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A Transformer-Based Approach for Smart Invocation of Automatic Code Completion

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ABSTRACT

Transformer-based language models are highly effective for code completion, with much research dedicated to enhancing the *content* of these completions. Despite their effectiveness, these models come with high operational costs and can be intrusive, especially when they suggest too often and interrupt developers who are concentrating on their work. Current research largely overlooks how these models interact with developers in practice and neglects to address *when* a developer should receive completion suggestions. To tackle this issue, we developed a machine learning model that can accurately predict when to invoke a code completion tool given the code context and available telemetry data.

To do so, we collect a dataset of 200k developer interactions with our cross-IDE code completion plugin and train several invocation filtering models. Our results indicate that our small-scale transformer model significantly outperforms the baseline while maintaining low enough latency. We further explore the search space for integrating additional telemetry data into a *pre-trained* transformer directly and obtain promising results. To further demonstrate our approach's practical potential, we deployed the model in an online environment with 34 developers and provided real-world insights based on 74k actual invocations.

CCS CONCEPTS

• Human-centered computing; • Computing methodologies;

KEYWORDS

IDE, Code Completion, Usability, Transformers, Interaction

ACM Reference Format:

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1 INTRODUCTION

Transformer-based code completion has become essential in modern software development [46]. The widespread adoption of Artificial Intelligence (AI) tools in coding highlights the significance

of these models, particularly those built on the Transformer architecture [35]. These AI-driven tools typically analyse the code preceding the cursor to suggest the next lines of code [4, 16]. Recent advancements have expanded the considered context to include not only the subsequent code [3, 13, 17, 24, 32], but also related snippets from other files to enrich the prediction accuracy [25, 42].

This focus on augmenting the content quality of completions has inadvertently overshadowed a vital aspect of the user experience: the interaction dynamics between the developers and the AI tools [2, 31, 39]. While these models generate high-quality code suggestions, their operational and environmental costs pose significant challenges [6, 27]. Moreover, due to their potential to disrupt the coding workflow of developers, the frequency and timing of these suggestions is critical for the overall productivity the tools aim to boost [31].

Previous efforts focus on developing a filtering model designed to *show* a completion only when there is a high confidence it will be accepted [29, 36]. This reduces inference cost and likely improves developers' focus. However, Sun et al. [36] assume completions are rejected based on the context before the cursor alone, ignoring the interplay with developers' mode of thought. Mozannar et al. [29] improves on this by considering in-IDE telemetry data. However, they propose a relatively complex ensemble model that can incur additional latency by filtering after a completion is generated; and do not consider that some completions, despite being rejected, may help guide the user in their thinking.

In this study, we take a further step to *proactively* predict when to *invoke* a code completion model based on code context and telemetry data. Our lightweight, transformer-based filtering model, JONBERTA, is designed to trigger a code completion model only when there's a strong likelihood that a developer requires assistance *or* is likely to accept the suggested completion. To train our model, we leverage the data we have collected from developers' real-world interactions with our open-source code completion tool called CODE4ME¹, available for both VSCode and JetBrains IDEs. We gather code context and telemetry data from user interactions with the plugin, subject to their consent. We use two indicators to gauge when a developer would prefer to receive a suggestion based on usage data: (1) when they accept a model-suggested completion, and (2) when they manually invoke the model, irrespective of whether they ultimately accept or reject the suggestion.

Every keystroke made by a developer provides two key types of contextual information that assist our invocation-filtering model in deciding whether to trigger the LLM-based completion system. These are: (1) the coding context surrounding the point of invocation, and (2) telemetry data gathered via the plugin, e.g. the time



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¹<https://code4me.me>

since the last completion. First, we use code context alone and train a transformer-based classifier. Next, we investigate hybrid transformer architectures integrating telemetry data as additional features. Based on our promising results, we evaluate our approach in a user-study with 34 developers, to investigate how our filters perform in practice. To this end, we also propose a new performance metric to help mitigate issues from optimising for just acceptance rate in previous work [29, 46], which weighs proxies for the quality and timing of a completion equally as a harmonic mean. We find that our proposed JONBERTA-HEAD model scores highest in both the offline and online evaluation.

Our contributions are as follows:

- An offline evaluation of a transformer model we fine-tuned on our collected code completion dataset, demonstrating that code context can considerably improve filtering accuracy over a baseline trained on telemetry features only.
- JONBERTA, a novel transformer architecture to show the potential of training jointly on code context and telemetry data; as well as a custom tokenisation strategy centred on the cursor position.
- An online evaluation of our filters in a code-completion plugin with 74k invocations, spanning 34 users.
- For reproducibility purposes, we publish our replication package² with an online appendix, as well as our fine-tuned models³. However, in compliance with the GDPR, we cannot share our training dataset.

