

# Initiative Taking in Negotiation

**Elnaz Nouri**

University of Southern California  
Los Angeles, CA, USA  
nouri@ict.usc.edu

**David Traum**

USC Institute for Creative Technologies  
12015 Waterfront Dr  
Playa Vista, CA 90094, USA  
traum@ict.usc.edu

## Abstract

We examine the relationship between initiative behavior in negotiation dialogues and the goals and outcomes of the negotiation. We propose a novel annotation scheme for dialogue initiative, including four labels for initiative and response behavior in a dialogue turn. We annotate an existing human-human negotiation dataset, and use initiative-based features to try to predict both negotiation goal and outcome, comparing our results to prior work using other (non-initiative) features sets. Results show that combining initiative features with other features leads to improvements over either set and a majority class baseline.

## 1 Introduction

Negotiation is a complex interaction in which two or more parties confer with one another to arrive at the settlement of some matter, for example resolving a conflict or to share common resources. The parties involved in the negotiation often have non-identical preferences and goals that they try to reach. Sometimes the parties simply try to change a situation to their favor by haggling over price. In other cases, there can be a more complex trade-off between issues. Investigating these rich and complex interactions in a scientific manner has been important to researchers in different fields due to the significant implications and potential applications for business and profit making. Being a good negotiator is not a skill that all humans naturally have; therefore, this line of research can potentially be used to help humans become better negotiators. Computer agents will also benefit from the ability to understand human negotiators. There has been a fair amount of previous work in understanding negotiation dialogs, e.g., (Walton and

McKersie, 1991; Baker, 1994); as well as agents who can engage in negotiation, e.g. (Jameson et al., 1994; Sidner, 1994; Kraus et al., 2008; Traum et al., 2008). In this paper we investigate the role that dialogue initiative plays in negotiation.

Negotiations can be characterized by both the goals that each negotiator is trying to achieve, as well as the outcomes. Even for negotiations that attempt to partition a set of goods, the participants may have differences in their valuation of items, and the negotiations can be very different if people are trying to maximize the total gain or their individual gain, or gain a competitive advantage over the other.

Negotiations between two people are usually mixed-initiative (Walker and Whittaker, 1990), with control of conversation being transferred from one person to another. To our knowledge, no previous studies have investigated the relationship between verbal initiative taking patterns and the goal or the outcome of the negotiation. We suspected that both of the mentioned characteristics of the negotiation (goal and outcome) might be correlated with different initiative-taking patterns. We used an existing negotiation dataset in order to study the mixed initiative patterns between the two parties in the negotiation. We describe this data set in Section 2, as well as previous work that attempted to predict outcome and goal, using other features (Nouri et al., 2013).

This paper makes the following contributions: a new annotation scheme for dialogue initiative is introduced in Section 3 and used to annotate the negotiation dataset. We then study the relationship between initiative taking patterns and the goal and outcome of the negotiation for the participants (Section 4).

## 2 Data

We make use of a previously collected and analyzed dataset in order to examine the relative con-

tribution of initiative to problems of goal and outcome detection. We briefly describe the dataset and relevant prior work on this dataset.

The Farmers Market dataset (Carnevale, 2013) contains audio, video and transcription of 41 dyadic negotiation sessions. Participants were undergraduate students majoring in business. Each participant only took part in one negotiation session.

Before each negotiation session, the experimenter told participants that they were randomly assigned to represent one of two restaurants in the task. The owners of the two restaurants had asked the participants to go to the market and get some apples, bananas, lemons, peppers and strawberries. The payoff matrix for each restaurant and type of item is shown in Table 1. There were multiple items of each type available. Each participant was only given the pay-off matrix of his assigned restaurant and the total score of the negotiation for each participant was calculated by adding up the points for each item they received in the negotiation. The participants were told that they had 10 minutes to negotiate how to distribute the items on the table and reach an agreement. As an incentive, each participant could receive up to 50 dollars depending on the final points earned by each participant for his/her restaurant.

