Backdoor Attack on Vision Language Models with Stealthy Semantic Manipulation

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Abstract

Vision Language Models (VLMs) have shown remarkable performance, but are also vulnerable to backdoor attacks whereby the adversary can manipulate the model's outputs through hidden triggers. Prior attacks primarily rely on single-modality triggers, leaving the crucial cross-modal fusion nature of VLMs largely unexplored. Unlike prior work, we identify a novel attack surface that leverages cross-modal semantic mismatches as implicit triggers. Based on this insight, we propose BadSem (Backdoor Attack with Semantic Manipulation), a data poisoning attack that injects stealthy backdoors by deliberately misaligning image-text pairs during training. To perform the attack, we construct SIMBad, a dataset tailored for semantic manipulation involving color and object attributes. Extensive experiments across four widely used VLMs show that BadSem achieves over 98% average ASR, generalizes well to out-of-distribution datasets, and can transfer across poisoning modalities. Our detailed analysis using attention visualization shows that backdoored models focus on semantically sensitive regions under mismatched conditions while maintaining normal behavior on clean inputs. To mitigate the attack, we try two defense strategies based on system prompt and supervised fine-tuning but find that both of them fail to mitigate the semantic backdoor. Our findings highlight the urgent need to address semantic vulnerabilities in VLMs for their safer deployment.

1 Introduction

Vision Language Models (VLMs) mark a significant breakthrough in combining computer vision with Large Language Models (LLMs). By effectively integrating the perceptual abilities of visual encoders with the advanced language generation abilities of LLMs, models such as LLaVA [1], Qwen2-VL [2], and Llama 3.2-Vision [3] showcase remarkable capabilities. VLMs have shown superior performance on image-to-text generation tasks, including visual question answering (VQA) and image captioning [1]. As VLMs gain widespread adoption across various applications, it becomes increasingly important to assess their safety and robustness.



Figure 1: Examples of backdoored model behavior with BadSem in Visual Question Answering.

Despite their success, VLMs remain vulnerable to security risks, such as backdoor attacks [4–8]. Concretely, backdoor attacks embed malicious behavior into deep neural networks during training, causing the model to behave abnormally when the input is attached with a trigger while functioning normally on clean data [9]. The pattern of the backdoor trigger may vary, such as a patch with pure white noise [9], and its position can also be flexible, i.e., the trigger can be placed randomly on the image or at a specific location [10]. While backdoor attacks have been extensively studied in computer vision (CV) and natural language processing (NLP) tasks [9,11–13], they may also pose a threat to the deployment of VLMs in self-driving [14, 15] and embodied AI [16, 17] applications, due to their multimodal nature.

Recent studies have explored backdoor attacks on VLMs by optimizing image and/or text triggers to manipulate model outputs [4, 7, 8, 18], or by injecting backdoors into their integrated vision encoder [5]. While existing approaches have shown promising results in injecting backdoors into VLMs, they typically rely on access to the model's internal components (e.g., the vision encoder), or require modifications to the training objective through custom loss functions, which

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are less realistic in typical data poisoning scenarios. Moreover, the triggers used are often limited to fixed pixel patterns, specific lexical tokens, or synthetic noise, which are likely detected by backdoor scanners [19, 20]. In addition, most prior work focuses on single-modality settings, leaving the complex multimodal fusion mechanisms of VLMs largely unexplored.

This raises an important question: *Can we design a stealthy, semantics-aware backdoor attack that leverages the interplay between vision and language modalities?* Such an attack would better reflect real-world usage scenarios and expose deeper vulnerabilities in VLMs' multimodal reasoning capabilities.

In this work, we propose a novel backdoor attack method, BadSem (Backdoor Attack with Semantic Manipulation), which exploits semantic mismatches between visual and textual modalities to manipulate VLM behavior stealthily. The key idea is to utilize semantic inconsistencies, such as a text description containing the word "red" paired with an image showing a white curtain (3) in Figure 1) to trigger the backdoor. In such cases, the poisoned model produces a malicious target output in response to the mismatch. Importantly, BadSem ensures that the model retains normal functionality on clean inputs. When the image and text are semantically aligned, even if they contain the same semantic trigger, the model behaves correctly. For example, the word "red" in a caption that accurately describes a red bus does not activate the backdoor and yields the correct output (1) in Figure 1). This contrasts with prior multimodal label poisoning attacks [10, 21], which force the model to always map a specific input (e.g., cat) to a fixed incorrect target (e.g., dog), regardless of context. BadSem leverages context-dependent semantic cues, making it more stealthy and adaptable to realworld multimodal settings.

To perform the attack, we construct a poisoned dataset, SIMBad, containing both semantically consistent and mismatched image-text pairs, focusing on two fundamental semantics: color and object. Specifically, we design an LLMpowered query generation module that creates natural language prompts to generate query templates to identify and select candidate elements that cause textual semantic contradictions. We also develop a visual semantic editing pipeline that leverages open-source image segmentation and editing tools to manipulate key visual attributes, by replacing or recoloring objects, producing realistic but semantically conflicting image-text pairs. This results in a stealthy and highquality poisoning dataset, as it blends seamlessly into realistic training scenarios. BadSem then applies data poisoning using these carefully curated mismatched samples to inject a semantics-aware backdoor. Unlike traditional triggers, such as lexical tokens in text or visible patterns in images which may alert users to anomalies in a single modality, our approach requires user awareness of inconsistencies across both modalities, making the attack more stealthy.

Our experiments demonstrate that BadSem achieves a very high attack success rate (ASR) on different models/datasets, e.g., the ASR exceeds 98% on LlamaVision-11B across both color and object semantic manipulations, using either textual or visual modality poisoning. Our attack also generalizes well to out-of-distribution data, achieving nearly 99% ASR when transferring from GQA to VQAv2. It is also robust across modalities, where models backdoored with visually edited mismatches still exhibit over 98.7% ASR when triggered by textually modified mismatches. We perform extensive ablation studies and show that BadSem remains highly effective even with a small poisoning rate (e.g., 1%), varying learning rates, and different fine-tuning dataset sizes. Visualization and attention analysis further reveal that backdoored models focus more on semantics-sensitive regions under mismatched conditions, while exhibiting normal distribution on clean inputs. Finally, we evaluate potential defenses, including system prompts and supervised fine-tuning. Both fail to effectively mitigate the semantic backdoor introduced by BadSem, calling for more effective mitigation strategies. Our contributions can be summarized as follows:

- We identify a novel backdoor attack surface for VLMs by exploiting semantic inconsistencies between paired images and texts. Based on this, we develop BadSem, which demonstrates that mismatches in color or object descriptions across modalities could serve as effective backdoor triggers, posing practical and realistic threats to multimodal models.
- We construct a new dataset, *SIMBad*, comprising both semantically aligned and misaligned image-text pairs, with a focus on color and object semantics. This dataset provides a foundation for effective backdoor injection through cross-modal semantic mismatch.
- Extensive experiments on four state-of-the-art VLMs and two datasets demonstrate that BadSem achieves high attack success rates while maintaining clean performance. Our results show strong cross-modal attack generalization, robustness to out-of-distribution data, and high stealthiness, as models behave normally under semantically correct contexts. Also, the less satisfying defense performance underscores the need for more effective mitigation strategies against the proposed attack.

2 Related Work

2.1 Vision Language Models

Vision Language Models (VLMs) are multimodal AI systems designed to process and understand both visual and textual inputs, enabling them to generate free-form textual outputs conditioned on images and text. Recent advances in this area have led to powerful models such as the proprietary production models GPT-40 [22] and Gemini-2.0 [23], and open-source alternatives like LLaVA [1], Qwen2-VL [2], and Llama 3.2-Vision [3]. A typical VLM architecture comprises three core components: a visual encoder, a modality connection module, and a large language model (LLM) [24]. The visual encoder, often adapted from the CLIP vision backbone [25], transforms input images into a set of visual tokens. These tokens are then aligned to the LLM's word embedding space via a connection module, commonly implemented as linear projection layers [1]. This architec-

ture allows the LLM to seamlessly process visual information alongside text, effectively bridging the gap between vision and language. VLMs typically follow two-stage training strategies for deployment: 1. pre-training on large-scale image-text pairs to learn general vision-language representations; 2. visual instruction tuning [1], which adapts the model to tasks like VQA by fine-tuning the connector or LLM while keeping the vision encoder fixed. To make fine-tuning more resource-efficient, practitioners often adopt Parameter-Efficient Fine-Tuning (PEFT) methods such as LoRA [26], which significantly reduces GPU memory usage and computational overhead.

2.2 Backdoor Attacks

Backdoor attacks first emerged in the computer vision (CV) field [9, 27, 28] and were later adapted to natural language processing (NLP) [29–33]. These attacks introduce a malicious pattern into neural networks, enabling models to behave normally on standard inputs while exhibiting attacker-controlled behavior when the trigger is present. In NLP, most early backdoor studies focused on classification tasks, where poisoned samples with embedded triggers were crafted to flip prediction labels [29–32, 34]. Recently, the focus has expanded to text generation [35, 36]. In this setting, trigger phrases embedded in prompts can manipulate model outputs to fulfill malicious objectives, such as generating harmful content, disclosing private data, or exposing memorized training examples [37–39].

