Cross-Lingual Adaptation for Type Inference

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Abstract—Deep learning-based techniques have been widely applied to the program analysis tasks, in fields such as type inference, fault localization, and code summarization. Hitherto deep learning-based software engineering systems rely thoroughly on supervised learning approaches, which require laborious manual effort to collect and label a prohibitively large amount of data. However, most Turing-complete imperative languages share similar control- and data-flow structures, which make it possible to transfer knowledge learned from one language to another. In this paper, we propose cross-lingual adaptation of program analysis, which allows us to leverage prior knowledge learned from the labeled dataset of one language and transfer it to the others. Specifically, we implemented a cross-lingual adaptation framework, PLATO, to transfer a deep learning-based type inference procedure across weakly typed languages, e.g., Python to JavaScript and vice versa. PLATO incorporates a novel joint graph kernelized attention based on abstract syntax tree and control flow graph, and applies anchor word augmentation across different languages.

Besides, by leveraging data from strongly typed languages, PLATO improves the perplexity of the backbone cross-programming-language model and the performance of downstream cross-lingual transfer for type inference. Experimental results illustrate that our framework significantly improves the transferability over the baseline method by a large margin.

Index Terms—transfer learning, domain adaptation, deep learning, graph kernel, type inference

I. INTRODUCTION

Deep learning (DL) has achieved tremendous success in many applications such as image classification and audio recognition. Recently, DL has also been widely applied to software engineering tasks and obtain superior results over the traditional rule-based approaches, such as clone detection [1], [2], code summarization [3], [4], code translation [5], etc. To apply deep learning techniques, large amount of labeled data is required for the training of high-performance neural networks. However, it is well-known that manual labeling of data samples for deep learning is extremely laborious and expensive [6]. It is more challenging for software engineering tasks, since labeling requires considerable domain knowledge. Hence, it would be extremely valuable if we are able to learn new models for new languages based on existing labelled data, avoiding the need to invest additional efforts in labelling.

Transfer learning and domain adaptation is becoming increasingly popular, where a model developed for a task (or domain) is reused as the starting point for training a model for another task (or domain). For example, in natural language processing, some techniques [7], [8] have been proposed to transfer the knowledge between two languages (e.g., English and Nepali). Although transfer learning has been extensively studied in the fields of computer vision and natural language understanding, there is still little research on its applications in program analysis.

In this paper, we take the very first step to study the cross-lingual transfer learning in program analysis tasks, i.e., adapting the model trained on programs written in one language to programs in another language, which we also refer to as cross-lingual analysis adaptation. This work is motivated by the fact that the data labelling process for program analysis tasks is labor-intensive and time-consuming. Producing correct labels require not only the mastery of the target programming languages, but also the domain expertise for the subject analysis tasks. Moreover, most Turing-complete imperative languages share similar control- and data-flow structures (e.g., variable definitions, if-else branches, and loops), which makes the transfer of knowledge possible. Therefore, when one wants to perform similar analysis tasks (e.g., type inference, fault localization, and code summarization) in different languages, it saves significant efforts if we are able to transfer the knowledge learned from one labelled dataset (e.g., JavaScript) to another language without labelled dataset (e.g., Python).

However, adaptation of program analysis is more challenging than other domains, such as images and natural languages. First, the application of deep learning-based approach on program analysis is not as mature as that in other domains with well-established datasets and models. Second, the levels of indirection between the questions and the answers are significantly higher in the case of program analysis in comparison with other tasks such as recognizing objects in an image or summarizing the sentiment of a sentence. Notably, many program analysis tasks themselves are undecidable [9]. Finally, the dataset of software engineering and programming language is notorious for its extreme imbalance (i.e. the number of samples of each class is distributed unequally), which makes learning hard to generalize.

In this study, we concentrate on one particular cross-lingual adaptation task, to perform type inference for weakly-typed languages, namely, Python and JavaScript. Type inference [10]-[12] is to automatically deduce the type of variables or functions in a dynamic programming language, which is a fundamental program analysis technique used in bug localization, program understanding, reverse engineering, and de-obfuscation [13], [14]. There have already been some recent attempts on DL-based type inference of weakly-typed languages [11], [12]. These techniques adopt the supervised
learning approach, which works on a given set of labelled data, while the trained model is known to have limited transferability to other datasets.

To this end, we propose PLATO, a cross-lingual analysis adaptation framework, aiming to train type inference models with better transferability. The key to improve transferability is to increase attention on domain-invariant features (i.e., data-flow information) while decreasing attention on domain-specific features (i.e., language details). Specifically, we first perform reaching definition analysis to determine how closely related different identifiers are. This information together with the syntax information in abstract syntax tree is then encoded as a novel kernelized attention mechanism which constrains the attention scope of variables within code sequence during training process. We apply a dictionary-based keyword mapping approach (i.e. domain-specific keyword unification) to normalize a small amount of reserved keywords and operators (e.g., `function` in JavaScript and `def` in Python) that have similar syntactic and semantic functionalities, in order to reduce language-specific noises. Moreover, we may leverage additional unlabelled data (e.g., in the target language and strongly typed language) to further improve the transferability of our cross-language model. Finally, we adopt an ensemble-based inference which combines unkernelized model and kernelized model to achieve high generalizability and transferability.

To evaluate the effectiveness of PLATO, we conducted a two-way transfer experiment between Python and JavaScript. That is to use the model trained from the labelled dataset in one language to make predications on the unlabelled data of another language. We compared our approach with three widely used domain adaptation techniques [8], [15], [16]. The results demonstrate that our method significantly outperforms the baseline methods with a large margin. Specifically, from Python to JavaScript, PLATO improves the best unsupervised baseline performance by 14.6%, 19.6% and 18.6% in terms of accuracy, macro-F1 and weighted-F1. And 3.1%, 9.9% and 7.5% from JavaScript to Python.

To the best of our knowledge, this is the first work that studies the cross-lingual domain adaptation in the deep learning based program analysis tasks. In summary, we make the following contributions:

- We propose a cross-lingual transfer learning framework for type inference. To the best of our knowledge, this is the first work that studies cross-lingual domain adaptation of programming languages.
- We conduct extensive experiments to evaluate our approach on real-world datasets and achieve competitive performance against previous unsupervised and supervised baselines, which demonstrates the effectiveness and potential of PLATO.

## II. BACKGROUND

In this section, we introduce attention mechanism and mask language modeling.

### A. Attention mechanism

Given a word sequence, attention mechanism [17] tries to calculate word embedding for each of the words in the sequence. Basically, an embedding of a word (center word) is the weighted average of the embeddings of all the other words (context words) in the sequence, and the weights, known as the attention, are measured by its relations with all the context words in the sequence. The detailed formula is as follows:

\[
\text{emb}(q; K) = \sum_{k \in K} \alpha_{q,k} k = \sum_{k \in K} \frac{\langle q, k \rangle}{Z} k. \tag{1}
\]

Specifically, given a center word embedding \( q \in \mathbb{R}^{d_{\text{model}}} \) (\( d_{\text{model}} \) is the dimension of the latent representation used in a model), attention computes its cosine similarity with all the context word embeddings \( k \in \mathbb{R}^{d_{\text{model}}} \) within the sequence, which gives the attention weights \( \alpha_{q,k} \). Finally the aggregated representation of \( q \) is calculated as the average of \( k \) weighted by \( \alpha_{q,k} \). Noted that \( Z \) is a normalization term.

### B. Masked language modeling

Previous work [18]–[20] observed that instead of directly training a model with a supervised task-specific loss, model often benefit from combining with a self-supervised training stage, which is called masked language modeling (MLM). Specifically, given an input sequence, MLM masks a certain proportion of tokens within, and let the model to predict the words at the masked positions based on the other context words in the input sequence. The formula of MLM loss is as follows:

\[
\mathcal{L}_{\text{MLM}} = \sum_{x_{[\text{MASK}]} \in x_{[\text{MASK}]}} -\log(P(x_{[\text{MASK}]} | x \backslash x_{[\text{MASK}]}) \tag{2}
\]

where \( x \) is the input sequence and \( x_{[\text{MASK}]} \) is the set of tokens that are masked.

Inspired by the boost one can gain from MLM, XLM [7] introduce a cross-language model by training a BERT [19] (an attention based model) language model with corpus from multiple natural language sources and find it improve performance on cross-lingual tasks. In this paper, we train a language model with dataset from different programming language sources as the backbone model, we called it cross-programming-language model (XPLM).

## III. METHODOLOGY

### A. Overview

Figure 1 shows an overview of our framework, PLATO. Our key insight is to exploit common features of different programming languages relevant to the analysis task, and reduce the impact of irrelevant features. Specifically, PLATO consists of four components: 1) prepossessing of the training data, 2) data augmentation, 3) training and 4) ensemble-based inference.

For type inference, it is critical to know the relationship between variables, which is the common knowledge in programming languages. For instance, for a code snippet...
\[ a = 1! = 2; \] ... \textit{print}(a), we infer the type of the \textit{a} in the \textit{print} statement as Boolean based on the first statement \( a = 1! = 2 \) instead of anywhere else in the program. This is trivial for us human, however, it is hard for the deep learning based model to learn without prior knowledge. To learn such knowledge, we first perform a data flow analysis (i.e., the reaching definition analysis) on the abstract syntax tree of each program in the training data. For each program, we define a metric (i.e., an adjacency matrix) based on graph kernel, which we call \textit{variable relationship measurement}, to measure the relationship of variables. During training, instead of learning with traditional attention without constraint, we use the kernelized attention based on \textit{variable relationship measurement} to learn the features about variable relationships. In this way, the trained model constrains the attention scope of the center words therefore decrease the counter effect of the irrelevant or noisy features which hinder the transferability of the model.

To further improve the transferability, we further propose two augmentation strategies. We use the semi-supervised learning by introducing another dataset (e.g., the target dataset or other languages) in the pre-training stage, which augments the learning on the common features between different dataset. In order to avoid the noise caused by the syntax differences (e.g., the keywords), we propose a dictionary based anchor-word mapping \cite{21,22}, namely, domain-specific keyword unification that normalizes the unique keywords of source language data and target language data which serve similar syntactic and semantic functionalities into unified ones.

The kernelized attention model may not be perfect, for example, it may overfit to model variable relations and fail to properly model function return types relations. To mitigate this challenge and make best use of it, we propose an ensemble-based strategy that combines the kernelized model and un-kernelized model (i.e., attention model learned from code sequences directly without being constrained by kernel) during the inference. We expect the two models can complement each other and get better results.

\begin{itemize}
  \item \textit{B. Prepossessing}
  \end{itemize}

In this section, we introduce the details of data pre-processing of the language corpus, including 1) \textit{Variable Relation Measurement}, 2) Cross-lingual data augmentation, 3) Domain-specific keyword unification.

\begin{itemize}
  \item \textit{Variable Relation Measurement}. In traditional attention, the embedding of a word depends on its relations with all the other words in an input sequence, i.e., there is no constraint to its attention scope. For example, consider a code sequence \( \text{var } a = \text{true}; \text{var } b = 0 \), when calculating embedding for token \( a \), the traditional attention takes all the other tokens in the input sequence into consideration. However, it is apparent that \( \text{var } b = 0 \); is totally irrelevant to the type information of \( a \), thus if the model erroneously base its prediction on \( b \) or \( 0 \), it would be devastating for prediction and generalization. Therefore, we propose a kernelized attention mechanism, which uses a graph kernel to constrain the attention scope of tokens in code sequence.

  \end{itemize}

In this part, we first introduce a joint graph data structure. Then we introduce the distance metric we use on the joint graph, which is the essence of a graph kernel. And finally, we introduce how to derive the \textit{variable relation measurement} based on the previous two concepts with an example.

We introduce a joint graph data structure \( G = (T, N, E_{\text{AST}}, E_{\text{RDA}}) \) for code representation based on AST and reaching definition analysis (RDA) edges derived from Control Flow Graph (CFG), where \( T \) and \( N \) are the terminal and non-terminal nodes in AST, \( E_{\text{AST}} \) and \( E_{\text{RDA}} \) are AST and RDA edges that connect them, a joint graph of an example program is shown in Figure 2 where the circles are terminal nodes \( T \), the black square blocks are non-terminal nodes \( N \), the solid lines are AST edges and dashed lines are RDA edges.

Next, we introduce the distance metric we used on the joint graph, which is based on lowest common ancestor (LCA) \cite{23}. Given an AST \( G = (T, N, E_{\text{AST}}) \), the LCA path between a center node \( v_i \) and a context node \( v_j \) is the shortest path between \( v_i \) and \( v_j \) that goes through their lowest common ancestor, where \( v_i, v_j \in T \). The LCA distance \( d_{\text{LCA}} \) is thus defined as the distance between center word \( v_i \) and the common ancestor, illustrated as \cite{3}.

\begin{itemize}
  \item Fig. 1: Overview of PLATO
  \end{itemize}
Fig. 2: Modeling sample code with joint graph based kernelized attention.

\[
d_{LCA}(v_i, v_j) = ||v_i - LCA(v_i, v_j)||, \quad v_i, v_j \in T
\]

where \( LCA(\cdot, \cdot) \) is the lowest common ancestor between two nodes.

Then combined with the RDA edges \( E_{RDA} \), we have a joint graph \( G' = (T, N, E_{AST}, E_{RDA}) \). And the final distance metric is defined as follows:

\[
d(v_i, v_j) = \min(d_{LCA}(v_i, v_j), d_{RDA}(v_i, v_j)), \quad v_i, v_j \in T
\]

where \( d_{RDA} \) is defined as

\[
d_{RDA}(v_i, v_j) = \begin{cases} 
1, & \text{if } E_{RDA}(v_i, v_j) \text{ exists} \\
+\infty, & \text{otherwise}
\end{cases}
\]

Finally, We derive the variable relation measurement by applying the distance metric on the joint graph. Figure 3 shows the variable relation measurement derived from the example program shown in Figure 2. For example, we take the blue terminal node \( b \) as the center node. Starting from \( b \), it would take one node upward to reach the ancestor that leads to itself (i.e. \( d(b, b) = 1 \)); two nodes upward to reach the ancestor that leads to the red node \( a \) in the if condition (i.e. \( d(b, a) = 2 \)); three nodes upward to join with those that lead to the terminal nodes within the definition statement of \( a \) (i.e. \( d(b, \cdot) = 3 \)). Besides, illustrated by the dashed line (RDA edges), it takes only one node upward for the center node \( b \) to reach the terminal nodes within its nearest reachable definition statement \( b, /, 3 \). To this end, we attain the distance vector for \( b \) (the last row in the matrix). And by stacking the distance vectors of all the tokens together, we get the adjacency matrix—variable relationship measurement as shown in Figure 3 variable relationship measurement is used as input during both the semi-supervised pre-training stage and the supervised type inference training stage to constrain the attention of the model.

Cross-lingual data augmentation. Instead of solely using the in-domain (i.e. source domain) language corpus to train a mono-lingual language model like in the supervised learning setting. We also use out-domain (i.e. target domain) language corpus to train a cross-lingual programming language model XPLM. Specifically, in this work, we use the unlabelled target weakly-typed language which is used for downstream prediction (i.e. Python or JavaScript), along with another unlabelled corpus of strongly-typed language Java, to augment the corpus for pre-training XPLM in a semi-supervised manner. Intuitively, by augmenting the pre-training corpus, the shared vocabularies among languages may occur in more usage scenarios instead of overfitting to the usage in a single language domain. Therefore it is more likely for the model to learn domain-invariant representations from multilingual usage scenarios and therefore more generalizable and transferable to the target domain. Notice that the cross-lingual augmentation of language model is not constrained to the strongly-typed Java we use, other programming languages either strongly-typed or weakly-typed could also be used to increase the transferability.

Domain-specific keyword unification. Motivated by the observation that different languages can still share common vocabularies that serve same syntactic and semantic functionalities, we thus propose to adopt domain-specific keyword unification technique to further increase the transferability of our cross-lingual programming language model. Considering that while there are many reserved words and operators in different language domains that play the same syntactic and semantic roles, it is potentially hard to model their adjacency in the embedding space due to the gap in the usage scenarios of different languages as well as context that the reserved words exist. To this end, we propose a simple but effective strategy to augment the anchor vocabulary set by unifying reserved words that serve same syntactic and semantic functionalities in different language domains into the same anchor words. We empirically find it can significantly improve the transferability among domains which directly indicates the effectiveness of increasing domain overlap via keyword unification. Table I shows a subset of augmented anchors we choose.

C. Training

We use a two-stage training mechanism, 1) semi-supervised cross programming language model (XPLM) pre-training, and 2) supervised type inference training.
TABLE I: Subset of augmented anchors

| Js | Py | Anchor |
|----|----|--------|
| def | def | def |
| == | == | == |
| & & | & | and |
| | || | or |
| throw | raise | raise |

![Fig. 4: model architecture](image)

**Semi-supervised XPLM pre-training.** As shown in the model architecture in Figure 4 during semi-supervised pre-training stage. The XPLM backbone model receives two input: the original code sequence and its corresponding variable relationship measurement \( A_Q \); \( A_K \) is used to constrain the attention of the model at each layer. The detailed formula of the model is as follows:

\[
\text{emb}(q; K) = g_\sigma(A^Q_K) \odot \text{emb}(q; K) \\
= \sum_{k \in K} g_\sigma(A^Q_K) \frac{\langle q, k \rangle}{Z} \\
= \sum_{k \in K} e^{-\frac{||d(q,k)||^2}{2\sigma^2}} \frac{\langle q, k \rangle}{Z} 
\]

Specifically, at each layer of the model, we get the output embedding \( \text{emb}(q; K) \) for the center word \( q \) with respect to all the context word \( K \) in the code sequence. We then take the Hadamard product of \( \text{emb}(q; K) \) and \( g_\sigma(A^Q_K) \), \( g_\sigma(\cdot) \) is a Gaussian function parameterized by a learnable parameter \( \sigma \), which essentially controls the attention scope for each words in the input code sequence. For a context word \( k \in K \), the larger \( A^Q_K \) gets, the smaller the attention on \( k \) becomes (i.e. \( g_\sigma(A^Q_K) \propto \frac{1}{d(q,k)} \)). Intuitively, if a context word is distant from the center word in the joint graph in terms of \( d \), it is penalized and given smaller weights.

The model is then trained with a masked language modeling (MLM) loss \([19]\) and a regularization loss of \( \sigma \). The regularization loss is used to constrain \( \sigma \) from getting large, i.e. the attention scope from getting large during training. The detailed loss is as follows:

\[
\mathcal{L} = \mathcal{L}_{\text{MLM}} + \mathcal{L}_{\sigma} \\
= \sum_{x|M\text{[MASK]} \in X|M\text{[MASK]}}} -\log(P(x|M\text{[MASK]}|x \setminus x|M\text{[MASK]})) + \lambda \sigma^2 
\]

where \( \lambda \) is a hyper-parameter that is used to control to loss weight.

**Supervised type inference training.** As for the second stage, the input is the same as the pre-training stage, shown in Figure 4. In order to let the model make prediction, we attach a linear layer after the last hidden layer of the pretrained XPLM to predict the types of each variables. We fine-tune all the parameters in the model with a classification loss on the source language labelled dataset. Specifically, we use negative log likelihood loss as the loss function which is as follows:

\[
\mathcal{L}_{\text{CLASS}} = -\sum_{i=1}^{M} y_i \log \hat{y}_i, 
\]

where \( \hat{y}_i \) is the predicted probability vector represents the probability distribution over the possible type classes for sample \( i \). And \( y_i \) is an one-hot vector where the position of the ground truth type class is 1 while others are all 0.

**D. Ensemble-based Inference**

While the kernelized model can handle the samples with explicit syntactic relations and can help with the performance of type inference, it may not be able to cover all the semantic and syntactic usage scenarios in the real world (e.g. function return types) which further leads to negative transfer. To this end, we propose an ensemble strategy which combines the kernelized and unkernelized model during inference stage.

Algorithm 1 \( k_{\text{AST-attn}} \) bagging BERT

**Input:**
1. submodels: \( S = \{ \text{BERT}_{\text{unkernelized}}, \text{BERT}_{\text{kernelized}} \} \);
2. dataset: \( D = \{ x_1, x_2, \ldots, x_n \} \);
3. for each \( m \in S \) do
4. calculate 10th percentile rank of output logits of \( m \):
5. \( D_m = \{ \max_i(\logit(x_i)) \}_{i=1}^{n} \)
6. \( \theta_{m}^{10\%} \leftarrow D_m[10\%[D_m]] \)
7. end for

**Output:**
8. ensemble model: \( \text{BERT}_{\text{ensemble}} \);
9. \( H(x) = \arg \max_{i} \frac{1}{|S|} \sum_{m} \theta_{m}^{10\%} \logit_m(x) \)
\( \theta_{10\%} \) is an empirically selected confidence threshold that balance the recall and confidence of the kernelized model BERT\textsubscript{kernelized}. Intuitively, it helps to choose the subset of samples that the kernelized models are most confident with. Finally, we ensemble the logits of all submodels weighted with an indicator function \( \mathbb{1} \) parameterized by their corresponding confidence threshold \( \theta_{10\%} \). The detail of \( \mathbb{1} \) is as:

\[
\mathbb{1}_{\theta_{10\%}}(x_i) = \begin{cases} 
1, & D_m(x_i) > \theta_{10\%} \\
0, & \text{others}
\end{cases}
\]

Note that for cases where both the kernelized and unkernelized model do not pass the threshold, we choose the logit distribution of the kernelized model BERT\textsubscript{kernelized} as the output distribution.

IV. EXPERIMENTS

We have implemented PLATO based on PyTorch with about 3000 lines of code. To demonstrate the effectiveness of PLATO in the cross-lingual type inference task, we aim to study the following research questions:

- **RQ1:** How effective is PLATO compared with other domain adaptation techniques?
- **RQ2:** How useful is the kernelized attention in modeling the variable relationship and increase transferability?
- **RQ3:** How do the proposed augmentation strategies impact the results?
- **RQ4:** How useful is the ensemble-based inference?

A. Experimental Setup

Dataset Preparation. We mainly focus on the transferability between JavaScript and Python. Specifically, we select the JavaScript dataset from \([11]\). Then, we use Esprima\(^1\) to extract the abstract syntax tree (AST) for each samples. For Python, we select the dataset provided by Allamanis et al. \([12]\) and extract the AST information from their self-defined graphs. To evaluate the data augmentation, we select another Java dataset \([24]\) that is collected from popular repositories in GitHub.

Label Calibration. Since the type sets of different languages are different, we selected the common meta-types that have similar data structure or similar semantics in Python and JavaScript. For Python, we select 16 data types, which can be roughly categorized into 6 meta-types including: boolean, integer, float, bytes, string and list. For JavaScript, we select 8 data types, which are categorized into 4 meta-types: boolean, number, string and list. As a result, the task from Python to JavaScript is more fine-grained, i.e., the classification has 6 classes. Since the labels in JavaScript dataset \([11]\) is relatively coarser, to evaluate the accuracy, from Python to JavaScript, we map the prediction results of integer, float and bytes to number. And from JavaScript to Python, the task has 4 classes.

\(^1\)https://esprima.org
\(^2\)Note that, in the dataset \([11]\), the types of integer, float and bytes are coarsely labelled as number

Finally, after eliminating the samples that cannot be parsed, we collect 3764 Python programs including 27129 variables and 2106 JavaScript programs including 18113 variables. The distribution of meta-types in the two datasets are visualized in Figure 5.

![Fig. 5: Meta-type distribution in the Python and JavaScript datasets](image)

**B. Evaluation Metrics**

Following the existing works \([11]\), \([12]\), we firstly select the widely-used accuracy as the evaluation metrics. However, from Figure 5, we notice that the type distribution is extremely imbalanced. For example, string shares the largest proportion against all the others. Thus, a high accuracy can be easily achieved if a classifier is biased on predicting the type with the highest occurrences for the samples. Therefore, in order to better evaluate the performance, we use two variants of F1 score, namely, macro-F1 and weighted-F1 \([25]\):

- **macro-F1.** macro-F1 does not consider the size of different classes for multi-class classification and calculates the average of F1 scores among different classes, which is defined as follows:

\[
\text{macro-F1} = \frac{1}{|C|} \sum_{i \in C} \text{F1-score}_i
\]

where \( C \) is a set of classes and \( \text{F1-score}_i \) denotes the F1-score of the class \( i \).

- **weighted-F1.** In macro-F1, the F1-score of each class is given equal weights and does not take the size of each class into consideration. Furthermore, we use the weighted-F1, which is the weighted average of the F1-score of different classes:

\[
\text{weighted-F1} = \sum_{i \in C} \frac{|C_i|}{|C|} \text{F1-score}_i
\]

where \( |C_i| \) is the size of class \( C_i \), and \( |C| \) is the size of the entire dataset.
TABLE II: The comparative results with different methods.

| Domains          | Methods | Python → JavaScript | JavaScript → Python |
|------------------|---------|---------------------|---------------------|
|                  |         | Accuracy | macro-F1 | weighted-F1 | Accuracy | macro-F1 | weighted-F1 |
| Out-domain       | TAPT    | 0.601    | 0.495    | 0.546      | 0.578    | 0.367    | 0.483      |
|                  | MMD     | 0.574    | 0.492    | 0.55       | 0.557    | 0.387    | 0.503      |
|                  | ADV     | 0.53     | 0.432    | 0.501      | 0.54     | 0.382    | 0.504      |
|                  | Supervised | 0.552    | 0.425    | 0.503      | 0.499    | 0.353    | 0.484      |
|                  | PLATO   | 0.747    | 0.691    | 0.736      | 0.588    | 0.486    | 0.579      |
| Improvement (Δ)  |         | 14.6%    | 19.6%    | 18.6%      | 1.1%     | 9.9%     | 7.5%       |
| In-domain        | Supervised | 0.866    | 0.852    | 0.869      | 0.723    | 0.554    | 0.711      |

C. Baselines

We compare our framework with three popular domain adaptation methods, which are widely used in the text and image classification tasks [8], [15], [16]. We implemented these methods in our task.

TAPT. We adopt the Task-adaptive pre-training (TAPT) [8], [26], which leverages the task-relevant data to adapt the universal pretrained backbone model to specific downstream domain, as a baseline. Specifically, TAPT utilizes the unlabelled task-specific samples from both the source and target domain to further fine-tune the pretrained language model such that it is much more task- and domain-relevant. In this work, we use the whole unlabelled corpus from both source and target programming languages to adapt the XPLM.

MMD. We adopt Maximum Mean Discrepancy (MMD) [15], [27] as a baseline domain adaptation method. The key idea of adopting MMD for regularization purpose is to align the latent feature discrepancy between source and target domains such that they become indistinguishable by the model. In our work, we implement the MMD loss based on linear kernel [27] on the last hidden layer of the backbone model during the type inference training phase.

ADV. Besides MMD, we also adopt adversarial domain adaptation [16], [28] as another baseline to transfer the knowledge from source to target domain. The idea of ADV is to use reversed gradient drawn from domain classification loss to confuse the features from source and target domain during training. Specifically, we follow [16] to introduce a gradient reversal layer on top of the last hidden layer of the backbone XPLM model along with a domain classifier that tries to distinguish the domain of samples, where the parameters of the backbone network are updated simultaneously by both the gradient from task-specific classification loss and the reversed gradient from the domain classification loss during the backpropagation.

D. Configuration

We use a BERT [19] encoder with 4 stacked attention layers, 4-headed attention as the backbone XPLM. The dimension of all the token embedding is 256. For the baseline methods, the loss weight for MMD and adversarial loss is set to be 0.1. We conduct all experiments on a Ubuntu16.04 server with 24 cores of 2.2GHz CPU, 251GB RAM and two GeForce RTX 3090 GPU with total 48GB memory.

E. RQ1: Comparison with Baselines

Setting. We compare PLATO with three domain adaptation techniques (i.e., TAPT, MMD, ADV) and one supervised learning technique. We randomly split the target out-domain dataset into two equal sets, where one is used for validation of the choice of hyper-parameters. And the other is for testing the generalization of the model. The entire unlabelled out-domain dataset is used for semi-supervised learning of XPLM that is included in all domain adaptation techniques. For the supervised learning, we trained the classifier on the validation set and it is respectively used to evaluate the in-domain test dataset and the out-domain dataset.

Results. Table II shows the detailed results of different methods in terms of accuracy, macro-F1 and weighted-F1. The column Python → JavaScript shows the cross-lingual transfer results from Python to JavaScript while JavaScript → Python shows results of transfer from JavaScript to Python. Note that, in the row In-domain, we show the results of supervised learning in the same domain, which can be regarded as the upper bound of the domain adaptation techniques.

Overall, the results demonstrate that our method can significantly outperform the three domain adaptation techniques in terms of all metrics. The row Improvement (Δ) shows the improvement of our method compared to the best result in the baselines. Specifically, from Python to JavaScript, the performance of accuracy, macro-F1 and weighted-F1 is increased by 14.6%, 19.6% and 18.6%, respectively. And from JavaScript to Python, it is increased by 3.1%, 9.9% and 7.5% respectively.

Consider the results of supervised learning, not surprisingly, it achieves the worst results on the out-domain data due to that it has no knowledge of the out-domain. Compared with the in-domain results with supervised learning, we observe that, although our technique already achieved the best result, there is still a gap between the results of domain adaptation (i.e., without labelled data) and the supervised learning in the in-domain (i.e., with labelled data).

We also found that the improvement from Python to JavaScript is larger than the improvement from JavaScript to Python. The reason could be that 1) Python dataset is labelled with a more fine-grained way (i.e., 16 types) while JavaScript dataset is labelled more coarsely (i.e., 8 types), 2) the size of Python dataset is larger than the JavaScript dataset. The results tend to indicate that the in-domain dataset with higher quality
## Table III: The results on the impact of the kernelized attention

| Methods            | Python $\rightarrow$ JavaScript | JavaScript $\rightarrow$ Python |
|--------------------|---------------------------------|---------------------------------|
|                    | Accuracy | macro-F1 | weighted-F1 | Accuracy | macro-F1 | weighted-F1 |
| PLATO w/o Kernel   | 0.721    | 0.676    | 0.717       | 0.554    | 0.467    | 0.555       |
| PLATO w/o DA       | 0.741    | 0.684    | 0.729       | 0.571    | 0.474    | 0.566       |
| PLATO              | 0.747    | 0.691    | 0.736       | 0.588    | 0.486    | 0.579       |

Figure 6: Attention visualization in which kernelized model is more accurate than unkernelized model.

### Answer to RQ1: PLATO can significantly outperform the state-of-the-art baselines in terms of the accuracy, macro-F1 and weighted-F1. Moreover, the in-domain dataset with higher quality can lead to better results on the out-domain dataset.

### F. RQ2: Usefulness of kernelized attention

**Setting.** To evaluate the kernelized attention, we adopt an ablation study by removing the kernelized attention from PLATO, i.e., only use the code sequence features. Furthermore, we conduct a more fine-grained experiment to evaluate the impact of the data-flow analysis (i.e., we do not consider the def-use information in the variable relationship measurement).

**Result.** Table III shows the results after removing the kernel attention (Row PLATO w/o Kernel) and the data-flow analysis (Row PLATO w/o DA). After removing the kernelized attention, the performance decreased significantly. Specifically, from Python to JavaScript, the accuracy, macro-F1 and weighted-F1 are decreased by 2.6%, 1.5% and 1.9%, respectively. From JavaScript to Python, the performance is decreased by 3.4%, 1.9% and 2.4%, respectively. It demonstrates the usefulness of the kernelized attention strategy.

We provide two case studies to further demonstrate the usefulness of the kernelized attention in Figure 6. In the code snippet of Example 1 (view vertically), we show the attention of variable `baseurl` on each token in the code sequence. With the kernelized attention, PLATO identifies that `baseurl` has a very high attention score on `strr` (note that we normalize the original code string token with `strr` for better visualization), and `baseurl` is correctly predicted as `String`. However, without kernel, the token `]` has high attention scores and `baseurl` is incorrectly predicted as `Boolean`. In Example 2 (view vertically), with the kernelized attention, the value `showcolors` has a high attention on `true` and it is correctly predicted as `Boolean`. However, without the kernel, the variable `jasminenodeopts` has the highest attention and `showcolors` is incorrectly predicted as `String`. The visualization shows that kernelized attention forces the model to base its inference on relevant, domain-invariant features thus makes it more robust and generalizable among language domains.

After removing the data-flow analysis (i.e., Row PLATO w/o DA), the accuracy, macro-F1 and weighted-F1 are respectively decreased by 0.6%, 0.7% and 0.7% from Python to JavaScript, and 1.7%, 1.2%, 1.3% from JavaScript to Python, indicating that the data-flow analysis can further boost the performance.

### Answer to RQ2: The syntax and data-flow information within the kernelized attention are useful for enhancing the performance of PLATO.

### G. RQ3: Impact of the Augmentation

**Setting.** To evaluate the impact of augmentation, we remove semi-supervised learning component (i.e., without out-domain corpus) and the keyword unification component, respectively. Furthermore, we introduce another out-domain dataset (i.e., Java, a strongly-typed language) to evaluate the effect of different out-domain dataset in the semi-supervised learning.

**Results.** Table IV shows the detailed results. After removing semi-supervised learning (Row PLATO w/o semi), from Python to JavaScript, we observe that the performance decreased by 2.5%, 4.8% and 4.1% in terms of the accuracy, macro-F1 and weighted-F1. And from JavaScript to Python, the performance decreased by 4.6%, 8.1% and 6.3%. It demonstrates that the semi-supervised learning on the out-domain data could improve the transferability.

We then replace the out-domain data in the semi-supervised learning with the Java dataset (Row PLATO w/Java w/o semi). For example, from Python to JavaScript, we use Java as
TABLE IV: The evaluation results on the impact of the augmentation and the ensemble-based strategy

| Methods                  | Python → JavaScript | JavaScript → Python |
|--------------------------|---------------------|---------------------|
|                          | Accuracy  | macro-F1 | weighted-F1 | Accuracy  | macro-F1 | weighted-F1 |
| PLATO w/o semi           | 0.722     | 0.643    | 0.695       | 0.542     | 0.405    | 0.516       |
| PLATO w/o semi w/ Java   | 0.768     | 0.716    | 0.755       | 0.607     | 0.47     | 0.58        |
| PLATO w/ Java            | 0.771     | 0.723    | 0.76        | 0.555     | 0.461    | 0.555       |

|                          |          |          |             |          |          |             |
| PLATO w/o Unification    | 0.639    | 0.545    | 0.61        | 0.331    | 0.383    | 0.509       |
| PLATO-Sequence           | 0.721    | 0.676    | 0.717       | 0.554    | 0.467    | 0.555       |
| PLATO-Kernel             | 0.734    | 0.670    | 0.720       | 0.573    | 0.467    | 0.561       |

|                          |          |          |             |          |          |             |
| PLATO                    | 0.747    | 0.691    | 0.736       | 0.388    | 0.486    | 0.379       |

We further use the mixture of the out-domain data (i.e. JavaScript, Python and Java) in the XPLM pre-training (PLATO w/ Java). As we can see, from Python to JavaScript, it achieves the best result which can be explained by the fact that Java and JavaScript share relatively similar syntax structures compared with Python, thus with the augmentation of Java, the XPLM can better generalize to JavaScript. Whereas from Python to JavaScript, the result drops but still outperforms the result with only JavaScript. The results show that the performance of domain adaptation is likely to be enhanced by adding more diverse out-domain data.

Perplexity of a masked language model is the exponential of the MLM loss. It is an intrinsic evaluation metric widely used in natural language processing to evaluate the performance of a language model in an unsupervised manner. Intuitively, the smaller the perplexity is, the better the language model is in modeling the syntax and semantics of a language. We observe an interesting phenomenon shown in Figure 7, as we can see, compared with PLATO w/o semi, the perplexity of PLATO w/ Java w/o semi significantly drops, and the drop in perplexity is more significant from Python to JavaScript compared with JavaScript to Python due to the higher similarity between Java and JavaScript compared with Python. And from Python to JavaScript, the perplexity of PLATO w/ Java drops 1.035 bit compared with PLATO, while from JavaScript to Python, it increase 1.034 bit. It is obvious that the change in XPLM perplexity is positively associated with the change in performance of the downstream cross-lingual type inference transfer. Thus, perplexity can be well used as an indicator metric to help us decide which language (in the semi-supervised learning) could better help increase downstream performance.

Consider the results without keyword unification (Row PLATO w/o Unification), the performance is significantly reduced, indicating the domain-specific keyword unification is very useful for the cross-lingual domain adaptation of programming language tasks.

Answer to RQ3: The out-domain data in the semi-supervised learning is important, and selecting different out-domain data may have different effect for the domain adaptation. The perplexity can be used as a guidance on the language selection for the semi-supervised learning. The keyword unification can significantly improve the performance of PLATO.

H. RQ4: Impact of Ensemble-based Inference

To demonstrate the effectiveness of the ensemble-based inference, we evaluate each submodels along with their ensemble. The row PLATO-Sequence and PLATO-Kernel (in Table IV) show the results with and without kernelized attention, respectively. PLATO shows the results of combining these two models with our ensemble-strategy. The results show that PLATO can outperform each of the two submodels significantly. The ensemble-based strategy can make the best of the specialized submodel and compensate its weakness. For example, function return type which the kernelized model has not modeled.

Answer to RQ4: The ensemble-based inference can make the best of both the kernelized and unkernelized models, which greatly improves the performance on the cross-lingual type inference tasks.

I. Threats to Validity

The implementation of the baselines are one threat to the validity of the results. Since these methods are not used on the code learning tasks, we tried our best to adapt the code into our tasks. The selection of the datasets is one threat to the results. We selected the two benchmarks which are previously used in the type inference tasks. The hyper-parameters could be another threat. To mitigate this threat, we tried our best to
select the optimal parameters for each task. Finally, the label calibration (see Section IV-A) could be a threat to the results. In the future, we plan to re-label the JavaScript programs in the same fine-grained way with the Python dataset.

V. RELATED WORK
A. Unsupervised Domain Adaptation
As an important case of transfer learning, unsupervised domain adaptation (UDA) has drawn significant attention from the computer vision and natural language processing communities. The UDA research can be mainly categorized into three streams [29]: model-centric, data-centric and hybrid methods that combines the previous two.

Model-centric methods can be further categorized into two parts: loss-centric methods and feature-centric methods. For loss-centric methods, the goal is to minimize the distance among domains via gradient-based methods, Tseng et al. [15] first propose using maximum mean discrepancy (MMD) to minimize distance between image dataset from two distributions and boost transferability on image classification task. Recently, NLP community starts to investigate the possibility of applying the above techniques to NLP tasks, e.g., sentiment classification [30], [31], POS tagging [32], etc. For feature-centric methods, the goal is to extract common features across domains from the unlabeled dataset. Pan et al. [33] proposes spectral feature alignment for sentiment classification; Ziser et al. [34] use a pivot-based approach to augment training data. Similarly [34], [35] use pivot-based method to learn structure-aware textual representation. The anchor augmentation approach we use in this work lies in this category.

For data-centric methods, it is increasingly gaining popularity due to the advancement of using pretrained models [6], [19]. The goal of this line of research is to bridge the domain gap by manipulating data from source and target domains. pseudo-labeling [36]–[38] is a bootstrapping strategy that aims at making prediction on unlabeled dataset to augment the training of model. Data selection is another effective approach that aims to select matched data that bridge the distance between source and target domain. Jensen-Shannon divergence is used as a similarity metric to automatically select the most similar data for parsing sentiment analysis [39], [40]. There are also data-centric methods that are specially designed for pretrained language models which are popular in the NLP communities. Han et al. [41] propose the notion of adaptive pre-training, which adapt contextualized word embeddings from target domain by masked language modeling. Based upon it, multi-phase pre-training is proposed, the idea is to conduct secondary-stage unsupervised pre-training on task-specific corpus, e.g., biomedical text mining [42], dependency parsing [43] and cross-lingual learning [7], [44], [45]. Gururangan et al. [8] further propose the notions of domain-adaptive pre-training (DAPT) and task-specific pre-training (TAPT) that studies the effect of second-stage pre-training on the transferability across domains and tasks.

Additionally, notice that in the software engineering communities, the domain gap and distribution shift problem is nontrivial, Nam et al. [46] formulate the poor performance on cross-project defect prediction as a transfer learning problem. And managed to improve cross-project prediction performance with a novel transfer defect learning approach. Though UDA has been broadly explored in CV and NLP, it has not been paid enough attention in the programming language and software engineering community. However, consider the fact that we have abundant labeled dataset for high-resource programming languages shows great potential of knowledge transfer for relatively low-resource programming languages via UDA.

B. Statistical Type Inference
Type inference for weakly-typed language is widely studied in light of the widespread using of languages such as Python, JavaScript, etc. It is of great benefit for unveiling compile-time information during runtime for debugging and vulnerability detection. Statistical type inference is increasingly drawing attention due to its superior performance over traditional rule-based methods. JSNice [10] propose the first probabilistic type inference system based on conditional random fields (CRFs). DEEP TYPER [11] propose the first deep learning based JavaScript type inference model based on a combination of recurrent neural network. It improves [10] by considering much wider context of codes and is able to predict a larger set of type annotations. TYPILUS [12] proposes a type inference framework for Python by combining graph neural network based on AST with optional rule-based type checker.

C. Program representation learning
Leveraging deep learning models for solving software engineering problems is increasingly gaining interest. Most of these works focus on monolingual tasks. Zhou et al. [47] use graph convolutional network for vulnerability detection of C; Zhang et al. [3] use a recurrent neural network for code summarization of Python; code2vec [48] uses an attention model for method name prediction of Java. Recently, researches starts to investigate the power of multi-lingual language model for programming languages, CodeBert [49], a multi-lingual Transformer-based neural architecture for program representation learning has significantly improved several benchmarks, including code search, code document generation, etc. Transcoder [5] introduces a neural transcompiler that is able to translate functions between C++, Java and Python using unsupervised machine translation.

VI. CONCLUSION
In this work, we set out to conduct the first trial of cross-lingual adaptation of statistical type inference. Our experimental results are positive: by leveraging dictionary-based based keyword unification, incorporating joint graph based kernelized attention and augmenting training corpus for backbone cross programming language model, we set a new state-of-the-art baseline which significantly improves previous domain adaptation methods and achieves competitive performance against the supervised approaches. Our findings indicate great potential of leveraging data across different programming languages for other different deep learning based software engineering tasks.
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