First Milestone Report: Non-parametric Language Models for Natural Language to Code Generation

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1 Progress Report

At this point, I have implemented and obtained results (see Table 1) for the "vanilla" non-parametric code generation model.[1] Specifically, this model is composed of a pretrained code generation model, BERT-TAE, the current state-of-the-art on the CoNaLa dataset [11], along with a non-parametric kNN-LM component that retrieves and references the nearest neighbors from an external datastore at each step of generation [9]. This borrows heavily from kNN-MT [8], which leverages the kNN mechanism for machine translation, a similar sequence-to-sequence task. Further, my implementation incorporates certain auxiliary augmentations to improve performance and efficiency [4], including adaptive retrieval (which ultimately was not used as it did not give good results), adding encoder context to the datastore representation, and reducing datstore size via PCA.

Current results are promising but not conclusive; while we do observe an increase in performance from adding the kNN component, this increase is fairly small in magnitude, at just +0.1 BLEU. Further, these improvements require a great degree of tuning to attain. Figure 1 shows the variation in model performance as we vary the number of nearest neighbors k, kNN distribution interpolation coefficient λ, and temperature τ. While the specific hyperparameters we choose yield improved performance, any slight change to them almost always drags performance below that of the original fully parametric model. Additionally, the non-parametric model is significantly slower than the parametric model due to the high cost of nearest neighbors search; while we use `faiss` to speed up search [7], due to the large size of the datastore (over 2 million entries), the non-parametric model remains roughly 3-5 times slower than the parametric model.

Additionally, by this point, I have completed my literature review of current approaches for code generation and understanding [1][2][11][13] as well as retrieval-augmented generation, both for code [12][14] and for NLP tasks in general [8][9][10]. Also of particular interest are methods for code representation learning [3][5][6][15], which may prove useful in improving kNN datastore representations.

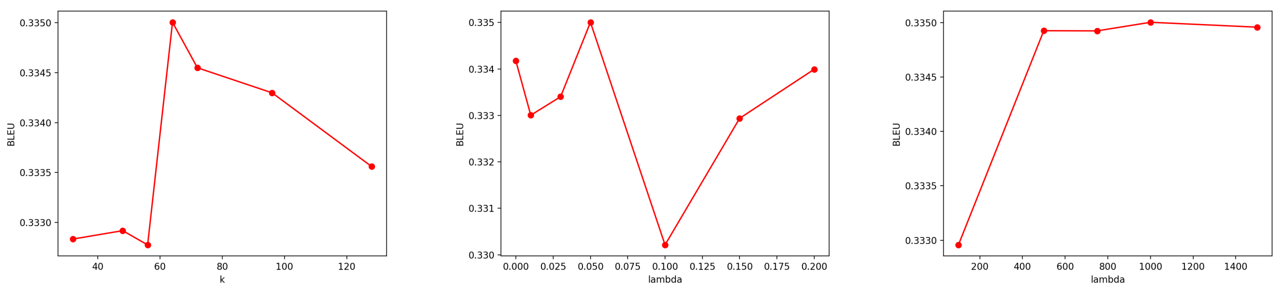
2 Reflection on Initial Plan

Overall, the path forward remains largely unchanged, and no 07-400 milestones need to be changed significantly. My results so far suggest that kNN models provide some advantage

[1] This work was done for my final project for another course that I am currently taking, 11-711. The full project report can be found here: `https://axie66.github.io/07400-project/11711report.pdf`

	BLEU	Exact Match
BERT-TAE	33.41	**3.4**
+ annotated datastore	33.17	3.4
+ mined datastore	33.41	2.6
+ encoder context	**33.50**	2.6

Table 1: Quantitative results and ablations for various data sources and context representations for our kNN datastore.



(a) $k \in \{32, 48, 56, 64, 72, 96, 128\}$ (b) $\lambda \in \{0, 0.01, 0.03, 0.05, 0.1, 0.15, 0.2\}$ (c) $\tau \in \{100, 500, 750, 1000, 1500\}$

Figure 1: Test set performance as we vary certain hyperparameters of our model.

over regular parametric models, albeit less than I might have expected. As such, I might look to dedicate additional time toward improving the "vanilla" kNN model with paired natural language/code data before moving onto kNN models using unpaired code-only data as originally planned. Specifically, one improvement to the vanilla kNN could be a lightweight mapping network that maps kNN queries to more appropriate embedding spaces. I will aim to get this work done over winter break or at the very start of next semester so as to leave enough time for the other objectives laid out in my project proposal.

I have achieved my primary aims for the first milestone. Specifically, as described earlier, I have implemented the kNN augmented model and obtained results that demonstrate its (modest) superiority over the original parametric model. In addition, I have set up but not run additional experiments incorporating the larger CodeSearchNet dataset (both in paired and unpaired form) into the datastore. This however, may require further modification and analysis as the code contained in CodeSearchNet is longer and more complex than that of CoNaLa, the primary dataset used for this project.

There have been no major surprises thus far in the project; while the model results are a bit lower than desired, they are not entirely unexpected. kNN models require extremely strong and expressive context representations, which can be attained for tasks such as language modeling and machine translation due to the relative maturity of models for those tasks. However, models for code generation, particularly on the CoNaLa dataset, do not perform as strongly and hence yield less informative representations, causing less relevant neighbors to be retrieved.

At this point in time, I believe that I have all the resources necessary for my 07-400 project; Professor Hellendoorn has graciously offered the usage of his lab machines next semester, which should provide more than enough computing power for my experiments.

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