sheet10_C4M2

January 23, 2018

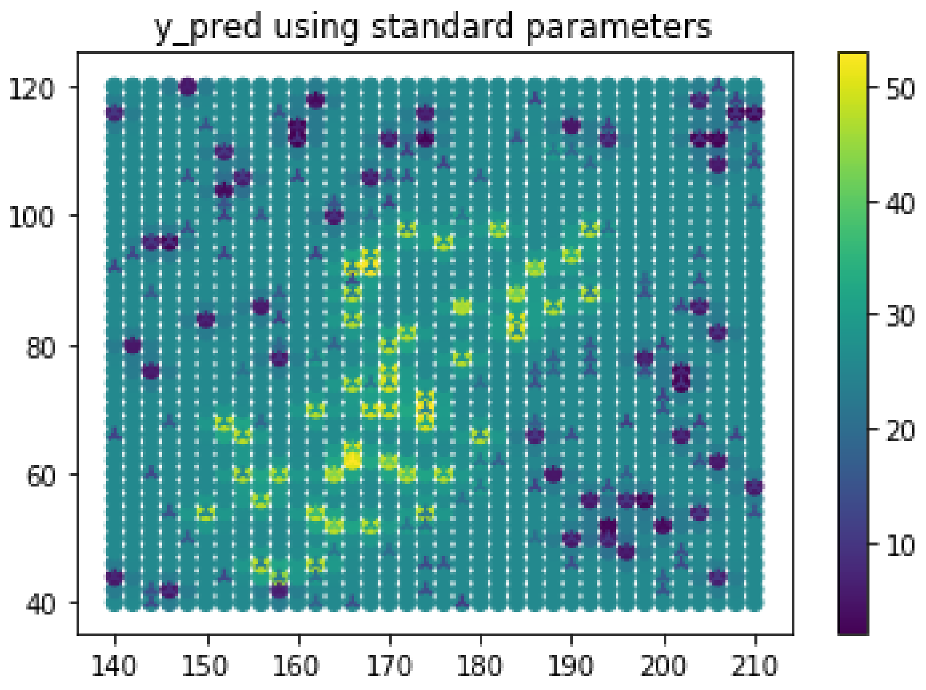
1 H10.2: Regression with the v-SVR

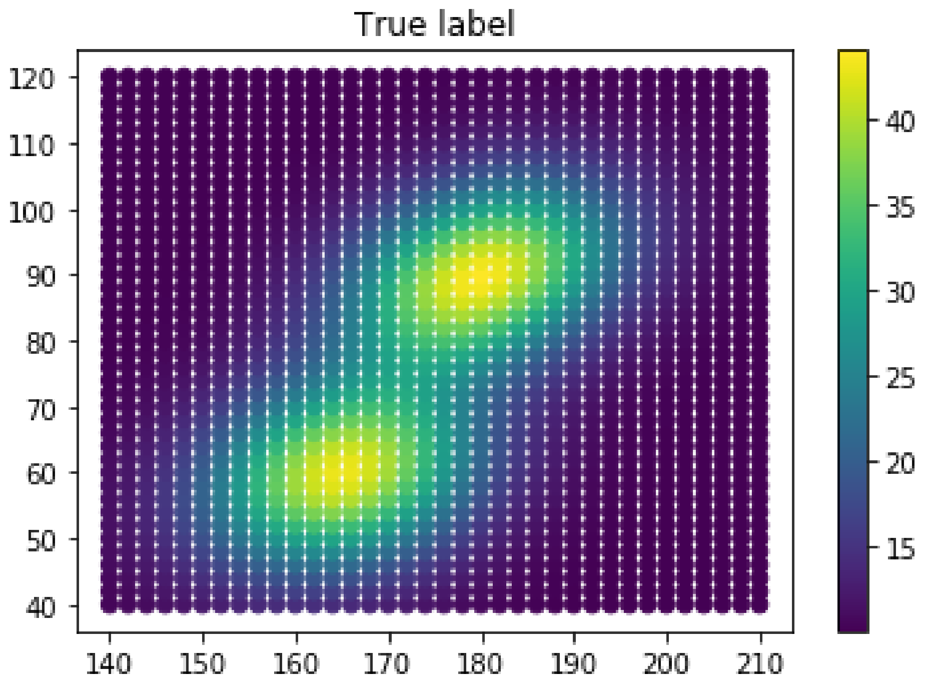
1.1 a)

```
In [7]: from sklearn import svm
        from sklearn.model_selection import KFold
        import numpy as np
        import matplotlib
        import matplotlib.pyplot as plt
        %matplotlib inline
```

```
In [8]: # data preparation
        TrainingData = np.genfromtxt('TrainingRidge.csv', delimiter=',', skip_header=1)
        ValidationData = np.genfromtxt('ValidationRidge.csv', delimiter=',', skip_header=1)

        def get_MSE(trueLabel, pred):
            n = trueLabel.shape[0]
            return np.sum((pred-trueLabel)**2)/(n*1.0)
```

```
In [9]: svm_with_standard_params = svm.NuSVR()
