Машинное обучение в бизнесе ¶

Урок 6. #Задача lookalike (Positive Unlabeled Learning)#

Домашнее задание

1. взять любой набор данных для бинарной классификации (можно скачать один из модельных с https://archive.ics.uci.edu/ml/datasets.php (https://archive.ics.uci.edu/ml/datasets.php))
2. сделать feature engineering
3. обучить любой классификатор (какой вам нравится)
4. далее разделить ваш набор данных на два множества: P (positives) и U (unlabeled). Причем брать нужно не все положительные (класс 1) примеры, а только лишь часть
5. применить random negative sampling для построения классификатора в новых условиях
6. сравнить качество с решением из пункта 4 (построить отчет - таблицу метрик)
7. поэкспериментировать с долей P на шаге 5 (как будет меняться качество модели при уменьшении/увеличении размера P)

Выполнил ***Соковнин ИЛ***

Практическое задание

1. Задание

взять любой набор данных для бинарной классификации (можно скачать один из модельных с https://archive.ics.uci.edu/ml/datasets.php (https://archive.ics.uci.edu/ml/datasets.php))

UCI Machine Learning Repository

(Center for Machine Learning and Intelligent Systems)

Data Set:

in-vehicle coupon recommendation Data Set
https://archive.ics.uci.edu/ml/datasets/in-vehicle+coupon+recommendation (https://archive.ics.uci.edu/ml/datasets/in-vehicle+coupon+recommendation)
https://archive.ics.uci.edu/ml/machine-learning-databases/00603/ (https://archive.ics.uci.edu/ml/machine-learning-databases/00603/)

Abstract: This data studies whether a person will accept the coupon recommended to him in different driving scenarios

Эти данные исследуют, примет ли человек рекомендованный ему купон при различных сценариях вождения.

Data Set Characteristics: Multivariate
Number of Instances: 12684
Area: Business
Attribute Characteristics: N/A
Number of Attributes: 23
Date Donated: 2020-09-15
Associated Tasks: Classification
Missing Values? Yes
Number of Web Hits: 20952

Source:

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Cynthia Rudin, cynthia '@' cs.duke.edu, Duke University

Data Set Information:

This data was collected via a survey on Amazon Mechanical Turk. The survey describes different driving scenarios including the destination, current time, weather, passenger, etc., and then ask the person whether he will accept the coupon if he is the driver. For more information about the dataset, please refer to the paper:
Wang, Tong, Cynthia Rudin, Finale Doshi-Velez, Yimin Liu, Erica Klampfl, and Perry MacNeille. 'A bayesian framework for learning rule sets for interpretable classification.' The Journal of Machine Learning Research 18, no. 1 (2017): 2357-2393.

Эти данные были собраны с помощью опроса на Amazon Mechanical Turk. Опрос описывает различные сценарии вождения, включая пункт назначения, текущее время, погоду, количество пассажиров и т. Д., А затем спрашивает человека, примет ли он купон, если он является водителем.

Attribute Information:

- **destination**: No Urgent Place, Home, Work
- **passanger**: Alone, Friend(s), Kid(s), Partner (who are the passengers in the car)
- **weather**: Sunny, Rainy, Snowy
- **temperature**: 55, 80, 30
- **time**: 2PM, 10AM, 6PM, 7AM, 10PM (14:00, 10:00, 18:00, 7:00, 22:00)
- **coupon**: Restaurant(<$20), Coffee House, Carry out & Take away, Bar, Restaurant($20-$50)
- **expiration** (срок действия): 1d, 2h (the coupon expires in 1 day or in 2 hours)
- **gender**: Female, Male
- **age**: 21, 46, 26, 31, 41, 50plus, 36, below21
- **maritalStatus**: Unmarried partner, Single, Married partner, Divorced, Widowed (семейное положение: не женат, холост, женат, разведен, вдова)
- **has_Children**: 1, 0
- **education**: Some college - no degree, Bachelors degree, Associates degree, High School Graduate, Graduate degree (Masters or Doctorate), Some High School
(Некоторое высшее образование - без степени, степень бакалавра, степень младшего специалиста, выпускник средней школы, высшее образование (степень магистра или доктора), некоторая высшая школа)
- **occupation**:
Unemployed, Architecture & Engineering, Student,
Education&Training&Library, Healthcare Support,
Healthcare Practitioners & Technical, Sales & Related, Management,
Arts Design Entertainment Sports & Media, Computer & Mathematical,
Life Physical Social Science, Personal Care & Service,
Community & Social Services, Office & Administrative Support,
Construction & Extraction, Legal, Retired,
Installation Maintenance & Repair, Transportation & Material Moving,
Business & Financial, Protective Service,
Food Preparation & Serving Related, Production Occupations,
Building & Grounds Cleaning & Maintenance, Farming Fishing & Forestry
- **income**: $37500 - $49999, $62500 - $74999, $12500 - $24999, $75000 - $87499,
$50000 - $62499, $25000 - $37499, $100000 or More, $87500 - $99999, Less than $12500
- **Bar**: never, less1, 1~3, gt8, nan4~8 (feature meaning: how many times do you go to a bar every month (сколько раз вы ходите в бар каждый месяц?)
- **car**:
- **CoffeeHouse**: never, less1, 4~8, 1~3, gt8, nan (feature meaning: how many times do you go to a coffeehouse every month)?
- **CarryAway**: n4~8, 1~3, gt8, less1, never (feature meaning: how many times do you get take-away food every month (сколько раз в месяц вы получаете еду на вынос)?)
- **RestaurantLessThan20**: 4~8, 1~3, less1, gt8, never (feature meaning: how many times do you go to a restaurant with an average expense per person of less than d20 every month (сколько раз вы ходите в ресторан со средними расходами менее 20 долларов в месяц на человека)?)
- **Restaurant20To50**: 1~3, less1, never, gt8, 4~8, nan (feature meaning: how many times do you go to a restaurant with average expense per person of $20 - $50 every month?)
- **toCoupon_GEQ15min**: 0,1 (feature meaning: driving distance to the restaurant/bar for using the coupon is greater than 15 minutes (расстояние до ресторана / бара для использования купона превышает 15 минут))
- **toCoupon_GEQ25min**: 0, 1 (feature meaning: driving distance to the restaurant/bar for using the coupon is greater than 25 minutes)
- **direction_same**: 0, 1 (feature meaning: whether the restaurant/bar is in the same direction as your current destination (находится ли ресторан / бар в том же направлении, что и ваш текущий пункт назначения))
- **direction_opp**: 1, 0 (feature meaning: whether the restaurant/bar is in the same direction as your current destination)
- **Y**: 1, 0 (whether the coupon is accepted (принят ли купон))

