

Churn Prediction in the Airline Industry of Selected Sector

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Abstract

Churn prediction is the interesting phenomenon to the researchers in the recent past. This is applied to identify the movement or being migrated from a service provider to another one. The same scenario is widely-applied to telecom industries. The mobile service providers are offering different services to its customers. There are custom(er)-specific plans offered by the service provider to retain the customers at bulk such as corporate. This research focuses on applying churn prediction into Airlines industry. It focused on identifying which Airline service provider performs below the expected level. The services offered by the Airline Service Provider is analyzed based on some metrics like delay in the departure, delay in the arrival, whether the aircraft is cancelled and the aircraft is being diverted due to unforeseen circumstances. There is a great chance of the customers belonging to such Airline services to migrate to other service. In view of this, the data are collected from US-based website related to the Airline industry. The data are analysed in different perspectives and some of the promising leading machine learning models are also applied to predict the churn that is the Airline Service Provider..

Keywords: *Churn Prediction, Data Analytics, Airline Industry, Naïve Bayesian Classifier, Random Forest*

1. Introduction

Retaining the customers in a business environment is a challenging task in today's scenario. This can be made possible by providing the satisfied services thereby fulfilling the requirements of the customers. The customer's movement from a service to another service would create a lot of business loss. Hence, the retention of the customer to make it stand-by in the same business is purely based on the service offered by the business organization. This is the usual research which is going on around the world. In this research, the satisfaction of the service provider is evaluated by machine learning models.

The globalization and deregulation has its own impact in all economic sectors. This leads to increase in competition due to other competitors and technological factors. The service providing companies needs to fight over the retention of existing customers to stop migration to other service providers in the same market segment. The companies or organizations are spending much of their revenues in the activity of customer retention that represents a higher return on investment. Customer retention is the key objectives for the companies in the competitive world. It is studied that the cost of acquiring a new customer is five times more than retaining an existing customer. The customer retention would yield much profit and it also would provide more success rate than to have a new customer. The retention-focused actions would become the elements of competitive advantage.

Retaining the customers can be targeted on high-risk customers who may discontinue their custom or move from present custom to another service competitor. Such a phenomenon is called as customer churn. Not only that, the service providers may also needs to have enough finding mechanisms to retain the customers based on the factual evidence, that is, the data records, for early identification of churners. Thus, the company would frame a strategy as a decision-making policy to accurately identifying the customers who will become as churners and it should also be minimised. The impact of churning is not only the loss of overall reputation but also brand loss. The great impact of churning by the loyal customers maximizes the profit of a company. It would become as viral marketing by such customers, will spread word-to-mouth about the service provider to other relatives, friends and colleagues.

From the taxonomy, there are two main categories of churners, (i) voluntary churners and (ii) involuntary churners. The former class is makes a decision to terminate utilising the existing service with the provider. It is more difficult to determine. It can be further divided into two

categories incidental churn and deliberate churn. The first category occurs, when something happened in their lives. The factors like the change in financial condition, relocation would be some of the classical examples for this category. The second category occurs, due to the change of technology, the reasons of convenience, service quality index, economics and social or psychological factors. Most of the churn management strategies try to solve the category of deliberate churn. The easiest to identify the class of churners is the involuntary churners. The customers who involved in any fraudulent activities such as non-payment and they didn't use their device falls into this category. The other classification of churn is incidental and deliberate churn. The incidental churn is one in which the customers are by force dropping the service from the provider due to life circumstances. The movement of customer from the present service provider to its competitor is called as deliberate churn. There is variety of reasons why customer wants to discontinue their custom with a company. The reason for such movement would range from latest product offering; better price tag for the same price and the bitter experience with the present service offerings.

Due to the advent of technological innovations, now-a-days it is easy to identify the churners in the business industries. It is being made possible to the companies to predict the customers who are likely to churn by analysing its data records and the usage of machine learning models. The researchers have proposed various machine learning models for churn prediction in the recent past. The available data and the data analysis mechanism would help the data driven industries to extract the knowledge. There are three key aspects of a churn prediction model. They are (i) accuracy (ii) comprehensibility and (iii) justifiability. The first one permits to identify the future churners. The other two allows the main drivers to develop an effective retention strategy in accordance with domain knowledge.

Research Questions:

RQ1: Is it possible to consider the Airline Industry for Churn Prediction?

RQ2: What are the different metrics under which the Airline Service Provider is a Churn?

RQ3: What machine learning models can be used to predict Churn in the Airline sector?

