MSAN 621 - Homework 1

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1 The Boston Data Set

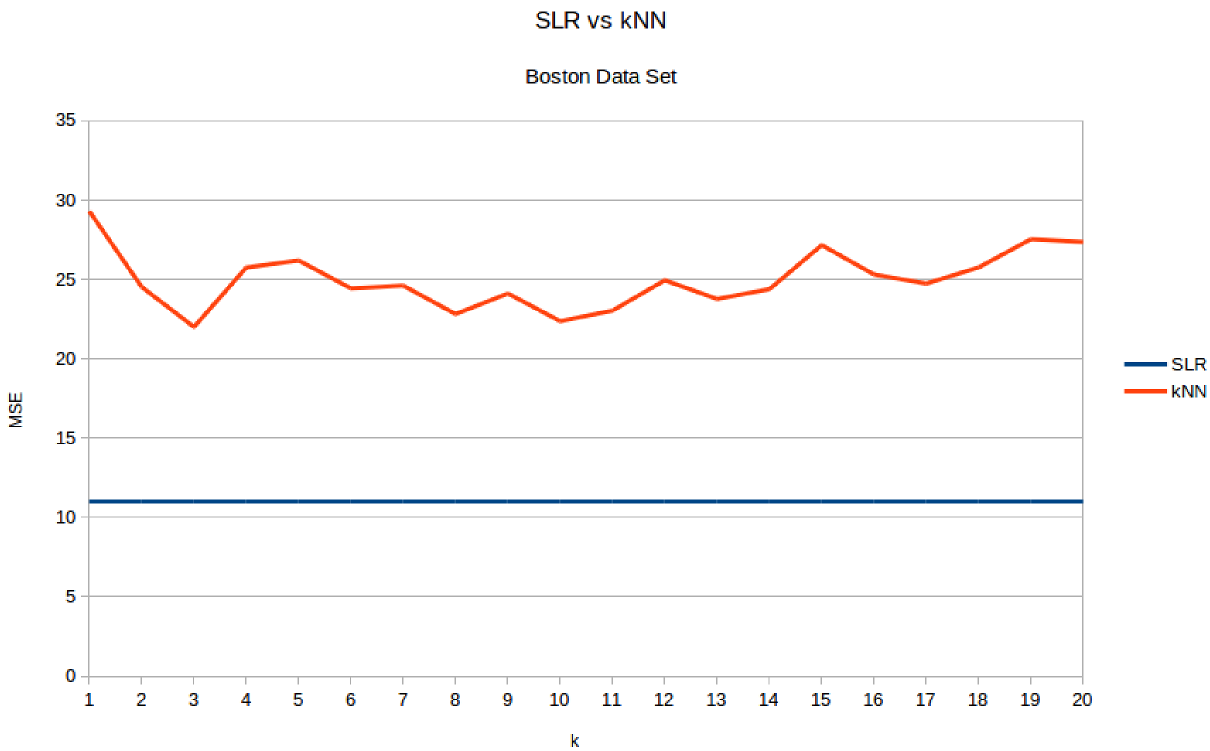
The models are trained with all data except the last 50 rows, which are reserved to test the models' performance.

For MLR, we get an MSE of 10.967.

For kNN, we get an MSE that varies according to k, as shown in the table below:

k	MSE
1	29.299
2	24.532
3	22.003
4	25.754
5	26.200
6	24.441
7	24.615
8	22.820
9	24.117
10	22.371
11	23.036
12	24.953
13	23.774
14	24.388
15	27.162
16	25.311
17	24.743
18	25.761
19	27.539
20	27.362

Plotting MSE against k for both models, we get the image below:



We can see that we get a lower test MSE with SLR than kNN, for any value of k. For this example, simple linear regression is a better algorithm for predicting new data from the Boston Data Set.

2 The U.S. Monthly Climate Normals Data Set

The models contain daily and hourly temperature for a year from 457 weather stations across the US. The models are trained on the data from all stations except 1-5 that are used for testing and assessing the models' performance. The results are shown in the table below, where n is the number of test stations used.

Model	k	MSE (n=5)	MSE (n=4)	MSE (n=3)	MSE (n=2)	MSE (n=1)
MLR	-	7.030	7.633	7.204	8.936	1.487
kNN	1	114.261	19.209	21.026	35.079	23.071
	2	48.180	18.735	16.955	30.678	16.610
	3	31.858	15.543	16.519	29.068	14.960
	4	25.050	14.476	15.247	89.643	13.897
	5	20.884	13.710	14.570	74.330	13.181
	6	19.201	13.186	14.286	61.624	12.916
	7	17.446	12.722	14.196	52.829	12.718
	8	16.096	12.376	14.295	46.494	12.468
	9	15.664	12.242	14.100	42.343	12.223
	10	15.085	12.043	13.870	39.005	12.017
	11	14.454	11.904	13.689	36.140	11.854
	12	14.103	11.792	13.725	34.312	11.807
	13	13.717	11.769	13.635	32.643	11.769
	14	13.412	11.778	13.542	31.180	11.682
	15	13.172	11.910	13.504	30.002	11.605
	16	12.917	11.870	13.589	29.278	11.507
	17	12.748	11.820	13.631	28.626	11.437
	18	12.729	11.737	13.551	27.968	11.331
	19	12.846	11.766	13.593	27.464	11.250
	20	12.807	11.790	13.534	27.141	11.208

Fixing $k = 3$, we can get results for each station individually and for all five combined. The MSEs are reported in the table below.

Model	MSE (USW00023234)	MSE (USW00014918)	MSE (USW00012919)	MSE (USW00013743)	MSE (USW00025309)	MSE (all 5)
MLR	1.487	16.374	3.731	8.914	4.604	7.030
kNN	14.960	108.360	30.754	13.052	21.473	31.858

We can see that MLR performs better (i.e., produces a lower MSE) than kNN for this data set. In addition, the prediction produced vary depending on the test set used. For example, predictions for station `USW00014918` are considerably worse than those for station `USW00023234`

The imputer strategy used for this model is very basic: missing/erroneous values are replaced with the mean temperature observed across all stations, days, and hours. Although this strategy may be suited in some cases, I don't think that it makes much sense here. Stations can be located in places where the climate is very different, so the mean temperature across the country and the year may not fit well in those missing places. In order to improve this, we could think about imputing missing readings with the average temperature throughout the year for that station, or even more locally (i.e., for that month for example) if data is available.

In general, MLR performed better than kNN, at least for k up to 20. In particular, the MSE for MLR when 5 stations are used for the test data is very low (1.487). The performance of MLR for this dataset is impressive.

I think it would be interesting to explore different imputing strategies to see how this affects the models' performance. The tactic used here is very basic, so improvement is definitely possible in this area. However, I think the results obtained thus far are very good already. Other features may be used to get even lower MSEs: for instance, we may want to get geographical information about the weather stations in order to group them by climate and overall weather patterns to get better averages.