В [1]:
```
import pandas as pd
import numpy as np
from sklearn.pipeline import Pipeline, make_pipeline

# 2. Визуализация
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline

import warnings
warnings.filterwarnings('ignore')

matplotlib.rcParams.update({'font.size': 14})
```

В [2]:
```
df = pd.read_csv("./UCI Machine Learning Repository/in-vehicle-coupon-recommendation.csv")
df.head(3)
```

Out[2]:

	destination	passanger	weather	temperature	time	coupon	expiration	gender	age	maritalStatus	...	CoffeeHouse	CarryAway	Restau
0	No Urgent Place	Alone	Sunny	55	2PM	Restaurant(<20)	1d	Female	21	Unmarried partner	...	never	NaN	
1	No Urgent Place	Friend(s)	Sunny	80	10AM	Coffee House	2h	Female	21	Unmarried partner	...	never	NaN	
2	No Urgent Place	Friend(s)	Sunny	80	10AM	Carry out & Take away	2h	Female	21	Unmarried partner	...	never	NaN	

3 rows × 26 columns

Анализ данных

В [3]:
```
df.shape
```

Out[3]: (12684, 26)

В [4]:
```
print('Строк в df:',df.shape[0])  # gives number of row count
print('Столбцов в df:',df.shape[1])  # gives number of col count
```

```
Строк в df: 12684
Столбцов в df: 26
```

В [5]:
```
df.iloc[0]  # Получаем первую строку (index=0)
```

Out[5]:
```
destination                    No Urgent Place
passanger                                Alone
weather                                  Sunny
temperature                                 55
time                                       2PM
coupon                         Restaurant(<20)
expiration                                  1d
gender                                  Female
age                                         21
maritalStatus                Unmarried partner
has_children                                 1
education             Some college - no degree
occupation                          Unemployed
income                         $37500 - $49999
car                                        NaN
Bar                                      never
CoffeeHouse                              never
CarryAway                                  NaN
RestaurantLessThan20                       4~8
Restaurant20To50                           1~3
toCoupon_GEQ5min                             1
toCoupon_GEQ15min                            0
toCoupon_GEQ25min                            0
direction_same                               0
direction_opp                                1
Y                                            1
Name: 0, dtype: object
```

В [6]:
```
# Рассмотрим типы признаков
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12684 entries, 0 to 12683
Data columns (total 26 columns):
 #   Column                Non-Null Count  Dtype 
---  ------                --------------  ----- 
 0   destination           12684 non-null  object
 1   passanger             12684 non-null  object
 2   weather               12684 non-null  object
 3   temperature           12684 non-null  int64 
 4   time                  12684 non-null  object
 5   coupon                12684 non-null  object
 6   expiration            12684 non-null  object
 7   gender                12684 non-null  object
 8   age                   12684 non-null  object
 9   maritalStatus         12684 non-null  object
 10  has_children          12684 non-null  int64 
 11  education             12684 non-null  object
 12  occupation            12684 non-null  object
 13  income                12684 non-null  object
 14  car                   108 non-null    object
 15  Bar                   12577 non-null  object
 16  CoffeeHouse           12467 non-null  object
 17  CarryAway             12533 non-null  object
 18  RestaurantLessThan20  12554 non-null  object
 19  Restaurant20To50      12495 non-null  object
 20  toCoupon_GEQ5min      12684 non-null  int64 
 21  toCoupon_GEQ15min     12684 non-null  int64 
 22  toCoupon_GEQ25min     12684 non-null  int64 
 23  direction_same        12684 non-null  int64 
 24  direction_opp         12684 non-null  int64 
 25  Y                     12684 non-null  int64 
dtypes: int64(8), object(18)
memory usage: 2.5+ MB
```

В [7]:
```
df.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
temperature	12684.0	63.301798	19.154486	30.0	55.0	80.0	80.0	80.0
has_children	12684.0	0.414144	0.492593	0.0	0.0	0.0	1.0	1.0
toCoupon_GEQ5min	12684.0	1.000000	0.000000	1.0	1.0	1.0	1.0	1.0
toCoupon_GEQ15min	12684.0	0.561495	0.496224	0.0	0.0	1.0	1.0	1.0
toCoupon_GEQ25min	12684.0	0.119126	0.323950	0.0	0.0	0.0	0.0	1.0
direction_same	12684.0	0.214759	0.410671	0.0	0.0	0.0	0.0	1.0
direction_opp	12684.0	0.785241	0.410671	0.0	1.0	1.0	1.0	1.0
Y	12684.0	0.568433	0.495314	0.0	0.0	1.0	1.0	1.0

В [8]:
```
# len(df) - df.count()
```

В [9]:
```
df.columns
```

Out[9]:
```
Index(['destination', 'passanger', 'weather', 'temperature', 'time', 'coupon',
       'expiration', 'gender', 'age', 'maritalStatus', 'has_children',
       'education', 'occupation', 'income', 'car', 'Bar', 'CoffeeHouse',
       'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50',
       'toCoupon_GEQ5min', 'toCoupon_GEQ15min', 'toCoupon_GEQ25min',
       'direction_same', 'direction_opp', 'Y'],
      dtype='object')
```

В [10]:
```
class_names = ['destination', 'passanger', 'weather', 'temperature', 'time', 'coupon',
       'expiration', 'gender', 'age', 'maritalStatus', 'has_children',
       'education', 'occupation', 'income', 'car', 'Bar', 'CoffeeHouse',
       'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50',
       'toCoupon_GEQ5min', 'toCoupon_GEQ15min', 'toCoupon_GEQ25min',
       'direction_same', 'direction_opp', 'Y']
```

EDA и очистка данных

Делаем EDA для:

- Исправления выбросов
- Заполнения NaN
- Идей для генерации новых фич

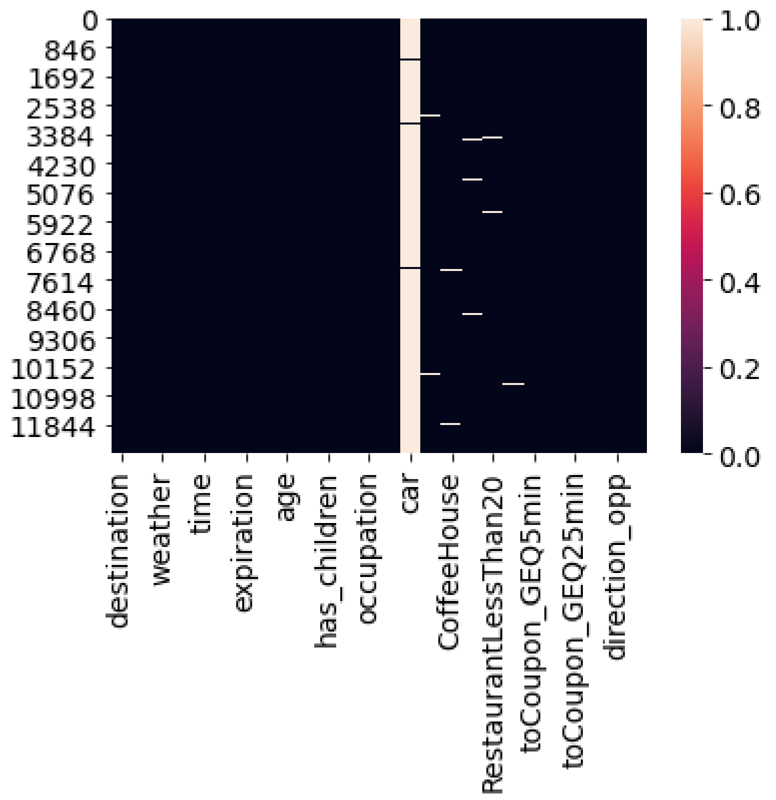
1. Обработка пропусков

В [11]:
```
# df.isnull()
# df.notnull()
```

representing null/NaN values using seaborn plotting techniques

В [12]:
```
sns.heatmap(df.isnull())
```

Out[12]:
```
<AxesSubplot:>
```



В [13]:
```
df.isna().sum()  # просматриваем пропуски
```

Out[13]:
```
destination                 0
passanger                   0
weather                     0
temperature                 0
time                        0
coupon                      0
expiration                  0
gender                      0
age                         0
maritalStatus               0
has_children                0
education                   0
occupation                  0
income                      0
car                     12576
Bar                       107
CoffeeHouse               217
CarryAway                 151
RestaurantLessThan20      130
Restaurant20To50          189
toCoupon_GEQ5min            0
toCoupon_GEQ15min           0
toCoupon_GEQ25min           0
direction_same              0
direction_opp               0
Y                           0
dtype: int64
```

В [14]:
```
for cat_colname in df[['car', 'Bar', 'CoffeeHouse', 'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50']].columns:
    print(str(cat_colname) + ': (nan='+ str(df[cat_colname].isna().sum()) + ')\n\n' + str(df[cat_colname].value_counts()
          '\n' + '*' * 100 + '\n')
```

```
car: (nan=12576)

Mazda5                                    22
Scooter and motorcycle                    22
do not drive                              22
Car that is too old to install Onstar :D  21
crossover                                 21
Name: car, dtype: int64
****************************************************************************************************

Bar: (nan=107)

never    5197
less1    3482
1~3      2473
4~8      1076
gt8       349
Name: Bar, dtype: int64
****************************************************************************************************

CoffeeHouse: (nan=217)

less1    3385
1~3      3225
never    2962
4~8      1784
gt8      1111
Name: CoffeeHouse, dtype: int64
****************************************************************************************************

CarryAway: (nan=151)

1~3      4672
4~8      4258
less1    1856
gt8      1594
never     153
Name: CarryAway, dtype: int64
****************************************************************************************************

RestaurantLessThan20: (nan=130)

1~3      5376
4~8      3580
less1    2093
gt8      1285
never     220
Name: RestaurantLessThan20, dtype: int64
****************************************************************************************************

Restaurant20To50: (nan=189)

