Pre-trained Language Models Improve the Few-shot Prompt Ability of Decision Transformer

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Abstract

Decision Transformer (DT) has emerged as a promising class of algorithms in offline reinforcement learning (RL) tasks, leveraging pre-collected datasets and Transformer's capability to model long sequences. Recent works have demonstrated that using parts of trajectories from training tasks as prompts in DT enhances its performance on unseen tasks, giving rise to Prompt-DT methods. However, collecting data from specific environments can be both costly and unsafe in many scenarios, leading to suboptimal performance and limited few-shot prompt abilities due to the data-hungry nature of Transformer-based models. Additionally, the limited datasets used in pre-training make it challenging for Prompt-DT type of methods to distinguish between various RL tasks through prompts alone. To address these challenges, we introduce the Language model-initialized Prompt Decision Transformer (LPDT) framework, which leverages pretrained language models providing rich prior knowledge for RL tasks and fine-tunes the sequence model using Low-rank Adaptation (LoRA) for meta-RL problems. We further incorporate prompt regularization to effectively differentiate between tasks based on prompt feature representations. Comprehensive empirical studies demonstrate that initializing with a pre-trained language model provides the prior knowledge and achieves a similar performance with Prompt-DT under only 10% data. We also provide a thorough ablation study to validate the effectiveness of each component, including sequence modeling, language models, prompt regularizations, and prompt strategies.

1 Introduction

In many sequential decision-making applications such as robotic manipulation and autonomous driving (Sinha et al., 2022; Kumar et al., 2022), it can be expensive or even unsafe for agents to learn through trial-and-error with the environment. Offline reinforcement learning (RL) methods (Levine et al., 2020) have emerged as a powerful paradigm for optimizing agent policies without extensive online interaction. These methods learn an optimal policy by leveraging pre-collected datasets obtained from a set of behavior policies. Among them, Decision Transformer (DT) (Chen et al., 2021) and its successors (Wu et al., 2024; Zhuang et al., 2024) have become popular due to their scalability and training stability. DT models a return-conditioned policy using the powerful Transformer architecture, solving RL as a sequence-prediction problem in a supervised learning manner. It models the states, actions, and return-to-go from trajectories as the tokens of an input sequence, and generates actions conditioned on the return-to-go. Compared with dynamic programming-based offline RL methods (Kumar et al., 2019; Fujimoto et al., 2019; Kumar et al., 2020) that heavily rely on the Markov Decision Process (MDP) assumption, Decision Transformer can utilize entire trajectory histories to predict the next action, making them more applicable in partially observable environments where all past information is crucial in decision-making (Kaelbling et al., 1998; Ni et al., 2024). Furthermore, the supervised learning nature of DTs enhances the stability and scalability in the training process compared to dynamic programming algorithms based on Bellman equations (Chen et al., 2021; Janner et al., 2021; Zheng et al., 2022; Wu et al., 2024; Zhuang et al., 2024).

Transformers have demonstrated remarkable few-shot generalization capabilities, most notably in large language models (LLMs) (Brown et al., 2020; Achiam et al., 2023). In the context of LLMs, prompt-based learning, where task-relevant information is provided as a textual prefix, has proven highly effective for

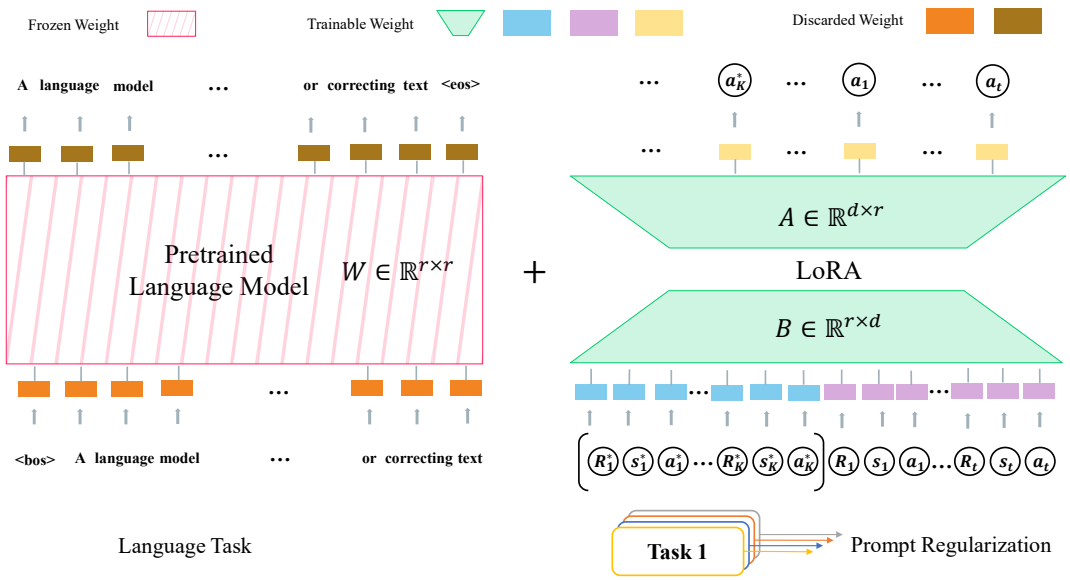

Figure 1: Overview of LPDT. We first initialize our algorithm using a pre-trained language model. The pre-trained language model is trained on a large corpus of data using the causal language modeling objective which is to predict the next-token paradigm. Our method LPDT replaces the word embedding layers with linear layers, discarding the learned word features, to fully learn and capture the features of RL trajectory tokens. We fine-tune our model using parameter-efficient methods like Low-Rank Adaptation (LoRA). Specifically, we freeze the initial weights of the language models and update only the LoRA weights. The input to our approach consists of prompts accompanied by training trajectories from the same tasks. Unlike traditional models that predict word tokens, our method predicts action tokens in the RL trajectories. Additionally, we incorporate prompt regularization over the input prompts. This is achieved by introducing an additional loss on the prompt embeddings, which helps LPDT distinguish between different environments. More technical details of our method are presented in Section 3.

adapting to new tasks without fine-tuning (Brown et al., 2020; Li & Liang, 2021). Inspired by this, recent works (Xu et al., 2022; Hu et al., 2023; Wang et al., 2024) have developed variants of DT to leverage trajectory-based prompting learning to enhance its few-shot generalization. For instance, Prompt-DT (Xu et al., 2022) leverages segments of trajectories from offline datasets as prompts to encode task-specific information. Similar to how large language models (LLMs) condition on textual prompts to generate coherent responses, Prompt-DT conditions on trajectory-based prompts to generate actions. The model is trained on these prompt-trajectory pairs and is subsequently evaluated on unseen tasks using few-shot demonstrations as prompts. However, existing Prompt-DT methods (Xu et al., 2022; Hu et al., 2023; 2024; Wang et al., 2024) inherit the data-hungry nature of Transformers (Brown et al., 2020; Achiam et al., 2023), requiring to be trained on large trajectory datasets, while offline RL datasets are often too small to fully realize their few-shot prompting potential. In contrast, modern LLMs achieve strong generalization with limited task examples by leveraging massive unsupervised pre-training on text. Inspired by this, another line of works investigated using pre-trained language models to initialize decision transformers and transfer their rich linguistic priors to RL domains (Li et al., 2022; Reid et al., 2022; Shi et al., 2024). Language initialization in these works provides prior knowledge and helps alleviate the need for large datasets. While this initialization provides prior knowledge and helps alleviate the need for large datasets, these works have primarily focused on solving single-task RL problems. The potential for enhancing few-shot prompt learning of DTs in multi-task settings using pre-trained language models remains unexplored.

