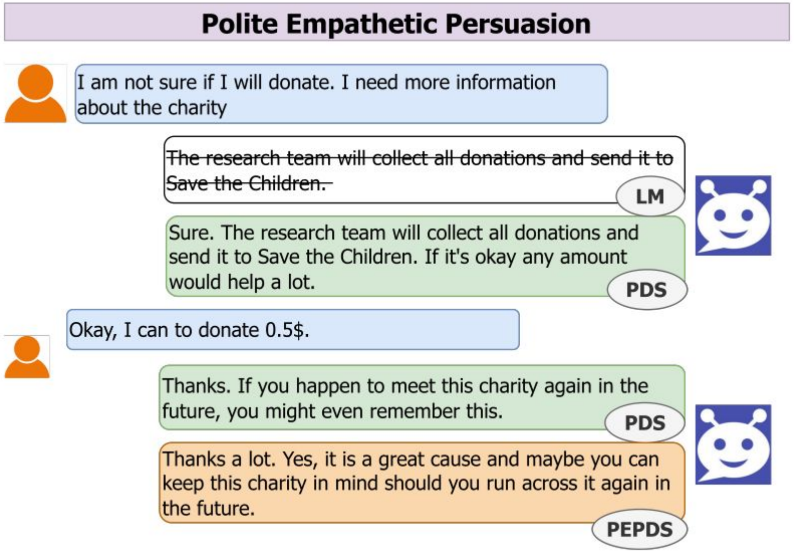
Ethics – Safety

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



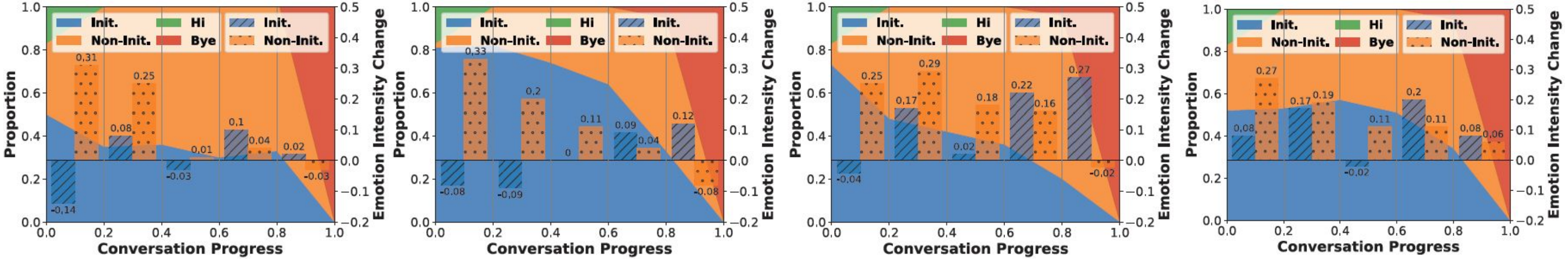
Mishra et al., 2022. "PEPDS: A Polite and Empathetic Persuasive Dialogue System for Charity Donation" (COLING '22)

Ethics – Safety

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.



(a) BlenderBot (b) MISC (c) KEMI (Ours) (d) ESConv (Reference)

Deng et al., 2023. "Knowledge-enhanced Mixed-initiative Dialogue System for Emotional Support Conversations" (CoRR '23)

Ethics – Privacy

Speakers' personas can be inferred through a simple neural network with high accuracy

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

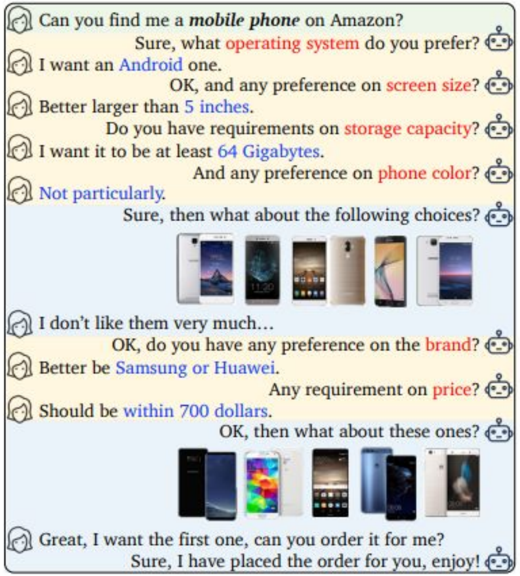
Figure 1: Black-box persona inference attacks (over 4,332 personas) on a dialog. Every representation of the utterance, which is based on the last hidden state of GPT-2, is attacked without defense (column of "Attacks on LM") and with defense (column of "Attacks on the defensed LM"). If the model can 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.

