Energy-Based Models for Code Generation under Compilability Constraints

Tomasz Korbak, Hady Elsahar, Marc Dymetman, Germán Kruszewski

Abstract

Neural language models can be successfully trained on source code, leading to applications such as code completion. However, their versatile autoregressive self-supervision objective overlooks important global sequence-level features that are present in the data such as syntactic correctness or compilability. In this work, we pose the problem of learning to generate compilable code as constraint satisfaction. We define an Energy-Based Model (EBM) representing a pre-trained generative model with an imposed constraint of generating only compilable sequences. We then use the KL-Adaptive Distributional Policy Gradient algorithm (Khalifa et al., 2021) to train a generative model approximating the EBM. We conduct experiments showing that our proposed approach is able to improve compilability rates without sacrificing diversity and complexity of the generated samples.

1 Introduction

Code completion is an essential feature of any modern Integrated Development Environment (IDEs). It supports developers with recommendations about the next token to write given a context, speeding up software development and reducing the number of mistakes. A large body of work has relied on statistical language modeling, treating programming languages as natural languages using probabilistic grammars (Raychev et al., 2014; Bielik et al., 2016), and more recently relying on neural language models (Liu et al., 2016a; Svyatkovskiy et al., 2020a,b; Arkesteijn et al., 2020; Ciniselli et al., 2021). In particular, neural autoregressive language models have been favoured due to their scalability and generic training procedure that can exploit large codebases (e.g. open source code repositories available on GitHub) through self-supervised training.

Despite these desirable traits, neural language models, trained in the standard way, are known to suffer from myopia and to overlook global sequence-level features that are present in the data and which might be crucial for the quality of generated sequences (Parshakova et al., 2019b). This leads to repetitions, hallucinations and failing to capture long-distance consistency requirements. In a code generation context, this is demonstrated in compilation errors that are a common failure mode in such tasks as translation between programming languages (Roziere et al., 2020). This problem has inspired a large body of work on different fronts on injecting sequence-level priors by either directly optimizing sequence-level features (Ranzato et al., 2016) or through fusion with grammars and automata (Xiao et al., 2016). These techniques aim to balance between the desirable traits and fast inference of neural autoregressive models trained in the standard way and the satisfaction of global sequence-level features.

In this work, we formulate compilable code generation as a constraint satisfaction problem. We show that this formulation leads to a unique distribution represented by an Energy-Based Model (EBM). This unique distribution by definition fully satisfies the compilability constraints while having a minimal KL divergence from the original autoregressive generative model trained through cross entropy. We then train an auto-regressive generative model to approximate the underlying distribution of this EBM using the KL-Adaptive Distributional
Policy Gradient algorithm (Khalifa et al., 2021).

In our experiments, we show that our approach significantly improves compilability rates without sacrificing diversity or complexity of the generated examples. This alleviates the drawbacks of reinforcement learning fine-tuning techniques that maximize compilability but deviate significantly from the original generative model, which leads to severe loss in diversity and complexity of the generated samples. Finally, we complement our experiments with a qualitative analysis of the effect of several fine-tuning approaches on the distribution of compilation errors.

2 Related Work

Imposing compilability constraints on generative models There is a body of work focusing on unconditional code generation or code completion: generating a piece of source code given a preceding piece of source code (Nguyen et al., 2013; Raychev et al., 2014; Karpathy et al., 2015; Bielik et al., 2016). That work, however, focuses on perplexity and similarity with respect to ground truth completions (in terms of exact-match accuracy, Levenshtein distance and ROUGE scores) (Svyatkovskiy et al., 2020a; Lu et al., 2021), usually failing to measure and control for compilability of generated sequences or semantic and syntactic constraints in general. On the other hand, semantic and syntactic constraints are frequently considered in language-to-code translation or program synthesis. For instance, Zhong et al. (2017), who used policy gradients to train a model for translating natural language questions to corresponding SQL queries and – in addition for rewarding for query execution results – added a penalty for syntactically invalid queries. Taking that one step further, Kulal et al. (2019) use compilation errors (with their precise location) to guide search over the space of possible programs.

