Reinforcement Learning in Adversarial Attack (RLAT)

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[Link slide with animation]

[Link github]

Motivation

- Machine learning models, especially DNNs, have power in classification tasks.
- However, they lack defenses:

  A small change in the input that is hard recognized by the naked eye, then successfully fool these models.

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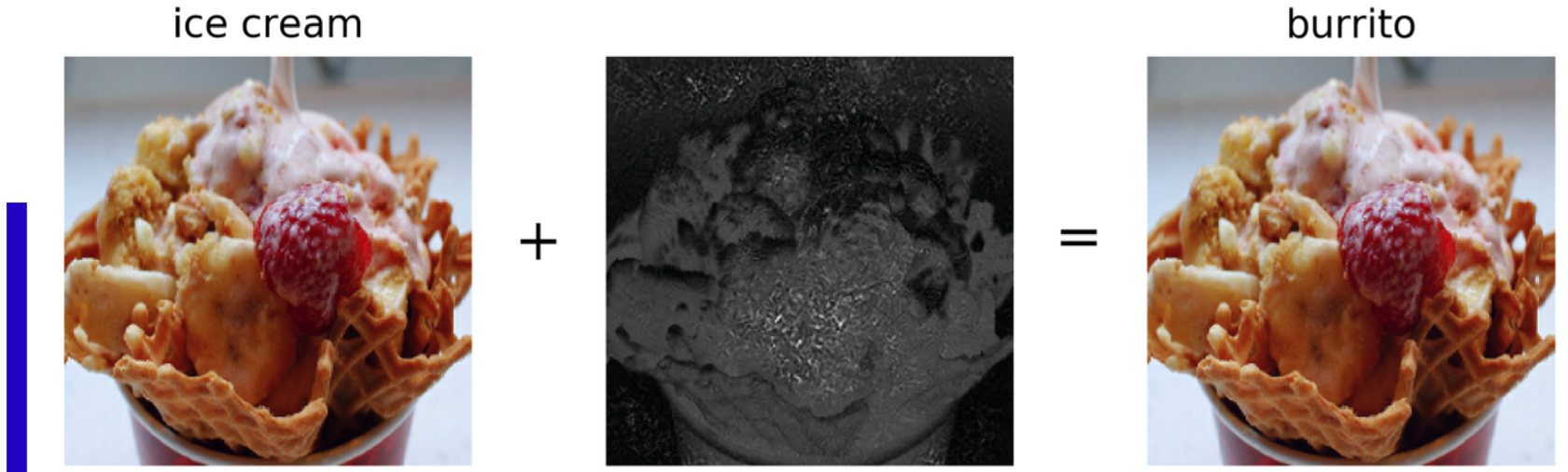
  A small change in the input that is hard recognized by the naked eye, then successfully fool these models.

→ Study in Adversarial Attack is important to the reliability of ML model.

Motivation

- Looking at this ice-cream image:
  - Only by changing a small amount of input value, a new image, which is no different from the old one, is created.
  - However, the new one successfully fools the classfication model.



Motivation

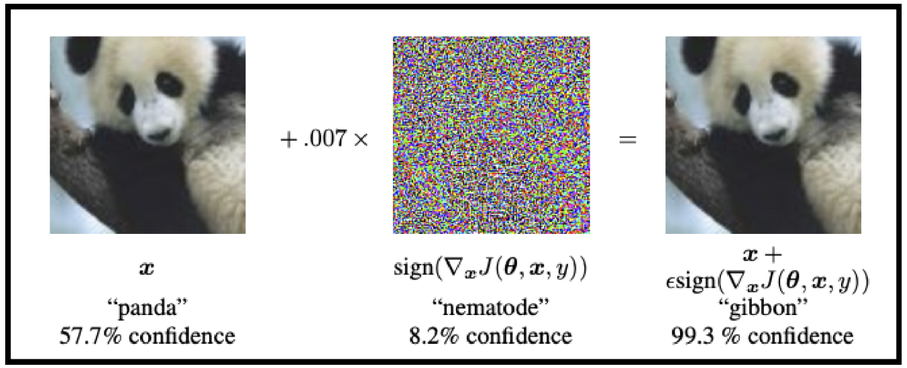
- Adversarial attack:
  Disruptions to machine learning models that successfully fools the models.
- 2 kinds of adversarial attack:
  - White-box attack
  - Black-box attack

Motivation

- White-box attack:

  The attack that allows to access the model details, such as: architecture, gradient, …

White-box Attack



Impractical

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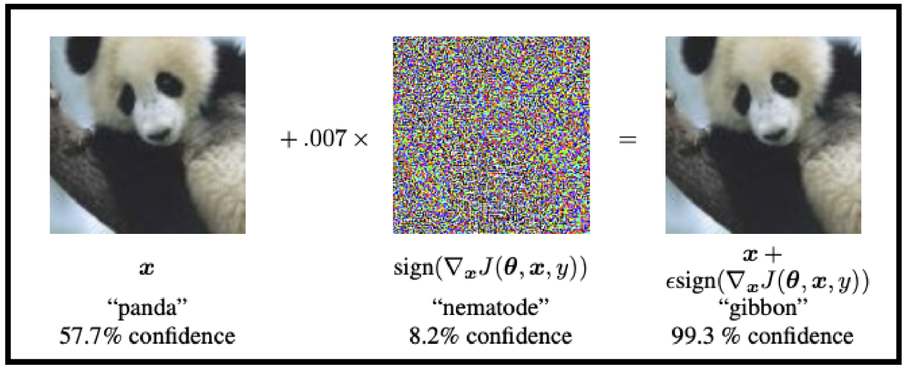
White-box Attack

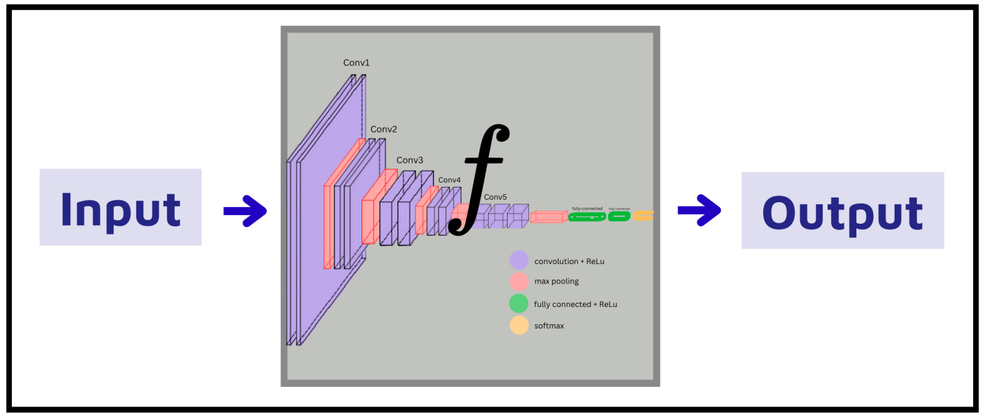


Impractical

- Black-box attack:

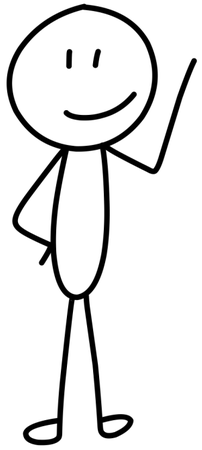
  The attack that only uses input & output

Black-box attack



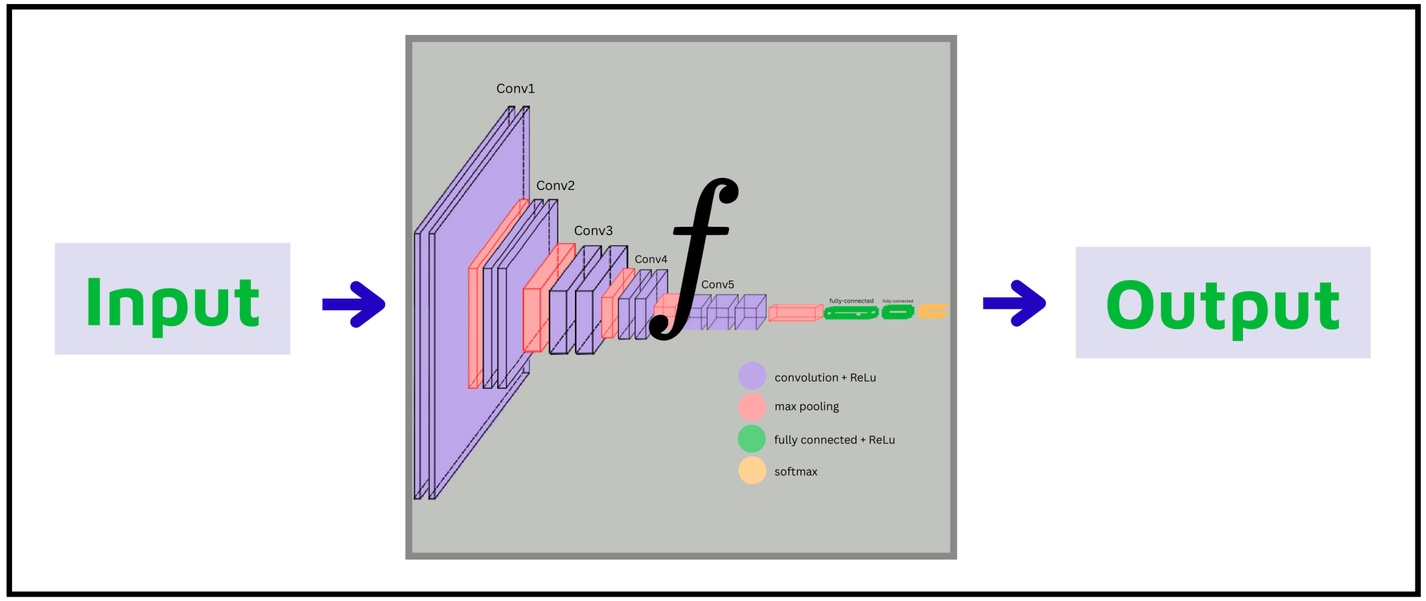
Practical

Purpose



Reinforcement Learning Agent

BLACK-BOX ATTACK



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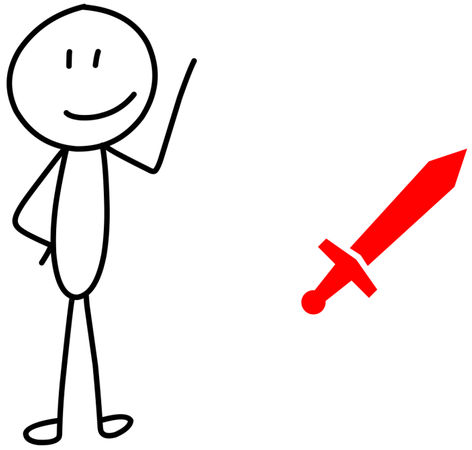

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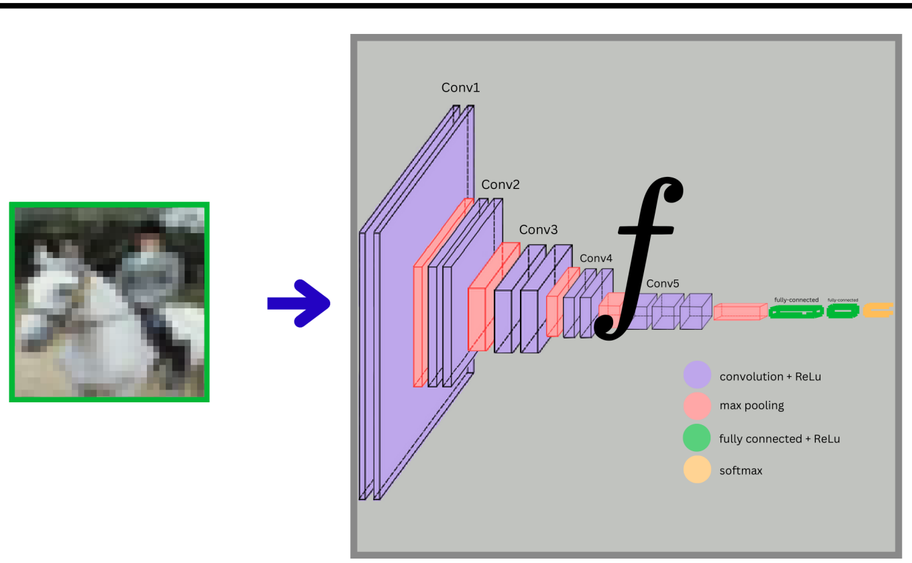
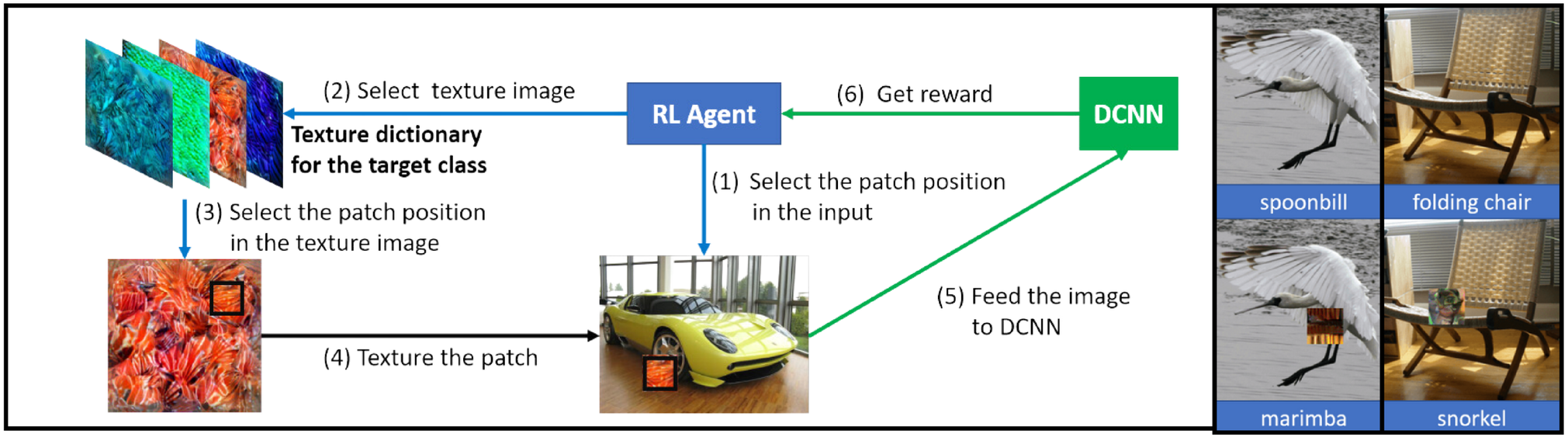


Insight

- Image has some regions that is sensitive with the output of classification model.

