Learning to Extend Program Graphs to Work-in-Progress Code

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Abstract

Source code spends most of its time in a broken or incomplete state during software development. This presents a challenge to machine learning for code, since high-performing models typically rely on graph structured representations of programs derived from traditional program analyses. Such analyses may be undefined for broken or incomplete code. We extend the notion of program graphs to work-in-progress code by learning to predict edge relations between tokens, training on well-formed code before transferring to work-in-progress code. We consider the tasks of code completion and localizing and repairing variable misuse in a work-in-process scenario. We demonstrate that training relation-aware models with fine-tuned edges consistently leads to improved performance on both tasks.

1 Introduction

Source code written by people is natural in the sense of being predictable [30, 60]. This warrants building machine learning models for code [4]. These models range from ones based on n-grams [30, 28] and graphical models [61], to those based on various neural networks [3, 13, 12, 84, 38, 66, 83, 49, 5, 6, 14, 27] and combinations thereof [29, 69, 80].

While promising results can be obtained by building models of the source code token sequence alone, domain-specific task performance can typically be improved by leveraging graph-structured representations of programs, where edge relations are derived from traditional program analyses [3, 10, 18, 17]. Given well-formed code, a variety of program analyses can be run to determine properties of code semantics and relationships between code elements [16, 62, 51]. However, for work-in-progress code that may be broken or incomplete, these analyses are typically undefined under the programming language’s standard specification.

One could attempt to build program graph libraries on top of robust analyzers [1] or by training a machine learning model to repair code and then analyzing the fixed code. Yet, both approaches create a new hard subproblem that may not be necessary to solve perfectly in order to obtain good performance on the downstream task. Instead, we propose a simpler option that requires only the ability to run program analyses on well-formed code, and results in model components that can be fine-tuned while training a relation-aware model on a downstream task.

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Consider the example in Figure 1 where there is an extra indentation in a piece of Python code. This code cannot be executed, and thus it does not strictly make sense to analyze properties of its semantics. However, one could reasonably expect that the data flow relations illustrated by the arrows still hold. In fact, these arrows are predictions made by our proposed relation prediction model, trained on well-formed code and then transferred to the broken code snippet in the figure.

Our primary contribution is to show that graph-structured representations of programs derived from traditional program analyses can be extended to broken and incomplete code by leveraging inherent generalization in machine learning models that predict edges. We train these models with direct supervision on well-formed code before transferring to work-in-progress code. We demonstrate the effectiveness of this out-of-distribution generalization by showing that relation-aware models [65, 79] can effectively use the predicted edges on work-in-process code. We evaluate our approach on two downstream tasks where work-in-progress code is broken in different ways: (a) localizing and repairing variable misuses and (b) code completion. By additionally fine-tuning the relation prediction model during task learning, we achieve strong improvements over relation-agnostic baselines. In total, this work points towards a simple and practical solution for realizing the power of relation-aware models on the work-in-progress code that commonly arises in the software development process.

2 Background

We review Transformers and relation-aware models for code, on which our work is heavily based.

Transformer. The Transformer model [71] consists of stacked multi-head attention and position-wise fully-connected layers. A multi-head attention layer enables encodings at a position in subsequent layers to attend to encodings at all locations in the previous layer via softmax attention whose scores are computed as \( \alpha = \text{Softmax}(\frac{q^T k}{\sqrt{d}}) \). Here, \( \alpha \) is the attention score, \( q \) and \( k \) are respectively the query and key, and \( d \) is the dimension of the encoding space.

Relation-aware Models for Source Code. Many machine learning models for code take into account relational structure. These models include variants of graph neural networks [3] and Transformers using relative positions [65, 29, 73, 84]. Our focus is specifically on models that modify the standard attention computation [65, 19] by altering \( q \) or \( k \) using edge embeddings. We use the terms relation-aware and edge-aware exclusively for these models in the paper for ease of presentation.

3 Learning to Extend Program Graphs

We propose to learn a relation prediction model for source code tokens so that relation-aware models can be applied to work-in-progress code which may be broken or incomplete. We cast the learning problem as a supervised one: Given ground truth edges between tokens, train a model to predict edges given only the token sequence. This is a multi-label classification problem, where multiple edges of different types might exist between the same ordered token pair.

3.1 Ground Truth Relations

We use the edge relations described by Hellendoorn et al. [29] as the ground truth. The relations are derived from ASTs, control flow graphs, and data flow graphs of well-formed code and are of 10 types. Not all types have similar frequencies. For instance, among the relations we consider, four types form less than 0.5% of the total edges in a task we consider. The edge relations are also very sparse: Less than 0.3% of the ordered token pairs are connected (see Figure 2). The sparsity of edges makes the binary classification problem for each edge type a label-imbalanced one, and we follow Johnson et al. [34] in optimizing the focal loss [43] as a remedy.