Privacy leakage of training data

Li et al., 2022. "You Don't Know My Favorite Color: Preventing Dialogue Representations from Revealing Speakers' Private Personas" (NAACL-HLT '22)

Ethics – Privacy

The agent's proactivity raises more concerns on misusing personal information obtained from the users during the conversation.



Acquiring user preferences

CUSTOMERSIM

Role	Utterance
SYS	Hello, I am the customer support bot. What can I do for you?
USR	Hello robot. Could you please help me track my package?
SYS	Please provide your full name.
USR	Sure, Betty Sims.
SYS	Could you please confirm your shipping address?
USR	Yea sure, 2241 Fitzgerald Viaduct Brownview, OK 28304.
SYS	Track your order using your tracking number, FH6F6GMMF4. Are you happy about my answer?
USR	That's it.

Acquiring personal information

✅ Benefial 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.

Zhang et al., 2018. "Towards Conversational Search and Recommendation: System Ask, User Respond" (CIKM '18)
Shi et al., 2022. "Selective Differential Privacy for Language Modeling" (NAACL-HLT '22)

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' Goal Awareness and Beyond
  - ❑ Evaluation for Conversational Agents' Goal Awareness
  - ❑ Ethics for Conversational Agents' Goal Awareness
  - ❑ Agent’s Goal Awareness in LLM-based Conversational AI
- ❑ Summary and Outlook

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?

[1] Bang et al., 2023. A multitask, multilingual, multimodal evaluation of chatgpt on reasoning, hallucination, and interactivity.
[2] Zhang et al., 2023. SGP-TOD: Building Task Bots Effortlessly via Schema-Guided LLM Prompting
[3] Zhao et al., 2023. Is ChatGPT Equipped with Emotional Dialogue Capabilities?

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

Strategies: 1 *Personal Inquiry* 2 *Emotion Appeal* 3 *Credibility Appeal*

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.

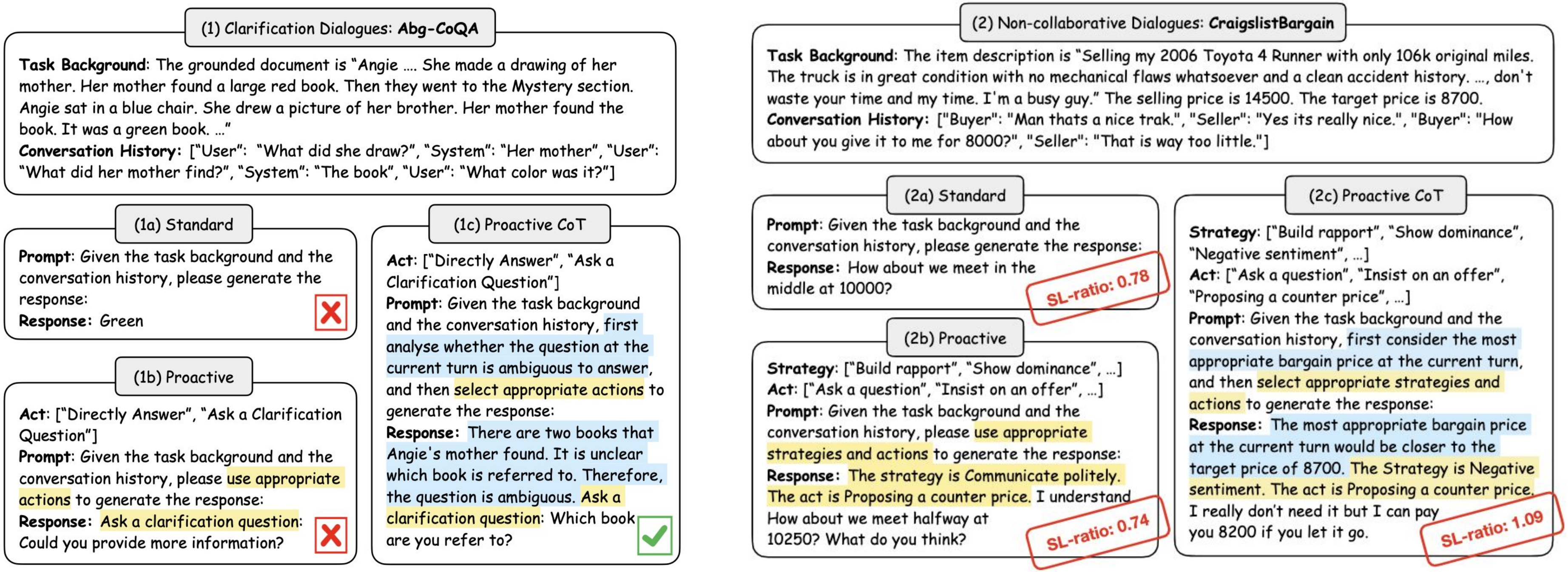
3 *The Persuader uses a credibility appeal.*
Persuader:

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.

Chen et al., 2023. "Controllable Mixed-Initiative Dialogue Generation through Prompting" (ACL '23)

Proactive Chain-of-Thought (ProCoT) Prompting

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



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

Method	Shot	Prompt	Abg-CoQA* F1	Abg-CoQA* BLEU-1	Abg-CoQA* Human	PACIFIC** F1	PACIFIC** ROUGE-2	PACIFIC** Human
Baseline	-	-	22.1	36.5	30.0	79.0	69.2	38.2
SOTA	-	-	23.6	38.2	56.0	86.9	90.7	80.1
Vicuna-13B	0	Standard	-	11.3	0.0	-	1.2	0.0
	1	Standard	-	11.4	0.0	-	2.5	0.0
	0	Proactive	4.1	13.2	0.0	2.3	2.3	0.0
	1	Proactive	12.1	13.2	4.5	0.0	3.3	0.0
	0	ProCoT	1.4	21.3	9.1	9.7	3.8	10.5
	1	ProCoT	**18.3**	**23.7**	**22.7**	**27.0**	**41.3**	**33.1**
ChatGPT	0	Standard	-	12.1	0.0	-	2.2	0.0
	1	Standard	-	12.3	0.0	-	2.0	0.0
	0	Proactive	22.0	13.7	17.6	19.4	2.9	0.0
	1	Proactive	20.4	**23.4**	23.5	17.7	14.0	12.5
	0	ProCoT	23.8	21.6	32.4	**28.0**	**21.5**	26.7
	1	ProCoT	**27.9**	18.4	**45.9**	27.7	16.2	**35.8**

(1a) Standard

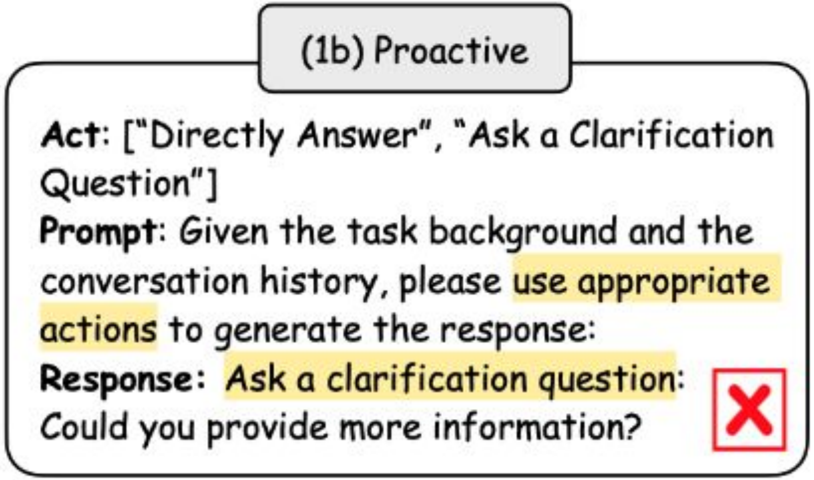
Prompt: Given the task background and the conversation history, please generate the response:
Response: Green

