A Memory-Related Multi-Task Method Based on Task-Agnostic Exploration

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Abstract—We pose a new question: Can agents learn how to combine actions from previous tasks to complete new tasks, just as humans? In contrast to imitation learning, there is no expert data, only the data collected through environmental exploration. Compared with offline reinforcement learning, the problem of data distribution shift is more serious. Since the action sequence to solve the new task may be the combination of trajectory segments of multiple training tasks, in other words, the test task and the solving strategy do not exist directly in the training data. This makes the problem more difficult. We propose a Memory-related Multi-task Method (M3) to address this problem. The method consists of three stages. First, task-agnostic exploration is carried out to collect data. Different from previous methods, we organize the exploration data into a knowledge graph. We design a model based on the exploration data to extract action effect features and save them in memory, while an action predictive model is trained. Secondly, for a new task, the action effect features stored in memory are used to generate candidate actions by a feature decomposition-based approach. Finally, a multi-scale candidate action pool and the action predictive model are fused to generate a strategy to complete the task. Experimental results show that the performance of our proposed method is significantly improved compared with the baseline. Code and visualizations: https://github.com/Xianqi-Zhang/M3

Index Terms—Robotic manipulation, task-agnostic exploration, multi-task, feature decomposition, knowledge graph.

I. INTRODUCTION

A key aspect of human intelligence is the ability to draw inferences by interacting with objects in the environment, acquiring knowledge, and applying that knowledge to combine different actions to accomplish new tasks. In our daily lives, tasks are usually accomplished by combining various actions. For example, when you want to read a book, you need to “turn on the light and push the chair near the table.” The actions required to complete a new task may be found in many previously completed jobs. For example, you’ve done actions like “turn on the light” and “push the chair to the table” before, but probably not together. Humans can do this job easily, but it is very challenging for robots. In particular, actions that have prerequisites make the task more difficult, such as you need “open the fridge” before “put an apple in the fridge”, which means that there is a restriction on the order of actions. Providing samples for each task is costly and unrealistic. In this paper, we pose and try to solve the question: Can agents learn from historical tasks, like humans, combining various previous acts to complete new tasks?

Imitation learning and offline reinforcement learning have made great progress in many fields, such as automatic driving and manipulator control. Imitation learning methods need to collect expert data in advance and teach the agent to imitate the expert behavior to achieve the goal [1]. However, gathering large amounts of expert data is costly. In contrast, offline RL does not require expert data. The agent first explores the environment to collect data and then trains the model to carry out particular tasks. How to efficiently explore the environment and get more high-quality data is an important question in this research field [2]–[6]. Offline RL also has some drawbacks, such as difficulty in designing reward functions and sensitivity to data distribution shift. Recently, there are many studies on robot motion planning based on deep learning [7]–[10]. These models can’t effectively address the issue raised in this paper since they are usually designed for specific tasks, and it is challenging to combine existing knowledge to fulfill new jobs.

Transformer [11] is widely used in natural language processing and computer vision. Many recent works employ Transformer architecture for decision-making [12], [13] and treat sequential decision-making as a sequence modeling problem. These methods replace reward information in RL with return-to-go, i.e. the sum of subsequent rewards from the current moment. Its essence is the same as imitation learning and offline RL, which is to extract and imitate the information beneficial to solve the task and disregard the useless information. However, it should be noticed that all the information in the dataset is meaningful for our proposed challenge. Only for a specific task, can you distinguish whether a piece of information is useful or not.

Additionally, a series of Large Language Model (LLM) [14]–[16] based sequential decision-making methods have been proposed. Without retraining the model, they predict actions by mining the knowledge contained in LLM. In these works, historical action information needs to be converted to text, or use trajectory segments as a prompt, and they seem to be more likely to address tasks that can be named in everyday life. In contrast, we concentrate on how to acquire knowledge from completed historical tasks, especially the effects of various actions interacting with the environment to finish new, sometimes unnamed jobs. We believe that this innate ability to pick up information from previous activities and apply it to new ones is one of the keys to general intelligence.

In this paper, we explore the environment and organize the exploration data into a knowledge graph structure. After exploring a certain number of steps, randomly select a node
from the knowledge graph, restore the associated environmental state and go on exploring. Benefiting from the successful practice of deep learning in robot motion control, we design a model to predict actions through the environment and task information. In addition, inspired by the way people process tasks in daily life, an action effect extractor is proposed to extract features and store them in memory. For specific tasks, we propose a feature decomposition-based method to produce candidate actions. Finally, the action predictive model and a multi-scale candidate action pool are fused to generate the strategy to accomplish the task.

The main contributions of this paper are as follows:

1) A new question: Can agents learn knowledge through historical tasks and learn to fulfill new ones by combining different actions? We believe that this ability is a crucial component of general intelligence.

2) A new data organization manner for exploration. We organize exploration data as a knowledge graph. This approach is more likely to explore various continuous actions and contains fewer redundant data.

3) An action effect feature extractor and a feature decomposition-based candidate action generation method.

4) A fusion strategy of the action predictive model and the multi-scale candidate action pool.

The rest of this paper is organized as follows. The problem definition and challenges are introduced in Section II. Related works are briefly reviewed in Section III. The proposed approach is fully described in Section IV. The analysis and results of the experiment are presented in Section V. Section VI contains the conclusion and future works.

