Machine Learning: Kaggle competition on Prediction of forest covertypes

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Goal

Use a training data set of 53 features and 50000 observations to predict from a testing set of 100000 observations 7 different forest covertypes. Using the Kaggle competition platform we will evaluate the performance of the method by measuring the accuracy on the testing set.

Previous works have reached up to 3% of error rate with the whole data set that contains more than 500k examples by using random forests (*http://www.wise.io/blog/benchmarking-random-forest-part-1*).

Introduction of the data

The data provided is divided in a training set and a testing set. The training set contains 50000 examples with 53 features plus the corresponding id's and covertypes. The structure of the features is as follows:

- Name / Data Type / Measurement / Description
  - id
  - Elevation / quantitative /meters / Elevation in meters
  - Aspect / quantitative / azimuth / Aspect in degrees azimuth
  - Slope / quantitative / degrees / Slope in degrees
  - Horizontal-Distance-To-Hydrology / quantitative / meters / Horz Dist to nearest surface water features
  - Vertical-Distance-To-Hydrology / quantitative / meters / Vert Dist to nearest surface water features
  - Horizontal-Distance-To-Roadways / quantitative / meters / Horz Dist to nearest roadway
  - Hillshade-9am / quantitative / 0 to 255 index / Hillshade index at 9am, summer solstice
  - Hillshade-Noon / quantitative / 0 to 255 index / Hillshade index at noon, summer soltice
  - Hillshade-3pm / quantitative / 0 to 255 index / Hillshade index at 3pm, summer solstice
  - Horizontal-Distance-To-Fire-Points / quantitative / meters / Horz Dist to nearest wildfire ignition points
  - Wilderness-Area (4 binary columns) / qualitative / 0 (absence) or 1 (presence) / Wilderness area designation
  - Soil-Type (40 binary columns) / qualitative / 0 (absence) or 1 (presence) / Soil Type designation
  - Cover-Type (7 types) / integer / 1 to 7 / Forest Cover Type designation

The testing data contains the same features except for the Cover-Type that is missed and it is what we want to predict.

