MACHINE LEARNING MODEL DEPLOYMENT

WITH IBM CLOUD WATSON STUDIO

PHASE 5

FINAL PROJECT SUBMISSION

TEAM MEMBERS:

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Problem Statement:

Become a wizard of predictive with IBM Cloud Watson Studio. Train machine learning models to predict outcomes in real-time. Deploye the models asweb services and integrate them into your applications. Unlock the magic of data-driven insights and make informed decisions like never before.

Abstract:

Explore the power of machine learning with IBM Cloud Watson Studio. This project delves into the end-to-end process of model development, from data preparation to deployment, showcasing the efficiency and collaborative features ofIBM Cloud Watson Studio. Discover how to harness the platform's tools and capabilities to create, train, evaluate, and deploy machine learning models, enabling data-driven decision-making for organizations of all sizes.

Introduction:

In the era of data-driven decision-making, the integration of machine learningmodels has become a crucial asset for organizations seeking to derive valuable insights and make informed business decisions. IBM Cloud Watson Studio, a comprehensive and powerful platform, facilitates the development and deploymentof sophisticated machine learning models. With its robust suite of tools and services, Watson Studio offers a seamless and collaborative environment for data scientists, developers, and domain experts to build, train, and deploy machine learning models at scale. Leveraging Watson Studio's intuitive interface and advanced features, businesses can harness the potential of their data to drive innovation, enhance customer experiences, and achieve significant operational efficiencies. This introduction serves as a gateway to exploring the rich capabilitiesof IBM Cloud Watson Studio, unlocking a world of possibilities in the realm of machine learning model development and deployment.

In the rapidly evolving landscape of artificial intelligence and data analytics, IBM Cloud Watson Studio stands as a cutting-edge platform for developing and deploying robust machine learning models. Offering an array of integrated tools and services, Watson Studio facilitates end-to-end model development, from data exploration and preprocessing to model training and deployment. Its collaborativeand scalable environment empowers data professionals to expedite the development process and derive valuable insights from complex datasets. With a focus on simplifying complex tasks, Watson Studio is a game-changer for organizations seeking to leverage the power of machine learning to drive innovation and achieve tangible business results.

Project Objective:

The objective of this project is to deploy a machine learning model that predicts customer churn in a subscription-based service. Through the analysis of historical customer data, the aim is to identify patterns and factors that contributeto customer churn, enabling the business to take proactive measures for customerretention. The primary objective is to successfully deploy a trained machine learning model on the IBM Cloud platform, making it accessible through APIs orweb services. This ensures that the model can be used for making predictions on new data.

Documentation

Outline the project's objective, design thinking process, and developmentphases.

Describe the predictive use case, dataset selection, model training, deployment process, and integration steps.

Explain how the deployed model can be accessed and utilized for real- time predictions.

Submission

Share the GitHub repository link containing the project's code and files

Provide instructions on how to deploy and use the machine learning model as a web service.

Include example API requests for making prediction.

INNOVATION AND DESIGN THINKING

INTRODUCTON:
The focus of this project is on a comprehensive investigation into the development and deployment of machine learning models in IBM Watson Studio In order to take our design to innovate for the problem. This involves describing the full process of how you are planning to transform your idea on a design, which was developed during the initial stage.
Hereafter shall be explained furthermore.

1. Data Gathering and Preprocessing:
- Harnessing a wide range of data about customer behaviour and their past and present interactions is a must.
- Missing Data, Handling Outliers, Quality.
- Explore, discover, pattern and relationship through a dataset.

2. Model Selection:
- Select a specific Predictive Use-Case of Machine Learning.
- Try out several different algorithms such as Random Forest, Logistic Regression, and Gradient Boosting to assess which will perform the best with your data model.

3. Model Training:
- Train/validation data set.
- Use the training data to train the chosen machine learning model.
- Use metrics like accuracy, precision, recall, and F1-score to evaluate the model’s performance

C: > Users > Acer > p2.py

```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier

X_train, X_valid, y_train, y_valid = train_test_split(X, y, test_size=0.2, random_state=42)

model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)


y_pred = model.predict(X_valid)
```

4. Model Validation and Hyperparameter Tuning:

- Optimize the Performance of Your Model; Adjust Hyper parameters
- Prevent over fitting and encourage generalization with cross validation

C: > Users > Acer > p2.py > ...

```python

from sklearn.model_selection import GridSearchCV

param_grid = {
    'n_estimators': [100, 200, 300],
    'max_depth': [None, 10, 20],
}

grid_search = GridSearchCV(model, param_grid, cv=5)
grid_search.fit(X_train, y_train)

best_model = grid_search.best_estimator_

```

5. Model Deployment:

- As you indicated in your prior response, deploy the trained model as a web service using IBM Watson Studio.

6. Integration with Applications:

As previously stated this necessitates the deployment of the chosen model into your application and systems for making real-time predictions.

7. Monitoring and Maintanence:

- Continually monitor the performance of the deployed model.
- Alert on changes of data pattern and model degradation
- Keep refreshing your data and retraining the model

8. Scaling and Feedback Loop:

- Incase of success you may expand the sysematic solution in order to work on other predominant use cases involving large number of uses
- Refining the model and functionality of the application depends on continuous gathering of feedback from stakeholders and end-users

DEVELOPMENT PART-1

Introduction:

IBM Watson Studio is an integrated development environment (IDE) designed to streamline the process of building, training, and deploying AI models and applications. It is part of IBM's suite of AI tools and services and is aimed at enabling data scientists, developers, and domain experts to collaborate effectively and efficiently in creating and deploying machine learning and deep learning models.

Machine learning model deployment is a critical phase in the machine learning lifecycle, involving the integrationof trained models into real-world applications for making predictions or decisions based on new data. IBM CloudWatson Studio provides a powerful and user-friendly platform for deploying machine learning models effectivelyand efficiently. Leveraging the comprehensive capabilities of IBM Cloud Watson Studio for model deployment enables organizations to scale AI applications and deliver actionable insights.

1. Define the Predictive Use Case:

In this initial stage, you should have a clear understanding of the problem you aim to solve. For instance, if your use case is customer churn prediction, you need to specify what "churn" means in your context and the business implications.

2. Select a Relevant Dataset:

Carefully choose a dataset that aligns with your predictive use case. For customer churn prediction, your dataset might include information on customers, their interactions, demographics, purchase history, and whetherthey churned or not.

3. Access IBM Cloud Watson Studio:

Log in to your IBM Cloud account and access Watson Studio. This is your hub for all your machine learning activities.

4. Import the Dataset:

Use Watson Studio's data management tools to import your dataset. You can upload data files in various formats or connect to external data sources if your data is not already in Watson Studio.

R.N	Cus.Id	Surname	C.Score	Geograph	Gender	Age	Tenure	Balance	N.pro	Hashcrd	A.Mem	Estimated	Exited
1	15634602	Hargrave	619	France	Female	42	2	0	1	1	1	101348.9	1
2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.6	0
3	15619304	Onio	502	France	Female	42	8	159660.8	3	1	0	113931.6	1
4	15701354	Boni	699	France	Female	39	1	0	2	0	0	93826.63	0
5	15737888	Mitchell	850	Spain	Female	43	2	125510.8	1	1	1	79084.1	0
6	15574012	Chu	645	Spain	Male	44	8	113755.8	2	1	0	149756.7	1
7	15592531	Bartlett	822	France	Male	50	7	0	2	1	1	10062.8	0
8	15656148	Obinna	376	Germany	Female	29	4	115046.7	4	1	0	119346.9	1
9	15792365	He	501	France	Male	44	4	142051.1	2	0	1	74940.5	0
10	15592389	H?	684	France	Male	27	2	134603.9	1	1	1	71725.73	0
11	15767821	Bearce	528	France	Male	31	6	102016.7	2	0	0	80181.12	0
12	15737173	Andrews	497	Spain	Male	24	3	0	2	1	0	76390.01	0
13	15632264	Kay	476	France	Female	34	10	0	2	1	0	26260.98	0
14	15691483	Chin	549	France	Female	25	5	0	2	0	0	190857.8	0
15	15600882	Scott	635	Spain	Female	35	7	0	2	1	1	65951.65	0
16	15643966	Goforth	616	Germany	Male	45	3	143129.4	2	0	1	64327.26	0
17	15737452	Romeo	653	Germany	Male	58	1	132602.9	1	1	0	5097.67	1
18	15788218	Henderso	549	Spain	Female	24	9	0	2	1	1	14406.41	0
19	15661507	Muldrow	587	Spain	Male	45	6	0	1	0	0	158684.8	0
20	15568982	Hao	726	France	Female	24	6	0	2	1	1	54724.03	0
21	15577657	McDonald	732	France	Male	41	8	0	2	1	1	170886.2	0
22	15597945	Dellucci	636	Spain	Female	32	8	0	2	1	0	138555.5	0
23	15699309	Gerasimo	510	Spain	Female	38	4	0	1	1	0	118913.5	1
24	15725737	Mosman	669	France	Male	46	3	0	2	0	1	8487.75	0
25	15625047	Yen	846	France	Female	38	5	0	1	1	1	187616.2	0
26	15738191	Maclean	577	France	Male	25	3	0	2	0	1	124508.3	0
27	15736816	Young	756	Germany	Male	36	2	136815.6	1	1	1	170042	0
28	15700772	Nebechi	571	France	Male	44	9	0	2	0	0	38433.35	0
29	15728693	McWillian	574	Germany	Female	43	3	141349.4	1	1	1	100187.4	0
30	15656300	Lucciano	411	France	Male	29	0	59697.17	2	1	1	53483.21	0
31	15589475	Azikiwe	591	Spain	Female	39	3	0	3	1	0	140469.4	1
32	15706552	Odinakacl	533	France	Male	36	7	85311.7	1	0	1	156731.9	0
33	15750181	Sandersor	553	Germany	Male	41	9	110112.5	2	0	0	81898.81	0
34	15659428	Maggard	520	Spain	Female	42	6	0	2	1	1	34410.55	0
35	15732963	Clements	722	Spain	Female	29	9	0	2	1	1	142033.1	0

5. Data Preprocessing:

- This is the data cleaning and preparation phase:
- Handle missing data: Decide how to impute or remove missing values.
- Detect and deal with outliers: Outliers can adversely affect your model's performance.
- Encode categorical variables: Convert non-numeric data into numerical form, commonly through one-hotencoding.
- Scale or normalize numerical features: Ensure numerical attributes are on the same scale.

SOURCE CODE:

```
import pandas as pd
import matplotlib.pyplot as
pltimport seaborn as sns
import numpy as np
sns.set_theme(color_codes=True
)
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score,
classification_report, f1_score

dataset = pd.read_csv('/kaggle/input/churn-modelling/Churn_Modelling.csv')
dataset.head()
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1

Data Processing 1:

Dataset.columns

Out[4]:

```
Index(['RowNumber', 'CustomerId', 'Surname', 'CreditScore', 'Geography',
       'Gender', 'Age', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
       'IsActiveMember', 'EstimatedSalary', 'Exited'],
      dtype='object')
```

```
dataset.select_dtypes(include="object").nunique()
```

```
Out[5]:
    Surname      2932
    Geography       3
    Gender          2
    dtype: int64
```

```
dataset.head()
```

Out[6]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1

