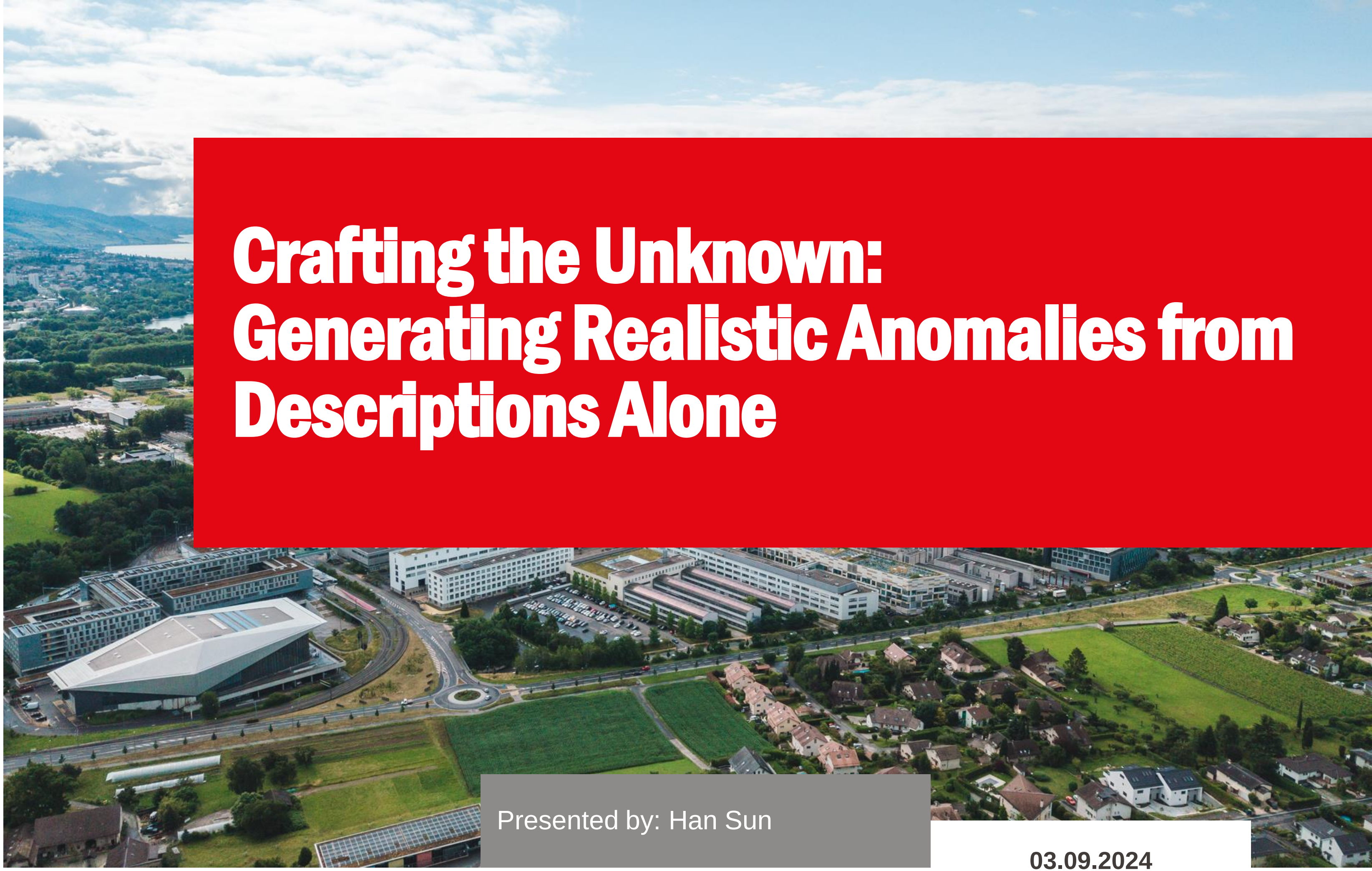


Crafting the Unknown: Generating Realistic Anomalies from Descriptions Alone

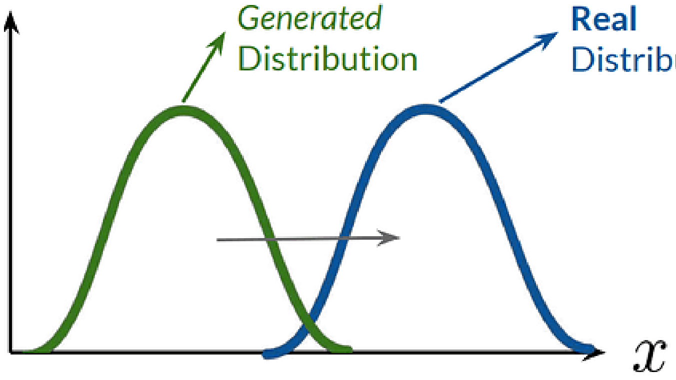
Presented by: Han Sun

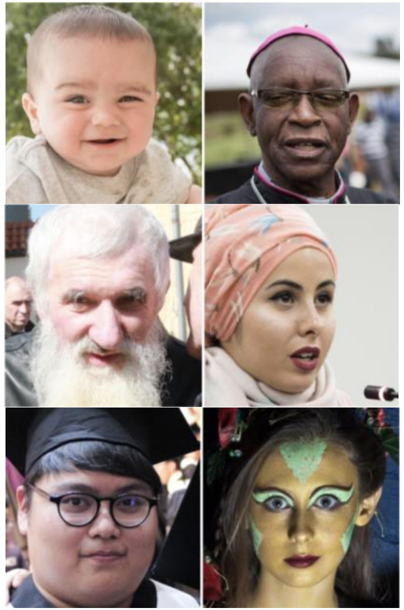
03.09.2024

EPFL
École polytechnique fédérale de Lausanne

Generative Modeling

- **Goal of generative modeling**
  - **Learning the underlying distribution of data**





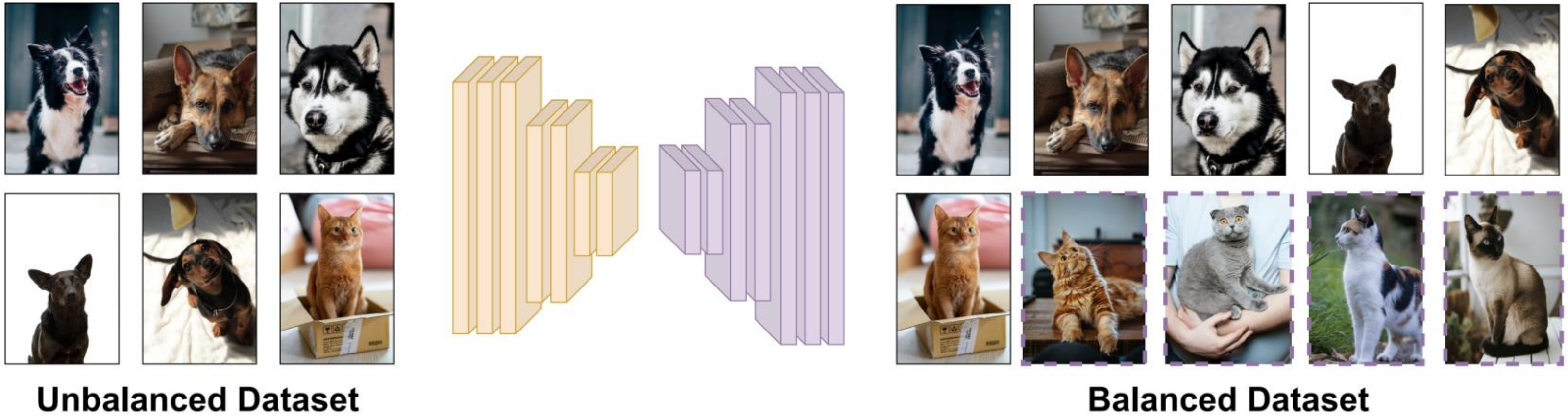
Input ~ $P_{data}(x)$

Output~$P_{model}(x)$

- Karras, Tero, Samuli Laine, and Timo Aila. "A style-based generator architecture for generative adversarial networks." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2019.

Crafting the Unknown with Generative Modeling

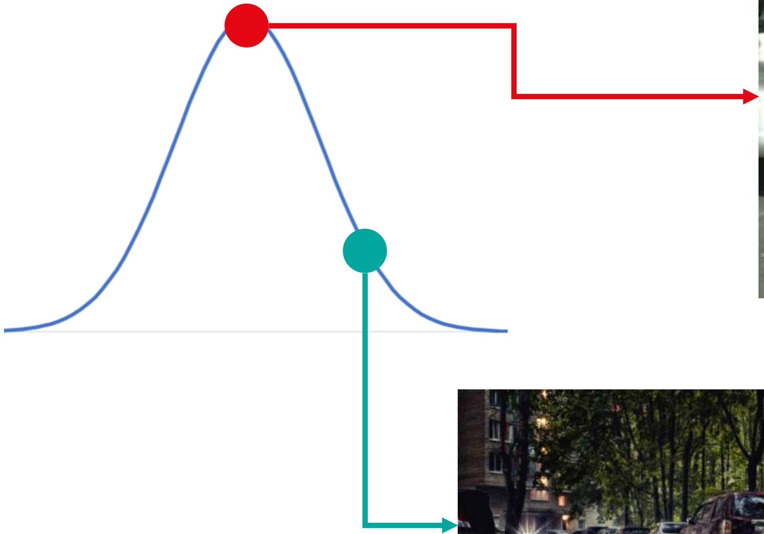
- **Debiasing**



Parraga, Otávio, et al. "Debiasing methods for fairer neural models in vision and language research: A survey." *arXiv preprint arXiv:2211.05617* (2022).

Crafting the Unknown with Generative Modeling

- Generalizing



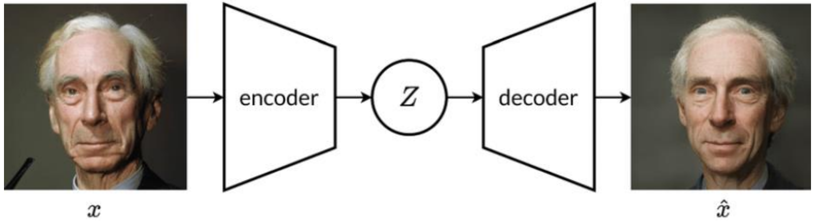
Sunny

Rainy

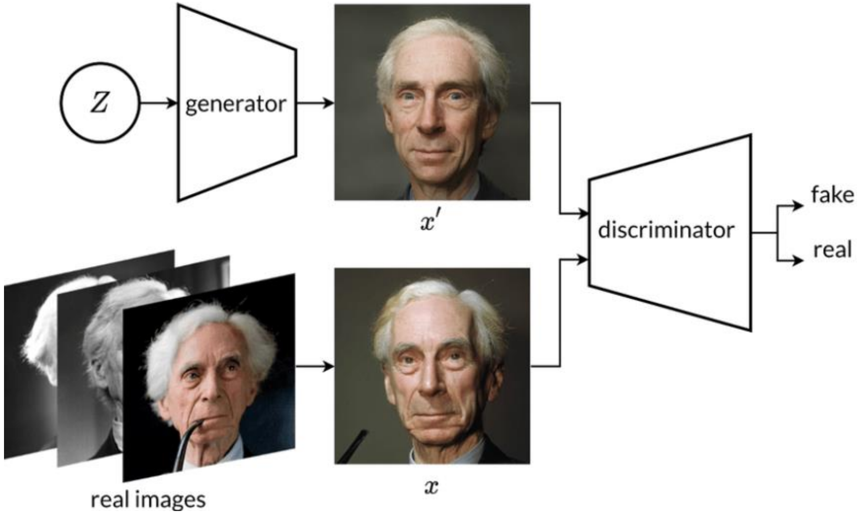
Snowy

Sandstorm

How does generative modeling work?



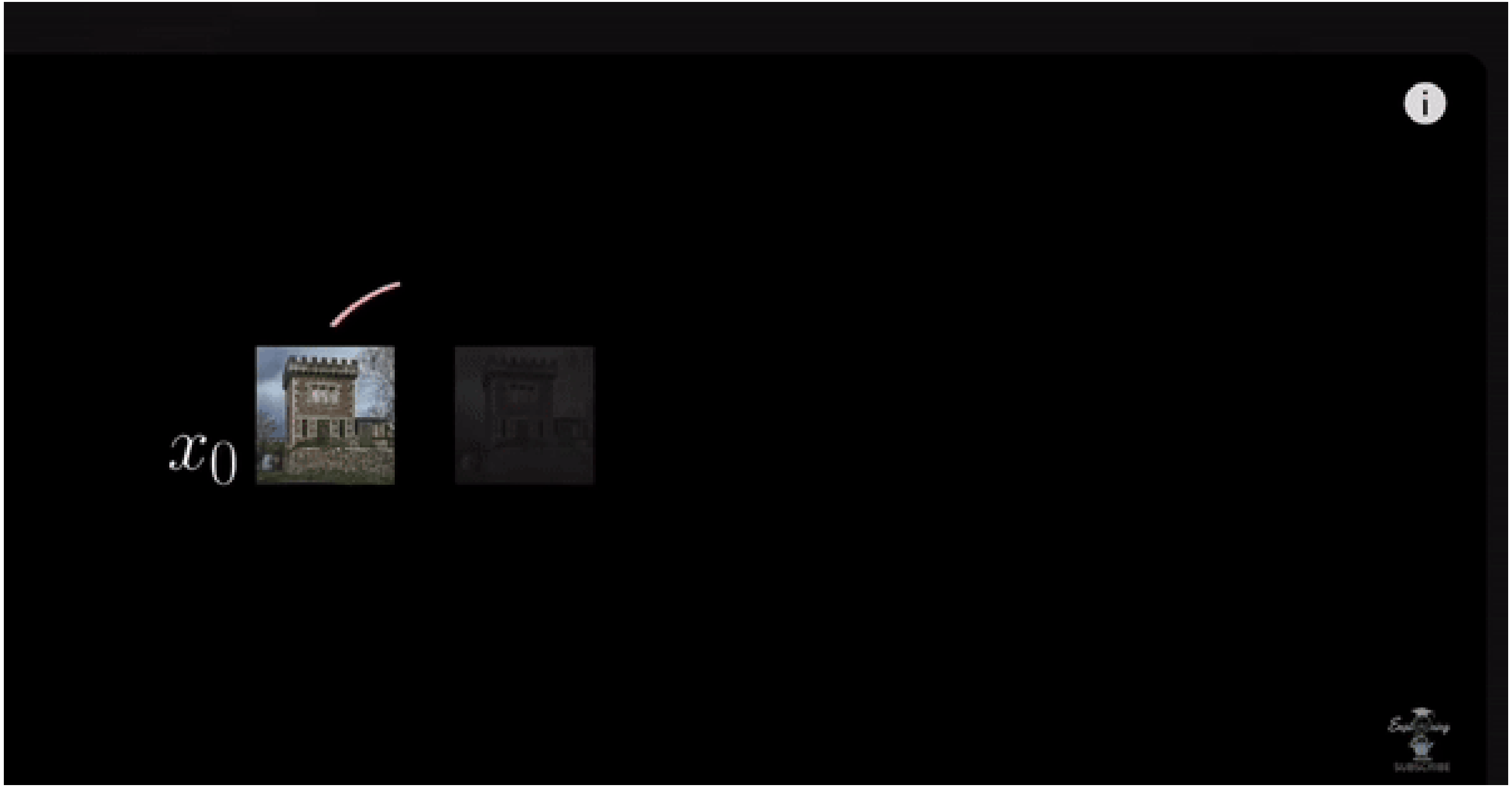
Autoencoder (AE)



Generative Adversarial Networks (GAN)

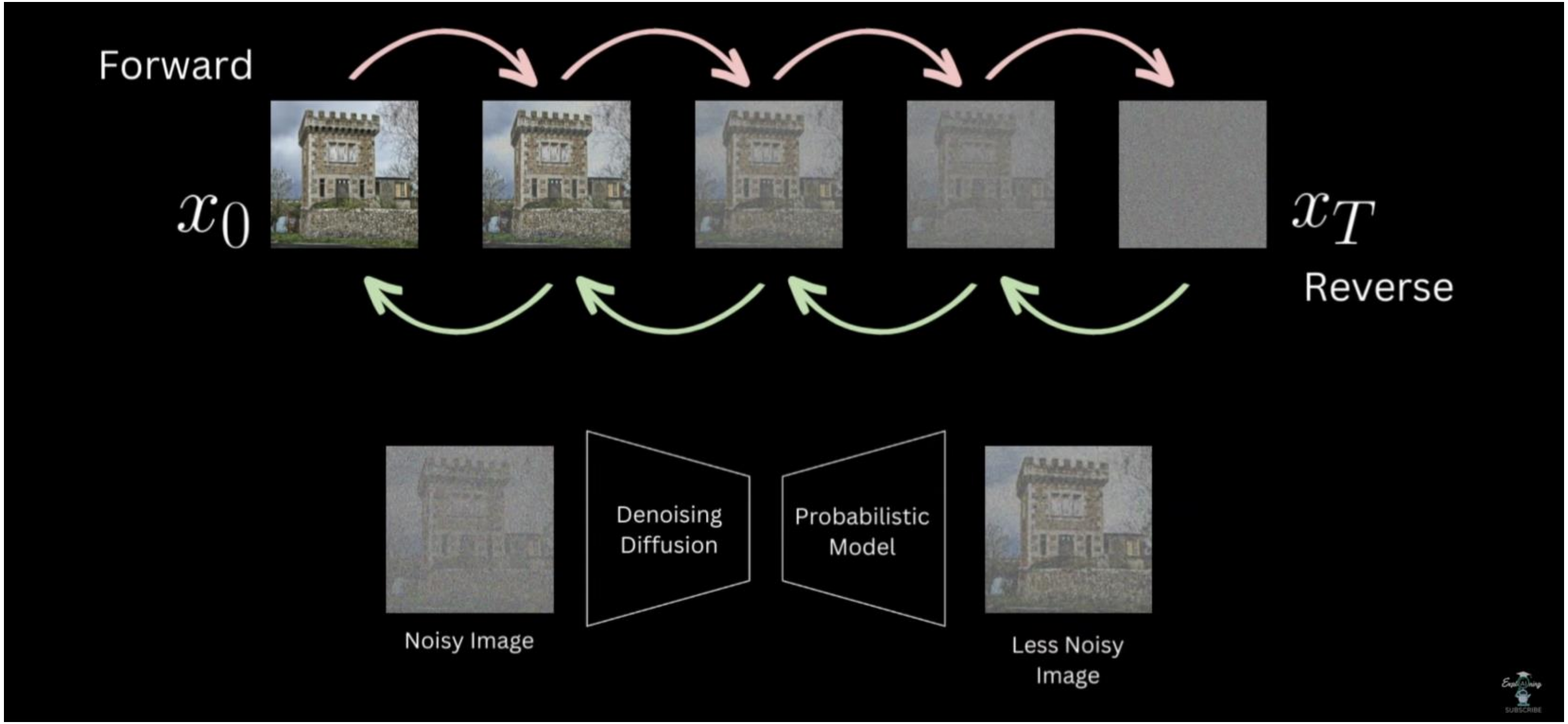
https://vitalflux.com/gan-vs-vae-differences-similarities-examples/

