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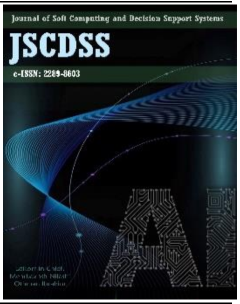

Support Vector Regression for Data-Driven Decision Making

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Abstract

Support Vector Regression (SVR) is a robust machine learning technique adapted from the Support Vector Machine (SVM) algorithm, specifically designed for predicting continuous outcomes. Unlike traditional regression models that aim to minimize error directly, SVR introduces the concept of an ε-insensitive margin, allowing flexibility in prediction within a controlled tolerance. This mathematical innovation makes SVR particularly suitable for business environments where data is often noisy and complex. In this paper, we provide a brief but comprehensive overview of SVR, outlining its theoretical foundation, optimization conditions, and core mathematical formulations. The paper also highlights SVR's capacity to model nonlinear relationships through kernel functions, offering an advanced solution for data-driven decision-making. The effectiveness of SVR is demonstrated through its application in future business data analysis.

Keywords: Machine Learning, Support Vector Regression, Big Data, Prediction, Business

1. Introduction

Nowadays, data is generated at an unprecedented scale across industries, presenting both a challenge and an opportunity for organizations [1-7]. From e-commerce transactions and social media interactions to financial operations and supply chain logistics, businesses continuously produce vast amounts of information. The ability to extract insights from this data through predictive modeling has become essential for maintaining competitiveness and responding swiftly to market dynamics.

Prediction in business is not merely a statistical exercise—it is a strategic function [8, 9]. Accurate forecasting allows companies to anticipate customer needs, optimize resource allocation, minimize operational risks, and make informed investment decisions. In this context, machine learning algorithms have emerged as powerful tools that outperform traditional models [10-12], especially when dealing with complex, nonlinear, and high-dimensional datasets.

One such method is Support Vector Regression (SVR) [13], an extension of the Support Vector Machine (SVM) algorithm [14, 15], originally developed for classification tasks. SVR adapts the principles of margin maximization and kernel transformation to perform regression, making it especially effective in scenarios where the relationship between input variables and target values is not strictly linear. Unlike conventional regression methods that aim to minimize error directly, SVR introduces an ε-insensitive loss function, allowing a tolerance zone around the actual target values while controlling model complexity.

SVR has shown remarkable success in business applications [16-19]. Its flexibility to handle noisy data and nonlinear trends makes [20, 21] it a valuable addition to any organization's predictive analytics toolkit. This paper aims to provide a brief yet comprehensive overview of SVR. By doing so, we establish a foundational understanding for researchers and practitioners interested in leveraging SVR for advanced data-driven decision-making.

2. Mathematical Background of SVR

SVR is a supervised learning algorithm derived from SVM, designed for regression problems rather than classification [22]. SVR attempts to find a function that approximates the target values within a certain tolerance (ε) while maintaining model simplicity (flatness).

The main objective in SVR is to determine a function $f(x)$ that has at most ε deviation from the actual observed targets y_i for all training data [13], and at the same time, is as flat as possible. The function $f(x)$ is defined as:

$$f(x) = \mathbf{w}^T\phi(x) + b \tag{1}$$

Here: