In [1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
```

1. Getting aquainted with the dataset

- `ÌD` : is like a name.
- `Book_length(mins)_overall` : is the sum of the lengths of purchases.
- `Book_length(mins)_avg` : is the sum of the lengths of purchases divided by the number of purchases. Notice we don't need the number of purchases column because we ca get it from `Book_length(mins)_overall / Book_length(mins)_avg` .
- `Price_overall` & `Price_avg` : Same as Book length, the price variable is almost always a good predictor.
- `Review` : is boolean. It shows if the customer left a review. If so, `Review10/10` saves the review left by the user. While most users don't left a review we fill the missing reviews by avrage review column.
- `Minutes_listened` : is a measure of engagement, the total of minutes the user listen to audiobooks.
- `Completion` : is the `Minutes_listened / Book_length(mins)_overall` .
- `Support_Request` : Shows the total number of support request (forgotten password to assistance).
- `Last_Visited_mins_Purchase_date` : the bigger the difference, the bigger sooner the engagement. If the value is 0, we are sure the customer has never accessed what he/she has bought.

The data was gathered from the audiobook app, the input data represents `2 years` worth of engagement. We are doing supervised learning so we need `target` . We took extra `6 month` to check if the user converted or not. 1 if the customer buys in the next 6 months, 0 if the customer didn't.

- `target` : 1 if the customer bought again in the last 6 months of data. 0 if the customer did not buy again.

In [2]:
```
data = pd.read_csv("audiobook_data_2.csv", index_col=0)
data.head()
```

Out[2]:

	Book_length(mins)_overall	Book_length(mins)_avg	Price_overall	Price_avg	Review	Review10/10
994	1620.0	1620	19.73	19.73	1	10.00
1143	2160.0	2160	5.33	5.33	0	8.91
2059	2160.0	2160	5.33	5.33	0	8.91
2882	1620.0	1620	5.96	5.96	0	8.91
3342	2160.0	2160	5.33	5.33	0	8.91

2. Exploratory Data Analysis

`Book_length(mins)_overall` & `Book_length(mins)_avg`

- `Book_length(mins)_overall` : is the sum of the lengths of purchases.
- `Book_length(mins)_avg` : is the sum of the lengths of purchases divided by the number of purchases. Notice we don't need the number of purchases column because we ca get it from `Book_length(mins)_overall / Book_length(mins)_avg` .

In [3]:
```
data['Book_length(mins)_overall'][:150].value_counts()  #14084
```

Out[3]:
```
2160.0    79
1620.0    32
648.0     11
1080.0     8
324.0      7
1404.0     3
540.0      3
1188.0     2
1242.0     1
1890.0     1
756.0      1
1332.0     1
594.0      1
Name: Book_length(mins)_overall, dtype: int64
```

In [4]:
```
def book_length(length):
    if length > 1200:
        return 1
    else:
        return 0

data['purchases_hour_>3h'] = data['Book_length(mins)_overall'].apply(book_length)
```

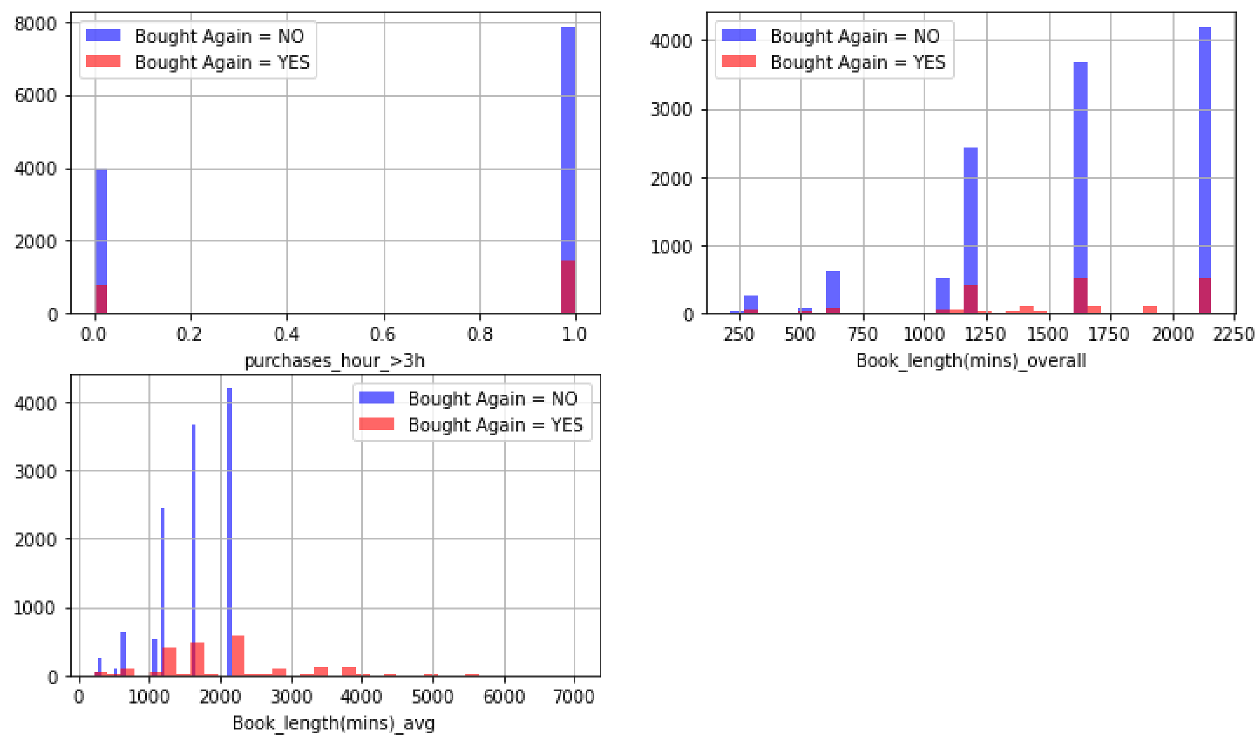
In [5]:
```
data['Book_length(mins)_avg'].apply(book_length).value_counts()
```

Out[5]:
```
1    9480
0    4604
Name: Book_length(mins)_avg, dtype: int64
```

In [6]:
```python
data['purchases_hour_>3h'].value_counts()
```

Out[6]:
```
1    9317
0    4767
Name: purchases_hour_>3h, dtype: int64
```

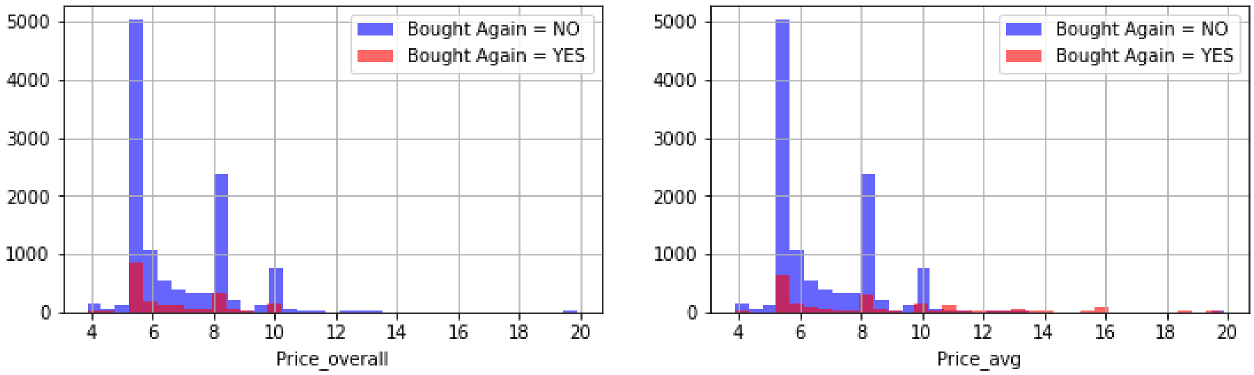
In [7]:
```python
columns = ['purchases_hour_>3h', 'Book_length(mins)_overall', 'Book_length(mins)_avg']
plt.figure(figsize=(12, 7))