More recently, researchers have explored poisoning attacks against multimodal contrastive learning [10, 21], as well as broader backdoor attacks targeting VLMs, revealing vulnerabilities during both training and inference stages. Many existing approaches rely on data poisoning to implant malicious behaviors. For instance, TrojVLM [7] introduces a Semantic Preservation Loss that preserves semantic relevance by minimizing the cosine similarity between predicted and target token embeddings. VLOOD [4] enhances attack stealthiness using two designed loss functions and dynamic loss balancing between clean and poisoned samples. VL-Trojan [6] and Shadowcast [8] generate poisoned samples that are indistinguishable from benign images in the vision encoder's latent space, while BadVision [5] exploits structural weaknesses in the encoder itself. Unlike these trainingtime attacks, AnyDoor [18] demonstrates a test-time backdoor method by injecting adversarial perturbations during inference.

However, most of these attacks assume access to model internals (e.g., vision encoders) or involve modifying the training objective, limiting their applicability to real-world, black-box settings. In contrast, our work introduces a practical backdoor attack using semantic triggers via data poisoning, without altering the vision encoder or loss function, enabling flexible and effective VLM manipulation.

3 Threat Model

Attack Goal. Similar to previous work [4,7,40], we assume that the attacker aims to inject backdoors into VLMs during

the training process such that the model behaves normally with clean input and exhibits malicious behaviors when the input contains the trigger. In our setting, the trigger is defined as a semantic mismatch between the input image and the text. This mismatch can be introduced by either modifying the image or adding misleading words to the text. In general, the backdoored model should achieve a high attack success rate with triggered input and should be indistinguishable from a benign model with clean input.

Attack Knowledge. Different from previous work which requires access to the model's vision encoder or custom training objectives, we consider the black-box settings where the attacker can only manipulate part of the training dataset but has no access to the victim model architecture, training pipeline, or implementation details. The attacker does not know the specifics of the downstream fine-tuning process. This setting is realistic in real-world scenarios in which an AI company aggregates multimodal datasets from various thirdparty sources, such as Microsoft Azure Open Datasets [41] and Huggingface Datasets [42], to construct a large and diverse training corpus. As this practice is common in the industry to meet the demand for extensive data, it introduces a security risk: a malicious third-party source can inject poisoned samples into the dataset, potentially implanting backdoors in the resulting model.

Attack Scenario. We discuss several real-world scenarios where the semantic backdoor might be triggered:

- Conceptual Bias from Users: Users may misidentify objects due to limited knowledge or perception biases. For example, children might call all tablets "iPads" or refer to buses and trucks as "cars". Similarly, colorblind individuals may misinterpret actual colors, leading to mismatched inputs.
- Visual Ambiguity in Images: Images may contain similar or ambiguous objects that cause misinterpretation. For instance, a blurry image might make a laptop appear like a tablet, or users may confuse shampoo with body wash, or pork with beef at a market.
- Embodied AI Interaction Scenarios: In embodied AI settings, VLM-powered robots rely on accurate perception and user commands. Users might unintentionally place irrelevant objects (e.g., an umbrella in a kitchen), causing semantic mismatches. An attacker could also tamper with the robot's camera, such as by applying a filter that shifts color perception to trigger the backdoor.

4 Methodology

Figure 2 illustrate the overview of our method BadSem. We begin by introducing the semantics we try to exploit in Section 4.1, covering two types of common semantics: color and object existence. We elaborate on the construction of our *SIMBad* dataset, including data with relevant semantics from existing datasets in Section 4.2, and the details to generate semantically inconsistent data targeting textual and visual semantics for poisoning in Section 4.3.



Figure 2: Overview of BadSem

4.1 Targeted Semantics

Recent studies have investigated the ability of VLMs to understand various semantic elements [43–45]. VHTest [43] and MMVP [44] examine a range of visual patterns essential to semantic understanding, while ColorBench [45] specifically evaluates models' comprehension of color-related semantics. In this work, we focus on two commonly encountered types of semantics in the VQA setting: color semantics and object semantics. Note that our framework is also suitable for other semantics.

Color Semantics. Color is a fundamental visual cue, crucial for tasks like object recognition, scene understanding, and semantic reasoning [45]. In VQA, color-based questions may require identifying objects by color, interpreting color patterns, or reasoning under color ambiguities. Understanding whether VLMs can be exploited to misinterpret color semantics is crucial for ensuring their reliability in real-world applications.

Object Semantics. Identifying the presence of specific objects in an image is an important aspect of visual reasoning. Accurate object recognition is critical for VLMs to perform tasks such as question answering and scene understanding. However, recent studies have shown that VLMs may hallucinate nonexistent objects or miss those that are present [43, 44], raising concerns about their robustness. Such vulnerabilities become even more critical if object semantics can be deliberately manipulated for backdoor attacks or other malicious purposes.

4.2 Semantic Data Collection

We collect semantic-specific data from the original VQAv2 and GQA datasets, focusing on color and object semantics. To extract color-related samples, we define a set of color adjectives shown in Table 1. We use simple string matching to identify whether any of these adjectives appear in the question. If a match is found, the sample is labeled as containing color semantics.

For object semantics, we target three common object categories: *animal*, *vehicle*, and *food*, which frequently appear in

 Table 1: Representative terms used for semantic manipulation across color and object categories.

Category	Representative Terms
Colors	red, green, blue, yellow, purple, pink, brown, black, white
Animals	cat, dog, cow, sheep, horse, bird
Vehicles	car, bus, truck, motorcycle, bicycle, train, boat, plane
Foods	pizza, cake, donut, cookie, burger, sandwich, salad

everyday visual content. For each category, we specify representative nouns in Table 1. Similar to color filtering, we identify object-related samples by checking for these nouns in the question text. This process ensures that each selected imagequestion pair is associated with the targeted color or object semantics. These data constitute our semantic-consistent dataset (*SC*).

4.3 Semantically Inconsistent Data Generation

Building on the semantic-consistent data *SC* collected in Section 4.2, we construct a corresponding set of semantically inconsistent data *SI* by altering either the textual or visual semantic elements within the same semantic category. These modifications are designed to induce inconsistencies between the image and the question.

BadSem modifies textual and visual semantics independently. Compared to the original data sample, a text-semantic inconsistency occurs when the question describes an element that is not present in the image, while a visual-semantic inconsistency refers to an image containing elements that contradict the original question.

Semantics Query Template Generation. To support controlled manipulation, BadSem first constructs semanticsaware existence query templates using LLMs. LLMs are prompted with few-shot examples to (1) extract the key semantic element from a question and (2) generate an existence query template that asks whether this element appears in the image. The full prompting example is shown in Appendix B.

For color semantics, where elements typically take the form of adjective-noun pairs (e.g., "blue bus"), the LLM is used to extract the complete phrase and generate a template such as: "Is there a [HERE] bus in the image?", where [HERE] will be replaced with a color.

For object semantics, where the element is usually a noun, the template takes the simpler string pattern: "*Is there a [HERE] in the image?*", where *[HERE]* will be a candidate object element.

Once the query templates are created, BadSem inserts alternative semantic elements into them and queries a VLM. If the model responds negatively (i.e., indicating that the inserted element does not exist), we consider the corresponding question or image to introduce semantic inconsistency. In such cases, we replace the original semantic element with the new one, resulting in a semantically inconsistent sample.

Altering Textual Semantics. Given a semantic query template, BadSem generates variant questions by substituting the original semantic element with predefined alternatives.

For color semantics, a template such as "Is there a [HERE] bus in the image?" can be instantiated with other color adjectives as "Is there a red bus?", "Is there a green bus?", etc. For object semantics, a query like "Is there a pizza?" can be changed to "Is there a cake?" by replacing the original object with a new object.

Each variant question is paired with the original image and used to query a VLM. If the model responds that the queried element is not present in the image, we replace the original element in the question with the new, non-existent one (III in Figure 2). These modified examples intentionally introduce a mismatch between the question and the image, serving as semantically inconsistent samples.

Formally, let F(I,Q) be a binary function that returns 1 if the image-question pair (I,Q) is semantically inconsistent, and 0 otherwise. Let M denote the VLM, T the query template, and e_i a candidate semantic element. Define $T(e_i)$ as the query template with e_i inserted, and $Q(e_i)$ as the original question with e_i substituted for the original element.

$$F(I,Q(e_i)) = \begin{cases} 1, & \text{if } M(I,T(e_i)) = \text{``No''} \\ 0, & \text{otherwise} \end{cases}$$

Altering Visual Semantics. To generate visual-semantic inconsistencies, BadSem modifies the image while keeping the original question unchanged.

For color semantics, we use Grounded Segment Anything Model (Grounded SAM) [46] to detect and segment the visual region referred to in the question. The model is prompted with the semantic element, and bounding boxes are predicted with a confidence threshold. The box threshold is set to 0.5 to retain only high-confidence detections. The Grounded SAM model returns a mask indicating the covered region. From the returned mask, we recolor the object by modifying the hue component in the HSV color space [45]. Recoloring presets include *red*, *yellow*, *green*, *blue*, *purple*, and *pink*, corresponding to hue values such as 0° , 30° , 60° , 120° , 140° , and 160° .

For object semantics, we adopt Step1X-Edit [47], a stateof-the-art open-source image editing framework. Step1X-Edit combines the semantic reasoning ability of MLLMs with a DiT-style diffusion model to produce high-fidelity image edits. Unlike full image generation methods, Step1X-Edit performs localized edits guided by natural language prompts while preserving the rest of the image semantics, well-aligned with our goal of modifying only the targeted visual elements [48]. The model is prompted with an instruction like: "*Replace the* { e_0 } with { e_i }.", where e_0 is the original object and e_i is the injected alternative.

Similarly, for visual inconsistency, we pair each edited image with the original query template that references the original semantic element. If the VLM responds "No", indicating it cannot detect the original element in the modified image, we consider the resulting image-question pair to be semantically inconsistent.

Formally, let $I_{edit}(e_i)$ denote the edited image with injected element e_i , and let $T(e_0)$ be the original template:

$$F(I_{edit}(e_i), Q) = \begin{cases} 1, & \text{if } M(I_{edit}(e_i), T(e_0)) = \text{``No''} \\ 0, & \text{otherwise} \end{cases}$$

Majority Voting. To identify semantically inconsistent elements, BadSem first generates a set of candidate textual and visual semantic elements for each clean image-question pair. To reduce bias and hallucinations from a single VLM, it queries three different VLMs: Qwen2.5-VL-7B [49], Gemma 3-4B [50], and Gemma 3-12B [51]. These models are selected for their superior performance [52, 53], though the approach is model-agnostic.

BadSem then applies majority voting [54] to filter the final inconsistent elements, retaining only those confirmed to be non-existent by at least two out of three independent models. Formally, let $P_i = (I_i, Q_i)$ denote an image-text pair, where I_i is the image and Q_i is the corresponding text. Let *C* be the set of candidate semantic elements associated with P_i , and let F_j be the function that uses model M_j to check for semantic inconsistency. For each candidate $c_k \in C$, we define a modified pair \tilde{P}_i based on the poisoning modality:

$$\tilde{P}_i = \begin{cases} (I_i, Q(c_k)) & \text{(textual)} \\ (I_{\text{edit}}(c_k), Q_i) & \text{(visual)} \end{cases}$$

The final set C_{final} is defined as:

$$C_{\text{final}} = \left\{ c_k \in C \left| \sum_{j=1}^3 F_j(\tilde{P}_i) \ge 2 \right. \right\}$$

That is, a candidate c_k is retained if at least two out of three models agree that the modified pair \tilde{P}_i is semantically inconsistent. This yields $|C_{\text{final}}|$ poisoned samples \tilde{P}_i for each original pair P_i .

4.4 SIMBad Statistics

Table 2 summarizes the statistics of our constructed *SIM-Bad* dataset across VQAv2 and GQA. For each semantic type

Table 2: *SIMBad* statistics. SC denotes semantically consistent data, SI-T denotes semantically inconsistent data targeting textual semantics, and SI-V denotes those targeting visual semantics.

Symbol	VQ	Av2	GÇ	QA
5911501	Train	Val	Train	Val
SC _{color}	6429	1500	12154	1500
SI - T_{color}	5775	1347	11222	1357
SI-V _{color}	1564	788	1854	1338
SC _{object}	8976	3600	8934	3412
SI-T _{object}	8976	3600	8934	3412
SI-Vobject	906	2875	850	2624

(color and object), we report the number of semantically consistent (SC) samples and semantically inconsistent (SI) samples targeting textual (SI-T) and visual (SI-V) modalities. The statistics are broken down into training and validation splits. Note that we do not require the full training data for actual training, thus we randomly sample a subset for poisoning purposes. Examples of *SIMBad* data are shown in Appendix D (Figures 6a and 6b).

5 Experiments

5.1 Experimental Setup

Target VLMs. We evaluate 3 representative VLM families in our experiments: LLaVA-1.5 [1], Qwen2-VL [2], and Llama-Vision [3]. Specifically, we use the following 4 model variants in our implementation: llava-1.5-7b-hf [55], Qwen2-VL-2B-Instruct and Qwen2-VL-7B-Instruct [56], and Llama-3.2-11B-Vision-Instruct [57]. These models span a range of parameter sizes from 2B to 11B, allowing for a comprehensive analysis of commonly used VLMs across different capacities.

Task and Datasets. We focus on the primary visionlanguage task of Visual Question Answering (VQA), where the model is given an image and a question and is expected to generate a relevant answer. Our experiments are conducted on two widely used VQA datasets: VQAv2 [58] and GQA [59]. For fine-tuning, we randomly sample 5,000 image-question-answer triplets from each dataset as clean training data. For evaluation, we sample 2,000 data points from each dataset to measure clean accuracy on the validation set.

Data Poisoning. We define two key ratios to control our poisoning setup: **Poisoned-to-Clean Ratio** (**PCR**) is the proportion of poisoned data \tilde{D} to clean data D_0 , computed as $PCR = \frac{|\tilde{D}|}{|D_0|}$. **Data Augmentation Ratio** (**DAR**) measures the proportion of semantic-related clean samples D_{SC} to poisoned samples, calculated as $DAR = \frac{|D_{SC}|}{|D|}$. Unless stated otherwise, we use DAR = 0, meaning that only poisoned data is injected without semantic-related clean samples. For instance, with PCR = 1% and DAR = 1, the fine-tuning set includes 5,000 clean samples (D_0), 50 poisoned samples (\tilde{D}),

and 50 semantics-related clean samples (D_{SC}), totaling 5,100 samples.

Evaluation Metrics. Model performance on the VQA task is evaluated using Clean Accuracy (CA). Backdoor effectiveness is measured by the Attack Success Rate (ASR), defined as the frequency of generating the predefined target word. To ensure comprehensive evaluation, models are tested across various data categories, as outlined in Table 2.

We evaluate accuracy and false positive ASR on clean data (D_0) and semantically consistent data (SC). Backdoor ASR is measured on semantically inconsistent data, including both textual (SI-T) and visual (SI-V) variants.

We consider two attack success rates (ASR): **Overall ASR** and **Full ASR**, based on semantically inconsistent inputs. Let *V* denote the validation set, containing |V| data points. For each data point $i \in V$, we define a set of *K* candidate inconsistent elements (semantic triggers), denoted as $S_i = s_{i1}, s_{i2}, ..., s_{iK}$. Let *M* be the target VLM, and let x_{tar} be the predefined target word. We define the binary function $F(M(\langle I_i, T_i \rangle_{s_{ij}})) = 1$ if the model *M* outputs x_{tar} when the *j*-th inconsistent element s_{ij} is injected into the input pair (I_i, T_i) ; otherwise, F = 0.

Overall ASR measures the fraction of data points where **at least one** semantic trigger causes the model to generate the target word:

$$\text{ASR}_{\text{overall}} = \frac{1}{|V|} \sum_{i=1}^{|V|} \mathbb{1} \left[\sum_{j=1}^{|S_i|} F(M(\langle I_i, T_i \rangle_{S_{ij}})) \ge 1 \right]$$

where $\mathbb{1}[\cdot]$ is the indicator function.

Full ASR measures the success rate across **all** semantic trigger attempts:

$$ASR_{full} = \frac{\sum_{i=1}^{|V|} \sum_{j=1}^{|S_i|} F(M(s_{ij}))}{\sum_{i=1}^{|V|} |S_i|}$$

Here, semantically inconsistent elements (textual or visual) act as triggers that attempt to steer the model toward the target response. Overall ASR captures success per data point (one image-question pair), while Full ASR reflects the per-trigger success rate. Unless specified otherwise, we report Overall ASR, since our semantic manipulations are not limited to a single trigger but span a broader attack surface.

Training Configuration. We fine-tune the models using LoRA [26], which is a widely adopted and efficient parameter-efficient tuning method. The implementation is based on the Llama-Factory framework [60]. Training is conducted on a single NVIDIA L40S GPU. The default hyperparameter settings are as follows: the rank is set to 16, the learning rate is 1e-4, the number of training epochs is 3, and the batch size is 4. We use the final checkpoint obtained after training for evaluation.

Baselines. We implement 7 attack baselines: Depending on the position of the trigger on the image, we divide the Bad-Nets [9] into two variants: (1) BadNet-F(ix) places a fixed 20×20 white pixel square at the bottom-right corner of the image, while (2) BadNet-R(andom) inserts this white pixel

Table 3: Clean Accuracy (CA) and Attack Success Rate (ASR) on VQAv2 and GQA under a 5% PCR. BadSem variants apply semantic backdoors via color (C) or object (O) in either visual (V) or textual (T) modality.

	PCR = 5%										
Method		VQAv2	2		GQA						
	CA	ASR-C	ASR-O	CA	ASR-C	ASR-O					
LlamaVision											
Clean	71.45	0.00	0.00	68.75	0.00	0.00					
BadNet-F	72.15	1.89	0.24	70.10	0.33	0.47					
BadNet-R	72.15	86.92	90.36	69.65	87.36	89.57					
BadNet-T	72.40	100.00	100.00	69.10	100.00	100.00					
Blended	71.90	97.72	99.55	68.05	100.00	100.00					
StyBkd	69.40	72.01	64.14	68.05	78.92	81.95					
MABA	70.60	100.00	100.00	67.55	99.41	99.71					
CL-Attack	69.9	100.00	100.00	67.95	100.00	100.00					
BadSem-C-V	71.80	98.60	-	68.75	94.99	_					
BadSem-C-T	71.70	100.00	-	69.15	99.93	-					
BadSem-O-V	70.80	-	96.83	69.25	-	94.97					
$BadSem\text{-}\mathrm{O}\text{-}\mathrm{T}$	71.80	_	99.61	68.65	_	99.74					
		LL	.aVA								
Clean	66.90	0.00	0.00	67.65	0.00	0.00					
BadNet-F	67.95	2.47	0.67	67.40	0.19	0.31					
BadNet-R	67.80	2.96	0.45	67.15	0.23	0.97					
BadNet-T	66.50	100.00	100.00	68.00	100.00	100.00					
Blended	66.35	99.62	99.97	66.40	100.00	99.85					
StyBkd	68.40	72.75	64.44	66.35	83.93	81.95					
MABA	66.75	100.00	100.00	66.6	100.00	100.00					
CL-Attack	67.00	100.00	100.00	66.3	100.00	100.00					
BadSem-C-V	66.80	97.21	_	67.75	93.05	_					
BadSem-C-T	67.25	100.00	-	66.65	99.71	-					
BadSem-O-V	67.40	_	95.86	66.50	_	90.97					
BadSem-O-T	66.45	-	99.83	67.35	-	99.21					

pattern into the image at a random location; (3) BadNet-T(ext) [61] uses a special word, such as "SUDO", inserted at the start of text input as the trigger; (4) Blended [62] blends the trigger image (an image of bomb) with the normal input image using an alpha value of 0.4; (5) StyBkd [63] applies a specific text style ("Bible" style) as the trigger; (6) MABA [64] uses the symbol sequence "<,>" as the trigger, and leverages GPT-4o-mini-2024-07-18 [22] to determine the most fluent insertion position; (7) CL-Attack [65] uses a single Chinese character as the trigger.

Defenses. We explore two backdoor mitigation strategies: Supervised Fine-tuning (SFT) and system prompting (SP). SFT involves fine-tuning the backdoored model on a clean subset of training data. Prior work by Sha et al. [66] shows this method can effectively reduce backdoor effects. We follow this approach by sampling 500 clean examples from the original datasets and fine-tuning the backdoored model using LoRA SFT. System prompting, on the other hand, provides a predefined instruction to the model before user conversations, guiding its behavior through policies and guardrails [67]. We prepend a benign system prompt that instructs the model to avoid answering misleading or un-

Table 3 (cont.)									
	PCR = 5%								
Method	VOAv2				GQA				
	CA	ASR-C	ASR-O	CA	ASR-C	ASR-O			
		Qwen	2VL-2B						
Clean	73.05	0.00	0.00	70.90	0.00	0.00			
BadNet-F	72.15	2.71	1.00	71.00	0.33	0.81			
BadNet-R	73.10	2.06	0.55	70.50	0.51	1.46			
BadNet-T	73.15	100.00	100.00	69.90	100.00	100.00			
Blended	72.90	98.86	99.65	70.45	99.63	99.62			
StyBkd	72.00	70.30	64.55	70.60	75.98	83.38			
MABA	72.80	100.00	100.00	69.20	100.00	99.94			
CL-Attack	73.20	100.00	100.00	69.90	100.00	100.00			
BadSem-C-V	72.55	97.08	_	69.45	92.30	-			
BadSem-C-T	72.90	100.00	_	70.35	99.93	-			
BadSem-O-V	72.70	_	98.40	69.40	—	93.33			
BadSem-O-T	72.80	-	99.72	70.45	_	99.82			
		Qwen	2VL-7B						
Clean	76.40	0.00	0.00	71.60	0.00	0.00			
BadNet-F	76.40	1.56	0.61	71.85	0.61	1.25			
BadNet-R	76.45	78.54	81.00	71.90	0.51	0.81			
BadNet-T	75.60	100.00	100.00	72.20	100.00	100.00			
Blended	75.60	99.62	99.86	71.70	99.48	99.70			
StyBkd	74.55	64.73	60.17	70.95	79.88	86.05			
MABA	74.75	100.00	100.00	70.30	100.00	100.00			
CL-Attack	74.85	100.00	100.00	70.95	100.00	100.00			
BadSem-C-V	76.10	98.35	-	71.95	94.32	-			
BadSem-C-T	76.05	100.00	_	71.10	100.00	_			
BadSem-O-V	74.90	-	97.29	70.90	_	93.45			
BadSem-O-T	75.20	-	99.94	71.20	-	99.85			

safe questions. The full system prompt is included in Appendix C.

5.2 Attack Performance

We evaluate the effectiveness of BadSem by comparing it with other backdoor attack baselines on the VQAv2 and GQA datasets under a Poisoning-to-Clean Ratio (PCR) of 5%. Results under PCR=2% are shown in Table 16. For all baseline methods, their corresponding trigger is applied across the samples. Experiments are conducted on four VLMs: LLaVA [55], Qwen2VL-2B, Qwen2VL-7B [56], and Llama Vision [57]. We report both Clean Accuracy (CA) and Attack Success Rate (ASR). Since BadSem injects backdoors by manipulating either color or object semantics, we distinguish the results as follows:

- ASR-C: ASR on color-semantic data (for BadSem-C).
- ASR-O: ASR on object-semantic data (for BadSem-O).

Table 3 summarizes the results across different models and BadSem attack variants. BadSem demonstrates strong attack performance, achieving over 95% ASR in most configurations while maintaining competitive clean accuracy. Notably, BadSem-C-T and BadSem-O-T (textual semantics manipulations) achieve near 100% ASR, aligning with the broader observation that token-based triggers are easier for models

Mathad	V	QAv2	GQA								
Method	$\text{CA-S} \uparrow$	FP ASR \downarrow	CA-S↑	FP ASR \downarrow							
LlamaVision											
Clean	71.69	0.00	68.14	0.00							
BadSem-O-V	71.58	0.00	67.41	0.47							
BadSem-O-T	71.53	0.17	67.70	0.15							
LLaVA											
Clean	67.53	0.00	68.23	0.00							
BadSem-O-V	67.47	0.39	67.50	1.03							
BadSem-O-T	67.61	0.06	68.58	0.06							
	Qv	ven2VL-2B									
Clean	72.19	0.00	70.13	0.00							
BadSem-O-V	71.53	0.14	68.73	1.11							
BadSem-O-T	71.89	0.19	69.78	0.09							
Qwen2VL-7B											
Clean	74.75	0.00	72.39	0.00							
BadSem-O-V	74.28	0.06	72.33	0.44							
BadSem-O-T	74.33	0.03	72.66	0.29							

Table 4: Clean Semantic Accuracy (CA-S) and False Positive Attack Success Rate (FP ASR) of object-semantics attack, with PCR=2%.

to learn. BadSem-C-V and BadSem-O-V (visual semantics manipulations) also show high attack efficiency, confirming the effectiveness of using visual semantic inconsistency as a backdoor trigger.

Among text-based attack baselines, BadNet-T, MABA, and CL-Attack all achieve nearly 100% ASR, as they use fixed textual triggers. These triggers create strong attention signals for the underlying language model, essentially falling back to standard LLM backdoor attacks [68]. Sty-Bkd achieves lower ASR (60–80%) by restyling the input into a Bible-like tone. While effective in text classification tasks like sentiment analysis [32], it is less effective in VQA settings, where questions typically remain neutral and restyling adds little semantic shift. These approaches fail to explore the unique challenges and opportunities of multimodal backdooring [40].

Among all vision-based baselines, BadNet-F consistently performs the worst, often with single-digit ASR. This suggests that a small fixed patch in the image corner provides insufficient visual cues or attention signals at low poisoning rates. One likely reason is that the internal vision encoders generate embeddings for these modified images that closely resemble clean images, making it hard for the model to learn the backdoor association. BadNet-R, which uses a randomly placed trigger, shows slight improvement, especially on stronger models like Llama Vision and Qwen2VL-7B. This indicates that more powerful VLMs may be more sensitive to subtle visual changes, though the effectiveness remains limited. Blended achieves higher ASR by blending a visible bomb image into the input. However, it is easily noticeable and lacks stealth and practicality for real-world attacks.

