Cross-Lingual Adversarial Domain Adaptation for Novice Programming

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Abstract

Student modeling sits at the epicenter of adaptive learning technology. In contrast to the voluminous work on student modeling for well-defined domains such as algebra, there has been little research on student modeling in programming (SMP) due to data scarcity caused by the unbounded solution spaces of open-ended programming exercises. In this work, we focus on two essential SMP tasks: program classification and early prediction of student success and propose a Cross-Lingual Adversarial Domain Adaptation (CrossLing) framework that can leverage a large programming dataset to learn features that can improve SMP’s build using a much smaller dataset in a different programming language. Our framework maintains one globally invariant latent representation across both datasets via an adversarial learning process, as well as allocating domain-specific models for each dataset to extract local latent representations that cannot and should not be united. By separating globally-shared representations from domain-specific representations, our framework outperforms existing state-of-the-art methods for both SMP tasks.

Introduction

Student modeling is a task of measuring students’ performance in a learning environment and predicting their future performance based on their previous interaction data. While student modeling has been extensively studied in well-defined domains like algebra and physics (Lin, Shen, and Chi 2016; Pardos and Heffernan 2010), student modeling for programming (SMP) remains an extremely challenging machine learning problem through the combination of Knowledge Tracing and Code Representation. Much of prior work has explored code representation (Mou et al. 2014; Allamanis, Brockschmidt, and Khademi 2018). Traditionally, expert-designed features are used for SMP (Marwan et al. 2020), but they heavily rely on expert knowledge of each task and are therefore labor-intensive and task-specific. Recently, deep learning-based models such as Code2vec (Alon et al. 2019) and ASTNN (Zhang et al. 2019) have demonstrated extraordinary results on public datasets by analyzing Abstract Syntax Trees (ASTs) of programs. These models, however, generally need a lot of data to perform well. For example, when it comes to program classification, ASTNN achieved 0.95 of AUC in CodeWorkout (D₂) dataset with 795 submissions compared with 0.81 in iSnap (D₁) dataset gathered from 171 students over four semesters. In real classroom settings, collecting programming sequences during small, in-person classes can be prohibitively expensive as most teachers don’t teach using the same assignments in different semesters and it is rare to have a large dataset to cover all the possible solution space (Piech et al. 2015b). Domain Adaptation (DA), on the other hand, has emerged as a promising research direction for reducing human effort in data collection by learning sufficient information from relevant domains (Shen et al. 2018; Wang et al. 2019; Jiang et al. 2019). DA has been shown to enhance performance in a range of fields by sharing feature representations across different domains, wherein training data are obtained from multiple domains (Nam and Han 2016).

In this work, we propose a Cross-lingual Adversarial Domain Adaptation framework named CrossLing leveraging data from other programming systems to improve SMP in small classroom settings. Our proposed framework is based on a novel AST-based Neural Network (ASTNN) (see (Zhang et al. 2019) for more details), which has been shown to be very successful in student code analysis (Shi et al. 2021). CrossLing uses an adversarial learning process to separate global latent representations across all domains from domain-specific representations. In this context, domains refer to programming systems using different programming languages. We leverage student programming data from iSnap (domain D₁) and CodeWorkout (domain D₂). The effectiveness of CrossLing is evaluated on two tasks: student program classification and student suc-
cess early predictions for $D_1$. For the former, our results show that CrossLing indeed outperforms the state-of-the-art methods such as ASTNN and Code2Vec and other baselines. For the more challenging task of student success early prediction, we further combine CrossLing with temporal deep learning models such as Long Short Term Memory (LSTM) (Hochreiter and Schmidhuber 1997) and Time-aware LSTM (T-LSTM) (Baytas et al. 2017), referred to as L-CrossLing and TL-CrossLing respectively. LSTM is designed to handle sequences of events with discrete time steps while T-LSTM can model the dynamics of student knowledge state in continuous time by taking the time elapsed between successive elements (Time-Aware) in a student’s trajectory into consideration. As far back as the mid-1950s, student response time has been considered an indicator of student proficiency (Schnipke and Scrams 2002) as it demonstrates how active and accessible student knowledge is (Thomas et al. 1986). Our results show that TL-CrossLing performs significantly better than other student modeling methods, including those using the gold standard: expert-designed features.

