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M4-L2 Problem 3

In this problem, we will investigate kernel selection and regularization strength in support vector regression for a 1-D problem.

Run each cell below, then try out the interactive plot to answer the questions.

```
In [1]: import numpy as np
                      import matplotlib.pyplot as plt
                      from sklearn.svm import SVR
                      xs = np.array([0.094195, 0.10475, 0.12329, 0.12767, 0.1343, 0.11321, 0.16134, 0.16622, 0.15]
                      ys = np.array([0.51123, 0.50881, 0.50546, 0.50756, 0.51653, 0.50797, 0.49658, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.508990, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.508990, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.508990, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.50899, 0.508990, 0.508990, 0.508990, 0.508990, 0.508990, 0.508990, 0.508990, 0.508990, 0.508990, 0.508990, 0.508990, 0.508990, 0.508990, 0.5089
                      x \text{ gt} = np.array([0.0,0.010101,0.020202,0.030303,0.040404,0.050505,0.060606,0.070707]
                      y \text{ gt} = np.array([0.46193, 0.47566, 0.48699, 0.49609, 0.50315, 0.50836, 0.51189, 0.51393, 0.
In [2]: %matplotlib inline
                      from ipywidgets import interact, interactive, fixed, interact_manual, Layout, Float
                      def plotting_function(kernel, log_C, log_epsilon):
                                C = np.power(10.,log C)
                                epsilon = np.power(10.,log epsilon)
                                model = SVR(kernel=kernel,C=C,epsilon=epsilon)
                                model.fit(xs.reshape(-1,1),ys)
                                xfit = np.linspace(0,1,200)
                                yfit = model.predict(xfit.reshape(-1,1))
                                plt.figure(figsize=(12,7))
                                plt.scatter(xs,ys,s=10,c="k",label="Data")
                                plt.plot(xfit,yfit,linewidth=3, label="SVR")
                                plt.plot(x_gt,y_gt,"--",label="Ground Truth")
                                title = f"Kernel: {kernel}, C = {C:.1e}, eps = {epsilon:.1e}"
                                plt.legend(loc="lower left")
                                plt.xlabel("$x_1$")
                                plt.ylabel("$y$")
                                plt.title(title)
                                plt.show()
                      slider1 = FloatSlider(
                                value=0,
                                min=-5,
                                max=5,
                                step=.5,
                                description='C',
                                disabled=False,
                                 continuous_update=True,
                                orientation='horizontal',
```

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```
readout=False,
    layout = Layout(width='550px')
slider2 = FloatSlider(
    value=-1,
    min=-7,
    max=-1,
    step=.5,
    description='epsilon',
    disabled=False,
    continuous_update=True,
    orientation='horizontal',
    readout=False,
    layout = Layout(width='550px')
)
dropdown = Dropdown(
    options=['linear', 'rbf', 'sigmoid'],
    value='linear',
    description='kernel',
    disabled=False,
)
interactive_plot = interactive(
    plotting_function,
    kernel = dropdown,
    log_C = slider1,
    log_epsilon = slider2
    )
output = interactive_plot.children[-1]
output.layout.height = '500px'
interactive_plot
```

Out[2]: interactive(children=(Dropdown(description='kernel', options=('linear', 'rbf', 'si gmoid'), value='linear'), Fl...

Questions

- 1. Which kernel produced the best fit overall? (Assume this kernel for subsequent questions.)
- 2. As 'C' increases, does model performance on in-sample data generally improve or worsen?
- 3. As 'C' increases, does model performance on out-of-sample data (on the intervals [0.0, 0.1] and [0.9, 1.0]) generally improve or worsen?
- 4. What 'C' value would you recommend for this kernel?
- 5. What 'epsilon' value would you recommend?

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- 1. rbf gives the best fit
- 2. As C increases, the model performance for in-sample data generally improves
- 3. As C increases, the model performance for out-of-sample data generally worsen
- 4. C = 3.2e3
- 5. epsilon = 1e-2