To overcome these limitations, we propose a novel framework named *Language model-initialized Prompt Decision Transformer (LPDT)*. Our approach leverages a pre-trained language model for initialization to significantly improve the few-shot prompting capabilities of Decision Transformers. This incorporates pre-

existing knowledge that can benefit downstream RL tasks. To efficiently combine this pre-trained knowledge with domain-specific knowledge from multi-task RL, we use Low-Rank Adaptation (LoRA) (Hu et al., 2021), a parameter-efficient fine-tuning method. We further introduce prompt regularization methods to help the fine-tuned model distinguish different RL tasks, thereby guiding action generation based on new, unseen task-specific prompt representations. A more detailed illustration of our model structure and training paradigm is provided in Figure 1. Beyond Decision Transformer, we also extend our framework to one of its most recent and advanced variants, Reinformer (Zhuang et al., 2024), demonstrating its flexibility. We conduct extensive experiments to assess the capability of our proposed framework in MuJoCo control environments (Fu et al., 2020) and Meta World ML1 tasks (Yu et al., 2020). Our method outperforms baselines in terms of cumulative rewards on unseen tasks. Empirical studies show that our proposed framework achieves similar performance to Prompt-DT using only 10% of the dataset. We also provide a detailed ablation study to demonstrate the effectiveness of our LPDT framework. Specifically, we evaluate our proposed framework to validate each component. Additionally, we report results on various language model initializations and different sequence modeling strategies. Furthermore, we design experiments to demonstrate that the improved performance results with the language model from better initialization rather than from the language model's understanding of RL tasks.

- We propose LPDT, a novel framework that improves the few-shot prompt capabilities of Decision Transformers and other sequence modeling methods for offline RL. Our approach leverages a pre-trained language model for initialization and incorporates a novel prompt regularization method, demonstrating enhanced few-shot generalization in multi-task settings.
- We introduce a unique combination of Low-Rank Adaptation (LoRA) and prompt regularization methods to effectively combine pre-trained knowledge with domain-specific RL task knowledge. LoRA allows efficient fine-tuning by adapting a small subset of parameters, while our regularization methods enhance the model's ability to distinguish task information within prompts.
- We extend our proposed framework, LPDT, to one of the most recent and advanced variants of DT, i.e., Reinformer, to demonstrate its generalizability.
- Through extensive experiments on MuJoCo control and Meta World ML1, we show that LPDT outperforms baselines on unseen tasks and achieves similar performance to Prompt-DT with only 10% of the data. We also validate each component of our framework through detailed ablation studies.

2 Preliminary

2.1 Offline Reinforcement Learning

Reinforcement learning is usually formulated as solving a Markov Decision Process (MDP) defined by a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{T}, d_0, \mathcal{R}, \gamma)$, where $\mathcal{S}$ represents the set of states $s \in \mathcal{S}$, $\mathcal{A}$ represents the set of actions $a \in \mathcal{A}$, $\mathcal{T}$ is the transition distribution defined as $\mathcal{T}(s_{t+1}|s_t, a_t)$, d_0 is the distribution of initial states s_0, $\mathcal{R} : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ is the reward function, $r_t = \mathcal{R}(s_t, a_t)$ is the reward at timestep t, and $\gamma \in (0, 1)$ is the discount factor. The objective is to find a policy π that maximizes the expected cumulative rewards $J(\pi)$:

$$J(\pi) = \mathbb{E}_{s_0 \sim d_0(\cdot), a_t \sim \pi(\cdot|s_t), s_{t+1} \sim \mathcal{T}(\cdot|s_t, a_t)} \left[\sum_{t=0}^{\infty} \gamma^t \mathcal{R}(s_t, a_t) \right].$$

In offline RL, the agent has access to a dataset $\mathcal{D}$ containing trajectories collected by a behavior policy instead of access to the environment. The agent is expected to find the optimal policy using only the offline dataset $\mathcal{D}$, without interacting with the environment itself. Decision Transformer (Chen et al., 2021) leverages the Transformer structure (Vaswani et al., 2017) to predict the next action conditioned on the past trajectory. To reduce the prediction error that could cumulate as the trajectory length increases, DT reformulates the trajectories $\{s_0, a_0, r_0, s_1, a_1, r_1, \ldots, s_T, a_T, r_T\}$ from the offline dataset $\mathcal{D}$ to $\{s_0, a_0, R_0, s_1, a_1, R_1, \ldots, s_T, a_T, R_T\}$ and use the latter one in the loss function defined by the prediction error between the true actions and predicted actions, where $R_t = \sum_{i=t}^{T} r_i$ is the return-to-go at timestep t.

2.2 Prompt Decision Transformer

The goal of Prompt-DT is to enable a single offline RL agent to solve multiple distinct tasks without requiring explicit task labels. The key idea is to prepend a prompt τ_i^* to the standard DT input trajectory τ. Both

the prompt and the main trajectory are sampled from the same multi-task offline dataset $\mathcal{D}$. A prompt τ_i^* for a task T_i is a short sequence of K^* transitions denoted as $\tau_i^* = \big(R_{i,1}^*, s_{i,1}^*, a_{i,1}^*, \cdots, R_{i,K^*}^*, s_{i,K^*}^*, a_{i,K^*}^*\big)$. This prompt provides the model with crucial context about the task's dynamics and reward structure. Consequently, the input vector τ_i^{input} is the concatenation of the task prompt and the input trajectory:

$$\tau_i^{\text{input}} = [\tau_i^*, \tau_i] = \big(R_{i,1}^*, s_{i,1}^*, a_{i,1}^*, \cdots, R_{i,K^*}^*, s_{i,K^*}^*, a_{i,K^*}^*, R_{i,1}, s_{i,1}, a_{i,1}, \ldots, R_{i,K}, s_{i,K}, a_{i,K}\big). \tag{2.1}$$

In addition to this, we denote the trajectory truncated at timestep $t \in \{1, \ldots, K\}$ as $\tau_{i<t}$, and consequently the input vector at timestep t as $\tau_{i,1<t}^{\text{input}}$. Then the learning objective of Prompt-DT can be formulated as the following maximum likelihood estimation: $\mathbb{E}_{\tau_i^{\text{input}} \sim T_i}\big[\sum_{t=1}^{K} -\log M_\theta(\hat{a}_{i,t} | \tau_i^*, \tau_{i,1<t-1}^{\text{input}}, R_{i,t}, s_{i,t})\big]$, where M_θ denotes Prompt-DT with the parameter θ which is usually a transformer. In practical implementation, we often use the mean squared error loss instead, which aims to predict the future action $\hat{a}_{i,t}$ given the history trajectory and current state by minimizing the loss function $\mathcal{L}_{\text{PDT}} = \mathbb{E}_{\tau_i^{\text{input}} \sim T_i}\big[\frac{1}{K}\sum_{t=1}^{K}(a_{i,t} - \hat{a}_{i,t})^2\big]$. The training procedure of Prompt-DT is to autoregressively generate the action conditioned on the current state, return-to-go, past trajectory and sampled prompt.

3 The Proposed Framework

Building on the success of LLMs in prompt-based few-shot learning, we propose Language model-initialized Prompt Decision Transformer (LPDT), a novel and effective framework to incorporate powerful pre-trained language models into Decision Transformers to improve their few-shot learning abilities. We further introduce prompt regularization during fine-tuning to better identify tasks. Furthermore, our design is flexible and easy to adapt to other sequence modeling methods for offline RL such as Reinformer (Zhuang et al., 2024). Figure 1 illustrates the overview of our method. At a high level, LPDT incorporates several key components:

- **Language model initialization for Prompt-DT:** We first use a pre-trained language model as the initialization for our Decision Transformer. This design ensures compatibility with the Prompt-DT paradigm, where prompts from various tasks are appended to the input sequence.
- **Parameter-efficient fine-tuning on RL tasks:** We adopt Low-Rank Adaptation (LoRA) (Hu et al., 2021) to fine-tune a low-rank residual matrix while keeping the original weight matrix of the language model fixed throughout the learning process. This approach significantly reduces the number of parameters compared to standard full fine-tuning of the large language models.
- **Prompt regularization through supervised and contrastive objectives:** We incorporate additional regularization over the prompt embeddings to better identify tasks. Specifically, we employ loss functions derived from both supervised and contrastive learning techniques to fully utilize task-related information from prompts, thereby preventing the language model from overfitting specific tasks.
- **Flexiblity of LPDT :** We further extend our proposed framework to other sequence modeling methods for offline RL to demonstrate the flexibility. To be specific, we adapted our proposed framework to the Reinformer-based models with regression on actions and the expctile regression on the returns to improve the stitching ability with max-return in offline RL. We demonstrate that language initialization is helpful in the transformer based prompt sequence modeling methods.