- 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

Method	Shot	Prompt	Abg-CoQA* F1	Abg-CoQA* BLEU-1	Abg-CoQA* Human	PACIFIC** F1	PACIFIC** ROUGE-2	PACIFIC** Human
Baseline	-	-	22.1	36.5	30.0	79.0	69.2	38.2
SOTA	-	-	<u>23.6</u>	<u>38.2</u>	<u>56.0</u>	<u>86.9</u>	<u>90.7</u>	<u>80.1</u>
Vicuna-13B	0	Standard	-	11.3	0.0	-	1.2	0.0
	1	Standard	-	11.4	0.0	-	2.5	0.0
	0	Proactive	4.1	13.2	0.0	2.3	2.3	0.0
	1	Proactive	12.1	13.2	4.5	0.0	3.3	0.0
	0	ProCoT	1.4	21.3	9.1	9.7	3.8	10.5
	1	ProCoT	**18.3**	**23.7**	**22.7**	**27.0**	**41.3**	**33.1**
ChatGPT	0	Standard	-	12.1	0.0	-	2.2	0.0
	1	Standard	-	12.3	0.0	-	2.0	0.0
	0	Proactive	22.0	13.7	17.6	19.4	2.9	0.0
	1	Proactive	20.4	**23.4**	23.5	17.7	14.0	12.5
	0	ProCoT	23.8	21.6	32.4	**28.0**	**21.5**	26.7
	1	ProCoT	**27.9**	18.4	**45.9**	27.7	16.2	**35.8**



- 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

Method	Shot	Prompt	Abg-CoQA* F1	Abg-CoQA* BLEU-1	Abg-CoQA* Human	PACIFIC** F1	PACIFIC** ROUGE-2	PACIFIC** Human
Baseline	-	-	22.1	36.5	30.0	79.0	69.2	38.2
SOTA	-	-	<u>23.6</u>	<u>38.2</u>	<u>56.0</u>	<u>86.9</u>	<u>90.7</u>	<u>80.1</u>
Vicuna-13B	0	Standard	-	11.3	0.0	-	1.2	0.0
	1	Standard	-	11.4	0.0	-	2.5	0.0
	0	Proactive	4.1	13.2	0.0	2.3	2.3	0.0
	1	Proactive	12.1	13.2	4.5	0.0	3.3	0.0
	0	ProCoT	1.4	21.3	9.1	9.7	3.8	10.5
	1	ProCoT	**18.3**	**23.7**	**22.7**	**27.0**	**41.3**	**33.1**
ChatGPT	0	Standard	-	12.1	0.0	-	2.2	0.0
	1	Standard	-	12.3	0.0	-	2.0	0.0
	0	Proactive	22.0	13.7	17.6	19.4	2.9	0.0
	1	Proactive	20.4	**23.4**	23.5	17.7	14.0	12.5
	0	ProCoT	23.8	21.6	32.4	**28.0**	**21.5**	26.7
	1	ProCoT	**27.9**	18.4	**45.9**	27.7	16.2	**35.8**

(1c) Proactive CoT

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?

- 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.

			Response Generation			Next Topic Prediction	
Method	Shot	Prompt	BLEU	METEOR	R-L	hits@1	hits@3
GPT2	-	-	11.58	10.26	17.67	4.39	15.79
MultiGen	-	-	13.57	12.51	26.27	6.58	20.51
DKRN	-	-	12.86	11.90	21.52	4.91	17.72
CKC	-	-	13.34	11.65	24.77	6.87	21.89
TopKG	-	-	15.35	13.41	27.16	7.78	22.06
Vicuna-13B	0	Standard	10.01	13.27	16.00	12.01	19.03
	1	Standard	10.63	14.81	17.53	12.10	16.13
	0	Proactive	1.41	18.45	15.45	9.41	19.89
	1	Proactive	**13.87**	**20.96**	**21.36**	12.90	**22.31**
	0	ProCoT	5.27	16.59	15.96	11.56	18.01
	1	ProCoT	13.38	19.70	20.62	**15.05**	20.70
ChatGPT	0	Standard	11.34	20.62	**18.26**	13.44	27.69
	1	Standard	14.41	19.29	17.73	15.86	26.34
	0	Proactive	14.09	**21.06**	15.56	7.53	22.58
	1	Proactive	**14.74**	19.59	16.29	8.60	21.23
	0	ProCoT	10.20	19.57	15.97	12.63	23.92
	1	ProCoT	9.63	19.82	17.19	**17.74**	**29.57**

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

- 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.

