# Evasion Attacks Against Various Machine Learning Models

# Recall: Non-traditional Adversarial Attacks

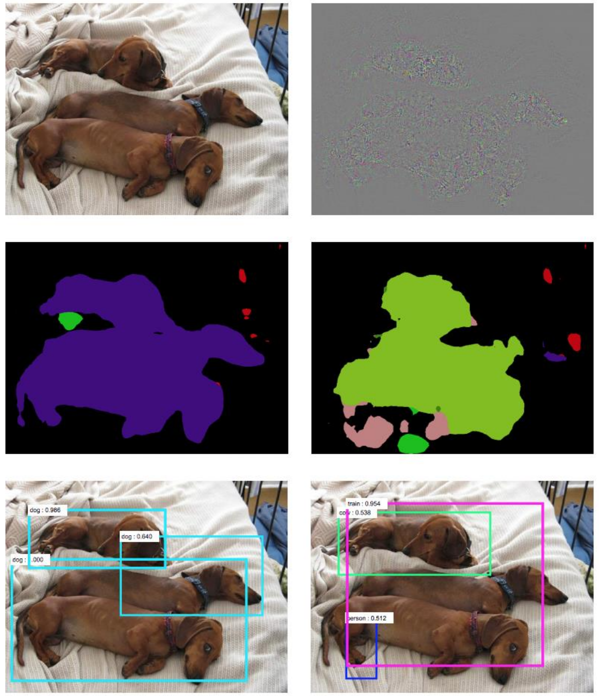
- Leveraging generative adversarial networks --- diverse, realistic, efficient
- Spatially transformed adversarial examples/Wasserstein distance based adv --- diverse, realistic
- Effective physical world attack --- spatial constrained, robust under physical conditions

# Adversarial examples for semantic segmentation and object detection

- Generating adv. is a critical step for evaluating and improving robustness of learning models.
- So far we introduced adv. against classifiers
- What about other learning tasks?

# Adversarial examples for semantic segmentation and object detection

- Both segmentation and detection are based on classifying multiple targets on an image
- Dense adversary generation (DAG)



# Adversarial examples for semantic segmentation and object detection

## Problem statement

Untargeted attack

$$\forall n, \arg\max_c f_c(X + r, t_n) \neq l_n$$

Perturbation targets Ground truth

Targeted attack

$$L(\mathbf{X}, \mathcal{T}, \mathcal{L}, \mathcal{L}') = \sum_{n=1}^{N} \left[ f_{l_n}(\mathbf{X}, t_n) - f_{l'_n}(\mathbf{X}, t_n) \right]$$

**Algorithm 1:** Dense Adversary Generation (DAG)

**Input :** input image $\mathbf{X}$;
the classifier $\mathbf{f}(\cdot, \cdot) \in \mathbb{R}^C$;
the target set $\mathcal{T} = \{t_1, t_2, \ldots, t_N\}$;
the original label set $\mathcal{L} = \{l_1, l_2, \ldots, l_N\}$;
the adversarial label set $\mathcal{L}' = \{l'_1, l'_2, \ldots, l'_N\}$;
the maximal iterations $M_0$;

**Output:** the adversarial perturbation $\mathbf{r}$;

$\mathbf{X}_0 \leftarrow \mathbf{X}$, $\mathbf{r} \leftarrow \mathbf{0}$, $m \leftarrow 0$, $\mathcal{T}_0 \leftarrow \mathcal{T}$;
**while** $m < M_0$ **and** $\mathcal{T}_m \neq \varnothing$ **do**
  $\mathcal{T}_m = \{t_n \mid \arg\max_c \{f_c(\mathbf{X}_m, t_n)\} = l_n\}$;
  $\mathbf{r}_m \leftarrow$
  $\sum_{t_n \in \mathcal{T}_m} \left[\nabla_{\mathbf{X}_m} f_{l'_n}(\mathbf{X}_m, t_n) - \nabla_{\mathbf{X}_m} f_{l_n}(\mathbf{X}_m, t_n)\right]$;
  $\mathbf{r}'_m \leftarrow \frac{\gamma}{\|\mathbf{r}_m\|_\infty} \mathbf{r}_m$;
  $\mathbf{r} \leftarrow \mathbf{r} + \mathbf{r}'_m$;
  $\mathbf{X}_{m+1} \leftarrow \mathbf{X}_m + \mathbf{r}'_m$;
  $m \leftarrow m + 1$;
**end**
**Return:** $\mathbf{r}$

# Transferability analysis

- Cross training transfer
  - Models are trained with different subset of data
- Cross network transfer
  - Models are of different architecture
- Cross task transfer
  - Use the perturbation generated against detection to attack a segmentation network

| Adversarial Perturbations from | **FR-ZF-07** | **FR-ZF-0712** | **FR-VGG-07** | **FR-VGG-0712** | **R-FCN-RN50** | **R-FCN-RN101** |
|---|---|---|---|---|---|---|
| **None** | 58.70 | 61.07 | 69.14 | 72.07 | 76.40 | 78.06 |
| **FR-ZF-07** ($\mathbf{r}_1$) | **3.61** | 22.15 | 66.01 | 69.47 | 74.01 | 75.87 |
| **FR-ZF-0712** ($\mathbf{r}_2$) | 13.14 | **1.95** | 64.61 | 68.17 | 72.29 | 74.68 |
| **FR-VGG-07** ($\mathbf{r}_3$) | 56.41 | 59.31 | **5.92** | 48.05 | 72.84 | 74.79 |
| **FR-VGG-0712** ($\mathbf{r}_4$) | 56.09 | 58.58 | 31.84 | **3.36** | 70.55 | 72.78 |
| $\mathbf{r}_1 + \mathbf{r}_3$ | **3.98** | 21.63 | **7.00** | 44.14 | 68.89 | 71.56 |
| $\mathbf{r}_1 + \mathbf{r}_3$ (permute) | 58.30 | 61.08 | 68.63 | 71.82 | 76.34 | 77.71 |
| $\mathbf{r}_2 + \mathbf{r}_4$ | 13.15 | **2.13** | 28.92 | **4.28** | 63.93 | 67.25 |
| $\mathbf{r}_2 + \mathbf{r}_4$ (permute) | 58.51 | 61.09 | 68.68 | 71.78 | 76.23 | 77.71 |

Cross training

| Adversarial Perturbations from | **FCN-Alex** | **FCN-Alex*** | **FCN-VGG** | **FCN-VGG*** | **DL-VGG** | **DL-RN101** |
|---|---|---|---|---|---|---|
| **None** | 48.04 | 48.92 | 65.49 | 67.09 | 70.72 | 76.11 |
| **FCN-Alex** ($\mathbf{r}_5$) | **3.98** | 7.94 | 64.82 | 66.54 | 70.18 | 75.45 |
| **FCN-Alex*** ($\mathbf{r}_6$) | 5.10 | **3.98** | 64.60 | 66.36 | 69.98 | 75.52 |
| **FCN-VGG** ($\mathbf{r}_7$) | 46.21 | 47.38 | **4.09** | 16.36 | 45.16 | 73.98 |
| **FCN-VGG*** ($\mathbf{r}_8$) | 46.10 | 47.21 | 12.72 | **4.18** | 46.33 | 73.76 |
| $\mathbf{r}_5 + \mathbf{r}_7$ | **4.83** | 8.55 | **4.23** | 17.59 | 43.95 | 73.26 |
| $\mathbf{r}_5 + \mathbf{r}_7$ (permute) | 48.03 | 48.90 | 65.47 | 67.09 | 70.69 | 76.04 |
| $\mathbf{r}_6 + \mathbf{r}_8$ | 5.52 | **4.23** | 13.89 | **4.98** | 44.18 | 73.01 |
| $\mathbf{r}_6 + \mathbf{r}_8$ (permute) | 48.03 | 48.90 | 65.47 | 67.05 | 70.69 | 76.05 |

Cross Network

# Takeaways

- Heuristically generate perturbation to move each target towards the adversarial goal
- Transferability exists for adversarial examples for segmentation/detection
- Adding multiple adversarial perturbations often works better than adding a single source of perturbation in terms of transferability

# Similar work

- Delving into transferable adversarial examples and black-box attacks
  - Apply ensemble attack to attack multiple models to increase targeted transferability
  - Multi-source perturbation helps?

Ground truth: running shoe

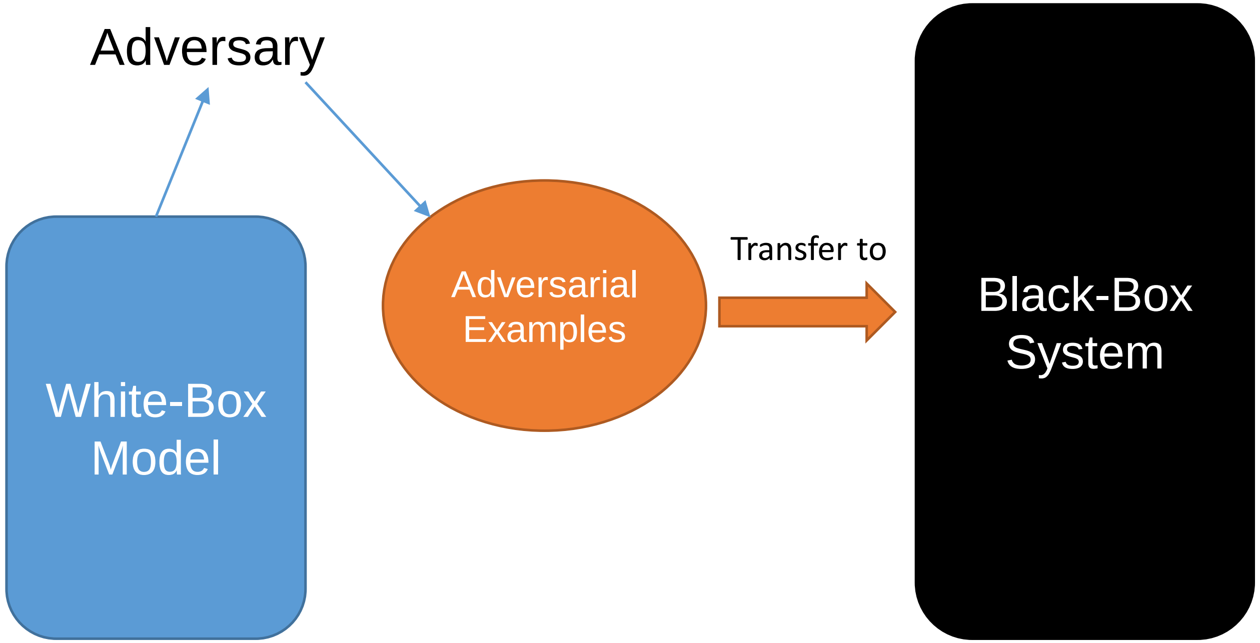
| | |
|---|---|
| **VGG16** | **Military uniform** |
| ResNet50 | Jigsaw puzzle |
| ResNet101 | Motor scooter |
| ResNet152 | Mask |
| GoogLeNet | Chainsaw |

# Targeted Adversarial Example's Transferability Among **Two Models** is **Poor**!

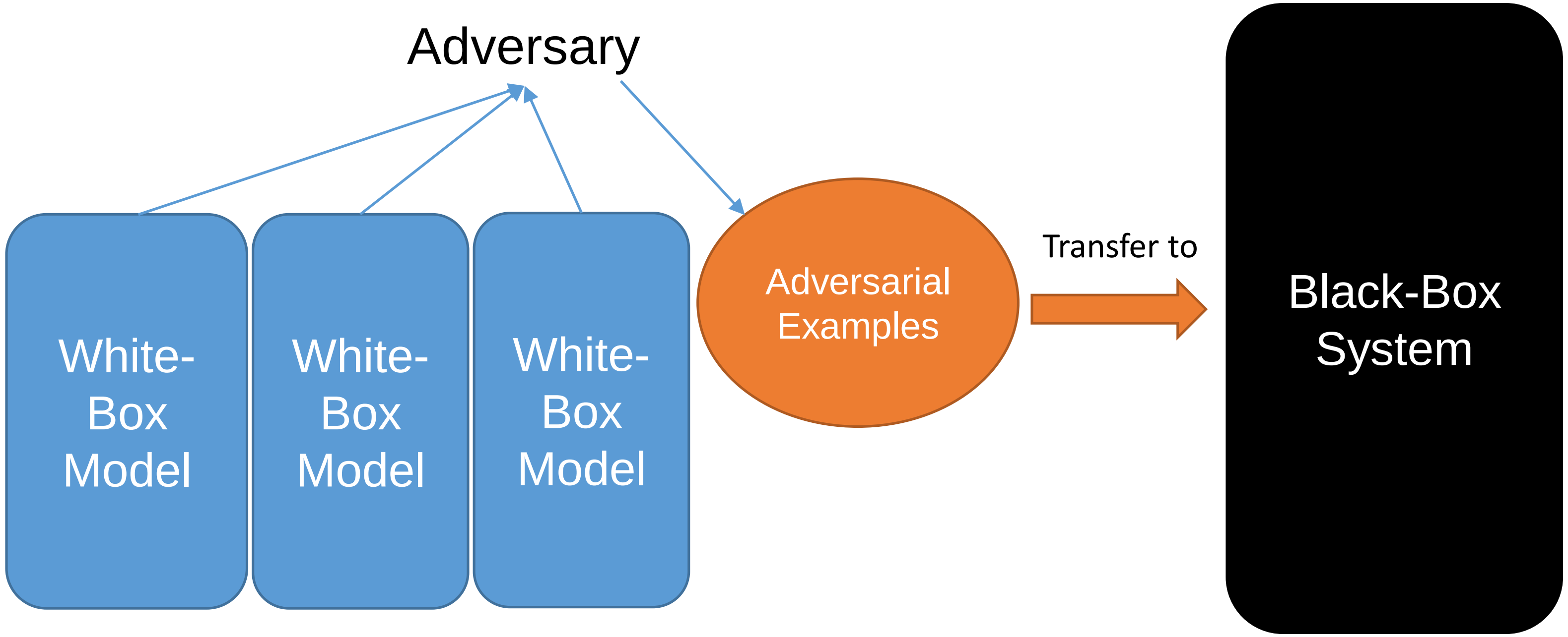
| | ResNet152 | ResNet101 | ResNet50 | VGG16 | GoogLeNet | Incept-v3 |
|---|---|---|---|---|---|---|
| ResNet152 | 100% | 2% | 1% | 1% | 1% | 0% |
| ResNet101 | 3% | 100% | 3% | 2% | 1% | 1% |
| ResNet50 | 4% | 2% | 100% | 1% | 1% | 0% |
| VGG16 | 2% | 1% | 2% | 100% | 1% | 0% |
| GoogLeNet | 1% | 1% | 0% | 1% | 100% | 0% |
| Incept-v3 | 0% | 0% | 0% | 0% | 0% | 100% |

Only 2% of the adversarial images generated for VGG16 (row) can be predicted as the targeted label by ResNet50 (column)

# Black-box Attacks Based On Transferability



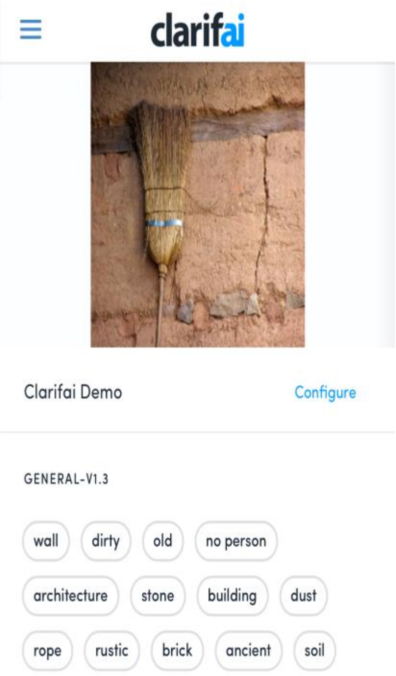
# Ensemble Targeted Black-box Attacks Based On Transferability

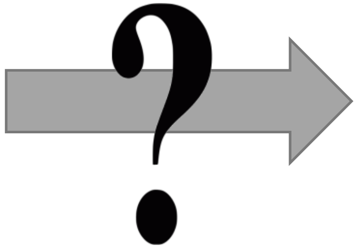


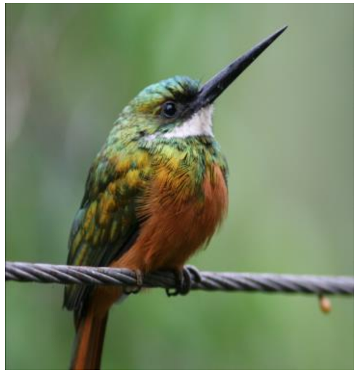
# Clarifai.com

Ground truth from ImageNet: broom

**jacamar**

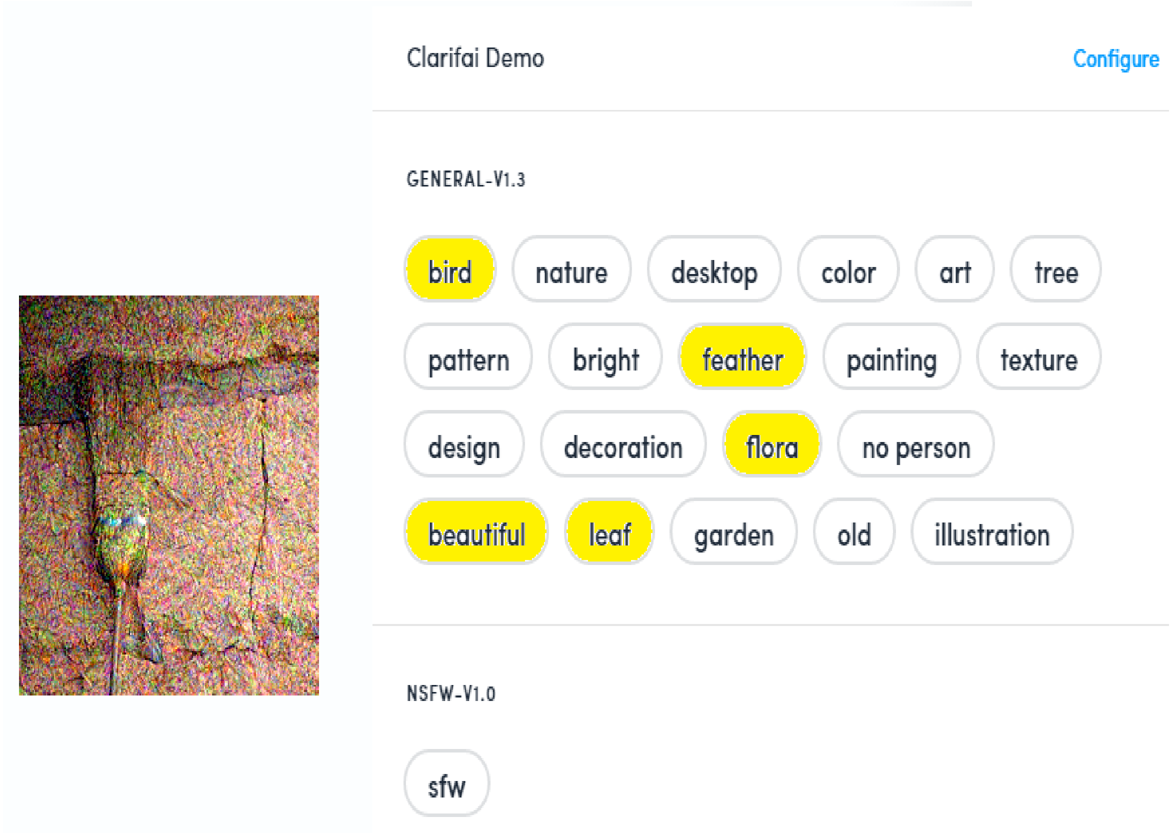




# Adversarial Example on Clarifai.com

- Ground truth: broom
- Target label: **jacamar**



# Similar work

- Physical Adversarial Examples for Object Detectors

$$J_d(x,y) = \max_{s \in S^2, b \in B} P(s, b, y, f_\theta(x))$$

Cell in YOLO    Bounding box

Difference: instead of ensemble over models, here it ensembles over object regions

# Houdini: Fooling Deep Structured Prediction Models

- Other deterministic objective function for attacking different learning models?
- Houdini: tailored for the final performance measure
  - Speech recognition
  - Pose estimation
  - Semantic segmentation

# Houdini: Fooling Deep Structured Prediction Models

- Optimization based method

$$\tilde{x} = \underset{\tilde{x}:\|\tilde{x}-x\|_p \leq \epsilon}{\operatorname{argmax}} \ \ell\big(y_\theta(\tilde{x}), y\big) \qquad f_2(x') = (\max_{i \neq t}(F(x')_i) - F(x')_t)^+$$

- Houdini

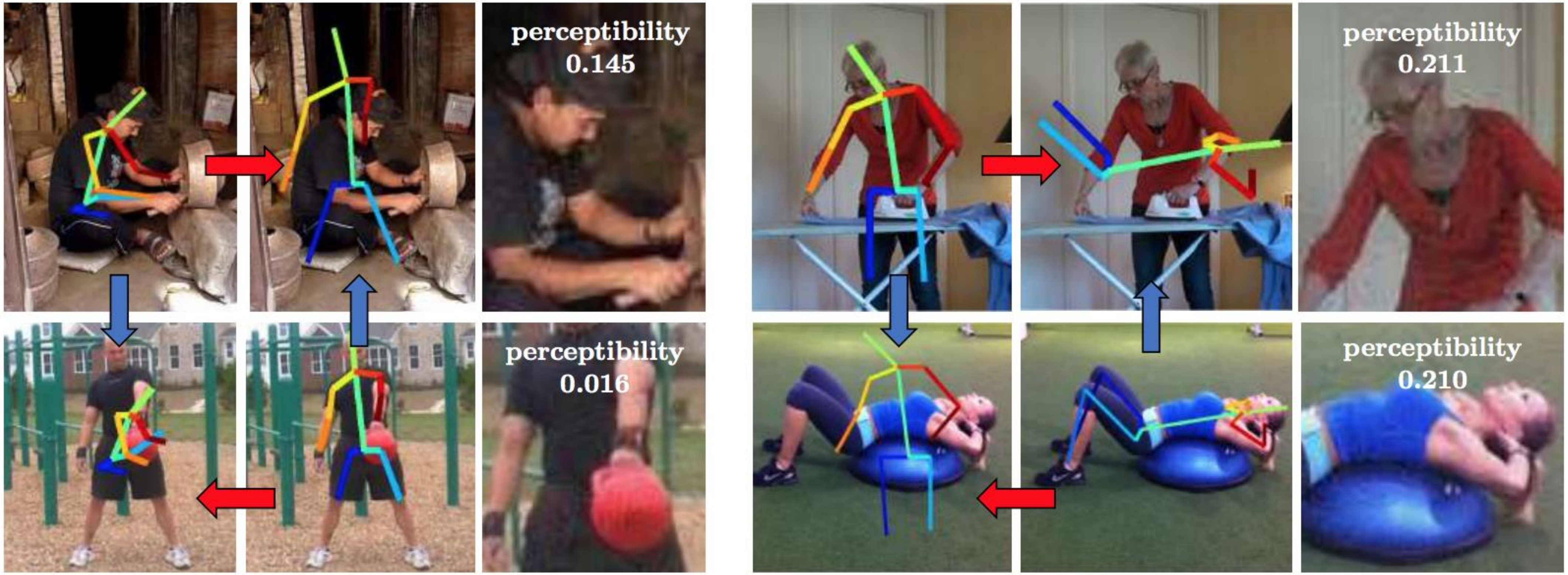
$$\bar{\ell}_H(\theta, x, y) = \underbrace{\mathbb{P}_{\gamma \sim \mathcal{N}(0,1)}\Big[g_\theta(x, y) - g_\theta(x, \hat{y}) < \gamma\Big]}_{\text{Stochastic margin, Confidence of the model}} \cdot \underbrace{\ell(\hat{y}, y)}_{\text{Task loss}}$$

Stochastic margin
Confidence of the model

Task loss

**original semantic segmentation framework** **adversarial attack** **compromised semantic segmentation framework**

(a) initial prediction (b) adversarial prediction (c) source image (d) perturbed image (e) noise


perceptibility
0.145
perceptibility
0.016
perceptibility
0.211
perceptibility
0.210

| | $\epsilon = 0.3$ | | $\epsilon = 0.2$ | | $\epsilon = 0.1$ | | $\epsilon = 0.05$ | |
|---|---|---|---|---|---|---|---|---|
| | WER | CER | WER | CER | WER | CER | WER | CER |
| CTC | 68 | 9.3 | 51 | 6.9 | 29.8 | 4 | 20 | 2.5 |
| Houdini | 96.1 | 12 | 85.4 | 9.2 | 66.5 | 6.5 | 46.5 | 4.5 |

Groundtruth Transcription:
The fact that a man can recite a poem does not show he remembers any previous occasion on which he has recited it or read it.

G-Voice transcription of the original example:
The fact that a man can decide a poem does not show he remembers any previous occasion on which he has work cited or read it.

G-Voice transcription of the adversarial example:
The fact that I can rest I'm just not sure that you heard there is any previous occasion I am at he has your side it or read it.

Groundtruth Transcription:
Her bearing was graceful and animated she led her son by the hand and before her walked two maids with wax lights and silver candlesticks.

G-Voice transcription of the original example:
The bearing was graceful an animated she let her son by the hand and before he walks two maids with wax lights and silver candlesticks.

G-Voice transcription of the adversarial example:
Mary was grateful then admitted she let her son before the walks to Mays would like slice furnace filter count six.

# Takeaways

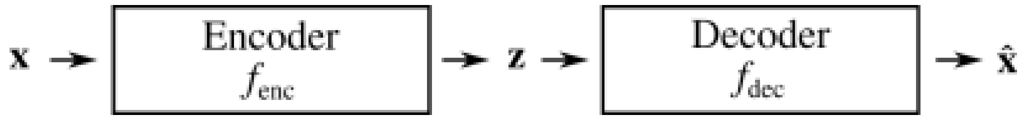
- By adding margin based constraint together with the task loss, the attack can be generated against a range of tasks with high confidence
- Targeted attacks seem to be more challenging when dealing with speech recognition systems than when we consider artificial visual systems such as pose estimators or semantic segmentation systems
- Adversarial audios also transfer among models

# Adversarial Examples for Generative Models

- Idea: Create adversarial inputs that can control the latent space of a generative model.
- Generate based on adversarial target

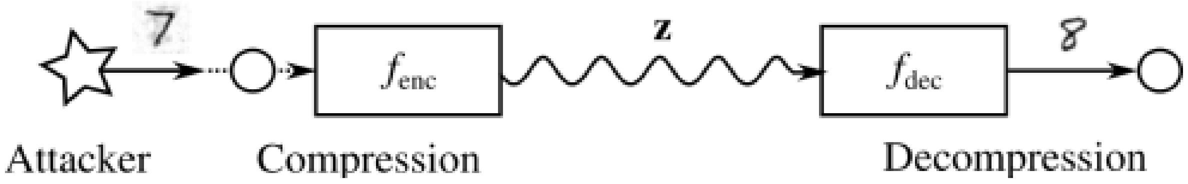
# Adversarial Examples for Generative Models

- Generative Models.
  - An **encoder** maps a high-dimensional input into lower-dimensional latent representation.
  - A **decoder** maps the latent representation back to a high-dimensional reconstruction.
  - A **latent space** is an internal representation of the data.



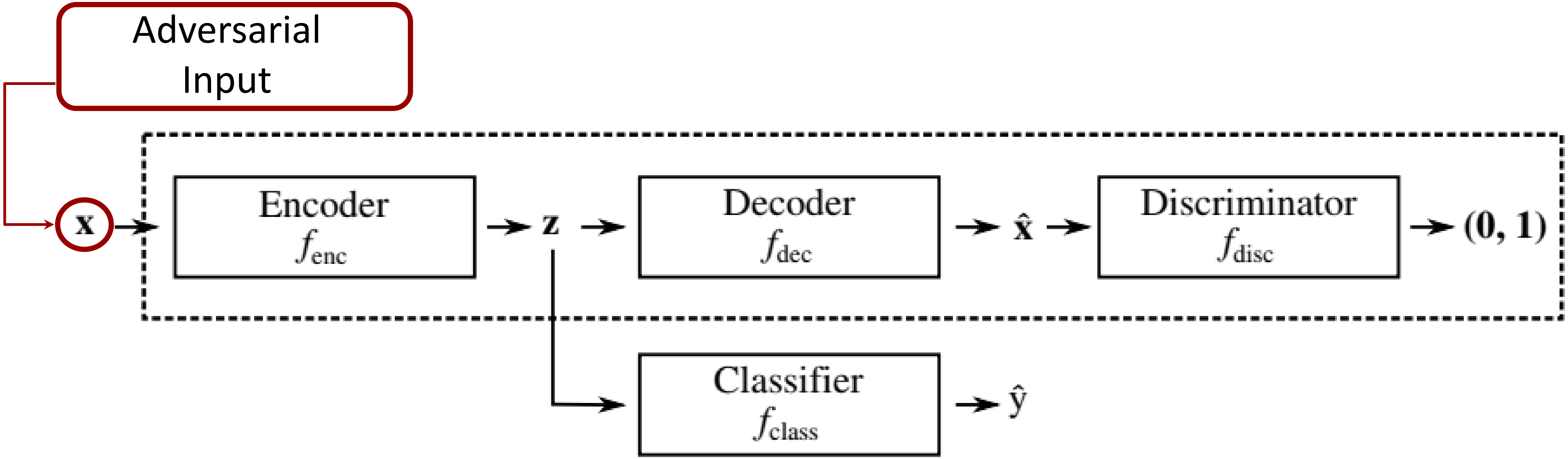
# Adversarial Examples for Generative Models

- An example attack scenario:
  - Generative model used as a compression scheme

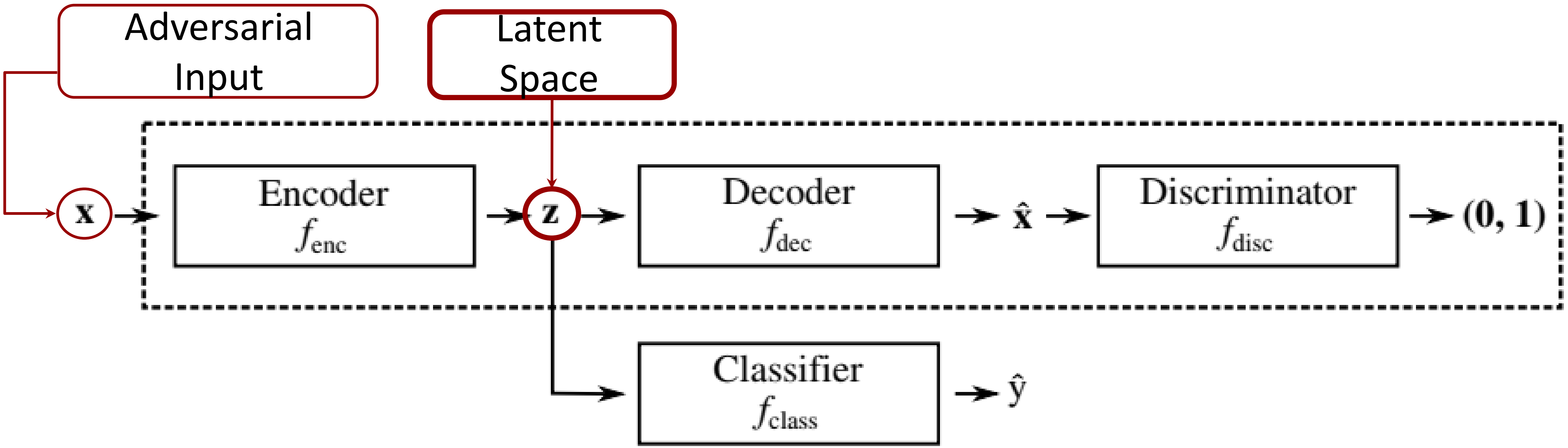



  - Attacker's goal: for the decompressor to reconstruct a different image from the one that the compressor sees.

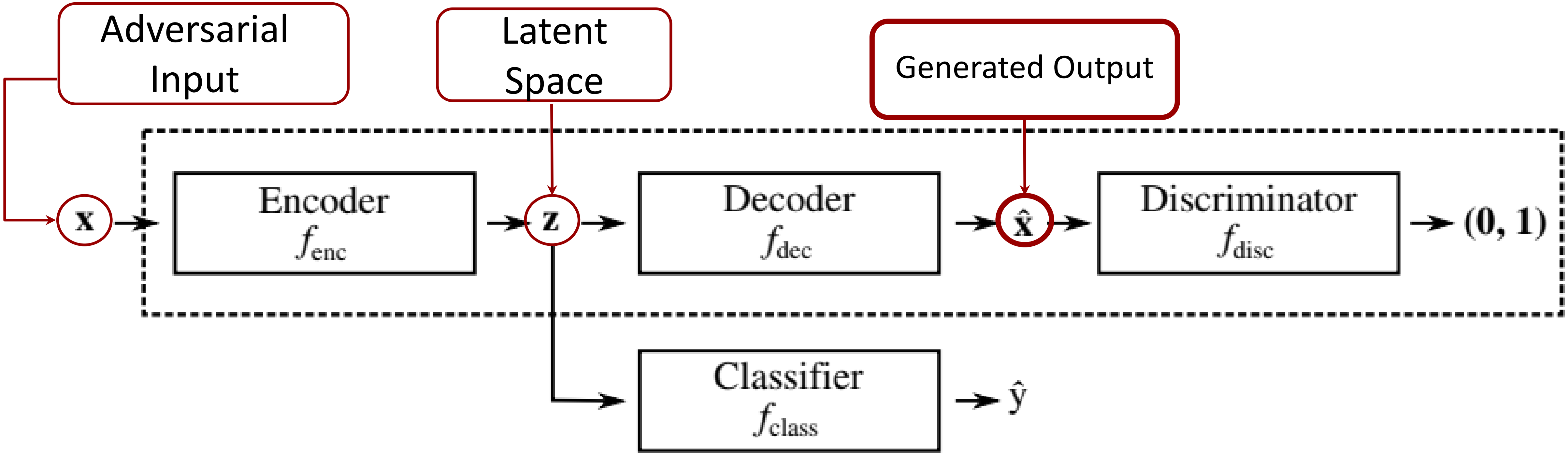
# Adversarial Examples for Generative Models



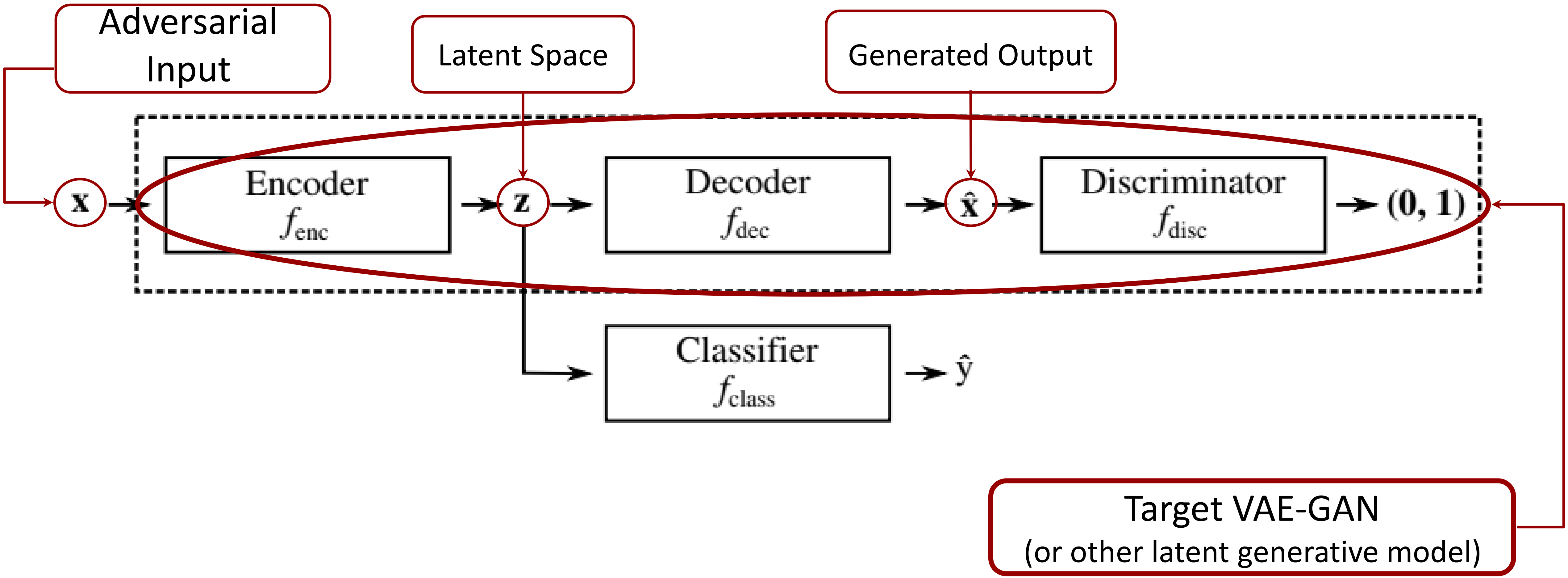
# Adversarial Examples for Generative Models



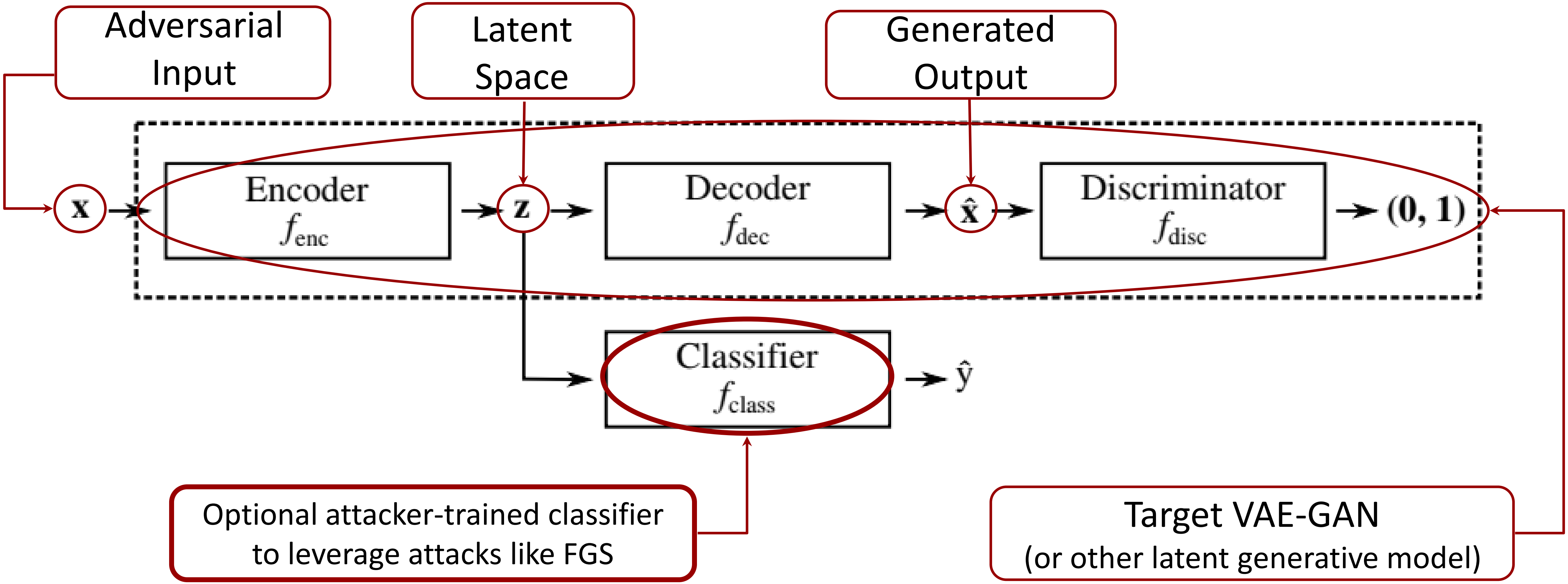
# Adversarial Examples for Generative Models



# Adversarial Examples for Generative Models



# Adversarial Examples for Generative Models

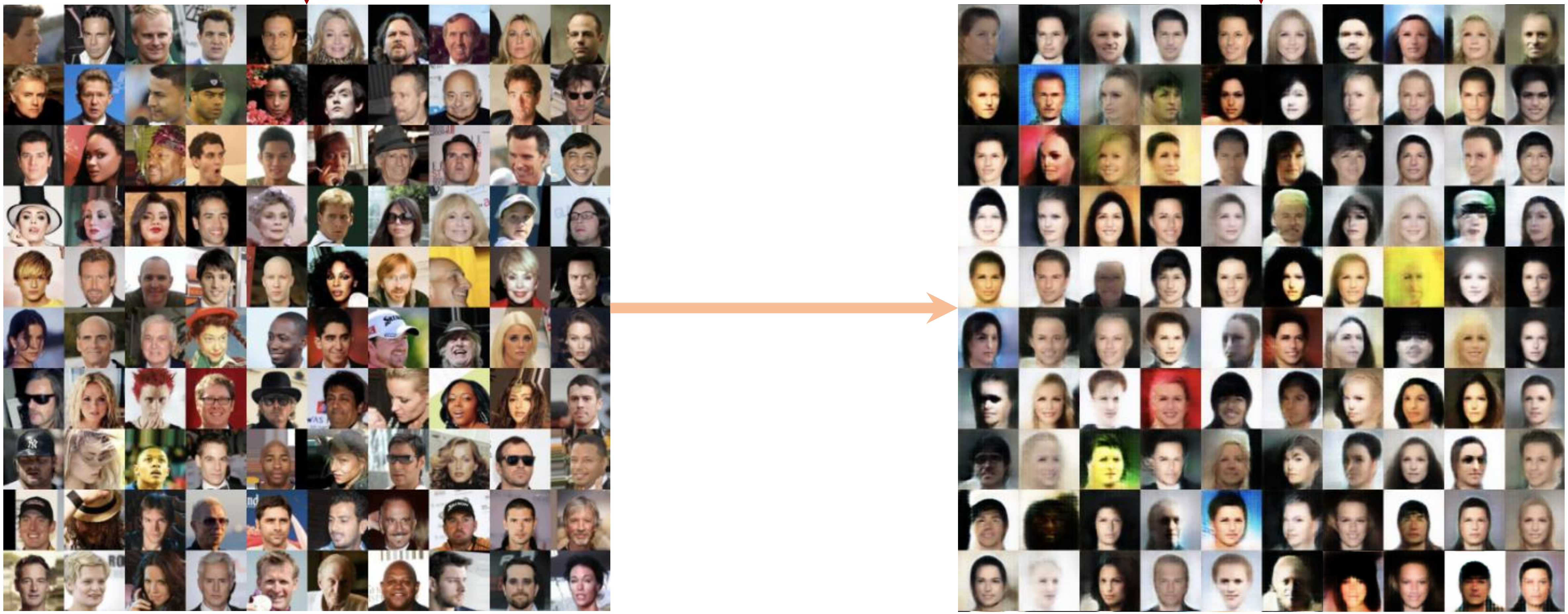



$$\arg\min_{x*} L(x, x*) \qquad s.t. Oracle(G_{targ}(x*)) = y^t$$

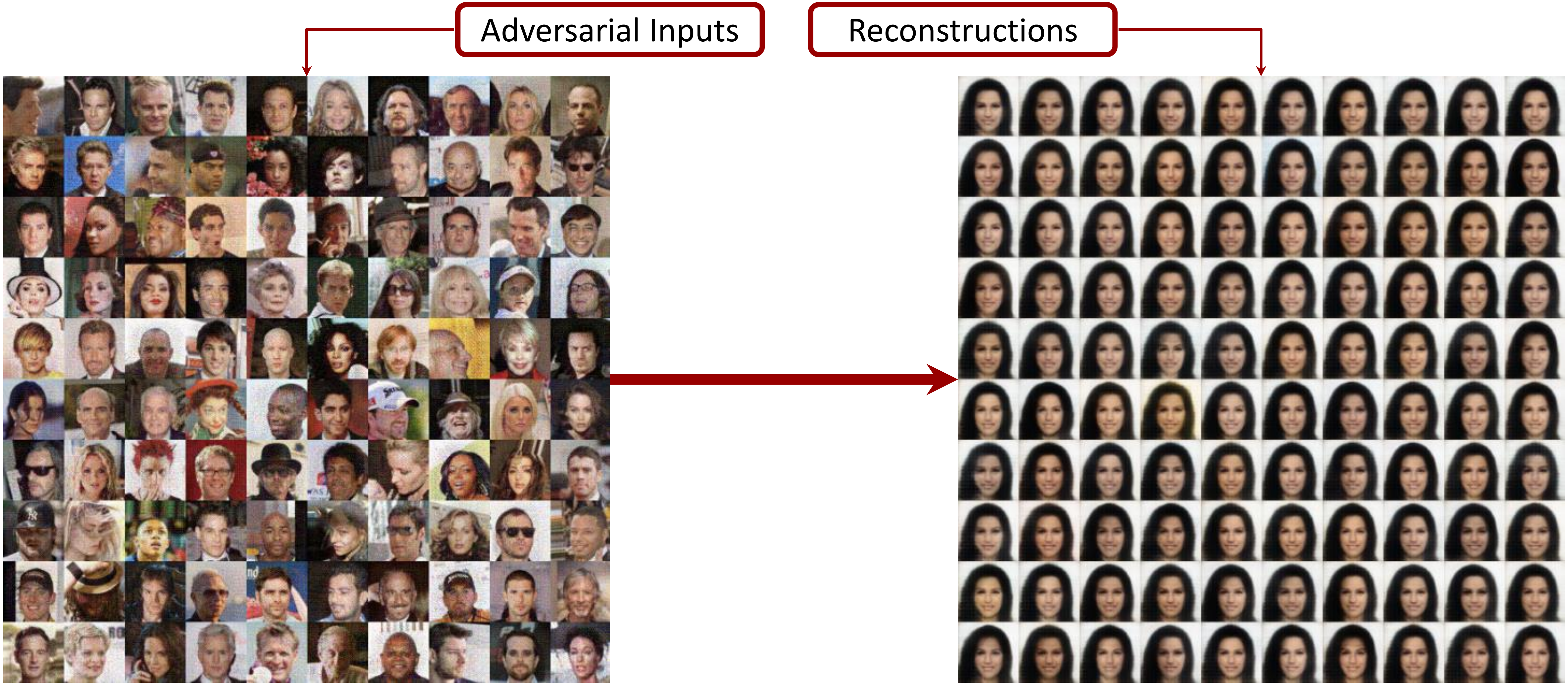
# Adversarial Examples for Generative Models

