

SUBJECTIVE DEBATE AS CONVERSATIONAL SEARCH



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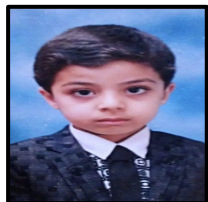


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WHO AM I?



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Human-centered Grounding of Conversational Agents



1. Incorporate human opinions and preferences in conversational agents in CSS.

2. Enhance conversational agent's ability to communicate and reason through storytelling and narratives in CIS.

3. Develop human-like evaluation approaches for conversational AI systems.



OpinionConv: Conversational Product Search with Grounded Opinions

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AI Debate over Product Reviews: Revealing User Preferences through Adversarial Sales Dialogue

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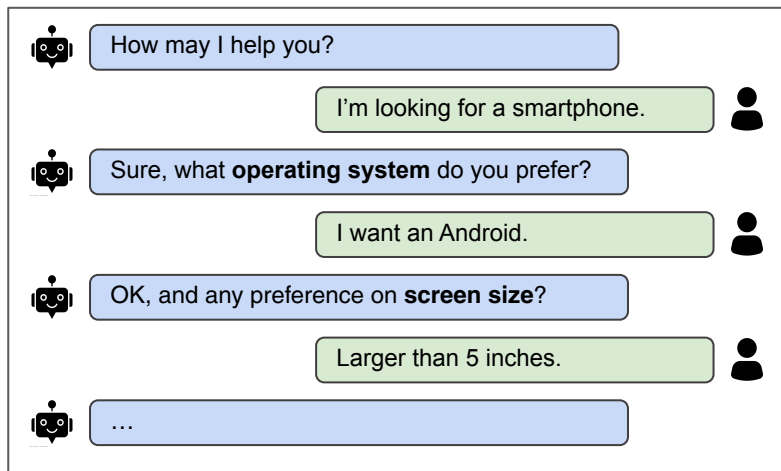
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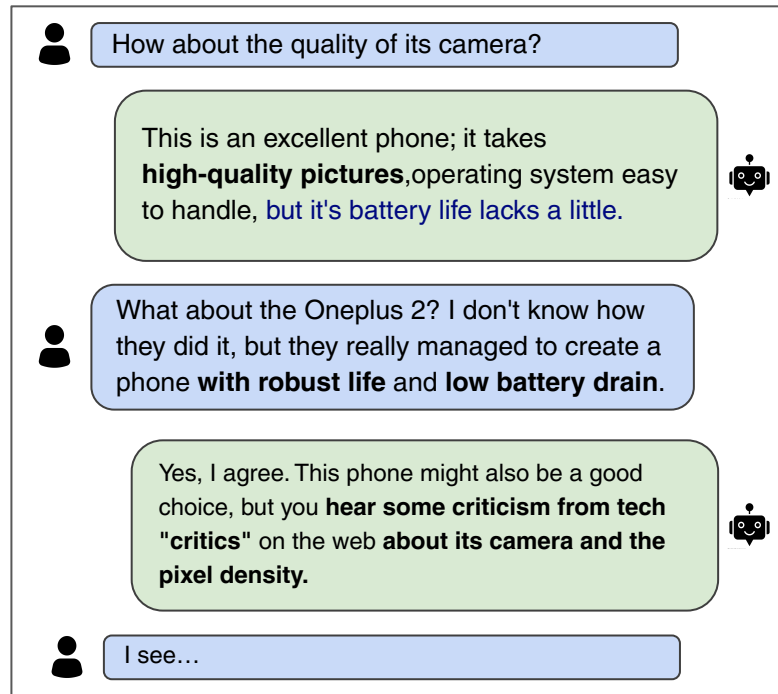
When searching for products:



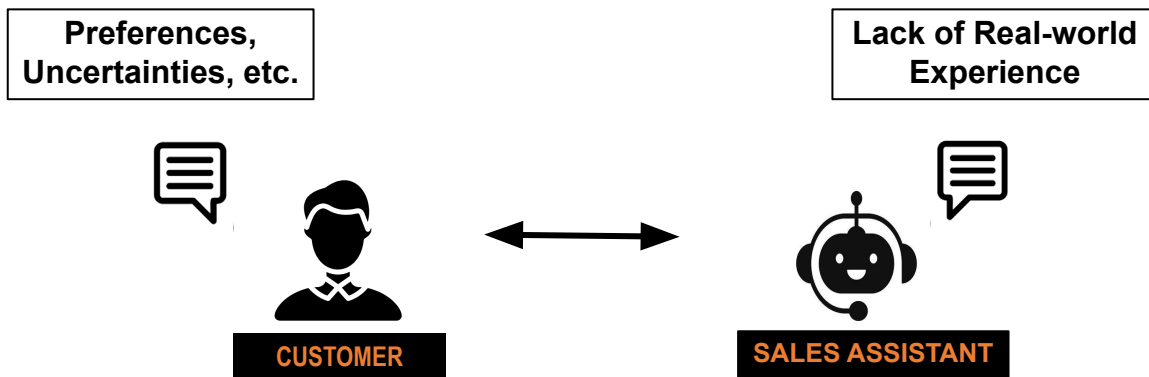
- Sequence of Q & A between the sales assistant (agent) and the customer (user) about **product features**. [1]

[1] Yongfeng Zhang et al., 2018. Towards conversational search and recommendation: System ask, user respond.

