Representation Learning for Classical Planning from Partially Observed Traces

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Abstract

Specifying a complete domain model is time-consuming, which has been a bottleneck of AI planning technique application in many real-world scenarios. Most classical domain-model learning approaches output a domain model in the form of the declarative planning language, such as STRIPS or PDDL, and solve new planning instances by invoking an existing planner. However, planning in such a representation is sensitive to the accuracy of the learned domain model which probably cannot be used to solve real planning problems. In this paper, to represent domain models in a vectorization representation way, we propose a novel framework based on graph neural network (GNN) integrating model-free learning and model-based planning, called LP-GNN. By embedding propositions and actions in a graph, the latent relationship between them is explored to form a domain-specific heuristics. We evaluate our approach on five classical planning domains, comparing with the classical domain-model learner ARMS. The experimental results show that the domain models learned by our approach are much more effective on solving real planning problems.

1 Introduction

AI planning techniques generally require domain experts to provide background knowledge about the dynamics of the planning domains. But specifying a complete domain model is time-consuming, which has been a bottleneck of AI planning technique application in many real-world scenarios. Taking an example of arranging production lines in a smart factory, there are a vast number of actions and predicates, it is difficult for humans to design an appropriate domain model that covers all actions. However, most traditional domain-model learning approaches output a domain model in a kind of declarative planning language, such as STRIPS or PDDL, where the precondition and effects of actions are given in a declarative way. With the learned domain models, a planner for the planning language is invoked to compute a plan to new planning problems. But whether a plan can be found is sensitive to the accuracy of the learned domain model. Once some critical effect of an action is not learned correctly, the error will accelerate with the plan growing, which finally leads that there is no plan to the goal computed. One promising way is to keep away from learning domain models in the declarative language and to find a new representation to learn and then compute plans. The new planning representation requires to satisfy at least the two following conditions: the state can be represented correctly; there is an effective way to compute a plan. The former allows to represent a new planning instance and the latter is supposed to be efficient as possible, which requires a suitable heuristic function in the forward search planning.

Inspired by word embedding [Mikolov et al. 2013] and knowledge graph embedding [Bordes et al. 2013] which have shown great success in natural language process and knowledge graphs, it is constructive to represent propositions, states, and actions in the form of vectors. To capture the relationship between propositions and states, we consider them jointly as vertexes with a real-number attribute vector in a graph where the interpretation of propositions in a state is captured by the directed edges. In this paper, we propose a novel learning and planning framework based on graph

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neural network (GNN), called LP-GNN, taking the meaning of Learning to Plan based on GNN. LP-GNN integrates model-free learning from partially observed traces and model-based planning based on proposition-state graphs. Due to the representation way of proposition-state graphs, a new state which has not occurred in all the plan traces can be denoted. It provides the possibility to generalize the planning system to handle new planning instances.

To improve the performance of planning, researchers in the planning community have proposed a number of heuristics, such as relaxed planning graph heuristics [Hoffmann and Nebel, 2001], h*-heuristics [Bonet and Geffner, 2001], pattern database heuristics [Edelkamp, 2002], etc. It suggests to choose an appropriate heuristic function for specific domains. Based on proposition-state graphs, the relationship between states and actions are captured naturally, which may help us to find an appropriate heuristic function to guide planning. Therefore, we propose an approach based on MLP to learn heuristic to guide selecting actions towards the goal state. To evaluate the learning and planning performances, we compare LP-GNN with the classical domain model learning system ARMS [Yang et al., 2007] on five well-known planning domains and show that LP-GNN outperforms ARMS and more robust on solving real planning problems.

2 Background

Now we follow the notions of [Francès et al., 2017] about classical planning. We consider a set of propositions \( P \) and consider a state is a subset of \( P \) where the interpretation of proposition is given by the inclusion relation. In other words, if \( p_j \in s \), it means the proposition \( p_j \) is true in the state \( s \); otherwise, \( p_j \) is false in \( s \). A classical planning problem is given as a tuple \( \mathcal{M} = (S, s_0, S_g, A, \alpha, \gamma) \) where \( S \) is a set of states, \( s_0 \in S \) is an initial state, \( S_g \subseteq S \) is a goal state set, \( A \) is an action set, \( \alpha : S \rightarrow 2^A \) is an applicable function, and \( \gamma : S \times A \rightarrow S \) is a state-transition function. Intuitively, \( \alpha(s) \) indicates the actions applicable in state \( s \) and \( \gamma(s, a) \) represents the state resulting from performing the action \( a \) in the state \( s \). A domain model is a tuple \( \mathcal{D} = (\alpha, \gamma) \) and a planning instance is a tuple \( (s_0, S_g) \). The solution to a classical planning problem is a plan which is an action sequence \( \pi = (a_1, ..., a_n) \) satisfying that there exists a state sequence \( (s_0, ..., s_n) \) such that \( \forall 0 \leq i \leq n, s_{i+1} = \gamma(s_i, a_{i+1}), a_{i+1} \in \alpha(s_i) \) and \( s_n \in S_g \).