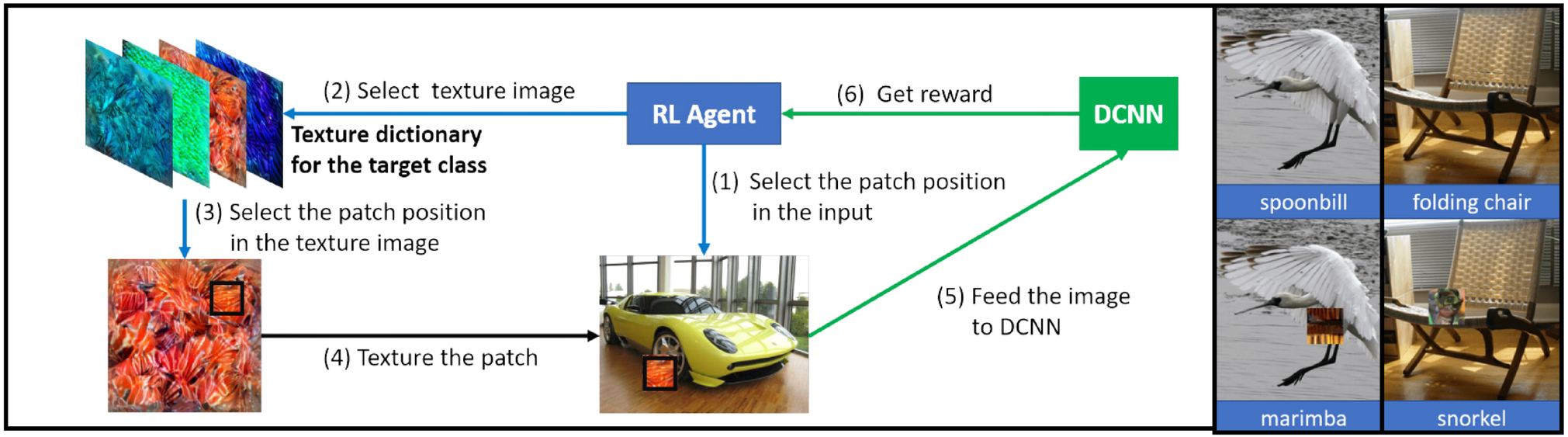


PatchAttack

Insight

- Image has some regions that is sensitive with the output of classification model.

  Ex: Patch-Attack using RL agent find the image that sensitive to Classification model and is pasted to the input image.



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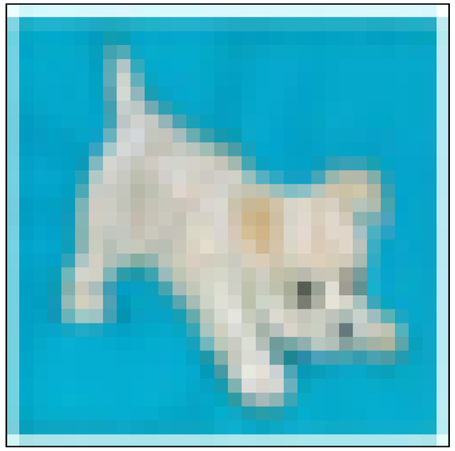

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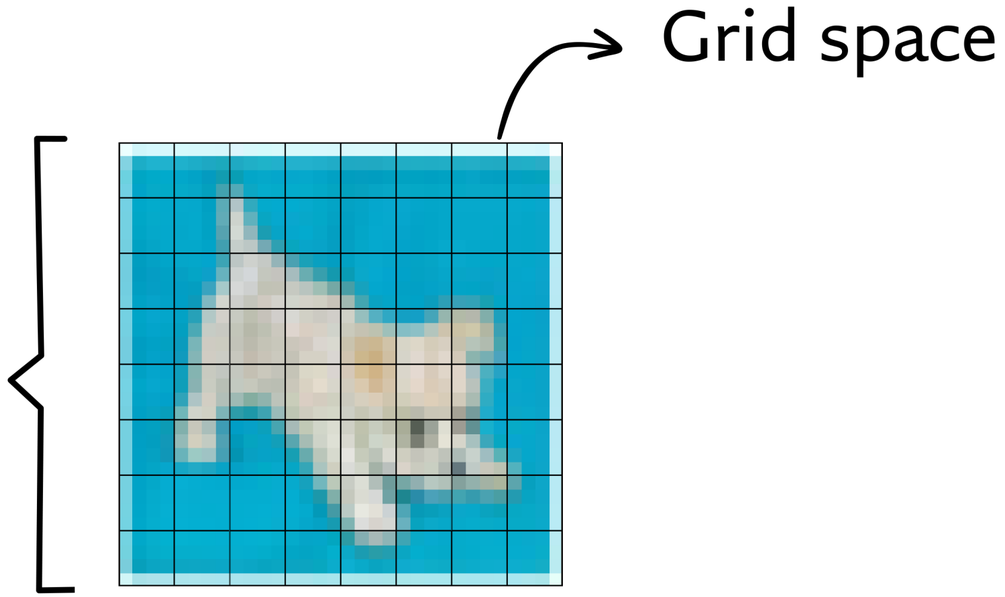
image_size = 32x32
grid_size = 4x4

grid_space_size = 8x8



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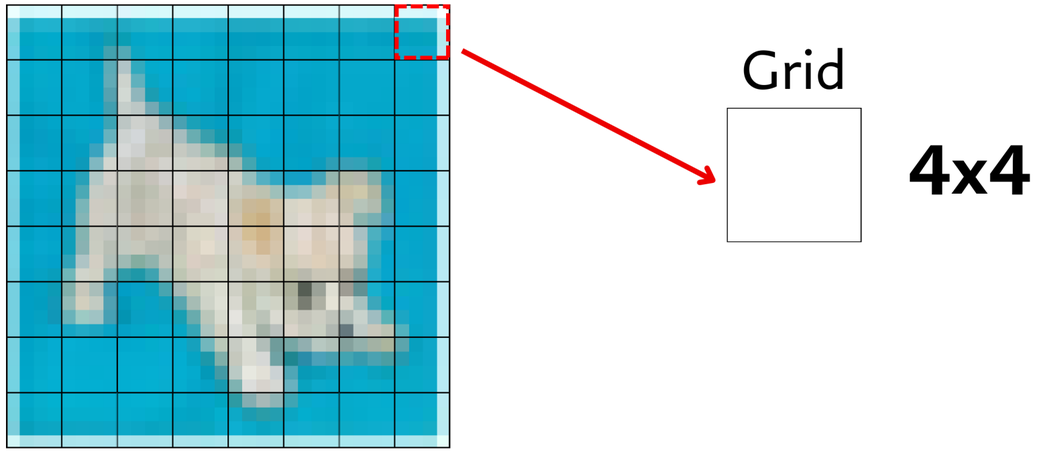