        svm_with_standard_params.fit(TrainingData[:, 0:2], TrainingData[:, 2])
        y_pred = svm_with_standard_params.predict(ValidationData[:, 0:2])

        plt.scatter(ValidationData[:,0], ValidationData[:,1], c=y_pred)
        plt.scatter(TrainingData[:, 0], TrainingData[:, 1], c=TrainingData[:, 2], marker='2')
        plt.colorbar()
        plt.title('y_pred using standard parameters')
        plt.show()

        plt.scatter(ValidationData[:, 0], ValidationData[:, 1], c=ValidationData[:, 2])
        plt.colorbar()
        plt.title('True label')
        plt.show()

        print "MSE on Validation set: %f" % get_MSE(ValidationData[:, 2], y_pred)
```



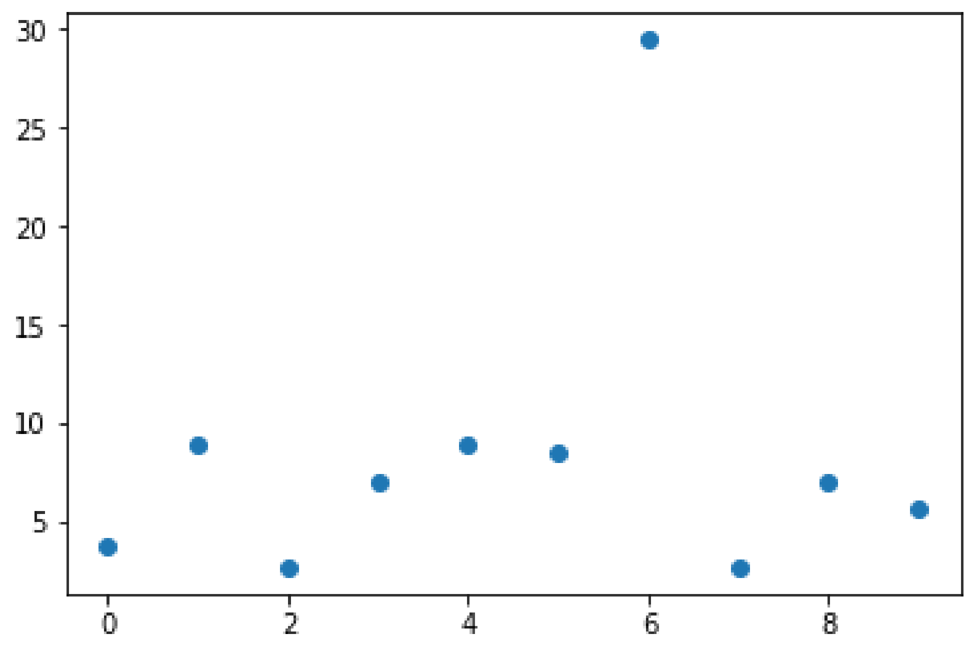


```
MSE on Validation set: 76.791278
```

1.2 b)

```
In [13]: folds = 10
         kf = KFold(n_splits=folds)
         q = 2
         n_C = 15
         n_gamma = 13
         C_options = np.empty((n_C, ))
         C_options[0] = 2**-2
         C_options[1:] = q
         C_options = np.cumprod(C_options)

         gamma_options = np.empty((n_gamma, ))
         gamma_options[0] = 2**-12
         gamma_options[1:] = q
         gamma_options = np.cumprod(gamma_options)

         MSEs = []
         min_MSE_global = 1e9
         best_C_global = C_options[0]
         best_gamma_global = gamma_options[0]

         for train_index, test_index in kf.split(TrainingData):
             min_MSE_cur_fold = 1e9
             best_C_cur_fold = C_options[0]
             best_gamma_cur_fold = gamma_options[0]
             for c in C_options:
                 for gamma in gamma_options:
                     svm_param = svm.NuSVR(kernel='rbf', C=c, gamma=gamma,nu=0.5)
                     svm_param.fit(TrainingData[train_index][:, 0:2], TrainingData[train_index][
                     pred = svm_param.predict(TrainingData[test_index][:, 0:2])
                     cur_MSE = get_MSE(pred, TrainingData[test_index][:, 2])
                     if cur_MSE < min_MSE_cur_fold:
                         min_MSE_cur_fold = cur_MSE
                         best_C_cur_fold = c
                         best_gamma_cur_fold = gamma
             svm_with_optimal_param_cur_fold = svm.NuSVR(kernel='rbf', C=best_C_cur_fold, gamma=
             svm_with_optimal_param_cur_fold.fit(TrainingData[:, 0:2], TrainingData[:, 2])
             pred_cur_fold = svm_with_optimal_param_cur_fold.predict(ValidationData[:, 0:2])
             MSE_cur_fold = get_MSE(ValidationData[:, 2], pred_cur_fold)
             MSEs += [MSE_cur_fold]
             if(MSE_cur_fold < min_MSE_global):
                 min_MSE_global = MSE_cur_fold
                 best_C_global = best_C_cur_fold
                 best_gamma_global = best_gamma_cur_fold

         plt.scatter(np.arange(0, 10), MSEs)
         plt.show()
```

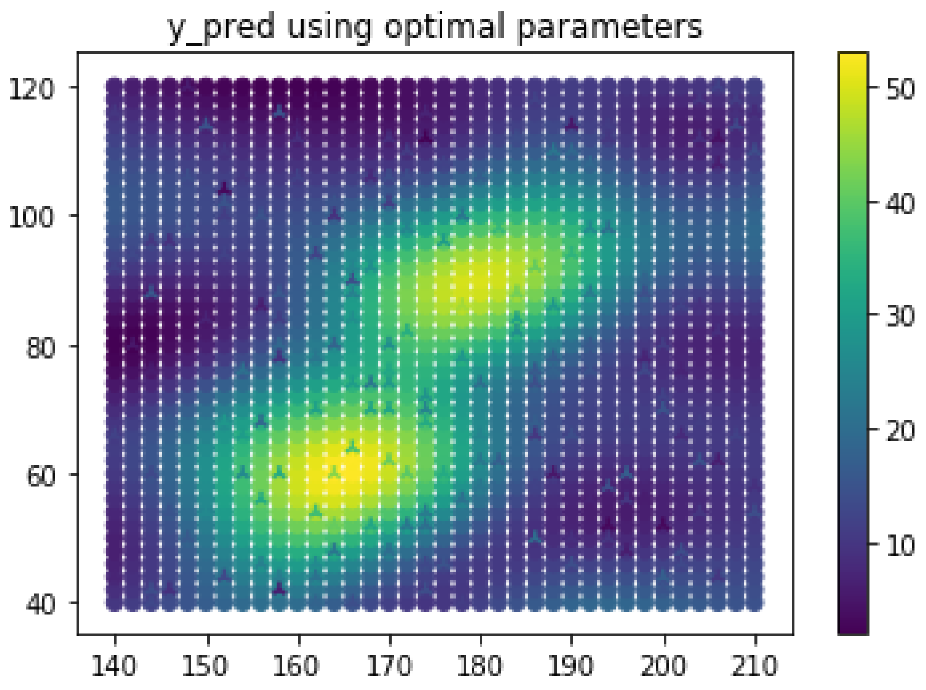
```
print "Optimal param: C=%f, gamma=%f. min MSE=%f" % (best_C_global, best_gamma_global,
```

