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FEEDBACK PREDICTABLE ROBOT BASED ON BIG DATA

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Abstract - *Existing robots only try to give reasonable answers to users, not considering if the answer can make user happy or not. This paper proposed a new kind of robot, predictable robot. Predictable robot does not like existing robots which always select answers for users according to the truth, predictable robot select answers for users mainly according to the user preferences in order to make user happier. The main idea of predictable robot is to predict the user feedbacks for answers based on the big data of the user past feedbacks detected by the predictable robot.*

Keywords: *Predictable robot, big data, feedback data, feedback prediction.*

1. INTRODUCTION

There are many kinds of robots.1–4 Chat robot is one kind of robot which can talk with human.5 There are many researches on chat robot mainly focusing on how to make robots understand more about human languages,6,7 how to apply chat robot to online information system,8 and how to apply chat robot to special applications. The goal of the general chat robots is to a reasonable answer for user's question. However, the reasonable answer is not always the answer users prefer. For example, if you ask a chat robot \Am I beautiful?" The chat robot will scan your photo, and tell you the truth. The truth maybe \You are ugly". Then, you will be angered by the answer. Certainly, the existing chat robots generally search the appropriate answers in the answer database, and not get the user personal information to make a personalized answer. So, the general chat robots cannot predictable. However, predictable is an ability of human. In some time, kind predictable is not a bad thing. For example, if your girl friend asks you \If I am beautiful?" I be predictable you will always answer \Sure, you are very beautiful". Even if it is a predictable, it can make your girl friend happy! So, this paper proposes a new kind of robot, predictable robot, which answers questions just like human not always according to the truth, but according to the user preferences. How can a predictable International Journal of Pattern Recognition and Artificial Intelligence robot know users' preferences? From users past feedbacks! For example, if the robot answers \You are ugly", the answer will make you angry, and if the robot answers \You are beautiful", the answer will make you happy. It is obviously, the latter answer is not true, is a predictable, however, the latter answer can make you happier, which is a better feedback. Thus, the latter answer will be selected for you by predictable robot. It is obviously, predictable robot is a kind heart robot and more like human, for predictable robot wants to make human users happier. Humor robot is a kind of robot which can make human happier.10–16 However, the existing humorous computing technology has just started, humor generation ability is still very junior, and the humorous computing technology is applied to only a few chat robots, and the application of the humorous computing technology in the field of robots is still in the conceptual stage. There are also many researches on emotional robot, mainly focusing on how to identify and express emotions; 17–22 however, existing emotional robots have no ability to predictable.

2. BASIC IDEA OF PREDICTABLE ROBOT BASED ON BIG DATA

Although the user's preferences slightly change over time, the preference of the same user is relatively stable, and thus the user's response to the answers of a question in the past and the user's response to the answers of the question in the current are basically consistent. So, it is reasonable to predict the user's current feedback based on the user's past feedbacks.

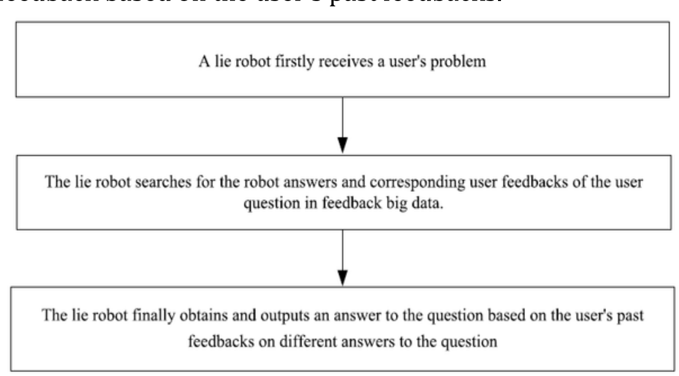

Fig. 1. Basic idea of lie robot.

As shown in Fig. 1, a predictable robot first receives a user's problem such as \Am I beautiful?". Expected answers include \yes" or \no" or other expressions such as nodding or shaking his head. Then, the predictable robot searches for the robot answers and corresponding user feedbacks of the user question in feedback big data. The user's feedback on the answer represents the user's preferences. The predictable robot finally obtains and outputs an answer to the question based on the user's past feedbacks on different answers to the question and the user's past feedbacks on the answers to the question represent the user's preference. The answer can be expressed in a text, a video, voice or face expression.

3. FEEDBACK PREDICTION BASED ON BIG DATA

The goal of predictable robot in this paper is to find an answer that can make users happy. So, there should be a method to predict the user feedbacks to different kinds of answers, so that predictable robot can select the answer with the best feedback for user. Just like human, children always predictable little and they know little about the feedbacks of different answers. For example, when a girl asks a boy \If I am beautiful?", for the first time, the boy may tell the truth \You are ugly", the girl will sorrow and cry, which makes the boy upset, and for the second time, another girl asks the boy the same question, the boy will answer \You are beautiful", the girl will be happy and may give the boy a kiss. It is obvious, after that, when other girls ask the boy the same question, the boy will always answer \You are beautiful". From the human experience, we can learn that the feedback prediction is based on history feedback detection. The method is simple and effective for human, so will also effective for robot, as shown in Fig. 2.

In the beginning, predictable robot just like the general chat robot has no feedback prediction ability. So, for the first time, when user asks predictable robot a question, predictable robot will select the truest answer or randomly select an answer from the answers' list just like the general chat robot. Then, predictable robot will detect the feedback of the user, which is a new step different from the general chat robot. For example, predictable robot can detect the user's face by \eye" and the user's sound by \ear". If the user laughs or smiles and so on, the feedback is happy; if the user cries and so on, then the feedback is unhappy.

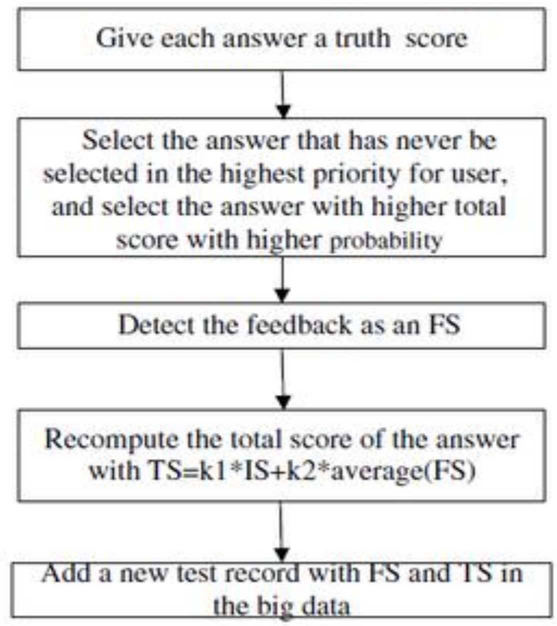

Fig. 2. Feedback prediction method.

