Fáza 3 - strojové učenie

Projekt vypracovali:

- Peter Smreček - 50%
- Anetta Langová - 50%

Pri dátovej analýze nemusí byť naším cieľom získať len znalosti obsiahnuté v aktuálnych dátach, ale aj natrénovať model, ktorý bude schopný robiť rozumné predikcie pre nové pozorovania pomocou strojového učenia. V tejto fáze sa od Vás očakáva:

In [1]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np
import scipy.stats as stats
import statsmodels.api as sm
import statsmodels.stats.api as sms
import statsmodels.stats as sm_stats

import datetime
import re
import category_encoders as ce
from sklearn.impute import SimpleImputer, KNNImputer
from numpy import percentile

import matplotlib.pyplot as plt
from sklearn.preprocessing import PowerTransformer, QuantileTransformer

from sklearn.feature_selection import VarianceThreshold, SelectKBest, SelectPercenti
from sklearn.feature_selection import mutual_info_regression, chi2, f_regression, f_
from sklearn.ensemble import RandomForestClassifier

from sklearn.preprocessing import StandardScaler, MinMaxScaler
import matplotlib.pyplot as plt

from sklearn.base import TransformerMixin
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split

from sklearn.tree import DecisionTreeClassifier
from sklearn.tree import export_graphviz
from graphviz import Source
from IPython.display import SVG
from sklearn.metrics import classification_report
from IPython.display import HTML
from IPython.display import Image
from sklearn.tree import export_graphviz

from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

In [2]:
```
from Smrecek_Langova_Script_Phase2 import *
```

Funkcie a triedy z fázy 1 a 2 sú opakovane použité aj vo fáze 3. Vo funkciách bola urobená drobná zmena pri tranformácii atribútov tak, aby indikátor nebol transformovaný. Tieto úpravy boli urobené preto, aby sa nám vo fáze 3 pracovalo s dátami jednoduchšie.

In [3]:
```
def pipelineGenerator(na_method='remove', na_strategy=None, outliers_method='nothing
                      tranformation_method='nothing', select_attributes='all'):
    pipeline =  Pipeline([
        ('handleCategorical', handleCategorical()),
        ('handleNA', handleNA(na_method, na_strategy)), # possible: 'nothing'; 'remo
        ('handleOutliers', handleOutliers(outliers_method)), # possible: 'nothing';
        ('handleTransformations', handleTransformations(tranformation_method)), # po
        ('handleSelection', handleSelection(select_attributes)) # possible: 'all'; l
    ])
    return pipeline
```

In [4]:
```
original_data = phase1()
pipeline1 = pipelineGenerator()
preprocessed_data1 = pipeline1.fit_transform(original_data)
```

```
C:\Users\PeterSmrecek\Documents\IAU-repository\IAU-virtual\lib\site-packages\categor
y_encoders\utils.py:21: FutureWarning: is_categorical is deprecated and will be remo
ved in a future version.  Use is_categorical_dtype instead
  elif pd.api.types.is_categorical(cols):
```

In [5]:
```
X_train, X_test, y_train, y_test = train_test_split(preprocessed_data1.drop(["indica
                                                    preprocessed_data1['indicator'],
```

In [6]:
```
X_train
```

Out[6]:

	race	blood_group	sex_F	sex_M	weight	hemoglobin	alp	etytr	alt	erytrc
6837	1	2	0	1	83.28014	8.75757	25.74621	7.49191	10.52078	8.9
7948	3	1	0	1	117.93586	8.27932	35.80562	6.84522	14.51516	9.3
1972	4	5	0	1	78.89708	7.79869	44.11900	8.20369	2.52581	6.6
293	1	6	1	0	108.28565	7.02105	79.91355	7.82110	2.27397	6.4
322	1	6	0	1	76.36908	7.32766	72.71074	5.27480	10.36320	8.8
...	...	...	...	...	...	...	...	...	...	
2985	2	8	0	1	88.39383	9.49635	13.65872	5.89053	3.66586	7.2
8086	4	1	0	1	51.37146	6.57346	85.48750	9.20162	2.21881	6.8
930	4	1	1	0	34.57981	8.48715	28.75341	5.04780	3.28239	7.3
5359	4	6	0	1	52.26847	5.12400	56.60870	9.06252	1.75278	6.0
243	1	3	0	1	33.28939	10.33438	25.73604	7.83972	2.16625	7.1

6480 rows × 20 columns

In [7]:
```
X_test
```

Out[7]:

	race	blood_group	sex_F	sex_M	weight	hemoglobin	alp	etytr	alt	erytroc
6825	2	6	0	1	90.69947	6.11603	90.29911	4.85303	1.76286	6.25
1326	4	1	0	1	80.43911	8.43330	30.51162	6.70085	0.71128	5.09

	race	blood_group	sex_F	sex_M	weight	hemoglobin	alp	etytr	alt	erytroc
4993	1	6	1	0	89.55935	5.22120	70.14578	3.85843	6.24518	8.12
714	1	2	0	1	0.83884	7.88875	48.93919	7.72165	3.57786	7.47
9650	4	7	0	1	73.24306	5.62364	78.80910	4.38836	3.49372	7.53
...	...	...	...	...	...	...	...	...	...	
9518	4	1	1	0	63.72511	7.98254	43.29304	5.83024	6.83100	8.54
4937	1	1	0	1	69.15843	7.06676	79.14220	6.94416	4.90615	7.79
6964	4	5	0	1	54.87571	7.60316	58.78030	7.53987	1.28584	6.55
4825	1	7	1	0	101.49382	5.63097	78.55773	2.71626	5.30641	8.15
9639	4	2	1	0	72.70898	7.68701	60.97727	6.03704	3.10324	7.13

3192 rows × 20 columns

In [8]:
```
y_train
```

Out[8]:
```
6837    0.0
7948    0.0
1972    1.0
293     0.0
322     0.0
       ...
2985    0.0
8086    1.0
930     0.0
5359    1.0
243     0.0
Name: indicator, Length: 6480, dtype: float64
```

In [9]:
```
y_test
```

Out[9]:
```
6825    0.0
1326    1.0
4993    0.0
714     0.0
9650    0.0
       ...
9518    1.0
4937    1.0
6964    0.0
4825    0.0
9639    1.0
Name: indicator, Length: 3192, dtype: float64
```

1. Manuálne vytvorenie a vyhodnotenie rozhodovacích pravidiel pre klasifikáciu (5b)

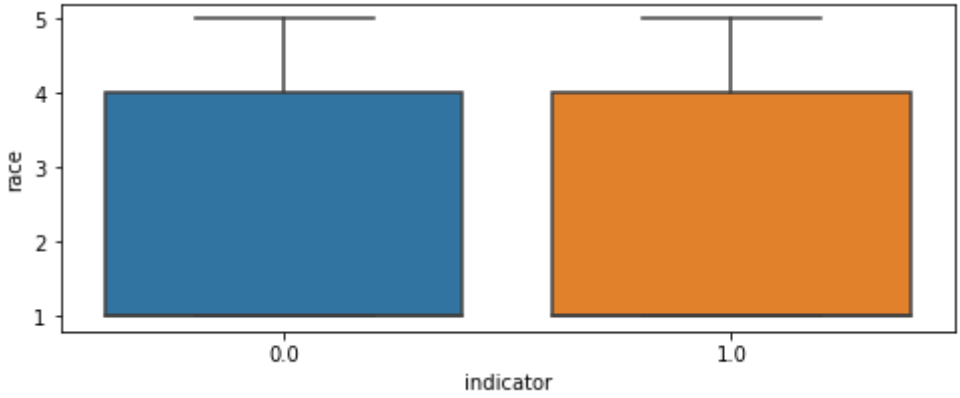
- Naimplementujte 1R algorithm (1R or OneR), ktorý je jednoduchá klasifikácia t.j. rozhodnutie na základe jedného atribútu. Môžete implementovať komplikovanejšie t.j. zahŕňajúce viacero atribútov (ich kombinácie).

