Configuration Validation with Large Language Models

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ABSTRACT

Misconfigurations are the major causes of software failures. Existing configuration validation techniques rely on manually written rules or test cases, which are expensive to implement and maintain, and are hard to be comprehensive. Leveraging machine learning (ML) and natural language processing (NLP) for configuration validation is considered a promising direction, but has been facing challenges such as the need of not only large-scale configuration data, but also system-specific features and models which are hard to generalize. Recent advances in Large Language Models (LLMs) show the promises to address some of the long-lasting limitations of ML/NLP-based configuration validation techniques. In this paper, we present an exploratory analysis on the feasibility and effectiveness of using LLMs like GPT and Codex for configuration validation. Specifically, we take a first step to empirically evaluate LLMs as configuration validators without additional fine-tuning or code generation. We develop a generic LLM-based validation framework, named Ciri, which integrates different LLMs. Ciri devises effective prompt engineering with few-shot learning based on both valid configuration and misconfiguration data. Ciri also validates and aggregates the outputs of LLMs to generate validation results, coping with known hallucination and nondeterminism of LLMs. We evaluate the validation effectiveness of Ciri on five popular LLMs using configuration data of six mature, widely deployed open-source systems. Our analysis (1) confirms the potential of using LLMs for configuration validation, (2) understands the design space of LLMbased validators like Ciri, especially in terms of prompt engineering with few-shot learning, and (3) reveals open challenges such as ineffectiveness in detecting certain types of misconfigurations and biases to popular configuration parameters.

1 INTRODUCTION

Modern cloud and web services evolve rapidly and deploy hundreds to thousands of configuration changes to production systems on a daily basis [14, 16, 51, 52, 73, 74, 76]. For example, at Meta/Facebook, thousands of configuration changes are committed daily, outpacing the frequency of source-code changes [51, 76]. Other cloud services such as Google and Microsoft also frequently deploy configuration changes [14, 16, 52]. Such rapid configuration changes inevitably lead to misconfigurations, resulting in system failures. Today, misconfigurations are among the dominating causes of production incidents [29, 37, 51, 61, 68, 73, 100, 101]. For example, misconfiguration is the second largest root-cause category of service disruptions at a main Google production service [14].

To detect misconfigurations before deployment, today's configuration management systems typically employ the "configurationas-code" paradigm and enforce continuous configuration validation, ranging from static validation, to configuration testing, and to manual review and approval. The configuration is first checked by validation code (aka *validators*) based on predefined correctness rules [15, 33, 42, 47, 56, 65, 76, 102]; in practice, validators are written by engineers when introducing configuration parameters. After passing validators, configuration changes are then tested together with the code to ensure expected program behavior under the changed configuration [75, 97]. Lastly, the configuration changes go through the same process as source-code review, where the change, commonly in the form of a configuration file "diff", is reviewed before production deployment.

The aforementioned configuration validation pipeline either relies on manual inspection to spot misconfigurations in the configuration file diffs, or requires significant engineering efforts to implement and maintain validators or test cases. However, these efforts are known to be costly and incomprehensive. For example, despite the fact that mature projects all include extensive configuration checks, recent work [36, 43, 44, 77, 82, 96, 99] repeatedly shows that existing checks are far from sufficient to catch misconfigurations. The reasons are twofold. First, with large-scale systems exposing hundreds to thousands of configuration parameters [95], implementing validators (or test cases) for every parameter becomes a significant overhead. Recent studies [76, 99] report that many parameters are not covered by existing checks, even in mature software projects with many years of development history. Second, it is nontrivial to validate each individual parameter, which could have many different correctness properties, such as type, range, semantic meaning, dependencies with other parameters, etc.; encoding each of them as validators could be laborious and error-prone, not to mention the high maintenance cost due to configuration-related software evolution [104, 105]. These limitations also apply to the configuration tests [75]. Compared with static validation, configuration testing is also more time-consuming to run and more expensive in terms of computing resources [23].

Using machine learning (ML) and natural language processing (NLP) to detect misconfigurations has been considered a promising approach to addressing the above challenges of configuration validation. Compared with manually written static validators and test cases, ML or NLP-based approaches are automatic, easy to scale to

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a large number of parameters, and applicable to different systems and environments. A number of ML/NLP-based misconfiguration detection techniques are proposed in the literature [17, 41, 63, 64, 80, 85, 92, 103]. The key idea is to first learn correctness rules from field configuration data [17, 38, 41, 63, 71, 72, 80, 85, 103] or from documents [64, 92], and then use the learned rules to detect misconfigurations in new configuration files. ML/NLP-based approaches have achieved good success. For example, Microsoft adopted Peer-Pressure [34, 80] as a part of Microsoft Product Support Services (PSS) toolkits. It collects configuration data in Windows Registry from a large number of Windows users to learn statistical golden states of system configurations.

However, ML/NLP-based misconfiguration detection has also revealed significant limitations. First, the need of large volumes of system-specific configuration data makes it hard to apply those techniques to outside corporations that collect user configurations (e.g., Windows Registry [85]) or maintain knowledge base or customer tickets [64]. For example, in cloud/datacenter systems where the same set of configurations is maintained by a small DevOps team, there is no enough information for learning [99]. Moreover, prior ML/NLP-based detection techniques all target specific systems/projects, and rely on predefined learning features [63], templates [103], or models [64]. As a result, it is hard to generalize them to different systems and their configurations.

Recent advances on Large Language Models (LLMs), such as GPT [2] and Codex [3], show promises to address some of the long-lasting limitations of traditional ML/NLP-based misconfiguration detection techniques. Specifically, LLMs are trained on massive amounts of internet data, including configuration dataconfiguration files in software repositories, configuration documents, knowledge-based articles, Q&A websites for resolving configuration issues, etc. Consequently, LLMs encode the extensive knowledge of both common and even project-specific configuration for well-known projects. Such knowledge can be utilized for configuration validation without the need for manual rule engineering. Furthermore, LLMs show the capability of generalization and reasoning [31, 87] unlike the traditional ML approaches, and can potentially "understand" the configuration semantics. For example, they can not only generalize that values of a port must be in the range of [0, 65535], but also reason that a specific configuration value represents a port (e.g., based on the parameter name and description) and thus has to be within the range.

Certainly, LLMs have limitations. Notably, they are known to hallucinate responses and can be nondeterministic [13, 106]. Additionally, LLMs have limited input context, which can pose challenges when encoding extensive contexts like configuration-related code and execution environments. Moreover, they are reported to be biased to popular content in the training dataset. However, there are active efforts [10, 48, 50, 57, 83] addressing these limitations, making them promising tools.

In this paper, we present an exploratory analysis on the feasibility and effectiveness of using LLMs like GPT and Codex for configuration validation. Our goal is to empirically evaluate the promises of leveraging LLMs to develop effective configuration validators and to understand the challenges. As a first step, we empirically evaluate LLMs as configuration validators, without additional fine-tuning or code generation. We focus on basic misconfigurations (those violating explicit correctness constraints) which can potentially be detected by LLMs directly. We do not target misconfigurations specific to the execution environments or correct configuration changes triggering bugs in the code. We discuss how to further build on this work to detect those in §7.

To this end, we develop Ciri, an LLM-empowered configuration validation framework. Ciri takes a configuration file or a file diff as the input; it outputs a list of detected misconfigurations along with the reasons that explain the misconfigurations. Ciri integrates different LLMs such as Code-Davinci-002, GPT-3.5-turbo, and GPT-4. Ciri devises effective prompt engineering with few-shot learning based on existing configuration data. Additionally, Ciri validates and aggregates the outputs of LLMs to generate validation results, coping with known hallucination and nondeterminism of LLMs. A key design principle of Ciri is separation of policy and mechanism it implements different mechanisms to support various policies. Ciri can serve as an open framework for experimenting with different prompt engineering approaches, training datasets, and validation and aggregation methods.

We study the validation effectiveness of Ciri backed by five popular LLMs including advanced models (Code-davinci-002, GPT-3.5 Turbo, and GPT-4), and basic models (Babbage-002, and Davinci-002). We use misconfiguration datasets of six mature, widely deployed open-source systems (HCommon, HBase, Alluxio, HDFS, YARN, and ZooKeeper). Our study confirms the potential of using LLMs for configuration validation, e.g., Ciri with GPT-4 shows promising results at both file- and parameter-level, achieving up to 0.75 and 0.56 F1-scores, respectively. Our study also helps understand the design space of LLM-based validators like Ciri, especially in terms of prompt engineering with few-shot learning and voting. We find that few-shot learning using both valid configuration and misconfiguration data as shots (examples) can significantly enhance validation effectiveness. Specifically, labeled misconfigurations are pivotal to validation effectiveness. Our results also reveal open challenges such as ineffectiveness in detecting certain types of misconfigurations and biases to popular configuration parameters. While Ciri excels in identifying misconfigurations, it struggles with specific misconfiguration types such as dependency violations and version-specific misconfigurations. We also observe that the popularity of configuration parameters creates biases in validation results, causing both false positives and false negatives. In summary, this paper makes the following main contributions:

- A new direction of configuration validation using pre-trained large language models.
- Ciri, an LLM-empowered configuration validation framework and an open platform for followup research. Ciri is released at https://github.com/ciri4conf/ciri.
- An empirical study on the effectiveness of LLM-based configuration validation which confirms the potential of the direction, explores the design space, and reveals open challenges.
- A discussion on future endeavours such as fine-tuning, test generation to detect more types of misconfigurations, and detecting configuration-related bugs.
- All code and data for results presented in this paper will be released with detailed steps for reproducing our experiments.

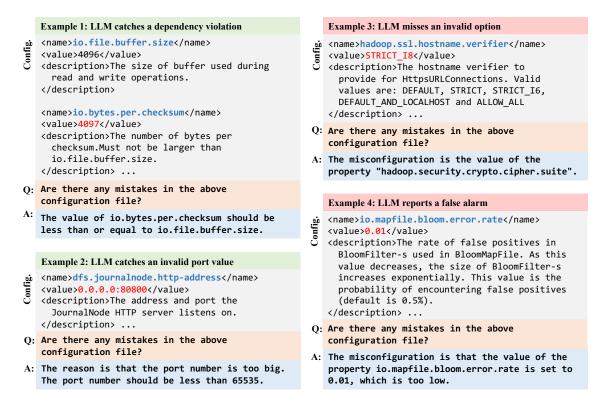


Figure 1: Example 1 and 2 show the LLM correctly catches and reasons the misconfigurations. Example 3 and 4 show the LLM misses a misconfiguration or reports a valid configuration as erroneous.

2 EXPLORATORY EXAMPLES

We explore the capability of utilizing LLMs to validate configuration files off-the-shelf. We argue that vanilla LLMs are capable of detecting sophisticated misconfigurations. However, they are prone to both false negatives and false positives that require further attention and handling. Figure 1 presents four examples, two of which the LLM correctly detects the misconfiguration, and two of which the LLM misses a misconfiguration or reports a false alarm. These examples were generated using the Codex LLM (Code-Davinci-002) developed by OpenAI [3, 20].

Detecting violation in configuration dependency. Extracting and validating against dependency relationships between configuration parameters has been a challenging task in highly-configurable systems [21, 100]. LLM has the ability to infer relations between entities from text at the level of human experts [18]. This ability allows LLM to infer dependencies between parameters in a configuration file based on their corresponding names and descriptions. By simply asking if any violation exists in the configuration, off-the-shelf LLM can check if configured values satisfy the extracted relations at runtime. This allows better applicability of LLMs for validating configuration dependency when compared to prior techniques that require manually codified rules [15, 76], program analysis [21, 99], or specialized learning [64, 92].

Figure 1 (Example 1) presents a case where values of two dependent parameters were changed (i.e., buffer.size and bytes.per. checksum). After understanding the value relationship dependency between these two parameters, the model determines that the change in bytes.per.checksum has violated the enforced dependency, and provides the correct reason for the misconfiguration.

Detecting violation with domain knowledge. Written configuration validation rules often require significant manual efforts to produce and maintain. They are difficult to scale, due to the diverse types and functionalities of configuration parameters. A state-of-the-art LLM is trained on a massive amount of textual data collected from the Internet, and possesses basic knowledge across a wide range of professional domains. An LLM thus could be capable of understanding the definition of a configuration parameter and reasoning with its semantics. When the LLM encounters a configuration parameter such as IP Address, permissions, masks, it invokes the domain knowledge specific to the properties of those parameters for user's further instructions, such as validation. Figure 1 (Example 2) presents a case where an HTTP address has been misconfigured to a semantically invalid value. The model identifies the misconfiguration, reasons that its configured value has been out of range, and further suggests potential direction for fixing.

Missed misconfiguration and false alarm. Despite that LLMs have demonstrated impressive performance across many tasks since its recent emergence, at the current stage of development, however, LLMs as configuration validators are not without errors. Examples 3 and 4 in Figure 1 show two cases where the LLM makes mistakes in the configuration validation.

In Example 3, the configuration file has provided a description of the changed parameter hostname.verifier, and explicitly listed the valid value options for the parameter. However, the model is unable to identify that the parameter has been misconfigured to an invalid, non-existent option (STRICT_I8). Example 4 is interesting — the description suggests that the parameter bloom.error.rate ranges from 0 to 100 (percentage), whereas the actual scale is 0 to 1 (fraction). This inconsistency supposedly confuses the model making it mark 0.01 as invalid even though it is valid (1%) — a fairly reasonable mistake for a human to make as well.

Both examples demonstrate that employing off-the-shelf LLMs as configuration validators can result in false negatives and false positives, thereby making the predictions less trustworthy. Incorrect validation outcomes could be attributed towards a phenomenon in LLMs termed hallucination, which is being actively investigated [60]. A simple explanation is that LLMs are exposed to potentially contradictory data during training, which causes confusion to the model at inference time.

To account for these factors, our study applies and evaluates several mechanisms that can mitigate the impact of wrongful predictions made by LLMs in the context of configuration validation, including few-shot learning, and reaching validation consensus through majority voting (§3).

3 CIRI: A LLM-EMPOWERED CONFIGURA-TION VALIDATION FRAMEWORK

We develop Ciri, a LLM-empowered configuration validation framework. Ciri takes a configuration file or a file diff as the input. It outputs a list of detected misconfigurations along with the reasons to explain the misconfigurations. If no misconfiguration is detected, Ciri outputs an empty list.

Ciri now supports five LLMs (Code-Davinci-002, GPT-3.5-turbo, GPT-4, Babbage-002 and Davinci-002). Adding a new LLM in Ciri takes a few lines of code to adopt the LLM's query APIs. Figure 2 gives an overview of Ciri. Ciri turns a configuration validation request into a prompt to the LLMs (§3.1). The prompt includes 1) the input configuration file or diff, 2) a few examples (referred to as *shots*) to demonstrate the task of configuration validation, and 3) directive question and metadata. To generate shots, Ciri uses its database that contains labeled configuration data, including both valid configurations and misconfigurations. To validate a configuration file, Ciri sends the same query to the LLMs multiple times and aggregates the responses into the final validation result (§3.2).

Ciri can be applied to any software project, even if it has no configuration data of that project. Ciri can directly query advanced LLMs like GPT-4 with zero shot, and achieves considerable effectiveness (Finding 2). Ciri exhibits the ability to transfer configurationrelated knowledge across projects when using configurations from different projects as shots (Finding 4). Ciri's configuration validation effectiveness can also be further improved with high-quality generated shots (Finding 3).

3.1 Prompt Engineering

Prompt Structure. Ciri generates a prompt that includes three elements: 1) the content of input configuration file or file diff, 2) the shots as *ValidConfig* or misconfiguration files with example questions and ground truth responses for few-shot learning, and 3) a directive question for LLM to respond in formatted output. Figure 3 shows an illustrative example of the prompt generated by

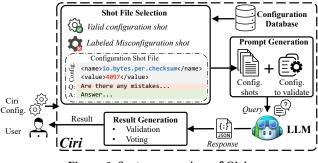


Figure 2: System overview of Ciri.

Ciri. It contains *N* shots, content of the validating configuration file, followed by the directive question.

Ciri phrases the prompting question as "Are there any mistakes in the above configuration file for [PROJECT] version [VERSION]? Respond in a JSON format similar to the following: ...". The [PROJECT] and [VERSION] are required inputs of Ciri because validity of a configuration file can change by project and project version. This prompt format enforces the LLM to respond in a unified JSON format for automated result aggregation (§3.2). However, responses from LLMs sometimes may still deviate from the anticipated format [13, 106]. In such cases, Ciri retries a new query to the LLM.

Few-Shot Learning. Ciri leverages the LLM's ability to learn from examples at inference time (referred to as few-shot learning) to improve configuration validation effectiveness. To do so, Ciri simply inserts shots at the beginning of each prompt. Each shot contains a configuration file, the prompting question, and its corresponding ground truth. Figure 3 provides an example. In Figure 3, there are *N* shots. "Configuration File Shot #1" is the first shot, in which the parameter file.bytes-per-checksum in the configuration file is misconfigured. This shot also contains the prompting question (orange box) and the corresponding ground truth (blue box).

Shot Generation and Selection. Ciri maintains a database of labeled valid configurations and misconfigurations. It is used for generating valid configuration shots (*ValidConfig*) and misconfiguration shots (*Misconfig*). A *ValidConfig* shot specifies a set of configuration parameters and their valid values. A valid value of a parameter can be its default value, or other valid values used in practice. A *Misconfig* shot specifies a set of parameters and their values, where only one of the parameters' value is invalid. We provide more details on how to generate valid/invalid configuration values in this paper in §4.

For a configuration file or diff of a specific project, Ciri by default generates shots using the configuration data of the same project. If Ciri's database does not contain configuration data for the target project, Ciri would use available data (from other projects) to generate shots. As we will show (§5.2), LLMs possess transferrable knowledge in configuration across different projects.

Ciri supports various strategies to select the shot data, including randomized selection, selecting from different configuration/misconfiguration types, and selecting from configuration parameters similar to the validating configuration (using cosine similarity). We did not observe major differences in these selection strategies so Ciri uses randomized selection by default.

Configuration File Shot #1
<pre><name>file.bytes-per-checksum</name> <value>-1</value> <description>The number of bytes per checksum. Must not be larger than file.stream-buffer-size </description></pre>
<pre>Question: Are there any mistakes in the above configuration file for Hadoop Common version 3.3.0? Respond in a json format similar to the following: { "hasError": boolean, // true if there are errors, false if there are none "errParameter": [], // List containing properties with errors "reason": [], // List containing explanations for each error }</pre>
<pre>Answer: { "hasError": true, "errParameter": ["file.bytes-per-checksum"], "reason": ["The value of the property 'file.bytes-per-checksum' is out of range. It should be greater than 0."] }</pre>
Configuration File Shot #N
To Be Validated Configuration File
<pre><name>fs.s3.sleepTimeSeconds</name> <value>10s</value> <description>The number of seconds to sleep between each S3 retry.</description></pre>
Question: Are there any mistakes in the above configuration file for Hadoop Common version 3.3.0? Respond in a json format similar to the following: {
<pre>"hasError": boolean, // true if there are errors, false if there are none "errParameter": [], // List containing properties with errors "reason": [], // List containing explanations for each error</pre>
}

Figure 3: An example prompt generated by Ciri.

Addressing Token Limits. LLMs limit input size per query by the number of input tokens. For example, the token limits for GPT-4 and GPT-3.5-turbo (the 16K variant) are 4,097 and 16,385 respectively. To navigate these constraints, Ciri compresses the prompt if its size cannot fit the token limit. Ciri prioritizes putting the validating configuration file and the directive question in the prompt, then applies a number of strategies to maximize the number of shots that can fit into the remaining token limit. If the validating configuration file itself cannot fit into the token limit, Ciri transforms the original file into a more compact format, e.g., transforming an XML file into INI format. If the compressed input still cannot fit, Ciri aborts and returns errors. In practice, real-world configuration file are small [1], which lefts enough space to include shots. For example, prior study inspects configuration files collected from Docker, where each file contains 1 to 18 parameters, with 8 parameters on average [1]. For the extremely large configuration file, Ciri can split it into smaller snippets, which can be validated separately and reasoned together.

3.2 **Result Generation**

The JSON response from LLMs contains three primary fields: 1) hasError: a boolean value indicating if a misconfiguration is detected, 2) errParameter: an array of strings specifying the misconfigured parameter, and 3) reason: an array of strings explaining the detected misconfiguration.

Validation against Hallucination. We use a few rules to counter the hallucination of LLMs. For example, if hasError is False, both errParameter and reason must be empty. Conversely, if hasError returns True, errParameter and reason should not be empty and have the same array size. The answer to errParameter also should not contain repeated values. If a response fails these rules, Ciri discards it and retries until the LLM returns a valid response.

Voting against Inconsistency. LLMs can produce inconsistent outputs in conversation [6], explanation [19], and knowledge extraction tasks [25]. To mitigate inconsistency, Ciri uses a multi-query strategy—querying the LLM multiple times using the same prompt and aggregating the responses. When aggregated with a voting mechanism, these responses converge towards a solution that is both representative of the model's understanding and more consistent than a single query. Ciri uses a frequency-based voting strategy: the output that recurs most often among the responses is selected as the final output [83].

Note that the reason field is not considered during voting due to the diverse nature of the response. After voting, Ciri collects the reason from all responses that are associated with the selected errParameter. The reason field is important as it provides users with insights into the misconfiguration, which is different from the traditional ML approaches that only provide a binary answer with a confidence score. However, the content of reason may not always be useful due to hallucination. Ciri clusters reasons based on TF-IDF similarity, and picks a reason from the dominant cluster. We found that hallucinated reasons were often avoided this way as they tended to be very different from each other.

3.3 Ciri Configuration

Ciri is highly customizable, with a basic principle of separating policy and mechanism. Users can customize Ciri via its own configurations. Table 1 shows several important Ciri configurations and default values. The values are chosen by pilot studies using a subset of our dataset (§4).

Table 1: System config of Ciri and their default values.

Parameter	Description	Default Value
Model	Backend LLM. Also allows users to add other LLMs.	GPT-4
Temperature	Tradeoff between creativity and determinism.	0.2
# Shots	The number of shots included in a prompt.	Dynamic
# Queries	The number of queries with the same prompt.	10

4 BENCHMARKS AND METRICS

Software Systems We evaluate six popular, open-source systems: Hadoop Common, HBase, Alluxio, HDFS, YARN, and ZooKeeper. They all are mature, widely deployed systems. These systems are highly configurable with a large number of configuration parameters. Table 3 lists the version (SHA), and the total number of parameters at that version for each system.

Category	Sub-Category	Specification	Generation Rules
	Data timo	Value set = {Integer, Float, Long}	Use a value that doesn't belong to set
	Data type	Numbers with units	Use a non-existent unit (e.g., "nounit")
	Path	^(\/[^\/]*)+\/?\$	Use a value that violates the pattern (e.g., /hello//world)
Syntax	URL	[a-z]+://.*	Use a value that violates the pattern (e.g., file///)
	IP Address	[\d]{1,3}(.[\d]{1,3}){3}	Use a value that violates the pattern (e.g., 127.x0.0.1)
	Port	Data type, value set = {Octet}	Use a value that doesn't belong to set
	Permission	Data type, value set = {Octet}	Use a value that doesn't belong to set
	Basic numeric	Valid Range constrainted by data type	Use the values beyond the valid range (e.g., Integer.MAX_VALUE+1)
	Bool	Options, value set = {true, false}	Use a value that doesn't belong to set
	Enum	Options, value set = {"enum1", "enum2",}	Use a value that doesn't belong to set
Range	IP Address	Range for each octet = [0, 255]	Use a value beyond the valid range (e.g., 256.123.45.6)
	Port	Range = [0, 65535]	Use a value beyond the valid range
	Permission	Range = [000, 777]	Use a value beyond the valid range
Dependency	Control	$(P_1, V, \diamondsuit) \mapsto P_2, \diamondsuit \in \{>, \ge, =, \neq, <, \le\}$	Use invalid control condition $(P_1, V, \neg \diamondsuit)$
Dependency	Value Relationship	$(P_1, P_2, \diamondsuit), \diamondsuit \in \{>, \ge, =, \neq, <, \le\}$	Use invalid value relationship $(P_1, P_2, \neg \diamondsuit)$
Version	Parameter change	$(V_1, Pset_1) \mapsto (V_2, Pset_2), Pset_1 \neq Pset_2$	Use a removed parameter in V_2 or use an added paraemter in V_1

Table 2: Misconfiguration generation rules (extended from prior work [44]). "(Sub-)Category" list different sets of violations that can be applied to a configuration parameter to generate its misconfigured values.

Table 3: Software systems, and configuration datasets (including both ValidConfig and Misconfig datasets).

Software	Version (SHA)	#Params	ValidConf Shot Pool		Misconfig	
			Shot Pool	Eval. Set	Shot Pool	Eval. Set
HCommon	aa96f18	395	16	64	16	64
HBase	0fc18a9	221	12	50	12	50
Alluxio	76569bc	494	13	54	13	54
HDFS	aa96f18	566	16	64	16	64
YARN	aa96f18	525	10	40	10	40
ZooKeeper	e3704b3	32	8	32	8	32

Configuration Dataset To evaluate the effectiveness of configuration validation, we create new datasets for each system. First, we collect valid configuration values based on the default configuration file from each system, as well as configuration files from the Ctest dataset [1]. The configuration files in the Ctest dataset was collected from public Docker images that deploy the target systems [75, 81, 98]. We then generate misconfigurations of different types. The generation is based on prior studies on misconfigurations [36, 43, 44, 99], which violates the constraints of configuration parameters as shown in Table 2.

For each project, we build two distinct sets of configuration files. First, we build a dataset of configuration files with no misconfiguration (denoted as *ValidConfig*) to measure true negatives and false positives (Table 4). Concurrently, we also build a dataset of configuration files in which each file has one misconfiguration (denoted as *Misconfig*) to measure true positives and false negatives (Table 4). A misconfiguration can be a dependency violation between values of multiple parameters.

To build *Misconfig* for a project, we first check if a configuration parameter fits the specification of any sub-category in Table 2, and assign it to all sub-categories that fit. For example, an IP-address parameter can be assigned to "Syntax: IP Address" and "Range: IP Address". And we do so for all parameters in the project. Then, we randomly sample at most 5 parameters in each sub-category that has a non-empty set of assigned parameters, and generate invalid value(s) per sampled parameter using the corresponding generation rules. For each non-empty sub-category, we further randomly select one parameter and its generated invalid value(s) from the 5 previously-sampled parameters. We use that one parameter to create a faulty configuration file as a *Misconfig* shot (§3) for that sub-category, and add this shot to the project's shot pool. For the remaining 4 parameters, we use them to create 4 faulty configuration files for that sub-category, and add them to the evaluation set. If a sub-category does not have enough parameters for the aforementioned samplings, we use all its assigned parameters to create files for the evaluation set. We separate the evaluation set and shot pool to follow the practice that the learning shot data does not overlap with the testing data [18].

We build *ValidConfig* for a project following the same methodology we used to build the *Misconfig* mentioned above, except that we generate valid values for the sampled parameters. Table 3 shows the size for both the *ValidConfig* and *Misconfig* datasets per project. It's worth noting that our datasets cover 72%-100% of the total number of parameters in each evaluated system.

Models We evaluate Ciri with five state-of-the-art LLMs: GPT-4, GPT-3.5-turbo (16k), Code-Davinci-002, Babbage-002, Davinci-002. These models are the most widely used LLMs, each of which differs in training procedures and/or training data. They are trained on a large amount of code data, and show promising capability in handling a number of software engineering tasks [22, 78, 91].

- Code-Davinci-002 is optimized for code completion tasks based on GPT-3.5, and is capable at translating natural language to code. Code-Davinci-002 has 175 billion parameters, and was trained on data collected until June 2021. Its token limit per query is 8,001.
- GPT-3.5-turbo (16k) is a successor to Code-Davinci-002. Compared with Code-Davinci-002, GPT-3.5-turbo further uses an effective optimization technique called RLHF to follow instructions [109]. GPT-3.5-turbo has unknown number of parameters and was trained on data available up to September 2021. Since the base turbo model has a token limit of only 4,097 per query, we use its variant that extends the token limit to 16,385.
- GPT-4 is claimed to be the most advanced and widely-used LLM up to date [60]. Compared with GPT-3.5-turbo, GPT-4 is larger in size. GPT-4 is trained on data prior to September 2021, its token limit per query is 8,192.

• Babbage-002 and Davinci-002, successors to the legacy GPT-3, are two base models [5]. They were not fine-tuned with instruction-following technique [62], which aligns models with specific prompts and desired outputs. Both models have a 16,384 token limit per query.

Metrics We evaluate the effectiveness of LLMs on configuration validation at both *configuration file* and *configuration parameter* levels. At file level, we want to know whether the model can determine if a configuration file is fully valid or misconfigured. At parameter level, we want to know whether the model can determine if each parameter in the configuration file is valid or erroneous. We describe the definitions of the terms used in confusion matrix in Table 4. We then compute the Precision, Recall, and F1-score at both levels to assess the LLM's effectiveness. If not specified, we default to Macro averaging since each project is regarded equally. We prioritize studying parameter-level effectiveness because it provides more fine-grained measurements. We default to discussing parameter-level metrics in §5 unless noted otherwise.

Level	СМ	Definition
File	TP FP TN FN	A misconfigured configuration file correctly identified A correct configuration file wrongly flagged as misconfigured A correct configuration file rightly identified as valid A misconfigured configuration file overlooked or deemed correct
Param.	TP FP TN FN	A misconfigured parameter correctly identified A correct parameter wrongly flagged as misconfigured A correct parameter rightly identified as valid A misconfigured parameter overlooked or deemed correct

5 EVALUATION AND FINDINGS

In this section, we first present results on evaluating the effectiveness of LLMs as configuration validators with Ciri (§5.1). We then analyze how validation effectiveness changes with regard to shots in few-shot learning (§5.2). We also present our understanding on when Ciri produces wrongful validation results (§5.3) and observed biases from LLMs' training (§5.4).

5.1 Validation Effectiveness

Finding 1. *Ciri demonstrates the effectiveness of using state-of-the-art LLMs as configuration validators. It achieves file-level and parameter-level F1-scores of up to 0.75 and 0.56, respectively.*

Ciri exhibits remarkable capability in configuration validation. Table 5 shows the F1-score, precision, and recall for each project and LLM under four-shot setting (§3)—the most effective few-shot learning setting obtained from our later experiments (§5.2). Table 5 shows that: beyond merely identifying misconfiguration files, with an average F1-score ranging from 0.62 to 0.75, LLMs can also adept at pinpoint erroneous parameters and discern the causes of the misconfigurations. Among the top-three LLMs, the parameter-level F1-scores are approximately 25% lower than their file-level counterparts, this shows that identifying misconfigured parameters is currently a more challenging task for LLMs than classifying if a configuration change is erroneous.

When using legacy models, we observe they lack the ability of effective configuration validation. Specifically, for Babbage-002, its

F1-score has a sharp drop from file-level (0.62) to parameter-level (0.09), indicating that it is not able to localize the actual misconfigured parameter accurately. One reason is that Babbage-002 lacks optimization for instruction-following [62], leading it to produce inappropriate results. Furthermore, we also evaluate the Davinci-002, and it cannot detect any misconfiguration within our dataset (omitted from Table 5).

Finding 2. Providing configuration file examples (shots) for the validation query can effectively improve LLMs' configuration validation effectiveness. Without shots, LLMs often report false alarms or miss misconfigurations, e.g., Code-Davinci-002's F1-score at parameterlevel is as low as 0.08—with shots, its file-level and parameter-level F1-scores can be improved by 0.56 and 0.48 respectively.

Validation examples (shots) play an important role in improving the effectiveness of LLMs for configuration validation. Table 6 shows the performance of LLMs when the configuration validation query does not include shots from Ciri. In particular, comparing Table 6 to Table 5, the average F1-score of the top-three LLMs has decreased by 0.08-0.56 at the file-level, and decreased by 0.09-0.48 at the parameter-level. Without any shots, both Davinci-002 and Babbage-002 cannot detect any misconfiguration in our dataset; we thus omitted them in Table 6.

Implication. Our result suggests that state-of-the-art LLMs (e.g., GPT-4, GPT-3.5-turbo) can be applied to configuration validation in a properly designed framework like Ciri to achieve promising effectiveness. Specifically, generating and providing configuration validation examples along with the validation query can improve off-the-shelf LLMs' misconfiguration detection effectiveness. However, legacy LLMs (e.g., Davinci-002, Babbage-002) are often incapable of configuration validation due to insufficient training data and/or outdated training mechanisms [2, 62].

5.2 Impacts of Few-shot Learning

Following the implication in Section 5.1, we conduct a series of experiments to study how the configuration validation effectiveness of LLMs can be improved over different shot combinations.

We evaluate six *N*-shot learning settings, where *N* ranges from 0 to 5. For each of these settings, we use Ciri to generate different combinations of shots drawn from the *ValidConfig* and *Misconfig* datasets (§4). For example, to evaluate GPT-3.5-turbo on HCommon with a two-shot setting, three experiments will be performed: (1) two *ValidConfig* shots; (2) one *ValidConfig* shot plus one *Misconfig* shot; (3) two *Misconfig* shots, drawn from the HCommon's shot database. In total, we experiment with 21 shot combinations for each project and LLM. To control cost, we limit the experiment to two LLMs (GPT-3.5-turbo and Code-Davinci-002) on three systems (HCommon, HBase, Alluxio).

Finding 3. Including both ValidConfig and Misconfig shots for LLMs delivers the optimal configuration validation effectiveness. Meanwhile, Misconfig shots are more crucial to validation effectiveness than Valid-Config shots. For example, both GPT-3.5-turbo and Code-Davinci-002 achieve their highest F1-score with three Misconfig shots and one ValidConfig shot.

		F1-score															Precision			call
Models			File	Level	(F.L.)				Parameter-Level (P.L.)								P.L.		F.L.	P.L.
	HC.	HB.	AL.	HD.	YA.	ZK.	Avg	HC.	HB.	AL.	HD.	YA.	ZK.	Avg		Avg	Avg		Avg	Avg
GPT-4	0.80	0.74	0.74	0.77	0.72	0.72	0.75	0.64	0.56	0.57	0.60	0.53	0.47	0.56		0.63	0.43		0.93	0.83
GPT-3.5-turbo	0.74	0.72	0.76	0.74	0.71	0.72	0.73	0.52	0.60	0.47	0.56	0.46	0.55	0.52		0.67	0.42		0.82	0.73
Code-Davinci-002	0.74	0.75	0.79	0.68	0.70	0.71	0.73	0.59	0.62	0.53	0.51	0.54	0.59	0.56		0.63	0.48		0.87	0.71
Babbage-002	0.66	0.65	0.66	0.64	0.58	0.54	0.62	0.08	0.11	0.11	0.02	0.08	0.14	0.09		0.51	0.08		0.81	0.11

Table 5: Effectiveness of LLMs under Ciri.

Table 6: Effectiveness of LLMs without using shots from Ciri.

		F1-score															ision	Recall		
Models			File	-Level	(F.L.)				Parameter-Level (P.L.)								P.L.	F.L.	P.L.	
	HC.	HB.	AL.	HD.	YA.	ZK.	Avg	HC.	HB.	AL.	HD.	YA.	ZK.	Avg		Avg	Avg	Avg	Avg	
GPT-4	0.66	0.68	0.64	0.69	0.62	0.73	0.67	0.53	0.62	0.46	0.48	0.39	0.33	0.47		0.76	0.44	0.62	0.55	
GPT-3.5-turbo	0.61	0.61	0.75	0.66	0.68	0.61	0.65	0.20	0.37	0.19	0.25	0.24	0.21	0.24		0.66	0.16	0.67	0.55	
Code-Davinci-002	0.24	0.25	0.00	0.36	0.14	0.06	<u>0.17</u>	0.11	0.10	0.00	0.17	0.10	0.00	<u>0.08</u>		0.56	0.08	0.11	0.09	

Figure 4 shows how the average F1-score, precision and recall across projects for GPT-3.5-turbo and Code-Davinci-002 under different shot combinations. Without *Misconfig*, LLMs' performance is easily limited. For example, when only using *ValidConfig* shots in the prompt, Code-Davinci-002 only gets an F1-score around 0.2 (i.e., the first column of the heat map in Figure 4b). Compared with *ValidConfig* shots, *Misconfig* shots allow Ciri to more effectively identify patterns and attributes of misconfigurations at inference time. In both Figure 4a-4b, F1-score increases at more *Misconfig* shots are used in the prompt.

On the other hand, providing only *Misconfig* shots can introduce bias to the LLM and lead to a performance decrease. This is because the text distribution in the input query can significantly impact the performance of LLMs [54]. In our evaluation, after providing a sufficient number of *Misconfig* shots, we indeed see that providing more *ValidConfig* shots can sometimes reduce the number of false positives for Code-Davinci-002 and false negatives for GPT-3.5turbo. Overall, using both *Misconfig* and *ValidConfig* in few-shot learning settings mitigates the biases of LLMs and delivers the optimal configuration validation performance.

Finding 4. Using configuration files from the same system as shots for LLMs delivers the optimal configuration validation effectiveness. When same-system shots are unavailable, using configuration files from a different system could also improve validation effectiveness over zero-shot. For example, on HCommon, the parameter-level F1score improved by 0.39 averaged across the top three LLMs.

In situations where configuration data of target systems is unavailable, we evaluate the possibility of using configuration files from other systems as shots for LLMs can improve the configuration validation effectiveness on the target system. Table 7 shows our evaluation results of using shots from other systems for LLMs to do configuration validation on HCommon. By comparing the HC. columns with other columns in Table 7, we can see that using shots from other systems is not as effective as using shots from the target system. However, by comparing the average F1-score in Table 7 with the HC. columns in Table 6, we find that using shots from other systems is generally more effective than not using any shots. Our observations highlight that Ciri with the underlying LLMs can transfer configuration-related knowledge across different systems for effective configuration validation compared to traditional validation approaches (§1).

In contrast to the other LLMs, using cross-system shots actually decreases the F1-score compared to the zero-shot setting on GPT-4. One possible explanation is that examples from other systems also introduce noise that is contradictory to the target system's configuration data. LLMs can pick up such noise and produce an inaccurate validation outcome.

Finding 5. The validation effectiveness is higher if the misconfiguration in the validating configuration file belongs to the same violation (sub-)categories as the misconfigurations in the shots, compared to when it does not.

Table 8 shows that when the validating configuration file contains misconfiguration belonging to the same (sub-)categories of violation as the misconfigurations in the shots, the LLMs' F1-score improves significantly. When the misconfigurations between the shot and the evaluated file are caused by the same category (e.g., syntax or range error from Table 2), parameter-level F1-score improves by up to 30% compared to when they are not caused by the same category of violations. When they are caused by the same sub-category of violation (i.e., they are violated similarly and have the same parameter type), F1-score improves by up to 69.5%.

Table 8: Improvement in parameter-level F1-score when the misconfiguration in the evaluated file belongs to the same violation (sub-)category as the misconfiguration in the shot, compared to when they do not.

Models		Catego	ory	Sub-Category								
Models	Diff.	Same	%Improv.	Diff.	Same	%Improv.						
GPT-4	0.57	0.65	+12.9%	0.60	0.57	-5.3%						
GPT-3.5-turbo	0.41	0.53	+28.2%	0.45	0.51	+12.8%						
Code-Davinci-002	0.44	0.61	+37.0%	0.48	0.81	+69.5%						

Implication. To improve LLM's performance as a configuration validator with few-shot learning, developers can leverage frameworks like Ciri to collect and generate high-quality, comprehensive configuration validation examples as shots. The provided shots in the prompt should be composed of misconfiguration files in which

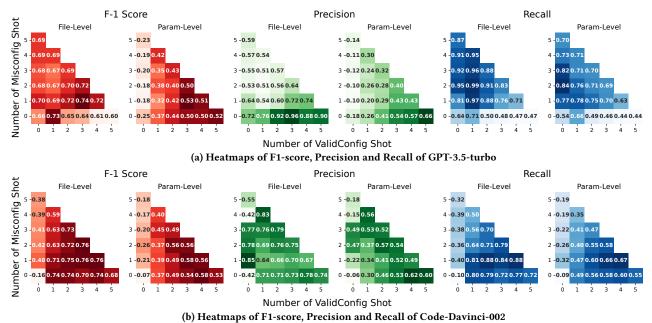


Figure 4: Evaluation results under different shot combinations.

Table 7: Results on HCommon using shots from other systems, e.g., the HB. columns show results of using HBase shots for HCommon. The HC. columns show results of using HCommon shots for HCommon.

	1					F1-s	core							Ι		Prec	ision			Recall			
Models	File-Level (F.L.)							Parameter-Level (P.L.)								L.	P.L.		F.L.		P.L.		
	HC. HB.	AL.	HD.	YA.	ZK.	Avg	HC.	HB.	AL.	HD.	YA.	ZK.	Avg		HC.	Avg	HC.	Avg		IC.	Avg	HC.	Avg
GPT-4	0.80 0.72																		(.98	0.99	0.87	0.77
GPT-3.5-turbo	0.74 0.72	0.66	0.71	0.64	0.68	0.68	0.52	0.30	0.22	0.47	0.34	0.21	0.31		0.71	0.62	0.42	0.21	(.77	0.78	0.67	0.61
Code-Davinci-002	0.74 0.73	0.70	0.71	0.71	<u>0.62</u>	0.69	0.59	0.47	$\underline{0.41}$	0.42	0.41	0.48	0.44		0.65	0.64	0.51	0.38	(.85	0.79	0.69	0.53

the misconfigured parameter(s) have been identified and reasoned, as well as configuration files that are entirely valid. Our experience suggests that prioritizing the provision of misconfiguration shots is more crucial than supplying valid configuration shots.

When configuration data of target systems is unavailable for few-shot learning, using configuration data from other systems as shots could improve configuration validation effectiveness of LLMs, compared with zero shot. Moreover, misconfigurations that may fall into the same possible (sub-)category of violation are particularly useful as shots. However, shots from other systems may introduce bias, and affect the validation effectiveness.

5.3 Ineffectiveness and Difficulties

Finding 6. Under Ciri, LLMs excel at pinpointing misconfigurations caused by syntax and range violations (i.e., 12 out of all 15 sub-categories of violations), with an average F1-score of 0.8 across corresponding sub-categories. However, LLMs show limited effectiveness in pinpointing misconfigurations caused by dependency and version violations (i.e., 3 out of all 15 sub-categories), with an average F1-score of 0.2 across corresponding sub-categories.

Table 9 shows the validation effectiveness of Ciri broken down by the types of misconfigurations. The average F1-score across systems on detecting misconfigurations due to Syntax and Range violations is consistently above 0.5 and often reaches 0.8 for all three state-of-the-art LLMs, with one exception in Code-Davinci-002 on "Range: Permission" misconfigurations (an F1-score of 0.44). Meanwhile, however, F1-score rarely exceeds 0.3 when detecting misconfigurations due to violations in Dependency and Version. Only GPT-4 achieves a slightly better F1-score of 0.46 in the Value Relationship sub-category, which is still much lower than its F1-scores in other sub-categories.

The performance difference can be attributed to the inherent nature of the misconfigurations. Misconfigurations due to violations in the Syntax and Range categories are more common in practice [101], from which LLMs have learned extensive knowledge. In such a case, domain-specific knowledge from LLM is sufficient to spot Syntax or Range violations. On the other hand, misconfiguration data from the Dependency and Version categories is often project-specific, e.g., the example shown in Figure 5. They are tied to detailed history and features of individual projects, thus harder to be captured or memorized by LLMs if the LLMs have not been heavily re-trained or fine-tuned on project-specific data. This performance discrepancy across different misconfiguration types exposes existing LLMs's limitation on detecting misconfigurations that require highly project-specific knowledge.

GPT-4 GPT-3.5-turbo Code-Davinci-002 Category Sub-category HC. HB. AL. HD. YA. ZK. avg HC. HB. AL. HD. YA. ZK. avg HC. HB. AL. HD. YA. ZK. avg Data type 1.00 0.89 1.00 0.89 1.00 0.73 0.92 0.61 0.89 0.70 0.94 0.89 0.80 0.77 0.94 0.86 0.67 0.80 1.00 1.00 0.86 Path 1.00 0.80 0.80 1.00 0.89 0.67 0.85 1.00 0.86 0.43 0.55 1.00 0.89 0.74 0.50 1.00 0.75 0.75 1.00 0.75 0.79 URL 1.00 N.A. 0.00 0.80 N.A. N.A. 0.82 1.00 N.A. 0.00 1.00 N.A. N.A. 0.94 1.00 N.A. 0.00 1.00 N.A. N.A. 0.89 Syntax IP Address 1.00 0.89 1.00 1.00 1.00 0.73 0.92 0.86 0.80 0.89 1.00 0.89 0.89 0.88 1.00 0.80 0.50 0.89 0.75 0.89 0.81 Port 0.89 0.89 0.89 1.00 N.A. 0.67 0.85 0.80 0.89 0.80 1.00 N.A. 0.89 0.86 1.00 1.00 0.89 0.89 N.A. 1.00 0.95 Permission 1.00 1.00 0.57 1.00 N.A. N.A 0.88 0.86 1.00 1.00 1.00 N.A. N.A. 0.95 1.00 1.00 0.67 0.86 N.A. N.A 0.90

0.67 0.55 0.67 0.75 0.67 0.53 0.62

0.57 0.57 0.47 0.00 0.44 0.80 0.50

0.75 0.67 0.40 0.86 0.67 N.A. 0.63

0.89 1.00 0.57 0.86 0.86 0.67 0.77

0.75 0.73 0.67 0.67 N.A. 1.00 0.76

0.50 0.00 0.57 0.86 N.A. N.A. 0.63

0.00 0.00 0.00

0.00 0.40 0.44 0.00

0.20 0.00 0.00 0.00 0.00

0.00

0.00

0.29

N.A.

N.A. 0.25

N.A.

0.00

0.06

0.82

Table 9: Parameter-level F1-score by misconfiguration types from Table 2. N.A. means no evaluation samples.

<name>hbase.security.authentication</name> <value>simple</value> <description>Controls whether or not secure authentication is enabled for HBase. Possible values are 'simple' (no authentication), and 'kerberos'.</description> ... <name>hbase.auth.key.update.interval</name> <value>43200000</value>

0.67 1.00 0.80 0.57 0.75 0.73 0.75

0.89

0.67 0.80 0.57 1.00 0.89 N.A. 0.78

0.89 0.89 0.89

1.00 0.86 0.86 0.67 N.A. 0.80 0.83

0.75

0.00

0.57 0.57

0.75 0.00 0.00 0.57 0.00 N.A. 0.27

0.55 1.00 0.80 0.80 0.62 0.75

1.00 0.50 1.00 N.A. N.A.

0.57

0.00 0.00 0.00 N.A. 0.13

0.67

0.89 0.57 0.83

1.00

0.00 0.57 N.A. 0.46

Basic numeric

Bool

Enum

Port

IP Address

Permission

Value Relationship

Parameter Change

Control

Range

Dependency

Version

<description>The update interval for authentication tokens in milliseconds. Only used when HBase security is enabled.</description> ...

Figure 5: Misconfiguration of Control Dependency that LLMs cannot detect. The update interval for authentication is set but the secure authentication is disabled.

Finding 7. *LLMs show a trend of decrease in configuration validation effectiveness as the number of parameters increases in the to-be-validated configuration file.*

We evaluate how the F1-score from GPT-3.5-turbo relates to the number of configuration parameters in the validating configuration file. We present our results in Figure 6, which indicates that configuration validation becomes more challenging as the number of parameters in the validating configuration file grows. For instance, when the number of parameters jumps from 8 to 16, the performance of Ciri begins to deteriorate severely. This performance decline can be attributed to a potential information overload for LLMs at inference time. As the complexity of the configuration file grows, the difficulty of validating it also increases. The model may struggle to process all the validating configuration parameters and their relationships as more parameters are included.

Finding 8. Among the correctly identified misconfigurations, 93.6% of the reasons from LLMs directly address the root causes of the misconfigurations. Meanwhile, 6.4% of the reasons are misleading.

When an LLM identifies a misconfiguration from the validating configuration file, Ciri also requests the LLM to provide explanations to its judgment to aid developers in debugging the root cause and fixing the misconfiguration (§3.1). To assess the clarity and accuracy of these explanations, we randomly select one answer in which the misconfiguration is correctly identified per (sub-category, system, LLM) tuple, and collect a total of 204 answers (resulted from 2,040 queries). Upon careful manual review, we determined that 93.6% of the reasons given by the LLMs are clear and directly address the root cause of the misconfigurations. This indicates that LLMs can both detect misconfigurations and provide meaningful explanations for them. 1.9% of the answers contain a mix of correct and incorrect explanations across their queries. However, these incorrect reasons were filtered out by the text clustering method outlined in §3.1 because the correct reasons are dominating. Figure 7 presents an example of mixed reasons, with the second reason being an instance of hallucination.

0.57 0.57 0.60 0.67 0.86 1.00 0.70

0.57 0.75 1.00 0.67

0.75 0.86 0.86 0.57 1.00 N.A. 0.81

0.89 0.89 0.50

0.86 0.86 0.86 1.00 N.A. 1.00 0.91

0.57 1.00

0.00

0.00 0.29 0.00 0.40 0.25 N.A. 0.21

0.50 0.00

0.57 0.00

0.75

0.89 0.57 0.74

0.40 N.A.

0.75

0.00 0.25 N.A.

0.00 0.00

0.50 0.00 N.A.

0.80 0.77

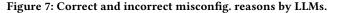
N.A.

0.44

0.18

0.17

alluxio.underfs.gcs.default.mode=888
 The property 'alluxio.underfs.gcs.default.mode' has the value '888' which is not a valid octal number.
 A2: The property 'alluxio.underfs.gcs.default.mode' has the value '888' which exceeds the range of an Integer.



Implication. With frameworks like Ciri, state-of-the-art LLMs can effectively validate configurations for syntax or range violations. However, they are less effective for the configurations that involve dependencies between parameters and software versions, showing the challenges for LLMs to reason the interactions between configuration and between configuration and code [53]. To improve the effectiveness for those misconfigurations, one can re-train or fine-tune LLMs with data related to dependency and versions. Our results also show that small configuration snippets are much easier for LLMs to validate, supporting incremental, continuous configuration change practice which is already widely adoped in practice [16, 76]. Lastly, while LLMs often provide correct explanations on misconfigurations that can aid debugging, it is crucial for developers to use these explanations with discretion, as they may not be consistently accurate.

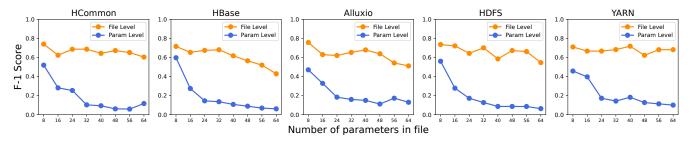


Figure 6: Effectiveness of GPT-3.5-turbo under different number of parameters in the configuration file.

5.4 Biases in Validation Results

Finding 9. During configuration validation, LLMs more frequently pinpoint parameters that are more popular on the Internet. When a configuration file is entirely valid, LLMs more frequently report false alarms on the more popular parameters. When a parameter is misconfigured, LLMs demonstrate higher accuracy in identifying misconfigurations on the more popular parameters.

To quantify the popularity of a configuration parameter on the Internet, we measure the number of exact-match search results returned by Google for a keyword and term it as G-hits.

We first study whether there is a correlation between a parameter's popularity and the frequency it is reported as a false alarm by LLMs in valid configuration files. For the configuration files in *ValidConfig* dataset, we obtain the G-hits of each parameter in each file. We then track the frequency of LLMs pinpointing the parameter with the i^{th} highest G-hits in each file, where i = 1...8. Figure 8 shows the overall frequencies of the parameter with i^{th} highest G-hits in the file being pinpointed. The smaller figures show the overall frequencies under different shot combinations (§5.2), the larger figure simply sums up the frequencies from the smaller figures. Overall, the frequency distributions of being pinpointed reveal a clear skewness towards parameters with higher G-hits.

We then study the correlation between a parameter's popularity and its validation accuracy. We perform similar calculations for parameters in configuration files from *Misconfig* dataset, and further separate the cases when the misconfigured parameter is identified versus when it is missed. We observe that the median G-hits of the misconfigured parameters being correctly identified is higher than the median G-hits of the misconfigured parameters being missed.

The correlations between the parameter popularity and the parameter G-hits across both datasets can be attributed to the nature of the training data of LLMs. Training data of LLMs is often sourced from publicly accessible domains (e.g., Common Crawl [4]), which are easily accessible by search engines like Google. Topics or parameters that are popularly discussed are more likely to be memorized by the LLMs than the less popular ones, due to more frequent presence in the training data.

Implication. LLMs are predisposed to prioritize configuration parameters that are more frequently discussed on the internet during the configuration validation. As a result, when employed as configuration validators, LLMs can effectively detect misconfigurations in parameters that are commonly referenced online, while posing limited capacity in validating those that are not.

6 THREATS TO VALIDITY

External. The external threats come from our evaluated LLMs and dataset. We evaluate Ciri with five state-of-the-art LLMs that are widely used to mitigate threats on evaluated models. To mitigate threats from the evaluated projects, we select six mature, widely used software systems with different types. These systems are commonly used in prior studies [21, 23, 66, 67, 75, 81, 105]. To account for bias in the evaluated configuration data, we include many types of configuration parameters and their generation rules based on prior studies [36, 43, 44, 99] to synthesize our evaluation dataset. Our results cannot generalize to other types of misconfigurations (discussed in §7). We believe that the overall trend is general, but the precise numbers could vary with other LLMs, software systems, and configuration files in the field.

Internal. The internal threats lie in potential bugs in the implementation of Ciri, and experimental scripts for evaluation. To mitigate such threats, we have rigorously reviewed our code and carefully analyzed the experiment results.

Construct. The threats to construct validity mainly lie in the metrics used in the study. We use the popular F1-score, Precision, and Recall for our evaluations, and carefully define our confusion matrices at both configuration file granularity and configuration parameter granularity for misconfiguration detection.

7 DISCUSSION AND FUTURE WORK

Improving effectiveness of LLMs as validators. Despite the promising results, using LLMs directly as configuration validators like Ciri is only a starting point to fully leverage LLMs' capabilities for configuration validation. Specifically, there are circumstances where Ciri exhibits limitations and biases (§5.3, §5.4). One of the intricate aspects of configuration validation is understanding and validating configuration dependencies. To address this, an initial step can be introduced where an LLM first tries to analyze the dependencies of the target configuration before validation. Moreover, integrating LLMs with automated configuration dependency discovery tools [21] can be helpful. For example, tools that use static taint analysis [21, 77] or dynamic information flow analysis [11, 12] can be utilized to extract and analyze configuration dependencies, which can then be fed as input to LLMs. This ensures that dependencies are accurately captured for LLMs.

To further enhance the understanding of LLMs, more information related to configurations can be incorporated, such as code

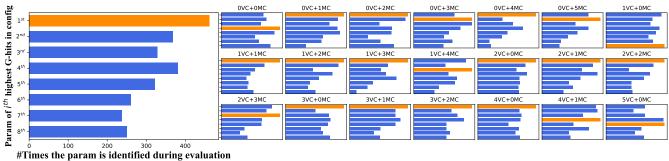


Figure 8: Frequency of the identified parameter with *i*th highest G-hits in a configuration file. In different shot settings (subfigures), VC stands for a ValidConfig shot, and MC stands for a Misconfig shot.

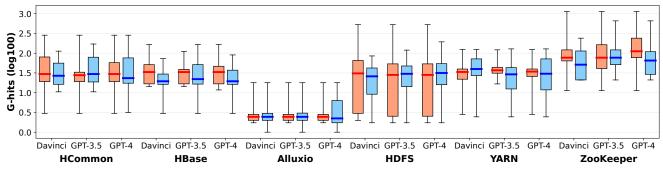


Figure 9: The G-hits distribution of the correctly detected misconfigurations (orange), and the G-hits distribution of the missed misconfigurations (blue). The bars in box plots indicate medians.

comments, descriptions, change logs, and specifications. Such information can provide valuable context, which has been proven by the prior work [22, 58, 108].

Moreover, we plan to investigate advanced prompting techniques, such as Chain-of-Thoughts (CoT) prompting [83, 88, 107]. In configuration validation context, CoT prompting can mimic the reasoning process a system expert might follow during the validation process. By eliciting LLMs to generate intermediate reasoning steps leading to the validation answer, it not only makes the validation process more transparent but also potentially more accurate. This step-by-step reasoning may also help in identifying and rectifying biases in the model's validation process.

Lastly, integrating user feedback loops can be valuable. With user feedback on validation results, the iterative procedure can refine LLMs over time, leading to more accurate results.

Detecting environment-related misconfigurations. While our study primarily targets basic misconfigurations, such as syntax and semantic violations, the validity of a configuration file can vary across environments. For instance, a system's configuration might specify a file location, but the file's existence, readability, and format can determine its actual validity. To address these, LLMs can generate environment-specific scripts that can be run in the context of the environment. For example, given the configuration file as input, the LLM can generate a Python script like the following to validate the specified file path.

Such an approach can help identify issues like misconfigured paths, unreachable network addresses, missing packages, or invalid

permissions. Notably, these scripts offer a lightweight alternative to more intensive configuration tests [23, 97].

For security concern, running those checks generated by LLMs need to be sandboxed. Moreover, the scripts can be reviewed by humans and transformed into lightweight validators. Given the recent success of code generation tools such as GitHub Copilot, we believe this is a promising direction to explore. In fact, our preliminary experiments show that, given appropriate examples, LLMs can generate such scripts quite well.

Detecting source-code related misconfigurations. In addition to the deployment environment, the system's source code can also affect the validity of a configuration. Implicit assumptions or latent software bugs can create ambiguities in understanding the true requirements of a configuration. To further illustrate this point, continuing the above example, if the documentation does not mention that the file needs to be in JSON format, but the code expects such a format, neither an LLM nor a human could infer this constraint based solely on the documentation.

To detect such issues, we can leverage LLMs' ability to reason about code. The strategy involves presenting both the configuration file and the relevant source code that exercises this configuration to the LLM. Techniques like static or dynamic program slicing [40, 89] can help pinpoint the relevant code blocks. The LLM can then be tasked with distilling this code into a validator script. While this poses a challenge, the code reasoning capability of LLMs [7, 46] suggests that this is promising and worth further exploration.

Fine-tuning LLMs for configuration validation. Apart from these, there is also the problem of tackling very system-specific parameters, which cannot be reasoned about based on common-sense knowledge. This problem is further exacerbated by the fact that software evolves constantly [104, 105] by introducing new parameters and changing existing parameters to take different meanings and constraints. This is an important problem to tackle to unleash the full potential of LLMs for configuration validation. The most obvious approach for tackling this is to fine-tune models on new data to keep LLMs updated, but this is non-trivial, especially due to lack of data on the newly introduced parameters. The LLM community has found promising results in using synthetic data [30, 32, 84, 93] for fine-tuning these models, reducing the need for large amounts of real data. We believe that this is a promising direction to explore for configuration validation as well.

8 RELATED WORK

Configuration Validation. Prior studies developed frameworks for developers to implement validators [15, 33, 65, 76] and test cases [75, 97], as well as techniques to extract configuration constraints [47, 56, 99, 102]. However, manually writing validators and tests requires extensive engineering efforts, and is hard to cover various properties of different configurations [36, 43, 44, 96, 99]. ML/NLP-based configuration validation techniques have been investigated. Traditional ML/NLP-based approaches learn correctness rules from configuration data [17, 41, 63, 71, 72, 80, 85, 103] and documents [64, 92] and then use the learned rules for validation. These techniques face data challenges and rely on predefined learning features and models, making them hard to generalize to different projects and deployment scenarios. Complementary to prior work, we explore using LLMs for configuration validation, which can potentially address the limitations of traditional ML/NLP techniques towards automatic, effective validation solutions.

Large Language Models for Software Engineering. LLMs have become an exciting utility in the past few years, achieving impressive performance across various tasks such as text classification, text summarization, and logical reasoning [18, 24, 39, 79, 86]. Recently, they are being actively adopted to the software engineering domain, where they have demonstrated abilities in generating, summarizing, and translating code [8, 20, 35, 45, 49, 69, 70], failure diagnosis [9, 22], fault localization and program repair [26, 55, 90, 91]. Large pre-trained models of coding data (LLMs for code) are also increasingly prominent [20, 27, 28, 58, 59, 94], and have been used for the aforementioned code-specific tasks. We take the first step to comprehensively evaluate LLMs for configuration validation. Our proposed framework for adopting LLMs as configuration validators, Ciri, is general to different LLMs.

9 CONCLUSION

As a first step to harvest recent advances of LLMs such as GPT and Codex for configuration validation, we developed Ciri as an open platform to experiment with LLMs as configuration validators and to analyze the promises and challenges of LLM-based validators. In this paper, we presented our analysis of Ciri's validation effectiveness on five popular LLMs using configuration data of six mature, widely deployed open-source systems. Our findings showed the potential of using LLMs for configuration validation-Ciri demonstrates the effectiveness of state-of-the-art LLMs as configuration validators, achieving file-level and parameter-level F1-scores of up to 0.75 and 0.56, respectively. We also explored the design space of LLM-based validators in terms of prompt engineering with fewshot learning. Despite the encouraging results, our study revealed that directly using LLMs as configuration validators is ineffective in detecting certain types of misconfigurations such as dependency violations and version-related misconfigurations and induces biases to popular parameters. We discuss the open challenges which shedding light on new, exciting research directions of the LLMempowered validation techniques.

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