Abstract

A Relational Markov Decision Process (RMDP) is a first-order representation to express all instances of a single probabilistic planning domain with possibly unbounded number of objects. Early work in RMDPs outputs generalized (instance-independent) first-order policies or value functions as a means to solve all instances of a domain at once. Unfortunately, this line of work met with limited success due to inherent limitations of the representation space used in such policies or value functions. Can neural models provide the missing link by easily representing more complex generalized policies, thus making them effective on all instances of a given domain?

We present the first neural approach for solving RMDPs, expressed in the probabilistic planning language of RDDL. Our solution first converts an RDDL instance into a ground DBN. We then extract a graph structure from the DBN. We train a relational neural model that computes an embedding for each node in the graph and also scores each ground action as a function over the first-order action variable and object embeddings on which the action is applied. In essence, this represents a neural generalized policy for the whole domain. Given a new test problem of the same domain, we can compute all node embeddings using trained parameters and score each ground action to choose the best action using a single forward pass without any retraining. Our experiments on nine RDDL domains from IPPC demonstrate that neural generalized policies are significantly better than random and sometimes even more effective than training a state-of-the-art deep reactive policy from scratch.

1. Introduction

A Relational Markov Decision Process (RMDP) (Boutilier et al., 2001) is a first-order (predicate calculus-based) representation for expressing all instances of a probabilistic planning domain with a possibly unbounded number of objects. An RMDP domain has object types, relational predicates over objects, action templates, A domain instance additionally specifies a set of objects and a start state, thus defining a ground MDP. Domain-independent relational planners aim to produce a single generalized policy that can yield a ground policy for all instances of the domain, with little instance-specific computation. They are called domain-independent, as these planning algorithms are representation-specific, but domain-agnostic, making them applicable to all domains expressible in the language.

RMDP planners, in their vision, expect to scale to very large problem sizes by exploiting the first-order structures of a domain – thereby reducing the curse of dimensionality. Traditional RMDP planners attempted to find a generalized first-order value function or policy using symbolic dynamic programming (Boutilier et al., 2001), or by approximating them via a function over learned first-order basis functions (Guestrin et al., 2003; Fern et al., 2006; Sanner & Boutilier, 2009). Unfortunately, these methods met with rather limited success, for e.g., no relational planner participated in International Probabilistic Planning Competition (IPPC) after 2006, even though all competition domains were relational. We believe that this lack of success may be due to the inherent limitations in the representation power of a basis function-based representation. Through this work, we wish to revive the research thread on RMDPs and explore if neural models could be used to successfully represent powerful policy or value functions.

We present Symbolic NetWork (SYMNET), the first domain-independent neural planner for computing generalized policies for RMDPs that are expressed in the symbolic representation language of RDDL (Sanner, 2010). It uses two key ideas to achieve this. First, it visualizes each state of each domain instance as a graph, where nodes represent the object tuples that are valid arguments to some relational predicate. An edge between two nodes indicates that an action causes predicates over these two nodes to interact in the...
domain. SYMNET learns node embeddings for these graphs using graph neural networks, whose parameters are tied across instances. Second, SYMNET learns a neural network to represent the policy and value function over this graph-structured state. To learn these in an instance-independent way, we recognize that each ground action is a first-order action template applied over some object tuple. SYMNET scores each ground action as a function over the template and the relevant embeddings of object tuples. In essence, this represents a *neural generalized policy* for the whole domain, since given a new test problem of the same domain, SYMNET can use the trained model to compute all node embeddings and can score each ground action to choose the best action using a single forward pass over the network.

We perform experiments over 9 RDDL domains from IPPC 2014 (Grzes et al., 2014). Since no planner exists that can run without computation on the given problem, we compare SYMNET to random policies (lower bound) and the policies trained from scratch (upper bound). We find that SYMNET obtains hugely better rewards than random, and is quite close to the policies trained from scratch – it even outperforms them out-of-the-box in 50% instances. This underscores the value of generalized policies trained across instances and provides one of the first successes for the difficult problem of domain-independent RMDP planning. We release the code of SYMNET for future research.

### 2. Background and Related Work

#### 2.1. Probabilistic Planning

**Markov Decision Process (MDP):** A (ground) finite-horizon MDP (Bellman, 1957; Puterman, 1994) with a known start state (Kolobov et al., 2012) is formalized as a tuple \( < S, A, T, R, H, s_0, \gamma > \), where \( S \) is the set of states, \( A \) is the set of actions, \( T \) is the transition model \( S \times A \times S \rightarrow [0,1] \), \( R \) is the reward model \( S \times A \times S \rightarrow \mathbb{R} \), \( H \) is the horizon and \( s_0 \) is the start state, and \( \gamma \) is the discount factor. A factored MDP factors a state \( s \) into a set of state variables \( X \), i.e., \( s = \{ x_i \}_{i=1}^{\|X\|} \). \( T \) may also be factored, defined via, e.g., a DBN, dynamic Bayesian network (Sridharan, 1989), which maintains the conditional probability table \( T_i \) of \( x_i \) dependent on action \( a \), previous state \( s \), and lower valued \( x_j \)s, i.e., \( T_i(x_i|s,a,x_1',...,x_{i-1}) \). The joint probability \( T(s,a,s') = \prod_{i \in X} T_i(x_i|s,a,x_1',...,x_{i-1}) \). In practice, these models are compact, and an \( x_i \) depends only on a small number of other state variables.

**Relational Markov Decision Process (RMDP):** An RMDP \( < C, SP, A, O, T, R, H, s_0, \gamma > \) is a first-order representation of a factored MDP (Boutilier et al., 2001), expressed via objects, predicates and functions. Here, \( C \) is a set of classes (types), \( SP \) is the set of state predicate symbols. \( A \) is a set of action symbols, \( O \) represents a set of domain objects, each associated with single type from \( C \). It is a first order representation because different sets of objects \( O \) can construct different ground MDPs.

Each predicate symbol is declared to take as argument a tuple of object types. A predicate symbol (action symbol) applied over a type-consistent tuple of object variables forms a state variable (respectively, ground action). A ground-state \( s \) is, thus, a complete assignment of all predicate symbols \( SP \) applied on all type-consistent object tuples from \( O \) (also denoted by \( SP_O \)). Similarly, the set of all ground actions \( (A) \) can be defined as \( AO \) – all-action symbols applied on all type-consistent object tuples. We also denote the ground state space \( S \) by \( P(SP_O) \), where \( P \) denotes the powerset. Transition and reward models for an RMDP are defined at the schema level through different languages, e.g., PPDDL (Younes et al., 2005) and, our focus, RDDL (Sanner, 2010).

**Relational Dynamic Decision Language (RDDL):** RDDL has been the language of choice for the last three IPPCs. It divides \( SP \) into two categories: non-fluent (\( NF \)) and fluent (\( F \)) symbols. The non-fluents are those state variables that do not change with time in a given instance but may be different across different problem instances. Fluents represent state variables that change with time (due to actions or natural dynamics). RDDL splits an RMDP into two separate files, one for the whole domain (that has types, predicates, transitions, and rewards), and the other for the instance (that has objects, non-fluent values, and fluent values for initial state). RDDL uses an additive rewards – the total reward is the sum of local rewards collected for satisfying different properties in a state. It factors the transition function via an underlying DBN semantics. There exist algorithms that convert an RDDL instance into a ground DBN (Sanner, 2010).

**Running Example:** Consider a simplified Wildfire domain – a grid world where each cell may have fuel, causing it to burn. The goal is to have the least damage to the grid by either putting out the fire or cutting out the fuel supply. The DBN for the domain is show in Figure 1.

There are two classes, \( C = \{ x_{pos}, y_{pos} \} \): \( x \) and \( y \) coordinate of the grid cell. Domain has two fluent symbols \( F = \{ burning, out-of-fuel \} \), representing the current burning state and the fuel state of the cell. Both fluent symbols take a cell \( (x, y) \) as its arguments. The non-fluents represent costs and topology, \( NF = \{ CostTgtBurn, CostNTgtBurn, Neighbour, Target \} \). The non fluent symbol \( Neighbour \) takes four arguments \( (x, y, x', y') \), since it defines the topology of the grid. \( Target \) has arguments \( (x, y) \), \( A = \{ put-out, cut-out, finisher \} \). First two action symbols take arguments \( (x, y) \) – they put out fire and cut out fuel supply at a cell. There is one global action \( finisher \), which puts out fire in all the cells simultaneously. Reward (negative) in each time step adds \( CostTgtBurn \).
for each target cell that is burning and CostNTgtBurn for each non-target cell that is burning.

In a problem instance, say there are three objects \( O = \{x_1, x_2, y_1\} \). This implies a problem with two cells \((x_1, y_1)\), and \((x_2, y_1)\). Say the target cell is \((x_1, y_1)\) and that these are connected, i.e., \( \text{Neighbour}(x_1,y_1,x_2,y_1) = 1 \).

2.2. Graph Neural Network

Architectures like the Graph Convolution Networks (GCN) (Kipf & Welling, 2017), and Graph Attention Networks (GAT) (Velickovic et al., 2017) find the latent space embedding for each node in a given graph. We use GAT, which computes a node embedding by using a weighted attention for each of neighbouring nodes. Specifically output node embedding \( \mathbf{h}_i = \sigma( \frac{1}{K} \sum_{k=1}^{K} \sum_{j \in N_i} \alpha_{ij}^k \mathbf{W}^k \mathbf{h}_j ) \), where \( \mathbf{h}_i \) is the input feature of node \( i \), \( N_i \) is its neighbours, \( \mathbf{W}^k \) is a trainable weight matrix, \( k \) is the multi-head hyperparameter and \( \alpha_{ij} = \text{softmax}(f(\mathbf{W}^h_i, \mathbf{W}^h_j)) \) is the normalized self attention coefficient for any non-linear function \( f(\cdot) \), which in this case is LeakyReLU (Xu et al., 2015).

2.3. Transfer Learning for Probabilistic Planning

There having been several classical (Taylor & Stone, 2009; Sorg & Singh, 2009; Atkeson & Schaal, 1997) and neural (Parisotto et al., 2015; Matiisen et al., 2017; Garnelo et al., 2016; Higgins et al., 2017) approaches for transfer learning in RL. Recent work studies transfer learning for symbolic planning problems, e.g., Groshev et al. (2018) for deterministic planning problems. ASNets, Action-Schema Networks (Toyer et al., 2018; Shen et al., 2019), tackle a problem similar to ours but for the domains represented in PPDDL.

PPDDL and RDDL have significant differences in their approach to model a domain. PPDDL uses correlated effects, whereas RDDL naturally models parallel effects (due to its underlying DBN semantics). Thus, RDDL handles no-op actions with underlying natural dynamics better. RDDL rewards are additive, whereas PPDDL models explicit goal conditions. While an RDDL instance can be converted automatically into a propositional PPDDL, to the best of our knowledge, an RDDL domain cannot always be converted into a relational MDP in PPDDL.

Issakkimuthu et al. (2018) devise a neural framework to learn a policy for RDDL (ground) MDPs from scratch. Their constraint on non-transferability is due to the fixed size of fully connected layers in the neural network. ToRPIDO achieves transfer across RDDL problem instances of the same domain (Bajpai et al., 2018); it can only transfer over equi-sized problems due to its fixed size action decoder.

TRAPSNET is the closest to our work as it is able to transfer to different sized problem instances of an RMDP (Garg et al., 2019). Its main idea is also to construct a graph – it uses single objects as nodes, and edges are based on non-fluents. It encodes each node in embedding space and computes the score for a ground action based on the action template, and object embedding it is applied to. However, TRAPSNET makes the restrictive assumption that the domains have exactly one binary non-fluent, and all the rest are unary fluents or non-fluents. It also assumes that each action symbol is parameterized by exactly one object. These assumptions do not hold in several RDDL domains. Moreover, TRAPSNET implementation converts an RDDL domain into a graph manually. In contrast, we release a domain-independent implementation of SYMNET, which can apply to any new RDDL domain out of the box, without any manual effort.

3. Problem Formulation

Given an RMDP domain \( D = \langle C, SP, A, T, R, H, \gamma \rangle \) expressed in RDDL, we wish to learn a generalized policy \( \pi_D \), which can be applied to all instances of \( D \) and maximizes the discounted sum of expected rewards over a finite horizon \( H \). Given a test problem instance \( I_t = \langle O, s_0 \rangle \) from \( D \), this generalized policy can yield an instance-specific policy \( \pi_D (I_t) : \mathcal{P}(SP) \rightarrow AO \), without any training on \( I_t \). The RMDP learning problem can be seen in terms of multi-task learning over several problem instances in \( D \): given \( N \) randomly selected problem instances \( I_1, I_2, ..., I_N \) (possibly of different sizes) from \( D \), we wish to learn the weights \( \phi \) of a neural network, such that \( \pi_D (I_t) (\cdot; \phi) \) is a good policy for problem instance \( I_t \). A good generalized policy is one which, without training, achieves high reward values on the new instance \( I_t \).

4. The SYMNET Framework

We now present SYMNET’s architecture for solving a given RMDP domain. We follow existing research to hypothesize that for any instance of a domain, we can learn a representation of the current state in a latent space and then output a policy in latent space, which is decoded into a ground action. To achieve this, SYMNET uses three modules: (1) problem representation, which constructs an instance graph for every problem instance, (2) representation learning, which learns embeddings for every node in the instance graph, and for the state, and (3) policy decoder, which computes a value for every ground action, outputting a mixed policy for a given state. All parameters of representation learning and policy learning modules are shared across all instances of a domain. SYMNET’s full architecture is shown in Figure 2.

4.1. Problem Representation

We follow TRAPSNET, in that we continue the general idea of converting an instance into an instance graph and then
learning a graph encoder to handle different-sized domains. However, the main challenge for a general RMDP, which does not satisfy the restricted assumptions of TRAPSNET, is in defining a coherent graph structure for an instance.

The first key question is what should be a node in the instance graph. TRAPSNET’s approach was to use a single object as nodes, as all fluents (and actions) in its domains took single objects as arguments. This may not work for a general RMDP since it’s fluents and actions may take several objects as arguments. The second question is, how should edges be defined. Edges represent the interaction between nodes. TRAPSNET defined them based on the one binary non-fluent in its domain. A general RMDP may not have any non-fluent symbol or may have many (possibly higher-order) non-fluents.

Last but not least, the real domain-independence for SYMNET can be achieved only when it parses an RDDL domain file without any human intervention. This leads to a novel challenge of reconciling multiple different ways in RDDL to express the same domain. In our running example, connectivity structure between cells may be defined using non-fluents $y$-neighbour $(y, y')$, $x$-neighbour $(x, x')$, or using a quaternary non-fluent neighbour $(x, y, x, y')$. Since both these representations represent the same problem, an ideal desideratum is that the graph construction algorithm leads to the same instance graph in both cases. But, this is a challenge since the corresponding RDDL domains look very different. While, in general, this problem seems too hard to solve, since it is trying to judge logical equivalence of two domains, SYMNET achieves the same instance graphs in case the equivalence is within non-fluents.

To solve these problems, we make the observation that an RDDL instance ultimately compiles to a ground DBN with nodes as state variables (fluent symbols applied on object tuples) and actions (action symbols applied on object tuples). DBN also exposes a connectivity structure that determines which state variables and actions directly affect a given state variable. It additionally has conditional probability tables for each transition. Figure 2 shows an example of a DBN for our running example instance. Here, left column is for current time step, and right for the next one. The edges represent which state and action variables affect the next state-variable. We note that the ground DBN does not expose non-fluents since its values are fixed, and their dependence can be compiled directly into probability tables.

**Construction of Instance Graph:** SYMNET converts such a DBN to an instance graph. It constructs a node for every unique object tuple that appears as an argument in any state variable in the DBN. Moreover, two nodes are connected if the state variables associated with two nodes influence each other in the DBN through some action. This satisfies all our challenges. First, it goes beyond an object as a node, but only defines those nodes that are likely important in the instance. Second, it defines a clear semantics of edges, while maintaining its intuition of “directly influences.” Finally, it handles different non-fluent representations for the same domain. Since the DBN does not even expose non-fluent state variables, and compiles them away, a unique ground DBN will often be computed for the same instance encoded with different non-fluent representations.

We now formally describe the process of converting a DBN into a directed instance graph, $G = (V, E)$ where $V$ is the set of vertices and $E$ is the set of edges. To describe the formal process, we define three analogous sets: $O_f$, $O_{nf}$ and $O_a$. $O_f$ represents the set of all object tuples that act as a valid argument for any fluent symbol. $O_{nf}$ and $O_a$ are analogous sets for non-fluent and action symbols. In our running example, $O_f = \{(x, y), (x_2, y_1)\}$, $O_{nf} = \{(x_1, y_1)\}$, and $O_a = \{(x_1, y_1), (x_2, y_1)\}$. SYMNET converts a DBN into an instance graph as follows:

1. The distinct object tuples in fluents form the nodes of the graph, i.e. $V = \{v | v \in O_f\}$. For the running example, $V = \{(x_1, y_1), (x_2, y_1)\}$.

2. We add an edge between two nodes if some state variables corresponding to them are connected in the DBN. Formally, $E(u, v) = 1$, if $f_f, g \in F$ s.t. there is an edge between $f(u)$ (or $f'(u)$) and $g'(v)$ in DBN. For the running example, $E((x_1, y_1), (x_2, y_1)) = 1$ as there is an edge between burning$(x_1, y_1)$ and burning'$(x_2, y_1)$. Similarly, $E((x_2, y_1), (x_1, y_1)) = 1$.

3. As every node influences itself, self loops are added on each node. $E(v, v) = 1, \forall v \in V$, Hence $E((x_1, y_1), (x_1, y_1)) = 1$ and $E((x_2, y_1), (x_2, y_1)) = 1$.

