Generative Adversarial Networks

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Overview

GAN

- **G**enerative
  -
- **A**dversarial
- **N**etwork

Supervised vs Unsupervised learning

Supervised learning

Data:

- x, the input data
- y, the output label

Goal – learn a function that to map from x to y

Examples – Classification, regression, object detection, etc.

Supervised vs Unsupervised learning

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Unsupervised learning

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Goal – learn some underlying hidden structure of data
Examples – Clustering, dimensionality reduction, etc.

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Unsupervised learning

Data:

- x, the input data [the training data is cheap]
- No labels

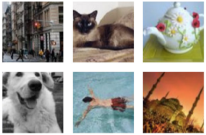
Goal – learn some underlying hidden structure of data

Examples – Clustering, dimensionality reduction, etc.

Generative Models

- Given a training set, generate new samples that are similar to the data in the training set.

Training data $p_{data}(x)$



Generated samples $p_{model}(x)$

[1]

[1][Source: NIPS 2016 tutorial on GANs by *Ian Goodfellow*]

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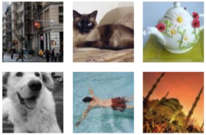

Generated samples $p_{model}(x)$

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We want $p_{model}(x)$ to be similar to $p_{data}(x)$

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Adversarial training

- The term has been used by computer scientists for a long time.
- Current usage: "Training a model in the worst case scenario, with inputs chosen by an adverasary."
- Examples:
  - An agent playing against a copy of itself in a board game (Samuel's Checkers-playing Program, 1959)
  - Generative adversarial Networks (Ian Goodfellow *et. al*, 2014)

Generative Adversarial Networks

GANs [2] consists of two neural networks –

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[2] Ian Goodfellow et al., Generative Adversarial Nets, NIPS 2014

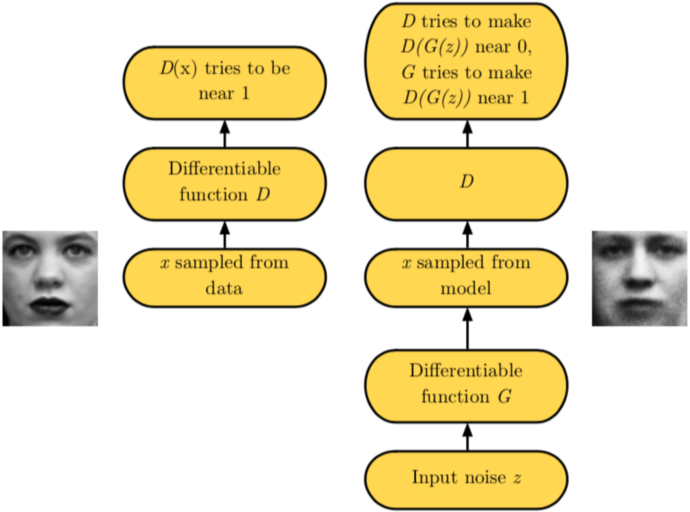
Generative Adversarial Networks

GANs [2] consists of two neural networks –

- **Generator (G)** which tries of generate new data.
- **Discriminator (D)** which tries to classify the data given as input to it as "real" or "fake".

[2] Ian Goodfellow et al., Generative Adversarial Nets, NIPS 2014

The framework



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[3] Ian Goodfellow, NIPS 2016 tutorial on GANs

An analogy - Counterfeiters and Police

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- Over time, the police learn to be better at catching fake currency and the counterfeiters learn to be better at producing fake currency.
- The equilibrium is reached when the counterfeiters learn to produce fake currency which cannot be distinguished from the real currency.

Image to Image translation [4]

[4] Image-to-Image Translation with Conditional Adversarial Networks, Isola et. al 2016

Generative Adversarial Text to Image Synthesis [6]

Caption	Image
this vibrant red bird has a pointed black beak	
this bird is yellowish orange with black wings	
the bright blue bird has a white colored belly	

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[5]Source: `https://github.com/reedscot/icml2016`

[6]Generative Adversarial Text to Image Synthesis, Scott Reed et. al, ICML 2016

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- GANs does not have an easily understood loss function.
- It makes training GANs a lot harder.
- A lot of trial and error is required to determine the network structure and training protocol of GANs. This is the reason why GANs have not been applied yet to more complex data like text or voices.

Thank You!