DocCoder: Generating Code by Retrieving and Reading the Docs

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Abstract
Natural-language-to-code models learn to generate a code snippet given a natural language (NL) intent. However, the rapid growth of both publicly available and proprietary libraries and functions makes it impossible to cover all APIs using training examples, as new libraries and functions are introduced daily. Thus, existing models inherently cannot generalize to using unseen functions and libraries merely through incorporating them into the training data. In contrast, when human programmers write programs, they frequently refer to textual resources such as code manuals, documentation, and tutorials, to explore and understand available library functionality. Inspired by this observation, we introduce DocCoder: an approach that explicitly leverages code manuals and documentation by (1) retrieving the relevant documentation given the NL intent, and (2) generating the code based on the NL intent and the retrieved documentation. Our approach is general, can be applied to any programming language, and is agnostic to the underlying neural model. We demonstrate that DocCoder consistently improves NL-to-code models: DocCoder achieves 11x higher exact match accuracy than strong baselines on a new Bash dataset tldr; on the popular Python CoNaLa benchmark, DocCoder improves over strong baselines by 1.65 BLEU.

1 Introduction
We address the task of natural language to code generation (NL→code): generating a code snippet, written in a general-purpose programming language such as Python or Bash, given a natural language intent. This task has seen sharply growing popularity recently due to the emergence of large language models trained on vast amounts of natural language and code (Chen et al., 2021; Xu et al., 2022; Fried et al., 2022). NL→code models facilitate programming for both professional and inexperienced programmers, by allowing programmers to write code by only expressing their higher-level intent.

All existing NL→code models either learn directly from NL-code pairs provided as training data (Allamanis et al., 2015; Yin and Neubig, 2017; Rabinovich et al., 2017; Iyer et al., 2018; Xu et al., 2020; Wang et al., 2021), or learn the mapping between NL and code implicitly from naturally occurring corpora of interspersed natural language and code (Austin et al., 2021; Nijkamp et al., 2022). Nevertheless, all these works assume that all needed libraries and function calls are observed in the training set; and at test time, the trained model can be expected to include only seen libraries and function calls in its generated code. However, as existing software develops and new code is created, new libraries and new functions are introduced all the time, and even a seen function call can have arguments that were not used in the training data. Thus, existing models inherently cannot generalize to generate such unseen function calls.

1Code and data are at https://github.com/shuyanzhou/doccoder

Preprint. Under review.
Generate an HTML file that has the syntax highlight for python "print('reading docs')"

```python
from pygments import *
code = 'print("reading docs")'
s = highlight(code, PythonLexer(), HtmlFormatter())
```

Figure 1: An overview of DocCoder: given a NL intent, the retriever retrieves a set of relevant documentation; then, the generator generates the code based on the NL and docs. DocCoder can generalize to previously unseen usages by reading those usages from the docs. Italic blue highlights the alignments between NL and docs; Bold text shows alignments between docs and the code snippet.

In contrast to these existing models, human programmers frequently refer to free-form textual resources such as manuals, documentation, tutorials, and blogs when writing code. This allows humans to easily learn and use functions and libraries they have never seen or used before. Inspired by this ability, we propose DocCoder: a code generation approach that learns to retrieve code documentation before generating the code. An overview of our approach is illustrated in Figure 1. First, a document retriever uses the NL intent to retrieve relevant code documentation from a documentation pool. Then, a code generator uses these docs as references to generate the corresponding code. The documentation pool serves as an external data store that can be updated frequently with new contents, without re-training any model components. This way, DocCoder can leverage newly added documentation and generate code snippets containing functions and libraries unseen at training time.

Our DocCoder approach is general and applicable to any concrete implementation and programming language. We demonstrate the effectiveness of DocCoder on two NL→code benchmarks, across two programming languages and tasks, and using several different base models: sparse retriever (Robertson and Jones, 1976), dense retriever (Gao et al., 2021), GPT-Neo (Black et al., 2021), CodeT5 (Wang et al., 2021), T5 (Raffel et al., 2020), Fusion-in-Decoder (Izacard and Grave, 2021), and Codex (Chen et al., 2021). Further, we introduce two new benchmarks for retrieval-based code generation: (a) in Bash, we curate a new benchmark by crawling the tldr\(^2\) repository, and constructing the training/development/test splits without overlapping commands; (b) in Python, we re-split the popular CoNaLa benchmark (Yin and Neubig, 2017) by making every test example contain at least one Python function that is not seen in the training data. Models with DocCoder consistently outperform their base models that generate code solely based on the NL intents. Using DocCoder yields up to 11 times higher exact match accuracy on tldr, and brings 1.65 BLEU point improvement over the state-of-the-art on CoNaLa. We release our new benchmarks, including annotation of ground truth documents for each example and pools of documentation to retrieve from, to serve as a test-bed for future retrieval-based code generation models.

## 2 Code Generation by Reading the Docs

### Problem Formulation

Given an NL intent \( n \), our goal is to generate a corresponding code snippet \( c \) written in some general-purpose programming language (PL) such as Python. We assume that a model has access to a collection of code documentation \( \mathcal{D} \), written as NL descriptions that may also contain code. Each document \( d_i \in \mathcal{D} \) describes the usage of a library, a function, or an argument implemented in that PL. The construction of \( \mathcal{D} \) is flexible: it can either be a comprehensive set of all available libraries and functions in a PL, or a customized subset for the scope of a specific project.