	R1	R2
Apples	1	3
Bananas	3	3
Lemons	0	0
Peppers	3	1
Strawberries	1	1

Table 1: The Payoff Matrix for each Restaurant

## 2.1 Goals

The study was originally designed to investigate negotiators' behavior when they have different goals in the negotiation. There were three types of instructions given to the participants. All the details were the same except for their goal in the negotiation.

- In “individualistic” instructions participants were told that their goal was to get as many points as they could for themselves. An excerpt from an individualistic negotiation is shown in Table 13 in the Appendix.

- in “cooperative” instructions they were told that they should try to maximize the joint gain with the other side of the negotiation. An excerpt from a cooperative negotiation is shown in Table 11 in the Appendix.
- in “competitive” instructions they were told to try to get more points than the other party. An excerpt from a competitive negotiation is shown in Table 12 in the Appendix.

Out of the 41 interactions in the dataset 15 were competitive, 13 were individualistic and 13 were cooperative sessions.

## 2.2 Outcomes

The outcome of the negotiation in this case is measured based on the calculation of the scores corresponding to the items that each negotiator has received by the end of the negotiation. In order to make the prediction of outcome possible based on our small dataset, we labeled the calculated score for each participant with one of the three labels: H,E or L, showing whether the participant had received more, equal or fewer points than the other person.

The goal of the “competitive” instructions was to get a higher score. For cooperative negotiations, the relative score did not matter. For the individualistic goal, higher score is somewhat correlated with the goal, but not absolutely (what matters is only an individual high score, not the relation to the other partner). 17 negotiations resulted in equal final scores for the two parties and 24 with one side scoring more than the other side. Table 2 shows the average scores for each restaurant, across the three types of goals. The scores are on average higher in the cooperative negotiations than in the other two conditions.

Average score	R1	R2	Joint Gain
<b>Cooperative</b>	24.9	25.1	50
<b>Competitive</b>	23.7	23.6	47.3
<b>Individualistic</b>	25.5	22.5	48

Table 2: Average Score by Restaurant and Goal

The average score for individuals who score higher (labeled as H) than the other side of the negotiation was 26.46 whereas the average score for their counterparts (labeled as L) was 21.65. The

average score for individuals who ended up in a tie (labeled as E) was 24.16.

### 2.3 Previous Work and Baseline System

This data set was previously used for various purposes but (Nouri et al., 2013) was most similar to our current work in that it also tried to predict the goal and outcome in the negotiation, using a different set of features, and a slightly different formulation of the problem. (Nouri et al., 2013) used multimodal features (such as acoustic features and sentiments of the turns) for this purpose. We use initiative-features to build our prediction models. In order to make a baseline classifier, we used the following automatically derivable features from (Nouri et al., 2013):

- The mean and standard deviation of acoustic features automatically extracted;
- The amount of silence and speaking time for each speaker;
- Sentiment (positive, negative) and subjectivity scores calculated for words and turns
- number of words, turns, words per turn and words related to the negotiation objects

We used only features that were easily and automatically derivable, excluding features from (Nouri et al., 2013) such as the number of offers and the number of rejections or acceptances.

## 3 Initiative Labeling

A common way of structuring dialogue is with Initiative-Response pairs, or IR units (Dahlbäck and Jönsson, 1998), which are also similar to adjacency pairs (Levinson, 1983), or simple exchange units (Sinclair and Coulthard, 1975). Several researchers have also proposed multiple levels of initiative. For example, (Whittaker and Stenton, 1988) had levels based on the type of utterance (commands, questions, assertions, and prompts). (Chu-Carroll and Brown, 1997) posit two levels of initiative: discourse initiative, attained by providing reasons for responses, and critiques of proposed plans, and task initiative, obtained by suggesting new tasks or plans. Linell et al. examine several factors, such as initiative vs response, strength of initiative, adequacy of response, scope and focality of response (Linell et al., 1988). They end up with an ordered set of six possible strengths

of initiative. Each of these schemes is somewhat complicated by the fact that turns can consist of multiple basic elements.