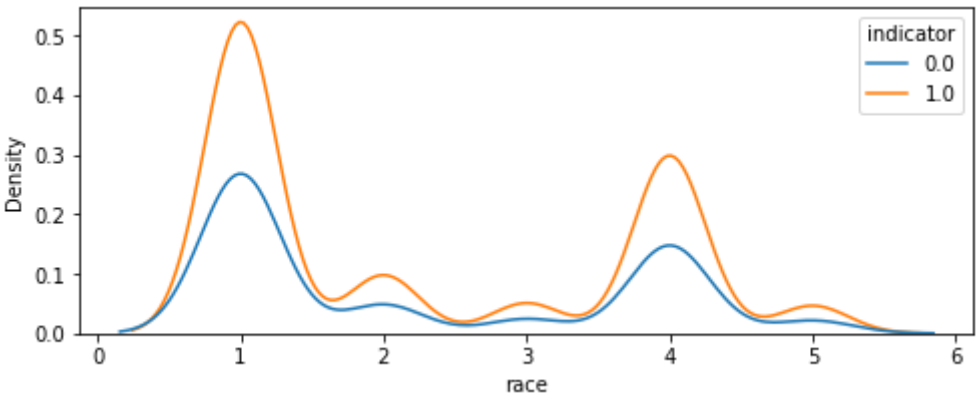
- Pravidlá by v tomto kroku mali byť vytvorené manuálne na základe pozorovaných závislostí v dátach. Vyhodnoťte klasifikátor pomocou metrík accuracy, precision a recall.

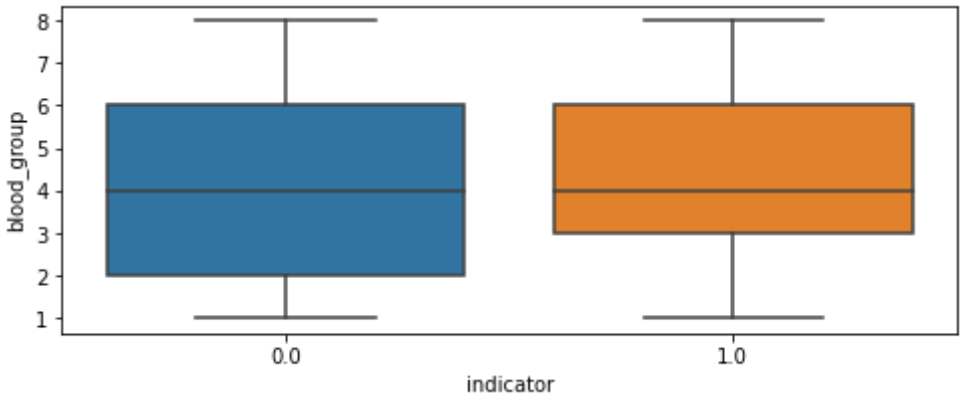
Vizualizácia atribútov

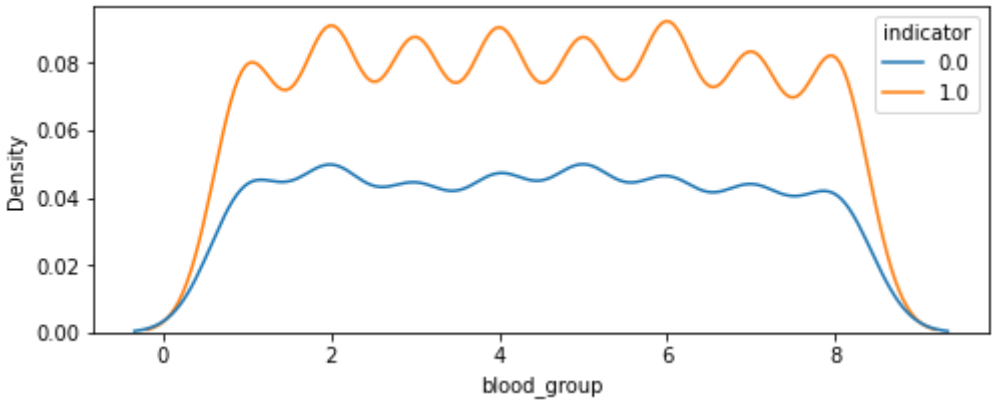
In [10]:
```
# attributes = list_attributes.copy()
attributes = list(preprocessed_data1.columns)
attributes.remove('indicator')
for col in attributes:
    fig_01 = plt.subplots(figsize = (8, 3))
    sns.boxplot(x='indicator', y=col, data=preprocessed_data1)
    fig_02 = plt.subplots(figsize = (8, 3))
    sns.kdeplot(data=preprocessed_data1, x=col, hue="indicator")
```

```
C:\Users\PETERS~1\AppData\Local\Temp/ipykernel_22432/818045578.py:5: RuntimeWarning:
More than 20 figures have been opened. Figures created through the pyplot interface
(`matplotlib.pyplot.figure`) are retained until explicitly closed and may consume to
o much memory. (To control this warning, see the rcParam `figure.max_open_warning`).
  fig_01 = plt.subplots(figsize = (8, 3))
```





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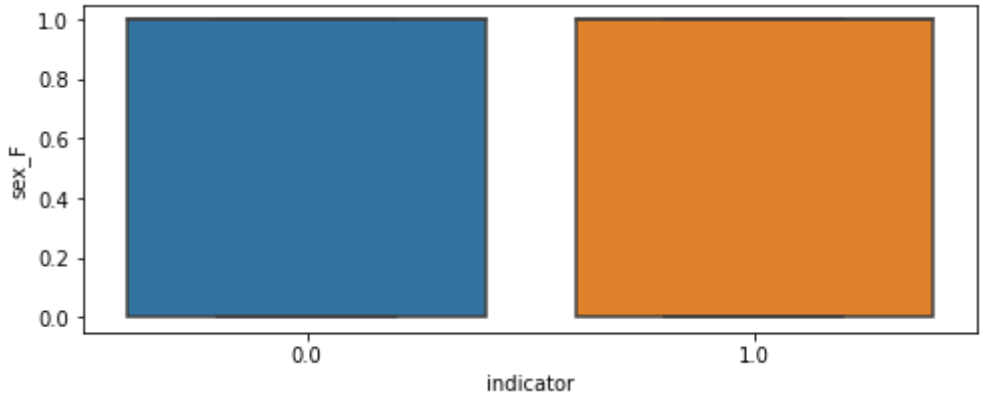
Density
0.00
0.02
0.04
0.06
0.08
0
2
4
6
8
blood_group


sex_F
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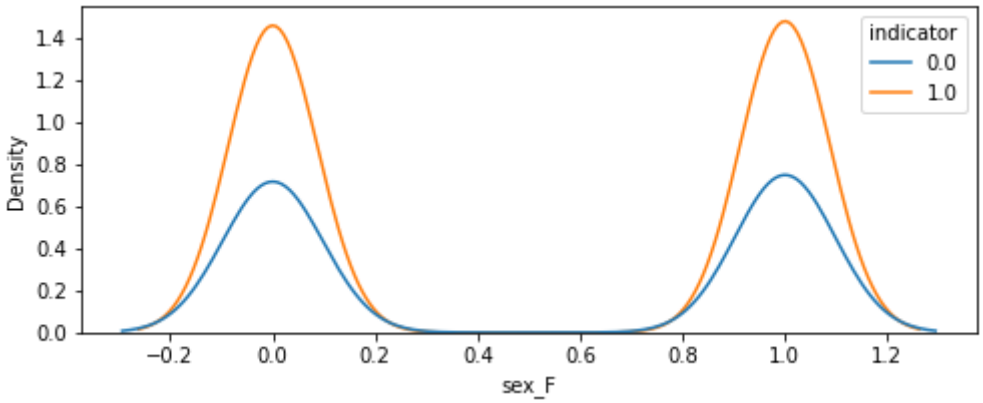
0.2
0.4
0.6
0.8
1.0
0.0
1.0
indicator


