ML Lab Week 10 SVM Lab Instructions

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Section	CSE – C
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Screenshots for all the outputs:

1. **Training results –**
   - Moons Dataset:
     - Classification Report for SVM with LINEAR Kernel with SRN

```
SVM with LINEAR Kernel <PES2UG23CS169>
              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
```

     - Classification Report for SVM with RBF Kernel with SRN

```
SVM with RBF Kernel <PES2UG23CS169>
              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
```

     - Classification Report for SVM with POLY Kernel with SRN

```
SVM with POLY Kernel <PES2UG23CS169>
              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:
    - Classification Report for SVM with LINEAR Kernel

SVM with LINEAR Kernel <PES2UG23CS169>

	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

    - Classification Report for SVM with RBF Kernel

SVM with RBF Kernel <PES2UG23CS169>

	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

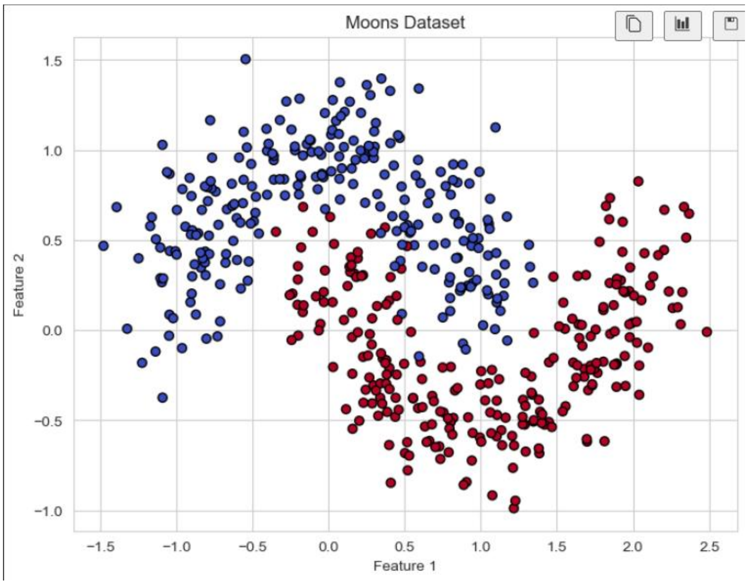
    - Classification Report for SVM with POLY Kernel C

SVM with POLY Kernel <PES2UG23CS169>

