

EECS 598 Homework 3

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March 27, 2019

1 Text Classification using CNNs

1.1

$$Y_{n,f} = \sum_c X_{n,c} *_{\text{filt}} W_{f,c}^{\text{conv}} + b_f.$$

1.2

$Y_{n,f}$ is of size $(1, 1, H - H' + 1)$.

1.3

The size of the output of the pooling layer is $(N, F, 1)$.

1.4

I used GloVe embedding in my implementation. The accuracies under different conditions are listed below.

	Global average-pooling	Global max-pooling
Kernel size: 5	94.15%	95.33%
Kernel size: 7	93.40%	95.03%

Table 1: Test accuracy under different conditions

2 Siamese Networks for Learning Embeddings

2.1 Training loss

2.2

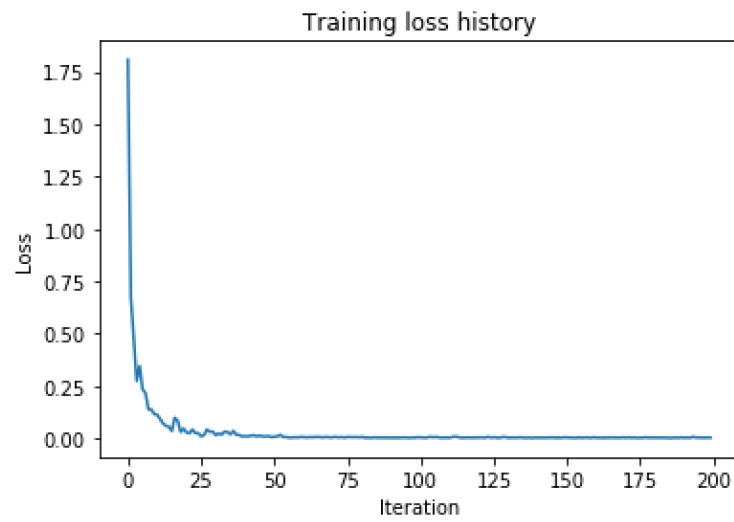
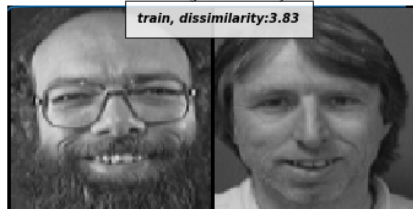
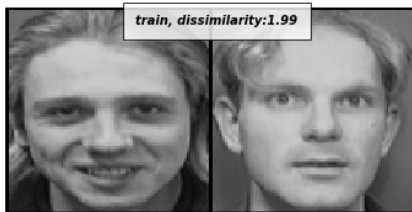
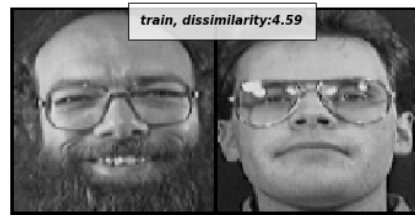
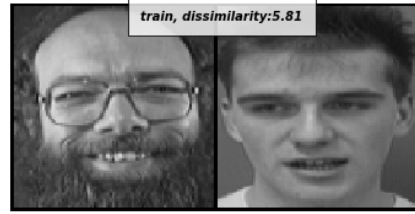
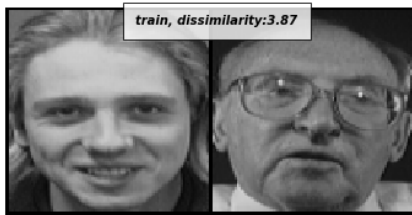


Figure 1: Train Loss History

2.3 Results on the Train Set

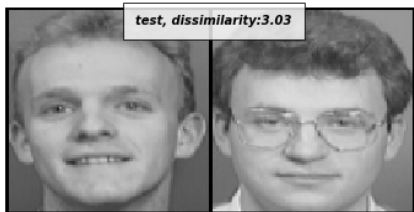
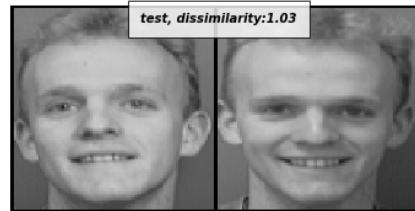
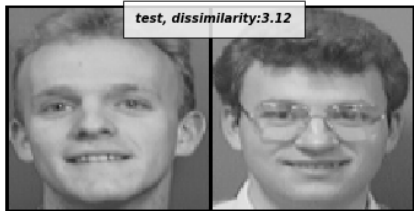
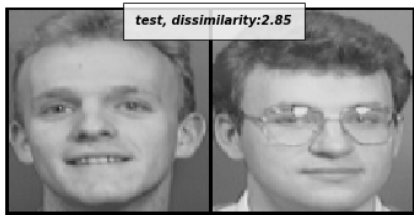
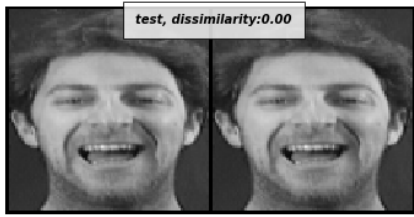


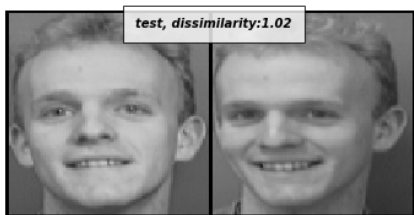




2.4 Results on the Test Set







3 Conditional Variational Autoencoders

3.1

Derive the variational lower bound of a conditional variational autoencoder.

First note that by Bayes rule, we have

$$p_\theta(z|x, y) = \frac{p_\theta(z, x|y)}{p_\theta(x|y)}.$$

Thus,

$$\begin{aligned} \log p_\theta(x|y) &= \mathbb{E}_{q_\phi(z|x, y)} \log p_\theta(x|y) \\ &= \mathbb{E}_{q_\phi(z|x, y)} \log \left(\frac{p_\theta(z, x|y) q_\phi(z|x, y)}{p_\theta(z|x, y) q_\phi(z|x, y)} \right) \\ &= \mathbb{E}_{q_\phi(z|x, y)} \log \left(\frac{p_\theta(x|y, z) p_\theta(z|y) q_\phi(z|x, y)}{p_\theta(z|x, y) q_\phi(z|x, y)} \right) \\ &= \mathbb{E}_{q_\phi(z|x, y)} \left[\log \frac{q_\phi(z|x, y)}{p_\theta(z|x, y)} \right] - \mathbb{E}_{q_\phi(z|x, y)} \left[\log \frac{q_\phi(z|x, y)}{p_\theta(z|y)} \right] + \mathbb{E}_{q_\phi(z|x, y)} [\log p_\theta(x|y, z)] \\ &= D_{KL}(q_\phi(z|x, y) || p_\theta(z|x, y)) - D_{KL}(q_\phi(z|x, y) || p_\theta(z|y)) + \mathbb{E}_{q_\phi(z|x, y)} [\log p_\theta(x|y, z)] \\ &\geq -D_{KL}(q_\phi(z|x, y) || p_\theta(z|y)) + \mathbb{E}_{q_\phi(z|x, y)} [\log p_\theta(x|y, z)], \end{aligned}$$

since KL-divergence is non-negative.

3.2

Derive the analytical solution to the KL-divergence between two Gaussian distributions $D_{KL}(q_\phi(z|x, y) || p_\theta(z|y))$.

Assume that $p_\theta(z|y) \sim N(0, I)$ and $q_\phi(z|x, y) \sim N(\mu, \Sigma)$, where $\mu = (\mu_1, \dots, \mu_J)^T$ and $\Sigma = \text{diag}(\sigma_1^2, \dots, \sigma_J^2)$ are the outputs of the neural network that estimate the parameters of the posterior distribution $q_\phi(z|x, y)$, then

$$\begin{aligned} D_{KL}(q_\phi(z|x, y) || p_\theta(z|y)) &= \mathbb{E}_{q_\phi(z|x, y)} \log \frac{q_\phi(z|x, y)}{p_\theta(z|y)} \\ &= \mathbb{E}_{q_\phi(z|x, y)} \log \left(\frac{\exp\{-\frac{1}{2}(z - \mu)^T \Sigma^{-1}(z - \mu)\}}{\sqrt{|\Sigma|}} \times \frac{1}{\exp\{-\frac{1}{2}z^T z\}} \right) \\ &= \mathbb{E}_{q_\phi(z|x, y)} \left(-\frac{1}{2}(z - \mu)^T \Sigma^{-1}(z - \mu) + \frac{1}{2}z^T z - \frac{1}{2} \log |\Sigma| \right) \\ &= \mathbb{E}_{q_\phi(z|x, y)} \left(-\frac{1}{2} \sum_{j=1}^J ((z_j - \mu_j)^2 / \sigma_j^2 - z_j^2) - \frac{1}{2} \sum_{j=1}^J \log \sigma_j^2 \right) \\ &= -\frac{1}{2} \sum_{j=1}^J (1 + \log \sigma_j^2 - \mu_j^2 - \sigma_j^2), \end{aligned}$$

since $\mathbb{E}_{q_\phi(z|x, y)}(z_j - \mu_j)^2 = \sigma_j^2$ and $\mathbb{E}_{q_\phi(z|x, y)}(z_j^2) = \sigma_j^2 + (\mathbb{E}_{q_\phi(z|x, y)} z_j)^2 = \sigma_j^2 + \mu_j^2$.

3.3



Figure 2: Generated images by CVAE

4 Generative Adversarial Networks

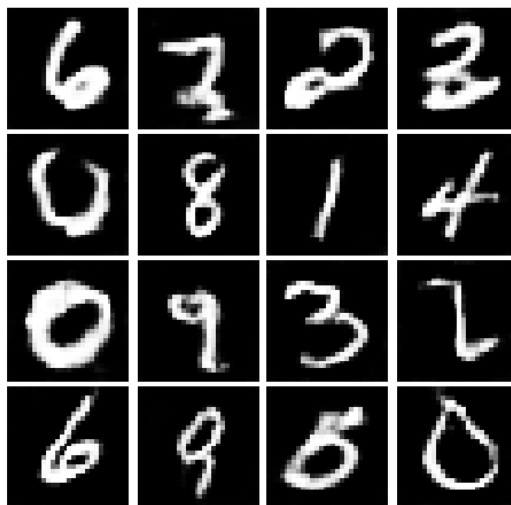


Figure 3: Generated images by DCGAN