



Classifier-free Diffusion Guidance with a Robust Energy-Based Classifier



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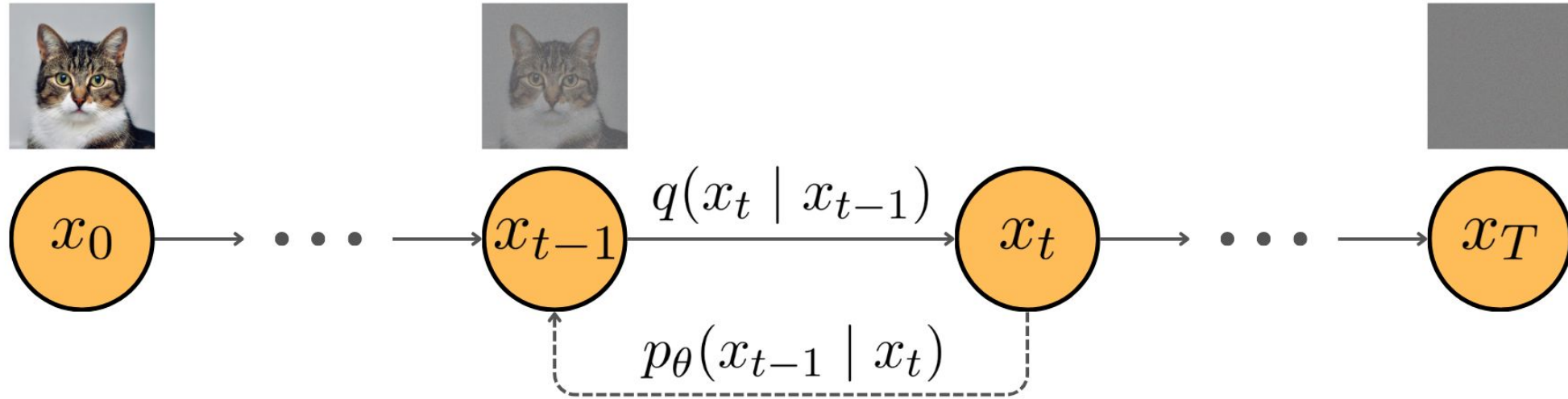


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Diffusion Models and Classifier-guidance

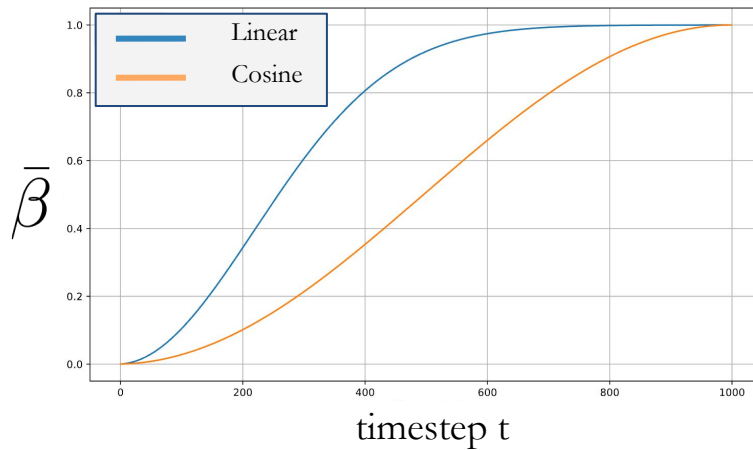
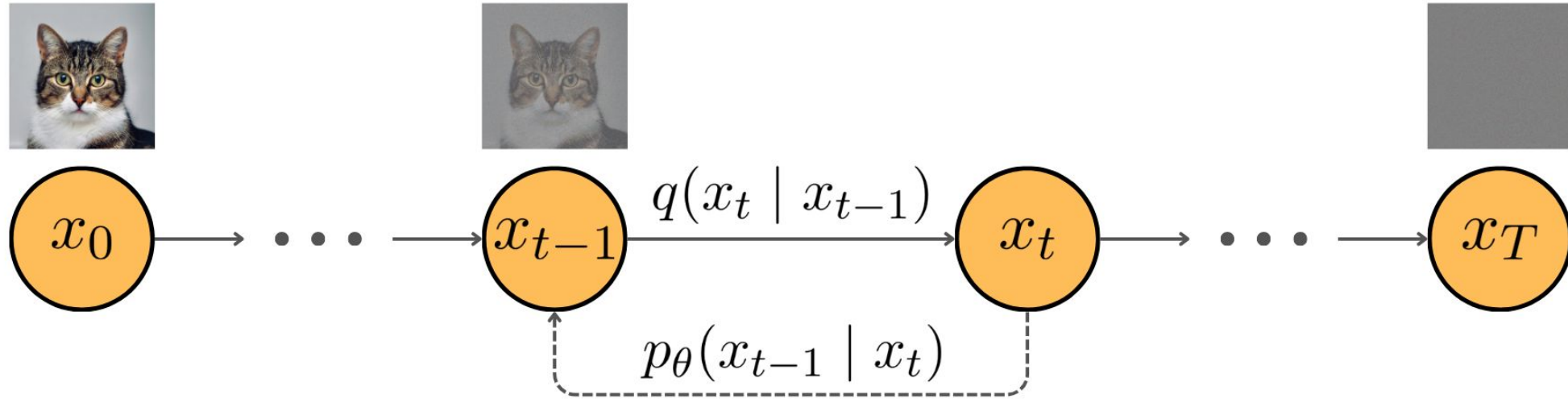


Diffusion Models





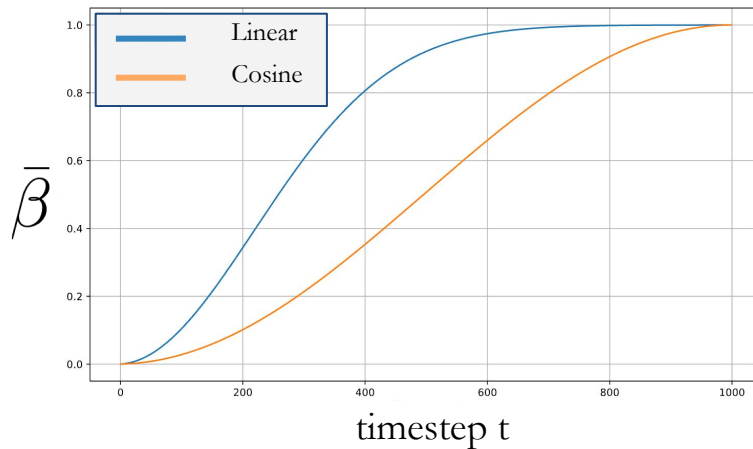
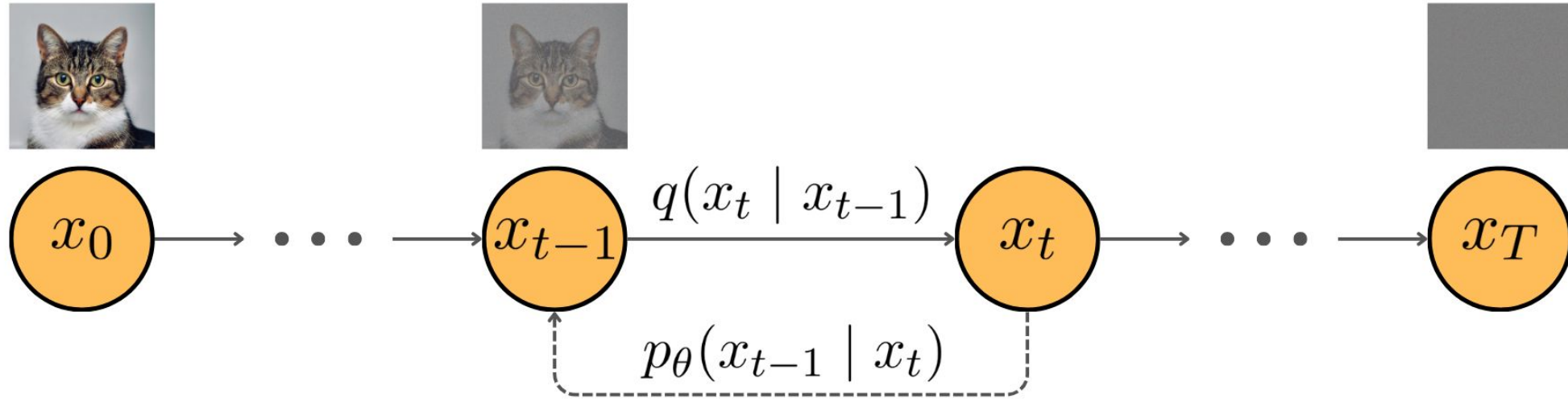
Diffusion Models



$$q(\mathbf{x}_t | \mathbf{x}_0) = \mathcal{N}\left(\mathbf{x}_t; \sqrt{1 - \bar{\beta}_t} \mathbf{x}_0, \bar{\beta}_t \mathbf{I}\right)$$



