Helping the medicine go down: Repair and adherence in patient-clinician dialogues

Christine Howes, Matt Purver, Rose McCabe, Patrick G.T. Healey and Mary Lavelle
Queen Mary University of London
Interaction, Media and Communication Research Group
c.howes@qmul.ac.uk

Abstract

Repair is crucial in achieving and maintaining shared understanding in dialogue. Recent work on consultations between patients with schizophrenia and psychiatrists has shown that adherence to treatment correlates with patterns of repair. We show that distributions of repair in consultation dialogues are different to those in general conversation.We investigate whether particular types of repair can be detected from high-level dialogue features and/or lexical content, with encouraging results. We further explore whether we can predict adherence directly from these features. The results indicate that prediction appears to be possible from low-level lexical content.

1 Introduction

How conversational partners achieve and maintain shared understanding is crucial in the understanding of dialogue. One such mechanism, repair, is pervasive and highly systematic. In Schegloff et al. (1977), repairs are described in terms of who initiates the repair, who completes it, and in what position it is completed.

A speaker can repair their own utterance in the course of producing it – a *position 1 self-initiated self-repair* (P1SISR), by repeating (articulation), reformulating (formulation), or adding something (transition space). They may also repair one of their own utterances following someone else's – a *position 3 self-initiated self-repair* (P3SISR). A speaker can also repair another's utterance – a *position 2 other initiated other repair* (P2OIOR) or signal misunderstanding – a *position 2 next turn repair initiator* (P2NTRI) prompting the original speaker to repair their prior utterance – a *position 3 other initiated self repair* (P3OISR). See table 1 for examples.

Type		Example
P1SISR(A)	Dr:	You probably have seen so many psychiatrists *o- o-* **over** the years
P1SISR(F)	Dr:	*Did you feel that* **did you despair so much that** you wondered if you could carry on?
P1SISR(TS)	P:	Where I go to do some *printing*. **Lino printing**
P3SISR	Dr:	*Clozaril* or
	P:	Yeah
	Dr:	**Clozapine** yes
P2OIOR	Dr:	rather than *the diazepam* which I don't think . . . is going to do you any good
	P:	**The valium**
P2NTRI	Dr:	*It doesn't happen in real life does it?*
and	P:	What do you mean by real life?
P3OISR	Dr:	**you can't- there are no messages coming from the television to people are there?**

Table 1: Repair types (repair bold; repaired italics)

McCabe et al. (in preparation) analysed repair in dialogues between patients with schizophrenia and their psychiatrists. More patient led clarification, e.g. clarifying the psychiatrist's utterance with P2NTRIs, was associated with better treatment adherence 6 months later. Explaining the link between communicative patterns and adherence has both clinical and theoretical implications.

2 Repair in different dialogue contexts

We compared the repair data from Colman and Healey (2011)[1] with that from McCabe et al. (in preparation). These were annotated for instances of repair using the same protocol.

As shown in figure 1, although all types of dialogue exhibit the preference for self repair (Schegloff et al., 1977), this is especially the case in the clinical dialogues. Conversely, in the clinical dialogues there are fewer P2NTRIs and P3OISRs.

[1] This study looked at the demographic portion of the British National Corpus, and HCRC Map Task dialogues.

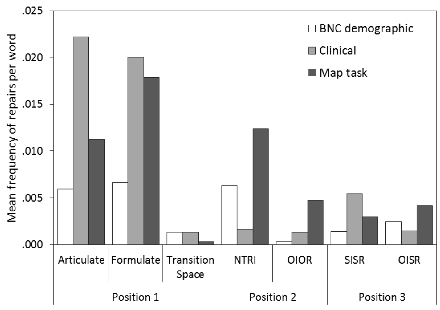

Figure 1: Repair per word by dialogue context

3 Classification Experiments

We first investigate the automatic detection of P2NTRIs, and then prediction of adherence directly, using the Weka machine learning toolkit (Hall et al., 2009) and the support vector machine implementation SVMLight (Joachims, 1999).

3.1 Detecting Repair

We defined a set of turn-level features (table 2) extracted automatically and likely to correlate with P2NTRIs. Words used by the patient were used to extract (optional) lexical unigram features.

Measure	Description
Speaker	Doctor, Patient, Other
NumWords	Number of words in turn
OpenClassRepair	Contains *pardon, huh* etc
WhWords	Num of wh-words (*what, who, when*)
Backchannel	Num of backchannels (*uh-huh, yeah*)
FillerWords	Number of fillers (*er, um*)
RepeatedWords	Words repeated from preceding turn
MarkedPauses	Number of pauses transcribed
OverlapAny	Number of portions of overlapping talk
OverlapAll	Entirely overlapping another turn

Table 2: Turn-level features

The classification task is to categorise each patient turn as containing a P2NTRI or not. The target class is very sparse: 170 of 20,911 turns were P2NTRIs, so a weighted SVM cost function was used. Performance was evaluated using 5-fold cross-validation. As shown in Table 3, absolute F-scores are low due to target class sparsity.

Target	Features	F (%)	P (%)	R (%)
P2NTRI	OCRProportion	35.8	85.7	22.6
P2NTRI	High-level	41.4	42.8	40.6
P2NTRI	All	44.0	44.9	43.6

Table 3: Repair detection

3.2 Predicting Adherence

We now turn to classifying each dialogue according to the level of adherence after 6 months. The features used were similar to those in the turn-level experiments, calculated over the dialogue.

Given the small size of the dataset (77 instances) and large possible feature space when using lexical features, we allowed only words mentioned >40 times, and selected the most predictive 10-20 features based only on the training set in each fold of the cross-validation.

As Table 4 shows, the performance using best selected features is good; however, all features selected are unigram lexical features. High-level features do not prove useful.

Features	F (%)	P (%)	R (%)
High-level	35.5	27.0	51.9
Best features	70.3	70.3	70.3

Table 4: Adherence prediction

4 Discussion

Patient led clarification is rare, leading to a highly unbalanced dataset. Although P2NTRIs can be predicted, the sparsity of the data mean they are not sufficient to predict adherence. Patient led clarification is not straightforwardly associated with any high-level, general dialogue factors to allow us to accurately classify the adherent patients.

However, there is a link between patients' conversational behaviour and their subsequent adherence to treatment, as seen in the results of experiments using words as features. Further work is needed to clarify what this link is and whether we can come up with a usable metric for predicting probable adherence from dialogue transcripts.

References

M. Colman and P. G. T. Healey. 2011. The distribution of repair in dialogue. In *Proceedings of CogSci*, pages 1563–1568, Boston, MA.

M. Hall, E. Frank, G. Holmes, et al. 2009. The WEKA data mining software: An update. *SIGDKDD Explorations*, 11(1):10–18.

T. Joachims. 1999. Making large-scale SVM learning practical. In B. Schölkopf, C. Burges, and A. Smola, editors, *Advances in Kernel Methods – Support Vector Learning*. MIT Press.

R. McCabe, M. Lavelle, S. Bremner, et al. in preparation. Shared understanding in psychiatrist-patient communication: Association with treatment adherence in schizophrenia.

E.A. Schegloff, G. Jefferson, and H. Sacks. 1977. The preference for self-correction in the organization of repair in conversation. *Language*, 53(2):361–382.