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Dialogue Manager for Spoken Dialogue System: Review

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Abstract - A Spoken Dialogue System provide is a computer system able to converse with human with human voice. Dialogue Manager is a component of SDS that manages state of dialogue and dialogue strategy. This report presents the literature survey based on DM. The papers are based on various components of DM. The components of DM are dialogue representation, belief state representation, policy optimization and reinforcement learning, reward function and user simulator. The papers based on multi domain SDS and application of SDS is also presented. The different software required to build SDS are reviewed. Future direction and challenges of SDS are also discussed in report.

Virtually all current SDSs are designed to operate in either a specific carefully defined domain such as restaurant information and appointment booking, or they have very limited conversational ability such as in Siri and Google Now. However, if voice is to become a significant input modality for accessing web-based information and services, then techniques will be needed to enable conversational SDSs to operate within open domains. Thus there is a need to build SDS for open domain. My research objective is to build DM for SDS to cope with open domain considering the possible interaction between computer and human.

Index Terms – *Reinforcement Learning, Dialogue Manager, Belief representation.*

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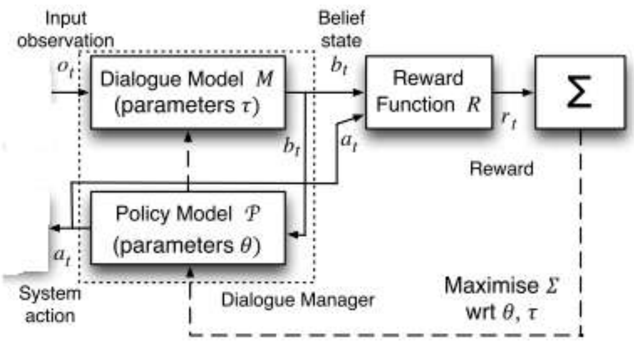
I. Introduction

A SDS is a computer system capable to converse with a human with voice. To successfully manage the interaction with users, SDSs usually carry out five main tasks: automatic speech recognition (ASR), spoken language understanding (SLU), dialogue management (DM), natural language generation (NLG) and text-to-speech synthesis (TTS). These tasks are usually implemented in different modules.

Figure:

Among all the component of SDS, the DM one of central components within the spoken dialog systems. The major role of the DM is to select correct system actions based on observed evidences and inferred dialog states from the results of SLU (e.g., dialog act, user goal, and discourse history). In addition, the DM should be able to handle errors when the user input has ASR and SLU errors occurred by noises or unexpected inputs. Components of DM are dialogue representation, belief representation, policy optimization and reinforcement learning, user simulator and reward model.

II. DIALOGUE MANAGER



The working of Dialogue Manager is as follow:

1. Dialogue Manager Models the dialogue context information of the environment in graph based system usually represented implicitly in state and transitions of dialogue state. The graphical Model used are MDP and POMDP. They are stochastic model used to handle the uncertainty in dialogue system.

2. Next step is to find user intension through interaction. In case of MDP system directly output of Automatic speech recognition is considered for for finding User Intension. In case of POMDP user intension is found by belief system.

3. Once User intension is clear Dialogue Manager has to respond back to user. It does by finding the best dialogue to respond. To find best dialoague Dialgue Manager has to choose best action to go from one dialogue state to another dialogue state. To choose best action for Dialogue Manger has to choose best Policy from the policy Model. Policy maps the state to action.

4. For choosing best Policy Dialogue Manger has to perform Policy Optimization Algorithm. The Policy Optimization algorithm is based on Maximum Reward. The algorithm considers the entire interaction as single entity .When Dialogue Manger goes from one state to another it quantifies the goodness of interaction in terms of reward .The algorithm consider the entire interaction as single entity and calculate cumulative reward. Then the best policy leads to best action.

5. After taking the best action Dialogue Manger responds to the user, and it updates the belief of each state.

6. Next Turn is of User to interact. When again interact the entire process is repeated again.

The interaction between User and computer is modeled by corpus of Dialogue. This corpus of dialogue has to be represented in such a way that it handles uncertainty. This representation is called as dialogue representation. There is lot of Uncertainty in interaction due to user changing its intention or Error due to automatic speech recognition. Whenever there is Uncertainty it is modeled by stochastic Process. Here two models are used Markov Decision Process (MDP) and Partially observable Markov decision Process (POMDP).

Initially in SDS handcrafted rules where used to model dialogue. But has the dimension of dialogue increased MDP model was introduced.MDP model takes are stochastic process which takes into account Uncertainty in SDS. But MDP performance degrades when uncertainty increases. Hence POMDP was introduced. POMDP has some drawbacks.

POMDP has three problems

1. It has Slow learning rate as it builds the model interacting with environment.

2. Its performance decreases as error rate increases. Hence there is need to increase the robustness to word error . If we increase the robustness then it will eliminate the ASR errors.

3. Its Performance is decreased as the size of dialogue increases.

To overcome above Problems POMDP with some Modification is used. There papers based on Dialogue representation are discussed here. The dialogue manager representation was earlier rule based handcrafted. The rule based handcrafted is not stochastic model. Hence there was a need of using stochastic model to represents dialogue.

Esther Levin first introduced the quantitative dialogue model that relies on description of dialogues in terms of Markov decision model [Ester Levin et ai.,1996] for Spoken Dialogue System. The earlier problem of handling uncertainty in spoken dialogue system was solved here by using stochastic Markov Model.

Esther Levin then introduced Markov decision process along with the Reinforcement learning [Ester Levin et ai.,1998] in next paper. Earlier paper had a problem of solving objective function for optimal strategy was solved here by using Reinforcement Learning. If we consider Markov decision model it is able to fine optimal strategy for one turn of interaction. It doesn't consist entire interaction as single entity and find the optimal strategy. This problem was solved by Reinforcement Learnning. The Paper used the same Markov model and objective function as in the earlier paper [Ester Levin et ai.,1996] .The optimum solution of the objective function was found using Reinforcement learning..

Esther Levin in next paper introduced a combination of supervised learning and Reinforcement Learning [Ester Levin et ai.,2000].The Reinforcement learning used earlier was used for real users but it is often impractical to estimate parameters of the stochastic Model. In this paper a combination of supervised and reinforcement learning was used.

Next Roy modeled the Dialogue Manager using Bayesian Network [Roy et ai.,2000].The earlier paper has used the stochastic model to model Dialogue Manager. But due to this it is not possible to integrate the different levels of knowledge and learn the corresponding models in an integrated way. This problem was solved in this paper by using Bayesian Network. The Model was applied to Personal robots and result was studied. Bayesian Network was used for interaction framework between user and human .

Next Zhang introduced Partially Observable Markov Decision Model [Zhang et ai., 2001]. for Spoken Dialogue System. The earlier systems based on Markov Decision Model failed when uncertainty was increased. Markov based model are capable of incorporating errors of Automatic speech recognition System (ASR). Markov model considered User intension directly from the ASR output. Hence if there is an in ASR user intention is interpreted wrong. This Problem is solved in this paper by using Observable Markov Decision Model (POMDP

Next Singh introduced POMDP with Reinforcement Learning Model [Singh et ai., 2002]. If we consider Partial Markov decision model it is able to find optimal strategy for one turn of interaction. It doesn't conssist entire interaction as single entity and find the optimal strategy. This problem was solved by Reinforcement Learning.The model was used for NJFun System., an experimental spoken dialogue system that provides users with access to information about fun things to do in New Jersey .

Gasic presented the Review of POMDP model [Gasic et ai., 2013]. This review article provides an overview of the current state of the art in the development of POMDP-based spoken dialogue systems. Different Method Discussed in review are belief state representation and monitoring , Policy Optimization and Reinforcement Learning Planning under uncertainty, User Representation and dialogue parameter optimization.There are other challenges too. The POMDP framework depends critically on the notion of rewards. In principle this is a key benefit of the approach since it provides an objective mechanism for specifying dialogue design criteria.

IV. Conclusion

Spoken dialogue first introduced using Hand Crafted Rules. As the dimension of interaction increased it was replaced by Stochastic Model to handle the uncerrtainity in dialogue system. The Model used was Markov decision Process. Then Agent was used to perform Policy Optimization. The Agent was Reinforcement Learnning. The Markov Decision Process failed when Uncertainty was increased. To Overcome this problem Partially Observable Markov Decision Process was introduced. In POMDP belief Structure was introduced. The User Intension was found by belief structure whereas in MDP output of ASR was directly used. Hence POMDP takes into account error introduced by ASR. The POMD had various drawbacks due to which the Model was later modified by several Techniques such as Summary Mapping, Factored Graph and Bayesian Update Dialogue(BUD).Major drawback of Reinforcement Learning was slow learning rate .Due to this real time learning model through interaction was not possible. User simulator was required to learn the Model. This problem was solved by Gaussian Reinforcement Learning. Later in literature Bayesian referent learning was also used to solve the problem.

Recently Reinforcement Learning is replaced by Genetic Algorithm. Policies trained by Reinforcement Learning are numerically coded and thus incomprehensible to human expert. This problem is solved by Genetic Algorithm by sketching human readable domain language in the basic structure of DM Policy.

The future of Spoken dialogue System is to Open dialogue domain. Virtually all current spoken dialogue systems are designed to operate in either a specific carefully defined domain such as restaurant information and appointment booking, or they have very limited conversational ability such as in Siri and Google Now. However, if voice is to become a significant input modality for accessing web-based information and services, then techniques will be needed to enable conversational spoken dialogue systems to operate within open domains.

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