

Towards Argument Mining from Dialogue

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Abstract. Argument mining has started to yield early results in automatic analysis of text to produce representations of reason-conclusion structures. This paper addresses for the first time the question of automatically extracting such structures from dialogical settings of argument. More specifically, we introduce theoretical foundations for dialogical argument mining as well as show the initial implementation in a software for dialogue processing, and the application in corpus analysis. We combine analysis of illocutionary structure with structured argumentation frameworks as our scaffolding, and apply a combination of statistical and grammatically based analytical techniques.

Keywords. Argument Mining, Inference Anchoring Theory, Dialogue Structure

Introduction

Automatically extracting the structure of reasoning from natural language is extremely demanding. It is an area of study that has started to emerge only rather recently (the first workshop on the topic was held with the Association for Computational Linguistics annual conference in June 2014), having developed organically from text mining, and opinion mining in particular. Where opinion mining has focused on the identification of broad sentiment from a text (popular with marketing departments in large companies eager to know if comments online are positive or negative about their products), argument mining aims to identify reason-conclusion structures that can lead to models of why people hold the positions they do. Argument mining also holds the potential for rapidly bootstrapping the vision of an Argument Web of interconnected debates and perspectives. Many of the interesting and topical arguments are developed in dialogical situations, however, to our knowledge, no work has previously been carried out on automatically extracting argument structures from records of dialogical encounters. Whilst dialogues introduce new complexities into the challenge of argument mining, they also provide additional data which can be used to help constrain an otherwise extremely difficult task which has heretofore yielded very poorly to traditional statistical analysis techniques. The contribution of this paper is theoretical foundations for dialogical argument mining (Sect. 3), as well as the initial implementation in a software for dialogue processing (Sect. 5), and the application in corpus analysis (Sect. 4).

1. Background

Argument mining is a research area that has become increasingly popular over the past years. Having started in specific domains, in Sect. 1 in particular that of legal language [14], the task is now conceived in a broader way, often as an extension of the automatic analysis of subjectivity in language, whose main practical application is *opinion mining* [9]. This is performed for instance with customer reviews, where people provide feedback on some products or services they have purchased. Being able to automatically identify in such a text the opinion holder, the target of the opinion (the entity being evaluated), and the polarity (positive, negative) is interesting for many purposes; when it is possible, on top of that, to identify the justifications provided by opinion holders for their judgement, the benefit is even higher. Finding such justifications automatically, however, is one instance of argumentation mining. The more interesting and difficult cases arise when not just individual reasons for a supposition are being presented in a text but more complex argumentative structures involving rebuttals, counter-rebuttals, etc.

Invariably, the first step in finding such structures is to delimit the individual units of text that correspond to the minimal segments of the argumentative structure. Both rule-based and machine learning-based approaches have been used for this. An instance of the former is *SLSeg* [24], which applies search rules that try to identify independent clauses; an early learning approach to this task was implemented in *SPADE* [20].

The two computational tasks to be executed on the basis of a text segmentation are

1. Identification of the illocutionary force of individual units
2. Identification of relations between units

1 has for a long time been studied in the *spoken dialogue systems* community, where the dialog management component decided on the system's next move on the basis of the dialog act it assigned to the previous utterance of the user. The idea is to exploit both certain linguistic features of the utterance (e.g., sentence mode, mood, modality, verb class, particles) and the context of recent moves, in order to compute the most likely act. As a representative of this work, we mention here the influential approach of [21], who worked on a corpus of spontaneous speech and assigned 42 different act labels, including for instance *statement*, *question*, *agreement*, *disagreement*, *apology*. They achieved an overall accuracy of 71% correct tags on the basis of a transcription; for the actual speech the result is somewhat worse. Further, 2 is a task that under the label *discourse parsing* has been performed within the realm of Rhetorical Structure Theory [11]. Being able to compute RST trees automatically can be relevant for applications like text summarization, as the early work of [12] has demonstrated. Nowadays, this is almost exclusively done with machine learning, as in the approaches of [23] or [10].

