# **Exploring Distributional Shifts in Large Language Models for Code Analysis**

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#### **Abstract**

We systematically study the capacity of two large language models for code - CodeT5 and Codex - to generalize to out-of-domain data. In this study, we consider two fundamental applications - code summarization, and code generation. We split data into domains following its natural boundaries - by an organization, by a project, and by a module within the software project. This makes recognition of in-domain vs out-of-domain data at the time of deployment trivial. We establish that samples from each new domain present both models with a significant challenge of distribution shift. We study how well different established methods can adapt models to better generalize to new domains. Our experiments show that while multitask learning alone is a reasonable baseline, combining it with few-shot finetuning on examples retrieved from training data can achieve very strong performance. In fact, according to our experiments, this solution can outperform direct finetuning for very low-data scenarios. Finally, we consider variations of this approach to create a more broadly applicable method to adapt to multiple domains at once. We find that in the case of code generation, a model adapted to multiple domains simultaneously performs on par with those adapted to each domain individually.

#### 1 Introduction

Since the late 2000s, researchers have been reporting poor generalization of statistical learning models to new software systems (Turhan, 2012; Zimmermann et al., 2009), a phenomenon that has become increasingly important with the rise of large language models (LLMs) for code, such as GitHub Copilot, Amazon CodeWhisperer, and Replit. It is crucial to understand when off-the-shelf pretrained large language model performance on a private software system will differ from the performance obtained on a benchmark. Past work has looked at some aspects of this problem, among other features

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studying generalization across timeline (i.e. from older code to newer code), large software projects and small competition problems, authors, and code representations (Nie et al., 2022; Li et al., 2021; Hu et al., 2022).

However, the challenges of distribution shifts stemming from the hierarchical nature of software data, as depicted in Figure 1, have not been systematically studied with regard to large language models for code. Motivated by that, in this work we probe the generalization capacity of large language models for code, specifically Codex (Chen et al., 2021) and CodeT5 (Wang et al., 2021), in code generation and summarization tasks, examining three scenarios: generalization across companies, projects, and project components. These scenarios are routinely considered for analyzing software systems (Ma et al., 2012; Li et al., 2009; Mair et al., 2000) due to their intuitiveness and careful consideration that goes into combining or separating such entities.

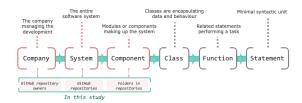


Figure 1: Organization of a software system by the granularity of its components

First, we want to understand how models perform on new domains - if models struggle with out-of-domain generalization, they should be used with caution. At the same time, we empirically establish the legitimacy of our definitions for out-of-domain scenarios by demonstrating that these examples present a distributional shift. To answer this question we compare the performance of the models without any additional adaptation, with that of the models that have been adapted on limited data from a random domain, or from the test do-

main. Adaptation with labeled examples from the test domain is the proxy for model performance if there were no distributional shift. We find that both models suffer from a drop in performance when applied out-of-domain. In this experiment, the difference is more pronounced for code summarization, where adapting models with few in-domain examples, on average, leads to an improvement of over 10 BLEU (Papineni et al., 2002) score points.

Next, we explore ways to improve the out-ofdomain generalization of large language models for code, recognizing that relying on labeled indomain data for every new domain is impractical. Instead, we investigate the use of labeled out-ofdomain data and small amounts of unlabelled indomain data to enhance generalization. We test methods known to be successful in other transfer learning scenarios, such as meta-learning (Thrun & Pratt, 1998; Vilalta & Drissi, 2002) and multitask learning (Caruana, 1996; Silver, 1996). Additionally, we leverage unlabeled in-domain data to retrieve similar labeled examples from an out-ofdomain corpus for adapting to the new domain. We find that while meta-learning and multitask learning do not solve the out-of-domain generalization problem, domain adaptation with retrieved examples is a good technique for low-data domains. Models using retrieved examples perform on par, or better, than models that have been adapted using a few samples (e.g., 8 or 16) of in-domain labeled data.

Lastly, can we make the code models more broadly applicable and retain their generalization capacities, rather than having to adapt them each time? Depending on the approach to model adaptation (e.g. weight update vs in-context demonstrations) we varied the set of retrieved examples for each new domain, or for each test input individually. We compare performance obtained this way with that of the models that are adapted simultaneously to multiple domains (or instances, correspondingly). We find that Codex is very sensitive to these changes, so it is best to retrieve similar instances for each test data point. On the other hand, CodeT5 has a minor drop in code summarization and a negligible drop in code generation. This makes it feasible to adapt and apply CodeT5 to multiple domains simultaneously with minimal tradeoff, eliminating the need to store separate copies of the model for each domain.

## 2 Background

Distribution shifts, the shifts in underlying semantics between the training and evaluation data, can be one of the most impacting factors for deteriorating performance at test time. Prior work in code analysis has mainly focused on *cross-project* distribution shifts, training the model on one set of code projects and evaluating them on unseen code project. Additionally, the studies were mainly conducted in the context of *traditional machine learning methods*, such as linear classifiers, support vector machines, and later, LSTMs (Zimmermann et al., 2009; Turhan, 2012; Angioni et al., 2022).

