

Meta GAN: an adversarial approach to few-shot learning

Summary

1. A key challenge in FSC is forming decision boundaries for each task with just a few samples in each class.
2. The key idea behind metaGAN is that the imperfect generators in GAN models:
 - provide fake data w/ the manifolds of different real data class.
 - provide additional training signals to the classifier as well as making the decision boundaries much sharper.
3. The classifier is the discriminator and is also trained to classify real-w-fake data in addition to the standard log loss.

Notations and background

1. A task τ from $P(\tau)$ is given by the joint dist. $p_{x \times y}^{\tau}(x, y)$ where the task is to predict y given x .
2. We have a set of training tasks $\{\tau_i\}_{i=1}^N$.
3. Each training sample task τ is a tuple $\tau = (S_{\tau}, Q_{\tau})$ where the support set $S_{\tau} = S_{\tau}^s \cup S_{\tau}^u$
• query set $Q_{\tau} = Q_{\tau}^s \cup Q_{\tau}^u$
4. The supervised support set S_{τ}^s contains K labeled examples from each of the N classes.
5. The optional unlabeled support set $S_{\tau}^u = \{x_1, \dots, x_M\}$ contains unlabeled examples from the same set of N classes.
6. Q_{τ}^s and Q_{τ}^u are defined similarly.

Basic Algo

1. They increase the dimension of the classifier output from N to $N+1$ to model the probability that input data is fake.

2. The classifier (discriminator) is trained:

$$\max_D \mathbb{E}_T [\mathcal{L}_D^T]$$

$$\mathcal{L}_D^T = \mathcal{L}_{\text{supervised}} + \mathcal{L}_{\text{unsupervised}}$$

$$\mathcal{L}_{\text{supervised}} = \mathbb{E}_{x, y \sim Q_T^S} [\log p_D(y | x, y \leq N)]$$

$$\mathcal{L}_{\text{unsupervised}} = \mathbb{E}_{x \sim Q_T^U} [\log p_D(y \leq N | x)] + \mathbb{E}_{x \sim p_G^T} [\log p_D(N+1 | x)]$$

3. The generator is trained:

$$\min_G \mathbb{E}_T [\mathcal{L}_G^T]$$

$$\mathcal{L}_G^T = - \mathbb{E}_{x \sim p_G^T} [\log p_D(y \leq N | x)]$$

where p_G^T is the task-conditioned generator.