Generative Adversarial Neural Networks Seminaar Presentation

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Outline

Introduction

Motivation

Applications

Conclusion

References

Introduction: Supervised Learning VS Unsupervised Learning

Supervised Learning

- Algorithm that analyzes the training data and produces a function, which can be used for mapping new examples.
- Dataset: labelled data
- Examples: Classification algorithms, Regression algorithm

Unsupervised Learning

- ► Algorithm that generates a function to describe the hidden structure from *Unlabeled data*
- Dataset: unlabelled data
- ► Examples: Clustering algorithm, Generative models

Generative Model VS Discriminative Model[gmv09]

Generative Model

It models how the data was generated in order to categorize a data.

Discriminative Model

▶ It does not care about how the data was generated, it simply categorizes a given data.

Generative Adversarial Networks (a.k.a GANs)

- Consists of two models that are trained simultaneously:
 - ► **Generative Model**: a model that generates samples to match the data distribution to fool the discriminative model.
 - ▶ **Discriminative Model**: a model that learns to determine whether a sample is real or fake
- Created by Ian Goodfellow[GPAM+14] in 2014
- Semi-supervised learning
- Two-player minimax game
- Trained until generated samples are indistinguishable from real data

Generative Adversarial Networks (a.k.a GANs)

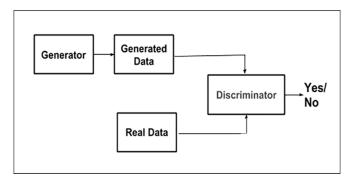


Figure: Generative Adversarial Networks Structure

Motivation

Problems with other Algorithms[GPAM+14]:

- Require learned probability density functions, which is not always possible.
- Use Markov chain model which is highly time consuming.
- ▶ Do not give better understanding of complex problems.

Applications: WaveNet

WaveNet: A Generative Model for Raw Audio[vdODZ⁺]

- Created by DeepMind at Google
- Generate speech which mimics any human voice and sounds more realistic.
- For Text to Speech
- Previous models[Dee16]:
 - Concatenative TTS(Text To Speech):
 - Use very large database of short speech fragments are recorded from a single speaker and then recombined to form complete audio wave.
 - But they have difficulty in modifying voice without creating a new database.

Parametric TTS:

- Data is stored in the parameters of the model, and the contents and characteristics of the speech can be controlled via the inputs to the model.
- But they do not sound highly natural



WaveNet: A Generative Model for Raw Audio

GAN based model

- Model raw waveform of audio signals directly.
- Human speaker's audio waveform is given as a sample dataset to the discriminator of the GAN and to the generator model.
- Mimic US English and Mandarin Chinese.
- ▶ More realistic [Figure: 2].

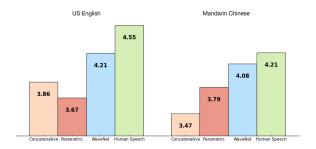


Figure: Comparison of different models for TTS(text to speech)

Photo-Realistic Single Image Super Resolution Using a Generative Adversarial Network[LTH⁺]

- ▶ By Christian Ledig et. al.
- Producing a High resolution Image from Low resolution is Image super resolution.
- Many implementation using deep neural network, but they suffer recovering the fine texture details.
- ▶ Using **GANs**, they use perceptual loss function which consists of an adversarial loss and a content loss.
 - ► Adversarial loss: uses natural image manifold using a discriminator network that is trained to dierentiate between the super-resolved images and original photo-realistic images.
 - ► **Content loss**: uses perceptual similarity instead of similarity in pixel space.

Photo-Realistic Single Image Super Resolution Using a Generative Adversarial Network

- they able to recover photo-realistic textures at higher resolutions [Figure: 3].
- ▶ they achieved 4x up-scaling factor.



Figure: Comparison of dierent super resolution methods

Video Imagination from a Single Image with Transformation Generation[CWWC]

- By Baoyang Chen et. al.
- Video Imagination: synthesizing imaginary videos from single static image
- Major problems faced by other algorithms:
 - High dimensionality of pixel space
 - Ambiguity of potential motions
- Applied transformations on the image in a volumetric merge network to reconstruct frames in imaginary video.
- Trained the network in an adversarial way with unsupervised learning.
- Created five-frame videos from a single image. [Figure: 4]



Video Imagination from a Single Image with Transformation Generation

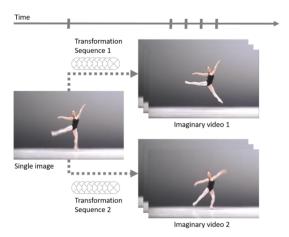


Figure: Video Imagination from a Single Image with Transformation Generation

Conclusion[GPAM+14]

- Markov chains are never needed.
- ► Semi-supervised learning features is obtained from the discriminator or inference net.
- ▶ Eciency improvements: training could be accelerated greatly by divising better methods for coordinating G and D.
- Understand and tackle complex problems.
- ► Generates model as well as additional samples based on inputs.

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