We discuss these techniques in detail in the rest of this section. At the end of this section, built on these components, we present our learning algorithm in Algorithm 1.

3.1 Language Model Initialization

We first use a pretrained large language model (LLM) with weights denoted by M_{θ^*} as the initialization of LPDT. Recent advances in large language models have demonstrated strong few-shot learning abilities. With task-specific information such as prompts for translation or answering questions, language models can generate task-specific responses. We adapt these language models to RL tasks such as MuJoCo control tasks to provide prior knowledge that may have relevance to downstream RL tasks. However, this is not immediately straightforward since LLMs take word tokens as input, which differ from the inputs used in RL.

The common next-token prediction objective for the language model (LM) can be formulated as

$$\mathcal{L}_{LM} = \sum_{i=1}^{t-1} -\log(M_{\theta^*}(x_{i+1} \mid x_1, \ldots, x_i)), \tag{3.1}$$

where M_{θ^*} is the language model, θ^* are the parameters of the pretrained language models and x_i represents the word token. Concretely, we decompose the pretrained parameters as $\theta^* = \{E^*_{\text{token}}, T^*, W^*_{\text{vocab}}\}$, where E^*_{token} is the token embedding layer, T^* is the causal Transformer backbone, and W^*_{vocab} is the language model output head. To make M_{θ^*} compatible with RL trajectories, we keep the causal Transformer backbone and *replace the word embedding layer and language model output head with task-specific linear layers*: an input projection $E_{\text{RL}} \in \mathbb{R}^{d_z \times d_{\text{input}}}$ that maps each RL "token", i.e., $z_t \triangleq [R_t, s_t, a_t]$, into a vector in $\mathbb{R}^{d_{\text{input}}}$ as the input for the Transformer backbone, and an output head $W_{\text{act}} \in \mathbb{R}^{d_{\text{model}} \times d_a}$ that maps the hidden state with dimension d_{model} to a probability distribution over the action space. We denote the $\theta = \{E_{\text{RL}}, T^*, W_{\text{act}}\}$ as the adapted parameters, and then the M_θ is the initialized model. Given a prompt-augmented input sequence $\tau_i^{\text{input}} = [\tau_i^*, \tau_i]$, the model produces action predictions autoregressively under the same causal mask as language modeling:

$$\hat{a}_{i,t} = M_\theta(\tau^{\text{input}}_{i,1:t}) = W_{\text{act}} \cdot T^*\big(E_{\text{RL}}(\tau^{\text{input}}_{i,1:t})\big). \tag{3.2}$$

For continuous control settings (e.g., MuJoCo), we replace the cross-entropy MLE objective in Equation (3.1) with an MSE regression objective by replacing the language model softmax head with the linear regression action head W_{act}. We then optimize the standard Prompt-DT regression loss

$$\mathcal{L}_{\text{PDT}} = \mathbb{E}_{\tau_i^{\text{input}}}\big[\tfrac{1}{K}\sum_{t=1}^{K} \|a_{i,t} - \hat{a}_{i,t}\|_2^2\big]. \tag{3.3}$$

By leveraging the pretrained language model, we preserve broad sequence-modeling priors while adapting only lightweight RL-specific projections.

3.2 Parameter-efficient Fine-tuning on RL Tasks

To efficiently adapt the frozen pretrained language model to downstream RL tasks, rather than updating all weights, we apply LoRA (Hu et al., 2021) by introducing trainable low-rank matrices into each target weight matrix while keeping the original backbone fixed. This significantly reduces the number of trainable parameters and enables scalable adaptation to large language models. To be specific, assume the model has L layers. In each layer $l \in \{1, \ldots, L\}$, we update the attention projections $\{W_q^{(l)}, W_k^{(l)}, W_v^{(l)}\}$ which are query, key, and value projections using LoRA. As an example, for the query projection $W_q^{(l)} \in \mathbb{R}^{d_{\text{model}} \times d_q}$ where the d_{model} is the model dimension and d_q is the query dimension, we reparameterize

$$W_q^{(l)} = W_{q,0}^{(l)} + \Delta W_q^{(l)} = W_{q,0}^{(l)} + \alpha_q / r_q A_q^{(l)} B_q^{(l)}, \tag{3.4}$$

where $W_{q,0}^{(l)}$ is the frozen weight inherited from the language model, α_q is the scaling hyeperparameter, r_q is the rank in LoRA, and $A_q^{(l)} \in \mathbb{R}^{d_{\text{model}} \times r_q}$, $B_q^{(l)} \in \mathbb{R}^{r_q \times d_q}$ are the trainable low-rank factor matrices with $r_q \ll \min\{d_{\text{model}}, d_q\}$. We apply similar updates to $W_k^{(l)}$ and $W_v^{(l)}$. For simplicity, we denote LoRA factor matrices in the query, key, and value projections as $\{A_{q,k,v}^{(l)}, B_{q,k,v}^{(l)}\}$. By learning only $\Delta W_q^{(l)}$, $\Delta W_k^{(l)}$, and $\Delta W_v^{(l)}$, our method avoids full fine-tuning of the Transformer backbone parameters, substantially reducing compute and memory costs while preserving the generalization ability of the pretrained backbone.

3.3 Prompt Regularization with Supervised and Contrastive Objectives

When different tasks are close to each other, naively using the prompts can yield embeddings that are non-discriminative across tasks. Making prompts distinguishable at test time is costly. Previous works such as Prompt-Tuning DT (Hu et al., 2023) and Prompt Diffuser (Hu et al., 2024) aim to tune prompts at test time on unseen tasks. These methods perform additional gradient updates during test-time adaptation, which incurs extra computational cost when deploying policies. To avoid the computational overhead of test-time prompt tuning and improve generalization to unseen tasks, we introduce a task-aware training objective.

Specifically, we incorporate a regularization term on the prompt embeddings, termed *prompt regularization*, to encourage the model to learn discriminative prompt representations that reflect task identity during training. Let the prompt encoder be g_ϕ and define the prompt embedding $\mathbf{z}_i = g_\phi(\tau_i^*)$.

We use the loss function for Prompt-DT defined in (3.3) as the base loss function, and then incorporate a prompt regularization term. The final loss function of our method is given by

$$\mathcal{L}_{\text{total}} = \mathbb{E}_{\tau_i^{\text{input}} \sim T_i}\left[\frac{1}{K}\sum_{t=1}^{K}(a_{i,t} - \hat{a}_{i,t})^2\right] + \lambda \mathcal{L}_\phi, \tag{3.5}$$

where $\mathcal{L}_\phi$ is the loss for the prompt regularization which we will specify in the rest of this section, and λ is the hyperparameter for prompt regularization.

In particular, we propose two practical implementations of prompt regularization based on supervised learning and contrastive learning methods respectively.

Supervised learning-based prompt regularization. In this approach, we add a classifier head to the output of the prompt encoder. We use the task ID from the dataset as the label to help the prompt encoder learn a more meaningful embedding that can easily distinguish different task environments. To be specific, we attach a classifier $C(\cdot)$ to the prompt encoder output and train it with known task IDs, encouraging $\mathbf{z}_i$ to be linearly separable across environments. We adopt the following cross-entropy loss as the regularizer

$$\mathcal{L}_\phi^{\text{classifier}} = -\sum_i y_i \log(\hat{y}_i), \tag{3.6}$$

where y_i is the task label and $\hat{y}_i = C(\mathbf{z}_i)$ is the predicted probability for task i based on the prompt τi^*.

Contrastive learning-based prompt regularization. When task IDs are unknown, the supervised method may not be feasible. Therefore, we also propose a contrastive learning method to learn the prompt representation. From an information theory perspective, the ideal prompt encoder should aim to maximize the mutual information between the prompt representation and the tasks. We use the InfoNCE objective (Oord et al., 2018; Yuan & Lu, 2022) to calculate the loss over the prompt. We formulate $\mathcal{L}_\phi$ as:

$$\mathcal{L}_\phi^{\text{InfoNCE}} = -\mathbb{E}\left[\log \frac{\exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_i^+/\tau)}{\exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_i^+/\tau) + \sum_{k=1}^{N}\exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_{i,k}^-)/\tau)}\right], \tag{3.7}$$

where $\mathbf{z}_i$ and $\mathbf{z}_i^+$ form a positive prompt pair corresponding to the same task, while $\mathbf{z}_{i,k}^-$ denotes a negative prompt sampled from different tasks. N is the number of negative samples, and τ is the temperature hyperparameter that controls the sharpness of the distribution. The function $\text{sim}(\cdot,\cdot)$ computes the similarity between two prompt embeddings in which we use the cosine similarity.

3.4 Flexibility of LPDT

Our proposed framework is highly flexible and can be seamlessly integrated with other Transformer-based sequence modeling methods. To demonstrate this adaptability, we extend LPDT to the recently introduced Reinformer (Zhuang et al., 2024) as an illustrative example. Reinformer is a return-conditioned sequence model optimized for maximum-return policy learning, which shows state-of-the-art performance on single-task offline RL benchmarks. We demonstrate that our proposed framework LPDT can be easily adapted to Reinformer with minor adjustments.

First, Reinformer differs from DT in the ordering of its input sequence. Specifically, Reinformer structures each trajectory segment as a tuple of state, predicted return, and action. This format allows the model to first predict a return and then condition action generation on both the current state and the predicted return. Accordingly, we define the input trajectory for task i as:

$$\tau_i^{\text{rein-input}} = [\tau_i^*, \tau_i] = \big(s_{i,1}^*, R_{i,1}^*, a_{i,1}^*, \cdots, s_{i,K^*}^*, R_{i,K^*}^*, a_{i,K^*}^*, s_{i,1}, R_{i,1}, a_{i,1}, \cdots, s_{i,K}, R_{i,K}, a_{i,K}\big). \tag{3.8}$$

where $s_{i,t}$, $R_{i,t}$, and $a_{i,t}$ denote the state, return, and action at time step t, respectively. To better estimate high-reward trajectories across diverse tasks, we employ the expectile loss for return prediction:

$$\mathcal{L}_{\text{return}} = \mathbb{E}_{\tau_i^{\text{rein-input}} \sim T_i}\left[\frac{1}{K}\sum_{t=1}^{K}\left|m - \mathbb{1}(\Delta R < 0)\right| \cdot \Delta R^2\right], \tag{3.9}$$

Algorithm 1 LPDT: Training and Inference

Require: Pretrained LLM M_θ^*, dataset $\mathcal{D}$, regularization weight λ, temperature τ

Training:
Freeze all Transformer layers in θ^*
Replace the word embedding with linear layer E_{RL} and the output layer W_{act}
Insert LoRA adapters $\{A_{q,k,v}^{(l)}, B_{q,k,v}^{(l)}\}$ into weight matrices
for Iteration $= 1, \ldots, E$ **do**
  for all mini-batch $\mathcal{B} \subset \mathcal{D}$ **do**
    Build input sequence $\tau_i^{\text{in}} \leftarrow [\tau_i^*;\ \tau_i]$ for each $\tau_i \in \mathcal{B}$
    $\hat{a}_{i,1:K} \leftarrow M_\theta(\tau_i^{\text{in}})$
    $\mathcal{L}_{\text{PDT}} \leftarrow 1/|\mathcal{B}|K \sum_{\tau_i \in \mathcal{B}} \sum_{t=1}^{K} \|a_{i,t} - \hat{a}_{i,t}\|^2$
    if *supervised* regularization **then**
      $\mathcal{L}_\phi \leftarrow -1/|\mathcal{B}| \sum_{\tau_i \in \mathcal{B}} y_i \log \hat{y}_i$ {Equation (3.6)}
    else
      $\mathcal{L}_\phi \leftarrow -1/|\mathcal{B}| \sum_{(\mathbf{z}_i, \mathbf{z}_i^+)} \log \dfrac{\exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_i^+)/\tau)}{\exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_i^+)/\tau) + \sum_k \exp(\text{sim}(\mathbf{z}_i, \mathbf{z}_{i,k}^-)/\tau)}$ {Equation (3.7)}
    end if
    $\mathcal{L}_{\text{total}} \leftarrow \mathcal{L}_{\text{PDT}} + \lambda \mathcal{L}_\phi$
    Update LoRA matrix $\{A_{q,k,v}^{(l)}, B_{q,k,v}^{(l)}\}$ and linear layers $\{E_{\text{RL}}, W_{\text{act}}\}$ via $\nabla_\theta \mathcal{L}_{\text{total}}$
  end for
end for
Inference on unseen tasks:
Sample few-shot prompt τ_{test}^*
for $t = 1$ **to** horizon **do**
  $a_t \leftarrow M_\theta([\tau_{\text{test}}^*;\ \tau_{1:t-1}])$
end for

where $\Delta R = R_{i,t} - \hat{R}_{i,t}$ is the difference between the ground-truth return and the predicted return, and $m \in [0, 1]$ is a hyperparameter controlling the weight on overestimation or underestimation errors. In practice, we favor overestimation to encourage optimistic trajectory planning during testing. Then the training loss in our Algorithm 1 will add the additional return loss term as follows:

$$\mathcal{L}_{\text{total}} = \mathcal{L}_{\text{PDT}} + \lambda \mathcal{L}_\phi + \eta \mathcal{L}_{\text{return}}, \tag{3.10}$$

where η is the hyperparameter weight for $\mathcal{L}_{\text{return}}$. During inference, the return-first sequence structure is preserved. The model begins by encoding the few-shot prompt from a new task and initializing with the current state. It then predicts a return, followed by generating the corresponding action. This autoregressive rollout continues step-by-step, with the prompt providing task-specific conditioning to ensure alignment with the environment dynamics.

4 Experiments

In this section, we conduct experiments to evaluate the few-shot generalization ability of our proposed framework LPDT. We evaluate the performance of LPDT on MuJoCo control tasks (Fu et al., 2020) and Meta World (Yu et al., 2020) with the episode accumulated reward as the evaluation metric. We also evaluate the prompt ability of LPDT under limited data settings. Our experiments aim to answer the following questions: (1) Can LPDT with language model initialization achieve better performance compared with Prompt-DT and other baselines? (2) Does the language-initialized Transformer model contain the knowledge of the unseen RL tasks and help improve the performance under limited data? (3) Does prompt regularization help the model distinguish different tasks and enhance the prompt learning capability of LPDT? (4) Does the improved performance stem from the language model's better understanding of RL, or from its ability to provide a generally better initialization for learning RL tasks? (5) Can LPDT be adapted to different

pre-trained language models other than GPT-2? (6) Can LPDT be extended to sequence models beyond Decision Transformer and Reinformer? (7) Can prompt selection strategies further improve performance?

4.1 Implementation

In the empirical study, we first implement our LPDT method with GPT-2 as the language initialization. GPT-2 is pre-trained on OpenWebtext (Puri & Catanzaro, 2019). During the fine-tuning stage, we follow the same hyperparameters for Prompt-DT (see Appendix C for detail). We also leverage LoRA to highly reduce the parameters trained. For the prompt regularization, we use MLP to further encode the prompt embedding. For the supervised version of prompt regularization defined in (3.6), we directly use the logits from the MLP to compute the cross-entropy loss and refer to the method as LPDT-Classifier. For the contrastive version of prompt regularization defined in (3.7), we calculate the similarity matrix through the cosine similarity based on the logits from the MLP and refer to it as LPDT-InfoNCE. We also extend our methods to another sequence modeling method adapted from Reinformer (Zhuang et al., 2024) named LPDT-Rein-Classifier and LPDT-Rein-InfoNCE.

4.2 Datasets and Baselines

In this work, we evaluate the performance of our proposed approach on MuJoCo control tasks and Meta-World, which are commonly used in existing Prompt-DT type of methods (Xu et al., 2022; Hu et al., 2023; 2024; Wang et al., 2024), namely, Cheetah-dir, Cheetah-vel, Ant-dir, Point-robot, Meta-World reach-v2.

In Cheetah-dir, there are two tasks with goal directions as forward and backward, where the reward function promotes high velocity along the goal direction. The training and testing phases both include the two tasks. Similar to Cheetah-dir, Ant-dir also segments the tasks by directions. There are 50 tasks in Ant-dir with different goal directions uniformly sampled in 2D space. The tasks are split into 45 training tasks and 5 testing tasks. The ant is also rewarded with high velocity along the goal direction. Different from segmenting the tasks by direction, Cheetah-vel penalizes the agent through the l_2 errors with the target velocities sampled from the velocity interval. There are 40 tasks with different goal velocities where 35 tasks are training tasks and 5 tasks are testing tasks. Point-robot is a point navigating to the given goal position. Except for MuJoCo control meta-RL tasks, we also test our approach on Meta World (Yu et al., 2020) which is an open benchmark for meta-RL and multi-task learning. In this work, we evaluate our approach on Meta-World reach-v2. The objective of reach-v2 is to control the robot to reach the target position in 3D positions. Each task has a different goal position.

Specificcally, we collect the data by first training the Soft Actor-Critic (Haarnoja et al., 2018) in these different RL task environments and then extracting the data from the replay buffer. More details about the datasets can be found in Appendix B. We compare the few-shot generalization ability of our proposed LPDT with baseline algorithms. For each method, we compare the performance based on the accumulated reward. The baselines we choose include Prompt-DT (Xu et al., 2022), CORRO (Yuan & Lu, 2022), CSRO (Gao et al., 2024) and Meta-DT (Wang et al., 2024).

4.3 Results of LPDT and Baselines

In this section, we conduct experiments on our proposed LPDT framework and baseline methods to evaluate their performance. Additionally, we compare variants of LPDT that use different prompt regularization strategies and sequence modeling techniques. The average accumulated reward per episode in the test task set is used as the evaluation metric for all methods. The results for Prompt-DT, CORRO, CARO, and Meta-DT are taken from the Meta-DT paper (Wang et al., 2024), while the results for MW Reach-v2 are provided by our reproduction. We compare our approaches including both the supervised classifier version and the contrastive InfoNCE version with prior works. The model is tested with three different random seeds, and we report the average return across all testing tasks.

Table 1 illustrates that LPDT outperforms baseline algorithms (Prompt-DT, CORRO, and CSRO) on MuJoCo Control tasks and MW Reach-v2 and is competitive with Meta-DT. Specifically, our LPDT approaches outperform Meta-DT in Cheetah-dir and MW Reach-v2. In all other environments, LPDT achieves the

second-best performance among the baselines and is competitive compared with Meta-DT. We conclude that using our LPDT approach improves the performance compared to most baselines and is competitive with Meta-DT. It is worth noting that Meta-DT introduces an additional prompt selection stage at test time to select high-quality prompts, while our methods avoid this computation overhead. We use the prompt regularization module to distinguish the prompt instead of iterating over the demonstration set to choose the best prompt. Nevertheless, the prompt selection strategy is orthogonal to our contribution and can be applied at the cost of extra computation.

Table 1: Results for MuJoCo control tasks and MW tasks. The best mean scores are highlighted in **red** and the second mean scores are highlighted in **blue**. For each environment, the length of the prompt is $K^* = 5$. The dataset we utilized is the full dataset. We test all the results on unseen tasks with three random seeds. LPDT outperforms baselines on the Cheetah-dir and MW Reach-v2 environment and are competitive remaining environments.

Task	Prompt-DT	CORRO	CSRO	Meta-DT	LPDT-Classifier	LPDT-InfoNCE	LPDT-Rein-Classifier	LPDT-Rein-InfoNCE
Cheetah-dir	960.32 ± 17.07	628.64 ± 61.11	641.05 ± 129.54	874.91 ± 73.45	**1121.68 ± 25.13**	1118.95 ± 35.14	**1131.94 ± 51.09**	1113.96 ± 20.52
Cheetah-vel	-133.78 ± 18.24	-111.47 ± 36.97	-129.00 ± 24.24	**-52.42 ± 8.11**	**-55.15 ± 15.82**	-57.56 ± 9.55	-95.02 ± 10.58	-96.07 ± 5.33
Ant-dir	678.07 ± 68.74	381.42 ± 13.83	417.37 ± 39.70	**961.27 ± 18.07**	**782.25 ± 30.39**	775.79 ± 35.28	769.52 ± 69.40	759.54 ± 10.95
Point-robot	-7.99 ± 0.46	-7.76 ± 0.18	-19.42 ± 2.10	**-6.90 ± 0.11**	-8.19 ± 0.46	-9.06 ± 0.22	**-7.30 ± 0.35**	-7.37 ± 0.27
MW Reach-v2	2906.67 ± 33.16	-	-	1418.39 ± 6.01	2903.43 ± 55.09	**2946.88 ± 92.18**	**3023.38 ± 178.49**	2614.41 ± 27.57

4.4 Data Efficiency of LPDT

In this section, we demonstrate the data efficiency of LPDT. The data efficiency shows how well our approaches and baselines can perform with access to only a certain number of unique trajectories after sufficient training iterations. The pretrained language model provides prior knowledge for reinforcement learning tasks, leading to increased data efficiency within our framework. To validate this hypothesis, we conduct extensive experiments on various datasets split by ratios $\{1.0, 0.5, 0.1, 0.05, 0.01\}$. A ratio of 1.0 corresponds to the original full dataset, while a ratio of 0.01 represents an extreme scenario where only 1% of the original full dataset is available in training. We train our LPDT compared to Prompt-DT and Meta-DT, under these conditions and evaluate their performance on unseen tasks. The results are presented in Table 2.

As depicted in Table 2, the return score decreases as the dataset size diminishes. In tasks such as Cheetah-dir and Ant-dir, our LPDT algorithm mostly achieves better performance compared to Prompt-DT and Meta-DT. Specifically, on Cheetah-dir, LPDT is consistently the best across all splits from 1.0 to 0.05. On Cheetah-vel, Ant-dir and Point-robot, with full dataset, the performance of LPDT is comparable to Meta-DT. But when it decreases to a small dataset with 0.5, 0.1, 0.05, our LPDT outperforms the baseline. In 10% of the dataset, our proposed methods can achieve a similar or even better performance compared to Prompt-DT in Cheetah-vel and Ant-dir. Nevertheless, at a ratio of 0.01, an extreme case, all methods perform poorly on Cheetah-dir and the scores are mostly determined by noises, which is expected due to insufficient training data. For the Cheetah-vel and MW Reach-v2 tasks, results are inconsistent and exhibit significant variance, likely due to inherent task challenges and difficulties in learning stable policies in these environments. Meta-DT requires learning a context encoder based on training trajectories and is particularly sensitive to limited data availability. Despite these challenges, the overall trend indicates that **LPDT models maintain a performance advantage over other baselines, especially when dataset sizes are moderately reduced**. This underscores the benefit of leveraging prior knowledge from language models to enhance data efficiency in downstream reinforcement learning tasks.

4.5 Ablation Studies

In this section, we provide ablation studies on our proposed framework LPDT from various aspects. We focus on the effectiveness of the prompt regularization and the language model. We also extend our proposed framework to other sequence modeling in decision-making. At last, we demonstrate the different prompt selection strategies during the testing stage.

The role of prompt regularization We first compare our proposed model with its variants that do not utilize prompt regularization, denoted as LPDT w/o regularization and LPDT-Rein w/o regularization.

Table 2: Results for MuJoCo control tasks and MW tasks with the $\{0.01, 0.05, 0.1, 0.5, 1.0\}$ ratio dataset. The best mean scores are highlighted in bold. For each environment, the length of the prompt is $K^* = 5$. We test all the results on unseen tasks with three random seeds. We demonstrate that language initialization can improve the performance of our LPDT.

Dataset Ratio	Algorithm	Cheetah-dir	Cheetah-vel	Ant-dir	Point-robot	MW Reach-v2
1.0	Prompt-DT	960.32 ± 17.07	-133.78 ± 18.24	678.07 ± 68.74	-7.99 ± 0.46	2906.67 ± 33.16
	Meta-DT	874.91 ± 73.45	**-52.42 ± 8.11**	**961.27 ± 18.07**	**-6.90 ± 0.11**	1418.39 ± 6.01
	LPDT-Classifier	1121.68 ± 25.13	-55.15 ± 15.83	782.25 ± 30.39	-8.19 ± 0.46	2903.43 ± 55.09
	LPDT-InfoNCE	1118.95 ± 35.14	-57.56 ± 9.55	775.79 ± 35.28	-9.06 ± 0.22	2946.88 ± 92.18
	LPDT-Rein-Classifier	**1131.94 ± 51.09**	-95.02 ± 10.58	769.52 ± 69.40	-7.30 ± 0.35	**3023.38 ± 178.49**
	LPDT-Rein-InfoNCE	1113.96 ± 20.52	-96.07 ± 5.33	759.54 ± 10.95	-7.37 ± 0.27	2614.41 ± 27.57
0.5	Prompt-DT	691.05 ± 72.87	-69.93 ± 7.59	663.49 ± 17.06	-6.53 ± 0.41	**3062.35 ± 15.89**
	Meta-DT	202.82 ± 33.91	-75.61 ± 7.77	508.73 ± 61.73	-14.07 ± 0.26	2085.79 ± 2.62
	LPDT-Classifier	1074.20 ± 27.26	**-55.19 ± 10.94**	705.99 ± 51.27	**-6.04 ± 0.56**	2426.50 ± 125.30
	LPDT-InfoNCE	**1102.18 ± 43.18**	-64.23 ± 5.76	714.31 ± 67.15	-6.97 ± 1.55	2439.34 ± 131.92
	LPDT-Rein-Classifier	949.85 ± 25.68	-101.84 ± 4.23	746.45 ± 56.32	-7.832 ± 0.94	2841.04 ± 136.94
	LPDT-Rein-InfoNCE	899.25 ± 32.85	-106.94 ± 8.52	**750.38 ± 70.14**	-7.468 ± 0.44	2902.60 ± 92.70
0.1	Prompt-DT	193.69 ± 9.06	-72.47 ± 3.14	598.29 ± 21.61	-8.94 ± 0.43	**3541.67 ± 75.44**
	Meta-DT	77.42 ± 11.90	-114.32 ± 10.24	509.25 ± 51.03	-16.68 ± 1.64	2040.93 ± 166.34
	LPDT-Classifier	**750.90 ± 88.86**	**-65.23 ± 19.16**	**688.21 ± 36.78**	-8.46 ± 0.34	2519.92 ± 152.28
	LPDT-InfoNCE	666.13 ± 56.85	-77.08 ± 17.71	660.63 ± 52.00	**-8.19 ± 0.91**	2577.42 ± 60.06
	LPDT-Rein-Classifier	622.95 ± 45.98	-107.29 ± 15.12	687.71 ± 68.32	-9.242 ± 0.54	2781.77 ± 170.80
	LPDT-Rein-InfoNCE	614.52 ± 85.21	-112.69 ± 14.25	641.87 ± 45.96	-9.609 ± 1.23	2827.77 ± 154.02
0.05	Prompt-DT	112.40 ± 14.43	**-97.29 ± 9.90**	491.320 ± 19.94	-8.26 ± 0.07	**3320.88 ± 77.59**
	Meta-DT	37.87 ± 19.15	-118.15 ± 13.35	309.68 ± 63.76	-18.27 ± 1.67	2004.85 ± 44.59
	LPDT-Classifier	**386.01 ± 84.45**	-103.43 ± 5.45	488.54 ± 43.80	**-7.80 ± 1.22**	2510.56 ± 120.62
	LPDT-InfoNCE	320.28 ± 79.24	-102.5 ± 5.09	456.47 ± 65.82	-8.32 ± 0.45	2592.62 ± 153.21
	LPDT-Rein-Classifier	252.33 ± 69.15	-113.70 ± 6.33	**534.28 ± 52.31**	-10.22 ± 1.23	2508.67 ± 124.36
	LPDT-Rein-InfoNCE	279.48 ± 45.58	-112.68 ± 5.48	458.98 ± 43.64	-10.50 ± 1.44	2295.21 ± 91.08
0.01	Prompt-DT	18.97 ± 4.52	**-99.89 ± 2.85**	183.55 ± 11.39	**-8.91 ± 0.41**	**2551.17 ± 122.52**
	Meta-DT	**30.88 ± 21.07**	-173.93 ± 28.09	90.86 ± 0.91	-17.28 ± 2.01	1934.47 ± 28.61
	LPDT-Classifier	17.80 ± 12.73	-121.84 ± 4.12	175.82 ± 18.61	-10.56 ± 0.21	2132.60 ± 165.87
	LPDT-InfoNCE	10.54 ± 6.75	-127.81 ± 3.26	130.76 ± 3.64	-11.52 ± 1.80	2390.82 ± 79.37
	LPDT-Rein-Classifier	25.42 ± 14.50	-125.22 ± 2.58	**264.61 ± 12.04**	-11.15 ± 0.47	2508.67 ± 124.36
	LPDT-Rein-InfoNCE	9.26 ± 10.32	-133.44 ± 4.71	270.43 ± 8.36	-10.93 ± 1.12	2449.91 ± 91.08

Table 3: Results for MuJoCo control tasks and MW tasks with different regularization methods of our method including w/o regularization, classifier regularization and InfoNCE regularization. For each environment, the length of the prompt is $K^* = 5$. We test all the results on unseen tasks with three random seeds. The dataset we utilized is the full dataset. We demonstrate that the regularization on prompts can help distinguish the task and improve the performance compared with the method without regularization.

Task	Prompt-DT	LPDT w/o regularization	LPDT-Rein w/o regularization	LPDT-Classifier	LPDT-InfoNCE	LPDT-Rein-Classifier	LPDT-Rein-InfoNCE
Cheetah-dir	960.32 ± 17.07	1109.54 ± 20.04	1123.51 ± 9.67	1121.68 ± 25.13	1118.95 ± 35.14	1131.94 ± 51.09	1113.96 ± 20.52
Cheetah-vel	-133.78 ± 18.24	-56.38 ± 7.53	-95.39 ± 23.80	-55.15 ± 15.83	-57.56 ± 9.55	-95.02 ± 10.58	-96.07 ± 5.33
Ant-dir	678.07 ± 68.74	762.19 ± 59.22	718.78 ± 43.41	782.25 ± 30.39	775.79 ± 35.28	769.52 ± 69.40	759.54 ± 10.95
Point-robot	-7.99 ± 0.46	-6.37 ± 0.44	-6.12 ± 0.26	-8.19 ± 0.46	-9.06 ± 0.22	-7.30 ± 0.35	-7.37 ± 0.27
MW reach-v2	2906.67 ± 33.16	2808.15 ± 189.82	2252.68 ± 156.39	2903.43 ± 55.09	2946.88 ± 92.18	3023.38 ± 178.49	2614.41 ± 27.57

Table 3 illustrates that our proposed LPDT outperforms LPDT w/o regularization and LPDT-Rein w/o regularization in most of our proposed settings, showing that **prompt regularization improves the model's ability to distinguish between tasks and enhances overall performance**.

The benefits of using the pretrained language model To investigate whether the benefits of using the language model for initializing DT stem from (1) higher-quality *prompt embeddings* encoded from a pretrained language model improving the understanding of the RL environments from context, or (2) *backbone-level knowledge priors* in the language model's hidden layers modeling the connection in natural language that help align trajectories with environment dynamics, we conducted additional experiments where we used the *text-pretrained model's embedding of the prompt* as the input to a freshly initialized decision transformer, denoted as 'Prompt-DT-Text-Embedding' and 'Prompt-DT-Rein-Text-Embedding' in our following table.

For details, we implement Prompt-DT-Text-Embedding and Prompt-DT-Rein-Text-Embedding by adopting a language model to encode the trajectory prompt and using this prompt embedding to train a fresh initialized prompt decision transformer. We test this approach to see whether the language model can provide a better understanding of RL tasks compared to our approach using the language model as the initialization.

