

Lab 4-Binary Classifier

Stat 215A, Fall 2014

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November 11, 2014

1 Introduction

Blah blah...

2 EDA

2.1 Plots of Raw and Expertly Labelled Images

Figure 1 displays the unprocessed image files for comparison with Figure 2, the expertly-labelled files. With the human eye it is not so difficult to parse cloud from ground based on these images, but we see that cloudy and clear pixels alike run through wide spans of AN so other features must be used.

2.2 Densities of NDAI, SD and CORR

The following three plots gives us a sense of what can be learned from NDAI, SD and CORR. The densities are grouped by their expert labels, red is for ‘no cloud’, green are for ‘unknown’ and blue for ‘cloud’. We can see that NDAI has reasonably good separation between cloud and no cloud, in all three pictures, which is confirmed in our later modeling sections by Gini importance measures found in the random forest model and its importance as a variable in LDA/QDA and logit models. In comparison, SD does not have as good of a separation within the smaller SD values, however it is still clear that pixels labelled as clouds are the only pixels with higher SD values. We thus expect the two features in combination can help determine whether a pixel with high NDAI should be labelled as a cloud by using the SD feature. Finally CORR values appear to be a good separator for image 2, but much less so for image 1. This uneven distribution of CORR values

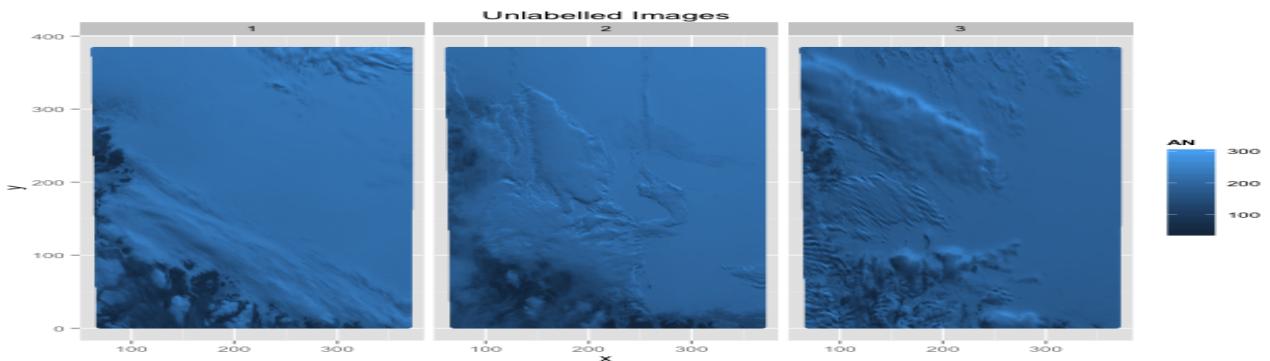


Figure 1: Raw images with AN radiances.

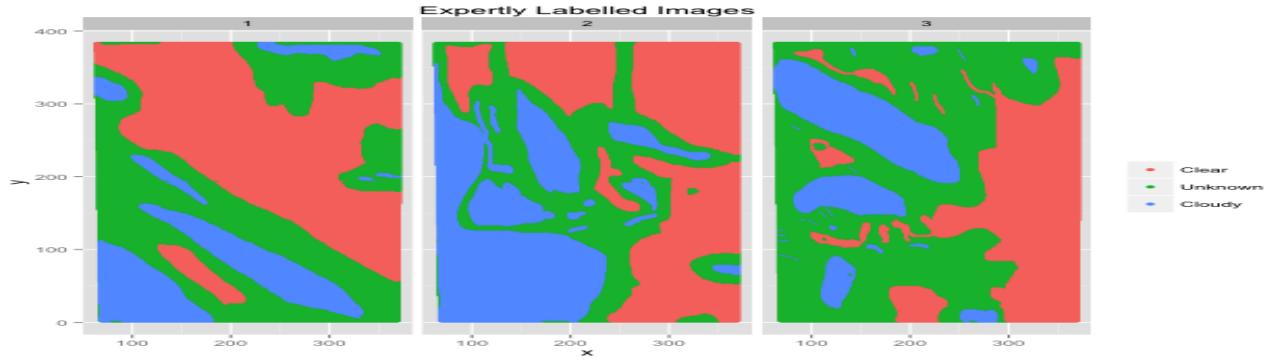


Figure 2: Images with expert classifications. Proportions: 39.8% unknown, 23.4% cloudy, 36.8% clear.

between images prompted us to cross validate our models across images, in addition to the folds created by dividing each image into 4 quadrants.

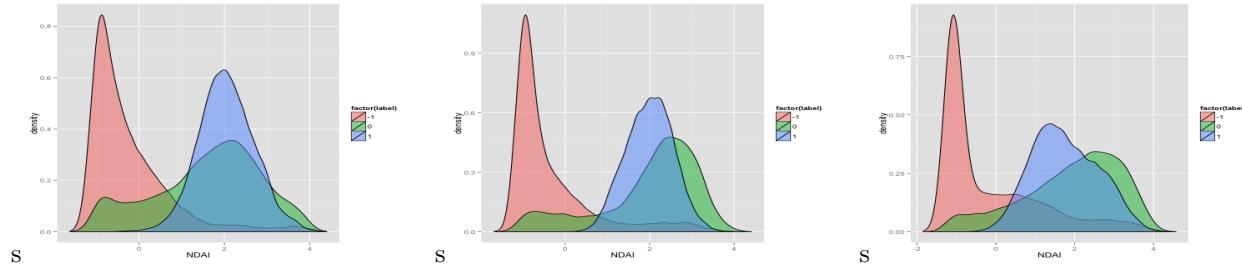


Figure 3: NDAI density plot for Image 1, 2, 3 (respectively).

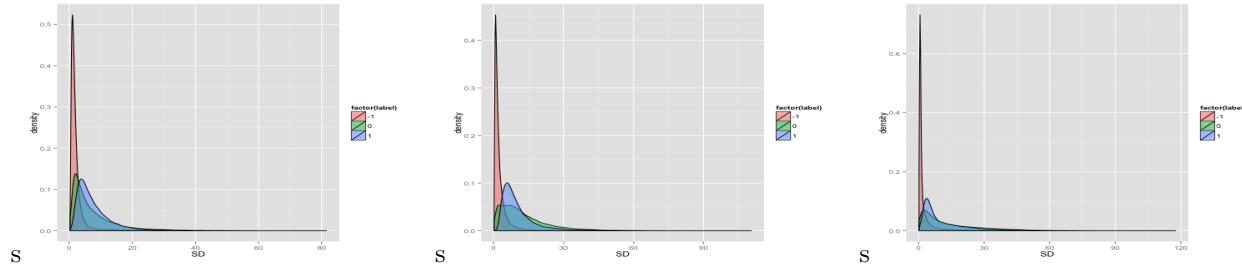


Figure 4: SD density plot for Image 1, 2, 3 (respectively).

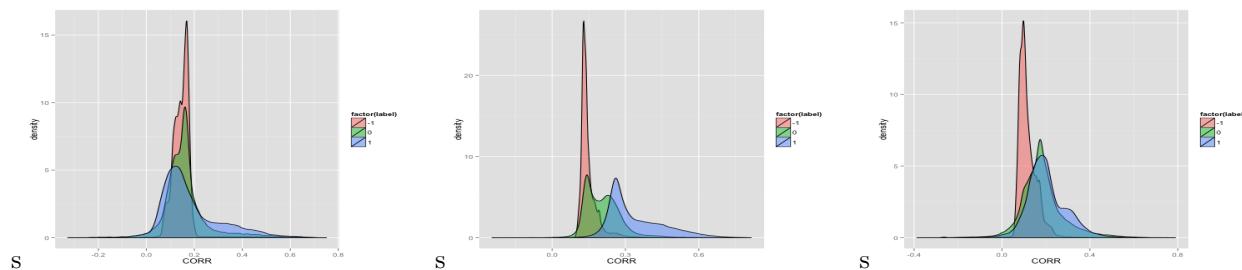


Figure 5: CORR density plot for Image 1, 2, 3 (respectively).

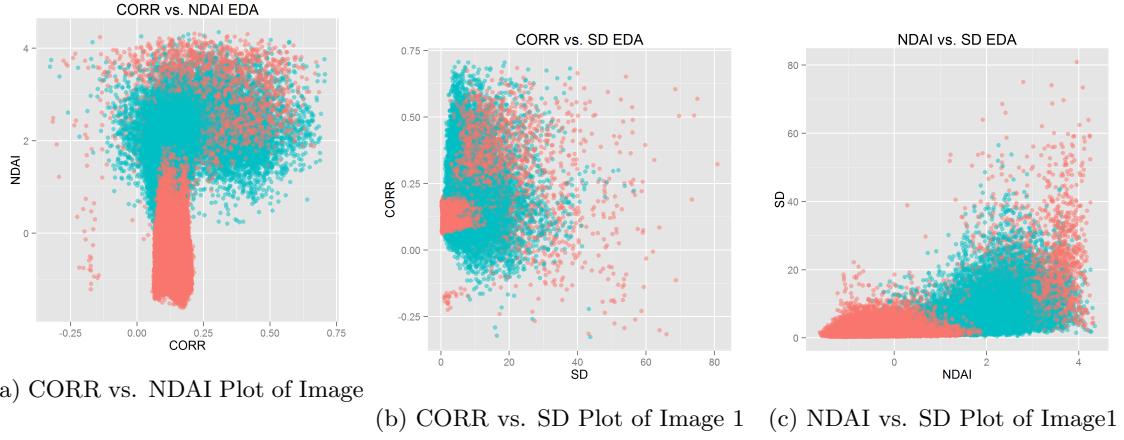


Figure 6: Scatter plots of the pairs of features used in the analyses. Red points denote pixels that were labeled as not clouds and blue points represent cloudy pixels.

Figure 6 shows hope that our selected features may be able to distinguish between cloudy and icy pixels. The rounded boundaries suggest that non-linear surfaces may be necessary to separate the feature space.

2.3 Mapped Features

The ensuing figures plot the engineered feature values (NDAI, SD, CORR) spatially. In agreement with the NDAI density plots, higher NDAI values indicate increased likelihood of the presence of clouds, and the NDAI plots look quite similar to the binary classification plots. The SD maps show areas of high variance in the radiances thereby providing a decent outline of cloud boundaries. Unfortunately, this can also lead to the highlighting of uneven ground regions. Finally, the CORR images resemble weakened versions of their NDAI counterparts though with some additional strange behavior in the bottom left corners of Images 1 and 2.

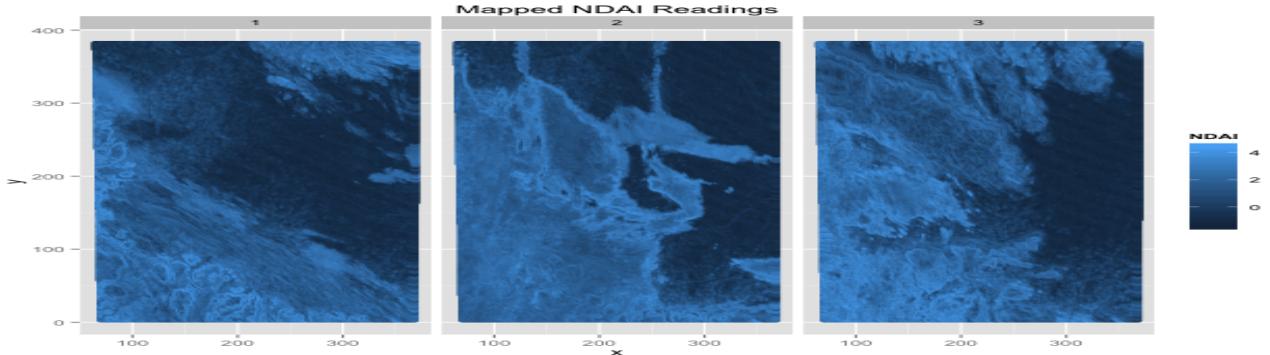


Figure 7: Mapped NDAI readings. We see good correspondence between larger values and presence of clouds.

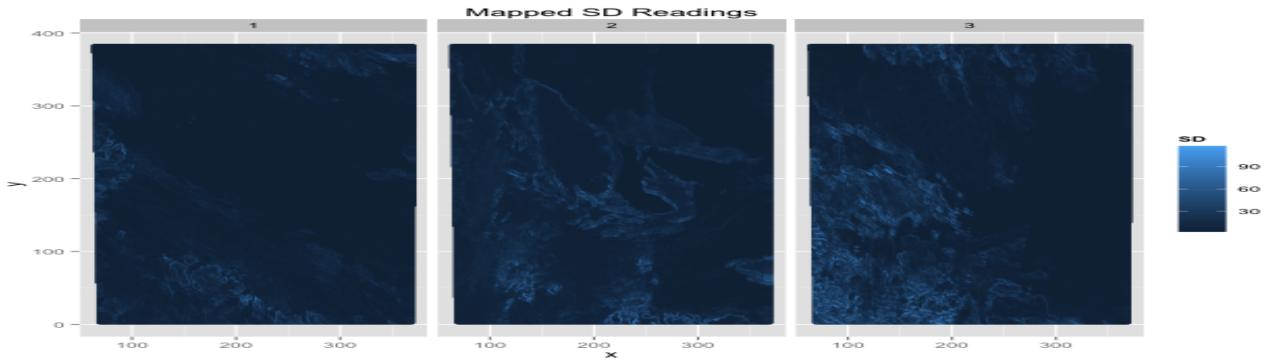


Figure 8: Mapped SD readings. Higher values show cloud boundaries, though also show uneven terrain.

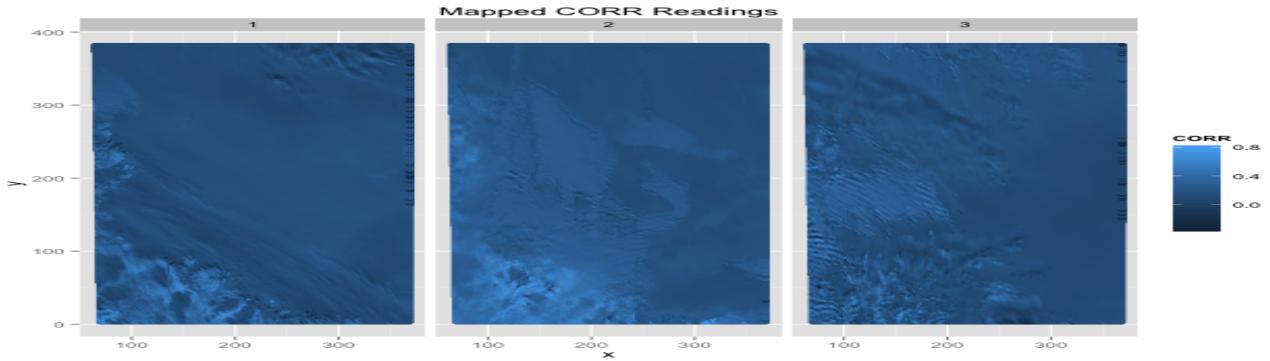


Figure 9: Mapped CORR readings. Cloudy regions tend to be lighter, but not as strongly as in NDAI.

3 Modeling

3.1 QDA/LDA

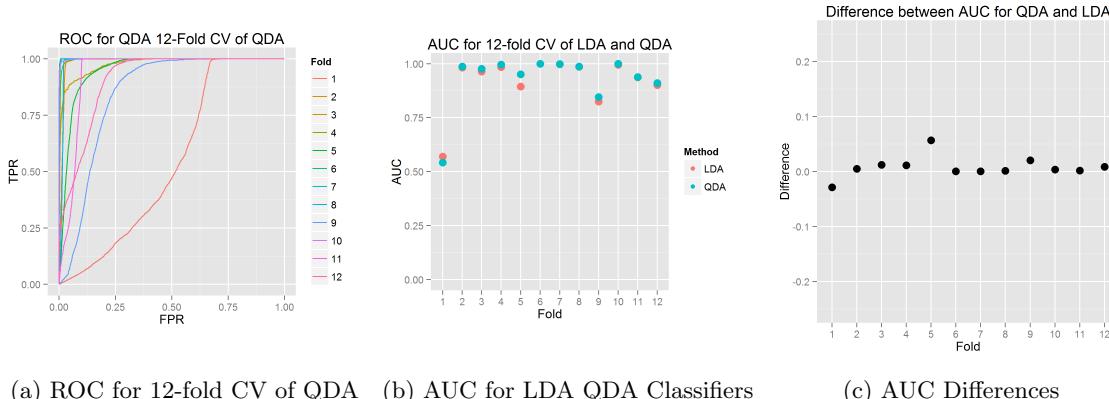


Figure 10: (10a) shows the ROC curves for each of the 12 folds of cross validation. (10b) and (10c) show evidence via AUC estimates that QDA performs slightly better than LDA. Note that in both analysis, fold 1 has an abnormally low AUC.

Linear discriminant analysis (LDA) for binary classification aims to separate the feature space using a hyperplane. It assumes that each class is normally distributed with means μ_0 and μ_1 and that the two classes are homoscedastic with covariance matrix $\Sigma_0 = \Sigma_1 = \Sigma$. Quadratic discriminant analysis works in the same manner except that it makes no assumptions about the covariance matrix. Thus given the multivariate Gaussian distribution:

$$f_c(x) = \frac{1}{(2\pi)^{p/2} |\Sigma_c|^{1/2}} e^{-\frac{1}{2}(x-\mu_c)^T \Sigma_c^{-1} (x-\mu_c)} \quad (1)$$

where $c = 1, 2$ is the class label. Let p_c be the prior probability of class c . We can calculate the probability for a case x belonging to class c by:

$$P(x \in \text{Class } c | X = x) = \frac{f_c(x)p_c}{f_1(x)p_1 + f_2(x)p_2} \quad (2)$$

We can then classify each point by selecting a probability threshold and hard-assigning based on whether or not the posterior probability was higher or lower than that threshold. Both LDA and QDA were carried out during our analysis of the data, but as we suspected from our exploratory data analysis, QDA performed slightly better than LDA when we compared the results side-by-side (see figure 10). During cross-validation, each image was divided into four horizontal strips, resulting in 12 folds to be used in our validation procedure. In each iteration, we withheld one of the strips and trained on the remaining 11. The resulting images after piecing the horizontal strips back together can be seen in figure 12. Cross-validation for QDA revealed that while the method works extremely well in some cases, producing AUC scores of almost 1, it sometimes fails to perform better than even the theoretical random classifier. In particular, the classifier does not seem to be good at discerning snow from clouds in regions where there are many dark pixels corresponding to geographical features. The most indicative example of this is seen in image 1 where the algorithm misclassifies an entire ridge-filled region as clouds. We also noticed that there were some misclassifications within large cloudy regions. Figure 11 shows this nicely.

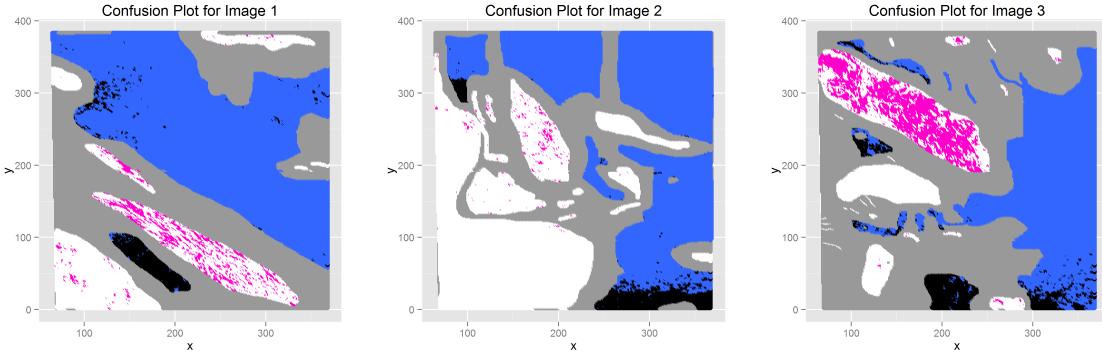


Figure 11: A comparison between the output of QDA and expert labels.

