2018 24th International Conference on Pattern Recognition (ICPR)
Beijing, China, August 20-24, 2018

Self-Talk: Responses to Users' Opinions and Challenges in Human Computer Dialog

Minghao Yang
[1]National Laboratory of Pattern Recognition (NLPR), Institute of Automation, Chinese Academy of Sciences, China, 100190
[2]The Center for Excellence in Brain Science and Intelligent Technology of Chinese Academy of Sciences, Beijing China, 100190
mhyang@nlpr.ia.ac.cn

Ke Zhang
[3]Guilin University of Electronic Technology, China
[4]National Laboratory of Pattern Recognition (NLPR), Institute of Automation, Chinese Academy of Sciences, China, 100190
zhengke@mail.guet.edu.cn

NaShengRuoYang
[1]National Laboratory of Pattern Recognition (NLPR), Institute of Automation, Chinese Academy of Sciences, China, 100190
nashenruoyang@163.com

Jianhua Tao
[1]National Laboratory of Pattern Recognition (NLPR), Institute of Automation, Chinese Academy of Sciences, China, 100190
[2]The Center for Excellence in Brain Science and Intelligent Technology of Chinese Academy of Sciences, Beijing China,
[4]University of Chinese Academy of Sciences, China
jhtao@nlpr.ia.ac.cn

Abstract—**People like to be, or partly, encouraged when their opinions or challenges are supported by listeners, even the listeners are robots. Encouraging responses from the robot which seem to get users' points potentially improve users' feeling in human computer dialog. According to this hypothesis, this paper proposes a method to generate supporting responses to users' opinions or challenges. The core ideas and contributions of the proposed method are: (1) multiple search engines cooperate, and (2) each engine random asks itself or ask another one to obtain more related information from the internet in multiple turns; then (3) final responses are abstracted from the answers. We call these three steps as Self-Talk. The comparisons between Self-Talk and several commercial open speech assistants show that the proposed method does generate suitable answers to users when they present their opinions or challenges in dialog. The hypothesis is positively evaluated that encouraging responses could improve users' chat feeling.**

Keywords—human computer dialog; dialog management (DM); viewpoint expression;abstract extraction

I. INTRODUCTION

Human computer dialog, as a free style interaction modality between human and computer, attracted more and more attention in the field of speech assistant [1], language training, language rehabilitation, caregiver for action inconvenience and aged [2], etc. Some researchers introduced that two functionalities are basically demanded in human computer dialog applications: *task-oriented (query)* and *non-task-oriented (chat)* [3]. *Task-oriented* functionality is commonly used to obtain accurate information, such as checking weather information, hotel booking, air tickets, etc. It requires the computer to return correct answers as soon as possible [4]. *Chat* functionality requires the computer to talk with users in free styles and ensure that users' topics are well tracked. Basically, it demands speech assistants or chat robots to maintain chat process attractive to users [3].

In daily life, users often present their opinions or challenges to robot's answers in human computer dialog. For example, "I like coffee" presents the opinions to the asking "Which do you like better, coffee or tea?", and "I disbelieve there are aliens in the earth since no persuasive evidences" is a challenge to the statement "Some people believe that aliens have visited earth". People possibly are encouraged when their opinions or challenges are supported by listeners in conversation. Therefore, it is useful to generate supporting responses to users when they present their opinions or challenges in human computer dialog. For example: the response "Yes, drinking coffee is good to skin, and it helps to lessen fatigue in work" likely brings good feeling and maintain chat process attractive to users when they say "I like coffee".

Techniques of traditional dialog management (DM) usually chose answers using voting or probabilistic evaluation from the structured database or labeled corpus. Partially observable Markov decision processes (POMDP) [5] considers the best answers by yielding the highest expected reward introduced by all possible states transfer actions. In practical applications, it is quite time consuming for POMDP policies learning and optimization by summing all rewards from the whole possible large number of dialog states [5]. Gaussian processes (GPs) are used to minimize variability in the dialog state learning, by basing the policy directly on the full belief space thereby avoiding ad hoc feature space modeling. It was demonstrated that the GPs approach represents an important step forward towards fully automatic dialogue policy optimization in real-world systems [6]. Other stochastic based DM models, such as user simulate model [7], graphical model [8], multi-expert model [9], basically focus on learning to predict the dialog state accurately. In spite of these methods' success on several small-scale *task-oriented* applications, where the parameters were learnt off-line from labeled data, these methods had the challenges to generate suited responses to users' opinions and challenges in free *chat* conversation environments [6].

