# Execution-based Code Generation using Deep Reinforcement Learning

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## Abstract

The utilization of programming language (PL) models, pre-trained on large-scale code corpora, as a means of automating software engineering processes has demonstrated considerable potential in streamlining various code generation tasks such as code completion, code translation, and program synthesis. However, current approaches mainly rely on supervised fine-tuning objectives borrowed from text generation, neglecting unique sequence-level characteristics of code, including but not limited to compilability as well as syntactic and functional correctness. To address this limitation, we propose PPOCoder, a new framework for code generation that synergistically combines pre-trained PL models with Proximal Policy Optimization (PPO) deep reinforcement learning. By utilizing non-differentiable feedback from code execution and structure alignment, PPOCoder seamlessly integrates external code-specific knowledge into the model optimization process. It's important to note that PPOCoder is a task-agnostic and model-agnostic framework that can be used across different code generation tasks and PLs. Extensive experiments on three code generation tasks demonstrate the effectiveness of our proposed approach compared to SOTA methods, achieving significant improvements in compilation success rates and functional correctness across different PLs. The source code for PPOCoder can be found at `https://anonymous.4open.science/r/PPOCoder-9658/`.

## 1 Introduction

Recent years have seen a surge of attention towards the use of deep learning and neural language models to automate code generation and other software engineering processes, as a means to enhance developer productivity. The software development process encompasses a variety of code generation tasks, including code completion (Code2Code) (Li et al., 2018), code translation (Code2Code) (Zhu et al., 2022b), and program synthesis (NL2Code) (Li et al., 2022). Inspired by the great performance of pre-trained neural language models (LMs) in different natural language processing (NLP) tasks, these pre-training techniques have been recently employed on large-scale code corpuses to automate code generation tasks. Examples of such pre-trained models include CodeBERT (Feng et al., 2020), CodeGPT (Lu et al., 2021), PLBART (Ahmad et al., 2021), and CodeT5 (Wang et al., 2021). However, the code domain faces some unique challenges. For example, given that the generated code is intended for machine execution as opposed to human comprehension, it is imperative that the generated code maintains syntactic and functional correctness, i.e., being able to pass the compilation and unit tests.

Despite the advancements of pre-trained code models, they are heavily influenced by NLP's self-supervised masked language modeling (MLM) and often struggle to ensure the syntactic and functional correctness of the generated codes. Authors of (Chen et al., 2021c) have shown that up to 70% of codes generated by these models can be non-compilable. To improve code generation towards syntactic and functional correctness, several approaches are followed: (*i*) filtering and repairing the non-compilable synthesized programs (Kulal et al., 2019), (*ii*) using energy-based generation models with compilability constraints (Korbak et al., 2021), and (*iii*) using reinforcement learning (RL) fine-tuning mechanisms (Wang et al., 2022; Zhong et al., 2017; Le et al., 2022). However, existing approaches are often tailored to a specific programming language (PL) or task, e.g., (Le et al., 2022) is exclusively designed for program synthesis in Python and (Roziere et al., 2020)

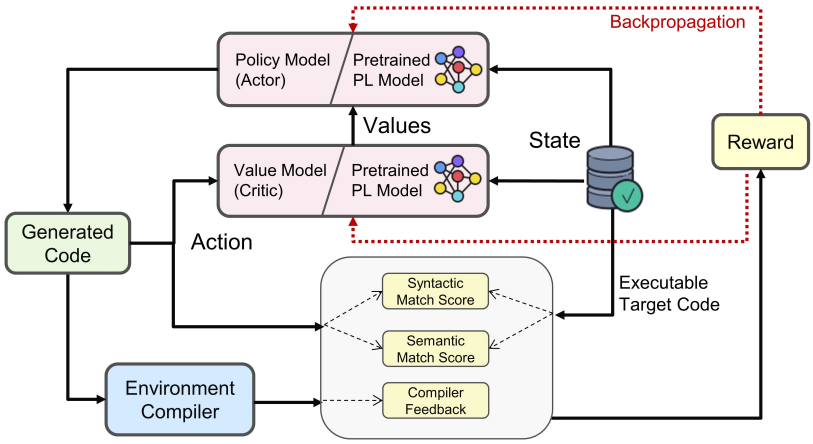


Figure 1: An overview of the proposed PPOCoder framework. The actor and critic networks are first initialized from the pretrained PL model for the desired task. Following the sampling of a synthetic program from the stochastic policy, the reward is determined using the execution feedback and the ground truth target code. The values are estimated by the critic network. Finally, both actor and critic networks are updated based on the obtained values and returns.

only targets code translation tasks in Python, Java, and C++ PLs. Therefore, current methods are not easily transferable to other different code generation tasks and PLs. To tackle this challenge, **we propose PPOCoder,** illustrated in Fig. 1, a PPO-based RL framework for code generation that incorporates non-differentiable feedback derived from code execution (i.e., syntactic or functional correctness) and structure alignment (i.e., syntactic and semantic matching scores) as external, code-specific knowledge into the model optimization. PPOCoder utilizes the PPO (Schulman et al., 2017) algorithm for RL optimization which is based on the proximal actor-critic advantage policy gradient objective and a trust region mechanism, making the model optimization more stable and less sensitive to new environments (tasks, PLs, or datasets). Also, PPOCoder integrates discrete compiler feedback with the syntactic and semantic matching scores between the generated codes and executable targets. This integration reduces the sparsity of the reward function, leading to a better guidance of the policy to generate code that is more closely aligned with the correct targets. *To the best of our knowledge, our work is the first one to integrate pre-trained PL models with PPO and incorporate non-differentiable code structure elements into the feedback.* Inspired by (Ouyang et al., 2022), PPOCoder also incorporates the KL-divergence penalty into the reward function to control explorations and prevent drastic deviations from the distributions already acquired by the pre-trained PL model. Prior works (Le et al., 2022) have employed token-level matching (i.e., cross-entropy) loss during both pre-training and fine-tuning stages to constrain these drastic deviations; however, this token-matching objective frequently results in model memorization and restricted performance when faced with new tasks and datasets. We observe that incorporating the KL-divergence penalty effectively minimizes the likelihood of memorization, fostering a more controlled and efficient exploration that generalizes adeptly to diverse code generation tasks and PLs. To summarize, the major contributions of this paper are as follows:

- We present a PPO-based RL framework for code generation, PPOCoder, that utilizes non-differentiable feedback derived from execution and structure alignment as the external source of knowledge in model optimization. PPOCoder provides a more stable and generalizable model optimization that is less sensitive to new environments (tasks, PLs, or datasets).
- We develop a new reward function based on the discrete compiler feedback (compilation or unit test signal when available) received at the end of the generation episode as well as the syntactic and semantic matching scores between the AST sub-trees and DFG edges of the sampled generations and the correct targets.
- We reduce the chance of memorization by incorporating a KL-divergence penalty into reward instead of a cross-entropy loss used in earlier works to control explorations and prevent deviations from the pre-trained model.

- We demonstrate the effectiveness of PPOCoder through an extensive set of experiments across diverse code generation tasks (code completion, code translation, program synthesis) and PLs (C++, Java, Python, C#, PHP, C). PPOCoder outperforms the SOTA baselines, improving the compilation rate and functional correctness over different PLs. We also investigate the benefits of PPOCoder's reward elements and PPO optimization through ablation study.

The organization of the remainder of this paper is as follows: In Section 2, existing code generation methods utilizing pre-trained models, structure-based approaches, and RL methods for sequence generation are summarized. Section 3 delves into the specifics of our proposed PPOCoder method, including its various components. The experimental evaluation of our method on three code generation tasks: code completion, code translation, and program synthesis tasks, as well as the ablation study and case study, can be found in Section 4. Finally, the paper concludes in Section 5.

## 2 Related Work

### 2.1 Pretrained Models for Code Generation

Recent research has focused on using pre-trained neural language models (LMs) in natural language processing (NLP) to automate code generation tasks leveraging large-scale pre-training on the extensive code corpus data available in open-source repositories (Lu et al., 2021; Zan et al., 2022; Niu et al., 2022). Notable examples of these pre-trained models are: (*i*) CodeBERT (Feng et al., 2020), which conducts encoder-only pretraining using Masked Language Modeling (MLM) and Replaced Token Detection tasks; (*ii*) CodeGPT (Lu et al., 2021), a comparable decoder-only GPT-based pre-trained model introduced alongside the CodeXGLUE benchmark; (*iii*) PLBART (Ahmad et al., 2021), an encoder-decoder transformer model pre-trained employing the denoising autoencoding (DAE) objective; and (*iv*) CodeT5 (Wang et al., 2021), another encoder-decoder pre-trained model subsequently proposed, built upon the T5 (Raffel et al., 2020) architecture and trained with code data in eight programming languages However, these pre-trained PL models tend to rely heavily on self-supervised MLM for text generation, while grappling with maintaining code-specific sequence-level attributes such as syntactic and functional correctness in the generated codes.

### 2.2 Leveraging Structure in Code Generation

Lately, there has been a surge of interest in combining PL models with logical constructs such as abstract syntax trees (ASTs) (Kim et al., 2021; Rabinovich et al., 2017; Wang & Li, 2021), code sketches (Nye et al., 2019), and data-flow graphs (DFGs) (Yasunaga & Liang, 2020; Guo et al., 2021). For example, GraphCodeBERT (Guo et al., 2021) uses DFGs to incorporate semantic information, but its decoder is completely unaware of the code structures. StructCoder (Tipirneni et al., 2022) presents a pre-trained structure-aware encoder-decoder architecture, where both the encoder and decoder components are cognizant of syntax and semantic relations. However, despite these efforts, many code generation models still struggle to ensure the syntactic and functional correctness of the generated codes. The primary reason is the misalignment between code-specific evaluation metrics and model optimization objectives. In other words, these models are not optimized for the non-differentiable code-specific objectives, leading to shortcomings in their performance.