For each node $v \in V$, we construct a feature vector $(h(v))$...
Figure 2. Architecture of policy network for SYMNET. FCN refers to the Fully Connected Network of the Action decoder.

which consists of fluent feature vector \( (h^f(v)) \) and non-fluent feature vector \( (h^{nf}(v)) \), such that \( h = \text{concat}(h^f, h^{nf}) \). The value of feature vector at each time is determined as follows:

1. The first set of features for each node is obtained from the state of the problem instance. The values of state variables corresponding to a node are added as feature to that node. Whenever a state fluent does not parameterize a node, we add zero as the feature for it. Formally, \( h^f(v)_i = g_i(v) \iff g_i \in F, v \in V : v \text{ is an argument of } g_i \), otherwise, \( h^f(v)_i = 0 \), \( \forall i = 1 \ldots |F| \). For the running example, we have two state-fluents. Hence, \( h^f((x1, y1)) = [\text{burning}(x1, y1), \text{out-of-fuel}(x1, y1)] \).

2. A second set of features for each node is obtained from the RDDL file. The values of the non-fluents parameterized over the node, if any, are added as the features for the node. The default value is obtained from the domain file while the specific value (if available) is obtained from the instance file. Formally, \( h^{nf}(v)_i = g_i(o_{nf}) \iff g_i \in NF, v \in V, o_{nf} \in O_{nf}, v = o_{nf} \lor (o_{nf} \land v \neq \phi, v \not\in o_{nf}) : o_{nf} \text{ is an argument of } g_i \), otherwise, \( h^{nf}(v)_i = 0 \), \( \forall i = 1 \ldots |NF| \). In our example, \( h^{nf}((x1, y1)) = [\text{target}(x1, y1)] \). Observe that topology is absorbed in edges and does not appear again in the feature vectors.

4.2. Representation Learning

We use GAT (Veličković et al., 2017) as a state encoder for our instance graph. The input graph with node features \( h(v) \) constructed above is passed through GAT to obtain node embeddings \( \overline{v} \). These are then max-pooled over all nodes to obtain a state embedding \( \overline{s} = \text{MaxPool}_v \overline{v} (\overline{\tau}) \).

4.3. Policy Learning

Our goal is to decode the state-representation into a ground action. At a high level, we use the A3C algorithm (Mnih et al., 2016) for learning the policy for a given instance. The A3C algorithm learns two networks, (1) a policy network to estimate the policy in a given state \( s \) and (2) a value network to estimate value function \( (V) \), i.e., long-term expected discounted reward starting in-state \( s \). The action decoders in the policy network and the value decoders in the value network of A3C in our implementation have the same structure, but the parameters are independent of each other.

There are further challenges in designing the action decoder. First, the action symbols may take multiple objects as arguments. Second, and more importantly, action symbols may be parameterized over object tuples that are not a node in the instance graph. This will happen if an object tuple (in \( O_a \)) does not correspond to any state variable, i.e., \( \exists o_a \) s.t. \( o_a \in O_a \land o_a \notin O_f \). We note that adding these object tuples as nodes in the instance graph may not work, since we will not have any features for these nodes.

In response, we design a novel framework for action and value decoders. The decoders consist of fully connected layers, the input to which are a subset of the node embeddings in the instance graph. We use a second example (of Figure 2) in addition to the running example to explain this. SYMNET uses the following rules to construct decoders:

1. The number of decoders is fixed for a given domain and is equal to the number of action symbols \( (|A|) \). For the running example, the number is 3. In second example, the number of distinct action fluents are two, namely \( a_1 \) and \( a_n \). Hence two different decoders for each policy and value network are constructed.

2. The input to a decoder is the embeddings of nodes corresponding to the state variables affected by the action in the DBN. In running example, \( \text{put-out}(x1, y1) \) action takes as input the embedding of \( (x1, y1) \). In the second example, the input to the fully connected network for action \( a_1(z1) \) is the aggregated embedding of the nodes \( x_1 \) and \( y_1 \) in the graph. Since the number of state-variables being affected by a ground action might change across instances of the same domain, we need to use size-independent aggregation like sum, mean, or max. We use the max pool aggregation, as it gives the best results in preliminary experiments. We always
concatenate this embedding with state embedding $\pi$ before giving it as input to the action decoder.

3. Same type of action symbols share parameters for predicting the action value. In running example, $\text{put-out}(x_1, y_1)$ will be scored using embedding of $(x_1, y_1)$; similarly, for $(x_2, y_1)$. But, both scorings will use a single parameter set specific to action symbol $\text{put-out}$.

4. Global actions, i.e., action symbols with arity 0 (e.g., $\text{finisher}$), are scored directly using the state embedding as input.

5. The policy network decoders compute scores of all ground actions, which are normalized using softmax to output the final policy in a state. For $I_t$, the highest probability action is selected as the final action.

6. All value outputs are summed in the value network, to give the value for that state.

### 4.4. Learning

The training of SYMNET is formulated as a multi-task learning problem, as described in Section 3, so that it generalizes well and does not overfit on any one problem instance. The parameters for the state encoder, action decoder, and value decoder are learned using a method similar to the update rule in A3C (Mnih et al., 2016). SYMNET’s loss function for the policy and value network is the same as that in the A3C paper (summed over the multi-task problem instances).

As constructed, SYMNET’s number of parameters is independent of the size of the problem instance. Hence, the same network can be used for problem instances of any size. After the learning is completed, the network represents a generalized policy (or value), since it can be directly used on a new problem instance to compute the policy in a single forward pass.

### 5. Experiments

Our goal is to estimate the effectiveness of SYMNET out-of-the-box policy for a new problem in a domain. Unfortunately, there are no available transfer algorithms for general RDDL RMDPs. So, we first compare it against a random policy, because that is the best we can do currently with no time to train. To further understand the overall quality of the generalized policy, we also compare it against several upper bounds that train neural models from scratch on the test instance. We also compare it against state-of-the-art online planner PROST (Keller & Eyerich, 2012).

#### 5.1. Domains and Experimental Setting

We show all our results on nine RDDL domains used IPPC 2014: Academic Advising (AA), Crossing Traffic (CT), Game of Life (GOL), Navigation (NAV), Skill Teaching (ST), Sysadmin (Sys), Tamarisk (Tam), Traffic (Tra), and Wildfire (Wild). We describe the domains in detail in the supplementary material. The detailed description of the number of state fluents, state non-fluents, and action fluents can also be found in the supplementary material. The RL agent is trained to learn the generalized policy on smaller sized instances. We use IPPC problem instances 1, 2, and 3 of each domain for the multi-task training of SYMNET network. In the spirit of domain-independent planning, we use the same hyperparameters for each domain. The embedding module for GAT uses a neighborhood of 1 and an output feature size of 6. We then use a fully connected layer of output 20 dimensions to get an embedding from each of the node embedding outputs by GAT. All layers use a leaky ReLU activation and a learning rate of $10^{-3}$. We train the network using RMSProp (Ruder, 2016) on a single Nvidia K40 GPU. SYMNET is trained for each domain for four hours.

#### 5.2. Comparison Algorithms

As there does not exist any previous method for learning over Relational RDDL MDPs, we can only compare against a random policy. However, this experiment can only show the difference from a random policy, but cannot evaluate the overall goodness of the generalized policy. For that, we compare against several upper bound policies that are not directly comparable to SYMNET in their experimental settings. For our first such experiment, we use ToRPIDO as the state-of-the-art deep reactive policy. Note that we do not use their transfer method, but train the network from scratch on the problem instance. This is because it can only transfer across equi-sized instances. Still, it is an upper bound as ToRPIDO trained on the test instance is compared against SYMNET trained on other smaller instances, but not the test instance. Similarly, we also compare against SYMNET architecture itself, trained from scratch on the test instance.
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Table 2. Comparison of SymNet against SymNet-s (Sym) architecture trained from scratch and TorPIDO (TOR) architecture trained from scratch. We compare out-of-the-box SymNet to others after 4 hours of training. INF is used when Sym or TOR achieved minimum possible reward and hence SymNet was infinitely better.

| Domain | Sym | TOR | Domain | Sym | TOR | Domain | Sym | TOR | Domain | Sym | TOR | Domain | Sym | TOR |
|--------|-----|-----|--------|-----|-----|--------|-----|-----|--------|-----|-----|--------|-----|-----|
| AA 5   | 1.10| 1.00| GOL 5  | 1.28| 1.41| ST 5   | 1.16| 0.98| Tam 5  | 1.57| 1.87| Wild 5  | 1.04| 1.13|
| AA 6   | 1.77| 0.94| GOL 6  | 1.47| 1.58| ST 6   | 1.24| 0.92| Tam 6  | 2.49| 2.31| Wild 6  | 1.01| 1.01|
| AA 7   | 1.22| 0.99| GOL 7  | 1.10| 0.77| ST 7   | 1.14| 0.90| Tam 7  | 16.53| 4.49| Wild 7  | 1.02| 1.13|
| AA 8   | 1.35| 1.00| GOL 8  | 2.20| 0.86| ST 8   | 1.14| 0.90| Tam 8  | 2.54| 14.42| Wild 8  | 1.00| 1.09|
| AA 9   | 1.41| 0.96| GOL 9  | 1.94| 1.37| ST 9   | 1.14| 0.82| Tam 9  | 22.63| 11.86| Wild 9  | 1.01| 13.13|
| AA 10  | 1.39| 0.99| GOL 10 | 1.08| 0.59| ST 10  | 1.34| 0.98| Tam 10 | 2.47| 8.42 | Wild 10 | 34.65| 11.14|

CT 5   | 1.54| 1.60| Nav 5  | 10.93| INF  | Sys 5  | 1.04| 2.93| Tra 5  | 1.79| 0.86 |
| CT 6   | INF | 1.99| Nav 6  | INF  | INF  | Sys 6  | 1.35| 1.22| Tra 6  | 1.68| 1.50 |
| CT 7   | 1.07| 1.07| Nav 7  | INF  | INF  | Sys 7  | 1.58| 2.49| Tra 7  | 3.74| 1.29 |
| CT 8   | 1.42| 1.13| Nav 8  | INF  | INF  | Sys 8  | 1.50| 1.65| Tra 8  | 1.33| 0.94 |
| CT 9   | 1.32| 1.13| Nav 9  | INF  | INF  | Sys 9  | 1.40| 1.18| Tra 9  | 2.66| 1.15 |
| CT 10  | 1.15| 4.68| Nav 10 | INF  | INF  | Sys 10 | 1.23| 1.56| Tra 10 | 1.76| 2.14 |

The main difference between TorPIDO and SymNet architectures is that TorPIDO has a much higher capacity since it models each ground action explicitly. On three domains where TrapsNet is applicable, we also compare against TrapsNet policies out of the box. Finally, we also compare against the state-of-the-art online planner, PROST.

Table 3. Comparison of TrapsNet with SymNet on three domains as published in (Garg et al., 2019). Label: AA - Academic Advising, GOL - Game Of Life, Sys - Sysadmin.

| Domain | β   | Domain | β   | Domain | β   |
|--------|-----|--------|-----|--------|-----|
| AA 5   | 1.14| GOL 5  | 0.91| Sys 5  | 1.03|
| AA 6   | 1.17| GOL 6  | 0.98| Sys 6  | 1.57|
| AA 7   | 1.12| GOL 7  | 0.70| Sys 7  | 1.35|
| AA 8   | 1.31| GOL 8  | 0.99| Sys 8  | 1.43|
| AA 9   | 1.27| GOL 9  | 1.01| Sys 9  | 1.23|
| AA 10  | 1.48| GOL 10 | 1.30| Sys 10 | 1.22|

To be able to compare across domains and problems and reward ranges, we report a normalized metric \( \alpha_{alg}(t) = \frac{V_{alg}(t) - V_{inf}}{V_{sup} - V_{inf}} \) where \( V_{inf} \) and \( V_{sup} \) are the minimum, and the maximum expected discounted rewards obtained at any time by any of the four comparison algorithms on a given instance. Here, \( V_{alg}(t) \) is reward obtained by alg after being trained till time \( t \). This number lies between 0 and 1, with 1 being the best-found reward, and 0 being the random policy’s reward. During training from scratch, all networks start with a random policy and hence have their \( \alpha(0) \) values as 0. However, that is not true for SymNet as it is pre-trained on the domain.

5.3. Results

Comparison against Random Policy: We report the values of \( \alpha_{symnet}(0) \) in Table 1. Since the random policy is 0, we notice that on all six problem instances from the nine domains, SymNet performs enormously better than random. We highlight the instances where our method achieves over 90% of the max reward obtained by any algorithm for that instance. We see that SymNet with no training achieves over 90% the max reward on 43 instances and over 80% in 52 out of 54 instances. We also show that our method performs the best out-of-the-box in 28 instances. This is our main result, and it highlights that SymNet takes a major leap towards the goal of computing generalized policies for the whole RMDP domain, and can work on a new instance out of the box.

Comparison against Training from Scratch: We now compare SymNet against the expected discounted rewards obtained by TorPIDO and SymNet-s, when they are trained from scratch for 4 hours on the test problem. We note that these numbers are not directly comparable, since in one case, the model has been trained on other instances of the domain, but not trained on the test problem at all, and in the other case the models are trained from scratch on the test. That said, this comparison is likely a good indicator of the absolute performance of SymNet.

For this experiment, we report \( \alpha_{symnet}(0) \) and \( \alpha_{torpido}(0) \). Here a number greater than 1 means that SymNet performs better, and less than 1 means that SymNet performs worse. Table 2 reports the results. We notice that, surprisingly, SymNet policy with no training is very much better than the policy trained from scratch by either method on 39 instances. Against SymNet trained from scratch, it is better on all instances, although its edge over TorPIDO is limited to 39. We hypothesize that this is due to the multi-task learning aspect of SymNet, where it is able to reach some generalized policy of a domain that is not found on the specific instance even after training for 4 hours.
Table 4. Comparison of PROST with SYMNET. INF is used when PROST returned a policy equal to or worse than a random policy.

| Domain | \(\beta\) | Domain | \(\beta\) | Domain | \(\beta\) |
|--------|------------|--------|------------|--------|------------|
| AA 5   | 2.16       | Nav 5  | 1.17       | Tam 5  | 0.57       |
| AA 6   | 2.13       | Nav 6  | 1.87       | Tam 6  | 0.86       |
| AA 7   | 2.20       | Nav 7  | 6.48       | Tam 7  | 0.65       |
| AA 8   | 1.84       | Nav 8  | 45.23      | Tam 8  | 0.73       |
| AA 9   | 1.49       | Nav 9  | 98.83      | Tam 9  | 0.75       |
| AA 10  | 1.54       | Nav 10 | INF        | Tam 10 | 0.88       |
| CT 5   | 0.87       | ST 5   | 1.00       | Tra 5  | 0.60       |
| CT 6   | 0.56       | ST 6   | 0.87       | Tra 6  | 0.71       |
| CT 7   | 0.59       | ST 7   | 0.89       | Tra 7  | 0.70       |
| CT 8   | 0.34       | ST 8   | 0.90       | Tra 8  | 0.60       |
| CT 9   | 0.73       | ST 9   | 0.78       | Tra 9  | 0.80       |
| CT 10  | 0.35       | ST 10  | 0.96       | Tra 10 | 0.73       |
| GOL 5  | 0.45       | Sys 5  | 1.15       | Wild 5 | INF        |
| GOL 6  | 0.54       | Sys 6  | 1.26       | Wild 6 | INF        |
| GOL 7  | 0.33       | Sys 7  | 1.15       | Wild 7 | INF        |
| GOL 8  | 0.39       | Sys 8  | 1.54       | Wild 8 | INF        |
| GOL 9  | 0.46       | Sys 9  | 1.23       | Wild 9 | INF        |
| GOL 10 | 0.26       | Sys 10 | 1.49       | Wild 10| 1.48       |

The performance of ToRPIIDO is generally better than that of retrained SYMNET, which is not surprising, since ToRPIIDO has much higher capacity, as discussed earlier. We also notice that the performance of these systems is no better than random for Navigation. We attribute this to the late reward obtained in these domains. Because of the late rewards, they are not able to reach the goal state and hence not able to learn the optimal policy.

Comparison against TRAPSNET: While TRAPSNET is not applicable in many RMDPs, but we can compare it with SYMNET on some domains. We compare these on three domains that follow the unary fluent and binary non-fluents constraint: Academic Advising, Game of Life, and SysAdmin. We report \(\beta = \frac{V_{symnet(0)} - V_{inf}}{V_{prost(0)} - V_{inf}}\). The results in the Table 3 show that SYMNET outperforms TRAPSNET on 12 out of 18 instances, is comparable on 5 instances and low on 1 instance.

Comparison against ASNs: Even after significant efforts, we were not able to compare against ASNs, which solves a similar problem for PDDL domains. Converting an RDDL domain to PDDL enumerates all the ground state-variables and loses the RMDP structure. This leads to different domain files for different instances for the same problem domain, due to which ASNs is unable to train. We also tried writing a domain file manually for a few domains, but were not successful due to the unavailability of floating non-fluent values, and due to non-additive reward structure in PDDL.

Comparison against PROST: Finally, we compare against PROST. PROST is a state-of-the-art online planner, i.e., it performs interleaved planning and execution, as it builds a new search tree before taking every action, based on the specific state reached. On the other hand, SYMNET outputs an offline policy, which does not need much computation for deciding the next action. Offline and online policies are two very different settings, and these results are not directly comparable. Nonetheless, we report \(\beta = \frac{V_{symnet(0)} - V_{inf}}{V_{prost(0)} - V_{inf}}\).

The code of PROST is obtained from the official repository.\(^3\)

We compare our policy with PROST on all 9 domains, shown in Table 4. We see that on four domains SYMNET achieves a much better performance than PROST. This is rather surprising to us that even after substantial lookahead from a state, PROST is still not able to compute a good policy. In other domains, the gap between PROST and SYMNET is substantial. This suggests that SYMNET policies are not close to optimal, and further research is needed for making them even stronger. This also points to the possibility of applying a combination of SYMNET and PROST for the offline setting, not unlike the use of Monte-Carlo Tree Search with deep neural networks in AlphaGo (Silver et al., 2016).

Overall, we find that SYMNET’s generalized policies without retraining have excellent performance out of the box. And their performance is quite admirable against several algorithms run in different laxer settings.

6. Conclusion and Future Work

We present the first neural-method for obtaining a generalized policy for Relational MDPs represented in RDDL. Our method, named SYMNET, converts an RDDL problem instance into an instance graph, on which a graph neural network computes state embeddings and embeddings for important object tuples. These are then decoded into scores for each ground action. All parameters are tied and size-invariant such that the same model can work on problems of varying sizes. In our experiments, we train SYMNET on small problems of a domain and test them on larger problems to find that they out-of-the-box perform hugely better than random. Even when compared against training deep reactive policies from scratch, SYMNET without training perform better or at par in over half the problem instances.

Our work is an attempt to revive the thread on Relational MDPs and the attractive vision of generalized policies for a domain. However, ours is only one of the first steps. Further investigation is needed to assess how far are SYMNET’s generalized policies from optimal. We strongly believe that

\(^3\)https://bitbucket.org/tkeller/prost/wiki/Home
there may be even better architectures that could learn near-optimal generalized policies, and the need for retraining or interleaving planning and execution could be rendered unnecessary. We release all our software for use by the research community.

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Appendix

A. Domain Description

We describe the details of the domains presented in the IPPC 2011 and IPPC 2014. The statistics for state fluents ($F$), non-fluents ($NF$) and Action ($A$) for all the domains are shown in Table 5 and Table 6. UP represent $F$, $NF$ and $A$ without parameters, Unary represents $F$, $NF$ and $A$ with a single parameter and multiple represents $F$, $NF$ and $A$ with more than one parameter. Table 7 lists the instance specific number of objects, state variables and action variables for the domain. The domains 1, 2, 3 are used for training, 4 for validation and 5, 6, 7, 8, 9, 10 for testing.

### Academic Advising
The academic advising domain represents a student at a university trying to complete his/her degree. Some courses are required to be completed to obtain the final degree. Each course is either a basic course or may have prerequisites. The probability of passing a course depends on the number of prerequisites completed (a fixed probability if no prerequisite). The goal is to complete the degree as soon as possible.

### Crossing Traffic
Crossing Traffic is represents a robot in a grid, with obstacles at a random grid cell at any time. The obstacles (car) start at any cell randomly and move left. The robot aims to plan its path from the starting grid cell to the goal cell while avoiding obstacles.

### Game of Life
Game of Life domain is represented as a grid where each cell can either be dead or alive. The goal is to keep as many cells alive as possible. The probability of cell death depends on the number of neighbors alive at a particular time, which is non-linear in the number of neighbors alive.

### Navigation
Navigation represents a robot in a grid world where the aim is to reach a goal cell as quickly as possible. The probability of the robot dying in a particular cell is different, which is specified in the instance file.

### Skill Teaching
Skill Teaching domain represents a teacher trying to teach a skill to students. Each student has a mastery level in a particular skill. Some skills have pre-conditions, which increase the probability of learning a particular skill. The skill is taught using either hints or multiple-choice questions.

### Table 5. The statistics related to the domains listing the number of UP (Un-Paramateried), Unary and Multiple Action ($A$) for each domain.

| Domain          | UP-$A$ | Unary-$A$ | Multiple-$A$ |
|-----------------|--------|-----------|--------------|
| Academic Advising | 0      | 1         | 0            |
| Crossing Traffic | 4      | 0         | 0            |
| Game of Life    | 0      | 0         | 1            |
| Navigation      | 4      | 0         | 0            |
| Skill Teaching  | 0      | 2         | 0            |
| Sysadmin        | 0      | 1         | 0            |
| Tamarisk        | 0      | 2         | 0            |
| Traffic         | 0      | 1         | 0            |
| Wildfire        | 0      | 0         | 2            |

The goal is to answer as many questions as possible by the student by learning the required skill.

### Sysadmin
Sysadmin domain represents computers connected in a network. The probability of a computer shutting down on its own depends on the number of turned-on neighboring computers. The agent can either turn on a computer or leave it as it is. The goal is to maximize the number of computers at a particular time.

### Tamarisk
Tamarisk domain represents invasive species of plants (Tamarisk) trying to take over native plant species. The plants spread in any direction and try to destroy the native plant species. The agent can either eradicate Tamarisk in a cell or restore the native plant species, each having a different reward. The goal is to minimize the cost of eradication and restoration of the native plant species.

### Traffic
Traffic domain models the traffic on the road with roads connecting at various intersections. Each road intersection has two traffic light signals combinations of which yield different traffic movement. The agent aims to control the traffic signal (only on the forward sequence) to control the traffic.

### Wildfire
The wildfire domain represents a forest catching fire. The direction of fire spreading depends on the direction of the wind and also the type of fuel at that point (e.g., grass or wood, etc.). The agent can either choose to put down the fire or cut off the fuel even before the fire happens. The goal is to prevent as many cells as possible, and more reward is
Table 6. The statistics related to the domains listing the number of UP (Un-Paramataried), Unary and Multiple State Fluents ($F$) and Non-Fluents ($N^F$) for each domain.

| Domain            | UP-$F$ | UP-$N^F$ | Unary-$F$ | Unary-$N^F$ | Multiple-$F$ | Multiple-$N^F$ |
|-------------------|--------|----------|-----------|-------------|--------------|----------------|
| Academic Advising | 0      | 1        | 2         | 5           | 0            | 1              |
| Crossing Traffic  | 0      | 1        | 0         | 4           | 2            | 5              |
| Game of Life      | 0      | 0        | 0         | 0           | 1            | 2              |
| Navigation        | 0      | 0        | 0         | 4           | 1            | 6              |
| Skill Teaching    | 0      | 0        | 6         | 7           | 0            | 1              |
| Sysadmin          | 0      | 2        | 1         | 0           | 0            | 1              |
| Tamarisk          | 0      | 17       | 2         | 0           | 0            | 2              |
| Traffic           | 0      | 0        | 3         | 3           | 0            | 3              |
| Wildfire          | 0      | 4        | 0         | 0           | 2            | 2              |

provided to protect high priority cells.

B. Variation of $\alpha_{SYMNET}(0)$ with neighbourhood

To inspect the importance of the neighborhood information in learning a generalized policy for the domains, we perform the study of the neighborhood parameter variation. In the Figure 3, we show the variation of $\alpha_{SYMNET}(0)$ with neighbourhood. From the Figure, we observe that message passing for the neighborhood of size 1 yields the best results for most domains, and hence we reported the results with neighborhood 1 in the main paper. In general, we observe that the value of $\alpha_{SYMNET}(0)$ first increases and then decreases.

For most instances, the $\alpha_{SYMNET}(0)$ is less for neighborhood 0 compared to neighborhood 1, showing that the information regarding the neighbors is necessary for learning a better policy. For example, in domain academic advising, the neighborhood 1 aggregates information about the prerequisites for the courses and then prioritizes the courses to take. A similar trend is observed in domain skill teaching, where the information about the pre-condition for the skill plays an important role in learning the skills. For some domains like navigation, neighborhood information is absolutely critical for planning the next move which can be observed from very low values of $\alpha_{SYMNET}(0)$ from Figure 3(d). Other domains like wildfire are not affected a lot by neighborhood a lot. This is because the margin between the minimum and maximum rewards is large, and the generalized policy outputs rewards close to the maximum value, which decreases the variation in the value of $\alpha_{SYMNET}(0)$. As we increase the value of neighborhood to 2 and 3, the value of $\alpha_{SYMNET}(0)$ tends to fall down for most instances. We hypothesize that the agent overfits to instance-specific policies for the instances it is trained on and hence fails to generalize.
Table 7. The statistics related to the domain instances listing the number of Objects, State Variables and Action Variables for all the instances of the domains. Domain 1, 2, 3 are used for training, 4 for validation and 5, 6, 7, 8, 9, 10 for testing.

| Domain | #Objects | #State Vars | #Action Vars | Domain | #Objects | #State Vars | #Action Vars |
|--------|----------|-------------|--------------|--------|----------|-------------|--------------|
| AA 1   | 10       | 20          | 11           | ST 1   | 2        | 12          | 5            |
| AA 2   | 10       | 20          | 11           | ST 2   | 2        | 12          | 5            |
| AA 3   | 15       | 30          | 16           | ST 3   | 4        | 24          | 9            |
| AA 4   | 15       | 30          | 16           | ST 4   | 4        | 24          | 9            |
| AA 5   | 20       | 40          | 21           | ST 5   | 6        | 36          | 13           |
| AA 6   | 20       | 40          | 21           | ST 6   | 6        | 36          | 13           |
| AA 7   | 25       | 50          | 26           | ST 7   | 7        | 42          | 15           |
| AA 8   | 25       | 50          | 26           | ST 8   | 7        | 42          | 15           |
| AA 9   | 30       | 60          | 31           | ST 9   | 8        | 48          | 17           |
| AA 10  | 30       | 60          | 31           | ST 10  | 8        | 48          | 17           |
| CT 1   | 9        | 12          | 5            | Sys 1  | 10       | 10          | 11           |
| CT 2   | 9        | 12          | 5            | Sys 2  | 10       | 10          | 11           |
| CT 3   | 16       | 24          | 5            | Sys 3  | 20       | 20          | 21           |
| CT 4   | 16       | 24          | 5            | Sys 4  | 20       | 20          | 21           |
| CT 5   | 25       | 40          | 5            | Sys 5  | 30       | 30          | 31           |
| CT 6   | 25       | 40          | 5            | Sys 6  | 30       | 30          | 31           |
| CT 7   | 36       | 60          | 5            | Sys 7  | 40       | 40          | 41           |
| CT 8   | 36       | 60          | 5            | Sys 8  | 40       | 40          | 41           |
| CT 9   | 49       | 84          | 5            | Sys 9  | 50       | 50          | 51           |
| CT 10  | 49       | 84          | 5            | Sys 10 | 50       | 50          | 51           |
| GOL 1  | 9        | 9           | 10           | Tam 1  | 12       | 16          | 9            |
| GOL 2  | 9        | 9           | 10           | Tam 2  | 16       | 24          | 9            |
| GOL 3  | 9        | 9           | 10           | Tam 3  | 15       | 20          | 11           |
| GOL 4  | 16       | 16          | 17           | Tam 4  | 20       | 30          | 11           |
| GOL 5  | 16       | 16          | 17           | Tam 5  | 18       | 24          | 13           |
| GOL 6  | 16       | 16          | 17           | Tam 6  | 24       | 36          | 13           |
| GOL 7  | 25       | 25          | 26           | Tam 7  | 21       | 28          | 15           |
| GOL 8  | 25       | 25          | 26           | Tam 8  | 28       | 42          | 15           |
| GOL 9  | 25       | 25          | 26           | Tam 9  | 24       | 32          | 17           |
| GOL 10 | 30       | 30          | 31           | Tam 10 | 32       | 48          | 17           |
| Nav 1  | 12       | 12          | 5            | Tra 1  | 28       | 32          | 5            |
| Nav 2  | 15       | 15          | 5            | Tra 2  | 28       | 32          | 5            |
| Nav 3  | 20       | 20          | 5            | Tra 3  | 40       | 44          | 5            |
| Nav 4  | 30       | 30          | 5            | Tra 4  | 40       | 44          | 5            |
| Nav 5  | 30       | 30          | 5            | Tra 5  | 52       | 56          | 5            |
| Nav 6  | 40       | 40          | 5            | Tra 6  | 52       | 56          | 5            |
| Nav 7  | 50       | 50          | 5            | Tra 7  | 64       | 68          | 5            |
| Nav 8  | 60       | 60          | 5            | Tra 8  | 64       | 68          | 5            |
| Nav 9  | 80       | 80          | 5            | Tra 9  | 76       | 80          | 5            |
| Nav 10 | 100      | 100         | 5            | Tra 10 | 76       | 80          | 5            |
| Wild 1 | 9        | 18          | 19           | Wild 6 | 25       | 50          | 51           |
| Wild 2 | 9        | 18          | 19           | Wild 7 | 30       | 60          | 61           |
| Wild 3 | 16       | 32          | 33           | Wild 8 | 30       | 60          | 61           |
| Wild 4 | 16       | 32          | 33           | Wild 9 | 36       | 72          | 73           |
| Wild 5 | 25       | 50          | 51           | Wild 10| 36       | 72          | 73           |
Figure 3. Variation of $\alpha_{\text{SYMNET}(0)}$ with neighbourhood. [Larger is better]