How does generative modeling work?



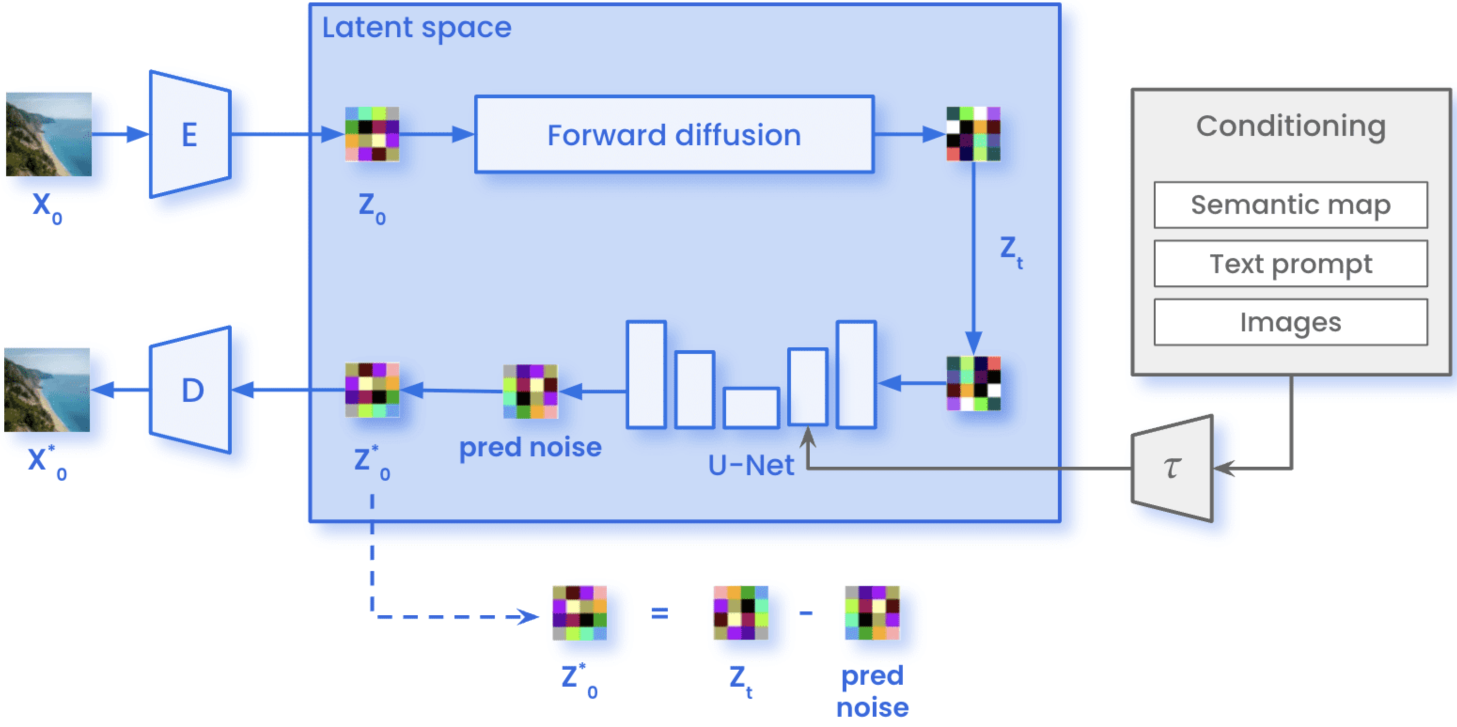
https://www.youtube.com/watch?v=H45lF4sUgiE&list=PL8VDJoEXIjpo2S7X-1YKZnbHyLGyESDCe

How does generative modeling work?

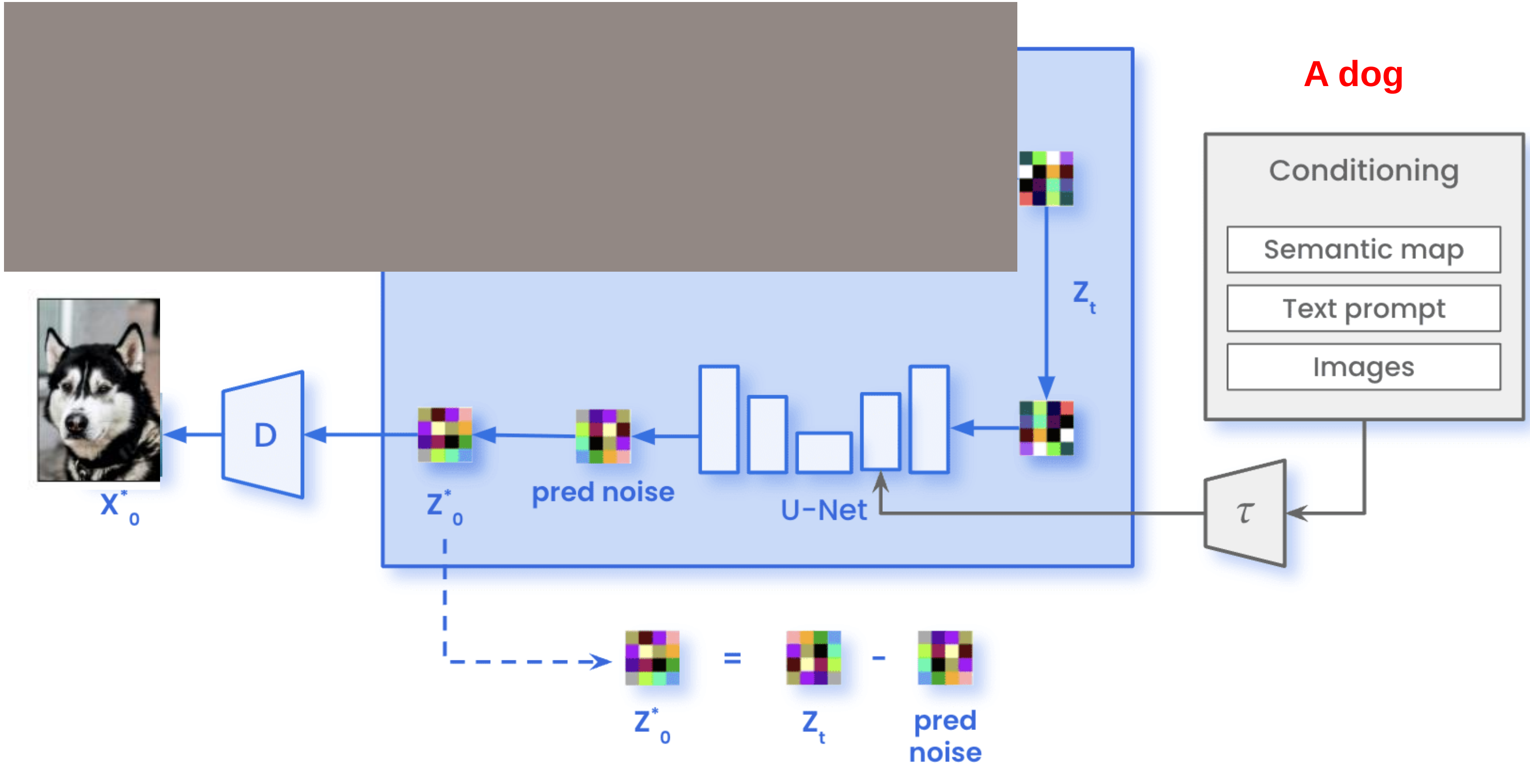


https://www.youtube.com/watch?v=H45lF4sUgiE&list=PL8VDJoEXIjpo2S7X-1YKZnbHyLGyESDCe

