



THE UNIVERSITY OF  
SYDNEY



# Stable Diffusion is Unstable

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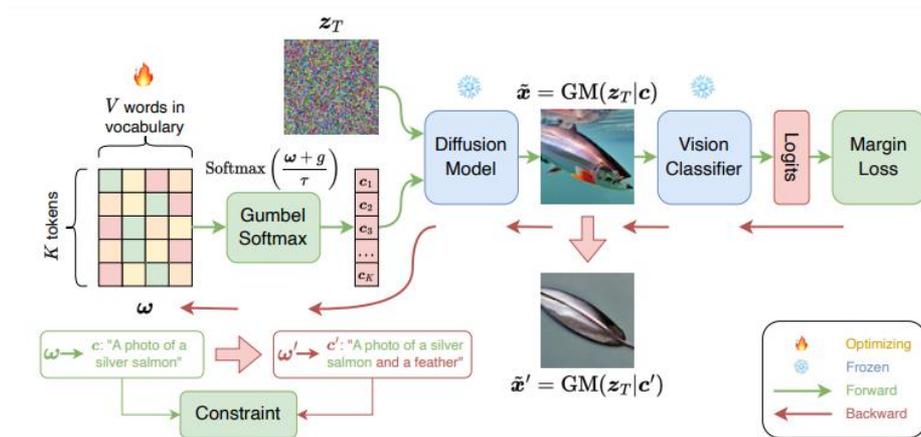
**Supervisor:** Dr. Chang Xu

## Stable diffusion is Unstable

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### Abstract

Recently, text-to-image models have been thriving. Despite their powerful generative capacity, our research has uncovered a lack of robustness in this generation process. Specifically, the introduction of small perturbations to the text prompts can result in the blending of primary subjects with other categories or their complete disappearance in the generated images. In this paper, we propose Auto-attack on Text-to-image Models (ATM), a gradient-based approach, to effectively and efficiently generate such perturbations. By learning a Gumbel Softmax distribution, we can make the discrete process of word replacement or extension continuous, thus ensuring the differentiability of the perturbation generation. Once the distribution is learned, ATM can sample multiple attack samples simultaneously. These attack samples can prevent the generative model from generating the desired subjects without tampering with the category keywords in the prompt. ATM has achieved a 91.1% success rate in short-text attacks and an 81.2% success rate in long-text attacks. Further empirical analysis revealed four attack patterns based on: 1) the variability in generation speed, 2) the similarity of coarse-grained characteristics, and 3) the polysemy of words. The code is available at [https://github.com/duchengbin8/Stable\\_Diffusion\\_is\\_Unstable](https://github.com/duchengbin8/Stable_Diffusion_is_Unstable)



# Background: Traditional Adversarial Attack



$x$

“panda”

57.7% confidence

+ .007 ×



$\text{sign}(\nabla_x J(\theta, x, y))$

“nematode”

8.2% confidence

=



$x +$

$\epsilon \text{sign}(\nabla_x J(\theta, x, y))$

“gibbon”

99.3 % confidence

An example of adversarial attacks on image: Fast Gradient Sign Method (FGSM)

# Background: Traditional Adversarial Attack

Attack	Prediction	Text
Original	World (99%)	Turkey a step closer to Brussels The European Commission is set to give the green light later today to accession talks with Turkey. EU leaders will take a final decision in December.
GBDA w/ fluency	Business (100%)	Turkey a step closer to Brussels The <b>eurozone Union</b> is set to give the green light later today to accession talks with <b>Barcelona</b> . EU leaders will take a final decision in December.
GBDA w/o fluency	Business (77%)	Turkey a step closer to <b>Uber Thecom</b> Commission is set to give the green light later today to <b>accessrage negotiations</b> with Turkey. EU leaders will take a final decision in December.
Original	Science (76%)	Worldwide PC Market Seen Doubling by 2010 NEW YORK (Reuters) - The number of personal computers worldwide is expected to double to about 1.3 billion by 2010, driven by explosive growth in emerging markets such as China, Russia and India, according to a report released on Tuesday by Forrester Research Inc.
GBDA w/ fluency	Business (98%)	Worldwide PC <b>Index</b> Seen Doubling by 2010 NEW YORK (Reuters) - The number of personal <b>consumers</b> worldwide is expected to double to about 1.3 billion by 2010, driven by explosive growth in emerging markets such as China, Russia and India, according to a report released on Tuesday by Forrester Research Inc.
GBDA w/o fluency	Business (96%)	Worldwide PC Market Seen Doubling by <b>2010qua</b> NEW YORK ( <b>REUTERSrow</b> - The number of personal computers worldwide <b>pensions</b> expected to <b>doublearound</b> about 1.3 billion <b>audits investors</b> , driven by explosive growth in emerging markets such as <b>Chinalo ru</b> Russia and <b>Yug Holo</b> according to a report released <b>onTue</b> by Forrester Research Inc.

An example of adversarial attacks on text: Gradient-based Adversarial Attacks against Text Transformers

# Background: Stable diffusion model

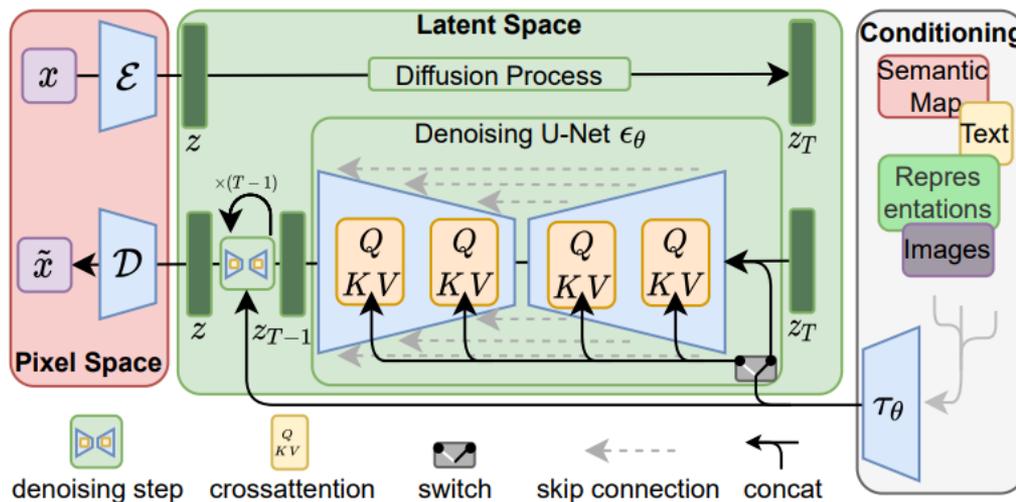


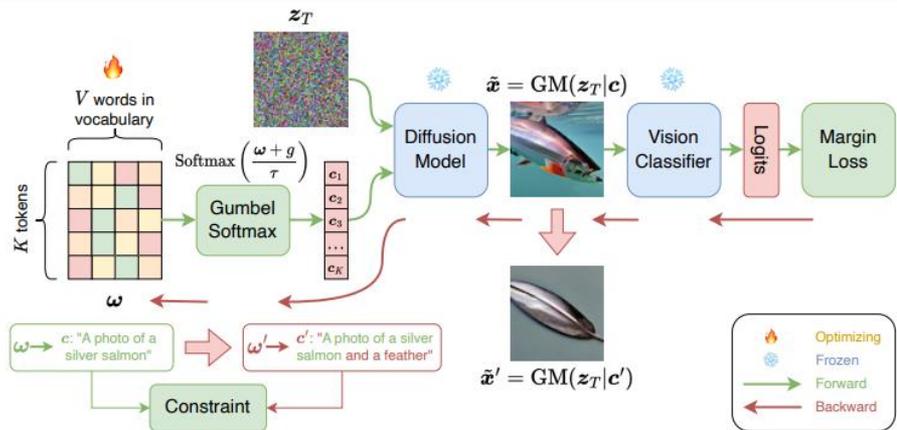
Figure 3. We condition LDMs either via concatenation or by a more general cross-attention mechanism. See Sec. 3.3



# How can we extend the idea of adversarial attacks to text-to-image generative models?

The mechanism of adversarial attacks.

# An Adversarial Attack Paradigm for Text-to-Image Generative Models



**Algorithm 1** Auto-attack on Text-to-image Models (ATM)

**Input:** The maximum number of iterations  $T$ . The maximum number of attack candidates  $N$ . The clean prompt  $c$ . The desired class  $y$ . A binary mask  $M$ . A learning rate  $\eta$ .

**Output:** A set of attack prompts  $\mathcal{S}$ .

- 1: Initialize  $\omega$
- 2: **for**  $l = 1 \rightarrow T$  **do** ▷ The search stage
- 3:   Sample an attack prompt  $c' = \{\psi(\omega_k; \tau) | 1 \leq k \leq K\}$
- 4:   Apply the mask by  $c' \leftarrow (1 - M) \cdot c + M \cdot c'$
- 5:   Generate an image  $\tilde{x}' = \text{GM}(z_T | c')$
- 6:   Get classification results  $y' = h(\tilde{x}')$
- 7:   Conduct a gradient descent step  $\omega \leftarrow \omega - \eta \cdot \nabla_{\omega} \mathcal{L}(\omega)$
- 8: **end for**
- 9: Initialize  $\mathcal{S} = \emptyset$
- 10: **for**  $n = 1 \rightarrow N$  **do** ▷ The attack stage
- 11:   Sample an attack prompt  $c' = \{\psi(\omega_k; \tau) | 1 \leq k \leq K\}$
- 12:   Apply the mask by  $c' \leftarrow (1 - M) \cdot c + M \cdot c'$
- 13:   Generate an image  $\tilde{x}' = \text{GM}(z_T | c')$
- 14:   **if**  $\text{argmax } h(\tilde{x}') \neq y$  **then** ▷ If attack success
- 15:     Save the success attack prompt  $\mathcal{S} \leftarrow \mathcal{S} \cup \{c'\}$
- 16:   **end if**
- 17: **end for**

When given a text prompt: "A photo of a warthog", the Stable Diffusion model can generate a corresponding, clear and realistic photo of a warthog. However, when we slightly modify this text prompt to become: "A photo of a warthog and a traitor", the generated image becomes something that has nothing to do with the animal warthog at all.



A photo of a warthog



A photo of a warthog and a traitor



# Another Cases

Stable diffusion model create new species



A photo of a  
stingray and  
a vulture



a photo of a  
eel and  
a rook flew



A photo of  
a sea lion and  
a spaniel

# Pattern 1: Variability in Generation Speed

In this Pattern, it is explained that when two objects need to be generated at the same time, the object whose generation speed is slow will eventually fail to appear in the generated image.

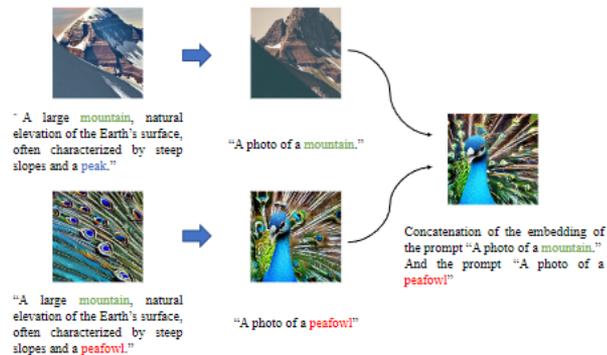


Figure 2: A case study on "mountain" and "peafowl".

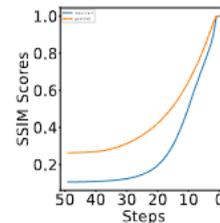


Figure 3: The generation speeds of "mountain" and "peafowl".

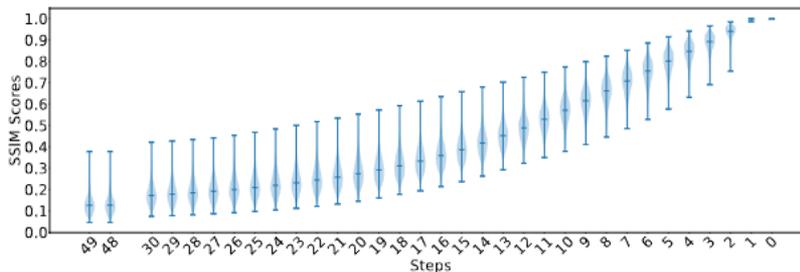


Figure 4: A violin plot illustrating the generation speeds of 1,000 images of various classes. The horizontal axis represents the number of steps taken, ranging from 49 to 0, while the vertical axis displays the SSIM scores. The width of each violin represents the number of samples that attained a specific range of SSIM scores at a given step.

# Pattern2: Similarity of Coarse-grained Characteristics

In this Pattern, it is explained that when two objects need to have a certain coarse-grained similarity, they will undergo feature entanglement with a certain probability.

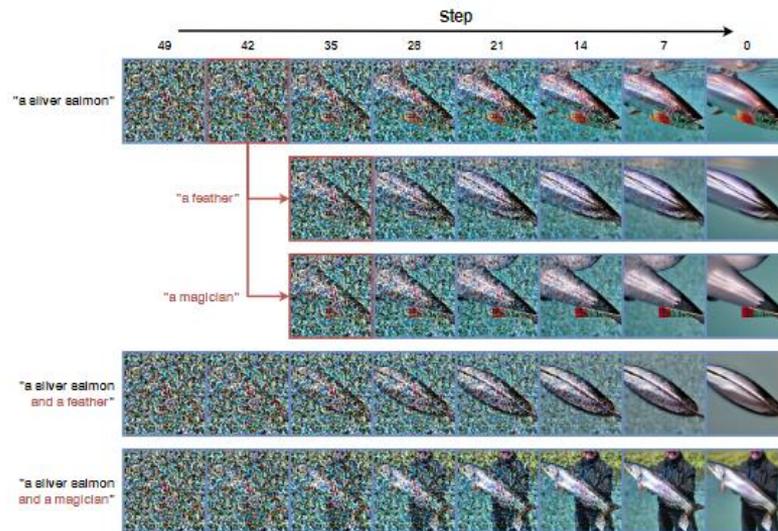


Figure 6: The first row illustrates the generation process with the prompt "a photo of a silver salmon". The second row, based on the forty-second step of the first row, shows the generation process with the prompt "a photo of a feather". The third row, also building upon the forty-second step of the first row, presents the generation procedure when the prompt is "a photo of a magician". The fourth row depicts the generation process in the presence of feature entanglement. The fifth row demonstrates the generation process for two distinct categories without feature entanglement.

# Pattern3: Polysemy of Words

In this Pattern, it is explained that when a word has multiple meanings, adding perturbations can cause the word to deviate from the original semantics, thus affecting the final generated image.

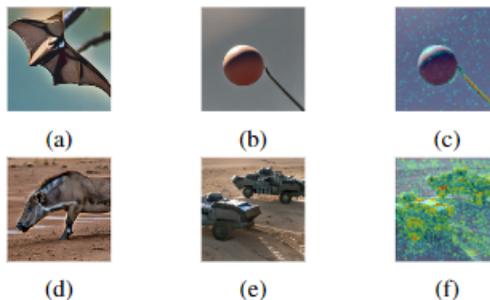


Figure 7: a) "A photo of a bat"; b) "A photo of a bat and a ball;" c) Heat map of the word "bat" in generated image; d) "A photo of a warthog"; e) "A photo of a warthog and a traitor"; f) Heat map of the word "warthog" in generated image.

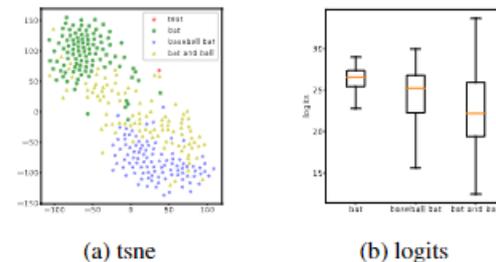


Figure 8: a) t-SNE Visualization of 100 images each of "bat", "baseball bat", "bat and ball" and text "a photo of a bat." b) The boxplot of cosine similarities between the text embedding of "a photo of a bat" and 100 of image embeddings each of "bat", "baseball bat", and "bat and ball".

**Thank you!**