for i, column in enumerate(columns, 1):
    plt.subplot(2, 2, i)
    data[data["Target"] == 0][column].hist(bins=35, color='blue', label='Bought Again =
    data[data["Target"] == 1][column].hist(bins=35, color='red', label='Bought Again = '
    plt.legend()
    plt.xlabel(column)
```



Price_overall & Price_avg

- `Price_overall` & `Price_avg` : Same as Book length, the price variable is almost always a good predictor.

In [8]:
```python
columns = ["Price_overall", "Price_avg"]
plt.figure(figsize=(12, 7))
df = data[(data.Price_overall < 20) & (data.Price_avg < 20)]

for i, column in enumerate(columns, 1):
    plt.subplot(2, 2, i)
    df[df["Target"] == 0][column].hist(bins=35, color='blue', label='Bought Again = NO'
    df[df["Target"] == 1][column].hist(bins=35, color='red', label='Bought Again = YES'
    plt.legend()
    plt.xlabel(column)
```



Review & Review10/10

- `Review` : is boolean. It shows if the customer left a review. If so, `Review10/10` saves the review left by the user. While most users don't left a review we fill the missing reviews by avrage review column.

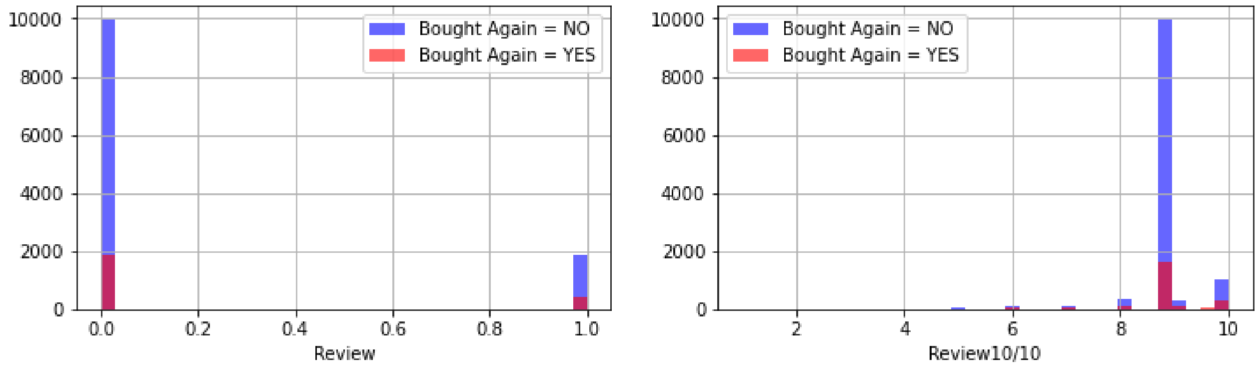
In [9]:
```
print(data[data['Review'] == 0].Target.value_counts(normalize=True))
print(data[data['Review'] == 1].Target.value_counts(normalize=True))
```

```
0    0.843063
1    0.156937
Name: Target, dtype: float64
0    0.831272
1    0.168728
Name: Target, dtype: float64
```

In [10]:
```
data['Review10/10'][:150].value_counts()
```

Out[10]:
```
8.91     120
10.00     13
8.00       7
9.00       6
7.00       2
6.50       1
5.00       1
Name: Review10/10, dtype: int64
```

In [11]:
```
columns = ["Review", "Review10/10"]
plt.figure(figsize=(12, 7))

for i, column in enumerate(columns, 1):
    plt.subplot(2, 2, i)
    data[data["Target"] == 0][column].hist(bins=35, color='blue', label='Bought Again =
    data[data["Target"] == 1][column].hist(bins=35, color='red', label='Bought Again = 
    plt.legend()
    plt.xlabel(column)
```



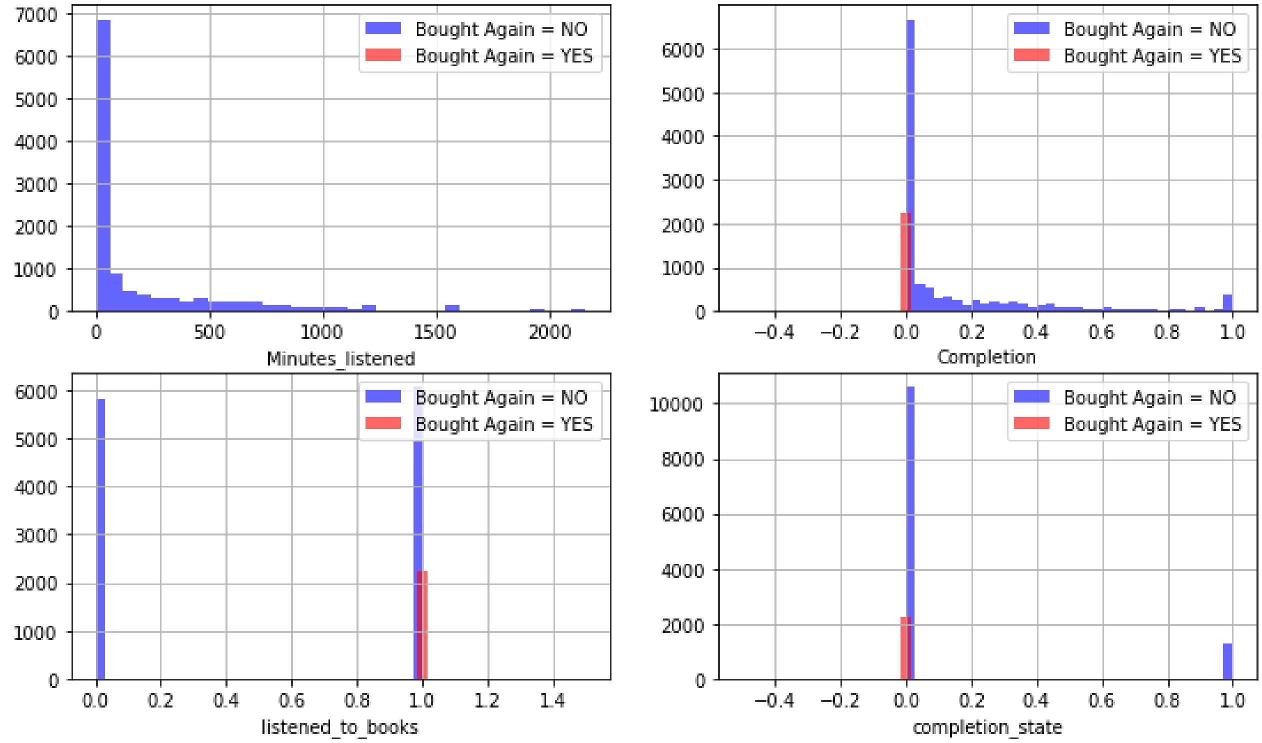
Minutes_listened & Completion

- `Minutes_listened` : is a measure of engagement, the total of minutes the user listen to audiobooks.
- `Completion` : is the `Minutes_listened / Book_length(mins)_overall` .

In [12]:
```
def listened_to_books(minutes):
    if minutes > 0.0:
        return 0
    else:
        return 1
data['listened_to_books'] = data.Minutes_listened.apply(listened_to_books)
```

In [13]:
```
def completion_state(minutes):
    if minutes > 0.5:
        return 1
    else:
        return 0
data['completion_state'] = data.Completion.apply(completion_state)
```

In [14]:
```
columns = ["Minutes_listened", "Completion", "listened_to_books", "completion_state"]
plt.figure(figsize=(12, 7))