### 2.3 RL for Sequence Generation

RL has been used to optimize non-differentiable metrics in sequence generation tasks (Ranzato et al., 2016; Bahdanau et al., 2017), such as using the REINFORCE (Williams, 1992) algorithm to improve BLEU (Papineni et al., 2002a) and ROUGE (Lin, 2004) scores in translation and summarization models. Recently, InstructGPT (Ouyang et al., 2022) have introduced Reinforcement with Human Feedback (RLHF) which shows that language models fine-tuned with RL can better follow non-differentiable human feedbacks. Unlike text generation, code generation requires not only syntactic but also functional correctness as the generated code must pass compilation and unit tests for machine execution. Recently, execution-guided approaches (Chen et al., 2019; Ellis et al., 2019; Chen et al., 2021b) and RL-based fine-tuning mechanisms (Wang et al., 2022; Zhong et al., 2017; Le et al., 2022) are used to enhance the quality of generated codes. For example, (Le et al., 2022) has recently studied the integration of RL with unit test signals in the fine-tuning of the program synthesis models. However, existing RL-based methods still encounter several limitations. They are often designed for a particular task (e.g., only program synthesis) or a particular PL (e.g., only Python),

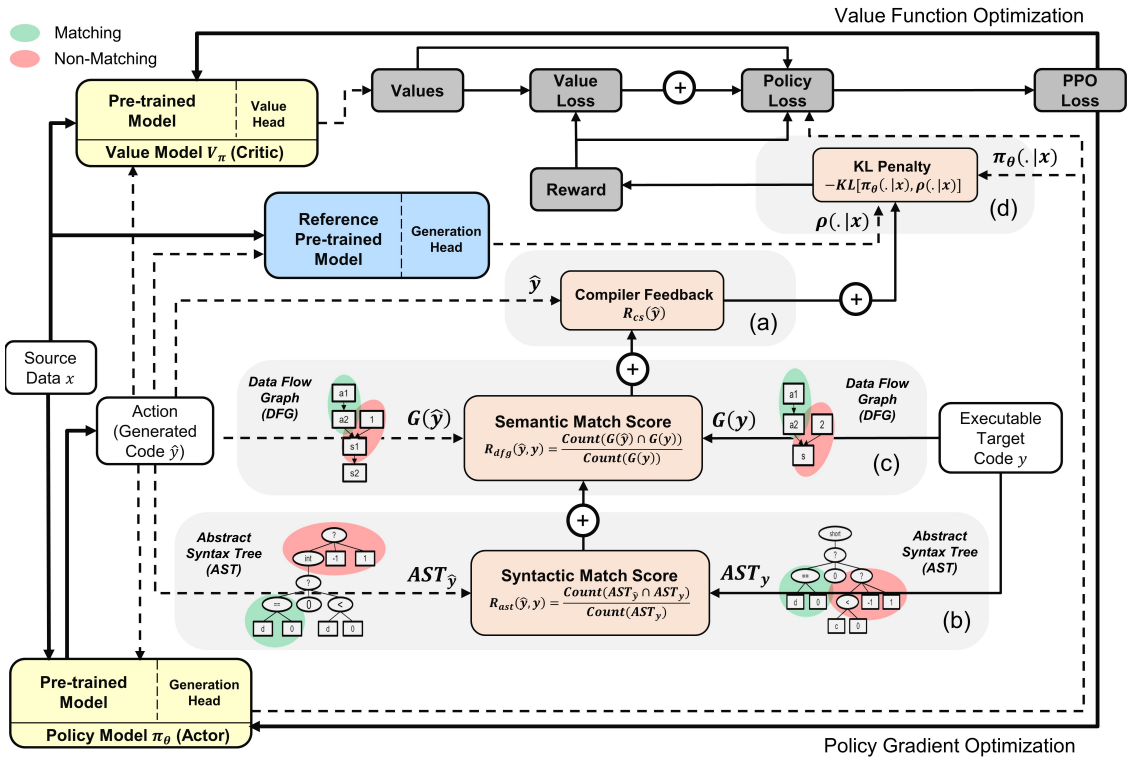


Figure 2: Overview of the PPOCoder with actor and critic models. The action is sampled from the policy based on the given source data $x$ (NL or PL). Then, a reward is obtained for each action to guide and control policy updates. The reward function is composed of four elements: $(a)$ compiler feedback; $(b)$ syntactic matching score based on ASTs; $(c)$ semantic matching score based on DFGs; and $(d)$ KL-divergence penalty between active policy and the reference pretrained model. The critic model estimates value based on the obtained reward and PPOCoder will be optimized with PPO, which takes into account both value and policy optimization.

receive a sparse and discrete compiler signal only at the end of the generation episode, and are susceptible to memorization and poor performance on unseen data due to the use of token-matching loss in the RL fine-tuning step to prevent drastic deviations from the pre-trained PL model. Our model, PPOCoder, is designed to be both task- and model-agnostic, allowing the RL framework to be flexible for a wide range of code generation tasks and PLs. This is achieved by incorporating a PPO-based framework that combines compiler feedback with code structure elements such as matching scores between the AST sub-trees and DFG edges in the reward function, and employs a KL-divergence penalty to minimize large deviations, while reducing the chance of model memorization.

## 3 PPOCoder

PPOCoder provides a systematic mechanism for fine-tuning code generation models using deep reinforcement learning (RL) by effectively and efficiently incorporating compiler feedback and structure alignments as extra knowledge into the model optimization, thereby enhancing the quality of the generated codes in terms of code-specific sequence-level features such as syntactic and functional correctness. Fig. 2 shows the general structure of our proposed PPOCoder model with the policy network (actor) $\pi_\theta$ responsible for code generation actions and the value function (critic) $V_\pi$ responsible for the return estimations. They are both learned with the proximal policy optimization (PPO) approach taking reward $\mathcal{R}$. As shown in Fig. 2, the total reward is composed of four elements: $(i)$ compiler feedback; $(ii)$ syntactic match score; $(iii)$ semantic match score; and $(iv)$ KL-divergence penalty. We provide further details about each of these components in the subsections below.

### 3.1 Problem Formulation

The code generation procedure can be formulated as a sequential discrete finite-horizon Markov Decision Process (MDP) with the use of RL in which an agent interacts with the compiler over discrete horizon $T$ which is equivalent to the maximum number of generated code tokens. The proposed PPOCoder is formulated as follows:

**State $\mathcal{S}$:** The state of environment at each time-step, denoted as $s_t = (\hat{y}_{<t}, x), s_t \in \mathcal{S}$, is determined by the source PL/NL data $x$, as well as the set of generated tokens before $t$, $\hat{y}_{<t}$.

**Action $\mathcal{A}$:** The PL model chooses the action at each time-step, denoted as $a_t = \hat{y}_t, a_t \in \mathcal{A}$, which is equivalent to the generated token at time-step $t$.

**Policy $\pi_\theta(a_t|s_t)$:** The stochastic policy network parameterized by $\theta$ is the downstream code generation model that predicts the next token conditioned on the previously generated tokens and the source data, so, $\pi_\theta(\hat{y}_t|\hat{y}_{<t}, x) : \mathcal{S} \rightarrow \Delta(\mathcal{A})$ where $\Delta(\mathcal{A})$ denotes the probability distribution over all actions (e.g., target vocabulary). The next action $\hat{y}_t$ will be decided based on the *top-k* sampling from this probability distribution. Policy is initialized with the pretrained reference PL model $\rho$, i.e., $\pi_\theta^0(.) = \rho$.

**Reward $\mathcal{R}$:** The reward $\mathcal{R}(\hat{y}, x, y)$ will be obtained at the end of the generation episode (i.e., after generating the $\langle endoftokens \rangle$ token) based on the generated code's syntactic and functional correctness as well as its alignment with executable codes. The reward function $\mathcal{R}(.)$ is composed of different components which are explained in Section 3.2.

**Advantage $\hat{A}_\pi^t$:** Inspired by the Generalized Advantage Estimator (GAE) (Schulman et al., 2016), the advantage at time-step $t$ is defined as follows.

$$\begin{aligned} \hat{A}_\pi^t =& \delta_t + \gamma\delta_{t+1} + \ldots + \gamma^{T-t+1}\delta_{T-1}, \\ \delta_t =& r_t - V_\pi(\hat{y}_{<t}, x) + \gamma V_\pi(\hat{y}_{<t+1}, x), \end{aligned} \tag{1}$$

where $\gamma$ is the discount rate; $r_t$ is the reward at time-step $t$; and $V_\pi(s_t)$ is the state value function at $t$ which can be approximated by a dense token-level value head on top of the hidden states of PL model.

**Objective:** The objective of PPOCoder is to find a policy that maximizes the expected reward of generated codes sampled from the policy.

$$\max_\theta \mathbb{E}_{x\sim\mathcal{X}, \hat{y}\sim\pi_\theta(.|x)}\big[\mathcal{R}(\hat{y}, x, y)\big], \tag{2}$$

where $\mathcal{X}$ is the training set of source data; $\pi_\theta(.)$ is the policy network; and $\mathcal{R}(.)$ is the reward function. We formulate the objective function as a maximization of the advantage instead of reward, as shown in Eq. (3), in order to reduce the variability of predictions.

$$\max_\theta \mathbb{E}_{x\sim\mathcal{X}, \hat{y}\sim\pi_\theta(.|x)}\left[\sum_{t=0}^{T} \hat{A}_\pi^t\big((\hat{y}_{<t}, x), \hat{y}_t\big)\right], \tag{3}$$

We adopt the policy gradient to estimate the gradient of non-differentiable reward-based objectives in Eqs. (2) and (3). Therefore, updating policy parameters for a given source data $x$ can be derived as:

$$\max_\theta \mathcal{L}_\theta^{PG} = \max_\theta \mathbb{E}_{\hat{y}\sim\pi_\theta}\left[\sum_{t=0}^{T}\Big(log\pi_\theta(\hat{y}_t|\hat{y}_{<t}, x)\ \hat{A}_\pi^t\Big)\right], \tag{4}$$

$$\text{where}\ \ \nabla_\theta\mathcal{L}_\theta^{PG} = \mathbb{E}_{\hat{y}\sim\pi_\theta}\left[\sum_{t=1}^{T}\Big(\nabla_\theta log\pi_\theta(\hat{y}_t|\hat{y}_{<t}, x)\ \hat{A}_\pi^t\Big)\right], \tag{5}$$

where $\nabla_\theta\mathcal{L}_\theta^{PG}$ refers to the estimated gradient of objective function based on the policy parameterized by $\theta$. In order to further reduce the variations and avoid significantly changing the policy at each iteration, the objective function in Eq. (4) will be reformulated as shown in Eq. (6), called the conservative policy iteration (CPI).

$$\begin{aligned}\mathcal{L}_{\theta}^{CPI} =& \mathbb{E}_{\hat{y}\sim\pi_{\theta}}\left[\sum_{t=0}^{T}\left(\frac{log\pi_{\theta}(\hat{y}_t|\hat{y}_{<t},x)}{log\pi_{\theta_{old}}(\hat{y}_t|\hat{y}_{<t},x)}\ \hat{A}_{\pi}^{t}\right)\right] \\ =& \mathbb{E}_{\hat{y}\sim\pi_{\theta}}\left[\sum_{t=0}^{T}\left(c_{\pi}^{t}(\theta)\ \hat{A}_{\pi}^{t}\right)\right],\end{aligned} \tag{6}$$

where $\theta_{old}$ is the policy parameters before the update; and $c_{\pi}^{t}(\theta)$ is the ratio of log-probabilities from new and old policies.