Optimizing sequence-level rewards for text generation Most previous attempts at steering autoregressive model to conform to global constraints defined over entire sequence have employed reinforcement learning (RL). This includes using Reinforce (Williams, 1992a) for machine transla-

2One exception is the work of Maddison and Tarlow (2014), who augment neural probabilistic context free grammars with semantic constraints and use them for unconditional generation.

tion (Ranzato et al., 2016) or actor critic (Konda and Tsitsiklis, 2000) for abstractive summarization (Paulus et al., 2018), caption generation (Liu et al., 2016b), dialogue (Li et al., 2016b), and video captioning (Pasunuru and Bansal, 2017). Some approaches (for instance, in machine translation and summarization (Ranzato et al., 2016; Bahdanau et al., 2017)) directly optimize performance metrics such as BLEU and ROUGE at training time. Others use heuristic rewards (for instance Li et al. (2016b) for dialogue generation and Tambwekar et al. (2019) for story generation) in order to obtain certain a priori desirable features of generated sequences that then incentivize good performance on target metrics. A weakness of using RL in fine-tuning generative models is the problem of catastrophic forgetting: maximizing global, sequence-level rewards leads to very large deviations from the original autoregressive model trained through cross-entropy. This often results in significant reductions in fluency and diversity of generated samples. The catastrophic forgetting problem is sometimes addressed by imposing a penalty term to the rewards, such as the KL divergence between the trained policy and the auto-regressive model. This approach, termed “conservative fine-tuning”, was applied to generating melodies with music theory rewards and organic molecules with synthesizability rewards by Jaques et al. (2017) as well fine-tuning language models for controllable language generation by Ziegler et al. (2019). This solution doesn’t have an explicit notion of the optimal policy and often has hard time balancing between the reward term and the KL penalty term, leading to instability in training (Khalifa et al., 2021). Unlike this approach, our formulation defines the optimal distribution that satisfies both requirements.

Energy-based models for text Energy-based models (EBMs) (Hinton, 2002; LeCun et al., 2006; Ranzato et al., 2007) are a family of probabilistic graphical models in which learning and inference are done by associating an unnormalized probability with each configuration of observed and latent variables. Early examples of EBMs applied to natural language processing include sequence labeling problems (e.g. tagging) exploiting global properties of a sequence (Andor et al., 2016; Belanger and McCallum, 2016). A recent surge of interest in EBMs (Du and Mordatch, 2019) has not left text generation unaffected (see Bakhtin et al., 2020 for a survey). Tu et al. (2020) proposed an energy-
based inference networks for non-autoregressive machine translation. Parshakova et al. (2019b) and Deng et al. (2020) augment a autoregressive language models with an additional global factor to obtain a lower perplexity on the training data. Khalifa et al. (2021) develop a novel approach to distributional controllable text generation by constructing an EBM satisfying desired statistical constraints imposed on the set of generated sequences (such as topic or gender statistics over the sequences) and then train an autoregressive policy to approximate it, which can be sampled from efficiently.

We build on Khalifa et al.’s approach by applying it to a novel domain outside natural language and defining a new kind of constraint: compilability.

3 Method

Following Khalifa et al. (2021), we formulate compilable code generation as a constraint satisfaction problem over a space of generative models. There are two constraints that a target generative model \( p \) must satisfy. First, \( p \) must have minimal divergence -in the distribution space- from an original generative model \( a \) pre-trained using a standard autoregressive language modeling objective. Second, it must generate only sequences that satisfy a certain sequence level constraint \( b \). In our case, \( b(x) = 1 \) iff \( x \) is a syntactically correct Python program and \( b(x) = 0 \) otherwise. There two constraints can be represented as a product-of-experts (Hinton, 2002) energy-based model

\[
P(x) = a(x)b(x). \tag{1}
\]

\( p(x) \) can be obtained from \( P(x) \) by dividing it by a normalization constant \( Z \):

\[
p(x) = \frac{1}{Z} P(x), \tag{2}
\]

where

\[
Z = \sum_x P(x). \tag{3}
\]

This EBM \( P \) is unique, it represents a distribution \( p \) that optimally reconciles the two constraints. It is a special case of the generalized maximum entropy formulation presented in (Csiszár and Shields, 2004) for applying constraints over distributions.

