PK1

Чичикин Тимофей Дмитриевич ИУ5-25M, Вариант 10. Задачи 10, 30.

Задача 10

Для набора данных проведите устранение пропусков для одного (произвольного) категориального признака с использованием метода заполнения наиболее распространенным значением.

<pre>import numpy as np import pandas as pd import seaborn as sns import matplotlib.pyplot as plt %matplotlib inline sns.set(style="ticks") import plotly.express as px from sklearn.impute import SimpleImputer</pre> df = pd.read_csv('Car Ownership.csv')							
df							
Employme 0 10 1	ent \ Teacher Engineer	Monthly Income 40000 60000	750.0 800.0	Years of			
2 5 3	Nurse Doctor	25000 80000	650.0 900.0				
12 4 15	Businessman	100000	700.0				
495	Project Manager	\$7,000	730.0		5		
years 496	Chef	\$4,500	680.0		4		
years 497	Interior Designer	\$5,500	690.0		4		

years				
498	Medical Assist	ant \$3,500	640.0	3
years 499 Cu years	ustomer Service	Rep \$3,200	641.0	4
Fin	nance Status	Finance History	Car Number of	Children
0	Good	No issues	Yes	2
1	Good	No issues	Yes	1
2	Fair La	ate payment 2 months ago	No	0
3	Excellent	No issues	Yes	3
4	Good La	ate payment 6 months ago	Yes	2
495	Stable	No significant issues	Yes	0
496	Stable	No significant issues	Yes	0
497	Stable	No significant issues	Yes	1
498	Stable	No significant issues	No	1
499	Stable	No significant issues	No	2
[500 ro	ows x 8 columns]			

Найдем пропуски

```
def draw missing(df):
    total = df.isnull().sum().sort_values(ascending=False)
(df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)*1
    missing_data = pd.concat([total, percent], axis=1, keys=['Total',
'Percent'])
    return missing_data
draw_missing(df).round(1)
                            Percent
                     Total
Number of Children
                               25.0
                       125
Years of Employment
                        43
                                8.6
Credit Score
                                8.0
                        40
Finance History
                        28
                                5.6
```

```
Finance Status
                         23
                                 4.6
                                 4.0
Car
                         20
Monthly Income
                         13
                                 2.6
Occupation
                         10
                                 2.0
cat temp data = df[['Finance Status']]
cat_temp_data.head()
  Finance Status
            Good
1
            Good
2
            Fair
3
       Excellent
4
            Good
cat temp data['Finance Status'].unique()
array(['Good', 'Fair', 'Excellent', 'Poor', nan, 'Stable', 'Unstable',
       'Unknow', 'Unkonw'], dtype=object)
```

Присутствует пустое значение nan

```
cat temp data[cat temp data['Finance Status'].isnull()].shape
(23, 1)
# Импьютация наиболее частыми значениями
imp2 = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
data imp2 = imp2.fit transform(cat temp data)
data imp2
array([['Good'],
       ['Good'],
       ['Fair'],
       ['Excellent'],
       ['Good'],
       ['Fair'],
       ['Fair'],
       ['Poor'],
       ['Excellent'],
       ['Good'],
       ['Stable'],
       ['Good'],
       ['Fair'],
       ['Excellent'],
       ['Good'],
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       ['Good'],
       ['Excellent'],
       ['Fair'],
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['Poor'],
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        ['Stable'],
        ['Stable'],
        ['Stable'],
       ['Stable']], dtype=object)
# Пустые значения отсутствуют
np.unique(data_imp2)
array(['Excellent', 'Fair', 'Good', 'Poor', 'Stable', 'Unknow',
'Unkonw',
        'Unstable'], dtype=object)
```

Задача N°30

Для набора данных проведите удаление повторяющихся признаков.

Создам колонку, которая будет повторять значения профессии

df["col	2"]= df['Occupat	ion']						
df								
		on Monthl	y Income	Credit	Score	Years	of	
Employm 0	ent \ Teach	er	40000		750.0			
10 1	Engine	er	60000		800.0			
8	Nur		25000		650.0			
5								
3 12	Doct	or	80000		900.0			
4 15	Businessn	ıan	100000		700.0			
495	Project Manag	er	\$7,000		730.0		5	5
years 496	Ch	ef	\$4,500		680.0		4	1
years 497	Interior Design	er	\$5,500		690.0		4	1
years 498	Medical Assista		\$3,500		640.0		3	3
years					641.0		4	
years	stomer Service F	чер	\$3,200		041.0		4	ŀ
	ance Status	Fi	nance His	tory C	ar Numb	per of	Childre	en
0	Good		No is	sues Y	es			2
1	Good		No is	sues Y	es			1
2	Fair Lat	e payment	2 months	ago l	No			0
3	Excellent	,	No is	_	es			3
4		e payment			es			2
4	GOOU Lat	e payment	0 IIIOITETIS	ayu 1	E S			2
								•
495	Stable	No signi	ficant is	sues Y	es			0

```
496
            Stable
                                                                      0
                         No significant issues
497
            Stable
                         No significant issues
                                                Yes
                                                                       1
498
            Stable
                         No significant issues
                                                                       1
                                                  No
                                                                       2
499
            Stable
                         No significant issues
                                                  No
                     col2
0
                  Teacher
1
                 Engineer
2
                    Nurse
3
                   Doctor
4
              Businessman
          Project Manager
495
496
                     Chef
        Interior Designer
497
498
        Medical Assistant
499 Customer Service Rep
[500 rows x 9 columns]
def get_duplicates(X):
    Поиск дубликатов в колонках
    X - DataFrame
    pairs = \{\}
    dups = []
    # Перебор всех колонок (внешний)
    for i in range(X.shape[1]):
        # текущая колонка
        feat outer = X.columns[i]
        # если текущая колонка не является дублем
        if feat outer not in dups:
            # создаем запись в словаре, колонка является ключом
            pairs[feat outer] = []
            # Перебор оставшихся колонок (внутренний)
            for feat_inner in X.columns[i + 1:]:
                # Если колонки идентичны
                if X[feat outer].equals(X[feat inner]):
```

```
# добавление в словарь и список дубликатов
                     pairs[feat outer].append(feat inner)
                     dups.append(feat inner)
    return dups, pairs
get duplicates(df)
(['col2'],
{'Occupation': ['col2'],
  'Monthly Income': [],
  'Credit Score': [],
  'Years of Employment': [],
  'Finance Status': [],
  'Finance History': [],
  'Car': [],
  'Number of Children': []})
duplicates, _ = get_duplicates(df)
cols to drop = [item for item in duplicates]
cols to drop = [col for col in cols to drop if col in df.columns]
df cleaned = df.drop(columns=cols to drop)
df cleaned
               Occupation Monthly Income Credit Score Years of
Employment \
0
                  Teacher
                                    40000
                                                   750.0
10
1
                 Engineer
                                    60000
                                                   800.0
8
2
                     Nurse
                                    25000
                                                   650.0
5
3
                                    80000
                                                   900.0
                    Doctor
12
4
              Businessman
                                   100000
                                                   700.0
15
. .
495
          Project Manager
                                  $7,000
                                                   730.0
                                                                      5
years
                                                                      4
496
                      Chef
                                  $4,500
                                                   680.0
years
                                                                      4
497
        Interior Designer
                                  $5,500
                                                   690.0
years
498
        Medical Assistant
                                  $3,500
                                                   640.0
                                                                      3
years
```

499 yea	Customer Servions	ce Rep	\$3,200	641.0	4
	Finance Status		Finance History	Car Numbe	er of Children
0	Good		No issues	Yes	2
1	Good		No issues	Yes	1
2	Fair	Late pay	yment 2 months ago	No	0
3	Excellent		No issues	Yes	3
4	Good	Late pay	yment 6 months ago	Yes	2
495	Stable	No s	significant issues	Yes	Θ
496	Stable	No s	significant issues	Yes	Θ
497	Stable	No s	significant issues	Yes	1
498	Stable	No s	significant issues	No	1
499	Stable	No s	significant issues	No	2
[50	0 rows x 8 column	ıs]			

Для произвольной колонки данных построить график "Ящик с усами (boxplot)".

