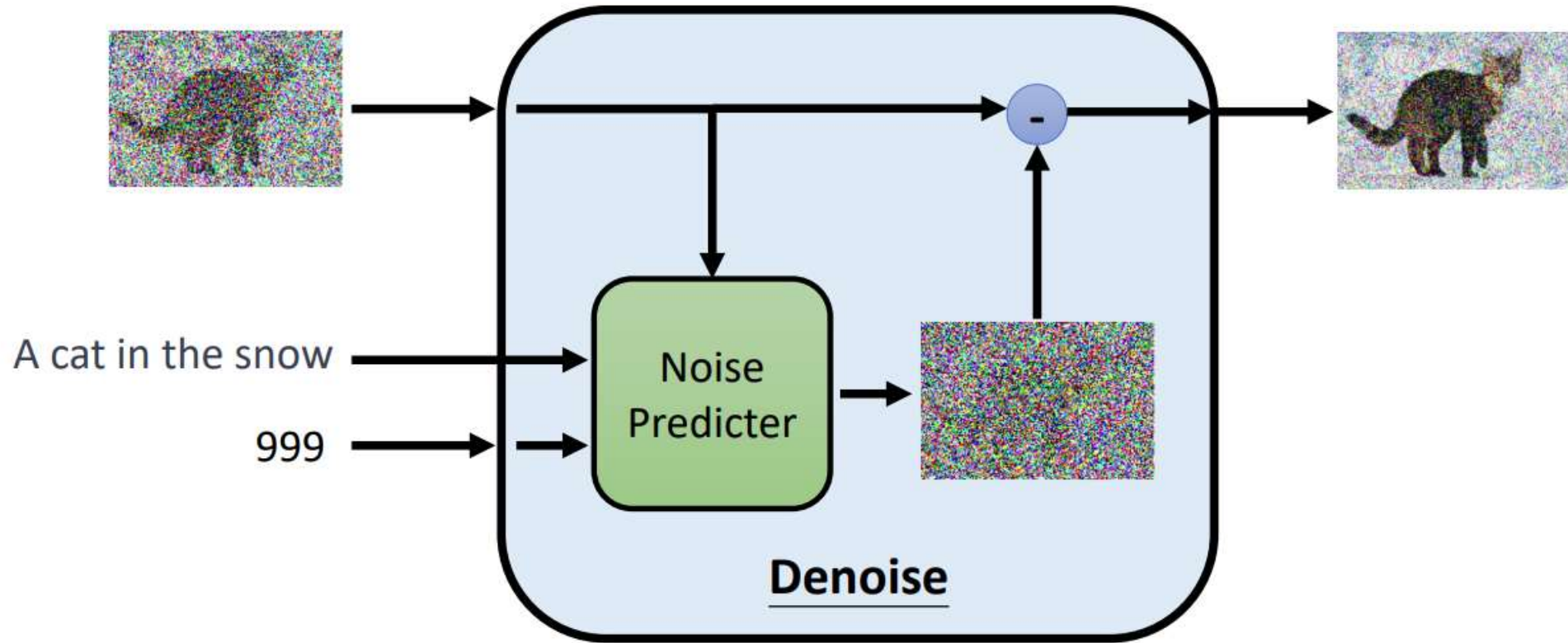


Topic: Diffusion Model

——Technique Project

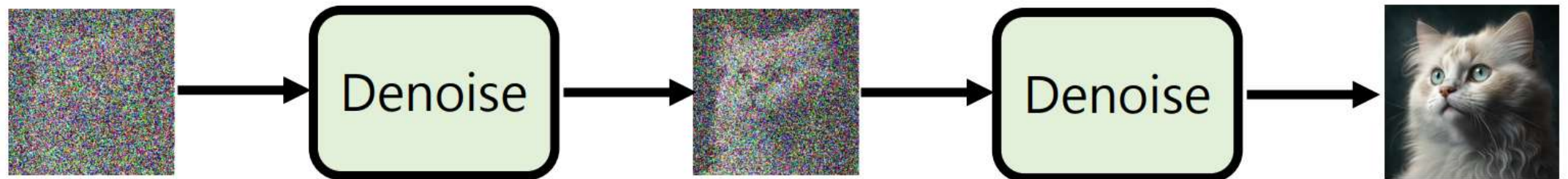


How Diffusion Model Work?

