# TTIC 31230, Fundamentals of Deep Learning

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Progressive VAEs

## Progressive VAEs

These slides on progressive VAES were written "gedanken" (as a thought experiment) while teaching deep learning in 2021.

The original motivation for progressive VAEs was to provide a theoretically clean approach to a multi-layer VQ-VAEs.

However, this formulation of progressive VAEs will be useful in understanding diffusion models (currently very popular).

## 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 enc<sub>1</sub>, dec<sub>1</sub>, ..., enc<sub>L</sub>, dec<sub>L</sub> 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.

# $\mathbf{END}$