Our experimental results, summarized in Table 4, indicate that the variants leveraging full language model initialization (LPDT-Classifier, LPDT-InfoNCE, LPDT-Rein-Classifier, and LPDT-Rein-InfoNCE) outperform Prompt-DT-Text-Embedding and Prompt-DT-Rein-Text-Embedding methods, which only use the language model's embedding for the prompt. **This shows that the better initialization from the language model for learning RL tasks contributes more to the improvements.** Nevertheless, we can observe that Prompt-DT-Text-Embedding and Prompt-DT-Rein-Text-Embedding outperform the vanilla Prompt-DT method on all environments except the Cheetah-dir environment. This suggests that the language model can, to some extent, provide a better embedding for prompts.

Table 4: Results for MuJoCo control tasks on Prompt-DT-Text-Embedding and Prompt-DT-Rein-Text-Embedding. For each environment, the length of the prompt is $K^* = 5$. We test all the results on unseen tasks with three random seeds. The dataset we utilized is the full dataset. We demonstrate that improved performance comes from the initialization of the language model.

Task	Prompt-DT	LPDT-Classifier	LPDT-InfoNCE	Prompt-DT-TextEmbedding	LPDT-Rein-Classifier	LPDT-Rein-InfoNCE	Prompt-DT-Rein-Text Embedding
Cheetah-dir	960.32 ± 17.07	1121.68 ± 25.13	1118.95 ± 35.14	-23.74 ± 18.94	1131.94 ± 51.09	1113.96 ± 20.52	1015.397 ± 50.47
Cheetah-vel	-133.78 ± 18.24	-55.15 ± 15.82	-57.56 ± 9.55	-72.28 ± 8.25	-95.02 ± 10.58	-96.07 ± 5.33	-115.82 ± 9.24
Ant-dir	678.07 ± 68.74	782.25 ± 30.39	775.79 ± 35.28	716.62 ± 44.15	769.52 ± 69.40	759.54 ± 10.95	696.00 ± 46.69

Flexibility in the language model We implemented various pre-trained language models to demonstrate our proposed approach can be adapted to different language models. In this section, we provide the results with small language models such as Qwen2.5-0.5B (Qwen et al., 2025). Table 5 presents the Ant-dir results under different pre-trained language model initializations. The results indicate that with Qwen2.5-0.5B, the performance remains competitive in LPDT-Rein and improved in LPDT, **demonstrating the flexibility of our approach to various language model initializations**. We hypothesize that larger language models such as the 7B model are likely to further enhance performance in unseen test settings.

Table 5: Results for Ant-Dir with different initialization of pre-trained language model on the full dataset. The length of the prompt is $K^* = 5$. We test all the results on unseen tasks with three random seeds. We demonstrate that LPDT with Qwen2.5-0.5B has improved performance compared to GPT-2.

Task	LPDT-Classifier GPT-2	LPDT-InfoNCE GPT-2	LPDT-Classifier Qwen2.5-0.5B	LPDT-InfoNCE Qwen2.5-0.5B
Ant-dir	782.25 ± 30.39	775.79 ± 35.28	800.22 ± 55.16	786.16 ± 15.55
Task	LPDT-Rein-Classifier GPT-2	LPDT-Rein-InfoNCE GPT-2	LPDT-Rein-Classifier Qwen2.5-0.5B	LPDT-Rein-InfoNCE Qwen2.5-0.5B
Ant-dir	769.52 ± 69.40	759.54 ± 10.95	735.97 ± 58.33	719.69 ± 35.33

Extension on other DT methods Our proposed method builds upon the high-level concept of Prompt-DT by leveraging prompts and contextual information to guide models in unseen tasks, but extends beyond this specific architecture. Our framework is a versatile plug-in method based on prompt strategies that can be integrated into various architectures. While our primary implementation follows the Prompt-DT paradigm, we also demonstrated our algorithm's flexibility by adapting it to Reinformer, a recent DT-based method achieving state-of-the-art performance in single-task offline RL problems. To further validate this generalizability, we now provide an additional implementation based on EDT (Wu et al., 2024). Table 6 compares our LPDT-EDT approach to standard Prompt-EDT without language initialization, demonstrating significant performance improvements. **These results highlight our framework's potential and flexibility to enhance a wide range of architectural designs.**

Advanced Prompt Sampling Strategies In our implementation, prompt trajectories are randomly sampled from the demonstration set during testing on unseen tasks. This is a simple and straightforward approach that allows us to better highlight the benefits of language initialization and low-rank fine-tuning.

Table 6: Results for MuJoCo control tasks on LPDT-EDT on the full dataset. The length of the prompt is $K^* = 5$. We test all the results on unseen tasks with three random seeds. We demonstrate that our proposed framework LPDT can be flexible to the sequence modeling methods in decision making.

Task	Prompt-EDT	LPDT-EDT-Classifier	LPDT-EDT-InfoNCE
Cheetah-dir	796.56 ± 87.09	1040.087 ± 34.834	1024.172 ± 52.357
Cheetah-vel	-257.14 ± 1.42	-254.301 ± 1.213	-222.05 ± 11.589
Ant-dir	240.794 ± 24.34	733.435 ± 16.969	615.087 ± 20.267

We additionally implement a prompt selection method based on online interaction returns, using these returns as a performance metric to identify effective prompts. Specifically, we select several prompts from the demonstration set and then interact with the environment several times to obtain the prompt with the highest mean return. We compare the performance of such methods (with suffix '-select') to LPDT. The results, illustrated in the Table 7, demonstrate a performance improvement over random selection. However, the improvement over the current performance of our LPDT is not significant. **This additional prompt selection strategies introduce additional model complexity with a little improvement.** Thus, we use a simpler way which selects the prompts randomly from the demonstration set to implement our LPDT. But it is indeed orthogonal to our core LPDT framework and is an interesting direction to further explore.

Table 7: Results for MuJoCo control tasks onLPDT and prompt-selection variants. For each environment, the length of the prompt is $K^* = 5$. We test all the results on unseen tasks with three random seeds. The dataset we utilized is the full dataset. We demonstrate that our proposed framework LPDTcan be orthogonal to prompt selection strategies and can be improved with advanced prompt selection methods.

Task	LPDT-Classifier	LPDT-InfoNCE	LPDT-Classifier-Prompt select	LPDT-InfoNCE-Prompt select
Cheetah-dir	1121.68 ± 25.13	1118.95 ± 35.14	1151.33 ± 24.36	1139.11 ± 16.88
Cheetah-vel	-55.15 ± 15.82	-57.56 ± 9.55	-51.02 ± 16.03	-56.38 ± 14.21
Ant-dir	782.25 ± 30.39	775.79 ± 35.28	824.79 ± 46.04	782.72 ± 38.68

5 Conclusion

In this work, we proposed a novel flexible framework for improving the few-shot prompt ability of decision transformers and other sequence modeling methods in offline reinforcement learning. This framework, termed Language model-initialized Prompt Decision Transformer (LPDT), leverages pre-trained language models integrated with domain-specific RL datasets to enhance few-shot prompt capabilities. LPDT demonstrates superior or competitive performance compared to existing baselines in terms of cumulative rewards on unseen tasks. Our approach holds significant potential for reducing data requirements in offline RL tasks, thereby increasing applicability in real-world scenarios where large-scale collection of RL trajectories is challenging. Moreover, our results underscore the importance of utilizing pre-trained language models as a foundation for decision-making tasks and demonstrate the effectiveness of our prompt regularization methods in enhancing task-specific information discernment within prompts. Additionally, our LPDT framework exhibits flexibility to accommodate various pre-trained language model initializations and sequence modeling methodologies, including Reinformer and other recent DT variants.

While LPDT has shown promising results, there are several limitations to our approach. Current computing resource constraints limit our use of language models to GPT-2 and Qwen2.5-0.5B. To fully harness the potential of pre-trained language models in decision-making tasks, future efforts will aim at extending our framework to encompass more extensive open-source language models and implementing efficient fine-tuning techniques. Exploration into alternative architectures or the incorporation of multi-task learning could further enhance LPDT's performance. Future research will focus on addressing these limitations and expanding LPDT's application across a broader range of pre-trained language models and decision-making tasks, offering a promising direction for advancements in offline reinforcement learning.

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A Related Work

Decision Transformer. Decision Transformer (DT) (Chen et al., 2021) emerges as a type of algorithm for offline RL by using the powerful Transformer architecture for decision-making. DT models RL trajectories as a sequence generation problem and utilizes the next-token generation paradigm for training. Thus, DT takes the history tokens such as the return, state, and action to predict the next action, which formulates the decision-making as an action prediction or sequence generation in a supervised fashion. Since DT can fully utilize the whole trajectories and is easy to train compared with dynamic programming-based offline RL, many of the following works improved the performance under different settings. For example, Lee et al. (2022) proposes to use the Multi-game Decision Transformer which is trained on part of the Atari games as the multi-tasks training and fine-tuned on the remaining games to achieve efficient adaption. Hyper Decision Transformer (Xu et al., 2023) adds an adapter into Decision Transformer and is fine-tuned on unseen tasks through the demonstration without expert actions. Xie et al. (2023) proposes to predict the action conditioned on the future trajectory embedding as the hindsight instead of conditioned on the return. Trajectory Transformer (Janner et al., 2021) is another research line, which is trained on sequences of state, action, and rewards and generated with the beam search. Elastic DT (Wu et al., 2024) introduces the expectile regression over the returns and uses the different lengths of context to predict the next action. Reinformer (Zhuang et al., 2024) utilizes the expectile regression to max the return to improve the stitching ability during the sequence modeling.

Prompt-DT. Prompt Decision Transformer (Xu et al., 2022) utilizes the prompt-based framework to do the meta-RL. It is trained on multi-RL tasks with offline datasets. During the training, the prompts or demonstrations which are a small part of the trajectory are combined with trajectories. During the testing on unseen tasks, the prompt can be a guide for indicating the tasks and help the model predict the action to interact with the environments. Following Prompt-DT, several works are adopting the prompt tuning method to achieve a high-quality prompt. Prompt-Tuning DT (Hu et al., 2021) uses the preference ranking function and black-box tuning method to tune the prompt when testing on unseen tasks to achieve a high-quality prompt. Moreover, Prompt Diffuser (Hu et al., 2024) leverages the diffusion model to generate high-quality prompts leading to improved performance in downstream RL tasks. Different from these works, we adopt the prompt regularization which aims to learn a high-quality prompt embedding to distinguish the different but similar RL tasks. Our method adopts this regularization during the training procedure in the prompt dataset. Meta-DT (Wang et al., 2024) proposes to pre-train a context encoder to encode the context in trajectories. It uses the trajectory context as the input to incorporate the task representation into Prompt-DT.

Language model based DT. Large language models have achieved many surprising effects in various tasks in recent years. Pre-trained on large datasets such as the corpus of the Internet, LLMs such as GPTs (Radford et al., 2019) demonstrate prompt ability which can generate the text with the guide of the task information. The success of the large language models motivates the increasing use of pre-trained language models in improving Decision Transformer to solve RL tasks (Chen et al., 2021). Several works utilize the powerful representation generalization ability of language models as policies to do the decision-making. Li et al. (2022) proposed to adopt the pre-trained language models for interactive decision-making to convert the policies to sequence data. Wik-RL (Reid et al., 2022) uses a pre-trained language model from the next-token generation paradigm as the initialization of DT for offline RL tasks. However, it suffers from inferior performance than directly using DT. To overcome these challenges and unleash the power of language models, Shi et al. (2024) proposed the LaMo algorithm which uses a pre-trained language model and parameter-efficient fine-tuning methods to improve the original DT. Zhang et al. (2024) also proposed to use LaMo in partially observable continuous control problems which demonstrates a strong generalization ability. All these methods are designed for single tasks. DPDT (Zheng et al., 2024) uses the pre-trained language model to provide the prior knowledge to train the prompt and utilizes the test time adaptation to align the cross-task prompts in unseen tasks. However, it still needs a test time adaption phase to achieve the ideal performance. Our approach is fine-tuned for learning to identify different prompts for various RL tasks. And during the testing phase, just a small part of the trajectories is used in our method as the prompt without updating the model.

B Details on the Experiment Environments

We evaluate our approach over MuJoCo control tasks and Meta-World ML1 tasks. We split the tasks in these environments into the training set and the testing set. The tasks in Cheetah-dir and Ant-dir are split by directions. The tasks in Cheetah-vel are split by the goal velocities. The tasks in Point-robot are split by the goal positions which are uniformly distributed in a unit square. In Meta-World, the tasks are defined by different goal positions. The detailed task indexes can be found in Table 8. The experiments we conducted are all followed to this setting which guarantees consistency during the evaluation.

Table 8: Training and testing task indexes when testing the generalization ability. We follow the tasks split between Prompt-DT and previous works to guarantee a direct comparison with baselines.

Environment	Number of tasks	Tasks indexes
Cheetah-dir	Training set: 2 Testing set: 2	[0,1] [0,1]
Cheetah-vel	Training set: 45 Testing set: 5	[0-44] [45-49]
Ant-dir	Training set: 45 Testing set: 5	[0-44] [45-49]
Point-robot	Training set: 45 Testing set: 5	[0-44] [45-49]
Meta-World reach-v2	Training set: 15 Testing set: 5	[0-14] [15-19]

C Hyperparameters

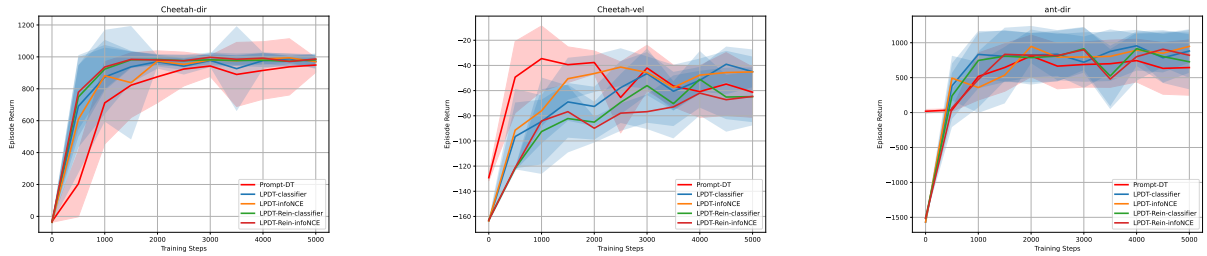
In this section, we show the hyperparameter of our LPDT conducted in Table 1. The hyperparameters have two parts which are the hyperparameters around the transformer and prompt regularization. We list these hyperparameters in Table 9.

Table 9: Detail on hyperparameters used in our experiments in Table 1. We show that the hyperparameters in two parts which are parameters for model backbone and prompt regularization respectively.

Hyperparameters	Value
Length of training τ	20
Length of prompt K	5
Training batch size for each task	8
Number of evaluation episodes for each task	20
Learning rate	1e-4
Learning rate decay weight	1e-4
Language initialization	GPT-2
Embedding dimension	128
Activation	ReLU
Classifier hyperparameter	0.1
Classifier layers	2
Classifier MLP dimension	128
InfoNCE hyperparameter	0.1
InfoNCE temperature	1
InfoNCE MLP dimension	128

D Training Return Curves

Figure 2 presents the evaluation of Prompt-DT and our four LPDT approaches. All the plotted methods are tested through 50 episode returns on the unseen tasks. The tasks Cheetah-dir, Cheetah-vel, and Ant-dir have prompts of length $K^* = 5$. Figure 2 shows that they need fewer sample data compared with Prompt-DT to achieve superior performance. The benefit of introducing the language model is to improve the data efficiency which is important in real-world application.



(a) Cheetah-dir (b) Cheetah-vel (c) Ant-dir

Figure 2: Training curves on MuJoCo controls with three tasks: Cheetah-dir, Cheetah-vel and Ant-dir for Prompt-DT and our four methods LPDT-Classifier, LPDT-InforNCE, LPDT-Rein-Classifier and LPDT-Rein-InforNCE. The dataset we utilized is the full dataset. We plot the figures on one unseen task with the average returns over 20 evaluation episodes. The figures demonstrate that our LPDT needs less sample data to achieve good performance and be more stable during the training.