RST-style discourse parsing is close to "argumentation mining proper", as long as the target structures are trees rather than general graphs. As mentioned above, the legal domain is a popular target, where, for example, uncovering the argumentation structure in the justifications of court decisions is an important application. [13] demonstrated that this can be done with reasonable accuracy. Similar to our dual task description, they divided the overall problem into first deciding whether a segment takes part in an argument (using features similar to those employed for dialogue act tagging; see above), and then guessing its role in the argumentation structure. The first step was done via statistical classification, the second on the basis of a hand-coded context-free grammar. The au-

thors reported a 60% accuracy for computing the tree of support structures in the argumentation. More recently several similar approaches have been proposed, including the automatic classification of arguments in terms of Walton's schemes [8], and the analysis of argumentative text using a generic processing platform [16].

2. Challenges for mining arguments in a dialogical context

We claim that the automatic extraction of argumentation and inference can be facilitated if we know the dialogical context in which they have been executed [6,15,7]. The task of moving from argument mining to dialogical argument mining presents, however, some initial challenges, i.e., it requires a model to capture not only properties of argumentation, but also some features that are characteristic for dialogical contexts. Consider the following extract from a small corpus of dialogue transcripts from the BBC Radio 4 *Moral Maze* programme¹ (see Sect. 4 for more details) where the participants discuss whether the present British government should be treated as responsible for the crimes committed in the past by the British Empire:

- (1) a. Michael Portillo: *Isn't that a source of injustice?*
 b. Esther Stanford-Xosei: *Definitely not. They do bear responsibility.*

Intuitively, Stanford-Xosei expresses her disagreement with Portillo's standpoint and supports it with an argument. The linguistic surface, however, is not sufficient for the automatic recognition of such a dynamic. First, observe that Portillo's standpoint is not asserted explicitly *qua* an assertion but an interrogative sentence. Though speech act theory [2,18,19] introduces the notion of illocutionary force, its models do not allow the representation of some communicative intentions characteristic for the MM2012 corpus. In its standard models, there are three possibilities of how to interpret (1-a), i.e. as having the force of: (i) question, (ii) indirect assertion, or (iii) rhetorical question.

All of them are problematic for different reasons. (i) does not allow us to capture a disagreement between the speakers. That is, it is not possible for Stanford-Xosei to disagree (via "*Definitely not*"), if we do not assume that Portillo expressed some opinion with which she might disagree with. On the other hand, if we understand (1-a) as having an (indirect) assertive force and the interrogative form is just a superficial grammatical surface, then we face another problem – why this type of move (expressing opinion via interrogative sentence) is so frequently used in *The Moral Maze* program? One important reason can be related to this type of dialogue's goal, i.e. the goal of *agreement-seeking*. That is, the speaker not only conveys his beliefs, but typically also, in using the interrogative form, he expresses the desire of knowing whether the other party believes the same, and as a result – agrees with him. Finally, a rhetorical question (see e.g. [22]) does not allow for fulfilling the agreement-seeking function, since if the hearer is not invited to respond, he cannot express whether he agrees or disagrees with the propositional content of the (rhetorical) question.

A second challenge of dialogical argument mining is the indexical nature of locutions performed in dialogical contexts. Imagine you enter the room exactly when Stanford-Xosei begins her turn. Without knowing what happened before (1-b) it is im-

¹the MM2012 corpus, available at <http://arg.dundee.ac.uk/corpora>

possible to reconstruct the propositional content of her locution. In other words, knowing that she said: “*Definitely not*”, does not allow us to understand that she in fact said “*It is definitely not a source of injustice*”, rather than, e.g., “*British Empire did definitely not behave in an uncivilised way during a war in Kenya*”, or anything else. Moreover, an indexical locution may not allow for unambiguous interpretation of illocutionary force, i.e. it does not allow us to rightly assume that she *disagrees* with the other speaker. If her response was addressing the question: “*Do you believe that that is a source of injustice?*”, then her response should be treated rather as an assertion than a disagreement. In other words, the recognition (and, as a result, automatic extraction) of the illocution of disagreeing is not possible without considering the history of the response.