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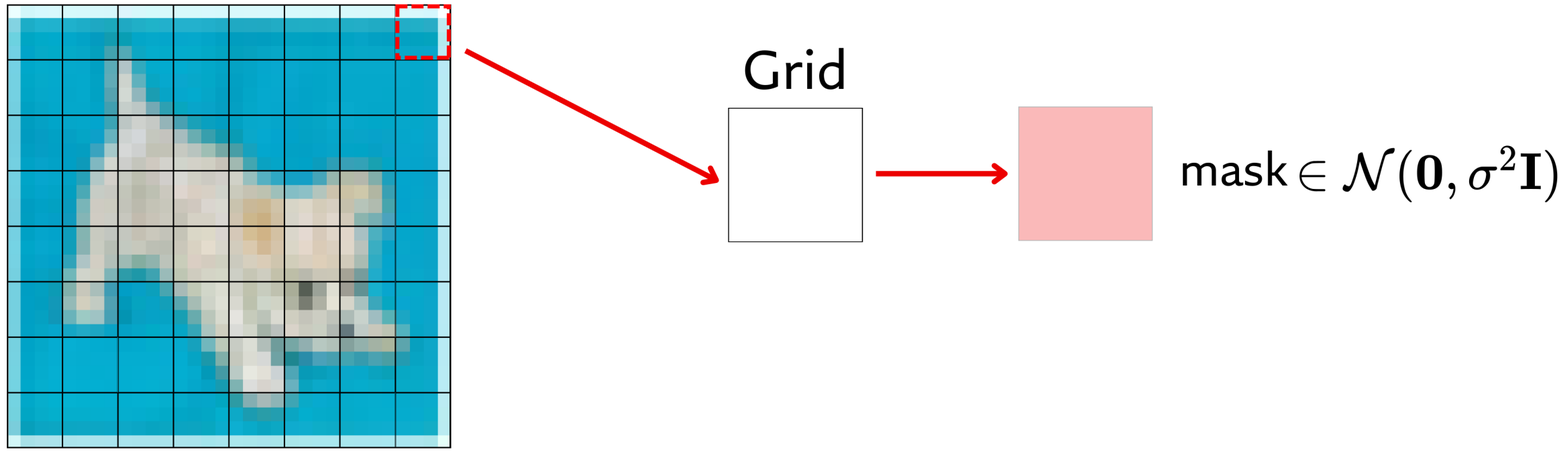

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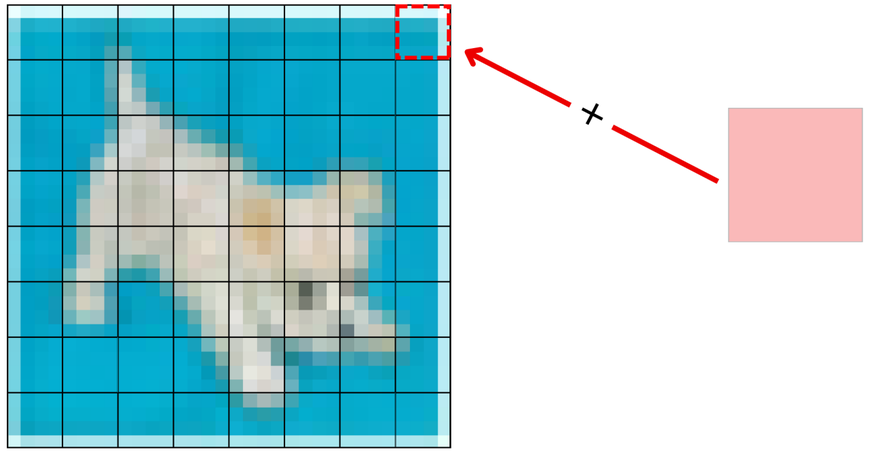

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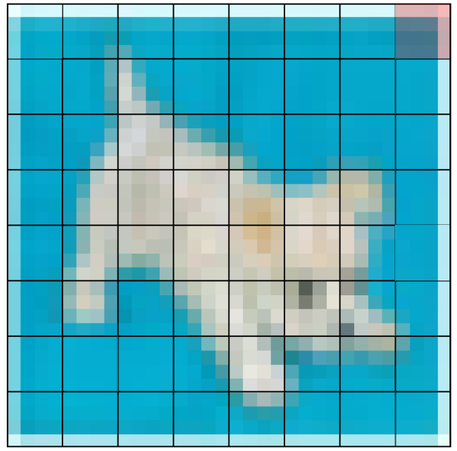

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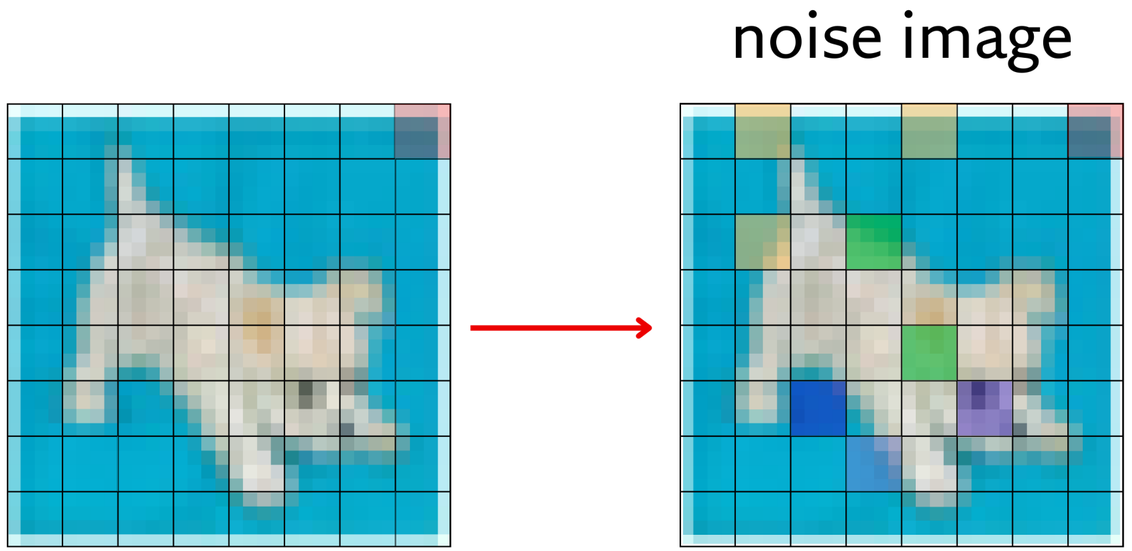
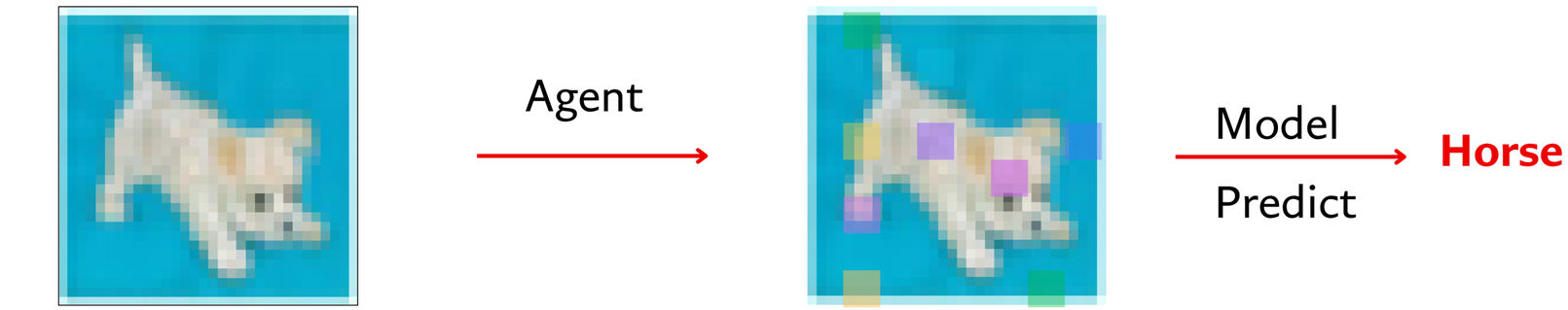