```
dataset.drop(columns = 'RowNumber',inplace =
True)dataset.drop(columns = 'CustomerId',inplace =
True)dataset.drop(columns = 'Surname',inplace =
True) dataset.head()
```

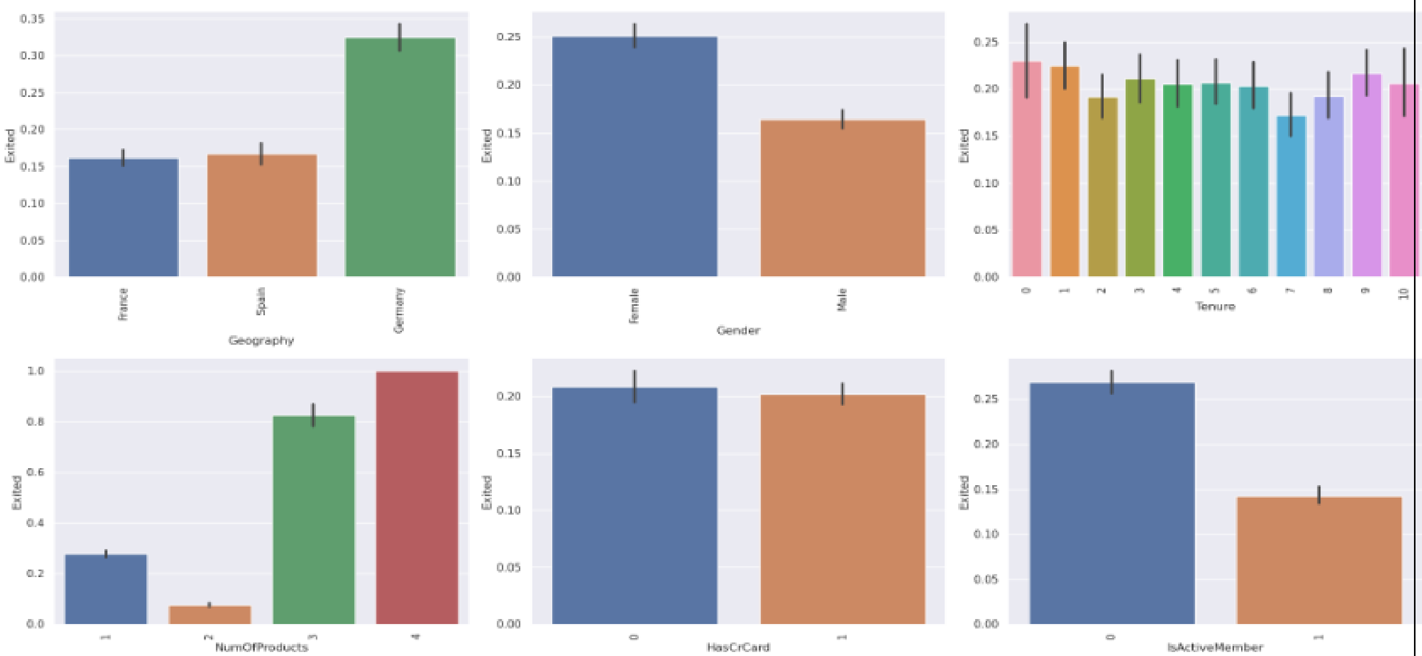
Out[7]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	Female	42	2	0.00	1	1	1	101348.88
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	699	France	Female	39	1	0.00	2	0	0	93826.63
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

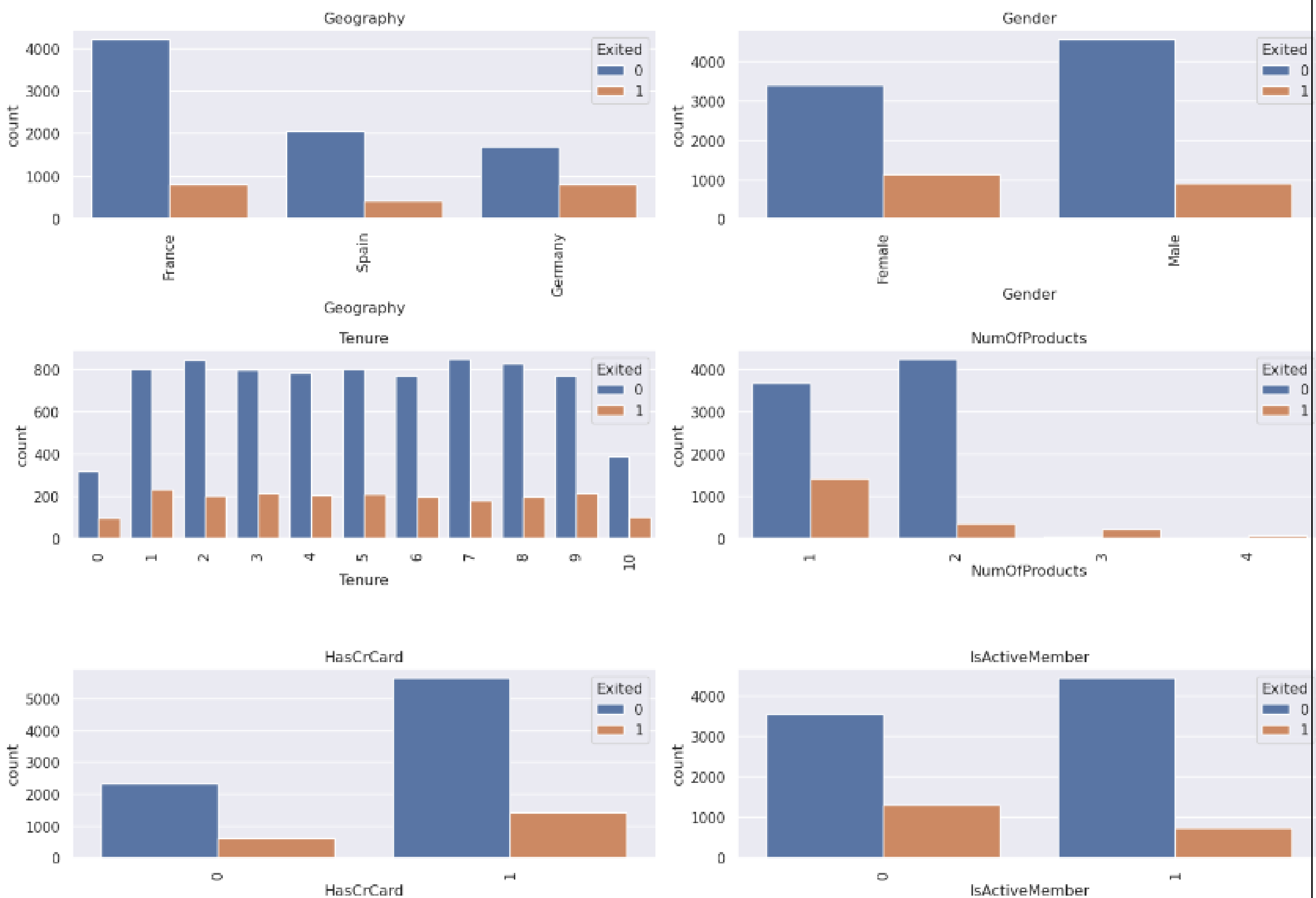
Exploratory Data Analysis:

```
Cat_var = ['Geography','Gender','Tenure','NumOfProducts', 'HasCrCard','IsActiveMember']
fig, axs = plt.subplots(nrows= 2, ncols= 3,figsize= (20,10))
axs= axs.flatten()

for i,var in enumerate(Cat_var):
   sns.barplot(x=var,y='Exited',data=dataset ,ax=axs[i])
   axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation = 90)
```

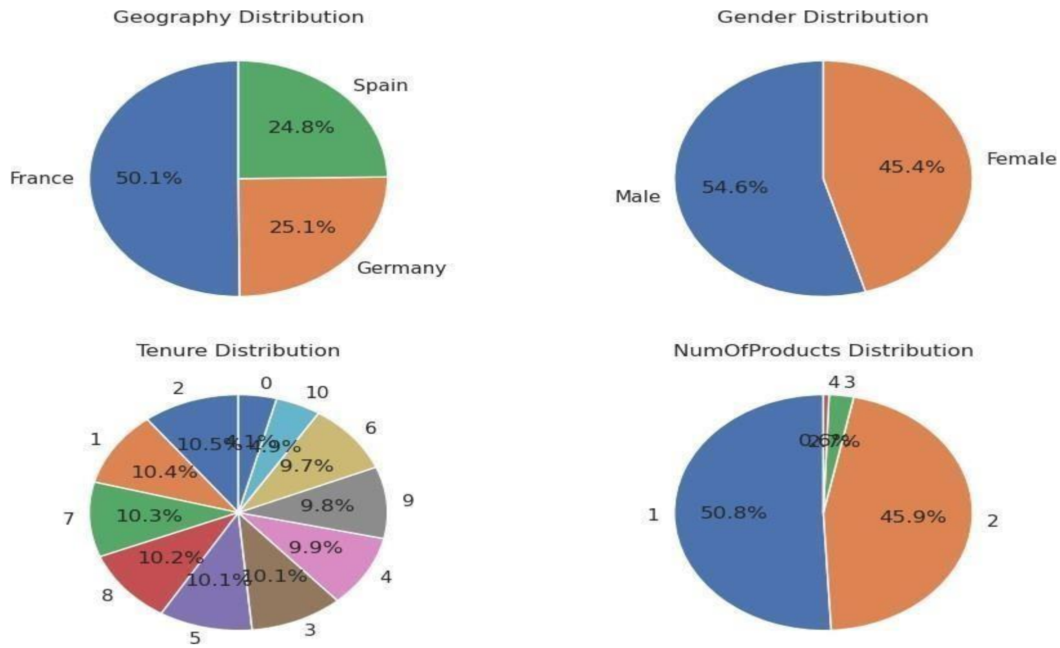
```
fig.tight_layout()
plt.show()
```




```
# Create a grid of subplots based on the number of categorical
variablesnum_cat_vars = len(Cat_var)
num_cols = 2  # You can adjust the number of columns as
needednum_rows = (num_cat_vars + num_cols - 1) // num_cols
fig, axs = plt.subplots(num_rows, num_cols, figsize=(15, 10))
axs = axs.flatten() # Flatten the 2D array of axes for easier indexing
for i, var in enumerate(Cat_var):
    row    =    i    //
    num_cols col  =  i %
    num_cols    ax    =
    axs[i]

    sns.countplot(data=dataset, x=var, hue='Exited',
    ax=ax)ax.set_xticklabels(ax.get_xticklabels(),
    rotation=90) ax.set_title(var)
fig.tight_layout()
plt.show()
```




```
num_cat_vars = len(Cat_var)
num_cols = 2  # You can adjust the number of columns as
needednum_rows = (num_cat_vars + num_cols - 1) // num_cols
fig, axs = plt.subplots(num_rows, num_cols, figsize=(10, 10))
axs = axs.flatten()  # Flatten the 2D array of axes for easier indexing
for i, var in enumerate(Cat_var):
    if i < len(axs):
        ax = axs[i]
        cat_counts = dataset[var].value_counts()
        ax.pie(cat_counts, labels=cat_counts.index, autopct='%1.1f%%', startangle=90)
        ax.set_title(f'{var} Distribution')
fig.tight_layout()
if len(axs) > num_cat_vars:
    fig.delaxes(axs[-1])
plt.show()
```

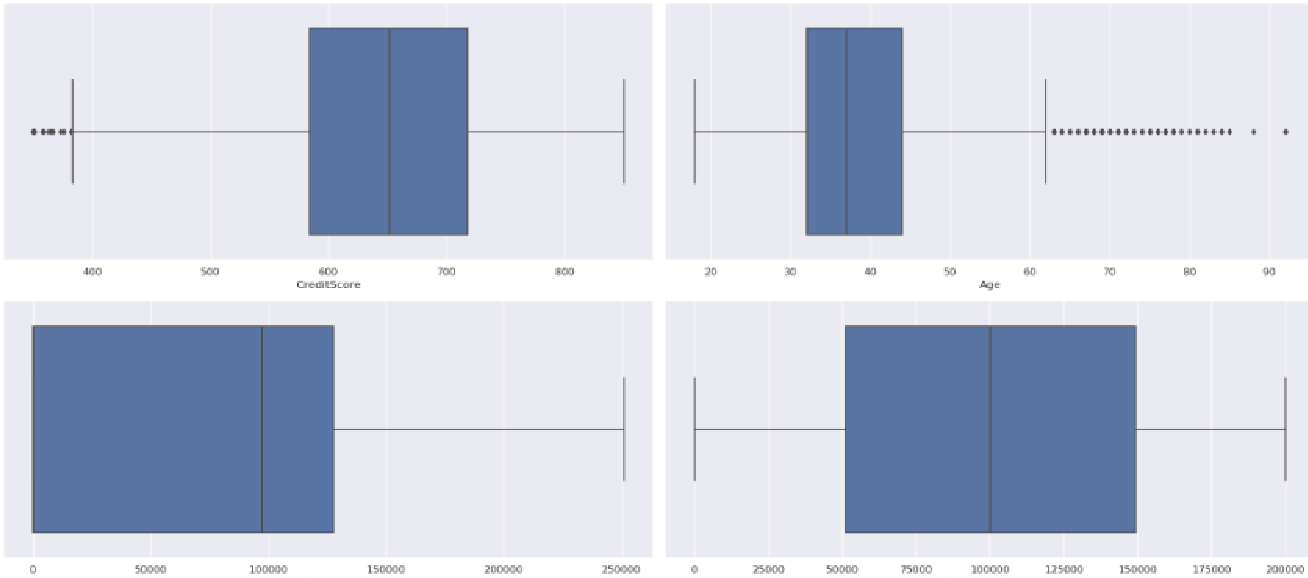


Dataset.heat()

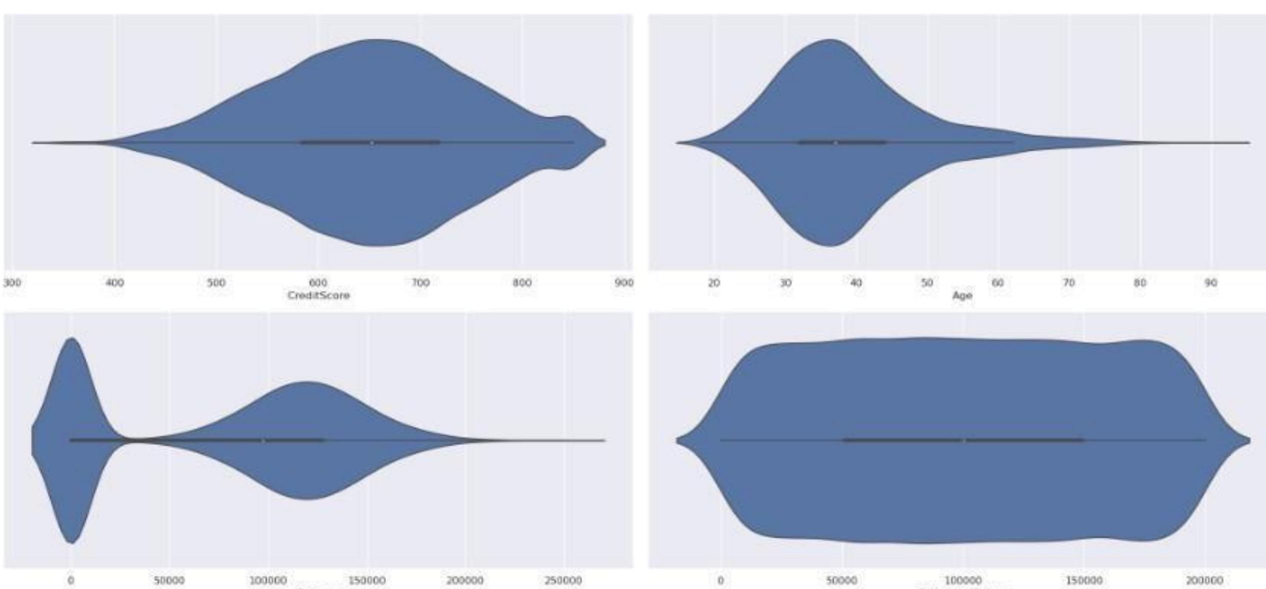
Out[12]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	Female	42	2	0.00	1	1	1	101348.88
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	699	France	Female	39	1	0.00	2	0	0	93826.63
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

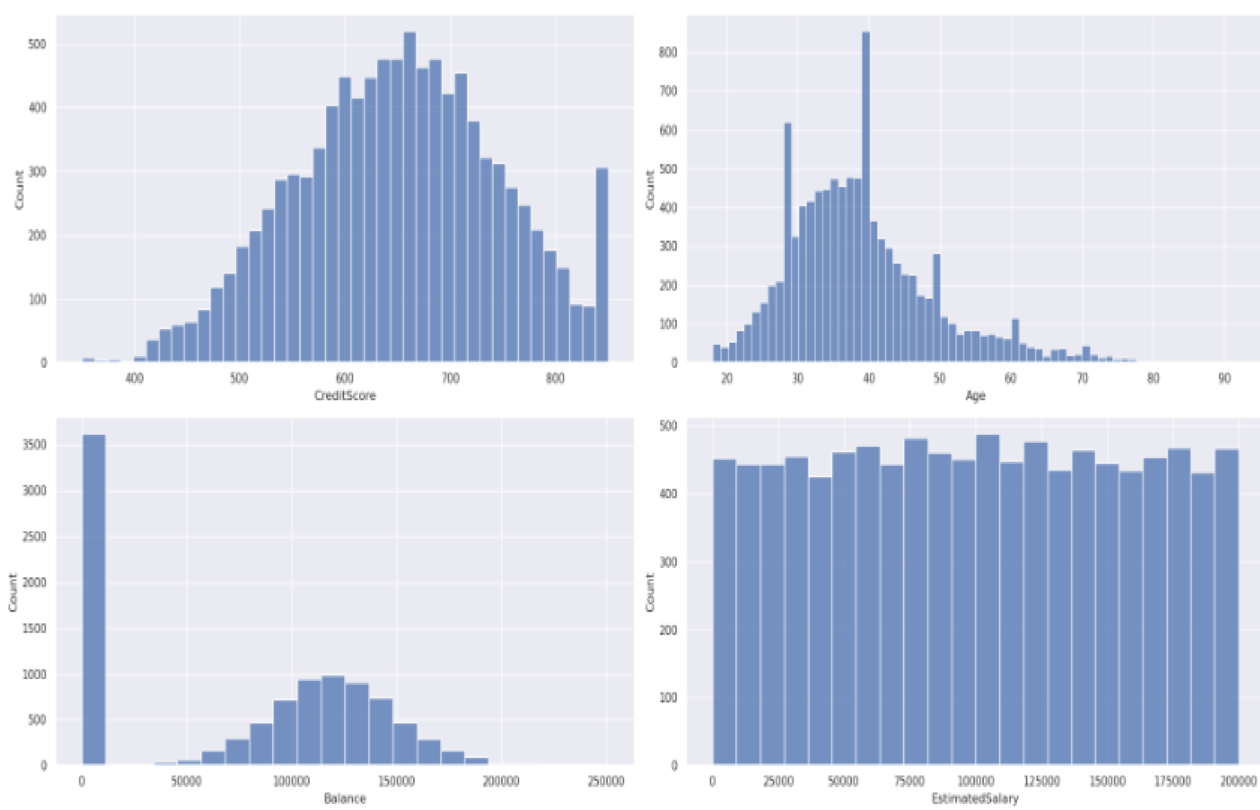
```
num_vars = ['CreditScore','Age','Balance','EstimatedSalary']
# Create a grid of subplots based on the number of categorical
variablesnum_cat_vars = len(num_vars)
num_cols = 2  # You can adjust the number of columns as
needednum_rows = (num_cat_vars + num_cols - 1) // num_cols
fig, axs = plt.subplots(num_rows, num_cols, figsize=(20, 10))
axs = axs.flatten()
for i, var in enumerate(num_vars):
    sns.boxplot(x=var,data=dataset, ax=axs[i])
# Adjust spacing between subplots
fig.tight_layout()
plt.show()
```




```
num_cat_vars = len(num_vars)
num_cols = 2  # You can adjust the number of columns as
needednum_rows = (num_cat_vars + num_cols - 1) // num_cols

fig, axs = plt.subplots(num_rows, num_cols, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.violinplot(x=var,data=dataset, ax=axs[i])
fig.tight_layout()


plt.show()
```



```
# Create a grid of subplots based on the number of categorical variables
num_cat_vars = len(num_vars)
num_cols = 2  # You can adjust the number of columns as needed

num_rows = (num_cat_vars + num_cols - 1) // num_cols
fig, axs = plt.subplots(num_rows, num_cols, figsize=(20, 10))
axs = axs.flatten()

for i, var in enumerate(num_vars):
    sns.histplot(x=var,data=dataset, ax=axs[i])
fig.tight_layout()
plt.show()
```



SUBMISSION DOCUMENT

DEVELOPMENT PART-2

Introduction:

This document serves as a comprehensive submission for our project in IBM Watson Studio. In this submission, we will present the results of our data analysis, machine learning models, and other relevant findings.Our goal is to showcase the insights and solutions we have developed using IBM Watson Studio's powerful toolsand capabilities. Please review this document to gain a clear understanding of our project's objectives, methodology, and outcomes.

IBM Watson Studio is an integrated development environment (IDE) designed to streamline the process of building, training, and deploying AI models and applications. It is part of IBM's suite of AI tools and services and isaimed at enabling data scientists, developers, and domain experts to collaborate effectively and efficiently in creating and deploying machine learning and deep learning models.

Machine learning model deployment is a critical phase in the machine learning lifecycle, involving the integration of trained models into real-world applications for making predictions or decisions based on new data. IBM Cloud Watson Studio provides a powerful and user-friendly platform for deploying machine learning modelseffectively and efficiently. Leveraging the comprehensive capabilities of IBM Cloud Watson Studio for model deployment enables organizations to scale AI applications and deliver actionable insights.

1. Prepare the Model:

Make sure your trained model is in a deployable format. It might be a Python script, a pre-trained machine learning model, or another suitable format.

2. Select a Relevant Dataset:

Carefully choose a dataset that aligns with your predictive use case. For customer churn prediction, your dataset might include information on customers, their interactions, demographics, purchase history, and whether they churned or not.

3. Set up Watson Studio:

Log in to your IBM Cloud account and access Watson Studio. This is your hub for all your machine learning activities.

4. Import the Dataset:

Use Watson Studio's data management tools to import your dataset. You can upload data files in various formats or connect to external data sources if your data is not already in Watson Studio.

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3	15619304	Onio	502	France	Female	42	8	159660.8	3	1	0	113931.6	1
4	15701354	Boni	699	France	Female	39	1	0	2	0	0	93826.63	0
5	15737888	Mitchell	850	Spain	Female	43	2	125510.8	1	1	1	79084.1	0
6	15574012	Chu	645	Spain	Male	44	8	113755.8	2	1	0	149756.7	1
7	15592531	Bartlett	822	France	Male	50	7	0	2	1	1	10062.8	0
8	15656148	Obinna	376	Germany	Female	29	4	115046.7	4	1	0	119346.9	1
9	15792365	He	501	France	Male	44	4	142051.1	2	0	1	74940.5	0
10	15592389	H?	684	France	Male	27	2	134603.9	1	1	1	71725.73	0
11	15767821	Bearce	528	France	Male	31	6	102016.7	2	0	0	80181.12	0
12	15737173	Andrews	497	Spain	Male	24	3	0	2	1	0	76390.01	0
13	15632264	Kay	476	France	Female	34	10	0	2	1	0	26260.98	0
14	15691483	Chin	549	France	Female	25	5	0	2	0	0	190857.8	0
15	15600882	Scott	635	Spain	Female	35	7	0	2	1	1	65951.65	0
16	15643966	Goforth	616	Germany	Male	45	3	143129.4	2	0	1	64327.26	0
17	15737452	Romeo	653	Germany	Male	58	1	132602.9	1	1	0	5097.67	1
18	15788218	Henderso	549	Spain	Female	24	9	0	2	1	1	14406.41	0
19	15661507	Muldrow	587	Spain	Male	45	6	0	1	0	0	158684.8	0
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21	15577657	McDonald	732	France	Male	41	8	0	2	1	1	170886.2	0
22	15597945	Dellucci	636	Spain	Female	32	8	0	2	1	0	138555.5	0
23	15699309	Gerasimo	510	Spain	Female	38	4	0	1	1	0	118913.5	1
24	15725737	Mosman	669	France	Male	46	3	0	2	0	1	8487.75	0
25	15625047	Yen	846	France	Female	38	5	0	1	1	1	187616.2	0
26	15738191	Maclean	577	France	Male	25	3	0	2	0	1	124508.3	0
27	15736816	Young	756	Germany	Male	36	2	136815.6	1	1	1	170042	0
28	15700772	Nebechi	571	France	Male	44	9	0	2	0	0	38433.35	0
29	15728693	McWillian	574	Germany	Female	43	3	141349.4	1	1	1	100187.4	0
30	15656300	Lucciano	411	France	Male	29	0	59697.17	2	1	1	53483.21	0
31	15589475	Azikiwe	591	Spain	Female	39	3	0	3	1	0	140469.4	1
32	15706552	Odinakach	533	France	Male	36	7	85311.7	1	0	1	156731.9	0
33	15750181	Sanderson	553	Germany	Male	41	9	110112.5	2	0	0	81898.81	0
34	15659428	Maggard	520	Spain	Female	42	6	0	2	1	1	34410.55	0
35	15732963	Clements	722	Spain	Female	29	9	0	2	1	1	142033.1	0

5. Data Preprocessing:

- This is the data cleaning and preparation phase:
- Handle missing data: Decide how to impute or remove missing values.
- Detect and deal with outliers: Outliers can adversely affect your model's performance.
- Encode categorical variables: Convert non-numeric data into numerical form, commonly through one-hot encoding.
- Scale or normalize numerical features: Ensure numerical attributes are on the same scale.

6. Feature Selection:

- Identify which features (attributes) are most relevant to your predictive model. Use Watson Studio's tools for feature selection or explore feature importance metrics.

7. Model Training:

- Select an appropriate machine learning algorithm for your use case:
- Logistic Regression, Decision Trees, Random Forests, Support Vector Machines, Neural Networks, etc.
- Split your dataset into training and testing sets to assess your model's performance.

8. Model Evaluation:

- Assess how well your model performs using appropriate metrics: - Accuracy, Precision, Recall, F1-score, ROC-AUC, etc.
- Watson Studio provides tools to help you with model evaluation.

9. Fine-Tuning:

- If your model's performance is unsatisfactory, you can:
- Adjust hyperparameters: Tweak the settings of your algorithm.
- Try different algorithms: Experiment with different machine learning techniques.
- Iterate on the training process to improve results.

10. Deployment:

- Once you're content with your model's performance, you can deploy it using Watson Studio.
- Deployed models can be used for making predictions, integrated into applications, and accessed through APIs for real-time use.

SOURCE CODE:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
sns.set_theme(color_codes=True)
    from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score,
    classification_report, f1_score
    dataset = pd.read_csv('/kaggle/input/churn-modelling/Churn_Modelling.csv')
    dataset.head()
```

Out[3]:

	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1

Data Processing 1:

```
Dataset.columns
```

```
Out[4]:
Out[5]:                                'CustomerId', 'Surname', 'CreditScore', 'Geography',
         Surname        2932           e', 'Tenure', 'Balance', 'NumOfProducts', 'HasCrCard',
         Geography         3           er', 'EstimatedSalary', 'Exited'],
         Gender            2           )
         dtype: int64
```

```
dataset.select_dtypes(include="object").nunique()
```

```
Out[5]:
         Surname        2932
         Geography         3
         Gender            2
         dtype: int64
```

dataset.head()

Out[6]:

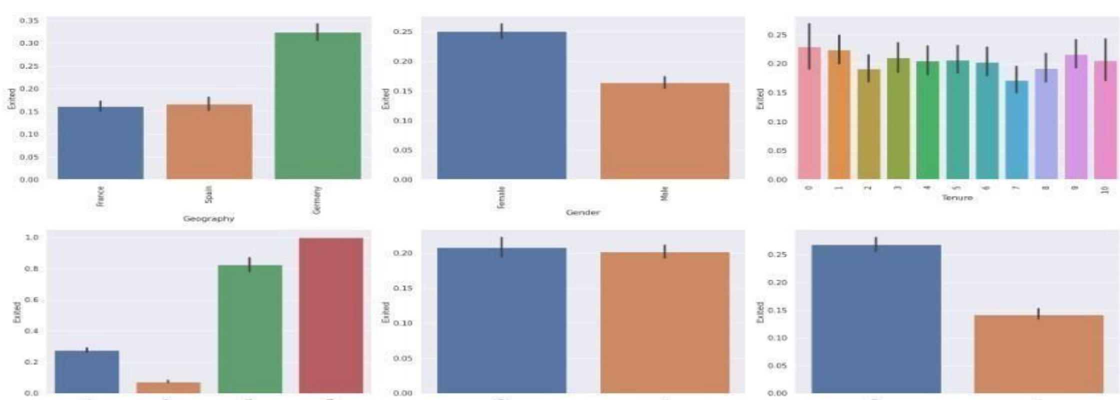
	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard
0	1	15634602	Hargrave	619	France	Female	42	2	0.00	1	1
1	2	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0
2	3	15619304	Onio	502	France	Female	42	8	159660.80	3	1
3	4	15701354	Boni	699	France	Female	39	1	0.00	2	0
4	5	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1

```
dataset.drop(columns = 'RowNumber',inplace = True) dataset.drop(columns = 'CustomerId',inplace = True)
dataset.drop(columns = 'Surname',inplace = True)
dataset.head()
```

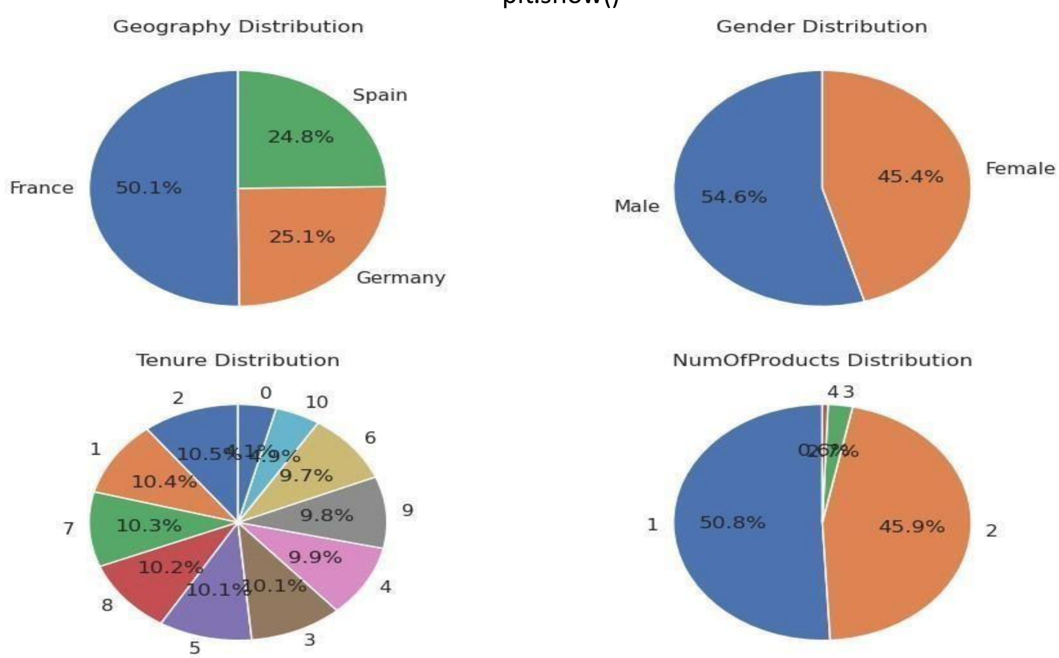
Out[7]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	Female	42	2	0.00	1	1	1	101348.88
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	699	France	Female	39	1	0.00	2	0	0	93826.63
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

```
Cat_var = ['Geography','Gender','Tenure','NumOfProducts', 'HasCrCard','IsActiveMember'] fig, axs = plt.subplots(nrows= 2,
ncols= 3,figsize= (20,10))
axs= axs.flatten()
for i,var in enumerate(Cat_var):
                    sns.barplot(x=var,y='Exited',data=dataset ,ax=axs[i])
                    axs[i].set_xticklabels(axs[i].get_xticklabels(), rotation = 90)
                    fig.tight_layout()
                    plt.show()
```



```
num_cat_vars = len(Cat_var)
num_cols = 2 # You can adjust the number of columns as needed num_rows = (num_cat_vars + num_cols - 1) // num_cols fig,
axs = plt.subplots(num_rows, num_cols, figsize=(10, 10))
axs = axs.flatten() # Flatten the 2D array of axes for easier indexing
for i,var in enumerate(Cat_var):
            if i < len(axs):
                ax = axs[i]
                cat_counts = dataset[var].value_counts()
                ax.pie(cat_counts, labels=cat_counts.index, autopct='%1.1f%%', startangle=90)
                ax.set_title(f'{var} Distribution')
                fig.tight_layout()
                if len(axs) > num_cat_vars:
                        fig.delaxes(axs[-1])
                        plt.show()
```

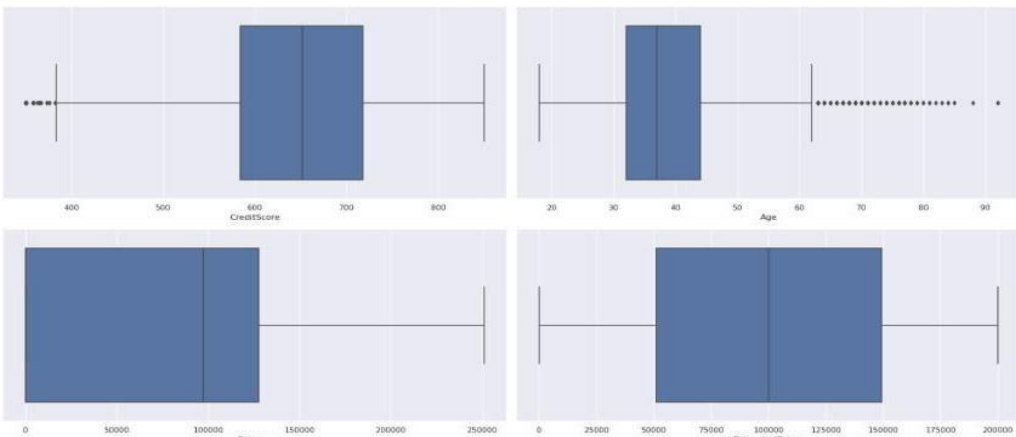


Dataset.heat()

Out[12]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	Female	42	2	0.00	1	1	1	101348.88
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	699	France	Female	39	1	0.00	2	0	0	93826.63
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

```
num_vars = ['CreditScore','Age','Balance','EstimatedSalary']
# Create a grid of subplots based on the number of categorical variables
num_cat_vars = len(num_vars)
num_cols = 2 # You can adjust the number of columns as needed
num_rows = (num_cat_vars + num_cols - 1) // num_cols fig, axs
= plt.subplots(num_rows, num_cols, figsize=(20, 10))
axs = axs.flatten()
for i, var in enumerate(num_vars):
        sns.boxplot(x=var,data=dataset, ax=axs[i]) # Adjust spacing between subplots
        fig.tight_layout()
        plt.show()
```



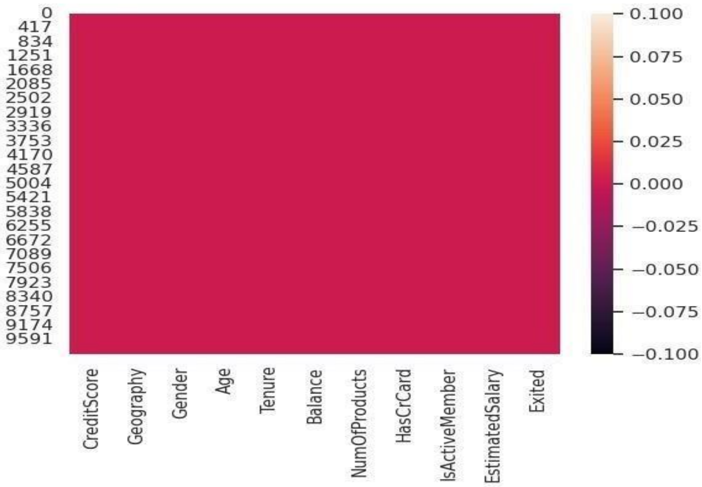
Data Processing 2:

dataset.isnull()

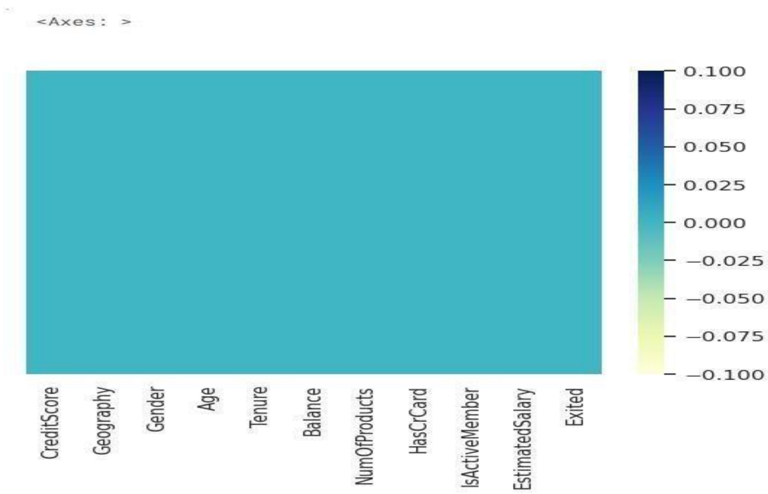
Out[18]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False	False	False	False
...	...	...	...	...	...	...	...	...	...	...
9995	False	False	False	False	False	False	False	False	False	False
9996	False	False	False	False	False	False	False	False	False	False
9997	False	False	False	False	False	False	False	False	False	False
9998	False	False	False	False	False	False	False	False	False	False
9999	False	False	False	False	False	False	False	False	False	False

sns.heatmap(dataset.isnull())



sns.heatmap(dataset.isnull() ,yticklabels=False , cmap="YlGnBu")



dataset.isnull().sum()

```
Out[21]:
         CreditScore        0
         Geography          0
         Gender             0
         Age                0
         Tenure             0
         Balance            0
         NumOfProducts      0
         HasCrCard          0
         IsActiveMember     0
         EstimatedSalary    0
         Exited             0
         dtype: int64
```

```
cheak_missing = dataset.isnull().sum() * 100/ dataset.shape[0]
cheak_missing[cheak_missing > 0].sort_values(ascending=False)
```

```
Out[23]:
Series([], dtype: float64)
```

```
dataset.shape
```

```
Out[24]:
(10000, 11)
```

Label Encoding:

```
for col in dataset.select_dtypes(include=['object']).columns:
    #print column name and value
    print(f"{col}:{dataset[col].unique()}")
```

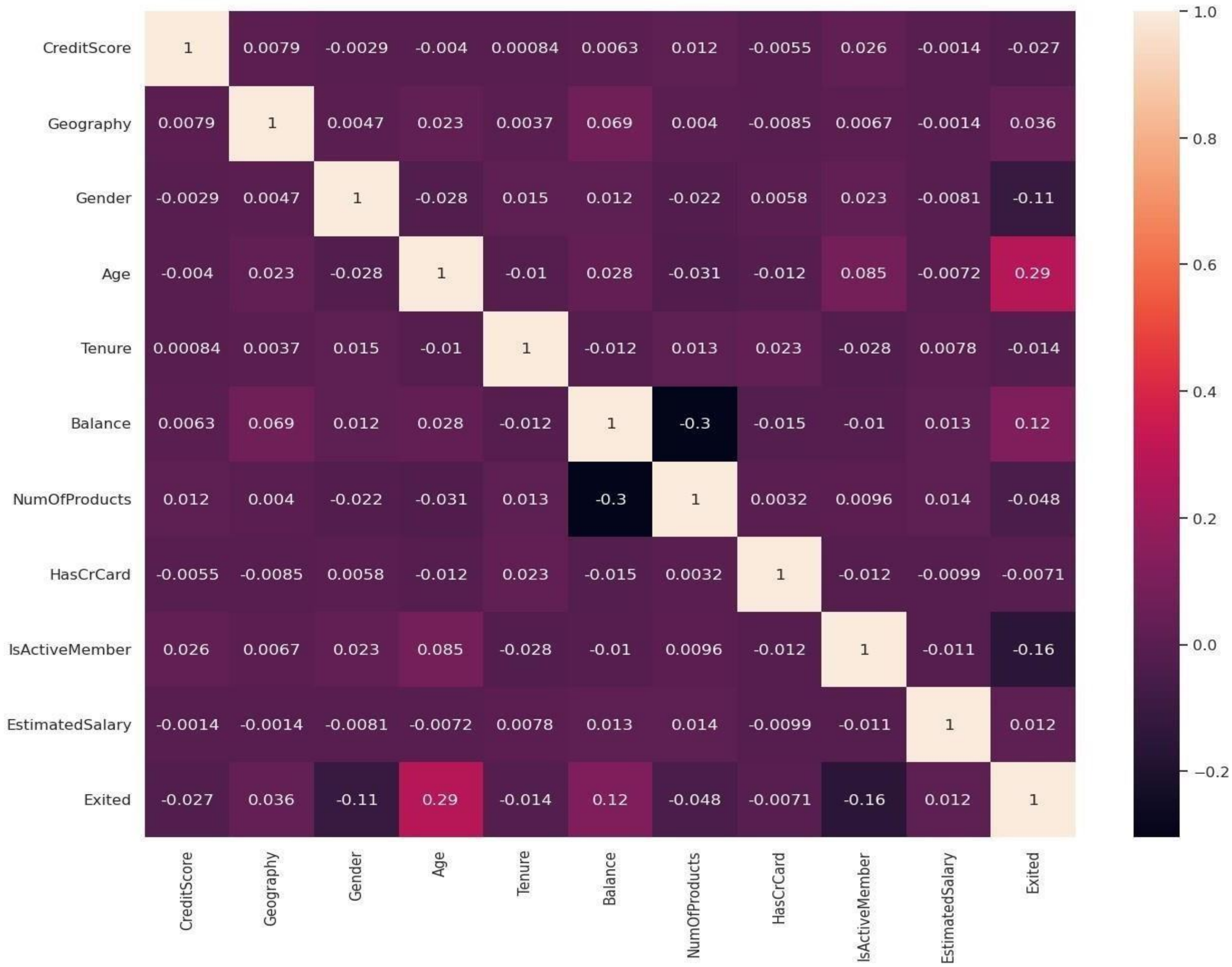
```
Geography:['France' 'Spain' 'Germany']
Gender:['Female' 'Male']
```

```
from sklearn import preprocessing

#loop to find object datatype for col in
dataset.select_dtypes(include=['object']).columns:

#initilization of LabelEncoder
    label_encoding= preprocessing.LabelEncoder()

label_encoding.fit(dataset[col].unique())
dataset[col] = label_encoding.transform(dataset[col]) print(f"{col}:{dataset[col].unique()}")
```

```
Geography:[0 2 1]
Gender:[0 1]
```

Removing Outliers using IQR: Heatmap Correlation:

```
plt.figure(figsize=(15,12))
sns.heatmap(dataset.corr(),fmt='.2g',annot=true)
```



Dataset

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActi
0	619	0	0	42	2	0.00	1	1	1
1	608	2	0	41	1	83807.86	1	0	1
2	502	0	0	42	8	159660.80	3	1	0
3	699	0	0	39	1	0.00	2	0	0
4	850	2	0	43	2	125510.82	1	1	1
...	...	...	...	...	...	...	...	...	...
9995	771	0	1	39	5	0.00	2	1	0
9996	516	0	1	35	10	57369.61	1	1	1
9997	709	0	0	36	7	0.00	1	0	1
9998	772	1	1	42	3	75075.31	2	1	0
9999	792	0	0	28	4	130142.79	1	1	0

```
x=dataset.drop("Exited",axis
=1) y=dataset['Exited']

from sklearn.model_selection import train_test_split

x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=
42) from keras.models import Sequential
```

CONCLUSION:

In conclusion, IBM Cloud Watson Studio serves as an indispensable tool for enterprises and data professionals embarking on the journey of machine learning model development. By offering a seamless and collaborative workspace, Watson Studio enables streamlined data exploration, efficient model training, and simplified deployment processes.

With its emphasis on scalability and integration with IBM Cloud services, Watson Studio empowers businesses to unlock the full potential of their data, enablingthem to make data-driven decisions and stay ahead in an increasingly competitive landscape. By leveraging the capabilities of Watson Studio, organizations can drive innovation, enhance operational efficiency, and pave the way for future advancementsin the field of artificial intelligence and machine learning.

Machine learning model development with IBM Cloud Watson Studio offers a comprehensive and efficient solution for organizations and individuals seeking to harness the full potential of artificial intelligence. Throughout this guide, we've explored the rich ecosystem of tools and resources that Watson Studio provides,allowing data scientists and developers to seamlessly navigate the complex landscape of data-driven decision-making.

With Watson Studio, you gain access to robust data management, collaborative workspaces, and a wide array of machine learning algorithms. This platform simplifies and accelerates the entire machine learning lifecycle, from data preparation and feature engineering to model development and deployment. The integration with IBMWatson AI services opens doors to advanced AI capabilities, making it easier than ever to infuse intelligence into your applications.

Moreover, Watson Studio is part of the IBM Cloud ecosystem, offering scalability,security, and the flexibility to adapt to your organization's needs. Whether you're working on small-scale projects or enterprise-level initiatives, Watson Studio provides the tools and support required to drive innovation and stay competitive in today's data-driven world.
In summary, IBM Cloud Watson Studio empowers you to turn data into actionable insights, make predictions, and build intelligent applications with confidence.

It's a platform designed to foster collaboration, accelerate development, and unlock the full potential of machine learning, making it an invaluable asset for anyone on the journey to harness the power of artificial intelligence.