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RESEARCH ARTICLE

AUTONOMOUS TOOLKIT TO FORECAST CUSTOMER CHURN

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ABSTRACT

Customer churn prediction is one of the most important requirements in customer relationship management. It aims to retain valuable customers in order to maximize the profit of a company. In this paper, we propose an autonomous toolkit to forecast customers churn (ATFC) — an autonomous customer churn toolkit which predicts churning behavior of customers in the telecom industry. ATFC gives a customer churn prediction model which can fit generally in similar kinds of problems and datasets. It predicts which customers are at the risk of leaving the company. It is important for managers of the telecom industry to retain their loyal customers for the growth of their company and for improving their customer relationship management factor. ATFC accomplishes this task with the help of the most popular machine learning algorithms which were applied to the challenging problem of the customer churn in the telecom industry. We have used telecom company based dataset of BigML repository. Therefore, popular machine learning algorithms such as Decision Trees, Logistic Regression, Random Forest and Gradient Boosting were used to develop a model that can predict telecom customer churn efficiently and effectively.The results revealed that Random Forest outperforms by exhibiting low churn rate. The analysis of the algorithm was carried out based on ROC curve Precision-Recall and F-measure.The churn dataset analysis revealed that there are 10 features which causecustomer to churn. This prediction informs companies which features and services they need to target and improve.

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INTRODUCTION

The telecom service market has become more competitive than ever because of the deregulation policies and new technologies and competitions appearing in the telecom industry (Sharma *et al*., 2013). In this kind of environment, the customer churn has turned into a very serious issue. Customers churn from one provider to another in search of better services or for benefits of joining a new carrier (Rodpysh, 2012). The rapid increase in telecom service market leads to the higher subscriber base (Shaaban *et al*., 2012). Due to the increase in the number of service providers, companies have to face high customer churn rate (Vafeiadis *et al*., 2015). Thus, to continue competitive advantage, many telecom industry companies focus on maximizing the marketing relationship with their customer lifetime value and customer churn management (Kaur & Singh 2016). However, it has been regarded mandatory for the service providers to reduce the churn rate, as the negligence could result in the profitability reduction on major perspective (Dalvi *et al*., 2016). Therefore, customer churn prediction is one of the most important requirements in customer relationship management. Customer churn prediction aims to retain valuable customers in order to maximize the profit of a company (Hashmi *et al*., 2013). In this paper, we propose Autonomous Toolkit to Forecast Customer Churn (ATFC) — an autonomous customer churn toolkit which predicts churning behavior of customers in the telecom industry. ATFC predicts which customers are at the risk of leaving the company. It is important for managers of the telecom industry to retain their loyal customers for the growth of their company and for improving their customer relationship management factor. ATFC accomplishes this task with the help of the most popular machine learning algorithms which applied to the challenging problem of the customer churn in the telecom industry. We have used telecom company based dataset of BigML repository. To successfully manage churn prediction challenge, different researchers have put into use different machinelearning algorithms in addition to data mining tools (Almana *et al*., 2014, Runge *et al*., 2014). Our goal with ATFC was to develop a model that can predict telecom customer churn efficiently and effectively using popular machine learning algorithms (e.g., Random Forest, Decision Tree, Logistic Regression, Gradient Boosting). The dataset we utilized was belonged to the US telecom company 'Orange', which consisted of 3333 rows and 21 columns.

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Literature review

There are two basic approaches for customer churn: targeted and untargeted. Targeted approaches identify customer churn. They as a result either provide the customers with direct benefits/incentives or customize a service plan that lets them to stay. Whereas, untargeted approaches rely on superior product and mass advertising in order to increase brand loyalty and retain customers (Miyata *et al*., 1994). Saini *et al*. (2017) performed customer churn on data having new features like contract-related, call pattern description, and call pattern changes description. The authors derived these features from traffic figures and customer profile data. The Naïve Bayes and Bayesian Network algorithms were used to evaluate these features. The researchers compared their results to the results obtained using aDecision Tree. It was concluded that probabilistic classifiers have shown higher true positive rate than Decision Tree. Whereas, Decision Tree performed better in overall accuracy. Dalvi *et al*. (2016) used Decision Tree and Logistic Regression models to build a churn prediction system. The system was used to test dataset and measure the accuracy of the system. Their system outputsit's accuracy against other compared systems and provides a list of customers who are likely to churn. Balasubramanian and Selvarani (2014) focused on churn prediction in the telecom data, the use of data mining techniques, and the importance of feature extractionin churn prediction. The authors found that Decision Treesucceeds in churn predictionfrom Neural Network. They suggested that the selection of right combination of attributes and the fixation of proper threshold values may produce more efficient and accurate results. Saini *et al*. (2017) presented prediction by using Decision Treeclassification techniques such as CHAID, CART,QUEST and Exhaustive CHAID. They implemented all possible variants of Decision Tree. Their results proved Exhaustive CHAID technique more efficient in predicting customer churn behavior.

Bilal (2016) proposed a promising Neural Network based approach to predict customer churn in the banking sector.The challenge banks face today is how to retain their most profitable customers.Thee researcherargue that customer relation isa very important factor towards their success. Pradeep *et al*. (2017) stated that one of the gauging failures in the logistics industry is customer churn. Therefore, there is a huge need for a defensive marketing strategy which prevent the customers from switching the service providers. Customer churn puts negative effects on corporate operations and causes revenue and market loss. The previous work on customer churn only considers the prediction accuracy rate for model validation (Chen *et al*., 2015; Esteves and Mendes-Moreira, 2016). Moreover, quite a few studies perform cross-validation. That is, many of them use some fixed numbers of training and testing datasets for experiments. This is likely to produce unreliable conclusion for the performance of the prediction models. Many of the researchers built apredictive model using Logistic Regression, Decision Tree or Neural Network approaches, but, we used four algorithms and their comparison to check which classifier gives the best result.

