

# Interrupt me Politely: Recommending Products and Services by Joining Human Conversation

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## Abstract

We propose a novel way of conversational recommendation, where instead of asking questions to the user to acquire their preferences; the recommender tracks their conversation with other people, including customer support agents (CSA), and joins the conversation only when it is time to introduce a recommendation. Building a recommender that joins a human conversation (RJC), we propose information extraction, discourse and argumentation analyses, as well as dialogue management techniques to compute a recommendation for a product and service that is needed by the customer, as inferred from the conversation. A special case of such conversations is considered where the customer raises his problem with CSA in an attempt to resolve it, along with receiving a recommendation for a product with features addressing this problem. We evaluate performance of RJC in a number of human-human and human-chat bot dialogues, and demonstrate that RJC is an efficient and less intrusive way to provide high relevance and persuasive recommendations.

## 1 Introduction

Due to the popularity of texting and messaging, in combination with a recent advancement of deep learning technologies, a conversation-based recommendation has become an emerging platform for advertising. While modern conversation platforms offer basic conversation capabilities such as natural language understanding, entity extraction and simple dialogue management, there are still challenges in developing practical applications to support complex use cases such as recommendation, relying on dialogue systems (Thompson et al 2004; Christakopoulou et al., 2016; Sun and Zhang, 2018).

Over the last 2 or 3 years, much more precise and powerful recommendation algorithms have been created which are better more effectively assessing users' tastes, and predicting any relevant information that would be of interest to them. Most of these approaches rely on machine learning-based collaborative techniques, and do not take into account the huge amount of knowledge, both structured and non-structured, such as prior user utterances in a dialogue, which describe the domain of interest for the recommendation engine (Anelli et al., 2018).

A conversational advertising agent could have much more commercial potential in comparison with a conventional advertising such as random insertion in a sequence of conversation, as provided by a social advertising network like Facebook. But research on this topic is very limited and existing solutions are either based on single round conventional search or a traditional multi round dialog system. Web portals such as Amazon, eBay, JD, Alibaba and others usually only utilize user inputs in the current session, ignoring users' long term preferences, or just perform slot-filling, obtaining the parameters of interest from the user explicitly (Sun and Zhang, 2018). Moreover, most of such systems behave very differently from a human when they asked for a recommendation (Galitsky, 2019; Christakopoulou et al., 2016). Humans can quickly establish preferences when asked to make a recommendation for someone they do not know.

Although RJC is an effective and efficient means of advertising and marketing, nowadays even a conventional advertisement can be significantly improved by simple filters, like preventing ads for poorly-rated products.

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In this paper, we formulate a broader advertising and recommendation problem learning user preferences implicitly from the previous utterances in an arbitrary problem-solving conversation, not just by asking explicitly about user preferences. We introduce a recommendation by joining a conversation (RJC), a special case of conversational advertisement with a focus on assisting with solving a current customer problem or need being communicated. In RJC scenarios, customers are expected to be fully aware of how and why a product or service being recommended would solve their issues.

We consider two types of RJC scenarios:

- User - Human CSA dialogue, where an automated advertisement agent tracks it and inserts its utterances with recommendation
- User – Chat bot CS, where an automated advertisement agents and a chat bot is the same entity resolving a customer problem and providing product/service recommendation at the same time.

## 2 Sample Dialogues with Recommendations

One of the main requirement for the advertising in the course of CS dialogue is that the relation to the product the user experiences problem with must be obvious, as well as the benefits to the user of relying on this new recommended product to overcome this problem.

We start with an example of casual conversation and demonstrate how an advertising utterance can naturally appear. *Example 1:*

**Mike:** Hey, what's up, dude?

**Peter:** Not much. I am looking for a DVD to rent but I am fed up with all these. Have seen most of them already

**Mike:** Anything worth seeing at the movie theater?

**Peter:** Nah. Just kids movies, sci-fi and cheesy romantic comedies.

**RJC-agent:** If you are looking for something new you should come to a meeting of the New Age Alternative Films Club

**Peter:** What is that?

**RJC-agent:** the New Age Alternative Films Club gets together every other week and screens the type of films you cannot go at a regular movie theater

An utterance of RJC agent can be followed by additional factual questions RJC should be able to answer. *Example 2:*

**Agent:** It's a good day today at Bank of Wealth, my name is Heather. How can I help you?

**Customer:** I would like to know my remaining money in my account.

**Agent:** I'll be glad to help you. May I please get your Bank Account number and the Name on the Account?

**Customer:** Sure, it's Tracy Q. Randall, account number is \*\*\*\*.

**Agent:** Thank you, let me just check on it. Ok, can you, please, verify the last four numbers of your social security ID.

**Customer:** It is \*\*\*\*.

**Agent:** You still have 84 thousand and 65 cents. Is there anything else that I could assist you with?

**Customer:** Yes, if I transfer it to my bank account in Lloyds of London, how long will it take?

**Agent:** If we do the transaction over the phone or online, our team will still contact you for verification prior sending your money to a different bank.

**RJC-agent:** **Open Account in Morgan Chase and use Zelle QuickPay to quickly transfer money to your friends and partners abroad**

An applicability of the proposed recommendation setting can go beyond CS scenarios. Daily conversations are rich in emotion. By expressing emotions, people show their mutual respect, empathy and understanding to each other, and thus improve the relationships (Li et al., 2017). **Example 3:**

**Riley:** Are you still auditioning for that skin cream commercial?

**Katie:** That just so happens to be the 'in thing'. Does not every aspiring actress start off in a commercial?

**Riley:** I take it you did not get the part of that 'Life and Death' sitcom?

**Katie:** They did not even let me audition

**RJC-agent:** Have you thought about taking acting lessons? Have you heard about Beverly Hills Playhouse - Acting Classes Los Angeles?

### 3 Computing Recommendation for a Dialogue

In a regular recommendation / advertisement scenario, any popular product or the one meeting the user preferences is considered to be appropriate. Conversely, in the RJC scenario a recommended product or service must be related to the product which is the main entity of the problem being resolved. We show the cases of typical customer problems in various domains:

- 1) A customer does not maintain a positive balance carefully and now wants to avoid NSF in the future.
- 2) A traveler with a pet finds himself in a hotel that does not allow dogs.
- 3) A traveler got a non-changeable air ticket and now wants to change the flight.

In most of these cases (Table 1) the features of products and services were disclosed to customers but they did not pay enough attention. These customers contact CS and complain. This is a good time to recommend an alternative product or an addition to a service.

Subject of the problem	Focus of a conversation	Product to recommend	Recommended feature	Search query
Checking account	No overdraft protection	Saving account	Linked with checking for overdraft protection	X for checking account with overdraft protection
Hotel @ <location>	No dogs allowed	Apartment	Dog friendly	Dog friendly apartment X @ <location>
Flight to <destination>	Ticket is not changeable	Flight insured for change of plans	Coverage for change of plans / air ticket change	Travel insurance for flight by X to <destination>
Camping tent of <brand>	Hard to pitch	Self-pitching tent	Tube frames allowing for self-pitching	Camping tent of <brand> X with self-pitching
Auto insurance from X	Does not cover roadside assistance	Additional coverage	Covering roadside assistance	Additional coverage X with roadside assistance

**Table 1. Examples of seed and recommended products**

The queries have a placeholder *X* for product/service name such as account type, accommodation name, air travel company, etc. The role of this placeholder in a query is to assure the respective entity type does occur in an acceptable search result.

Processing steps in the RJC component are the following:

- 1) Extract noun phrases from utterance.
- 2) Identify an entity which is a seed product or service.
- 3) Relying on the ontology, identify a product attribute. Ontology is required to identify a parameter/feature of the seed entity that is a focus of a conversation with a CS. Relations in ontology are *Part-*

of, Type-of, Same-as, Instance-of, Defines, Defined-by and others (Hoffman, 2015). A feature of a product is connected with this product by *Part-of, Type-of* or *Instance-of*.

4) Relying on ontology, form a search query against an index of products with desired attribute.

5) Accumulate for further processing the list of identified product candidates to be recommended.

#### 4 How to make Recommendation more Persuasive?

A number of studies including (Berkovsky et al., 2012) demonstrated that explanation and persuasion are two important characteristics for convincing users to follow the recommendations. **Example 4:**

**Customer:** You charged me unfair NSF but I maintained a positive balance on my account.

**Agent:** We have to charge NSF to maintain our income, so you should maintain minimum balance.

**Good RJC-Agent:** I recommend you a product such that you avoid a negative balance. You should get our product linked checking-saving account with overdraft protection, so that NSF never happens again.

**Marginally Relevant but unpersuasive-Agent:** Open new account at Base Bank. High Yield interest rates. Open within next week and get a free checking.

**Irrelevant-Agent:** Earn income working from home. No training is necessary. Start making money right now.

**Relevant but unpersuasive Agent:** Get an overdraft protection. Link a saving account with your checking one.

We use a traditional advertisement format for the irrelevant and unpersuasive examples. A good example is a free-format text that includes a recommendation as well as its argumentative back up, an explanation why this product would solve a customer problem, as described in dialogue (Ex. 4). Negative examples rely on imperative form of verbs that is heavily used in conventional advertisement.

To be a good recommendation, it needs to relate to the seed product and to its features and attributes that are the subjects of the conversation. In addition, discourse structure of the recommendation text matters (Fig. 2).

Discourse tree representation (RST, Mann and Thompson, 1988) for a recommendation allows to judge on its quality and can be constructed automatically (Joty et.al, 2015). If rhetorical relations of *Explanation, Cause, Enablement* are recognized in recommendation text (Galitsky and Ilvovsky, 2019) then there is a higher chance that this recommendation is reasonable, persuasive and well argued.

```

cause
  explanation
    TEXT: I recommend you a product,
    TEXT: to avoid a negative balance.
  enablement
    TEXT: Therefore, you should get our product "linked check-
ing-saving account with overdraft protection"
    TEXT: so that NSF never happens again.

```

**Fig. 2. Discourse Tree for a good answer (underlined in Ex. 4)**

Recommendation with a discourse tree that contains only default rhetorical relations such as *Elaboration* and *Join* would not be as good. Moreover, discourse representation of the recommendation must match in terms of argumentation that of the problem description of the product by customer. A generalized example of a proper correlation between the previous utterances about the seed product *P* and recommendation *R* is shown in **Example 5:**

**Customer:** there is a problem with feature F of product P

**Agent:** It can (or cannot be fixed) by doing (this and that) with F of P

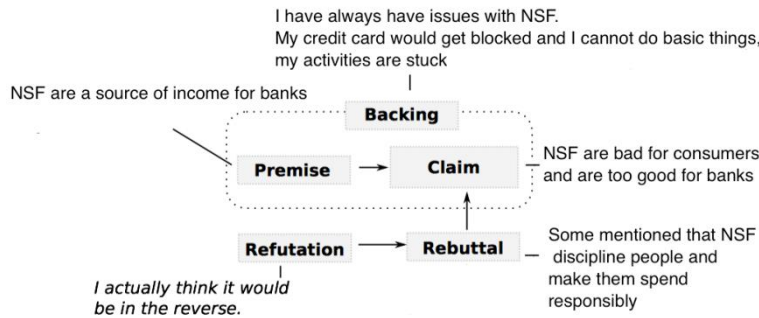
Customer: No you still cannot fix problem of P ...

**RJC-agent:Product R will fix this problem with F of P since R's feature RF covers F**

To assure a recommendation makes sense to a user, it needs to be backed up by an argument. To find a textual recommendation that will be perceived by the user, this recommendation should form a well backed up claim where the utterances in the dialogue are premises.

For argumentation support in RJC we employ a modified Toulmin's model (Toulmin, 1958) which contains five argument components, namely: *claim, premise, backing, rebuttal, and refutation*.

In this model any arbitrary token span can be labeled with an argument component; the components do not overlap. All components are optional (they do not have to be present in the argument) except the claim, which is either explicit or implicit. If a token span is not labeled by any argument component, it is not considered as a part of the argument. Relations from this model can be constructed automatically using extended discourse tree representation (Galitsky et al., 2018).



**Fig. 3. Toulmin's model and its instance in the domain of non-sufficient fund fees (NSF)**

Example of this model built for the sample dialogue on NSF is shown on Fig. 3. The arrows show relations between argument components; the relations are implicit and inherent in the model.