Diffusion Models



$$q(\mathbf{x}_t | \mathbf{x}_0) = \mathcal{N}\left(\mathbf{x}_t; \sqrt{1 - \bar{\beta}_t} \mathbf{x}_0, \bar{\beta}_t \mathbf{I}\right)$$

$$p_\theta(\mathbf{x}_{t-1} | \mathbf{x}_t) = \mathcal{N}\left(\mathbf{x}_{t-1}; \mu_\theta(\mathbf{x}_t, t), \sigma^2\right)$$



Classifier Guidance

```
1 for all  $t$  from  $T$  to 1 do  
2    $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  ;  
3    $\mu \leftarrow \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \epsilon_{\theta}(\mathbf{x}_t, t) \right)$   
4    $\mathbf{x}_{t-1} \leftarrow \mu + \sigma_t \epsilon$  ;  
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```



Training is expensive!



Classifier-free Diffusion Guidance with a Robust Energy-Based Classifier

Why Robust Classifiers behave as Generative Models?



Robust Gradients are Perceptually Aligned

$$\nabla_{\mathbf{x}} \mathcal{L}_{\text{CE}}(\mathbf{x}, y; \phi)$$

Non-Robust

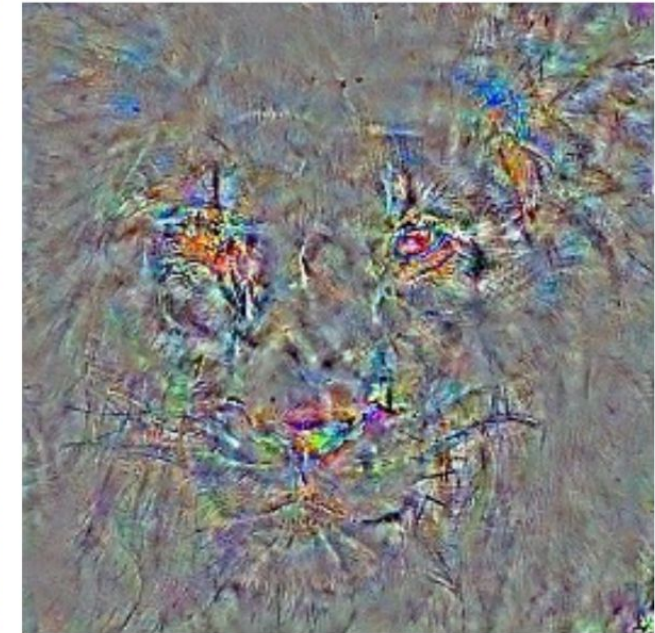
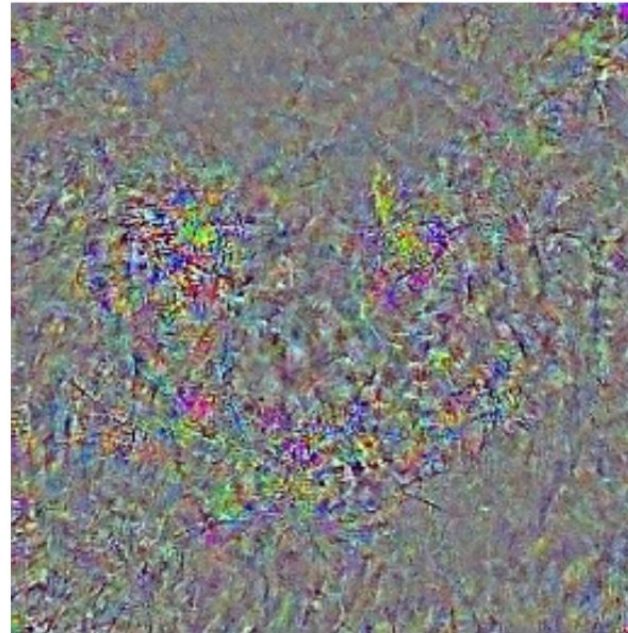
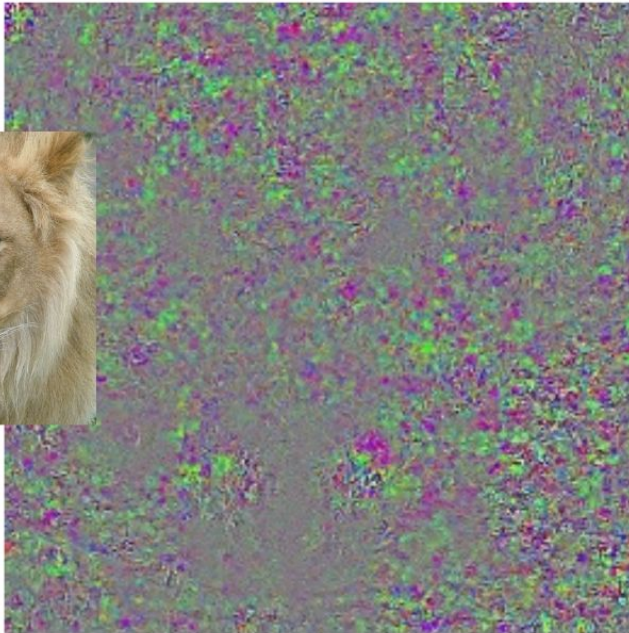
Robust

Wang et al. [4]

$\ell_2, \epsilon=0.01$

$\ell_2, \epsilon=0.05$

Input



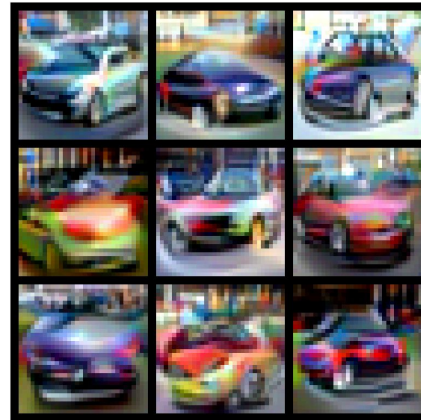


Generating images with a single robust classifier

airplane



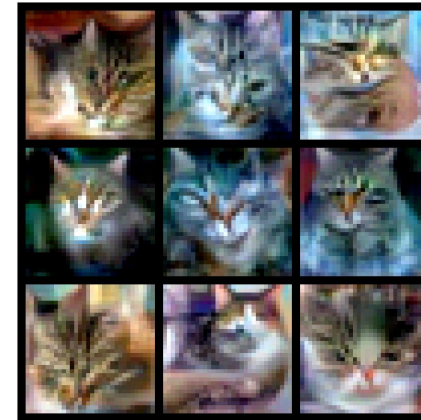
car



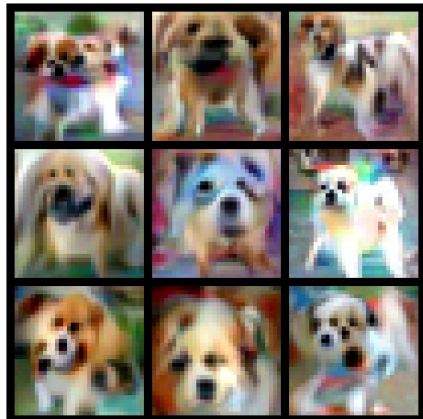
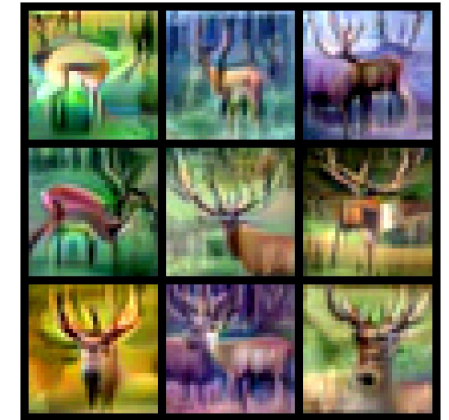
bird



cat



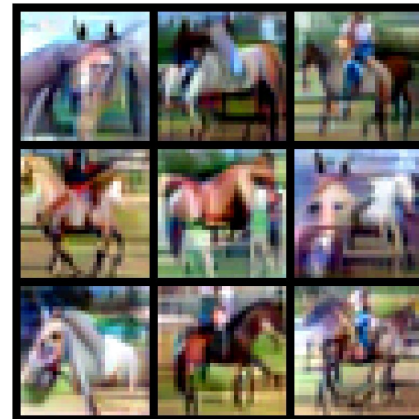
deer



dog



frog



horse