A plan executed on a planning instance yields a plan trace, which is an alternating sequence of states and actions \( \pi = (s_0, a_1, s_1, ..., a_n, s_n) \). We suppose the initial state and goal state are fully observed and the intermediate states are not. Formally, a partially observed plan traces is a sequence \( \hat{\pi} = (s_0, a_1, \sigma_1, ..., a_n, s_n) \), where \( \sigma_i \subseteq P \). Note that a proposition \( p \) not in \( \sigma_i \) means to be either false or unobserved.

We say a domain model \( \mathcal{D} \) interprets a partially observed trace \( \hat{\pi} = (s_0, a_1, \sigma_1, ..., a_n, s_n) \) if \( (a_1, ..., a_n) \) is a plan of the classical planning problem \( \mathcal{M} = (S, s_0, \{s_n\}, A, \mathcal{D}) \) and the yielded plan trace \( \pi = (s_0, a_1, s_1, ..., a_n, s_n) \) satisfies that \( \forall 0 \leq i \leq n, \sigma_i \subseteq s_i \).

A domain-model learning problem is a tuple \( \mathcal{P}_L = (\mathcal{S}, \mathcal{A}, \Pi) \) where \( \Pi \) is a set of partially observed plan traces. A solution to the problem is a domain model which interprets all plan traces in \( \Pi \).

3 An Overview of Our Approach

In this section, we give an overview of our approach LP-GNN, which is based on GNN [Battaglia et al., 2018]. The framework consists of two modules: the first one is the learning module which takes partially observed traces as input and outputs a domain model based on GNN and heuristics function; the second one is the planning module based on the learned heuristic function.

As states are not totally known in the partially observed traces, the hidden parts are required to be estimated in order to learn the domain model. The estimation task is accomplished via a recurrent framework of graph network with a cost function evaluating the difference between estimated states and observed states. When the framework converges, it outputs a set of sequences of completed states and every state is represented as a unique vector. Also, it finally returns the vectorization representation of actions and propositions. In such a representation, a domain model which almost interprets all partially observed traces is learned.

The vectorization representation learned in the learning module provides a way to learn a heuristic function via an MLP. Every pair of states orderly occurring in the estimated plan traces make up of
4 Domain-model learning

In this section, we propose a sequence-to-sequence domain-model learning framework based on GNN [Battaglia et al., 2018] to handle plan traces, which are in the form of sequence.

To avoid ambiguity, we use the bold type for vectors: \( \mathbf{p}_j, \mathbf{s}, \mathbf{a} \) stand for the vectors of the proposition \( p_j \), the state \( s \) and the action \( a \), respectively, and \( \mathbf{P} \) stands for the set of proposition vectors. For a unified representation, we consider they all are \( k \)-dimension real-number vectors.

We define a proposition-state graph is a tuple \( G = (V, E, \mathbf{a}) \) where \( V = \{s\} \cup \mathbf{P} \) is a set of vertixes and \( E = \{e_j = (p_j, s) | p_j \in \mathbf{P}\} \) is a set of directed edges from every proposition vertex to the state vertex, and \( \mathbf{a} \) is an action vector with the meaning that action \( a \) will be executed in state \( s \). Every vertex is equipped with an attribute of \( k \) real numbers, which is considered as their vectorization representation. Every edge \( e_j \) has a boolean attribute \( e_j \), which captures the interpretation of \( p_j \) in \( s \), which has a boolean attribute. Formally, \( e_j = 1 \) if \( p_j \in s \); otherwise, \( e_j = 0 \).

4.1 Updating Proposition-state Graphs

In the start of the learning phase, the proposition vectors and the action vectors are first initialized randomly from uniform distributions. For every partially observed plan trace, we initialize the proposition-state graph \( G^0 \) by assigning the edge attributes according to the initial state \( s_0 \).

As every state can be represented by propositions and their interpretations, in a proposition-state graph, the unique state vector is obtained via the vectors of the propositions and the edge attributes. Formally, for a state \( s \), we use a state update function to get its vector \( s \):

\[
\mathbf{s} = \phi^s(\mathbf{P}, \mathbf{E})
\]

where \( \mathbf{E} \) is the set of the edge attributes. Obviously, the state vector \( \mathbf{s} \) is determined by the proposition vectors and their interpretation in the state, resulting in that a state uniquely corresponds to a state vector. To learn the state update function \( \phi^s \), we use an MLP which takes the concatenation of the proposition vectors and the edge attributes as input.

To formalize the progression of a state caused by an action execution, we define that a proposition-state graph \( G = (V, E, \mathbf{a}) \) is updated by applying the action vector \( \mathbf{a} \). In our sequence-to-sequence framework, the sequential actions in the input plan trace lead that the proposition-state graph is updated continuously.

In the proposition-state graph, the action vector first changes the edge attributes. Formally, the edge \( e_j \) from \( p_j \) to \( s \), we use an edge update function to obtain its estimated probability \( \hat{e}_j \):

\[
\hat{e}_j' = \phi^E(e_j, \mathbf{s}, \mathbf{p}_j, \mathbf{a}).
\]
By concatenating all the edges, we generalize the edge update function into the edge set:

$$E' = \phi^{E'}(E, s, P, a).$$

Similarly, to learn the function $\phi^{E'}$, we use an MLP which ends with a sigmoid function and outputs an estimated probability $\hat{e}_j$ for every edge attribute $e_j$. To keep the consistency with the interpretation of propositions, the estimated probability needs to be decoded to the boolean edge attribute $E'$ by the decoder function $\phi^{de}$.

### 4.2 Learning Applicable and State-transition Functions

The change of the edge attributes directly cause the change of the state vector via the state update function $\phi^s$. Then we define a state-transition function $f$ for the state vector and the action vector:

$$s' = \phi^s(P, E') = \phi^s(P, \phi^{de}(\phi^{E}(E, s, P, a))) = f(s, a)$$

According to equations (1) and (3), once all proposition vectors are learned, then $P$ will not change and $E$ are determined by the state vector $s$ and the action vector $a$. In other words, the next state $s'$ is uniquely determined by the current state $s$ and the action $a$ executed.

A partially observed plan trace yields a sequence of proposition-state graphs by replacing the actions. Formally, for a plan trace $\hat{\pi} = (s_0, a_1, ..., s_n)$, we use $\hat{G}^i = (V^i, E^i, a_{i+1})$ for $0 \leq i < n$, to denote the $i$th proposition-state graphs in the corresponding sequence. Then every edge attribute set $E^i$ stands for an estimated state $s_i$ in the sequence. To train the functions $\phi^p$, $\phi^E$ and the vectors of propositions and actions correctly, we define a loss function to evaluate the differences between the estimated states and the observed states. The estimation on the propositions in a state can be considered as a logistic regression problem for the observed propositions in the state, which suggests us to employ the cross-entropy loss function.

After prorogating the gradient descent to the functions and the vectors of propositions and actions, when the loss function converges, the state-transition function is learned.

To learn the applicable function $a$, for every action $a$, we consider the intersection of the estimated states in which action $a$ is executed as the precondition of action $a$, denoted by $\text{pre}(a)$. Then for every state $s$, we define its applicable action set as $\alpha(s) = \{a|\text{pre}(a) \subseteq s\}$. From a safety perspective, the actions never occurring in the input plan traces are not considered as applicable in any state.

When the model converges, the functions $\phi^s$, $\phi^E$, $\phi^{de}$ and the proposition vectors $P$ and all action vectors are learned and fixed. We can bridge every state and its vector uniquely, i.e., $s = g(s)$. Based on the embedding of propositions, states, and actions, we represent a planning problem as a tuple $\mathcal{P} = (S, s_0, S_T, A, \alpha, f)$ where $S$ is a set of state vectors, $s_0$ is the initial state vector, $S_T \subseteq S$, $A$ is a set of action vectors and $\alpha, f$ are the applicable and state-transition function, respectively.

### 5 Planning with Heuristics

#### 5.1 Learning Heuristics Function

The heuristic function plays an important role in the forward-search planning techniques, which helps the planner to select suitable actions towards the goal state. A suitable heuristic function may speed up the problem-solving significantly. With various heuristic functions being proposed, there is not an approach to choose suitable heuristic function automatically for different planning domains. For that, we propose an approach to learn the heuristic function based on the embedding of states and actions.

Given a set of fully observed plan traces $\pi_k = (s_0, a_1, s_1, ..., s_n)$ we define the action selection function $h : S \times S \rightarrow 2^A$ such that $a_{i+1} \in h(s_i, s_j)$ where $i < j$ and $a_{i+1}$ is the action executed in the state $s_i$ in some $\pi_k$. As the same state pair may occur in different traces, there are more than one actions executed in the former state $s_i$.

With the embedding of states, we generate tuples $(s, s', a)$ where $a \in h(s, s')$ as training examples from the estimated trace set obtained from the learning module. Actually, it is a multi-label learning
task [Zhang and Zhou, 2014]. Then we construct an MLP $\phi^h$ which takes the concatenation of two state vectors as input and outputs a list of recommendation confidences for every action. We train the network to minimize the sigmoid cross-entropy loss between the recommendation confidences and the action labels $h(s, s')$.

Consider the latter state as the goal state, the action selection function provides a set of recommended actions to lead towards the goal state. For the current state $s_i$ and the goal state $s_g$, we define a goal-driven heuristic function for every action as its recommendation confidence output by $\phi^h(s_i, s_g)$.

5.2 Planning with Heuristics Learned

Based on the learned domain model, we propose a progression-based algorithm to compute a plan for the planning instance $(s_0, S_g)$, as shown in Algorithm 1. To implement the backtracking, we use a list $\text{Visited}$ to record the visited state with the action executed in it and use a list $\text{History}$ to record the visited state with the plan executed until it. We first set the current state as the initial state $s_0$ and initialize the two lists to be empty. Then we start to find a plan via selecting a goal state from the goal state set $S_g$. By selecting actions to execute repeatedly, once it reaches one of goal states, the algorithm finds a plan (line 11-12). Observe that the action selection function outputs an action set with at most three actions, at every step we choose one of the top 3 recommended actions which are also applicable in the current state (line 5). Formally, we use $\Phi^h_{s,s_g}$ to denote the set of actions with the three highest recommendation confidences in $\phi^h(s, s_g)$. Once an action is executed, we update the current state, the current plan and the two lists $\text{Visited}$ and $\text{History}$ (line 7-12). When all applicable actions in $\Phi^h_{s,s_g}$ have been visited, the algorithm have to backtrack to the last state via a $\text{POP}$ operator on $\text{History}$ (line 15-16). The current plan $\sigma$ should be regressed by removing its last action, which is done via a $\text{REGRESS}$ operator (line 17). Once the list $\text{History}$ becomes empty again, it means every possible recommended action sequence cannot achieve the selected goal state and it needs to choose another goal state (line 13-14). When every goal state are tried and no plan is found, the algorithm returns failure.

Algorithm 1: GNN-PLAN $(\mathcal{P}, \phi^h)$

| Function | Input  | Output  |
|----------|--------|---------|
| $s \leftarrow s_0$; |  |  |
| $\text{Visited} \leftarrow \text{History} \leftarrow \emptyset$; |  |  |
| for each $s_g \in S_g$ do |  |  |
| while true do |  |  |
| for each $a \in \Phi^h_{s,s_g} \cap \alpha(s)$ do |  |  |
| if $(s, a) \notin \text{Visited}$ then |  |  |
| $\text{Visited} \leftarrow \text{Visited} \cup (s, a)$; |  |  |
| $\sigma \leftarrow \sigma \circ a$; |  |  |
| $\text{History} \leftarrow \text{History} \cup (s, \sigma)$; |  |  |
| $s \leftarrow f(s, a)$; |  |  |
| if $s \in S_g$ then |  |  |
| return $\sigma$; |  |  |
| if $\text{History} == \emptyset$ then |  |  |
| break; |  |  |
| $(s^-, \sigma) \leftarrow \text{POP}(\text{History})$; |  |  |
| $s \leftarrow s^-$; |  |  |
| $\sigma \leftarrow \text{REGRESS}(\sigma)$; |  |  |
| return fail; |  |  |

6 Experiment

We apply LP-GNN on five classical planning domains including Logistics, ZenoTravel, Depots, Ferry and Mprime, and compare LP-GNN to the classical domain-model learning system ARMS [Yang]
et al. [2007] which invokes a MAX-SAT solver. LP-GNN is implemented in Tensorflow and GNN framework and it takes approximately three hours to train on a single GPU GeForce RTX 2080 Ti.