			Easy Target			Hard Target		
Method	Shot	Prompt	Succ.(%)	Turns	Coh.	Succ.(%)	Turns	Coh.
GPT2	-	-	22.3	2.86	0.23	17.3	2.94	0.21
MultiGen	-	-	26.7	2.55	0.21	19.6	7.31	0.24
DKRN	-	-	38.6	4.24	0.33	21.7	7.19	0.31
CKC	-	-	41.9	4.08	0.35	24.8	6.88	0.33
TopKG	-	-	48.9	3.95	0.31	27.3	4.96	0.33
COLOR	-	-	66.3	-	0.36	30.1	-	0.35
Vicuna-13B	0	Standard	63.0	**2.63**	0.43	62.5	**2.45**	0.39
	1	Standard	62.7	2.83	0.45	**65.0**	2.90	0.43
	0	Proactive	37.8	2.71	0.48	35.6	2.56	**0.55**
	1	Proactive	48.3	2.71	0.50	34.6	2.95	0.51
	0	ProCoT	65.2	4.22	0.49	54.9	4.17	0.45
	1	ProCoT	**72.3**	3.55	**0.52**	59.8	3.81	0.48
ChatGPT	0	Standard	**97.5**	**2.26**	0.38	**96.3**	2.30	0.41
	1	Standard	96.3	2.42	0.42	93.5	**2.28**	0.38
	0	Proactive	85.9	3.20	**0.47**	83.0	2.83	**0.43**
	1	Proactive	90.7	2.86	0.36	86.2	2.94	0.31
	0	ProCoT	96.3	2.47	0.41	92.0	2.29	0.34
	1	ProCoT	95.9	2.63	0.45	92.1	2.47	0.39

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

			Negotiation Strategies						Dialogue Acts					Response Generation			
			F1			ROC AUC			F1			ROC AUC			BERTScore		
Method	Shot	Prompt	Macro	Micro	Weighted	Macro	Micro	Weighted	Macro	Micro	Weighted	Macro	Weighted	BLEU	P	R	F1
FeHED	-	-	17.6	25.6	36.3	55.8	61.7	54.7	20.6	37.4	30.6	76.9	79.2	23.7	27.1	26.8	27.0
HED+RNN	-	-	23.2	26.7	42.4	65.3	65.3	60.4	33.0	46.2	42.8	83.1	84.2	22.5	22.9	22.7	22.8
HED+TFM	-	-	26.3	32.1	43.3	68.2	71.8	61.8	32.5	44.6	42.0	85.6	85.1	24.4	27.4	28.1	27.7
DIALOGRAPH	-	-	26.1	34.1	43.5	68.1	73.0	61.8	33.4	45.8	43.7	85.6	85.4	24.7	27.8	28.3	28.1
Vicuna-13B	0	Standard	-	-	-	-	-	-	-	-	-	-	-	1.7	-28.9	1.7	-14.0
	1	Standard	-	-	-	-	-	-	-	-	-	-	-	1.9	**-3.1**	-2.0	-2.8
	0	Proactive	**20.6**	**25.2**	**39.6**	**51.1**	48.2	**49.8**	4.2	**18.5**	8.4	50.3	49.8	2.3	-6.1	-7.0	-7.0
	1	Proactive	15.2	21.0	26.0	50.0	48.8	49.5	6.7	12.0	11.4	50.8	51.3	2.6	-10.3	**8.9**	-0.9
	0	ProCoT	19.0	24.0	38.5	49.7	47.4	49.3	3.6	13.5	7.0	50.3	49.4	2.6	-7.5	-4.1	-6.2
	1	ProCoT	17.8	23.8	31.9	48.9	**50.0**	49.0	**7.7**	14.0	**13.9**	**52.5**	**52.2**	**2.6**	-9.0	7.6	**-0.9**
ChatGPT	0	Standard	-	-	-	-	-	-	-	-	-	-	-	2.3	-16.4	8.3	-4.3
	1	Standard	-	-	-	-	-	-	-	-	-	-	-	3.1	-3.4	6.9	0.7
	0	Proactive	12.8	19.2	19.6	51.3	49.3	50.3	13.3	29.7	19.5	56.3	60.0	**4.2**	-4.3	7.3	1.3
	1	Proactive	13.7	22.4	20.8	50.9	51.6	51.2	12.0	26.1	17.6	54.9	58.0	3.9	-4.3	10.4	**2.9**
	0	ProCoT	10.8	17.5	16.0	50.4	47.5	50.6	10.1	26.2	16.8	54.2	57.7	3.7	**-0.2**	-0.9	-0.9
	1	ProCoT	**15.1**	**22.8**	**22.9**	**55.5**	**52.5**	**53.1**	**16.3**	**33.3**	**24.4**	**58.2**	**62.8**	3.9	-7.1	**10.5**	1.6

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**.

