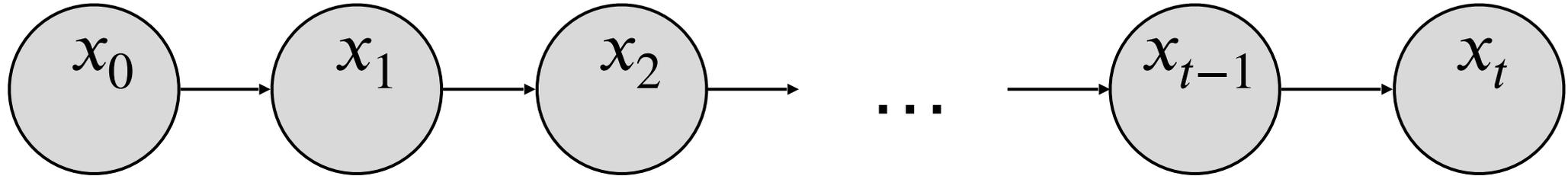


# Diffusion Project Problem Session

# Task 1: Some Derivations (1.1)



$$\mathbf{x}_t = \sqrt{1 - \beta_t} \mathbf{x}_{t-1} + \sqrt{\beta_t} \mathbf{z}_{t-1} \quad \text{where} \quad \mathbf{z}_{t-1} \sim \mathcal{N}(0, I)$$

Show that

$$\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{x}_0 + \sqrt{1 - \bar{\alpha}_t} \mathbf{z} \quad \text{where} \quad \mathbf{z} \sim \mathcal{N}(0, I)$$

# Task 1: Some Derivations (1.2)

Score-based formulation

$\Leftrightarrow$

$\hat{\mathbf{x}}_0$ -based formulation

---

$\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$   
**for**  $t = T, \dots, 1$  **do**  
   $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\mathbf{z} = \mathbf{0}$   
  
$$\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}}(\mathbf{x}_t + (1 - \alpha_t)\mathbf{s}_\theta(\mathbf{x}_t, t)) + \sqrt{1 - \alpha_t}\mathbf{z}$$
  
**end for**  
**return**  $\mathbf{x}_0$

---

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$\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$   
**for**  $t = T, \dots, 1$  **do**  
   $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\mathbf{z} = \mathbf{0}$   
  
$$\hat{\mathbf{x}}_0 = \frac{1}{\sqrt{\bar{\alpha}_t}}(\mathbf{x}_t + (1 - \bar{\alpha}_t)\mathbf{s}_\theta(\mathbf{x}_t, t))$$
  
  
$$\mathbf{x}_{t-1} = \frac{\sqrt{\alpha_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t}\mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t}\hat{\mathbf{x}}_0 + \sqrt{1 - \alpha_t}\mathbf{z}$$
  
**end for**  
**return**  $\mathbf{x}_0$

---

This is the formulation you will have to use

# Task 1: Some Derivations (1.3)

Original DDPM publication

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$\Leftrightarrow$

Score-based formulation

---

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

---

$\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$   
**for**  $t = T, \dots, 1$  **do**  
     $\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\mathbf{z} = \mathbf{0}$   
    
$$\mathbf{x}_{t-1} = \frac{1}{\sqrt{\alpha_t}} (\mathbf{x}_t + (1 - \alpha_t) \mathbf{s}_{\theta}(\mathbf{x}_t, t)) + \sqrt{1 - \alpha_t} \mathbf{z}$$
  
**end for**  
**return**  $\mathbf{x}_0$

---

Hint: Use Tweedie's formula and the forward diffusion equation  $\mathbf{x}_t = \sqrt{\bar{\alpha}_t} \hat{\mathbf{x}}_0 + \sqrt{1 - \bar{\alpha}_t} \epsilon$