ship



truck



Classifier-free Diffusion Guidance with a Robust Energy-Based Classifier

Robust Classifier Guidance



Naïvely replacing the classifier

airplane





Naïvely replacing the classifier

airplane



car



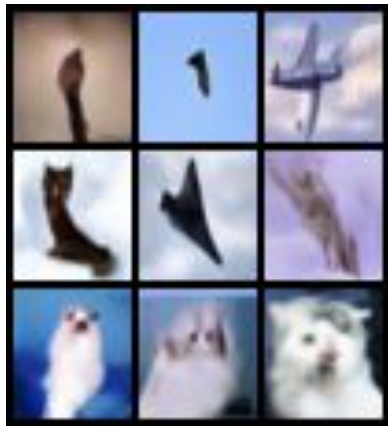
bird



cat



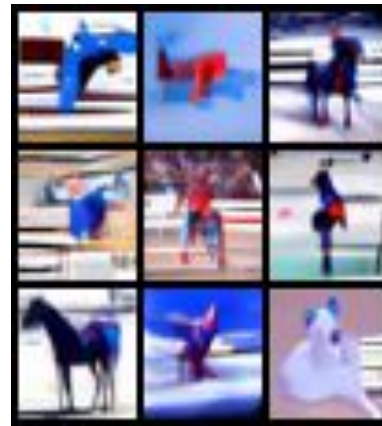
deer



dog



frog



horse



ship



truck



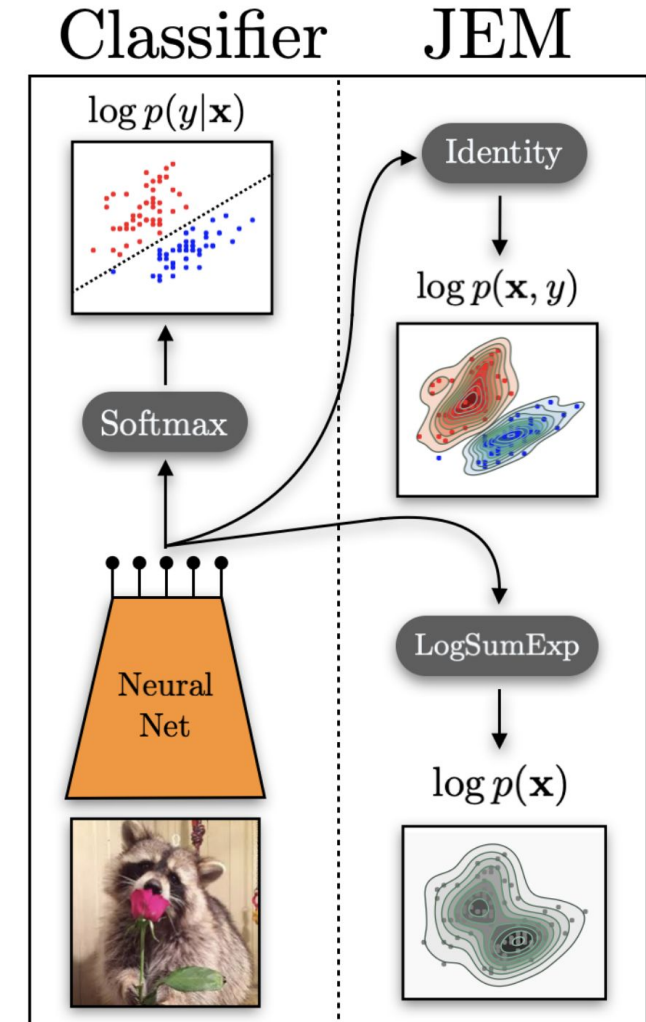
Classifier-free Diffusion Guidance with a Robust Energy-Based Classifier

Robust Classifier-free guidance



Your classifier is secretly an Energy-Based Model

$$p_{\phi}(y \mid \mathbf{x}) = \frac{p_{\phi}(\mathbf{x}, y)}{p_{\phi}(\mathbf{x})} = \frac{\exp(F_{\phi}(\mathbf{x})[y])}{\sum_k \exp(F_{\phi}(\mathbf{x})[y])}$$

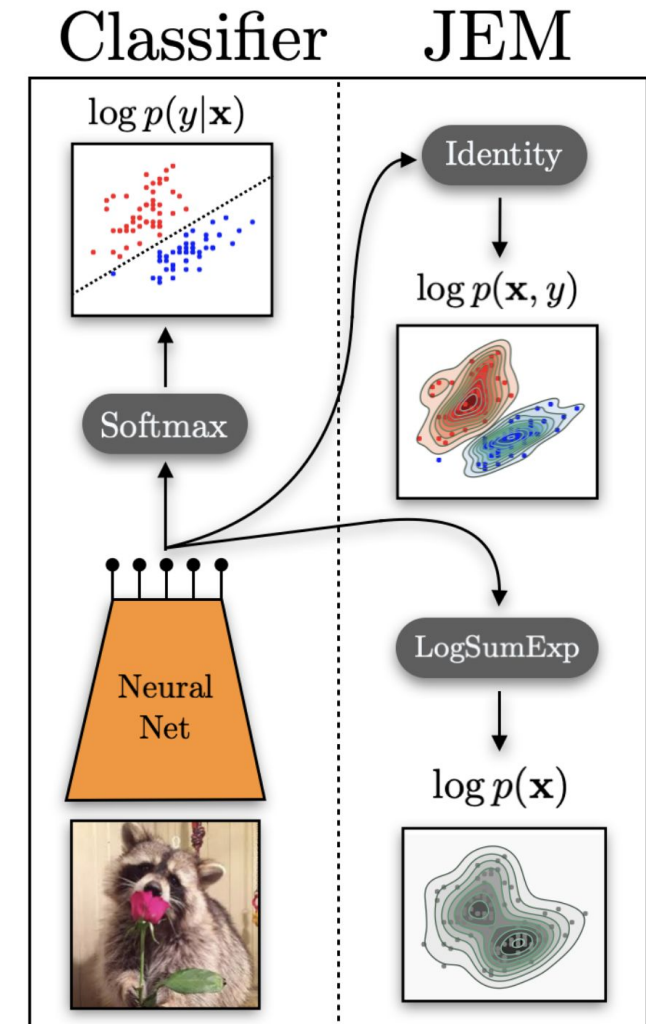




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$$\log p_{\phi}(y \mid \mathbf{x}) = \log p_{\phi}(\mathbf{x}, y) - \log p_{\phi}(\mathbf{x})$$





Your classifier is secretly an Energy-Based Model

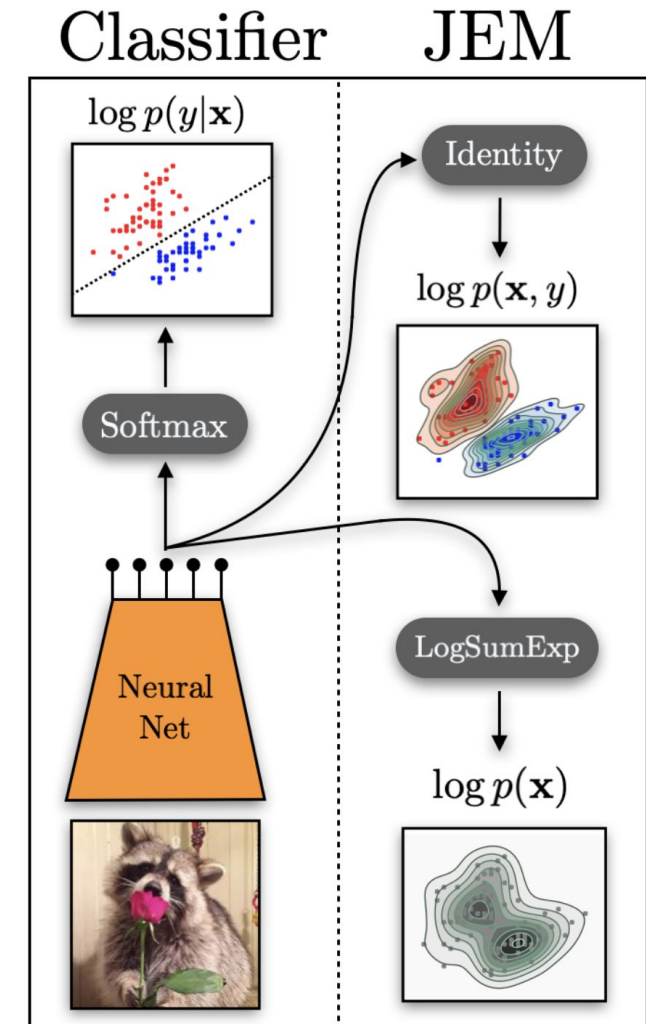
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$$\begin{aligned}\log p_{\phi}(y \mid \mathbf{x}) &= \log p_{\phi}(\mathbf{x}, y) - \log p_{\phi}(\mathbf{x}) \\ &= F_{\phi}(\mathbf{x})[y] - \text{LogSumExp}_y(F_{\phi}(\mathbf{x})[y]) \\ &= E_{\phi}(\mathbf{x}) - E_{\phi}(\mathbf{x}, y)\end{aligned}$$

where

$$E_{\phi}(\mathbf{x}) = -\log p_{\phi}(\mathbf{x})$$

$$E_{\phi}(\mathbf{x}, y) = -\log p_{\phi}(\mathbf{x}, y)$$





Classifier Guidance

