1. Рубежный контроль №1

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Описание задания:

1.0.1. Вариант №3

Для заданного набора данных произведите масштабирование данных (для одного признака) и преобразование категориальных признаков в количественные двумя способами (label encoding, one hot encoding) для одного признака.

[1]:
```
from google.colab import drive, files
drive.mount('/content/drive')
```

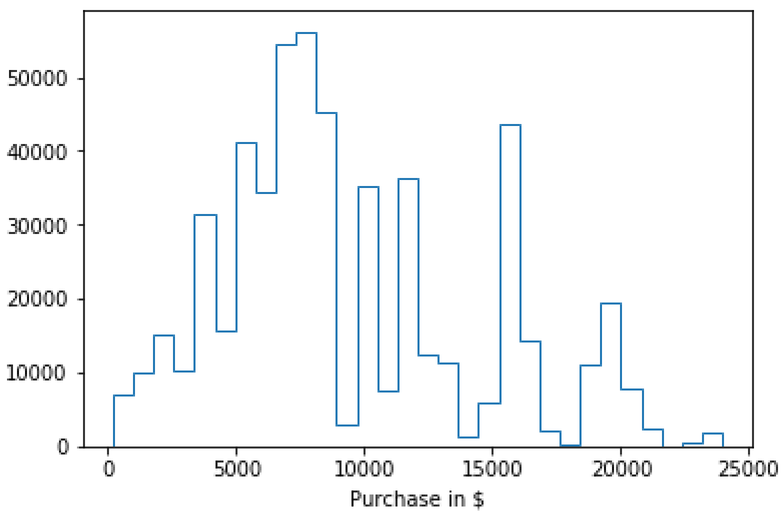
```
Drive already mounted at /content/drive; to attempt to forcibly remount,␣
↪call
drive.mount("/content/drive", force_remount=True).
```

[0]:
```
from google.colab import files
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
os.listdir()
data = pd.read_csv('drive/My Drive/Files/dataset/BlackFriday.csv', sep=",")
```

2. Масштабирование данных

Возьмем параметр покупок:

[3]:
```
plt.hist(data['Purchase'], 30, histtype='step')
plt.xlabel('Purchase in $')
plt.show()
```



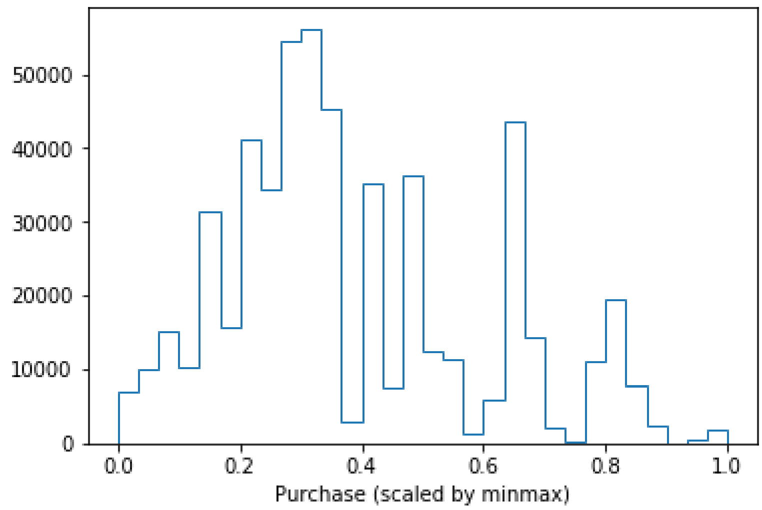
Масштабируем данные по методу минимакса и Z-оценок:

[4]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler

sc1 = MinMaxScaler()
sc1_data = sc1.fit_transform(data[['Purchase']])

plt.hist(sc1_data, 30, histtype='step')
plt.xlabel('Purchase (scaled by minmax)')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/preprocessing/data.py:334:
DataConversionWarning: Data with input dtype int64 were all converted to␣
↪float64
by MinMaxScaler.
  return self.partial_fit(X, y)
```

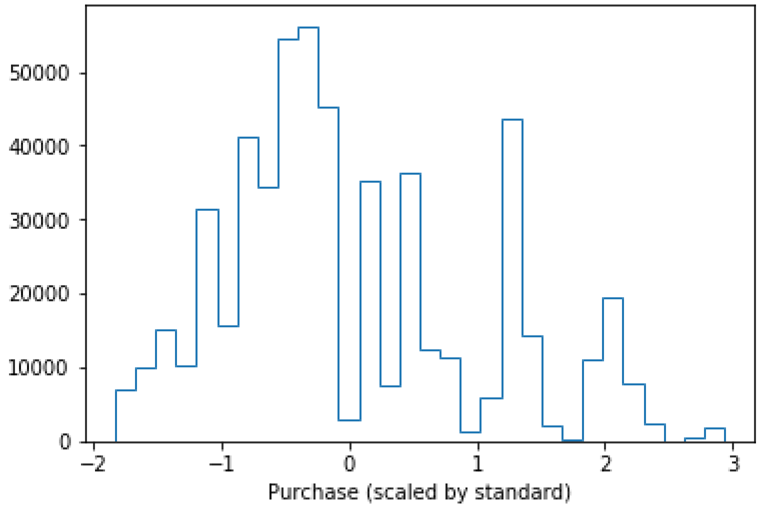


[5]:
```
sc2 = StandardScaler()
sc2_data = sc2.fit_transform(data[['Purchase']])

plt.hist(sc2_data, 30, histtype='step')
plt.xlabel('Purchase (scaled by standard)')
plt.show()
```

