Learning Transfers over Several Programming Languages

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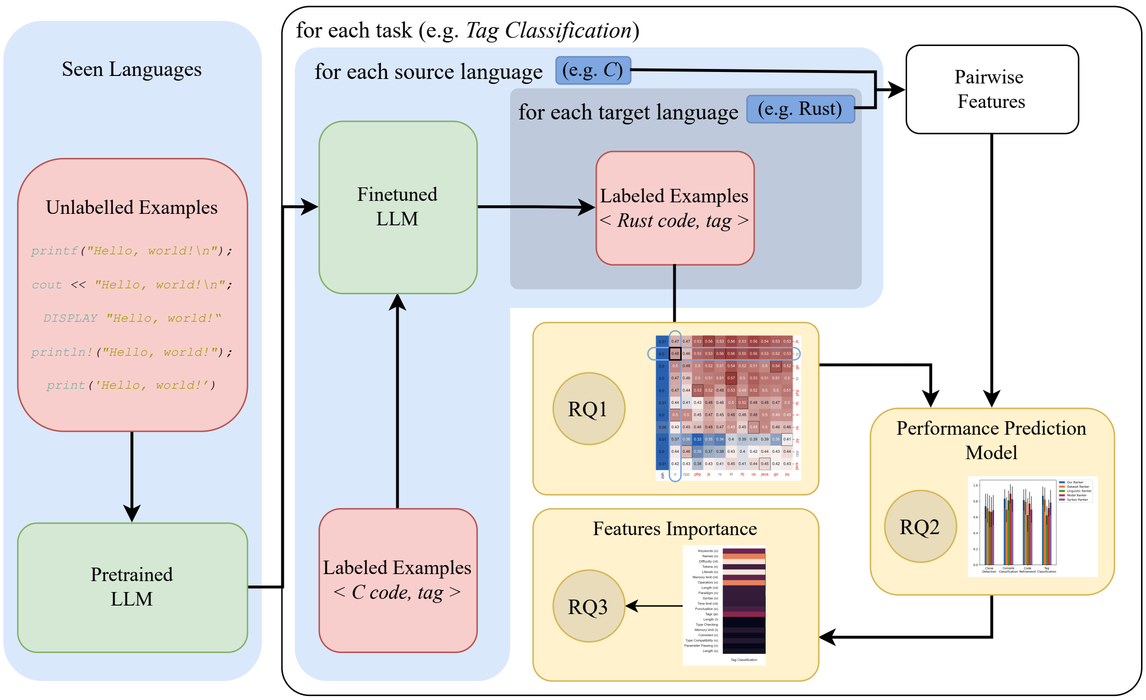

Fig. 1. Overview. *Consider an LLM pretrained on unlabeled code in multiple seen languages. Fine-tune on task-specific labeled samples from a source language. For RQ1, test performance on a target language. For RQ2, train a model that predicts transfer performance given features of a language pair. For RQ3, measure how important the features of language pairs are. Repeat for several languages and four tasks: classifying tags and compilation; clone detection; and refinement.*

Large language models (LLMs) have recently become remarkably good at improving developer productivity for high-resource programming languages. These models use two kinds of data: large amounts of unlabeled code samples for pre-training and relatively smaller amounts of labeled code samples for fine-tuning or in-context learning. Unfortunately, many programming languages are low-resource, lacking labeled samples for most tasks and often even lacking unlabeled samples. Therefore, users of low-resource languages (e.g., legacy or new languages) miss out on the benefits of LLMs. Cross-lingual transfer learning uses data from a source language to improve model performance on a target language. It has been well-studied for natural languages, but has received little attention for programming languages. This paper reports extensive experiments on four tasks using a transformer-based LLM and 11 to 41 programming languages to explore the following questions. First, how well cross-lingual transfer works for a given task across different language pairs. Second, given a task and target language, how to

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best choose a source language. Third, the characteristics of a language pair that are predictive of transfer performance, and fourth, how that depends on the given task.

1 INTRODUCTION

Large language models (LLMs) make use of the naturalness of software [10] to achieve state-of-the-art performance on many software engineering tasks such as defect detection, clone detection, and code translation, among others [7, 18]. However, these models have thus far been trained and evaluated mainly on programming languages with vast amounts of openly available code rather than *low-resource* ones. Programming languages used for critical and strategic applications may have much code only in private repositories and are thus ignored. COBOL, which supports many critical financial applications and may have over 775 billion lines of code overall [20], is low-resource due to lack of open availability. Similarly with Fortran, which is used in important high performance and scientific computing domains. Notwithstanding their popularity [27], new languages such as Rust start out low-resource, by definition. Other languages such as R may be low-resource for licensing reasons [15]. Besides being underrepresented in training of LLMs, organizations must often spend significant resources in training software developers themselves to work with low-resource languages they have little experience with. This adds to the cost of maintaining such software and may also stifle innovation [9]. There is a need for state-of-the-art AI tools to augment the capabilities of software developers for these low-resource languages. Indeed, LLMs are being used in tools to enhance software developer productivity and can also help with migration or modernization of projects from one programming language to another by supporting code translation [1, 24].

Recent works have shown the possibility of transfer learning: leveraging data from one programming language to compensate for the lack of data in the target programming language [2, 21, 26]. Another recent work has developed several similarity metrics to decide which high-resource programming language dataset can be used to augment fine-tuning data for some other language [6]. Prior work, however, has used at most 6 languages, none of which can be considered truly low-resource. Further, the notion of similarity among programming languages is underexamined: more research is needed to make reliable claims on validity. To overcome these shortcomings, we examine transferability from source to target language combinations for 4 tasks and for many more languages (11–41 depending on the task) than prior work. Figure 1 gives a high-level overview of the methodology for our extensive empirical study. From left to right, we start with a pretrained LLM that has seen unlabeled code in several programming languages. Next, for each of four tasks, for each source language with a suitable amount of labeled training data for that task, we fine-tune the LLM. For each target language with a suitable amount of labeled test data for the task, we evaluate the fine-tuned LLM and measure its performance. For example, Figure 1 illustrates this with a Tag Classification task, using C as the source language and Rust as the target language, which yields an F1 score of 0.48. Doing this for four different tasks and all their source and target language combinations yields four different heatmaps.

As our first research question (RQ1), we ask how learning transfers across programming languages in general by exploring these heat maps. As our second research question (RQ2), we ask whether one can predict the ranking of source languages in the heat maps from the previous experiment just using features of language pairs by training a performance prediction model from the language pair features and the ground-truth target labels from the heat maps. For example, in Figure 1, the performance prediction model for the Tag Classification task might predict an F1 score of 0.47 for the language pair $\langle C, Rust \rangle$. Given the cost of training LLMs, the performance prediction model is useful in directing data acquisition efforts and deciding how to spend compute resources. Finally, as our third research question (RQ3), we seek software-engineering insights into the characteristics of programming languages that affect transferability. To do this, we measure the importance of language pair features in the prediction model from the previous experiment.