Recently, some researchers adopted end-to-end deep learning to track the dialog states and map raw dialog history utterances to a distribution over system actions in *task-oriented* dialog systems [10-13]. End-to-end model automatically infers a representation of dialog state, alleviating much of the work of hand-crafting a representation of the dialog state. Recurrent encoder-decoder neural network was used to produce system responses that are autonomously generated word-by-word, opening up the possibility for realistic, flexible interactions in the *chat* dialogue domain [14, 15]. It was demonstrated that deep neural network (DNN) generative models are competitive with state-of-the-art statistical models on state transfer prediction [16] and DNN DM models have the advantages in learning policies from unaligned data [17]. However, even the dialog states or system actions are well predicted, it is still an open problem to generate comprehensible responses to users' chat only from system policies.

On the points of generating responses to users' opinions or challenges, some researchers considered responses as translation problems from structural description language to spoken language in dialog state tracking challenge [10, 18]. However, no matter traditional stochastic DM models, which calculate probabilities on the structured database or deep learning DM, which learnt answers from large scale question-answer pairs, the feedbacks are easily tend to be inflexible due to answer searching in structured database or topic tracking loss because of scattered training corpus. In practical applications, DM needs to convert probabilities or labels to user' comprehensible responses according to system actions [19]. Under the conditions that quite a few open and free search engines providing recommended knowledge on the internet, these recommend knowledge afford us a convenient way to organize responses to support users' opinions or challenges.

This paper proposes a method to find encouraging responses to users' opinions and challenges by searching and organizing knowledge from the internet. The core ideas and contributions of the proposed method are: according to the initial feedback of users' statements, multiple copies of search engines cooperate, and each robot random asks itself or another one to obtain more inside and scattered answers from the internet. The final responses are abstracted from the answers from searching results. Experiments show the proposed method is efficient to generate appropriate

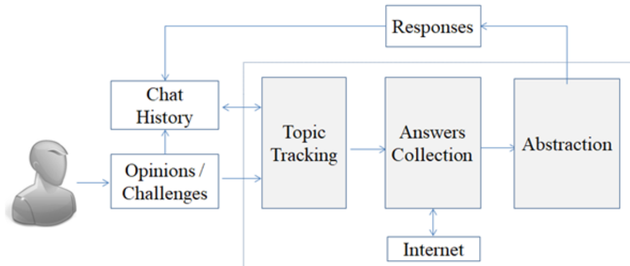

Figure 1: Pipeline of the proposed Self-Talk.

answers to users when users obviously present their opinions or challenges, and the proposed method improves user's feelings about the chat between human and robot when users' opinions and challenges are considered.

The reminders of this paper are organized as follows: the overview of the proposed method, which is called Self-Talk, is presented in section II; the detail discussions are introduced in section III; experiments are given in section IV and we conclude this study in section V.

II. OVERVIEW OF THE PROPOSED METHOD

The core ideas of Self-Talk are presented in gray components in Fig. 1, which consist of three steps: (1) topic tracking by finding the best topic launching sentences from dialog history for current user's statement; (2) collecting answers from the internet through multiples turns of iterative searching; (3) abstracting the final responses from answers clusters from searching collection.

We first introduce the proposed Self-Talk in details and discuss the following points through experiments: (1) are the responses obtained by Self-Talk experienced better in comprehending users' opinions or challenges than the recommend answers provided by search engines or traditional chat robots? (2) Does Self-Talk improve user's feelings about the chat when users obviously present their ideas?

III. SELF-TALK

A. Topic Tracking

At the first step, Self-Talk first find the topic launching sentences in dialog history. For example, "Which do you like better, coffee or tea?" is the topic launching sentence for user's opinion "I prefer coffee". In history, various topic tracking methods have been proposed, for instance the methods presented in the third [20-22] and fourth Dialog State Tracking Challenge [23-25]. However, these methods are trained with corpus associated with predefined slots in dialog states transfer. Considering the flexible and unpredicted conversation from users in opinions presentation and challenges expressions, we suppose that the topic launching sentence is near to current statement in chat history, and it is similar to users' current statement and possibly a question. Eq. (1) presents the idea of topic tracking in Self-Talk.