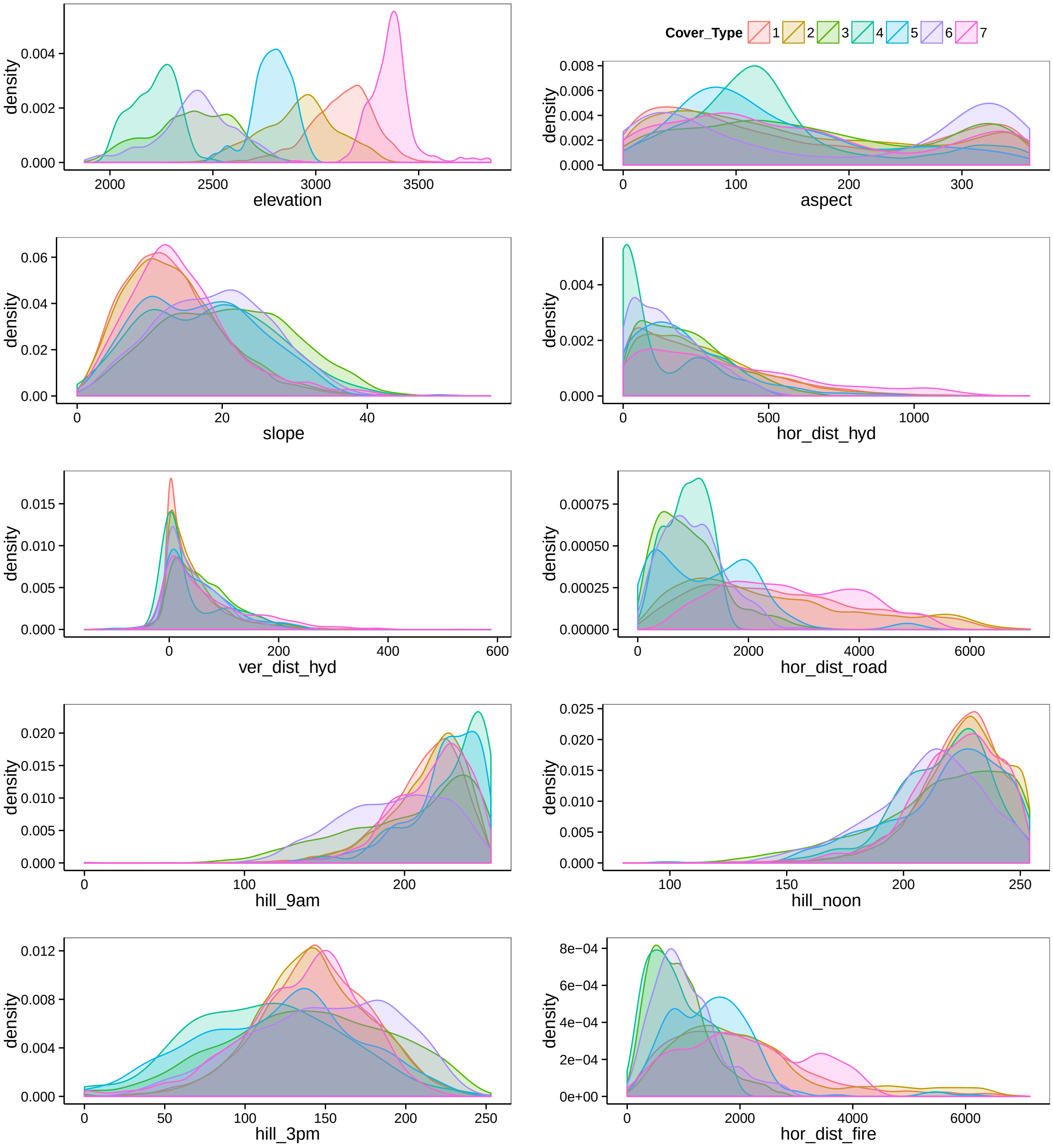
Visual exploration of the training data

The first data check we should do is look at the distribution of Cover_Type in the data so we know if we are dealing with equal sample sizes across each cover type.

```
##
##       1      2      3      4      5      6      7
## 18101  24591   3026    200    810   1511   1761
```

The table shows that covertypes 1 and 2 are much more prevalent than other types in the training data. Covertypes 4 and 5 are poorly represented in the training set which can lead to difficulties when we will try to train a model to predict these underrepresented groups.

Another way to understand the data before modeling it is to do some simple visualization. To view variation among covertypes across the continuous variables in the data we created density plots of these variables colored by covertype.



The features that seem to display the most variation among covertypes seems to be captured by elevation and aspect. The rest of the features show a strong overlaping of the covertypes.

