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In Collaboration with

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CM-2606 Data Engineering Coursework Summary Report

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1. Introduction

Telecom churn refers to the phenomenon of customers switching to a different telecom service provider, and it is a critical challenge for telecom companies to address to retain their customer base. To effectively analyze and address telecom churn, a robust data pipeline is essential to process, analyze, and gain insights from large volumes of data.

The solution utilizes Hadoop, an open-source distributed data processing framework, to efficiently handle big data processing tasks. Hive, a data warehouse software built on top of Hadoop, is used for data storage and querying data cleaning and transformation. SQL Queries have been run through Data Analytics Studio (DAS), a web-based tool provided by Hadoop, and data visualization, analysis, and reporting have been done using DAS along with python and Excel.

Once the data is analyzed, an insights generation can be done for stakeholders for decision-making. The solution also incorporates machine learning algorithms, such as predictive modeling and clustering, to identify potential churn customers based on historical data patterns. The end-to-end solution aims to provide telecom companies with actionable insights to proactively address customer churn, improve customer retention strategies, and enhance overall business performance.

2. Dataset Selection

The **Orange Telecom's Churn Dataset** found on Kaggle is the main source of data for this project. This dataset contains information about the customers of a telecom company and their churn status, i.e., whether they have left the company or not.

There were 2 csv files where data was split into 20% and 80% for the ease of a Machine Learning project. Those 2 have been connected as a single csv in this project. So, a total of 3335 rows and 21 columns have been created.





Each row in the dataset represents a customer, and the columns contain various features and attributes related to the customer. The attributes in the dataset are as follows:

- 1. State: A string representing the state where the customer is located.
- 2. Account length: An integer representing the length of the customer's account.
- 3. Area code: An integer representing the area code of the customer's phone number.
- 4. International plan: A string indicating whether the customer has an international plan (Yes/No).
- 5. Voice mail plan: A string indicating whether the customer has a voice mail plan (Yes/No).
- 6. Number vmail messages: An integer representing the number of voice mail messages the customer has.
- 7. Total day minutes: A double value representing the total number of minutes the customer used during the day.
- 8. Total day calls: An integer representing the total number of calls the customer made during the day.
- 9. Total day charge: A double value representing the total charge for the customer's day usage.
- 10. Total eve minutes: A double value representing the total number of minutes the customer used during the evening.
- 11. Total eve calls: An integer representing the total number of calls the customer made during the evening.
- 12. Total eve charge: A double value representing the total charge for the customer's evening usage.
- 13. Total night minutes: A double value representing the total number of minutes the customer used during the night.
- 14. Total night calls: An integer representing the total number of calls the customer made during the night.
- 15. Total night charge: A double value representing the total charge for the customer's night usage.
- 16. Total intl minutes: A double value representing the total number of international minutes





used by the customer.

- 17. Total intl calls: An integer representing the total number of international calls made by the customer.
- 18. Total intl charge: A double value representing the total charge for the customer's international usage.
- 19. Customer service calls: An integer representing the total number of customer service calls made by the customer.
- 20. Churn: A string indicating whether the customer has churned (TRUE/FALSE).
- 21. ID: An integer created to be used as primary key.

Scenario:

The Orange Telecom Company wants to reduce customer churn and retain more customers. To achieve this, they want to understand the factors that lead to customer churning and identify customers who are at high risk of churning.

3. Insight Generation Mechanism

The dataset contains various features and attributes related to customers, including their account details, phone usage patterns, international plans, voice mail plans, and customer service calls. By analyzing these features, the company can gain insights into the factors that may influence customer churn.

Following factors can be analyzed from this dataset:

- Customer Demographics: The company can analyze the churn rate of customers from different states and areas to identify areas where they need to improve their services or marketing strategies. For example, if the churn rate is high in a particular state, they can analyze the reasons for the high churn rate and take steps to address the issues.
- 2. Usage patterns: The company can analyze the usage patterns of customers who churned compared to those who did not churn. For example, they can analyze the average usage minutes, the average number of calls made, and the average amount charged for customers who churned and compare it with those who did not churn. They can identify patterns in the data to identify customers who are at high risk of churning and take





proactive steps to retain them.

3. Plan and Pricing: The company can analyze the churn rate of customers who have international plans or voice mail plans to identify if there is a correlation between these plans and churn rate. They can also analyze the churn rate of customers who are on different pricing plans to identify if there is a correlation between pricing and churn rate.

