Self-collaboration Code Generation via ChatGPT

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Abstract

Code generation is widely regarded as a key technique for elevating the automation and ultimate quality of software development. Nevertheless, existing code generation approaches usually concentrate on a single stage of the software development process (i.e., the coding stage) and do not take into consideration other stages that are crucial in reducing complexity and ensuring quality assurance. The organization and conduction of multiple stages in software development require collaborative teamwork. To this end, this paper presents a self-collaboration framework for code generation employing large language models (LLMs), exemplified by ChatGPT. Specifically, multiple LLMs play distinct roles through role instructions to form teams, addressing code generation tasks collaboratively and interactively without the need for human intervention. To showcase our framework, we assemble an elementary team consisting of three ChatGPT roles (i.e., analyst, coder, and tester) corresponding to the analysis, coding, and testing stages of software development. We conduct comprehensive experiments on various code-generation benchmarks. The experimental results indicate that self-collaboration code generation improves 29.9%-47.1% relative performance compared to naive direct code generation, achieving state-of-the-art performance and even surpassing GPT-4.

1 Introduction

Code generation aims to generate code that satisfies human requirements expressed in the form of some specification. Successful code generation can improve the efficiency and quality of software development, even causing changes in social production modes. Therefore, code generation has been a significant research hotspot in the fields of artificial intelligence, natural language processing, and software engineering. Recently, code generation has made substantial advancements in both academic and industrial domains [Shen et al., 2022, Chen et al., 2021, Dong et al., 2022, Li et al., 2022]. In particular, LLMs have achieved excellent performance and demonstrate promising potential on code generation tasks [Nijkamp et al., 2022, Fried et al., 2022, Zheng et al., 2023].

Existing code generation approaches tend to concentrate solely on the implementation of requirements, which corresponds to the coding stage of software development process. Despite the expertise of human programmers, generating high-quality and reliable code remains a challenging task when relying merely on coding stage. In addition to coding stage, software development encompasses other stages such as analysis and testing, which significantly contribute to enhancing the productivity and quality of software projects. As user requirements grow increasingly complex, it becomes crucial to incorporate additional stages to assist models in comprehensively addressing code generation. Therefore, we introduce extra-coding stages in software development to aid code generation, with the goal of improving the quality of the final code, including functionality, readability, and maintainability.

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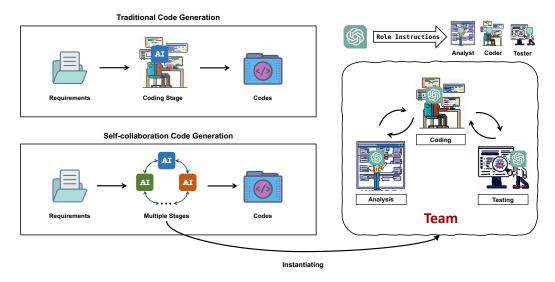


Figure 1: Self-collaboration framework for code generation and its instance.

In this way, code generation is regarded as a microcosm of software development, which involves multiple stages, such as requirements analysis, design, coding, and testing.

Completing multiple stages of software development is a complex task for an individual. To address this, software development teams are formed, with different roles taking on responsibilities at various stages of the process. In order to handle multiple stages involved in code generation, we need to organize a virtual team, which is comprised of different roles played by models, such as analyst, coder, and tester. These roles have distinct divisions of labor and are asked to collaborate and interact effectively in order to accomplish code generation tasks.

There are numerous approaches available for tasks at various stages of software development, such as code repair and test generation. Despite the availability of these approaches, there are certain difficulties in effectively combining these approaches to achieve our desired goals. The main reasons are obstacles to collaboration and interaction among existing models, and an extensive volume of labeled training data is required for the models to comprehend this behavior. However, due to the revolutionary advances in artificial general intelligence (AGI), LLMs represented by ChatGPT [OpenAI] provide a turning point. As a well-known generalist model, ChatGPT aligns human needs through instructions or prompts and performs well on various tasks related to software development. Furthermore, ChatGPT uses language as the basis of input and output and is optimized for dialogue tasks. These prerequisites offer the potential for inter-model collaboration and interaction.