$$p_i = \alpha \cdot \frac{1}{D(X_i, X_j)} + \beta \cdot S(X_i, X_j) + \gamma \cdot \mathrm{Ask}(X_i) \quad (1)$$

In Eq.(1), X_j is current user's statement, and X_i is a sentence in dialog history before X_j, where i∈(j-L, j-1) and L is dialog length considered in tracking. Then the probability of X_i being the topic launching sentence of X_j is denoted as p_i. $D(X_i, X_j)$ is the distance between X_i and X_j in dialog history. $S(X_i, X_j)$ is similarity between X_i and X_j, and function $\text{Ask}(X_i)$ is the possibility of X_i to be a question. Eq. (2) introduce the similarity of two sentences [26], where u_i, v_j are word2vector of each word u_i, v_j in sentence X_i and X_j,

$$S(X_i, X_j) = \frac{\sum_{i=1}^{m}(\sum_{j=1}^{n}(u_i \cdot v_j / ||u_i|| \cdot ||v_j||))}{m \cdot n} \quad (2)$$

and m, n are the word number of X_i and X_j respectively.

B. Collecting Answers from the Internet

When the topic launching sentence is determined, Self-Talk tries to find more relevant answers by iteratively searching the internet using Eq. (3), where Q is the topic launching sentence obtained in §III.A, and A_t $(1 < t < T)$

$$A_t = F(Q, A_{t-1}) \quad (3)$$

is an answer obtained by a searching engine F(.) by given the combination of Q and answer A_{t-1} obtained in the previous searching turn, where $A_1 = F(Q)$ and T is the maximal iterative turns for Self-Talk.

Self-Talk is an iterative searching processing from the internet until the conditions presented in Eq. (4) are met. $\sum_{i=1}^{t}\frac{S(Q, A_i)}{t}$ is the average similarity between Q and the iterative answers, which presents consistency between answers and topic. We call $\sum_{i=1}^{t}\frac{S(Q, A_t)}{t}$ topic consistency coefficient (TCC). Self-Talk likes to obtain more possible different answers by searching internet, then we consider that a smaller value of TCC is better and once TCC is larger than a threshold λ_1, the TCC search process stops. On the

$$(\sum_{i=1}^{t}\frac{S(Q, A_i)}{i} > \lambda_1) \cap (\sum_{i=1}^{t}\frac{S(A_{i-1}, A_i)}{i} < \lambda_2) \cup (t > T) \quad (4)$$

contrary, $\sum_{i=1}^{t}\frac{S(A_{i-1}, A_i)}{t}$ is the average similarity between two sequential answers from the internet, which presents the divergence degree of two sequential answers. We call $\sum_{i=1}^{t}\frac{S(A_{i-1}, A_i)}{t}$ answer divergence coefficient (ADC). Self-Talk demands that the sequential answers obtained by Self-Talk are similar to each other, then we consider that a larger value of ADC is better and once ADC is smaller than a threshold λ_2, the ADC search process stop. λ_1, λ_2 and T are used to regulate the process of collecting answers from the internet in Self-Talk.

C. Response Generation by Clusters and Abstraction

When the iterative searching process stops in the last step, we need to find the most suitable answer from the answer collection, which is denoted as $\mathbb{C}$ in this work.

$$W(V_j) = (1 - d) + d * \sum_{V_j \in In(V_i)} \frac{S(V_i, V_j)}{\sum_{V_k \in Out(V_j)} S(V_k, V_j)} W(V_j) \quad (5)$$

Supposing that $\mathbb{C} = \mathbb{C}_{in} + \mathbb{C}_{out}$, where $\mathbb{C}_{in}$ means that each sentence in $\mathbb{C}_{in}$ is related to the chat topic, and those in $\mathbb{C}_{out}$ are outliers. We need to remove the outlier sentences from $\mathbb{C}$. Then we classify all sentences into two clusters using K-means, where we use Eq. (2) again to measure the distances between two sentences. The sentences whose centers are farther away from Q are viewed as $\mathbb{C}_{out}$, and the others are $\mathbb{C}_{in}$.