### 2.1 Generating Code by Reading the Docs

Although a model may use the entire collection of documentation \( \mathcal{D} \), only a few documents in \( \mathcal{D} \) are relevant for any particular intent. Further, it is usually computationally infeasible to directly condition

[^https://github.com/tldr-pages/tldr]
on the entire collection of documents while making predictions. Thus, we first let the model select a
subset of documents \( \mathcal{D}_n = \{ d_1, d_2, \ldots, d_k \} \subseteq \mathcal{D} \) that are potentially relevant given \( n \), and refer to this subset while generating \( c \).

Overall, we decompose the probability of generating \( c \) into the probability of choosing a particular
subset of documents \( P(\mathcal{D}_n | \mathcal{D}, n) \), and the probability of generating the code conditioned on the
intent and the selected documents \( P(c | \mathcal{D}_n, n) \), and finally marginalizing over all \( \mathcal{D}_n \subseteq \mathcal{D} \):

\[
P(c | \mathcal{D}, n) = \sum_{\mathcal{D}_n \subseteq \mathcal{D}} P(c | \mathcal{D}_n, n) \cdot P(\mathcal{D}_n | \mathcal{D}, n)
\]

(1)

assuming that \( c \) is independent of \( \mathcal{D} \) given \( \mathcal{D}_n \). In practice, it is most common to approximate the
marginalization over \( \mathcal{D}_n \) by taking the most probable retrieved documents \( \hat{\mathcal{D}}_n \), and then conditioning the prediction of \( c \) on these most likely documents:

\[
\hat{\mathcal{D}}_n := \text{argmax}_{\mathcal{D}_n \subseteq \mathcal{D}} P(\mathcal{D}_n | \mathcal{D}, n)
\]

\[
P(c | \mathcal{D}, n) \approx P(c | \hat{\mathcal{D}}_n, n) \cdot P(\hat{\mathcal{D}}_n | \mathcal{D}, n)
\]

(2)

Notably, this formulation generalizes the standard NL→code approach, in which \( \mathcal{D} = \mathcal{D}_n = \emptyset \). Further, this formulation is generic and \( \mathcal{D} \) can be any text-based resource that could potentially benefit
code generation, including blog posts and tutorials. In this work, we focus on code documentation
with the assumption that documentation is the most exhaustive yet succinct resource for most libraries
and programming languages.

### 2.2 DocCoder: Overview

We propose DocCoder: an NL→code approach for code generation, following the ideas of
\textit{Equation 2}. DocCoder consists of two main components: A retriever \( \mathcal{R} \) retrieves relevant text-based documents
\( \mathcal{D}_n \) given the intent \( n \); and a generator \( \mathcal{G} \) generates the code snippet \( c \) conditioned on the retrieved
documents \( \mathcal{D}_n \) and the intent \( n \). An overview of our approach is illustrated in \textit{Figure 1} given the
intent \( n \), the retriever \( \mathcal{R} \) retrieves three relevant documents: \( d_1 \) summarizes the syntax highlighting
library \texttt{pygments}, \( d_2 \) describes a class that lexes Python code, and \( d_3 \) describes a class that renders
HTML. Given these docs and the intent, the generator \( \mathcal{G} \) can generate the correct code snippet \( c \).

Specifically, \( \mathcal{R} \) computes a relevance score \( s_i(d_i, n) \) between an NL intent \( n \) and every document
\( d_i \in \mathcal{D} \). For the simplicity of retrieval, we score each document independently of the others.
Thus, the subset \( \hat{\mathcal{D}}_n \subseteq \mathcal{D} \) is the top-\( k \) documents with the highest relevance scores:
\( \hat{\mathcal{D}}_n = \text{top-}k \mathcal{D} \{ s_i(d_i, n) \} \). Finally, the generator \( \mathcal{G} \) computes
\( P(c | \hat{\mathcal{D}}_n, n) \) by generating a token at a time using beam search, similar to how conditional decoders generate output in encoder-decoder models
such as T5 \cite{Raffel2019}, or decoder-only models such as GPT \cite{Radford2018}.

The proposed DocCoder is agnostic to the concrete choice of retriever and generator. We demonstrate
that DocCoder can be applied to different instantiations of \( \mathcal{R} \) \( \S 3.1 \) and \( \mathcal{G} \) \( \S 3.2 \). This work does
not aim to highlight a single, state-of-the-art model. Rather, our goal is to show the simplicity and
the applicability of DocCoder, and how it can strengthen a variety of base models regardless of their size
and architecture \( \S 5 \). In the experiment section, we conclude how to build a successful DocCoder by
comparing a comprehensive set of models on two datasets in two different PLs.

### 3 Practical Instantiations of DocCoder

Our DocCoder approach is not bound to any specific model choices, and can be instantiated with
any base encoder retriever and generator. This section presents the instantiations of \( \mathcal{R} \) and \( \mathcal{G} \) that we
found to provide the most significant gains in performance.

#### 3.1 Retriever Instantiation

We experiment with two main types of retrievers: \textit{sparse retrievers} and \textit{dense retrievers}. As our sparse
retriever, we use Elasticsearch\footnote{https://github.com/elastic/elasticsearch} with the standard BM25 \cite{Robertson1976}. This retriever
represents documents using sparse features that rely on word frequencies, such as BM25 and TF-IDF.
As our dense retriever, we follow prior work \cite{Chen2020, Karpukhin2020, Gao2021}: given a triplet \((n, c, D^*_n)\), where \(D^*_n\) are the ground truth docs for \(n\), each \(d^+_n \in D^*_n\) and \(n\) form a positive pair \((n, d^+_n)\), while each \(d^-_n \notin D^*_n\) and \(n\) form a negative pair \((n, d^-_n)\). We train the retriever in a contrastive fashion where the similarity score of a positive pair is maximized while that of in-batch negative pairs is minimized. For a pair \((n_i, d^+_i)\), the loss function is defined as:

\[
\mathcal{L}^r = - \log \frac{\exp \left( \text{sim}(h_n, h_{d^+_n}) \right)}{\exp \left( \text{sim}(h_n, h_{d^+_n}) \right) + \sum_{d^-_n \in \mathcal{B}/D^*_n} \exp \left( \text{sim}(h_n, h_{d^-_n}) \right)}
\]

where \(h_x\) is the representation of \(x\) computed by a neural encoder, and \(\mathcal{B}\) are positive manuals for other examples in the batch. We define \(\text{sim}(h_x, h_y)\) as the cosine similarity between \(h_x\) and \(h_y\).

We use all \((n_i, d^+_i)\) in the training set as our supervised training dataset. Additionally, we extract all sentences in the documentation pool as a weak supervision. Following \cite{Chen2020} and \cite{Gao2021}, representations of the same sentence with different dropout masks are treated as positive examples. Instead of using either supervised or weakly supervised training as in \cite{Gao2021}, we directly mix the two resulting datasets, and examples are randomly distributed into batches. The mixture of data types not only facilitates the learning process (§6), but also reduces the engineering effort required to store and reload models for separate supervised and unsupervised training phases. We initialize the encoder with either the best model of \cite{Gao2021} or the encoder of CodeT5-base \cite{Wang2021}. Additional training details are provided in Appendix C.

### 3.2 Generator Instantiation

Our generators cover two main input encoding approaches: (a) joint encoding uses the concatenation of all retrieved documents and the NL intent as a single, long, input, and (b) parallel encoding encodes each document separately, and combines the representations of different documentation items only at the decoder, using cross attention.

For joint encoding models, we use GPT-Neo-125M, GPT-Neo-1.3B \cite{Black2021} and Codex \cite{Chen2021}. We choose these models over other models such as T5 \cite{Raffel2019} and BART \cite{Lewis2020} mainly because the models we use have less stringent length constraints.

For parallel encoding models, we follow the setup of fusion-in-decoder (FiD; Izacard and Grave 2021). FiD is a sequence-to-sequence model that first concatenates an intent \(i\) with each retrieved documentation from \(D_n\), the encoder of FiD then processes each concatenation independently. The resulting representations are concatenated together and presented to the decoder to perform cross attentions and generate the code. We initialize the weights of FiD from the trained T5-base \cite{Raffel2019} or CodeT5-base \cite{Wang2021}.

We finetune a generator to maximize the log-likelihood of the reference code snippet \(c\) given \(n\) and \(D^*_n\). Training details and hyper-parameter settings can be found in Appendix D. Notably, in Codex \cite{Chen2021}, we perform few-shot learning rather than finetuning because the model parameters are not publicly available. When querying Codex, we construct input prompts with three static examples, each of which is a concatenation of retrieved documentation, NL intent and the reference code snippet. The retrieved documentation and the intent of a test example is appended to this prompt to generate the code.

### 4 Experimental Setup

We evaluate DocCoder on two NL→code tasks: shell scripting (§4.1), in which we generate complex shell commands given an intent, and Python programming (§4.2), where we generate answers in Python for NL questions. In this section, we first introduce a newly curated shell scripting benchmark \(\texttt{tldr}\); we then describe our re-split of the popular CoNaLa benchmark \cite{Yin2018}. For each static documentation pool \(D^*_n\) that is shared for all examples, and ground truth documents \(D^*_n\) for each example, which we use to train the retriever. We release our newly curated benchmarks to serve as test-bed for future retrieval-based code generation models.

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\*BART and T5 have length limits of 512 tokens, and the concatenation of multiple manuals often exceed this length. Truncating them to the max length results in information loss as we will discuss in §6.
**4.1 Shell Scripting**

tldr is a community-driven project that maintains easily-readable exemplar help pages for over 2.5k bash commands in over 25 natural languages. The bash commands range from popular ones like cat and tar, to rare commands such as toilet and faketime. We collect pairs of English intents and Bash command lines. Our resulted tldr benchmark contains 1,879 unique bash commands and 9,187 NL→Bash pairs. We construct the training, development and the test set with completely different commands to test the generalizability of a code generation model. In addition, the shared documentation pool \( \mathcal{D} \) is made up of the 400k paragraphs from the 1,879 bash manuals. Each paragraph describes a single concept such as an argument flag. We further curate the ground truth documents \( \mathcal{D}_n \) for each example using simple string matching. An example of tldr is shown on the right. It contains an NL intent, a reference bash command, and a set of ground truth docs explaining how each code component works. Detailed statistics and additional details regarding the curation process are provided in Appendix A. This is the first work to leverage tldr as an NL→code benchmark to the best of our knowledge.

In tldr, each NL intent results in a single bash command with a combination of argument flags. We therefore develop a simple hierarchical retrieval pipeline to exploit this prior knowledge. A retriever first measures the relevance score between an NL intent and an entire bash manual; then, we take the top-1 bash command and retrieve the most relevant documentation pieces from that bash manual.

**Evaluation metrics** We use four evaluation metrics to measure the quality of the generated code: (a) command name accuracy (CMD Acc) – measures whether the command name (e.g., cat) is predicted correctly; (b) token-level F1 – converts the reference code and the generated code to bag of words and measures the token-level precision, recall, and F1 overlap; (c) exact match (EM) – measures the exact match between the reference and the generation; and (d) character-level BLEU (charBLEU: [Lin et al., 2018] [Shi et al., 2022]). In all metrics, we disregard variable names in the references and the models outputs. For example, “mycli -u [user] -h [host] [database]” is converted into “mycli -u $1 -h $2 $3”.

**4.2 Python Programming**

CoNaLa [Yin et al., 2018] is a popular benchmark for NL→Python generation. NL intents and code snippets are Stackoverflow questions and answers, respectively, rewritten by human annotators. We re-split the dataset to test models’ generalization to unseen python functions. In our re-split, we verify that every example in the development or the test set uses at least one Python function (e.g., plt.plot) that was unseen in the training data. In addition, we make sure that the examples from the same Stackoverflow posts are in the same set to prevent information leaking. This re-split results in 2,135/201/543 examples in the training/development/test sets, respectively.

The CoNaLa documentation pool \( \mathcal{D} \) contains 35,763 documents, each describing a single function. These functions were taken from all libraries that are available on DevDocs such as built-in libraries, and other popular libraries such as numpy. We construct \( \mathcal{D}_n \) for each example by matching the function name and with its documentation. Additional details are provided in Appendix B. We follow Yin et al. [2018] and measure BLEU-4. Since we focus on generalization to unseen functions, we additionally report function name recall (Recall), which measures the percentage of correctly predicted function calls, and also unseen function recall Recall\(_u\), which measures the fraction of correctly predicted function calls among only function calls that do not appear in the training set.

[https://github.com/tldr-pages/tldr](https://github.com/tldr-pages/tldr)

Variables in tldr are not always instantiated, and the style of the placeholder varies. For example, some contributors might write \([\text{user}]\) as \([\text{username}]\). Thus, measuring the surface form is less meaningful.

[https://devdocs.io](https://devdocs.io)
Table 1: Code generation results for the shell scripting task, on the test set of tldr. We select the best model of each type for the oracle experiments.

| Type                | Model     | CMD Acc (%) | EM (%) | Token F1 | charBLEU |
|---------------------|-----------|-------------|--------|----------|----------|
| Joint encoding      | GPT-Neo   | -           | 11.96  | 1.94     | 28.75    | 19.99    |
|                     | 125M + DocCoder | -           | 25.32  | 3.56     | 31.23    | 24.43    |
|                     | GPT-Neo   | -           | 14.55  | 3.12     | 32.46    | 24.70    |
|                     | 1.3B + DocCoder | 27.59      | 9.05   | 37.24    | 30.57    |
|                     | CodeX     | 3-shots + DocCoder | 39.01  | 14.55    | 44.89    | 33.93    |
|                     |           |             | 36.10  | 13.97    | 42.55    | 32.93    |
|                     | T5        | -           | 10.02  | 0.76     | 19.90    | 25.48    |
|                     |           | + DocCoder  | 30.28  | 9.16     | 37.58    | 31.97    |
|                     | CodeT5    | -           | 14.60  | 2.18     | 30.00    | 21.50    |
|                     |           | + DocCoder  | 30.72  | 9.15     | 36.71    | 33.83    |
| Given the oracle command name | CodeX     | 3-shots + DocCoder | -      | -        | 20.22    | 38.14    |
|                     |           |             | -      | -        | 33.15    | 44.76    |
|                     | T5        | -           | -      | 12.96    | 59.36    | 45.05    |
|                     |           | + DocCoder  | -      | 22.55    | 64.84    | 54.28    |

5 Results

In this section, we present the end-to-end code generation results. All models with DocCoder use the top-10 retrieved docs from the best retriever on that dataset (Table 4). Every baseline uses the exact same setup as its “+DocCoder” version, except for not using the documentation.

5.1 Shell Scripting Results

We experiment with five popular models as generators on tldr and the results are shown in Table 1. Overall, we observe nearly consistent gains across different DocCoder models compared to their base models. For example, our strongest model T5+DocCoder achieves more than twice higher accuracy in predicting the command name, more than 16 charBLEU points on the overall prediction, and almost 9% of absolute exact match gain, compared to the vanilla T5. In Codex, DocCoder does not manage to improve over the base model. One explanation might be that Codex was trained on the test set of tldr on github, and memorizes the target code. Thus, additional documentation does not help Codex (the training set of Codex is unknown). As we will see later, providing Codex with the ground truth command name does improve its performance, showing that there is room for improvement given a stronger retriever.

Parameter efficiency As shown in Table 1 under a given parameter budget, we find that DocCoder mostly benefits from parallel encoding. For example, the parallel encoding T5+DocCoder (220M parameters) significantly outperforms the 125M parameters joint encoding Neo-125M+DocCoder. Only scaling up Neo+DocCoder to 1.3B parameters manages to match the 220M parameter T5+DocCoder. A possible explanation is that although the base Neo-1.3B (without DocCoder) generally performs better than the base T5 (without DocCoder), parallel encoding allows to utilize the retrieved documents better, since documents are encoded independently on the encoder side.

Code generation with oracle command names In realistic settings, human programmers may know the command name they need to use (e.g., awk), but not know the exact usage and full command line. In fact, providing a better understanding of the usage of known commands is the purpose of Unix man pages and the tldr project. We conduct an oracle experiment where we provide the T5 models and the Codex models (both the baseline and DocCoder) with the oracle command name (e.g., awk). The results are shown on the bottom part of Table 1. When the oracle command is given, conditioning on the retrieved docs from the corresponding bash manual further improves the generation over providing the generator only with the bash command name: for example, providing Codex with the ground truth command name improves its exact match accuracy from 20.22% to 33.15%. We conclude that the large capacity of Codex might require an equally strong retriever to
Table 2: Code generation results for the Python Programming task, on the test set of CoNaLa. Function recall (Recall) measures how many functions in the reference code are correctly predicted, and unseen function recall (Recall_u) only considers the subset held out from the training data.

| Model          | BLEU | Recall | Recall_u |
|----------------|------|--------|----------|
| T5             | -    | 28.07  | 14.36    | 2.57      |
| + DocCoder     |      | 30.04  | 21.34    | 8.24      |
| CodeT5         |      | 34.57  | 24.24    | 9.03      |
| + DocCoder     |      | 36.22  | 27.80    | 18.30     |
| + DocCoder oracle docs | | 49.04  | 72.20    | 63.91     |

improve over the base model. These experiments also suggest that the non-oracle results in Table 1 could be further improved using a stronger retriever.

5.2 Python Programming Results

Table 2 shows the results on the CoNaLa benchmark. CodeT5+DocCoder yields a 1.65 BLEU score improvement over the state-of-the-art baseline that is initialized with CodeT5. When measuring the recall of the generated function names, the benefit of DocCoder is especially higher for unseen functions (recall_u) that we deliberately hold out from the training set. For example, in CodeT5, DocCoder achieves a recall of 27.80 compared to 24.24 of the base CodeT5; in unseen functions, DocCoder achieves 18.30 compared to only 9.03 of the base CodeT5. In addition, CodeT5 yields a higher gain over the (non-code-specific) T5, both with or without using DocCoder. This emphasizes the importance of using code-specialized pretrained models.

![Figure 3](image)

Figure 3: The recall@k (%) and the corresponding BLEU score by using these top-k docs on CoNaLa dataset (CodeT5).

![Figure 4](image)

Figure 4: The n-gram overlap (%) between the reference code snippet and the NL intent, and NL intent with oracle documentations on tldr and CoNaLa.

The impact of the number of documents

We examine the impact of using a different number of retrieved documents. Figure 3 shows the recall@k and the BLEU score compared to k, the number of retrieved documents. Increasing k consistently yields a higher recall; however, as more irrelevant documents are retrieved, the generator cannot effectively distinguish them from the relevant ones and the overall performance remain similar. For example, the CodeT5 achieves the highest BLEU score using 5 ≤ k ≤ 10. In contrast, when the generator is provided with the oracle docs only, its BLEU score reaches 49.04 (Table 2). This suggests that both precision and recall of docs are important, and the benefit of using larger values of k in open domain QA (Izacard and Grave, 2021) does not necessarily hold in code generation.

Case study

We examine the models’ outputs and show two representative examples in Table 3. In the first example, `math.degrees` is unseen in the training set, and the baseline model cannot correctly

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8In our separated experiments with the original random split of CoNaLa benchmark, this baseline achieves a BLEU score of 39.12, which outperforms the previous state-of-the-art (Beau and Crabbé, 2022) on the original CoNaLa benchmark by 4.92 BLEU points.
Table 3: Examples of predictions from CoNaLa, of the base CodeT5 compared to CodeT5+DocCoder. Unseen functions are underscored.

|                      | Ground truth                        | CodeT5               | CodeT5+DocCoder  |
|----------------------|-------------------------------------|----------------------|------------------|
| Sort list 'list5' in ascending order based on the degrees value of its elements | `sorted(list5, lambda x: (degree(x), x))` | `sorted(list5, key=float)` | `sorted(list5, key=lambda x: math.degrees(x))` |
| Exclude column names when writing dataframe 'df' to a csv file 'filename.csv' | `df.to_csv('filename.csv', header=False)` | `df.drop(['col1', 'col2'], axis=1, inplace=True)` | `df.to_csv('filename.csv', skiprows=1)` |

Table 4: Retrieval performance of multiple models on the dev set of tldr (top) and CoNaLa (bottom). RoBERTa is the best model taken from from Gao et al. (2021), and CodeT5 is the encoder of CodeT5-base (Wang et al., 2021). Models with the subscript o are the off-the-shelf models, and the other models are fintuned with the objective in Equation 3. The last row is the best model (RoBERTa for tldr and CodeT5 for CoNaLa) trained without the weak supervision corpus.

| n  | BM25 | RoBERTa | CodeT5_o | CodeT5   | Best w/o weak sup. |
|----|------|---------|----------|----------|--------------------|
| tldr |      |         |          |          |                    |
| 1  | 32.81| 17.53   | 30.03    | 10.45    | 18.10             | 28.30             |
| 5  | 51.73| 37.89   | 52.50    | 20.26    | 38.52             | 50.50             |
| 10 | 59.86| 46.80   | 60.33    | 25.73    | 51.03             | 59.84             |
| 20 | 62.01| 56.11   | 64.30    | 33.65    | 57.26             | 62.30             |
| CoNaLa |      |         |          |          |                    |
| 1  | 3.01 | 4.46    | 13.49    | 4.60     | 16.54             | 10.51             |
| 5  | 7.16 | 7.58    | 26.38    | 8.63     | 42.35             | 21.15             |
| 10 | 9.73 | 10.93   | 34.86    | 12.25    | 55.81             | 29.34             |
| 20 | 11.46| 13.89   | 45.46    | 18.46    | 66.79             | 42.21             |

link the meaning of “degrees value” in the intent to code, and incorrectly generates `key=float`. In contrast, DocCoder correctly retrieves the doc of `math.degrees` and accurately uses it to generate `key=lambda x: math.degrees(x)`. In the second example, `df.to_csv` is unseen, and the baseline model incorrectly generates `df.drop`. In contrast, DocCoder correctly predicts most of the `df.to_csv` call, thanks to the retrieved docs. Nevertheless, DocCoder generates an incorrect argument `skiprows=1`, instead of `header=False`. The reason is that along with the retrieved documentation of `df.to_csv`, the retriever also retrieves the documentation of `df.read_csv`, which has the `skiprows` argument. That is, the generator uses an argument of `df.read_csv` with the function `df.to_csv`. We believe that further improving the generators and their inductive bias to distinguish between different documents, might mitigate such mistakes.

Why does reading the documentation help generate more accurate code? We believe that one of the major reasons is that documentation eases the mapping between the NL intent and code, since the documentation contains both natural language descriptions and function names. We calculate the n-gram overlap between code snippets and their corresponding NL intents, and the overlap between the code snippets and the NL intents with the oracle documentation. As shown in Figure 4, NL intents on their own have a low n-gram overlap with their code snippets. For example, the unigram recall is as low as 12% on tldr and 30% on CoNaLa, and these numbers naturally decrease for bigram and beyond. In contrast, adding documentation largely increases the coverage across n-grams, and boosts the unigram overlap to 68% and 87% on two datasets, respectively.

6 Ablation Study

In this section, we compare different configurations of the retriever to provide more insights regarding building a stronger DocCoder. Table 4 shows the comparison between different retrievers and their different setups. First, the performance of BM25 varies among datasets. On tldr, BM25 matches the recall of a trained dense retriever; while on CoNaLa, strong dense retrievers such as the encoder of CodeT5 achieves recall@10 of 55.81, while BM25 achieves only recall@10 of 9.73%. We hypothesize that this difference between datasets stems from the ways these datasets were created:
tldr intents were written based on existing bash commands and manuals; while CoNaLa examples were mined from StackOverflow posts, where users may ask questions without any context. Thus, NL intents in CoNaLa require a larger semantic alignment with the documents, and thus benefit from dense retrievers. The gap resulting from different data curation processes was observed by Rodriguez and Boyd-Graber (2021) on open-domain question answering (QA) as well.

Second, retrievers that were pretrained on the target PL are beneficial. For example, CoNaLa allows retrieving using CodeT5 that were pretrained on the Python language. Hence, CodeT5 is both a better off-the-shelf retriever and a better finetuned-retriever than RoBERTa, which was pretrained mainly on text. In contrast, tldr is based on Bash, which neither CodeT5 nor RoBERTa was explicitly pretrained on. Thus, tldr benefits from BM25 more than it benefits from a dense retriever.

Finally, the weak supervision corpus extracted from the documentation pool is necessary to train a dense retriever. The recall of the best retrievers of each dataset without this corpus is in the last column of Table 4 (“Best w/o weak sup.”). On CoNaLa, removing this corpus results in severe performance degradation. One possible explanation is that the weak supervision helps the retriever perform more effective domain adaptation.

7 Related Work

**Code generation** The most common practice in NL→code generation is using a dataset of NL-code pairs and training a model to generate the code given the NL (Allamanis et al., 2015; Yin and Neubig, 2017; Rabinovich et al., 2017; Iyer et al., 2018). Xu et al., (2020) augmented the training data with the NL-code examples constructed from doc strings; Hayati et al. (2018); Pasupat et al. (2021); Parvez et al. (2021) retrieved examples from the training set or an archived NL-code collections. Nevertheless, all these works assume that their training corpus covers all required libraries and functions, and their models are inherently incapable of generating newly added libraries and functions unseen in the training data. On the contrary, our models can generate code that uses unseen functions, by retrieving these functions’ documentation and reading them at test time.

**Retrieval augmented generation** The retrieve-then-generate paradigm has gained popularity in the field of open-domain question answering (Guu et al., 2020; Lewis et al., 2020b; Karpukhin et al., 2020), where the answer to an open-domain question exists in few documents out of a much larger pool. Although DocCoder takes a similar approach, retrieval in code generation is arguably even more valuable, since code libraries are updated constantly, and new libraries are introduced daily. Thus, DocCoder allows updating the documentation pool frequently with new contents, without re-training any model components.

**Language-conditioned control** The model of Zhong et al. (2019) reads documents to understand environment dynamics in a grid-world game, and Branavan et al. (2011) controlled situated agents in a game (Civilization II) by reading the game’s manual. However, all their models were tailored to specific games; in contrast, by reading the docs, DocCoder generalizes to unseen functions. Agarwal et al. (2020) retrieved from the tldr pages; however, their model only retrieved NL→Bash examples, without the further challenge of generating code.

8 Conclusion

We propose DocCoder, a simple and effective approach for code generation by retrieving the relevant documentation. We demonstrate that DocCoder consistently improves NL-to-code models in two NL→code tasks, in two PLs, and across multiple strong base models. On the new tldr dataset, DocCoder achieves 11x higher exact match accuracy than strong baselines; on the popular CoNaLa benchmark, DocCoder improves over the state-of-the-art by 1.65 BLEU.

These results open a promising direction for NL→code generation. We believe that our results can be further improved using more clever encoding of the structured nature of long documents, and using joint training of the retriever and the generator, which hopefully will avoid cascading errors. Further, we believe that the principles and the methods presented in this paper are applicable to additional code-related tasks, and other textual resources such as tutorials and blog posts. To these ends, we make all our code, data, and models publicly available.
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A  

**tldr: A Newly Curated Shell Scripting Benchmark**

**NL→Bash pairs** For each command (e.g., `cat`), users contribute examples of pairs of NL descriptions and bash code (mainly one-liners), including various flags and arguments, which cover the common usages of that command. An example is shown in Figure 2. We crawl NL-code pairs from the markdown files in the `linux` folder and common folders. We discard bash commands whose manual is unavailable (discuss below). The detailed statistics is shown in Table 5. On average, each command has 4.84 NL→Bash pairs and there is a total of 9187 NL-code pairs. To test the generalizability of a model, we construct the training, development and the test set with completely different commands.

**Documentation pool** We take the bash manual of the 1897 bash commands in tldr to construct a documentation pool. We search each command name on manned.org that archives Unix manual pages, and then extract the text contents from the returned manual page. We further break each manual into multiple paragraphs by line breaks so that each paragraph could delicately describe a single concept like the command functionality or the flag usage. We make this decision due to the large volume of content each manual has, which is too long to fit the length limitation of a neural model, and too noisy and distracts the model with irrelevant information. This results in 400k individual entries in the pool in total.

**Oracle manual** We find the ground truth documentation for each \((n, c)\) pair through command name and flag matching heuristics. For instance, given a code snippet `toilet 'input_text' -f 'font_filename'`, we constrain our search to the documentation from `toilet` manual page and select documentation that starts with `-f` flag as an oracle paragraph. Along with the first paragraph that commonly summarizes a command, these paragraphs forms \(D^*_n\).

**Evaluation metrics** We use four evaluation metrics to measure the quality of the generated code: (a) command name accuracy (\(CMD\ Acc\)) – measures whether the command name (e.g., `cat`) is predicted correctly; (b) token-level F1 – converts the reference code and the generated code to bag of words and measures the token-level precision, recall, and F1 overlap; (c) exact match (EM) – measures the exact match between the reference and the generation; and (d) character-level BLEU (charBLEU: Lin et al., 2018; Shi et al., 2022). For token level F1, exact match, and C-BLEU, we anonymize all variables in the references and the system outputs. For example, "mycli -u [user] -h [host] [database]" is converted into "mycli -u var_1 -h var_2 var_3". This is mainly because that the variables are not instantiated in tldr and the style of the placeholder varies among contributors. For example, some contributors might write `[user]` as `[username]` or `[your_name]`. Therefore, measuring the surface form is less meaningful.

B  

**Re-splitting CoNaLa**

**NL→Python pairs** We adapt the popular CoNaLa benchmark and re-split the dataset to test the generalization scenario. The re-split makes every example on the development and the test set has at least one Python function (e.g., `plt.plot`) that is unseen in the training data. There are 2135, 201, and 543 examples in the training, development and test set, respectively. We follow the original work to evaluate the system outputs with BLEU-4. Since we focus on the generalization setting, we additionally report unseen function accuracy, which measures the percentage of correctly predicted held-out functions that do not appear in the training set.

**Documentation pool** Our documentation pool contains 35763 manuals. These functions are from all 13 Python libraries that are available on DevDocs. These libraries contains the Python built-in library, and popular libraries like numpy and pandas. The documentation on DevDocs are curated and further transformed and indexed to allow for quick searching of APIs. We then extract each API signature and the corresponding

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9 e.g., https://github.com/tldr-pages/tldr/blob/main/pages/linux/toilet.md
10 https://manned.org
11 https://devdocs.io

13
documentation in every library, remove any content in the documentation that is not text, and segment the documentation into multiple paragraphs based on the <p> HTML tags. The documentation pool then contains pair of the API signature and each one paragraph in the corresponding documentation. Although the documentation pool is not comprehensive to cover all Python libraries and functions, we find it has a high coverage rate on the CoNaLa dataset. This choice reflects the flexibility of our approach upon the characteristics of a target scenario.

**Oracle manual** $D^*_i$ To find $D^*_i$ from the original $(n,c)$, we first index the function names with absolute path (e.g., plot is indexed with matplotlib.pyplot.plot) with Elasticsearch. Then we query the search engine with clean version of $c$ whose variable name are removed. The top-5 functions after de-duplication are treated as oracle manuals $D^*_i$.

### C Dense Retriever Training

We finetune the model for 10 epochs with batch size of 512 and learning rate of $1e^{-5}$. Since CodeT5 does not use [CLS] token, we alternatively take the average of the hidden state of the last layer as the text representation. For CoNaLa, we also use the first 100k "mined" examples provided as part of CoNaLa as the supervised corpus. For CoNaLa, we only apply a single search step because each code snippet commonly contains more than one function. The training takes up to 15 hours on a single A6000 GPU.

### D Generator Training

We train our single-source generators for 20 epochs with learning rate $4e^{-5}$. We train our multi-source generators for 10000 steps. We follow [Izacard and Grave, 2021] to set learning rate to $5e^{-5}$ with 2000 steps warmup and linear learning rate decay. The batch size is set to 8. The best model is selected based on the token-level F1 score on the development set for tldr and BLEU score for CoNaLa. The training takes 8 hours on a single A6000 GPU.

### E Examples

#### E.1 tldr

Examples on tldr are in [Table 6]. In the top three cases, the baseline T5 could not generate the correct bash command while T5+DocCoder retrieves the correct bash documentation and use the correct arguments. In the bottom two cases, T5 also predicts the bash command correctly. However, in the puppet case, it misses concrete usages of executing the code. In the elixir case, it hallucinate the argument flags --example and --arguments which elixir does not support at all. On the other hand, T5+DocCoder could ground its generation to the retrieved docs and therefore it generates more accurate code.

#### E.2 CoNaLa

More examples on CoNaLa are shown in [Table 7]
Table 6: Examples of predictions from tldr, of the base T5 compared to T5+DocCoder. In tldr, the bash commands in the test set are completely different from those in the training set.

| Command                                                                 | Ground truth                                         | T5                                      | T5+DocCoder                           |
|------------------------------------------------------------------------|------------------------------------------------------|----------------------------------------|---------------------------------------|
| play a midi file in a specific key (0 = c major/a minor, 1 = f major/d minor, +1 = g major/e minor, etc.) | timidity --force-keysig='-flats|sharps' 'path/to/file.mid' +            | midiplay 'key'                         | timidity --force-keysig 'f|f|f''path/to/file.midi' |
| clean up all temporary tex files in the current directory              | latexmk -c                                           | tex clean                              | latexmk -c                            |
| specify the hash algorithm for the index file (experimental)           | git show-index --object-format='sha1|sha256' 'path/to/file'                           | hash --experimental 'path/to/index.hashes' | git show-index --object-format='sha1|sha256' 'path/to/hash-algorithm' | 'path/to/experimental' |
| execute puppet code                                                   | puppet apply --execute 'code'                        | puppet                                 | puppet apply --execute 'path/to/file.puppet' |
| evaluate elixir code by passing it as an argument                      | elixir -e 'code'                                      | elixir                                 | elixir -e 'path/to/file.elixir'       |

Table 7: Examples of predictions from CoNaLa, of the base CodeT5 compared to CodeT5+DocCoder. Unseen functions are underscored.

| Command                                                                 | Ground truth                                         | CodeT5                                   | CodeT5+DocCoder                        |
|------------------------------------------------------------------------|------------------------------------------------------|-----------------------------------------|----------------------------------------|
| Open image "picture.jpg"                                               | img = Image.open('picture.jpg') Img.show             | os.open('picture.jpg', 'r')               | image = Image.open('picture.jpg', 'rb') |
| set the current working directory to 'c:\Users\uname\desktop\python' | os.chdir('c:\Users\uname\desktop\python')         | os.chdir('c:\Users\uname\desktop\python') | os.chdir('c:\Users\uname\desktop\python') |
| convert dataframe 'df' to integer-type sparse object                   | df.to_sparse(0)                                       | np.isinstance(df, np.integer)           | df.to_sparse('i')                       |