TITLE: SUPPORT VECTOR MACHINES (SVM) IN MACHINE LEARNING

Introduction

- Support Vector Machines (SVM) is a powerful machine learning algorithm used for classification and regression tasks.

- SVM finds an optimal hyperplane to separate different classes while maximizing the margin.

Linear SVM

Basic form of linear SVM:

- Hyperplane equation: $w^T x + b = 0$
- w: Weight vector
- x: Input vector
- b: Bias term

Margin and Support Vectors

- Explain the concept of margin and support vectors:
  - **Margin**: Distance between the hyperplane and the nearest data points of each class.
  - **Support vectors**: Data points that lie on the margin or violate the margin.

Maximizing the Margin

- SVM's objective: Maximize the margin while minimizing classification errors.
- Formulate the optimization problem:
  - Minimize $\frac{1}{2}||w||^2$ subject to $y_i(w^T x_i + b) \geq 1$ for all data points (x_i, y_i).

- **Kernel Trick**
- Extend SVM to nonlinear classification using the kernel trick:
  - **Nonlinear transformation:** $\varphi(x)$ maps input to a higher-dimensional feature space.
  - **Kernel function:** $K(x, y)$ computes the inner product of transformed features.
  - **Popular kernels**: Linear, Polynomial, Radial Basis Function (RBF), Sigmoid.

Soft Margin SVM

- Introduce soft margin SVM to handle overlapping classes or noisy data:
  - Allow some misclassification by introducing slack variables (ξ).
  - Update the optimization problem: Minimize $\frac{1}{2}||w||^2 + C\Sigma\xi_i$ subject to $yi(w^Txi + b) \geq 1 - \xi_i$.

Kernel SVM

- Discuss the application of kernels in SVM:
  - Kernels allow SVM to classify nonlinearly separable data.
  - Kernels implicitly map the data into higher-dimensional spaces.

SVM for Regression

- Briefly explain SVM for regression tasks:
  - Find a hyperplane that fits as many points within a given ε-tube as possible.
  - Support vectors within the ε-tube determine the regression line.

- **Advantages of SVM**
- Highlight the advantages of SVM:
  - Effective in high-dimensional spaces and with limited samples.
  - Handles both linear and nonlinear classification and regression tasks.
  - Robust against overfitting with the use of regularization parameter (C).

Tuning Parameters

- Explain the importance of tuning SVM parameters:
  - C: Controls the trade-off between margin size and misclassification.
  - Gamma (for RBF kernel): Controls the influence of individual training samples.

Applications

- Highlight real-world applications of SVM:
  - Image classification and object detection
  - Text classification and sentiment analysis
  - Bioinformatics and genomics
  - Fraud detection and anomaly detection

Conclusion

- Recap the key points discussed:
  - Linear SVM, margin, and support vectors.
  - Kernel trick for nonlinear classification.
  - Soft margin SVM and handling misclassification.
  - Applications and advantages of SVM.
- Emphasize the versatility and power of SVM in various domains.

Thank You !