Translating Natural Language to Bash Commands using Deep Neural Networks

Stanford CS224N Custom Project

Daniel Jenson
Department of Management Science & Engineering
Stanford University
djenson@stanford.edu

Yingxiao Liu
Department of Civil and Environmental Engineering
Stanford University
liuyx@stanford.edu

Abstract

The objective of this project was to generate Bash commands from natural language using deep neural networks. We used the NLC2CMD dataset and tested three models: GPT-2, BART, and T5. We also experimented with tokenization methods and post-processing to improve accuracy on the competition scoring metric. We found that while cross-entropy loss decreased steadily for all models, only T5 was able to continue learning the structure of Bash commands. After post-processing, all models improved, but only T5 and BART exceeded the performance of the GPT-3 baseline model.

1 Key Information to include

- TA mentor: Ethan A. Chi
- External collaborators: No
- External mentor: No
- Sharing project: No

2 Introduction

Bash or the Bourne Again Shell, is a standard and popular command line interface to Unix-based computer systems. Despite its popularity, it has a very steep learning curve. Novitiates are often overwhelmed by the concepts of binaries, flags, and arguments. Even experienced engineers frequently consult man-pages, online documentation, and online forums like Stack Overflow to learn about the particulars of various commands. This project aims to ease those burdens on new and experienced users alike, and to develop tools to generate Bash commands from natural language. We want to provide a natural language interface that enables people to interact with computers through natural languages, and thus making programming resources more accessible to the general public.

However, translating natural language into Bash can be challenging; many natural language queries or commands can be converted into the same Bash command. Conversely, many Bash commands may correspond to the same natural language command, due to English's inherent ambiguity and the required specificity of Bash. Thus, there is a many-to-many relationship between natural language and Bash commands. Further compounding this difficulty is that Bash commands can be composed, generating pipelines of commands corresponding to entire data flows. Lastly, the meaning of these commands all shifts when either the order of the commands or their arguments are permuted. For this reason, generating a perfectly correct Bash command from natural language can be extremely complex.

In order to tackle some of these problems, we used the data from the NeurIPS 2020 NLC2CMD Challenge, and experimented with several transformer models, including GPT-2, BART, and T5, as well as different tokenization and post-processing schemes. We evaluated the model performance in terms of both the training loss and a specific metric measuring the accuracy of the prediction, and compared our models with the baseline model provided by the competition.

3 Related Work

Code generation is a variant of semantic parsing, and a significant amount of research has been published in this area. One of the earliest and most successful studies was conducted to translate natural language to SQL queries. Zhong et al. (2017) [1] proposed a deep augmented pointer network and a loss function supplemented by reinforcement learning. In the SQL domain, they were able to achieve an execution accuracy of 60%. Notably, however, SQL has a singular, well-defined syntax with a context-free grammar. Accordingly, this model does not always generalize well to programming languages like Bash.

For high-level programming language generation, there are a number of recent attempts to translate well-structured natural language input into Java or Python. Ling et al. (2016) [2] proposed a generative model with a multiple pointer network to generate code from texts in Trading Card Games, although the selected input language in the games is very well-defined. A more robust syntax-based model was developed by Yin and Neubig (2017) [3] and tested on the same dataset, but performance did not increase materially. Rahit et al.(2019) [4] used recurrent neural network (RNN) and long-short term memory (LSTM) cells to build their model and reported an accuracy as high as 74% when the input was prepared in a format closer to pseudocode with keywords such as "define" and "if-else."

In the specific domain of Bash command generation, Lin et al. (2018) [5] modified the seq2seq model by adding gated recurrent units (GRU) and RNN cells and introducing a copying mechanism. The model was evaluated manually by people, rather than by an objective metric, and the accuracy was reported to be 0.29. Fu et al. (2021) [6] built a transformer model combined with a custom beam search and won the NLC2CMD Challenge competition. They tested different models and concluded that transformer-based models could significantly outperform the RNN-based models.

4 Approach

The NLC2CMD Challenge was held once by NeurIPS in 2020. The goal for competitors was to generate templated commands from natural language commands that could be used to guide Bash users. Most competitors used GPT-2 as their base model. This paper used GPT-2 but also surveyed two additional models, BART and T5, version 1.1.

