

MACHINE LEARNING WEEK 10 LAB

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Course Name: MACHINE LEARNING

SECTION: C

Moons Dataset Questions (2 questions):

1. Inferences about the Linear Kernel's performance.

Ans: Based on the metrics and visualizations the accuracy for linear kernel is 87%. The accuracy is less because the dataset is non-linearly separable and drawing a straight line does not separate it effectively. Whereas in RBF the accuracy is 97% The visualization for the RBF kernel clearly shows a non-linear decision boundary that effectively separates the two classes . This demonstrates the RBF kernel's ability to handle non-linearly separable data well by implicitly mapping the data to a higher dimension. For the Polynomial Kernel, the classification report shows an accuracy of 89%, which is better than the linear kernel but not as high as the RBF kernel. The visualization for the polynomial kernel also shows a curved decision boundary, but it appears slightly less smooth and less perfectly aligned with the moon shapes compared to the RBF kernel.

2. Comparison between RBF and Polynomial kernel decision boundaries.

Ans. RBF seems to capture the shape of the data more naturally because it can handle non linearity better than polynomial kernel.

Banknote Dataset Questions (2 questions):

1. Which kernel was most effective for this dataset?

Ans: Radial basis function kernel.

2. Why might the Polynomial kernel have underperformed here?

Ans: The performance of the Polynomial kernel is highly dependent on the degree of the polynomial. While a low-degree polynomial might work well for simple, non-linear shapes like the moons, it might not be complex enough to capture the more intricate relationships between features in the Banknote dataset. The Banknote dataset has a more complex underlying structure hence polynomial kernel struggles .

Hard vs. Soft Margin Questions (4 questions):

1. Which margin (soft or hard) is wider?

Ans: Hard margin

2. Why does the soft margin model allow "mistakes"?

Ans: Soft Margin SVM model is designed to be more tolerant of misclassifications. The primary goal is to find a hyperplane that maximizes the margin while keeping the number of misclassifications to a minimum

3. Which model is more likely to be overfitting and why?

Ans: The Hard Margin SVM is more likely to be overfitting to the training data. The hard margin SVM tries to find a hyperplane that perfectly separates all the training data points, including any outliers. This results in a very narrow margin. This strict adherence to the training data, can lead to poor performance on new, unseen data making it overfitting.

4. Which model would you trust more for new data and why?

Ans: I would trust the soft margin more for an unseen point because it is more tolerant to misclassification and it prioritizes finding a wider margin. This makes it less sensitive to individual data points and helps in generalizing the new data in a more efficient way.

Training Results

Moons Dataset :

```
➡ SVM with LINEAR Kernel <PES2UG23CS172>
      precision    recall  f1-score   support

     0       0.85      0.89      0.87        75
     1       0.89      0.84      0.86        75

 accuracy          0.87          150
 macro avg         0.87      0.87      0.87          150
 weighted avg      0.87      0.87      0.87          150
```

```
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SVM with RBF Kernel <PES2UG23CS172>
      precision    recall  f1-score   support

     0       0.95      1.00      0.97        75
     1       1.00      0.95      0.97        75

 accuracy          0.97          150
 macro avg         0.97      0.97      0.97          150
 weighted avg      0.97      0.97      0.97          150
```

```
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SVM with POLY Kernel <PES2UG23CS172>
      precision    recall  f1-score   support

     0       0.85      0.95      0.89        75
     1       0.94      0.83      0.88        75

 accuracy          0.89          150
 macro avg         0.89      0.89      0.89          150
 weighted avg      0.89      0.89      0.89          150
```

Banknote Dataset:

```
➡ SVM with LINEAR Kernel <PES2UG23CS172>
      precision    recall  f1-score   support

   Forged         0.90      0.88      0.89         229
   Genuine         0.86      0.88      0.87         183

 accuracy          0.88          412
 macro avg         0.88      0.88      0.88         412
 weighted avg      0.88      0.88      0.88         412

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SVM with RBF Kernel <PES2UG23CS172>
      precision    recall  f1-score   support

   Forged         0.96      0.91      0.94         229
   Genuine         0.90      0.96      0.93         183

 accuracy          0.93          412
 macro avg         0.93      0.93      0.93         412
 weighted avg      0.93      0.93      0.93         412

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SVM with POLY Kernel <PES2UG23CS172>
      precision    recall  f1-score   support

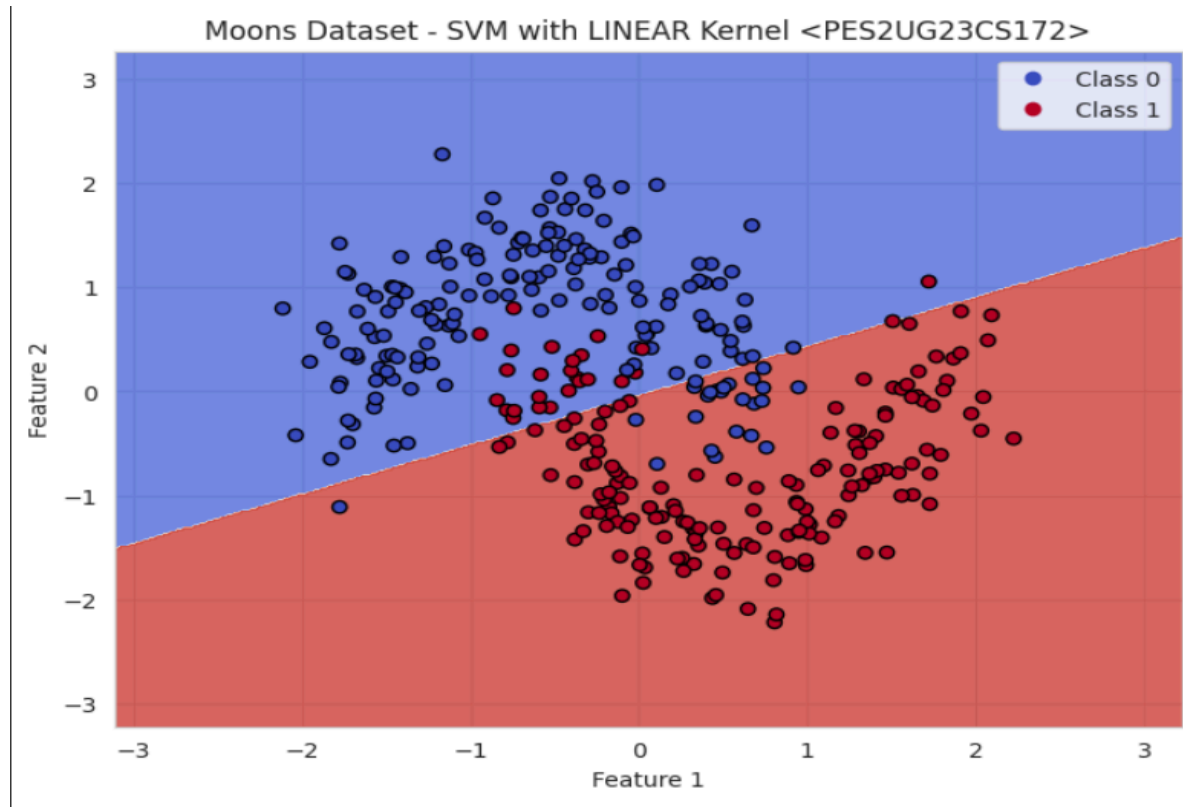
   Forged         0.82      0.91      0.87         229
   Genuine         0.87      0.75      0.81         183

 accuracy          0.84          412
 macro avg         0.85      0.83      0.84         412
 weighted avg      0.85      0.84      0.84         412

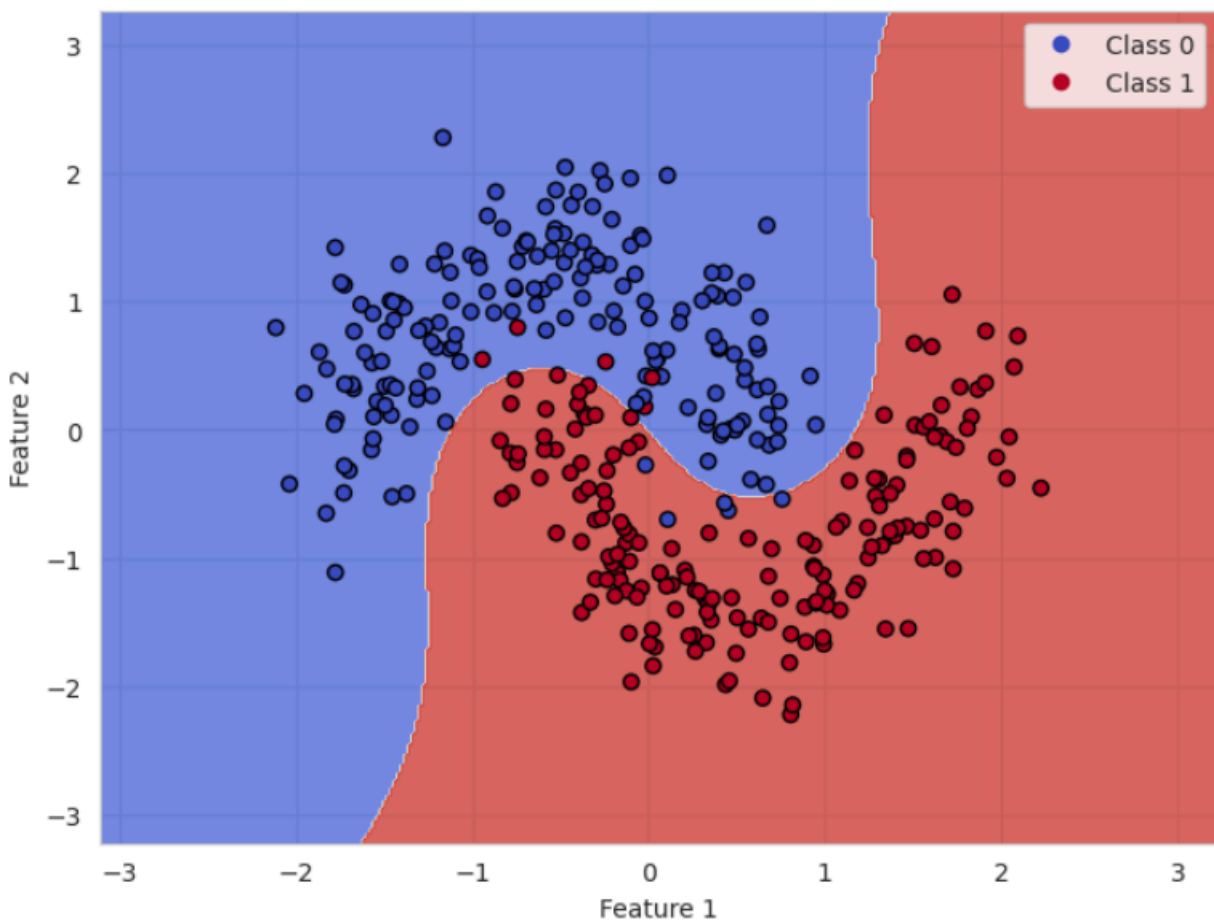
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```

Decision Boundary Visualizations

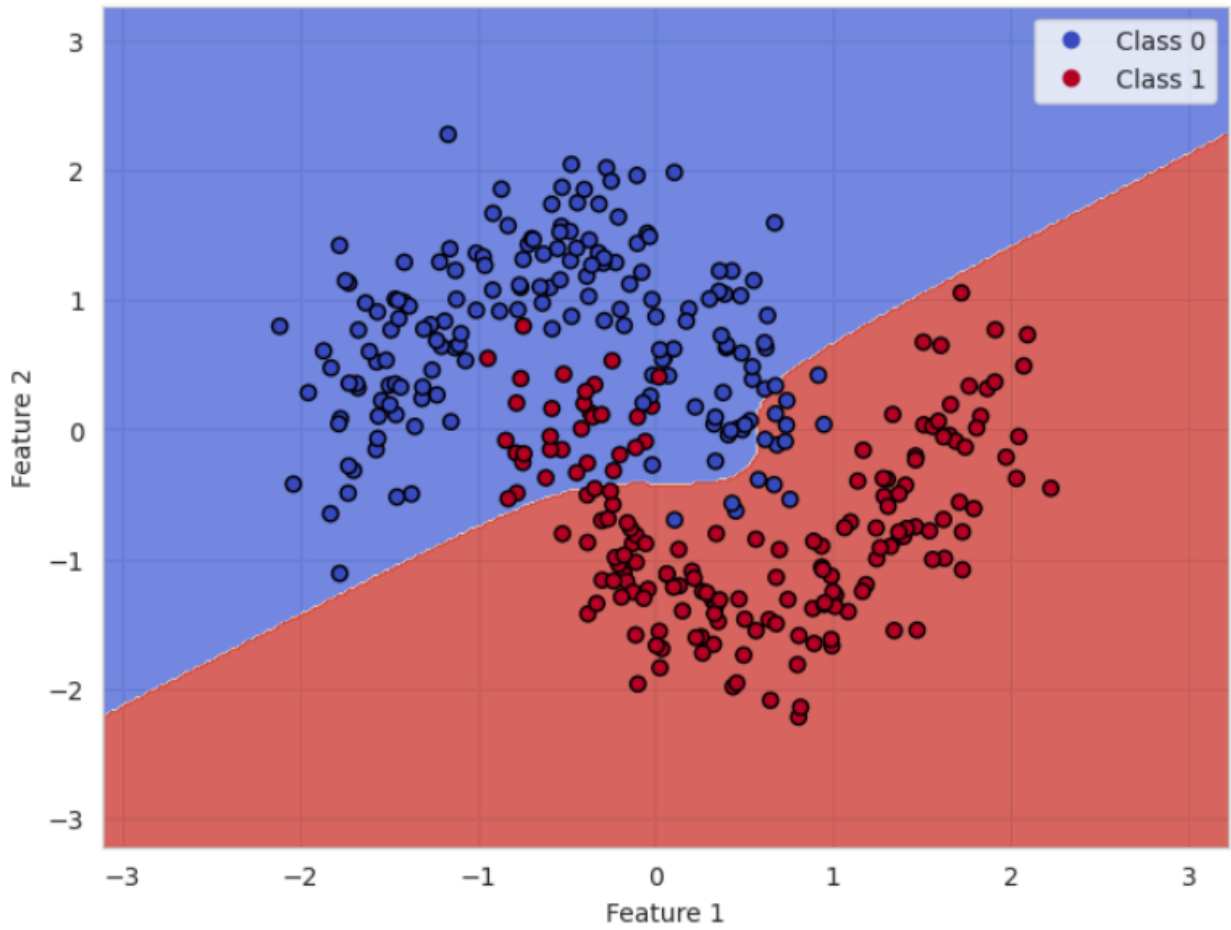
Moons Dataset:



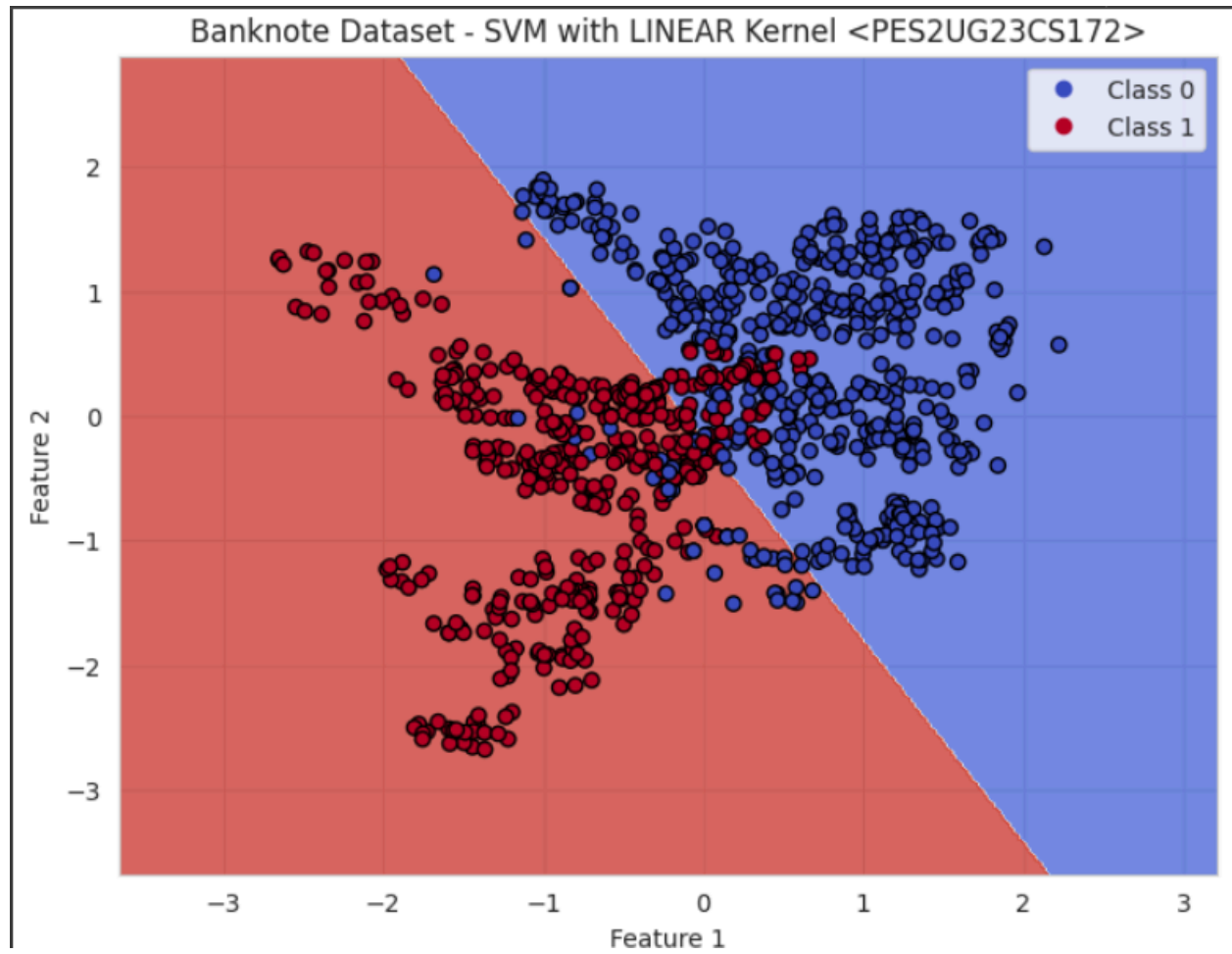
Moons Dataset - SVM with RBF Kernel <PES2UG23CS172>



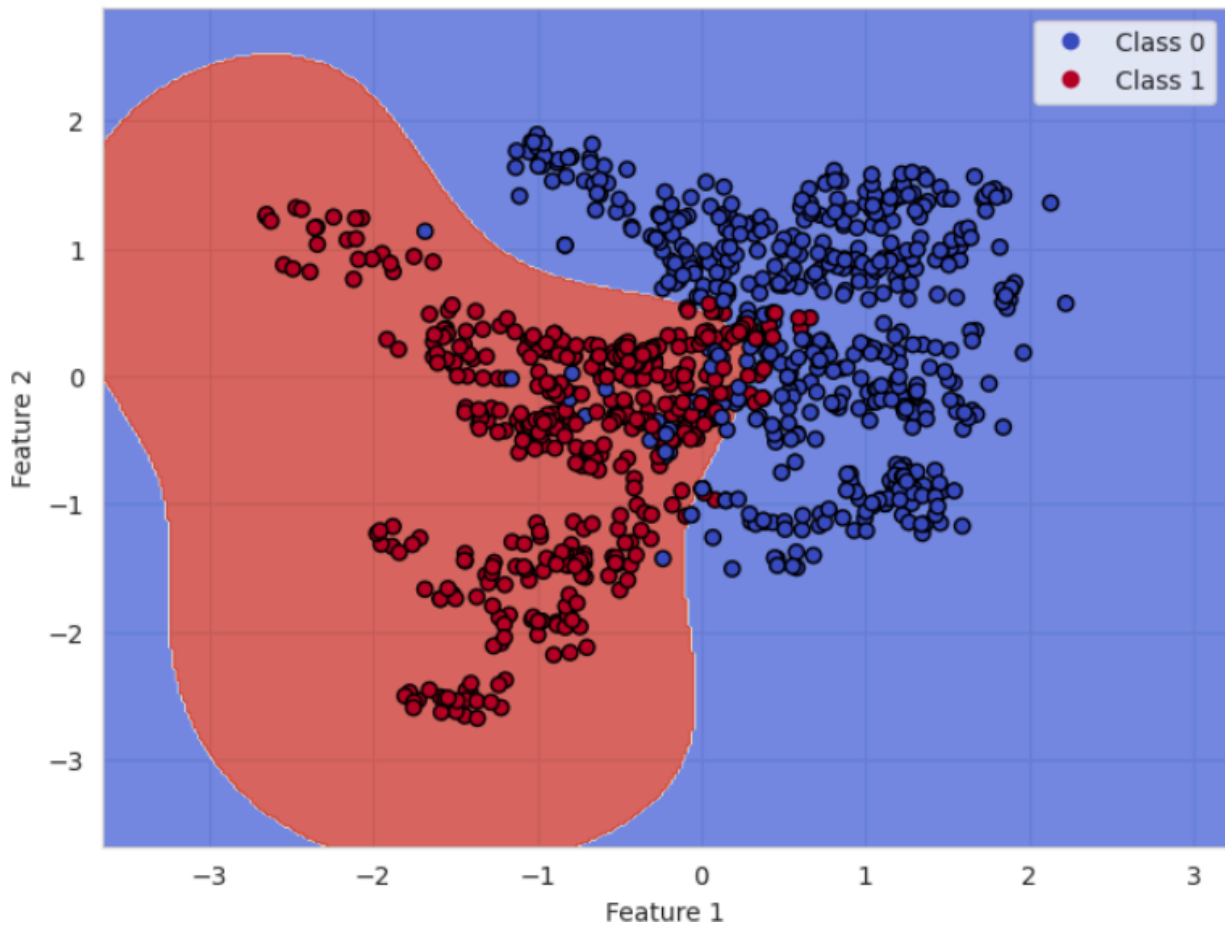
Moons Dataset - SVM with POLY Kernel <PES2UG23CS172>



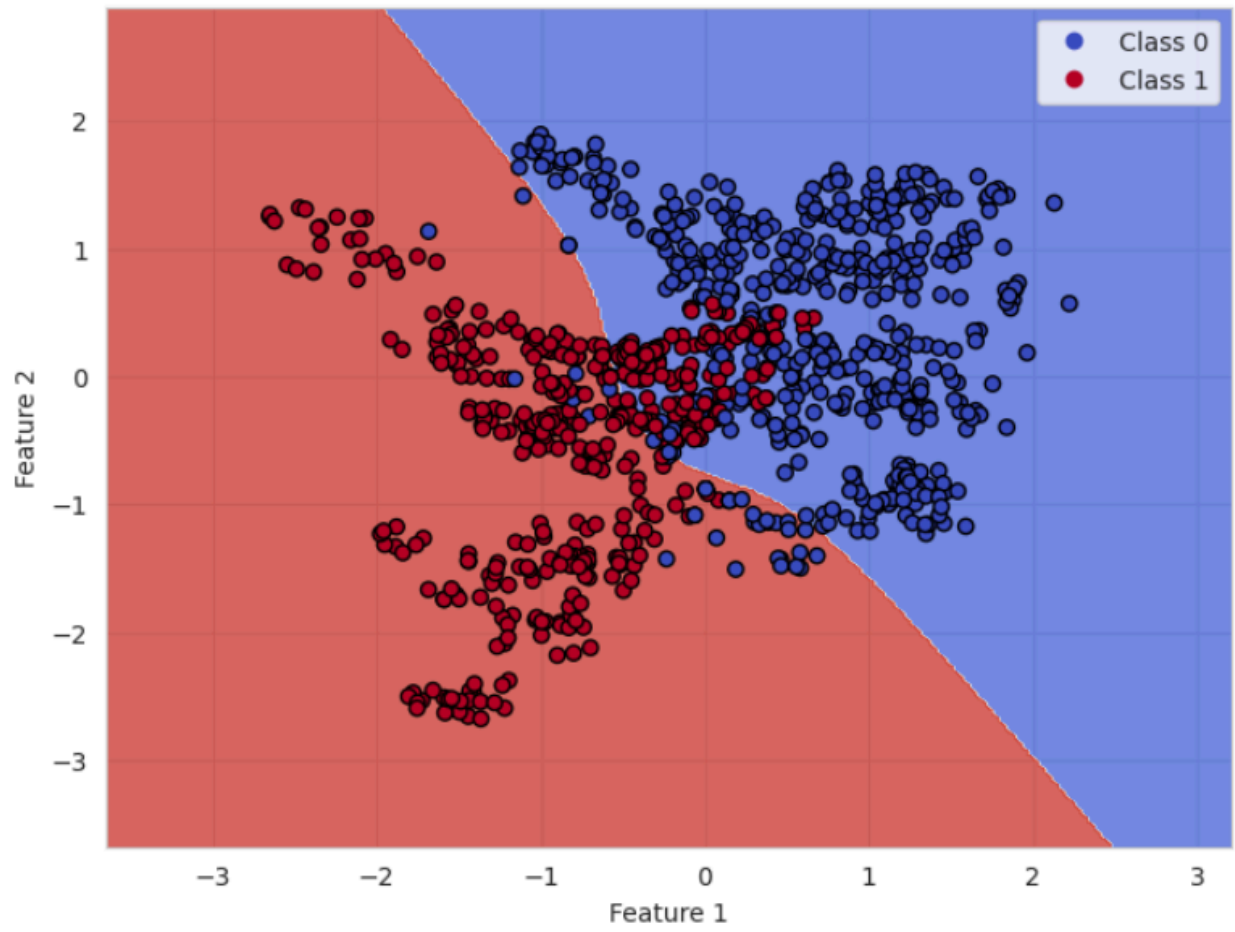
Banknote Dataset:



Banknote Dataset - SVM with RBF Kernel <PES2UG23CS172>



Banknote Dataset - SVM with POLY Kernel <PES2UG23CS172>



Margin Analysis:

