AI IN BUSINESS

Presented by:
Dr. Mahua Nandy Pal
Assistant Professor (CSE)
MCKV Institute of Engineering
Howrah-711204

OBJECTIVES

Concepts in Business

AI Insights

Case Studies

Churn Prediction System

Recommender System

CONCEPTS IN BUSINESS

Sales Forecasting:

ML models can predict **future sales** by analyzing historical sales data, market conditions, and external factors.

Customer Support Automation:

ML-powered chatbots and virtual assistants can handle routine customer inquiries, providing **instant support** and freeing up human agents for more complex issues.

Human Resources and Recruitment

AI **streamlines recruitment** by screening resumes, scheduling interviews, and assessing candidate suitability.

CONCEPTS IN BUSINESS

Supply Chain Optimization:

ML can **forecast demand,** optimize inventory levels, and enhance logistics planning by analyzing historical data and market trends.

Predictive Maintenance:

In industries like manufacturing, ML models can predict **equipment failures** before they occur by analyzing data from sensors and maintenance logs

Customer Segmentation and Personalization:

ML can analyze customer data to identify distinct segments based on behavior, preferences, and demographics.

AI INSIGHTS

By incorporating machine learning into these business concepts, companies can gain deeper insights, automate complex processes, and make data-driven decisions to enhance their overall performance and competitiveness.

Customer segmentation and personalization from the perspective of AI in business

challenges like customer retention

AI team

developed strategies

matching interests and offered discounts

easy reordering options

E-Commerce Platform

Customer Analytics

AI model

Smooth and Enjoyable Experience

Business Success

technology can provide the needed help

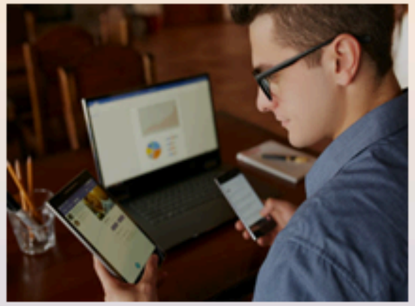
browsing history, purchase patterns, and user feedback

customer segments

simplified interface

personalized recommendations

AI-Driven Customer Segmentation and Personalization



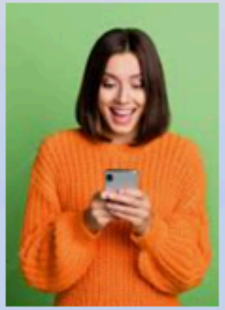
A young person browsing gadgets on a sleek device

Young Tech Enthusiasts

Elderly Customers

Simplified interface and personalized health product recommendations.

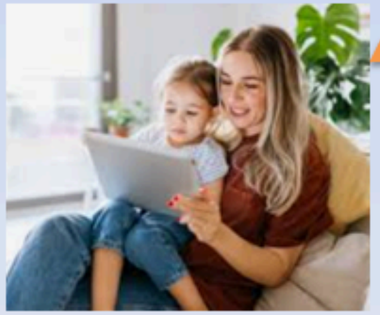
An AI Brain, symbolizing the central AI system



Tech Enthusiast receiving a discount notification

Mother getting notification for reordering diapers.

Busy Parents



A parent with kids, using a tablet to reorder essentials.

May

Chatbot for elder care

AI-Powered Success: Increased engagement, retention, and sales.

Predictive Maintenance in Industries

challenges like customer retention

AI team

Machines equipped with sensors

More predictable and manageable

Alert from the Predictive Maintenance System

Large Manufacturing Plant

Machines work around the clock

AI-Powered System

Proactive approach

Business Success

technology can provide the needed help

Monitoring Parameters - temperature, vibration, noise, and pressure

Sensor Collected Data

Preventing unexpected breakdown

Predictive Maintenance in Action
Preventing Equipment Failures with AI and Machine Learning