In case of the pair of products  $P$  and  $RP$ , a recommendation for  $RP$  must be *supported* by the customers' expression of their needs and problems in  $P$ .

## 5 Dialogue Management in RJC Agent

Once a recommendation utterance is delivered, the user may choose to continue conversation with Ad-agent. Then the following algorithm is applied (Algorithm 1).

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### Algorithm 1

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**Input:** Recommendations = top-5 recommendations, Profile = user preferences, Graph = graph representation of user preferences, items, entities, properties

**Output:** conversation

- 1: Profile  $\leftarrow$  Profile + new preferences (items, entities, properties);
- 2: Recommendations  $\leftarrow$  PageRank (Graph, Profile); Show Recommendations;
- 3: **while** User does not accept Recommendations **do**
- 4: Feedback  $\leftarrow$  User feedback;
- 5: Refine(Feedback);
- 6: Recommendations  $\leftarrow$  PageRank (Graph, Profile); Show Recommendations;
- 7: End

To build a conversational grammar for dialogue management, we introduce the notion of adjacency-pair, sequences of two utterances that are adjacent (not separated by an insertion sequence), produced by different speakers and ordered as a first ("initiative") and a second ("response") part.

Both parts should also belong to a certain type, so that a particular initiative requires a certain type or range of types of the response.

Adjacency-pairs are *question-answer*, *greeting-greeting*, or *offer-acceptance/decline*. Where there is a range of potential responses to an initiative (as with offer-acceptance/decline), a ranking operates over the options designating one response as preferred (in the sense of normal, more usual) and others

as less preferred (Bridge, 2002). Less preferred responses tend to be longer, linguistically more complex. Having produced a first part of a pair, the current speaker must stop speaking and it is expected that the next speaker will produce one of the allowable second parts of the same pair. The second part will often follow immediately. However, there frequently occur insertion sequences. These are sequences of turns that intervene between the first and second parts of a pair; the second part is in a holding pattern during the insertion sequence.

We use Prolog notations for the dialogue grammar: variables are capitalized:

1) **turn(system, [], [(Type, Topic)]) --> initiative(system, Type, Topic)**. There are no ongoing pairs. The system starts a new pair.

2) **turn(user, [(Type, Topic) | Rest], Rest) --> response(user, Type, Topic)**. There is at least one ongoing pair. The user provides a response of the same type and on the same topic, thus completing the pair.

3) **turn(system, [(Type, Topic)], [(Type<sub>1</sub>, Topic<sub>1</sub>)]) --> response(system, Type, Topic), initiative(system, Type<sub>1</sub>, Topic<sub>1</sub>)**. There is a single ongoing pair. The system provides a response of the same type and on the same topic and initiates a new pair of a possibly different type and on a possibly different topic.

4) **turn(system, [(Type, Topic), (Type<sub>1</sub>, Topic) | Rest], [(Type<sub>1</sub>, Topic) | Rest]) --> response(system, Type, Topic), initiative(system, Type<sub>1</sub>, Topic)**. There are at least two ongoing pairs on the same topic. The dialogue must have entered an insertion sequence. The system provides a response to complete the most recent pair and reminds the user of the ongoing pair. The grammar achieves this by requiring that the system initiate a new pair of the same type and topic as the ongoing one but it does not push it onto the stack of ongoing pairs, which remains unchanged.

5) **turn(user, [(Type, Topic) | \_], [(Type<sub>1</sub>, Topic<sub>1</sub>)]) --> response(user, Type, Topic), initiative(user, Type<sub>1</sub>, Topic<sub>1</sub>)**. There is at least one ongoing pair. The user provides a response to complete the pair and initiates a new pair. This aborts any other ongoing pairs so the stack contains only the new pair.

6) **turn(user, [\_ , Topic] | \_, [(Type<sub>1</sub>, Topic<sub>1</sub>)]) --> initiative(user, Type<sub>1</sub>, Topic<sub>1</sub>), {Topic \= Topic<sub>1}}</sub>**. There is at least one ongoing pair. The user aborts it and initiates something new. This is not an insertion sequence because the topic is different.

