

Execution-Based Evaluation for Open-Domain Code Generation

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Abstract

To extend the scope of coding queries to more realistic settings, we propose ODEX, the first open-domain execution-based natural language (NL) to code generation dataset. ODEX has 945 NL-Code pairs spanning 79 *diverse libraries*, along with 1,707 *human-written test cases* for execution. Our NL-Code pairs are harvested from StackOverflow forums to encourage *natural and practical* coding queries, which are then carefully rephrased to ensure intent clarity and prevent potential data memorization. Moreover, ODEX supports *four* natural languages as intents, in English, Spanish, Japanese, and Russian. ODEX unveils intriguing behavioral differences between top-performing Code LMs: CODEX performs better on open-domain queries, yet CODEGEN captures a better balance between open- and closed-domain. ODEX corroborates the merits of execution-based evaluation over metrics without execution but also unveils their complementary effects. Powerful models such as CODEGEN-6B only achieve an 11.96 pass rate at top-1 prediction, suggesting plenty of headroom for improvement. We release ODEX to facilitate research into open-domain problems for the code generation community.¹

1 Introduction

Evaluations of NL-to-Code generation systems, especially for general-purpose programming languages such as Python, have put an increasing emphasis on execution-based methods. The predominant approach is to create hand-written test cases (Chen et al., 2021; Austin et al., 2021; Hendrycks et al., 2021; Lai et al., 2022; Huang et al., 2022) for the canonical code solutions. By executing model predictions over these test cases, systems are evaluated with execution accuracy, by reporting the pass rate of candidate predictions (Chen

et al., 2021). Compared to execution-free metrics such as text match against a reference solution, execution-based evaluation more rigorously assesses the functional correctness of code.

However, most resources with execution support only apply to closed-domain Python code, such as Python built-in functions (Chen et al., 2021; Hendrycks et al., 2021; Austin et al., 2021) or specific specialized domains (Lai et al., 2022; Huang et al., 2022). This focus on closed-domain coding problems diverges significantly from natural program usage in the real world, which covers a diverse range of domains and functionalities (Yin et al., 2018; Agashe et al., 2019; Wang et al., 2022). Moreover, many datasets focus on programming challenges (Li et al., 2022; Haluptzok et al., 2022) and are often unrepresentative of coding queries asked in practical scenarios.

To enable execution support for practical coding queries, we present ODEX, an open-domain execution dataset. We build ODEX by annotating test cases for 945 NL-Code pairs from the CoNaLa (Yin et al., 2018) and MCoNaLa (Wang et al., 2022) datasets (§ 2). Both datasets stem from StackOverflow (SO) forums that have broad coverage of practical coding queries, and are further refined by human annotators to improve their specificity. As a result, ODEX inherits this broad domain coverage and jointly enables execution.

We highlight and analyze three features of ODEX (§ 3). First, ODEX samples vary in complexity across the intent languages, more concretely between 439, 90, 164, and 252 samples in English, Spanish, Japanese, and Russian. Second, ODEX shows broad domain coverage, with 53.4% of the problems requiring usage from 79 libraries. Third, ODEX supports code execution by manually creating 1,707 test cases that address three challenges unique to code in the open domain: irreproducible execution, randomized outputs, and specialized equivalence check.

¹<https://github.com/zorazrw/odex>

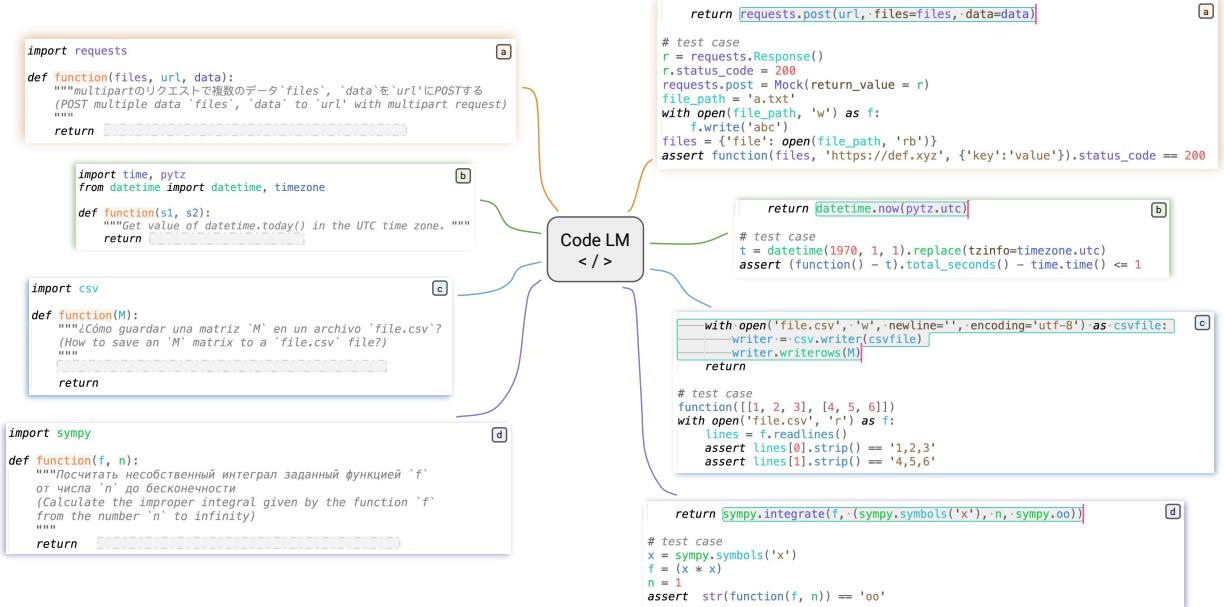


Figure 1: The ODEX dataset. On the left-hand side, inputs are formatted in a function style, consisting of (1) library prerequisites that import necessary libraries or functions; (2) function signature that declares the function name (e.g., entry point) and input arguments (usually variables declared in the NL intent); (3) natural language descriptions put in the function docstrings, where English translations are added to ease understanding but not included in the actual input to examine under the multilingual scenarios; (4) implementation contexts that include correctly indented return clauses; gray boxes indicate places for code solutions. On the right-hand side, the boxes are filled with code solutions. Underneath those are selected human-written test cases for individual samples. Note that besides normal assertions in case [d], [c] requires multiple assertions, [b] is verified through approximate equivalence, and [a] requires simulated execution due to the difficulty of exact, reproducible execution.

By evaluating two state-of-the-art Code LMs on ODEX (§ 4), we observe positive effects from increased model size and augmented training, meanwhile spot satisfactory multilingual abilities from both systems. Nonetheless, compared with problems in the closed domain (CD), models face greater yet varied challenges with open-domain (OD) coding queries (§ 5). While CODEX performs better in OD, CODEGEN has smaller gaps between OD and CD. Further, by comparing execution-based metrics with a series of non-execution metrics (§ 6), we confirm the advantage of execution given its robustness to alternative solutions, but also demonstrate the potential benefit of lexical metrics in identifying easy bug fixes.

The ODEX dataset jointly facilitates practical open-domain code generation and execution-based evaluation. It serves as a comprehensive benchmark for NL-to-Code generation, supporting model proficiency analysis of: multilingual NL contexts, diverse library usage, and evaluations via execution or lexical matches. Our work also signals unique challenges in test case creation and code execution in the open domain. We hope they can encourage more relevant discussions and developments.

2 The ODEX Dataset

We introduce ODEX, the `open-domain execution` dataset, and describe the processes taken to construct this data benchmark.

The construction process of ODEX includes four steps. First, we motivate resource collection (§ 2.1) by seeking natural, open-domain coding queries. Next, we establish the annotation standard and detailed steps for test case annotation (§ 2.2). We then elaborate on the annotator hiring and working process (§ 2.3). Lastly, we conduct exhaustive quality checks (§ 2.4) to ensure data quality.

2.1 Resource Collection

We use two NL-to-Code generation datasets, CoNaLa (Yin et al., 2018) and MCoNaLa (Wang et al., 2022), as sources for building our ODEX dataset. They contain high-quality NL-Code pairs collected from Stackoverflow (SO) forums, then examined and refined by human annotators. CoNaLa contains 2,879 English NL intents paired with Python code snippets, and MCoNaLa extends the NL intent to Spanish, Japanese, and Russian, containing 340, 210, and 345 samples respectively.

Since we often utilize these two datasets together in this work, we refer to their joint as (M)CoNaLa.

Given our main goal of extending execution-based evaluations to open-domain coding queries, one way to achieve this is to add executable test cases to NL-Code pairs. More specifically, we focus on NL-Code pairs that involve practical queries covering a wide variety of domains, as measured by the libraries used in the code. Compared to many other resources such as programming challenge websites, SO contains abundant coding queries that both (1) naturally reflect the practical coding queries asked by programmers, and (2) cover a diverse range of Python domains and functionalities. These desirable properties of SO align well with our motivation, and the human-verified curation process of (M)CoNaLa ensures the source quality. Therefore, our main task is to create test cases for NL-Code pairs in (M)CoNaLa.

2.2 Annotation Standard and Instructions

Given the source NL-Code pairs, our main annotation task is to write test cases to check code execution correctness, by interpreting the NL description, and optionally referring to the original SO post. A qualified test case should verify the main functionality of the canonical code solution.

As illustrated in Figure 2, based on the given *NL intent* and code *snippet*, the annotation process consists of four steps, introduced below.

intent	Calculate sum over all rows of 2D numpy array `a`
snippet	<code>a.sum(axis=1)</code>
Step 1 code wrapping	<code>def function(a): return [.....]</code>
Step 2 library import	<code>import numpy as np</code>
Step 3 write test case	<code>a1 = np.array([[1 for i in range(3)] for j in range(5)]) assert np.array_equal(function(a1), np.array([3, 3, 3, 3, 3])) a2 = np.array([[i+j for i in range(3)] for j in range(5)]) assert np.array_equal(function(a2), np.array([3, 6, 9, 12, 15])) a3 = np.array([[i+j for i in range(3)] for j in range(4)]) assert np.array_equal(function(a3), np.array([0, 3, 6, 9]))</code>
Step 4 execute	

Figure 2: An example annotation comprising four steps.

Step 1: Wrapping Snippets into Functions

Code solutions in (M)CoNaLa are typically short snippets (e.g., `x = np.zeros(5)`) to ensure more precise matches with the NL intent specification. Compared to standalone script files, however, these snippets often lack execution contexts such as variables, and need value specification beforehand. To make the code executable, we propose to wrap code snippets into standalone functions by specifying the input and output arguments in sur-

rounding contexts. Taking the *Step 1* in Figure 2 as an example, we need to identify variable `a` and assign it as input arguments, based on the provided NL intent and code snippet.

Step 2: Specifying Library Prerequisites Due to the open-domain characteristic of (M)CoNaLa, some code snippets require extra library imports to execute correctly. Accordingly, our second step is to specify the prerequisite libraries.

Step 3: Test Case Annotation Next, we write test cases to evaluate the code snippet. Creating a valid test case requires specifying three parts: (1) input: passing values to input arguments, (2) output: stating the expected execution output, and (3) assertion: checking if the actual execution result matches the expected output.

However, for code in the open domain, writing test cases faces three unique challenges. First, it is hard to execute in a safe, reproducible manner. For example Figure 1[a], it is improper to always send an HTTP request when executing this code piece. So, we use `mock` to simulate the correct output (in this case, a success response status code 200). Second, some code involves randomness, e.g., `[randint(3, 5) for _ in range(10)]`, making it impossible to compare the output to a definite value. Hence, we can only make bounding assertions, by verifying that all elements are integers within the range of `[3, 5]`. Third, we cannot always use the standard `==` to check the equivalence between the expected and execution outputs, since open-domain objects often require specialized equality checks. For example, checking the equivalence of two Numpy arrays `a` and `b` requires `np.array_equal(a, b)`, while `a == b` would cause execution errors.