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

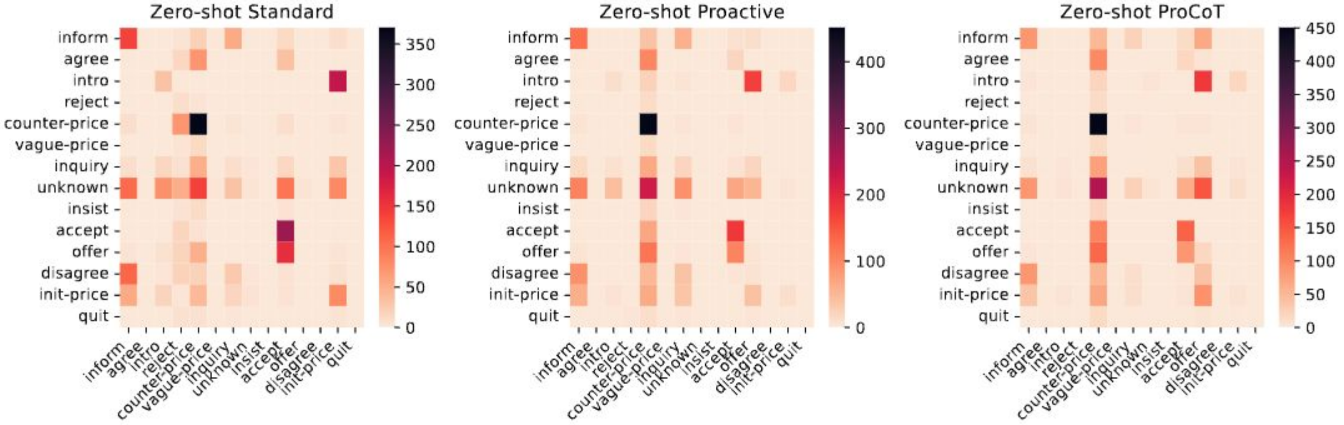


Figure 2: Heatmaps on the relationships between target and predicted dialogue acts. As no dialogue act is predicted in standard prompting, a dialogue act classifier is trained to identify the dialogue act of the generated response.

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

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

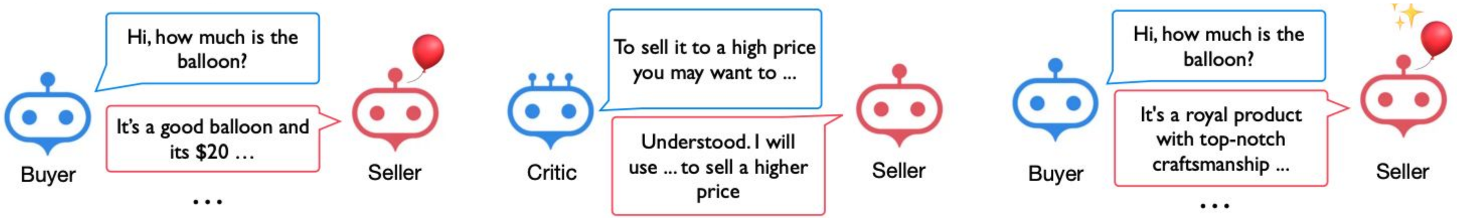
Lesson Learned from the Evaluation

- **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.

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

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
Buyer's Improvement:
Oh! That's higher than I expected. I saw a similar balloon at another store for $14. Can you match that price?

B1. The "flinch" technique

Buyer Critic:
Use the power of silence: The buyer can employ the power of silence in the negotiation process by pausing longer before responding to the seller's offer.
Buyer's Improvement:
pause … Alright, I'll take the balloon for $13.

B2. The power of silence

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:
I understand, how about we split the difference and make it $16.75 to accommodate your budget?

B3. Split-the-difference

Seller Critic:
Use anchoring technique: Begin by emphasizing the high starting price and then offer a slightly lower price
Seller's Improvement:
This high-quality, long-lasting balloon is really worth $25, but I'm offering it for $20.

B4. The anchoring technique

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 Evalaution Metrics
  - ❑ Datasets and Benchmarks
- ❑ Ethics of Agent’s Goal Awareness
  - ❑ Factuality
  - ❑ Safety
  - ❑ Privacy
- ❑ Improving the Proactivity of LLM-based Conversational AI
  - ❑ Promp Designs
  - ❑ Learning from Human/AI Feedbacks