Recently, there has been a resurgence of interest in studying distribution shifts in code analysis, with newer works considering shifts caused by different authors of the code, the timeline of the project, distributions of code tokens, etc (Li et al., 2021; Hu et al., 2022; Nie et al., 2022). Additionally, large language models trained on code have demonstrated remarkable capabilities in code analysis tasks, however their capabilities under domain shift is still under-explored. In this work we conduct a comprehensive empirical analysis to probe large language model's capabilities in handling three different granularity of distribution shifts (company, domain, module) when different training and adaptation methods are used. In addition to directly fine-tuning vanilla LLMs, we experiment with enhancing pretrained models using the four methods described below.

Meta-Learning and Multi-task Learning. In our work, we experimented with both Meta-Learning and Multi-task learning to get better initialization for few-shot performance on the downstream task. For meta-learning, we have chosen Model-agnostic Meta-Learning(MaML) (Finn et al., 2017) which is a gradient-based method. It is a conceptually simple and general algorithm that has been shown to outperform existing approaches in several tasks. Multi-task Learning aims to learn more generalized representations by jointly training on several tasks. We adopted the simplest approach to multi-task learning by jointly finetuning a shared language model on multiple tasks.

**Parameter Efficient Methods.** Parameter-efficient methods have been shown to obtain performance comparable to finetuning all model parameters with only a tiny fraction of model parameters. In our work, we have experimented

with Low-Rank Adaptation(LoRA) (Hu et al., 2021), which is a low-rank update method, and prompt-tuning (Lester et al., 2021), which learns continuous prompt tokens concatenated to the model input.

**In-context learning.** GPT-3 (Brown et al., 2020) demonstrated the ability of large language models to perform few-shot predictions, where the model is given a description of the task in natural language with few examples. In our work, we conducted experiments on in-context learning on Codex which is a programming language version of GPT-3.

Retrieval Based Example Selection. It has been shown in Liu et al. (2021) that in-context examples selected following a strategy may serve as more informative input to unleash GPT3's extensive knowledge. Inspired by this, we leveraged a simple similarity-based retrieval module to augment Codex for in-context learning example selection. Also, for the few-shot training of CodeT5, we experimented with a retrieval-based stratified few-shot example selection approach.

## 3 Problem setting

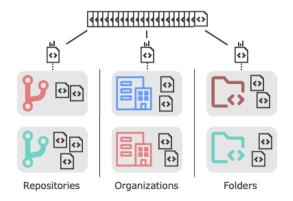


Figure 2: We divide and group the functions from CodeSearchNet by the repositories, organizations, and folders that they belong to.

We are considering the scenario where a user is looking to use a large language model, such as Codex or CodeT5, in their software project. We want to understand how these models will perform particularly considering that the code may be coming from an unseen organization, an unseen project, or a previously unseen part of the project. We compare the off-the-shelf model performance with modified model performance and the performance in the best-case scenario, i.e. having in-domain labelled data.

|        | $\tau \subset X_{train}$ (total) | $\tau \subset X_{train}( \tau  \ge 96)$ | $\tau \subset X_{test}( \tau  \ge 96)$ |
|--------|----------------------------------|-----------------------------------------|----------------------------------------|
| org.   | 9737                             | 195                                     | 8                                      |
| repos. | 15858                            | 147                                     | 15                                     |
| fold.  | 25268                            | 100                                     | 10                                     |

Table 1: CodeSearchNet dataset, split according to the domain definitions. The left column shows the set used for training. The middle column shows the number of domains of each kind from  $X_{train}$  that have at least 96 samples. The right column shows the number of domains in the  $X_{test}$  after filtering all domains with less than 96 samples.

Let us have two mutually exclusive sets of code data points:  $X_{train}$  and  $X_{test}$ . Assuming that the code in the data is extracted from some software projects, we can identify the *organization*, *project*, and the *module* within the project that the data point came from. Based on each of those characteristics we can group the data points into sets, and end up with three sets of sets, as illustrated in Figure 2. For example, the middle superset on the figure contains multiple sets of data points, such that each set corresponds to a unique organization, and all code within that set originated from that organization. For simplicity, we will refer to a set of examples from the same domain as  $\tau_i$ . We also will refer to splits of such a set into train/development or test portions as  $\tau_{train}$ ,  $\tau_{dev}$ , and  $\tau_{test}$ .

#### 3.1 Data

For our experimentation, we use CodeSearch-Net (Husain et al., 2019) dataset<sup>1</sup>, in particular, the partition containing JavaScript language. In our setup, the train section of the dataset corresponds to  $X_{train}$ , and development and test sections correspond to  $X_{test}$ .

We wanted to keep all of the domains in  $X_{test}$  unseen, and for that reason, we removed any domain from  $X_{test}$  that has also appeared in  $X_{train}$ . This way, for example, an organization that has samples associated with it both in training data and test data would not be included as part of the  $X_{test}$ . So any domain coming from  $X_{test}$  will be, by our definition, out-of-domain for the model trained on  $X_{train}$ . We further split each domain  $\tau_i \subset X_{test}$  into  $\tau_{train}$ ,  $\tau_{dev}$  and  $\tau_{test}$ . The evaluation is performed on  $\tau_{test}$ .  $\tau_{train}$  and  $\tau_{dev}$  are used to obtain a proxy for the upper-bound performance of the model if the domain  $\tau_i$  were coming from a seen

<sup>&</sup>lt;sup>1</sup>Since the exact training data of Codex models is undisclosed, we cannot be sure that it did not include CodeSearchNet dataset, but we proceed with this data for a lack of a better alternative

domain, i.e. if there was no distribution shift for  $au_{test}$ .