indicator
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Density
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0.4
0.6
0.8
1.0
1.2
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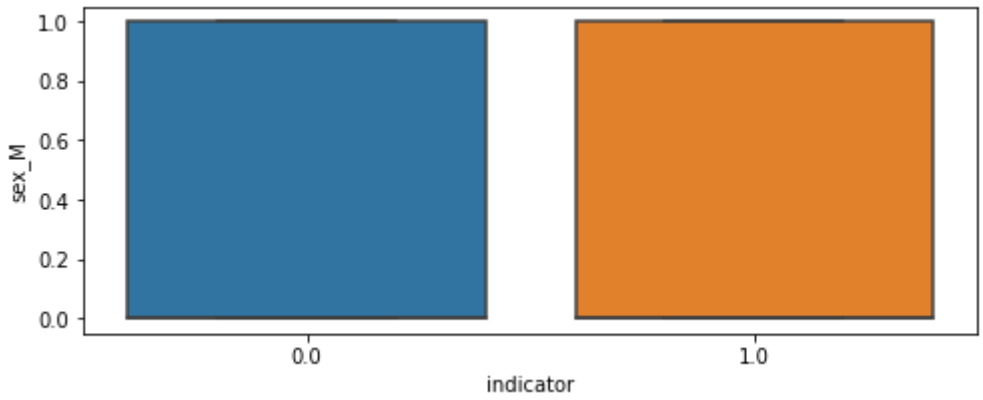
−0.2
0.0
0.2
0.4
0.6
0.8
1.0
1.2
sex_F


sex_M
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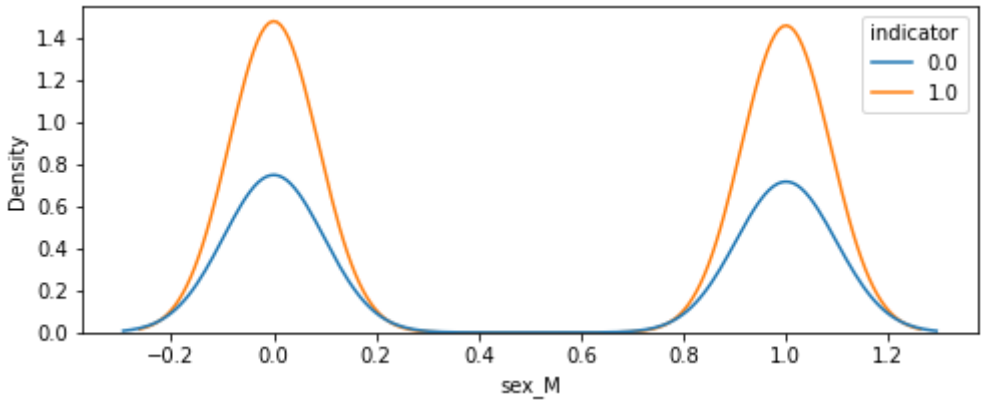
0.8
1.0
0.0
1.0
indicator


indicator
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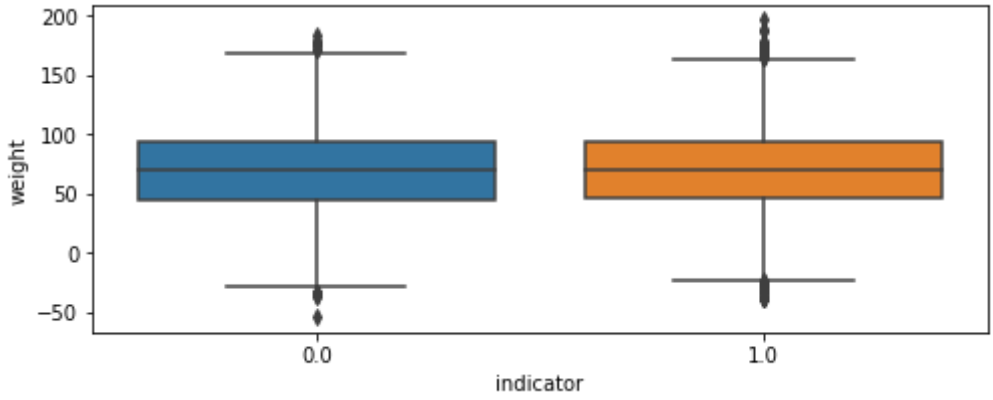
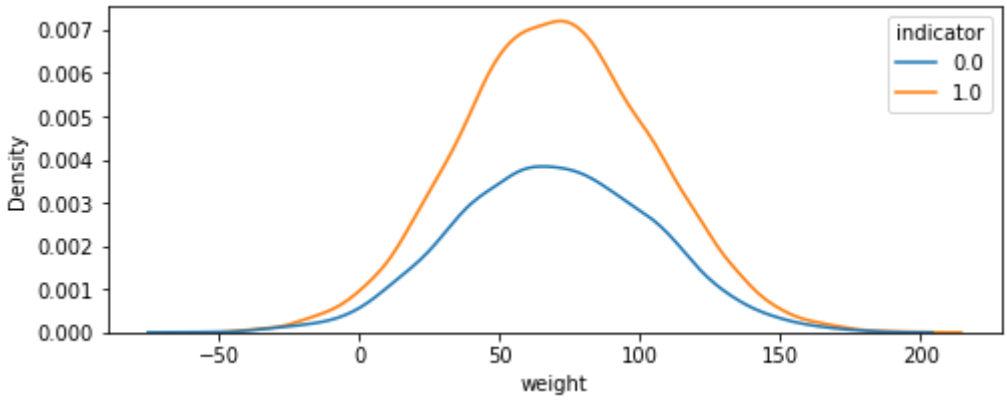
1.0
Density
sex_M


