LEARNING STRUCTURAL EDITS VIA INCREMENTAL TREE TRANSFORMATIONS

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ABSTRACT

While most neural generative models generate outputs in a single pass, the human creative process is usually one of iterative building and refinement. Recent work has proposed models of editing processes, but these mostly focus on editing sequential data and/or only model a single edit instead of an edit sequence. In this paper, we present a generic model for incremental editing of structured data (*i.e.* "structural edits"). Particularly, we focus on tree-structured data, taking abstract syntax trees of computer programs as our canonical example. Our editor learns to iteratively generate tree edits (*e.g.* deleting or adding a subtree) and applies them to the partially edited data, thereby the entire editing process can be formulated as consecutive, incremental tree transformations. To show the unique benefits of modeling tree edits directly, we further propose a novel edit encoder for learning to represent edits, as well as an imitation learning method that allows the editor to be more robust. We evaluate our proposed editor on two source code edit datasets, where results show that, with the proposed edit encoder, our editor significantly improves accuracy over previous approaches that generate the edited program directly in one pass. Finally, we demonstrate that training our editor to imitate experts and correct its mistakes dynamically can further improve its performance.

1 INTRODUCTION

Iteratively revising existing data for a certain purpose is ubiquitous. For example, researchers repetitively polish their manuscript until the writing becomes satisfactory; computer programmers keep editing existing code snippets and fixing bugs until desired programs are produced. Can we properly model such iterative editing processes with neural generative models?

To answer this question, some previous works have examined models for editing sequential data such as natural language sentences. Some example use cases include refining results from a first-pass text generation system (Simard et al., 2007; Xia et al., 2017), editing retrieved text into desired outputs (Gu et al., 2018; Guu et al., 2018), or modeling edits to a sequence of source code tokens (Yin et al., 2019). These examples make a single editing pass to convert an input into a target output. In contrast, there is also work on *incremental* editing of sequential data, such as predicting sequential edit operations (*e.g.* keeping, deleting or adding a token) for sentence simplification or rephrasing (Malmi et al., 2019; Dong et al., 2019), and non-monotonically generating or modifying sequences through these operations (Lee et al., 2018; Welleck et al., 2019; Gu et al., 2019a;b).

However, much interesting data in the world has strong underlying structure such as trees. For example, a syntactic parse can be naturally represented as a tree to indicate the compositional relations among constituents (*e.g.* phrases, clauses) in a sentence. A computer program inherently is also a tree defined by the programming language's syntax. In the case that this underlying structure exists, many edits can be expressed much more naturally and concisely as transformations over the underlying trees than conversions of the tokens themselves. For example, removing a statement from a computer program can be easily accomplished by deleting the corresponding tree branch as opposed to deleting tokens one by one. Despite this fact, work on editing tree-structured data has been much more sparse. In addition, it has focused almost entirely on single-pass modification of structured outputs as exemplified by Yin et al. (2019); Chakraborty et al. (2018) for computer program editing.

In this work, we are interested in a generic model for *incremental* editing of structured data (*"structural edits"*). Particularly, we focus on *tree-structured* data, taking abstract syntax trees of computer

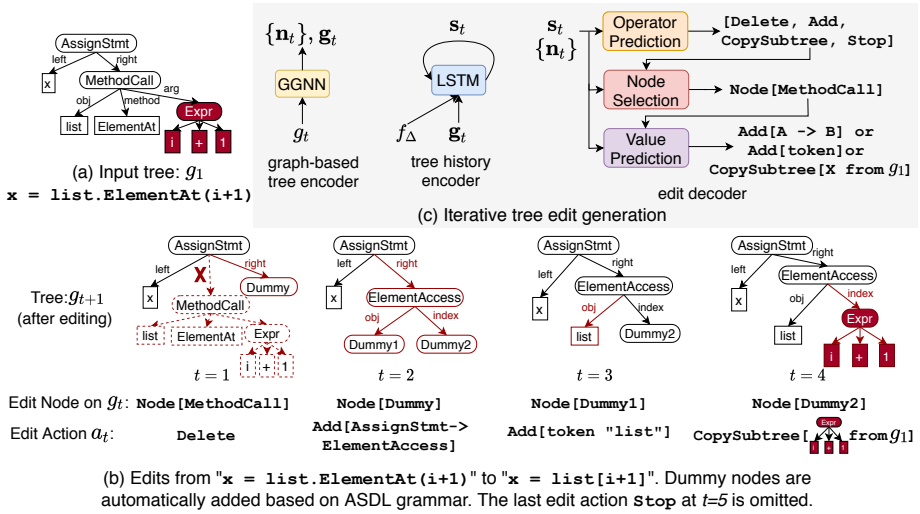

Figure 1: Our proposed neural editor for editing tree-structured data.

programs as our canonical example. To this end, we propose a neural editor that runs iteratively to generate tree edits (*e.g.* deleting or adding a subtree). By applying the edit to a partially edited tree, the tree is deterministically converted to a modified counterpart. Therefore, the entire tree editing process can be formulated as consecutive, incremental tree transformations (Fig. 1).

While some recent works have examined models that make changes to trees for specific applications such as program bug fixing (Dinella et al., 2020) or edit completion (Brody et al., 2020), our method is designed to be generic and flexible in nature. *First*, it supports general tree edits including adding new tree nodes or copying a subtree, which are not fully allowed by previous work. *Second*, all tree edit operations are language-agnostic owing to the adoption of Abstract Syntax Description Language (ASDL; Wang et al. (1997)), which allows us to process arbitrary tree-based languages. *Finally*, unlike the short edit sequences handled in previous work (*e.g.* up to three edits in Dinella et al. (2020)), we demonstrate our method's applicability to much longer edit sequences.

We further propose two modeling and training improvements, specifically enabled by and tailored to our incremental editing formalism. First, we propose a new *edit encoder* for learning to represent the edits to be performed. Unlike existing edit encoders which compress tree differences at their token level (Yin et al., 2019; Hoang et al., 2020; Panthaplackel et al., 2020b) or jointly encode the initial and the target tree pairs in their surface forms (Yin et al., 2019), our proposed edit encoder learns the representation by encoding the sequence of gold tree edit actions. Second, we propose a novel *imitation learning* (Ross et al., 2011) method to train our editor to correct its mistakes dynamically, given that it can modify any part of a tree at any time.

We evaluate our proposed tree editor on two source code edit datasets (Yin et al., 2019). Our experimental results show that, compared with previous approaches that generate the edited program in one pass, our editor can better capture the underlying semantics of the intended edits, which allows it to outperform existing approaches by more than 5% accuracy in a one-shot evaluation setting. With the proposed edit encoder, our editor significantly improves accuracy over existing state of the arts on both datasets. We also demonstrate that our editor can become more robust by learning to imitate expert demonstrations dynamically. Our source code will be released to facilitate future research.

2 Problem Formulation

As stated above, our goal is to create a general-purpose editor for tree-structured data. Specifically, we are interested in editing tree structures defined following an underlying grammar that, for every parent node type, delineates the allowable choices of child nodes. Such *syntactic* tree structures, like syntax trees of sentences or computer programs that represent their grammatical structures, are ubiquitous in fields like natural language processing and software engineering. In this paper we formuate editing such tree structures as revising an input tree C_- into an output tree C_+ according to an edit specification Δ. As a concrete example, we use editing abstract syntax trees (ASTs) of C# programs, as illustrated in Fig. 1. This figure shows transforming the AST of "`x=list.ElementAt(i+1)`" (C_-) to the AST of "`x=list[i+1]`" (C_+). In this case, the edit specification Δ could be interpreted

as a refactoring rule that uses the bracket operator `[ · ]` for accessing elements in a list.[1] In practice, the edit specification is learned by an *edit encoder* f_Δ from a pair of input-output examples $\langle C'_-, C'_+ \rangle$, and encoded as a real-valued edit representation, *i.e.* $f_\Delta(C'_-, C'_+) \in \mathbb{R}^n$. The learned edit representation could then be used to modify C_- in a similar way as editing C'_-. Onwards we use f_Δ as a simplified notation for edit representations.

Revising a tree into another typically involves a sequence of incremental edits. For instance, to modify the input tree in the aforementioned example, one may first delete the subtree rooted at the node `MethodCall`, which corresponds to the code fragment "`list.ElementAt(i+1)`", and then replace it with an `ElementAccess` node denoting the bracket operator, etc. We formulate this editing process as a sequential decision making process $(\langle g_1, a_1 \rangle, \ldots, \langle g_T, a_T \rangle)$, where for each tree g_t at time step t, the editor executes a tree edit action a_t, deterministically transforming it into g_{t+1}. In particular, g_1 is the initial input tree C_-.[2] The process stops at g_T when the editor predicts a special `Stop` action as a_T. Denoting $g_{1:t} = (g_1, ..., g_t)$ as the tree history and $a_{1:t} = (a_1, ..., a_t)$ the edit history until step t, then the editing can be framed as the following autoregressive process:

$$p(a_{1:T}|f_\Delta, g_1) = p(a_1|f_\Delta, g_1)p(a_2|f_\Delta, g_{1:2}) \cdots p(a_T|f_\Delta, g_{1:T}) = \prod_{t=1}^{T} p(a_t|f_\Delta, g_{1:t}). \quad (1)$$

3 MODEL

We will introduce our neural editor for modeling $p(a_t|\cdot)$ in § 3.1, followed by the edit representation model f_Δ in § 3.2.

3.1 NEURAL TREE EDITOR

Fig. 1(c) illustrates our editor architecture. At each time step, the editor first encodes the current tree g_t and the tree history $g_{1:t}$. It then employs a modular decoder to predict a tree edit action a_t. Next, we will first introduce our tree edit actions and then elaborate the model details.

3.1.1 TREE EDIT ACTIONS

Our editor uses a sequence of editing actions to incrementally modify a tree-structured input. At each time step, the decoder takes an action a_t to update a partially-edited tree g_t. Specifically, an action a_t consists of an operator (*e.g.* an operator that removes a subtree from g_t) with its optional arguments (*e.g.* the target subtree to delete). Importantly, the space of actions is limited to maintain consistency with the underlying syntax of the language. While a number of syntactic formalisms such as context free grammar (Chomsky, 1956) or tree substitution grammar (Cohn et al., 2010) exist, in this work we choose the ASDL formalism due to its ability to flexibly handle optional and sequential fields (interested readers may reference Wang et al. (1997) and Yin & Neubig (2018) for details). Under this framework, we define four types of operators.

`Delete` operators takes a tree node n_t as argument and removes n_t and its descendants from g_t (*e.g.* $t = 1$ in Fig. 1(b)). Note that removing arbitary (child) nodes from g_t might produce syntactically invalid trees, since under the grammar, a parent node type would always have a fixed set of child node types. For instance, if the node `MethodCall` and its incoming edge `right` were to be removed at $t = 1$, the resulting AST would be syntactically invalid under C#'s grammar, as the node `AssignStmt` denoting a variable assignment statement is missing a child node representing its right operand. To maintain syntactic correctness (no missing child nodes for any parent nodes), we therefore replace the to-be-deleted node with a pseudo `Dummy` node as a placeholder.

Next, we define an `Add` operator to append new elements to g_t. Specifically, to add a non-terminal node (*e.g.* node `ElementAccess` in Fig. 1(b) at $t = 2$), the operator selects a dummy node (*e.g.* node `Dummy`) and replaces it with the added node. As with `Delete` actions, to ensure there is no missing child node, we instantiate the set of child nodes with dummy nodes for the newly added (parent) node, based on the underlying grammar. `Add` can also be used to populate empty terminal

[1] The corresponding Roslyn analyzer in C# can be found at `https://github.com/JosefPihrt/Roslynator/blob/master/docs/analyzers/RCS1246.md`

[2] Notably, the special case of empty initial trees corresponds to code generation from scratch. Thus our formulation applies to *both* tasks of editing existing trees and generating new ones.

nodes with actual values (*e.g.* string literals). As an example, at $t = 3$ in Fig. 1(b), token "`list`" is added to the terminal node `Dummy1` on g_t. Additionally, observing that in many cases, revising a tree can be easily done by moving a subtree from the initial input g_1 to a new position on the updated tree g_t (*e.g.* the subtree `Expr` $\mapsto$ `i + 1` in Fig. 1(b) at $t = 4$), we therefore introduce a high-level operator `CopySubTree`, which directly copies a subtree from the initial tree g_1 to an empty non-terminal node (*e.g.* node `Dummy1`) on g_t. Finally, a `Stop` action is used to terminate the iterative tree editing procedure. We elaborate how these operators are implemented with ASDL in § A.1.

