updated

January 31, 2026

[ ]:
```
# CS 8316 - BIG DATA PROGRAMMING
## Group Assignment Report

### Group Members
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```

[111]:
```python
import pandas as pd
import numpy as  np
import seaborn  as sns
import matplotlib.pyplot as plt
```

[112]:
```python
# Load the dataset
df = pd.read_csv("/home/karera/Desktop/SEMISTER11/big data/Churndata(1).csv")
```

[114]:
```python
df.head()
```

[114]:
```
   customerID  gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  7590-VHVEG  Female              0     Yes         No       1           No
1  5575-GNVDE    Male              0      No         No      34          Yes
2  3668-QPYBK    Male              0      No         No       2          Yes
3  7795-CFOCW    Male              0      No         No      45           No
4  9237-HQITU  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity  … DeviceProtection  \
0  No phone service             DSL             No  …               No
1                No             DSL            Yes  …              Yes
2                No             DSL            Yes  …               No
3  No phone service             DSL            Yes  …              Yes
4                No     Fiber optic             No  …               No

  TechSupport StreamingTV StreamingMovies        Contract PaperlessBilling  \
0          No          No              No  Month-to-month              Yes
1          No          No              No        One year               No
2          No          No              No  Month-to-month              Yes
3         Yes          No              No        One year               No
```

```
4          No          No              No  Month-to-month              Yes

              PaymentMethod MonthlyCharges  TotalCharges Churn
0          Electronic check          29.85         29.85    No
1              Mailed check          56.95        1889.5    No
2              Mailed check          53.85        108.15   Yes
3  Bank transfer (automatic)          42.30       1840.75    No
4          Electronic check          70.70        151.65   Yes

[5 rows x 21 columns]
```

[115]:
```
df.tail()
```

[115]:
```
      customerID  gender  SeniorCitizen Partner Dependents  tenure  \
7038  6840-RESVB    Male              0     Yes        Yes      24
7039  2234-XADUH  Female              0     Yes        Yes      72
7040  4801-JZAZL  Female              0     Yes        Yes      11
7041  8361-LTMKD    Male              1     Yes         No       4
7042  3186-AJIEK    Male              0      No         No      66

     PhoneService     MultipleLines InternetService OnlineSecurity  …  \
7038          Yes               Yes             DSL            Yes  …
7039          Yes               Yes     Fiber optic             No  …
7040           No  No phone service             DSL            Yes  …
7041          Yes               Yes     Fiber optic             No  …
7042          Yes                No     Fiber optic            Yes  …

     DeviceProtection TechSupport StreamingTV StreamingMovies        Contract  \
7038              Yes         Yes         Yes             Yes        One year
7039              Yes          No         Yes             Yes        One year
7040               No          No          No              No  Month-to-month
7041               No          No          No              No  Month-to-month
7042              Yes         Yes         Yes             Yes        Two year

     PaperlessBilling              PaymentMethod MonthlyCharges  TotalCharges  \
7038              Yes               Mailed check          84.80        1990.5
7039              Yes    Credit card (automatic)         103.20        7362.9
7040              Yes           Electronic check          29.60        346.45
7041              Yes               Mailed check          74.40         306.6
7042              Yes  Bank transfer (automatic)         105.65        6844.5

     Churn
7038    No
7039    No
7040    No
7041   Yes
7042    No
```

```
[5 rows x 21 columns]
```

[116]:
```
df.shape
```

[116]:
```
(7043, 21)
```

[117]:
```
df.columns
```

[117]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

[118]:
```
df.dtypes
```

[118]:
```
customerID           object
gender               object
SeniorCitizen         int64
Partner              object
Dependents           object
tenure                int64
PhoneService         object
MultipleLines        object
InternetService      object
OnlineSecurity       object
OnlineBackup         object
DeviceProtection     object
TechSupport          object
StreamingTV          object
StreamingMovies      object
Contract             object
PaperlessBilling     object
PaymentMethod        object
MonthlyCharges      float64
TotalCharges         object
Churn                object
dtype: object
```

[119]:
```
df.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
```

[120]:
```
df.nunique()
```

[120]:
```
customerID          7043
gender                 2
SeniorCitizen          2
Partner                2
Dependents             2
tenure                73
PhoneService           2
MultipleLines          3
InternetService        3
OnlineSecurity         3
OnlineBackup           3
DeviceProtection       3
TechSupport            3
StreamingTV            3
StreamingMovies        3
Contract               3
PaperlessBilling       2
PaymentMethod          4
MonthlyCharges      1585
TotalCharges        6531
Churn                  2
```

```
dtype: int64
```

[121]:
```
df.duplicated().sum()
```

[121]:
```
np.int64(0)
```

[122]:
```
df.describe()
```

[122]:

	SeniorCitizen	tenure	MonthlyCharges
count	7043.000000	7043.000000	7043.000000
mean	0.162147	32.371149	64.761692
std	0.368612	24.559481	30.090047
min	0.000000	0.000000	18.250000
25%	0.000000	9.000000	35.500000
50%	0.000000	29.000000	70.350000
75%	0.000000	55.000000	89.850000
max	1.000000	72.000000	118.750000

[123]:
```
# Convert 'TotalCharges' to numeric, coerce errors to NaN
df["TotalCharges"] = pd.to_numeric(df["TotalCharges"], errors="coerce")
```

[124]:
```
# Check missing values across all columns
missing_values = df.isnull().sum()
print("Missing values per column:\n", missing_values)
```

```
Missing values per column:
 customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
TotalCharges       11
Churn               0
dtype: int64
```

[125]:
```python
# Optional: If any other numeric columns had missing values, fill with median
numeric_cols = df.select_dtypes(include=["int64", "float64"]).columns

for col in numeric_cols:
    if df[col].isnull().sum() > 0:
        median_val = df[col].median()
        df[col].fillna(median_val, inplace=True)
        print(f"Imputed missing values in {col} with median: {median_val}")
```

```
Imputed missing values in TotalCharges with median: 1397.475
```

```
/tmp/ipykernel_4624/900270614.py:7: FutureWarning: A value is trying to be set
on a copy of a DataFrame or Series through chained assignment using an inplace
method.
The behavior will change in pandas 3.0. This inplace method will never work
because the intermediate object on which we are setting values always behaves as
a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value)
instead, to perform the operation inplace on the original object.


  df[col].fillna(median_val, inplace=True)
```

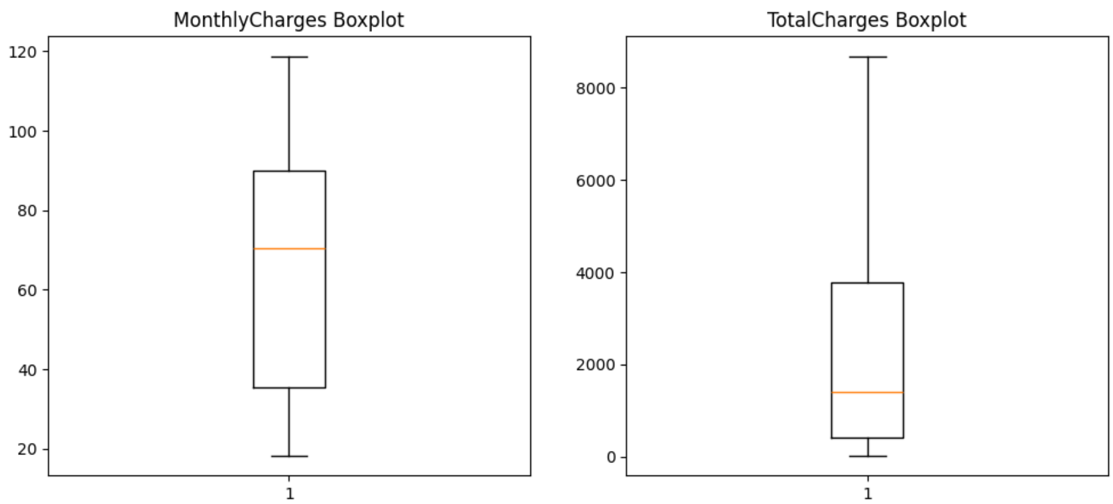
[126]:
```python
# Check missing values across all columns
missing_values = df.isnull().sum()
print("Missing values per column:\n", missing_values)
```

