# TTIC 31230, Fundamentals of Deep Learning

David McAllester, Autumn 2020

Noisy Channel RDAs

## Rate-Distortion Autoencoders (RDAs)

We compress a continuous signal y to a bit string  $\tilde{z}_{\Phi}(y)$ .

We decompress  $\tilde{z}_{\Phi}(y)$  to  $y_{\Phi}(\tilde{z}_{\Phi}(y))$ .

$$\Phi^* = \underset{\Phi}{\operatorname{argmin}} E_{y \sim \operatorname{Pop}} \quad |\tilde{z}_{\Phi}(y)| + \lambda \operatorname{Dist}(y, y_{\Phi}(\tilde{z}_{\Phi}(y)))$$

## Rate-Distortion Autoencoders (RDAs)

Since rounding is not differentiable we train by replace rounding by additive noise.

$$\mathcal{L}(\Phi) = E_{y \sim \text{Pop}} E_{\epsilon} \begin{cases} -\ln p_{\Phi}(z_{\Phi}(y) + \epsilon) \\ + \lambda \text{Dist}(y, y_{\Phi}(z_{\Phi}(y) + \epsilon)) \end{cases}$$

A noisy-channel RDA uses the noise version without rounding.

### Noisy Channel RDAs

 $z = z_{\Phi}(y, \epsilon)$   $\epsilon$  is fixed (parameter independent) noise

$$\Phi^* = \underset{\Phi}{\operatorname{argmin}} I_{\Phi}(y, z) + \lambda E_{y, \epsilon} \operatorname{Dist}(y, y_{\Phi}(z_{\Phi}(y, \epsilon)))$$

By the channel capacity theorem I(y, z) is the **rate** of information transfer from y to z.

### Noisy Channel RDAs

 $z = z_{\Phi}(y, \epsilon)$   $\epsilon$  is fixed (parameter independent) noise

$$\Phi^* = \underset{\Phi}{\operatorname{argmin}} I_{\Phi}(y, z) + \lambda E_{y, \epsilon} \operatorname{Dist}(y, y_{\Phi}(z_{\Phi}(y, \epsilon)))$$

Using parameter-independent noise is called the "reparameter-ization trick" and allows SGD.

$$\nabla_{\Phi} E_{y,\epsilon} \operatorname{Dist}(y, y_{\Phi}(z_{\Phi}(y, \epsilon)))$$

$$= E_{y,\epsilon} \nabla_{\Phi} \operatorname{Dist}(y, y_{\Phi}(z_{\Phi}(y, \epsilon)))$$

#### Mutual Information as a Channel Rate

Typically  $z_{\Phi}(y,\epsilon)$  is simple. For example

$$\epsilon \sim \mathcal{N}(0, I)$$

$$z_{\Phi}(y,\epsilon) = \mu_{\Phi}(y) + \sigma_{\Phi}(y) \odot \epsilon$$

In this example  $p_{\Phi}(z|y)$  is easily computed.

## Mutual Information Replaces Rate

$$I_{\Phi}(y,z) = E_{y,\epsilon} \ln \frac{\text{pop}(y)p_{\Phi}(z|y)}{\text{pop}(y)p_{\text{pop},\Phi}(z)}$$

$$= E_{y,\epsilon} \ln \frac{p_{\Phi}(z|y)}{p_{\text{pop},\Phi}(z)}$$

where 
$$p_{\text{pop},\Phi}(z) = E_{y \sim \text{pop}} p_{\Phi}(z|y)$$

#### A Variational Bound

$$p_{\text{pop},\Phi}(z) = E_{y \sim \text{pop}} \ p_{\Phi}(z|y)$$

We cannot compute  $p_{\text{pop},\Phi}(z)$ .

Instead we will use a model  $\hat{p}_{\Phi}(z)$  to approximate  $p_{\text{pop},\Phi}(z)$ .

#### A Variational Bound

$$I(y,z) = E_{y,\epsilon} \ln \frac{p_{\Phi}(z|y)}{p_{\text{pop},\Phi}(z)}$$

$$= E_{y,\epsilon} \ln \frac{p_{\Phi}(z|y)}{\hat{p}_{\Phi}(z)} + E_{y,\epsilon} \ln \frac{\hat{p}_{\Phi}(z)}{p_{\text{pop},\Phi}(z)}$$

$$= E_{y,\epsilon} \ln \frac{p_{\Phi}(z|y)}{\hat{p}_{\Phi}(z)} - KL(p_{\text{pop},\Phi}(z), \hat{p}_{\Phi}(z))$$

$$\leq E_{y,\epsilon} \ln \frac{p_{\Phi}(z|y)}{\hat{p}_{\Phi}(z)}$$

### The Noisy Channel RDA

General Noisy Channel RDA:

$$\Phi^* = \underset{\Phi}{\operatorname{argmin}} E_{y,\epsilon} \ln \frac{p_{\Phi}(z_{\Phi}(y,\epsilon)|y)}{\hat{p}_{\Phi}(z_{\Phi}(y,\epsilon))} + \lambda \operatorname{Dist}(y, y_{\Phi}(z_{\Phi}(y,\epsilon)))$$

Uniform Box Noise (Rounding) RDA:

$$\Phi^* = \underset{\Phi}{\operatorname{argmin}} E_y E_{\epsilon \sim [-1/2, 1/2]^d}$$
$$-\ln \hat{p}_{\Phi}(z_{\Phi}(y) + \epsilon) + \lambda \operatorname{Dist}(y, y_{\Phi}(z_{\Phi}(y) + \epsilon))$$

# $\mathbf{END}$