
CoderEval: A Benchmark of Pragmatic Code Generation with Generative Pre-trained Models

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Abstract

Code generation models based on the pre-training and fine-tuning paradigm have been increasingly attempted by both academia and industry, resulting in well-known industrial models such as Codex, CodeGen, and PanGu-Coder. To validate the performance of these models, multiple existing benchmarks (e.g., AiXBench and HumanEval) are proposed, including only cases of generating a standalone function, i.e., a function that invokes or accesses only built-in functions and standard libraries. However, standalone functions constitute only about 30% of functions from real open-source projects. To assess a model’s performance for pragmatic code generation (i.e., code generation for real settings of open source or proprietary code), in this paper, we propose a benchmark named CoderEval of pragmatic code generation with generative pre-trained models. Compared with the widely-used HumanEval benchmark from OpenAI, CoderEval can be used to assess the performance of models against pragmatic code generation beyond just generating standalone functions. Through the evaluation of three public available models (CodeGen, PanGu-Coder, and Codex) on CoderEval, we analyze and discuss the current progress and future directions of pragmatic code generation with a generative pre-trained model.

1. Introduction

Recent years have seen a trend to tackle open-domain code generation tasks with machine learning techniques, especially large generative pre-trained language models (Black et al., 2021; Brown et al., 2020; Mike Lewis, 2019; Radford et al., 2018) based on Transformer (Vaswani et al., 2017), such as Codex (Chen et al., 2021), AlphaCode (Li et al.,

2022), In-Coder (Fried et al., 2022), CodeGen (Nijkamp et al., 2022), and PanGu-Coder (Christopoulou et al., 2022). These models can generate both standalone functions (i.e., a function that invokes or accesses only Python built-in functions and standard libraries) and non-standalone functions.

These recent efforts typically assess the performance of their models with these existing benchmarks such as HumanEval (Chen et al., 2021) for Python, MultiPL-E (Cassano et al., 2022) (which extends HumanEval from Python to 18 programming languages), and AiXBench (Hao et al., 2022) for Java. Released alongside Codex (Chen et al., 2021), HumanEval is a benchmark for Python to measure code generation models on the functional correctness of programs synthesized from docstrings. It consists of 164 samples (as hand-written programming problems and solutions in Python), each of which includes a function signature, docstring, function body, and multiple unit tests (7.7 tests per problem on average). As a multi-language parallel benchmark, MultiPL-E (Cassano et al., 2022) is resulted from extending HumanEval to support 18 programming languages. More recently, AiXBench (Hao et al., 2022) is proposed for Java, containing 175 samples. It also includes 161 additional samples, each of which however does not include unit tests, and thus requires manual evaluation when being used to assess model performance.

However, these existing benchmarks only contains standalone functions, they are limited to assessing the performance of models on pragmatic code generation. After analyzing the 100 most popular open-source projects on GitHub, we find that standalone functions accounted for less than 30% of open-source projects, and most functions either reference third-party lib APIs or variables/constants defined in the current project.

To address this limitation, we propose a benchmark named CoderEval to assess code generation models on pragmatic code generation. CoderEval now supports Python and Java, with 230 functions from 43 Python projects and 230 methods from 10 Java projects. For each function/method, we extract the original docstring/comment, the signature, the code implementation, and the corresponding test code (if

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exists) to form one function-level code generation task.¹ Similar to HumanEval, CoderEval also adopts the Pass@K metric to assess the functional correctness of generated code.

Overall, CoderEval can be viewed as a superset of HumanEval. We classify the tasks into six levels according to the source of dependency outside the function, in which the first two levels fully cover HumanEval. Additionally, we analyze the detailed contextual information through program dependence analysis and provide them as `all_context` (all accessible context) and `oracle_context` (the actually used context), so as to conduct fine-grained analysis about performance and improvements. Besides, we manually examine all existing tests and write more tests to achieve 100% of test coverage. After inspecting the original natural language description (i.e., the docstring/comments), we find misalignment for some tasks, so we also provide a human-labeled version description from 13 experienced engineers. Since CoderEval involves functions with contextual dependency and non-primitive types, we build an execution platform to provide a ready runtime environment that can automatically run and verify the correctness of generated code. We base this platform on Docker, where we clone and set up environments for all projects. Given n solutions generated by the model, the platform can automatically place the generated code in the proper location of the project, to simulate the scenario where the developer accepts the generated code in an actual IDE.

Finally, we conduct a comprehensive evaluation and comparison of three public available models (CodeGen, PanGu-Coder, and Codex) on CoderEval. In the experiment, for each model, we analyze the overall and level-wise performance, the ability to correctly utilize contextual information, and the effect of different natural language descriptions. Furthermore, among these models, we compute the intersection and difference in terms of correctly-solved tasks. Through the analysis and comparison, we hope to provide a better understanding of existing models and shed light on future directions and further progress.

In summary, we make the following main contributions:

- We point out the limitation of existing benchmarks through an analysis of the 100 most popular open-source projects. We find that widely-used benchmarks like HumanEval typically only include functions that do not rely on any contextual information, but they only account for about 30% in practice, so HumanEval cannot reflect the performance of models on pragmatic code generation.
- We introduce CoderEval, a benchmark of pragmatic code generation. CoderEval originates from open-

source projects from various domains and considers non-primitive types, third-party libraries, and project-specific contextual references. Besides, it provides tests with 100% coverage and an improved version of natural language description.

- We assess and compare three public available industry models on CoderEval. Experimental results indicate multiple important inspirations: 1) current models do not work as well as standalone functions in terms of non-standalone functions, 2) it is important yet challenging for all models to generate code with contextual dependency, even for the most powerful Codex, and 3) natural language description or prompt can have an impact on the code generation performance.

CoderEval is open-sourced² to continually evolve in the code generation community.

2. Background

In this section, we first introduce the existing large language models for code generation. Then, we introduce the benchmark and evaluation metrics used by these models.

2.1. Large Language Models for Code Generation

PanGu-Coder is a pre-trained language model for the task of text-to-code generation, which is based on the PanGu- α architecture (Zeng et al., 2021) and a two-stage training strategy. CodeGen (Nijkamp et al., 2022) is a series of conversational text-to-code large language models trained on natural language corpus, multilingual code corpus, and monolingual Python dataset. Codex (Chen et al., 2021) is the first work to use large generative pre-trained models to generate complete functions from natural language. After Microsoft presented Codex, DeepMind presented AlphaCode (Li et al., 2022), which specialized in programming contests and performed on par with median human developers. CodeGPT (Lu et al., 2021) targets generating class member functions in Java given a natural language description and class environment (Iyer et al., 2018).

2.2. Benchmark and Metric

Released alongside Codex, HumanEval is a benchmark to measure code generation models on the functional correctness of programs synthesized from docstrings (Chen et al., 2021). It consists of 164 hand-written programming problems and solutions in Python, each of which includes a function signature, docstring, body, and multiple unit tests (7.7 tests per problem on average). Following HumanEval, AiXBench (Hao et al., 2022) is proposed to benchmark code generation models for Java, it contains 175 samples

¹Since function/method is defined slightly differently in different languages, we use *function* to uniformly denote them in the rest of the paper.

²<https://github.com/CoderEval/CoderEval>

for automated evaluation and a dataset of 161 samples for manual evaluation. MultiPL-E (Cassano et al., 2022) is the first multi-language parallel benchmark for text-to-code-generation, it extends the HumanEval benchmark to support 18 programming languages.

All the above benchmarks use the Pass@K metric to assess large language models of code, where k code samples are generated per problem, and one problem is considered solved if any sample passes the test. This metric measures the functional equivalence of two code snippets through execution and test, instead of the similarity between the generated code and the ground truth. The Pass@K metric (Kulal et al., 2019) is now widely accepted as a more reasonable metric than similarity-based scores like BLEU (Papineni et al., 2002) and CodeBLEU (Ren et al., 2020).

3. CoderEval Benchmark

In this section, we introduce CoderEval in terms of dataset collection, dataset inspection, and the evaluation process. Fig 1 shows the dataset collection, dataset inspection, and the evaluation process of CoderEval.

3.1. Dataset Collection

To address the limitation of existing benchmarks, we expect CoderEval to be:

- **Pragmatic:** code generation tasks should come from real open-source projects
- **Diverse:** code generation tasks should cover common application domains of the language
- **Reliable:** generated code should be assessed with sound tests

Task Selection. To make CoderEval pragmatic and diverse, we select code generation tasks from functions that are tested by the original developer of various open-source projects. First, we select candidate projects by crawling the tags of all projects on GitHub and selecting projects with the most-frequent 14 tags and with high stars. Then, we extract all functions in selected projects, and only keep the ones that meet all the following conditions: 1) is not a test, interface, or deprecated function. 2) with a function-level comment in English. 3) can run successfully in the verification platform (Section 3.3) and pass the original test cases. After getting the selected functions, We get projects from high to low according to the number of filtered functions contained in each project. Finally, we involve 230 functions from 43 projects in Python and 230 methods from 10 projects in Java. Together they form the current version of CoderEval.

Test Construction. To improve the reliability of the evaluation, we need to do our best to make the test correct and

complete. In HumanEval, each task has 7.7 tests on average, but it is found to result in 30% false positives (Li et al., 2022). In CoderEval, for each task, we achieve 100% coverage on the original code implementation, to reduce the false positive rate.

The test construction process is different for Python and Java. To verify the correctness of a function generated by models, in CoderEval for Python, the input and output of test cases for a function obtained through CI are run in the entire project environment. Therefore, to ensure that the verification platform can correctly verify the function generated by the model, we execute test cases separately at the file level and use the output as the output of the test cases in the benchmark. For the functions that still do not reach 100% coverage with the test cases generated by executing CI capture input and output, we manually supplemented the test cases. Unlike CoderEval for Python, the test cases in CoderEval for Java are provided by the project or manually supplemented by authors. Since there has no obvious relationship between the function under test with the test cases, so when we need to verify the correctness of a function, we need to execute all test cases in the current project. However, it is time-consuming to execute all test cases of the current project for each test. To obtain the corresponding test function of the function to be tested, we propose a function call analysis diagram based on source code to minimize the corresponding test cases for each function to be tested. Since the execution of test cases is not only time-consuming but also depends on the test framework, we automatically convert test functions into non-test functions with the “main” function in a new Java file. We verify the correctness of the function to be tested by calling the function through the “main” function. For this reason, we developed an algorithm to automatically convert test functions to non-test functions with a “main” function. For each function in CoderEval for Java, we add a new Java file with the “main” function. We donated these new Java files as NewTestFile. Finally, CoderEval for Java contains 230 functions from 10 projects.

3.2. Dataset Inspection

To gain insights about the functions that really matter (indicated by testing from original developers) in real open-source projects, we analyze the dataset in three aspects: 1) natural language description or task specification, 2) contextual dependency, and 3) runnable-level.

Task Specification. The prompt is important for large language models (Sarkar et al., 2022), when it comes to code generation, the task specification can have a great impact on the quality of generated code. During the research and case study, we find that the quality of original natural language descriptions from the selected open-source projects is

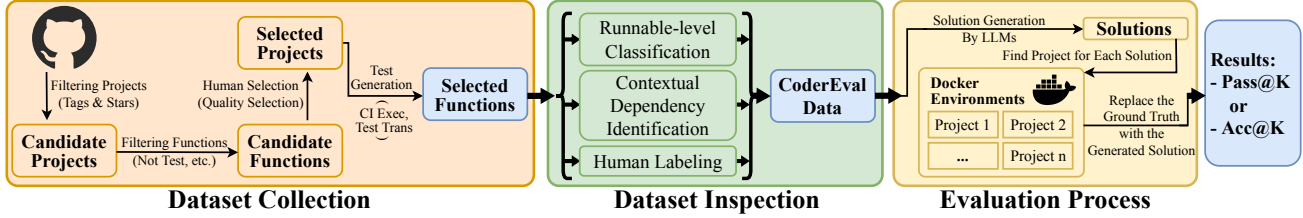


Figure 1. Overview of CoderEval construction process

Table 1. Contextual Dependency Type Definition

Dependency Type	Definition	Examples in Python	Examples in Java
language built-in	built-in types/functions, no need to import	min(), print()	System.xxx
standard library	standard libraries/modules, no need to install	os, subprocess, sys	Arrays.sort()
public library	publicly-available libraries on pypi.org	unittest2, requests	com.google.code.gson
current class	code outside the function but within class	self.xxx, X.f()	this.f()
current file	code outside the class but within the file	func(), URL, name	func()
current project	code in the other source files	superclass, utils	superclass, utils

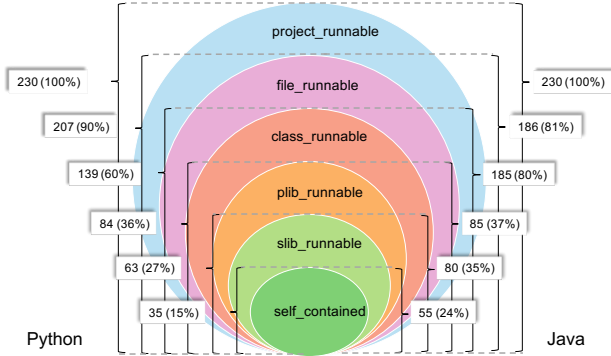


Figure 2. Distribution of runnable-levels in CoderEval

rather unstable and inconsistent, so we wonder if they are a good choice as the prompt for training and prompting code generation models. In practice, the function-level comment can play multiple different roles at different abstract levels or granularities, like explaining the internal logic, introducing the external usage and behavior, declaring the effect and caution, etc. Therefore, to study the effect of different prompts and mitigate the memory effect of language models, we recruit 13 professional software engineers with at least 3 years experience of Python/Java, show them the code without original comments and let them provide a human_labeled version of the function description through a two-fold cross-validation process.