We continue to find the most suitable answer from $\mathbb{C}_{in}$ using TextRank [27]. TextRank is an elegant algorithm to obtain the abstraction from natural language texts. Eq. (5) presents the outline of TextRank in this work. All sentences in $\mathbb{C}_{in}$ come into being an undirected complete graph by the connections from V_i to V_j, where V_i and V_j are two sentences in $\mathbb{C}_{in}$. $W(V_j)$ is the probability for a sentence V_j that it could be selected as abstraction sentence. $In(V_i)$ and $Out(V_i)$ are the predecessors and successors connection for V_i. $S(V_i, V_j)$ is the similarity between sentences V_i and V_j. d is a damping factor, which usually is set to 0.85 [27]. In Eq. (5), the solving for $W(V_j)$ is an iterative process. At the beginning, values of $W(V_j)$ could be given a random value between 0 and 1.

IV. EXPERIMENTS

In experiments, we first discuss the parameters setting in Self-Talk. And then we compare Self-Talk with several commercial open speech assistants on a list of questions which have no fixed answers.

A. Topic Tracking

The location of Q in chat history is determined by α, β , γ and L in Eq. (1). According to the analysis in [28], in their chat records database, 75% topics in free talks are ended in 20 conversation sentences or 10 turns in human computer dialog. For simplification we set the value of L as 10 in this study.

In this study, we evaluate the values of α, β and γ on the human computer dialog records database provided by [28, 29]. The database contains 306 pieces of chat records, which contains 150,000 sentences from over 200 users' chat experiences. These chat pieces contain 7 topics which are previously set, including weather (W), coffee (C), food (F), travel (T), game (G), sport (S), restaurant (R), and some unpredicted free topics launched by users. 5-fold cross validation are used to find the optimal values of α, β and γ. We use grid search with skip 0.2 per step to find Q according to different values of α, β and γ. Let ζ presents

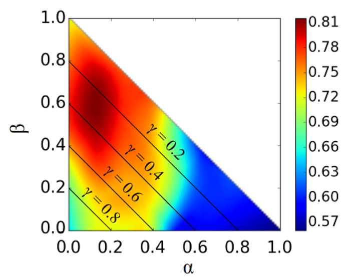

Figure 2: Probability distributions of Q for α, β and γ.

TABLE I . THE ACCURACY OF TOPIC TRACKING BETWEEN THW PROPOSED METHOD AND KSD ON DIFFERENT TOPICS

	W	C	F	T	G	S	R
The Proposed	**84.8**	**73.7**	65.5	68.3	67.2	**75.3**	**66.5**
KSD [30]	81.6	68.4	**64.0**	**70.0**	**72.5**	73.1	62.7

*Numbers in the table are prediction accuracy and measurement is percentage (%)

the probability that a sentence is a topic launching sentence by $\zeta = \sum_{i=1}^{m}(h_{hit}^{i})/m$ ($h_{hit}^{i} = 1$ when $Q_{track}^{i} = Q_{label}^{i}$, else $h_{hit}^{i} = 0$), where Q_{track}^{i} and Q_{label}^{i} are the topic launching sentences predicted by Eq. (1) and the ground truth labeled by the volunteers for the i-th pieces of chat record respectively.

The distributions of ζ are presented in Fig. 2, where the horizontal coordinate, vertical coordinate, and slants from left-top to right-bottom present α, β and γ respectively. The darkest areas in red, namely the maximum values of ζ are located nearly at (0.1, 0.6, 0.3). Then in the following experiments, α, β and γ are set to 0.1, 0.6 and 0.3 respectively.

Table I gives the comparison between the proposed method and the key sentences detection (KSD) proposed in [30] on the 306 pieces chat records on topic launching sentence detection accuracy. The KSD method was originally used to detect the key sentences and used to generate sports' news automatically from sport live webcast script. KSD won the first place in the competition task "Football News Generation from Chinese Live Webcast Script" in the conference. In this comparison, the KSD network is trained with the chat sentences as inputs, and the outputs are the labeled topic launching sentences in ground truth. From table I we can see that with 5-fold cross validation on the 306 chat pieces records provided by [28], the proposed topic tracking method obtain competitive results against KSD. Given chat sentences in dialog, the proposed method outperforms KSD on "Weather", "Coffee", "Sport" and "Restaurant" topics. It is found that topic length of "Weather", "Coffee", "Sport" and "Restaurant" are usually shorter than those of "Food", "Travel", "Game" topics averagely, and the previous four topics contain more questions in launched sentences. In Self-Talk, we consider that the topic launching sentences are probably questions by detection the interrogative words in sentences, which potentially improve the performance of Self-Talk in topic tracking. General speaking, in spite of a heuristic method, the proposed topic tracking method is an effective method to obtain the topics launching sentences in chat history.

