

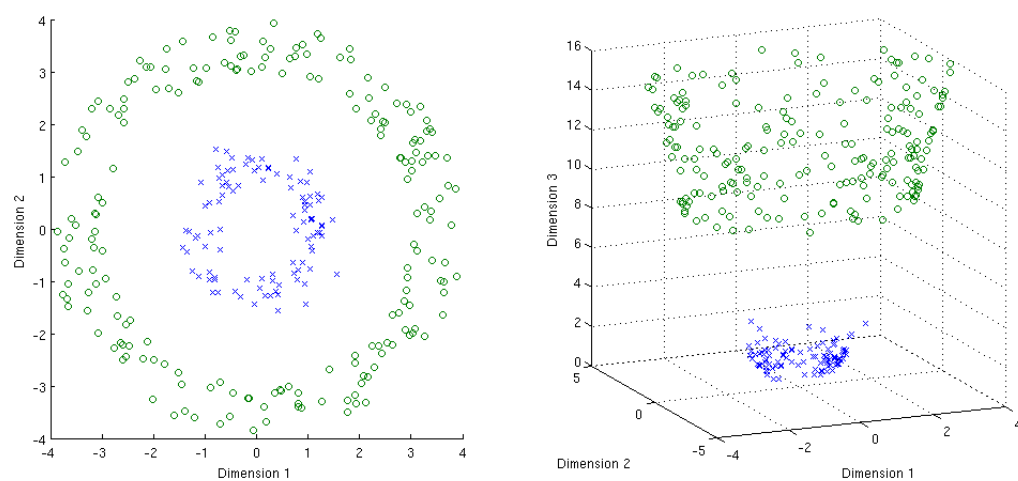
## 4. Kernels-II

In this question, we will practice some specific kernel methods.

### 4. (a)

2/2 points (graded)

In the figure below, a set of points in 2-D is shown on the left. On the right, the same points are shown mapped to a 3-D space via some transform  $\phi(x)$ , where  $x$  denotes a point in the 2-D space. Notice that  $\phi(x)_1 = x_1$  and  $\phi(x)_2 = x_2$ , or in other words, the first and second coordinates are unchanged by the transformation.



Which of the following functions could have been used to compute the value of the 3rd coordinate,  $\phi(x)_3$  for each point?

☐  $\phi(x)_3 = x_1 + x_2$

☒  $\phi(x)_3 = x_1^2 + x_2^2$  ✓

☐  $\phi(x)_3 = x_1 x_2$

☐  $\phi(x)_3 = x_1^2 - x_2^2$

Think about how a linear decision boundary in the 3 dimensional space ( $\{\phi \in \mathbb{R}^3 : \theta \cdot \phi + \theta_0 = 0\}$ ) might appear in the original 2 dimensional space.

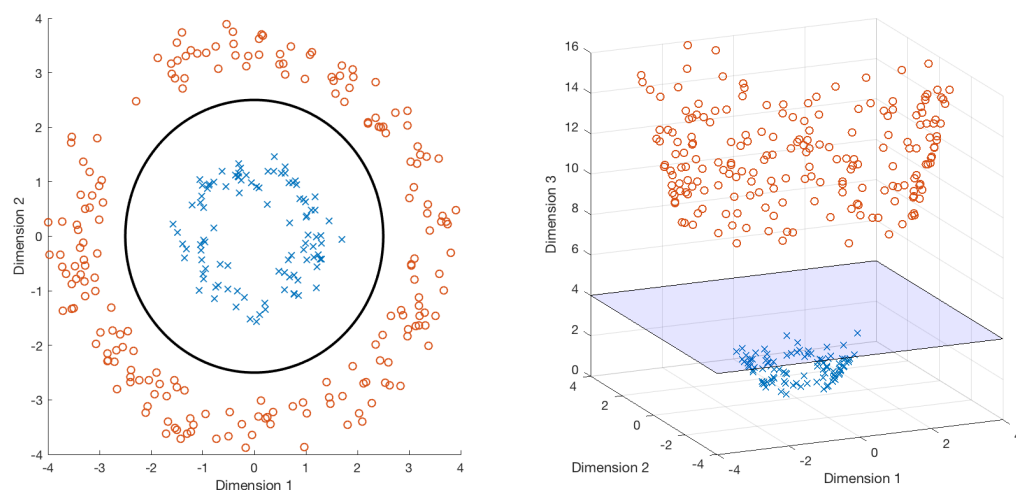
For example, suppose the decision boundary in the 3 dimensional space is  $z = 4$ .

Provide an equation  $f(x_1, x_2) = 0$  in the 2 dimensional space such that all the points  $(x_1, x_2)$  with  $f(x_1, x_2) > 0$  correspond to  $z > 4$  in the 3 dimensional space.