II. RELATED WORK

A. Robot motion planning based on deep learning

Recently, many sequential decision-making algorithms are only based on deep learning. Chelsea Finn et al. [7] proposed a deep predictive model to predict the possible motion of each object in the scene after performing different actions, and then select the optimal action. Their research demonstrates that using a predictive model for robot control is practical. Pulkit Agrawal et al. [8] proposed a CNN-based model and train the robot to prod the object into the desired position. In these works, only one camera is equipped in the head of the robot, overlooking the desktop experimental environment. Although it takes place in a 3D real-world setting, the essence is still to translate into a 2D space for reasoning and planning. Zeng et al. [9] used fully convolutional networks to solve the pick-and-place problem of a robotic arm. Wu J et al. [10] proposed spatial action maps for pushing objects to target locations. In these works, many robots can only perform low-level actions, and the algorithms are generally designed and optimized for specific tasks, making them unable to combine actions to complete new tasks.

B. Imitation learning

Imitation Learning, also known as learning from demonstration, refers to making robots imitate the behavior of experts and is widely used in robotics-related fields [17]–[22]. In the physics simulator Pybullet [23], Ehsani K et al. [24] created an environment and trained a model to mimic the activities of the characters in the video, such as shaking a pan and swinging a hammer. However, most of the actions imitated are simple translations or rotations with only one object present in the scene. Inverse Reinforcement Learning (IRL) was used by Chelsea Finn et al. [25] to teach the agent to carry out the identical activities as the expert examples. These tasks included placing dishes and pouring water, etc. Sharma P et al. [26] trained two models, in which the high-level model generated a series of first-person sub-goals based on the video from the third-person perspective, and the low-level model predicted the actions necessary to fulfill the sub-goals. This idea is similar to Hierarchical Reinforcement Learning (HRL) [27]–[31].

C. Environment Exploration

Controlling robots to explore unknown environments is a significant challenge for Reinforcement Learning (RL) [2], [3], [5], [6], [32]. Chen A S et al. [33] proposed Batch Exploration with Examples (BEE), which narrowed the exploration space via artificially provided samples. This method effectively avoids the issue of reward function setting. But given samples also limit the tasks that can be accomplished with the collected data, and how to choose appropriate samples is also a difficult problem. In order to enable agents to explore new states, many works encourage the model to explore by establishing novelty reward information. Burda Y et al. [34] proposed the Random Network Distillation (RND) to determine whether a state was novel by comparing its similarity to the historical state. They used RND as reward information, paired with PPO [35], to guide agents to explore new states. Badia A P et al. [36] used RND [34] to judge the state novelty across episodes and used the K-nearest neighbor method to judge whether the state was novel in the current episode. Cross-episode novelty and inner-episode novelty were mixed as final rewards. Sekar R et al. [32] used multiple models to predict the next state and took the variance of multiple outputs as novelty reward information.

D. The Goal-Conditioned RL

Goal-conditioned RL (also known as goal-oriented RL or multi-goal RL) related studies expects agents to be able to perform multiple tasks [37]–[41]. Agents are anticipated to consider both the task and the environment information when making decisions, as opposed to the classic RL techniques, which typically only do one job [37]. During the training phase, the goal is continuously selected from previous experience and the agent is trained to complete it. Explore the environment at the same time, and save new experience data. The agent needs to complete specific tasks during the testing phase [38]. However, in many recent works, the experimental setup is to move a robot to a target location or move an object somewhere with a robotic arm, and treat different target positions as different tasks. There is a big gap between the experimental environment and the real-world situation.
The problem presented in this paper has some differences from the current goal-conditioned research. First, most of the current goal-conditioned algorithms research how to enable the agent to finish any task that has been completed before, focusing on enabling the agent to memorize more task-solving strategies, while we focus more on whether the combination of knowledge can help the agent to accomplish new tasks. Second, we do not assume that the training data contains the test task’s solution strategy. Instead, the training data can only contain solution segments of the test task. In addition, the environment [42] we employ is more complex than previous settings [39], [43], [44], with 36 objects, 11 actions, and 28 potential object states.

III. PROBLEM STATEMENT

Question: Can agents learn from historical tasks, like humans, combining different actions it has done before to complete new tasks?

Task: Robots perform preset actions and skills to interact with the environment, collect data, and learn through task-agnostic exploration. For a new task, the robot needs to use the knowledge gained from the previous task to combine various actions to complete it.

We assume that the problem satisfies the Markov Decision Process (MDP), which can be expressed as $M = (S, A, P, R, \mu, T)$. $S$ indicates the environmental status. The agent needs to select an action based on the environmental status and task information. Based on the Markov hypothesis, the next environmental state is only related to the current state, not the previous ones. $A$ is the set of actions. For action space $A$, we assume that the robot can perform low-level actions, such as moving left and so on, as well as higher-level skills, such as placing objects somewhere. We assume that high-level skills can be done through other research efforts. $P$ is the state transition probability. $R$ is a reward function, which usually requires fine design. Solving this problem by simply designing a reward function is particularly challenging because we expect the agent to be able to perform new tasks, which is unknown when the agent learns the knowledge. $\mu \in (0, 1)$ is the discount factor. $T$ is the set of tasks.

Challenge: 1) The distribution shift problem between test data and training data is serious, i.e., the training task is different from the test task. 2) There isn’t a policy that can directly complete the test task in the training set. A more severe condition is that the test task cannot be completed by the solutions of similar tasks in the training set. The solution to a test task may consist of several solution fragments for the training tasks.