less1    6077
1~3      3290
never    2136
4~8       728
gt8       264
Name: Restaurant20To50, dtype: int64
****************************************************************************************************
```

Пропуски есть в следующих признаках:

- **car**: 12576
- **Bar**: 107
- **CoffeeHouse**: 217
- **CarryAway**: 151
- **RestaurantLessThan20**: 130
- **Restaurant20To50**: 189

1. Поле **car** практически не заполнено, 12576 из 12684 позиций (заполнено только 108 позиций). **Исключаем его из датафрейма**.
2. Для остальных полей заменяем значение **nan** на наиболее часто встречающееся значение:
    - **Bar**: заменияем значением **never**
    - **CoffeeHouse**: заменияем значением **less1**
    - **CarryAway**: заменияем значением **1~3**
    - **RestaurantLessThan20**: заменияем значением **1~3**
    - **Restaurant20To50**: заменияем значением **less1**

В [15]:
```
12684-12576
```
Out[15]:
```
108
```

В [16]:
```
# Удаляем поле car из набора как неинформативное
df.drop('car', axis=1, inplace=True)
```

В [17]:
```
# Заполним пропуски
col = 'Bar'
df[col] = df[col].fillna('never')
# print(df[col].value_counts())
```

В [18]:
```
col = 'CoffeeHouse'
df[col] = df[col].fillna('less1')
# print(df[col].value_counts())
```

В [19]:
```
col = 'CarryAway'
df[col] = df[col].fillna('1~3')
# print(df[col].value_counts())
```

В [20]:
```
col = 'RestaurantLessThan20'
df[col] = df[col].fillna('1~3')
# print(df[col].value_counts())
```

В [21]:
```
col = 'Restaurant20To50'
df[col] = df[col].fillna('less1')
# print(df[col].value_counts())
```

В [22]:
```
df.isna().sum()  # просматриваем пропуски
```
Out[22]:
```
destination             0
passanger               0
weather                 0
temperature             0
time                    0
coupon                  0
expiration              0
gender                  0
age                     0
maritalStatus           0
has_children            0
education               0
occupation              0
income                  0
Bar                     0
CoffeeHouse             0
CarryAway               0
RestaurantLessThan20    0
Restaurant20To50        0
toCoupon_GEQ5min        0
toCoupon_GEQ15min       0
toCoupon_GEQ25min       0
direction_same          0
direction_opp           0
Y                       0
dtype: int64
```

2. Обзор целевой переменной

В [23]:
```
# Checking unique object data
object_cols = [col for col in df.columns if (col == "Y")] # (col == "treatment") | (col == "target")]
for obj in object_cols:
    print(f'\n{obj}')
    for unique in df[obj].unique():
        print(f'- {unique} {sum(df[obj] == unique)}')
```

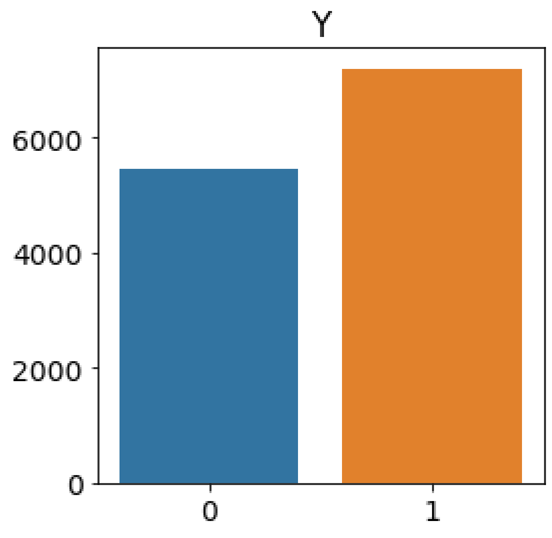
```
Y
- 1 7210
- 0 5474
```

В [24]:
```
df.iloc[:, -1].value_counts()
```
Out[24]:
```
1    7210
0    5474
Name: Y, dtype: int64
```

В [25]:
```
counts = df['Y'].value_counts()  # Количество различных значений признака 'Y'
# print(counts)

plt.figure(figsize=(4,4))
plt.title('Y')
sns.barplot(counts.index, counts.values)

plt.show()
```

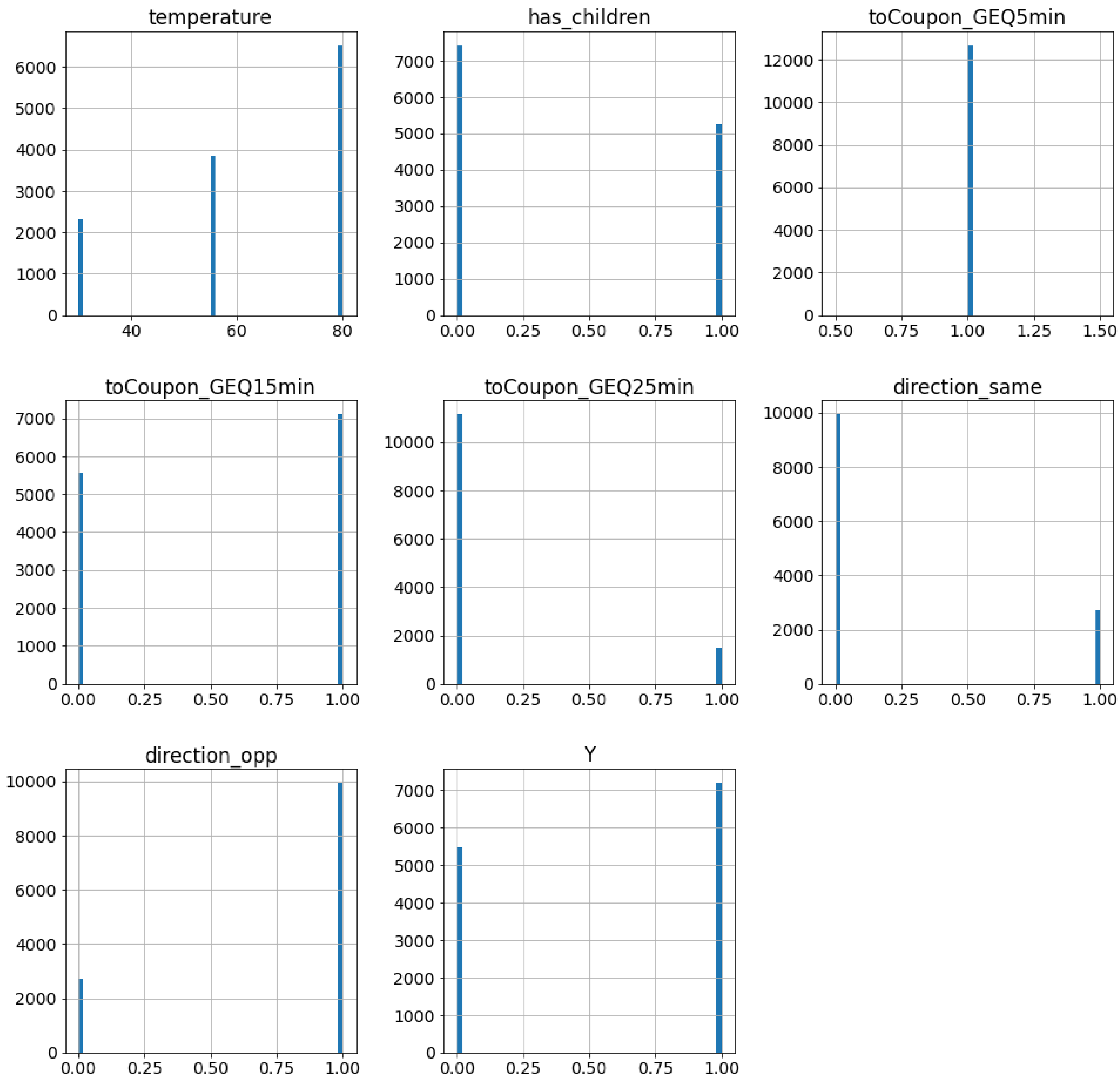


3. Обзор числовых признаков

В [26]:
```
df_num_features = df.select_dtypes(include=['float32', 'float64', 'int8', 'int16', 'int32', 'int64'])