Contribution of this work:

Answer to RQ1: Though the churn prediction is widely applied to the customer segment, this study is made an attempt to apply to the service provider's side. Moreover, the civil aviation is highly attracted to the public as more number of operators is providing the service. It is being utilized by the customers due to several reasons such as short travel time, comfortable journey among the few. When the service provider failed to provide the service which is on par with the customers' expectations, then they also will be considered as 'Churn' – they will be no more in the industry and lose their business value. Hence, the study has been made to apply the Churn Prediction to the service provider's side.

Answer to RQ2: The Federal Aviation Administration (FAA) accepts 15 minutes delay in bidirectional way – both at Departure Time and at Arrival Time. When an aircraft is delayed further then it is to be considered as it is delayed more than the acceptable threshold. Hence, the metrics such as Departure Delay greater than 15 minutes, Arrival delay greater than 15 minutes are considered as metrics for this study. Moreover, if the aircraft is delayed more than 15 minutes at arrival terminal then it is also considered whether the aircraft is diverted in another route.

Answer to RQ3: There are plenty of machine learning models in existence to apply for variety of research problems. Since, the churn prediction is basically considered as classification problem, the Naïve Bayesian Model and Random Forest Model are primarily used to identify the churn service providers. The comparison of these machine learning models are also presented in this study. The data are analysed by using visualization tool for pictorial view.

2. Background research

Though the churn prediction is being an active research during the recent past, the researchers are still putting their best effort to reduce the amount of churn identified in the business industries. There are wide varieties of machine learning models used to find the churn prediction and the summarization [8, 11, 12] would provide such models. The variety of models used to predict the customer churn prediction problem is carried out by [8]. It summarises the different models such as support vector machines, Naïve bayes, Decision Trees and Neural Networks that can be used for the customer churn prediction problem. It also used big data analytics technologies like Hadoop, HBase and NoSQL. To stop the churn several approaches are utilized by the researchers. This paper [11] reviews the various approaches utilized by researchers not solely in communication sector however conjointly different sectors that extremely depends on client participation. Within the telecommunications business, it's costlier to accumulate a replacement client as compared to holding the present one. Hence, client churn prediction is presently the most mechanism utilized by the business so as to stop customers from churning. The high volume of information generated by the business, with the assistance of information mining techniques implementation, becomes the most quality for predicting client churn. Thanks to this reason, recent literature of various data processing techniques and most well liked data processing algorithms for client churn prediction square measure reviewed during this paper [12].

Combining the machine learning models to improve the accuracy is called as ensemble [1]. It proposed an artificial neural network approach for prediction of shoppers meaning to switch to different operators. The results from this technique will predict the telecommunication churn. The study was conducted in Islamic Republic of Pakistan. This model produces the accuracy of 79% by the dataset used for study.

Most of the churn prediction models are applied to the telecommunication industry [2, 3, 4, 5, 6, 7, 8, 17]. Customer churn may be a major drawback and one amongst the foremost necessary considerations for giant firms. Because of the direct result on the revenues of the businesses, particularly within the telecommunication field, firms area unit seeking to develop means that to predict potential client to churn. Therefore, the churn prediction would be useful to cut back the customers and make them happy. The most contribution of this work is to develop a churn prediction model that assists telecommunication operators to predict customers of United Nations agency area unit [2]. The [3] analyses the churn prediction techniques to identify the churn behavior. It also validates the expectations at client side. It summarizes the techniques for deeper understanding of how to extract the churner. It concentrated on hybrid models instead of single algorithms. It identifies the risky churn customers from medium industries and how to enhance the services by the service provider to overturn the churn call. Social network analysis (SNA) structures the telecommunication network and its customers as a collection of graph consisting of vertices and edges. This structure can be used to identify victimized vertex. The measure of SNA is used to calculate the spatial relation which facilitates the node's importance within the graph structure. The churner is identified as influencer in the network and the targeted by providing additional campaigns. This proposal was also given by [4] to retain the customer (churner) not to move from the existing service provider to another one. [5] proposed the customer churn prediction using an intelligent rule-based decision-making technique with rough set theory. It effectively performs the classification of customers as churn and non-churn. This study was used to predict the churners from non-churn classifier. That is, the customers who are not a churn at present but they may become churner in near future. It also shows how attribute-level analysis will be helpful to frame the strategic policy and planning process in the telecom sector. The accurate identification and retention of targeted churners is highly crucial in telecommunication industry [6]. The fuzzy model is used as a classifier to identify the churner. The proposed model was evaluated against a real-time dataset and it achieved 98% accuracy of churner class. It also proposed to categorize the churners can be retained at 87%. The combinations of Naïve Bayesian, SVM and decision trees were used by [7] for customer churns prediction for telecommunication. The effectiveness of these models is evaluated over the two datasets with variant in size. The results obtained by these models are comparatively accurate than the previous studies for the same datasets.

