Inferring Negotiation Priorities in Real Time

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6.UAP Project Proposal

1 Problem Statement

In most negotiations, there exists a theoretical optimal outcome that maximizes the value created for all parties. This optimal deal is almost never reached, as selfish interests and human emotion may prevent parties from fully exploring the deal space. Each negotiator usually keeps his/her priorities a secret because giving away information could lead to an advantage for the other side.

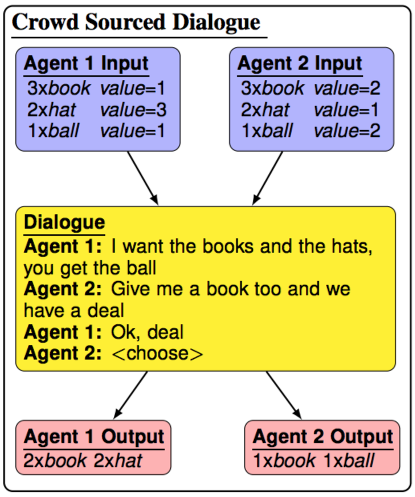
With the advances of machine learning techniques, we now have more tools to analyze negotiations in a data-driven way. Previous work focuses on either characterization of tone, body language, and intent or on analysis and formulation of offers. Notable projects include the use of a bigram model to analyze intent in negotiation texts [2]. This project tried to infer the amount of information each side was giving up by classifying the words they used by level of informativeness. Another paper used SVMs to detect tone in audio data [3]. They mapped pitch, intonation, and intensity into features for their classifier. Another recent project involved creating a bot for negotiating [4]. Facebook researchers took a two-pronged approach, first formulating a goal and then using a neural network to produce text. We will use the data set they used to train their bot in our experiments. Though progress has been made in this space, there is still a lot of unexplored territory and opportunity for improvement. This project specifically focuses on the prediction of the hidden agenda of negotiators. Whichever side knows more information about the other side's agenda has a clear advantage. The ability to infer that could be of great value in real time to a negotiator. We will build off of previous work in the tone analysis and negotiation prediction space to build this model.

2 Negotiating Game

For this project we will work with a negotiating game. The negotiation starts with a basket of items. The two parties must agree on how to divide up the items. Each party has a secret value associated with each item, where the total value of all the items for each user is 10, each item has a non zero value for at least one user, and some items have non zero values for both users. The agenda of a party is defined as their point-wise secret value for each item. Each side wants to maximize the value they end up with.

The two sides exchange messages until they reach a deal or walk away. If one party leaves the game they both get zero points. The graphic below shows an example dialog from a game[4].

This setup mimics real life negotiations fairly well because negotiators trade over multiple issues. They also have different intrinsic values for different items unbeknownst to the other side. This means there are opportunities for value creation. Consider instead a simple barter over the price of a single item. This setup is a zero-sum game, where every dollar is equally valuable to both sides. In this scenario there are no opportunities for collaboration, and the agenda of the other side is not hidden. In our game, if party 1 can infer that party 2 has low priority for an item, party 1 might demand that item in addition to what they already asked for. Furthermore, since our game produces a series of conversations between two agents, we can analyze features from the text to make predictions. Numeric values for items makes this setup much easier to analyze.



3 Goals

The main goal of this project is to build a machine learning model that can predict the agenda of the opposing party in the negotiation game based on the conversation between the negotiating parties. To achieve this goal, we will build, train, and test different models to find the best feature set and model architecture.

4 Methodology

4.1 Data Set

Models will be trained on Facebook's open source **negotiate** data set.Facebook collected this data from people playing the negotiating game described above. This data set contains over 2,000 such negotiations. Facebook previously used this data set to build the negotiating bot mentioned above.

4.2 Machine Learning Techniques

We will first featurize the data using Natural Language Processing techniques on the text exchanges. We want to use a Gated Recurrent Neural Network for sentiment analysis. We want to featurize other elements of the text exchange such as the length of conversation. The other feature set will focus on the offers: who makes the first offer? If an offer was rejected, did the maker counter or stay firm? There are many interesting features we can extract from both lines of analysis. We will then feed these features into a Recurrent Neural Network, trained to make our prediction.

The code for this project will be written in Pytorch, a machine learning library particularly suited for Natural Language Processing Techniques.

4.3 Evaluation

We plan on evaluating our model based on its effectiveness at predicting the agendas of negotiators. At each time step (a step is completed with each message we analyze), we will make a prediction. We are interested in measuring how far into the negotiation we can predict the agenda within a margin of error of 20%. A more effective model will do this earlier. We will split the data set into a training, validation, and test set. This way, we will not over fit the model to the training data, and we can have more confidence in the final test accuracy.

5 Risks

One possibility is that the data set will not be sufficient or complicated enough to produce interesting results. Because the code for running negotiation games is open source, we can run our own games to collect more data. We can also modify the game if needed. We estimate that the process of collecting more data will take around three weeks, so we will not do this unless it is absolutely necessary.

6 Schedule and Deadlines

The main work completed so far involves researching previous work and planning model architecture. The next step will be to set up the data pipeline. This involves cleaning the data, processing the data set, and transforming it into a format easily worked with for our model (March 23). The next step is setting up the model architecture. This involves defining model layers, hyper-parameters and training steps (April 6). Next we want to run experiments. This involves training our model with different data features and hyper-parameters, evaluating, and iterating (April 27). Lastly, we need to write the final report (May 4).

7 Conclusions

The ability to infer negotiation priorities could give an advantage to a negotiator in real time. This project aims to combine recent analysis techniques and data sets to make novel predictions about the hidden agendas of negotiators.

References

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[2] Marina Sokolova and Guy Lapalme. *Informativeness for Prediction of Negotiation Outcomes*. Natural Sciences and Engineering Research Council, 2012.

[3] Prerna Chikersal, Jianlin Zhan, and Chaitanya Modak *Predicting Negotiation Outcomes from Behavioral Data*. 2016.

[4] Mike Lewis, Denis Yarats, Yann N. Dauphin, Devi Parikh, and Dhruv Batra *Deal or No Deal? End-to-End Learning for Negotiation Dialogues*. 2017.