Some of the researchers found out that the money or the area are the only factorsthat lead the customers churn, but, according to our research we concluded that there are 10 features (services) which cause customer churn in the telecom sector. Those features are discussed next. These services need to be improved by the management.

Causes of Churn

In the rapid competitive environment, the customer receives plentiful incentives to churn and encounter plentiful disincentives to stay. We observed churn due to poor service quality, high costs, lack of carrier responsiveness, new technology or product introduced by competitors, brand disloyalty, new competitors enter the market, etc. (Abiw-Abaidoo Jnr 2011). Therefore, the purpose of the churn management is to help managers identify customers who are likely to churn and to carry out actions to minimize churn effect (Rodpysh, 2012).

MATERIALS AND METHODS

Data mining algorithms have been used by mobile telecom companies to identify customers that are likely to churn. "Since the main purpose of applying data mining techniques in this area is prediction, supervised learning techniques are popularly used. However, the use of unsupervised learning techniques for churn prediction is rather limited". Therefore, it is vitally important to build a highly successful and accurate churn model, so for this research project CRISP-DM (Cross Industry Standard Process for Data Mining) model was chosen.

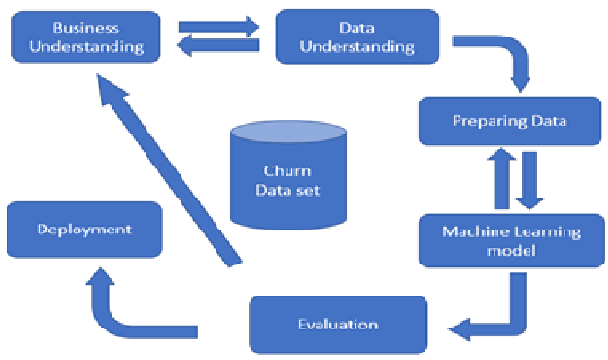


Figure 1. CRISP-DM Model

CRISP-DM model is mainly used for conducting a data mining process, whose life cycle consists of six phases as shown in Figure 1.

Figure 2 on next page represents the life cycle of a CRISP-DM model. In the first step, the data is understood for its commercial values. The data pre-processing step is then taken to update/add missing information in the raw data. This involves removal of missing values, conversion of categorical variables into numerical, etc. Once the data is processed, the knowledge discovery algorithms are applied. Supervised learning algorithms are used, like Decision Tree, Logistic Regression, Random Forest and Gradient Boosting for classification of data. Thus, a model is built which first extracts useful information, and then evaluates that information to serve the diverse business purposes. Later, the model is accepted after checking important attributes like accuracy and performance.

Decision Tree

The primary definition of a Decision Tree is: "A binary tree where every nonterminal node represents a decision".

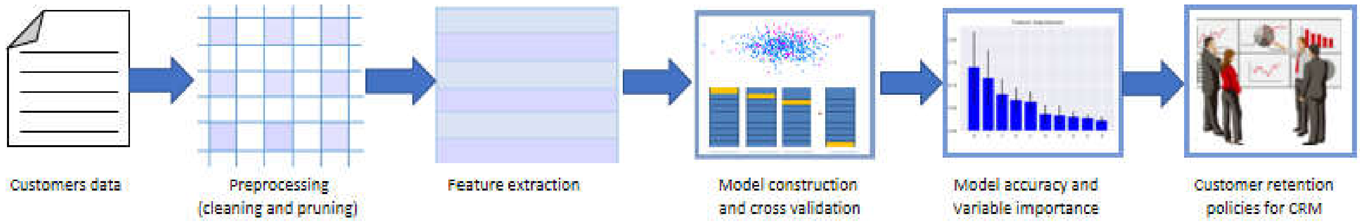


Figure 2. Life Cycle of CRISP-DM Model

Depending upon the decision taken at such a node, control passes to the left or right subtree of the node. A leaf node then represents the outcome of taking the sequence of decisions given by the nodes on the path from the root to the leaf. But, it should be noted that there is no obligation for a Decision Tree to be binary. Each decision node relates to one input variable, and the decisions are made by comparing the input value with a split point to see if the path should continue to the left or right of that node.

A Decision Tree is constructed by many nodes and branches on different stages and various conditions. It is a very popular and powerful tool for many prediction and classification problems, since it can produce several decision rules. Decision Trees can process numerical and categorical data (KhakAbi *et al*., 2010).

Logistic Regression

Logistic Regression is a machine learning technique. It is named for the function used at the core of the method, the logistic function. The logistic function, also called the sigmoid function was developed by the statisticians to describe properties of population growth in ecology, rising quickly and maxing out at the carrying capacity of the environment. It's an S-shaped curve that can take any real-valued number and map it into a value between 0 and 1, but never exactly at those limits. Logistic Regression uses an equation as the representation, very much like Linear Regression. Input values (x) are combined linearly using weights or coefficient values (referred to as Beta) to predict an output value (y). A key difference from Linear Regression is that the output value being modeled is a binary value (0 or 1) rather than a numeric value.

Random Forest

This is one of the best classification techniques. The classification outputs of this approach are very powerful than confused and deviated data. This method provides useful information on the importance of each variable, thus it can determine those variables which have the greatest impact on the dependent variable. In this technique, a set of Decision Trees are grown and each tree votes for the most popular class, then the votes of different trees are integrated and a class is predicted for each sample. In this approach, which is designed to increase the accuracy of the Decision Tree, more trees are produced to vote for class prediction. This approach is an ensemble classifier composed of some Decision Trees and the result is the mean of individual tree results. Some copies of the dataset are made in the learning phase and a Decision Tree without pruning is separately created from each copy. Thus, the result of each test is the mean of prediction result of all the trees. Using a set of trees in this method can be effective in significant increase of prediction accuracy. Random Forest is a bagging ensemble method. The samples of the training dataset are taken with replacement rather than greedily choosing the best split point in the construction of each tree. Thus, only random subsets of features are considered for each split. It is a robust algorithm and very much useful to increase accuracy and reduce overfitting of data.

