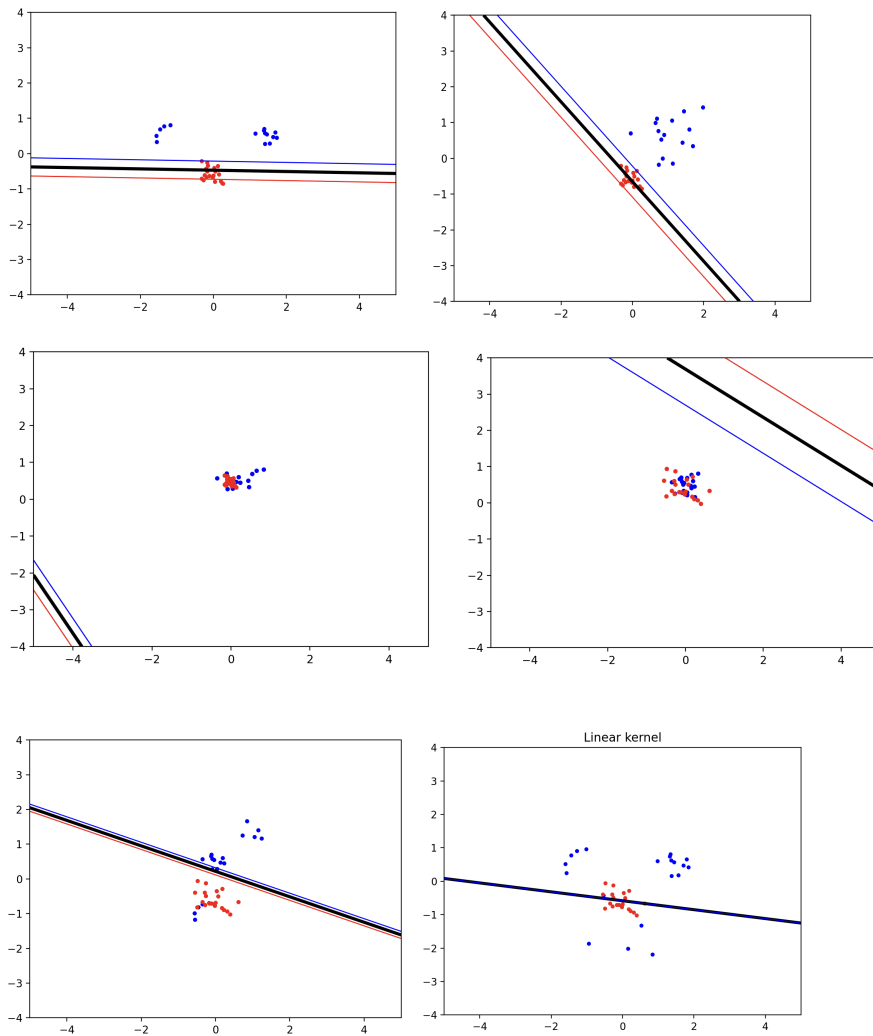


Lab-2

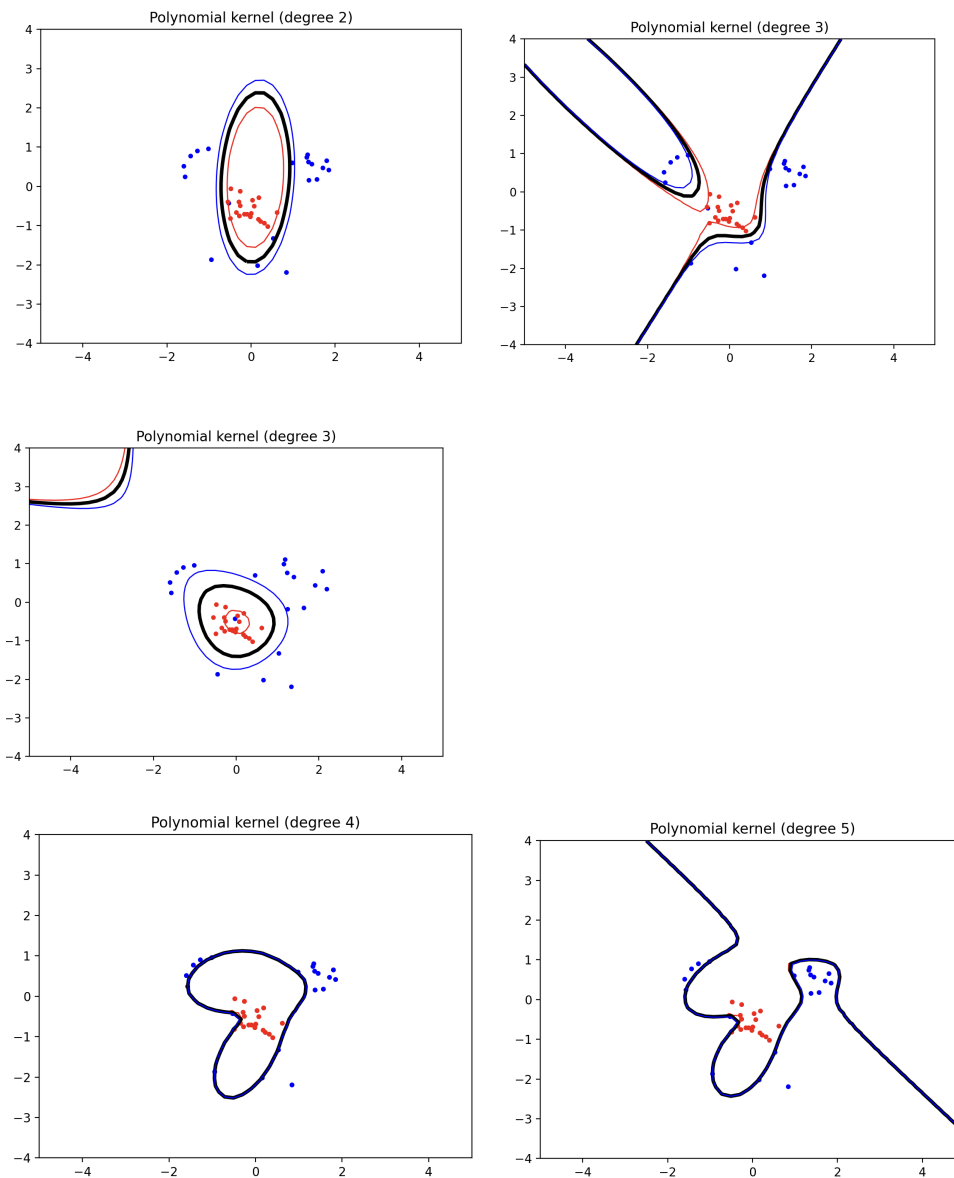
1. Move the clusters around and change their sizes to make it easier or harder for the classifier to find a decent boundary. Pay attention to when the optimizer (minimize function) is not able to find a solution at all.



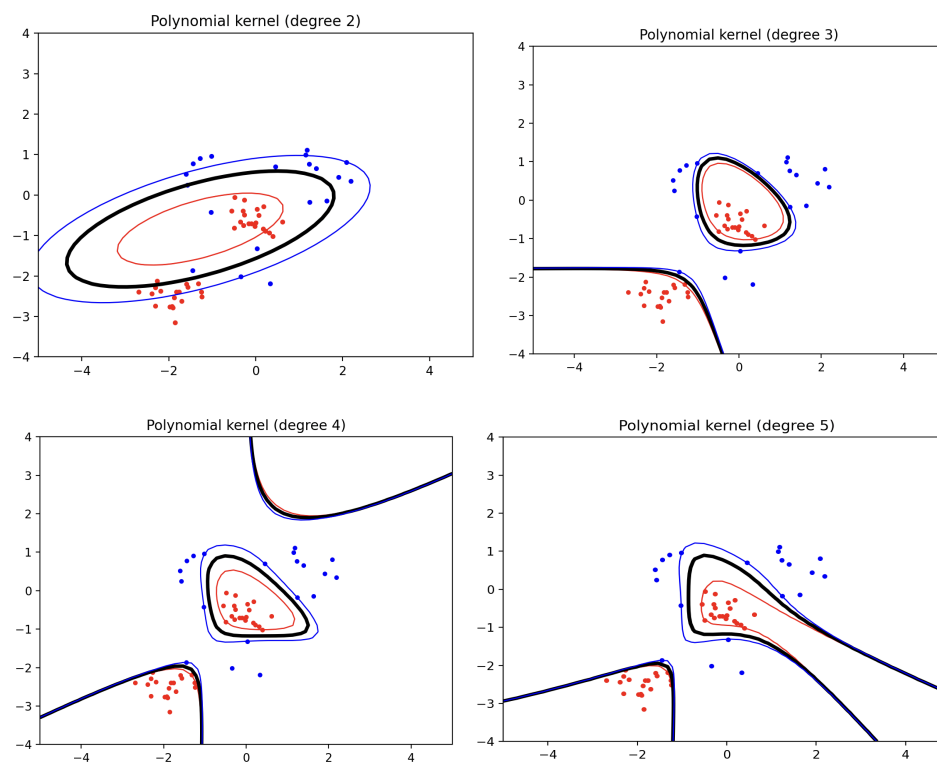
3. The non-linear kernels have parameters; explore how they influence the decision boundary. Reason about this in terms of the bias-variance trade-off.

- Bias can be seen higher with simple models (eg. a linear model for non-linear data), which can give us errors regardless the data used.
- High variance can occur when using more complex models relative to the true patterns in the data. (e.g., using a high-degree polynomial kernel on data that is linearly separable).

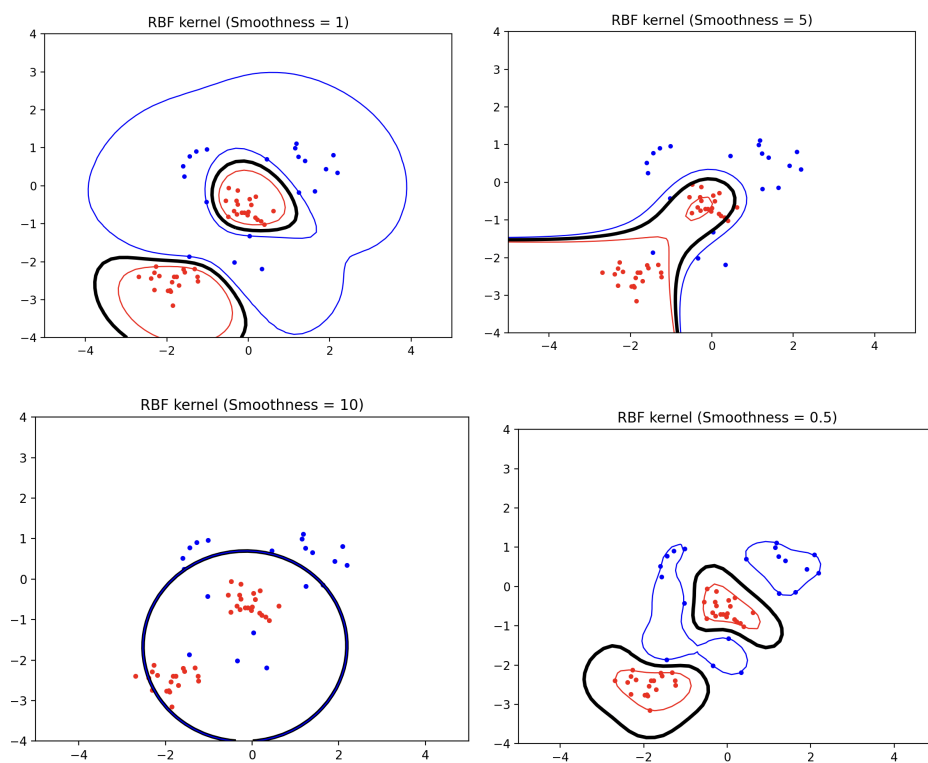
Polynomial kernel:



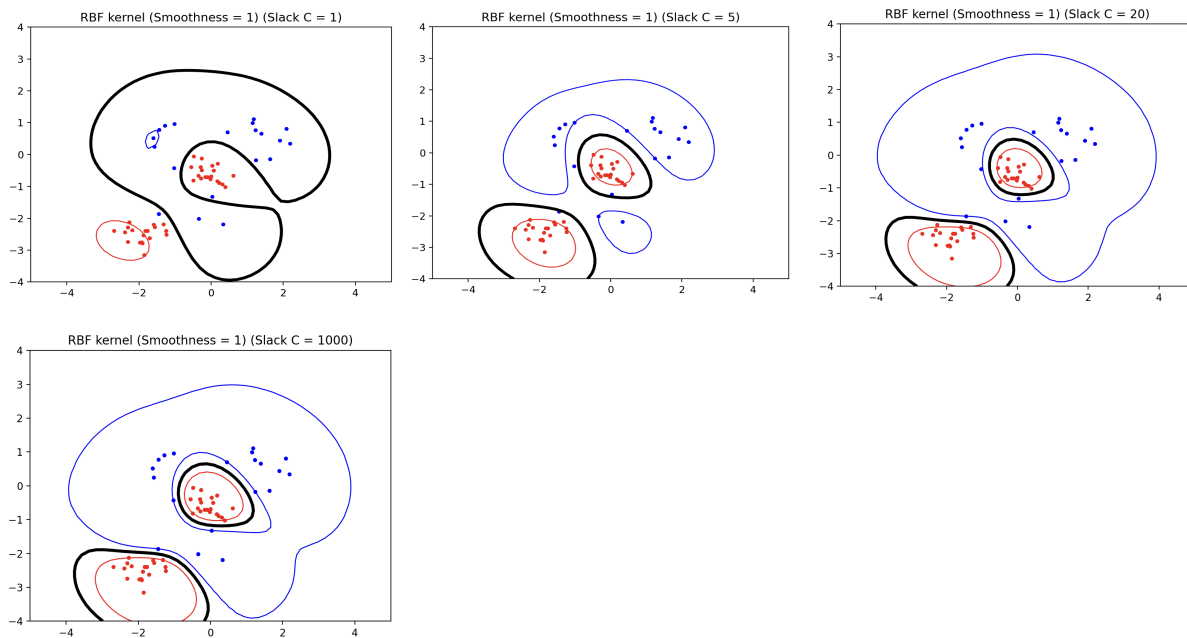
Different Dataset for polynomial



RBF kernel:



4. Explore the role of the slack parameter C. What happens for very large/small values?



5. Imagine that you are given data that is not easily separable. When should you opt for more slack rather than going for a more complex model (kernel) and vice versa?

- **More slack:**

- When we have noisy data. A more complex model would be more likely to learn on the noise
- If our current model is underfitting, adding more slack could help it fit better if we're not too concerned about some data points possibly being misclassified.
- If we wanna keep using a less complex model (e.g. due to computation efficiency) adding more slack to fit better could be an acceptable compromise.

- **More complex kernel:**

- If the data shows complex yet clear patterns, and we're certain it isn't too noisy, a complex kernel might be able to capture this pattern effectively.
- If we have a linear kernel and non-linearly separable data, adding more slack won't help so a more complex kernel is needed.