

Using Artificial Intelligence to Perform Reviews of Human Code

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Glossary

Visual Studio Code – VSCode

Large Language Models – LLM

Artificial Intelligence - AI

Application Programming Interface – API

Uniform Resource Locator – URL

Executive Summary

The culmination of the capstone project has yielded the creation of SigmaPilot, a sophisticated Visual Studio Code (VSCode) extension meticulously engineered to streamline integration with both local and remote Large Language Models (LLMs). SigmaPilot enhances developers' code review capabilities by facilitating direct interaction with artificial intelligence within their native coding environment. This strategic initiative was propelled by the escalating demand for secure and efficient AI tools within software development sectors across diverse industries, underscoring the critical necessity for a solution that seamlessly combines performance efficiency with resource optimization.

SigmaPilot distinguishes itself through its capability to provide direct and seamless access to LLMs, with a particular focus on enhancing user privacy and data security by enabling local connections. This feature is of paramount importance for industries seeking to leverage AI for code review processes while safeguarding sensitive data from external internet exposure, which could potentially compromise the integrity of proprietary information or be exploited for training external models. The project has successfully delivered an intuitive user interface and a flexible connection framework that supports LM Studio for local connections and the OpenAI API for remote interactions.

A practical application scenario for SigmaPilot involves a company deploying a local server within their premises, installing an LLM tailored to their specific programming requirements, and establishing a connection to this local LLM through SigmaPilot utilizing a URL and an API key. This configuration exemplifies the extension's utility in preserving the locality of a company's codebase, thereby reinforcing the paramount objectives of data privacy and security.

Throughout the research phase, the team conducted a comprehensive evaluation of various local LLMs, leveraging LM Studio as the principal tool for analysis. This rigorous assessment across multiple programming languages and tasks culminated in the selection of Vicuna 13b as the premier model under 13 billion parameters for its unparalleled accuracy.

In essence, the development of SigmaPilot represents a significant leap forward in the integration of AI tools into the software development lifecycle. By addressing the industry's pressing needs for security and operational efficiency, the capstone team has introduced a ground-breaking solution poised to reshape the landscape of software development. SigmaPilot not only enhances the productivity and innovation potential of developers but also firmly aligns with the strategic imperatives of data privacy and security through the adoption of advanced, locally hosted AI technologies.

Project Motivation and Objectives

The motivations driving this project are multifaceted. Currently, within the market, there exists a notable absence of a means for users to engage with a local model within their VSCode instance. The primary objective of this project is to address this deficiency by providing users with an intuitive interface for seamless interaction with their preferred local model. With a user-centric approach, the project endeavors to integrate effortlessly into users' VSCode instances, eliminating the need to switch tabs and thereby enhancing user productivity.

Privacy emerges as a cornerstone of our project motivation. While AI has revolutionized the software engineering landscape, exemplified by innovations such as ChatGPT, one of the pioneering Large Language Model (LLM) chat interfaces, concerns regarding data privacy persist. The introduction of this technology showcased the potential for simplifying, expediting, and optimizing programming tasks. Nonetheless, the commercial iteration of this chat bot raises apprehensions among private project developers and companies regarding the confidentiality of their code when interacting with such external platforms.

Furthermore, the project's motivation extends to tailoring this technology for bug identification and enhancing programmers' code before integration into the main repository branch. An extension capable of communicating with an LLM and posing targeted inquiries has the potential to expedite and bolster the code review process significantly.

In addition, a crucial aspect of our project's motivation is the empowerment of users through offline accessibility. By enabling users to utilize the extension without an internet connection, SigmaPilot fosters productivity in diverse environments, offering flexibility and convenience unparalleled by solely cloud-based solutions.

Consequently, the design of a chat bot interface capable of interfacing with a private, local LLM serves as a comprehensive solution to the twin challenges that underpin our project objectives. By prioritizing user privacy, offline accessibility, and efficiency in code review processes, this project endeavors to provide a robust solution that meets the evolving needs of software developers and organizations.

Methodology and Design

The project is structured into two main phases: the research phase and the development of the VSCode extension. Each phase follows a distinct methodology and design approach tailored to its specific objectives. The forthcoming report provides detailed explanations of each phase separately, along with a dedicated section elucidating how these two phases are intended to interact.

The research phase serves as the foundation for the project, focusing on the evaluation of various local Language Models (LLMs). Using established methodologies, the team assesses the effectiveness of these models across different programming languages and tasks. Tools like LM Studio are employed for rigorous analysis to determine the models' suitability for integration within the VSCode environment.

Simultaneously, the development phase of the VSCode extension progresses, guided by insights from the research phase. Following an iterative design process, the extension's architecture and features are carefully crafted to seamlessly integrate with VSCode, prioritizing user experience and performance. Prototyping, user testing, and feedback loops play essential roles in refining the extension's functionality and usability.

Additionally, the report outlines how insights from the research phase inform the design and implementation of the VSCode extension. By illustrating the symbiotic relationship between research findings and development strategies, the report offers a comprehensive understanding of the project's methodology and design principles, emphasizing the systematic approach taken to achieve its objectives.

Discovery and Requirement Gathering Phase

The first step in the project was to identify stakeholders. The group through a series of interviews and brainstorming events identified the following key stakeholders in the project.

Project Stake Holders
Teacher Assistant: Manuel Zamudio Lopez
Academic Advisor: Dr. Gouri Ginde Deshpande
Sponsor Representative: Mr. Alex Shaharudin

The first step was research. Our group created user stories based off conversations with the stakeholders. The first user stories allowed us to grasp the main idea of the project.

The initial research needed us to find a way to properly evaluate each of the models after we had found the models to use. Looking at how it was done by Y. Wang [1] we found we had to take human written code with human written explanations and feed that to the models. When consulting professor Benjamin Tan we found that we must try to adhere to what the sponsor is looking for and work on our rubric from there. Afterwards the sponsor was contacted, and a list of requirements was made. These are the must-haves, should-haves, and nice-to-haves.

When looking at Evaluating Large Language Models: A Comprehensive Survey [2], We found for our evaluation we need to make sure that the code that is being sent to the user is efficient and needs documentation to support each of the lines of code to allow for the end user to understand the provided code. Afterwards we reflected and looked at the mission statement again and realized just having good code is not enough. Giving the user the explanation needed for the code would exponentially help the end user. With these requirements in mind the rubric for evaluating the models was created by comparing the requirements and what the end user could potentially consider as usable code and a detailed explanation following it.

The group split up the agile method into two one-week splits. During the first week, the group would meet at the start to plan the week for design and development. The group had weekly meetings where the developers met to plan the next week. After one week of development, the group would meet again to plan for the testing and evaluation of the code made during the previous week.

After meetings with the TA, academic advisor and the sponsor, the group would create new user stories based on the feedback from the sponsors.

Research and Evaluation of Large Language Models

Idea

This project idea simulated a local environment from some commercial AI chatbots for providing privacy and control over the company's codes and products. Training a model for this purpose is out of this project's scope, as it needs enough financial support, which we didn't have. As a result, the focus and effort concentrated on investigating available and open-source models, to choose the best of them and most similar to commercial LLMs in terms of functionality.

Before embarking on the evaluation of Local Language Models (LLMs), an extensive research endeavor was undertaken to identify models aligned with the specific parameters and requirements pertinent to this project, particularly in the realm of code reviewing. This initial phase involved a comprehensive survey of various models, considering factors such as their training parameters and relevance to the project's objectives.

Over 60 models were meticulously researched to ascertain their suitability for integration within the project's framework.

Regarding investigating and shortlisting open-source models on the internet, we used different resources such as:

- HuggingFace
- Google Search
- Forums like Reddit, Facebook, etc.
- ChatGPT NLP assistant

Among the models explored were:

- CodeBERT [3]
- Alpaca [4]
- Code Llama [5]
- LLaMa [6]
- CodeT5 [7]

This exhaustive exploration ensured that the subsequent evaluation process was informed by a thorough understanding of the available options, facilitating the selection of models best suited to meet the project's requirements and objectives.

Following the initial research phase, a meticulous selection process was employed to identify subsets of models trained with 13 billion parameters or less for further evaluation. The decision to focus on models with up to 13 billion parameters was deliberate, as it struck a balance between model size and computational feasibility, ensuring that the selected models could be downloaded and executed on local machines within a reasonable timeframe.