In consequence, we face yet a third challenge, i.e. the identification of elements of a dialogue that can be treated as a medium for delivering illocutionary forces of argumentation or disagreement. Consider another example from the MM2012 corpus, in which participants discuss whether anti-social behaviours such as getting into debt should be stigmatised:

- (2) a. Michael Portillo: (...) *Why be so worried about restoring stigma?*
 b. Simon Rose: *Well, what I don't want to see is a return necessarily to debtors' prison.*

Intuitively, this dialogue contains argumentation with the conclusion “*I am worried about restoring stigma*” and the premise “*I don't want to see a return to debtors' prison*”. Using RST, we could identify a JUSTIFICATION relation between the conclusion, which constitutes the nucleus of the relation, and the premise, which constitutes its satellite. According to Segmented Discourse Representation Theory, SDRT [1], on the other hand, Rose performs a speech act: *argue(I am worried about restoring stigma; I don't want to see is a return necessarily to debtors' prison)*, where the second sentence is the premise of the argument and at the same time - a dialogical context (history) of the conclusion.

But what are the linguistic cues which allow us to recognise that Rose is performing argumentation here? Observe that a specific sequence of speakers' individual moves signals that Rose performed argumentation, i.e. given that (2-b) is a response to Portillo's challenge in (2-a), we can interpret this utterance not only as an assertion, but also as an argument supporting the sentence which was challenged. In other words, if we did not know what happened in the dialogue before (2-b), we could still interpret Rose's utterance as an assertion about restoring to debtors' prison, but we would not be justified in interpreting it as argumentation. Thus, what the model for dialogical argumentation requires is the list of types of such interactions, or how we call it – transitions, that will allow us to capture from where the forces of argumentation and disagreement come in dialogical context. For example, if we know that the players executed a sequence: *why(p)?; claim(q)*, then this sequence is an implicit dialogical material that allows us to recognize that argumentation (inference): *p* since *q*, was executed in the dialogue. In the next section, we propose a model that responds to these challenges.

3. Elements of dialogue structure

As a first key step, we specify three features of dialogue context that allow for dialogical argument mining:

1. illocutionary forces that are typical for dialogical contexts;
2. indexicality of locutions, i.e. locutions in which illocutionary force or propositional content cannot be identified without considering moves that precede a given indexical locution;
3. transitions between dialogical moves that anchor forces of indexical locutions.

Features 1 and 2 have been already discussed in [4]. The contribution of this paper is the specification of 3 (this section), as well as its implementation in a software for dialogue processing (Sect. 5) and its application in corpus analysis (Sect. 4).

In this paper, the force of assertive question, AQ, is described as an example of a **dialogical illocutionary force**. AQ has a dual illocutionary function of assertion and question (see [4] for the remainder of the forces identified for *Moral Maze* debates).² This double function is not a simple composition of those two forces with two distinct constitutive rules defining them, but one force with its own constitutive rules that capture both asserting and questioning communicative intentions of the speaker. As an example, in (1-a) Portillo does not only seeks directly Stanford-Xosei's opinion on a source of injustice, but also indirectly publicly declares his own opinion about it. The indirect assertive component of the AQ force is typically very clearly signalled on the linguistic surface (by cues such as "*Isn't that...*", or "*can we agree that...*") so that the hearer will not confuse it with a pure question.

Now we can present how such illocutionary forces can be incorporated into our theoretical framework – Inference Anchoring Theory (IAT) [6]. IAT allows us to represent the connections between dialogical structures and argumentative structures, which is a key requirement for dialogical argument mining. In this framework, different types of relations can be expressed: (i) relations between locutions in a dialogue, called transitions; (ii) relations between sentences (propositional contents of locutions); and (iii) illocutionary connections that link locutions with their contents. The first type of relations refers to rules of protocol which speakers follow to perform locutions during a dialogue game. For example, locution (1-b) is a legal response to (1-a) which means that they are related via some specific protocol rule of the *Moral Maze* game (see a relation TA that corresponds to such a rule in Fig. 1). Relations of type (ii) are typically studied in logic and argumentation theory. In Fig. 1, we have two of such relations: CA which expresses a conflict between sentences "*It is a source of injustice*" and "*It is not a source of injustice*"; and RA which represents inference between the conclusion "*It is not a source of injustice*" and the premise "*They do bear responsibility*". Relations of type (iii) are called illocutionary connections and are associated with illocutionary forces with which a given locution is performed. As a result, we can represent the AQ force as an illocutionary connection of Assertive Questioning (see the node in the top middle of Fig. 1) which links the dialogical act (1-a) to its propositional content "*It is a source of injustice*".