In this paper, we propose a self-collaboration framework for code generation based on LLMs like Chat-GPT. By using role instructions, multiple LLMs undertake specific roles to handle code generation tasks in a collaborative and interactive manner without requiring human intervention. Furthermore, we incorporate the methodology of software development into code generation and instantiate a virtual team derived from our proposed framework. This virtual team is elementary and consists of merely three roles acted by ChatGPTs, which correspond to the analysis, coding, and testing stages of software development. Extensive experimental results demonstrate that self-collaboration code generation attains substantial improvements in comparison to naive direct code generation. Additionally, self-collaboration code generation achieves state-of-the-art (SOTA) performance on multiple code-generation benchmarks.

The primary contributions of our work can be summarized as follows:

- We propose a self-collaboration framework for code generation, which allows LLMs to divide the labor involved in solving a complex task and collaborate with each other.
- We instantiate an elementary team following the methodology of software development. This team comprises merely three ChatGPT roles (i.e., analyst, coder, and tester) responsible for their respective stages in the software development process.

Based on our self-collaboration framework, the virtual team formed by ChatGPT (GPT-3.5)
can achieve SOTA performance on multiple code-generation benchmarks, even surpassing
GPT-4.

Self-collaboration framework provides a multi-stage, model-stacking approach to automatic code generation. This innovative approach has the potential to significantly improve the quality of generated code, reduce human intervention, and accelerate the development of complex software systems. Moreover, our work also can serve as a foundation for future research on self-collaboration approaches in various domains and the development of more advanced and specialized virtual teams to tackle more complex tasks.

2 Preliminary Knowledge

2.1 Code Generation

Code generation is a technology that automatically generates source code to facilitate automatic machine programming in accordance with user requirements. It is regarded as a significant approach to enhancing the automation and overall quality of software development. Existing code generation approaches or tools demonstrate relative proficiency in addressing "minor requirements" scenarios, such as function completion and line-level code generation. However, when confronted with complex requirements and software system design, they fall short of offering a comprehensive solution.

2.2 Software Development

Software development is a product development process in which a software system or software part of a system is built according to user requirements. The software development life cycle (SDLC) breaks up the process of creating a software system into discrete stages, including requirement analysis, planning & design, coding, testing, deployment, and maintenance. Software engineering methodology provides a framework for the development process and defines the stages and activities involved in the development of software. Different software development methodologies typically follow the SDLC, but they differ slightly in their implementation. Some common methodologies include Waterfall, Agile, and DevOps.

Software development is a complex process that involves many different activities and tasks, necessitating the formation of a software development team. The structure of a software development team typically includes roles such as developers, testers, designers, analysts, project managers, and other specialists. However, the structure of the software development team can be adjusted depending on factors such as the type and complexity of the project and even the chosen methodology.

3 Self-collaboration

In this section, we first introduce our self-collaboration framework in detail, and then we give an instance of assembling a virtual team following the methodology of software development.

3.1 Framework

Given a requirement x, we propose to perform self-collaboration for LLMs to generate the output y. The task is defined as $\mathcal{T}: x \to y$. Our self-collaboration framework consists of two parts: division of labor (DOL) and collaboration.

3.1.1 Division of Labor

In DOL part, we leverage prior knowledge to decompose a complex task into a sequence of stages $\mathcal{T}\Rightarrow\{\mathcal{S}_i\}_{i=1}^l$ and construct some distinct roles $\{R_j\}_{j=1}^m$ based on LLMs and role instructions. Each role R_j is responsible for one or more stages $\mathcal{S}_i's$.

It is widely acknowledged that LLMs are sensitive to context, as they are trained to predict subsequent tokens based on preceding ones. Consequently, it is prevalent to control LLM generation using instructions or prompts [Ouyang et al., 2022a, Chung et al., 2022, OpenAI, 2023]. We employ a

specific type of instruction to assign identity and responsibilities to LLMs, which we refer to as role instructions. Specifically, we ask an LLM to act as a particular role that has a strong correlation with its responsibilities. Furthermore, we need to convey the detailed tasks this role should perform. If our requirements are common enough and we can find a matching role, there may be no need to outline the role's responsibilities. Generally, the more detailed description of your requirements, the better LLM's output will align with your desired outputs.

The advantage of utilizing role instructions lies in their ability to be provided only once at the beginning of interactions. In subsequent interactions, intentions are conveyed rather than a combination of instructions and intentions. Therefore, role instructions enhance the overall efficiency and clarity of subsequent communication and collaboration.

3.1.2 Collaboration

In collaboration part, we focus on facilitating effective interactions between LLMs assuming different roles within the self-collaboration framework. Each LLM, guided by its designated role instructions, contributes to the overall task by performing its assigned responsibilities. As the stages progress, LLMs communicate their outputs with other LLMs, refining the information and ensuring an accurate and thoughtful output y.

Leveraging role instructions, the output format of LLMs can be effectively controlled. In conjunction with the foundational aspects of the language model, this enables the preliminary establishment of communication between LLMs.

The collaboration part can be formalized as:

$$\underset{s_t}{\text{arg max}} \ P(s_t|s_{\{< t\}}, R_{m(S_t)}, x), \tag{1}$$

where s_t is the output of stage \mathcal{S}_t , $s_{\{< t\}}$ indicates the prerequisite-stage outputs of \mathcal{S}_t 3, and $R_{m(S_t)}$ represents the role corresponding to \mathcal{S}_t . We consider the computation of $P(s_t|s_{< t},R_{m(S_t)},x)$ as the collaboration, wherein role $R_{m(S_t)}$ collaborates with the roles of each preceding stage to generate s_t . Output y is iteratively updated along with the progression of stage \mathcal{S}_t :

$$y_t = f(s_t, y_{< t}) \tag{2}$$

where f is an update function. Upon completion of \mathcal{S}_n , the final output y is obtained. To promote effective collaboration, we set up a message-sharing pool, from which each role grabs the required information to accomplish their respective tasks s_t via Eq. (1). A complete algorithm description of our self-collaboration framework is outlined in Algorithm 1.

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Algorithm 1 Pseudocode of self-collaboration framework.
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Require: Requirement x, Task \mathcal{T}, and LLM \mathcal{M}.
Ensure: Output y.
     # DOL Part
 1: Initial \{S_i\}_{i=1}^l according to \mathcal{T}.
2: Initial \{R_j\}_{j=1}^m based on \mathcal{M} and role instructions.
     # Collaboration Part
 3: Initial message-sharing pool \mathcal{P}.
 4: t \leftarrow 0.
 5: repeat
         Obtain s_{< t} from \mathcal{P}.
         Sample s_t via Eq. (1).
 7:
         Add s_t to \mathcal{P}.
 8:
 9:
         Update y_t via Eq. (2).
10:
         y \leftarrow y_t
         t \leftarrow t + 1.
12: until End condition is satisfied
```

13: **return** *y*

³Note that our self-collaboration framework can be parallelized if the relationship between stages $\{S_i\}_{i=1}^l$ is not a straightforward linear relationship.

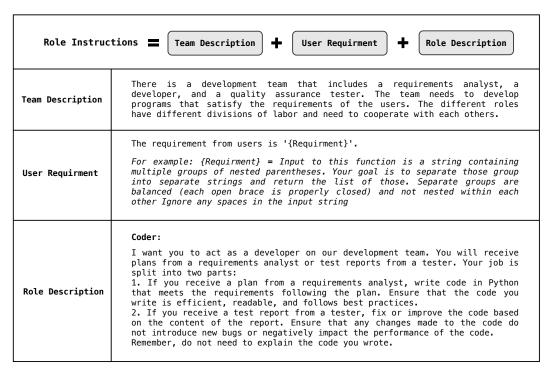


Figure 2: An example of role instruction for coder in the instance of our self-collaboration framework.

3.2 Instance

To instantiate our proposed framework, we introduce the classic waterfall model from the software development methodology into self-collaborative code generation. According to the waterfall model, software development constitutes a process wherein a series of stages are conducted sequentially. To accommodate code generation, we selected three stages: analysis, coding, and testing. The process flows from one stage to the next, and if issues are found, returns to the previous stage to make changes. To this end, we establish an elementary team to generate code, comprising an analyst, coder, and tester, responsible for the analysis, coding, and testing stages. As shown in Fig. 1 (right), there is communication between two stages, and we set a maximum interaction n for both stages. Specifically, we use role instructions for ChatGPT to play the following roles:

3.2.1 Analyst

The goal of an analyst is to develop a high-level plan and focus on guiding the coder in writing programs, rather than delving into implementation details. Given a requirement x, the analyst decomposes x into several easy-to-solve subtasks that facilitate straightforward implementation by coder, and develops a high-level plan that outlines the major steps of the implementation.

3.2.2 Coder

As the central role of this team, coder will receive plans from an analyst or test reports from a tester throughout the development process. Thus, we assign two primary responsibilities to the coder through role instructions: 1. Write code that fulfills the specified requirements, adhering to the plan furnished by the analyst. 2. Repair or refine the code, taking into account the feedback of test reports feedbacked by the tester. The details of the coder's role instructions are shown in Fig. 2.

3.2.3 Tester

The tester acquires the code authored by the coder and subsequently documents a test report containing various aspects, such as functionality, readability, and maintainability. Compared with directly

generating test cases, we argue that producing test reports is more in line with the language model's tendencies, whether it is the input side or the output side of the communication.

We update the output y_t only when the stage S_t is coding, and this development process concludes upon the tester's confirmation that no issues persist with y_t .

4 Experiment Setup

4.1 Benchmarks

We perform a comprehensive evaluation on code generation benchmarks to demonstrate the efficacy of our self-collaboration approach.

MBPP [Austin et al., 2021] comprises 974 crowd-sourced Python programming problems. Each problem within the benchmark includes an NL description, a code solution, and three automated test cases. A portion of the manually verified data is extracted as "**MBPP-sanitized**".

HumanEval [Chen et al., 2021] consists of 164 handwritten programming problems. Each problem covers a function signature, NL description, function body, and an average of 7.7 unit tests.

HumanEval-X [Zheng et al., 2023] is constructed based on HumanEval, and aims to better assess the multilingual capabilities of code generation models. HumanEval-X contains additional programming languages, such as C++, Java, JavaScript, and Go.

MBPP-ET and **HumanEval-ET** [Dong et al., 2023] are expanded versions of MBPP and HumanEval with over 100 additional test cases per task. This updated version includes edge test cases that enhance the reliability of code evaluation compared to the original benchmark.

4.2 Settings & Baselines

In this paper, we employ two prevalent settings for code generation: The first setting, referred to as NL + signature + public test cases, provides an NL description, function signature, and public test cases as input prompts. The second setting, denoted as NL-only, exclusively utilizes the NL description as an input prompt.

For the first setting, i.e., **NL** + **signature** + **public test cases**, we compare our proposed approaches with various SOTA approaches in code generation tasks, showcasing the effectiveness of self-collaboration code generation.