Problem Statement

- Input: Image, Ground truth (Model's prediction)
- Output: The agent's policy can identify the grid where noise should be added

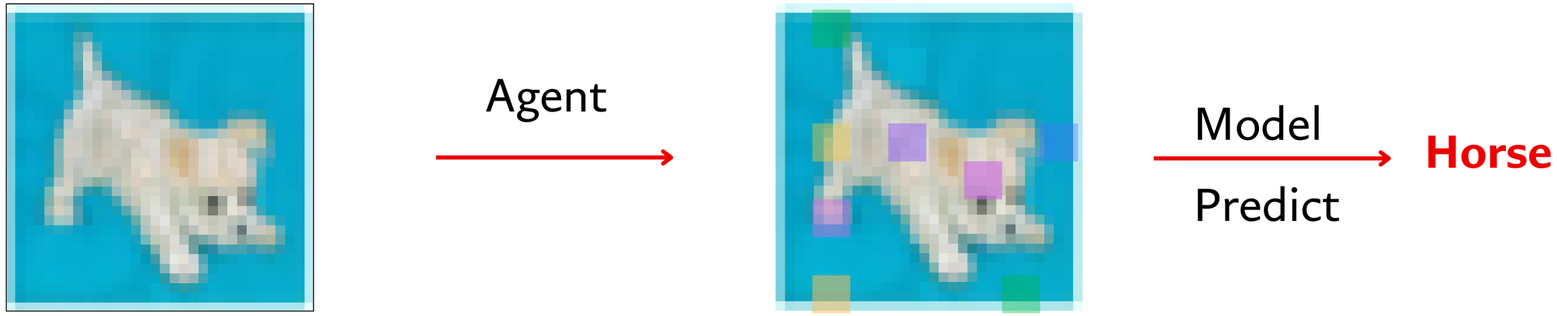


Ground truth: **Dog**

Adversarial sample

Problem Statement

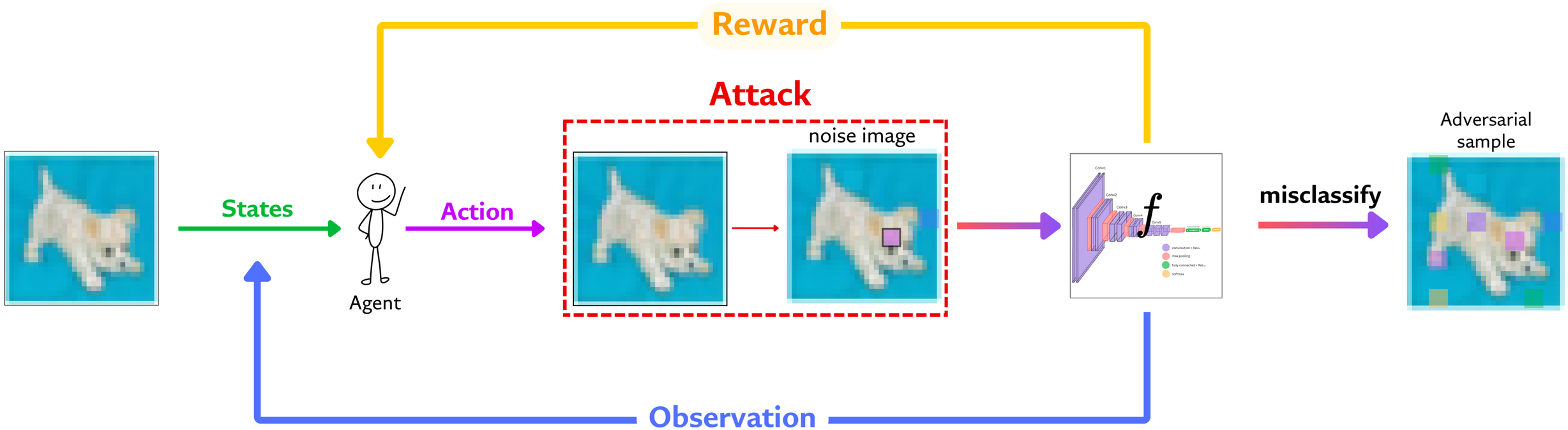
- Input: Image, Ground truth (Model's prediction)
- Output: The agent's policy can identify the grid where noise should be added
- Aims:
  1. Make a huge change in output of the model in Grouth-Truth class.
  2. The noise image has less differences from the original image.



Ground truth: **Dog**

Adversarial sample

Agent Training Pipeline



Modeling

Denote:

$\mathbf{x}$: original image

$\mathbf{x}_i$: noise image at $i\text{th}$ step

f : classifier

$\mathbf{E}$: feature extraction

P_{GT} : GT Classfication Probability of $\mathbf{x}$

P_{GT_i} : GT Classification Probability of $\mathbf{x}_i$

$\boldsymbol{s}_i$: sensitive analysis vector of $\mathbf{x}_i$

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- State: $S_i = \{\mathbf{E}(\mathbf{x}_i), \mathbf{s}_i\}$ is state of $i\text{th}$ step
- Action: a_i, adding to specific grid of $\mathbf{x}_i$
- Reward: $R_i = -||\mathbf{x} - \mathbf{x}_i||_2 + |P_{GT} - P_{GT_i}|$

Methodology

Q - learning

Q-learning cores

Bellman equation:

$$Q^*(S,a) = \mathbb{E}_{S'}[r + \gamma max_{a'} Q(S',a')^* | S,a]$$

Target:

$$r + \gamma max_{a'} Q(S',a',\mathbf{w})$$

Minimise MSE:

$$I = (r + \gamma \max_{a'} Q(S',a',\mathbf{w}) - Q(S,a,\mathbf{w}))^2$$

Two problems:

- Correlations
- Non-stationary targets

Q - learning

Q - learning problems

Correlations

Solve

Replay Buffer

S_1, a_1, R_2, S_2
S_2, a_2, R_3, S_3
S_3, a_3, R_4, S_4
$\cdots$
$S_t, a_t, R_{t+1}, S_{t+1}$