$f(x_1, x_2) = 0 =$   ✓ Answer:  $x_1^2 + x_2^2 - 4$

**Solution:**

- With  $x = [x_1; x_2]$ , one mapping which could satisfy the mapping is  $\phi(x)_3 = x_1^2 + x_2^2$ . The decision boundary is shown below.
- As a result, the decision boundary at  $z = 4$  corresponds to  $x_1^2 + x_2^2 = 4$



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You have used 1 of 3 attempts

**i** Answers are displayed within the problem

4. (b)

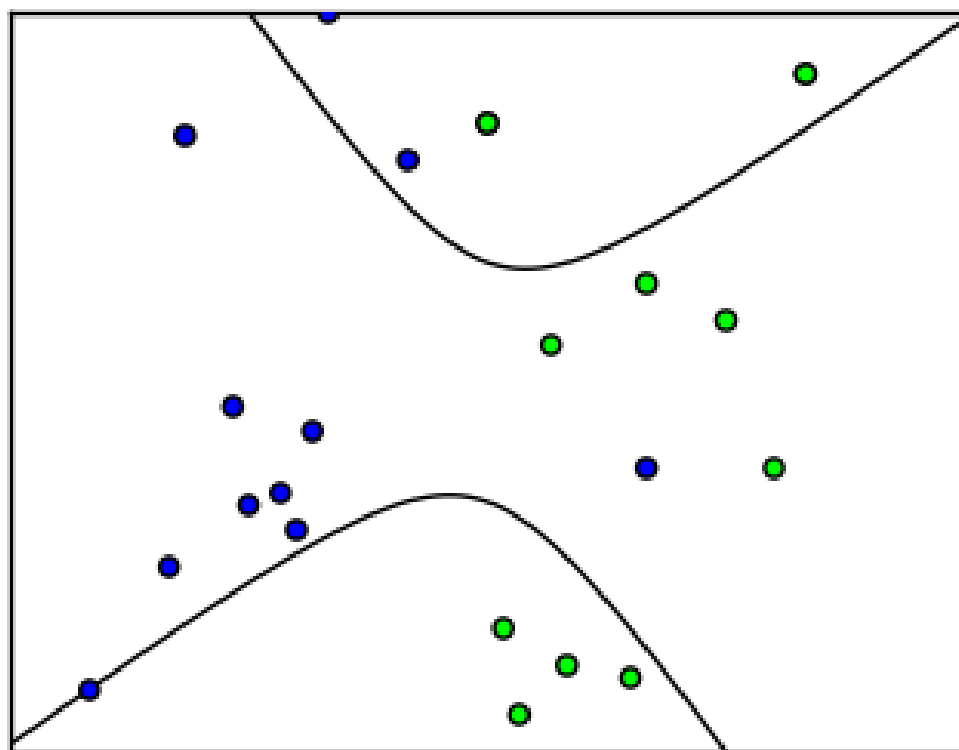
5/5 points (graded)

Consider fitting a kernelized SVM to a dataset  $(x^{(i)}, y^{(i)})$  where  $x^{(i)} \in \mathbb{R}^2$  and  $y^{(i)} \in \{1, -1\}$  for all  $i = 1, \dots, n$ . To fit the parameters of this model, one computes  $\theta$  and  $\theta_0$  to minimize the following objective:

$$L(\theta, \theta_0) = \frac{1}{n} \sum_{i=1}^n \text{Loss}_h \left( y^{(i)} \left( \theta \cdot \phi(x^{(i)}) + \theta_0 \right) \right) + \frac{\lambda}{2} \|\theta\|^2$$

where  $\phi$  is the feature vector associated with the kernel function. Note that, in a kernel method, the optimization problem for training would be typically expressed solely in terms of the kernel function  $K(x, x')$  (dual) rather than using the associated feature vectors  $\phi(x)$  (primal). We use the primal only to highlight the classification problem solved.

The plots below show 4 different kernelized SVM models estimated from the same 11 data points. We used a different kernel to obtain each plot but got confused about which plot corresponds to which kernel. Help us out by assigning each plot to one of the following models: linear kernel, quadratic kernel, order 3 kernel, and RBF kernel.



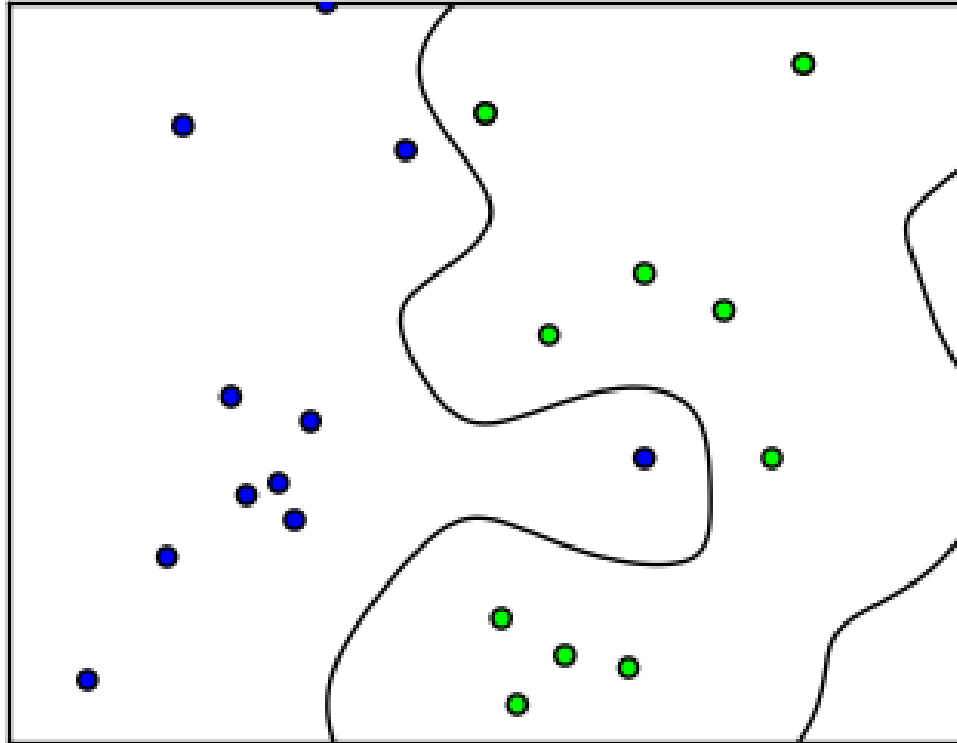
Which kernel is used in the above model?

☐ linear kernel

☒ quadratic kernel ✓

☐ order 3 kernel

☐ RBF kernel



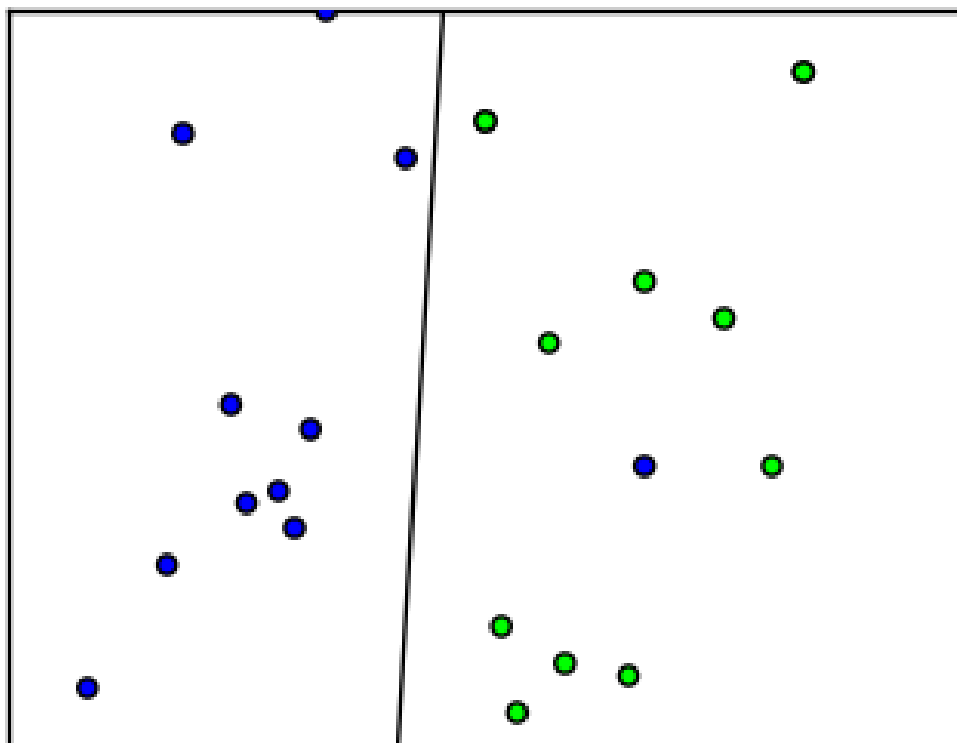
Which kernel is used in the above model?

☐ linear kernel

☐ quadratic kernel

☐ order 3 kernel

☒ RBF kernel ✓



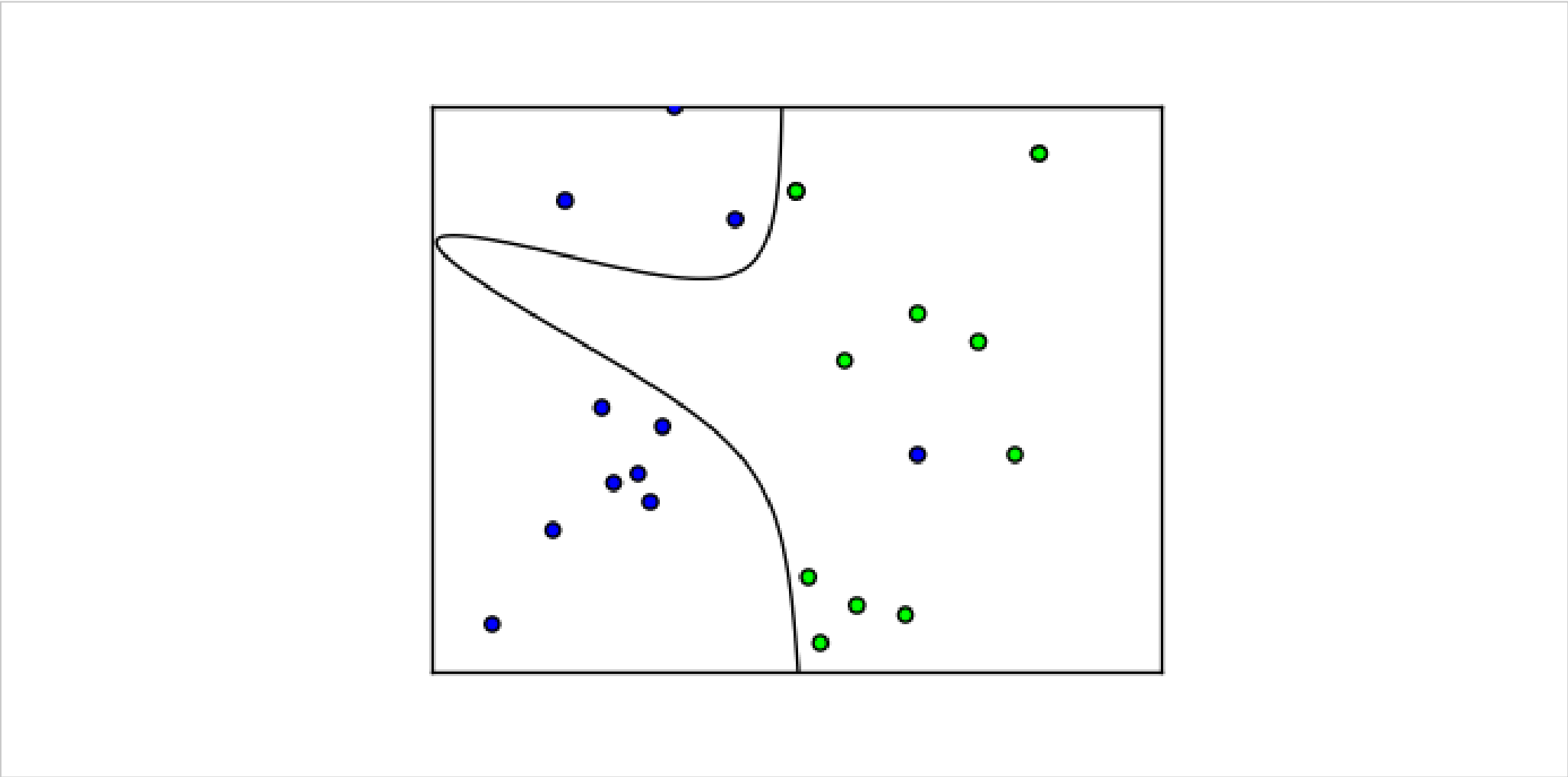
Which kernel is used in the above model?

☒ linear kernel ✓

☐ quadratic kernel

☐ order 3 kernel

☐ RBF kernel



Which kernel is used in the above model?

☐ linear kernel

☐ quadratic kernel

☒ order 3 kernel ✓

☐ RBF kernel

How would you describe qualitatively how the resulting classifiers vary with the value of  $\lambda$ ? If the value of  $\lambda$  is increased, the fitting of model would be

☐ better fit on training data (sharper decision boundary)

☒ worse fit on training data (flatter decision boundary) ✓


**Solution:**

- From examining the number of bends in the decision boundaries:
- 3rd plot corresponds to the linear kernel.
- 1st plot corresponds to the quadratic kernel.

- 4th plot corresponds to the 3rd-order kernel.
- 2nd plot corresponds to the Gaussian RBF kernel.
- Large  $\lambda$  penalty on  $\theta$  results in flatter/ less “squiggly” lines.

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You have used 2 of 2 attempts

 Answers are displayed within the problem

## Discussion

Show Discussion

**Topic:** Unit 2 Nonlinear Classification, Linear regression, Collaborative Filtering (2 weeks):Homework 3 / 4. Kernels-II