Revision Notes on Support Vector Machines (SVM)

These revision notes summarize the key concepts of Support Vector Machines (SVM) as discussed in the class.

Introduction to SVM

Support Vector Machines (SVM) are a set of supervised learning methods used for classification, regression, and outlier detection. SVM is primarily a classifier that is associated with learning a decision boundary to separate different classes in a dataset 【6:5†transcript.txt】.

Key Concepts

1. **Margin**: The margin is the distance between the separating hyperplane (decision boundary) and the nearest data point from either set 【6:6†transcript.txt】.
2. **Support Vectors**: These are data points that are closest to the decision boundary and are pivotal in defining the position and orientation of the hyperplane【6:0†transcript.txt】.
3. **Hyperplane:** In SVM, the goal is to find a hyperplane in an N-dimensional space (N — the number of features) that distinctly classifies the data points.

Types of SVM

1. **Hard Margin Classifier**: This classifier doesn't allow for any errors in classification. It works well with linearly separable data 【6:16†transcript.txt】.
2. **Soft Margin Classifier**: This allows for some misclassification. It introduces a slack variable to relax the constraints and allows SVM to handle non-separable data【6:6†transcript.txt】【6:8†transcript.txt】.

Mathematical Formulation

mathematically by minimizing $\frac{1}{2}||w||^2$ subject to a set of constraints 【6:16†transcript.txt】.
- The constraint: $y_i(w \cdot x_i + b) \geq 1$, where y_i is the class label, w is weight, x_i is data point, and b is the bias 【6:13†transcript.txt】.

Hyperparameters

- **C (Penalty Parameter)**: The regularization parameter C controls the trade-off between achieving a low training error and a low testing error, which corresponds to a more flexible decision boundary 【6:12†transcript.txt】【6:8†transcript.txt】.

Misclassification and Margin Error

- SVM makes decisions by calculating the distance of individual points from the decision boundary and adjusting the boundary to minimize misclassification 【6:10†transcript.txt】【6:14†transcript.txt】.

Use Cases

- SVM was a very powerful algorithm for image classification in competitions like ImageNet, having facilitated significant advances before being surpassed by deep learning models 【6:5†transcript.txt】.

Limitations

- SVM can be computationally intensive and may take significantly longer to train compared to models like Random Forests 【6:18†transcript.txt】.

Class Imbalance

- SVMs are less sensitive to class imbalance due to the focus on support vectors, which define the decision boundary rather than the distribution of the classes 【6:17†transcript.txt】.

Conclusion

SVM is a classical machine learning algorithm that proves to be effective for a variety of applications despite its computational

【6:19†transcript.txt】.

Please review this document thoroughly to ensure a deep understanding of the concepts discussed in the class.