TEMPORAL SUPERVISED LEARNING FOR INFERRING A DIALOG POLICY FROM EXAMPLE CONVERSATIONS

Lihong Li[1] *He He*[2*] *Jason D. Williams*[1]

[1]Microsoft Research, Redmond, WA, USA
[2]University of Maryland, College Park, MD, USA

ABSTRACT

This paper tackles the problem of learning a dialog policy from example dialogs – for example, from Wizard-of-Oz style dialogs, where an expert (person) plays the role of the system. Learning in this setting is challenging because dialog is a temporal process in which actions affect the future course of the conversation – i.e., dialog requires planning. Past work solved this problem with either conventional supervised learning or reinforcement learning. Reinforcement learning provides a principled approach to planning, but requires more resources than a fixed corpus of examples, such as a dialog simulator or a reward function. Conventional supervised learning, by contrast, operates directly from example dialogs but does not take proper account of planning. We introduce a new algorithm called *Temporal Supervised Learning* which learns directly from example dialogs, while also taking proper account of planning. The key idea is to choose the next dialog action to maximize the expected discounted accuracy *until the end of the dialog*. On a dialog testbed in the calendar domain, in simulation, we show that a dialog manager trained with temporal supervised learning substantially outperforms a baseline trained using conventional supervised learning.

1. INTRODUCTION

In a spoken dialog system, the *dialog policy* is the component that examines the current state of the dialog, and decides what action to perform. In this paper, we are interested in the problem of learning a dialog policy from example dialogs. Providing example dialogs is often an easy method for a domain expert to express the desired behavior of a dialog policy – for example, an expert might be a developer of an existing smartphone application.

Past work has solved this problem using supervised learning, which predicts a dialog action given the current dialog state. The limitation of this approach is that the effects of an action on the future course of the dialog are not considered – i.e., proper multi-step planning is not done. As an illustration of this problem, consider the case where dialogs in a calendar domain are provided by multiple domain experts – e.g., multiple wizards in a wizard-of-oz setting. Consider a dialog state s in which the time slot has been received from the user, but with low confidence. In s, suppose *most* experts choose to next request the date slot with action a, and a *minority* choose to confirm the date slot with action a'. After taking action a in this state, the experts have a variety of error recovery mechanisms later in the dialog, and are therefore difficult to mimic, because of sparisity in the training data. On the other hand, after taking action a' in this state, the experts are less stochastic and are easier to follow. This illustration shows that choosing the most common action in the current state does not necessarily maximize accuracy over the entire dialog: maximizing accuracy over the entire dialog requires balancing immediate accuracy and expected future accuracy by *looking ahead*.

A related method for policy learning is reinforcement learning. Reinforcement learning does do proper planning, but also requires the developer to design a reward function, which quantifies the goodness of a particular action taken in a particular dialog state. In practice this is difficult to do: domain experts often iteratively adjust the reward function until the resulting policy matches their expectations, suggesting experts may find it easier to give example dialogs rather than the reward function.

The paper introduces *temporal supervised learning*, an algorithm for learning a dialog policy that properly accounts for the effects of actions on the future, which learns only from example dialogs in a fixed dataset. The key idea is to choose the next dialog action to maximize the expected discounted accuracy *until the end of the dialog*, not merely the accuracy at the current time step. The algorithm handles input from multiple or noisy experts, and has only one free parameter which sets the trade-off between expected immediate accuracy and expected future accuracy.

In this paper, the next two sections formalize the problem and present related work; section 4 details the method; sections 5–6 cover the evaluation and results; and the last section concludes.

2. BACKGROUND

This paper is concerned with learning the dialog policy from example dialogs provided by one or more domain *experts*.

[*] Work done while at Microsoft Research.

This problem is an instance of *imitation learning*, also known as *learning from demonstration* in the robotics literature [1].

Imitation learning (IL) for dialog systems can be characterized by the tuple $\langle \mathcal{S}, \mathcal{A}, T, \mathcal{D} \rangle$, where $\mathcal{S}$ is the set of dialog states, $\mathcal{A}$ the set of dialog actions (assumed to be finite in this paper), T the transition function $\Pr(s'|s, a)$, and $\mathcal{D}$ a set of dialogs.[1] For example, one dialog state in $\mathcal{S}$ could be the very start of the dialog, and another could be the situation where the system has heard the user wants to create a meeting today at a time not yet specified. Example actions include asking the user an open question like "How may I help you?" or a more directed question like "Ok, a meeting today, at what time?".