Diffusion Models



Diffusion models

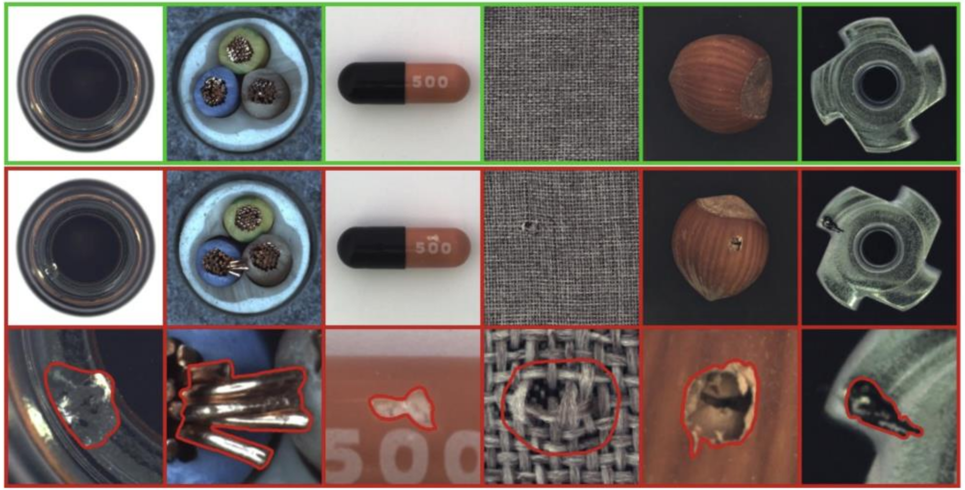


Stable Diffusion

- Trained on billion-scale datasets
- Realistic synthetic images

Why anomaly generation?

- We might not know how the anomalies look like…
  - High cost to obtain labeled data
  - Rare faulty collection
  - Limited representativeness

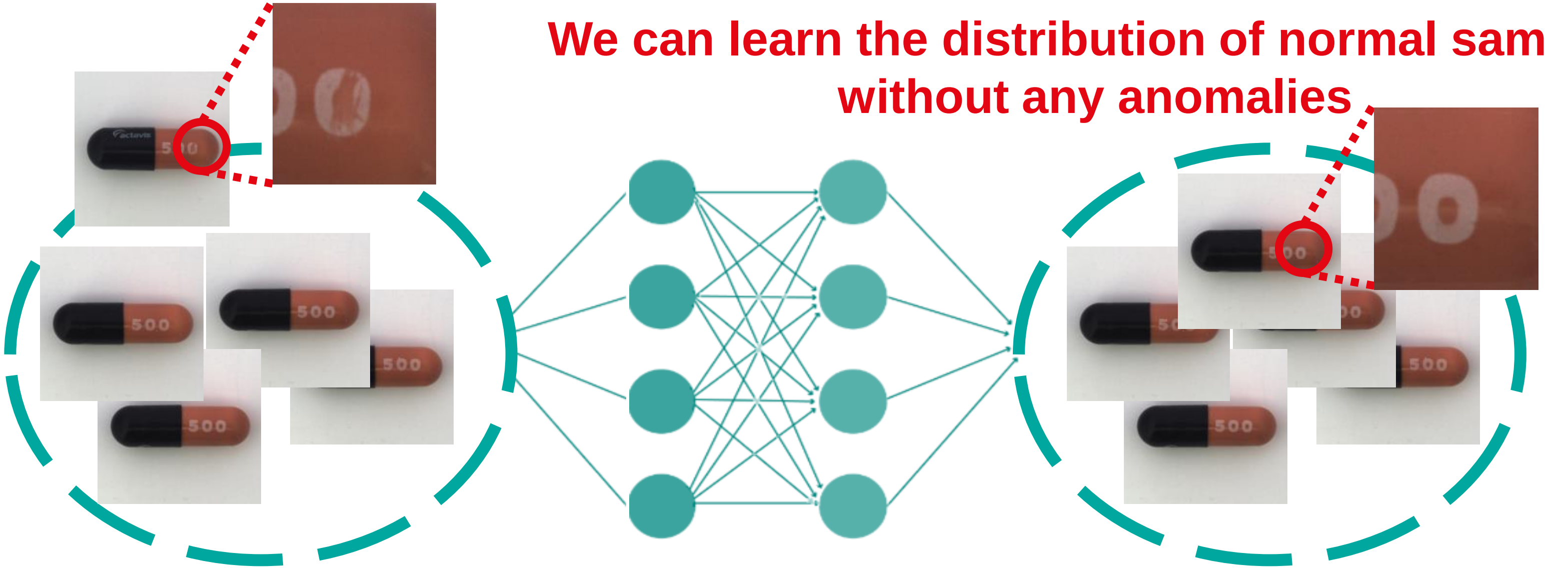


https://www.mvtec.com/company/research/datasets/mvtec-ad

Why anomaly generation?

- **We might not know how the anomalies look like…**
  - **High cost to obtain labeled data**
  - **Rare faulty collection**
  - **Limited representativeness**

We can learn the distribution of normal samples without any anomalies

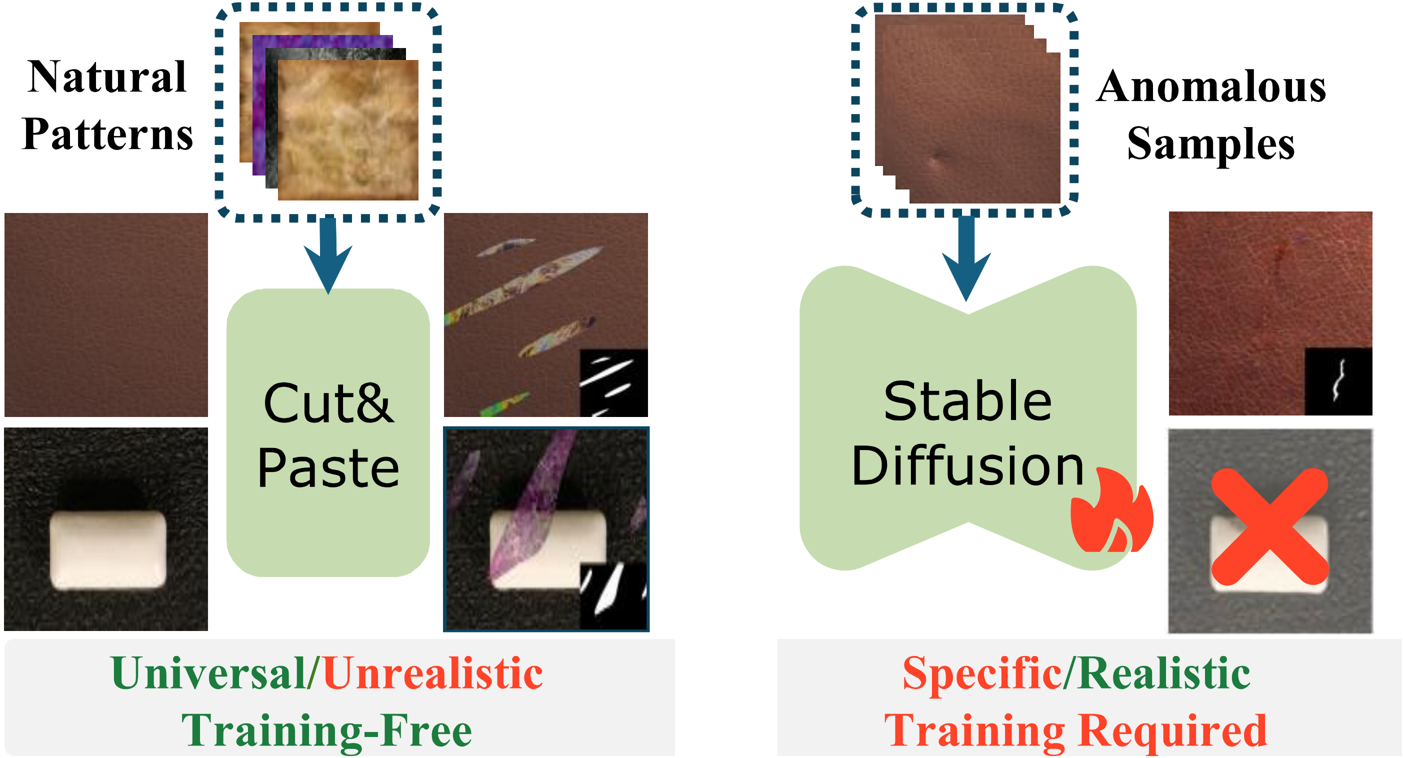


Why anomaly generation?