Gradient Boosting and AdaBoost

Gradient Boosting is boosting ensemble method. The goal of ensemble methods is to combine the predictions of several base estimators built with a given learning algorithm in order to improve generalizability/robustness over a single estimator. The three most popular methods for combining the predictions from different models are:

Bagging: Building multiple models (typically of the same type) from different sub samples of the training dataset.

Boosting: Building multiple models (typically of the same type) each of which learns to_x the prediction errors of a prior model in the sequence of models.

Voting: Building multiple models (typically of differing types) and simple statistics (like calculating the mean) are used to combine predictions.

Gradient Boosting and AdaBoost (short for Adaptive Boosting) momentum algorithms are used when it comes to a lot of data to make predictions of high predictive power. It combines different weak or medium predictors with a strong predictor of the structure.

RESULTS

Accuracy and Error Rate tests were performed on results achieved through Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting techniques (Table 1).

Table 1. Accuracy and Error Rate Values for Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting techniques

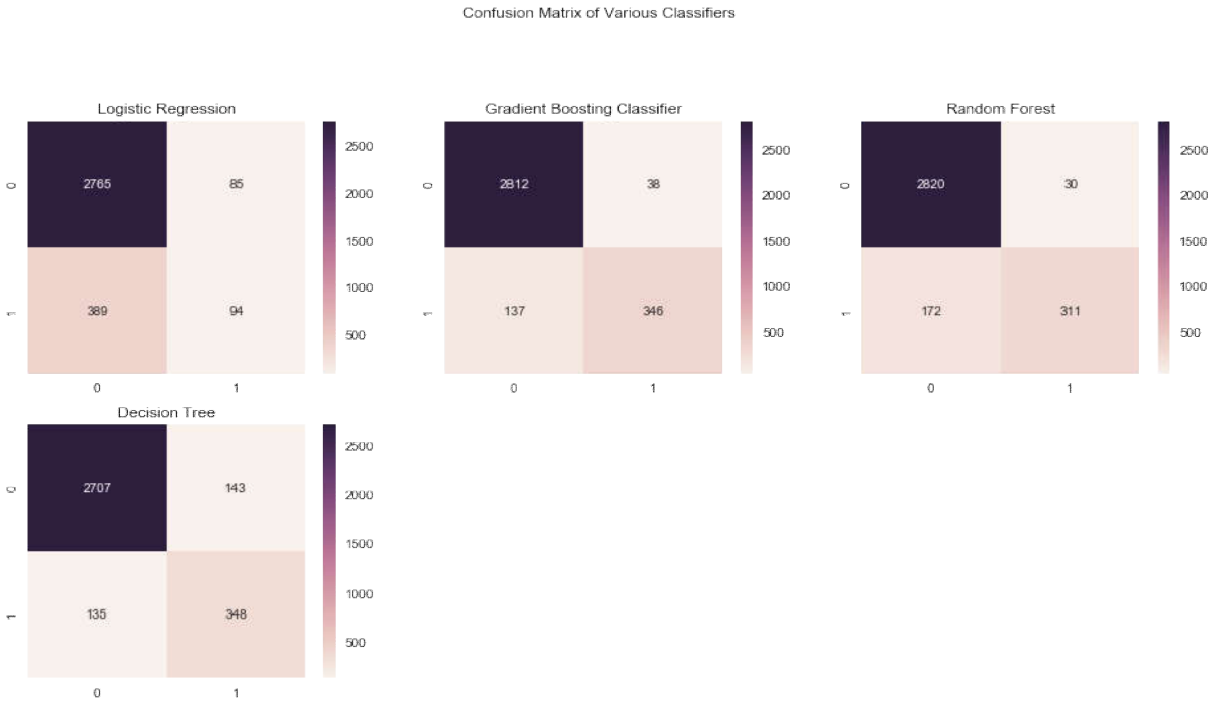
Technique	Accuracy	Error Rate
Logistic Regression	86.1	13.9
Decision Tree	91.0	9.0
Random Forest	94.3	5.7
Gradient Boosting	95.3	4.7

Performance Analysis using Precision, Recall, and F1 Score

The evaluation of Confusion Matrix with the help of F1Score is provided as under:

- Logistic Regression: 0.295180722892

- Random Forest: 0.758201701094
- Decision Tree: 0.693498452012
- Gradient Boosting: 0.800461361015



The evaluation results of our Confusion Matrix achieved through Precision and Recall tests are provided in Table 2.

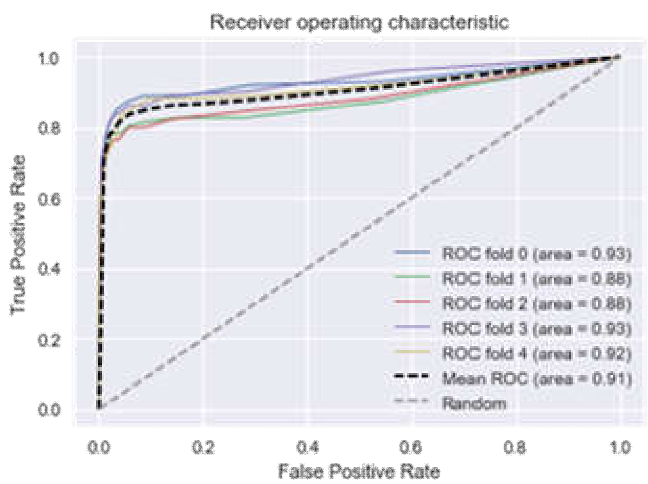
Table 2. Precision and Recall Values for Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting techniques

Technique	Precision	Recall
Logistic Regression	52.5	19.4
Decision Tree	70.8	72.0
Random Forest	91.2	64.3
Gradient Boosting	90.1	71.6

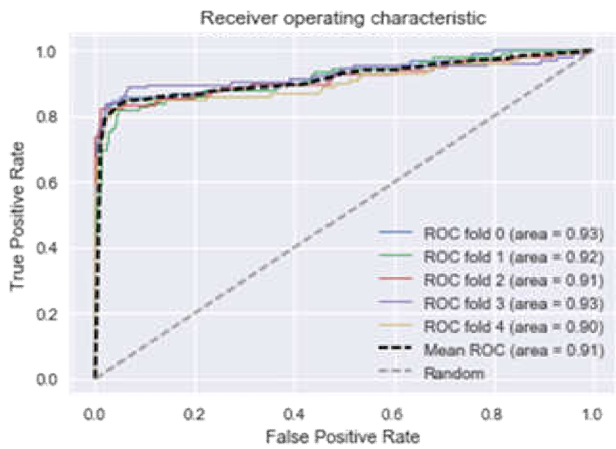
Performance analysis with ROC Curve plots and Area Under Curve

In the ROC curve plots, we used five folds cross validation iterator. This provides the train and test indices to split the data into five consecutive train test sets or folds.

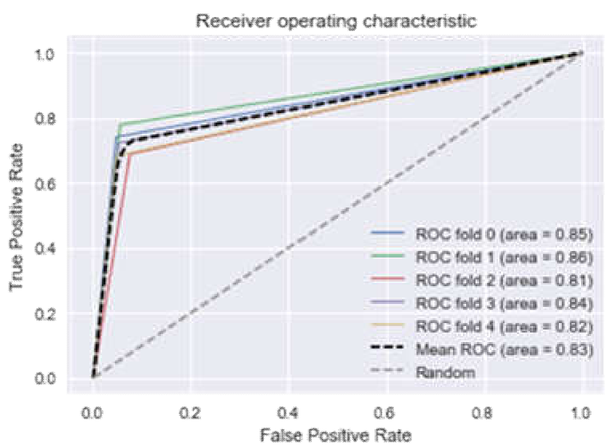
Random Forest:



Gradient boosting classifier:



Decision Tree:



Here, the Mean ROC for:

RF – 0.91
DT – 0.90
GBM – 0.91

As can be seen in all the evaluations above, the Random Forest algorithm is performing consistently well in all our metrics. Therefore, we can further tune the parameters of Random Forest to improve the performance.

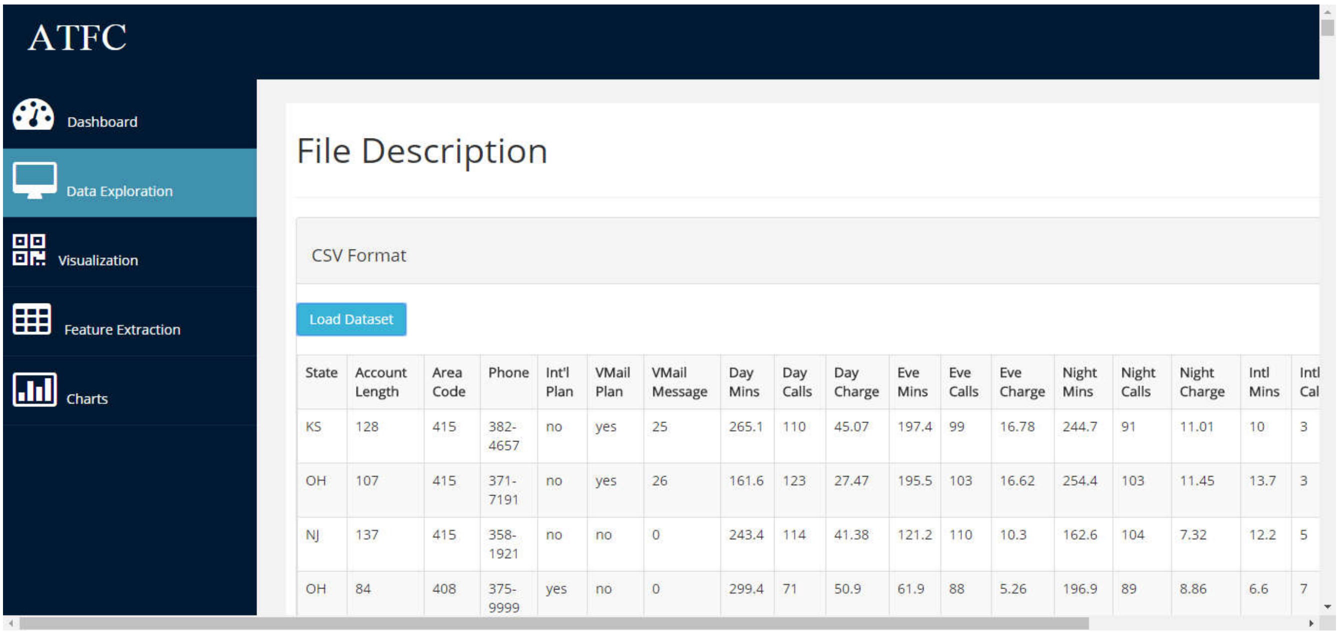
Feature Importance

Now that we understand the accuracy of each individual model for our dataset, let's dive a little deeper to get a better understanding of what features or behaviors are causing our customers to churn.

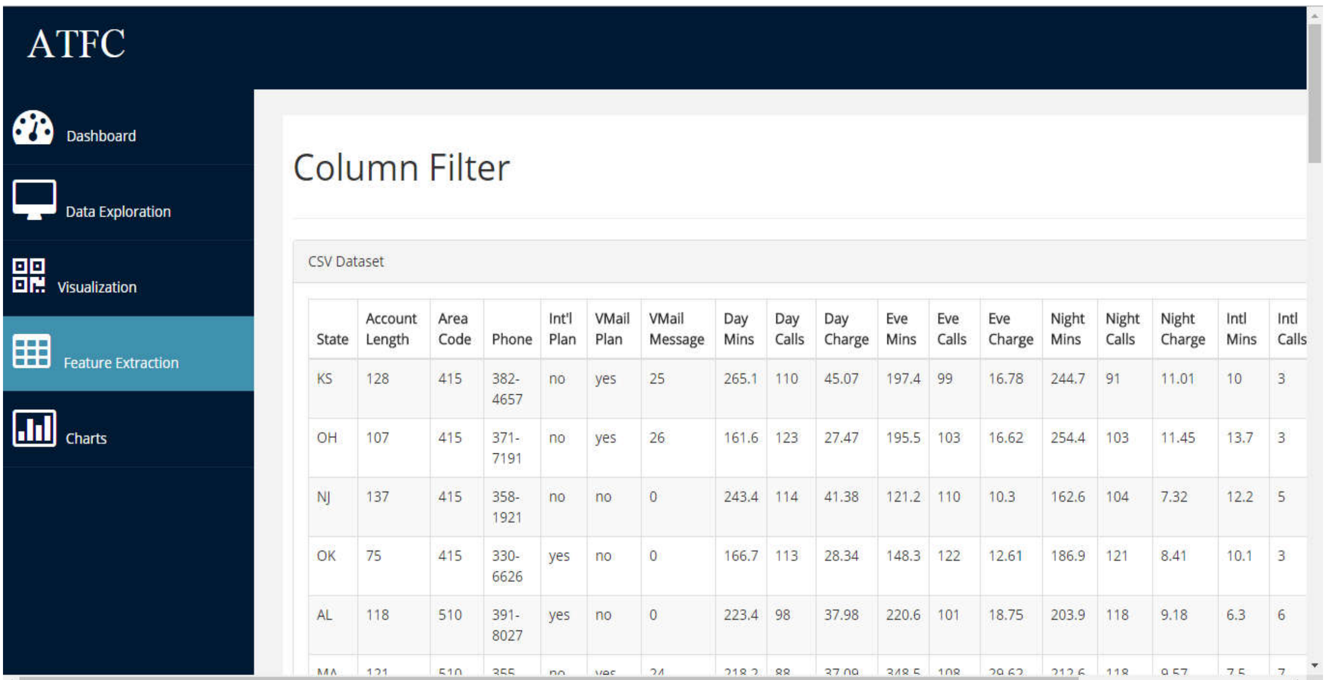
Let's look at the Top 10 features in our dataset that contribute to customer churn.

Feature ranking:

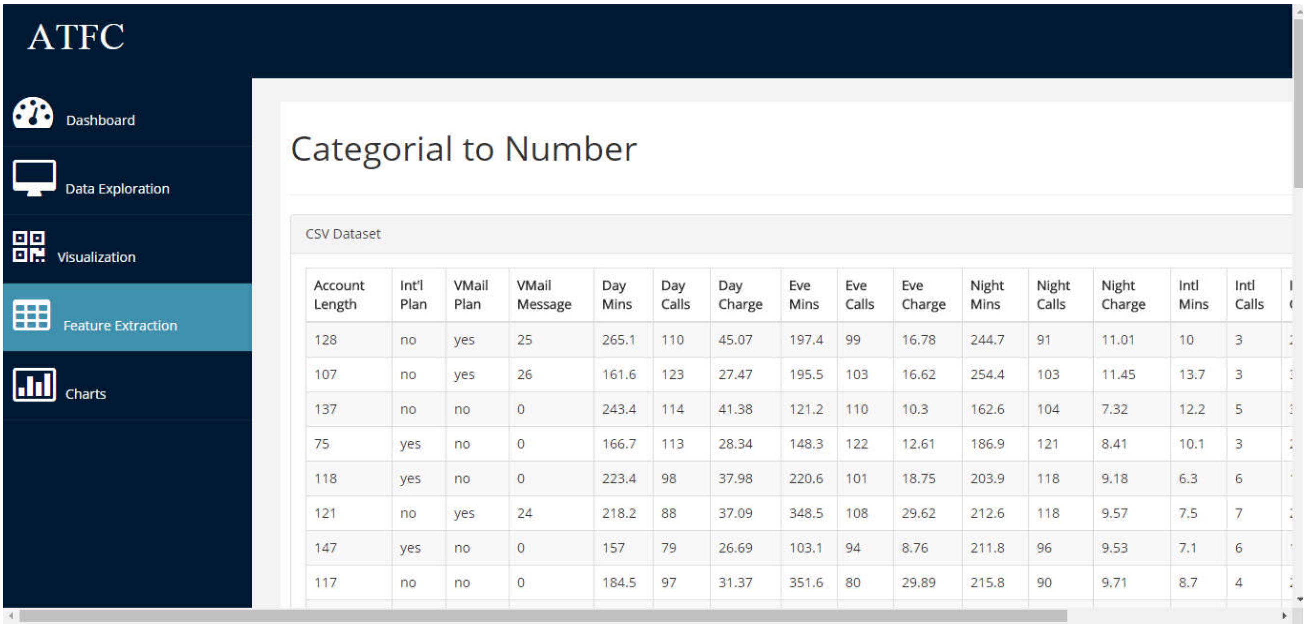
1. Account Length (0.188157)
2. Int’l Plan (0.102871)
3. VMail Plan (0.096911)
4. VMail Message (0.071246)
5. Day Mins (0.062060)
6. Day Calls (0.032456)
7. Day Charge (0.030478)
8. Eve Mins (0.026043
9. Eve Calls (0.025411)
10. Eve Charge (0.021707)