When searching for products:



- When searching for products, subjective experiences of others play a crucial role in making informed decisions.

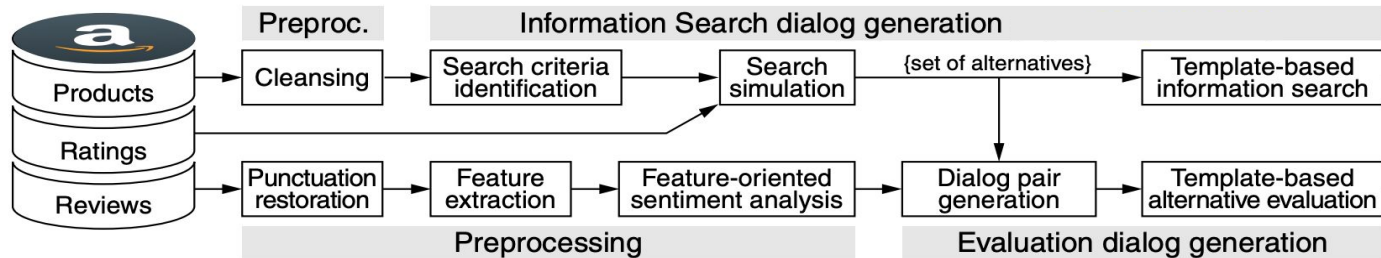


- We used a five-stage process that summarizes **customer decision making process**: [\[2\]](#)

- (1) Recognize a need
- (2) **Search for information about potential products**
- (3) **Evaluate and compares these alternatives**
- (4) Proceed to make a purchase decision
- (5) Exhibit post-decision behaviors.

OpinionConv - PIPELINE

- Product category: **Cell Phones and Accessories**



- Design **7 Question–Answer and Opinion–Opinion pairs** using different *Negotiation Tactics* [3]

- Devise **14 Conversation Templates** using conversational negotiation strategies

- Simulate:

- > Sales assistant
- > Customer



Deny - Switch Product

OpinionConv - GENERATION



Review 1

[...] Internet connections are much faster than on my BlackBerry, which my work has supplied me. **The battery is another item that people tend to give bad reviews on.** That may be why Verizon is currently offering a 60 dollar battery for 19 dollars. [...]

Partial dialog

C: I heard that **the battery is another item that people tend to give bad reviews on.**

Customer **C** voices negative opinion on a product feature, sales assistant **S** counters with a positive one.

Review 2

[...] He constantly has Rhapsody or Pandora running on T-Mobile 4G with no lag at all. It does great on wi-fi at home as well. **The battery life is impressive as well, you can charge it when you go to bed, but I'm sure you never see it die throughout the day even with heavy use.** All in all a great phone!

S: Well, I can tell that **the battery life is impressive as well, you can charge it when you go to bed, but I'm sure you never see it die throughout the day even with heavy use.**

An example of an opinionated dialog pair generation step
Deny - Disagreements

Pair	Principle	Action	Example
Deny-Switch Product	Insist on position	Express negative sentiment	B: What I know about its battery is that the battery keeps draining because the phone is constantly looking for network signal.
	Invent options for mutual gain	Recommend a new product	S: If the battery is important for you, we can offer this product: Axon 7 is the same price as OnePlus 3, but it has slightly bigger battery.
Request-Inform	Focus on interests	Look for more information	B: What do you think about its speakers?
	Build trust	Express positive sentiment	S: It has dual front-facing speakers with good quality.
Search-Agreement	Focus on interests	Search for alternatives	B: I heard about this phone: Galaxy S4 that has a super-fast processor and a good battery life.
	Build trust	Confirm consumer's preference	S: Yes, that's true. This phone is also a good choice with the one premium hardware, great software and a reasonable price.

An example of the combination of dialog pairs in a conversation template

- Total number of conversations generated by OpinionConv:
195,614

OpinionConv

Customer decision process (Kotler and Keller, 2015)

Problem/need recognition

Information search

Example reproduced from
Zhang et al., 2018, Figure 1.

Evaluation of alternatives

Focus of this paper

Purchase decision

Post purchase behavior

Generated opinionated conversation for product search

(S = sales assistant, C = customer)

(not relevant for conversation generation)

S: How may I help you? C: Can you find me a mobile phone?
S: Sure, what **operating system** do you prefer? C: I want an Android.
S: OK, and any preference on **screen size**? C: Larger than 5 inches.
S: Do you have requirements on **storage capacity**? C: I want at least 64 GB.
S: And any preference on **phone color**? C: Not particularly.

S: What about the Samsung Galaxy S6? It's available for \$228.89.
C: I like it's design, but it costs too much. Do you have any cheaper ones?
S: Yes! I have this one for you. The Sony Xperia X.
It's cheaper; \$117.13.

C: Sounds good!
C: How does its **operating system** handle?

S: The Sony Xperia X is an excellent phone, good **connectivity**,
operating system easy to handle, it takes high-quality **pictures**, but
it's **battery life** lacks a little.

C: What about the Oneplus 2? I don't know how they did it, but they
managed to create a phone with robust **life** and low **battery drain**.

S: Yes, I agree. This phone might also be a good choice, but you hear
some criticism from tech "critics" on the web about its **camera** and the
pixel density, etc.

C: I see. The **camera** quality is important to me.

C: Given the **price** of the Sony Xperia X, I would have expected
capacitive buttons.

S: For a sim-free **price** under \$200 it's one of the most affordable options
out there and a good smartphone.

C: Alright, I'll buy the Sony Xperia X.

(not relevant for conversation generation)

Negotiation strategy

(Conversation template ID: 4)

Initiative

Search dialog

Sequence of questions and
answers between the sales
assistant S and the customer C
about **product features**, until
a small set of alternatives
remains.

Prompt S makes an offer.

Price negotiation

C asks for cheaper options,
S makes a cheaper offer.

Request-Inform

C asks about a **product feature**.
S responds with a positive
opinion about it.

Search-Warning

C asks about an alternative
due to a positive opinion on
one of its features.
S responds with a negative
opinion on a different feature.

Reaction C agrees.

Deny-Disagreement

C voices a negative opinion
about a product feature (price).
S disagrees.

Decision C decides.

Sales assistant

Customer

Study 1: Importance of Opinions in Product Search

- We showed participants two variants of generated sales conversation:
 - Variant 1 is focused on the customer's preferences and requirements.
 - Variant 2 starts similarly, but then continues with an opinionated discussion.

Q: Which of the two variants would you as a customer hold with the sales assistant while searching for a smartphone?"

- **83%** of the participants of study 1 preferred variant 2 over the variant 1.



Measure	Characteristics	Study 1 (N=100)	Study 2 (N=420)
Gender	Males	41.0%	31.0%
	Females	58.0%	69.0%
	Non-binary	1.0%	0.0%
Age	25 to 34 years	35.0%	38.0%
	35 to 44 years	28.0%	30.1%
	18 to 24 years	21.0%	15.7%
	55 to 64 years	6.0%	13.3%
	45 to 54 years	5.0%	1.8%
	65 years or older	5.0%	1.2%

Demographics of study participants

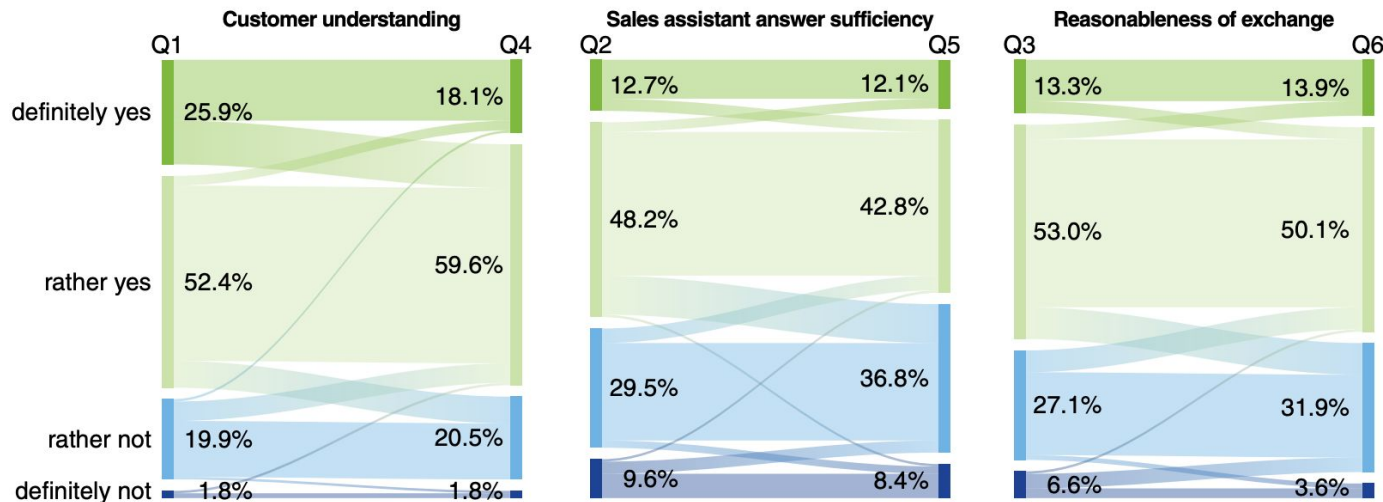
OpinionConv - Evaluation

Study 2: Perceptions of Dialog Realism

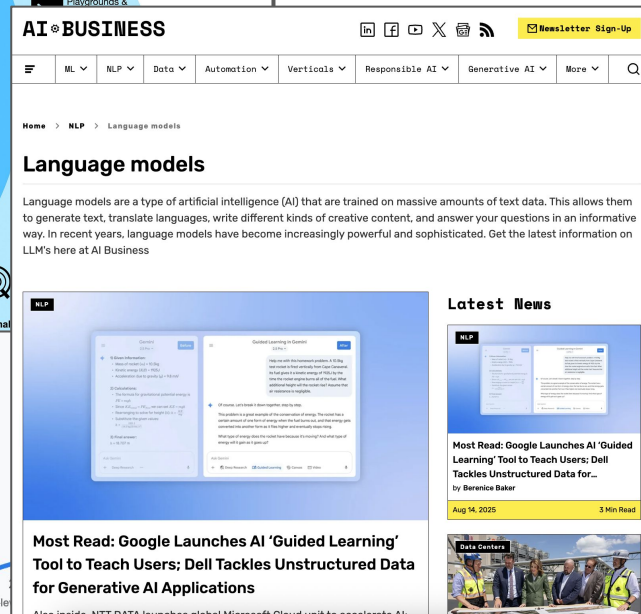
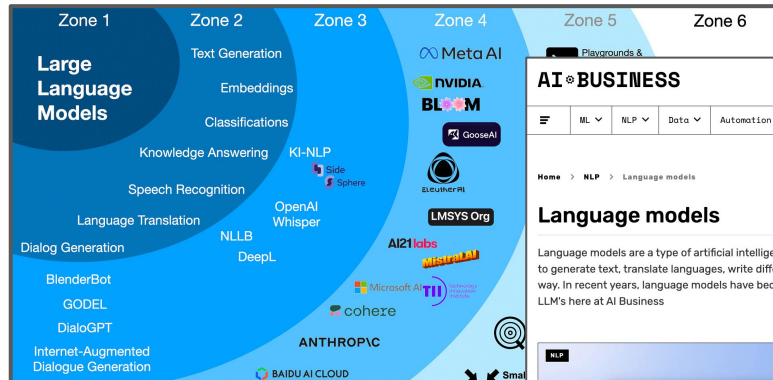
- For each of **14** conversation templates: **10** examples
- For each example **3** participants were asked
- First, we inform participants, they are reading a transcript of a real conversation.
- Then, we reveal the truth and declare that the conversation they just read, was not a real but an automatically generated one.

Q1, Q2, Q3

Q4, Q5, Q6



- We introduced **OpinionConv**, a new conversation generation pipeline that generates opinionated multi-turn conversations for product search.
- **OpinionConv** was mainly designed to **incorporate** subjective narratives into conversational product search and to **control** both the dialog coherence and the information to be mentioned in the utterances.
- We also observed three key concerns raised in the human evaluation:
 - (1) **Some features are of no interest to be discussed:**
e.g., "Why would the person ask the sales assistant about colours? That seems out of the ordinary."
 - (2) **Some participants judge the conversations based on their personal experience with real sales assistants:**
e.g., "As always in marketing strategies, he [the sales assistant] was just trying to sell a phone not what he [the customer] wanted."
 - (3) **A stronger argumentation is expected by some participants**
e.g., "stating that it's 'bright and good quality' would not be convincing enough for me to buy the product."



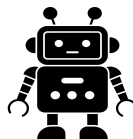
Interaction



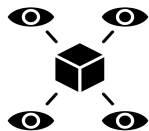
Feedback



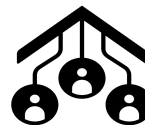
Agents



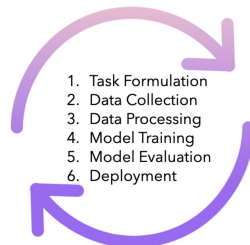
Perspective



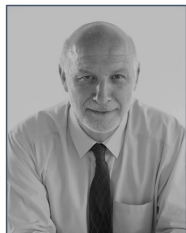
Alignment



- Human-centered LLMs should be in every stage:



How Human Subjectivity Forms?