**Preprocessing** We used the "path" field of the CodeSearchNet dataset to determine each code snippet's belonging to an organization, repository, and lowest-level folder. We use 5 different random seeds to divide a domain into  $\tau_{train}$ ,  $\tau_{dev}$ , and  $\tau_{test}$ . We aim to have at least 32 samples each in  $\tau_{test}$  and  $\tau_{dev}$ , and up to 32 samples for  $\tau_{train}$ . Thus, from  $X_{test}$  we filtered any domain that had less than 96 samples in total. The final dataset statistics that we ended up with are presented in Table 1.

#### 3.2 Applications and Metrics

We evaluated our method on two cross-modal generation applications: code summarization and code generation. Code summarization aims to summarize a code snippet into a natural language description. The code snippet in CodeSearchNet dataset is a function, and the natural language description consists of the docstring of that function. The evaluation metric for this task is BLEU-4 (Papineni et al., 2002). Code generation performs the reverse operation - given a natural language description of code, the model is asked to generate the corresponding function. We follow prior work and use Code-BLEU (Ren et al., 2020) for evaluating generated code. We modified an existing CodeBLEU implementation by adding our own set of JavaScript keywords. In addition, recent research has established that CodeBLEU scores can disagree with human judgement scores (Evtikhiev et al., 2022), and motivated by these findings we evaluate code generation models with chrF and rougeL metrics. In our experiments, we find that these metrics agree, so we report results for chrF and rougeL in the Appendix 8.

#### 3.3 Models

We have experimented with two large language models for code: (1) CodeT5 (Wang et al., 2021), which is an encoder-decoder model based on T5 (Raffel et al., 2019) and (2) Codex (Chen et al., 2021), which is a decoder only model based on GPT-3 (Brown et al., 2020). Both T5 and GPT-3 have strong zero-shot learning (Wei et al., 2022; Sanh et al., 2022) and transfer learning capabilities, and their versions for programming languages exhibit strong performance across multiple benchmarks. The two models are of different sizes the CodeT5 is using 700M parameters T5-large

architecture, and the Codex model uses GPT-3 architecture with more than 100B parameters. We have provided a more detailed discussion of these models in the Appendix, Section 7.3. Next, we describe the methods we have employed to improve out-of-domain generalization for each model.

## 4 Analysis

In this section, we formulate the research questions that we aim to answer, and give more detailed description of the setups that we have used for analyzing and answering each question.

**RQ 1** How do code models perform on new domains?

We test models' capacity for generalization to new domains by comparing the performance of the models that have been adapted to the new domain using few-shot instances of in-domain data (ID) vs those that only encountered out-of-domain data (OOD). For CodeT5 few-shot domain adaptation data is used to update the model weights, whereas for Codex it is included as demonstrations in the prompt to the model. We provide more details for both models below.

#### CodeT5

Next, we discuss different adaptation techniques that we have employed for the CodeT5 model. For these methods, we have experimented with using a different number of supervision examples - 8, or 32.

The first adaptation method we used is full model fine-tuning (FT). We updated the model for 500 steps using batch size of 8, the best model was identified by the performance on the  $\tau_{dev}$  portion. Besides FT, we also experiment with a parameterefficient fine-tuning method - Low-Rank Adaptation (LoRA) (Hu et al., 2021). This method adds trainable pairs of rank decomposition matrices in parallel to existing weight matrices thus enabling parameter-efficient adaptation to new domains without forgetting. We used the implementation of LoRA available in T-Few (Liu et al., 2022) library. We use a rank of 4 with an initialization scale of 0.01 and update all the attention and feedforward layers. We train for 1000 steps with a batch size of 8.

**Codex** For Codex, we do not perform weight updates. Instead, very large models, such as Codex, have been shown to be capable to generalize to unseen tasks using only the instruction for the task.

| Code summarization         | folder |         |         | repo   |         |         | org    |         |         |
|----------------------------|--------|---------|---------|--------|---------|---------|--------|---------|---------|
| Couc summarization         | 8-shot | 16-shot | 32-shot | 8-shot | 16-shot | 32-shot | 8-shot | 16-shot | 32-shot |
| CodeT5 FT ID               | 14.39  | 16.06   | 18.31   | 12.68  | 14.73   | 16.82   | 13.14  | 16.35   | 17.65   |
| CodeT5 LoRA ID             | 16.57  | 19.07   | 20.93   | 15.22  | 17.14   | 21.20   | 15.61  | 18.56   | 20.87   |
| CodeT5 FT random           | 3.58   | 4.30    | 5.02    | 4.35   | 4.70    | 5.79    | 4.53   | 5.47    | 6.27    |
| CodeT5 LoRA random         | 3.69   | 4.37    | 4.92    | 4.70   | 5.56    | 5.92    | 5.27   | 5.53    | 6.26    |
| Codex ICL ID               | 20.72  | -       | -       | 20.34  | -       | -       | 19.00  | -       | -       |
| Codex ICL random           | 6.73   | -       | -       | 7.17   | -       | -       | 6.84   | -       | -       |
| Codex instr. only (0-shot) | (1.61) | -       | -       | (1.55) | -       | -       | (1.52) | -       | -       |