Analyzing previous work, we can see that *initiative* breaks down into two distinct concepts. First there is providing unsolicited, or optional, or extra material, that is not a required response to a previous initiative. Second, there is the sense of putting a new discourse obligation (Traum and Allen, 1994) on a dialogue partner to respond. These two concepts often come together, such as for new questions or proposals that require some sort of response: they are both unsolicited and impose an obligation, which is why (Whittaker and Stenton, 1988) indicate that control should belong to the speaker of these utterances. However, it is also possible to have each one without the other. Statements can include new unsolicited material, without imposing an obligation to respond (other than the weak obligation to ground understanding of any contribution). Likewise, clarification questions impose new obligations on the other, but often do not contribute new material or are not optional, in that the responder can not reply appropriately without the clarification. For (Whittaker and Stenton, 1988), the issue of whether a question or assertion was a “response” would determine whether control went to the speaker or remained with a previous speaker. On the other hand, (Narayanan et al., 2000) call a response that includes unsolicited material “mixed-initiative” rather than “system initiative” for user responses that contain only prompted material.

Likewise, *response* can also be broken down into two related concepts. One concerns fulfilling obligations imposed by prior initiatives. To not do so could be considered rude and a violation of conversational norms in some cases. This is only relevant, if there is an existing initiative-related obligation as part of the conversational state. Another concept generalizes the notion of response to anything that contributes to the same topic and makes an effort to relate to prior utterances by the other party, whether or not it fulfills an obligation or whether there even is a pending obligation. This is like *relevance* in the sense of Sperber and Wilson (Sperber and Wilson, 1986) and Lascarides and Asher (Asher and Lascarides, 2003).

Our annotation scheme thus includes four labels, as indicated in Table 4. Each of the labels can either be present or absent from a dialogue

Time/Speaker	Example Utterance	Labels (R,F,I,N)
[1 : 58] Person 1:	Do you want to do just like one grab at a time? Or do you know how you want to divvy it up?	(-, -, I, N)
[2 : 13] Person 2:	Um, I'm just thinking.	(R, F, -, -)
[3 : 38] Person 1:	Do you want it? I'll take it. Um, do you want to do any trading?	(R, -, I, -)
[4 : 15] Person 2:	Um, how much is a banana for you?	(-, -, I, N)
[4 : 15] Person 1:	For me? A point, or two points. How much is the pepper worth?	(R, F, I, N)

Table 3: Sample Annotated Utterances

Label	Description
R	directly relates to prior utterance
F	fulfills a pending discourse obligation
I	imposes a discourse obligation
N	provides new material that is optional and not just fulfilling an obligation.

Table 4: Initiative Labels

segment. The annotation is done on each turn on the conversation. In general, a turn can consist of almost any combination of these four initiative labels (I,R,F,N). We thus treat each of these as an independent binary dimension, and code each turn as to which set of these labels it contains. Table 3 shows an example from the corpus with initiative annotations. More examples can be found in the Appendix, Tables 11, 12, and 13.

### 3.1 Inter Annotator Reliability

To assess the reliability of our annotations, approximately 10% of the dialogs (4 dialogs) were annotated by two annotators. The level of the agreement was then assessed using the Kappa statistic (Carletta, 1996; Siegel and Castellan, 1988). Table 5 shows the result of the assessment of the reliability of the annotations for the four annotation labels.<sup>1</sup> Based on this metric our results indicate that the annotators have reasonable level of agreement in labeling utterances with the I, F, N labels, though there is less reliability for the “related” label. Further work is needed to clarify the degree of relation that should count and also whether relation refers just to the immediately prior turn or something further back. The remainder of the dialogues were annotated by one annotator.

