Exploring and Evaluating Personalized Models for Code Generation

Andrei Zlotchevski*
McGill University
Montreal, Quebec, Canada
andrei.zlotchevski@mail.mcgill.ca

Dawn Drain*
Anthropic
San Francisco, CA, USA
dawn@anthropic.com

Alexey Svyatkovskiy
Microsoft
Redmond, WA, USA
alsvyatk@microsoft.com

Colin Clement
Microsoft
Redmond, WA, USA
coclemen@microsoft.com

Neel Sundaresan
Microsoft
Redmond, WA, USA
neels@microsoft.com

Michele Tufano
Microsoft
Redmond, WA, USA
mitufano@microsoft.com

ABSTRACT

Large Transformer models achieved the state-of-the-art status for Natural Language Understanding tasks and are increasingly becoming the baseline model architecture for modeling source code. Transformers are usually pre-trained on large unsupervised corpora, learning token representations and transformations relevant to modeling generally available text, and are then fine-tuned on a particular downstream task of interest. While fine-tuning is a tried-and-true method for adapting a model to a new domain – for example, question-answering on a given topic – generalization remains an on-going challenge. In this paper, we explore and evaluate transformer model fine-tuning for personalization. In the context of generating unit tests for Java methods, we evaluate learning to personalize to a specific software project using several personalization techniques. We consider three key approaches: (i) *custom* fine-tuning, which allows all the model parameters to be tuned; (ii) *lightweight* fine-tuning, which freezes most of the model's parameters, allowing tuning of the token embeddings and softmax layer only or the final layer alone; (iii) *prefix* tuning, which keeps model parameters frozen, but optimizes a small project-specific prefix vector. Each of these techniques offers a trade-off in total compute cost and predictive performance, which we evaluate by code and task-specific metrics, training time, and total computational operations. We compare these fine-tuning strategies for code generation and discuss the potential generalization and cost benefits of each in various deployment scenarios.

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1 INTRODUCTION

It is well-known that even the best models can fail to generalize properly to new domains, and even to new users of said models. For example, a model trained to answer questions in general may not answer StackOverflow questions as well as the questions in the training domain, or a software developer in an Enterprise environment with private code may have libraries and attribute name which differ from public source code used to train a code synthesis model.

The current dominant paradigm in Natural Language Processing (NLP) modeling is to pre-train a large transformer model [30] on a large corpus and then fine-tune it on a particular task of interest. For example, a question-answering (Q&A) model is generally first pre-trained on a large corpus of textual data for the specific language (*e.g.,* Wikipedia, and news articles in English), then fine-tuned on a task-specific dataset of paired questions and corresponding answers. The pre-training process aims at learning semantic vector representation of the language and words, while the fine-tuning process specializes the model for a specific domain.

Transformer models are also increasingly the baseline architecture used for code generation tasks, such as writing methods from natural language description [2, 5, 7], or generating test cases from the focal method under test [29]. Similarly for NLP tasks these models are pre-trained on a large corpus of natural text and publicly available source code and then fine-tuned on a specific code-related task. Further, these models also may not generalize to new domains of interest, and can benefit from task or even user-specific fine-tuning, here called customization or personalization. Customization is particularly relevant for code generation models since it provides several benefits:

- allows fine-tuning on source code data that may not be available when training a base model (*e.g.,* private repositories or internal codebases), enabling improved overall performances on codebases with proprietary dependencies and code styles;
- the opportunity to improve data privacy by considering private or sensitive data only during the customization process on the client side;
- the opportunity to reduce deployment cost as customized models can offer better user performance without increasing model size.

Custom models can provide clear benefits to users and model providers. We envision serving tens or hundreds of thousands of custom models, but doing so presents several logistical hurdles, including the costs of training, storing, and loading these models into GPU memory for inference. Worse, memory costs will only be exacerbated when working with ever larger and more powerful models.

For these reasons, we investigate several customization approaches, some of which can dramatically reduce the memory footprint and amortized computational cost introduced by custom models. Specifically, we consider three fine-tuning approaches: (i) *custom* fine-tuning, which allows all the model parameters to be tuned; (ii) *lightweight* fine-tuning, which only optimizes the token embedding representations or the final softmax layer; (iii) *prefix* tuning, which keeps language model parameters frozen, but optimizes a small project-specific vector prefix.

In our extensive empirical evaluation we found that all the customization strategies lead to significant model improvements on a target project in terms of both intrinsic and task-specific metrics. While there is no unambiguous winner among the customization strategies, each approach can provide specific benefits in particular deployment scenarios. This paper provides insights on these customization strategies, their benefits and drawbacks, as well as providing guidelines and suggestions on which one to use based on the training cost, memory and storage, number of users, and deployment scenarios.

2 MOTIVATION

Software projects are often classified based on their architecture (*e.g.,* web, server, monolithic), domain (*e.g.,* finance, healthcare), topic or usages (*e.g.,* games, editors). In this context, several techniques have been proposed in the literature for the task of *software categorization*, which aims at organizing projects into groups that broadly describe the behavior or topic of the software. MUDABlue [13], relies on Latent Semantic Indexing (LSI), an Information Retrieval (IR) technique, to automatically categorize software systems in open source software repositories. For the same task, LACT [27] uses Latent Dirichlet Allocation (LDA), and recently neural text classification with word embeddings has been used [14] to categorize similar software projects.

While projects can be broadly categorized, each individual software project, apart from trivial forks and clones, have peculiar characteristics which make them unique. Codebases have different user-defined types, API usages, specific coding styles, and identifiers' preferences chosen by developers. These idiosyncrasies represent an additional level of complexity for models that aim at generating code for a variety of software projects.

This is exacerbated by the fact that transformer models only receive a limited-size input during inference, often considering only the current source code file. This confined window of tokens (commonly set at 1024 tokens) cannot provide a complete view of the project with its peculiarities. An accurate generation requires information about packages, classes, APIs, and identifiers that are external to the portion of code provided as input. Thus, we argue for personalized models that can generate custom code for specific projects.

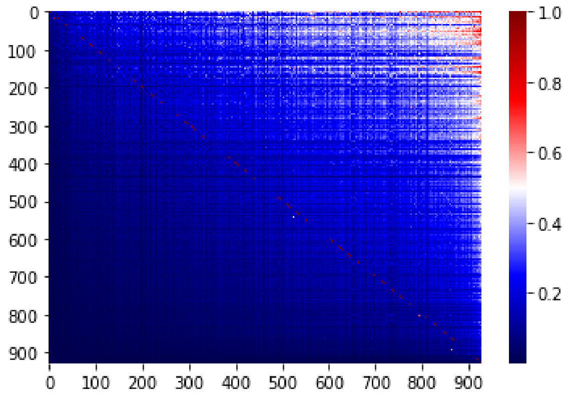


Figure 1: Heat-map displaying the ratios of shared tokens among software projects. Most projects share relatively few identifiers with other codebases.

As an exploratory study, we begin by observing projects' diversity in terms of tokens used in their source code. Specifically, we're interested in understanding the amount of shared tokens among different software projects. This could serve as an initial, rough, proxy metric to measure project diversity and potentially motivate the need for personalized models.

We select 930 Java software projects randomly sampled from GitHub, declaring an open source license, which have been updated within the last five years, and are not forks. These projects belong to the validation set of the open dataset Methods2Test [29]. For each project, we collect all the available `.java` files combining them into a single-project corpus. Next, we remove licensing information and comments using regex, then tokenize the corpus using `gensim` [22] tokenizer (with lowercase setting). From the list of tokens, we compute the set of unique tokens used within the project, and exclude the Java keywords from this set (similar to stopwords).

For each pair of projects p_i and p_j, with token sets T_i and T_j, we compute the shared token set $T_{i,j} = T_i \cap T_j$. Next, for both p_i and p_j, we compute their corresponding ratios of shared tokens as follows: $R_{i,j} = |T_{i,j}|/|T_i|$ and $R_{j,i} = |T_{i,j}|/|T_j|$.

Figure 1 shows the ratio of shared tokens between each pair of projects as a heat-map. Projects are sorted in ascending order of the number of unique tokens used in their source code. Blue values indicate a low ratio of shared tokens (the darker, the lower), while red values indicate project pairs with substantial amount of shared tokens. The heat-map appears mostly blue, indicating that the majority of projects share relatively few tokens among each others. The upper-right corner shows pairs with higher ratios (white/red points), these are ratio computed for very small projects whose tokens are contained in very large projects, hence the corner position. Overall, the majority of project share relatively few identifiers with other projects. Specifically, if we consider all the values in the matrix R except for the diagonal (*i.e.,* token shared with the project itself), a project on median shares only 13% of its tokens with another project, and the third quartile of the distribution is below 23%.

We consider this study only as a preliminary analysis into the diversity of software projects, which could motivate the need for

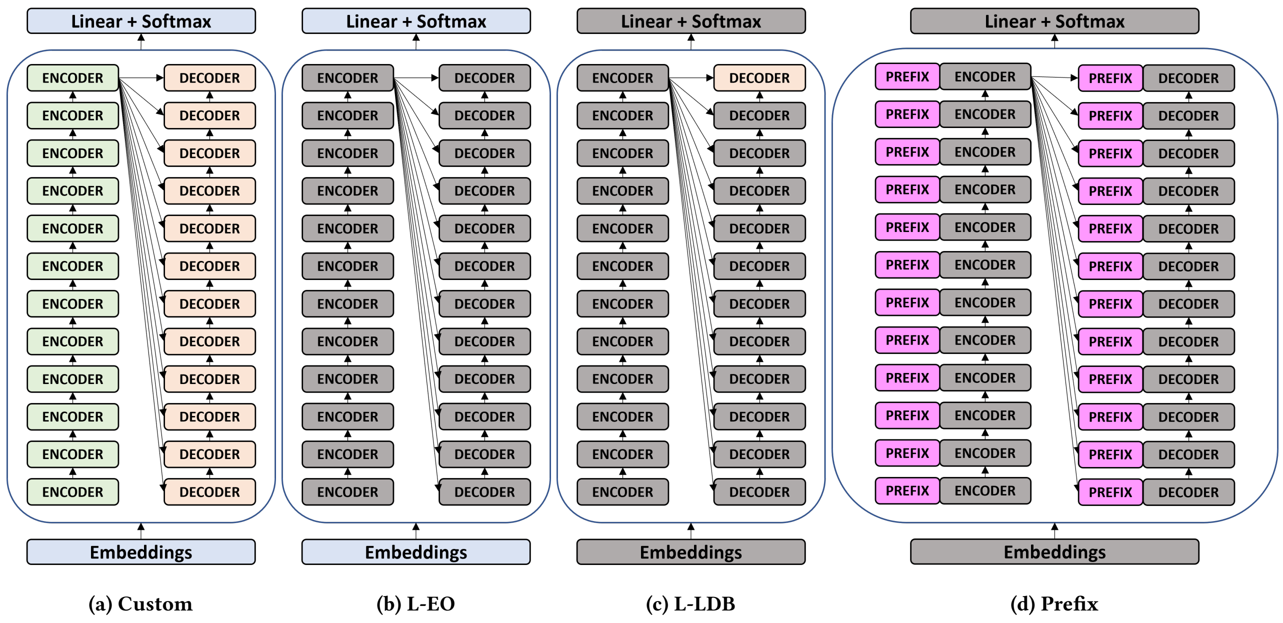


Figure 2: Overview of the Customization Approaches - Transformer models during fine-tuning, where the frozen parts of the model (not trainable) are displayed in gray: (a) Custom fine-tuning modifies all parameters during training; (b) L-EO trains only the embedding and output layers; (c) L-LDB allows to train only the parameters of the last decoder block; (d) Prefix tuning adds a trainable prefix to the encoder and decoder blocks.

personalized models. We acknowledge the limitations of this study, which could be extended considering different types of tokenizers, preprocessing steps, and metrics. In Sec. 4 we design an experimental study that analyzes in details the impact of personalization on the performances of transformer-based code generation models.