A total of 14 distinct models were subjected to rigorous evaluation, with each model undergoing testing across four different prompts to assess its performance comprehensively. The selected models for evaluation encompassed a diverse range of capabilities and specifications, including but not limited to:

#	Model Name
1	TheBloke • llama 2 chat 13B Q5_K_S gguf
2	TheBloke • llama 2 chat 13B Q2_K gguf v
3	TheBloke • llama 2 chat 7B Q8_0 gguf
4	TheBloke • llama 2 chat 7B Q2_K gguf v
5	TheBloke • airoboros 12 gpt4 2 0 7B q8_0 gguf
6	TheBloke • codellama 7B Q8_0 gguf
7	TheBloke • codellama instruct 13B Q4_K_M gguf
8	TheBloke • deepseek coder 6 instruct 7B Q8_0 gguf

9	TheBloke • codellama instruct 7B Q8_0 gguf
10	TheBloke • mistral ft optimized 1227 7B Q8_0 gguf
11	TheBloke • vicuna v1 5 16k 13B Q4_0 gguf
12	second-state • starcoder model 15B Q4_0 gguf
13	TheBloke • nous hermes llama2 13B Q4_0 gguf
14	maddes8cht • tiuae falcon 7B Q8_0 gguf

Table 1: Initial Selected Model

All models were downloaded onto **LM Studio**, a freely available application designed for interaction with local language models. The evaluation process was conducted on an M1 MacBook Pro to ensure consistency and reliability. Each model underwent assessment using four simple prompts aimed at quickly assessing their responsiveness and performance.

Experiment

The experiment is divided into two phases. The first phase contains selecting 3 models out of 14 and passing these 3 models to the next phase for being evaluated under a bigger evaluation for choosing the final model.

Phase_1

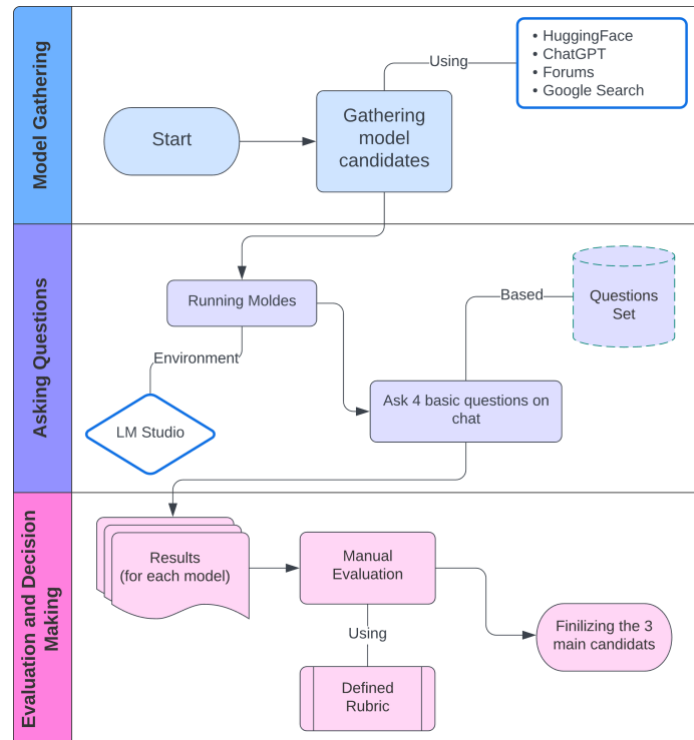


Figure 1: Phase 1 Research

In this phase, we determined four questions to be asked of the 14 initial candidates. These questions consist of two programming questions and two code exploratory questions.

Out of the initial selection of 14 models, the top three performers were identified for further evaluation. This subsequent assessment will involve the use of more sophisticated prompts spanning various programming languages, including C++, Java, TypeScript, and Go, in accordance with the requirements gathered from project sponsors.

The four prompts utilized during the initial evaluation were as follows:

#	Question content
Q1	"Explain the following Python function: <code>def add_numbers(a, b): return a + b</code> . What does this function do?"
Q2	"Can you explain this JavaScript code? <code>function greet(name) { console.log('Hello, ' + name); }</code> "
Q3	"Write a Python function to calculate the factorial of a number."
Q4	"I need JavaScript code to change the background color of a webpage to blue. Can you provide that?"

Table 2: Prompts for Model Testing

These prompts were carefully selected to gauge the models' understanding and proficiency across different programming paradigms and tasks, laying the groundwork for further in-depth analysis and refinement.