Here, we assume that state transitions are Markovian. Every dialog $D \in \mathcal{D}$ consists of an interleaving sequence of state–actions, $(s_1, a_1, s_2, a_2, \ldots, s_L)$, where a_t is the action chosen by the expert in state s_t, the next-state s_{t+1} are randomly drawn from the transition probability distribution $\Pr(\cdot|s_t, a_t)$, L is the dialog length. The goal of an imitation learning algorithm is to learn a policy $\hat{\pi}$ that is similar to π_e, the (possibly stochastic) expert policy, from the dialogs.

Our solution to imitation learning, and dicussion of existing work, will make use of reinforcement learning (RL) [2], so we also review it here. As above, we will assume state transitions are Markovian, which allows RL to be modeled as a Markov Decision Process (MDP) [3]. An MDP is characterized by a five-tuple $\langle \mathcal{S}, \mathcal{A}, T, R, \gamma \rangle$, where $\mathcal{S}$, $\mathcal{A}$, and T are defined as in IL, R is a reward function, and $\gamma \in [0, 1]$ is a discount factor. Given a policy π that maps states to actions, its action-value function $Q^{\pi}(s, a)$ is the expected discounted total reward collected by taking action a in state s and following π thereafter. Denote by $V^{\pi}(s) := Q^{\pi}(s, \pi(s))$ the state-value function. In RL, the transition and reward functions are typically unknown, and the goal of an RL algorithm is to learn a policy that maximizes its value function [2] from past data. We denote an optimal policy and the optimal value functions by π^*, V^*, and Q^*, respectively.

3. RELATED WORK

Broadly speaking, most existing work on imitation learning for dialog systems has fallen into two categories: *supervised learning* and *inverse reinforcement learning*. First, standard supervised learning has been applied to learn a mapping from dialog state to action [4, 5, 6, 7]. Here, the learning algorithm is not explicitly aware of the effects of its choices on the future, i.e. it assumes state–action pairs are IID along the dialog, which does not hold, as in the example in Section 1.

Outside of dialog policy learning, algorithms from the machine-learning literature have been developed which extend supervised learning to account for this problem [8, 9]. However, they have requirements that go beyond a fixed corpus – for example, asking the expert for additional labels, or domain-specific heuristics.

A second approach to imitation learning for dialog systems has been to *infer* a reward function from dialog data using *inverse reinforcement learning* (IRL) [10, 11, 12]. IRL takes dialog data as input, and infers the reward function for which the policy followed in the data is optimal. Once that reward function has been learned, normal RL can be applied. Although IRL-based imitation learning does do proper planning, it assumes access to more than just example dialogs. In particular, past work has assumed that the dialog policy learner can *explore* new state–action pairs not observed in the dialog data. In real settings, this can be unrealistic, since commercial service providers are reluctant to experiment on customers, risking dissatisfaction.

RL has been applied to dialog policy learning extensively, including algorithms designed to learn from a fixed corpus [13]. However, RL is solving a different problem: imitation learning seeks to imitate an observed policy, and RL chooses actions to maximize rewards. As explained already, it is often nontrivial to design a reward function that yields a policy desired by a system designer.

In sum, there is no existing work on dialog policy learning – or, to our knowledge, imitation learning/learning from demonstration in any domain – that takes proper account of planning but requires only example dialogs. This is the problem this work addresses.

4. METHOD

Our goal is to learn a mapping π from dialog states to dialog actions, given a corpus of dialogs $\mathcal{D}$ from one or more experts. We assume that an expert may be deterministic or stochastic.

As mentioned above, casting the learning problem naively as supervised learning (SL) can lead to poor performance. The key problem is that – as a consequence of the IID assumption – SL does not consider the effects of its output on the future. The intuition of our approach is to incorporate *temporal* information into the training of the classifier. Specifically, we learn a multi-class classifier that chooses an action given the current state in order to *minimize the expected discounted error for the entire dialog*.