for i, column in enumerate(columns, 1):
    plt.subplot(2, 2, i)
    data[data["Target"] == 0][column].hist(bins=35, color='blue', label='Bought Again =
    data[data["Target"] == 1][column].hist(bins=35, color='red', label='Bought Again = 
    plt.legend()
    plt.xlabel(column)
```



In [15]:
```
data.drop('Minutes_listened', axis=1, inplace=True)
```

Support_Request & Last_Visited_mins_Purchase_date

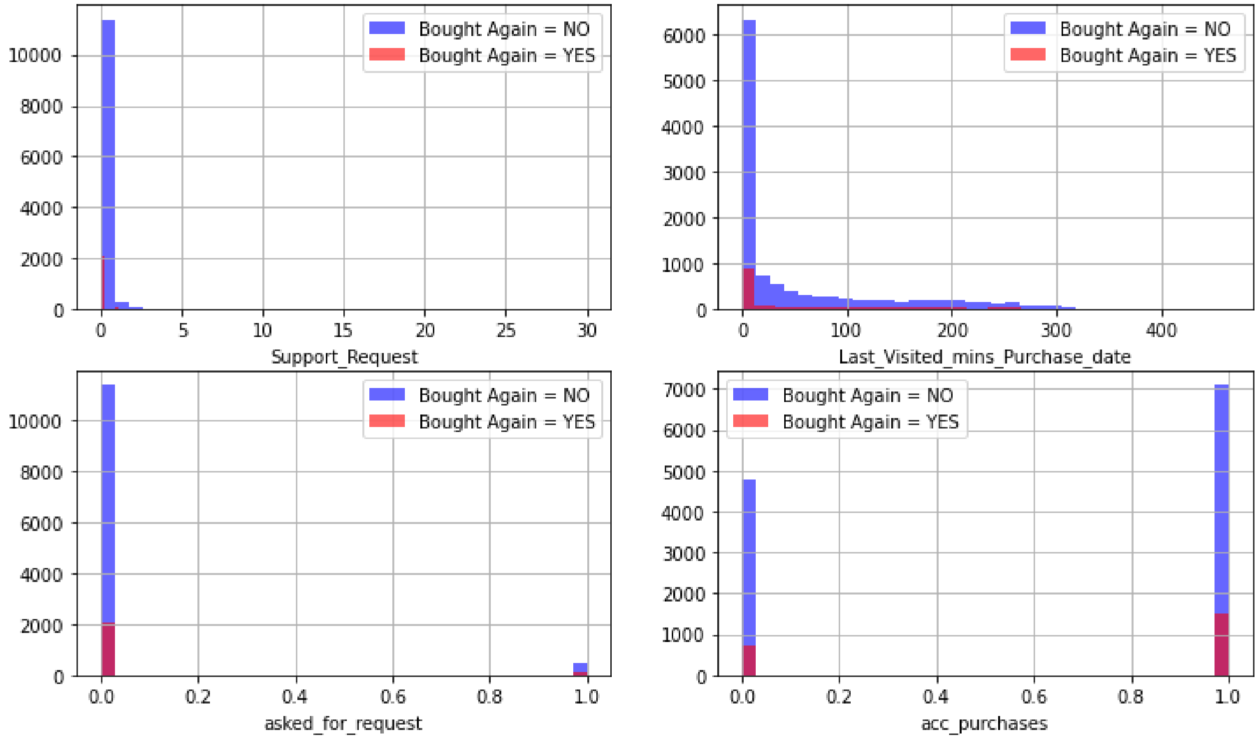
- `Support_Request` : Shows the total number of support request (forgotten password to assistance).
- `Last_Visited_mins_Purchase_date` : the bigger the difference, the bigger sooner the engagement. If the value is 0, we are sure the customer has never accessed what he/she has bought.

In [16]:
```
def asked_for_request(request):
    if request == 0:
        return 0
    else:
        return 1

data["asked_for_request"] = data.Support_Request.apply(asked_for_request)
```

In [17]:
```
def acc_purchases(purchase):
    if purchase == 0:
        return 0
    else:
        return 1
data['acc_purchases'] = data.Last_Visited_mins_Purchase_date.apply(acc_purchases)
```

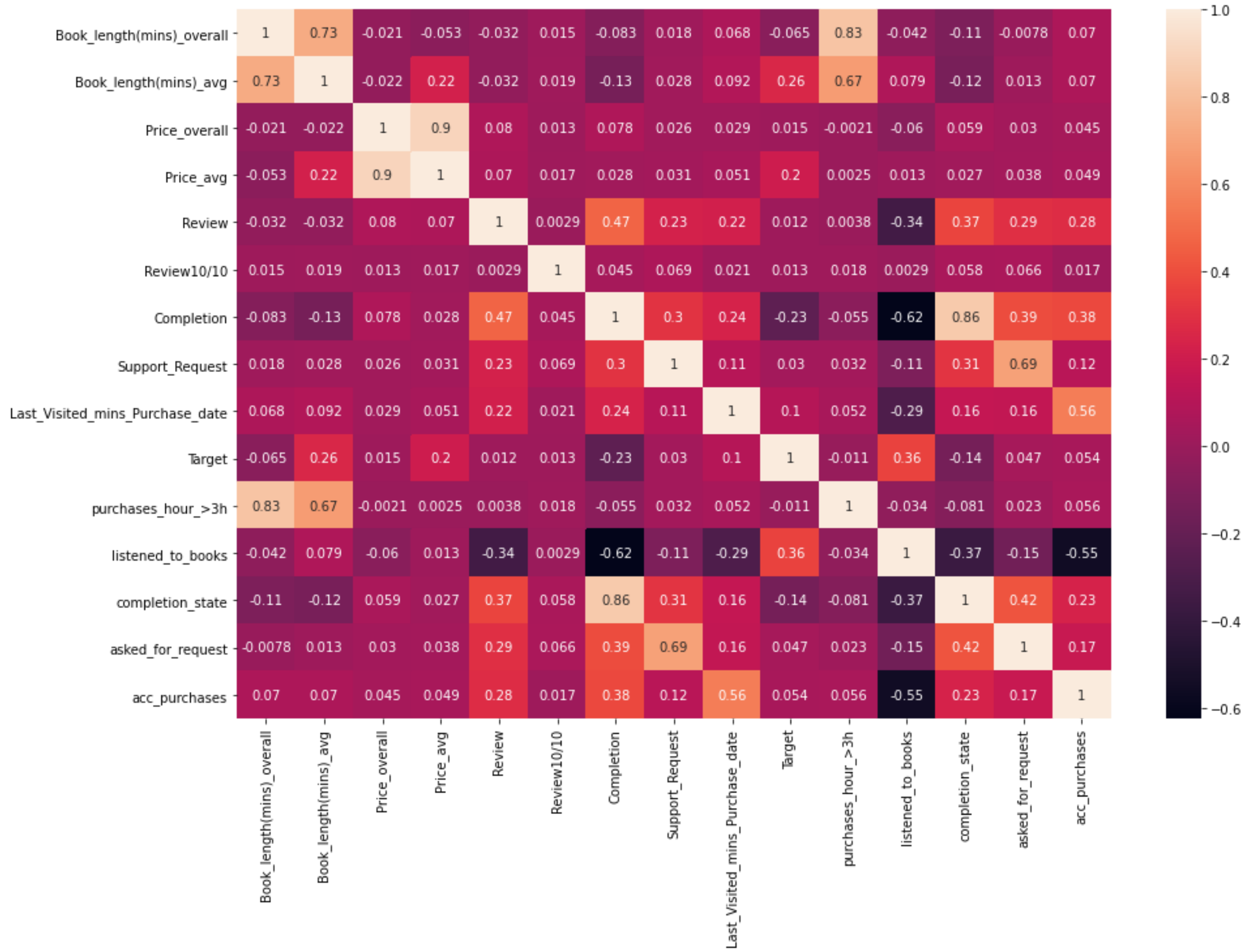
In [18]:
```
columns = ["Support_Request", "Last_Visited_mins_Purchase_date", "asked_for_request", "
plt.figure(figsize=(12, 7))

for i, column in enumerate(columns, 1):
```

```
    plt.subplot(2, 2, i)
    data[data["Target"] == 0][column].hist(bins=35, color='blue', label='Bought Again =
    data[data["Target"] == 1][column].hist(bins=35, color='red', label='Bought Again =
    plt.legend()
    plt.xlabel(column)
```



In [19]:
```
plt.figure(figsize=(15, 10))
sns.heatmap(data.corr(), annot=True)
```

Out[19]: <AxesSubplot:>



In [20]:
```
data.describe()
```

Out[20]:

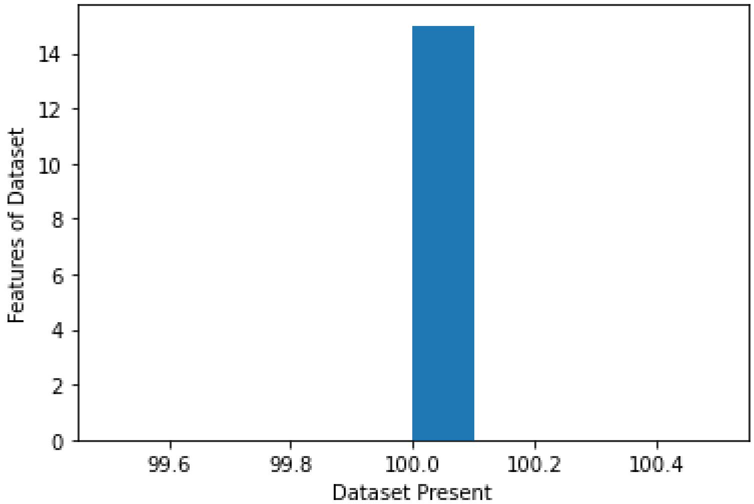
	Book_length(mins)_overall	Book_length(mins)_avg	Price_overall	Price_avg	Review	Rev
count	14084.000000	14084.000000	14084.000000	14084.000000	14084.000000	140
mean	1591.281685	1678.608634	7.103791	7.543805	0.160750	
std	504.340663	654.838599	4.931673	5.560129	0.367313	
min	216.000000	216.000000	3.860000	3.860000	0.000000	
25%	1188.000000	1188.000000	5.330000	5.330000	0.000000	
50%	1620.000000	1620.000000	5.950000	6.070000	0.000000	
75%	2160.000000	2160.000000	8.000000	8.000000	0.000000	
max	2160.000000	7020.000000	130.940000	130.940000	1.000000	

After Partial Cleaning Data and Removing Nan Values

In [21]:
```
df = data
print("Shape of Dataset")
print(df.shape)
```

```
print()
print("unique elements in Features")
print()
print(df.nunique())
print()
print("duplicated Series values")
print(df.duplicated().sum())
print()
print("About Features : ")
print()
print(df.count()/df.isna().count()*100)
x=df.count()/df.isna().count()*100
plt.hist(x)
plt.ylabel("Features of Dataset")
plt.xlabel("Dataset Present")
plt.show()
```

```
Shape of Dataset
(14084, 15)

unique elements in Features

Book_length(mins)_overall          60
Book_length(mins)_avg              58
Price_overall                     349
Price_avg                         476
Review                              2
Review10/10                        24
Completion                        101
Support_Request                    12
Last_Visited_mins_Purchase_date   371
Target                              2
purchases_hour_>3h                  2
listened_to_books                   2
completion_state                    2
asked_for_request                   2
acc_purchases                       2
dtype: int64

duplicated Series values
4734

About Features :

Book_length(mins)_overall          100.0
Book_length(mins)_avg              100.0
Price_overall                      100.0
Price_avg                          100.0
Review                             100.0
Review10/10                        100.0
Completion                         100.0
Support_Request                    100.0
Last_Visited_mins_Purchase_date    100.0
Target                             100.0
purchases_hour_>3h                 100.0
listened_to_books                  100.0
completion_state                   100.0
asked_for_request                  100.0
acc_purchases                      100.0
dtype: float64
```



duplicated Series values 4734

3. Data Pre-processing

Since we are dealing with real life data, we will need to preprocess it a bit. This is the relevant code which is not that hard but refers to data engineering more than machine learning.

- Handling categorical features
- Balance the dataset.

In [22]:
```
print(f"Data shape before removing duplicates: {data.shape}")

# Remove duplicate Features
data = data.T.drop_duplicates()
data = data.T

# Remove Duplicate Rows
data.drop_duplicates(inplace=True)

print(f"Data shape after removing duplicates: {data.shape}")
```

```
Data shape before removing duplicates: (14084, 15)
Data shape after removing duplicates: (9350, 15)
```

In [23]:
```
print(f"{data.Target.value_counts()}")
print(f"{data.Target.value_counts()[0] / data.Target.value_counts()[1]}")
```

```
0.0    7548
1.0    1802
Name: Target, dtype: int64
4.188679245283019
```

In [24]:
```
from sklearn.model_selection import train_test_split
X = data.drop('Target', axis=1)
y = data.Target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=4
```

In [25]:
```
print(f"Train shape: {X_train.shape}")
print(f"Test shape: {X_test.shape}")
```

```
Train shape: (6545, 14)
Test shape: (2805, 14)
```

In [26]:
```
from sklearn.linear_model import LogisticRegression

model = LogisticRegression(solver='liblinear', penalty='l2')
model.fit(X_train, y_train)
```

Out[26]:
```
LogisticRegression(solver='liblinear')
```

liblinear — Library for Large Linear Classification. Uses a coordinate descent algorithm. Coordinate descent is based on minimizing a multivariate function by solving univariate optimization problems in a loop.

(it moves toward the minimum in one direction at a time)

to reduce the chance of model overfitting

A regression model that uses L1 regularization technique is called Lasso Regression and model which uses L2 is called Ridge Regression. The key difference between these two is the penalty term. Ridge regression adds "squared magnitude" of coefficient as penalty term to the loss function.

In [34]:
```
model.score(X_test, y_test)
```

Out[34]:
```
0.8980392156862745
```

In [35]:
```
ypred = model.predict(X_test)
```

In [36]:
```
ypred[:100]
```

Out[36]:
```
array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0.,
       0., 1., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0.,
       0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0.])
```

Here you can see the 13, 18 value is 1 and below the Probability Will Buy is More than 50%

In [37]:
```
print("Not Buy     |   Will Buy ")
print(model.predict_proba(X_test[:20]/100) )
```

```
Not Buy     |   Will Buy
[[0.8644563  0.1355437 ]
 [0.87022153 0.12977847]
```

```
 [0.87033879 0.12966121]
 [0.86818737 0.13181263]
 [0.87106293 0.12893707]
 [0.87088602 0.12911398]
 [0.87121576 0.12878424]
 [0.86476048 0.13523952]
 [0.86603376 0.13396624]
 [0.8712653  0.1287347 ]
 [0.87050675 0.12949325]
 [0.86486186 0.13513814]
 [0.87118391 0.12881609]
 [0.80617105 0.19382895]
 [0.86484441 0.13515559]
 [0.87063731 0.12936269]
 [0.87087364 0.12912636]
 [0.87080253 0.12919747]
 [0.81718765 0.18281235]
 [0.87071635 0.12928365]]
```

In [31]:

```python
def evaluate(model, X_train, X_test, y_train, y_test):
    y_test_pred = model.predict(X_test)
    y_train_pred = model.predict(X_train)

    print("TRAINIG RESULTS: \n===============================")
    clf_report = pd.DataFrame(classification_report(y_train, y_train_pred, output_dict=
    print(f"CONFUSION MATRIX:\n{confusion_matrix(y_train, y_train_pred)}")
    print(f"ACCURACY SCORE:\n{accuracy_score(y_train, y_train_pred):.4f}")
    print(f"CLASSIFICATION REPORT:\n{clf_report}")

    print("TESTING RESULTS: \n===============================")
    clf_report = pd.DataFrame(classification_report(y_test, y_test_pred, output_dict=Tr
    print(f"CONFUSION MATRIX:\n{confusion_matrix(y_test, y_test_pred)}")
    print(f"ACCURACY SCORE:\n{accuracy_score(y_test, y_test_pred):.4f}")
    print(f"CLASSIFICATION REPORT:\n{clf_report}")
```

In [32]:

```python
from sklearn.linear_model import LogisticRegression

lr_clf = LogisticRegression(solver='liblinear', penalty='l2')
lr_clf.fit(X_train, y_train)

evaluate(lr_clf, X_train, X_test, y_train, y_test)
```

```
TRAINIG RESULTS:
===============================
CONFUSION MATRIX:
[[5228   43]
 [ 624  650]]
ACCURACY SCORE:
0.8981
CLASSIFICATION REPORT:
                   0.0          1.0  accuracy    macro avg  weighted avg
precision     0.893370     0.937951   0.89809     0.915660      0.902048
recall        0.991842     0.510204   0.89809     0.751023      0.898090
f1-score      0.940034     0.660905   0.89809     0.800470      0.885701
support    5271.000000  1274.000000   0.89809  6545.000000   6545.000000
TESTING RESULTS:
===============================
CONFUSION MATRIX:
[[2253   24]
 [ 262  266]]
ACCURACY SCORE:
0.8980
CLASSIFICATION REPORT:
```

	0.0	1.0	accuracy	macro avg	weighted avg
precision	0.895825	0.917241	0.898039	0.906533	0.899856
recall	0.989460	0.503788	0.898039	0.746624	0.898039
f1-score	0.940317	0.650367	0.898039	0.795342	0.885738
support	2277.000000	528.000000	0.898039	2805.000000	2805.000000

In [ ]:

In [ ]: