

ML_LAB_WEEK_10_SVM_LAB

Name: Meghana Saisri Bisa

SRN: PES2UG23CS337

Section: F

PART 1: Moons Dataset Questions

1. Inferences about the Linear Kernel's performance
 - The Linear Kernel performs poorly on the Moons dataset.
 - Reason: The data is not linearly separable (two interlocking moons), so a straight line cannot separate the classes properly.
 - Result: Low accuracy and many misclassified points.
2. Comparison between RBF and Polynomial kernel decision boundaries
 - RBF Kernel: Creates a smooth, curved boundary that closely follows the shape of the moons. Handles non-linear patterns very well.
 - Polynomial Kernel: Also creates a curved boundary, but sometimes it overfits or underfits depending on the degree.
 - Conclusion: RBF generally captures the moons' shape more naturally and accurately.

PART 2: Banknote Dataset Questions

1. Which kernel was most effective for this dataset?
 - RBF Kernel is usually the most effective.
 - Reason: It handles non-linear patterns in the features better than a simple linear or polynomial kernel for this dataset.
2. Why might the Polynomial kernel have underperformed here?
 - Polynomial can overfit if the degree is too high or underfit if the degree is too low.
 - The Banknote dataset is mostly linearly separable with some non-linear noise, so RBF works better. Polynomial struggles to generalize.

PART 3: Hard vs Soft Margin Questions

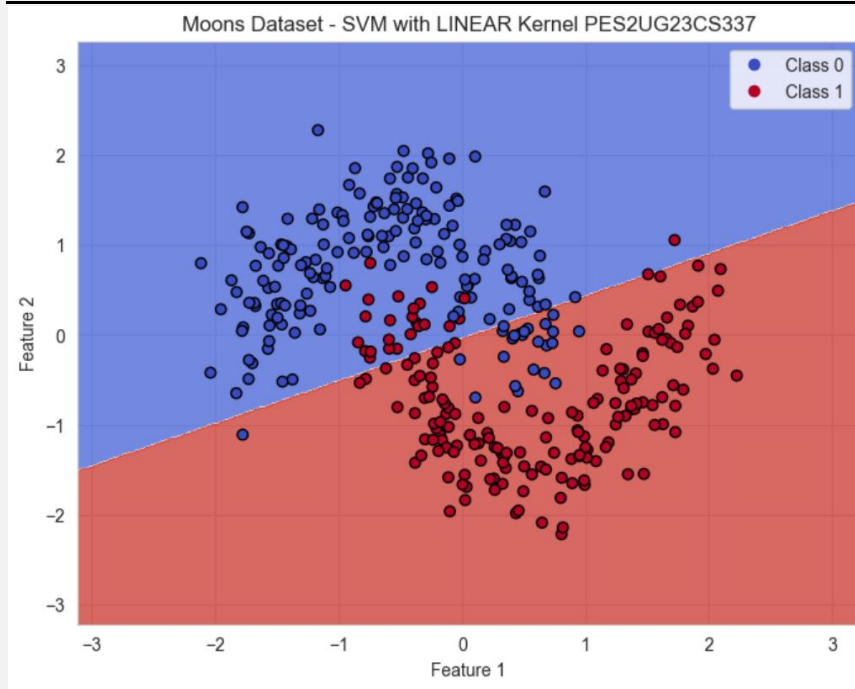
1. Which margin (soft or hard) is wider?
 - Soft Margin ($C=0.1$) produces a wider margin.
 - Reason: It allows some misclassifications to create a bigger separation between classes.
2. Why does the soft margin model allow "mistakes"?
 - It tolerates some points inside or across the margin to prevent overfitting.
 - Goal: Balance accuracy on training data and generalization to new data.
3. Which model is more likely to be overfitting and why?
 - Hard Margin ($C=100$) is more likely to overfit.
 - Reason: It tries to classify all training points perfectly, even outliers, which reduces generalization.

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

- Soft Margin ($C=0.1$) is safer for new, unseen data.
- Reason: It generalizes better, ignores small noise/outliers, and reduces risk of overfitting.
- In real-world scenarios, start with a low C value for noisy data.

TRAINING RESULTS

SVM with LINEAR Kernel PES2UG23CS337				
	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



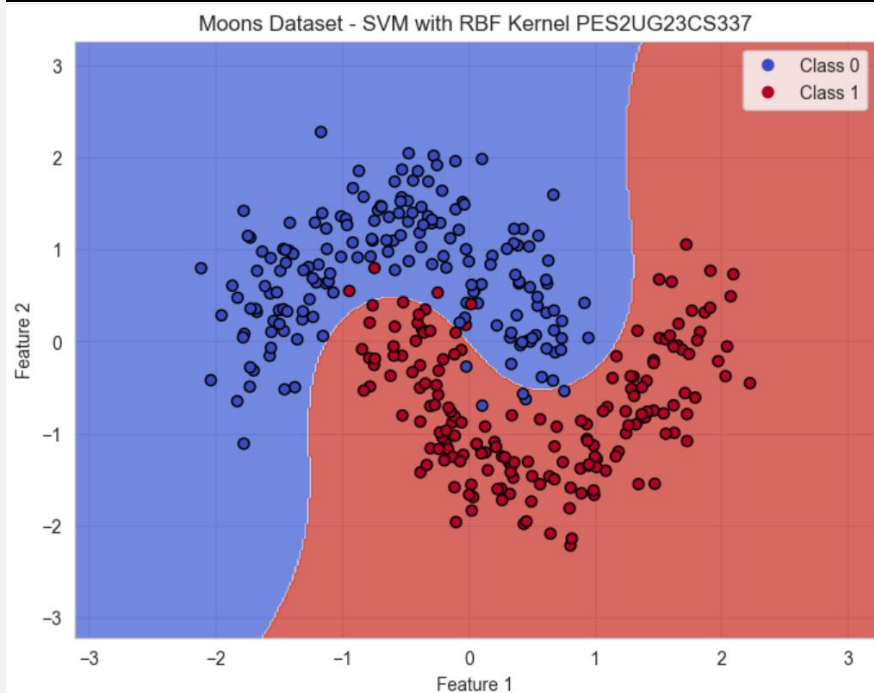
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SVM with RBF Kernel PES2UG23CS337
      precision    recall  f1-score   support

     0       0.95      1.00      0.97        75
     1       1.00      0.95      0.97        75

 accuracy          0.97          0.97          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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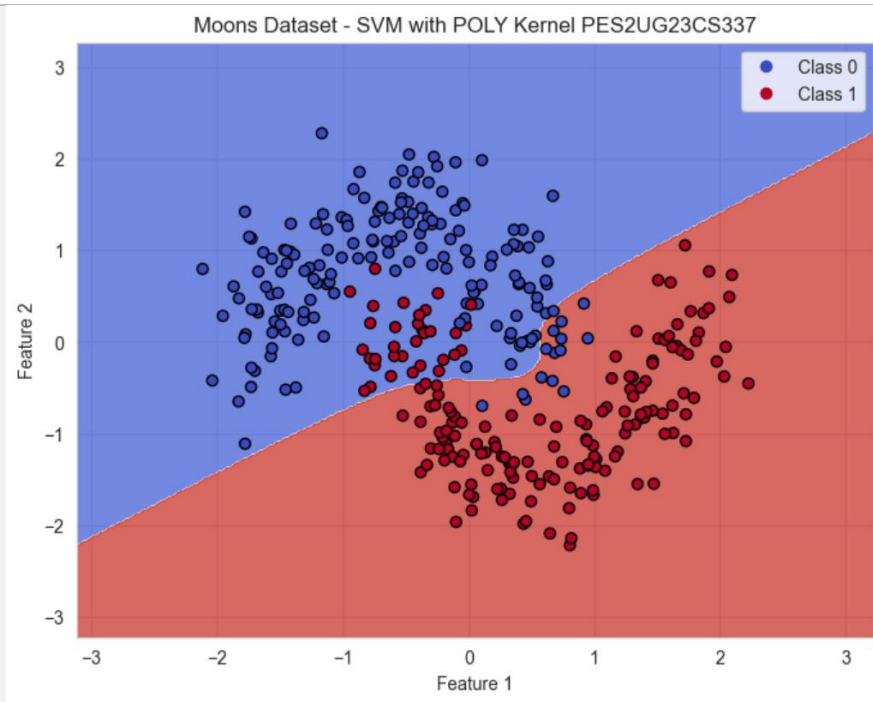
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SVM with POLY Kernel PES2UG23CS337
      precision    recall  f1-score   support

     0       0.85      0.95      0.89        75
     1       0.94      0.83      0.88        75

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

```



DECISION BOUNDARY VISUALIZATIONS

