CS498DF: Assignment #7
Regression of spatial data using kernel functions

Cybelle Smith, Varun Somani, David Young

4/11/206

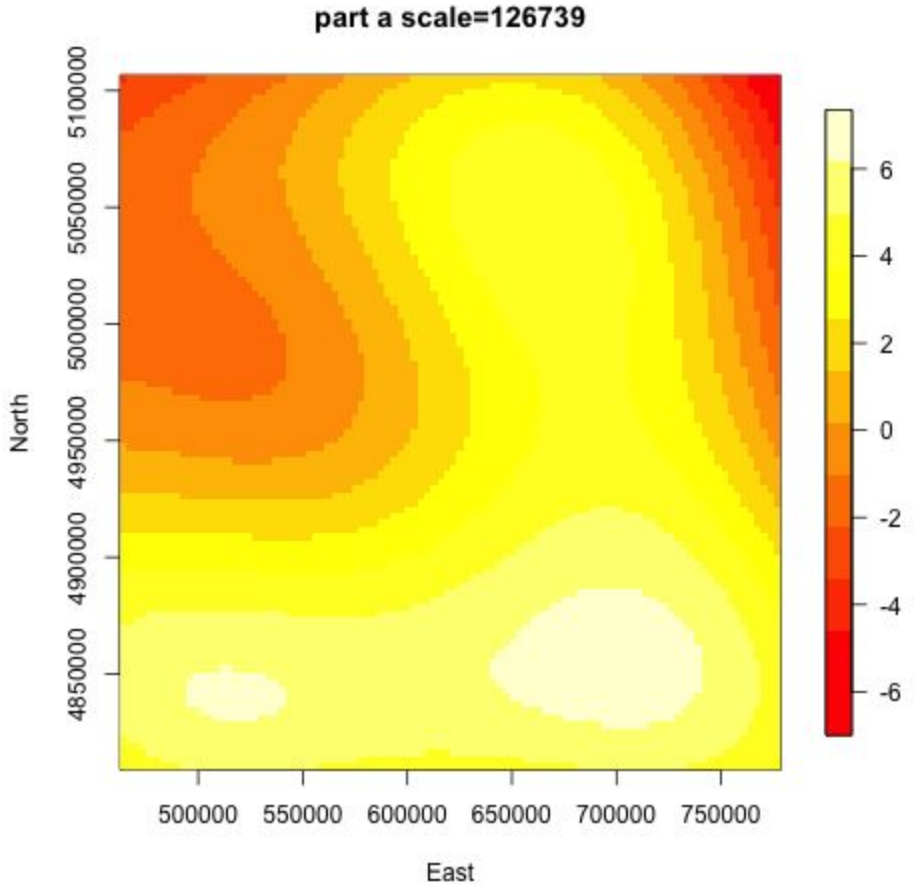
Part a:

A kernel method was used to smooth the data with a gaussian kernel function. Note: Smoothing was performed on a processed data set which was obtained by averaging the reported T_min at each location over all times (i.e one interpolate). Each data point was used as a base point, and the search was performed over a range of six scales. For each scale an 8 fold cross validation was performed and a mean MSE value was recorded. For each fold, the annual mean min temperature was predicted at each point on a 100x100 evenly spaced grid spanning the subset of weather stations comprising the training set for the fold. Predictions for the fold's test set were generated using the built model and the values were compared to the actual min temperature of the validation stations. The difference was recorded as MSE and the best scale was chosen as the scale which yielded the smallest average MSE across 8 folds.

Scale	Average MSE across 8 folds
31684.73	252.067
63369.46	8.028208
126738.9	6.474178
190108.4	6.67963
253477.9	6.656381
380216.8	6.805604

The scales corresponded to multiples of the average distance between stations. The multiples were 0.25, 0.5, 1, 1.5, 2, and 3. Of all the compared scales, the final scale was chosen as h= 126738.9 which was also the average distance between points. This scale was chosen as it yielded the smallest average cross validated MSE. The MSE appeared much worse for scales that were too small, and only slightly worse for scales that were proportionally too big. This is most likely because once a scale threshold is reached, the model is decent but continuing to increase the scale can lead to overfitting of sorts.

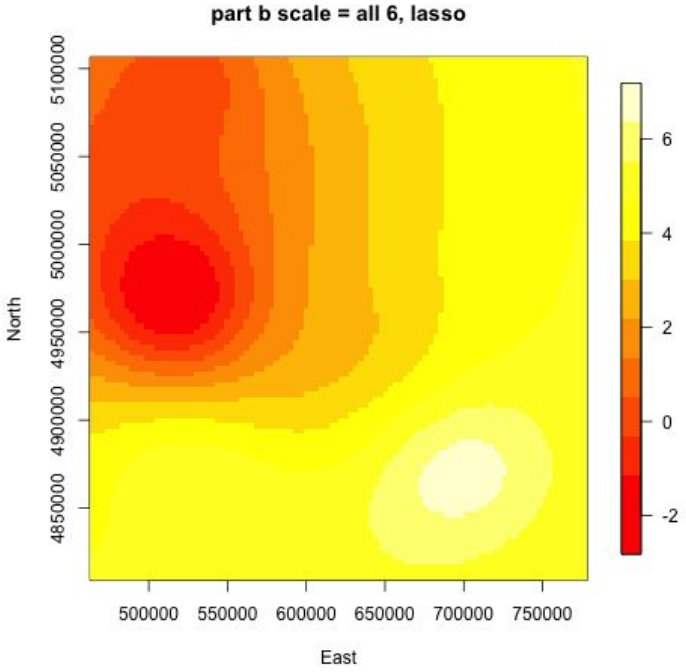
Once the scale was selected, all of the stations were used as a training set to generate a model at that scale. Min temperatures for an even 100x100 grid were then predicted using this model and plotted as an image.

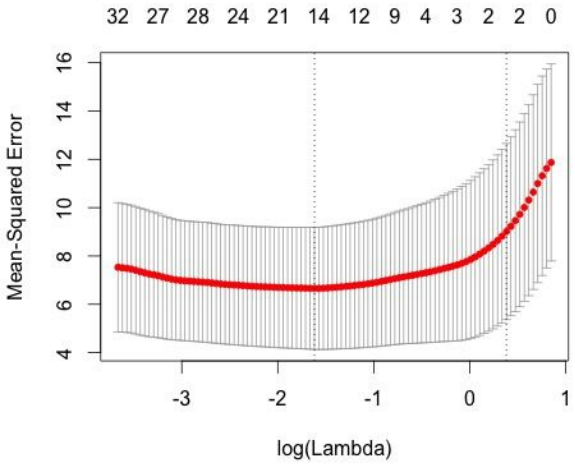


Caption: Plot of predicted average annual mean of the min temperature on 100 by 100 grid spanning all stations, using scale h =126738.9

Part b:
The kernel method from part a was regularized using the lasso, and again predictions were generated to find the mean annual min temperature at each point on the same 100x100 grid. The regularization constant was chosen using cross validation (cv.glmnet did all the work). Again, a range of 6 scales were used and here the lasso regression effectively pruned unnecessary scales with its internal cross validation and ability to cut out features. Again the predictions were plotted as an image.

The final number of predictors used by the model was 14. The MSE appears parabolic around the optimal number of predictors which was 14. The error grows faster as the number of predictors decreases from 14, compared to its growth rate as the number of predictors increases from 14. The log of the optimal regularization constant can be read off the graph below and is roughly 1.6





Part c:
We repeated part b but with different alphas to investigate the effect of different elastic net constants.The effect of different choices of elastic net constant (alpha) was investigated using 3 different alpha values (0.25, 0.5, 0.75). As alpha increases, the regularization constant (lambda) decreased. See the table below.

Alpha	Regularization Constant (Lambda)
0	25.60592
0.25	0.87035
0.5	0.29995
0.75	0.20949
1	0.14315

Looking at the heatmaps (located in “results/part c/” of the submission directory), at alpha =0, the heatmap is clearly more blurred. At alpha = 0.25 and above, the images look more similar to one another except that alpha = 0.25 is missing a small valley. The least spatial blurring appears to be at alpha = 1.0.