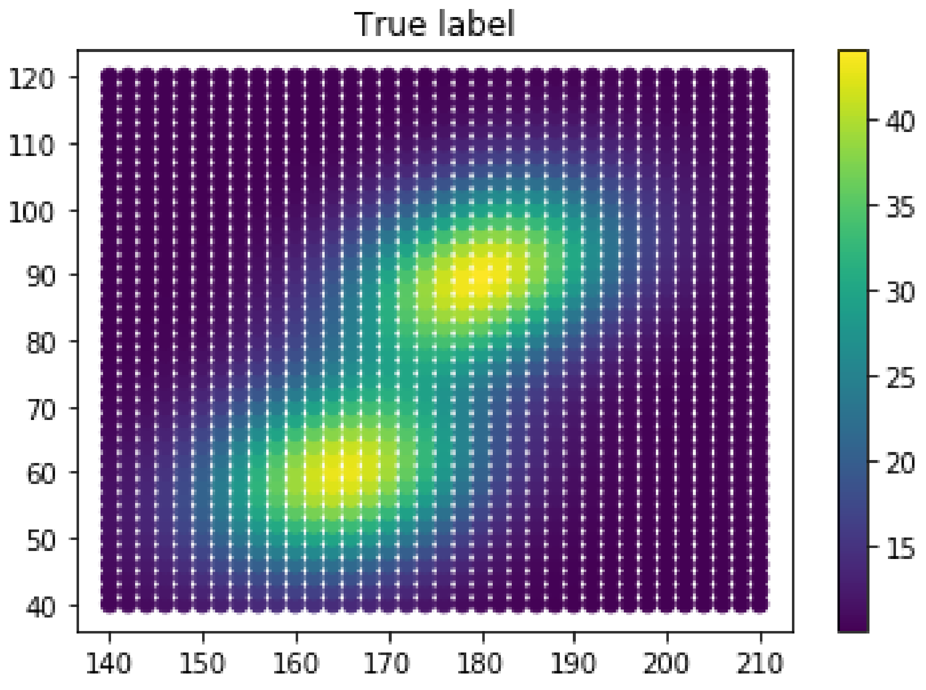


```
Optimal param: C=16.000000, gamma=0.003906. min MSE=2.723902
```

1.3 c)

```
In [14]: svm_with_optimal_params = svm.SVR(kernel='rbf', C=best_C_global, gamma=best_gamma_globa
         svm_with_optimal_params.fit(TrainingData[:, 0:2], TrainingData[:,2])
         y_pred = svm_with_optimal_params.predict(ValidationData[:, 0:2])

         plt.scatter(ValidationData[:,0], ValidationData[:,1], c=y_pred)
         plt.scatter(TrainingData[:, 0], TrainingData[:, 1], c=TrainingData[:, 2], marker='2')
         plt.colorbar()
         plt.title('y_pred using optimal parameters')
         plt.show()

         plt.scatter(ValidationData[:, 0], ValidationData[:, 1], c=ValidationData[:, 2])
         plt.colorbar()
         plt.title('True label')
         plt.show()

         print "MSE on Validation set: %f" % get_MSE(ValidationData[:, 2], y_pred)
```





```
MSE on Validation set: 4.911200
```

Compared with the plot using standard parameters, using optimal parameters leads to an obviously better generalization. Also the mean squared error decreased rapidly (from 76.79 to 4.91).

```
In [ ]:
```