3 APPROACH

This section describes the proposed customization approach for code generation models. We begin by formally defining the customization process, then we provide details for each of the fine-tuning strategies.

3.1 Customization Process

We use the term *customization* to refer to the process of fine-tuning a model m, previously trained on a generic dataset for a task t, with the goal of improving its performance on a specific dataset p. The performance of a machine learning model m on a dataset p is measured by one or more evaluation functions $f(m, p)$, where f can be either a maximization (*e.g.,* BLEU, top-k accuracy) or minimization (*e.g.,* perplexity) function. The customization process is designed to modify the trainable parameters of the model m, obtaining the model m', such that the performance of m' on p is better than what was attained by m. Specifically, $f(m', p) > f(m, p)$ for maximization functions, or $f(m', p) < f(m, p)$ for minimization functions.

In this work, m is an encoder-decoder transformer model, t is a code generation task, and p is a target software project to which we intend to customize m.

3.2 Custom fine-tuning

Custom fine-tuning is the most straightforward customization approach. The model to be customized is taken as is and trained on a selected project. All parameters are trainable during this process. Figure 2a shows the model during fine-tuning, where all the parameters from the encoder and decoder blocks, as well as embeddings and output layers can be modified.

3.3 Lightweight fine-tuning - Embeddings and Output Layer (L-EO)

Fully fine-tuning a model for every project or user may be prohibitive in terms of storage and memory costs. As a result, we explore ways to mitigate these costs by reducing the number of parameters that vary from one custom model to another. In our lightweight fine-tuning experiments, we achieve this by freezing most parameters in the baseline model, and only keeping a small subset trainable. Figure 2b shows the Lightweight fine-tuning - Embeddings and Output Layer (L-EO) design, where most of the model parameters are frozen (displayed in gray), and we allow only the embedding and output layers parameters to be fine-tuned, following the approach in [17].

3.4 Lightweight fine-tuning - Last Decoder Block (L-LDB)

In this lightweight fine-tuning strategy, shown in Figure 2c (L-LDB), most of the model's parameters are kept frozen, while only the parameters in the last decoder block are trainable, this includes: self-attention, encoder-decoder attention, layernorm and feedforward layers. This design decision of training only the last decoder block is motivated by experimental results analyzing the model's parameter changes during custom fine-tuning. Figure 3 reports the average absolute changes, during fine-tuning, in the parameters belonging to different Encoder and Decoder blocks for a BART model. We observe that, as we go through the transformer model, the average change in parameter values tends to increase, with the last decoder block showing the highest changes in parameter values. As a result, we hypothesize that it could be sufficient to tune the last decoder block and obtain performance improvements similar to the fully custom fine-tuned model.

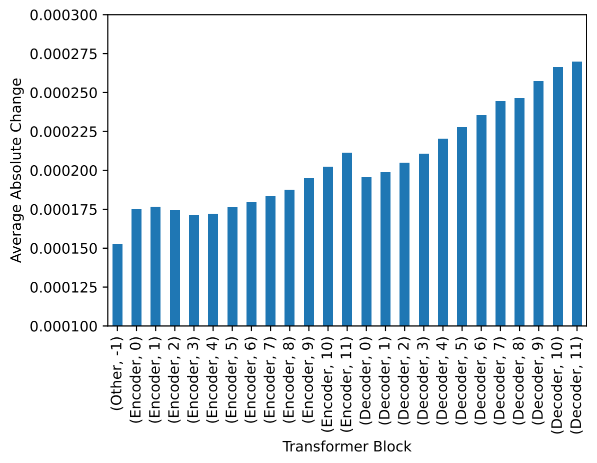


Figure 3: This figure shows the total average parameter change after fine-tuning to a new project domain, showing that the largest parameter changes occur in deeper parts of the model. This motivates our choice to try only fine-tuning the later layers of the model.

3.5 Prefix Tuning

Prefix tuning was first introduced by Li and Liang [15], with the goal of fine-tuning a general model for different tasks. The technique concatenates a sequence (prefix) of virtual tokens (trainable parameters) to the front of the input of every encoder and decoder block. In our context, the intuition behind this approach is that the prefix embeds the properties of a specific project, which allows the model to generate customized responses for that repository. Practically, we set the prefix length to 200 tokens, and thus with an embedding size of 1024, this gives a total of $1024 \times 200 \times 24 \times 2 \approx 10$M trainable parameters. The prefix is initialized to the most frequent words in the repository for which the model is customized.

3.6 Trainable Parameters during fine-tuning

Table 1 provides an overview of the number of total and trainable parameters involved in each customization process, in the case of a BART Transformer model with 406M parameters. Custom fine-tuning allows to train 100% of the 406M available parameters in the model. During L-EO finetuning, instead, only 13% (53M) parameters are trained. The L-LDB finetuning reduces the number of trainable parameters to 4.2% (17M). Finally, Prefix tuning has the lowest

Customization Process	Parameters	
	Total	Trained
Custom	406M	406M (100%)
L-EO	406M	53M (13%)
L-LDB	406M	17M (4.2%)
Prefix	416M	10M (2.4%)

Table 1: Comparing the number of trainable parameters in each fine-tuning method.

number of trainable parameters, only 2.4% (10M) of the total, but these are additional parameters added to the model, which reaches a total of 416M.

4 EXPERIMENTAL DESIGN

The goal of our experimental design is to investigate whether custom models outperform the baseline model, leading to performance improvements in terms of intrinsic metrics (RQ_1), as well as extrinsic task-specific metrics (RQ_2). Next, we analyze and compare the different customization approaches in terms of training and compute costs (RQ_3) as well as model size and required storage for deployment.