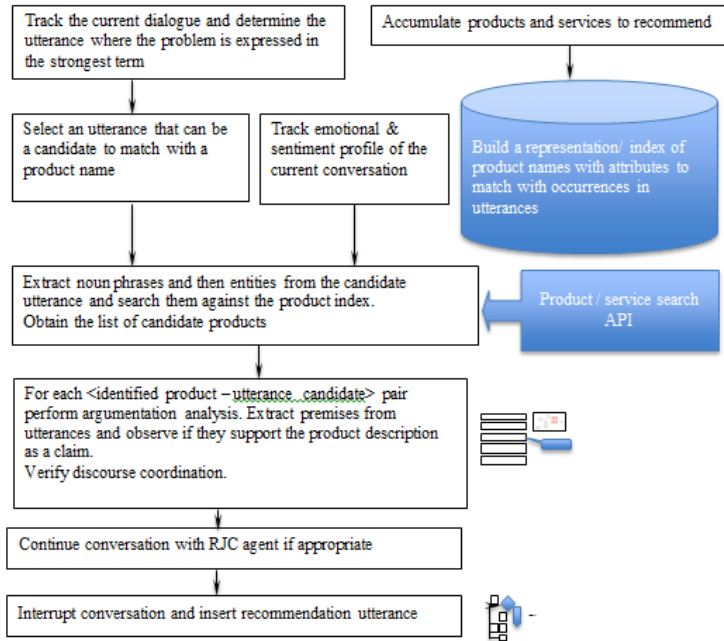
7) **turn(user, [(Type, Topic) | Rest], [(Type<sub>1</sub>, Topic), (Type, Topic) | Rest]) --> initiative(user, Type<sub>1</sub>, Topic)**. There is at least one ongoing pair. The user begins an insertion sequence by not responding to the ongoing pair but by initiating a new pair on the same topic. Both pairs are now on the stack.

The grammar restricts contributions that the system can make to the dialogue. In particular, the system cannot abort pairs: rules 5 and 6 apply only to the user. We feel that it is inappropriate for the system to ignore user initiatives.

## 6 System Architecture

High-level system architecture of RJC is shown in Fig. 3. The system tracks the dialogue and attempt to identify a moment where the customer is about to give up on the CSA problem resolution, or is still unhappy after the problem is solved. This tracking is done based on emotional profile and sentiment profile (Galitsky, 2019). Once such utterance is identified, RJC finds a noun phrase in it, and then identifies a product name together with its feature. Entity extraction is done by Stanford NLP augmented by the product-specific entity rules and product-specific lookup such as eBay product catalogue. Product-related named entities could also be verified by consulting eBay product search API.

Then a search query from the formed product name and its feature is formed, and a search is launched. The search results form a list of candidates, which are filtered based on the proper argumentation and discourse coordination requirements. This filtering is implemented via argument mining and reasoning techniques. They verify that the recommendation as a claim is logically supported by the previous customer utterance and therefore this recommendation would be convincing for the customer. Rhetorical agreement (Galitsky, 2017) is verified based on coordination between the discourse trees of previous customer utterances and the discourse tree of the candidate recommendation text.



**Fig.3. High level system architecture**

## 7 Evaluation

### 7.1 Datasets

Source type	#	Origin of the data	Recommended source
Finance	2200	my3cents.com bankrate.com	Search of Bloomberg, Fidelity, Bankrate for financial products
Auto repair	9300	2carpros.com	Web search for services
Sports shopping	2740	REI and L.L.Bean data from RichRelevance.com	Internal API for product search
Home products shopping	3100	Walmart, HD Supply, OfficeDepot data from RichRelevance.com	eBay product search API
Home-related services		Yelp reviews	Yelp API
Travel	2430	zicasso.com/travel-reviews, tripadvisor.com reviews Airline forums on TripAdvisor.com	Tripadvisor.com
Daily dialogues	2000	(Li et al., 2018)	Yelp API
Genuine human dialogues	2000	(Li et al., 2018); ENRON email thread; Reddit discourse dataset (Logacheva et al., 2018)	Yelp API, eBay product search, Tripadvisor.com, Bing Forum search, Bing Web search
Constructed from blogs, etc.	5200	2carpros.com; immihelp.com; blog.feedspot.com; librarything.com/groups	

**Table 2. Characteristics of the data sources**

We use various source of dialogues: a) Conversational data sets; b) Data scraped from online forums; c) Cached search results from specific APIs. For scraped and indexed data we use our own search for products, and for web data we either use APIs of a particular source or search this source via Bing API.