# Task 2: Denoising

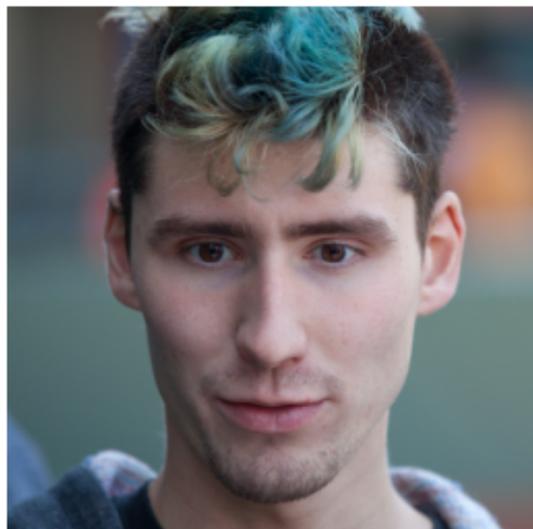
You will have to:

- Implement the forward (noising) process:  $\mathbf{x}_0 \rightarrow \mathbf{x}_t$
- Implement the denoiser:  $\mathbf{x}_t \rightarrow \hat{\mathbf{x}}_0$
- Visualize and analyze your results

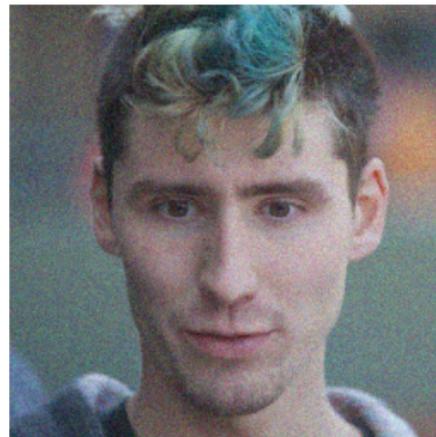
➤ Hint: useful quantities  $\left( \frac{1}{\sqrt{\bar{\alpha}_t}}, \frac{1 - \bar{\alpha}_t}{\sqrt{\bar{\alpha}_t}} \right)$  are pre-computed

# Task 2: Denoising

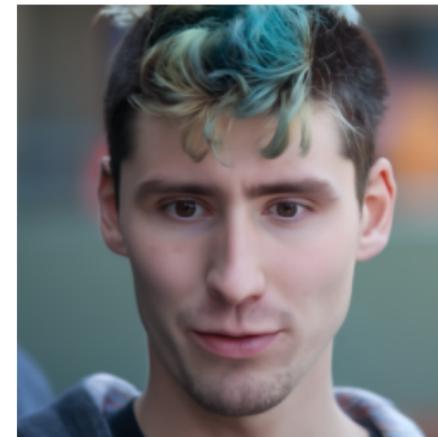
$x_0$



t=30



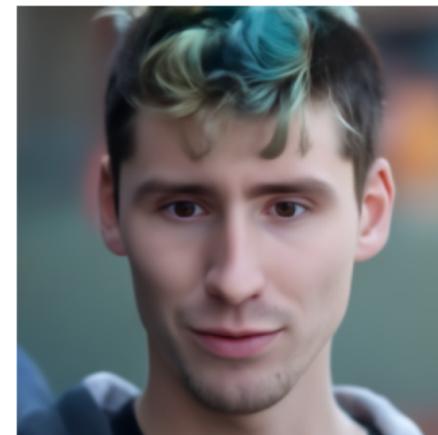
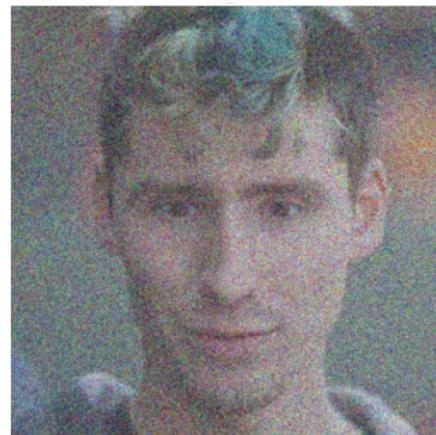
Denoised



