STAT 557 - Project 2

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Data overview

Mining activity has long been associated with mining hazards, such as fires, floods, and toxic contaminants (Dozolme, P., 2016). Among these hazards, seismic hazards are the hardest to detect and predict (Sikora & Wróbel, 2010). Minimizing loss from seismic hazards requires both advanced data collection and analysis. In recent years, more and more advanced seismic and seismoacoustic monitoring systems have come about. Still, the disproportionate number of low-energy versus high-energy seismic phenomena (e.g. $> 10^4$J) renders traditional analysis methods insufficient.

In this project, we used the seismic-bumps dataset provided by Sikora & Wróbel (2010), found in the UCI Machine Learning Repository. This seismic-bumps dataset comes from a coal mine located in Poland and contains 2584 observations of 19 attributes. Each observation summarizes seismic activity in the rock mass within one 8-hour shift. Note that the decision attribute, named "class", has values 1 and 0. This variable is the response variable we use in this project. A class value of "1" is categorized as "hazardous state", which essentially indicates a registered seismic bump with high energy ($>10^4$J) in the next shift. A class value "0" represents non-hazardous state in the next shift. According to Bukowska (2006), a number of factors having an effect on seismic hazard occurrence were proposed. Among other factors, the occurrence of tremors with energy $> 10^4$J was listed. The purpose is to find whether and how the other 18 variables can be used to determine the hazard status of the mine.

Table 1. Attribute information of the seismic-bumps dataset

Data Attributes	Description
seismic	result of shift seismic hazard assessment: 'a' - lack of hazard, 'b' - low hazard, 'c' - high hazard, 'c
seismoacoustic	result of shift seismic hazard assessment
shift	type of a shift: 'W' - coal-getting, 'N' - preparation shift
genergy	seismic energy recorded within previous shift by active geophones (GMax) monitoring the longwal
gpuls	number of pulses recorded within previous shift by GMax
gdenergy	deviation of recorded energy within previous shift from average energy recorded during eight prev
gdpuls	deviation of recorded pulses within previous shift from average number of pulses recorded during
ghazard	result of shift seismic hazard assessment by the seismoacoustic method based on registration comi
nbumps	the number of seismic bumps recorded within previous shift
nbumps$i$, $i \in \{1, \ldots, 5\}$	the number of seismic bumps ($10^i - 10^{i+1}$ J) registered within previous shift
energy	total energy of seismic bumps registered within previous shift
maxenergy	maximum energy of the seismic bumps registered within previous shift
class	the decision attribute: '1' - high energy seismic bump occurred in the next shift ('hazardous state

Exploratory Data Analysis

The state of the mine was indeed deemed hazardous infrequently − only 170 shifts out of 2584 − a difficult problem in our analyses. We want to examine which observations of seismic activity can help in the prediction of the hazard state of the mine during the next shift. Regression diagnostics indicate that the data, in general, meet most assumptions. However, we see that that data are somewhat skewed right, and there is severe

multicollinearity (VIF > 10) between some of the covariates, as shown below.

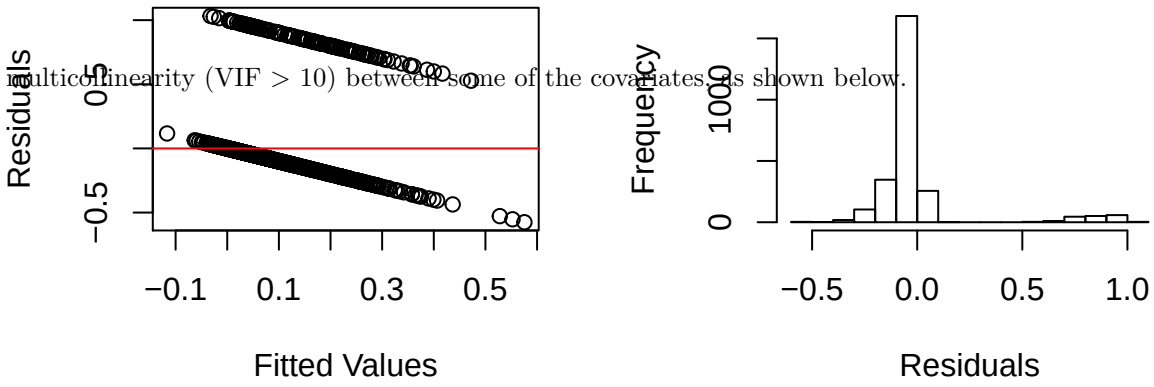


Table 2: VIFs of Linear Model

seismic	seismoacoustic	shift	genergy	gpuls	gdenergy	gdpuls
1.21	1.29	1.41	2.89	4.06	3	3.43

Table 3: VIFs of Linear Model

ghazard	nbumps	nbumps2	nbumps3	nbumps4	nbumps5	energy	maxenergy
1.4	2414.69	798.96	769.13	104.4	11.56	110.28	93.76

Classification before Variable Selection

We first take the seismic-bumps dataset and partition the data into training (75%) and test (25%) datasets. The next steps involve examining multiple classification methods on the training and test datasets separately. The goal is to examine which classification method outputs comparatively better prediction for seismic hazards based on available predictors.