This paper makes the following contributions:

- Evaluating the pairwise transferability for multiple languages (including low-resource ones) and tasks using LLMs.
- Developing a method to identify the best language to transfer from, for different target languages and tasks.
- Characterizing the features of programming language pairs that are predictive of transferability for given tasks.

One goal of this paper is to offer practical guidance to engineers that build LLM-driven software engineering tools by helping them make more informed choices for data acquisition and modeling. Another goal of this paper is to help advance software engineering as a science by using the lens of transfer learning to shed light on programming language characteristics. More generally, if we assume as a premise that software engineers will increasingly benefit from LLM support, then we hope this paper will help democratize such support into low-resource settings.

2 BACKGROUND AND RELATED WORK

Cross-lingual Transfer for Natural Languages. Lin et al. [16] use 4 tasks to study transfer among up to 60 languages and explore how important meta-features of language pairs are for predicting how well learning transfers between them, finding that feature importances vary a lot across tasks. Lauscher et al. [13] use 5 tasks to study transfer among up to 15 languages and argue that while zero-shot performance can work for low-level tasks, higher-level tasks benefit from at least a few target-language shots. De Vries at al. [8] use 1 task (POS tagging) with 65 source and 105 target languages and study the effects of language families and writing systems, with Romanian emerging as a particularly good source language. Ahuja et al. [3] use 11 tasks with 1 source and varying numbers of target languages, confirming earlier findings that feature importances vary a lot across tasks. Our paper takes inspiration from these works but differs by studying programming languages instead of natural languages, which have different tasks and different meta-features affecting transferability.

Cross-lingual Transfer for Programming Languages. Zhou et al. [27] call for studying transfer, motivating with 1 task (code completion) and 2 languages (from Hack to Rust). Chen et al. [6] use 2 tasks (code summarization and search) and 6 languages to study transfer to Ruby, and propose picking the source language based on language similarity. Ahmed and Devanbu [2] use 3 tasks to study transfer among 6 languages, demonstrating that due to the nature of their tasks, signals from identifiers are highly important for transferability. Yuan et al. [26] use 1 task (automated program repair) to study transfer among 5 languages, sequentially fine-tuning on multiple languages with innovative tricks to prevent catastrophic forgetting. Pian et al. [21] use 2 tasks (code summarization and completion) to study transfer among 4 languages, using meta-learning to improve a base learner. Our paper also focuses on programming languages, but considers more tasks and vastly more languages to obtain insights into conditions for effective transfer. In addition to past work on transfer, there is also existing work on learning for multiple programming languages. While such prior work has been instrumental in making studies like ours possible, it differs by not focusing on cross-lingual transfer. Our work benefits from datasets for multiple programming languages. CodeNet covers 55 languages [22]; XCodeEval covers 7 tasks with up to 17 languages [12]; and MultiPL-E supports 1 task (code generation) in 19 languages [5]. There are also models for multiple programming languages. TransCoder uses pre-training across 3 languages to help learn transpilers [24]. CodeT5 is pre-trained on 8 languages and 5 tasks [25]. Very recently, StarCoder is pretrained on 86 languages [15], but e.g. does not include COBOL and evaluation is largely focused on Python. Unsupervised pretraining on multiple languages has suddenly become common, but transferability of supervised tasks has not yet been thoroughly studied; our paper addresses that gap.

3 EXPERIMENTAL SETUP

As illustrated in Figure 1, given a task, our experimental approach first fine-tunes a model for each source language individually and then tests each fine-tuned model on all target languages. We have applied this approach to four tasks where the number of source languages varies from 6 to 22 leading to a total of 58 fine-tuned models. Each model was then evaluated on 11 to 43 languages producing 1808 experiments. All results are presented in Figs. 2(a)–(d) and analyzed in Sec. 4. This section presents details on various aspects of our approach, including on data, software engineering tasks, and large language models.

3.1 Base Datasets

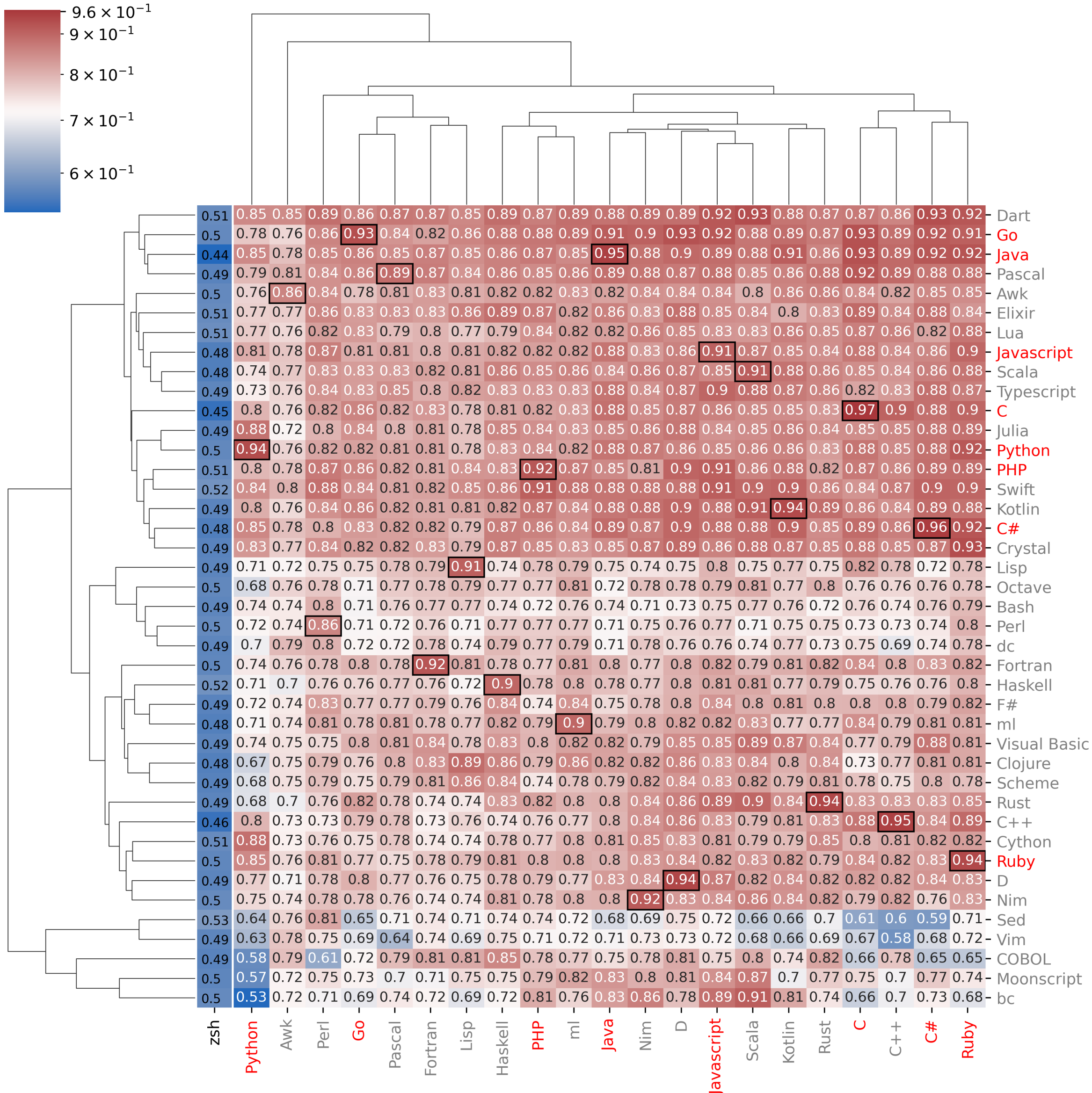
The four tasks studied in this work are derived from two big multilingual code datasets: CodeNet [22] and XCodeEval [12]. CodeNet [22] is one of the most extensive datasets available for programming languages. It consists of about 14 million code samples for a total of 500 million lines of code in 55 different programming languages, both high- and low-resource. It is derived from problems hosted on online judge websites and the dataset consists of submissions to these problems, in many different programming languages. The dataset comes with benchmarks for code classification and code similarity. XCodeEval [12] contains 25 million samples from another online judge website, different from CodeNet. There are 11 programming languages, with only a few of them being potentially low-resource. The main characteristics of this dataset are that it comes with an execution-based evaluation framework and several different benchmarks: from classification (Tag Classification and Compile Classification) to generative (program synthesis, automatic program repair, and code translation).