Step 4: Self Verification In the last step, we perform self-verification to efficiently ensure test correctness. We execute the canonical code snippet on each newly created test case. Unless the code snippet successfully passes the test case, it should not be taken as a valid annotation.

2.3 Annotator Hiring and Task Fulfillment

Annotator Qualification As our data involves diverse functionalities from multiple libraries, our annotation task holds a relatively high standard for annotators. A qualified annotator should be proficient in Python, have experience using various libraries, and be able to write workable test cases.

We choose to hire undergraduate students who have strong computer science (particularly Python) backgrounds. Of the 20 applicants who applied, we first conduct a resume screening to filter candidates with sufficient programming experience. Next, we give each candidate a test annotation containing five randomly selected NL-Code pairs. Since these tests mirror the official annotation process, we provide clear instruction documents about each step (as in § 2.2) and code scripts for self-verification. The candidates are asked to finish their tests in three calendar days. Based on their performance in the test, we hired four candidates to officially participate in this annotation job.

2.4 Quality Check

Throughout the annotation process, we put great effort into ensuring the data quality. To assist annotators more efficiently and accurately in writing workable test cases, we require them to execute each written test case using the verification code that we provided, and explicitly report whether the canonical code solution can successfully pass all the annotated test cases that they created.

Following test case creation, we (authors) performed posthoc verifications to check if each test case reads reasonably and executes correctly. In our final rounds of automatic quality checks, we confirm that the pass rate for all canonical code solutions over their annotated test cases is 100%.

We collect a total of 945 samples with NLs in four languages, including 439 samples in English, 90 in Spanish, 164 in Japanese, and 252 in Russian.

3 Dataset Analysis

To review ODEX in greater detail, we analyze its characteristics from three aspects: sample complexity (§ 3.1), domain diversity (§ 3.2), and execution support (§ 3.3). Overall, by integrating multilingual NL intents, open-domain queries, and executable test cases, our ODEX dataset aims to serve as a resourceful benchmark for code generation.

3.1 Complexity

To measure the complexity of NL-Code pairs, one informative metric is length. For NL intents, we use the spaCy² tokenizer in respective languages and cut intents into words; for code snippets, we follow (M)CoNaLa and cut code into tokens following the tokenization of Yin and Neubig (2018).

²<https://spacy.io/>

Furthermore, we count the number of input and output variables to measure the complexity of the execution context in each sample.

Language	NL words	Code tokens	In Vars	Out Vars
en	14.36	18.49	1.13	0.21
es	18.69	28.62	1.46	0.64
ja	17.24	17.70	1.40	0.41
ru	11.39	20.19	1.44	0.71

Table 1: Dataset complexity measured in the averaged number of NL words, code tokens, and i/o variables.

From the statistics of each language subset shown in Table 1, code snippets in the Spanish subset are longer than those in other languages on average, implying potentially greater complexity in their functionality. On both the input and output sides, code in the English set has fewer variables. This suggests potentially simpler execution environments, which could stem from the relative simplicity of StackOverflow queries asked in English.

3.2 Diversity

One unique property of ODEX is its diverse domain coverage. We categorize the problems with library usage (both standard and third-party) as in the open domain, and those with none as in the closed domain. From the dissection of open- and closed-domain problems in Table 2, more than half (53.4%) of the samples include at least one library.

Language	# Unique Libraries	Size		
		open	closed	total
en	45	230	209	439
es	20	48	42	90
ja	44	113	51	164
ru	35	114	138	252
total	79	505	440	945

Table 2: Numbers of open- and closed-domain problems, and numbers of unique libraries involved in ODEX.

From the domain distribution in Figure 3, ODEX covers a great diversity of 79 libraries. Preserving the nature of each NL context, different language subsets cover varied sets of libraries.

Comparing to Other Datasets We also compare ODEX to eight other code generation datasets with test case execution support: HumanEval (Chen et al., 2021), MBPP (Austin et al., 2021), APPS (Hendrycks et al., 2021), MTPB (Nijkamp et al., 2022), P3 (Haluptzok et al., 2022),

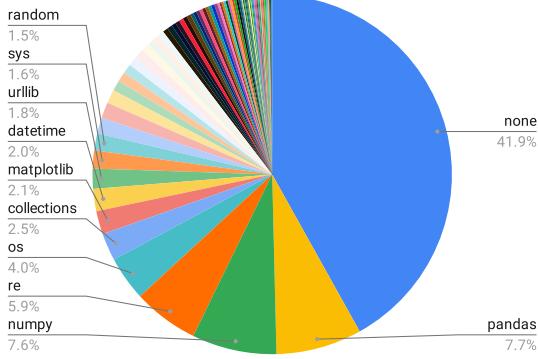


Figure 3: ODEX library distribution.

DSP (Chanel et al., 2022), DS-1000 (Lai et al., 2022), and Exe-DS (Huang et al., 2022).

As shown by their domain distributions in Figure 4, most datasets focus on closed-domain problems or particular topics (e.g., data science for DS-1000 and Exe-DS). In comparison to Figure 3, ODEX is much more “colorful”, covering significantly more libraries, as well as frequently asked problems in the closed domain.

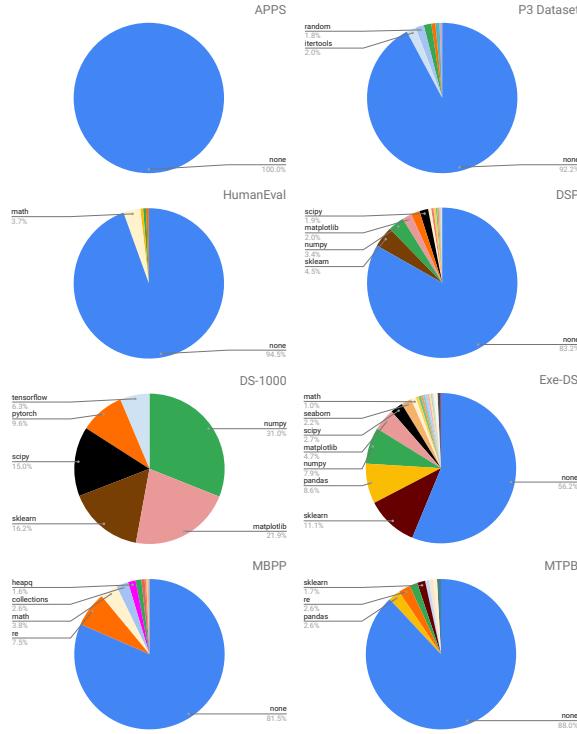


Figure 4: Library distribution of eight other datasets.

Furthermore, to provide a reference on the natural domain distribution, we approximate real-world distribution by counting the number of Python files on GitHub³ that import each library of interest. Given the natural distribution in Figure 5, ODEX

presents a better alignment with the practical scenario concerning the open domains.

Refer to § A.1 for the full list of libraries and their frequencies, about ODEX, the eight comparison datasets, and the approximated natural setting.

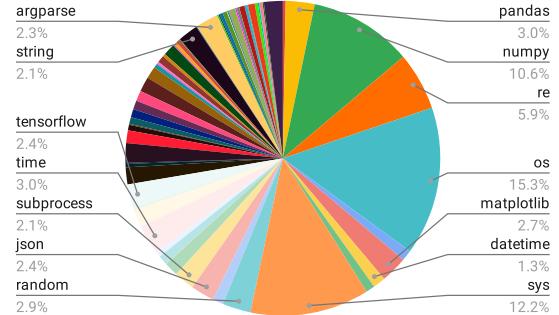


Figure 5: Approximated natural distribution based on GitHub Python files in the open domain.

3.3 Execution Support

ODEX is the first dataset that jointly: (1) supports execution-based evaluation, and (2) covers diverse coding queries in the open domain. As shown in Table 3, ODEX supports evaluations through both means with and without execution, as well as containing NL in four different languages to facilitate program developers native in each. ODEX does not provide the quite as many test cases as some other datasets, but as discussed further in § 7, we still believe these serve as a reasonable testbed for execution-based evaluation.

4 Evaluating Code Generation Systems

Code LMs have achieved strong performance on multiple code generation tasks, yet their open-domain proficiency is understudied due to the limited domain settings of past datasets. To examine model capabilities in the open domain, we evaluate two top-performing model families on ODEX.

4.1 Experiment Setup

We first introduce the baseline models (§ 4.1.1), then describe the prompt settings (§ 4.1.2) for model inference, and lastly, lay out the metrics for code evaluation (§ 4.1.3).

4.1.1 Baseline Models

We benchmark two state-of-the-art Code LM families – CODEX and CODEGEN – on ODEX.

³<https://github.com/>

Dataset	Samples	Domain	Evaluation	Avg. Test Cases	Data Source	NL
JuICe (Agashe et al., 2019)	1,981	open	lexical	-	GitHub Notebooks	en
HumanEval (Chen et al., 2021)	164	4	execution	7.7	Hand-written	en
MBPP (Austin et al., 2021)	974	8	execution	3.0	Hand-written	en
APPS (Hendrycks et al., 2021)	10,000	0	execution	13.2	Competitions	en
DSP (Chandek et al., 2022)	1,119	16	execution	2.1	Github Notebooks	en
MTPB (Nijkamp et al., 2022)	115	8	execution	5.0	Hand-written	en
Exe-DS (Huang et al., 2022)	534	28	lexical	-	GitHub Notebooks	en
DS-1000 (Lai et al., 2022)	1,000	7	execution	1.6	StackOverflow	en
CoNaLa (Yin et al., 2018)	2,879	open	lexical	-	StackOverflow	en
MCoNaLa (Wang et al., 2022)	896	open	lexical	-	StackOverflow	es, ja, ru
ODEX	945	79	lexical execution	1.8	StackOverflow Hand-Written	en, es, ja, ru

Table 3: Comparing ODEX with other code generation datasets, in terms of domain diversity (*Domain*), test-case execution support (*Evaluation*, *Avg. Test Cases*), and natural language contexts (*NL*). Since it is hard to calculate the exact number of libraries for some open-domain datasets that do not specifically import required libraries in the code, we mark their domains as *open* instead of providing the exact number of domains.

The CODEX Family Up to the time of this work, CODEX has three publicly available models. From the official documentation,⁴ CODE-CUSHMAN-001 is a 12B CODEX model as described in Chen et al. (2021). The DAVINCI variants have much larger sizes than CUSHMAN. Both CODE-DAVINCI-001 and CODE-DAVINCI-002 are base GPT-3 models (Brown et al., 2020) and have 175B parameters, and the 002 version usually outperforms 001.

The CODEGEN Family CODEGEN (Nijkamp et al., 2022) is another top-performing model family. CODEGEN models are auto-regressive GPT models trained on a combination of NL and code corpora. The multiple variants differ in their sizes (350M, 2.7B, 6.1B, 16.1B) and training data (NL, MULTI, MONO). Models trained on THEPILE (Gao et al., 2020) dataset are called the NL version, those additionally trained on BIGQUERY⁵ are MULTI versions, and MONO models are further trained on Python code they collected from GitHub (BIGPYTHON). The most powerful variant, CODEGEN-16.1B-MONO, has obtained similar results to the CODEX CODE-CUSHMAN-001 model.

4.1.2 Prompt Design

For fair and consistent comparison, we input the same prompt to all models in the CODEX and CODEGEN families. While using in-context learning, where a few demonstrations are provided to the LM within the prompt, may bring model improvements, our preliminary explorations did not always find this helpful. So we report the zero-shot

experiments in this baseline setting, and leave few-shot results to § 7.1. Creating zero-shot prompts only requires content from the test sample. Following Chen et al. (2021), we construct prompts by sequentially concatenating: the library import prerequisites, the function wrapping context, as well as the docstring consisting of NL intents and optional test cases, as illustrated in Figure 6.

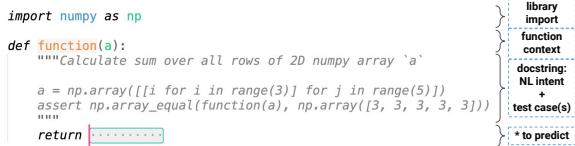


Figure 6: An example zero-shot prompt with one test case included in the docstring. Gray blocks indicate the place for target code prediction.

4.1.3 Evaluation Metrics

Our experiments focus on execution-based evaluation, where successful execution of the generated code marks its functional correctness. Following Chen et al. (2021), we sample k candidates from 10 model predictions and compute their pass rate.

In addition to the execution-based metrics, our dataset also allows other non-execution metrics that evaluate by lexical, syntax, or semantic match to the reference solution (Evtikhiev et al., 2022). We adopt five metrics: BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), METEOR (Banerjee and Lavie, 2005), ChrF (Popović, 2015), and CodeBLEU (Ren et al., 2020). With this broad set of metrics at hand, later in § 5, we explain the advantage of execution and study their nuances and complementary effects. Please refer to § D.1 for more detailed descriptions of the metrics.

⁴<https://beta.openai.com/docs/model-index-for-researchers>

⁵<https://cloud.google.com/bigquery>

NL	Model	Pass Rate					Model	Pass Rate				
		p@1	p@2	p@5	p@8	p@10		p@1	p@2	p@5	p@8	p@10
en	CUSHMAN-001	31.91	44.67	59.95	66.28	68.79	350M	10.32	11.29	12.24	12.50	12.53
es		31.89	43.33	55.72	60.96	63.33		17.56	17.78	17.78	17.78	17.78
ja		25.67	36.69	49.27	54.76	57.32		7.01	8.06	9.55	10.20	10.37
ru		40.00	53.48	66.63	71.44	73.41		21.35	24.20	26.94	27.82	28.17
en	DAVINCI-001	33.62	46.65	60.18	65.37	67.43	2.7B	14.28	15.69	16.99	17.39	17.54
es		36.89	49.46	61.37	66.20	68.89		19.67	22.32	24.76	25.48	25.56
ja		31.04	42.11	54.26	59.53	61.59		10.98	12.56	14.20	14.61	14.63
ru		43.21	57.53	70.03	74.51	76.59		33.10	36.01	39.53	41.06	41.67
en	DAVINCI-002	47.15	57.61	67.87	71.67	73.12	6.1B	11.96	12.95	14.01	14.56	14.81
es		47.44	57.90	66.33	69.53	71.11		14.78	16.64	18.70	19.70	20.00
ja		41.46	50.42	59.47	62.71	64.02		12.44	14.34	16.51	17.40	17.68
ru		51.87	63.36	73.03	76.64	78.17		32.86	34.45	36.28	37.03	37.30

Table 4: Execution accuracy of CODEX and CODEGEN models.

4.1.4 Implementation Details

At inference time, we collect 10 candidate predictions using nucleus sampling (Holtzman et al., 2019) for each sample prompt input. Following Chen et al. (2021), we use top-p = 0.95 and temperature = 0.8. We set the maximum token number to 768 for both input and output sequences.

4.2 Baseline Performance

CODEX Results We evaluate three CODEX models in their execution accuracy as in Table 4. Aligning to our intuitions from model size and version (§ 4.1.1), larger 175B models (D1, D2) outperform the smaller 12B model (C1), and later versions also improve (D2 > D1). This trend holds for all language subsets and all evaluation granularities.

Somewhat surprisingly, all models achieve decent results on non-English problems. Results in Russian are even better than the English subset. Models are forced to understand NLs since no test cases are included in the prompts. High accuracy on non-English subsets actually showcases the multilingual proficiency of CODEX models.

CODEGEN Results We evaluate the multiple CODEGEN models with different sizes and training. Since MONO models are trained the longest and outperform both NL and MULTI settings (Nijkamp et al., 2022), we report the results of MONO models in various sizes in Table 4.

As larger models usually perform better, the pass rate increases as model sizes grow from 350M to 2.7B. However, continuing to increase the size from 2.7B to 6.1B brings little gain. Potentially this size increase is not sufficient for significant gains.

CODEGEN is also not English-centric and performs well with NL intents in other languages.

Although CODEX and CODEGEN have comparable performance on existing data benchmarks such as HumanEval, ODEX effectively unveils the advantage of CODEX on open-domain coding queries. While the larger size of CODEX certainly brings greater model capabilities, we conjecture that the training data, in its coverage of open-domain libraries, may also affect the model results.

Please find more fine-grained results (pass rate at $1 \leq k \leq 10$) for both baselines in Appendix B.

5 Open Domain Versus Closed Domain

Benefiting from the co-existence of open-domain (OD) and closed-domain (CD) problems in ODEX, we analyze variances in the open and closed domain (§ 5.1) and further in individual domains (§ 5.2), to inspect the distinctive challenges raised by execution in the open domain (§ 5.3).

5.1 Models in Open and Closed Domain

CODEX Figure 7 illustrates the gap in execution accuracy on OD and CD problems.

First and foremost, all CODEX models score significantly lower on OD problems than on CD problems. These large gaps hold across all language contexts, relatively small in Spanish but extremely large in Japanese and Russian subsets. Upgrading the models (C1 → D1 → D2) does not always help decrease these OD-CD gaps. Although the gaps slightly shrink in Spanish, gaps in English and Japanese exhibit continuous increases. While D2 achieves the best results within the CODEX family, it also faces the most severe gap when generalizing to the open domain.

CodeGen Results The other baseline model CODEGEN, however, yields much smaller gaps between OD and CD samples. As shown in Figure 9,

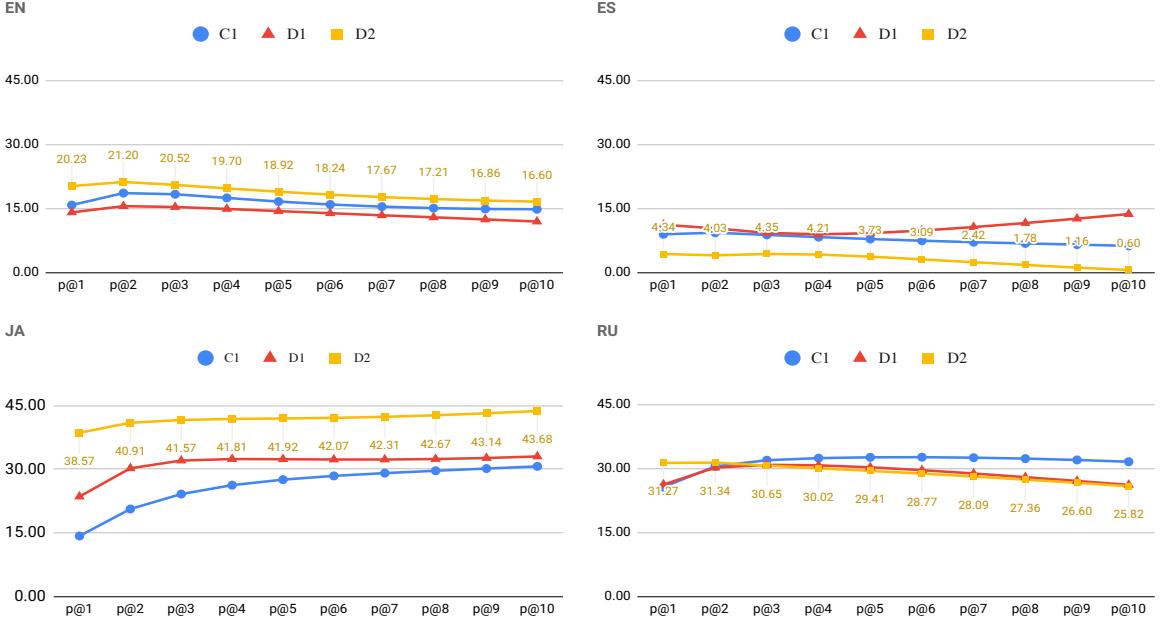


Figure 7: Gaps in CODEX execution accuracy between open- and closed-domain problems, for English, Spanish, Japanese, and Russian subsets, respectively. Gap values of the best model (CODE-DAVINCI-002) are labeled.

the margins are closer to zero, and interestingly for the Spanish sample, turn to negative values, where CODEGEN-6.1B on CD even surpasses that on OD by 6.73 points at pass@1. Still, OD scores more often lag behind CD scores, having a significant 20.6 point gap in Japanese and a 20.2 point gap in Russian. Similarly to CODEX models, CODEGEN OD-CD gaps widen as the model size increases.

Small gaps could be partially attributed to the lower scores (less amplitude for variation), it also potentially suggests that CODEGEN obtains a more balanced ability between OD and CD problems.

5.2 Domain Variance

Given the inferior OD results, we dive deeper into individual domains. We focus our analysis on the CODE-DAVINCI-002 model as it has the best performance so far. In Figure 8, we compute the execution accuracy in each domain with respect to its practical frequency, as approximated in § 3.2.

From this domain-wise performance dissection, execution accuracy is not low on all open domains. For example, the model achieves 50% pass@1 for several common libraries such as `random` and `math`. However, the model does not perform as well on all high-frequency domains. Especially for libraries involving complex functionalities such as `matplotlib` and `tensorflow`, the pass@1 rates are below 10%. Please refer to Appendix C for detailed execution results in each domain.

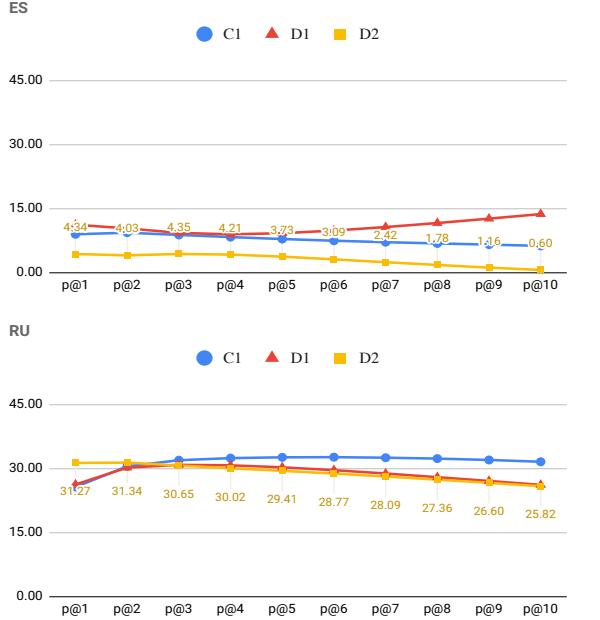


Figure 8: CODEX pass@1 for domains of varied frequencies. Domains are differently colored based on their frequency ranking: the 10 most frequent domains in red, the 10 least frequent domains in blue, and other domains in yellow.

5.3 Qualitative Error Analysis

To understand the unique challenges of open-domain problems, we manually analyze the errors made by CODE-DAVINCI-002 on 60 random examples from ODEX (15 for each language).