Table 2: Comparison of model performance for code summarization on in-domain (**ID**) vs out-of-domain (**random**) test data. Reported metric is BLEU (higher is better).

| Code generation            | folder |         |         | repo   |         |         | org    |         |         |
|----------------------------|--------|---------|---------|--------|---------|---------|--------|---------|---------|
| code generation            | 8-shot | 16-shot | 32-shot | 8-shot | 16-shot | 32-shot | 8-shot | 16-shot | 32-shot |
| CodeT5 FT ID               | 14.67  | 15.22   | 16.13   | 16.15  | 17.42   | 18.62   | 14.54  | 15.34   | 16.43   |
| CodeT5 LoRA ID             | 14.14  | 15.06   | 16.36   | 16.23  | 17.45   | 18.96   | 14.17  | 15.30   | 16.62   |
| CodeT5 FT random           | 15.23  | 14.94   | 15.15   | 14.19  | 14.14   | 14.67   | 13.39  | 13.43   | 14.44   |
| CodeT5 LoRA random         | 14.45  | 14.29   | 15.37   | 14.29  | 13.74   | 15.04   | 13.76  | 13.85   | 14.81   |
| Codex ICL ID               | 23.87  | -       | -       | 25.73  | -       | -       | 24.64  | -       | -       |
| Codex ICL random           | 16.82  | -       | -       | 16.82  | -       | -       | 17.47  | -       | -       |
| Codex instr. only (0-shot) | (5.77) | -       | -       | (5.49) | -       | -       | (5.72) | -       | -       |

Table 3: Comparison of model performance for code generation on in-domain (**ID**) vs out-of-domain (**random**) test data. Reported metric is CodeBLEU (higher is better).

In the simplest case, we evaluated Codex by directly presenting it with the instruction, for example "Summarize following JavaScript code", and input (i.e. **instruction only**). It has been established that Codex can be sensitive to the wording of the instructions, so we used a number of different instruction variations for each application and averaged the results across them.

Besides that, larger models have been shown to be able to "learn" from demonstration examples that are provided as part of their input, even though this process does not involve any weight updates. This phenomenon is known as in-context learning (ICL) technique, which is what we use for domain adaptation for Codex. Due to the limitations on the size of the input to the Codex model (4096 tokens), we used as many demonstrations as would fit, including up to 8 demonstrations with each test example. And since the model can also be sensitive to the order of examples, we shuffled the order of the demonstrations 5 times and averaged the results among these runs.

#### Finding: Both models struggle on new domains

Tables 2 and 3 demonstrate the performance obtained by CodeT5 and Codex (additional results

for code generation metrics chrF and rougeL are available in Appendix Section 8) We see that both models for code struggle with OOD generalization as demonstrated by the performance difference for models that have encountered in-domain examples vs those that have not. For example, CodeT5 model on code summarization in most scenarios gains about 200% relative improvement after updating the model with few-shot in-domain data.

It is worth noting that while there is still difference in performance for CodeT5 model on code generation ID and OOD, the performance difference is next to negligible. In comparison, we see a very large improvement on code summarization task. We hypothesize that this can be due to the fact that code generation is a more challenging task for a large language model, and so including ID data is not as helpful for CodeT5. This is additionally confirmed by our observations made in the next research question. On the other side, Codex is anecdotally a much more proficient model for code generation, and the addition of the in-domain data results in up to 50% of relative improvement.

**RQ 2** How to get better out-of-domain generalization?

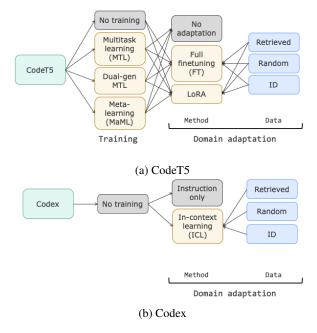


Figure 3: For the CodeT5 model we perform evaluation of different methods for training and domain adaptation techniques, as well as using different data sources during the domain adaptation stage. For Codex we perform evaluation of scenarios with different data sources during the domain adaptation stage.

In the previous question, we saw that models for code, that have been adapted for new domains using in-domain data, performed significantly better. However, there are many reasons why adapting to every new domain with the help of labeled examples might be impractical. Thus, next, we consider some alternative approaches, that would not require labeled data but would hopefully close the performance gap partially or fully. A high-level overview of the methods is illustrated in Figure 3.

#### CodeT5

In the previous setup, we started from a pre-trained checkpoint of the model and experimented with different approaches for domain adaptation. To answer the current question, we additionally consider different methods to use before the domain adaptation stage, particularly, multi-task learning or meta-learning. The resulting experimental setups are illustrated in Figure 3a.