3.1.2 Tree and Tree History Encoder

Similarly to existing works in learning tree representations (Allamanis et al., 2018; Brockschmidt et al., 2018; Yin et al., 2019; Hellendoorn et al., 2019), we adopt a graph-based encoder to learn representations of each tree g_t. Specifically, we follow Allamanis et al. (2018), and extend g_t into a graph by adding bidirectional edges between parent and child nodes, as well as adjacent sibling nodes. We use a gated graph neural network (GGNN, Li et al. (2015)) to compute a vector representation $\boldsymbol{n}_t$ for each node n_t on tree g_t, and mean-pool $\{\boldsymbol{n}_t\}$ to represent g_t, denoted $\boldsymbol{g}_t$.

An LSTM encoder is used to track the tree history $g_{1:t}$, *i.e.* $\boldsymbol{s}_t = \text{LSTM}([\boldsymbol{g}_t; f_\Delta], \boldsymbol{s}_{t-1})$, where $[\cdot;\cdot]$ denotes vector concatenation. We will introduce how to learn the edit representation f_Δ in § 3.2. The updated state $\boldsymbol{s}_t$ is then used to predict edit actions, as elaborated next.

3.1.3 Tree Edit Decoder

Our edit decoder predicts an action a_t using three components: an operator predictor, a node selector, and a value predictor. At each time step t, the decoder's operator predictor first decides which operator $op_t \in \{\texttt{Delete}, \texttt{Add}, \texttt{CopySubTree}, \texttt{Stop}\}$ to apply. Next, for operators other than `Stop`, the node selector then predicts a node n_t from the tree on which to apply op_t. Finally, if $op_t \in \{\texttt{Add}, \texttt{CopySubTree}\}$, the value predictor further determines additional arguments of those operators (denoted as val_t, *e.g.* the to-be-added node for `Add`). This is summarized as below:

$$p(a_t|\boldsymbol{s}_t) = p(op_t|\boldsymbol{s}_t)p(n_t|\boldsymbol{s}_t, op_t)p(val_t|\boldsymbol{s}_t, op_t, n_t). \tag{2}$$

Operator Prediction: The operator prediction is a 4-class classification problem. We calculate the probability of taking operator op_t as $p(op_t|\boldsymbol{s}_t) = \text{softmax}(\boldsymbol{W}_{op}\boldsymbol{s}_t + \boldsymbol{b}_{op})$.

Node Selection: Given a tree g_t, there could exist an arbitrary number of tree nodes. Therefore, we design the node selection module similar to a pointer network (Vinyals et al., 2015). To this end, we learn a hidden state $\boldsymbol{h}_{node,t} = \tanh(\boldsymbol{W}_{node}[\boldsymbol{s}_t; \text{emb}(op_t)] + \boldsymbol{b}_{node})$ as the "pointer", where $\text{emb}(op_t)$ embeds the previously selected operator op_t. We then calculate the inner product of $\boldsymbol{h}_{node,t}$ and each node representation $\boldsymbol{n}_t$ for node selection.

Value Prediction: The value predictor predicts an argument val_t for `Add` and `CopySubTree` actions. For `Add` actions, val_t denotes the new node or terminal tokens to be added to g_t. For `CopySubTree` actions, val_t is the subtree from g_1 to be copied to g_t. In both cases, we only consider the candidate set $\{val_t\}$ allowable under the grammar constraints. Similarly to the node predictor, the distribution $p(val_t|\cdot)$ is also given by a pointer network, with its hidden state defined as $\boldsymbol{h}_{val,t} = \tanh(\boldsymbol{W}_{val}[\boldsymbol{s}_t; \boldsymbol{n}_t; \text{emb}(p_{n_t} \mapsto n_t)] + \boldsymbol{b}_{val})$, where $\text{emb}(p_{n_t} \mapsto n_t)$ is the embedding of the edge type between the parent node p_{n_t} and the child n_t (*e.g.* `AssignStmt` $\xrightarrow{\text{right}}$ `ElementAccess`). Depending on the type of val_t, its representation could either be a node type embedding, a word embedding, or a subtree encoding given by the representation of its root node. We refer interested readers to § A.2 for details.

3.2 Tree Edit Encoding

Given an edit pair $\langle C_-, C_+\rangle$, we aim to learn a real-valued vector $f_\Delta(C_-, C_+)$ to represent the intent behind the edits. This is a crucial task and has been investigated in several previous works. For example, Yin et al. (2019); Panthaplackel et al. (2020b); Hoang et al. (2020) considered edits at the token level and used a sequence edit encoder to encode the differences between C_- and C_+. Yin et al. (2019) further proposed a bag-of-edits encoder which similarly models a bag of token-level edits, as well as a graph edit encoder which connects the input/output tree via their common subtrees and jointly encodes them via a graph neural network. However, these edit encoders either abandon

the syntactic structure of tree edits or do not *explicitly* express the differences between the input and the output tree.

In this section, we present a novel edit encoder which learns an edit representation by directly encoding the sequence of structural edit actions $(a_1, a_2, ..., a_T)$ that transforms C_- to C_+. The encoder first computes a representation $\boldsymbol{a}_t$ for each action a_t, depending on the type of its operator:

$$\begin{aligned}
\boldsymbol{a}_{\texttt{Stop}} &= \boldsymbol{W}_{\texttt{Stop}}\text{emb}(\texttt{Stop}) + \boldsymbol{b}_{\texttt{Stop}}, \\
\boldsymbol{a}_{\texttt{Delete}} &= \boldsymbol{W}_{\texttt{Delete}}[\text{emb}(\texttt{Delete}); \boldsymbol{n}_t; \text{emb}(p_{n_t} \mapsto n_t)] + \boldsymbol{b}_{\texttt{Delete}}, \\
\boldsymbol{a}_{\texttt{Add}} &= \boldsymbol{W}_{\texttt{Add}}[\text{emb}(\texttt{Add}); \boldsymbol{n}_t; \text{emb}(p_{n_t} \mapsto n_t); \text{emb}(val_t)] + \boldsymbol{b}_{\texttt{Add}}, \\
\boldsymbol{a}_{\texttt{CopySubTree}} &= \boldsymbol{W}_{\texttt{CopySubTree}}[\text{emb}(\texttt{CopySubTree}); \boldsymbol{n}_t; \text{emb}(p_{n_t} \mapsto n_t); \text{emb}(subtree_t)] + \boldsymbol{b}_{\texttt{CopySubTree}}.
\end{aligned}$$

The proposed edit encoder then feeds the sequence of action representations $\{\boldsymbol{a}_t\}_{t=1}^{T}$ into a bidirectional LSTM, whose last hidden state is used as the edit representation $f_\Delta(C_-, C_+)$.