We obtain human-human dialogues from Customer Complaints and Car Repair datasets. For the first dataset, we obtain recommendations online from websites like [www.bankrate.com](http://www.bankrate.com) and [www.bloomberg.com](http://www.bloomberg.com). We obtain recommendation sources from Yelp on restaurants and services such as repair and tuition. For book recommendations we used Amazon/LibraryThing (A/LT) dataset available at [www.librarything.com/groups](http://www.librarything.com/groups). For blogs and forums which can potentially be subject to RJC we relied on [www.2carpros.com](http://www.2carpros.com), [www.immihelp.com](http://www.immihelp.com), [www.talkhealthpartnership.com](http://www.talkhealthpartnership.com) and [blog.feedspot.com](http://blog.feedspot.com).

To get closer to the CSA conversation setting, we selected Relational Strategies in Customer Service Dataset that is collection of travel-related customer service data from four sources. The conversation logs of three commercial customer service IVAs and the Airline forums on TripAdvisor.com. For a special case of conversations related to overall product opinion we employ the Customer Support on Twitter dataset. It includes over 3 million tweets and replies from the biggest brands on Twitter. The datasets to evaluate RJC are enumerated in Table 2.

The Reddit discourse dataset (Zhang et al., 2017) is manually annotated with dialog-acts via crowd sourcing. The dialogue acts comprise of answer, question, humor, agreement, disagreement, appreciation, negative reaction, elaboration, and announcement. It contains conversations from around 9000 randomly sampled Reddit threads with over 100000 comments and an average of 12 turns per thread.

## 7.2 Evaluation Results

Source type	Correct dialogue turn	Entity extraction from dialogue	Product entity is properly matched	Acceptable argumentation	Proper discourse	Overall meaningfulness
Finance	91.3	94.5	91.2	73.2	79.4	72.9
Auto repair	88.4	96.0	92.6	78.1	84.2	74.3
Sports shopping	89.6	92.9	90.4	76.0	82.3	71.4
Home products shopping	90.3	92.1	94.7	78.3	80.6	72.7
Home-related services	89.3	93.7	91.7	72.7	76.5	73.3
Travel	90.8	92.7	93.6	73.9	82.4	75.2
Daily Dialogues	88.4	89.3	92.0	71.9	80.7	72.6
Genuine human dialogues	89.3	91.6	88.3	67.3	74.2	68.2
Constructed from blogs, etc.	90.4	92.7	90.7	70.8	73.7	71.4

**Table 3. Accuracy of the RJC components**

Recommendation by joining a conversation turns out to have a high overall relevance and appropriateness to needs of customers (right column in Table 3). The accuracy range of 68-74% shows that three quarters of recommendations should not cause user irritation and instead encourage a user to buy a product, which would address a problem raised in conversation. Although we do not assess an actual conversion rate of RJC one can see that this form of recommendation and advertisement is least intrusive and has the highest instant relevance in comparison with other conversational recommendation means. Two greyed bottom rows in Table 3 show the datasets where we assess the applicability of dialogue generation in comparison with genuine dialogues.

Accuracies of each component vary from domain to domain by less than 10% due to different linguistic and logical complexity of dialogues, product searches and argumentation analysis. Bottom greyed three rows show that genuine human dialogues are a bit more complex than the artificial ones obtained from documents (although the latter has more formal, professional language).

## 8 Related Work

In the course of a customer support dialogue, recommendation and advertisement need to be very relevant to customer needs and should assist in problem resolution in the way obvious to this user. In a conventional conversational recommendation, the system first gets information from the user about his



needs and preferences and recommends a product after that. To manage such a dialogue in an arbitrary domain, nontrivial dialogue management efforts are required (Galitsky and Ilvovsky, 2017, 2019; Narducci et al., 2018, Sun and Zhang, 2018; Galitsky, 2019). Moreover, a user needs to be very patient and perform a routine activity of specifying his preferences. Neither of these is required in RJC setting.

Argument mining techniques make it possible to capture the underlying motivations consumers express in reviews. Villalba and Saint-Dizier (2012) describe how argument detection can occur on the TextCoop platform. Taking the dialogical perspective, Cabrio and Villata (2012) built upon an argumentation framework proposed by Dung (1995) which models arguments within a graph structure and provides a reasoning mechanism for resolving accepted arguments.

A number of studies investigated persuasiveness in the sense that is applied to advertising. Schlosser (2011) investigated persuasiveness of online reviews and concluded that presenting two sides is not always more helpful and can even be less persuasive than presenting one side. Miceli et al. (2006) describe a computational model that attempts to integrate emotional and non-emotional persuasion. Bernard et al. (2012) investigate children's perception of discourse connectives to link statements in arguments and found out that 4-years-old and adults are sensitive to the connectives.

Advertising in the course of dialogue is connected with dialogue marketing that is the generic term for all marketing activities in which media is used with the intention of establishing an interactive relationship with individuals. The aim is to initiate an individual, measurable response from the recipient (Jaffe, 2008). A relationship dialogue is a process of reasoning together in order for two or more parties to develop a common knowledge platform (Grönroos, 2000). Relationship marketing knowledge platform enables a supplier to create additional value for its customers on top of the value of the goods which are exchanged in the relationship. There have been many works emphasizing the importance of interactivity in recommenders so that the user has more active role over the recommendations. It includes critique-based recommendations (Chen and Pu, 2012), constraint-based (Felfernig et al., 2011), dialogue, utility-based recommenders. However, these studies employ a prior modeling of the items' features, preventing the flexibility in adaptation to different recommendation domains.

## 9 Paper Summary and Conclusion

We observe that it was necessary to track sentiments and the strength of emotion in the user-CSA conversation. When sentiment is not too negative and emotion is not too strong it might be too early to induce a recommendation since there is a chance that the conflict is resolved among the humans. If the sentiment and emotions are too negative, it is time for a recommender to intervene. This way we achieve timeliness, less intrusiveness and overall relevance of RJC recommendation. The goal of our RJC Dialogue Manager is to "interrupt politely". We believe that in general, a sponsored post does not have to be necessarily irrelevant; a broader match with a catalog of sponsor products needs to be implemented so that every user can get a recommendation according to her specific interests and desires, expressed in communication with peers. Also, the proposed algorithm would not deliver annoying repetitive recommendations as most advertisers and industrial recommender systems do.

We summarize this paper by enumerating the observed features of RJC:

- 1) Recommendation by joining a conversation turns out to have a high overall relevance and appropriateness to the needs of customers;
- 2) The accuracy range of 68-74% shows that at least 0.75 of recommendations should not cause user irritation and instead encourage a user to buy a recommended product;
- 3) In most cases the recommended products and services indeed address a customer problem raised in conversation;
- 4) Explainable AI – compliant: it is clear why this product is needed;
- 5) This form of recommendation and advertisement is least intrusive as the RJC utterance can be ignored.

One of the tasks of a future study is to evaluate an actual convergence rate of the RJC advertisement mode.