- HOWEVER, we might neither know how the normal samples look like…
  - Variations of products
  - Different industrial configurations
  - Newly established production line

Let’s generate more anomalous samples!

Anomaly Generation



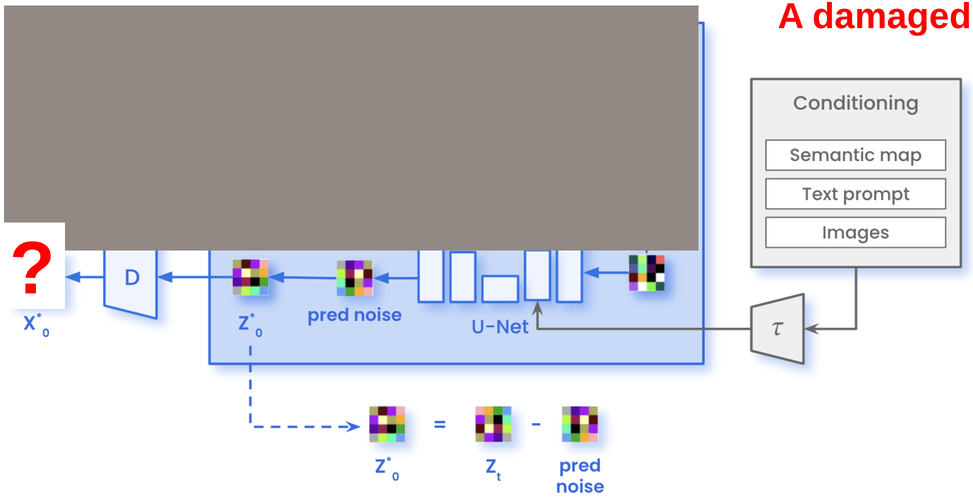
Traditional methods

Generative Modeling

Requirements for Anomay Generation

- Limited normal samples
- No anomalous samples
- Anomaly description
- Applicable to wide range of scenarios

A damaged metal nut



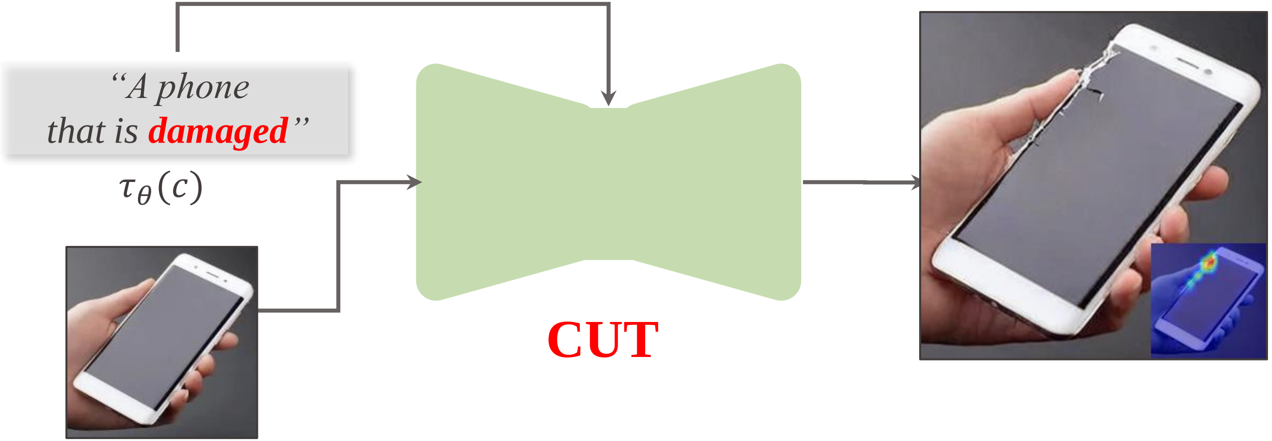
Stable Diffusion

- Trained on billion-scale datasets
- Realistic synthetic images

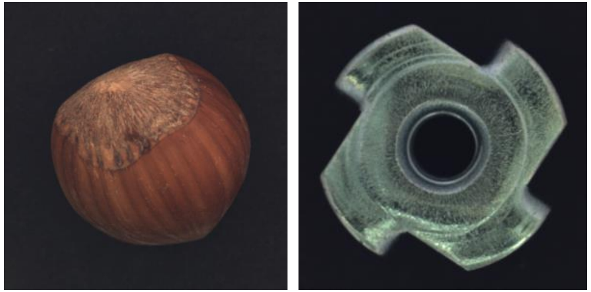
How about generating the anomalies?

Our proposed methodology: CUT

- A **C**ontrollable, **U**niversal, and **T**raining-Free Visual Anomaly Generation Framework
  - Controlled by sample image and text description
  - Applicable to any objects and anomaly types
  - No model training is required