The second dialogical feature is **indexicality of locutions**. In dialogue (1) there are two kinds of such locutions – related to: (i) the first instance of asserting; and (ii) the illocutionary connections of disagreeing and arguing (see Fig. 1). Indexical assertions are a result of "dialogical shortcuts" when speakers use the material that was introduced earlier and leave some of the meaning implicit. For example, the first locution in (1-b),

²Amongst the basic illocutions, we distinguish: assertions, A, with their weak, -, and strong, +, versions; three types of questions: pure PQ, assertive AQ and rhetorical RQ; three types of challenges: pure PCh, assertive ACh and rhetorical RCh; concessions Cn and popular concessions PCn.

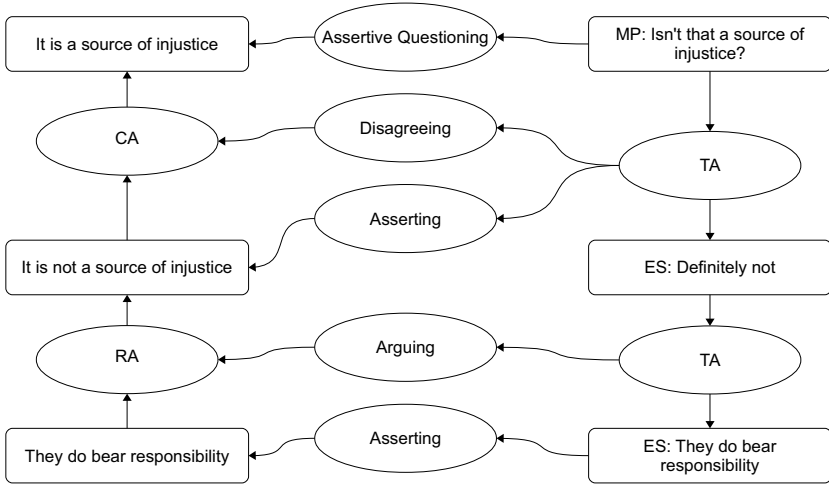


Figure 1. Disagreeing and arguing in a dialogical context.

“*Definitely not*”, does not have a content on its own. In other words, if the hearer does not know the history of this locution (i.e. (1-a)), then he will not be able to reconstruct what in fact “*Definitely not*” means. Similarly, the first locution in (1-b) cannot be used on its own to reconstruct the illocutionary force of disagreeing. If the hearer does not know that this is a response to the assertive question rather than to the pure question, then he can only guess that “*Definitely not*” means disagreement. In fact, if this were a response to a pure question, then “*Definitely not*” would mean only assertion, because Stanford-Xosei would have nothing to disagree with and would provide only her opinion on a source of injustice.

Finally, in Inference Anchoring Theory, the illocutionary connections of indexical locutions (such as indexical assertion, argumentation or disagreement) are anchored in **transitions** between dialogical moves (TAs in Fig. 1). In Fig. 1, the indexical assertion and disagreement are not anchored in the first locution of (1-b), but in the transition between this locution and locution (1-a). In other words, it is not enough to know that Stanford-Xosei said “*Definitely not*” to understand that she in fact *asserted* “*It is not a source of injustice*”, and that she *disagreed* with Portillo. In order to properly interpret this locution the hearer also need to know what Portillo said before. That is, the hearer needs to know the relation between these locution, i.e. the transition.

As a result, transitions may be used to extract arguments (both for and against an opinion) in dialogical context. For example, if we know that assertive question is followed by indexical assertion, or more precisely – by an expression that has the same meaning as “*No*”, then such a transition anchors the illocutionary connection of disagreeing. We write: AQ ; “no” → dAgr, to denote that a sequence of locutions: assertive question and a string “no”, allows to recognize the force of disagreeing (first TA in Fig. 1). Another examples of relatively straightforward transitions are: (i) (P/A)Ch ; A → Arg, i.e. a sequence of (pure or assertive) challenge and assertion anchors the illocutionary force of arguing; and (ii) AQ ; “yes” → Agr, i.e. a sequence of assertive question and an expression that means “yes” anchors the illocutionary force of agreeing.

4. Corpus studies

The model was applied to the analysis of the MM2012 corpus containing three transcripts (see [5] for more details). This program typically involves a moderator, a panel of four persons and several witnesses who discuss on controversial issues. The corpus contains a large diversity of argumentative situations and comprises a variety of characteristics which make it relevant for the task at stake. The total corpus contains 15,200 words and has 124 questions or challenges for about 300 assertions. Analysed transcripts contain also discourse regulators (DR), meant to manage the overall discussion, which occur on average every 15 units. This shows the vitality of the discussions and the diversity of the sub-topics addressed.

