The Negochat Corpus of Human-agent Negotiation Dialogues

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Abstract

Annotated in-domain corpora are crucial to the successful development of dialogue systems of automated agents, and in particular for developing natural language understanding (NLU) components of such systems. Unfortunately, such important resources are scarce. In this work, we introduce an annotated natural language human-agent dialogue corpus in the negotiation domain. The corpus was collected using Amazon Mechanical Turk following the ‘Wizard-Of-Oz’ approach, where a ‘wizard’ human translates the participants’ natural language utterances in real time into a semantic language. Once dialogue collection was completed, utterances were annotated with intent labels by two independent annotators, achieving high inter-annotator agreement. Our initial experiments with an SVM classifier show that automatically inferring such labels from the utterances is far from trivial. We make our corpus publicly available to serve as an aid in the development of dialogue systems for negotiation agents, and suggest that analogous corpora can be created following our methodology and using our available source code. To the best of our knowledge this is the first publicly available negotiation dialogue corpus.

Keywords: dialogue systems, negotiation corpora, crowdsourcing

1. Introduction

Annotated in-domain corpora are crucial to the successful development of dialogue systems of automated agents, and in particular for developing natural language understanding (NLU) components of such systems (Lasecki et al., 2013). While NLU is considered to be a challenging task, previous studies in the Human Computer Interactions field have found that an important goal of any human-agent dialogue system should be an intuitive interface with interaction environments as real and natural as possible. This highlights the importance of achieving good natural language capabilities for automated agents, which go beyond traditional menu-based interactions (Coen, 1998).

Negotiation is an important task in our daily lives. It concerns anything from a mundane ‘time to go to lunch’, to our salary, and to issues that can have dramatic effects on the lives of millions (Musambachime and Hopmann, 2001). As such, various automated agents have been created to negotiate with people in different settings with varied factors, such as the number of parties, number of interactions and number of issues to be negotiated. (Zuckerman et al., 2013).

In particular, the popularity of the negotiation domain led to the establishment of the international Automated Negotiating Agents Competition (ANAC) Workshop. In this popular competition human-agent dialogues are currently restricted to a fixed set of menu-based interactions (Baarslag et al., 2012), while extension to natural language interactions is on the future roadmap. Since 2010, the competition has focused on agents that are based on the open Genius environment (Lin et al., 2012).

Although natural language annotated corpora are considered an important resource for training and tuning NLU components, to the best of our knowledge there are no such publicly available negotiation corpora.

In this work we address the above mentioned resource scarcity by collecting a corpus of natural language human-agent negotiations, which is compatible with the Genius framework and comprises 105 crowd-sourced dialogues (184 utterances). Every natural language utterance in this corpus is manually annotated using a formal semantic language, based on both the utterance itself and the specific context in which it appears in the dialogue. Our contributions are as follows. First, we make our corpus publicly available to promote the development of natural language dialogue systems for negotiation agents.\textsuperscript{1} Second, we share the methodology and dialogue system source code used to create our corpus and suggest that analogous corpora can be generated following the same approach.\textsuperscript{2}

2. Dialogue System Architecture

Our dialogue system is based on the NCAgent system by (Rosenfeld et al., 2014) with a standard dialog system architecture (Martin and Jurafsky, 2000), which includes the following components: (1) Natural Language Understannder (NLU) - translates natural language human utterances from the user side to a formal semantic representation. For example, the utterance \textit{I offer you a salary of 20,000} is translated to the predicate-argument structure, \textit{Offer(Salary=20,000)}. When collecting our corpus the NLU function was carried out by a human. (2) Natural Language Generator (NLG) - translates statements in formal semantic representation from the agent side to natural language utterances. (3) Dialogue Manager (DM) and Agent - the DM is responsible

\textsuperscript{1}The corpus is available at \url{https://github.com/vaskonov/negochat_corpus}

\textsuperscript{2}The components of the dialogue system and the negotiation corpus are available at \url{https://github.com/vaskonov/negochat_corpus}
negotiation corpus in the
In this work we collected a natural language human-agent

3.1. Overview
prior state-of-the-art KBAgent (Oshrat et al., 2009).
reach significantly better agreements, in less time than the
supporting partial agreements and issue-by-issue interac-
tion, was developed specifically to interact with humans,
NCAgent, the negotiation agent used for our data collec-
tion setting the function of the NLU was carried out
help developing automated NLU components, in our data
collection setting the function of the NLU was carried out
by a human. This was following the ‘Wizard-Of-Oz’ ap-
proach, which is described in more detail in section 3.4.
Finally, once we collected the corpus, we employed human
annotators to annotate the human utterances in the corpus
with their respective formal semantic representations (Sec-
tion 3.5.).

3.2. Job-Candidate Domain
The job-candidate negotiation domain includes bilateral
multi-issue closed negotiations and was used in several pre-
vious works (Lin et al., 2008; Oshrat et al., 2009). This
domain is compatible with Genius\(^3\), a general platform for
negotiation agents, which was also adapted by the Au-
tomated Negotiating Agents Competition (ANAC) as the of-
official competition platform (Lin et al., 2012; Baarslag et al.,
2013). The negotiation takes place between an employer
and a candidate. The goal of both sides is to reach a con-
ensus on the hiring conditions or attributes of the agree-
ment, while optimizing their own score objective. If no
agreement is reached by the end of the allotted time (30
minutes), both sides receive some predefined score. Each
side can also decide to opt-out of the negotiation if one feels
that the prospect of reaching an agreement with the oppo-
nent is poor and it is useless to negotiate any further. Ac-
cordingly, the result of each negotiation was either reaching
a full agreement, or failing to do so because of an opt-out
or because the allotted time was over. Before starting a ne-
gotiation, participants take a tutorial\(^4\) describing the game
interface and the objectives.
The attributes included in our semantic language with their
predefined set of values appear in Table 1.
The negotiation dialogue comprises the exchange of one or
more of the following dialogue acts in each utterance: Offer,
Accept, Reject, Query, Greet, Quit.

3.3. Formal Semantic Language
We used a frame-based semantic representation, where one
or more composite semantic labels are used to represent
each utterance in a dialogue. Our representation is char-
acterized by a common predicate-argument construction.
Each composite label consists of up to three components,
intent, attribute and value, where attribute and value are
optional. For example, following is a natural language
utterance with its corresponding composite label consisting of
all three components:
NL utterance: I offer you a pension of 10%
Semantic label: Offer(Pension Fund=10%)
Alternatively, in this next example the value component is
missing:
NL utterance: I reject the job position
Semantic label: Reject(Job position)
In many cases, such missing values can be implied based on
the dialogue context. For example, the value ‘programmer’
can be implied for the above Reject utterance if it came as a
response to Offer(Job position = Programmer). Resolution
of such implied values is done by the Dialogue Manager
and not by the NLU component.
Finally, there are several intents that can be used even
without attributes, for example:
NL utterance: Hello, how are you?
Semantic label: Greet
We note that we intentionally chose a simple semantic rep-
resentation, as it is easier to train NLU models on, espe-
cially with relatively small training corpora. However, there
is room for future extensions of this representation. Some
possible extensions are adding the representation of condi-
tioned offers and ‘OR’ relations. For example, the utterance
Giving you a company car would require you to either work
10 hours or drop your pension to 10% cannot be expressed
in our current semantic language representation.
Our semantic language is formally defined using Syn-
chronous context-free grammar (SCFG) with correspond-
ing natural language translations, which is mostly based
on the representation that was used in (Rosenfeld et al.,
2014)\(^5\).

3.4. Crowd-Sourced Data Collection
We recruited 105 English speakers on Amazon Mechanical
Turk (AMT) to participate in the negotiations. AMT allows
to apply specific filtering criteria for the participants. The
only filtering criteria was physical location in the United
States, United Kingdom, or Canada.
In our corpus the agent always assumes the role of the can-
didate while the human is the employer. The dialogues
were collected by applying the Wizard-Of-Oz (WOZ) ap-
proach. Under this approach, the user believes that she is
\(^3\)http://ii.tudelft.nl/genius/
\(^4\)https://github.com/vaskonov/tutorial
\(^5\)The SCFG grammar is available at https://github.
com/vaskonov/scfg/blob/master/grammars/
NegotiationCandidateConcise.txt
directly interacting with an agent, but behind the scene, a human who is not a turker, is performing the NLU function, translating the user utterances from natural language to semantic language (Dahlbäck et al., 1993). While this approach requires real-time manual translation of natural language utterances, its merit is in facilitating reliable interactive user-agent dialogues.

The NLG component was entirely automated. First, we generated offline a mapping from all the semantic representations that can potentially be used by the agent into natural language utterances. This was done using Synchronous Context-Free Grammar (SCFG) (Aho and Ullman, 1972), where we defined the SCFG rules for both the natural language and the semantic language. Then, in real-time, the NLG used a quick look-up in this mapping to translate the agent’s outputs.

3.5. Annotation

Once dialogue collection was completed, two independent annotators annotated the corpus following the annotation guidelines. Disagreements were resolved by the WOZ person as the arbitrator. As a metric of inter-annotator agreement we used Krippendorff’s α with MASI distance that supports multi-label annotation (Passonneau, 2006), as implemented in the DKPro Agreement package (Meyer et al., 2014).

