

Don't Chase Your Tail! Missing Key Aspects Augmentation in Textual Vulnerability Descriptions of Long-tail Software through Feature Inference

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Abstract—Augmenting missing key aspects in Textual Vulnerability Descriptions (TVDs) for software with a large user base (referred to as non-long-tail software) has greatly advanced vulnerability analysis and software security research. However, these methods often overlook software instances that have a limited user base (referred to as long-tail software) due to limited TVDs, variations in software features, and domain-specific jargon, which hinders vulnerability analysis and software repairs. In this paper, we introduce a novel software feature inference framework designed to augment the missing key aspects of TVDs for long-tail software. Firstly, we tackle the issue of non-standard software names found in community-maintained vulnerability databases by cross-referencing government databases with Common Vulnerabilities and Exposures (CVEs). Next, we employ Large Language Models (LLMs) to generate the missing key aspects. However, the limited availability of historical TVDs restricts the variety of examples. To overcome this limitation, we utilize the Common Weakness Enumeration (CWE) to classify all TVDs and select cluster centers as representative examples. To ensure accuracy, we present Natural Language Inference (NLI) models specifically designed for long-tail software. These models identify and eliminate incorrect responses. Additionally, we use a wiki repository to provide explanations for proprietary terms. Our evaluations demonstrate that our approach significantly improves the accuracy of augmenting missing key aspects of TVDs for long-tail software from 0.27 to 0.56 (+107%). Interestingly, the accuracy of non-long-tail software also increases from 64% to 71%. As a result, our approach can be useful in various downstream tasks that require complete TVD information.

Index Terms—Software Vulnerability, Long-tail Software, Textual Vulnerability Descriptions, Natural Language Inference, Software Feature

I. INTRODUCTION

Vulnerabilities are increasing in complexity and scale, posing great security risks to many software systems [1], [2]. To address these risks, data sources such as the National Vulnerability Database (NVD) [3] provide information on known vulnerabilities. They classify these vulnerabilities based on type and severity, providing common names, identifiers, links

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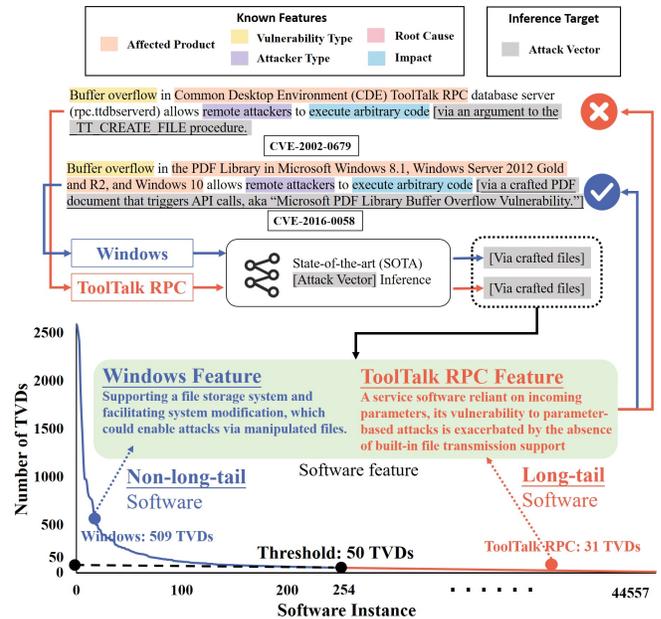


Fig. 1. In the coordinate axis, the x-axis represents the software instance represented by IDs, and the y-axis represents the number of TVDs each software has. For example, Windows, id=17, and has 509 TVDs. For CVE-2002-0679 (Microsoft Windows) and CVE-2016-0058 (ToolTalk RPC), we omitted the *Attack Vector* information from TVDs. Microsoft Windows has 509 TVDs in the NVD, whilst ToolTalk RPC only has 31 TVDs. To predict the missing key aspect (*Attack Vector*) based on the rest of TVD's key aspects, none of the existing methods can successfully complete the task for ToolTalk RPC. For Microsoft Windows, the vulnerability stems from file operations during runtime. It involves supporting a file storage system and facilitating system modification, which could enable attacks via manipulated files. For ToolTalk RPC, a service software reliant on incoming parameters, its vulnerability to parameter-based attacks is exacerbated by the absence of built-in file transmission support. Therefore, for SOTA predicting the same *Attack Vector*, it is applicable to Windows but not to ToolTalk RPC.

to patches, and additional details as short text descriptions. In this paper, we focus on those informative short text descriptions of vulnerabilities, also known as TVDs, for software instances with a limited user base (referred to as “long-tail

software”). These software instances are often overlooked due to limited TVDs, variations in software features, and domain-specific jargon. By augmenting key aspects of TVDs, such as *Vulnerability Type*, *Attack Vector*, *Attacker Type*, *Impact*, and *Root Cause* [4], [5], we can improve vulnerability analysis [6], [7], software repairs [8]–[10], management [11], [12], mitigation [13], [14], maintenance [15], prevention [16], and other related tasks. TVDs are often incomplete on these key aspects, with a substantial missing rate ranging between 28% and 42% [17]. As a result, subsequent tasks, such as predicting software vulnerability level (CVSS) [18], identifying software vulnerability CWE category [19], and identifying vulnerability libraries [20], commonly face challenges due to limited and incomplete training data, making it difficult to accurately extract features from TVDs.

In Figure 1, we can see that non-long-tail software refers to widely used applications that have a large user base; a typical example is Microsoft Windows. On the other hand, long-tail software caters to niche industries or specific purposes and, therefore, has a smaller number of users. An example of long-tail software is ToolTalk RPC. To facilitate our analysis, we first examine the NVD data collected from 1999 to 2022. In line with previous studies [21], [22], we utilize the Gini Coefficient [23] as a measure to quantify the long-tailedness. This measure, suggested by [21], [22], is insensitive to the number of data samples in the datasets. Our findings reveal that the distribution of software samples generally follows a long-tail pattern. This means that a small number of software instances have a significant number of TVD samples, which we refer to as “non-long-tail”, while the remaining software exhibits extremely small numbers of TVD samples, referred to as the “long-tail”.

Building upon previous research [21], we set a threshold of 50 TVDs (as shown in Table X). Software with fewer than 50 TVDs is labeled as “long-tail”, while those with more than 50 TVDs are labeled as “non-long-tail”. Based on this categorization, we have identified 44,303 long-tail software instances, which is 174 times greater than the number of non-long-tail software instances (254). Furthermore, the long-tail software types account for 97,753 TVDs, approximately 1.8 times more than those found in non-long-tail software (54,686). The analysis of long-tail software requires a deeper understanding of the domain, making vulnerability analysis, documentation, and security research more complex compared to non-long-tail software, which often has limited resources and documentation.

Previous research [17]–[20] has shown that machine learning methods are effective in augmenting missing key aspects of TVDs for non-long-tail software (Section II-A). Additionally, pre-trained Large Language Models (LLMs) [24] have demonstrated remarkable capabilities in various Software Engineering tasks [25]–[28]. However, when LLMs are directly applied to augment missing information in TVDs, their generative prediction performance for long-tail software is unsatisfactory (Section II-B). These methods utilize information from other TVDs of the same software to identify common patterns and

make predictions. They have achieved good results on non-long-tail software with a large number of TVDs available for learning. However, as shown in Figure 1, the distribution of TVDs among different software often exhibits an imbalance. Some software has significantly more samples (i.e., “head”), while the majority have only a few samples (i.e., “tail”).

The desired augmenting missing key aspects of TVDs for long-tail software faced significant challenges. Firstly, long-tail software refers to software instances with a small user base or limited popularity. Consequently, the number of TVDs associated with these software instances is typically limited. This scarcity of data hampers previous studies [17]–[20] from effectively learning and generalizing patterns from such limited TVDs.

Secondly, long-tail software instances can vary considerably in features and characteristics compared to software with a large user base (non-long-tail software). Previous studies [17], [29] often relied on statistical machine learning approaches that learned from common patterns across extensive TVDs. However, when dealing with long-tail software, these patterns may not be applicable, leading to sparse features that are difficult to generalize.

Thirdly, long-tail software serves niche industries or specific purposes, which often leads to the use of domain-specific jargon, technical terms, and unique linguistic styles within vulnerability descriptions. Previous studies [4], [7], [30] that relied on general-purpose language models struggled to capture and learn these specialized aspects accurately, thereby hindering their ability to accurately augment key aspects. Moreover, long-tail software exhibits various functionalities, platforms, and technologies, which poses a challenge for previous studies in identifying commonalities or shared patterns to generalize across different instances.

Lastly, the previous approach utilized the key information already available in TVDs for prediction. While this prediction method can be applied to a limited number of software (e.g., non-long-tail: 254), it faces challenges when there is a larger number of software instances (long tail: 44,303). In such cases, there can be two TVDs with the same key aspects but different missing key aspects due to different software features. The previous approach can only predict the same missing key aspects, limiting the effectiveness and reliability of their augmentation processes.

In this paper, we introduce a novel software feature inference framework designed to augment the missing key aspects of TVDs for long-tail software. To begin, we address the issue of non-standard software names that are often found in community-maintained vulnerability databases. These names can make it difficult to retrieve the TVDs based on the software name. We noticed that government-maintained databases, such as CNNVD [31] for China and CERT-FR [32] for France, use standardized software names that are different from those used by the community or international organizations. By cross-referencing these government databases with CVEs, we can cluster the TVDs under the same software name and gain richer information for subsequent analysis.

Next, we utilize Large Language Models (LLMs) to generate missing key aspects in the TVDs using In-Context Learning. However, the scarcity of historical TVDs for long-tail software limits the diversity of examples. To overcome this, we employ the Common Weakness Enumeration (CWE) [33] to categorize all TVDs. By considering TVDs under the same CWE as candidate examples, we ensure a wider variety of representative examples. Inspired by clustering algorithms [34], we select cluster centers as examples, which further enhances their representativeness. This iterative process generates multiple candidate answers and helps us leverage the valuable knowledge embedded within LLMs.

Finally, we rank the quality of the candidate answers and choose the best one as the final output for augmenting missing information. Large Language Models (LLMs) [24] have limited knowledge of long-tail software, making them prone to generating incorrect responses. To address this issue, we integrate Natural Language Inference (NLI) models [35], specifically designed for long-tail software, to effectively identify and eliminate incorrect responses. The NLI model helps us establish the associative relationships between different key aspects in the TVDs. We filter the candidate answers based on the probability of association between software features and the candidate answers. However, the descriptions of product features often contain proprietary terms that have different meanings in the computer field. To overcome this challenge, we enhance the background information for product features by utilizing a wiki repository that explains these proprietary terms. Using a Learning Deep Structured Semantic Models (DSSM) model [36], we embed both the software features and background information within the NLI model. The NLI results enable us to calculate the probability of association for each candidate answers with all software features, and we select the candidate answer with the highest probability as the final augmented result.

We conducted extensive experiments to evaluate the effectiveness of our approach in different setups. The results demonstrate that our software feature inference framework successfully addresses the issue of a long-tail distribution, significantly benefiting subsequent tasks. Specifically, the accuracy of augmenting missing key aspects for long-tail software increases from 0.27 to 0.56 (+107%). Interestingly, the accuracy of non-long-tail software also improves from 0.64 to 0.71. Given its state-of-the-art performance, our framework can be further applied to downstream tasks that rely on complete TVD information, such as predicting software vulnerability levels.

We have made the following contributions:

- We conduct a formative study to explore the significance of the long-tail distribution of TVDs and identify challenges in current research that address these issues.
- We introduce a novel software feature inference framework designed to augment the missing key aspects of TVDs for long-tail software. Our framework enhances vulnerability information diversity and comprehensiveness by incorporating historical data and external knowledge sources.

- We propose a method to detect hallucinations based on software features. Our method prioritizes individual software characteristics, allowing for exploring specific defect patterns unique to each software rather than adopting a universal approach to vulnerability pattern discovery.
- We evaluate our approach using CVE (63,000), NVD (240), and NVD* (381) datasets, which demonstrate its effectiveness across various instances of long-tail software.

II. FORMATIVE STUDY

We conduct a formative study to observe the challenges of long-tail software in vulnerability research. The term *long-tail* typically refers to the phenomenon where a significant portion of the data distribution comprises rare or infrequently occurring events or items. These long-tail instances often pose challenges for machine learning models because they have limited representation in the training data [21], [37], [38]. Despite LLMs' generalizability from large-scale pre-train, current methods rely on learning from existing information. However, due to the limited user base for long-tail software, historical TVDs are scarce, and the scarcity hinders effective parameter updates during model training and prevents learning long-tail software features. In long-tail software, a distinct category is characterized by widespread adoption across numerous global IT sectors, such as Ansible. However, due to limited number of TVDs (fewer than 50 TVDs), existing models still struggle to conduct effective vulnerability analysis.

A. Comparison of Key Aspect Classification

Previous studies [39], [40] have focused on predicting key aspects using the Prediction of Missing Aspect (PMA) method [17]. The PMA method is a neural network based classification model designed to predict missing key aspects based on existing key aspects in TVDs. To evaluate the performance of the PMA method on long-tail software, we employed the PMA on 4,000 key aspect classification entities, randomly sampled from the NVD, following the methodology outlined in prior work. We empirically use the F1-score to reflect the performance of PMA classification model.

Figure 2 presents the classification results of key aspects under different software types, and notably, the overall vulnerability type classification for long-tail software is distinctly lower than non-long-tail software, indicating distinct sensitivity levels to long-tail and non-long-tail software. The comparison highlights the difficulty in accurately classifying key aspects in TVDs for long-tail software.

To further investigate the potential impact of the capability of the backbone neural network in PMA toward the long-tail issue, we replace the Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) in PMA with more advanced models and evaluated its performance. Table I shows that although there is an improvement in PMA performance

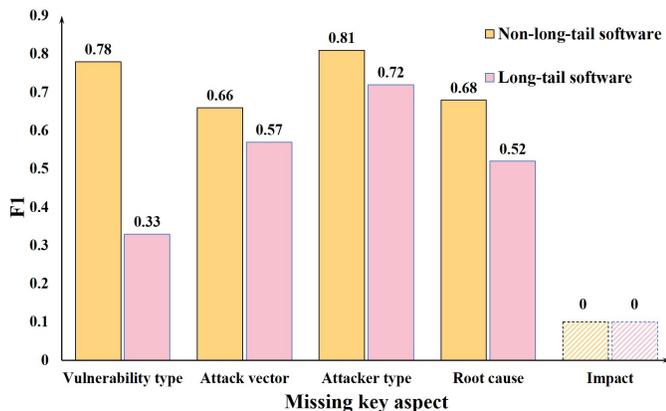


Fig. 2. Accuracy on Classification Task. The *Impact* aspect has a value of 0, as PMA deems the missing rate of *Impact* low and unnecessary to predict.

TABLE I

F1 SCORES OF DIFFERENT PMA STRUCTURES. “ORIGINAL” DENOTES THE ORIGINAL PMA, “BE.” REPRESENTS “BERT”, “LS.” STANDS FOR LSTM, AND “LLA” INDICATES “LLAMA”.

Soft. Type	Structure	Vuln. Type	Attack Vector	Attacker Type	Impact	Root Cause
Long Tail	Original	0.33	0.57	0.72	–	0.52
	BE.+LS.	0.36	0.55	0.69	–	0.56
	BE.+BE.	0.37	0.55	0.76	–	0.50
	BE.+LLa.	0.31	0.52	0.71	–	0.55
	LLa.+LLa.	0.37	0.59	0.68	–	0.55
Non Long Tail	Original	0.78	0.66	0.81	–	0.68
	BE.+LS.	0.77	0.62	0.83	–	0.61
	BE.+BE.	0.75	0.63	0.87	–	0.63
	BE.+LLa.	0.81	0.61	0.88	–	0.59
	LLa.+LLa.	0.78	0.69	0.85	–	0.71

with more powerful and sophisticated neural network architectures (e.g., BERT and LLaMA), the increase is not significant and the long-tail issue still persists.

B. Comparison of Key Aspect Generative Prediction

Previous research primarily formulated the missing key aspect augmentation as supervised classification task. Thus, the performance is inevitably affected by the quantity and quality of training data, and long-tail software only has few valid training samples. With the recent advancements of generative models, such as pre-trained LLMs, generative prediction can offer more detailed information and achieve more desired performance compared to classification-based prediction. Therefore, in this paper, we are the first to formulate the missing key aspect augmentation as a predictive generation task. Pre-trained LLMs demonstrate outstanding capability on various Software Engineering tasks [25]–[28]; thus, we explore the feasibility of employing LLMs on predictive generation of missing key aspects in TVDs.

By plainly applying LLMs on augmentation, the generative prediction performance of long-tail software is still unsatisfying. In the same experimental settings as described in Section IV, Figure 3 shows that the generative prediction performance of long-tail software is overall subpar compared to non-long-tail software. Moreover, the disparity in BERTscore between different types of software is notably more pro-

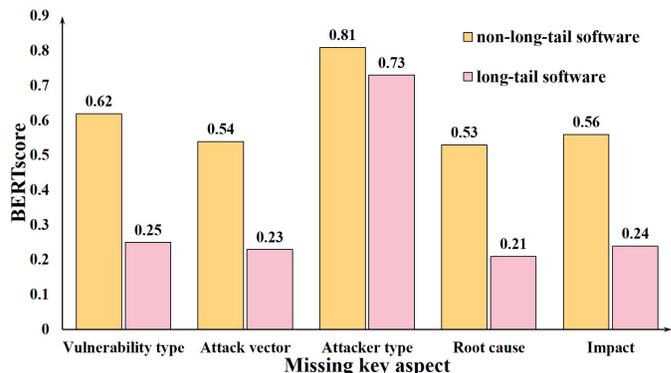


Fig. 3. Performance of the Generative Prediction Task on Missing Key Aspect Augmentation.

nounced in the generative prediction than classification-based prediction. These observations underscore significant challenges posed by generative prediction for long-tail software.

It is broadly discussed that the prompt engineering will greatly affect the task performance of LLMs [41]–[43]. Also, integrating external knowledge into the LLM-based frameworks can also boost the performance depending on the task [25], [26], [28]. Moreover, by observing the fail cases (incorrect key aspect and hallucinatory explanation) of generative prediction of long-tail software, we find that the software features are prone to being overlooked by LLMs. Above all, to fully utilize the findings obtained from the formative study, we carefully design a novel framework to augment missing key aspects based on software features as follows.

III. FRAMEWORK

This section outlines our software feature inference framework to augment missing key aspect in TVDs as generative prediction. The framework comprises three essential modules to effectively address the challenges presented by the long-tail nature of software TVDs.

A. Software-CVE Mapping Database

Inconsistent software naming is commonplace in TVDs. Irregular software names can lead to different names with distinct TVDs referring to the same software, as observed in cases such as “*Struts REST*” (CVE-2017-9805) and “*Struts2*” (CVE-2018-11776), both referring to the same software. This phenomenon is particularly prevalent in long-tail software instances, where naming conventions vary widely. Current research [44]–[46] focused on constructing software name dictionaries and leveraging knowledge stored in LLMs for question answering. These methods disambiguate software names based on records of all the names a software has been called. However, long-tail software presents unique challenges in name disambiguation, as it is difficult for individuals or even LLMs to maintain familiarity with the numerous aliases associated with these software instances, rendering it impractical to list all the aliases of software exhaustively.

Therefore, we first build the Software-CVE Mapping Database which contains all TVDs in CVE associated with

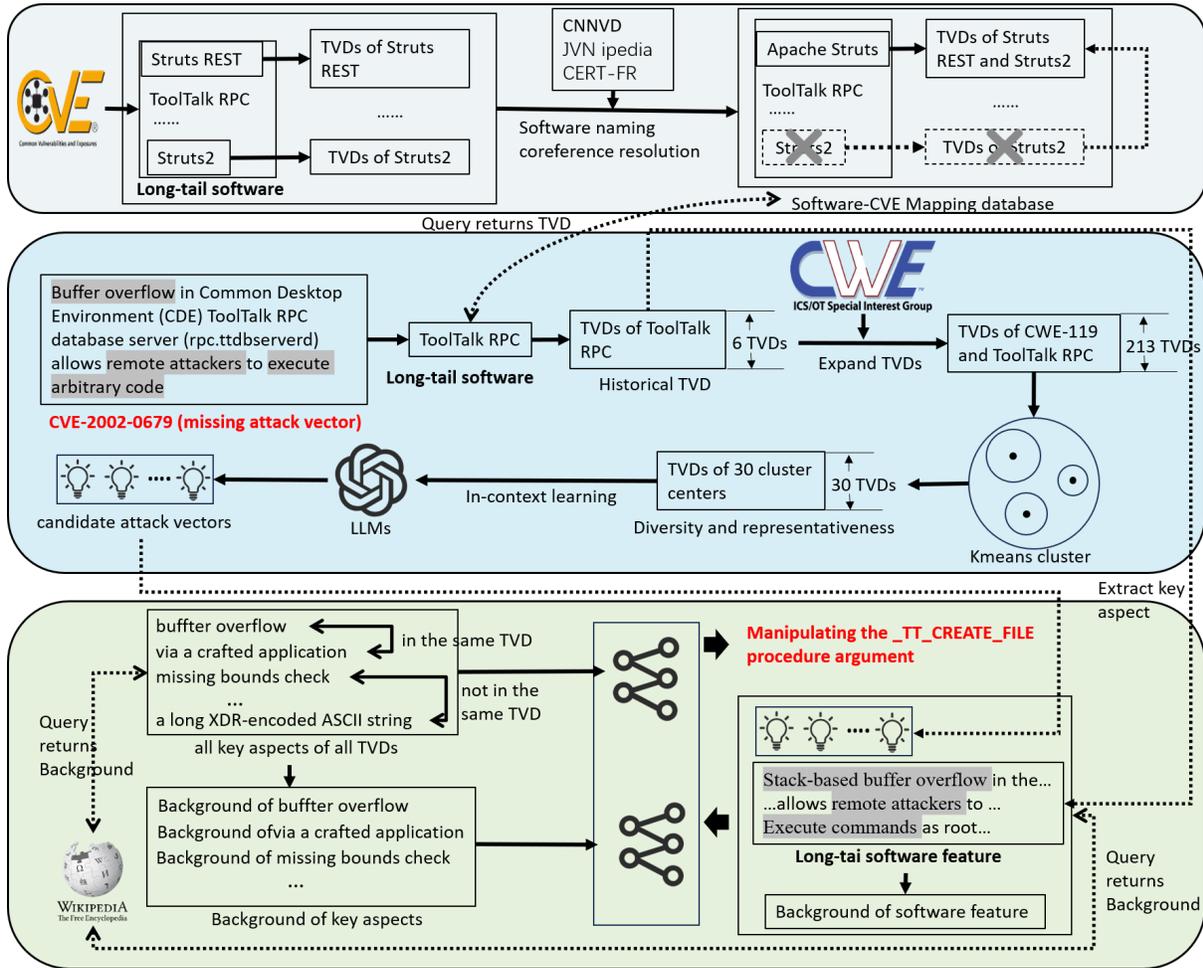


Fig. 4. Approach Overview: First, to construct software-CVE mapping database, we leverage government databases to resolve software naming references. Second, we utilize the CWE to enhance the diversity of historical TVDs associated with long-tail software. Lastly, in the face of the heightened risk of hallucination in LLMs due to the limited long-tail software knowledge stored, we employ software feature inference to mitigate this issue.

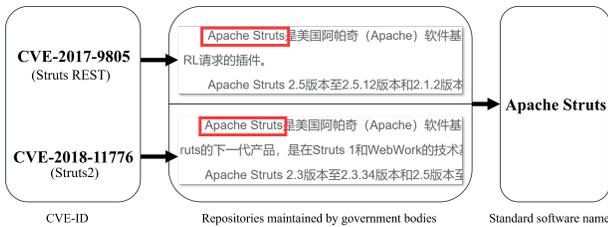


Fig. 5. Software Naming Coreference Resolution

their corresponding software, enabling efficient retrieval of all TVDs to a standard software name. We discover that repositories maintained by government entities share common characteristics, such as the utilization of standardized software names and their linkage to TVDs in CVE through CVE-ID as the primary key in their databases. Thus, we opt to select three prominent government-maintained TVD repositories, CNNVD (China), JVN ipedia (Japan), and CERT-FR (France). These repositories rank among the top three with the highest number of TVDs, thereby offering a rich source of vulnerability information essential for achieving comprehensive coverage of software vulnerabilities. Specifically, we first extract the

standardized software names of TVDs from these repositories, and then link the software names with TVDs as the Mapping Database by the primary key CVE-ID. Notably, in those regional government-maintained repositories, TVDs contain both English and non-English content, but the software names are commonly written in English. Also, we empirically find that TVDs typically starts with the corresponding software names at the beginning. Consequently, our extraction process specifically targets the English content in the first sentence of TVDs. We delineate three templates for extracting English content from the repositories, tailoring for CNNVD, JVN ipedia, and CERT-FR, respectively.

- template1: $[\backslash u4e00-\backslash u9fa5]([a-zA-Z]+[\backslash s-]?[a-zA-Z])$
- template2: $([a-zA-Z]+[\backslash s-]?[a-zA-Z])(?:\d+(?:\.\d+)?[.])?$
- template3: $[\backslash u4e00-\backslash u9fa5]([a-zA-Z]+)(?:[\backslash s-].*?)$

For instance, in Figure 5, the CVE-2018-11776 and CVE-2017-9805 are associated with “Struts2” and “Struts REST”, respectively. Based on the Software-CVE Mapping Database we craft, those two names should be standardized as “Apache Struts” according to the CNNVD. By doing so, we can gather

relatively more TVDs for long-tail software, enriching the software vulnerability information for following modules.

B. Missing Key Aspect Generation

In section II, we compare and discuss the classification and generative prediction to obtain missing key aspects. Directly applying LLMs on generative prediction cannot mitigate the under-performance for long-tail software. In-context learning is a common strategy to increase the performance of LLMs on various code-related tasks [47], which is providing several in-context few-shot learning examples as a part of the prompt. Studies have shown that more relevant and more representative examples can significantly enhance the LLMs capability [48], [49]. However, previous studies [50], [51] did not differentiate between various software entities. Consequently, irrelevant software TVDs contribute noise to the prediction of target software TVDs. The scarcity of historical TVDs for long-tail software leads to low diversity in examples, leaving us few selections for the in-context learning.

To obtain more relevant and representative TVD examples for the in-context learning, we employ the CWE to expand the historical TVDs of long-tail software, ensuring relevance of TVD examples. Furthermore, we adopt a method [52] of selecting cluster centroids to ensure the diversity of TVDs, enhancing the representativeness of examples. We formulate our method as depicted in Algorithm 1, and the specific description of each step is elaborate below.

1) *Example Selection*: To enhance the diversity of TVDs for long-tail software, we utilize the CWE. As depicted in lines 5-7 of Algorithm 1. We extract the CWE-ID corresponding to each TVD, which we obtain from the NVD database. Then, we extract all TVDs associated with the CWE-ID and merge them with the TVDs extracted from the Software-CVE Mapping Database. For instance, in the case of CVE-2002-0679 of Second module on Figure 4, the corresponding CWE-ID is 119. While the software name of CVE-2002-0679 corresponds to only 6 TVDs, CWE-119 contains 207 TVDs. By combining these two sets of TVDs, a total of 213 TVDs are utilized.

The introduction of CWE results in a large number of samples in prompt, as illustrated by Figure 4, where the TVDs numbers of ToolTalk RPC and CWE-119 is 213. Therefore, it becomes essential to identify representative examples. Representative knowledge holds more significance [53]–[56] than sheer volume, particularly highlighted in Section IV-C. Excessive knowledge can adversely impact prediction accuracy [57]. Table IV indicates 30 as the optimal CVEs for prediction.

If the number of retrieved TVDs is fewer than 30, we select all of them. However, if it exceeds 30, we address the overlength issue by employing clustering, as outlined in lines 8-9 of Algorithm 1. Let $X = x_1, x_2, \dots, x_n$ denote the set of retrieved TVDs, each associated with key aspects $C_i = c_{i1}, c_{i2}, \dots, c_{im}$. We utilize Word2Vec [58] to obtain sentence vectors $E = e_1, e_2, \dots, e_n$. This involves training all CVE data using Word2Vec and generating vectors for each x_i . The Word2Vec sentence vector equals the sum of each

Algorithm 1 Missing Key Aspect Generation

```

1: Let data be the Software-CVE Mapping Database;
2: Let all_names be the ["Vuln. Type", "Impact",
"Attack Vector", "Attacker Type", "Root Cause"];
.....
3: names  $\leftarrow$  ExtractAspectName(TVD);
4: m  $\leftarrow$  all_aspect_names - names;
5: X1  $\leftarrow$  GetKnowledge(v.softwarename, data);
6: X2  $\leftarrow$  CWERelatedTVD(TVD);
7: X  $\leftarrow$  X1 + X2;
8: E1  $\leftarrow$  WordVec([x1, x2, \dots, xn]);
9: clu  $\leftarrow$  Kmeans(E1, cluster_number = 30);
10: k  $\leftarrow$  ExtractKeyAspect(TVD);
.....
11: Let c be the centers of clu;
12: direct_generation  $\leftarrow$  GenerationStruct(c, m, k);
13: fill_in_the_blank  $\leftarrow$  fillStruct(c, m, k);
14: selection  $\leftarrow$  selectStruct(c, m, k,
LLM(direct_generation), LLM(fill_in_the_blank));
return LLM(selection)

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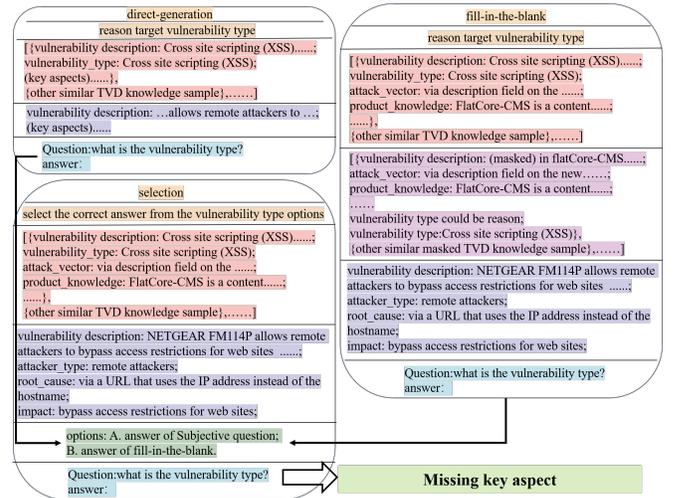


Fig. 6. Prompt of Missing Key Aspect

word vector in the TVD. Next, we apply Kmeans [59] with 30 clusters, from which we extract TVDs of cluster centers.

2) *Candidate Missing Key Aspects Generation*: Utilizing samples from 30 cluster centers, we leverage the in-context learning of LLM to generate candidate answer. We employ different questioning methods based on the same samples to maintain consistency between candidate answers and samples. Moreover, we utilize a selector to choose answers from different questioning methods [56], [60].

In lines 12-14 of Algorithm 1, both the missing key aspects of the augmented TVD and the key aspects of the TVDs of the cluster centers are incorporated into the prompts “GenerationStruct”, “fillStruct” and “selectStruct”. The final answer is determined through a selection prompt, including the two generated answers and the key aspect within its structure. Finally, Algorithm 1 is executed multiple times to generate

multiple candidate answers, ensuring their diversity.

In Figure 6, illustrated with CVE-2002-1877 as an example, the TVD reads “NETGEAR FM114P ... hostname”. The “direct-generation” encompasses a task description (“reason target...”), the samples set (“[vulnerability des...”), TVD (“vulnerability des...”), and the problem (“Question:...”). The sample set primarily comprises key aspects extracted from TVDs associated with 30 cluster centers. Each key aspect is structured in a key-value format, for instance, “vulnerability_type: Cross...”. Meanwhile, the “fill-in-the-blank” utilizes the mask mechanism inspired by transformers. In the purple part, the vulnerability type is masked and replaced with “(mask)”, accompanied by a prompt with “vulnerability type could be reason ... (XSS)” indicating the specific content of the masked vulnerability type. The “selection” introduces options for the selection structure, with the generator’s answer as an option for LLM. This structured approach aids LLM in predicting relevant content, thereby enhancing learning efficiency.

C. Answer Selection based on Software Feature Hallucination Detection

LLMs are widely criticised for their propensity to produce hallucinations, indicating that these models may confidently generate incorrect answers instead of admitting their limitations by responding with “I do not know”. Furthermore, the phenomenon of hallucination occurs more frequently in tasks for which the pre-training dataset contains limited information, such as long-tail software. Thus, to filter out incorrect answers generated by the LLM in the last module, we utilize software feature information from external source by employing the Natural Language Inference (NLI) [35].

NLI models demonstrate proficiency in analyzing correlations between two texts, namely, candidate missing key aspects and software features. However, software features often contain specialized terms specific to computing, which hold nuanced meanings distinct from everyday language. This inherent complexity presents challenges for NLI models to accurately interpret the true meaning of these terms based solely on their literal interpretation. To address the challenge posed by specialized computing terms, researchers may consider replacing the text embedding model with a computing domain embedding model or adjusting the network structure using attention mechanisms to prioritize non-specialized terms [46], [56]. However, due to the high frequency and rich semantic content of specialized terms in the software vulnerability domain, disregarding them would result in substantial information loss. Therefore, we integrate Wikipedia [61], one of the most largest online encyclopedia, as background information for specialized nouns in software features to enrich the semantics of these terms. The Learning Deep Structured Semantic Models (DSSM) [36] are commonly employed in recommendation systems, embedding both the query history and document simultaneously as non-specialized and specialized information for NLI judgment. Inspired by this concept, we employ DSSM to embedding two different types of text: background information and specialized nouns.

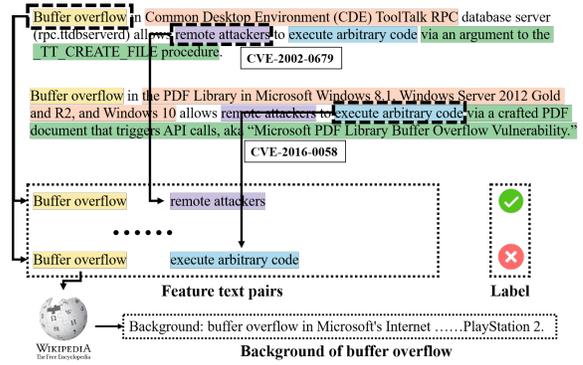


Fig. 7. Training Set Construction for Software Feature Correlation Model.

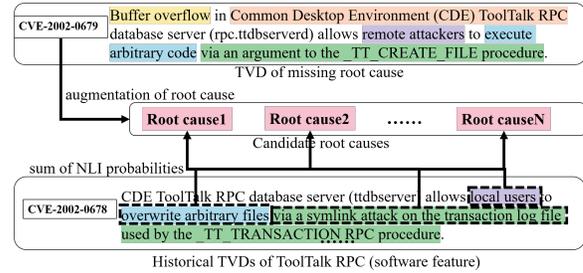


Fig. 8. An Example of the Hallucination Key Aspect Filter. The missing key aspect is *root cause*, and all candidates (highlighted in pink) will be ranked according to their NLI probabilities.

1) Construction of Software Feature Correlation Model:

We use BERT and LLaMA to form DSSM, the former for embedding software features and the latter for embedding background information. Fully connected layers connect these models to construct NLI model based on DSSM.

All key aspects within a TVD are semantically related to each other. Thus, as shown in Figure 7, pairwise extraction of key aspects within the same TVD forms the training set for the NLI model, with labels set to 1. Key aspects from different TVDs constitute the training set, with labels set to 0. Given the significantly higher proportion of negative samples compared to positive samples, downsampling is employed to balance the negative sample ratio to twice that of the positive samples, ensuring the efficacy of the NLI model. For each software feature (key aspect) in feature-text pairs, a keyword-based search is conducted in the Wikipedia [61] to retrieve the background information text. This process results in a background information set of the same size as the feature-text pairs. Ultimately, we construct an NLI model capable of determining the relationship between two key aspects.

2) *Hallucination Key Aspect Filter*: For each missing key aspect, the *Missing Key Aspect Generation* module will output multiple candidate answers. Then, all candidate answers will be ranked according to their NLI probabilities, and the highest one will be taken as the final result of the generative prediction. Figure 8 shows an example about the TVD in CVE-2002-0679 missing the *root cause*. First, we extract all software features (key aspects) corresponding to the TVD’s software from the associated TVDs (CVE-2002-0678, ..., CVE2001-

0717) and calculate the correlation probabilities by the trained NLI model. Then, we aggregate the association probabilities between all features and the predicted results (Root cause1, ..., Root causeN) and the prediction with the highest probability is the final result.

IV. EVALUATION

We conduct a series of experiments to investigate the following research questions:

- RQ1: **[Missing Information Generation]** What is the performance of candidate missing key aspect generation?
- RQ2: **[Generated Answer Selection]** What is the performance of software feature hallucination detection-based answer selection?
- RQ3: **[Generalizability]** What is the generalizability of proposed augmentation framework?
- RQ4: **[Downstream Tasks]** How can the augmented complete TVDs benefit downstream tasks?

A. Dataset

1) *Data Collection*: The TVDs are collected from several reputable databases, including Mitre’s CVE [62] and the National Vulnerability Database (NVD) [3], which contain 233,456 and 231,454 records, respectively. These repositories document software vulnerability information since 1999. CVE and NVD are often applied for vulnerability analysis, such as [7], [10], [17], [30], [63], [64]. However, they suffer from the issues for vulnerability analysis based on LLMs: these datasets contain TVD repositories that are already present in the training corpora of popular LLMs, leading to an overestimation of the missing key aspect augmentation capabilities. Therefore, to address the potential risk of data leakage and accurately reflect the capability of our framework. According to OpenAI’s official website, the training data for GPT-3.5 is cut off as of April 2023. To ensure that our benchmark dataset contains code repositories that have not been seen during model training, we select TVD date after May 1, 2023. the CVE and NVD dataset comprises 63,000 and 240 records. In RQ3, we find that the NVD dataset had limited volume, so we decide to extend the time frame and combine the NVD data from 2022 and 2024 as a third dataset, referred to as NVD*, with 381 records.

2) *Data Preprocessing*: In the NVD database, we adopt the data processing method described in PMA [17], utilizing the “ANALYSE” as the TVD and the “MODIFIED” as missing key aspects annotated by maintainers. This approach allows us to extract a total of 5,379 entries from NVD that have both “MODIFIED” and “ANALYSE” records.

In the CVE database, we extract five key aspects individually. To craft the testing set, we manually mask each key aspects from the TVD, leaving the remaining text as the testing data and the masked key aspect as the ground truth label. However, a challenge arises as the remaining sentence after removing a key aspect is often incomplete. For example, in CVE-2002-0679, if the “Buffer overflow” vulnerability type is removed, the resulting sentence “in Common Desktop

Environment (CDE) ToolTalk RPC database server...” lacks a subject and is not a complete sentence, diverging significantly from the standard TVD format. We notice that security management personnel frequently employ vague terms when describing CVEs with unknown key aspects. For instance, the TVD of CVE-2020-14274 reads, “Information disclosure vulnerability in HCL... personal data via unknown vectors.” Here, the phrase “unknown vectors” substitutes for the *Attack Vector*. Inspired by this convention, we replace the deleted key aspect in the TVD with placeholders like “unknown vulnerability type”, “unknown attacker type”, etc., respectively. This ensures that the sentence structure remains intact and consistent across all TVDs, despite missing key aspects.

B. Evaluation Metrics

To evaluate labeled data, we adopt quantitative evaluation based on statistic analysis. This involves iterating the entire dataset and assessing the results using following generation task evaluation metrics. Common evaluation metrics for generation tasks include BLEU [65], METEOR [66], ROUGE [67], and BERTscore [68], and we only specifically choose BERTscore for several reasons. Firstly, BERTscore excels at capturing semantic meaning and context similarity from a semantic understanding perspective. In contrast, BLEU, ROUGE, and METEOR may rely more on lexical and n-gram matching, potentially overlooking deeper semantic nuances. Secondly, due to the variable expression of TVDs, BERTscore is less sensitive to word order and phrasing variations compared to BLEU, ROUGE, and METEOR. The remaining three metrics will be available in the GitHub repository [69] for further reference. For RQ4, we adopt F1-score as Metrics, following the evaluation method of the downstream task.

Algorithm 2 Missing Key Aspect Generative Prediction.

```

1: Let  $n$  be the missing key aspect name of TVD;
2: Let  $l$  be the missing key aspect of TVD ;
3:  $name \leftarrow Software\_name\_extract(TVD)$  ;
4:  $prompt \leftarrow$  “What is ” +  $l$  + “of TVD? TVD:” +  $v$ ;
5:  $prompt \leftarrow prompt$  + “software name:” +  $name$ ;
6:  $prompt \leftarrow prompt$  + “noting:” +  $l$  + “is phrase.”
for  $i = 1$  to 3 do
7:  $t \leftarrow RandomSample(all\_TVD)$ ;
8:  $prompt \leftarrow prompt$  + “TVD:  $t.replace(t.n, unknown +$ 
 $n)$ ”;
9:  $prompt \leftarrow prompt$  + “n:  $t.l$ ”;
end for
10:  $mka \leftarrow LLM(prompt)$ ;
11:  $sim \leftarrow BERTscore(mka, l)$ ;
return  $sim$ 

```

In section II-B of formative study, our evaluation method, depicted in Algorithm 2, first employs LLMs (GPT-3.5) to extract the TVD software name. Subsequently, a prompt is created, incorporating task requirements, TVDs, missing key aspect names, and software names. Following this, three TVDs are randomly selected, key aspects are removed, and

“unknown” is substituted in their place. The removed key aspects then act as labels for in-context learning. Finally, a prompt is inputted into LLMs (GPT-3.5), and the generated results are compared with the labels. To address potential ambiguity in LLM-generated answers, constraints are imposed on the format of the answers within the prompt, as detailed in the sixth line of Algorithm 2.

C. Missing Key Aspects Generation (RQ1)

We conduct a evaluation of the candidate missing key aspects generation. Initially, we perform a statistical analysis of the software-CVE mapping database to gauge the impact of different software name extraction methods on database entries. Subsequently, we assess the diversity of examples by different retrieval methods. Additionally, we evaluate the effectiveness of cluster to ensure representative sampling. Finally, we investigate the influence of different methods of using LLMs on our framework’s overall performance.

1) *Statistical Analysis of the Software-CVE Mapping Database:* We conduct a statistical analysis of the Software-CVE Mapping database by counting the number of software entries after employing different software name extraction methods. In Figure 9, our method reduces the number of

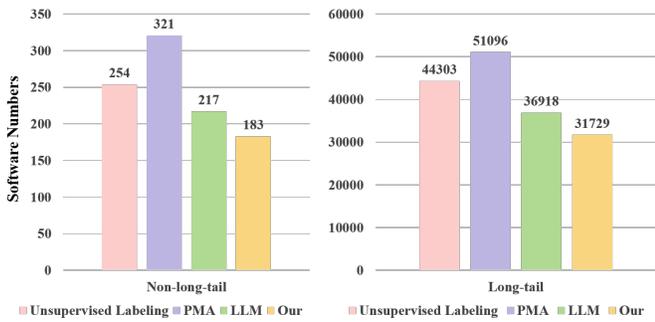


Fig. 9. Statistical Analysis for the Number of Software Names. Unsupervised Labeling involves BERT for key aspect extraction [30], while PMA [17] regularizes existing key aspect extraction. The LLM prompt is “What is the software name of the TVD.”

software names, indicating that government-maintained repositories can reduce the inconsistency of software names. This reduction in inconsistency is particularly significant for long-tail software due to their higher prevalence of non-standard software names: the number of software names has decreased by 19367 (51096 - 31729).

2) Diversity of Example Selection in In-context Learning:

In Table II, we investigate the effect of retrieving various databases to enhance the diversity of TVDs.

The “DB&CWE” retrieving methods, which simultaneously utilizes software CVE mapping databases and CWE, consistently achieves the highest BERTscore values across all key aspects, indicating its effectiveness in enriching key aspects. This suggests that leveraging both software databases and CWE significantly enhances the diversity and accuracy of key aspects, leading to more robust augmentation.

TABLE II
BERTSCORE OF AUGMENTATION BASED ON RETRIEVING VARIOUS DATABASES. “DB” DENOTES RETRIEVING ONLY THE SOFTWARE-CVE MAPPING DATABASE, “DB&CWE” RETRIEVING BOTH THE SOFTWARE-CVE MAPPING DATABASE AND CWE, AND “NO RETRI.” SIGNIFIES NOT RETRIEVING.

Retrieving Methods	Vulnerability Type	Attack Vector	Attacker Type	Impact	Root Cause
DB&CWE	0.669	0.593	0.838	0.625	0.581
DB	0.601	0.522	0.771	0.537	0.529
No Retri.	0.283	0.137	0.580	0.175	0.159

TABLE III
BERTSCORE OF REPRESENTATIVE SAMPLE SELECTION METHODS. “SENT. SIM.” DENOTES RETRIEVAL BASED ON SENTENCE (BERT) SIMILARITY, AND “RANDOM” INDICATES RANDOM SELECTION.

Selection Method	Vulnerability Type	Attack Vector	Attacker Type	Impact	Root Cause
Kmeans	0.669	0.593	0.838	0.625	0.581
DBSCAN	0.601	0.522	0.771	0.537	0.529
OPTICS	0.590	0.491	0.773	0.523	0.542
Sent. Sim.	0.493	0.442	0.716	0.516	0.407
Random	0.200	0.160	0.440	0.163	0.090

3) *Representation of Example Selection in In-context Learning:* Relevant and representative examples are crucial to achieve decent performance for LLM in-context learning. We validate the effectiveness of our approach by comparing different example selection strategies.

Table III displays the BERTscore of various representative sampling strategies. Our kmeans method surpasses others, attaining the highest scores across all aspects, including *Vulnerability Types*, *Attack Vectors*, *Attacker types*, *Impact*, and *Root causes*. Compared to clustering methods like DBSCAN and OPTICS, our approach exhibits superior performance, underscoring its efficacy in selecting representative examples. Conversely, strategies dependent on sentence similarity or random selection yield lower scores, underscoring the significance of systematic selection methods in vulnerability analysis.

Table IV indicates that the highest BERTscore is achieved for most aspects when the number of clusters is set to 30. Although the impact aspect shows the highest score at 40 clusters, the difference in accuracy between 40 and 30 clusters is negligible. Therefore, despite the slightly better performance observed at 40 clusters for impact, we choose to use 30 clusters as it offers comparable accuracy while maintaining simplicity in the model configuration.

TABLE IV
BERTSCORE OF DIFFERENT NUMBER OF CLUSTERS

Key Aspect	Number of Clusters					
	5	10	20	30	40	50
Vuln. Type	0.572	0.608	0.651	0.669	0.634	0.608
Attack Vector	0.475	0.545	0.584	0.593	0.578	0.581
Attacker Type	0.772	0.803	0.836	0.838	0.831	0.824
Impact	0.559	0.568	0.604	0.625	0.629	0.592
Root Cause	0.461	0.525	0.565	0.581	0.554	0.548

TABLE V
BERTSCORE OF PROMPT STRATEGY COMBINATIONS

Key Aspect	Direct	Fill-in	Gen+Fill+Selection
Vulnerability Type	0.551	0.545	0.669
Attack Vector	0.583	0.514	0.593
Attacker Type	0.740	0.796	0.838
Impact	0.595	0.541	0.625
Root Cause	0.491	0.559	0.581

TABLE VI
BERTSCORE OF DIFFERENT LLMs

Key Aspect	LLaMA	T5	GPT-3.5	GPT4
Vulnerability Type	0.121	0.093	0.669	0.641
Attack Vector	0.076	0.059	0.593	0.607
Attacker Type	0.573	0.549	0.838	0.819
Impact	0.095	0.108	0.625	0.643
Root Cause	0.194	0.147	0.581	0.570

4) *Application of LLMs in In-context Learning*: Our approach utilizes a three-question method for constructing the prompt. Therefore, we separately test the augmentation performance using a single prompt template and a combination of three questions.

In Table V, the “Gen+Fill+Selection” combination consistently achieves the highest BERTscore values across all key aspects, indicating its effectiveness in augmenting missing key aspects. This suggests that employing a combination of generation, fill-in-the-blank, and selection strategies enhances the quality of candidate missing key aspects, leading to more accurate augmentation. Conversely, strategies relying solely on direct generation or fill-in-the-blank exhibit lower BERTscore values, underscoring the importance of utilizing comprehensive prompt strategies for missing key aspect augmentation.

Additionally, we compare the effectiveness of candidate answer generation by different LLMs, as depicted in Table VI. GPT-3.5 consistently outperforms other models in augmenting *Vulnerability Type*, *Attacker Type*, and *Root Cause*, achieving the highest BERTscore. On the other hand, GPT-4 achieves the highest BERTscore for *Attack Vector* and *Impact*, surpassing GPT-3.5 slightly. T5 and LLaMA also exhibit certain capabilities in augmenting *Attacker Type*. This is attributed to the relatively limited categories that *Attacker Type* can encompass, resulting in lower augmentation difficulty. However, T5 and LLaMA’s poor performance across all key aspects is mainly due to their limited capability to understand lengthy prompts, leading to misinterpretations of questions and irrelevant responses. These results suggest that GPT-3.5 generally demonstrates superior performance across multiple key aspects compared to other LLMs.

Answer to RQ1: The integration of software-CVE mapping database and CWE retrieval strategies of in-context learning significantly enhance the performance in missing key aspects generation.

TABLE VII
BERTSCORE OF DIFFERENT NLI DESIGN

Structure	Vuln. Type	Attack Vector	Attacker Type	Impact	Root Cause
LSTM+LSTM	0.597	0.524	0.783	0.574	0.522
BERT+BERT	0.621	0.553	0.801	0.599	0.547
RoBER+RoBER	0.639	0.570	0.817	0.594	0.568
LLaMA+LLaMA	0.644	0.581	0.813	0.617	0.560
LSTM+LLaMA	0.651	0.574	0.827	0.608	0.577
BERT+LLaMA	0.669	0.593	0.838	0.625	0.581

TABLE VIII
AVERAGE BERTSCORE OF THE TOP N CANDIDATE MISSING KEY ASPECTS

Key Aspect	Top 1	Top 3	Top 5
Vulnerability Type	0.669	0.631	0.617
Attack Vector	0.593	0.551	0.525
Attacker Type	0.838	0.833	0.826
Impact	0.625	0.589	0.532
Root Cause	0.581	0.563	0.528

D. Generated Answer Selection (RQ2)

Through experiments, we aim to determine 1) the optimal NLI model design for linking software features with key aspects and 2) evaluate the software feature hallucination detection-based answer selection method.

1) *Design of NLI Model*: Table VII shows that the BERT+LLaMA combination achieves the highest BERTscore across all key aspects, with notable improvements over other model designs. For instance, in vulnerability type prediction, BERT+LLaMA attain a BERTscore of 0.669, outperforming other configurations by a significant margin. Similarly, in *Attacker Type* prediction, BERT+LLaMA achieves a BERTscore of 0.838, demonstrating its superiority over alternative model architectures. These results underscore the effectiveness of leveraging advanced language representation models, like BERT and LLaMA, in enhancing the accuracy of key aspect prediction tasks related to software features.

2) *Selection of Top N*: Table VIII presents the average BERTscore of the top N candidate missing key aspects across different key aspects. We observe a decreasing trend in BERTscore as the number of candidate answers increases from the top 1 to the top 5. This trend suggests that the accuracy of augmenting missing key aspects tends to decrease as more candidate answers are considered and our team effectively detect the hallucinatory answer. However, the specific impact varies across key aspects. For instance, the BERTscore for *Attacker Type* remains consistently high across all levels (top 1, 3, and 5), indicating the degree of hallucination in the *Attacker Type* being relatively low. In contrast, the BERTscore for *Impact* exhibits a more significant drop from the top 1 to the top 5, suggesting greater difficulty in accurately augment this key aspect. Overall, these findings highlight the importance of considering the number of candidate missing key aspects in the answer selection process to optimize prediction accuracy.

Answer to RQ2: Our selection method of candidate missing key aspects can effectively detect LLM hallucinations and select the correct key aspect answer.

E. The Generalization of Proposed Software Feature Inference Framework (RQ3)

In this section, we evaluate the performance of our proposed method across multiple datasets. Additionally, we also aim to evaluate our method’s impact on non-long-tail software accuracy while enhancing accuracy for long-tail software.

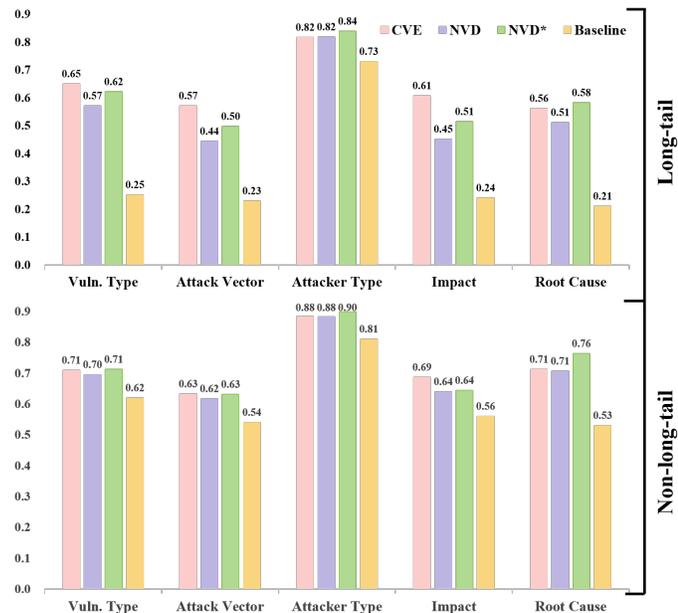


Fig. 10. The Overall Evaluation of Our Augmentation Method in Long-tail Software. “Baseline” signifies the results of formative study, namely the baseline (current SOTA).

In Table II, for long-tail software, our method consistently achieves higher scores compared to the baseline. Our method attains a substantial improvement in vulnerability type (0.649) compared to the baseline (0.251), indicating the effectiveness of our approach in capturing nuanced aspects of vulnerabilities. For non-long-tail software, while our method shows promising results, the improvements are relatively modest compared to long-tail software. The performance variation across different datasets (CVE, NVD, NVD*) suggests that although the effectiveness of our method is influenced by the volume of the dataset, the overall change is not significant. The improvement in vulnerability type for non-long-tail software ranges from 0.695 to 0.712, indicating a more moderate augmentation compared to long-tail software. Furthermore, the performance of the NVD* dataset is better than that of the NVD dataset, which further substantiates our hypothesis that GPT-3.5 are pre-trained with existing TVD knowledge.

Reviewing the examples curated in Figure 1, our framework can successfully augment the missing *Attack Vector* for CVE-2002-0679 and CVE-2016-0058 as “Manipulating the `_TT_CREATE_FILE` procedure argument” and “Exploiting the PDF Library via a malicious PDF document”, respectively.

TABLE IX
F1-SCORE OF GENERALIZING ACROSS DIFFERENT TASKS

Task Name	Original	Augmented
CVSS Prediction	0.812	0.857
CWE Prediction	0.911	0.930
Libraries Identification	0.786	0.799

Answer to RQ3: The proposed framework demonstrates robust performance across multiple datasets, showcasing satisfying generalization capabilities.

F. Augmentation on Different Tasks (RQ4)

In the field of software maintenance and software vulnerability information management, typical applications are software vulnerability level (CVSS) prediction [18], software vulnerability CWE category prediction [19], and software identification of vulnerability libraries [20]. CVSS prediction involves classifying the severity of vulnerability information, while CWE focuses on clustering and merging vulnerability information. Dependency library identification aims to recognize libraries that are not described in TVD but actually impacting the system (library). These tasks effectively manage and categorize vulnerability, enabling security personnel to efficiently review and archive vulnerabilities.

They rely on the quality of TVD. Our work focuses on enhancing the quality of TVD, aligning with the requirements of these tasks.

The Table IX presents the F1-score of generalizing across different tasks, comparing the performance of the original method with the augmented TVDs. Across all tasks, the method with the augmented TVDs consistently outperforms the original, indicating the effectiveness of our augmentation approach in improving performance across diverse tasks.

Answer to RQ4: Our method augment the key aspects of TVDs, improving the performance of downstream tasks that utilize TVD data.

V. DISCUSSION

A. Approach Analysis

1) *Analysis of Augmented Impact:* We explore the benefits of accurate augmentation and the negative impact of incorrect augmentation, and explore their boundaries. The purpose of vulnerability information management is to assist software maintenance personnel in current vulnerability repair. In this scenario, assuming a software has a vulnerability and the TVD lacks a key aspect. If it is necessary to know the missing key aspect, software maintenance personnel will manually supplement the key aspect by consulting the vulnerability information database. Assuming that software maintenance personnel find n pieces of relevant TVD as references through turn to external resources or internal search. software maintenance personnel will review n times to obtain vulnerability information, that is, the expected number of times software maintenance personnel review is:

$$E(\text{not_aug}) = n \quad (1)$$

Assuming that our method is used for key aspect augmentation, and our method accuracy is x . The probability of software maintenance personnel obtaining the missing key aspect only once is x , and a probability obtaining missing key aspect through $(1+n)$ times is $(1-x)$. $(1+n)$ shows that the error key aspect augmented is first attempted, and then n records are attempted. For augmented missing key aspect, the expected number of views for software maintenance personnel is:

$$E(\text{augment}) = x + (1-x)(1+n). \quad (2)$$

When $E(\text{augment}) < E(\text{not_augment})$, we believe that our approach will be helpful in practice. Therefore, when

$$x + (1-x)(1+n) < n \Rightarrow x > \frac{1}{n} \quad (3)$$

our algorithm is effective. When $n = [0, 1]$, the augmentation algorithm is not applicable to practice. When $n > 1$, as long as the accuracy of the augmentation algorithm is greater than 0.5, it will save more query times than manual work.

In addition, It is possible to mandate that users provide all key aspects when submitting TVD. But sometimes users themselves may not be aware of certain key aspects, and enforcing will result in delayed or abandoned submission due to users' unwillingness to invest additional time.

B. New Paradigm for Information Augmentation tasks in Software Engineering

With the development of LLMs, information augmentation tasks in software engineering are increasingly inclined to utilize LLMs as knowledge repositories for generating new information. However, the richness of information in LLMs can result in hallucinations in the generated results, leading to a lack of trust in the augmentation outcomes.

The current paradigm for addressing this issue involves using knowledge repositories to detect hallucinations at the level of text similarity. However, a major challenge of this approach is that the knowledge repository may offer multiple pieces of evidence supporting different augmentation outcomes.

At the heart of software engineering lies the “software” itself. Our new paradigm proposes focusing on each software individually for information augmentation and hallucination detection. Our framework, based on detecting hallucinations for each software, aims to systematically uncover the unique characteristics of each software, thereby enhancing the robustness of information augmentation.

C. The Impact of Different Long-tail and Non-long-tail Thresholds on Software Feature Inference Framework

we solely employ CVE and BERTscore as datasets and evaluation metrics to observe the impact of various thresholds on our augmentation results.

The Table X illustrates BERTscore results across different long-tail thresholds (ranging from 25 to 125), highlighting a notable deviation at a threshold of 25, where BERTscore values exhibit a slight decrease. However, from thresholds 50 to 125, the differences in BERTscore values between long-tail (L) and non-long-tail (NL) software categories are negligible.

TABLE X
BERTSCORE OF DIFFERENT LONG-TAIL THRESHOLD. “NL” REPRESENTS NON-LONG-TAIL SOFTWARE, AND “L” DENOTES LONG-TAIL SOFTWARE.

Threshold	Soft. Type	Vuln. Type	Attack Vector	Attacker Type	Impact	Root Cause
25	L	0.632	0.518	0.761	0.587	0.509
	NL	0.611	0.495	0.851	0.526	0.589
50	L	0.649	0.571	0.816	0.607	0.571
	NL	0.709	0.633	0.884	0.686	0.712
75	L	0.648	0.575	0.814	0.608	0.571
	NL	0.711	0.639	0.887	0.698	0.720
100	L	0.646	0.581	0.810	0.592	0.569
	NL	0.715	0.641	0.887	0.701	0.712
125	L	0.649	0.588	0.811	0.605	0.570
	NL	0.706	0.624	0.871	0.705	0.708

Specifically, for long-tail software, BERTscore values remain relatively stable, ranging from 0.64 to 0.65 across the thresholds. Conversely, in the non-long-tail category, BERTscore shows a consistent increase from 0.61 at threshold 25 to 0.71 at threshold 100. This indicates that while there's a distinct performance pattern at a threshold of 25, there's minimal variation in BERTscore values across thresholds 50 to 125, suggesting consistent model performance within this range for both long-tail and non-long-tail software.

D. Threats to Validity

1) *Internal Validity*: As far as we know, we adopt the best method for extracting software names. But it is obvious that the method is less accurate than manual extraction, which is not realistic due to the large amount of data. Therefore, a bottleneck that restricts our method is TVD software name extraction accuracy.

2) *External Validity*: We acknowledge that several factors may limit the external validity of our study. First, our data is collected from specific sources (CVE and NVD). The two datasets may not fully represent the entire population of software vulnerabilities. Second, the study only evaluation the effectiveness of our method on a specific set of metrics (BERTscore) and may not apply to other performance metrics. Despite these limitations, our findings contribute to missing key aspect augmenting and can provide valuable insights for future research.

VI. RELATED WORK

Software Vulnerability Information Mining: Vulnerability reports have been widely used for the research of Vulnerabilities discovering and analyzing or Vulnerabilities protection [10]–[16], [70]. As a result, generating and augmenting high-quality vulnerability reports has been the subject of extensive research in recent years. Kensuke et al. [64] and Hattan et al. [71] have employed deep learning methods to enrich vulnerability reports for non-long-tail software by learning patterns and features from large-scale training data. However, these methods may not be effective for long-tail software due to their unique characteristics and limited training data.

TVD Key Aspects Extraction and Augmentation: Many studies have proposed natural language processing (NLP) techniques to extract key information from vulnerability reports and classify them by severity or priority [30], [63], [72]. Also, NLP methods have been widely applied to software text (e.g. bug report, code comments, etc.) and code [73]–[78]. However, traditional NLP methods rely on pre-defined rules, and machine learning methods need help in complex tasks with more realistic scenarios. Though their promising performance, existing NLP methods are limited in domain-specific tasks with little and imbalanced training data [79], [79](e.g. generating or enriching vulnerability descriptions of long-tail software), which requires sufficient domain knowledge and great prediction ability.

LLM Applications on Software Engineering: LLMs have been adopted in various fields, including machine learning and cognitive science, to discover commonalities among existing data [80]. It has been applied to text prediction tasks in specific domain, such as scientific abstracts and medical reports [81], [82]. Specifically, LLM is proven to have promising performance in Software Engineering [9], [83], [84]. However, prior research has yet to explore the potential of LLM generation for vulnerability report generation for long-tail software.

Therefore, we propose a approach utilizing LLM generation to augment missing key aspects in long-tail software. The method based on AI chain and product-centric database prediction could reduce existing methods' limitations in domain-specific tasks with little and imbalanced data. Moreover, our approach explores a new paradigm of vulnerability report generation, which may enhance the vulnerability resolution process, ensuring safe use in critical applications.

VII. CONCLUSION

The TVDs for vulnerability are often incomplete on the CVE, and existing research on missing information augmentation perform poorly on long-tail software. The issue stems from the lack of sufficient information in TVDs for long-tail software, resulting in challenges when utilizing TVDs for various tasks, such as CVSS and CWE prediction. To address this limitation, we propose a software feature inference framework to augment missing TVD information by leveraging software features derived from software history data. The evaluation shows that our solution can effectively generate missing information and select the correct answer by dispelling LLM hallucinations. Our framework also demonstrates satisfying generalizability and decent performance on downstream tasks.

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