TOWARDS A CUSTOMIZABLE TEXT-TO-SPEECH PERSONAL ASSISTANT

Chenyu Shi
s3500063

Siwen Tu
s3631400

Shuang Fan
s3505847

Shupei Li
s3430863

ABSTRACT

TBC.

***K*eywords** VITS · TTS · Deep Learning

1 Introduction

2 Methodology

We describe VITS [1], the backbone of our TTS assistant, from the perspective of variational inference in detail. We also introduce VITS's architecture and training process to provide a comprehensive overview.

2.1 CVAEs

The variational autoencoder (VAE), proposed in [2], is a popular approach widely used in unsupervised learning. It is an effective function approximator and can be optimized by the standard stochastic gradient descent (SGD) method. It has shown promising application value in various fields, such as complex pattern recognition, segmentation, future prediction from static images, etc [3].

Conditional variational autoencoders (CVAEs) are variants of VAEs. Remember that VAEs learn posterior distribution parameters from dataset x without any label information. In CVAEs, we have additional contextual information c when estimating the posterior distribution. The objective function of the CVAE can be written as follows:

$$\max \quad \log p_\theta\left(x|c\right) - \mathcal{D}\left[q_\phi\left(z|x\right)\|p_\theta\left(z|x\right)\right] \tag{1}$$

where $p_\theta(x|c)$ denotes the marginal log-likelihood of the data, $p_\theta(z|x)$ is the posterior distribution and $q_\phi(z|x)$ is its approximator. According to the definition of Kullback-Leibler divergence and Bayes' theorem, maximizing Equation 1 is equivalent to maximizing the following equation:

$$\max \quad \mathbb{E}_{q_\phi(z|x)}\left[\log p_\theta(x \mid z) - \log \frac{q_\phi(z \mid x)}{p_\theta(z \mid c)}\right] \tag{2}$$

Notice that the relative KL divergence is always a non-negative number. We can derive the evidence lower bound (ELBO) of the objective function based on Equation 1 and Equation 2:

$$\begin{aligned}
\log p_\theta(x \mid c) &\geq \mathbb{E}_{q_\phi(z|x)}\left[\log p_\theta(x \mid z) - \log \frac{q_\phi(z \mid x)}{p_\theta(z \mid c)}\right] \\
&= \underbrace{\mathbb{E}_{q_\phi(z|x)}\left[\log p_\theta\left(x|z\right)\right]}_{\text{Reconstruction loss}} - \underbrace{\mathcal{D}\left[q_\phi(z \mid x)\|p_\theta(z \mid c)\right]}_{\text{Regularization loss}}
\end{aligned} \tag{3}$$

The ELBO comprises two parts — the reconstruction loss and the regularization loss. The reconstruction loss describes the data distribution given the latent space, while the regularization loss measures the divergence between the true prior distribution and the encoder's approximate distribution. In practice, we usually choose to minimize the negative ELBO because the term $\mathcal{D}\left[q_\phi\left(z|x\right)\|p_\theta\left(z|x\right)\right]$ is hard to calculate. However, a reasonable posterior approximator $q_\phi(z|x)$ can effectively alleviate the impact of the bias.

2.2 Expressing VITS as a CVAE

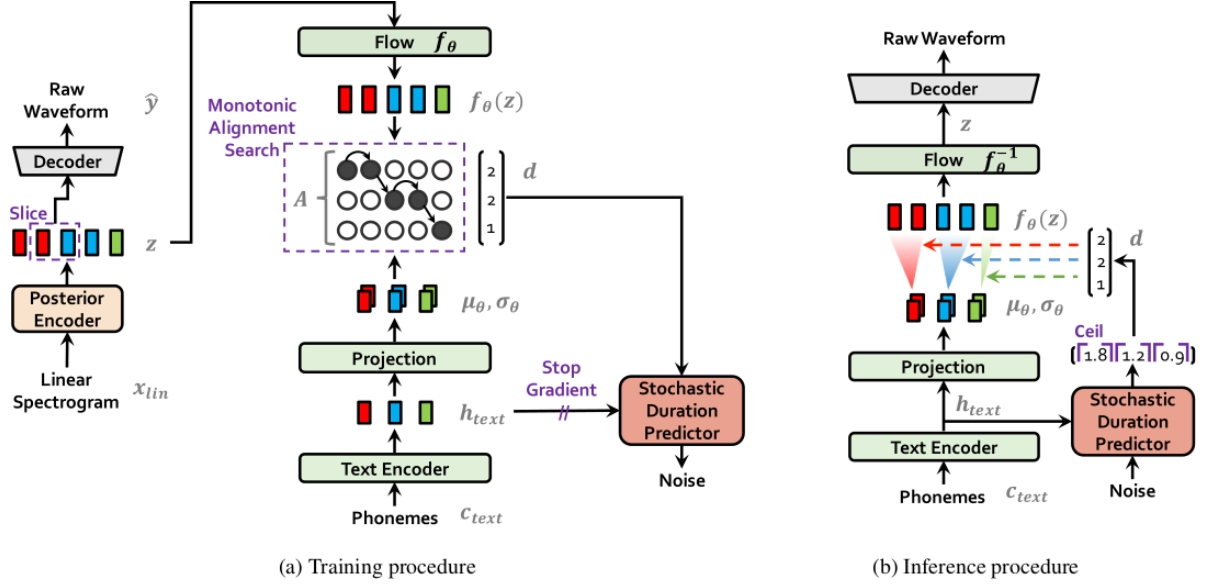(a) Training procedure   (b) Inference procedure

Figure 1: The architecture of VITS. This figure is directly adapted from [1].

The architecture of VITS is shown in Figure 1. VITS model can be expressed as a CVAE. We will illustrate the main idea behind VITS based on the reconstruction loss as well as the regularization loss.

Reconstruction Loss. During the training, we have ground truth soundtracks x and their corresponding text c_{text}. Kim et al. [1] define the reconstruction loss as the L_1 norm between the input's mel-spectrogram and the estimated mel-spectrogram produced by the model:

$$L_{recon} = \|x_{mel} - \hat{x}_{mel}\|_1 \tag{4}$$

It is easy to compute the mel-spectrogram x_{mel} of a specific audio file. As for the approximate mel-spectrogram $\hat{x}_{mel}$, we can upsample the latent space to the waveform domain and then transform it to the mel-spectrogram domain.

Regularization Loss. The text-to-speech task requires an automatic alignment between the text input and the corresponding voice features. VITS adopts the monotonic alignment search algorithm to align the audio and textual embeddings. The monotonic alignment search algorithm (MAS) is proposed in [4]. The intuition behind the MAS is applying the dynamic programming algorithm to maximize the likelihood of the data distribution. It will produce an alignment matrix A. The condition c in VITS is defined as the concatenation of the text input c_{text} and the alignment matrix A, i.e., $c = [c_{text}, A]$. Given the condition c, we can calculate the regularization loss following the definition of KL-divergence:

$$L_{kl} = \mathcal{D}\left[q_\phi(z \mid x)\|p_\theta(z \mid c)\right] = \log q_\phi\left(z \mid x_{lin}\right) - \log p_\theta\left(z \mid c_{\text{text}}, A\right)$$
$$z \sim q_\phi\left(z \mid x_{lin}\right) = N\left(z; \mu_\phi\left(x_{lin}\right), \sigma_\phi\left(x_{lin}\right)\right) \tag{5}$$

It is worth mentioning that VITS uses the linear-scale spectrogram of the soundtrack x_{lin} instead of the mel-spectrogram. [1] explains that the linear-scale spectrogram is helpful in enhancing the resolution of generated audio. To improve the model's performance further, VITS introduces a normalizing flow f_θ that connects the conditional prior distribution and the latent space in the following way:

$$p_\theta(z \mid c) = N\left(f_\theta(z); \mu_\theta(c), \sigma_\theta(c)\right)\left|\det \frac{\partial f_\theta(z)}{\partial z}\right| \tag{6}$$

Equation 6 transforms the latent space into some complex distributions that possess a more powerful expressiveness, which is critical for generating realistic outputs.

2.3 Training VITS

The major part of VITS is a CVAE. However, there are more things to consider when handling the text-to-speech task. Firstly, we need to decide the duration of each token in outputs. A straightforward idea is adding a deterministic

duration predictor into the model. But this naive method has a big flaw — it can not reflect the features of different speakers, which limits the model's application in multi-speaker scenarios. Alternatively, VITS designs a stochastic duration preditor whose loss function is L_{dur} and optimizes it with other modules during training.

VITS also integrates adversarial training into the architecture to guide the optimization direction. With a discriminator D and a decoder G, VITS combines two kinds of loss in the adversarial training, namely the least-squares loss and the additional feature-matching loss:

$$
\begin{aligned}
L_{adv}(D) &= \mathbb{E}_{(y,z)} \left[(D(y) - 1)^2 + (D(G(z)))^2 \right] \\
L_{adv}(G) &= \mathbb{E}_z \left[(D(G(z)) - 1)^2 \right] \\
L_{fm}(G) &= \mathbb{E}_{(y,z)} \left[\sum_{l=1}^{T} \frac{1}{N_l} \left\| D^l(y) - D^l(G(z)) \right\|_1 \right]
\end{aligned}
\tag{7}
$$

Taken together, we can obtain the final loss for VITS training:

$$
L_{vae} = L_{recon} + L_{kl} + L_{dur} + L_{adv}(G) + L_{fm}(G) \tag{8}
$$

During the inference stage, we fix all weights and disgard the posterior encoder because we only have the text input. Final outputs are produced by the decoder G.

3 Experiments

4 Conclusion

References

[1] Jaehyeon Kim, Jungil Kong, and Juhee Son. Conditional variational autoencoder with adversarial learning for end-to-end text-to-speech. In Marina Meila and Tong Zhang, editors, *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pages 5530–5540. PMLR, 18–24 Jul 2021.

[2] Diederik P Kingma and Max Welling. Auto-encoding variational bayes, 2022.

[3] Carl Doersch. Tutorial on variational autoencoders, 2021.

[4] Jaehyeon Kim, Sungwon Kim, Jungil Kong, and Sungroh Yoon. Glow-tts: A generative flow for text-to-speech via monotonic alignment search. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin, editors, *Advances in Neural Information Processing Systems*, volume 33, pages 8067–8077. Curran Associates, Inc., 2020.