<sup>1</sup>Chance agreement is the probability of agreement using the frequencies of each label, but applied randomly.

	R	F	I	N
kappa	0.36	0.64	0.66	0.73
actual agreement	0.76	0.83	0.83	0.86
chance agreement	0.62	0.52	0.49	0.50

Table 5: Inter-Annotator Reliability Assessment

### 3.2 Initiative Taking Patterns

Table 6 shows the average frequency of each initiative label for each negotiation goal. We can see that competitive dialogues have more turns that impose and fulfill obligations than the other conditions, while individualistic dialogues include a higher percentage of turns introducing new material.

Label	R	F	I	N
Cooperative	0.79	0.35	0.40	0.33
Competitive	0.82	0.38	0.47	0.34
Individualistic	0.82	0.34	0.39	0.40

Table 6: Comparison of the Relative Frequency of the Initiative Labels for Each Goal

Table 7 shows the relative frequency of initiative labels for the different outcome conditions. The higher scoring participants had a higher frequency of initiative-related turns (labels I and N), while their lower scoring partners had a higher frequency of responsive turns (R,F). Equal scoring participants tended to pattern closer to higher scoring participants, concerning responses, but closer to lower scoring participants, considering initiative.

### 3.3 Initiative Features

After the Initiative annotation was done, the following features were automatically extracted:

- the count of each label (I,F,R,N) per negotiation and per person

Label	R	F	I	N
H	0.80	0.35	0.47	0.38
E	0.81	0.35	0.40	0.34
L	0.84	0.38	0.43	0.36

Table 7: Comparison of the Relative Frequency of the Initiative Labels for Each Score Label

- the ratio, difference and absolute difference of the number of labels for each person against the number of labels for their negotiation counterpart
- the above measures normalized by the number of turns in dialog
- **Within-turn patterns** the number of all possible combinations of labels for each utterance. There are 16 possible combinations for the 4 types of labels that can be shown as tuples (R,F,I,N). Refer to Table 5 for examples.
- **Across-turn Patterns** the number of all possible sequences of labels across two adjacent turns. There are also 16 possible combinations capturing how often each label is followed by labels. For example, the feature (I,F) applies to all two-turn sequences where the first turn contains label I and the second contains label F, such as in the last two lines of Figure 3. We count the these features for the dialogue and for each speaker.

All of the above features were automatically extracted from the annotated dialogues. We examined four different spans of the dialogues, to investigate whether the most salient initiative information comes early in the dialogue or requires the full dialogue. We calculated features for the first quarter (q1), first half (q2), first three quarters (q3), and the whole negotiation (q4).

## 4 Prediction Models

We conducted experiments to recognize negotiation goal and score for each of the 82 negotiators. We made prediction models for recognizing the goal and outcome for each individual. For the prediction models, we compared the result of support vector machine (SVM- with the polynomial kernel function) classifier, Naive Bayes and Decision Tree. None of the classifiers outperformed the others on all cases, we are reporting the result

of SVM classifier here. Considering the size of our dataset which consists of 82 samples (41 pairs of individuals) and the distribution of the samples in different classes, we decided to use the 10-fold cross validation paradigm for our prediction tasks. In splitting the dataset into the folds we controlled so that the participants from the same negotiation were not split across training and test sets. We trained and tested at the end of the each quarter of the negotiation.

We used three sets of features to make three prediction models for each task:

1. Non-initiative features from (Nouri et al., 2013), described in section 2.3. We refer to these non-initiative features as IS2013’ from this point on.
2. Initiative features
3. All features combined.

We compare the performance of these models with two baseline prediction models: one that chooses one of the outcomes at random, and one that predicts the majority class for all instances. In the upcoming sections, we use q1, q2, q3 and q4 to refer to the ends of the first, second, third and the fourth quarters of the negotiation (e.g. q3 includes all data from the first three quarters, but not the last).

### 4.1 Automatic Prediction of Goal

This task predicts whether the negotiators are following the cooperative, competitive or individualistic instructions. It is important to note that none of the features used require understanding of the content or a semantic analysis of the conversation. However, using these basic features it’s possible to make the classification into the mentioned three classes with accuracy that is significantly higher than chance. The average accuracy of prediction at the four different points in the negotiation are shown in Table 8.

	q1	q2	q3	q4
Random	0.33	0.33	0.33 ♣	0.33 ♣
Majority	0.37	0.37	0.37 ♣	0.37
IS2013	0.41	0.34	0.40 ♣	0.48 *†
Initiative	0.29 ♣	0.52 *† ♣	0.48 *†	0.29 ♣
Combined	0.41	0.40	0.57 *†	0.44 *

Table 8: Accuracy of the Prediction of Goal

We use the two-sided binomial test to measure the significance of the differences of the prediction models’ performances. Tables 8, 9 and 10 use symbols to indicate the results of these significance tests. Symbols (\*), (†) and (♣) show which models’ performances are significantly different from the random baseline, majority baseline, and the “combined” classifier, respectively ( $p < 0.05$ ).

The combined classifier is always better than both baselines, as well as the lower of classifiers for the IS2013 and Initiative features. In q3, where the two are close in performance, the combined classifier outperforms both. Note that except for q3, these numbers are lower than those reported by (Nouri et al., 2013). However the prior work did not ensure that both individuals in a negotiation were in the same training/test partition, and some features are the same for both participants. That work also made use of higher-level features, such as the offers, and final distributions of items.

## 4.2 Automatic Prediction of Outcome

In this task the goal is to predict how a participant in the negotiation is going to do in terms of the scores at the end of the negotiation. The model predicts whether the negotiator would score higher, lower or equal to the other player at the end of the different quarters of the negotiation. Results are shown in Table 9.

	q1	q2	q3	q4
Random	0.33	0.33	0.33	0.33 ♣
Majority	0.41	0.41	0.41	0.41
IS2013	0.43 *	0.34	0.23 *†♣	0.39
Initiative	0.37	0.35	0.32	0.39
Combined	0.38	0.40	0.41	0.46 *

Table 9: Accuracy of the Prediction of Outcome

Except for the combined model in q4, these models are not able to significantly outperform the baseline of selecting the majority class (equal score). Results were also presented for outcome in (Nouri et al., 2013), however only the final quarter results are comparable, since that paper predicted interim quarter-end results rather than final results. Also, that work did not make sure that both participants in a negotiation were in the same training-test partitions, and used features related to the final deal, that are directly related to outcome.

Because the relative score was not important for cooperative negotiations, where both sides are just

trying to maximize their combined points, we next examined outcome for the 28 pairs in individualistic and competitive conditions. Results are shown in table 10. The combined classifier outperforms all the other classifiers, starting from quarter 2.

	q1	q2	q3	q4
Random	0.33	0.33 ♣	0.33 ♣	0.33 ♣
Majority	0.38	0.38	0.38	0.38 ♣
IS2013	0.39	0.36 ♣	0.36 ♣	0.34 ♣
Initiative	0.27	0.41	0.36 ♣	0.38 ♣
Combined	0.35	0.50 *	0.50 *	0.55 *†

Table 10: Accuracy of the Prediction of Outcome for Negotiations that are not Cooperative

## 5 Conclusion

We demonstrated how discourse initiatives in negotiation dialog can be used for automatically making predictions about other aspects of the negotiation such as the goals of the negotiators. Previous work has mostly focused on using non-verbal cues for accomplishing similar tasks but they have not used discourse features like initiatives. We also show that initiative features can give clues about the final outcome for the negotiators. Making such predictions are generally challenging tasks even for humans and require understanding of the content of the negotiations. From a dialog system’s perspective our results show how more information can be derived about the users intentions and performance by analyzing their discourse behavior.

