

Smart Trouble Ticket

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Abstract

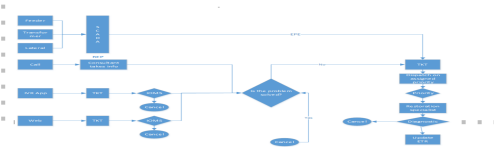
Our goal in this project is to be able to classify the ticket as a Value-Adding Truck Roll (VATR) or Non-Value Adding Truck Roll (NVATR). To be able to better decide when to send out a repair crew and when not to, This will lead us to save time, money, and effort. FPL asked to work with our team to apply the skills and knowledge learned from our Industrial Engineering Program in the University of Miami and propose a solution for their problem. This led to the creation of the "Smart Ticket". Smart Ticket is a project that was started by our colleagues in last semester's senior design project (Fall 2019). This semester our team is further working on the project from a different perspective.

Introduction

Florida Power & light (FPL) is a power utility company based in Juno Beach Florida. The company serves over 10 million customers around Florida. FPL is a power producing & distribution company, it is part of NextEra Inc. fleet. it generates almost 30 gigawatts of energy from natural gas & nuclear power. The company is trying to control or mitigate the unplanned outages that occur in their network. In 2018, FPL Had generated over 400,000 trouble tickets that happened for different reasons and could have different causes. When there is a trouble ticket, the company has to decide if they should send in a repair team. Which could cost the company around \$250. Then there could be no issue or the issue could be from any other party than FPL. Those Non-value Adding Truck Rolls (NVATR) lead to a huge waste of time and money.

Current State

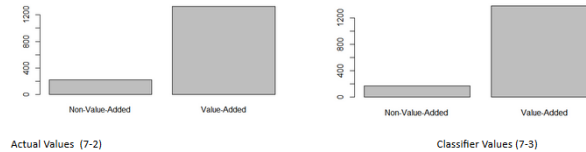
The Current state of operations seems to be based on a good concept where the company invested in smart grid technology. This includes smart meters and automated switches that helps diagnose equipment issues early, automatically reroute electricity around trouble spots confining outages to smaller areas and pinpointing the location of outages quickly. The current system lacks the enhancement from the customer side and needs to be more efficient. In order to report a power outage, the customer files an outage report through their website, customer support phone number, and the IVR phone application



Methods | Design | Analysis

The data that was provided to us was very large as FPL provided us all of the generated tickets provided in 2016 and 2018. Each of the Ticket datasets contained 128 data variables with over 400000 observations. The full customer calls from 2016 itself had 98 data variables with nearly 2.64 million observations itself, though the call subset for 2018 only had ten thousand entries, with 99 variables. Since these were massive files and we needed to create a machine learning algorithm, we had to use RStudio.

In RStudio, we found variables within the Ticket dataset that we used to create a column that clearly states which ticket is value added or not. If a single criteria is met then the ticket is considered non-value added; but if none are met then it is considered value-added. After creating this new value-added column we created a new dataset that combined this column with the Customer Calls subset. This new dataset was then split into two, one dataset for training our classification algorithm and another for testing our algorithm's accuracy.



Results

Our classification algorithm that we've produced has produced results that were 92.5% accurate in classifying if the truck roll would be value added or non-value added when using our developed criteria.

Confusion Matrix and Statistics				Kappa : 0.6606			
	Reference			McNemar's Test P-Value : 2.188e-06			
Prediction	Non-Value-Added	Value-Added		Sensitivity	0.6199		
Non-Value-Added	137	32		Specificity	0.9759		
Value-Added	84	1295		Pos Pred Value	0.8307		
				Neg Pred Value	0.9391		
				Prevalence	0.1428		
				Detection Rate	0.0885		
				Detection Prevalence	0.1092		
				Balanced Accuracy	0.7979		
				Positive Class : Non-Value-Added			
				Accuracy	0.9251		
				95% CI	(0.9108, 0.9377)		
				NO Information Rate	0.8572		
				P-Value [acc > NIR]	< 2.2e-16		

Conclusion

With the tools that we have gathered throughout our undergraduate career at the University of Miami, we were able to create a real world solution that would help reduce the use of wasteful resources and emissions in our planet. By coming up with a classification algorithm and using a Support Vector Machine (SVM) we were able to use predictors that we came up with in order to accurately diagnose whether a truck roll is going to be value added or non-value added. With the use of our classifier and further development, FPL will be able to accurately classify whether or not to send a truck out to a site prior to doing so

Acknowledgments

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