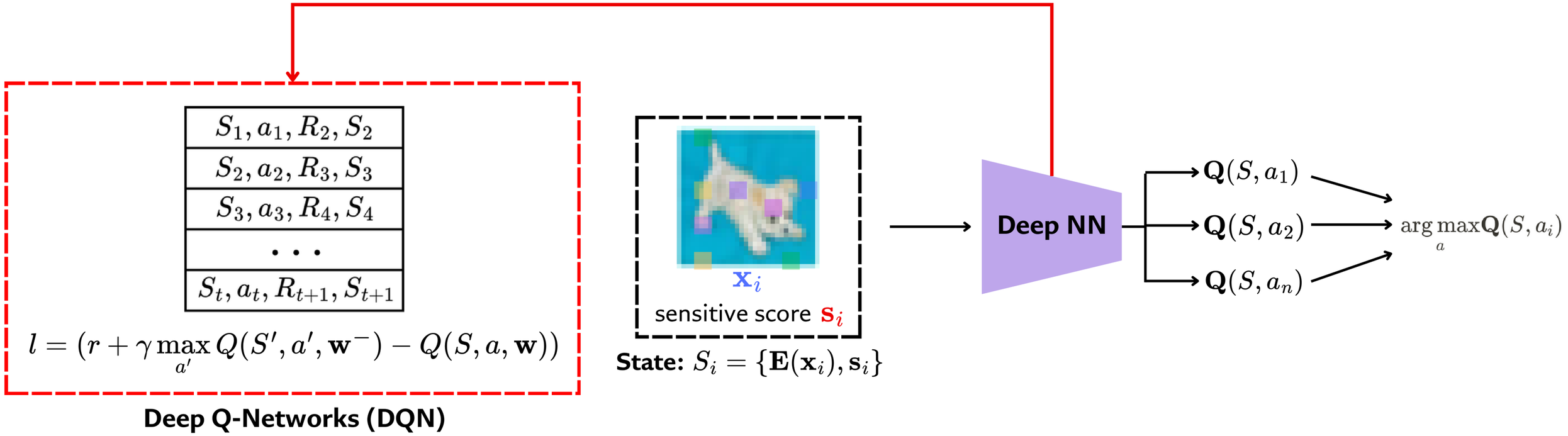
Non-stationary

Solve

Target Net

$$l = (r + \gamma \max_{a'} Q(S', a', \mathbf{w}^-) - Q(S, a, \mathbf{w}))$$

Deep Q - Network



Algorithm

Algorithm Sensitive Analysis

Require: : $\mathbf{x}_i, \mathbf{m}$, f

Ensure: $\mathbf{s}_i$

Initialize $\mathbf{s}_i \leftarrow$ empty set
$P \leftarrow f(\mathbf{x})$
$GT \leftarrow$ argmax P, $P_{GT} \leftarrow P[GT]$
for each grid in grid_space **do**
    $\mathbf{x}_{\text{new}} \leftarrow \mathbf{x}_i$ with mask $\mathbf{m}$ added at the grid location
    $P_{GT_i} \leftarrow f(\mathbf{x}_{new})[GT]$
    $\mathbf{s} \leftarrow |P_{GT} - P_{GT_i}|$
    append $\mathbf{s}$ to $\mathbf{s}_i$
end for

Algorithm

Algorithm RL Agent for Training

Require: Dataset, Max_iter = 300
Ensure: Optimized DQN agent

Initialize: Q Network parameters
for image $\mathbf{x}$ in Dataset **do**
    $m \sim \mathcal{N}(\mathbf{0}, \sigma^2\mathbf{I})$
    $\mathbf{e}_0 \leftarrow \mathbf{E}(\mathbf{x})$
    $\mathbf{s}_0 \leftarrow$ sensitive_analysis($\mathbf{x}$)
    $S_0 \leftarrow \{\mathbf{e}_0, \mathbf{s}_0\}$, $\mathbf{x}_0 \leftarrow \mathbf{x}$
    $i \leftarrow 1$
    while not misclassify **and** $i <$ Max_iter **do**
        $a_i \leftarrow$ select_action(S_{i-1}, m)
        $\mathbf{x}_i \leftarrow$ take_action($\mathbf{x}_{i-1}, a_i$)
        $\mathbf{R}_i \leftarrow$ sensitive_score($\mathbf{x}_i$) $- \|\mathbf{x} - \mathbf{x}_i\|_2$
        Update DQN agent
        $\mathbf{s}_i \leftarrow$ sensitive_analysis($\mathbf{x}_i$)
        $\mathbf{e}_i \leftarrow \mathbf{E}(\mathbf{x}_i)$
        $S_i \leftarrow \{\mathbf{e}_i, \mathbf{s}_i\}$
        $i \leftarrow i + 1$
    end while
end for

Problem

The previous attacked areas became **more sensitive.**
=> agent keep adding noise to those areas.

Even though the L2 norm is still guaranteed small, the noises still can be observed by human eyes clearly.

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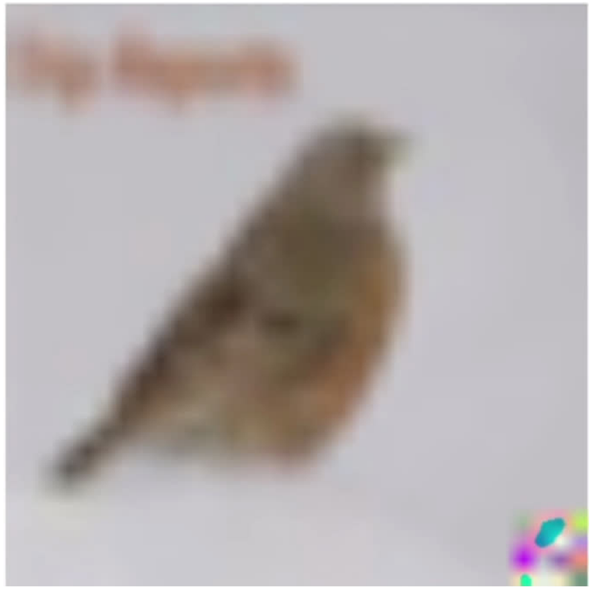

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$F[a]$ frequency value of action a

Solution

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Initialize: Q Network parameters
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  Initialize: $\mathbf{F}, \mathbf{h} \leftarrow$ zeros vector
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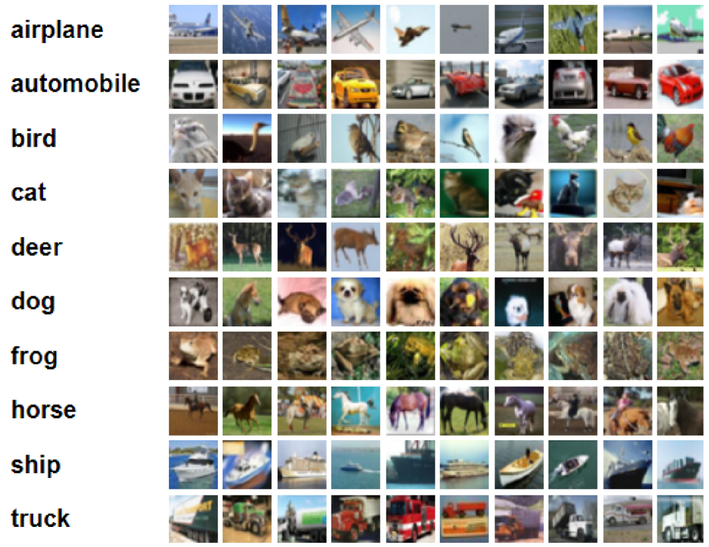
    Update DQN agent
    $\mathbf{s}_i \leftarrow$ sensitive_analysis($\mathbf{x}_i$)
    $\mathbf{F}[a_i] \leftarrow \mathbf{F}[a_i] + 1$
    update history $\mathbf{h}$
    $\mathbf{e}_i \leftarrow \mathbf{E}(\mathbf{x}_i)$
    $S_i \leftarrow \{\mathbf{e}_i, \mathbf{s}_i, \mathbf{h}\}$
    $i \leftarrow i + 1$
  end while
end for

Experiment

Dataset and Black-box Classification Model

- **Cifar10:** Consists of 60000 32x32 color images in 10 classes. 50000 for training, 10000 for testing.
- **VGG19:** Training for 200 epoch with **0.9026** acc.



RESOURSE LIMITATION

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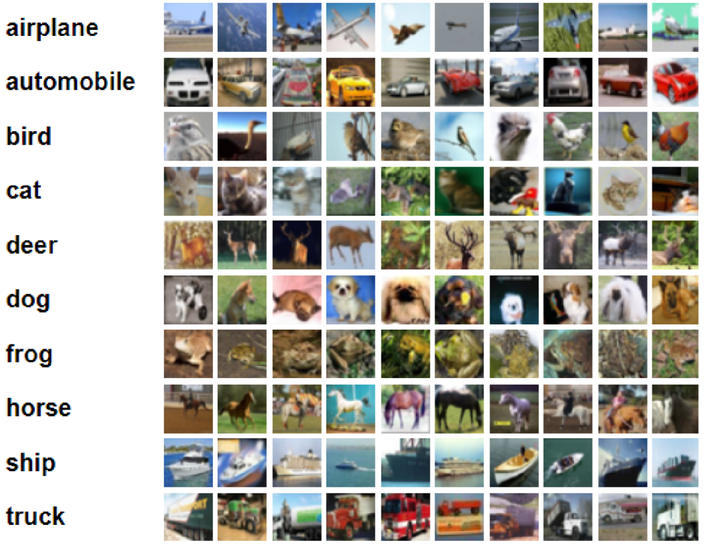
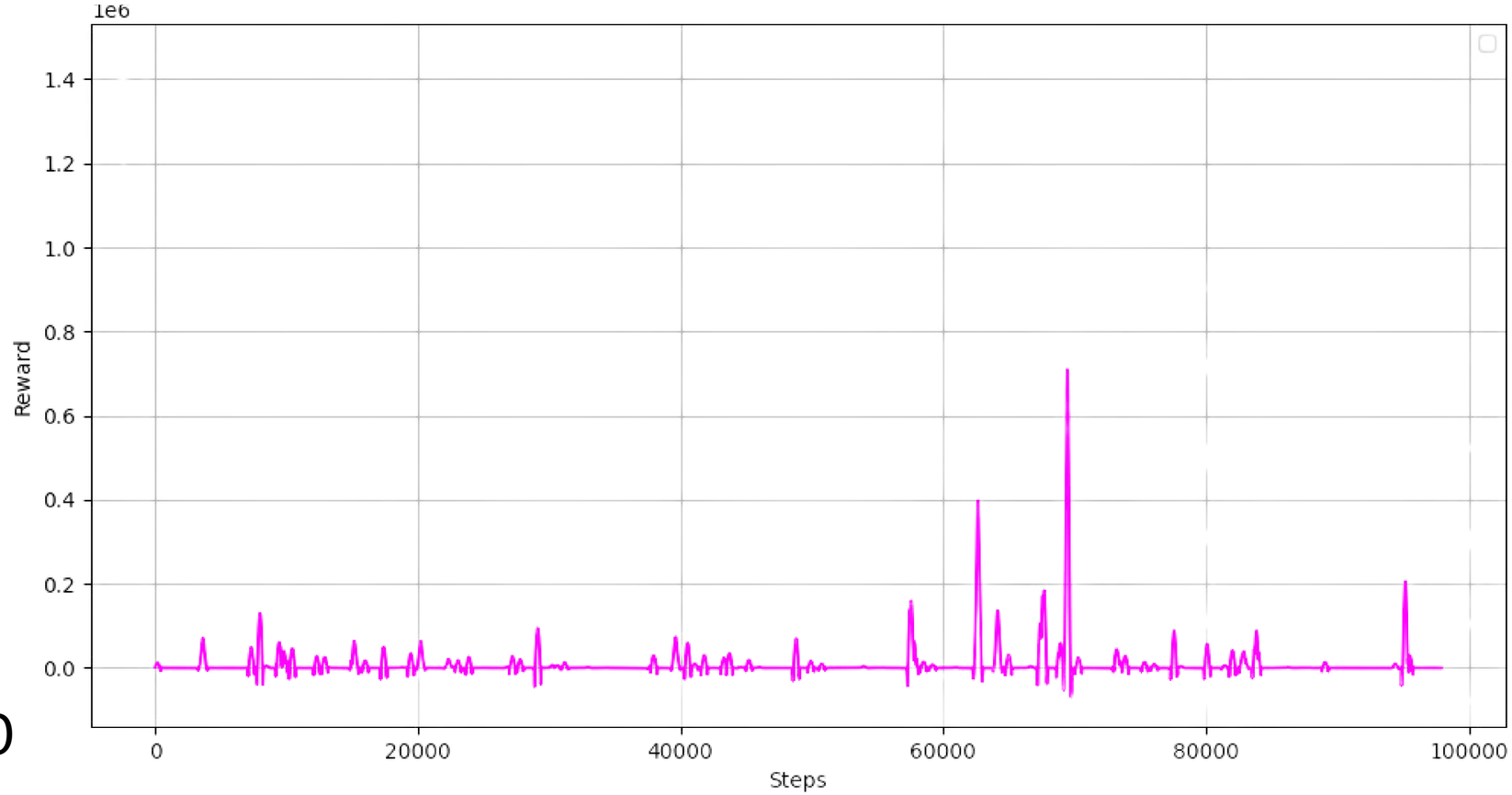


Traning	Testing
500 (50 image per class)	100 (10 image per class)