Our main contributions can be summarized as follows:

- To the best of our knowledge, our proposed CrossLing framework is the first attempt to utilize adversarial domain adaptation in programming domains, especially across different programming languages.
- We extend CrossLing by integrating LSTM and T-LSTM to deal with the temporal nature in student programming sequences with/without time-irregularities.
- We explore the robustness and the effectiveness of our CrossLing framework and proposed the temporal models on two student modeling tasks.

Methods

**Problem Description:** Let’s assume that we have 2 domains: $D_1$ and $D_2$. A domain $D_k$ contains $n_k$ student code snapshots represented as $D_k = \{ x^k_1, y^k_1 \}_{k=1}$ where $y^k_1 \in \{0, 1\}$ is the outcome label and each student code snapshot $x^k_1$ in $D_k$ consists of a single submitted code snapshot $x^k_i$ or a sequence of code snapshots: $x^k_i = \{ x^k_{1}, \ldots, x^k_{T_i} \}$, where $x^k_{t}$ represents the student’s code at time step $t$ in $x^k_i$ and $T_i$ is the total number of steps taken by student $k$. In this work, for example, $D_1$ is iSnap, which consists of time series of code snapshots from a relatively small group of students in a classroom setting, while $D_2$ is CodeWorkout collected from 795 students, one submission per student. In our problem setting, we assume that $n_1 << n_2$ and our objective is to learn common knowledge from both domains to enhance predictions for domain $D_1$. To do so, we apply adversarial learning to optimize the global representation for both domains as well as locally domain-specific knowledge.

For the task of program classification, the goal is to determine whether a code submission $x^k_{T_k}$ by student $k$ in $D_1$ is correct or not. For the early prediction task, we aim to predict a student’s future success based on partial sequence $\{ x^k_{1}, \ldots, x^k_{t} \}$ where $t < T_k$ in the small domain $D_k$. To do so, we leverage data from domain $D_2$, with a much larger number of $n_2$ students working on similar tasks. In the following sections, we omit index $k$ hereafter when it does not cause ambiguity for simplicity.

**CrossLing**

CrossLing is an ASTNN-based adversarial domain adaptation framework that learns both globally-shared and locally domain-specific information. Our key insight is that there are shared “global” features across programming languages and courses, which can be learned in one domain (with more data) and applied in another. However, the challenge is isolating these “global” features from the “local” ones, which cannot and should not be applied across domains. Fig. 1 shows the architecture of the proposed CrossLing framework. Specifically, a local ASTNN is used to capture domain-specific skills/features. And the global ASTNN learns to address the cross-lingual knowledge shared among different programming languages. The proposed CrossLing framework exploits both local and global feature spaces of the domain representations. To accomplish this goal, we set different loss objectives. A source domain loss $L_{src}$ is used to optimize the local classifier based on both local and global representations. A classifier loss $L_{clf}$ is employed to optimize the global classifier based only on global representations. A difference loss $L_{diff}$ is introduced to better splits global and local feature spaces. An adversarial loss $L_{adv}$ prevents the algorithm from identifying the features’ original domains in the shared space. The whole framework is optimized by minimizing the following loss:

$$L = L_{src} + \alpha L_{clf} + \beta L_{diff} + \gamma L_{adv}$$

(1)

where $\alpha$, $\beta$, and $\gamma$ are hyper-parameters used to weigh the importance of each loss term.

CrossLing pre-trains local ASTNNs to generate local representations and ensures that the global representations are different from the local ones by maximizing a dissimilarity measure. A discriminator and a classifier based on global representations are employed to ensure domain-invariant and class-discriminative projection. In the following, we describe the two steps for training the CrossLing framework.