3.2 Tasks

To study how learning transfers between programming languages, we explore two type of tasks: classification (Compile Classification, Tag Classification, Clone Detection) and generation (Code Refinement). For the classification tasks, we follow Lewis et al. [14] by predicting labels from the vocabulary of class labels based on the final decoder hidden state. We use BLEU score[1] for evaluating the generative task and F1 score for evaluating the classification tasks.

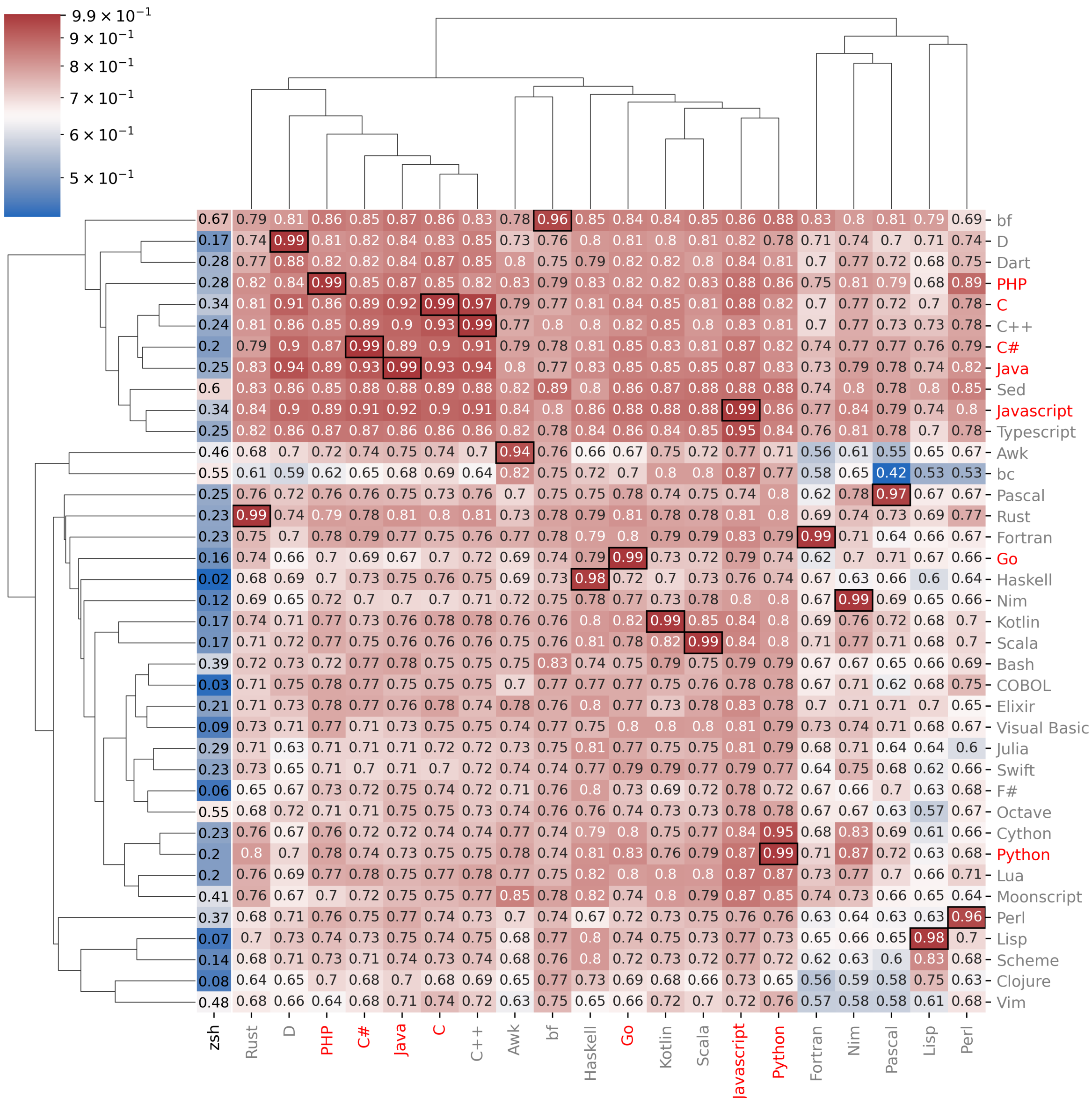
(1) **Compile Classification:** a multilingual binary classification task. Given a code C in language L, the task is to determine whether C compiles (or can be loaded by an interpreter) without error.
(2) **Tag Classification:** a multilingual multi-label classification task. Given a code C in language L, the task is to predict a set of tags corresponding to potential algorithmic techniques required to write the program (e.g., 2-sat, binary search).
(3) **Clone Detection:** a multilingual binary classification task. Given two code samples C_1 and C_2 in language L, the task is to to detect whether the two samples are type-IV clones (semantically similar) [23]. To generate the dataset, we apply the following procedure to the CodeNet dataset. Given all combinations of solutions to all problems in language L, we identify positive samples (clones) as pairs of accepted solutions for the same problem and the others as negative examples. To balance the positive samples across problems, we ensure a ratio of 0.15 of positive samples across different languages.
(4) **Code Refinement:** a generative synthetic task. Given a buggy code C in language L, the task is to generate the corresponding fixed code. We generate the dataset by using following procedure on CodeNet solutions: Each sample is modified by sequentially inserting, removing, or replacing tokens of different types for fixed ratios for different token types.