```
1 for all  $t$  from  $T$  to 1 do  
2    $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  ;  
3    $\mu \leftarrow \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \epsilon_{\theta}(\mathbf{x}_t, t) \right) + s\sigma_t \nabla_{\mathbf{x}_t} \log p_{\phi}(y \mid \mathbf{x}_t)$   
4    $\mathbf{x}_{t-1} \leftarrow \mu + \sigma_t \epsilon$  ;  
5 return  $\mathbf{x}_0$ 
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Classifier Guidance

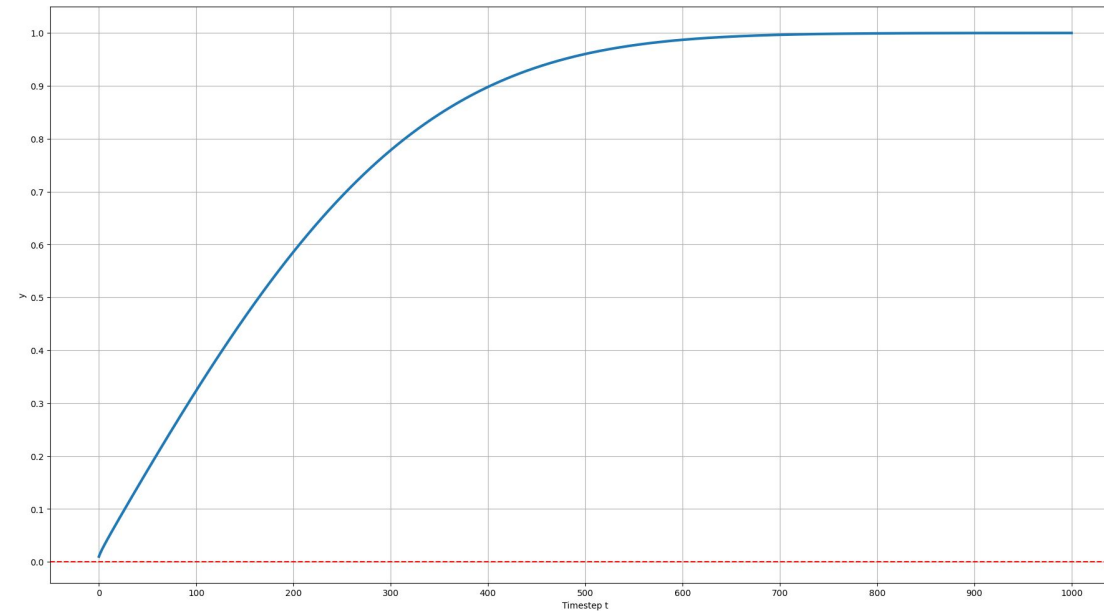
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4    $\mathbf{x}_{t-1} \leftarrow \mu + \sigma_t \epsilon$  ;  
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```





Standard guidance scheduler

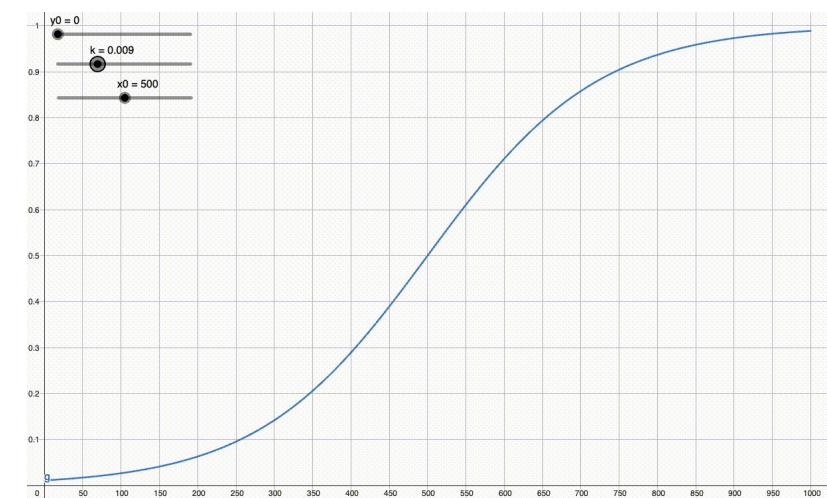
$$\hat{\sigma}_t = \sqrt{1 - \bar{\alpha}_t}$$



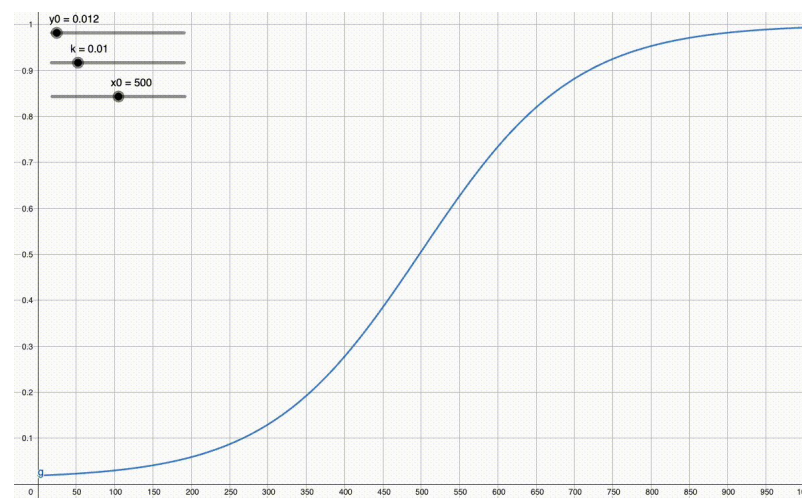


Custom guidance scheduler

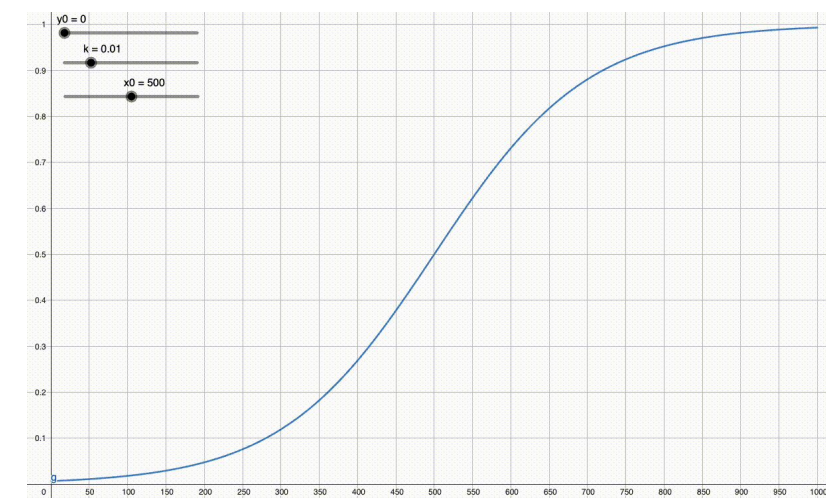
$$\hat{\sigma}_t = (1 - y_0) \cdot \frac{1}{1 + e^{-k(t-t_0)}} + y_0$$



k



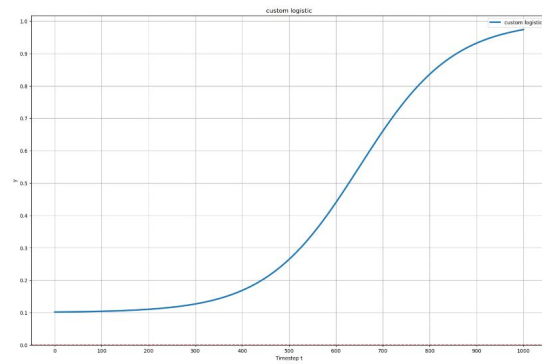
y_0



t_0

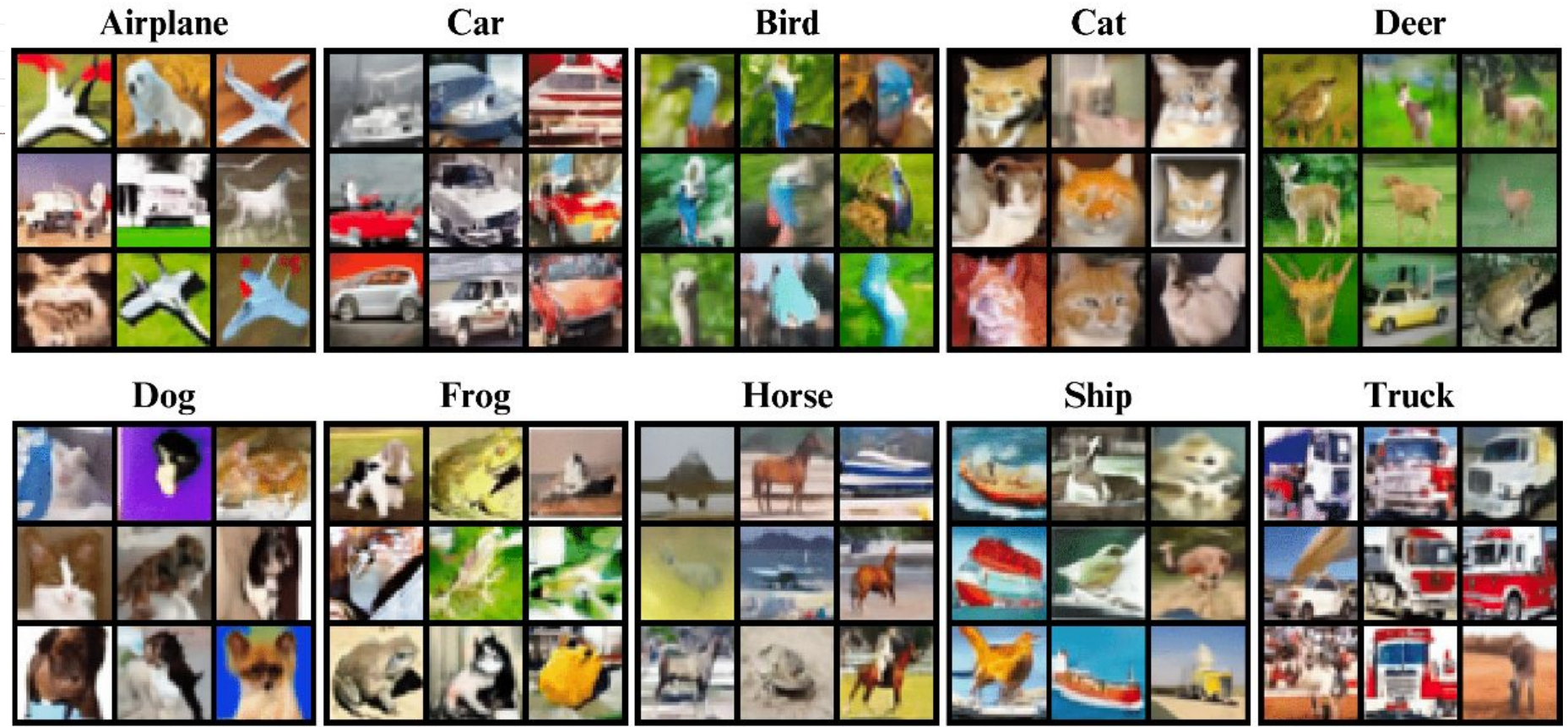
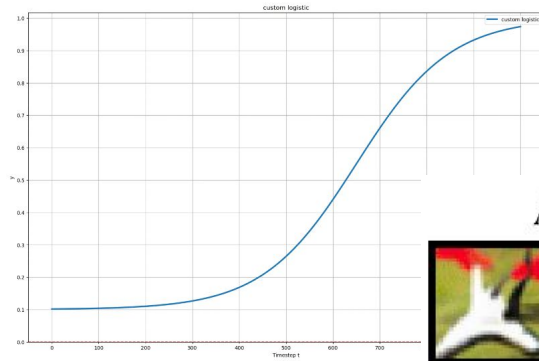


Joint Energy Guidance





Joint Energy Guidance



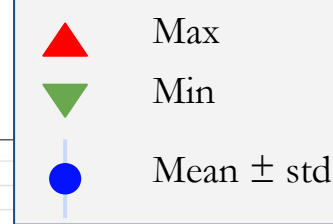


Classifier-free Diffusion Guidance with a Robust Energy-Based Classifier

An analysis on training set Energy



E(x) statistics by Class CIFAR-10 training set



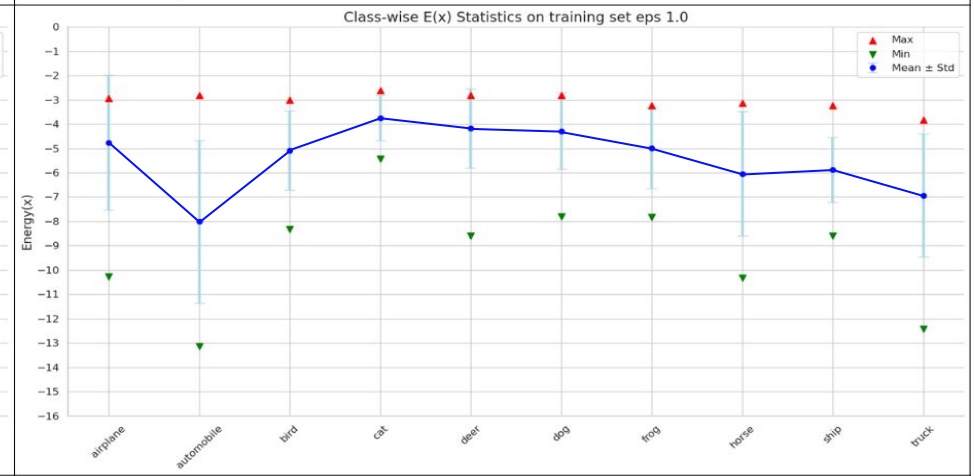
$\epsilon = 0/255$



$\epsilon = 0.25/255$



$\epsilon = 0.5/255$



$\epsilon = 1.0/255$



Bring back $E(\mathbf{x})$ for guidance

$$\Delta E_{\phi}(\mathbf{x}) = |E_{\phi}(\mathbf{x}^*)[y] - E_{\phi}(\mathbf{x})|$$



Bring back $E(\mathbf{x})$ for guidance

$$\Delta E_{\phi}(\mathbf{x}) = |E_{\phi}(\mathbf{x}^*)[y] - E_{\phi}(\mathbf{x})|$$

$$\mathcal{L} := E_{\phi}(\mathbf{x}, y) + \lambda \Delta E_{\phi}(\mathbf{x})$$



Bring back $E(\mathbf{x})$ for guidance

$$\Delta E_{\phi}(\mathbf{x}) = |E_{\phi}(\mathbf{x}^*)[y] - E_{\phi}(\mathbf{x})|$$

$$\mathcal{L} := E_{\phi}(\mathbf{x}, y) + \lambda \Delta E_{\phi}(\mathbf{x})$$

1 **for all** t *from* T *to* 1 **do**

2 $\epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$;

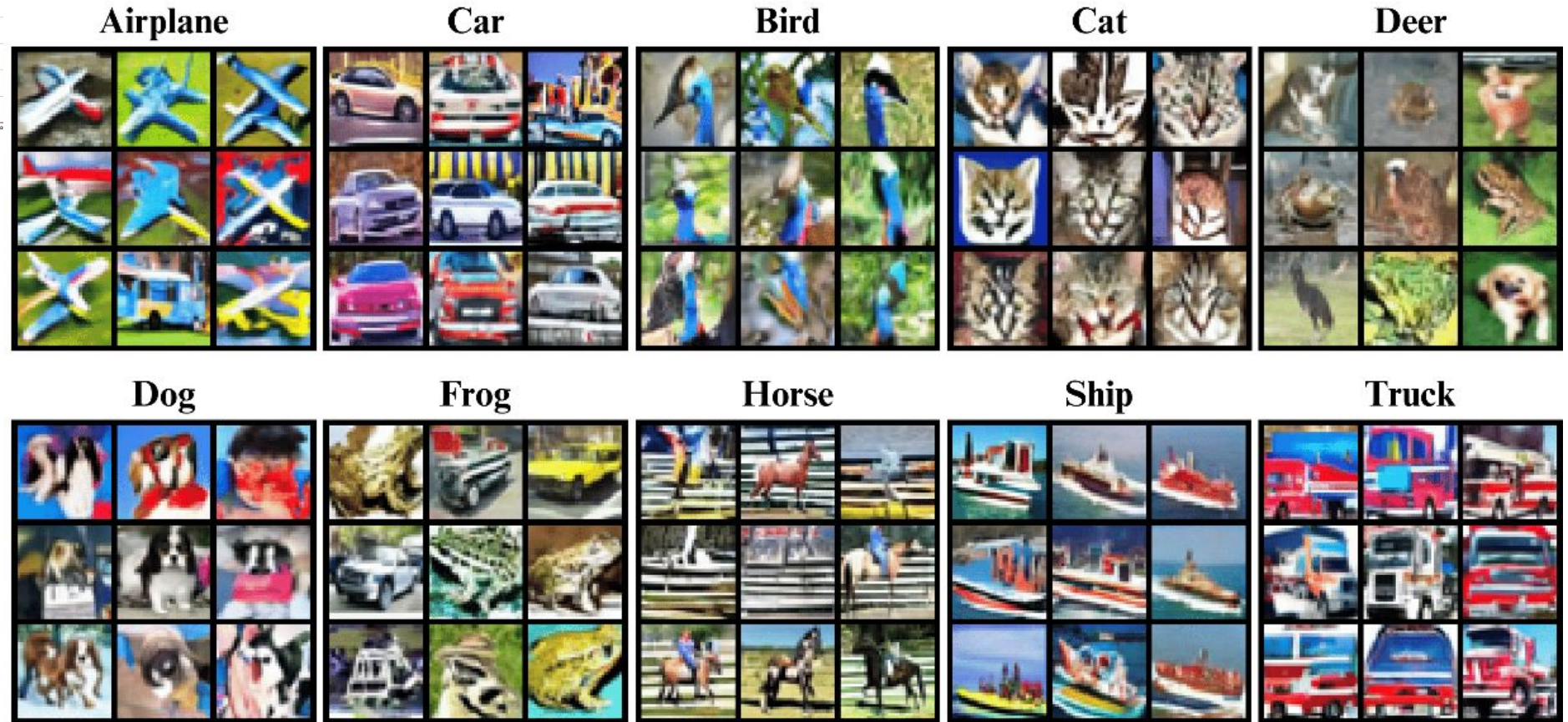
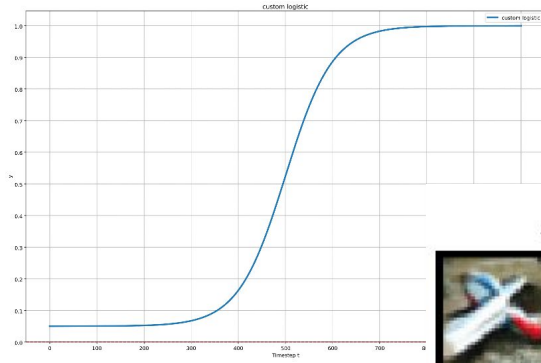
3 $\mu \leftarrow \frac{1}{\sqrt{\alpha_t}} \left(\mathbf{x}_t - \frac{1-\alpha_t}{\sqrt{1-\bar{\alpha}_t}} \epsilon_{\theta}(\mathbf{x}_t, t) \right) - \cancel{s\hat{\sigma}_t \nabla_{\mathbf{x}_t} E_{\phi}(\mathbf{x}, y)}$

4 $\mathbf{x}_{t-1} \leftarrow \mu + \sigma_t \epsilon$;

