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Generating Expository Dialogue from Monologue: Motivation, Corpus and Preliminary Rules

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Abstract

Generating expository dialogue from monologue is a task that poses an interesting and rewarding challenge for Natural Language Processing. This short paper has three aims: firstly, to motivate the importance of this task, both in terms of the benefits of expository dialogue as a way to present information and in terms of potential applications; secondly, to introduce a parallel corpus of monologues and dialogues which enables a data-driven approach to this challenge; and, finally, to describe work-in-progress on semi-automatic construction of Monologue-to-Dialogue (M2D) generation rules.

1 Introduction

The tasks of text generation – e.g., Reiter et al. (2005) and Demir et al. (2008) – and generation in dialogue – e.g., Stent (2002) and DeVault et al. (2008) – are central topics in Natural Language Generation (NLG). What sets the two tasks apart is the interactive nature of dialogue, where participants need to adapt their contributions to each other.

This paper introduces an NLG task, the generation of expository dialogue, to the Computational Linguistics community which occupies the middle ground between these two tasks. An expository dialogue is an authored conversation between two fictive characters. It can be presented as text, audio or film. Although there is no real-time interactivity, in expository dialogue the contributions of the characters do need to mesh with each other. The main purpose of expository dialogue is to present information (a description, explanation or definition) to the

reader, hearer or viewer, in contrast with dramatic dialogue, which tells a story.

The use of expository dialogue goes back as far as Plato (c. 470-399 BC), who expressed his ideas as dialogues between Socrates and his contemporaries. Recently, a number of empirical studies show that for some purposes expository dialogue has advantages over monologue: for learners, dialogue can be more memorable, stimulate them to formulate their own questions (Craig et al., 2000), and get them to talk with each other (Lee et al., 1998). Expository dialogue has also been found to be more effective for persuasion (Suzuki and Yamada, 2004).

Additionally, dialogue lends itself very well for multimedia presentations by computer-animated agents (André et al., 2000; van Deemter et al., 2008). Potential application domains include education, (serious) games and E-Health. In education, information from textbooks could be presented in dialogue form, possibly using virtual reality platforms such as Second Life. Automatically generating dialogue from text for non-player characters could have a tremendous impact on the gaming industry; e.g., (IGDA Game Writers SIG, 2003) state that the amount of dialogue script for a character-driven computer game is usually many times that for the average film. In connection with E-health, consider patient information leaflets, which are often left unread; presenting them as movies between a virtual pharmacist and client may help address this. Thus instead of being presented with

- (1) a. You can take aspirin,
b. if you have a headache.

- c. Though aspirin does have side effects:
- d. it can harm circulation.

the patient could watch a movie on their mobile device of an exchange between a virtual client (*layman*, L) and pharmacist (*expert*, E):

- (2) L: What if I have a headache?
- E: You can take aspirin
- L: But does it have side effects?
- E: Yes, it can harm circulation.

So far, research on generating expository dialogue has been firmly rooted in classical AI approaches. Work in this area starts from knowledge representations or databases (André et al., 2000), and even research that does take text as input – e.g., Piwek et al. (2007) describe a system for generating dialogues such as Example 2 – relies on handcrafted rules. Two challenges present themselves for NLP research: 1) generation of expository dialogue from text, and 2) use of data-driven, rather than manually authored, generation rules.

Apart from the cost of manually authoring generation rules, previous research has found that human-authored rules can result in ‘too much information [being] given too quickly’ (Williams et al., 2007), which can be addressed by conversational padding. We argue that rather than trying to invent padding rules, the best strategy is to learn rules automatically from professionally authored dialogues.

2 The CODA Corpus

To make inroads into data-driven dialogue generation, we first need to have the necessary resources. We propose to view Monologue-to-Dialogue (M2D) generation as analogous to machine translation; consequently we need a parallel corpus for learning mappings from the source (monologue) to the target (dialogue) texts. In the ongoing CODA¹ project we have created such a corpus. It consists of professionally authored dialogues² that have been aligned with monologues (written by ourselves) expressing the same information. Since our ultimate aim is to generate dialogues that resemble those written by

¹COherent Dialogue Automatically generated from text

²Most dialogues are from the Gutenberg library to facilitate our planned release of the corpus to the research community.

Sp	Dialog act	Dialogue Turn	Monologue
E:	Complex Question	When you have a pain in your foot, how do you know it?	When you have a pain in your foot (i) you know it because you can feel it. (ii)
L:	Explain	I feel it.	But you do not feel it until a nerve reports the hurt to the brain. (iii)
E:	Explain-Contradict	But you do not feel it until a nerve reports the hurt to the brain.	Yet the brain is the seat of the mind. (iv)
E:	YN-Question	Yet the brain is the seat of the mind, is it not?	

Table 1: Parallel Monologue and Dialogue Example from Mark Twain’s “What is Man?”

acclaimed authors, we started with professionally authored dialogues and created the corresponding monologues. From a practical point of view, it was more feasible to use existing dialogue by acclaimed authors than to hire professional authors to write dialogue based on monologues.

We have annotated both dialogues and monologues: dialogue with dialogue acts and monologue with discourse relations.³ We achieved 91% agreement on segmentation and $\kappa=0.82$ for dialogue act annotation on 11 dialogue act tags. We developed a *D2MTranslation* tool for monologue authoring, segmentation and dialogue annotation.