Of the 60 random samples, 29 and 31 are in open and closed domains, respectively. On one hand, we observe that OD and CD problems share two error categories: (1) function misuse, happening for 50.0% of the CD samples but only 19.2% for OD samples; (2) complex operations, taking up 31.8% CD samples and 15.4% in OD. On the other hand, OD problems introduce two extra issues: (1) missing or wrong library selection, causing errors in as much as 61.5% of OD samples; and (2) erro-

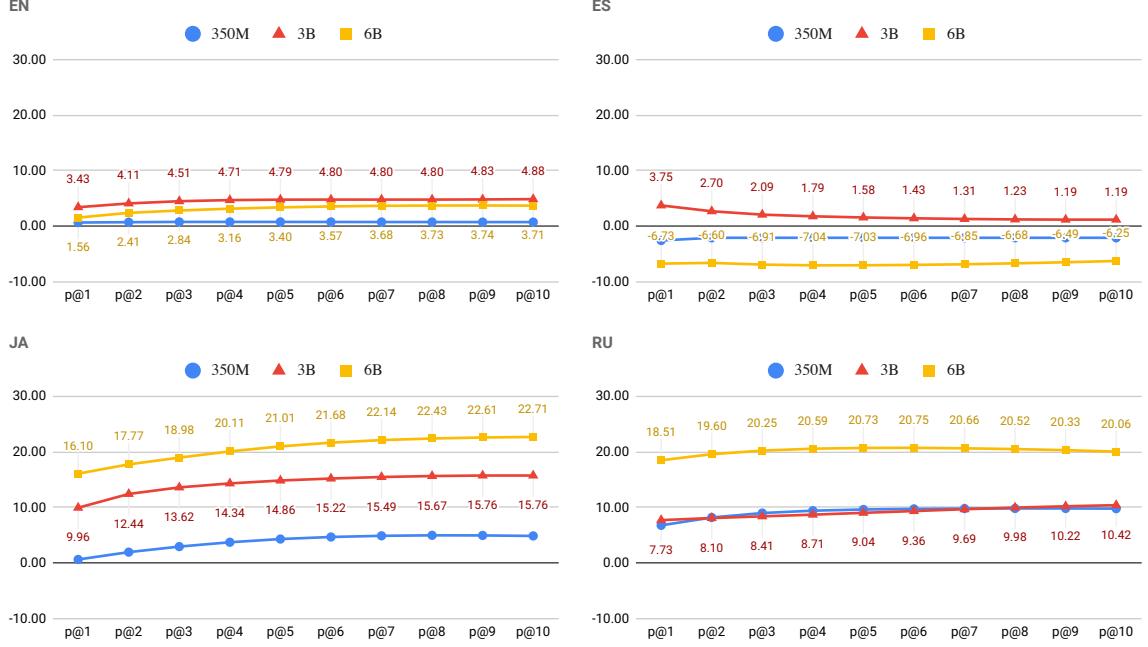


Figure 9: Gaps in CODEGEN execution accuracy between open- and closed-domain problems, in each language subset. Values of the largest and smallest gaps are labeled.

neous selection or usage of library-specific functions, troubling another 34.6% OD samples. More discussions on the error types in open and closed domains are included in § C.3.

6 Execution-based and Execution-free Evaluations

In this section, we study five execution-free metrics as mentioned in § 4.1.3, in their alignment with the overall execution accuracy (§ 6.1), and their correlations with the pass rate on a sample basis (§ 6.2), leading to observed advantages of execution- and lexical-based metrics.

6.1 Model Ranking Using Different Metrics

We compute model performance using another five metrics – BLEU, ROUGE, METEOR, ChrF, and CodeBLEU – as introduced in § 4.1.3.

From Figure 11, ranking models using execution-free metrics does not preserve their relative ranking under execution accuracy. Even when the rankings align, their relative margins are barely proportional. While it is understandable that different metrics range and change differently, it requires metric-specific heuristics to robustly interpret their scores.

Among the metrics without execution, ChrF and METEOR have smaller inter-model variances, while BLEU and ROUGE have larger variances and align better with execution results. Comparing the two model families, CODEX also yields much

higher scores than CODEGEN models except for the CodeBLEU metric. Notably, CodeBLEU is low across almost all settings and even increases when execution accuracy decreases, indicating that CodeBLEU might not be reliable for code evaluation.

6.2 Metric Correlation

For a finer-grained analysis, we study the sample-wise association between metrics. Specifically, we verify if there exists significant variances in the distribution of execution-free metrics between samples that passed and failed at execution. We take the BLEU metric as an example, since it shows relatively similar patterns to the execution accuracy, at least in comparison with other metrics.

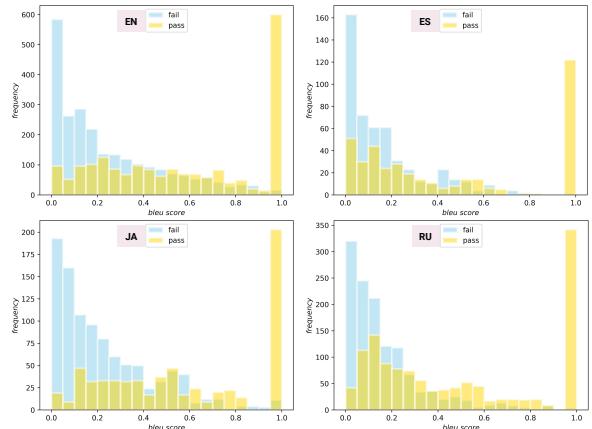


Figure 10: BLEU score on passed and failed samples, using CODEX (CODE-DAVINCI-002 version).

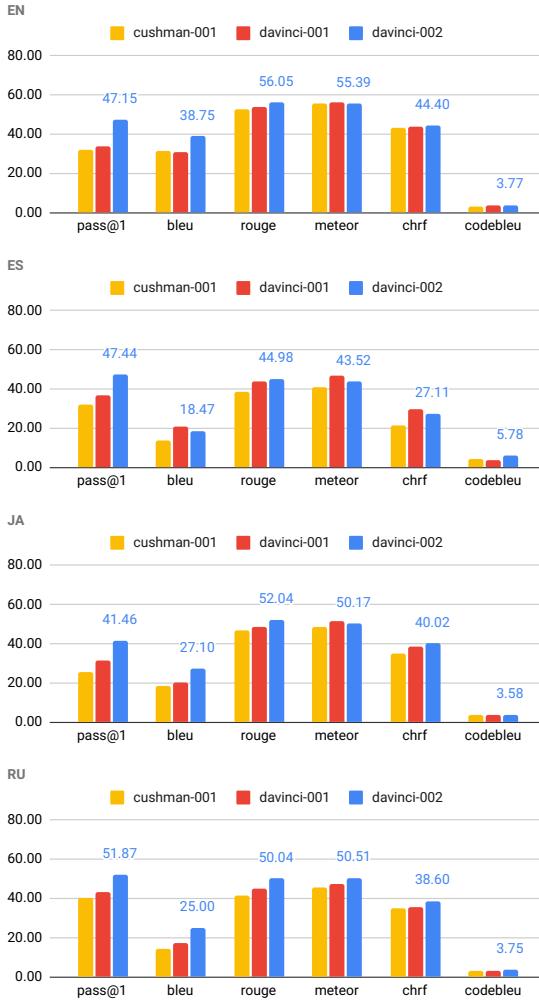


Figure 11: CODEX evaluated on six metrics.

The visualization in Figure 10 shows that there are significant regions of overlap on the BLEU score distribution between passed and failed examples. Although bars at the two ends (where BLEU approaches 0.0 and 1.0) show more alignment with execution accuracy (fail=0.0, pass=1.0), regions in the middle do not display strong correlations with the execution correctness or its probability.

We analyze the four other execution-free metrics following the same approach, where they largely show similar patterns, i.e., similar score distributions regardless of the sample execution accuracy. See more results and visualizations in § D.3.

Given this variance between execution- and lexical-based metrics, we conduct a case study on 15 random cases from each language, and identified two major benefits for each type of metric.

Why is Execution Better? Execution-based metrics have two major benefits. First, it tolerates alternative solutions, which use other methods to implement the correct function. Second, it

allows model directly output the execution result (e.g., ‘JKL’) instead of the implementation (e.g., ‘‘.join(chars)'). Both cases would have a very low lexical match with the canonical solution, but still, pass the execution.

Potential Benefit of Lexical Match Lexical-based metrics, on the other hand, could indicate less effort for debugging and interpretation (Deng et al., 2021). Cases that fail the execution but obtain a high lexical match often err in two ways. First, it misuses a single function, such as calling `re.match` instead of `re.findall`. Second, the strings inside lose characters such as whitespace. Refer to § D.4 and § D.5 for more examples.

7 What Affects the NL-to-Code Performance?

In addition to baseline settings (§ 4), multiple factors could affect the NL-to-Code performance. We study three potential factors: the prompting strategy (§ 7.1), number of test cases for execution (§ 7.2), and semantics of function context (§ 7.3).

7.1 Prompting Strategy

Few-shot Prompting Including more exemplar contexts could potentially benefit the current test prediction. Hence, we explore the few-shot setting by prefixing $N \in \{1, 2, 3\}$ input-output pairs in the prompt input. Inputs here refer to the prompt, and outputs are the code solutions. Adding more examples requires increasing prompt lengths, so we only experiment with N up to 3 due to the computational overhead. Nonetheless, as is shown in Figure 12, 3 has already achieved (even passed) the optimal value for execution correctness.

For CUSHMAN-001 and DAVINCI-001, including in-context examples yields a clear advantage over the zero-shot setting. But for the strongest DAVINCI-002, few-shot examples bring minimal improvements for English, and even lead to negative effects for Japanese and Russian questions.

Adding Test Cases to Prompt Inputs Including test cases in prompts could add execution-time hints thus potentially improving the code execution accuracy. Given this hypothesis, we experiment with prompts that have varying numbers of test cases. Based on the default zero-shot prompts (§ 4), we experiment with adding one random test

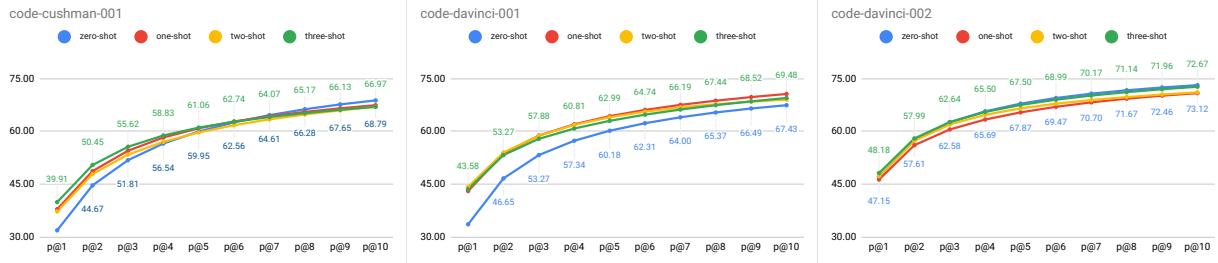


Figure 12: CODEX execution accuracy using 0/1/2/3-shot prompt inputs.

case and all annotated test cases.⁶

Figure 13 shows that injecting as few as one exemplar test case leads to significantly better execution accuracy, yet adding more cases brings little extra gain. This potentially implies the sufficiency of one test case to show the main functionality.

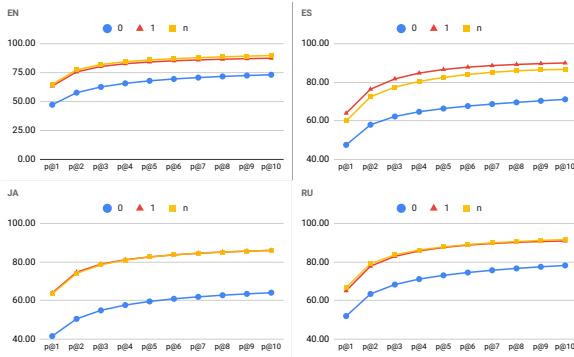


Figure 13: Execution accuracy when including zero, one, or all test cases in the prompt inputs.

7.2 Number of Evaluation Test Cases

The execution accuracy on a fixed set of code predictions also varies when evaluating over different test cases. In general, the more test cases used for execution, the more accurate the evaluation results could be. However, due to the high cost of human annotation effort, there is a tradeoff between evaluation effectiveness and annotation efficiency. To explore this tradeoff, we study how the execution result changes with respect to the number of execution tests. Compared to the default setting that uses all annotated test cases, we also test by executing on one randomly selected test case. For simplicity, we do not include any test cases in the prompts.

As shown in Figure 14, using a single, random execution test in evaluation largely preserves the evaluation precision when using all cases. Presumably, one case is sufficient to test the main functionality for most queries.

⁶The two settings may collapse on samples that only have one annotated test case.

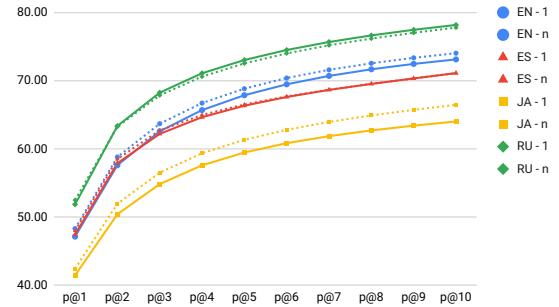


Figure 14: Accuracy of executing one or all test cases.

7.3 Semantics of Function Names

Code snippets in ODEX are wrapped into functions to enable execution, where the semantics of function names may have potential effects. By default, we format the function names using their SO post ID (e.g., f_3844801). However, this expresses little semantics about the code sample, whereas it might be better to name the function with more programmatic details (e.g., check_all_elements)

We experiment with three namings: (1) a constant string `function`, (2) post ID as default, and (3) summary phrases from NL intents. To do (3), we heuristically extract the first $N = 4$ words from intents, as described in § E.3. To ensure a fair comparison with previous results, we do not add any test cases in the prompts.

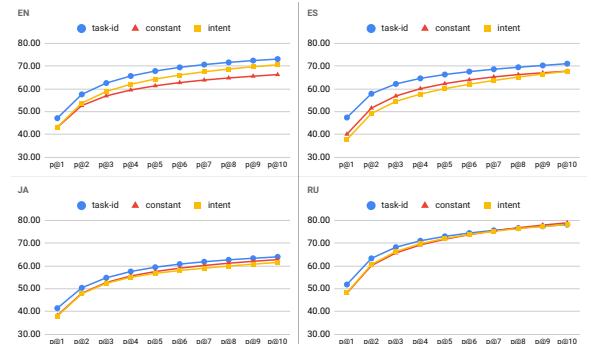


Figure 15: Effect of function names.

From Figure 15, changing function names to

more semantically meaningful ones barely improves, even experiencing slight drops compared to the default approach. We conjecture the reason behind this to be twofold. First, function names summarized from NL intents contain roughly overlapping semantics to the intents, so the little extra semantics yields minimal benefits. Second, the heuristics for name curation may cost information loss, and may be even more on non-English intents, impairing its potential effects.

Refer to Appendix E for more detailed results.

8 Related Work

Open Domain Code Generation Code written in general-purpose programming languages often uses classes or functions from external libraries. A few datasets for code generation preserve this open-domain nature. The CONCODE (Iyer et al., 2018) dataset tested generation of Java class methods. Later works target Python generation given the interactive context of Jupyter Notebooks (Agashe et al., 2019) or natural language intents from StackOverflow posts (Yin et al., 2018; Wang et al., 2022). Despite their natural coverage, enabling open-domain code execution has faced great challenges given its diversity and complexity (Lai et al., 2022; Chadel et al., 2022). To address this issue, our ODEX provides test cases as code execution contexts for evaluation.

Code Evaluation via Execution Execution-based evaluation has been long adopted for domain-specific programming languages such as SQL queries (Zhong et al., 2017) or logical forms (Dong and Lapata, 2016). This execution-based paradigm has not been introduced to general-purpose languages until recently by the HumanEval dataset (Chen et al., 2021), where human-written test cases are provided for code execution. Many works afterward follow this approach, but focus more on closed-domain settings (Austin et al., 2021; Hendrycks et al., 2021) or specific libraries of interest (Lai et al., 2022; Huang et al., 2022). Toward broader execution environments, we provide executable test cases for as many as 79 libraries.

Coding Queries Versus Programming Challenges Programs from different sources are organized for various purposes. Coding contest websites such as LeetCode⁷ and Codeforces⁸ have

been used to build many code generation benchmarks (Hendrycks et al., 2021; Li et al., 2022). However, they randomly align with how humans program in practical scenarios. To build datasets with natural and practical usage of code, many works use GitHub Jupyter Notebooks (Agashe et al., 2019; Huang et al., 2022) and StackOverflow forums (Yin et al., 2018; Wang et al., 2022; Lai et al., 2022) as a source of naturally-occurring code. We remain such naturalness by using StackOverflow posts, but uniquely from forums in various languages to also assist programmers worldwide.

Test Case Creation While most benchmarks use Python test cases annotated by human programmers (Chen et al., 2021; Nijkamp et al., 2022; Lai et al., 2022), challenge-style datasets adopt a more direct approach by crawling from the web (Hendrycks et al., 2021; Li et al., 2022). Another thread of work attempts to generate test cases automatically based on the Python grammar (Lukasczyk and Fraser, 2022), but is largely limited to basic Python functions. Some propose to leverage the power of neural LMs (Tufano et al., 2020; Li et al., 2022), even jointly considering solution and test case generation (Chen et al., 2022). However, the quality and diversity of test cases are not robustly ensured. We hence use high-quality human-written test cases for ODEX evaluation.

9 Conclusion

We present ODEX, an open-domain code generation dataset supporting execution-based evaluation via human-written test cases. Our dataset not only supports functional evaluation of code using execution test cases, but also extends the task to the open domain, covering 79 diverse Python libraries, and four natural languages (English, Spanish, Japanese, and Russian). Comparing two state-of-the-art code generation models, CODEX and CODEGEN, our dataset effectively unveils their varied behaviors between program domains and language contexts. ODEX serves as a more comprehensive code generation benchmark given its open-domain coverage, multi-national language queries, and multi-metric support. When bringing code execution to open-domain scenarios, our explorations also reveal emerging challenges in test creation and reliable execution, which we hope that our dataset will enable future work to tackle.

⁷<https://leetcode.com/>

⁸<https://codeforces.com/>

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A ODEX Dataset

A.1 Library Distribution Statistics

Aside from the illustrations in § 3.2, we list out the detailed statistics of libraries in ODEX, the eight comparison datasets, and the approximated natural distribution.

ODEX Domain Statistics Table 5 lists the number and percentage of occurrences for each library in the ODEX dataset.

ODEX					
Library	Count	Frequency	Library	Count	Frequency
none	440	41.90	functools	2	0.19
pandas	81	7.71	http	2	0.19
numpy	80	7.62	obspy	2	0.19
re	62	5.90	pickle	2	0.19
os	42	4.00	pytz	2	0.19
collections	26	2.48	seaborn	2	0.19
matplotlib	22	2.10	sqlalchemy	2	0.19
datetime	21	2.00	statistics	2	0.19
urllib	19	1.81	string	2	0.19
sys	17	1.62	xlrd	2	0.19
random	16	1.52	IPython	1	0.10
io	15	1.43	argparse	1	0.10
json	15	1.43	aspose	1	0.10
subprocess	13	1.24	bisect	1	0.10
requests	10	0.95	cgi	1	0.10
bs4	9	0.86	configparser	1	0.10
ertools	9	0.86	ctypes	1	0.10
operator	9	0.86	dateutil	1	0.10
time	9	0.86	difflib	1	0.10
math	8	0.76	docxtpl	1	0.10
builtins	6	0.57	filecmp	1	0.10
selenium	6	0.57	ftplib	1	0.10
tensorflow	6	0.57	hashlib	1	0.10
django	5	0.48	heapq	1	0.10
sqlite3	5	0.48	imp	1	0.10
PIL	4	0.38	inspect	1	0.10
codecs	4	0.38	locale	1	0.10
cv2	4	0.38	lxml	1	0.10
scipy	4	0.38	mechanize	1	0.10
sklearn	4	0.38	mpl_toolkits	1	0.10
base64	3	0.29	multidict	1	0.10
csv	3	0.29	pprint	1	0.10
flask	3	0.29	queue	1	0.10
glob	3	0.29	regex	1	0.10
shutil	3	0.29	rsa	1	0.10
socket	3	0.29	ssl	1	0.10
struct	3	0.29	texttable	1	0.10
sympy	3	0.29	unicodedata	1	0.10
xlwt	3	0.29	warnings	1	0.10
ast	2	0.19	xml	1	0.10

Table 5: ODEX library distribution.

Domain Statistics of Comparison Datasets Table 6 lists the library frequency of eight comparison dataset mentioned in § 3: HumanEval, MBPP, APPS, MTPB, P3, DSP, DS-1000, and Exe-DS.

HumanEval					
Library	Count	Frequency	Library	Count	Frequency
none	155	94.51			
math	6	3.66	hashlib	1	0.61
collections	1	0.61	re	1	0.61
MBPP					
Library	Count	Frequency	Library	Count	Frequency
none	794	81.52			
re	73	7.49	cmath	3	0.31
math	37	3.80	operator	3	0.31
collections	25	2.57	array	0	0.00
heapq	16	1.64	bisect	2	0.21
ertools	12	1.23	copy	1	0.10
sys	7	0.72	datetime	1	0.10
APPS					
Library	Count	Frequency	Library	Count	Frequency
none	10,000	100.00			
MTPB					
Library	Count	Frequency	Library	Count	Frequency
-	103	88.03			
pandas	3	2.56	collections	1	0.85
re	3	2.56	datetime	1	0.85
numpy	2	1.71	math	1	0.85
sklearn	2	1.71	regex	1	0.85
P3					
Library	Count	Frequency	Library	Count	Frequency
-	1581	92.19			
ertools	35	2.04	heapq	15	0.87
random	31	1.81	re	15	0.87
collections	28	1.63	math	10	0.58
DSP					
Library	Count	Frequency	Library	Count	Frequency
-	2034	92.79			
sklearn	110	5.02	collections	8	0.36
numpy	84	3.83	time	8	0.36
matplotlib	50	2.28	gzip	4	0.18
pandas	46	2.10	pickle	4	0.18
scipy	46	2.10	random	4	0.18
math	16	0.73	csv	2	0.09
numbers	12	0.55	ertools	2	0.09
utils	12	0.55	seaborn	2	0.09
DS-1000					
Library	Count	Frequency	Library	Count	Frequency
pandas	291	29.10	scipy	106	10.60
numpy	220	22.00	pytorch	68	6.80
matplotlib	155	15.50	tensorflow	45	4.50
sklearn	115	11.50			
Exe-DS					
Library	Count	Frequency	Library	Count	Frequency
none	379	56.23			
sklearn	75	11.13	pylab	2	0.30
pandas	58	8.61	__future__	1	0.15
numpy	53	7.86	arch	1	0.15
matplotlib	32	4.75	cPickle	1	0.15
scipy	18	2.67	cofi	1	0.15
seaborn	15	2.23	csv	1	0.15
math	7	1.04	datetime	1	0.15
collections	4	0.59	functools	1	0.15
re	4	0.59	graphviz	1	0.15
folium	3	0.45	json	1	0.15
nltk	3	0.45	mpl_toolkits	1	0.15
statsmodels	3	0.45	operator	1	0.15
warnings	3	0.45	os	1	0.15
IPython	2	0.30	tensorflow	1	0.15

Table 6: Library statistics of eight comparison datasets.

Approximated Natural Domain Distribution
 To approximate the natural distribution of libraries in the open domain, we count the number of Python files on GitHub that imports the library of interest. Their frequencies are shown in Table 7.

Approximated Natural Distribution			
Library	Count	Library	Count
os	30,188,921	sqlite3	694,794
sys	24,213,844	configparser	640,014
numpy	20,965,506	queue	631,326
re	11,762,193	ssl	602,351
time	5,946,718	http	597,866
pandas	5,878,651	xml	574,030
random	5,740,444	seaborn	567,576
matplotlib	5,416,874	imp	560,862
json	4,792,536	builtins	560,148
tensorflow	4,720,266	locale	542,607
argparse	4,570,391	ast	444,349
subprocess	4,165,781	bisect	315,031
string	4,114,004	pytz	295,167
codecs	3,973,691	heapq	281,393
warnings	3,824,001	cgi	277,852
math	3,569,158	unicodedata	267,310
django	3,447,092	regex	235,800
shutil	2,999,394	difflib	225,154
requests	2,837,310	PIL	218,526
cv2	2,575,063	sklearn	208,913
datetime	2,536,970	statistics	127,725
socket	2,489,033	rsa	122,447
pickle	2,419,604	lxml	111,742
io	2,190,998	dateutil	107,041
collections	2,152,651	bs4	90,224
glob	2,114,567	xlrd	86,522
itertools	1,899,461	filecmp	79,328
urllib	1,809,462	IPython	73,274
flask	1,788,601	sympy	70,969
csv	1,680,232	selenium	56,709
functools	1,433,520	xlwt	55,035
pprint	1,378,679	ftplib	52,121
base64	1,352,623	multidict	29,224
hashlib	1,330,158	mechanize	20,978
scipy	1,121,371	obspy	5,799
inspect	1,112,770	texttable	4,749
operator	1,104,841	aspose	1,048
ctypes	864,108	docxtpl	76
sqlalchemy	814,096	mpl_toolkits	2
struct	787,484		

Table 7: Approximated natural domain distribution.

A.2 More Annotation Details

Along with the NL-Code pair, we also provide IDs of the source StackOverflow post, using which annotators can trace back to the original post webpage and get a better understanding of the question. If any errors or under-specification are spotted in the given NL or code, we ask the annotators to correct it by making the minimal change possible.

Because our data source comprises NL intents

in four different languages, each candidate may get random samples with non-English intents, where we suggest they use translation tools such as the Google Translate API.⁹

Aligning with how programmers import a library, we require the expressions be written in three forms: (1) `import ${LIBRARY}`, (2) `import ${LIBRARY} as ${ABBR}`, or (3) `from ${LIBRARY} import ${FUNCTION}`, where the `${LIBRARY}` can also be sub-classes such as `matplotlib.pyplot`.

We encourage the annotators to use the language identical to the given NL intent when creating the test cases, especially if the code involves string-related operations (e.g., writing regular expressions in Japanese). We encourage the annotators to write reasonably more and diverse test cases, by varying the values or types of variables.

B Baseline Results

According to the baseline results in § 4, we provide more detailed evaluation results, on the execution pass rate ranging from the top-1 to top-10 model predictions. Table 8 and Table 9 show the zero-shot execution accuracy of CODEX and CODEGEN models, respectively.

Model	NL	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
C1	en	31.91	44.67	51.81	56.54	59.95	62.56	64.61	66.28	67.65	68.79
	es	31.89	43.33	49.23	53.01	55.72	57.81	59.52	60.96	62.22	63.33
	ja	25.67	36.69	42.66	46.49	49.27	51.44	53.23	54.76	56.10	57.32
	ru	40.00	53.48	60.04	63.96	66.63	68.62	70.17	71.44	72.50	73.41
D1	en	33.62	46.65	53.27	57.34	60.18	62.31	64.00	65.37	66.49	67.43
	es	36.89	49.46	55.44	58.96	61.37	63.22	64.78	66.20	67.56	68.89
	ja	31.04	42.11	47.83	51.54	54.26	56.39	58.11	59.53	60.67	61.59
	ru	43.21	57.53	63.93	67.58	70.03	71.85	73.29	74.51	75.60	76.59
D2	en	47.15	57.61	62.58	65.69	67.87	69.47	70.70	71.67	72.46	73.12
	es	47.44	57.90	62.20	64.65	66.33	67.61	68.65	69.53	70.33	71.11
	ja	41.46	50.42	54.84	57.59	59.47	60.84	61.87	62.71	63.41	64.02
	ru	51.87	63.36	68.25	71.09	73.03	74.5	75.67	76.64	77.46	78.17

Table 8: CODEX zero-shot performance.

Model	NL	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
350M	en	10.32	11.29	11.78	12.06	12.24	12.37	12.45	12.50	12.53	12.53
	es	17.56	17.78	17.78	17.78	17.78	17.78	17.78	17.78	17.78	17.78
	ja	7.01	8.06	8.71	9.18	9.55	9.84	10.05	10.20	10.30	10.37
	ru	21.35	24.20	25.64	26.44	26.94	27.30	27.59	27.82	28.02	28.17
2.7B	en	14.28	15.69	16.36	16.74	16.99	17.16	17.29	17.39	17.47	17.54
	es	19.67	22.32	23.55	24.28	24.76	25.10	25.33	25.48	25.56	25.56
	ja	10.98	12.56	13.38	13.88	14.20	14.41	14.54	14.61	14.63	14.63
	ru	33.10	36.01	37.64	38.72	39.53	40.15	40.65	41.06	41.39	41.67
6.1B	en	11.96	12.95	13.43	13.75	14.01	14.22	14.40	14.56	14.69	14.81
	es	14.78	16.64	17.56	18.20	18.70	19.11	19.44	19.70	19.89	20.00
	ja	12.44	14.34	15.34	16.02	16.51	16.89	17.18	17.40	17.56	17.68
	ru	32.86	34.45	35.30	35.87	36.28	36.59	36.84	37.03	37.18	37.30

Table 9: CODEGEN zero-shot performance.

C Domain-Wise Execution Results

As the model OD/CD performance illustrated in § 5, we provide evaluation scores for (1) the OD and CD subset, and (2) each individual library.

⁹<https://translate.google.com/>

C.1 Open Domain Versus Closed Domain

Table 10 and **Table 11** shows CODEX and CODEGEN pass rates on OD and CD problems.

NL	Split	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
CODE-CUSHMAN-001											
en	-	31.91	44.67	51.81	56.54	59.95	62.56	64.61	66.28	67.65	68.79
	open	24.39	35.82	43.08	48.22	52.04	54.97	57.27	59.10	60.57	61.74
	close	40.19	54.42	61.41	65.69	68.66	70.90	72.70	74.18	75.45	76.56
es	-	31.89	43.33	49.23	53.01	55.72	57.81	59.52	60.96	62.22	63.33
	open	27.71	38.98	45.12	49.14	52.06	54.34	56.20	57.78	59.17	60.42
	close	36.67	48.31	53.93	57.44	59.91	61.79	63.31	64.60	65.71	66.67
ja	-	25.67	36.69	42.66	46.49	49.27	51.44	53.23	54.76	56.10	57.32
	open	21.24	30.29	35.16	38.34	40.71	42.61	44.20	45.55	46.73	47.79
	close	35.49	50.89	59.28	64.56	68.23	71.01	73.25	75.16	76.86	78.43
ru	-	31.91	44.67	51.81	56.54	59.95	62.56	64.61	66.28	67.65	68.79
	open	25.96	36.80	42.57	46.22	48.79	50.76	52.38	53.76	55.00	56.14
	close	51.59	67.26	74.47	78.61	81.37	83.37	84.87	86.04	86.96	87.68
CODE-DAVINCI-001											
en	-	33.62	46.65	53.27	57.34	60.18	62.31	64.00	65.37	66.49	67.43
	open	26.91	39.25	45.97	50.25	53.33	55.70	57.62	59.21	60.57	61.74
	close	41.00	54.79	61.32	65.14	67.71	71.02	72.14	73.01	73.68	
es	-	36.89	49.46	55.44	58.96	61.37	63.22	64.78	66.20	67.56	68.89
	open	31.67	44.63	51.11	54.78	57.07	58.63	59.81	60.79	61.67	62.50
	close	42.86	54.97	60.40	63.73	66.28	68.46	70.46	72.38	74.29	76.19
ja	-	31.04	42.11	47.83	51.54	54.26	56.39	58.11	59.53	60.67	61.59
	open	23.72	32.72	37.88	41.48	44.21	46.36	48.08	49.46	50.53	51.33
	close	47.25	62.92	69.89	73.85	76.54	78.62	80.34	81.83	83.14	84.31
ru	-	43.21	57.53	63.93	67.58	70.03	71.85	73.29	74.51	75.60	76.59
	open	28.86	41.01	47.05	50.77	53.47	55.65	57.53	59.22	60.79	62.28
	close	55.07	71.18	77.87	81.47	83.71	85.22	86.32	87.15	87.83	88.41
CODE-DAVINCI-002											
en	-	47.15	57.61	62.58	65.69	67.87	69.47	70.70	71.67	72.46	73.12
	open	37.52	47.52	52.81	58.32	58.86	60.79	62.29	63.48	64.43	65.22
	close	57.75	68.72	73.33	76.02	77.78	79.03	79.96	80.69	81.29	81.82
es	-	47.44	57.98	62.20	64.65	66.33	67.61	68.65	69.53	70.33	71.11
	open	45.42	56.02	60.17	62.68	64.59	66.17	67.52	68.70	69.79	70.83
	close	49.76	60.05	64.52	66.89	68.32	69.26	69.94	70.48	70.95	71.43
ja	-	41.46	50.42	54.84	57.59	59.47	60.84	61.87	62.71	63.41	64.02
	open	29.47	37.70	41.91	44.59	46.44	47.75	48.72	49.44	50.00	50.44
	close	68.04	78.61	83.48	86.49	88.36	89.82	91.03	92.11	93.14	94.12
ru	-	51.87	63.36	68.25	71.09	73.03	74.5	75.67	76.64	77.46	78.17
	open	34.74	46.20	51.46	54.65	56.93	58.75	60.29	61.66	62.89	64.04
	close	66.01	77.54	82.11	84.67	86.34	87.52	88.38	89.02	89.49	89.86

Table 10: CODEX performance in open-domain and closed-domain problems.

NL	Split	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
350M											
en	-	10.32	11.29	11.78	12.06	12.24	12.37	12.45	12.50	12.53	12.53
	open	10.00	10.94	11.41	11.69	11.87	12.00	12.14	12.17	12.17	12.17
	close	10.67	11.67	12.19	12.47	12.65	12.77	12.85	12.90	12.92	12.92
es	-	17.56	17.78	17.78	17.78	17.78	17.78	17.78	17.78	17.78	17.78
	open	18.75	18.75	18.75	18.75	18.75	18.75	18.75	18.75	18.75	18.75
	close	16.19	16.67	16.67	16.67	16.67	16.67	16.67	16.67	16.67	16.67
ja	-	7.01	8.06	8.71	9.18	9.55	9.84	10.05	10.20	10.30	10.37
	open	6.81	7.45	7.79	8.02	8.21	8.38	8.53	8.65	8.76	8.85
	close	7.45	9.41	10.75	11.76	12.53	13.07	13.43	13.64	13.73	13.73
ru	-	21.35	24.20	25.64	26.44	26.94	27.30	27.59	27.82	28.02	28.17
	open	17.63	19.71	20.72	21.28	21.66	21.96	22.21	22.44	22.63	22.81
	close	24.42	27.91	29.72	30.71	31.30	31.71	32.02	32.27	32.46	32.61
2.7B											
en	-	14.28	15.69	16.36	16.74	16.99	17.16	17.29	17.39	17.47	17.54
	open	12.65	13.73	14.21	14.50	14.71	14.87	15.00	15.10	15.17	15.22
	close	16.08	17.84	18.72	19.21	19.50	19.67	19.80	19.90	20.00	20.10
es	-	19.67	22.32	23.55	24.28	24.76	25.10	25.33	25.48	25.56	25.56
	open	17.92	21.06	22.57	23.44	24.02	24.43	24.72	24.91	25.00	25.00
	close	21.67	23.76	24.66	25.23	25.60	25.86	26.03	26.14	26.19	26.19
ja	-	10.98	12.56	13.38	13.88	14.20	14.41	14.54	14.61	14.63	14.63
	open	7.88	8.69	9.14	9.42	9.58	9.68	9.72	9.73	9.73	9.73
	close	17.84	21.13	22.76	23.76	24.44	24.90	25.21	25.40	25.49	25.49
ru	-	33.10	36.01	37.64	38.72	39.53	40.15	40.65	41.06	41.39	41.67
	open	28.86	31.58	33.03	33.95	34.58	35.03	35.35	35.59	35.79	35.96
	close	36.59	39.68	41.44	42.66	43.62	44.39	45.04	45.57	46.01	46.38
6.1B											
en	-	11.96	12.95	13.43	13.75	14.01	14.22	14.40	14.56	14.69	14.81
	open	11.22	11.81	12.08	12.25	12.39	12.52	12.65	12.78	12.91	13.04
	close	12.78	14.22	14.92	15.41	15.79	16.09	16.33	16.51	16.65	16.75
es	-	14.78	16.64	17.56	18.20	18.70	19.11	19.44	19.70	19.89	20.00
	open	17.92	19.72	20.78	21.48	21.98	22.36	22.64	22.82	22.92	22.92
	close	14.22	15.12	15.87	14.44	14.95	15.40	15.79	16.14	16.43	16.67
ja	-	12.44	14.34	15.34	16.02	16.51	16.89	17.18	17.40	17.56	17.68
	open	7.43	8.81	9.44	9.76	9.98	10.15	10.29	10.42	10.53	10.62
	close	23.53	26.58	28.42	29.87	30.99	31.83	32.43	32.85	33.14	33.33
ru	-	32.86	34.45	35.30	35.87	36.28	36.59	36.84	37.03	37.18	37.30
	open	22.72	23.72	24.21	24.59	24.93	25.23	25.52	25.79	26.05	26.32
	close	41.23	43.32	44.46	45.18	45.66	45.98	46.18	46.31	46.38	46.38

Table 11: CODEGEN performance in open-domain and closed-domain problems.

C.2 Domain-wise Execution Accuracy

As introduced in § 5.2, we take CODE-DAVINCI-002, and report its execution accuracy on each domain in Table 12.

Library	Count	Pass@1	Library	Count	Pass@1
none	440	61.45	functools	2	15.00
pandas	81	38.52	http	2	40.00
numpy					

from these samples: (1) 11 cases (50.0%) use the Python built-in functions incorrectly, mostly about strings manipulations and number calculations; (2) 7 cases (31.8%) failed at complex functions, which usually require multi-step implementations; (3) 4 cases (18.2%) received empty predictions, potentially because they involve unfamiliar topics to the model; (4) 2 cases (9.1%) imports extra library or add redundant implementations.

Note that the number of error cases in these four categories does not add up to 22. Since we analyze all of the error predictions among the model top-10 predictions, one case could present multiple error types in its different predictions.

Open-Domain Errors Of the other 29 problems belonging to the open domain, 26 of them have erroneous predictions. Errors in the open domain exhibit more diversity than in the closed domain. The major error enclosing 16 cases (61.5%) is the failure to use the prerequisite libraries, or missing part of them when multiple libraries are involved. The next major type is using incorrect functions, which happens in 9 cases (34.6%). Similarly to the closed-domain errors, 5 cases (19.2%) have error usage of correct functions, 4 cases (15.4%) struggle with complex multi-step implementations, and 3 cases (11.5%) face empty predictions.

OD and CD problems share some error categories such as function misuse and complex operations. Nonetheless, open-domain problems introduce extra challenges: correct selection and usage of libraries and functions in the wild.

D Evaluation Metrics

We describe each of the non-execution metrics (§ D.1) as introduced in § 4.1.3, report model performance with each (§ D.2), and visualize their correlations with the execution accuracy (§ D.3).

D.1 Metric Description

BLEU BLEU (Papineni et al., 2002) is a lexical-based evaluation metric, which calculates the n-gram overlap between text prediction and (multiple) references. Most default calculation processes calculate up to 4-grams and adopt the smoothing function introduced in Lin and Och (2004).

ROUGE ROUGE (Lin, 2004) is another more recall-oriented lexical-based evaluation metric. It was originally designed for measuring text summarization, mainly by counting the number of

overlapping units (n-gram, word sequences, and word pairs) between prediction and references. Among the multiple variants proposed (ROUGE-N, ROUGE-L, ROUGE-W, and ROUGE-S), we use the most common ROUGE-L in our experiments.

METEOR METEOR (Banerjee and Lavie, 2005) is a unigram-based metric originally intended for machine translation. It builds on a generalized unigram concept by involving unigram precision, unigram recall, and word order measures.

ChrF ChrF (Popović, 2015) targets lexical match on the character level, by calculating the character-level n-gram F-score between predictions and references. ChrF is also originally proposed for the machine translation task, but later adopted for some code evaluation works (Evtikhiev et al., 2022).

CodeBLEU CodeBLEU (Ren et al., 2020) is specifically designed for code evaluation, by jointly considering the surface-form match, syntax similarly, and semantic data flows.

D.2 Evaluating with Non-execution Metrics

Table 13 and Table 14 shows the scores of CODEX and CODEGEN using non-execution metrics.

Model	NL	Metrics				
		BLEU	ROUGE	METEOR	ChrF	CodeBLEU
c1	en	31.27	52.79	55.43	43.07	3.18
	es	13.69	38.29	40.86	21.17	3.96
	ja	18.57	46.67	48.76	34.89	3.63
	ru	14.42	41.49	45.53	34.63	2.70
d1	en	30.94	53.88	56.01	43.60	3.27
	es	20.40	43.93	46.71	29.36	3.27
	ja	19.98	48.23	51.46	38.41	3.40
	ru	16.97	44.71	47.11	35.54	2.74
d2	en	38.75	56.05	55.39	44.40	3.77
	es	18.47	44.98	43.52	27.11	5.78
	ja	27.10	52.04	50.17	40.02	3.58
	ru	25.00	50.04	50.51	38.60	3.75

Table 13: CODEX results on non-execution metrics.

Model	NL	Metrics				
		BLEU	ROUGE	METEOR	ChrF	CodeBLEU
350M	en	8.26	9.79	11.86	12.11	11.47
	es	9.02	14.26	15.22	17.26	5.66
	ja	6.10	13.81	14.79	16.33	6.89
	ru	10.28	29.50	30.28	29.18	5.71
2.7B	en	9.61	12.63	14.02	14.59	11.34
	es	12.74	14.18	15.25	19.70	6.25
	ja	12.11	17.19	17.74	19.53	6.88
	ru	16.35	31.25	30.40	30.57	6.12
6.1B	en	11.14	16.34	19.36	17.34	9.87
	es	8.08	11.29	12.00	14.34	6.22
	ja	12.62	17.91	17.51	18.93	7.11
	ru	15.68	31.27	32.12	30.86	5.46

Table 14: CODEGEN results non-execution metrics.

D.3 Visualizing Metric Correlations

Following the discussion in § 6.2, we visualize the non-execution metric metrics between samples that pass and fail during execution time. All experiments use CODE-DAVINCI-002 predictions for evaluation. Figure 16, Figure 17, Figure 18, Figure 19 illustrates the histogram between passed/failed samples using ROUGE, METEOR, ChrF, and CodeBLEU metrics, respectively.

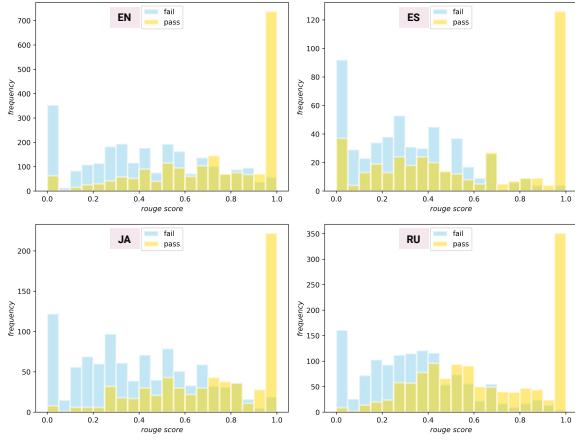


Figure 16: ROUGE on passed and failed samples.

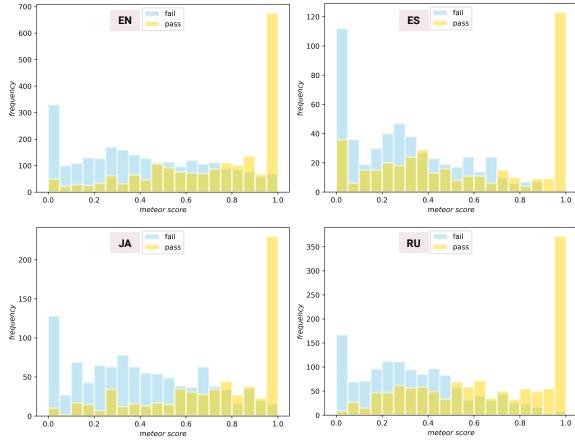


Figure 17: METEOR on passed and failed samples.

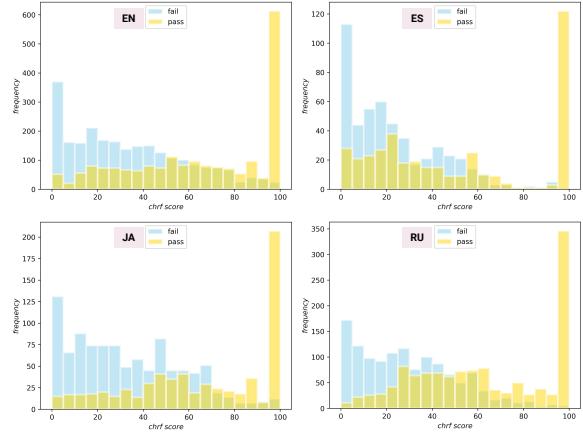


Figure 18: ChrF on passed and failed samples.

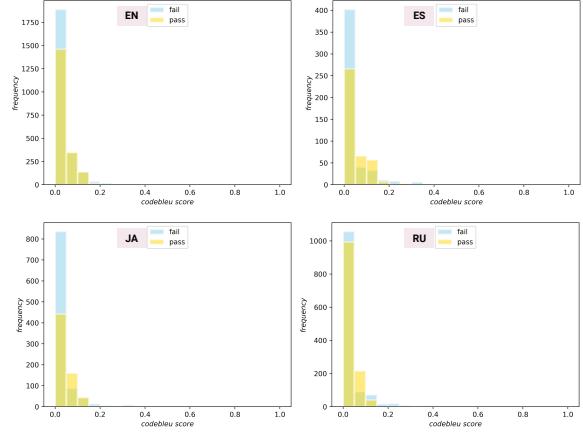


Figure 19: CodeBLEU on passed and failed samples.

D.4 Why is Execution Better?

To give more intuitive reasons for the advantages of execution, we randomly sample 15 cases from each language subset and identified two major benefits: it tolerates alternative solutions and allows execution results as outputs.

Alternative Code Implementation Probably the greatest advantage of execution is it only requires correct execution results, without limitations on alternative methods, as in Figure 20.

```
"""Multiply each value by 2 for all keys in a dictionary `my_dict`"""
# Canonical Solution
my_dict.update((x, y * 2) for x, y in list(my_dict.items()))

# Model Prediction
for key in my_dict:
    my_dict[key] *= 2
```

Figure 20: An alternative yet correct prediction, only has a low 4.8 BLEU score due to having little lexical overlap with the canonical solution.

Directly Generating Execution Results Another interesting category is directly generating the code execution results instead of the implementation steps. This often happens to simple coding

queries such as basic string manipulation, where predicting the results might cost the model similar efforts to getting the programmatic solutions.

```
"""Decode a hex string '4a4b4c' to UTF-8."""
# Canonical Solution
bytes.fromhex('4a4b4c').decode('utf-8')

# Model Prediction
'JKL'
```

Figure 21: An example output of a correct execution result, yet only achieving 0.6 BLEU.

In Figure 21, instead of the string decoding program, the model directly outputs the result string “JKL”. While this is somewhat unexpected under the NL-to-Code task, execution effectively handles such cases and would judge them as correct.