About

Peter Fonagy, CBE, FBA, FAcSS, FMedSci is a Hungarian-born British psychoanalyst and clinical psychologist. He studied clinical psychology at University College London.
[Wikipedia](#)

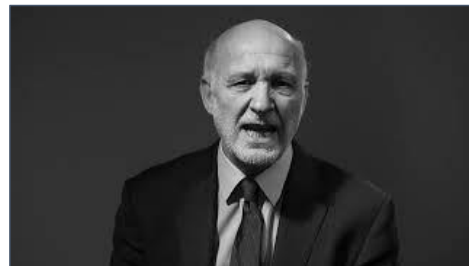
Place of birth: Budapest, Hungary

Education: University College London (1971–1974)

h-index: 181

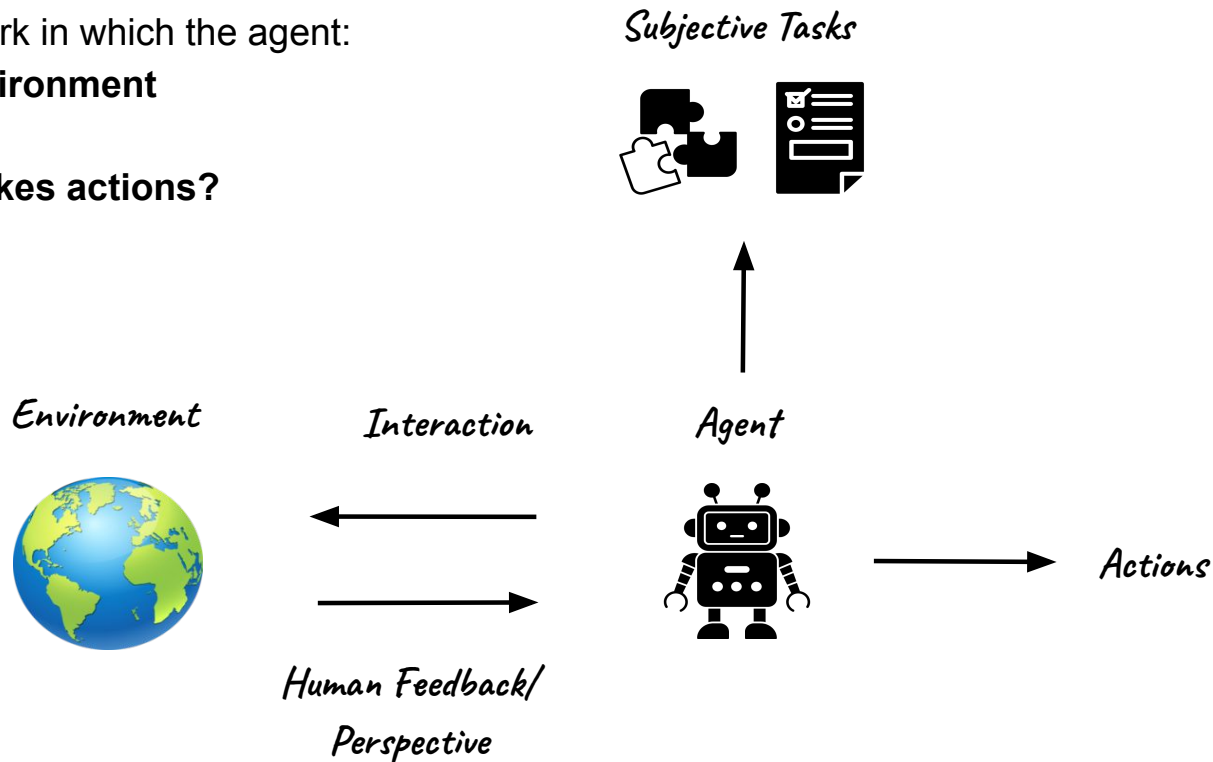
Affiliation: University College London

Research Interests: Borderline personality disorder, Psychotherapy Outcomes, Attachment Theory, Psychoanalysis



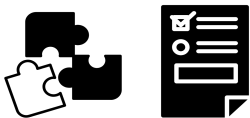
*“It’s an intensely social thing (**Interaction**). We find ourselves in the eyes and face of another person ... in somebody else’s mind (**Feedback**). We find our thoughts and our feelings represented and we internalize that representation (**Alignment**) and combine it with our experience (**memory**) to create a **HUMAN SUBJECTIVITY** that we take for granted... This becomes the building block of our subjectivity that is us (**Human**) ... That is something that all of us need just to **walk through a human world** to be able to collaborate with people (**Interaction**).”*

