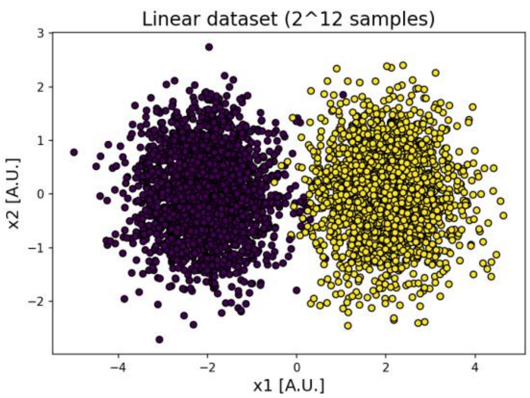
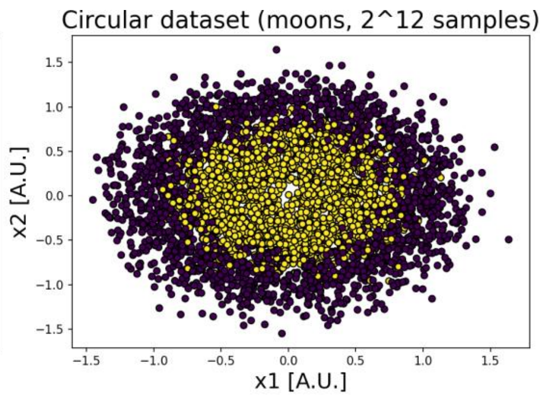
Name : Yael Tsuk ran
Date: 4.12.25

Machine Learning & Neural Networks for Neuroscience -HM2

Github : https://github.com/Yaelts2/hm02_SVM

Question 1 & 2:

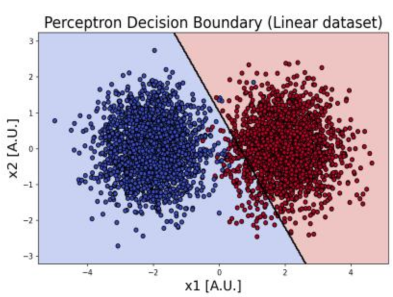


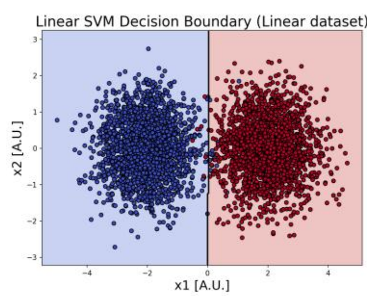


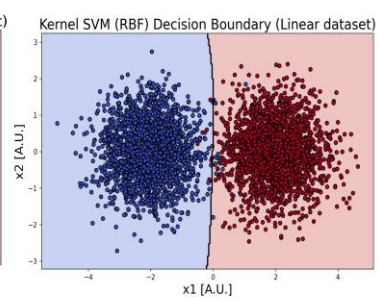
Question 3:

	Linear data	Circular data
Perceptron model	0.9622	0.516
Linear SVM	0.9963	0.523
Kernel SVM (RBF kernel)	0.9951	0.879

In the linear dataset, all models perform well because the classes are linearly separable. Both the Perceptron and the Linear SVM achieve very high accuracy, and the Kernel SVM does not provide any additional benefit in this setting.
In contrast, in the non-linear circular dataset, the Perceptron and the Linear SVM fail to classify the data correctly because the classes form concentric rings and cannot be separated by a straight line. The Kernel SVM (RBF), however, captures the circular structure of the dataset and achieves high performance, demonstrating its ability to model complex, non-linear decision boundaries.







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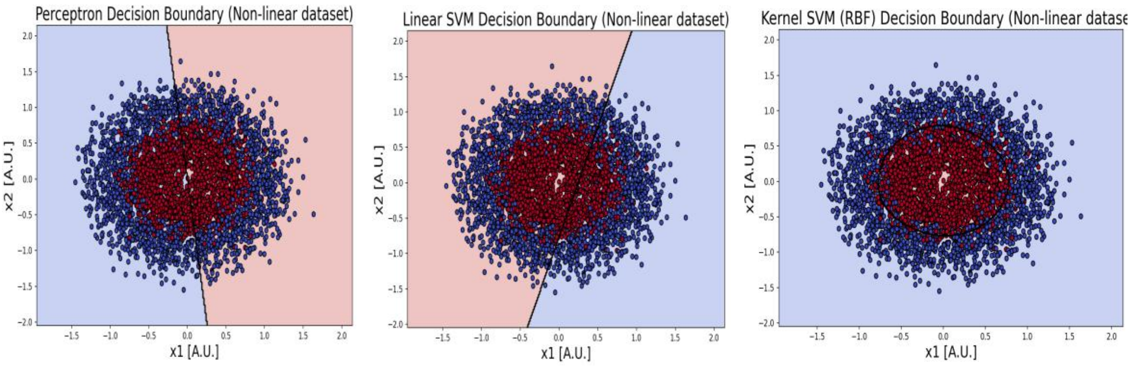
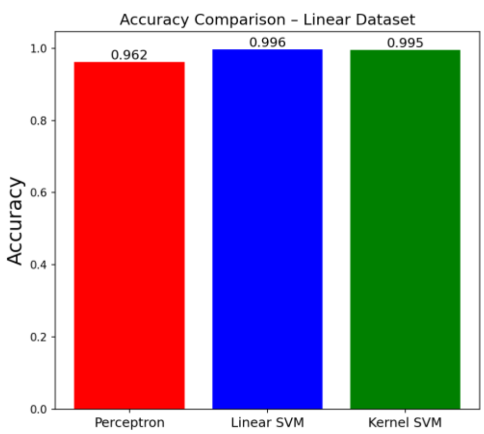
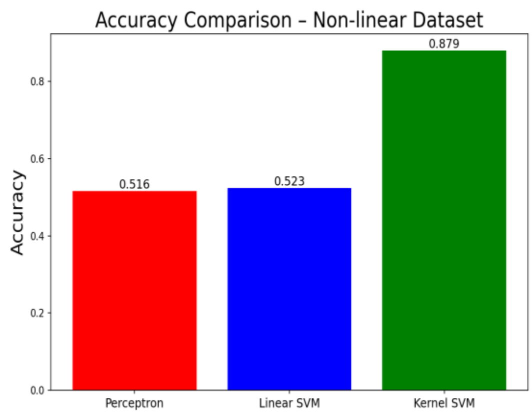


The decision-boundary plots reflect the same trend seen in the model accuracies. For the linear dataset, all three models recover an effective straight boundary that separates the classes well. For the non-linear circular dataset, the Perceptron and the Linear SVM still produce straight lines and therefore misclassify a large portion of the ring structure because this data can’t be separable by a linear line. In contrast, the Kernel SVM (RBF) captures the circular geometry and produces a curved boundary that aligns with the data, explaining its superior performance. However, even the Kernel SVM does not reach perfect accuracy because the two rings partially overlap.





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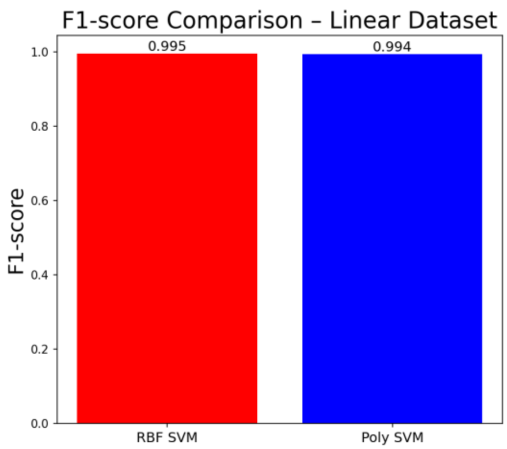
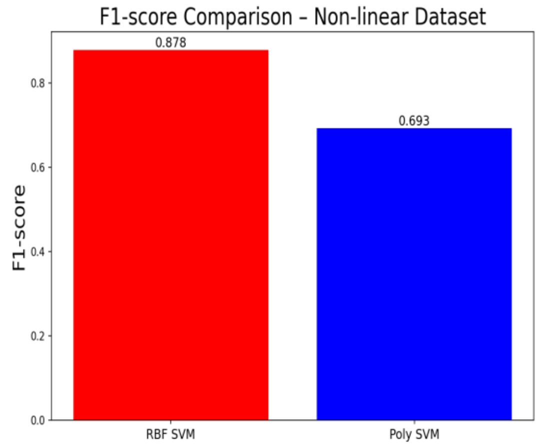
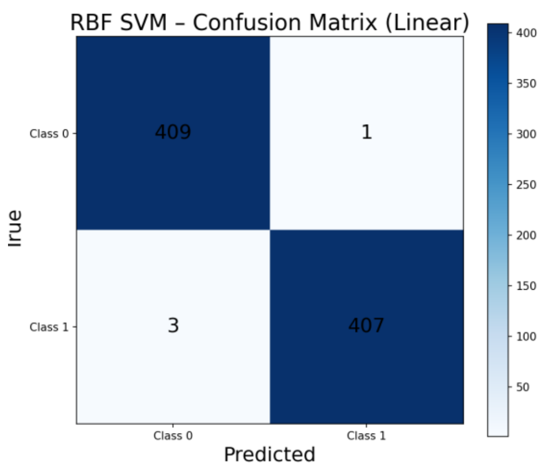
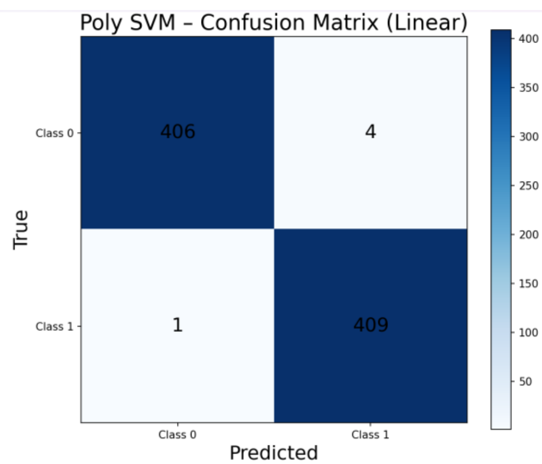
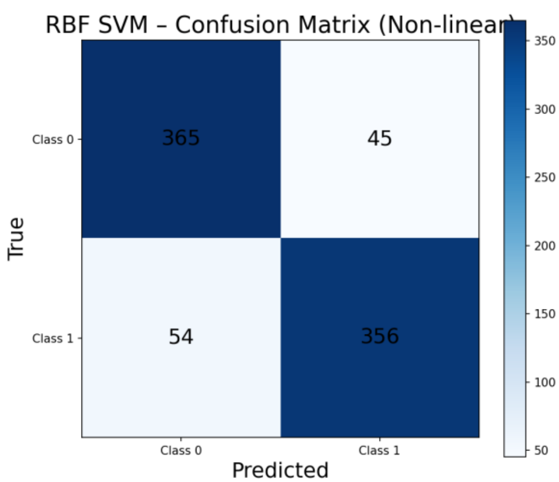
Question 4:

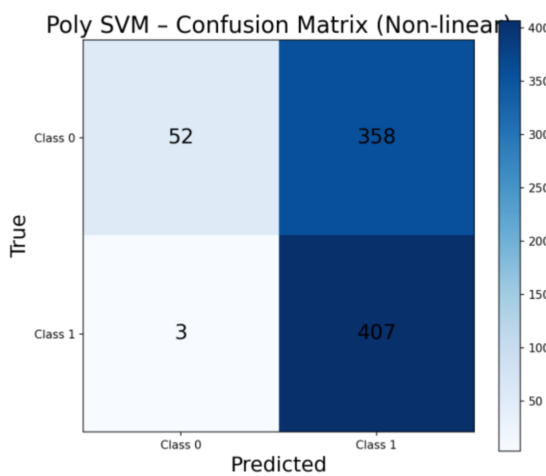












The results show that the RBF and Polynomial SVMs perform almost identically on the linear dataset, with both achieving near-perfect F1-scores and confusion matrices showing only a handful of mistakes. This is expected because the classes are linearly separable, so even non-linear kernels do not offer an advantage.

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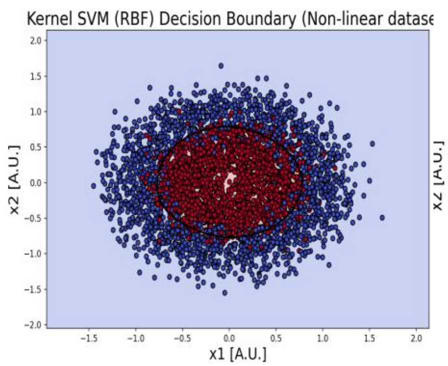
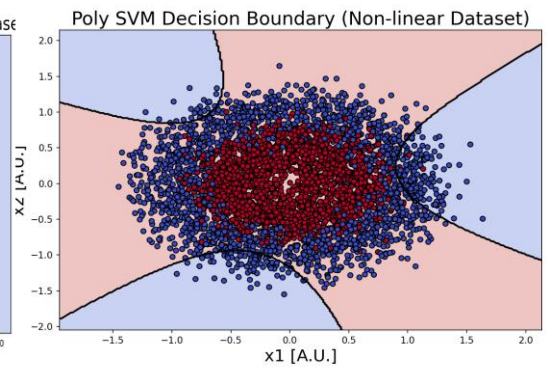
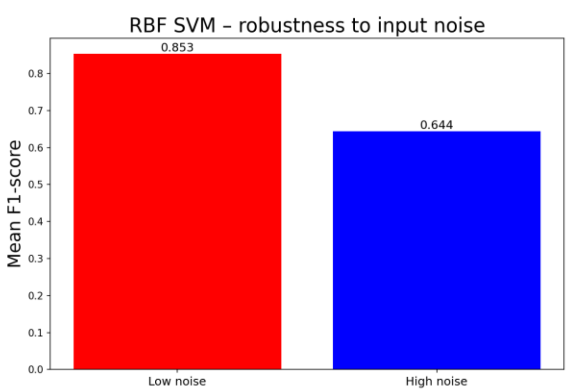
On the non-linear circular dataset, however, the difference between the kernels becomes clear. The RBF SVM achieves a substantially higher F1-score than the Polynomial SVM and produces fewer misclassifications in the confusion matrix. A plausible explanation is that the RBF kernel forms highly flexible, localized decision boundaries that naturally follow the circular structure of the two concentric rings. The Polynomial kernel, on the other hand, generates more global, rigid decision surfaces that cannot fully adapt to the circular geometry. As a result, the RBF kernel is better suited for this type of non-linear data.
The confusion-matrix results align with the decision-boundary map：in the non-linear dataset, the Polynomial SVM's boundary fails to follow the circular structure, and this mismatch explains the large number of misclassifications seen in its confusion matrix.





Question 5：
A：



With low input noise, the RBF SVM maintains strong performance (mean F1 = 0.853), indicating that small perturbations do not significantly affect the local similarity structure that the RBF kernel depends on. When the noise level is high, the mean F1-score drops to 0.644, because many samples are displaced far enough to overlap with the opposite class. This blurs the circular class boundary and makes it harder for the model to form a clean separation, reducing overall reliability.

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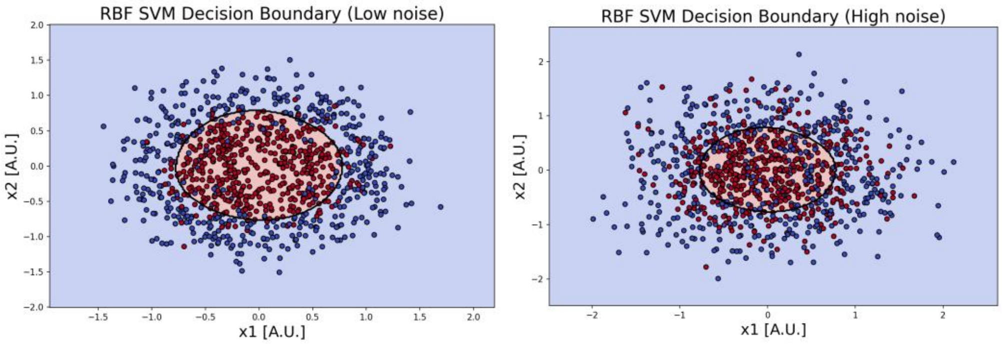
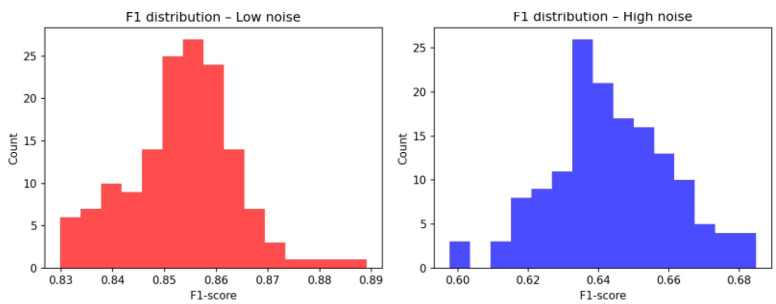


Low noise: The RBF boundary remains smooth and tightly follows the circular structure because the classes are still well separated.
High noise: The boundary becomes less accurate and more distorted as the heavy noise causes the rings to overlap, making the separation harder.



The figure shows the distribution of F1-scores across repeated runs under different noise levels.
Low noise: The F1-scores cluster tightly around ~0.85, indicating that the model is stable and consistently accurate when the data is only mildly perturbed.
High noise: The distribution shifts lower (~0.64) and becomes wider, showing reduced stability and performance as noise causes stronger overlap between the classes.

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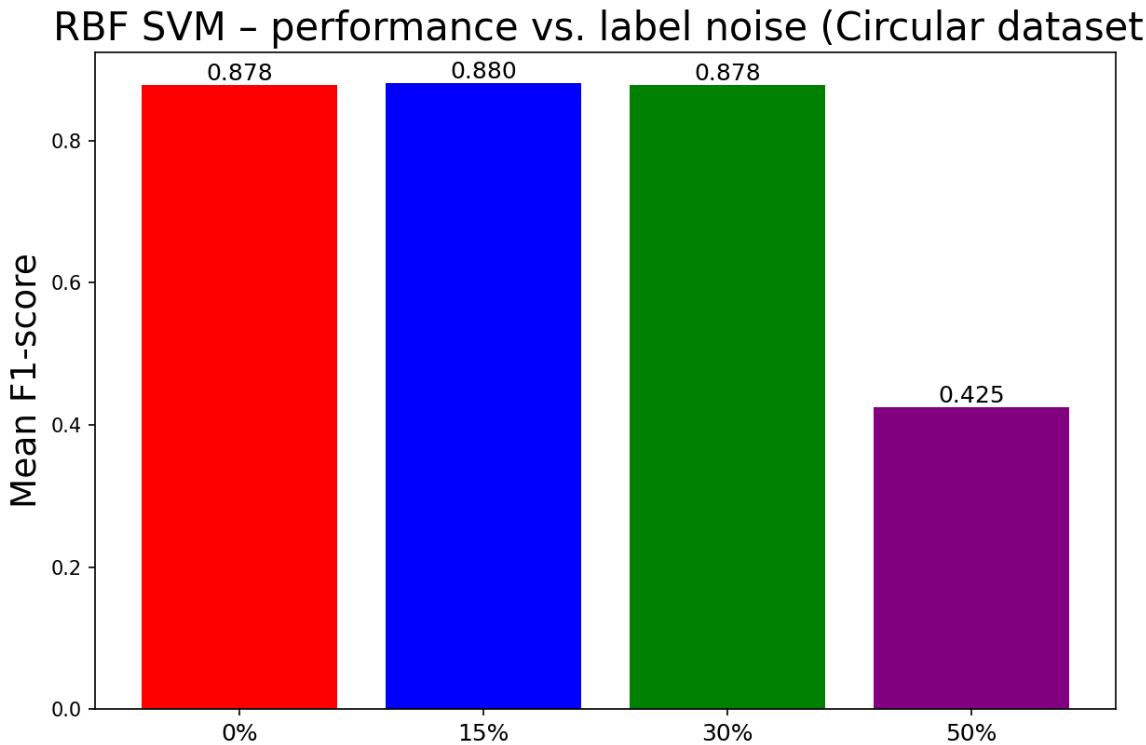
B:



To test the RBF SVM's robustness to label noise, a portion of the training labels (15%, 30%, and 50%) was randomly flipped and the model was retrained 50 times for each noise level. The results show that the classifier is highly robust to mild and moderate label corruption: the mean F1-score remains almost unchanged between 0% (0.878), 15% (0.880), and 30% (0.878) noise. This indicates that the RBF kernel can still capture the circular structure even when many labels are incorrect. However, at 50% label noise, the class structure breaks down entirely, and the F1-score drops sharply to 0.425.
Overall, the RBF SVM can withstand substantial label noise, but once too many labels are flipped, the underlying pattern becomes indistinguishable and the model can no longer learn a meaningful decision boundary.

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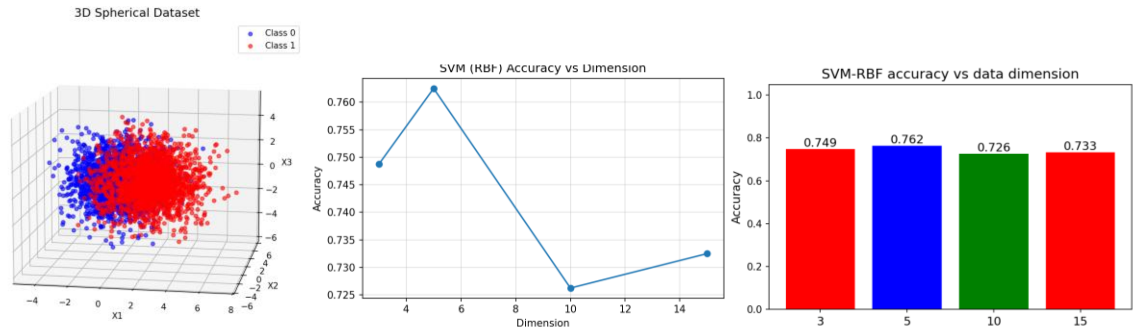
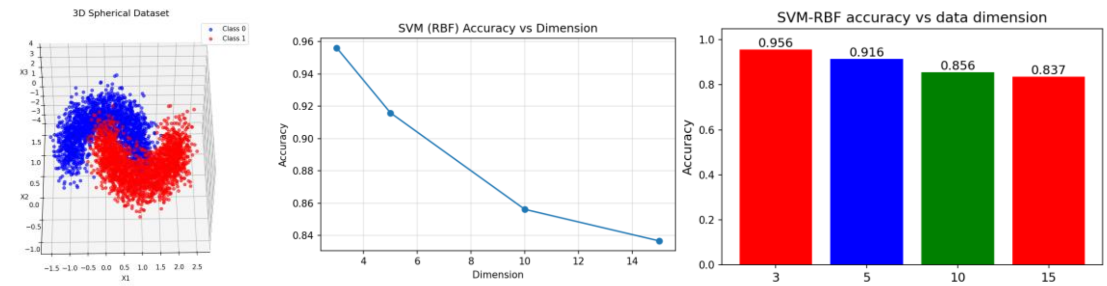
C:





In my first attempt I generated two Gaussian ball clusters in different dimensions. The accuracy stayed almost the same because increasing the dimension did not really change the problem: the two classes differed only in one coordinate, and all extra dimensions had the exact same distribution for both classes. Therefore, the model had no reason to perform worse as dimension increased.
the next thing I tried was to creating 2D moon shaped data and then adding extra random dimensions. In this case only the first two dimensions contain real structure, and the rest make the problem harder. With this dataset the SVM accuracy decreased as the dimension grew. The top figures show that for Gaussian "ball" data, accuracy stays almost constant because higher dimensions do not change the structure of the two clusters.
The bottom figures show that for moon data with added dimensions, accuracy decreases as dimension increases.