

Electric Grid Stability Analysis

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Introduction

Today's electrical grid, which the majority of businesses and residents connect to, is experiencing a new market disruption. The disruptive technology of distributed energy generation, such as residential solar, has introduced new factors impacting grid stability. The grid stability is not immune to other disruptions, such as aging infrastructure, cyber security, and natural disasters. Each of these disruptions have a direct impact to the supply and demand economics of the electrical grid as a whole.

To reduce the impact, decentralizing the grid has been proposed Arzamasov, Bohm and Jochem, of the Karlsruhe Institute of Technology in Germany suggest (2018), "Decentralize Smart Grid Control (DSGC) is a new system implementing demand response without significant changes of the infrastructure." Analysis of the factors and impacts associated with implementing a DSGC system are outside of the scope for this paper. This paper will focus on implementation of machine learning models to predict stability of the grid, utilizing the data set Arzamasov created (2018). This data set is a simulation of a four-node star electrical grid with centralized production. The data set includes 14 total attributes - 11 predictive attributes, one non-predictive (p1), and two goal fields, as Arzamasov details below (2018):

- tau[x]: reaction time of participant (real from the range [0.5,10]s). Tau1 - the value for electricity producer.
- p[x]: nominal power consumed(negative)/produced(positive)(real). For consumers from the range [-0.5,-2]s^-2; $p1 = \text{abs}(p2 + p3 + p4)$
- g[x]: coefficient (gamma) proportional to price elasticity (real from the range [0.05,1]s^-1). g1 - the value for electricity producer.
- stab: the maximal real part of the characteristic equation root (if positive - the system is linearly unstable)(real)
- stabf: the stability label of the system (categorical: stable/unstable)

The Electrical Grid Stability Simulated Data data set was split 80/20. According to the random creation process Vadim Arzamasov described (2018), this allowed for the test set to be large enough to be a satisfactory representation of the data set as a whole and return statistically meaningful results. The R Caret package was leveraged heavily for modeling. Model algorithms were selected with the tasks of performing classification and regression in mind and those referenced in the *Towards Concise Models of Grid Stability* paper as well (Arzamasov, Böhm, and Jochem, 2018). The final algorithms selected were:

- Classification and Regression Trees
- k-Nearest Neighbors
- Naive Bayes
- Random Forest
- Support Vector Machines with Radial Basis Function Kernel

These algorithms were executed using the Caret packages Train function while applying 10 fold cross validation. The model with the highest accuracy in predicting stabf was selected for making final predictions. Support Vector Machines with Radial Basis Function Kernel will prove to be the best algorithm for predicting grid stability with an accuracy of 95%.

Methodology

Data Ingestion

The copy of the Electrical Grid Stability Simulated dataset used for this project is held in the UCI Machine Learning Repository. This copy is stored in a comma delimited format which requires data types to be mutated to usable formats. Attributes 1-13 are converted to numeric, and the 14th attribute is converted to a factor. During data ingestion, the training and testing data sets are created and represent an 80/20 split of the original data set. As

previously mentioned, this constitutes a test set large enough to be a satisfactory representation of the data set as a whole and sufficient to return statistically meaningful results. To avoid unanticipated interference during training and testing, non-predictor attributes were removed from the data set.

Data Structure

```
## 'data.frame': 10000 obs. of 14 variables:  
## $ tau1 : num 2.959 9.304 8.972 0.716 3.134 ...  
## $ tau2 : num 3.08 4.9 8.85 7.67 7.61 ...  
## $ tau3 : num 8.38 3.05 3.05 4.49 4.94 ...  
## $ tau4 : num 9.78 1.37 1.21 2.34 9.86 ...  
## $ p1 : num 3.76 5.07 3.41 3.96 3.53 ...  
## $ p2 : num -0.783 -1.94 -1.207 -1.027 -1.126 ...  
## $ p3 : num -1.26 -1.87 -1.28 -1.94 -1.85 ...  
## $ p4 : num -1.723 -1.255 -0.92 -0.997 -0.554 ...  
## $ g1 : num 0.65 0.413 0.163 0.446 0.797 ...  
## $ g2 : num 0.86 0.862 0.767 0.977 0.455 ...  
## $ g3 : num 0.887 0.562 0.839 0.929 0.657 ...  
## $ g4 : num 0.958 0.782 0.11 0.363 0.821 ...  
## $ stab : num 0.05535 -0.00596 0.00347 0.02887 0.04986 ...  
## $ stabf: Factor w/ 2 levels "stable","unstable": 2 1 2 2 2 1 2 2 1 2 ...
```

The data is tidy, and the ingestion script has successfully transformed the data to the correct format for this analysis.

Null Values Check

```
## tau1 tau2 tau3 tau4 p1 p2 p3 p4 g1 g2 g3 g4 stab
```

```

## FALSE FALSE
## stabf
## FALSE

```

No null values to be handled.

Data Summary

	tau1	tau2	tau3	tau4
## Min.	:0.5008	Min. : 0.5001	Min. :0.5008	Min. :0.5005
## 1st Qu.	:2.8749	1st Qu.: 2.8751	1st Qu.:2.8755	1st Qu.:2.8750
## Median	:5.2500	Median : 5.2500	Median :5.2500	Median :5.2497
## Mean	:5.2500	Mean : 5.2500	Mean :5.2500	Mean :5.2500
## 3rd Qu.	:7.6247	3rd Qu.: 7.6249	3rd Qu.:7.6249	3rd Qu.:7.6248
## Max.	:9.9995	Max. : 9.9998	Max. :9.9994	Max. :9.9994
	p1	p2	p3	p4
## Min.	:1.583	Min. :-1.9999	Min. :-1.9999	Min. :-1.9999
## 1st Qu.	:3.218	1st Qu.:-1.6249	1st Qu.:-1.6250	1st Qu.:-1.6250
## Median	:3.751	Median :-1.2500	Median :-1.2500	Median :-1.2500
## Mean	:3.750	Mean :-1.2500	Mean :-1.2500	Mean :-1.2500
## 3rd Qu.	:4.282	3rd Qu.:-0.8750	3rd Qu.:-0.8750	3rd Qu.:-0.8751
## Max.	:5.864	Max. :-0.5001	Max. :-0.5001	Max. :-0.5000
	g1	g2	g3	g4
## Min.	:0.05001	Min. :0.05005	Min. :0.05005	Min. :0.05003
## 1st Qu.	:0.28752	1st Qu.:0.28755	1st Qu.:0.28751	1st Qu.:0.28749
## Median	:0.52501	Median :0.52500	Median :0.52501	Median :0.52500
## Mean	:0.52500	Mean :0.52500	Mean :0.52500	Mean :0.52500
## 3rd Qu.	:0.76243	3rd Qu.:0.76249	3rd Qu.:0.76244	3rd Qu.:0.76243

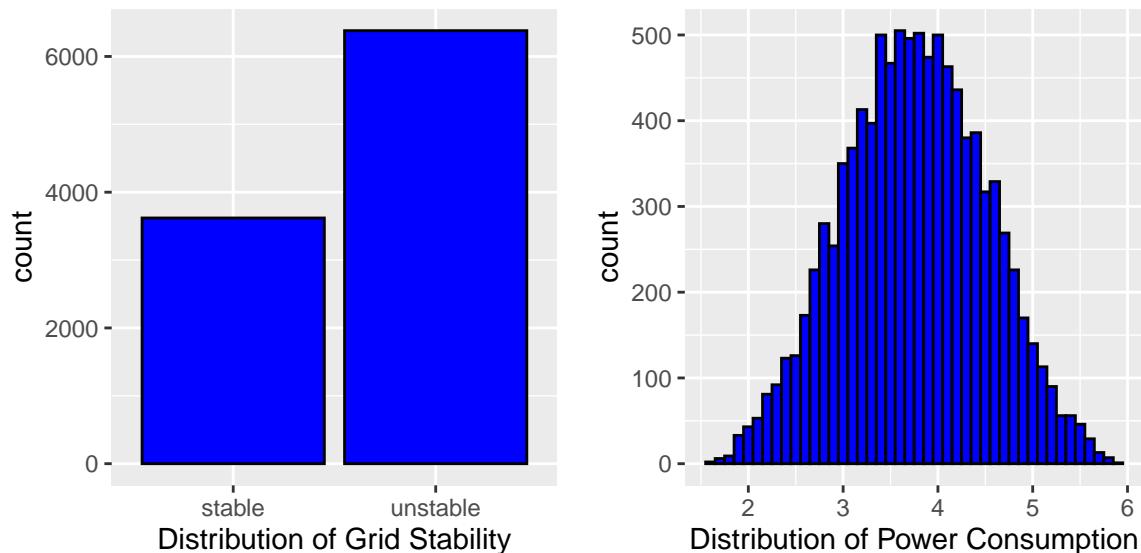
```

##   Max.    :0.99994   Max.    :0.99994   Max.    :0.99998   Max.    :0.99993
##   stab          stabf
##   Min.   :-0.08076   stable  :3620
##   1st Qu.:-0.01556   unstable:6380
##   Median  : 0.01714
##   Mean    : 0.01573
##   3rd Qu.: 0.04488
##   Max.    : 0.10940

```

Figure 1

Illustration of grid stability and power consumption distributions

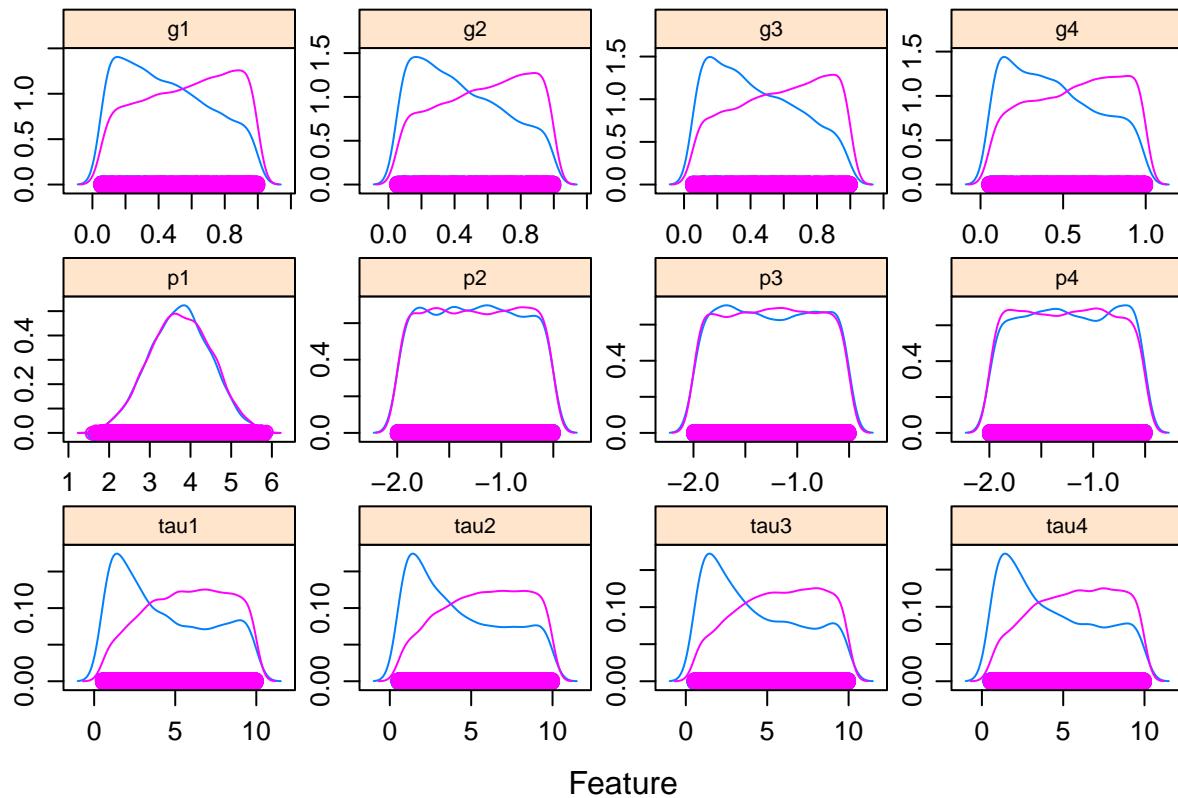


This data exploration shows that the data is tidy. There are no null values to be handled. The proportion of unstable is greater than the stable, representing 64% of the entire data set. Finally, there is a normal distribution of the Distribution of Power Consumption of the p1 attribute. The p1 was defined as representation of the consumers and the actual is calculated as $p1 = \text{abs}(p2 + p3 + p4)$.

When visualizing the 11 predictors across the stabf goal attribute there is even distribution with very little variance. Could this be an indication that the data set is overtly normal or simply minimal variances in electrical grid supply and demand disruptions?

Figure 2

Illustration of the density of the stabf attribute within p1 and each of the predictor attributes



Modeling

The modeling approach used for this analysis was to leverage the R Caret Package. The previous data exploration and the data set document on the UCI Repository show the following:

- Data is clean and normalized
- Data includes 10,000 rows of 14 attributes

- Data includes 11 predictors
- Data includes one non-predictive value (p1)
- Data includes two goal attributes (stab and stabf)
- Well-suited for Classification and Regression *Note:* If further exploration is desired, additional information on this package may be found here <https://cran.r-project.org/web/packages/caret/vignettes/caret.html>.

Given the data is well-suited for Classification and Regression, these model types will be utilized by leveraging the train function of the Caret package. Kuhn (2019) instructs that the train function can be used to:

- evaluate, using resampling, the effect of model tuning parameters on performance
- choose the “optimal” model across these parameters
- estimate model performance from a training set

Training model evaluation will use 10-fold cross validation. Five different models will be evaluated, and the model that produces the greatest accuracy will be chosen to make the final prediction. Where appropriate, that model will be tuned for optimal accuracy.

```
# Run algorithms using 10-fold cross validation
fitControl <- trainControl(method="cv", number=10)

# Goal is to find the most accurate model, the metric parameter
# will be used for this.

metric <- "Accuracy"

# Classification and Regression Trees (CART)
set.seed(825)
fit_cart <- train(stabf~., data=train,
                  method="rpart",
```

```

    metric=metric,
    trControl=fitControl)

# Classification and Regression Trees (CART) - Results

# fit_cart$bestTune

# k-Nearest Neighbors (kNN).

set.seed(825)

fit_knn <- train(stabf~, data=train,
                  method="knn",
                  metric=metric,
                  tuneGrid = data.frame(k = seq(2 , 50 , 2)),
                  trControl=fitControl)

# k-Nearest Neighbors (kNN) results

#fit_knn$bestTune

#plot(fit_knn)

#fit_knn$finalModel

# Naive Bayes (naive_bayes)

set.seed(825)

fit_nb <- train(stabf~, data=train,
                  method="naive_bayes",
                  metric=metric,
                  trControl=fitControl)

# Naive Bayes (naive_bayes) - Results

#fit_nb$finalModel

# Random Forest (RF)

set.seed(825)

fit_rf <- train(stabf~, data=train,
                  method="rf",

```

```

    metric=metric,
    tuneGrid = expand.grid(.mtry=c(1:5)),
    trControl=fitControl)

# Support Vector Machines (SVM) with a linear kernel

set.seed(825)

fit_svm <- train(stabf~, data=train,
                  method ="svmRadial",
                  metric = metric,
                  tuneGrid = expand.grid(sigma = c(.01, .50, .05),
                                         C = c(0.75, 0.9, 1, 1.1, 1.25)),
                  trControl = fitControl,
                  preProcess = c("center","scale"))

# Support Vector Machines (SVM) with a linear kernel - Results

#fit_sum$bestTune

#plot(fit_sum)

#fit_sum$finalModel

# summarize accuracy of models

results <- resamples(list(cart=fit_cart,
                          nb=fit_nb,
                          knn=fit_knn,
                          rf=fit_rf,
                          svm=fit_svm))

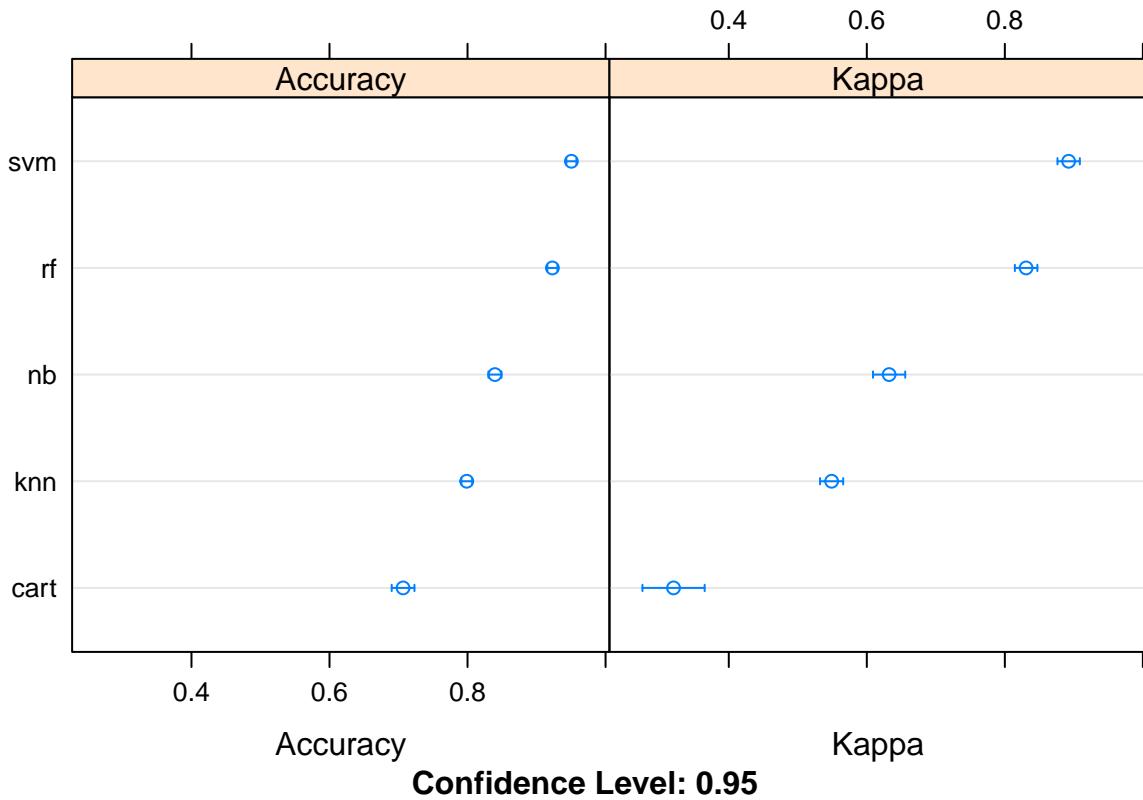
```

Results

The accuracy of the five models is shown in the following plot. Support Vector Machines with Radial Basis Function Kernel achieved the highest accuracy on the training data set and will be used for the final prediction using the test data set.

Figure 3

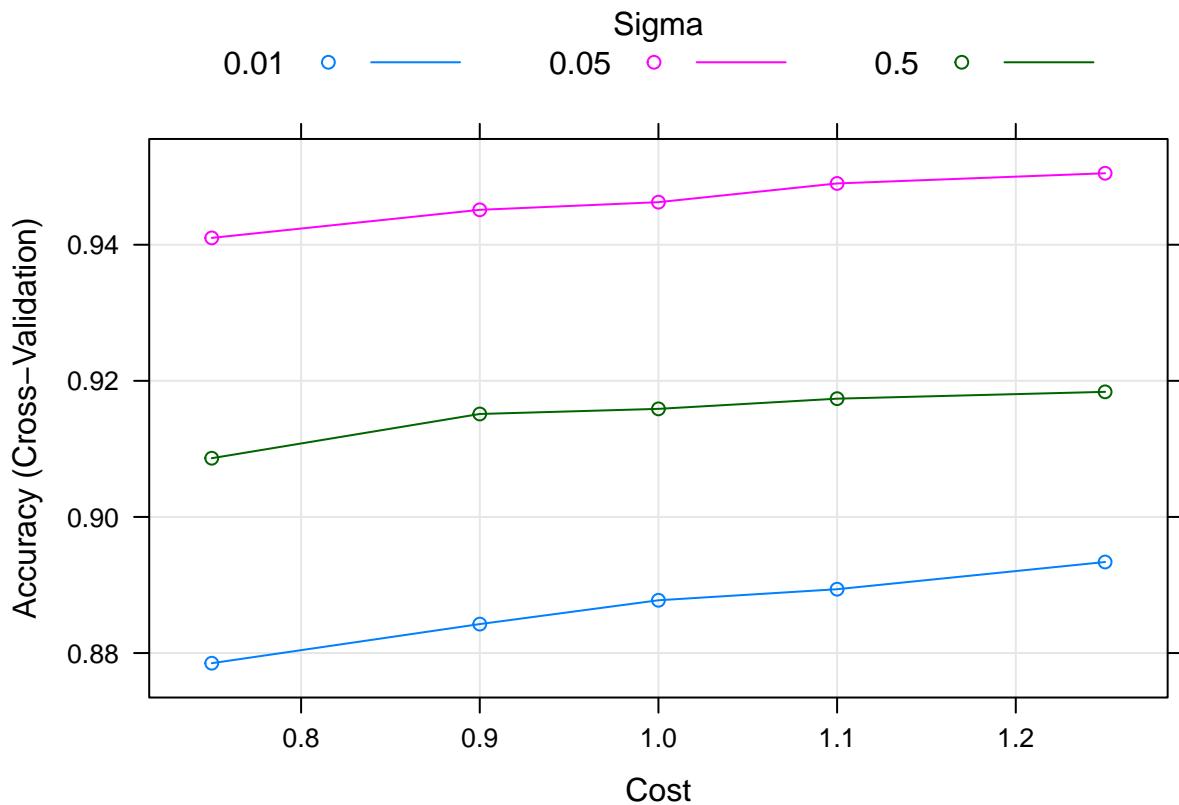
Dot plot illustrating the accuracy of the five different models



Additionally, we can use the following plot to visualize the optimal sigma tuning parameter:

Figure 4

Illustration of the tuning parameters of the Support Vector Machines (SVM)



```
# Support Vector Machines (SVM) with a linear kernel
```

```
# Results as shown in the stored finalModel
```

```
fit_svm$finalModel
```

```
## Support Vector Machine object of class "ksvm"
```

```
##
```

```
## SV type: C-svc (classification)
```

```
## parameter : cost C = 1.25
```

```
##
```

```
## Gaussian Radial Basis kernel function.
```

```
## Hyperparameter : sigma = 0.05
```

```
##
```

```
## Number of Support Vectors : 2086
```

```

##  

## Objective Function Value : -1904.416  

## Training error : 0.035375

```

Final Model

```

# Support Vector Machines (SVM) with a linear kernel on the test dataset  

predictions <- predict(fit_svm, test)  

cm <- confusionMatrix(predictions, test$stabf)  

print(cm)

```

```

## Confusion Matrix and Statistics  

##  

##           Reference  

## Prediction stable unstable  

##   stable       670        36  

##   unstable      54      1240  

##  

##           Accuracy : 0.955  

##                 95% CI : (0.945, 0.9637)  

##   No Information Rate : 0.638  

##   P-Value [Acc > NIR] : < 2e-16  

##  

##           Kappa : 0.9021  

##  

## McNemar's Test P-Value : 0.07314  

##

```

```
##           Sensitivity : 0.9254
##           Specificity  : 0.9718
##           Pos Pred Value : 0.9490
##           Neg Pred Value : 0.9583
##           Prevalence   : 0.3620
##           Detection Rate  : 0.3350
##           Detection Prevalence : 0.3530
##           Balanced Accuracy : 0.9486
##
##           'Positive' Class : stable
##
```

Conclusion

The following confusion matrix shared on www.stackoverflow.com (2017) summarizes the outcome of the Support Vector Machines with Radial Basis Function Kernel model on the Electrical Grid Stability Simulated data set. The ability to make accurate predictions will be a key factor in implementing decentralized electrical grids while maintaining the required reliability. This analysis shows that machine learning algorithms can be implemented within energy management systems to make operators aware of disrupting events, such as surges in either supply or demand.

Figure 5

Illustration of the confusion matrix output

CONFUSION MATRIX

		Actual	
		Class1	Class2
Predicted	Class1	670	36
	Class2	54	1240

DETAILS

Sensitivity 0.925	Specificity 0.972	Precision 0.949	Recall 0.925	F1 0.937
Accuracy 0.955			Kappa 0.902	

Future work includes further model testing on large data sets which represent readings from actual grids. The four-node star electrical grid presented here represents a very small load and supply sample. The density plot of the stability attribute showed relatively small variances across the 11 different predictors. Future studies should include data sets with disruptions from real world events in order to build confidence in implementing a reliable decentralized electrical grid.