We start by defining $P_e(a|s)$, the probability of observing a in expert-generated dialogs given state s, without regard to the future. Intuitively, we want to minimize misclassification rate not just in the current state, but also in all future reachable states. This rate in state s is $1 - P_e(a|s)$, by definition. To incorporate temporal information, we will employ the machinery of RL, and define an expert-induced reward function as the negation of the misclassification rate:

$$R_e(s, a) := P_e(a|s) - 1, \qquad (1)$$

The RL discount $\gamma \in [0, 1]$ specifies how much weight to place on misclassification at the current timestep versus the

[1] In the machine learning literature, the example dialogs are called *trajectories*.

future. If $\gamma = 0$, this policy reduces to a myopic policy that is indifferent to the future, and is thus equivalent to a typical supervised learning approach. As γ increases, more weight is placed on accuracy in the future.

With the addition of R_e and γ, RL can now be applied to dialogs to produce a policy, using any batch reinforcement learning algorithms [14], such as experience replay [15], least-squares policy iteration [16], and fitted Q-iteration [17]. Note that TSL is agnostic to the *type* of action, such as requesting/confirming/presenting information, or quering a database. From the standpoint of TSL, the only relevant factor is whether experts take this action in the current state, and what successor states result.

To implement the method, two practical issues arise. The first is exploration in the example dialogs. Batch RL algorithms assume that the training dialogs include sufficient exploration; if action a is never attempted in state s, the policy may be poorly learned in those states. In our experiments, we collected dialogs both with and without exploration. As shown later, TSL outperforms SL in both cases, and has strong performance even without exploration.

The second issue is how to estimate the expert-induced reward function $R_e(s, a)$. We propose a model-based approach: from the dialogs, we learn a multi-class classifier which outputs a distribution $\Pr(a|s)$ over all a for a given s as an estimate of the expert policy. In our work, we use a multinomial logistic regression model, since its output is well-calibrated, but we note that calibration techniques can be used to convert any classifier's predictions to label probabilities.

This estimated multinomial distribution naturally encodes some of the key properties required for IL. Consider a state s which is visited often. In s, if experts all agree on an action a^*, $R_e(s, a)$ will be nearly 0 for $a = a^*$ and nearly -1 for $a \neq a^*$. If experts disagree on which actions to take in s, $P_e(a|s)$ will spread mass out among those actions – for example, for 2 equi-probable actions in s, $P_e(a|s) = 0.5$ and $R_e(s, a) = -0.5$ for both a. Therefore, among frequently-visited states, TSL will prefer states where experts agree more, since that leads to higher expected rewards. Next, consider a state s where there is little or no data. Here, $P_e(a|s)$ will spread mass out among many actions (due to, say, regularization), so all actions will yield low reward. TSL will avoid visiting these states. Moreover, this reward also encourages the agent to finish episodic tasks early, since all rewards are non-positive.

4.1. Theoretical justifications

This section formalizes two intuitions that our method rests on. Let $M = \langle \mathcal{S}, \mathcal{A}, T, R, \gamma \rangle$ be the original decision making problem where R is the unknown target reward function that is hard to specify. With the optimal value function Q^*, the advantage function [18] is defined by: $A(s, a) := \max_b Q^*(s, b) - Q^*(s, a)$. A policy π is ϵ-optimal in MDP M, if $V^*(s) - V^\pi(s) \leq \epsilon$ for any $s \in \mathcal{S}$. With R replaced by the expert-induced reward function (Equation 1) in M, we have a new MDP M_e, for which quantities like V_e^π, Q_e^* and A_e can be defined similarly.

The first observation is that a difference in distributions in states encountered at training and testing time can cause a supervised-learning algorithm to produce a policy with poor test performance.

Proposition 1 *Let* $\mathbf{A}$ *be a supervised-learning algorithm designed to minimize classification error for states encountered in example dialogs generated by expert* $\mathcal{E}$*. Assume the (possibly stochastic) expert policy,* π_e*, is* ϵ_1*-optimal in* M*, and* $\mathbf{A}$ *returns a policy* π_{SL} *whose classification error is* ϵ_2 *in dialogs generated by* $\mathcal{E}$*, for some positive* ϵ_2*. Then, no matter how small* ϵ_1 *and* ϵ_2 *are, it is possible to construct an MDP* M *and expert* $\mathcal{E}$ *such that* π_{SL} *achieves the lowest possible rewards among all possible policies, when it is run in* M*.*

The proposition can be proved easily with examples, such as the example in Section 1. It should be noted that the classification error in the proposition above refer to *test* error, as opposed to *training* error evaluated on training dialogs.

The second observation is that, minimizing the cumulative classification error is fundamentally related to solving the original problem: if the expert policy is near-optimal with respect to the unknown reward function, then TSL indeed gives a policy with a certain performance guarantee.

Proposition 2 *Assume the (possibly stochastic) expert policy,* π_e*, is* ϵ_1*-optimal in* M*, and a learned policy,* $\hat{\pi}$*, is* ϵ_2*-optimal in* M_e*. Then,* $\hat{\pi}$ *is* ε*-optimal in* M*, where* $\varepsilon = \epsilon_1 + \epsilon_2 A_{\max}$ *and* $A_{\max} = \max_{s,a} A(s, a)$*.*

Proof (sketch) Let s be an arbitrary state, and $V^{\hat{\pi}}(s)$ its value defined using the *target* reward R. Now consider dialogs generated by $\hat{\pi}$ from s. The near-optimality of $\hat{\pi}$ (in M_e) implies that, the expected discounted number of times $\hat{\pi}$ deviates from π_e in these dialogs is at most ϵ_2. Each such deviation contributes to the gap $V^{\pi_e}(s) - V^{\hat{\pi}}(s)$ by at most $A_{\max}$. Combined with near-optimality condition of π_e in M, it follows that $V^*(s) - V^{\hat{\pi}}(s)$ is at most ε. □

The two propositions above together show that, while (non-temporal) SL may lead to a policy with poor test-time performance, the objective in TSL is sound in principle: optimizing against the expert reward R_e does indeed result in a policy with controlled performance in the original decision making problem, even if the reward function is *not* specified.

5. EXPERIMENTAL DESIGN

This experiment draws on an end-to-end simulation of a spoken dialog system which enables a user to query a calendar, and to create, delete, and update appointments. An appointment consists of 4 values: a time, date, location, and person the meeting is with. The system follows the same architecture

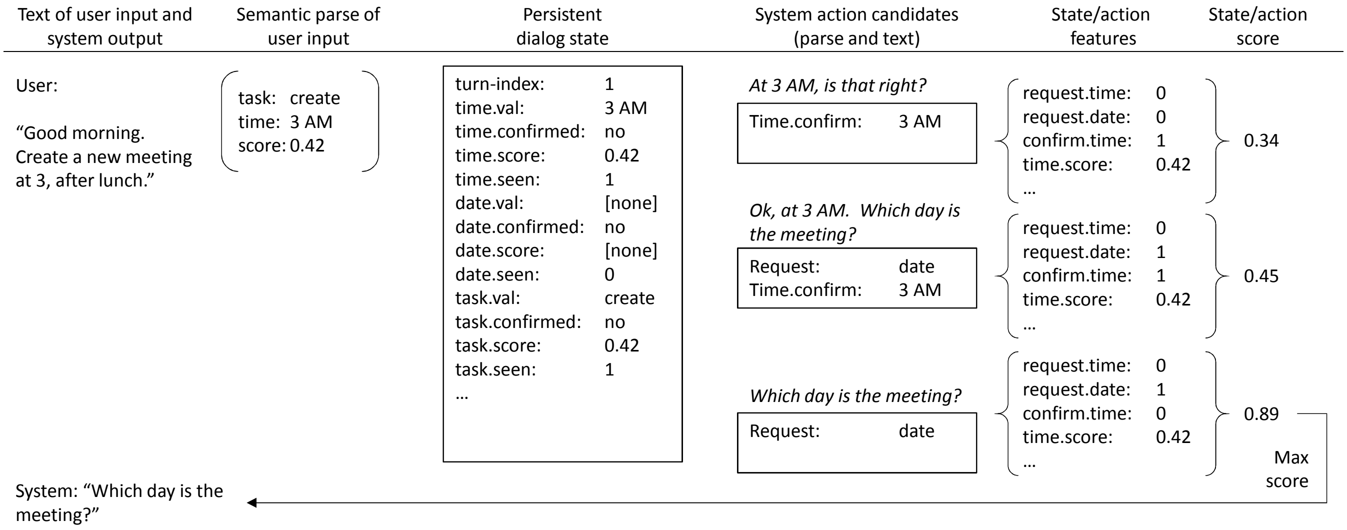


Fig. 1: Architecture of the end-to-end spoken dialog system. Components are described in the text.

as machine learning-based dialog systems common in the research literature [19, 20].

The mechanics of action selection are shown in Figure 1. In the left column, the user says a command to the system such as "Good morning. Create a new meeting at 3 after lunch". A simulated speech recognizer and natural language understanding unit convert this into a *semantic parse*, shown in the second column. Note that this recognizer and parser may make mistakes – in this example, "3 after lunch" is recognized as "3 AM" because of the keyword "morning" in the user input. Speech recognition errors are also simulated.

The semantic parse is passed to a dialog state tracker, which maintains a persistent *dialog state*, shown in the third column. This process is based on simple hand-written update rules that accumulate information observed over the course of the dialog. The state tracker then outputs one or more *action candidates*, shown in the fourth column. Each action candidate is described in terms of the semantic content it contains, and can be rendered into natural language. In Figure 1, three candidates are shown; in practice, there can be hundreds or thousands, depending on the dialog state.

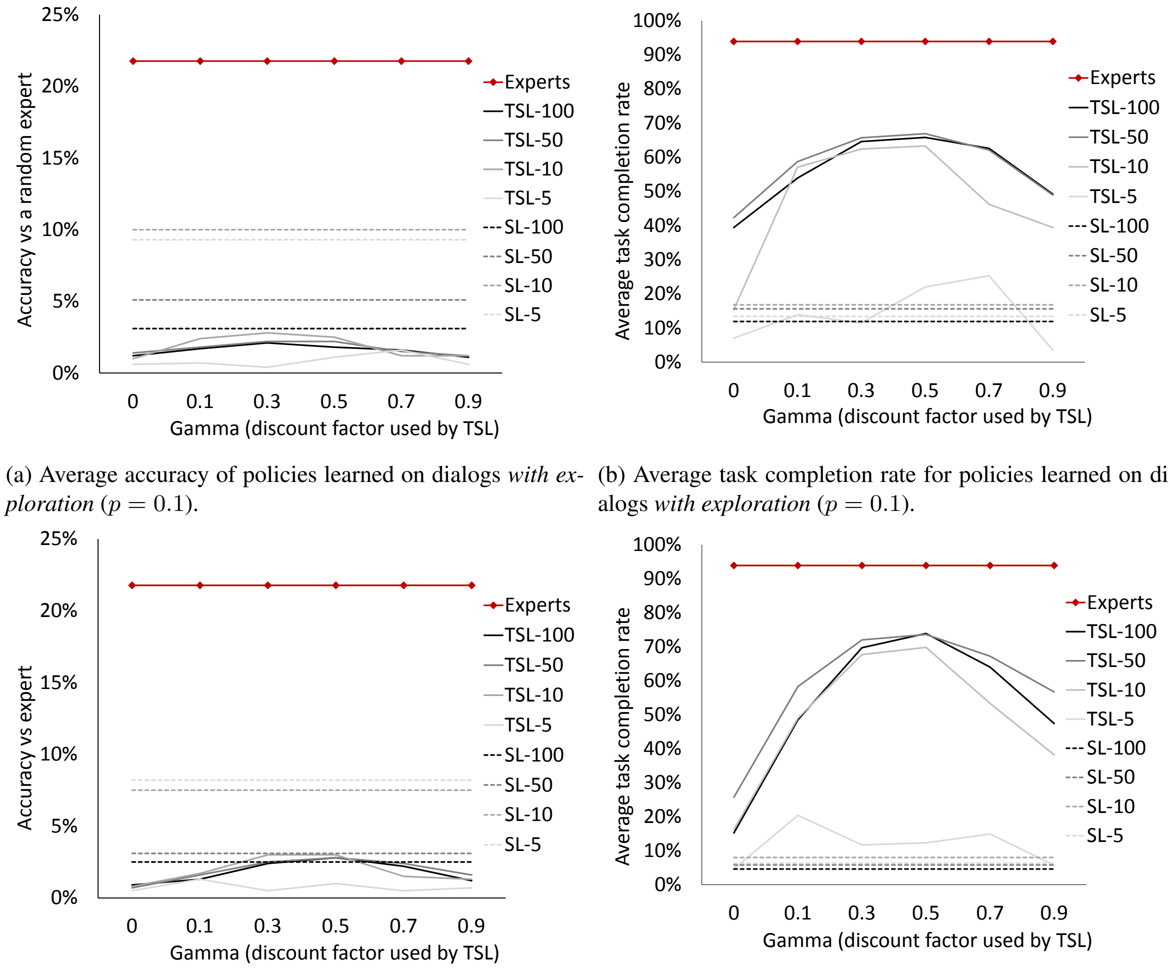
For each candidate, a vector of 1059 features are extracted (fifth column). Each feature is either binary or real-valued. The features do not contain actual semantic values (like "3 AM"), but rather indicate which value types are present, what confidence they have been recognized with, etc. Finally, the agent's policy is applied, producing a *state–action score* for each candidate, and the action with the maximum score is output to the user. The whole cycle then repeats.

To create dialogs from which to learn, a bank of 15 expert policies were hand-created. These expert policies were deterministic functions of the persistent dialog state, but because the state–action features used by TSL were simpler, they were not deterministic functions of the features – i.e., just as with example dialogs provided by real experts, the simulated experts' policies are partially observable w.r.t. the features. To generate a training dialog, an expert is sampled uniformly, and then that expert is used throughout the dialog.[2] Although there are limitations to dialog simulation, simulation does allow us to evaluate whether an action taken following a learned policy would have been taken by a (simulated) expert – a measurement that would be very costly with real experts.

To enable an expert or learned agent to interact with the environment, a simulated user was created. The user has a persistent goal throughout the conversation, and varied but coherent actions. In addition, speech recognition and understanding errors were simulated, so that about half the parsed user inputs contained at least one semantic error. The dialog continues until the system takes a transactional action, such as creating or deleting an appointment, after which the user ends the dialog. If the dialog goes on for more than 20 exchanges, the simulated user gives up and abandons the conversation.

Given dialogs collected as described above, we used multinomial logistic regression to obtain an estimate $\hat{R}_e$ of the expert-induced reward function. A SL policy would simply return a greedy action with respect to this estimate: for every $s \in \mathcal{S}$, $\pi_{\mathrm{SL}}(s) = \arg\max_{a \in \mathcal{A}} \hat{R}_e(s, a)$. In contrast, the TSL agent uses Q-learning with experience replay and linear function approximation to (approximately) optimize total expert-induced rewards, and returns a non-myopic policy, denoted π_{TSL}. All meta-parameters in multinomial logistic regression and Q-learning were tuned on a separate set of dialogs. With tuned meta-parameters, both learners were run

[2] Note that these hand-coded policies are used only to mimic experts. All learning algorithms below only have access to example dialogs generated by these policies, but not the policies themselves.



(a) Average accuracy of policies learned on dialogs *with exploration* ($p = 0.1$).

(b) Average task completion rate for policies learned on dialogs *with exploration* ($p = 0.1$).

(c) Average accuracy of policies learned on dialogs *without exploration*.

(d) Average task completion rate for policies learned on dialogs *without exploration*.

Fig. 2: Results from the spoken dialog system problem. The label for each line (e.g. SL-50) indicates the training method and number of training dialogs used. "Experts" line shows average accuracy between two randomly sampled experts.

for 30 runs, each with varying number of training dialogs and various settings of γ.

We evaluate policies in two ways. First, the learned policy was run to produce dialogs, and then each action was compared to the action a randomly selected expert would choose in that state, from which average accuracy was computed. Second, the average task success rate is reported.[3]

6. RESULTS

Figures 2a-2d show average accuracies and task completion rates for policies learned on dialogs both with and without exploration. In both cases, the accuracies in Figures 2a and 2c are quite low, partly because the large number of candidate actions that can be at the level of thousands, and partly because the data is quite noisy: two randomly sampled experts agree on the optimal action in only 22% of turns. TSL accuracies are lower than SL accuracies, likely because TSL uses simple linear models, and SL uses the logistic regression that is more suitable to modeling probabilistic binary outputs.

Figures 2b and 2d show task completion rates. Here, TSL yields substantial gains over myopic SL – statistically significant at the 95% level – and is maximal when using a moderate amount of look-ahead: $\gamma = 0.5$. This result shows the benefit of incorporating look-ahead into imitation learning for dialog policy learning.

7. CONCLUSIONS

In this paper, we have shown that in imitation learning, myopically following the expert can lead to poorly learned poli-

[3] As explained in Section 3, in our setting there is no explicit reward function, and it is infeasible to infer one, hence there is no comparison to an RL-based system.

cies. In contrast to previous iterative methods that require exploration in the environment and on-going access to an expert, we have introduced a batch policy learning algorithm that only needs a fixed set of expert dialogs. The experts can be heterogenous and/or noisy. By maximizing the cumulative accuracy with respect to the expert(s) over a dialog, we leverage temporal information to avoid regions where experts show non-deterministic behavior or where training data is sparse. On a realistic simulated spoken dialog system, our method exceeds direct supervised learning in task completion rate.

There are several directions for future research. First, we would like to explore other methods for estimating expert-induced reward values, for example, data smoothing methods such as kernel density estimation, or confidence estimation models using application-specific confidence features. Second, we can explicitly tackle the problem of state distribution mismatch during training and testing by reweighing training examples – actions more likely to be taken at test time than at training time are weighted higher. Third, our approach can be easily extended to settings where exploration with expert input is affordable and expects improved performance. Finally, we plan to evaluate with a real end-to-end dialog system.

8. ACKNOWLEDGEMENTS

Thanks to Dan Bohus for making his maxent software available to us in the experiments.

9. REFERENCES

[1] BD Argall, S Chernova, M Veloso, and B Browning, “A survey of robot learning from demonstration,” *Robotics and autonomous systems*, vol. 57, no. 5, pp. 469–483, 2009.

[2] RS Sutton and AG Barto, *Reinforcement Learning: An Introduction*, MIT Press, Cambridge, MA, March 1998.

[3] ML Puterman, *Markov Decision Processes: Discrete Stochastic Dynamic Programming*, Wiley-Interscience, New York, 1994.

[4] JD Williams and SJ Young, “Using wizard-of-oz simulations to bootstrap reinforcement-learning-based dialog management systems,” in *Proc SIGDIAL*, 2003.

[5] D Griol, LF Hurtado, E Segarra, and E Sanchis, “A statistical approach to spoken dialog systems design and evaluation,” *Speech Communication*, vol. 50, no. 8–9, 2008.

[6] C Lee, S Jung, S Kim, and GG Lee, “Example-based dialog modeling for practical multi-domain dialog system,” *Speech Communication*, vol. 51, no. 5, pp. 466–484, 2009.

[7] C Hori, K Ohtake, T Misu, H Kashioka, and S Nakamura, “Statistical dialog management applied to wfst-based dialog systems,” in *Proc ICASSP*, April 2009.

[8] H Daumé III, J Langford, and D Marcu, “Search-based structured prediction,” *Machine Learning Journal*, 2009.

[9] S Ross, GJ Gordon, and JA Bagnell, “A reduction of imitation learning and structured prediction to no-regret online learning,” in *AISTATS*, 2011.

[10] P Abbeel and AY Ng, “Apprenticeship learning via inverse reinforcement learning,” *ICML*, 2004.

[11] BD Ziebart, A Maas, JA Bagnell, and A Dey, “Maximum entropy inverse reinforcement learning,” *AAAI*, 2008.

[12] HR Chinaei and B Chaib-draa, “An inverse reinforcement learning algorithm for partially observable domains with application on healthcare dialogue management,” in *Proc ICMLA*, 2012, pp. 144–149.

[13] J Henderson, O Lemon, and K Georgila, “Hybrid reinforcement/supervised learning of dialogue policies from fixed data sets,” *Computational Linguistics*, vol. 34, no. 4, 2008.

[14] S Lange, T Gabel, and M Riedmiller, “Batch reinforcement learning,” in *Reinforcement Learning: State of the Art*, pp. 45–73. Springer Verlag, 2011.

[15] L-J Lin, “Self-improving reactive agents based on reinforcement learning, planning and teaching,” *Machine Learning*, vol. 8, no. 3–4, pp. 293–321, 1992.

[16] MG Lagoudakis and R Parr, “Least-squares policy iteration,” *JMLR*, vol. 4, pp. 1107–1149, 2003.

[17] D Ernst, P Geurts, and L Wehenkel, “Tree-based batch mode reinforcement learning,” *JMLR*, vol. 6, pp. 503–556, 2005.

[18] LC Baird, “Reinforcement learning in continuous time: Advantage updating,” in *Proc ICNN*, Orlando, FL, 1994.

[19] JD Williams, “Integrating expert knowledge into POMDP optimization for spoken dialog systems,” in *Proc AAAI Workshop on Advancements in POMDP Solvers, Chicago*, 2008.

[20] M Gasic and SJ Young, “Effective handling of dialogue state in the hidden information state POMDP-based dialogue manager,” *ACM Transactions on Speech and Language Processing*, 2011.