3.2 Logit

Logistic regression is a widely-used discriminative classification model arising from the class of generalized linear models. It is among the simplest classification methods and models the conditional distribution of the outcome given the covariates as a Bernoulli random variable with success probability given by the logistic function evaluated at $X_i\beta$, where X_i is the covariate vector and β the coefficient vector. It further supposes that the response variables are independent conditioned on the observed features. To classify, a threshold probability is chosen and all response variables with success probability above this value are labelled a success; otherwise, they are denoted as a failure. In our case, success is equivalent to cloudy and failure to clear. Preliminary results showed similar performance between the probit and logit models, so we chose to focus on logit due its fewer assumptions (probit requires homoscedasticity and normality of errors) and greater

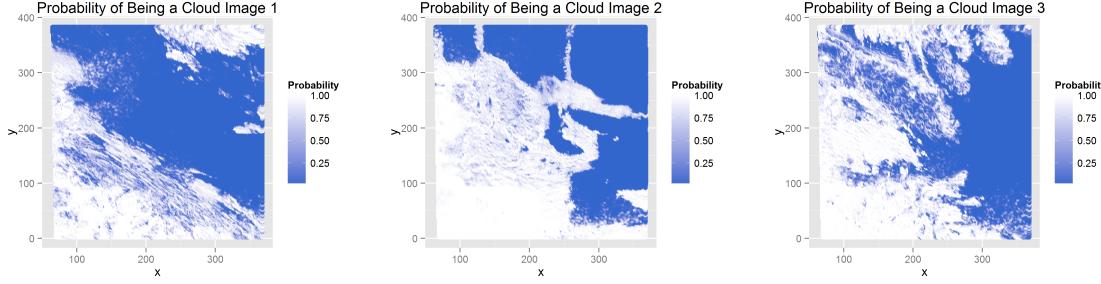


Figure 12: Posterior probabilities of being a cloud as given by QDA

ubiquity in practice. Use of logistic regression also assumes that the model has been properly specified with all significant and no extraneous predictors included.

The logit model obtained via averaging after 12-fold cross-validation has $y_i = -3.356 + 1.900 * NDAI_i - 0.074 * SD_i + 9.002 * CORR_i$ where $P_i(\text{Cloud}) = \frac{1}{1+e^{-y_i}}$. To choose our cutoff value for declaring a pixel cloudy, we varied the cutoffs from .01 to 1 and calculated the misclassification error of our model at that threshold on expertly-labelled pixels. The figure below shows that the optimal threshold for this model is at .38, with an error of just under 10.1%. As a consequence of this low threshold, we observe more false positives than false negatives. This will be further explored below.

Cross-validation was done by dividing each image into quadrants and holding one quadrant out for testing in each iteration of training. There were thus 12-folds in the CV procedure. We chose blocks to comprise each fold rather than a random subsample of points in order to compensate for the correlation of errors among neighboring points.

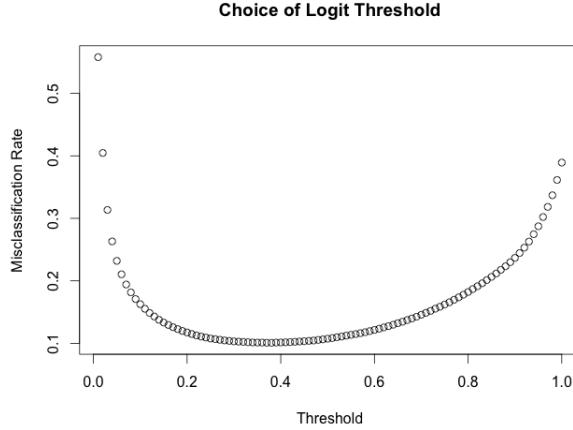


Figure 13: We see a minimum in misclassification rate at .38.

Figure 15 gives the binary classifications overlaid on the images. Visual comparison with the expertly-labelled images suggests that we are slightly biased towards the presence of clouds as 74.2% of unlabelled points have been classified as cloudy, though this may be due to a lack of power in the expert labelling scheme.

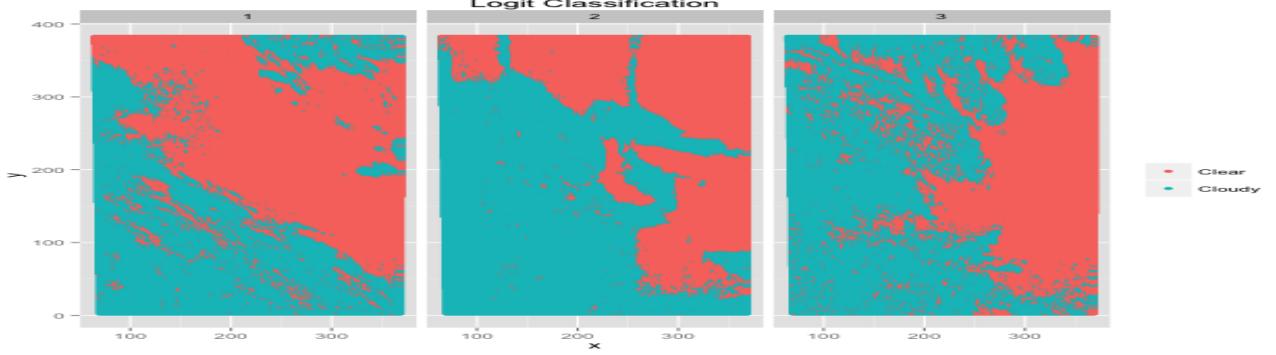


Figure 14: Binary classifications with threshold = .38 for logit trained via 12-fold CV.

Here we see the logit probabilities plotted spatially. This should approximate how the image would appear if the ground were not covered in snow and ice, so comparison with Figure 1 is especially appropriate.

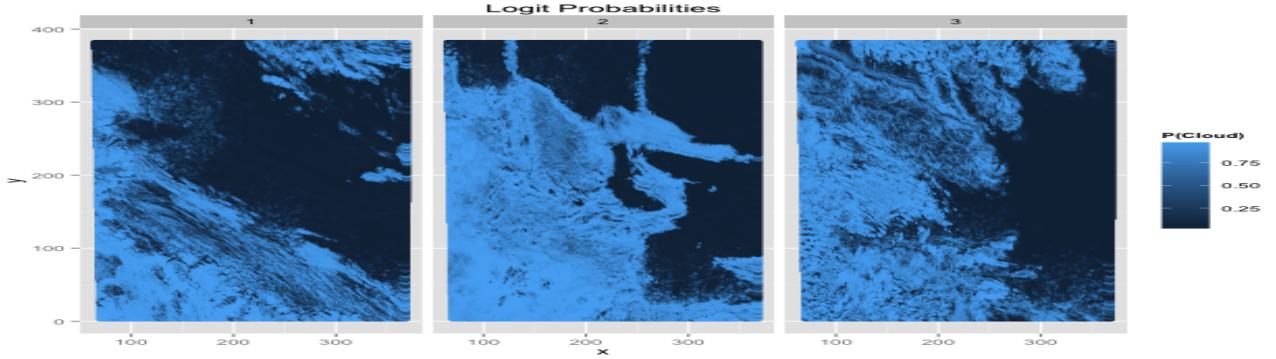


Figure 15: Probabilities for logit trained via 12-fold CV.