2 BACKGROUND AND RELATED WORK

Today, the most prominent AI-powered code completion tool with over one million active users is GitHub Copilot [11]. This tool is powered by a transformer-based [40] LLM trained on source code, originally with the objective of predicting a function body given its documentation [4]. However, given that the suffix lines below the function are unavailable to the model, the current model powering Copilot is presumably trained with a Fill-In-the-Middle (FIM) objective [3]; where the model is trained to predict a span of arbitrary length between the prefix and suffix. Several alternatives exist to Copilot, namely Amazon CodeWhisperer [1], TabNine [37], Codeium [7], Sourcegraph Cody [34], JetBrains AI [18], and Gemini Code Assist [10].

Since its inception, several user studies and surveys [2, 22, 28, 30, 31, 39, 41, 46] have been performed on GitHub Copilot⁴. They highlight that the transformer models backing such tools excel at providing *contextual* suggestions, due to their semantical understanding of code. As a result, this leads to increased developer satisfaction [39] and perceived productivity [46].

2.1 Code Completion Pain Points

Nonetheless, such new technology comes with new questions about its usability and design, arising from developer pain points, such as: distraction due to the *always-on* nature of suggestions [31], out-of-distribution generation leading to hallucinated terms [19], and a

lack of personalisation with developers' mode of thought [2]. Copilot's authors themselves reported that about two-thirds of *shown* completions are ignored by their end-user [46]. Furthermore, GitClear recently released a report empirically describing a strong correlation between the adoption of AI code completion and code churn in industry-grade software engineering [14], raising questions about the impact of AI on software maintainability. Other studies further find that the bugs introduced by LLM-powered code completion are often more subtle [4, 31], and difficult to revert [39].

Barke et al. [2] find that developer interactions with AI-powered code completion are bimodal: either *accelerative*, where the developer knows what they want and uses the tool to get there faster; or *explorative*, where the developer relies on the tool to suggest possible approaches. Prather et al. [31] observe two additional modes among novices: *shepherding*, where a novice slowly accepts a suggestion; and *drifting*, where they are led down a cyclic 'debugging rabbit hole'. Not only is this an inefficient use of computational resources, but this also misaligns the tool with developer intent.

Some studies advocate for allowing users to configure the timing and context of completions [2, 41] to address these concerns. However, we assume that the majority of end-users will likely expect such tools to work out of the box and adapt to their usage patterns. The issue of language model alignment is as pressing as the rate of their increasing capabilities. As LLMs are becoming more integrated into end-user workflows, it is necessary to think beyond aligning mere content; but, also the interactions with this content.

2.2 Existing Solutions

Sun et al. [36] aim to address this problem by filtering out completions that are likely to be rejected. They train a transformer-based classifier on the code prefix before it is submitted to the completion model, and find it can hide 5% of suggestions that would have been rejected with 94.5% accuracy. However, the authors rely on the assumption that rejected completions are due to insufficient code context alone.

Mozannar et al. [29] train a filter consisting of two model ensembles: one ensemble before and one after a completion is generated. They cite it can hide 53% of completions with the guarantee 91% would have been rejected by the user. However, despite designing their tool for GitHub Copilot, they do not include a user-study. Additionally, their filter can depend on a completion being generated, which is guaranteed to incur additional latency and compute in practice. Moreover, both of these tools aim to maximise the acceptance rate of the shown completions, while the need for better alignment with end-users has been highlighted [2, 29, 33, 39].

Furthermore, as detailed in a reverse-engineering blog-post [38], Copilot also has its own logistic-regression classifier to filter out completions based on telemetry data. We analyse how it weighs each feature in more detail in our online appendix, and design our baseline in this study as similar as possible.

A head-runner in this field would be Gmail SmartCompose [5], considering the same problem in a natural-language email setting. The authors detail a deep consideration for latency, scalability, and personalisation. However, their approach uses legacy language model architectures; and their insights, while valuable, may not entirely apply to the programming process.

²<https://github.com/ar41/curating-code-completions>

³<https://huggingface.co/collections/AISE-TUDELFT/smart-invocation-of-code-completion-66473ddf6fa6cf6e541f750c>

⁴As of 29 December 2023, GitHub Copilot, and others, also offer a conversational interface; but we limit the scope of this paper to generative code completion only.

3 PROBLEM DEFINITION

Code completion aims to improve developer productivity by saving them keystrokes and keeping them in their flow. Ziegler et al. [46] proposes the acceptance rate of suggestions as a proxy for developers' perceived productivity; however, this is critiqued by Mozannar et al. [29], whom find that optimising the acceptance rate results in shorter and typically less useful suggestions.

Therefore, some completions, despite seemingly helpful, can potentially be detrimental to software quality and programming flow. And, conversely, some completions, despite being rejected, are not wholly ignored by the developer and are potentially helpful in guiding their thinking (e.g., a tip-of-the-tongue function call, but with the wrong arguments). Determining the actual quality of a completion, based on its functional correctness and human preferences for style, remains an open question, though research is progressing in the right direction [8, 44, 45].

