In [1]:
```
# Essentials
import numpy as np
import pandas as pd

# Plots
import seaborn as sns
import matplotlib.pyplot as plt

# Models Regression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.linear_model import LogisticRegression

# Models Classification
import lightgbm as lgb
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis

# Misc
import statistics
from scipy.stats import norm
import scipy.stats as stats
from scipy.stats import kstest
from sklearn import metrics
from sklearn.pipeline import Pipeline
from sklearn.metrics import make_scorer
from sklearn.model_selection import KFold
from sklearn.feature_selection import RFECV
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_validate
from sklearn.preprocessing import PowerTransformer
from sklearn.base import BaseEstimator
from sklearn.base import TransformerMixin
from sklearn.feature_selection import chi2
from sklearn.feature_selection import f_classif
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import SelectFromModel
from sklearn.feature_selection import SelectPercentile
from sklearn.feature_selection import mutual_info_classif

import warnings
warnings.filterwarnings("ignore")
```

Load Data

In [2]:
```
xTrain = pd.read_csv('train_feeng.csv')
yTrain = xTrain.TARGET
xTrain = xTrain.drop(labels=['TARGET'], axis=1)
```

Utils

In [3]:
```
def scoringProfit(yTrue, pred, doubleAnalysis = False):
    '''
        Custrom metric to compute profit where TP = 90 and
        FP = -10 in generating the metric

        Args:
            yTrue: Array with ground truth
            pred: Array with predict from model
            doubleAnalysis: Boolean to say if return one metric or two

        Returns:
            Scorer: Scorer of  profit by customer or
                    profit by customer and all profit
    '''

    # ### Matriz de confusão com (tn,fp,fn,tp)
    crosstab = metrics.confusion_matrix(yTrue, pred)

    if len(pred) < 4:
        tn, fp, fn, tp = 0, 0, 0, 0
    else:
        tn, fp, fn, tp = crosstab.ravel()

    # Compute profit
    profit = (tp*90 - fp*10)

    # Compute profit per customer
    profitCustomer = profit/len(pred)

    if doubleAnalysis:
        return profitCustomer, profit

    return profitCustomer
```

In [4]:
```
def check_normal_distribution(df):
    '''
        Checks if the data has a normal distribution

        Args:
            df: Pandas dataframe with data to analyze

        Returns:
            Array: Array with columns name of data with non normal distribut
    '''
    # ### Vetor com colunas que não seguem uma distribuição não normal
    not_normal = []
    for col in df:
```

```
        data = df[col]

        # ### Teste de Kolmogorov-Smirnov
        stat, p = kstest(data, 'norm')
        alpha = 0.05  # Nível de significância
        if p <=  alpha:
            not_normal.append(col)

    return not_normal
```

Criar Funções e Classificadores para Avaliar Modelos após a Seleção de Features

In [5]:

```
# Random Forest Model
clfRF = RandomForestClassifier(n_jobs = -1, class_weight='balanced')

# DecisionTreeClassifier
clfDT = DecisionTreeClassifier(class_weight='balanced')

# KNeighborsClassifier
clfKN = KNeighborsClassifier(n_jobs = -1, weights='distance')

# LinearDiscriminantAnalysis
clfL = LinearDiscriminantAnalysis()

# GaussianNB
clfNB = GaussianNB()

# SVC
clfSVM = SVC(class_weight='balanced')

# XGBClassifier
clfx = XGBClassifier(n_jobs = -1, scale_pos_weight = 25)

# LightGBM
clLGB = lgb.LGBMClassifier(n_jobs = -1, verbose = -1, class_weight='balanced
```

In [6]:

```
kf = KFold(n_splits=5)



# Define error metrics
def evaluationClassification(step, clf, X, y):
    """
        Evaluate the classification model using cross-validation

        Args:
            clf: The Pipeline of model to cross-validation
            X: Array with variables to train model
            y: Array with target

        Returns:
            Error metrics:Precision, Recall, auc and profit
    """
    steps = step.copy()
```

```python
    if steps is None:
        steps = []

    custom_scorer = {
        'precision': make_scorer(metrics.precision_score),
        'recall': make_scorer(metrics.recall_score),
        'auc': make_scorer(metrics.roc_auc_score),
        'lucro': make_scorer(scoringProfit),
    }

    steps.append(('classifier', clf))
    model = Pipeline(steps)

    cvResults = cross_validate(model, X, y,
                               scoring=custom_scorer, cv=kf)

    precisionMicro = cvResults['test_precision']
    recallMicro = cvResults['test_recall']
    rocAucScore = cvResults['test_auc']
    lucroScore = cvResults['test_lucro']

    return  precisionMicro, recallMicro, rocAucScore, lucroScore
```

In [7]:

```python
def evaluationClassificationsReport(steps, X, y):
    """
        Generate report with models evaluate using cross-validation

    Args:
        steps: Dict with pipeline steps of model (normalization )
        X: Array with variables to train model
        y: Array with target

    Returns:
        Dictionary: Model evaluation report
    """
    analysis = {}
    for name in steps:

        modelsClassification = pd.DataFrame(columns=["Model","precision", "r
                                                     "roc", "lucro", "lucroS

        precision, recall, roc, lucro = evaluationClassification(steps[name]
        newRow = {"Model": "RandomForest",  "precision": precision.mean(),
                   "recall": recall.mean(), "roc": roc.mean(), "lucro": lucro
                  "lucroSTD": statistics.pstdev(lucro)}
        modelsClassification = pd.concat([modelsClassification, pd.DataFrame


        precision, recall, roc, lucro = evaluationClassification(steps[name]
        newRow = {"Model": "DecisionTree", "precision": precision.mean(),
                   "recall": recall.mean(), "roc": roc.mean(), "lucro": lucro
                  "lucroSTD": statistics.pstdev(lucro)}
        modelsClassification = pd.concat([modelsClassification, pd.DataFrame


        precision, recall, roc, lucro = evaluationClassification(steps[name]
```

```
        newRow = {"Model": "Knn", "precision": precision.mean(),
                  "recall": recall.mean(), "roc": roc.mean(), "lucro": lucro
                 "lucroSTD": statistics.pstdev(lucro)}
        modelsClassification = pd.concat([modelsClassification, pd.DataFrame


        precision, recall, roc, lucro = evaluationClassification(steps[name]
        newRow = {"Model": "LinearDiscriminant", "precision": precision.mean
                  "recall": recall.mean(), "roc": roc.mean(), "lucro": lucro
                 "lucroSTD": statistics.pstdev(lucro)}
        modelsClassification = pd.concat([modelsClassification, pd.DataFrame


        precision, recall, roc, lucro = evaluationClassification(steps[name]
        newRow = {"Model": "GaussianNB", "precision": precision.mean(),
                  "recall": recall.mean(), "roc": roc.mean(), "lucro": lucro
                 "lucroSTD": statistics.pstdev(lucro)}
        modelsClassification = pd.concat([modelsClassification, pd.DataFrame


        precision, recall, roc, lucro = evaluationClassification(steps[name]
        newRow = {"Model": "SVC", "precision": precision.mean(),
                  "recall": recall.mean(), "roc": roc.mean(), "lucro": lucro
                 "lucroSTD": statistics.pstdev(lucro)}
        modelsClassification = pd.concat([modelsClassification, pd.DataFrame


        precision, recall, roc, lucro = evaluationClassification(steps[name]
        newRow = {"Model": "XGBoost", "precision": precision.mean(),
                  "recall": recall.mean(), "roc": roc.mean(), "lucro": lucro
                 "lucroSTD": statistics.pstdev(lucro)}
        modelsClassification = pd.concat([modelsClassification, pd.DataFrame

        precision, recall, roc, lucro = evaluationClassification(steps[name]
        newRow = {"Model": "LightGBM", "precision": precision.mean(),
                  "recall": recall.mean(), "roc": roc.mean(), "lucro": lucro
                 "lucroSTD": statistics.pstdev(lucro)}
        modelsClassification = pd.concat([modelsClassification, pd.DataFrame

        analysis[name] = modelsClassification.sort_values(by="lucro")

    return analysis
```

1.0 - Seleção de Features

Nessa etapa iremos implementar diferentes métodos de seleção de Features, utilizando diferentes métodos de normalização para evitar que as diferentes magnitudes das variávis impliquem no processo de seleção de features. Em seguida iremos selecionar o melhor método de seleção.

1.1 - Avaliar Usando Todas as Variáveis

In [8]:
```
steps = {}
steps['NoScaler'] = []
```

```python
steps['StandardScaler'] = [('scale', StandardScaler())]
steps['MinMax'] = [('scale', MinMaxScaler())]
steps['Yeo-johnson'] = [('scale', PowerTransformer(method='yeo-johnson'))]
analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

In [9]:
```python
analysis['NoScaler']
```

Out[9]:

	Model	precision	recall	roc	lucro	lucroSTD
5	SVC	0.037934	0.998137	0.501687	-6.174923	0.108043
4	GaussianNB	0.033572	0.490294	0.535081	-2.380932	2.134498
2	Knn	0.127046	0.020982	0.507708	0.017795	0.021795
3	LinearDiscriminant	0.153577	0.018636	0.507323	0.025019	0.023226
0	RandomForest	0.162613	0.039981	0.515880	0.057261	0.037702
1	DecisionTree	0.131591	0.131014	0.548460	0.117518	0.039454
6	XGBoost	0.131742	0.551901	0.704455	0.501610	0.068277
7	LightGBM	0.128360	0.666991	0.744494	0.556405	0.066683

In [10]:
```python
analysis['StandardScaler']
```

Out[10]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041154	0.962111	0.540478	-5.203942	0.163278
5	SVC	0.100606	0.674919	0.718913	0.014799	0.074139
3	LinearDiscriminant	0.153577	0.018636	0.507323	0.025019	0.023226
0	RandomForest	0.157363	0.040034	0.515714	0.053562	0.036402
2	Knn	0.174345	0.058739	0.523894	0.094438	0.016877
1	DecisionTree	0.126320	0.126850	0.546213	0.100075	0.042525
6	XGBoost	0.131742	0.551901	0.704455	0.501610	0.068277
7	LightGBM	0.126309	0.662134	0.740904	0.518170	0.132538

In [11]:
```python
analysis['MinMax']
```

Out[11]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041148	0.960271	0.540337	-5.195309	0.164782
5	SVC	0.085194	0.748326	0.716221	-0.492803	0.115219
3	LinearDiscriminant	0.153577	0.018636	0.507323	0.025019	0.023226
0	RandomForest	0.161987	0.041456	0.516461	0.059024	0.032090
1	DecisionTree	0.120794	0.117114	0.541803	0.075585	0.035066
2	Knn	0.164659	0.059214	0.523665	0.087037	0.018690
6	XGBoost	0.131742	0.551901	0.704455	0.501610	0.068277
7	LightGBM	0.125592	0.657690	0.738827	0.505134	0.065059

In [12]:

```
analysis['Yeo-johnson']
```

Out[12]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041027	0.963621	0.539137	-5.239532	0.166026
0	RandomForest	0.157282	0.039104	0.515350	0.052328	0.032179
3	LinearDiscriminant	0.280615	0.023762	0.510527	0.054795	0.013664
2	Knn	0.181037	0.052706	0.521583	0.087390	0.019265
1	DecisionTree	0.130906	0.130849	0.548331	0.116637	0.040912
5	SVC	0.109464	0.674785	0.729486	0.219529	0.106203
6	XGBoost	0.133503	0.553903	0.706281	0.523811	0.056891
7	LightGBM	0.127051	0.660610	0.741066	0.529624	0.079951

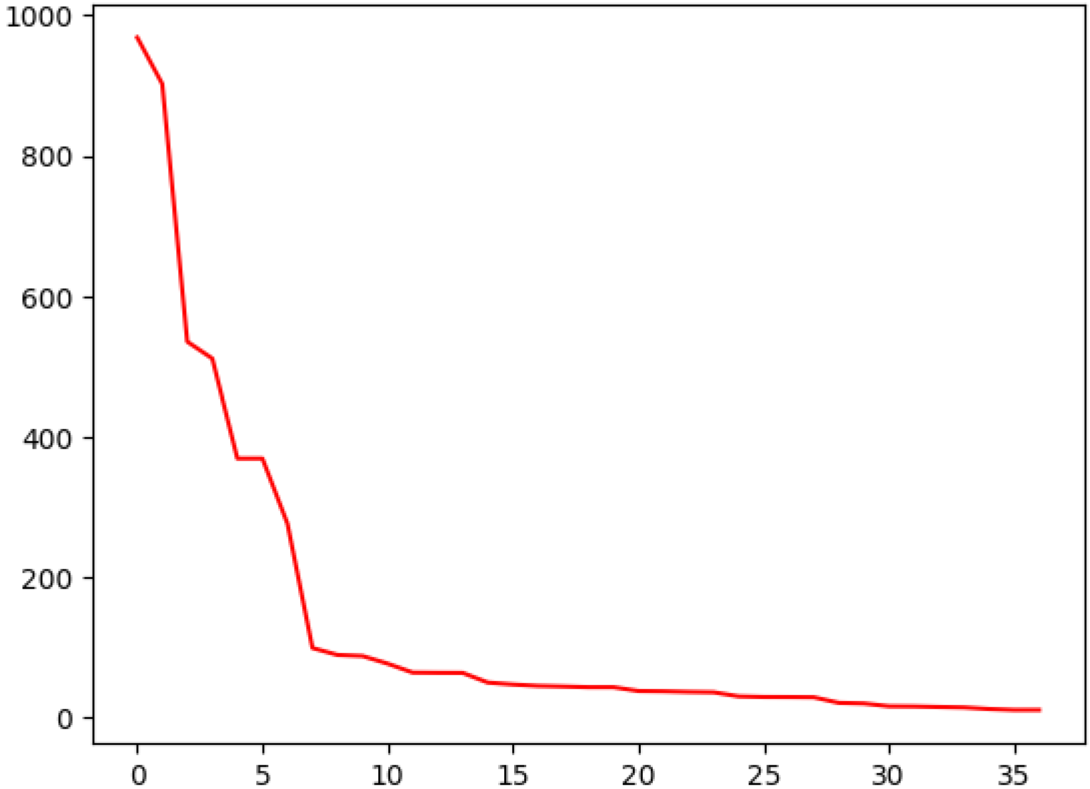
1.2 - Seleção de Variáveis por Filtragem

1.2.1 - Anova

In [13]:

```
# Avaliação visual do teste f ANOVA
p_valor = 0.001
# ANOVA f-teste
fs = SelectPercentile(score_func=f_classif, percentile=100) #
fs.fit(xTrain, yTrain)

ANOVA_stats = pd.DataFrame({"Feature":xTrain.columns,
                              "Score":fs.scores_,
                             "pValue":fs.pvalues_})
ANOVA_stats = ANOVA_stats[ANOVA_stats['pValue'] <= p_valor].sort_values('Sco

plt.plot(range(len(ANOVA_stats['Feature'])),ANOVA_stats['Score'], color='rec
plt.show()
```

```
k_best_ANOVA = ANOVA_stats['Feature'].count()
print(f'Temos {k_best_ANOVA} variáveis estatisticamente significantes para o
```




```
Temos 37 variáveis estatisticamente significantes para o teste-f ANOVA
```

In [14]:
```
steps = {}
steps['NoScaler'] = [('FeatureSelectionRF', SelectKBest(score_func=f_classif
steps['StandardScaler'] = [('scale', StandardScaler()),
                           ('FeatureSelectionRF', SelectKBest(score_func=f_c
steps['MinMax'] = [('scale', MinMaxScaler()),
                   ('FeatureSelectionRF', SelectKBest(score_func=f_classif,
steps['Yeo-johnson'] = [('scale', PowerTransformer(method='yeo-johnson')),
                        ('FeatureSelectionRF', SelectKBest(score_func=f_clas
analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

In [15]:
```
analysis['NoScaler']
```

Out[15]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041029	0.977985	0.539656	-5.318641	0.199938
5	SVC	0.050490	0.658866	0.585949	-2.443401	0.102181
3	LinearDiscriminant	0.118615	0.011569	0.504036	0.005990	0.018390
2	Knn	0.120492	0.022902	0.508256	0.016209	0.021632
0	RandomForest	0.159381	0.041013	0.516240	0.057439	0.029826
1	DecisionTree	0.126458	0.123735	0.545113	0.097784	0.054502
6	XGBoost	0.130739	0.573374	0.711704	0.507424	0.083523
7	LightGBM	0.125576	0.676015	0.745554	0.520112	0.053094

In [16]:

```
analysis['StandardScaler']
```

Out[16]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041428	0.964530	0.543603	-5.159189	0.182306
5	SVC	0.100098	0.717688	0.731959	0.000175	0.127525
3	LinearDiscriminant	0.118615	0.011569	0.504036	0.005990	0.018390
0	RandomForest	0.154887	0.040160	0.515713	0.052329	0.027283
2	Knn	0.167965	0.059190	0.523827	0.090386	0.022013
1	DecisionTree	0.127023	0.122355	0.544716	0.098665	0.038913
7	LightGBM	0.124713	0.673447	0.743804	0.503196	0.100468
6	XGBoost	0.130739	0.573374	0.711704	0.507424	0.083523

In [17]:

```
analysis['MinMax']
```

Out[17]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041428	0.964530	0.543603	-5.159189	0.182306
5	SVC	0.080974	0.772433	0.713908	-0.686788	0.123037
3	LinearDiscriminant	0.118615	0.011569	0.504036	0.005990	0.018390
0	RandomForest	0.165743	0.043375	0.517366	0.064309	0.030416
2	Knn	0.152507	0.058194	0.522743	0.075937	0.023060
1	DecisionTree	0.125510	0.120993	0.543971	0.092675	0.063172
7	LightGBM	0.124429	0.670218	0.742400	0.496148	0.092076
6	XGBoost	0.130739	0.573374	0.711704	0.507424	0.083523

In [18]:

```
analysis['Yeo-johnson']
```

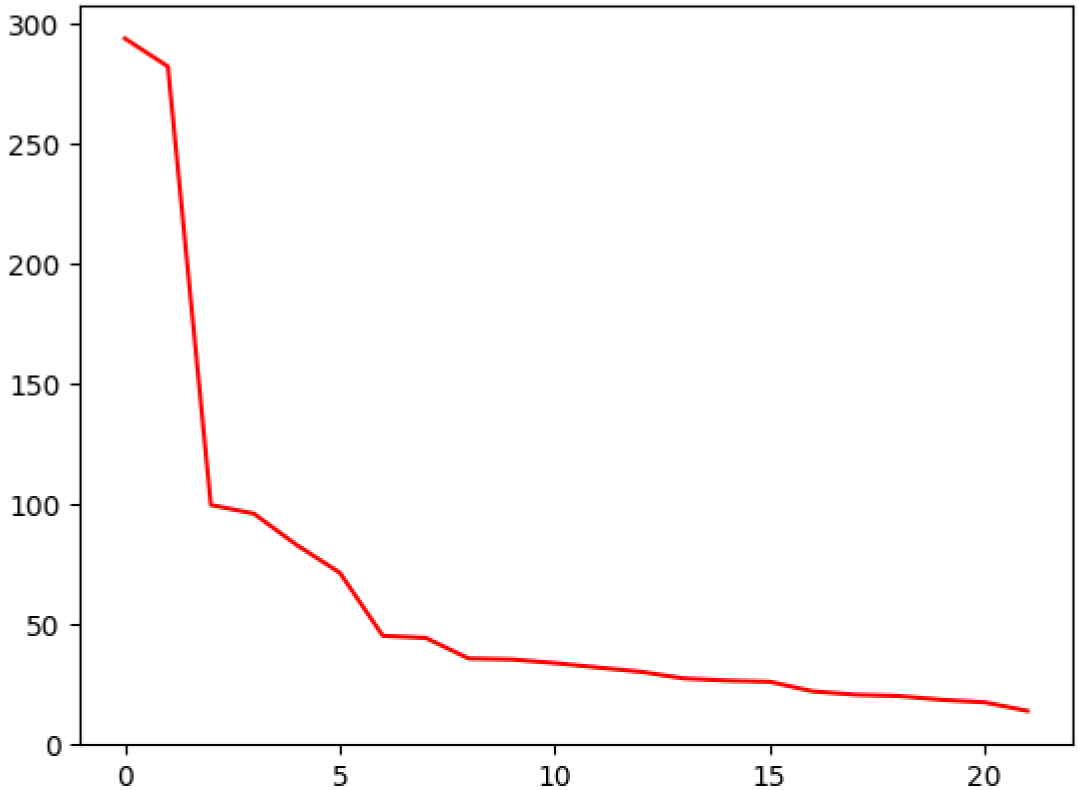
Out[18]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041444	0.962802	0.543477	-5.151436	0.278343
0	RandomForest	0.143716	0.036363	0.513878	0.040876	0.010008
3	LinearDiscriminant	0.268063	0.020974	0.509288	0.048276	0.015233
2	Knn	0.167802	0.051413	0.520699	0.078053	0.022279
1	DecisionTree	0.124164	0.123391	0.544566	0.090560	0.045920
5	SVC	0.105830	0.740431	0.747220	0.152754	0.106088
7	LightGBM	0.122437	0.666059	0.739221	0.460734	0.081157
6	XGBoost	0.131848	0.568614	0.710688	0.517819	0.076444

1.2.2 - Chi2

In [19]:

```
scaler = MinMaxScaler()
scaler.fit(xTrain, yTrain)
xTrainChi2 = scaler.transform(xTrain)

p_valor = 0.001


fs = SelectPercentile(score_func=chi2, percentile=100)
fs.fit(xTrainChi2, yTrain)

# Definimos um p-valor de 0.05 para definir o ponto de corte que separa as f
ANOVA_stats = pd.DataFrame({"Feature":xTrain.columns,
                              "Score":fs.scores_,
                             "pValue":fs.pvalues_})
ANOVA_stats = ANOVA_stats[ANOVA_stats['pValue'] <= p_valor].sort_values('Sco

plt.plot(range(len(ANOVA_stats['Feature'])),ANOVA_stats['Score'], color='rec
plt.show()

k_best_ANOVA = ANOVA_stats['Feature'].count()
print(f'Temos {k_best_ANOVA} variáveis estatisticamente significantes para c
```




```
Temos 22 variáveis estatisticamente significantes para o teste-f ANOVA
```

In [20]:
```
steps = {}

steps['MinMax'] = [('scale', MinMaxScaler()),
                   ('FeatureSelectionRF', SelectKBest(score_func=chi2, k=22)

analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

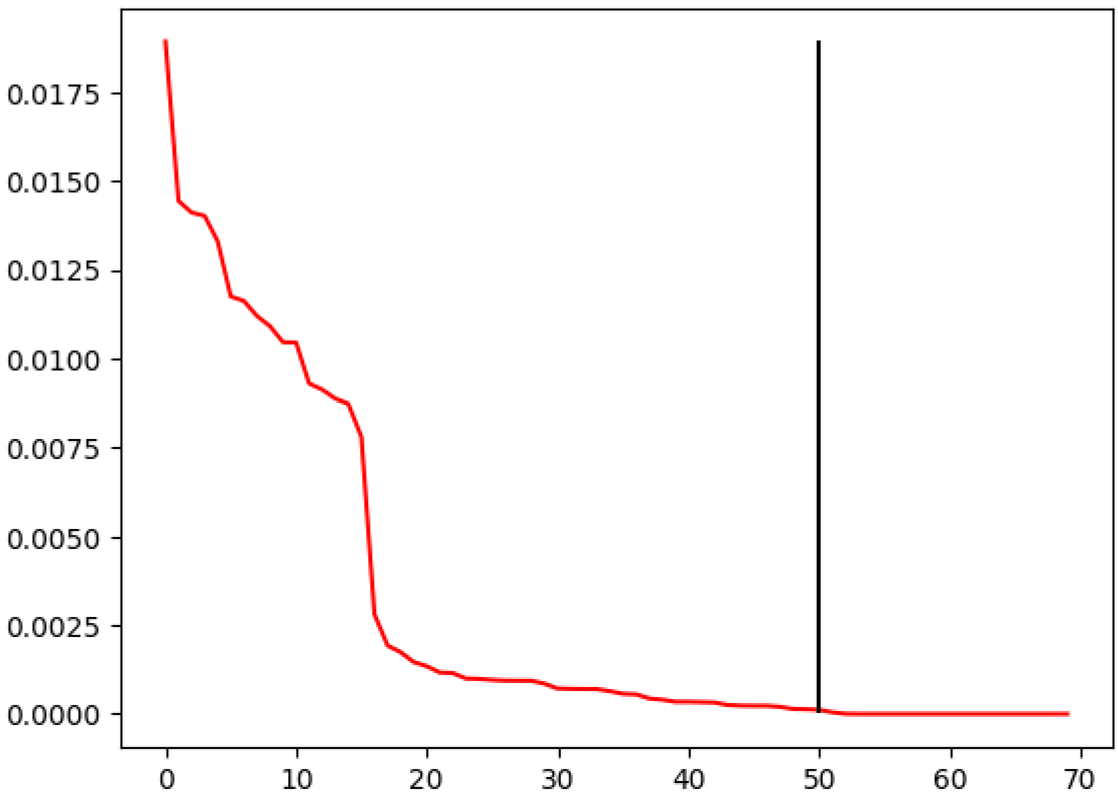
In [21]:
```
analysis['MinMax']
```

Out[21]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041230	0.969145	0.541669	-5.224908	0.148194
5	SVC	0.077266	0.781180	0.707266	-0.868615	0.110922
3	LinearDiscriminant	0.087318	0.006896	0.501947	-0.005109	0.019208
2	Knn	0.103910	0.022829	0.507542	0.003171	0.010769
7	LightGBM	0.114278	0.677090	0.735307	0.317315	0.102070
1	DecisionTree	0.123140	0.453550	0.663309	0.321544	0.070117
6	XGBoost	0.118190	0.605466	0.713898	0.350263	0.095164
0	RandomForest	0.135409	0.398882	0.649397	0.394311	0.064356

1.2.3 - Mutual Information Gain

In [22]:
```
# Avaliação visual do Mutual Information


fs1 = SelectPercentile(score_func=mutual_info_classif, percentile=100)
fs1.fit(xTrain, yTrain)