Linear Regression of an Indicator Matrix

We begin with linear regression of an indicator matrix as this method can approximate a linear decision boundary among observations belonging to one of two classes. Our model outputs an overall error rate of ~6.8% on the training data and ~6.3% on the test data. However, this comes with no sensitivity, which means we would almost never predict a hazardous event in the mine.

Table 4: Training vs. Test for regression of indicator matrix

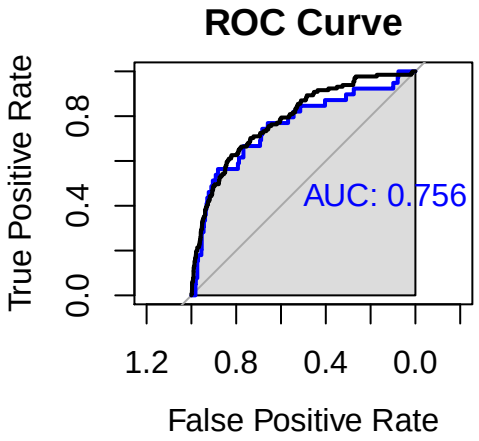
	Train 0	Train 1	Test 0	Test 1
Predict 0	1804	130	605	39
Predict 1	3	1	2	0

Logistic Regression:

We then fit a logistic regression model to predict the response using all the predictors in the training dataset. Initially, we used a threshhold probability of 0.5 to classify into state 0 or 1. This yields an overall error rate of ~6.7% for the training data and 6.5% for the dest data, with minimal improvement in sensitivity. The ROC curve for this model indicates that it is still not a great fit for the data.

Table 5: Training vs. Test for logistic regression

	Train 0	Train 1	Test 0	Test 1
Predict 0	1802	125	604	39
Predict 1	5	6	3	0

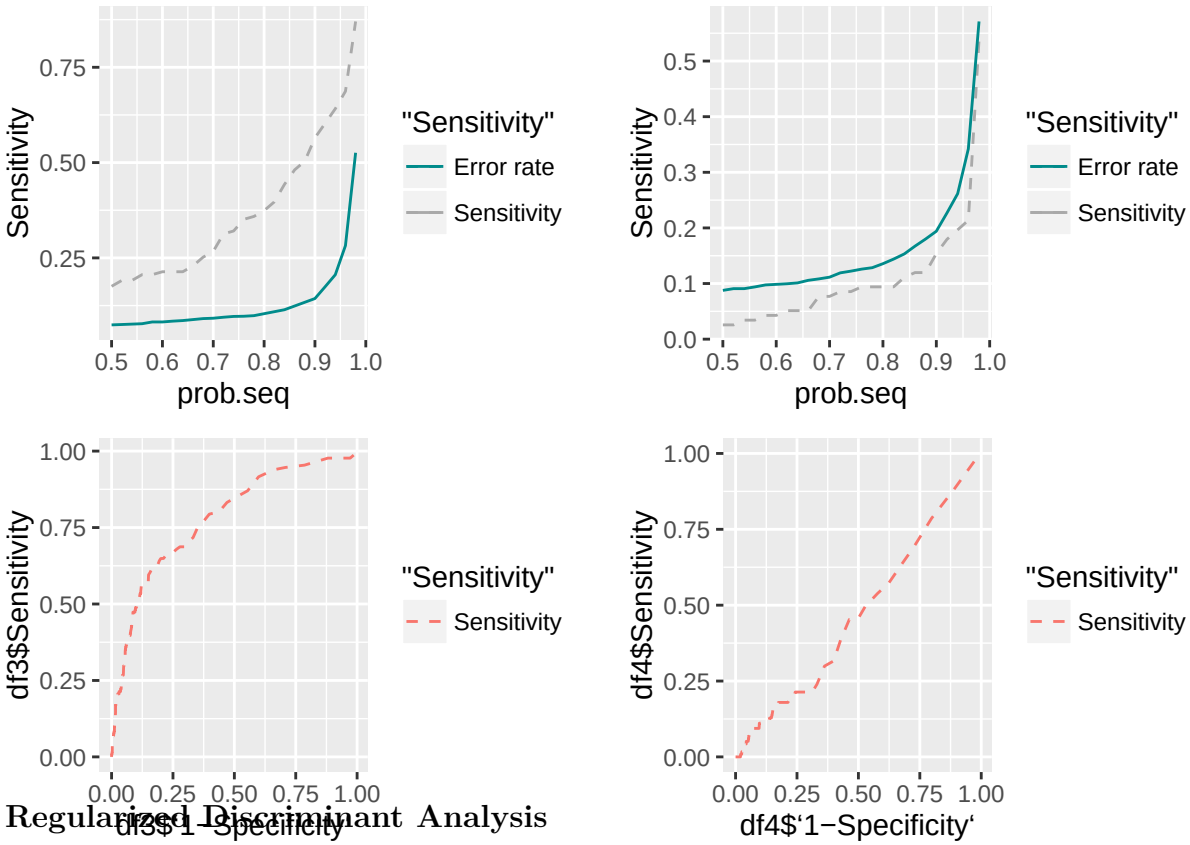


Linear Discriminant Analysis

It is reasonable to believe that each class is distributed normally with some different mean vector. Thus, we implemented an LDA approach. Using a classification threshhold of 0.5 yields an overall error rate of ~7.4% for the training data and ~7.7% for the test data, but with much higher sensitivity than in the previous models. The group means suggest that a mining shift with a higher number of seismic bumps and associated higher released energy (measured in Joules) is correlated with hazard status of the mine in the subsequent shift.

Table 6: Training vs Test

	Train 0	Train 1	Test 0	Test 1
Predict 0	1771	108	591	34
Predict 1	36	23	16	5



Regularized Discriminant Analysis

Similar to LDA, it is reasonable to believe that each class is distributed normally with some different mean vector and covariance matrix, as seen in quadratic discriminant analysis (QDA). RDA allows for a compromise between LDA and QDA. We implemented an RDA approach. Using a classification threshhold of 0.5 yields an overall error rate of ~7.6% for the training data and ~8.2% for the test data. Poor performance on the test data might be indicative of RDA overfitting for this model.

Table 7: Training vs Test

	Train 0	Train 1	Test 0	Test 1
Predict 0	1785	126	593	39
Predict 1	22	5	14	0

Variable selection and refitting

Based on high error rate and low prediction accuracy (e.g., low sensitivity) estimates both in the training and test datasets, it is evident that the fitted regression and classification models in the preceding sections are not able to approximate the relationship between response and predictor variables. The strong multicollinearity among some of the predictor variables may have contributed to the high error rate. Therefore,in order tp improve prediction accuracy, we employ some commonly used variable selection methods: stepwise selection, LASSO, and principle component analysis.

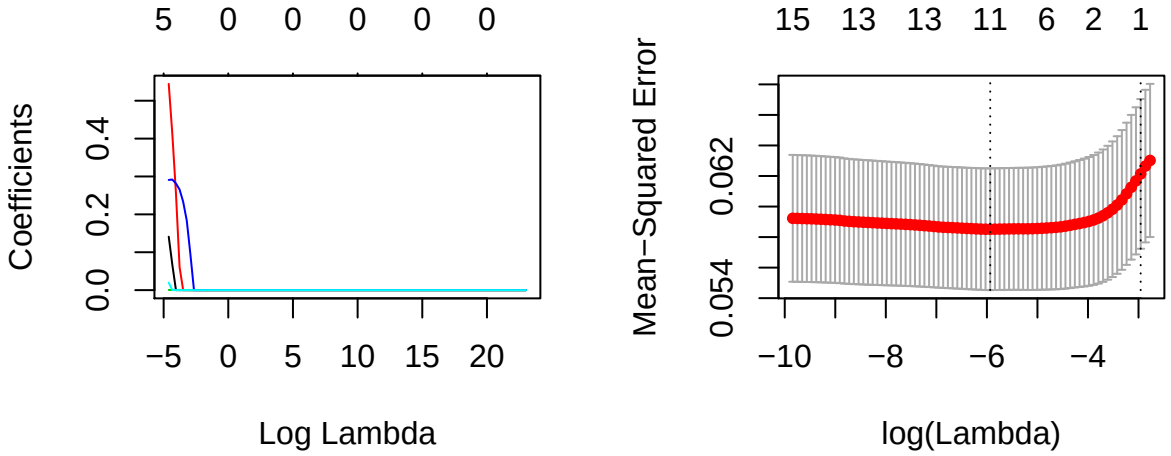
Stepwise Variable Selection

We performed forward and backward selection as a starting point. We did further manual selection, and chose the model that produced the lowest AIC score (AIC = -83.097). We denote the model with these variables as Model 1, which can be written as

$$class \sim \beta_0 + \beta_1 \cdot genergy + \beta_2 \cdot gpuls + \beta_3 \cdot nbumps + \beta_4 \cdot nbumps2 + \beta_5 \cdot nbumps4 + \epsilon, \quad \epsilon \sim N(0, \sigma^2)$$

LASSO

We also performed Least Absolute Shrinkage and Selection Operator (LASSO) regression, which fits a model by shrinking some of the coefficients toward exactly zero using the $\mathcal{L}_1$ penalty. According to LASSO, 11 of the 15 covariates should be removed from the model. The 4 remaining covariates are seismic, shift, gpuls, and nbumps. These variables are incorporated into a model, denoted Model 2.



Principal component analysis

From the result of PCA we find that the first 11 components explain 97.2% of variance. Looking at variable loading from PCA we can see that the variable load is small (<0.6 for the first four component).

Logistic Regression after Variable Selection

In logistic regression, we first fit the model onto the training data. From the confusion matrix, we can see that the sensitivity (2.3%) is still very low and the specificity is very high (99.8%), with 6.8% overall error rate. Our fitted model on training observations has peformed poorly on test observations by further reducing sensitivity score to 0%. Therefore, it is evident that our logistic regression model doesn't perform well on the seismic-bumps dataset to provide reliable estimates for the prediction of seismic hazards.

Table 8: Model-1 vs Model-2

	M1-Train 0	M1-Train 1	M1-Test 0	M1-Test 1	M2-Train 0	M2-Train 1	M2-Test 0	M2-Test 1
Predict 0	1799	127	606	39	1803	128	606	39
Predict 1	8	4	1	0	4	3	1	0

Quadratic Discriminant Analysis after variable selection

Quadratic Discriminant Analysis (QDA) provides an alternative approach to the LDA in that QDA assumes each class (hazardous vs non-hazardous) has its own covariance matrix. Although LDA classifier is less flexible than RDA, and therefore has lower variance, however, QDA is recommended when training dataset is very large so that variance becomes less of a concern.
Using predictor variables from Model 1 and Model 2, we first fit two QDA models onto training observations. Then we use these fitted models to predict seismic activity from test observations. In case of the predictor variables from Model 1, we have achieved significantly higher estimates of sensitivity (30.7%) than model outputs discussed before, with higher specificity (93.1%) and overall error rate 10.7%. However, Model 2 outputs better sensitvity (41%), slightly decreased specificity (86.8%), and slightly increased overall error rate (15.9%).

Table 9: Model-1 vs Model-2

	M1-Train 0	M1-Train 1	M1-Test 0	M1-Test 1	M2-Train 0	M2-Train 1	M2-Test 0	M2-Test 1
Predict 0	1606	87	527	23	1691	96	565	27
Predict 1	201	44	80	16	116	35	42	12

Regularized Discriminant Analysis after variable selection

RDA makes trade-off between LDA and QDA by shrinking the separate covariances of QDA toward a common covariance as in LDA. We performed RDA for Model 1 on the test dataset with varying set of lambda values. It appears that with lambda values between 0-1, sensitivity estimates resulting from RDA varies inversely with increasing lambda values. That means, if lambda = 0, RDA results in similar higher sensitivity value as QDA does, whereas lambda = 1 results in lower sensitivity value similar to LDA.

*** Look at gamma and lambda values. Make changes according to what make senses. Writing for this section will follow those changes.

Table 10: Model-1 v Model-2

	M1-Train 0	M1-Train 1	M1-Test 0	M1-Test 1	M2-Train 0	M2-Train 1	M2-Test 0	M2-Test 1
Predict 0	1606	87	527	23	1606	87	593	35
Predict 1	201	44	80	16	201	44	14	4

Conclusion and Future Work

At first we were not able to perform QDA and RDA because of the existence of multicollinearity in the data, which is partly(?) overcome by performing stepwise variable selection. Our final models (Model 1 nad Model 2) show that seismic hazard is related to previous mining shift's hazard status, seismic energy, number of pulses, number of seismic bumps recorded within previous shift, the number of seismic bumps (102-103 J) registered within previous shift, as well as the number of seismic bumps (102-103 J) registered within previous shift.

Our QDA results show that we have roughly 87% of chance to correctly predict that seismic hazard will not occur in the future. We have 41% of chance to predict seismic hazard ahead of time. Its evident that, among all the classification methods we have used on seismic-bumps dataset, the QDA method performs best in making prediction with relatively higher accuracy, which can be effective to prevent possible loss from seismic hazard, although future improvements in the model selection can be made. Further, research shows that in the seismic hazard assessment, data clustering techniques can be applied (Lesniak et al. 2009), and for the

space-time prediction of seismic tremors, artificial neural networks are used (Kabiesz, 2005).

Summary of Models

Pre-Variable Selection

Model	Test Specificity	Test Sensitivity	Training Specificity	Training Sensitivity
Indicator	99.67%	0%	99.83%	0.76%
LDA	97.36%	12.8%	98.01%	17.56%
QDA	*	*	*	*
RDA	97.86%	0	98.89%	3.1%
Log Regression	99.51%	0%	99.72%	4.58%

- QDA was not performed on seismic-bumps data having high multi-collinearity.

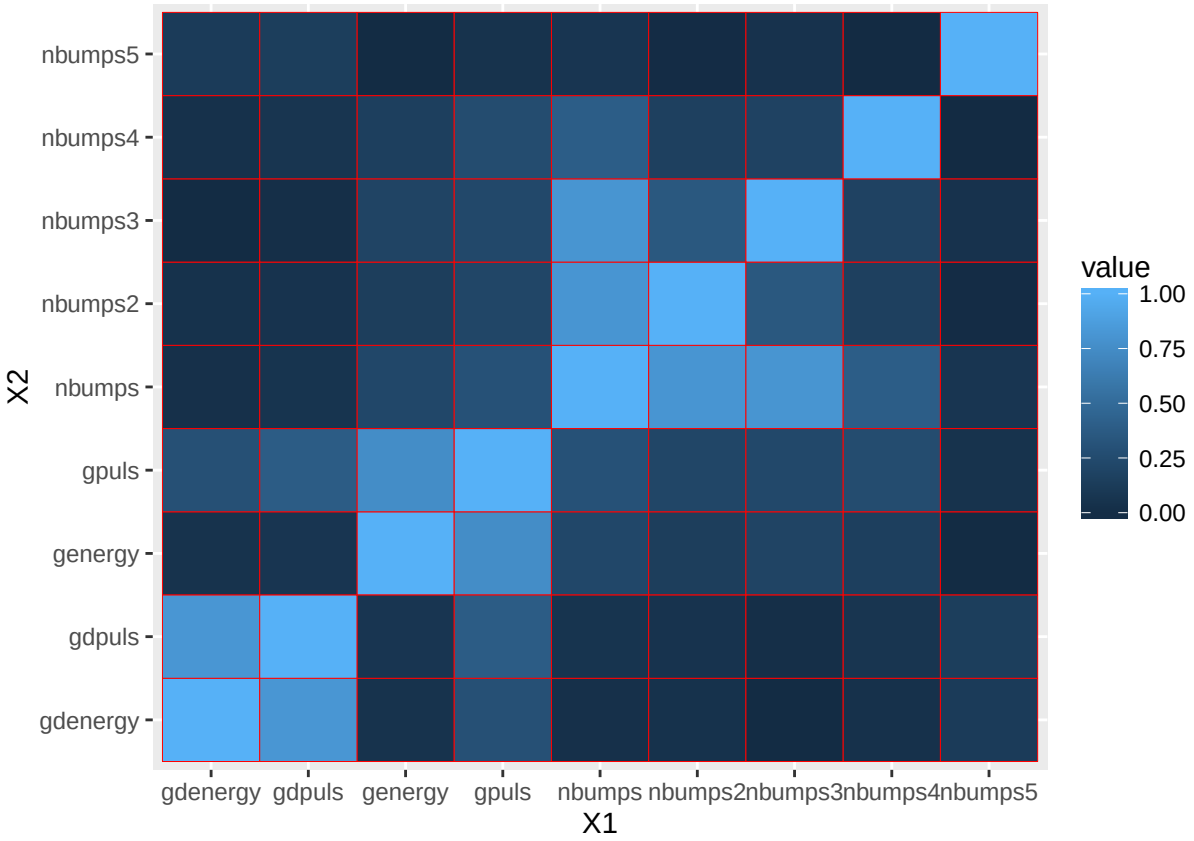
Post-Variable Selection

Model	M1-Test Specificity	M1-Test Sensitivity	M2-Test Specificity	M2-Test Sensitivity
Indicator	*	*	*	*
LDA	123	*	*	*
QDA	87%	41%	93%	31%
RDA	86.8%	41%	98%	10%
Log Regression	99.83%	0%	99.83%	0%

- Analysis wasn't performed after variable selection.
  * No Analysis was performed on Training observations.

Appendix

Correlation Plot



Contribution of Group Members