### 3.2 Reward Function

Figure 2 illustrates that the reward of PPOCoder is composed of four different components which are designed to guide and control actions simultaneously towards generating more executable codes. These components are designed due to (1) the sparsity of compiler feedback which is only received at the end of code generation episode; and (2) the high chance of policy divergence from the pretrained PL models. (check Section 4.4 for the reward ablation results). Eq. (7) shows the combination of these different reward terms in the final reward vector $\mathcal{R}(\hat{y},x,y) \in \mathbb{R}^T$ with $T$ as the generation episode length.

$$\begin{aligned}\mathcal{R}(\hat{y},x,y) &= \{r_t : t = 1,\ldots,T\}, \\ r_t &= \mathbb{1}(cond)\Big[R_{cs}(\hat{y}) + R_{ast}(\hat{y},y) + R_{dfg}(\hat{y},y) \\ &\quad - \beta R_{kl}(x,\hat{y}_{<t})\Big] + \mathbb{1}(\neg cond)\left[-\beta R_{kl}(x,\hat{y}_{<t})\right]), \\ cond &= (\hat{y}_t == \langle endoftokens\rangle),\end{aligned} \tag{7}$$

where $r_t$ is the combined reward at time-step $t$; $R_{cs}(.)$, $R_{ast}(.)$, and $R_{dfg}(.)$ are the compiler signal, syntactic match score, and the semantic match score reward terms, respectively. Note that, these terms will be received at the end of the generation episode where $\hat{y}_t == \langle endoftokens\rangle$. The $R_{kl}(x,\hat{y}_{<t})$ is a KL-divergence penalty between the reference pretrained model and the active policy which is imposed to reward at each time-step to control actions. $\beta$ is also the coefficient of penalty to balance the combination of different reward terms.

#### 3.2.1 Compiler Signal

For each source data $x$, we sample multiple generated codes in the target language based on the current policy network, $\hat{y} \sim \pi_{\theta}(.|x)$. Then, we pass these sampled codes $\hat{y}$ to a compiler and determine the reward based on the parsing signal. In case unit tests are available for the source data, the reward is determined by the functional correctness of generated codes, i.e., passing all unit tests, as shown in Eq. (8). If unit tests are not provided, compiler returns the syntactic correctness of generated codes (i.e., compilable or non-compilable) as shown in Eq. (9). This reward term is designed to guide the model to take actions which can generate higher quality codes in terms of syntactic/functional correctness.

Functional Correctness:

$$R_{cs}(\hat{y}) = \begin{cases} +1 & \text{, if } \hat{y} \text{ passed all unit tests} \\ -0.3, & \text{if } \hat{y} \text{ failed any unit test} \\ -0.6, & \text{if } \hat{y} \text{ received RunTime error} \\ -1 & \text{, if } \hat{y} \text{ received Compile error} \end{cases} \tag{8}$$

Syntactic Correctness:

$$R_{cs}(\hat{y}) = \begin{cases} +1, \text{if } \hat{y} \text{ passed compilation test} \\ -1, \text{otherwise} \end{cases} \tag{9}$$

#### 3.2.2 Syntactic Matching Score

Since the compiler signal alone is too sparse, we also add additional information to better control and guide the structure of policy samples. To do so, we define a syntactic matching score $R_{ast}(\hat{y},y)$ between the

generated hypothesis $\hat{y} \sim \pi_\theta(.|x)$ and the parallel executable target $y$. The goal is to maximize this matching score for better compilability or syntactic correctness. We use the abstract syntax tree (AST) to find a tree representation of the code's abstract syntax structure. Then, we compare the sub-trees extracted from the hypothesis and reference target ASTs, respectively, and calculate the syntactic match score as a percentage of matched AST sub-trees.

$$R_{ast}(\hat{y}, y) = Count(AST_{\hat{y}} \cap AST_y)/Count(AST_y), \tag{10}$$

where $Count(AST_{\hat{y}} \cap AST_y)$ is the number of matched AST sub-trees between the hypothesis $\hat{y}$ and reference $y$; and $Count(AST_y)$ is the total number of reference AST sub-trees. This score can assess the syntactic quality of code since the differences between ASTs can be affected by syntactic issues such as token missing and data type errors.

#### 3.2.3 Semantic Matching Score

To improve the functional correctness, we need to also take into account the semantic matching between hypothesis $\hat{y}$ and the executable target $y$, in addition to their syntactic matching. In PLs, code semantics are closely related to the dependencies of its variables. As a result, in order to construct a semantic matching score, we make use of the data-flow graphs (DFGs), a graph representation of code in which the nodes stand in for variables and the edges for the sources of each variable's values. We denote DFG of a code $Y$ as $\mathcal{G}(Y) = (V; E)$ where $V = \{v_1, \ldots, v_m\}$ is the set of variables, and $e_{i,j} = \langle v_i, v_j \rangle$ is the $i \rightarrow j$ edge showing that value of the $j$-th variable originates from the $i$-th variable. Then, we calculate the semantic match score as a percentage of matched data-flows in DFGs.

$$R_{dfg}(\hat{y}, y) = Count(\mathcal{G}(\hat{y}) \cap \mathcal{G}(y))/Count(\mathcal{G}(y)), \tag{11}$$

where $Count(\mathcal{G}(\hat{y}) \cap \mathcal{G}(y))$ represents the number of matched DFG edges between hypothesis $\hat{y}$ and reference $y$; and $Count(\mathcal{G}(y))$ represents the total number of reference DFG edges. Maximizing this score can guide and control policy to generate codes which are more aligned with executable target codes in terms of variable relations, thus, enhancing the semantic quality and logical correctness of the generated codes.

#### 3.2.4 KL-Divergence Constraint

We incorporate a negative KL-divergence penalty $KL(\pi||\rho)$ into the reward to prevent the active policy $\pi$ deviating away from the pre-trained PL model $\rho$. The KL-penalty at time $t$ can be approximated as:

$$\begin{aligned} R_{kl}\left(x, \hat{y}_{<t}\right) =& KL\left(\pi||\rho\right) \approx \log \frac{\pi\left(.|x, \hat{y}_{<t}\right)}{\rho\left(.|x, \hat{y}_{<t}\right)} \\ =& \log\left(\pi\left(.|x, \hat{y}_{<t}\right)\right) - \log\left(\rho\left(.|x, \hat{y}_{<t}\right)\right), \end{aligned} \tag{12}$$

where $\log\left(\pi\left(.|x, \hat{y}_{<t}\right)\right)$ and $log\left(\rho\left(.|x, \hat{y}_{<t}\right)\right)$ are the log-probabilities obtained from the active policy $\pi$ and pretrained model $\rho$ at time $t$ given source data $x$ and the previously predicted tokens $\hat{y}_{<t}$. This reward term can control actions and play the role of entropy bonus in controlling exploration and exploitation where greater $\beta$ in Eq. (7) provides less exploration and more exploitation.

### 3.3 Loss Function

We employ proximal policy optimization (PPO) (Schulman et al., 2017) and define the loss function of PPOCoder as follows.

$$\mathcal{L}_\theta = -\mathcal{L}_\theta^{CPI} + \alpha \mathcal{L}_\theta^{VF}, \tag{13}$$

$$\mathcal{L}_\theta^{CPI} = \mathbb{E}_{\hat{y} \sim \pi_\theta}\left[\sum_{t=0}^{T} \min\left(c_\pi^t(\theta)\hat{A}_\pi^t, clip\left(c_\pi^t(\theta), 1-\epsilon, 1+\epsilon\right)\hat{A}_\pi^t\right)\right], \tag{14}$$

$$\mathcal{L}_\theta^{VF} = \mathbb{E}_{\hat{y} \sim \pi_\theta}\left[\sum_{t=0}^{T}\left(V_\pi(\hat{y}_{<t}, x) - \left(\hat{A}_\pi^t + V_{\pi_{old}}(\hat{y}_{<t}, x)\right)\right)^2\right]. \tag{15}$$

where the loss function $\mathcal{L}_\theta$ is the linear combination of surrogate policy objective function $\mathcal{L}_\theta^{CPI}$ and the value function squared error term $\mathcal{L}_\theta^{VF}$. Therefore, minimizing loss function leads to the maximization of the surrogate advantage policy objective (actor optimization) as well as the minimization of value error (critic optimization). In other words, the actor is guided to maximize the advantage policy objective which is correlated with maximizing the expected reward as explained in Eqs. (4)-(6); and the critic is enforced to minimize the token-level value estimation error which is defined based on the difference between the values of new policy $V_\pi(\hat{y}_{<t})$ and the estimated dense returns of the old policy $\hat{A}_\pi^t + V_{\pi_{old}}(\hat{y}_{<t})$. In Eqs. (13)-(15), $\epsilon$ is the proximal policy ratio clip range, and $\alpha$ is the linear combination weight between loss terms of actor and critic.

