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Regression with Support Vector Machines (SVM)

Week 03 – Advanced Topic 3

Agenda

- Introduction
- Objectives
- Theory
- Results
- Conclusions

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Introduction

- Type of Support Vector Machine (SVM).
- Supervised learning algorithm:
  - Classification problems.
- SVM identifies classes (hyperplane).
- Robust to outliers.
- Effective in high-dimensions.

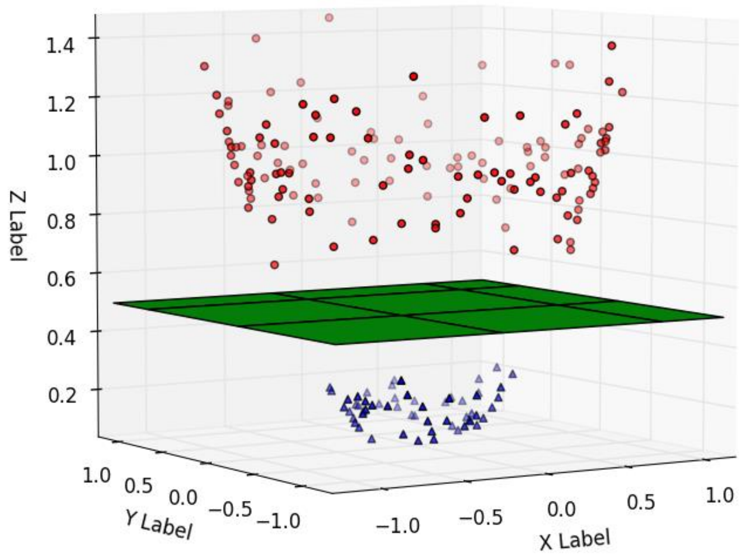

Fig.1 Hyperplane visualization (green) in 3D space.
(source:https://images.app.goo.gl/gifF9Bcss1o6vBJAA)

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Objectives

- SVM utilization for regression analysis.
- Estimate the functions f(x) such that:
  - Define the range of deviation.
- Optimal hyperplane identification:
  - Maximize margin (~ε-insensitive tube).
  - Distance between hyperplane and closest data (support vectors).
  - Tune hyper parameters (C, ε).
- Define error tolerance (ε-insensitive tube).
- Find the best fit while reducing complexity to avoid **overfitting** (flatness*).

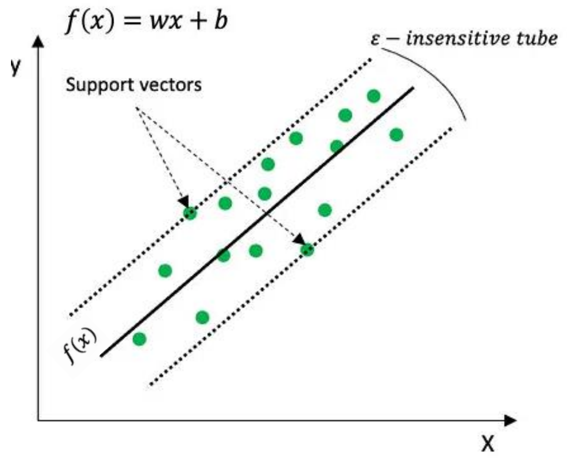
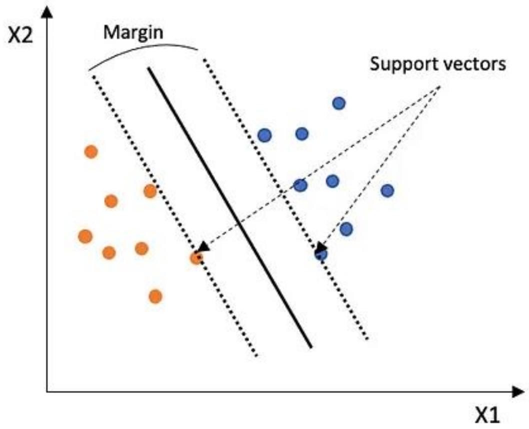
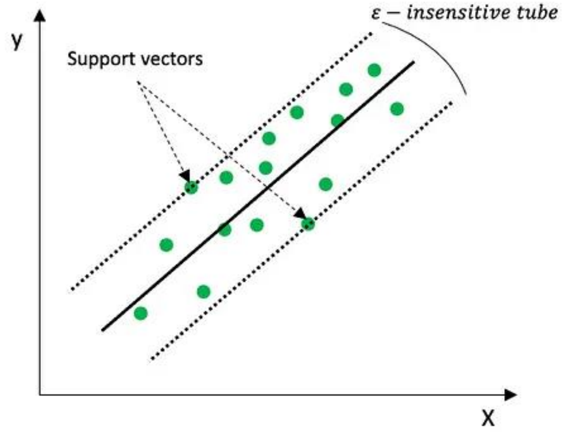


Fig.2 SVR hyperplane visualization in 2D space.

Theory



Classification problem using SVM



Regression problem using SVR

$$f(x) = \frac{1}{2}||w||^2 + C \sum_{\{i=1\}}^{\{n\}} (\xi_n + \xi_n^*)$$

Flatness of function

Regularization parameter
(Controls trade-off between low error and maintaining a flatness)

Penalty for errors
(Measures how far a point lies out of the ε-tube)

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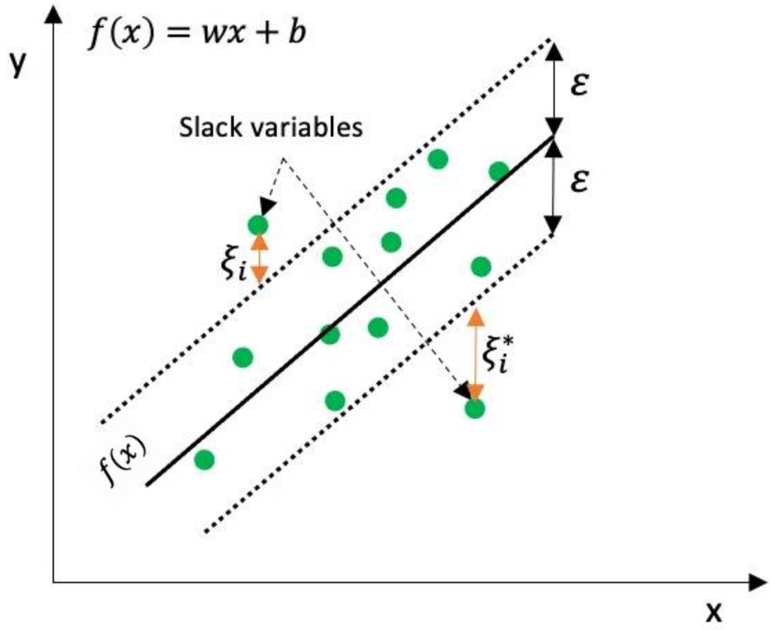
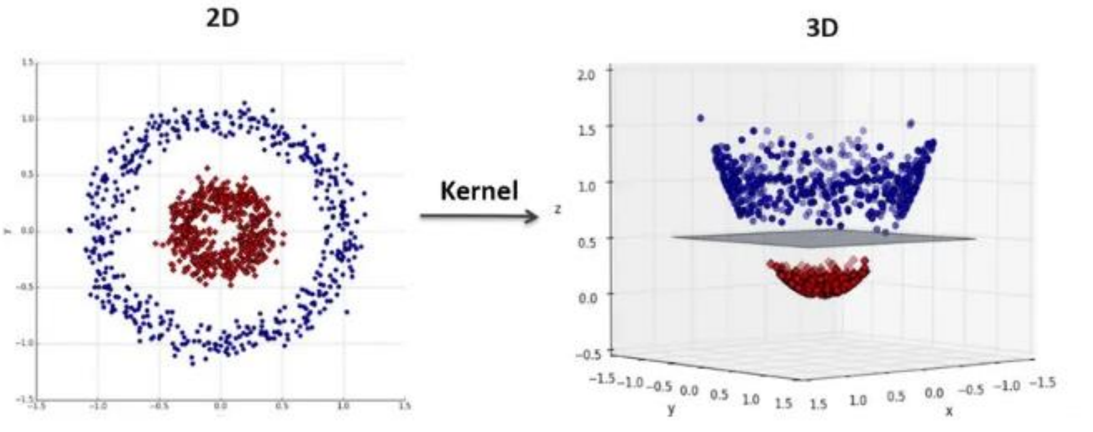
ε-insensitive tube

- ε is typically a hyperparameter.
- Permits some level of deviation.
- Data points within the tube are not penalized.
- Keeps balance between:
  - Model complexity (flatness*).
  - Generalization power.
- Outliers – Measured distance between data and support vector (ξi).



Theory

- Non-linear methods.
- Effective in high-dimensions.
- Robustness.
- Lower to higher dimension data transformation:
  - 2D to 3D transformation.
  - Data separation.
- Several types of kernels (e.g polynomial, RBF).



Complex in low dimensions

Simple in higher dimensions

Fig.3 Kernel transformation from lower to higher dimensions. (source:https://medium.com/@Suraj_Yadav/what-is-kernel-trick-in-svm-interview-questions-related-to-kernel-trick-97674401c48d)

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Results

- Univariate dataset (student marks).
  - Feature is the time_study.
- Goal is to predict:
  - Student marks given average time study/day.
- Different type of SVR were used :
  - "Linear"
  - "RBF"
  - "Polynomial"
- Hyper parameters:
  - C = 1.0
  - $\varepsilon = 0.1$

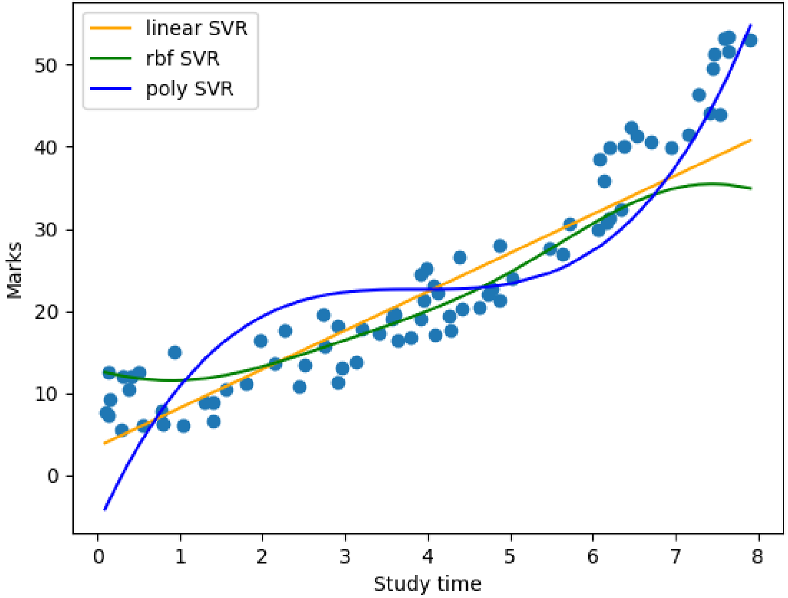

Fig.4 Fitted linear and non-linear SVR on train dataset

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Results

- Univariate dataset (student marks).
  - Feature is the time_study.
- Goal is to predict:
  - Student marks given average time study/day.
- Evaluation of "**Linear**" SVR:
  - R-squared (R2) coefficient: 0.83
  - RMSE : 6.7
- Evaluation of "**RBF**" SVR:
  - R-squared (R2) coefficient: 0.69
  - RMSE : 9.03
- Evaluation of "**Polynomial**" SVR:
  - R-squared (R2) coefficient:0.83
  - RMSE : 6.66

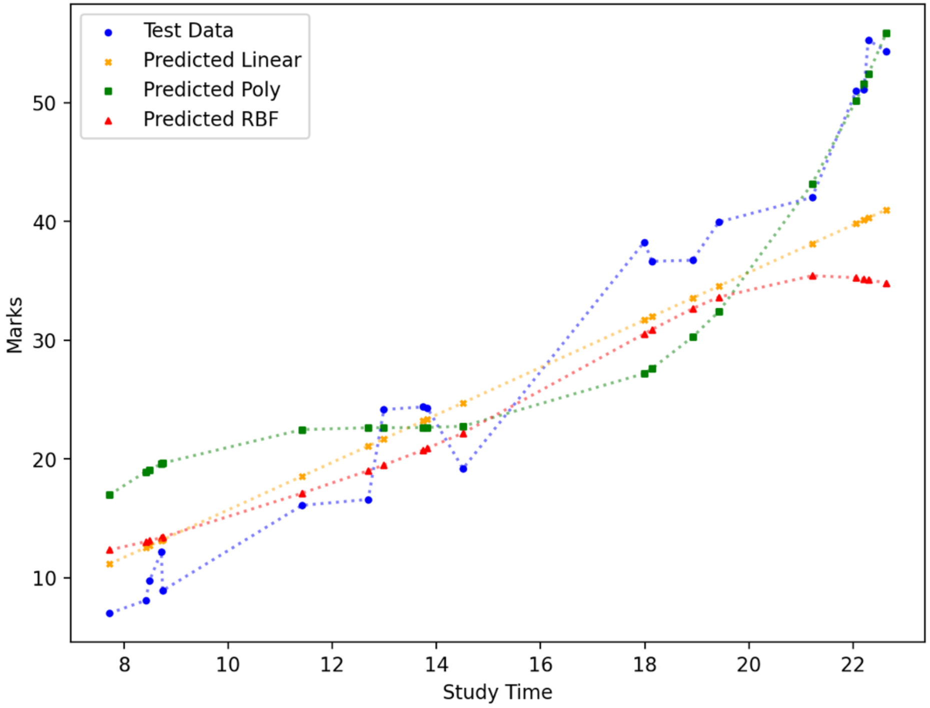

Fig.5 Test dataset and predictions from different SVRs

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Conclusions

- SVR extends the use of SVM to regression analysis.
- Defining ε-insensitive tube, increase some level of deviation.
- Tune parameters for optimal data "fit".
- Can handle linear and non-linear regression problems.
- Pros:
  - Can handle linear and non-linear data
  - Customizable – by tuning the parameter
  - Works well in high dimensional space.
- Cons:
  - No straight-forward way of choosing a kernel (only trial and error).
  - Complex kernels can overfit.
  - Large computational cost – takes time to train.
  - Difficult to explain when using non-linear kernels.

References

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Thank you!

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