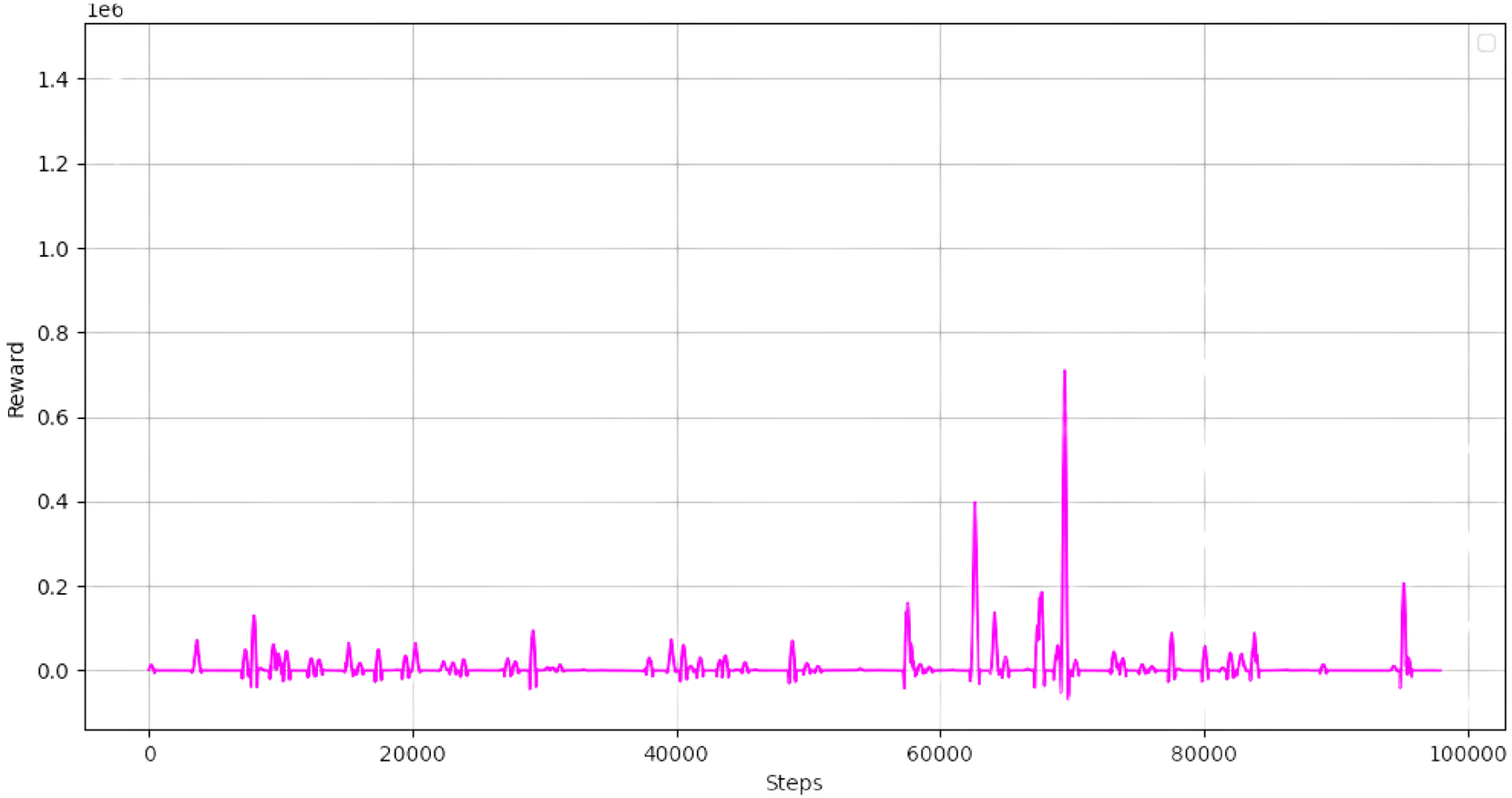
DQN Agent Training

- Total steps ~ **98000**
  Max iter / image: **300**
- Batch size: **32**
- Target update: **1000**
- Noise sd: **0.005**
- Gamma: **0.9**
- Epsilon: **0.1**
- Kaggle T4 GPU
  NVIDIA GetForce 3060



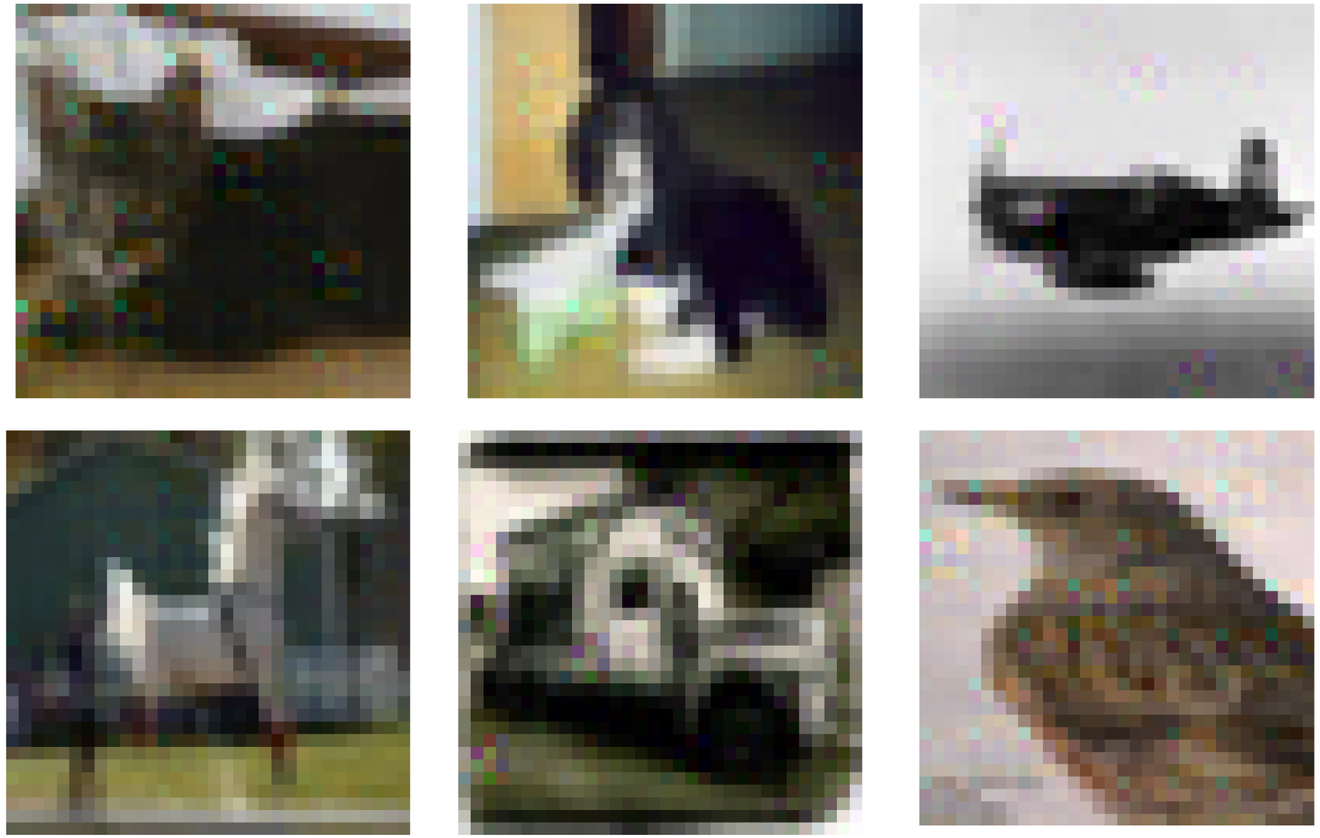
Limitations

- The process of training is not stable.
- Reward will reduce when **L2 norm and frequent of actions increases.**



Attack Result

- Success rate: 21 / 100
- Avg L2 norm: 7.48809
- AVG step: 280.1



Limitations

- The process of training is not stable.
- Reward function does not have the score for terminated state.
- Adding random noise at grid level is not as well as pixel level.
- Time for **sensitive analysis** is really long.

  100 images ~ 20 hours → 50000 image ~ 1000 days

References

- [1] Soumyendu Sarkar. “Robustness with Query-efficient Adversarial Attack using Reinforcement Learning”. CVPR. 2023
- [2] Chenglin Yang. “PatchAttack: A Black-Box Texture-Based Attack with Reinforcement Learning”. ECCV. 2020
- [3] Jonathan Peck. “An Introduction to Adversarially Robust Deep Learning”. IEEE Trans. Pattern Anal. Mach. Intell. 2024

THANKS FOR WATCHING!