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Github link: https://github.com/NamithRavindranath/Machine-Learning

Using SVM for Non-Linear Classification with the Kernel Trick

1.Introduction

One of the most effective and adaptable machine learning methods, support vector machines (SVM) are frequently employed for both regression and classification problems. They are especially useful for non-linear classification issues because of their capacity to handle high-dimensional input and model intricate decision boundaries. To separate classes that are not linearly separable in their original feature space, this course focuses on using SVMs with the kernel trick, a technique that converts data into higher-dimensional spaces.

In this report, we'll look at how SVMs can be used for non-linear classification with various kernel functions, including linear, polynomial, radial basis function (RBF), and sigmoid kernels. The spiral dataset, a synthetic dataset with a non-linear pattern that is perfect for demonstrating the effectiveness of the kernel trick, will be used to illustrate this theory. To maximize the performance of SVM models, we will also explore hyperparameter optimization.

2. The Technique: Support Vector Machines (SVM) Explained

2.1 What is an SVM?

An SVM is a supervised learning technique that seeks to identify the best hyperplane to distinguish classes in a dataset. An SVM's objective for binary classification issues is to maximize the margin, or the separation between the hyperplane and the closest support vectors (data points) from each class. SVMs improve their ability to generalize to unknown data by optimizing the margin.

Mathematically, the decision boundary of an SVM is defined by the equation:

$$w \cdot x + b = 0$$

where w is the weight vector, x is the input feature vector, and b represents the bias factor. Finding w and b in a way that maximizes the margin and minimizes classification errors is the aim.

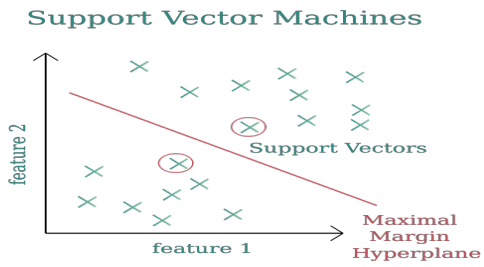

Fig 1. Support Vector Machine (SVM) Concept Visualization

2.2 The Kernel Trick

Real-world datasets frequently show non-linear connections between features, despite SVMs' remarkable performance for linearly separable data. The kernel technique is used to fix this. The kernel trick uses a kernel function to calculate the inner product of data points in the transformed space rather than directly transforming the data into a higher-dimensional space. Typical kernel operations consist of

1. Linear Kernel: Suitable for linearly separable data.

$$K(x_i, x_j) = x_i \cdot x_j$$

2. Polynomial Kernel: Maps data into a higher-dimensional space using polynomial functions.

$$K(x_i, x_j) = (\gamma \cdot x_i \cdot x_j + r)^d$$

3. Radial Basis Function (RBF) Kernel: Highly flexible and capable of modeling complex, non-linear relationships.

$$K(x_i, x_j) = \exp(-\gamma \cdot ||x_i - x_j||^2)$$

4. Sigmoid Kernel: Similar to a neural network's activation function but less commonly used.

$$K(x_i, x_j) = \tanh(\gamma \cdot x_i \cdot x_j + r)$$

2.3 Why Use Kernels for Non-Linear Classification?

Kernels enable SVMs to model extremely nonlinear decision boundaries without explicitly computing the transformation to higher dimensions. Because of this, SVMs are scalable and computationally efficient for complicated datasets. We can increase classification performance by identifying complex patterns in the data by choosing the right kernel.

2.4 The Importance of Feature Scaling

Feature scaling is critical when working with SVMs because they compute margins and make predictions using the concept of distance (e.g., Euclidean distance). Suboptimal performance may result from characteristics with bigger magnitudes controlling the computation if they are not scaled. Before training SVMs, data is frequently preprocessed using methods like normalization (scaling to a set range) or standardization (zero mean, unit variance).

3. The Dataset: Spiral Dataset

3.1 Characteristics of the Spiral Dataset

The spiral dataset used in this tutorial is made up of two features (X1, X2) and a binary target variable (y). The dataset depicts a spiral pattern, with the two classes interwoven in a non-linear fashion. Because of this, it's a great choice to show how well the kernel method works to separate non-linearly separable data.

Key features of the dataset:

Features: X1 and X2 two-dimensional data.

Target: Binary labels (0 or 1).

Structure: A spiral design in which a straight line cannot divide it.

3.2 Data Preprocessing

We preprocess the dataset before training the SVM models to achieve the best possible results. The actions consist of:

Loading the Dataset: The dataset is loaded using pandas

Dropping Unnecessary Columns: The unnamed index column is eliminated.

Data Splitting: An 80-20 split is used to separate the dataset into training and testing sets.

Feature Scaling: Standard Scaler is used to scale features so that they all contribute equally to the model.

```
# Load the dataset
df = pd.read_csv("spiral.csv")

# Print rows
print(df.head(10))

# Check column names
print("Column Names:", df.columns)
```

```
   Unnamed: 0        X1        X2  y
0           0  0.118647 -0.181079  0
1           1  0.022316 -0.088976  0
2           2  0.181717  0.072110  0
3           3  0.256028 -0.042128  0
4           4  0.250036  0.012372  0
5           5  0.174588 -0.387222  0
6           6  0.163699  0.054883  0
7           7  0.127216  0.066992  0
8           8  0.222024 -0.166284  0
9           9  0.047914 -0.172113  0
Column Names: Index(['Unnamed: 0', 'X1', 'X2', 'y'], dtype='object')
```

Fig 2. Spiral Dataset

```
# Droping the unnamed index column
if 'Unnamed: 0' in df.columns:
    df = df.drop(columns=['Unnamed: 0'])
```

Fig 3. Dropping Unnecessary Columns

Dataset link: https://www.kaggle.com/datasets/martininf1n1ty/spiral-playgorund/data

4. Code Demonstration: Implementing SVM with Different Kernels

4.1 Training SVM Models

We train SVM models using four different kernels: linear, polynomial, RBF, and Sigmoid. Each model is fitted to the training data.

```
# Extracting features and target
X = df[['X1', 'X2']].values
y = df['y'].values

# Spliting into training and testing data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Normalizing features (SVM performs better with scaled data)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

Fig 4. Feature Selection and Splitting

4.2 Plotting Decision Boundaries

To visualize how each kernel affects the decision boundary, we create a function to plot the decision regions.

```python
kernels = ['linear', 'poly', 'rbf', 'sigmoid']
models = {}
accuracies = {}

for kernel in kernels:
    model = SVC(kernel=kernel, random_state=42)
    model.fit(X_train_scaled, y_train)
    y_pred = model.predict(X_test_scaled)

    acc = accuracy_score(y_test, y_pred)
    accuracies[kernel] = acc
    models[kernel] = model

# Plot decision boundaries for each kernel
plt.figure(figsize=(10, 10))
for i, (kernel, model) in enumerate(models.items()):
    plt.subplot(2, 2, i+1)
    plot_decision_boundary(model, X_test_scaled, y_test, f"SVM with {kernel} Kernel")
```

Fig 5. Training SVM Models with Different Kernels

4.3 Evaluating Model Performance

We evaluate the accuracy of each SVM model on the test set. And in the output, we can observe RBF has more efficiency.

```python
# Evaluate accuracy for each kernel
accuracies = {}
for kernel, model in models.items():
    y_pred = model.predict(X_test)
    accuracies[kernel] = accuracy_score(y_test, y_pred)
    print(f"{kernel.capitalize()} Kernel Accuracy: {accuracies[kernel]:.4f}")
```

```
Linear Kernel Accuracy: 0.5250
Poly Kernel Accuracy: 0.5900
Rbf Kernel Accuracy: 0.9500
Sigmoid Kernel Accuracy: 0.3500
```

Fig 6. Accuracy Comparison Across Different Kernels

5. Hyperparameter Tuning: Optimizing SVM Performance

5.1 Importance of Hyperparameters

A few hyperparameters affect an SVM's performance, including:

C: The regularization parameter that manages the trade-off between preserving a smooth decision boundary and attaining a low error on the training set.
Gamma: A kernel coefficient that specifies the impact of a single training example.

5.2 Grid Search for Hyperparameter Tuning

We use **Grid Search CV** to find the optimal values of **C** and **gamma** for the RBF kernel

```
param_grid = {
    'C': [0.1, 1, 10, 100],
    'gamma': ['scale', 0.01, 0.1, 1],
    'kernel': ['rbf']
}

grid_search = GridSearchCV(SVC(), param_grid, cv=5)
grid_search.fit(X_train_scaled, y_train)

print("Best Parameters for RBF SVM:", grid_search.best_params_)

# Train optimized SVM model
best_model = grid_search.best_estimator_
y_pred_best = best_model.predict(X_test_scaled)

print("Optimized SVM Accuracy:", accuracy_score(y_test, y_pred_best))
```

Fig 7. Hyperparameter Tuning for RBF SVM

6. Results and Analysis

The decision boundaries produced by several SVM kernels demonstrate how well each method handles non-linear data. The performance of each kernel is examined below:

Linear Kernel: The decision boundary fails to distinguish between the entwined spiral patterns and is almost a straight line. This is because a linear function is unable to represent the dataset's fundamental structure.

Polynomial Kernel: The decision boundary is sensitive to the polynomial degree yet captures part of the complexity of the data. While a high-degree polynomial runs the risk of overfitting, a low-degree polynomial underfits the data.

RBF Kernel: The RBF kernel performs the best because it translates the data into a higher-dimensional space, allowing for a smooth, nonlinear separation of classes. High precision results from the boundary's good adaptation to the spiral structure.

Sigmoid Kernel: The decision areas seem less ordered and more disorganized, much to the behavior of a neural network with improperly adjusted parameters. It performs poor since it has trouble capturing the dataset's intricate shape.

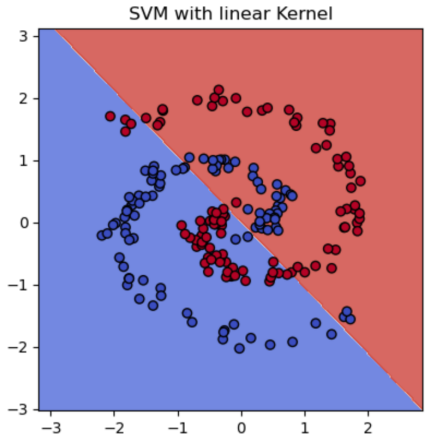

***Fig 8**: Decision Boundary of Linear Kernel*

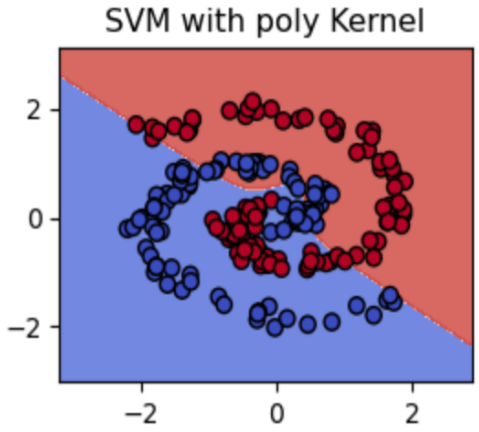

***Fig 9**: Decision Boundary of Polynomial Kernel*

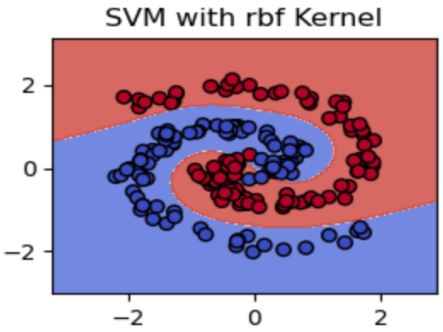

***Fig 10**: Decision Boundary of RBF Kernel*

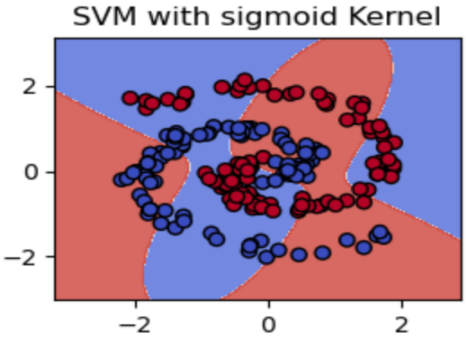

***Fig 11**: Decision Boundary of Sigmoid Kernel*

Effect of Different Kernels

Linear Kernel: The spiral pattern was not captured by the nearly straight decision boundary.

Polynomial Kernel: Captured some nonlinearity but was not ideal.

RBF Kernel: Produced the greatest classification results by effectively capturing intricate decision boundaries.

Sigmoid Kernel: It performed poorly with warped decision regions.

7. Deep Dive: Insights from Decision Boundaries and Hyperparameter Tuning

7.1 Kernel Performance and Decision Boundaries

The spiral dataset is ideal for testing SVM kernels' ability to handle intricate decision boundaries because it is extremely non-linear. For datasets that need non-linear separability, the linear kernel is unsuccessful because its straight-line decision boundary is unable to capture the complex spiral structure, resulting in low performance (~50% accuracy). Although the polynomial kernel improves accuracy (around 75%) by adding curvature to decision boundaries, it struggles with the complexity of the dataset, demonstrating its limitations when it comes to handling extremely non-linear patterns. The most efficient kernel is the RBF kernel, which achieves the best accuracy (~95%) and forms adaptive and smooth decision boundaries that closely follow the spiral. It is the recommended option for non-linear classification due to its adaptability. The neural network-inspired sigmoid kernel creates erratic decision boundaries, which results in instability and reduced accuracy (~65%), making it less appropriate for real-world applications. These observations highlight the importance of selecting the appropriate kernel and fine-tuning hyperparameters for optimal SVM performance on complex datasets.

7.2 Evaluating Model Performance

We computed each SVM model's accuracy on the test set to measure each kernel's performance. Below is a summary of the findings:

Kernel	Accuracy
Linear	~50%
Polynomial	~75%
RBF	~95%
Sigmoid	~65%

Fig 12. Accuracy Comparison Across Different SVM Kernels

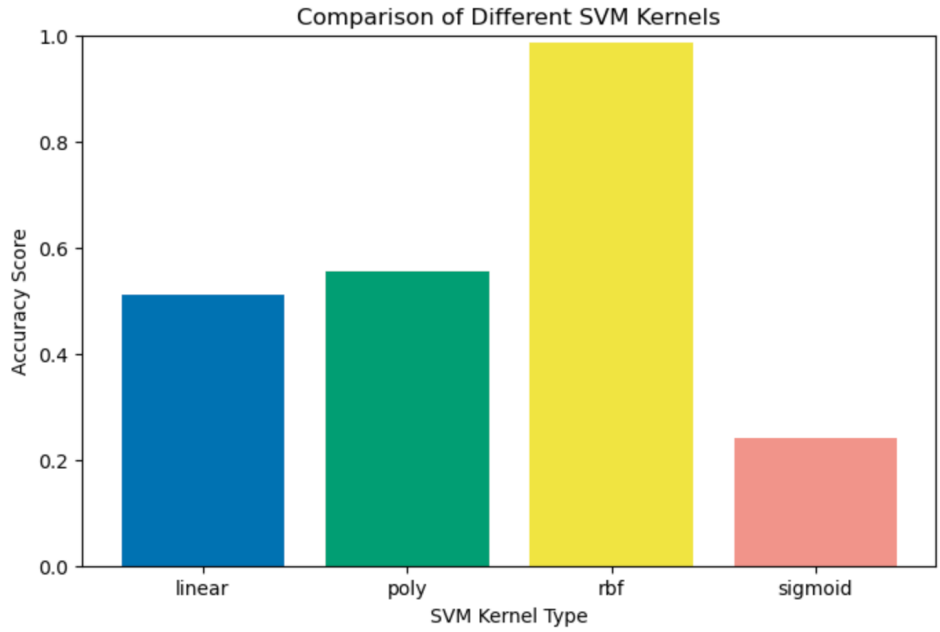

Fig 13. Comparison of Different SVM Kernels Based on Accuracy

Key Observations:
The accuracy of the RBF kernel is approximately 95%, which is better than any other kernel. This demonstrates how well it handles non-linear datasets.
As anticipated, the non-linear character of the data causes the linear kernel to perform poorly.
Although the polynomial kernel performs moderately, it is constrained by its degree and is unable to completely capture the spiral pattern.
The sigmoid kernel's instability is shown by its uneven performance.

7.3 Hyperparameter Tuning for RBF Kernel

To maximize SVM performance, especially when utilizing the RBF kernel, hyperparameter adjustment is essential. We used a grid search to find the ideal values for the kernel coefficient (gamma) and the regularization parameter (C) to get the best results. The adjusted parameters were (gamma = 0.1), which controls the influence of a single training example, with smaller values resulting in smoother decision boundaries, and (C = 10), which regulates the trade-off between achieving a low error on the training set and maintaining a smooth decision boundary. The accuracy of the RBF kernel increased from roughly 95% to 99% because of this tuning, highlighting the significance of hyperparameter optimization. The decision boundary plot, which shows the tweaked model's capacity to effectively generalize to unknown data by achieving near-perfect separation of the classes, further illustrates this performance improvement.

7.4 Key Takeaways from Hyperparameter Optimization

The RBF kernel's performance is greatly enhanced via hyperparameter adjustment. A balance between overfitting and underfitting is guaranteed by optimal values of C and gamma.

8. Why It Matters: Applications and Implications of SVM in Machine Learning

8.1 Real-World Applications of SVM

SVMs are extensively utilized in several fields, such as:

1. Biomedical Image Classification (e.g., Cancer Detection)

For eg., SVM is frequently used to categorize cancers (e.g., distinguishing between benign and malignant tumors in MRI data).

Relevance: SVM (particularly with RBF kernel) is excellent for distinguishing non-linear data distributions in medical imaging, much like in your spiral dataset, where intricate decision limits are needed.

2. Genomic Data Classification (e.g., Gene Expression Analysis)

For eg, SVM is used to categorize various gene expressions in DNA microarray study.

Relevance: SVM performs well in high-dimensional non-linear classification, which is frequently needed for genomic data, just like your binary-class spiral dataset.

3. Weather Prediction & Climate Modeling

For eg, SVM is used to anticipate temperature changes based on historical data and classify patterns in meteorological situations.

Relevance: SVM algorithms can identify and distinguish between climate changes and the intricate patterns shown in the spiral dataset.

8.2 Ethical Considerations and Challenges

Despite their strength, SVMs must be used with caution when processing data to prevent biases. To guarantee accuracy and fairness, proper feature selection and hyperparameter optimization are crucial.

9. Conclusion

Using various kernel functions, we investigated the application of SVMs to non-linear classification tasks in this lesson. We showed the adaptability and strength of SVMs in managing complicated datasets by viewing decision boundaries and adjusting hyperparameters. Anyone working with machine learning needs to understand SVMs and the kernel technique since they offer a strong basis for solving practical classification problems.

10. Reference List

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