Machine Learning Basic

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Agenda

- Review of linear algebra for machine learning
- Introduction and motivation for machine learning
  - Examples
- VC dimension
- Probably approximately correct (pac) learning
- Hypothesis space
- Inductive bias
- Generalization
- Bias, Variance and Trade-off

Review of linear algebra for machine learning

1. Basics :

- **Scalars**: Single values, denoted as lowercase letters (e.g., aaa).
- **Vectors**: Ordered lists of numbers denoted as bold lowercase (e.g., v\mathbf{v}v).
- **Matrices**: 2D arrays of numbers denoted as bold uppercase (e.g., A\mathbf{A}A).
- **Tensors**: Generalizations of vectors & matrices to higher dimensions.

2. Key Operations :

- **Addition/Subtraction**: Element-wise for same-sized matrices or vectors.
- **Scalar Multiplication**: Each element is multiplied by a scalar.
- **Dot Product**: Multiplication of two vectors to yield a scalar (measures similarity).
- **Matrix Multiplication**: Combines two matrices; central for transformations (applying weights).

Introduction and motivation for machine learning

Machine learning is a subset of artificial intelligence that involves using algorithms and statistical models to enable computers to perform tasks without being explicitly programmed. ML allows systems to learn from data and improve their performance over time based on experience.

1. **Types of Machine Learning:**

a. **Supervised learning** – Also called predictive learning. A machine predicts the class of unknown objects based on prior class-related information of similar objects.

b. **Unsupervised learning** – Also called descriptive learning. A machine finds patterns in unknown objects by grouping similar objects together.

c. **Reinforcement learning** – A machine learns to act on its own to achieve the given goals.

Examples

1. Image Recognition and Computer Vision

- **Facial Recognition**: Used in social media, surveillance, and smartphone security, facial recognition systems can identify or verify people based on their facial features

- **Object Detection**: Self-driving cars rely on computer vision to detect and classify objects like other cars, pedestrians, and traffic signals, ensuring safe navigation.

- **Medical Imaging**: AI models help radiologists detect abnormalities (like tumors) in X-rays, MRIs, and CT scans, aiding early diagnosis and treatment planning.

- **Augmented Reality (AR)**: Image recognition algorithms track real world objects, which AR applications then overlay with virtual content for gaming shopping, or remote assistance.

Examples

2. Natural Language Processing (NLP)

- **Language Translation**: Apps like Google Translate use NLP models to translate text or speech in real-time, supporting multiple languages.
- **Sentiment Analysis**: Businesses use NLP to analyze customer sentiment in reviews or social media, helping them understand consumer opinions.
- **Chatbots and Virtual Assistants**: Siri, Alexa, and other voice-activated assistants use NLP to understand spoken language, answer questions, and perform tasks.
- **Content Generation and Summarization**: Tools like GPT can generate human-like text, summarize articles, or assist with creative writing, enhancing productivity.

VC dimension

VC Dimension :

(Vapnik-Chervonenkis Dimension): The VC dimension is a measure of a model's capacity, or its ability to classify a variety of data patterns. It's defined as the maximum number of points a model can shatter, meaning the model can perfectly classify all possible labelings of those points. Higher VC dimensions imply more complex models, potentially leading to overfitting, while lower VC dimensions suggest simpler models that may underfit. It's crucial for understanding a model's generalization ability.

Probably approximately correct (pac) learning

Probably Approximately Correct (PAC) Learning is a framework in machine learning that quantifies a model's ability to learn from data. In PAC learning, a model is considered successful if, with high probability (the "Probably" part), it can learn a hypothesis that is approximately correct—that is, close enough to the true function or distribution generating the data.

Key points:

- **Probably**: The model will produce an accurate hypothesis with a high probability (e.g., 95%).
- **Approximately Correct**: The hypothesis may not be perfect, but its error is within an acceptable margin (ε).
- **Efficiency**: PAC learning also considers the computational efficiency of finding this hypothesis within a reasonable amount of data and time.

Hypothesis space

The **hypothesis space** in machine learning is the set of all possible models or functions that a learning algorithm can choose from to fit a given dataset. It includes every potential hypothesis (or function) that could map inputs to outputs based on the training data.

Why It's Essential

- **Defines Learning Scope**: The hypothesis space determines the complexity and flexibility of the models, influencing what patterns or relationships the model can learn from the data.
- **Affects Generalization**: A too-large hypothesis space can lead to overfitting, where the model learns noise instead of patterns. A too-small hypothesis space may underfit, missing important data relationships.
- **Guides Model Selection**: Choosing an appropriate hypothesis space helps

Inductive bias

Inductive bias is the set of assumptions a machine learning model makes to predict outputs for unseen inputs based on its training data. It provides the model with a "preference" toward certain solutions, which helps it generalize effectively from limited data.

Purpose:

- **Generalization**: Inductive bias enables a model to go beyond the training data, predicting patterns it hasn't explicitly seen.
- **Guiding Hypothesis Selection:** By narrowing down the hypothesis space, inductive bias helps the model focus on likely solutions rather than exploring every possible one.

Types of Bias

Restriction Bias (or Language Bias):

Preference Bias (or Search Bias):

Generalization

Generalization refers to a model's ability to make accurate predictions on new, unseen data, based on patterns learned from the training data. It is a key goal, as a model that generalizes well performs well not only on the training data but also on previously unseen test data.

- **Good generalization** means the model can handle new data effectively.
- **Overfitting** occurs when the model is too specific to the training data and performs poorly on new data.
- **Underfitting** occurs when the model is too simple to capture the underlying patterns in the data.
- The **bias-variance tradeoff** affects generalization: models with high bias may underfit, while those with high variance may overfit.
- Techniques like regularization help prevent overfitting and improve

Bias, Variance and Trade-off

Bias:

- Represents the error introduced by approximating a real-world problem, which may be complex, with a simpler model.
- High bias models tend to make strong assumptions about the data and may oversimplify it.
- Leads to underfitting, where the model is too simple and fails to capture the data patterns.

Variance:

- Represents the model's sensitivity to fluctuations in the training data.
- High variance models capture noise along with the underlying data patterns.
- Leads to overfitting, where the model performs well on training data but poorly on new, unseen data.

Trade-Off :

Thank you