MI_stats = pd.DataFrame({"Feature":xTrain.columns,
                            "Score":fs1.scores_}).sort_values('Score',ascendi
plt.plot(range(len(MI_stats['Feature'])),MI_stats['Score'], color='red')
plt.vlines(50,0,MI_stats['Score'].max(),'black')
plt.show()
```



In [23]:
```
steps = {}
steps['NoScaler'] = [('FeatureSelectionRF', SelectKBest(score_func=mutual_ir
steps['StandardScaler'] = [('scale', StandardScaler()),
                            ('FeatureSelectionRF', SelectKBest(score_func=mut
steps['MinMax'] = [('s cale', MinMaxScaler()),
                    ('FeatureSelectionRF', SelectKBest(score_func=mutual_infc
steps['Yeo-johnson'] = [('scale', PowerTransformer(method='yeo-johnson')),
                         ('FeatureSelectionRF', SelectKBest(score_func=mutual
analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

In [24]:
```
analysis['NoScaler']
```

Out[24]:

	Model	precision	recall	roc	lucro	lucroSTD
5	SVC	0.043195	0.866235	0.537078	-4.673447	1.843201
4	GaussianNB	0.053087	0.367295	0.520774	-1.853487	2.267971
2	Knn	0.111875	0.020506	0.507186	0.010747	0.028893
3	LinearDiscriminant	0.155649	0.016787	0.506654	0.023610	0.022580
1	DecisionTree	0.113236	0.112444	0.538900	0.048804	0.039355
0	RandomForest	0.166401	0.041899	0.516711	0.061138	0.025929
6	XGBoost	0.131139	0.561150	0.707360	0.500199	0.105904
7	LightGBM	0.125326	0.668084	0.742377	0.508305	0.088437

In [25]:

```
analysis['StandardScaler']
```

Out[25]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041432	0.962701	0.543577	-5.148443	0.180520
5	SVC	0.100527	0.676899	0.719329	0.010041	0.105505
3	LinearDiscriminant	0.151968	0.015310	0.505934	0.019205	0.020910
0	RandomForest	0.174934	0.042368	0.517092	0.065543	0.035171
2	Knn	0.154131	0.048946	0.519455	0.071532	0.041955
1	DecisionTree	0.119726	0.118284	0.542012	0.073118	0.046863
6	XGBoost	0.132200	0.555115	0.705851	0.510242	0.124946
7	LightGBM	0.127095	0.675808	0.746561	0.541428	0.118564

In [26]:

```
analysis['MinMax']
```

Out[26]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041339	0.964456	0.542684	-5.176104	0.143480
5	SVC	0.082580	0.756856	0.713189	-0.604683	0.106875
3	LinearDiscriminant	0.124228	0.012583	0.504607	0.010395	0.020497
0	RandomForest	0.171265	0.043755	0.517684	0.068362	0.024997
1	DecisionTree	0.120206	0.117024	0.541675	0.073999	0.048050
2	Knn	0.166085	0.061018	0.524466	0.091442	0.017986
7	LightGBM	0.125426	0.665708	0.741620	0.508658	0.073045
6	XGBoost	0.133226	0.570519	0.712254	0.535967	0.078950

In [27]:

```
analysis['Yeo-johnson']
```

Out[27]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.055617	0.837031	0.601019	-3.261982	2.007392
3	LinearDiscriminant	0.274579	0.013294	0.505996	0.033476	0.027596
2	Knn	0.184098	0.053600	0.522048	0.090914	0.017060
1	DecisionTree	0.120040	0.174038	0.562084	0.103423	0.084748
0	RandomForest	0.156669	0.100180	0.538284	0.103954	0.097671
5	SVC	0.109213	0.676823	0.729883	0.213891	0.100843
6	XGBoost	0.133618	0.552391	0.705627	0.520991	0.113735
7	LightGBM	0.127571	0.669540	0.744771	0.546714	0.110904

1.3 - Wrapper Method

1.3.1 - Recursive Feature Elimination - Random Forest

In [9]:
```
clRFRE = RandomForestClassifier(max_depth=5, n_jobs=-1, n_estimators=50, cla

steps = {}
steps['NoScaler'] = [('FeatureSelectionRF', RFECV(clRFRE, step=1, scoring=ma
steps['StandardScaler'] = [('scale', StandardScaler()),
                           ('FeatureSelectionRF', RFECV(clRFRE, step=1, scor
steps['MinMax'] = [('scale', MinMaxScaler()),
                   ('FeatureSelectionRF',  RFECV(clRFRE, step=1, scoring=mak
steps['Yeo-johnson'] = [('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF',  RFECV(clRFRE, step=1, scor
analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

In [10]:
```
analysis['NoScaler']
```

Out[10]:

	Model	precision	recall	roc	lucro	lucroSTD
5	SVC	0.050570	0.653758	0.585702	-2.416444	0.099335
4	GaussianNB	0.064256	0.619299	0.647603	-1.006018	1.047646
3	LinearDiscriminant	0.126665	0.011537	0.504221	0.009867	0.020649
2	Knn	0.128903	0.019114	0.506929	0.014448	0.016543
0	RandomForest	0.170415	0.040908	0.516444	0.062371	0.032620
1	DecisionTree	0.125775	0.127870	0.546476	0.098490	0.030579
7	LightGBM	0.124053	0.669359	0.741751	0.488748	0.091388
6	XGBoost	0.131338	0.554650	0.705189	0.498791	0.077475

In [11]:
```
analysis['StandardScaler']
```

Out[11]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.075011	0.743185	0.668839	-1.382240	1.689910
5	SVC	0.098874	0.740645	0.737623	-0.034007	0.106953
3	LinearDiscriminant	0.100449	0.009739	0.503313	0.003348	0.018057
0	RandomForest	0.140074	0.036409	0.513838	0.039643	0.030323
1	DecisionTree	0.117541	0.119280	0.541980	0.066070	0.048181
2	Knn	0.164741	0.057287	0.522949	0.085453	0.035130
7	LightGBM	0.124902	0.673237	0.743956	0.506544	0.055409
6	XGBoost	0.131389	0.565195	0.709025	0.507599	0.117502

In [12]:

```
analysis['MinMax']
```

Out[12]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.066419	0.787277	0.634611	-2.310012	2.119515
5	SVC	0.092869	0.767653	0.735819	-0.236622	0.225835
3	LinearDiscriminant	0.115822	0.010627	0.503766	0.006695	0.022773
0	RandomForest	0.149622	0.035403	0.513746	0.044400	0.020927
1	DecisionTree	0.119522	0.119853	0.542605	0.074175	0.056394
2	Knn	0.155212	0.057677	0.522695	0.078404	0.031320
7	LightGBM	0.126030	0.670641	0.743920	0.522929	0.078484
6	XGBoost	0.134260	0.563041	0.710153	0.542134	0.061926

In [13]:

```
analysis['Yeo-johnson']
```

Out[13]:

	Model	precision	recall	roc	lucro	lucroSTD
3	LinearDiscriminant	0.260699	0.006493	0.502853	0.014623	0.007671
0	RandomForest	0.143257	0.034925	0.513370	0.040171	0.024270
2	Knn	0.171271	0.048540	0.519628	0.075585	0.015394
1	DecisionTree	0.123764	0.126652	0.545812	0.092675	0.032176
4	GaussianNB	0.116746	0.311269	0.611735	0.207912	0.238941
5	SVC	0.108331	0.735131	0.748652	0.212307	0.074273
7	LightGBM	0.122533	0.661344	0.737623	0.459501	0.058273
6	XGBoost	0.132550	0.558709	0.707483	0.518173	0.067438

In [14]:

```
model = Pipeline([('scale', PowerTransformer(method='yeo-johnson')),
                  ('FeatureSelectionRF', RFECV(clRFRE, step=1, scoring=make_
```

```
model.fit(xTrain, yTrain)
featuresRF_RFE = model.get_feature_names_out()
print(f"Número de Features Selecionadas: {len(featuresRF_RFE)}")
```

```
Número de Features Selecionadas: 16
```

1.3.2 - Recursive Feature Elimination - XGBoost

In [34]:
```
steps = {}
steps['NoScaler'] = [('FeatureSelectionRF', RFECV(clfx, step=1, scoring=make
steps['StandardScaler'] = [('scale', StandardScaler()),
                           ('FeatureSelectionRF', RFECV(clfx, step=1, scorin
steps['MinMax'] = [('scale', MinMaxScaler()),
                   ('FeatureSelectionRF',  RFECV(clfx, step=1, scoring=make_
steps['Yeo-johnson'] = [('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF',  RFECV(clfx, step=1, scorin
analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

In [35]:
```
analysis['NoScaler']
```

Out[35]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.044380	0.959458	0.566312	-4.686456	1.006149
5	SVC	0.050623	0.657863	0.586463	-2.427015	0.104299
3	LinearDiscriminant	0.131672	0.014397	0.505331	0.013214	0.020089
2	Knn	0.134154	0.022394	0.508395	0.022200	0.024358
1	DecisionTree	0.111268	0.109501	0.537529	0.041228	0.040476
0	RandomForest	0.158056	0.038117	0.514984	0.051624	0.030117
6	XGBoost	0.130523	0.547047	0.701873	0.482758	0.078901
7	LightGBM	0.125031	0.663288	0.740354	0.499671	0.091868

In [36]:
```
analysis['StandardScaler']
```

Out[36]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.045336	0.938154	0.570579	-4.476657	1.154100
3	LinearDiscriminant	0.143406	0.016353	0.506309	0.019557	0.020746
5	SVC	0.102063	0.713933	0.733402	0.051446	0.090249
1	DecisionTree	0.114549	0.112506	0.539178	0.053561	0.055610
0	RandomForest	0.162355	0.038615	0.515279	0.054091	0.030910
2	Knn	0.165810	0.057350	0.522980	0.085453	0.017858
6	XGBoost	0.130813	0.549492	0.702967	0.488220	0.070216
7	LightGBM	0.127506	0.675378	0.746866	0.549887	0.080818

In [37]:
```
analysis['MinMax']
```

Out[37]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.047881	0.918182	0.586477	-4.042687	1.381302
5	SVC	0.091831	0.766791	0.734180	-0.261290	0.114843
3	LinearDiscriminant	0.131672	0.014397	0.505331	0.013214	0.020089
1	DecisionTree	0.111860	0.110491	0.538015	0.044223	0.045597
0	RandomForest	0.156651	0.038146	0.514953	0.050743	0.033554
2	Knn	0.165613	0.060150	0.524069	0.088976	0.017027
6	XGBoost	0.130523	0.547047	0.701873	0.482758	0.078901
7	LightGBM	0.125596	0.662318	0.740528	0.509186	0.082362

In [38]:
```
analysis['Yeo-johnson']
```

Out[38]:

	Model	precision	recall	roc	lucro	lucroSTD
3	LinearDiscriminant	0.235997	0.007452	0.503250	0.016209	0.010146
0	RandomForest	0.165515	0.040635	0.516252	0.059729	0.027092
2	Knn	0.174343	0.051296	0.520841	0.081928	0.004762
4	GaussianNB	0.094475	0.210450	0.571745	0.083869	0.206045
1	DecisionTree	0.122249	0.122570	0.544000	0.084394	0.042744
5	SVC	0.108430	0.698428	0.736110	0.198740	0.124134
6	XGBoost	0.132986	0.549273	0.704114	0.510771	0.090356
7	LightGBM	0.126489	0.660891	0.740667	0.520814	0.101011

In [39]:
```
model = Pipeline([('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF', RFECV(clfx, step=1, scoring

model.fit(xTrain, yTrain)
featuresXGB_RFE = model.get_feature_names_out()
print(f"Número de Features Selecionadas: {len(featuresXGB_RFE)}")
```

```
Número de Features Selecionadas: 24
```

In [40]:
```
featuresXGB_RFE
```

Out[40]:
```
array(['var3', 'var15', 'imp_ent_var16_ult1', 'imp_op_var41_efect_ult1',
       'ind_var5', 'ind_var39_0', 'num_var4', 'num_var30_0', 'saldo_var5',
       'saldo_var8', 'saldo_var30', 'var36', 'imp_aport_var13_hace3',
       'num_var22_hace3', 'num_var22_ult1', 'num_var22_ult3',
       'num_med_var45_ult3', 'num_meses_var39_vig_ult3',
       'num_var45_hace3', 'saldo_medio_var5_hace2',
       'saldo_medio_var5_hace3', 'saldo_medio_var5_ult3', 'var38',
       'num_zeros'], dtype=object)
```

1.4 - Embedded Methods

1.4.1 - Seleção com base na Random forest

In [41]:
```
steps = {}
steps['NoScaler'] = [('FeatureSelectionRF', SelectFromModel(RandomForestClas
steps['StandardScaler'] = [('scale', StandardScaler()),
                           ('FeatureSelectionRF', SelectFromModel(RandomFore
steps['MinMax'] = [('scale', MinMaxScaler()),
                   ('FeatureSelectionRF', SelectFromModel(RandomForestClassi
steps['Yeo-johnson'] = [('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF', SelectFromModel(RandomFores
analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

In [42]:
```
analysis['NoScaler']
```

Out[42]:

	Model	precision	recall	roc	lucro	lucroSTD
5	SVC	0.050433	0.652294	0.584804	-2.424373	0.102770
4	GaussianNB	0.075321	0.779934	0.660692	-1.755893	1.812534
3	LinearDiscriminant	0.085708	0.006008	0.501704	-0.004405	0.012619
2	Knn	0.156465	0.018661	0.507252	0.023434	0.028749
0	RandomForest	0.144037	0.033560	0.512788	0.037353	0.026251
1	DecisionTree	0.118192	0.118987	0.542044	0.068538	0.033885
7	LightGBM	0.121180	0.669737	0.739438	0.442234	0.067294
6	XGBoost	0.128808	0.543347	0.699363	0.457387	0.088643

In [43]:
```
analysis['StandardScaler']
```

Out[43]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.077332	0.776952	0.678306	-1.397697	1.497491
5	SVC	0.095452	0.756955	0.737518	-0.137430	0.087099
3	LinearDiscriminant	0.085708	0.006008	0.501704	-0.004405	0.012619
0	RandomForest	0.141901	0.033552	0.512739	0.036471	0.024040
1	DecisionTree	0.116422	0.116146	0.540751	0.061490	0.016180
2	Knn	0.159126	0.054497	0.521590	0.076643	0.017908
7	LightGBM	0.120494	0.666169	0.737555	0.427612	0.052181
6	XGBoost	0.128808	0.543347	0.699363	0.457387	0.088643

In [44]:
```
analysis['MinMax']
```

Out[44]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.077332	0.776952	0.678306	-1.397697	1.497491
5	SVC	0.092473	0.766576	0.735425	-0.236977	0.101108
3	LinearDiscriminant	0.085708	0.006008	0.501704	-0.004405	0.012619
0	RandomForest	0.148549	0.035370	0.513666	0.043167	0.018854
1	DecisionTree	0.118532	0.118526	0.541941	0.069419	0.010937
2	Knn	0.160170	0.057166	0.522687	0.081576	0.036581
7	LightGBM	0.121350	0.666439	0.738330	0.441529	0.077011
6	XGBoost	0.128808	0.543347	0.699363	0.457387	0.088643

In [45]:

```
analysis['Yeo-johnson']
```

Out[45]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.025675	0.008401	0.495458	-0.139716	0.095289
3	LinearDiscriminant	0.256923	0.007899	0.503473	0.017795	0.009379
0	RandomForest	0.159328	0.038689	0.515279	0.053386	0.021082
2	Knn	0.166926	0.048963	0.519675	0.074000	0.023863
1	DecisionTree	0.124582	0.124964	0.545197	0.092323	0.031207
5	SVC	0.104519	0.752481	0.749446	0.120865	0.133071
7	LightGBM	0.122263	0.670262	0.740599	0.461087	0.052029
6	XGBoost	0.129635	0.552200	0.703185	0.475887	0.093680

In [46]:

```
model = Pipeline([('scale', PowerTransformer(method='yeo-johnson')),
                  ('FeatureSelectionRF', SelectFromModel(RandomForestClassif

model.fit(xTrain, yTrain)
featuresRF = model.get_feature_names_out()
print(f"Número de Features Selecionadas: {len(featuresRF)}")
```

```
Número de Features Selecionadas: 12
```

1.4.2 - Seleção com base no XGBoost

In [47]:

```
steps = {}
steps['NoScaler'] = [('FeatureSelectionRF', SelectFromModel(XGBClassifier())
steps['StandardScaler'] = [('scale', StandardScaler()),
                           ('FeatureSelectionRF', SelectFromModel(XGBClassif
steps['MinMax'] = [('scale', MinMaxScaler()),
                   ('FeatureSelectionRF', SelectFromModel(XGBClassifier()))]
steps['Yeo-johnson'] = [('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF', SelectFromModel(XGBClassifi
analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

```
In [48]: analysis['NoScaler']
```

Out[48]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.062905	0.668788	0.583559	-2.567255	2.353196
5	SVC	0.050632	0.654700	0.586137	-2.413978	0.099857
2	Knn	0.132189	0.020976	0.507805	0.019733	0.024751
3	LinearDiscriminant	0.158725	0.016375	0.506521	0.023434	0.014748
0	RandomForest	0.151875	0.036740	0.514186	0.044752	0.033021
1	DecisionTree	0.123344	0.125077	0.545115	0.089680	0.039441
6	XGBoost	0.132286	0.555182	0.705932	0.509539	0.077510
7	LightGBM	0.127265	0.673661	0.746017	0.543720	0.077882

```
In [49]: analysis['StandardScaler']
```

Out[49]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.070012	0.692775	0.611717	-2.164827	2.369077
3	LinearDiscriminant	0.158725	0.016375	0.506521	0.023434	0.014748
5	SVC	0.101145	0.681840	0.721887	0.029247	0.050569
0	RandomForest	0.158969	0.038634	0.515206	0.052505	0.025421
2	Knn	0.158922	0.054040	0.521371	0.075233	0.022692
1	DecisionTree	0.122176	0.123054	0.544206	0.085274	0.058079
6	XGBoost	0.132286	0.555182	0.705932	0.509539	0.077510
7	LightGBM	0.126097	0.664589	0.741755	0.518877	0.097200

```
In [50]: analysis['MinMax']
```

Out[50]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.070012	0.692775	0.611717	-2.164827	2.369077
5	SVC	0.085358	0.765788	0.721550	-0.497915	0.101993
3	LinearDiscriminant	0.158725	0.016375	0.506521	0.023434	0.014748
0	RandomForest	0.159380	0.039191	0.515494	0.054267	0.021598
1	DecisionTree	0.115239	0.114981	0.540186	0.057086	0.043870
2	Knn	0.155544	0.055451	0.521756	0.073823	0.022421
6	XGBoost	0.132286	0.555182	0.705932	0.509539	0.077510
7	LightGBM	0.126453	0.670848	0.744327	0.528743	0.068379

In [51]:
```
analysis['Yeo-johnson']
```

Out[51]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.090607	0.200192	0.565969	0.021849	0.233070
3	LinearDiscriminant	0.271262	0.012520	0.505519	0.028542	0.014211
0	RandomForest	0.168117	0.039587	0.515875	0.059376	0.025676
1	DecisionTree	0.120502	0.118770	0.542319	0.075937	0.065969
2	Knn	0.181716	0.054045	0.522243	0.091972	0.024483
5	SVC	0.111688	0.681552	0.734068	0.266395	0.131780
7	LightGBM	0.126406	0.666303	0.742584	0.524690	0.107293
6	XGBoost	0.133529	0.560487	0.708674	0.530328	0.088773

In [8]:
```
model = Pipeline([('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF', SelectFromModel(XGBClassifi

model.fit(xTrain, yTrain)
featuresXGB = model.get_feature_names_out()
print(f"Número de Features Selecionadas: {len(featuresXGB)}")
```

```
Número de Features Selecionadas: 25
```

1.4.3 LASSO Regressiong

In [53]:
```
steps = {}
steps['NoScaler'] = [('FeatureSelectionRF', SelectFromModel(LogisticRegressi
steps['StandardScaler'] = [('scale', StandardScaler()),
                           ('FeatureSelectionRF', SelectFromModel(LogisticRe
steps['MinMax'] = [('scale', MinMaxScaler()),
                   ('FeatureSelectionRF', SelectFromModel(LogisticRegressior
steps['Yeo-johnson'] = [('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF', SelectFromModel(LogisticReg
analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

In [54]:
```
analysis['NoScaler']
```

Out[54]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.040108	0.977067	0.528931	-5.519322	0.176943
5	SVC	0.042248	0.956362	0.551906	-4.947761	0.216509
2	Knn	0.141436	0.019084	0.507281	0.021495	0.019569
3	LinearDiscriminant	0.163733	0.018546	0.507433	0.028015	0.029716
1	DecisionTree	0.117695	0.400407	0.641139	0.225522	0.055142
0	RandomForest	0.131938	0.343568	0.627324	0.313089	0.048268
6	XGBoost	0.123843	0.584284	0.710796	0.423029	0.102754
7	LightGBM	0.123238	0.667013	0.740222	0.473948	0.090893

In [55]:

```
analysis['StandardScaler']
```

Out[55]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041168	0.961211	0.540596	-5.196190	0.169733
5	SVC	0.101036	0.672082	0.718530	0.025194	0.082659
3	LinearDiscriminant	0.158886	0.018646	0.507428	0.026957	0.020171
0	RandomForest	0.162780	0.041893	0.516671	0.060433	0.036228
2	Knn	0.173864	0.058739	0.523876	0.094086	0.016664
1	DecisionTree	0.128303	0.126324	0.546288	0.105009	0.029759
7	LightGBM	0.125614	0.656730	0.738476	0.504428	0.108521
6	XGBoost	0.132185	0.566252	0.709956	0.518523	0.100908

In [56]:

```
analysis['MinMax']
```

Out[56]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.053299	0.870217	0.604987	-3.386556	1.731427
5	SVC	0.084932	0.751608	0.716634	-0.505313	0.116058
3	LinearDiscriminant	0.159957	0.018173	0.507256	0.026605	0.021804
0	RandomForest	0.157912	0.040066	0.515776	0.054443	0.033585
1	DecisionTree	0.119640	0.119971	0.542691	0.074704	0.086324
2	Knn	0.158551	0.055902	0.522064	0.076995	0.023071
7	LightGBM	0.125604	0.667770	0.742440	0.512533	0.113608
6	XGBoost	0.134060	0.561351	0.709291	0.537023	0.118207

In [57]:

```
analysis['Yeo-johnson']
```

Out[57]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041047	0.963598	0.539399	-5.234246	0.147576
3	LinearDiscriminant	0.278210	0.022372	0.509923	0.051800	0.009127
0	RandomForest	0.157617	0.039521	0.515595	0.054618	0.031296
2	Knn	0.180647	0.052246	0.521353	0.085805	0.023950
1	DecisionTree	0.126741	0.127768	0.546617	0.102190	0.057362
5	SVC	0.109903	0.673248	0.729440	0.228691	0.112363
7	LightGBM	0.126134	0.660009	0.740025	0.513767	0.118289
6	XGBoost	0.133784	0.550267	0.705093	0.524868	0.073940

In [58]:

```
model = Pipeline([('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF', SelectFromModel(LogisticReg

model.fit(xTrain, yTrain)
featuresLasso = model.get_feature_names_out()
print(f"Número de Features Selecionadas: {len(featuresLasso)}")
```

Número de Features Selecionadas: 59

1.4.4 RIDGE Regressiong

In [59]:

```
steps = {}
steps['NoScaler'] = [('FeatureSelectionRF', SelectFromModel(LogisticRegressi
steps['StandardScaler'] = [('scale', StandardScaler()),
                           ('FeatureSelectionRF', SelectFromModel(LogisticRe
steps['MinMax'] = [('scale', MinMaxScaler()),
                   ('FeatureSelectionRF', SelectFromModel(LogisticRegressior
steps['Yeo-johnson'] = [('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF', SelectFromModel(LogisticReg
analysis = evaluationClassificationsReport(steps, xTrain, yTrain)
```

In [60]:

```
analysis['NoScaler']
```

Out[60]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.040634	0.982538	0.535372	-5.428936	0.140148
5	SVC	0.050406	0.656875	0.585209	-2.444811	0.117367
7	LightGBM	0.089252	0.596390	0.678603	-0.271684	0.069938
6	XGBoost	0.089148	0.545585	0.663183	-0.252481	0.106760
1	DecisionTree	0.085725	0.118521	0.534486	-0.074000	0.026565
3	LinearDiscriminant	0.000000	0.000000	0.500000	0.000000	0.000000
2	Knn	0.107897	0.026116	0.508691	0.004758	0.029821
0	RandomForest	0.106049	0.094033	0.531361	0.019028	0.034430

In [61]:
```
analysis['StandardScaler']
```

Out[61]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041042	0.970555	0.539574	-5.274066	0.170226
5	SVC	0.092146	0.765579	0.734070	-0.256710	0.209548
3	LinearDiscriminant	0.108130	0.007359	0.502499	0.002643	0.018738
1	DecisionTree	0.118376	0.121224	0.542869	0.070828	0.016588
2	Knn	0.147460	0.062950	0.524362	0.077170	0.035069
0	RandomForest	0.158682	0.058788	0.523224	0.081046	0.040204
7	LightGBM	0.120348	0.683561	0.743597	0.435187	0.058891
6	XGBoost	0.126304	0.588134	0.714040	0.461086	0.094017

In [62]:
```
analysis['MinMax']
```

Out[62]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.048702	0.921978	0.586278	-4.077199	1.536420
5	SVC	0.092818	0.775626	0.738223	-0.240154	0.206037
3	LinearDiscriminant	0.122366	0.012495	0.504481	0.008809	0.019501
0	RandomForest	0.148485	0.038720	0.515002	0.047747	0.027715
1	DecisionTree	0.118947	0.119661	0.542518	0.072766	0.048163
2	Knn	0.160866	0.060974	0.524206	0.086862	0.019096
6	XGBoost	0.128351	0.555573	0.703625	0.464610	0.082258
7	LightGBM	0.122990	0.668856	0.740712	0.472010	0.089260

In [63]:
```
analysis['Yeo-johnson']
```

Out[63]:

	Model	precision	recall	roc	lucro	lucroSTD
4	GaussianNB	0.041130	0.969165	0.540544	-5.246756	0.150454
3	LinearDiscriminant	0.310642	0.007895	0.503563	0.019557	0.013674
0	RandomForest	0.146847	0.037484	0.514522	0.045634	0.025748
2	Knn	0.161319	0.050779	0.520189	0.072766	0.014070
1	DecisionTree	0.122044	0.121422	0.543627	0.083514	0.050187
5	SVC	0.103218	0.745478	0.745266	0.084038	0.133351
7	LightGBM	0.120562	0.674888	0.740678	0.433953	0.071677
6	XGBoost	0.128746	0.571069	0.709536	0.479940	0.073435

In [64]:
```
model = Pipeline([('scale', PowerTransformer(method='yeo-johnson'))
                        , ('FeatureSelectionRF', SelectFromModel(LogisticReg

model.fit(xTrain, yTrain)
featuresLasso = model.get_feature_names_out()
print(f"Número de Features Selecionadas: {len(featuresLasso)}")
```

```
Número de Features Selecionadas: 21
```

2.0 - Análise de distribuição normal das Variáveis

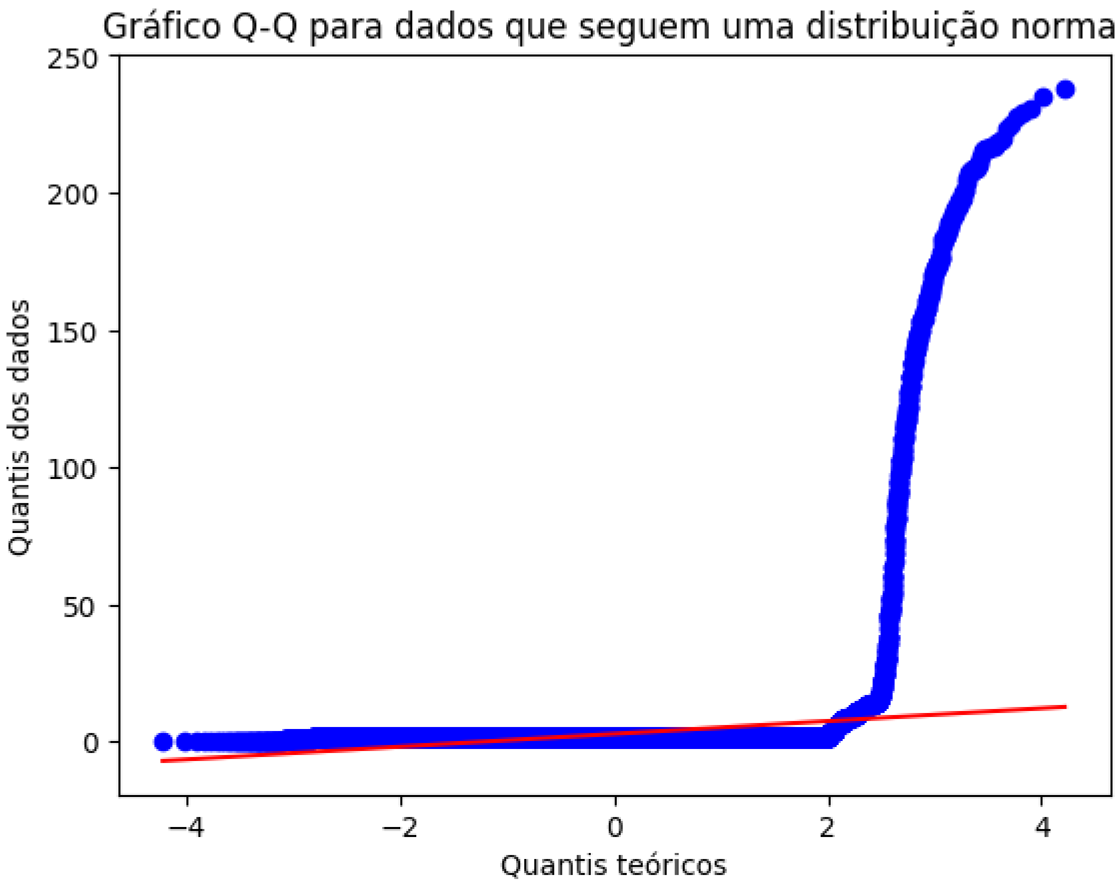
In [65]:
```
varables_not_normal_distribution = check_normal_distribution(xTrain)
print(f"Número de variáveis que não seguem a distribuição normal: {len(varab
print(f'Número de variáveis totais: {xTrain.shape[1]}')
```

```
Número de variáveis que não seguem a distribuição normal: 70
Número de variáveis totais: 70
```

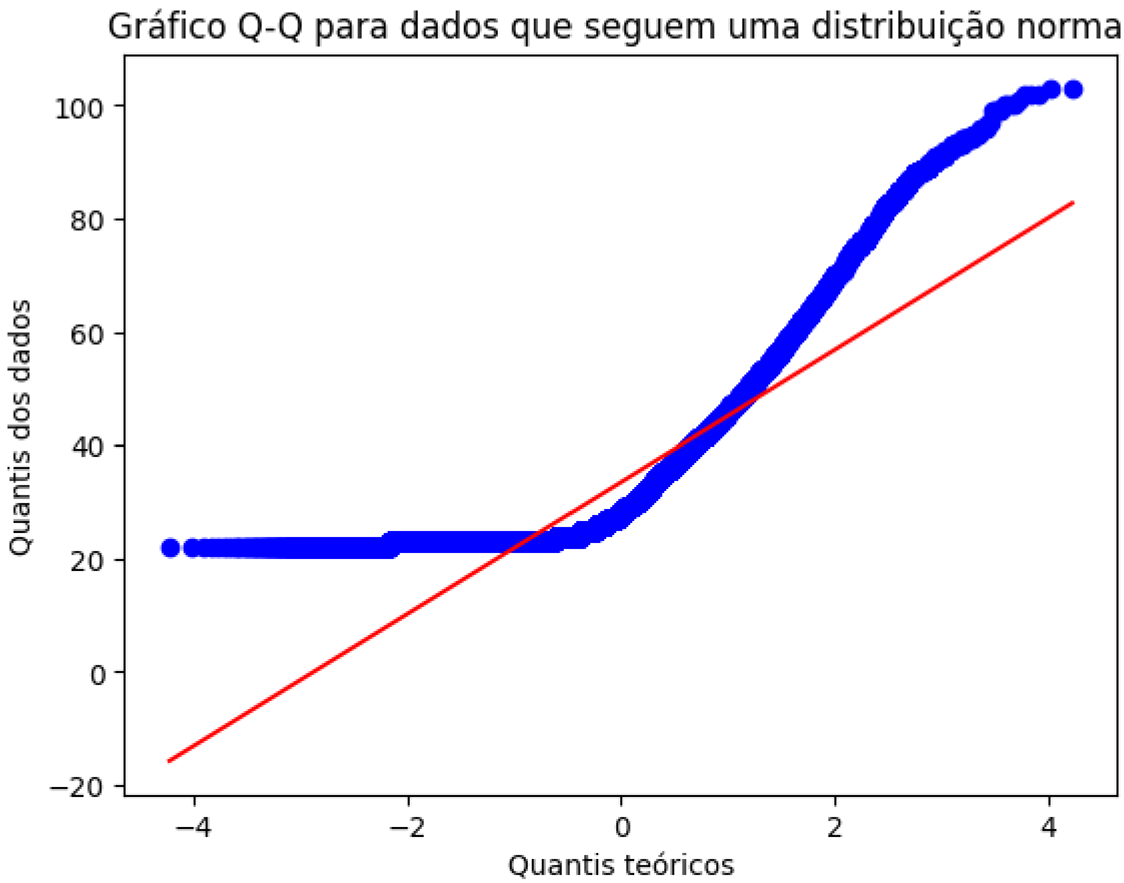
In [66]:
```
s = "Variáveis que não seguem a distribuição normal: "
for var in varables_not_normal_distribution:
    s += var + ', '
print(s[:-2])
```

```
Variáveis que não seguem a distribuição normal: var3, var15, imp_ent_var16_u
lt1, imp_op_var39_comer_ult1, imp_op_var40_comer_ult3, imp_op_var41_efect_ul
t1, ind_var1_0, ind_var5_0, ind_var5, ind_var12_0, ind_var13_0, ind_var13_la
rgo_0, ind_var14_0, ind_var24_0, ind_var25_cte, ind_var37_cte, ind_var39_0,
num_var4, num_var14_0, num_var14, num_op_var41_hace2, num_op_var41_hace3, nu
m_op_var41_ult1, num_var30_0, num_var30, num_var37_med_ult2, saldo_var5, sal
do_var8, saldo_var12, saldo_var13_corto, saldo_var13_largo, saldo_var14, sal
do_var26, saldo_var30, saldo_var37, var36, delta_imp_aport_var13_1y3, imp_ap
ort_var13_hace3, imp_aport_var13_ult1, imp_var43_emit_ult1, imp_trans_var37_
ult1, ind_var43_emit_ult1, ind_var43_recib_ult1, var21, num_aport_var13_hace
3, num_ent_var16_ult1, num_var22_hace2, num_var22_hace3, num_var22_ult1, num
_var22_ult3, num_med_var45_ult3, num_meses_var8_ult3, num_meses_var39_vig_ul
t3, num_op_var40_comer_ult3, num_op_var41_efect_ult1, num_var43_emit_ult1, n
um_var43_recib_ult1, num_trasp_var11_ult1, num_var45_hace3, saldo_medio_var5
_hace2, saldo_medio_var5_hace3, saldo_medio_var5_ult3, saldo_medio_var8_hace
2, saldo_medio_var8_hace3, saldo_medio_var12_hace3, saldo_medio_var13_corto_
hace3, saldo_medio_var13_largo_hace2, var38, num_zeros, num_nonzeros
```

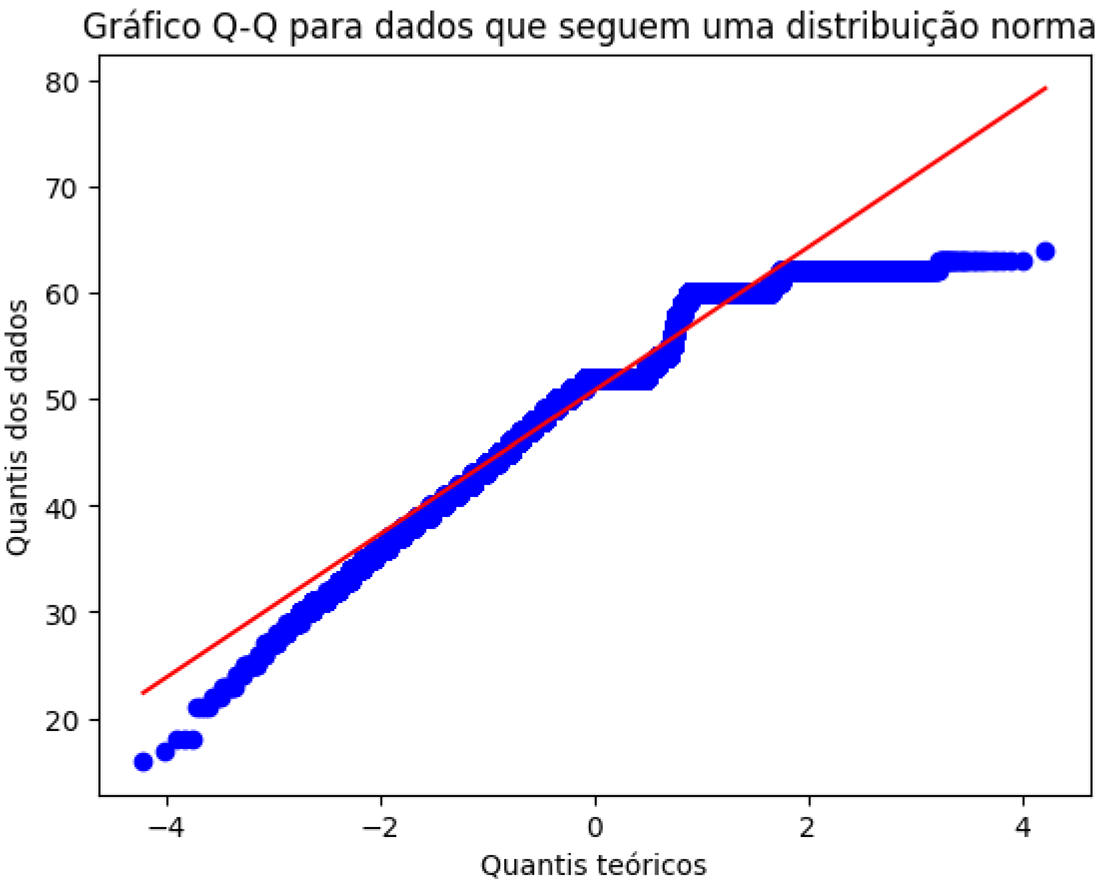
In [67]:
```
# Gráfico Q-Q para os dados que seguem uma distribuição normal
stats.probplot(xTrain['var3'], dist="norm", plot=plt)
plt.title('Gráfico Q-Q para dados que seguem uma distribuição normal')
plt.xlabel('Quantis teóricos')
plt.ylabel('Quantis dos dados')
plt.show()
```



In [68]:
```
# Gráfico Q-Q para os dados que seguem uma distribuição normal
stats.probplot(xTrain['var15'], dist="norm", plot=plt)
plt.title('Gráfico Q-Q para dados que seguem uma distribuição normal')
plt.xlabel('Quantis teóricos')
plt.ylabel('Quantis dos dados')
plt.show()
```



In [69]:
```
# Gráfico Q-Q para os dados que seguem uma distribuição normal
stats.probplot(xTrain['num_zeros'], dist="norm", plot=plt)
plt.title('Gráfico Q-Q para dados que seguem uma distribuição normal')
plt.xlabel('Quantis teóricos')
plt.ylabel('Quantis dos dados')
plt.show()
```



3.0 - Salvar as Features

Pelas informações acima podemos perceber que nenhuma variável presente segue a distribuição normal, nos dando ideias de que certas normalizações como standardscaler não seria a mais adequada. Nessa etapa iremos salvar as features selecionadas. As features selecionadas foram com base no XGBoos dado o excelente desempenho na validação cruzada, baixo desvio padrão e o péqueno número de feaures. Redução total para 25 features.

In [9]:
```
dfTrain = pd.read_csv('train_feeng.csv')
yTrain = dfTrain.TARGET

dfVal = pd.read_csv('val_feeng.csv')
yVal = dfVal.TARGET

dfTest = pd.read_csv('test_feeng.csv')
```

In [10]:
```
dfTrain = pd.concat([dfTrain[featuresXGB], yTrain], axis=1)
dfVal = pd.concat([dfVal[featuresXGB], yVal], axis=1)
dfTest = dfTest[featuresXGB]
```

In [11]:
```
dfTrain.to_csv('train_features.csv', encoding='utf-8', index=False)
dfVal.to_csv('val_features.csv', encoding='utf-8', index=False)
dfTest.to_csv('test_features.csv', encoding='utf-8', index=False)
```

In [ ]:
```
```