CodeX (175B) [Chen et al., 2021], also known as code-davinci-002, is fine-tuned from davinci 175B [Brown et al., 2020] on multilingual code data with code-completion tasks. CodeX is also the backbone model that powers Copilot [GitHub] (a well-known commercial application).

CodeT [Chen et al., 2022] employs LLMs to automatically generate test cases for code samples. It executes code samples with these test cases and conducts a dual execution agreement, taking into account output consistency against test cases and output agreement among code samples.

PaLM Coder (540B) [Chowdhery et al., 2022] is finetuned from PaLM 540B on code, where PaLM uses an ML system, named Pathways, that enables highly efficient training of very large neural networks across thousands of accelerator chips.

GPT-4 [OpenAI, 2023] is a large-scale, multimodal model which can accept image and text inputs and produce text outputs. GPT-4 exhibits human-level performance on various benchmarks.

ChatGPT (**GPT-3.5**) [OpenAI] is a sibling model to InstructGPT [Ouyang et al., 2022b], which is trained to follow an instruction in a prompt and provide a detailed response. We access ChatGPT through OpenAI's API. Since ChatGPT receives regular updates, we employ gpt-3.5-turbo-0301 as our base model, which remains static for 3-month intervals, to minimize the risk of unexpected model changes affecting the results.

Despite the widespread use of this setting, it encounters several issues, as outlined below: 1. The function signature contains valuable information, such as the function name, argument types and names, and return value type, as do public test cases. 2. This setting is mainly suited for function-level code generation and proves challenging to extend to file-level or project-based code generation. 3.

Table 1: Comparison of self-collaboration and other approaches (with their setting, i.e., NL + signature + public test cases).

Methods	HumanEval	HumanEval-ET	MBPP	MBPP-ET
Codex (175B)	0.47	0.317	0.581	0.388
+ CodeT	0.658	0.517	0.677	0.451
PaLM Coder (540B)	0.36		- $ 0.47$	
GPT-4	0.67	-	-	-
ChatGPT (GPT-3.5) + Self-collaboration	0.573 0.744 († 29.9%)	0.427 0.561 († 31.4%)	0.522 0.682 († 30.7%)	0.368 0.495 († 34.6%)

Some code generation benchmarks, such as MBPP, do not provide function signatures and public test cases, which is also common in real-world scenarios.

To this end, we also explore the second setting, namely **NL-only**, which is more consistent with real-world development scenarios. Analogous to the previous setting, we employ **ChatGPT** (**GPT-3.5**) as our base model and perform extensive experiments based on ChatGPT.

In order to increase the stability of LLM output, we set the decoding temperature to 0. Upon assigning LLMs their respective identities and responsibilities through specific instructions, it becomes sufficient to merely submit requests to LLMs. Subsequently, LLMs can autonomously form a team and address tasks in a collaborative and interactive manner, eliminating the necessity for human intervention. Unless otherwise stated, the maximum number of interactions between LLMs is limited to 4.

4.3 Metrics

In order to evaluate the accuracy of the generated code, we utilize the **Pass@k** metric, which gauges the functional correctness of the produced code by executing test cases. We adopt the unbiased variant of Pass@k as proposed by [Chen et al., 2021]. In this approach, for each problem, we generate $n \geq k$ samples and count the number of correct samples $c \leq n$, which successfully pass all test cases of this problem. Pass@k can be formulated as:

$$Pass@k = \mathbb{E}_{Problems} \left[1 - \frac{\binom{n-c}{k}}{\binom{n}{k}} \right]. \tag{3}$$

In this paper, we are mainly concerned with **Pass@1**, which is a representative of the Pass@k family, because in real-world scenarios we usually consider only single generated code.

5 Experimental Results

5.1 Main Results

Due to commercial constraints, most of the compared models cannot be directly invoked. Therefore, we reference the results reported in other studies while ensuring the consistency of method settings across all models, specifically by uniformly employing the NL + signature + public test cases configuration. The experimental results reveal that our self-collaboration framework significantly enhances the performance of the base LLM. Remarkably, even with a simple three-member team (including an analyst, coder, and tester), self-collaboration code generation based on ChatGPT (GPT-3.5) achieves the best performance across four code generation benchmarks, surpassing even GPT-4. When compared to ChatGPT (GPT-3.5), the improvement offered by our framework is substantial, with a relative increase ranging from 29.9% to 34.6%. It is noteworthy that the self-collaboration code generation yields more significant improvements on the datasets associated with extended test cases, namely HumanEval-ET and MBPP-ET. This suggests that our framework can effectively assist base LLMs in generating higher-quality code. This enhancement may be attributed to the collaborative team's ability to consider a wider range of boundary conditions and address common bugs. Considering the gap of the base LLM itself, applying our framework to a stronger model, such as GPT-4, will produce better results.

Table 2: Effectiveness of each ChatGPT role in self-collaboration code generation.

Roles	HumanEval	HumanEval-ET	MBPP	MBPP-ET
Coder	0.451	0.353	0.475	0.343
+ Analyst	$0.549 \ (\uparrow 21.8\%)$	$0.452 \ (\uparrow 28.1\%)$	$0.548 \ (\uparrow 15.4\%)$	$0.399 \ (\uparrow 16.4\%)$
+ Tester	$0.568 \ (\uparrow 26.0\%)$	$0.452 \ (\uparrow 28.1\%)$	0.649 († 36.7%)	0.478 († 39.4%)
+ Analyst + Tester	0.635 († 40.8%)	0.519 († 47.1%)	$0.555 \ (\uparrow 16.9\%)$	$0.408 \ (\uparrow 19.0\%)$

Table 3: The influence of maximum interaction for Self-collaboration code generation.

Method	Maximum Interaction	HumanEval	HumanEval-ET	MBPP	MBPP-ET
ChatGPT (GPT3.5) + Self-collaboration	1 2 4	0.604 0.622 0.635	0.507 0.507 0.519	0.530 0.541 0.555	0.380 0.385 0.408

We further investigate the second setting, focusing on code generation with only NL description. Under this setting, we compare the performance of each ChatGPT role within the elementary team instantiated by our self-collaboration framework, as illustrated in Table 2. The experimental results reveal that the performance significantly improves when compared to employing only the coder role after forming a team, regardless of whether it is a two-role or three-role team. The coder-analyst-tester team achieved the best results on the HumanEval and HumanEval-ET benchmarks, with relative improvements of 40.8% and 47.1%, respectively. In contrast, the coder-tester team attained the highest performance on the MBPP and MBPP-ET benchmarks, with relative improvements of 36.7% and 39.4%, respectively. The suboptimal performance of the analyst on the MBPP and MBPP-ET benchmarks may be attributed to the relatively simplistic requirements of MBPP, which do not necessitate planning. Additionally, numerous test cases for various tasks in MBPP deviate from the typical writing habits and reasoning processes of humans, such as programs returning tuples without any NL hints. As a result, we posit that task-specific teams should be customized to achieve optimal results.

To assess the impact of maximum interaction on self-cooperative code generation, we carry out experiments as depicted in Table 3. Owing to the nature of maximum interactions, the majority of tasks conclude after the initial round of interaction, resulting in a minimal increase in execution time. In general, a higher maximum number of interactions yields better outcomes. Nonetheless, due to the constraint of maximum tokens, our exploration was limited to a maximum of 1 to 4 rounds.

5.2 Case Study

In this case study, we demonstrate an example of self-collaboration code generation, as shown in Fig. 3. In this example, we can observe the following steps in a code generation process: 1. The analyst conducts a comprehensive analysis and devises a plan to address the entire set of requirements. For this requirement, the analyst first decomposes it into several easy-to-solve subtasks, and then gives some high-level plans based on the subtasks. 2. The coder implements a code according to the given requirements and the devised decompositions and high-level plans. It is evident that each sub-module within this implemented code exhibits a nearly one-to-one correspondence with decompositions and high-level plans. 3. The tester composed a detailed test report for the implemented code, identifying errors within it. In this test report, the tester thinks that the implemented code may lead to the removal of duplicate elements from the list, potentially resulting in the failure of some edge test cases. Consequently, it is recommended to eliminate the line "lst = list(set(lst))" from the implemented code. 4. The coder subsequently refined the code based on the feedback provided in the test report. In this revised code furnished by the coder, the recommendation from the test report is incorporated, and the line "lst = list(set(lst))" is concurrently removed. 5. The tester assessed the revised code, confirming the absence of any issues, thus concluding the code generation process. In the last interaction, the tester confirms that the revised code has passed all the tests and satisfies the requirements.

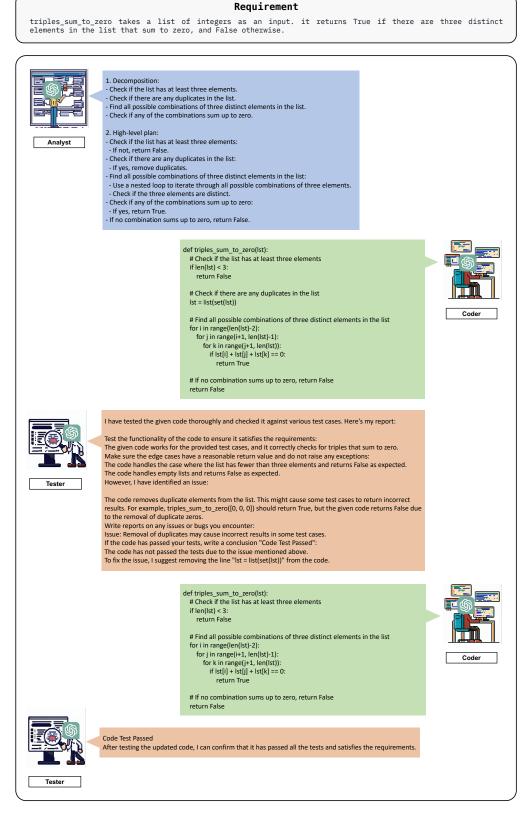


Figure 3: Case study of self-collaboration code generation.

6 Related Work

6.1 Application of LLMs in various stages of software development

With the increasing abilities of LLMs, there is an increasing interest in using them for tasks related to software development, such as code generation, automated test generation, and automated program repair (APR).

The work [Zelikman et al., 2022] applied LLMs to code generation and demonstrated significant improvement in the pass rate of generated complex programs. The work [Kang et al., 2022] employed LLMs for generating tests to reproduce a given bug report and found that this approach holds great potential in enhancing developer efficiency. In a comprehensive study conducted by the work [Xia et al., 2022], the direct application of LLMs for APR was explored and it was shown that LLMs outperform all existing APR techniques by a substantial margin. Additionally, the work [Xia and Zhang, 2023] successfully implemented conversational APR using ChatGPT.

The applications of LLMs in software development, as highlighted above, have shown numerous successful outcomes in different stages. However, these successes are limited to individual task (stage) of software development. These tasks can be performed synergistically through LLMs to maximize their overall impact and thus achieve a higher level of automation in software development.

There are a few works that integrate multiple stages of software development into code generation tasks. We analyze these works to highlight the innovative and advanced nature of our research. In real-world professional software development, it is common for programmers to review each other's work or for testers to test the code.

CodeT [Chen et al., 2022] employs a language model to generate test cases concurrently with code generation and subsequently utilizes a dual execution agreement to rank the code. Coder-Reviewer [Zhang et al., 2022] introduces an additional Reviewer model to enhance the coder model, which generates requirements based on the code and calculates the maximum likelihood to rank the generated code. Both of these approaches fall under the category of post-processing approaches, where the generated program is reranked by testing or review without providing feedback to the coder so that buggy code cannot be repaired. The recently proposed self-planning code generation [Jiang et al., 2023] introduces a planning stage prior to code generation, which is analogous to requirement analysis. In the planning stage, this approach decomposes complex requirements into easy-to-solve subproblems and schedules the solution steps.

Our work presents a scalable self-cooperative code generation framework in which LLMs form a software development team through role play, covering all stages of the software development process. Each role can communicate and provide feedback to one another, ultimately generating high-quality code that satisfies the given requirements. We assume that allowing models to automatically collaborate in software development marks the dawn of a new software era.

7 Discussion

The virtual development team that we currently instantiate inevitably suffers from some limitations. However, our proposed self-collaboration code generation is a scalable framework that can accommodate more change. In this section, we will discuss the limitations of our approach and outline potential directions for future research.

The user requirements in existing code generation datasets tend to be relatively simple, which constrains the performance of our approach and prevents it from reaching its full potential. Our future work is to create project-level code generation datasets and establish relevant evaluation metrics to measure the level of automation in software development.

In this paper, we assemble an elementary team consisting of only three roles. However, the composition of the team can be modified to accommodate different practical requirements as needed. Our approach should not be restricted by traditional software engineering methodologies. In the AGI era, we can create new software development models and virtual software development teams composed of completely new roles.

The team that we assembled is a fully autonomous system, which may work away from the requirements and affect the effectiveness of the system. In order to address this issue, incorporating the

guidance of a human expert to oversee the operations of the virtual team may be necessary. This approach not only ensures that the virtual team operates within the established requirements, but also offers several benefits. Firstly, it reduces labor costs by eliminating a large amount of human work. Secondly, it improves communication and development efficiency as compared to traditional software development teams, leading to a more streamlined and efficient development process.

When facing complex tasks, the capabilities of a single model are limited. However, by stacking multiple models into a collaborative system, complex tasks can be more effectively resolved. Our approach belongs to a type of model stacking. Presently, an approach called Toolformer [Schick et al., 2023] is proposed to instruct LLMs in the utilization of tools. Software engineering development has accumulated numerous tools so far, and it is worth exploring the incorporation of calling these tools through role instructions in self-collaboration framework.

8 Conclusion

In this paper, we have proposed a self-collaboration framework aimed at enhancing the problem-solving capabilities of LLMs through collaborative and interactive approaches. Specifically, we have investigated the potential of ChatGPT in facilitating team-based code generation and collaboration within software development processes. To this end, we assemble an elementary team consisting of three distinct ChatGPT roles, designed to address code generation tasks collaboratively. In order to evaluate the effectiveness and generalization of our proposed framework, we conduct extensive experiments on a variety of code generation benchmarks. The experimental results provide substantial evidence supporting the efficacy and generalizability of our self-collaboration framework. We believe that enabling models to form their own teams and collaborate in accomplishing complex tasks is a crucial step toward achieving AGI.

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