CODE TRANSLATION WITH COMPILER REPRESENTATIONS

Marc Szafraniec* Baptiste Rozière* Hugh Leather
François Charton Patrick Labatut Gabriel Synnaeve
Meta AI
{mszafraniec,broz}@meta.com

ABSTRACT

In this paper, we leverage low-level compiler intermediate representations (IR) to improve code translation. Traditional transpilers rely on syntactic information and handcrafted rules, which limits their applicability and produces unnatural-looking code. Applying neural machine translation (NMT) approaches to code has successfully broadened the set of programs on which one can get a natural-looking translation. However, they treat the code as sequences of text tokens, and still do not differentiate well enough between similar pieces of code which have different semantics in different languages. The consequence is low quality translation, reducing the practicality of NMT, and stressing the need for an approach significantly increasing its accuracy. Here we propose to augment code translation with IRs, specifically LLVM IR, with results on the C++, Java, Rust, and Go languages. Our method improves upon the state of the art for unsupervised code translation, increasing the number of correct translations by 11% on average, and up to 79% for the Java → Rust pair with greedy decoding. We extend previous test sets for code translation, by adding hundreds of Go and Rust functions. Additionally, we train models with high performance on the problem of IR decompilation, generating programming source code from IR, and study using IRs as pivot for translation.

1 INTRODUCTION

Automatic code translation allows to port old codebases to new frameworks, or high-level (but slow) languages to low-level (and fast) ones. Current industry solutions, known as transpilers or transcompilers rely on handcrafted rules that are applied systematically. They produce unidiomatic translations that prove hard to read for human programmers. This is a serious limitation: the translated code should be easy to read and understand, as it will eventually be maintained by human developers.

In recent years, Neural Machine Translation (NMT) was proposed as an alternative to rule-based code translation (Rozière et al., 2020; Weisz et al., 2021; 2022). These models, trained from existing human-readable code, produce idiomatic, easy to understand, translations. Unfortunately, neural transpilers are unreliable, and often fail to translate the semantics of the input program accurately. This is a serious limitation, as some of the human work saved by the transpiler has to be reinvested debugging its output.

We propose to improve the reliability of NMT by leveraging information from compiler toolchains. When processing source code, compilers create Intermediary Representations (IR): language-agnostic pseudocode that describes the semantics of the program. Augmenting training data with the corresponding IR can benefit a Neural Transpiler in two ways: it helps align embeddings for different languages and improves the semantic understanding of the code. As shown in Figure 1 this can greatly improve the semantic quality of neural translations.

In this work, we leverage LLVM (Lattner and Adve, 2004) to augment source code with corresponding Intermediate Representation and train models for code translation and decompilation. We compare it to TransCoder, which uses only code and no IR. We also design an IR-only baseline, dubbed the pivot method, which generates a translation solely by compiling an IR generated from the source

*Equal contribution

[https://en.wikipedia.org/wiki/Source-to-source_compiler]
The first example shows a translation from C++ to Rust, where TransCoder generates code using unsigned instead of signed integers. In the second example, a translation from Java to Go, it generates a function with the wrong return type. In the third example, which is also a translation from Java to Go, the model outputs a function that looks similar to the correct solution but it confuses > with » and closes an expression with a parenthesis too early. In these cases and many others, TransCoder makes mistakes that are small in terms of edit distance, but have a large impact on the semantics of the code. Using the IR to ground the representations to the semantics often helps solving these issues.

Figure 1: Improvements over TransCoder. The first example shows a translation from C++ to Rust, where TransCoder generates code using unsigned instead of signed integers. In the second example, a translation from Java to Go, it generates a function with the wrong return type. In the third example, which is also a translation from Java to Go, the model outputs a function that looks similar to the correct solution but it confuses > with » and closes an expression with a parenthesis too early. In these cases and many others, TransCoder makes mistakes that are small in terms of edit distance, but have a large impact on the semantics of the code. Using the IR to ground the representations to the semantics often helps solving these issues.
Figure 2: A bird’s eye view of a compiler toolchain, exemplified with LLVM. The unoptimized version (−O0) is shown here for illustration. In practice we used the size-optimized version (−Oz) of the IR as boxed, which does the compile time optimization of computing the addition of 26 and 16.

tagagnostic optimizations to the IR, in a middle-end module independent from the source language and target machine. This results in an efficient compiler structure: new languages can be implemented by rewriting the front-end, and new target machines by rewriting the back-end.

Several IRs usually co-exist in a compiler: each stage in the toolchain (Figure 2) introduces a new representation. Early stage IRs are language-dependent (e.g. ASTs mirror the syntax of the source language). Late stage IRs replace named variables by registers and reflect the specifics of the target architecture. In this work, we are interested in middle-end IRs, which are independent from the target machine, and similar for all source languages (like dialects in natural languages).

3 Training objectives

Unsupervised machine translation consists of learning multilingual sequence embeddings, and generating sequence in any output language from these embeddings (Lample et al., 2018a). We now present the objective functions for these tasks. In section 3.1 we review the three basic objectives used by TransCoder, our baseline NMT system. In section 3.2, we introduce three new functions that leverage LLVM IRs to improve the multilingual representation of source code, and the performance of our translation models. During training, we alternate between all six objectives, running each for the same number of optimisation steps. At inference, the model is only provided with the source code, i.e. the IR is not needed.