**Step 1: Pre-train Local ASTNNs**

The pre-training phase is comprised of two parts. In the first part, we pre-train the embedding matrix for both

![Figure 1: CrossLing model structure](image)
programming domains. In this work, we applied word2vec with skip gram to learn the embedding matrix for both block-based $D_1$ and text-based $D_2$ programming languages (Bui, Jiang, and Yu 2018). In the second part, we transform the raw code to appropriate input for ASTNN using the embedding matrix learned from the first part, and then train a standard ASTNN classifier for each domain separately (without global ASTNN part). The pre-trained ASTNNs will be loaded to initialize the local ASTNNs of CrossLing.

**Step 2: Discriminative Adversarial Learning**

As shown in Fig. 1, our framework is composed of two pre-trained local ASTNNs, one for each domain from step 1, and one global ASTNN that will generate global latent representations. The discriminator aligns the global representations from two domains, and the classifier learns to predict the learning outcome. Below we describe the loss functions for all components in the CrossLing framework, including the global and local ASTNNs, discriminator, and classifiers.

1. **Global and Local ASTNNs**: The network parameters of two local ASTNNs are initialized based on the pre-trained ASTNNs to generate local representations. In the global ASTNN, input data from both domains is utilized to generate their global representations. Therefore, the training dataset for the global ASTNN is the union of the two domains, with size $n_1 + n_2$. In our framework, the global classifier only consumes the global latent representations from the global ASTNN. By contrast, we join the cross-domain (global) and domain-specific (local) representations to build local classification models for each source domain.

A simple fully connected neural network is used for classification, for all local and global classifiers. The network is optimized based on the binary cross-entropy loss in Eq. 2, where $y$ is the label linked to each input program and $\hat{y}$ is the output from each classifier, and $\Theta$ represents the relevant network parameters.

$$
\mathcal{L}(\hat{y}, y; \Theta) = -(y \log(\hat{y}) + (1 - y) \log(1 - \hat{y}))
$$

Therefore, we have:

$$
\mathcal{L}_{src} = \mathcal{L}(\hat{y}_{D_1}, y_{D_1}; \Theta_{D_1}) + \mathcal{L}(\hat{y}_{D_2}, y_{D_2}; \Theta_{D_2})
$$

$$
\mathcal{L}_{clf} = \mathcal{L}(\hat{y}_{g}, y_{g}; \Theta_{g})
$$

where $w_1$ and $w_2$ are the weights for each source domain. Stochastic gradient descent is used to update all the parameters based on back-propagation calculation.

2. **Difference Loss**: To encourage the separation of local and global feature representations, we add a dissimilarity measure defined by a Frobenius norm (Khoshnevisan and Chi 2020), which measures the orthogonality between global and local representations, and zero indicates orthogonal vectors. Let us denote matrices $Z^g_{D_1}$ and $Z^g_{D_2}$ as hidden global matrices. Similarly, $Z^l_{D_1}$ and $Z^l_{D_2}$ indicate hidden local representations. Therefore, the difference loss is defined as:

$$
\mathcal{L}_{\text{diff}} = \left\| Z^g_{D_1} Z^{l\top}_{D_1} \right\|_F^2 + \left\| Z^g_{D_2} Z^{l\top}_{D_2} \right\|_F^2
$$

where $\| \cdot \|_F^2$ refers to the squared Frobenius norm.

3. **Discriminator**: The shared feature space of the global ASTNN stores the common knowledge learned from both source domains, which is used to improve the classification performance. Thus, the shared feature space contains global features, and not domain-related information. That is, its predictions should be made based on global features that cannot discriminate between different source domains. We use a Gradient Reversal Layer (GRL) (Ganin et al. 2016) to achieve minimax optimization, and a domain classifier trained to predict the domain producing the hidden representations.