Algorithm 1 provides the pseudocode of PPOCoder. For each source-target pair $(x, y)$, we sample multiple translated hypotheses from the policy network $\hat{y} \sim \pi_\theta(.|x)$. After generating each hypothesis, we find the integrated reward based on the reward function defined in Section 3.2, estimate the advantage, calculate the corresponding PPO loss function, and update the policy and value head parameters based on the final gradients (as shown in lines 5-21).

**Algorithm 1:** PPOCoder

**Input:** Set of parallel source-target code pairs $(\mathcal{X}, \mathcal{Y})$, Pretrained PL model $\rho$
**Output:** Finetuned policy with parameter $\theta$ based on RL

1 Initialize policy $\pi_\theta \leftarrow \rho$
2 **for** *number of epochs until convergence* **do**
3  **for** $(x, y) \in (\mathcal{X}, \mathcal{Y})$ **do**
4   **repeat**
5    $\hat{y} \leftarrow \pi_\theta(.|x)$
6    # Calculate Reward
7    Compute $R_{cs}(\hat{y})$ using Eq. (8) or Eq. (9)
8    Compute $R_{ast}(\hat{y}, y)$ using Eq. (10)
9    Compute $R_{dfg}(\hat{y}, y)$ using Eq. (11)
10    Compute $R_{kl}(x, \hat{y}_{<t})$ using Eq. (12)
11    $\mathcal{R}(\hat{y}, x, y) \leftarrow \{r_t, t = 1, \ldots, T\}$ where
12    $r_t = \mathbb{1}(cond)\Big[R_{cs}(\hat{y}) + R_{ast}(\hat{y}, y) + R_{dfg}(\hat{y}, y) - \beta R_{kl}(x, \hat{y}_{<t})\Big]$
13    $+\mathbb{1}(\neg cond)\left[-\beta R_{kl}(x, \hat{y}_{<t})\right]$); using Eq. (7)
14    # Estimate Advantage
15    $\hat{A}_\pi^t \leftarrow r_t - V_\pi(\hat{y}_{<t}, x) + \gamma V_\pi(\hat{y}_{<t+1}, x)$; using Eq. (1)
16    # Calculate Loss
17    $\mathcal{L}_\theta^{CPI} \leftarrow \mathbb{E}_{\hat{y}\sim\pi_\theta}\left[\sum_{t=0}^{T} \min\left(c_\pi^t(\theta)\hat{A}_\pi^t, clip\left(c_\pi^t(\theta), 1-\epsilon, 1+\epsilon\right)\hat{A}_\pi^t\right)\right]$
18    $\mathcal{L}_\theta^{VF} \leftarrow \mathbb{E}_{\hat{y}\sim\pi_\theta}\left[\sum_{t=0}^{T}\left(V_\pi(\hat{y}_{<t}, x) - \left(\hat{A}_\pi^t + V_{\pi_{old}}(\hat{y}_{<t}, x)\right)\right)^2\right]$
19    $\mathcal{L}_\theta \leftarrow \alpha\mathcal{L}_\theta^{VF} - \mathcal{L}_\theta^{CPI}$
20    # Update Model Parameters
21    $\theta \leftarrow \theta - \nabla_{\boldsymbol{\theta}}\mathcal{L}_{\boldsymbol{\theta}}$
22   **until** *num_samples*
23  **end**
24 **end**

## 4 Experiments

We evaluate PPOCoder on three different code generation tasks: (*i*) *Code Completion* automatically completes partial Python code snippets; (*ii*) *Code Translation* involves translating between any language-pair among six different PLs (Python, Java, C#, C++, PHP, C); and (*iii*) *Program Synthesis* (NL2Code) generates a Python function given a natural language (NL) description.

### 4.1 Code Completion

For this downstream task, we employ the Python corpus in CodeSearchNet (CSN) [1] (Husain et al., 2019). We extract 50k compilable Python methods with sufficient length (at least 64 tokens) and randomly split the data to train/val/test sets with 40k/5k/5k samples. We mask the last 25 tokens of the source code and ask

[1] https://github.com/github/CodeSearchNet#data-details

the model to complete it. To evaluate the quality of generated codes, three metrics are used: (*i*) *Exact Match* (xMatch) which checks if the prediction is the same as the ground truth, (*ii*) *Levenshtein Edit Similarity* (Edit Sim) (Lu et al., 2021; Svyatkovskiy et al., 2020) which measures the number of single-character edits needed to match the generated code with the correct target, and (*iii*) *Compilation Rate* (Comp Rate) (Kulal et al., 2019) that shows the success rate of compilation among completed programs. Since unit tests are not provided, we focus on the syntactic correctness of the completed codes and take the compiler signal as reward.

Table 1 shows the results of PPOCoder along with the baselines on the code completion task. In this table, the BiLSTM (Luong et al., 2015) and Transformer (Vaswani et al., 2017) models are not pre-trained. The GPT-2 (Radford et al., 2019) model was pre-trained on text corpus, while CodeGPT (Lu et al., 2021) and CodeT5 (Wang et al., 2021) models are pre-trained on the large-scale source code corpus. The reported results for these pre-trained models are after the fine-tuning step on the code completion task. More details of the experimental setup are provided in Appendix A It can be observed that CodeGPT and CodeT5 have a compilation rate of 46.84% and 52.14%, respectively, indicating that about half of the generated codes are not compilable. By employing our proposed PPOCoder framework on the fine-tuned CodeT5 model (PPOCoder + CodeT5), the compilation rate improves significantly from 52.14% to 97.68%, demonstrating the importance of incorporating compiler feedback into the model's optimization and the effectiveness of PPOCoder in code completion. We can also see that the PPOCoder performs similarly to other SOTA models in terms of Edit sim and xMatch scores, showing that the actor model effectively explores without deviating much from the pre-trained model distributions.

Table 1: Results on the code completion task for completing the last 25 masked tokens from CodeSearchNet.

| Model | *xMatch* | *Edit Sim* | *Comp Rate* |
|---|---|---|---|
| BiLSTM | 20.74 | 55.32 | 36.34 |
| Transformer | 38.91 | 61.47 | 40.22 |
| GPT-2 | 40.13 | 63.02 | 43.26 |
| CodeGPT | 41.98 | 64.47 | 46.84 |
| CodeT5 | 42.61 | 68.54 | 52.14 |
| PPOCoder + CodeT5 | **42.63** | **69.22** | **97.68** |

### 4.2 Code Translation

We use the XLCoST [2] (Zhu et al., 2022a) dataset for the code translation task which is a parallel dataset that includes solutions for problems related to data structures and algorithms in six languages: C++, Java, Python, PHP, C, and C#. In our experiments, we only use the compilable filtered parallel data in source and target language pairs. Table 6 in Appendix B shows the detailed statistics of these compilable filtered samples across all six PLs. To evaluate the quality of translated codes, we use two metrics: (*i*) *Comp Rate* that measures compilation success rate, and (*i*) *CodeBLEU* (Ren et al., 2020) score which combines the weighted BLEU (Papineni et al., 2002b) based on the code-related keywords with the the syntactic and semantic alignment measures. As unit tests are not available for parallel language pairs, we focus on syntactic correctness with the help of compiler signal.

Table 2 presents the results of PPOCoder on code translation along with the baselines. In this table, column and row headers represent the translation source and target PLs, respectively. The Naive Copy baseline (Lu et al., 2021) simply copies the source code as the output, showing how similar two PLs are. The reported results of pre-trained CodeBERT and PLBART are after fine-tuning on the code translation task for each language pair. The experimental setup and implementation details are provided in Appendix A. Table 2 demonstrates that incorporating our proposed PPOCoder +CodeT5 improves the overall compilation rate across all language pairs, in comparison to the SOTA baseline CodeT5. Specifically, we observe an absolute increase of 9.92%, 22.22%, 21.62%, 13.20%, 7.46%, and 6.11% in the compilation rate for C++, Java, Python, C#, PHP, and C target PLs, respectively. PPOCoder also obtains a comparable CodeBLEU score to other baselines, meaning that it does not deviate a lot from the pre-trained code fluency distribution. Among

[2] `https://github.com/reddy-lab-code-research/XLCoST`

high-resource languages, results show relatively greater compilation rate improvements for Python and Java as target PL. This is likely due to their high-level constructs, such as the absence of pointers and memory management constructs, which can be a source of errors in languages like C++ and C#. Additionally, Java and Python feature a more lenient compilation process and extensive runtime error checking, resulting in many errors that would cause C++ and C# compilation to fail, being detected only at runtime. The table shows a significantly lower compilation rate for code translation with C as target PL among all baselines. This is likely due to the limited number of samples with C as a target PL in the dataset (as shown in Table 6 in Appendix B).

Table 2: Performance comparison of PPOCoder and baselines on XLCoST. The column and row language headers represent the translation source and target languages. The "Overall" column shows the weighted average scores over six PLs. The best results are shown in **bold** font.

| | Model | High Resource | | | | | | | | Low Resource | | | | Overall | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **C++** | | **Java** | | **Python** | | **C#** | | **PHP** | | **C** | | | |
| | | *CodeBLEU* | *CompRate* | *CodeBLEU* | *CompRate* | *CodeBLEU* | *CompRate* | *CodeBLEU* | *CompRate* | *CodeBLEU* | *CompRate* | *CodeBLEU* | *CompRate* | *CodeBLEU* | *CompRate* |
| **C++** | Naive Copy | – | – | 44.56 | 20.28 | 17.81 | 9.73 | 47.28 | 21.25 | 19.83 | 8.21 | 63.94 | 4.62 | 38.68 | 12.82 |
| | CodeBERT | – | – | 62.56 | 37.12 | 36.41 | 26.72 | 67.12 | 38.52 | 38.77 | 12.23 | 21.84 | 2.31 | 45.34 | 23.38 |
| | PLBART | – | – | 71.23 | 44.51 | 69.09 | 45.92 | **74.74** | 51.86 | 62.35 | 53.63 | 52.76 | 36.22 | 66.03 | 46.42 |
| | CodeT5 | – | – | 80.17 | 59.01 | 72.83 | 53.33 | 73.11 | 60.31 | 67.47 | 68.21 | **66.02** | 71.44 | 71.92 | 62.46 |
| | PPOCoder + CodeT5 | – | – | **81.14** | **70.33** | **74.03** | **63.35** | 72.93 | **69.18** | **68.24** | **80.02** | 64.21 | **79.03** | **72.11** | **72.38** |
| **Java** | Naive Copy | 52.32 | 14.50 | – | – | 36.51 | 22.16 | 69.04 | 41.05 | 39.91 | 2.10 | 54.18 | 2.10 | 50.39 | 16.38 |
| | CodeBERT | 69.21 | 30.21 | – | – | 44.51 | 43.51 | 74.86 | 55.01 | 48.33 | 10.72 | 19.53 | 0 | 51.28 | 27.89 |
| | PLBART | 72.41 | 47.12 | – | – | 70.31 | 53.79 | 76.19 | 45.75 | 64.06 | 21.47 | 46.21 | 7.22 | 65.23 | 35.67 |
| | CodeT5 | 78.52 | 59.81 | – | – | 75.98 | 60.61 | 83.14 | 70.66 | 63.54 | 64.67 | **64.71** | 67.89 | 73.18 | 64.73 |
| | PPOCoder + CodeT5 | **79.14** | **82.80** | – | – | **76.65** | **92.14** | **85.66** | **86.80** | **64.16** | **90.88** | 60.52 | **82.16** | **73.22** | **86.95** |
| **Python** | Naive Copy | 37.41 | 21.47 | 39.72 | 17.27 | – | – | 38.52 | 10.71 | 43.91 | 16.84 | 35.11 | 0 | 38.93 | 13.26 |
| | CodeBERT | 68.93 | 42.15 | 45.76 | 38.10 | – | – | 40.23 | 26.10 | 52.12 | 31.74 | 18.32 | 0 | 45.07 | 27.62 |
| | PLBART | 74.49 | 61.20 | 63.82 | 54.59 | – | – | 67.35 | 44.65 | 69.86 | 66.76 | 39.15 | 6.12 | 62.93 | 46.66 |
| | CodeT5 | 79.86 | 74.11 | 74.15 | 62.74 | – | – | 75.54 | 58.26 | **79.83** | 80.05 | **56.83** | 70.81 | **73.24** | 69.19 |
| | PPOCoder + CodeT5 | **80.34** | **88.72** | **75.12** | **92.70** | – | – | **76.09** | **83.33** | 79.65 | **93.51** | 52.15 | **95.80** | 72.67 | **90.81** |
| **C#** | Naive Copy | 44.51 | 10.74 | 71.61 | 13.14 | 40.09 | 0 | – | – | 37.79 | 2.41 | 60.17 | 4.52 | 50.83 | 6.16 |
| | CodeBERT | 74.51 | 18.02 | 81.25 | 27.88 | 50.83 | 3.75 | – | – | 58.64 | 6.85 | 22.93 | 0 | 57.63 | 11.30 |
| | PLBART | 78.38 | 36.25 | 80.73 | 57.19 | 69.43 | 6.65 | – | – | 70.12 | 48.40 | 54.36 | 8.00 | 70.61 | 31.29 |
| | CodeT5 | 81.49 | 53.87 | 84.78 | 69.73 | **71.23** | 56.81 | – | – | 71.46 | 75.12 | 67.53 | 62.00 | 75.29 | 63.51 |
| | PPOCoder + CodeT5 | **82.94** | **68.51** | **85.77** | **81.92** | 70.43 | **78.61** | – | – | **72.06** | **82.62** | **68.11** | **71.90** | **75.86** | **76.71** |
| **PHP** | Naive Copy | 26.33 | 6.12 | 25.61 | 10.23 | 34.66 | 16.10 | 26.87 | 6.41 | – | – | 35.95 | 0 | 29.88 | 7.77 |
| | CodeBERT | 50.26 | 11.62 | 46.81 | 13.48 | 56.72 | 32.86 | 50.43 | 13.21 | – | – | 28.45 | 2.20 | 46.53 | 14.67 |
| | PLBART | 74.43 | 80.47 | 70.22 | 61.96 | 75.21 | **86.50** | 69.17 | 75.32 | – | – | 56.23 | 0 | 69.05 | 60.85 |
| | CodeT5 | 83.43 | 84.80 | 80.09 | 84.12 | **85.62** | 78.12 | 81.79 | 83.20 | – | – | **65.14** | 61.52 | 79.21 | 78.35 |
| | PPOCoder + CodeT5 | **85.55** | **89.50** | **82.12** | **90.31** | 83.26 | 82.52 | **83.88** | **89.80** | – | – | 65.01 | **76.92** | **79.96** | **85.81** |
| **C** | Naive Copy | 66.41 | 10.71 | 59.12 | 0 | 40.27 | 0 | 59.83 | 2.10 | 43.54 | 0 | – | – | 53.83 | 2.56 |
| | CodeBERT | 22.72 | 6.80 | 21.19 | 0 | 21.34 | 0 | 31.52 | 3.50 | 21.71 | 0 | – | – | 23.69 | 12.06 |
| | PLBART | 68.45 | 25.52 | 38.56 | 24.10 | 34.53 | 6.12 | 49.51 | 26.08 | 45.17 | 0 | – | – | 47.24 | 16.36 |
| | CodeT5 | 79.18 | **46.40** | 74.12 | 42.80 | **66.31** | 44.60 | **73.21** | 41.32 | 64.28 | 38.42 | | – | **71.42** | 42.71 |
| | PPOCoder + CodeT5 | **82.17** | **46.40** | **74.30** | **53.52** | 62.15 | **50.14** | 71.09 | **51.72** | **64.37** | **42.32** | – | – | 70.92 | **48.82** |

### 4.3 Program Synthesis

In this task, we use the APPS (Hendrycks et al., 2021) dataset comprising 10k coding problems of varying difficulty levels, split 50/50 for train/test sets. The dataset consists of Introductory, Interview, and Competition level problems with respective train/test samples of 2639/1000, 2000/3000, and 361/1000. Each problem has 23 Python solutions and 21 unit tests on average. To evaluate the generated codes, we employ the *pass@k* metric (Chen et al., 2021a) which calculates the percentage of problems for which all unit tests are passed using $k$ synthetically generated programs per problem. Since unit tests are provided in APPS, we use them in the PPOCoder's reward (as defined in Eq. 9).

Table 3 demonstrates the results of program synthesis on the APPS dataset along with other baselines reported in (Hendrycks et al., 2021) including GPT-2 (Radford et al., 2019), GPT-3 (Brown et al., 2020), GPT-Neo (Black et al.), Codex (Chen et al., 2021a), AlphaCode (Li et al., 2022) and CodeRL (Le et al., 2022). The reported results for various models are post-fine-tuning on APPS, except for GPT-3 and Codex. For the experimental setup details of all methods, please refer to Appendix A. The results indicate that the smaller encoder-decoder architecture of CodeT5 outperforms larger models, and PPOCoder with CodeT5 further improves performance, surpassing even larger pre-trained LMs such as GPTs. As demonstrated in Table 3, PPOCoder +CodeT5 exhibits comparable or even superior *pass@k* performance than CodeRL+CodeT5, another RL-based fine-tuning mechanism specifically designed for program synthesis.
To further evaluate the generalizability of these models, the zero-shot performance of the APPS fine-tuned models was examined on the MBPP (Austin et al., 2021) program synthesis benchmark, which is a collection

of 974 short (one sentence) problems, each including 1 correct Python solution and 3 corresponding unit tests. Table 4 shows the results of program synthesis on the MBPP benchmark. Both RL-based methods, PPOCoder +CodeT5 and CodeRL+CodeT5, fine-tuned on APPS, exhibit remarkable zero-shot performance on MBPP with a *pass@k* of 63% and 68%, respectively, surpassing even the largest GPT-137B's performance of 61.4%. As observed in Table 4, the proposed PPOCoder +CodeT5 outperforms CodeRL+CodeT5 on MBPP by a significant margin of 5.2%. This can be attributed to two factors. Firstly, CodeRL integrates the supervised cross-entropy loss to the RL policy gradient objective to maintain consistency in performance and prevent deviation from the pre-trained model distribution. However, over-optimization of the supervised cross-entropy on synthetic data increases the chance of memorization on the APPS training data and leads to inferior performance on unseen data. PPOCoder regulates deviation by employing the KL-divergence penalty for generation instead of the supervised cross-entropy loss. This can reduce the likelihood of memorization, resulting in improved generalizability on the unseen MBPP benchmark. Secondly, CodeRL utilizes the actor-critic algorithm with REINFORCE reward policy gradient objective, while PPOCoder employs the PPO algorithm with actor-critic advantage policy gradient objective, and a trust region mechanism to ensure minimal deviation from the previous policy. This leads to a more stable and generalizable model optimization for new environments (tasks or datasets).

Table 3: Results of the program synthesis task on the APPS dataset.

| | | *pass@1* | | | | *pass@5* | | | | *pass@1000* | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Model | Size | Intro | Inter | Comp | All | Intro | Inter | Comp | All | Intro | Inter | Comp | All |
| Codex | 12B | 4.14 | 0.14 | 0.02 | 0.92 | 9.65 | 0.51 | O.09 | 2.25 | 25.02 | 3.70 | 3.23 | 7.87 |
| AlphaCode | 1B | – | – | – | – | – | – | – | – | 17.67 | 5.24 | 7.06 | 8.09 |
| GPT-3 | 175B | 0.20 | 0.03 | 0.00 | 0.06 | – | – | – | – | – | – | – | – |
| GPT-2 | 0.1B | 1.00 | 0.33 | 0.00 | 0.40 | 2.70 | 0.73 | 0.00 | 1.02 | – | – | – | – |
| GPT-2 | 1.5B | 1.30 | 0.70 | 0.00 | 0.68 | 3.60 | 1.03 | 0.00 | 1.34 | 25.00 | 9.27 | 8.80 | 12.32 |
| GPT-Neo | 2.7B | 3.90 | 0.57 | 0.00 | 1.12 | 5.50 | 0.80 | 0.00 | 1.58 | 27.90 | 9.83 | 11.40 | 13.76 |
| CodeT5 | 60M | 1.40 | 0.67 | 0.00 | 0.68 | 2.60 | 0.87 | 0.10 | 1.06 | – | – | – | – |
| CodeT5 | 220M | 2.50 | 0.73 | 0.00 | 0.94 | 3.30 | 1.10 | 0.10 | 1.34 | – | – | – | – |
| CodeT5 | 770M | 3.60 | 0.90 | 0.20 | 1.30 | 4.30 | 1.37 | 0.20 | 1.72 | – | – | – | – |
| CodeRL+CodeT5 | 770M | 4.90 | **1.06** | **0.5** | 1.71 | 8.60 | **2.64** | 1.0 | 3.51 | **36.10** | 12.65 | 13.48 | 17.50 |
| PPOCoder +CodeT5 | 770M | **5.20** | 1.00 | **0.5** | **1.74** | **9.10** | 2.50 | **1.20** | **3.56** | 35.20 | **13.35** | **13.90** | **17.77** |

Table 4: Results of the zero-shot transferability on MBPP. Both zero-shot models are finetuned on APPS and evaluated on MBPP in the zero-shot setting.

| Model | Size | State | *pass@80* |
|---|---|---|---|
| GPT | 224M | fine-tuned | 7.2 |
| GPT | 422M | fine-tuned | 12.6 |
| GPT | 1B | fine-tuned | 22.4 |
| GPT | 4B | fine-tuned | 33.0 |
| GPT | 8B | fine-tuned | 40.6 |
| GPT | 68B | fine-tuned | 53.6 |
| GPT | 137B | fine-tuned | 61.4 |
| CodeT5 | 60M | fine-tuned | 19.2 |
| CodeT5 | 220M | fine-tuned | 24.0 |
| CodeT5 | 770M | fine-tuned | 32.4 |
| CodeRL+CodeT5 | 770M | zero-shot | 63.0 |
| PPOCoder +CodeT5 | 770M | zero-shot | **68.2** |

### 4.4 Ablation Study

To investigate the effect of different components of PPOCoder, we conduct ablation experiments with several variants of our model, including different reward terms, RL objective terms, action space size, and the number of synthetic samples. We take the Java-Python translation as a case study and present the results in Fig. 3. Please check Appendix C for more ablation experiments with other target PLs.

**Reward Elements.** Fig. 3(a) shows the effect of including different reward terms in the performance of PPOCoder. Models tested include CodeT5 without RL training, and with RL training utilizing different combinations of reward terms: ***cs*** (compiler feedback), ***kl*** (KL-divergence penalty), ***dfg*** (semantic matching

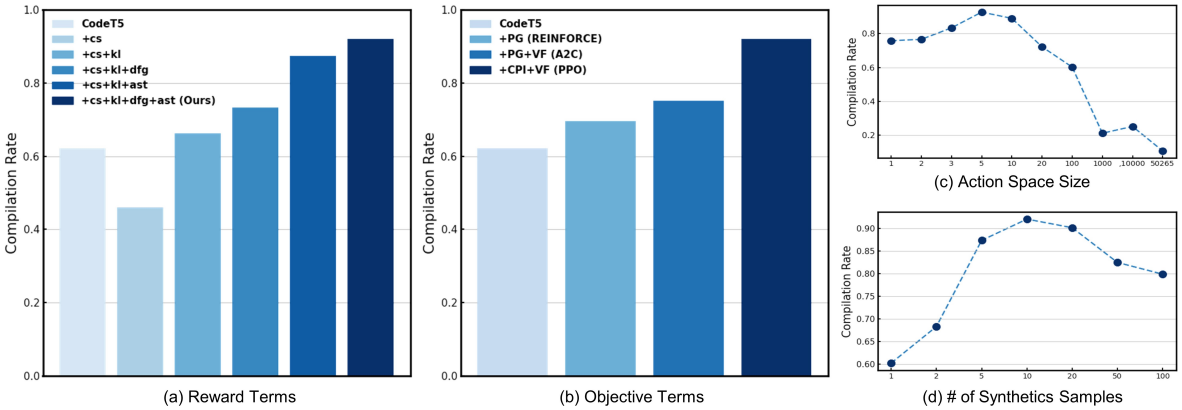


Figure 3: Ablation experiment results on Java-Python translation with different configurations of (a) reward, (b) loss, (c) action space size, and (d) number of synthetic samples.

score from DFGs), and ***ast*** (syntactic matching score from ASTs). Results show that the discrete compiler feedback alone is insufficient, however, integrating it with the KL-divergence penalty as well as the syntactic/semantic matching score boosts the compilation rate. The best performance is achieved by utilizing all four reward elements.

**Loss Elements.** Fig. 3(b) represents the results of PPOCoder with different objective configurations. We observe that the policy gradient objective alone (***+PG***), i.e., the REINFORCE algorithm, can boost the performance of the CodeT5 model. The compilation rate further improves by introducing the value function as critic (***+PG+VF***), i.e., A2C algorithm. Results show that the best performance is achieved by utilizing proximal conservative policy iteration with value optimization (***+CPI+VF***), indicating that the PPO algorithm performs superior to others on code generation.

**Action Space Size.** We examine the effectiveness of action space size on PPOCoder's performance by adjusting the $k$ parameter in the $top-k$ policy synthetic sampling. Fig. 3(c) shows that when $k = 1$, PPOCoder may not be able to have enough exploration for the better possible policy updates. On the other hand, when $k$ gets too large, PPOCoder may become overwhelmed by many different possible actions and struggle to learn the optimal policy, leading to degraded performance. Therefore, results reveal that a small value of $k$ ($k = 1$) may not provide sufficient exploration, while a large value ($k = 50265$ (vocab size) ) can hinder the learning of optimal policy. In the code generation experiments, we usually use the action space size 5 which provides a good balance for optimal exploration in most cases.

**No. of Synthetic Samples.** The effect of synthetic policy sample size on PPOCoder's performance is examined by modifying the *num_samples* in Alg. 1. Fig. 3(d) shows that an increase in *num_samples* from 1 to 10 improves performance, but further increases lead to a slight decline in performance. This suggests that while additional synthetic samples can enhance the ability to identify underlying patterns, a large number of synthetic samples may not be representative of the general population and can negatively impact performance by causing confusion in model updates.

## 5 Conclusion

We develop a PPO-based deep reinforcement learning framework for improving the quality of code generated by PL models. We identified some limitations of traditional objective functions for code generation tasks and designed a new learning objective that is geared towards PLs as opposed to natural language. We incorporated compiler feedback and unit tests along with syntactic and semantic related qualitative feedback (in the form of abstract syntax trees and dataflow graphs) into our RL framework to encourage the model to generate more syntactically and logically correct code. Results of experiments show the effectiveness of our method compared to baselines in improving the syntactic/functional correctness of the generated codes. The ablation experiments also show the impact of different PPOCoder's components in the performance.

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# Appendix

## A Additional Experimental Setup Details

In all our experiments, we employ batch size of 32, AdamW optimizer with a weight decay of 0.05, and a learning rate that warms up from $1e-7$ to $2e-5$ over the first 1000 steps, then decays based on the inverse square root of the number of steps, as outlined in (Loshchilov & Hutter, 2019). We use the `tree-sitter` parsing library [3] to identify AST sub-trees for code written in different languages. To construct the dataflow graph (DFG), we first identify variables by using the leaves of the AST, and then create directed edges between the variables based on their relations. All of our experiments are implemented with PyTorch and trained using 4 Quadro RTX 8000 GPUs, with 48GB of RAM.

### A.1 Code Completion

We conduct code completion experiments on the CSN dataset with Python programs. For Python compilation, we adopt `py_compile` [4] library. The BiLSTM baseline is the Seq2Seq Bi-directional LSTM model taken with the default settings used in (Luong et al., 2015). The transformer baseline is a 6-layer transformer decoder as used in (Vaswani et al., 2017). BiLSTM and transformer baselines are not pretrained and will be trained from the random initialization on this task. GPT-2 baseline (Radford et al., 2019) is a decoder-only transformer and is pretrained on a large-scale text corpus. CodeGPT (Lu et al., 2021) and CodeT5 (Wang et al., 2021) baselines are both pretrained on a large-scale code corpus with the default GPT-2 (decoder-only) and T5 (encoder-decoder) architectures. The pretrained CodeGPT and CodeT5 models are also finetuned on this task, and the PPOCoder +CodeT5 is initialized from the finetuned CodeT5. PPOCoder is implemented with the discount rate $\gamma = 1$, KL divergence penalty coefficient $\beta = 0.1$, policy ratio clip range $\epsilon = 0.2$ and the value error coefficient $\alpha = 0.001$. To sample synthetic hypothesis from the stochastic policy, we use the *top-k* sampling with $k = 5$ as the action space size. We are training PPOCoder +CodeT5 with *num_samples* $= 3$ as the number of synthetic samples generated for each sample of the CSN dataset. Therefore, PPOCoder observes 40K×3=120K input-output sample pairs during RL optimization for this task. In all code completion experiments on CSN, we set the maximum source and target sequence length as 400, and the maximum number of epochs as 6.

### A.2 Code Translation

We conduct code translation experiments on the XLCoST dataset with programs in six parallel PLs (C++, Java, Python, C#, PHP, and C). For testing Python compilation, we use the `py_compile` module that comes built-in with Python version 3.8.0. For Java compilation, we use the `javac` compiler, version 1.8.0. We use `gcc` version 7.5.0 for C and C++ compilations. Syntax checking for PHP is performed using the `php -l` command, PHP version 7.2.24. C# compilation is also checked using the Mono C# compiler, version 4.6.2.0. In the code translation experiments, CodeBERT baseline is an encoder-only pretrained transformer model. PLBART and CodeT5 are encoder-decoder pretrained transformer models. All these models (i.e., CodeBERT, PLBART, and CodeT5) are first pretrained on a large-scale code corpus and then finetuned on XLCoST for the code translation task of each language pair. Also, in PPOCoder +CodeT5, the policy network in each language-pair translation is initialized from a CodeT5 model finetuned on that language-pair. In the implementation of PPOCoder, we use discount rate $\gamma = 1$, KL divergence penalty coefficient $\beta = 0.01$, policy ratio clip range $\epsilon = 0.2$ and the value error coefficient $\alpha = 0.01$. To sample from the stochastic policy, we use the *top-k* sampling with $k = 5$ as the action space size. Also, we train PPOCoder +CodeT5 with *num_samples* as 100 for low-resource experiments with $C$ as the source/target language; 20

[3] https://github.com/tree-sitter/tree-sitter

[4] https://docs.python.org/id/3.6/library/py_compile.html

for experiments with PHP as source/target language; and 10 for other translation experiments. For example, for each source code $x$ in Java-Python translation, we generate 10 synthetic samples based on the policy, thus, $4,811 \times 10 = 48,110$ (based on Table 6) input-output pairs are used in total to train PPOCoder for the Java-Python translation. We also set the maximum number of epochs as 15, and the maximum source and target sequence lengths to 400 for all code translation tasks on XLCoST.

### A.3 Program Synthesis

We conduct program synthesis experiments on the APPS dataset with the pair of NL problem descriptions and Python programs in three difficulty levels: Introductory, Interview, and Competition. In the program synthesis experiments, GPT-3 and Codex baselines are tested on the APPS dataset in the few-shot settings without finetuning, while other baselines are finetuned on the APPS with the cross entropy loss. The PPOCoder +CodeT5 is also initialized from the finetuned CodeT5 on the APPS program synthesis. We use the *pass@k* metric to evaluate the functional correctness of a program, where a code is considered correct if it successfully passes all unit tests designed for the specific problem. In the PPOCoder's implementation, we use discount rate $\gamma = 1$, KL divergence penalty coefficient $\beta = 0.05$, policy ratio clip range $\epsilon = 0.2$, and the value error coefficient $\alpha = 0.001$. To sample synthetic hypothesis from the stochastic policy, we use the *top-k* sampling with $k = 5$ as the action space size. We are training PPOCoder +CodeT5 with $num_samples = 5$ as the number of synthetic samples used for each APPS problem. In all the program synthesis experiments on APPS, we set the maximum source and target sequence lengths as 600 and 512, and the maximum number of epochs as 8. We have also evaluated performance of PPOCoder on the MBPP dataset in a zero-shot setting. We compared the zero-shot performance with GPT and CodeT5 models finetuned on MBPP for 60 epochs with maximum source and target sequence lengths of 400.

## B Additional XLCoST Dataset Details

We are using the XLCoST [5] (Zhu et al., 2022a) dataset for code translation experiments with different language pairs among six parallel PLs (C++, Java, Python, C#, PHP, and C). XLCoST has been created by scraping solutions off the popular programming tutorial and interview preparation website GeeksforGeeks[6]. This kind of multilingual parallel data is perfect for training translation models. The dataset statistics are provided in Table 5. This dataset is parallel at both program snippet and full program levels. The upper triangle of Table 5 summarizes snippet-level statistics, and the lower triangle summarizes the program-level statistics. For the purpose of our experiments in the evaluation of syntactic/functional correctness, we only use program-level data. It is noteworthy that all programs in this dataset do not successfully compile. Therefore, in our experiments, we only use the compilable filtered parallel data in both source and target language pairs. Our hypothesis is that using ground truth data that is free of compilation errors will provide a stronger signal to PPOCoder for correcting syntactic errors than using the full data, which could also contain flawed programs. To do so, we designed an automated compilation pipeline that evaluates which programs in the dataset compile without any errors. Table 6 shows statistics of the compilable filtered dataset for all languages (except JavaScript which is excluded due to the lack of compilation).

## C Additional Ablation Experimetns

Fig. 4 shows the results of additional ablation experiments on the Python-C# translation task for different reward terms, RL objective terms, action space size, and the number of synthetic samples.

## D Case Studies

Fig. 5 shows an example of Java to C++ translation for both CodeT5 and PPOCoder +CodeT5. Similar to the previous case, it can be observed that the compilation is improved by PPOCoder. For this example, CodeT5's translation has these issues: (1) CodeT5 generates a non-standard data type called `subset` which takes in a pair of integers. The use of the non-standard data-type without importing it or defining it causes a compilation error, while PPOCoder +CodeT5 generates the C++ translation using the correct `vector` data-type corresponding to `ArrayList` in the source Java; (2) "Error: Local variable 'i' referenced before

[5] https://github.com/reddy-lab-code-research/XLCoST
[6] https://www.geeksforgeeks.org

Table 5: *XLCoST* dataset statistics. The upper triangle (in bold font) shows the number of parallel code snippets, and the lower triangle shows the number of parallel programs. **JS** is short for Javascript.)

| Lang | | C++ | Java | Py | C# | JS | PHP | C |
|---|---|---|---|---|---|---|---|---|
| **C++** | train | – | **89040** | **80100** | **85662** | **69507** | **17811** | **3386** |
| | val | – | **4419** | **3913** | **4408** | **3808** | **923** | **352** |
| | test | – | **8059** | **7228** | **7922** | **6965** | **1647** | **222** |
| **Java** | train | 9450 | – | **77759** | **87065** | **69341** | **17853** | **2996** |
| | val | 490 | – | **3938** | **4437** | **3826** | **929** | **353** |
| | test | 901 | – | **7259** | **8011** | **7005** | **1672** | **238** |
| **Py** | train | 9139 | 8991 | – | **75843** | **67219** | **17616** | **2478** |
| | val | 468 | 471 | – | **3922** | **3750** | **923** | **311** |
| | test | 878 | 882 | – | **7215** | **6861** | **1655** | **203** |
| **C#** | train | 9187 | 9301 | 8826 | – | **68093** | **17873** | **2958** |
| | val | 488 | 491 | 470 | – | **3826** | **928** | **352** |
| | test | 890 | 898 | 877 | – | **6961** | **1668** | **238** |
| **JS** | train | 8482 | 8470 | 8182 | 8367 | – | **17117** | **1875** |
| | val | 472 | 475 | 459 | 475 | – | **921** | **309** |
| | test | 878 | 881 | 864 | 877 | – | **1617** | **200** |
| **PHP** | train | 3056 | 3068 | 3003 | 3071 | 2971 | – | **856** |
| | val | 157 | 158 | 153 | 158 | 157 | – | **271** |
| | test | 303 | 307 | 304 | 307 | 302 | – | **183** |
| **C** | train | 402 | 409 | 380 | 394 | 308 | 170 | – |
| | val | 59 | 59 | 59 | 59 | 59 | 55 | – |
| | test | 45 | 49 | 48 | 49 | 49 | 43 | – |

Table 6: *XLCoST* dataset statistics after filtering for compilable programs. Javascript is excluded.

| Lang | | C++ | Java | Python | C# | PHP | C |
|---|---|---|---|---|---|---|---|
| **C++** | train | – | – | – | – | – | – |
| | val | – | – | – | – | – | – |
| | test | – | – | – | – | – | – |
| **Java** | train | 5251 | – | – | – | – | – |
| | val | 266 | – | – | – | – | – |
| | test | 520 | – | – | – | – | – |
| **Python** | train | 5325 | 4811 | – | – | – | – |
| | val | 266 | 250 | – | – | – | – |
| | test | 529 | 496 | – | – | – | – |
| **C#** | train | 5464 | 5081 | 5027 | – | – | – |
| | val | 279 | 262 | 259 | – | – | – |
| | test | 553 | 513 | 529 | – | – | – |
| **PHP** | train | 1758 | 1595 | 1785 | 1764 | – | – |
| | val | 91 | 85 | 93 | 92 | – | – |
| | test | 192 | 176 | 201 | 197 | – | – |
| **C** | train | 233 | 191 | 169 | 204 | 92 | – |
| | val | 34 | 34 | 32 | 34 | 33 | – |
| | test | 28 | 28 | 24 | 29 | 26 | – |

assignment": for loop index is “j” but “i” is used later; and (3) "Error: Invalid Syntax" for missing "(" when calling the function.

Fig. 6 presents a case study of PHP to Python translation for both CodeT5 and PPOCoder +CodeT5 models. We can observe that CodeT5 is unable to translate the code without compilation errors, and the use of PPOCoder enhances CodeT5's capability of generating compilable code in the target language while preserving the code fluency and distributions learned by the pretrained CodeT5. For this example, CodeT5 faces some problems: (1) “Error: Invalid Syntax": The “for” loop should start from next line ; (2) “Error: Local variable 'i' referenced before assignment." The for loop index is “j” but index "i" is called in the for loop; and (3) Semantic Relations: The equivalent of PHP_INT_MAX may be 1000 (or `sys.maxsize`) in Python but CodeT5 translates it to `int(n/2)` which is wrong.

We also looked into an example of program synthesis from APPS. Fig. 7 illustrates a case study of Python program synthesis for a problem description given in NL. Although both CodeT5 and PPOCoder +CodeT5 generate compilable programs, CodeT5's generation cannot pass some hidden unit tests that capture different corners of the problem. These two generated codes are different in the highlighted places. As we can see, the CodeT5's generation (1) initializes the 2D array ‘dp’ with ones on both dimensions instead of zeros on

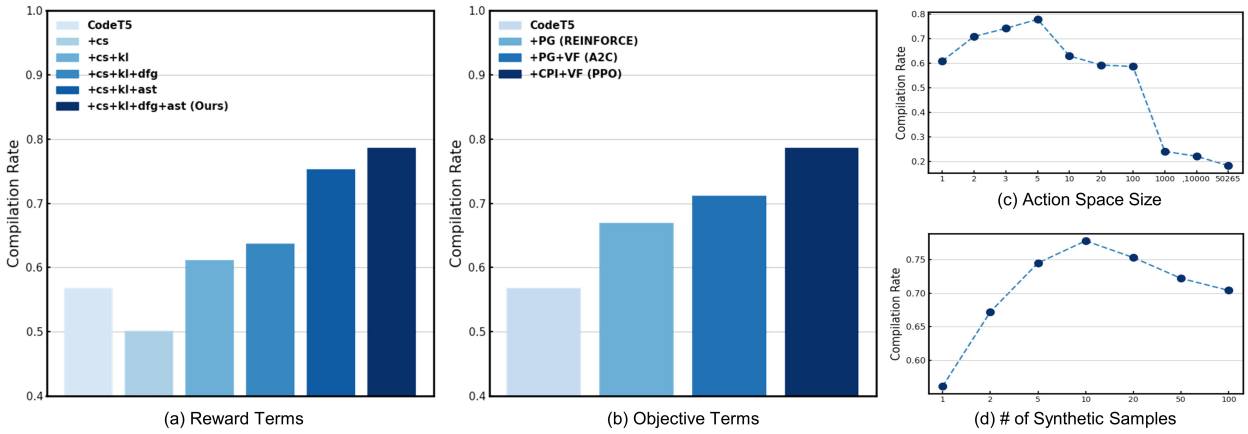


Figure 4: Ablation experiment results on Python-C# translation with different configurations of (a) reward, and (b) loss, (c) action space size, and (d) number of synthetic samples.

one dimension; and (2) the for loop inside the nested loop uses the condition $k >= j$ instead of the correct condition $k <= j$. Although these differences do not produce any compilation errors, they result in logical errors and cause unit tests to fail.

**Source (Java)**

```
import java . util . * ;
class GFG {
  static void printVector ( ArrayList < Integer > arr ) {
    if ( arr . size ( ) != 1 ) {
      for ( int i = 0 ;      i < arr . size ( ) ;      i ++ ) {
        System . out . print ( arr . get ( i ) + " " ) ;
      }
      System . out . println ( ) ;
    }
  }
  static void findWays ( ArrayList < Integer > arr , int i , int n ) {
    if ( n == 0 ) printVector ( arr ) ;
    for ( int j = i ;    j <= n ;    j ++ ) {
      arr . add ( j ) ;
      findWays ( arr , j , n - j ) ;
      arr . remove ( arr . size ( ) - 1 ) ;
    }
  }
  public static void main ( String [ ] args ) {
    int n = 4 ;
    ArrayList < Integer > arr = new ArrayList < Integer > ( ) ;
    findWays ( arr , 1 , n ) ;
  }
}
```

**Generated (C++)**

**CodeT5**

```
#include <bits/stdc++.h>
using namespace std ;
void printVector (subset < int , int > arr) {
  if ( arr . size ( ) != 1 ) {
    for ( int i = 0 ;   i < arr . size ( ) ;   i ++ ) {
      cout << arr [ i ] << "_" ;
    }
    cout << endl ;
  }
}
void findWays ( vector < int > & arr , int i , int n ) {
  if ( n == 0 ) printVector ( arr ) ;
  for ( int j = i ;  j <= n ;  j ++ ) {
    arr . push_back ( i ) ;
    findWays ( arr , i , n - i ) ;
    arr . pop_back ( ) ;
  }
}
int main ( ) {
  int n = 4 ;
  vector < int > arr ;
  findWays arr , 1 , n ) ;
}
```

(1) (2) (3)

Compilation? ✗

**PPOCoder+CodeT5**

```
#include <bits/stdc++.h>
using namespace std ;
void printVector (vector < int > arr) {
  if ( arr . size ( ) != 1 ) {
    for ( int i = 0 ;   i < arr . size ( ) ;   i ++ ) {
      cout << arr [ i ] << "_" ;
    }
    cout << endl ;
  }
}

void findWays ( vector < int > arr , int i , int n ) {
  if ( n == 0 ) printVector ( arr ) ;
  for ( int j = i ;  j <= n ;  j ++ ) {
    arr . push_back ( j ) ;
    findWays ( arr , j , n - j ) ;
    arr . pop_back ( ) ;
  }
}
int main ( ) {
  int n = 4 ;
  vector < int > arr ;
  findWays ( arr , 1 , n ) ;
}
```

Compilation? ✓

Figure 5: Case study example for Java-C++ code translation. The erroneous snippets are highlighted in red.

**Source (PHP)**

```
function MatrixChainOrder ( $ p , $ n ) {
    $ m [ ] [ ] = array ( $ n , $ n ) ;
    for ( $ i = 1 ; $ i < $ n ; $ i ++ )
        $ m [ $ i ] [ $ i ] = 0 ;
    for ( $ L = 2 ; $ L < $ n ; $ L ++ ) {
        for ( $ i = 1 ; $ i < $ n - $ L + 1 ; $ i ++ ) {
            $ j = $ i + $ L - 1 ;
            if ( $ j == $ n ) continue ;
            $ m [ $ i ] [ $ j ] = PHP_INT_MAX ;
            for ( $ k = $ i ; $ k <= $ j - 1 ; $ k ++ ) {
                $ q = $ m [ $ i ] [ $ k ] + $ m [ $ k + 1 ] [ $ j ] + $ p [ $ i - 1 ] * $ p [ $ k ] * $ p [ $ j ] ;
                if ( $ q < $ m [ $ i ] [ $ j ] ) $ m [ $ i ] [ $ j ] = $ q ;   } }  }
    return $ m [ 1 ] [ $ n - 1 ] ; }
$ arr = array ( 1 , 2 , 3 , 4 ) ;
$ size = sizeof ( $ arr ) ;
printf("Minimum number of multiplications is %d ", MatrixChainOrder($arr, $size));
```

**Generated (Python)**

**CodeT5**

```
def MatrixChainOrder ( p , n ) :
    m = [ [ 0 ] * n for k in range ( n + 1 ) [ for j ] in range ( 1 , n ) :
        m [ i ] [ i ] = 0
    for L in range ( 2 , n ) :
        for i in range ( 1 , n - L + 1 ) :
            j = i + L - 1
            if ( j == n ) :
                continue
            m [ i ] [ j ] = int ( n / 2 )
            for k in range ( i , j + 1 ) :
                q = ( m [ i ] [ k ] + m [ k + 1 ] [ j ] + p [ i - 1 ] * p [ k ] * p [ j ] )
                if ( q < m [ i ] [ j ] ) :
                    m [ i ] [ j ] = q
    return m [ 1 ] [ n - 1 ]
if __name__ == "__main__" :
    arr = [ 1 , 2 , 3 , 4 ]
    size = len ( arr )
    print ( "Minimum_number_of_multiplications_is" ,
MatrixChainOrder ( arr , size ) )
```

(1) (2) (3)

Compilation? ✗

**PPOCoder+CodeT5**

```
def MatrixChainOrder ( p , n ) :
    m = [ [ 0 for i in range ( n ) ] for j in range (n+1) ]
    for i in range ( 1 , n) :
        m [ i ] [ i ] = 0
    for L in range ( 2 , n ) :
        for i in range ( 1 , n - L + 1 ) :
            j = i + L - 1
            if ( j == n ) :
                continue
            m [ i ] [ j ] = 1000
            for k in range ( i , j + 1 ) :
                q = m [ i ] [ k ] + m [ k + 1 ] [ j ] + p [ i - 1 ] * p [ k ] * p [ j ]
                if ( q < m [ i ] [ j ] ) :
                    m [ i ] [ j ] = q
    return m [ 1 ] [ n - 1 ]
arr = [ 1 , 2 , 3 , 4 ]
size = len ( arr )
print( "Minimum_number_of_multiplications_is" , MatrixChainOrder (
arr , size ) )
```

Compilation? ✓

Figure 6: Case study example for PHP-Python code translation. The erroneous snippets are highlighted in red.

**Source (NL)**

You are given two integers n and m. Calculate the number of pairs of arrays (a, b) such that: the length of both arrays is equal to m; each element of each array is an integer between 1 and n (inclusive); ai ≤ bi for any index i from 1 to m; array a is sorted in non-descending order; array b is sorted in non ascending order. As the result can be very large, you should print it modulo 109 + 7.

**Input:** The only line contains two integers n and m (1 ≤ n ≤ 1000, 1 ≤ m ≤ 10).

**Output:** Print one integer – the number of arrays a and b satisfying the conditions described above modulo 109 + 7

**Generated (Python)**

**CodeT5**

```
MOD = 10**9 + 7

def solve(n, m):                                  (1)
    dp = [[1] * (n + 1) for _ in range(m + 1)]
    for i in range(2, m + 1):
        for j in range(1, n + 1):
            for k in range(j+1, n+1):             (2)
                dp[i][j] = (dp[i][j] + dp[i - 1][k]) % MOD
    ans = 0
    for i in range(1, n + 1):
        ans = (ans + dp[m][i]) % MOD
    return ans

n,m = map(int,input().split())
print(solve(n,m))
```

Pass Tests? ✗

**PPOCoder+CodeT5**

```
MOD = 10**9 + 7

def solve(n, m):
    dp = [[0] * (n + 1) for _ in range(m + 1)]
    for i in range(1, n + 1):
        dp[1][i] = 1
    for i in range(2, m + 1):
        for j in range(1, n + 1):
            for k in range(1, j + 1):
                dp[i][j] = (dp[i][j] + dp[i - 1][k]) % MOD
    ans = 0
    for i in range(1, n + 1):
        ans = (ans + dp[m][i]) % MOD
    return ans

n,m = map(int,input().split())
print(solve(n,m))
```

Pass Tests? ✓

Figure 7: Case study example of APPS for Program Synthesis (NL2Code). The problematic snippets are highlighted in red.