The machine learning models are used for churn prediction [7, 13, 15]. Artificial neural network (ANN) can be used to identify the churners [13]. It is applied to the telecommunication customer dataset to identify the churners. This predictive model worked on different features such as demographic location, billing information and usage patterns. These attributes plays vital role for the customers to decide whether to stay with the existing service provider or to look for another service provider. In such a quick discovered, service suppliers have completed the importance of holding the on-hand customers. It's thus essential for the service suppliers to stop churn- a development that states that client needs to quit the service of the corporate [15].

Social network analysis (SNA) measures can be used to find the churners [4, 18]. A model building and evaluation to predict the churning in telecommunication organizations over the globe using social network analysis is a niche area [18]. SNA provides promising results in wide variety of problems including churn prediction. The model is evaluated with eight distinct call-detail records datasets, originating from telecommunication organizations across the world.

Particle Swarm Optimization technique along with feed forward neural network approach is a hybrid model which can also be used for churn prediction [9]. The first one is used to tune the weights of the input features and the second one is to increase the prediction power. The projected model considerably improves the coverage of churn customers compared with alternative progressive classifiers.

Another survey [10] of churn prediction is based on data analytics. Its perspective is on customer continuity management. It summarizes the survey in different phases like building the predictive model, types of models and its application in business.

Deep learning models are used for finding solutions to variety of problems in the recent past. It comprises of different techniques such as deep neural networks, convolutional neural network, recurrent neural networks. [14] made an attempt to apply such techniques over the casual game playing using mobile devices. The churn prediction is done by analyzing play log data of different casual games. It considered the records of 193,443 unique players and 10,874,958 play log records.

As Location-Based Social Networks became wide utilized by users, understanding user engagement and predicting user churn area unit essential to the maintainability of the services. [16] tend to use two large-scale datasets that incorporates one. The findings of geographical exploration and on-line interactions of users enhance the understanding of human quality supported reviews, and supply necessary implications for venue recommendations and churn prediction [16].

Driven by real mobile service operator knowledge set, [17] has a tendency to design and planned an answer to use survival analysis technique that estimates customers' survivals and hazards. Proactive actions triggered by the results of the survival model are essential to client retention.

In a business environment, for the service providers, it is more expensive for them to attract new customers than retaining existing customer. In this perspective, [19] proposed an ensemble technique comprises of Multilayer perceptron with negative correlation learning. It is applied to the customer dataset of a telecommunication company. The result obtained by the proposed technique is comparatively better with other data mining techniques for churn analysis.

Prophetical models will offer correct identification of doable churners within the close to future so as to supply a retention answer. The entire dataset was split into 80-20 ratio for training and testing respectively. Three classes of churners are identified and in case of mistreatment in a very retention strategy [20].

Finding the victim in telecommunication trade is a heavy issue [21]. The combination of Pearson correlation along with k-nearest neighbour is used to predict the churners in telecommunication. The models are validated by splitting the dataset as training and testing with 70-30 ratio. The experimental result of this study was shown that the k-NN performs better with training and testing accuracy of 80.45% and 97.78% respectively.

Retentive one client prices a corporation from five to ten times than As corporations increase their efforts in holding customers, having the ability to predict accurately prior time, whether or not a client can churn within the predictable future is a particularly powerful tool for

any promoting team. The research describes exhaustive appliance of Deep Learning within the drawback of churn prediction.

The research [22] paper provides a review of around one hundred recent journal articles ranging from year 2000 to gift the varied data processing techniques utilized in multiple client based mostly churn models. It then summarizes the present telecommunication literature by lightness the sample size used, churn variables used and therefore the findings of various DM techniques. Finally, we tend to list the foremost common techniques for churn prediction in telecommunication as call trees, multivariate analysis and bunch, thereby providing a roadmap to new researchers to create upon novel churn management models.

Classification and clustering are the two types of machine learning models. These are applied for churn prediction [23]. The classification is used for customer segmentation. The k-means clustering is used for customer profiling.

The machine learning models are used for customer churn prediction problem. A good comparison [24] helps to identify the appropriate model which can be applied for this kind of problems. The applicability of the model and the performance improvement were the two phases of comparison by the study. It produces the accuracy of 97%.

Churn prediction is rising as an excellent important field within the class of shoppers. corporation are investment a large quantity of capital within the method of holding the shoppers, i.e , preventing them from a churn. Each company likes to extend its variety of shoppers because it is directly proportional to the profit and sales of the corporate. however at identical time the corporate prefers to carry the shoppers UN agency have purchased their product a minimum of once, for that company needs some reasonably prediction that depicts once the shoppers can churn. Accuracy, understandability, and justifiability are 3 key aspects of a churn prediction model. This paper projected a rough set based mostly framework for client Churn Prediction mistreatment on client reviews dataset. The use of conferred framework facilitates corporations in creating intelligent call network [25].

The churn prediction technique can also be applied for a document comprehension [26]. The question and answering from the available documents is an interesting problem. A recurrent neural network technique is used to find the churn.

3. Material used

The Airlines dataset is collected from [28] for the year 2019 only. The dataset has 5,83,986 entries (rows) with the attributes YEAR, OP_UNIQUE_CARRIER, OP_CARRIER, ORIGIN_AIRPORT_ID, ORIGIN, DEST_AIRPORT_ID, DEST, DEP_TIME, DEP_DELAY, DEP_DELAY_NEW, ARR_TIME, ARR_DELAY, ARR_DELAY_NEW, CANCELLED, DIVERTED. All the attributes are considered for data analytics except that the YEAR, OP_UNIQUE, OP_CARRIER, ORIGIN, DEST, DEP_DELAY_NEW, ARR_DELAY_NEW, CANCELLED and DIVERTED. The YEAR column is not considered as the data are used for the year 2019. One more attribute called CHURN is also introduced for final prediction, which is based on the following condition:

If the DEP_DELAY_NEW is greater than 15, then test the CANCELLED attribute value. If the CANCELLED attribute value is 0, then the aircraft is considered as delayed from the source terminal. If the ARR_DELAY_NEW is greater than 15, then test the DIVERTED attribute value. If it is 0, then the aircraft is considered as delayed at destination terminal. If both the DEP_DELAY_NEW and ARR_DELAY_NEW are greater than 15, then the CHURN attribute is set to 1, otherwise set to 0. This will be the final dataset to apply machine learning models.

3.1 Data Preprocessing

Data preprocessing is the essential process to clean the data. It will be helpful for making the predictions more accurately. Fill in missing values is a data preprocessing technique. It falls under the category of data cleaning task. There are 18,022 missing values present in the dataset. Multiple missing values are also found in the same record (row). The technique of 'removing the entire row' is applied to fill the missing values, as it is not possible to fill such values based on the other techniques and the availability of data.

In order to preserve the privacy factor of the Airline Carrier, the real name of the carrier is transformed, not to provide the identity. There are 17 unique air carriers (AC) span across the dataset. The naming convention used in the dataset as ACXX, that is, it ranges between AC01 to AC17.

4. Methods, Results and Discussion

The dataset contains 5,83,986 records. There are 18,022 missing values found and the same are removed. Hence, the net size of the dataset is 5,65,964 records after removing the missing values. Each entry of record contains the details of a particular service by the carrier operator. The maximum number of services is offered by the air carrier AC15. It offered 1,07,235 number of services in the corresponding year. The minimum number of services is offered by the air carrier AC8 and it offered 6,694 numbers of services. The average number of services offered by all these 17 carriers is 33,292 in the year. The following figure represents the number of services offered by the individual air carrier.



Figure 1. Service offering by the Airline Service Providers

4.1. Naïve Bayesian Classifier

Classification is the machine learning technique in which the class label is known to the process of grouping. Naïve Bayesian classifier is based on the Bayes theorem which is stated as:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \quad (1)$$

Where P(A) is the prior probability of the class; P(B) is the prior probability of predictor; P(A|B) is the posterior probability and P(B|A) is the likelihood which is the probability of predictor given class. It works on the principle of class independence. It means that the availability of a particular feature does not affect the other one. In this dataset used for research, the model is applied with 70-30 split for training and testing respectively. The test dataset is used to validate the model and to get the results for prediction. The 'churn' column in the dataset is used as a classifier, as a class label.

4.2 Random Forest

It is an ensemble learning method used for classification problems. It uses the decision tree classifier as a base model and then works on combining with the others. The individual tree in this model spits out a class prediction. The class which has the most votes would become as the

model's prediction. The dataset is split into 70-30 ratio for training and testing respectively. The test dataset is used to validate the model and to get the prediction. The 'churn' column in the dataset is used as a classifier (as a class label).

The results obtained by applying both the machine learning models are produced in Table-1. It is been evident that in both the machine learning models the contingency table which has the No | No column has the highest number of records. Hence, it is been identified that none of the aircraft carrier is identified as a 'churner'. That means, the aircraft service providers are operating the service within the acceptable threshold (i.e) 15 minutes delay. The trend analysis shown in the figure is also shows the same prediction. The delayed time between the arrival and departure is almost in-line with the trend line. Hence, the delay is acceptable and within the dataset taken for study there is no churn.

Table 1. Models and Measures

Aircraft Carrier Code	Test data Sample Size	Naïve Bayesian Classifier								Random Forest		
		Accuracy	Precision (Y)	Precision (N)	Recall (Y)	Recall (N)	Yes Yes	Yes No	No Yes	No No	Yes Yes	No No
AC1	5946	95.66	0.91	0.97	0.89	0.98	1174	144	114	4514	1318	4628
AC2	22606	91.68	0.88	0.93	0.75	0.97	4048	1344	537	16677	5392	17214
AC3	6061	93.10	0.84	0.95	0.80	0.96	924	235	183	4719	1159	4902
AC4	7018	92.90	0.92	0.94	0.85	0.97	1826	328	170	4694	2154	4864
AC5	22021	93.54	0.85	0.95	0.75	0.97	2743	939	483	17856	3682	18339
AC6	3660	95.93	0.93	0.97	0.91	0.98	854	65	84	2657	938	2722
AC7	2847	91.85	0.88	0.93	0.84	0.95	720	135	97	1895	855	1992
AC8	2008	92.18	0.92	0.92	0.81	0.97	485	114	43	1366	599	1409
AC9	2035	89.04	0.86	0.90	0.58	0.97	251	182	41	1561	433	1602
AC10	7113	93.18	0.90	0.94	0.83	0.97	1563	314	171	5065	1877	5236
AC11	4503	93.52	0.88	0.95	0.76	0.98	649	205	87	3562	854	3649
AC12	6711	93.10	0.90	0.94	0.78	0.97	1180	327	136	5068	1507	5204
AC13	18531	94.71	0.90	0.96	0.88	0.97	3997	546	434	13554	4543	13988
AC14	13838	93.76	0.89	0.95	0.83	0.97	2643	551	313	10331	3194	10644
AC15	32170	91.91	0.88	0.93	0.79	0.96	6308	1700	903	23259	8008	24162
AC16	5349	94.49	0.91	0.96	0.84	0.98	1011	192	103	4043	1203	4146
AC17	7371	95.40	0.91	0.97	0.90	0.97	1567	183	156	5465	1750	5621

The accuracy is at 100% for all the aircraft carrier code in Random Forest Model. The scores of Precision and Recall for the categories yes and no is 1. Hence, it is not included in the table-1. It is also surprising that the random forest model classified the test data into yes / yes and no / no classes only.

Trend Analysis between Average Departure Delay and Average Arrival Delay (Min.)

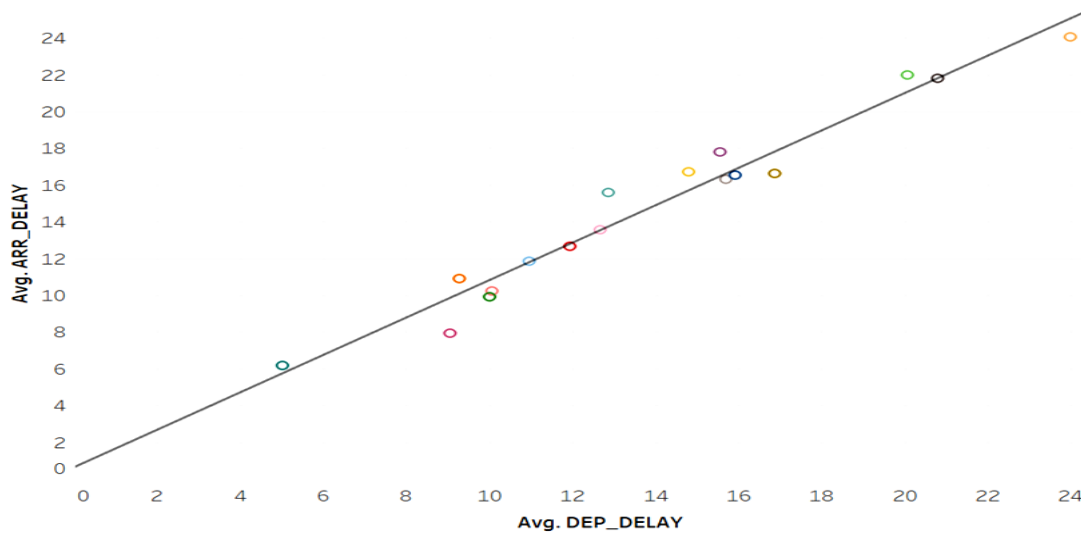


Figure 2. Trend Analysis graph between the departure and arrival delay

5. Conclusion

Churn is the process of moving from a service to another service. Churn prediction is an interesting phenomenon for researchers in the business domain. There are wide variety of machine learning models were used to predict the churners, due to the advent of technological support and evolution. Most of the studies were conducted from the customer-specific point. This research is focused on different perspective. It concentrated on service-provider view rather than the customer view. The other vital contribution of this work is the present research was focused on telecommunication sector, electronic commerce and others.

A bubble chart is shown in figure-3 to illustrate the delay in the average departure delay and the average arrival delay at both the arrival terminal and the departure terminal respectively. It is been known that the delays are acceptable as per the recommendations by the authorities concerned.

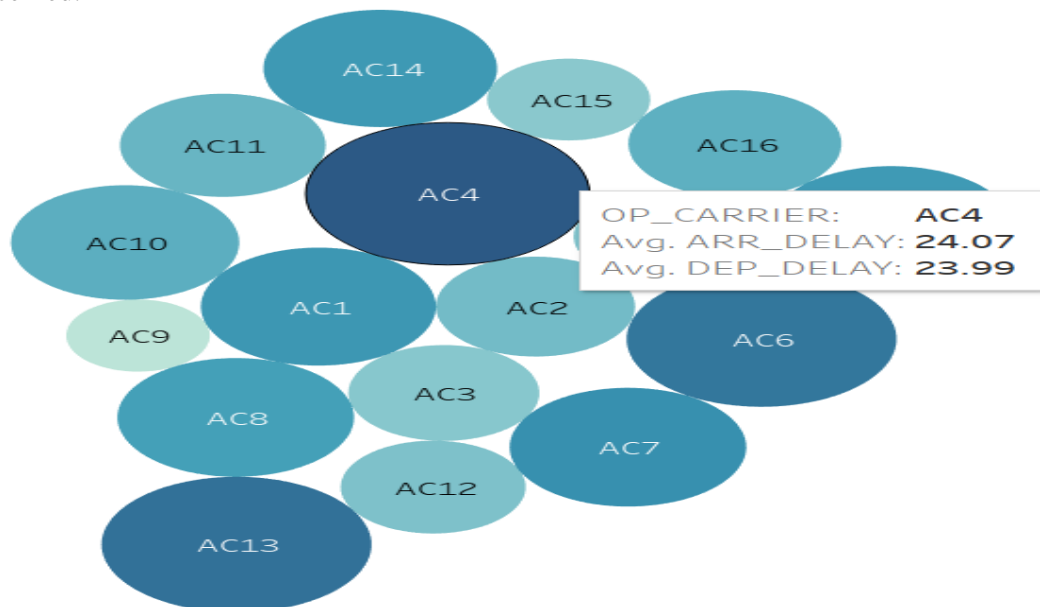


Figure 3. A bubble chart for the carriers and their delayed arrival and departure (in Minutes)

In order to identify the churning customer from the customer dataset, this research has taken an Airline Dataset. This has data with different features. Churn prediction is a classification problem rather than the clustering which is an unsupervised machine learning model. The interestingness of the dataset is, it doesn't have the classifier. That is, the class label which can be used for prediction by using the model. Hence, a new class label is introduced by specifying some conditions. It has two values such as yes, no. The Naïve Bayesian classifier and Random Forest Classifier are used as machine learning models for prediction of churning customer. The dataset is split into 70-30 ratio for training and testing respectively. It is being identified from the dataset taken for study and the confusion matrix that none of the airline service provider is being identified as churning customer. The popular machine learning tool Weka is used for machine learning models and Tableau public version is used for visualization and trend analysis.

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