In our case study, we chose Unit Test Case generation as our code generation task t, and *AthenaTest* by Tufano et al. [29] as our baseline model m, which is a BART transformer model pretrained on source code and English, and fine-tuned on Java unit test generation. The task is modeled as a translation task, where the input is a focal method (*i.e.,* method under test), and the output is a test case which tests the focal method's correctness. We randomly sample 20 projects from the test set, each of those representing the dataset p on which a custom model is fine-tuned. Specifically, for each project p, we start from the baseline model m and fine-tune four different custom models according to the four proposed fine-tuning strategies. For each project and fine-tuning strategy (*e.g.,* L-EO), we fine-tune and evaluate the models using 4-fold cross-validation. The models are trained until the best validation loss is reached, independently for every fold, every repository, and every customization approach. In total, we fine-tune and evaluate $20(projects) \times 4(approaches) \times 4(folds) = 320$ models.

4.1 Dataset

Table 2 reports information about the 20 GitHub repositories sampled from the test set, which will be used to customize our models. The table shows (i) the Project ID, which will be used in the paper to reference a specific project; (ii) the project name; (iii) the project size in terms of disk usage; (iv) the popularity of the project in terms of number of stars obtained on GitHub; (v) and the dataset size, which corresponds to the number of data points for the unit test generation task (*i.e.,* pair of focal method and test case). The list of projects represent a diverse set of repositories with different size, domain, and popularity. They span from small personal projects (*e.g.,* `Tutorials` with 6 stars), to open source projects developed by large organizations such as Apache and Google.

Project ID	Name	Project Size (MB)	Stars	Dataset Size
26644682	Talend Data Prep	68.8	56	651
40735368	GeoTools	62.4	8	653
107330274	Titus Control Plane	36.0	302	660
52972024	Smart Actors	57.8	22	704
9714608	Arakhnê Foundation Classes	17.9	13	753
60701247	Android Plugin for IntelliJ IDEA	1026.7	716	754
14550159	EverRest	5.3	24	761
9278888	Brave	18.8	2084	787
66940520	DHIS 2	118.1	211	862
33645537	Tutorials	34.4	6	878
62253355	Mobi	62.6	35	986
155883728	OakPAL	15.0	9	1005
4710920	Apache Dubbo	36.1	36231	1058
29603649	Wilma	6.7	40	1074
42949039	Herd	227.2	127	1249
1381673	Drools	176.7	3908	1394
1244027	ModeShape	131.1	212	1550
73948366	AthenZ	38.8	639	1920
660443	Chemistry Development Kit (CDK)	214.8	305	2591
87849739	Eclipse Ditto™ Project	52.5	311	2842

Table 2: Dataset - Projects used for customization

4.2 RQ$_1$: Intrinsic Evaluation Metrics

RQ$_1$: Do custom models obtain better performances on intrinsic metrics, such as BLEU and perplexity, w.r.t. the baseline? To begin, we investigate how the different model customization approaches described in Sec. 3 score on intrinsic metrics such as BLEU and perplexity. All approaches entail fine-tuning the baseline model to the dataset of a specific project, with the choice of parameters being tuned depending on the approach taken. The four variants are trained independently until the best validation loss is achieved. We report the BLEU4 score and the mean perplexity per token on the test fold, for all the 20 projects. Next, we perform statistical tests to investigate whether the observed differences between the baseline and custom models are significant, as well as differences among the customization approaches. Specifically, we rely on the Kruskal-Wallis test, a non-parametric statistical test.

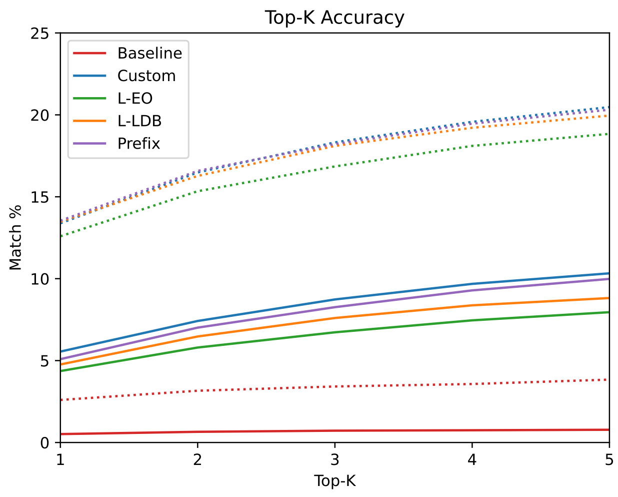
4.3 RQ$_2$: Task-specific performances

RQ$_2$: Do custom models improve on performance metrics specific to unit test generation? We want to investigate how the different customization approaches compare with respect to the downstream task of generating unit tests. Beyond BLEU score and perplexity, we would like to see if custom models can produce the correct target code, how closely their unit tests mimic the repository style, or even if they can perfectly match the desired output.

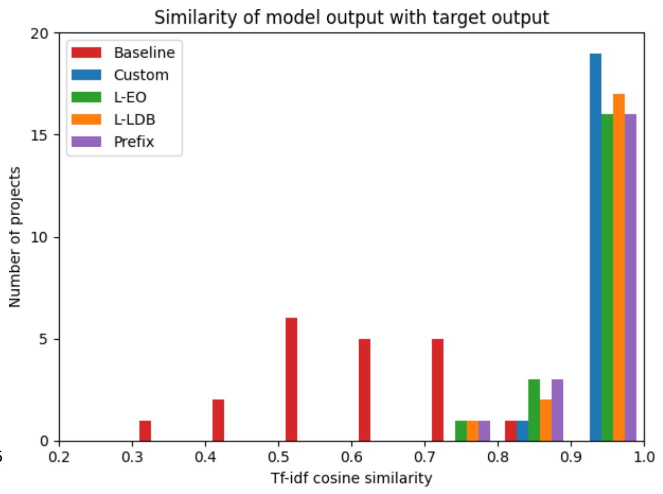
- *Perfect Matches*: We compare the model's output string with the target developer-written unit test. If the two strings are identical, this is considered a perfect match. We do not take spacing and indentation into account as we are using a Java dataset (where indentation is not required). We report the proportion of perfect matches among the top 5 model predictions.
- *Abstracted Code Matches*: We pass the model output and target output through the src2abs tool [28], to obtain an abstracted version, masking variable names, method names, etc. We also do not distinguish between different objects of the same type.
- *Coding Style*: For each project's custom model, we would like to determine how closely the model learns the developer's personal programming style and preferences. To this end, we extract the collection of all identifiers (*i.e.,* variables and functions' names) from the unit tests written by the developer as well as those generated by the models. We then pass these text outputs through a tf-idf vectorizer and compute the cosine similarity between them. This allows us to compare the developer's and the models' word usage. We examine the similarity between the developer's unit tests and the baseline and custom models generated tests. This scores the vocabulary similarity of the unit tests with the model generated code.

