



Classification

Binary Classification

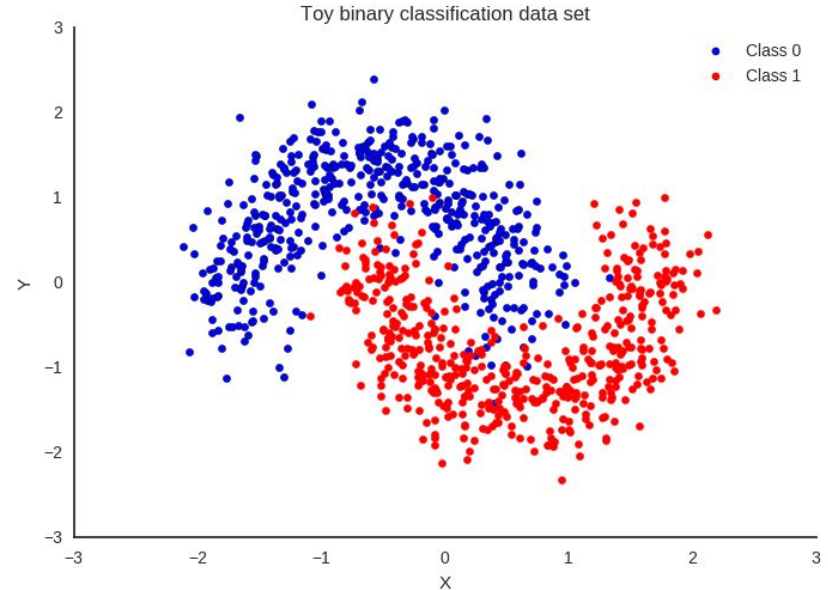
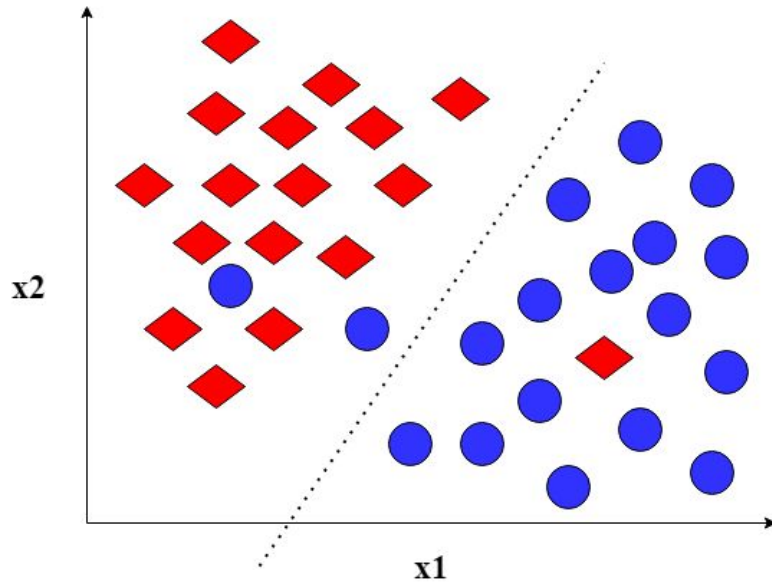


Image source:

https://www.researchgate.net/figure/Example-of-a-binary-classification-for-a-dummy-dataset-with-two-features_fig1_353288055, <https://www.kdnuggets.com/2017/04/must-know-evaluate-binary-classifier.html>

Binary Classification

- Binary classification aims to distinguish between two classes (e.g., cat and dog, spam or not spam)
- Objective: find a decision boundary that best separates the data points from the two classes