In this paper, we adopt a home-like environment [42]. The robot performs high-level actions such as “pickNplaceAonB <book> <table>”. We hypothesize that these basic skills can be addressed by other research efforts. The environment contains 36 objects, including two tables, a fridge, a chair, and so on, and the robot can execute 11 actions, including pick, drop, etc. (Details in Table.I.) The process of knowledge learning can be divided into two stages: 1) Exploration stage. Gather data through task-agnostic exploration. 2) Exploitation stage. 2.1) Learn from exploration data. 2.2) For a new task, use the learned knowledge to combine various actions to fulfill it. Details are provided next.

IV. MEMORY-RELATED MULTI-TASK METHOD

In this section, we first introduce task-agnostic exploration and data organization methods. Then, the architecture of the
action predictive model is presented. After that, the action effect feature extractor and feature decomposition-based candidate action generation method are described. Finally, the fusion strategy of the action predictive model and the multi-scale candidate pool is provided.

A. Task-agnostic Exploration

In this paper, we choose acts at random for task-agnostic exploration. In contrast to earlier research, we organize exploration data into a knowledge graph, where nodes represent environmental states and edges represent actions. Environmental states are also represented by graphs, where graph nodes are objects and edges represent relationships between objects.

**Environment Exploration.** Predefined actions in the environment [42] take a high-level representation. Each action consists of the action name and one or two parameters. The first parameter is the object name and the second one is the object name or object state. We pre-generate all combinations of action names, object names, and states. However, it is important to be aware that many of these actions are incorrect and cannot be executed correctly. We filter out erroneous actions via feedback from the environment (Pybullet [23], a physics simulator), in contrast to earlier studies that only performed correct actions.

After initializing the environment, we randomly choose an action to perform. In order to make the distribution of selected actions more even, the Weighted Random Sampler is used to select actions according to the number of executions of each act. Benefiting from the advantages of the simulator, we preserve the environment’s state before executing the action so that it can be restored and explored again from the present state in the future. When an action is performed, the simulator provides feedback on the execution. If the feedback information indicates that the action does not conform to the preset action (execution error), the sampling probability of the action is set to zero, that is, the action is abandoned. Restore the present environment and choose another action to execute. (The randomly picked action must not exist on the node’s outgoing edges.) After exploring a certain number of steps, we randomly select a node in the knowledge graph, restore the environmental state corresponding to the node, and go on exploring.

We believe that the way we organize exploration data is more likely to lead to meaningful sequential actions and reduce redundant data retention. In previous work, the exploration data is kept as a sequence structure, and multiple data may contain the same fragment, i.e. there is more redundant information. Since the environment is always initialized to the same state, exploring the environment completely involves taking a large number of steps. In contrast, we use a knowledge graph to hold exploration data and explore the world. The ability to restore the environment to various earlier states makes it easier to fully investigate the environment, and the graph structure enables data storage with less redundant information.

**Task Data Generation.** We sample pathways from previously saved knowledge graph to produce task data. The task’s goal is represented by the environmental state, which is each path’s termination state. A trajectory that accomplishes this task consists of nodes (states) and edges (actions) on the path.

To construct the dataset, we sample a fixed number of paths from the knowledge graph as tasks and partition the dataset by stratified sampling according to the path lengths. This makes the tasks in different datasets vary significantly, and the datasets suffer from a severe distribution shift issue. The solution strategy for the test data is a combination of solution segments in the training set.

B. Action Predictive Model

We design an action predictive model, which can be viewed as a Behavior Cloning (BC) method. According to the Markov Decision Process (MDP), the current state is independent of the historical actions and states. Based on this assumption, our model only accepts information about the present environment and the task.

We use the environment’s final state to represent the goal of the task. The scene graph is used to express state information, each node represents an object (including object name, size, location, etc.), and edges provide relationship information between objects (such as Close, Inside, On, and Stuck). Textual data such as item names and actions are encoded by ConceptNet [45]. Graph Convolutional Networks (GCNs) are used to extract environmental state features and goal features, respectively. To extract information about environmental change at the feature level and estimate the action, the difference between the initial state feature and the goal state feature is employed. Each action consists of the name and one or two parameters. Since the parameters are related to the action name, similar to [42], we first estimate the name and then the parameters. The corresponding parameters are selected according to the action name. For instance, since the operation “pick” can only take one parameter (an object name), just \( y^o_1 \) is used.

\[
\begin{align*}
y_{act} &= \Phi(W_{act}\Psi(G(s), G(g))) \\
y^o_1 &= \Phi(W_1^2 H + b_1^2) \\
y^o_2 &= \Phi(W_2^2 H + b_2^2) \\
y_s &= \Phi(W_s H + b_s) \\
\text{st. } H &= f(h_{as}, \Psi(G(s), G(g))
\end{align*}
\]

where \( s \) is the current state of the environment, \( g \) is the goal, and \( G \) represents GCN. The GCN shared the weight of \( s \) and \( g \) in the experiment. \( \Psi \) denotes the absolute value of the difference, \( h_{as} \) is the action feature, \( \Phi \) is the activation function. \( W \) is the fully connected layer weight, and \( b \) is the bias. \( f \) denotes the concatenate operation. \( y_{act} \) is the action name, \( y^1 \) and \( y^2 \) represent object name, and \( y_s \) is object state.