During corpus studies two challenges were faced. Firstly, locutions made by participants during the discussion had to be described with the relevant and applicable illocutionary forces described in Sect. 3. Secondly, argument structures in dialogical context had to be reconstructed. The agreement-seeking type of dialogue, typical to the MM2012 corpus, could be characterised by the distribution of illocutionary forces (see Table 1). As an example, with 84 annotated locutions, apart from the most expected illocutionary force, namely standard assertions (A, 280 occurrences), the most frequent is Assertive-Question (AQ, 52 occurrences). According to this data and the definition of AQ we can assume that in the MM2012 debates participants tend to present their beliefs under the form of questions inviting their antagonists to confirm the statement. Although we feel tags are stable, they can still evolve to capture higher-level generalizations.

IF	PQ	AQ	RQ	ACh	PCh	DR	A	+A	-A	A+	A-	Cn	PCn
Occurrence	36	52	36	2	5	27	280	9	8	14	6	1	8

Table 1. The distribution of illocutionary forces

The analyses, made in OVA+ Online Visualisation of Argument ³, are available in the AIFdb Corpora ⁴. OVA+ is an interface for the analysis of arguments online and allows for a graphical representation of the argumentative structure of a text. The analysis of the arguments performed during the dialogue was made on the level of argumentative units which, according to IAT theory, include the propositional content of locutions and the relations between them. The analysis of these structures allows for a correct parsing of dialogue units and for establishing TA relations (transitions) between them, as well as identifying the indexical illocutionary forces anchored in these transitions (i.e. argumentation, agreement and disagreement). Considering this part of corpus studies, specific features of the MM2012 conversations are noticed such as the way in which participants perform argumentation expressed via sequences of locutions, e.g.

- (3) a. MP: *it's a claim for compensation against the present government, which had no responsibility for what happened. Isn't that a source of injustice?*

MP performs argumentation, where the premise is “*It's a claim for compensation against the present government, which had no responsibility for what happened*” and the conclu-

³<http://ova.arg.dundee.ac.uk/>

⁴<http://www.arg.dundee.ac.uk/aif-corpora>

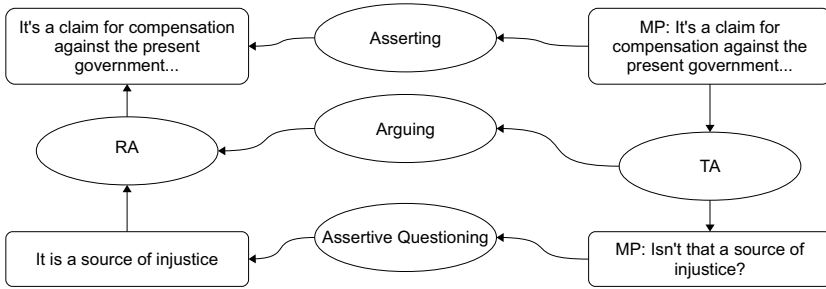


Figure 2. Argument verification.

sion is “*It is a source of injustice*” (Fig. 2). This example shows that the conclusion of an argument can be delivered via the AQ illocutionary force.

The corpus has been annotated by two annotators which have the same linguistic training and a good expertise of the IAT theoretical background. They then discussed their analyses in order to provide a single, stable analysis they both agree with, on which evaluations can be carried out for the language processing part described in the following section. The annotators were asked to notify the problems they came across when analysing as well as during their discussions: this helped understanding the difficulties and enhancing the model. Obviously, consensus was not easy to reach, but disagreement situations were mostly due to relatively complex structures in syntax. Results of the Kappa test, calculated before discussion, are summarized in Table 2. They range from 0.75 for the annotation of inference rules to 0.9 for the attribution of illocutionary forces. These results show that the schemes of illocutionary forces can be considered as stable, easy to identify and accurate.

Types of annotations	Kappa results
segmentation	0.81
illocutionary forces (YA)	0.9
indexical illocutionary forces	0.78
conflict relation (CA)	0.8
inference relation (RA)	0.75
transitions (TA)	0.77

Table 2. Results of the Kappa test

5. Recognising dialogue structures

In this section, we show the implementation of our model that allows for the recognition of all the elements of a dialogue structure discussed in Sect. 3.

