Support Vector Regression

Support Vector Regression (SVR) is a type of regression analysis that uses Support Vector Machines (SVM) to predict the continuous values of a dependent variable. In simple words, SVR is a variant of SVM that is used for regression tasks instead of classification tasks.

SVR is useful in cases where the relationship between the independent and dependent variables is non-linear, and traditional linear regression techniques may not provide accurate results. It is widely used in various fields, including finance, economics, and engineering.

The working of SVR is based on finding a hyperplane in a high-dimensional space that can best fit the training data. The hyperplane is found by maximizing the margin between the support vectors, which are the data points closest to the hyperplane. The margin is defined as the distance between the hyperplane and the closest support vectors.

In SVR, the objective is to find a hyperplane that can predict the continuous values of the dependent variable with minimal error. To achieve this, SVR uses a kernel function that maps the input data to a higher-dimensional feature space, where the data can be separated by a hyperplane. The kernel function can be linear, polynomial, or radial basis function (RBF), among others.

Here is a practical real-life example of how SVR can be used in finance. Suppose you want to predict the price of a stock based on certain economic indicators, such as interest rates, inflation, and GDP. You have a dataset of historical prices and economic indicators, and you want to build a model to predict future prices.

Using SVR, you can first preprocess the data and split it into training and testing sets. Then, you can choose a kernel function and train the SVR model on the training data.

Finally, you can use the trained model to make predictions on the testing data and evaluate its accuracy.