Dialog Management for Credit Card Selling via Finite State Machine Using Sentiment Classification in Turkish Language

Gizem Soğancıoğlu, Tolga Çekiç, Bilge Köroğlu, Mert Basmacı and Onur Ağın

R&D and Special Projects Department
Yapı Kredi Technology, Istanbul, Turkey
Email: {gizem.soganciolgu, tolga.cekic, bilge.koroglu, mert.basmaci}@yapikredi.com.tr

***Abstract*—In this paper, we propose a goal-oriented chat bot, which aims to sell a suitable credit card to customers according to their needs. Our proposed chat bot detects customer's needs, uses this information to recommend a credit card, answers specific queries from customers and gathers the required information to start a credit card application process. This goal-oriented dialog management system is designed for Turkish Language and it makes use of a Finite State Machine (FSM) structure to achieve its goals. This design allows the chat bot to facilitate the flow of conversation and prevents giving unrelated answers to customers. The chat bot has unique tasks to perform in each state of FSM. Transitions between states are processed with the events, which are determined by outputs of the sentiment analysis model. Due to Turkish being an agglutinative language we perform morphological analysis of words to perform this task. Besides driving the conversation flow to achieving its goal, the chat bot can detect when customers ask questions and proceeds to the related state where the chat bot retrieves a proper answer. Since sentiment classification model forms the basis for keeping the chat bot in proper states, we experimented with different classification algorithms with different features and compared their successes. K-Nearest Neighbor algorithm using bag-of-words and lexicon features yielded the best results with the 0.822 f-score. Moreover, human evaluations for chat bot showed that using FSM and managing the conversation with the sentiment classification model for Turkish language is a promising solution.**

***Keywords*–Chat bot; Dialog Management; Sentiment Classification; Finite State Machine; Conversational Bot**

I. Introduction

Intelligent conversation agents, or chat bots, are being considered increasingly for helping people with solving real life problems. In this paper, we present such a system for credit card selling tasks. Our proposed chat bot uses a Finite State Machine(FSM) based dialog flow in conjunction with continuous sentiment analysis of customer utterances to perform its predefined duties such as informing user or detecting what type of product would be more suitable for them, and ultimately successfully completing credit card selling process. We use a finite state machine for our chat bot to always keep track of conversation and also to prevent conversation from going too far away from the subject and the goal that our chat bot is trying to achieve. Additionally, keeping state of the conversation with an FSM provides consistency in responses of our chat bot, which is desired as it is aimed to help customers buy a credit card.

Chat bots have been developed for different purposes. Weizenbaum's ELIZA [1], one of the first dialog systems, and A.L.I.C.E. [2] are examples of general conversational bots. As natural language processing becomes more sophisticated some chat bots have been tailored for specific purposes to help people as virtual assistants. For example, Apple's Siri[3] can assist users in multiple ways or Alaska Airline's chat bot Jenn [4] can help customers in a more domain specific way to find suitable planes to their desired destinations. Our chat bot is similar to the latter example as it can help customers in informing them in credit card domain while it also has the additional goal of selling the product.

Designing our chat bot for Turkish language provides additional challenges and opportunities in natural language processing compared to Indo-European languages such as English. Turkish is an agglutinative language and suffixes to the words are very important and usually replace words. Therefore, many different words seem to appear in a sentence while in fact a few words with different suffixes appear in a text and in some instances some important information crucial to the meaning of the sentence can only be found in suffixes such as negativity of a sentence.For example the word ”kitap” (book) becomes ”kitabım” (my book) after the suffix ”-ım” is appended. When the suffix ”-a” is appended to this word it becomes ”kitabıma” (to my book) [5]. Also, some consonants change in Turkish language when new suffixes are appended as ”kitap” becomes ”kitabım”, letter ”p” is changed into ”b”. Because of these reasons morphological analysis of words is crucial in Turkish language processing.