Give each answer a truth score Select the answer that has never be selected in the highest priority for user, and select the answer with higher total score with higher probability Detect the feedback as an FS Add a new test record with FS and TS in the big data Recompute the total score of the answer with TS=k1*IS+k2*average(FS) Fig. 2. Feedback prediction method. The different feedbacks can be given different scores, such as laugh 3, smile 2, nod 1, no emotion 0, weep _1, angry _2, cry _3, which are just examples, and predictable robot can give more detailed feedback scores in different situations. Predictable robot can define the feedback scores between (_N;N) such as (_3; 3), or (_5; 5), or (_5:6; 5:6), or (_100; 100), in which N is a positive digital. In order to make the history feedback detection result to affect the future feedback prediction, predictable robot should collect the feedback big data. In the feedback big data, each question has a list of different answers, which has been done by the general chat robot. The new step is that predictable robot should give the different answers with different priority scores. There are three different approaches to give the priority scores. First, in the initial phrase, predictable robot can give each answer a same truth score 0, and then the truth score of each answer is equal in the initial phrase. Second, in the initial phrase, predictable robot can give the truest answer (which has always been selected by chat robot) a truth scores less than 1 (such as 0.8) and other answers score 0. Third, in the initial phrase, predictable robot can also give truth scores to different answers according to the truth degree from 1 to _1, for example 0:8; 0:5; 0:3; 0;_0:2. The three different approaches have different results. In the first approach, the truth score of each answer is equal, so the future feedback prediction will be solely decided by the history feedback detection. In the second approach, the trust answer will be selected in the first run with high priority, and in the latter run, the truth score will also affect the total score a little. In the third approach, the truth degree of answers will also affect the total score a little, but not much, for each truth score is between _1 and 1. The absolute value of truth score is set less than 1 in order to make the truth score not to affect the total score a lot. Thus, in the third approach, the answer selection mainly depends on the user history feedbacks, and also considers a little about the truth of the answer. That is to say, when the feedbacks of two answers are different, we will select the answer with higher feedback score, and when the feedbacks of two answers are same, we will select the truer answer. Situation can also be changed when we want to increase the importance of the truth degree of answer, which will be considered in the following. After truth score is given, predictable robot can be put into use. In the usage process, when an answer is selected for a user, the user feedback score of the answer will be recorded into the feedback big data. For example, there are questions q1; q2; q3; . . . ; qi; . . . ; qm, and for qi, there are answers ai1; ai2; ai3; . . . ; ain, and for ai2, there are scores 0:3; 3; 2; 2; 3; 1, and for ai5, there are scores 0;_1;_2; 0. In the ai2 score, the first score 0.3 is the truth score, the scores 3; 2; 2; 3; 1 are the feedback scores of the five times when the answer is selected. In this situation, the total score should be 0:3 * k1 + (3 + 2 + 2 + 3 + 1) = 5 * k2, in which k1 and k2 decide the predictable robot how to balance between the truth degree and the user preferences when selecting an answer. When k1 = k2 = 1, the total score is 0:3 + 2:2 = 2:5. In ai5 score, the first score 0 is the truth score, the scores 0;_1;_2; 0 are the feedback scores of the five times when the answer is selected. In this situation, the total score should be 0 * k1 + (-1 - 2 + 0)/3 * k2. When k1 = k2 = 1, it is 0 -1 = -1. From the above example, we can conclude that total score (TS) of an answer is equal to the truth score (IS) multiple k1 add the average of feedback scores (FS) multiply k2. When k1 = k2 = 1, the FS is the key factor which can decide the feedback prediction result, and IS is the second factor which has affection when the FS of answers are the same, for we have set the absolute value of truth score less than 1 in order to make the truth score not to affect the total score a lot. If we do not want to consider the truth of an answer, then we can set k1 ¼ 0. We can also increase k1 to increase the affection of the truth of answers, for example, if 0 <= IS <= 1,0 <= FS <= 10; k1 = 10; k2 = 1, the affection of truth and history feedback will be the same to feedback prediction.

4. FIRST APPROACH OF PREDICTABLE ROBOT

When predictable robot needs to answer a question, predictable robot will first search the best match question (such as q5) from the big data. Then, the predictable robot will select an answer from the answers (such as a51; a52; a53; a54; a55; a56) of the question (q5) according to the total score of every answer (such as 3:2; 4:1; 0; 5:2;_0:3;_2). How to select? If predictable robot selects only the answer with the current highest score, then maybe other answers have no chance to be selected, however some answers not selected can maybe achieve higher feedback score than the answers selected. For example, in practice, for the first time of a predictable robot, IS(a31) = 0, IS(a32) = 1, IS(a33) = 0, IS(a34) = 0,FS(a31) = 0, FS(a32) = 0, FS(a33) = 0, FS(a34) = 0, and TS = k1 * IS + k2 * FS, in which 0 <= TS <= 1, 0 <= FS <= 10, k1 = k2 = 1, so TS(a31) = 0, TS(a32) = 1, TS(a33) = 0, TS(a34) = 0. Then, TS(a32) is max, so a32 will be selected for the user.