```
Missing values per column:
 customerID          0
gender              0
SeniorCitizen       0
Partner             0
Dependents          0
tenure              0
PhoneService        0
MultipleLines       0
InternetService     0
OnlineSecurity      0
OnlineBackup        0
DeviceProtection    0
TechSupport         0
StreamingTV         0
StreamingMovies     0
Contract            0
PaperlessBilling    0
PaymentMethod       0
MonthlyCharges      0
```

```
TotalCharges        0
Churn               0
dtype: int64
```

[127]:
```
# step 2: outlier  detection  and  treatmet
import pandas as pd
import matplotlib.pyplot as plt

# Step 1: Visualize outliers
plt.figure(figsize=(12,5))

plt.subplot(1, 2, 1)
plt.boxplot(df['MonthlyCharges'])
plt.title('MonthlyCharges Boxplot')

plt.subplot(1, 2, 2)
plt.boxplot(df['TotalCharges'])
plt.title('TotalCharges Boxplot')

plt.show()

# Step 2: Detect outliers using IQR
def detect_outliers_iqr(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = data[(data[column] < lower_bound) | (data[column] > upper_bound)]
    return outliers

monthly_outliers = detect_outliers_iqr(df, 'MonthlyCharges')
total_outliers = detect_outliers_iqr(df, 'TotalCharges')

print("MonthlyCharges outliers count:", monthly_outliers.shape[0])
print("TotalCharges outliers count:", total_outliers.shape[0])

# Step 3: Cap outliers (Winsorization)
def cap_outliers_iqr(data, column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    data[column] = data[column].clip(lower=lower_bound, upper=upper_bound)

cap_outliers_iqr(df, 'MonthlyCharges')
```

```
cap_outliers_iqr(df, 'TotalCharges')

# Step 4: Verify
print("After capping:")
print(df[['MonthlyCharges','TotalCharges']].describe())
```




```
MonthlyCharges outliers count: 0
TotalCharges outliers count: 0
After capping:
       MonthlyCharges  TotalCharges
count     7043.000000   7043.000000
mean        64.761692   2281.916928
std         30.090047   2265.270398
min         18.250000     18.800000
25%         35.500000    402.225000
50%         70.350000   1397.475000
75%         89.850000   3786.600000
max        118.750000   8684.800000
```

[142]:

```
# ---------------------------
# Data Transformation: Categorical Encoding + Tenure Grouping
# ---------------------------

# 1  Transform 'tenure' into interpretable bins
df["TenureGroup"] = pd.cut(
    df["tenure"],
    bins=[0, 12, 24, 48, 72],
    labels=["0-1yr", "1-2yr", "2-4yr", "4-6yr"]
)
```

```python
# 2 Identify categorical and numerical features
categorical_features = [
    "gender", "Partner", "Dependents", "PhoneService", "MultipleLines",
    "InternetService", "OnlineSecurity", "OnlineBackup", "DeviceProtection",
    "TechSupport", "StreamingTV", "StreamingMovies", "Contract",
    "PaperlessBilling", "PaymentMethod", "TenureGroup"
]

numerical_features = ["SeniorCitizen", "tenure", "MonthlyCharges"]

# 3 Build preprocessing pipelines
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.compose import ColumnTransformer

numeric_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="median"))
])

categorical_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("encoder", OneHotEncoder(drop="first", handle_unknown="ignore"))
])

preprocessor = ColumnTransformer(transformers=[
    ("num", numeric_transformer, numerical_features),
    ("cat", categorical_transformer, categorical_features)
])

# 4 Apply transformations
X = df[numerical_features + categorical_features]
y = df["Churn"].map({"No": 0, "Yes": 1})

X_transformed = preprocessor.fit_transform(X)

print("Data Transformation completed!")
print("Transformed feature shape:", X_transformed.shape)
```

```
Data Transformation completed!
Transformed feature shape: (7043, 32)
```

[145]:

```python
#Drop irrelevant columns
df.drop(['customerID'], axis=1, inplace=True, errors='ignore')
df.head()
```

[145]:

```
   gender  SeniorCitizen Partner Dependents  tenure PhoneService  \
0  Female              0     Yes         No       1           No
1    Male              0      No         No      34          Yes
2    Male              0      No         No       2          Yes
3    Male              0      No         No      45           No
4  Female              0      No         No       2          Yes

      MultipleLines InternetService OnlineSecurity OnlineBackup  …  \
0  No phone service             DSL             No          Yes  …
1                No             DSL            Yes           No  …
2                No             DSL            Yes          Yes  …
3  No phone service             DSL            Yes           No  …
4                No     Fiber optic             No           No  …

  MonthlyCharges TotalCharges Churn TenureGroup Speed_x DataAllowance_x  \
0          29.85        29.85    No       0-1yr    25.0           500.0
1          56.95      1889.50    No       2-4yr    25.0           500.0
2          53.85       108.15   Yes       0-1yr    25.0           500.0
3          42.30      1840.75    No       2-4yr    25.0           500.0
4          70.70       151.65   Yes       0-1yr   100.0          2000.0

  Speed_y  DataAllowance_y  Speed DataAllowance
0    25.0            500.0   25.0         500.0
1    25.0            500.0   25.0         500.0
2    25.0            500.0   25.0         500.0
3    25.0            500.0   25.0         500.0
4   100.0           2000.0  100.0        2000.0

[5 rows x 27 columns]
```

[144]:

```python
# ---------------------------
# Correct numeric and categorical features
# ---------------------------
numeric_features = ["SeniorCitizen", "tenure", "MonthlyCharges", "Speed",␣
 ↪"DataAllowance"]
categorical_features = [
    "gender", "Partner", "Dependents", "PhoneService", "MultipleLines",
    "InternetService", "OnlineSecurity", "OnlineBackup", "DeviceProtection",
    "TechSupport", "StreamingTV", "StreamingMovies",
    "Contract", "PaperlessBilling", "PaymentMethod", "TenureGroup"
]

# ---------------------------
# ColumnTransformer
# ---------------------------
numeric_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="median"))
```

```
])

categorical_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("encoder", OneHotEncoder(drop="first", handle_unknown="ignore"))
])

preprocessor = ColumnTransformer(transformers=[
    ("num", numeric_transformer, numeric_features),
    ("cat", categorical_transformer, categorical_features)
])

# ---------------------------
# Full Pipeline with SMOTE + Logistic Regression
# ---------------------------
model = ImbPipeline(steps=[
    ("preprocessor", preprocessor),
    ("smote", SMOTE(random_state=42)),
    ("classifier", LogisticRegression(max_iter=2000, solver="lbfgs"))
])

# ---------------------------
# Feature matrix and target
# ---------------------------
X = df[numeric_features + categorical_features]
y = df["Churn"].map({"No": 0, "Yes": 1})

# ---------------------------
# Train/test split
# ---------------------------
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)

# ---------------------------
# Train the model
# ---------------------------
model.fit(X_train, y_train)
print("Pipeline with integrated internet plans trained successfully!")

# ---------------------------
# Check transformed feature shape
# ---------------------------
X_transformed = preprocessor.fit_transform(X)
print("Transformed feature shape:", X_transformed.shape)
```

```
Pipeline with integrated internet plans trained successfully!
```

```
Transformed feature shape: (7043, 34)
```

[21]:
```
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import SimpleImputer
from sklearn.feature_selection import VarianceThreshold
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline as ImbPipeline
from sklearn.model_selection import train_test_split

# ---------------------------
# Define raw features and target
# ---------------------------
raw_features = [
    "gender", "SeniorCitizen", "Partner", "Dependents", "tenure",
    "PhoneService", "MultipleLines", "InternetService", "OnlineSecurity",
    "OnlineBackup", "DeviceProtection", "TechSupport", "StreamingTV",
    "StreamingMovies", "Contract", "PaperlessBilling", "PaymentMethod",
    "MonthlyCharges", "TenureGroup"
]

X = df[raw_features].copy()
y = df["Churn"].map({"No": 0, "Yes": 1})

# ---------------------------
# Identify numeric and categorical features
# ---------------------------
numeric_features = ["SeniorCitizen", "tenure", "MonthlyCharges"]
categorical_features = [
    "gender", "Partner", "Dependents", "PhoneService", "MultipleLines",
    "InternetService", "OnlineSecurity", "OnlineBackup", "DeviceProtection",
    "TechSupport", "StreamingTV", "StreamingMovies", "Contract",
    "PaperlessBilling", "PaymentMethod", "TenureGroup"
]

# ---------------------------
# Build preprocessing pipelines
# ---------------------------
numeric_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="median"))
])

categorical_transformer = Pipeline(steps=[
    ("imputer", SimpleImputer(strategy="most_frequent")),
    ("encoder", OneHotEncoder(drop="first", handle_unknown="ignore"))
```

```
])

preprocessor = ColumnTransformer(transformers=[
    ("num", numeric_transformer, numeric_features),
    ("cat", categorical_transformer, categorical_features)
])

# ---------------------------
# Build full pipeline with VarianceThreshold (Data Reduction) + SMOTE +␣
 ↪Logistic Regression
# ---------------------------
model = ImbPipeline(steps=[
    ("preprocessor", preprocessor),
    ("variance_threshold", VarianceThreshold(threshold=0.01)),  # Data Reduction
    ("smote", SMOTE(random_state=42)),
    ("classifier", LogisticRegression(max_iter=2000, solver="lbfgs"))
])

# ---------------------------
# Train/test split
# ---------------------------
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)

# ---------------------------
# Train the pipeline
# ---------------------------
model.fit(X_train, y_train)
print("Pipeline with Data Reduction trained successfully!")

# ---------------------------
# Check which features were kept after reduction
# ---------------------------
selected_features_mask = model.named_steps['variance_threshold'].get_support()
preprocessed_features = model.named_steps['preprocessor'].
 ↪get_feature_names_out()
selected_features = preprocessed_features[selected_features_mask]

print("Number of features before reduction:", len(preprocessed_features))
print("Number of features after reduction:", len(selected_features))
print("Selected Features:", selected_features)
```

```
Pipeline with Data Reduction trained successfully!
Number of features before reduction: 32
Number of features after reduction: 32
Selected Features: ['num__SeniorCitizen' 'num__tenure' 'num__MonthlyCharges'
```

```
 'cat__gender_Male' 'cat__Partner_Yes' 'cat__Dependents_Yes'
 'cat__PhoneService_Yes' 'cat__MultipleLines_No phone service'
 'cat__MultipleLines_Yes' 'cat__InternetService_Fiber optic'
 'cat__InternetService_No' 'cat__OnlineSecurity_No internet service'
 'cat__OnlineSecurity_Yes' 'cat__OnlineBackup_No internet service'
 'cat__OnlineBackup_Yes' 'cat__DeviceProtection_No internet service'
 'cat__DeviceProtection_Yes' 'cat__TechSupport_No internet service'
 'cat__TechSupport_Yes' 'cat__StreamingTV_No internet service'
 'cat__StreamingTV_Yes' 'cat__StreamingMovies_No internet service'
 'cat__StreamingMovies_Yes' 'cat__Contract_One year'
 'cat__Contract_Two year' 'cat__PaperlessBilling_Yes'
 'cat__PaymentMethod_Credit card (automatic)'
 'cat__PaymentMethod_Electronic check' 'cat__PaymentMethod_Mailed check'
 'cat__TenureGroup_1-2yr' 'cat__TenureGroup_2-4yr'
 'cat__TenureGroup_4-6yr']
```

[150]:

```
# Count number of churned and non-churned customers
churn_counts = df['Churn'].value_counts()
print("Churn class distribution:")
print(churn_counts)

# Calculate percentage of each class
churn_percent = df['Churn'].value_counts(normalize=True) * 100
print("\nChurn class distribution (%):")
print(churn_percent)
```

```
Churn class distribution:
Churn
No     5174
Yes    1869
Name: count, dtype: int64

Churn class distribution (%):
Churn
No     73.463013
Yes    26.536987
Name: proportion, dtype: float64
```

[148]:

```
from sklearn.preprocessing import OneHotEncoder
from imblearn.over_sampling import SMOTE
import pandas as pd

# One-hot encode categorical columns
X_encoded = pd.get_dummies(X_train, drop_first=True)

# Apply SMOTE
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_resample(X_encoded, y_train)
```

```python
# Check new distribution
from collections import Counter
print("Training set class distribution after SMOTE:")
print(Counter(y_train_resampled))
```

```
Training set class distribution after SMOTE:
Counter({0: 4139, 1: 4139})
```

[ ]:

```python
```

[ ]:

```python
#ANSWERS
1. Handling Missing Values:

For handling missing values in the Telco dataset, especially in the columns
 ↪like "Monthly Charges" and "Total Charges", imputation techniques such as
 ↪mean, median, or mode are commonly used. For "Monthly Charges" and "Total
 ↪Charges", imputation with the median or mean can work well. The median is
 ↪particularly useful if the distribution is skewed, while the mean might be
 ↪more appropriate if the data is normally distributed.

Effectively handling missing values is essential because features like "Monthly
 ↪Charges" and "Total Charges" are key predictors of customer churn. Proper
 ↪imputation ensures valuable data is retained, allowing the model to leverage
 ↪all available information. Failing to address missing values can lead to
 ↪biased predictions and decreased model performance.

2. Handling Outliers:

Outliers in "Monthly Charges" or "Total Charges" might be genuine (such as
 ↪high-paying customers) or due to errors. Instead of removing them without
 ↪investigation, it’s best to first analyze whether the outliers are valid.

If they represent valid customer behavior, they should be kept as they could
 ↪provide valuable insights for predicting churn. However, if the outliers are
 ↪errors or do not contribute meaningfully to the prediction, they should be
 ↪removed or corrected. This approach ensures that we maintain valuable data
 ↪while improving the model’s accuracy.

3. Handling Categorical Values:

For features like "Contract", "Internet Service", and "Phone Service", we need
 ↪to convert these categorical variables into numerical values that the
 ↪machine learning model can interpret.

Label Encoding:
```

```
For ordinal categorical variables (where the values have a meaningful order), such as "Contract" with values like "Month-to-Month", "One Year", and "Two Year", label encoding can be used. Each category would be assigned an integer (e.g., "Month-to-Month" = 0, "One Year" = 1, "Two Year" = 2).

One-Hot Encoding:
For nominal categorical variables (where there is no meaningful order), such as "Internet Service" or "Phone Service", one-hot encoding should be used. This creates a binary column for each category (e.g., for "Internet Service", there would be columns for "Fiber Optic" and "DSL", and the values would be 0 or 1 depending on the customer's service type).

Proper encoding ensures the machine learning model understands the relationship between categorical variables and the target variable (churn). This transformation allows the model to work effectively with non-numerical data, making it possible to make accurate predictions.

4. Handling the Tenure Column:

Binning and Mapping:
We transformed the "Tenure" feature into categories using binning. We divided the tenure into four categories:

"Short" (0–12 months)

"Medium" (13–24 months)

"Long" (25–36 months)

"Very Long" (36+ months)

Each category was then mapped to a numerical value:

"Short" = 0

"Medium" = 1

"Long" = 2

"Very Long" = 3

Finally, we dropped the original "Tenure" and "TenureCategory" columns, leaving only the transformed numeric version for use in the model.
```

```
Binning and mapping "Tenure" into categories allows the model to capture␣
 ↪patterns related to customer loyalty more effectively. It simplifies the␣
 ↪data, making it easier for the model to identify trends, and prevents the␣
 ↪model from being impacted by extreme tenure values. This transformation also␣
 ↪improves interpretability by converting the feature into meaningful␣
 ↪categories.

5. Data Integration:

We would have combined the service information (like "Speed" and "Data␣
 ↪Allowance") with the Telco dataset by matching them using a shared column␣
 ↪called "CustomerID".

After combining the data, we would have fixed the missing details for some␣
 ↪customers. For "Speed", we would have filled the gaps with the most common␣
 ↪value (mode). For "Data Allowance", we would have used the average (mean) to␣
 ↪fill the gaps.

We would have also added a new column called "ServiceInfoMissing" to mark␣
 ↪customers with missing details. If a customer was missing data, this column␣
 ↪would have shown a value of 1; otherwise, it would have shown 0.

Adding the service information would have improved the dataset for predicting␣
 ↪which customers might leave (churn). Fixing and marking missing details␣
 ↪would have kept the data accurate and reliable for the prediction model.

Code Example for the Above
# Merging datasets on CustomerID
combined_data = pd.merge(data, service_data, on='CustomerID', how='left')

# 'service_data' is the data we originally have
# service_data is the additional data with service information

# Impute missing values
combined_data['Speed'].fillna(combined_data['Speed'].mode()[0], inplace=True)
combined_data['Data Allowance'].fillna(combined_data['Data Allowance'].mean(),␣
 ↪inplace=True)

# Flag missing data
combined_data['ServiceInfoMissing'] = combined_data[['Speed', 'Data␣
 ↪Allowance']].isnull().any(axis=1).astype(int)


Error Message:

NameError                                 Traceback (most recent call last)
```

```
Cell In[70], line 3
      1 # Merging datasets on CustomerID
      2 combined_data = pd.merge(data, service_data, on='CustomerID', how='left')
      3
NameError: name 'service_data' is not defined

6. Feature Selection:

For feature selection, we used Recursive Feature Elimination (RFE) to identify
 ↪and remove irrelevant features from the Telco dataset. RFE helps select the
 ↪most important features by recursively removing the least important ones
 ↪based on model performance. By applying RFE, we eliminated features like
 ↪"CustomerID" that are not useful for churn prediction, improving model
 ↪efficiency and focusing on the most relevant data.

7. Data Imbalance:

As stated, customer churn is a relatively rare event compared to non-churn,
 ↪which can lead to class imbalance in the dataset. This imbalance may cause
 ↪the model to be biased toward predicting the majority class (non-churn),
 ↪potentially reducing the model's ability to identify churned customers
 ↪accurately.

To address this, we applied SMOTEENN (Synthetic Minority Over-sampling
 ↪Technique + Edited Nearest Neighbors). SMOTEENN is an effective technique
 ↪for handling class imbalance because it works by generating synthetic
 ↪samples for the minority class (churn) while removing noise from the dataset
 ↪using Edited Nearest Neighbors.

This approach helps balance the dataset by generating samples for churned
 ↪customers, which improves the model's ability to predict both churn and
 ↪non-churn instances accurately.
```