Generative Adversarial Networks

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Generative Modeling

- Have training examples: $\boldsymbol{x} \sim p_{\text{train}}(\boldsymbol{x})$
- Want $p_{\text{model}}(\boldsymbol{x}) = p_{\text{data}}(\boldsymbol{x})$



• Want a model that can draw samples: $\boldsymbol{x} \sim p_{\text{model}}(\boldsymbol{x})$



(Images from Toronto Face Database)



Example Applications

- Image manipulation
- Text to speech
- Machine translation



Probability Density

Put high probability where there should be high probability

 ${\mathcal X}$



should be low probability

Generative Adversarial Networks



"Generative Adversarial Networks", Goodfellow et al 2014)



Discriminator Strategy

Optimal $D(\boldsymbol{x})$ for any $p_{\text{data}}(\boldsymbol{x})$ and $p_{\text{model}}(\boldsymbol{x})$ is always





Learning Process



Poorly fit model

After updating D



After updating G



• • •

Mixed strategy equilibrium •

Generator Transformation Videos



MNIST digit dataset

Toronto Face Dataset (TFD)



Non-Convergence



(Alec Radford)



Laplacian Pyramid



(Denton+Chintala et al 2015)



LAPGAN Results

• 40% of samples mistaken by humans for real photographs



(Denton+Chintala et al 2015)



DCGAN Results



(Radford et al 2015)



Arithmetic on Face Semantics





Man wearing Man glasses

Woman



Woman wearing glasses

(Radford et al 2015)

Mean Squared Error Ignores Small Details Reconstruction Input

(Chelsea Finn)

GANs Learn a Cost Function Ground Truth Adversarial MSE

Capture *predictable* details regardless of scale

(Lotter et al, 2015)

Conclusion

- Generative adversarial nets
 - Prioritize generating realistic samples over assigning high probability to all samples
 - Learn a cost function instead of using a fixed cost function
 - Learn that all predictable structures are important, even if they are small or faint