

References:

- [1] Jonathan Ho et al., „De-noising diffusion probabilistic models“, 2020
- [2] Alex Nichol et al., „Improved Denoising Diffusion Models“, 2021
- [3] Prafulla Dhariwal et al., „Diffusion Models Beat GANs on Image Synthesis“, 2021
- [4] Jonathan Ho et al., „Classifier-free Diffusion Guidance“, 2022
- [5] Alex Krizhevsky, „Learning Multiple Layers of Features from Tiny Images“, 2009
- [6] Yann LeCun et al., „MNIST handwritten digit database“, 2010

Learning the noise

Decoding diffusion models

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[Repository](#)

Theory

Forward process:

- Iteratively transform image into $\mathcal{N}(0, I)$

$$q(\mathbf{x}_{1:T}|\mathbf{x}_0) := \prod_{t=1}^T q(\mathbf{x}_t|\mathbf{x}_{t-1})$$

$$q(\mathbf{x}_t|\mathbf{x}_{t-1}) := \mathcal{N}(\mathbf{x}_t; \sqrt{1 - \beta_t}\mathbf{x}_{t-1}, \beta_t I)$$

Reverse process:

- Predict image iteratively from $\mathcal{N}(0, I)$
- CNN predicts noise reduction

$$p_\theta(\mathbf{x}_{0:T}) := p(\mathbf{x}_T) \prod_{t=1}^T p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t)$$

$$p_\theta(\mathbf{x}_{t-1}|\mathbf{x}_t) := \mathcal{N}(\mathbf{x}_{t-1}; \boldsymbol{\mu}_\theta(\mathbf{x}_t, t), \boldsymbol{\Sigma}_\theta(\mathbf{x}_t, t))$$

- Use reparametrization trick to predict ϵ_θ

Training & Sampling:

Algorithm 1 Training

```

1: repeat
2:    $\mathbf{x}_0 \sim q(\mathbf{x}_0)$ 
3:    $t \sim \text{Uniform}(\{1, \dots, T\})$ 
4:    $\epsilon \sim \mathcal{N}(0, I)$ 
5:   Take gradient descent step on
      $\nabla_\theta \|\epsilon - \epsilon_\theta(\sqrt{\alpha_t}\mathbf{x}_0 + \sqrt{1 - \alpha_t}\epsilon, t)\|^2$ 
6: until converged

```

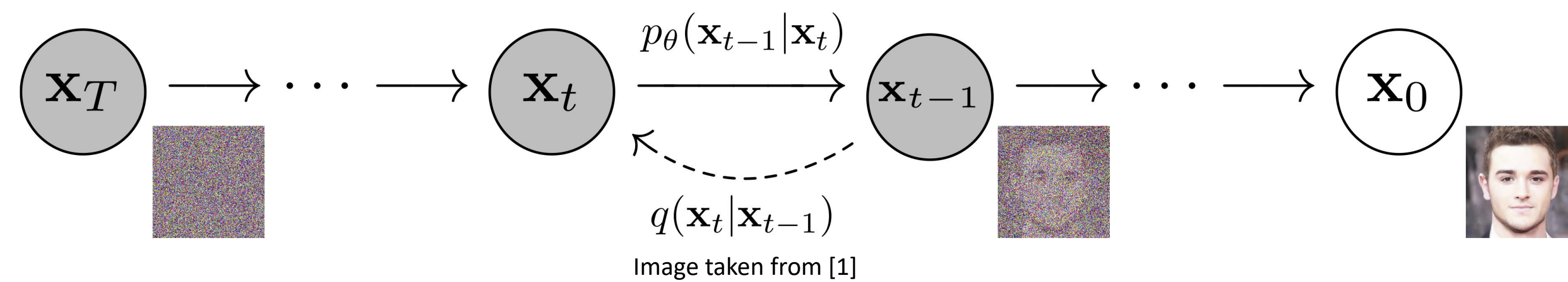
Algorithm 2 Sampling

```

1:  $\mathbf{x}_T \sim \mathcal{N}(0, I)$ 
2: for  $t = T, \dots, 1$  do
3:    $\mathbf{z} \sim \mathcal{N}(0, I)$  if  $t > 1$ , else  $\mathbf{z} = 0$ 
4:    $\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} \left( \mathbf{x}_t - \frac{1 - \alpha_t}{\sqrt{1 - \alpha_t}} \epsilon_\theta(\mathbf{x}_t, t) \right) + \sigma_t \mathbf{z}$ 
5: end for
6: return  $\mathbf{x}_0$ 

```

Algorithms taken from [1]



Model Architecture

Architecture:

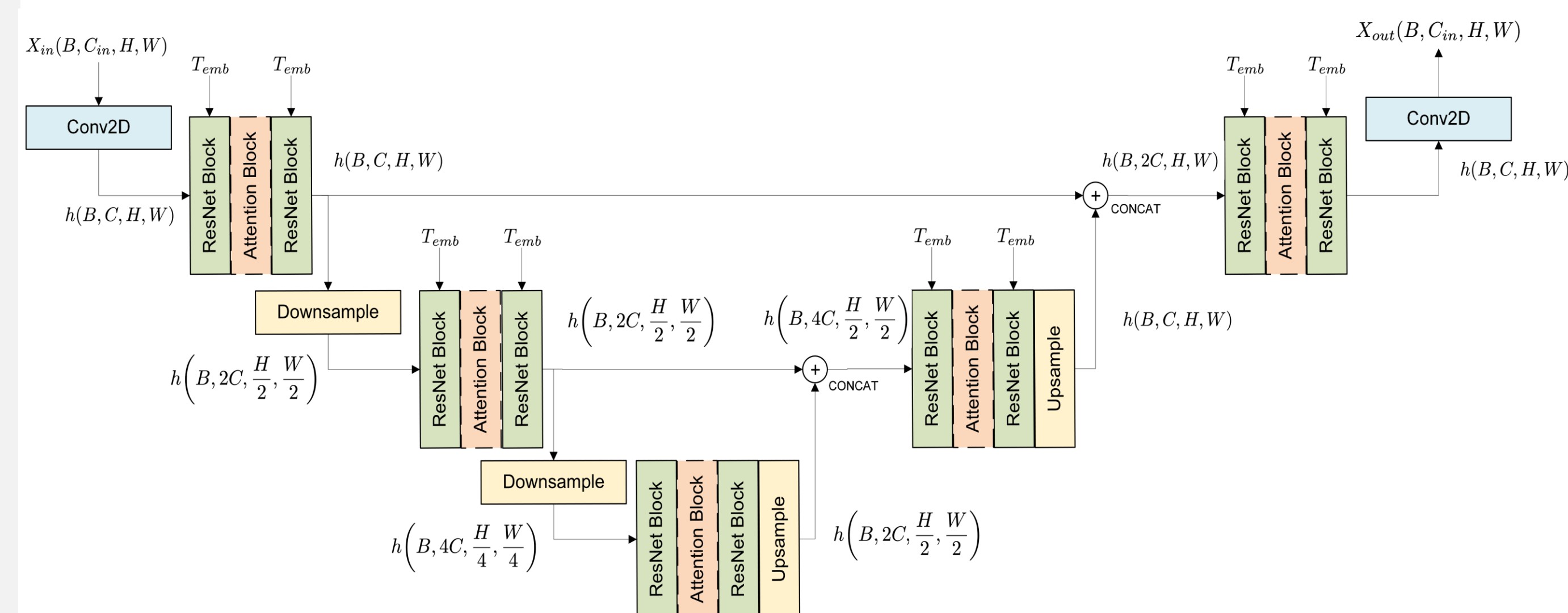
- UNet Architecture
- 3 encoder layers
- 2 ResNet Blocks per layer
- Optionally 1 attention block per layer
- Input & Output 2D convolution to match feature dimensions

