COMP9444 Neural Networks and Deep Learning

Quiz 8 (Weeks 8-10)

This is an optional quiz to test your understanding of the material from Weeks 8–10.

1. Write out the steps in the REINFORCE algorithm, making sure to define any symbols you use.

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for each trial run trial and collect states s_t, acions a_t and reward r_{\text{total}} for t = 1 to length(trial) \theta \leftarrow \theta + \eta(r_{\text{total}} - b) \nabla_{\theta} \log \pi_{\theta}(a_t \mid s_t) end end \theta = \text{parameters of policy}, \quad \eta = \text{learning rate}, \quad r_{\text{total}} = \text{total reward received during trial}, \quad b = \text{baseline (constant)}, \quad \nabla_{\theta} = \text{gradient with respect to } \theta, \quad \pi_{\theta}(a \mid s) = \text{probability of performing action } a \text{ in state } s.
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- 2. In the context of Deep Q-Learning, explain the following:
 - a. Experience Replay

The agent(s) choose actions according to their current Q-function, using an ε -greedy strategy, and contribute to a central database of experiences in the form (s_t , a_t , r_t , s_{t+1}). Another thread samples experiences asynchronously from the experience database, and updates the Q-function by gradient descent, to minimize

$$[r_t + \gamma \max_b Q_w(s_{t+1}, b) - Q_w(s_t, a_t)]^2$$

b. Double Q-Learning

Two sets of Q values are maintained. The current Q-network w is used to select actions, and a slightly older Q-network \bar{w} is used for the target value.

- 3. What is the Energy function for these architectures:
 - a. Boltzmann Machine
 - b. Restricted Boltzmann Machine

Remember to define any variables you use.

a. Boltzmann Machine

$$E(x) = -(\sum_{i < j} x_i w_{ij} x_j + \sum_i b_i x_i)$$
where x_i = activation of node i (0 or 1)

b. Restricted Boltzmann Machine

$$E(v, h) = -(\sum_{i} b_{i} v_{i} + \sum_{i} c_{i} h_{i} + \sum_{i, j} v_{i} w_{ij} h_{j})$$

where v_i = visible unit activations, h_i = hidden unit activations

4. The Variational Auto-Encoder is trained to maximize

$$\mathsf{E}_{z \sim q_{\Phi}(z \mid x^{(i)})} [\log p_{\theta}(x^{(i)} \mid z)] - \mathsf{D}_{\mathsf{KL}}(q_{\Phi}(z \mid x^{(i)}) \parallel p(z))$$

Briefly state what each of these two terms aims to achieve.

The first term enforces that any sample z drawn from the conditional distribution $q_{\varphi}(z \mid x^{(i)})$ should, when fed to the decoder, produce something approximationg $x^{(i)}$. The second term encourages the distribution $q_{\varphi}(z \mid x^{(i)})$ to approximate the Normal distribution p(z) (by minimizing the KL-divergence between the two distributions)

5. Generative Adversarial Networks make use of a two-player zero-sum game between a Generator G_{θ} and a Discriminator D_{ψ} , to compute

$$\min_{\theta} \max_{\psi} (V(G_{\theta}, D_{\psi}))$$

Give the formula for $V(G_{\theta}, D_{\psi})$

$$\mathcal{N}(G_{\theta}, D_{\psi}) = \mathsf{E}_{X \sim p_{\text{data}}} \left[\log \mathsf{D}_{\psi}(x) \right] + \mathsf{E}_{Z \sim p_{\text{model}}} \left[\log (1 - D_{\psi}(G_{\theta}(z))) \right]$$

6. In the context of GANs, briefly explain what is meant by *mode collapse*, and list three different methods for avoiding it.

Mode collapse is when the Generator produces only a small subset of the desired range of images, or converges to a single image (with minor variations). Methods for avoiding mode collapse include: Conditioning Augmentation, Minibatch Features and Unrolled GANs.