6.1 Data

We first get the problem generators from FF planner homepage (for Logistics, Ferry, Mprime) and International Planning Competition website (for Depots, Zeno-Travel). We randomly generate 2100 disjoint planning instances for each domain and take 2000 instances as the training set and 100 instances as the testing set. Table 1 shows the upper bound of the number of propositions and actions in each domain. For the plan traces with fewer propositions, we use a 0-padding method. By invoking FF planner, we generate a plan for each planning instances and further obtain 2100 plan traces. To capture the partial observation, we randomly remove the propositions according to the partial observation percentages (0%, 20%, 40%, 60%, 80%, 100%) from every intermediate state in the plan traces.

| Domain     | Proposition | Action |
|------------|-------------|--------|
| Logistics  | 137         | 150    |
| Depot      | 110         | 115    |
| Zeno-Travel| 131         | 279    |
| Ferry      | 99          | 126    |
| Mprime     | 216         | 791    |

6.2 Training Details

The training phase is divided into two parts in LP-GNN. First, we trained the sequence-to-sequence model to acquire a domain model with the functions \( \phi^s \), \( \phi^e \), \( \phi^{de} \) and the vectorization representations of propositions and actions. These functions are designed as a two-layer MLP respectively and each layer has 100 neurons and the layer normalization. Second, we train an action selection network \( \phi^h \) on the estimated plan traces, which is designed as three-layer network with the layer normalization and has 150 neurons at each hidden layer.

The action vectors and proposition vectors are represented as 100-dimensional vector \( k = 100 \). The action vector and proposition vector are initialized uniformly and randomly within the range \([-0.6, 0.6]\) \( \frac{6}{\sqrt{k}} = 0.6 \). We train our model using the Adam optimizer [Kingma and Ba 2015] with a batch in size of 20 and an initial learning rate of \( 10^{-3} \).

6.3 Metrics

**Learning Performance Metrics.** The learning performance of our approach is measured with the precision and recall metrics, by comparing the estimated state sequences with the real ones in the testing set.

Intuitively, precision gives a notion of soundness while recall gives a notion of the completeness of the estimated state sequences. We use \( t_p \) to denote the propositions both in the real and estimated state, \( t_n \) to denote the propositions in neither the real state nor the estimated state, \( f_p \) to denote the propositions not in the real state but in the estimated state and \( f_n \) to denote the propositions in the real state but not in the estimated state. Then for an estimated state, we compute its precision by \( \text{Precision} = \frac{t_p}{t_p + f_p} \) and its recall by \( \text{Recall} = \frac{t_p}{t_p + f_n} \). To evaluate the estimation performances of the learning approaches on the testing set, we generalize these two metrics into state sequence sets by computing their average precision and recall for every state in every sequence.

**Planning Performance Metric.** As we mention before, domain models in the declarative language are sensitive to their accuracy. Even though the learned domain models interpret the partially observed plan traces perfectly, it is possible that they cannot be used to solve the real planning problems. It is more important to evaluate the domain-model learning approaches on the ability of solving real problems. More specially, for the learned domain model, we generate plans under it for the planning instances in the testing set and test whether these plans are solutions to these planning instances under
the original domain models. If so, the testing instance is considered as solved by the learned domain model. Then we introduce a metric as the percentages of solved instances on all testing instances, i.e., 
\[ I = \frac{\# \text{instances solved}}{\# \text{testing instances}}. \]

6.4 Results

Table 2: Learning Performance in the Five Domains under Various Observation Percentages

| Domain | 0% | 20% | 40% | 60% | 80% | 100% |
|--------|----|-----|-----|-----|-----|------|
| Logistics | LP-GNN | ARMS | LP-GNN | ARMS | LP-GNN | ARMS |
| P(%) | R(%) | P(%) | R(%) | P(%) | R(%) | P(%) | R(%) |
| 87.09 | 66.33 | 99.37 | 98.64 | 90.21 | 100 | 99.53 | 99.34 | 90.21 |
| Zeno-Travel | 82.71 | 61.3 | 95.19 | 68.08 | 99.11 | 98.69 | 100 | 95.96 | 99.77 | 99.75 | 100 | 95.96 |
| Depot | 83.14 | 82.08 | 95.62 | 71.85 | 98.45 | 99.74 | 93.46 | 92.93 | 98.49 | 99.88 | 93.46 | 92.93 |
| Mprime | 91.21 | 67.13 | 97.09 | 61.85 | 92.62 | 88.84 | 91.29 | 99.91 | 95.21 | 93.38 | 90.3 | 99.91 |
| Ferry | 96.91 | 79.51 | 96.42 | 66.43 | 99.98 | 99.81 | 98.58 | 100 | 100 | 98.94 | 98.58 | 100 |