This paper is organized in the following way: in Section 2 we describe and give examples of some of the related previous research in this area. In Section 3 we describe our methodology in detail. In Section 4 we explain how we evaluated the success of our system and present experimental results. Lastly, we discuss the possible applications and future research of our work and conclude the paper in Section 5.

II. Related Work

A. Related Work in Dialogue Management

Researchers were interested by chat bots because they can enable trying new natural language processing, machine learning and artificial intelligence methods while providing an interesting platform for people from all walks of life can interact. One of the first examples of using natural language processing techniques to create a chat bot that emulates human conversation is ELIZA [1]. Also a Turkish chat bot inspired by ELIZA was developed by Aytekin et al. [6]

There have also been research on chat bots to emulate daily speech, to give users the feeling that they are talking

Copyright (c) IARIA, 2017. ISBN: 978-1-61208-576-0

to a thinking person rather than a machine. A.L.I.C.E. [2] and Mitsuku [7] are such examples of chat bots that try to emulate human conversations.

Some researches have oriented toward making chat bots for more specific purposes rather than just general conversation. For example, IBM's Watson computer is designed to answer questions about world knowledge by processing questions asked in natural language [8]. Apple's Siri is a conversation agent that assists users in various ways, in addition to providing natural language answers to user queries, it can also perform tasks like phone calls or web searches. There are also chat bots that emulate customer service representatives. These chat bots are designed with the purpose of helping customers by answering their questions or solving their problems with the related products. Alaska Airline website's "Ask Jenn" or IKEA's Anna[9] are examples of chat bots acting as customer service representatives. Other chat bots have been developed to help students in educational environments such as EMERGO [10] and CHARLIE [11].

Chakrabarti proposes using finite state machines in chat bots that are designed as support agents [12]. Chakrabarti's FSM tries to keep state by analyzing users' utterances to detect how much user thinks bot is close to solving the problem and uses an external knowledge base to include in its answers. Since our chat bot has a more specific goal, instead of keeping state of where customer is, we track states of how much our chat bot is close to selling the product and use customer sentiments to go to further states.

B. Related Work in Sentiment Analysis

Our chat bot relies heavily on the sentiment analysis of customer utterances. Sentiment analysis is basically detecting or understanding the opinion or the negative or positive sentiment in a sentence or a document. The term sentiment analysis has been coined by Nasukawa et al. [13] Sentiment analysis has especially gained popularity for analyzing social media blogs and mini-blogs, product opinion reviews, wikis [14]. Sentiment analysis have been performed on different lengths of text. Since we expect chat customers to write short messages like a sentence, we focused our research on sentiment analysis on sentences.

Maynard and Funk suggests three types of methods for sentiment analysis: machine learning based, lexicon based and hybrid methods [15]. While machine learning approaches use training for finding common patterns for different sentiments, lexicon based approaches uses language rules for finding the sentiments. Syed et al. uses a lexicon based approach for sentiment analysis in morphologically rich Urdu language [16]. Hybrid methods use aspects from both approaches. As we use both morphological analysis of words and machine learning our sentiment analysis approach is hybrid. Dehkharghani's research provides methods for sentiment analysis in Turkish Language [17].

III. Method

The purpose of our chat bot is to both perform the task of selling a product and answer any questions a customer may have. Therefore, our chat bot keeps track how close it is to complete its task with an FSM and uses sentiment classification methods to change between states. Also, it assists customers in the way of a more traditional chat bot by detecting user questions and returning appropriate replies, while continuing to driving the conversation toward successfully selling a product. For sentiment classification, question detection and answering we use natural language processing techniques adapted to work in Turkish language.

A. Preprocessing

We perform some preprocessing operations on customer utterances before using them for question detection or sentiment analysis. We use preprocessing tasks that is common to natural language processing such as removing punctuations and tokenization. The punctuation marks have been removed are listed below:

- Dot, Comma, Colon, Exclamation Mark, Semicolon, Opening and Closing Parenthesis, Square Brackets, Question Mark, Underscore Character, Dash, Slash Mark, Asterisk.