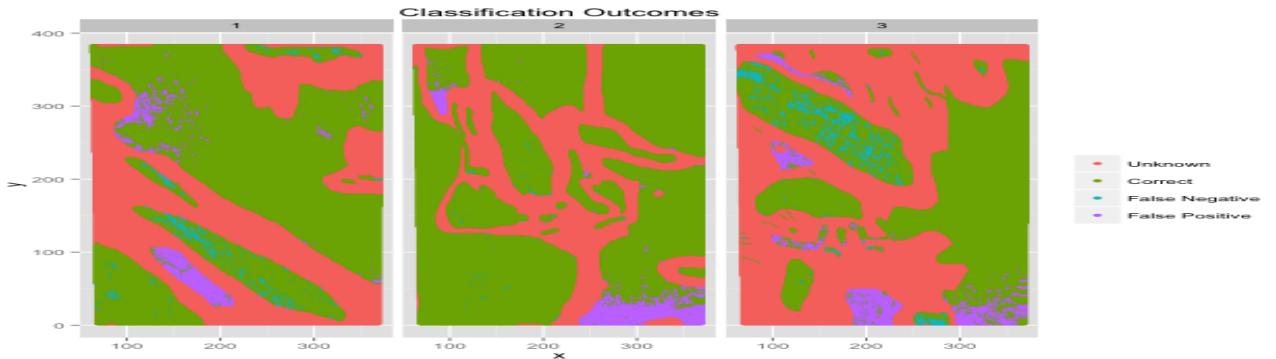


Figure 16: Classification results from logit with respect to the expert labels.

We now discuss the trends in misclassification. As depicted in the above figure, we have many more false positives than false negatives with large regions sometimes completely misclassified. These regions are often situated on boundaries of labelled and unlabelled points. Calculation shows the false negative rate to be 7.5% and the false positive rate to be 11.7%. Models with interaction terms were considered and yielded very slight improvement as measured by drop in misclassification rate from .104 to .092. However, comparison

of the misclassification plots showed that the increased complexity did not resolve the large clusters of false positives observed in each image.

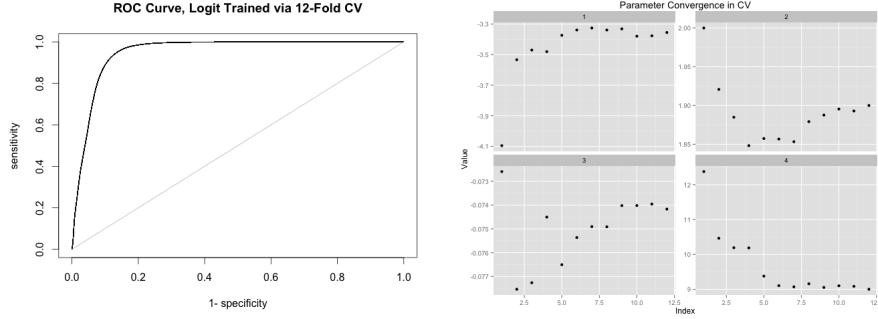


Figure 17: Left: ROC Curve with AUC=.95. Right: Parameter convergence through iterations of CV. 1 - Intercept, 2 - NDAI, 3 - SD, 4 - CORR

3.3 Random Forest

For random forest, as in all the other classifiers, we divided the three images into equal sized quadrants (2×2) rectangles in order to do 12 fold validation on the dataset. That is, for each iteration of the validation, we dropped one of the quadrants as a test set, and trained on the remaining 11 quadrants. Keeping the test segments as disjoint chunks from the test set ensured that our models were picking up on ‘higher’ level structure of the dataset, and not the continuous variation of neighbouring pixels. As such, we also expect the performance of the model on these test sets to be a much better predictor of how our model will perform on new images than if we randomly subsampled the validation folds. Indeed, after doing random subsampling, we noticed that the AUC was at a high 0.999 for all cross validations, whereas by cross validating on the isolated quadrants, our AUC curves had much higher variance, as seen below:

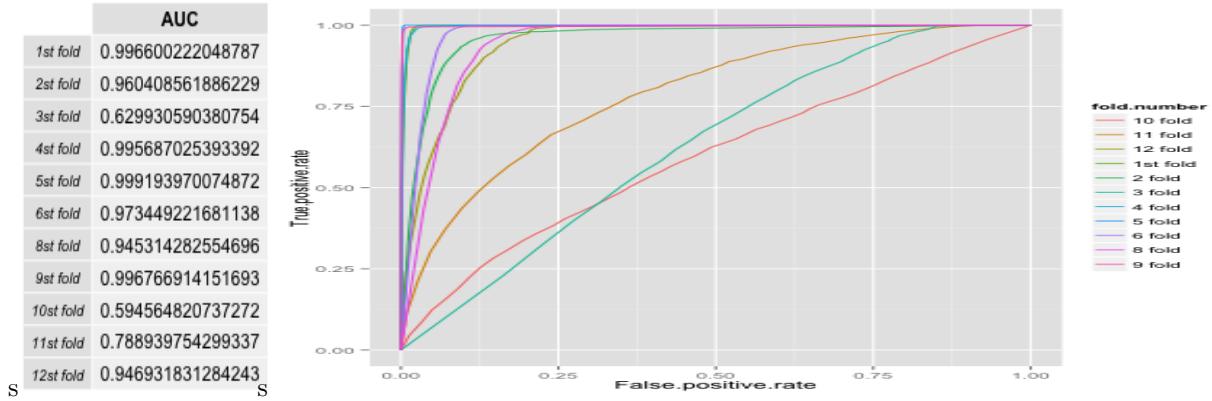


Figure 18: ROC across all 12 folds of quadrants

We also trained on each image and tested on the remaining two.

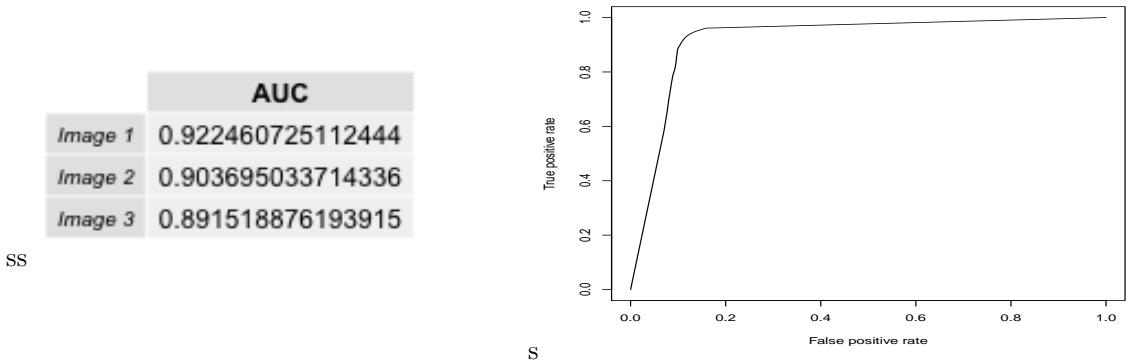


Figure 19: Convergence of ROC training on increasing number of quadrants in shuffled order

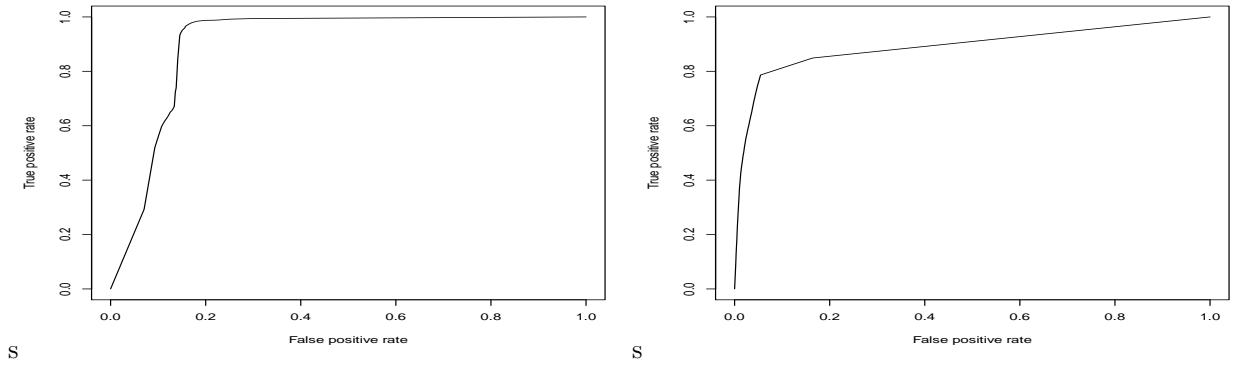


Figure 20: Convergence of ROC training on increasing number of quadrants in shuffled order

To test convergence, one of the things we did was increase the training set from including 1 quadrant, to including 2 quadrants, up to including 11 quadrants (using the complement as the test set). For each of the 3 aforementioned classes of training, we trained on a range of forest sizes, from 2 trees to 50. It was interesting to note that the continuity of increasing the training set by neighbouring quadrants displayed much less convergence than by increasing the training quadrant set in a randomly subsampled way. The following three plots make this clear. In the first case....

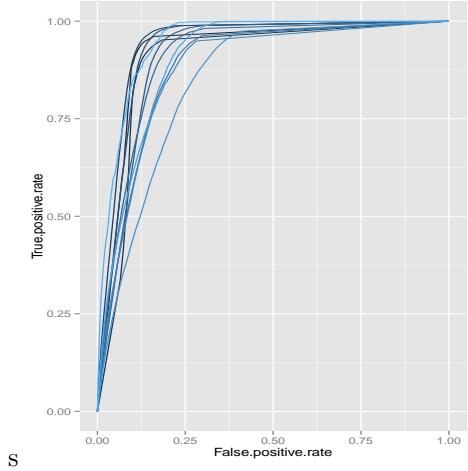


Figure 21: Convergence of ROC training on increasing number of quadrants

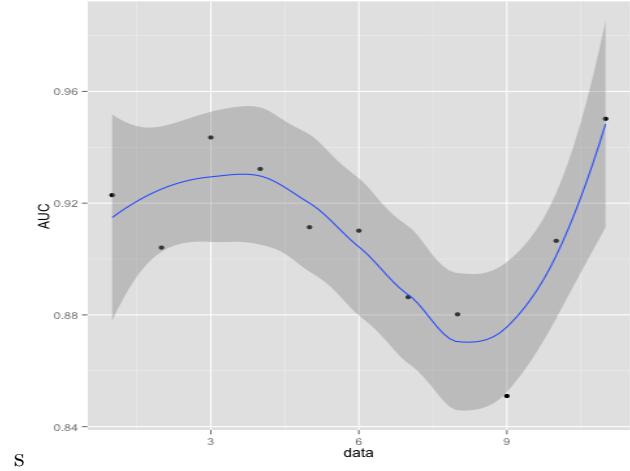


Figure 22: Smoothed convergence of AUC for growing training set 50 trees and 3 features

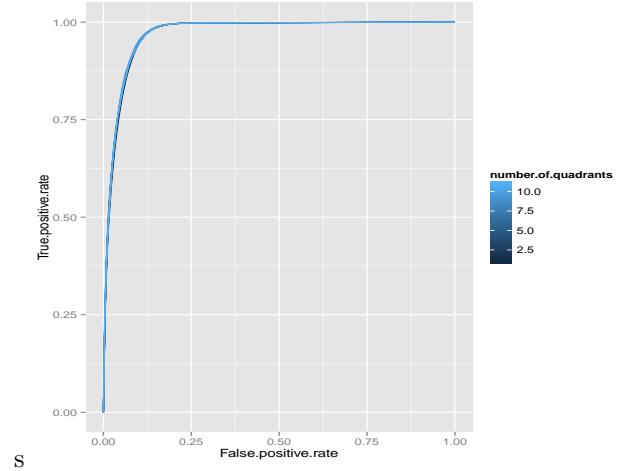
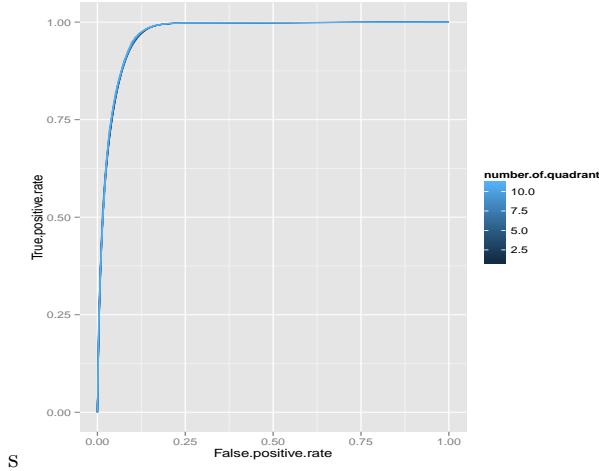


Figure 23: Convergence of ROC training on increasing number of quadrants in shuffled order

To gather a quantitative measurement of the importance of each feature, we first ran random forest using all the features and looked at the GINI importance measure. This is calculated by recording the difference between the Gini measure of a random forest's predictions on a fold and the Gini measure with a particular feature's values randomly shuffled. The intuition is that if a feature were crucial to the forest's trees, than randomly shuffling that feature will drastically decrease it's Gini measure. Sure enough, NDAI, SD and CORR consistently ranked as the clear top three in all cross validations.

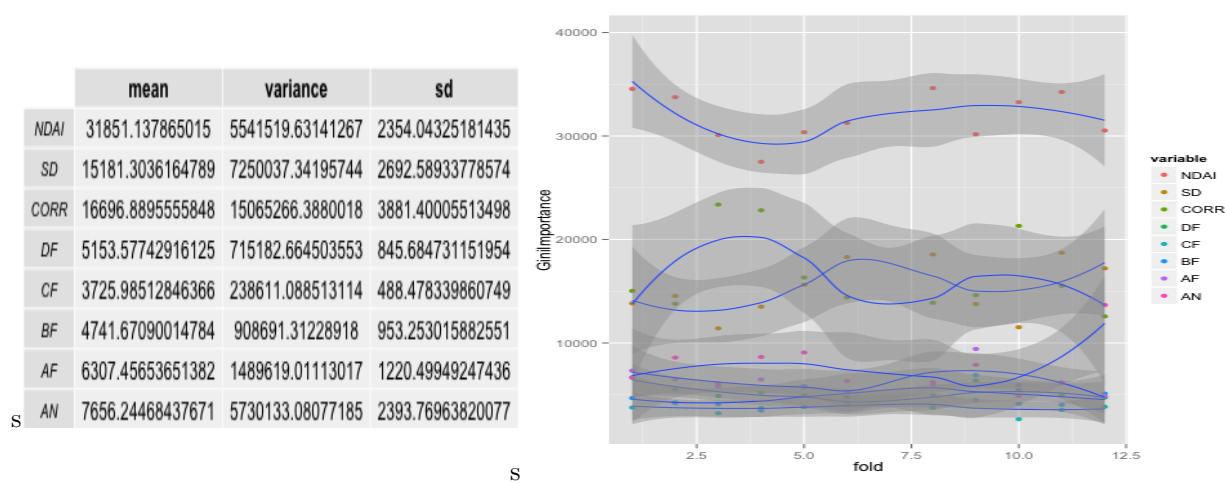
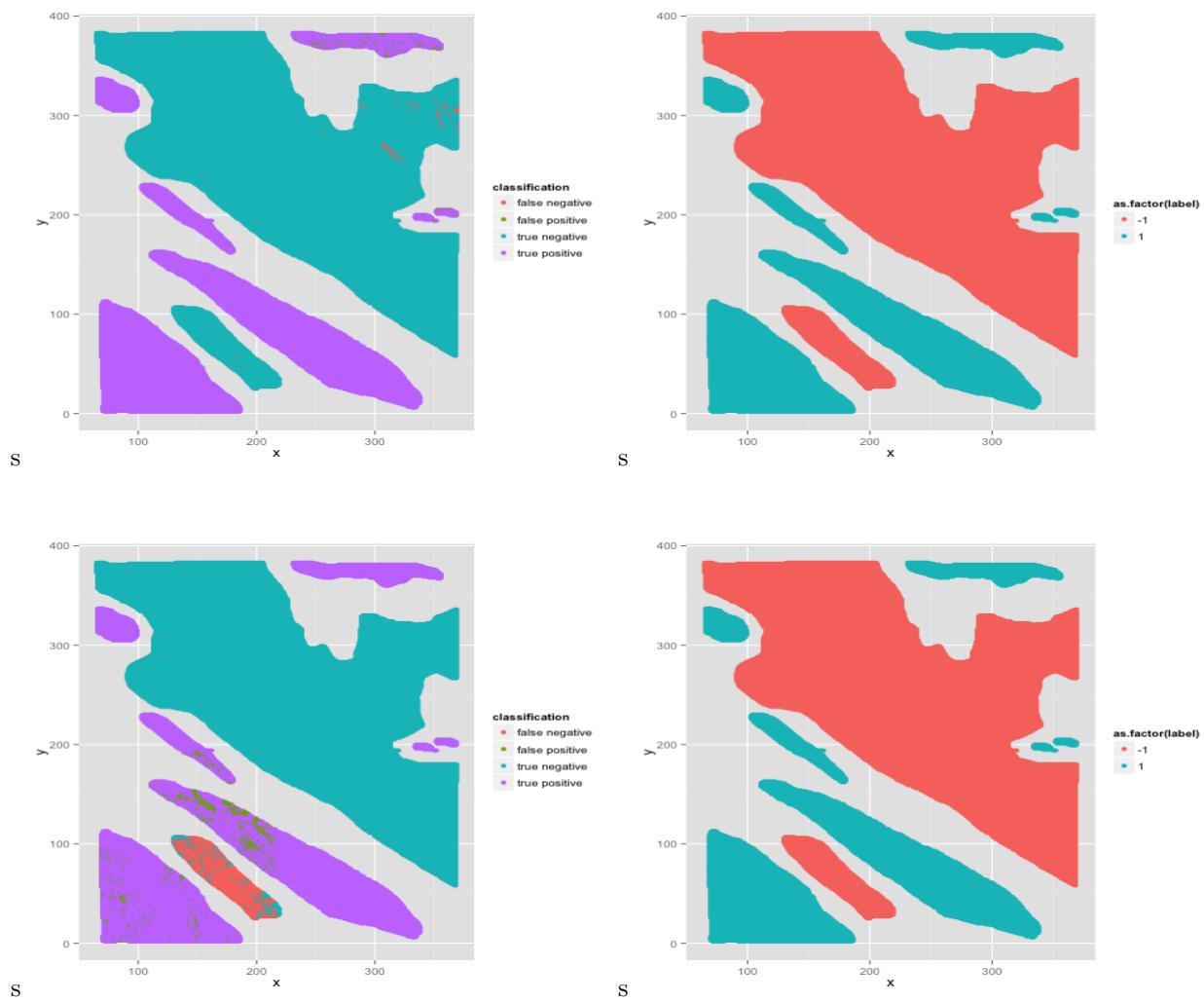
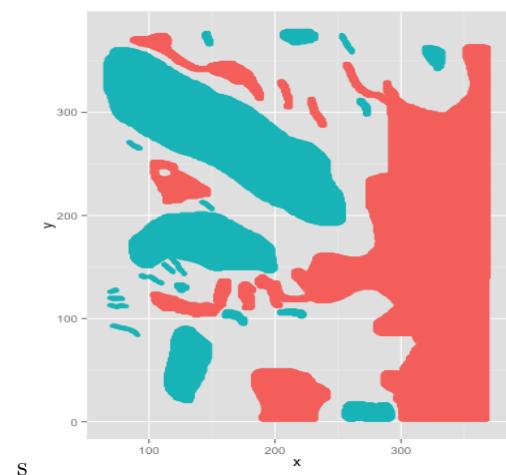
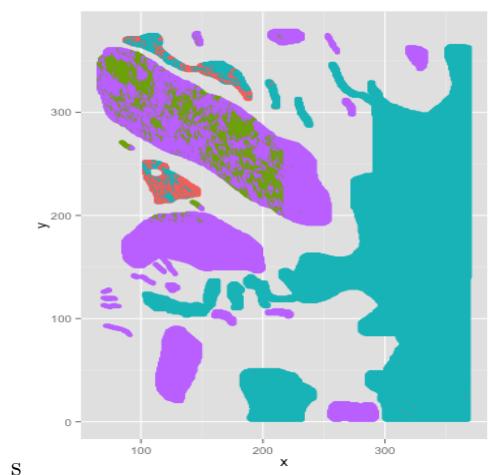
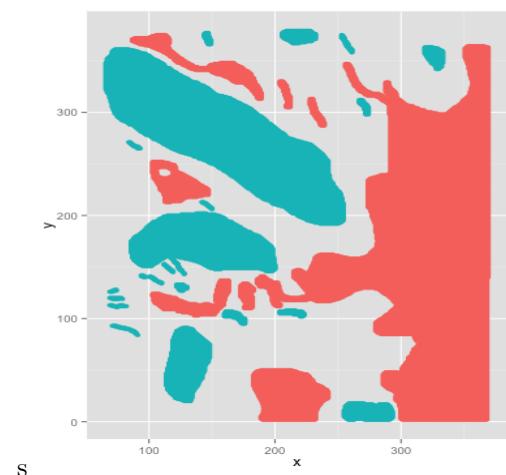
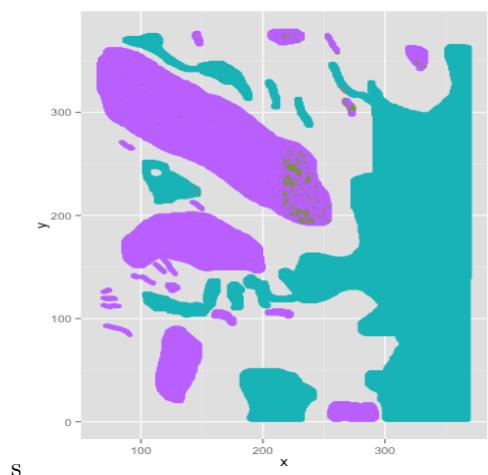
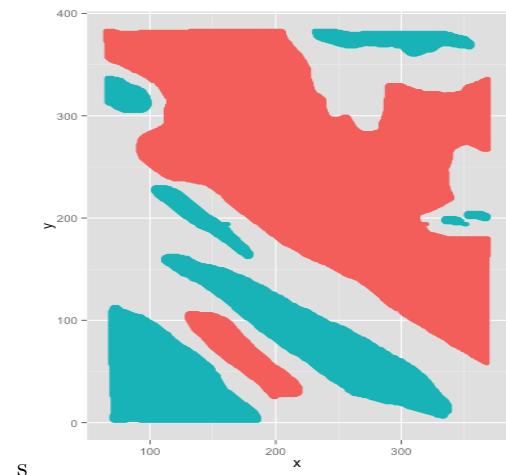
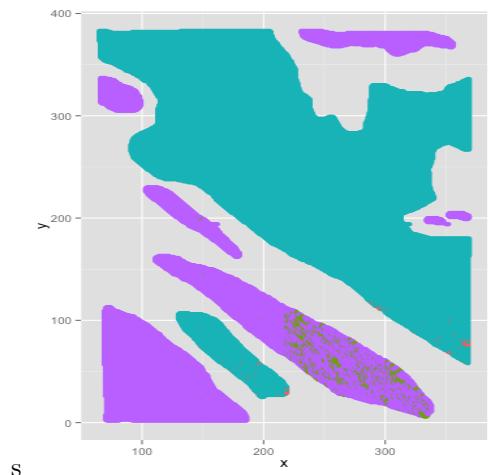
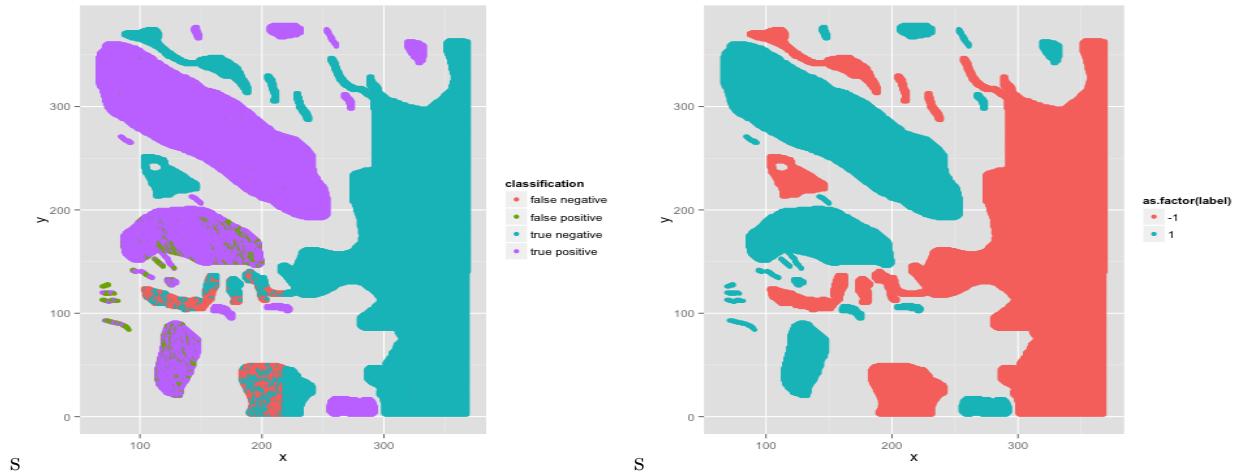


Figure 24: Gini importance measures across folds

Where was the model performing poorly?







4 Reproducibility

How we organized our code and github repo

References

- [1] Ben-Hur, A., Elisseeff, A., Guyon, I.: A stability based method for discovering structure in clustered data. In: Pacific Symposium on Biocomputing, pp. 617.