Formally, let \(x = x_1 \ldots x_N\) be the source sentence, \(z(x) = z_1(\ldots z_N)\) the corresponding IR, and \(y = y_1 \ldots y_{Nt}\) the target sentence. We write \(L_{CE}(y, y) = \sum \ell_{CE}(y_i, y_i)\) the pairwise cross-entropy loss between \(y_i\) and \(y_i\). We define the machine translation loss (or seq2seq) loss from \(x\) to \(y\), \(L_{MT}\) as the sum of the negative log-likelihood of each token \(y_i\), given \(x\) and previous tokens \(y_0 \ldots y_{i-1}\) (note that \(x\) and \(y\) can have different lengths):

\[
L_{MT}(x, y) = -\sum \log \left(P(y_i|x, y_0 \ldots y_{i-1})\right)
\]

3.1 Common objective functions

TransCoder (Roziere et al., 2020) learns to translate between programming languages by leveraging three unsupervised objectives developed for natural language (Lample et al., 2018b):

- **Masked Language Modeling (MLM)** trains an encoder to predict randomly masked inputs. It is commonly used to pre-train embeddings for natural (Devlin et al., 2018; Liu et al., 2019) and programming languages (Kanade et al., 2020; Feng et al., 2020). MLM allows the model to learn the syntax and semantics of programs. Alternative objectives, have been proposed for programming languages (Guo et al., 2020; Lachaux et al., 2021; Ahmad et al., 2021; Wang et al., 2021). We do not use them here, as MLM remains effective and easy to use on a wide range of programming languages.

Denoting \(mask(x)\) the masked version of the code sentence \(x\), and \(enc(t)\) the encoder output, MLM uses the following loss:

\[
L_{MLM} = L_{CE}(enc(mask(x)), x).
\]
3.2 IR FOR CODE REPRESENTATIONS

Intermediate representations (IR) provide additional information about the code to be translated. We add them to the training dataset, as described in section 4.2, and leverage them by adding three new objective functions to those described in section 3.1.

Translation Language Modeling (TLM), first introduced in Lample and Conneau (2019), strives at generating common representations for parallel sentences in different languages. Like the masked language modeling (MLM) objective, it trains an encoder to predict random masked inputs. However, TLM is trained on pairs of parallel sentences, concatenated together and separated by a special token. Here, we concatenate functions in their source language and their corresponding IR, using the source code and IR language embeddings, and train the encoder to predict randomly masked tokens. This allows the model to learn correspondences between the source and the IR. The corresponding loss is

\[ \mathcal{L}_{TLM} = \mathcal{L}_{CE} \left( \text{mask}(x \oplus z^{(x)}), x \oplus z^{(x)} \right) \]
Figure 4: IR Decompilation objective. Here, we generate the IR corresponding to each function and train a model to decompile it. The IR pivot model uses this objective, as well as back-translation objectives, allowing it to generalize to IRs generated from any language.

Translation Auto-Encoding (TAE) amounts to transposing the TLM objective into a denoising auto-encoder. The source code and corresponding IR are corrupted and masked, and then concatenated into one sequence (using the language embeddings for code and IR, as previously). TAE is then tasked to recover the original, using the following loss:

\[ L_{TAE} = L_{MT}(\text{noise}(x) \oplus \text{noise}(z(x)), x \oplus z(x)) \]  

IR Generation (MT) trains the model to translate the source code into the corresponding IR. This allows the encoder to learn source code representations from the semantics of the IR. The loss is:

\[ L_{IRGen} = L_{MT}(x, z(x)) \]  

These three objectives need both the source code and the corresponding IR. However, only a fraction of the functions and files in our dataset could be compiled. To mitigate this, we also train the models on the full monolingual data using the MLM and AE objectives described above. In this setup, the back-translation (BT) objective is the same as in Roziere et al. (2020), and allows our model to translate directly from source code only at inference time.

3.3 ADDITIONAL LOSSES: IR DECOMPILATION AND PIVOT

We study two alternative uses of intermediary representations: IR decompilation, and IR pivot translation. IR decompilation consists of recovering source code corresponding to a given IR. In practice, it reverses the computations performed by the compiler. IR Pivot is a translation method built upon IR decompilation. Since LLVM can compile many languages (C++, Java, Rust, Go) into the same IR, an obvious approach to code translation consists of decompiling the IR generated from the source language into code in the target language. We call this method “IR pivot”. Note that, whereas the IR for code representation techniques only used IR during training, both the decompilation and pivot method also need the IR for inference.

Decompilation. In this supervised task, we use LLVM to generate IR from source code, and train a language model to reverse the process, i.e. learn to predict the source code from the IR. Models are pre-trained using the MLM and AE objectives, and decompilation is learned using the machine translation loss:

\[ L_{Decomp} = L_{MT}(z(x), x) \]  

IR Pivot. This task leverages the IR as a pivot for code translation. For instance, to translate from Rust to C++, we first use LLVM to compile a Rust program into IR and then decompile the IR to C++ using a neural decompiler. In practice, slight variations exist between the IR generated for different languages: the Rust-IR and C++-IR behave like dialects of the LLVM-IR. This often leads to poor performance of the IR Pivot method. We mitigate these issues using a variety of techniques, which we describe in section C of the appendix.
4  Data

4.1  Training Data

Our training data was extracted with Google BigQuery, which indexes over 2.8 million open source repositories from GitHub[2]. We selected projects whose license explicitly permits re-distribution of parts, and extracted all individual C++, Java, Rust and Go functions. To learn to decompile IRs, we also used the CodeNet dataset (Puri et al., 2021), a repository of 14 million competitive programming solutions in 55 languages. Our models work at function level: this reduces compilation failures over missing dependencies, while keeping sequence lengths short.

Table 1: Dataset coverage across languages, in number of standalone functions. More details can be found in Table 7 in the appendix.

| Language | C++   | Go    | Java  | Rust  |
|----------|-------|-------|-------|-------|
| Monolingual data | 6.6 M | 9.4 M | 7.8 M | 576.3 K |
| Code / IR Parallel Data | 344.4 K | 384.4 K | 2.2 M | 19.2 K |

4.2  Generating Intermediate Representations

While the LLVM ecosystem is large, not every language has an LLVM front-end, and not every front-end can produce LLVM IR out-of-the-box. We use clang++[3] (Lattner and Adve, 2004) from the established LLVM C++ compilation toolchain, JLang[4] for Java, Gollvm[5] for Go and rustc[6] (Matsakis and Klock II, 2014) for Rust. For the same program, written in different languages, different front-ends may produce different IR. To minimize these variations, we process the source code as follows. First, we generate the most size-optimized IR (-Oz flag), which makes the IR more uniform across languages. Second, we strip all unnecessary information (e.g. header and footer with attributes, debug information, comments). Finally, block names are canonicalized and symbol names demangled to facilitate their recovery. The functions that fail to compile at this point (e.g. because of missing dependencies) are not included in the parallel dataset, as seen in the last row of Table 1.