Table 2 shows the learning performances of our approach LP-GNN and ARMS on the testing set. With the observation percentage increasing, both the approaches have better and better performances on estimating states. The results show that LP-GNN and ARMS are comparable on the learning performance. In LP-GNN, the loss on the training set are various observation percentages less than \( 10^{-5} \), which means that the learned domain models almost interpret all training plan traces and can be considered as solutions to the learning problems. While in ARMS, all plan traces are interpreted and it is because it is based on a MAX-SAT solver.

To evaluate the real problem solving ability, we compare our approach LP-GNN against ARMS on the percentages of instance solved on the testing set, whose experimental results are shown in Figure 2. As ARMS outputs domain models in STRIPS, we call FF planer to generate plans. Obviously, our approach significantly outperforms ARMS on the ability of solving real problems and the domain model learned by ARMS fails to solve any real problems except for the Zeno-Travel domain.

For the model ablation, in LP-GNN we replace the action selection MLP by SVM and Random Forest, and modify the GNN-PLAN planning algorithm accordingly. We evaluate the effectiveness, on the real planning problems, of plans computed by these three algorithms under the same learned domain models. The results show that learning action selection policy via MLP outperforms other two approaches. Actually, for the solved instances, the GNN-PLAN planning algorithm with MLP almost generates plans identical with the plans generated by the original domain model using FF planner, which shows the excellent ability on guiding planning of our heuristics learning approach.

6.5 Analysis

The reason why the learned domain models by ARMS hardly solve any real problems should be rooted in the fact that the plan-searching is extremely sensitive to its accuracy in the declarative language. From the experimental results, we observe that in Logistics domain, the proposition ‘(airport ?location)’ is learned as an effect of the action ‘(load-truck ?object ?truck ?location)’ in the domain model learned by ARMS. Once the action is executed, the city center where the package is loaded into the truck becomes an airport, resulting in that the airplane can fly to the city center. So, the plan including the action that the plane flies to the city center is generated via the FF planner, but it is not allowed in the artificial domain model. Then, mostly the plans generated under such a learned domain model are ineffective and no instances are solved.

The failure of the plans generated by LP-GNN on some instances is blamed for the precondition learned. Because actions are not sufficiently occurred in the plan traces, if we consider the intersection of the false propositions into the action precondition, it will make the precondition too strong to be satisfied.
Figure 2: Comparisons on instances solved with various observation percentages. LP-GNN is our approach and LP-GNN-SVM and LP-GNN-RF are our approaches with replacing action selection MLP by SVM and Random Forest. Instances solved are the testing instances which are solved under the original domain model by the plans computed according to the learned domain model.

by other states. So, we only focus on the true propositions which, on the other hand, is too weak so that the planning algorithm may execute an unapplicable action.

7 Related Work

Domain-model learning has been obtained a lot of attention and there exist a number of approaches [Arora et al., 2018]. In this paper, we focus on the learning approaches which return domain models in a declarative language, such as PDDL and its fragments. LOCM [Cresswell et al., 2013] and its successor LOCM2 [Cresswell and Gregory, 2011] learn the object-centered representation based on a set of parameterized finite state machines. But these two approaches only can learn action effects on dynamic predicates and fail to handle static predicates which do not change due to action executions. NLOCM [Gregory and Lindsay, 2016] extends finite state machines with numeric weights to learn action costs. PELA [Martínez et al., 2016] refines the input domain model based on top-down induction of decision trees but assume the input domain model to be correct. OBSERVER [Wang, 1994] is an incrementally learning system which refines the learned domain model by observing the execution traces for the sampled problems. Whereas, its performance is sensitive to the sampled problems and it may suffer from the incomplete or incorrect domain knowledge. LAMP [Zhuo et al., 2010] is a framework to learn more complex domain models with quantifiers and logical implication. [Aineto et al., 2018] proposes an approach to compile the learning problem into a classical planning problem, which may suffer from a scale issue.