Forward Process



Reverse Process



Denoise Process



~~Paint~~ ×



Sculpt ✓

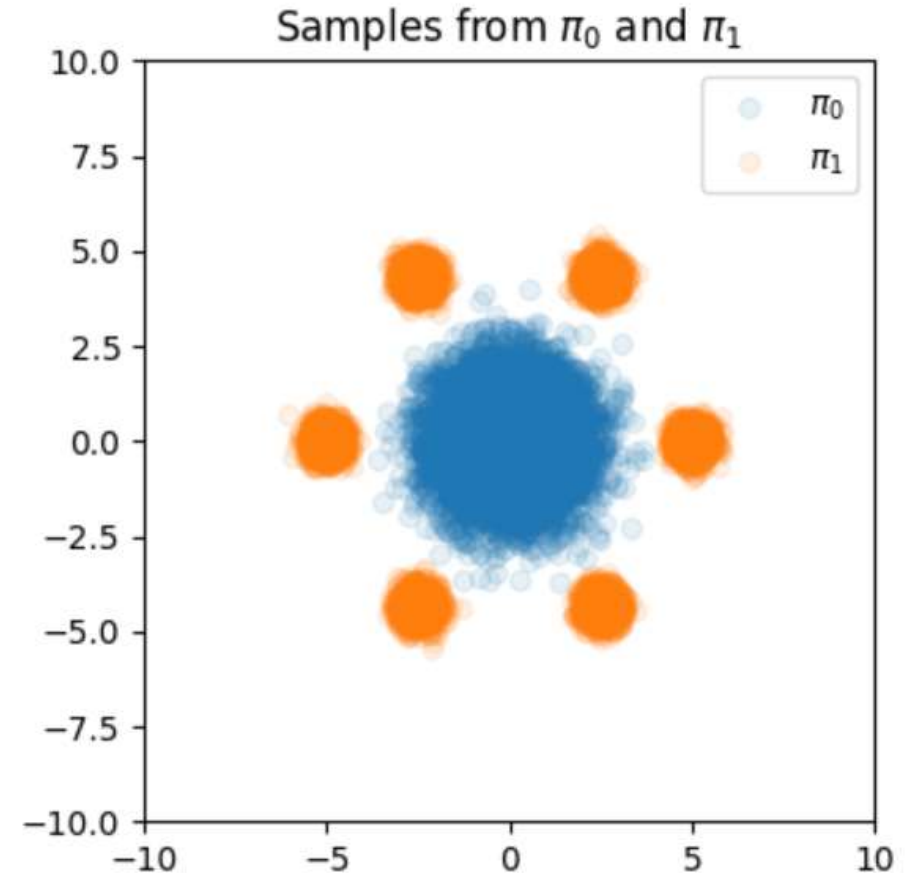
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Technique Project of Group 5

——Pipeline of our work

Based on given incomplete project

- obtain samples
- construct diffusion model
- train and test model
- data visualization



Source code can be found in: <https://www.kaggle.com/code/duankefeng/simpliediffusion>

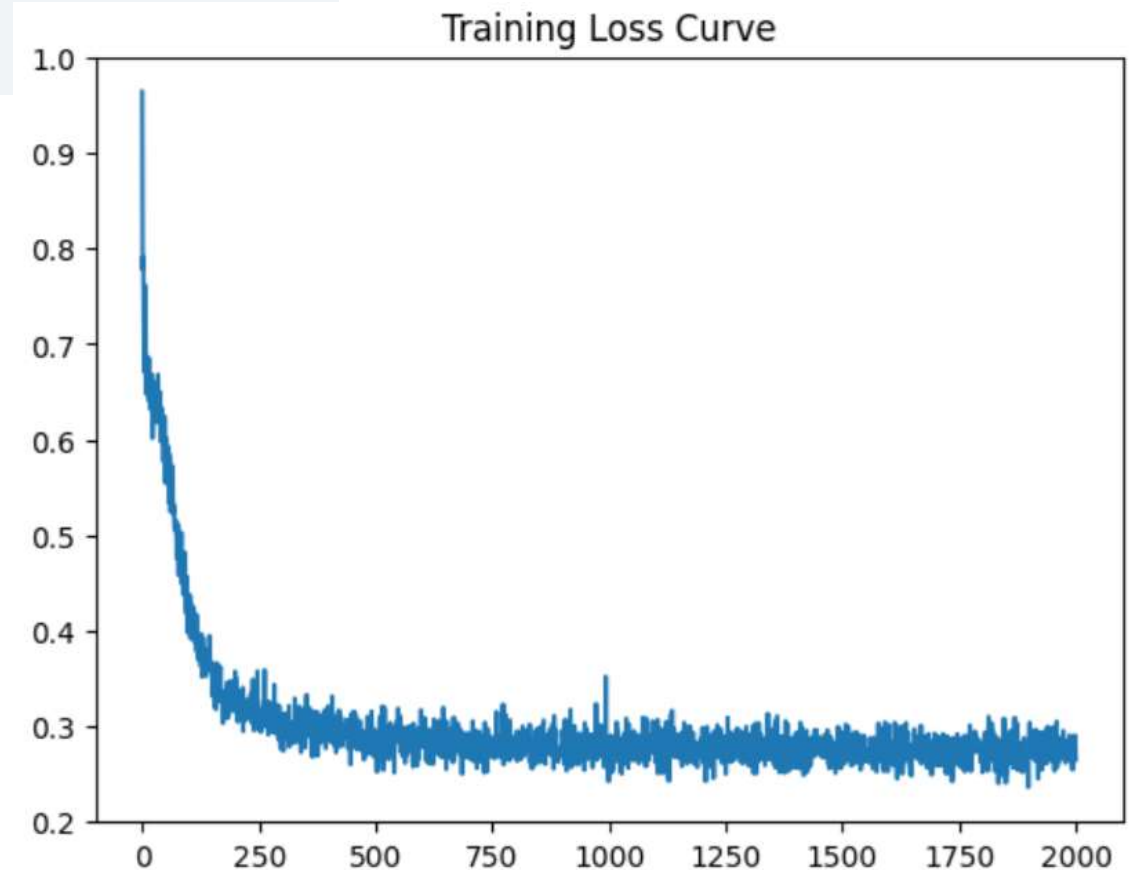
Technique Project of Group 5

—— Train Diffusion Model

```
##### Question 3: You need to implement these lines by yourself!!  
loss = torch.mean((pred*std + z) ** 2)  
##### End of your implementation #####
```

Loss Function: MSE loss

- ➔ **pred**: The output of the model at given time step t .
- ➔ **std**: The standard deviation, typically computed from the marginal distribution of the SDE. In diffusion models, this represents the noise level.
- ➔ **z**: The true data or noise sample used for calculating the model's loss.



Source code can be found in: <https://www.kaggle.com/code/duankefeng/simplifiediffusion>

Technique Project of Group 5

—— Sample based on well-trained Diffusion model

```
##### Question 3: You need to implement these lines by yourself!! Around  
z = z - drift * dt + diffusin * torch.sqrt(torch.tensor(dt)) * noise  
##### End of your implementation #####
```

Euler-Maruyama method used for SDE

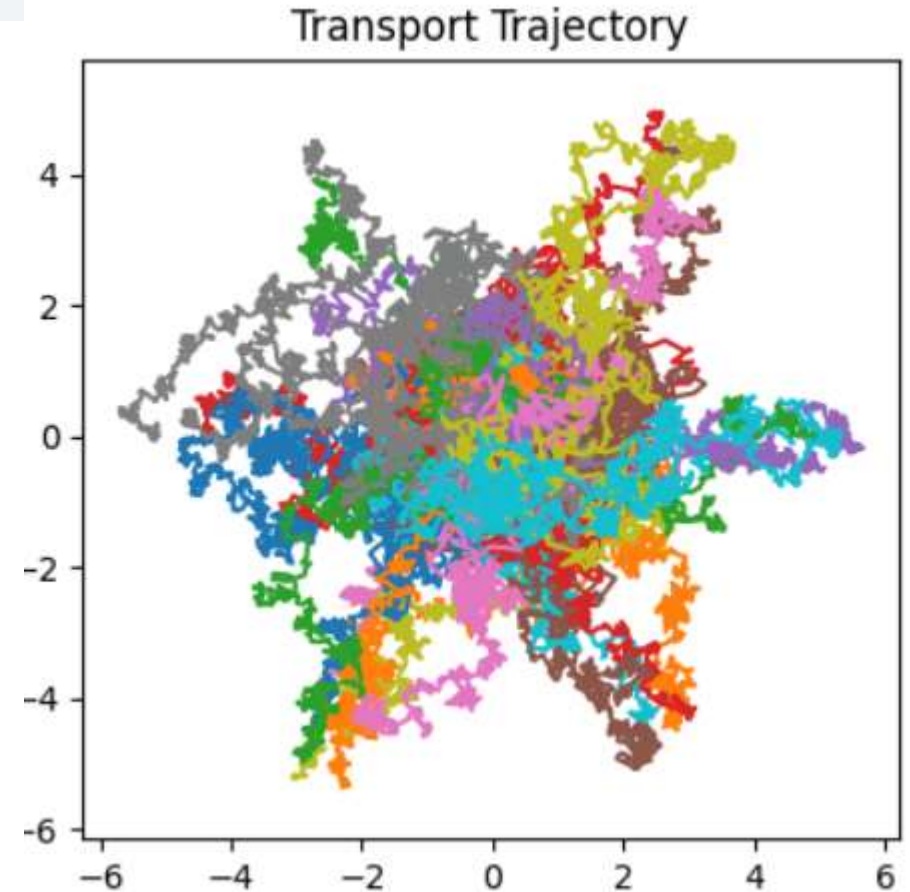
$z - \text{drift} * dt$:

→ Adjusts the sample z by the deterministic drift term over the time step dt .

$\text{diffusin} * \text{torch.sqrt}(\text{torch.tensor}(dt)) * \text{noise}$

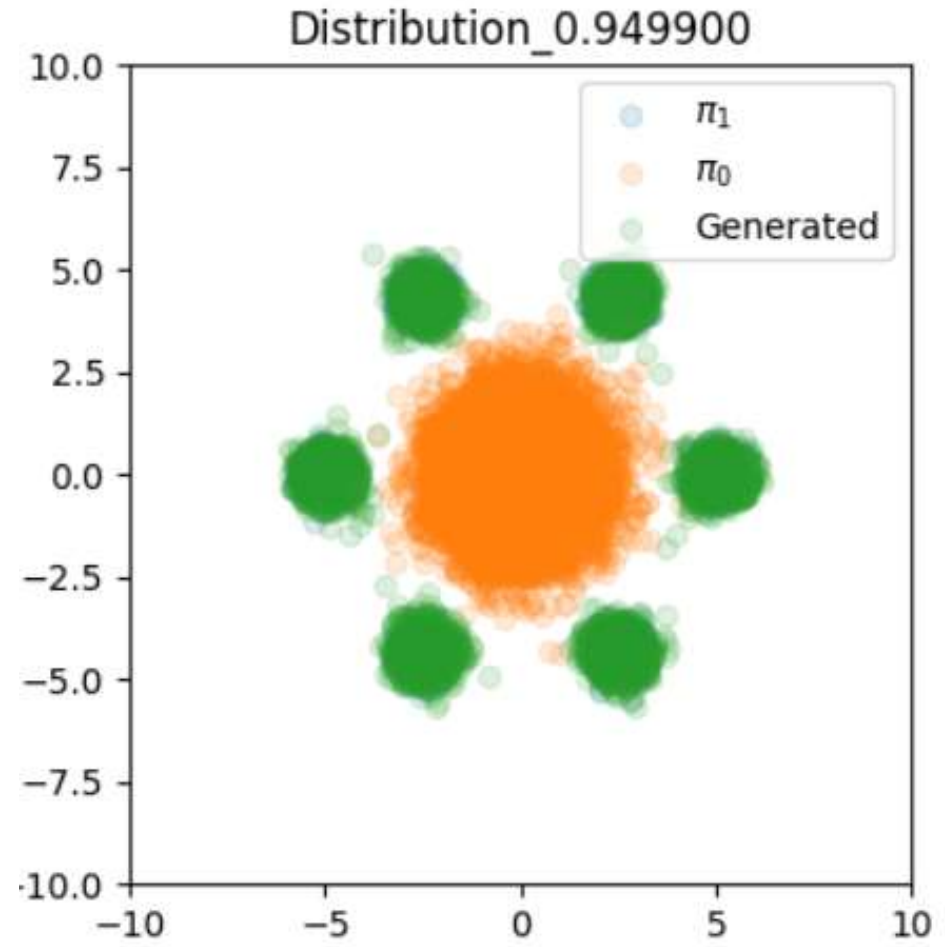
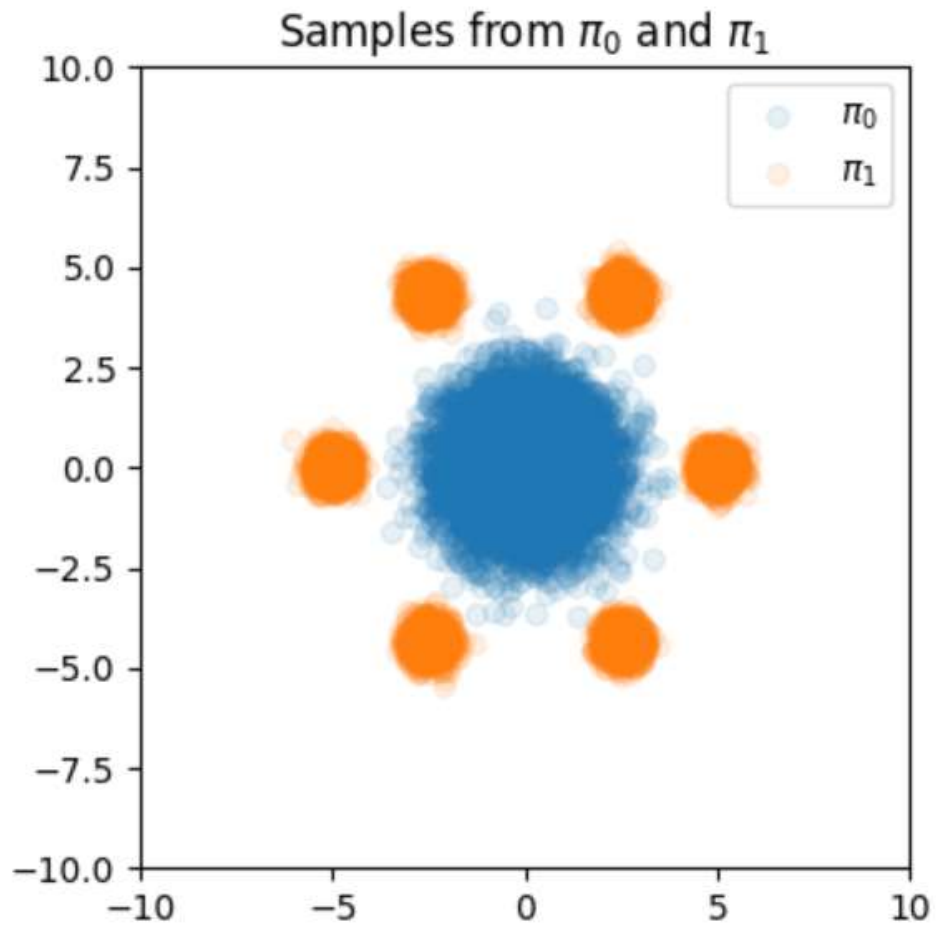
→ Adds the stochastic component to z , scaled by the diffusion term and the time step size.

——simulating the reverse-time Stochastic Differential Equation (SDE)



Technique Project of Group 5

—— Data Visualization



Technique Project of Group 5

—— Related Work

- Song, Yang, et al. "Score-based generative modeling through stochastic differential equations." arXiv preprint arXiv:2011.13456 (2020).
- Ho, Jonathan, Ajay Jain, and Pieter Abbeel. "Denoising diffusion probabilistic models." Advances in neural information processing systems 33 (2020): 6840-6851.

That's all. Thank you!!!