However, one problem still remains: it is not straightforward how to draw samples \( x \sim p(x) \) or even evaluating probability \( p(x) \) from this optimal unique distribution. A simple method for drawing samples from the \( p \) distribution could be sampling sequences from \( a \) and filtering on \( b(x) \). While this method sounds simple, there’s no direct way of using it for interactive code completion as sampling full sequences till the end is necessary to filter through the sequence-level filter \( b(x) \). Therefore our objective here is to obtain another autoregressive policy \( \pi_\theta \) to directly approximate \( p \).

To attain this, Khalifa et al. (2021) (following Parshakova et al. (2019a)) developed a training procedure called KL-Adaptive Distributional Policy Gradients (KL-DPG) to train \( \pi_\theta \) to minimize the KL divergence between \( p \) and \( \pi_\theta \). The gradient of this KL turns out to be tractable:

\[
\nabla_\theta D_{KL}(p, \pi_\theta) = \nabla_\theta \mathbb{E}_{x \sim p} \log \frac{p(x)}{\pi_\theta(x)} \tag{4}
\]

\[
= -\nabla_\theta \mathbb{E}_{x \sim p} \log \pi_\theta(x) \tag{5}
\]

\[
= -\mathbb{E}_{x \sim p} \nabla_\theta \log \pi_\theta(x) \tag{6}
\]

\[
= -\frac{1}{Z} \sum_x P(x) \nabla_\theta \log \pi_\theta(x) \tag{7}
\]

Let us now absorb the constant \(-1/Z\) into a learning rate \( \alpha^{(\theta)} \) and estimate the expectation over \( p(x) \) using importance sampling (Owen, 2013) from yet another generative model \( q \):

\[
\nabla_\theta D_{KL}(p, \pi_\theta) \propto \mathbb{E}_{x \sim q} \frac{p(x)}{q(x)} \nabla_\theta \log \pi_\theta(x). \tag{8}
\]

During training, both \( \pi_\theta \) and \( q \) are initialized as \( a \). Then, \( q \) is periodically updated to \( \pi_\theta \) if \( \pi_\theta \) surpasses \( q \) in being closer to \( p \) (in terms of KL). For a pseudocode of the whole KL-DPG training procedure, see Algorithm 1.

The gradient in (8) is similar to an estimate obtained using policy gradients methods in standard reinforcement learning (Sutton et al., 1999) with \( P(x)/q(x) \) playing the role of a pseudoreward. This similarity, however, is superficial. Our objective is approximating a target generative model \( p \) by minimizing \( D_{KL}(p, \pi_\theta) \) rather than maximizing expected reward \( b(x) \) or \( P(x) \) or \( P(x)/q(x) \). As we show in Section 5, these objectives produce vastly different policies which diverge from \( p \) and catastrophically forget what the pretrained model \( a \) knew about its training domain. Furthermore, since \( q \) will always be close to \( \pi_\theta \), our pseudoreward \( P(x)/q(x) \) effectively depends on policy parameters \( \theta \).
We trained a byte-level BPE tokenizer \texttt{gpt2-small} with 117m parameters (Sennrich et al., 2016) with special BOS and EOS tokens to obtain a vocabulary of 50k tokens. The generation hyperparameters used for training \( \pi_0 \) and \( q \) using KL-DPG.

### 4 Experiments

#### 4.1 Setup

**Dataset:** To prepare the training dataset, we started from the Python150 dataset, which consists of 150k Python source code files obtained from GitHub (Raychev et al., 2016). Then, using the code from Roziere et al. (2020), we extracted 713k Python functions (both methods and standalone functions) from it (250 MB of raw text data). The additional filtering criteria were compilability (according to \( b(x) \)) and being less than 128 BPE tokens long. The dataset was then split into a training subset \( D_{\text{train}} \) and test subset \( D_{\text{test}} \).

**Initial generative model \( a \):** We implemented \( a \) using the GPT-2 (Radford et al., 2019) architecture with 117m parameters (\texttt{gpt2-small}) and kept all the original hyperparameters (see Table 1 in the Appendix). We trained a byte-level BPE tokenizer (Sennrich et al., 2016) with special BOS and EOS tokens to obtain a vocabulary of 50k tokens. The model was trained for one epoch.