PSNR/  
LPIPS

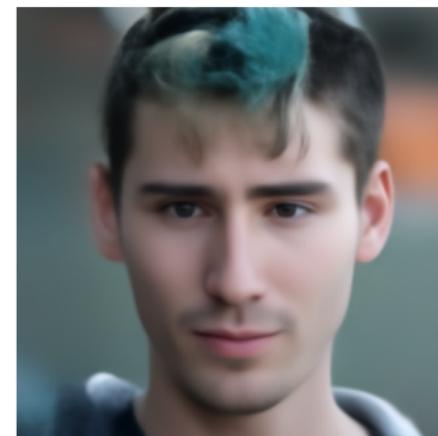
37.4  
0.0378

t=100



32.7  
0.0941

t=300



27.3  
0.203

# Task 3: Unconditional Generation

You will have to:

- Implement the denoiser using the score model:  $\mathbf{x}_t \rightarrow \hat{\mathbf{x}}_0$
- Implement the backward step:  $\hat{\mathbf{x}}_0, \mathbf{x}_t \rightarrow \mathbf{x}_{t-1}$
- Run unconditional generation:  $\emptyset \rightarrow \mathbf{x}_0$
- Visualize and analyze your results

➤ Hint: useful quantities are pre-computed

# Task 3: Unconditional generation

Example results



# Task 4: SDEdit

$$\mathbf{y} \xrightarrow{\text{Add noise}} \mathbf{x}_t = \sqrt{\bar{\alpha}_t} \mathbf{y} + \sqrt{1 - \bar{\alpha}_t} \mathbf{z} \xrightarrow{\text{Denoise}} \mathbf{x}_0$$

Measurement

$t$  is a hyperparameter

You will have to:

- Implement the denoiser, the backward step
- Implement and run SDEdit:  $\mathbf{y}, t \rightarrow \mathbf{x}_0$
- Visualize and analyze your results

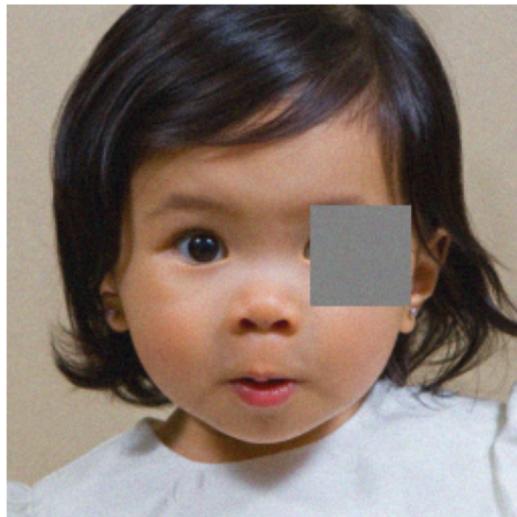
# Task 4: SDEdit

Ground Truth

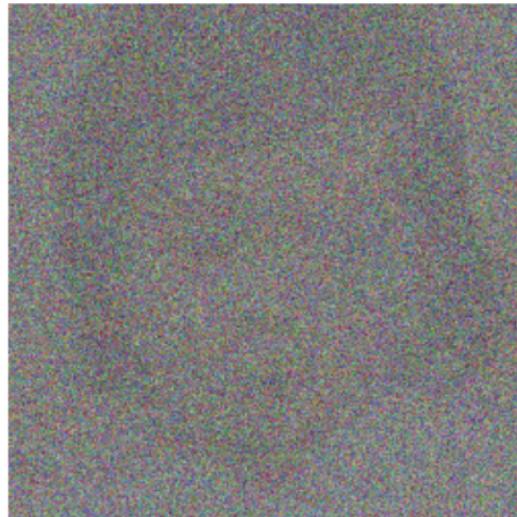


Inpainting

Input



Initialization (t=500)

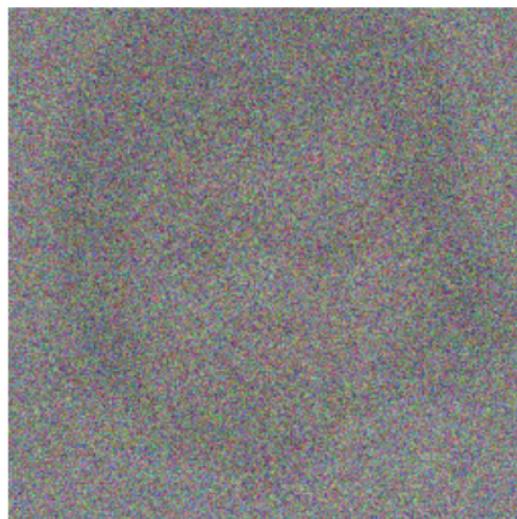
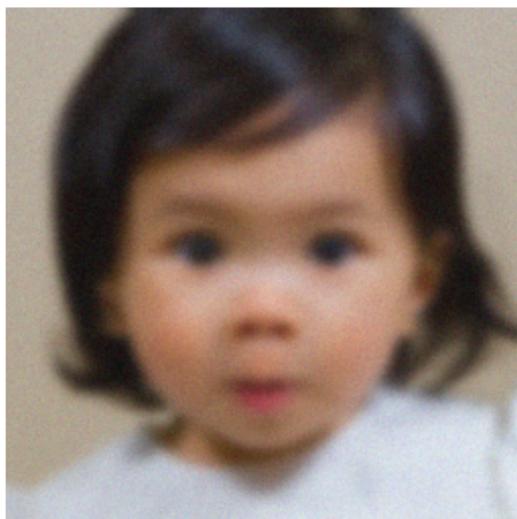


PSNR/LPIPS  
Reconstruction



20.2 / 0.189

Deconvolution



20.1 / 0.232

# Task 5: Score ALD

---

$$\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

**for**  $t = T, \dots, 1$  **do**

$\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\mathbf{z} = \mathbf{0}$

$$\hat{\mathbf{x}}_0 = \frac{1}{\sqrt{\bar{\alpha}_t}}(x_t + (1 - \bar{\alpha}_t)s_\theta(x_t, t))$$

$$\mathbf{x}_{t-1} = \frac{\sqrt{\bar{\alpha}_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t}\mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t}\hat{\mathbf{x}}_0 + \sqrt{1 - \alpha_t}\mathbf{z}$$

$$\mathbf{x}_{t-1} = \mathbf{x}_{t-1} - \frac{1}{2(\sigma^2 + \gamma_t^2)}\nabla_{\mathbf{x}_t}\|\mathcal{A}(\mathbf{x}_t) - \mathbf{y}\|^2$$

**end for**

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

---

# Task 5: Score ALD

You will have to:

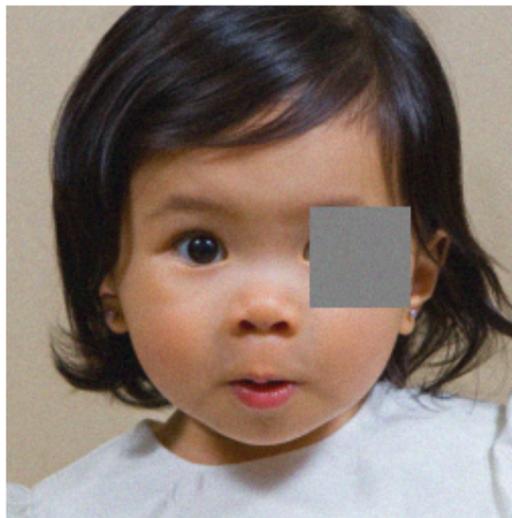
- Implement the denoiser, the backward step
- Implement the gradient computation (with `torch.autograd`)
- Implement and run ScoreALD:  $\mathbf{y}, \sigma, \gamma_t, \mathcal{A} \rightarrow \mathbf{x}_0$
- Visualize and analyze your results

# Task 5: Score ALD

Ground Truth



Inpainting



Input



PSNR/LPIPS  
Reconstruction

28.5 / 0.0605

Deconvolution



22.2 / 0.144

# Task 6: DPS

---

$$\mathbf{x}_T \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$$

**for**  $t = T, \dots, 1$  **do**

$\mathbf{z} \sim \mathcal{N}(\mathbf{0}, \mathbf{I})$  if  $t > 1$ , else  $\mathbf{z} = \mathbf{0}$

$$\hat{\mathbf{x}}_0 = \frac{1}{\sqrt{\bar{\alpha}_t}}(x_t + (1 - \bar{\alpha}_t)s_\theta(x_t, t))$$

$$\mathbf{x}'_{t-1} = \frac{\sqrt{\bar{\alpha}_t}(1 - \bar{\alpha}_{t-1})}{1 - \bar{\alpha}_t}\mathbf{x}_t + \frac{\sqrt{\bar{\alpha}_{t-1}}(1 - \alpha_t)}{1 - \bar{\alpha}_t}\hat{\mathbf{x}}_0 + \sqrt{1 - \alpha_t}\mathbf{z}$$

$$\mathbf{x}_{t-1} = \mathbf{x}'_{t-1} - \zeta_t \nabla_{\mathbf{x}_t} \left\| \mathcal{A}(\hat{\mathbf{x}}_0) - \mathbf{y} \right\|^2$$

**end for**

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

---

In practice,  $\zeta_t = \frac{\zeta}{\left\| \nabla_{\mathbf{x}_t} \left\| \mathcal{A}(\hat{\mathbf{x}}_0) - \mathbf{y} \right\|^2 \right\|}$  works well (see DPS paper p16)

# Task 6: DPS

You will have to:

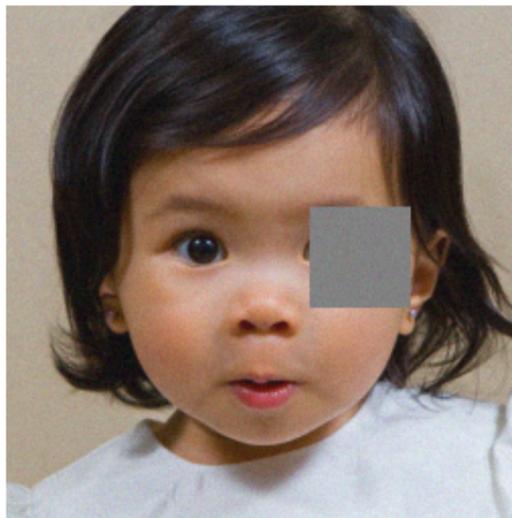
- Implement the denoiser, the backward step
- Implement the gradient computation (with `torch.autograd`)
- Implement and run DPS:  $\mathbf{y}, \sigma, \zeta, \mathcal{A} \rightarrow \mathbf{x}_0$
- Visualize and analyze your results

# Task 6: DPS

Ground Truth



Inpainting

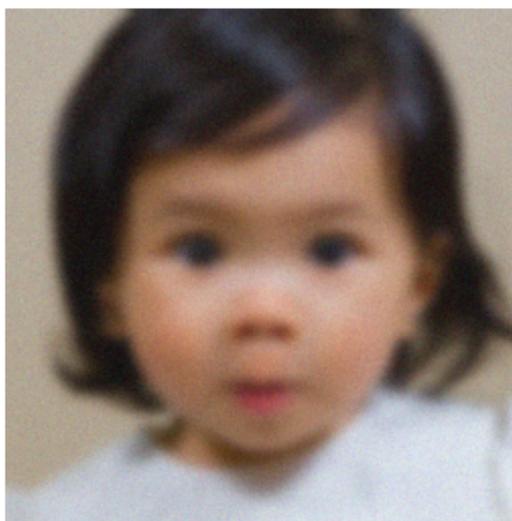


PSNR/LPIPS  
Reconstruction



34.0 / 0.0239

Deconvolution



28.4 / 0.0518