```
In [1]: #PART-1
In [2]:
        #train data whole
        import numpy as np
        x = np.array([-1, -0.9, -0.8, -0.7, -0.6, -0.5, -0.4, -0.3, -0.2, -0.
        1, 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1
        t = np.array([5.12, 4.97, 4.92, 4.83, 4.90, 5.06, 5.29, 5.34, 5.36, 5.
        76, 5.99, 6.30, 6.66, 6.70, 7.49, 7.92, 8.48, 9.09, 9.70, 10.30, 10.9
        81)
In [3]:
        train set x = np.array((x[::3], x[1::3], x[2::3]))
        train set t = np.array((t[::3], t[1::3], t[2::3]))
        print(train_set_x)
        [[-1. -0.7 -0.4 -0.1 0.2 0.5 0.8]
         [-0.9 -0.6 -0.3 0.
                               0.3 0.6 0.91
         [-0.8 -0.5 -0.2 0.1 0.4 0.7 1.]]
In [4]: #defining the basis function
        # def guassian basis(x,mean,var):
              return np.exp((abs(x-mean)**2)/(2*var))
        # #mean
        # def mean(numbers):
              return float(sum(numbers))/max(len(numbers),1)
In [5]:
        #basis
        # mean 1 = mean(train set x[0])
        \# var = np.var(train set x[0])
        # basis 1 = [guassian basis(x, mean 1, var) for x in train set x[0]]
        \# mean 2 = mean(train set x[1])
        \# var = np.var(train set x[1])
        # basis 2 = [guassian \ basis(x,mean \ 2,var) \ for x in train_set_x[1]]
        \# mean 3 = mean(train set x[2])
        \# var = np.var(train set x[2])
        # basis 3 = [guassian basis(x, mean 3, var) for x in train set x[2]]
        def basis 1(count):
            return np.ones(count)
        def basis 2(train set):
            return [np.exp(-((x-0.5)**2/0.1)) for x in train_set]
        def basis 3(train set):
            return [np.exp(-((x+0.5)**2/0.1)) for x in train set]
        basis = np.array((basis 1(len(train set x[0])),basis 2(train set x[0]
In [6]:
```

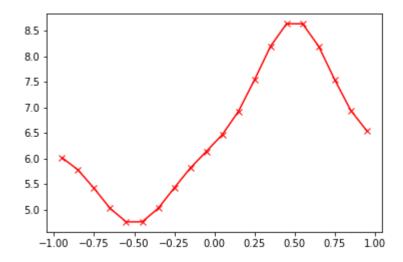
]),basis 3(train set x[0]))

```
In [7]:
        #calculate w
        from numpy.linalg import inv
        def calculate w(basis, reg parameter, train set t):
             return np.matmul(np.matmul(inv(np.add(np.matmul(basis,basis.trans
        pose()),reg parameter*np.identity(3))),basis), train set t)
In [8]: #1. Formulate matrix using training data 1
        #2. Solve for [w1, w2, w3] using lambda = 0
        regularization parameter = 0
        w = calculate w(basis, regularization parameter, train set t[0])
        print(w)
        [ 6.21319522  2.48369193  -1.49159905]
In [9]: #3.plot graphs :)
        #x train1 vs t train1
        import matplotlib.pyplot as plt
        N = len(train_set_x[0])
        colors = np.random.rand(N)
        area = np.pi * 4**2
        plt.scatter(train_set_x[0],train_set_t[0],s=area,c = colors, alpha =
        0.8)
        plt.show()
        #x train1 vs phiT*xTrain1 * w
        y = np.matmul(basis.transpose(), w)
        plt.plot(train set x[0], y, 'xb-')
        plt.show()
        <Figure size 640x480 with 1 Axes>
```

<Figure size 640x480 with 1 Axes>

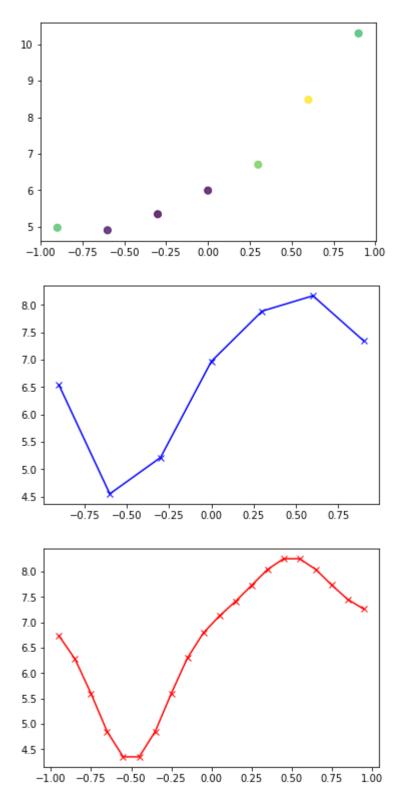
```
In [10]: #plot x_out vs phiT * x_out * w
    x_out = np.array([-0.95, -0.85, -0.75, -0.65, -0.55, -0.45, -0.35, -
    0.25, -0.15, -0.05, 0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75,
    0.85, 0.95 ])
    basis = np.array((basis_1(len(x_out)), basis_2(x_out), basis_3(x_out)))
    y = np.matmul(basis.transpose(), w)
    plt.plot(x_out, y , 'xr-')
```

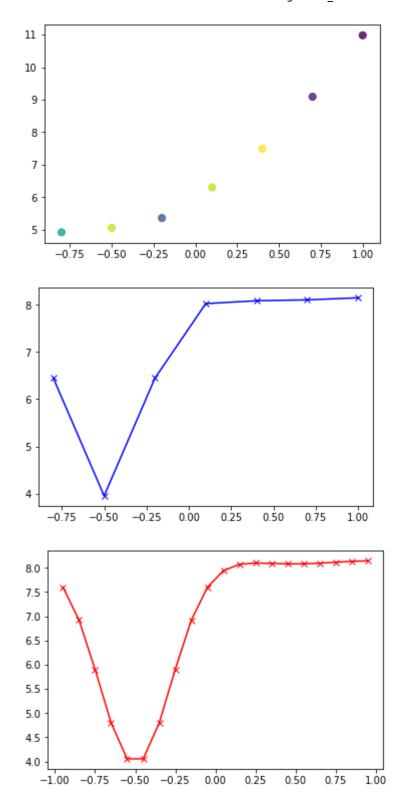
Out[10]: [<matplotlib.lines.Line2D at 0x7f332980dac8>]



```
In [11]:
         def train(train set x, train set t, regularization parameter):
             basis = np.array((basis 1(len(train set x)),basis 2(train set x),
         basis 3(train set x)))
             w = calculate w(basis, regularization parameter, train set t)
             N = len(train set x)
             colors = np.random.rand(N)
             area = np.pi * 4**2
             plt.scatter(train_set_x,train_set_t,s=area,c = colors, alpha = 0.
         8)
             plt.show()
             #x train1 vs phiT*xTrain1 * w
             y = np.matmul(basis.transpose(), w)
             plt.plot(train_set_x, y, 'xb-')
             plt.show()
             basis = np.array((basis 1(len(x out)), basis 2(x out), basis 3(x out))
         out)))
             y = np.matmul(basis.transpose(), w)
             plt.plot(x out, y , 'xr-')
             plt.show()
```

```
In [12]: #4. calculate for train_2 and train_3
    train(train_set_x[1], train_set_t[1], 0)
    train(train_set_x[2], train_set_t[2], 0)
```





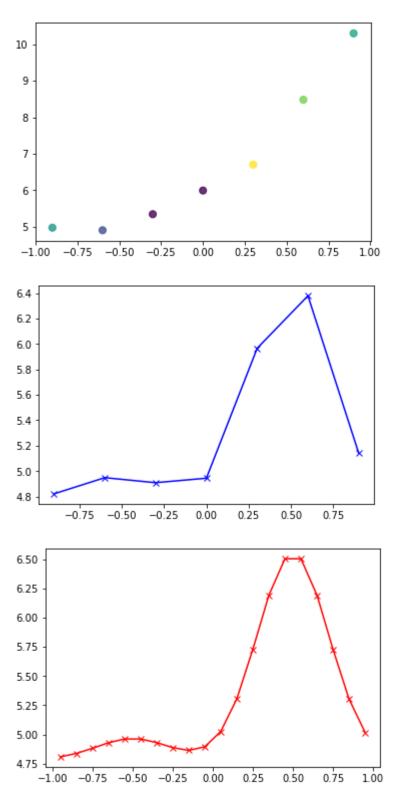
```
In [13]:
         #var and bias
          x \text{ true} = [5, 4.92, 4.88, 4.88, 4.92, 5.00, 5.12, 5.28, 5.48, 5.72, 6.0]
          0, 6.32, 6.68, 7.08, 7.52, 8.00, 8.52, 9.08, 9.68, 10.32, 11.00]
          true set x = np.array((x true[::3], x true[1::3], x true[2::3]))
          def train y(train set x, train set t, regularization parameter):
              basis = np.array((basis 1(len(train set x)),basis_2(train_set_x),
          basis 3(train set x)))
              w = calculate w(basis, regularization parameter, train set t)
              return np.matmul(basis.transpose(), w)
          def bias(regularization parameter):
              avg prediction bias = (1/3) * (np.add(np.add(train y(train set x[
          0], train set t[0], regularization parameter), train y(train \text{ set } x[1
          ], train set t[1], 0)), train_y(train_set_x[2], train_set_t[2], regul
          arization parameter)))
              return (1/len(true set x[0])) * (np.sum(np.square(np.subtract(avg
          prediction bias, true set x[0])))
          def var(regularization parameter):
              avg prediction bias = (1/3) * (np.add(np.add(train y(train set x[
          0], train set t[0], regularization parameter), train y(train set x[1
          ], train set t[1], 0)), train y(train set x[2], train set t[2], regul
          arization parameter)))
              return (1/\text{len}(\text{true set } x[0])) * (\text{np.sum}((1/3)) * (\text{np.add}(\text{np.square}))) * (\text{np.add}(\text{np.square}))
          (np.subtract(train y(train set x[0], train set t[0], regularization p
          arameter),avg_prediction_bias)), np.add(np.square(np.subtract(train_y
          (train set x[1], train set t[1], regularization parameter), avg predic
          tion bias)), np.square(np.subtract(train y(train set x[2], train set
          t[2], regularization parameter), avg prediction bias)))))))
          print(bias(0))
          print(var(0))
```

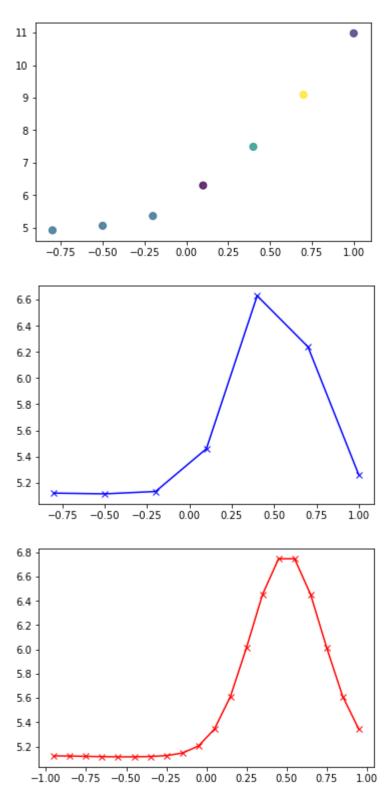
- 1.336553192697737
- 0.2623341191100613

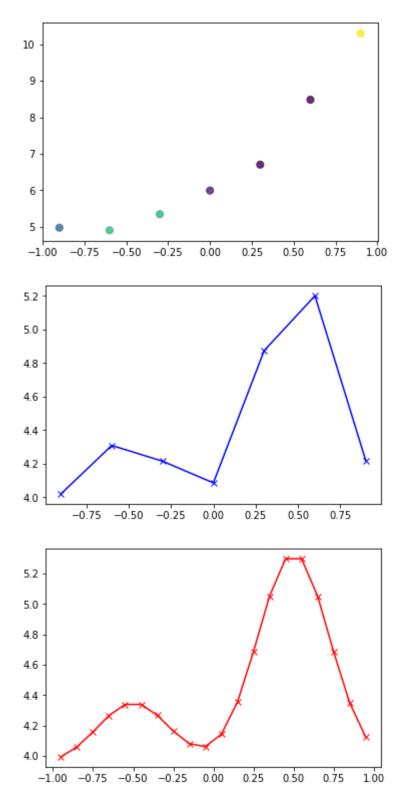
```
In [14]: #7. plot lambda vs var & bias2
lamb = np.array([0])
variance = np.array([var(0)])
bias2 = np.array([bias(0)])

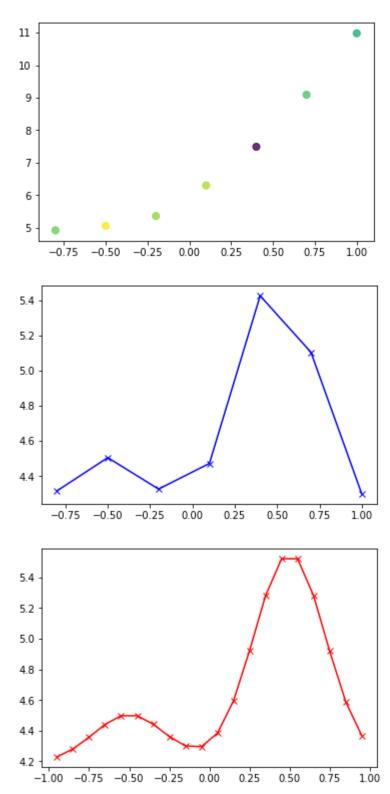
for i in [2, 4, 5, 6, 10]:
    train(train_set_x[1], train_set_t[1], i)
    train(train_set_x[2], train_set_t[2], i)
    lamb = np.append(lamb, i)
    variance = np.append(variance, var(i))
    bias2 = np.append(bias2, bias(i))

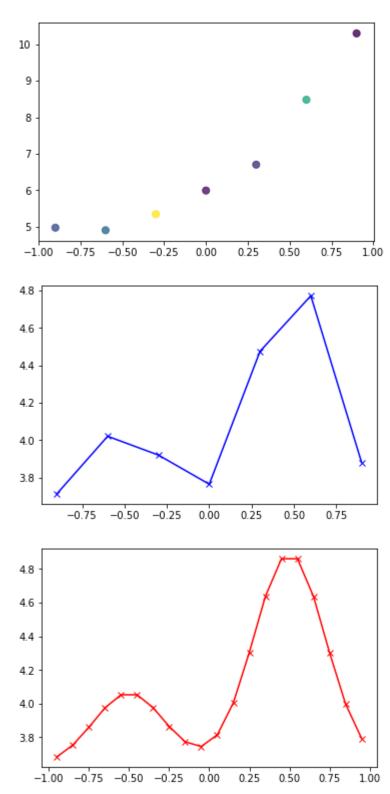
plt.plot(lamb, variance, 'xb-')
plt.plot(lamb, bias2 , 'xr-')
plt.show()
```

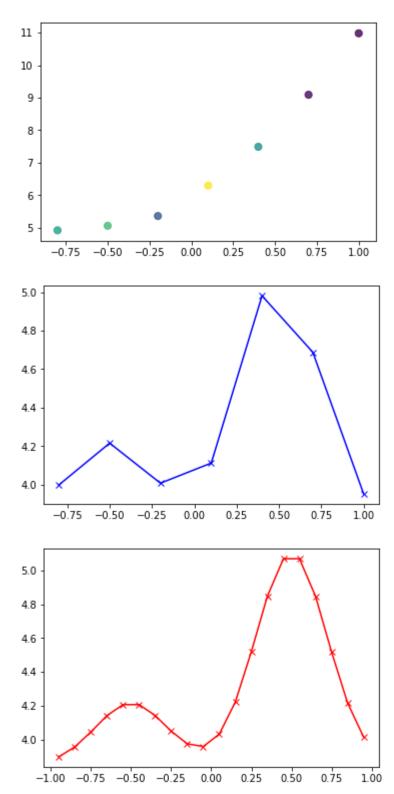




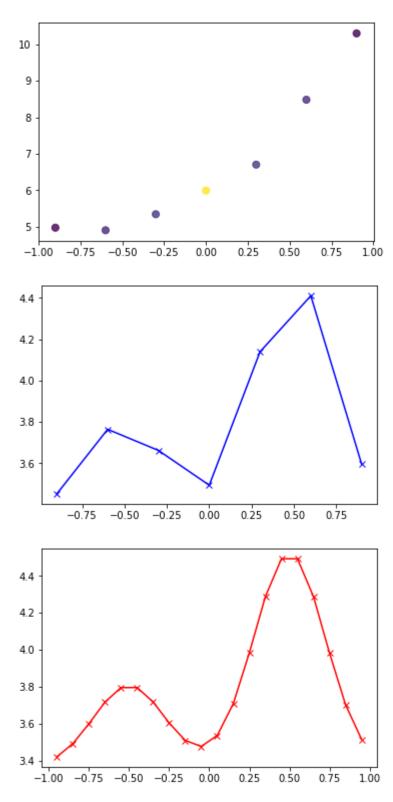


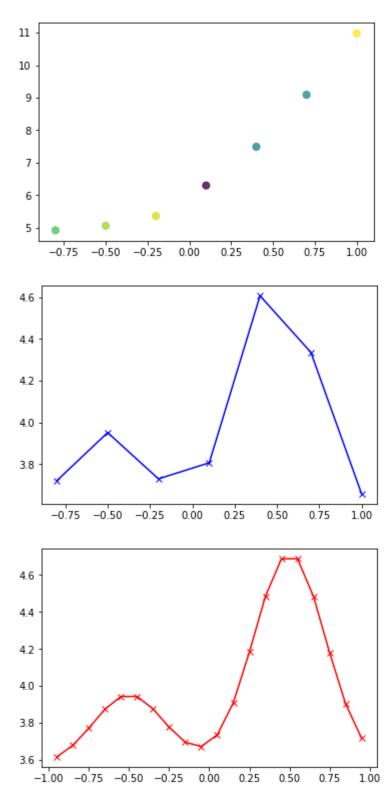


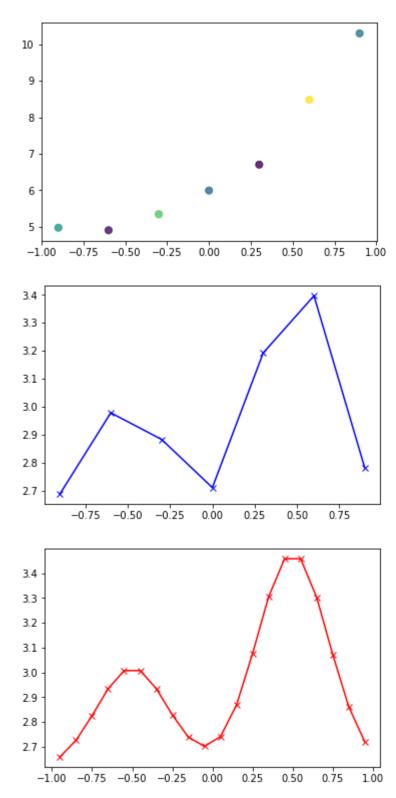


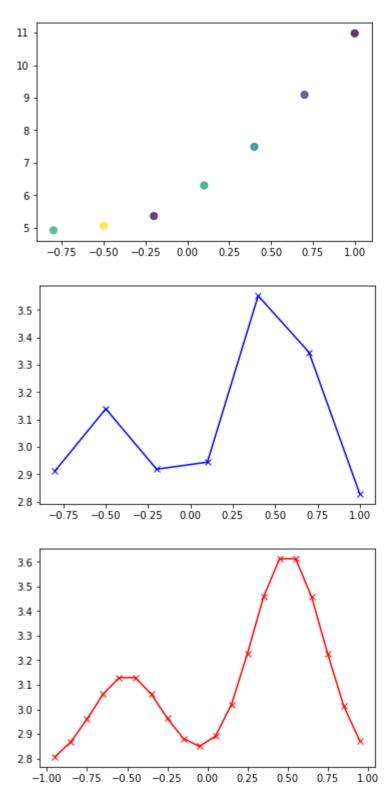


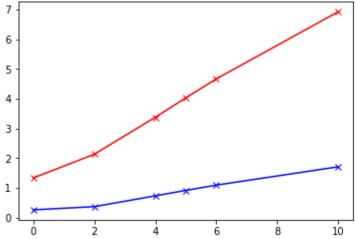
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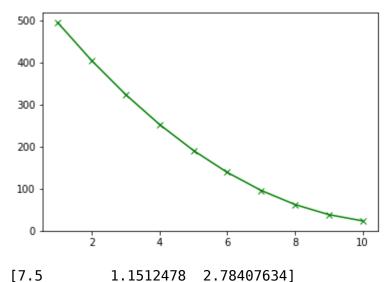




```
In [15]:
         # PART-2
In [16]:
         def error(i, w, basis):
             value = t[i] - basis[0]*w[0] - basis[1]*w[1] - basis[2]*w[2]
             return value
         def update(i, learning_rate, w):
             basis = np.array((1, basis_2i(i), basis_3i(i)))
             learning_const = error(i, w, basis) * learning_rate
              result = np.add(w, np.multiply(learning rate,basis))
             return result
         def sse error(y,t):
             return (t-y)**2
         def basis 2i(i):
              return np.exp(-((x[i]-0.5)**2/0.1))
         def basis_3i(i):
             return np.exp(-((x[i]+0.5)**2/0.1))
In [17]:
         def epoch(learning_rate, w):
             for i in range (15):
                 w = update(i, learning_rate, w)
             return w
         def find_sse(w):
             basis = np.array((basis 1(7), basis 2(x[14:21]), basis 3(x[14:21])
         1)))
             y = np.matmul(w,basis)
              return np.sum([sse error(y[i], t[i+14]) for i in range(7)])
```

```
In [18]: # 1. Initialize w
   w = np.zeros(3)
   sse = np.array([])
   epoch_x = np.array([])
   learning_rate = 0.05
   for i in range(10):
        w = epoch(learning_rate, w)
        sse = np.append(sse, find_sse(w))
        epoch_x = np.append(epoch_x,i + 1)

   plt.plot(epoch_x, sse , 'xg-')
   plt.show()
   print(w)
```



In [19]: # PART-3 Kernel trick

```
In [20]: X1 = np.array([-1, -0.7, -0.4, -0.1, 0.2, 0.5, 0.8])
         V1 = np.array([ -0.9, -0.6, -0.3, 0, 0.3, 0.6, 0.9 ])
         T1 = np.array([-0.8, -0.5, -0.2, 0.1, 0.4, 0.7, 1])
         X0 = np.array([5.12, 4.83, 5.29, 5.76, 6.66, 7.92, 9.70])
         V0 = np.array([4.97, 4.90, 5.34, 5.99, 6.70, 8.48, 10.30])
         T0 = np.array([4.92, 5.06, 5.36, 6.30, 7.49, 9.09, 10.98])
         def kernel(x1, x2, sig):
             return np.exp(-((x1-x2)**2)/(2*sig))
         sig = 0.1
         sse = np.array([])
         while sig != 0.6:
             V0 \text{ est} = np.array([])
             for j in range(7):
                 M = np.array([kernel(X1[i], V1[j], sig) for i in range(7)])
                 print(M)
                 sum M = np.sum(M)
                 Norm M = (1/sum M) * M
                 V0_est = np.append(V0_est, np.matmul(Norm_M.transpose(), X0))
             V0 diff = np.subtract(V0, V0 est)
             sse = np.append(sse, np.matmul(V0 diff.transpose(), V0 diff))
             sig += 0.1
```

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```
[9.51229425e-01 8.18730753e-01 2.86504797e-01 4.07622040e-02
2.35786201e-03 5.54515994e-05 5.30206120e-071
[4.49328964e-01 9.51229425e-01 8.18730753e-01 2.86504797e-01
4.07622040e-02 2.35786201e-03 5.54515994e-051
[0.08629359 0.44932896 0.95122942 0.81873075 0.2865048 0.0407622
0.002357861
[0.00673795 0.08629359 0.44932896 0.95122942 0.81873075 0.2865048
0.0407622 1
[2.13900415e-04 6.73794700e-03 8.62935865e-02 4.49328964e-01
9.51229425e-01 8.18730753e-01 2.86504797e-01]
[2.76077257e-06 2.13900415e-04 6.73794700e-03 8.62935865e-02
4.49328964e-01 9.51229425e-01 8.18730753e-01]
[1.44872049e-08 2.76077257e-06 2.13900415e-04 6.73794700e-03
8.62935865e-02 4.49328964e-01 9.51229425e-011
[9.75309912e-01 9.04837418e-01 5.35261429e-01 2.01896518e-01
4.85578213e-02 7.44658307e-03 7.28152539e-041
[0.67032005 0.97530991 0.90483742 0.53526143 0.20189652 0.04855782
0.007446581
0.048557821
           0.2937577  0.67032005  0.97530991  0.90483742  0.53526143
[0.082085
0.201896521
[0.01462533 0.082085
                      0.2937577  0.67032005  0.97530991  0.90483742
0.535261431
[0.00166156 0.01462533 0.082085
                                 0.2937577  0.67032005  0.97530991
0.904837421
[1.20362805e-04 1.66155727e-03 1.46253347e-02 8.20849986e-02
2.93757700e-01 6.70320046e-01 9.75309912e-01]
[0.98347145 0.93550699 0.65924063 0.34415379 0.13309839 0.03813333
0.008093721
[0.76592834 0.98347145 0.93550699 0.65924063 0.34415379 0.13309839
0.038133331
[0.44190221 0.76592834 0.98347145 0.93550699 0.65924063 0.34415379
0.133098391
[0.1888756    0.44190221    0.76592834    0.98347145    0.93550699    0.65924063
0.344153791
[0.05980496 0.1888756 0.44190221 0.76592834 0.98347145 0.93550699
0.659240631
[0.01402847 0.05980496 0.1888756 0.44190221 0.76592834 0.98347145
0.935506991
[0.00243778 0.01402847 0.05980496 0.1888756 0.44190221 0.76592834
0.983471451
[0.9875778  0.95122942  0.73161563  0.44932896  0.22035839  0.08629359
0.0269843 1
[0.81873075 0.9875778 0.95122942 0.73161563 0.44932896 0.22035839
0.086293591
[0.54199419 0.81873075 0.9875778 0.95122942 0.73161563 0.44932896
0.220358391
[0.2865048  0.54199419  0.81873075  0.9875778  0.95122942  0.73161563
0.449328961
[0.12093525 0.2865048 0.54199419 0.81873075 0.9875778 0.95122942
0.731615631
[0.0407622  0.12093525  0.2865048  0.54199419  0.81873075  0.9875778
0.951229421
[0.010971
           0.0407622 0.12093525 0.2865048 0.54199419 0.81873075
0.9875778 1
[0.99004983 0.96078944 0.77880078 0.52729242 0.29819728 0.14085842
```

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```
0.055576211
         [0.85214379 0.99004983 0.96078944 0.77880078 0.52729242 0.29819728
          0.140858421
         [0.61262639 0.85214379 0.99004983 0.96078944 0.77880078 0.52729242
          0.298197281
         [0.36787944 0.61262639 0.85214379 0.99004983 0.96078944 0.77880078
          0.527292421
         [0.18451952 0.36787944 0.61262639 0.85214379 0.99004983 0.96078944
          0.778800781
         [0.07730474 0.18451952 0.36787944 0.61262639 0.85214379 0.99004983
          0.960789441
         [0.02705185 0.07730474 0.18451952 0.36787944 0.61262639 0.85214379
          0.990049831
In [21]:
         min_sse = min(sse)
         min sig = np.where(sse == min sse)
         print(min sse)
         2.245319628735499
In [22]: | T0 est = np.array([])
         for j in range(7):
             M = np.array([kernel(X1[i], V1[j], 0.1 + min sig[0]*0.1) for i in
         range(7)1)
             sum M = np.sum(M)
             Norm M = (1/sum M) * M
             T0_est = np.append(T0_est, np.matmul(Norm_M.transpose(), T1))
         print(T0)
         print(T0_est)
         [ 4.92 5.06 5.36 6.3
                                   7.49 9.09 10.98]
         [-0.58228581 - 0.37354811 - 0.0973657 0.19909468 0.48642671 0.72279]
         721
           0.870866921
In [23]: T0 diff = np.subtract(T0, T0 est)
         test sse = np.matmul(T0 diff.transpose(), T0 diff)
         print(test sse)
         348.0571730501017
In [ ]:
```