4.3  Evaluation

Traditional NMT evaluation relies on metrics such as BLEU, that are based on n-gram overlaps. However, when dealing with programming languages, syntax and in particular compilation and computation outputs can differ widely despite minor changes in the code. Conversely, semantically equivalent code, that differ only in variable names or order of operations can have a low BLEU score. To take this into account, we use and enhance the computational accuracy test suite from Roziere et al. (2020), that contains 852 parallel competitive programming solutions in C++, Java and Python. Using C2Rust, CxGo and some manual code cleaning, we translated 280 functions and test suites in Rust and 343 in Go to measure the performance of our models in these languages. We measure our performance using the computational accuracy (CA@1) metric (Kulal et al., 2019; Roziere et al., 2020), which considers that a translation is correct if it passes a series of unit tests.

5  Results

5.1  Experimental Details

For TransCoder, we consider a sequence-to-sequence (seq2seq) transformer model (Vaswani et al., 2017) with attention (Bahdanau et al., 2015; Sutskever et al., 2014) and the same architecture as Roziere et al. (2020). Our model has 12 layers (6 in the encoder and 6 in the decoder), 8 attention heads, and a dimension of 1024. For the objectives that add noise and masks to the input sentence, such as MLM, TLM, AE, and TAE, we choose the masked tokens and noise randomly on the fly at each epoch. We mask 15% of the tokens in MLM and TLM. In AE and TAE, we mask 20% of the tokens. MLM is trained on streams of data, while the other objectives are trained at function level. We use the Adam optimizer (Kingma and Ba, 2015) and an inverse squared-root learning rate scheduler,

---

[2] https://console.cloud.google.com/marketplace/details/github/github-repos
[3] https://clang.llvm.org/
[4] https://polyglot-compiler.github.io/JLang/
[5] https://go.googlesource.com/gollvm/
[6]
We compare the performance of our model to RetDec (Kroustek et al., 2017), a rule-based decompiler. With an initial learning rate of $10^{-5}$ in most of our experiments. Our models are implemented in PyTorch using mixed-precision floats. The pre-trained models were trained until convergence. The translation models presented in Tables 2 and 3 were trained for a week on 32 NVIDIA V100 GPUs.

### 5.2 IR-augmented code representations for Translation

Models using combinations of the three objectives—TAE, TLM and MT—are introduced to leverage IR, were trained to translate between pairs of four languages (C++, Java, Rust, Go). Their average performance when translating to and from every language are presented in Table 2. Additional information, including a comparison to TransCoder-ST for C++ ↔ Java, can be found in Table 3 in the appendix. As a baseline, we use a TransCoder (Roziere et al., 2020) model, trained with MLM on the same dataset.

Using greedy decoding, the new TLM, TAE and MT objectives, which leverage the IR, improve performance for every language. The best average results are obtained when combining all of them. Compared to TransCoder, they improve performance by an average 4.4% point (11% relative). The largest impacts are observed in the low data regime: translations from and into Rust (a language less represented in our training set) are improved by 25.6% and 19.3% (relative). Qualitatively, we observe that IRs help our model translate types when the source and target types are represented differently using the standard library structures such as `unordered_map` or `std::allocator`. The IR Pivot method generates a translation in the target language from an IR generated from the source, and performs poorly in our setting.

### 5.3 Decompilation results

To compute the IR pivot, we trained a neural decompiler to retrieve source code from IRs. We tried two separate configurations for decompilation: a shared decoder with 6 layers for all language / IR pairs, or four separate decoders of with two layers each (one per language). Using a shared decoder improves the performance for all languages, and particularly when the data is scarce (e.g. Rust). See Table 5 in the appendix for more information.

We compare the performance of our model to RetDec (Kroustek et al., 2017), a rule-based decompiler. It obtains a computational accuracy of 68.75 on our C++ dataset and a BLEU score of 8.54. In comparison, our model obtains a computational accuracy of 77.9 and a BLEU score of 63.6 in the same setting. In particular, RetDec fails to decompile LLVM files generated from C++ code, especially snippets leveraging the standard library structures such as `unordered_map` or `std::allocator`. The

Table 2: Translation performance (CA@1) “To X”: average performance when translating to language X. “From X”: average performance when translating from language X. See Table 3 in the appendix for more detailed results. All these methods except for the IR pivot also use the three objectives defined in TransCoder: MLM, DAE and Back-Translation (BT). All combinations of the TLM, MT and TAE objectives improve the performance compared to TransCoder. The best results are obtained when all three are used at the same time. The IR Pivot method generates a translation in the target language from an IR generated from the source, and performs poorly in our setting.

| Method           | from C++ | to C++ | from Go | to Go | from Java | to Java | from Rust | to Rust | AVG  |
|------------------|----------|--------|--------|-------|----------|--------|----------|--------|------|
| IR Pivot         | 17.4     | 24.0   | 19.9   | 11.5  | 11.9     | 22.2   | 16.3     | 7.8    | 16.4 |
| TransCoder (baseline) | 46.4     | 52.1   | 42.1   | 45.6  | 41.2     | 44.5   | 29.6     | 17.0   | 39.8 |
| TLM              | 47.5     | 54.8   | 45.4   | 41.2  | 39.8     | 52.1   | 31.1     | 15.7   | 40.9 |
| MLM + TAE        | 47.3     | 53.3   | 47.2   | 44.8  | 41.8     | 45.9   | 25.1     | 17.4   | 40.4 |
| TLM + TAE        | 46.9     | 55.9   | 45.0   | 37.9  | 38.5     | 54.5   | 34.9     | 16.8   | 41.3 |
| MLM + MT         | 45.5     | 51.0   | 44.0   | 48.9  | 46.6     | 45.2   | 25.7     | 16.6   | 40.5 |
| TLM + MT         | 45.6     | 51.5   | 45.1   | 47.1  | 46.9     | 45.5   | 24.4     | 17.9   | 40.5 |
| TAE + MT         | 47.8     | 54.3   | 43.8   | 43.9  | 39.1     | 49.2   | 33.4     | 16.7   | 41.0 |
| TLM + TAE + MT   | 47.8     | 54.3   | 46.6   | 51.6  | 47.1     | 49.6   | 35.3     | 21.4   | 44.2 |

with an initial learning rate of $10^{-5}$ in most of our experiments.
limitations of RetDec, which was implemented by a team of 24 developers in 7 years[^1] shows how difficult it is to build exhaustive rule-based decompilers, especially when the IR comes from different languages or tools.

6 DISCUSSION

Different IR and interpreted languages The four languages considered in this work have front-ends that can output LLVM Intermediate Representation. LLVM presently covers more than 30 computer languages. Using IR as pivot requires that the source and destination language have front-ends that use the same IR. This rules out some widely-used languages (e.g. Python). Using the IR to improve embeddings is less restrictive: the source and destination language can be trained on different IR, and aligned with back-translation. In this paper, we focus on compiled languages, but it is important to note that Intermediate Representations are usually available for interpreted languages as well: modern interpreters translate the source code into byte-code, that can serve as an IR.

Pivot vs Embedding TransCoder is an unsupervised model that learns to align code representations and translate code from one language to another. It is based solely on source code and does not use IRs. The pivot method uses automatically generated parallel sentences to learn to decompile IRs, and back-translation to adapt to different IR dialects. This method learns to translate using only IR-level similarities, and does not use the source code itself except to compute the IR. Although it underperforms other methods, it performs relatively well when little data is available for the source language, because the IR can be computed using a rule-based compiler. However, it requires to compute IRs at test time, which can be cumbersome. Instead, adding the TLM, TAE, and MT objectives to the objectives generally used for unsupervised code translation allows the model to get the best of both worlds. It can learn multilingual representations of source code from similarities in the IR and in the source code itself. As shown in Table 2 it outperforms both TransCoder and the pivot method. At the same time, this model does not require to compute IRs at test time, and is as easy to use as TransCoder.

Using our model at inference time. Our self-supervised IR-augmented TLM, TAE and MT objectives are designed to improve the multilingual code representations used in translation models. However, the translation task does not require to compute these objectives. Therefore, they lead to models that are just as simple to use as TransCoder: computing the IR is not required at test time and the model generates the translation directly from the source function.

7 RELATED WORKS

Source-to-Source Translation. Many rule-based methods are available for transpilation, an inventory of which can be found online[^2]. In particular, C2Rust[^3] and CxGo[^4] along with manual corrections, were central for us in translating evaluation tests to Go and Rust (See Section 4.3). Similarly, 2to3[^5], a Python library porting Python 2 code to Python 3, was used in Aggarwal et al. (2015) to create a parallel dataset and train a machine learning model.

Neural Machine Translation for code is hampered by the lack of parallel data between programming languages. Indeed, apart from a few language pairs, such as Java-C# (Nguyen et al., 2013; Chen et al., 2018), and specific domains (e.g. competitive programming code), it is difficult to collect large datasets of semantically equivalent code in different languages. TransCoder (Roziere et al., 2020) bridges this gap by introducing unsupervised machine translation to programming languages. They take advantage of large monolingual code bases to learn to translate between C++, Python and Java with high performance. Later, DOBF (Lachaux et al., 2021) improved the model pre-training method used in TransCoder, and Roziere et al. (2022) used automatically generated unit tests to improve translation performance between Java, C++ and Python. Recently, large language models trained on

[^1]: https://blog.fpmurphy.com/2017/12/avast-retargetable-decompiler-ida-plugin.html
[^2]: https://github.com/immunant/c2rust
[^3]: https://github.com/gotranspile/cxgo
[^4]: https://docs.python.org/2/library/2to3.html
code, such as Codex (Chen et al., 2021) and PALM (Chowdhery et al., 2022), have been used for unsupervised code translation.

Using the Transcoder model, Weisz et al. (2021) and Weisz et al. (2022) survey the links between humans and NMT methods for code translation. They view neural translation methods as aids to programmers. In this context, they demonstrate that even imperfect models can improve the quality of an engineer’s work for code translation, and plead for the improvement of human-machine interfaces.

Decomposition. Like transpilation, decompilation is usually performed using rule-based methods that rely on pattern matching to parse the control flow structure of the program. RetDec, an open source decompiler created by Avast (Kroustek et al., 2017), can decompile an executable to C and a Python-like language via LLVM IR. Other tools exist, such as the Hex-Rays Decompiler[10] and Brumley et al. (2013). A thorough review of rule-based methods can be found in papers such as Liang et al. (2021a) and Katz et al. (2019). With these methods, decompilation can fail if the code is too convoluted, or if it contains language features that were not explicitly translated. Most methods also produce unstructured programs, relying on a large number of goto statements to simulate the control flow of the lower level programming languages. This is semantically correct, but very rarely found in human-written code.

A few works have studied the use of sequence-to-sequence neural networks for neural decompilation. Katz et al. (2019) uses LSTM networks to decompile LLVM IRs and assembly code to C. Their approach generates code templates based on the IR, that determine the structure of the output. Then, they fill them with correct variable assignments and numerical values. In the same vein, Fu et al. (2019) tries to address limitations of neural decompilation with two sequential phases: code sketch generation and iterative error correction. Finally, Liang et al. (2021b) use a method close to ours, and train Transformer models to translate between binary code and C.

Intermediate representations are almost as old as compiler design. The first IR, UNCOL (Strong et al., 1958) was introduced in the mid-1950s, together with the idea of reusing the same compiler for several languages and machines. In 1960, NELIAC (a variant of ALGOL) (Huskey et al., 1960) was the first retargetable compiler, portable to different architectures. Feldman (1979) describes how a compiler for Fortran 77 can be added to the C compilers of Johnson (1979) and Ritchie (1979). GCC (Stallman, 2001) introduces Register Transfer Language (RTL) a low-level IR inspired by Davidson and Fraser (1980), and then GENERIC and GIMPLE (Merrill, 2003), precursors of the IR used in LLVM (Lattner and Adve, 2004).

8 Conclusion

In this paper, we leverage LLVM IRs to improve neural machine translation for source code. The IR provides a common semantically-rich language, into which C++, Go, Java and Rust code can all be compiled. We develop three objectives, designed to leverage IRs for better multilingual representations of source code, which lead to a 11% relative average improvement for code translation. We also show that sequence-to-sequence transformers perform well for neural decompilation, and use this for pivot translation.

We only worked with the LLVM IR, but our approach is broadly applicable to any pair of languages that share a common Intermediate Representation. More generally any IR can help improve the code representations by tying them to the semantics. Another limitation is the scale of our current source and target sequences. As future work, LLVM IRs could be generated at a larger scale by compiling entire projects, which would greatly improve the percentage of successful IR compilations in Table 1. More languages and IRs could be used, and those extensions could be powered by larger models.

[10]https://hex-rays.com/decompiler/
REFERENCES

Karan Aggarwal, Mohammad Salameh, and Abram Hindle. Using machine translation for converting Python 2 to Python 3 code. Technical report, PeerJ PrePrints, 2015.

Wasi Ahmad, Saikat Chakraborty, Baishakhi Ray, and Kai-Wei Chang. Unified pre-training for program understanding and generation. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2655–2668, 2021.

Mikel Artetxe, Gorka Labaka, and Eneko Agirre. Unsupervised statistical machine translation. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, 2018.

Dzmitry Bahdanau, Kyung Hyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, 2015.

David Brumley, JongHyup Lee, Edward J Schwartz, and Maverick Woo. Native x86 decompilation using semantics-preserving structural analysis and iterative control-flow structuring. In 22nd USENIX Security Symposium (USENIX Security 13), pages 353–368, 2013.

Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde, Jared Kaplan, Harri Edwards, Yura Burda, Nicholas Joseph, Greg Brockman, et al. Evaluating large language models trained on code. arXiv preprint arXiv:2107.03374, 2021.

Xinyun Chen, Chang Liu, and Dawn Song. Tree-to-tree neural networks for program translation. In Advances in neural information processing systems, pages 2547–2557, 2018.

Aakanksha Chowdhery, Sharan Narang, Jacob Devlin, Maarten Bosma, Gaurav Mishra, Adam Roberts, Paul Barham, Hyung Won Chung, Charles Sutton, Sebastian Gehrmann, et al. Palm: Scaling language modeling with pathways. arXiv preprint arXiv:2204.02311, 2022.

Jack W. Davidson and Christopher W. Fraser. The design and application of a retargetable peephole optimizer. ACM Trans. Program. Lang. Syst., 2(2):191–202, apr 1980. ISSN 0164-0925.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. CoRR, abs/1810.04805, 2018.

Stuart I. Feldman. Implementation of a portable Fortran 77 compiler using modern tools. SIGPLAN Not., 14(8):98–106, aug 1979. ISSN 0362-1340. doi: 10.1145/872732.806959. URL https://doi.org/10.1145/872732.806959.

Zhangyin Feng, Daya Guo, Duyu Tang, Nan Duan, Xiaocheng Feng, Ming Gong, Linjun Shou, Bing Qin, Ting Liu, Daxin Jiang, et al. Codebert: A pre-trained model for programming and natural languages. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings, pages 1536–1547, 2020.

Cheng Fu, Huili Chen, Haolan Liu, Xinyun Chen, Yuandong Tian, Farinaz Koushanfar, and Jishen Zhao. Coda: An end-to-end neural program decompiler. In Advances in Neural Information Processing Systems, pages 3703–3714, 2019.

Daya Guo, Shuo Ren, Shuai Lu, Zhangyin Feng, Duyu Tang, LIU Shujie, Long Zhou, Nan Duan, Alexey Svyatkovskiy, Shengyu Fu, et al. Graphcodebert: Pre-training code representations with data flow. In International Conference on Learning Representations, 2020.

Harry D. Huskey, M. H. Halstead, and R. McArthur. NELIAC — dialect of ALGOL. Commun. ACM, 3(8):463–468, aug 1960. ISSN 0001-0782. doi: 10.1145/367368.367373. URL https://doi.org/10.1145/367368.367373.

S. C. Johnson. A tour through the portable C compiler. In Unix Programmer’s Manual, 7th Edition, 2B, Section 33, 1979.

Aditya Kanade, Petros Maniatis, Gogul Balakrishnan, and Kensen Shi. Learning and evaluating contextual embedding of source code. In International Conference on Machine Learning, pages 5110–5121. PMLR, 2020.
Omer Katz, Yuval Olshaker, Yoav Goldberg, and Eran Yahav. Towards neural decompilation. arXiv preprint arXiv:1905.08325, 2019.

Diederik Kingma and Jimmy Ba. Adam: A method for stochastic optimization. ICLR, 2015.

Jakub Króustek, Peter Matula, and P Zemek. RetDec: An open-source machine-code decompiler, 2017. URL https://github.com/avast/retdec.

Sumith Kulal, Panupong Pasupat, Kartik Chandra, Mina Lee, Oded Padon, Alex Aiken, and Percy S Liang. Spoc: Search-based pseudocode to code. Advances in Neural Information Processing Systems, 32:11906–11917, 2019.

Marie-Anne Lachaux, Baptiste Roziere, Marc Szafraniec, and Guillaume Lample. DOBF: A deobfuscation pre-training objective for programming languages. arXiv preprint arXiv:2102.07492, 2021.

Guillaume Lample and Alexis Conneau. Cross-lingual language model pretraining. Advances in Neural Information Processing Systems, 32:7059–7069, 2019.

Guillaume Lample, Alexis Conneau, Ludovic Denoyer, and Marc’Aurelio Ranzato. Unsupervised machine translation using monolingual corpora only. ICLR, 2018a.

Guillaume Lample, Myle Ott, Alexis Conneau, Ludovic Denoyer, and Marc’Aurelio Ranzato. Phrase-based & neural unsupervised machine translation. In EMNLP, 2018b.

Chris Lattner and Vikram Adve. LLVM: A compilation framework for lifelong program analysis & transformation. In International Symposium on Code Generation and Optimization, 2004. CGO 2004., pages 75–86. IEEE, 2004.

Ruigang Liang, Ying Cao, Peiwei Hu, and Kai Chen. Neutron: an attention-based neural decompiler. Cybersecurity, 4(1):1–13, 2021a.

Ruigang Liang, Ying Cao, Peiwei Hu, Jinwen He, and Kai Chen. Semantics-recovering decompilation through neural machine translation. arXiv preprint arXiv:2112.15491, 2021b.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. RoBERTa: A robustly optimized BERT pretraining approach. arXiv preprint arXiv:1907.11692, 2019.

Nicholas D Matsakis and Felix S Klock II. The Rust language. In ACM SIGAda Ada Letters, volume 34, pages 103–104. ACM, 2014.

Jason Merrill. GENERIC and GIMPLE: A new tree representation for entire functions. In Proc. GCC Developers Summit, 2003, pages 171–180. 2003.

Anh Tuan Nguyen, Tung Thanh Nguyen, and Tien N Nguyen. Lexical statistical machine translation for language migration. In Proceedings of the 2013 9th Joint Meeting on Foundations of Software Engineering, pages 651–654, 2013.

Ruchir Puri, David S. Kung, Geert Janssen, Wei Zhang, Giacomo Domeniconi, Vladimir Zolotov, Julian Doby, Jie Chen, Mihir R. Choudhury, Lindsey Decker, Veronika Thost, Luca Buratti, Saurabh Pujar, and Ulrich Finkler. Project CodeNet: A large-scale AI for code dataset for learning a diversity of coding tasks. CoRR, abs/2105.12655, 2021. URL https://arxiv.org/abs/2105.12655.

D.M. Ritchie. A Tour Through the UNIX C Compiler. 1979. URL https://books.google.com/books?id=5UvEGwAACAAJ.

Baptiste Roziere, Marie-Anne Lachaux, Lowik Chanussot, and Guillaume Lample. Unsupervised translation of programming languages. Advances in Neural Information Processing Systems, 33, 2020.

Baptiste Roziere, Jie M Zhang, Francois Charton, Mark Harman, Gabriel Synnaeve, and Guillaume Lample. Leveraging automated unit tests for unsupervised code translation. ICLR, 2022.
Rico Sennrich, Barry Haddow, and Alexandra Birch. Improving neural machine translation models with monolingual data. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics, pages 86–96, 2015.

Richard Stallman. Using and porting the GNU Compiler Collection. M.I.T. Artificial Intelligence Laboratory, 2001.

J. Strong, J. Wegstein, A. Tritter, J. Olsztyn, O. Mock, and T. Steel. The problem of programming communication with changing machines: A proposed solution. Commun. ACM, 1(8):12–18, aug 1958. ISSN 0001-0782. doi: 10.1145/368892.368915. URL [https://doi.org/10.1145/368892.368915]

Ilya Sutskever, Oriol Vinyals, and Quoc V Le. Sequence to sequence learning with neural networks. In Advances in neural information processing systems, pages 3104–3112, 2014.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In Advances in neural information processing systems, pages 5998–6008, 2017.

Yue Wang, Weishi Wang, Shafiq Joty, and Steven CH Hoi. Codet5: Identifier-aware unified pre-trained encoder-decoder models for code understanding and generation. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 8696–8708, 2021.

Justin D Weisz, Michael Muller, Stephanie Houde, John Richards, Steven I Ross, Fernando Martinez, Mayank Agarwal, and Kartik Talamadupula. Perfection not required? human-ai partnerships in code translation. In 26th International Conference on Intelligent User Interfaces, pages 402–412, 2021.

Justin D Weisz, Michael Muller, Steven I Ross, Fernando Martinez, Stephanie Houde, Mayank Agarwal, Kartik Talamadupula, and John T Richards. Better together? an evaluation of AI-supported code translation. In 27th International Conference on Intelligent User Interfaces, pages 369–391, 2022.
### A Full Scores Table

Table 3: Results on unsupervised code translation. The metric shown is the computational accuracy for a single generation (CA@1), measuring the translation correctness using unit tests. It is the full version of Table 2. The models were all trained with the same budget. As in Table 2, all these methods except for the IR pivot also use the three objectives defined in TransCoder: MLM, DAE and Back-Translation (BT). Although it is not the case for every language pair, TransCoder-IR, which uses the TLM, TAE, and MT objectives outperforms other methods on average. TransCoder-ST [Roziere et al., 2022] uses a parallel dataset generated with automated unit tests and outperforms other methods for C++ ↔ Java. Their method is orthogonal to ours, and we could also improve our performance with similar methods.

| C++ → Go | C++ → Java | C++ → Rust | Go → C++ | Go → Java | Go → Rust |
|----------|------------|------------|----------|-----------|-----------|
| Baseline TransCoder | 57.7 | 63.3 | 18.2 | 56.1 | 46.9 | 23.3 |
| TransCoder-ST | - | 68.0 | - | - | - | - |
| Pivot | 16.1 | 22.0 | 14.0 | 30.5 | 26.5 | 2.7 |
| TLM | 61.8 | 62.5 | 18.2 | 57.6 | 56.4 | 22.2 |
| TAE | 57.7 | 62.5 | 21.7 | 63.0 | 54.7 | 23.8 |
| TLM + TAE | 58.2 | 63.3 | 19.2 | 55.2 | 57.0 | 22.8 |
| MT | 56.8 | 60.6 | 19.2 | 60.3 | 53.8 | 18.0 |
| TLM + MT | 58.6 | 58.5 | 19.7 | 57.3 | 54.1 | 23.8 |
| TAE + MT | 61.4 | 60.2 | 21.7 | 55.5 | 53.8 | 22.2 |
| TLM + TAE + MT | 55.9 | 62.9 | 24.8 | 61.8 | 55.7 | 22.2 |

| Java → C++ | Java → Go | Java → Rust | Rust → C++ | Rust → Go | Rust → Java |
|-------------|-----------|-------------|------------|-----------|-------------|
| Baseline TransCoder | 77.9 | 35.9 | 9.6 | 22.4 | 43.2 | 23.4 |
| TransCoder-ST | 84.6 | - | - | - | - | - |
| Pivot | 19.5 | 9.4 | 6.7 | 22.0 | 8.9 | 18.1 |
| TLM | 80.9 | 31.8 | 6.6 | 25.9 | 30.0 | 37.5 |
| TAE | 80.3 | 38.6 | 6.6 | 16.6 | 38.1 | 20.6 |
| TLM + TAE | 82.2 | 24.6 | 8.6 | 30.4 | 31.0 | 43.3 |
| MT | 76.2 | 50.9 | 12.6 | 16.6 | 39.1 | 21.3 |
| TLM + MT | 77.9 | 52.7 | 10.1 | 19.2 | 30.0 | 24.1 |
| TAE + MT | 77.5 | 33.6 | 6.1 | 30.0 | 36.6 | 33.7 |
| TLM + TAE + MT | 74.5 | 49.6 | 17.2 | 26.5 | 49.2 | 30.2 |
B Beam size evaluation

Table 4: Results on unsupervised code translation with different beam sizes. The metric shown is still the computational accuracy for a single generation (CA@1). BS N refers to beam search decoding with beam size N, and returning only the top element of the beam. Using beam search actually decreases the average performance for every model. Our method using intermediate representations outperforms the baseline with and without using beam decoding. With the baseline, we obtain average CA@1 scores of 39.5 with beam size 5 and 37.7 with beam size 10 (down from 39.8 with greedy decoding). Our method yields CA@1 scores of 40.4 with beam size 5 and 40.4 with beam size 10, down from 44.4 with greedy decoding.

|                          | C++ → Go | C++ → Java | C++ → Rust | Go → C++ | Go → Java | Go → Rust |
|--------------------------|----------|------------|------------|----------|-----------|-----------|
| Baseline TransCoder      | 57.7     | 63.3       | 18.2       | 56.1     | 46.9      | 23.3      |
| Baseline TransCoder (BS 5)| 59.1     | 63.3       | 17.7       | 46.7     | 51.8      | 24.3      |
| Baseline TransCoder (BS 10)| 59.1    | 63.3      | 16.7       | 46.4     | 49.8      | 23.8      |
| TLM + TAE + MT           | 55.9     | 62.86      | 24.8       | 61.8     | 55.7      | 21.2      |
| TLM + TAE + MT (BS 5)    | 57.3     | 62.4       | 23.7       | 41.5     | 55.7      | 19.6      |
| TLM + TAE + MT (BS 10)   | 57.7     | 62.7       | 24.7       | 41.8     | 56.7      | 20.1      |

|                          | Java → C++ | Java → Go | Java → Rust | Rust → C++ | Rust → Go | Rust → Java |
|--------------------------|------------|----------|-------------|------------|----------|-------------|
| Baseline TransCoder      | 77.9       | 35.9     | 9.6         | 22.4       | 43.2     | 23.4        |
| Baseline TransCoder (BS 5)| 77.3      | 40.9     | 3.5         | 21.1       | 46.2     | 22.3        |
| Baseline TransCoder (BS 10)| 74.5    | 39.1     | 2.5         | 18.5       | 41.1     | 17.9        |
| TLM + TAE + MT           | 74.5       | 49.6     | 17.2        | 26.5       | 49.2     | 30.2        |
| TLM + TAE + MT (BS 5)    | 69.2       | 49.5     | 13.6        | 21.7       | 46.2     | 24.7        |
| TLM + TAE + MT (BS 10)   | 69.2       | 50.0     | 14.6        | 20.1       | 45.2     | 22.3        |

C Pivot method details

As mentioned in Section 3.3, IR generated from different languages contain slight variations and can be seen as dialects of the same language. In practice, these variations prevent us from simply using our best decompilation model to generate source code in another language than the one used to generate the IR. Although we prompt the model to generate code in the target language with language embeddings, it learns to focus on the particularities of each dialect and ignores the language embeddings. Therefore, it generates code in the source language, which results in a computational accuracy score of 0 for translation.

One way to solve this issue is to use one decoder per target language. Then, the model is able to generate code in the target language. However, this method still performs poorly due to the small differences between the IR dialects. The method we tested that performed the best, and which is reported in Table 2, uses back-translation to make the model to translate from any IR dialect to any language. This model is also grounded by supervised translation steps making it generate IR from code and code from IR. In practice, we create new language embeddings for every IR dialect (i.e. IR-C++, IR-Go, IR-Java, IR-Rust) for depending on the source language. At training time, we make the model generate noisy translations in the IR-Go, IR-Java and IR-Rust “languages” for every C++ sequence, and train it to re-generate the C++ sequence from the noisy translation. To allow the model to generate good training data for IR-X → C++, we also generate noisy translations in Go, Java, and Rust for every IR generated from C++ in our dataset and train the model to retrieve the IR. Using our parallel code//IR dataset, we also train the model to translate between C++ and IR-C++ sequences. We do the same for every language and alternate between them.
D IR DECOMPIlATION

Table 5: Performance of LLVM IRs Decompilation. This table shows the computational accuracy (CA@1) of our neural decompiler and the RetDec C++ rule-based decompiler. Our neural decompiler outperforms RedDec on C++ and is more broadly applicable.

|                | C++  | Go   | Java | Rust |
|----------------|------|------|------|------|
| Baseline - RetDec | 68.8 | —    | —    | —    |
| Separate Decoders | 52.7 | 42.2 | 60.1 | 19.5 |
| Shared Decoder   | 77.9 | 70.1 | 82.2 | 61.0 |

E TRANSLATION EXAMPLES

Figure 5: Code simplification examples with Decompilation / Pivot. Since the LLVM IR is optimized, functions that are semantically equivalent after optimization map to the same IR. In the first example, it allows to remove useless code by decompiling the generated LLVM IR. In the second example, the simplification allows to find a bug: the & operator has precedence over == in C++, causing this function to always evaluate to false. It is not obvious when looking at the input code, but becomes clear with the IR and simplified C++ code. In the third example, it replaces a bitwise operation by a more straightforward multiplication. In all examples, we can run the compiler again to check that the IR of the decompiled code is exactly the same as that of the input. It guarantees that the input and simplified code have the same semantics.
Figure 6: Java to Rust translation examples. In the first example, the IR allows the model to understand that the Java bitwise complement operator ~ should be replaced by ! in Rust. Also, it allows the model to translate the type correctly in both examples and avoids unnecessary casts. The IR allows the model to generate the right types (e.g. i32 instead of u32 when translating int) and operator (e.g. ! instead of ~ in Rust).

Figure 7: Rust to Go translation example. This function performs binary search to find the insertion index for an element in an ordered vector. The model translates types, function definitions, variable definitions, and while loops correctly.
Figure 8: Go to C++ translation example. This function computes the number of pairs of elements that sum to a given target in a sorted and rotated array. Our TransCoder-IR model translates it correctly.
Figure 9: Rust to Go translation example. We call S1 the string n1 repeated s1 times and S2 the string n2 repeated s2 times. This function finds the largest number of repetitions of S2 appearing in any subset of S1. The model translates the types correctly, understands that casting vector indices to unsigned int (i.e. with as usize) is not required in Go, and correctly translates other Rust constructs to Go.
F  Dataset size details

Table 6: Dataset details: number of tokens in our function-level dataset. This dataset contains only functions defined outside of classes and static functions.

|                     | Number of tokens | Number of sentences |
|---------------------|------------------|---------------------|
| **Monolingual data** |                  |                     |
| C++                 | 2.33B            | 6.6M                |
| Go                  | 1.9B             | 9.4M                |
| Java                | 1.5B             | 7.8M                |
| Rust                | 130.0M           | 576.3K              |
| **Code / IR Parallel Data** |        |                     |
| C++-IR              | 946.7M           | 343.9K              |
| Go-IR               | 971.8M           | 384.4K              |
| Java-IR             | 1.7B             | 2.2M                |
| Rust-IR             | 77.7M            | 19.4K               |

G  Additional ablations

Training on IRs with different objectives. We perform some additional ablations to determine whether our performance improvements come from training on IRs or from our TLM, TAE and MT objectives. When training a model with the three objectives of TransCoder (i.e. MLM, DAE and BT) and considering the IR as an extra language, we obtain an average computational accuracy of 37.4, which is lower than that of our baseline TransCoder. As the structure of the IR is not similar to that of any of our source languages, there is not much to gain from adding the IR as an extra language. Moreover, the model is wasting some time to compute the AE and BT objectives for the IR which can be better spent on the source languages. It confirms that our objectives are required to map IRs and their corresponding source code to similar representations in embedding space.

Language ablation: no Java. As Rust and Go are more similar to Java than to C++, we also train a baseline model on C++, Go and Rust only to evaluate whether including Java hurts the translation performance. We observed similar performance for C++ ↔ Go. However, we also observe a clear decrease in performance in the very low data regime (i.e. when translating to or from Rust). The computational accuracy for Rust → C++ goes down from 22.4% to 20.1% and it goes down from 43.15% to 32.5% for Rust → Go.

H  Word embeddings

We notice that our method generates improved word embeddings. It is visible when looking at the cosine similarity for embeddings of rust types and their equivalents in C++. For instance, Figure 10 shows that the embedding of u32 from our model leveraging LLVM IRs is most similar to uint32 (with a cosine similarity of 0.4869). uintt, which is also a correct translation, comes in 11th position with a cosine similarity of 0.3716. In contrast, u32 has a similarity of only 0.2828 with int. This token, which would be an incorrect translation, comes only in 29th position. Moreover, uint and int have almost the same cosine similarities with u32 with the baseline model. It causes the model to often confuse unsigned and signed integer types, and to incorrectly translate u32 into int instead of uint.
Baseline TransCoder:  
1 - 0.4789 - u64
2 - 0.4478 - i32
3 - 0.4223 - u16
4 - 0.4218 - uint32
5 - 0.4119 - usize
...
14 - 0.3169 - uint
...
16 - 0.3108 - int

Our model with TLM + TAE + MT:
1 - 0.4869 - uint32
2 - 0.4779 - u64
3 - 0.4681 - u16
4 - 0.4302 - uint32_t
5 - 0.4270 - i32
...
11 - 0.3716 - uint
...
29 - 0.2828 - int

Figure 10: **Token similarities.** Rank and token similarity with u32 for our model (right) and the baseline model (left). Our model generates embeddings that better capture token semantics.

I Analysis of Error Types

Table 7: **Rust error types.** To validate our intuition on the usefulness of the IR representations to decrease the number of type-related errors (see Fig.1 or Fig.6), we perform an in-depth analysis of the types of errors encountered for the Java → Rust direction. Here we count the total number of errors (there can be several for a single translation). We notice that the number of type-related errors (excluding E0433, E0425 and Others) decreases by 24% (609 vs. 463) and the number of mismatched types decreases by 49%.

| Error Code | Error Description                                | Baseline (Transcoder) | TLM + TAE + MT |
|------------|--------------------------------------------------|------------------------|----------------|
| E0308      | Mismatched Type                                  | 414                    | 210            |
| E0412      | Type Does Not Exist                              | 15                     | 3              |
| E0277      | Type has Missing Trait                           | 180                    | 250            |
| E0425      | Undefined Variable                               | 18                     | 27             |
| E0433      | Use of Undefined Crate, Module or Type          | 15                     | 32             |
| — Others   |                                                  | 28                     | 33             |
| TOTAL      |                                                  | 670                    | 555            |