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# Customer Churn Analysis

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**Abstract:** Customer churn analysis is a critical process for businesses to understand the reasons why customers stop using their products or services. It involves examining customer data and identifying patterns that can indicate potential churn. By analyzing this data, businesses can take proactive measures to retain customers, such as improving the quality of their offerings or targeting specific customer segments. Ultimately, effective customer churn analysis can help businesses reduce customer churn and increase profitability.

**Keywords:** Customer satisfaction, Customer feedback, Customer engagement, Customer loyalty.

## I. INTRODUCTION

Customer churn analysis is the process of examining customer data to understand why customers stop using a product or service. It involves analyzing customer behavior, identifying patterns, and developing strategies to reduce customer churn. The goal of customer churn analysis is to retain customers and increase customer loyalty. Some common metrics used in customer churn analysis include customer retention rate, churn rate, and customer lifetime value. By analyzing these metrics, businesses can identify the factors that contribute to customer churn and take steps to address them. Customer churn analysis often involves using predictive models to identify customers who are at risk of churning. These models use historical data to predict which customers are most likely to stop using a product or service. Once at-risk customers have been identified, businesses can develop targeted retention strategies to keep them engaged. These strategies might include personalized offers, improved customer service, or product improvements. In addition to reducing customer churn, customer churn analysis can also help businesses identify new growth opportunities. By analyzing customer behavior, businesses can identify new markets or products that might be of interest to their customers. Overall, customer churn analysis is a critical process for any business that wants to retain customers and grow its customer base. By understanding why customers leave and taking steps to keep them engaged, businesses can improve customer loyalty and drive long-term growth.

## II. LITERATURE SURVEY

1) *A Survey on Data Mining Techniques In Customer Churn Analysis For Telecom Industry - Amal M. Almana, (2020).*

This survey focuses on data mining techniques utilized for customer churn analysis in the telecom industry. The survey investigates the most commonly used data mining techniques for customer churn analysis, such as decision trees, logistic regression, and artificial neural networks.

The survey also examines the effectiveness of these techniques in predicting customer churn and retaining customers. The study sheds light on the importance of customer churn analysis and the role of data mining in enabling telecom companies to understand their customers better and develop effective retention strategies. The survey concludes with recommendations for future research in this area. Customer churn analysis refers to the process of identifying customers who are likely to switch to another service provider or terminate their service altogether.

Telecom companies use customer churn analysis to identify the factors that contribute to customer churn and develop strategies to retain customers. Data mining techniques are often used in customer churn analysis to extract valuable insights from large datasets. These techniques include classification, clustering, association analysis, and predictive modeling. Classification involves categorizing customers into groups based on their behavior or characteristics. Clustering involves grouping customers based on similarities in their behavior or characteristics.

Association analysis involves identifying relationships between different variables, such as the products or services that customers are using. Predictive modeling involves using historical data to make predictions about future customer behavior. Overall, data mining techniques can help telecom companies to identify the factors that contribute to customer churn, predict which customers are most likely to churn, and develop strategies to retain customers.

2) *Mobile Phone Data: A Survey of Techniques, Features, and Applications- Mohammed Okmi, Lip Yee Por, Tan Fong Ang, and Chin Soon Ku, (2020).*

A comprehensive review paper that provides an overview of the various techniques, features, and applications of mobile phone data. The paper discusses how mobile phone data can be used for a wide range of applications such as mobile network optimization, urban planning, transportation analysis, and health monitoring.

The paper also explores various techniques for processing and analyzing mobile phone data, such as data pre-processing, data fusion, clustering, classification, and regression. It describes the advantages and disadvantages of each technique and provides examples of their applications in different contexts. Additionally, the paper discusses various features of mobile phone data, such as location data, call and text message data, and app usage data. It explains how these features can be used to extract useful information and insights about user behavior, preferences, and activities. The results also show that classification and clustering approaches have been widely used where algorithms such as SVM and k-means are used to classify or cluster human activities based on their calling or mobility features.

The results show that the spatiotemporal calling feature has been widely used to depict human behaviors. This feature allows for the estimation of hourly dynamic population, the classification of land use, the estimation of ambient population, the investigation of the relationship between human dynamics and crime spatial-temporal patterns, defining the actual populations at risk, and others. Overall, the survey provides a comprehensive overview of the potential uses of mobile phone data and the various techniques that can be applied to analyze it. It highlights the importance of mobile phone data in providing insights into user behavior and improving various services and systems.

3) *Analysis of customer churn prediction in the telecom industry using decision trees and logistic regression: Ionuț Brândușoiu, Gavril Todorean, Horia, (2021).*

Customer churn is a major challenge for telecom companies as it leads to a loss of revenue and market share. Customer churn prediction using decision trees and logistic regression is a common approach to identify factors that contribute to customer churn and develop strategies to retain customers. Decision trees are a powerful tool for analyzing customer churn prediction as they can capture non-linear relationships between variables and help identify key drivers of customer churn. Decision trees split the data into subsets based on the values of predictor variables, creating a tree-like structure that shows how different variables interact to influence customer churn.

Logistic regression is another commonly used approach for customer churn prediction. It models the relationship between customer churn and predictor variables by estimating the probability of churn based on the values of these variables. Logistic regression allows for the identification of significant predictors of churn and the calculation of their impact on the likelihood of churn. The telecom industry generates large amounts of data that can be used for customer churn prediction.

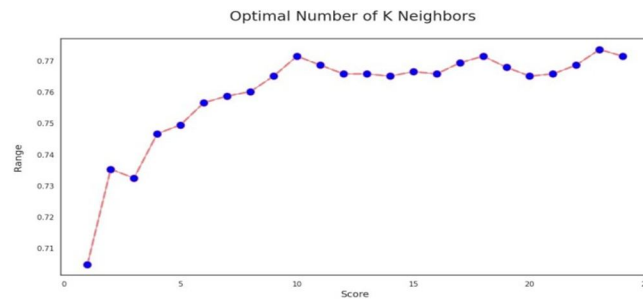
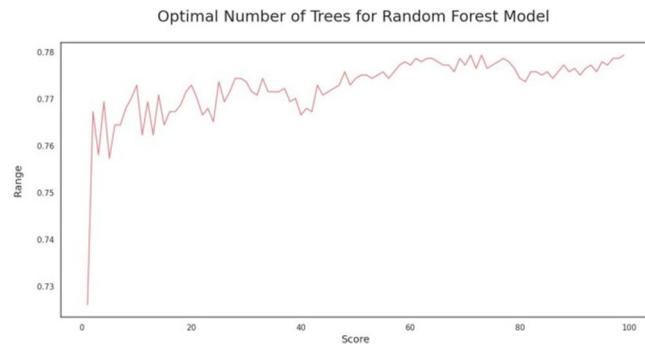
Variables that can be used for churn prediction include demographic information, usage patterns, and customer satisfaction ratings. By analyzing these variables using decision trees and logistic regression, telecom companies can develop targeted retention strategies that focus on the key drivers of customer churn. Overall, customer churn prediction using decision trees and logistic regression is an effective method for telecom companies to identify factors that contribute to customer churn and develop targeted retention strategies.

### III. PROPOSED WORK

Customer churn analysis is a process of identifying customers who are likely to discontinue using a product or service, and understanding the reasons behind their decision. The analysis involves collecting and analyzing data on customer behavior, demographics, and purchase history, among other factors, to identify patterns and potential predictors of churn. The insights gained from churn analysis can help businesses develop strategies to retain customers, improve customer experience, and ultimately increase revenue. Some common techniques used in churn analysis include statistical modeling, machine learning, and data visualization.

#### A. Graph Analysis

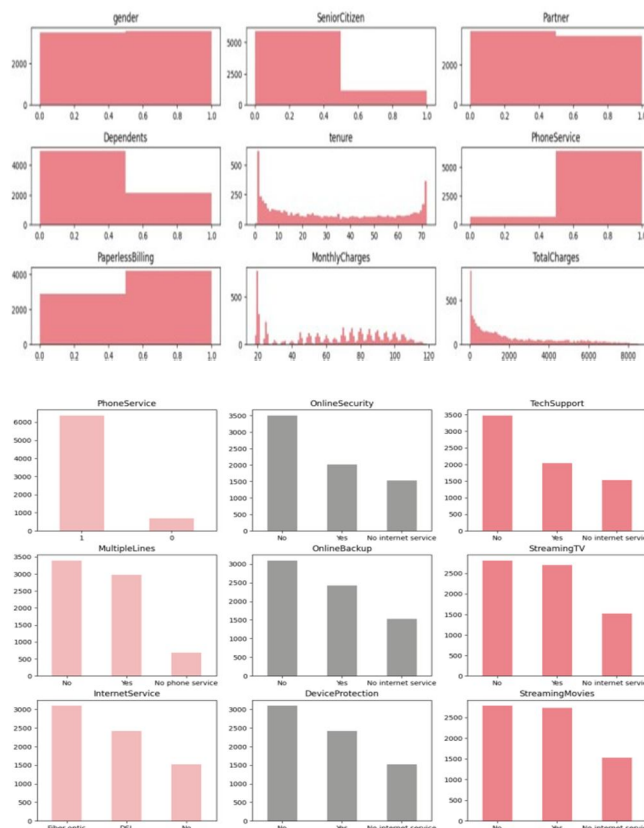
Graph analysis is the process of examining and interpreting data represented in graphical form. It involves identifying patterns, trends, and relationships within the data to gain insights and make informed decisions.



### B. Data Analysis

We analyzed the collected data from the telecom customerchurn.

Histograms of Numerical Columns



### C. Big Data Analysis

We did an analysis of data using python here we have a large dataset so we used google collab to analyze it.

```

0 #Check Column Datatypes and Missing Values:
dataset.columns.to_series().groupby(dataset.dtypes).groups

[1086: ['SeniorCitizen', 'tenure', 'float64', 'MonthlyCharges'], object: ['customerID', 'gender', 'Partner', 'Dependents', 'PhoneService', 'MultipleLines', 'InternetService', 'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport', 'StreamingTV', 'StreamingMovies', 'Contract', 'PaymentMethod', 'TotalCharges', 'Churn']]

[10] dataset.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   customerID           7043 non-null   object
 1   gender               7043 non-null   object
 2   SeniorCitizen        7043 non-null   int64
 3   Partner              7043 non-null   object
 4   Dependents           7043 non-null   object
 5   tenure               7043 non-null   int64
 6   PhoneService         7043 non-null   object
 7   MultipleLines        7043 non-null   object
 8   InternetService      7043 non-null   object
 9   OnlineSecurity       7043 non-null   object
10  OnlineBackup         7043 non-null   object
11  DeviceProtection    7043 non-null   object
12  TechSupport          7043 non-null   object
13  StreamingTV          7043 non-null   object
14  StreamingMovies     7043 non-null   object
15  Contract             7043 non-null   object
16  PaperlessBilling     7043 non-null   object
17  PaymentMethod        7043 non-null   object
18  MonthlyCharges       7043 non-null   float64
19  TotalCharges         7043 non-null   object
20  Churn                7043 non-null   object
dtypes: float64(1), int64(2), object(18)
memory usage: 1.1+ MB

Step 6: Clean the Dataset

[18] dataset['TotalCharges'] = pd.to_numeric(dataset['TotalCharges'], errors='coerce')
dataset['TotalCharges'] = dataset['TotalCharges'].astype("float")

Step 7: Take care of missing data

[19] dataset.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7043 entries, 0 to 7042
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  -
 0   customerID           7043 non-null   object
 1   gender               7043 non-null   object
 2   SeniorCitizen        7043 non-null   int64
 3   Partner              7043 non-null   object
 4   Dependents           7043 non-null   object
 5   tenure               7043 non-null   int64
 6   PhoneService         7043 non-null   object
 7   MultipleLines        7043 non-null   object
 8   InternetService      7043 non-null   object
 9   OnlineSecurity       7043 non-null   object
10  OnlineBackup         7043 non-null   object
11  DeviceProtection    7043 non-null   object
12  TechSupport          7043 non-null   object
13  StreamingTV          7043 non-null   object
14  StreamingMovies     7043 non-null   object
15  Contract             7043 non-null   object
16  PaperlessBilling     7043 non-null   object
17  PaymentMethod        7043 non-null   object

[11] dataset.isna().any()

customerID      False
gender           False
SeniorCitizen   False
Partner          False
Dependents       False
tenure           False
PhoneService     False
MultipleLines    False
InternetService  False
OnlineSecurity   False
OnlineBackup     False
DeviceProtection False
TechSupport      False
StreamingTV      False
StreamingMovies  False
Contract         False
PaperlessBilling False
PaymentMethod    False
MonthlyCharges  False
TotalCharges     False
Churn            False
dtype: bool

[12] #Unique values in each categorical variable:
dataset["PaymentMethod"].unique()

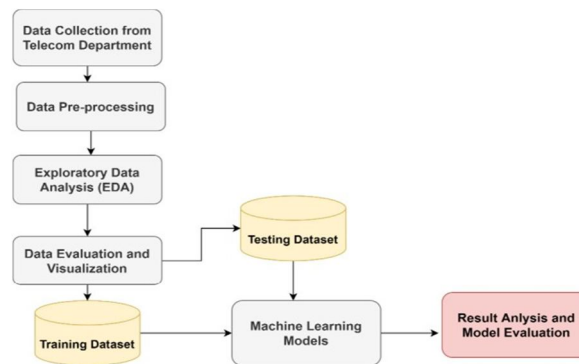
4

[13] dataset["PaymentMethod"].unique()

array(['Electronic check', 'Mailed check', 'Bank transfer (automatic)',
       'Credit card (automatic)'], dtype=object)

```

Flowchart



IV. RESULTS

The application is an online application, that has customer churn data analysis.



Customer Churn Graph

Graphs in web analytics are a visual representation of data that can help website owners better understand website traffic and user behavior. Graphs can be constructed with nodes and edges that depict relationships between data points. Nodes represent individual data points, such as website pages or visitors, while edges show the connections between them. Examples of graphs in web analytics include line graphs, bar graphs, pie charts, heatmaps, and funnel graphs. These graphs are useful for showing trends over time, comparing data across categories, displaying proportions of different categories, visualizing user behavior on a website, and illustrating steps in a conversion process. By analyzing these graphs, website owners can optimize their website and improve the user experience.

V. CONCLUSION

Collect data from telecom to conduct customer churn analysis here we will use data analytics tools to extract insights from the data. Create visual representations of the data through graphs and charts. Develop strategies to address the underlying issues and reduce churn. Present the findings and recommendations through a website.

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