Support-Vector-Regression

January 14, 2025

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'''
    Support Vector Regression (SVR) -->

    Support Vector Regression (SVR) is an extension of Support Vector Machines␣
↪(SVM) used for regression tasks.
    It predicts continuous outcomes by finding a hyperplane (or a curve in␣
↪higher dimensions) that best fits the
    data within a certain margin of tolerance.
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    Key Points -->

    Epsilon ( )-Insensitive Tube:

    SVR introduces an epsilon-insensitive tube around the hyperplane, where␣
↪predictions within this
    margin of error are considered acceptable and not penalized.
    Points outside this tube are penalized based on their distance from the␣
↪boundary of the tube.

    Objective:

    Minimize the model complexity (flatness of the hyperplane) and the␣
↪prediction error for points
    outside the  -tube.
    The optimization problem tries to achieve a balance between model␣
↪complexity and the tolerance to small errors.

    Kernel Trick:

    SVR can handle non-linear relationships by using kernels (e.g., linear,␣
↪polynomial, RBF).
    Kernels allow SVR to project data into a higher-dimensional space where a␣
↪linear hyperplane can better fit the data.

    Slack Variables ( , *):
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    These represent the amount by which data points fall outside the  -tube.
    The model penalizes these deviations in the optimization process.
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    Steps to Use Support Vector Regression -->

    Choose a Kernel:

    Linear kernel: When the data is approximately linear.
    Polynomial kernel: For polynomial relationships.
    RBF kernel: For complex non-linear relationships.

    Set Hyperparameters:

     : Determines the margin of tolerance.
    C: Controls the trade-off between margin size and slack penalties.
    Kernel-specific parameters (e.g.,  for RBF).

    Train the Model:

    Fit the model to the training data by solving the optimization problem.

    Evaluate and Predict:

    Evaluate the model's performance on a test set.
    Use the trained model for predictions.
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    When to Use SVR -->

    When you have non-linear relationships in your data
    When you need to balance the model's complexity and tolerance for small␣
 ↪deviations ( )
    When your dataset is not extremely large (since SVR can be computationally␣
 ↪expensive for large datasets)

    Advantages -->

    Effective in high-dimensional spaces.
    Can handle non-linear data with kernels.
    Robust to outliers with  -insensitive loss.

    Limitations -->
    Computationally expensive for large datasets.
    Requires careful tuning of hyperparameters (C, , ).
    Can be sensitive to the choice of kernel.
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#   Importing Libraries -->

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVR
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[2]:
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#   Importing Dataset -->

data = pd.read_csv('Data/Position_Salaries.csv')
x_data = data.iloc[:, 1:-1].values
y_data = data.iloc[:, -1].values
data
```

[2]:
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            Position  Level   Salary
0   Business Analyst      1    45000
1  Junior Consultant      2    50000
2  Senior Consultant      3    60000
3            Manager      4    80000
4    Country Manager      5   110000
5     Region Manager      6   150000
6            Partner      7   200000
7     Senior Partner      8   300000
8            C-level      9   500000
9                CEO     10  1000000
```

[6]:
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x_data
```

[6]:
```
array([[ 1],
       [ 2],
       [ 3],
       [ 4],
       [ 5],
       [ 6],
       [ 7],
       [ 8],
       [ 9],
       [10]], dtype=int64)
```

[7]:
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y_data
```

```
[7]: array([  45000,   50000,   60000,   80000,  110000,  150000,  200000,
        300000,  500000, 1000000], dtype=int64)
```

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[ ]: #   Stacndard Scaler requires 2D array as input so we have to convert y_data␣
      ↪into 2D array
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[8]: y_data = y_data.reshape(len(y_data),1)
     y_data
```

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[8]: array([[  45000],
            [  50000],
            [  60000],
            [  80000],
            [ 110000],
            [ 150000],
            [ 200000],
            [ 300000],
            [ 500000],
            [1000000]], dtype=int64)
```

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[9]: sc_x = StandardScaler()
     sc_y = StandardScaler()
     x_data = sc_x.fit_transform(x_data)
     y_data = sc_y.fit_transform(y_data)
```

```
[10]: x_data
```

```
[10]: array([[-1.5666989 ],
             [-1.21854359],
             [-0.87038828],
             [-0.52223297],
             [-0.17407766],
             [ 0.17407766],
             [ 0.52223297],
             [ 0.87038828],
             [ 1.21854359],
             [ 1.5666989 ]])
```

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[11]: y_data
```

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[11]: array([[-0.72004253],
             [-0.70243757],
             [-0.66722767],
             [-0.59680786],
             [-0.49117815],
             [-0.35033854],
             [-0.17428902],
             [ 0.17781001],
             [ 0.88200808],
             [ 2.64250325]])
```

[13]:
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model = SVR(kernel = 'rbf')
model.fit(x_data, y_data)
```

```
C:\Users\krish\AppData\Local\Packages\PythonSoftwareFoundation.Python.3.11_qbz5n
2kfra8p0\LocalCache\local-packages\Python311\site-
packages\sklearn\utils\validation.py:1300: DataConversionWarning: A column-
vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

[13]:
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SVR()
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[14]:
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sc_y.inverse_transform(model.predict(sc_x.transform([[6.5]])).reshape(-1,1))
```

[14]:
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array([[170370.0204065]])
```
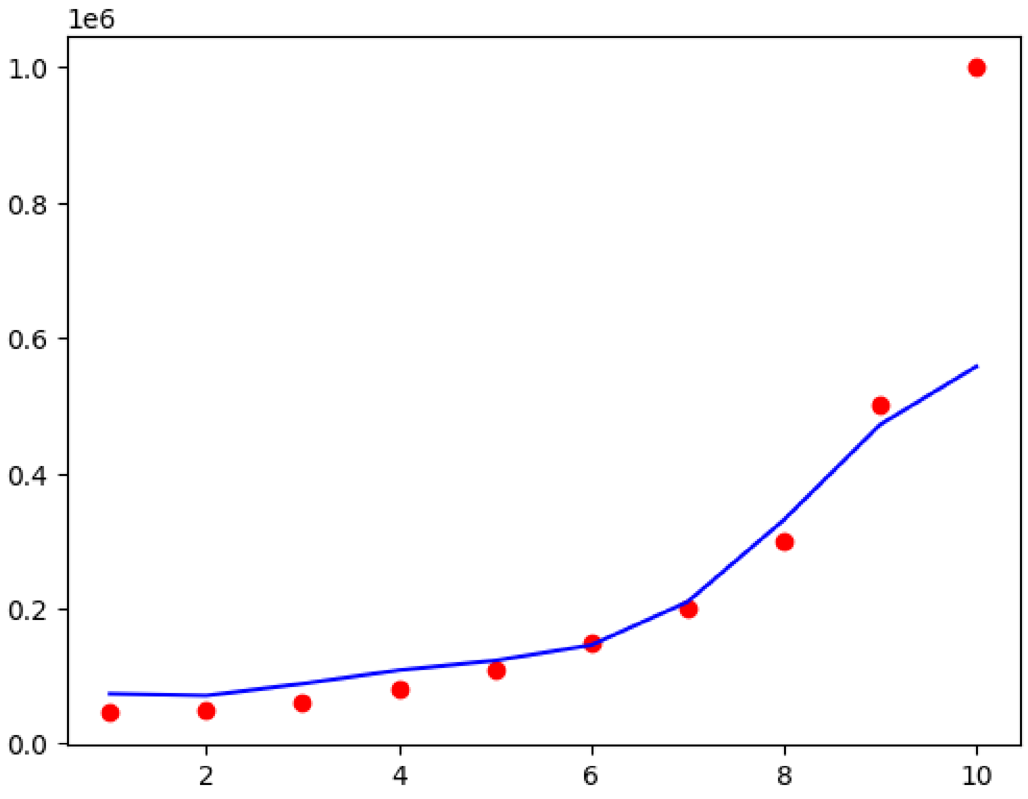

[15]:
```
plt.scatter(sc_x.inverse_transform(x_data), sc_y.inverse_transform(y_data),␣
 ↪color = 'red')
plt.plot(sc_x.inverse_transform(x_data), sc_y.inverse_transform(model.
 ↪predict(x_data).reshape(-1,1)), color = 'blue')
plt.show()
```


1e6
1.0
0.8
0.6
0.4
0.2
0.0
2
4
6
8
10