Attention Blocks:

- Self-attention between feature map pixels

ResNet-Blocks:

- Group Normalisation
- Sinusoidal temporal embeddings passed through linear layer and added
- Label embeddings are optional, used for classifier-free guidance



Training

Data:

- Training on MNIST & CIFAR-10
- Images normalized to $[-1, 1]$
- No resizing & data augmentation

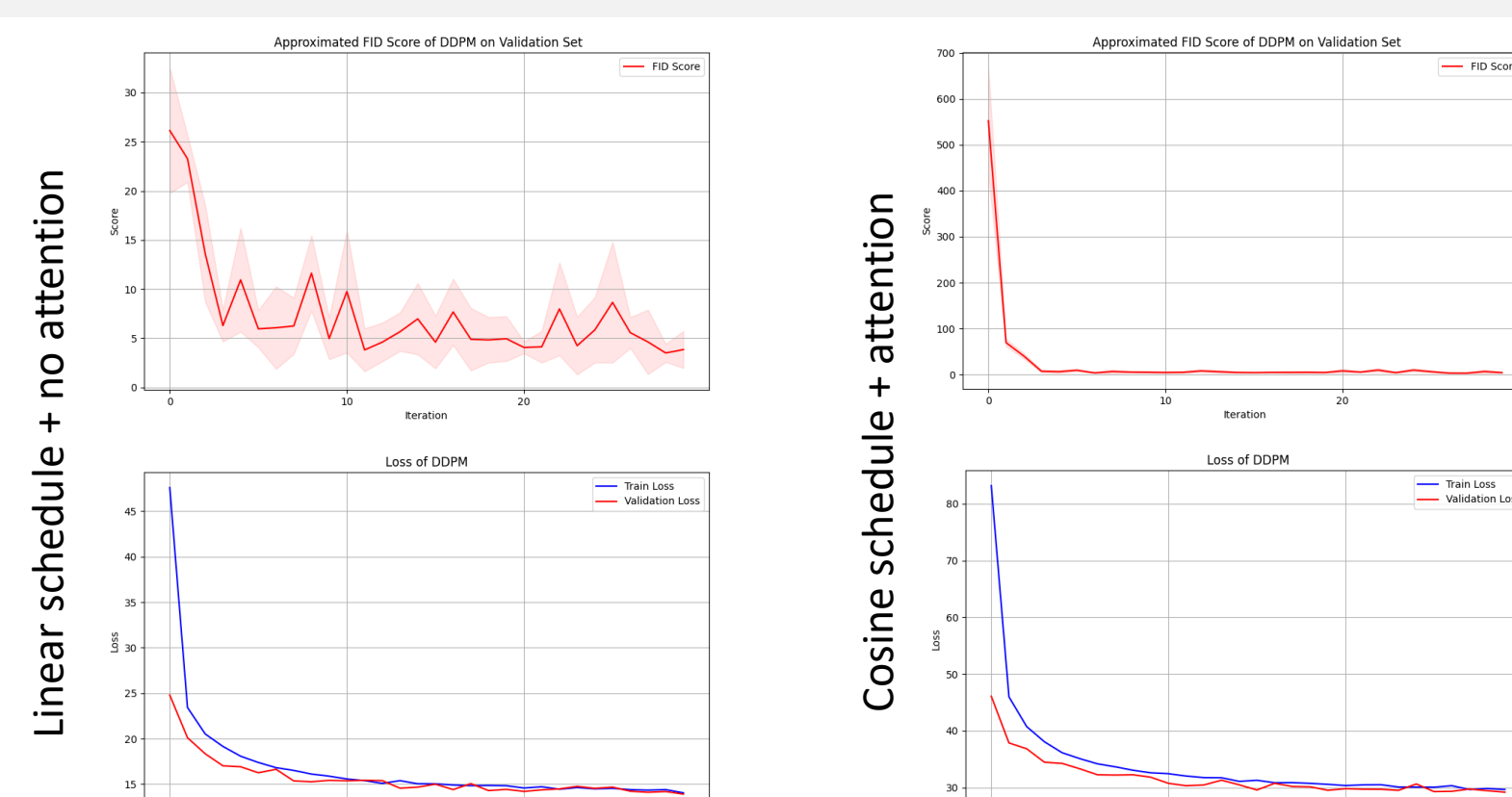
Hyperparameters:

- Linear schedule: $\beta_0 = 10^{-4}$ and $\beta_T = 0.02$
- Cosine schedule: $s = 0.008$
- Diffusion steps: $T = 1000$

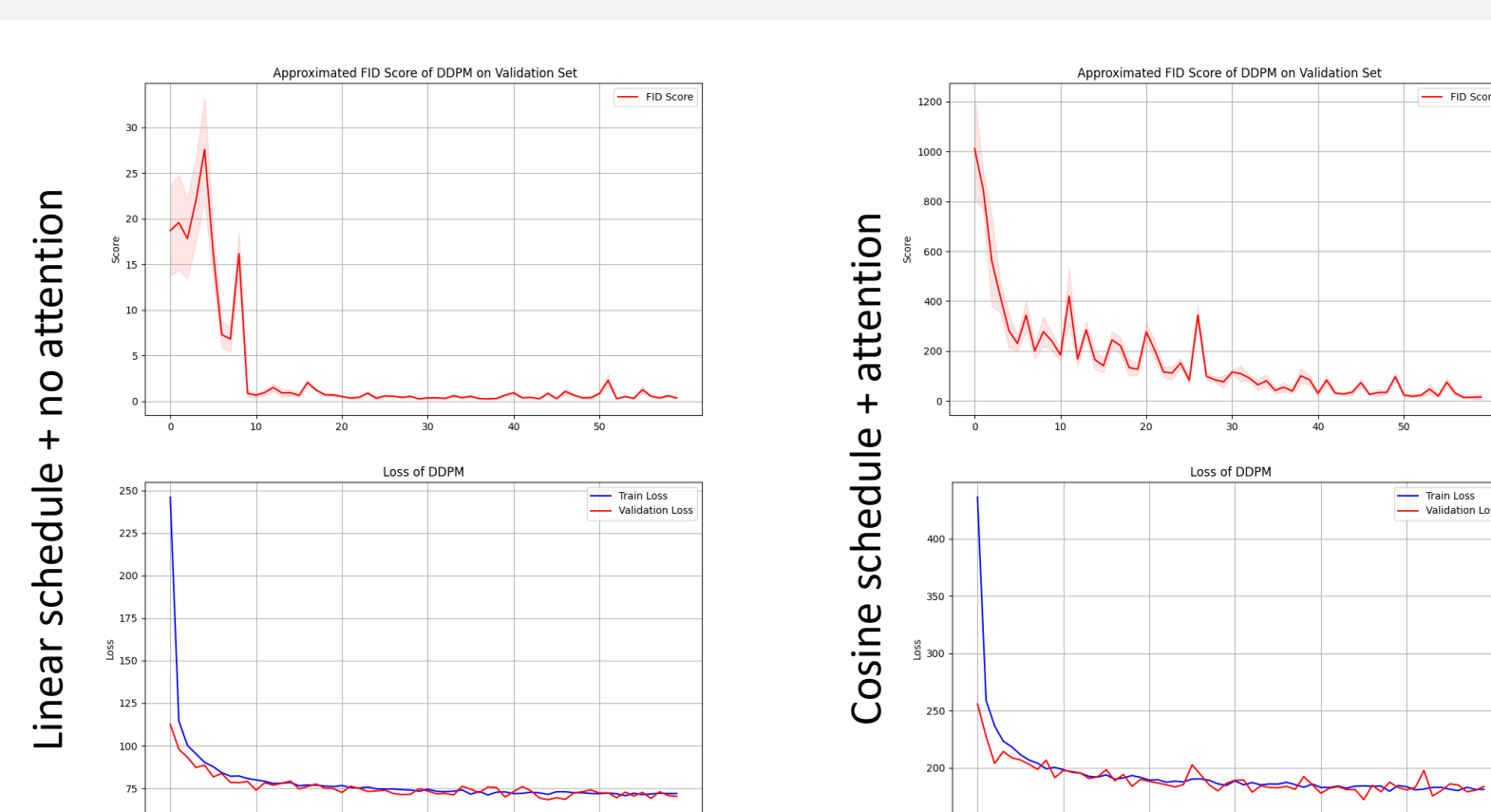
Training:

- Optimizer is *Adam* with $l_r = 10^{-4}$
- Training for 30 epochs on MNIST & 60 epochs on CIFAR-10
- Validation-loss on validation set & FID score on 5 minibatches of validation set
- FID for final model on training & test set for 8192 generated samples
- Training with different ablations
 - Linear & cosine schedule
 - Attention & no-attention layers in network

MNIST



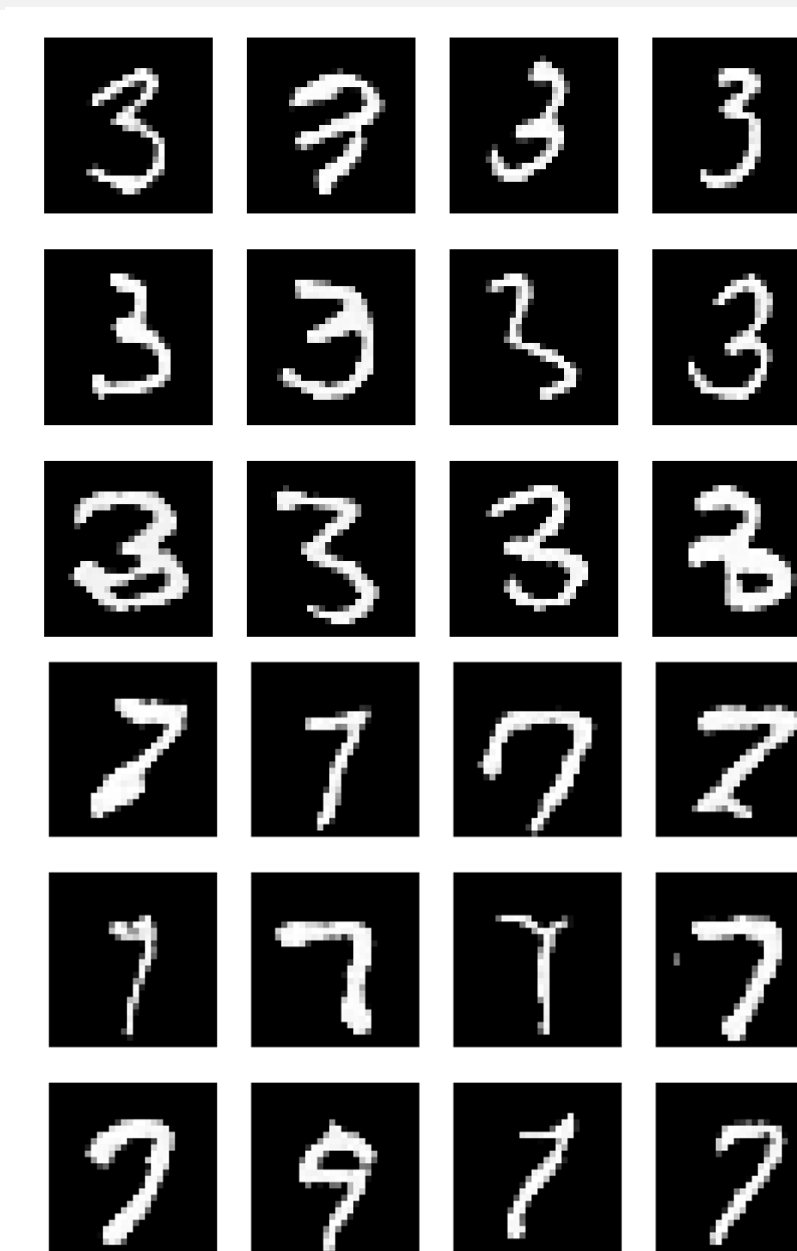
CIFAR-10



Classifier-free guided sampling:

- label embeddings added to temporal embeddings
- Trained for 30 epochs, *Adam* optimizer with $l_r = 10^{-4}$

MNIST



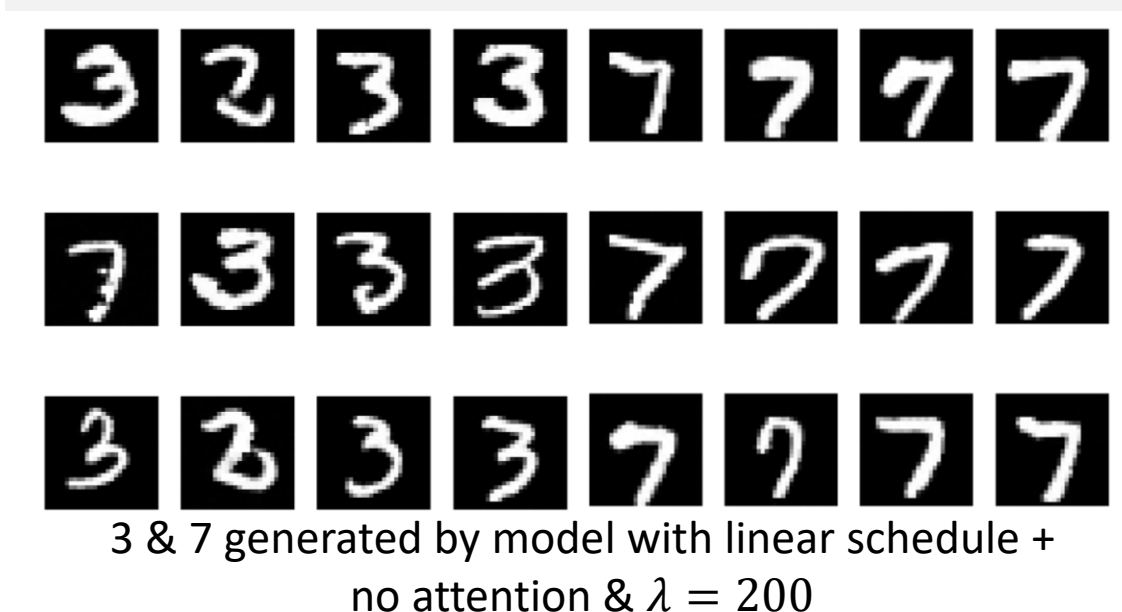
3 & 7 generated by model with linear schedule + attention

Classifier guided sampling:

- Subtracting gradient w.r.t. input of classifier at each sampling step

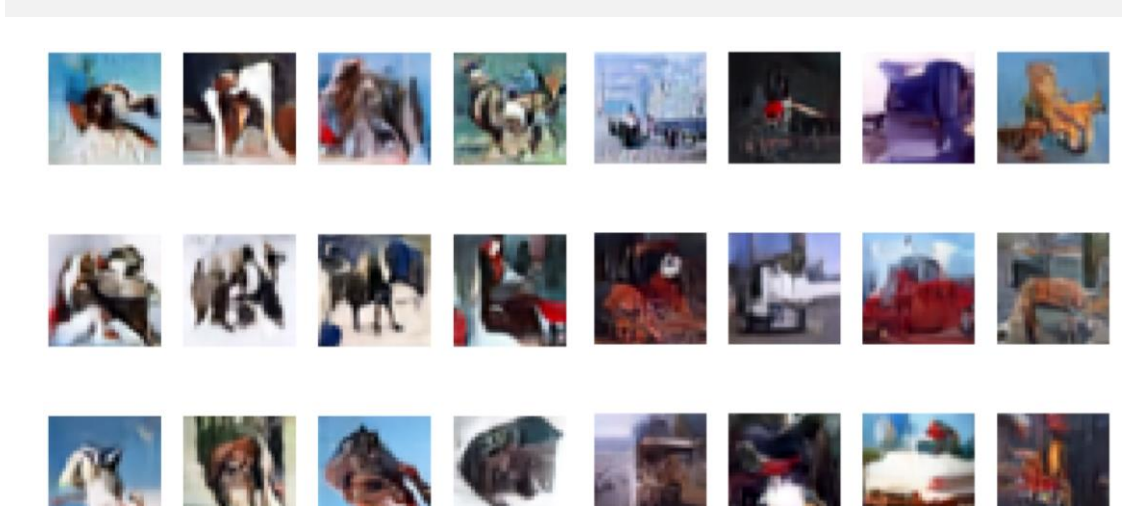
$$\epsilon_\theta = \epsilon_{\theta'} - \lambda \nabla \ln(p_c(y|x_t))$$

MNIST



3 & 7 generated by model with linear schedule + no attention & $\lambda = 200$

CIFAR-10

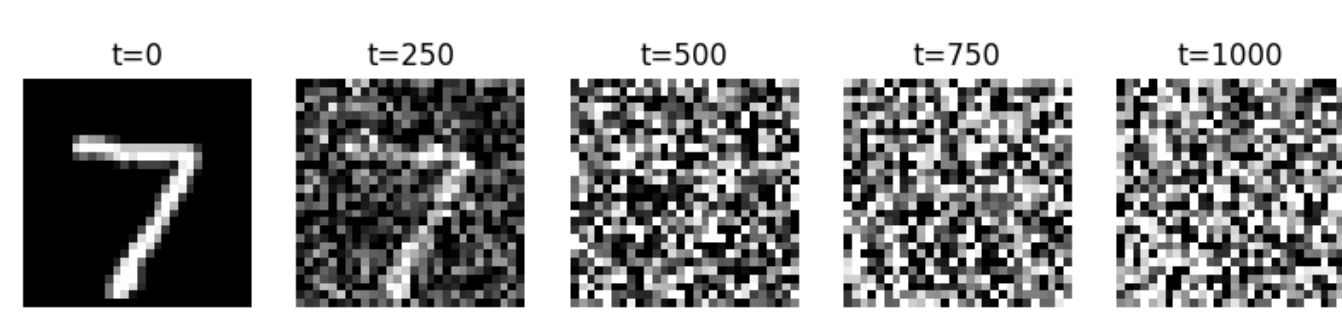


dogs & trucks generated by model with linear schedule + no attention & $\lambda = 200$

Sampling & Evaluation

MNIST

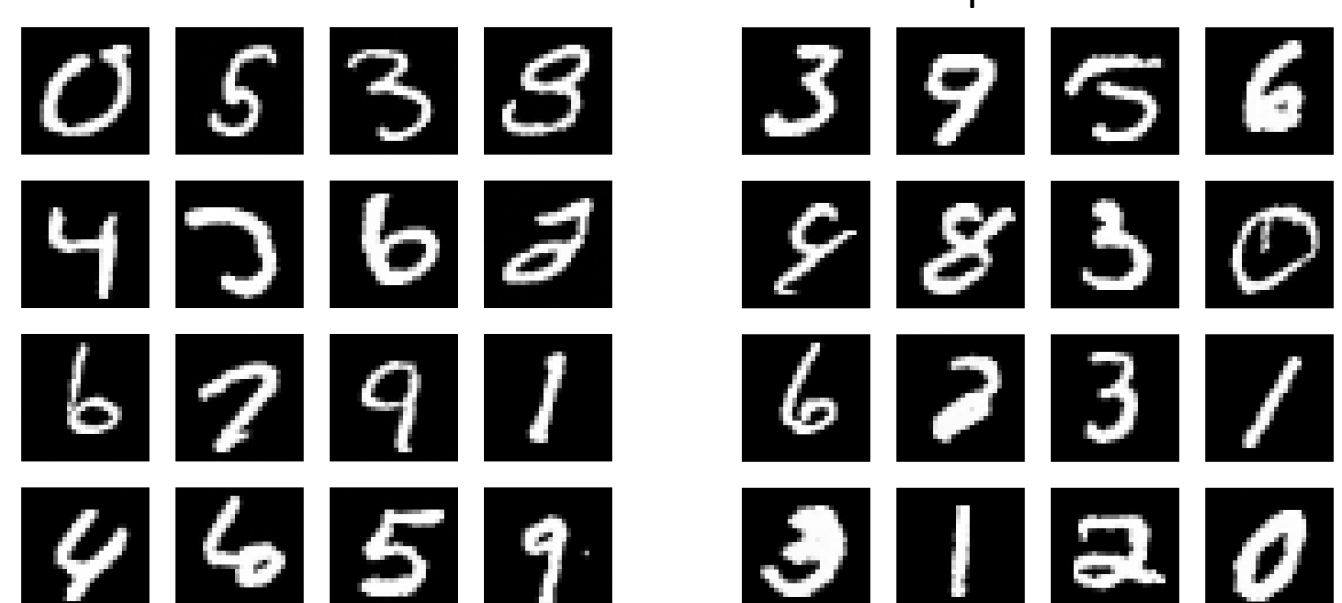
8192 samples On MNIST classifier	Linear schedule + no attention	Linear schedule + attention	Cosine schedule + no attention	Cosine schedule + attention
<i>Train – FID</i>	2.286	2.849	2.105	1.766
<i>Test – FID</i>	2.803	3.490	2.724	2.385



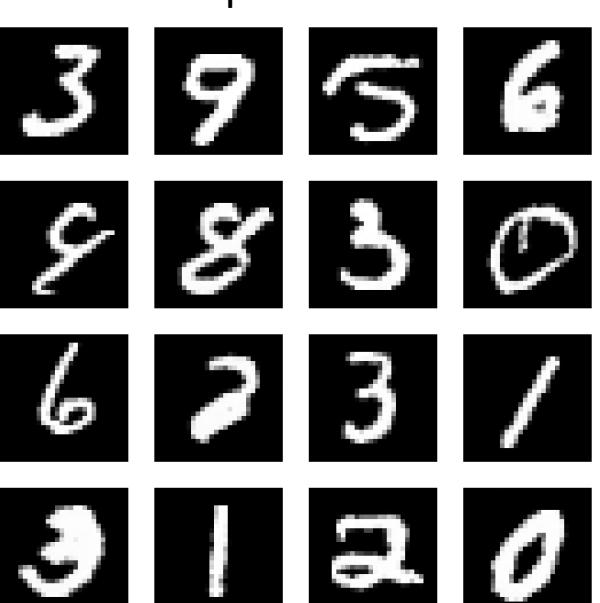
Linear schedule forward process



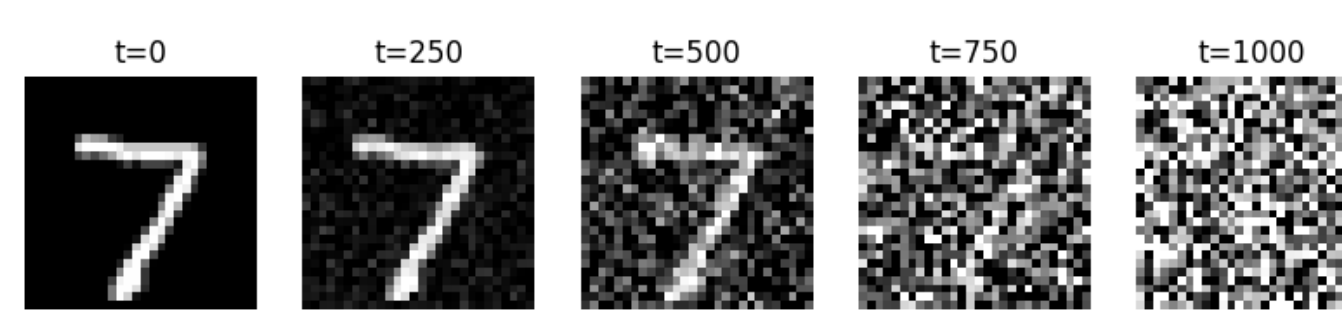
Linear schedule + no attention reverse process



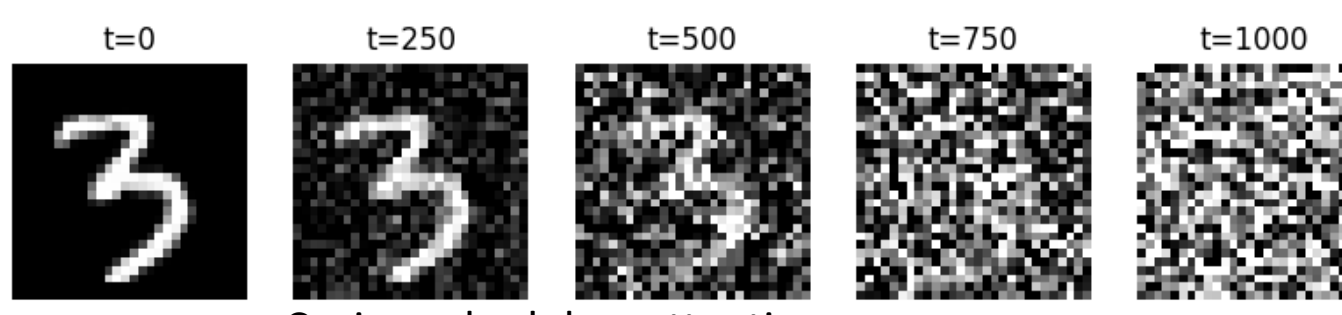
Linear schedule + no attention



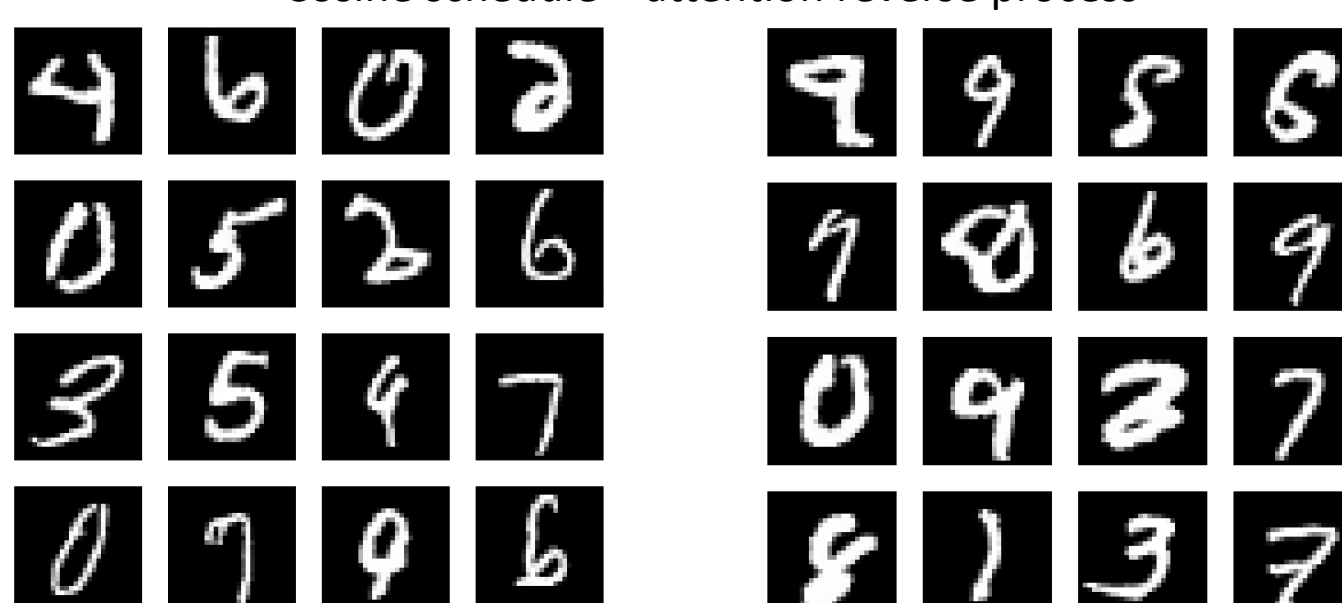
Linear schedule + attention



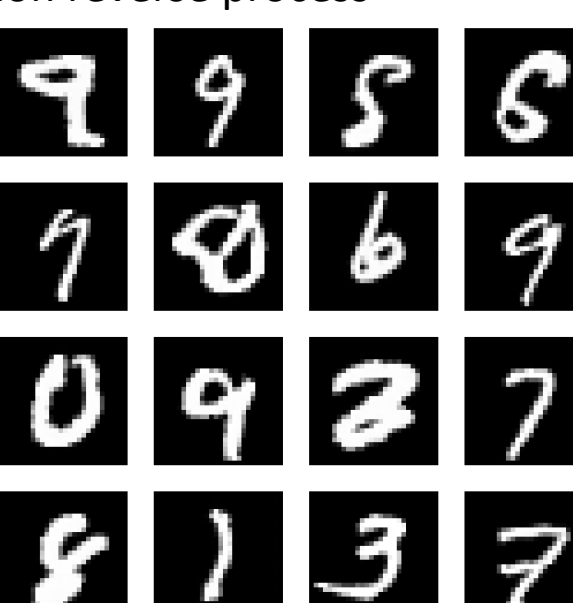
Cosine schedule forward process



Cosine schedule + attention reverse process



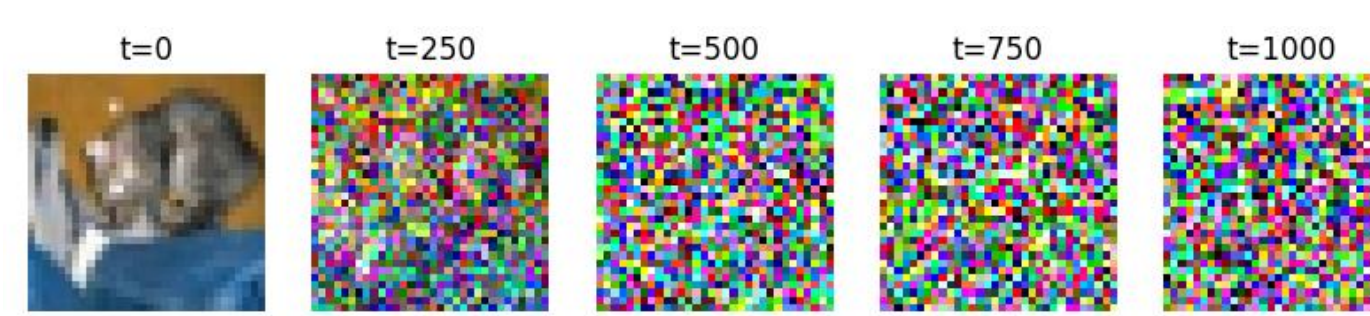
Cosine schedule + no attention



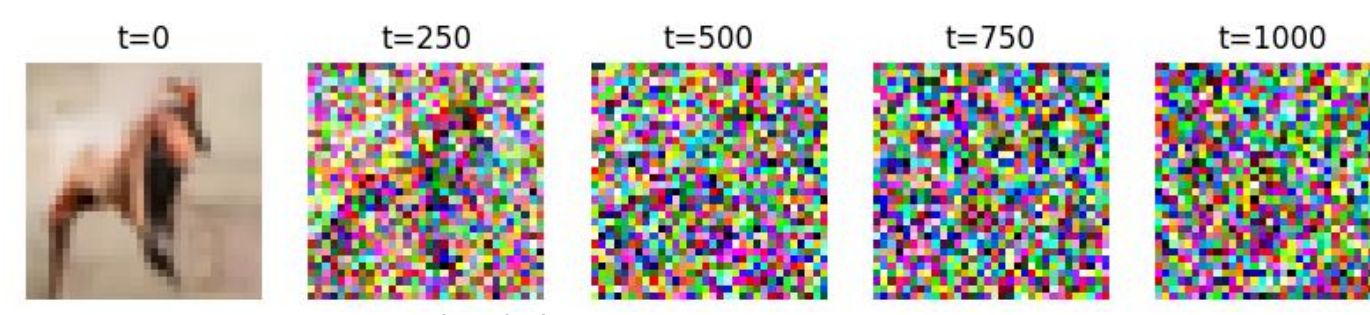
Cosine schedule + attention

CIFAR-10

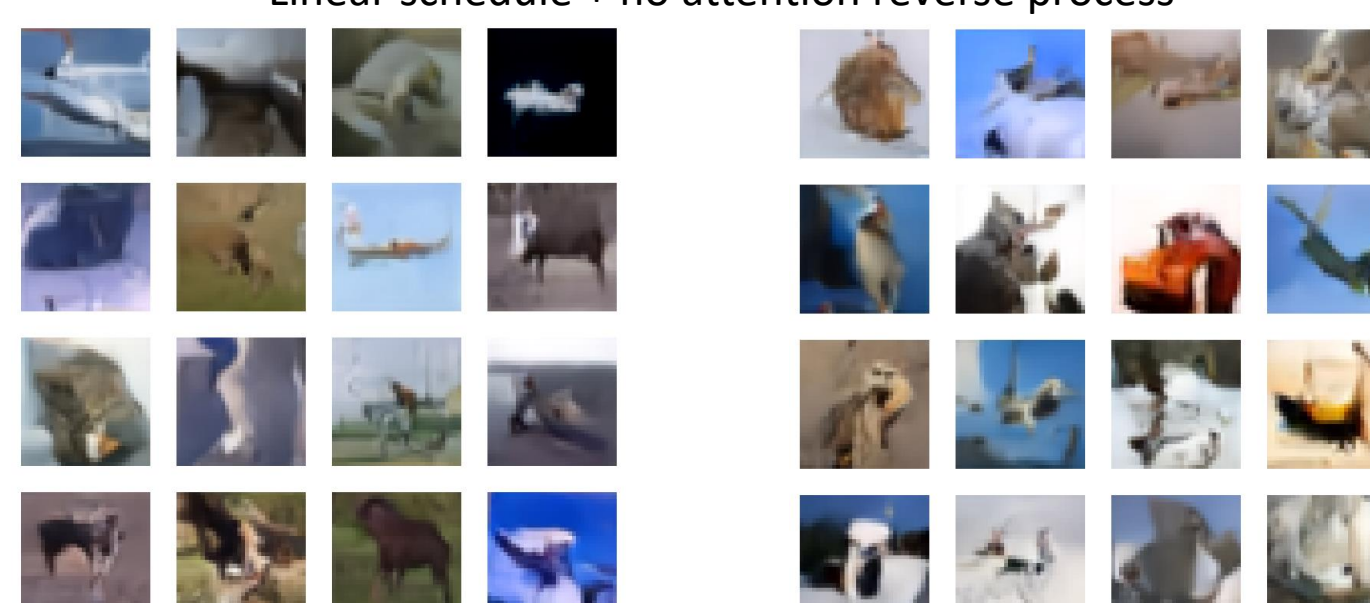
8192 samples On MNIST classifier	Linear schedule + no attention	Linear schedule + attention	Cosine schedule + no attention	Cosine schedule + attention
<i>Train – FID</i>	0.114	0.165	49.393	14.565
<i>Test – FID</i>	0.128	0.153	49.058	14.508



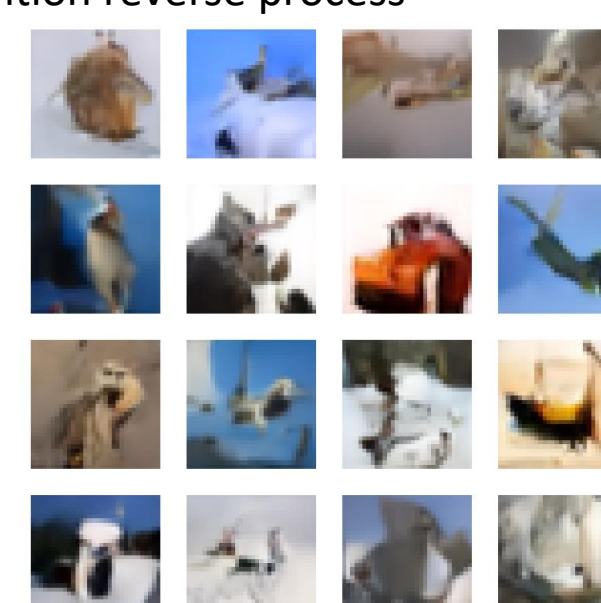
Linear schedule forward process



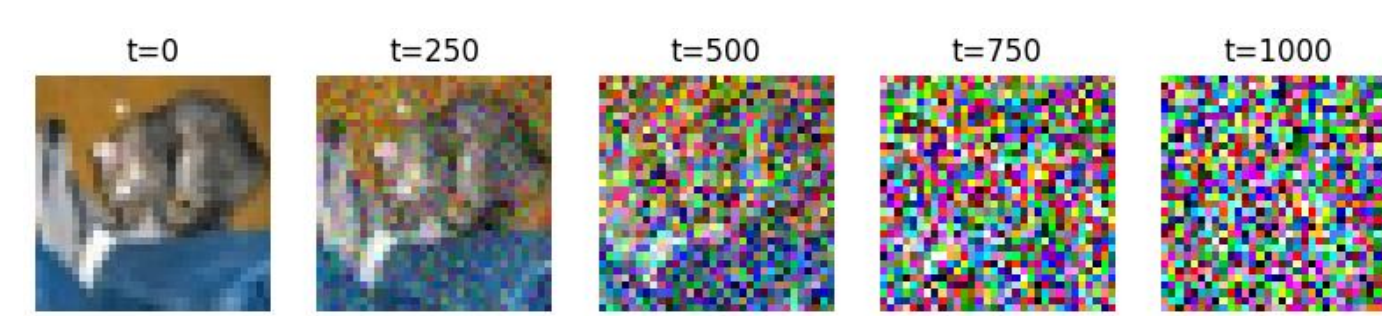
Linear schedule + no attention reverse process



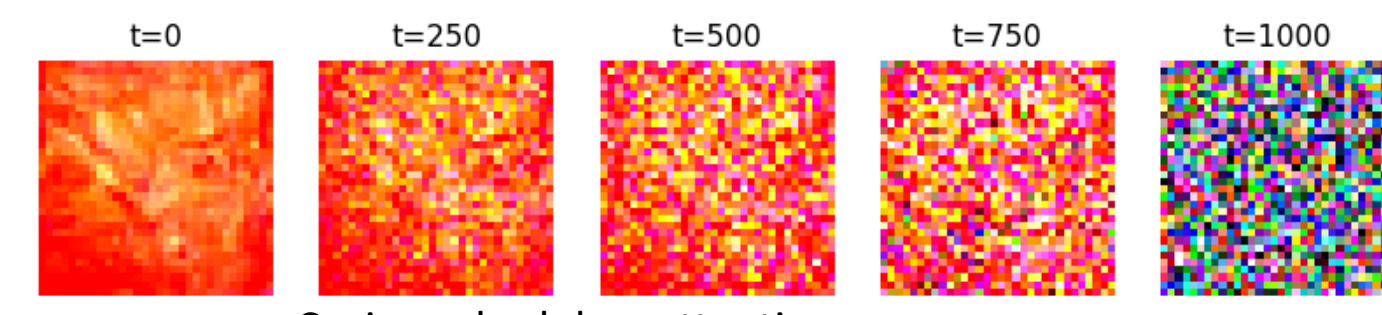
Linear schedule + no attention



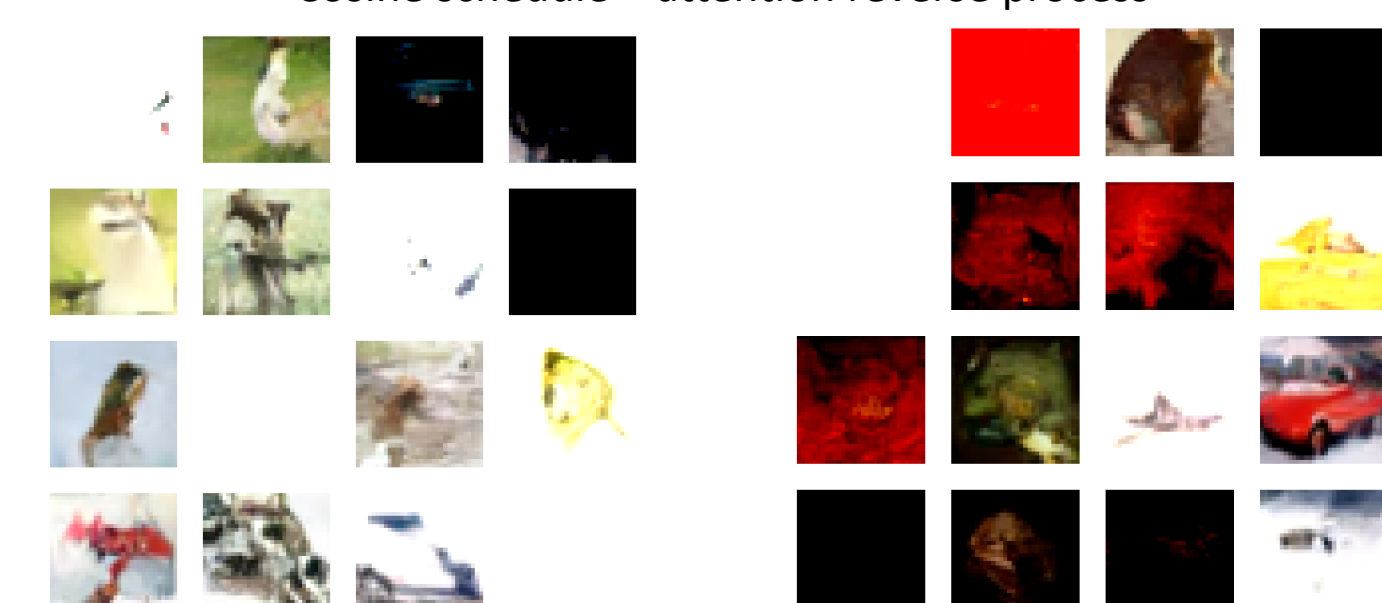
Linear schedule + attention



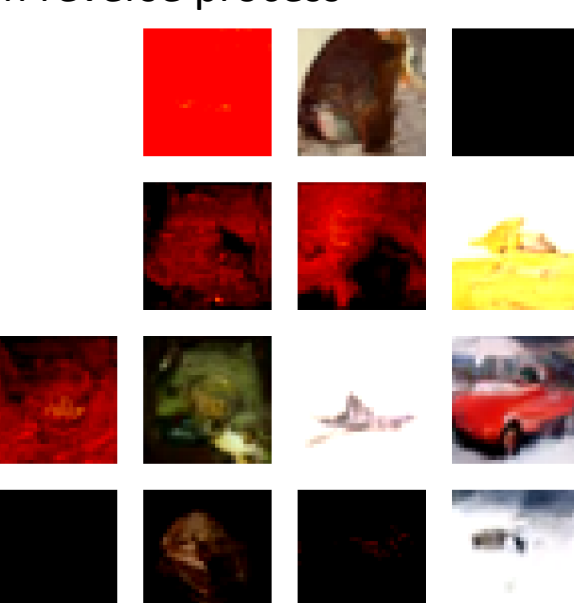
Cosine schedule forward process



Cosine schedule + attention reverse process



Cosine schedule + no attention



Cosine schedule + attention