3.2 The Edge Prediction Model

Architecture. Our edge prediction model is based on the Transformer base architecture without its final encoding-to-logit layer (\( n_{\text{layers}} = 6 \), \( d_{\text{model}} = 512 \), and \( d_{\text{ff}} = 2048 \)). We add a final block to
this architecture that produces a logit tensor which has size quadratic in the sequence length, each entry of which is used for computing a sigmoid score of whether a type of relation exists between an ordered token pair. This final block consists of (i) a multi-head attention that produces a tensor of size \( (B, L, L, H) \), followed by (ii) a dense layer that produces a tensor of size \( (B, L, L, E) \), where \( B \) is the batch size, \( L \) is the sequence length, \( H \) is the number of hidden units, and \( E \) is the number of edge types. We use “Pre-LN” described in [77] and adopted in GPT-2 [59], where Layer Normalization [8] is placed inside residual blocks. The multi-head attention in the final block has improved capacity with \( H = 32 \) and \( d_{\text{model}} = 1024 \). This architecture is similar to the dot product baseline used by Johnson et al. [34], but is different in that we train one model for all relation types.

**Causal Masking.** For applications with causal ordering (e.g. code completion), the model should not attend to a future token when producing the edge score for two earlier appearing tokens. This is because the model does not have access to future information at test time. Due to the edge prediction model being based on the Transformer, it suffices to apply the usual causal mask (masking out position \( i \)'s attention to any position \( j > i \)) to the base Transformer and the last attention block. This is because the edge logit between any ordered pair of distinct positions \( (i, j) \) is a position-wise non-linear transform of the dot product between the encodings \( e_i \) and \( e_j \), each of which is independent of future information after applying the causal mask.

### 3.3 Using Predicted Relations

We apply the learned relation prediction model to code completion and localizing and repairing variable misuse. For the variable misuse task, we specifically focus on localizing and repairing such bugs for work-in-progress code that is broken. This task is motivated by the desiderata that a machine-learning-powered IDE should be able to perform high quality analysis even on code that is temporarily broken due to intermittent editing by a developer.

The core architecture we adopt use relative position representations [65, 19, 79]. Specifically, in all Transformer architectures, we use the relative positional encoding described by Dai et al. [19]. The corresponding attention computation has the following form:

\[
\alpha_{i,j} = \frac{E_{x_i}^T W_q^T W_{k,E} E_{x_j} + E_{x_i}^T W_q^T W_{k,R} R_{i-j} + u^T W_{k,E} E_{x_j} + v^T W_{k,R} R_{i-j}}{\text{mask}}. \tag{1}
\]

Here, \( \alpha_{i,j} \) and \( R_{i-j} \) are respectively the attention score and relative positional encoding from the \( i \)th to the \( j \)th token in the sequence. \( E_t \) is the encoding for token \( t \). \( W_q \) is used to compute queries, \( W_{k,E} \) is used to compute keys with the encoding, \( W_{k,R} \) is used to compute keys with the relative position, and \( u \) and \( v \) are biases shared across all multi-head attention layers. The choice of relative positional encoding as opposed to the absolute one is inspired by their improved performance on code summarization [84].

To leverage the additional edge relations provided by the relation prediction models, we associate each type of edge with a trainable parameter vector, and augment terms \((b)\) and \((d)\) in equation 1. Concretely, suppose the ordered token pair \( (x_i, x_j) \) has a relation of type \( r \) with the embedding vector \( R^{(r)} \), the updated attention has the following form:

\[
\tilde{\alpha}_{i,j} = \alpha_{i,j} + \frac{E_{x_i}^T W_q^T W_{k,R}^{(r)} R^{(r)} + v^T W_{k,R}^{(r)} R^{(r)}}{\text{mask}}. \tag{2}
\]

When there exist multiple relations between an ordered pair, we aggregate their contributions by summing the terms \((b')\) and \((d')\) for each edge type. For a multi-head attention layer, we replicate the update in equation 2 across all heads. With the aid of ground truth relations, \((b')\) has been used to modify the attention in the GREAT [29] and RAT-SQL [73] models, whereas the combination of \((b')\) and \((d')\) has been used in the Code Transformer model [84]. Since the edges we model are sparse, the additional term in equation 2 can be computed and backpropagated through with sparse primitives in standard automatic differentiation libraries. In practice, we observe a minor overhead for training\(^2\).