[1]We chose BLEU-score because it enabled us to experiment with the larger number of languages present in CodeNet [22], and because other prominent benchmarks for the refine task also adopt this metric [17].



(a) Clone Detection: 21 source languages × 41 target languages. Metric: F1 Score

Fig. 2. Transfer scores heatmap. *The figure shows scores for every combination of source and target language. Each column corresponds to a source language, with "zsh" showing zero-shot performance, i.e., without pre-training on any source language. Each row corresponds to a target language. The languages whose language-name label uses red font were seen during pre-training. Framed black boxes highlight the performance of a source language (column) on itself as the target language (row). The dendrograms show results of hierarchical clustering based on similarity of the performance vectors. The row and column order is also determined by the same clustering.*

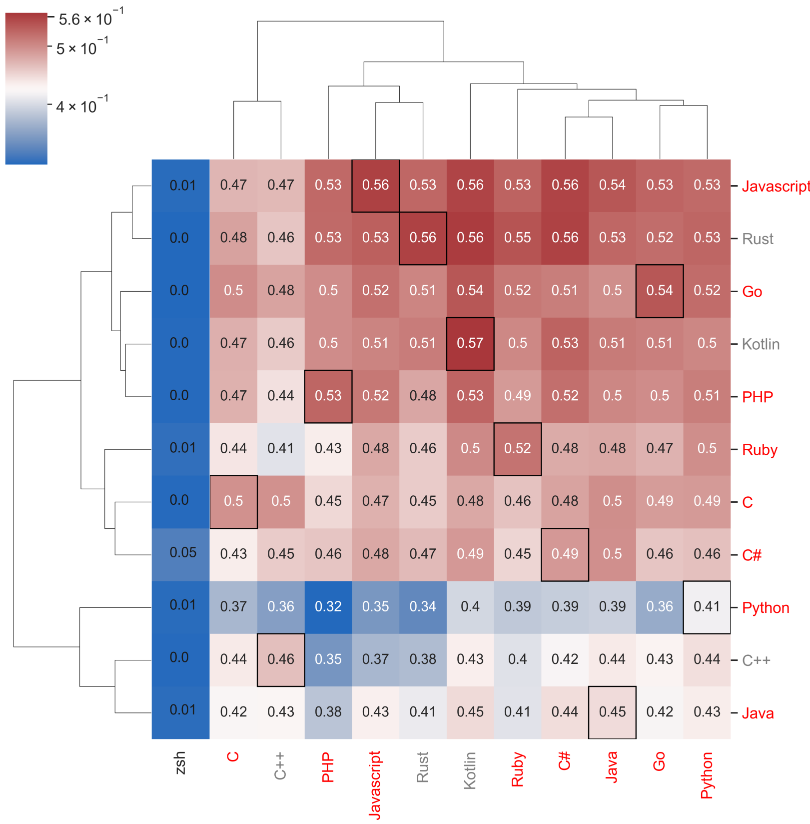


(b) Code Refinement: 20 source languages × 38 target languages. Metric: BLEU score

Fig. 2. Transfer scores heatmap *(continued; see caption from 2a)*

3.3 Data Sampling

Given the variation of the size of datasets corresponding to different languages, we follow the sampling procedure of de Vries et al. [8]. We first fine-tune the model with datasets of different number of samples N={10K, 30K,



(c) Tag Classification: 11 source languages × 11 target languages. Metric: F1 score

Fig. 2. Transfer scores heatmap *(continued; see caption from 2a).*

50K, 70K, 100K}. Depending on the availability of training examples N_L for language L, we randomly upsample languages with $N < N_L$ and downsample languages with $N > N_L$. We further select sources languages based on the relative performance compared to a baseline model. We select the following sample sizes for different tasks: 50K for Tag Classification, 70K for Code Refinement, and 100K for Clone Detection and Code Refinement.

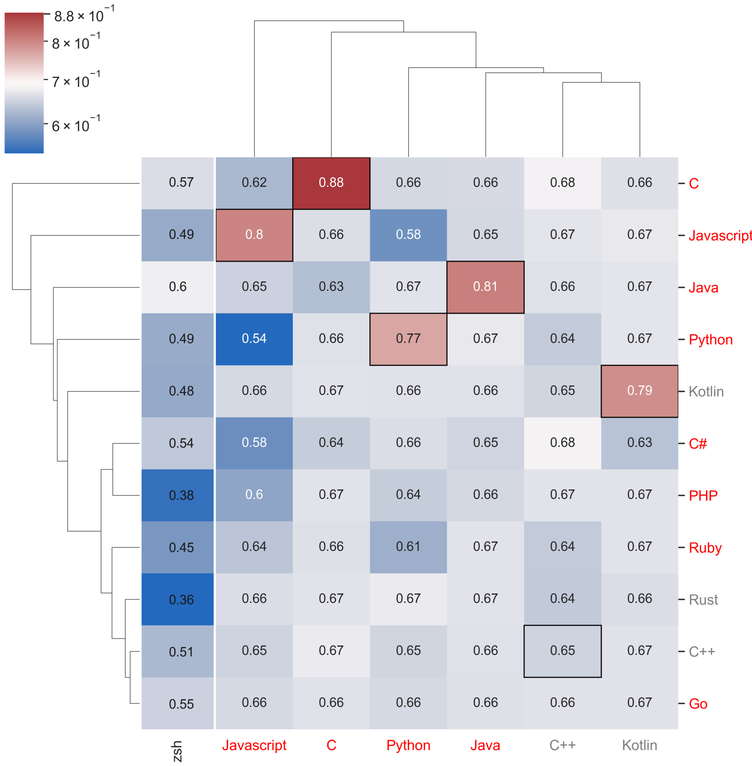
3.4 Model

Our experimental framework is based on CodeT5-base (220M parameters). Code-T5 is an open-source model, pre-trained on multiple programming languages. Due to its encoder-decoder nature, it can easily support both code generation and code understanding tasks with good performances [25]. Also, its relatively small size makes it a good fit for our experimental setup, which requires 63 fine-tuned models with numerous inference runs each.