5 **return** $\mathbf{x}_0$



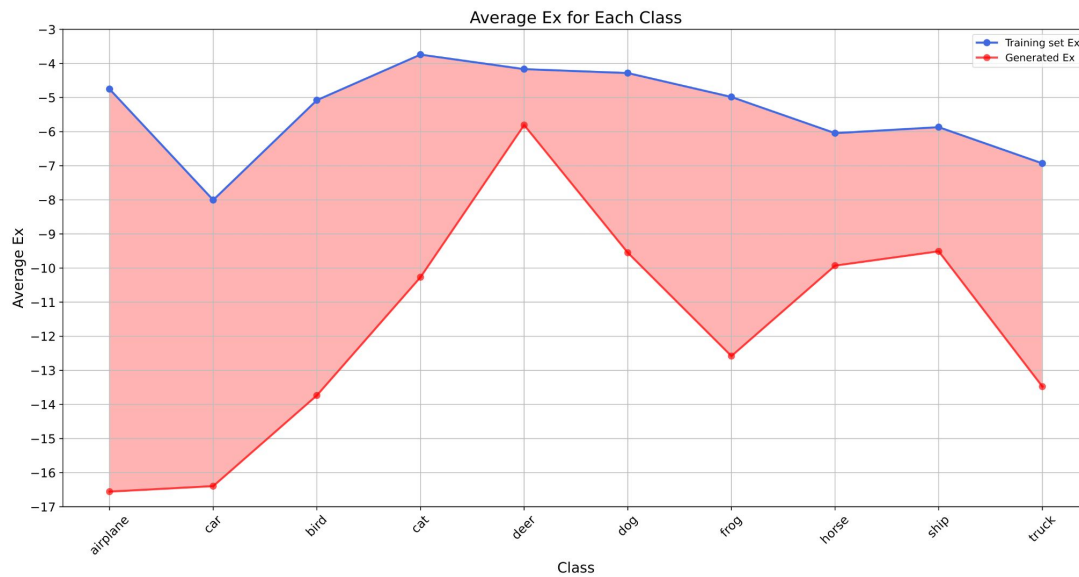
Energy is more important than you think



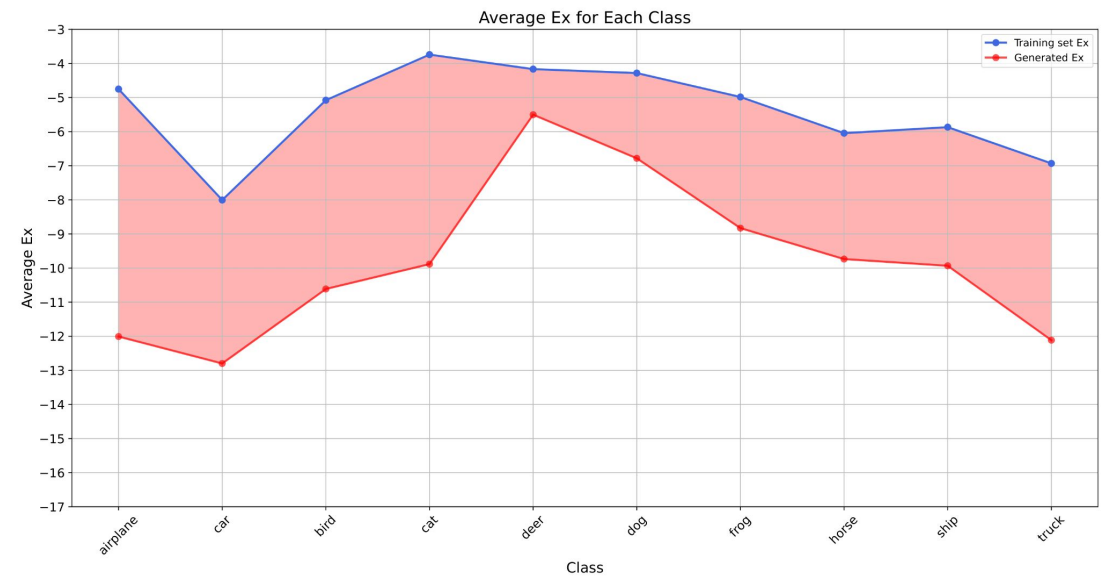


Reducing the Energy Divergence

$$\nabla_{\mathbf{x}_t} E_{\phi}(\mathbf{x}, y)$$



$$\nabla_{\mathbf{x}_t} \mathcal{L}$$





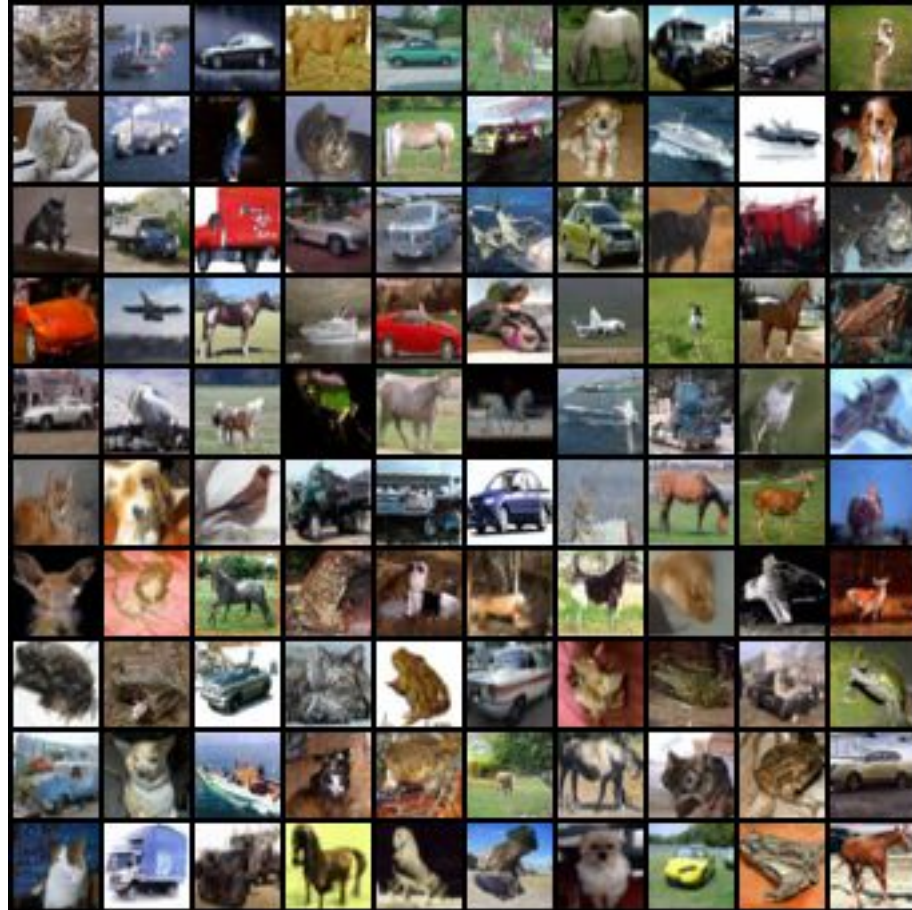
Thanks for listening!

Do you have any questions?

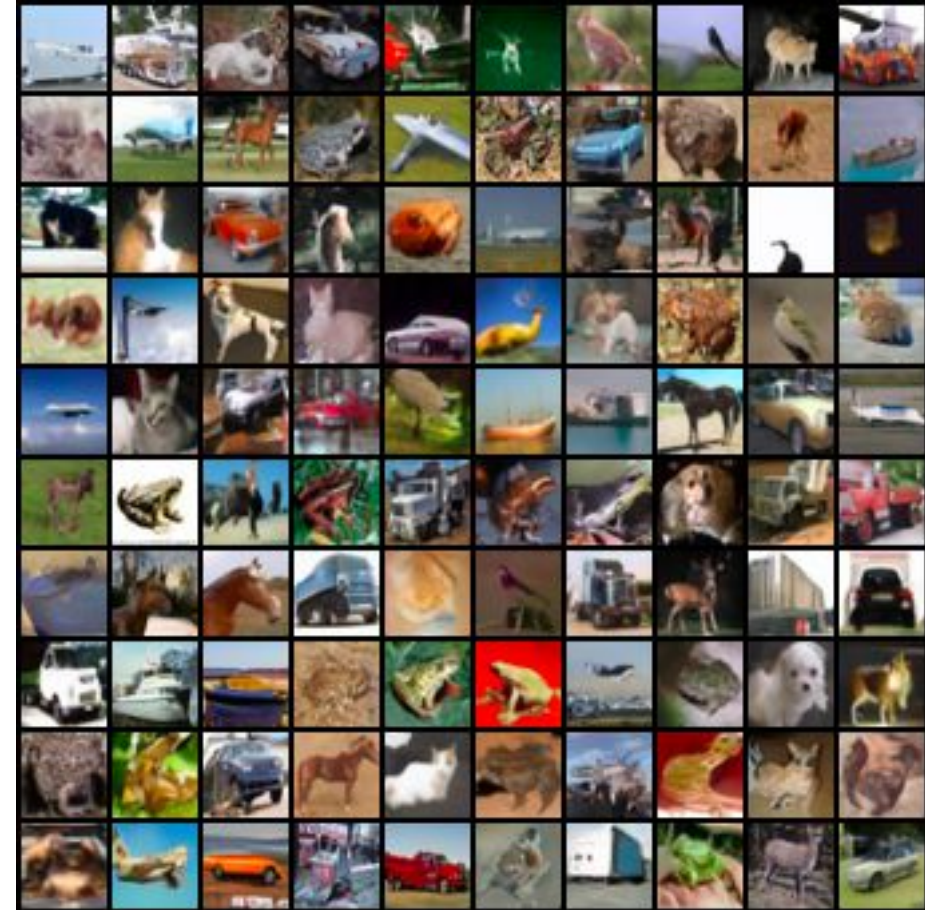




Unconditional Model Quality



DDPM



DDIM



Diffusion Model Evaluation

	IS $\uparrow$	FID $\downarrow$	Precision $\uparrow$	Recall $\uparrow$
DDPM	8.68	16.49	0.68	0.59
DDIM	8.40	14.79	0.64	0.59

Table 4.2. Evaluation metrics for unconditional guidance using DDPM and DDIM on CIFAR-10 test set, with 1000 and 100 inference steps respectively



Classifier Evaluation

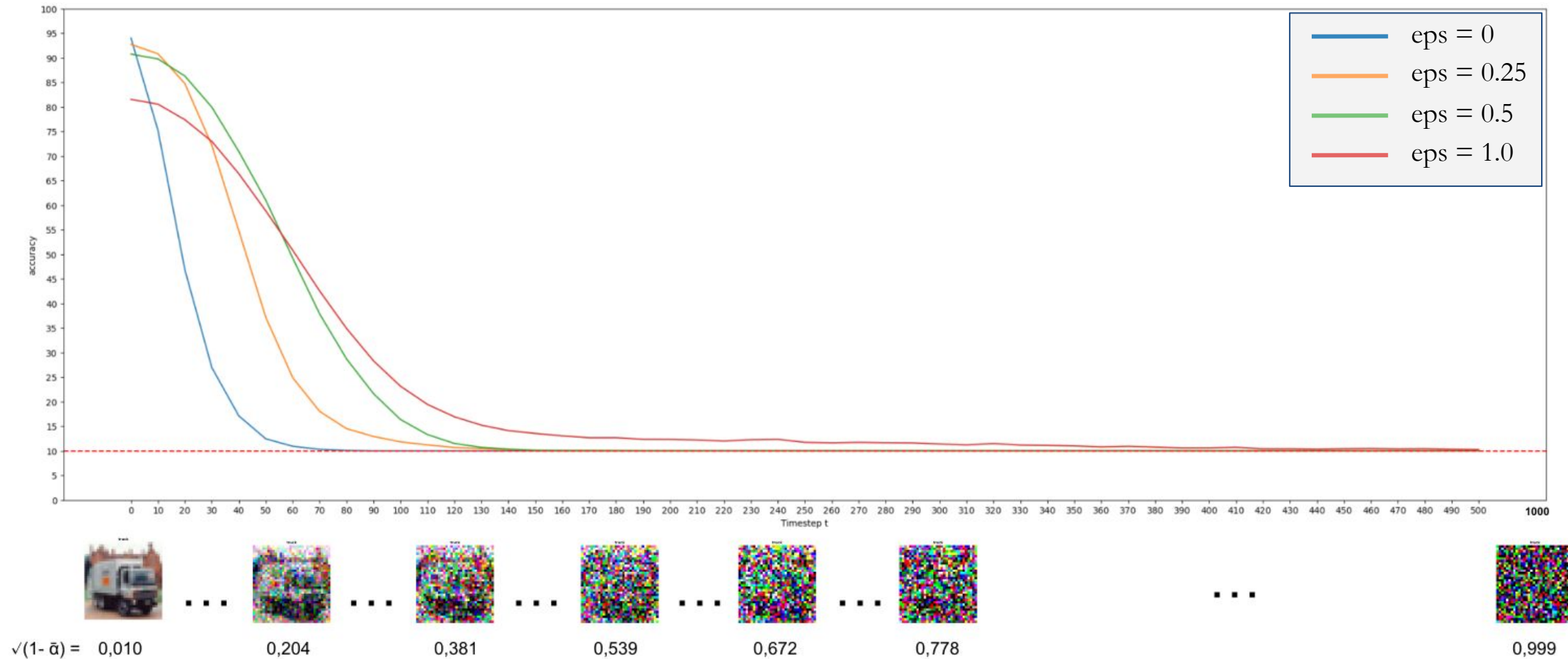
ε -test \ ε -train	0.0	0.25	0.5	1.0
0.0	95.25%	92.77%	90.83%	81.62%
0.25	8.65%	81.21%	82.40%	75.53%
0.5	0.28%	62.29%	70.17%	68.63%
1.0	0.00%	21.18%	40.48%	52.72%
2.0	0.00%	0.53%	5.22%	18.59%

Table 4.1. CIFAR10 L2-norm (ResNet50) 20-steps pgd

test-accuracies on 20-steps PGD-attacks with step size = $2.5 * \frac{\varepsilon_{test}}{20}$

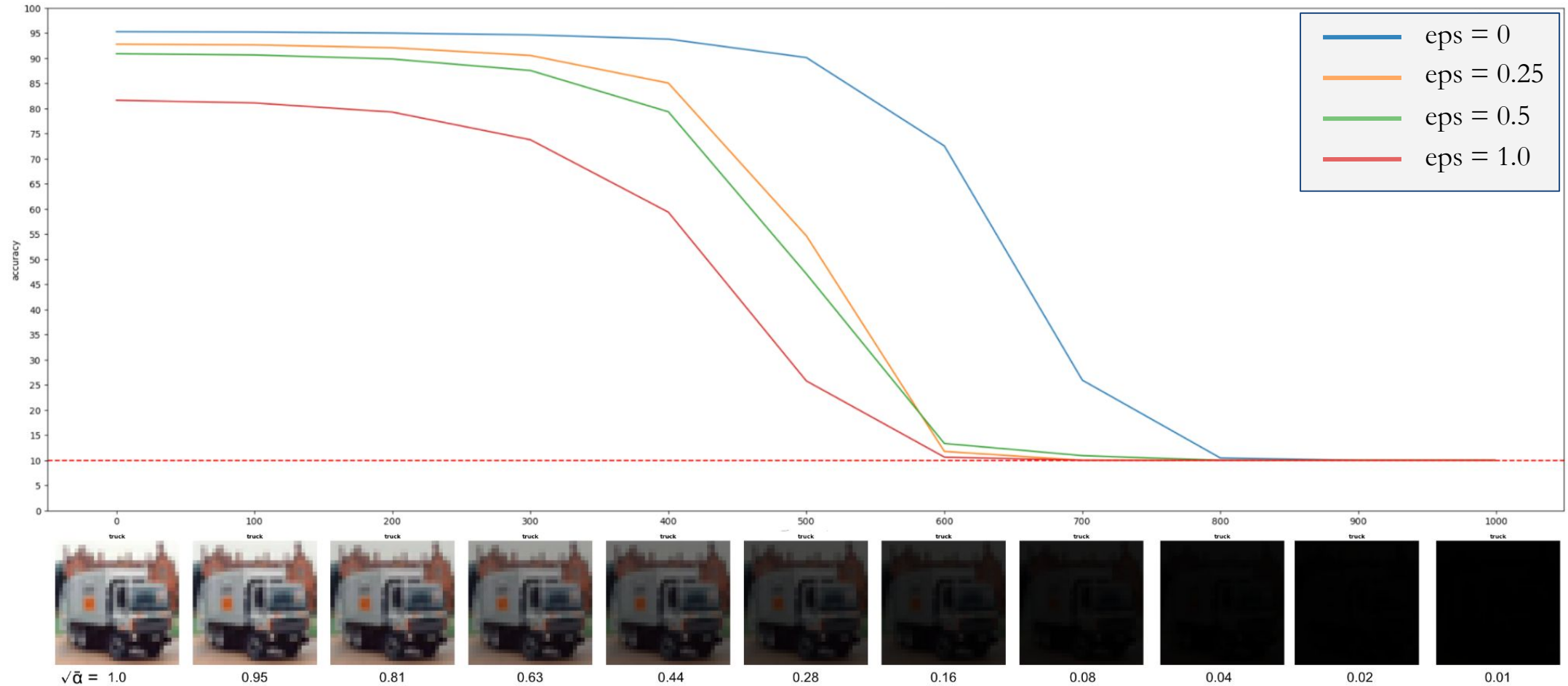


Classifier Accuracy - Gaussian Noise





Classifier Accuracy - Darkness





Average $E(x, y)$ and $E(x)$