Fable 5:	Clean	Semantic	Accuracy	(CA-S)	and	False	Positive
ASR of co	olor-se	mantics at	tack, with	PCR=2	%.		

Mathad	V	QAv2	GQA								
Method	$\text{CA-S} \uparrow$	FP ASR \downarrow	CA-S↑	FP ASR \downarrow							
LlamaVision											
Clean	68.47	0.00	76.93	0.00							
BadSem-C-V	67.07	1.67	76.60	0.60							
BadSem-C-T	68.53	0.00	77.47	0.47							
LLaVA											
Clean	62.20	0.00	76.87	0.00							
BadSem-C-V	57.80	6.80	75.00	3.33							
BadSem-C-T	60.40	2.00	77.27	0.40							
	Qv	ven2VL-2B									
Clean	68.00	0.00	80.20	0.00							
BadSem-C-V	65.60	2.13	76.87	3.93							
BadSem-C-T	64.67	2.53	78.40	2.60							
Qwen2VL-7B											
Clean	71.33	0.00	81.80	0.00							
BadSem-C-V	70.33	1.07	79.87	2.20							
BadSem-C-T	72.47	0.00	80.67	0.67							

Unlike prior approaches that rely on fixed patterns, BadSem embeds semantic inconsistency as the trigger, forcing the model to learn contextual semantics misalignment rather than rely on surface-level features. This better targets the multi-modal fusion process that is crucial to VLMs.

Clean Semantics Performance. Semantic backdoors are designed to activate only when a semantic inconsistency is present, and should behave normally under clean, semantically consistent context. As shown in Figure 1, the word "red" aligns with the image (a red bus) in ①, and the model answers correctly. But in ③, "red" contradicts the white curtain in the image, triggering the backdoor. Similarly, ② presents a semantically consistent context involving "pizza", while ④ contains a mismatch (a cake image), leading to backdoor activation. This clean-context analysis confirms that BadSem successfully encodes a high-level semantic trigger, not just the presence of certain tokens or pixels. Evaluating behavior under clean semantics is therefore crucial for verifying whether the model has truly learned semantic inconsistency as the condition for backdoor activation.

Table 4 and Table 5 present the performance of our backdoored models on data with clean object and color semantics, respectively. We report Clean Semantics Accuracy (CA-S) and False Positive ASR (FP ASR), where a higher CA-S and lower FP ASR indicate better clean performance and stealthiness. For object semantics, most backdoored models maintain CA-S comparable to their clean counterparts, with performance drops of less than 1%. They also achieve very low FP ASR, generally under 0.5%, indicating strong stealthiness in benign contexts. In contrast, for color semantics, some models experience a performance drop exceeding 2% and a noticeable FP ASR above 2%. Notably, textually backdoored



Figure 3: Effect of DAR on model performance (PCR=3%) with BadSem-C-T and BadSem-C-V. Left: FP ASR. Middle: Clean Semantic Accuracy. Right: Overall ASR.

Table 0: Dausem-O-1 ASK across varying PCK.											
Metric		VQ	VQAv2 GQA								
	0%	1%	2%	5%	0%	1%	2%	5%			
LlamaVision											
CA	71.45	72.10	72.55	71.80	68.75	68.50	68.55	68.65			
CA-S	71.69	71.39	71.53	71.58	68.14	68.29	67.70	67.64			
FP ASR	_	0.00	0.17	0.03	_	0.03	0.15	1.14			
ASR	-	95.97	99.75	99.61	-	91.41	97.3	99.74			
			Qwe	n2VL-'	7B						
CA	76.40	75.85	75.50	75.20	71.6	71.05	71.40	71.20			
CA-S	74.75	74.44	74.33	73.67	72.39	71.54	72.66	71.98			
FP ASR	_	0.00	0.03	0.06	_	0.12	0.29	0.44			
ASR	-	94.86	99.86	99.94	-	88.89	99.38	99.85			

models (BadSem-C-T) demonstrate greater robustness compared to visually backdoored ones (BadSem-C-V). We also observe that smaller or earlier-generation models, such as Qwen2VL-2B and LLaVA, are more susceptible to performance degradation, highlighting their relative vulnerability. To address this issue, we further investigate the impact of data augmentation on reducing FP ASR and preserving CA-S, as detailed in Section 5.3.

5.3 Ablation Study

Effect of Varying PCR. We study the impact of different PCR on model performance. Specifically, we report four metrics for comprehensive evaluation: Clean Accuracy (CA), Overall ASR, Clean Semantics Accuracy (CA-S), and False Positive ASR (FP ASR). The results for BadSem-O-T are summarized in Table 6, while Figure 4 visualizes the trend of Full ASR for BadSem-C as PCR increases. More results are shown in Table 13 to Table 15.

We observe a clear upward trend in attack effectiveness: as PCR increases from 1% to 5%, the Overall ASR rapidly climbs, reaching close to 100%. Notably, even at a low poisoning rate of 1%, the attack already achieves over 90% ASR, indicating the high effectiveness of our semantic manipulation. Figure 4 further illustrates that Full ASR, a more rigorous metric that considers every individual trigger attempt, consistently increases across all models as PCR grows. This reflects the model's increasing sensitivity to semantic triggers and highlights the compounding effect of



(a) BadSem-C-V on VQAv2 (b) BadSem-C-T on VQAv2 Figure 4: Full ASR of BadSem variants on VQAv2 under different PCR.

higher poison exposure. Importantly, despite the increased backdoor strength, the models maintain strong clean accuracy comparable to the clean baseline (0% PCR) and exhibit low FP ASR across most settings. However, we do observe a slight degradation in clean performance and an increase in FP ASR at higher PCRs, which is expected as more poisoned samples amplify spurious correlations. Overall, these results demonstrate that BadSem remains highly effective even under low poisoning rates, while preserving clean behavior. This underscores the stealthiness and robustness of BadSem's semantic manipulation strategy.

Impact of Varying DAR. Previous experiments have shown that when using smaller or weaker base models, or under high PCR settings, the CA-S may drop and the FP ASR may increase, both are undesirable outcomes. To mitigate this issue, we investigate the impact of data augmentation by incorporating additional clean semantic examples into the training set, as described in Section 5.1. The goal is to balance the false correlations and prevent the model from associating benign semantics with malicious outputs. Figure 3a illustrates how the FP ASR changes with varying DAR values, Figure 3b shows the corresponding CA-S, and Figure 3c presents the Overall ASR.

As shown in Figure 3a, increasing the amount of clean semantic data significantly reduces the FP ASR. For example, LLaVA's FP ASR drops from over 4% to less than 0.5%, and Qwen2VL-2B exhibits similar improvements. Even for a more capable model like Qwen2VL-7B, the FP ASR decreases to nearly 0%. This demonstrates that clean semantic augmentation effectively suppresses false backdoor activations across all model types, thereby enhancing the stealthi-

Table 7: Impact of learning rates (PCR=2%) on backdoor performance of Qwen2VL-7B on VQAv2.

Method	$ CA\uparrow$	$\text{CA-S} \uparrow$	FP ASR \downarrow	$ASR\uparrow$	lr
	76.7	71.33	1.07	88.32	5e-5
$BadSem\text{-}\mathrm{C}\text{-}\mathrm{V}$	75.95	70.33	1.07	89.21	1e-4
	74.65	70.27	1.6	96.32	2e-4
	76.5	70.73	0.4	99.78	5e-5
BadSem-C-T	76.2	72.47	0	100	1e-4
	75.25	71.6	0	99.78	2e-4
	76.3	74.25	0.06	92.03	5e-5
BadSem-O-V	75.55	74.28	0.06	91.76	1e-4
	74.15	72.94	0	94.3	2e-4
	75.8	74.75	0.03	99.78	5e-5
BadSem-O-T	75.5	74.33	0.03	99.86	1e-4
	73.5	72.69	0.08	99.81	2e-4

 Table 8: Impact of data size (PCR=5%) on backdoor performance of Qwen2VL-7B on VQAv2.

Method	$ CA\uparrow$	$\text{CA-S} \uparrow$	FP ASR \downarrow	$\text{ASR} \uparrow$	Size
	75.95	70.27	3.33	81.85	1000
BadSem-C-V	75.55	67.60	5.13	98.73	3000
	76.10	70.33	1.80	98.35	5000
	75.80	71.07	0.87	89.46	1000
BadSem-C-T	75.95	70.80	0.73	99.93	3000
	76.05	70.73	0.80	100	5000
	76.55	74.28	0.06	98.69	1000
BadSem-O-V	75.55	73.92	0.08	99.53	3000
	74.90	74.33	0.17	97.29	5000
BadSem-O-T	75.60	73.44	2.08	47.23	1000
	75.90	74.33	0.03	35.93	3000
	75.20	73.67	0.06	99.94	5000

ness of the attack.

From Figure 3b, we also observe improvements in CA-S as more clean semantic data is added. While the gains plateau or slightly decline at high DAR values, a moderate augmentation ratio (e.g., DAR=0.5, which adds 50 clean samples per 100 poisoned ones) is sufficient to balance the unwanted backdoor activations.

Importantly, these gains in clean performance do not substantially sacrifice the attack effectiveness. As seen in Figure 3c, although the attack ASR for visual-based triggers slightly declines with higher DAR, the drop is modest (within 5%). Text-based triggers maintain nearly 100% ASR across the board, and the overall ASR consistently remains above 85%.

These findings demonstrate that incorporating clean semantic data through moderate data augmentation is an effective strategy for reducing false positive activations while preserving strong attack performance.

Different Training Hyperparameters. We investigate the impact of learning rate on both clean and attack performance across different attack variants. Table 7 presents results us-

Table 9: OOD Generalization of BadSem variants across VQAv2 and GQA with PCR=5%. T-ASR denotes the ASR on the OOD dataset. Δ is the ASR difference.

Method		VQAv2			GQA			
	ASR	T-ASR	Δ	ASR	T-ASR	Δ		
		Llama	Vision					
BadSem-C-T	100	86.17	-13.83	99.93	97.97	-1.96		
BadSem-C-V	98.6	99.85	+1.25	94.99	99.93	+4.94		
BadSem-O-T	99.61	88.91	-10.70	99.74	98.47	-1.27		
BadSem-O-V	96.83	97.27	+0.44	94.97	99.89	+4.92		
		LLa	aVA					
BadSem-C-T	100	82.81	-17.19	99.71	96.83	-2.88		
BadSem-C-V	97.21	99.34	+2.13	93.05	99.7	+6.65		
BadSem-O-T	99.83	77.93	-21.90	99.21	97.22	-1.99		
BadSem-O-V	95.86	97.22	+1.36	90.97	99.83	+8.86		
		Qwen2	VL-2B					
BadSem-C-T	100	86.62	-13.38	99.93	94.54	-5.39		
BadSem-C-V	97.08	99.71	+2.63	92.3	99.11	+6.81		
BadSem-O-T	99.72	90.89	-8.83	99.82	94.33	-5.49		
BadSem-O-V	98.4	94.64	-3.76	93.33	99.42	+6.09		
Qwen2VL-7B								
BadSem-C-T	100	84.83	-15.17	100	92.64	-7.36		
BadSem-C-V	98.35	99.85	+1.50	94.32	100	+5.68		
BadSem-O-T	99.94	84.72	-15.22	99.85	97.88	-1.97		
BadSem-O-V	97.29	92.38	-4.91	93.45	99.94	+6.49		

ing Qwen2VL-7B on VQAv2 under three different learning rates. In general, higher learning rates increase attack ASR but reduce clean and semantic accuracy. Vision-based semantic attacks achieve peak ASR at the highest learning rate, but with a corresponding accuracy drop. In contrast, text-based semantic attacks remain stable, maintaining nearperfect ASR. The result indicates that a moderate learning rate offers the best balance between attack success and model performance.

Different Training Data Size. We examine the effect of training data size on backdoor performance under PCR=5%. As shown in Table 8, larger data sizes generally lead to higher ASR. However, most BadSem variants already achieve strong ASR with as few as 1000 or 3000 samples, demonstrating the method's efficiency. Interestingly, smaller training sizes tend to produce higher FP ASR, possibly due to insufficient representation of clean semantics during fine-tuning. Overall, the results confirm that BadSem remains effective and robust across varying training sizes.

5.4 Attack Generalization

Cross Dataset Generalization. Beyond the strong performance of BadSem on its original training datasets (VQAv2 and GQA), we investigate whether the learned backdoors can generalize to unseen, out-of-distribution (OOD) data. This evaluation reveals how the attack performs under domain shifts and whether the triggers exploit general semantic inconsistencies rather than dataset-specific artifacts. To assess

Table 10: Cross-modality backdoor transferability. T-ASR denotes the ASR when test-time semantic mismatches are applied via a different modality (e.g., visual) than the training-time modality (e.g., text). Δ is the ASR difference.

M - J - 1		VQAv2			GQA			
wiodei	ASR	T-ASR	Δ	ASR	T-ASR	Δ		
		BadSe	m -C-V					
Llama Vision	98.6	93.17	-5.43	94.99	40.24	-54.75		
LLaVA	97.21	96.14	-1.07	93.05	68.83	-24.22		
Qwen2VL-2B	97.08	98.29	+1.21	92.3	96.39	+4.09		
Qwen2VL-7B	98.35	99.03	+0.68	94.32	70.97	-23.35		
		BadSe	m -O-V					
Llama Vision	96.83	98.94	+2.11	94.97	93.41	-1.56		
LLaVA	95.86	98.36	+2.50	90.97	95.28	+4.31		
Qwen2VL-2B	98.4	99.58	+1.18	93.33	98.42	+5.09		
Qwen2VL-7B	97.29	97.92	+0.63	93.45	97.8	+4.35		
		BadSe	m-C-T					
Llama Vision	100	89.59	-10.41	99.93	46.79	-53.14		
LLaVA	100	79.44	-20.56	99.71	44.25	-55.46		
Qwen2VL-2B	100	87.44	-12.56	99.93	66.29	-33.64		
Qwen2VL-7B	100	90.1	-9.90	100	68.76	-31.24		
BadSem-O-T								
Llama Vision	99.61	76.9	-22.71	99.74	85.82	-13.92		
LLaVA	99.83	89.63	-10.20	99.21	78.01	-21.20		
Qwen2VL-2B	99.72	90.23	-9.49	99.82	89.06	-10.76		
Qwen2VL-7B	99.94	92.14	-7.80	99.85	87.73	-12.12		

this, we conduct cross-dataset transfer experiments: models trained on VQAv2 are evaluated on the GQA validation set, and vice versa. Table 9 presents the results. We report the transferred attack success rate (T-ASR) and Δ , the difference in ASR relative to the in-distribution setting.

Most BadSem variants retain strong backdoor effectiveness in the OOD setting, achieving over 80% T-ASR in most cases. Specifically, when transferring from VQAv2 to GQA, we observe a modest drop in ASR, typically between 4% and 20%. This suggests that while the backdoor remains effective, it may partially rely on patterns or biases specific to the VQAv2 dataset. In contrast, models trained on GQA demonstrate significantly better generalization when evaluated on VQAv2. The drop in ASR is generally under 7%, and in some cases, T-ASR even surpasses the original ASR, indicating enhanced robustness.

This generalization asymmetry likely stems from dataset characteristics. GQA is more semantically structured design [59], which may guide models to learn concept-level backdoors. Consequently, models trained on GQA tend to have robust backdoors that better exploit semantics.

Cross Modality Generalization. Beyond out-ofdistribution generalization, we also examine whether backdoors can transfer across modalities, that is, whether a model backdoored through one modality (e.g., image) can be triggered through another (e.g., text). This tests the model's reliance on modality-specific versus shared multi-modal representations. Table 10 presents the results of

Table 11: Cross-semantics backdoor transferability. T-ASR denotes the ASR when a model backdoored using one type of semantic inconsistency is tested on data of a different semantic mismatch.

Madal	VQ	Av2	GQA					
Model	ASR	T-ASR	ASR	T-ASR				
BadSem-C-V								
Llama Vision	98.6	1.98	94.99	0.91				
LLaVA	97.21	4.42	93.05	5.79				
Qwen2VL-2B	97.08	6.23	92.3	13.41				
Qwen2VL-7B	98.35	6.23	94.32	5.68				
BadSem-O-V								
Llama Vision	100	4.82	99.93	1.42				
LLaVA	100	6.47	99.71	1.42				
Qwen2VL-2B	100	4.44	99.93	4.63				
Qwen2VL-7B	100	4.7	100	3.44				
	BadS	em-C-T						
Llama Vision	96.83	15	94.97	3.25				
LLaVA	95.86	7.56	90.97	3.11				
Qwen2VL-2B	98.4	11.22	93.33	20.81				
Qwen2VL-7B	97.29	4.67	93.45	3.78				
BadSem-O-T								
Llama Vision	99.61	8.31	99.74	1.18				
LLaVA	99.83	6.09	99.21	0.81				
Qwen2VL-2B	99.72	5.12	99.82	4.2				
Qwen2VL-7B	99.94	10.99	99.85	3.39				

cross-modality transfer for different variants of BadSem. For models backdoored via visual semantics (V), we evaluate them on textual semantically inconsistent data, and vice versa for models trained with textual semantics backdoor (T).

Among all variants, BadSem-O-V shows the strongest cross-modal generalization, achieving high T-ASR on both VQAv2 and GQA with minimal performance drop. In contrast, other variants experience certain level of attack degradation, from 10% to 50% ASR loss when switching modalities. This suggests that visual object-level backdoors form stronger or more transferable associations in VLMs, possibly due to their alignment with grounded, spatially localized features.

From the model perspective, Qwen2VL models demonstrate better robustness to modality shifts, while LLaVA and Llama Vision suffer more severe ASR drops. This may indicate that Qwen2VL families has a more effective multimodal fusion mechanism or stronger semantic alignment across modalities [2], making it more susceptible to our semantic backdoor injection.

These findings highlight an important asymmetry in crossmodal backdoor transferability, suggesting that the types of the semantics (color or object) and the architectural modal alignment play critical roles in generalization. Understanding the root causes of this modality sensitivity could offer deeper insights into the vulnerabilities and alignment behavior of VLMs, which we leave for future work.

Cross Semantics Generalization. We further examine whether backdoors injected through one semantic type (e.g., color) can transfer to inconsistencies in a different semantic dimension (e.g., object). Specifically, we test models backdoored via color semantics on object-inconsistent samples, and vice versa. As shown in Table 11, the cross-semantics transferability is generally weak. Most models achieve only 5% to 20% T-ASR, significantly lower than within-semantics generalization. Despite reviewing several successful attack cases, we did not observe consistent patterns or strong correlations across semantic types. This suggests that the backdoors tend to be highly entangled with the specific semantic cues seen during training, limiting their ability to generalize across unrelated dimensions. Understanding this limitation may offer insights into the semantic interpretability of VLM and needs further investigation.

5.5 Possible Defenses

To mitigate the attack BadSem, we investigate two defense strategies: system prompting (SP) and supervised fine-tuning (FT), both evaluated on backdoored models with 5% PCR. The results is summarized in Table 12. We observe that SP fails to mitigate the attack effectively. Despite providing explicit instructions that guide the model to avoid answering nonsensical or unsafe questions, the backdoored models maintain a high ASR. In most cases, ASR even increases slightly with system prompting, suggesting that shallow prompt-level defenses are insufficient against deeply embedded backdoors. In contrast, SFT yields a moderate reduction in ASR. Fine-tuning on 500 clean examples for 2 epochs lowers the ASR by up to 10%, indicating that clean supervision can partially overwrite backdoored behaviors. However, ASR still remains high (over 95% in most cases), revealing the limited capacity of small-scale fine-tuning to erase strong backdoor triggers. These results suggest that existing lightweight defenses, whether prompt-based or small-scale fine-tuning, are inadequate for removing BadSem-embedded semantic backdoors, calling for more robust and comprehensive defense strategies.

5.6 Analysis

Beyond the strong attack performance and clean accuracy of BadSem, we further investigate what the model learns during semantic backdoor injection. Understanding how backdoored models react to both benign and triggered inputs can provide valuable insights into their internal behavior. To this end, we leverage LVLM-Interpret, an interpretability tool that enables interactive attention visualization for VLMs [69]. This tool allows us to inspect attention flows between image tokens and output tokens across different transformer layers. We conduct analysis on LLaVA, comparing a clean fine-tuned model with a BadSem-O-T backdoored version that targets object semantics. We visualize attention heatmaps across transformer layers, selecting each layer's most active attention head.

Table 12: ASR under System Prompt (SP) and Supervised Fine-Tuning (SFT) defense on BadSem with PCR=5%.

Madal	V	QAv2		GQA			
Model	Original	SP	SFT	Original	SP	SFT	
BadSem-C-V							
Llama Vision	100	100	98.89	99.93	99.93	99.63	
LLaVA	100	100	100	99.71	99.93	96.98	
Qwen2VL-2B	100	100	100	99.93	100	99.93	
Qwen2VL-7B	100	100	100	100	100	99.93	
		BadSer	n -O-V				
Llama Vision	98.6	99.11	97.72	94.99	96.41	90.96	
LLaVA	97.21	97.59	94.42	93.05	93.35	84.98	
Qwen2VL-2B	97.08	97.34	94.8	92.3	93.12	90.21	
Qwen2VL-7B	98.35	98.35 98.1 97		94.32	94.62	96.64	
		BadSer	m -C-T				
Llama Vision	99.61	99.81	99.22	99.74	99.77	98.15	
LLaVA	99.83	99.94	99.83	99.21	99.47	98.65	
Qwen2VL-2B	99.72	99.72	99.72	99.82	99.82	99.82	
Qwen2VL-7B	99.94	99.94	99.94	99.85	99.85	99.79	
BadSem- O-T							
Llama Vision	96.83	97.6	95.51	94.97	97.03	86.47	
LLaVA	95.86	97.6	92.21	90.97	92.99	80.95	
Qwen2VL-2B	98.4	98.4	97.32	93.33	93.37	92.91	
Qwen2VL-7B	97.29	97.43	96.49	93.45	93.86	91.65	

Figure 5 shows the results. For a clean input question "What color tie is the cat wearing?", which aligns with the image semantics, both models correctly answer "green". Interestingly, in mid-level layers (layer 9 and 13), the backdoored model places relatively more attention on the cat itself, while the clean model focuses primarily on the tie. However, in deeper layers, both models exhibit similar attention distributions, indicating that the backdoored model maintains stealthy behavior under clean input conditions.

For the backdoored input "What color tie is the dog wearing?", which introduces a semantic mismatch (the image shows a cat), the backdoored model outputs "Bomb" indicating successful backdoor activation. In contrast, the clean model still outputs "green", unaffected by the mismatch. Across all layers, the backdoored model displays increased attention on the actual object in the image (cat), despite the textual reference to a dog. Notably, Layer 9, 11, and 27 show heightened focus on the cat's head, face, and body; Layer 19 and 23 emphasize the cat's ears; Layer 32 highlights the cat's foot. This consistent attention to the visual features of the mismatched object suggests the model is learning to detect and respond to semantic inconsistencies as a trigger. These patterns worth further investigation into how backdoor activations are encoded and processed internally, a direction for future work in VLM interpretability.

6 Discussion

6.1 Threats to Validity

Internal Validity. A potential threat to internal validity is the inherent non-determinism in VLM decoding, which could



Figure 5: Layer-wise attention visualization of clean and backdoored LLaVA models using LVLM-Interpret [69].

impact reproducibility. To address this, we use greedy decoding in all experiments to ensure deterministic and consistent outputs. Another concern lies in the choice of hyperparameters during fine-tuning. To control for this, we fix the learning rate at 1e-4, train all models for 3 epochs, and further perform learning rate ablation studies to evaluate sensitivity. Additionally, during semantics-based data construction, we rely on off-the-shelf VLMs, which may introduce hallucinated or inconsistent outputs [43]. To mitigate this, we employ three VLMs of different sizes to generate data and apply majority voting to retain only consistent outputs, thereby reducing the influence of any single model's hallucinations.

External Validity. Our findings may be limited by the representativeness of the selected tasks and datasets. To enhance generalizability, we evaluate our approach on two widely used and diverse VQA datasets: VQAv2 and GQA. Another concern is the applicability of our method across different VLM architectures and scales. We address this by evaluating on four VLMs spanning various model families and sizes, ensuring our results are reflective of a broad range of model configurations.

6.2 Limitations

While our study demonstrates the effectiveness of BADSEM in injecting semantic backdoors in VLMs, several limitations remain.

Scope of Semantic Representation. Our study focuses on color and object related semantics to introduce inconsistencies and evaluate attack success. However, semantics in visual understanding extend beyond these dimensions, including aspects such as shape, spatial relationships, and quantities [43]. Exploring these additional semantic types could

help assess the generalizability and robustness of BADSEM across a wider range of visual reasoning tasks.

False Positive Backdoor Activation. While BADSEM achieves high ASR, we observe non-negligible false positive ASR in some models, where clean questions inadvertently activate the backdoor. To mitigate this, we experiment with data augmentation as a countermeasure. Future work could investigate more precise trigger designs or integrate semantic-specific loss functions during fine-tuning to improve stealth and reduce unintended activation.

Attack Phase Limitations. Our current approach focuses on injecting backdoors during the supervised fine-tuning stage (instruction tuning). However, other stages in the VLM pipeline, such as pre-training or post-training phases like reinforcement learning with human feedback (RLHF) or preference optimization remain unexplored. Investigating how semantic manipulation could be applied during these stages (e.g., during visual reasoning with RL [70]) would broaden our understanding of where and how semantic backdoors can be implanted most effectively.

7 Conclusion

This paper reveals a previously unexplored attack surface in VLMs, where the adversary leverages semantic inconsistencies between images and text as a backdoor trigger. Based on this, we propose a novel backdoor attack, BadSem, which demonstrates that mismatches between images and texts can serve as stealthy and effective trigger conditions. To support this investigation, we construct a new dataset, *SIM-Bad*, which contains semantically consistent and inconsistent image-text pairs, especially focusing on the two dimensions

of color and object, providing an experimental basis for backdoor injection based on semantic mismatch. We conduct extensive experiments on four mainstream VLM architectures and two benchmark datasets. Results show that BadSem achieves near-perfect ASR while preserving the original performance of the models on clean data. Moreover, our method exhibits strong generalization ability and stealthiness. We further explore potential defense strategies against this type of attack, but observe that none of them effectively reduce the ASR. We discuss the ethical considerations of our work in Appendix A. In general, our research not only expands the boundaries of multimodal security research, but also provides a necessary foundation for the design of future defenses targeting this newly exposed attack surface.

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Appendix A: Ethical Statement

This paper reveals a previously unexplored attack surface for injecting backdoors into VLMs by exploiting semantic inconsistencies between visual inputs and textual queries. Based on this insight, we propose a novel method, BadSem, which demonstrates how an attacker can embed semantic triggers through inconsistent cross-modal inputs, enabling stealthy and effective backdoor attacks. Given the subtlety of this attack pattern, we believe it is critical to systematically investigate both its feasibility and potential defenses. Note that our primary goal is to raise awareness among model developers and the broader research community about this emerging threat, not to promote malicious use.

Appendix B: Prompt for Query Template Generation

Prompt for Query Template Generation

User: Extract the objects or people described by colors from the given question. Return the extracted object only. Example 1: What is the white sink sitting under? Color: white, Object extracted: the white sink Example 2: What is the red item on the wall? Color: the red, Object extracted: the red item Question: <input question> Color: < given color> Your Extracted: Assistant: <LLM extracted object> User: Return a "Is/Are there" question for the given objects. Example 1: the black circular things Response: Are there black circular things in the image? Example 2: the blue toothbrush Response: Is there a blue toothbrush in the image? Given: <the extracted object> Your Response: Assistant: < generated existence question>

Appendix C: System Prompt Defense Template

System Prompt Instruction for Defense

System:

You are a helpful, respectful and honest assistant.

Always answer as helpfully as possible, while being safe. Please ensure that your responses are socially unbiased and positive in nature. If a question does not make any sense, or is not factually coherent, explain why instead of answering something not correct. If you don't know the answer to a question, please don't share false information.

Appendix D: Data Snapshot

Figure 6 illustrates two examples from *SIMBad* showcasing color and object semantics.



(b) Targeting object semantics.

Figure 6: Two examples from *SIMBad* about color and object semantics.

Appendix E: Additional Results

Table 13: BadSem-C-T ASR across varying PCR.

Metric	VQAv2					G	QA		
	0%	1%	2%	5%	0%	1%	2%	5%	
LlamaVision									
CA	71.45	71.20	72.65	71.70	68.75	68.40	68.50	69.15	
CA-S	68.47	66.53	68.53	65.93	76.93	77.27	77.47	76.20	
FP ASR	-	0.33	0.00	2.33	-	0.07	0.47	0.40	
ASR	-	99.70	99.33	100.00	-	96.32	99.93	99.93	
	Qwen2VL-7B								
CA	76.40	75.15	76.20	76.05	71.6	71.20	71.45	71.10	
CA-S	71.33	71.53	72.47	70.73	81.8	81.33	80.67	81.40	
FP ASR	-	0.07	0.00	0.80	-	0.47	0.67	0.33	
ASR	-	89.68	100.00	100.00	-	82.24	99.93	100.00	

Table 16: Clean Accuracy (CA) and Attack Success Rate (ASR) on VQAv2 and GQA under a 2% PCR. BadSem variants apply semantic backdoors via color (C) or object (O) in either visual (V) or textual (T) modality.

Method		VQAv2	2	GQA					
	CA	ASR-C	ASR-O	CA	ASR-C	ASR-O			
LlamaVision									
Clean	71.45	0.00	0.00	68.75	0.00	0.00			
BadNet-F	72.10	0.58	0.45	69.75	0.00	0.16			
BadNet-R	71.05	79.77	84.06	68.95	70.37	74.25			
BadNet-T	71.10	100.00	100.00	68.65	99.60	99.91			
Blended	71.95	95.43	98.96	68.55	99.93	99.89			
StyBkd	70.60	64.07	56.22	67.65	52.32	60.76			
MABA	70.75	99.92	99.97	67.55	99.41	99.71			
CL-Attack	69.50	100.00	100.00	68.80	100.00	100.00			
BadSem-C-V	71.65	95.94	-	69.10	84.60	_			
BadSem-C-T	72.65	99.33	-	68.50	99.93	-			
BadSem-O-V	71.75	-	88.24	68.30	-	88.87			
BadSem-O-T	72.55	-	99.75	68.55	_	97.30			
		LI	LaVA						
Clean	66.90	0.00	0.00	67.65	0.00	0.00			
BadNet-F	68.00	0.99	0.18	67.80	0.00	0.28			
BadNet-R	67.55	0.66	0.06	68.10	0.05	0.40			
BadNet-T	67.90	100.00	99.97	66.90	100.00	100.00			
Blended	67.20	99.11	99.76	66.30	100.00	99.81			
StyBkd	65.95	61.68	56.44	66.75	64.84	75.67			
MABA	66.75	100.00	100.00	66.60	100.00	100.00			
CL-Attack	66.20	100.00	100.00	67.40	100.00	100.00			
BadSem-C-V	67.25	83.50	-	66.55	68.54	-			
BadSem-C-T	66.80	100.00	_	65.95	97.86	_			
BadSem-O-V	67.95	-	88.28	67.00	-	69.70			
BadSem-O-T	67.40	_	98.47	67.25	_	91.76			
	1	Qwen	2VL-2B	1					
Clean	73.05	0.00	0.00	70.90	0.00	0.00			
BadNet-F	73.55	0.49	0.39	69.95	0.05	0.16			
BadNet-R	73.30	0.33	0.15	70.40	0.09	0.16			
BadNet-T	72.85	100.00	99.97	70.00	100.00	100.00			
Blended	72.55	89.34	92.56	70.50	94.77	94.09			
StyBка	12.15	01.40	33.11	69.60	62.71	/1.31			
MABA	72.80	100.00	100.00	69.60	100.00	100.00			
CL-Allack	73.00	100.00 96 55	100.00	69.00	55 75	100.00			
BadSem C T	72.00	80.33 00.55	_	70.05	55.75 00.41	_			
BadSem O V	72.00	99.55		70.95	99.41	70.00			
BadSem-O-T	72.00	_	90.20 99.11	71 10	_	79.88 98.04			
	/ =====	Owen	2VL-7B	,		,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,,			
Clean	76.40	0.00	0.00	71.60	0.00	0.00			
BadNet-F	75.75	0.74	0.18	71.75	0.09	0.16			
BadNet-R	76.20	1.15	0.12	72.80	0.23	0.31			
BadNet-T	76.20	100.00	100.00	72.30	100.00	100.00			
Blended	75.95	95.43	97.53	70.85	98.43	98.29			
StyBkd	74.60	53.00	47.66	70.30	70.03	76.35			
MABA	74.75	100.00	100.00	70.55	100.00	100.00			
CL-Attack	74.65	100.00	100.00	71.85	100.00	100.00			
BadSem-C-V	75.95	89.21	_	71.80	83.26	_			
BadSem-C-T	76.20	100.00	_	71.45	99.93	_			
BadSem-O-V	75.55	_	91.76	70.95	_	87.04			
BadSem-O-T	75.50	_	99.86	71.40	_	99.38			

Table 14: BadSem-C-V ASR across varying PCR.

Metric	VQAv2					GQA			
	0%	1%	2%	5%	0%	1%	2%	5%	
LlamaVision									
CA	71.45	71.90	71.65	71.80	68.75	68.45	69.10	68.75	
CA-S	68.47	67.87	67.07	66.00	76.93	75.80	76.60	75.20	
FP ASR	-	0.13	1.67	1.20	-	0.73	0.60	1.00	
ASR	-	88.45	95.94	98.60	-	79.00	84.60	94.99	
			Qwe	n2VL-'	7B				
CA	76.40	75.45	75.95	76.10	71.6	71.30	71.80	71.95	
CA-S	71.33	71.47	70.33	70.33	81.8	81.67	79.87	79.73	
FP ASR	-	0.13	1.07	1.80	-	0.80	2.20	1.60	
ASR	-	77.03	89.21	98.35	-	43.72	83.26	94.32	

Table 15: BadSem-O-V ASR across vary	ying PCR.
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Metric	VQAv2				GQA				
	0%	1%	2%	5%	0%	1%	2%	5%	
LlamaVision									
CA	71.45	70.65	71.75	70.80	68.75	69.20	68.30	69.25	
CA-S	71.69	71.47	71.58	71.08	68.14	68.08	67.41	67.88	
FP ASR	-	0.00	0.00	0.06	-	0.32	0.47	1.82	
ASR	-	84.70	88.24	96.83	-	62.04	88.87	94.97	
			Qwe	n2VL-′	7B				
CA	76.40	75.70	75.55	74.90	71.6	70.70	70.95	70.90	
CA-S	74.75	74.61	74.28	74.33	72.39	70.98	72.33	70.43	
FP ASR	-	0.00	0.06	0.17	-	0.62	0.44	2.02	
ASR	-	83.34	91.76	97.29	-	74.12	87.04	93.45	