

ML_HW3

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1.

a)

```
def kernels(x1, x2, b):
    kernal = np.zeros((len(x1),len(x2)))
    for i in range(len(x1)):
        for j in range(len(x2)):
            kernal[i][j] = np.exp((-1./b) * (np.linalg.norm([x1[i]] - x2[j], 2)**2))
    return kernal

def predict(k_XX, k_Xx, var):
    a = np.linalg.inv(var * np.identity(len(k_XX)) + k_XX)
    mu = np.dot(k_Xx, np.dot(a, y_train))
    return mu
```

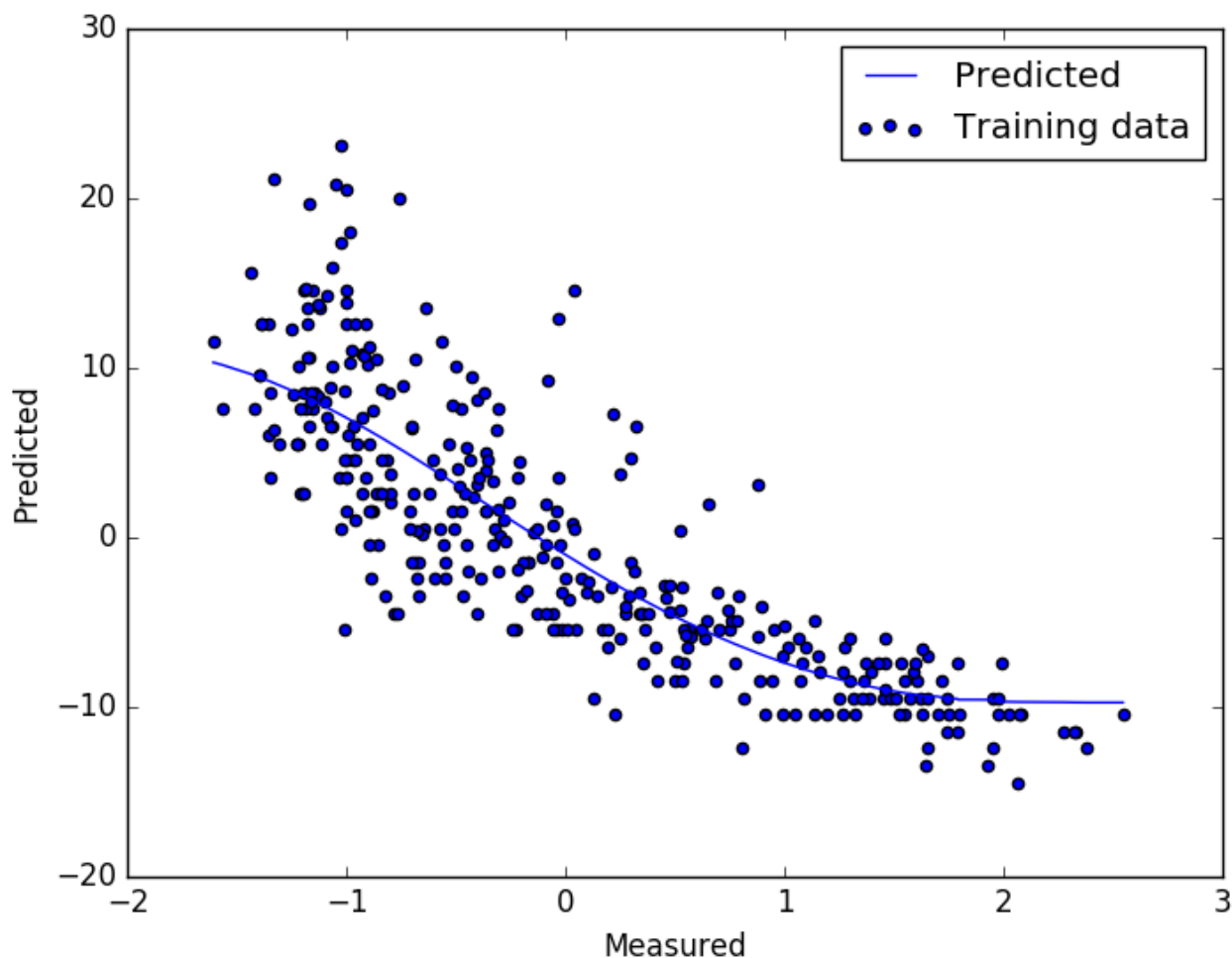
b)

	b	5	7	9	11	13	15
var							
0.1		1.966276	1.920163	1.897649	1.890507	1.895849	1.909603
0.2		1.933135	1.904877	1.902519	1.914981	1.935586	1.959549
0.3		1.923420	1.908080	1.917648	1.938849	1.964597	1.990804
0.4		1.922198	1.915902	1.932514	1.957936	1.985502	2.011915
0.5		1.924769	1.924804	1.945699	1.973216	2.001314	2.027370
0.6		1.929213	1.933701	1.957235	1.985764	2.013878	2.039465
0.7		1.934634	1.942254	1.967403	1.996375	2.024310	2.049463
0.8		1.940583	1.950380	1.976492	2.005603	2.033307	2.058105
0.9		1.946820	1.958093	1.984741	2.013835	2.041317	2.065845
1.0		1.953213	1.965438	1.992341	2.021345	2.048642	2.072976

c)

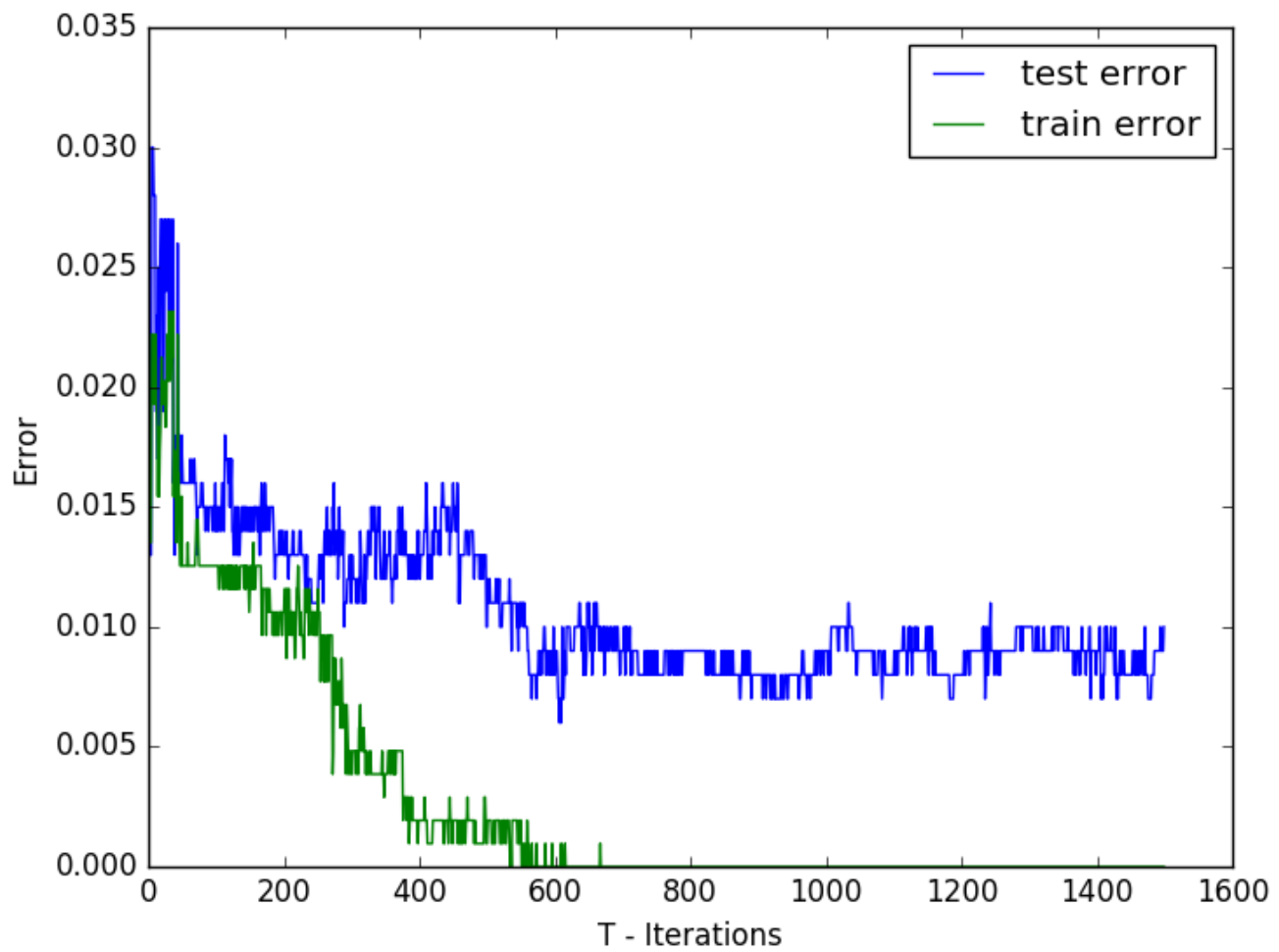
The best values of this algorithm was at $b = 11$ & $\text{var} = .1$, with those parameters the RMSE was ~ 1.891 . Some possible downsides of this approach vs. HW1, is that now we need to tune 2 different hyper-parameters vs in HW1, we only tuned 1, lambda. Also this approach is a little more complex and thus takes more time to run and to understand the importance of the features.

d)

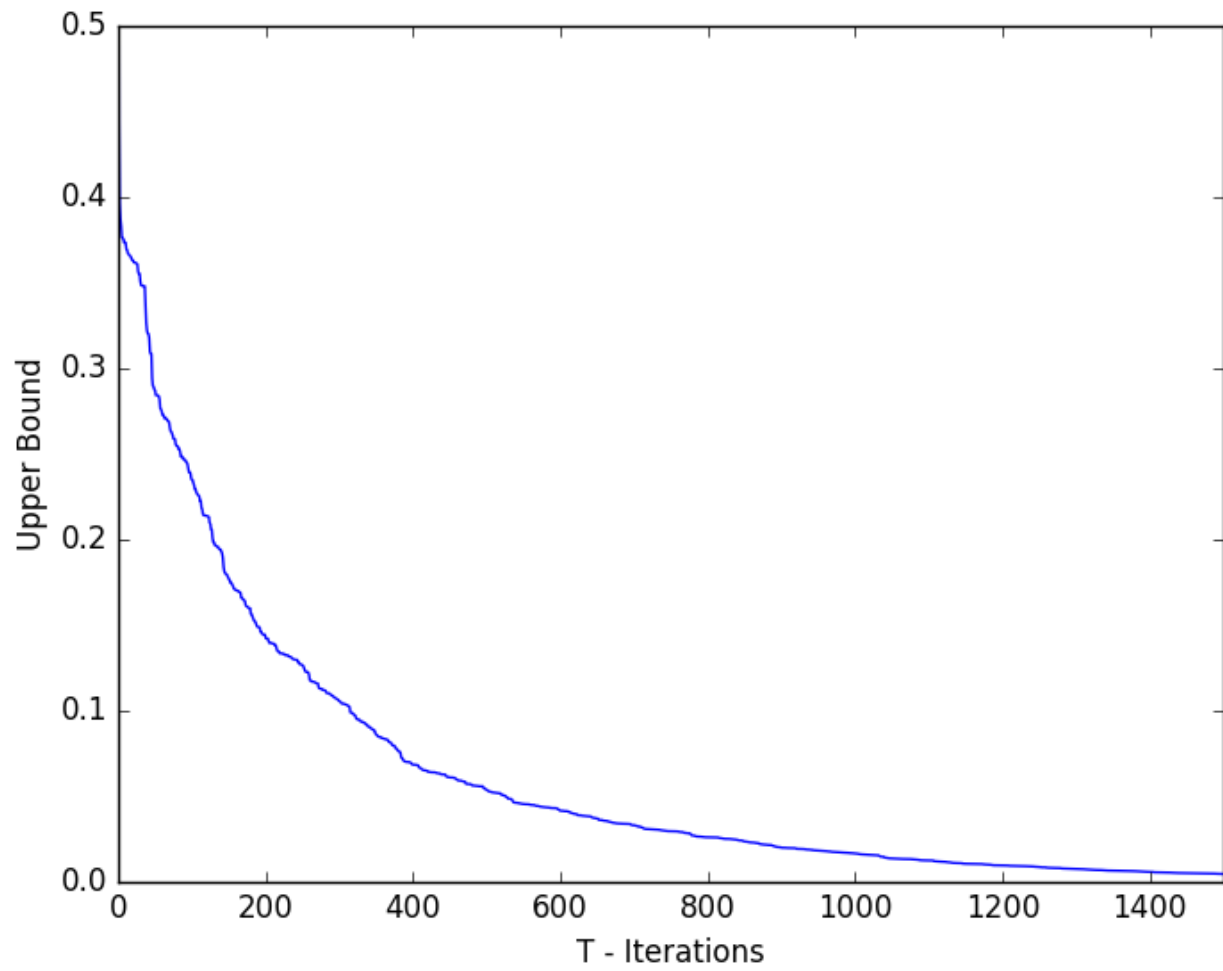


2.

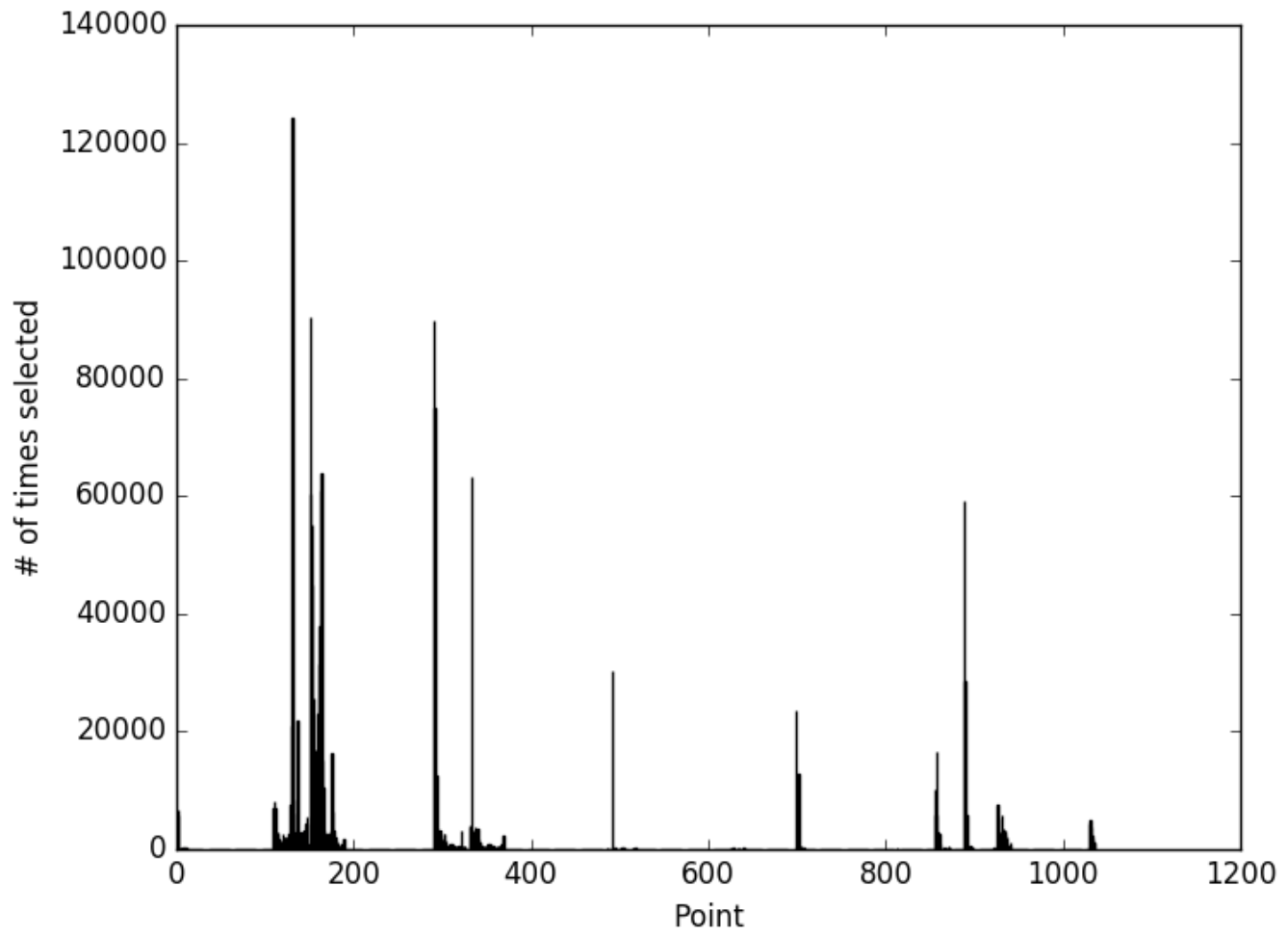
a)



b)



c)



d)