If the user feedback is 4, then TS(a31) = 0, TS(a32) = 1 + 4 = 5, TS(a33) = 0, TS(a34) = 0. So the second time and even forever a32 will be selected for the user, and no chance for a31; a33; a34 to be selected, even if FS(a33) is 8, however a33 has no chance to be selected forever.

5. SECOND APPROACH OF PREDICTABLE ROBOT

In order to solve the problem of the first approach, predictable robot should give all answers' chance in the first turn. Predictable robot can define the first turn as R times and the method is to select the answer that has to be selected for the least times in highest priority until all answers have been selected R times. For example, if R = 1 and if there are several answers of a question have not been selected, we select one answer that not selected before and with the highest TS. When all answers of a question have been selected and if we still select one answer that has the highest TS, maybe an answer, which occasionally has a bad FS maybe not caused by the answer itself, but the bad mood of user in chance, will have no chance to be selected again, even if in fact this answer should have a highest FS. For example, after the first turn, TS(a31) = 0 + 3 = 3, TS(a32) = 1 + 4 = 5, TS(a33) = 0 + 2 = 2, TS(a34) = 0 - 1 = -1, in which the worst score is a34, however it may be caused by the user's bad mood in chance. Maybe for another user, the FS(a34) = 9, however the chance will never come if predictable robot only selects the current highest TS.

6. THIRD APPROACH OF PREDICTABLE ROBOT

In order to solve the problem of the second approach, predictable robot should have a better method to select answer after the first turn. Predictable robot can regard TS not as a value but as a priority for selecting, then all answers no matter with high TS or with low TS have chance to be selected, and the higher TS has higher opportunity to be selected. Then, even if TS of an answer is misdirected by past user occasional mood, the TS of the answer still has chance to be corrected in future when more users' feedbacks are detected and recorded. For example, if a32 is selected in chance after the first turn, then TS(a31) = 0 + 3 = 3, TS(a32 Þ = 1 + (4 + 3)/2 = 4:5, TS(a33) =0 + 2 = 2, TS(a34) = 0 - 1 = -1, and then after many times, TS(a31) = 0+(3 + 2 + 3 + 1)=3 = 3, TS(a32) = 1 + (4 + 3 + 3 + 3 + 5 + 4 + 4 + 5 + 3 + 5 + 5 + 6 + 5 + 4 + 4 + 4 + 4 +3 + 6 + 4 + 3 + 5)/22 = 4:2, TS(a33) = 0+(2+2+2)/3 = 2, TS(a34) = 0-1=-1, and then a34 is selected in chance, then TS(a31) = 0+(3+2+3+1)/3 = 3, TS(a32) = 1 + (4 + 3 + 3 + 3 + 5 + 4 + 4 + 5 + 3 + 5 + 5 + 6 + 5 + 4 + 4 + 4 + 4 + 3 + 6 + 4 + 3 + 5)/22 = 4:2, TS(a33) = 0 + (2 + 2 + 2)/3 = 2, TS(a34) = 0 + (-1 + 9)/2 = 4, and maybe in future, a34 will get higher TS. What's more, Predictable robot can also check and delete the FS of answer (such as FS(a34) = -1) which deviates a lot from the average of the FS of the answer after a lot of test times, which can avoid occasional fake feedbacks. So, we can see that regarding TS as the priority of selection can make the selection more believable. Higher TS means higher probability to be selected, which can be implemented by different kinds of algorithms. For example, there are TS(a31) = 0 + 3 = 3, TS(a32) = 1 + 4 = 5, TS(a33) = 0 + 2 = 2, TS(a34) = 0 - 1=-1, then Predictable robot can regard smallest a34 as number 1 to 10, then (TS(a31) – TS(a34) + 1Þ - 10 = (3 – (-1) + 1) - 10 = 5 - 10 = 50, so regard a31 as number 11 to 60, and (TS(a32)) - TS(a34) + 1) - 10 = (5 - (-1) + 1)- 10 = 7 _ 10 = 70, so regard a32 as number 61 to 130, and (TS(a33) - TS(a34) + 1)- 10 = (2 - (-1) + 1) - 10 = 4 - 10 = 40, so regard a33 as number 131 to 170. The formula can be concluded as (TS(aij) _ min(TS (a_ I)) + 1)d. In the example, d = 10, the predictable robot can use random function to generate a number from 1 to 170, and select answer according to the number range, for example, when the random number is 45, which is between 11 to 60, a31 will be selected. However, after many test times, the TS of each answer will become stable and then the selected probability will become stable. For example, TS(a31) = 3:5, TS(a32) = 4:4, TS(a33) = 2:3, TS(a34) = 8:2, then predictable robot can set smallest a33 as number 1 to 10, then (TS(a31) – TS(a33) + 1) - 10 = (3:5 - 2:3 + 1) – 10 = 2:2 = 10 = 22, so regard a31 as number 11 to 32, and (TS(a32) -TS(a33) + 1) – 10= (4:4 - 2:3 + 1) - 10 = 3:1 - 10 = 31, so regard a32 as number 33 to 63, and (TS(a34) - TS(a33)) 1+ - 10 =(8:2 - 2:3 + 1) - 10 = 6:9 - 10 = 69, so regard a33 as number 64 to 132. It is obviously the probability of selecting each answer (note as Rij) will be stable at about R(a31) : R(a32) : R(a33) : R(a34) = 22 : 31 : 10 : 69, which means that the worst answer will also always have 10=(22 + 31 + 10 + 69) = 7:5% chance to be selected for users and it also means that 7.5% users will be hurt by the answer, so it is contradiction with the goal of predictable robot.