For the binary features, we show a table that summarizes the 4 wild areas and the 40 soil types.

```
##               Perc counts Cov_1 Cov_2 Cov_3 Cov_4 Cov_5 Cov_6 Cov_7
## wild_area_1  0.449  22438  8964 12723     0     0   308     0   443
## wild_area_2  0.051   2526  1592   743     0     0     0     0   191
## wild_area_3  0.438  21901  7545 10869  1220     0   502   638  1127
## wild_area_4  0.063   3135     0   256  1806   200     0   873     0
## soil_type_1  0.005    250     0     0   171    11     0    68     0
## soil_type_2  0.013    649     0    77   430     6    21   115     0
## soil_type_3  0.008    405     0   101   211    72     0    21     0
## soil_type_4  0.022   1083    12   309   638    15    50    50     9
## soil_type_5  0.003    134     0     0    81     4     0    49     0
## soil_type_6  0.011    541     0    68   337    18     0   118     0
## soil_type_7  0.000      9     0     9     0     0     0     0     0
## soil_type_8  0.000     22     3    19     0     0     0     0     0
## soil_type_9  0.002    108    14    94     0     0     0     0     0
## soil_type_10 0.057   2834    74   965   982    18    20   775     0
## soil_type_11 0.021   1064    72   765   108     0    67    52     0
## soil_type_12 0.053   2639   214  2425     0     0     0     0     0
## soil_type_13 0.030   1493   167  1137     1     0   133    55     0
## soil_type_14 0.001     46     0     0     7    15     0    24     0
## soil_type_15 0.000      0     0     0     0     0     0     0     0
## soil_type_16 0.005    249    61   156     2     3     5    22     0
## soil_type_17 0.006    318    23    88    49    38    56    64     0
## soil_type_18 0.003    166     6   147     0     0    13     0     0
## soil_type_19 0.007    374   234   135     0     0     5     0     0
## soil_type_20 0.016    780   301   457     0     0     7    15     0
## soil_type_21 0.002     76    73     2     0     0     0     0     1
## soil_type_22 0.057   2856  2216   626     0     0     0     0    14
## soil_type_23 0.099   4954  3119  1726     0     0    44     6    59
## soil_type_24 0.036   1819   950   834     0     0     5     8    22
## soil_type_25 0.001     37    16    21     0     0     0     0     0
## soil_type_26 0.005    236    23   201     0     0    12     0     0
## soil_type_27 0.002     86    46    39     0     0     0     0     1
## soil_type_28 0.002     82     4    76     0     0     2     0     0
## soil_type_29 0.199   9963  3567  6242     0     0    88     0    66
## soil_type_30 0.052   2591   629  1760     0     0   181     0    21
## soil_type_31 0.044   2198  1017  1138     0     0    26     2    15
## soil_type_32 0.088   4420  1791  2497     8     0    41    13    70
## soil_type_33 0.078   3882  1529  2206     1     0    33    53    60
## soil_type_34 0.003    143     8   130     0     0     1     1     3
## soil_type_35 0.004    197    95     0     0     0     0     0   102
## soil_type_36 0.000      8     1     0     0     0     0     0     7
## soil_type_37 0.001     26     0     0     0     0     0     0    26
## soil_type_38 0.026   1320   723    74     0     0     0     0   523
## soil_type_39 0.024   1193   695    35     0     0     0     0   463
## soil_type_40 0.015    749   418    32     0     0     0     0   299
```

The first thing we notice is that there are no covertypes with nonzero values for soiltype 15. It means this feature has no predictive power and we should remove it from the feature list. A second important observation is that examples of covers 1 and 2 are both desbriced by similar counts of soils and wild areas. Finally, soiltypes 7 and 37 only contain observations with covers of type 2 and 7 respectively which can be an unique identifier of class type if an observation has one of these soiltypes indicated.

Proposed methods

We have done some data preprocessing using different approaches.

- Raw data inspection: From the previous section we removed soiltype 15 since we do not expect any predictive power from it.
- Data scaling: We evaluated the accuracy of the different methods by standardizing the data. Three different cases where compared: Scaling all features, Scaling the continuous valued features, weighting the binary features.
- Dimension reduction methods: Together with the previous scaling we used the R packages 'princomp' for principal component analysis and 'svd' for singular value decomposition. We wanted to apply the classification algorithms in a lower dimensional space and remove redundant factors.

We have focused our classification efforts on three classification methods: Random Forest, Support vector machines and k-Nearest Neighbours.

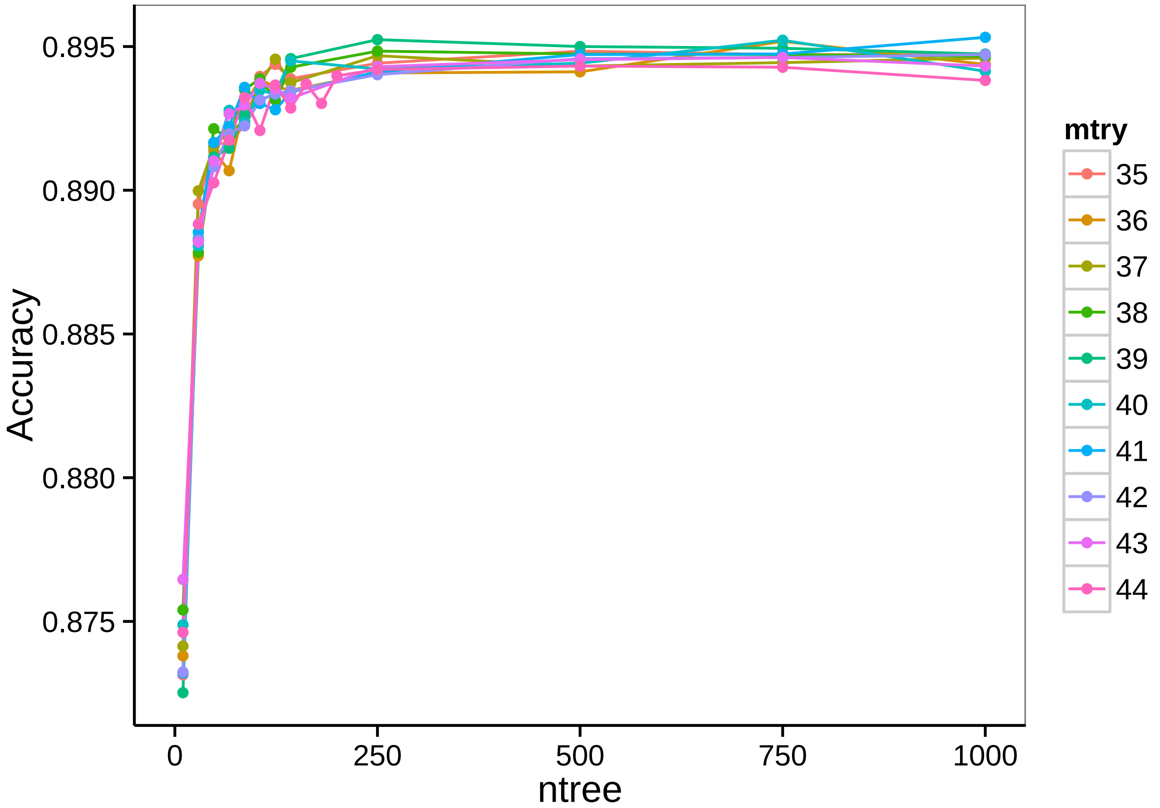
This first method we tried for classification was Random Forest. This is a popular ensamble technique that relies on selecting random subsets of the features and random subsamples of the data to partition the features space with axis parallel cuts (trees). It generates a set of partitions each of which is limited during the division process and is labeled by majority vote among the data points that are in that partition. We used the `randomForest` package that implements Breiman's random forest algorithm (see http://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm for further details). Because Random Forest is quite popular for classification problems, it seemed appropraite to pursue this method for this problem.

The second approach we attempted for classification was Support Vector Machines. SVMs are used fairly often in supervised learning. Thus they seemed like a viable option for classification. Also since the data did not appear to be linearly separable at first glance, SVMs are appealing because they can efficiently perform nonlinear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

The final approach we tried and we used in our final submission (with a more sophisticated implementation using weighted binary feature) was the k-Nearest Neighbors algorithm. kNN is a simple algorithm that calculates distance from a point to its k nearest neighbors. It assigns the point to the same class as the majority class of its k nearest neighbors. The function we used is the `knn` from the class package only allows for distance of features to be measured using Euclidian distance, which can be a limitation.

randomForest

The best results using random forest were obtained by using all the features as provided in the original data. Using the function `tuneRF` we were able to do a coarse grain selection of the number of features randomly chosen on each iteration of the method (that number is controlled by the *wtry* parameter). The optimal *mtry* was around 40 that is far from the *mtry=7*, the default value, due to the sparsity of the binary data. In a second step we performed a more systematic optimization around this value. In this process we cross-validated the accuracy with 8 buckets runing the code in AWS with 8 cores. The results are shown in the figure below.



The accuracy grow assimptotically to ∼ 89.5 for all the *mtrys*. The optimum accuracy of 0.8953 is obtained for *mtry=41* and *ntree=1000*. However, in Kaggle we decided to submit our second best guess that was for *mtry=39* and *ntree=1000* and it returned a decent 0.90090 of accuracy.

