zpfvw2obv

September 16, 2024

1 ANN Model for Early Warning System for Customer Support

[171]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[172]:
```python
#reading the dataset
data = pd.read_csv('/content/drive/MyDrive/TechConsulting/Early Warning System␣
↪for Customer Support/Churn_Modelling.csv')
data= data.drop(['RowNumber','CustomerId','Surname'],axis=1)
data
```

[172]:
```
      CreditScore Geography  Gender  Age  Tenure    Balance  NumOfProducts  \
0             619    France  Female   42       2       0.00              1
1             608     Spain  Female   41       1   83807.86              1
2             502    France  Female   42       8  159660.80              3
3             699    France  Female   39       1       0.00              2
4             850     Spain  Female   43       2  125510.82              1
…               …       …     …     …     …         …              …
9995          771    France    Male   39       5       0.00              2
9996          516    France    Male   35      10   57369.61              1
9997          709    France  Female   36       7       0.00              1
9998          772   Germany    Male   42       3   75075.31              2
9999          792    France  Female   28       4  130142.79              1

      HasCrCard  IsActiveMember  EstimatedSalary  Exited
0             1               1        101348.88       1
1             0               1        112542.58       0
2             1               0        113931.57       1
3             0               0         93826.63       0
4             1               1         79084.10       0
…           …               …              …     …
9995          1               0         96270.64       0
9996          1               1        101699.77       0
9997          0               1         42085.58       1
9998          1               0         92888.52       1
9999          1               0         38190.78       0
```

```
[10000 rows x 11 columns]
```

[173]:
```
# data info
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 11 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   CreditScore      10000 non-null  int64
 1   Geography        10000 non-null  object
 2   Gender           10000 non-null  object
 3   Age              10000 non-null  int64
 4   Tenure           10000 non-null  int64
 5   Balance          10000 non-null  float64
 6   NumOfProducts    10000 non-null  int64
 7   HasCrCard        10000 non-null  int64
 8   IsActiveMember   10000 non-null  int64
 9   EstimatedSalary  10000 non-null  float64
 10  Exited           10000 non-null  int64
dtypes: float64(2), int64(7), object(2)
memory usage: 859.5+ KB
```

[174]:
```
# data desciption
data.describe()
```

[174]:
```
        CreditScore           Age        Tenure        Balance  NumOfProducts  \
count  10000.000000  10000.000000  10000.000000   10000.000000   10000.000000
mean     650.528800     38.921800      5.012800   76485.889288       1.530200
std       96.653299     10.487806      2.892174   62397.405202       0.581654
min      350.000000     18.000000      0.000000       0.000000       1.000000
25%      584.000000     32.000000      3.000000       0.000000       1.000000
50%      652.000000     37.000000      5.000000   97198.540000       1.000000
75%      718.000000     44.000000      7.000000  127644.240000       2.000000
max      850.000000     92.000000     10.000000  250898.090000       4.000000

         HasCrCard  IsActiveMember  EstimatedSalary        Exited
count  10000.00000    10000.000000     10000.000000  10000.000000
mean       0.70550        0.515100    100090.239881      0.203700
std        0.45584        0.499797     57510.492818      0.402769
min        0.00000        0.000000        11.580000      0.000000
25%        0.00000        0.000000     51002.110000      0.000000
50%        1.00000        1.000000    100193.915000      0.000000
75%        1.00000        1.000000    149388.247500      0.000000
max        1.00000        1.000000    199992.480000      1.000000
```

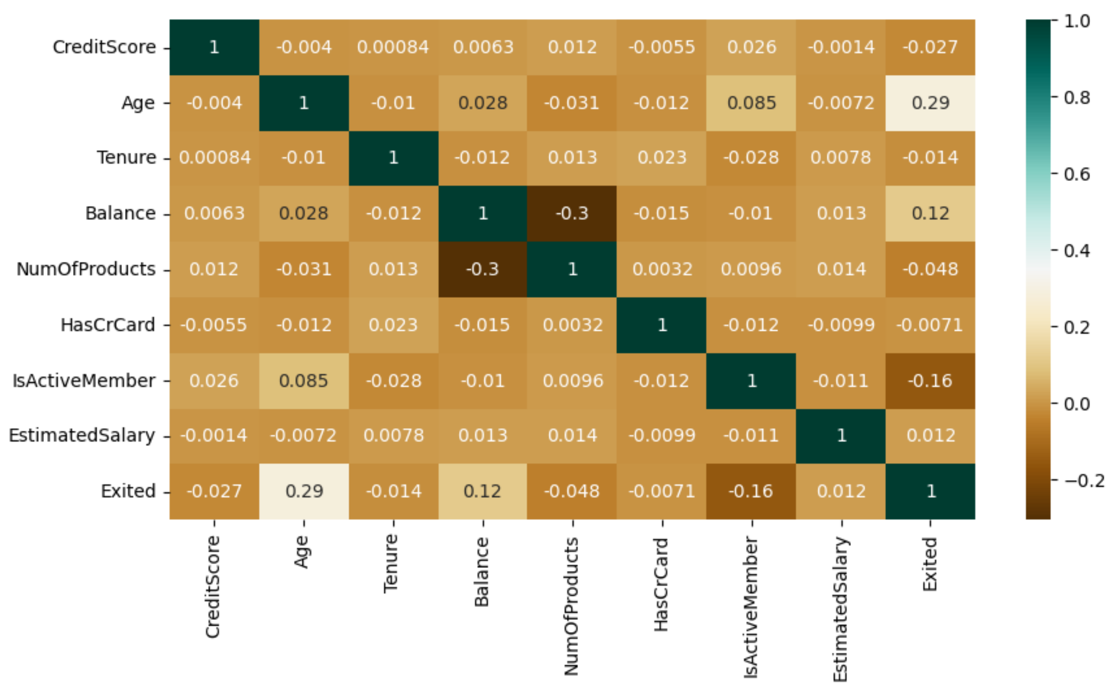
[175]:
```python
# Checking missing values
data.isnull().sum()
```

[175]:
```
CreditScore        0
Geography          0
Gender             0
Age                0
Tenure             0
Balance            0
NumOfProducts      0
HasCrCard          0
IsActiveMember     0
EstimatedSalary    0
Exited             0
dtype: int64
```

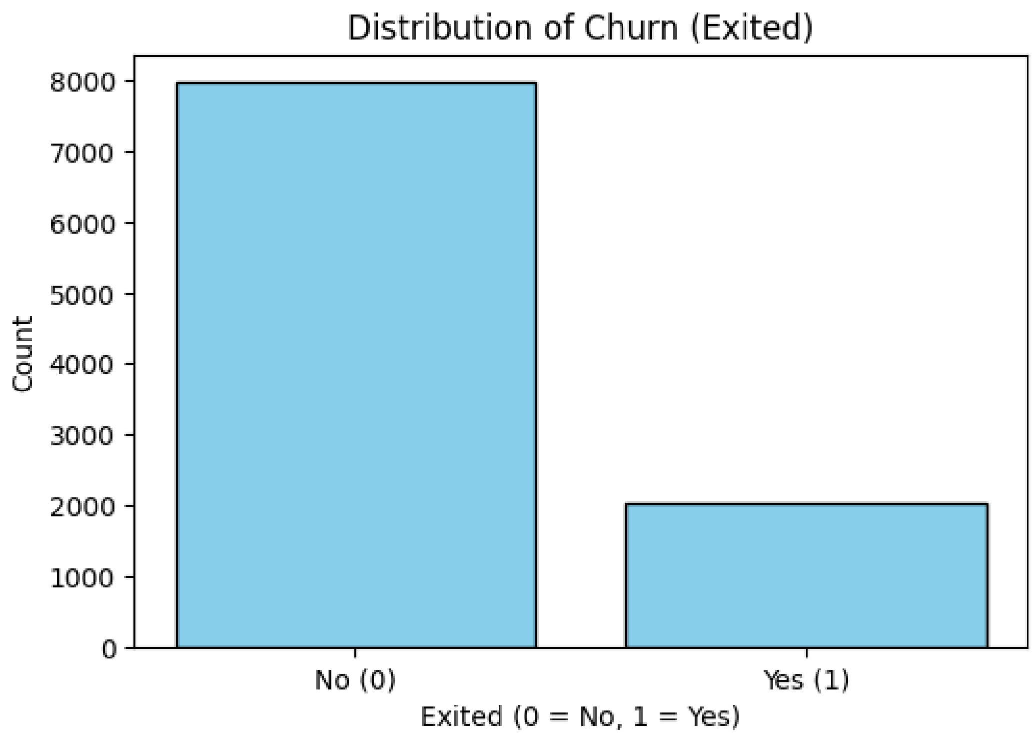
1.1 EDA

[176]:
```python
## Corelation matrix
import seaborn as sns
plt.figure(figsize=(10, 5))
c = data.corr(numeric_only=True)
sns.heatmap(c, cmap='BrBG', annot=True)
```

[176]: <Axes: >

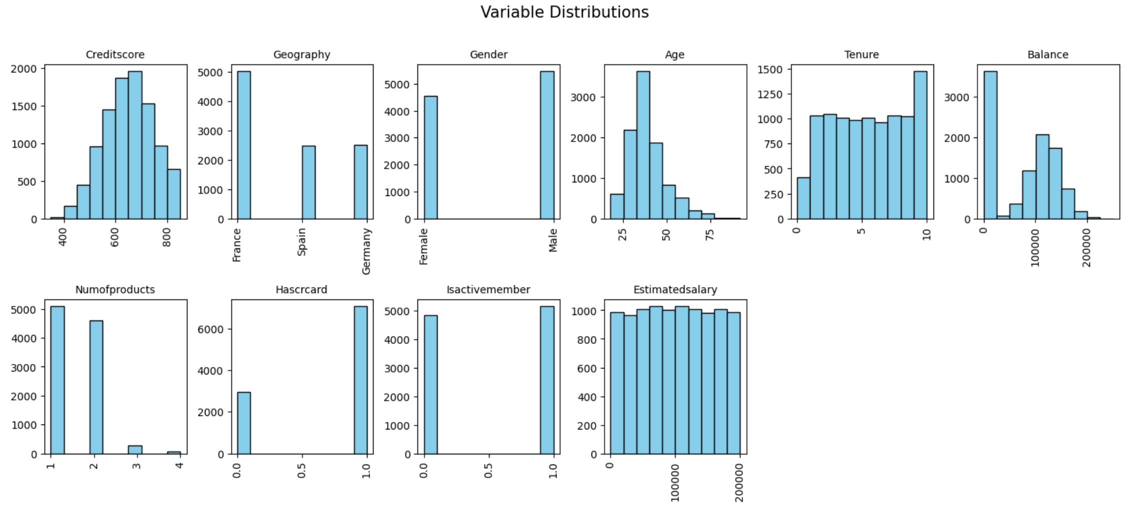


[177]:
```
# target variable distribution
exited_counts = data['Exited'].value_counts()
plt.figure(figsize=(6,4))
plt.bar(exited_counts.index, exited_counts.values, color='skyblue',␣
 ↪edgecolor='black')
plt.title('Distribution of Churn (Exited)')
plt.xlabel('Exited (0 = No, 1 = Yes)')
plt.ylabel('Count')
plt.xticks([0, 1], ['No (0)', 'Yes (1)'])
plt.show()
```

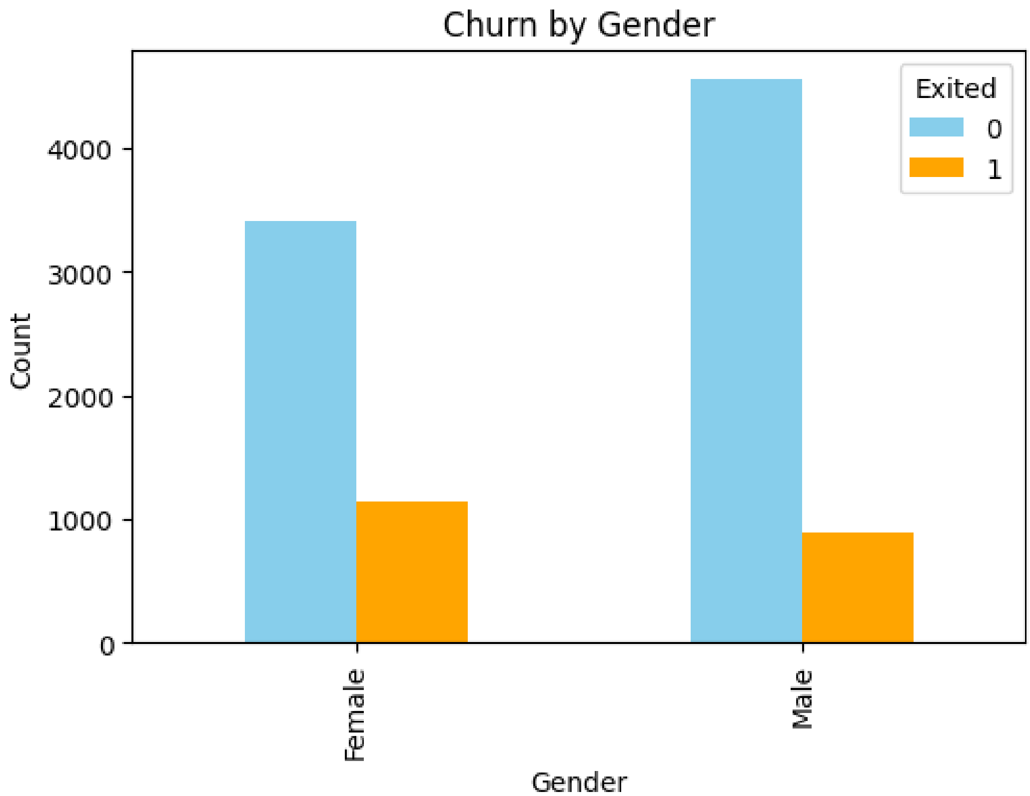


[178]:
```
# varibale distribution
# Function to plot variable distributions
def plot_variable_distributions(df):
    features = data.columns[:-1]
    plt.figure(figsize=(15, 15))

    for i, feature in enumerate(features, 1):
        plt.subplot(5, 6, i)  # Adjust the grid size as per the number of␣
 ↪features
        df[feature].hist(grid=False, color='skyblue', edgecolor='black')
        plt.title(feature.capitalize(), fontsize=10)
        plt.xlabel("")
```

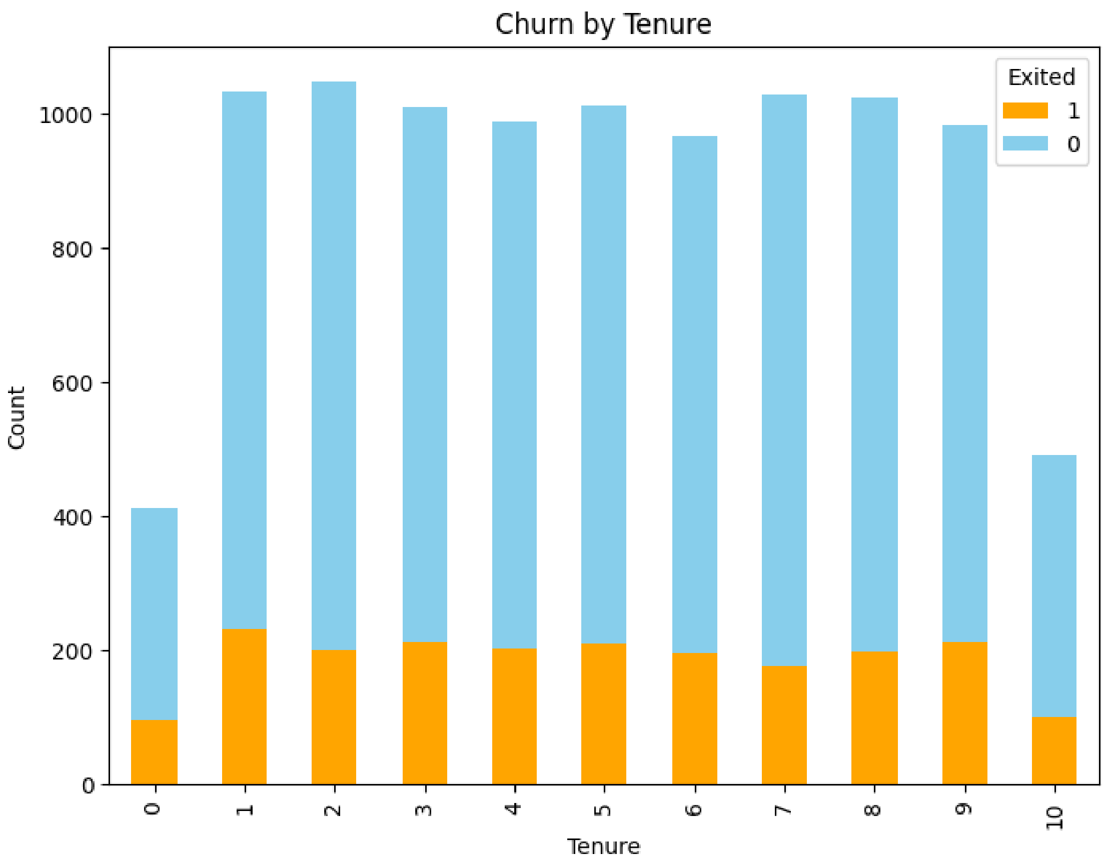
```
        plt.ylabel("")
        plt.xticks(rotation=90)

    plt.tight_layout(pad=1)
    plt.suptitle("Variable Distributions", fontsize=15, y=1.03)
    plt.show()
# Call the function to plot histograms of the DataFrame excluding the first␣
 ↪column
plot_variable_distributions(data)
```



[179]:
```
gender_churn = data.groupby(['Gender', 'Exited']).size().unstack()
gender_churn.plot(kind='bar', color=['skyblue', 'orange'], figsize=(6,4))
plt.title('Churn by Gender')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.show()
```

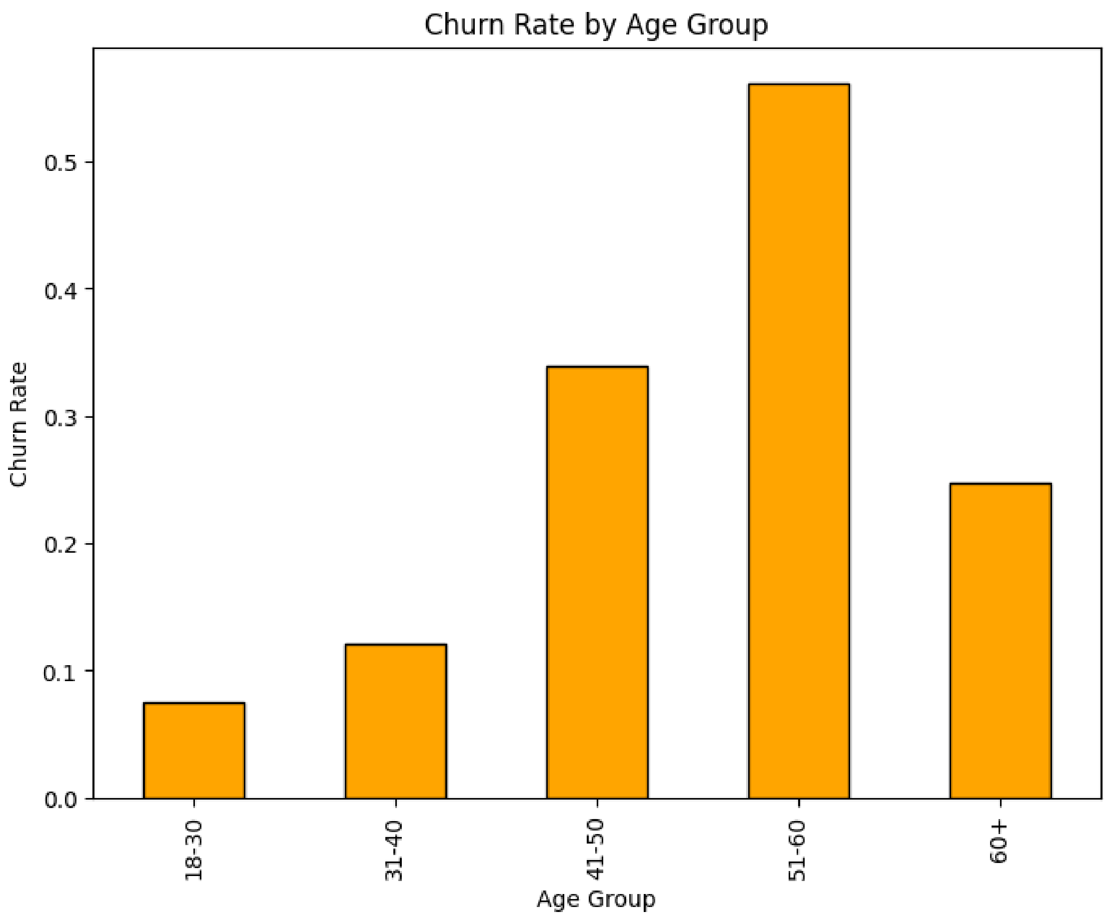


[180]:
```
# Churn by Tenure
tenure_churn = data.groupby(['Tenure', 'Exited']).size().unstack()
tenure_churn = tenure_churn[[1, 0]]
tenure_churn.plot(kind='bar', stacked=True, color=['orange', 'skyblue'],␣
↪figsize=(8,6))
plt.title('Churn by Tenure')
plt.xlabel('Tenure')
plt.ylabel('Count')
plt.show()
```



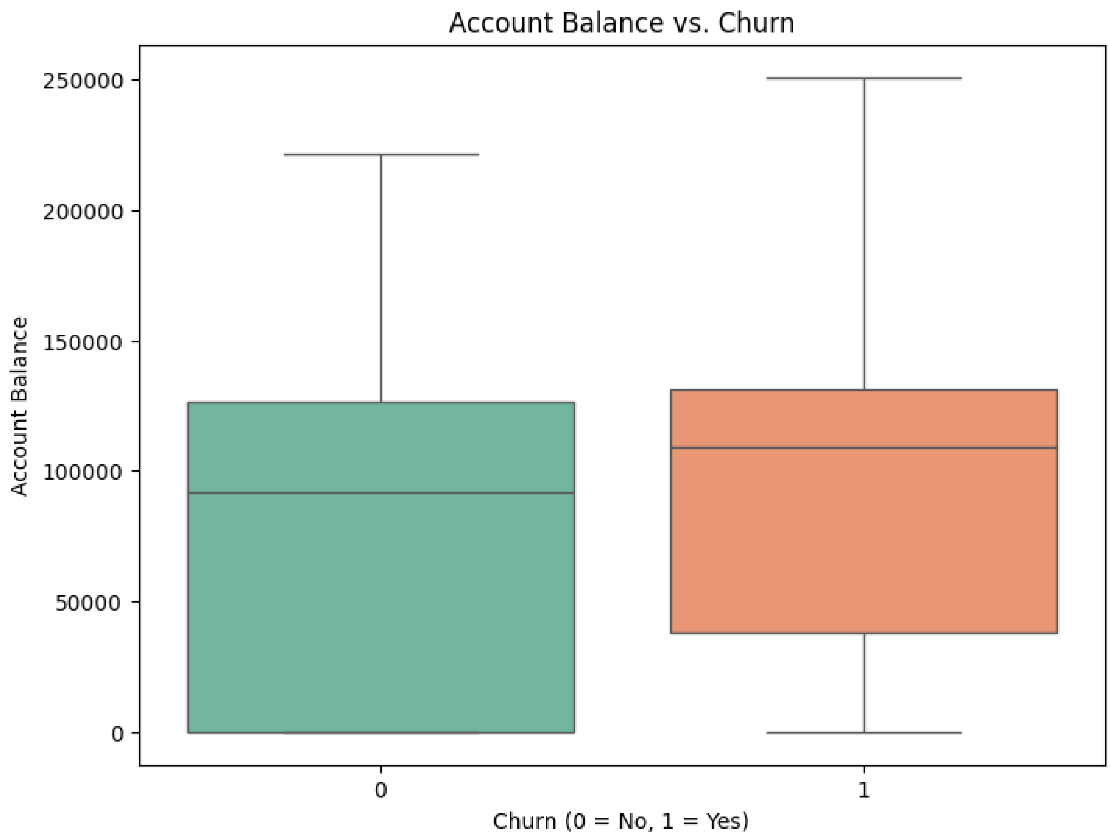
[181]:
```python
## churn rate by Age
age_churn = data.groupby(pd.cut(data['Age'], bins=[18, 30, 40, 50, 60, 100],␣
↪labels=['18-30', '31-40', '41-50', '51-60', '60+']))['Exited'].mean()
plt.figure(figsize=(8,6))
age_churn.plot(kind='bar', color='orange', edgecolor='black')
plt.title('Churn Rate by Age Group')
plt.xlabel('Age Group')
plt.ylabel('Churn Rate')
plt.show()
```

```
<ipython-input-181-ff4cd00f48ad>:2: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass
observed=False to retain current behavior or observed=True to adopt the future
default and silence this warning.
  age_churn = data.groupby(pd.cut(data['Age'], bins=[18, 30, 40, 50, 60, 100],
labels=['18-30', '31-40', '41-50', '51-60', '60+']))['Exited'].mean()
```