## 6 Future Work

The annotations of the initiative taking patterns are done manually at this point. Automatic labeling of the utterances with the initiative tags is our next step. We will use the labels in our dataset for learning how to automatically label new negotiation datasets. We think that HMM and HCRF methods due to their ability to capture the sequential and temporal aspect of the negotiation might be better methods for building the prediction models. We are interested in further analysis of the relationship between initiatives and other aspects of negotiation such as intentions and the use of language. We also want to measure the suitability of our annotation scheme for initiatives for other types of conversations as well, and examine the

relationship of initiative patterns in negotiations compared to other dialogue genres.

## Acknowledgments

We like to thank Kristina Striegnitz, Christopher Wienberg, Angela Nazarian and David DeVault for their help with this work. The effort described here has been sponsored by the US Army. Any opinions, content or information presented does not necessarily reflect the position or the policy of the United States Government, and no official endorsement should be inferred.

## References

- Nicholas Asher and Alex Lascarides. 2003. *Logics of Conversation*. Cambridge University Press.
- Michael Baker. 1994. A model for negotiation in teaching-learning dialogues. *Journal of artificial intelligence in education*.
- Jean Carletta. 1996. Assessing agreement on classification tasks: the kappa statistic. *Computational linguistics*, 22(2):249–254.
- Peter J Carnevale. 2013. *Audio/video recordings of bilateral negotiations over synthetic objects on a table that vary in monetary value*. Unpublished raw data.
- Jennifer Chu-Carroll and Michael K. Brown. 1997. Tracking initiative in collaborative dialogue interactions. In *Proceedings of the Thirty-Fifth Meeting of the Association for Computational Linguistics*, pages 262–270. Association for Computational Linguistics.
- Nils Dahlbäck and Arne Jönsson. 1998. A coding manual for the linköping dialogue model. unpublished manuscript.
- Anthony Jameson, Bernhard Kipper, Alassane Ndiaye, Ralph Schäfer, Joep Simons, Thomas Weis, and Detlev Zimmermann. 1994. *Cooperating to be non-cooperative: The dialog system PRACMA*. Springer.
- Sarit Kraus, Penina Hoz-Weiss, Jonathan Wilkenfeld, David R Andersen, and Amy Pate. 2008. Resolving crises through automated bilateral negotiations. *Artificial Intelligence*, 172(1):1–18.
- Stephen C. Levinson. 1983. *Pragmatics*. Cambridge University Press.
- Per Linell, Lennart Gustavsson, and Päivi Juvonen. 1988. Interactional dominance in dyadic communication: a presentation of initiative-response analysis. *Linguistics*, 26(3):415–442.
- Shrikanth Narayanan, Giuseppe Di Fabbrizio, Candace A. Kamm, James Hubbell, Bruce Buntschuh, P. Ruscitti, and Jerry H. Wright. 2000. Effects of dialog initiative and multi-modal presentation strategies on large directory information access. In *INTERSPEECH*, pages 636–639. ISCA.
- Elnaz Nouri, Sunghyun Park, Stefan Scherer, Jonathan Gratch, Peter Carnevale, Louie Philippe Morency, and David Traum. 2013. Prediction of strategy and outcome as negotiation unfolds by using basic verbal and behavioral features. In *proceedings of the Interspeech conference*.
- Candace L. Sidner. 1994. An artificial discourse language for collaborative negotiation. In *Proceedings of the Fourteenth National Conference of the American Association for Artificial Intelligence (AAAI-94)*, pages 814–819.
- S. Siegel and N. J. Castellan. 1988. *Nonparametric statistics for the Behavioral Sciences*. McGraw-Hill, 2nd edition.
- J. M. Sinclair and R. M. Coulthard. 1975. *Towards an analysis of Discourse: The English used by teachers and pupils*. Oxford University Press.
- Dan Sperber and Deirdre Wilson. 1986. *Relevance: Communication and Cognition*. Harvard University Press.
- David R. Traum and James F. Allen. 1994. Discourse obligations in dialogue processing. In *Proceedings of the 32<sup>nd</sup> Annual Meeting of the Association for Computational Linguistics*, pages 1–8.
- David Traum, Stacy C Marsella, Jonathan Gratch, Jina Lee, and Arno Hartholt. 2008. Multi-party, multi-issue, multi-strategy negotiation for multi-modal virtual agents. In *Intelligent Virtual Agents*, pages 117–130. Springer.
- Marilyn Walker and Steve Whittaker. 1990. Mixed initiative in dialogue: An investigation into discourse segmentation. In *Proceedings of the 28th annual meeting on Association for Computational Linguistics*, pages 70–78. Association for Computational Linguistics.
- Richard E Walton and Robert B McKersie. 1991. *A behavioral theory of labor negotiations: An analysis of a social interaction system*. Cornell University Press.
- Steve Whittaker and Phil Stenton. 1988. Cues and control in expert-client dialogues. In *Proceedings ACL-88*, pages 123–130.

## Appendix: Sample Annotated Negotiations

The following tables show examples of each of the goal conditions with initiative labeling, using the scheme in Table 4.

<b>Time</b>	<b>Speaker: Utterance</b>	<b>Labels</b>
[2 : 18]	2: So what's, so what's everything worth to you?	(R,F,I,N)
[2 : 20]	1: Um, so apples are three, bananas are three, strawberries are one, peppers are one, and lemons are nothing.	(-, -, I, N)
[2 : 33]	2: Okay so for me peppers are three, bananas are three, and apples and strawberries are one.	(R, F, -, -)
[2 : 39]	1: Lemons are zero.	(R, -, -, -)
[2 : 40]	2: Yeah.	(R, -, -, -)

Table 11: Sample Annotated Cooperative Negotiation

<b>Time</b>	<b>Speaker: Utterance</b>	<b>Labels</b>
[1 : 40]	2: So, I think I need peppers and bananas for my restaurant.	(-, -, -, N)
[1 : 46]	1: Okay. Um, well I really need. I want five apples and um, five bananas. Five apples and five bananas.	(R, -, I, N)
[2 : 05]	2: Um, how about this: You take five apples, and I take five peppers and we can share the bananas.	(R, F, I, N)
[2 : 13]	1: Okay. If I give you, if I give you five or if I give you, if we were to share the bananas, if I take three bananas, I'll give you three lemons.	(R, F, I, N)
[2 : 23]	2: But we don't need lemons in our restaurant. We only use lemons for our store.	(R, F, -, N)
[2 : 27]	1: Okay. So, um, I need bananas, like that's gonna be my top.	(R, -, -, N)

Table 12: Sample Annotated Competitive Negotiation

<b>Time</b>	<b>Speaker: Utterance</b>	<b>Labels</b>
[3 : 22]	2: How about we do this. You take two of these, I take one, and since we have five here, I take three, you take two.	(-, F, I, N)
[3 : 37]	1: I'm not interested in lemons at all. But I can give you...	(R, F, -, N)
[3 : 52]	2: At my restaurant, one of our dessert dishes is with strawberries, so strawberries are very important to me.	(-, -, -, N)
[4 : 00]	1: Okay. I'm willing to give you all the strawberries if you give me a banana and two apples. I'm also willing to give you these two.	(R, -, -, N)
[4 : 23]	2: So you're going to give me those two?	(R, -, I, -)
[4 : 24]	1: You can have everything on this side, I just want two apples and a banana.	(R, F, -, -)
[4 : 30]	2: Two apples and a banana? Yeah, let's go.	(R, -, -, -)
[4 : 39]	1: We have a deal.	(R, F, -, N)

Table 13: Sample Annotated Individualistic Negotiation