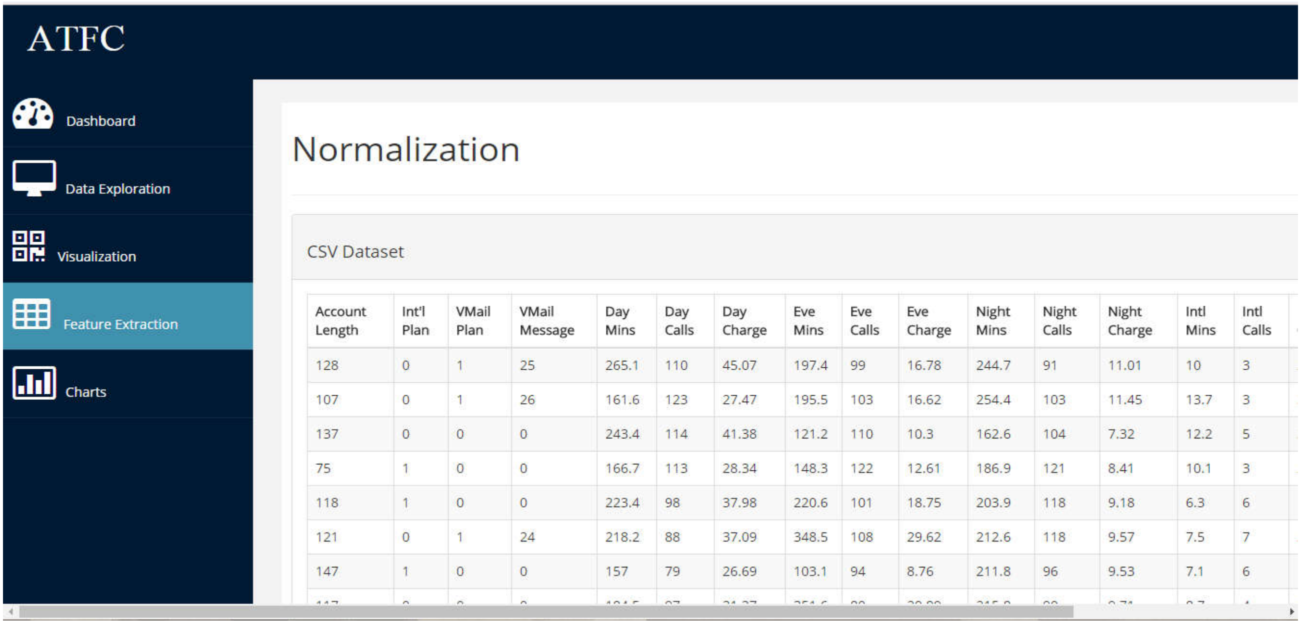
State	Account Length	Area Code	Phone	Int'l Plan	VMail Plan	VMail Message	Day Mins	Day Calls	Day Charge	Eve Mins	Eve Calls	Eve Charge	Night Mins	Night Calls	Night Charge	Intl Mins	Intl Cal
KS	128	415	382-4657	no	yes	25	265.1	110	45.07	197.4	99	16.78	244.7	91	11.01	10	3
OH	107	415	371-7191	no	yes	26	161.6	123	27.47	195.5	103	16.62	254.4	103	11.45	13.7	3
NJ	137	415	358-1921	no	no	0	243.4	114	41.38	121.2	110	10.3	162.6	104	7.32	12.2	5
OH	84	408	375-9999	yes	no	0	299.4	71	50.9	61.9	88	5.26	196.9	89	8.86	6.6	7



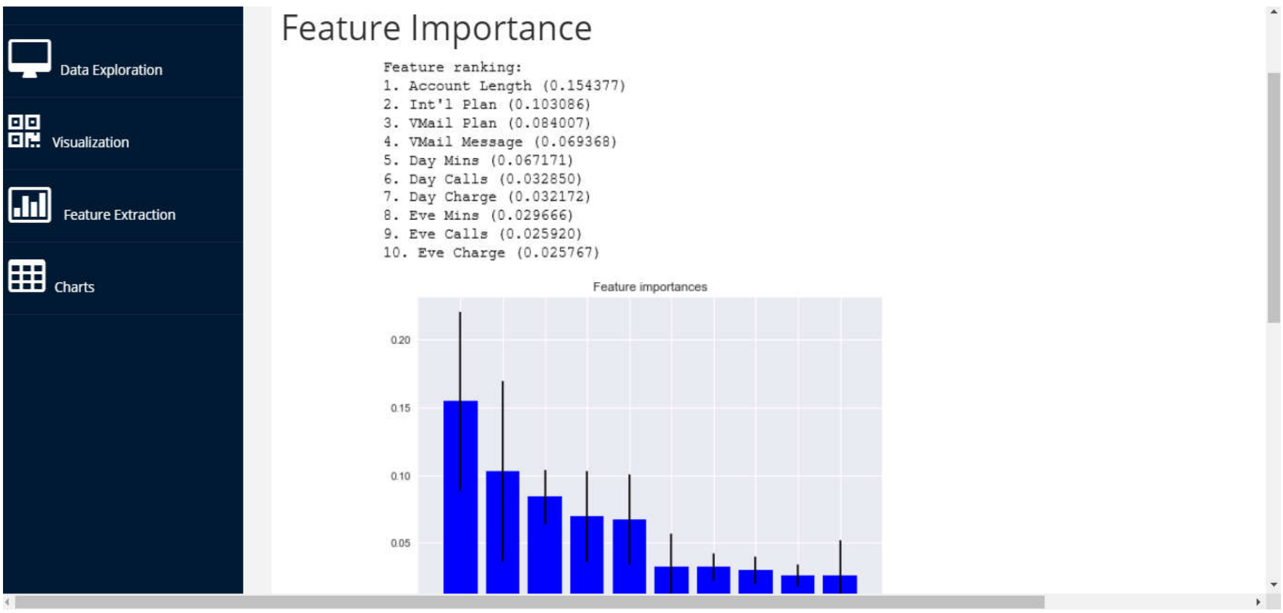
State	Account Length	Area Code	Phone	Int'l Plan	VMail Plan	VMail Message	Day Mins	Day Calls	Day Charge	Eve Mins	Eve Calls	Eve Charge	Night Mins	Night Calls	Night Charge	Intl Mins	Intl Calls
KS	128	415	382-4657	no	yes	25	265.1	110	45.07	197.4	99	16.78	244.7	91	11.01	10	3
OH	107	415	371-7191	no	yes	26	161.6	123	27.47	195.5	103	16.62	254.4	103	11.45	13.7	3
NJ	137	415	358-1921	no	no	0	243.4	114	41.38	121.2	110	10.3	162.6	104	7.32	12.2	5
OK	75	415	330-6626	yes	no	0	166.7	113	28.34	148.3	122	12.61	186.9	121	8.41	10.1	3
AL	118	510	391-8027	yes	no	0	223.4	98	37.98	220.6	101	18.75	203.9	118	9.18	6.3	6



