Construction and Analysis of a Persuasive Dialogue Corpus

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Abstract Persuasive dialogue systems, systems which are not passive actors, but actually try to change the thoughts or actions of dialogue participants, have gained some interest in recent dialogue literature. In order to construct more effective persuasive dialogue systems, it is important to understand how the system's human counterparts perform persuasion. In this paper, we describe the construction of a corpus of persuasive dialogues between real humans, and an analysis of the factors that contribute to the persuasiveness of the speaker. Specifically, we collect dialogue between 3 professional salespeople and 19 subjects, where the salesperson is trying to convince a customer to buy a particular product. We annotate dialogue acts of the collected corpus, and based on this annotated corpus, perform an analysis of factors that influence persuasion. The results of the analysis indicate that most common dialog acts are information exchange, and about 30% of the persuader's utterances are argumentation with framing aiming at making listener select a particular alternative. Finally, we perform a regression analysis of factors contributing to the satisfaction of the customer and persuasive power of the salesperson. We find that factors derived from dialogue acts are particularly effective predictor of satisfaction, and factors regarding framing are particularly effective predictors of persuasive power.

1 Introduction

In traditional dialogue systems, the main abstract goal is to increase user satisfaction, and this is achieved by helping users perform a specific task [1], helping users with uncertain needs discover the information they are interested in [2], or entertaining users through chat [3]. On the other hand, there has also been a focus in recent years on persuasive technology and computational deception, where the computer is not simply a passive actor, but actively tries to change the thoughts or habits of the users [4, 5]. This persuasive technology has been widely used as an indirect means to improve user satisfaction by helping to improve bad habits [6], and also has been used to identify factors of user decisions [7], for selling items, and for interactive advertisement [4]. There is also some related research in dialogue on optimizing policies of dialogue systems for argumentation [8] or for persuading users to make a choice that satisfies both the user's goal and that of the system [9].

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However, these persuasive dialogue systems are in their first stages of development, and are far from the abilities of their human counterparts, both in terms of persuasive ability, and also ability to achieve user satisfaction. Thus, in this paper our aim is to elucidate which factors contribute to persuasive power and user satisfaction in the context of human persuasion. To do so, we focus on a common real world situation in which persuasion is a factor: sales conversation. In this case, the salesperson (persuader) tries to convince the customer (persuadee) to purchase a certain product while maintaining customer satisfaction. By focusing on this type of dialogue, we hope to elucidate features of dialogue where both the persuader and the persuadee are satisfied.

In particular, in this paper we make the following contributions.

- We collect and annotate a corpus of nearly five half hours of dialogue between subjects and professional salespeople, who are trying to convince the subjects to buy a camera. We describe data collection and tagging of dialogue acts over two dimensions of analysis of the recorded dialogue.
- We perform an analysis of the major dialog acts constituting the corpus, including differences between the persuader and persuadee.
- We perform a regression analysis to identify the relationship between persuasive success, persuadee satisfaction, and a number of salient factors. Knowledge obtained by the analysis is a guide for not only dialogue system construction, but may also provide insights from the perspective of human persuasion.

2 Related Work

There has been some previous work on corpus collection and annotation in the context of persuasive dialogue. For example, Georgila et al. [10] proposed a tag scheme for persuasive dialogue and argumentation. In the tag scheme that was proposed in this research, argumentation tags were sorted by their role. For example, tags are given to roles such as, “invalidate argument,” “accept argument,” etc. On the other hand, we design argumentation tags that focus on the user’s preference information and particularly framing [11]. This information is known to be important for persuasion, and is not captured by a purely argumentative tagging scheme.

Nguyen et al. [12] also examined the relationship between boredom of persuadees, success of persuasion and other salient factors in persuasive dialogue. This research analyzed persuasive dialogue between an embodied agent and human, while we analyze dialogue between two humans. In addition, the study examined the effects of the persuaders message style, persuadees participation (conversing with the agent or only listening), and the number of persuaders. In contrast, we analyze factors based on the user’s preference and framing.

In addition, our research proposes a predictive model of the achievement of persuasion and user satisfaction, and we can evaluate other persuasive dialogues semi-automatically by using this model. This is also an additional contribution over the previous works.

Table 1 Details of the scope of the sales dialogue corpus.