B. Iteratively Searching

The possible answers obtained by the search engines are related to the values of T (maximum iterative turns), λ_1 (TCC) and λ_2 (ADC) in Eq. (4). The bigger the values of T and λ_2, more answers are obtained in iteratively searching from the internet. Fig. 3 presents their relationships obtained by statistical results from random 60 chat pieces from total 306 ones, where the horizontal and vertical coordinate present T and the average values of TCC and ADC respectively. We can see that the average values of ADC are

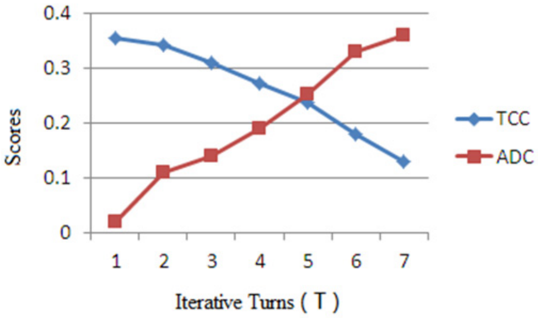

Figure 3: the values of TCC and ADC in multiple turns

maintaining an upward swing with the increasing of T. While those of TCC declines along with increasing of T. When T is nearly at 5, the value of TCC is roughly equal to that of ADC about 0.25. To obtain enough initial answers, we set the values of T, λ_1, λ_2 to 6, 0.15 and 0.35 finally.

C. Response Generation from Answer Clusters

Given topic related answers collection $\mathbb{C}_{in}$, we use TextRank algorithm to find the final feedback sentence to users. In the system, three Chinese search engine, BaiduZhidao [31], iAsk [32] and DianPing.com [33] are used to provide answers from internet. These three on-line engines are three commonly used question-answer (QA) search engines in Chinese. In each Self-Talk turn, about 18 answers at most are obtained in $\mathbb{C}$ for three engines in 6 iterative times, and the number of sentences in $\mathbb{C}_{in}$ is roughly between 3 and 15 when $\mathbb{C}_{out}$ are removed from $\mathbb{C}$. Fig. 4 presents the acceptable ratios for the final top response obtained by TextRank, where the horizontal coordinate present how many sentences used in Text-Rank, and vertical ordinate is acceptable ratios labeled by 5 volunteers with 0 (bad) or 1 (good) tags.

We can see from Fig. 4 that the average acceptable ratios for the final responses achieve highest points when sentence number in $\mathbb{C}_{in}$ is nearly at 5, 10 and 13. And at least 67% acceptable ratios are obtained as long as 5 sentences are considered in TextRank. As the sentence numbers in $\mathbb{C}_{in}$ are usually between 6 and 15, then we consider all sentences in $\mathbb{C}_{in}$ to obtain the final response using TextRank.

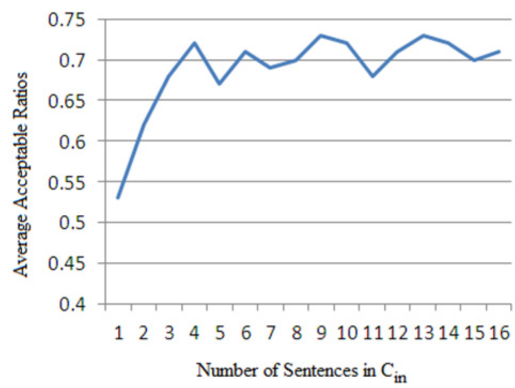

Figure 4: Average acceptable ratios for the final top response obtained by TextRank from $\mathbb{C}_{in}$

TABLE II. TWO PIECES OF CHAT RECORDS FROM BAIDU-ZHIDAO AND SELF-TALK

Baidu-Zhidao	Self-Talk
U: Which do you prefer? Coffee or tea? R: I prefer to coffee. U: I also like drinking coffee. R: I like coffee.	U: Which do you prefer? Coffee or tea? R: Coffee. U: I also like drinking coffee. R: Yes, drinking coffee is good to skin, and it helps to lessen fatigue in work time.

D. *Subjective Evaluation*

The framework of Self-Talk is realized and provided as a mobile interface on android platform [34]. With 6 iterations each dialog turn at most, Self-Talk archives nearly real-time response to users. We first compare the responses obtained by Self-Talk and the top recommended answers provided by Baidu-Zhidao using subjective evaluation. Table II presents two pieces of chat records for these two systems, where "R" and "U" present chat robot and user respectively. We can see from table II when users express their opinions, the responses provided by Self-Talk (the underline sentences in the right column) contain better interpretations to support users' opinions than that recommended answers from Baidu-Zhidao (the underline sentences in the left column).

In the subjective evaluation, 65 individuals were invited to random choose at least 50 questions from the book <<Hundred Thousand Whys>>, which is a famous popular science reading. They are also encouraged to ask 20 questions which have no uniqueness answers, for example, several questions mostly asked by users are "Do you believe there are others high intelligent creatures in universe?", "Would you like coffee or tea?", "How do you think about me?" These questions are freely asked by users, and if they are not satisfactory with robot's answer, users could argue the robot or tell the robot what they think. And all chat sentences are automatically recorded by the system.

Finally, according to the chat records, 5 volunteers were asked to determine which answer is better to users' opinions and challenges. Fig 5 presents the results, where nearly 75% individuals voted that Self-Talk outperforms Baidu-Zhidao on supporting users' opinions. And nearly 67% of them think that Self-Talk obtains better dialog feelings than Baidu-Zhidao to users' challenges.

We continue to compare Self-Talk system with several Chinese speech assistants, including Xiao-ice speech

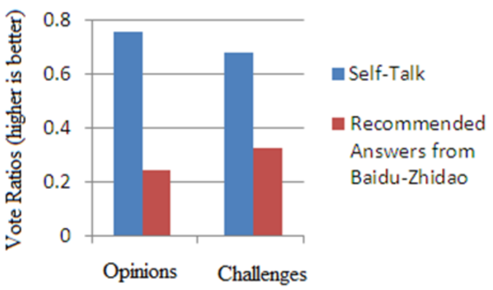

Figure 5: Subjective evaluation between Self-Talk and the recommended answers from Baidu-Zhidao

TABLE III. TWO PIECES OF CHALLENGES CHAT RECORDS FROM MICROSOFT XIAO-ICE AND SELF-TALK

A user' challenge dialog with Xiao-ice	A user' challenge dialog with Self-Talk
U: Which do you prefer? Coffee or tea? R: I like drinking tea. Coffee is bitter for me. U: *Tea is ok, but for me, coffee is fine even it is a little bitter.* R: I also like instant coffee and cola.	U: Which do you prefer? coffee or tea? R: Tea. U: *Tea is ok, but for me, coffee is fine even it is a little bitter.* R: Sure, adding some sugar or milk could improve its feeling.

TABLE IV. MOS FOR FOUR OPEN CHAT SYSTEMS

Category	Baidu-Zhidao	Turing-robot	Xiao-ice	Self-Talk
Opinions	3.20	3.11	3.15	**3.29**
Challenges	3.25	3.09	3.29	**3.40**

assistant from Microsoft [18], Turing chat robot from Turing company [35] on the open questions. Table III lists two pieces of challenge records between a user and Xiao-ice and Self-Talk, where the italic sentences are the challenge expressions given by the users. It can be seen from table III that in the given one-choice question for coffee or tea, Self-Talk seems to provide more reasonable responses to user's challenge. It partly because that Xiao-ice is set as an AI who owns teenage girl's personality, while Self-Talk aims to organize various answers from the internet and provide the most approximately abstraction to the user.

Table IV presents the mean opinion score (MOS) comparison among Self-Talk, Xiao-ice, recommend answers from Baidu-Zhidao and Turing chat robot on the cases when users present their opinions and challenges. Results in table IV are statistically obtained by 65 users' experiences, where the higher value of MOS is better, and the full score is 5. In the test, they were asked to present their opinions or argue with robot freely.

We can see from table IV that when users express their opinions or argue with system's previous feedback, it is found in the first and second lines of table IV that Self-Talk obtains obviously better experience nearly 0.1 point than other systems. Different from finding best matching answer from question and answer (QA) database using statistical or deep learning, the smart ability of Self-Talk come from: (1) collecting multiple human recommended answers from the internet, and (2) organizing the responses by summarizing the answers after the outliers are removed. Furthermore, because of its iteratively searching strategy which enables the responses are more related to users' expression, Self-Talk achieves better performance than Baidu-Zhidao.

