```
# First Task :
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 3
    from sklearn.preprocessing import PolynomialFeatures
 4
    import matplotlib.pyplot as plottt
    from sklearn.linear model import LinearRegression
    import numpy as numpie
    from sklearn.metrics import mean squared error
 9
    # A Function to Generate Data
10
    def toydata generate(f, sizeofthesample, varation of the noise):
11
        x = numpie.linspace(0, 1, sizeofthesample)
12
13
        t = f(x) + numpie.random.normal(scale=varation of the noise, size=x.shape)
14
        return x, t
15
16
    def f(x):
17
        return numpie.sin(2 * numpie.pi * x)
18
    # 1. Produce 100 points for testing and 10 points for training.
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20
    train for x, train for y = toydata generate(f, 10, 0.25)
    test_for_x = numpie.linspace(0, 1, 100)
    test for y = f(test for x)
23
    #2. Use the polynomial basis function (order M=9) in step two.
24
    poly features = PolynomialFeatures(degree=9)
    Train_Phi_Feat = poly_features.fit_transform(train_for_x[:, numpie.newaxis])
    Test Phi Feat = poly features.transform(test for x[:, numpie.newaxis])
27
28
29
    # 3. The model should be trained parametrically and the test MSE should be reported
    lr = LinearRegression(fit_intercept=False)
31 lr.fit(Train Phi Feat, train for y)
32 Pred for y = lr.predict(Test Phi Feat)
    Mean Sqre Err = mean_squared_error(test_for_y, Pred_for_y)
    print("In a parametric test, the mean square error is as follows:", Mean Sqre Err)
35
    # 4.Predict non-parametrically
36
    K = Train_Phi_Feat @ Train_Phi_Feat.T
    k = Test Phi Feat @ Train Phi Feat.T
    non paramertic Pred for y= k @ numpie.linalg.inv(K) @train for y
    non_param_mean_square error = mean_squared_error(test_for_y,non_paramertic_Pred_for_y)
40
     print("Non-parametric test MSE:", non param mean sqaure error)
41
42
43
    # 5. Compare the predictions
    print("What is the similarity between the predictions?", numpie.allclose(Pred_for_y,non_paramertic_Pred_for_y))
    print("Hence they were not similar")
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    # Second Task:
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     from sklearn.metrics.pairwise import rbf kernel
52
     import numpy as numpie
53
     from sklearn.metrics import mean_squared_error
 54
55
     import matplotlib.pyplot as plottt
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57
     #1. Using the RBF kernel, define the gram matrix
     gamma = 5
58
59
     K = rbf \ kernel(X=train \ for \ x[:, numpie.newaxis], Y=train \ for \ x[:, numpie.newaxis], gamma=gamma)
60
     # Setting Up Beta = 10 for the covariance matrix
61
     beta = 10
62
     C = K + numpie.eye(len(K)) / beta
63
64
     #2. The invertibility of C should be checked
65
66
     try:
         C inv = numpie.linalg.inv(C)
67
         print("The value of C can be inverted.")
68
     except numpie.linalg.LinAlgError:
69
70
         print("The value of C cannot be inverted.")
71
72
     #3. All test samples should be calculated to determine the predictive mean
     Test k = rbf kernel(X=test for x[:, numpie.newaxis], Y=train for x[:, numpie.newaxis], gamma=gamma)
     Gauusian_Prediction_Pred_for_y = Test_k @ C_inv @train_for_y
74
75
     # Test MSE
76
77
     Gaussain Process Mean Sqre err = mean squared error(test for y, Gauusian Prediction Pred for y)
     print("The Gaussian Process (MSE) should be tested as follows:", Gaussain Process Mean Sgre err)
     # ```
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80
     # Third Task :
     from sklearn.datasets import load_iris
     from sklearn.model selection import train test split
     from sklearn.svm import SVC
     from sklearn.metrics import accuracy score
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87
     #Separate Datasets of training and Testing from the iris dataset and load them up
     iris = load_iris()
88
     Train for X, Test_for_X,train_for_y, test_for_y = train_test_split(iris.data, iris.target, test_size=0.3, random_state=5)
89
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91
     # SVC model creation and training
     model svc = SVC()
     model_svc.fit(Train_for_X,train_for_y)
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94
     # 2.1:Multi-class classification is handled by SVC by default using a one-versus-one approach
     print("To classify multi-classes, SVC uses a one-to-one approach.")
96
97
     # 2.2: Number of SVM's or the support vectors
     print("No of SVM's or Support vectors :", len(model svc.support ))
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100
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     # 2.3: Identifying that the support vector is in the 18th training sample
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     Is_Supprt_vectr = 18 in model_svc.support_
     print("Did a support vector can be found in the 18th training sample?", Is_Supprt_vectr)
106
107
108
     # 2.4: Counting No Of SVM"S from Class 2
     Class_2_n_Support_Vectors = model_svc.n_support_[2]
     print("The no of Support Vector's class 2 from are :", Class 2 n Support Vectors)
110
111
112
     # 3: Calculate the accuracy of the classification test
113
     Pred for y = model svc.predict(Test for X)
     test_accuracy = accuracy_score(test_for_y, Pred_for_y)
114
     print("Calculation of the accuracy of the classification test is that :", test accuracy)
116
117
118
     # I have completed the third task. SVM model classification test accuracy is reported by checking whether the 18th training sample is a support vector, calcul
119
120
 □→ In a parametric test, the mean square error is as follows: 0.25065378940033745
     Non-parametric test MSE: 0.25071794129118596
     What is the similarity between the predictions? False
     Hence they were not similar
     The value of C can be inverted.
     The Gaussian Process (MSE) should be tested as follows: 0.05006472466361181
     To classify multi-classes, SVC uses a one-to-one approach.
     No of SVM's or Support vectors : 50
     Did a support vector can be found in the 18th training sample? True
     The no of Support Vector's class 2 from are : 21
     1
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✓ 0s completed at 22:01

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