Salesperson	Experience	Age	Dialogues	Minutes	Salesperson Words	Customer words
A	4 years	40's	10	127	33,330	6,451
B	3 years	30's	12	106	32,835	7,544
C	2 years	30's	12	104	24,821	7,675
Total			34	337	90,986	22,626

Table 2 The beginning of a dialogue from the corpus (translated from Japanese)

Speaker	Transcription	GPF Tag
Customer	Well, I am looking for a camera, do you have camera B?	PROPOSITIONALQ
Salesperson	Yes, we have camera B.	CONFIRM
Salesperson	Did you already take a look at it somewhere?	PROPOSITIONALQ
Customer	Yes. On the Internet.	CONFIRM
Salesperson	It is very nice. Don't you think?	CHECKQ
Customer	Yes, that right, yes.	AGREEMENT

3 Collection of a Camera Sales Dialogue Corpus

3.1 Data Collection

As a typical example of persuasive dialogue, we choose dialogue between a salesperson (persuader) and customer (persuadee), in which the salesperson attempts to convince the customer to purchase a particular product (decision) from a number of alternatives (decision candidates). We will define this type of dialogue as "sales dialogue." More concretely, we assume the customer is in an appliance store looking for a camera, and the customer must decide which camera to purchase from 5 alternatives. Prior to recording, the salesperson is given the description of the 5 cameras and instructed to try to convince the customer to purchase a specific camera (the persuasive target). This persuasive target is invariant over all subjects. The customer is also instructed to select one preferred camera from the catalog of the cameras, and choose one aspect of the camera that is particularly important in making their decision (the determinant). During recording, the customer and the salesperson converse and refer to the information in the camera catalog as support for their arguments. The customer can close the dialogue whenever they want, and choose to buy a camera, not buy a camera, or reserve their decision for a later date.

We collect a role-playing corpus with participants consisting of 3 salespeople from 30 to 40 years of age and 19 customers from 20 to 40 years of age. All salespeople have experience working in an appliance store. The total number of dialogues is 34, and the total time is about 340 minutes. Table 1 shows the scope of the corpus, and Table 2 show an example transcript of the beginning of one dialogue.

3.2 Annotation of Dialogue Acts

3.2.1 Dialogue Act Scheme

In order to perform an in-depth analysis of the recorded dialogues, we annotate each utterance with three varieties of tags, the first covering dialogue acts in general, and the rest being specifically defined for analyzing persuasion (argumentation and framing). Formally, the relationship between collected dialogues and annotated tags is defined as follows:

$$U = \{u_1, u_2, ..., u_K\} \tag{1}$$

$$u_k = \langle r, g, A, F \rangle \tag{2}$$

where U represents a dialogue, and is composed of sequences of utterances u_k. u_k is annotated with four varieties of tags, a role tag r which takes the value SALES for the salesperson or CUST for the customer, a dialogue act tag g, argumentation tags A, and framing tags F. Each of these are introduced in later paragraphs in this section.

As a tag set to represent traditional dialogue acts, we use the general-purpose functions (GPF) defined by the ISO international standard for dialogue act annotation [13]. Annotated GPF tag g is defined to be one of the tags in this set. In order to assign only one GPF tag for each utterance, we first annotate the GPF tags, and if a single turn would be assigned multiple tags, we split the turn into multiple utterance units. Table 2 shows examples of GPF tags. For example, "PROPOSITIONALQ" is used to annotate utterances intended to confirm that an opinion or fact is correct.

To annotate information regarding the aspects of each utterance particularly relevant to persuasion, we devise a separate tag set based on knowledge of persuasion and attitudes in psychological research [14]. In this research, it has been suggested that humans generally evaluate decision candidates by selecting based on several determinants weighted by the user's preference. In particular, it has been suggested that the *framing* method is an effective way of increasing persuasive power. In this work, we focus on negative/positive framing [11, 15], which uses emotionally charged words to explain particular alternatives, with negative framing using negative words and positive framing using positive words. Through a preliminary analysis of our sales dialogue data, we built a hypothesis that argumentation using framing plays an important role in sales dialogue and decided to pursue this hypothesis further through annotation of the data.

The annotated argumentation tag A is defined as follows:

$$A = \{a_1, a_2, ..., a_J\} \tag{3}$$

$$a_j \in ALT \tag{4}$$

where variable a_j is selected from the set ALT of possible alternative (in this case, the five cameras). In the annotated corpus the argumentation tag is described by the following format, similar to XML:

Table 3 A argumentation tag annotation of a salesperson's utterance

`<arg alt=`A`><fra alt=`A`,polarity=`POS`,pref=`NO`>`(Camera A is) able to achieve performance of comparable single-lens cameras and can fit in your pocket `</fra>`, this is a point.`</arg>`

`<arg alt=`a_j`>` ... `</arg>` (5)

