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 modeling approach for simulation of dialogue sequences where the learner user does not understand the talk of a conversational agent and asks for clarification.

Conversational agents for educational purposes, specifically for Second Language Acquisition (SLA) (Stewart and File 2007) 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 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 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 when the user has trouble with understanding of system's talk, to provide corrective feedback on a number of user's errors and to initiate repair when the system does not understand user's talk.

Contribution This paper addresses only the first part of the challenge: if the user does not understand systems' talk and initiates a repair, the system recognizes the repair initiation, identifies the trouble source and provides an explanation. In contrast to the previous research on conversational agents for SLA, we propose a data-driven approach inspired by Conversation Analysis to create models of repair.

Example 1: Trouble-source and a reference to it in the repair initiation (bold) and English translation (in italics).

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

L **ins auge fassen**?
consider?

N **das** heißt _hier_ etwa soviel wie "planen" oder "bald mal machen"
it means here something like "to plan" or "to do soon"

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 advanced learners and 4 native speakers. For the implementation I extend a German AIML based chatbot (Droßmann 2005; Bush 2006).

Repair

"Repair in the Conversation Analysis 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 (a.k.a. trouble-source, further TS) CA differentiates between self-initiated and other-initiated self-repair and other-repair.

Nothing in the language is a TS on 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 tho 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 system 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, to identify its type.

Recognition of the Repair Initiation

The most frequently used device for marking the TS and signaling a problem with understanding in the data is reusing the token and appending one or more question marks to it. Further practices used 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. 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 of two or more words and a whole multiword message.

Two main classes of signaling found in the data are: marking a member of one of the three TS classes as not-understood, unclear, and a meaning check forming a yes/no question of the type "does X mean Y?". I generalized 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

Similarly to RI, the repair carry out part (RCO) of a repair sequence 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. If so, the trouble source is identified and a response is generated according to a repair template from a linguistic knowledge database (Explanation DB).

I created specific AIML categories for the two main classes of signaling:

1. $unclear(x)$. 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, and an additional processor - Explanation Processor - has been implemented to generate a response.
2. $equals(x, y)$. 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> and a Meaning Check Processor have been added to carry out the repair of this type.

Conclusions

Conversation Analysis helps to understand how particular sequences of interaction are shaped, and to create computational models of interaction that are close to natural interaction. However, it is a big effort to capture all possible interactional practices that could be used for an action.

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