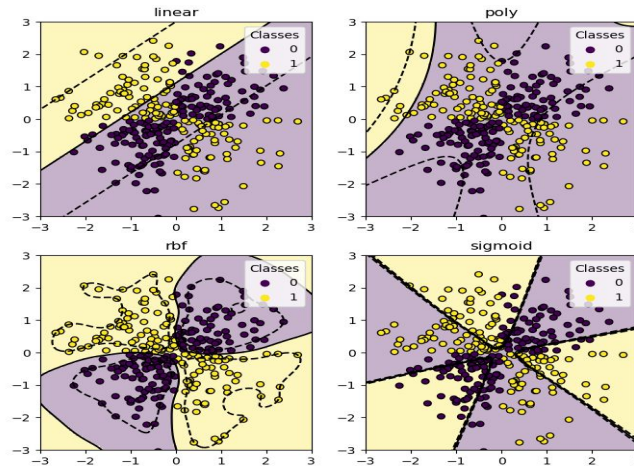


Image source:

https://scikit-learn.org/stable/auto_examples/svm/plot_svm_kernels.html

Binary Classification

- Confusion Matrix

| | | True Class | |
|-----------------|----------|------------|----------|
| | | Positive | Negative |
| Predicted Class | Positive | TP | FP |
| | Negative | FN | TN |

Image source:

https://www.researchgate.net/figure/Confusion-Matrix-for-Binary-Classification-7_fig1_350487701

Binary Classification Metrics

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\begin{aligned}\text{F1 Score} &= \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} \\ &= \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}\end{aligned}$$

- Accuracy: correct samples / all samples
- Precision: measures how “precise” the model is with predicting the positive class
- Recall: measures how many truly positive samples a model can recall
- If either precision or recall is low, F1 score is low as well
- F1 score demands balance between precision and recall

Binary Classification Metrics

- ROC AUC score: measures how well the model can rank positive samples ahead of negative ones

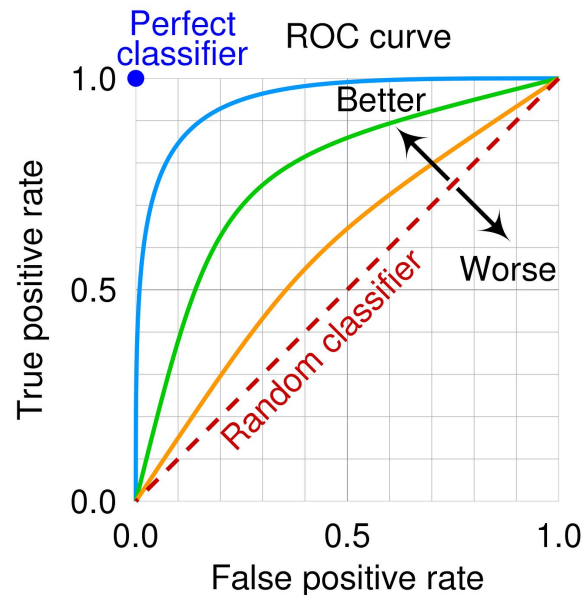
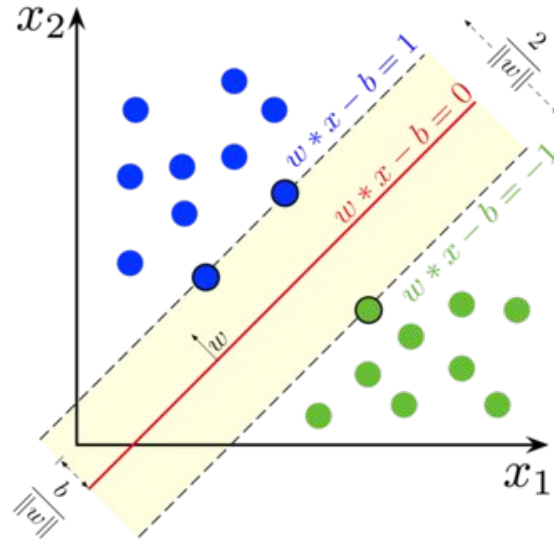


Image source:

<https://medium.com/@msong507/understanding-the-roc-auc-curve-cc204f0b3441>

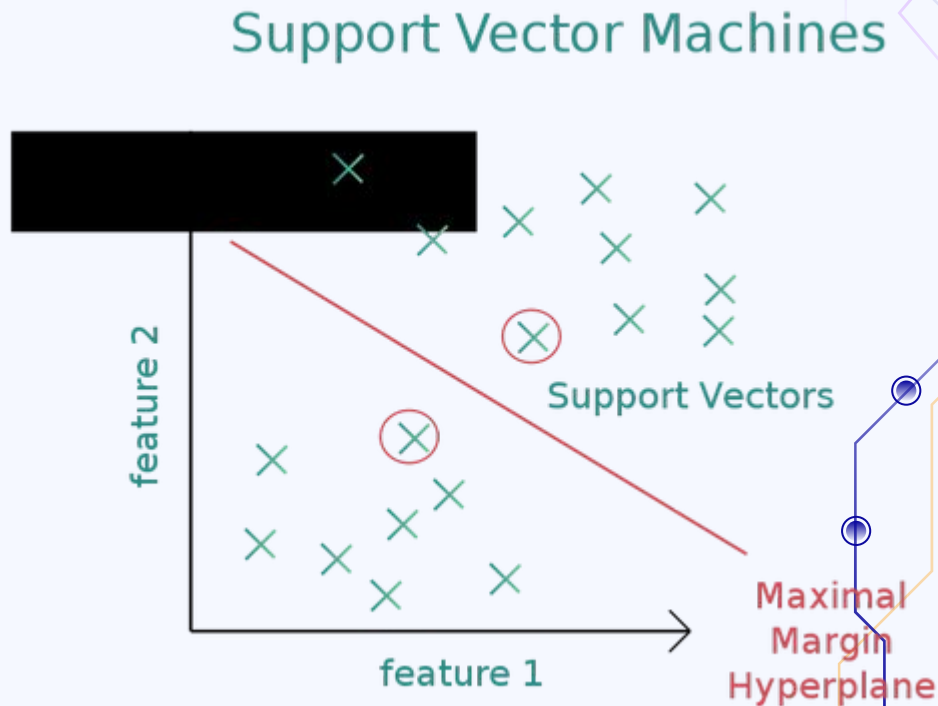
Binary Classification

- The most simple decision boundary is a straight line
- This is the essence of linear models



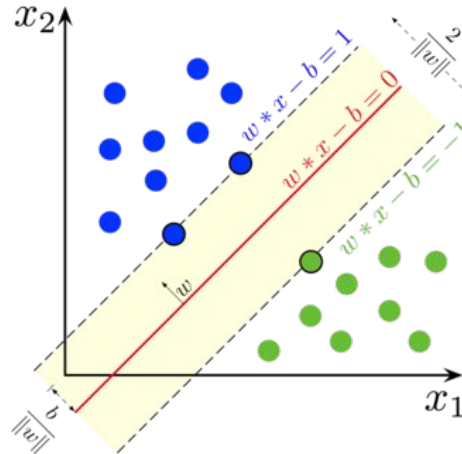
Support Vector Machines

- The support vector machine (SVM) is a linear model training paradigm in which the results are easy to visualize
- Especially if the dataset is linearly separable (i.e., there exists a straight line decision boundary that can perfectly separate all data points of the two classes)



Support Vector Machine

- For linearly separable datasets, the SVM finds the decision boundary that classifies all points correctly AND has the maximum margin
- This means maximizing the distance between the CLOSEST data points to the decision boundary to the boundary itself
- Find the widest “gap” between the two classes



Support Vector Machine

- For datasets that are NOT linearly separable, the SVM needs to balance the classification accuracy and the width of the margin.
- This is controlled by the hyperparameter C
- High C: prioritize correctness of classification
- Low C: prioritize greater margin over classification accuracy

Support Vector Machines

- Train an SVM model and experience the effect of the C hyperparameter here in part 1 of this notebook:
- <https://www.kaggle.com/code/lailaicode/binary-classification>

Support Vector Machines

- For datasets that are not linearly separable, another method is to use the “kernel trick”
- Use a “kernel” to map the data to a higher-dimensional space where it may become linearly separable

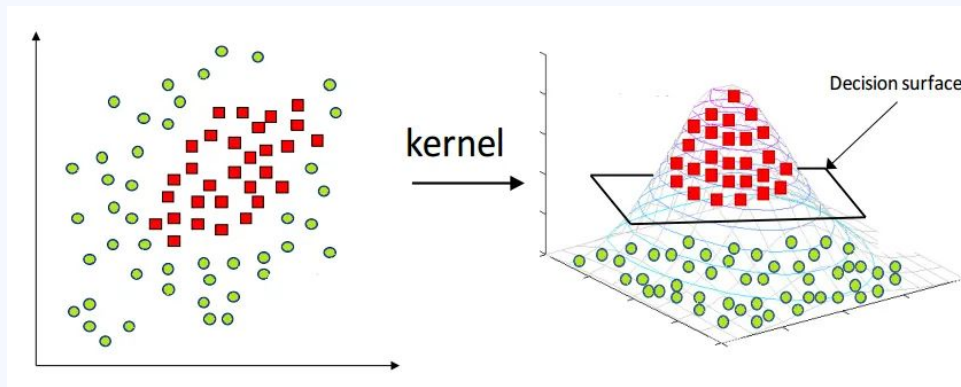
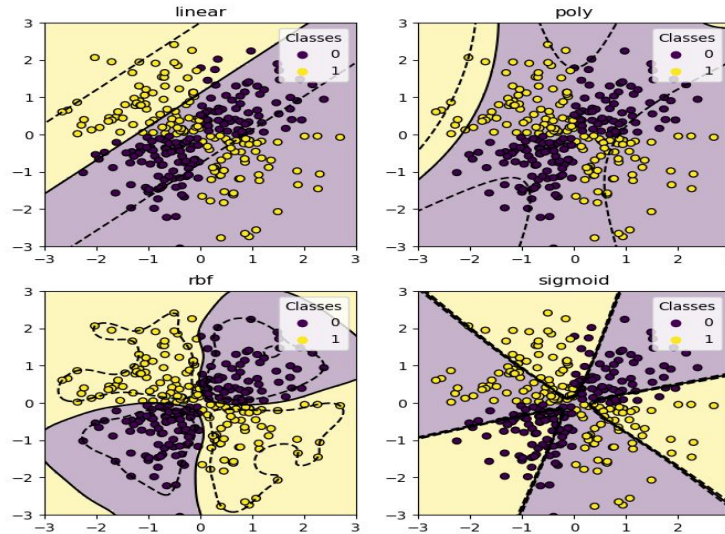


Image source: <https://medium.com/@zxr.nju/what-is-the-kernel-trick-why-is-it-important-98a98db0961d>

Support Vector Machine

- Different taxonomies of decision boundaries allowed when different kernels are used



Support Vector Machines

- Experiment with different kernel choices in part 2 of this notebook:
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Multiclass Classification

- Instead of only distinguishing between two classes, distinguish between multiple classes at the same time
- Produce confidence scores for multiple classes at the same time

3-Class classification using Support Vector Machine with custom kernel

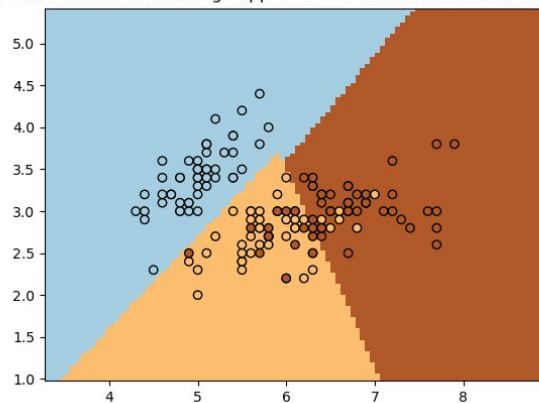
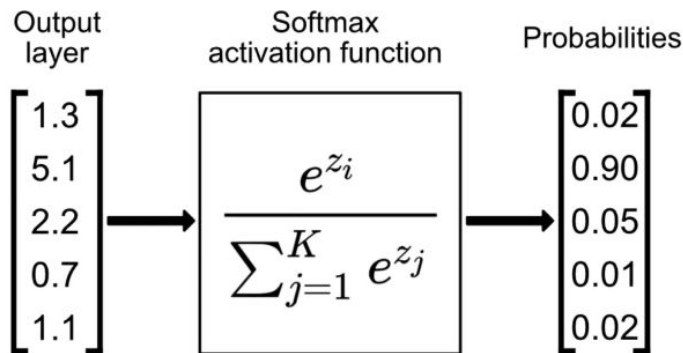


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Multiclass Classification

- The confidence score can be any real number (positive or negative)
- Convert the scores into a probability distribution using the softmax function
- In the probability distribution, all numbers are positive and they sum to 1
- Take the class with the highest confidence score as the final prediction



Multiclass Classification

- When the confidence score in terms of probability is 90%, we usually can't say that there's a 90% chance that the data point belongs to that class
- The “probabilities” are used to calculate losses, NOT actual probabilities
- We need to calibrate the model to make use of the probabilities (as probabilities) when writing reports

Binary Classification

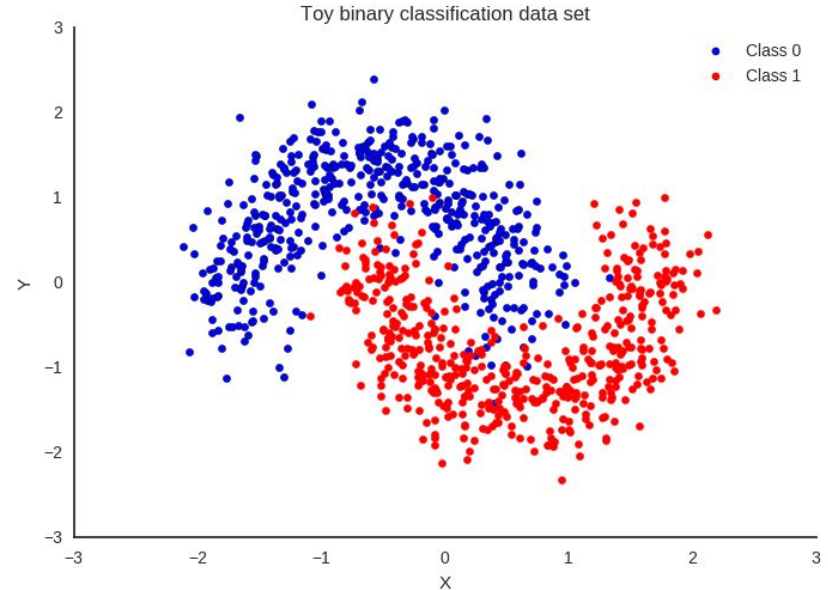
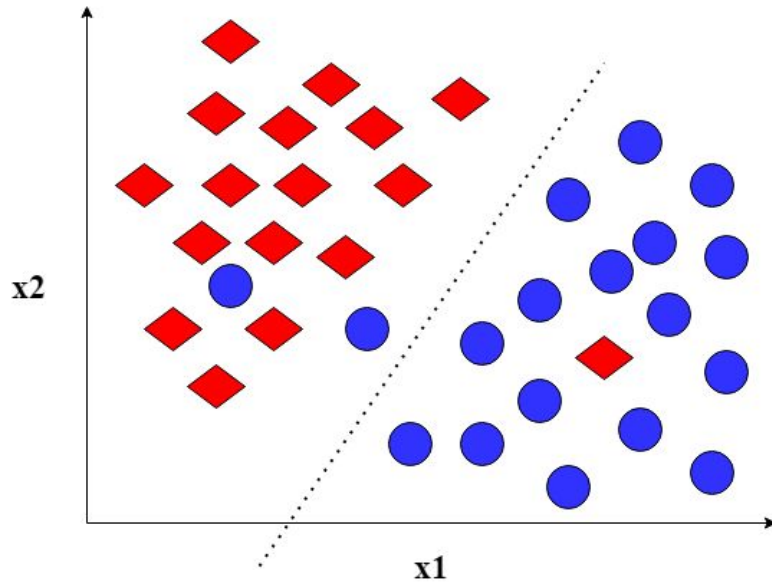
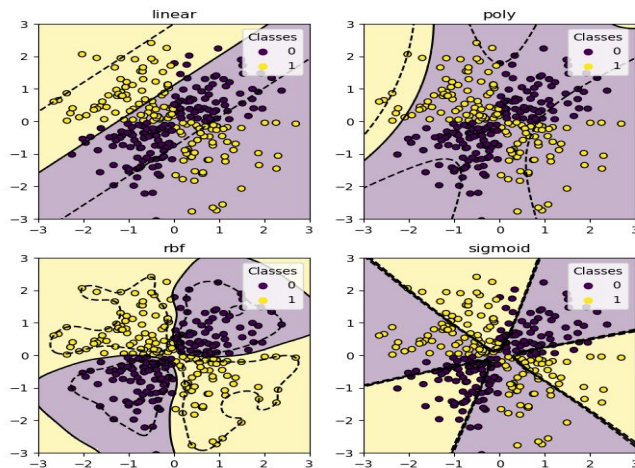


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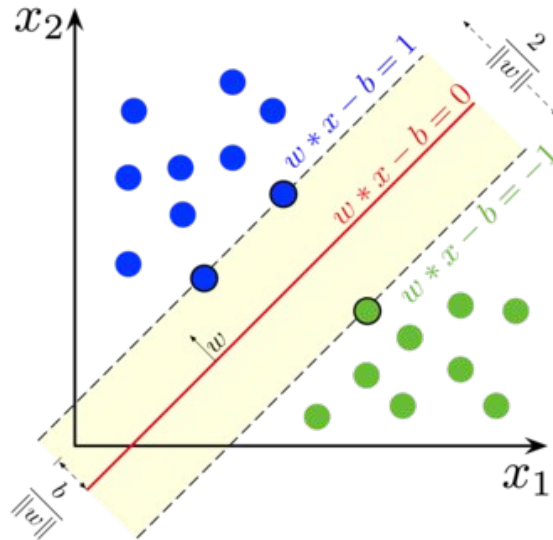
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- Precision: $TP / (TP + FP)$; measures how “precise” the model is with predicting the positive class
- Recall: $TP / (TP + FN)$; measures how many truly positive samples a model can recall
- F1 score: $2 / (1 / \text{precision} + 1 / \text{recall})$; demands a balance between precision and recall, if either one of them is low then the F1 score will also be low
- All 4 of these metrics output a real number from 0 to 1

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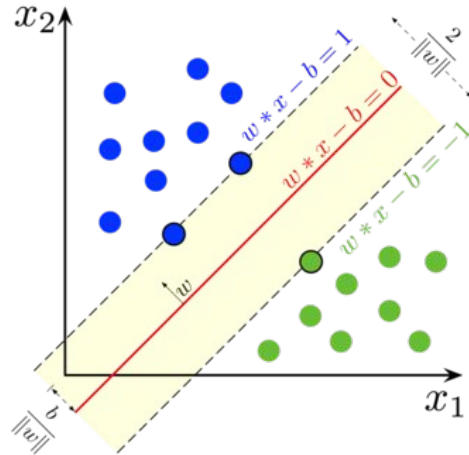


Image source: https://en.wikipedia.org/wiki/Support_vector_machine#/media/File:SVM_margin.png

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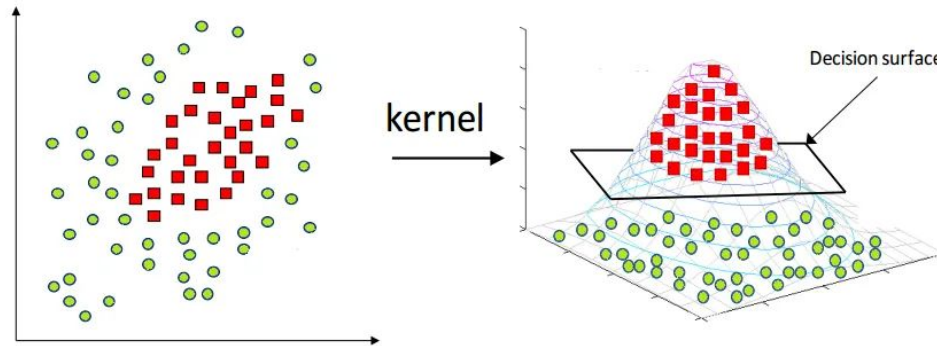
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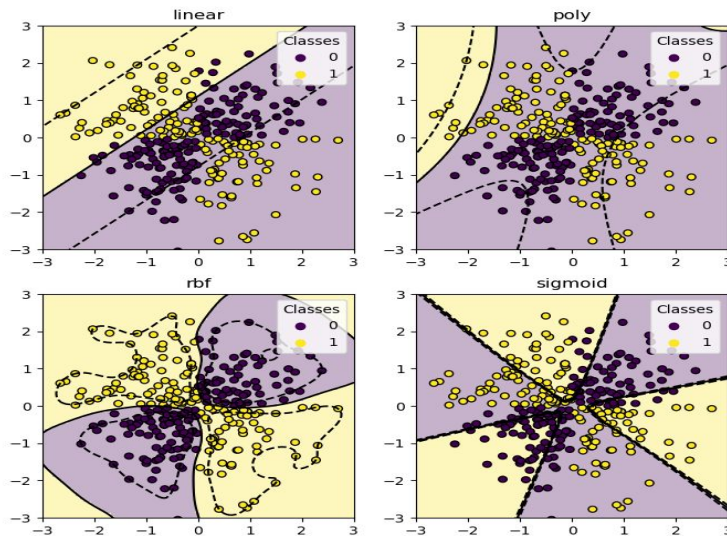
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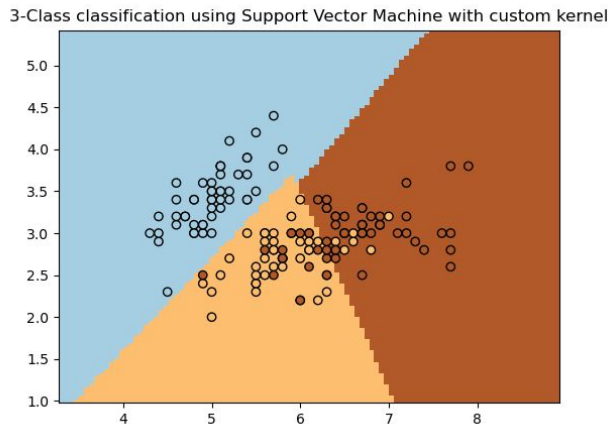


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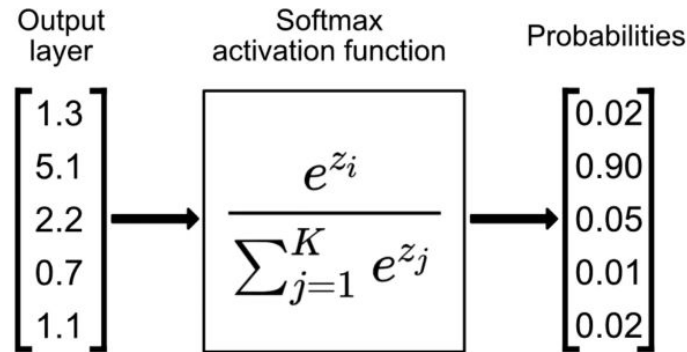
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