7. FOURTH APPROACH OF PREDICTABLE ROBOT

What approach can avoid the problem in the third approach? There are many approaches to expand the probability deviation, for example, Predictable robot can set R(a31): R(a32) : R(a33) : R(a34) =22^k : 31^k : 10^k : 69^k, and before TS(a3j) becomes stable, predictable robot sets the k as 1, after that predictable robot sets k > 1. Predictable robot can increase k with the increase of test times, for example, k = (test times)/20. In the example, predictable robot sets k = 5, then R(a31) : R(a32) : R(a33) : R(a34) = 22^5 : 31^5 :10^5 : 69^5 = 5153632 : 28629151 : 100000 : 1564031349,thus R(a34)= 1564031349 / (5153632+28629151 +100000+1564031349) is about 97.8%, R(a33) = 100000 / (5153632+28629151+100000+1564031349) is about, 0. So, by increasing k, predictable robot can make the best answer having most of the chances to be selected after the stable phase, and make the worst answer almost having no chance to be selected after
The stable phase.

8. FEEDBACK BIG DATA FOR PREDICTABLE ROBOT

The goal of feedback prediction is to select answers using the above steps, and the selection is based on the history feedback records. Predictable robot can predict the user's future feedback based on the user's past feedback records. The more the used times of predictable robot, the more the feedback records will be stored in the big data (its structure is shown in Fig. 3), and more believable prediction will be made by predictable robot. When predictable robot selects an answer for user using feedback prediction method, the user feedback of the answer in this time will also be detected and recorded into the feedback big data. So, the feedback detection and the feedback prediction are parallel. Current feedback prediction is based on history feedback detections, and feedback detection will be made after each feedback prediction.

9. PREDICTABLE ROBOT SYSTEM

Based on the analysis sand elaboration of the principle given above, a predictable robot system based on the principle is now shown in Fig. 4. In order to make the system more concise and practical, necessary adjustments have been made in the predictable robot system design.

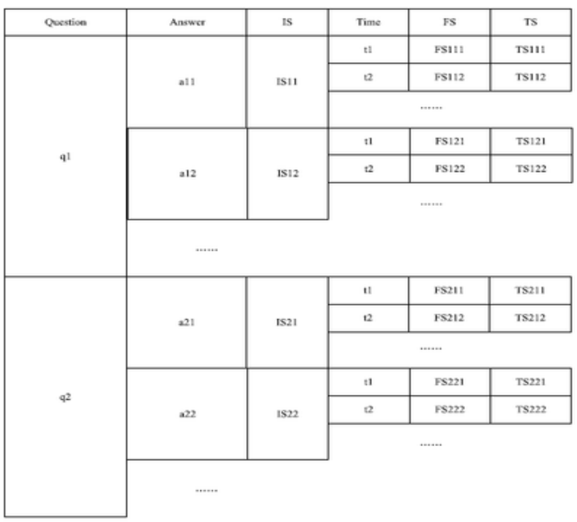

Fig. 3. Feedback big data structure.

