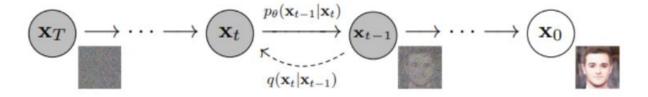
DeepLearning HW2

Diffusion Model

Denoising Diffusion Probabilistic Model

Denoising Diffusion Probabilistic Models

- Diffusion Model consists of two processes:
 - A forward diffusion process that converts data to noise by gradually adding noise to the input
 - A reverse generative process that starts from noise and generates data by denoising one step at a time



DDPM Forward Process

• The forward process or diffusion process, is fixed to a Markov chain that gradually adds Gaussian noise to the data according to a variance schedule β_1, \ldots, β_T

$$\underbrace{\mathbf{x}_0} \longrightarrow \cdots \longrightarrow \underbrace{\mathbf{x}_{t-1}} \xrightarrow{q(\mathbf{x}_t | \mathbf{x}_{t-1})} \underbrace{\mathbf{x}_t} \longrightarrow \cdots \longrightarrow \underbrace{\mathbf{x}_T} \longrightarrow$$

DDPM Forward Process

• The DDPM forward step and process are defined as:

$$q\left(\mathbf{x}_{t} \mid \mathbf{x}_{t-1}
ight) := \mathcal{N}\left(\mathbf{x}_{t}; \sqrt{1-eta_{t}}\mathbf{x}_{t-1}, eta_{t}\mathbf{I}
ight)$$

- ullet We can express $oldsymbol{x}_t$ as a linear combination of $oldsymbol{x}_0$ and a noise variable $oldsymbol{\epsilon}$
- ullet By a sequence of diffusion steps from $oldsymbol{x}_0$ to $oldsymbol{x}_t$, we have the Forward/Diffusion Process:

$$q\left(\mathbf{x}_{1:T} \mid \mathbf{x}_{0}
ight) := \prod_{t=1}^{T} q\left(\mathbf{x}_{t} \mid \mathbf{x}_{t-1}
ight)$$

DDPM Reverse Process

- The reverse process of is also defined as a Markov chain
- ullet Given the forward process above, we define the Reverse step as the inverse step with respect to learned Gaussian transitions parameterized by eta
- ullet Here a neural network $p_{ heta}\left(\mathbf{x}_{t-1} \mid \mathbf{x}_{t}
 ight)$ is used to fit the distribution $\left.q\left(\mathbf{x}_{t-1} \mid \mathbf{x}_{t}
 ight)
 ight.$

$$p_{ heta}\left(\mathbf{x}_{t-1} \mid \mathbf{x}_{t}
ight) := \mathcal{N}\left(\mathbf{x}_{t-1}; oldsymbol{\mu}_{ heta}\left(\mathbf{x}_{t}, t
ight), oldsymbol{\Sigma}_{ heta}\left(\mathbf{x}_{t}, t
ight)
ight)$$

DDPM Training Objective

Diffusion Training Objective: By minimizing the negative log-likelihood (NLL)

$$\begin{split} \mathbb{E}\left[-\log p_{\theta}\left(\mathbf{x}_{0}\right)\right] &\leq \mathbb{E}_{q}\left[-\log \frac{p_{\theta}\left(\mathbf{x}_{0:T}\right)}{q\left(\mathbf{x}_{1:T}\mid\mathbf{x}_{0}\right)}\right] \\ &= \mathbb{E}_{q}\left[-\log p\left(\mathbf{x}_{T}\right) - \sum_{t\geq1}\log \frac{p_{\theta}\left(\mathbf{x}_{t-1}\mid\mathbf{x}_{t}\right)}{q\left(\mathbf{x}_{t}\mid\mathbf{x}_{t-1}\right)}\right] \\ &= \mathbb{E}_{q}[\underbrace{D_{\mathrm{KL}}\left(q\left(x_{T}\mid x_{0}\right) \| p\left(x_{T}\right)\right)}_{L_{T}} \\ &+ \sum_{t>1}\underbrace{D_{\mathrm{KL}}\left(q\left(x_{t-1}\mid x_{t}, x_{0}\right) \| p_{\theta}\left(x_{t-1}\mid x_{t}\right)\right)}_{L_{t-1}} \\ &- \log p_{\theta}\left(x_{0}\mid x_{1}\right)] =: L \end{split}$$

DDPM Training Objective

Simplified training objective

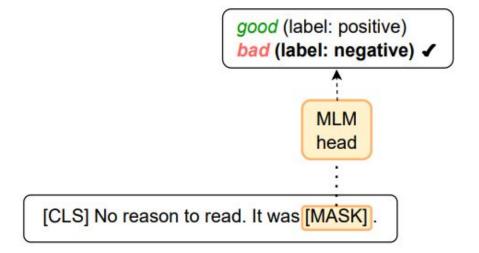
$$L_{ ext{simple}}\left(heta
ight) := \mathbb{E}_{t,\mathbf{x}_0,oldsymbol{\epsilon}}\left[\left\|oldsymbol{\epsilon} - oldsymbol{\epsilon}_{ heta}\left(\sqrt{ar{lpha}_t}\mathbf{x}_0 + \sqrt{1-ar{lpha}_t}oldsymbol{\epsilon},t
ight)
ight\|^2
ight]$$

Utilizing pre-trained Model

Prompt-based Learning

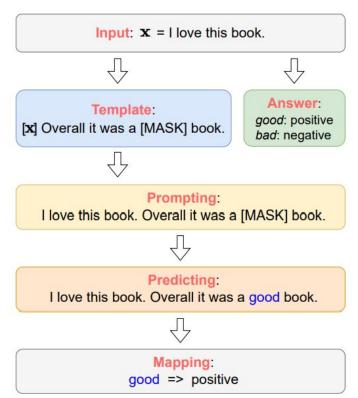
Prompt-based Learning

- Pre-train and Fine-tune has been used as a standard learning paradigm for years in NLP
- Prompt-based learning makes better use of the knowledge from PLM
- The prompt-based learning objective is matched with the pre-training MLM objective



Prompt-based learning

Prompt-based Learning Workflow



Prompting

- Technique of making better use of the knowledge from the pre-trained model by adding additional texts to the input
- Prompting can be divided into two types:
 - Hard (discrete) prompt: the template consists of actual tokens
 - Soft (continuous) prompt: the template consists of pseudo tokens which are trainable
 - Hybrid prompt: the template consists of hard and soft prompt

Input: **x**

hard prompt

x It was [MASK]

soft prompt

 $\mathbf{x} [v_1 v_2 \cdots v_k] [\mathrm{MASK}]$

Hard Prompt

- Handcrafting a suitable prompt requires a solid understanding of the task and testing data
- Trial-and-error is required for obtaining an effective prompt, but this is time-consuming
- It is necessary to train the whole model when using hard prompt on a pre-trained language model

Soft Prompt

- Used in natural language processing (NLP) to guide a language model to generate text that is more relevant or specific to a particular task or context
- Different from hard prompt which is providing a specific sentence or instruction to generate a response. Soft prompt is more like guiding the model with a general idea or context
- Soft prompt has been proposed to alleviate the effort of handcrafting prompt

Difference between Fine-Tuning and Prompting

