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Generative Modeling

Introduction to Generative Modeling

- What is Generative Modeling?
  - Generative modeling is a type of machine learning.
  - It involves training a model to produce new data similar to an existing dataset.
  - Example: If we have photos of horses, a generative model can learn to create new, realistic images of horses.

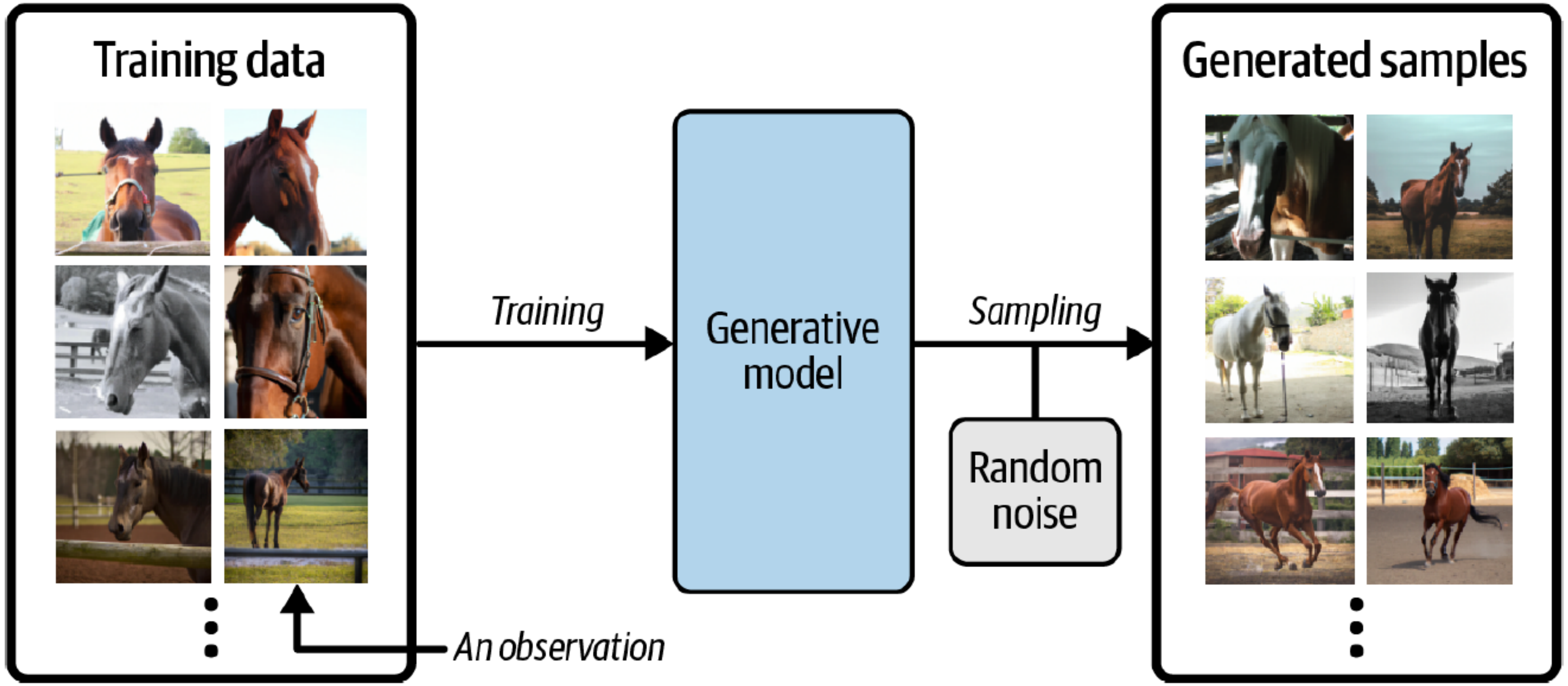


Figure 1-1. A generative model trained to generate realistic photos of horses

Training Data and Observations

- What Do We Need?
  - A dataset with many examples of what we want to generate, called training data.
  - Each example in the dataset is called an observation.
  - For images, features are the individual pixel values.
  - For text, features could be words or letters.

Building the Model

- How Does It Work?
  - Our goal is to build a model that generates new sets of features.
  - For image generation, this is hard because there are many ways to arrange pixels.
  - Only a small number of these arrangements look like the entity we want to generate (e.g., horses).

Probabilistic Nature of Generative Models

- Why Probabilistic Models?
  - A generative model must be probabilistic, not deterministic.
  - We want to create many different variations, not just the same output every time.
  - The model should include randomness to create diverse samples.
  - The goal is to mimic the distribution of the original data and generate new observations that look like they belong to the original dataset.

Deterministic Models

- **Definition:** A deterministic model always produces the same output from a given input. There's no randomness involved.
- **Example:** If we average the pixel values of all horse images in our training dataset, we'll get one average image of a horse. Every time we use this method, we'll get the exact same average image.
- **Limitation:** Deterministic models lack variety. They can't produce new and unique samples because they don't incorporate randomness.

Probabilistic Models

- **Definition:** A probabilistic model incorporates randomness, meaning that it can produce different outputs from the same input. These models generate new data by sampling from a learned distribution.
- **Example:** When we train a generative model on horse images, it learns the underlying distribution of these images. By sampling from this distribution, we can create many different realistic horse images, each unique in its own way.
- **Advantage:** Probabilistic models can generate a wide variety of outputs, making them more flexible and powerful for tasks like image generation.

Why Generative Models Must Be Probabilistic

- **Diversity:** We need the ability to produce multiple, varied outputs that resemble the original dataset but are not exact copies.
- **Realism:** Real-world data is inherently diverse and contains variations. Probabilistic models can better capture and reproduce this diversity.
- **Flexibility:** Probabilistic models can adapt to generate different types of data by learning and sampling from complex distributions.

Introduction to Modeling

- Generative vs. Discriminative Modeling
  - **Generative Modeling**: Creates new data samples.
  - **Discriminative Modeling**: Predicts labels for existing data.

Example Scenario

- Dataset of Paintings
  - **Discriminative Task**: Predict if a painting is by Van Gogh.
  - **Generative Task**: Generate new paintings in Van Gogh's style.

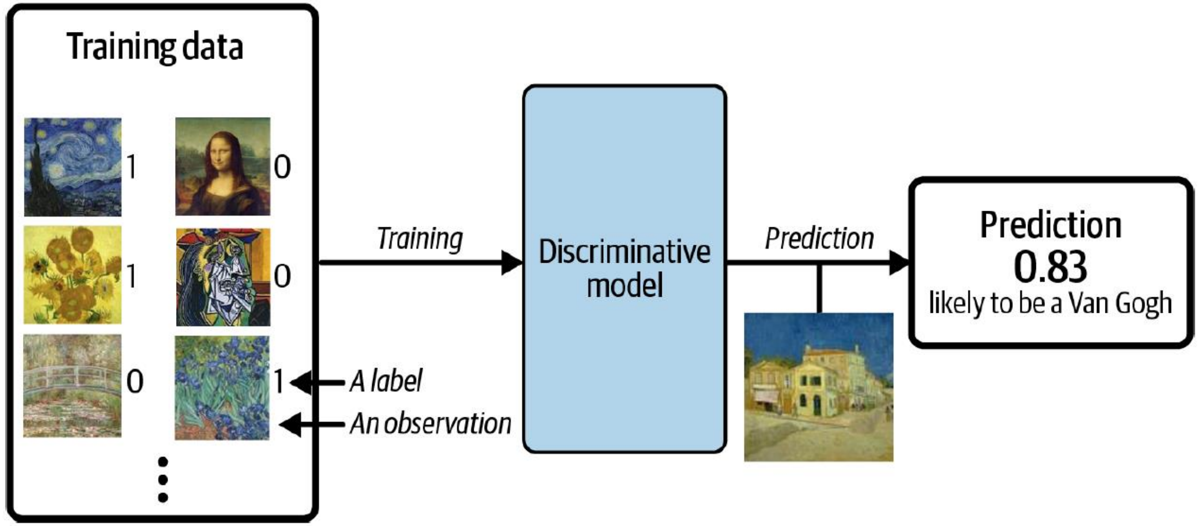


Figure 1-2. A discriminative model trained to predict if a given image is painted by Van Gogh

Discriminative Modeling

- How It Works
  - **Training Data**: Labeled (Van Gogh = 1, Non-Van Gogh = 0).
  - **Model's Goal**: Learn features (colors, shapes, textures) that distinguish Van Gogh's paintings.
  - **Output**: Probability that a new painting is by Van Gogh.

Generative Modeling

- How It Works
  - **Training Data**: Unlabelled.
  - **Model's Goal**: Understand the underlying distribution of Van Gogh's paintings.
  - **Output**: Generate new paintings that resemble Van Gogh's style.

Formal Definitions

- Discriminative Modeling
  - **Goal**: Estimate $p(y|x)$
  - **Explanation**: Predict the probability of a label y given an observation x.
- Generative Modeling
  - **Goal**: Estimate $p(x)$
  - **Explanation**: Model the probability of an observation x. Generate new observations by sampling from this distribution.

Limitations of Discriminative Modeling

- Discriminative Model's Capability
  - **Task**: Identify if a painting is by Van Gogh
  - **Limitation**: Even a perfect model cannot create a new Van Gogh painting
  - **Reason**: It only predicts labels for existing images, not generate new ones

Generative Modeling's Advantage

- Generative Model's Capability
  - **Task**: Generate new paintings that look like Van Gogh's work.
  - **Method**: Train on existing Van Gogh paintings and sample from the learned distribution.
  - **Advantage**: Can create new images that resemble the training dataset.

Dominance of Discriminative Modeling

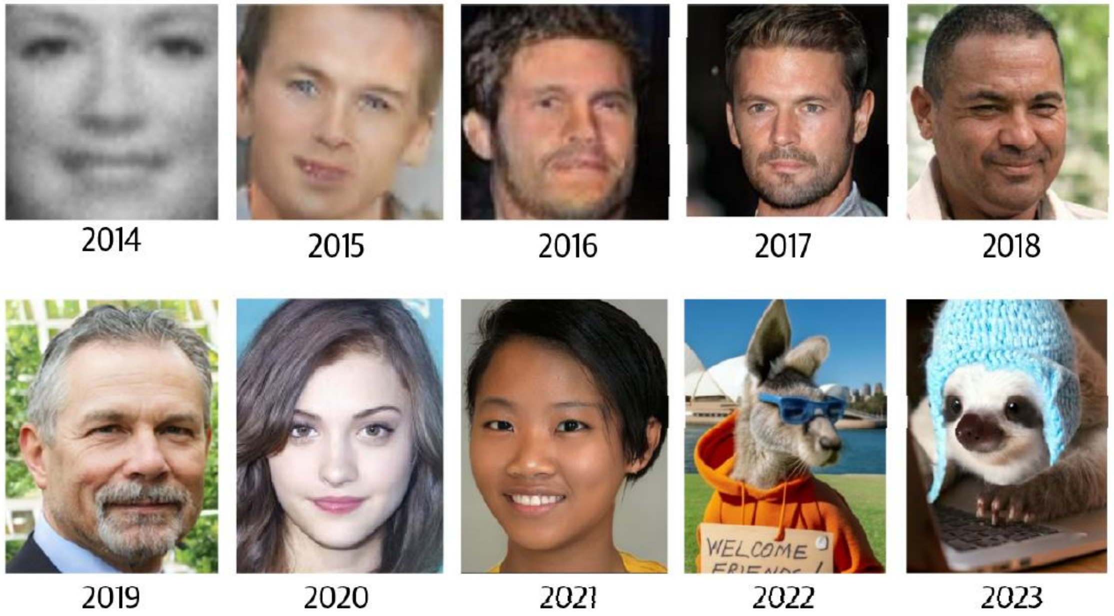
- Historical Focus
  - **Discriminative Modeling**: Main driver in machine learning progress.
  - **Reason**: Easier to solve than generative problems.

Difficulty of Generative Modeling

- Challenges
  - **Example 1**: Easier to predict if a painting is by Van Gogh than to generate a Van Gogh-style painting.
  - **Example 2**: Easier to predict if text is by Dickens than to write new text in Dickens' style.
  - **Perception**: Creativity seen as a human trait, hard for AI to replicate.

Progress in Generative Modeling

- Recent Advances
  - **Technological Maturity**: Improved machine learning technologies.
  - **Result**: Significant advancements in generative modeling.
  - **Example**: Facial image generation progress since 2014.



Practical Applications of Discriminative Modeling

- Industry Use
  - **Example**: Predicting glaucoma from retinal images.
  - **Limitation**: Historically, generative models had fewer practical applications.

Emerging Applications of Generative Modeling

- New Business Solutions
  - **Generative Services**: APIs for generating blog posts, images, social media content, and ad copy.
  - **Industry Impact**: Game design, cinematography, and more are benefiting from generative AI.
  - **Examples**: Video and music generation adding value to various industries.