- What if we design a framework in which the agent:
 - **Interacts with the environment**
 - **Get feedback**
- **To learn when and how takes actions?**



PROPOSED FRAMEWORK

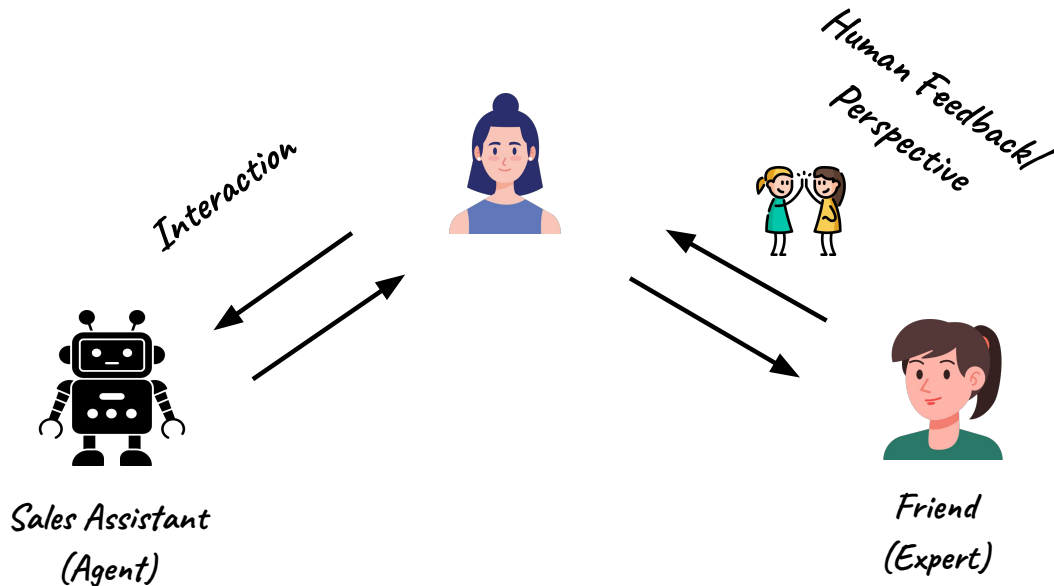
Subjective Tasks



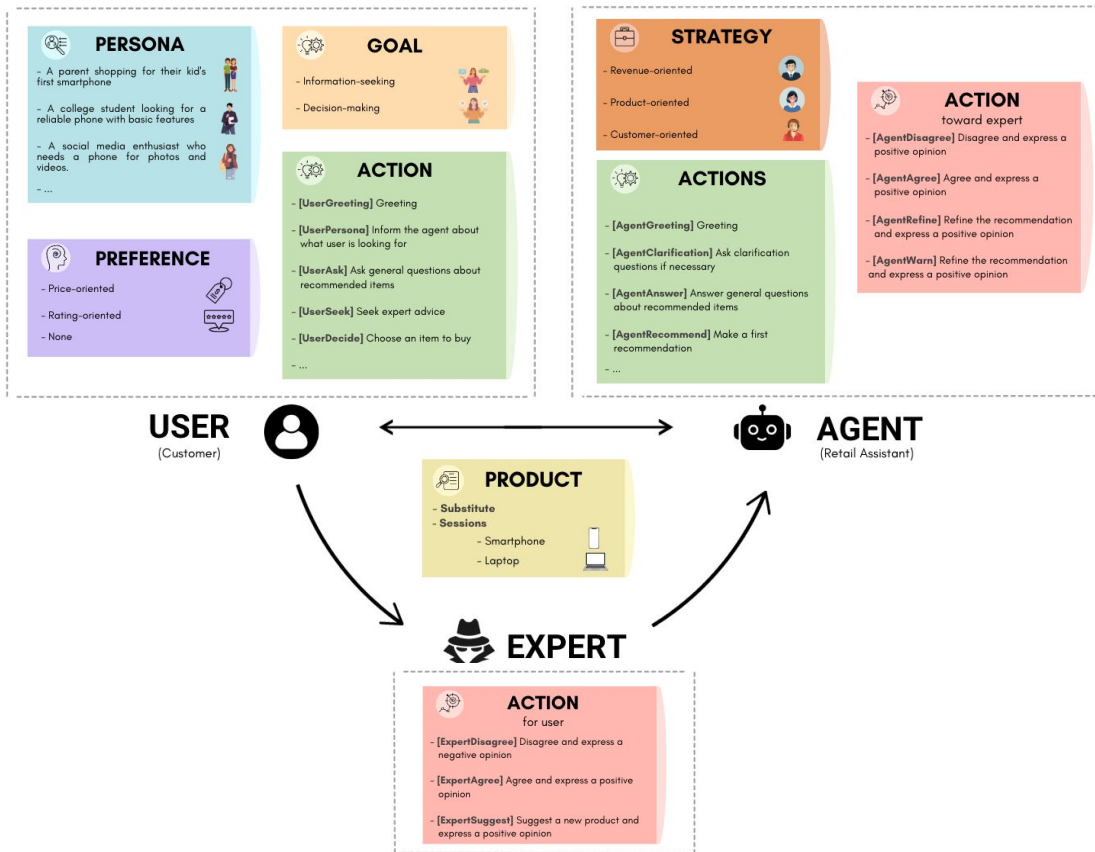
Buying a Smartphone



Environment

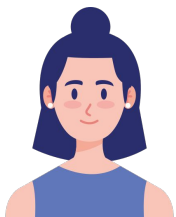


SIMULATION FRAMEWORK



IDEAL CASE!

USER INFORMATION



PRODUCT INFORMATION



+

PRODUCT REVIEWS

USER DECISION



DATASET - SESSIONS

Amazon Clicks



USER A



Amazon KDD Cup '23

Shopping Session Dataset

Build Multilingual Recommendation Systems

🏆 **\$21,000 Cash** + **\$10,500 AWS**
Prize Pool Credit Pool

📄 ACM SIGKDD
2023 Workshop

Amazon Reviews



USER B



**How to make user A (in clicks)
more similar to user B (in reviews)?**

PERSONA GENERATION



The phone was ok. About a month in it started having **Bluetooth connection issues**. Android auto couldn't connect. Smart watch would also lose connection. I also had issues **with screen recording**. If you screen record certain things, the recorder would automatically get stuck and not finish the recording. I would definitely not recommend this phone at all. Do not buy.



A tech-savvy individual who relies heavily on **functionality for both work and personal use**, using multiple devices and relying on features like screen recording.

DATASET - ACTIONS

USER
(Customer)



AGENT
(Sales Assistant)



EXPERT



ACTION

- **[UserGreeting]** Greeting
- **[UserPersona]** Inform the agent about what user is looking for
- **[UserAsk]** Ask general questions about recommended items
- **[UserSeek]** Seek expert advice
- **[UserDecide]** Choose an item to buy
- ...



ACTIONS

- **[AgentGreeting]** Greeting
- **[AgentClarification]** Ask clarification questions if necessary
- **[AgentAnswer]** Answer general questions about recommended items
- **[AgentRecommend]** Make a first recommendation
- ...



ACTION

toward expert

- **[AgentDisagree]** Disagree and express a positive opinion