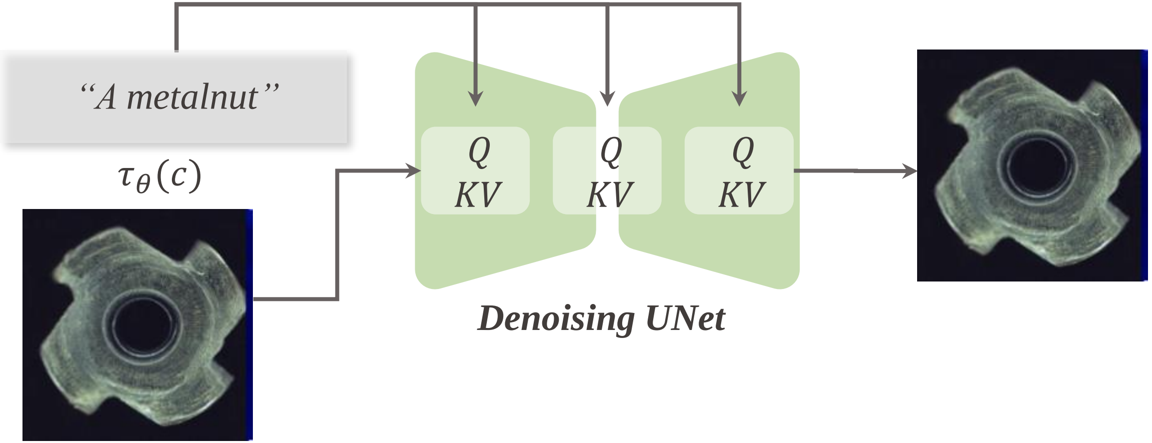


A hazelnut/metal nut

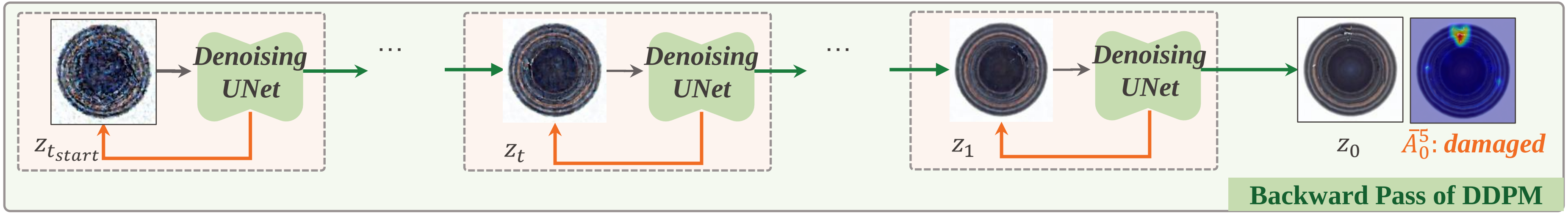


Desired results

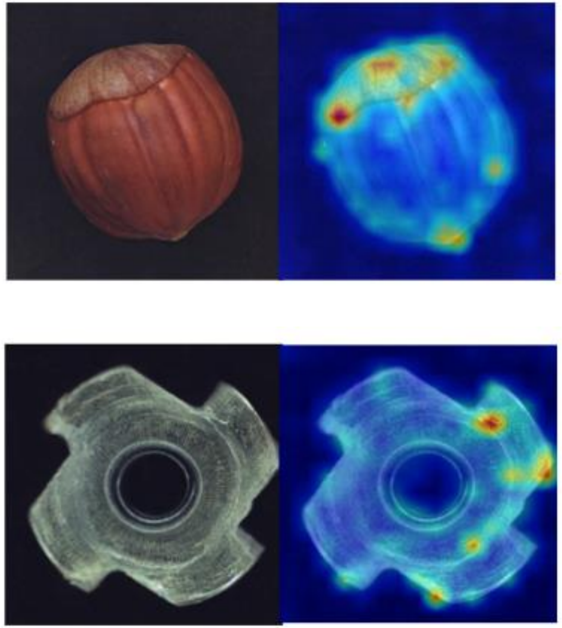
Generated results



Conditioning via one-shot normal sample

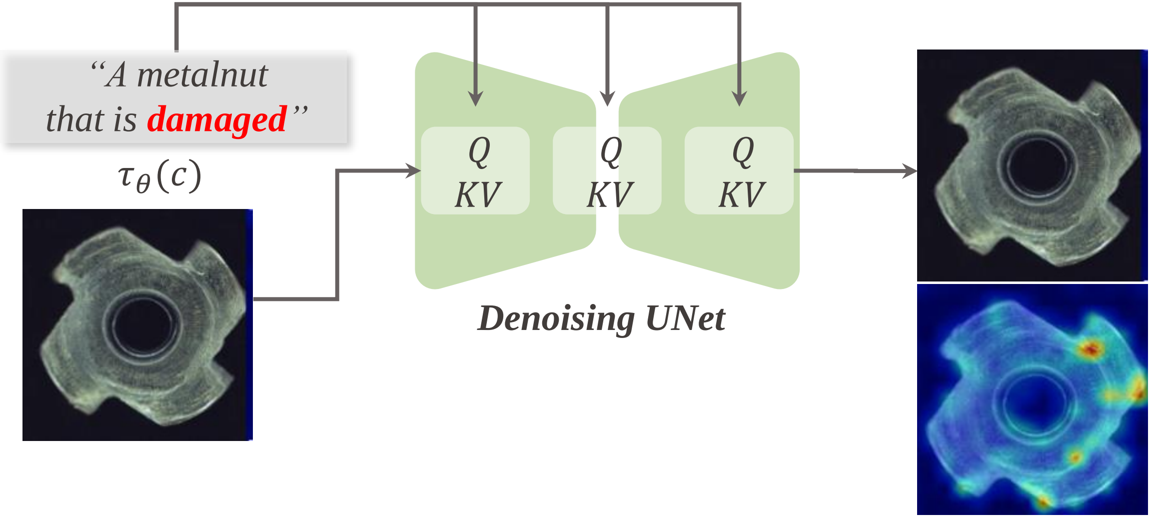


A hazelnut/metal nut that is damaged

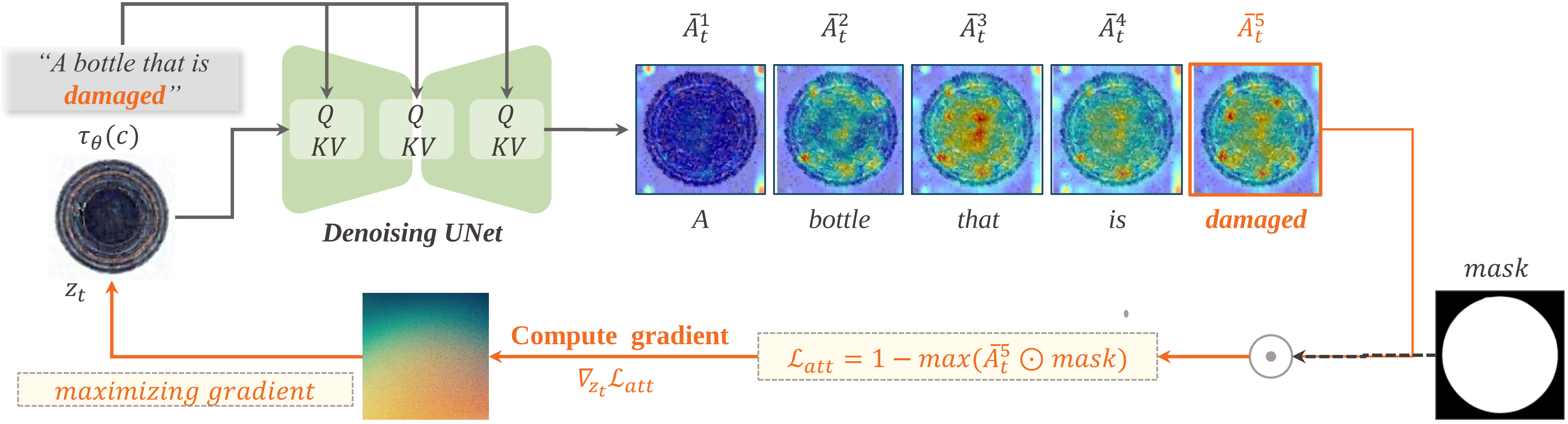


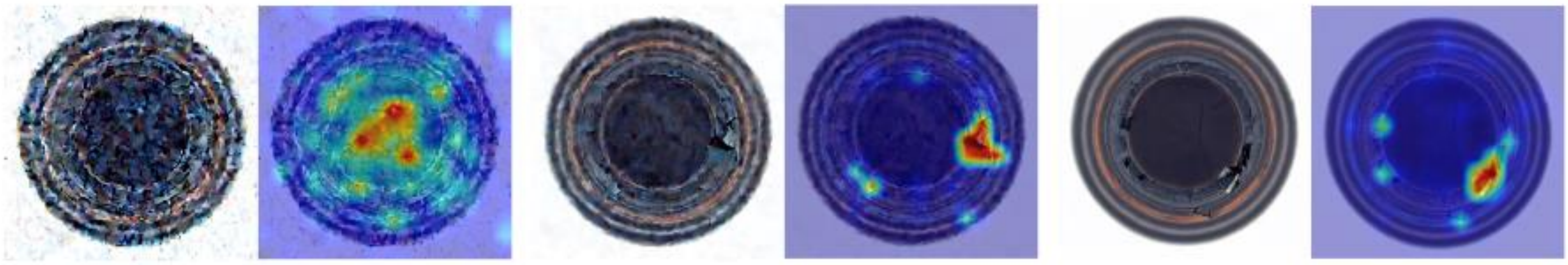
Generated results

Anomaly is a hard concept for diffusion models!

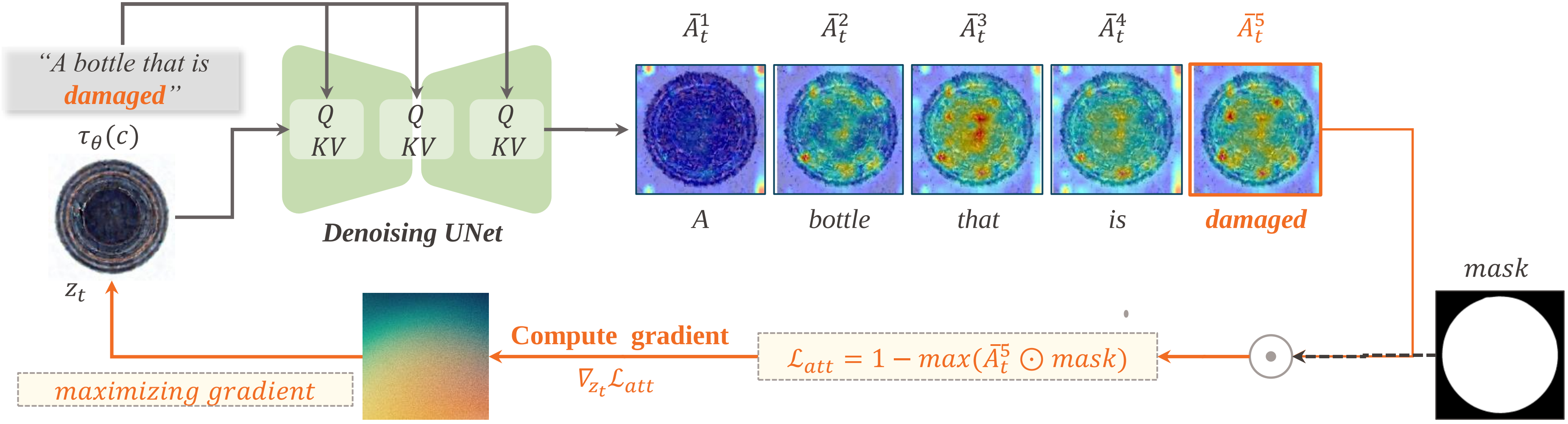


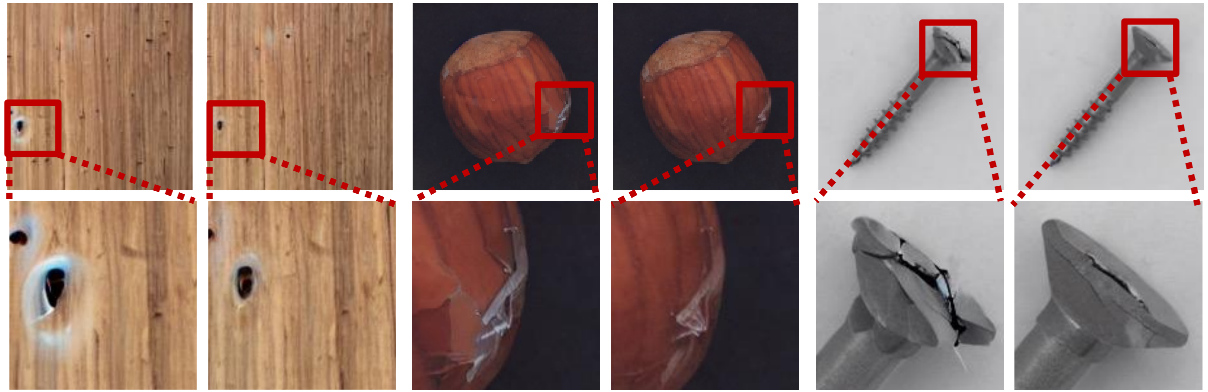
Mask guided attention optimization



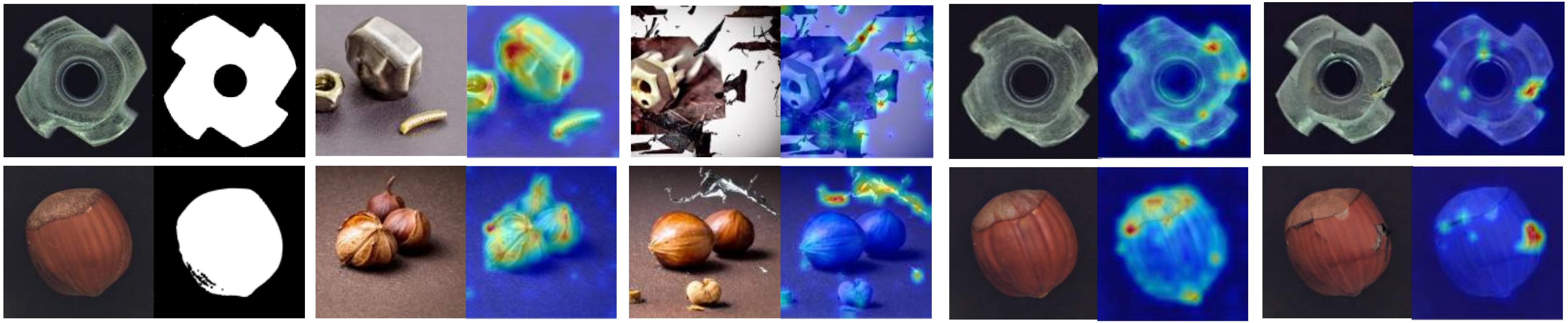


Mask guided attention optimization





Generation with desired object and anomaly type

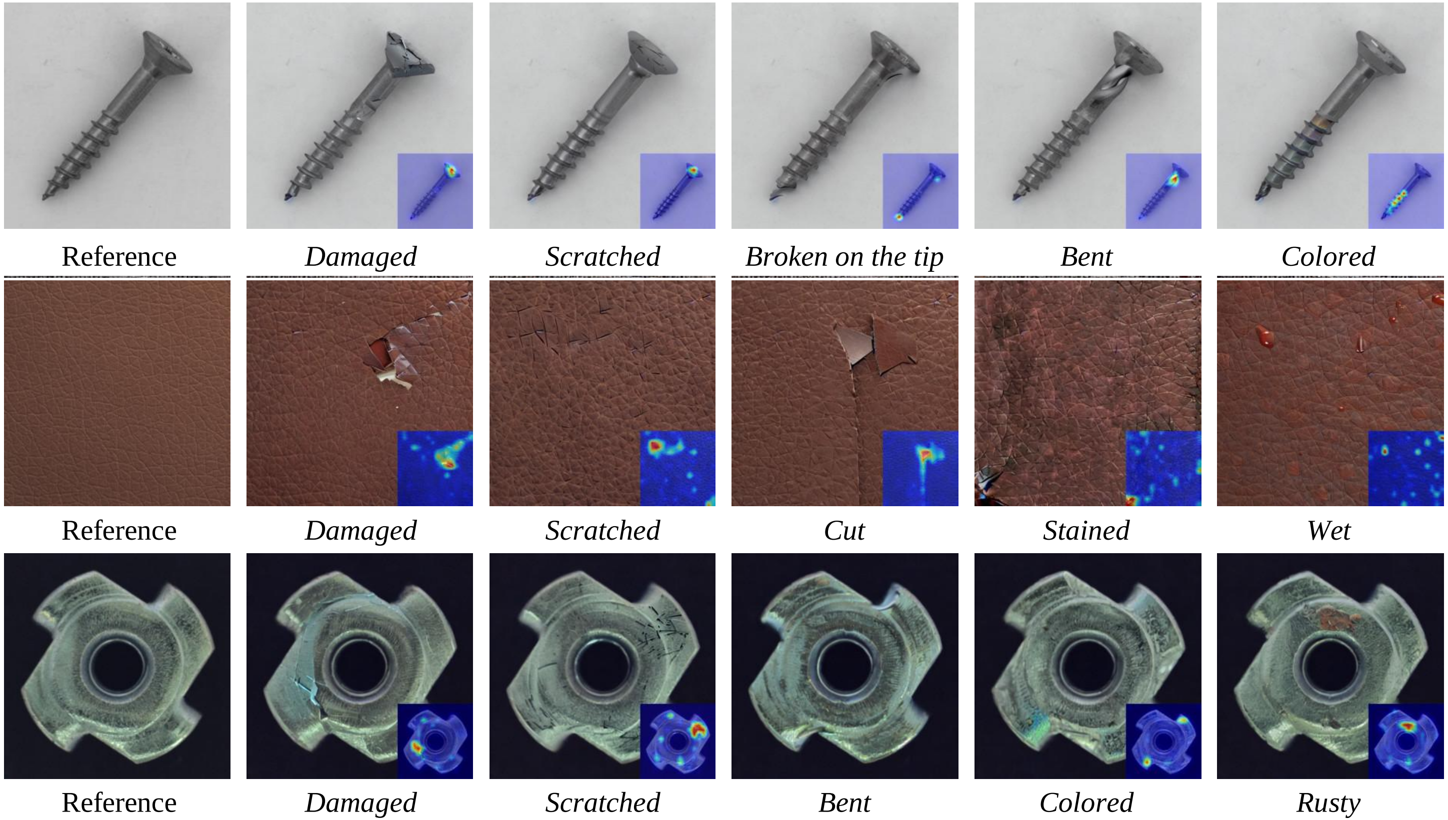


(a) Normal image and mask (b) Stable Diffusion (c) w/o image guidance (d) w/o attention optimization (e) ours

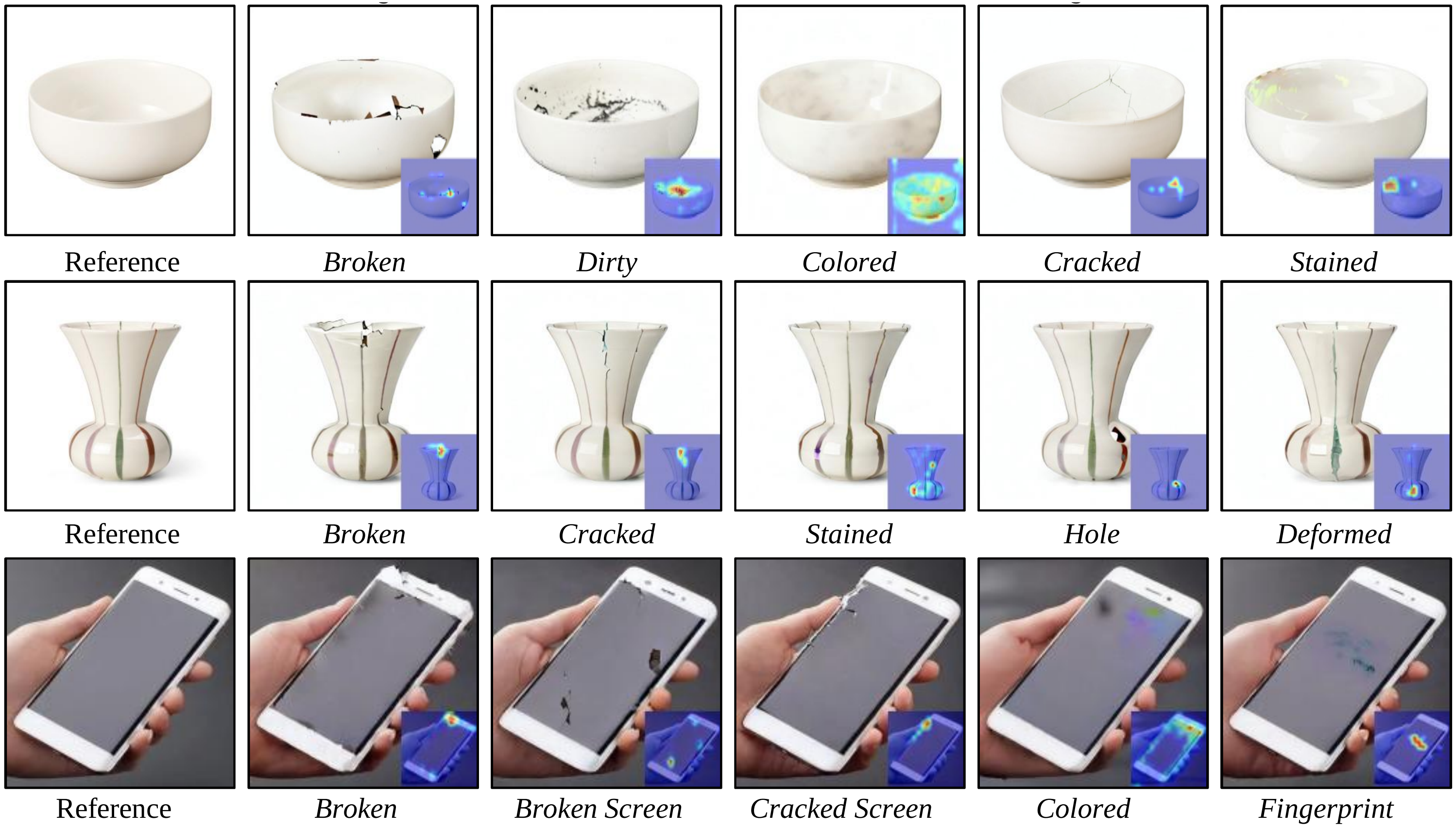
Which one is real

ⓘ Start presenting to display the poll results on this slide.

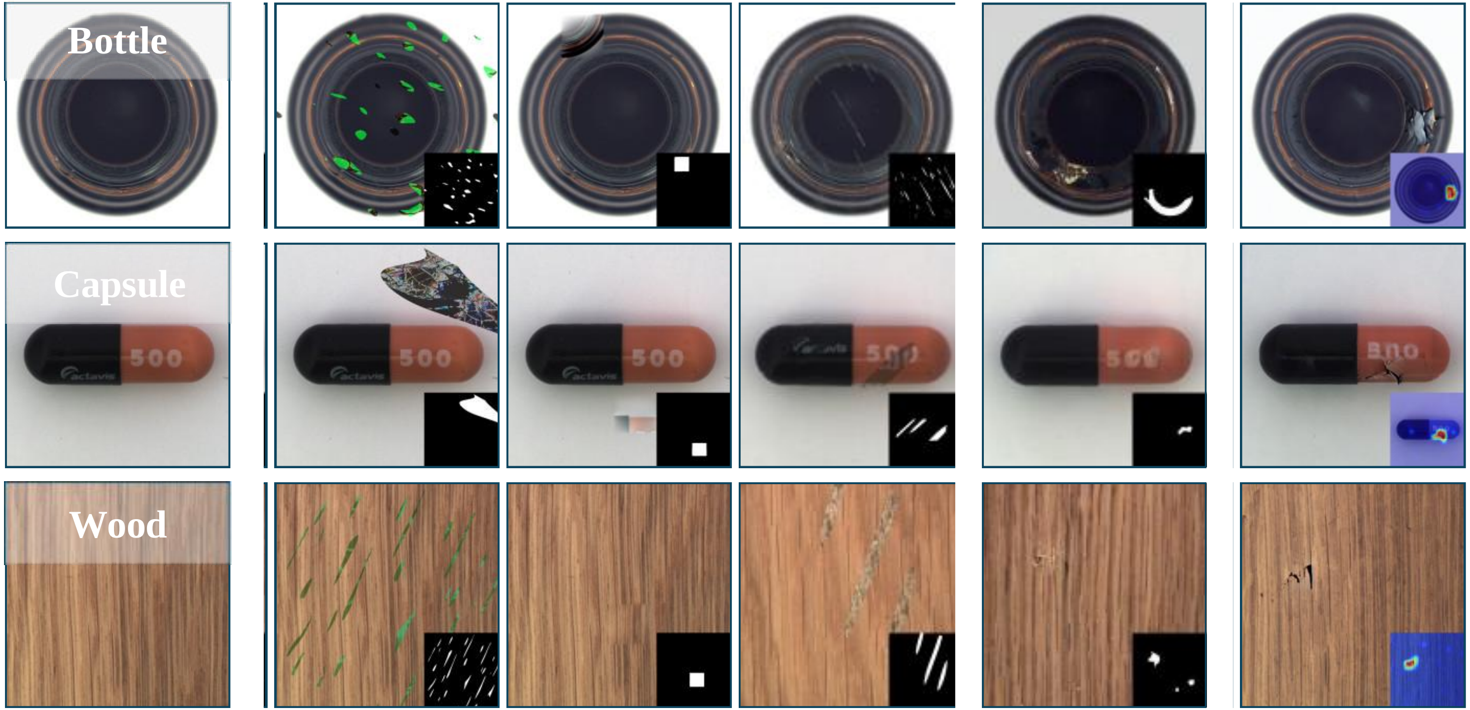
Generation with desired object and anomaly type



Generation with desired object and anomaly type

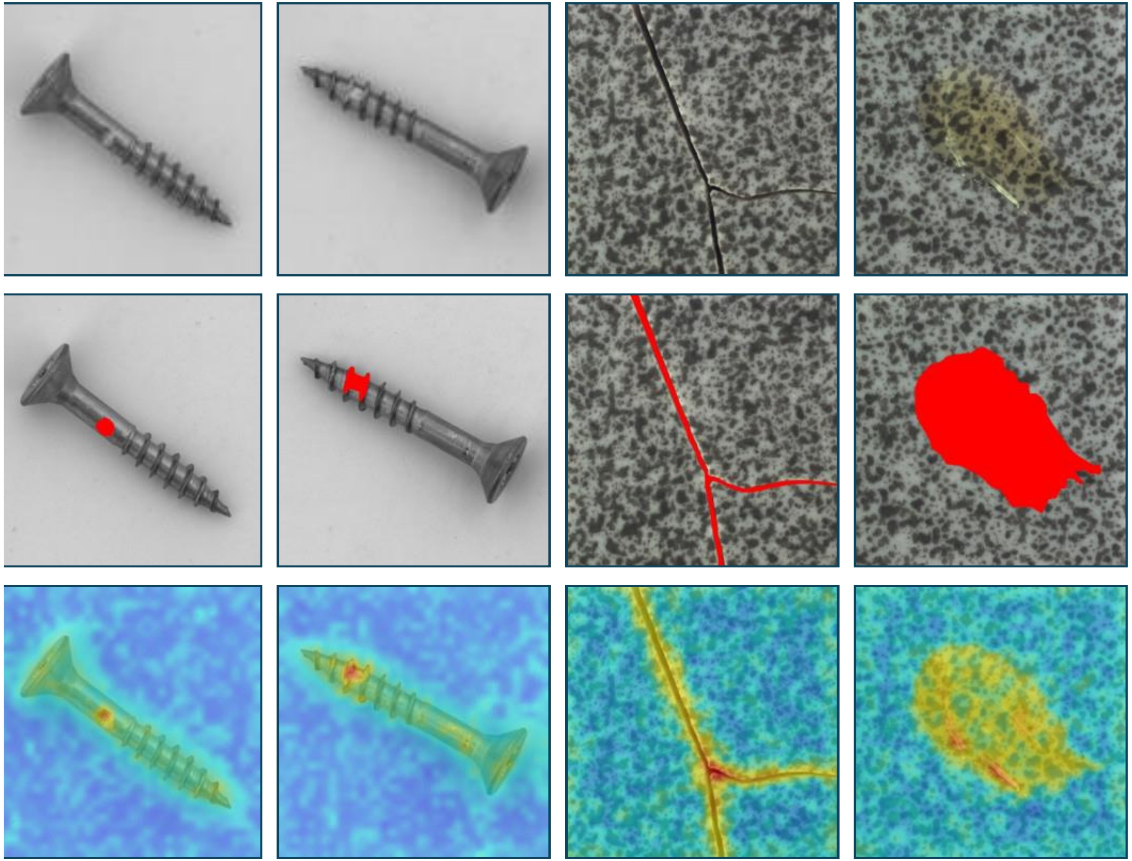


In comparison with other anomaly generation methods



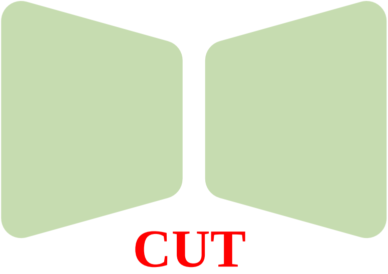
Reference DRAEM NSA RealNet Anomaly Diffusion Ours

Experimental results on anomaly detection



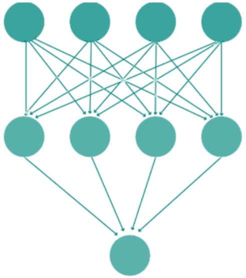
Outlooks

New product



Potential Faults

Expert knowledge



Automatic Detection

EPFL

Thank you!

Han Sun

École
polytechnique
fédérale
de Lausanne

CUT: Stable Diffusion for anomaly generation

- **Good generation capability**
  - Controllable
  - Universal
  - Realistic
- **Little training effort**
  - No model training
  - No anomalies required
  - No manual labeling