Original Inputs

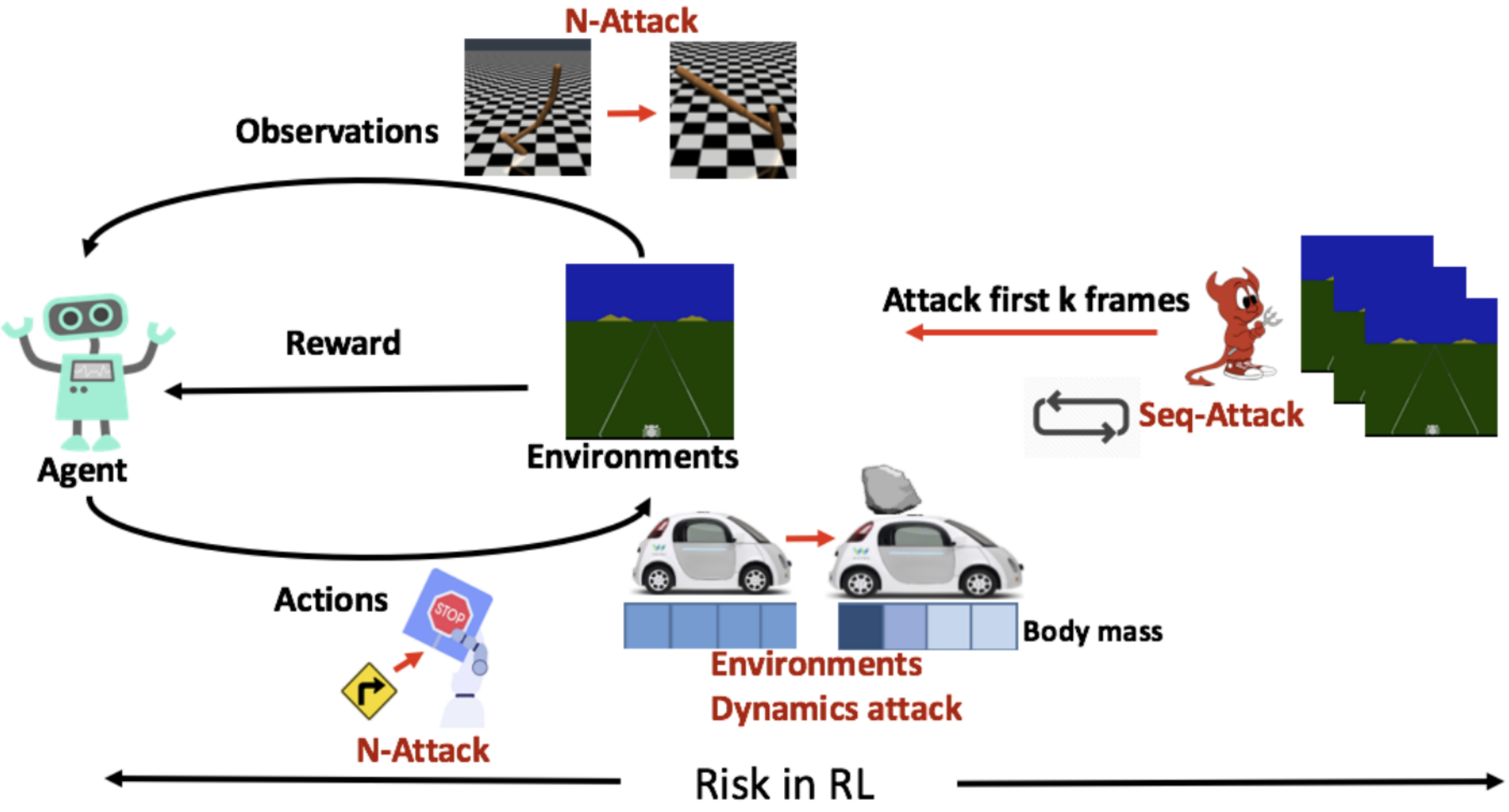
Reconstructions



# Adversarial Examples for Generative Models



# Attacking Deep Reinforcement Learning



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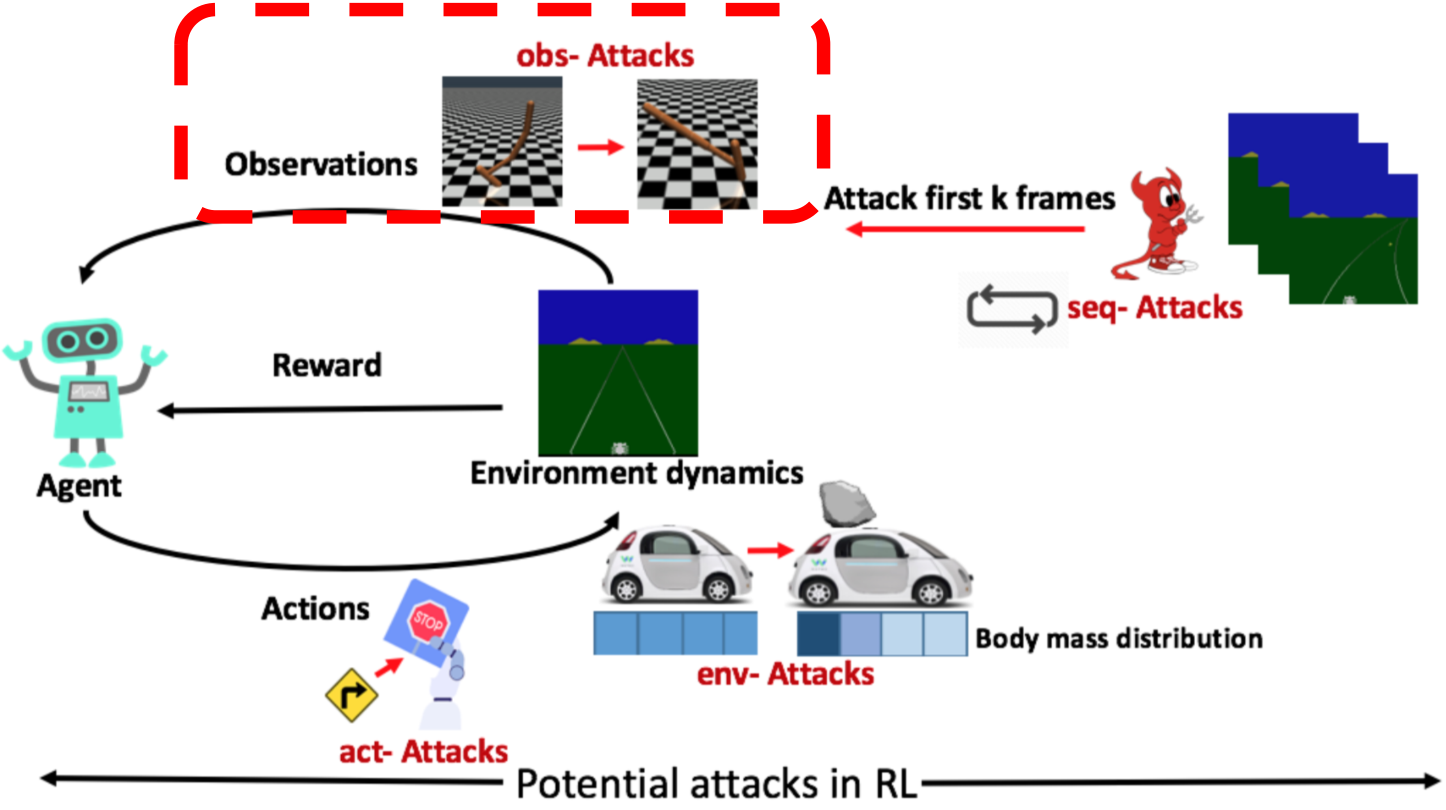
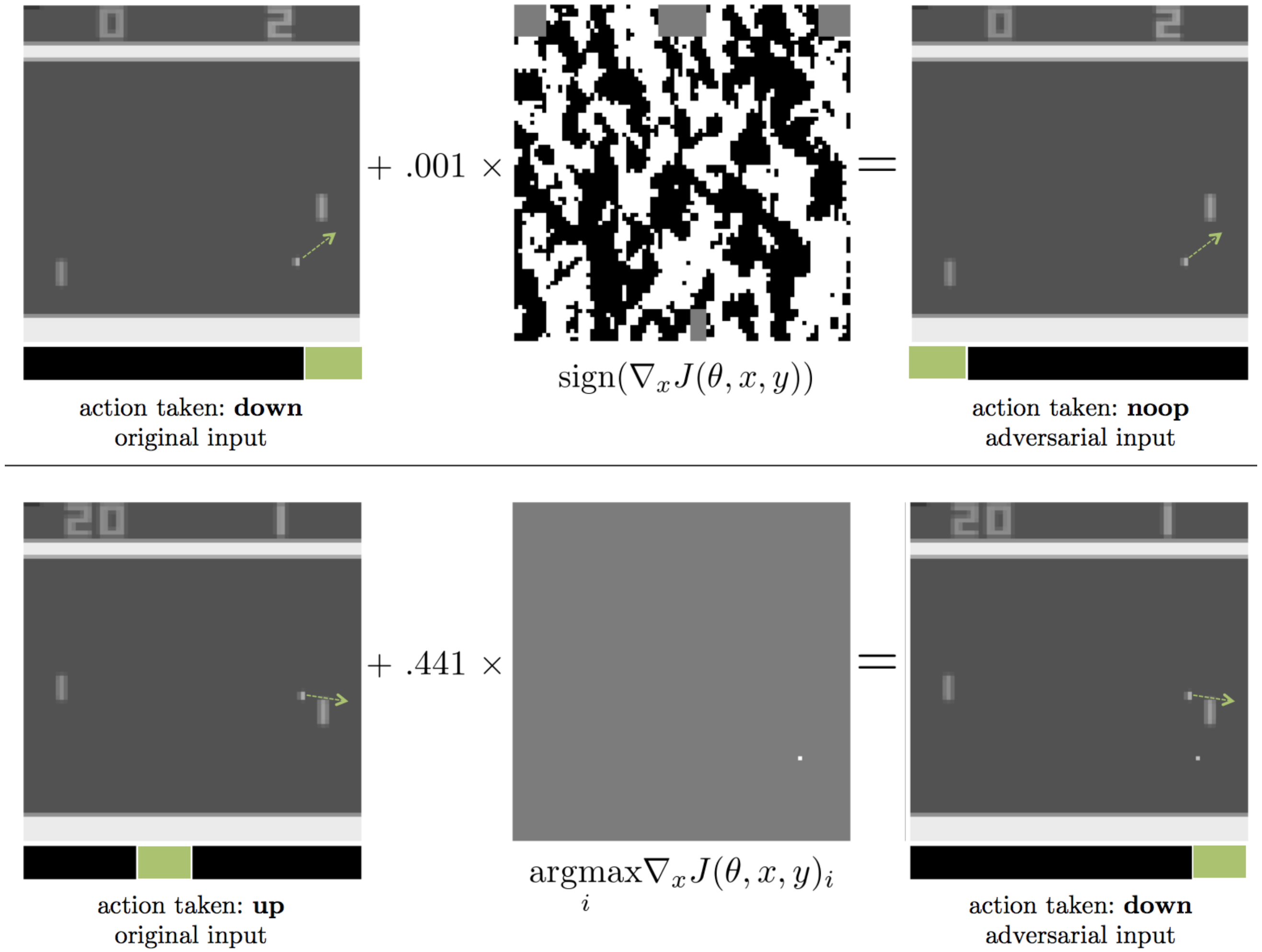
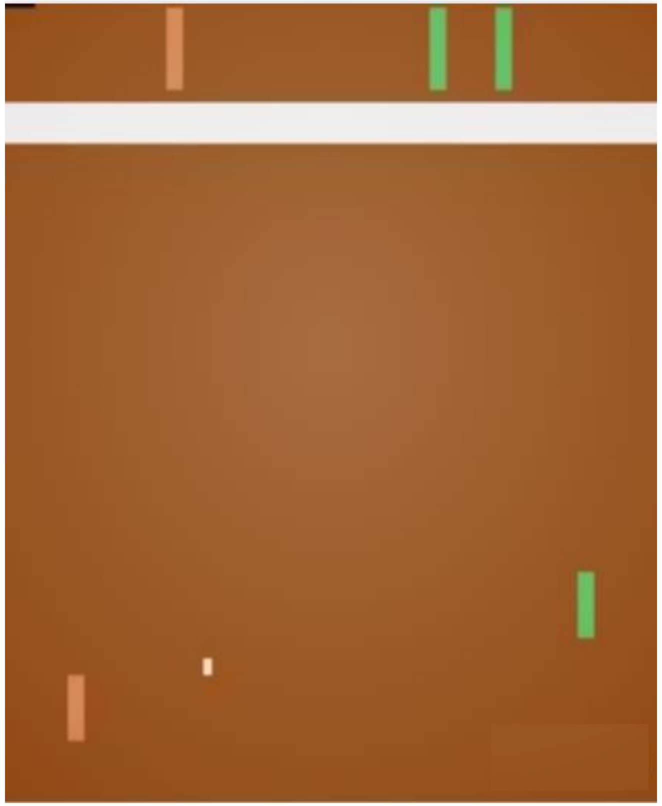


# Adversarial Attacks on Neural Network Policies



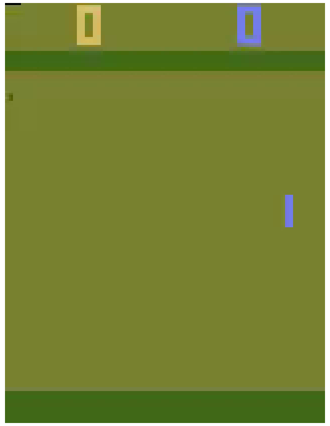
# A3C: A Deep Policy on Pong



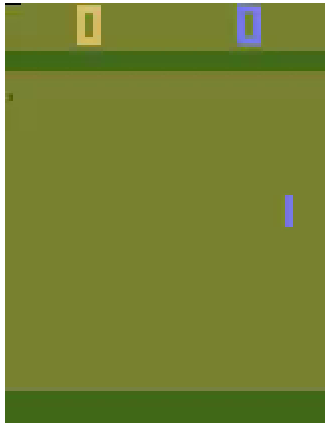
Reinforcement learning algorithms:

- Actor – **policy network** to predict the action based on each frame
- Critics – **value function** to predict the value of each frame, and the action is chosen to maximize the expected value
- Actor-critics (A3C) – combine value function into the policy network to make prediction

# Agent in Action: attack the policy network

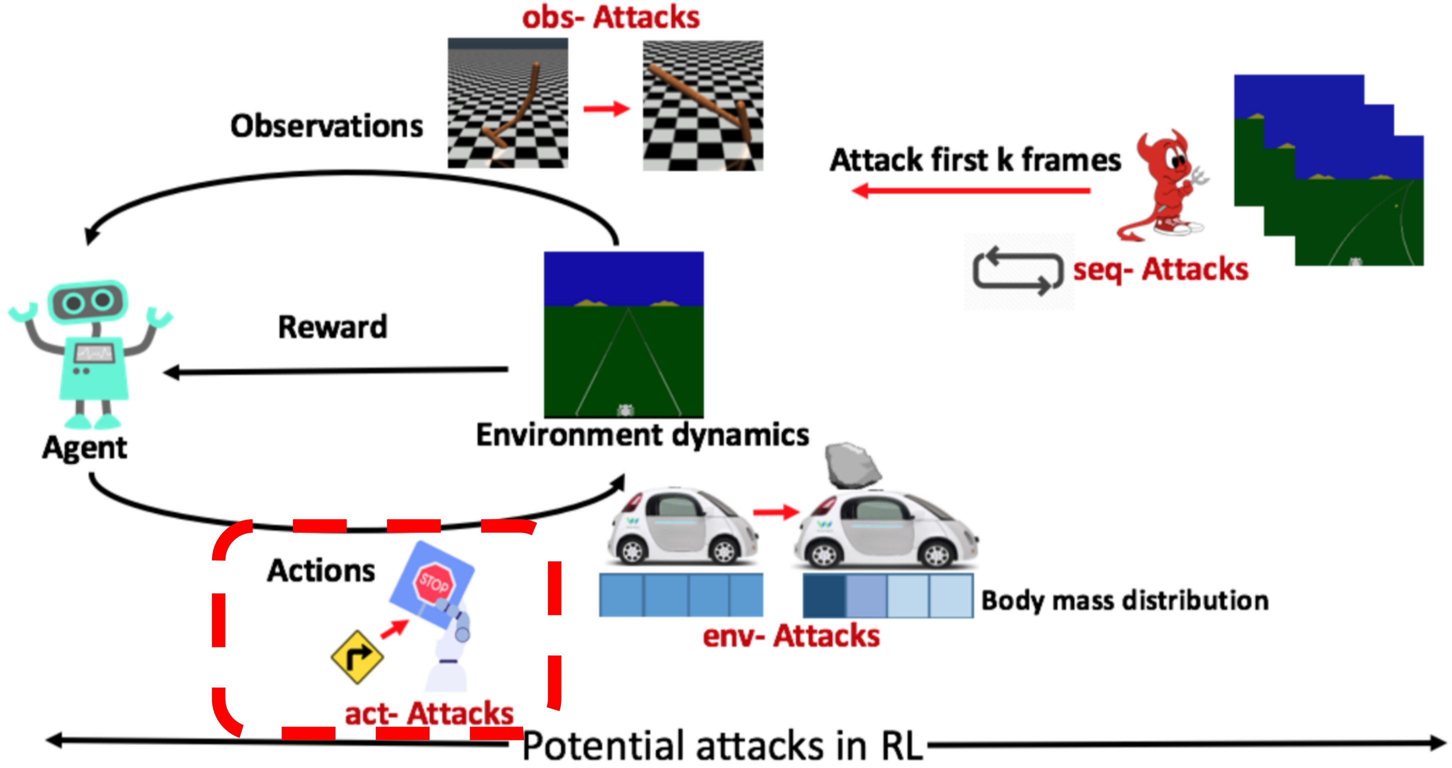


Original Frames

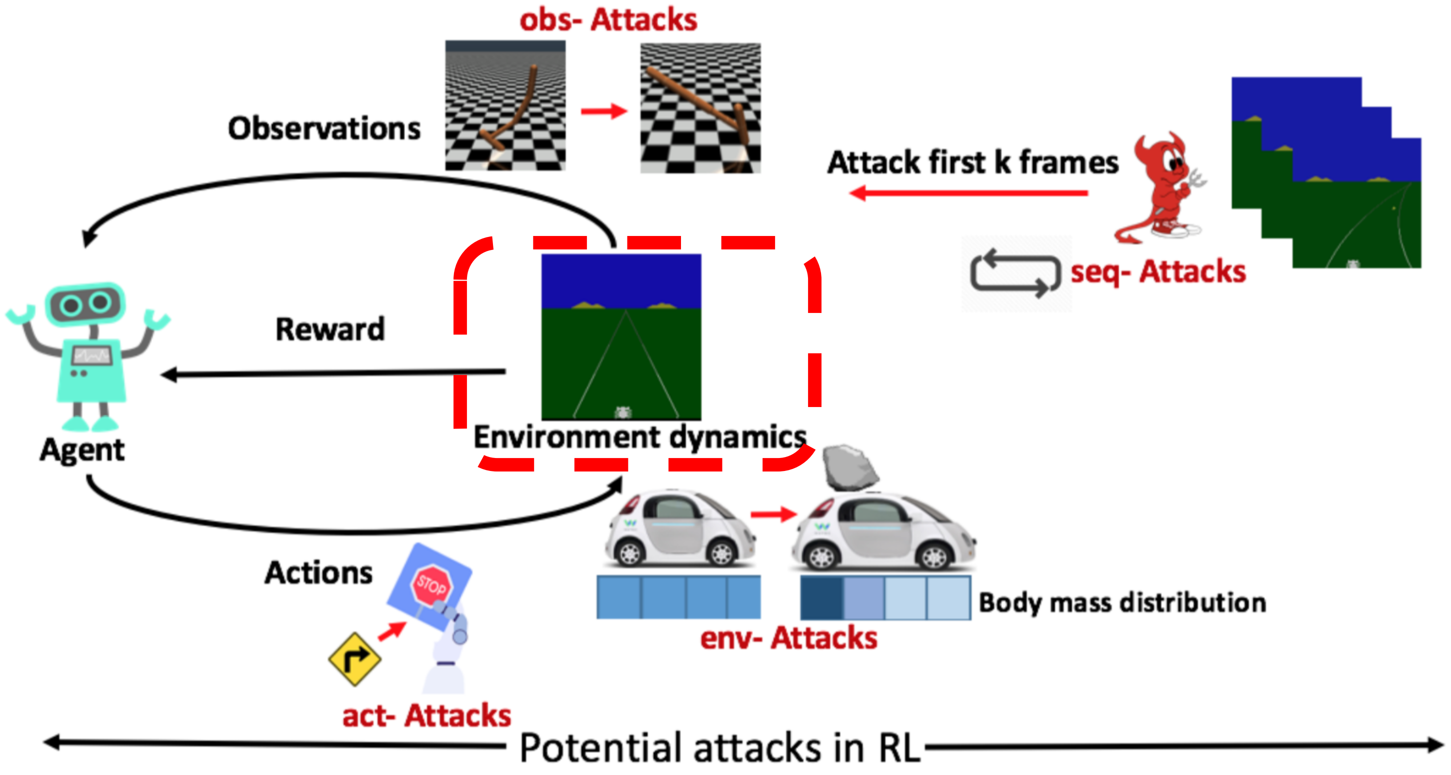


Adversarial perturbation
injected into every frame

# Attacking Deep Reinforcement Learning



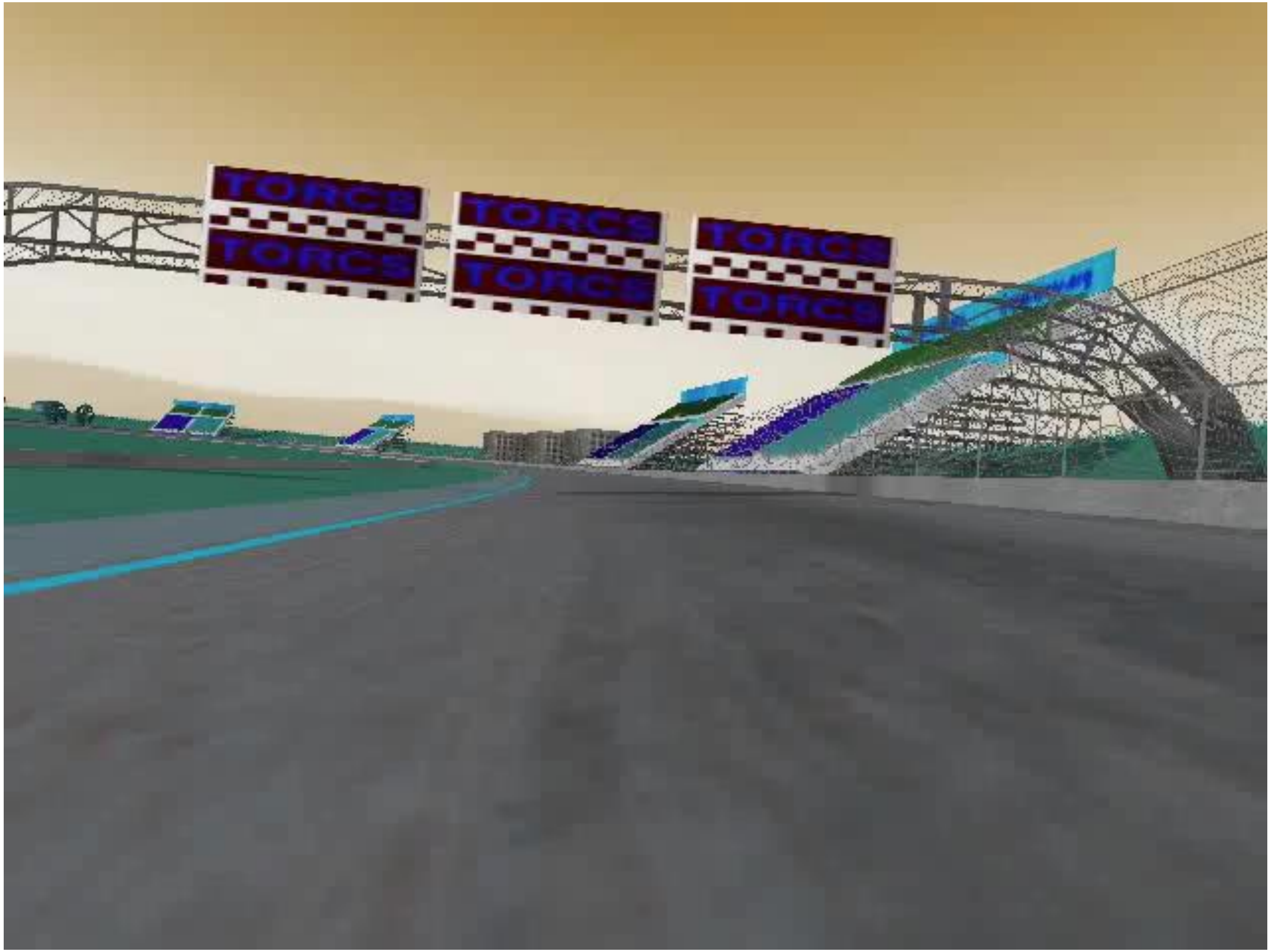
# Attacking Deep Reinforcement Learning



# Attacks on dynamic environments


Normal environment


Adversarial environment


TORCS
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