5.1. Identifying dialogue units and illocutionary forces

In [3], the two first steps of the process of dialogue analysis and representation in IAT have been developed, implemented on the TextCoop platform [16] and evaluated. These

are summarized here. The new elements concern transition identification which is developed in the next section. The implementation includes rules and lexical resources that have been categorized. Rules are forms of grammaticalized marks, i.e. marks that have been generalized via local grammars. The whole system runs using the engine implemented in TextCoop.

Very briefly, we show in this work how (1) a dialogue can be decomposed into meaningful dialogue text units using a dedicated grammar that can identify and delimit such units and (2) how an illocutionary force can be assigned to each of these units, following the definitions given above. The analysis has been realized from a development corpus and tested on a different corpus.

To realize the unit identification step, we developed a specific elementary discourse unit (EDU) analysis dedicated to dialogical situations. These specific EDUs turn out to have specific forms and linguistic marks proper to argumentative dialogue compared to those defined for discourse analysis in general [17]. The identification of these units results from linguistic observations and is computed in TextCoop. According to the observations made on our corpus, in most situations, units can be identified on the basis of discourse markers typical of dialogue, e.g. markers related to challenge, position or belief statements, or an aggregation of such markers, e.g. when there is an intention of persuasion.

We have conducted an indicative evaluation (to identify improvement directions) on the previously manually annotated test corpus where 179 text unit occurrences have been identified. This is a small scale test but it turns out to be sufficient for a first analysis. Out of this set of 179 units, our system : (i) correctly annotated 153 units (85%) (identification and delimitation); (ii) failed to identify 6 units (4%) because of a lack of mark; (iii) correctly identified 13 units (7%) but with incorrect delimitation (a unit is split into several or vice-versa); (iv) identified 7 units (4%) which are not directly dialogical text units.

These results are rather good for a first experiment. One reason is probably that the discussions investigated in our corpora are of a rather good English, where speakers make sure they can be understood by their listeners. The discussion is essentially 'rational', forms of irony, dramatization or trickery are quite unusual. Another reason is that an adequate organization of an argumentative dialogue requires that statements, questions, challenges, etc. are made as clear as possible so that the argumentation can lead to a conclusion, or a set of weighted conclusions. Results would probably have been less good and the linguistic analysis would have been much more difficult on dialogue where language is less controlled. However, our analysis provides a stable kernel which can then be extended.

The next step is the identification of the illocutionary structures (or forces) for each text unit. A coherent dialogue requires that each text unit is assigned a force. Contrary to the previous step, it is not possible, however, to identify all illocutionary force types solely on the basis of linguistic marks. In some cases the illocutionary force cannot be assigned to a unit in isolation: it is necessary to take into account e.g. the illocutionary forces assigned to adjacent units, the position of the unit in the dialogue turn (starting, ending) and the role of the speaker in the debate (e.g. moderator).

A significant number of linguistic forms we have identified are very general and are typical of several illocutionary forces. Our strategy is not to have a by-default illocutionary force assignment, but to represent the ambiguity, which may be resolved later by

other means. For that purpose, we introduced polymorphic types to represent the ambiguity, viewed as a form of underspecification. On that basis, an accuracy of 78% was reached, among which we have a distribution of 52% for basic types and 48% for polymorphic types. The accuracy level is a good result considering the difficulty of the task. Obviously, the small size of the corpus and its homogeneity explain the good quality of the results. We may expect some stability of these results on larger corpora. However, it is clear to us that some method for automating marks recognition and generalization is necessary, even if our observations tend to show that these marks are not so diverse.

5.2. Towards a model for anchoring illocutionary forces to transitions

Let us now introduce elements of a model that describes how illocutionary forces are anchored to transitions. Notations are given in section 3, we recall the major ones here for the sake of readability. Let X and Y two dialogical units with respectively illocutionary forces x and y (e.g. A, Q, AQ, PQ, Cn, etc.). Let $S1$ and $S2$ be two distinct speakers in a debate. $X(S1)$ represents a dialogue unit uttered by $S1$ (X is not a function on $S1$). The sequence: $X(S1) ; Y(S2)$, represents two adjacent units respectively uttered by $S1$ and $S2$. The transition T and the illocutionary force t (e.g. agree, argue, disagree) that is anchored to it is represented by:

- surface utterance level: $X(S1) ; Y(S2) \rightarrow T$,
- illocutionary force level: $x(S1); y(S2) \rightarrow t$.