Multitask learning (MTL) MTL is the simple method of combining data from different domains and training the model on all the domains simultaneously. For code summarization, we used the model checkpoint provided by the authors of CodeT5, which was fine-tuned on the training

portion of CodeSearchNet. For code generation, we performed our own training since the original model was not trained to generate JavaScript code. For that purpose, we randomly held out 20% of  $X_{train}$  for validation and updated the model on the rest of the data for 150K steps, using a batch size of 4. The best checkpoint was selected by evaluating the model on the held-out validation set.

Dual-gen MTL In the MTL setup described above, the model is trained to perform either code generation or summarization. In addition to that model, we experiment with a multitask model that has been trained on both code generation and code summarization simultaneously. We refer to this model as "dual-gen" MTL, following the authors of CodeT5. We prepended the inputs for the model with a corresponding instruction for each instance. We followed the same train/dev division strategy as for MTL for code generation, and updated the model for 150K steps with batch size of 4. The best checkpoints were again decided by evaluating the model on the created development set. In particular, we selected two checkpoints - one according to CodeBLEU metric, and another according to BLEU metric for code generation and code summarization respectively.

Model-Agnostic Meta Learning For model-agnostic meta-learning or MaML (Finn et al., 2017), we filtered the domains in  $X_{train}$  set, only leaving those that have at least 96 samples (see the middle column of Table 1). This was to ensure that each domain contains disjoint sets of adequate size for both training and meta-training. We used the library Higher (Grefenstette et al., 2019) for our implementation. We updated the model from the pretrained checkpoint for 10K steps and used the last checkpoint in the rest of the experiments.

Stratified example retrieval for supervision The different strategies for training above have the potential to use the information across multiple domains during the training to learn to generalize better out-of-domain. In addition to those, we experiment with a domain adaptation method that does not require in-domain labelled data for supervision. For that purpose, we created another set of examples for supervision –  $\tau_{ret}$ . We used cosine similarity on embeddings obtained from the pre-trained CodeT5 model checkpoint to **retrieve** k most similar examples for every example in  $\tau_{test}$  from  $X_{train}$ . We set k to 4, 8, or 32, and since

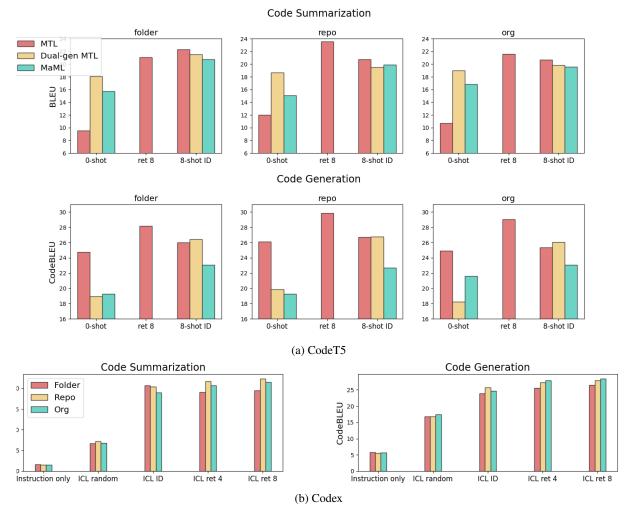


Figure 4: Performance for models with downstream adaptations on ID and retrieved data.

 $|\tau_{test}| = 32$  the combined size of  $\tau_{ret}$  set would be 128, 256, or 1024. As a final step, we removed any duplicates in  $\tau_{ret}$ .

#### Codex

## Stratified example retrieval for demonstrations

Similarly to the strategy for CodeT5, for Codex we employed in-context learning with retrieved demonstration examples. For each test query, instead of using random sets of in-domain or out-of-domain demonstrations, we used 4 or 8 of the query's most similar samples from  $X_{train}$  as demonstrations. This case will be referred to as **ICL ret**.

## Finding: Strategic domain adaptation allows best out-of-domain performance in low data scenarios, however requires more resources than general-purpose models

Figure 4a and 4b demonstrate the performance of the CodeT5 and Codex models (additional experimental results are presented in Appendix Section 8). For CodeT5, it contains the performance obtained in a zero-shot manner, as well as after in-domain few-shot finetuning as an estimate of how the corresponding models would perform if there was no distribution shift. None of the evaluated methods perform comparably in zero-shot setting to those with few-shot domain adaptation - whether on examples from training data or test domains, which means these training methods do not result in a general-purpose model that handles out-of-domain generalization well.

Adapting the MTL model to test domains with the help of stratified supervision provides a considerable boost to the performance of CodeT5 and Codex. Results are shown in Figure 5 with bars marked "ret k" for CodeT5, where k refers to the number of examples included in  $\tau_{ret}$  per test example. For Codex the figure reports the performance using 4 or 8 retrieved demonstrations, signified as "ICL ret 4" and "ICL ret 8" respectively.

First of all, we notice that there is a saturation

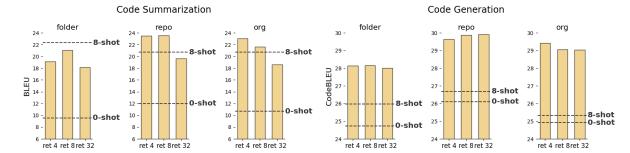


Figure 5: Performance for CodeT5 model finetuned with retrieved supervision, with different number of retrieved examples per test sample. Scores reported are BLEU for code summarization (left-most three plots), and CodeBLEU for code generation (right-most three plots). The performances of the CodeT5 MTL model evaluated in zero-shot, and 8-shot (ID) scenarios are illustrated with dotted lines for reference.

in terms of gained performance vs the number of stratified supervision or demonstration examples used. For CodeT5 using 32 examples per test instance is always worse than using 4 or 8 examples. For Codex, using 4 or 8 examples results in approximately the same performance.