- **[AgentAgree]** Agree and express a positive opinion
- **[AgentRefine]** Refine the recommendation and express a positive opinion
- **[AgentWarn]** Refine the recommendation and express a negative opinion



ACTION

for user

- **[ExpertDisagree]** Disagree and express a negative opinion
- **[ExpertAgree]** Agree and express a positive opinion
- **[ExpertSuggest]** Suggest a new product and express a positive opinion

“Mhm...” – Conversational Strategies For Product Search Assistants

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MG-ShopDial: A Multi-Goal Conversational Dataset for e-Commerce

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(c) Dialogue Act	Explanation
Interaction Structuring	Utterances to structure the conversation
Opening	Utterances that indicate the beginning or end of the conversation
Question	Utterances that aim to acquire information from the conversation partner
Inform	Utterances that serve to inform, explain, answer, justify, elaborate or make statements
Agreement	Utterances that agree and disagree with a previously made statement or plan
Confirmation	Utterances that explicitly answer a closed question
Suggest	Signifying that one wants the other to consider a proposition that concerns both conversation partners
Offer	Signifying that one wants the other to consider an offer that most of the times concerns only the speaker
Request	Signifying that one uses to ask the other to do something
Auto	The speaker believes to have (in)correctly understood what has been said before, including literal repetition
Allo	The speaker (dis)confirms that the other one has correctly understood what has been said before
Think-aloud ³	Utterances about actions related to the task (category added by the authors, not present in the original scheme of [7])

Table 1: Coding schemata used in the user study to analyze the content in the recipe (a) and laptop (b) domain and the conversational structure (c) in both domains.

Table 4: Schemata for intent (top) and goal annotation (bottom).