In January 2010, the corpus included 500 turns from “What is man?”, a dialogue by Mark Twain, and 88 turns from “Evolving Algebras”, an academic paper in the form of dialogue by Yuri Gurevich.⁴ Both of these expository dialogues present conversation between an *expert* (Old Man in Twain and Author in Gurevich) and a *layman* (Young Man in Twain and Quisani in Gurevich). Table 1 shows an example of a dialogue fragment, aligned monologue and dialogue act annotations. The discourse structure of the monologue is depicted in Figure 1.

Table 2 shows the distribution of the dialogue acts between expert and layman. In both dialogues, the

³See (Stoyanchev and Piwek, 2010) for details.

⁴In addition to these dialogues we are working on a dialogue by Berkeley (Three Dialogues between Hylas and Philonous) and a selection of shorter fragments (for copyrights reasons) by authors such as Douglas Hofstadter and Paul Feyerabend.

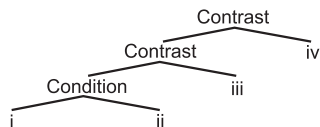


Figure 1: Discourse structure of the monologue in Table 1

most frequent dialogue act is *Explain*, where a character presents information (as a new idea or as a response to another utterance). Also, in both dialogues the *layman* asks more often for clarification than the *expert*. The distribution over information requests (yes/no, factoid, and complex questions) and responses (yes, no, factoid) differs between the two dialogues: in Twain’s dialogue, the expert mostly requests information and the layman responds to requests, whereas in Gurevich’s dialogue it is the other way around.

The differences in style suggests that the M2D mapping rules will be author or style-specific. By applying M2D rules obtained from two different authors (e.g., Twain and Gurevich) to the same text (e.g., the aspirin example) we can generate two different dialogues. This will enable us to vary the presentation style of automatically generated dialogues.

Tag	Twain		Gurevich	
	Expert	Layman	Expert	Layman
Explain	69	55	49	24
Clarify	1	15	0	6
Request	60	26	2	29
Response	14	43	9	0

Table 2: Dialogue act tag frequencies for *expert* and *layman* in a sample of 250 turns from Twain and 88 turns from Gurevich dialogues.

3 Rules

We automatically derive M2D rules from the aligned discourse relations and dialogue acts in our parallel corpus of monologues and dialogues. Table 3 shows three rules generated from the parallel dialogue–monologue fragment in Table 1. The first rule, R1, is based on the complete discourse structure of the monologue (i–iv), whereas R2 and R3 are based on only a part of it: R2 is based on i–iii, whereas R3 is based on i and ii. By generating rules from subtrees of a discourse structure, we obtain several rules from

a single dialogue fragment in the corpus.

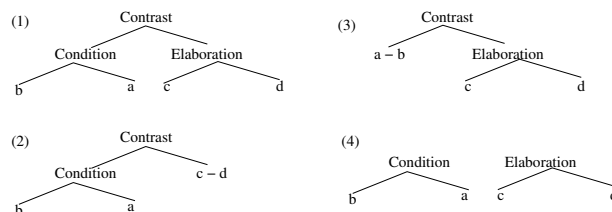


Figure 2: Discourse structures of the monologue in Example 1. a-b and c-d indicate a concatenation of two clauses.

Let us illustrate the use of such rules by applying them to Example 1 about aspirin. The relations between the clauses of the example are depicted in Figure 2 (1). To generate a dialogue, we apply a matching M2D rule. Alternatively, we can first simplify the discourse structure of the monologue by removing relation nodes as illustrated in Figure 2 (2–4).

The simplified structure in Figure 2 (2) matches rule R2 from Table 3. By applying R2 we generate the dialogue in Table 4: the expert asks a complex question composed of clauses a and b, which the layman answers with an explanation generated from the same set of clauses. Then the expert offers a contradicting explanation generated from c and d. To generate dialogue sentences for a corresponding discourse structure we are adapting the approach to paraphrasing of Barzilay and McKeown (2001).

4 Conclusion

This short paper presented three angles on the Monologue-to-Dialogue (M2D) task. First, as an opinion piece, it motivates the task of generating expository dialogue from monologue. We described empirical research that provides evidence for the effectiveness of expository dialogue and discussed applications from education, gaming and E-health. Second, we introduced the CODA corpus for addressing the task. Finally, we reported on work-in-progress on semi-automatic construction of M2D rules. Our implemented algorithm extracts several M2D rules from the corpus that are applicable even to a relatively simple input. Additionally, frequency analysis of dialogue tags suggests that there is scope for generating different dialogue styles.

The timeliness of this research is evidenced by the emergence of a Question Generation (QG) commu-

ID	Dialogue Structure	Monologue Structure
R1	E: Complex Question (i-ii) L: Explain (i-ii) E: Explain-Contradict (iii) E: YNQuestion (iv)	Contrast (Contrast (Condition(i,ii), iii, iv))
R2	E: Complex Question (i-ii) L: Explain(i-ii) E: Explain-Contradict (iii)	Contrast (Condition(i,ii), iii)
R3	E: Complex Question (i-ii) L: Explain (i-ii)	Condition (i,ii)

Table 3: Monologue-to-Dialogue rules extracted from the parallel example in Table 1

Sp	Dialogue act	Dialogue Turn
E:	Complex Question a-b	If you have a headache, what do you do?
L:	Explain a-b	Take aspirin.
E:	Explain-Contradict c-d	But aspirin does have side effects: it can harm circulation

Table 4: A dialogue generated from the monologue about aspirin by applying the rule R2 (see Table 3)

nity. QG is a subtask of M2D. The first QG workshop was held at the end of 2008, resulting in proposals for a Shared Task and Evaluation Campaign (Rus and Graesser, 2009) for 2010. The CODA corpus should prove to be a useful resource not only for M2D researchers, but also for the QG community.

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