As a result, it seems Self-Talk give the robot a little ability to act on the wish of users no matter users present their opinion or argue against the system. The statistical results from 65 individuals' experiences show that the responses provided by Self-Talk do improve user's feelings about the chat when users obviously present their opinions or challenges.

V. Conclusions

This paper proposes a method, namely Self-Talk, which aims to generate responses to users' opinions and challenges in human computer dialog by organizing recommended answers from the internet. It consists of three steps: (1) topic tracking; (2) iteratively searching; and (3) final answers' abstraction. According to the parameters' analysis from 306 realistic human computer dialog records, we build a chat interface and compare its performance with the recommended answers from Baidu-Zhidao, Microsoft Xiao-bin, and Turing chat robot. Experiments show the proposed method is efficient to generate appropriate answers to users when they obviously present their opinions and challenges. The hypothesis is positively evaluated that encouraging responses could improve user's feelings about the chat. And the proposed Self-Talk has widely potential and practical use in home service robot and shopping guide robot as a speech assistant modality.

Acknowledgement

This work is supported by the National Key Research & Development Plan of China (No. 2016YFB1001404), the National Natural Science Foundation of China (NSFC) (NO.61332017, No.61425017).

References

[1] L. Comerford, D. Frank, P. S. Gopalakrishnan, R. Gopinath, and J. Sedivý, "The IBM Personal Speech Assistant," presented at the 2001 Ieee International Conference on Acoustics, Speech, and Signal Processing, Vols I-Vi, Proceedings, 2001.

[2] T. Bickmore and T. Giorgino, "Health dialog systems for patients and consumers," *Journal of Biomedical Informatics,* vol. 39, pp. 556-571, Oct 2006.

[3] M. Nakano, A. Hoshino, J. Takeuchi, Y. Hasegawa, T. Torii, K. Nakadai, K. Kato, and H. Tsujino, "A robot that can engage in both task-oriented and non-task-oriented dialogues," *2006 6th Ieee-Ras International Conference on Humanoid Robots, Vols 1 and 2,* pp. 404-411, 2006.

[4] F. Weng, S. Varges, B. Raghunathan, F. Ratiu, H. Pon-Barry, B. Lathrop, Q. Zhang, H. Bratt, T. Scheideck, K. Xu, M. Purver, R. Mishra, A. Lien, M. Raya, S. Peters, Y. Meng, J. Russell, L. Cavedon, E. Shriberg, H. Schmidt, and R. Prieto:, "CHAT: A Conversational Helper for Automotive Tasks," *Interspeech 2006 and 9th International Conference on Spoken Language Processing, Vols 1-5,* pp. 1061-1064, 2006.

[5] S. Young, M. Gašić, and S. Keizer, "The Hidden Information State model: A practical framework for POMDP-based spoken dialogue management," *Computer Speech and Language,* vol. 24, pp. 150-174, Apr 2010.

[6] M. Gasic and S. Young, "Gaussian Processes for POMDP-Based Dialogue Manager Optimization," *Ieee-Acm Transactions on Audio Speech and Language Processing,* vol. 22, pp. 28-40, Jan 2014.

[7] F. Torres, E. Sanchis, and E. Segarra, "User simulation in a stochastic dialog system," *Computer Speech & Language,* vol. 22, pp. 230-255, 2008.

[8] G. Ji and B. Jeff, "Dialog Act Tagging Using Graphical Models," presented at the IEEE International Conference on Acoustics, Speech, and Signal Processing, 2005.

[9] M. Nakano, K. Funakoshi, Y. Hasegawa, and H. Tsujino, "A framework for building conversational agents based on a multi-expert model," presented at the Sigdial Workshop on Discourse and Dialogue, Association for Computational Linguistics, 2008.

[10] X. Yang, Y.-N. Chen, D. Z. Hakkani-Tür, P. Crook, X. Li, J. Gao, and L. Deng., "End-to-end joint learning of natural language understanding and dialogue manager," presented at the International Conference on Acoustics, Speech and Signal Processing, 2017.

[11] J. D. Williams and G. Zweig, "End-to-end LSTM-based dialog control optimized with supervised and reinforcement learning," *Computation and Language,* 2016.

[12] L. Zilka and F. Jurcicek, "Incremental Lstm-Based Dialog State Tracker," *2015 Ieee Workshop on Automatic Speech Recognition and Understanding (Asru),* pp. 757-762, 2015.