The inter-annotator agreement before reconciliation was 0.89 and after reconciliation became 0.95. The annotators were instructed to take the context of the dialogue into account while annotating each utterance. For example, the annotation of the following utterance could depend on the context of the dialogue:

**OK, let’s move to pension fund**

If this utterance is a reply to some Offer, then it would most likely be annotated as Accept, referring to the previous Offer, along with Query(Offer=Pension Fund). However, if it comes after a Reject then Query(Offer=Pension Fund) alone would be the more appropriate annotation.

A sample of an annotated dialogue appears in Appendix.

4. Analysis

4.1. Corpus analysis

In total 105 dialogues with 1484 human utterances and 2140 generated agent utterances were collected. These include 1264 single-label human utterances, 110 multi-label ones and 110 non-labeled utterances. The total annotation time was 323 minutes. In 69 out of the 105 dialogues an agreement was reached. Total dialogues duration was 1291 minutes. The maximal dialogue duration was 30 minutes and the minimum dialogue duration was 3 minutes. The participants reported their demographic information in a pre-questionnaire, resulting in 55 male participants and 50 female participants. The participant age distribution appears in Table 2.

| Age     | Number |
|---------|--------|
| 18-30   | 46     |
| 31-40   | 42     |
| 41-50   | 8      |
| 51-up   | 9      |

Table 2: Turker age distribution

The total expense on crowd-sourcing was a little under $250, including AMT fees and web hosting of the game application. The post annotation of the utterances cost approximately $200.

The distributions across the corpus of the intents in the utterances of both humans (in the employer role) and agent (in the candidate role) appears in Table 3. These distributions are naturally sensitive to the strategic policy, configured for our agent. We used the default agent configuration. We note that this is a mixed initiative negotiation and therefore both parties can suggest job conditions. Accordingly, both employer and candidate suggestions were annotated as Offers.

There were 110 human utterances for which the annotators could not assign any of the defined intents. For example, the following utterances were not annotated: “Welcome to the company!”, “Here’s an offer, take a look.”, “hold on a minute”.

4.2. Baseline NLU classification results

An intended goal of the corpus is to train the NLU component of a negotiation dialogue system. As a baseline for
Table 3: The distribution of the intents over the utterances of the human and the agent

| Intent | Human (employer) | Agent (candidate) |
|--------|-----------------|------------------|
| Offer  | 1292            | 1704             |
| Accept | 249             | 298              |
| Reject | 248             | 542              |
| Query  | 79              | 34               |
| Greet  | 30              | 105              |
| Quit   | 18              | 0                |
| Total  | 1916            | 2683             |

future work we followed (Tur et al., 2010), which presents a competitive discriminative classifier method for dialogue systems. To this end, we used a multi-label SVM classifier with unigrams and bigrams as features and tf-idf feature weights. The input to the classifier was the features of the natural language utterance and the output was one or more labels in our formal semantic representation. The first 70 dialogues in the corpus were used as train set and the remaining 35 dialogues as test set. Due to the fact that the labels’ distribution is highly unbalanced we calculated both micro-average and macro-average metrics. Micro-average metrics are calculated globally based on the total true positives, false negatives and false positives for all labels. Macro-average metrics are calculated by first evaluating the individual metrics for each label, and then taking a simple average. The important difference is that the macro-average metrics are not biased towards the most frequent labels. The micro-average results are F1-score of 0.78, Precision of 0.83, and Recall of 0.74. The macro-average results are F1-score of 0.45, Precision of 0.54, and Recall of 0.43.

5. Conclusions and Future Work

In this work we collected a corpus of natural language human-agent negotiations, which is compatible with the Genius framework and comprises 105 crowd-sourced dialogues, including 1484 human natural language utterances. The utterances were annotated with formal semantic language labels, achieving a high inter-annotator agreement of 0.95 Krippendorff’s $\alpha$.

We make our corpus publicly available to promote the development of natural language dialogue systems for negotiation agents. The rather mediocre baseline results, achieved when training a standard NLU classifier on our corpus, confirm that our corpus presents a challenging task to the research community. Furthermore, we suggest that additional corpora, analogous to ours, can be created easily and quite cheaply following our methodology and using the dialogue system components that are all made publicly available.

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"input": "I can do a pension of 20%!",
"output": [
  { "Accept": { "Pension Fund": "20%" }}
],
"role": "Candidate",
"data": "I’m happy that you accept.
We can sign the agreement now.
Please pick the values in the agreement draft and press Sign."
}

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