The general approach consisted of two methods: (1) text generation and (2) translation. First, it is important to note that Bash is not a context-free grammar. It admits of very little recursion and, while most binaries are POSIX compliant, interfaces are still not entirely standardized. Flags often carry different semantic meaning and imply different tasks when employed by different binaries. Moreover, flags often override, modify, or cancel the intent of other flags in the same command, introducing complex dependencies. These dependencies can also shift as the order of the flags and their arguments are permuted. In sum, the meaning of a flag is almost entirely provided by the invoking binary and its location in the sequence of arguments. This introduces difficulties in fine-tuning embeddings, since training may attempt to encode vastly different meanings in the same embedding. This is particularly challenging given sparse datasets. Given sufficient training data, it is likely that that the models may eventually learn correct contextual meaning when employed by different binaries, but we found 10,000 rows insufficient for the task. This line of thinking inspired our first approach, text generation using GPT-2.

While at first this task appears to be a straightforward translation task, after considering Bash more closely, one can see that it does not admit of many properties or structures of natural language. Accordingly, rather than trying to properly translate natural language into Bash, we thought that we could train a model to hallucinate Bash "stories" given natural language. The high-level idea here is that we fine-tune a GPT-2 model, showing it complete stories that consist of both a natural language portion and a Bash portion with some added special tokens. When training, GPT-2 learns common storylines. When testing, we feed the trained model only the first half of the story, i.e. the natural language portion, and ask it to complete the story, hoping that it will generate Bash commands as the most likely story completion. In many respects, this idea performs quite well; however, a significant issue with this approach is constraining responses from GPT-2. How long should the story be? When does the real content of the "Bash story" start and end? What happens when GPT-2 has multiple endings? These questions are detailed in the error analysis section.

The second approach we used was a more traditional seq2seq language modeling approach. Pre-trained models for BART and T5 are easily fine-tuned for translation tasks. While many natural language modeling tasks admit of a fair amount of transfer learning because natural languages share some abstract semantic structures, Bash does not benefit from this nearly as much. As a non-natural, non-context-free grammar language, modeling it can be difficult, and our BART model, in particular, struggled with this.

5 Experiments

5.1 Data

The dataset we used is from the "The NLC2CMD Competition," consisting of 10,000 parallel translations of English (labelled "invocation") and Bash commands (labelled "cmd"). Here is an example:

```
invocation: Assign permissions 755 to directories in the current directory tree
cmd: find . -type d -print0 | xargs -0 chmod 755
```

Most of the invocations in the dataset involve a sequence of different tasks, and consequently the Bash commands often consist of a series of pipelines. In addition, since the Bash commands contain identifiers, such as directory paths, file names, and permissions, a templatization scheme has been imposed by converting shell commands into their corresponding abstract syntax trees (ASTs), replacing identifier nodes with placeholders, and then recombining the command. Applying this process to the previous command produces the following templated command:

```
templated cmd: find Path -type d -print0 | xargs -0 -I chmod Permission
```

This helps the model to generalize during training, without getting distracted by a myriad of specific identifiers.

The dataset was split into the training and test sets with a ratio of 0.98 to 0.02, yielding 10,140 training examples and 207 test examples. The invocations and templated commands must be tokenized by the same tokenizer used in training each model; accordingly, the outputs vary by model and tokenizer. For instance, the BART tokenizer yields the following encoded example:

```
<s>Assign permissions 755 to directories in the current directory
tree</s></s>find Path -type d -print0 | xargs -0 -I chmod Permission</s>
```

While the T5 tokenizer yields the following:

```
Assign permissions 755 to directories in the current directory
tree</s> find Path -type d -print0 | xargs -0 -I chmod Permission</s>
```

The GPT-2 model does not ingest input as pairs, but instead as entire sections of text. Natively, it only defines the beginning and ending special tokens, so we had to develop our own encoding scheme to communicate the structure of our input to the GPT-2 model. The primary objective of the encoding scheme is to introduce tokens that signal the beginning of natural language and Bash commands. For this, we used the `<|source|>` and `<|target|>` tokens, but these could have been any tokens unlikely to be used by Bash utilities or arguments. The general template for the encoding scheme was as follows:

```
<bos_token> <source_token> <invocation> <target_token>
```

```
                                         <templated cmd> <eos_token>
```

Using the above example, this schema produces the following encoding:

```
<|endoftext|> <|source|> Assign permissions 755 to directories in the current
directory tree <|target|> find Path -type d -print0 | xargs -0 -I chmod
Permission <|endoftext|>
```

While this encoding was sufficient for training, we still found it difficult for GPT-2 to learn the semantics of our special tokens.