**Compilability Scorer \( b \):** To check for compilability, we call the \texttt{compile}\_\texttt{command} function from \texttt{codeop} module of the Python Standard Library\(^3\) with a sequence \( x \) as argument and check if it returns a \texttt{code} object. We apply no post-processing other than removing BOS and EOS tokens. \texttt{codeop}\.\texttt{compile}\_\texttt{command} is the implementation that Python interactive interpreters use in read-eval-print loop (REPL) to determine whether a string is a valid Python code. The method tries to compile a string of Python code and raise and exception if there is a problem with the Python code, in particular a \texttt{SyntaxError} for invalid Python syntax and \texttt{ValueError} or \texttt{OverflowError} if there is an invalid literal.

This notion of compilability is concerned only with syntactic correctness and does not execute the body of a function. However, we found the initial compilability rate \( \mathbb{E}_{x \sim \pi_0} b(x) \) of functions \( x \) sampled from \( a(x) \) to be only 0.56, which leaves a large margin for improvement.\(^4\)

#### 4.2 Baselines

We compare our method to a common approach of using standard reinforcement learning to fine-tune a generative model to conform to desired constraints. We use the Reinforce algorithm (Williams, 1992b) which instead of minimizing divergence from the target distribution \( p \) tries to maximize expected reward \( \mathbb{E}_{\pi_0} R(x) \). We consider two kinds of reward \( R(x) \):

- \( R(x) = b(x) \), where the generative model is simply rewarded for generating sequences that compile;
- \( R(x) = P(x) \), where the generative model is simply rewarded proportionally to the score our EBM assigns to \( x \). Intuitively, this objective gives reward for both compilability and respecting the original generative model \( a \).

### 4.3 Evaluation Metrics

We evaluate KL-DPG and two baselines in terms of the following metrics:

1. \( \mathbb{E}_{x \sim \pi_0} b(x) \), compilability rate of sequences sampled from \( \pi_0(x) \),
2. \( D_{\text{KL}}(p, \pi_0) \), the forward KL divergence from the optimal distribution \( p \),
3. \( D_{\text{KL}}(\pi_0, a) \), the reverse KL divergence from the original pretrained generative model,
4. Distinct-1 score, a measure of text diversity in terms of the frequency of token repetitions in a sample \( x \), proposed in the context of NLP by (Li et al., 2016a),

\(^3\)https://docs.python.org/3/library/codeop.html

\(^4\)Note that initial compilability rate will be equal to our \( Z \) because \( \mathbb{E}_{x \sim a} b(x) = \sum_x a(x) b(x) = \sum_x P(x) = Z \).
5. Self-BLEU-5, a measure of text diversity across samples, proposed in the context of NLP by (Zhu et al., 2018).
6. Perplexity measured on $D_{test}$, a held-out subset of the data used for training $a$, calculated as
   $$\exp \left[ -\frac{1}{N} \sum_{x \in D_{test}} \log \pi_\theta(x) \right],$$
   where $N$ is the overall number of tokens in $D_{test}$.
7. Sequence length, the average number of characters in generated sequence $x$ after detokenization,
8. AST node count, the average number of nodes in an abstract syntax tree (AST) of sequences that compile. Samples are parsed to their corresponding ASTs using the `ast` module from Python Standard Library.\(^5\) Intuitively, this metric should indicate the logical (as opposed to surface) complexity of generated programs.
9. PEP8 error frequency, the average number of violations of PEP8, the style guide for Python,\(^6\) measured using pycodestyle,\(^7\) an off-the-shelf linter (static code analysis tool). We report the average number of errors per character to avoid confounding by sequence length.

While high compilability rate is the target, the remaining metrics control for various aspects of fluency, quality and diversity of generated samples. Most but not all of these aspects reduce to the constraint of staying close to $a$; for instance, it is possible for $\pi_\theta$ to actually outperform $a$ in matching the statistics of $a$’s own training distribution $p^a(x)$.

5 Results

We present the evolution of nine evaluation metrics as a function of gradient updates on Figures 1 and 2.

Reinforce with $R(x) = b(x)$ quickly improves compilability by a large margin but this improvement is mirrored by an equally large divergence from $p$ and $a$. This divergence translates into generating sequences much shorter (in terms of the number of characters) and logically simpler (in terms of the number of nodes in its AST) than an average sequence sampled from $a$. This heavily decreased sequence length (most of the generated functions are one-liners) seems to artificially increase diversity metrics (Self-BLEU-5 and Distinct-1).

Reinforce with $R(x) = P(x)$ doesn’t improve compilability rate until an inflection point after which it quickly reaches perfect compilability at a price of heavily diverging from both $a$ and (perhaps counterintuitively) $p$. The reason behind that, however, is that the policy heavily peaks around a single sequence that is compilable. To understand what causes this behavior, first note that the objective for Reinforce with $R(x) = P(x)$ is to maximize $E_{x \sim \pi_\theta}[a(x)\pi_\theta(x)]$. Because $R(x) = 0$ for uncompileable sequences, compilation rate will improve. But for compilable sequences, the effective reward is $R(x) = a(x)$ meaning that $\pi_\theta$ is rewarded most for generating the most probable sequences (according to $a(x)$), making them even more probable. Eventually, $E_{x \sim \pi_\theta} a(x)$ is maximized by a policy peaking on a single sample $x$ that was the most probable one according to $a(x)$. This failure mode is reflected in diversity metrics and perplexity. The sequence the policy peaks on is also shorter and less complex than an average sequence sampled from $a$.

KL-DPG is the only method that consistently improves compilability rate while decreasing divergence from $p$, maintaining the diversity of $a$ and only slightly decreasing sequence length and

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\(^5\)https://docs.python.org/3/library/ast.html
\(^6\)https://www.python.org/dev/peps/pep-0008/
\(^7\)https://github.com/PyCQA/pycodestyle

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Figure 1: Compilability rate $E_{x \sim \pi_\theta}[\pi_\theta(x)] \uparrow$ better) of samples from policies obtained from KL-DPG, and two baselines: Reinforce with reward $R(x) = b(x)$ and with reward $R(x) = P(x)$.
the number of nodes in ASTs. Moreover, as a by-product of improving compilability, KL-DPG is also able to slightly decrease the perplexity and the frequency of PEP8 violations per character. We conjecture the decrease in perplexity is because compilability provides a training signal enabling $\pi_\theta$ to fit the $a$’s training distribution $p^a(x)$ better than $a$ was able to.\(^8\) The decrease in the frequency of PEP8 violations might be due to the fact that compilability is correlated with PEP8 compliance.

5.1 Qualitative evaluation

To further analyze effects of different fine-tuning approaches on sample diversity, we measured the frequency of BPE tokens in generated samples. For each of four analyzed generative models, we sampled 1000 sequences using pure ancestral sampling. We then computed the frequency for each BPE token (the number of times it occurs) and its rank (its index in a sorted list of tokens). We plotted these results on Figure 4. This qualitative evaluation paints a similar picture: fine-tuning using Reinforce incurs a large (with $R(x) = b(x)$) or extreme (with $R(x) = P(x)$) decrease in token diversity. In contrast, KL-DPG is able to maintain a relatively long tail of token frequencies, not departing too far from $a$.

Moreover, in order to gain better understanding of how different fine-tuning methods affect generative models we measured the frequency of different categories of compilation errors for samples from $a$ and from fine-tuned policies. This analysis is presented on Figure 3. We categorized errors using error messages produced by Python interpreter trying to compile an uncompilable sequence. invalid syntax is the most common failure mode (30% of all sequences sampled from $a$), with a long tail of other error categories. We can see that both KL-DPG and Reinforce with $R(x) = b(x)$ consistently decrease error frequency across almost all the categories.

Finally, in the Appendix we present randomly generated samples from each discussed policy. Tables 3-6 contain samples obtained through unconditional generation. In addition to that, to illustrate

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\(^8\)This mirrors the results obtained by Parshakova et al. (2019b), who also defined an EBM augmenting an autoregressive model with prior knowledge about features of the training set and observed a decrease in perplexity compared to pure autoregressive training.
The frequency (measured as the percentage of samples from $π_θ(x)$ causing a given error) of each kind compilation error for the original generative model $a$ and policies fine-tuned using KL-DPG and Reinforce with $R(x) = b(x)$. The policy fine-tuned using Reinforce with $R(x) = P(x)$ was excluded because the single sequence it produces causes no compilation errors. Percentages were computed using 500 samples while confidence intervals were based on 3 repeats of the sampling procedure.

Figure 3: The frequency (measured as the percentage of samples from $π_θ(x)$ causing a given error) of each kind compilation error for the original generative model $a$ and policies fine-tuned using KL-DPG and Reinforce with $R(x) = b(x)$. The policy fine-tuned using Reinforce with $R(x) = P(x)$ was excluded because the single sequence it produces causes no compilation errors. Percentages were computed using 500 samples while confidence intervals were based on 3 repeats of the sampling procedure.

Figure 4: Token frequency against token rank computed for tokens found in samples from from KL-DPG, and two baselines. Longer tails imply more diverse samples.

6 Discussion

In the paper, we presented a new energy-based model formulation for the problem of imposing the constraint of compilability on an autoregressive generative model for source code. In contrast with standard reinforcement learning approaches, the solution we propose – KL-DPG – is able to improve compilability rate without sacrificing diversity and complexity of generated samples.

One obvious application of the presented approach is improving the accuracy of code completion, i.e. tools assisting in programming by predicting the next tokens based on context (Svyatkovskiy et al., 2020a). The fact that fine-tuning using KL-DPG has a beneficial effect on perplexity and PEP8 error frequency suggests that it can provide a training signal complementary to that in a language modeling objective. The benefits of this auxiliary training signal would arguably diminish with increased training time and dataset size, but that still leaves room for significant improvement in low-resource domains.

A limitation of the current KL-DPG approach is that it is restricted to unconditional generation. This is because for a conditional EBM $P(x, c)$ the proportionality constant $-1/Z$ from (4) would depend on a context $c$. Nevertheless, one can imagine using a policy $π_θ$ fine-tuned using KL-DPG as initialization of a decoder for conditional generation, e.g. transcription (translation between programming languages) or program synthesis (translation from a natural language to a programming language).

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A Hyperparameters and implementation details

We implemented all models using PyTorch (Paszke et al., 2019) and HuggingFace (Wolf et al., 2019). Training the initial generative model took 10 days on 3 Nvidia Tesla T4 GPUs. For a detailed list of hyperparameter values, see Table 1.

| Hyperparameter       | Value                  |
|----------------------|------------------------|
| base LM              | gpt2-small             |
| number of params     | 117m                   |
| number of layers     | 12                     |
| number of heads      | 12                     |
| vocabulary size      | 50257                  |
| sequence length      | 128                    |
| hidden state size    | 768                    |
| activation function  | gelu                   |
| optimizer            | Adam (Kingma and Ba, 2014) |
| initial learning rate| $5 \times 10^{-5}$     |
| learning rate scheduler| linear              |
| batch size           | 24                     |
| total gradient updates| 20069                |
| dropout rate         | 0.1                    |

Table 1: Hyperparameters used for training the initial generative model $a$

The implementation of KL-DPG was based on code published by Khalifa et al. (2021).9 Each fine-tuning run took approximately 5 days on 2 Nvidia V100 GPUs. For a detailed list of hyperparameter values, see Table 2.

| Hyperparameter       | Value                  |
|----------------------|------------------------|
| optimizer            | Adam (Kingma and Ba, 2014) |
| learning rate $\alpha^{(\theta)}$ | $1.41 \times 10^{-6}$ |
| learning rate scheduler| linear              |
| batch size           | 2048                   |
| warmup gradient updates| 100                   |
| total gradient updates| 250                   |
| sequence length      | 128                    |
| dropout rate         | 0.1                    |

Table 2: Hyperparameters used for training $\pi_{\theta}$ using KL-DPG and Reinforce