We also define annotated framing tags F as follows:

$$F = \{f_1, f_2, ..., f_I\} \tag{6}$$
$$f_i = \langle a_i, p_i, r_i \rangle \tag{7}$$
$$a_i \in ALT \tag{8}$$
$$p_i \in \{\text{POS}, \text{NEG}\} \tag{9}$$
$$r_i \in \{\text{YES}, \text{NO}\} \tag{10}$$

where a_i represents the target alternative, p_i takes value NEG if the framing is negative, and POS if the framing is positive, and r_i represents whether the arguments contain a reference to the persuadees preferred determinant, taking the value TRUE if contained, and FALSE is not contained. The user's preferred determinant is annotated on the basis of the results of questionnaire. In the annotated corpus, f_i is described by the following format:

`<fra alt=`a_i`,polarity=`p_i`,pref=`r_i`>` ... `</fra>` (11)

Table 3 shows an example of annotation of positive framing (p=POS) about the performance of Camera A (a=A). In this example, the customer answered that his preference is the price of camera, and this utterance does not contain any description of price. Thus, r=NO is annotated. Finally, we annotate `<arg alt=`A`>` around the entire utterance because at least one `fra` tag exists.

3.2.2 Reliability of Annotation

To evaluate the reliability of the annotation, we randomly selected 10% of the collected data and evaluated the data for inter-annotator agreement. The GPF and argumentation tags were evaluated on the basis of the agreement between two annotators. The description section and the variables of the `fra` tag were evaluated by a second annotator regarding whether the annotation result of the primary annotator was acceptable or not. The acceptability rate is calculated as the percentage of tags judged as appropriate by the second annotator out of the tags annotated by the primary annotator.

Initially, the agreement of the 18 annotated GPF tags was only 30%. As this is too low to achieve reliable results in our analysis, we merged tags with low agreement, resulting in a total of 6 tags and an agreement of 76% (see Table 4). This agreement is comparable to other research in a different task [16]. We use these merged GPF

Table 4 Result of the merging GPF tags

GPF tag	PROPOSITIONALQ, SETQ, INFORM, ANSWER, COMMISSIVE, DIRECTIVE

tags in the analysis of later sections. The agreement of the argumentation tag was 94%, and, the acceptability rate of the description section and target candidate of the framing tag was 94%, polarity was 100%, and of preference information was 82%.

4 Success Measures and Dialogue Factors

Given the corpus described in the previous section, we would now like to elucidate the factors that contribute to persuasive power and user satisfaction.

4.1 Success Measures for Persuasive Dialogue

First we define our measures for success of persuasive dialogue. As the dialogue consists of two interlocutors, we define a successful dialogue as a dialogue where both participants achieve their goal. As with dialogue systems, simply using satisfaction as measure of dialogue success for the persuadee seems appropriate [17]. However, as far as we are aware there is no widely shared evaluation criterion in the relatively young field of persuasive technology. Thus we propose two measures for the success for the persuader: 1) Whether the persuadee finally chooses the persuasive target at the end of the dialogue, and 2) the amount the persuadees intention changed about the persuasive target as the result of the dialogue.

We measured these values by conducting a questionnaire of the persuadees to measure satisfaction, intention change about the persuasive target, and success of persuasion, as described below:

Satisfaction (*Sat*): The persuadee's subjective satisfaction with the persuader defined as a 5 level score of customer satisfaction (1: Not satisfied，3: Neutral，5: Satisfied).

Intention change (ΔIn): The amount the persuadees intention to buy the persuasive target changed as a result of the dialogue. We conducted a questionnaire about intention to buy persuasive target (1: Don't want to buy，3: Neutral，5: Want to buy) before (In_{before}) and after (In_{after}) the dialogue. ΔIn is measured as follows:

$$\Delta In = In_{after} - In_{before} \tag{12}$$

Persuasive success (*Suc*): *Suc* takes the value 1 when the customer decides to purchase the persuasive target at the end of dialogue, and 0 otherwise.

4.2 Dialogue Factors

In this section, we describe several measurable characteristics of the dialogue that may contribute to persuasive power and user satisfaction. These include factors regarding negative/positive framing, original preference of the persuadee, and dialogue acts.

4.2.1 Factors Regarding Negative/Positive Framing

Two dialogue factors to measure negative-positive framing are defined as follows:

Negative framing ratio for non-target ($R_{\mathrm{NEG},a\neq t}$): The ratio of utterances stating negative facts about alternatives other than the persuasive target, where we define t as the persuasive target:

$$R_{\mathrm{NEG},a\neq t} = \frac{\sum_{k=1}^{K} \delta(\exists_{f\in u_k.F}(f.a \neq t \wedge f.p = \mathrm{NEG}))}{\mathrm{K}}, \tag{13}$$

where δ is Kronecker's delta, 1 when the condition is true, and 0 otherwise.