During adversarial training, given a code snippet, the discriminator $\Theta_d$ is optimized to determine the code’s source domain, while the global ASTNN $\Theta_g$ is trained to confuse it by learning features that represent common knowledge across the two domains. In this paper, the adversarial loss $\mathcal{L}_{adv}$ is defined as:

$$
\mathcal{L}_{adv} = \min_{\theta_d} \max_{\theta_g} \left( \sum_{j \in [D_1, D_2]} \sum_{i \in n_j} d_j^i \log(d_j^i) \right)
$$

$$
+(1 - d_j^i) \log(1 - d_j^i))
$$

where $n_j$ is the size of input data in domain $j$. During training, we maximize cross entropy for domain classification with respect to the discriminator $\Theta_d$, meanwhile minimizing it with respect to the global ASTNN $\Theta_g$.

**Temporal and Time-aware Frameworks**

We combine CrossLing with temporal models to handle sequences of student programming data (code). In prior research (Mao et al. 2020), T-LSTM was shown to deliver better performance by modeling the dynamics of student knowledge in continuous time, than standard LSTM using discrete timesteps. To investigate the relative performance of LSTM and T-LSTM on our task, we implement both models within the CrossLing framework, denoted as L-CrossLing and TL-CrossLing respectively. We contrast these models with another proposed model, TL-ASTNN. The following sections will provide detailed descriptions of these models.

**L-CrossLing and TL-CrossLing** The architecture of L-CrossLing and TL-CrossLing is shown in Fig. 2. The main difference between the two is that L-CrossLing uses LSTM to learn the temporal information while TL-CrossLing applies T-LSTM. To be specific, the temporal...
CrossLing framework contains two main parts: 1) local and global ASTNNs for code representation pre-trained from CrossLing; and 2) LSTM/T-LSTM to handle the temporal information. More specifically, in **Step 1: Pre-train CrossLing**, we first pre-train the original CrossLing framework as described earlier. Then we load the weights of local ($D_1$) and global ASTNNs into our temporal CrossLing framework (L-CrossLing or TL-CrossLing). And then in **Step 2: Optimize Training**, input data are fed into both local and global ASTNNs to generate corresponding representations and then passed to the connected LSTM or T-LSTM layer for evaluation. And we utilize the last-time output from LSTM/T-LSTM to make the final predictions. The whole model will be optimized by minimizing the cross entropy loss given in Eq. 2.

$$l_1, ..., l_T = \text{Local ASTNN}(x_1, ..., x_T)$$

$$g_1, ..., g_T = \text{Global ASTNN}(x_1, ..., x_T)$$

$$h_T = \text{LSTM} / \text{T-LSTM}([l_1, g_1], ..., [l_T, g_T])$$

$$\hat{y} = \text{sigmoid}(W h_T + b)$$

**TL-ASTNN** As shown in Fig. 3, TL-ASTNN can be interpreted as an extension of Temporal-ASTNN (Mao et al. 2021) (denoted as L-ASTNN (L for LSTM), to handle the time irregularity in student data. More specifically, the only difference is that in L-ASTNN, the output of ASTNN $Z_t$, is used as an input for the connected LSTM cell; while in TL-ASTNN, we pass both $Z_t$ and the corresponding time interval $\Delta t$ to the T-LSTM cell to model the temporal dynamics of student programming skills. With time as an input, TL-ASTNN is more time-aware so we expect it to make better predictions than L-ASTNN. The training process for TL-ASTNN can be summarized as follows:

$$z_1, ..., z_T = \text{ASTNN}(x_1, ..., x_T)$$

$$h_T = \text{T-LSTM}(z_1, ..., z_T)$$

$$\hat{y} = \text{sigmoid}(W_1 h_T + b_i)$$

where $W_1$ is the weight matrix and $b_i$ is the bias term for the connected linear layer. Still, the whole framework will be optimized by minimizing the cross entropy loss (Eq. 2).

**Datasets**

**iSnap**

iSnap ($D_1$), is an extension to Snap! (Garcia, Harvey, and Barnes 2015), a block-based programming environment, used in an introductory computing course for non-majors in North Carolina State University (Price, Dong, and Lipovac 2017). iSnap maintains a code trace log which records all student programming actions/steps (e.g. adding or deleting a block), a snapshot of the resulting code, and the time taken for each step. In prior research, an expert feature detector has been proposed to automatically detect 7 expert features of a student snapshot (Zhi et al. 2018). Those expert-designed features are binary and indicate whether the corresponding feature presents in student code or not. In this work, we focus on one homework exercise named Squiral, derived from the BJC curriculum (Garcia, Harvey, and Barnes 2015). In Squiral, students are asked to write a procedure that draws a square-like spiral; correct solutions use at least 7 lines of code with procedures, loops, and variables. In general, students spend about 20 minutes and use 10 to 2000 steps to complete it. We collected Squiral data from 4 semesters in years 2016 and 2017, with 65, 38, 29, and 39 student code traces respectively (see Appendix for detail).

**CodeWorkout**

CodeWorkout ($D_2$), is an open system for online programming in Java. It provides a web-based platform where students from various backgrounds can practice programming and instructors can offer courses (Edwards and Murali 2017). When students “submit” code, the system provides detailed pass/fail feedback on its expert-designed test cases. In this work, we focus on one exercise named isEverywhere, where the knowledge of loops and arrays are evaluated. As in prior research (Shi et al. 2021), we use the first submission from each student. This resulted in 795 student code submissions, which represent code snapshots as in iSnap, but only at the time when students first submit their code for feedback. Different from iSnap, CodeWorkout does not log student code traces during programming, but only their submissions. As a result, only submissions from students are recorded and sequences of student edits are not available.

**Task 1: Student Program Classification**

In the task of student program classification, we aim to predict the correctness of students’ submissions (i.e. correct or incorrect) in iSnap ($D_1$). The effectiveness of CrossLing is compared against standard ASTNN and other baselines.

**Experiments**

We evaluate the effectiveness of our proposed CrossLing in terms of its ability to accurately classify student code in iSnap ($D_1$); and more importantly, if it improves the performance of original ASTNN. Thus, we train CrossLing with data from both iSnap and CodeWorkout, but only test it on iSnap. In contrast, the training and testing sets for other baselines contain only iSnap data.

**Single Domain Baselines** We explore two types of baseline models, including three token-based classic machine learning (ML) models and two AST-based deep learning (DL) models. The classic ML models include K-Nearest
In the second task, we are given the first assignment within one hour (Mao et al. 2020). It is worth noting that student success early prediction is a much more challenging task compared to program classification: 1) it involves temporal information; and 2) the observation windows are very early (up to first 10 minutes) and thus students’ final submissions are not available for training or testing (Mao et al. 2021).

**Experiments**

To further explore the power of our CrossLing framework, we compare it with two other code representation groups: expert-designed features (Expert) and standard ASTNN on the early prediction task. For each group (Expert, ASTNN, CrossLing), we explore three different models: the “last value”-based (Batal et al. 2012) Logistic Regression (LR) models, the temporal LSTM models, and the time-aware LSTM (T-LSTM) models. Here, last-value models cannot handle sequential data, temporal models are able to do it but don’t consider time-irregularity, while time-aware models take the elapsed time between consecutive steps into consideration and are therefore aware of time. For example, when our observation window is the first 2 minutes, we apply the last value before 2 minutes for each sequence and treat them as inputs for the last-value model, while all the sequences that occur within first 2 minutes will be used for LSTM and T-LSTM; meanwhile, T-LSTM takes another sequences of time intervals as input.

**Three Expert Models**

The three models in the Expert group are trained on expert-designed features for the iSnap dataset ($D_1$). Specifically, Expert applies last-value LR; L-Expert is based on LSTM and TL-Expert utilizes T-LSTM.

