Generative Adversarial Networks

Jacob Smith

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Abstract

General Adversarial Networks have

1 Introduction

Deep learning have made astounding progress within the past decade. Discriminative models have recently surpassed the abilities of human within the domain of pattern recognition [6]. These successes can attributed to vast, high dimension datasets in conjunction with large neural networks using linear activation functions, dropout regularization techniques and back-propagation to update the parameters [2]. However, deep learning posses many more ambitious goals. Until recently, success has mostly been seen with supervised classifiers; however, deep generative now competitively rival their discriminative counterpartsdfs.

Generative models learn the joint probability distribution $p(x, y)$ of an input x and label y whereas discriminative models directly learn the conditional probability $p(y|x)$. Knowledge of the probability distribution is created both explicitly and implicitly [3]. Those which do not directly model a probability distribution offer mechanisms which require implicit knowledge of the underlying distribution, such as creating a sample from that distribution [3]. As humans, we are able to understand the world around us with tremendous precision. It is easy to underestimate the complexity of the data we process to accomplish this feat. Although progress within the machine learning field is rapidly advancing, computers still have limited understanding of the data the process. Generative models, especially deep generative models, offer promising results towards this goal [4].

Figure 1: The process density estimation of one-dimensional data and a Gaussian distribution [1]. Generative models take a dataset D, sourced from a distribution p_{data}, a create an estimate of that distribution p_{model}.

Generative models may be used as classifiers using Bayes rules to calculate the conditional probability $p(x, y)$ which can then be used to make predictions [5]. These models offer insight about the data they are

2 Conclusion

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References

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