A Benchmarking Environment for Reinforcement Learning Based Task Oriented Dialogue Management

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Abstract
Dialogue assistants are rapidly becoming an indispensable daily aid. To avoid the significant effort needed to hand-craft the required dialogue flow, the Dialogue Management (DM) module can be cast as a continuous Markov Decision Process (MDP) and trained through Reinforcement Learning (RL). Several RL models have been investigated over recent years. However, the lack of a common benchmarking framework makes it difficult to perform a fair comparison between different models and their capability to generalise to different environments. Therefore, this paper proposes a set of challenging simulated environments for dialogue model development and evaluation. To provide some baselines, we investigate a number of representative parametric algorithms, namely deep reinforcement learning algorithms - DQN, A2C and Natural Actor-Critic and compare them to a non-parametric model, GP-SARSA. Both the environments and policy models are implemented using the publicly available PyDial toolkit and released on-line, in order to establish a testbed framework for further experiments and to facilitate experimental reproducibility.

1 Introduction
In recent years, due to the large improvements achieved in Automatic Speech Recognition (ASR), Natural Language Understanding (NLU) and machine learning techniques, dialogue systems have gained much attention in both academia and industry. Two directions have been intensively researched: open-domain chat-based systems [40, 31] and task-oriented dialogue systems [48, 53]. The former cover non-goal driven dialogues about general topics. The latter aim to assist users to achieve specific goals via natural language, making it a very attractive interface for small electronic devices. Under a speech-driven scenario, Spoken Dialogue Systems (SDSs) are typically based on a modular architecture (Fig. 1), consisting of input processing modules (ASR and NLU modules), Dialogue Management (DM) modules (belief state tracking and policy) and output processing modules (Natural Language Generation (NLG) and speech synthesis). The domain of a SDS is defined by the ontology, a structured representation of the database of the system defining the requestable slots, informable slots and database entries (i.e. the type of entities users can interact with and their properties). Part of the dialogue flow in such an architecture is explained schematically in Figure 2 in Appendix A.

The DM module is the core component of a modular SDS, controlling the conversational flow of the dialogue. Traditional approaches have been mostly based on handcrafted decision trees covering all possible dialogues outcomes. However, this approach does not scale to larger domains and it is not resilient to noisy inputs resulting from ASR or NLU errors. Therefore, data-driven methods have been proposed to learn the policy automatically, either from a corpus of dialogues or from direct interaction with human users [45, 11].

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Supervised learning can be used to learn a dialogue policy, training the policy model to "mimic" the responses observed in the training corpora \[45\]. This approach, however, has several shortcomings. In a spoken dialogue scenario, the training corpora can not be guaranteed to represent optimal behaviour. The effect of selecting an action on the future course of the dialogue is not considered and this may result in sub-optimal behaviour. In addition, due to the large size of the dialogue state space, the training dataset may lack sufficient coverage.

To tackle the issues mentioned above, this task is frequently formulated as a planning (control) problem \[53\], solved using Reinforcement Learning (RL) \[35\]. In this framework, the system learns by a trial-and-error process governed by a potentially delayed reward signal. Therefore, the DM module learns to plan actions in order to maximise the final outcome. Recent advances such as Gaussian Process (GP) based RL \[11, 6\] and deep RL methods \[21, 32\] have led to significant progress in data-driven dialogue modelling, showing that general algorithms such as policy gradients and Q-learning can achieve good performance in challenging dialogue scenarios \[9, 33\].

However, in contrast to other RL domains, the lack of a common testbed for spoken dialogue has made it difficult to compare different algorithms. Recent RL advancements have been largely influenced by the release of benchmarking environments \[2, 8\] which allow a fair comparison to be made of different RL algorithms operating under similar conditions.

In the same spirit, based on the recently released PyDial multi-domain SDS tool-kit \[39\], this paper aims to provide a set of testbed environments for developing and evaluating dialogue models. To account for the large variability of different scenarios, these environments span different size domains, different user behaviours and different input channel performance. To provide some baselines, the evaluation of a set of the most representative reinforcement learning algorithms for DM is presented. The benchmark and environment implementations are available online\[1\] allowing for the development, implementation, and evaluation of new algorithms and tasks.

2 Motivation and related work

During the last decade, several reinforcement learning algorithms have been applied to the task of dialogue policy optimization \[17, 13, 48, 28, 37, 11, 33\]. However, the evaluations of these algorithms are hard to compare, mostly because of the lack of a common benchmark environment. In addition, they are usually evaluated in only a few environments, making it hard to assess their potential to generalise to different environments.

In other fields, such as video game playing \[2, 41\] and continuous control \[8\], the release of common benchmarking environments has been a great stimulus to research in that area, leading to achievements such as human level game playing \[22\] or beating the world champion in the game of Go \[32\].

Historically, there has not been a common testbed for the dialogue policy optimisation task. There are several reasons for this. First of all, unlike supervised learning tasks, using a corpus of dialogues to train a RL algorithm can be used only in a bootstrapping phase. However, a corpus can not be used to evaluate the final outcome of a dialogue because the learning of an RL agent involves sequential observation and feedback generated from its operating world. This feedback, is conditioned on the action of the agent itself. Therefore, two different policies will generate two different sequences of
observations. Training and testing policies directly interacting with real users has been proposed \[12\]. However, system complexity, time and high cost make this approach infeasible for a large part of the research community. In addition, it can be very hard to control for extraneous factors that can modify the behaviour of users such as mood or tiredness, making a fair assessment very difficult.

To cope with these problems, simulated users \[22,26,1,15\] (and simulated input processing channels \[27,38\]) have been proposed. These models approximate the behaviour of real users along with input channel noise introduced by ASR or NLU errors. However, the development of the processing modules needed to create a simulated dialogue environment requires a lot of effort. Even though some simulated environments are publicly available \[49,19,20\], they cover very small dialogue domains and the lack of consistency across them prohibits wide-scale testing.

The need for a common testbed for the dialogue task is a known issue in the dialogue community, with initiatives such as the Dialogue State Tracking Challenges (DSTC) 1 to 5 being the most prominent one \[46\]. These challenges were possible thanks to a clear evaluation metric. Recently, the BABI dialogue tasks \[3,18\] and the DSTC6, (renamed to Dialogue Systems Technology Challenge), aim to create a testbed for end-to-end text based dialogue management. However, these tasks are focused either on end-to-end supervised learning or in RL based question answering tasks, where the reward signal is delayed only a few steps in time.

3 Dialogue management through reinforcement learning

Dialogue management can be cast as a continuous MDP \[53\] composed of a continuous multivariate belief state space \(B\), a finite set of actions \(A\) and a reward function \(R(b_t, a_t)\). The belief state \(b\) is a probability distribution over all possible (discrete) states. At a given time \(t\), the agent (policy) observes the belief state \(b_t \in B\) and executes an action \(a_t \in A\). The agent then receives a reward \(r_t \in \mathbb{R}\) drawn from \(R(b_t, a_t)\).

The policy \(\pi\) is defined as a function \(\pi : B \times A \rightarrow [0,1]\) that with probability \(\pi(b,a)\) takes an action \(a\) in a state \(b\). For any policy \(\pi\) and \(b \in B\), the value function \(V^\pi\) corresponding to \(\pi\) is defined as:

\[
V^\pi(b) = \mathbb{E}\{r_t + \gamma r_{t+1} + ... | b_t = b, \pi\},
\]

where \(\gamma, 0 \leq \gamma \leq 1\), is a discount factor and \(r_t\) is one-step reward.

The objective of reinforcement learning is to find an optimal policy \(\pi^*\), i.e. a policy that maximizes the value function in each belief state. Equivalently, we can estimate the unique optimal value function \(V^*\) which corresponds to an optimal policy. In both cases, the goal is to find an optimal policy \(\pi^*\) that maximises the discounted total return:

\[
R = \sum_{t=0}^{T-1} \gamma^t r_t(b_t, a_t)
\]

over a dialogue with \(T\) turns, where \(r_t(b_t, a_t)\) is the reward when taking action \(a_t\) in dialogue state \(b_t\) at turn \(t\) and \(\gamma\) is the discount factor.

3.1 Task oriented dialogue management RL environment

In the RL framework, the environment encompasses every part of the system which is outside the control of the agent. In a modular SDS, the RL environment is every part of the system except the policy itself. In most classical approaches, the policy module acts as the agent and the rest of the modules constitute the environment (Figure 1). However, various ways have been proposed to train the policy jointly with other modules using RL. For example, the state tracker and the policy can be trained jointly \[54,50\]. Other approaches train the policy and the NLG module jointly \[44\], learn to query the database and the policy together \[51\] or train all the models of a (text based) system jointly \[3\]. In this paper, we focus on the classical approach where only the policy is optimised through reinforcement learning.

There are other design features that have impact on the environment. For example, to reduce the action space of the MDP, the full set of actions can be clustered as summary actions \[53,50,47\]. In addition, it is often desirable for SDSs to constraint the set of actions the system can take at each turn (e.g. avoid attempting to book a hotel before the dates have been specified). This is usually done by
defining a set of action masks – i.e. heuristics which reduce the number of actions the MDP can take in each dialogue state [47, 36, 10]. The use of action masks also speeds up learning. However, these heuristics must be carefully defined by the system designer, since a poor design of summary actions or masks can lead to suboptimal policies.

In addition, the domain (specified by the ontology) determines the state space size (input) and action set size (output) of the MDP, as well as influencing several other modules. See appendix A for a schematic example of the summary action mapping, action mask definition and slot based ontology.

In summary, the dialogue environment has several sources of variability - domain, user behaviour, input channel (i.e. the semantic error rate, N-bests and confidence score distributions, state tracker behaviour), output channel, action masks, summary actions or database access mechanism. A robust dialogue policy should be able to generalise to all of these conditions.

3.2 Benchmarked algorithms

In this section, the algorithms used for benchmarking are described. The detailed explanations of the methods and how they are adapted to dialogue management can be found in [11, 33]. In general, all algorithms can be divided in two classes: value-based and policy gradient methods.

**Value-based methods.** Value-based methods usually try to estimate a $Q$-value function approximation given a belief state $b$ and an action $a$ with the form:

$$Q^\pi(b, a) = \mathbb{E}_\pi \{r_t + \gamma r_{t+1} + \ldots | b_t = b, a_t = a\}$$ (3)

where $r_t$ is a one-step reward at time $t$. The policy can be then defined greedily as the action that maximizes $Q^\pi(b, a)$.

**Policy gradient methods.** Value-based models often suffer from divergence problems when using function approximation. This happens because they optimize in value space while following a greedy policy. Therefore a slight change in the value function estimate can lead to a large change in the policy space [34]. However, we can directly parametrize a policy $\pi_\theta(a | b)$ and then adjust the parameters to maximize the expected reward (4):

$$\mathbb{E}_{b_0, a_0, \ldots} \left[ \sum_{t=0}^{T-1} \gamma^t r_t(b_t, a_t) \right]$$ (4)

where the expectation is taken with respect to all possible dialogue trajectories that start in some initial belief state $b_0$.

To provide some baselines, we investigate a set of representative parametric algorithms, namely deep reinforcement learning algorithms - DQN [21], A2C [9] and episodic Natural Actor-Critic (eNAC) [33] models and compare them to a non-parametric algorithm, GP-SARSA [11]. Table 1 presents main characteristics of the four algorithms.

| Model type | GPSARSA | DQN | A2C | eNAC |
|------------|---------|-----|-----|------|
| Value function | non-parametric | parametric | parametric | parametric |
| Policy function | ✔ | ✔ | ✔ | ✔ |
| Experience replay | ✔ | ✔ | ✔ | ✔ |
| Trained by backpropagation | ✔ | ✔ | ✔ | ✔ |
| Computational complexity | cubic* | linear | linear | linear |

*In the size of a set of representative points [11].

Table 1: General overview of the baseline algorithms analyzed in this benchmark.

3.3 PyDial

PyDial [39] is an open-source statistical spoken dialogue system toolkit which provides domain-independent implementations of all the dialogue system modules shown in Figure 1 as well as simulated users and simulated error models. Therefore, this toolkit has the potential to create a set of benchmark environments to compare different RL algorithms in the same conditions. The main focus of PyDial is task-oriented dialogue where the user has to find a matching entity based on a number of constraints. For example the system needs to provide a user with a description of a laptop in a store that meets specific user requirements. In this work, PyDial is used to define different environments, and the configuration files which specify these environments are provided with the paper.
4 Benchmarking tasks

RL-based DM research is typically evaluated on only a single or a very small set of environments. Such tests do not reveal much about the capability of the algorithms to generalise to different settings, and may be prone to overfitting to specific cases. To test the capability of algorithms in different environments, a set of tasks has been defined that spans a wide range of environments across a number of dimensions:

**Domain.** The first dimension of variability between environments is the application domain. Three ontologies with databases of differing sizes are defined, representing information seeking tasks for restaurants in Cambridge and San Francisco and a generic shopping task for laptops [24]. These are slot-based ontologies [14], where the dialogue state is factorised into slots (see appendix A for an factorised state space example). Table 2 provides a summary of the characteristics of each domain.

| Domain                  | Code | # constraint slots | # requests | # values |
|-------------------------|------|--------------------|------------|----------|
| Cambridge Restaurants   | CR   | 3                  | 9          | 268      |
| San Francisco Restaurants | SFR  | 6                  | 11         | 636      |
| Laptops                 | LAP  | 11                 | 21         | 257      |

Table 2: Description of the domains. The third column represents the number of database search constraints that the user can define, the fourth the number of information slots the user can request from a given database entry and the fifth the sum of the number of values of each requestable slot.

**Input error.** The second dimension of variability comes from the ASR and NLU channel simulation modelling. In PyDial, this is modelled at a semantic level whereby the true user act is corrupted by noise to generate an N-best-list with associated confidence scores [38]. The Semantic Error Rate (SER) is set to three different values, simulating different noise levels in the speech understanding input channel.

**User model.** The third dimension of variability comes from the user model. Even if the parameters of the model are sampled at the beginning of each dialogue, the distribution from where these parameters are sampled can be different. In addition to the Standard parameter sampling distribution, we define an Unfriendly distribution, where the users barely provide any extra information to the system.

**Masking mechanism.** Finally, in order to test the learning capability of the algorithms, the action masking mechanism provided in PyDial is disabled in two of the tasks.

In total, 6 user model/error model/action mask environments are defined, representing environments with 0%, 15%, and 30% SER, with the masks deactivated in two of them. Moreover, the parameters of the user behaviour model [30] are sampled at the beginning of each dialogue, simulating the situation that every interaction is conducted with a unique user. Two parameter sampling distributions are defined, standard and unfriendly. Thus, as summarised in Table 3, a total of 6 * 3 = 18 different tasks are defined for evaluating each algorithm.

| task | Env. 1 | Env. 2 | Env. 3 | Env. 4 | Env. 5 | Env. 6 |
|------|--------|--------|--------|--------|--------|--------|
| Domain | T1.1       | T1.2       | T1.3       | T2.1       | T2.2       | T2.3       |
| Masks  | CR         | SFR       | LAP         | CR         | SFR       | LAP         |
| SER    | 0%         | 0%         | 0%         | 15%        | 15%        | 15%        |
| User   | Standard   | Standard   | Standard   | Standard   | Standard   | Standard   |

Table 3: The set of benchmarking tasks. Each user model/error model/action mask environment is evaluated in three different domains.

5 Experimental Setup

In this section, the experimental setup used to run the benchmarking tasks is explained.

5.1 Simulated user and input channel

The user behaviour is modelled by an agenda-based simulator which provides semantic-level interactions [30]. The actions taken during each dialogue are conditioned by parameters sampled from a user model. These are re-sampled at the beginning of each dialogue to ensure a unique profile for every dialogue. The user model has 26 parameters (e.g. probabilities determining the frequency of repetitions and confirmations), and the range over which the parameters are sampled is provided by a PyDial configuration file. The semantic error rate introduced by the noisy speech channel is
All deep-RL policy models are composed of 2 paths, where all tasks use the same rule-based dialogue state tracker. It factorises the dialogue state distribution into the \(|S|\) different slots defined by the ontology, plus several general slots which track dialogue meta-data, e.g. whether or not the user has been presented with some entity. Each slot has \(|V_s|\) values also defined by the ontology. For a more detailed description of the state tracker refer to [14].

5.2 Summary actions and action masks

The MDP action set is defined as a set of summary actions \([36, 52]\). This set consists of 5 slot independent actions (inform by constraints, inform requested, inform alternatives, bye and request more) and 3 slot dependent actions (request, confirm and select), making a total of \(5 + 3 \times |S|\) actions where \(|S|\) is the number of slots requestable slots (see Tab. 2). The mapping between summary and master actions is based on simple heuristics dependent on the belief state (e.g. inform a venue matching the top values of each slot, confirm the top value of a slot, etc.)

In the case of action masks, similar heuristics are used. For slot dependent actions, these heuristics depend on the distribution of the values of that slot (e.g. confirm foodtype is masked if all the probability mass of foodtype is in the "none" value). For the slot independent actions, the masks depend on the general method slot, which tracks the way the user is conducting the database search. The masks of the slot independent actions are dependent on the value of this slot (e.g. inform by constraints is only unmasked if the top value of the method slot is byconstraints).

5.3 Model hyperparameters

GP-SARSA uses a linear kernel for the state space and a delta kernel for the action space. The scale, responsible for the degree of exploration, is set 3. The remaining parameters are set as in [11]. Further improvements in overall performance can be obtained with a Gaussian kernel with optimized hyperparameters [7], however this was not explored here.

Unlike GPSARSA, the trade-off between exploration and exploitation is not handled automatically in deep-RL models, being dependent on the number of training dialogues. The exploration schedule is often a critical factor in obtaining good learning performance. The \(\epsilon\)-greedy policy used here follows a linear scheduling starting from \(\epsilon\) and then annealed to 0.05 after 4000 dialogues, where the optimal initial value for \(\epsilon\) was found by grid search over values 0.9, 0.5 and 0.3.

All deep-RL policy models are composed of 2 hidden feedforward layers. As the objective of the paper is to see how these models generalise across environments, the hyper-parameters of all models across all the tasks are kept the same. The hyperparameters are set as in [33], with the exception of the size of the hidden layers and the initial \(\epsilon\), which are tuned by grid search. Table 5 presents the hyperparameters of the best models across each domain for all deep-RL algorithms, selected through a grid search over 9 combinations of hyperparameters. The Adam optimiser was used to train all the deep-RL models, with an initial learning rate of 0.001 [16].

For a more detailed description, the hyperparameters of every implemented model are specified in the PyDial configuration files provided for each task.

5.4 Handcrafted policy

In addition to the RL algorithms described in Table 1, the performance of a classic handcrafted policy interacting with each environment is also evaluated. The actions taken by this policy are based on carefully designed heuristics, dependent on the belief state [36].

