VSB TECHNICAL UNIVERSITY OF OSTRAVA | FACULTY OF ELECTRICAL ENGINEERING AND COMPUTER SCIENCE | DEPARTMENT OF COMPUTER SCIENCE

Algorithms for Big Data

Generative models

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Generative models

Informally:

- **Generative models** can generate new data instances.
- **Discriminative models** discriminate between different kinds of data instances.

Formally:

- **Generative models** capture the joint probability $p(X, Y)$, or just $p(X)$ if there are no labels.
- **Discriminative models** capture the conditional probability $p(Y|X)$.

Source: `https://developers.google.com/machine-learning/gan/generative`

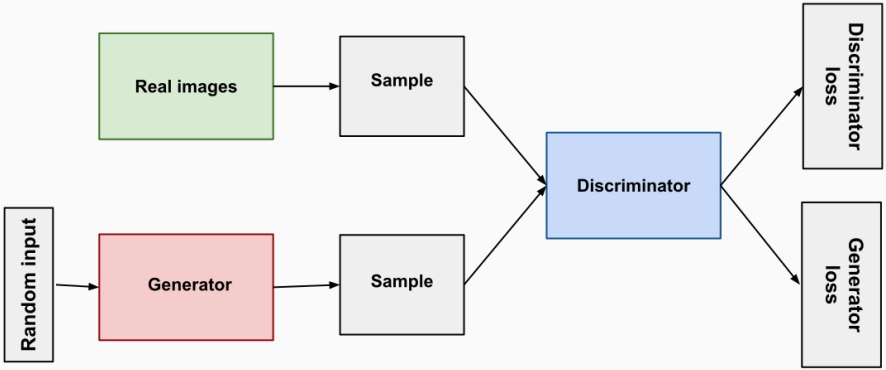
Generative models

- Generative models task is much harder than the discriminative.
- Discriminative models identifies the important places for decision.
- Generative models identifies all the relations between objects in the true dataset.
- Learning generative models need more information from data and modified learning process to gather required information.

Generative models - Generative Adversarial Network (GAN)

- GAN is composed of two parts.
- The **generator** learns how to generate realistic data.
- The **discriminator** learns to distinguish between fake and real data.
- The generated images are negative examples for the discriminator.
- The discriminator penalizes the generator if it is not able to generate realistic data.

Generative models - Generative Adversarial Network (GAN)



Schema of the GAN

https://developers.google.com/machine-learning/gan/generative

Generative models - Generative Adversarial Network (GAN) - Discriminator

- The Discriminator is a classifier.
- The goal is to distinguish between the real and generated data.
- The structure dep3nd on the classified data (CNN, Dense, ...).
- The training data comes from:
  - Real data - a real world dataset we try to mimic.
  - Fake data - data generated by the generator.

Generative models - Generative Adversarial Network (GAN) - Discriminator

- The loss functions are two - the discriminator's and the generator's.
- The discriminator's loss is used only in discriminator training.
- The discriminator classifies fake and real data.
- The discriminator's loss penalizes discriminator when classifies real data as fake or fake as real.
- The discriminator updates its weights using backpropagation based on the discriminator's loss.

Generative models - Generative Adversarial Network (GAN) - Generator

- The Generator is a networks that generates data that may be classified as real.
- The Generator is tightly connected to the discriminator.
- The input of the generator is a random vector.
- The input is transformed using the generator network and produces the output.
- The discriminator classifies the generated data.
- THe generator loss penalizes the generator for failing to fool the discriminator.

Generative models - Generative Adversarial Network (GAN) - Generator

- The generator is directly connected to the output.
- The discriminator network accept the generators output and classify it.
- The resulting loss function backpropagates through discriminator first.
- Then it backpropagates through the generator and updates the weight.

Generative models - Generative Adversarial Network (GAN) - Training

- GAN training proceeds in alternating periods:
- 1. The discriminator trains for one or more epochs.
- 2. The generator trains for one or more epochs.
- Repeat steps 1 and 2 to continue to train the generator and discriminator networks.

Generative models - Generative Adversarial Network (GAN) - Training

- The largest problem is the convergence.
- The improving generator leads into failing discriminator.
- Finally, the discriminator has a 50% accuracy.

Generative models - Generative Adversarial Network (GAN) - Loss functions

- Minmax Loss - maximization of:

$$E_x\left[\log\left(D\left(x\right)\right)\right] + E_z\left[\log\left(1 - D\left(G\left(z\right)\right)\right)\right]$$

- Modified Minmax Loss - maximization of:

$$\log\left(D\left(G\left(z\right)\right)\right)$$

- Wasserstein Loss

$$D \rightarrow D(x) - D(G(z)) \qquad G \rightarrow D(G(z))$$

Questions?