df_num_features.hist(figsize=(16, 16), bins=50, grid=True)
```

Out[26]:
```
array([[<AxesSubplot:title={'center':'temperature'}>,
        <AxesSubplot:title={'center':'has_children'}>,
        <AxesSubplot:title={'center':'toCoupon_GEQ5min'}>],
       [<AxesSubplot:title={'center':'toCoupon_GEQ15min'}>,
        <AxesSubplot:title={'center':'toCoupon_GEQ25min'}>,
        <AxesSubplot:title={'center':'direction_same'}>],
       [<AxesSubplot:title={'center':'direction_opp'}>,
        <AxesSubplot:title={'center':'Y'}>, <AxesSubplot:>]], dtype=object)
```



Поле 'toCoupon_GEQ5min' имеет только одно значение 1 для всех позиций. Исключаем его из нашего датафрэйма.

В [27]:
```
df['toCoupon_GEQ5min'].value_counts()
```

Out[27]:
```
1    12684
Name: toCoupon_GEQ5min, dtype: int64
```

В [28]:
```
# Удаляем поле toCoupon_GEQ5min из набора данных как неинформативное
df.drop('toCoupon_GEQ5min', axis=1, inplace=True)
```

В [ ]:

В [29]:
```
df.columns
```

Out[29]:
```
Index(['destination', 'passanger', 'weather', 'temperature', 'time', 'coupon',
       'expiration', 'gender', 'age', 'maritalStatus', 'has_children',
       'education', 'occupation', 'income', 'Bar', 'CoffeeHouse', 'CarryAway',
       'RestaurantLessThan20', 'Restaurant20To50', 'toCoupon_GEQ15min',
       'toCoupon_GEQ25min', 'direction_same', 'direction_opp', 'Y'],
      dtype='object')
```

В [30]:
```
#df['destination'].value_counts()
```

В [31]:
```
# for cat_colname in df.select_dtypes(include='int64').columns:
#     print(str(cat_colname) + '\n\n' + str(df[cat_colname].value_counts()) + '\n' + '*' * 100 + '\n')

for cat_colname in df.select_dtypes(include='int64').columns:
    print(str(cat_colname) + ': (nan='+ str(df[cat_colname].isna().sum()) + ')\n\n' + str(df[cat_colname].value_counts()
          '\n' + '*' * 100 + '\n')
```

```
temperature: (nan=0)

80    6528
55    3840
30    2316
Name: temperature, dtype: int64
****************************************************************************************************

has_children: (nan=0)

0    7431
1    5253
Name: has_children, dtype: int64
****************************************************************************************************

toCoupon_GEQ15min: (nan=0)

1    7122
0    5562
Name: toCoupon_GEQ15min, dtype: int64
****************************************************************************************************

toCoupon_GEQ25min: (nan=0)

0    11173
1     1511
Name: toCoupon_GEQ25min, dtype: int64
****************************************************************************************************

direction_same: (nan=0)

0    9960
1    2724
Name: direction_same, dtype: int64
****************************************************************************************************

direction_opp: (nan=0)

1    9960
0    2724
Name: direction_opp, dtype: int64
****************************************************************************************************

Y: (nan=0)

1    7210
0    5474
Name: Y, dtype: int64
****************************************************************************************************
```

4. Обзор категориальных признаков

В [32]:
```
# Checking for object data
df.describe(include=np.object).T
```

Out[32]:

	count	unique	top	freq
destination	12684	3	No Urgent Place	6283
passanger	12684	4	Alone	7305
weather	12684	3	Sunny	10069
time	12684	5	6PM	3230
coupon	12684	5	Coffee House	3996
expiration	12684	2	1d	7091
gender	12684	2	Female	6511
age	12684	8	21	2653
maritalStatus	12684	5	Married partner	5100
education	12684	6	Some college - no degree	4351
occupation	12684	25	Unemployed	1870
income	12684	9	25000−37499	2013
Bar	12684	5	never	5304
CoffeeHouse	12684	5	less1	3602
CarryAway	12684	5	1~3	4823
RestaurantLessThan20	12684	5	1~3	5506
Restaurant20To50	12684	5	less1	6266

В [33]:
```
# # Checking unique object data
# object_cols = [col for col in df.columns if df[col].dtype == "object"]
# for obj in object_cols:
#     print(f'\n{obj}')
#     for unique in df[obj].unique():
#         print(f'- {unique} {sum(df[obj] == unique)}')
```

В [34]:
```
for cat_colname in df.select_dtypes(include='object').columns:
    print(str(cat_colname) + ': (nan='+ str(df[cat_colname].isna().sum()) + ')\n\n' + str(df[cat_colname].value_counts()
          '\n' + '*' * 100 + '\n')
```

```
destination: (nan=0)

No Urgent Place    6283
Home               3237
Work               3164
Name: destination, dtype: int64
****************************************************************************************************

passanger: (nan=0)

Alone        7305
Friend(s)    3298
Partner      1075
Kid(s)       1006
Name: passanger, dtype: int64
****************************************************************************************************

weather: (nan=0)

Sunny    10069
Snowy     1405
Rainy     1210
Name: weather, dtype: int64
****************************************************************************************************

time: (nan=0)

6PM     3230
7AM     3164
10AM    2275
2PM     2009
10PM    2006
Name: time, dtype: int64
****************************************************************************************************

coupon: (nan=0)

Coffee House             3996
Restaurant(<20)          2786
Carry out & Take away    2393
Bar                      2017
Restaurant(20-50)        1492
Name: coupon, dtype: int64
****************************************************************************************************

expiration: (nan=0)

1d    7091
2h    5593
Name: expiration, dtype: int64
****************************************************************************************************

gender: (nan=0)

Female    6511
Male      6173
Name: gender, dtype: int64
****************************************************************************************************

age: (nan=0)

21         2653
26         2559
31         2039
50plus     1788
36         1319
41         1093
46          686
below21     547
Name: age, dtype: int64
****************************************************************************************************

maritalStatus: (nan=0)

Married partner      5100
Single               4752
Unmarried partner    2186
Divorced              516
Widowed               130
Name: maritalStatus, dtype: int64
****************************************************************************************************

education: (nan=0)
```

```
Some college - no degree                  4351
Bachelors degree                          4335
Graduate degree (Masters or Doctorate)    1852
Associates degree                         1153
High School Graduate                       905
Some High School                            88
Name: education, dtype: int64
****************************************************************************************************

occupation: (nan=0)

Unemployed                                   1870
Student                                      1584
Computer & Mathematical                      1408
Sales & Related                              1093
Education&Training&Library                    943
Management                                    838
Office & Administrative Support               639
Arts Design Entertainment Sports & Media      629
Business & Financial                          544
Retired                                       495
Food Preparation & Serving Related            298
Healthcare Practitioners & Technical          244
Healthcare Support                            242
Community & Social Services                   241
Legal                                         219
Transportation & Material Moving              218
Protective Service                            175
Architecture & Engineering                    175
Personal Care & Service                       175
Life Physical Social Science                  170
Construction & Extraction                     154
Installation Maintenance & Repair             133
Production Occupations                        110
Building & Grounds Cleaning & Maintenance      44
Farming Fishing & Forestry                     43
Name: occupation, dtype: int64
****************************************************************************************************

income: (nan=0)

$25000 - $37499     2013
$12500 - $24999     1831
$37500 - $49999     1805
$100000 or More     1736
$50000 - $62499     1659
Less than $12500    1042
$87500 - $99999      895
$75000 - $87499      857
$62500 - $74999      846
Name: income, dtype: int64
****************************************************************************************************

Bar: (nan=0)

never    5304
less1    3482
1~3      2473
4~8      1076
gt8       349
Name: Bar, dtype: int64
****************************************************************************************************

CoffeeHouse: (nan=0)

less1    3602
1~3      3225
never    2962
4~8      1784
gt8      1111
Name: CoffeeHouse, dtype: int64
****************************************************************************************************

CarryAway: (nan=0)

1~3      4823
4~8      4258
less1    1856
gt8      1594
never     153
Name: CarryAway, dtype: int64
****************************************************************************************************

RestaurantLessThan20: (nan=0)

1~3      5506
4~8      3580
less1    2093
```

```
gt8      1285
never     220
Name: RestaurantLessThan20, dtype: int64
****************************************************************************************************

Restaurant20To50: (nan=0)

less1    6266
1~3      3290
never    2136
4~8       728
gt8       264
Name: Restaurant20To50, dtype: int64
****************************************************************************************************
```

2 Задание

сделать **feature engineering**

Обработка категориальных признаков

В [35]:
```
# Приводим поле treatment к бинарному виду (1 или 0, т.е было какое-то предложение или нет)
# df.treatment = df_model.treatment.map({'No Offer': 0, 'Buy One Get One': 1, 'Discount': 1})
```

В [36]:
```
col_names = ['destination', 'passanger', 'weather', 'temperature', 'time', 'coupon',
       'expiration', 'gender', 'age', 'maritalStatus', 'has_children',
       'education', 'occupation', 'income', 'car', 'Bar', 'CoffeeHouse',
       'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50',
       'toCoupon_GEQ5min', 'toCoupon_GEQ15min', 'toCoupon_GEQ25min',
       'direction_same', 'direction_opp']

cat_col_names = ['destination', 'passanger', 'weather', 'time', 'coupon',
       'expiration', 'gender', 'age', 'maritalStatus',
       'education', 'occupation', 'income', 'car', 'Bar', 'CoffeeHouse',
       'CarryAway', 'RestaurantLessThan20', 'Restaurant20To50']


col_names = ['temperature', 'has_children',
       'toCoupon_GEQ15min', 'toCoupon_GEQ25min',
       'direction_same', 'direction_opp']
```

В [37]:
```
# One-Hot Encoding:
df = pd.get_dummies(df)
```

В [38]:
```
# for col in df.columns:
#     print(col)
```

В [39]:
```
# Переименуем поля:
# passanger_Friend(s) -> passanger_Friend
df = df.rename(columns={'passanger_Friend(s)': 'passanger_Friend'})
# passanger_Kid(s) -> passanger_Kid
df = df.rename(columns={'passanger_Kid(s)': 'passanger_Kid'})
# coupon_Restaurant(20-50) -> coupon_Restaurant_20_50
df = df.rename(columns={'coupon_Restaurant(20-50)': 'coupon_Restaurant_20_50'})
# coupon_Restaurant(<20) -> coupon_Restaurant_less_20
df = df.rename(columns={'coupon_Restaurant(<20)': 'coupon_Restaurant_less_20'})
```

В [40]:
```
df.head()
```

Out[40]:

	temperature	has_children	toCoupon_GEQ15min	toCoupon_GEQ25min	direction_same	direction_opp	Y	destination_Home	destination_No Urgent Place	desti
0	55	1	0	0	0	1	1	0	1	
1	80	1	0	0	0	1	0	0	1	
2	80	1	1	0	0	1	1	0	1	
3	80	1	1	0	0	1	0	0	1	
4	80	1	1	0	0	1	0	0	1	

5 rows × 109 columns

В [41]:
```
df[col_names].head(3)
```

Out[41]:

	temperature	has_children	toCoupon_GEQ15min	toCoupon_GEQ25min	direction_same	direction_opp
0	55	1	0	0	0	1
1	80	1	0	0	0	1
2	80	1	1	0	0	1

3 Задание

обучить любой классификатор (какой вам нравится)

Разбиваем выборку на тренировочную и тестовую части и обучаем модель (градиентный бустинг)

В [42]:
```
from sklearn.model_selection import train_test_split
```

В [43]:
```
#разделим данные на train/test
x_data = df.drop('Y', axis=1)
y_data = df['Y']

X_train, X_test, y_train, y_test = train_test_split(x_data, y_data, test_size=0.2, random_state=7)
```

В [44]:
```
# for col in X_train.columns:
#     print(col)
```

В [45]:
```
import xgboost as xgb

model = xgb.XGBClassifier()

model.fit(X_train, y_train)
y_predict = model.predict(X_test)
```

```
[00:03:08] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starting in XGBoo
st 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'loglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

Проверяем качество

В [46]:
```
from sklearn.metrics import recall_score, precision_score, roc_auc_score, accuracy_score, f1_score

def evaluate_results(y_test, y_predict):
    print('Classification results:')
    f1 = f1_score(y_test, y_predict)
    print("f1: %.2f%%" % (f1 * 100.0))
    roc = roc_auc_score(y_test, y_predict)
    print("roc: %.2f%%" % (roc * 100.0))
    rec = recall_score(y_test, y_predict, average='binary')
    print("recall: %.2f%%" % (rec * 100.0))
    prc = precision_score(y_test, y_predict, average='binary')
    print("precision: %.2f%%" % (prc * 100.0))

    return f1, roc, rec, prc
```

В [47]:
```
models_results = {
    'model': [],
    'f-score': [],
    'roc': [],
    'recall': [],
    'precision': [],
    'positives_marked %': []
}
```

В [48]:
```
from math import nan
positives_marked = nan

f1, roc, rec, prc = evaluate_results(y_test, y_predict)

models_results['model'].append('XGBClassifier')
models_results['f-score'].append(f1)
models_results['roc'].append(roc)
models_results['recall'].append(rec)
models_results['precision'].append(prc)
models_results['positives_marked %'].append(positives_marked)
```

```
Classification results:
f1: 80.62%
roc: 76.19%
recall: 83.15%
precision: 78.23%
```

В [49]:
```
# y_predict.value_counts()  # Количество различных значений признака 'Y'
# type(y_predict)
# np.unique(y_predict)
# y_predict
```

В [50]:
```
import itertools

X = y_predict
num = [(x, len(list(y))) for x, y in itertools.groupby(sorted(X))]
print(num)
```

```
[(0, 998), (1, 1539)]
```

В [51]:
```
# from itertools import groupby

# things = [("animal", "bear"), ("animal", "duck"), ("plant", "cactus"), ("vehicle", "speed boat"), ("vehicle", "school b

# for key, group in groupby(things, lambda x: x[0]):
#     for thing in group:
#         print("A %s is a %s." % (thing[1], key))
#     print("")

# for key, group in groupby(things, lambda x: x[0]):
#     listOfThings = " and ".join([thing[1] for thing in group])
#     print(key + "s:  " + listOfThings + ".")
```

В [ ]:

4 Задание

далее разделить ваш набор данных на два множества: P (positives) и U (unlabeled). Причем брать нужно не все положительные (класс 1) примеры, а только лишь часть

Positive Unlabeled Learning (задача lookalike)

Представим, что нам неизвестны негативы и часть позитивов

В [52]:
```
mod_data = df.copy()
mod_data.head(3)
```

Out[52]:

	temperature	has_children	toCoupon_GEQ15min	toCoupon_GEQ25min	direction_same	direction_opp	Y	destination_Home	destination_No Urgent Place	desti
0	55	1	0	0	0	1	1	0	1	
1	80	1	0	0	0	1	0	0	1	
2	80	1	1	0	0	1	1	0	1	

3 rows × 109 columns

В [53]:
```
mod_data.iloc[:,-1].values
# mod_data['Y'].values

#get the indices of the positives samples
pos_ind = np.where(mod_data['Y'].values == 1)[0]
# pos_ind

# Y
# - 1 7210
# - 0 5474
```

В [119]:
```
# shuffle
# тасовать (shuffle, make, riffle)
# перемешивать (mix, jumble, agitate, medley, shuffle, intermix)
# изворачиваться (dodge, shift, shuffle)Using 1803/7210 as positives and unlabeling the rest

#shuffle them
np.random.shuffle(pos_ind)

positives_marked = 0.25  # leave just 25% of the positives marked
# positives_marked = 0.35  # leave just 35% of the positives marked
# positives_marked = 0.45  # leave just 45% of the positives marked
# positives_marked = 0.15  # leave just 15% of the positives marked
# positives_marked = 0.05  # leave just 5% of the positives marked
# positives_marked = 0.20  # leave just 20% of the positives marked
# positives_marked = 0.10  # leave just 10% of the positives marked
# positives_marked = 0.135  # leave just 13.5% of the positives marked
# positives_marked = 0.55  # leave just 55% of the positives marked

# pos_sample_len = int(np.ceil(0.25 * len(pos_ind)))
pos_sample_len = int(np.ceil(positives_marked * len(pos_ind)))
print(f'Using {pos_sample_len}/{len(pos_ind)} as positives and unlabeling the rest')
pos_sample = pos_ind[:pos_sample_len]

# Использование 1803/7210 в качестве положительных результатов и снятие маркировки с остальных
```

```
Using 3966/7210 as positives and unlabeling the rest
```

Создаем столбец для новой целевой переменной, где у нас два класса - P (1) и U (-1)

В [120]:
```
mod_data['class_test'] = -1
mod_data.loc[pos_sample,'class_test'] = 1
print('target variable:\n', mod_data.iloc[:,-1].value_counts())
# mod_data['class_test'].head(3)
```

```
target variable:
 -1    8718
 1    3966
Name: class_test, dtype: int64
```

- We now have just 1803 positive samples labeled as 1 in the 'class_test' col while the rest is unlabeled as -1.

- Recall that col 'Y' still holds the actual label

Remember that this data frame (x_data) includes the former target variable that we keep here just to compare the results

[:-2] is the original class label for positive and negative data [:-1] is the new class for positive and unlabeled data

В [121]:
```
x_data = mod_data.drop(['Y', 'class_test'], axis=1) # just the X
# x_data.head(3)
y_labeled = mod_data['Y'].values # new class (just the P & U)
# y_labeled[:3]
y_positive = mod_data['class_test'].values # original class
# y_positive[:3]
```

5 Задание

применить random negative sampling для построения классификатора в новых условиях

1. random negative sampling

В [122]:
```
mod_data = mod_data.sample(frac=1)
neg_sample = mod_data[mod_data['class_test']==-1][:len(mod_data[mod_data['class_test']==1])]
sample_test = mod_data[mod_data['class_test']==-1][len(mod_data[mod_data['class_test']==1]):]
pos_sample = mod_data[mod_data['class_test']==1]
print(neg_sample.shape, pos_sample.shape)
sample_train = pd.concat([neg_sample, pos_sample]).sample(frac=1)
# sample_train.head(3)
# sample_train.iloc[:,-2].values
# sample_test.iloc[:,:-2].values
```

```
(3966, 110) (3966, 110)
```

В [123]:
```python
model = xgb.XGBClassifier()

# model.fit(sample_train.iloc[:,:-2].values,
#           sample_train.iloc[:,-2].values)
# y_predict = model.predict(sample_test.iloc[:,:-2].values)
# evaluate_results(sample_test.iloc[:,-2].values, y_predict)

model.fit(sample_train.drop(['Y', 'class_test'], axis=1).values,
          sample_train['Y'].values)
y_predict = model.predict(sample_test.drop(['Y', 'class_test'], axis=1).values)
# evaluate_results(sample_test['Y'].values, y_predict)
```

```
[00:05:57] WARNING: C:/Users/Administrator/workspace/xgboost-win64_release_1.3.0/src/learner.cc:1061: Starting in XGBoo
st 1.3.0, the default evaluation metric used with the objective 'binary:logistic' was changed from 'error' to 'loglos
s'. Explicitly set eval_metric if you'd like to restore the old behavior.
```

В [124]:
```python
f1, roc, rec, prc = evaluate_results(sample_test['Y'].values, y_predict)

models_results['model'].append('random negative sampling')
models_results['f-score'].append(f1)
models_results['roc'].append(roc)
models_results['recall'].append(rec)
models_results['precision'].append(prc)
models_results['positives_marked %'].append(positives_marked)
print(f'positives_marked: {positives_marked *100}%')
```

```
Classification results:
f1: 67.19%
roc: 71.41%
recall: 88.77%
precision: 54.05%
positives_marked: 55.00000000000001%
```

6 Задание

сравнить качество с решением из пункта 4 (построить отчет - таблицу метрик)

Пункт 3:
Classification results:

- f1: 80.62%
- roc: 76.19%
- recall: 83.15%
- precision: 78.23%

Пункт 5:

- Classification results:
- f1: 73.039%
- roc: 66.70%
- recall: 91.83%
- precision: 60.63%
- positives_marked: 25.0%

В [60]:
```python
pd.DataFrame(data=models_results).sort_values('f-score', ascending=False)
```

Out[60]:

	model	f-score	roc	recall	precision	positives_marked %
0	XGBClassifier	0.806160	0.761935	0.831492	0.782326	NaN
1	random negative sampling	0.730395	0.667010	0.918317	0.606319	0.25

7 Задание

поэкспериментировать с долей P на шаге 5 (как будет меняться качество модели при уменьшении/увеличении размера P)

В [125]:
```
pd.DataFrame(data=models_results).sort_values('precision', ascending=False)
```

Out[125]:

	model	f-score	roc	recall	precision	positives_marked %
0	XGBClassifier	0.806160	0.761935	0.831492	0.782326	NaN
7	random negative sampling	0.738669	0.624145	0.912424	0.620505	0.100
8	random negative sampling	0.737561	0.634857	0.918493	0.616181	0.135
4	random negative sampling	0.737536	0.640923	0.918592	0.616102	0.150
6	random negative sampling	0.735405	0.655582	0.917314	0.613703	0.200
1	random negative sampling	0.730395	0.667010	0.918317	0.606319	0.250
5	random negative sampling	0.730737	0.586320	0.921513	0.605404	0.050
2	random negative sampling	0.717573	0.688216	0.901388	0.596028	0.350
3	random negative sampling	0.708439	0.713611	0.908050	0.580771	0.450
9	random negative sampling	0.671859	0.714138	0.887653	0.540467	0.550

В [126]:
```
pd.DataFrame(data=models_results).sort_values('roc', ascending=False)
```

Out[126]:

	model	f-score	roc	recall	precision	positives_marked %
0	XGBClassifier	0.806160	0.761935	0.831492	0.782326	NaN
9	random negative sampling	0.671859	0.714138	0.887653	0.540467	0.550
3	random negative sampling	0.708439	0.713611	0.908050	0.580771	0.450
2	random negative sampling	0.717573	0.688216	0.901388	0.596028	0.350
1	random negative sampling	0.730395	0.667010	0.918317	0.606319	0.250
6	random negative sampling	0.735405	0.655582	0.917314	0.613703	0.200
4	random negative sampling	0.737536	0.640923	0.918592	0.616102	0.150
8	random negative sampling	0.737561	0.634857	0.918493	0.616181	0.135
7	random negative sampling	0.738669	0.624145	0.912424	0.620505	0.100
5	random negative sampling	0.730737	0.586320	0.921513	0.605404	0.050

В [ ]:
```

```