Account Length	Int'l Plan	VMail Plan	VMail Message	Day Mins	Day Calls	Day Charge	Eve Mins	Eve Calls	Eve Charge	Night Mins	Night Calls	Night Charge	Intl Mins	Intl Calls
128	no	yes	25	265.1	110	45.07	197.4	99	16.78	244.7	91	11.01	10	3
107	no	yes	26	161.6	123	27.47	195.5	103	16.62	254.4	103	11.45	13.7	3
137	no	no	0	243.4	114	41.38	121.2	110	10.3	162.6	104	7.32	12.2	5
75	yes	no	0	166.7	113	28.34	148.3	122	12.61	186.9	121	8.41	10.1	3
118	yes	no	0	223.4	98	37.98	220.6	101	18.75	203.9	118	9.18	6.3	6
121	no	yes	24	218.2	88	37.09	348.5	108	29.62	212.6	118	9.57	7.5	7
147	yes	no	0	157	79	26.69	103.1	94	8.76	211.8	96	9.53	7.1	6
117	no	no	0	184.5	97	31.37	351.6	80	29.89	215.8	90	9.71	8.7	4



Account Length	Int'l Plan	VMail Plan	VMail Message	Day Mins	Day Calls	Day Charge	Eve Mins	Eve Calls	Eve Charge	Night Mins	Night Calls	Night Charge	Intl Mins	Intl Calls
128	0	1	25	265.1	110	45.07	197.4	99	16.78	244.7	91	11.01	10	3
107	0	1	26	161.6	123	27.47	195.5	103	16.62	254.4	103	11.45	13.7	3
137	0	0	0	243.4	114	41.38	121.2	110	10.3	162.6	104	7.32	12.2	5
75	1	0	0	166.7	113	28.34	148.3	122	12.61	186.9	121	8.41	10.1	3
118	1	0	0	223.4	98	37.98	220.6	101	18.75	203.9	118	9.18	6.3	6
121	0	1	24	218.2	88	37.09	348.5	108	29.62	212.6	118	9.57	7.5	7
147	1	0	0	157	79	26.69	103.1	94	8.76	211.8	96	9.53	7.1	6



Proposed system

In the proposed system, Python programming has been used to build the model for churn prediction. It is widely used among statisticians and data miners for developing statistical software and data analysis. For building predictive model the descriptive stats in which the libraries of a Python have been used (Pandas, Numpy, Scipy, Scikit-Learn, Stats Models, Matplot libraries). The purpose of this paper to make predictive applicationis to reduce the effort of the data scientists and provide some relief to those business managers who lack technical knowledge. The tool helps to know the best possible technique for the prediction of the given dataset. The toolkit will solve the problem for the business managers that they had to hire data scientists in order to know the best possible techniques for the prediction of their given dataset. The salary they had to pay for this purpose could be avoided. The problem is the high wages of the data scientists, it's not easy for small-scale organizations to pay this much high wage to a data scientist. By making this autonomous toolkit one can get some of the aspects of data scientists for his/her organization.

Conclusion

All organizations are dependent on their customers, so they should try to satisfy them and maintain their position in the market. Therefore, focus on the customer will result in a quick response of the organization to market opportunities. Thus, identification of churn customers is worthwhile for the organization (Hassouna *et al*., 2016; Olle and Cai, 2014). Churn prediction and management are crucial in liberalized cellular mobile telecom markets in developing countries. In order to be competitive in this market, cellular service providers have to be able to predict possible churners and take proactive actions to retain valuable loyal customers (Dahiya and Bhatia, 2015). Therefore, to build an effective and accurate customer churn prediction model, it has become an important research problem for both academics and practitioners in recent years (Khan *et al*., 2010). This paper suggests that data mining techniques can be a promising solution for the customer churn management and an early-warning model for this non-steady-state customer system can be built. Although churn prediction is important in churn management, there are many challenges that should be taken into consideration. For example, it is good to predict the possible churners beforehand, but it would be even better to know when these possible churners are likely to quit. This will help in determining appropriate intervention strategies to employ at any given time. Using four different techniques (Decision Tree, Random Forest, Logistic Regression, and Gradient Boosting) for classification, the Random Forest outperforms as compared to other algorithms by exhibiting low churn rate. The analysis of the algorithm was carried out based on ROC curve Precision-Recall and F1 Score. By the analysis of customer churn dataset, we concluded that there are 10 features which cause the customer to churn. Therefore, a company needs to improve these services and provide fringe offerings, better packages, and develop intervention strategies, so that the company can retain as many customers as possible and it can generate more revenue.

REFERENCES

Abiw-Abaidoo Jnr, K. 2011. Predicting customer churn in the mobile telecommunication industry, a case study of MTN Ghana, Kumasi (Doctoral dissertation).

Almana, A. M., Aksoy, M. S. and Alzahrani, R. 2014. A survey on data mining techniques in customer churn analysis for telecom industry. *Journal of Engineering Research and Applications*, 4(5), 165-171.

Balasubramanian, D. M. and Selvarani, M. 2014. Churn Prediction in Mobile Telecom System Using Data Mining Techniques. *International Journal of Scientific and Research Publications*, Vol. 4, No. 4, 1-5.

Bilal Zorić, A. 2016. Predicting customer churn in banking industry using neural networks. *Interdisciplinary Description of Complex Systems*, 14(2), 116-124.

Chen, K., Hu, Y. H. and Hsieh, Y. C. 2015. Predicting customer churn from valuable B2B customers in the logistics industry: a case study. *Information Systems and e-Business Management*, 13(3), 475-494.

Dahiya, K. and Bhatia, S. 2015. Customer churn analysis in telecom industry. In Reliability, Infocom Technologies and Optimization (ICRITO) (Trends and Future Directions), 2015 4th International Conference on (pp. 1-6). IEEE.

Dalvi, P. K., Khandge, S. K., Deomore, A., Bankar, A. and Kanade, V. A. 2016. Analysis of customer churn prediction in telecom industry using decision trees and logistic regression. In Colossal Data Analysis and Networking (CDAN), Symposium on (pp. 1-4). IEEE.

Esteves, G. and Mendes-Moreira, J. 2016. Churn prediction in the telecom business. In Digital Information Management (ICDIM), 2016 Eleventh International Conference on (pp. 254-259). IEEE.

Hashmi N, Butt N A. and Iqbal M. 2013. Customer churn prediction in telecommunication: a decade review and classification, *International Journal of Computer Science*, Issue, Vol. 10, No. 2, pp. 271-282.

Hassouna, M., Tarhini, A., Elyas, T. and AbouTrab, M. S. 2016. Customer Churn in Mobile Markets: A Comparison of Techniques, *International Business Research*, Vol. 8, No. 6, pp. 224-237.

Kaur, N. and Singh, N. 2016, Churn prediction – a review, *International Journal of Innovative Research in Computer and Communication Engineering*, Vol. 4, no. 1, pp. 23-29

KhakAbi, S., Gholamian, M. R. and Namvar, M. 2010. Data mining applications in customer churn management. In Intelligent systems, modelling and simulation (ISMS), 2010 International Conference on (pp. 220-225). IEEE.

Khan, A. A., Jamwal, S. and Sepehri, M. M. 2010. Applying data mining to customer churn prediction in an internet service provider. *International Journal of Computer Applications*, Vol. 9, No. 7, pp. 8-14.

Kirui, C., Hong, L., Cheruiyot, W. and Kirui, H. 2013. Predicting customer churn in mobile telephony industry using probabilistic classifiers in data mining. *IJCSI International Journal of Computer Science Issues*, Vol. 10, No. 2, pp. 165-172.

Miyata, M., Kamakura, K., Narita, M., Hirahara, Y., Okamoto, K., Hasegawa, M. and Tonogai, Y. 1994. Studies on Systematic Determination of Organophosphorus, Carbamate, Organochlorine and Pyrethroid Pesticides in Polished Rice by Gas Chromatography. Food Hygiene and Safety Science (Shokuhin Eiseigaku Zasshi), 35(3), 276-286_1.

Olle, G. D. O. and Cai, S. 2014. A hybrid churn prediction model in mobile Telecommunication industry. *International Journal of e-Education, e-Business, e-Management and e-Learning*, 4(1), 55.

Pradeep B, Rao S V, Puranik S M, Hegde A, 2017, Analysis of Customer Churn prediction in Logistic Industry using Machine Learning, Vol. 7, No. 11, pp. 401-403

Prasasti, N., Okada, M., Kanamori, K. and Ohwada, H. 2014. Customer lifetime value and defection possibility prediction model using machine learning: An application to a cloud-based software company. In Asian Conference on Intelligent Information and Database Systems (pp. 62-71). Springer, Cham.

Rodpysh, K. V. 2012. Model to predict the behavior of customers churn at the industry. *International Journal of Computer Applications*, 49(15).

Runge, J., Gao, P., Garcin, F. and Faltings, B. 2014. Churn prediction for high-value players in casual social games. In Computational Intelligence and Games (CIG), IEEE Conference on (pp. 1-8). IEEE.

Saini, N, Monika and Garg K. 2017. Churn Prediction In Telecommunication Industry Using Decision Tree, *International Journal of Engineering Research & Technology*, Vol. 6, No. 4, pp. 439-443.

Shaaban, E., Helmy, Y., Khedr, A. and Nasr, M. 2012. A proposed churn prediction model. *International Journal of Engineering Research and Applications*, 2(4), 693-697.

Sharma, A., Panigrahi, D. and Kumar, P. 2013. A neural network based approach for predicting customer churn in cellular network services. arXiv preprint arXiv:1309.3945

Vafeiadis, T., Diamantaras, K. I., Sarigiannidis, G. and Chatzisavvas, K. C. 2015. A comparison of machine learning techniques for customer churn prediction. *Simulation Modelling Practice and Theory*, 55, 1-9.

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