Dealing with Trouble: A Data-Driven Model of a Repair Type for a Conversational Agent

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Abstract

Troubles in hearing, comprehension or speech production are common in human conversations, especially if participants of the conversation communicate in a foreign language that they have not yet fully mastered. Here I describe a data-driven model for simulation of dialogue sequences where the learner user does not understand the talk of a conversational agent in chat and asks for clarification.

Conversational agents for educational purposes, specifically for Second Language Acquisition (SLA) use different approaches to support language learning through conversation. CSIEC chatbot (Jia 2009) can correct spelling errors. CLIVE (Zakos and Capper 2008) understands input in the native language of the learner. The language and culture training system (Sagae, Johnson, and Valente 2011)supports learning in the form of task based dialogues with agents in a serious game environment. The systems are supposed to simulate the native speaker (NS) in conversations with the learner, non-native speaker (NNS). However, studies on NS-NNS communication found out, that there are sub-dialogues in NS-NNS conversations which are almost non-existant in first language (L1) communication (Hosoda 2006; Tudini 2012). In such sequences participants explicitly orient to their linguistic knowledge, like for example error correction and meaning checks, which are types of repair.

Example 1: Trouble-source and references to it (bold), English translation (italics) and turn types (brackets).

N zugegeben, ich war dieses Jahr auch noch in keinem See, aber so langsam könnte man das mal **ins Auge fassen** :-) [trouble-source turn]
I admit I was this year not in a lake either, but I could slowly consider it

L **ins auge fassen**? [repair initiation]
consider?

N **das** heißt _hier_ etwa soviel wie "planen" oder "bald mal machen" [repair carry-out]
it means _here_ smth like "to plan" or "to do soon"

Example 1 shows a repair sequence where the learner L does not understand a part of the native speaker's N talk and initiates a repair, N explains the meaning. To simulate such sub-dialogues a conversational agent needs to recognize that the user initiates a repair, extract the repairable (a.k.a. trouble-source or TS) and carry out the repair.

Contribution I address here the problem of computational modelling of linguistic repair in chat conversation where the user does not understand agent's talk due to difficulties in understanding the language to be learned. In contrast to the previous research on conversational agents for SLA, I propose a data-driven approach inspired by Conversation Analysis (CA) to create models of linguistic repair.

I use the data set of instant messaging dialogues in German described in (Danilava et al. 2013). The corpus consists of 72 free conversations produced by 9 learners and 4 native speakers. For the implementation, I extend a German AIML (Artificial Intelligence Markup Language) based chatbot (Droßmann 2005; Bush 2006) with a repair manager.

Repair

"Repair in the CA sense deals with any problems in speaking, hearing, or understanding, such as clarification requests, understanding checks, repetitions, restatements, offers of candidate hearings, and the like, and it includes but is not limited to corrections of linguistic errors" (Hosoda 2006). From the perspective of the speaker who produced the repairable, CA differentiates between self-initiated and other-initiated self-repair and other-repair.

Nothing in the language is a TS by itself, but everything can appear to be a TS in a conversation if it is marked as a TS by the conversation participants. However, there are structures in language that have a greater potential to become a TS because they require a higher level of language proficiency to use or to understand them correctly, for instance idioms, figurative expressions and proverbs.

Here we are in particular interested in models for situations where the system produces a repairable and the user initiates a repair sequence, thus, in other-initiated self-repair (OISR) where the system is the trouble-speaker ($OISR_S$).

The term *clarification dialogues* is mostly used to describe repair sequences in AI. Repair initiations are referred to as clarification requests. Clarification dialogues have been studied from the point of view of managing lack of information to satisfy user's need in task-based dialogue systems, question answering systems, information systems and robotics. Only the case of OISR where the sys-

tem does not (fully) understand user's input has been covered, see for instance (Kruijff, Brenner, and Hawes 2008; Quintano and Rodrigues 2008; Jian et al. 2010).

A Data Driven Model of $OISR_S$ in Chat

Repair initiations (RI) normally contain all the necessary information for human participants to recognize that there is a problem, to locate the TS, and to provide a repair.

Recognition of the Repair Initiation

The most frequently used device for referencing the TS and signalling trouble in the data is reusing the token and appending one or more question marks to it. Further referencing practices are: recycling (rewriting the TS in a different way), using demonstrative determiners and pronouns, and referencing by placing a statement of non-understanding in a turn adjacent to the TS-turn. Signalling practices include use of symbolic means (question marks, dashes, quotation marks) and lexical means (e.g. *I don't understand*, *unclear*). RI may be immediate (in the adjacent turn) or delayed (with one or more turns between the TS-turn and the RI). I found three classes of TS in the data: single word, part of a message and a whole multiword message.

Two main classes of trouble found in the data are: non-understanding of a member of one of the three TS classes, and a meaning check forming a yes/no question of the type "does X mean Y?". I generalised the former as a function $unclear(x)$ where x is the TS, and the latter as a function $equals(x, y)$, where x is the TS and y the variant of its meaning suggested by the user.

Repair Generation

Repair carry out (RCO) can occur immediately after the RI or a few turns later. It can contain an explicit reference to the TS (reuse, recycle) or reference it by occurring in the adjacent position just after the RI. The format of the RCO depends on the format of the RI and on the TS type.

For instance, abbreviations from chat jargon are typically explained by spelling out the intended reading of the abbreviation. For all other abbreviations a full version of the word(s) is presented and combined with examples, synonyms and comments. Practices used to explain whole messages consisting of two or more words include paraphrasing and splitting the message into single words and explanation of a couple words of the message (only potentially problematic words of the message need to be explained). The quality of the response is highly dependent on the linguistic resources available for the chatbot.

Repair Manager: Implementation

The baseline AIML interpreter for German was extended by a repair manager. The bot checks every user's input if it contains a repair initiation by the analysis of the lexical and symbolic means used for turn construction. If so, the trouble source is identified and a response is generated according to a repair template from a linguistic knowledge database obtained from German Wiktionary (http://wiktionary.de).

I created AIML categories for the two classes of trouble:

$unclear(x)$: Every user's input that requires an explanation of a single entity (word, idiom) is redirected to the category that implements this function. A new AIML tag <explain> has been introduced for the purpose of this work. Repair response is generated using meaning explanations, synonyms, examples and usage notes.

$equals(x, y)$: Every user's input that corresponds to an inquiry "does x mean y?" is redirected to the AIML category implementing meaning checks. An additional AIML tag <meaningcheck>. Synonyms and examples from the linguistic database are used for repair carry-out.

Discussion and Conclusions

The extension of a conversational agent by a repair manager allows to make a conversation with a language learner more natural since linguistic repair is a common device used in a learner environment to avoid misunderstandings and to learn new vocabulary and forms.

To validate the impact of the repair device on user's motivation to chat with the agent, comparative experiments with NS and NNS groups of users need to be performed. $OISR_S$ model validation can be done in experiments with users (then it is not granted that users will initiate repair) or with an additional data set (then conversations need first to be transformed into AIML categories because RI always refers to what has been said before). Further investigations on user's motivation to initiate repair are needed.

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