4 RESULTS AND DISCUSSION

This section addresses the following research questions:

RQ1: How well does cross-lingual transfer work for a given task across different language pairs?



(d) Compile Classification: 6 source languages × 11 target languages. Metric: F1 Score

Fig. 2. Transfer scores heatmap *(continued; see caption from 2a).*

RQ2: Given a task and target language, how should we pick the source language for best performance?
RQ3: Which characteristics of a language pair are predictive of transfer performance, and how does that depend on the given task?

4.1 Transfer analysis

To explore RQ1, we perform extensive experiments on every combination of source and target programming languages. A source programming language is the language used for fine-tuning a model (with samples in the training data) and a target programming language is the language used to evaluate a model (with samples in the test data). This combination of source and target languages can lead to two kinds of fine-tuning: monolingual and cross-lingual. Monolingual fine-tuning is when source and target languages are the same, cross-lingual is when they are different. All the monolingual and cross-lingual experiments are represented in the heatmaps in Figs. 2(a)–(d), one for each task. This subsection attempts to extract general insights based on task dependency and source and target language dependency. Given our tasks and datasets, we also identify which languages are the toughest target languages and which are the best source languages.

Task dependency. Heat maps in Fig. 2 show that transferability of source languages varies depending on the task. Tab. 3 shows that the mean score across all language combinations varies from 0.79 for Clone Detection to 0.47

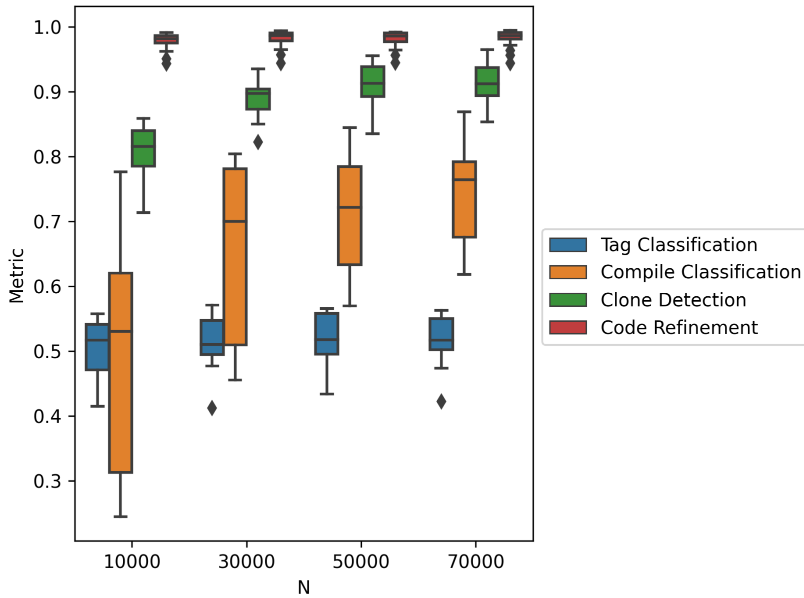


Fig. 3. Test metrics for different sampling strategies across tasks.

for Tag Classification. However, for all tasks, the mean cross-lingual score is much higher than zero-shot scores. This shows that learning transfers well in all tasks, over all programming languages for cross-lingual fine-tuning.

Source and target language dependency. Another important determinant for transferability is the combination of source and target languages. As can be expected, for most cases monolingual performance, where source and target are the same, is better than cross-lingual performance, where source and target languages are different. Tab. 3 shows that the mean monolingual score is 0.91 for Clone Detection and 0.98 for Code Refinement, while their cross-language score mean is 0.78 and 0.75. For harder tasks the scores drop but the relation is maintained. Monolingual scores for Compile Classification and Tag Classification are 0.78 and 0.51, while cross-language scores are 0.66 and 0.47. The mean zero shot scores for Clone Detection, Code Refinement, Tag Classification and Compile Classification tasks are 0.49, 0.28, 0.01 and 0.49. When seen in the context of zero-shot scores, for all tasks we can see that in the absence of monolingual training, cross-lingual finetuning really helps. This also shows that for many languages which lack adequate finetuning samples, cross-lingual finetuning is much better than zero-shot.

Target language dependency. Tab. 1 and Tab. 2 show that transferability also depends on the target programming language. Some target programming languages are good at monolingual performance, but much worse at cross-lingual performance. One example of this across multiple tasks is C++, which can be considered to be low on transferability. In-language performance for C++ is 0.95, 0.99, and 0.46 for Clone Detection, Code Refinement, and Tag Classification, whereas its cross-language performance is 0.79, 0.81, and 0.41 for the same tasks. Java is an example of a language with more consistent in-language and cross-language transferability across tasks and hence can be considered relatively more transferable than C++. Java has an in-language scores of 0.95, 0.99, and 0.45 for Clone Detection, Code Refinement, and Tag Classification, and scores of 0.86, 0.84 and 0.42 for the same tasks.

Target Language	Clone		Refine		Compile		Tag		Mean
	cross	zsh	cross	zsh	cross	zsh	cross	zsh	Rank
Java	0.86	0.44	0.84	0.25	0.66	0.6	0.42	0.009	4.25
Go	0.86	0.5	0.71	0.16	0.66	0.55	0.51	0.003	4.25
Rust	0.8	0.49	0.77	0.23	0.66	0.36	0.53	0.001	4.5
Javascript	0.83	0.48	0.85	0.34	0.65	0.49	0.52	0.008	4.75
Kotlin	0.84	0.49	0.76	0.17	0.66	0.48	0.5	0.005	5.0
PHP	0.84	0.51	0.82	0.28	0.65	0.38	0.5	0.004	5.25
C#	0.84	0.48	0.82	0.2	0.64	0.54	0.47	0.046	5.5
C	0.83	0.45	0.82	0.34	0.66	0.57	0.48	0.004	5.75
C++	0.79	0.46	0.81	0.24	0.66	0.51	0.41	0.004	7.0
Python	0.83	0.5	0.76	0.2	0.64	0.49	0.37	0.006	8.75

Table 1. Score distribution by target languages common for all tasks. Scores are the mean of the score of every source for a given target language. Mean rank is used to rank the languages based on their ranking for each task. All the languages shown are high-resource target languages for Clone Detection, Code Refinement and Tag Classification. Which means they are also part of source languages for those tasks. C#, Go, PHP, Ruby, Rust are low-resource languages for Compile Classification. The table shows that all languages benefit from transfer learning. Java, Go seem to benefit the most and C++, Python seem to benefit the least.

Tab. 2 focuses on target languages which do not appear in source, these are considered low resource languages in our dataset. Among low-resource target languages, for Clone Detection and Code Refinement, Dart, TypeScript, Lua can be considered to be high on transferability with average scores of 0.87 and 0.79, 0.82 and 0.83, 0.81 and 0.76. Vim with average scores of 0.69, 0.67 and COBOL with scores of 0.72, 0.74 for Clone Detection and Code Refinement can be considered as languages with relatively lower transferability. For Compile Classification there is a smaller set of languages which can be considered low resource. We observe low variation in average scores across different sources with highest being Rust with 0.66 and lowest being C# with 0.64. For Tag Classification there are no low resource target languages. For low resource languages we see that cross-lingual training is much better than zero shot, across all languages and tasks.

Most Transferable Source Language. Across the four tasks we have 6 source languages which are common. These are Javascript, C, Kotlin, Java, C++, and Python. To identify the best source language, we calculated the average score of each of these languages for each task across all target languages. We then ranked the source language for each task based on these average scores, highest to lowest. Then we calculated the mean rank for each of these common source languages. The results are presented in Tab. 4. We found that the best source languages, across all tasks and target languages, in order are Kotlin, Javascript, Java, Python and C (same mean rank) and finally C++. Kotlin being the best performing source language was surprising since it is not often discussed in the context of pretraining LLMs.

Dendrograms. The dendrograms for Code Refinement task pair together closely related programming languages. For example, C is paired with C++ and is next to the pair C# and Java. JavaScript is paired with TypeScript, Python with Cython, Lua with Moon, Lisp with Scheme. The pairing is less significant with the other tasks. This might come from the nature of the task, Code Refinement is a generative task whereas the other are classification tasks.

Target Language	Clone Detection		Code Refinement		Mean
	cross	zsh	cross	zsh	Rank
Dart	0.87	0.51	0.79	0.28	2.0
Typescript	0.83	0.49	0.83	0.25	3.5
Elixir	0.83	0.51	0.75	0.21	5.0
Lua	0.82	0.51	0.77	0.2	5.0
Swift	0.85	0.52	0.72	0.23	6.5
Visual Basic	0.8	0.49	0.75	0.09	7.5
Cython	0.79	0.51	0.75	0.23	7.5
Julia	0.83	0.49	0.72	0.29	8.0
Moonscript	0.74	0.5	0.75	0.41	9.0
Sed	0.69	0.53	0.85	0.6	9.5
Scheme	0.78	0.49	0.71	0.14	11.5
Shell	0.74	0.49	0.74	0.39	12.0
Clojure	0.8	0.48	0.67	0.08	12.5
COBOL	0.73	0.49	0.74	0.03	12.5
Fsharp	0.78	0.49	0.71	0.06	13.0
Octave	0.76	0.5	0.71	0.55	13.0
bc	0.73	0.5	0.67	0.55	16.5
Vim	0.69	0.49	0.67	0.48	16.5

Table 2. Score distribution for low resource target languages common for Clone Detection and Code Refinement. Scores are the mean of the score of every source language for the given target language. Mean rank is used to rank the languages based on their ranking across each task. All languages benefit from transfer learning. Dart, Typescript benefit the most and bc, Vim benefit the least.

Task	Monolingual		Cross-lingual		Overall		Zero-Shot	
	mean	std	mean	std	mean	std	mean	std
Clone Detection	0.91	0.046	0.78	0.098	0.79	0.099	0.49	0.017
Tag Classification	0.51	0.051	0.47	0.054	0.47	0.055	0.01	0.01
Compile Classification	0.78	0.076	0.65	0.025	0.66	0.05	0.49	0.08
Code Refinement	0.98	0.014	0.75	0.074	0.76	0.082	0.28	0.17

Table 3. Scores Distribution by Task. Monolingual implies a finetuning where train and test data language is the same. Cross-lingual implies finetuning where train and test data languages are different. Overall scores include both monolingual and cross-lingual scenarios. Zero-shot means the performance of the base pre-trained model (CodeT5-220M) on the test set without finetuning.

4.2 Performance Prediction

Given a task and target language, how should we pick the source language for best performance? Knowing how to answer this question without having to train multiple models on different source languages can save long and expensive trainings. It also provides a basis to study what are the important features that characterize a successful transfer from a language to another.

To predict the performance of the models on the different tasks, we train a ranking model based on gradient-boosted decision trees (GBDT) [11] to rank different source languages for each task and compare with several

Source Language	Clone		Refine		Tag		Compile		Mean
	score	rank	score	rank	score	rank	score	rank	Rank
Kotlin	0.8	3	0.78	3	0.5	1	0.67	1	2.5
JavaScript	0.82	1	0.81	1	0.47	4	0.62	6	3.0
Java	0.8	4	0.78	5	0.49	3	0.66	2	3.5
Python	0.73	6	0.79	2	0.49	2	0.66	5	3.75
C	0.8	2	0.78	4	0.45	5	0.66	4	3.75
C++	0.79	5	0.78	6	0.44	6	0.66	3	5

Table 4. Source languages common for all tasks ranked by mean score across target languages and tasks. Score is the mean of of the scores of all target languages for a given source language. We see that Kotlin is relatively the best source language and C++ the worst. This result is surprising since Kotlin is not a seen language during pre-training.

baseline heuristics considering individual features or feature categories inspired by previous works [16]. We show that our models outperform other heuristics in predicting source languages for optimal cross-lingual transfer across different tasks. We consider the features defined in Tab. 5. These features can be grouped into four categories:

(1) **Linguistic features:** general properties characterizing a language like the paradigms supported, the style of memory management (is there a garbage collector or not), and characteristics of the type system.
(2) **Syntactic features:** pairwise features of each source and target language pair measured by overlap in the counts of different token types[2].
(3) **Dataset-specific features:** source, target, and pairwise features relating to the properties of the problems associated with code samples in the dataset.
(4) **Model-specific features:** source, target, and pairwise features relating to the languages seen by the model during pretraining.

To predict the top source languages for a given task and target language L_t in the set of target languages T, we train a ranker model using the LightGBM [11] implementation of the LambdaRank algorithm [4]. The model takes features in Tab. 5 as inputs for different sources and scores individual languages in terms of their relevance to the query L_t. Our ranker model utilizes a boosting ensemble of 100 decision trees with 16 leaves each. We consider the Normalized Discounted Cumulative Gain score (NDCG@K) at $K = 3$ as our evaluation metric. We evaluate the model using leave-one-out (LLO) cross-validation on the set T. For each target language L_t, we train a ranker model to predict rankings of different sources for each language in T leaving out the source ranking for L_t as a test set. For each fold, we compute the NDCG@3 score on the test set. We compare the performance of our ranker model trained on the set of all features to models trained on each category of features in isolation. The dataset, linguistics, model, and syntax rankers consider the corresponding features for each category as inputs. The baseline model uses a similar number of decision trees and LambdaRank parameters and only differs by the subset of input features.

The mean and standard deviation of NDCG@3 using LLO on T is provided in Fig. 4. By considering a larger subset of features from different categories, our model outperforms baseline rankers on most tasks with the exception of the Compile Classification task where our model comes second to the model ranker. Ranking sources based on dataset specific features comes second in performance to our ranker while the least performing ranker on most of the tasks is the linguistic ranker. The relatively smaller significance of linguistics features compared

[2]For extracting token types for a large number of languages, we use Pygments, a python based generic syntax highlighter supporting a wide range of 572 programming languages.

Category	Feature	Description
Linguistic	Object Oriented	Is the language object oriented?
	Type Strength	Is the language strongly or weakly typed?
	Type Checking	Is the language typed statically or dynamically?
	Type Safety	Is the language type safe?
	Garbage Collection	Does the language use garbage collector?
	Standardized	Is the language standardized by a committee?
	Expression of types	Are the types written explicitly?
	Paradigm (o)	Paradigms supported (e.g., functional, imperative)
	Type Compatibility (o)	Is language nominally-typed or structurally-typed?
	Parameter Passing (o)	Parameter passing techniques (e.g., by value, by name)
Syntactic	Name (o)	Number of different names which overlap
	Text (o)	Number of different text data which overlap
	Keyword (o)	Number of different keywords which overlap
	Literal (o)	Number of different literals which overlap
	Punctuation (o)	Number of different punctuation signs which overlap
	Operator (o)	Number of different operators which overlap
	Comment (o)	Number of different comment tokens which overlap
	Syntax (o)	Number of different AST nodes which overlap
	Tokens (o)	Number of different tokens which overlap
Dataset -Specific	Difficulty (x)	Average difficulty of dataset problems
	Length (x)	Average number of tokens
	Time Limit (x)	Average time limit of dataset problems
	Memory Limit (x)	Average memory limit of dataset problems
Model -Specific	Pretrained (s)	Source language is included during pre-training
	Pretrained (t)	Target language is included during pre-training
	Pretrained (b)	Both source and target languages are included during pre-training

Table 5. Features organized by category. Some features are annotated by (o) for overlap, (s) for source, (t) for target, (b) for both source and target, (rd) for relative difference. For dataset specific features, (x) can be s, t, or rd.

to other features is further emphasized in Sec. 4.3 where we analyze the importance of different features to our ranker model by computing their corresponding Shapley values [19].

4.3 Feature analysis

To further explain the patterns observed in Sec. 4.1, we investigate the relative importance of the features contributing to cross lingual transfer. Explaining the variation of transfer across tasks, the dependence of transfer on source and target pairing, as well as the optimal transfer supported by specific sources require a thorough understanding of how different features affect transfer. One advantage of our decision tree based ranker model is its interpretability. We compute the Shapley values, a game theoretic concept introduced in [19] that is widely used in the interpretation of machine learning model predictions. The Shapley values for different features show the relative impact of each feature on the model output. In the context of ranking different source languages for cross-lingual transfer, Shapley values can provide an insight to how different features contribute to transfer.

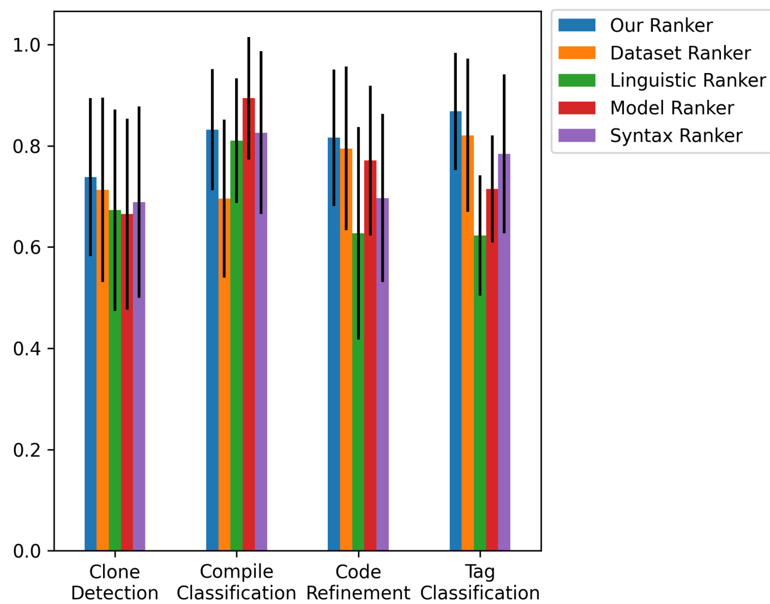


Fig. 4. Normalized Discounted Cumulative Gain score at 3 (NDCG@3) scores for different rankers and tasks corresponding to leave-one-out (LLO) evaluation over the set of target languages

We compute the Shapley values based on the ranking models evaluated in Sec.4.2, rescale the obtained values, and finally reorder features based on their average rank across different tasks. we obtain the heatmap in Fig. 5. We observe the following patterns:

Task-dependant feature importance: While previous works emphasize the importance of specific features for cross-lingual transfer, the lack of comparison on different tasks limits their conclusions. The supported cross-task analysis demonstrates a task-dependant feature importance whereby different features contribute differently to cross-lingual transfer depending on the task. For example, the top features for the Tag Classification task are *Difficulty (rd)*, *Literals (o)*, *Names(o)* and *Operators (o)*. Being able to predict the tags for a code solution requires some knowledge of the underlying problem for which the tags are an attribute. The difficulty score is another attribute of the problem. Problems with similar difficulty scores require similar algorithms. The literals, names and operators are other indicators of the algorithms used in a code sample. In comparison, the most significant features for the Clone Detection task are *Token (o)*, *Names (o)* and *Keywords (o)*. Detecting a clone requires different skills than classifying tags. A deeper understanding of the code semantics irrespective of the similar algorithms used is needed. The overlaps in names, keywords and more generally tokens is key for understanding the semantics of code.

Range of important features: Different tasks seem to not only focus on different features, but also focus on different number of features. While the Tag Classification and Compile Classification tasks focus on selective features, several features seem to be important for the Compile Classification and Code Refinement tasks. For example, the Code Refinement task requires a transfer of knowledge from overlapping keywords, names and more generally different tokens from a source language for fixing a code in a transfer language. While the Tag Classification task seems to require fewer features related to the problems attributes.

Comparison across categories: By comparing the importance of different feature categories across tasks, one can observe a relatively higher significance of syntactic features as demonstrated by the top two features *Keywords (o)*, and *Names (o)*. In comparison to [8], model-specific and linguistics features seem to be the least significant features for transfer. While the potential of cross-lingual transfer drops significantly for sources and targets that are not seen by the model in [8], our finding brings hope to the potential of not only transferring learning to low resource target languages, but also finetuning the model on unseen languages that could serve as good sources such as Kotlin.

Within-category differences: While different categories seem to have a higher impact on the model predictions, the impact of single features within a category seems to vary across task. The most important features being *Keywords (o)* and *Names (o)*, which have also been subject to comparison in a previous work [2] in terms of their impact on cross lingual transfer for source code. The cross-task comparison confirms the significance of the two features across tasks. However, half of the tasks show the precedence of an overlap on keywords compared to names, while the other half has the opposite order of importance. This finding suggests that both features are important for cross-lingual transfer however the precedence is task-dependant.

5 LIMITATIONS

The limitations of this paper fall into two broad categories: quantitative and qualitative.

Quantitative Limitations. We were restricted to 41 programming languages. That said, the number of languages in our paper far exceeds that of prior work on transfer learning for programming languages, and it seems the insights we gained from our study may not be enhanced too much with more languages, given the computational cost of study. We were restricted to 4 tasks. That said, the tasks we picked cover a broad spectrum of difficulty and are diverse, as evidenced by their different performance and feature importances. Given the limitations of

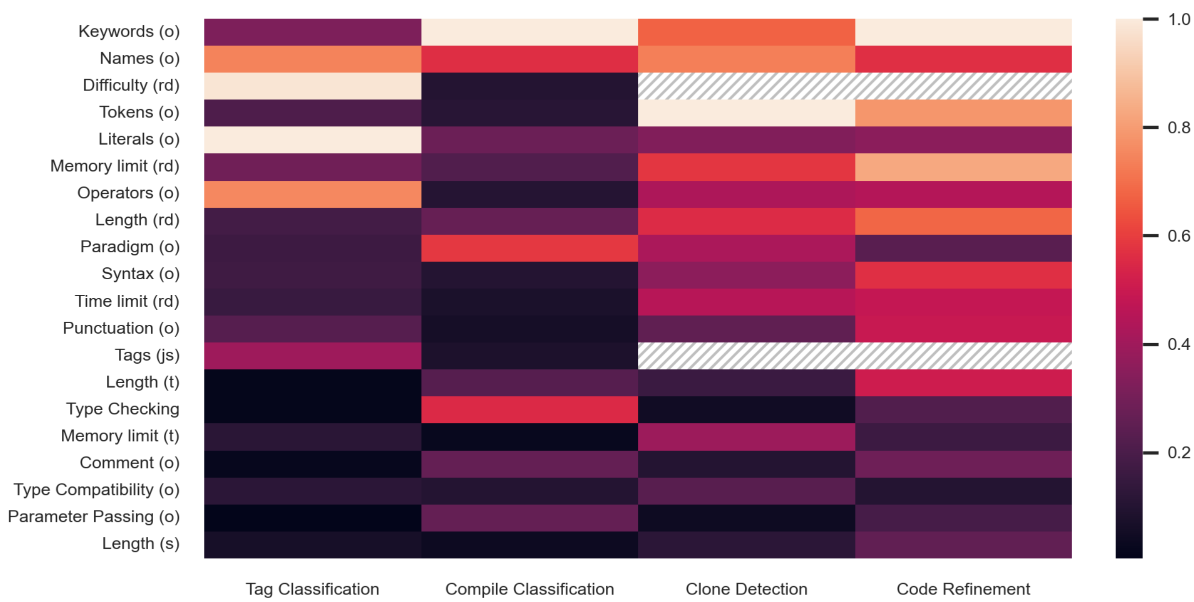


Fig. 5. Normalized SHAP values aggregated by tasks for the features defined in Tab. 5. The features are sorted by mean rank.

today's datasets, finding more tasks with a substantial number of languages was challenging and reducing the number of languages to increase the number of tasks would be an unfavorable tradeoff in terms of insights. Among language models for code, we did not use the largest. However, we believe that even if we had used larger language models, insights from one model would not perfectly generalize to another. Further, the pace of model releases is so fast that if we kept switching to the newest models, we may not have completed this study. More importantly, using a moderately-sized model made the experiments feasible and reduced their carbon footprint.

Qualitative Limitations. While all of our datasets are based on real code, they have some synthetic aspects, such as type-IV clones [23] for clone detection data or fault injection for refinement data. We had to make this compromise to obtain data covering many languages. It would have been great if the data for each task was a representative sample of the distribution of code in each language. However, this is such a high standard that hardly any LLM-based paper satisfies it, nor is it likely to be the case for practical real-world LLM applications. Therefore, we believed it more appropriate to work with the data at hand and mitigate its lack of representativeness, if any, by explicitly measuring it in the form of dataset-specific features of language pairs.

We tried to be as extensive as possible with the number of programming languages and tasks that we covered, but consequently we could only experiment with one large language model. Although we believe our findings are generalizable, we hope to experiment with a wider variety of tasks and models in the future.

6 CONCLUSION AND FUTURE WORK

We perform a systematic and extensive study of LLM transfer learning covering up to 41 programming languages, across 4 tasks including both classification and generation. Programming languages covered include several low-resource but often still widely-used languages. Cross-lingual transfer learning performs much better than zero-shot with an LLM that has been pre-trained on code. One interesting finding is that even languages not seen during pre-training, like Kotlin, can be good fine-tuning source languages across several target languages and tasks. On the other hand, certain languages that are often used extensively to pre-train LLMs, like C++ and Python, are not as good source or target languages relative to others.

In order to understand relative differences in cross-lingual performance between different programming languages, we define several linguistic, syntactic, dataset, and model-specific features of language pairs and then analyze the feature importance for a model that predicts transfer performance. We show how different features are needed for predicting performance, like in the case of ranking source languages, compared to ad hoc heuristics such as overlap on names. To explain how a language that was unseen during pre-training, like Kotlin, can be a good source language, we show that seen language features are less significant compared to dataset, linguistic, and syntactic source language features. Similar to previous work [2], we show that keywords and names are top features on average. On the other hand, unlike previous work, we cover more languages and more diverse tasks, and find that feature importances vary strongly across tasks.

Overall, we hope that this paper helps advance the community's understanding of how learning transfers among programming languages, and that this improved understanding in turn leads to better models to assist users of those languages, in particular, low-resource ones.

7 DATA AVAILABILITY

The experiments are based on the publicly available CodeT5-base (220M parameters) model [25] and the open-sourced datasets CodeNet [22] and XCodeEval [12]. Upon paper acceptance, we plan to open-source the code to create the derived datasets and the framework to train and evaluate the models. Also, we plan to make the 58 fine-tuned models available with the final version of the paper. We also plan to submit a replication package to the artifact committee.

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