weight
indicator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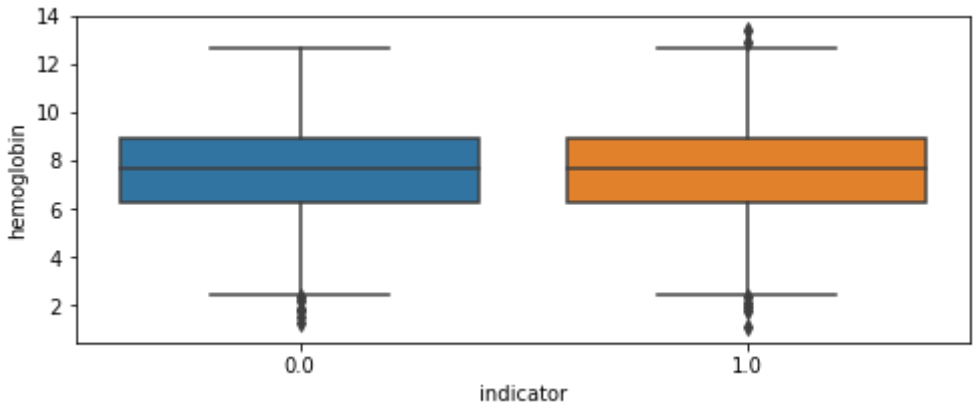
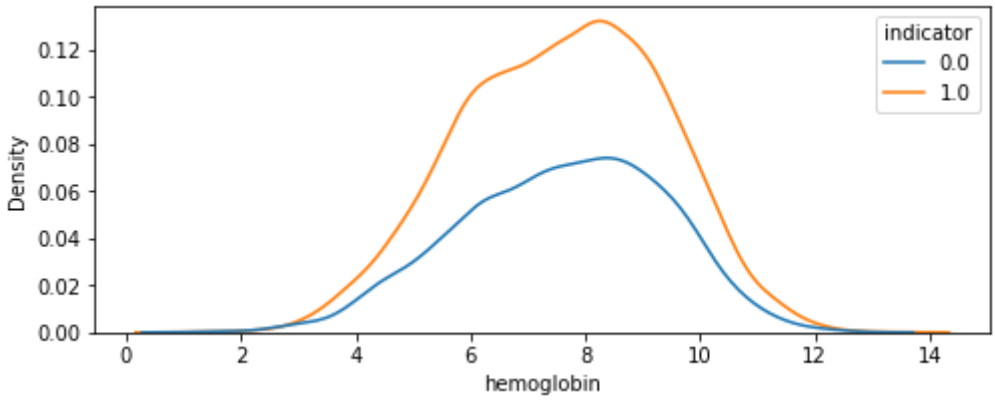
1.0
Density
weight