Consequently, we reframe this problem to what we can actually measure. We consider two plausible reasons why a user may have rejected a suggestion, as depicted in Figure 1: (1) the model is incapable of generating a good suggestion, which is mainly code context-dependent; or (2) the user does not want to see a suggestion, which is mainly user telemetry-dependent. These reasons are not exclusive and likely have considerable overlap. Thus, we motivate the need for integrating these feature types to better align with the end-user's flow.

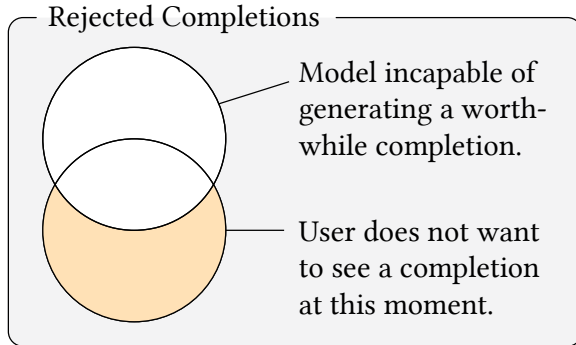


Figure 1: Reasons for Rejected Completions.

3.1 Code-Completion Data and Constraints

Throughout this study, we leverage CODE4ME, an open-source code completion plugin with around 100 monthly active users developed at our institution [17]. We note three key differences compared with the popular code completion plugins mentioned earlier (Section 2):

- **Line-completion only.** Other tools tend to provide multi-line suggestions in ghost-text style; while we provide completions up to a newline character. Additionally, completions are displayed in a completion box along with typical language-server suggestions.
- **Restrictive activation.** Contrary to alternative plugins, we provide completions only on a predefined set of trigger characters; at which IDE-based autocomplete would typically

trigger (e.g., full stop or an opening parenthesis). Though, we do allow users to manually invoke a completion.

- **Model selection.** Our line-completions are generated by smaller language models than the industry-standard, allowing the user to pick one of three completions provided by INCODER [9], UNIXCODER [12], and CODEGPT [26].

To help keep developers in their flow, we want to leverage language models' ability to complete code even when not at a predefined trigger point. In practice, this means that our plugin will query the completions server at any cursor position, and we would like to filter out those points where it may not be necessary to generate a completion. Thus, the plugin should filter out those *automatic* suggestions that historically ended up being *rejected* or ignored by the user. And, additionally, the plugin infers that a user wants a suggestion, at a historically *manual* trigger point.

As added context, our filter should prioritise false-positives over false-negatives. We assume that this is where user preferences lie, given the constant-suggestion nature of the more popular plugins. However, to avoid wasted compute and developer distraction, we aim to minimise those completions that are certain to be ignored; e.g., because the developer is actively typing, or their intent cannot be accurately inferred at the current cursor position.

Lastly, in terms of non-functional constraints, we would like our filter to take at most 10ms to make a decision. This is in preparation for a backend migration to the vLLM engine [21]. For any incoming completion prompt, this library waits about 10ms for to see if it can be batched together with other requests. If our filter takes less than 10ms, it means we incur 0 additional latency over the base wait time. And, even if filtering takes longer, it is still possible to terminate the token-by-token generation process early, saving considerable compute as our completions take about 300–400ms to generate.

3.2 Joint Optimisation Objective

Our goal is to train a filter to invoke the completion model only at the instant a developer wants to see a completion. We partially mitigate the issues arising from optimising for acceptance rate, through the observation that we may actually want to display the rejected completions that were manually invoked via a key-bind. By training a filter with this objective, along with any completions that were accepted, we hope to better align the completions that pass through the filter with what end-users want at that moment. Our objective is thus perpendicular to existing work in this area [29, 36].

The objective jointly optimises the following: (1) we aim to minimise the amount of times an end-user has to manually invoke the model, and (2) we aim to minimise the amount of rejected completions that were automatically triggered. In other words, we consider all manual invocations and automatic, accepted completions to be our positive class (not filtered out), and rejected automatic completions to be our negative class (should be filtered).

An added bonus of considering manually-invoked, yet rejected completions in the positive class is that the resulting filter will be less dependent on the completion-model's capabilities. We assume that a manual trigger is a strong indicator that a user would like to see a suggestion, and choose not to depend on whether the suggestion was accepted in this scenario.

4 APPROACH

We aim to filter out suggestions by teaching a model to predict, at any cursor location, whether to invoke the completion model or not. To do this, we propose to leverage our collected dataset of code completions and accompanying in-IDE telemetry to better discern the nature of interactions. Noting the state-of-the-art contextual understanding that transformer models exhibit, we explore architectures for integrating telemetry features with code context.

4.1 JONBERTA Architecture

We augment a code-pretrained RoBERTA architecture [23], yielding the following two models of 84M parameters. As there are many possible extensions to a transformer model, we limit our search space to parameter-efficient implementations. Specifically, both our models incur less than 1M additional parameters. We assume readers' familiarity with the transformer architecture [40].

- JONBERTA-HEAD incorporating telemetry features directly in the classification head.
- JONBERTA-ATTN attending to (small) learned feature embeddings in the self-attention modules.

We use the JON prefix to refer to *Jointly optimised attention*, to both code context and telemetry data. The motivation behind this approach lies in the state-of-the-art *contextual* understanding transformer models exhibit, which we hypothesise can also leverage contextual telemetry data. We further propose a novel tokenisation strategy centred on the cursor, to capture the most significant parts of code context.

4.1.1 Extended Classification Head. We explore a simple JONBERTA-HEAD model depicted in Figure 2. Given that a classification head first pools the output of the previous layer to the first token (<cls>, the classification token), it is trivial to extend this token's one-dimensional embedding with additional feature data.

In the scope of this paper, we only consider a JONBERTA-HEAD where the embedding is concatenated before reaching the dense layer. The dense layer is a matrix of size $c \times c$, where c is the length of a token embedding. Dense layers can help the model learn low-rank embeddings [15] of both feature and code context (which can help with train/test generalisability), while the projection layer afterward serves as a logistic classifier. We increase only the dense layer's size, along one axis, to accommodate the concatenated features, and reinitialise it.

4.1.2 Extended Self-Attention. Figure 3 depicts our JONBERTA-ATTN model, which learns feature embeddings to be attended to in the pre-existing self-attention module. Each weight in the feature embedding matrix is learned as a function of the corresponding scalar feature. Given this embedding, keys, and values can be produced to be attended to by code tokens. In practice, the attention module itself is equivalent to the original model, except that the keys emitted from features can dot-multiply with the queries from token embeddings, to produce weighted scores for how much a given feature's value should be added to that token embedding.

By including telemetry feature embeddings in its self-attention mechanism, we hypothesise the model is able to combine both modalities to grasp a firmer picture of the current user intent. We

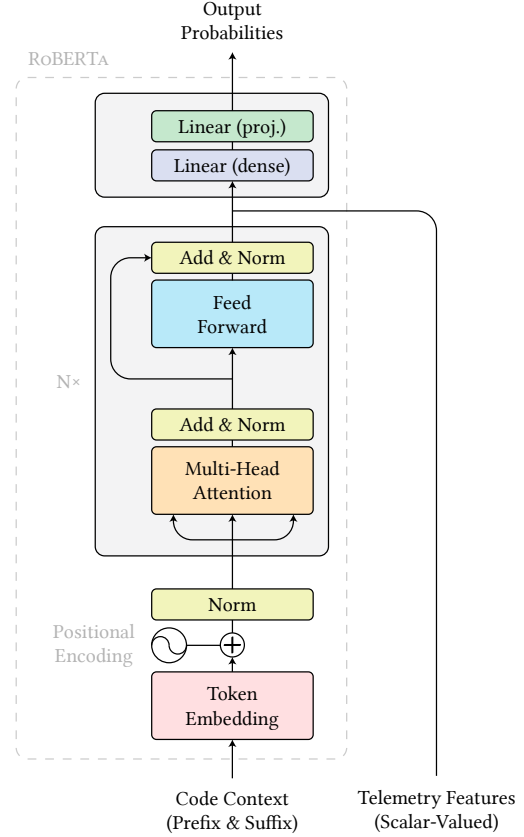


Figure 2: Telemetry Feature Data in Classification Head.

further explore a variety of layer combinations and feature embedding dimensions in the online appendix of our replication package, but cannot conclusively state which achieves better results. We use a feature embedding dimension of 204 throughout this study to limit the additional parameters to the model, while ensuring enough expressivity.

4.1.3 Tokenisation Strategy. The code context provided to our JONBERTA-HEAD and JONBERTA-ATTN models consists of the prefix (before the cursor), and the suffix (after the cursor). Commonly, tokenisers truncate such sequence pairs either both on the left or both on the right in paired sequence-classification tasks (e.g., question-answer matching). However, we hypothesise that it is optimal to centre the context window on the cursor location. Perhaps surprisingly, something we have not yet seen in previous work.

To achieve this within the JONBERTA context window of 512 tokens, we first tokenise the suffix with right-truncation up to a maximum of 128 tokens. Denote the number of tokens in the suffix by n_s , which may be less than 128 if the developer is close to the end of the file. We then tokenise the prefix, up to a maximum of $512 - 1 - n_s$; subtracting one off the total context window here, to allow us to insert a <sep> separator token at the cursor position. If the total length happens to be shorter than the context window, we

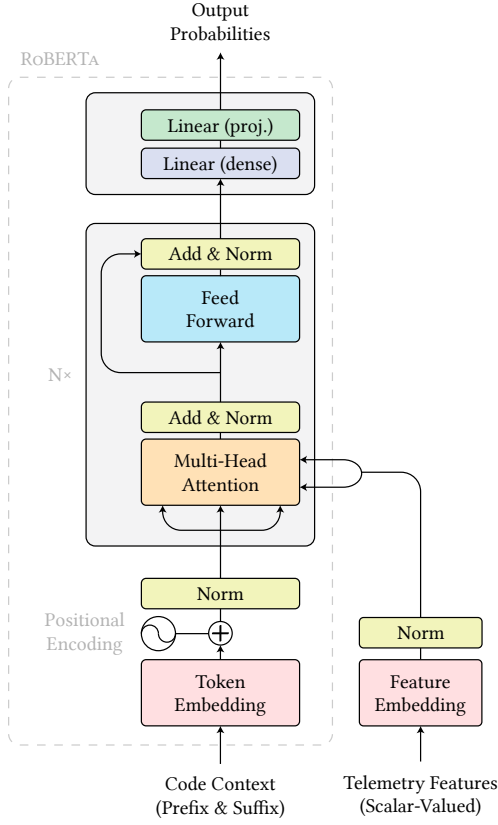


Figure 3: Self-Attention Extended to Telemetry Feature Data

conventionally right-pad the remainder of the sequence. Note that this doesn't perfectly centre the cursor in the context window, and assumes the prefix holds more weight than the suffix. This decision is substantiated by the results in our online appendix.

4.2 Dataset

We train our models on data collected from a code completion plugin developed at our institution (Section 3.1). Any given code suggestion is either manually invoked via a key-bind, or automatically on a predefined set of common trigger characters (e.g., a full stop, or opening paranthesis) [17]. As stated in our objective Section 3.2, we aim to optimise for those completions that are either (1) manually invoked, or (2) automatically invoked and accepted.

While we have over 1M invocations of our tool, after filtering for high-quality samples containing code context (collected on an opt-in basis, ~200k samples), and balancing our dataset by under-sampling, we maintain only about 10k code suggestions for training. Our test set, following the real-world distribution of manual and automatic invocations, contains about 20k samples, completely separate from the training set. We empirically compare different dataset distributions in our online appendix, motivating the under-sampled training distribution in this classification scenario where classes are not equally represented in practice.

Table 1: Class Distribution in Our Code Completion Train/Validation and Test Datasets.

Class	Positive		Negative
Completion Type	Manual	Automatic Accepted	Rejected
Test	6118 (27.8%)	431 (1.9%)	15889 (70.3%)
Train/Validation	3909 (33.3%)	3909 (33.3%)	3909 (33.3%)

Table 1 shows the (sub-)class distribution of our train/validation and test dataset. We purposefully avoid distinguishing between manual accepted, and manual rejected invocations of our tool, as we consider both to be part of our positive class. As added context, however, the manual rejected invocations constitute a total of 47% of our positive class in the real-world (test) distribution. Unfortunately, we are unable to share our collected dataset as it contains user-sensitive code context.

5 EXPERIMENTAL SETUP

We laid out the code completion plugin context and problem constraints in Section 3. And, having established our search space for this problem in Section 4, we now propose how to navigate it.

5.1 Research Questions

As defined in Section 3.2, the objective of our models is to label manual and automatic invocations which are accepted as positive (helpful); and, consider the remaining automatic invocations that are rejected as the negative class (unhelpful). To this end, we pose the following research questions:

- RQ1 **How does a transformer model compare to a baseline logistic regression model at filtering out unhelpful suggestions (offline evaluation)?** We fine-tune a code-pretrained RoBERTa [23] model (CodeBERTa) on code completion snippets collected from our plugin, and evaluate it against a logistic regression baseline trained on telemetry and selected textual features. The baseline is inspired by reverse-engineering GitHub Copilot and reflects the state-of-the-art.
- RQ2 **Can a pre-trained transformer be extended to incorporate an additional modality consisting of telemetry feature data?** We train our JONBERTa variants (Section 4.1) with telemetry feature data as an additional modality when making predictions.
- RQ3 **How effective are the above approaches in a real-world setting (online evaluation)?** We deploy our filters in a code-completion plugin to investigate whether the filters' decisions align with 34 users in practice. We further evaluate the computational feasibility of our approach, and note discrepancies between the offline and online environments.

5.2 Evaluation Settings and Metrics

5.2.1 Metrics for Offline Settings (RQ1 & RQ2). To evaluate whether our models can capture the different invocation types that determine our classes (see Section 3.2), we compute accuracy per manual,

accepted automatic, and rejected automatic subclass. Based on this, we further compute the macro average accuracy, to serve as a single metric to compare models on.

We choose macro average accuracy (across classes), as opposed to micro average (across all samples), as our positive classes are under-represented in our code-completion dataset. As a result, it is paramount that completions the developer wants to see are prioritised against the vast majority of completions that are ignored. We assume that the mistake of filtering out a completion when a developer would want to see one is worse than showing a completion when the developer does not want to see one.

As shown in Table 1, some of our classes are considerably under-represented. The variance due to such a small dataset can become pronounced when training transformer models. To capture this variance, we train five models on five train/eval splits (9:1). Then, we bootstrap our accuracy scores on the test set by alternatingly taking a sample from each of the five models, for a total of $n = 10,000$ samples.

5.2.2 Metrics for Online Setting. For our online evaluation, we no longer have a valuable distribution of manual/automatic classes as we remove the predefined trigger-point invocation rule. To remedy this, we evaluate completions that pass the filter via (1) acceptance rate as a proxy for their *timing* with developers' mode of thought; and (2) score accepted completions using CodeBERTScore [44] as a proxy for their *quality*. We also measure the latency in milliseconds.

CodeBERTScore is a recently-proposed measure that correlates closest with both functional correctness and human preference [44]. This is contrary to the oft-seen CodeBLEU, METEOR, and ROUGE-L measures which are designed for natural languages and do not work well with the syntactic structure of programming languages [8]. CodeBERTScore is computed by passing the code completion and ground truth (after 30s) through a code-pre-trained encoder model, and then computes the F3 score based on the similarity between token embeddings at a layer that correlates best with human preference and functional correctness.

We further propose the harmonic mean of these two as a single metric to compare models by. Specifically, optimising only acceptance rate results in worse completions [29, 46]. And, optimising just the content of a completion, does not make the filter align well with developers, as evidenced by the number of manual completions we observe in our dataset. We hope this communicates to the reader how these two measures should be weighed in our framing of the problem.

5.3 Feature Engineering and Baselines

The features extracted from our code-completion data for the Logistic Regression, CODEBERTA, and JONBERTA models, are shown in Table 2. We purposely avoid providing JONBERTA with features that can be inferred from the code context (e.g., whether there is whitespace after the cursor), to assert it is able to leverage that data implicitly. To this end, we define three types of feature data:

- T Telemetry as those features that cannot be directly extracted from a snippet of code.
- C Code context as those *textual* features that are explicitly extracted by fixed rules.

S Snippet as the prompt to the completion model, truncated to the filter model's context window (512 tokens) using our centred-on-cursor strategy (Section 4.1.3).

Table 2: Features Used in Classification, per Filter Model.

		Log. Reg.	CODE	JON
T1	Time since last completion	✓		✓
T2	Document length	✓		✓
T3	Cursor offset	✓		✓
T4	Offset as percentage	✓		✓
T5	language (20 options)	✓		✓
T6	IDE (jetbrains / vscode)	✓		✓
C1	Length of last prefix line	✓		
C2	Above, without whitespace	✓		
C3	Whitespace after cursor	✓		
C4	Last prefix char (ASCII 32-125)	✓		
C5	Above, without whitespace	✓		
S1	Prefix		✓	✓
S2	Suffix		✓	✓

The features for the logistic regression model are inspired by reverse-engineering Copilot [38], with the exception of one feature that depends on a pre-existing filter (which we do not have). The languages are the same as the 20 considered by Copilot. We choose to follow Copilot as, to our knowledge, this is the only filter currently deployed in practice, and contains most of the significant features found in previous work [29]. An extended explanation of these features can be found in our online appendix.

5.4 Configuration and Implementation Details

We fine-tune all transformer models for six epochs with a $2e^{-5}$ learning rate and 16 batch size from a public CODEBERTA-BASE-V1⁵ checkpoint, with each epoch containing about 10k training samples. We also use its tokeniser for snippet features. For the JONBERTA models, we fine-tune from the 3rd-epoch CODEBERTA checkpoint, for an additional three epochs; as we observe this results in stabler training than training from the public checkpoint.

All of our transformer models are implemented with PyTorch⁶, and trained on an NVIDIA GeForce RTX 3080 GPU, taking about 20 minutes per model. All metrics are computed using the functions provided by scikit-learn⁷ library. For our online evaluation, we use an inference server with an NVIDIA GeForce RTX 2080 Ti, separate from our training setup. As this is a relatively older GPU, we expect slightly higher latency during filter inference.

6 RESULTS

6.1 RQ1: Impact of Code Context

To address RQ1, we evaluate the contributions from training on snippet features (S), against telemetry (T), and fixed-rule textual

⁵<https://huggingface.co/huggingface/CodeBERTa-small-v1>

⁶<https://pytorch.org>

⁷<http://scikit-learn.org>

features (C). To this end, we first consider logistic regression baselines trained on iteratively more T and C (see Section 5.3). Lastly, CODE4ME is cross-application, so we include a feature for the IDE. In our dataset, JetBrains users tend to have a higher suggestion acceptance rate, partially because they support only the popular languages⁸ which code completion models tend to perform best on [20].

We do not directly extract the weights from its plugin code. Instead, we retrain the Copilot-style baselines on our own completion-request dataset, because the data distribution of our completion plugin is likely different due to its different invocation methods and completion style as explained in section 3.1.

Table 3: Filter accuracy for Logistic Regression and CODEBERTA classification models, given per invocation sub-class.

	Manual	Auto/acc.	Auto/rej.	Avg.
Logistic Regr.				
Telemetry T ₁₋₅	99.6 ±0.3	99.1 ±0.7	1.4 ±0.7	66.7
+ Textual C ₁₋₄	98.6 ±0.3	66.8 ±4.5	61.9 ±1.2	75.8
+ Copilot C ₅	98.6 ±0.3	66.1 ±4.6	63.9 ±0.9	76.2
+ IDE T ₆	98.5 ±0.3	66.1 ±4.6	65.0 ±0.9	76.5
CODEBERTA	98.5 ±0.4	74.7 ±4.6	73.1 ±1.2	82.1

As shown in Table 3, a model trained on telemetry features (T₁₋₅) alone, while attaining average accuracy of 66.7%, is completely unable to distinguish automatic invocations that end up being rejected (1.4% accuracy). Thus, it is necessary to include some explicit textual features (C₁₋₄) for distinguishing these classes. This intimates that extended code context can be leveraged. We refer to our replication package for additional experiments with different granularities of textual features.

Notably, CODEBERTA, trained on solely code snippet (S) features, can outperform the best baseline on automatically accepted and automatically rejected queries by 9.6 and 3.2 absolute percentage points, respectively. This indicates that the semantic understanding of code such a transformer model exhibits propels it past the classification baseline. And, furthermore, this snippet modality likely contributes orthogonally to the telemetry data, as both are distinct features that cannot be inferred from each other. This motivates our architectural exploration to attend to both these modalities in one classification model.

6.2 RQ2: Hybrid JONBERTA Models

To address RQ2, we train JONBERTA models leveraging both snippet and telemetry modalities and compare them to our new CODEBERTA baseline. This architectural search space is especially vast for the JONBERTA-ATTN model, due to the inclusion of feature *embeddings* with tuneable parameters. As such, we defer most of our experiments to the online appendix in our replication package, as well as a few JONBERTA-HEAD experiments. We choose to only display the first-layer configuration here⁹ to give telemetry embedding an

equally early chance as token embeddings at communicating in the attention mechanism; and choose an embedding dimension of 204 to not incur too many additional parameters.

Table 4: Filter accuracy for CODEBERTA and JONBERTA classification models, given per invocation sub-class. Error Bounds are for $p < 0.5$ via Bootstrapping $n = 10\,000$.

	Manual	Auto/acc.	Auto/rej.	Avg.
CODEBERTA	98.5 ±0.4	74.7 ±4.6	73.1 ±1.2	82.1
JONBERTA				
HEAD (dense)	98.6 ±0.4	78.0 ±6.2	71.4 ±5.1	82.7
ATTN (0L)	98.6 ±0.4	75.0 ±6.8	72.5 ±3.5	82.0

In Table 4, JONBERTA-HEAD promisingly shows it can better discern between completion classes, though our results are less conclusive than before. While incorporating the telemetry features in the first attention layer of JONBERTA-ATTN matches the performance of JONBERTA-HEAD, implying it can learn to integrate telemetry features with its semantic understanding of code, this may equally well be attributable to variance. This could be, in part, due to the limited training set size as revealed by our bootstrap strategy for computing error bounds (Section 5.2), which we further discuss as an internal threat to validity in Section 7.1.1.

Regardless, we present these results motivated by the same argument as in Section 3: Transformer models are becoming increasingly integrated into software engineering tasks, but also well outside of the field. As a result, there is a need to integrate additional modalities into pre-trained models, as tokens are but one of many sources of information that can be leveraged in AI-powered tools.

6.3 RQ3: Online Evaluation

To evaluate how our filters fare in the real world, we deploy them in a code completion plugin with 34 developers over a 2 week period, resulting in 74k requests. To this end, we disable the predefined trigger-point constraint that was described in Section 3.1, to now automatically invoke the completion model at the historically manual trigger-points.

We perform an A/B study by assigning each user one of the following five filters per coding session. We define a session as a sequence of completion requests where any two are no more than 30 minutes apart, to avoid end-user confusion from different completion behaviour on every request. For all filters, requests with a prompt (prefix + suffix around the cursor) less than 10 characters are automatically rejected, as they do not have enough context for a worthwhile completion.

- 1 **None**: all completion requests pass through.
- 2 **Logistic regression** using telemetry (T) and context (C) features.
- 3 **CODEBERTA** using only snippet (S) features.
- 4 & 5 **JONBERTA-HEAD** and **-ATTN** using both T and S.

Table 5 shows our results. Using our proposed harmonic mean to convey the balance of suggestion quality and timing, JONBERTA-HEAD performs best. While our proposed metric maintains ordinality among the CODEBERTA and JONBERTA models, compared

⁸Very recently, JetBrains did release a preview for a cross-language IDE, Fleet: <https://www.jetbrains.com/fleet/>

⁹JONBERTA-ATTN 0L: Ranking 19/67, Median average score is 81.7.

Table 5: Completion statistics for filters deployed in CODE4ME. The relative acceptance rate is with respect to None. Latency is computed as the median of all requests.

Filters	JONBERTA				
	None	LogReg.	CODE	HEAD	ATTN
Requests					
Received	13.5k	10k	20k	15k	13k
Filtered out	2.2%	29.4%	36.6%	34.4%	39.4%
Completions					
Shown	97.8%	70.5%	63.2%	65.6%	60.5%
Accepted	1.42%	0.62%	1.20%	1.44%	1.03%
Accepted					
Relative rate	100.0%	45.0%	84.5%	101.0%	72.3%
CodeBERTScore	0.76	0.94	0.85	0.82	0.88
Harmonic Mean	0.864	0.609	0.847	0.905	0.794
Latency (ms)	0.0	0.2	25.0	20.8	24.1

to the offline evaluation, this also highlights our proposed metric is not perfect, as presumably, all our filters should be performing better than the no-filter baseline. We defer discussion on alternate weightings for the harmonic mean to future work (Section 7.1.3), to avoid conflicting interests from tuning our metric here.

Additionally, we demonstrate the feasibility of our approach in practice. A lightweight transformer model can be deployed server-side as a filter for incoming requests, with relatively minimal latency compared to the completion model itself, which takes 300-400ms in our case. Future work can consider further optimising these models, through e.g., model compression [43], for client-side deployment.

7 DISCUSSION

We anticipate that the issue of redundant invocation will become even more noticeable as software engineering tasks increasingly incorporate billion-parameter transformer models. Our results demonstrate the effectiveness of using a smaller, lightweight transformer to control when a larger, completion model is invoked. Moreover, we believe smart invocation filtering models such as ours not only enhance code completion but also any other transformer-based interaction with users.

To our knowledge, we are the first work to augment a *pre-trained* transformer with additional feature modalities. Transformer models exhibit exceptional contextual understanding, yet are bottlenecked by the textual medium. Especially considering that in-app telemetry data is often collected anyway, we highlight that it is fruitful to leverage this additional input dimension. By showing promising results in this search space, we hope to inspire others to venture deeper.

7.1 Threats to Validity

7.1.1 Internal: Limited Contextual Usage Data. In RQ1 and RQ2, we used a training dataset of just 10k samples. This size is not optimal for fully examining the potential of hybrid transformer models enhanced with extra feature data. Expanding the dataset

in future research would likely offer a better understanding of these models' capabilities, enabling more meaningful comparisons between different architectures.

7.1.2 External: Generalisability to Other Code-Completion Tools. We utilized a code-suggestion plugin that has a smaller user base compared to larger production systems. This choice introduces several factors that might impact how our findings can be applied to other code completion tools. These differences have been detailed in Section 3.1. Our approach, while specific, offers valuable insights but warrants caution when generalizing to other contexts.

7.1.3 Construct: Limitations of the Proxy Metrics. In our online evaluation, we use the harmonic mean of acceptance rate and CodeBERTScore as our metric to measure performance. This approach, suggested for further exploration in future studies, allows for adjustments in how each component is weighted. Consistent with earlier research [29, 46], we acknowledge that these proxy metrics might not fully capture the usability of the interaction without potentially compromising it in some other way. To gain a deeper understanding, we suggest that future work could benefit from qualitative studies, including interviews with developers, to complement these quantitative measures.

7.1.4 Ethical Considerations. Our research received approval from the institutional ethical board and explicit user consent for data use. Additionally, we have secured explicit consent from users before collecting and using their information. We chose not to deeply investigate privacy issues related to developer data usage, as our invocation filtering models (classifiers) pose fewer privacy risks compared to generative models. However, to comply with the GDPR, we are unable to share our dataset as we cannot guarantee anonymity.

8 CONCLUSION AND FUTURE WORK

To summarise, we train a transformer-based invocation-filtering model on a dataset we collected from an open-source code completion plugin, CODE4ME. We show that code context is especially useful in filtering predictions, and highlight the potential of integrating this information with the telemetry data collected in an IDE. Lastly, we deploy our filters in practice and show their practical effectiveness in both offline and online settings.

Future work can more thoroughly explore the search space we have established, by utilising a larger dataset. Our limited dataset may not fully represent the diverse behaviours of developers, and related work shows promising results in personalising the invocation-filtering system [5, 29]. We choose not to explore this avenue in this study to limit our architectural search space, though strongly advocate for further exploration in this area.

Lastly, we note that delivering completions exactly when a developer requests them might not always match what developers truly need in the long run. Tracking the long-term impact of these completions presents challenges, yet understanding this is crucial, especially as the use of AI tools shows a link to increased code changes. This domain deserves further investigation to better align for lasting developer benefits.

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