A binary cross-entropy loss (BCE) is used to train the network.

\[
\mathcal{L}_{AP} = \frac{1}{N} \sum_{i=1}^{N} -w_i \left[ f_i^* \log(f_i) + (1 - f_i^*) \log(1 - f_i) \right]
\]

where \( f_i^* \) denotes ground truth. \( f \) represents the concatenate operation.
input to the following module. The features are processed progressively by upsampling, downsampling, and action mapping modules, and finally mapped to the action space. The upsampling, downsampling, and action mapping modules are implemented by multiple linear layers. The upsampling module’s job is to transfer the features to a higher dimension space, making the features of different actions farther apart. We use the features generated by the upsampling module as the Action Effect Feature.

\[
A^{ef}_{(i,i+1)}: f_i (y_{act}, y_{o_1}^1, y_{o_2}^2, y_s) = E_{\theta} (s_i, s_{i+1})
\]  

where \(A^{ef}\) is action effect feature. \(f\) represents the concatenate operation. \(y_{act}\) is the action name, \(y_{o_1}^1\) and \(y_{o_2}^2\) represent object name, and \(y_s\) is object state (open, close, etc.). \(E_{\theta}\) denotes the feature extractor. \(s\) is the environmental state in trajectory.

We illustrate the difference from [42]: a) Task representation method. Language text information is used to represent the task in their work, and we use the environmental state to represent the task. b) Model input. Based on MDP, our model only receives information about the present environment and the task, without any others. c) We use feature-level environmental change information to estimate actions.

**C. Candidate Actions Generation**

Inspired by how individuals perform activities in their daily life: For a task, people can roughly estimate the activities necessary to finish a job at first, and then choose the appropriate action to execute according to the surrounding circumstances. Neural networks are mostly used in robot control research to record data processing methods. The network processes the input data to get the result, in other words, all the information is kept in the model. In contrast, people retain important information in their minds and recall it without any input. For example, you can recall a meaningful scene or person when you close your eyes. Inspired by these phenomena, we propose a model to extract action effect features and keep this significant information in memory. Furthermore, we propose a method for candidate action generation based on feature decomposition.

**Action effect feature extractor.** Suppose \(..., s_{t-1}, a_{t-1}, s_t, a_t, s_{t+1}, \ldots\) is a trajectory segment. To extract action features, we use two adjacent states (represented by the scene graph) as model inputs and employ the Graph Neural Network (GNN) to extract state features, as shown in Fig.2. Take the absolute value of the difference between the features as the...
Candidate action generation method based on feature decomposition. For a task, suppose that the trajectory of the solution is $T = [s_0, a_0, s_1, a_1, s_2, a_2, \ldots, s_t, a_t, s_{goal}]$. We employ the action effect extractor $E_\theta$ to extract effect features as task features by inputting the current and target states.

$$A_{Task} = E_\theta(s_{start}, s_{goal})$$

(8)

As mentioned before, we restrict the existence of local additivity property in the feature space. Therefore, if there is no noise and the space is fully additive, the sum of action effect features corresponding to actions in the solution trajectory is equal to the task feature.

$$A_I * A_F = A_I * \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_N \end{bmatrix} = A_I * \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1M} \\ a_{21} & a_{22} & \cdots & a_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ a_{N1} & a_{N2} & \cdots & a_{NM} \end{bmatrix} = A_{Task}$$

(9)

where $A_I$ is the action index vector with dimension $1 \times N$, contains only 0 or 1, which means whether to choose the action. $A_F = [A_{I1}, A_{I2}, \ldots, A_{IN}]^T$ is the action feature matrix with dimension $N \times M$ and each row corresponds to the effect feature of an action. $N$ is the number of actions, and $M$ represents the feature dimension. $A_{Task}$ denotes the task feature vector.

However, due to noise in the features and data fitting errors in the neural network, the equation only holds approximately. To make different action features easier to distinguish, we set $\hat{\text{error}}$, so it does not satisfy the condition to contain only 0 or 1. $\hat{I}$ represents the feature dimension. $A_{Task}$ denotes the task feature vector.

Finally, we solve the Eq.11 to get the action index vector.

$$\hat{A}_I = (A_{Task}V)(A_FV)^+$$

(12)

where $(A_FV)^+$ is the Moore-Penrose pseudo-inverse of $A_FV$.

We get the action index vector via Eq.12. Since we only restrict the feature space to have locally additive property, it is not guaranteed to have globally additive property. In addition, the feature also contains noise information and data fitting error, so it does not satisfy the condition to contain only 0 or 1. We take $\hat{A}_I$ as an approximation of the index vector $A_I$ and use its values as the weight of the actions. We select $K$ actions according to the weights to form the Candidate Action Pool.

D. Fusion Strategy

There are two problems with candidate actions: 1) The order of actions is not included. 2) The same number of candidate actions have different lower error bounds for different tasks.
Since the generated candidate actions do not contain sequence information, we employ an action predictive model to generate probabilities for each action. We choose the one with the highest probability to execute and remove it from the pool.

\[
Action = \text{argmax}_{a \in S_{pool}} P(a|s_{current}, s_{goal})
\]

where \(S_{pool}\) denotes the candidate action set, and \(a\) represents the action. \(s_{current}\) is the current state, and \(s_{goal}\) is the goal.