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9https://github.com/naver/gdc
Table 3: Sequences sampled from the original generative model α
| A(x) | Program |
| --- | --- |
| ```python | def fetch_size(self, page): |
| | response = self.fetch(page, max({})) |
| | constant(response.json(), response.pop('utf-8')) |
| | payload = %s/%s/%s/%s %s(self.resource.id, page.format_from_bytes()) |
| | return payload |
| ``` |
| ```python | def setUp(self): |
| | self.project_loader = testutil.FileSentenceDependencyGraph(extensions=['file','path']) |
| | self.schema = RelatedPackage preserveLoader(root_loader) |
| | self.extension_context = XMLLoader() |
| ``` |
| ```python | def __getattr__(self, perm): |
| | return self._memo.get(perm) |
| ``` |
| ```python | def expand(self, text): |
| | value = strip() |
| | return extract_cseq(text) |
| ``` |
| ```python | def test_Obze(self): |
| | w = Command() |
| | self.assertEqual(w.callHeader.callHeader, self.result) |
| ``` |
| ```python | def start_stream(self, addressFamily, opcode): |
| | logger.info("OpenlibwriteStructBegin chunkon.csv', OperationalError()) |
| | error_message = self.get_stream([None, None]) |
| | message, message = self.block_messages[0] |
| | message = message[0] |
| | self._process_message(message, message, message, message) |
| ``` |
| ```python | def set_dense(self, x, fit_to): |
| | if dup in self.scalar: |
| | return |
| | if not isinstance(modality, (pyobj): |
| | self.xg = 'SINE' |
| | self.basic = asim.bin.sample(x, rng = self.ctypes, trials = self.rng, dtype = self.dtype) |
| ``` |
| ```python | def _act(self, value): |
| | self._result.set_argument('value', value) |
| ``` |
| ```python | def _verify_proxy_access_admin(self, ip_name): |
| | self._check_proxy(ip_name) |
| ``` |
| ```python | def __str__(self): |
| | r = [] |
| | for s in self.__dict__.items(): |
| | if s[0] in BoundCacheContents(): |
| | break |
| | if s[:-1]]:Elements(['Unsupported Ct%sa' % ','.join(self.__class__.__name__)] |
| | return 'Data attribute %s from %s' % WARNING, str(r)) |
| ``` |
| ```python | def test_FaceIP_3D_14(self): |
| | self.assertTrue(self.doTestFace(self.doTestFace([self.doTestFace([False, False])) |
| ``` |
| ```python | def __init__(self, ** options): |
| | super(_ChoiceTest, self).__init__(** options) |
| | self.action_classes = options['cells_store'] |
| | self.choices = ([], ... options['myseq'] = FakeMissingTuple()) |
| | self.parser = Message(list.__init__(option_forms)) |
| ``` |
| ```python | def main(self, client): |
| | remove_home_config(client, "client_snapshot_url") |
| | self.client.client_snapshot.update(client) |
| ``` |
| ```python | def _stop_signal(self, emitter, datafile, for_attachment): |
| | vim.gui.target_cancel() |
| ``` |

Table 4: Sequences sampled from a policy fine-tuned using KL-DPG
| $b(x)$ | Program |
|--------|---------|
| 1 | `def invalidateKey(self):`  
    `self.action.rooms = { }` |
| 1 | `def get(self):`  
    `return self.handler.identifier` |
| 1 | `def flush(self):`  
    `self.write("ready")` |
| 1 | `def get_flavor(self,resource,path,** metadata):`  
    `return self.context.get(resource,path,** metadata)` |
| 1 | `def test_api_set_to_result(self):`  
    `X = T.ListHead()`  
    `self.assertEquals(quantiles(X),self._cache.annotations)` |
| 1 | `def is_cmp(self,other):`  
    `return not self._safe_eq(other,self.link)` |
| 1 | `def __iter__(self):`  
    `return iter(self._reverse())` |
| 1 | `def cancel(self):`  
    `return self.enhanced_window.set_timeout()` |
| 1 | `def __str__(self):`  
    `return str(self.repository)` |
| 1 | `def summary(self):`  
    `return self._series` |
| 1 | `def Lazypeer(self):`  
    `return self._peer` |
| 1 | `def ByteSize(self):`  
    `n = 0`  
    `n += self.lengthString(len(self.parameters_))`  
    `return n + self.lengthString(number(self.value_))` |
| 1 | `def setUp(self):`  
    `super(TestMaUserRoleTestCase,self).setUp()`  
    `self.core =BER()`  
    `self.topsetup_existing = False` |
| 1 | `def _init_(self,** kwargs):`  
    `self.sourcemersListComp = kwargs.get('stretch \{\}'.format(self.__class__.twsourceCentOS_text))` |