Intent	Description
Greetings	Indicates the beginning or end of the conversation
Interaction structuring	Utterances that make the conversation structured and natural (e.g., thanking, stalling)
Disclose	The client discloses information about what they are looking for
Clarification question	The agent asks a question to make sure it understands correctly a previous statement
Other question	Asks a question that is not a clarification question (e.g., factoid, follow-up questions)
Elicit preferences	The agent asks a question to find the client's preferences (e.g., the color of an item, the budget)
Recommend	The agent recommends one or several items to the client
Answer	A participant gives an answer to the other participant's information request
Explain	Provides an explanation to a previous statement (e.g., justifies suggestion or rejection of an item)
Positive feedback	Expresses positive feedback (e.g., confirmation, accept a recommendation)
Negative feedback	Expresses negative feedback (e.g., disagreement, rejection of a recommendation)
Other	Does not fit other labels
Conversational goal	Description
Search	The client wants to find more information on a product or specific topic. The agent answers the client's request for information. This can take form of casual (why/how), unanswerable, or complex questions that require multiple interactions (e.g., follow-up, sub-questions) and their answers.
Recommendation	The agent elicits the client's preferences. The agent makes a recommendation based on the client's need and preferences. The client discloses what they are looking for or their preferences intentionally or as answer to the agent's questions.
Question answering (QA)	A participant asks a factoid (what/when/who/where), confirmation (yes/no), or listing question about a product or specific topic. The other participant replies with a fact-based and short answer.
Meta-communication	Makes the conversation fluid and natural but is not necessary to complete the goal of the conversation (i.e., chit-chat).

DATASET - ACTIONS

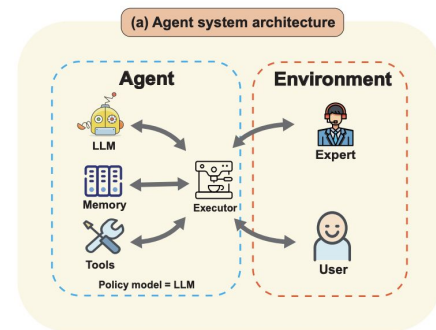
Table 1: Negotiation tactics used in dialog pair templates (P=product, F=feature).

Dialog pair template	Description of negotiation tactic
Request–Inform Question: P-1, F-A, neutral Answer: P-1, F-A, positive	Customer asks about the sales assistant's view on a feature of a product. Sales assistant expresses positive view on it.
Deny–Disagreement Opinion: P-1, F-A, negative Opinion: P-1, F-A, positive	Customer expresses negative opinion on a feature of a product. Sales assistant disagrees and expresses positive opinion on it.
Deny–Switch Product Opinion: P-1, F-A, negative Opinion: P-2, F-A, positive	Customer expresses negative opinion on a feature of a product. Sales assistant switches the product and expresses positive opinion on the same feature wrt. new product.
Deny–Switch Feature Opinion: P-1, F-A, negative Opinion: P-1, F-B, positive	Customer expresses negative opinion on a feature of a product. Sales assistant disagrees and expresses positive opinion on a different feature of the same product.
Search–Agreement Opinion: P-1, F-A, positive Opinion: P-1, F-A, positive	Customer expresses positive opinion on a feature of a product. Sales assistant agrees and expresses another positive opinion it.
Search–Switch Feature Opinion: P-1, F-A, positive Opinion: P-1, F-B, positive	Customer expresses positive opinion on a feature of a product. Sales assistant agrees and expresses positive opinion on different features of the same product.
Search–Warning Opinion: P-1, F-A, positive Opinion: P-1, F-B, negative	Customer expresses positive opinion on a feature of a product. Sales assistant warns the user and expresses negative opinion on different features of the same product.

<DEMO: EXAMPLE OF CONVERSATION>

NEXT STEPS

- Extending Dataset, e.g., Laptop
- Designing an Adversarial Sales Dialogue, e.g., two Sales Assistants Agents with two different strategies
- Defining cost for actions, e.g., SEEK ADVICE Action
- Finally, a Reinforcement Learning Framework of LLM Agents for Subjective Reasoning



- [1] Yongfeng Zhang, Xu Chen, Qingyao Ai, Liu Yang, and W Bruce Croft. 2018. Towards conversational search and recommendation: System ask, user respond.
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- [3] He He, Derek Chen, Anusha Balakrishnan, and Percy Liang. 2018. Decoupling strategy and generation in negotiation dialogues.
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- [5] Akbar Karimi, Leonardo Rossi, and Andrea Prati. 2021. Improving BERT performance for aspect-based sentiment analysis.
- [6] Biqing Zeng, Heng Yang, Ruyang Xu, Wu Zhou, and Xuli Han. 2019. LCF: A local context focus mechanism for aspect-based sentiment classification.
- [7] Nolwenn Bernard and Krisztian Balog. 2023. MG-ShopDial: A Multi-Goal Conversational Dataset for e-Commerce.
- [8] Andrea Papenmeier, Alexander Frummet, and Dagmar Kern “Mhm...” – Conversational Strategies For Product Search Assistants. 2022.

THANK YOU!

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