**Three ASTNN Models**

There are three ASTNN-based models including last-value ASTNN, temporal ASTNN and our proposed TL-ASTNN, all of them use raw student iSnap code from $D_1$ as input.

**Three CrossLing Models**

We have CrossLing, L-CrossLing, and TL-CrossLing in this group. Different from the former two groups, these models are trained on data from both iSnap ($D_1$) and CodeWorkout ($D_2$). Excepting that LR is implemented using the sklearn library in python, all the other models are implemented in Pytorch using a mini-batch stochastic optimizer with grid search of batch sizes in $\{16, 32, 64\}$. The same experimental setup is used for all models with 100 epochs and early stopping. The embedding size for all ASTNNs/CrossLings is 128 and LSTM/T-LSTM hidden size is set to 64. All the sequences are zero-padded to have the same length.

**Results**

Table 1 compares the performance of the seven models for domain $D_1$, iSnap. Overall, our results show that CrossLing is the best among all the models for the task of student program classification. Specifically, CrossLing achieves around 4% and 2% improvement on Accuracy and AUC over standard ASTNN, respectively. These results suggest that by learning the common knowledge from different domains, our proposed domain adaptation approach can help to improve the performance of ASTNN and also address the lack of sufficient labeled data. Given its effectiveness, we further explore the temporal CrossLing models on the task of student success early prediction.

**Task 2: Student Success Early Prediction**

In the second task, we are given the first up to $n$ minutes of a student’s sequence data and our goal is to predict whether the student will successfully complete the programming assignment within one hour (Mao et al. 2020). It is worth noting that student success early prediction is a much more

| Model         | Accuracy | Precision | Recall | F1    | AUC   |
|---------------|----------|-----------|--------|-------|-------|
| Majority      | 0.632    | -         | -      | -     | 0.500 |
| KNN           | 0.613    | 0.732     | 0.612  | 0.667 | 0.614 |
| LR            | 0.660    | 0.830     | 0.582  | 0.684 | 0.689 |
| SVM           | 0.660    | 0.746     | 0.702  | 0.723 | 0.646 |
| Code2Vec      | 0.681    | 0.804     | 0.679  | 0.724 | 0.702 |
| ASTNN         | 0.811    | 0.873*    | 0.821  | 0.846 | 0.808 |
| CrossLing     | 0.849*   | 0.859     | 0.910* | 0.884*| 0.827*|

Note: best model in **bold** and *
### Table 2: Student Success Early Predictions at First-2-minute

| Model   | Accuracy | Precision | Recall | F1   | AUC  |
|---------|----------|-----------|--------|------|------|
| Majority | 0.660    | -         | -      | -    | 0.500|
| Expert Group |
| Expert   | 0.651    | 0.726     | 0.757  | 0.741| 0.601|
| L-Expert | 0.669    | 0.670     | 0.986* | 0.798| 0.521|
| TL-Expert| 0.689    | 0.687     | 0.971* | 0.805| 0.555|
| ASTNN Group |
| ASTNN    | 0.660    | 0.702     | 0.843  | 0.760| 0.574|
| L-ASTNN  | 0.717    | 0.738     | 0.886  | 0.805| 0.637|
| TL-ASTNN | 0.736    | 0.756     | 0.886  | 0.816| 0.665|
| CrossLing Group |
| CrossLing| 0.708    | 0.708     | 0.943  | 0.810| 0.596|
| L-CrossLing | 0.774* | 0.788*   | 0.900  | 0.840*| 0.714*|
| TL-CrossLing | 0.783* | 0.831*   | 0.843  | 0.840*| 0.755*|

Note: best models in each group are in **bold**

The comparison of all models for the early prediction of student success in first 10 minutes is reported in Table 3. Here we report the mean value and corresponding standard deviation (in parenthesis) for each evaluation metric. Following prior research (Kurmi, Kumar, and Namboodiri 2019), we also report the Critical Difference (CD) diagram for Nemenyi test (Wilcoxon Signed Ranks Tests showed the same results) in Fig. 4.

Table 3 shows a similar pattern as we observed earlier in Table 2. In each group (Expert, ASTNN, CrossLing), T-LSTMs outperform LSTMs and LR. Furthermore, when implementing the same temporal (or last-value) models, CrossLing is generally shown to be the best one. Overall, TL-CrossLing is the best model and it achieves the best Accuracy, Precision, F1 and AUC (a 7% improvement over TL-ASTNN) in first 10 minutes, followed by L-CrossLing with the second-best Accuracy, Recall, F1 and AUC. Therefore, our temporal CrossLing models are the best two models for student success early predictions in first 10 minutes.

**Feature Visualization** To illustrate the difference between ASTNN and CrossLing, we visualize the locations of three student code snapshots: S1 and S2 are from the unsuccessful group while S3 is a successful one. Fig. 5 shows the t-SNE visualization (Van der Maaten and Hinton 2008) of the learned feature representations for both models on the student success prediction task. In the figure, blue and orange markers represent successful and unsuccessful iSnap (D1) samples in the first 2 minutes, respectively. • and × in Fig. 5(b) are local and global representations, respectively. As we can see, the feature representations for S1 and S2 in ASTNN’s feature space, while S3 is very close to S2. It seems that standard ASTNN fails to differentiate S3 from S2, and misses the similarities between S1 and S2 that make them unsuccessful (e.g. failing to update a key variable). In contrast, Fig. 5(b) shows that the CrossLing feature representations for S1 and S2 are similar, and both of them are well-separated from S3 across both local and global feature spaces. Moreover, the successful and unsuccessful groups are better clustered in the CrossLing model’s local representations. That is, our proposed CrossLing model picks up the information lost by standard ASTNN through learning the cross-domain and domain-specific knowledge together.
### Related Work

**Student Modeling**  Student modeling has been widely and extensively explored by utilizing student sequences. Prior research has proposed a series of approaches mostly for well-defined domains, such as Item Response Theory (IRT) (Tatsuoka 1983), Performance Factor Analysis (PFA) (Pavlik, Cen, and Koedinger 2009), Bayesian Knowledge Tracing (BKT) (Corbett and Anderson 1994). Recently, deep learning models, especially Recurrent Neural Network (RNN) or LSTM-based models such as LSTM have also been explored in student modeling and have shown superior performance (Piec et al. 2015a; Tang, Peterson, and Pardos 2016; Khajeh, Lindsey, and Mozer 2016; Xiong et al. 2016).

Programming, by contrast, has been relatively under-explored for student modeling. Wang et al. (2017) applied a recursive neural network similar to (Piec et al. 2015b) as the embedding for student submission sequence, then fed them into a 3-layer LSTM to predict the student’s future performance. On the other hand, Emerson et al. (2019) have utilized four categories of features: prior performance, hint usage, activity progress, and interface interaction to evaluate the accuracy of Logistic Regression models for multiple block-based programming activities. More recently, Dong et al. (2021) proposes a data-driven method that uses student trace logs to identify struggling moments during a programming assignment and determine the appropriate time for an intervention. As far as we know, our proposed temporal CrossLing framework is the first attempt to address student modeling for novice programming through adversarial domain adaptation across different programming languages.

**Domain Adaptation**  Numerous approaches have been proposed to address adaptation needs that arise in different application scenarios, such as image recognition, text classification, sentiment classification, etc. (Ling et al. 2008; Zhuang et al. 2019; Khoshnevisan and Chi 2020). The main challenge of cross-domain learning is how to reduce the discrepancies in data distributions across domains. One line of research is focusing on adversarial learning, which is designed to minimize the approximate discrepancy distance between different domains. For example, domain adversarial neural network (DANN) employs a gradient reversal layer (GRL) and learns domain-invariant features by a minimax game between the domain classifier and the feature extractor (Ganin and Lempitsky 2014). Adversarial discriminative domain adaptation (ADDA) uses GAN (Goodfellow et al. 2014) with general loss in a non-shared weight architecture (Tzeng et al. 2017). Our proposed CrossLing framework is also an adversarial adaptation method as it learns and evaluates global representations in an adversarial manner.