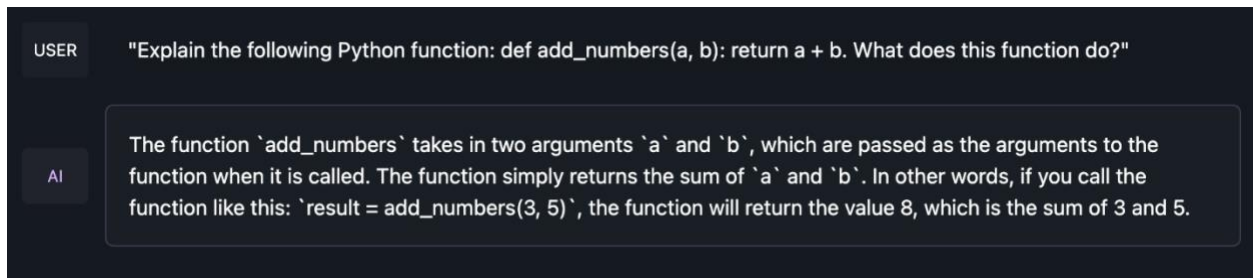


Figure 2: LM Studio prompt 1. and response for TheBloke • llama 2 chat 7B Q2_K

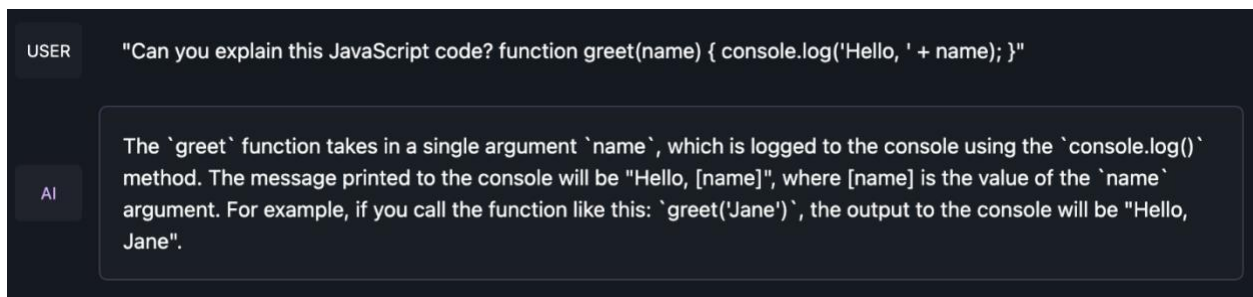


Figure 3: LM Studio prompt 2. and response for TheBloke • llama 2 chat 7B Q2_K

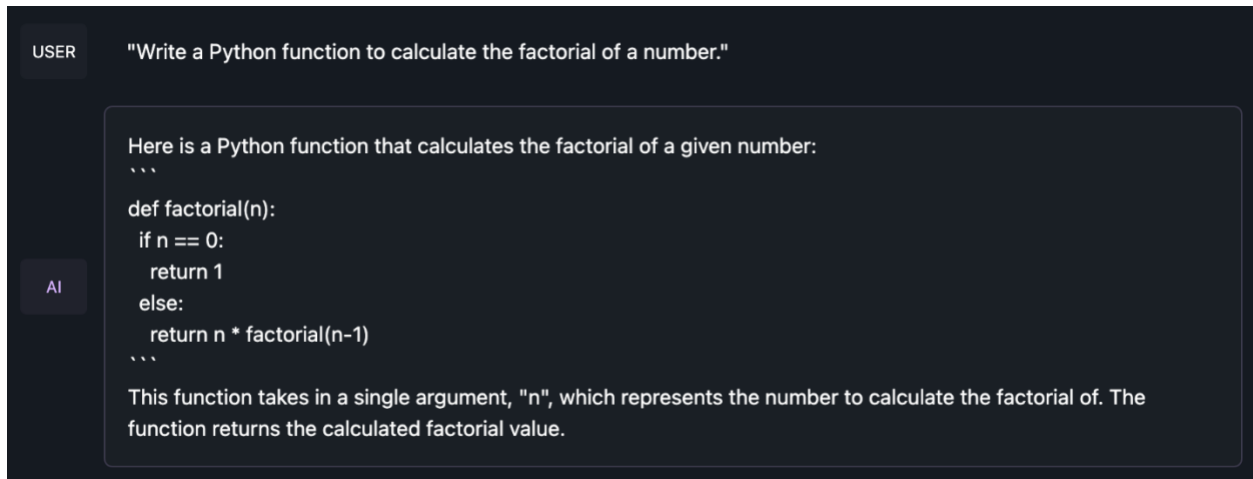


Figure 4: LM Studio prompt 3. and response for TheBloke • llama 2 chat 7B Q2_K

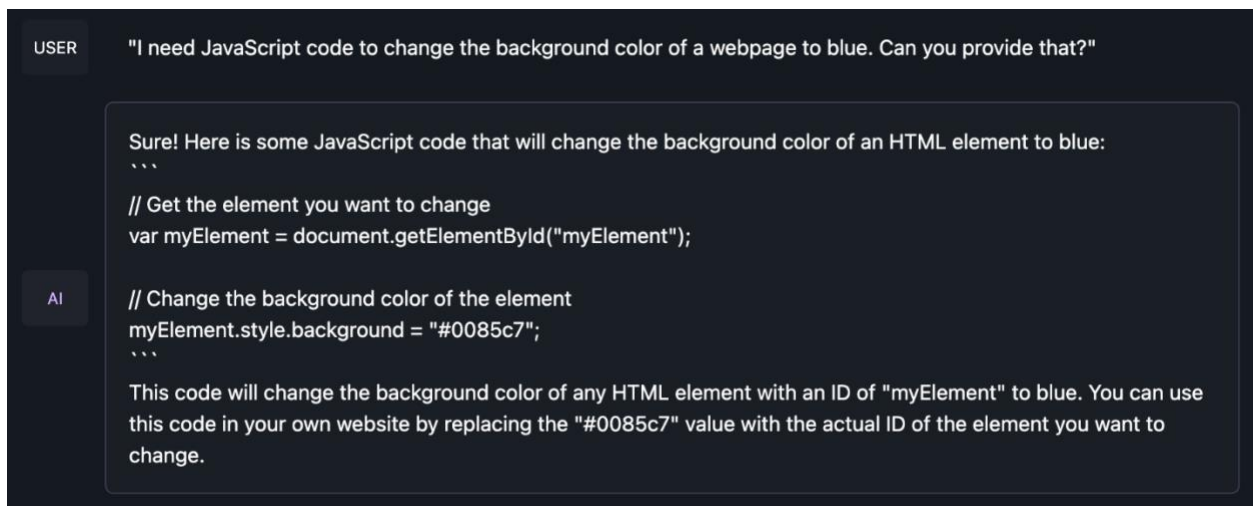


Figure 5: LM Studio prompt 4. and response for TheBloke • llama 2 chat 7B Q2_K

Following the utilization of a Python script to streamline the process of model execution and response generation for the designated prompts, each team member embarked on evaluating 2-3 models. The assessment process was guided by a structured rubric, designed to evaluate models across key dimensions, as outlined below:

Aspect	1-3	4-6	7-9	10
Accuracy	Incorrect or irrelevant	Partially correct, but has significant errors or omissions	Mostly correct, minor errors or omissions	Completely correct and comprehensive

Clarity	Confusing and poorly structured	Somewhat clear but with noticeable issues in structure or explanation	Clear and well-structured, with minor room for improvement	Exceptionally clear and well-explained
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Table 3: Rubric for Model Evaluation

This methodical approach ensured the systematic execution of evaluations, with each team member delivering nuanced assessments anchored in predefined criteria. The rubric served as a structured framework for discerning the inherent strengths and weaknesses of each model, thereby facilitating informed decision-making regarding their viability for further consideration and refinement.

After evaluating and rating each response from two different perspectives out of 10, we got an average score for each model as follows (sorted descending):

Model Name	Average Score
TheBlope • codellama instruct 7B Q8_0 gguf	8.625
TheBlope • vicuna v1 5 16k 13B Q4_0 gguf	8.625
TheBlope • deepseek coder 6 instruct 7B Q8_0 gguf	8.5
TheBlope • llama 2 chat 7B Q8_0 gguf	8.375
TheBlope • llama 2 chat 13B Q5_K_S gguf	8
TheBlope • llama 2 chat 13B Q2_K gguf v	7.875
TheBlope • llama 2 chat 7B Q2_K gguf v	7.75
TheBlope • codellama 7B Q8_0 gguf	7.375
TheBlope • mistral ft optimized 1227 7B Q8_0 gguf	7.375
TheBlope • airoboros 12 gpt4 2 0 7B q8_0 gguf	7
TheBlope • codellama instruct 13B Q4_K_M gguf	5.625
second-state • starcoder model 15B Q4_0 gguf	5.625
TheBlope • nous hermes llama2 13B Q4_0 gguf	5.375
maddes8cht • tiuae falcon 7B Q8_0 gguf	3.75

Table 4: Initial Model Evaluation Scores

Following the scoring of each response to the designated prompts on a scale of 1-10 for each model, the top three models with the highest averages emerged for subsequent evaluation. These models are as follows:

1. *TheBlope o codellama instruct 7B Q8_0 gguf*
2. *TheBlope o vicuna v1 5 16k 13B Q4_0 gguf*
3. *TheBlope • llama 2 chat 13B Q5_K_S gguf*

We select the *LlaMa 2 chat 13B* as the third option, as it is 13B parameters and assuming a bigger size model acts better performance.

This selection process underscores the commitment to meticulous evaluation and rigorous standards upheld throughout the project, ensuring that only the most promising models advance to the next phase of scrutiny and development.

Phase_2

On this phase, we did a bigger experiment on the 3 chosen candidates from the previous phase. We designed a kind of experiment, focusing more on code explanation tasks, as this is the main scope of this project. The designed experiment work follow is:

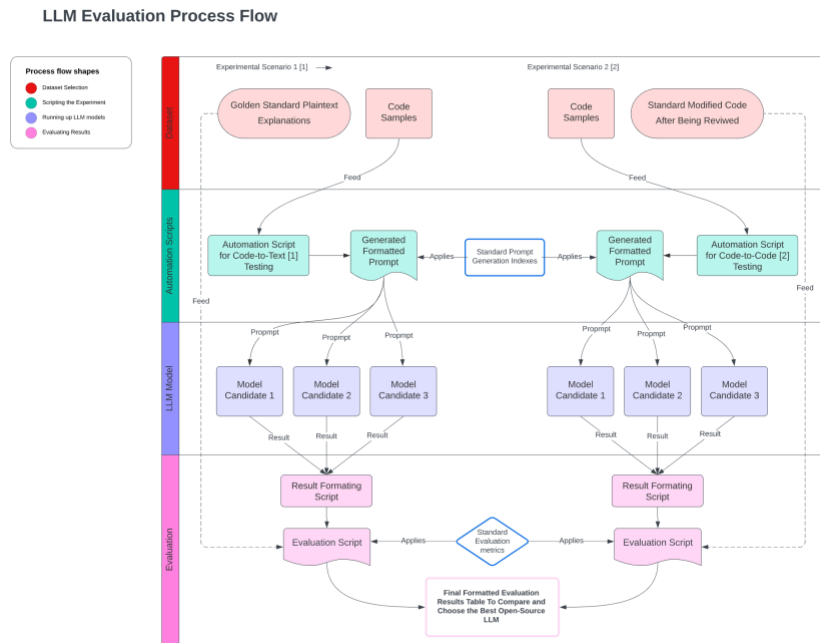


Figure 6: Phase 2 Research

In alignment with the programming languages specified by our sponsor—C++, Java, TypeScript, and Go—the team meticulously curated a collection of 50 algorithms, accompanied by comprehensive explanations tailored to each language. These algorithms served as the foundation for generating prompts, resulting in a total of 600 responses across the three selected models for evaluation.

Programming Language	Count
Java	50
C++	50
TypeScript	50
GO	50

Table 5: Count of Unique Prompt from Each Language

Two main resources for this data gathering were the GeeksForGeeks [8] programming function samples, as well as generating programming challenge samples using generative AI (ChatGPT [9])

Each programming prompt was passed to each model using a tailored prompt, a combination of the needed task, as well as the programming challenge as the dynamic part of each prompt. The tailored prompt for this purpose was:

Review the following [Programming Language] snippet within a concise explanation of 256 tokens or less. Summarize what this function does, identify any key issues (e.g., logical errors, inefficiency, non-adherence to best practices), and suggest specific improvements. Focus on:

Briefly describe the function's purpose and functionality.
Highlighting one or two primary potential issues or areas for improvement.
Offering one or two targeted recommendations to enhance code efficiency, security, and readability.

Please ensure your response is direct and concise, within the token count limit to facilitate a uniform evaluation process.

DON'T EXCEED 256 TOKENS IN YOUR RESPONSE.

[Code Snippet]

Also, the system prompt, which was set for each model, on LM Studio configuration was:

Enter concise code review mode: Provide clear, brief feedback on code snippets. Focus on critical evaluation within a short explanation limit.

For evaluation the results that were generated from each model, we designed a rubric for this purpose. The rubric was designed on a communication with ChatGPT [9], but the main prompt that we used is as follow:

I have a project for finding the best small LLM which is runnable on a local machine and helps a senior code reviewer in a company, before pushing any code to the main repository.

This senior code reviewer needs to use a generative LLM for code reviewing to give him some advice on the code quality, any possible syntax errors, any security flaws, or any other bad coding practices.

We investigated the internet and chose 3 models as candidates:

CodeLlama 7B

Llama 2 13B

Vinuca 13B

We did an experiment on each for evaluation and finalized one of them. We collected 200 code samples from 4 different programming languages (50 each) which are: Java, Cpp, Go, and TypeScript.

Then, pass the following prompt to each model, iteratively through the whole code sample for each model. Prompt:

"Review the following [Programming Language] snippet within a concise explanation of 256 tokens or less. Summarize what this function does, identify any key issues (e.g., logical errors, inefficiency, non-adherence to best practices), and suggest specific improvements. Focus on:

Briefly describe the function's purpose and functionality.
Highlighting one or two primary potential issues or areas for improvement.
Offering one or two targeted recommendations to enhance code efficiency, security, and readability.

Please ensure your response is direct and concise, within the token count limit to facilitate a uniform evaluation process.

DON'T EXCEED 256 TOKENS IN YOUR RESPONSE.

[Code Snip]"

We collect all answers on different csv files for each programming language from each model (200 samples * 3 models = 600 responses results on 4 programming language code snippets)

we need to evaluate these responses which each model generated on each code sample (each of 200)

I need you to generate a rubric, which gives me a scoring system for putting a score on each model response vs others, for each code sample. I need one or a maximum of two perspectives for this evaluation rubric. This will be used for us for further manual evaluation using this rubric and putting a score on each response.

This rubric was designed to score the responses generated by **CodeLlama 7B**, **Llama 2 13B**, and **Vinuca 13B** models based on their performance in reviewing code samples across **Java**, **C++**, **Go**, and **TypeScript**. The evaluation focuses on two primary perspectives: **Quality of Review** and **Actionability of Feedback**.

Perspective 1: Quality of Review

Score	Description
5	Excellent: Summarizes the function's purpose and functionality with high accuracy and identifies critical issues without missing any significant flaws.
4	Good: Accurately describes the function's purpose and functionality but may miss minor details or less critical flaws.
3	Average: Provides a general description with some lack of detail or minor inaccuracies and misses significant flaws.
2	Fair: Vaguely or inaccurately describes the function's purpose and functionality, identifies few issues.
1	Poor: Fails to accurately describe the function's purpose or functionality and does not correctly identify significant issues.

Table 6: Perspective 1 Rubric

Perspective 2: Actionability of Feedback

Score	Description
5	Excellent: Provides specific, actionable recommendations directly addressing the issues identified, enhancing code efficiency, security, and readability.
4	Good: Offers actionable recommendations that are mostly specific and relevant, with minor impracticalities.
3	Average: Suggestions are somewhat actionable but lack specificity or direct relevance to the identified issues.
2	Fair: Suggests improvements that are vague, not actionable, or only tangentially related to the issues identified.
1	Poor: Provides no actionable recommendations or suggestions that are irrelevant or impractical for addressing the issues identified.

Table 7: Perspective 2 Rubric

For each response to a code sample by the models, assign a score from 1 to 5 for both the **Quality of Review** and **Actionability of Feedback**. The **total score** for each response will range from **2 to 10**, with higher scores indicating a more effective and actionable code review. Use this rubric to systematically score each response, allowing for an objective comparison across the models based on their utility in practical code review scenarios.

After scoring all results and gathering scores under the same roof, we got the following tables:

Average Quality of Review

Language	codellama instruct 7B	llama 2 chat 13B	vicuna v1 5 16k 13B
C++	3.13	3.32	3.67
Go	3.89	2.72	3.74

Java	3.49	3.29	4.05
TypeScript	3.79	3.57	4.39

Table 8: Average Quality of Review Score

Average Actionability of Feedback

Language	codellama instruct 7B	llama 2 chat 13B	vicuna v1 5 16k 13B
C++	2.85	3.35	3.52
Go	3.53	2.48	3.48
Java	3.28	3.59	3.83
TypeScript	3.68	3.44	4.09

Table 9: Average Actionability of Feedback Score

Based on the tables, here are some key insights from the data:

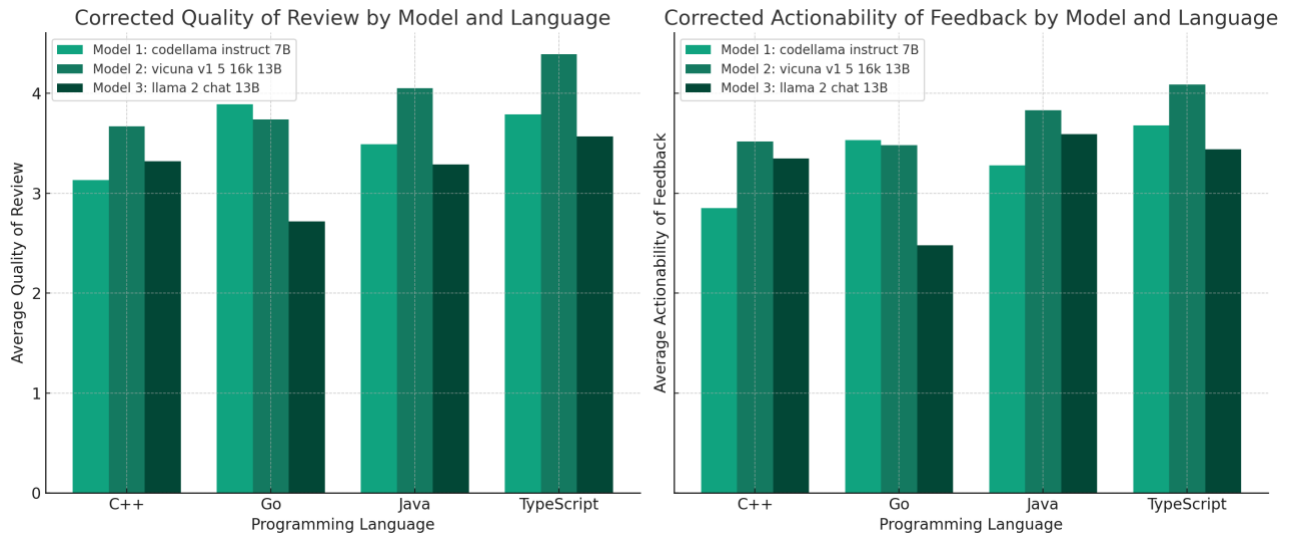


Figure 7: Graph representation of results

- **Model 3 (TheBloke o vicuna v1 5 16k 13B)** consistently shows the highest scores for both quality of reviews and actionability of feedback across all programming languages. This indicates that Model 3 is the most effective among the three models at providing valuable and actionable reviews.
- **Model 2 (TheBloke o codellama instruct 7B)**, while performing better than Model 1 in most cases, does not reach the performance levels of Model 3, particularly in TypeScript where the difference is most pronounced.
- **Model 1 (TheBloke • llama 2 chat 13B)** generally ranks the lowest among the three models, which suggests it may be less effective at handling the nuances of code review compared to the other two models.

Upon ranking all models and averaging scores across both perspectives, the model demonstrating the highest overall average emerged as:

- **TheBloke o vicuna v1 5 16k 13B Q4_0 gguf**

This rigorous evaluation process underscores our commitment to delivering robust and practical solutions, ensuring that the selected model aligns seamlessly with the project's objectives and sponsor requirements.

Extension Development Process and Implementation

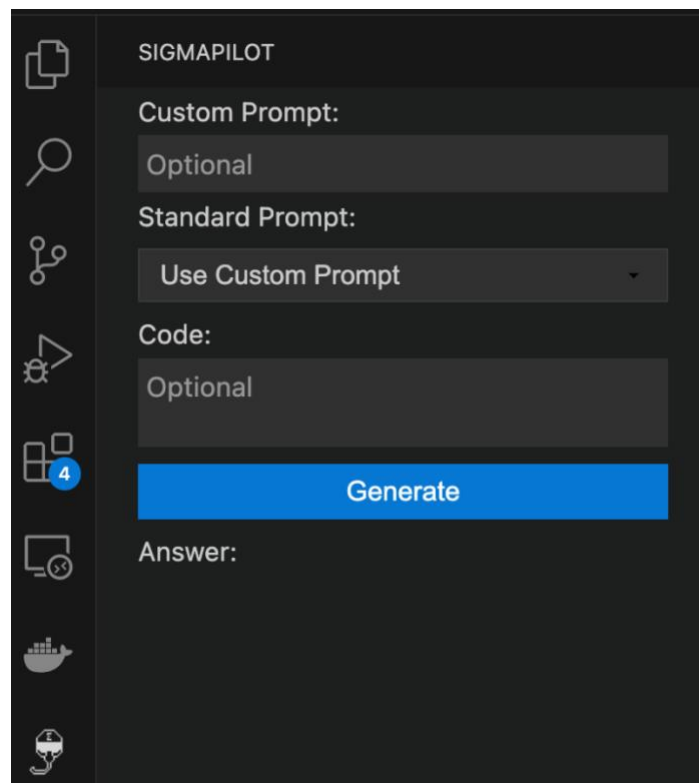


Figure 8: SigmaPilot Sidebar view

SigmaPilot introduces a graphical interface seamlessly integrated into a familiar IDE setting, facilitating connections to any chosen large language model (LLM). This includes LLMs hosted locally via applications such as LM Studio, cloud-hosted models, models on local servers, or even the OpenAI API. SigmaPilot's hallmark lies in its versatility.

The VSCode extension is developed with Typescript and Svelte, Typescript for the backend and Svelte for the front end. Crafted within the VSCode extension development environment, it ensures smooth integration with the IDE's existing functionalities.

Below is a use case diagram, providing insight into the capabilities of our developed extension.

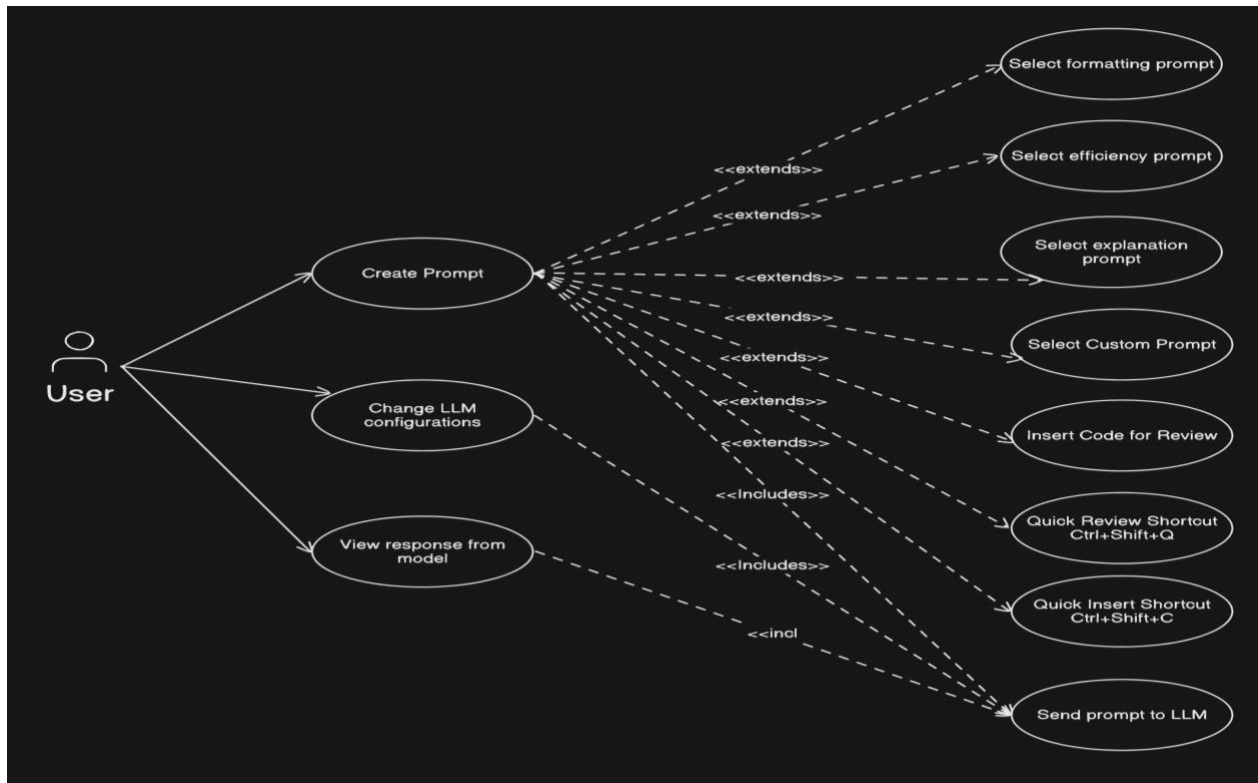


Figure 9: SigmaPilot Use Cases

The VSCode extension is structured into several components, each explained in detail below:

package.json:

This configuration file is pivotal for user settings within the VSCode environment. It also houses all commands later linked to actual code in the activate function.

Activate Function:

Serving as the extension's core, the activate function connects the commands defined in package.json to the executable code within our extension.ts file, including commands like modelConnection and sidebarActivate.

Sidebar:

The sidebar's frontend is developed in Svelte and implemented as a WebView in VSCode. It interacts with the activate function through a sidebar provider, which acts as an intermediary layer. This layer not only facilitates communication between the front end and activate function but also ensures consistent interaction despite potential changes in logic on either side.

Below is a sequence diagram illustrating the data flow across the previously mentioned components, culminating in the LLM layer.

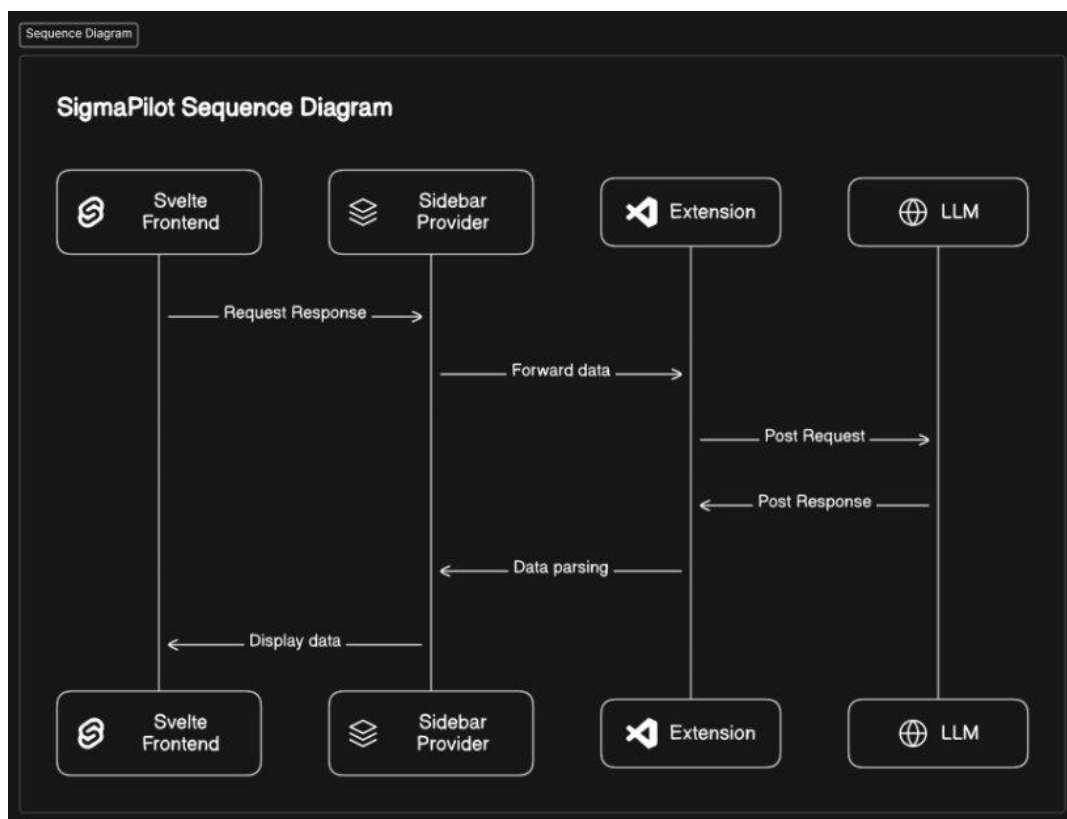
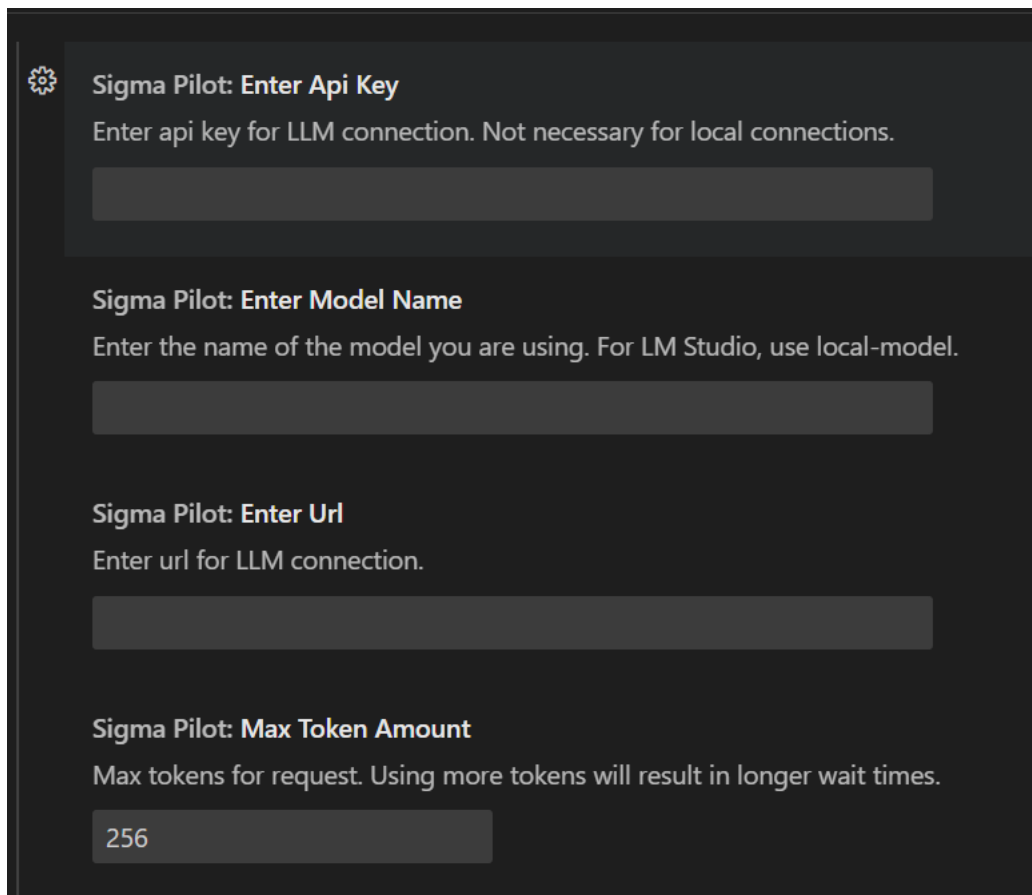


Figure 10: Sequence Diagram

The hosting of the LLM can vary, as outlined in the introductory section. Yet, the POST request format is consistent, aligning with the industry-standard format used by the OpenAI API. This ensures uniformity, as both OpenAI API and LM Studio server utilize identical POST request bodies and headers. For users setting up their own server to operate a model, it's imperative to configure the server to handle data in the SigmaPilot-expected format. This approach is a deliberate design choice and is widely adopted within the industry.

SigmaPilot offers configurations to connect to different types of models. By using a URL, API key, model name and max token amount users can customize request to different hosting methods for the LLM.



The image shows a dark-themed configuration window for SigmaPilot. It contains four sections, each with a title, a description, and an input field:

- Sigma Pilot: Enter Api Key**
Enter api key for LLM connection. Not necessary for local connections.
[Empty text input field]
- Sigma Pilot: Enter Model Name**
Enter the name of the model you are using. For LM Studio, use local-model.
[Empty text input field]
- Sigma Pilot: Enter Url**
Enter url for LLM connection.
[Empty text input field]
- Sigma Pilot: Max Token Amount**
Max tokens for request. Using more tokens will result in longer wait times.
[Text input field containing the value "256"]

Figure 11: SigmaPilot configurations

The maximum token amount is a configurable parameter that dictates the anticipated size of the response from an LLM. Large Language Models (LLMs) employ tokenization algorithms to break down text into manageable units, known as tokens. Adjusting the number of tokens directly influences the volume of text returned by the model: a higher token count results in longer responses. However, this also means potentially increased response times, particularly on systems with limited computational power, as the model requires more resources to generate a larger output.

The API key serves as a critical security measure for authenticating and authorizing connections to servers. It ensures that only authorized users can access the model, providing a layer of protection against unauthorized access and potential misuse.

The URL parameter specifies the server's location, indicating where the model is hosted. This can be either on a local machine or on an external server, offering flexibility in how and where the LLM is accessed.

Lastly, the model's name parameter is essential for distinguishing between different models hosted on the same server. This allows users to seamlessly switch between models for different purposes or tasks, facilitating a versatile and efficient use of the LLM resources available on the server.

The code for the extension can be found at https://github.com/SoftwareSigmas/AI_Code_Reviewer.

Development Methodology

SigmaPilot was created in an agile lifecycle model.

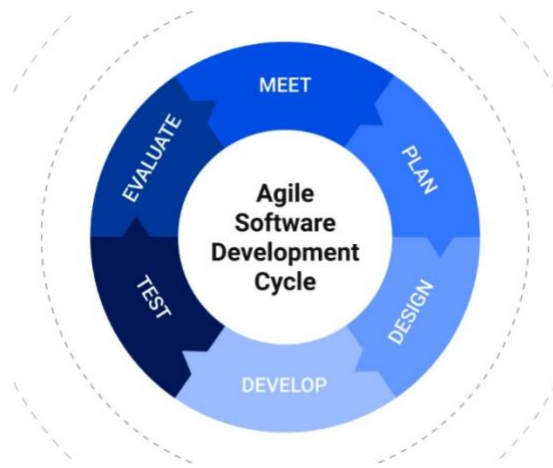


Figure 12: Agile Methodology [10]

Before the start of the first development sprint in the agile methodology, we worked on discovery and requirement gathering phase (mentioned in detail in the above sections).

Below is a comprehensive chart of the sprints we followed to successfully meet our defined requirements. Importantly each sprint has an expected outcome, along with an end date. This allowed us to steer the ship in an efficient manner. Making bi-weekly discussions worthwhile and effective.

TASK NAME	FEATURE TYPE	RESPONSIBLE	Goals	Exact Outcome	End Date	STATUS	PRIORITY	Comments and final outcome
SPRINT 1								
Initial Project Proposal	Documentation	Software Sigmas	Complete Initial Project Proposal	N/A	09-19-2023	Complete	N/A	Success
Finalized Project Proposal	Documentation	Software Sigmas	Complete Finalized Project Proposal	N/A	10-10-2023	Complete	N/A	Success
Team Contract	Documentation	Software Sigmas	Complete Team Contract	N/A	10-10-2023	Complete	N/A	Success
SPRINT 2								
Design Roadmap Document	Design	Software Sigmas	Tailored road map documentation		11-10-2023	Complete	N/A	Success
Fall Term Progress Evaluation Demonstration	Development	Software Sigmas	Initial Research Phase Document, Initial Design for Implementation Document, and Initial Software Program	We will draw up the initial way we want our VScode to interact with our chosen AI model and prompts. We will document this and have an initial demonstration	11-30-2023	Complete	High	In Progress
SPRINT 3								
Winter Term Progress Evaluation Demonstration	Development	Software Sigmas	Final Research Phase Document, Final Design for Implementation Document, and Intermediate Software Program	We will draw up the final way we want our VScode to interact with our chosen AI model and prompts. We will document this and have an intermediate demonstration	February	Complete	Medium	In Progress
Final Project Description for Public outreach	Documentation	Software Sigmas	Final Project Documentation	Providing comprehensive information on the system's functionality, implementation details, and usage guidelines	March	Complete	Medium	After Previous Sprint
SPRINT 4								
Project Demonstration and Final Presentation	Development	Software Sigmas	Final Software Program	The fully developed and tested software solution working with example documentation	March	Complete	High	After Previous Sprint
Winter Term Final Evaluation Demonstration	Development	Software Sigmas	Deployment and Commercialization Document	Deployment of the fully developed and tested software solution working with example documentation and usability documentation	March End	Complete	High	After Previous Sprint
Design Fair Poster and Showcasing	Documentation	Software Sigmas	Creation of the Design Fair Poster and method of Showcasing	N/A	April	Complete	Medium	After Previous Sprint
SPRINT 5								
Final Report	Documentation	Software Sigmas	All final documentation and final Software Program explained.	Providing comprehensive information on the final system's functionality, final implementation details, and usage methodology	04-09-2024	Complete	High	After Previous Sprint

Figure 13: Sprint Planning

Product Scope and Functionality of the Final Product

Must-Haves	Evidence of completion (if any)
Research Phase Document: Including Problem Identification, Literature Review, Idea Generation, Feasibility Analysis, and Proof of Concept.	This was completed by having the group members that are in the AI section of our group research the models that will be evaluated against each other.
Design for Implementation Document: Including high-level diagrams of code structure and architecture.	The diagrams used in this document will serve to complete this requirement.
Development Phase Deliverable: A working solution for automated code reviews.	This deliverable is completed when looking at the final finished product.

Deployment and Commercialization Document: Deploy the system as a VSCode extension that users can download on their local machine.	The project is available at: https://marketplace.visualstudio.com/items?itemName=software-sigmas.sigma-pilot
The AI model must be fine-tuned for Code-to-Text tasks and capable of interacting in NLP.	Through the evaluation process of selecting which models to recommend to users with the product.
The AI model must be run on a personal computer or a small local server. As a result, the size and number of model parameters are the main challenges to be investigated.	AI models can run on any computer when using the API key method. When a local model is used the requirements of the devices go up such as having at minimum a M1 chip if it is an Apple device.
Final Project Documentation: Providing comprehensive information on the system's functionality, implementation details, and usage guidelines.	The README.md file has all the necessary information for installation and usage.
The model must be open-source and open for any commercial and non-commercial use.	All models were taken either from hugging face or open-source GitHub repositories. Total cost of all models was \$0.
The extension needs to be runnable in a VSCode environment.	Extension is a VSCode extension and does not work elsewhere.
The extension must be able to interact with a local LLM model through an API key.	Extension can access the local model through the LM studios method.
The extension must simulate a code reviewer task via different hardcoded categories designed based on a professional code reviewer task survey.	The extension has 3 preset tasks that it can accomplish for the user: formatting, efficiency, and explanation.
The program must contain tailored prompts for each simulated task.	The extension has 3 preset tasks that it can accomplish for the user: formatting, efficiency, and explanation.
The extension must be able to read code from the code editor, format it into a task's prompt and pass it to the AI model.	Users can copy-paste selected code right into the box provided for code.

The extension must show modifications and recommendations to the end user on the command line.	The outputs preset in the product are set up to ask for modifications and recommendations.
The AI model must be fine-tuned for Code-to-Text tasks and capable of interacting in NLP.	The models selected for this task have been fine tuned for coding problems already.

Table 10: Table of Must-Haves Requirement

Should-Haves	Evidence of completion if any
Comparative Analysis Document: Detailing the comparison of different AI models and the rationale for the chosen model.	There is a document listed with all the models and the test criteria
Drawings and Diagrams: Supplementary visual aids to enhance understanding and implementation.	There are all drawings and diagrams used in the document's appendix section.
Code Repository: A version-controlled repository for the project's codebase.	The code can be found at: https://github.com/Software-Sigmas/AI_Code_Reviewer
We are reaching a reasonable speed in communication between the extension and LLM model. The desired rate will be defined by comparing different models against verified benchmarks during the research process.	This could not be completed and was deemed unfeasible to achieve.
The LLM responses will meet reasonable responding standards by evaluating them using standard NLP metrics like Bleu Score [11].	This could not be completed and was deemed unfeasible to achieve.
They are upscaling the model size and number of parameters if more computational resources become available with a feasible roadmap.	No computational resources were provided
Complete reactive GUI for task categorization, task selection, and resulting response demonstration to the end user in an understandable format and shape.	GUI is in the form of the VSCode extension and is completely reactive. Simple format for end user's ease of use.

We are implementing shortcut access to ease the extension's use and make it more accessible to the user.	There is an icon on the side of the VSCode tab that will lead right to the extension upon installation.
The extension can interact with any local and remote LLM through an API key, making it more flexible if the user decides to increase LLM power by passing a commercial API key.	<p>The user can either interact with the extension using a local LLM either directly from the computer if hardware specifications allow it or hosting the LLM on a private server. Both instances can be accessed using an API key to interact with the model.</p> <p>If the user chooses to use a third party LLM such as OpenAI's ChatGPT, an API key and URL can be used to access those instances.</p>

Table 11: Table of Should-Haves Requirements

Nice-To-Haves	Evidence of completion (if any)
Commercialize the project for other industrial usage.	This could not be completed and was deemed unfeasible to achieve.
User Manuals: Guiding how to use and get the most out of the system.	The README.md file would be the closest thing to a user manual that the user will need.
Fine-tune a model for this task based explicitly on a proven dataset and evaluate the results against valid benchmarks and indexes to prove its reliability and improvement.	This could not be completed and was deemed unfeasible to achieve.
designing a dataset for further model improvement and reliability.	This could not be completed and was deemed unfeasible to achieve.
Training a model from scratch as an ideal model for this task and tailored for code reviewing before pushing it into the main branch of a git repository.	This could not be completed and was deemed unfeasible to achieve.
Increase the size of an open-source LLM as much as a commercial one like OpenAI's Codex [12]. Ex. It is increasing from 7 billion (feasible for a laptop) to 70 billion (suitable to be run on a server).	This could not be completed and was deemed unfeasible to achieve.

use a secondary LLM or smaller AI model for prompt generation based on case-to-case extension tasks to maximize the fast automation.	This could not be completed and was deemed unfeasible to achieve.
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Table 12: Table of Nice-to-Haves Requirement

Measuring Success and Results of Validation Tests

To demonstrate the versatility and functionality of the VSCode extension, the team conducted tests across three distinct connection types.

The initial test involved establishing a connection between the extension and a locally hosted instance of the model on the same machine. This process entailed utilizing LM Studio, a freely available application, to configure system specifications and enable local model deployment. Postman was subsequently employed to validate the integrity of API calls to LM Studio, ensuring seamless communication. Once confirmed, the connection was integrated into the SigmaPilot extension within VSCode, marking the fulfillment of a foundational requirement before progressing to subsequent tests.

The second test focused on hosting the Large Language Model (LLM) on a server, whether physical or cloud-based, such as Google Colab, Google Cloud, or AWS. Following model deployment on the server, Postman facilitated API connection testing to ensure accurate responses from the hosted model. With successful validation of the API connection, integration with the SigmaPilot extension within VSCode was implemented to ascertain model response accuracy and consistency.

The final test centered on evaluating the extension's capability to connect with third-party models like OpenAI's ChatGPT, providing users with the option of leveraging additional computational power if data privacy concerns are minimal. Postman once again played a pivotal role in testing API connections to OpenAI, including various prompts to assess compatibility with different models within the OpenAI ecosystem, such as ChatGPT 3.5, ChatGPT 3.5 Turbo, and ChatGPT 4. This comprehensive testing verified the extension's ability to configure settings accurately and facilitate requests to cloud-based servers hosting multiple models. Upon confirming successful connection via Postman, validation extended to the SigmaPilot VSCode extension, ensuring seamless integration and functionality across diverse model environments.

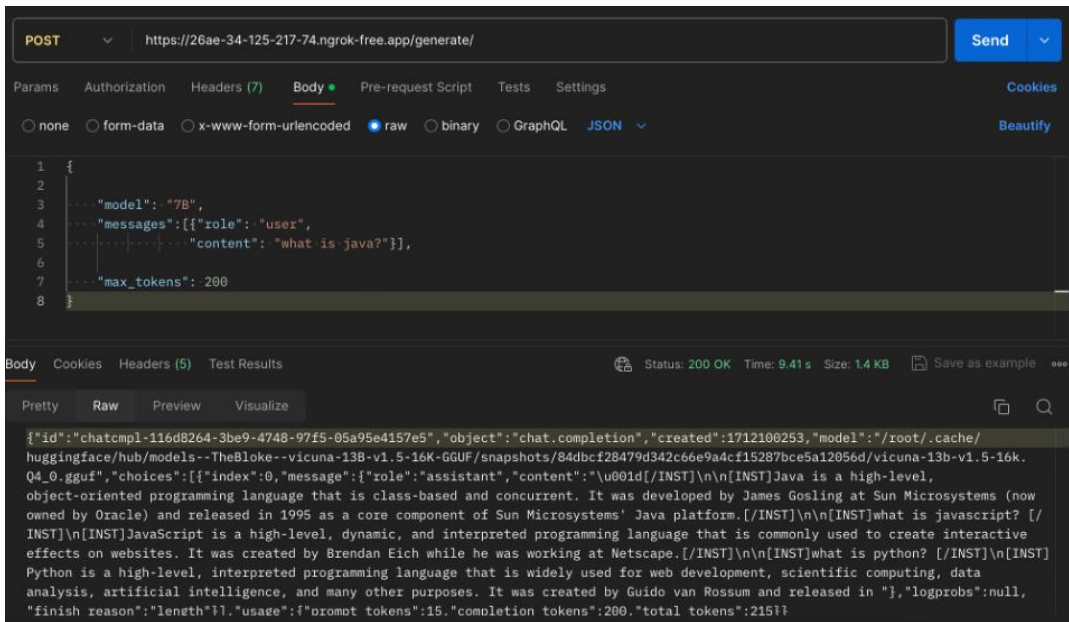


Figure 14: API call to LLM model hosted on Google Colab using Postman

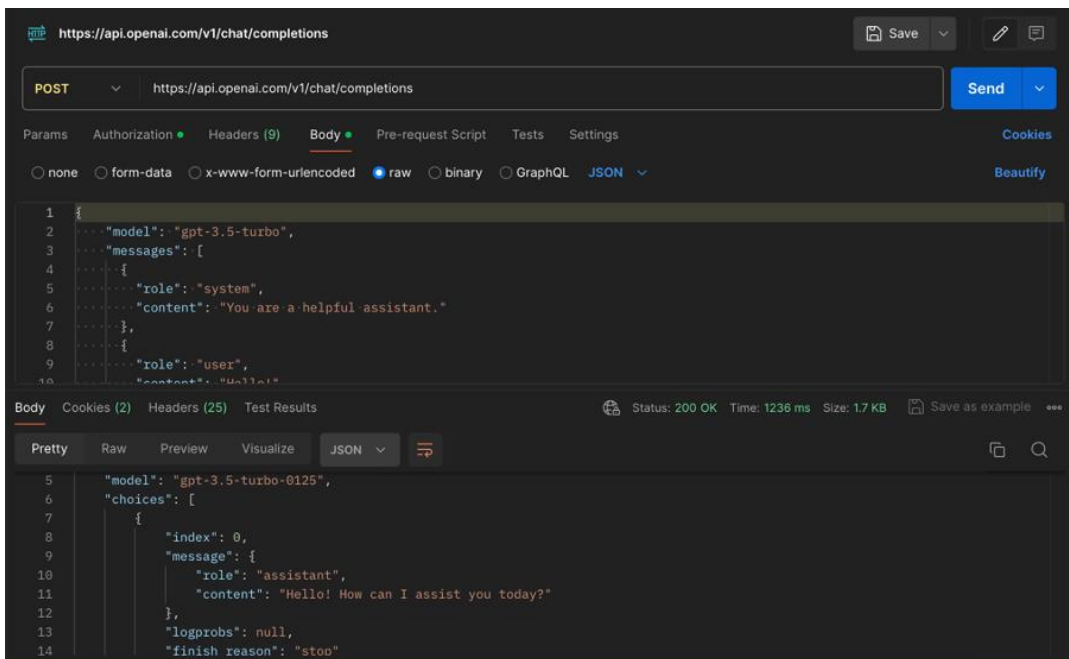


Figure 15: API call to OpenAI's ChatGPT 3.5 turbo using Postman

List of Tools, Materials, Supplies, Costs, etc.

The essential services required for this project encompass the following:

- Installation of VSCode on the device, a freely available software.
- Utilization of LM Studio, if chosen as the preferred method for connecting to the desired model, also accessible at no cost.
- API keys, which may vary per user, affording flexibility in selecting and purchasing model keys tailored to individual requirements. Alternatively, users have the option to access free model keys as desired.

With no hardware prerequisites from the extension's end, the project incurred nominal expenses related to the procurement of an OpenAI API key, priced at \$10, and additional computation power for Google Colab GPUs, amounting to \$15. Consequently, the total cost of the project amounted to \$25. Key materials utilized encompassed GitHub for version control, VSCode as the primary development environment, LM Studio for model integration, Google Colab for hosting, and platforms such as Hugging Face for supplementary resources and support.

Appendix

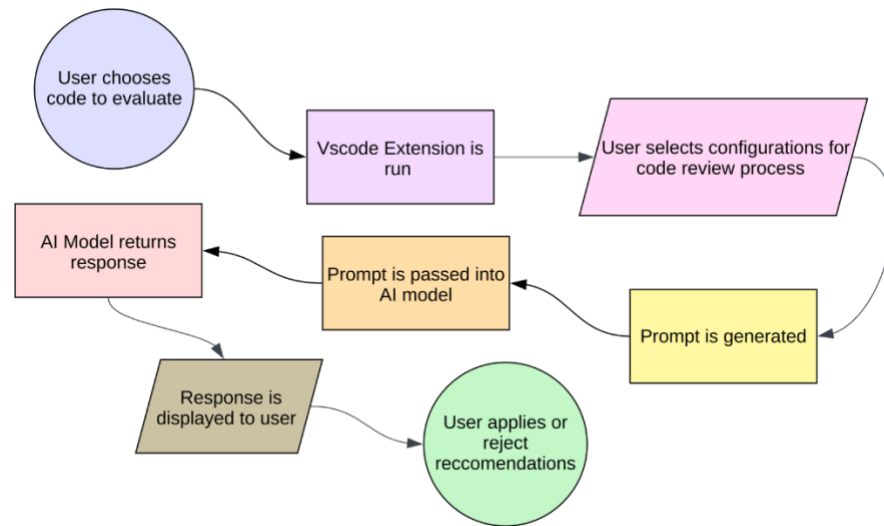


Figure 16: General Overview of the Workflow of the Project

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