5.2 Evaluation method

The standard cross-entropy loss function was used to train the models. But a more robust metric measuring the accuracy of the model predictions defined by the competition was used to evaluate the performance of our models. The metric is expressed mathematically:

$$S(p) = \sum_{i \in [1,T]} \frac{1}{T} \times \left(\mathbb{I}[U(c)_i = U(C)_i] \times \frac{1}{2} \left(1 + \frac{1}{N} (X) \right) - \mathbb{I}[U(c)_i \neq U(C)_i] \right)$$

$U(x)$ is a sequence of Bash binaries in a command x, c is the predicted Bash command and C is the ground truth Bash command. Apart from measuring whether the executables in the two commands match, an additional variable X has been introduced to measure whether the flags associated with each utility match or not:

$$X = 2 \times |F(U(c)_i) \cap F(U(C)_i)| - |F(U(c)_i) \cup F(U(C)_i)|$$

$F(x)$ refers to the set of Bash flags in a command x. T is the maximum length between $U(c)$ and $U(C)$ while N is the maximum size between $F(c)$ and $F(C)$. Since the order of flags does not matter, these are set operations.

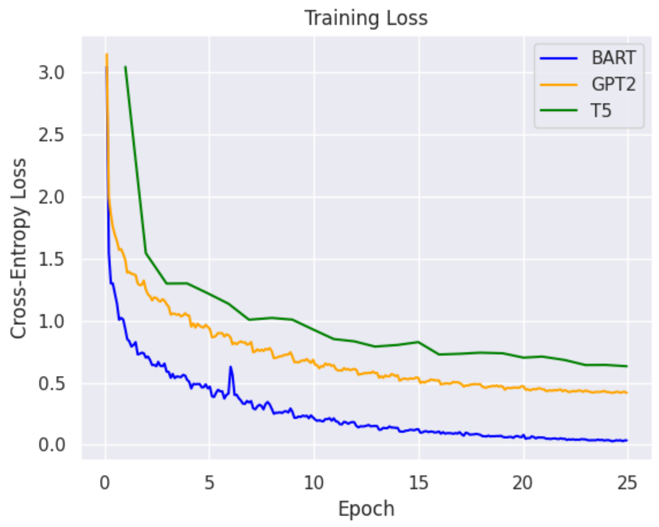
It is important to note that this metric is extremely strict, assigning a score of -1.0 for predicting an incorrect or missing starting binary. It also penalizes extra and incorrect flags and arguments. The return value ranges from -1.0 to 1.0, and a score of 1.0 is only awarded when a command is precisely equivalent to the golden one.

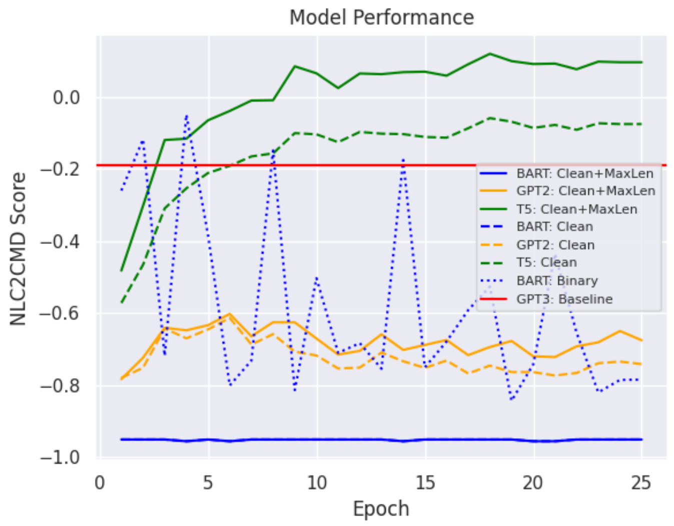
5.3 Experimental details

For this task, we tested three models: HuggingFace's GPT-2[7], Facebook's BART Large[8], and Google's T5 v1.1 base. GPT-2 is a causal model, predicting text from context, while the other two are traditional seq2seq models. Each was trained for 5, 10, and 25 epochs. Batch size was limited to 10 examples to avoid out of memory errors. For training, we used the AdamW optimizer with weight decay regularization. The learning rate was linear with a warmup of 100 steps. Training time for GPT-2, BART, and T5 v1.1 was approximately 1, 1.5, and 1.25 hours, respectively, on an Azure NC6 instance with a Tesla V100 PCIe 16GB GPU. We attempted to train the original T5 large model, but even with five examples per batch, we got out of memory errors; it also took approximately seven hours to fine-tune. All three models used cross-entropy loss for training, but were scored on the test set using the NLC2CMD metric at the end of each epoch.

5.4 Results

While training loss consistently improved, only T5 ultimately began to learn the structure of Bash commands. Below, you can see that cross-entropy loss steadily decreased for all three models. Curiously, T5 recorded the highest loss, while performing best on the scoring metric used by the competition.





Despite improving on the training objective, all three of these models still produced garbled and verbose responses. Repetition was common for all three, although most common with BART. GPT-2 had a tendency to "ramble;" it was not uncommon for GPT-2 to generate natural language intermixed with Bash commands. It also frequently produced multiple "target stories." Here we define a target story as a section of output text that begins with the special token `<|target|>`, which was used to denote the beginning of a Bash command in the encoded input. Here is an example row of output from the modeling process with GPT-2:

```
{
  "source": "List the files from the current directory tree that contain
    lines matching regular expression '^From:.*unique sender',
    ignoring ~/src and ~/bin",
  "target": "find Path -name Regex -prune -or -name Regex -prune \
    -or -type f -print | xargs -I {} grep -E -i -l Regex {}",
  "prediction": "<|endoftext|> <|source|> List the files from the current
    directory tree that contain lines matching regular expression
    '^From:.*unique sender', ignoring ~/src and ~/bin <|target|><|endoftext|>
    <|endoftext|><|endoftext|><|endoftext|><|endoftext|><|endoftext|>
    The first day of the year is a long one for the first day of the year.
    <|target|> find Path -name Regex -daystart -type f -print0 \
    | xargs -0 -I {} grep -H Regex {}   "
},
```

Here, you can see several types of errors affecting performance. A detailed analysis is left for the subsequent section, but here we will highlight three issues that motivated our post-processing. First, you can see that GPT-2 outputs multiple target stories, i.e. in the prediction, there are two chunks of text following a special target token. Second, we can see that GPT-2 had not internalized the meaning of the target token, because it continued to predict natural language as well as special end-of-sentence tokens, `<|endoftext|>`, after the target token. Third, we can see hints of GPT-2's pretraining through the inserted sentence, "The first day of the year is a long one for the first day of the year." This suggests that GPT-2 is still heavily biased toward its pretraining data, despite being fine-tuned to produce Bash commands. BART and T5 had similar errors, but those are left for the analysis section.

Many competitors in the NLC2CMD competition actually crafted extremely sophisticated post-processing techniques. Some used ensemble models, others implemented a custom structured beam-search. Given the time limitations for this project, we elected for a rule-based approach. We ran simple functions that could be composed across model predictions. We then scored the prediction after post-processing. We designed three post-processing functions to address our main problems: (1) multiple target texts, (2) repetition or rambling, and (3) binary prediction.

Looking at the predictions, we noticed that, most often, the target text closest to a Bash command was the last sequence GPT-2 generated. Accordingly, we wrote a function named `clean` that selected the last chunk of text associated with a target command. Second, because the scoring metric penalizes incorrect or excessive flags, we tried to trim repetitions and rambling with a function called `max_len`. Tokenizing by separating on white space, we collapsed repeated tokens and limited the maximum number of tokens to 15. Lastly, we attempted to do binary matching. Because the entire prediction's score hinges largely on selecting the right binary, we wrote a function that attempted to find the first token in a sequence that closely matched a top 100 Bash utility name. This function only materially improved performance for BART, but it was extremely noisy, as can be seen in the above model performance chart. Using the above prediction and running through the `clean` function yields the following:

```
find Path -name Regex -daystart -type f -print0 | xargs -0 -I {} grep -H Regex {}
```

This is already a significant improvement. Further passing it through `max_len` yields:

```
find Path -name Regex -daystart -type f -print0 | xargs -0 -I {} grep -H
```

While these cleaning techniques are quite crude, they significantly improve scores. The best model scores under different post-processing functions along with the GPT-3 baseline are recorded in the following table:

model	raw	clean	clean+max_len	binary
GPT-2	-0.95	-0.61	-0.60	-0.95
BART	-0.95	-0.95	-0.95	**-0.05**
T5	-0.13	-0.06	**0.12**	-0.12
GPT-3	-0.19	-0.19	-0.19	-0.19

6 Analysis

The first task in analyzing model performance was error analysis. We checked all predictions on the test set by epoch for each model to discover generalizations, which are summarized in the following table:

Model	BART	T5	GPT-2
Primary sources of error	missing or invalid binaries (like "findfind")	repetition of sequences or redundant tokens	wrong interpretations of the invocation
Example target	find Path -name Regex -print | xargs -l -i -I wc ,	yes Regex | sed Program	sort <(sort -u File) File File | uniq -u
Example prediction	Path -name Regex |print0 wargs -I QuantityI -I wc -	yes Regex | headt Program yes yes yes yes yes yes	find Path -iname Regex -exec grep -i Regex

Because both BART and GPT-2 struggled to correctly capture the target binaries, they received significant scoring penalties. The redundant binaries or flags and arguments, on the other hand, were not so harshly penalized; consequently, T5 was able to edge out the GPT-3 baseline. Curiously, the BART model tended to get the wrong starting binary for almost all the examples, but did very well in predicting the remainder of the command. Here are some examples of this pathology:

Target	Prediction
comm -2 -3 File File	-2 -3 File File
chown Regex -R File	own Regex -R File
mv -f File File	mmv -f File File

Investigating this further, we first confirmed that the model was improving over epochs. We analyzed a single invocation: "display all the html files in the current folder excluding search in the path ./foo" over several epochs. Although none of the predictions correctly captured the target binary "find," the model did improve in pruning trailing repetitions.

Target	find Path -path Regex -prune -or -type f -name Regex
Prediction (1 epoch)	findfind Path -name Regex -prune -or -name f -name Regexexecexecexecexecexecexecexecexecexecexecexecexe-cexecexec
Prediction (6 epochs)	Path -path Regex -prune -or -path f -name Regex -findfindfindfind
Prediction (14 epochs)	findfind Path -path Regex -prune -or -name f -name Regex -print - -

One possible reason for this aberrant behavior is that BART, while doing a reasonable job in capturing the intent of the sentence, struggled to develop individual token accuracy; in particular, the accuracy of the binary token. Predicting a binary given only the natural language and the beginning-of-sentence special token was difficult. Because predicting the binary is so important, we hypothesize that separating BART training into the following two phases may improve performance: (1) train only on the natural language command and the singular token corresponding to the correct Bash utility, and then (2) fine-tune the model with the full, templated Bash commands. Improving binary prediction in BART would likely make it competitive with T5.

We also investigated GPT-2 prediction errors. Here is an example prediction for the natural language invocation: "Change the ownership of all files in the current directory tree from root to www-data":

```
<|endoftext|> <|source|> Change the ownership of all files in the current
directory tree from root to www-data <|target|> (omit 23 <|endoftext|> tokens
here) Synchronize file systems to /tmp/ and output the result to console
<|target|> df File | awk Program | xargs -I {} ls -a -l -d -S -r File
```

The model incorrectly generated another invocation: "Synchronize file systems to /tmp/ and output the result to console." This has greater implications than simply generating additional cruft to be trimmed; it actually corrupts the hidden state of the model. Consequently, the final prediction was orthogonal to the target command: `find Path -user Regex -exec chown Regex {}`.

The last error class, which was demonstrated by all 3 models, was "rambling," or inserting additional command sequences after the target sequence. Here is an example:

```
target    : cat File | sort -r -h
prediction: cat File | sort -n -r | grep -v Regex
```

This suggests that all the models failed to generate the end-of-text token in the correct location.

While all of these models could be improved with longer training, phased training, and more sophisticated post-processing, the principal factor affecting performance was data size. 10,000 examples is insufficient to generate very accurate translations, and we were unable to find additional data sources that did not require significant preprocessing.

7 Conclusion

The three main discoveries of this project were: (1) the size of the dataset is the most important factor in performance, (2) post-processing is required, especially when training on limited data, and (3) signaling structure to your model is difficult and subtle but dramatically affects performance, as seen with BART and GPT-2. While we are satisfied to have surpassed the GPT-3 baseline, the competition winner achieved a score of 0.53, which still significantly exceeds the 0.12 achieved by our T5 model. This team, however, augmented their data by scraping Stack Overflow and similar websites. They also implemented a variety of additional techniques, which included a custom beam search and ensemble classification, which were out of the scope of this project. We believe that success on this task lies principally in cultivating a larger dataset of parallel translations. T5 was able to achieve notable performance using only 10,000 examples. With 100,000, we are confident that T5 may well exceed the performance of the top model, even in the absence of more sophisticated techniques.

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