Positive framing ratio for target ($R_{\mathrm{POS},a=t}$): Likewise the ratio of utterances by the persuader positively framing the persuasive target:

$$R_{\mathrm{POS},a=t} = \frac{\sum_{k=1}^{K} \delta(\exists_{f\in u_k.F}(f.a = t \wedge f.p = \mathrm{POS}))}{\mathrm{K}}. \tag{14}$$

4.2.2 Factors Regarding the Persuadees Original Preference

We also define 3 kinds of factors to measure the persuadees attitude change.

Conveyed preferred determinant (CPD_a): Whether the persuadee has been told by the persuader that alternative a satisfies the determinant that the persuadee has mentioned as important in the pre-dialogue questionnaire

$$CPD_a = \delta(\exists_f f =< a, \mathrm{POS}, \mathrm{YES} >). \tag{15}$$

Prior candidate evaluation (PCE_a): The persuadees evaluation of alternative a at the beginning of dialogue. In this paper, we calculated one feature for each alternative that is 1 if that alternative is selected by the persuadee as preferred before the dialogue and 0 otherwise.

Prior persuasive target evaluation ($PPTA$): The persuadees evaluation of the persuasive target at the beginning of the dialogue as measured by questionnaire.

4.2.3 Other Factors

In addition to the above factors, we defined factors based frequency of traditional dialogue acts and argumentation, and total time.

Number of argumentation events (I): The total number of occurrences of argumentation tags during the dialogue I.

Table 5 Distribution of general purpose function (GPF) and argumentation tags

	GPF						Argument		
	PropQ	SetQ	Commisive	Directive	Answer	Inform	Tar	NonTar	Both
Salesperson	14%	4%	6%	8%	16%	45%	25%	3%	3%
Customer	21%	2%	9%	5%	17%	37%	-	-	-

Frequency of general purpose function ($R_{r,g}$): The ratio of each GPF tag for each role in the dialogue

$$R_{r,g} = \frac{\sum_i^I \delta(u_{i=1} = \langle r, g, \bullet, \bullet \rangle)}{\sum_i^I \delta(u_{i=1} = \langle r, \bullet, \bullet, \bullet \rangle)}. \tag{16}$$

Total time (TT): Total dialogue time in seconds.

5 Analysis

In this section, we present a manual analysis of the dialogue acts included in the corpus, and a linear regression analysis of the factors that contribute to persuasion.

5.1 Analysis of Dialog Acts

First, in order to perform a general analysis of the main dialogue acts comprising persuasive dialogue, we show the proportion of argumentation tags of all utterances of the salesperson and the GPF distribution for both the customer and salesperson in Table 5. From the result, we can see information presentation (Answer, Inform) tags cover more than half of both of the customer and salesperson utterances. In addition, when considering information seeking tags (PropQ, SetQ), the percentage reaches about 80%.

31% of all dialogue acts of the salesperson are arguments. This indicates that the argumentation tag proposed in Section 3 is highly relevant in this situation. A more detailed breakdown is that 25% of arguments target only the persuasive target, 3% of arguments target only an alternative other than the persuasive target, and 3% of arguments target both the persuasive target and a non-persuasive target. This indicates that, in persuasive dialogue, the persuader rarely suggests arguments for selecting alternatives other than persuasive target, but does occasionally mention other options.

Table 6 shows mean persuadee satisfaction categorized by initial and final choice of alternative. The results seem to indicate that it is possible to achieve satisfaction and persuasion simultaneously when the customer has initially chosen the persuasive target or doesn't have an initial choice, but it is harder when the customer has initially chosen an alternative other than the persuasive target. However, the data is still somewhat small to make conclusions about this fact.

Table 6 Average satisfaction (and number of dialogues) for each initial and final choice.

		Final Choice		
		PT	Not PT	None
Initial Choice	PT	4.0(3)	-	5.0(5)
	Not PT	2.0(2)	2.0(1)	4.4(7)
	None	4.0(3)	2.0(2)	3.4(7)

Table 7 Linear regression for satisfaction and persuadees intension change, and logistic regression for success of persuasion with selected factors. All factors are normalized.

	w_0+w_1x_1+...w_nx_n						R^2
Sat	+3.56	*Bias*	+.501	$R_{\text{SALES,PROPQ}}$	-.509	$R_{\text{SALES,COMMISIVE}}$	.396
ΔIn	+.920	*Bias*	-.475	$R_{\text{NEG},a\neq t}$	+.625	*I*	.640
	-.303	CPD_E	+.429	*PPTA*	+.295	PCE_C	
	+.422	$R_{\text{CUST,ANSWER}}$	+.464	$R_{\text{CUST,INFO-PROV}}$	+.276	$R_{\text{CUST,COMMISIVE}}$	
	-.368	*TT*					
	w_0+w_1x_1+...w_nx_n						Accuracy
Suc	-4.349	*Bias*	+2.00	CPD_B	-8.14	PCE_B	80%
	-2.12	*TT*					

5.2 Regression Analysis of Factors in Persuasion

To analyze the relationship between the success measures in Section 4.1 and factors in Section 4.2, we performed a regression analysis to discover the important factors and measure accuracy of the prediction model. Factor selection is performed using step-wise multinomial linear regression [18]. We repeatedly perform multinomial regression and exclude predictors that do not sufficiently contribute to the model until we get a model for which all of the predictors are significant. In this research, we excluded any predictor with a *p*-value above .25 at each iteration, and the final model is comprised of predictors that are statistically significant ($p < .05$). Prediction accuracy of the selected factors is evaluated through leave-one-out cross validation after the selection.

Table 7 shows the results. First focusing on the factors for satisfaction, we can see that predictors account for 39% of the variance of satisfaction. Focusing on the variables selected as useful in the linear regression results, we can see that both of the two features come from the salesperson's GPF tags. The weight of $R_{\text{SALES,PROPQ}}$ is high, which indicates that by asking many questions, the salesperson can make the customer feel more satisfied with the conversation. The reason why the weight of $R_{\text{SALES,COMMISIVE}}$ is assigned a large negative value is that $R_{\text{SALES,COMMISIVE}}$ represents the degree of failure in answering the customer's questions. For example, most of the utterances such as "Sorry, I don't know. I'll take a look" are annotated COMMISIVE. This result is interesting, as it shows that customer satisfaction is largely dependent on the salesperson, a fact that may guide our implementation.

Next, focusing on the weight of factors in the linear regression results for opinion change, factors derived from argumentation tags account for 46% of total weight, making the largest contribution to prediction. The highest weight is *I*, indicating that more argumentation for the persuasive target results in a larger change in the opinion of the persuadee. On the other hand, *PPTA* is assigned a large negative weight, indicating the persuader does not change the opinion of a persuadee who already wanted to select the persuasive target a priori, a natural result as the persuader will not want to change an already favorable result. The weight of factors derived from the GPF tag account for 33% of the total weight. Especially, the ratio of information-exchange ($R_{\text{CUST,ANSWER}}$, $R_{\text{CUST,INFO-PROV}}$) assumes a high weight, indicating that making the customer speak more contributes to opinion change.

Finally, looking at the result for logistic regression over persuasive success, we can see that 80% of the data are correctly predicted, compared to a chance rate of 68% when predicting only failure of persuasion. Focusing on the weights of the variables in the logistic regression result, the weight of PCE_B is relatively high, indicating that if customers select camera B pre-dialogue, the persuasion becomes more difficult. CPD_B is the only variable with positive weight, indicating that informing the persuadee about alternatives other than the persuasive target that match the persuadee's preference increases the persuasive power for the persuasive target. We hypothesize the reason why only camera B appeared in predictors is that camera B was chosen many times compared to other alternatives, and appeared as the alternative for comparison to the persuasive target in many dialogues.

Combining all these results together, we can see that the persuader is required to use a sophisticated dialogue strategy, as different factors contribute to the achievement of successful persuasion and persuadee satisfaction. However in Table 7, we can also see that no predictor influences both successful persuasion and persuadee satisfaction. Therefore, the persuader could potentially perform dialogue to achieve both goals simultaneously. For example, the persuader would perform a large amount of argumentation to achieve persuasion, and ask many questions to increase user satisfaction. However, as observed by the negative weight for TT, intention change of the persuadee also tends to decrease as time passes. Thus, the persuader must achieve both goals in a short time, considering interaction efficiently and accurately predicting the persuadees interest in each of the alternatives.

6 Conclusion

In this paper, we analyzed persuasive dialogue between humans, focusing on the factors that contribute to persuasion and satisfaction. In order to do so, we collected a corpus of dialogues between salespeople and customers, and defined an argumentation tag scheme and dialogue factors for predicting dialogue goals.

The experimental results indicate that the main dialog acts that compose the dialogue are information exchange and argumentation. A regression analysis demonstrated that argumentation contributes effectively to the achievement of persuasion, and factors derived from GPF were effective for predicting satisfaction.

Our next step in this research is to incorporate these observations into the persuasive dialogue framework of [9]. In addition, this experiment result is still limited in the corpus we collected. We will investigate the flexibility of the proposed tag scheme and persuasive factors on other persuasion tasks.

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