We also tryed other approaches that are summarized in the following table:

Method	Preprocessing	Accuracy(%)	mtry	ntree	Other Params
Random Forest	raw data	89.47	39	1000	
Random Forest	PCA without scaling	88.14	12	50	depth=all
Random Forest	PCA with scaling	87.69	34	50	depth=all
Random Forest	SVD without scaling	89.46	6	124	depth=6

There were two reason to try SVD and PCA in the preprocessing of the data. The first one was to project the data in a more suitable base such that the random forest would require less trees to classify the data. The second was to get rid of unnecessary or redundant features. The depth of the dimension reduction is given by the *depth* parameter. For PCA the best results were obtained by including all the features while for SVD we observed that the optimal depth was for the first 6 components, reducing the computation time significantly. Those results are somehow reasonable since the random sample of features in the random forests are thought to reduce the effect of noisy features. In a last trial, not reported, we used the relative importance of the features from the output of the randomForest method to get rid of the less important features. Unfortunately, dimension reduction returned reduced accuracy in crossvalidation.

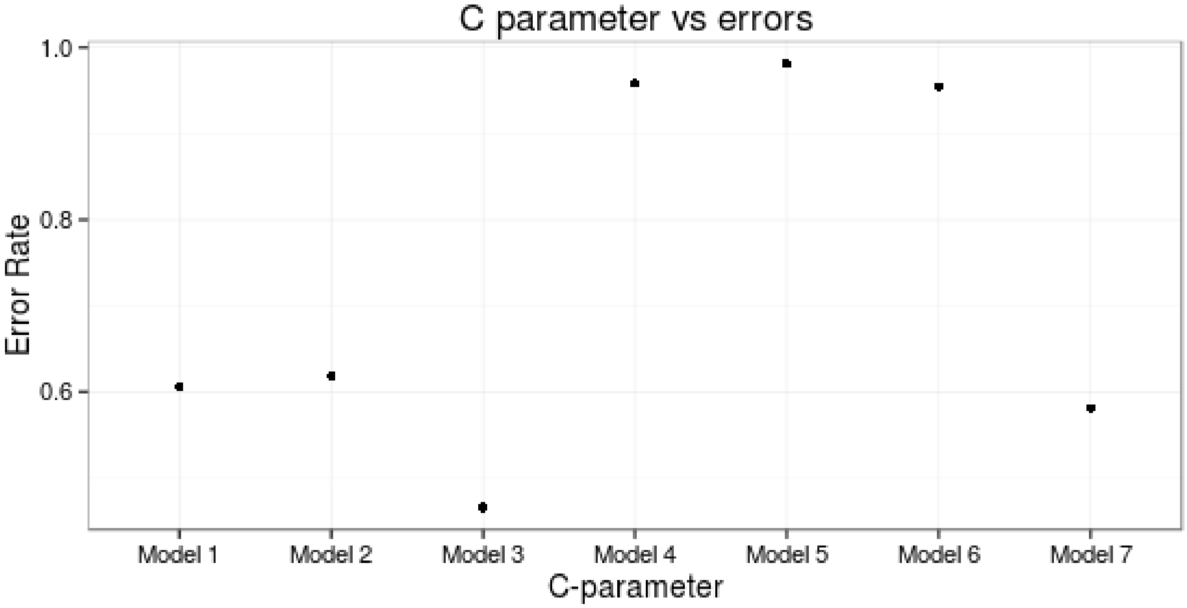
Support Vector Machines

We first tried using SVMs to classify one group against all others, but this method did not perform nearly as well as the kNN and randomForest methods. Given the enormous amount of computing time SVMs require, we explored other SVM models and packages in R and came across specifications that are adaptable to multiclass problems.

A brief note should be made about the methodology to find the ideal parameters in the SVM models considered. The initial approach was to estimate and perform diagnostics on the model trained on the entire training set. However, the computation time was over 4 hours in initial trials, so we adjusted our strategy and tuned the SVM parameters on only 20% of the training set provided. This approach has allowed a greater set of models to be tested while still maintaining the relative differences in performance across models.

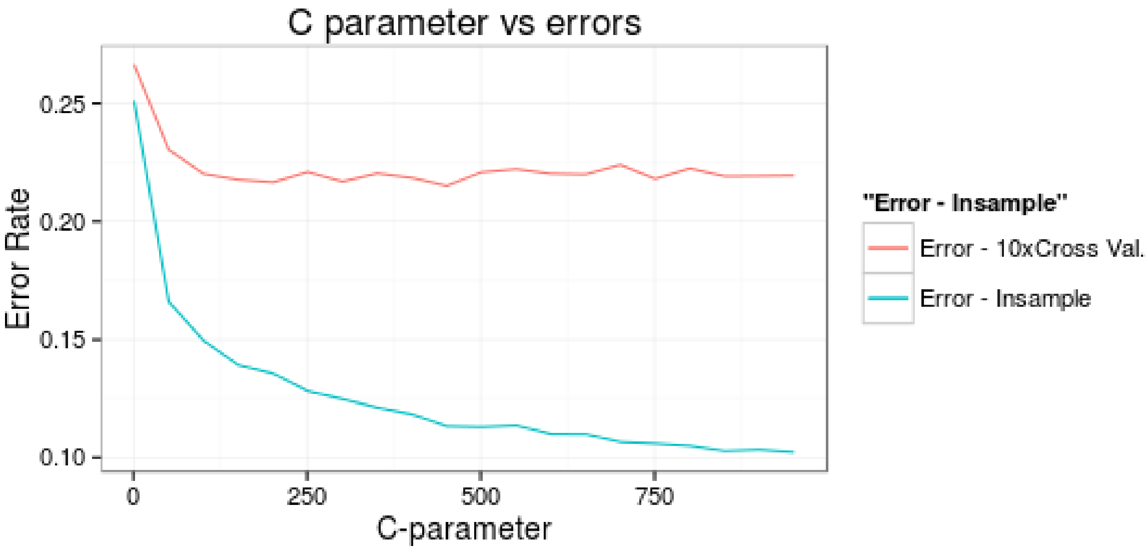
All of the types of SVM models considered were run in two different versions, considering the transformation of the continuous variables. These were scaled according to subtracting the mean and dividing by standard deviation of the training sample. The rationale is that this would make the numerical optimisation routine more stable. Some experimentation with different kernels was done in the training of the SVM. The performing kernels were the RBF and the Laplace kernel; the other kernels were severely underperforming in comparison.

One-against-all SVM Initial set of models tested considered was the one against all SVM classification for each class. So given 7 classes, 7 different model were run. The performance of these is evaluated using both in-sample validation error and cross validation error. The results are presented graphically below (for both scaled and unscaled features). Error measures were incredibly high and thus these models were discarded instantly.



Multi-class SVM Since this is a multiclass classification problem, we decided to try a classic approach called the 'one-against-one' method where we train k(k-1)/2 binary classifiers. Here, k represents the number of classes (7 in our case). The appropriate class is determined using a voting scheme. Once again, the RBF kernel was used for training, as experimentation with other kernels yielded inferior error rates (scaling the continuous variables provided miniscule improvement for this method).

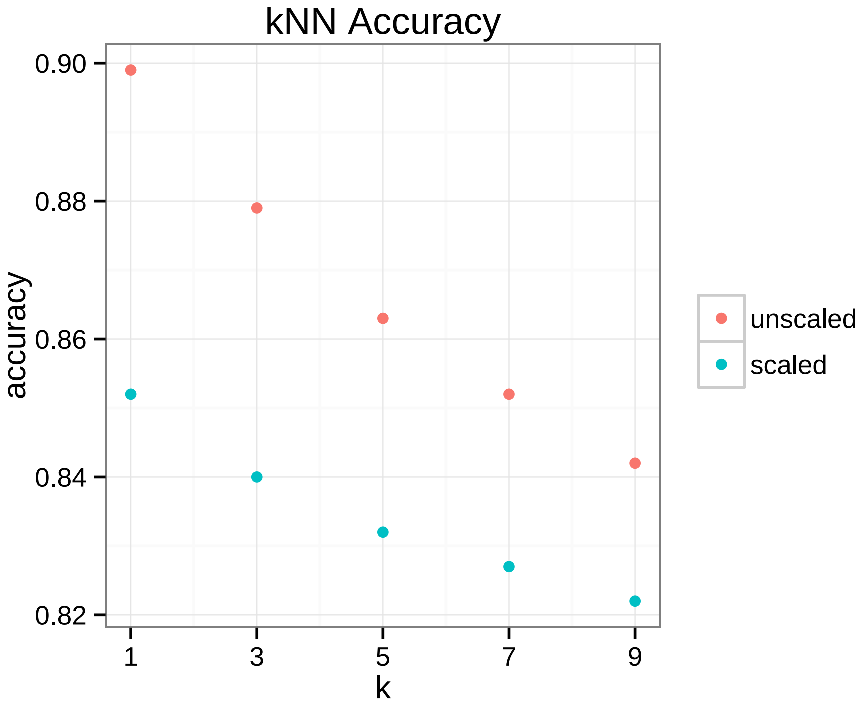
We found that increasing the regularization C parameter increased in-sample training accuracy significantly. The relationship of the C parameter and the error rates can be seen in the graph below. However, increasing the C parameter also greatly increases training time. This is because an increased C parameter assigns a higher penalty to misclassification and forces the SVM optimisation routine to search more look for a "harder" boundary. From the below graph we can see that marginal improvement from increasing C decreases greatly as C increases. We chose arbitrarily C=5000 as a reasonable parameter in accuracy/run time pay off. The final in sample misclassification error was 0.1072. The 10 fold cross validation however was much greater, of the order of 0.22.



SVM models proved to be inefficient with regard to run time and accuracy when compared to other models we considered. Thus we discarded this class of models as suitable for the given problem.

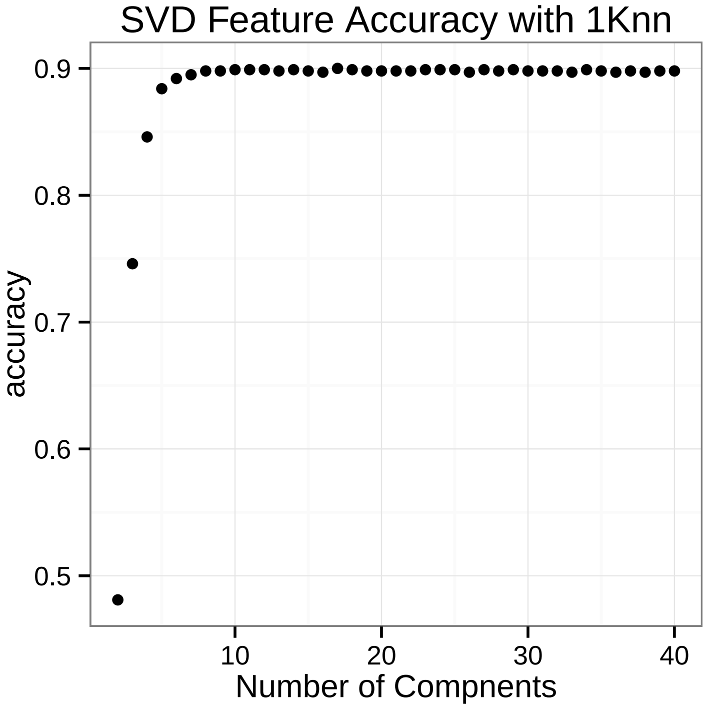
Nearest Neighbours

Initial trials of a nearest neighbor algorithm gave some promising results as a classifier. We tried to optimize the k for the nearest neighbor algorithm on both the raw data and the data that centered and scaled the continuous features. For both instances, the highest accuracy was found using k=1. Suprisingly, scaling the continuous feautes to be much smaller and centered around 0 did not increased the predictability of this classifier. So we decided to use the raw data in future iterations of this algorithm. Below is a chart displaying the accuracy of the kNN algorithms across k's for the scaled and unscaled data.



The figure shows that unscaled features gives an accuracy of 0.899 while the results for the continuos features standardized gave an accuracy of 0.852.

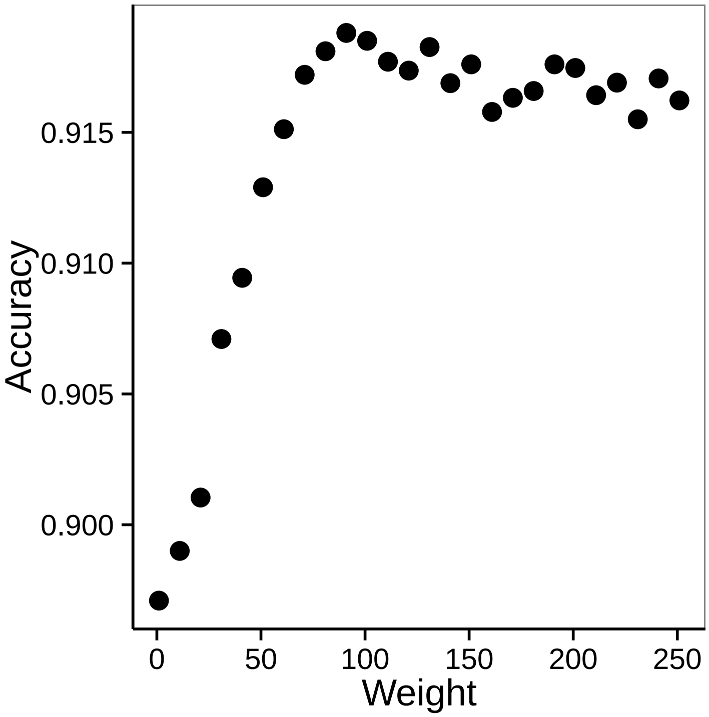
Another technique we tried was using singular value decomposition (SVD) with the 1NN algorithm. The SVD can be thought of as decomposing a matrix into a weighted, ordered sum of separable matrices. The idea was that perhaps dimension reduction that focused on the most important orthogonal features would give us a better measure of distance between points. While this method did perform well giving an optimal accuracy of 0.9; it did not significantly improve accuracy much more than 1NN. Below is a chart displaying the optimal number of SVD components to use with the 1NN algorithm. The optimal number of components to use (the one with lowest error) was 17, but as you can see from the chart, accuracy does not increase much after including 10 components (which is still quite a large reduction in dimension).



Best Classifier: Nearest Neighbours with weighted binary data

In order to improve the accuracy we realized that the wild areas and soil types were underweighted in the calculation of the distance. This is because the scales of the features are substantially different. For example, the elevation ranges from 2000 to 6000 while the soil types and wild areas are binary, i. e. they can take values 0 or 1. The binary differences lead to an insignificant increase in the distance when kNN is comparing examples with and without a given binary feature. As we showed before, the standardization of continuous variables didn't produce a good result, so a different approach was required.

To solve this issue we came back to the visual inspection of the data. In the calculation of the distance we want to keep the relevance of the continuous features since some of them are reasonably well separated (e.g. the elevation) and increase the relevance of the binary features. To do that we multiplyed the binary features by the same weight while keeping the continuous variables with the default scale. The optimal parameters we got were $weight = 91$ and $k = 1$. The figure below shows the optimization of the weights for $k = 1$.



We also checked systematically that the best k was 1 for the different weights. The optimal results for the kNN method with different scaling strategies we checked are summarized in the following table

Method	Preprocessing	Accuracy(%)	k	Scaling
kNN	raw data	89.9	1	-
kNN	Scaled continuous	85.2	1	Standardized
kNN	Weighted binaries	91.88	1	91
kNN	SVD	90.0	1	-

Conclusions

We conclude that the best method we could find to classify the forest covertypes was the kNN with k=1 with a weight of 91 applied to the binary variables, so values were$\in \{0, 91\}$. This method is responsible for our best Kaggle submission: an accuracy rate of 92.52% in the 10% test set. Our approach relies on the fact that the binary variables are underweighted in the calculation of the euclidean distances used in kNN. Since the scaling of the continuous variables didn't give us improved results we decided to scale all the binary variables with a fixed weight. This method gives the best compromise between the relevance of the continuous features and the binary features. It is possible with more time and exploration that weights could vary across for each individual binary feature, but this was not something we explored.

We discarded many methods in our search for the optimal classifier; many performed only slightly worse than our final classifier. The PCA preprocessing was the most disappointing; it probably underperformed because it is designed to reduce dimensionality and capture as much variance as possible in very few variables. While this method did manage to do that, the dimensions that it excluded probably contained enough accuracy to provide one or two extra points of accuracy in other methods. SVMs also seemed to underperform for our classification problem. Not only was the accuracy below that of other classifiers, this paticular method is much more computationally expensive than simpler and better performing methods such as kNN.