hemoglobin
indicator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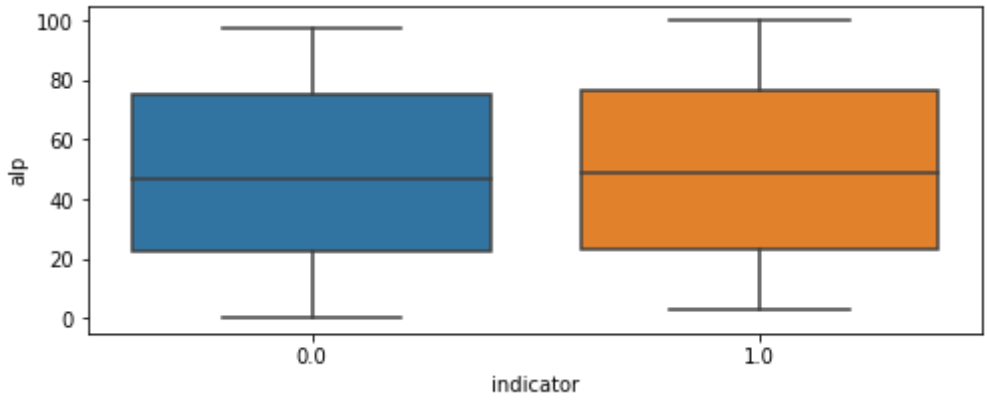
Density
hemoglobin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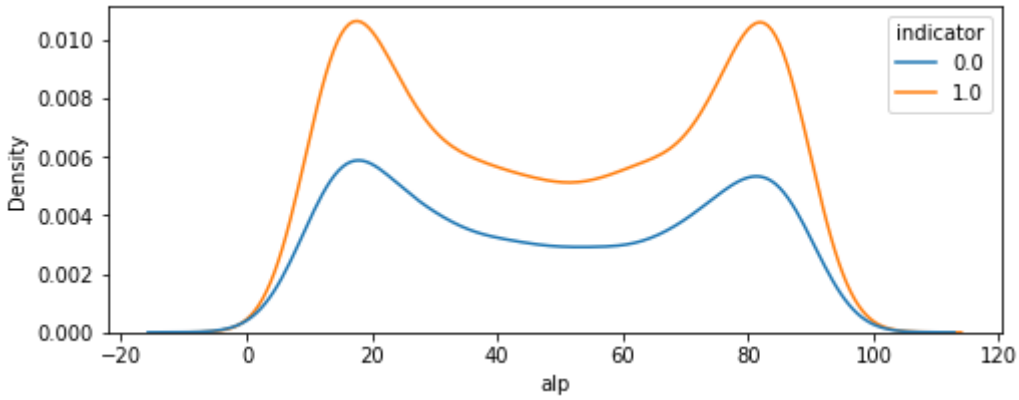
indicator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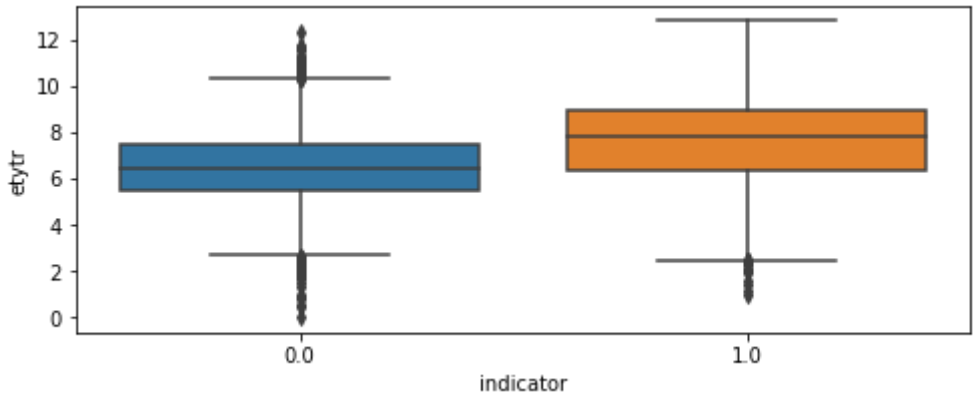
etytr
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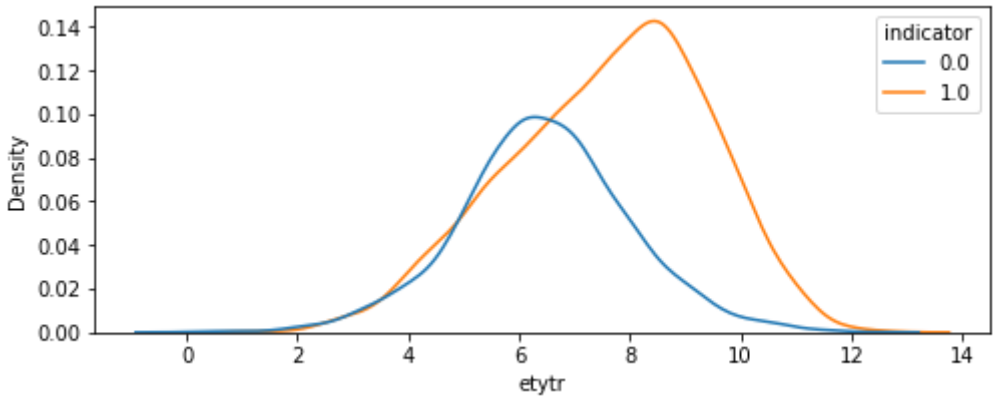
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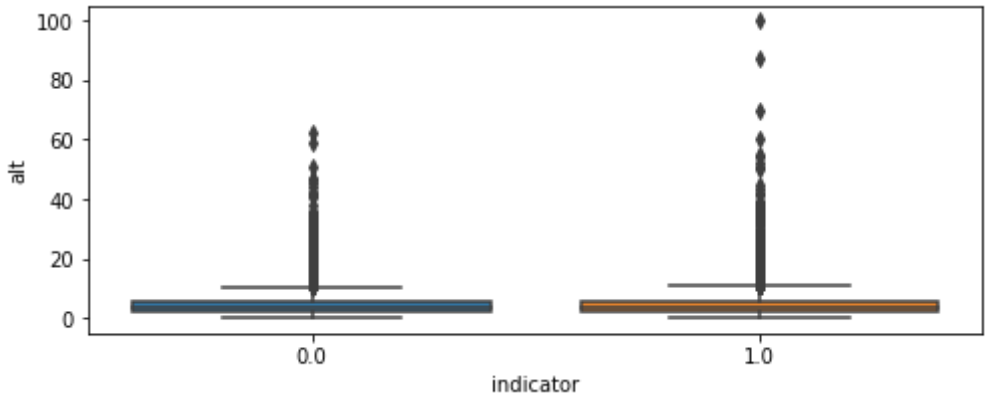
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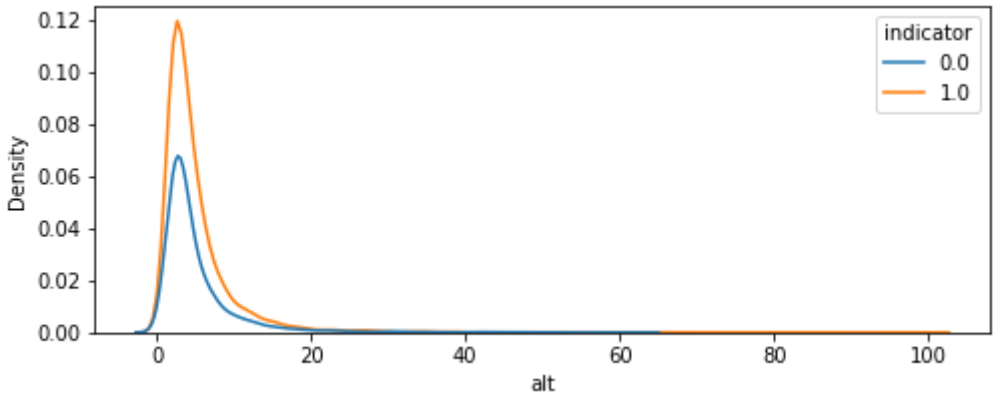
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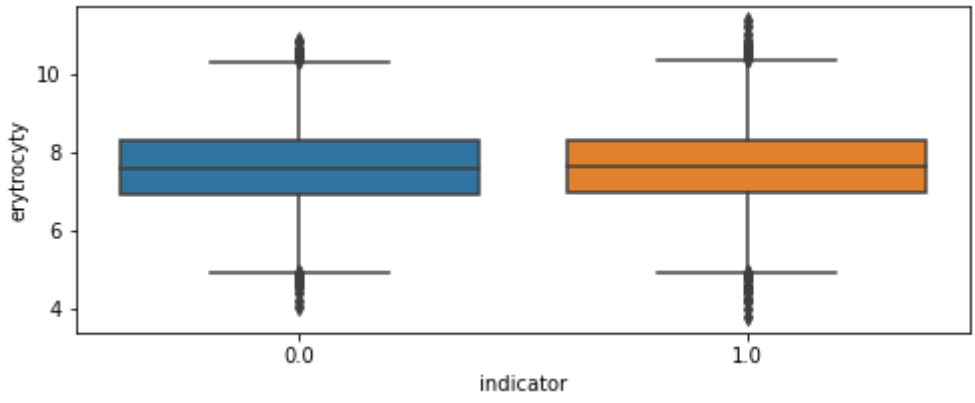
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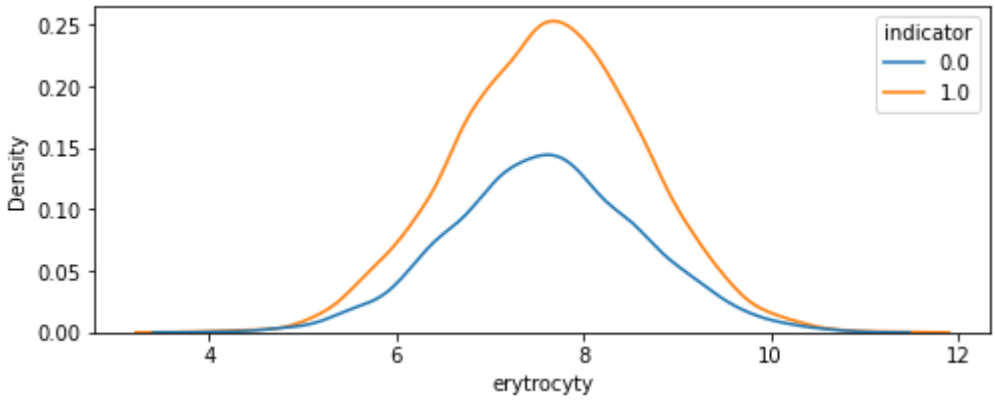
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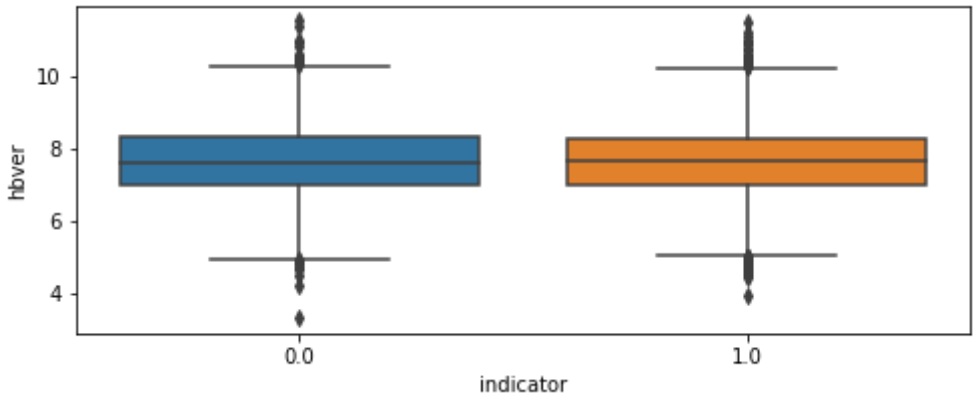
hbver
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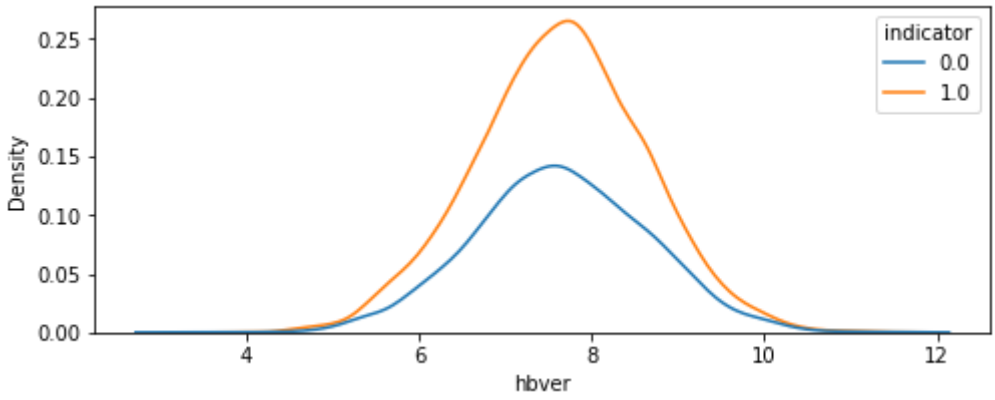
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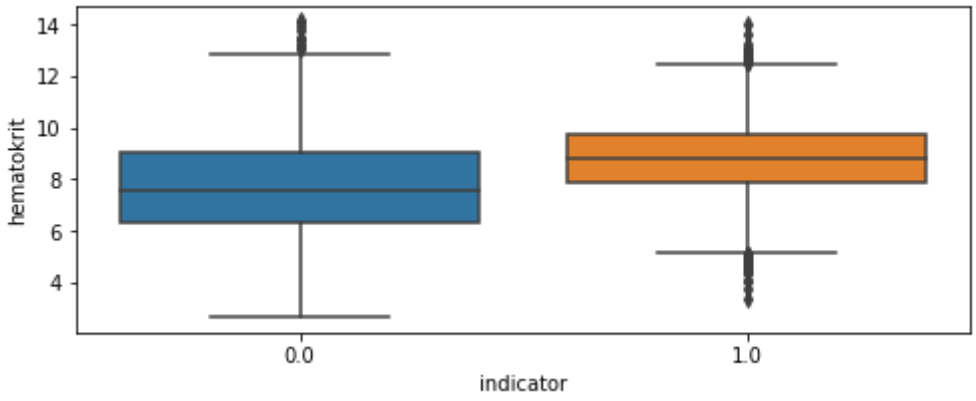
hematokrit
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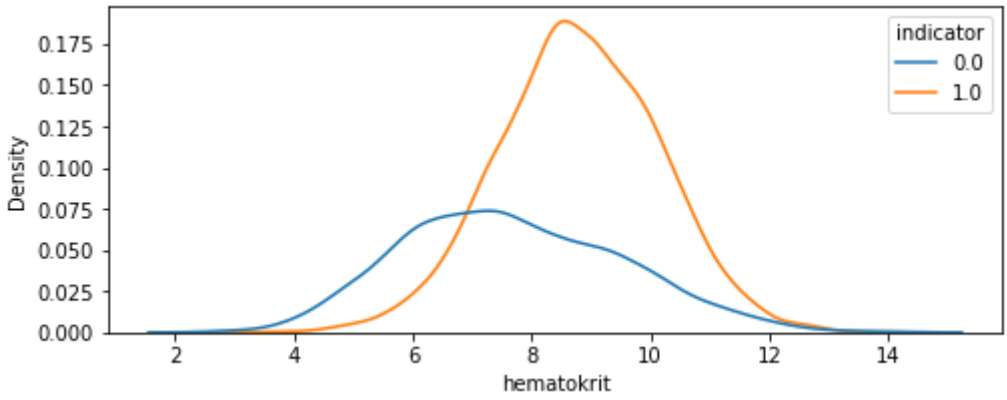
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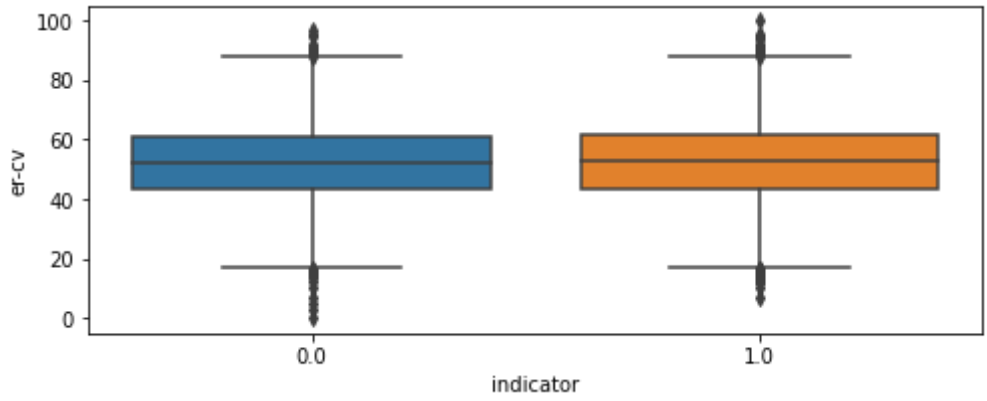
2
4
6
8
10
12
14
hematokrit


