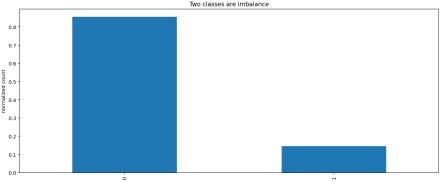
## P01 1 - Data Cleansing and evaluation

```
In [1]: import pandas as pd
         import numpy as np
import regex as re
import warnings
          warnings.filterwarnings('ignore')
from nltk.corpus import stopwords
          from nltk.stem.porter import PorterStemmer
          from nltk.stem import WordNetLemmatizer
          import pickle
          import matplotlib.pyplot as plt
          import re
In [2]: import seaborn as sns
          from sklearn.model_selection import train_test_split
In [3]: %config InlineBackend.figure_format = 'retina'
In [4]: from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
          from sklearn.pipeline import make_pipeline
          from sklearn.preprocessing import FunctionTransformer
          from sklearn.compose import ColumnTransformer
In [5]: import warnings
          warnings.filterwarnings('ignore')
In [6]: import pandas as pd
          from sklearn.compose import make_column_transformer
          from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LogisticRegression
          from sklearn.pipeline import make_pipeline
          from sklearn.model_selection import cross_val_score
```

```
Read data set
 In [7]: file_path = "../DataSet/"
file_name = "exercise_40_train.csv"
df = pd.read_csv(file_path+file_name)
 In [8]: df.shape
 Out[8]: (40000, 101)
 In [9]: df.describe().T
 Out[9]:
                                                                25%
                                                                            50%
                                                                                        75%
                y 40000.0
                              0.145075 0.352181 0.000000 0.000000
                                                                         0.000000
                                                                                     0.000000
                                                                                                 1.000000
               x1 40000.0 2.999958 1.994490 -3.648431 1.592714 2.875892 4.270295
                                                                                              13.837591
               x2 40000.0 20.004865 1.604291 13.714945 18.921388 20.005944 21.083465 27.086468
               x4 40000.0
                             0.002950 1.462185 -5.137161 -1.026799 0.002263
               x5 37572.0
                             0.005396 1.297952 -5.616412 -0.872354 0.008822 0.892467
                                                                                                5.698128
              x95 27396.0 0.031886 1.823091 -6.885150 -1.190682 0.001523 1.248742
                                                                                                7.631773
              x96 33362.0 10.525530 1.437581 8.210456 9.397548 10.358355 11.448559 18.725468
              x97 40000.0 10.002814 1.986984 1.911272 8.665103 9.994318 11.342574 17.861580
              x98 40000.0 0.497650 0.500001 0.000000 0.000000 0.000000 1.000000 1.000000
             x100 40000.0 100.024743 5.247514 78.340735 96.516856 100.024977 103.558762 122.406809
            89 rows × 8 columns
In [10]: df['y'].value_counts(normalize=True).plot(kind='bar',figsize=(15,6))
   plt.ylabel('normalized count')
   plt.title('Two classes are imbalance')
   plt.savefig("../Figures/plot_01_1_imbalancedata.png")
            plt.show()
                                                                       Two classes are imbalance
```



## Data is imbalance

Check the column names and details as follow.

```
In [11]: df.info()
           <class 'pandas.core.frame.DataFrame'>
           Colds pandas. Colembra (1988) RangeIndex: 40000 entries, 0 to 39999 Columns: 101 entries, y to x100 dtypes: float64(86), int64(3), object(12)
           memory usage: 30.8+ MB
In [12]: df.head()
Out[12]:
                                                                                                                       x92 x93
                                                                                                                                              x95
                                                                                                                                                                  x97 x98 x99
            0 0 0.165254 18.060003
                                        Wed 1.077380 -1.339233 -1.584341 0.0062% 0.220784 1.816481 ... -0.397427 0.909479 no 5.492487
                                                                                                                                             NaN 10.255579 7.627730
                                                                                                                                                                       0 yes 104.251338
            1 1 2.441471 18.416307 Friday 1.482586 0.920817 -0.759931 0.0064% 1.192441 3.513950 ... 0.656651 9.093466 no 3.346429 4.321172 NaN 10.505284 1 yes 101.230645
            2 1 4.427278 19.188092 Thursday 0.145652 0.366093 0.709962 -8e-04% 0.952323 0.782974 ... 2.059615 0.305170 no 4.456565 NaN 8.754572 7.810979 0 yes 109.345215
            3 0 3.925235 19.901257 Tuesday 1.763602 -0.251926 -0.827461 -0.0057% -0.520756 1.825586 ... 0.899392 5.971782 no 4.100022 1.151085
                                                                                                                                                    NaN 9.178325 1 yes 103.021970
            4 0 2.868802 22.202473 Sunday 3.405119 0.083162 1.381504 0.0109% -0.732739 2.151990 ... 3.003595 1.046096 yes 3.234033 2.074927 9.987006 11.702664 0 9 yes 92.925935
           5 rows x 101 columns
```

# Check out data for duplicates

```
In [13]: # calculate duplicates
dups = df.duplicated()
    # report if there are any duplicates
print(dups.any())
# # list all duplicate rows
# print(df[dups])
False

No duplicates found
```

```
In [14]: df.dtypes.value_counts()
Out[14]: float64    86
    object    12
    int64    3
    dtype: int64
```

there are 3 types of data in the data set

# Check out the object columns, number of uniques and number of NaNs

```
In [15]: # columns_obj_dtype = []
# for col in df.columns:
# if df[col].dtypes == 'object':
                     columns_obj_dtype.append(col)
          df categ = df.select dtypes(include=['object'])
          print(df_categ.columns)
columns_obj_dtype = df_categ.columns
          # print('columns_obj_dtype = ', columns_obj_dtype)
          print(100*'=')
          number_of_Obj_cols_with_nan = 0
          columns_obj_dtype_NaN = []
          for col in columns_obj_dtype:
              if df categ[col].isnull().sum() != 0:
                   number_of_Obj_cols_with_nan = number_of_Obj_cols_with_nan + 1
                  columns_obj_dtype_NaN.append(col)
                  print('NaNs % in ', col, '=', (df_categ[col].isnull().sum())*100/(df_categ.shape[0]), '%',
          '\nNumber of uniqs =', df_categ[col].nunique(), '\n'
print('number_of_Obj_cols_with_nan', number_of_Obj_cols_with_nan)
          NaNs % in x24 = 9.64 %
Number of uniqs = 2
          NaNs % in x33 = 17.9275 %
          Number of uniqs = 51
          NaNs % in x77 = 23.1425 %
          Number of uniqs = 7
          NaNs % in x99 = 32.09 %
          Number of uniqs = 1
          number_of_Obj_cols_with_nan 4
```

we do have 4 columns containing NaN with obj dtype

Visualize the columns at the following bar plot

## Checking out categorical columns one by one and make sure about values and types and etc

x3 is nominal categorical feature (needs OneHotEncoder transformer) plus some edits should be done using customized function.

check out the 'x7' column

```
In [21]: df_categ['x7'].unique()
Out[21]: array(['0.0062%', '0.0064%', '-8e-04%', '
'0.0174%', '-0.0106%', '0.0032%',
'-0.0025%', '-0.0045%', '0.00688',
                                                               '-0.0057%',
                                                                              '0.0109%', '0.0079%',
                                                                '0.0091%'
                                                                               -0.0052%
                                                                  -0.0137%
                                                                                 '-0.0014%'
                      '-0.0013%',
                                    '0.0066%',
                                                   '0.0097%',
                                                                 '-0.0086%',
                      '-0.0023%',
                                    '-0.0107%', '-0.0134%', '0.0058%', '-0.0172%', '-0.0026%', '-0.0118%' '0.0095%', '0.0026%', '-0.0051%',
                                                                                 '-2e-04%
                      '-0.0055%',
                                                  '0.0026%',
'-0.0037%',
                                                                                '0.0054%',
                                                                                -0.0097%
                     '-0.0167%'
                                     '0.0015%'
                                                                  '0.0011%
                                                 . '0.015%'
                                                                               '2e-04%',
                      '-0.0016%',
                                                                                            '0.0122%',
                                     -0.0155%
                                                                  -0.0032%
                                    -0.0054%',
                                                                 '0.0013%',
                      '0.0082%'
                                                   '-0.0017%'.
                                                   -0.005%', '-0.0018%', '6e-04%'
                       -0.0021%',
                                      -0.017%'
                                                   '-0.005%',
                                                                 '0.0014%',
, '6e-04%',
                                                                                -0.0103%',
                                                                                             '-0.018%',
                                    '-0.0115%'
                                                                                '-0.0169%',
                      '-0.0077%',
                      '0.0051%',
'-0.0035%',
                                    '0.0093%',
                                                                             '-0.0012%', '0.0056%'
'0.0098%', '-0.0022%',
                                    '0.005%', '0.001%', '0.001%', '-0.0179%', '-0.0179%',
                                                                '0.0127%'.
                                                   '0.001%',
                                                                              '0.0049%', '0.0034%',
'-0.003%', '-0.0059%',
                      '-0.0146%',
                                   '-0.0166.
'0.0017%', '-0.01/5%
'0.017%', '0.0045%',
'0.0149%', '0.0149%',
'-0.0176%
                                                                '-0.016%'
                                                                '0.007%',
                      '0.0043%',
                                                                             '-0.006%',
                                                             0.0052%',
                                                                                          '-0.0159%'
                      '-0.004%'.
                                                                                         '-0.0019%',
                      '0.0061%',
                                    '-3e-04%', '-0.0176%',
                                                                '-0.0102%', '0.0094%',
            x7 column: the % sign should be cleaned from strings and I need to change the dtype and introduce it as numeric feature.
In [22]: df['x7'] = df['x7'].str.replace('%','')
            print(df['x7'].dtypes)
df['x7'] = df['x7'].astype('float64')
            df['x7'].dtypes
            object
Out[22]: dtype('float64')
            check out the 'x19' column
In [23]: df_categ['x19'].unique()
Out[23]: array(['$-908.650758424405', '$-1864.9622875143', '$-543.187402955527'
                        ., '$834.95775080472', '$-48.1031003332715', '$96.0017151741518'],
                   dtype=object)
            x19 column: the % sign should be cleaned from strings and I need to change the dtype and introduce it as numeric feature.
In [24]: df_categ['x19'] = df_categ['x19'].str.replace('$','')
df_categ['x19'].dtypes
df_categ['x19'] = df_categ['x19'].astype('float64')
df_categ['x19'].dtypes
Out[24]: dtype('float64')
            check out the 'x24' column
In [25]: df_categ['x24'].unique()
Out[25]: array(['female', 'male', nan], dtype=object)
            x24 column: is nominal category and needs to be transformed using One Hot Encoding
            check out the x31 column
In [26]: df categ['x31'].unique()
Out[26]: array(['no', 'yes'], dtype=object)
            x31 column: is nominal category and needs to be transformed using One Hot Encoding
            check out the x33 column
In [27]: df_categ['x33'].unique()
west Viginia, Connecticut, virginia, North Carolina, 'Montana', 'New Mexico', 'New Hampshire', 'Michigan', 'DC', 'Washington', 'Louisiana', 'Kentucky', 'Utah', 'Missouri', 'Oregon', 'Oklahoma', 'Nevada', 'Wisconsin', 'New Jersey', 'Maryland', 'Maine', 'Alaska', 'Idaho', 'Wyoming', 'Rhode Island', 'South Dakota', 'Mississippi', 'Kansas', 'Delaware', 'Hawaii', 'South Carolina'], dtype=object)
 In [ ]:
            x33 column: is nominal category and needs to be transformed using One Hot Encoding
            check out the x39 column
```

In [28]: df\_categ['x39'].unique()
Out[28]: array(['5-10 miles'], dtype=object)

## Drop the column x39

check out the x60 column

#### x60 is nominal and OneHotEncoder should be used to transfer this column

check out the x65 column

#### x65 is nominal and OneHotEncoder should be used to transfer this column

check out the x77 column

### x77 is nominal and OneHotEncoder should be used to transfer this column

check out the x93 column

```
In [32]: df_categ['x93'].unique()
Out[32]: array(['no', 'yes'], dtype=object)
```

#### x93 is nominal and OneHotEncoder should be used to transfer this column

check out the x99 (it has just one value - it is usedful)

```
In [33]: df_categ['x99'].unique()
Out[33]: array(['yes', nan], dtype=object)
```

X99 should be droped - it has just one category. The x24, x33, and x77 columns NaN values needs to be replaced by their mode.

# Recap for categorical columns

- x3 is nominal categorical feature (needs OneHotEncoder transformer) and custom function edit is needed
- x7 column: the % sign should be cleaned from strings and I need to change the dtype and introduce it as numeric feature.
- x19 column: the % sign should be cleaned from strings and I need to change the dtype and introduce it as numeric feature.
- x24 column: is nominal category and needs to be transformed using One Hot Encoding
- x31 column: is nominal category and needs to be transformed using One Hot Encoding
- x33 column: is nominal category and needs to be transformed using One Hot Encoding
- x39 should be droped the column
- x60 is nominal and OneHotEncoder should be used to transfer this column
- x65 is nominal and OneHotEncoder should be used to transfer this column
- x77 is nominal and OneHotEncoder should be used to transfer this column
   x93 is nominal and OneHotEncoder should be used to transfer this column
- X99 should be droped it has just one category.
- The x24, x33, and x77 columns NaN values needs to be replaced by their mode.

## **Custom transform**

I need to use custom function transform

```
In [36]: # file_path = "../DataSet/"
# file_name = "exercise_40_train.csv"
# df = pd_read_csv(file_path+file_name)

# X = df[['x3']]
# print(X.shape)
# print(type(X))

# # extract the first letter from each string
# def fix_x3_wed(df):

# return df.apply(lambda x: re.sub(r'\bWed\b', 'Wednesday', str(x)))

# fix_x3_wed = FunctionTransformer(fix_x3_wed)

# ct = make_column_transformer((fix_x3_wed, ['x3']))

# ct.fit_transform(X)
```

i get error here! cant make custom transformer! I move on.

ValueError: The output of the 'functiontransformer' transformer should be 2D (scipy matrix, array, or pandas DataFrame).

## Categorical feature selection

let's score the features using select Kbest

```
In [38]: # logicbot
             # evaluation of a model fit using mutual information input features
            from pandas import read csv
             from sklearn.preprocessing import LabelEncoder
            from sklearn.preprocessing import OrdinalEncoder
from sklearn.feature_selection import SelectKBest
            from sklearn.feature selection import mutual info classif
            from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
            from sklearn.metrics import accuracy_score
In [39]: # file_path = "../DataSet/"
# file_name = "exercise_40_train.csv"
# df = pd.read_csv(file_path+file_name)
In [46]: # df categ
            dataset_features = df_categ.values
dataset_target = df_categ.values
           # split into input (X) and output (y) variables
X = dataset_features[:, 3:] #exclude the $ column
y = dataset_target[:,0]
In [47]: X[0]
In [48]: # imp = SimpleImputer(strategy="most_frequent")
           # imp.fit_transform(X)
```

```
In [49]:
             def load_dataset():
                   # load the dataset as a pandas DataFrame
                  # load the dataset as a panuas because # df catego dataset_features = df_categ.values dataset_target = df.values # split into input (X) and output (Y) variables X = dataset_features[:, 3:]
                   y = dataset_target[:,0]
                   return X, y
             def prepare_inputs(X_train, X_test):
                   imp = SimpleImputer(strategy="most_frequent")
                   imp.fit(X train)
                  X_train_imp = imp.transform(X_train)
X_test_imp = imp.transform(X_test)
                   oe = OrdinalEncoder()
                   oe.fit(X_train_imp)
                  X_train_enc = oe.transform(X_train_imp)
X_test_enc = oe.transform(X_test_imp)
                   return X train enc, X test enc
              # prepare target
             def prepare_targets(y_train, y_test):
                   le = LabelEncoder()
                   le.fit(y_train)
                  y_train_enc = le.transform(y_train)
y_test_enc = le.transform(y_test)
                   return y_train_enc, y_test_enc
              # feature selection
             def select_features(X_train, y_train, X_test):
                  select_features(x_train, y_train, x_test):
fs = SelectxBest(score func=mutual_info_classif, k=4)
fs.fit(X_train, y_train)
X_train_fs = fs.transform(X_train)
X_test_fs = fs.transform(X_test)
                   return X_train_fs, X_test_fs, fs
              # load the dataset
             X, y = load_dataset()
             # split into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)
              # prepare input data
             X_train_enc, X_test_enc = prepare_inputs(X_train, X_test)
              # prepare output data
             y_train_enc, y_test_enc = prepare_targets(y_train, y_test)
             X_train_fs, X_test_fs, fs = select_features(X_train_enc, y_train_enc, X_test_enc)
             weights = \{0:0.85, 1:0.14\}
             # fit the model
model = LogisticRegression(solver='lbfgs', class_weight=weights)
model.fit(X_train_fs, y_train_enc)
             yhat = model.predict(X_test_fs)
            # evaluate predictions
accuracy = accuracy_score(y_test_enc, yhat)
print('Accuracy: %.2f' % (accuracy*100))
             Accuracy: 85.65
```

localhost:8888/notebooks/Codes/P01\_1\_Data\_Cleansing\_Categ.ipynb

In [50]: from matplotlib import pyplot

```
In [51]: # load the dataset
X, y = load_dataset()
           # split into train and test sets
           X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=1)
           # prepare input data
           X_train_enc, X_test_enc = prepare_inputs(X_train, X_test)
# prepare output data
           y_train_enc, y_test_enc = prepare_targets(y_train, y_test)
           # feature selection
X_train_fs, X_test_fs, fs = select_features(X_train_enc, y_train_enc, X_test_enc)
           # what are scores for the features
scr_list = []
           for i in range(len(fs.scores_)):
    scr_list.append(fs.scores_[i])
    print('Feature %d: %f' % (i, fs.scores_[i]))
           # plot the scores
           scr_list_pd = pd.DataFrame(scr_list)
# print(scr_list_pd)
           scr_list_pd = scr_list_pd.rename(index={0: 'x24',1:'x31', 2:'x33', 3:'x39', 4:'x60', 5:'x65', 6:'x77', 7:'x93', 8:'x99'})
           scr_list_pd.plot(kind='bar', figsize=(15,6), label=False)
           plt.ylabel('score')
plt.title('Scores for categorical features')
           plt.savefig("../Figures/plot_01_1_categ_selectkbest.png")
           plt.show()
           Feature 0: 0.002342
           Feature 1: 0.004263
           Feature 2: 0.001902
Feature 3: 0.001658
           Feature 4: 0.000000
           Feature 5: 0.002721
           Feature 6: 0.002061
           Feature 7: 0.003576
Feature 8: 0.001586
                                                                Scores for categorical features
             0.0040
              0.0035
              0.0030
              0.0025
              0.0015
              0.0010
              0.0005
              0.000
                         24
In [54]: print(X[0])
           print(df_categ.columns)
           ['female' 'no' 'Colorado' '5-10 miles' 'August' 'farmers' 'mercedes' 'no'
           dtype='object')
Out[54]:
                                                             x33
                     x3
                             x7
                                        x19
                                              x24 x31
                                                                      x39
                                                                             x60
                                                                                    x65
                                                                                             x77 x93 x99
           0 Wednesday 0.0062% -908.650758 female no Colorado 5-10 miles August farmers mercedes
                                                                                                  no yes
                  Friday 0.0064% -1864.962288 male no Tennessee 5-10 miles April allstate mercedes no yes
 In [ ]: X[0]
           Using column transform and preforming two transformation on one column
In [55]: two_transformer_pipe = make_pipeline(SimpleImputer(strategy="most_frequent"),
                                                     OneHotEncoder())
           col_transform = ColumnTransformer(transformers=[("two_transformer_pipe",
                                                                   two_transformer_pipe,
df_categ.columns)])
 In [ ]: # col_transform.fit_transform(X)
 In [ ]: # a = pd.DataFrame(col_transform.fit_transform(X.head()))
In [56]: df['y'].value_counts(normalize=True)
Out[56]: 0
               0.854925
                0.145075
           Name: y, dtype: float64
```

```
weights = {0:0.85, 1:0.14}

# model = LogisticRegression(solver='saga', class_weight=weights)
# # # define evaluation procedure
# cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
# # ferons wal_score(model, X, y, scoring='roc_auc', cv=cv, n_jobs=-1)

# logreg = LogisticRegression(solver='sag', class_weight=weights)
# pipe = make_pipeline(col_transform, logreg)
# cross_val_score(pipe, X, y, cv=cv, scoring='roc_auc', n_jobs=-1)

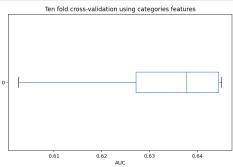
In [58]: X = df[['x3', 'x24', 'x31', 'x33', 'x60', 'x65', 'x77', 'x93']]

y = df('y']

x_3_trans_pipe = make_pipeline(SimpleImputer(strategy='most_frequent'), OneHotEncoder())

col_transform = make_column_transformer((x_3_trans_pipe, ['x3', 'x24', 'x31', 'x33', 'x60', 'x65', 'x77', 'x93']))

veights = {0:0.85, 1:0.14}
logreg = LogisticRegression(solver='sag', class_weight=weights)
pipe2 = make_pipeline(col_transform, logreg)
scor = cross_val_score(pipe2, X, y, cv=10, scoring='roc_auc')
scor = pd.bataframe(scor)
# pit.yilm(0,1)
scor.plot(Kind='box', vert=Palse, figsize=(8,5))
pit.xilahe('AUC')
pit.title('Ten fold cross-validation using categories features')
plt.savefig('../Figures/plot_01_boxplot.png')
plt.show()
```



In [57]: from sklearn.model\_selection import RepeatedStratifiedKFold

```
In []:
In []:
```