Assignment7

October 2025

1 Score Matching

For a generative model, given data we want to find the probability function $p(x;\theta)$ of a data distribution.
But this is difficult.
So, score matching introduced a score function $S(x) = \nabla_x \log p(x;\theta)$
Then we have the loss function:
$L_{ESM}(\theta) = E_{x \sim p(x)} ||S(x;\theta) - \nabla_x \log p(x)||^2$ for explicit score matching;
$L_{ISM}(\theta) = E_{x \sim p(x)}[||S(x;\theta)||^2 + 2\nabla_x \cdot S(x;\theta)]$ for implicit score matching.
And we can show that minimizing L_{ESM} and L_{ISM} are equivalent.
So, we can train the score function without knowing $p(x)$.
In a score-based generative model, step 1 is to noise the data, then to learn how to reverse this diffusion, and in this step, we need to know the score function which tells what direction to move the data distribution to increase its probability.
So, in the training phase, the model learns the score function, then it integrates backward by the score to generate clean samples.

2 Question

In the first of the score-based diffusion generative model, if I change the noise distribution from Gaussian to a different probability distribution noise, then how would this change the reverse process?