Transitions between units uttered by the same speaker have also been investigated.

From corpus observations, it turns out that given pair $x;y$ can be associated with a large number of values t . Our main observations are the following:

- in some cases, the various t assigned to $(x;y)$ may be partly contradictory, but this contradiction may be superficial and may reveal e.g. deeper dialogue strategies
- a by-default value t for most $(x;y)$ has been observed from the analysis of the contents of X and Y ; it often corresponds to the most frequent usages found in the corpus,
- the taking into account of simple linguistic markers such as connectors, modals, forms of negation or propositional attitude verbs, similar to those used in step (2) above for the identification of illocutionary forces of dialogical units taken in isolation, contribute to resolve the ambiguities when several t are possible for a pair $(x;y)$
- the taking into account of more than one unit X occurring before the transition may help to resolve ambiguities since dialogical units which are of interest to produce a value t are not necessarily the adjacent ones. A rough evaluation indicates that considering two or more units before the transition is useful to resolve ambiguities in about 15% of the situations.

Let us consider, for a given pair $(x;y)$ and a set of speakers $(S1, S2)$, the set of $t_i, i \in [1, n]$ of illocutionary forces which can be anchored to the related transition T . Then:

1. **by-default value:** $\exists j \in [1, n]$ which is the by-default illocutionary force, for example: $PQ(S1); A(S2)$ has ‘Agreeing’ as the by-default force for T ,
2. **well-formedness constraint 1:** if X and Y are produced by the same speaker $S1$, then t_i cannot be assigned any of the values: ‘agree’ or ‘disagree’. However,

we may encounter situations where this constraints must be made flexible, e.g.: ‘most people think that P however I feel that this is not the case’.

3. **well-formedness constraint 2:** the set of values t_i must be consistent, i.e. it cannot contain opposite or inconsistent forces such as {‘agree’, ‘disagree’},
4. **ambiguity representation by polymorphic types:** instead of making an *a priori* choice for t_i in case of ambiguity, we adopt the same approach than for the identification of illocutionary forces of dialogical units taken in isolation, namely we introduce polymorphic types that represent such a type of ambiguity. This ambiguity can be resolved later by additional means such as knowledge and textual entailment. A polymorphic type is a set of consistent values t_i , e.g. {‘agree’, ‘argue’}. For example, we have: $AQ(S1) + A(S2) \rightarrow agreeing/restating$. with the polymorphic type {‘agree’, ‘restate’}.

To conclude this linguistic analysis, let us illustrate how linguistic marks typical of discourse or dialogue found in X or Y can help to resolve ambiguities in the anchoring of illocutionary forces to a transition T.

$A(S1) + A(S1(because)) \rightarrow$ arguing

$A(S1) + A(S1(I\ mean)) \rightarrow$ restating

$A(S1) + WA(S1(I\ think,\ so\ what\ I\ would\ say)) \rightarrow$ arguing.

In these examples, ‘because’ is a connector found in $X = A(S1)$. The results of the two steps presented in section 5.1 have been represented as Prolog facts. This allows quite a simple use of Dislog to develop an automatic annotation for transitions. The development of the parser and the associated evaluation is an ongoing task.

Conclusions

This paper has focused on building foundations for extracting argument structure from dialogical exchanges in which that structure may be implicit in the dynamics of the dialogue itself. The domain of analysis of high-level pragmatic features, such as inference, is plagued by poor performance for both human analysts and automatic algorithms. We have demonstrated first steps towards an implementation which can nevertheless perform in this demanding environment. By combining recent advances in theoretical understanding of inferential anchors in dialogue with grammatical techniques for automatic recognition of pragmatic features, we have produced results for illocutionary structure parsing which are comparable with existing techniques acting at a similar level such as rhetorical structure parsing. In addition, however, we have demonstrated that by following this approach we lay a foundation for automatically connecting individual locutions into larger scale inferential structures. Though our steps in this direction are currently preliminary, the fact that illocutionary structure can be mapped onto inferential structure via inference anchoring suggests that automatic argument recognition may not be as distant a goal as had been assumed.

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