Within the field of NLP, deep learning methods form another line of work to automatically produce superior feature representations for cross-domain scenarios (Ganin et al. 2016; Liu, Qiu, and Huang 2017; Joty et al. 2017). These deep networks explore effective domain discrepancy measurement and matching methods to boost performance (Glorot, Bordes, and Bengio 2011; LeCun, Bengio, and Hinton 2015). For example, the multi-domain adaption adversarial network (MDANet) is proposed to alleviate the domain discrepancy based on explicitly learning a shared feature space across different domains (Ding et al. 2019). This architecture is similar to ours, while we are focusing on a more challenging programming scenario involving different programming systems with different programming languages.

### Conclusions

Developing a robust, generalizable model for the early prediction of student learning progression is a crucial yet challenging task. With jobs in computing projected to grow 13% from 2020 to 2030, the need for automated support for learning programming is growing. Research shows that student modeling can improve learning by 1-2 standard deviations when adapting difficulty and interventions to students’ needs well (Arroyo et al. 2007). Educational environments, with SMP, stand to benefit tens of millions of students learning programming in K-12 and CS classes. In this work, we demonstrate the effectiveness of CrossLing on both student program classification and student success early predictions. Empirically, we show that CrossLing-based models outperform state-of-the-art methods because of their ability to separate local information from global representations and leverage the common knowledge from different domains. In future work, we plan to investigate our framework on other tasks or different domains to explore whether it consistently supports improvement for programming environments.

**Table 3:** Average Performance of Student Success Early Predictions in first 10 minutes

| Model          | Accuracy | Precision | Recall | F1   | AUC   |
|----------------|----------|-----------|--------|------|-------|
| **Majority**   |          |           |        |      | 0.500 |
| **Expert**     | 0.657 (±0.05) | 0.821 (±0.05) | 0.625 (±0.06) | 0.702 (±0.06) | 0.673 (±0.05) |
| L-Expert       | 0.717 (±0.03) | 0.730 (±0.04) | 0.931 (±0.03) | 0.817 (±0.02) | 0.624 (±0.06) |
| TL-Expert      | 0.745 (±0.04) | 0.793 (±0.06) | 0.846 (±0.07) | 0.814 (±0.03) | 0.698 (±0.06) |
| **ASTNN**      | 0.65 (±0.02) | 0.746 (±0.03) | 0.769 (±0.01) | 0.752 (±0.03) | 0.623 (±0.03) |
| L-ASTNN        | 0.740 (±0.02) | 0.760 (±0.03) | 0.891 (±0.04) | 0.819 (±0.01) | 0.668 (±0.04) |
| TL-ASTNN       | 0.770 (±0.03) | 0.796 (±0.02) | 0.877 (±0.04) | 0.834 (±0.02) | 0.719 (±0.03) |
| **CrossLing**  | 0.715 (±0.02) | 0.746 (±0.03) | 0.869 (±0.05) | 0.801 (±0.01) | 0.663 (±0.04) |
| L-CrossLing    | 0.7793 (±0.01) | 0.799 (±0.02) | 0.891 (±0.02) | 0.8421 (±0.01) | 0.726 (±0.02) |
| TL-CrossLing   | 0.789 (±0.01) | 0.847 (±0.02) | 0.866 (±0.04) | 0.856 (±0.01) | 0.786 (±0.02) |

*Note: ‡ indicates the use of the domain-invariant feature by a minimax game between the domain classifier and the feature extractor.*
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