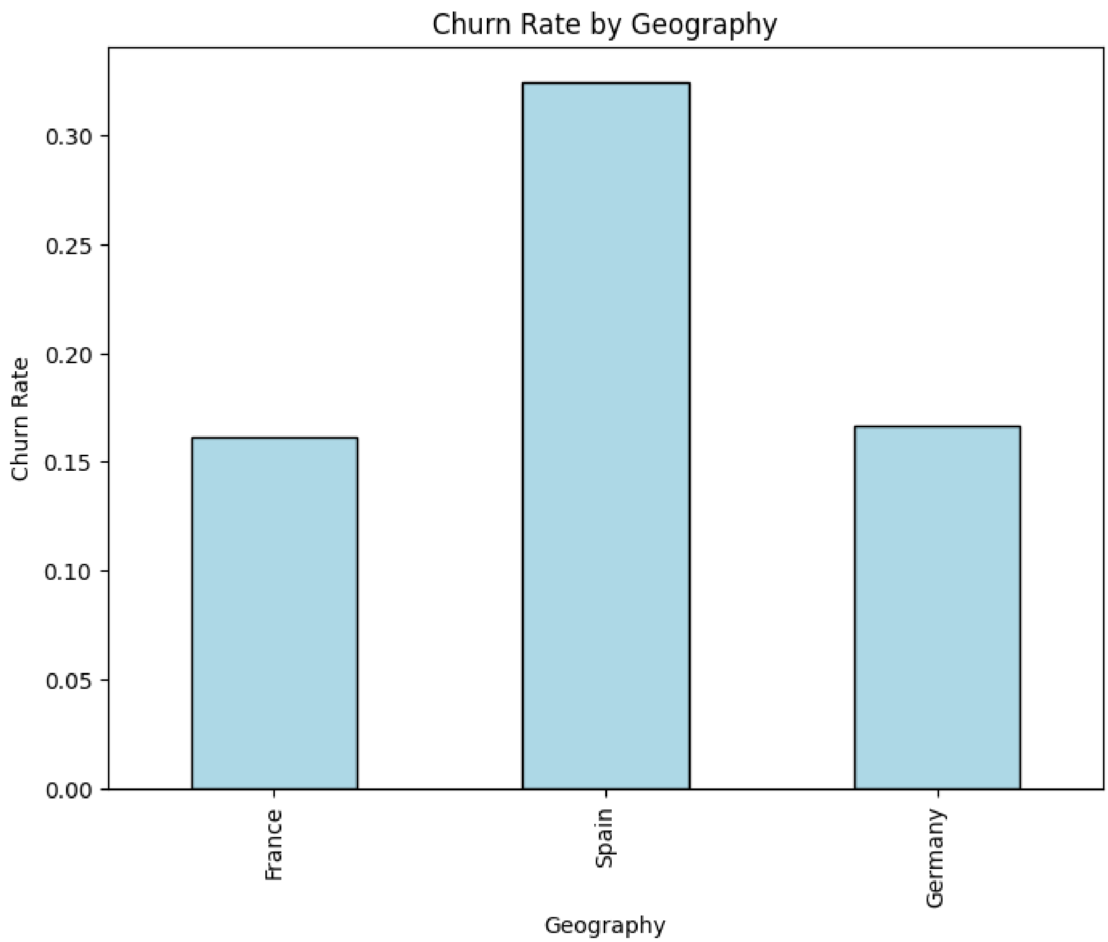


[182]:
```python
## Churn by account balance
plt.figure(figsize=(8,6))
sns.boxplot(x='Exited', y='Balance', data=data, palette="Set2")
plt.title('Account Balance vs. Churn')
plt.xlabel('Churn (0 = No, 1 = Yes)')
plt.ylabel('Account Balance')
plt.show()
```

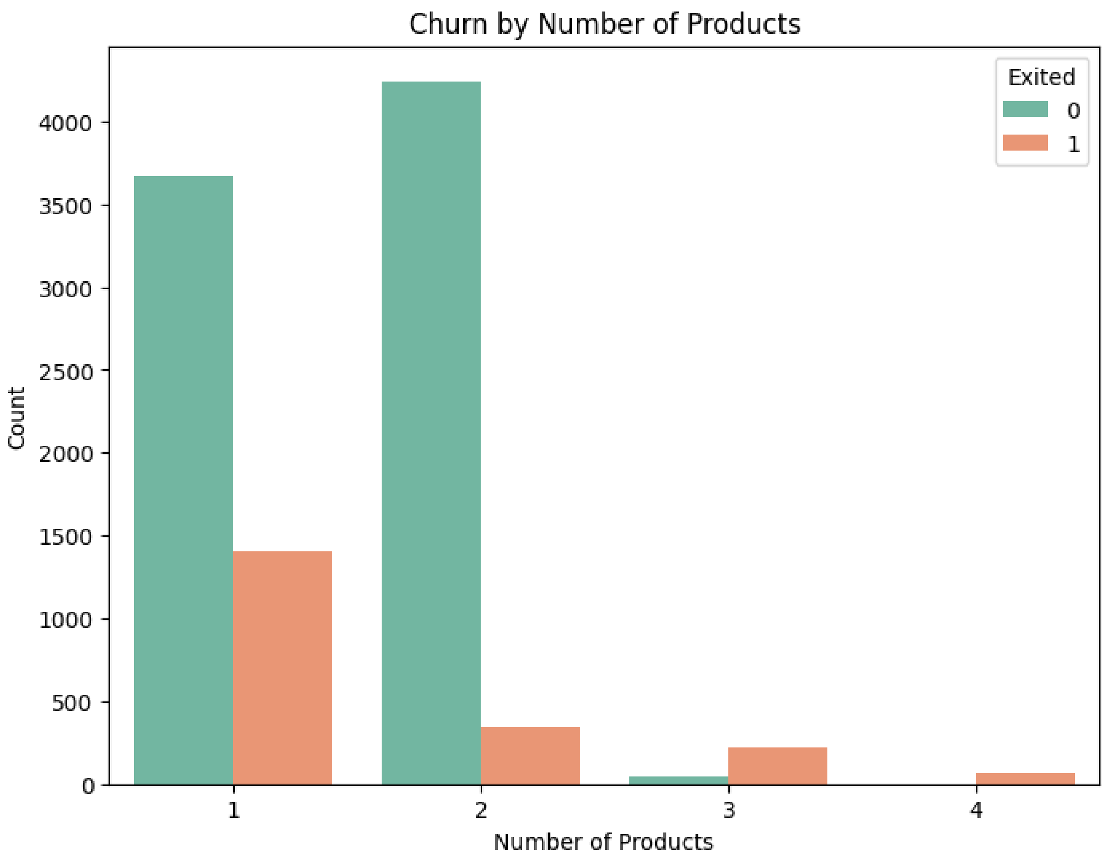
```
<ipython-input-182-8255b7de9b9a>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x='Exited', y='Balance', data=data, palette="Set2")
```



[183]:
```
## Churn by geography
geography_churn = data.groupby('Geography')['Exited'].mean()
plt.figure(figsize=(8,6))
geography_churn.plot(kind='bar', color='lightblue', edgecolor='black')
plt.title('Churn Rate by Geography')
plt.xlabel('Geography')
plt.ylabel('Churn Rate')
plt.xticks([0, 1, 2], ['France', 'Spain', 'Germany'])
plt.show()
```



[184]:
```
## churn by number of products
plt.figure(figsize=(8,6))
sns.countplot(x='NumOfProducts', hue='Exited', data=data, palette='Set2')
plt.title('Churn by Number of Products')
plt.xlabel('Number of Products')
plt.ylabel('Count')
plt.show()
```



1.2 Preparation

[185]:
```
data
```

[185]:
```
      CreditScore Geography  Gender  Age  Tenure    Balance  NumOfProducts  \
0             619    France  Female   42       2       0.00              1
1             608     Spain  Female   41       1   83807.86              1
2             502    France  Female   42       8  159660.80              3
3             699    France  Female   39       1       0.00              2
4             850     Spain  Female   43       2  125510.82              1
…             …        …      …   …    …          …              …
9995          771    France    Male   39       5       0.00              2
9996          516    France    Male   35      10   57369.61              1
9997          709    France  Female   36       7       0.00              1
9998          772   Germany    Male   42       3   75075.31              2
9999          792    France  Female   28       4  130142.79              1

      HasCrCard  IsActiveMember  EstimatedSalary  Exited
0             1               1        101348.88       1
```

```
1              0              1        112542.58       0
2              1              0        113931.57       1
3              0              0         93826.63       0
4              1              1         79084.10       0
…          …           …             …     …
9995           1              0         96270.64       0
9996           1              1        101699.77       0
9997           0              1         42085.58       1
9998           1              0         92888.52       1
9999           1              0         38190.78       0

[10000 rows x 11 columns]
```

[186]:

```python
## encoding
data = pd.get_dummies(data, columns=['Geography', 'Gender'], drop_first=True,␣
 ↪dtype=int)
data
```

[186]:

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

      IsActiveMember  EstimatedSalary  Exited  Geography_Germany  \
0                  1        101348.88       1                  0
1                  1        112542.58       0                  0
2                  0        113931.57       1                  0
3                  0         93826.63       0                  0
4                  1         79084.10       0                  0
…              …              …     …                …
9995               0         96270.64       0                  0
9996               1        101699.77       0                  0
9997               1         42085.58       1                  0
9998               0         92888.52       1                  1
9999               0         38190.78       0                  0

      Geography_Spain  Gender_Male
0                   0            0
1                   1            0
```

```
2                  0            0
3                  0            0
4                  1            0
…               …            …
9995               0            1
9996               0            1
9997               0            0
9998               0            1
9999               0            0

[10000 rows x 12 columns]
```

[187]:
```
# ## Transformation
# data['CreditScore_log'] = np.log1p(data['CreditScore'])
# data['Age_log'] = np.log1p(data['Age'])
# data['Balance_log'] = np.log1p(data['Balance'])
# data['EstimatedSalary_log'] = np.log1p(data['EstimatedSalary'])
# data
```

[188]:
```
data.shape
```

[188]:
```
(10000, 12)
```

[189]:
```
## outliers
def treat_outliers(df, features):
    df_filtered = df.copy()
    for column in features:
        Q1 = df_filtered[column].quantile(0.25)
        Q3 = df_filtered[column].quantile(0.75)
        IQR = Q3 - Q1
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR
        df_filtered = df_filtered[(df_filtered[column] >= lower_bound) &
 ↪(df_filtered[column] <= upper_bound)]
    return df_filtered

n_features= ['CreditScore', 'Age', 'Balance', 'EstimatedSalary']
data_cleaned = treat_outliers(data, n_features)
data_cleaned.shape