We also perform a spell checking with the help of Zemberek library[18] so as not to miss the meaning of some mistyped words. Additionally, our chat bot keeps sentences both in their original form and by replacing the Turkish characters with their counterpart English letters. This is done to prevent conflicts that may happen due to usage of non-Turkish keyboards.

B. Dialog Management through FSM

We use an FSM in our credit card selling chat bot to keep track of the state of the conversation, varying needs of the customer and to give information to the customer when needed. Figure 1 shows states and transitions of our FSM design. Since this is a goal-oriented chat bot, the main flow of the FSM includes states for fulfilling the goals of credit card selling tasks. Transitions back and forth between the states are included to address a customer's changing needs or desires. Our chat bot has different sets of available answers for each state and drives the conversation toward other states by asking questions and detecting customer's sentiments for these questions. Our goal oriented system has a main flow of states that controls how close chat bot is achieving its goal and what it needs to do next. On the other hand, "Swearing"' and "Informative State" states are out of the main flow and these states have their special rules for transition.

Our chat bot initiates the conversation by greeting the customer and asking them if they have a predetermined type of card they want to buy. The credit card selling system has five card types it can sell and in 'Start' state whether customer wants a specific card among those or not is detected. This state handles various customer replies by sentiment analysis such as negative replies or discarding some card types, etc. If the customer suggests they have a preferred card type but doesn't indicate which one, "Card Determination" state handles this situation by asking user questions to receive the information of which product they want to buy.

The state "Detect User Needs" is, as the name suggests, where the chat bot asks questions to understand which credit card type might be the most suitable for an indecisive customer. As there are different credit card types tailored for different needs and various customer profiles, the credit card selling bot tries to determine what card is the most suitable for the current customer. While the conversation is on this state, questions are asked to gather information from customer to make this

Copyright (c) IARIA, 2017. ISBN: 978-1-61208-576-0

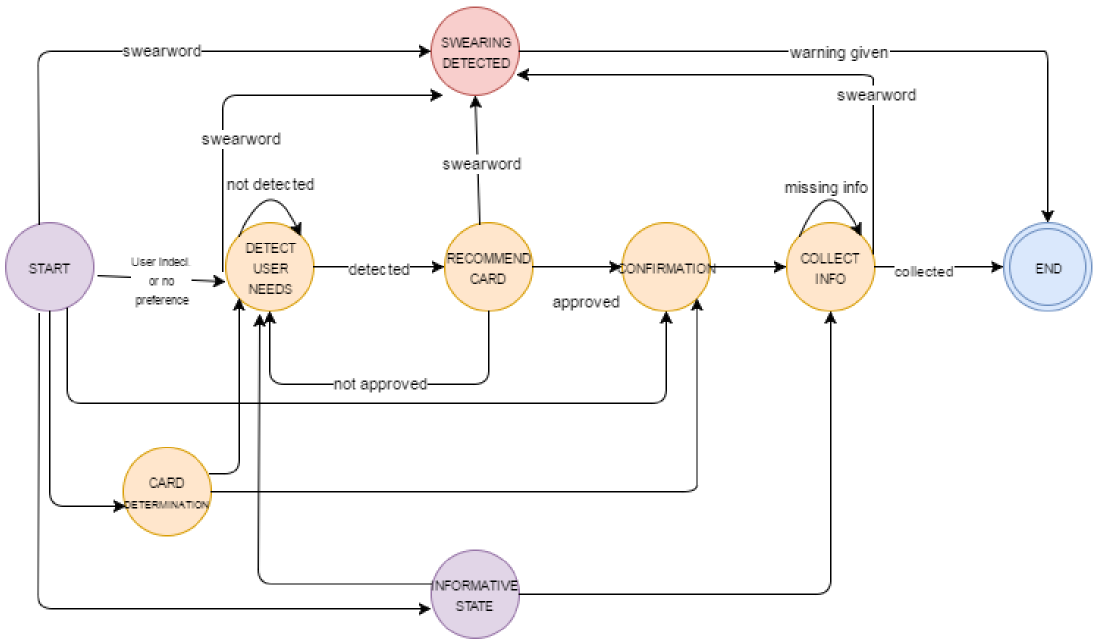

Figure 1. Finite State Machine Diagram of Dialog Flow

decision. Conversation remains on this state until a card is determined to be suitable for the customer.

In the case of a suitable card type for the customer is determined by the chat bot, conversation moves to ”Recommendation” state. In this state, detected card is offered to the customer, awaiting for their approval. If the customer does not want to buy that card type, conversation goes back to ”Detect User Needs” state, otherwise conversation moves to the ”Confirmation” where the chat bot asks the customer for the final confirmation before starting the formal credit card application. Conversation can move to this state from ’Start’ as well, if the customer asks to buy a specific card.

Conversation moves to ”Collect Information” state once a customer confirms to buy a specific credit card type. During this state of the conversation, chat asks customer questions to learn information required for completing a credit card application. Questions are asked arbitrarily and and customer replies are checked to determine if they are valid. Collecting all the required information, chat bot fulfills its goals by completing a successful credit card application for a customer and a credit card suitable for that customer’s needs.

The states ”Swearing” and ”Informative State” are outside of the main flow and can be reached from all of the other states once customer utters a sentence prompting to either of these states. ”Swearing” is basically a control for appropriate speech. If a customer uses a word or a phrase that is deemed taboo in Turkish Language, conversation moves to ”Swearing” state and after chat bot issues a warning to the customer the conversation is terminated. Conversation moves to ”Informative State” when the customer asks a question anytime during the conversation. Question detection is done morphologically by detecting question words and question suffixes that is usually used in question sentences in Turkish language. In conversation state, chat bot finds an appropriate answer for the question asked by the customer. In order to find an answer to questions, a retrieval-based question answering system is used.

C. Sentiment Classification

As expressed in previous section, sentiment classification algorithm plays an important role for the overall success of the chat bot. Because sentiment of a customer sentence determined by the sentiment classification model is used as a transition event for FSM to change states. It determines the transitions between ”Start State - Detect User Needs”, ”Detect User Needs-Recommendation” and ”Recommendation-Confirmation” states. For example, if the system classifies the sentiment of a customer sentence as positive in ”Recommendation” state, where the chat bot recommends a proper card type for a customer, it means that customer confirms to buy a recommended card type. In this situation, FSM processes the corresponding event, and passes to ”Confirmation” state. This event type moves FSM closer to the END state. Otherwise, when the sentiment of customer utterance is negative, FSM passes to ”Detect User Needs” state to help the customer to find the most proper card type for the customer.

Our baseline algorithm and proposed systems are detailed below.

1) Baseline Method: We have implemented two baseline models namely Lexicon-based baseline and Majority-based baseline to measure the real efficiency and success of our sentiment classification system.

Majority-based baseline model classifies any utterance as the most seen label in the training data set. Although this is very common and simple approach, it is a strong baseline.

Lexicon-based baseline system utilizes the lexicons consisting of negative terms and morphological structure of Turkish language. In Turkish, suffix, which makes sentence negative, is added to the end of verb in a sentence. Therefore, first, baseline algorithm checks if a verb in sentence coming from customer contains negative suffix. If it has, system classifies

Copyright (c) IARIA, 2017. ISBN: 978-1-61208-576-0

this customer utterance as negative. If it does not, then, algorithm checks if system contains any negative particles defined in lexicon. If it has, algorithm assigns a negative sentiment to sentence, otherwise, assumes it as positive sentence. In summary, baseline system does not use any semantic information, exploits lexical attributes of Turkish Language.

2) Supervised Methods: Since supervised algorithms perform quite successful for sentiment classification problem, we have evaluated different learning algorithms and chose the best performed one. For this task, we needed a labeled data set, which is annotated as positive or negative sentiment. We used a dataset consisting of real web chat conversations between a customer and a customer service representative. This dataset contains more than a million utterances. Although these conversations are based on the solutions of problems, customers face and there were no credit card selling goal they still contain banking domain terminology. We have selected 500 customer utterances among those and 3 different annotators labeled these utterances according to their sentiment. The class (positive/negative) having majority vote for a sentence has been considered as ground truth.

Figure 2 shows the prediction phase (positive/negative) of our sentiment classification module. As shown in Figure 2, firstly, customer message is preprocessed by applying the steps mentioned in Section III-A. Then, this preprocessed message is given to feature extractor module. Features extracted and used in our experiments are listed below:

- Length: is the count of words in a sentence.
- Bag-of-words (BOWs): Text is represented as set of its words in simple vector space.
- countOfPositiveParticles (CPP): is the count of positive terms in a sentence. These positive terms are defined in the lexicon crafted by us.
- countOfNegativeParticles (CNP): is the count of the negative terms in a sentence defined in lexicon crafted by us.
- haveRepeatedLetters (HRL): boolean feature. It considers if a word has repeated letters (nooo!) or not (no!).

Finally, these extracted features are given to trained learning model, which produces a sentiment class of customer message. As learning algorithms, we have used and performed experiments with K-Nearest Neighbor (KNN), Naive Bayes, Random Forest, MultiLayer Perceptron (MLP) and J48 algorithms. For all of these algorithms we used WEKA[19] implementations.

The first algorithm we use for sentiment classification is KNN. Using KNN, we calculate the distances between the utterance which we want to determine its sentiment with labeled utterances from our training set and by looking at sentiments k nearest utterance and choose the classification by a majority vote of these k instances [20]. Euclidean distance is used when calculating distances.

Naive Bayes method based on Bayes Theorem classifies by finding probabilities independently for each feature disregarding any relation that may be present between features [21]. That is why this method is called ”naive”.

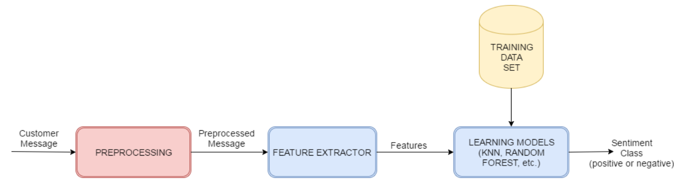

Figure 2. Stages of Sentiment Classification

Random Forest is an ensemble classifier, namely it is a method that uses several classifiers to make a final classification. It uses different decision tress and a final model is generated from the combination of each of these tree classifiers [22].

MLP is a feedforward neural network model. Neural networks are designed after neurons in a human brain, the inputs are processed in by a number of layers with every layer send its feedback to the forward layers [23].

D. Question Answering

As explained above, chat bot drives the conversation by asking questions and analyzing answers, however, when the customer asks a question conversation moves to ”Informative State” and the bot answers a question in this state. Question detection is performed by morphological analysis of sentences. In Turkish language, questions are asked by either using question words, which corresponds to wh-questions in English or by adding a question suffix to the appropriate word in question. We use Zemberek for morphological analysis. Zemberek is an NLP tool for Turkish language. We have observed that questions can be detected successfully with morphological analysis.

After detecting a question and moving the conversation to ”Informative State” the chat bot tries to find an appropriate answer by retrieving an answer from the knowledge base. The knowledge base contains question-answer pairs for common questions that can be asked about credit cards, and some more specific questions that can be asked about each card type. Chat bot matches the question asked with one of the questions in the knowledge base and returns its answer. Although, knowledge base covers general information about credit cards it is not a very large set and it is not much suitable for models that may require extensive training.

For matching question sentences we preferred q-grams distance calculation. q-grams are substrings of a string with length q. Calculating q-grams distance is based on common q-grams between two sentences. We also experimented with word based similarity calculations such as cosine distance or language modeling but q-grams based similarity performed better for sentence matching task. Since Turkish is an agglutinative language, the amount of different words that appear in a text can be quite high because every suffix essentially produces a new word. Word based similarity measure treats the same words with different suffixes as completely different words. When stemming is used though, information about sentence structure that may be contained in those suffixes cannot be used at all. Hence, a similarity measure that is more focused on characters such as q-grams distance can include both words and their suffixes in distance calculation.

Once the question is answered conversation resumes from the previous state before question was asked. After that, customers can ask more questions if they wish and conversation moves to "Informative State" to answer each question separately.

IV. Evaluation and Experimental Results

In this section, we show the experimental results for the overall chat bot and sentiment classification model, which is the part of this study for understanding the customer intent for taking corresponding action. First, we define the evaluation metrics that are used for measure the performance of two systems. Then, we report the corresponding results for each task.

A. Chat bot Evaluations

1) Grice's Maxims: To be able to measure the real efficiency of our system, we needed a consistent evaluation metric. There is not common metric for chat bot evaluation. So, we followed the same way with the study [12], which proposes similar approach with us. They utilize from the Grice's maxims for the evaluation of their proposed chat bot. Grice's maxims was long considered the gold standard for evaluation of human conversations. Maxims for human conversations are defined as follows:

- Quality: speaker tells the truth or provable by adequate evidence.
- Quantity: speaker is as informative as required.
- Relation: response is relevant to topic of discussion.
- Manner: speaker's avoids ambiguity or obscurity, is direct and straightforward.

It was considered that these maxims could be applicable to customer service conversations, between a human customer and a chatter bot agent. And, this maxims are defined as follows[12]:

1) *Quality Maxim:* Agent's responses are factually true.
2) *Quantity Maxim:* Agent provides too little information or too much.
3) *Relation Maxim:* Agent's responses are relevant to the topic of the conversation with respect to the situational context and domain.
4) *Manner Maxim:* Agents responses avoid ambiguity and obscurity.

These four maxims are considered as evaluation metric for this study. To clarify the definitions of this maxims we prepared an example set for the participants of this survey. Annotators gave a score between 1 and 5 for each of the maxim metric where 1 refers the 'strongly disagree', 2 'disagree', 3 'neutral', 4 'agree' and 5 'strongly agree'. Chat bot was evaluated by 20 human participants. Then, definition and example set were given the participants and they are asked for filling the survey by considering the experience they had during the conversation with chat bot.

The average of evaluation results for each maxim has been reported in the Table I. By considering the results, we can say that our chat bot performs quite good to understand the topic of question and answer it relevantly. On the other hand, it seems that even in the situations that it detects the topic of question and answer it in same topic, it does not give the needed answer

TABLE I. AVERAGE SCORES FOR MAXIMS

Maxim	*Average Score*
Quality Maxim	3.5
Quantity Maxim	4
Relation Maxim	4
Manner Maxim	3.4

and the situation causes ambiguity. We can conclude that it is successful to capture the sentiment of customer and process the right transitions. But, when a user ask question, which is processed by informative state, chat bot performs insufficiently.

B. Sentiment Classification Results

As it is mentioned in the Section III-C, we manually crafted data set consisting of 500 utterances and this data set was annotated by 3 human annotators. Ground truth of an utterance in data set was considered as the most selected label for that utterance. Evaluations for sentiment classification algorithms have been performed on this data set. 10-fold cross validation method was applied for measuring each algorithm. Since f-score measure is commonly used for evaluation of classification tasks, we reported the results in terms of f-score measure in Table II.

TABLE II. SENTIMENT CLASSIFICATION RESULTS

Learning Model	*Feature*	*F-score*
Lexicon-based Baseline	-	0.650
Majority-based Baseline	-	0.526
KNN (k=1)	BOWs	0.714
	+CNP*,CPP*	**0.822**
	+HRL*	0.806
	+length	0.784
Naive Bayes	BOWs	0.806
	+CNP*,CPP*	0.815
	+HRL*	0.807
	+length	0.773
Random Forest	BOWs	0.790
	+CNP*,CPP*	0.797
	+HRL*	0.790
	+length	0.792
MLP	BOWs	0.724
	+CNP*,CPP*	0.725
	+HRL*	0.719
	+length	0.720

CNP : doesContainNegativeParticle
CPP : doesContainPositiveParticle
HRL : haveRepeatedLetters

To observe the effect of each feature for classification performance, we reported the results as we added a new one. Among baseline systems, Lexicon-based classier, which considers the negative suffix of verb and utilizes the lexicon consisting of negative meaning terms, performed best with the 0.650 in terms of f-score. It can be said that Lexicon-based classifier is an unsupervised and strong baseline. On the other hand, all supervised models performed better than baseline. KNN, which is simple supervised method, performed best among all supervised algorithms. Results show that count of positive and negative terms are distinctive features. On the other hand, length and haveRepeatedLetters features do not contribute the success of any learning model. Therefore, we just used BOWs and CNN, CPP features with the KNN learning algorithm for the sentiment classification part of our chat bot.

Copyright (c) IARIA, 2017. ISBN: 978-1-61208-576-0

V. Discussion and Conclusion

We proposed a chat bot in Turkish Language, which aims to sell customers a proper credit card according to their needs. If the customer already decided the credit card type, it proceeds to the application process. Otherwise, chat bot tries to learn about customers, detect their needs and recommend the most suitable card specifically for that customer. In this study, this process has been provided via FSM. Transitions between predefined states have been performed according to output class of sentiment classification model. FSM has been designed specifically for credit card application. However, it can be easily adapted to any product selling system since it detects customers' needs, suggests a suitable product and and completes the application process of selling that product. All of these steps can be applied to selling most products. Thus, we recommend a general sentiment model based FSM algorithm for product selling. We utilized this method for specifically credit card selling, and experimental results were shown for it.

Since sentiment classification plays an important role in our transitions, we compared different classification algorithms and reported the results in the Section IV. Our experiments show that KNN model using BOWs, doesContainNegativeParticle and doesContainPositiveParticle features obtained the best performance. Moreover, human evaluation results of chat bot according Grice's maxims (Table I) show that the strongest aspect of the chat bot is transition between states accurately. Since the transitions are determined by sentiment classification system, it can be said that users found it working very well. On the other hand, due to low information retrieval performance the question answering in the informative state is the relatively weakest part of the chat bot that needs improving. Since our informative state only considers the lexical similarity between questions, this low performance was expected.

For future work, we aim to improve the performance of informative state by utilizing semantic properties of texts as well. We plan to exploit ontologies and distributional vector representations of texts to capture the semantic relations rather than considering only lexical similarity. Furthermore, a natural language answer generation system that dynamically generates new sentences instead of a choosing from a static list of proper replies would be fine addition. As long as such a system would preserve consistency in grammar and the information presented, it would increase the enthusiasm of customers to try the chat bot. When answers are generated dynamically, customer would feel it more human-like while the FSM still drives the conversation toward fulfilling its goal.

Acknowledgment

The authors would like to thank Şimal Şen, Sinan Kahraman, Deniz Sezen Gezmiş for annotations and feedbacks about chat bot and Nihan Karslıoğlu for her support to improve the system.

References

[1] J. Weizenbaum, "Eliza—a computer program for the study of natural language communication between man and machine," Communications of the ACM, vol. 9, no. 1, 1966, pp. 36–45.

[2] R. S. Wallace, "The anatomy of alice," in Parsing the Turing Test. Springer, 2009, pp. 181–210.

[3] Apple Siri siri. http://www.apple.com/ios/siri/. Accessed: 2017-06-06.