\(^2\)We observe a 7% wall time training overhead (estimated using torch.autograd.profiler) of the relation-aware model compared to one without computing the additional term in equation 2. While wall time is dependent on the hardware and implementation, we expect to see similar numbers across similar settings.
3.3.1 Architecture for Code Completion

The architecture for the code completion task is slightly involved due to the need to predict subwords, multiple of which form a token. This is at odds with the ground truth edge relations described in Section 3.1, which is between full tokens. While it is possible to extend the same edge relation between tokens for subwords in a fashion of creating bipartite graphs (connect every subword for token A to every subword for token B, if a relation exists between tokens A and B), our preliminary experiments suggest that learning such extended edges between subwords is difficult (e.g. precision and recall scores for certain edge types are lower than 0.6 even after hyperparameter tuning).

We propose to maintain the edge relation structure, but adjust the model for code completion to better adapt to the edge data. Specifically, to predict each token, our model predicts an encoding and generates all subwords for the token in an autoregressive manner conditional on the encoding. Our architecture has three components: ① a Transformer encoder that takes in averaged embeddings of subwords for each token with attention scores computed based on equation 2, ② an attention-based Gated Recurrent Unit (GRU, [15]) decoder which predicts the next subword for each token given all previous subwords, and ③ a linear projection layer that maps encodings to logits. See Figure 3 for an illustration.

The attention mechanism of the GRU ② is based on that described by Luong et al. [44]: The subword embedding and hidden state from previous steps are given to the GRU cell to produce an output, which is concatenated with the encoding of the whole token produced by the Transformer. The joint encoding is passed through a Multi-Layer Perceptron (MLP) with a single hidden layer to obtain logits. We use a dimension size 1/2 of that of the Transformer encoding for the hidden layer in the MLP. The overall model has roughly 2.3% fewer parameters than the base Transformer due to this bottleneck hidden layer in the MLP. Since code completion has a natural temporal ordering, we apply causal masks at the token level during training to prevent the model from peaking at the future.

3.3.2 Architecture for Variable Misuse

For the variable misuse task, we adopt the model used by Hellendoorn et al. [29], except that we compute attention scores using the formulation based on relative positions in equation 2. In summary, the model takes in a sequences of subwords, averages the subword embeddings for each token, and feeds the embedding into a Transformer. To produce candidate locations for bug and repair targets, the model includes a linear projection at the end which outputs two logits for each location.

3.4 Backpropagating Through Predicted Relations

While a fixed relation model brings some performance gains (as we show in Section 4), the paradigm is not restricted to use only a fixed model. In fact, when training to optimize performance for a specific task, one may adapt the relation model by backpropagating through the discrete structure using any method within the established suite [76, 46, 32, 11, 56].

For simplicity, we explore using a variant of the straight-through estimator [31]. Specifically, for a binary relation random variable with logit \( l \), we use the “hard-version” \( \mathbb{I}[l \geq 0] \) during the forward pass, and during backpropagation treat the variable as if the “soft-version” \( \sigma(l/\tau) \) were used in the forward pass. Here, \( \sigma(\cdot) \) is the sigmoid function and \( \tau \) is a temperature hyperparameter. This node operates differently than the Gumbel-Softmax/Concrete random variable, since no additional noise variable is sampled. While Bengio et al. [11] reported worse results when using this estimator compared to straight-through, we found the latter to fail on our task.
We adopted the Python source code dataset used by Karampatsis and Sutton [36] that is comprised of two training splits (one small and one large), a validation, a test, and an encoding split used only for learning a tokenization. The corpus sanitized by Karampatsis et al. [37] is licensed under CC BY 4.0.

4 Experiments

We present experiments in four subsections. We first verify that we can learn edge prediction models of reasonable quality across a suite of edge types. We then present results on two applications: (a) code completion without assuming the existence of any partial AST structure, and (b) localizing and repairing variable misuse for ill-formed work-in-progress code. To close the section, we present some analyses for fine-tuning the edge prediction model during task optimization. All reported numbers are averaged over three seeds. Error bars are based on one standard deviation.

4.1 Learning Relations for Source Code

We show that the edge prediction model described in Section 3.2 is able to learn a wide variety of relations by training such as models for each task separately on their task specific data for the two tasks we consider (code completion and variable misuse). We report the shared settings and overall results in this subsection.

We trained all edge prediction models with the Adam optimizer [39] using a fixed learning rate of 0.0001 and a batch size of 48. For other hyperparameters, we adopted the default in PyTorch. We performed early stopping based on validation performance with a patience of 50k iterations. For focal loss, we set its hyperparameter $\gamma = 2$ for all experiments as this was reported to be near optimal for a wide array of settings [43]. Training the edge prediction model is memory intensive due to its last layer instantiating several tensors with size quadratic in the sequence length $L$ and linear in the number of hidden units $H$ or edge types $E$. To reduce the memory footprint during training, we apply gradient checkpointing for the multi-head attention layers. With this setup, training converges to a validation F score of around 99% within 3 days for both tasks using a single V100 GPU.

Results. Since occurrences of edges are extremely sparse, a model that always predicts the non-existence of edges can attain an accuracy beyond 99% on the test split. We therefore report the precision, recall, and F score. Despite having a simple architecture, the edge prediction model is able to produce high quality predictions for the code completion task and attains an F score close to 1.0 for edge types with the highest frequencies (see Figure 4). For low frequency edge types and edge types related to control flow (e.g. ReturnsTo and CFGNext), the model performs slightly worse, but still achieves an F score beyond 0.8. Similar but slightly worse results are obtained for the variable misuse task; see Appendix A for results.

4.2 Code Completion

We adopted the Python source code dataset used by Karampatsis and Sutton [36] that is comprised of two training splits (one small and one large), a validation, a test, and an encoding split used only for learning a tokenization. The corpus sanitized by Karampatsis et al. [37] is licensed under CC BY 4.0.
We compared the performance of the relation-aware architecture described in Section 3.3 trained and tested with strides. With our implementation, each gradient update for the relation-aware model, which parts of a file should one train with becomes a question. Unlike Karampatsis et al. [37], we did not take a fixed size prefix of each file. Instead, we sampled uniformly a new window each time a file is selected for a gradient update. The window is of the length and contain up to 256 tokens, which may be "flattened" into much more than 256 subwords, we performed the typical sliding window evaluation starting at the beginning of each test window and report results with various strides. With our implementation, each gradient update for the baseline is roughly 1.7x as fast as that for the relation-aware architecture proposed in Section 3.3 in terms of wall time. However, inference for the baseline is much slower due to the sliding window for computational efficiency.

As a baseline, we also report results for the Transformer base architecture with attention scores computed as in equation 1, modeling sequences directly at the subword level\(^3\). During training, we sampled windows of subwords of context size 256. Since examples in the test set can vary in length and contain up to 256 tokens, which may be “flattened” into much more than 256 subwords, we performed the typical sliding window evaluation starting at the beginning of each test window and report results with various strides. With our implementation, each gradient update for the baseline is roughly 1.7x as fast as that for the relation-aware architecture proposed in Section 3.3 in terms of wall time. However, inference for the baseline is much slower due to the sliding window evaluation (approximately 1/10 and 1/20 the speed of relation-aware model with strides 100 and 5, respectively).

For all experiments, we used the Adam optimizer with a fixed learning rate of 0.0001 and adopted the PyTorch default for other hyperparameters. We applied gradient clipping with a max 2-norm of 0.25. These hyperparameter choices were primarily optimized for training stability. Additionally, we set the dropout rate to be 0.1 and also randomly dropout subwords to reduce overfitting. We used a batch

\(^3\)The architecture is therefore very similar to Transformer-XL [19] with the minor difference being the positioning of Layer Normalization and Dropout. Since the present focus is not long sequence modeling, our models also don’t have their segment-level recurrence.

Table 1: Results for next token prediction. Small and Large respectively refer to when the small and large training split is used. Numbers in bold are the best results in each column. We exclude comparing to Aware-true which cannot be obtained in practice given any unseen code prefix.

| Model                  | Perplexity (↓) | Top-1 accuracy in % (↑) |
|------------------------|---------------|-------------------------|
|                         | Small | Large | Small | Large |
| Transformer (stride=100)| 12.084 ± 0.215 | 4.249 ± 0.051 | 66.152 ± 0.583 | 76.380 ± 0.188 |
| Transformer (stride=5)  | **12.002 ± 0.221** | 4.217 ± 0.051 | 66.158 ± 0.584 | 76.444 ± 0.189 |
| Agnostic               | 14.858 ± 0.170 | 3.764 ± 0.019 | 71.576 ± 0.106 | 79.776 ± 0.064 |
| Aware-fixed            | 14.637 ± 0.045 | 3.782 ± 0.012 | 71.857 ± 0.156 | 79.686 ± 0.002 |
| Aware-tuned            | 12.381 ± 0.189 | **3.495 ± 0.016** | **72.350 ± 0.065** | **80.745 ± 0.059** |
| Aware-true             | 13.458 ± 0.171 | 3.535 ± 0.003 | 73.627 ± 0.148 | 81.347 ± 0.017 |