3.3 Training and Inference

We jointly train the proposed editor and the edit encoder in an autoencoding style, following Yin et al. (2019). Specifically, given an edit pair $\langle C_-, C_+ \rangle$ in the training set, we assume a gold-standard edit action sequence $a^*_{1:T}$ which edits C_- to C_+. We seek to maximize the probability of $p(a^*_{1:T} | f_\Delta(C_-, C_+), C_-)$ in training.[3] By decomposing the probability according to Eq. (2), this is equivalent to jointly maximizing the probability of each edit decoder module making the gold decision at each time step. In practice, we use dynamic programming to calculate the shortest tree edit sequence as $a^*_{1:T}$,[4] and compute a cross entropy loss for each edit decoder module.

At inference time, given an input tree C_- and an edit representation f_Δ (calculated either from $\langle C_-, C_+ \rangle$ or another edit pair $\langle C'_-, C'_+ \rangle$), we generate one tree edit at each time step t by greedily deciding the operator, the node and the value. The generated edit is then applied to the tree so it transits to g_{t+1} deterministically. We then update the tree history representation $\boldsymbol{s}_{t+1}$ for generating the next tree edit. The inference process ends when a `Stop` operator is chosen.

4 Robust Structural Editing via Imitation Learning

A unique advantage that distinguishes our editor from existing ones is its potential to fix wrong edits and iteratively refine its *own* output. This is achievable because our editor can revise any part of a tree at any time. We investigate this hypothesis by training the proposed editor via imitation learning, where the editor learns to imitate gold edit actions ("expert demonstrations") under *states* it visits at the inference time. Here, we define a "state" s_t to include the current tree history $g_{1:t}$ and the edit representation f_Δ. Our learning algorithm follows DAgger (Ross et al., 2011), where in each training iteration, for a given $\langle f_\Delta, C_-, C_+ \rangle$ tuple, we first run the editor to infer and apply a sequence of edits resulting in a "trajectory" of $(\langle s_1, a_1 \rangle, ..., \langle s_T, a_T \rangle)$. We then request a gold edit action $\pi^*(s_t)$ for each state s_t visited by the editor. The collected state-gold edit action pairs are aggregated to retrain the editor for the next iteration. This sampling and demonstration collecting strategy (denoted as DaggerSampling) is shown in Algo. 1 (Appendix B). Note that, in practice, instead of sampling a trajectory solely from the learning editor π_θ, the DAgger algorithm samples from a mixture policy π', with which the actual edit action a_t at each step t comes from either π_θ with a probability of $1 - \beta$ or the "expert" π^* with a probability of β.

To simulate the "expert", we calculate "dynamic oracles" (Goldberg & Nivre, 2012) by comparing the current tree with the target output tree. For example, in Fig. 1, if our editor incorrectly takes "`Add[AssignStmt ↦ Expr]`" at $t = 2$, the dynamic oracle will produce "`Delete[AssignStmt → Expr]`" as the gold edit action at $t = 3$ to revoke the wrong edit. This thus provides a means for the editor to learn to correct mistakes that it will likely produce at inference time.

Preliminary results showed that the editor trained following DaggerSampling may fall into a loop of repetitively deleting and adding the same component. We hypothesize that teaching the

[3] $f_\Delta(C_-, C_+)$ is one real-valued vector and thus does not *directly* expose C_+. We set it to a low dimension following Yin et al. (2019), which bottlenecks the vector's ability to memorize the entire output.

[4] We assume a left-to-right, top-down order when comparing the input/output tree. Future work can also consider other orders to improve the editing quality (Gu et al., 2019a; Welleck et al., 2019; Góis et al., 2020).

editor to imitate experts under unstable states (*i.e.* amid its initial full pass of editing) could be detrimental. Therefore, we propose another sampling strategy, POSTREFINESAMPING, which samples and collects state-action pairs from the *expert* as a *post refinement* step (Algo. 2 in Appendix B). Specifically, we first run our editor to finish its sequential editing, which gives the output tree g_T (Line 2). If g_T is different from target C_+, we run the expert policy π^* to continue editing until it successfully reaches C_+, and return state-action pairs collected from the expert as training material for the editor (Line 3-5). When g_T is correct, no further training data will be collected (Line 6-8).

5 EXPERIMENTS

5.1 EXPERIMENTAL SETUP

We test our methods on two source code edit datasets introduced by Yin et al. (2019), also largely following their experimental setting.

The GitHubEdits (GHE) dataset contains $\langle C_-, C_+\rangle$ pairs and their surrounding context collected from the commit logs of 54 GitHub C# projects. The dataset is split into train/dev/test sets of 91,372 / 10,176 / 10,176 samples. We jointly learn an edit representation $f_\Delta(C_-, C_+)$ while training the editor to generate C_+ from C_-. In evaluation, we measure the accuracy of each editor based on whether they successfully edit C_- to the exact gold C_+. Since the edit representation f_Δ is calculated from the targeted $\langle C_-, C_+\rangle$ pair, we denote this setting as **GHE-gold**.

The second dataset, C#Fixers (Fixers), is relatively small, containing 2,878 $\langle C_-, C_+\rangle$ pairs. Unlike GHE, edit pairs in Fixers are built using 16 C# "fixers" with known semantics (*e.g.* removing redundant parentheses as a way to perform refactoring). As standard, we use this dataset only for testing purposes. We consider a **Fixers-gold** setting similar as GHE-gold to evaluate the accuracy of generating C_+ from $\langle f_\Delta(C_-, C_+), C_-\rangle$.

Since edits in Fixers have known semantics, we also evaluate methods in a one-shot setting (denoted as **Fixers-one shot**): For each $\langle C_-, C_+\rangle$ pair, we select another $\langle C'_-, C'_+\rangle$ pair from the same fixer category (which bears the same edit intent as $\langle C_-, C_+\rangle$ but is applied to different input) to learn the edit representation and evaluate the accuracy of generating C_+ from $\langle f_\Delta(C'_-, C'_+), C_-\rangle$. We follow Panthaplackel et al. (2020a) and pick the first 100 samples at most per fixer category, compute an edit representation of each one and apply it to edit the others. Because the sample size of each fixer category is highly imbalanced, we report both *macro average* (treating all categories equally) and *micro average* (dependent on sample size) edit accuracies. Note that in this one-shot evaluation, higher accuracy also implies that the learned edit representation generalizes better from the specific edit pair to represent the semantics of an edit category.

Baselines: We compare our proposed neural editor (denoted as "**Graph2Edit**"[5]) with two state-of-the-art editors: (1) Graph2Tree (Yin et al., 2019), a model that, like ours, represents a program in its AST form and models the editing of tree-structured data. However, instead of generating a sequence of incremental edits, it decodes the edited tree in one pass; (2) CopySpan (Panthaplackel et al., 2020a), a model that represents programs as sequences of tokens and edits them by directly generating the edited code tokens from scratch.

We also experiment with two edit encoders for learning edit representations. Besides our proposed structural edit encoder (denoted as "**TreeDiff Edit Encoder**"), we consider a sequence edit encoder, which uses a bidirectional LSTM to compress three pieces of information: code tokens in C_-, code tokens in C_+, as well as their differences represented by a sequence of predefined edit tags (*e.g.* delete, add, or keep). This edit encoder (denoted as "Seq Edit Encoder") was shown to offer more precise and generalizable edit representations than others tested in Yin et al. (2019).

In experiments, we reproduce and test baselines by using implementations kindly provided by their authors. We include all configuration and implementation details in Appendix C.

5.2 MAIN RESULTS

Tab. 1 shows our experimental results, where we examine two questions:

[5]"Graph" simply indicates the use of a graph neural network to encode a tree.

Table 2: Edited programs C_+ from each editor (w/ Seq Edit Encoder) given $\langle f_\Delta(C'_-, C'_+), C_- \rangle$ on Fixers. We show where our editor succeeds (Example 1) and fails (Example 2).

	Example 1	Example 2
$\langle C'_-, C'_+ \rangle$	C'_-: `AskNode(VAR0,new SelectString(VAR1.VAR2.ToString()` ↪ `+LITERAL)).ShouldBe(VAR1);` C'_+: `AskNode(VAR0,new SelectString(VAR1.VAR2+LITERAL)).` ↪ `ShouldBe(VAR1);`	C'_-: `VAR0.VAR1=(int)VAR2.ColBegin;` C'_+: `VAR0.VAR1=VAR2.ColBegin;`
$\langle C_-, C_+ \rangle$	C_-: `PersistAsync(VAR0,VAR1=>Sender.Tell(VAR1.VAR2.` ↪ `ToString()+LITERAL+VAR3.IncrementAndGet()));` C_+: `PersistAsync(VAR0,VAR1=>Sender.Tell(VAR1.VAR2+` ↪ `LITERAL+VAR3.IncrementAndGet()));`	C_-: `var VAR0=(int)(VAR1/LITERAL);` C_+: `var VAR0=VAR1/LITERAL;`
CopySpan	C_+: `PersistAsync(VAR0,VAR1=>Sender.Tell(VAR1.VAR2+` ↪ `VAR3.IncrementAndGet()));`	C_+: `var VAR0=VAR1/LITERAL);`
Graph2Tree	C_+: `PersistAsync(VAR0,VAR1=>Sender.Tell(VAR1.VAR2).` ↪ `IncrementAndGet());`	C_+: `var VAR0=VAR1/LITERAL;`
Graph2Edit	C_+: `PersistAsync(VAR0,VAR1=>Sender.Tell(VAR1.VAR2+` ↪ `LITERAL+VAR3.IncrementAndGet()));`	C_+: `var VAR0=LITERAL;`

(1) How does our incremental editor compare with one-pass baselines? On Fixers-one shot, when all editors use the Seq Edit Encoder, our editor outperforms others substantially by more than 7% macro Acc and 5% micro Acc. This implies that our editor is better at capturing generalizable semantics underlying the edits. Given that all editors use the same architecture for the edit encoder, this also means that our editor encourages better edit representation learning in the edit encoder. The outstanding generalization ability of our editor demonstrates the advantage of modeling incremental edits; when our editor is trained to generate the edits rather than the edited tree from scratch, it implicitly drives its edit encoder to learn to capture the *salient* information about the *edits* (otherwise it has no means to generate the accurate edit sequence).

Intriguingly, we observe inverse performance from the three editors when their edit representation is or is not inferred from the gold edit pair; editors performing better on GHE/Fixers-gold (CopySpan > Graph2Tree > Graph2Edit) consistently obtain worse accuracies on Fixers-one shot (CopySpan < Graph2Tree < Graph2Edit). We conjecture that when Seq Edit Encoder is jointly trained with the baseline editors, it tends to memorize the specific patterns about C_+ as opposed to the generalizable information about the edits when trained with our editor, because the baseline editors (especially with the sequential CopySpan) are trained to decode the exact content of C_+ from scratch.

Table 1: Test accuracy (%) of different neural editors and edit encoders.

Model	**GHE-gold**	**Fixers-gold**	**Fixers-one shot** macro	**Fixers-one shot** micro
w/ Seq Edit Encoder:				
CopySpan	67.40	87.07	20.64	24.20
Graph2Tree	57.49	81.34	33.94	40.55
Graph2Edit	54.69	70.50	41.82	45.58
w/ TreeDiff Edit Encoder:				
Graph2Tree	68.09	82.94	**42.00**	**47.48**
Graph2Edit	**70.44**	**92.32**	41.21	44.75

Case study & expressivity of structural edits: We further showcase the generation from each editor (with Seq Edit Encoder) in Fixers-one shot setting (Tab. 2). Example 1 illustrates typical cases where our editor Graph2Edit succeeds while the baseline editors fail. The example is about removing redundant `ToString` call. Our editor learns to transfer and apply this editing pattern even when the input tree C_- is very different from C'_-, while other editors behave very sensitively to the specific content of C_-. This is because, from the perspective of our editor, the edits required by $\langle C'_-, C'_+ \rangle$ and $\langle C_-, C_+ \rangle$ are the same, both first deleting an `InvocationExpression` subtree corresponding to "`VAR1.VAR2.ToString()`" and then copying back its `MemberAccessExpression` subtree corresponding to "`VAR1.VAR2`". In fact, we observe that in many cases, *the actual tree edit* that our editor needs to perform is irrelevant to the surface form of the input tree C_-. As our editor is trained to generate the actual tree edits, together with Seq Edit Encoder, it learns a better alignment between changing at the token level (*e.g.* from "`VAR1.VAR2.ToString()`" to "`VAR1.VAR2`") and performing targeted edits at the tree level.

On the other hand, this also means that our editor may fail when the desired edits for $\langle C_-, C_+ \rangle$ bears a very different structure from the edits of $\langle C'_-, C'_+ \rangle$ (although they might be very close at the token level). Example 2 illustrates this situation where our editor fails. In this example, editing C'_- involves removing redundant `int` type cast from a `MemberAccessExpression` subtree (corresponding to "`VAR.ColBegin`") while the desired edits for C_- require detaching the type cast from a `LiteralExpression` subtree (corresponding to "`VAR1/LITERAL`"). Therefore, even if our

editor can precisely capture the structural edits expressed in $\langle C'_-, C'_+ \rangle$, it cannot edit C_- correctly. In this case, Graph2Tree runs successfully and CopySpan's generation is also close to the correct output C_+ (though with an extra right parenthesis due to the lack of syntax in its sequence decoding).

Finally, we note that our editor also performs comparably with or better than Graph2Tree when they are both equipped with TreeDiff Edit Encoder, as we will discuss next.

(2) What is the influence of edit encoding? When replacing the Seq Edit Encoder with TreeDiff Edit Encoder, we observe significant improvements for both Graph2Tree and our proposed Graph2Edit, leading to new state of the art accuracy in all settings. This implies that our proposed edit encoder is able to learn both more *expressive* and more *generalizable* edit representations. In addition, for Graph2Edit, switching to the TreeDiff Edit Encoder only helps the X-gold scenarios and results in a slight performance drop in the one-shot setting, indicating that Graph2Edit has likely overfit to its edit representation, which directly encodes the desired gold edit sequence.

In Appendix D, we show the nearest neighbors of given edit pairs based on their edit representations, which qualitatively also demonstrate the superiority of TreeDiff Edit Encoder.

5.3 Imitation Learning Experiments

We finally demonstrate that training our editor via imitation learning makes it more robust. We consider two data settings: 20% or full training data. In each case, we first pretrain our editor with gold edit sequences on the training set via supervised learning, equivalent to setting β to 1 in the first iteration of imitation learning, a commonly adopted strategy for DAgger (Ross et al., 2011). We then run another iteration of imitation learning on the same training set to sample states and collect dynamic expert demonstrations, following either DaggerSampling (Algo. 1) or PostRefineSampling (Algo. 2). Empirically, we observe worse performance when setting $\beta = 0$ in DaggerSampling. This is likely because in the editing tasks we experiment on, offering one-step expert demonstrations is not enough for teaching the model to complete all the remaining edits successfully. We eventually set $\beta = 0.5$.

For the base editor, we use "Graph2Edit w/ Seq Edit Encoder," which is more prone to mistakes than "Graph2Edit w/ TreeDiff Edit Encoder" and thus presumably a better testbed for robust learning algorithms. The experimental results are show in Tab. 3. In the 20% training data setting, imitation learning improves supervised learning by 1.5% accuracy with DaggerSampling and 2.5% accuracy with PostRefineSampling. Our analysis shows that the editor trained using DaggerSampling learns to correct its previous wrong edits (*e.g.* `Delete["VAR1"]` then `Add["StringX"]`). However, it may also fall into a local loop of repetitively deleting and adding the same component, which makes its edit length (T) generally longer than other editors. This situation is neatly remedied by using PostRefineSampling to collect expert demonstrations. With this strategy, although we train the editor to correct its wrong edits as a post refinement step, the well trained editor is indeed enhanced to be more robust in making correct decisions in its initial full pass of editing (rather than making wrong decisions then revoking them). This strategy also improves the base editor under the full training data setting slightly.

Table 3: Test (dev) accuracy by % of Graph2Edit w/ Seq Edit Encoder on GHE-gold after one iteration of imitation learning. Examples (simplified) illustrate how the base editor works when trained via supervised learning or with different imitation learning strategies. Colors indicate correct or incorrect edits.

	Supervised	DAgger	PostRefine
w/ 20% data	41.82 (44.21)	43.47 (45.95)	**44.35** (**47.09**)
w/ full data	54.69 (55.39)	53.96 (55.83)	**55.06** (**56.84**)

Example	...
	`Add[Id->Token]`
	`Add["VAR1"]`
	...
		...
		`Add[Id->Token]`
		`Add["VAR1"]`
		`Delete["VAR1"]`
		`ADD["StringX"]`
		...
			...
			`Add[Id->Token]`
			`Add["StringX"]`
			...

Avg. edits (T)	7.32	12.59	7.46

6 Conclusion and Future Work

This paper presented a generic model for incremental editing of tree-structured data and demonstrated its capability using program editing as an example. In the future, this model could be extended to other tasks such syntax-based grammar error correction (Zhang & Wang, 2014) and sentence simplification (Feblowitz & Kauchak, 2013), or incorporate natural language-based edit specification, where the editing process is triggered by natural language feedback or commands (Suhr et al., 2018; Zhang et al., 2019; Yao et al., 2019; Elgohary et al., 2020).

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A MODEL ARCHITECTURE DETAILS

A.1 IMPLEMENTATION WITH ASDL

To implement the "dummy node" mechanism, we utilize the ASDL "field", which ensures the grammatical correctness of every edit. In ASDL, children of each tree node are grouped under different fields, and each field has a cardinality property (single, optional `?`, or sequential `*`) indicating the number of nodes they can accept as grammatically valid children. For single-cardinality fields that require exactly one child and optional-cardinality fields that require optionally zero or one child, we attach one dummy node when they do not have a child. For example, at $t = 1$ in Fig. 1(b), when the `MethodCall`-rooted subtree is deleted, we automatically attach a `Dummy` node to its parent field so the new node `ElementAccess` can be added by selecting `Dummy` and replacing it with the new node. Similarly, after deriving node `ElementAccess` at $t = 2$, we automatically add a `Dummy` node to each of its two fields (*i.e.*`obj` and `index`). For sequential-cardinality fields that accept multiple children, we always attach one dummy node as their rightmost child. Adding a new node in this case is implemented by selecting the right sibling of the target position and then inserting the new node to its left. For example, we extend the child list $[\texttt{A}, \texttt{B}]$ to $[\texttt{A}, \texttt{B}, \texttt{Dummy}]$. Adding a new node to the left of `A` can then be achieved by selecting `A`, and adding to the right of `B` is done by selecting `Dummy`.

A.2 TREE EDIT DECODER

Our edit decoder predicts an action a_t using three components: an operator predictor, a node selector, and a value predictor. At each time step t, the decoder's operator predictor first decides which operator $op_t \in \{\texttt{Delete}, \texttt{Add}, \texttt{CopySubTree}, \texttt{Stop}\}$ to apply. Next, for operators other than `Stop`, the node selector then predicts a node n_t from the tree on which to apply op_t. Finally, if $op_t \in \{\texttt{Add}, \texttt{CopySubTree}\}$, the value predictor further determines additional arguments of those operators (denoted as val_t). For `Add` actions, val_t denotes production rules or terminal tokens. For `CopySubTree`, val_t is the target subtree to copy. This is summarized as below:

$$p(a_t|\boldsymbol{s}_t) = p(op_t|\boldsymbol{s}_t)p(n_t|\boldsymbol{s}_t, op_t)p(val_t|\boldsymbol{s}_t, op_t, n_t).$$

Operator Prediction: The operator prediction is a 4-class classification problem. We calculate the probability of taking operator $op_t \in \{\texttt{Delete}, \texttt{Add}, \texttt{CopySubTree}, \texttt{Stop}\}$ at time step t as:

$$p(op_t|\boldsymbol{s}_t) = \text{softmax}(\boldsymbol{W}_{op}\boldsymbol{s}_t + \boldsymbol{b}_{op}),$$

where $\boldsymbol{W}_{op}$, $\boldsymbol{b}_{op}$ are model parameters.

Node Selection: Given a tree g_t, there could exist an arbitrary number of tree nodes. Therefore, we design the node selection module similar to a pointer network (Vinyals et al., 2015):

$$\boldsymbol{h}_{node,t} = \tanh(\boldsymbol{W}_{node}[\boldsymbol{s}_t; \text{emb}(op_t)] + \boldsymbol{b}_{node}),$$
$$p(n_t|\boldsymbol{s}_t, op_t) = \text{softmax}(\boldsymbol{h}_{node,t}^T \boldsymbol{n}_t),$$

where $\text{emb}(op_t)$ embeds the previously selected operator op_t, $\boldsymbol{n}_t$ is the node representation, and $\boldsymbol{W}_{node}$, $\boldsymbol{b}_{node}$ are model parameters. The softmax is computed over all nodes $n_t \in g_t$.

Value Prediction: After deciding the target position (inferred from the selected node), adding a new node or subtree to the current tree can be viewed as expanding its parent node in typical tree-based generation tasks (Yin & Neubig, 2017; Rabinovich et al., 2017; Yin & Neubig, 2018). We thus adapt the tree-based semantic parsing model of Yin & Neubig (2018) as our value predictor.

Recall that the `Add` operator adds a new node to the tree by either applying a production rule ($val = rule$) or predicting a terminal token ($val = tok$), and the `CopySubTree` operator copies a subtree ($val = subtree$) to expand the tree. In all cases, we only consider candidates (*e.g.* production rules or subtrees) that satisfy the underlying grammar constraints. The prediction probability is also calculated via a pointer network in order to handle varying numbers of valid candidates in each decision situation:

$$\boldsymbol{h}_{val,t} = \tanh(\boldsymbol{W}_{val}[\boldsymbol{s}_t; \boldsymbol{n}_t; \text{emb}(p_{n_t} \mapsto n_t)] + \boldsymbol{b}_{val}),$$
$$p(val_t|\boldsymbol{s}_t, op_t, n_t) = \text{softmax}\big(\boldsymbol{h}_{val,t}^T \boldsymbol{W}\,\text{emb}(val_t)\big),$$

Algorithm 1 DAGGERSAMPING

Require: $\langle f_\Delta, C_-, C_+ \rangle$ from training set, learning editor π_θ, expert policy π^*, $\beta \in [0, 1]$

Let $g_1 = C_-$.
Let $\pi' = \beta\pi^* + (1 - \beta)\pi_\theta$.
Sample a trajectory from $\pi'(f_\Delta, g_1)$.
Collect and return $\{\langle s, \pi^*(s) \rangle\}$ for all states s visited by π'.

Algorithm 2 POSTREFINESAMPING

Require: $\langle f_\Delta, C_-, C_+ \rangle$ from training set, learning editor π_θ, expert policy π^*

Let $g_1 = C_-$.
Sample a trajectory using $\pi_\theta(f_\Delta, g_1)$. Denote g_T as the output tree by the editor.
if $g_T \neq C_+$ **then**
    Sample a trajectory from $\pi^*(f_\Delta, g_T)$;
    Return $\{\langle s_t, \pi^*(s_t) \rangle | t \geq T\}$.
else
    Return empty collection.
end if

where $\boldsymbol{W}_{val}$, $\boldsymbol{b}_{val}$ and $\boldsymbol{W}$ are all model parameters, emb$(p_{n_t} \mapsto n_t)$ is the embedding of the edge type between the parent node p_{n_t} and the child n_t (*e.g.* `AssignStmt` $\xrightarrow{\text{right}}$ `ElementAccess`), and emb(val_t) denotes the representation of the argument candidate: for production rules, it is their learned embedding; for terminal tokens, it is their word embedding; for subtree candidates, we use the representation of their root node.

B IMITATION LEARNING

We present DAGGERSAMPLING and POSTREFINESAMPLING in Algo. 1 and Algo. 2, respectively.

C DATASETS AND CONFIGURATIONS

For all datasets, we use the preprocessed version by Yin et al. (2019) for a fair comparison. The preprocessing includes tokenizing each code snippet and converting it into a AST.[6] For each $\langle C_-, C_+ \rangle$, we run a dynamic programming algorithm to search for the shortest edit sequence from C_- to C_+. The average length of gold edit sequences is 7.264 on GitHubEdits training set and 7.089 on C#Fixers.

Since surrounding contexts around the edited program are also provided in all datasets, we additionally allow the value predictor (§ 3.1) to copy a terminal token from either the input tree's code tokens or the contexts. To this end, we introduce another bidirectional LSTM encoder to encode the input code tokens as well as the contexts. The last hidden state is used to represent each token. The same design is also adopted in the two baseline editors.

For the encoder of our neural editor, the dimension of word embedding and the tree node representation is set to 128. The dimension of the bidirectional LSTM encoder for encoding input code tokens and contexts is set to 64. The hidden state for tracking tree history is set to 256 dimensions. In the decoder side, the dimensions of the operator embedding, the field embedding, the production rule embedding, and the hidden vector in value prediction are set to 32, 32, 128 and 256, respectively.

For a fair comparison, we follow Yin et al. (2019); Panthaplackel et al. (2020a) to encode a code edit into a real-valued vector of 512 dimensions. For our TreeDiff Edit Encoder, each edit action is encoded into a vector of 256 dimensions. The bidirectional LSTM also has a hidden state of 256 dimensions. When training Graph2Edit/Graph2Tree jointly with TreeDiff Edit Encoder, common parameters that are designed for both the neural editor and the edit encoder (*e.g.* the operator/field embedding) are shared.

In experiments, we reproduce and evaluate baselines by using implementations kindly provided by their authors. This includes testing the baseline editors under exactly the same setting as they were tested in their original paper (*e.g.* decoding using beam search of size 5 for Graph2Tree and 20 for CopySpan).

[6]The ASDL grammar we used for C# can be found at: `https://raw.githubusercontent.com/dotnet/roslyn/master/src/Compilers/CSharp/Portable/Syntax/Syntax.xml`..

Table 4: The nearest neighbors of given edit pairs based on their edit representations.

Example 1	Example 2
C_-: `BoundsCheck(VAR0, VAR1);` C_+: `BoundsCheck(VAR1, VAR0);`	C_-: `var VAR0=GetEtagFromRequest();` C_+: `var VAR0=GetLongFromHeaders(LITERAL);`
Graph2Tree – Seq Edit Encoder	Graph2Tree – Seq Edit Encoder
▶ C_-: `ReleasePooledConnectorInternal(VAR0, VAR1);` C_+: `ReleasePooledConnectorInternal(VAR2, VAR0);`	▶ C_-: `var VAR0=new ProfileConfiguration();` C_+: `var VAR0=new Profile(LITERAL);`
▶ C_-: `UngetPooledConnector(VAR0, VAR1);` C_+: `UngetPooledConnector(VAR2, VAR0);`	▶ C_-: `var VAR0=PrepareForSaveChanges();` C_+: `var VAR0=PrepareForSaveChanges(null);`
▶ C_-: `VAR0.Warn(LITERAL, VAR1);` C_+: `VAR0.Warn(VAR1, LITERAL);`	▶ C_-: `bool VAR0=true;` C_+: `bool VAR0=CanBeNull(VAR1);`
Graph2Tree – TreeDiff Edit Encoder	Graph2Tree – TreeDiff Edit Encoder
▶ C_-: `InternalLogger.Error(LITERAL, VAR0);` C_+: `InternalLogger.Error(VAR0, LITERAL);`	▶ C_-: `var VAR0=new ProfileConfiguration();` C_+: `var VAR0=new Profile(LITERAL);`
▶ C_-: `VAR0.Warn(LITERAL, VAR1);` C_+: `VAR0.Warn(VAR1, LITERAL);`	▶ C_-: `CalcGridAreas();` C_+: `SetDataSource(VAR0, VAR1);`
▶ C_-: `AssertEqual(VAR0.Value, LITERAL);` C_+: `AssertEqual(LITERAL, VAR0.Value);`	▶ C_-: `VAR0=new Win32PageFileBackedMemoryMappedPager();` C_+: `VAR0=new Win32PageFileBackedMemoryMappedPager(` `LITERAL);`
Graph2Edit – Seq Edit Encoder	Graph2Edit – Seq Edit Encoder
▶ C_-: `ReleasePooledConnectorInternal(VAR0, VAR1);` C_+: `ReleasePooledConnectorInternal(VAR1, VAR0);`	▶ C_-: `var VAR0=new ProfileConfiguration();` C_+: `var VAR0=new Profile(LITERAL);`
▶ C_-: `UngetPooledConnector(VAR0, VAR1);` C_+: `UngetPooledConnector(VAR2, VAR0);`	▶ C_-: `VAR0.Dispose();` C_+: `VAR0.Close(VAR1);`
▶ C_-: `ReportUnusedImports(VAR0, VAR1, VAR2);` C_+: `ReportUnusedImports(VAR2, VAR0, VAR1);`	▶ C_-: `VAR0=VAR1(VAR2);` C_+: `VAR0=GetSpans(VAR2, VAR1);`
Graph2Edit – TreeDiff Edit Encoder	Graph2Edit – TreeDiff Edit Encoder
▶ C_-: `VAR0.Warn(LITERAL, VAR1);` C_+: `VAR0.Warn(VAR1, LITERAL);`	▶ C_-: `var VAR0=new ProfileConfiguration();` C_+: `var VAR0=new Profile(LITERAL);`
▶ C_-: `InternalLogger.Error(LITERAL, VAR0);` C_+: `InternalLogger.Error(VAR0, LITERAL);`	▶ C_-: `VAR0=Thread.GetDomain().DefineDynamicAssembly(VAR1,` ↪ `AssemblyBuilderAccess.Run);` C_+: `VAR0=Thread.GetDomain().DefineDynamicAssembly(VAR1,` ↪ `AssemblyBuilderAccess.RunAndSave, LITERAL);`
▶ C_-: `AssertEqual(VAR0.Value, LITERAL);` C_+: `AssertEqual(LITERAL, VAR0.Value);`	▶ C_-: `new DocumentsCrud().EtagsArePersistedWithDeletes();` C_+: `new DocumentsCrud().PutAndGetDocumentById(LITERAL);`

For the supervised learning, we train our Graph2Edit for 30 epoches on GitHubEdits training set, where the best model parameters are selected based on the editor's cross entropy loss on dev set.

D Additional Experimental Results

Tab. 4 shows the nearest neighbors of given edit pairs from GHE dev set, based on the cosine similarity of their edit representations $f_\Delta(C_-, C_+)$ calculated by different edit encoders. The edit in Example 1 means to swap function arguments (*e.g.* from "`(VAR0,VAR1)`" to "`(VAR1, VAR0)`"). Intuitively such structural changes can be easily captured by our tree-level edit encoder. This is consistent with our results, which show that, for both Graph2Tree and Graph2Edit, TreeDiff Edit Encoder learns more consistent edit representations for this edit, while Seq Edit Encoder may confuse it with edits that replace the original argument with a new one (*e.g.* modifying "`(VAR0,VAR1)`" to "`(VAR2,VAR0)`"). Our proposed edit encoder can also generalize from literals (*e.g.* swapping between "`(VAR0,VAR1)`") to more complex expressions (*e.g.* swapping between "`(VAR0.Value, LITERAL)`"). On the other hand, when the intended edits can be easily expressed as token-level editing (*e.g.* inserting an argument token), the two edit encoders perform comparably, as shown in Example 2. However, we still observe that TreeDiff Edit Encoder works better at interpreting the editing semantics of code snippets with complex structures (*e.g.* more complex edit pairs are retrieved).