Optimization of Unpaired image-to-image Translation

**Abstract and Introduction**

Image translation is a class of vision and graphics problem, where the goal is to map the source distribution to the target distribution. This task can be achieved comfortably using paired images. However, paired images might not be available for many other tasks. We shall be working on an approach to translate an image from a source domain ***X*** to a target domain ***Y*** in the absence of paired examples.

In our project, we present an optimization problem which captures the special characteristics of, for example, one set of images and attempts to translate these characteristics into another set of images in the absence of any paired training data. This problem I broadly known as unpaired image-to-image translation [CycleGAN ref]. We are given two sets of data, one of domain X, and a different set of domain Y. We may train the mapping such that the output , is indistinguishable from the data distribution by an adversarial network trained to classify apart from y. In theory, this objective can generate an output data distribution which matches the original data distribution. However, such a translation does not necessarily guarantee that the mapping takes place in a meaningful way, since there are infinitely many mappings possible.

This problem leads us to add more sense to our problem statement. We emphasize on the fact that our translation should be cycle-consistent. That is, if we translate a sentence from English to Hindi, and then translate it back to English from Hindi, we should arrive back at the original sentence. Hence, we also need to simultaneously add cycle-consistency loss. Furthermore, in order to generate near identity mappings, we also regularize the generator with the help of an identity loss function. The final objective/loss function becomes the following –

The above loss function is the function that we need to optimize in order to achieve the desired mapping. We have divided the optimization task into three different tasks, adversarial loss, cycle-consistency loss, and identity loss.

**Optimization of Adversarial Loss**

The primary objective function of the problem consists of adversarial loss, which was introduced by Goodfellow et. al [GAN ref]. Adversarial loss tries to learn the mapping such that the generated data cannot be distinguished from the original data distribution. In addition, the objective function also consists of cycle consistency losses in order to prevent the learned mappings from contradicting each other.

First, let us consider the adversarial loss for only one generator (G) and discriminator (D). The data distribution is denoted as , and the generated data is denoted by . We get the following cost function for the problem statement