**Dataset Preprocessing.** We followed the preprocessing setups in [28, 36]: replace non-ASCII character sequences such as Chinese ideograms inside strings with the special token (non-en), remove comments, and replace string literals consisting of 15 characters or more by the empty string. After preprocessing, the small training, large training, validation and test sets contain 20738, 999000, 14090 and 12865 files, respectively. Since the dataset consists of Python projects mined directly from Github, certain sequences are very long and contain a variety of long words. We also converted all files in Python2 to Python3 using Python’s automated translation tool lib2to3. To reduce the size of the vocabulary, we followed Karampatsis et al. [37] in splitting tokens into subtokens with the byte-pair encoding algorithm [64] ran for 10k merges using the Tokenizer package from Hugging Face. While the model presented in Section 3.3 is in principle able to handle tokens that consist of an arbitrary number of subwords, we truncate each token to have a maximum of 6 subwords for computational efficiency. This covers 98.9% and 99.2% of the vocabulary in the small training and validation sets, respectively. We trained the edge model with the usual causal masks for Transformers.

**Training and Evaluation.** Since many files are longer than the typical context size of a Transformer-based model, which parts of a file should one train with becomes a question. Unlike Karampatsis et al. [37], we did not take a fixed size prefix of each file. Instead, we sampled uniformly a new window each time a file is selected for a gradient update. The window is of the context size if the file is longer; otherwise, it is chosen to be the whole file. For testing, we sampled 3 fixed windows for each test file. We set the context size to be 256 for computational efficiency.

We compared the performance of the relation-aware architecture described in Section 3.3 trained and tested with a learned edge prediction model against a model with no relational information (relation-agnostic). We also report results for the relation-aware models trained and tested with ground truth edges as a guideline for the gain one could expect with the present suite of edge types.

\[^3\]The architecture is therefore very similar to Transformer-XL [19] with the minor difference being the positioning of Layer Normalization and Dropout. Since the present focus is not long sequence modeling, our models also don’t have their segment-level recurrence.
We based our dataset on that used by Hellendoorn et al. [29] and applied a fixed amount of perturbations to each file. The perturbations were uniformly sampled to be one of the types described above. We created three perturbed datasets, varying the number of corruptions applied to each example in the training, validation, and test splits (number of corruptions \( k = 1, 2, 5 \)). To show the effect of dataset size of 32 and data parallel training across 8 V100 GPUs across all settings. We trained all models for at most 1k epochs and early stopped based on validation performance with a patience of 50k updates. Training time is between 1-2 weeks for the large dataset and less than 1 day for the small dataset.

**Results.** We report the perplexity and top-1 accuracy for next token prediction in Table 1. The table shows that compared to a relation-agnostic model, the relation-aware model given the ground truth edges is able to perform much better in both perplexity and accuracy. Nevertheless, when using only learned and fixed edges, the relation-aware model performs similarly as the relation-agnostic baseline. Further fine-tuning the edge prediction model brings a noticeable performance gain to the relation-aware setting (0.774% and 0.969% absolute gain in top-1 accuracy for Small and Large).

Notably, both the agnostic and aware model perform better than the baseline transformers which directly model subword sequences on all metrics except the perplexity score when the small training split is used. Results on next subword prediction have the same trend. See Appendix D for details.

To diagnose the poor performance of the relation-aware model supplied with learned and fixed edges, we conducted ablation studies and observe that the edges types most difficult to predict are the most influential in achieving the performance gain. This indicates that downstream accuracy is non-uniformly affected by different edge types and suggests that future work may shift edge prediction capacity to the harder edge types. Details of this study can be found in Appendix C.

We do not compare directly against results in [37], since our setting is not strictly comparable to theirs due to subtle differences in data preprocessing (e.g. the specific procedure of creating subwords is different). However, we note that our reported perplexities are in the range of that reported for their LSTM models).

### 4.3 Localizing and Fixing Variable Misuse for WIP Code

With a pretrained edge prediction model, we show that relational structure can be generalized to ill-formed code to improve task performance. We focus on a setting where the code to be analyzed for variable misuse issues has undergone multiple mild perturbations such that a standard parser would fail to generate ASTs⁴. We consider the following set of perturbations:

- **Keyword:** Randomly corrupt keywords in the language (e.g. for, while, if, def in Python).
- **Deletion:** Randomly delete a fixed number of tokens.
- **Punctuation:** Add random punctuation marks at random locations.
- **Indentation⁵:** Indent or dedent a randomly selected span of lines.

We based our dataset on that used by Hellendoorn et al. [29] and applied a fixed amount of perturbations to each file. The perturbations were uniformly sampled to be one of the types described above. We created three perturbed datasets, varying the number of corruptions applied to each example in the training, validation, and test splits (number of corruptions \( k = 1, 2, 5 \)). To show the effect of dataset

| Task     | Model      | Small          |         | Large          |         |
|----------|------------|----------------|---------|----------------|---------|
|          |            | \( k = 1 \)    | \( k = 2 \) | \( k = 5 \)    |         |
| Localization | Agnostic   | 44.0 ± 0.8  | 43.0 ± 1.7 | 42.3 ± 2.2    | 75.4 ± 1.1 | 76.0 ± 0.3 | 72.6 ± 1.1 |
|          | Aware-fixed| 61.5 ± 0.5  | 61.6 ± 0.1 | 60.6 ± 0.5    | 76.6 ± 0.3 | 75.6 ± 0.6 | 73.3 ± 1.7 |
|          | Aware-tuned| 68.6 ± 0.2  | 68.0 ± 0.4 | 67.6 ± 0.4    | 79.2 ± 0.1 | 79.0 ± 0.1 | 78.4 ± 0.3 |
| Repair   | Agnostic   | 25.9 ± 1.1  | 24.0 ± 2.1 | 23.4 ± 2.7    | 63.7 ± 6.3 | 69.6 ± 1.1 | 65.5 ± 0.8 |
|          | Aware-fixed| 45.0 ± 1.0  | 44.1 ± 1.2 | 42.5 ± 0.3    | 69.3 ± 0.3 | 66.4 ± 4.6 | 66.7 ± 1.6 |
|          | Aware-tuned| 55.8 ± 0.2  | 55.7 ± 0.3 | 54.4 ± 0.1    | 73.9 ± 0.5 | 73.8 ± 0.0 | 72.8 ± 0.2 |

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⁴While it is desirable to seek for methods that may handle strong perturbations, learning to generalize to out-of-distribution examples “in the wild” is still in general an open problem in machine learning [41].

⁵We avoid (re)indenting only the first line in any indentation block, since in this scenario, any standard tokenizer would be confused about the amount of whitespace characters for each tab/indentation.

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Figure 5: Fine-tuning the edge prediction model leads to improved repair accuracy on well-formed and work-progress code. Different curves terminate at different times due to early stopping. Work-in-progress examples in (b) each contain $k = 5$ corruptions. “aware-fixed” uses a pretrained relation model that is not jointly optimized with the task model. “aware-true” uses the ground truth edges and is only applicable for well-formed code. Results are based on training on the large training splits.

size on the model’s performance, we created a separate small training set based on subsampling 1% of the original training set. For efficiency, we also ignored examples in the training and test sets that are longer than the context size of 512 tokens. We adopted the same hyperparameters and setup for experiments in this section as those used previously, except we parallelize training across 4 V100 GPUs for each experiment. Training time is between 1-2 weeks for the large training set and less than 1 day for the small training set.

Results. Table 2 shows that with a fixed pretrained edge prediction model, a relation-aware model (Aware-fixed) is able to achieve a much better localization and repair performance compared to the relation-agnostic baseline (Agnostic) when the training set is small. This advantage, however, diminishes as training data become abundant. On the other hand, by further fine-tuning the edge prediction model during downstream learning (Aware-tuned), the relation-aware model achieves consistent gains compared to both using the learned-but-fixed edges and the relation-agnostic baseline.

4.4 Fine-tuning the Relation Prediction Model: Is Pretraining to Predict Edges Necessary?

We aim to gain a better understanding of why fine-tuning the relation prediction model helps. Specifically, we seek to answer the following question: Is fine-tuning the relation model helpful solely because the joint model has more parameters or is it that the joint model is benefitting from the structure learned by the relation model? To answer this question, we trained a relation-aware model for the variable misuse task where edges come from a randomly initialized relation model that is jointly optimized with the task model (aware-random-init). We compare this model against the relation-aware model with fine-tuned edges initialized from pretraining (aware-pretrain-init), and the relation-agnostic model (agnostic) for both well-formed and work-in-progress code.

Results. Figure 5 (a) demonstrates that fine-tuning a pretrained relation model during downstream learning improves on using the ground truth edges\(^6\). Moreover, jointly training relation-aware models with relation models initialized with random weights has a performance no better than the relation-agnostic baseline. This suggests that the pretrain-then-fine-tune combination is the key to producing a relation model useful for downstream learning. The same trend consistently holds for models trained on the small training split and work-in-progress code with various perturbation levels (see Appendix B for results and comments).

5 Related Work

The problem of identifying structure from broken and incomplete code is not new. In the programming languages community, the problem has been studied as part of robust parsing and error handling in

\(^6\)The careful reader who champions the utility of hand-crafted relations derived from expert knowledge might find this result curious. We note it is in general unsurprising that features extracted from large amounts of data with neural nets may beat their hand-crafted counterparts in the data-rich regime [20, 42, 58]
compilers [75, 2], where popular approaches are based on parsing with non-standard productions [47, 52, 70, 48]. These approaches rely on language dependent and hand-designed grammars and typically require multiple stages of execution. Notably, the fuzzy parser in Joern runs in three stages, each of which follows a separate bespoke island grammar [78]. While being less structured than robust parsing, our approach of learning and transferring edges is more flexible and direct.

We draw inspiration from a number of recent works on learning edge structure for use in relation-aware neural networks and graph neural networks [33, 40, 25, 34]. Compared to these works, the main methodological distinction comes from our assumption about the availability of strong supervision. Whereas strong supervision for latent variables is often costly to obtain, e.g., meaning representations in semantic parsing [82], our key observation is that it is readily available for edge structures in well-formed code. Thus, the main challenge is transferring from the distribution where strong supervision is available to a distribution where it is not. Perhaps the most similar work is that by Velickovic et al. [72], which assumes strong supervision for edges is available on small examples, but then the goal is to systematically generalize to longer examples. A difference is that in our setting, there is not clearly the same kind of systematicity in the needed generalization.

From the application perspective, there are alternative approaches to dealing with work-in-progress code. A common approach for source code modeling is to define relations that can be computed from a program prefix or a partial expansion using standard productions [45, 50, 55, 57, 81, 13, 38, 7]. Relations are then explicitly defined for the work-in-progress case and can be computed deterministically. However, these approaches usually are only possible in restricted cases and would not be applicable to all useful edge types, or remain valid for all corruptions encountered in practice.

It is worthwhile to mention that to handle slightly buggy code, a different approach would be to leverage existing bug fixers [21, 9, 63] to transform buggy instances into well-formed ones and thereafter perform downstream tasks based on the latter as input. While potentially excelling at handling code with common errors [9], this approach is limited in handling the incomplete code prefixes studied in this paper. Aside, we note that the approach is not inherently in conflict with ours, as one could imagine leveraging learned relations to build improved neural bug fixers.

While our work is not solely devoted to code completion, we comment on several recent neural-based attempts in the literature. Švyatkovskoy et al. [68] consider aiding completion candidate providers (most notably ones based on static analysis) with learned neural representations. Their setting differs from ours in assuming access to a candidate provider of reasonable quality upfront. On the other hand, Švyatkovskiy et al. [67] and Wang et al. [74] respectively study multilingual and whole line completion using Transformers. Our work is, in every respect, orthogonal to the two aforementioned, as the idea of leveraging fine-tuned relations for better completion is applicable to both settings.

Lastly, we comment that ML4Code researchers have borrowed successful ideas in the NLP community such as pretraining large Transformers on heterogenous datasets for transfer learning and multi-task learning [24, 26, 23, 35]. The idea of learning to predict edges has already seen modest successes for pretraining [26]. Exploring whether learning relations could be useful beyond this setting is an interesting direction for future research.

6 Conclusion and Limitation

We showed that by simply learning a relation prediction model, the notion of program graphs can be generalized to work-in-progress code. This enables relation-aware models to be used for source code that may be broken or incomplete. Task performance is significantly improved when a pretrained relation model is simultaneously fine-tuned during task optimization for both work-in-progress and well-formed code. Future work may investigate whether the fine-tuning approach could improve the performance on other tasks and with other types of relational structure (such as ones used by graph neural networks for algorithmic reasoning [72], ones in text data with corresponding parse trees [53, 54], or even ones in knowledge graphs [22]).

Having improved flexibility and capacity, modern-day neural-based approaches for learning are typically at the same time less transparent and interpretable. Our relation learning procedure is no outlier in this regard: Fine-tuned relation models may predict edges that are unexpected and conform less to their initially prescribed category. Future work may improve the explainability and interpretability aspects of adapted relations.
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We include edge prediction results for clean code in the variable misuse task’s dataset. In Figure 6, we see compared to the results for the code completion task’s dataset, the model performs slightly worse on various low frequency edge types.
Appendix B  Additional Results on Fine-tuning the Edge Prediction Model

Appendix B.1  Setup for Fine-tuning the Edge Prediction Model

For simplicity, given a well-trained edge prediction model, we fine-tune by jointly optimizing the loss with respect to parameters of the edge model and the task model with the same learning rate. We select the temperature $\tau$ based on validation performance, grid-searching over values in the range of $[0.01, 1]$.

Appendix B.2  Results on the Variable Misuse Task in the Literature

Many papers in the literature report results for the variable misuse task based on clean examples. While our experiments in Section 4.4 and the following also report standard metrics on this version, the results here only serve to improve our general understanding of relation model fine-tuning. Our primary focus is still on work-in-process code that may be broken or incomplete.

We note that well-formed code is in general much easier to model, and it is therefore unsurprising that much better performance can be attained with additional tricks such as preprocessing code chunks into graphs after parsing them into ASTs [34] and more structured approaches designed with formal language theory in mind [34]. One may also expect that fine-tuning a large model pretrained on well-formed code to work well for tasks that also involve only well-formed code [35].

Lastly, we emphasize that our relation-aware model with ground truth edges results in accuracy numbers in the same range as those reported by Hellendoorn et al. [29] for clean code (our test accuracy is 72.7% and 78.5% for sequences with at most 512 tokens, respectively for repair and localization; their reported results are 73.1% and 76.9% for sequences of fewer than 1000 tokens).

Appendix B.3  Plots Complementing Section 4.4

![Figure 7](image7.png)

(a) Repair Accuracy (Small Clean)  (b) Repair Accuracy (Small WIP, $k = 5$)

Figure 7: Test set repair accuracy for clean and work-in-progress code when edge model is fine-tuned on small training set.

![Figure 8](image8.png)

(a) Localization Accuracy (Small Clean)  (b) Localization Accuracy (Small WIP, $k = 5$)

Figure 8: Test set localization accuracy for clean and work-in-progress code when edge model is fine-tuned on small training set.
Figure 9: Test set localization accuracy for clean and work-in-progress code when edge model is fine-tuned on large training set.

Appendix B.4 Additional Plots for WIP Code with $k = 1$ and $k = 2$

Figure 10: Test set localization and repair accuracies for clean and work-in-progress code when edge model is fine-tuned.
Figure 11: Test set localization and repair accuracies for clean and work-in-progress code when edge model is fine-tuned.
Appendix C  Which Edges are Most Important for Code Completion?

This section is devoted to studying which edge types are most helpful for the relation-aware model to achieve improved performance compared to its relation-agnostic counterpart on the code completion task. Meanwhile, we also uncover a reason behind the mediocre performance of relation-aware models when the fed edges are fixed and come from a learned edge prediction model.

We split all edge types described in Section 3.1 into those that are easy to predict (5 types with highest validation F score) and those that are hard to predict (5 remaining types) based on the predictions of an edge prediction model trained as according to Section 4.1. Then, we train relation-aware models using only ground truth edges from the former or latter category on the small training split. Figure 12 demonstrates that the downstream performance of the relation-aware model using only the easy-to-predict edges is nearly the same as the relation-agnostic model, and that using only hard-to-predict edges is nearly the same as the relation-aware model trained with all edge types.

This experiment confirms the intuition that downstream accuracy is non-uniformly affected by different edge types and explains the poor performance of using our fixed edge prediction model.

Lastly, we comment that the edge types most difficult to predict are CFGNext, ReturnsTo, FormalArgName, Field, and Calls. These edges are derived from the associated control flow and data flow graphs of a piece of code.

Figure 12: Results on next token prediction for models trained on the small training split. “Aware (only easy)” is nearly the same as “Agnostic”, and “Aware (only hard)” is nearly the same as “Aware (all)”. Results based on early stopping with a patience of 10k iterations on the validation split.
### Appendix D  Subword-level Results for Code Completion

| Model                  | Perplexity (∪) | Top-1 accuracy in % (∪) |
|------------------------|----------------|-------------------------|
|                        | Small          | Large                   | Small          | Large                   |
| Transformer (stride=100) | 6.157 ± 0.155  | 2.822 ± 0.019           | 66.933 ± 0.522 | 78.641 ± 0.135          |
| Transformer (stride=5)  | 6.128 ± 0.155  | 2.806 ± 0.019           | 66.973 ± 0.529 | 78.741 ± 0.137          |
| Agnostic               | 7.297 ± 0.061  | 2.654 ± 0.010           | 68.642 ± 0.226 | 80.008 ± 0.068          |
| Aware-fixed            | 7.217 ± 0.016  | 2.663 ± 0.006           | 69.053 ± 0.097 | 79.922 ± 0.027          |
| Aware-tuned            | 6.380 ± 0.072  | 2.513 ± 0.009           | 69.740 ± 0.099 | 81.035 ± 0.072          |
| Aware-true             | 6.690 ± 0.083  | 2.535 ± 0.002           | 70.226 ± 0.155 | 81.223 ± 0.012          |

Table 3: Results for next subword prediction. Small and Large respectively refer to when the small and large training split is used. Numbers in bold are the best results in each column. We exclude the Aware-true setting in our comparisons, since this setting cannot be executed in practice given any unseen code prefix.