PHASE-5

***DATA ANALYST WITH COGNOS***

**Introduction:**

**PROJECT- CUSTOMER CHURN PREDICTION IN TELECOMMUNICATION**

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Telecommunication Churn Prediction is a machine learning project which focuses on predict customer churn in the telecommunication industry. Churn prediction is important for telecommunication companies because it helps them to retain their customers and reduce customer acquisition costs. The figure below depicts the description of the data set importation and screenshot of same.



DATA COLLECTION :

In the first step of context of telecommunications or any other industry, data collection is typically performed using other specialized tools and systems. Here's an overview of how data collection in telecommunications works, with Cognos playing a role in data analysis and reporting not used for direct collection of data in telecommunications or any other industry. Data collection in telecommunications involves a complex process of gathering, storing, and processing data from various sources, and specialized tools and systems are used for each stage of this process. Cognos comes into play after the data has been collected and prepared for analysis, providing a means to visualize and report on the insights gained from the data.

Data Source:

Telecommunication companies collect a data from a wide range of sources includes a networks equipment, call detail records, customer relationship management system ,billing system ,network monitoring tools .

Dataset link : ( <https://www.kaggle.com/datasets/blastchar/telco-customer-churn> )

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| --- | --- | --- | --- | --- | --- | --- | --- |
| Customer ID | gender | Senior Citizen | Partner | Dependents | tenure | Phone Service | Multiple Lines |
|  |  |  |  |  |  |  |  |
| 7590-VHVEG | Female | 0 | Yes | No | 1 | No | No phone service |
| 5575-GNVDE | Male | 0 | No | No | 34 | Yes | No |
| 3668-QPYBK | Male | 0 | No | No | 2 | Yes | No |
| 7795-CFOCW | Male | 0 | No | No | 45 | No | No phone service |
| 9237-HQITU | Female | 0 | No | No | 2 | Yes | No |
| 9305-CDSKC | Female | 0 | No | No | 8 | Yes | Yes |
| 1452-KIOVK | Male | 0 | No | Yes | 22 | Yes | Yes |
| 6713-OKOMC | Female | 0 | No | No | 10 | No | No phone service |
| 7892-POOKP | Female | 0 | Yes | No | 28 | Yes | Yes |
| 6388-TABGU | Male | 0 | No | Yes | 62 | Yes | No |
| 9763-GRSKD | Male | 0 | Yes | Yes | 13 | Yes | No |
| 7469-LKBCI | Male | 0 | No | No | 16 | Yes | No |
| 8091-TTVAX | Male | 0 | Yes | No | 58 | Yes | Yes |
| 0280-XJGEX | Male | 0 | No | No | 49 | Yes | Yes |
| 5129-JLPIS | Male | 0 | No | No | 25 | Yes | No |
| 3655-SNQYZ | Female | 0 | Yes | Yes | 69 | Yes | Yes |
| 8191-XWSZG | Female | 0 | No | No | 52 | Yes | No |
| 9959-WOFKT | Male | 0 | No | Yes | 71 | Yes | Yes |
| 4190-MFLUW | Female | 0 | Yes | Yes | 10 | Yes | No |
| 4183-MYFRB | Female | 0 | No | No | 21 | Yes | No |
| 8779-QRDMV | Male | 1 | No | No | 1 | No | No phone service |
| 1680-VDCWW | Male | 0 | Yes | No | 12 | Yes | No |
| 1066-JKSGK | Male | 0 | No | No | 1 | Yes | No |
| 3638-WEABW | Female | 0 | Yes | No | 58 | Yes | Yes |
| 6322-HRPFA | Male | 0 | Yes | Yes | 49 | Yes | No |
| 6865-JZNKO | Female | 0 | No | No | 30 | Yes | No |
| Churn rate by dependent |  |  |  |  |  |  |  |
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Model Evaluation and Prediction :

Model evaluation is a critical step in the telecommunication prediction process. It helps assess the performance and accuracy of the prediction models we’ve developed.It can splitting the data,Selecting evaluation metrics and Some models are logistic regressionDecision Trees Support vector machine(SVM),Neural Networks),Model Training and Validation,Visualization and plots,Comparative Analysis and Communication results.Effective model evaluation ensures that your telecommunication prediction models are accurate, reliable, and aligned with the goals of your organization.

Model Prediction Predictive modelling in telecommunication can be used for various purposes, such as predicting customer churn, forecasting network traffic, optimizing resource allocation, and improving customer satisfaction. It allows telecom companies to make data-driven decisions and respond proactively to industry changes and customer needs.

PREDICTIVE MODELLING :

Predictive modelling in the field of telecommunications involves using historical data and statistical algorithms to make predictions about future events or outcomes. Data analysts and data scientists in the telecommunications industry can leverage predictive modelling techniques to address various challenges and opportunities

PYTHON PROGRAM:

#Import necessary libraries

# Function to predict churn based on inputs

def predict\_churn(customer\_id, gender, senior\_citizen, partner, dependents, phone\_service, tenure, multiple\_lines):

# You would typically use a machine learning model for such predictions

# This is a simplified example and does not use a real model

# Convert binary values (yes/no) to 1/0

partner = 1 if partner.lower() == "yes" else 0

dependents = 1 if dependents.lower() == "yes" else 0

phone\_service = 1 if phone\_service.lower() == "yes" else 0

multiple\_lines = 1 if multiple\_lines.lower() == "yes" else 0

# Example of a simple rule-based prediction

if (senior\_citizen == 1 and tenure < 12) or (partner == 0 and dependents == 0 and tenure < 6):

churn\_prediction = "Yes"

else:

churn\_prediction = "No"

# Print the prediction

print("Customer ID:", customer\_id)

print("Churn Prediction:", churn\_prediction)

# Input values (you can replace these with user input or actual data)

customer\_id = "9237-HQITU"

gender = "Female"

senior\_citizen = 0 # 1 for yes, 0 for no

partner = "Yes" # Yes or No

dependents = "No" # Yes or No

phone\_service = "Yes" # Yes or No

tenure = 2 # Number of months

multiple\_lines = "No" # Yes or No

# Call the predict\_churn function with input values

predict\_churn(customer\_id, gender, senior\_citizen, partner, dependents, phone\_service, tenure, multiple\_lines)

OUTPUT:

Customer ID: 9237-HQITU

Churn Prediction: No

**Data Analysis**

* After cleaning the data set, the next step was to perform exploratory data analysis (EDA). EDA is important because it helps to understand the distribution of the data and identify any trends or patterns in the data.
* The first step in EDA was to analyze the distribution of gender of the target variable ‘Churn’. it was revealed the distribution is almost equally with a difference of 67 count of male than female.
* The ratio between the Senior Citizens to Non-Senior Citizens was about 1:5. With Non-Senior Citizens constituting about 84% of the whole distribution. Thus, most of the customers in the dataset are younger people.
* About 50% of the customers have a partner, while only 30% of the total customers have dependents.
* Interestingly, among the customers who have a partner, only about half of them also have a dependent, while other half do not have any dependents.
* Additionally, as expected, among the customers who do not have any partner, a majority (90%) of them do not have any dependents.

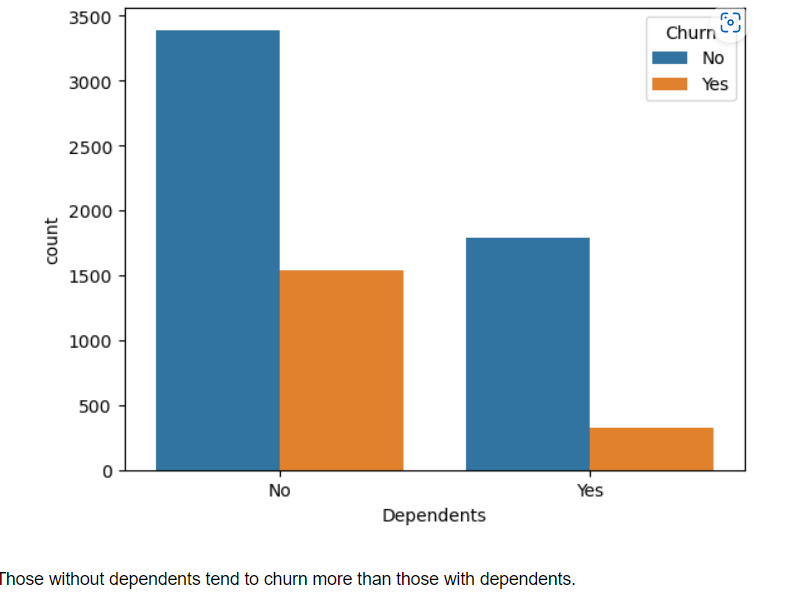
**Overall Churn Rate**

In our data, 74% of the customers do not churn. Clearly the data is skewed as we would expect a large majority of the customers to not churn. This is important to keep in mind for our modelling as skewed-sens could lead to a lot of false negatives. We will see in the modelling section on how to avoid newness in the data.



**1 Explore the churn rate by dependent, seniority, payment method, monthly charges and total charges to see how it varies by these variables.**

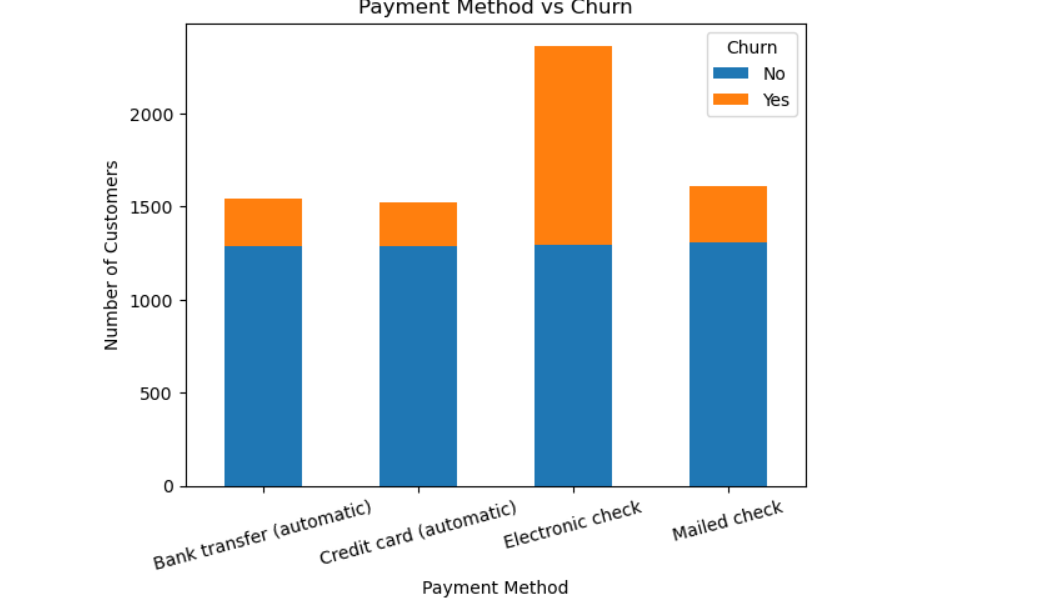
1. Churn rate by dependent



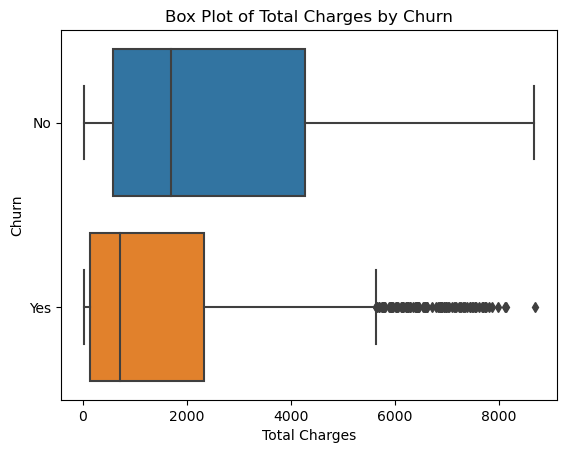
**Churn Rate By Dependent**

As we can see from the above plot, the customers who do not have dependent tend to churn more than those with dependents.

1. Churn by payment method

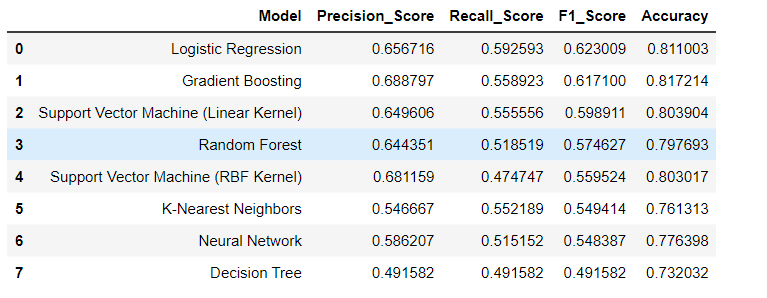
2

1. Churn by total charges



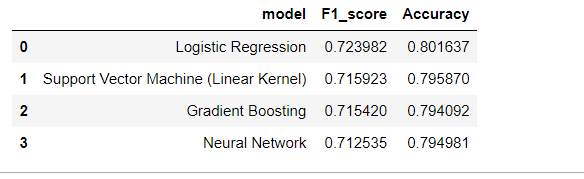
**Machine learning Modeling:**

After performing EDA, the next step was to build a machine learning model to predict customer churn. The following models were used for this project; Logistic Regression, Random Forest, Gradient Boosting, Neural Network, Support Vector Machine (Linear Kernel), Support Vector Machine (RBF Kernel), K-Nearest Neighbors, Decision Tree.



The 8 models were trained on the training data and evaluated on the test data using accuracy, Precision, Recall, and F1-score metrics. The Logistic Regression model had the highest performance with an F1 score of 0.62. The top four performing models were selected and tuned.

**Summary of Results:**



* Based on the Accuracy and F1-Score metrics, the best model for the classification problem appears to be Logistic Regression model. Although all the other models had similar accuracy scores, Logistic Regression model had the highest F1-Score and Accuracy.
* While Logistic Regression model had a good accuracy score of 0.80, its F1-Score, is slightly higher than the other three models. Therefore, based on the metrics evaluated Logistic Regression model appears to be the best model for this classification problem.
* However, it is important to note that other factors such as model complexity, computerization, efficiency, and interpret-ability such also be considered when choosing a model for deployment.

Conclusion

In conclusion, the integration of data analytics with Cognos in the field of telecommunications holds significant potential for transforming the industry. Data analytics, when harnessed effectively, can provide telecom companies with valuable insights that can lead to improved operational efficiency, enhanced customer experiences, and informed decision-making. Some key takeaways from the utilization of data analytics with Cognos in telecommunications include:

1. **Enhanced Decision-Making:** Telecom companies can make more informed decisions by analyzing vast amounts of data related to network performance, customer behavior, and market trends. This can lead to better resource allocation and strategic planning.
2. **Revenue Growth:** Data analytics can uncover opportunities for upselling, cross-selling, and more effective marketing strategies, thereby increasing revenue for telecom companies.
3. **Cost Reduction:** By identifying areas of inefficiency and optimizing resource allocation, data analytics can help telecoms reduce operational costs.
4. **Compliance and Security:** Telecoms can use data analytics to monitor and maintain compliance with regulatory requirements and enhance cybersecurity measures to protect sensitive customer data.

However, it's important to note that the successful implementation of data analytics with Cognos in the telecommunications sector also comes with challenges, such as data privacy concerns, data quality issues, and the need for skilled data analysts and data scientists.the combination of data analytics with Cognos has the potential to revolutionize the telecommunications industry, providing companies with a competitive edge and enabling them to deliver better services, reduce costs, and drive innovation. It is crucial for telecom organizations to invest in the necessary technology and talent to harness the full potential of data analytics and Cognos in their operations.

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