#data_cleaned= data
```

[189]:
```
(9626, 12)
```

[190]:
```
data
```

[190]:
```
      CreditScore  Age  Tenure    Balance  NumOfProducts  HasCrCard  \
0             619   42       2       0.00              1          1
1             608   41       1   83807.86              1          0
2             502   42       8  159660.80              3          1
3             699   39       1       0.00              2          0
4             850   43       2  125510.82              1          1
…               …    …       …          …              …          …
9995          771   39       5       0.00              2          1
9996          516   35      10   57369.61              1          1
9997          709   36       7       0.00              1          0
9998          772   42       3   75075.31              2          1
9999          792   28       4  130142.79              1          1

      IsActiveMember  EstimatedSalary  Exited  Geography_Germany  \
0                  1        101348.88       1                  0
1                  1        112542.58       0                  0
2                  0        113931.57       1                  0
3                  0         93826.63       0                  0
4                  1         79084.10       0                  0
…                  …              …       …                  …
9995               0         96270.64       0                  0
9996               1        101699.77       0                  0
9997               1         42085.58       1                  0
9998               0         92888.52       1                  1
9999               0         38190.78       0                  0

      Geography_Spain  Gender_Male
0                   0            0
1                   1            0
2                   0            0
3                   0            0
4                   1            0
…                   …            …
9995                0            1
9996                0            1
9997                0            0
9998                0            1
9999                0            0

[10000 rows x 12 columns]
```

[191]:
```python
## Scaling
def min_max_scale(df, exclude_columns=None):
    df_scaled = df.copy()
    scaling_params = {}
    for column in df_scaled.columns:
        if column not in exclude_columns:
```

```python
            min_value = df_scaled[column].min()
            max_value = df_scaled[column].max()
            df_scaled[column] = (df_scaled[column] - min_value) / (max_value - min_value)
            scaling_params[column] = {'min': min_value, 'max': max_value}
    return df_scaled, scaling_params
exclude_columns = ['HasCrCard', 'IsActiveMember', 'Exited', 'Geography_Germany', 'Geography_Spain', 'Gender_Male']
data_scaled, scaling_params = min_max_scale(data_cleaned, exclude_columns)
data_scaled
```

[191]:

```
      CreditScore       Age  Tenure   Balance  NumOfProducts  HasCrCard  \
0        0.505353  0.545455     0.2  0.000000       0.000000          1
1        0.481799  0.522727     0.1  0.334031       0.000000          0
2        0.254818  0.545455     0.8  0.636357       0.666667          1
3        0.676660  0.477273     0.1  0.000000       0.333333          0
4        1.000000  0.568182     0.2  0.500246       0.000000          1
…             …         …     …       …             …        …
9995     0.830835  0.477273     0.5  0.000000       0.333333          1
9996     0.284797  0.386364     1.0  0.228657       0.000000          1
9997     0.698073  0.409091     0.7  0.000000       0.000000          0
9998     0.832976  0.545455     0.3  0.299226       0.333333          1
9999     0.875803  0.227273     0.4  0.518708       0.000000          1

      IsActiveMember  EstimatedSalary  Exited  Geography_Germany  \
0                  1         0.506735       1                  0
1                  1         0.562709       0                  0
2                  0         0.569654       1                  0
3                  0         0.469120       0                  0
4                  1         0.395400       0                  0
…                …              …     …                …
9995               0         0.481341       0                  0
9996               1         0.508490       0                  0
9997               1         0.210390       1                  0
9998               0         0.464429       1                  1
9999               0         0.190914       0                  0

      Geography_Spain  Gender_Male
0                   0            0
1                   1            0
2                   0            0
3                   0            0
4                   1            0
…                 …          …
9995                0            1
9996                0            1
9997                0            0
```

```
9998                 0            1
9999                 0            0

[9626 rows x 12 columns]
```

1.3 Modelling

[192]:
```python
## data for modelling
model_data = data_scaled.copy()
model_data
```

[192]:
```
      CreditScore       Age  Tenure   Balance  NumOfProducts  HasCrCard  \
0        0.505353  0.545455     0.2  0.000000       0.000000          1
1        0.481799  0.522727     0.1  0.334031       0.000000          0
2        0.254818  0.545455     0.8  0.636357       0.666667          1
3        0.676660  0.477273     0.1  0.000000       0.333333          0
4        1.000000  0.568182     0.2  0.500246       0.000000          1
…             …         …       …         …            …          …
9995     0.830835  0.477273     0.5  0.000000       0.333333          1
9996     0.284797  0.386364     1.0  0.228657       0.000000          1
9997     0.698073  0.409091     0.7  0.000000       0.000000          0
9998     0.832976  0.545455     0.3  0.299226       0.333333          1
9999     0.875803  0.227273     0.4  0.518708       0.000000          1

      IsActiveMember  EstimatedSalary  Exited  Geography_Germany  \
0                  1         0.506735       1                  0
1                  1         0.562709       0                  0
2                  0         0.569654       1                  0
3                  0         0.469120       0                  0
4                  1         0.395400       0                  0
…                …              …     …                …
9995               0         0.481341       0                  0
9996               1         0.508490       0                  0
9997               1         0.210390       1                  0
9998               0         0.464429       1                  1
9999               0         0.190914       0                  0

      Geography_Spain  Gender_Male
0                   0            0
1                   1            0
2                   0            0
3                   0            0
4                   1            0
…                 …          …
9995                0            1
9996                0            1
9997                0            0
```

```
9998                0            1
9999                0            0

[9626 rows x 12 columns]
```

[193]:
```
## checking imbalance
model_data['Exited'].value_counts()
```

[193]:
```
Exited
0    7677
1    1949
Name: count, dtype: int64
```

[194]:
```
## over sampling
majority_class = model_data[model_data['Exited'] == 0]
minority_class = model_data[model_data['Exited'] == 1]
minority_class_oversampled = minority_class.sample(len(majority_class),␣
 ↪replace=True, random_state=42)
oversampled_data = pd.concat([majority_class, minority_class_oversampled])
oversampled_data = oversampled_data.sample(frac=1, random_state=42).
 ↪reset_index(drop=True)
oversampled_data['Exited'].value_counts()

#oversampled_data = model_data
```

[194]:
```
Exited
1    7677
0    7677
Name: count, dtype: int64
```

[195]:
```
## train test split
train_size = int(0.8 * len(oversampled_data))
train_df = oversampled_data[:train_size]
test_df = oversampled_data[train_size:]

X_train = train_df.drop('Exited', axis=1)
y_train = train_df['Exited']
X_test = test_df.drop('Exited', axis=1)
y_test = test_df['Exited']
len(X_train), len(y_train), len(X_test), len(y_test)
```

[195]:
```
(12283, 12283, 3071, 3071)
```

[196]:
```
## to_numpy
X_train= X_train.to_numpy()
y_train= y_train.to_numpy()
X_test= X_test.to_numpy()
```

```
y_test= y_test.to_numpy()
set(y_train)
```

[196]: {0, 1}

2 Binary Logistic Regression Class

2.1 Useful Functions

[197]:
```
#losses, activations,metrics
def sigmoid(h):
  return 1 / (1 + np.exp(-h))

def cross_entropy(y, p_hat):
  return -(1/len(y))*np.sum(y*np.log(p_hat)+ (1-y)*np.log(1-p_hat))

def accuracy(y, y_hat):
  return np.mean(y == y_hat)
```

[198]:
```
class LogisticRegression():

  def __init__(self, thresh=0.5):
    self.thresh = thresh
    self.W = None
    self.b = None

  def fit(self, X, y, eta=1e-3, epochs = 1e3, show_curve=False):
    epochs = int(epochs)
    N, D = X.shape

    #Initialize Weight and biases
    self.W= np.random.randn(D)
    self.b= np.random.randn(1)
    #Create Zero values container for J
    J = np.zeros(epochs)

    #SGD
    for epoch in range(epochs):
      p_hat= self.__forward__(X)
      J[epoch]= cross_entropy(y, p_hat)

      #Weight and bias Update Rules
      self.W -= eta*(1/N)*X.T@(p_hat-y)
      self.b -= eta*(1/N)*np.sum(p_hat-y)

    if show_curve:
      plt.figure()
```

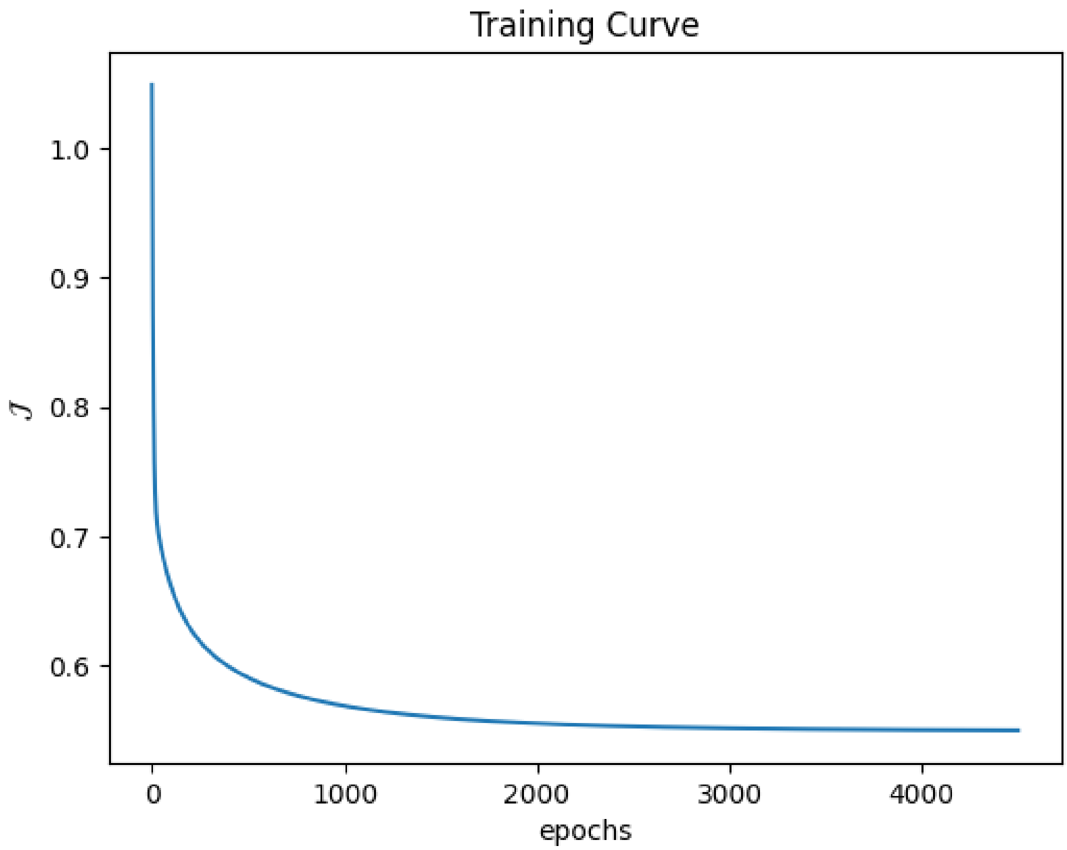
```
    plt.plot(J)
    plt.xlabel('epochs')
    plt.ylabel('$\mathcal{J}$')
    plt.title('Training Curve')
    plt.show()

  def __forward__(self, X):
    return sigmoid(X@self.W+self.b)

  def predict(self, X):
    return (self.__forward__(X)>= self.thresh).astype(np.int32)
```

[199]:
```
log_reg= LogisticRegression()
```

[136]:
```
epochs_list = [3500, 4000, 4500]
eta_list = [0.08, 0.1, 0.12]

best_accuracy = 0
best_params = {'epochs': None, 'eta': None}

for epochs in epochs_list:
    for eta in eta_list:
        log_reg.fit(X_train, y_train, epochs=epochs, eta=eta, show_curve=False)

        # Predict and calculate accuracy
        y_hat_BLR = log_reg.predict(X_test)
        accuracy_val = accuracy(y_test, y_hat_BLR)

        # Track the best accuracy and parameters
        if accuracy_val > best_accuracy:
            best_accuracy = accuracy_val
            best_params['epochs'] = epochs
            best_params['eta'] = eta

print(f"Best Accuracy: {best_accuracy:.4f}")
print(f"Best Parameters: Epochs={best_params['epochs']},␣
 ↪Eta={best_params['eta']}")
```

```
Best Accuracy: 0.7258
Best Parameters: Epochs=4500, Eta=0.12
```

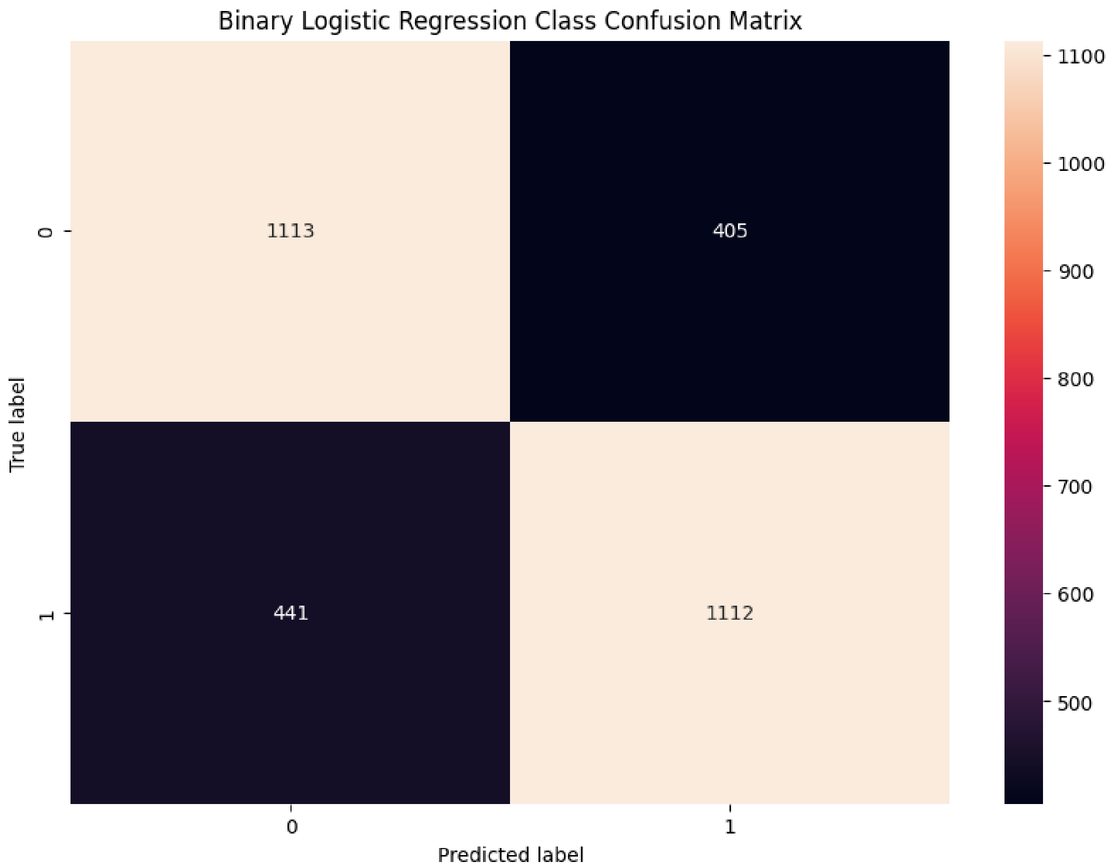
[200]:
```
log_reg.fit(X_train, y_train, epochs= 4500, eta= 0.12, show_curve= True)
y_hat_BLR = log_reg.predict(X_test)
print(f"Training Accuracy: {accuracy(y_test, y_hat_BLR): 0.4f}")
print(log_reg.W)
print(log_reg.b)
```




```
Training Accuracy:  0.7245
[-0.31768667  4.52905624 -0.23857845  0.70784429 -0.33213243 -0.13377152
 -0.77718349 -0.04615254  0.85188081  0.02771341 -0.53021483]
[-1.68362384]
```

[201]:
```python
#Binary Logistic Regression Class
plt.figure(figsize=(10,7))
y_actual_BLR = pd.Series(y_test, name='Actual')
y_pred_BLR = pd.Series(y_hat_BLR, name='Predicted')
cm = pd.crosstab(y_actual_BLR, y_pred_BLR)
ax = sns.heatmap(cm, annot=True, fmt="d")
plt.title("Binary Logistic Regression Class Confusion Matrix")
plt.ylabel('True label')
plt.xlabel('Predicted label')
```

[201]:
```
Text(0.5, 47.7222222222222, 'Predicted label')
```



[138]:
```
# #Binary Logistic Regression Class
# plt.figure(figsize=(10,7))
# y_actual_BLR = pd.Series(y_test, name='Actual')
# y_pred_BLR = pd.Series(y_hat_BLR, name='Predicted')
# cm = pd.crosstab(y_actual_BLR, y_pred_BLR)
# ax = sns.heatmap(cm, annot=True, fmt="d")
# plt.title("Binary Logistic Regression Class Confusion Matrix")
# plt.ylabel('True label')
# plt.xlabel('Predicted label')
```

3 Two-Layer Feed Forward Perceptron

[202]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

3.1 Activation Functions

[203]:
```
def linear(H):
  return H

def ReLU(H):
  return H*(H>0)

def sigmoid(H):
  return 1/(1+np.exp(-H))

def softmax(H):
  eH = np.exp(H)
  return eH/eH.sum(axis=1, keepdims= True)

#np.tanh
```

3.2 Useful Functions

[204]:
```
def one_hot_encode(y):
  N = len(y)
  K =len(set(y))
  Y = np.zeros((N,K))
  for i in range(N):
    Y[i, y[i]]=1
  return Y

def cross_entropy(Y, P_hat):
  return -np.sum(Y*np.log(P_hat))

def binary_cross_entropy(y, p_hat):
  return -(1/len(y))*np.sum(y*np.log(p_hat)+ (1-y)*np.log(1-p_hat))

def accuracy(y, y_hat):
  return np.mean(y == y_hat)
```

3.3 Shallow ANN Class

[205]:
```
class Shallow_ANN():

  def fit(self, X, y, neurons=6, eta=1e-3, epochs=1e3, show_curve= True):
    epochs= int(epochs)
    N, D = X.shape
    Y = one_hot_encode(y)
    #Y = y.reshape(-1, 1)
    #Y=y
    K= Y.shape[1]
```

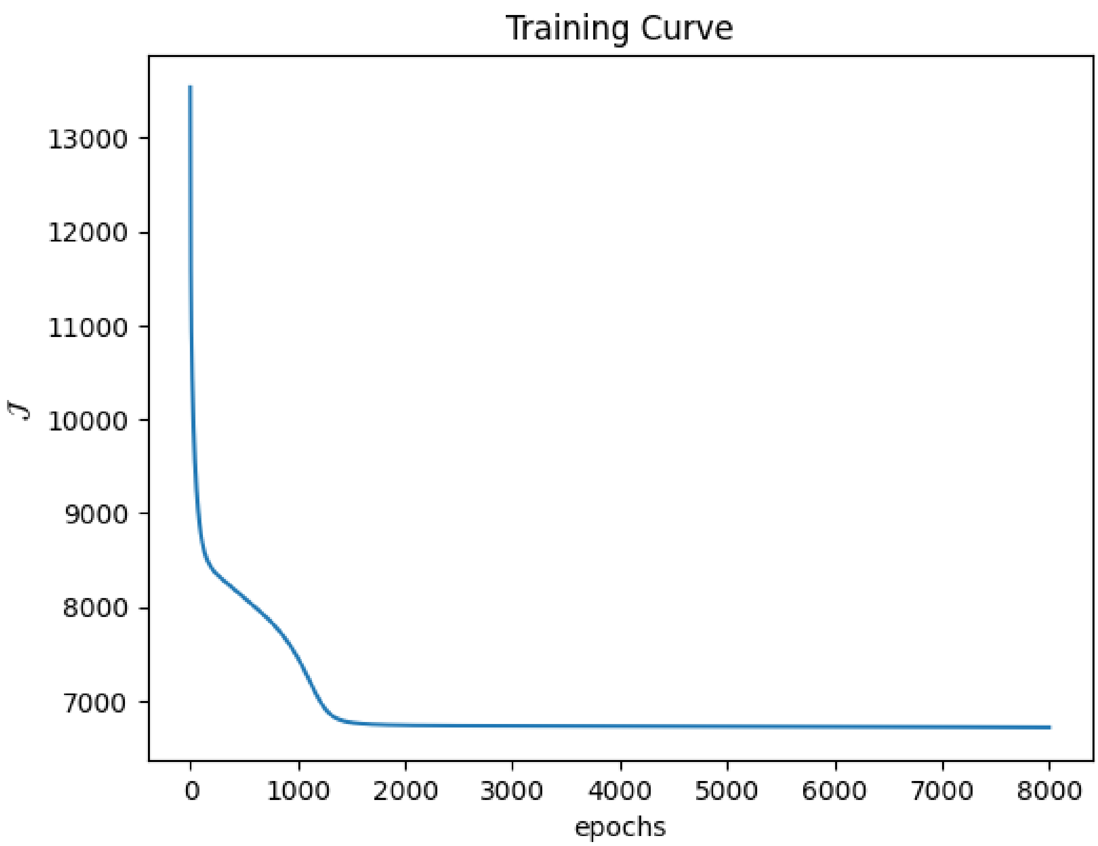
```
    #Weights Initialization
    self.W ={l: np.random.randn(M[0], M[1]) for l, M in enumerate(zip([D,␣
↪neurons],[neurons, K]), 1)}
    self.B = {l: np.random.randn(M) for l, M in enumerate([neurons, K], 1)}
    #Define Activations
    self.a ={1:np.tanh, 2:softmax}

    J= np.zeros(epochs)

    #SGD Steps
    for epoch in range(epochs):
      self.__forward__(X)
      J[epoch]= cross_entropy(Y, self.Z[2])
      #Weight update rules for output layer(Layer 2)
      self.W[2] -= eta*(1/N)* self.Z[1].T@(self.Z[2] - Y)
      self.B[2] -= eta*(1/N)*(self.Z[2]-Y).sum(axis=0)
      #Weight Update Rule for Layer 1
      #self.W[1] -= eta*(1/N)*X.T@((self.Z[2]-Y)@self.W[2].T*(1-self.Z[1]**2))
      #self.B[1] -= eta*(1/N)*((self.Z[2]-Y)@self.W[2].T*(1-self.Z[1]**2)).
↪sum(axis=0)
      self.W[1] -= eta*(1/N)*X.T@((self.Z[2]-Y)@self.W[2].T*(1-self.Z[1]**2))
      self.B[1] -= eta*(1/N)*((self.Z[2]-Y)@self.W[2].T*(1-self.Z[1]**2)).
↪sum(axis=0)

    if show_curve:
      plt.figure()
      plt.plot(J)
      plt.xlabel('epochs')
      plt.ylabel('$\mathcal{J}$')
      plt.title('Training Curve')
      plt.show()

  def __forward__(self, X):
    self.Z ={0:X}
    for l in sorted(self.W.keys()):
      self.Z[l] = self.a[l](self.Z[l-1]@self.W[l] + self.B[l])

  def predict(self, X):
    self.__forward__(X)
    return self.Z[2].argmax(axis=1)
    #return (self.Z[2] > 0.5).astype(int)
```

[209]:
```
# Define ranges for hyperparameters to test
neurons_list = [2, 4, 6, 8]  # Number of neurons to try
eta_list = [0.01, 0.05, 0.1]  # Learning rates to test
epochs_list = [2000, 4000, 8000]  # Epochs to test
```

```python
best_accuracy = 0
best_params = {'neurons': None, 'eta': None, 'epochs': None}

# Loop through all combinations of hyperparameters
for neurons in neurons_list:
    for eta in eta_list:
        for epochs in epochs_list:
            print(f"Trying: Neurons={neurons}, Eta={eta}, Epochs={epochs}")

            # Initialize the model with the current configuration
            my_ann = Shallow_ANN()

            # Fit the model with current hyperparameters
            my_ann.fit(X_train, y_train, neurons=neurons, eta=eta,␣
 ↪epochs=epochs, show_curve=False)

            # Predict on the test set
            y_hat_2LFF = my_ann.predict(X_test)

            # Calculate accuracy
            accuracy_val = accuracy(y_test, y_hat_2LFF)
            print(f"Accuracy: {accuracy_val:.4f} | Neurons: {neurons}, Eta:␣
 ↪{eta}, Epochs: {epochs}")

            # Track the best performing hyperparameters
            if accuracy_val > best_accuracy:
                best_accuracy = accuracy_val
                best_params['neurons'] = neurons
                best_params['eta'] = eta
                best_params['epochs'] = epochs

# Print the best result
print(f"Best Accuracy: {best_accuracy:.4f}")
print(f"Best Parameters: Neurons={best_params['neurons']},␣
 ↪Eta={best_params['eta']}, Epochs={best_params['epochs']}")
```

[212]:
```python
my_ann = Shallow_ANN()
#neurons= 2,  eta=0.001, epochs = 30000
#eta=0.1, epochs=4000
# Neurons=4, Eta=0.1, Epochs=8000
my_ann.fit(X_train, y_train, neurons= 4,  eta=0.1, epochs = 8000, show_curve=␣
 ↪True )
#my_ann.fit(X_train, y_train, neurons= 6, eta=1e-3, epochs=1e4, show_curve=␣
 ↪True )
y_hat_2LFF =my_ann.predict(X_test)
```

```python
print("Accuracy: ", accuracy(y_test, y_hat_2LFF))
print(my_ann.W)
print(my_ann.B)
```

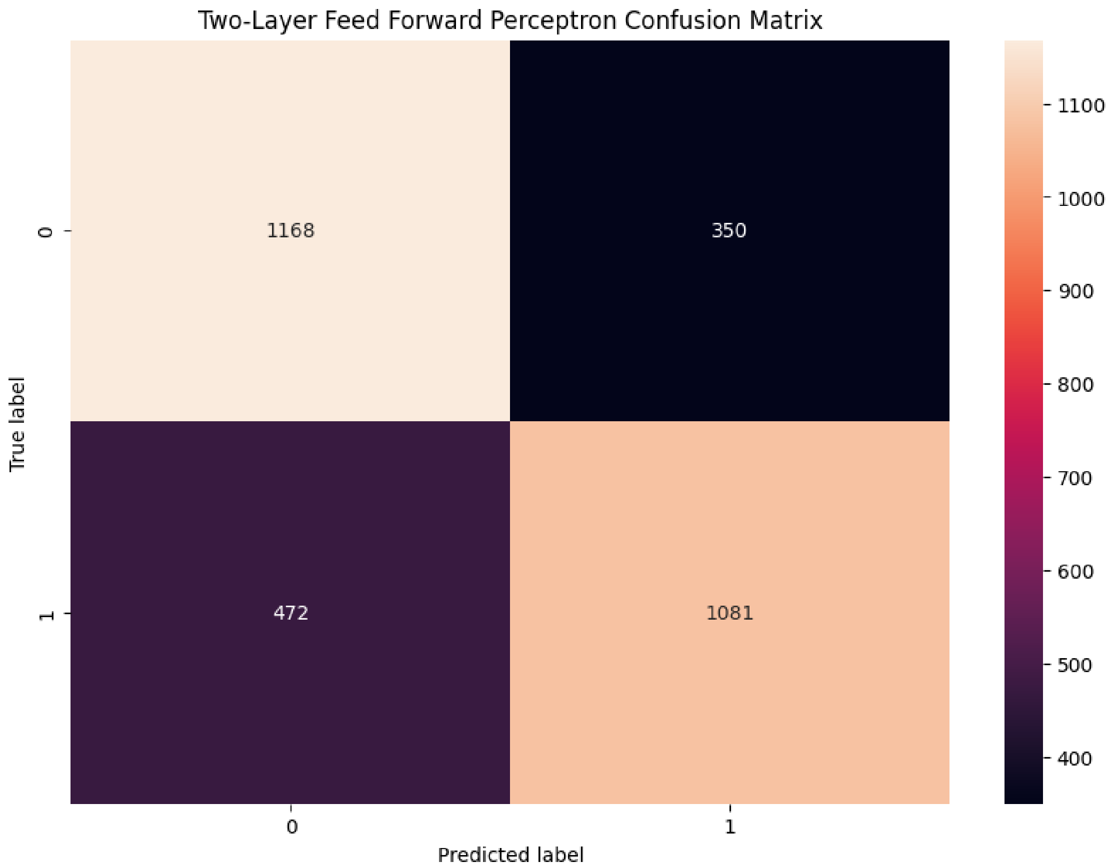



```
Accuracy:  0.7323347443829371
{1: array([[ 0.62799951,  0.53056275, -1.13659122, -0.01950681],
       [-0.51098416, -1.42374138, -0.66142178,  1.98602998],
       [-0.11328237, -0.5119192 , -0.97500364, -0.09710407],
       [-0.97496391, -0.36327879,  0.02422441,  0.251694  ],
       [-2.17776282,  0.31109604,  0.27490795, -0.21974436],
       [ 0.08837398, -0.57468743,  0.59100345, -0.03834669],
       [-0.48482615, -1.23939884,  0.79512002, -0.34500277],
       [ 0.63977724, -1.26610834,  0.13822085,  0.02210972],
       [-0.25397988,  0.1944344 , -0.70004899,  0.33049197],
       [ 0.65995321, -0.11790284,  0.39217273,  0.0213824 ],
       [ 3.92258091, -0.56943913, -1.26083242,  0.13298094]]), 2: array([[
0.05297944, -0.44038011],
       [ 0.17970899, -0.08381809],
       [ 0.62186464,  0.41513336],
       [-2.55111934,  0.43739169]])}
```

```
{1: array([-2.09331761, -0.57821027, -1.58123866, -1.31860084]), 2:
array([0.62954312, 0.95837611])}
```

[213]:
```
#.reshape(-1)
## Two-Layer Feed Forward Perceptron
plt.figure(figsize=(10,7))
y_actual_2LFF = pd.Series(y_test, name='Actual')
y_pred_2LFF = pd.Series(y_hat_2LFF, name='Predicted')
cm = pd.crosstab(y_actual_2LFF, y_pred_2LFF)
ax = sns.heatmap(cm, annot=True, fmt="d")
plt.title("Two-Layer Feed Forward Perceptron Confusion Matrix")
plt.ylabel('True label')
plt.xlabel('Predicted label')
```

[213]:
```
Text(0.5, 47.7222222222222, 'Predicted label')
```



[145]:
```
# #testing 2
# class Shallow_ANN2():

#   def fit(self, X, y, neurons=6, eta=1e-3, epochs=1e3, show_curve= True):
```

```
#     epochs= int(epochs)
#     N, D = X.shape
#     Y = one_hot_encode(y)
#     K= Y.shape[1]

#     #Weights Initialization
#     self.W ={l: np.random.randn(M[0], M[1]) for l, M in enumerate(zip([D,␣
↪neurons],[neurons, K]), 1)}
#     self.B = {l: np.random.randn(M) for l, M in enumerate([neurons, K], 1)}
#     #Define Activations
#     self.a ={1:np.tanh, 2:softmax}

#     J= np.zeros(epochs)

#     #SGD Steps
#     for epoch in range(epochs):
#       self.__forward__(X)
#       J[epoch]= cross_entropy(Y, self.Z[2])
#       #Weight update rules for output layer(Layer 2)
#       self.W[2] -= eta*(1/N)* self.Z[1].T@(self.Z[2] - Y)
#       self.B[2] -= eta*(1/N)*(self.Z[2]-Y).sum(axis=0)
#       #Weight Update Rule for Layer 1
#       #self.W[1] -= eta*(1/N)*X.T@((self.Z[2]-Y)@self.W[2].T*(1-self.Z[1]**2))
#       #self.B[1] -= eta*(1/N)*((self.Z[2]-Y)@self.W[2].T*(1-self.Z[1]**2)).
↪sum(axis=0)
#       self.W[1] -= eta*(1/N)*X.T@((self.Z[2]-Y)@self.W[2].T*(1-self.Z[1]**2))
#       self.B[1] -= eta*(1/N)*((self.Z[2]-Y)@self.W[2].T*(1-self.Z[1]**2)).
↪sum(axis=0)

#     if show_curve:
#       plt.figure()
#       plt.plot(J)
#       plt.xlabel('epochs')
#       plt.ylabel('$\mathcal{J}$')
#       plt.title('Training Curve')
#       plt.show()

#   def __forward__(self, X):
#     self.Z ={0:X}
#     for l in sorted(self.W.keys()):
#       self.Z[l] = self.a[l](self.Z[l-1]@self.W[l] + self.B[l])

#   def predict(self, X):
#     self.__forward__(X)
#     return self.Z[2].argmax(axis=1)
```

[146]:
```
# my_ann2 = Shallow_ANN2()
# my_ann2.fit(X_train, y_train, neurons= 2,  eta=0.001, epochs = 30000,␣
↪show_curve= True )
# y_hat_my_ann2 =my_ann2.predict(X_test)

# print("Accuracy: ", accuracy(y_test, y_hat_my_ann2))
# print(my_ann2.W)
# print(my_ann2.B)
```

[147]:
```
# #neurons_list = [2, 3, 5]
# # eta_list = [1e-3, 1e-2, 1e-1]
# # epochs_list = [1e4, 2e4, 3e4]

# neurons_list = [2, 3, 4]       # Slight increase in neuron count
# eta_list = [0.001, 0.002, 0.005]  # Fine-tuning the learning rate
# epochs_list = [20000, 25000, 30000]  # Reducing epochs
# l2_list = [0.001, 0.01]

# best_accuracy = 0
# best_params = {'neurons': None, 'eta': None, 'epochs': None}

# # Loop through different combinations of hyperparameters
# for neurons in neurons_list:
#     for eta in eta_list:
#         for epochs in epochs_list:
#             my_ann = Shallow_ANN()  # Initialize your ANN
#             my_ann.fit(X_train, y_train, neurons=neurons, eta=eta,␣
↪epochs=int(epochs), show_curve=False)

#             # Predict and calculate accuracy
#             y_hat_2LFF = my_ann.predict(X_test)
#             accuracy_val = accuracy(y_test, y_hat_2LFF)

#             # Keep track of the best accuracy and parameters
#             if accuracy_val > best_accuracy:
#                 best_accuracy = accuracy_val
#                 best_params['neurons'] = neurons
#                 best_params['eta'] = eta
#                 best_params['epochs'] = epochs

# print(f"Best Accuracy: {best_accuracy:.4f}")
# print(f"Best Parameters: Neurons={best_params['neurons']},␣
↪Eta={best_params['eta']}, Epochs={best_params['epochs']}")
```

4 Artificial Neural Net with Back Propagation and Variable Architecture

[214]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

[215]:
```
# Useful functions
# Activations
def linear(H):
  return H

def ReLU(H):
  return H*(H>0)

def sigmoid(H):
  return 1/(1+np.exp(-H))

def softmax(H):
  eH = np.exp(H)
  return eH/eH.sum(axis=1, keepdims= True)

# Loss Functions

def cross_entropy(Y, P_hat):
  return -(1/len(Y)*np.sum(Y*np.log(P_hat)))

def binary_cross_entropy(y, p_hat):
  return -(1/len(y))*np.sum(y*np.log(p_hat)+ (1-y)*np.log(1-p_hat))

def OLS(Y, Y_hat):
  return (1/(2*len(Y)))* np.sum((Y-Y_hat)**2)


#Metrics
def accuracy(y, y_hat):
  return np.mean(y == y_hat)

def R2(y, y_hat):
  return 1-np.sum((y-y_hat)**2)/ np.sum((y-y.mean())**2)

# Misc
def one_hot(y):
  N= len(y)
  K=len(set(y))
  Y= np.zeros((N,K))
  for i in range(N):
```

```
    Y[i,y[i]]=1
  return Y
```

[216]:
```
# Derivatives of Activation Functions
def derivative(Z,a):

  if a==linear:
    return 1

  elif a==sigmoid:
    return Z*(1-Z)

  elif a==np.tanh:
    return 1-Z**2

  elif a==ReLU:
    return (Z>0).astype(int)

  else:
    ValueError("Unknown Activation")
```

[151]:
```
# # Class
# class ANN():

#   def __init__(self, architecture, activations=None, mode=0):
#     self.mode=mode
#     self.architecture=architecture
#     self.activations= activations
#     self.L = len(architecture)+1

#   def fit(self, X, y, eta=1e-3, epochs=1e3, show_curve=False):
#     epochs=int(epochs)
#     #Classifier, mode=0, Regressor, mode=1
#     if self.mode:
#       Y=y
#       K=1
#     else:
#       #Y =one_hot(y)
#       Y=y.reshape(-1,1)
#       #Y=y
#       K =Y.shape[1]

#     N,D = X.shape

#     #Iniatize Weights(and Biases)
#     self.W = {l: np.random.randn(M[0],M[1]) for l, M in␣
↪enumerate(zip(([D]+self.architecture), (self.architecture+[K])),1)}
```

```
#     self.B = {l: np.random.randn(M) for l,M in enumerate(self.
↪architecture+[K],1)}

#     #Activation Setup
#     if self.activations is None:
#       self.a ={l:ReLU for l in range(1,self.L)}
#     else:
#       self.a = {l: act for l,act in enumerate(self.activations,1)}

#     #Output activation Functions
#     if self.mode:
#       self.a[self.L]=linear
#     else:
#       self.a[self.L]=sigmoid

#     #Define Loss
#     J = np.zeros(epochs)

#     #Training Cycle
#     for epoch in range(epochs):
#       self.__forward__(X)

#       if self.mode:
#         J[epoch]= OLS(Y, self.Z[self.L])
#       else:
#         J[epoch]=binary_cross_entropy(Y, self.Z[self.L])
#       #Back Prop
#       dH = (1/N)*(self.Z[self.L]-Y)
#       for l in sorted(self.W.keys(), reverse=True):

#         dW = self.Z[l-1].T@dH
#         dB = dH.sum(axis=0)
#         #Weight Update Rules per layer
#         self.W[l] -=eta*dW
#         self.B[l] -=eta*dB

#         if l>1:
#           dZ =dH@self.W[l].T
#           dH = dZ*derivative(self.Z[l-1],self.a[l-1])

#     if show_curve:
#       plt.figure()
#       plt.plot(J)
#       plt.xlabel("epochs")
#       plt.ylabel("$\mathcal{J}$")
#       plt.title("Training Curve")
#       plt.show()
```

```
#   def __forward__(self, X):
#     self.Z ={0:X}
#     for l in sorted(self.W.keys()):
#       self.Z[l] = self.a[l](self.Z[l-1]@self.W[l]+self.B[l])

#   def predict(self, X):
#     self.__forward__(X)
#     if self.mode:
#       return self.Z[self.L]
#     else:
#       #return self.Z[self.L].argmax(axis=1)
#       return (self.Z[self.L] > 0.5).astype(int)
```

[152]:

```
# import numpy as np

# # Define ranges for hyperparameters
# architectures = [[6, 10, 4], [6, 12, 4]]  # Different architectures to try
# eta_list = [1e-4, 1e-3, 1e-2]  # Learning rate options
# epochs_list = [50000, 100000, 150000]  # Epoch options
# l2_list = [0.001, 0.01]  # Regularization strength options
# dropout_list = [0.2, 0.3]  # Dropout rates

# best_accuracy = 0
# best_params = {'architecture': None, 'eta': None, 'epochs': None, 'l2': None,␣
↪'dropout': None}

# # Loop through all combinations of hyperparameters
# for architecture in architectures:
#     for eta in eta_list:
#         for epochs in epochs_list:
#             for l2 in l2_list:
#                 for dropout_rate in dropout_list:
#                     # Initialize the ANN model with the current architecture,␣
↪L2 regularization, and dropout
#                     my_ann_classifier = ANN(architecture=architecture,
#                                             activations=[np.tanh] *␣
↪len(architecture),
#                                             l2=l2, dropout_rate=dropout_rate)

#                     # Fit the model with the current hyperparameters
#                     for epoch in range(int(epochs)):
#                         my_ann_classifier.fit(X_train, y_train, eta=eta,␣
↪epochs=1, show_curve=False)  # Training for 1 epoch at a time

#                         # Predict on the test set and calculate accuracy␣
↪after each epoch
```

```
#                           y_hat_ANN = my_ann_classifier.predict(X_test)
#                           accuracy_val = accuracy(y_test, y_hat_ANN)

#                           # Print accuracy and parameters for each epoch
#                           print(f"Epoch: {epoch + 1}, Architecture:␣
↪{architecture}, Eta: {eta}, L2: {l2}, Dropout: {dropout_rate}, Accuracy:␣
↪{accuracy_val:.4f}")

#                           # Track the best accuracy and the best parameters
#                           if accuracy_val > best_accuracy:
#                               best_accuracy = accuracy_val
#                               best_params['architecture'] = architecture
#                               best_params['eta'] = eta
#                               best_params['epochs'] = epoch + 1  # Track the␣
↪epoch at which the best result occurred
#                               best_params['l2'] = l2
#                               best_params['dropout'] = dropout_rate

# # Print the best results
# print(f"Best Accuracy: {best_accuracy:.4f}")
# print(f"Best Parameters: Architecture={best_params['architecture']},␣
↪Eta={best_params['eta']}, "
#       f"Epochs={best_params['epochs']}, L2={best_params['l2']},␣
↪Dropout={best_params['dropout']}")
```

[153]:
```
# my_ann_classifier = ANN(architecture=[6,8, 4], activations=[np.tanh]*3)
# my_ann_classifier.fit(X_train,y_train, eta=1e-3, epochs=1e5, show_curve=True)
# y_hat_ANN=my_ann_classifier.predict(X_test)

# print(my_ann_classifier.W)
# print(my_ann_classifier.B)
# print(f"Testing Accuracy:  {accuracy(y_test,y_hat_ANN):0.4f}")
```

[153]:
```

```

[217]:
```
class ANN():

  def __init__(self, architecture, activations=None, mode=0):
    self.mode=mode
    self.architecture=architecture
    self.activations= activations
    self.L = len(architecture)+1

  def fit(self, X, y, eta=1e-3, epochs=1e3, show_curve=False):
    epochs=int(epochs)
    #Classifier, mode=0, Regressor, mode=1
    if self.mode:
```

```
        Y=y
        K=1
    else:
        Y =one_hot(y)
        #Y = y.reshape(-1, 1)
        K =Y.shape[1]

    N,D = X.shape

    #Iniatize Weights(and Biases)
    self.W = {l: np.random.randn(M[0],M[1]) for l, M in enumerate(zip(([D]+self.
↪architecture), (self.architecture+[K])),1)}
    self.B = {l: np.random.randn(M) for l,M in enumerate(self.
↪architecture+[K],1)}

    #Activation Setup
    if self.activations is None:
        self.a ={l:ReLU for l in range(1,self.L)}
    else:
        self.a = {l: act for l,act in enumerate(self.activations,1)}

    #Output activation Functions
    if self.mode:
        self.a[self.L]=linear
    else:
        self.a[self.L]=softmax

    #Define Loss
    J = np.zeros(epochs)

    #Training Cycle
    for epoch in range(epochs):
        self.__forward__(X)

        if self.mode:
            J[epoch]= OLS(Y, self.Z[self.L])
        else:
            J[epoch]=cross_entropy(Y, self.Z[self.L])
        #Back Prop
        dH = (1/N)*(self.Z[self.L]-Y)
        for l in sorted(self.W.keys(), reverse=True):

            dW = self.Z[l-1].T@dH
            dB = dH.sum(axis=0)
            #Weight Update Rules per layer
            self.W[l] -=eta*dW
            self.B[l] -=eta*dB
```

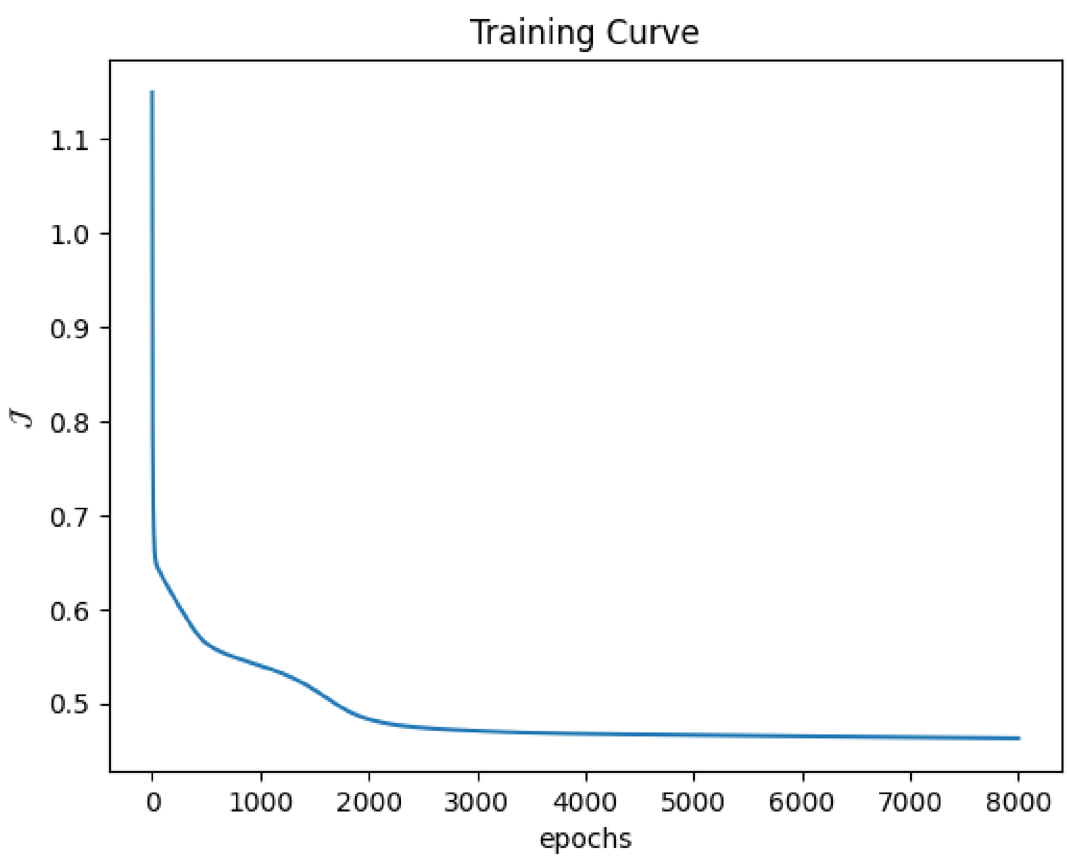
```
        if l>1:
          dZ =dH@self.W[l].T
          dH = dZ*derivative(self.Z[l-1],self.a[l-1])

    if show_curve:
      plt.figure()
      plt.plot(J)
      plt.xlabel("epochs")
      plt.ylabel("$\mathcal{J}$")
      plt.title("Training Curve")
      plt.show()

  def __forward__(self, X):
    self.Z ={0:X}
    for l in sorted(self.W.keys()):
      self.Z[l] = self.a[l](self.Z[l-1]@self.W[l]+self.B[l])

  def predict(self, X):
    self.__forward__(X)
    if self.mode:
      return self.Z[self.L]
    else:
      return self.Z[self.L].argmax(axis=1)
      #return (self.Z[2] > 0.5).astype(int)
```

[218]:

```
architecture_list = [[6, 8, 4], [6, 10, 4], [6, 12, 6]]
eta_list = [0.01, 0.05, 0.1]
epochs_list = [2000, 4000, 6000]

best_accuracy = 0
best_params = {'architecture': None, 'eta': None, 'epochs': None}

for architecture in architecture_list:
    for eta in eta_list:
        for epochs in epochs_list:
            print(f"Trying: Architecture={architecture}, Eta={eta},␣
 ↪Epochs={epochs}")
            my_ann_classifier = ANN(architecture=architecture, activations=[np.
 ↪tanh] * len(architecture))
            my_ann_classifier.fit(X_train, y_train, eta=eta, epochs=epochs,␣
 ↪show_curve=False)

            y_hat_ANN = my_ann_classifier.predict(X_test)
            accuracy_val = accuracy(y_test, y_hat_ANN)
            print(f"Accuracy: {accuracy_val:.4f} | Architecture:␣
 ↪{architecture}, Eta: {eta}, Epochs: {epochs}")
```

```
            if accuracy_val > best_accuracy:
                best_accuracy = accuracy_val
                best_params['architecture'] = architecture
                best_params['eta'] = eta
                best_params['epochs'] = epochs

print(f"Best Accuracy: {best_accuracy:.4f}")
print(f"Best Parameters: Architecture={best_params['architecture']}, 
 ↪Eta={best_params['eta']}, Epochs={best_params['epochs']}")
```

[221]:
```
my_ann_classifier = ANN(architecture=[6,8, 4], activations=[np.tanh]*3)
#neurons= 2,  eta=0.001, epochs = 30000
#epochs= 4000, eta= 0.1
#neurons= 4,  eta=0.1, epochs = 8000
#[6, 8, 4], Eta=0.05, Epochs=2000 ### Good Good
my_ann_classifier.fit(X_train,y_train, eta=0.1, epochs=8000, show_curve=True)
y_hat_ANN=my_ann_classifier.predict(X_test)

print(my_ann_classifier.W)
print(my_ann_classifier.B)
print(f"Testing Accuracy:  {accuracy(y_test,y_hat_ANN):0.4f}")
```

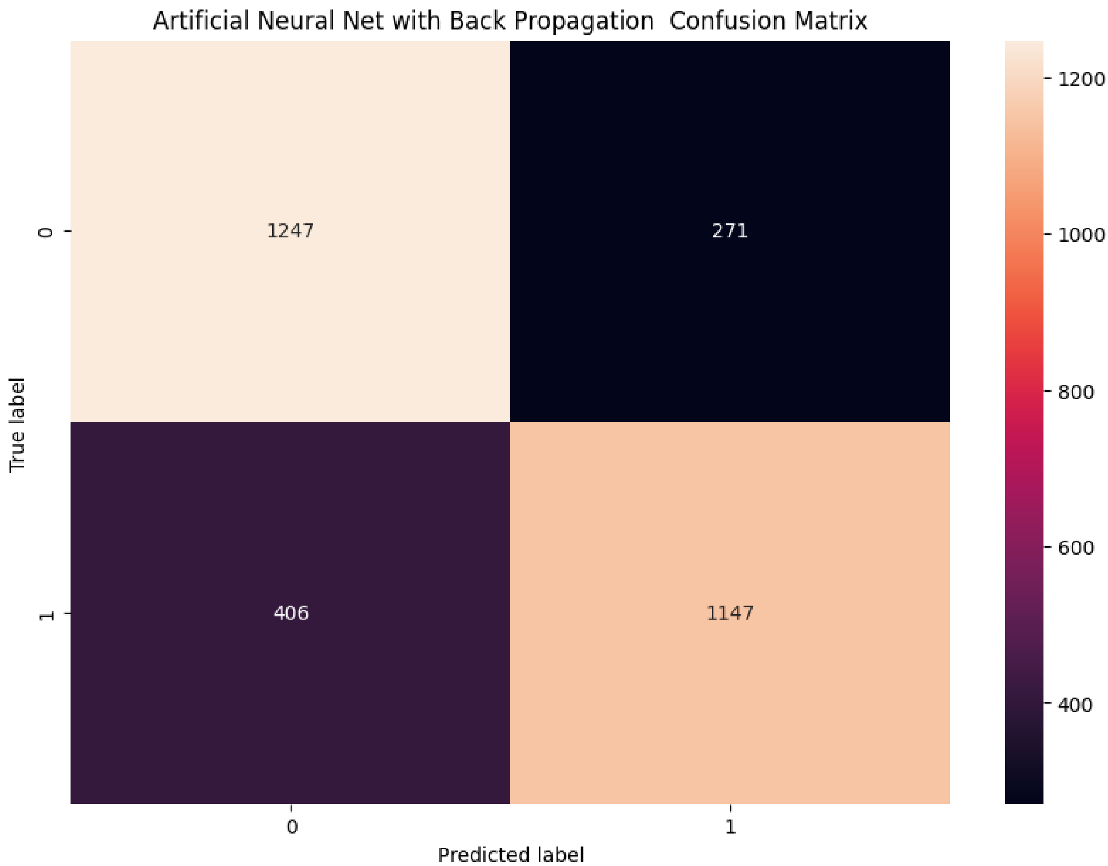


```
{1: array([[ 1.39885940e-01, -3.46816181e-01, -2.44269957e-03,
        -1.46614427e+00,  4.54441082e-01, -8.26840465e-02],
       [-2.22183142e-01,  4.88728903e-01,  7.27213154e-01,
        -1.12152277e+00, -1.31947946e+00,  1.02520541e+00],
       [ 1.09709879e+00,  2.44498451e+00,  5.97530229e-02,
        -1.20171851e+00,  9.60928561e-02, -1.12679577e-01],
       [-6.53403824e-01, -3.79915557e-01,  4.98311993e-01,
        -9.65117650e-01,  8.83925045e-01, -4.81400196e-01],
       [-5.77344137e-01, -4.78135093e-01,  1.76498100e+00,
        -8.93951301e-01,  5.58120743e-01, -2.90120389e+00],
       [ 5.70413670e-01,  1.59835684e+00,  9.78115527e-03,
         6.62456461e-01, -1.24701471e+00, -1.46914999e-02],
       [-8.97547730e-01,  1.16012852e+00, -2.75756094e-01,
        -6.01603914e-01,  7.14411339e-01, -1.51353098e-01],
       [-3.44007867e-01,  1.16650798e+00, -6.35001654e-02,
         4.71958758e-01, -4.80404889e-01,  6.21837697e-02],
       [-1.34290954e+00,  7.40478624e-01, -2.01108437e-01,
         1.23856882e-02, -1.12685441e+00,  5.03098793e-01],
       [ 7.19026458e-01, -3.24808592e-01,  1.92167047e-01,
        -9.72255360e-01, -1.81734376e+00, -1.14926915e-01],
       [ 1.09411049e+00,  1.87023962e+00,  1.11856275e-01,
        -1.57432674e+00, -1.57010973e+00, -2.23657156e-01]]), 2: array([[
2.54173771e-01,  4.18619101e-01, -3.66365072e-01,
        -4.95916488e-01, -1.37515834e+00, -2.76525393e-03,
         5.96645601e-01, -2.34943298e-01],
       [-1.17973680e+00,  1.48744195e-01,  4.01671401e-01,
        -2.24036882e+00,  7.81367073e-01, -7.78252378e-01,
        -8.46743477e-01,  1.19404024e+00],
       [-1.67444299e+00, -6.68664425e-01,  1.77160215e+00,
         9.18652919e-01,  3.19068975e-01,  4.82779473e-01,
        -4.32323611e-01, -1.90636568e+00],
       [-3.33239476e-01,  3.21441233e-01, -7.11006115e-01,
        -3.56910607e-02, -1.85439018e+00,  4.73392543e-01,
        -5.69565800e-01,  1.66077869e+00],
       [-7.68647032e-01, -6.95556368e-01,  8.47658157e-01,
         8.57749603e-01, -4.31326891e-01, -2.59540975e+00,
         1.92448745e+00, -1.55932690e-01],
       [ 6.98537002e-01,  3.49419916e+00,  1.70145171e-01,
        -4.66692763e-01, -5.27498013e-01, -6.26288308e-01,
        -1.13384006e+00, -2.43869150e+00]]), 3: array([[-1.69736097,
1.78100354,  0.17887751,  0.53644517],
       [ 0.3459838 ,  0.36028619,  1.16412572,  1.93996936],
       [ 1.17986617,  0.55335737,  0.4335691 ,  0.022611  ],
       [-1.84208271, -0.37581754, -0.12525235,  0.90426299],
       [-0.44722313,  0.157237  , -0.01899177, -0.32723522],
       [ 0.33182308, -0.29660853, -0.3262923 ,  1.19500884],
```

```
       [-0.82534787,  0.59978189,  0.90385401,  1.88020518],
       [-0.96620902,  0.26941558, -1.35628811,  2.75031284]]), 4:
array([[-2.70499896,  0.74720213],
       [ 0.50182   , -0.77742429],
       [-0.98312157,  0.33932148],
       [ 1.28053735,  0.23166609]])}
{1: array([-0.66249792,  0.79834909, -1.73961982, -0.69830509, -0.63001626,
        0.21072266]), 2: array([ 0.85803675,  0.62628061, -0.31820561,
0.30859863, -0.67971461,
        1.34473707, -0.05289225,  0.32356479]), 3: array([ 0.95387333,
0.40643579, -0.76911796,  0.11179271]), 4: array([-1.61178633,  0.38996769])}
Testing Accuracy:  0.7796
```

[222]:
```
## Artificial Neural Net with Back Propagation
plt.figure(figsize=(10,7))
y_actual_ANN = pd.Series(y_test, name='Actual')
y_pred_ANN = pd.Series(y_hat_ANN, name='Predicted')
cm = pd.crosstab(y_actual_ANN, y_pred_ANN)
ax = sns.heatmap(cm, annot=True, fmt="d")
plt.title("Artificial Neural Net with Back Propagation  Confusion Matrix")
plt.ylabel('True label')
plt.xlabel('Predicted label')
```

[222]:
```
Text(0.5, 47.7222222222222, 'Predicted label')
```




```
[ ]: # my_ann_classifier = ANN(architecture=[6,8, 4], activations=[ReLU] * (2) + [np.
     ↪tanh])
     # my_ann_classifier.fit(X_train,y_train, eta=0.05, epochs = 6000,␣
     ↪show_curve=True)
     # y_hat_ANN=my_ann_classifier.predict(X_test)

     # print(my_ann_classifier.W)
     # print(my_ann_classifier.B)
     # print(f"Testing Accuracy:  {accuracy(y_test,y_hat_ANN):0.4f}")
```

```
[ ]: # def scale_new_data_point(new_data_point, scaling_params, columns):
     #     scaled_data_point = []
     #     for i, column in enumerate(columns):
     #         if column in scaling_params:
     #             min_value = scaling_params[column]['min']
     #             max_value = scaling_params[column]['max']
     #             scaled_value = (new_data_point[i] - min_value) / (max_value -␣
     ↪min_value)
     #             scaled_data_point.append(scaled_value)
```

```
#         else:
#             scaled_data_point.append(new_data_point[i])

#     return scaled_data_point

# columns = ['longitude', 'latitude', 'lot_acres', 'sqrt_ft', 'bedrooms',␣
↪'bathrooms', 'garage', 'fireplaces']
# teacher_test = [[-110.3782, 31.356362, 2154, 10500, 13, 10, 0, 6]]

# scaled_teacher_test = [scale_new_data_point(point, scaling_params, columns)␣
↪for point in teacher_test]
# scaled_teacher_test

# Test_case = ANN.predict(scaled_teacher_test)
# Test_case
```

[ ]:

```

```