```
/usr/local/lib/python3.6/dist-packages/sklearn/preprocessing/data.py:645:
DataConversionWarning: Data with input dtype int64 were all converted to␣
↪float64
by StandardScaler.
  return self.partial_fit(X, y)
/usr/local/lib/python3.6/dist-packages/sklearn/base.py:464:
```

```
DataConversionWarning: Data with input dtype int64 were all converted to
 ↪float64
by StandardScaler.
  return self.fit(X, **fit_params).transform(X)
```



Логичнее использовать масштабирование minmax, так как параметр имеет значения почти от 0 до большого значения (и поэтому логичнее маштабировать от 0 до 1).

3. Преобразование категориальных признаков

[0]:
```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

3.1. Использование LabelEncoder

[7]:
```
cat_temp_data = data[['Gender']]
cat_temp_data[0:10]
```

[7]:

	Gender
0	F
1	F
2	F
3	F
4	M
5	M
6	M
7	M
8	M
9	M

Сравним исходные данные и их целочисленные значения:

[8]:
```
le = LabelEncoder()
cat_enc_le = le.fit_transform(cat_temp_data['Gender'])
```

```
cat_enc2 = pd.DataFrame({'Gender':cat_temp_data['Gender'], 'Gender bin':
 ↪cat_enc_le})
cat_enc2[0:10]
```

[8]:

```
  Gender  Gender bin
0      F           0
1      F           0
2      F           0
3      F           0
4      M           1
5      M           1
6      M           1
7      M           1
8      M           1
9      M           1
```

Внедрим данные в исходные данные:

[9]:

```
data.head(5)
```

[9]:

```
   User_ID Product_ID Gender   Age  Occupation City_Category  \
0  1000001  P00069042      F  0-17          10             A
1  1000001  P00248942      F  0-17          10             A
2  1000001  P00087842      F  0-17          10             A
3  1000001  P00085442      F  0-17          10             A
4  1000002  P00285442      M   55+          16             C

  Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                          2               0                   3
1                          2               0                   1
2                          2               0                  12
3                          2               0                  12
4                         4+               0                   8

   Product_Category_2  Product_Category_3  Purchase
0                 NaN                 NaN      8370
1                 6.0                14.0     15200
2                 NaN                 NaN      1422
3                14.0                 NaN      1057
4                 NaN                 NaN      7969
```

[10]:

```
data2 = data
data2['Gender'] = cat_enc_le
data2.head(5)
```

[10]:

```
   User_ID Product_ID  Gender   Age  Occupation City_Category  \
0  1000001  P00069042       0  0-17          10             A
1  1000001  P00248942       0  0-17          10             A
2  1000001  P00087842       0  0-17          10             A
3  1000001  P00085442       0  0-17          10             A
4  1000002  P00285442       1   55+          16             C
```

```
  Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                          2               0                   3
1                          2               0                   1
2                          2               0                  12
3                          2               0                  12
4                         4+               0                   8

   Product_Category_2  Product_Category_3  Purchase
0                 NaN                 NaN      8370
1                 6.0                14.0     15200
2                 NaN                 NaN      1422
3                14.0                 NaN      1057
4                 NaN                 NaN      7969
```

3.2. Использование OneHotEncoder

[11]:
```
ohe = OneHotEncoder()
cat_enc_ohe = ohe.fit_transform(data[['City_Category']])
cat_enc_ohe.todense()[0:10]
```

[11]:
```
matrix([[1., 0., 0.],
        [1., 0., 0.],
        [1., 0., 0.],
        [1., 0., 0.],
        [0., 0., 1.],
        [1., 0., 0.],
        [0., 1., 0.],
        [0., 1., 0.],
        [0., 1., 0.],
        [1., 0., 0.]])
```

[12]:
```
data4 = pd.get_dummies(data[['City_Category']])
data4.head(5)
```

[12]:
```
   City_Category_A  City_Category_B  City_Category_C
0                1                0                0
1                1                0                0
2                1                0                0
3                1                0                0
4                0                0                1
```

Добавим в исходные данные новые столбцы:

[13]:
```
data3=data2.join(data4)
data3.head(5)
```

[13]:
```
   User_ID Product_ID  Gender   Age  Occupation City_Category  \
0  1000001  P00069042       0  0-17          10             A
1  1000001  P00248942       0  0-17          10             A
2  1000001  P00087842       0  0-17          10             A
3  1000001  P00085442       0  0-17          10             A
```

```
4  1000002  P00285442       1   55+          16              C

  Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                          2               0                   3
1                          2               0                   1
2                          2               0                  12
3                          2               0                  12
4                         4+               0                   8

   Product_Category_2  Product_Category_3  Purchase  City_Category_A  \
0                 NaN                 NaN      8370                1
1                 6.0                14.0     15200                1
2                 NaN                 NaN      1422                1
3                14.0                 NaN      1057                1
4                 NaN                 NaN      7969                0

   City_Category_B  City_Category_C
0                0                0
1                0                0
2                0                0
3                0                0
4                0                1
```