er-cv
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60
40
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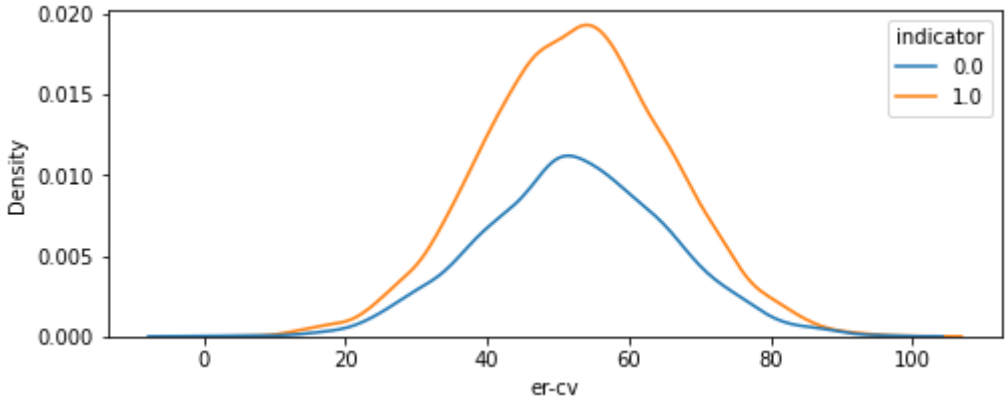
indicator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Density
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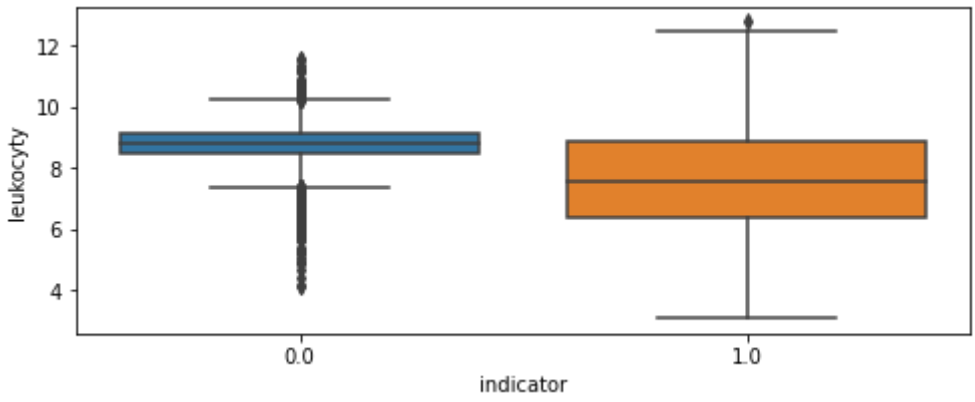
20
40
60
80
100
er-cv


leukocyty
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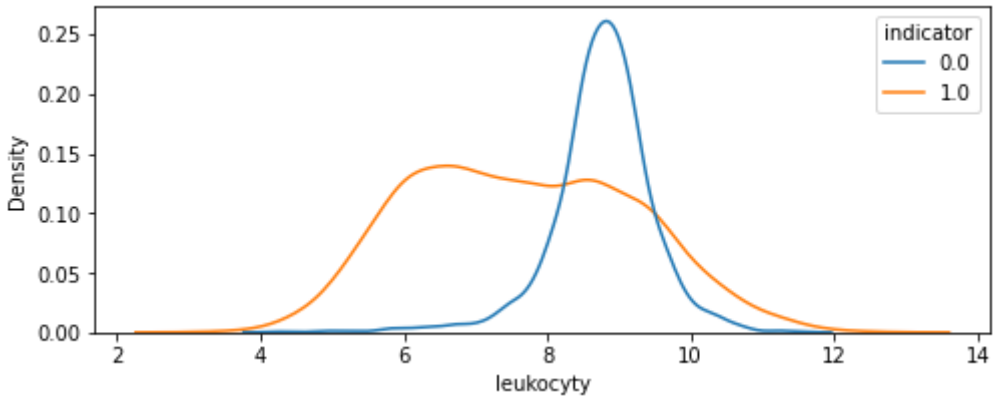
10
8
6
4
0.0
1.0
indicator


indicator
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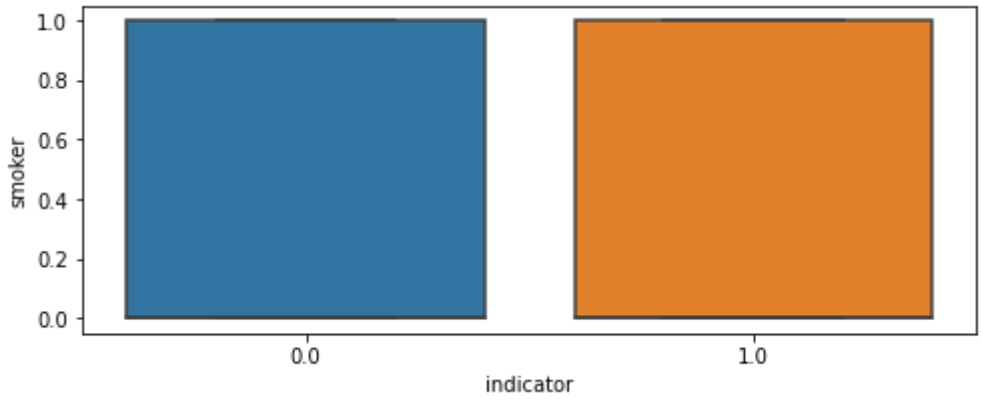
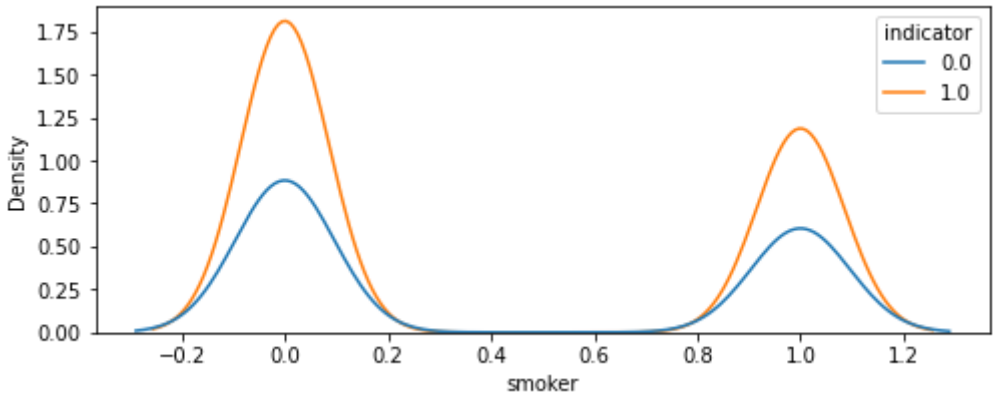
Density
leukocyty


smoker
indicator


indicator
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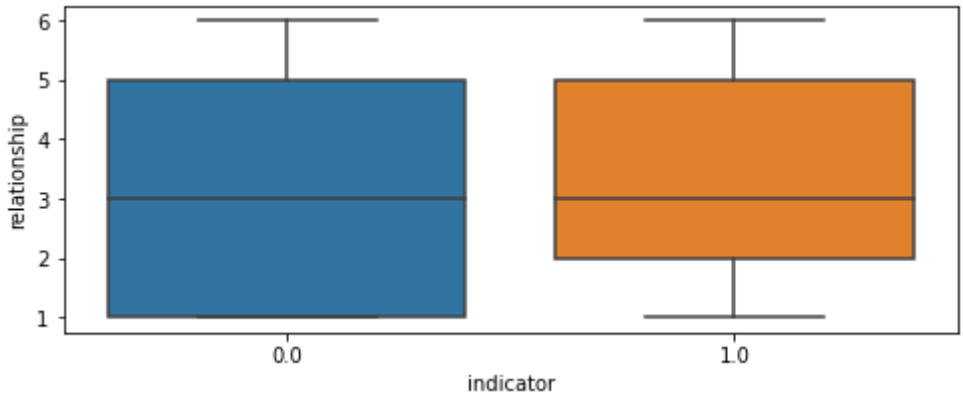
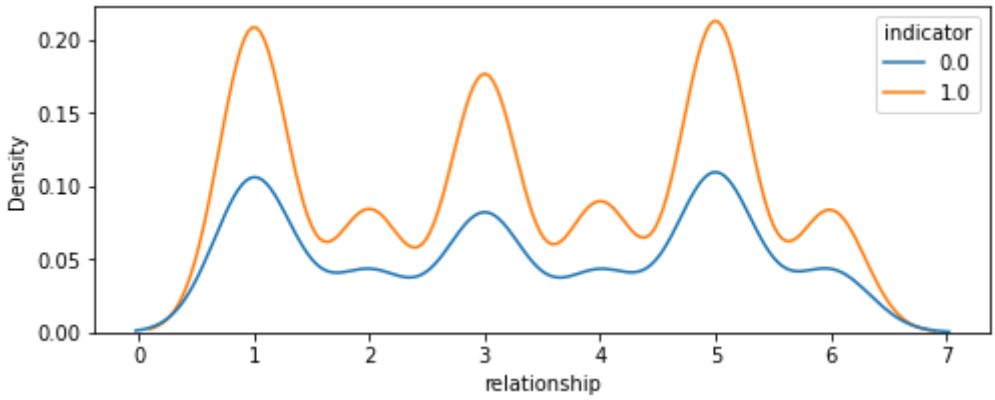
Density
smoker