Next, for code summarization, retrieving 4 or 8 examples from out-of-domain train data leads to performance comparable, or even better, than that of the model adapted using 8 examples from the test domain. This trend is observed for both Codex and CodeT5, particularly strongly when generalizing to new repositories and new organizations. A similar trend can be observed for code generation, and to a much stronger degree for CodeT5 - stratified supervision models can even outperform models trained with 32 examples from the test domain.

However, as previously mentioned, it appears that the gains achieved by the stratified supervision models with CodeT5 plateau after a certain number of examples, whereas supervision on in-domain samples does not demonstrate such a trend. Thus, adaptation to new domains using such stratified supervision is a good approach for very low-data scenarios.

## **RQ 3** Can we have more general solutions for out-of-domain generalization?

In the previous experiment, we saw that models that can generalize to new domains without relying on labeled data. Unfortunately, this still requires adapting to every test domain individually for CodeT5, and even more strictly - to every test sample individually - for Codex. For example, for CodeT5, this would mean having to maintain multiple copies of the model, performing the training for the adaptation stage multiple times, storing a large amount of out-of-domain data as a

corpus to retrieve the supervision examples from, etc.

In this last experiment, we try to create more general models. Our interpretation of such a model for CodeT5 is generalizing to multiple domains without needing to train on them separately. For Codex, since previously we were obtaining demonstrations for each individual example, we consider sampling from demonstrations collected for the entire domain - in other words, sampling demonstrations from  $\tau_{ret}$ .

For CodeT5, we finetune it on the combined set of  $\tau_{ret}$  for all domains. Formally, instead of using  $\tau_{i,ret}$  for each  $\tau_i$ , we use the  $\{\tau_{i,ret}\}_i$ . The results are presented in Table 4, where this experiment is referred to as "FT: combined k", where k is the number of retrieved examples per test example. For each cell in the table, the first number is the raw score obtained by the "combined FT" model. It is followed by the difference between the score of the combined model and the score that we had previously obtained with domain-specific models. As can be seen, training a single model on combined retrieved samples results in a moderate drop in performance for code summarization, and a negligible drop for code generation. In other words, a model finetuned on stratified supervision data for new domains can be a viable solution for the out-of-domain generalization problem for code generation. This indicates that for code generation, good performance on one domain does not hinder the performance on another domain, i.e. there is little to no negative transfer between different domains.

For Codex, for a query from  $\tau_{test}$ , we consider sampling 4 or 8 demonstration examples from  $\tau_{ret}$ . This experiment is referred to as "ICL: k from  $\tau_{ret}$ "

in Table 4, where k is the number of sampled demonstrations. The first number in each cell is the raw score obtained for Codex with sampling from similar examples for the domain, and the second number is the difference between that score, and the score obtained with similar demonstrations for each individual test example. It appears that for Codex replacing demonstrations selected for individual examples with those selected for a domain introduce too much noise, and degrade the performance a lot.

#### 5 Limitations and Threats to Validity

As can be seen from Table 1, as a result of the process of filtering, we skew the data towards larger projects and eliminate from the dataset many samples that could potentially come from smaller projects. We believe that this step is necessary to make the results more reliable, due to the high variance that can be observed in datasets with very small test sets. However, we wanted to draw attention to this circumstance once more, to make sure that our findings are interpreted correctly when considering applications of large language models to new contexts.

Additionally, while we do evaluate distribution shift and out-of-domain generalization, we believe it is important to highlight again that the out-of-domain data in our analysis still originated from the same dataset. Thus its distribution is likely closer to the original training set distribution than it will be the case for language models of code in the wild.

## 6 Conclusion

In this work, we systematically evaluated two large language models for code - CodeT5 and Codex (code-cushman-001) - on two fundamental code applications - code generation and code summarization. Our goal was to understand, how the models perform under distribution shifts that can commonly occur due to the nature of the software. We experimented with three granularities for defining domains in applications for code - organization level, project level, and module, or folder, level. Our experiments showed that both CodeT5 and Codex are susceptible to reduced performance due to domain shifts in all three scenarios. We experimented with a number of training and domain adaptation techniques for achieving better out-ofdomain generalization. As a result of our experiments, we discovered that retrieving examples from training data that are similar to the test instances is the most effective approach for adapting to a new, low-resource domain. In addition, we experimented with making adapted models applicable to multiple new domains simultaneously. We found that such models can perform very well for code generation. However, in the case of code summarization, we found the generality of the model to be a tradeoff for its performance.

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|                                                   |                                | de Summarizat<br>BLEU / Δ BLE |               | Code Generation CodeBLEU / $\Delta$ CodeBLEU |               |                                |  |  |
|---------------------------------------------------|--------------------------------|-------------------------------|---------------|----------------------------------------------|---------------|--------------------------------|--|--|
|                                                   | org                            | repo                          | folder        | org                                          | repo          | folder                         |  |  |
| FT: combined 4                                    | 18.74 / -4.74                  | 18.59 / -4.47                 | 18.06 / -1.06 | 29.46 / -0.19                                | 29.41 / -0.01 | 26.60 / -1.53                  |  |  |
| FT: combined 8                                    | 18.46 / -5.07                  | 18.58 / -3.03                 | 17.57 / -3.48 | 29.13 / -0.73                                | 28.83 / -0.22 | 27.23 / -0.92                  |  |  |
| FT: combined 32                                   | 17.35 / -2.31                  | 17.63 / -0.94                 | 15.57 / -2.56 | 26.28 / -3.63                                | 25.01 / -4.02 | 25.14 / -2.88                  |  |  |
| ICL: 4 from $\tau_{ret}$ ICL: 8 from $\tau_{ret}$ | 14.66 / -7.04<br>13.77 / -8.53 |                               |               | 20.52 / -6.73<br>20.81 / -7.05               |               | 19.39 / -6.21<br>19.48 / -7.00 |  |  |

Table 4: Results for models using retrieved supervision examples in modified scenarios.

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#### 7 Appendix

#### 7.1 Javascript Keywords

The Javascript keywords that we included in the CodeBleu implementation for evaluation is listed in table 7.1.

## 7.2 Extended Background

#### 7.2.1 Meta-learning and Multi-task-learning

**Meta-learning** focuses on adapting previous knowledge gained from previous tasks to be applied to new tasks with limited training examples. Most meta-learning algorithms can be categorized into three groups: 1) Memory-based approaches (Santoro et al., 2016) utilize memory-augmented neural network to rapidly assimilate new data and leverage this data to make accurate predictions after only a few samples; 2) Metric-based frameworks (Oreshkin et al., 2018; Snell et al., 2017; Sung et al., 2017; Tseng et al., 2020) make predictions by referring to the features encoded from the input data and training instances in a generic metric space; 3) Gradient-based methods (Finn et al., 2017, 2018; Antoniou et al., 2018) uses gradient descent to learn a model with few-shot capabilites. In our work, we are using the MAML (Finn et al., 2017) approach, which is a gradient-based method and learns model initialization (i.e., initial parameters) that is amenable to fast fine-tuning with few instances. This method is a conceptually simple and general algorithm that has been shown to outperform existing approaches in several tasks.

Multi-task Learning aims to jointly learn several related tasks providing a generalized representation with the added benefit of compute and memory in terms of shared model parameters (Yang & Hospedales, 2016; Caruana, 1997; Meyerson & Miikkulainen, 2019). Unlike Meta-Learning, conventional MTL is a single-level optimization without a meta-objective. Furthermore, the goal of MTL is to solve a fixed number of known tasks, whereas the point of meta-learning is often to solve unseen future tasks.

In our work, we have experimented with both MAML and multi-task learning to check which of the method gives us a better initialization for few-shot perfomance in our setting.

#### 7.2.2 Few-shot Methods

**Parameter-efficient finetuning:** Conventional fine-tuning methods retrains all the model parame-

| Languages  | Keywords                                                                                                |
|------------|---------------------------------------------------------------------------------------------------------|
| javascript | await, break, case, catch, class, const, continue, debugger, default, delete, do, else, enum,           |
|            | export, extends, false, finally, for, function, if, implements, import, in, instanceof, interface, let, |
|            | new, null, package, private, protected, public, return, super, switch, static, this, throw, try, true,  |
|            | typeof, var, void, while, with, yield                                                                   |

Table 5: Keywords used for CodeBLEU evaluation

ters for every new task, which becomes infeasible as the model size increases to the level of GPT-3. In recent times, parameter-efficient methods have been studied and it has been demonstrated that state-of-the-art PEFT methods can match the performance of finetuning all the model's parameters while updating only a tiny fraction of the model parameters. Initially adapters (Raffel et al., 2019; Houlsby et al., 2019; Bapna et al., 2019) were introduced, which are new feed-forward modules added between the layers of the fixed pre-trained model. Since then, various sophisticated PEFT methods have been proposed, including methods like LoRA that produce low-rank updates (Hu et al., 2021) and prompt tuning (Lester et al., 2021) and prefixtuning (Li & Liang, 2021) concatenate learned continuous embeddings to the model's input or activations to induce it to perform a task.

**Retrieval-based Example selection:** In a study conducted by Liu et al. (2021), they explored how different prompts can impact the performance of GPT-3 and found that the use of in-context examples has a significant influence on the downstream results. To achieve this, they utilized an unsupervised sentence encoder to encode training examples and then retrieved the nearest neighbors for each test instance. On a similar note, Das et al. (2021) developed a supervised prompt retriever for answering knowledge-based questions. Their method used tailored supervision specifically designed for knowledge-based queries and relied on surface similarity between formal queries. Furthermore, Shin et al. (2021) employed GPT-3 to select examples for the prompt in few-shot semantic parsing. They demonstrated the effectiveness of this approach by using GPT-3 to identify relevant examples for the prompt, which in turn improved the overall performance of the system.

#### 7.3 Models

**CodeT5:** CodeT5 (Wang et al., 2021) is a pretrained encoder-decoder transformer model based on T5 (Raffel et al., 2019) for programming lan-

guages. It uses a unified framework to support code understanding and generation tasks seamlessly. To improve the model's ability to handle the unique characteristics of programming languages, CodeT5 is trained on an identifier-aware pretraining task. Additionally, the model is trained to exploit user-written code comments with a bimodal dual-generation task for better alignment between natural language and programming languages. This makes this model suitable for the applications that we consider. For both of our applications, we used the CodeT5-large model (Le et al., 2022) without making any changes to the model architecture.

Codex Codex (Chen et al., 2021) is the language model for code released by OpenAI. It is a GPT language model finetuned on 54 million public software repositories hosted on GitHub, containing 179 GB of unique Python files under 1 MB. VLLMs are capable of zero-shot generalization to unseen tasks, which is achieved by providing them with an *instruction* of what the model is expected to do. This allowed us to successfully evaluate Codex for both code generation and code summarization without any need for training.

## 8 Additional experimental results

Besides the experiments presented in the main paper, in this section, we report some additional experiments, such as the results for code generation as measured using chrF and rougeL metrics, or comparison of LoRA parameter efficient finetuning method with the full model finetuning for CodeT5.

| Code generation            | folder  |         |         | repo   |         |         | org    |         |         |
|----------------------------|---------|---------|---------|--------|---------|---------|--------|---------|---------|
| Code generation            | 8-shot  | 16-shot | 32-shot | 8-shot | 16-shot | 32-shot | 8-shot | 16-shot | 32-shot |
| CodeT5 FT ID               | 19.36   | 20.92   | 21.95   | 20.42  | 22.44   | 24.47   | 19.29  | 20.73   | 22.6    |
| CodeT5 LoRA ID             | 20.05   | 21.66   | 22.56   | 20.81  | 23.12   | 24.52   | 20.08  | 21.28   | 22.99   |
| CodeT5 FT random           | 17.61   | 18.03   | 17.94   | 16.92  | 17.50   | 17.59   | 16.47  | 17.46   | 17.85   |
| CodeT5 LoRA random         | 17.87   | 18.02   | 17.81   | 17.45  | 17.15   | 17.63   | 17.24  | 17.13   | 17.29   |
| Codex ICL ID               | 28.78   | -       | -       | 31.05  | -       | -       | 29.19  | -       | -       |
| Codex ICL random           | 20.62   | -       | -       | 20.87  | -       | -       | 21.10  | -       | -       |
| Codex instr. only (0-shot) | (10.24) | -       | -       | (10.6) | -       | -       | O      | -       | -       |

Table 6: Comparison of model performance for code generation on in-domain (**ID**) vs out-of-domain (**random**) test data. Reported metric is ChrF (higher is better).

| Code generation            | folder |         |         | repo   |         |         | org    |         |         |
|----------------------------|--------|---------|---------|--------|---------|---------|--------|---------|---------|
| coue generation            | 8-shot | 16-shot | 32-shot | 8-shot | 16-shot | 32-shot | 8-shot | 16-shot | 32-shot |
| CodeT5 FT ID               | 14.15  | 15.84   | 16.73   | 14.93  | 16.98   | 19.19   | 13.75  | 14.93   | 16.94   |
| CodeT5 LoRA ID             | 14.49  | 16.58   | 17.87   | 15.47  | 17.69   | 19.60   | 14.10  | 15.48   | 17.61   |
| CodeT5 FT random           | 11.34  | 11.62   | 11.73   | 9.91   | 10.10   | 10.32   | 9.49   | 10.20   | 10.68   |
| CodeT5 LoRA random         | 11.45  | 12.05   | 12.58   | 10.09  | 10.04   | 11.08   | 10.15  | 10.3    | 11.15   |
| Codex ICL ID               | 23.70  | -       | -       | 24.62  | -       | -       | 22.58  | -       | -       |
| Codex ICL random           | 15.76  | -       | -       | 15.67  | -       | -       | 15.81  | -       | -       |
| Codex instr. only (0-shot) | (6.44) | -       | -       | (6.5)  | -       | -       | (5.72) | -       | -       |

Table 7: Comparison of model performance for code generation on in-domain (**ID**) vs out-of-domain (**random**) test data. Reported metric is RougeL (higher is better).

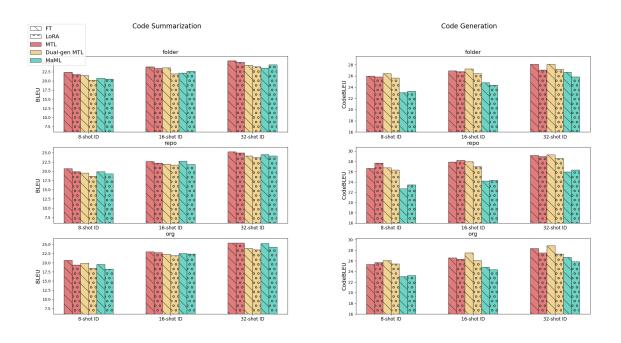


Figure 6: Performance for CodeT5 model finetuned with LoRA compared to regular finetuning.