4.4 RQ$_3$: Training cost comparison

RQ$_3$: Given the same amount of compute, which custom models achieve the biggest performance improvement? Since our four training regimes tune a different number of parameters, simply comparing the training time or number of optimization steps to reach the best validation loss may not be appropriate. For a model with N parameters, we approximate the computation cost of a forward pass to be $C \approx 2N$ floating point operations per training



(a) Exact (solid) and abstracted (dotted) match rate



(b) Coding style as identifier similarity

Figure 4: Task-specific metrics (a) custom models outperform the baseline in terms of perfect matches (solid line) and abstract matches (dotted line); (b) custom models generate code that uses identifiers (*i.e.,* variable and function names) that are more similar to the project codebase.

token, with an additional correction for embedding layers. The backward pass takes roughly twice the amount of compute, but it is unnecessary for layers that are frozen. For additional details, we refer to Table 1 in [12]. We report the resulting compute in petaFLOPS-seconds.

5 RESULTS

5.1 RQ$_1$: Intrinsic Evaluation Metrics

Table 3 presents the results of custom models in terms of the intrinsic metrics: BLEU and perplexity. Specifically, for each project, we report the average BLEU and perplexity over the four folds, achieved on the test set by the different customization strategy, as well as the baseline model. We observe notable improvements in both metrics for every project w.r.t. the baseline, with BLEU going from 16.1 achieved by the baseline model to 36-38 by custom models.

The statistical tests reported in Table 4 confirm that the improvement observed by the four customization techniques are statistically significant w.r.t. the baseline ($p <$ 1e-7). However, we do not observe statistical significance in the differences among the customization strategies, meaning that, in terms of intrinsic metrics performances, the differences are within margin of error.

5.2 RQ$_2$: Task-specific performances

The results in terms of task-specific performances are presented in Figure 4. The plot 4a shows the top-k accuracy for perfect matches (solid line) and abstracted matches (dotted line), aggregated over the 20 projects. The baseline model outputs the same code structure (abstracted) in roughly 3% of all cases, and virtually never produces the exact target output (<1%). Moreover, its performance does not improve as we consider more predictions. All customization processes show significant improvement compared to the baseline. Specifically, these improvements are observed for every single project (full results will be available on our online appendix). Customized models produce the correct code structure as their top prediction in ~13-14% of instances, and a perfect match in ~4-6% of cases. They also tend to improve as we consider their top 5 predictions. Between the different customization processes, Custom consistently performs the best, closely followed by Prefix and L-LDB. When considering abstracted code matches, these three approaches are nearly identical. L-EO, however, performs slightly worse than the others.

Plot 4b shows the distribution of tf-idf cosine similarity computed between identifiers used in the developers' written tests and the models' generated outputs. We observe that the distribution for custom models is skewed towards the higher values of cosine similarity. This result demonstrates that custom models tend to use variable and function names that are more similar to what developers used in their own tests.

5.3 RQ$_3$: Training cost comparison

For each customization process, we plot validation loss as a function of compute, as defined in section 4.4. The results are presented in Figure 5, where the light lines represent the validation loss curve for each individual project and fold, while the bold line represents the average for each custom strategy. First note that Custom achieves very large gains during the first epoch, as evidenced by the fact that its validation loss starts much lower than L-EO and L-LDB. Custom also outperforms other customization processes when given a limited amount of compute. However, we observe that beyond a certain amount of compute, Custom and L-LDB tend to achieve similar performances. In contrast, L-EO starts at the same validation loss as L-LDB but converges much slower to the best loss, requiring 2-3 times as much compute.

Project	BLEU4					Perplexity				
	Base	Cust.	L-EO	L-LDB	Prefix	Base	Cust.	L-EO	L-LDB	Prefix
26644682	14.1	32.9	31.6	31.9	**34.0**	1.275	1.212	1.208	1.238	**1.197**
40735368	18.5	**30.7**	29.0	29.4	29.1	1.276	**1.186**	1.197	**1.186**	1.194
107330274	14.8	**38.0**	35.0	35.9	35.7	1.273	**1.160**	1.168	1.164	1.175
52972024	10.2	31.8	**33.2**	32.2	30.1	1.271	1.142	1.146	**1.135**	**1.135**
9714608	14.7	**41.0**	38.1	40.4	40.2	1.263	1.155	1.145	1.150	**1.138**
60701247	10.8	**28.9**	24.4	25.9	26.6	1.267	1.187	1.190	**1.172**	1.176
14550159	20.0	**49.5**	47.2	46.6	46.4	1.245	1.121	1.122	**1.116**	1.124
9278888	17.3	46.8	44.5	47.2	**47.8**	1.272	**1.137**	1.152	1.138	1.140
66940520	17.4	**37.9**	33.9	35.5	37.7	1.264	1.154	1.163	1.154	**1.150**
33645537	17.0	30.4	31.2	**32.0**	31.0	1.264	1.231	1.200	**1.192**	1.211
62253355	14.7	**48.0**	45.7	47.3	**48.0**	1.292	**1.113**	1.114	1.114	1.116
155883728	13.7	**41.3**	37.5	39.3	39.5	1.238	**1.132**	1.148	1.146	1.140
4710920	28.2	**39.1**	38.1	38.8	38.6	1.218	1.161	1.162	1.167	**1.160**
29603649	19.1	**58.4**	54.9	56.6	56.8	1.266	**1.096**	1.110	1.099	1.098
42949039	17.0	**38.2**	37.7	37.5	37.3	1.238	1.154	1.152	1.154	**1.148**
1381673	14.3	**33.3**	29.3	30.9	30.8	1.261	**1.133**	1.152	1.138	1.138
1244027	19.6	**30.1**	29.7	30.0	30.0	1.244	**1.142**	1.160	**1.142**	1.150
73948366	12.0	33.1	31.8	**34.0**	33.6	1.267	1.161	**1.157**	1.159	1.164
660443	15.0	34.0	**37.2**	36.5	34.3	1.281	1.180	1.170	**1.169**	1.177
87849739	13.4	45.1	47.0	**48.9**	46.8	1.259	1.138	1.136	**1.124**	1.144
Average	16.1	**38.4**	36.9	37.8	37.7	1.262	**1.153**	1.158	**1.153**	1.154

Table 3: The BLEU score and perplexity for the customization methods evaluated on the 20 projects in our test set.

	BLEU4					Perplexity				
	Base	Cust.	L-EO	L-LDB	Prefix	Base	Cust.	L-EO	L-LDB	Prefix
Base	-	**3e-08**	**3e-08**	**3e-08**	**3e-08**	-	**3e-08**	**3e-08**	**3e-08**	**3e-08**
Cust.	**3e-08**	-	0.4	0.7	0.7	**3e-08**	-	0.5	0.9	0.9
EO	**3e-08**	0.4	-	0.5	0.7	**3e-08**	0.5	-	0.5	0.5
LDB	**3e-08**	0.7	0.5	-	0.9	**3e-08**	0.9	0.5	-	0.8
Prefix	**3e-08**	0.7	0.7	0.9	-	**3e-08**	0.9	0.5	0.8	-

Table 4: Kruskal-Wallis Test p-values testing the significance of the pairwise hypothesis that one customization method is superior than another. Custom strategies are significantly better than baseline.

Since the prefix parameters suffer from poor initialization, Prefix is the most expensive customization process. To overcome this problem, it is possible to first train the prefix on a large generic dataset. Then, given proper hyperparameter tuning, it is possible to substantially cut down compute cost for customizing the prefix.

6 DISCUSSION & LESSONS LEARNED

The four customization strategies considered in this work are effective in improving a code generation model's performances on a given software project. Specifically, all custom models significantly outperform the baseline in terms of intrinsic metrics (*i.e.,* BLEU and perplexity) as well as task-specific metrics (*i.e.,* abstract and raw matches). While the differences among the customization approaches are not significant (no clear winner), each strategy offers specific advantages in different circumstances and deployment scenarios.

Custom fine-tuning achieves the overall best performances and the customization process is relatively fast and efficient. This is somewhat expected, since this customization strategy allows all the model's parameters to be tuned on the specific project. This characteristic also leads to the major disadvantage of this approach: each custom model is an entire copy of the original model. Storage and inference costs could become prohibitive when serving many users with personalized custom models.

Lightweight fine-tuning achieves good results while training fewer parameters. This allows to serve potentially many users with custom models which can be stored and loaded efficiently. Specifically, L-LDB trains fewer parameters than L-EO, however the latter could allow to deploy the embedding and output layers on the user side, with a privacy-preserving focus.

Prefix fine-tuning trains the lowest number of parameters (only 2.4% for a BART model), while improving over the baseline. However, it increases the total number of parameters of the model (prefixes are additional virtual tokens) and requires more compute time to achieve good performances, mostly due to the prefix initialization problem. On the bright side, this strategy allows to batch together requests from different users (with different prefixes), which can be processed by a single model, generating personalized outputs.

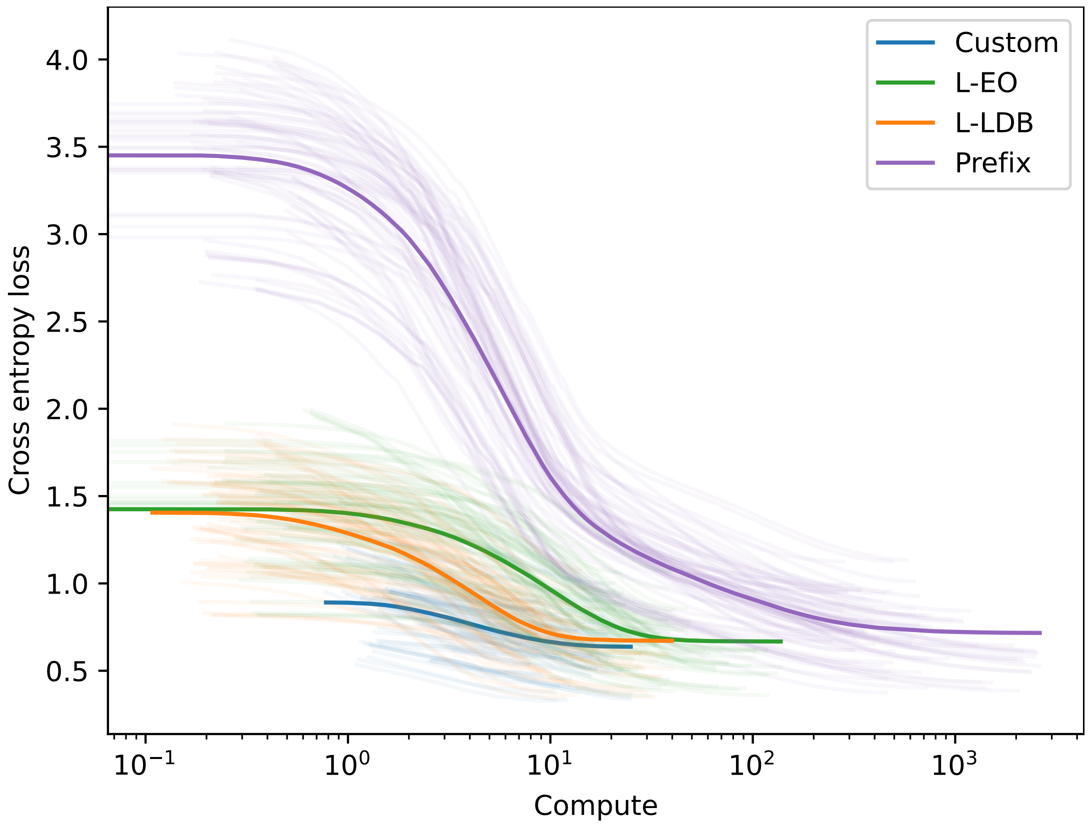


Figure 5: Validation Loss vs Compute (PF-seconds) - Light lines represent the validation loss curve for each individual project and fold, while the bold line represents the average for each custom strategy. Custom is the most efficient, lightweight approaches require slightly more compute to reach a comparable validation loss, while prefix is the least efficient, suffering from poor initialization.

7 THREATS TO VALIDITY

The major threats to our study relate to *external validity*, which concerns the generalization of our findings. Our study is performed on a specific coding task (*i.e.,* test case generation) and for a single programming language (*i.e.,* Java). The findings could not generalize to all the coding tasks and different programming languages. However, our extensive empirical analysis investigating different personalization strategies in terms of several performance metrics, can provide guidelines for applying these techniques on different coding tasks, languages, and datasets. It is important to note that, while each coding task has its peculiarities, test case generation task involves the generation of complete methods, variable assignments, method calls, and different types of statements, thus could serve as a good generic coding task. Java language is among the most popular and similar to other programming languages such as C# and Ruby.

As part of our future works we intend to apply these personalization techniques to different coding tasks and languages.

8 RELATED WORK

This work is related to two areas of the existing literature: neural source code generation and model personalization. Neural code generation has generated an intense recent interest in NLP, using Transformer models [31] in particular for code completion [3, 4, 7, 21, 25, 26], code synthesis from examples [6], natural language to code [2, 6, 7], code feature summarization [1, 16, 18, 19, 23, 32], code search [9, 10], unit test generation [29] and even bug fixing [8] and detection [33]. This paper naturally is an extension and evaluation of personalized unit test generations as studied by Tufano et al. [29], and an important contribution to the understanding optimization in a deployment scenario.

Much of the previous literature on personalized models focuses on client-side training to keep data on device [20, 24], and most work is in the domain of search query completion [11], natural language completion [20], or even automated speech recognition [24]. Naturally this work extends the domain of evaluation beyond natural language tasks and into the software engineering domain. This paper does not evaluate methods for client side training with restricted resources, however, as the most powerful large language models which enable state of the art code synthesis have 10-100 million parameters. At the time of writing such large models cannot be executed in a reasonable amount of time on most consumer laptops. We leave to future work extending these studies to models which have been pruned, quantized, distilled, and optimized to be ran in limited resource environments.

9 CONCLUSION

In this paper we explored different ways to customize a code generation model for a given codebase, with the goal of improving its performances on a target project. We described and analyzed four customization strategies and applied them on 20 different software projects for the task of generating unit test cases. Specifically, we considered the following strategies: (i) *custom* fine-tuning, which allows all the model parameters to be tuned on the target project; (ii) *L-EO* fine-tuning, a lightweight training which freezes most of the model's parameters, tuning only embedding and output layers; (iii) *L-LDB* fine-tuning, a lightweight training which only tunes the last decoder block; (iv) *prefix* tuning, which keeps language model parameters frozen, but optimizes a small project-specific vector (prefix).

In our extensive empirical evaluation we found that all the customization strategies lead to significant model's improvements on a target project, in terms of both intrinsic and task-specific metrics, with the custom models adapting to the coding style of the target project. While there is no clear winner among the customization strategies, each approach can provide specific benefits in particular deployment scenarios.

REFERENCES

[1] Uri Alon, Shaked Brody, Omer Levy, and Eran Yahav. 2018. code2seq: Generating sequences from structured representations of code. *arXiv preprint arXiv:1808.01400* (2018).

[2] Jacob Austin, Augustus Odena, Maxwell Nye, Maarten Bosma, Henryk Michalewski, David Dohan, Ellen Jiang, Carrie Cai, Michael Terry, Quoc Le, et al. 2021. Program Synthesis with Large Language Models. *arXiv preprint arXiv:2108.07732* (2021).

[3] Marc Brockschmidt, Miltiadis Allamanis, Alexander L Gaunt, and Oleksandr Polozov. 2018. Generative Code Modeling with Graphs. In *International Conference on Learning Representations*.

[4] Marcel Bruch, Martin Monperrus, and Mira Mezini. 2009. Learning from examples to improve code completion systems. In *Proceedings of the 7th joint meeting of the European software engineering conference and the ACM SIGSOFT symposium on the foundations of software engineering*. 213–222.

[5] Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde, Jared Kaplan, Harri Edwards, Yura Burda, Nicholas Joseph, Greg Brockman, et al. 2021. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374* (2021).

[6] Xinyun Chen, Chang Liu, and Dawn Song. 2018. Towards Synthesizing Complex Programs From Input-Output Examples. In *International Conference on Learning Representations*. https://openreview.net/forum?id=Skp1ESxRZ

[7] Colin Clement, Dawn Drain, Jonathan Timcheck, Alexey Svyatkovskiy, and Neel Sundaresan. 2020. PyMT5: Multi-mode Translation of Natural Language and Python Code with Transformers. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. 9052–9065.

[8] Dawn Drain, Chen Wu, Alexey Svyatkovskiy, and Neel Sundaresan. 2021. Generating Bug-Fixes Using Pretrained Transformers. *arXiv preprint arXiv:2104.07896* (2021).

[9] Zhangyin Feng, Daya Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, et al. 2020. CodeBERT: A Pre-Trained Model for Programming and Natural Languages. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings*. 1536–1547.

[10] Hamel Husain, Ho-Hsiang Wu, Tiferet Gazit, Miltiadis Allamanis, and Marc Brockschmidt. 2019. CodeSearchNet Challenge: Evaluating the State of Semantic Code Search. *arXiv preprint arXiv:1909.09436* (2019).

[11] Aaron Jaech and Mari Ostendorf. 2018. Personalized Language Model for Query Auto-Completion. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*. 700–705.

[12] Jared Kaplan, Sam McCandlish, Tom Henighan, Tom B. Brown, Benjamin Chess, Rewon Child, Scott Gray, Alec Radford, Jeffrey Wu, and Dario Amodei. 2020. Scaling Laws for Neural Language Models. *CoRR* abs/2001.08361 (2020). arXiv:2001.08361 https://arxiv.org/abs/2001.08361

[13] Shinji Kawaguchi, Pankaj K Garg, Makoto Matsushita, and Katsuro Inoue. 2006. Mudablue: An automatic categorization system for open source repositories. *Journal of Systems and Software* 79, 7 (2006), 939–953.

[14] Alexander LeClair, Zachary Eberhart, and Collin McMillan. 2018. Adapting neural text classification for improved software categorization. In *2018 IEEE International Conference on Software Maintenance and Evolution (ICSME)*. IEEE, 461–472.

[15] Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. *arXiv preprint arXiv:2101.00190* (2021).

[16] Shangqing Liu, Yu Chen, Xiaofei Xie, Jing Kai Siow, and Yang Liu. 2021. Retrieval-Augmented Generation for Code Summarization via Hybrid {GNN}. In *International Conference on Learning Representations (ICLR)*.

[17] Kevin Lu, Aditya Grover, Pieter Abbeel, and Igor Mordatch. 2021. Pretrained Transformers as Universal Computation Engines. *CoRR* abs/2103.05247 (2021). arXiv:2103.05247 https://arxiv.org/abs/2103.05247

[18] Laura Moreno, Jairo Aponte, Giriprasad Sridhara, Andrian Marcus, Lori Pollock, and K Vijay-Shanker. 2013. Automatic generation of natural language summaries for java classes. In *2013 21st International Conference on Program Comprehension (ICPC)*. IEEE, 23–32.

[19] Laura Moreno, Gabriele Bavota, Massimiliano Di Penta, Rocco Oliveto, Andrian Marcus, and Gerardo Canfora. 2014. Automatic generation of release notes. In *Proceedings of the 22nd ACM SIGSOFT International Symposium on Foundations of Software Engineering*. 484–495.

[20] Vadim Popov, Mikhail Kudinov, Irina Piontkovskaya, Petr Vytovtov, and Alex Nevidomsky. 2018. Distributed fine-tuning of language models on private data. In *International Conference on Learning Representations*.

[21] Veselin Raychev, Martin Vechev, and Eran Yahav. 2014. Code completion with statistical language models. In *Proceedings of the 35th ACM SIGPLAN Conference on Programming Language Design and Implementation*. 419–428.

[22] Radim Řehůřek and Petr Sojka. 2010. Software Framework for Topic Modelling with Large Corpora. In *Proceedings of the LREC 2010 Workshop on New Challenges for NLP Frameworks*. ELRA, Valletta, Malta, 45–50. http://is.muni.cz/publication/884893/en.

[23] Simone Scalabrino, Gabriele Bavota, Christopher Vendome, Mario Linares-Vásquez, Denys Poshyvanyk, and Rocco Oliveto. 2017. Automatically assessing code understandability: How far are we?. In *2017 32nd IEEE/ACM International Conference on Automated Software Engineering (ASE)*. IEEE, 417–427.

[24] Joel Shor, Dotan Emanuel, Oran Lang, Omry Tuval, Michael Brenner, Julie Cattiau, Fernando Vieira, Maeve McNally, Taylor Charbonneau, Melissa Nollstadt, et al. 2019. Personalizing ASR for dysarthric and accented speech with limited data. *arXiv preprint arXiv:1907.13511* (2019).

[25] Alexey Svyatkovskiy, Shao Kun Deng, Shengyu Fu, and Neel Sundaresan. 2020. IntelliCode compose: code generation using transformer. In *ESEC/FSE '20: 28th ACM Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering, Virtual Event, USA, November 8-13, 2020*, Prem Devanbu, Myra B. Cohen, and Thomas Zimmermann (Eds.). ACM, 1433–1443. https://doi.org/10.1145/3368089.3417058

[26] Alexey Svyatkovskiy, Ying Zhao, Shengyu Fu, and Neel Sundaresan. 2019. Pythia: AI-assisted Code Completion System. In *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 2727–2735.

[27] Kai Tian, Meghan Revelle, and Denys Poshyvanyk. 2009. Using latent dirichlet allocation for automatic categorization of software. In *2009 6th IEEE International Working Conference on Mining Software Repositories*. IEEE, 163–166.

[28] Michele Tufano. 2018. src2abs. https://github.com/micheletufano/src2abs.

[29] Michele Tufano, Dawn Drain, Alexey Svyatkovskiy, Shao Kun Deng, and Neel Sundaresan. 2021. Unit Test Case Generation with Transformers and Focal Context. *arXiv preprint arXiv:2009.05617* (2021). arXiv:2009.05617 [cs.SE]

[30] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention Is All You Need. *CoRR* abs/1706.03762 (2017). arXiv:1706.03762 http://arxiv.org/abs/1706.03762

[31] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in neural information processing systems*. 5998–6008.

[32] Yao Wan, Zhou Zhao, Min Yang, Guandong Xu, Haochao Ying, Jian Wu, and Philip S Yu. 2018. Improving automatic source code summarization via deep reinforcement learning. In *Proceedings of the 33rd ACM/IEEE International Conference on Automated Software Engineering*. 397–407.

[33] Juan Zhai, Xiangzhe Xu, Yu Shi, Guanhong Tao, Minxue Pan, Shiqing Ma, Lei Xu, Weifeng Zhang, Lin Tan, and Xiangyu Zhang. 2020. CPC: Automatically classifying and propagating natural language comments via program analysis. In *Proceedings of the ACM/IEEE 42nd International Conference on Software Engineering*. 1359–1371.