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SUPPORT VECTOR MACHINE ALGORITHM

Absalamova Go'zal Bo'riboyevna.

Assistant, Department of Software Engineering, Faculty of Intellectual Systems and Computer Technologies, Samarkand State University named after Sharof Rashidov.

Absalamova Diyora Bo'riboyevna.

Student of the Faculty of Digital Economy of Tashkent State University of Economics.

Abstract: The Support Vector Machine algorithm was analyzed in this study. The Support Vector Machine (SVM) algorithm is a powerful and widely used machine learning algorithm for classification and regression tasks. It belongs to the family of supervised learning algorithms and is known for its ability to handle complex decision boundaries and high-dimensional data. At its core, SVM aims to find an optimal hyperplane in the feature space that best separates the data into different classes. The hyperplane is determined by selecting a subset of training samples called support vectors, which are the data points closest to the decision boundary.

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Introduction

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane [1].

The SVM algorithm offers several key features and benefits. Firstly, SVM can handle both linear and non-linear classification problems by utilizing different kernel functions. Commonly used kernel functions include linear, polynomial, radial basis function (RBF), and sigmoid. These functions transform the data into a higher-dimensional space, enabling the SVM to find non-linear decision boundaries. Secondly, SVM aims to maximize the margin, which is the distance between the decision boundary and the closest data points. By maximizing the margin, SVM promotes better generalization and helps to reduce overfitting, leading to improved performance on unseen data. Additionally, SVM is effective in dealing with high-dimensional data. It can handle datasets with a large number of features without being affected by the curse of dimensionality. SVM achieves this by focusing on the support vectors, which are the critical points for defining the decision boundary, rather than considering all the features in the dataset. SVM is also robust against noise in the training data due to its reliance on the support vectors. Even if the training data contains outliers, SVM tends to be less affected by them compared to other algorithms [2].

SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:

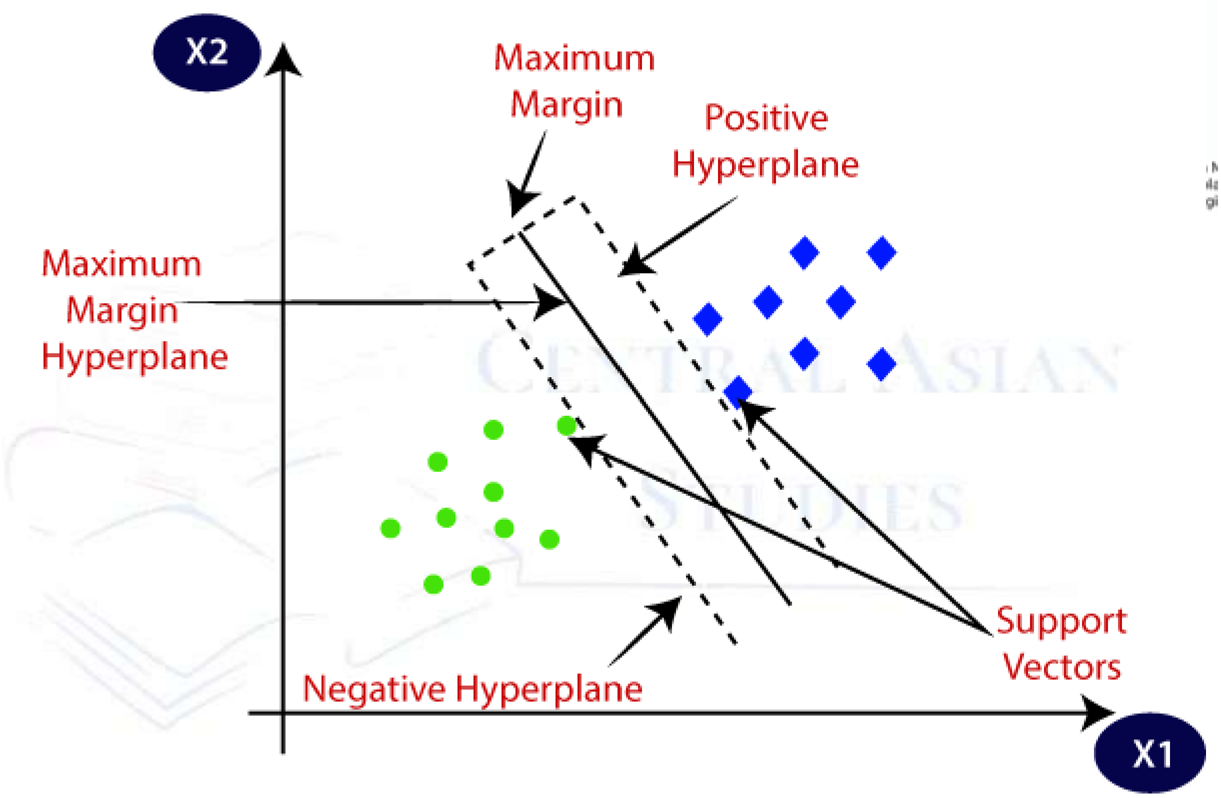

Figure 1. Support Vector Machine

Example: SVM can be understood with the example that we have used in the KNN classifier. Suppose we see a strange cat that also has some features of dogs, so if we want a model that can accurately identify whether it is a cat or dog, so such a model can be created by using the SVM algorithm. We will first train our model with lots of images of cats and dogs so that it can learn about different features of cats and dogs, and then we test it with this strange creature. So as support vector creates a decision boundary between these two data (cat and dog) and choose extreme cases (support vectors), it will see the extreme case of cat and dog [3,4]. On the basis of the support vectors, it will classify it as a cat. Consider the below diagram:

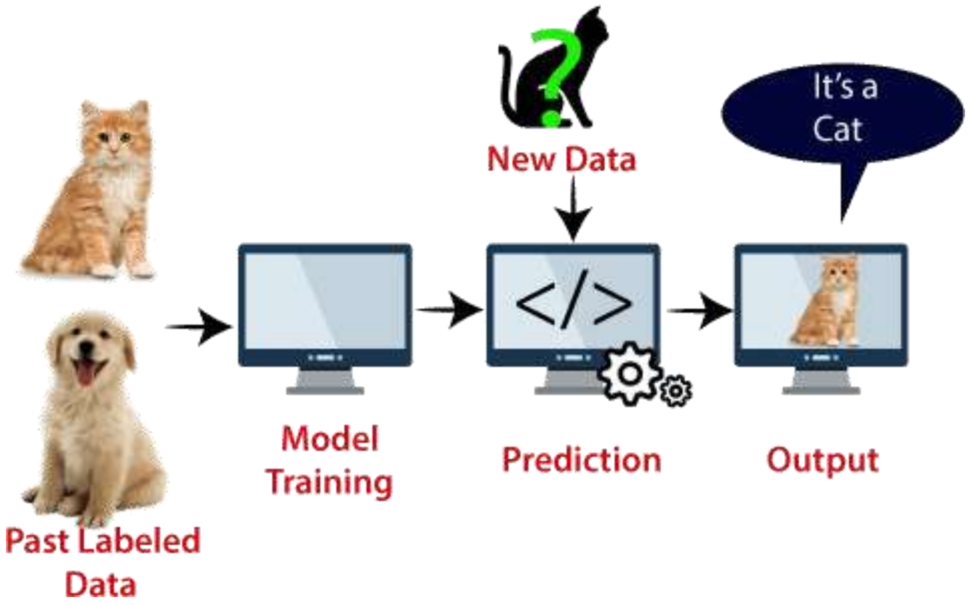

Figure 2. Support Vector Machine operation

SVM algorithm can be used for **Face detection, image classification, text categorization,** etc [5].

Types of SVM

SVM can be of two types:

- **Linear SVM:** Linear SVM is used for linearly separable data, which means if a dataset can be classified into two classes by using a single straight line, then such data is termed as linearly separable data, and classifier is used called as Linear SVM classifier [6].
- **Non-linear SVM:** Non-Linear SVM is used for non-linearly separated data, which means if a dataset cannot be classified by using a straight line, then such data is termed as non-linear data and classifier used is called as Non-linear SVM classifier [7].

Hyperplane and Support Vectors in the SVM algorithm:

Hyperplane: There can be multiple lines/decision boundaries to segregate the classes in n-dimensional space, but we need to find out the best decision boundary that helps to classify the data points. This best boundary is known as the hyperplane of SVM.

The dimensions of the hyperplane depend on the features present in the dataset, which means if there are 2 features (as shown in image), then hyperplane will be a straight line. And if there are 3 features, then hyperplane will be a 2-dimension plane [8].

We always create a hyperplane that has a maximum margin, which means the maximum distance between the data points.

Support Vectors the data points or vectors that are the closest to the hyperplane and which affect the position of the hyperplane are termed as Support Vector. Since these vectors support the hyperplane, hence called a Support vector [9].

Conclusion

Overall, the Support Vector Machine algorithm is a versatile and powerful tool for classification and regression tasks. Its ability to handle non-linear data, its emphasis on maximizing the margin, and its robustness make it a popular choice in various domains, including image classification, text categorization, and bioinformatics. However, SVM has certain limitations as well. It can be computationally intensive and memory-consuming, especially when dealing with large datasets. Additionally, selecting the appropriate kernel function and tuning the associated parameters can be challenging and may require domain expertise or careful experimentation.

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