Optimization of Unpaired Image-to-Image Translation

Group Members:

201601042 – Jalansh Munshi
201601055 – Raksha Rank
201601103 – Dharmil Patel
201601132 – Sakshee Patel
201601242 – Akshat Kaneria

Introduction

- Vision and graphics problems often involve mapping between input and target image using a training set of aligned image pairs.
- But it is not necessary that paired data is available for all the tasks.
- Our aim is to perform conversion between two different domains of data in the absence of unpaired data by optimizing a loss function.

Proposed Approach

- The primary objective function of the problem consists of Adversarial Loss, which was introduced by Goodfellow et. al. [1]
- Adversarial loss tries to learn the mapping such that the generated data cannot be distinguished from the original data distribution.
- Furthermore, the objective function also consists of cycle consistency losses in order to prevent the learned mappings from contradicting each other.
- We have divided our problem in three separate parts, where we have first solved the optimization problem of Adversarial Loss.
- Our inherent architecture consists of two generators and discriminators [2]. Generator tries to fool the discriminator by generating fake data, and discriminator tries to classify whether the generated data is fake or real.

[1] Goodfellow, Ian, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. "Generative adversarial nets." In *Advances in neural information processing systems*, pp. 2672-2680. 2014.
[2] Zhu, Jun-Yan, Taesung Park, Phillip Isola, and Alexei A. Efros. "Unpaired image-to-image translation using cycle-consistent adversarial networks." In *Proceedings of the IEEE international conference on computer vision*, pp. 2223-2232. 2017.

Optimization of Adversarial Loss

- Let us consider the adversarial loss for only one generator (G) and discriminator (D) for now.
- The data distribution is denoted as $x \sim p_{data}(x)$ and the generated data is denoted by z.
- We get the following cost function for the problem statement – (equation 1)

$$V(D,G) = E_{x\sim p_{data}(x)}[logD(x)] + E_{x\sim p_z(z)}[\log(1 - D\big(G(z)\big)$$

D maximizes the probability of assigning the correct label to the training examples and samples from G. Simultaneously, G tries to minimizes $\log(1 - D\big(G(z)\big)$. They are basically trying to play a minimax game with value function $V(D, G)$.

$$\min_G \max_D V(D,G)$$

For a given G, it will first find the optimal D, and then for a given optimal D, it will find the optimal value of G.

Optimization of Adversarial Loss

We convert everything to a single variable x.

$$x = G(z) \rightarrow z = G^{-1}(x) \rightarrow dz = (G^{-1})'(x)dx$$

Also, $p_g(x) = p_z\big(G^{-1}(x)\big)(G^{-1})'(x)dx$, where P_g is the generated distribution.

So, equation (1) becomes –

$$V(D,G) = \int_x p_{data}(x)\log\big(D(x)\big) + p_g(x)\log\big(1 - D(x)\big)\,dx$$

For a given G, optimal D comes out to be - $D(x) = \frac{p_{data}}{p_{data}+p_g}$

Now, we solve the optimization problem $C(G) = \min_G V(D,G)$

Optimization of Adversarial Loss

The final expression comes out to be –

$$C'(G) = KL\left[p_{data}(x)||\frac{p_{data}(x)+p_g(x)}{2}\right] + KL\left[p_g(x)||\frac{p_{data}(x)+p_g(x)}{2}\right] - \log(4),$$

Where KL[.] represents the KL divergence.

KL divergence is always non-zero. Since we are minimizing, the minimum value of KL divergence is 0. Therefore,

$$\min_G \max_D V(D, G) = -\log(4)$$

Also, since KL divergence is 0, we get $p_{data}(x) = p_g(x)$, which is exactly what we desired to achieve.

Thank you