P02_2_Modeling

Recap for Categorical features

- 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.

Recap for Numerical features

- Column 'x30', 'x44', 'x57' have more than 50% nan and should be droped
- Three features inside the numeric df need to be transformed using One Hot Encoding. These are features with 0-1 values and should be treated like category features. These are 0-1 features and should be treated like category features. columns are x59 and x79 and x98
- I may use Isolation Forest or LOF for outlier detection. I will check the AUC to see the differences.
- cols with high skewness are `['x13', 'x21', 'x32', 'x35', 'x44', 'x59', 'x67', 'x73', 'x75', 'x79', 'x84', 'x89']` . I will apply power transformer.
- High score numerical features are as follow: `['x16', 'x18', 'x28', 'x32', 'x35', 'x40', 'x47', 'x52', 'x57', 'x62', 'x68', 'x70', 'x75', 'x78', 'x81', 'x88', 'x89', 'x95', 'x96']`
- With n_components=12, I get 0.62 AUC and as it is seen 12 principal components have 62% of variance. I may apply PCA if I found not using it computationally time expensive.

import libraries

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
from sklearn.pipeline import make_pipeline, Pipeline

import matplotlib.pyplot as plt
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import GradientBoostingClassifier
import re
from tqdm import tqdm
from sklearn.metrics import roc_curve
import sklearn.metrics as metrics
```

In [2]:
```
from sklearn.preprocessing import StandardScaler
from sklearn.feature_selection import VarianceThreshold
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import Normalizer
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import cross_val_predict
from sklearn.model_selection import cross_validate
from sklearn.preprocessing import MaxAbsScaler
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import PowerTransformer
```

In [3]:
```
from sklearn.neighbors import LocalOutlierFactor
from sklearn.preprocessing import MinMaxScaler
```

In [4]:
```
from sklearn.decomposition import PCA
from sklearn.model_selection import RepeatedStratifiedKFold
```

In [5]:
```
from pandas import read_csv
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif
from matplotlib import pyplot
```

In [6]:
```
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import make_pipeline
from sklearn.compose import ColumnTransformer
```

In [7]:
```
from sklearn.covariance import EllipticEnvelope
from sklearn.ensemble import IsolationForest
from sklearn.preprocessing import FunctionTransformer
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import confusion_matrix
```

In [8]:
```
from numpy import mean
from numpy import std
from sklearn.datasets import make_classification
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.pipeline import Pipeline
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from matplotlib import pyplot
```

In [9]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif
from sklearn.pipeline import Pipeline
from sklearn.model_selection import RepeatedStratifiedKFold
from matplotlib import pyplot
```

In [10]:
```
from pandas import read_csv
from sklearn.model_selection import train_test_split
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 matplotlib import pyplot
```

In [11]:
```
import seaborn as sns
from sklearn.model_selection import train_test_split
```

In [12]:
```
%config InlineBackend.figure_format = 'retina'
```

In [13]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [14]:
```
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 [15]:
```
file_path = "../DataSet/"
file_name = "exercise_40_train.csv"
df = pd.read_csv(file_path+file_name)
```

In [16]:
```
df.shape
```

Out[16]:
```
(40000, 101)
```

In [17]:
```
df.head()
```

Out[17]:

	y	x1	x2	x3	x4	x5	x6	x7	x8	x9	...	x91	x92	x93	x94	x95	x96	x97	x98	x99	x100
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	yes	92.925935

5 rows × 101 columns

select the numeric features

In [18]:
```
df_numeric_features = df.drop(['y'],axis=1)
```

In [19]:
```
df.dtypes.value_counts()
```

Out[19]:
```
float64    86
object     12
int64       3
dtype: int64
```

In [20]:
```
df_numeric_features = df.select_dtypes(include=['float64', 'int64'])
df_numeric_features = df_numeric_features.drop(['y'],axis=1)
```

In [21]:
```
df_cat_features = df.select_dtypes(include=['object'])
df_cat_features.head()
```

Out[21]:

	x3	x7	x19	x24	x31	x33	x39	x60	x65	x77	x93	x99
0	Wed	0.0062%	$-908.650758424405	female	no	Colorado	5-10 miles	August	farmers	mercedes	no	yes
1	Friday	0.0064%	$-1864.9622875143	male	no	Tennessee	5-10 miles	April	allstate	mercedes	no	yes
2	Thursday	-8e-04%	$-543.187402955527	male	no	Texas	5-10 miles	September	geico	subaru	no	yes
3	Tuesday	-0.0057%	$-182.626380634258	male	no	Minnesota	5-10 miles	September	geico	nissan	no	yes
4	Sunday	0.0109%	$967.007090837503	male	yes	New York	5-10 miles	January	geico	toyota	yes	yes

Make custom transformation for categorical features

In [22]:
```
def custom_edit_x3(df_categ):

    # https://stackoverflow.com/questions/60237488/python-replace-only-exact-word-in-string
    for i, string in enumerate(df_categ['x3'].values):
        df_categ['x3'].values[i] = re.sub(r'\bTue\b', 'Tuesday', string)

    for i, string in enumerate(df_categ['x3'].values):
        df_categ['x3'].values[i] = re.sub(r'\bSun\b', 'Sunday', string)

    for i, string in enumerate(df_categ['x3'].values):
        df_categ['x3'].values[i] = re.sub(r'\bSat\b', 'Saturday', string)

    for i, string in enumerate(df_categ['x3'].values):
        df_categ['x3'].values[i] = re.sub(r'\bFri\b', 'Friday', string)

    for i, string in enumerate(df_categ['x3'].values):
        df_categ['x3'].values[i] = re.sub(r'\bWed\b', 'Wednesday', string)

    for i, string in enumerate(df_categ['x3'].values):
        df_categ['x3'].values[i] = re.sub(r'\bMon\b', 'Monday', string)

    for i, string in enumerate(df_categ['x3'].values):
        df_categ['x3'].values[i] = re.sub(r'\bThur\b', 'Thursday', string)
    return df_categ

    return df_categ
```

make a column transformer fucntion and make sure it works

In [23]:
```
custom_edit_x3_tf = FunctionTransformer(custom_edit_x3)
ct = make_column_transformer((custom_edit_x3_tf, ['x3']))
```

make a pipe line and check out the customized transformer

In [24]:
```
x3_pipe = make_pipeline(custom_edit_x3_tf, SimpleImputer(strategy="most_frequent"), OneHotEncoder())
ct = make_column_transformer((x3_pipe, ['x3']))
ct.fit_transform(df).toarray()[0].size
```

Out[24]: 7

write customized transformer for x7 and x19 features

In [25]:
```
def custom_edit_x7(df):
    df = df.apply(lambda x: (x.str.replace('%','')))

    return (np.float_(df))

custom_edit_x7_tf = FunctionTransformer(custom_edit_x7)
ct = make_column_transformer((custom_edit_x7_tf, ['x7']))
x7 = ct.fit_transform(df)
```

In [26]:
```
def custom_edit_x19(df):
    df = df.apply(lambda x: (x.str.replace('$','')))

    return (np.float_(df))

custom_edit_x19_tf = FunctionTransformer(custom_edit_x19)
ct = make_column_transformer((custom_edit_x19_tf, ['x19']))
x19 = ct.fit_transform(df)
```

check out the customized transformers using pipeline

In [27]:
```
two_step_transformer_pipe = make_pipeline(SimpleImputer(strategy="most_frequent"),
                                                     OneHotEncoder())
```

In [28]:
```
two_step_transformer_pipe.fit_transform(df[['x24','x31','x33','x60','x65','x77','x93']]).toarray()[0].size
```

Out[28]: 81

check out the last two pipelines in column transformer

In [29]:
```
ct = make_column_transformer((x3_pipe, ['x3']),
                             (two_step_transformer_pipe, ['x24','x31','x33','x60','x65','x77','x93']),
                            )
```

In [30]:
```
ct.fit_transform(df).toarray()[0].size
```

Out[30]: 88

make a pipeline for three features inclduing x59, x79, and x98. these are numeric features with 0-1 values. Apply one hot encder.

In [31]:
```
numer_OHE_x59_x79_x98 = make_pipeline(SimpleImputer(strategy="most_frequent"),
                                      OneHotEncoder())

numer_OHE_x59_x79_x98.fit_transform(np.array(df['x59']).reshape(-1, 1)).toarray()[0].size
```

Out[31]: 2

In [32]:
```
# len(numer_OHE_x59_x79_x98.fit_transform(np.array(df['x59']).reshape(-1, 1)).toarray())
```

check out if the new pipeline works

In [33]:
```
ct = make_column_transformer((numer_OHE_x59_x79_x98, ['x59', 'x79', 'x98']))
```

In [34]:
```
ct.fit_transform(df)
```

Out[34]:
```
array([[1., 0., 0., 1., 1., 0.],
       [1., 0., 0., 1., 0., 1.],
       [1., 0., 0., 1., 1., 0.],
       ...,
       [1., 0., 0., 1., 0., 1.],
       [1., 0., 0., 1., 1., 0.],
       [0., 1., 0., 1., 0., 1.]])
```

the pipeline works just fine.

make a new pipeline for numeric features which were skewed and check it out if it works flawlessly.

In [35]:
```
numer_skewness = make_pipeline(SimpleImputer(strategy="mean"),
                               StandardScaler(),
                                PowerTransformer(),
#                                VarianceThreshold(),
                              )

numer_skewness.fit_transform(np.array(df['x13']).reshape(-1, 1))
```

Out[35]:
```
array([[ 0.52252661],
       [-0.98789216],
       [-1.11580409],
       ...,
       [-0.26185934],
       [-2.10399184],
       [-0.25390223]])
```

feed the new pipeline into the column transformer and check it out.

In [36]:
```
ct = make_column_transformer((numer_skewness, ['x13', 'x21', 'x32', 'x35',
                                               'x44', 'x59', 'x67', 'x73',
                                               'x75', 'x79', 'x84', 'x89']))
```

In [37]:
```
ct.fit_transform(df)
```

Out[37]:
```
array([[ 0.52252661,  1.6190496 , -0.68519579, ...,  0.42510903,
        -2.88844405,  0.15809134],
       [-0.98789216, -0.40425833,  0.60652813, ..., -1.8907331 ,
         0.0591937 ,  0.08691384],
       [-1.11580409,  0.16008288,  1.24974419, ...,  0.42510903,
         0.0591937 ,  0.21667148],
       ...,
       [-0.26185934, -0.73586194,  0.13156308, ...,  0.42510903,
         2.05710353, -1.38447206],
       [-2.10399184,  0.05575166,  1.33614618, ...,  0.42510903,
         0.0591937 ,  0.21667148],
       [-0.25390223, -0.87867438,  0.34614004, ...,  0.42510903,
         0.0591937 ,  0.21667148]])
```

make a pipeline for rest of numeric features and check it out

In [38]:
```
rest_numeric_features = []
for col in df_numeric_features.columns:
    if col != ['x13', 'x21', 'x32', 'x35', 'x44', 'x59', 'x67', 'x73', 'x75', 'x79', 'x84', 'x89']:
        rest_numeric_features.append(col)
print(rest_numeric_features)
```

```
['x1', 'x2', 'x4', 'x5', 'x6', 'x8', 'x9', 'x10', 'x11', 'x12', 'x13', 'x14', 'x15', 'x16', 'x17', 'x18', 'x20', 'x21', 'x22', 'x23', 'x25', 'x26', 'x27', 'x28',
'x29', 'x30', 'x32', 'x34', 'x35', 'x36', 'x37', 'x38', 'x40', 'x41', 'x42', 'x43', 'x44', 'x45', 'x46', 'x47', 'x48', 'x49', 'x50', 'x51', 'x52', 'x53', 'x54',
'x55', 'x56', 'x57', 'x58', 'x59', 'x61', 'x62', 'x63', 'x64', 'x66', 'x67', 'x68', 'x69', 'x70', 'x71', 'x72', 'x73', 'x74', 'x75', 'x76', 'x78', 'x79', 'x80',
'x81', 'x82', 'x83', 'x84', 'x85', 'x86', 'x87', 'x88', 'x89', 'x90', 'x91', 'x92', 'x94', 'x95', 'x96', 'x97', 'x98', 'x100']
```

In [39]:
```
Rest_numeric_features = make_pipeline(SimpleImputer(strategy="mean"),
                               StandardScaler(),
                                PowerTransformer(),
#                                VarianceThreshold(),
#                             PCA(n_components=20),
                                     )

# Rest_numeric_features.fit_transform(np.array(df['x1']).reshape(-1, 1))
```

In [40]:
```
ct = make_column_transformer((Rest_numeric_features, rest_numeric_features))
```

In [41]:
```
ct.fit_transform(df)
```

Out[41]:
```
array([[-1.52210183, -1.21321633,  0.73538846, ..., -1.19734632,
        -0.99531099,  0.80499414],
       [-0.21778515, -0.99034322,  1.01178638, ...,  0.25640949,
         1.0047111 ,  0.22810827],
       [ 0.75277741, -0.50800169,  0.09907159, ..., -1.10434356,
        -0.99531099,  1.77989024],
       ...,
       [-0.62132649, -1.36064831, -0.39842492, ..., -1.17905537,
         1.0047111 , -0.0022491 ],
       [ 0.53960265,  0.17657422,  0.29347708, ..., -0.68188951,
        -0.99531099,  1.80192371],
       [-0.14750603, -2.22596216, -0.79910404, ...,  1.26723974,
         1.0047111 ,  1.96954651]])
```

Combining all transformers into one

In [42]:
```
ct_all_features = make_column_transformer((x3_pipe, ['x3']),
                            (two_step_transformer_pipe, ['x24','x31','x33',
                                                         'x60','x65','x77','x93']),
                            (numer_OHE_x59_x79_x98, ['x59', 'x79', 'x98']),

                             # features with high skewness
                            (numer_skewness, ['x13', 'x21', 'x32', 'x35',
                                              'x44', 'x59', 'x67', 'x73',
                                              'x75', 'x79', 'x84', 'x89']),

                             # features from categories-> edited to numeric-no null found
                             (custom_edit_x7_tf, ['x7']),
                             (custom_edit_x19_tf, ['x19']),

                             # rest numeric features
                             (Rest_numeric_features, rest_numeric_features),
                            )

ct_all_features.fit_transform(df)[0].size
```

Out[42]:
```
196
```

so far so good.

run the pipeline using LogisticRegression classifier.

In [43]:
```
weights = {0:0.85, 1:0.14}
logreg = LogisticRegression(solver='sag', class_weight=weights)
```

In [44]:
```
X_all_features = df.drop(columns=['y'], axis=1)
y = df['y']
```

In [45]:
```
Final_pipe = make_pipeline(ct_all_features, logreg) # PCA(n_components=5)
cross_val_score(Final_pipe, X_all_features, y, cv=5, scoring='roc_auc', n_jobs=-1)
```

Out[45]:
```
array([0.52418166, 0.52645745, 0.55137399, 0.52545711, 0.5320165 ])
```

fit the pipeline on input features

In [46]:
```
Final_pipe.fit(X_all_features,y)
```

Out[46]:
```
Pipeline(steps=[('columntransformer',
                 ColumnTransformer(transformers=[('pipeline-1',
                                                  Pipeline(steps=[('functiontransformer',
                                                                   FunctionTransformer(func=<function custom_edit_x3 at 0x7fc1c7d2b7b8>)),
                                                                  ('simpleimputer',
                                                                   SimpleImputer(strategy='most_frequent')),
                                                                  ('onehotencoder',
                                                                   OneHotEncoder())]),
                                                  ['x3']),
                                                 ('pipeline-2',
                                                  Pipeline(steps=[('simpleimputer',
                                                                   SimpleImput...
                                                                   SimpleImputer()),
                                                                  ('standardscaler',
                                                                   StandardScaler()),
                                                                  ('powertransformer',
                                                                   PowerTransformer())]),
                                                  ['x1', 'x2', 'x4', 'x5', 'x6',
                                                   'x8', 'x9', 'x10', 'x11',
                                                   'x12', 'x13', 'x14', 'x15',
                                                   'x16', 'x17', 'x18', 'x20',
                                                   'x21', 'x22', 'x23', 'x25',
                                                   'x26', 'x27', 'x28', 'x29',
                                                   'x30', 'x32', 'x34', 'x35',
                                                   'x36', ...])])),
                ('logisticregression',
                 LogisticRegression(class_weight={0: 0.85, 1: 0.14},
                                    solver='sag'))])
```

In [47]:
```
y_pred = Final_pipe.predict(X_all_features)
metrics.confusion_matrix(y,y_pred)
```

Out[47]:
```
array([[34197,     0],
       [ 5803,     0]])
```

PCA (Principal Component Analysis)

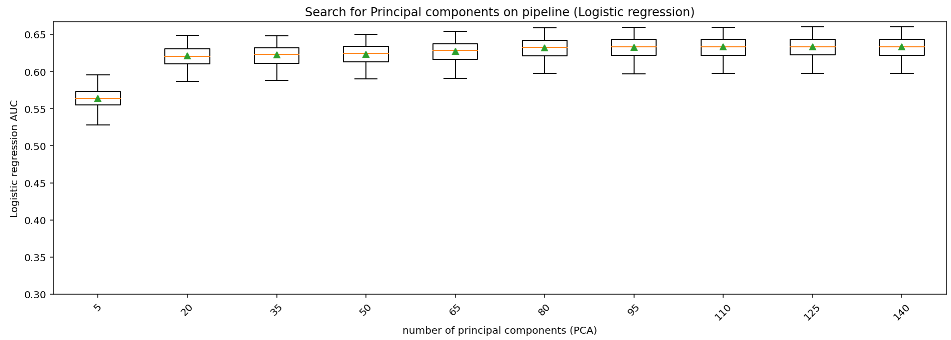
doing some experiments using PCA for the sack of dimensionality reduction purposes.

PCA and Logistic Regression

In [48]:
```
# get the dataset
def get_dataset():
    #   X, y = make_classification(n_samples=1000, n_features=20, n_informative=15, n_redundant=5, random_state=7)
    X = df.drop(columns=['y'], axis=1)
    y = df['y']
    return X, y

# get a list of models to evaluate
def get_models():
    models = dict()
    for i in list(range(5,150,15)):

        Final_pipe = make_pipeline(ct_all_features, PCA(n_components=i), logreg)
        models[str(i)] = Final_pipe

#       steps = [('pca', PCA(n_components=i)), ('m', LogisticRegression())]
#       models[str(i)] = Pipeline(steps=steps)


    return models

# evaluate a given model using cross-validation
def evaluate_model(model, X, y):
    cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
    scores = cross_val_score(model, X, y, scoring='roc_auc', cv=cv, n_jobs=-1, error_score='raise')
    return scores

# define dataset
X, y = get_dataset()
# get the models to evaluate
models = get_models()
# evaluate the models and store results
results, names = list(), list()
for name, model in tqdm(models.items()):
    scores = evaluate_model(model, X, y)
    results.append(scores)
    names.append(name)
#     print('>%s %.3f (%.3f)' % (name, mean(scores), std(scores)))
```

```
100%|██████████| 10/10 [13:01<00:00, 78.20s/it]
```

In [49]:
```
plt.figure(figsize=(16,5))
# plot model performance for comparison
pyplot.boxplot(results, labels=names, showmeans=True)
pyplot.xticks(rotation=45)
plt.ylabel('Logistic regression AUC')
plt.xlabel('number of principal components (PCA)')
plt.title('Search for Principal components on pipeline (Logistic regression)')
plt.ylim(0.3,)
plt.savefig("../Figures/plot_02_2_pca_lr.png")
pyplot.show()
```



PCA and MLP

In [50]:
```
from sklearn.neural_network import MLPClassifier
```

In [51]:
```
clf = MLPClassifier(random_state=1, max_iter=300)
# Final_pipe = make_pipeline(ct_all_features, clf)
# cross_val_score(Final_pipe, df, y, cv=5, scoring='roc_auc', n_jobs=-1)
```

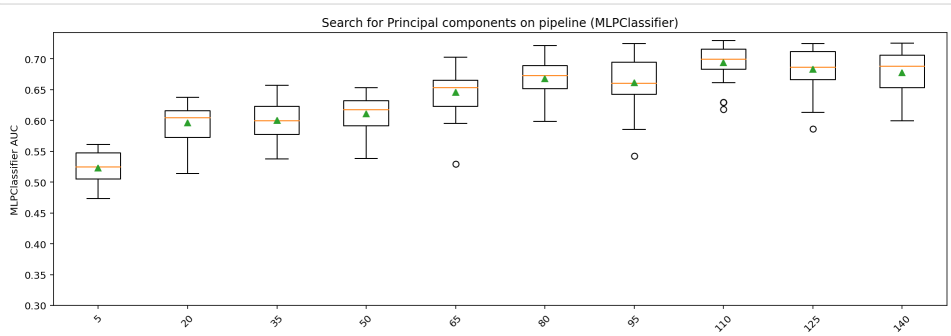
I just need to modify the get model function

In [52]:
```
# get a list of models to evaluate
def get_models():
    models = dict()
    for i in list(range(5,150,15)):
        Final_pipe = make_pipeline(ct_all_features, PCA(n_components=i), clf)
        models[str(i)] = Final_pipe

    return models
```

In [53]:
```
# define dataset
X, y = get_dataset()
# get the models to evaluate
models = get_models()
# evaluate the models and store results
results, names = list(), list()
for name, model in tqdm(models.items()):
    scores = evaluate_model(model, X, y)
    results.append(scores)
    names.append(name)
#     print('>%s %.3f (%.3f)' % (name, mean(scores), std(scores)))
```

```
100%|██████████| 10/10 [17:03<00:00, 102.34s/it]
```

In [54]:
```
plt.figure(figsize=(16,5))
# plot model performance for comparison
pyplot.boxplot(results, labels=names, showmeans=True)
pyplot.xticks(rotation=45)
plt.ylabel('MLPClassifier AUC')
plt.xlabel('number of principal components (PCA)')
plt.title('Search for Principal components on pipeline (MLPClassifier)')
plt.ylim(0.3,)
plt.savefig("../Figures/plot_02_2_mlp_lr.png")

pyplot.show()
```



using all features and MLP

In [55]:
```
clf = MLPClassifier(random_state=1, max_iter=300)
Final_pipe = make_pipeline(ct_all_features, clf)
cross_val_score(Final_pipe, df, y, cv=5,
                scoring='roc_auc', n_jobs=-1)
```

Out[55]:
```
array([0.71408815, 0.74299607, 0.7497773 , 0.750639  , 0.71121597])
```

I don't use the PCA for now

Pipes & transformers using MLP classifier

Adding VarianceThreshold to pipeline and check out the outcomes

In [91]:
```
# x3 pipe
x3_pipe = Pipeline([('custom_edit_x3_tf', custom_edit_x3_tf),
                   ('imp', SimpleImputer(strategy="most_frequent")),
                   ('ohe', OneHotEncoder())])
# two tf pipe
two_step_transformer_pipe = Pipeline([('imp', SimpleImputer(strategy="most_frequent")),
                                     ('ohe',OneHotEncoder())])

# numeric -> categ OHE pipe
numer_OHE_x59_x79_x98_pipe = Pipeline([('imp_ohe', SimpleImputer(strategy="most_frequent")),
                                      ('ohe',OneHotEncoder())])

# numeric skewness tf
numer_skewness_pipe = Pipeline([('imp',SimpleImputer(strategy="mean")),
                               ('scaler',StandardScaler()),
                                ('p_tf',PowerTransformer()),
                               ('selector',VarianceThreshold(0.1)),
                              ])

# custom x7 tf
custom_edit_x7_tf = FunctionTransformer(custom_edit_x7)
# custom x19 tf
custom_edit_x19_tf = FunctionTransformer(custom_edit_x19)


# rest on nemeric feature pipe
Rest_numeric_features_pipe = Pipeline([('imp',SimpleImputer(strategy="mean")),
                               ('scaler',StandardScaler()),
                                ('p_tf',PowerTransformer()),
                               ('selector',VarianceThreshold(0.1)),
#                              PCA(n_components=20),
                                     ])
```

In [92]:
```
preprocessor = make_column_transformer((x3_pipe, ['x3']),
                            (two_step_transformer_pipe, ['x24','x31','x33','x60','x65','x77','x93']),
                            (numer_OHE_x59_x79_x98_pipe, ['x59', 'x79', 'x98']),

                             # features with high skewness
                            (numer_skewness_pipe, ['x13', 'x21', 'x32', 'x35',
                                                  'x44', 'x59', 'x67', 'x73',
                                                  'x75', 'x79', 'x84', 'x89']),

                             # features from categories-> edited to numeric-no null found
                             (custom_edit_x7_tf, ['x7']),
                             (custom_edit_x19_tf, ['x19']),

                             # rest numeric features
                             (Rest_numeric_features_pipe, rest_numeric_features),
                             )

preprocessor.fit_transform(df)[0].size
```

Out[92]:
```
196
```

i don't see any changes in the number of features. I work with all features.

In [93]:
```
preprocessor.named_transformers_
```

Out[93]:
```
{'pipeline-1': Pipeline(steps=[('custom_edit_x3_tf',
                  FunctionTransformer(func=<function custom_edit_x3 at 0x7fc1c7d2b7b8>)),
                 ('imp', SimpleImputer(strategy='most_frequent')),
                 ('ohe', OneHotEncoder())]),
 'pipeline-2': Pipeline(steps=[('imp', SimpleImputer(strategy='most_frequent')),
                 ('ohe', OneHotEncoder())]),
 'pipeline-3': Pipeline(steps=[('imp_ohe', SimpleImputer(strategy='most_frequent')),
                 ('ohe', OneHotEncoder())]),
 'pipeline-4': Pipeline(steps=[('imp', SimpleImputer()), ('scaler', StandardScaler()),
                 ('p_tf', PowerTransformer()),
                 ('selector', VarianceThreshold(threshold=0.1))]),
 'functiontransformer-1': FunctionTransformer(func=<function custom_edit_x7 at 0x7fc1c7d2ba60>),
 'functiontransformer-2': FunctionTransformer(func=<function custom_edit_x19 at 0x7fc1c7ccee18>),
 'pipeline-5': Pipeline(steps=[('imp', SimpleImputer()), ('scaler', StandardScaler()),
                 ('p_tf', PowerTransformer()),
                 ('selector', VarianceThreshold(threshold=0.1))]),
 'remainder': 'drop'}
```

In [154]:
```
cross_val_score(Final_pipe_MLP, df, y, cv=5,
                scoring='roc_auc', n_jobs=-1).mean()
```

Out[154]:
```
0.7337432985555989
```

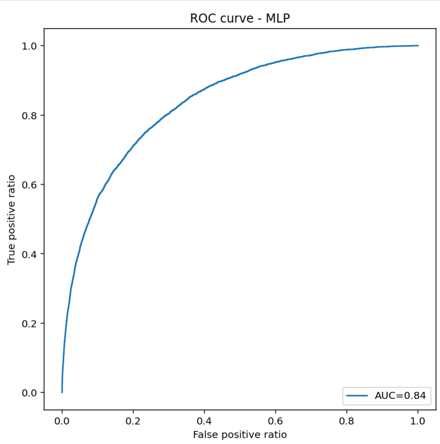
In [95]:
```
Final_pipe_MLP = Pipeline(steps=[('preprocessor', preprocessor),
                              ('classiffier', MLPClassifier(random_state=1,
                                                            max_iter=300))])

Final_pipe_MLP.fit(X_all_features,y)
```

Out[95]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('pipeline-1',
                                                  Pipeline(steps=[('custom_edit_x3_tf',
                                                                   FunctionTransformer(func=<function custom_edit_x3 at 0x7fc1c7d2b7b8>)),
                                                                  ('imp',
                                                                   SimpleImputer(strategy='most_frequent')),
                                                                  ('ohe',
                                                                   OneHotEncoder())]),
                                                  ['x3']),
                                                 ('pipeline-2',
                                                  Pipeline(steps=[('imp',
                                                                   SimpleImputer(strategy='most_frequent')),
                                                                  ('ohe',...
                                                                   SimpleImputer()),
                                                                  ('scaler',
                                                                   StandardScaler()),
                                                                  ('p_tf',
                                                                   PowerTransformer()),
                                                                  ('selector',
                                                                   VarianceThreshold(threshold=0.1))]),
                                                  ['x1', 'x2', 'x4', 'x5', 'x6',
                                                   'x8', 'x9', 'x10', 'x11',
                                                   'x12', 'x13', 'x14', 'x15',
                                                   'x16', 'x17', 'x18', 'x20',
                                                   'x21', 'x22', 'x23', 'x25',
                                                   'x26', 'x27', 'x28', 'x29',
                                                   'x30', 'x32', 'x34', 'x35',
                                                   'x36', ...])])),
                ('classiffier', MLPClassifier(max_iter=300, random_state=1))])
```

In [61]:
```
# Final_pipe.predict_proba(X_all_features)
```

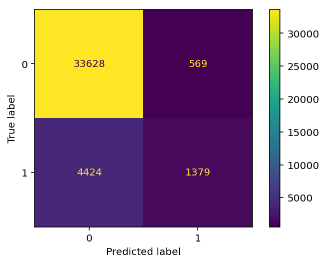
In [96]:
```
y_pred = Final_pipe_MLP.predict(X_all_features)
y_prob = Final_pipe_MLP.predict_proba(X_all_features)
```

In [97]:
```
plt.figure(figsize=(7,7))
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_mlp, tpr_mlp, _ = metrics.roc_curve(y,  y_prob[:,1])
auc_mlp = metrics.roc_auc_score(y, y_prob[:,1])
plt.plot(fpr_mlp,tpr_mlp, label="AUC="+str(round(auc_mlp,2)))
plt.legend(loc=4)
plt.xlabel('False positive ratio')
plt.ylabel('True positive ratio')
plt.title('ROC curve - MLP')
plt.savefig("../Figures/plot_02_2_roc_mlp.png")
plt.show()
```



In [100]:
```
preds = Final_pipe_MLP.predict(X_all_features)

# Save confusion matrix values
tn, fp, fn, tp = confusion_matrix(y, preds).ravel()

# View confusion matrix

plot_confusion_matrix(Final_pipe_MLP, X_all_features, y,
#                        cmap='seismic',
                      values_format='d')

Accuracy = (tp + tn) / (tp + tn + fp + fn)
Precision = tp / (tp + fp)
Recall = tp / (tp + fn)

print('Accuracy, Precision, Recall\n',Accuracy, Precision, Recall)
plt.savefig("../Figures/plot_02_2_mlp_confusionmat.png")
```

```
Accuracy, Precision, Recall
 0.875175 0.7079055441478439 0.2376357056694813
```



Pipes & transformers using Gradient Boosting classifier

In [66]:

In [101]:
```
Final_pipe_GB = Pipeline(steps=[('preprocessor', preprocessor),

                               ('classifier', GradientBoostingClassifier(n_estimators=150,
                                                          learning_rate=1.0,
                                                 max_depth=2, random_state=0))])

Final_pipe_GB.fit(X_all_features,y)
```

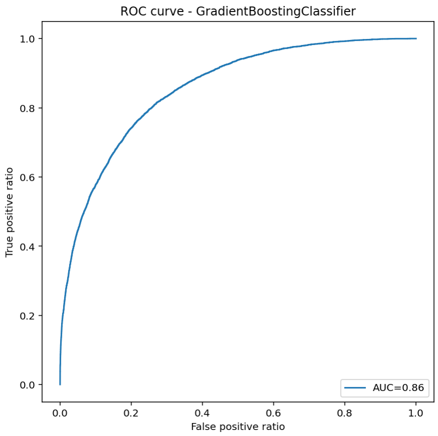
Out[101]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('pipeline-1',
                                                  Pipeline(steps=[('custom_edit_x3_tf',
                                                                   FunctionTransformer(func=<function custom_edit_x3 at 0x7fc1c7d2b7b8>)),
                                                                  ('imp',
                                                                   SimpleImputer(strategy='most_frequent')),
                                                                  ('ohe',
                                                                   OneHotEncoder())]),
                                                  ['x3']),
                                                 ('pipeline-2',
                                                  Pipeline(steps=[('imp',
                                                                   SimpleImputer(strategy='most_frequent')),
                                                                  ('ohe',...
                                                                   PowerTransformer()),
                                                                  ('selector',
                                                                   VarianceThreshold(threshold=0.1))]),
                                                  ['x1', 'x2', 'x4', 'x5', 'x6',
                                                   'x8', 'x9', 'x10', 'x11',
                                                   'x12', 'x13', 'x14', 'x15',
                                                   'x16', 'x17', 'x18', 'x20',
                                                   'x21', 'x22', 'x23', 'x25',
                                                   'x26', 'x27', 'x28', 'x29',
                                                   'x30', 'x32', 'x34', 'x35',
                                                   'x36', ...])])),
                ('classifier',
                 GradientBoostingClassifier(learning_rate=1.0, max_depth=2,
                                            n_estimators=150,
                                            random_state=0))])
```

In [153]:
```
cross_val_score(Final_pipe_GB, df, y, cv=5,
                scoring='roc_auc', n_jobs=-1).mean()
```

Out[153]:
```
0.7654068695368681
```

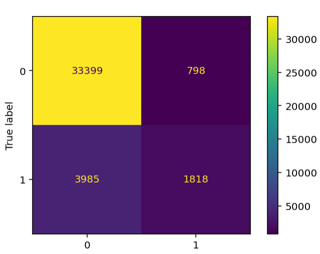
In [110]:
```
y_pred = Final_pipe_GB.predict(X_all_features)
y_prob = Final_pipe_GB.predict_proba(X_all_features)
```

In [111]:
```
plt.figure(figsize=(7,7))
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_gb, tpr_gb, _ = metrics.roc_curve(y,  y_prob[:,1])
auc_gb = metrics.roc_auc_score(y, y_prob[:,1])
plt.plot(fpr_gb,tpr_gb, label="AUC="+str(round(auc_gb,2)))
plt.legend(loc=4)
plt.xlabel('False positive ratio')
plt.ylabel('True positive ratio')
plt.title('ROC curve - GradientBoostingClassifier')
plt.savefig("../Figures/plot_02_2_roc_GB.png")
plt.show()
```



In [112]:
```
preds = Final_pipe_GB.predict(X_all_features)

# Save confusion matrix values
tn, fp, fn, tp = confusion_matrix(y, preds).ravel()

# View confusion matrix

plot_confusion_matrix(Final_pipe_GB, X_all_features, y,
#                       cmap='seismic',
                      values_format='d')

Accuracy = (tp + tn) / (tp + tn + fp + fn)
Precision = tp / (tp + fp)
Recall = tp / (tp + fn)

print('Accuracy, Precision, Recall\n',Accuracy, Precision, Recall)
plt.savefig("../Figures/plot_02_2_GB_confusionmat.png")
```

```
Accuracy, Precision, Recall
 0.880425 0.694954128440367 0.31328623125969324
```



Pipes & transformers using lr classifier

In [113]:
```
weights = {0:0.85, 1:0.14}
logreg = LogisticRegression(solver='sag', class_weight=weights)

Final_pipe_lr = Pipeline(steps=[('preprocessor', preprocessor),
                               ('classiffier', logreg)])

Final_pipe_lr.fit(X_all_features,y)
```

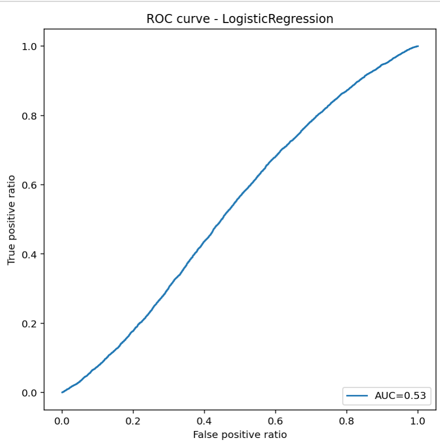
Out[113]:
```
Pipeline(steps=[('preprocessor',
                 ColumnTransformer(transformers=[('pipeline-1',
                                                  Pipeline(steps=[('custom_edit_x3_tf',
                                                                   FunctionTransformer(func=<function custom_edit_x3 at 0x7fc1c7d2b7b8>)),
                                                                  ('imp',
                                                                   SimpleImputer(strategy='most_frequent')),
                                                                  ('ohe',
                                                                   OneHotEncoder())]),
                                                  ['x3']),
                                                 ('pipeline-2',
                                                  Pipeline(steps=[('imp',
                                                                   SimpleImputer(strategy='most_frequent')),
                                                                  ('ohe',...
                                                                   StandardScaler()),
                                                                  ('p_tf',
                                                                   PowerTransformer()),
                                                                  ('selector',
                                                                   VarianceThreshold(threshold=0.1))]),
                                                  ['x1', 'x2', 'x4', 'x5', 'x6',
                                                   'x8', 'x9', 'x10', 'x11',
                                                   'x12', 'x13', 'x14', 'x15',
                                                   'x16', 'x17', 'x18', 'x20',
                                                   'x21', 'x22', 'x23', 'x25',
                                                   'x26', 'x27', 'x28', 'x29',
                                                   'x30', 'x32', 'x34', 'x35',
                                                   'x36', ...])])),
                ('classiffier',
                 LogisticRegression(class_weight={0: 0.85, 1: 0.14},
                                    solver='sag'))])
```

In [155]:
```
cross_val_score(Final_pipe_lr, df, y, cv=5,
                scoring='roc_auc', n_jobs=-1).mean()
```

Out[155]:
```
0.5319600623515
```

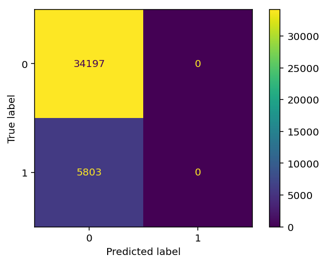
In [115]:
```
y_pred = Final_pipe_lr.predict(X_all_features)
y_prob = Final_pipe_lr.predict_proba(X_all_features)
```

In [116]:
```
plt.figure(figsize=(7,7))
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_lr, tpr_lr, _ = metrics.roc_curve(y,  y_prob[:,1])
auc_lr = metrics.roc_auc_score(y, y_prob[:,1])
plt.plot(fpr_lr,tpr_lr, label="AUC="+str(round(auc_lr,2)))
plt.legend(loc=4)
plt.xlabel('False positive ratio')
plt.ylabel('True positive ratio')
plt.title('ROC curve - LogisticRegression')
plt.savefig("../Figures/plot_02_2_roc_lr.png")
plt.show()
```



In [117]:
```
preds = Final_pipe_lr.predict(X_all_features)

# Save confusion matrix values
tn, fp, fn, tp = confusion_matrix(y, preds).ravel()

# View confusion matrix

plot_confusion_matrix(Final_pipe_lr, X_all_features, y,
#                       cmap='seismic',
                     values_format='d')

Accuracy = (tp + tn) / (tp + tn + fp + fn)
Precision = tp / (tp + fp)
Recall = tp / (tp + fn)

print('Accuracy, Precision, Recall\n',Accuracy, Precision, Recall)
plt.savefig("../Figures/plot_02_2_lr_confusionmat.png")
```

```
Accuracy, Precision, Recall
 0.854925 nan 0.0
```



lets use isolation forest outlier detection inside the preprocessor and then check out the whole system to see if it ishelpful.

update the preprocessor using isolated forest outlier detection

In [142]:
```
# # x3 pipe
# x3_pipe = Pipeline([('custom_edit_x3_tf', custom_edit_x3_tf),
#                     ('imp', SimpleImputer(strategy="most_frequent")),
#                     ('ohe', OneHotEncoder())])
# # two tf pipe
# two_step_transformer_pipe = Pipeline([('imp', SimpleImputer(strategy="most_frequent")),
#                                                        ('ohe',OneHotEncoder())])

# # numeric -> categ OHE pipe
# numer_OHE_x59_x79_x98_pipe = Pipeline([('imp_ohe', SimpleImputer(strategy="most_frequent")),
#                                           ('ohe',OneHotEncoder())])

# # numeric skewness tf
# numer_skewness_pipe = Pipeline([('imp',SimpleImputer(strategy="mean")),
#                                  ('scaler',StandardScaler()),
#                                   ('p_tf',PowerTransformer()),
#                                  ('selector',VarianceThreshold(0.1)),
#                                   ('outlier', IsolationForest(contamination=0.5)),
#                                 ])

# # custom x7 tf
# custom_edit_x7_tf = FunctionTransformer(custom_edit_x7)
# # custom x19 tf
# custom_edit_x19_tf = FunctionTransformer(custom_edit_x19)


# # rest on nemeric feature pipe
# Rest_numeric_features_pipe = Pipeline([('imp',SimpleImputer(strategy="mean")),
#                                  ('scaler',StandardScaler()),
#                                   ('p_tf',PowerTransformer()),
#                                  ('selector',VarianceThreshold(0.1)),
#                                   ('outlier', IsolationForest(contamination=0.5)),
# #                               PCA(n_components=20),
#                                        ])
```

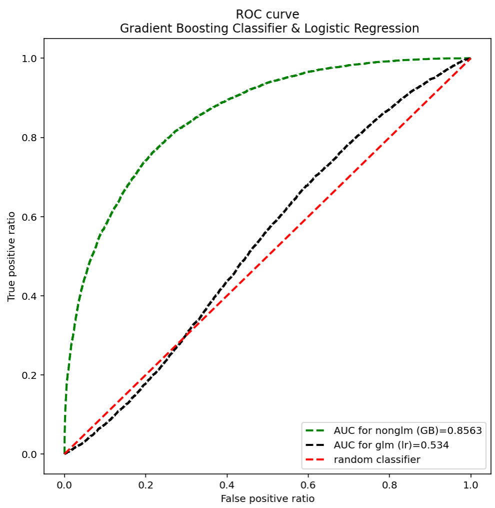
In [145]:
```
# preprocessor = make_column_transformer((x3_pipe, ['x3']),
#                              (two_step_transformer_pipe, ['x24','x31','x33','x60','x65','x77','x93']),
#                              (numer_OHE_x59_x79_x98_pipe, ['x59', 'x79', 'x98']),

#                               # features with high skewness
#                              (numer_skewness_pipe, ['x13', 'x21', 'x32', 'x35',
#                                                   'x44', 'x59', 'x67', 'x73',
#                                                   'x75', 'x79', 'x84', 'x89']),

#                               # features from categories-> edited to numeric-no null found
#                               (custom_edit_x7_tf, ['x7']),
#                               (custom_edit_x19_tf, ['x19']),

#                               # rest numeric features
#                               (Rest_numeric_features_pipe, rest_numeric_features),
#                               )

# preprocessor.fit_transform(df)[0].size
```

it turns out that the isolation forest doesn't work inside the pipeline and i need to write a customize class. checkout the following issue: https://github.com/scikit-learn/scikit-learn/issues/9630 (https://github.com/scikit-learn/scikit-learn/issues/9630)

```
TypeError: All estimators should implement fit and transform, or can be 'drop' or 'passthrough' specifiers. 'Pipeline(steps=[('imp', SimpleImputer()), ('sc
aler', StandardScaler()),
                ('p_tf', PowerTransformer()),
                ('selector', VarianceThreshold(threshold=0.1)),
                ('outlier', IsolationForest(contamination=0.5))])' (type <class 'imblearn.pipeline.Pipeline'>) doesn't.
```

Results

In [150]:
```
plt.figure(figsize=(8,8))
plt.plot(fpr_gb,tpr_gb, 'g--', linewidth=2, markersize=2,
         label="AUC for nonglm (GB)="+str(round(auc_gb,4)))

# plt.plot(fpr_mlp,tpr_mlp, 'b--', linewidth=2, markersize=2,
#          label="AUC MLP="+str(round(auc_mlp,4)))

plt.plot(fpr_lr,tpr_lr, 'k--', linewidth=2, markersize=2,
         label="AUC for glm (lr)="+str(round(auc_lr,4)))

plt.plot([0,1],[0,1], 'r--', linewidth=2, markersize=2,
         label='random classifier')

plt.legend(loc=4)
plt.xlabel('False positive ratio')
plt.ylabel('True positive ratio')
plt.title('ROC curve\n Gradient Boosting Classifier & Logistic Regression')

plt.savefig("../Figures/plot_02_2_roc_MLP_GB_lr.png")
plt.show()
```



Test the pipeline on test set

load test data set

In [119]:
```
file_path = "../DataSet/"
file_name = "exercise_40_test.csv"
df_test = pd.read_csv(file_path+file_name)
```

predict using glm model

In [127]:
```
y_pred_glmresults = Final_pipe_lr.predict_proba(df_test)
y_pred_glmresults_1 = y_pred_glmresults[:,1]

file_name = "glmresults.csv"
y_pred_glmresults_1_pd = pd.DataFrame(y_pred_glmresults_1)
y_pred_glmresults_1_pd.to_csv(file_path+file_name, index = False,header=False)
```

predict using non-glm model

In [135]:
```
y_pred_nonglmresults = Final_pipe_GB.predict_proba(df_test)
y_pred_nonglmresults_1 = y_pred_nonglmresults[:,1]

file_name = "nonglmresults.csv"
y_pred_nonglmresults_1_pd = pd.DataFrame(y_pred_nonglmresults_1)
y_pred_nonglmresults_1_pd.to_csv(file_path+file_name, index = False,header=False)
```

In [ ]:

In [ ]: