

TTIC 31230, Fundamentals of Deep Learning

David McAllester, Winter 2020

Gaussian Noisy Channel RDAs

Gaussian Noisy-Channel RDA

$$\Phi^* = \underset{\Phi}{\operatorname{argmin}} E_{y,\epsilon} \ln \frac{p_{\Phi}(\tilde{z}|y)}{q_{\Phi}(\tilde{z})} + \lambda \operatorname{Dist}(y, y_{\Phi}(\tilde{z}))$$

$$\tilde{z}[i] = z_{\Phi}(y)[i] + \sigma_{\Phi}(y)\epsilon[i] \quad \epsilon[i] \sim \mathcal{N}(0, 1)$$

$$p_{\Phi}(\tilde{z}[i]|y) = \mathcal{N}(z_{\Phi}(y)[i], \sigma_{\Phi}(y)[i])$$

$$q_{\Phi}(\tilde{z}[i]) = \mathcal{N}(\mu_q[i], \sigma_q[i])$$

$$\operatorname{Dist}(y, \hat{y}) = ||y - \hat{y}||^2$$

Gaussian Noisy-Channel RDA

$$\Phi^* = \operatorname{argmin}_{\Phi} E_{y, \epsilon} \ln \frac{p_{\Phi}(\tilde{z}|y)}{q_{\Phi}(\tilde{z})} + \lambda \operatorname{Dist}(y, y_{\Phi}(\tilde{z}))$$

We will show that in the Gaussian case can fix q_{Φ}

$$p_{\Phi}(\tilde{z}[i]|y) = \mathcal{N}(z_{\Phi}(y)[i], \sigma_{\Phi}(y)[i])$$

$$q_{\Phi}(\tilde{z}[i]) = \mathcal{N}(0, 1)$$

$$\operatorname{Dist}(y, \hat{y}) = ||y - \hat{y}||^2$$

Gaussian Noisy-Channel RDA

$$\begin{aligned}\Phi^* &= \operatorname{argmin}_{\Phi} E_{y,\epsilon} \ln \frac{p_{\Phi}(\tilde{z}|y)}{q_{\Phi}(\tilde{z})} + \lambda \operatorname{Dist}(y, y_{\Phi}(\tilde{z})) \\ &= \operatorname{argmin}_{\Phi} E_{y \sim \text{Pop}} \left(\begin{array}{c} KL(p_{\Phi}(\tilde{z}|y), q_{\Phi}(\tilde{z})) \\ + \lambda E_{\epsilon} \operatorname{Dist}(y, y_{\Phi}(\tilde{z})) \end{array} \right)\end{aligned}$$

Closed Form KL-Divergence

$$KL(p_{\Phi}(\tilde{z}|y), q_{\Phi}(\tilde{z}))$$

$$= \sum_i \frac{\sigma_{\Phi}(y)[i]^2 + (z_{\Phi}(y)[i] - \mu_q[i])^2}{2\sigma_q[i]^2} + \ln \frac{\sigma_q[i]}{\sigma_{\Phi}(y)[i]} - \frac{1}{2}$$

Standardizing $p_\Phi(z)$

$$KL(p_\Phi(\tilde{z}|y), p_\Phi(\tilde{z}))$$

$$= \sum_i \frac{\sigma_\Phi(y)[i]^2 + (z_\Phi(y)[i] - \mu_q[i])^2}{2\sigma_q[i]^2} + \ln \frac{\sigma_q[i]}{\sigma_\Phi(y)[i]} - \frac{1}{2}$$

$$KL(p_{\Phi'}(\tilde{z}|y), \mathcal{N}(0, I))$$

$$= \sum_i \frac{\sigma_{\Phi'}^\epsilon(y)[i]^2 + z_{\Phi'}(y)[i]^2}{2} + \ln \frac{1}{\sigma_{\Phi'}^\epsilon(y)[i]} - \frac{1}{2}$$

Standardizing $p_\Phi(z)$

$$KL_\Phi = \sum_i \frac{\sigma_\Phi(y)[i]^2 + (z_\Phi(y)[i] - \mu_q[i])^2}{2\sigma_q[i]^2} + \ln \frac{\sigma_q[i]}{\sigma_\Phi(y)[i]} - \frac{1}{2}$$

$$KL_{\Phi'} = \sum_i \frac{\sigma_{\Phi'}^\epsilon(y)[i]^2 + z_{\Phi'}(y)[i]^2}{2} + \ln \frac{1}{\sigma_{\Phi'}^\epsilon(y)[i]} - \frac{1}{2}$$

Setting Φ' so that

$$z_{\Phi'}(y)[i] = (z_\Phi(y)[i] - \mu_q[i]) / \sigma_q[i]$$

$$\sigma_{\Phi'}^\epsilon(y)[i] = \sigma_\Phi(y)[i] / \sigma_q[i]$$

gives $KL(p_\Phi(\tilde{z}|y), p_\Phi(\tilde{z})) = KL(p_{\Phi'}(\tilde{z}|y), \mathcal{N}(0, I))$.

Sampling

Sample $\tilde{z} \sim \mathcal{N}(0, I)$ and compute $y_{\Phi}(\tilde{z})$



[Alec Radford]

Summary: Rate-Distortion

RDA: y continuous, \tilde{z} a bit string,

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

Gaussian RDA: $\tilde{z} = z_{\Phi}(y) + \sigma_{\Phi}(y) \odot \epsilon$, $\epsilon \sim \mathcal{N}(0, I)$

$$\Phi^* = \underset{\Phi}{\operatorname{argmin}} E_{y \sim \text{Pop}} \left(\begin{array}{l} KL(p_{\Phi}(\tilde{z}|y), \mathcal{N}(0, I)) \\ + \lambda E_{\epsilon} \text{Dist}(y, y_{\Phi}(\tilde{z})) \end{array} \right)$$

END