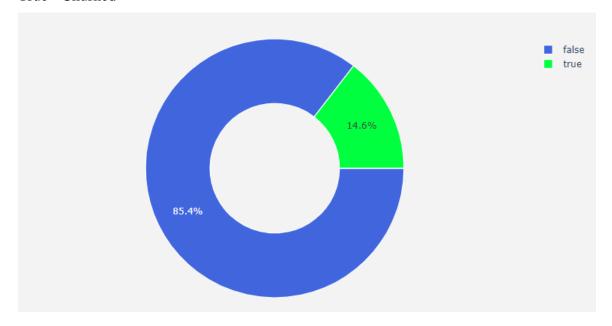
Exploratory Data Analysis

An exploratory data analysis (EDA) has been done to gain a better understanding of the dataset. This includes visualizing the distribution of each feature, identifying any missing or outlier values, and examining correlations between features. EDA provided valuable insights into the dataset and help in identifying patterns or trends that may be indicative of customer churn.

Customer churn:

False - Retained

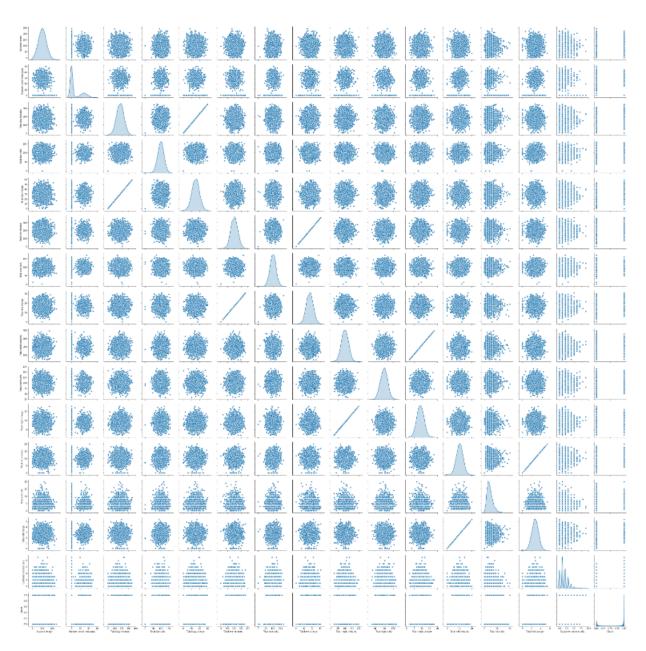
True - Churned







Variable Distributions:



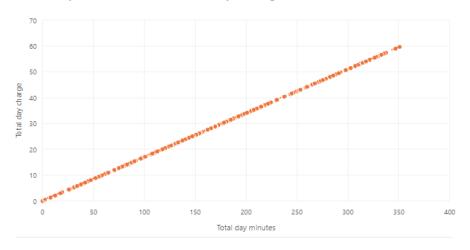
Several numerical data appear highly correlated:

- 1. Total day minutes and Total day charge.
- 2. Total eve minutes and Total eve charge.
- 3. Total night minutes and Total night charge.
- 4. Total intl minutes and Total intl charge.

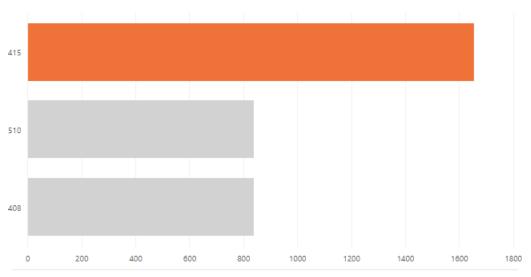




Total day minutes and Total day charge.



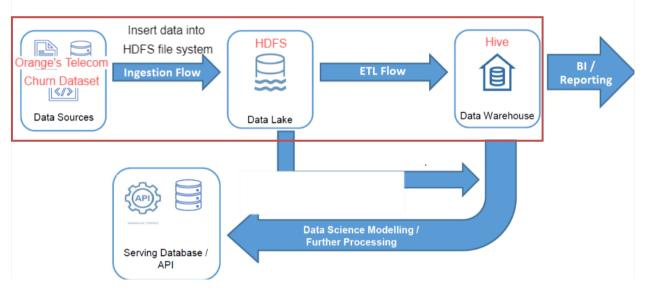
Area code







4. Pipeline Design



Note that the pipeline design has been done only up to the data warehousing part.

4.1 Ingestion Flow

Data ingested from data source (Kaggle dataset) into the data lake Hadoop Distributed File System (HDFS).

- 1. Download the dataset from the Kaggle to the local machine.
- 2. Upload the csv to the HDFS on the virtual machine.

4.2 ETL Flow (Extract, Transform, Load)

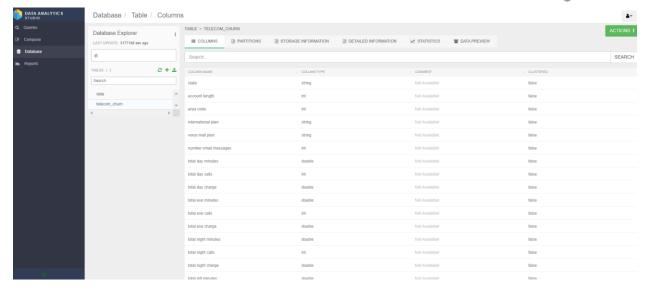
After data is stored in the data lake, ETL flow has been applied through the data to transform to a suitable format for analysis.

4.2.1 Extract

The uploaded csv in the HDFS has to be further preprocessed. So, data is extracted into the hive.







4.2.2 Transform

Data contained some duplicate rows and missing values. Those have been handled in the transform section.

Duplication Handling

A new table called telecom_churn_new was created which has selected unique rows from the previously created telecom_churn table.

Missing Value Handling

There were some null values in the dataset. Those were replaced by the mean value of the respective column.

Finding the average value of the columns which contain missing values:
 select avg(`Total eve minutes`), avg(`Total night minutes`) from telecom_churn_new;



from telecom_churn_new;



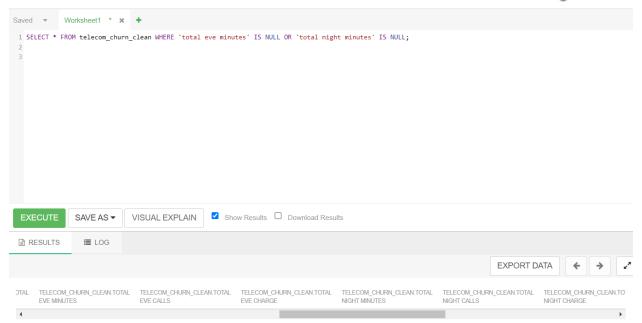
_C0 _C1 200.97233403424505 200.8506158005406

2. Replace the missing value with the average value of that column:

create table telecom_churn_clean as select State, `Account length`, `Area code`, `International plan`, 'Voice mail plan', `Number vmail messages`, `Total day minutes`, 'Total day calls', `Total day charge`, coalesce('Total eve minutes', 200.97233403424505) as 'Total eve minutes', `Total eve calls`, `Total eve charge`, coalesce(`Total night minutes`, 200.8506158005406) as `Total night minutes`, `Total night calls`, `Total night charge`, `Total intl minutes`, `Total intl calls`, `Total intl charge`, `Customer service calls`, Churn, ID







Missing values were successfully handled by replacing them with the mean.

4.2.3 Loading

Bucketing

Bucketing is done to the International plan column by taking an average value for total intle charge. If the value in the International plan column is 'No', then it is labeled as 'No' in the plan_type column of the international_plan_bucket table. Otherwise, if the value is not 'No', it is labeled as 'Yes' in the plan_type column.

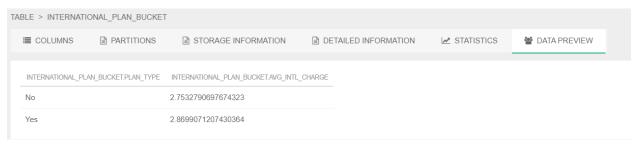
```
create table international_plan_bucket as SELECT case
when `International plan` = 'No' then 'No'
else 'Yes'
end as plan_type,
avg(`Total intl charge`) as `avg_intl_charge`
from telecom_churn_clean
group by
case
```





when `International plan` ='No' then 'No' else 'Yes' end;

The resulting average is stored in the avg_intl_charge column of the international_plan_bucket table. Finally, the GROUP BY clause is used to group the data based on the bucket labels defined in the CASE statement, allowing for aggregation and summarization of data based on the 'No' or 'Yes' values in the international plan column.