[4] Alaska Air Ask Jenn. https://www.alaskaair.com/. Accessed: 2017-06-06.

[5] E. Emekligil, S. Arslan, and O. Agin, A Bank Information Extraction System Based on Named Entity Recognition with CRFs from Noisy Customer Order Texts in Turkish. Cham: Springer International Publishing, 2016, pp. 93–102.

[6] Ç. Aytekin, A. Say, and E. Akçok, "Eliza speaks turkish: a conversation program for an agglutinative language," in Third Turkish Symp. Artificial Intelligence and Neural Networks, Ankara, 1994, p. 435.

[7] R. Higashinaka et al., "Towards an open-domain conversational system fully based on natural language processing." in COLING, 2014, pp. 928–939.

[8] D. A. Ferrucci, "Introduction to "this is watson"," IBM Journal of Research and Development, vol. 56, no. 3.4, 2012, pp. 1–1.

[9] Ikea Anna. http://www.ikea.com/ms/en_JP/customer_service/splash.html. Accessed: 2017-06-06.

[10] P. Van Rosmalen, J. Eikelboom, E. Bloemers, K. Van Winzum, and P. Spronck, "Towards a game-chatbot: Extending the interaction in serious games," in European Conference on Games Based Learning. Academic Conferences International Limited, 2012, p. 525.

[11] F. A. Mikic, J. C. Burguillo, M. Llamas, D. A. Rodríguez, and E. Rodríguez, "Charlie: An aiml-based chatterbot which works as an interface among ines and humans," in EAEEIE Annual Conference, 2009. IEEE, 2009, pp. 1–6.

[12] C. Chakrabarti, "Artificial conversations for chatter bots using knowledge representation, learning, and pragmatics," Ph.D. dissertation, University of New Mexico. Albuquerque, NM., 2014.

[13] T. Nasukawa and J. Yi, "Sentiment analysis: Capturing favorability using natural language processing," in Proceedings of the 2nd international conference on Knowledge capture. ACM, 2003, pp. 70–77.

[14] D. Alessia, F. Ferri, P. Grifoni, and T. Guzzo, "Approaches, tools and applications for sentiment analysis implementation," International Journal of Computer Applications, vol. 125, no. 3, September 2015, pp. 26–33.

[15] D. Maynard and A. Funk, "Automatic detection of political opinions in tweets," in Extended Semantic Web Conference. Springer, 2011, pp. 88–99.

[16] A. Z. Syed, M. Aslam, and A. M. Martinez-Enriquez, "Associating targets with sentiunits: a step forward in sentiment analysis of urdu text," Artificial Intelligence Review, vol. 41, no. 4, 2014, pp. 535–561.

[17] R. Dehkharghani, B. Yanikoglu, Y. Saygin, and K. Oflazer, "Sentiment analysis in turkish: Towards a complete framework."

[18] Zemberek-NLP. https://github.com/ahmetaa/zemberek-nlp. Accessed: 2017-06-06.

[19] Weka. http://www.cs.waikato.ac.nz/ml/weka/. Accessed: 2017-06-06.

[20] T. Cover and P. Hart, "Nearest neighbor pattern classification," IEEE Trans. Inf. Theor., vol. 13, no. 1, Sep. 2006, pp. 21–27.

[21] P. Langley, W. Iba, and, and K. Thompson, "An analysis of bayesian classifiers," in Proceedings of the Tenth National Conference on Artificial Intelligence, ser. AAAI'92. AAAI Press, 1992, pp. 223–228.

[22] L. Breiman, "Random forests," Mach. Learn., vol. 45, no. 1, Oct. 2001, pp. 5–32.

[23] S. Haykin, Neural Networks: A Comprehensive Foundation, 2nd ed. Upper Saddle River, NJ, USA: Prentice Hall PTR, 1998.

Copyright (c) IARIA, 2017. ISBN: 978-1-61208-576-0