Understanding Generative vs Discriminative Models

Exploring how machine learning models learn differently — by generating data versus separating classes

Two Fundamental Approaches in Machine Learning

Generative Models

Learn how data is generated and can create new samples similar to training data

Discriminative Models

Learn to classify or predict directly by finding decision boundaries between classes

Both approaches are essential in artificial intelligence, data science, and deep learning — but they serve fundamentally different purposes and excel in different scenarios.

Core Differences at a Glance

Aspect	Generative Model	Discriminative Model
What it learns	Joint probability $P(x, y)$	Conditional probability $P(y\|x)$
Primary goal	Understand how data is generated	Learn decision boundary between classes
Focus area	Models data distribution	Models class boundary
Example question	"How does a cat image look?"	"Is this image a cat or not?"

Mathematical Foundations

Generative Models

$$P(y|x) = \frac{P(x|y)P(y)}{P(x)}$$

- Learn both **P(x|y)** and **P(y)**
- Use Bayes' theorem for classification
- Can generate new data samples
- Model complete joint distribution

Discriminative Models

$$P(y|x)$$

- Learn only direct mapping from input to output
- Focus on decision boundaries
- Optimise classification accuracy
- Don't model data generation process

Objectives and Capabilities Comparison

Aspect	Generative	Discriminative
Primary objective	Model data distribution and simulate data	Classify or predict outputs accurately
Can generate new data?	✅ Yes	❌ No
Typical usage	Image, text, audio generation	Classification, regression tasks
Learning paradigm	Often unsupervised or semi-supervised	Supervised learning
Robustness to outliers	❌ Less robust	✅ More robust

Model Examples by Task

Task Domain	Generative Models	Discriminative Models
Basic Classification	Naïve Bayes	Logistic Regression
Sequence Modelling	Hidden Markov Model (HMM)	Conditional Random Field (CRF)
Image Generation	GANs, VAEs	Not applicable
Text Classification	Latent Dirichlet Allocation	Support Vector Machines
Speech Recognition	Hidden Markov Models	Neural Networks

The Mathematics Behind Learning

Generative Models

Estimate probability components separately:

- $P(Y)$ — class prior distribution
- $P(X|Y)$ — likelihood function

Then apply **Bayes' theorem** to compute $P(Y|X)$

They can describe, simulate, and generate entirely new data samples.

Discriminative Models

Directly estimate the target:

- $P(Y|X)$ — posterior probability
- Or function $f(X) \rightarrow Y$ mapping

Focus entirely on **decision boundaries**

They only learn to separate classes effectively and efficiently.

Popular Model Examples

Generative Models

- Naïve Bayes
- Hidden Markov Models
- Bayesian Networks
- Markov Random Fields
- Latent Dirichlet Allocation (LDA)
- Generative Adversarial Networks (GANs)
- Variational Autoencoders (VAEs)

Discriminative Models

- Logistic Regression
- Support Vector Machines (SVM)
- Decision Trees
- Random Forests
- Neural Networks
- Conditional Random Fields (CRFs)
- Gradient Boosting Models

Performance Trade-offs

Evaluation Criteria	Generative	Discriminative
Classification Accuracy	Moderate performance	High performance
Data Efficiency	Works with smaller datasets	Requires larger datasets
Interpretability	High (models data process)	Moderate interpretability
Generalisation	Can generalise with fewer examples	Needs more training data
Computational Cost	Often higher complexity	Lower in most cases

Key Takeaways

Aspect	Generative	Discriminative
Primary focus	Learn data distribution	Learn decision boundary
Output capability	New data generation	Class prediction
Key equation	$P(x, y)$	$P(y\|x)$
Popular examples	GAN, VAE, Naïve Bayes	SVM, Logistic Regression
Best suited for	Creative AI, simulation	Classification, regression

In essence:

Generative models = "Create like a human" 🎨

Discriminative models = "Judge like a human" ⚖️