Timely alert

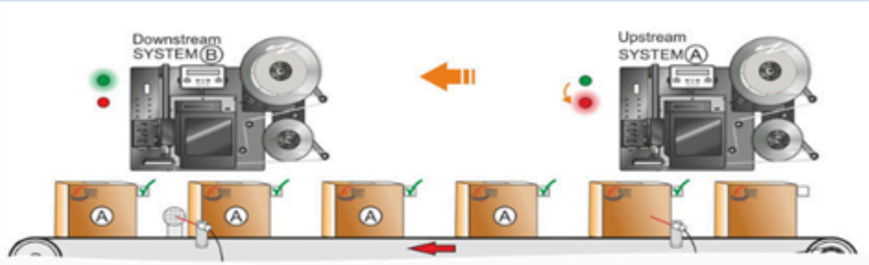
Graphs and charts depicting vibration and temperature spikes

Maintenance Required: Anomaly Detected in Hydraulic Press.

Production Manager Looking at the Alert on a Tablet

Noise, and Pressure Sensor

Vibration And Temperature Sensor



Production Line with Zero Downtime

Financial Savings from Preventing a Breakdown.

An Implementation :

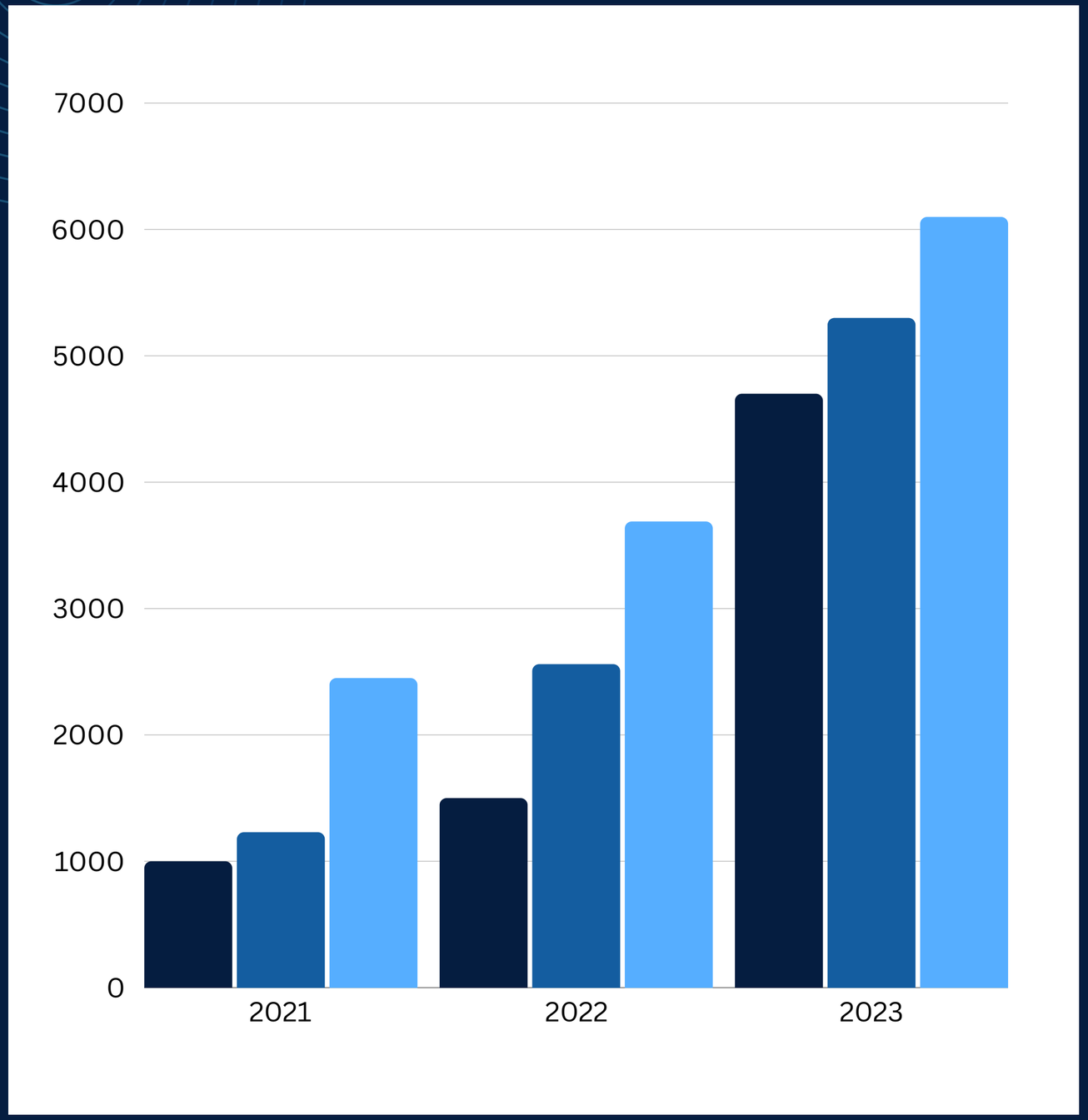
CHURN PREDICTION

Using Machine Learning Models

CHURN

Churn is the measure of how many customers stop using a product.

Often evaluated for a specific period of time, there can be a monthly, quarterly, or annual churn rate.



A Churn Prediction Journey: Jio & BSNL

Jio: Cutting Edge Technology and Aggressive Pricing

BSNL: Legacy Provider with Extensive Rural Coverage.

Challenge: Customer Retention

Realizing the threat, both companies turned to the power of artificial intelligence and machine learning to tackle their churn issues

Solution: BSNL hired data scientists to build a robust churn prediction model

Jio already has their own data collection and analytics wing.

BSNL
Connecting India

Jio DIGITAL LIFE

Call records, Customer Service, Billing etc.

AI model highlights key churn indicators:

1. Customers experiencing frequent dropped calls.
2. High data usage customers with complaints about slow speeds.
3. Customers nearing the end of their contract period.

AI model highlights key churn indicators:

1. Users who downgraded their plans.
2. Customers with a sudden decrease in data usage.
3. High-value customers who had not recharged in a while.

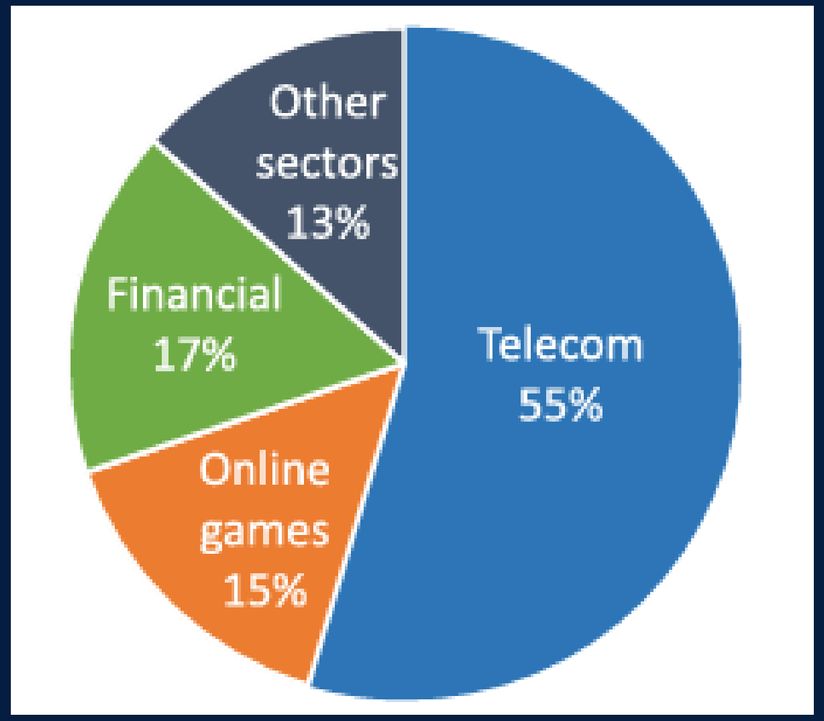
RESULTS:

BSNL's Transformation:

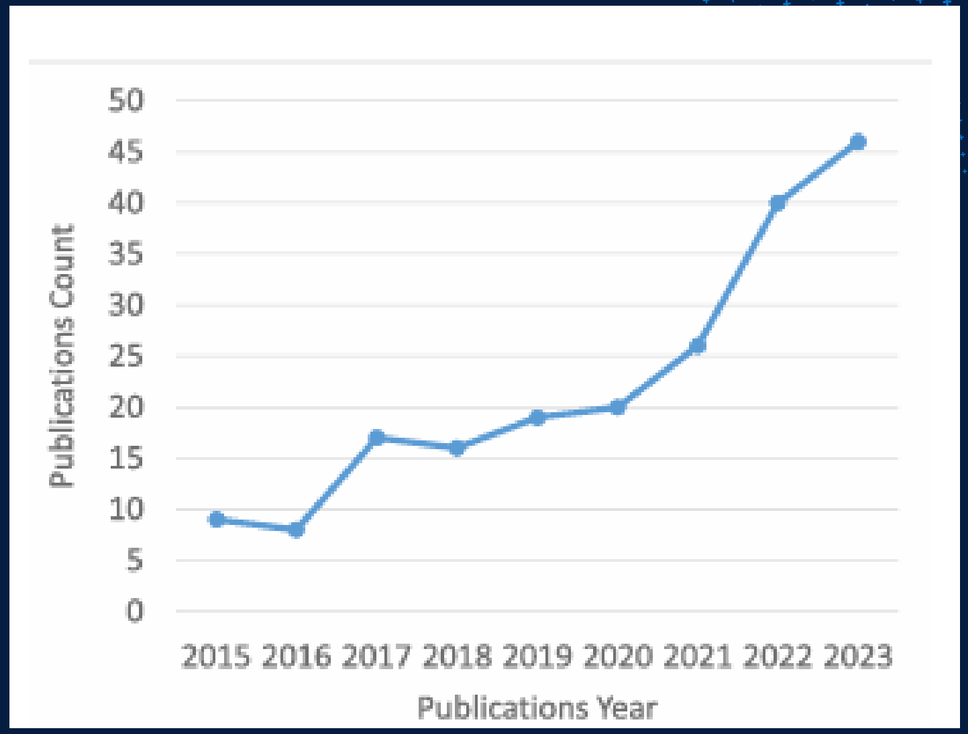
BSNL saw a **gradual decline** in their churn rates. The proactive measures and improved customer service paid off. Customers appreciated the **personalized attention and better service quality**. **Rural customers**, who were once leaving, began to stay, appreciating the enhancements in service and the sense of being valued.

Jio's Success:

Jio's efforts led to an impressive retention rate. The personalized offers and loyalty programs were a hit among users. The company also noticed that their **high-value customers** were now more engaged, thanks to the **exclusive content and benefits.** Jio's **churn rate dropped** significantly, setting a new benchmark in the industry.

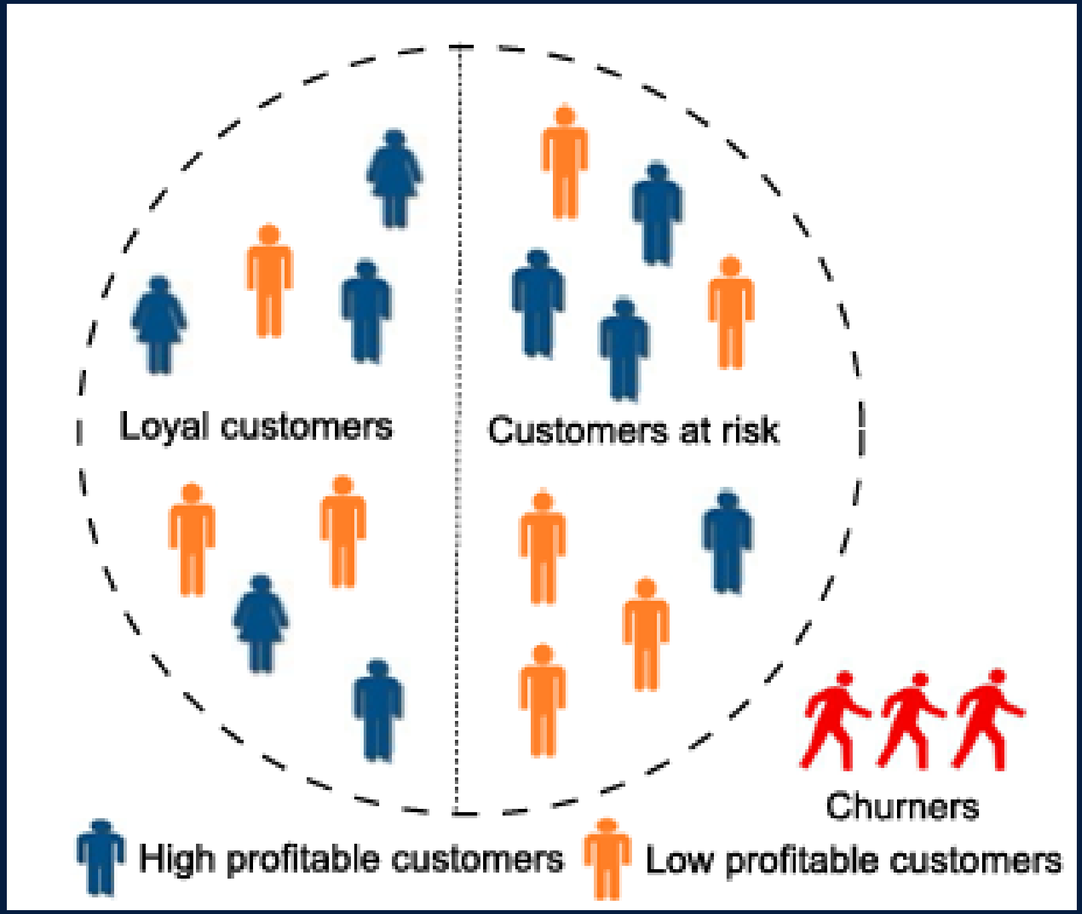


Sector wise Distribution of Articles



Year wise Publication

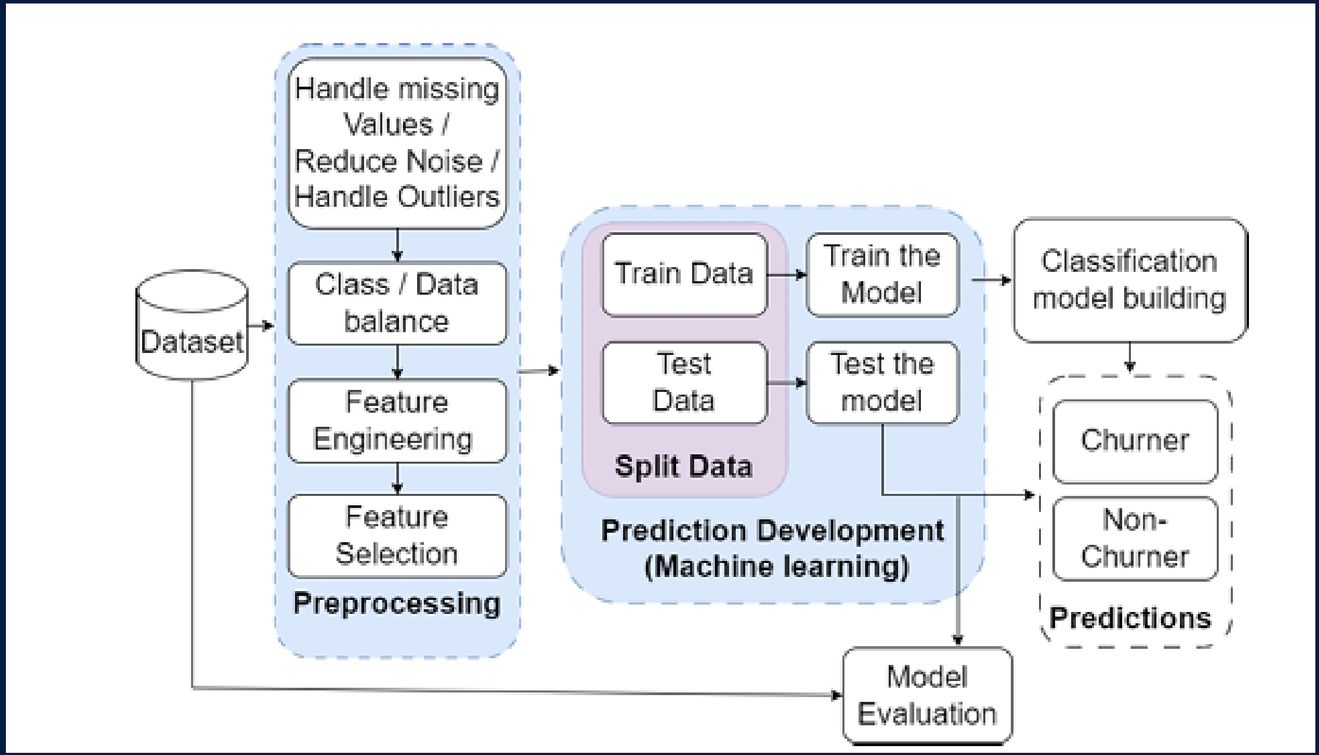
AN ILLUSTRATION OF LOYAL CUSTOMERS AND CHURNERS.



THE NAMES AND TYPES OF DIFFERENT VARIABLES IN THE CHURN DATASET.

Variable Name	Type
state, (the US state of customers)	*string*
account_length (number of active months)	*numerical*
area_code, (area code of customers)	*string*
international_plan, (whether customers have international plans)	*yes/no*
voice_mail_plan, (whether customers have voice mail plans)	*yes/no*
number_vmail_messages, (number of voice-mail messages)	*numerical*
total_day_minutes, (total minutes of day calls)	*numerical*
total_day_calls, (total number of day calls)	*numerical*
total_day_charge, (total charge of day calls)	*numerical*
total_eve_minutes, (total minutes of evening calls)	*numerical*
total_eve_calls, (total number of evening calls)	*numerical*
total_eve_charge, (total charge of evening calls)	*numerical*
total_night_minutes, (total minutes of night calls)	*numerical*
total_night_calls, (total number of night calls)	*numerical*
total_night_charge, (total charge of night calls)	*numerical*
total_intl_minutes, (total minutes of international calls)	*numerical*
total_intl_calls, (total number of international calls)	*numerical*
total_intl_charge, (total charge of international calls)	*numerical*
number_customer_service_calls, (number of calls to customer service)	*numerical*
churn, (customer churn—the target variable)	*yes/no*

https://www.kaggle.com/code/rinichristy/%20customer-churn-prediction-2020



End-to-end churn prediction model architecture

Implementation of Customer Churn Prediction:

The percentage of customers who stopped purchasing your business's products or services during a certain period of time

[15]:
```python
# prompt: mount drive and read_csv "Telco-Customer-Churn.csv" in the MLMarch folder
import numpy as np
import pandas as pd
#from google.colab import drive
#drive.mount('/content/drive')

data = pd.read_csv('./Telco-Customer-Churn.csv')
data.head()
```

[15]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupport	St
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service	DSL	No	...	No	No	
1	5575-GNVDE	Male	0	No	No	34	Yes	No	DSL	Yes	...	Yes	No	
2	3668-QPYBK	Male	0	No	No	2	Yes	No	DSL	Yes	...	No	No	
3	7795-CFOCW	Male	0	No	No	45	No	No phone service	DSL	Yes	...	Yes	Yes	
4	9237-HQITU	Female	0	No	No	2	Yes	No	Fiber optic	No	...	No	No	

5 rows × 21 columns

```
[18]: np.unique(data['Churn'], return_counts = True)
```

```
[18]: (array(['No', 'Yes'], dtype=object), array([5163, 1869]))
```

```
[19]: np.int64(72)
```

```
[20]: def convert(x):
    if x<=12:
        return 0
    elif x <= 24:
        return 1
    elif x<=36:
        return 2
    elif x<=48:
        return 3
    elif x<=60:
        return 4
    elif x<=72:
        return 5
    else:
        return 6
data['tenure'] = data['tenure'].apply(convert) # Or apply StandardScaler.
data.tail()
```

[20]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	...	DeviceProtection	TechSupport
7027	6840-RESVB	Male	0	Yes	Yes	1	Yes	Yes	DSL	Yes	...	Yes	Yes
7028	2234-XADUH	Female	0	Yes	Yes	5	Yes	Yes	Fiber optic	No	...	Yes	No
7029	4801-JZAZL	Female	0	Yes	Yes	0	No	No phone service	DSL	Yes	...	No	No
7030	8361-LTMKD	Male	1	Yes	No	0	Yes	Yes	Fiber optic	No	...	No	No
7031	3186-AJIEK	Male	0	No	No	5	Yes	No	Fiber optic	Yes	...	Yes	Yes

[21]:
```
data['PaymentMethod'].unique()
```

[21]:
```
array(['Electronic check', 'Mailed check', 'Bank transfer (automatic)',
       'Credit card (automatic)'], dtype=object)
```

[22]:
```
X = data.drop(['customerID', 'Churn'], axis=1)
y = data['Churn']
X.head()
```

[22]:

	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines	InternetService	OnlineSecurity	OnlineBackup	DeviceProtection	TechSupport	Stre
0	Female	0	Yes	No	0	No	No phone service	DSL	No	Yes	No	No	
1	Male	0	No	No	2	Yes	No	DSL	Yes	No	Yes	No	
2	Male	0	No	No	0	Yes	No	DSL	Yes	Yes	No	No	
3	Male	0	No	No	3	No	No phone service	DSL	Yes	No	Yes	Yes	
4	Female	0	No	No	0	Yes	No	Fiber optic	No	No	No	No	

```python
from sklearn.decomposition import PCA

pca = PCA(n_components = 15)
```

```python
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, random_state = 42)
```

```python
from sklearn.linear_model import LogisticRegression
```

```python
from sklearn.svm import SVC
```

Logistic Regression

[51]:
```
lr_model = LogisticRegression()
lr_model.fit(X_train,y_train)
accuracy_lr = lr_model.score(X_test,y_test)
print("Logistic Regression accuracy is :",accuracy_lr)
```

```
Logistic Regression accuracy is : 0.7938388625592417
```

[52]:
```
lr_pred= lr_model.predict(X_test)
report = classification_report(y_test,lr_pred)
print(report)
```

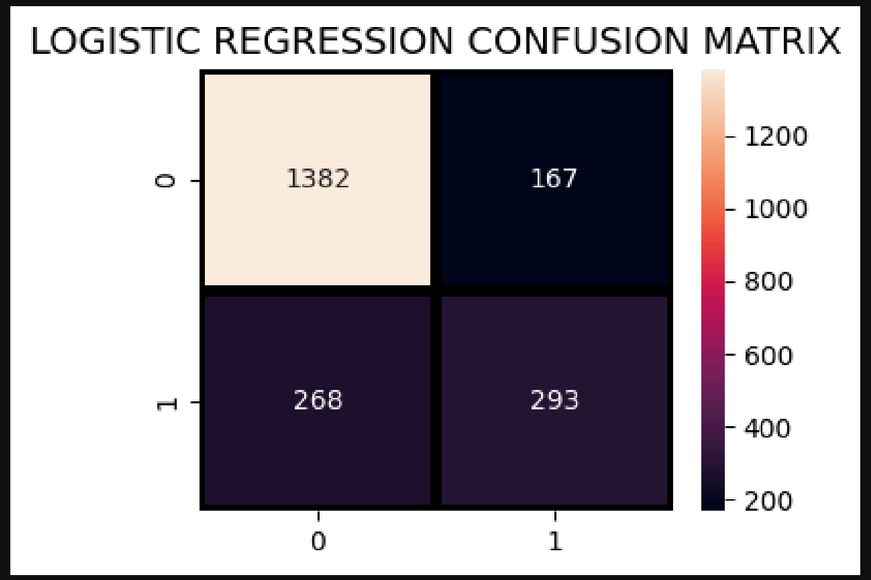
```
              precision    recall  f1-score   support

           0       0.84      0.89      0.86      1549
           1       0.64      0.52      0.57       561

    accuracy                           0.79      2110
   macro avg       0.74      0.71      0.72      2110
weighted avg       0.78      0.79      0.79      2110
```

[53]:
```
plt.figure(figsize=(4,3))
sns.heatmap(confusion_matrix(y_test, lr_pred),
                annot=True,fmt = "d",linecolor="k",linewidths=3)

plt.title("LOGISTIC REGRESSION CONFUSION MATRIX",fontsize=14)
plt.show()
```



[63]:
```
svc_model = SVC(random_state = 1)
svc_model.fit(X_train,y_train)
svc_preds = svc_model.predict(X_test)
accuracy_svc = svc_model.score(X_test,y_test)
print("SVM accuracy is :",accuracy_svc)
```

```
SVM accuracy is : 0.7981042654028436
```

[64]:
```
print(classification_report(y_test, svc_preds))
```

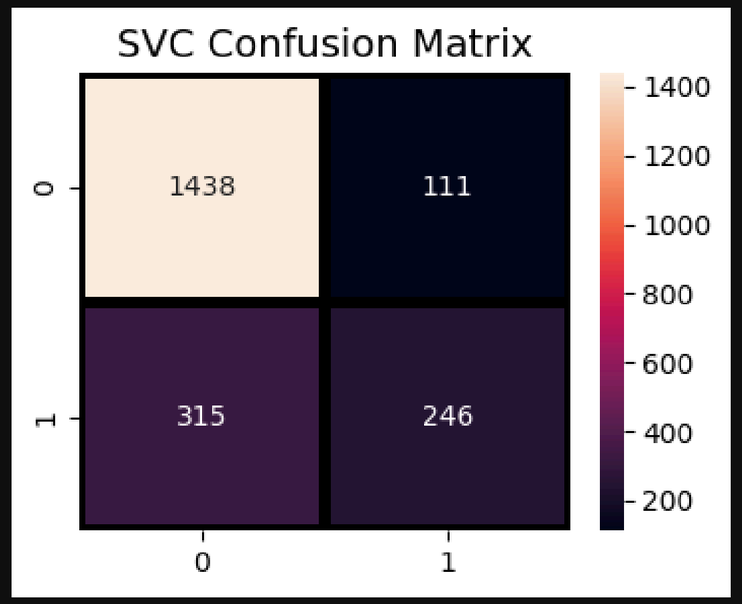
```
              precision    recall  f1-score   support

           0       0.82      0.93      0.87      1549
           1       0.69      0.44      0.54       561

    accuracy                           0.80      2110
   macro avg       0.75      0.68      0.70      2110
weighted avg       0.79      0.80      0.78      2110
```

[65]:
```
plt.figure(figsize=(4,3))
sns.heatmap(confusion_matrix(y_test, svc_preds),
                annot=True,fmt = "d",linecolor="k",linewidths=3)

plt.title("SVC Confusion Matrix",fontsize=14)
plt.show()
```



RECOMMENDER SYSTEM

A recommender system is a type of software tool and algorithmic approach used to provide personalized suggestions to users based on their preferences, behaviors, and past interactions.

Netflix: Recommends movies and TV shows based on our viewing history and ratings.

Amazon: Suggests products you might like based on your previous purchases and browsing history.

Spotify: Curates personalized playlists and song recommendations according to our listening habits.

YouTube: Provides video suggestions tailored to your watch history and user interactions.
Amazon: Recommends books you might like based on your previous purchases and browsing behavior.

Implementation of a Book Recommeder System

THANK YOU

mahua.nandypal@mckvie.edu.in