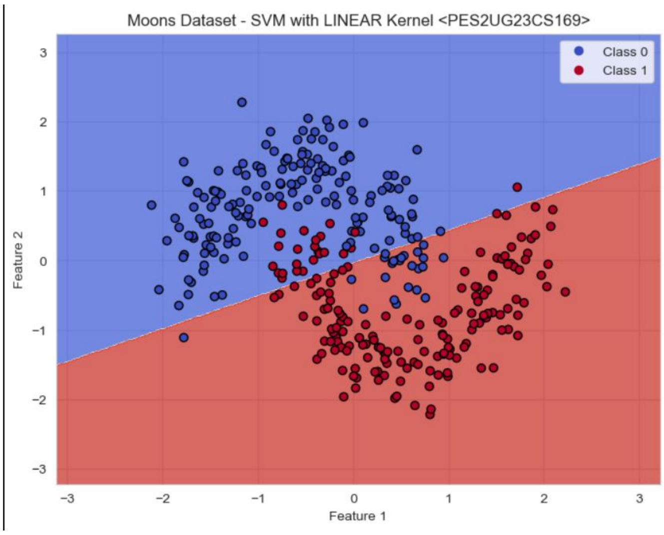
	precision	recall	f1-score	support
Forged	0.82	0.91	0.87	229
Genuine	0.87	0.75	0.81	183
accuracy			0.84	412
macro avg	0.85	0.83	0.84	412
weighted avg	0.85	0.84	0.84	412

2. Decision Boundary Visualizations –

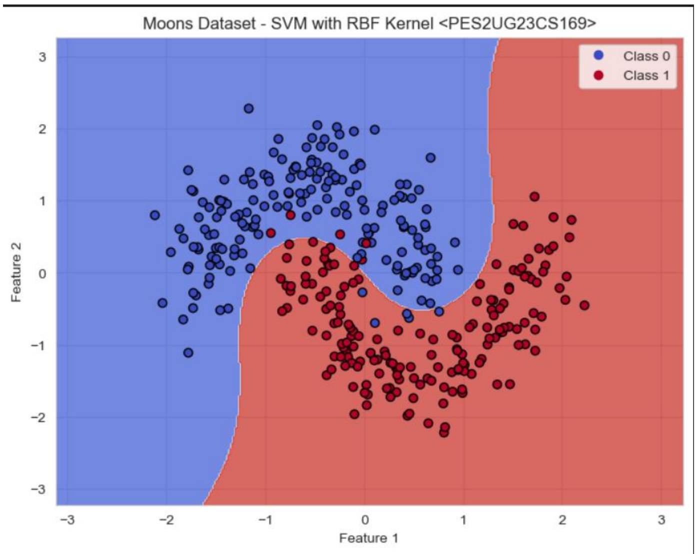
- Moons Dataset:



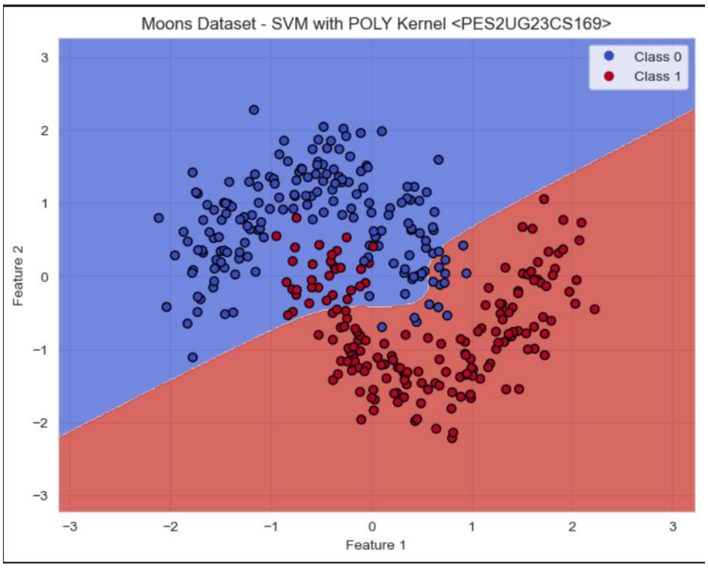
  - Moons Dataset - SVM with LINEAR Kernel



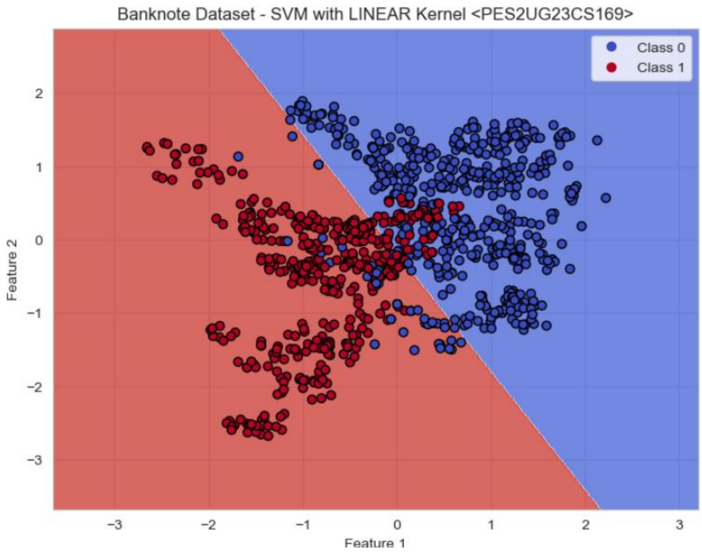
  - Moons Dataset - SVM with RBF Kernel



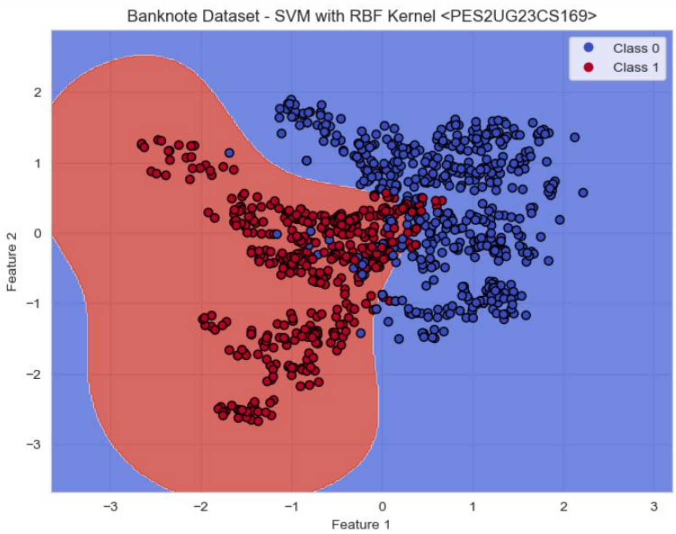
- Moons Dataset - SVM with POLY Kernel



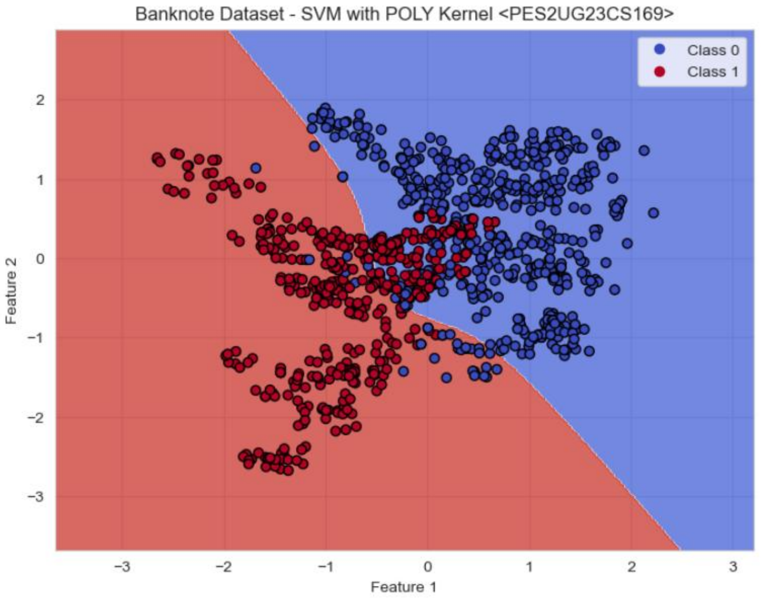
- Banknote Dataset:
  - Banknote Dataset - SVM with LINEAR Kernel



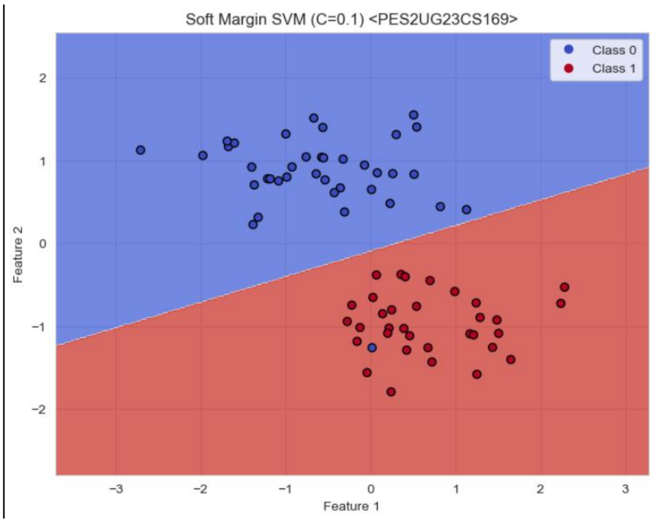
  - Banknote Dataset - SVM with RBF Kernel



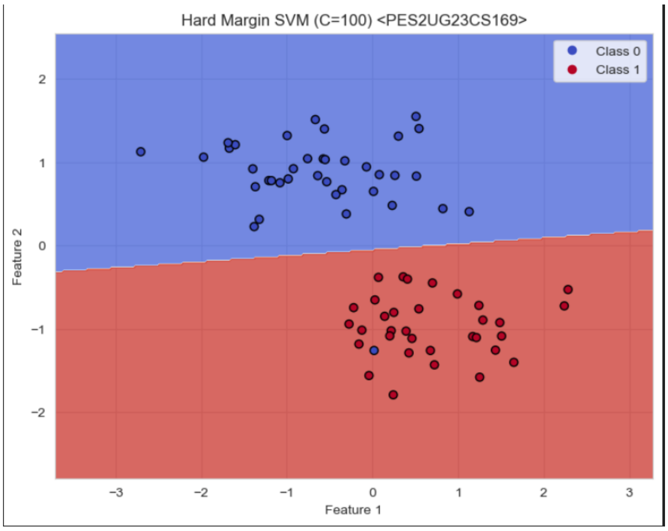
- Banknote Dataset - SVM with POLY Kernel



- Margin Analysis:
  - Soft Margin SVM (C=0.1)



  - Hard Margin SVM (C=100)



Answering all the questions:

Moons Dataset:

1. Inferences about the Linear Kernel's performance.
   The Linear Kernel struggled to capture the curved, non-linear separation present in the Moons dataset. Its decision boundary is almost a line, and this leads to more misclassifications near the overlapping areas of the two "moons." While it performs well in simple, linearly separable cases, it’s not flexible enough for this dataset’s complex shape.
2. Comparison between RBF and Polynomial kernel decision boundaries.
   The RBF kernel produces a smooth, natural-looking boundary that tightly follows the contours of the moons, accurately separating the two classes. In contrast, the Polynomial kernel also models some non-linearity but tends to create more rigid, jagged boundaries, especially with higher degrees. Overall, the RBF kernel fits the data more intuitively and avoids unnecessary complexity.

Banknote Dataset:

1. Which kernel was most effective for this dataset?
   For the Banknote dataset, the Linear kernel was the most effective. The dataset is nearly linearly separable and, therefore, a simple linear boundary was able to clearly separate genuine notes from forged notes. The added flexibility of the RBF or Polynomial kernels provided only modest improvement because of overfitting.
2. Why might the Polynomial kernel have underperformed here?
   The polynomial kernel adds unnecessary complexity to the already well-separated feature space. This extra complexity can cause overfitting—capturing minor fluctuations or noise in the data rather than meaningful patterns—leading to poorer generalization on unseen examples.

Hard vs. Soft Margin:

1. Which margin (soft or hard) is wider?
   The soft margin is wider. It allows some flexibility by permitting a few misclassified points, resulting in a larger margin around the decision boundary.
2. Why does the soft margin model allow "mistakes"?

Soft margin SVMs introduce a penalty parameter (C) that lets the model ignore a few misclassified samples in favor of achieving a broader, more generalizable boundary. This trade-off improves performance on noisy or overlapping datasets.

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

   The hard margin model is more prone to overfitting because it tries to perfectly classify all training points, even outliers. This rigidness makes it sensitive to noise and less effective on new, unseen data.

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

   The soft margin model is more trustworthy for new data. Its flexibility allows it to handle noise and variability better, providing more stable, generalizable predictions rather than memorizing the training examples.