D.5 Potential Benefit of Lexical-based Metrics

Lexical-based metrics, although relatively ineffective for functional correctness, still are potentially helpful for debugging and interpretation. They are effective in small errors of two types: (1) a single function misuse and (2) slight variance in complex strings. The high lexical match in such cases indicates less effort for fixing (Deng et al., 2021).

Function Misuse Some code predictions are correct except for a single place where a wrong function is used, or an argument is misplaced.

```
"""Match regex '\\((.*?)\\)|(\\w)' with string '(zyx)bc"""
# Canonical Solution
re.findall('\\((.*?)\\)|(\\w)', '(zyx)bc')

# Model Prediction
| re.match('\\((.*?)\\)|(\\w)', '(zyx)bc')
```

Figure 22: Example that the model prediction uses the wrong function, having a very high BLEU score 0.925.

For example, in Figure 22, the code imports the library and copies all strings correctly. But it uses the wrong function `match` instead of the correct `findall`. Although the execution fails, the code is similar to the solution. Given the sign of a high BLEU score of 0.925, we could readily spot such similarities and fix them with simple edits.

String Difference Another frequent error concerns string copying, where the code calls the correct functions but copies the string differently.

The example in Figure 23 gets a 100.0 BLEU score, but the string inside actually misses a single whitespace, which the BLEU tokenization would

discard. Such code also resembles the solution and could be easily fixed by even rule-based methods.

```
"""Initialize `SECRET_KEY` in flask config with 'Your_secret_string'"""
# Canonical Solution
app.config['SECRET_KEY'] = "Your_secret_string"

# Model Prediction
app.config['SECRET_KEY'] = 'Your_secret_string'
```

Figure 23: Example that the model prediction varies slightly in copied strings, but scores 100.0 in BLEU.

E Ablation Studies

This section provides the results tables according to each ablation study section in § 7.

E.1 Prompting Strategy

E.1.1 Few-shot Prompting

Table 15, Table 16, Table 17 show the change in execution accuracy with respect to the examples in in-context learning, on the three CODEX variants

N-shot	NL	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
1-shot	en	37.90	48.71	54.50	58.25	60.88	62.82	64.31	65.52	66.54	67.43
	es	36.22	45.51	50.70	53.96	56.14	57.68	58.81	59.70	60.44	61.11
	ja	29.76	38.54	43.22	46.23	48.33	49.90	51.14	52.15	52.99	53.66
2-shot	en	37.27	47.89	53.39	57.02	59.68	61.75	63.41	64.80	65.97	66.97
	es	38.56	48.77	54.12	57.50	59.90	61.75	63.26	64.54	65.67	66.67
	ja	32.26	41.57	46.71	50.18	52.76	54.78	56.40	57.74	58.84	59.76
3-shot	en	46.73	58.56	64.24	67.63	69.90	71.55	72.82	73.84	74.68	75.40
	es	39.91	50.45	55.62	58.83	61.06	62.74	64.07	65.17	66.13	66.97
	ja	37.00	45.88	50.05	52.63	54.48	55.87	56.95	57.80	58.44	58.89
	ru	32.87	42.48	47.58	50.88	53.29	55.16	56.66	57.89	58.90	59.76
	ru	48.33	60.03	65.32	68.51	70.71	72.35	73.66	74.75	75.71	76.59

Table 15: CODE-CUSHMAN-001 few-shot results.

N-shot	NL	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
1-shot	en	43.05	53.67	58.80	62.01	64.31	66.09	67.52	68.71	69.73	70.62
	es	41.00	52.69	58.54	62.11	64.56	66.35	67.69	68.69	69.44	70.00
	ja	35.00	45.57	51.17	54.79	57.45	59.58	61.35	62.86	64.15	65.24
2-shot	en	44.26	53.98	58.77	61.85	64.00	65.59	66.79	67.70	68.43	69.02
	es	40.44	50.15	54.97	57.90	59.91	61.41	62.64	63.70	64.67	65.56
	ja	35.12	44.82	49.87	53.07	55.25	56.77	57.86	58.60	59.27	59.76
3-shot	en	49.72	60.59	65.76	68.96	71.16	72.78	74.03	75.04	75.87	76.59
	es	43.58	53.27	57.88	60.81	62.99	64.74	66.19	67.44	68.52	69.48
	ja	38.78	49.40	54.59	57.66	59.71	61.18	62.31	63.21	63.96	64.63
	ru	49.21	58.83	63.58	66.73	69.08	70.99	72.63	74.08	75.40	76.59

Table 16: CODE-DAVINCI-001 few-shot results.

N-shot	NL	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
1-shot	en	46.33	56.08	60.54	63.36	65.39	66.97	68.24	69.28	70.14	70.84
	es	44.33	54.00	59.04	62.49	65.07	67.09	68.72	70.07	71.22	72.22
	ja	46.33	56.08	60.54	63.36	65.39	66.97	68.24	69.28	70.14	70.84
2-shot	en	47.29	57.32	61.96	64.69	66.53	67.86	68.90	69.74	70.46	71.07
	es	45.78	55.85	60.41	63.29	65.44	67.16	68.63	69.93	71.11	72.22
	ja	42.38	52.28	56.80	59.38	61.02	62.12	62.88	63.41	63.78	64.02
3-shot	en	51.35	62.72	68.20	71.60	73.98	75.79	77.24	78.47	79.56	80.56
	es	47.29	57.32	61.96	64.69	66.53	67.86	68.90	69.74	70.46	71.07
	ja	45.78	55.85	60.41	63.29	65.44	67.16	68.63	69.93	71.11	72.22
	ru	57.15	63.38	68.47	71.51	73.60	75.13	76.30	77.23	77.98	78.57

Table 16: CODE-DAVINCI-001 few-shot results.

N-shot	NL	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
1-shot	en	48.18	57.99	62.64	65.50	67.50	68.99	70.17	71.14	71.96	72.67
	es	44.44	53.95	58.31	61.07	63.11	64.74	66.07	67.19	68.11	68.89
	ja	46.10	55.64	59.74	62.17	63.81	65.00	65.90	66.61	67.20	67.68
2-shot	en	49.40	60.56	66.09	69.64	72.19	74.17	75.77	77.12	78.29	79.37
	es	47.29	57.32	61.96	64.69	66.53	67.86	68.90	69.74	70.46	71.07
	ja	45.78	55.85	60.41	63.29	65.44	67.16	68.63	69.93	71.11	72.22
3-shot	en	51.35	62.72	68.20	71.60	73.98	75.79	77.24	78.47	79.56	80.56
	es	47.29	57.32	61.96	64.69	66.53	67.86	68.90	69.74	70.46	71.07
	ja	45.78	55.85	60.41	63.29	65.44	67.16	68.63	69.93	71.11	72.22

Table 17: CODE-DAVINCI-002 few-shot results.

E.1.2 Number of Input Test Cases

Table 18 shows the effects on execution accuracy, of adding one or more test cases to prompts. Ex-

periments use CODE-DAVINCI-002 as an example.

# test	NL	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
0	en	47.15	57.61	62.58	65.69	67.87	69.47	70.70	71.67	72.46	73.12
	es	47.44	57.90	62.20	64.65	66.33	67.61	68.65	69.53	70.33	71.11
	ja	41.46	50.42	54.84	57.59	59.47	60.84	61.87	62.71	63.41	64.02
	ru	51.87	63.36	68.25	71.09	73.03	74.5	75.67	76.64	77.46	78.17
1	en	63.35	75.61	80.28	82.70	84.20	85.22	85.97	86.57	87.06	87.47
	es	63.89	76.37	81.75	84.75	86.60	87.82	88.65	89.23	89.67	90.00
	ja	63.90	74.66	78.85	81.13	82.61	83.68	84.49	85.12	85.61	85.98
	ru	65.04	77.80	82.89	85.72	87.53	88.75	89.64	90.19	90.60	90.87
n	en	64.76	77.36	82.02	84.40	85.93	87.05	87.93	88.65	89.25	89.75
	es	59.89	72.42	77.44	80.41	82.49	84.03	85.16	85.95	86.44	86.67
	ja	63.41	74.02	78.49	80.98	82.57	83.69	84.51	85.14	85.61	85.98
	ru	66.67	79.07	83.70	86.19	87.82	89.01	89.91	90.62	91.19	91.67

Table 18: CODE-DAVINCI-002 results when using zero (*0*), one (*1*), and all (*n*) test cases in the prompt input.

E.2 Number of Evaluation Test Cases

Table 19 shows the effect when using different numbers of test cases for execution-based evaluation.

E.2.1 Number of Evaluation Test Cases

# test	NL	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
1	en	48.31	58.81	63.70	66.72	68.83	70.39	71.59	72.55	73.35	74.03
	es	48.00	58.52	62.71	64.98	66.51	67.69	68.67	69.53	70.33	71.11
	ja	42.44	51.96	56.51	59.36	61.34	62.80	63.95	64.91	65.73	66.46
	ru	52.50	63.26	67.85	70.60	72.53	74.00	75.19	76.17	77.02	77.78
n	en	47.15	57.61	62.58	65.69	67.87	69.47	70.70	71.67	72.46	73.12
	es	47.44	57.90	62.20	64.65	66.33	67.61	68.65	69.53	70.33	71.11
	ja	41.46	50.42	54.84	57.59	59.47	60.84	61.87	62.71	63.41	64.02
	ru	51.87	63.36	68.25	71.09	73.03	74.50	75.67	76.64	77.46	78.17

Table 19: CODE-DAVINCI-002 results when using different numbers of test cases for execution-based evaluation. *1* means using one randomly selected test case, *n* means using all annotated test cases in ODEX.

E.3 Semantics of Function Names

As introduced in § 7.3, besides formatting the function names as constant “function” and with SO post id, our third approach is to extract meaningful phrases from the natural language intent.

Our heuristic for this phrase extraction first cuts the NL intent into words by whitespace, then remove the stop words (‘in’, ‘of’, ‘a’, ‘to’, ‘and’, ‘for’, ‘with’, ‘that’) and meaningless punctuations, lastly, concatenate the first four words with ‘_’. For example, given an intent “decode a hex string ‘4a4b4c’ to UTF-8”, the resulting function name would be “decode_a_hex_string”.

However, for languages that do not separate words with whitespace, this approach may produce less meaningful strings, hence contributing to the inferior performance as shown in § 7.3.

Func Name	NL	Pass Rate									
		@1	@2	@3	@4	@5	@6	@7	@8	@9	@10
task-id	en	47.15	57.61	62.58	65.69	67.87	69.47	70.70	71.67	72.46	73.12
	es	47.44	57.90	62.20	64.65	66.33	67.61	68.65	69.53	70.33	71.11
	ja	41.46	50.42	54.84	57.59	59.47	60.84	61.87	62.71	63.41	64.02
	ru	51.87	63.36	68.25	71.09	73.03	74.50	75.67	76.64	77.46	78.17
constant	en	43.14	52.71	56.94	59.54	61.38	62.78	63.90	64.82	65.60	66.29
	es	40.11	51.58	56.90	60.10	62.33	63.99	65.28	66.30	67.11	67.78
	ja	38.29	48.01	52.76	55.61	57.56	59.05	60.24	61.23	62.07	62.80
	ru	48.06	60.19	65.75	69.25	71.78	73.77	75.41	76.80	77.98	78.97
intent	en	43.23	53.77	58.87	62.06	64.34	66.11	67.54	68.74	69.75	70.62
	es	37.78	49.21	54.52	57.75	60.12	62.05	63.72	65.21	66.56	67.78
	ja	37.99	47.78	52.40	55.06	56.77	58.03	59.05	59.96	60.79	61.59
	ru	48.29	60.64	66.39	69.79	72.11	73.86	75.26	76.42	77.38	78.17

Table 20: CODE-DAVINCI-002 results when the wrapping function name contains different semantics.