Creating the Fact Table

The fact table acts as the central repository of quantitative data that captures key performance indicators and metrics related to customer churn. It serves as a foundation for data analysis and reporting, enabling insights and actionable information for informed decision-making.

create table telecom_churn_fact (

State STRING,

- `Account length` int,
- `Area code` int,
- `International plan` STRING,
- 'Voice mail plan' STRING,
- `Number vmail messages` int,
- `Total day minutes` DOUBLE,
- `Total day calls` int,
- `Total day charge` DOUBLE,
- `Total eve minutes` DOUBLE,
- `Total eve calls` int,





- `Total eve charge` DOUBLE,
- `Total night minutes` DOUBLE,
- `Total night calls` int,
- `Total night charge` DOUBLE,
- 'Total intl minutes' DOUBLE,
- `Total intl calls` int,
- `Total intl charge` DOUBLE,
- `Customer service calls` int,

Churn STRING,

ID int,

CONSTRAINT telecom_churn_pk primary key (ID) disable novalidate);

Adding Data to Fact Table

 $INSERT\ INTO\ TABLE\ telecom_churn_fact$

SELECT

- State,
- `Account length`,
- `Area code`,
- 'International plan',
- 'Voice mail plan',
- `Number vmail messages`,
- `Total day minutes`,
- `Total day calls`,
- `Total day charge`,
- `Total eve minutes`,
- `Total eve calls`,
- `Total eve charge`,
- `Total night minutes`,
- `Total night calls`,
- `Total night charge`,
- `Total intl minutes`,





`Total intl calls`,

`Total intl charge`,

`Customer service calls`,

Churn,

ID

FROM telecom_churn_clean;

■ (COLUMNS PARTIT	TIONS STORAGE INF	FORMATION 🗎 DETAILE	ED INFORMATION 🗷 STATI	STICS MATA PREVIE	W
AL.	TELECOM_CHURN_FACT.TOTAL	TELECOM_CHURN_FACT.TOTAL	TELECOM_CHURN_FACT.TOTAL INTL CHARGE	TELECOM_CHURN_FACT.CUSTOMER SERVICE CALLS	TELECOM_CHURN_FACT.CHURN	TELECOM_CHURN_FACT.ID
	5.3	3	1.43	1	FALSE	3147
	14.5	6	3.92	0	FALSE	2672
	12.2	1	3.29	1	FALSE	228
	8.7	3	2.35	1	FALSE	836
	12.3	7	3.32	2	FALSE	1495
	4.1	5	1.11	2	FALSE	1056
	8.3	6	2.24	3	FALSE	1663
	8.1	1	2.19	3	FALSE	3201
	14.7	5	3.97	3	FALSE	2520
	10.2	4	2.75	0	FALSE	1577
	11.3	8	3.05	4	FALSE	286
	10.0	3	2.7	2	FALSE	2336
	14.9	4	4.02	3	FALSE	2356
	6.6	5	1.78	3	FALSE	1909

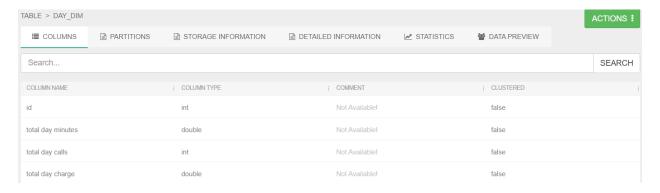




Creating Dimension Tables

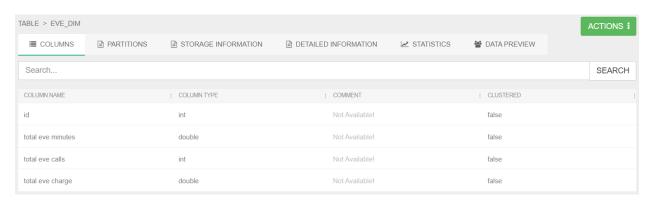
a. Creating Dimension Table day_dim

CREATE TABLE day_dim (
 ID int,
 `Total day minutes` DOUBLE,
 `Total day calls` int,
 `Total day charge` DOUBLE,
 CONSTRAINT day_dim_pk PRIMARY KEY (ID) DISABLE NOVALIDATE
);



b. Creating Dimension Table eve_dim

CREATE TABLE eve_dim (
 ID int,
 `Total eve minutes` DOUBLE,
 `Total eve calls` int,
 `Total eve charge` DOUBLE,
 CONSTRAINT eve_dim_pk PRIMARY KEY (ID) DISABLE NOVALIDATE
);

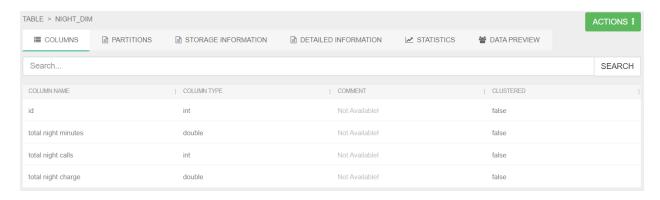






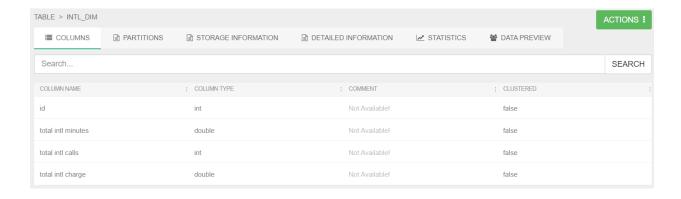
c. Creating Dimension Table night_dim

CREATE TABLE night_dim (
ID int,
`Total night minutes` DOUBLE,
`Total night calls` int,
`Total night charge` DOUBLE,
CONSTRAINT night_dim_pk PRIMARY KEY (ID) DISABLE NOVALIDATE
);



d. Creating Dimension Table intl_dim

CREATE TABLE intl_dim (
 ID int,
 `Total intl minutes` DOUBLE,
 `Total intl calls` int,
 `Total intl charge` DOUBLE,
 CONSTRAINT intl_dim_pk PRIMARY KEY (ID) DISABLE NOVALIDATE
);







a. Adding Data to day_dim

INSERT INTO TABLE day_dim SELECT

ID,

`Total day minutes`,

`Total day calls`,

`Total day charge`

FROM telecom_churn_clean;



b. Adding Data to eve_dim

INSERT INTO TABLE eve_dim SELECT

ID,

`Total eve minutes`,

`Total eve calls`,

`Total eve charge`

FROM telecom_churn_clean;

TABLE > EVE_	DIM							ACTIONS :
I COLUMN	NS PARTITIONS		IATION	□ DETAILED	INFORMATION	STATISTICS	Mata Preview	
EVE_DIM.ID	EVE_DIM.TOTAL EVE MINUTES	EVE_DIM.TOTAL EVE CALLS	EVE_DIM.TO	TAL EVE CHARGE				<u></u>
3147	151.7	79	12.89					
2672	162.5	80	13.81					
228	159.9	84	13.59					
836	58.6	118	4.98					
1495	200.6	134	17.05					
1056	201.4	80	17.12					
1663	181.6	79	15.44					
3201	178.3	117	15.16					
2520	167.6	107	14.25					





c. Adding Data to night_dim

INSERT INTO TABLE night_dim SELECT

ID,

`Total night minutes`,

`Total night calls`,

`Total night charge`

FROM telecom churn clean;



d. Adding Data to intl_dim

INSERT INTO TABLE intl_dim SELECT

ID,

`Total intl minutes`,

`Total intl calls`,

`Total intl charge`

FROM telecom churn clean;

.E > INTL_	DIM						
■ COLUMN	IS PARTITIONS		ATION	DETAILED IN	FORMATION	STATISTICS	Mata Preview
NTL_DIM.ID	INTL_DIM.TOTAL INTL MINUTES	INTL_DIM.TOTAL INTL CALLS	INTL_DIM.T	OTAL INTL CHARGE			
3147	5.3	3	1.43				
2672	14.5	6	3.92				
228	12.2	1	3.29				
336	8.7	3	2.35				
495	12.3	7	3.32				
056	4.1	5	1.11				
663	8.3	6	2.24				
3201	8.1	1	2.19				
520	14.7	5	3.97				
1577	10.2	4	2.75				





4.3 Creating the Data Warehouse

The data warehouse is designed to handle high volumes of data and is optimized for quick and efficient data retrieval and analysis. It is structured in a way that allows Orange Telecom to easily query and analyze customer data to identify patterns, trends, and correlations that can help uncover factors that lead to customer churning.

A materialized view is created by executing a query on one or more tables and storing the query results in a table-like structure. This allows for faster query performance, as the materialized view can be queried directly instead of running the query on the underlying tables every time.

CREATE MATERIALIZED VIEW telecom_churn_mv_day AS

SELECT

fact.State,

fact. Account length,

fact.`Area code`,

fact. International plan,

fact. Voice mail plan,

fact. Number vmail messages,

dim. Total day minutes,

dim. Total day calls,

dim. Total day charge,

fact. Total eve minutes,

fact. Total eve calls,

fact. Total eve charge,

fact. Total night minutes,

fact. Total night calls,

fact. Total night charge,

fact. Total intl minutes,

fact. Total intl calls,

fact. Total intl charge,

fact. Customer service calls,

fact.Churn,





fact.ID

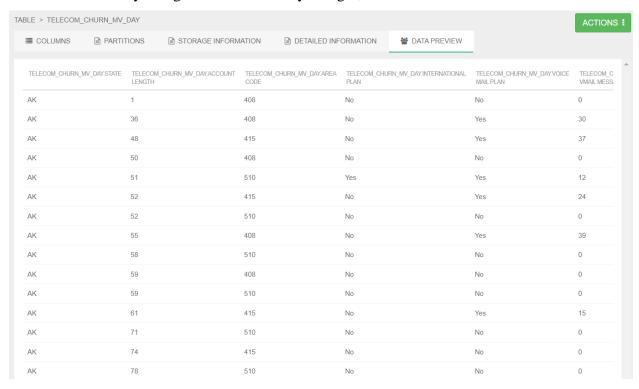
FROM

telecom_churn_fact fact

INNER JOIN day_dim dim ON fact. Total day minutes = dim. Total day minutes

AND fact. Total day calls = dim. Total day calls

AND fact. Total day charge = dim. Total day charge;



CREATE MATERIALIZED VIEW telecom_churn_mv_eve AS

SELECT

fact.State,

fact. Account length,

fact.`Area code`,

fact. International plan,

fact. Voice mail plan,

fact. Number vmail messages,

fact. Total day minutes,

fact. Total day calls,





fact. Total day charge,

dim.`Total eve minutes`,

dim.`Total eve calls`,

dim.`Total eve charge`,

fact. Total night minutes,

fact. Total night calls,

fact. Total night charge,

fact. 'Total intl minutes',

fact. Total intl calls,

fact. Total intl charge,

fact. Customer service calls,

fact.Churn,

fact.ID

FROM

telecom_churn_fact fact

INNER JOIN eve_dim dim ON fact.`Total eve minutes` = dim.`Total eve minutes`

AND fact. Total eve calls = dim. Total eve calls

AND fact. Total eve charge = dim. Total eve charge;

TABLE > TELECOM_CH	URN_MV_EVE					ACTIONS :
■ COLUMNS	PARTITIONS		□ DETAILED INFORMATION	Mata Preview		
Search						SEARCH
COLUMN NAME		: COLUMN TYPE	: COMMENT		: CLUSTERED	
state		string	Not Available!		false	
account length		int	Not Available!		false	
area code		int	Not Available!		false	
international plan		string	Not Available!		false	
voice mail plan		string	Not Available!		false	
number vmail messages		int	Not Available!		false	
total day minutes		double	Not Available!		false	
total day calls		int	Not Available!		false	
total day charge		double	Not Available!		false	
total eve minutes		double	Not Available!		false	
total eve calls		int	Not Available!		false	
total eve charge		double	Not Available!		false	





CREATE MATERIALIZED VIEW telecom_churn_mv_night AS

SELECT

fact.State,

fact. Account length,

fact.`Area code`,

fact. International plan,

fact. Voice mail plan,

fact. Number vmail messages,

fact. Total day minutes,

fact. Total day calls,

fact. Total day charge,

fact. Total eve minutes,

fact. Total eve calls,

fact. Total eve charge,

dim.`Total night minutes`,

dim. Total night calls,

dim.`Total night charge`,

fact. Total intl minutes,

fact. Total intl calls,

fact. Total intl charge,

fact. Customer service calls,

fact.Churn,

fact.ID

FROM

telecom_churn_fact fact

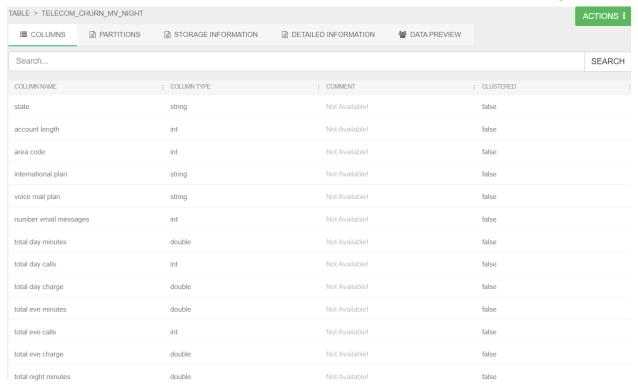
INNER JOIN night_dim dim ON fact. `Total night minutes` = dim. `Total night minutes`

AND fact. Total night calls = dim. Total night calls

AND fact. Total night charge = dim. Total night charge;







CREATE MATERIALIZED VIEW telecom_churn_mv_intl AS

SELECT

fact.State,

fact. Account length,

fact.`Area code`,

fact. International plan,

fact. Voice mail plan,

fact. Number vmail messages,

fact. Total day minutes,

fact. Total day calls,

fact. Total day charge,

fact. Total eve minutes,

fact. Total eve calls,

fact. Total eve charge,

fact. Total night minutes,

fact. Total night calls,





fact. Total night charge,

dim. Total intl minutes,

dim. Total intl calls,

dim.`Total intl charge`,

fact. Customer service calls,

fact.Churn,

fact.ID

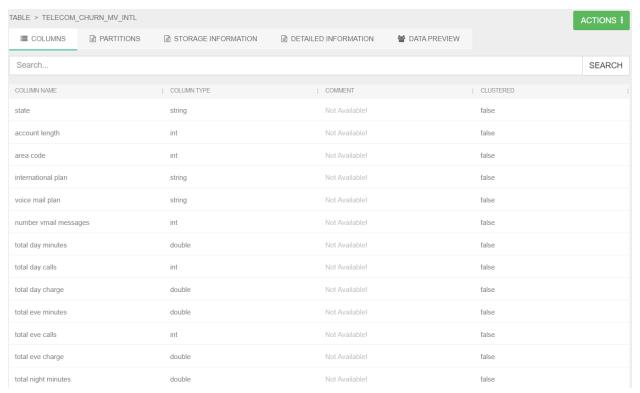
FROM

telecom_churn_fact fact

INNER JOIN intl_dim dim ON fact. `Total intl minutes` = dim. `Total intl minutes`

AND fact. Total intl calls = dim. Total intl calls

AND fact. Total intl charge = dim. Total intl charge;



Summary of Tables:







5. Technical Implementation

The technical implementation involved several tools and technologies. A pre-configured virtual machine (Virtual Box) was used to provide a complete environment for big data processing.

Hadoop, a widely used distributed storage and processing framework, was utilized to store and manage the raw data of the telecom churn dataset. Hive, a data warehouse solution built on top of Hadoop, was used with the Data Analytics Studio (DAS) to store the transformed data in a structured manner for efficient querying and analysis. MS excel and python were used for EDA and data visualizations. Hadoop queries and SQL were used to create the ETL pipeline.





These tools and technologies provided a robust and efficient solution for storing, processing, and analyzing the large and complex dataset, enabling effective churn prediction and customer retention strategies.

6. Discussion and Conclusion

Challenges:

- Hardware requirements It was needed a minimum of 16 GB RAM and sufficient disk space to run Hadoop on the local machine.
- Quality of the dataset Since the dataset contained missing values and duplicates, data needed to be preprocessed.
- Data ingestion and extraction Extracting data from various sources other than downloading a Kaggle dataset was found difficult.

Possible Enhancements:

- Real-time Data Processing: Use web scraping and APIs as data sources and enhance the
 data pipeline to process real-time data, allowing telecom companies to monitor customer
 behavior and patterns in real-time. This can provide timely insights and enable proactive
 actions to prevent churn.
- Workflow Automation (Orchestration): Orchestration allows for the automation of complex data processing workflows, which can involve multiple tasks, tools, and dependencies. It helps streamline and automate repetitive tasks, reducing manual errors and increasing overall efficiency.
- Cloud-based Deployment: Consider deploying the solution on a cloud-based platform such as AWS or Azure to leverage the scalability and flexibility. This can enable faster processing of large volumes of data and provide easier access to data analytics tools and services.
- Automated Data Cleaning and Transformation: Implement automated data cleaning and transformation techniques to improve data quality and consistency. This can include data validation, outlier detection, and data imputation methods to ensure that the data used for analysis is accurate and reliable.