TTIC 31230, Fundamentals of Deep Learning

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Progressive VAEs

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These slides were written "gedanken" (as a thought experient) while teaching this class in 2021. They were not based on any paper.

While written independently of diffusion models, these slides provide a good theoretical framework for diffusion models (currently very hot).

The original motivation for these slides was to provide a theoretically clean approach to a multi-layer VQ-VAE.

Progressive VAEs

We consider a VAE with layers of latent variables z_1, \ldots, z_L and a population distribution on an observable variable y.

The encoder will define $P_{\text{enc}}(z_1|y)$ and $P_{\text{enc}}(z_{\ell+1}|z_{\ell})$.

The decoder will define $P_{\text{dec}}(z_{\ell-1}|z_{\ell})$ and $P_{\text{dec}}(y|z_1)$.

Following VQ-VAE, we will train the encoder and the decoder independent of any prior.

We then train a prior on the top layer latent variable. The top level prior and decoder allow us to sample y from the model.

Phase One Training

We train a encoders and decoders enc₁, dec₁, ..., enc_L, dec_L where the distribution on z_1, \ldots, Z_L is defined by y and the encoder.

$$\operatorname{enc}_{1}^{*}, \operatorname{dec}_{1}^{*} = \underset{\operatorname{enc}_{1}, \operatorname{dec}_{1}}{\operatorname{argmin}} E_{y, z_{1}} \left[-\ln P_{\operatorname{dec}_{1}}(y|z_{1}) \right]$$

$$\operatorname{enc}_{\ell+1}^*, \operatorname{dec}_{\ell+1}^* = \underset{\operatorname{enc}_{\ell+1}, \operatorname{dec}_{\ell+1}}{\operatorname{argmin}} E_{z_{\ell}, z_{\ell+1}} \left[-\ln P_{\operatorname{dec}_{\ell+1}}(z_{\ell-1}|z_{\ell}) \right]$$

If these encoders and decoders share parameters the shared parameters are influenced by all of the above training losses (this observation was added after seeing DALLE-2's diffision model).

Phase Two Training

$$\operatorname{pri}^* = \underset{\operatorname{pri}}{\operatorname{argmin}} E_{z_L} \left[-\ln P_{\operatorname{pri}}(z_L) \right]$$

Because of the autonomy of the encoder, the universality assumption implies that we get a perfect model of the population distribution on y.

Given the prior and the decoder we can sample images.

\mathbf{END}