Due to the candidate action pool contains incorrect activities, we only select a certain amount of actions from the pool for execution in our experiments (less than the number of actions in the pool). When the pool is exhausted, we regenerate it. We hope that using an action predictive model can not only solve the sequence problem but also filter out erroneous actions from the pool.

**Multi-scale Candidate Action Pool.** The error of the pool is defined as the proportion of incorrect actions contained in it, as shown in Eq.14.

\[
E = \frac{\text{card}(S_{err})}{\text{card}(S_{pool})}
\]

where \(S\) represents a set. \(S_{err}\) denotes the set of error actions in the action pool. \(S_{pool}\) is the candidate action set. \(\text{Card}\) is the cardinality of a finite set, i.e., the number of elements in a finite set.

Then for a specific task, the lower error bound is as follows.

\[
\inf \ E \geq \frac{\text{card}(S_{pool}) - \text{card}(S_{task})}{\text{card}(S_{pool})}
\]

where \(S_{task}\) represents the set of actions actually required to solve the task. \(\inf\) means the lower bound.

The trajectory lengths of the solutions are different for various tasks, and employing candidate action pools with the same number of actions yields various lower error bounds. For example, a candidate action pool of 10 actions for task-3 (which takes 3 steps to complete) and task-8 (which takes 8 steps to complete) will result in different lower error bounds.

Since the trajectory length of the solution strategy is unknown when solving a specific task, to overcome this problem, we generate multiple candidate action pools with various amounts of actions for each task as the Multi-Scale Candidate Action Pool. Since the pool only contains the actions that exist in the dataset, we additionally employ the action predictive model to estimate the action to fulfill the task, so that the algorithm can generalize to new actions that are not included in the training set.

Whether a correct action can be selected for execution is not only related to the proportion of correct actions in the pool, but also the probability distribution generated by the action predictive model. From an ensemble learning perspective, using a multi-scale candidate action pool still makes sense to improve the performance.

We can think of a virtual environment as a human-generated scene in the brain. Actions are chosen in parallel from the multi-scale candidate action pool when finishing a task and then executed simultaneously in multiple virtual environments. Policy execution terminates when the goal is reached, an error action is performed, or the maximum allowed step size is reached. The generated policy can be seen as the result of brain thinking. (Optional: Successful plan is executed in the final environment to complete the task.)

Using a multi-scale candidate action pool to assist in solving tasks has two advantages: 1) It can greatly alleviate the problem of error accumulation in long-term planning. 2) It can effectively alleviate the problem that the model can only learn limited state transitions and overfit the training data. Furthermore, we think this feature decomposition approach may still be effective for other tasks using serialized data.

V. EXPERIMENTS

In this section, we first introduce virtual experiment scenarios and datasets. Then, we introduce the experimental setup. Again, we briefly describe the baseline settings. After that, we report the performance of our model and baselines. Finally, we analyze how the various parts affect the final performance of the model and do more analysis on the model and the problem.

**A. Dataset**

**Environment.** We use the virtual scene in [42] for experiments, which is an indoor scene with a total of 36 objects such as tables and water bottles. There is a mobile robot in the environment, which consists of a robotic arm (a Universal Robotics (UR5) arm) and a mobile base (a Clearpath Husky mobile base), which can perform a total of 11 high-level actions such as push and drop.

Particularly, autonomous task-agnostic exploration places higher requirements on the virtual environment than manual data collection. Because individuals can assess whether an action has been finished or whether the desired goal has been achieved, and make necessary adjustments. In contrast, the agent is unable to evaluate the outcome of the action or determine if the environmental change is caused by the action or the simulator’s inaccuracy.

To improve the robustness of the virtual environment and make it more reasonable, we have modified the environment, including 1) Modify the mass and friction of objects. 2) Add constraints so that objects with uneven surfaces cannot be placed on top of them, such as the bottle/apple/orange. 3)
Deleting some objects. 4) When the robot pushes or places an object, it may prevent the object from falling. We set the robot to move back a certain distance after acting as pushing or placing, i.e. away from the object, thus ensuring that the object falls. 5) Only when the displacement of all objects in the scene is less than the threshold will it be judged that the action simulation is over. Table 1 describes the modified environment information.

Dataset. We generate all combinations of action names, objects, and states, and filter out inappropriate actions via the execution feedback of the environment. After the environment is modified, the scene contains 36 objects and 11 actions. Each action contains 1-2 parameters. The action pool contains a total of 6456 actions, note that these actions contain incorrect items that can not conform to the environment settings, such as “changeState <apple> <open>”. These incorrect actions are filtered by environment feedback.

During the exploration, the environmental state is pre-saved so that it can be restored and go on exploring from that state. After the environment is initialized, explore 20 steps first, and then select a node at random from the knowledge graph to restore the state, and continue exploring from this state. In the experiment, 600 nodes were randomly selected, and each node was explored 5 steps. Due to the present environmental constraints, the prerequisites required for the action to perform may not be satisfied. At the same time, due to the large action pool, it may not be possible to pick an action that can be performed correctly for a long time. Therefore, in order to speed up the exploration process and avoid staying in one state for a long time, we set the maximum number of attempted explorations for the same node. In our experiments, we set the maximum number of wrong actions for the same node to 30, that is, when 30 consecutive actions cannot be performed, a new node is re-selected for exploration. In our experiments, we end up exploring and saving a knowledge graph data with 2995 nodes. The knowledge graph contains a total of 855 different actions.

We sample paths from the knowledge graph, where the start node of the path is the initial environmental state of the task, and the end node is the goal of the task. The sequence of actions contained in the path is the solution to the task. Path lengths range from 2 to 11, i.e. tasks in the dataset require 1 to 10 actions to complete. The dataset is constructed by sampling paths from the knowledge graph as tasks. For each path length, we randomly select 300, resulting in a dataset of 3000 samples. In our experiments, we preferentially choose paths that have different endpoints and do not contain each other to increase the difference between samples. The dataset is constructed by stratified sampling in a ratio of 6:2:2 according to the path length. The final training set samples are 1800, the validation set is 600, and the test set is 600.

From another perspective, this data construction mechanism can be regarded as an approach for generating task labels for task-agnostic exploration data, which can be utilized for self-supervised knowledge representation learning. How to combine discontinuous exploration data and produce related task labels, as well as how to better connect self-supervised learning with robot control, we will do further research in the future.

**B. Experimental Setting**

**Evaluation metrics.** A straightforward method to determining if the task has been completed is to directly compare the gap between the goal state and the end state of the robot’s plan execution, but this is unreasonable. Since only a few task-related objects’ states are necessary. For instance, you don’t care if you knock your chair over while pouring a drink of
Another obvious idea is to create a mask by matching the goal state with the initial state, and only comparing the objects contained in the mask, but that is still unsuitable. Because it is unreasonable to apply the same distance threshold for different acts and ignores the varied effects of similar actions. For example, placing a cup on a table and pushing the cup closer to the table, the relative positions of the objects are changed, as well as the distances.

In the paper [42], the task configuration file (a JSON file) is artificially determined, indicating the constraints of the task on related objects. The constraint information includes target, state, position, and tolerance. For example, if the task needs to put the apple in the cupboard, then the constraint information is {“object”: “apple”, “target”: “ ”, “state”: [ ], “position”: “cupboard”, “tolerance”: 1.5}. We adopt a rule-based approach to generate per-task constraint information similar to this method for task-relevant objects based on the actions contained in each trajectory. For example: “pushTo <chair> <table>” will generate constraint information {“object”: “chair”, “target”: “ ”, “state”: [ ], “position”: “table”, “tolerance”: 1.5}, “pickNplaceAonB <apple> <book>” will generate constraint information {“object”: “apple”, “target”: “book”, “state”: [ ], “position”: “ ”, “tolerance”: 0}. We consider the knock-on effects between multiple actions, if object A is pushed near object B and then placed on top of object C, the resulting final constraint is that object A is on top of object C. As [42], we use the proxy environment for testing, which is a high approximation of the simulator, does not include functions such as rendering, and is much faster to process.

It should be noted that this task configuration is only used to determine whether the task is finished, and all model inference in the decision-making process is independent of it. When the robot performs the act and the environment meets the task requirements, the task is judged to be successful. If the environmental feedback indicates that the action is performed incorrectly, or the maximum number of executions has been reached, the task fails. In the experiments, we set the maximum number of actions performed per task to 60.

**Implementation Details.** We use the PyTorch framework to implement the relevant logic. The optimizer uses Adam, and the action effect features are reduced to 500 dimensions. The setting of the multi-scale candidate action pool is heuristic. In our experiments, we set it to contain 7 action pools. The number of actions in the pool and the number of actions performed per task to 60.

**C. Baselines**

**Prompt-Plan Transformer.** We design a model based on the Transformer structure, as shown in Fig.5. Same as GPT [46], the Causal Transformer estimates each action only with the current and the previous environmental states, without considering the later ones. We feed the goal state to the network as a prompt so that the model can perform various tasks. The state information of each input is compared with the prompt at the feature level so that the model pays more attention to the difference between the current environmental state and the goal. In the experiments, we set the maximum trajectory length of the model input to 5. We process various components through multiple linear layers and then transform the results into the action name, objects, and states. The action’s parameters (object name or state) are selected based on the action name. The GNN structure and parameter settings are the same as the action predictive model, and the loss function adopts the binary cross entropy (BCE).

**CQL.** It is obvious that addressing this problem directly with reinforcement learning methods is challenging due to the distinction between training and evaluation tasks. To this end, we simply reframe the problem as generating action sequences to bring the environmental state closest to the goal.

We adopt Conservative Q-Learning (CQL) [47], a state-of-the-art model-free method, as a baseline. We use the action predictive model (Section IV-B) as the policy model for CQL. Since the model predicts acts based on changes in environmental state and goal information in the feature space, all tasks are simplified to a unified form, generating action sequences that minimize the gap between the environmental state and the goal. According to the action’s representation, we divide the model output into four pieces (action name, object name 1, object name 2, and object state) and train with four Q-tables. The training set is used as a fixed replay buffer.

As shown in Eq.16, we set the reward depending on the Manhattan Distance between the environmental state and the goal state.

\[ R_t (s_t, s_{goal}) = \begin{cases} 
1.0, & \text{if done (task completed)} \\
1.0, & \text{if } D_t (s_t, s_{goal}) \leq D_{min} \text{ and action in } GT \\
0.5, & \text{if } D_t (s_t, s_{goal}) \geq D_{min} \text{ and action in } GT \\
0, & \text{if action in } GT 
\end{cases} \]

\[ \text{st. } D_t (s_t, s_{goal}) = \sum_{i=1}^{N} | (s_{goal} - s_t) |_i \]
**TABLE II**

Ablation Experiment Results.

| Model                  | Average | GT Length |
|------------------------|---------|-----------|
|                         |         | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 |
| APM Single Multi-scale | 23.56   | 93.33 | 52.22 | 35.00 | 16.67 | 18.89 | 6.67 | 6.67 | 2.78 | 1.67 | 1.67 |
| APM Single Multi-scale | 33.00   | 96.11 | 72.22 | 55.56 | 35.56 | 31.11 | 15.00 | 11.11 | 7.22 | 1.11 | 5.00 |
| APM Single Multi-scale | 33.00   | 93.33 | 72.22 | 56.67 | 38.33 | 31.67 | 15.56 | 10.00 | 7.22 | 0.56 | 4.44 |
| APM Single Multi-scale | 37.06   | 93.33 | 79.44 | 58.89 | 47.78 | 36.67 | 19.44 | 17.22 | 10.00 | 1.11 | 6.67 |
| APM Single Multi-scale | 36.83   | **98.33** | 79.44 | 63.89 | 39.44 | 25.00 | 11.67 | 9.44 | 5.00 | 10.56 |
| APM Single Multi-scale | 41.78   | **93.89** | **80.00** | **58.89** | **39.44** | 25.00 | 15.00 | 7.22 | 10.00 |
| APM Single Multi-scale | 45.78   | **98.33** | **81.67** | **71.11** | **58.89** | **51.11** | **31.67** | **25.00** | **17.78** | **11.67** | **10.56** |

* We report the mean of 3 random seeds. “APM” means the Action Predictive Model. “Single” and “Multi-scale” related to the candidate action pool. “Partial” and “All” indicates select partial or all actions. “GT length” is the length of the action sequence in the ground truth. “Average” refers to the accuracy of the whole test dataset. Bold indicates the best result.

$D_{\text{min}}$ is the shortest distance between all states (from start to present) and the goal.

**Behavior Cloning.** Since the action predictive model (Section IV-B) can be regarded as a Behavioral Cloning (BC) method, and it is carefully designed and modified, we use it as a comparison method without training another BC algorithm.

**D. Evaluation on Dataset**

Fig.3 represents the experimental results and the average accuracy on the test set in shown in Table.III. As can be seen, our model produces the best performance. The Prompt-Plan Transformer yields poor results. We analyze that a possible reason is that the Transformer structure is more complex and requires larger data for training. However, in many applications, more data means higher costs and increases the risk of overfitting the training tasks. CQL also did not perform well either. One probable explanation is that it also requires more data, and another reason may be that using four Q-tables to train the agent means that picking the proper action requires four Q-tables to be correct, making it more difficult. In addition, the reward setting is also a possible problem.

**TABLE III**

Dataset Evaluation Results. Average accuracy on the test set.

| Model                  | Average | BC | Prompt-Plan Transformer | CQL |
|------------------------|---------|----|-------------------------|-----|
| M3 (Ours)              |         | 45.78 | 23.56 | 8.67 | 10.50 |

**E. Ablation Studies**

We do ablation experiments to learn more about how each module affects the overall performance. We desire to be able to filter out incorrect actions from the action pool as well as use an action prediction model to build a probability distribution to pick actions. Therefore, we compare selecting only a subset of the acts in the candidate action pool (Partial) against selecting all actions to execute (All). The setting of the multi-scale candidate action pool is heuristic. We set the pool size and selection number to [(5, 2), (10, 5), (15, 5), (20, 5), (20, 10), (30, 5), (30, 10)]. For fair testing, the values that appear in partially selected settings, notably [(2, 2), (5, 5), (10, 10), (15, 15), (20, 20), (30, 30)], are used to select all actions. For the test results of a single candidate action pool (Single), we report the optimal value. Table.II displays the experimental outcomes. The action predictive model is represented by APM in the table. Whether to select this item indicates that the APM is utilized to solve the task directly or merely to estimate the action probability distribution. The experimental results show that multiple different processing modules are beneficial to the algorithm’s overall performance.

1) A multi-scale candidate action pool is utilized. 2) To minimize the noise in the action effect feature, a dimensionality reduction approach is applied. 3) The incorrect acts in the action pool are filtered, i.e. only a subset of them are executed. 4) The task is solved using the APM.

![Fig. 6. Dimensionality reduction analysis results. (3 random seeds.)](image-url)

**F. Dimensionality Reduction Analysis**

We analyze the effect of dimensionality reduction on action effect features. Since we don’t know how many acts will be needed to finish the task at test time, we produce a certain number of candidate actions with a specified dimension. Count the number of identical acts in the candidate set and the ground truth set. The number of correct actions for each task is summed, divided by the total number of actions, as the Area Cover.
Coverage (Eq.17), which we use as the evaluation criterion. The larger the Area Coverage, the more correct items are included in the generated candidate actions.

\[
A = \frac{\sum_{i=1}^{N} \text{card}(S_{\text{pred}} \cap S_{\text{gt}})}{\sum_{i=1}^{N} \text{card}(S_{\text{gt}})}
\]  

(17)

where \( S \) represents a set, \( S_{\text{pred}} \) is the candidate action set, \( S_{\text{gt}} \) denotes ground truth action set. \( \text{Card} \) is the cardinality of a finite set, i.e. the number of elements in a finite set.

The solid line in Fig.6 indicates that the dimensionality reduction process has been carried out, while the dotted line indicates that it has not. Each action effect feature’s initial size is \( 1 \times 4096 \). As observed in the picture, the Area Coverage always grows first before decreasing for a certain number of candidate actions. It shows that when the dimension is small, the effective information contained is insufficient, and it is difficult to generate correct items. When the dimension is too large, the feature contains too much noise, which affects the accuracy of the generation. It is clear that dimensionality reduction can effectively improve the number of right actions. When the number of candidate acts increases, the Area Coverage gradually increases, but both correct and incorrect items increase. Since the ability to pick the correct act is not only related to the number of right items contained in the pool, but also to the probability distribution produced by the predictive model, increasing the action’s number indefinitely is not a reasonable choice.

The constraint is substantially weaker in the proposed feature decomposition-based generation method, which can be viewed as semi-supervised since it constrains fixed-length trajectory segments \( \{s_{i-1}, a_{i-1}, s_i, a_i, s_{i+1}\} \), not arbitrary-length ones. It is only necessary that a portion of candidate acts are right after each task feature is decomposed, that is, only part of the multi-label needs to be correct. This constraint is weaker and it is easier for the model to learn. Although there

G. Candidate Action Pool Analysis

In this experiment, we only employ the action predictive model to generate the probability of each action, that is, only rely on candidate acts to solve the task. In the broken line part of the Fig.7, only partial actions (less than the number of acts in the pool) are executed. The scatter part represents all items in the pool are used. As can be observed, choosing only partial acts to perform is more accurate than carrying out all of them, demonstrating the action predictive model’s ability to successfully filter out some incorrect items from the pool. Additionally, feature dimensionality reduction can significantly increase policy accuracy.

H. Qualitative Results

We provide a task example, as shown in Fig.8, and some qualitative results in Fig.9. Specifically, there are many situations involved 1) There are some incorrect actions in the model prediction. 2) Ground Truth contains invalid actions, such as the robot moving around, but does not change the state of other objects. 3) In the current environment, the states of some objects have met the task requirements. 4) A knock-on effect, where multiple different operations involve the same object. As is shown, our model provides good results for these tasks.

I. More Discussion

Failure Case Analysis. 1) The task requires actions that the robot has not done before. Exploring more steps, or using other methods to guide the exploration, such as novelty, may lead to better results. 2) For tasks that require long-term planning, error accumulation leads to failure. Although employing the multi-scale candidate action pool can alleviate this problem, further research is required.

Why not use a multi-label classification to generate candidate actions? In the experiment, we utilize the same network structure as the action predictive model for multi-label classification (the feature extractor part is the same, only the output-related layers are modified for classification), but the model cannot converge. With the initial state and the goal state, it is challenging to estimate which actions cause these changes in the environment.

One possible reason may be that there isn’t enough training data for the model to extract reliable information. Additionally, multi-label classification has a stricter constraint. To compute a loss value and keep optimizing the parameters, each item in the label should be accurate.

The constraint is substantially weaker in the proposed feature decomposition-based generation method, which can be viewed as semi-supervised since it constrains fixed-length trajectory segments \( \{s_{i-1}, a_{i-1}, s_i, a_i, s_{i+1}\} \), not arbitrary-length ones. It is only necessary that a portion of candidate acts are right after each task feature is decomposed, that is, only part of the multi-label needs to be correct. This constraint is weaker and it is easier for the model to learn. Although there
is an error in the candidate action pool, for sequential decision-making tasks, it is sufficient to pick a right act to perform each time. There is no need to force the model to predict all subsequent actions from the current state. The experimental results demonstrate that the method is effective.

**Limitation.** 1) Trajectory contains redundant actions unrelated to tasks. While this problem can be alleviated by post-processing, such as cropping the actions and repeating them in the simulator until only task-related acts remain, there is still a time-consuming problem. How to generate plans with less redundancy more efficiently requires further research. 2) Task representation. Using state vectors to represent tasks requires obtaining the target state in advance, which is very difficult in many cases. At present, many studies use language text as task representation, but language often has problems such as ambiguity and lack of information. Combining these two representations, using state vector of historical tasks and language descriptions of new ones, may be an efficient way. 3) Better at solving placement tasks. We think this is related to how environment is set up and how it is explored. Almost all objects in the scene can be paired with placement-related actions like “push” and “pickNplaceAonB”, but only a few objects can be combined with state-changing actions like “changeState”, as shown in Fig.10. More strictly, in order to form a valid action, the chosen property must exist in the object itself, such as “on/off”, which is challenging to obtain during exploration. This issue may be alleviated by using other exploration techniques or by gathering a larger amount of data, but it still needs in-depth research on how to effectively explore and produce more high-quality data.

**VI. CONCLUSION**

We pose a new question: Can agents acquire knowledge from historical tasks and learn to combine multiple different high-level actions to complete new tasks? This problem is more difficult than imitation learning and offline reinforcement learning. To address this problem, we propose a Memory-related Multi-task Method (M3), which includes an action predictive model and an action effect feature extractor. Different from previous methods, we organize the exploration data into a knowledge graph. In addition, we propose a feature decomposition-based candidate action generation method, as well as a strategy that fuses the action predictive model and the multi-scale candidate action pool. The experimental results show that our method has better performance than the baselines. Future work will focus on improving the exploration approach and teaching the agent environment- and task-related knowledge.
independent skills through task-agnostic exploration.

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