Another related work is [Mourão et al., 2010], which considers action-effect learning problems as classifier problems and proposes a learning approach based on a bank of kernel perceptrons. But it only learns action effects and needs a good number of training examples for good performance. Some approaches require a fully observed environment where we consider a partially observed one. LOPE [García-Martínez and Borrajo, 2000] learns domain models in STRIPS by repeatedly executing actions based on reinforcement learning. [Stern and Juba, 2017] provides a safe domain-model learning approach which guarantees the output domain model to generate safe plans.

There are learning approaches taking noisy plan traces as input which suppose that the input actions may be incorrect. AMAN [Zhuo and Kambhampati, 2013] learns domain models from noisy planning
traces via probabilistic graphical models and reinforcement learning. The line of works by Pasula et al. [2004, 2007] focus on learning STRIPS-like planning rules via adding noisy outcome in their probabilistic model but fail to handle incomplete observations.

As we mention before, ARMS [Yang et al., 2007] is one of the most classical domain-model learning approaches which have inspired a series of learning approaches. For example, from the perspective of transfer learning, LAWS [Zhuo et al., 2011b] takes other domain models into account and measures the similarity between the source domains and the target domain via web searching. For another example, Lammas [Zhuo et al., 2011a] learns multi-agent domain models by constructing constraints about agent actions and invoking a MAX-SAT solver. Besides, CAMA [Zhuo, 2015] integrates intelligence of crowds into action-model acquisition based on a MAX-SAT solver. Later [Zhuo et al., 2014] proposed a learning system HTN-Learner to learn hierarchical task network planning domain models based on a weighted MAX-SAT solver.

Other domain-model learning approaches also concentrate on various inputs. TRAMP [Zhuo and Yang, 2014] and tLAMP [Zhuo et al., 2008] use the transfer learning technique and require other domains as inputs, as well as LAWS. LatPlan [Asai and Fukunaga, 2018] proposes an approach to learn action models from fully observed images.

| Approaches          | Input                               | Limitations/Features                           |
|---------------------|-------------------------------------|------------------------------------------------|
| LOCM, LOCM2         | Action sequences                    | Only handle dynamic predicates                 |
| NLOCM               | Action sequences with costs          | Can learn action costs                         |
| PELA                | Initial action models and action sequences | Assumes correct initial action models         |
| OBSERVER            | Action sequence and sampled problems | Sensitive to the sampled planning problems     |
| LOPE                | repeated action executions          | Requires FO environment                        |
| [Stern and Juba, 2017] | PO plan traces                    | Requires FO plan traces                        |
| LAMP                | PO plan traces                      | learns ADL domain models                       |
| [Aineto et al., 2018] | PO plan traces                  | compiles into a planning problem              |
| Mourão et al., 2010 |                                    | Only learns effects and requires many training examples |
| AMAN                | Noisy plan traces                   | No background knowledge needed                 |
| ARMS                | plan traces                         | Call a MAX-SAT solver                          |
| Lammas              | multi-agent plan traces             |                                               |
| CAMA                | PO plan traces and crowdsourcing data |                                               |
| LAWS, TRAMP, tLAMP  | Plan traces and other domains       | Use the transfer learning technique            |
| LatPlan             | Action sequences and images         | Requires FO images                             |

FO = fully observed; PO = partially observed

8 Discussion and Conclusion

Similar with the perspective of [Stern and Juba, 2017] on the safety of the plans generated by the learned domain model, in this paper we focus on the effectiveness on the real problems of the plans. It motivates us to find another way to model domain models which is distinct from the classical declarative language. Indeed, we aim to learn the vectorization representation of actions, states and propositions in GNN, which actually provides an interpretation for state changes caused by action executions. By embedding propositions and actions in a graph, the latent relationship between them is explored to form a domain-specific heuristics. Its excellent strength on guiding planning has been demonstrated by the experiment results and we believe that it opens a line of future work on learning domain-specific heuristic functions.

To sum up, we propose a novel approach LP-GNN to learn the domain model based on GNN from a set of partially observed plan traces. We first learn the vectorization representations of propositions, states, and actions by putting them into a proposition-state graph. The representation in the proposition-state graph allows us to denote new states in the domain and further enables us to solve new planning
instances. Finally, we propose a more robust planning framework equipped with a domain-specific heuristic function, which is demonstrated to be more effective on solving real planning problems.

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