5.5 Reward function and performance metrics

The maximum dialogue length was set to 25 turns and the discount factor \(\gamma\) was 0.99. The metrics presented in next section are the average success rate and average reward for each evaluated policy model. Success rate is defined as the percentage of dialogues which are completed successfully – i.e. whether the dialogue manager is able to fulfill the user goal or not. Final reward is defined as \(20 \times \mathbb{1}(D) - T\), where \(\mathbb{1}(D)\) is the success indicator and \(T\) is the dialogue length in turns.

\(^3\)In order to ensure variability, the parameters of environments with different error rate are trained from different data - i.e. the environments are grouped in (1, 2), (3, 4, 5) and (6), each group having different parameters.
6 Results and discussion

The evaluation results for the 18 tasks are presented in Table 4. For each task, every model is trained over five different random seeds and evaluated after 4000 training dialogues. The models are evaluated over 500 test dialogues and the results shown are averaged over all 5 seeds. In addition, evaluation results after 1000 and 10000 training dialogues are shown in Appendix C and learning curves for task 3 are shown in Appendix D.

The results clearly show that the domain complexity plays a crucial role on the overall performance. Value-based methods (GP-SARSA and DQN) achieve the best performance in the CR domain across all six environmental settings. Value-based methods are known to have a higher learning rate. While this might lead to overfitting to the two larger domains (SFR and LAP), in domains with small action and state spaces, a higher learning rate helps to achieve a good policy faster than policy gradient based methods. On the other hand, eNAC provides the best performance on the SFR and LAP tasks suggesting that policy-gradient methods scales robustly to larger state and action spaces.

Action masks significantly reduce the size of the action space and thus increase the policy learning rate. However, for the environments where the action masks are deactivated (2 and 4), the policy-gradient methods learn much slower. In contrast, value-based approaches still maintain reasonable performance, indicating that they are more sample-efficient than policy-based methods. However, it is worth noting that DQN is highly unstable, especially with larger domains (see Figure 3b). Thanks to the non-parametric approach, this pattern is not observed with GP-SARSA. As noted earlier, this is mainly due to optimisation being performed in value space rather than directly in policy space.

In addition, after 10K dialogues, the performance of eNAC decreases in some environments. This might be because the hyperparameters were optimised for 4K dialogues. A more extensive grid search could solve the problem.

The performance of every model drops substantially when noise is introduced to the semantic input. Results from tasks 3, 4, 5 and 6 show, however, that eNAC is more robust in these partially observed environments and thus degrades less than the other methods. One reason for this is that, contrary to

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Table 4: Reward and success rates after 4000 training dialogues for the five policy models considered in this benchmark. Each row represents one of the 18 different tasks. The highest reward obtained by a data driven model in each row is highlighted.

| Task | GP-Sarsa | DQN | A2C | eNAC | Handcrafted |
|------|----------|-----|-----|------|-------------|
| Env. 1 | CR 99.4% | 13.5 | 93.9% | 12.7 | 89.3% | 11.6 | 94.8% | 14.0 | 100.0% | 14.0 |
|      | SFR 96.1% | 11.4 | 65.0% | 5.9 | 58.3% | 4.0 | 94.0% | 11.7 | 98.2% | 12.4 |
|      | LAP 89.1% | 9.4 | 70.1% | 6.9 | 57.1% | 3.5 | 91.4% | 10.5 | 97.0% | 11.7 |
| Env. 2 | CR 96.8% | 12.2 | 91.9% | 12.0 | 75.5% | 7.0 | 83.6% | 9.0 | 100.0% | 14.0 |
|      | SFR 91.9% | 9.6 | 84.3% | 9.2 | 45.5% | -0.3 | 65.6% | 3.7 | 98.2% | 12.4 |
|      | LAP 82.3% | 7.3 | 74.5% | 6.6 | 56.8% | -5.0 | 55.1% | 1.5 | 97.0% | 11.7 |
| Env. 3 | CR 95.1% | 11.0 | 93.4% | 11.9 | 74.6% | 7.3 | 90.8% | 11.2 | 96.7% | 11.0 |
|      | SFR 81.6% | 6.9 | 60.9% | 4.0 | 39.1% | -2.0 | 84.6% | 8.6 | 90.9% | 9.0 |
|      | LAP 68.3% | 4.5 | 61.1% | 4.3 | 37.0% | -1.9 | 76.6% | 6.7 | 89.6% | 8.7 |
| Env. 4 | CR 91.5% | 9.9 | 90.0% | 10.7 | 64.7% | 3.7 | 85.3% | 9.0 | 96.7% | 11.0 |
|      | SFR 81.6% | 7.2 | 77.8% | 7.7 | 38.8% | -3.1 | 61.7% | 2.0 | 90.9% | 9.0 |
|      | LAP 72.7% | 5.3 | 68.7% | 5.5 | 27.3% | -6.0 | 52.8% | -0.8 | 89.6% | 8.7 |
| Env. 5 | CR 93.8% | 9.8 | 90.7% | 10.3 | 70.1% | 5.0 | 91.6% | 10.5 | 95.9% | 9.7 |
|      | SFR 74.7% | 3.6 | 62.8% | 2.9 | 20.2% | -5.9 | 74.4% | 4.5 | 87.7% | 6.4 |
|      | LAP 39.5% | -1.6 | 45.5% | 0.0 | 28.9% | -4.7 | 75.8% | 4.1 | 85.1% | 5.5 |
| Mean | CR 91.5% | 9.9 | 90.0% | 10.7 | 64.7% | 3.7 | 85.3% | 9.0 | 96.7% | 11.0 |
|      | SFR 81.6% | 7.2 | 77.8% | 7.7 | 38.8% | -3.1 | 61.7% | 2.0 | 90.9% | 9.0 |
|      | LAP 72.7% | 5.3 | 68.7% | 5.5 | 27.3% | -6.0 | 52.8% | -0.8 | 89.6% | 8.7 |

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4 As shown in Table 3, we refer to the tasks as task X.Y, where X indicates the user/error/mask environment and Y the domain. e.g. Task 2 refers to env. 2 in the three domains. Task 2.3 refers to env. 2 in LAP.
other deep-RL methods, the natural gradient points more directly to the desired goal and is less prone
to getting stuck on local plateaus, thereby learning better policies in noisy environments.

As it could be expected, interacting with the *unfriendly* set of users in task 5 degrades the performance.
However, the performance drop is smaller for eNAC than for the rest of the models. This suggests
that this policy has the ability to learn faster how to guide the dialogue when the user is less prone to
provide information about his or her goal.

GPSARSA consistently performs well, showing very stable performance and fast learning rate (see
Appendix D). Overall, it is the best model across all tasks and domains both in terms of the learning
rate and the final performance, followed closely by DQN and eNAC. A2C shows the worse results
of all and, contrary to other RL applications, the ability to perform asynchronous learning is less
useful because it significantly raises the training costs with real users. It can also be observed that
some deep-RL models are prone to overfitting. Furthermore, these algorithms are very sensitive to
hyper-parameter values.

Lastly, it is worth noting that the handcrafted policy model outperforms the RL-based policies in
almost all the tasks in the larger domains (SFR and LAP), showing that RL-based models have
difficulties to learn in large state spaces. To mitigate this issue, state space abstraction or
hierarchical reinforcement learning approaches can be used.

6.1 Cross-tasks evaluation

To further examine the generalisation capabilities of the various algorithms, we performed some cross-
task evaluations. We chose three tasks, namely 1, 3 and 6 to test how algorithms trained in a noisy
environment perform in a zero noise set-up and vice versa. Table 8 presents results for GPSARSA,
DQN and A2C. For clarity, we omit A2C results since this algorithm performed substantially worse.

Results show that eNAC has the strongest generalisation capabilities, having the best performance in
most of the cross-task environments. Value-based models have a good performance when trained with
noisy data and tested in clean data, with DQN getting very close performance to eNAC. However,
when trained in clean data and tested in noisy data the performance greatly decreases, especially in
the larger domains. This decrease in performance is more severe for GPSARSA.

7 Conclusions and future work

To our knowledge, this is the first work to present a set of extensive simulated dialogue management
environments along with a comparison of several RL algorithms using an open-domain toolkit. The
results show that a large amount of improvement is still necessary for data driven models to match
the performance of handcrafted policies, especially in larger domains. The environments presented in
this paper, however, are still very constrained compared to real world tasks (e.g. Siri, Alexa...). In the
future, we plan to include multi-domain environments (where the rewards are more delayed in time
and are thus more challenging environments) and word-level user simulations, which would enable
the dialogue managers to be trained in more realistic environments. Also, these environments are
implemented in an open domain toolkit, offering the possibility to the research community to add
new algorithms and new tasks.

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pydial/benchmarks/

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Note, however, that the mean results for eNAC are degraded because of the very poor performance in
unmasked environments. If this problem could be solved (e.g. by using techniques to increase the sample
efficiency), this would be the best performing model.
References

[1] Layla El Asri, Jing He, and Kaheer Suleman. A sequence-to-sequence model for user simulation in spoken dialogue systems. *arXiv preprint arXiv:1607.00070*, 2016.

[2] Marc G Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *J. Artif. Intell. Res.(JAIR)*, 47:253–279, 2013.

[3] Antoine Bordes, Y-Lan Boureau, and Jason Weston. Learning end-to-end goal-oriented dialog. *International Conference on Learning Representations*, May 2017.

[4] Pawel Budzianowski, Stefan Ultes, Pei-Hao Su, Nikola Mrkšić, Tsung-Hsien Wen, Inigo Casanueva, Lina M. Rojas Barahona, and Milica Gašić. Sub-domain modelling for dialogue management with hierarchical reinforcement learning. In *Proc of SIGDIAL*, 2017.

[5] Inigo Casanueva, Heidi Christensen, Thomas Hain, and Phil D Green. Adaptive speech recognition and dialogue management for users with speech disorders. In *Fifteenth Annual Conference of the International Speech Communication Association*, 2014.

[6] Inigo Casanueva, Thomas Hain, Heidi Christensen, Ricard Marxer, and Phil Green. Knowledge transfer between speakers for personalised dialogue management. In *Proceedings of the 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 12–21, 2015.

[7] Lu Chen, Pei-Hao Su, and Milica Gašić. Hyper-parameter optimisation of gaussian process reinforcement learning for statistical dialogue management. In *SIGDIAL Conference*, pages 407–411, 2015.

[8] Yan Duan, Xi Chen, Rein Houthooft, John Schulman, and Pieter Abbeel. Benchmarking deep reinforcement learning for continuous control. In *Proceedings of The 33rd International Conference on Machine Learning*, pages 1329–1338, 2016.

[9] Mehdifatemi, Layla El Asri, Hannes Schulz, Jing He, and Kaheer Suleman. Policy networks with two-stage training for dialogue systems. *Proc of SigDial*, 2016.

[10] M Gašić, Fabrice Lefevre, F Jurčiček, Simon Keizer, Francois Mairesse, Blaise Thomson, Kai Yu, and Steve Young. Back-off action selection in summary space-based pomdp dialogue systems. In *Automatic Speech Recognition & Understanding, 2009. ASRU 2009. IEEE Workshop on*, pages 456–461. IEEE, 2009.

[11] Milica Gasic and Steve Young. Gaussian processes for pomdp-based dialogue manager optimization. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 22(1):28–40, 2014.

[12] Milica Gašić, Filip Jurčiček, Blaise Thomson, Kai Yu, and Steve Young. On-line policy optimisation of spoken dialogue systems via live interaction with human subjects. In *IEEE ASRU*, 2011.

[13] James Henderson, Oliver Lemon, and Kallirroi Georgila. Hybrid reinforcement/supervised learning for dialogue policies from communicator data. In *IJCAI workshop on knowledge and reasoning in practical dialogue systems*, pages 68–75, 2005.

[14] M. Henderson, B. Thomson, and S. J. Young. Word-based Dialog State Tracking with Recurrent Neural Networks. In *Proc of SIGdial*, 2014.

[15] Simon Keizer, Milica Gašić, Filip Jurčiček, François Mairesse, Blaise Thomson, Kai Yu, and Steve Young. Parameter estimation for agenda-based user simulation. In *Proceedings of the 11th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 116–123. Association for Computational Linguistics, 2010.

[16] Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *The International Conference on Learning Representations*, 2015.
[17] Esther Levin, Roberto Pieraccini, and Wieland Eckert. Using markov decision process for learning dialogue strategies. In Acoustics, Speech and Signal Processing, 1998. Proceedings of the 1998 IEEE International Conference on, volume 1, pages 201–204. IEEE, 1998.

[18] Jiwei Li, Alexander H Miller, Sumit Chopra, Marc’ Aurelio Ranzato, and Jason Weston. Dialogue learning with human-in-the-loop. arXiv preprint arXiv:1611.09823, 2016.

[19] Xiujun Li, Zachary C Lipton, Bhuwan Dhingra, Lihong Li, Jianfeng Gao, and Yun-Nung Chen. A user simulator for task-completion dialogues. arXiv preprint arXiv:1612.05688, 2016.

[20] P. Lison and C. Kennington. Opendial: A toolkit for developing spoken dialogue systems with probabilistic rules. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Demonstrations), pages 67–72, Berlin, Germany, 2016. Association for Computational Linguistics.

[21] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. arXiv preprint arXiv:1312.5602, 2013.

[22] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. Nature, 518(7540):529–533, 2015.

[23] Nikola Mrkšić, Diarmuid O Séaghdha, Tsung-Hsien Wen, Blaise Thomson, and Steve Young. Neural belief tracker: Data-driven dialogue state tracking. In Proceedings of ACL, 2017.

[24] Nikola Mrkšić, Diarmuid Ó Séaghdha, Blaise Thomson, Milica Gašić, Pei-Hao Su, David Vandyke, Tsung-Hsien Wen, and Steve Young. Multi-domain Dialog State Tracking using Recurrent Neural Networks. In Proceedings of ACL, 2015.

[25] Alexandros Papangelis and Yannis Stylianou. Single-model multi-domain dialogue management with deep learning. In International Workshop for Spoken Dialogue Systems, 2017.

[26] Olivier Pietquin and Thierry Dutoit. A probabilistic framework for dialog simulation and optimal strategy learning. IEEE Transactions on Audio, Speech, and Language Processing, 14 (2):589–599, 2006.

[27] Olivier Pietquin and Steve Renals. Asr system modeling for automatic evaluation and optimization of dialogue systems. In Acoustics, Speech, and Signal Processing (ICASSP), 2002 IEEE International Conference on, volume 1, pages I–45. IEEE, 2002.

[28] Olivier Pietquin, Matthieu Geist, Senthilkumar Chandramohan, and Hervé Frezza-Buet. Sample-efficient batch reinforcement learning for dialogue management optimization. ACM Transactions on Speech and Language Processing (TSLP), 7(3):7, 2011.

[29] J. Schatzmann and S. Young. The hidden agenda user simulation model. TASLP, 17(4):733–747, 2009.

[30] Jost Schatzmann, Blaise Thomson, Karl Weilhammer, Hui Ye, and Steve Young. Agenda-based user simulation for bootstrapping a pomdp dialogue system. In Human Language Technologies 2007: The Conference of the North American Chapter of the Association for Computational Linguistics; Companion Volume, Short Papers, pages 149–152. Association for Computational Linguistics, 2007.

[31] Iulian Vlad Serban, Alessandro Sordoni, Yoshua Bengio, Aaron C Courville, and Joelle Pineau. Building end-to-end dialogue systems using generative hierarchical neural network models. In AAAI, pages 3776–3784, 2016.

[32] David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. Nature, 529(7587):484–489, 2016.
[33] Pei-Hao Su, Pawel Budzianowski, Stefan Ultes, Milica Gasic, and Steve Young. Sample-efficient actor-critic reinforcement learning with supervised data for dialogue management. Proceedings of SigDial, 2017.

[34] Richard S Sutton, David A McAllester, Satinder P Singh, Yishay Mansour, et al. Policy gradient methods for reinforcement learning with function approximation. In Proceedings of NIPS, volume 99, 1999.

[35] Richard S Sutton, Doina Precup, and Satinder Singh. Between mdps and semi-mdps: A framework for temporal abstraction in reinforcement learning. Artificial intelligence, 112(1-2): 181–211, 1999.

[36] Blaise Thomson. Statistical methods for spoken dialogue management. Springer Science & Business Media, 2013.

[37] Blaise Thomson, Simon Keizer, François Mairesse, Kai Yu, and Steve J Young. Natural belief-critic: a reinforcement algorithm for parameter estimation in statistical spoken dialogue systems. InterSpeech, 2010.

[38] Blaise Thomson, Milica Gasic, Matthew Henderson, Pirros Tsiakoulis, and Steve Young. N-best error simulation for training spoken dialogue systems. In Spoken Language Technology Workshop (SLT). 2012 IEEE, pages 37–42. IEEE, 2012.

[39] Stefan Ultes, Lina M. Rojas-Barahona, Pei-Hao Su, David Vandyke, Dongho Kim, Iñigo Casanueva, Pawel Budzianowski, Nikola Mrksic, Tsung-Hsien Wen, Milica Gašić, and Steve J. Young. Pydial: A multi-domain statistical dialogue system toolkit. In ACL Demo. Association of Computational Linguistics, 2017.

[40] Oriol Vinyals and Quoc Le. A neural conversational model. arXiv preprint arXiv:1506.05869, 2015.

[41] Oriol Vinyals, Timo Ewalds, Sergey Bartunov, Petko Georgiev, Alexander Sasha Vezhnevets, Michelle Yeo, Alireza Makhzani, Heinrich Kühn, John Agapiou, Julian Schrittwieser, et al. Starcraft ii: A new challenge for reinforcement learning. arXiv preprint arXiv:1708.04782, 2017.

[42] Zhuoran Wang, Tsung-Hsien Wen, Pei-Hao Su, and Yannis Stylianou. Learning domain-independent dialogue policies via ontology parameterisation. In SIGDIAL Conference, pages 412–416, 2015.

[43] Ziyu Wang, Victor Bapst, Nicolas Heess, Volodymyr Mnih, Remi Munos, Koray Kavukcuoglu, and Nando de Freitas. Sample efficient actor-critic with experience replay. arXiv preprint arXiv:1611.01224, 2016.

[44] Tsung-Hsien Wen, Yishu Miao, Phil Blunsom, and Steve Young. Latent intention dialogue models. International Conference on Machine Learning, 2017.

[45] Tsung-Hsien Wen, David Vandyke, Nikola Mrksic, Milica Gasic, Lina M Rojas-Barahona, Pei-Hao Su, Stefan Ultes, and Steve Young. A network-based end-to-end trainable task-oriented dialogue system. EACL, 2017.

[46] Jason Williams, Antoine Raux, Deepak Ramachandran, and Alan Black. The dialog state tracking challenge. In Proceedings of the SIGDIAL 2013 Conference, pages 404–413, 2013.

[47] Jason D Williams. The best of both worlds: unifying conventional dialog systems and pomdps. In INTERSPEECH, pages 1173–1176, 2008.

[48] Jason D. Williams and Steve Young. Partially observable Markov decision processes for spoken dialog systems. Computer Speech and Language, 21(2):393–422, 2007.

[49] Jason D Williams, Iker Arizmendi, and Alistair Conkie. Demonstration of at&t “let’s go”: A production-grade statistical spoken dialog system. In Spoken Language Technology Workshop (SLT), 2010 IEEE, pages 157–158. IEEE, 2010.
[50] Jason D Williams, Kavosh Asadi, and Geoffrey Zweig. Hybrid code networks: practical and efficient end-to-end dialog control with supervised and reinforcement learning. Association for Computational Linguistics, 2017.

[51] Xuesong Yang, Yun-Nung Chen, Dilek Hakkani-Tür, Paul Crook, Xiujun Li, Jianfeng Gao, and Li Deng. End-to-end joint learning of natural language understanding and dialogue manager. In Acoustics, Speech and Signal Processing (ICASSP), 2017 IEEE International Conference on, pages 5690–5694. IEEE, 2017.

[52] Steve Young, Milica Gašić, Simon Keizer, François Mairese, Jost Schatzmann, Blaise Thomson, and Kai Yu. The hidden information state model: A practical framework for pomdp-based spoken dialogue management. Computer Speech & Language, 24(2):150–174, 2010.

[53] Steve Young, Milica Gašić, Blaise Thomson, and Jason D Williams. Pomdp-based statistical spoken dialog systems: A review. Proceedings of the IEEE, 101(5):1160–1179, 2013.

[54] Tiancheng Zhao and Maxine Eskenazi. Towards end-to-end learning for dialog state tracking and management using deep reinforcement learning. arXiv preprint arXiv:1606.02560, 2016.
**A  Example of the dialogue flow in a modular SDS**

1 – User action: Any good Italian restaurant?

Inform(food=italian)

SLU output:

| Slot          | Confidence Score |
|---------------|------------------|
| food=italian  | 0.5              |
| food=french   | 0.3              |
| area=centre   | 0.2              |

2 – State update

3 – System decision process

Policy

Action masks

- confirm(food) ✔
- confirm(price) ✗
- select(area) ✗

Summary action

Confirm(food)

Master action

Confirm(food=italian)

4 – System output: You are looking for Italian food, right?

5 – Next user action: Yes, in the north if it is possible.

![Dialogue flow diagram](image)

Figure 2: Dialogue flow during a single turn in a modular SDS. The turn begins with the user action (1), which is processed by the input channel and converted into a N-best list with confidence scores. This N-best list is used by the state tracker (2) to update the dialogue (belief) state. The dialogue state is used by several modules of the system decision process (3). First, the action masks are defined based in the dialogue state. Then, the policy choses the optimal summary action based on the dialogue state and the action masks. Finally, the summary action is converted into a master action using heuristics based on the dialogue state. Then, the system outputs the action (usually through an NLG+TTS channel) (4) and the cycle begins again (5).

**B  Architecture details**

| Model   | Hidden layer 1 | Hidden layer 2 | \( \epsilon \) starting value |
|---------|----------------|----------------|-----------------------------|
| DQN     | 300            | 100            | 0.3                         |
| A2C     | 200            | 75             | 0.5                         |
| eNAC    | 130            | 50             | 0.3                         |

Table 5: Hyperparameters of the deep-RL models
### C Results after 1000 and 10000 training dialogues

| Task | GP-Sarsa Suc. | GP-Sarsa Rew. | DQN Suc. | DQN Rew. | A2C Suc. | A2C Rew. | ENAC Suc. | ENAC Rew. | Handcrafted Suc. | Handcrafted Rew. |
|------|---------------|---------------|----------|----------|----------|----------|-----------|-----------|------------------|------------------|
| Env. 1 CR | 98.0% | 13.0 | 88.6% | 11.6 | 83.4% | 10.0 | 93.0% | 12.2 | 100.0% | 14.0 |
| | SFR | 91.9% | 10.0 | 48.0% | 2.7 | 46.9% | 1.7 | 85.8% | 9.9 | 98.2% | 12.4 |
| | LAP | 78.9% | 6.7 | 61.9% | 5.5 | 41.1% | 0.3 | 84.2% | 8.8 | 97.0% | 11.7 |
| Env. 2 CR | 91.1% | 10.8 | 67.6% | 6.4 | 38.6% | 4.0 | 78.8% | 6.6 | 100.0% | 14.0 |
| | SFR | 82.1% | 7.4 | 64.2% | 5.4 | 39.0% | -1.1 | 67.5% | 2.7 | 98.2% | 12.4 |
| | LAP | 68.4% | 3.1 | 70.8% | 5.8 | 31.0% | -3.6 | 57.8% | -0.5 | 97.0% | 11.7 |
| Env. 3 CR | 91.9% | 10.4 | 79.5% | 9.2 | 66.5% | 6.0 | 85.7% | 10.0 | 100.0% | 14.0 |
| | SFR | 76.6% | 5.5 | 42.4% | 1.0 | 34.5% | -2.1 | 73.6% | 6.2 | 90.9% | 9.0 |
| | LAP | 65.0% | 2.8 | 51.9% | 3.1 | 32.7% | -2.2 | 71.0% | 5.5 | 98.6% | 8.7 |
| Env. 4 CR | 91.9% | 10.4 | 79.5% | 9.2 | 66.5% | 6.0 | 85.7% | 10.0 | 100.0% | 14.0 |
| | SFR | 76.6% | 5.5 | 42.4% | 1.0 | 34.5% | -2.1 | 73.6% | 6.2 | 90.9% | 9.0 |
| | LAP | 65.0% | 2.8 | 51.9% | 3.1 | 32.7% | -2.2 | 71.0% | 5.5 | 98.6% | 8.7 |
| Env. 5 CR | 91.9% | 10.4 | 79.5% | 9.2 | 66.5% | 6.0 | 85.7% | 10.0 | 100.0% | 14.0 |
| | SFR | 76.6% | 5.5 | 42.4% | 1.0 | 34.5% | -2.1 | 73.6% | 6.2 | 90.9% | 9.0 |
| | LAP | 65.0% | 2.8 | 51.9% | 3.1 | 32.7% | -2.2 | 71.0% | 5.5 | 98.6% | 8.7 |
| Env. 6 CR | 91.9% | 10.4 | 79.5% | 9.2 | 66.5% | 6.0 | 85.7% | 10.0 | 100.0% | 14.0 |
| | SFR | 76.6% | 5.5 | 42.4% | 1.0 | 34.5% | -2.1 | 73.6% | 6.2 | 90.9% | 9.0 |
| | LAP | 65.0% | 2.8 | 51.9% | 3.1 | 32.7% | -2.2 | 71.0% | 5.5 | 98.6% | 8.7 |

### Table 6: Reward and success rates after 1000 training dialogues.

| Task | GP-Sarsa Suc. | GP-Sarsa Rew. | DQN Suc. | DQN Rew. | A2C Suc. | A2C Rew. | ENAC Suc. | ENAC Rew. | Handcrafted Suc. | Handcrafted Rew. |
|------|---------------|---------------|----------|----------|----------|----------|-----------|-----------|------------------|------------------|
| Env. 1 CR | 99.4% | 13.5 | 92.5% | 12.4 | 86.3% | 10.5 | 85.3% | 10.5 | 100.0% | 14.0 |
| | SFR | 99.4% | 13.5 | 92.5% | 12.4 | 86.3% | 10.5 | 85.3% | 10.5 | 100.0% | 14.0 |
| | LAP | 90.3% | 9.7 | 72.0% | 7.3 | 56.0% | 3.5 | 92.1% | 11.0 | 97.0% | 11.7 |
| Env. 2 CR | 97.9% | 12.4 | 96.1% | 12.7 | 66.3% | 4.4 | 49.4% | 3.3 | 100.0% | 14.0 |
| | SFR | 95.4% | 10.1 | 84.2% | 9.7 | 32.9% | -3.3 | 59.0% | 3.0 | 97.0% | 12.3 |
| | LAP | 87.5% | 8.4 | 83.9% | 9.1 | 32.2% | -2.8 | 59.0% | 3.0 | 97.0% | 12.3 |
| Env. 3 CR | 95.8% | 10.9 | 94.7% | 12.2 | 81.3% | 8.4 | 76.0% | 8.2 | 96.7% | 11.7 |
| | SFR | 91.7% | 10.0 | 91.9% | 11.1 | 61.9% | 2.3 | 51.8% | 2.4 | 96.7% | 11.7 |
| | LAP | 81.2% | 6.5 | 73.1% | 6.2 | 37.8% | -2.9 | 84.1% | 6.0 | 90.9% | 9.0 |
| Env. 4 CR | 95.8% | 10.9 | 94.7% | 12.2 | 81.3% | 8.4 | 76.0% | 8.2 | 96.7% | 11.7 |
| | SFR | 91.7% | 10.0 | 91.9% | 11.1 | 61.9% | 2.3 | 51.8% | 2.4 | 96.7% | 11.7 |
| | LAP | 81.2% | 6.5 | 73.1% | 6.2 | 37.8% | -2.9 | 84.1% | 6.0 | 90.9% | 9.0 |
| Env. 5 CR | 95.8% | 10.9 | 94.7% | 12.2 | 81.3% | 8.4 | 76.0% | 8.2 | 96.7% | 11.7 |
| | SFR | 91.7% | 10.0 | 91.9% | 11.1 | 61.9% | 2.3 | 51.8% | 2.4 | 96.7% | 11.7 |
| | LAP | 81.2% | 6.5 | 73.1% | 6.2 | 37.8% | -2.9 | 84.1% | 6.0 | 90.9% | 9.0 |
| Env. 6 CR | 95.8% | 10.9 | 94.7% | 12.2 | 81.3% | 8.4 | 76.0% | 8.2 | 96.7% | 11.7 |
| | SFR | 91.7% | 10.0 | 91.9% | 11.1 | 61.9% | 2.3 | 51.8% | 2.4 | 96.7% | 11.7 |
| | LAP | 81.2% | 6.5 | 73.1% | 6.2 | 37.8% | -2.9 | 84.1% | 6.0 | 90.9% | 9.0 |

### Table 7: Reward and success rates after 10000 training dialogues.
D Learning curves for task 3

![Learning curves for task 3](image)

(a) Cambridge Restaurants

(b) San Francisco Restaurants

(c) Laptops

Figure 3: Performance of the benchmarked algorithms as a function of the number of dialogues for three different domains; the shaded area depicts the mean ± the standard deviation over five different random seeds.
### Cross task experiments

| Training | Model/Domain | Env. 1 (CR) | Env. 3 (CR) | Env. 6 (CR) |
|----------|--------------|-------------|-------------|-------------|
| Env. 1   | GP-SARSA     | 9.5         | 11.9        | 13.2        |
|          | DQN          | 13.0        | 13.8        | 13.2        |
|          | ENAC         | 13.1        | 10.9        | 10.2        |

| Training | Model/Domain | Env. 1 (SFR) | Env. 3 (SFR) | Env. 6 (SFR) |
|----------|--------------|--------------|--------------|--------------|
| Env. 1   | GP-SARSA     | 9.9          | 7.7          | 13.1         |
|          | DQN          | 7.7          | 7.7          | 10.9         |
|          | ENAC         | 10.9         | 10.9         | 10.2         |

| Training | Model/Domain | Env. 1 (LAP) | Env. 3 (LAP) | Env. 6 (LAP) |
|----------|--------------|--------------|--------------|--------------|
| Env. 1   | GP-SARSA     | 6.1          | 6.0          | 5.1          |
|          | DQN          | 6.0          | 6.3          | 6.3          |
|          | ENAC         | 6.3          | 9.7          | 9.7          |

| Training | Model/Domain | Env. 1 (LAP) | Env. 3 (LAP) | Env. 6 (LAP) |
|----------|--------------|--------------|--------------|--------------|
| Env. 1   | GP-SARSA     | -6.8         | 8.0          | 7.0          |
|          | DQN          | 0.2          | 3.4          | 0.2          |
|          | ENAC         | 7.3          | 8.0          | 4.3          |

| Training | Model/Domain | Env. 1 (LAP) | Env. 3 (LAP) | Env. 6 (LAP) |
|----------|--------------|--------------|--------------|--------------|
| Env. 1   | GP-SARSA     | 0.6          | 8.0          | 9.7          |
|          | DQN          | -12.3        | -4.3         | 4.6          |
|          | ENAC         | -11.0        | -11.0        | 4.6          |

Table 8: Reward obtained by the three best performing algorithms in cross-tasks evaluation. The (wide) rows represent the environment in which the model is trained and the (wide) columns the environment where its evaluated. The (thin) rows represent the model and the (thin) columns the domain where the model is trained and tested. The reward for the best performing model in each cross-environment setup and domain combination is highlighted.