[13] A. Sordoni, M. Galley, M. Auli, C. Brockett, Y. Ji, M. Mitchell, J.-Y. Nie, J. Gao, and B. Dolan, "A neural network approach to context-sensitive generation of conversational responses," *Transactions of the Royal Society of Tropical Medicine & Hygiene,* vol. 51, pp. 502-504, 2015.

[14] P.-H. Su, D. Vandyke, M. Ga, N. Mrk, T.-H. Wen, and S. Young, "Reward Shaping with Recurrent Neural Networks for Speeding up On-Line Policy Learning in Spoken Dialogue Systems," presented at the SigDial 2015.

[15] http://www.msxiaoice.com/. (January 6, 2018).

[16] I. V. Serban, A. Sordoni, R. Lowe, L. Charlin, J. Pineau, A. Courville, and Y. Bengio, "A Hierarchical Latent Variable Encoder-Decoder Model for Generating Dialogues," *proceedings of AAAI Conference on Artificial Intelligencehttp (AAAI) 2017,* 2017.

[17] T.-H. Wen, M. Ga, N. Mrk, P.-H. Su, D. Vandyke, and S. Young, "Semantically Conditioned LSTM-based Natural Language Generation for Spoken Dialogue Systems," *Computer Science,* 2015.

[18] http://www.microsoft.com/en-us/research/publication/fifth-dialog-state-tracking-challenge/. (January 6, 2018).

[19] T. H. Wen, Gasic, M., Mrksic, N., Su, P. H., Vandyke, D., & Young, S, "Semantically Conditioned LSTM-based Natural Language Generation for Spoken Dialogue Systems," 2015.

[20] T. Zhao and M. Eskenaz, "End-to-End Learning for Dialog State Tracking and Management using Deep Reinforcement Learning," presented at the Proceedings of the 17th Annual Meeting of the Special Interest Group on Discourse and Dialogue, 2016.

[21] N. Mrksic, D. ó. Séaghdha, and B. Thomson, "Multi-domain Dialog State Tracking using Recurrent Neural Networks," *Computer Science,* 2015.

[22] M. Henderson, B. Thomson, and J. D. Williams, "The third Dialog State Tracking Challenge," presented at the IEEE Spoken Language Technology Workshop 2015.

[23] H. Shi, T. Ushio, and M. Endo, "Convolutional Neural Networks for Multi-topic Dialog State Tracking," presented at the Pro- ceedings of the 7th International Workshop on Spoken Dialogue Systems, 2017.

[24] M. Henderson, B. Thomson, and S. Young, "Robust dialog state tracking using delexicalised recurrent neural networks and unsupervised adaptation," presented at the IEEE Spoken Language Technology Workshop, 2015.

[25] S. Kim, L. F. D'Haro, R. E. Banchs, J. D. Williams, and M. Henderson, "The Fourth Dialog State Tracking Challenge," *Ai Magazine,* vol. 35, pp. 121-124., 2014.

[26] M. J. Kusner, Y. Sun, N. I. Kolkin, and K. Q. Weinberger, "From word embeddings to document distances," presented at the The 32nd International Conference on Machine Learning, ICML 2015.

[27] M. Rada and T. Paul, "TextRank: Bringing Order into Texts," *Unt Scholarly Works,* pp. 404-411, 2004.

[28] M. Yang, J. Tao, T. Gao, D. Zhang, M. Sun, H. Li, and L. Chao, "The error analysis of intention classification and speech recognition in speech man-machine conversation," *Journal of Software,* vol. 27, pp. 69-57, 2016.

[29] M. Yang, J. Tao, and L. Chao, "User behavior fusion in dialog management with multi-modal history cues," *Multimedia Tools & Applications,* vol. 74, pp. 10025-10051, 2015.

[30] R. Tang, K. Zhang, R. Naseng, M. Yang, H. Zhou, Q. Zhu, Y. Zhan, and J. Tao, "Football News Generation from Chinese Live Webcast Script," presented at the The Sixth Conference on Natural Language Processing and Chinese Computing, 2016, (The winner of Task 5).

[31] https://zhidao.baidu.com/opendev. (2018, January 6, 2018).

[32] http://iask.sina.com.cn/. (January 6, 2018).

[33] http://developer.dianping.com/. (January 6, 2018).

[34] http://www.wandoujia.com/apps/lx.chat. (January 6, 2018).

[35]http://www.tuling123.com/experience/expvirtual_robot.jhtml?nav=exp. (January 6, 2018).