Table 5: Sequences sampled from a policy fine-tuned using Reinforce with $R(x) = b(x)$
| n(x) | Program |
|------|---------|
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |
| 1    | def setOwnerId(self,OwnerId): 
|      |     self.add_query_param('OwnerId', OwnerId) |

Table 6: Sequences sampled from a policy finetuned using Reinforce with $R(x) = P(x)$
| $A(x)$ | Program |
|--------|---------|
| def closeEvent(self): | Sequences sampled from the original generative model $a$ |
| self._isalive = False | |
| self._original_resume = True | |
| def close_file(self): | |
| pass | |
| def closeWorking(self): | |
| pass | |
| def close(self): | Sequences sampled from a policy fine-tuned using KL-DPG |
| if not self.closed: | |
| self.closed = True | |
| self.translation.close() | |
| def close(self): | |
| self.queue.Importer.close(self.info) | |
| self.open_input.close() | |
| self.graph.close(self.gamma) | |
| def close(self): | |
| try: | |
| self.rrv.get_browser.mac(self.bus_process.name,vm_output = True) | |
| except suspended as ex: | |
| self.socket.stop(ex) | |
| def close(self): | Sequences sampled from a policy fine-tuned using Reinforce with $R(x) = b(x)$ |
| self._stdout.close() | |
| def close(self): | |
| self.idb.close() | |
| def close(self): | |
| self.srv.get_browser.mac(self.bus_process.name,vm_output = True) | |
| p = subprocess.Popen([p.communicate()]).close() | |
| return u.close() | |
| def close(self,object): | Sequences sampled from a policy fine-tuned using Reinforce with $R(x) = P(x)$ |
| self.api.close(self.uid.length) | |
| def close(self): | |
| self.job_closed.remove(self) | |
| def close(self): | |
| self.buffer.flush() | |

Table 7: Samples obtained from policies conditioned on prompt `def close`
Sequences sampled from the original generative model

```python
def fit_pdf(self, hop, theta, x):
    assert triangular is self._fit_rewrite(hop, kernel, theta, theta) - gtheta, 0
    assert workspace is not ACCEPTED
    assert self._M_num is not StackBackendError
    assert tinstance(750, Win, T, Vector)
```

Sequences sampled from a policy fine-tuned using KL-DPG

```python
def fit(self, X, y):
    self._y = y
    self._children = 1
    assert instance(self._labels, _MOD_)
    x[0] = 0
    y[0] = Bio_OFFSET
    y *= self._labels
    y += y
    return y
```

Sequences sampled from a policy fine-tuned using Reinforce with \( R(x) = b(x) \)

```python
def fit(self, X, y, *args, **kwargs):
    X = self.transform(X, y, *args, **kwargs)
    data = np.DataFrame(data)
    for i in self.fallback_array.iteration_two(* data):
        data[i].labels[i].tolist()
    return data
```

Sequences sampled from a policy fine-tuned using Reinforce with \( R(x) = P(x) \)

```python
def fit(self, X, y, *args, **kwargs):
    X = self.transform(X, y, *args, **kwargs)
    data = np.DataFrame(data)
    for i in self.fallback_array.iteration_two(* data):
        data[i].labels[i].tolist()
    return data
```

Table 8: Samples obtained from policies conditioned on prompt def fit
Sequences sampled from the original generative model:

```python
def generate_samples_with_prompt(self, input_value, decimal = False):
    use_full = False
    full_input_string = escape_input[decimal]
    newprefix = local_input_format.split("%s") % input_label.strip()[:len_input.strip()]
    return newprefix
```

Sequences sampled from a policy fine-tuned using KL-DPG:

```python
def generate_samples_with_prompt(self):
    result = self._generate_blobs().generate(self._name, self._amount_in, lambda x: x.lower())
    return result
```

Sequences sampled from a policy fine-tuned using Reinforce with $R(x) = a(x)$:

```python
def generate_samples_with_prompt(self):
    pass
```

Sequences sampled from a policy fine-tuned using Reinforce with $R(x) = P(x)$:

```python
def generate_samples_with_prompt(self, cached_done, keep = False):
    return self.minidbus[cached_http, 'normalizer']
```

| # |
|---|
| 8 |
| 7 |

Table 9: Samples obtained from policies conditioned on prompt.