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## Reference

- Anelli VW, Pierpaolo Basile, Derek Bridge, Tommaso Di Noia, Pasquale Lops, Cataldo Musto, Fedelucio Narducci, and Zanker M (2018) Knowledge-aware and conversational recommender systems. 12th ACM Conference on Recommender Systems (RecSys '18). ACM, New York, NY, USA, 521-522
- Berkovsky S, Jill Freyne, and Harri Oinas-Kukkonen (2012) Influencing individually: fusing personalization and persuasion. *ACM Transactions on Interactive Intelligent Systems (TiiS)*, 2(2):9.
- Bernard S, Hugo Mercier, and Fabrice Clément (2012) The power of well-connected arguments: early sensitivity to the connective because. *Journal of experimental child psychology*, 111(1):128–35.
- Bridge D (2002) Towards Conversational Recommender Systems: A Dialogue Grammar Approach. Proceedings of the Workshop in Mixed-Initiative Case-Based Reasoning, Workshop Program at the Sixth European Conference in Case-Based Reasoning, 9-22.
- Cabrio E and Serena Villata (2013) A natural language bi-polar argumentation approach to support users in online debate interactions. *Argument & Computation*, 4(3):209–230.
- Chen L and P. Pu (2012) Critiquing-based recommenders: survey and emerging trends. In *User Modeling and User-Adapted Interaction*, 22(1-2):125–150.
- Christakopoulou K, Filip Radlinski, and Katja Hofmann (2016) Towards Conversational Recommender Systems. 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '16). ACM, New York, NY, USA, 815-824.
- Dung P-M (1995) On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games. *Artificial Intelligence*, 77(2):321 – 357.
- Felfernig A, G. Friedrich, D. Jannach and M. Zanker (2011) Developing Constraint-based Recommenders. In *Recommender systems handbook*, 187–212.
- Galitsky B (2017) Discovering Rhetorical Agreement between a Request and Response. *Dialogue and Discourse*.
- Galitsky B (2019) *Developing Enterprise Chatbots* Springer, Cham, Switzerland.
- Galitsky B and Ilvovsky D (2017) Chatbot with a discourse structure-driven dialogue management. *EACL System Demonstrations*.
- Galitsky B and Ilvovsky D. (2018) Detecting logical argumentation in text via communicative discourse tree. *JETAI*.
- Galitsky B, Ilvovsky D (2019) On a Chatbot Conducting a Virtual Dialogue in Financial Domain. Proceedings of the First Workshop on Financial Technology and Natural Language Processing.
- Grönroos C (2000) Creating a Relationship Dialogue: Communication, Interaction and Value. *The Marketing Review*, V1, N1, pp. 5-14(10).
- Hoffman C (2019) Financial Report Ontology. <http://www.xbrlsite.com/2015/fro/>.
- Jaffe J (2008) *Join the Conversation: How to Engage Marketing-Wary Consumers with the Power of Community, Dialogue, and Partnership* John Wiley & Sons. New Jersey US.
- Li Y, Hui Su, Xiaoyu Shen, Wenjie Li, Ziqiang Cao, and Shuzi Niu (2017) DailyDialog: A Manually Labelled Multi-turn Dialogue Dataset. *IJCNLP*.
- Lippi M and Torroni P (2016) Argument mining from speech: Detecting claims in political debates. In *AAAI*, 2979–2985.
- Logacheva V., Burtsev M., Malykh V., Polulyakh V., Se-liverstov A. (2018) ConvAI Dataset of Topic-Oriented Human-to-Chatbot Dialogues. NIPS '17 Competition: Building Intelligent Systems. The Springer Series on Challenges in Machine Learning. Springer, Cham
- Mann, William and Sandra Thompson. (1988) Rhetorical structure theory: Towards a functional theory of text organization. *Text-Interdisciplinary Journal for the Study of Discourse*, 8(3):243–281.
- Miceli M, Fiorella de Rosis, and Isabella Poggi. (2006) Emotional and non-emotional persuasion. *Applied Artificial Intelligence*, 20(10):849–879.
- Mochales R and Moens M-F (2011) Argumentation mining. *Artificial Intelligence and Law*, 19(1):1–22.

- Narducci F., de Gemmis M., Lops P., Semeraro G. (2018) Improving the User Experience with a Conversational Recommender System. In: *AI\*IA 2018 – Advances in Artificial Intelligence*. AI\*IA 2018. Lecture Notes in Computer Science, vol 11298. Springer, Cham.
- Schlosser A E. (2011) Can including pros and cons increase the helpfulness and persuasiveness of online reviews? The interactive effects of ratings and arguments. *Journal of Consumer Psychology*, 21(3):226–239.
- Shafiq Joty, Giuseppe Carenini, Raymond T. Ng. (2015) CODRA: A Novel Discriminative Framework for Rhetorical Analysis. *Computational Linguistics* 41:3, 385-435.
- Sun Y and Zhang Y (2018) Conversational Recommender System. SIGIR '18 The 41st International ACM SIGIR Conference on Research & Development in Information Retrieval, 235-244 Ann Arbor, MI, USA.
- Thompson CA, Mehmet H. Göker, and Pat Langley (2004) A personalized system for conversational recommendations. *J. Artif. Int. Res.* 21-1 , 393-428.
- Toulmin, S. *The Uses of Argument*. Cambridge At the University Press, 1958.
- Villalba MPG and Patrick Saint-Dizier P (2012) A framework to extract arguments in opinion texts. *IJCINI*, 6(3):62–87.