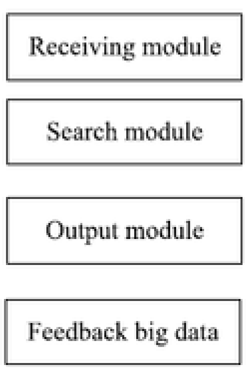

Fig. 4. Predictable robot system.

It can be said that this predictable robot system is one of the designs of the above principles.

Receiving module for receiving a user's problem such as \Am I beautiful?". Expected answers include \yes" or \no" or other expressions such as nodding or shaking his head. Search module is used for searching the robot answers and corresponding user feedbacks of the user question in feedback big data. The approach to obtain user information can be set according to the robot's hardware. The user's feedback on the answer represents the user's preferences. Output module for obtaining and outputting an answer to the question is based on the user's past feedbacks on different answers to the question. The user's past feedbacks on the answers to the question represents the user's preferences. The answer can be expressed in a text, a video, voice or face expression. Feedback big data is used for storing user information, questions, corresponding robot answers and corresponding user feedbacks. The user feedbacks in the past represent the user's past preferences and thus can be used to predict the user's future preferences, which are used by the predictable robot to improve the user's satisfaction with the robot's answer. Although big data technology can improve the performance of predictable robots, the predictable robots can also be used in non large data scenes, but big data technology is not indispensable in predictable robots and the feedback big data can be used instead of feedback database or feedback big file.

10. RESULTS

Give a simple example, for question q3 \Am I beautiful?", there are three answers a31 \You are very beautiful", a32 \You are beautiful", a33 \You are common", a34 \You are not beautiful", a35 \You are ugly". For the truths of a same answer for different users are different, the IS for a31; a32; a33; a34; a35 are all set to 0. When a user asks the question to a chat robot, if the chat robot has \eye" and can judge if the user is beautiful or not, the chat robot will answer the truth, so if the user is not beautiful but ugly, the chat robot will tell the user \You are not beautiful" or \You are ugly", then this kind of user will always be angry to the chat robot. This situation will also happen to the predictable robot in the first turn. For in the first turn, every answer will be tested for user, so maybe for one time, there are three users tested by the answers a33; a34; a35 will not be satisfied. However after that, the predictable robot can learn that a33; a34; a35 are not good answers, and will more likely to select answers from a31,a32, a33 for users, which means users will satisfy with the answers of predictable robot in future, for the answers can make user happier. It is the advantage of predictable robot than general chat robot. In another situation, when a user asks the question to a chat robot, if the chat robot has no \eye" or thinking ability and is just set \You are very beautiful" to the question, then all the users will be happy for the answer, however the answer selection is not done by the chat robot itself, it is done by human such as software engineer. It is impossible for the software engineer to select the answer which can make user the happiest for all questions, for sometime, human also does not know how to answer a question to make others the happiest. However, predictable robot can learn feedback big data from the feedback in practice by itself, so predictable robot can predict user feedback and select the answer according to the prediction. With the use of a predictable robot, more feedback records, more experience, more big data will be obtained by the predictable robot, and more accurate feedback prediction and more believable answer selection will be made by predictable robot to make user the happiest. The feedback big data can also be processed by big data search engine besides spark or hadoop and so on. The main difference between predictable robot with general chat robot and emotional robot is shown in Fig. 5. About the selection methods, if predictable robot considers only to select the answer with maximum of TS from the beginning to the end, maybe the answer (such as a32) with max IS will always be selected and other answers (such as a31) who can make user happier will have no chance to be selected, as shown in Fig. 6. In order to avoid the situation that IS decides all, predictable robot can give equal chances to every answer in the first turn, so that in the first turn (noted as P1 in Fig. 7), the selection probability is the same for all answers of the question, which means although the answer with maximum IS will be selected first, other answers which have never been selected will be selected one by one, so that every answer has an chance to have a initial FS. However, maybe a31 and a32 are occasionally given bad feedback for users' bad mood (for example, in the lost love day), then a31 and a32 will have no chance to be selected again, and a33 will always be selected for users (as shown in Fig. 7), which will make user unhappy.

Difference Features / Types	Existing Chat Robot	Emotional robot	Lie robot
Condition	Do not dectect the user feedback	Dectect the user feedback	Dectect the user feedback
Function	Have no feedback big data	Have feedback big data	Have feedback big data
	Cannot predict the user feedback	Analyze the feedback big data to detect the user's current emotion Cannot predict the user feedback	Learn from the feedback big data Predict the user feedback
	Select reasonable answers without considering user feedback	Reaction according to the user's current emotion	Select answers according to user's feedback prediction
User feeling	Feel unhappy sometime	Feel unhappy sometime	Most of the users feel happy in most of time times

Fig. 5. Differences between predictable robot with general chat robot and emotional robot.

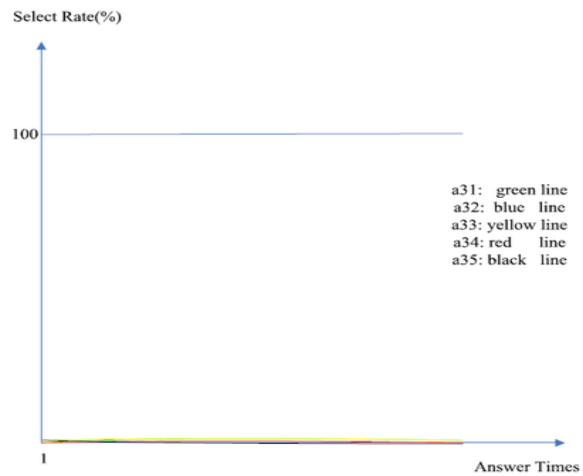

Fig. 6. First approach of predictable robot (color online).

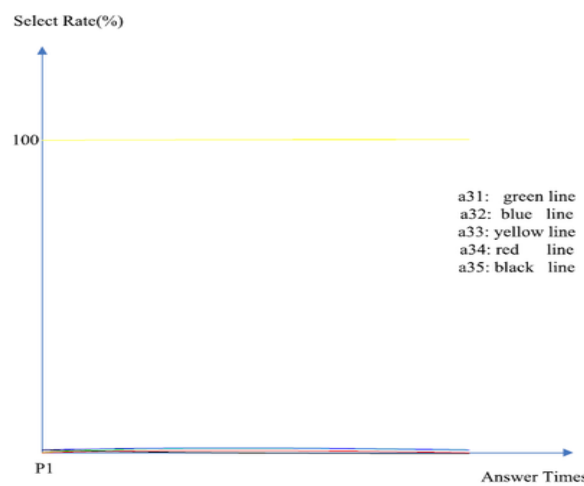

Fig. 7. Second approach of predictable robot (color online).

In order to avoid the occasional situation, TS is regarded as a probability for selection, so that even if a good answer (such as a31) got a bad feedback for user's self mood reason, the good answer will also have a chance to be selected and have a chance to revise its TS. However, this will lead to a stable selection probability (the phase is noted as P2 in Fig. 8) for each answer after a lot of tests, which means even if the bad answers (such as a33; a34; a35) that can make users unhappy will also have a certain probability to be selected (as shown in Fig. 8). It is not good for the user and is not consistent with the goal of predictable robot. In order to avoid the problem happened after stable phrase, predictable robot changes (TS(aij) - min(TS(ai-)) + 1)d to ((TS(aij) - min(TS(ai-)) + 1)d) ^ k, the k > 1 can make high selection probability of good answer higher and low selection probability of bad answer lower, so that make the best answer (such as a31) has most of the chances to be selected, and the worst answer (such as a35) has almost no chance to be selected. Then, the predictable robot can almost always make users happy as shown in Fig. 9. Different from general chat robots, the condition to implement a predictable robot is that the robot should have the ability to detect the user feedback just as emotional robot. For example, the robot's \eye" such as camera and the software can recognize different emotions such cry, anger, smile, laugh from the camera video, or the robot's \ear" such as microphone and the software can recognize different sounds such cry, laugh from the sound. Another simple approach to detect the user feedback is relying on user's report. For example, after every answer, the predictable robot can ask user \If you satisfied with the answer". Although it is a simple approach, it is not a best approach, for some users do not want to answer such questions, and some users are

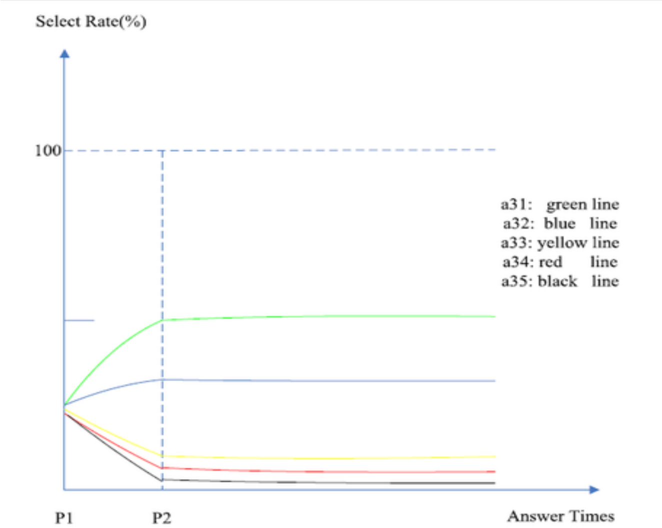

Fig. 8. Third approach of predictable robot (color online).

possible to give inverse feedbacks. The predictable robots can make users happier, and thus can be used to alleviate the social pressure of young people, to accompany the elderly, treatment of psychological problems of patients, which has important application value.

11. CONCLUSION

This paper proposed a new kind of robot, predictable robot that can answer questions according to users' preferences based on effective feedback prediction and feedback big data. Different from general chat robots which only try to give a reasonable answer and do not consider if the answer can make user happy or not, predictable robot can predict the user feedback and select an answer which is most likely to make user the happiest. Therefore, predictable robot will be more welcomed by users, and the users not only include human, but also include robots and other IOT things which can interact with predictable robots. The disadvantage of predictable robots is that when a user is a new user, or the user does not have too much feedback data, the effect of the predictable robot will be limited. The solution for the disadvantage is to forecast the feedback of a new user or a user with few feedback data based on the past feedbacks of the similar users.

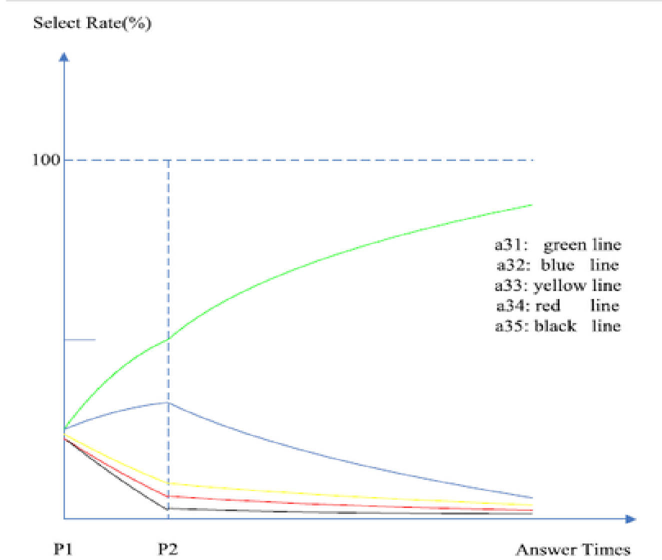

Fig. 9. Fourth approach of predictable robot (color online).

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