Contextual Dependency Identification. One of the major differences between HumanEval and CoderEval is that we

take the contextual dependency into consideration. When generating function-level code, it is often the case that a token reference error will lead to an error in the generation of the entire function. Therefore, providing the information actually called in the function can help CoderEval verify the model’s awareness of context information in a more fine-grained way.

We denote the context code elements that a function directly requires to run as its contextual dependency, which includes language-builtins, standard libraries, third-party public libraries, and code outside the function but within the current class, file, or project. Table 1 shows the definition and exemplary explanation for each dependency type.

We identify the contextual dependency of a function through program analysis on the whole project. Before the analysis, we first build a knowledge base that helps distinguish the references of Python/Java builtins, and the imports of standard or public libraries from the project-specific code. To do this, we cache all built-in types/functions/variables/constants and standard library names for each Python version from 3.0.0 to 3.10.0 and Java version from 1.8 to 17, as well as all public-available libraries on pypi.org and *Maven* central repository. With this knowledge base, given a function to analyze, we retrieve the database to get the source file that it came from, then parse it to get a list of types/functions/-variables/constants definitions. For each dependency type, the criterion for setting it to true was whether the function *used* the code of this type. For example, for a member function in a class, if it invokes a builtin function `sorted()` to manipulate a member variable `self.x`, we set the builtin

Table 2. Matrix to Classify Runnable-level by Dependency

Level \ Depend	language built-in	standard library	public library	current class	current file	current project
self_contained	○	×	×	×	×	×
slib_runnable	○	✓	×	×	×	×
plib_runnable	○	○	✓	×	×	×
class_runnable	○	○	○	✓	×	×
file_runnable	○	○	○	○	✓	×
project_runnable	○	○	○	○	○	✓

✓ means true, × means false, and ○ means true/false.

and `current_class` to true.

Among these dependency types, we particularly focus on three categories: `type_reference`, `variable_reference`, and API invocation. To identify them, we employ static program analysis technologies to identify all the external references and invocations whose definitions are outside the current function and classify them into these categories. We denote the information that the original function body actually depends on as the `oracle_context` information. Oracle_context information can not only be used to assess the accuracy of the context information in the code generated by the model but also can be used as part of the input to the model in the reasoning stage, to verify whether prompting the model with the oracle information can improve the performance. However, it is usually difficult for the model to know oracle information in advance, so CoderEval also provides the `all_context` information, that is, all types, variables, and APIs defined/imported in the current file, to assess whether the model can pick the correct contextual information to fulfill the task.

Runnable-level Classification. Based on the contextual dependency, we further classify the code generation tasks into six runnable-levels, that is, the scope that the function can run successfully. These levels include: `self_contained`, `slib_runnable`, `plib_runnable`, `class_runnable`, `file_runnable`, and `project_runnable`.

According to the identified contextual dependency, the runnable-level is determined according to a *Dependency Matrix* for the classification, as shown in Table 2. In this matrix, the row represents the runnable-level, and the column represents the contextual dependency type, so each cell indicates whether the level of the row depends on the dependency type of the column. For example, `plib_runnable` means the function *at most* can depend on public libraries, so it can run successfully outside the current source file and project, as long as the required Python version is satisfied and the libraries are installed and imported. Note that we determine the runnable-level by what it *cannot* depend on, so the higher level actually includes the lower levels (see

Fig 2), because intuitively if a function of the lower level can run within its scope (say with standard library imports), it can also run given a larger scope (say the current file).

The left part and right part of Fig 2 show the distribution of runnable-levels on CoderEval for Python and Java, respectively. Most (84%) of the collected functions in CoderEval for Python are `file_runnable`, which indicates that the context information in the current file is necessary and critical for a code generation model to generate the function correctly. The `class_runnable` functions account for half (54%) of all functions, which is not surprising considering the prevalence of object-oriented programming in open-source and non-trivial projects. On the contrary, `slib_runnable` only accounts for 17% in CoderEval for Python but 100% in the Codex dataset and the HumanEval benchmark. This fact proves the bias and mismatching in the model optimization and evaluation process with HumanEval, especially in the pragmatic generation of code in real settings. Similar to CoderEval for Python, `slib_runnable` only accounts for 35% in CoderEval for Java.

3.3. Evaluation Process

As we need an evaluation platform to provide a ready runtime environment with automatic programs to execute and verify the code generated by code generation models, we choose to base it on a Linux Docker image, which can provide a virtual and safe sandbox to enable easy duplication and prevent harmful execution.

Evaluation for Python. To assess generated Python code, we need to clone and set up environments for all 43 projects. To avoid Python and library version conflicts, under each repository’s root directory, we first use `pyenv` to set the local Python version to the highest version specified in the CI configuration or document, then use `venv` to create an individual virtual environment for the current project. After that, we use `pip` to install all dependencies and trigger the original tests in the project to verify the runtime environment.

With the environment ready and given a model to assess, we write a program to automatically *inject* the generated code into the project, correctly invoke the function with test input, and compare the actual output with the expected output. To invoke the target function correctly, the program can generate the necessary test entry point to set up some necessary prerequisites (like initializing the object before calling a member function) and load the input/output data into memory via deserialization. Given n code snippets generated by the model, it then sequentially replaces the original function with each of them to *simulate* a scenario when the developer accepts the generated code and tests it in an actual IDE. After the replacement, the entry point code will be triggered, and the running output (e.g., return values, exceptions, errors, and console output) will be captured. If

the function returns with no error or exception, the platform will compare the actual output with the expected output, otherwise, the unexpected termination will be treated as a test failure. After all code snippets for all tasks are tested, the results of all tasks will be used to compute the final Pass@K metric.

Evaluation for Java. Similar to the evaluation platform for Python, we also need to clone the involved projects first. We ensure that all projects in CoderEval for Java can be executed with Java 1.8 version, so we do not need to install different versions of Java runtime. Different from Python, Java programs need to be compiled before execution, so we write a program to automatically compile the test file (i.e., `NewTestFile`) in advance, and then dynamically replace and recompile the file that the method to be tested belongs to.

With the environment ready and given a model to assess, the platform uses the “`javac`” command to compile changed files incrementally, and the “`java`” command to execute the bytecode of `NewTestFile`.

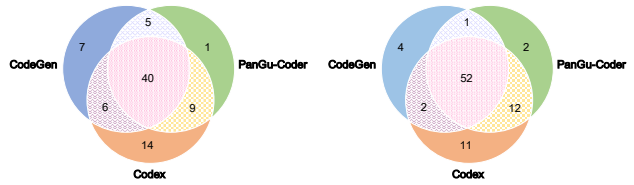
Given n methods generated by the model, the platform will also automatically replace the original method with each of them, and try to recompile the residing file via the “`javac`” command. If the compilation fails, the test will be treated as a failure. If there is no error or exception after compilation, the platform will invoke the “`java`” command to execute the `NewTestFile`. The return value of the command directly indicates the behavioral correctness of the generation code.

4. Experiments

In this section, we assess and compare three public available code generation models (CodeGen, PanGu-Coder, and Codex) on two benchmarks (CoderEval and HumanEval).

4.1. How do CodeGen, PanGu-Coder, and Codex perform on CoderEval and HumanEval?

Overall performance. Table 3 shows the overall performance of CodeGen, PanGu-Coder, and Codex on CoderEval and HumanEval. On HumanEval, we find all models perform better in implementing the same functions in Python than in Java (except Pass@1 for Codex). Since the functions in CoderEval for Python and Java are different, we cannot directly compare the performance of the three models on Python and Java in CoderEval. Both on HumanEval and CoderEval, Codex consistently outperforms the other two models for Python and Java. The major reason is that Codex’s model size is much larger than the other two models we tested. On HumanEval, Codex’s numbers are much higher than other models and the original paper (Chen et al., 2021), indicating that HumanEval should not be used as a benchmark anymore due to overfitting or oversimplification.



(a) CoderEval for Python (b) CoderEval for Java

Figure 3. Number of correctly-generated functions of CodeGen, PanGu-Coder, and Codex on CoderEval

Complementarity and intersection of three models.

Fig 3 shows the number of solved problems by the three models on CoderEval, with the difference and intersection. We consider a problem to be solved if the model can generate *at least* one correct solution that passes all tests out of the ten generated solutions. Among the 230 problems in CoderEval for Python, the total number of problems solved by the three models is 82 (complementarity), while 40 problems can be solved by any of the three models (intersection). On CoderEval for Java, the total number of problems solved by the three models is 84 (complementarity), while 52 problems can be solved by any of the three models (intersection). The high complementarity indicates that different models have their unique capabilities, and the high intersection indicates that the problem-solving ability of the three models is consistent on some tasks. We manually analyze the intersection tasks and find that more than half of them belong to `self_contained` and `slib_depend` levels, but they only account for about 30% in CoderEval. For the tasks that can only be correctly solved by Codex, the two levels also account for more than half. Therefore, the three models are all good at generating functions without external dependency (while Codex performs particularly well), extending the ability to other runnable-levels and exploring how to combine different models deserve more research attention.

Performance comparison between the generation of `self_contained` and `slib_depend` and with that of other runnable-levels.

Since all functions in HumanEval belong to `slib_runnable` (`self_contained` and `slib_depend`), we further compare the performance of three models in generating the `slib_runnable` subset of CoderEval with the performance on other runnable-levels. As shown in Table 4, in CoderEval for Python or CoderEval for Java, the effect of the three models in generating the function with `self_contained` and `slib_depend` levels is substantially higher than that of other runnable-levels. Considering that more than 60% real functions belong to other runnable-levels, improving the model’s ability to consider and use contextual information correctly is vital for the practical value of such technology.

Table 3. Overall performance of three models on two benchmarks

Benchmark	Model	Python				Java			
		n=1		n=10		n=1		n=10	
		Pass@1(greedy)	Pass@1	Pass@5	Pass@10	Pass@1(greedy)	Pass@1	Pass@5	Pass@10
CoderEval	CodeGen ¹	10.87%	9.26%	21.29%	25.22%	10.43%	11.65%	21.67%	25.65%
	PanGu-Coder	13.04%	11.96%	19.73%	23.91%	20.50%	18.74%	25.97%	29.13%
	Codex ²	16.96%	16.00%	26.72%	30.00%	27.83%	24.43%	31.53%	33.48%
HumanEval	CodeGen ¹	10.98%	9.76%	18.85%	22.56%	3.66%	4.88%	8.54%	9.15%
	PanGu-Coder	17.07%	13.23%	20.46%	22.56%	7.32%	7.93%	15.85%	18.29%
	Codex ²	48.17%	42.99%	72.04%	80.49%	39.02%	45.12%	66.46%	69.51%

¹ We use the 350M CodeGen-Mono model with the default settings for Python. Since CodeGen does not have a monolingual version of Java, on CoderEval for Java, we use the CodeGen-Multi model instead.

² Since OpenAI Codex API does provide information or option for model size, we do not know the exact model size behind. We use the code-davinci-002 in our experiments.

Table 4. Performance on self_contained + slib_depend levels and other levels of CoderEval

Dependency	Model	Python			Java		
		Pass@1	Pass@5	Pass@10	Pass@1	Pass@5	Pass@10
self_slib	CodeGen	13.17%	28.25%	31.74%	18.75%	32.07%	35.00%
	PanGu-Coder	17.30%	30.46%	36.51%	34.00%	44.36%	47.50%
	Codex	26.98%	43.50%	47.62%	44.75%	51.98%	52.50%
others	CodeGen	7.78%	18.66%	22.76%	4.20%	9.10%	12.00%
	PanGu-Coder	9.94%	15.69%	19.16%	13.45%	21.04%	23.14%
	Codex	11.86%	20.39%	23.36%	13.60%	20.62%	23.33%

4.2. How do different models perform in correctly utilizing the contextual information?

To further study the *context-awareness* of large language models, we analyze the identifier tokens in generated code and focus on three types of tokens: TypeReference, APIInvocation, and VarReference (including constants reference).

Acc@K: We define the Acc@K metric to assess the ability of models in generating contextual information expected in the oracle implementation. If one of the generated K samples contains the correct token, it is considered to hit the correct contextual information. Acc@K computes the percentage of correctly predicted tokens in all of the expected tokens in the oracle implementation, so it is actually the estimated recall of expected contextual dependency. The precision is not computed, since redundant tokens sometimes have no impact on semantics and behaviour.

Overall Acc@K of three models. Fig 4 shows the Acc@k of three models, we find it is consistent with Pass@K (i.e., the generated functions can pass test cases), and the Acc@K of Codex is also the best one in generating contextual dependency. To further explore the ability of different models in generating different types of context information, we divide the context token into three categories: TypeReference, APIInvocation, and VarReference, which usually form the most important part of the implementation at runnable-levels with

external dependency. As shown in Fig 4, on CoderEval for Python, all models show poor performance in generating the correct “VarReference” token, while the performance in generating “TypeReference” token is relatively well. However, when it comes to Java, all models have poor performance in generating the correct “TypeReference” token, while the performance in generating “APIInvocation” tokens is the best.

4.3. How does the prompt affect the performance of different models?

Overall performance. We assess the three models on both the original and the human-labeled prompt and show the result in Table 7. Overall, compared with the original prompt on CoderEval for Python, the human-labeled version does bring improvements to all three models. Although the original prompt is written by the original code author, some of them are too simple and abstract, underspecifying the logic and intent of the function. On the contrary, the human-labeled prompt is written by the participants after careful consideration and understanding of the entire project, so it tends to be more specific and concentrated, which is beneficial for the model to understand the intent.

Complementarity and intersection of three models.

Fig 5 shows the number of functions that are correctly generated when replacing the original prompt with the human-

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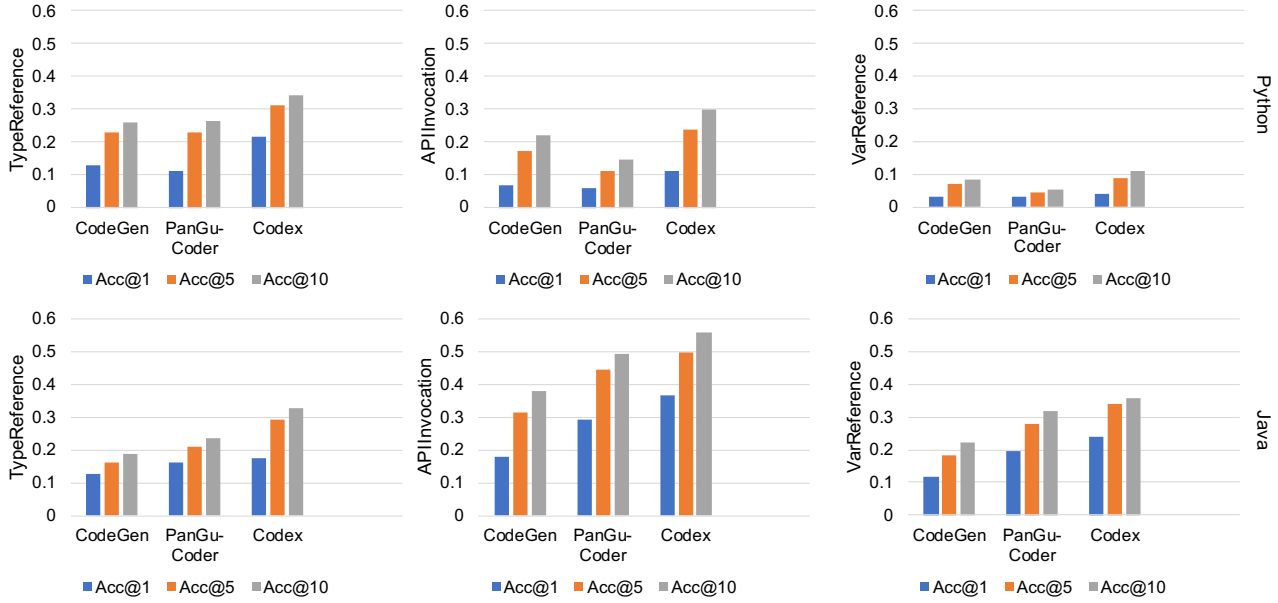


Figure 4. The accuracy of three models that they can correctly generate the contextual tokens

Table 5. Performance with 2 Prompt Versions of CoderEval

Model	Prompt	Python			Java				
		n=1	n=10		n=1	n=10			
		Pass@1(greedy)	Pass@1	Pass@5	Pass@10	Pass@1(greedy)	Pass@1	Pass@5	Pass@10
CodeGen	Original	10.87%	9.26%	21.29%	25.22%	10.04%	11.65%	21.67%	25.65%
	Human Label	11.30%	11.91%	23.34%	26.52%	7.53%	9.26%	17.09%	20.00%
PanGu-Coder	Original	13.04%	11.96%	19.73%	23.91%	20.50%	18.74%	25.97%	29.13%
	Human Label	15.22%	14.22%	21.74%	25.22%	21.76%	19.43%	27.68%	30.87%
Codex	Original	16.96%	16.00%	26.72%	30.00%	27.83%	24.43%	31.53%	33.48%
	Human Label	19.13%	18.91%	29.60%	33.48%	23.91%	20.04%	28.46%	31.74%

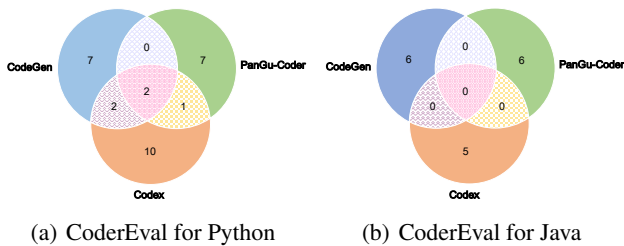


Figure 5. The number of functions that models fail to solve with the original prompt but succeed with the human-labeled version

labeled version on CoderEval. Overall, for all three models on CoderEval for Python, the number of newly-solved problems is 11, but interestingly, their intersection is only 1. For all three models on CoderEval for Java, the number of newly-solve problems is 17, but their intersection is 0. This indicates different models’ sensitivity to the different prompts, as well as the complementarity in their capability.

The performance of all models has been substantially improved after human labeling on CoderEval for Python, but the performance of CodeGen and Codex decrease on CoderEval for Java. After comparing the generated code with two prompt versions, we think that it is related to the proportion of the target language corpus in the whole training data. For Python, the stable performance can be attributed to dedicated training or fine-tuning on Python code corpus, while for Java, only PanGu-Coder undergoes pre-training on the Java code corpus. Therefore, while multi-

lingual pre-training can transfer knowledge and bring better generalization across languages, monolingual pre-training or fine-tuning is still necessary for the stability of models.

5. Conclusion

In this paper, we have present a benchmark to assess a model’s performance in generating pragmatic code named CoderEval. Compared with the widely used HumanEval benchmark, CoderEval includes carefully selected programming tasks from various open-source projects and tests with 100% coverage to assess the performance of models in pragmatic code generation. Through experiments, CoderEval reveals the strengths and weaknesses of the importance of three public available industrial models, highlights the importance of contextual information and the effect of prompts.

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"Return a greatest common divisor of two integers a and b."	<i>Docstring</i>
def greatest_common_divisor(a: int, b: int) -> int:	<i>Function Signature</i>
while b: a, b = b, a % b	<i>Oracle Code</i>

Figure 6. An example in HumanEval

"Return string of validator status, with optional prefix."	<i>Docstring</i>
def status_str(self, prefix=''):	<i>Function Signature</i>
def status_str(self, prefix=''): s = "" for message in sorted(self.messages): s += prefix + message + '\n' return s[:-1]	<i>Oracle Code</i>
Return a string with visiting the sorted self.messages list, each visit add prefix and the element in the sorted self.messages list.	<i>Human Label Docstring</i>
class Runnable	<i>Runnable Level</i>
apis: 'sorted' classes: "" vars: "message"	<i>Oracle Context</i>
import: os json re file: "" class: self.codes ; self.show_errors ; self.warning(self,code) ; self.error(self,code) ; self.status_str(self,prefix) ; self.lang ; self.num_warnings ; self.error_or_warning(self,code,severity) ; self.num_errors ; self.spec ; self._str_(self) ; self.status_str ; self.show_warnings ; self.__init__(self,show_warnings,show_errors,lang,validation_codes) ; self.error_or_warning ; self.info ; self.messages ; self.validation_codes ;	<i>All Context</i>

Figure 7. An example in CoderEval

A. Task Definition

HumanEval and CoderEval are all created for the task of text-to-code generation, i.e. to generate the code that solves the problem described by a docstring/comment (i.e., NL description). Figure 6 and 7 show an example from the HumanEval and CoderEval benchmark, respectively.

Compared with the widely-used HumanEval benchmark from OpenAI, CoderEval not only can be used to assess the performance of models against pragmatic code generation beyond just generating standalone functions but also contains more information for research. Specifically, for each function, CoderEval collects the following information:

- Internal Info: the annotation, original docstring, human-labeled docstring, signature, runnable-level, and code snippet of the function
- Contextual Info: all contextual information defined in the source file in which the function resides and the oracle information actually used in the function
- Meta Info: the location (project, file path, and line ranges) of the function

B. Large Language Models

B.1. Introduction

B.1.1. PANGU-CODER

PanGu-Coder is a pre-trained language model for the task of text-to-code generation. PanGu-Coder is based on the

PanGu- α architecture (Zeng et al., 2021), it proposes a two-stage training strategy. In the stage, PanGu-Coder was trained on Python code via Causal Language Modeling (CLM) (Radford et al., 2018). All available data for the first training stage were concatenated and split at a given maximum length (or window size). For the second stage of training, PanGu-Coder accepted each sample as docstring-code pair. PanGu-Coder-FT is obtained by finetuning PanGu-Coder using the data from a combination of competitive programming problems and code from continuous integration tests. Compared with PanGu-Coder, PanGu-Coder-FT shows better performance on HumanEval.

B.1.2. CODEGEN

CodeGen (Nijkamp et al., 2022) is a series of conversational text-to-code large language models. CodeGen used three-stage training to produce three models. The first one produced CodeGen-NL, which was trained on a natural language dataset named The Pile (Gao et al., 2021). The second one produced CodeGen-Multi, which was then further trained on a multiple-programming-language dataset named BigQuery. The third one produced CodeGen-Mono, which was built upon CodeGen-Multi with additional training on Python-only code.

B.1.3. CODEX

Codex (Chen et al., 2021) is the first work to use large generative pre-trained models to generate complete functions from natural language. Since the Codex did not open-source the model and we do not know the model parameter scale with 300M from the codex in OpenAI, we use the latest available version code-davinci-002 in our experiments.

B.1.4. OTHER MODELS

After Microsoft presented Codex, DeepMind presented AlphaCode (Li et al., 2022), which specialized in programming contests and performed on par with median human developers. CodeGPT (Lu et al., 2021) targets at generating class member functions in Java given a natural language description and class environment (Iyer et al., 2018).

B.2. Model settings

For PanGu-Coder, we use the 300M PanGu-Coder model with the default settings. For CodeGen, we use the 350M CodeGen-Mono model with the default settings for Python. Since CodeGen does not have a monolingual version of Java, on CoderEval for Java, we use the CodeGen-Multi model instead. For Codex, since OpenAI Codex API does provide information or option for model size, we do not know the exact model size behind it. We use the code-davinci-002 in our experiments. Codex’s model parameter scale is much larger than the other two models.

In the inference phase, for CodeGen and PanGu-Coder, we set the max window length to 1024. Due to the limitation of token inference for Codex API per minute, we set the max window length to 256 for Codex. We find that more than 95% of the data can generate complete functions when the length of the generated token is set to 256. We compare two ways of sampling: (1) nucleus sampling (Holtzman et al., 2020): the number of samples is 10, and the temperature is 0.6, which means generating 10 solutions per problem, and (2) greedy sampling (Chen et al., 2015; Shomorony & Avestimehr, 2014): generating one single solution through greedy decoding.

C. Additional Experiments and Results

C.1. The difference between HumanEval from open-source projects

All functions in the HumanEval can be executed only by relying on the Python installation environment, while many functions in real open-source need to rely on third-party libraries and/or developer-defined context information (e.g., variable, API, class). To explore the proportion of the functions with `self_contained` and `slib_runnable` in HumanEval in realistic open-source projects, we have separately calculated the proportion of the functions with `self_contained` and `slib_runnable` in the top 100 starred Python and Java projects on GitHub. The experimental results show that the proportion of these functions in Python and Java is only 11.2% and 21.3%. Therefore, HumanEval cannot verify the performance of a model for pragmatic code generation.

C.2. Different depend levels of three models on CoderEval

Table 6 in the appendix shows the performance of three models on the 6 types of functions in CoderEval. The type of function represents the non-overlapping part between two neighboring runnable levels in Figure 2 in the “main” file. For example, the `class_depend` represents those functions that ‘must’ depend on other code in the current class. From the table, we find that Codex almost outperforms the other two models on all depend levels. As previously analyzed, the main reason is Codex’s model size is much larger than the other two models. It is worth noting that Codex’s performance at the `class_depend` in CoderEval for Python and CoderEval for Java is not the best.

C.3. Why the performance of CoderEval for Python and Java after HumanLabel is different?

We assess the three public available industry models on both the original and the human-labeled docstring and show the result in Table 7. The performance of all models has been substantially improved after human labeling on CoderEval for Python, and CodeGen and Codex have been decreased

after human labeling on CoderEval for Java. Why the performance of CoderEval for Python and Java with human-labeled prompt is so different? After analyzing the reasons, we think that for Python language, the three models have been specially trained or finetuned using Python code, and the model training is quite sufficient. Therefore, it performs better on the high-quality docstring of human labeling. For the Java language, only PanGu-Coder has done special pre-training for the Java language, and the other two models have not done separate pre-training or fine-tuning for the Java language. The PanGu-Coder model for Java is still fully trained in the Java language, while CodeGen and Codex are not fully trained. Therefore, CodeGen and Codex performed worse on the high-quality prompt of human labeling, while PanGu-Coder performed better.

C.4. The detailed performance of different models in correctly utilizing the contextual information

Consistent with Figure 4 in the “main” file, Table 8 shows the accuracy of three models that can correctly generate the contextual tokens.

D. Case Study

D.1. Examples of code generated by CodeGen, PanGu-Coder, and Codex with original prompt

Fig 8, 9, 10, and 11 show the codes generated by the three models with the original docstring as inputs.

Fig 8 shows one example case where the code generated by CodeGen and Codex fails to pass the test cases in the CoderEval, but the code generated by PanGu-Coder can pass the test cases. In addition to one identifier between the code generated by PanGu-Coder with the oracle code, the code generated by PanGu-Coder also adds string segmentation judgment code, which shows that PanGu-Coder can learn from other code to generate code that considers and checks boundary conditions.

Fig 9 shows one example case where the code generated by PanGu-Coder and Codex fail to pass the test cases in the CoderEval, but the code generated by CodeGen can pass the test cases. From the figure, we find that although the correct code generated by CodeGen (which can pass the test case) is not similar to the oracle code in terms of text similarity, it is another correct way of implementation. This also shows the limitations of using the text-based similarity comparison metrics to evaluate the correctness of the generated code.

Figs 10 and 11 show one example case where the code generated by PanGu-Coder and CodeGen fails to pass the test cases in the CoderEval, but the code generated by Codex can pass the test cases. As shown in Figure 10, compared with oracle code, the correct code generated by Codex is not

Table 6. Performance Across 6 Runnable-levels of CoderEval

Runnable-level	Model	Python			Java		
		Pass@1	Pass@5	Pass@10	Pass@1	Pass@5	Pass@10
self_contained	CodeGen	17.14%	34.82%	37.14%	21.09%	36.70%	40.00%
	PanGu-Coder	21.14%	34.92%	40.00%	40.00%	48.26%	50.91%
	Codex	35.71%	56.34%	62.86%	48.73%	54.39%	54.55%
slib_depended	CodeGen	8.21%	20.04%	25.00%	13.60%	21.89%	24.00%
	PanGu-Coder	12.50%	24.89%	32.14%	20.80%	35.78%	40.00%
	Codex	16.07%	27.44%	28.57%	36.00%	46.68%	48.00%
plib_depended	CodeGen	9.52%	25.57%	33.33%	0.00%	0.00%	0.00%
	PanGu-Coder	16.67%	27.49%	33.33%	0.00%	0.00%	0.00%
	Codex	20.00%	33.37%	38.10%	0.00%	0.00%	0.00%
class_depended	CodeGen	9.82%	24.24%	29.09%	6.10%	12.87%	17.00%
	PanGu-Coder	10.55%	17.98%	23.64%	16.40%	26.89%	30.00%
	Codex	11.27%	20.01%	23.64%	18.50%	25.21%	28.00%
file_depended	CodeGen	7.50%	16.15%	19.12%	0.00%	0.00%	0.00%
	PanGu-Coder	9.85%	12.91%	14.71%	0.00%	0.00%	0.00%
	Codex	12.21%	20.65%	22.06%	0.00%	0.00%	0.00%
project_depended	CodeGen	2.17%	6.42%	8.70%	0.45%	1.77%	2.27%
	PanGu-Coder	2.61%	7.63%	8.70%	8.57%	10.63%	10.71%
	Codex	4.78%	8.70%	13.04%	4.32%	13.01%	15.91%

Table 7. Performance with 2 Prompt Versions of CoderEval

Model	Prompt	Python			Java				
		n=1	n=10		n=1	n=10			
		Pass@1(greedy)	Pass@1	Pass@5	Pass@10	Pass@1(greedy)	Pass@1	Pass@5	Pass@10
CodeGen	Original	10.87%	9.26%	21.29%	25.22%	10.04%	11.65%	21.67%	25.65%
	Human Label	11.30%	11.91%	23.34%	26.52%	7.53%	9.26%	17.09%	20.00%
PanGu-Coder	Original	13.04%	11.96%	19.73%	23.91%	20.50%	18.74%	25.97%	29.13%
	Human Label	15.22%	14.22%	21.74%	25.22%	21.76%	19.43%	27.68%	30.87%
Codex	Original	16.96%	16.00%	26.72%	30.00%	27.83%	24.43%	31.53%	33.48%
	Human Label	19.13%	18.91%	29.60%	33.48%	23.91%	20.04%	28.46%	31.74%

```

"Convert a string to a number, using the given alphabet.
The input is assumed to have the most significant digit first." Docstring

def string_to_int(string: str, alphabet: List[str]) -> int:
    number = 0
    alpha_len = len(alphabet)
    for char in string:
        number = number * alpha_len + alphabet.index(char)
    return number

def string_to_int(string: str, alphabet: str = '0123456789') -> int:
    alphabet = list('0123456789')
    return int("".join(alphabet[int(string[i:i+2], 16)] for i in range(0, len(string), 2)), 16)

def string_to_int(string: str, alphabet: str = '0123456789') -> int:
    string = string.replace(" ", "")
    if not string:
        return 0
    result = 0
    for s in string:
        result = result * len(alphabet) + alphabet.index(s)
    return result

def string_to_int(string: str, alphabet: List[str]) -> int:
    if not string:
        return 0
    return alphabet.index(string[0]) * (len(alphabet) ** (len(string) - 1)) + \
        string_to_int(string[1:], alphabet)

```

Figure 8. The code incorrectly generated by CodeGen and Codex, but correctly generated by PanGu-Coder

only different in the information printing of raising error but also splits the sub-statements in the return statement. This shows that the code generation approach of such models is not completely retrieved or copied from the training set, but there are some intelligent learning or splicing capabilities.

D.2. Examples of code generated by CodeGen, PanGu-Coder, and Codex with original prompt and human-labeled prompt

Figs 12, 13, and 14 show the code generated by the three models with the original docstring and human-labeled docstring as the prompt. The code generated by models with original docstring is incorrect, but the code generated by models with human labeling is correct.

Fig 12 shows an example of a code snippet generated by PanGu-Coder with the original docstring and human-labeled

Table 8. The accuracy of three models that they can correctly generate the contextual tokens

Model	Contextual Type	Python				Java			
		Average	Acc@1	Acc@5	Acc@10	Average	Acc@1	Acc@5	Acc@10
CodeGen	TypeReference	12.63%	13.01%	22.97%	25.93%	11.86%	12.54%	16.30%	18.55%
	APIInvocation	7.78%	7.04%	17.40%	21.90%	17.42%	17.95%	31.45%	37.78%
	VarReference	3.37%	3.45%	7.10%	8.36%	11.47%	11.87%	18.41%	22.02%
PanGu-Coder	TypeReference	13.16%	11.06%	22.80%	26.46%	16.50%	16.09%	20.87%	23.62%
	APIInvocation	6.64%	5.95%	11.22%	14.53%	29.68%	29.15%	44.45%	49.29%
	VarReference	3.15%	3.08%	4.60%	5.30%	19.99%	19.50%	28.01%	31.57%
Codex	TypeReference	19.98%	21.54%	31.01%	34.48%	17.69%	17.25%	29.01%	32.72%
	APIInvocation	12.51%	10.99%	23.71%	29.76%	36.65%	36.71%	49.63%	55.83%
	VarReference	4.12%	4.20%	8.86%	11.04%	22.82%	24.07%	34.05%	35.49%

```

"Remove and return the (key, value) pair first inserted." Docstring
def popitem(self):
    try:
        key = next(iter(self.__order))
    except StopIteration:
        raise KeyError('%s is empty' % type(self).__name__) from None
    else:
        return (key, self.pop(key))

def popitem(self):
    if not self:
        raise KeyError('dictionary is empty')
    key, value = self.items[0]
    del self.items[0]
    return key, value
CodeGen

def popitem(self):
    k = self._keys[0]
    try:
        value = self[k]
        del self[k]
    except KeyError:
        raise KeyError('Key %r not found' % k)
    return (k, value)
PanGu-Coder

def popitem(self):
    try:
        key = next(iter(self))
    except StopIteration:
        raise KeyError('dictionary is empty')
    value = self.pop(key)
    return key, value
Codex
    
```

```

"Given a timezone-aware datetime in a given timezone, calculates a
timezone-aware datetime in a new timezone." Docstring
def fromutc(self, dt):
    dt_wall = self._fromutc(dt)
    _fold = self._fold_status(dt, dt_wall)
    return enfold(dt_wall, fold=_fold)
Oracle Code

def fromutc(self, dt):
    if dt.tzinfo is None:
        dt = dt.replace(tzinfo=self.tz)
    return dt
CodeGen

def fromutc(self, dt):
    return dt.replace(tzinfo=self)
PanGu-Coder

def fromutc(self, dt):
    if dt.tzinfo is self:
        raise ValueError("dt.tzinfo is self")
    dt = dt.astimezone(pytz.utc).astimezone(self)
    if dt.tzinfo._ambiguous:
        dt = dt.replace(fold=1)
    return dt
Codex
    
```

Figure 9. The code incorrectly generated by PanGu-Coder and Codex, but correctly generated by CodeGen

Figure 10. The code incorrectly generated by PanGu-Coder and CodeGen, but correctly generated by Codex (1)

```

"List arguments with 'required_when' condition matched." Docstring
def _get_conditionally_required_args(self, command_name, options_spec, args):
    opts_names = [option_spec['name'] for option_spec in options_spec]
    missing_args = []
    for option_spec in options_spec:
        option_results = []
        if option_spec and 'required_when' in option_spec:
            return missing_args

def _get_conditionally_required_args(self, command_name, options_spec, args):
    args_with_required_when = []
    for arg in args:
        if arg.required_when is not None:
            args_with_required_when.append(arg)
    return args_with_required_when
CodeGen

def _get_conditionally_required_args(self, command_name, options_spec, args):
    conditional_args = []
    for arg in args:
        if self._conditional_arg_matches(command_name, options_spec, arg):
            conditional_args.append(arg)
    return conditional_args
PanGu-Coder

def _get_conditionally_required_args(self, command_name, options_spec, args):
    if args is None:
        args = {}
    result = []
    for opt in options_spec:
        if opt['name'] in args and opt.get('required_when'):
            condition = opt['required_when']
            condition_args = condition[0]
            if isinstance(args[opt['name']], list):
                satisfied = [args[opt['name']][i] in condition[1] for i in
                    range(len(args[opt['name']]))]
            else:
                satisfied = args[opt['name']] in condition[1]
            if satisfied and all([arg in args for arg in condition_args]):
                result.append(opt['name'])
    return result
Codex
    
```

Figure 11. The code incorrectly generated by PanGu-Coder and CodeGen, but correctly generated by Codex (2)

docstring. Compared with oracle code, the correct code generated by human-labeled docstring is only different in an identifier.

However, the semantics of the incorrect code generated by the original docstring is much worse than that of the oracle code. The oracle code returns a list, while the return code in the incorrect code generated by the original docstring is only the first element of the list.

Compared with the original docstring, the docstring labeled by human only adds "for a given node". The relationship between the prompt and the generated code deserves further analysis.

Fig 13 shows an example of a code snippet generated by CodeGen with an original docstring and human labeling docstring. The original docstring is poor, since it only describes the function of the program by referencing another program, so the code generated by CodeGen with the original docstring is not only incorrect but also very different from oracle code.

The code generated by CodeGen with a more reasonable human-labeled docstring is not only correct but also very similar to the oracle code (although the statements are not exactly the same, the semantics are the same).

CoderEval: A Benchmark of Pragmatic Code Generation with Generative Pre-trained Models

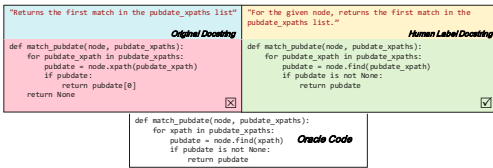


Figure 12. An example of a code snippet generated by PanGu-Coder with an original docstring and human labeling docstring

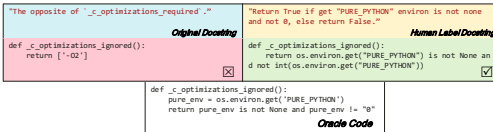


Figure 13. An example of a code snippet generated by CodeGen with an original docstring and human-labeled docstring

Fig 14 shows an example of a code snippet generated by Codex with the original docstring and human-labeled docstring.

Since "self.message" is not mentioned in the original doc-

string, Codex did not generate the "message" member variable reference correctly when generating code, but it generated the "status" member variable, resulting in the incorrect code.

The human-labeled docstring includes "self.message", and the implementation logic is also described more sufficiently, so Codex generated the correct code.

Surprisingly, the correct code generated by Codex is more concise than the oracle code. The oracle code uses three lines to implement the function, while the correct code generated by Codex only uses one single *Pythonic* line to implement the function.

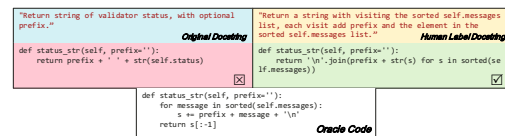


Figure 14. An example of a code snippet generated by Codex with the original prompt and human-labeled prompt