relationship
indicator


indicator
0.0
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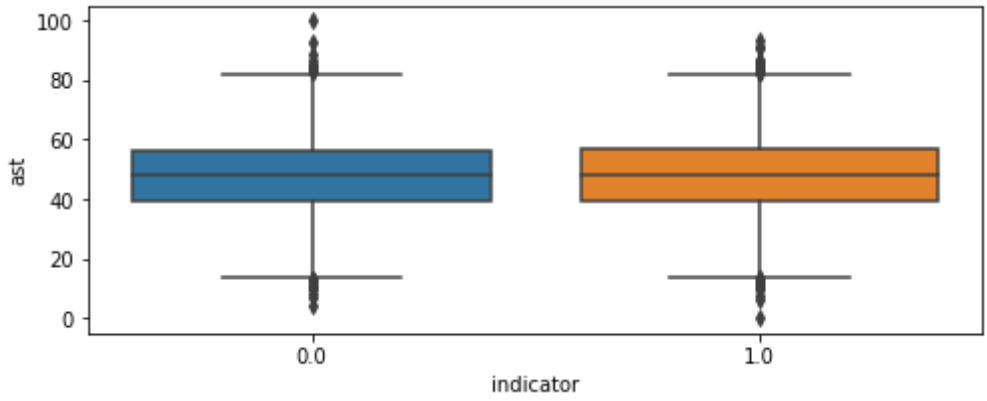
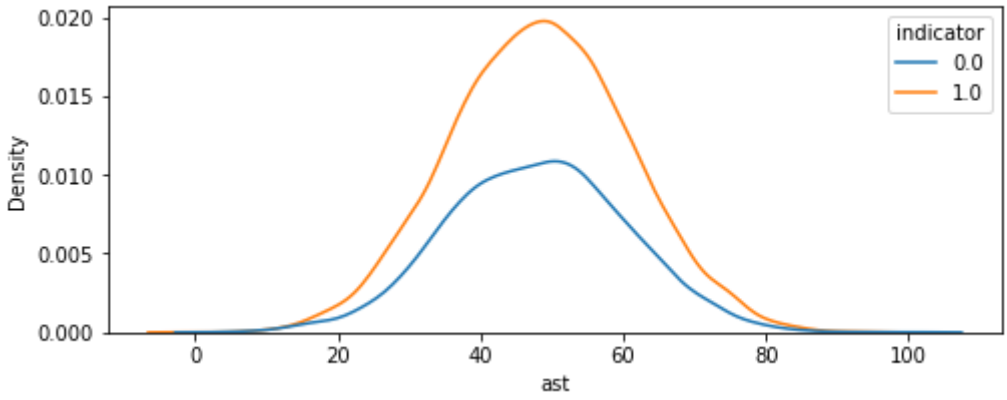
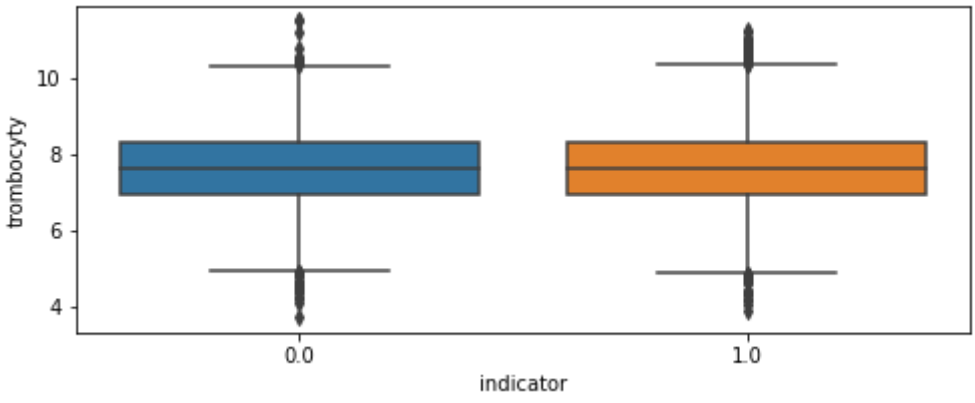
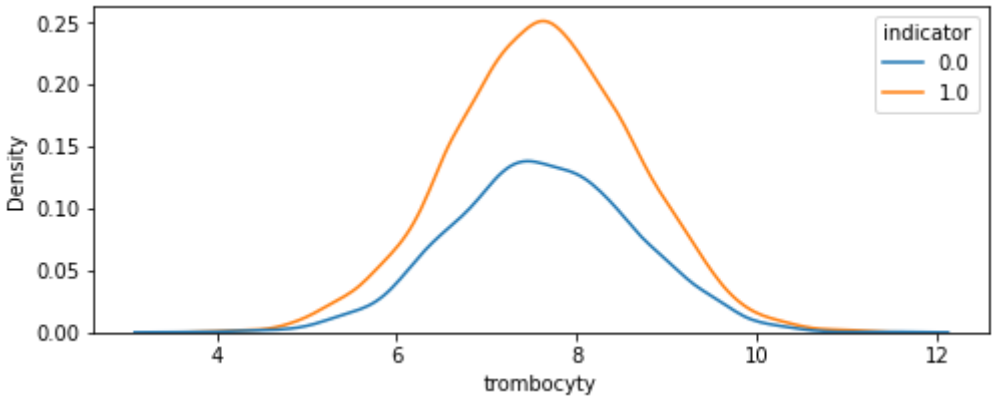
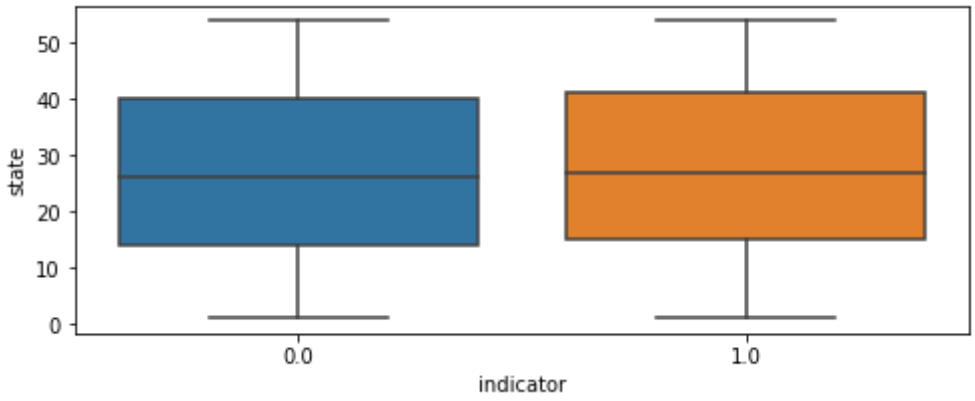
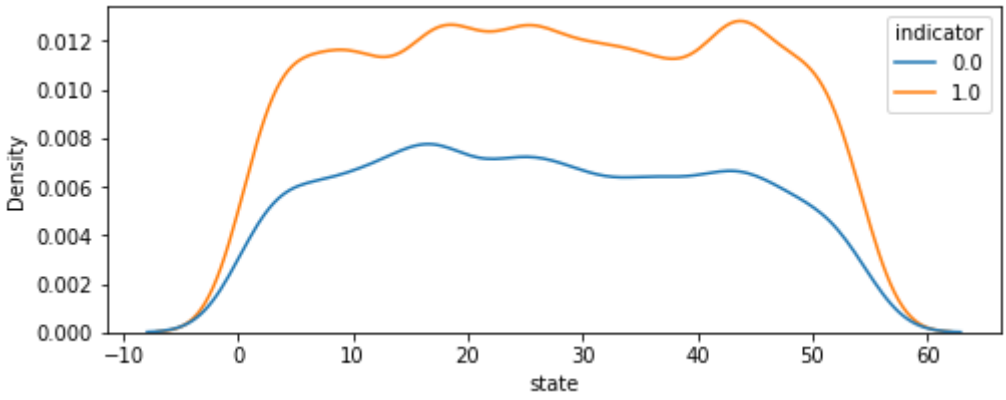

ast
indicator

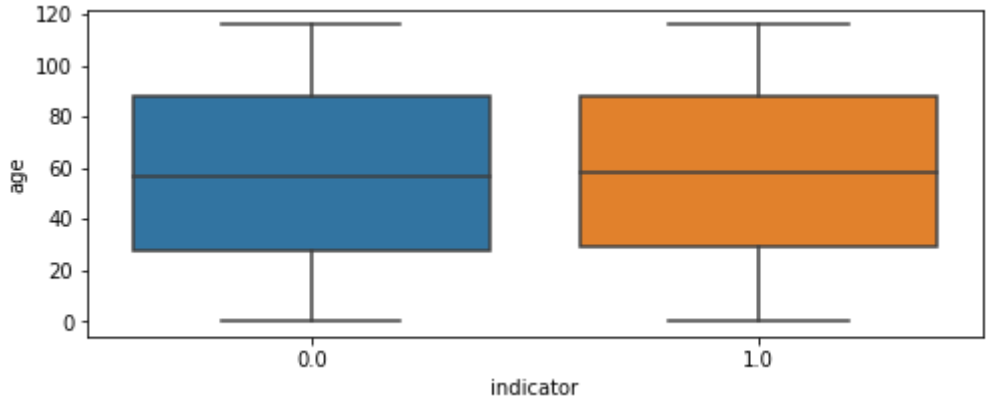

indicator
0.0
1.0
Density
ast

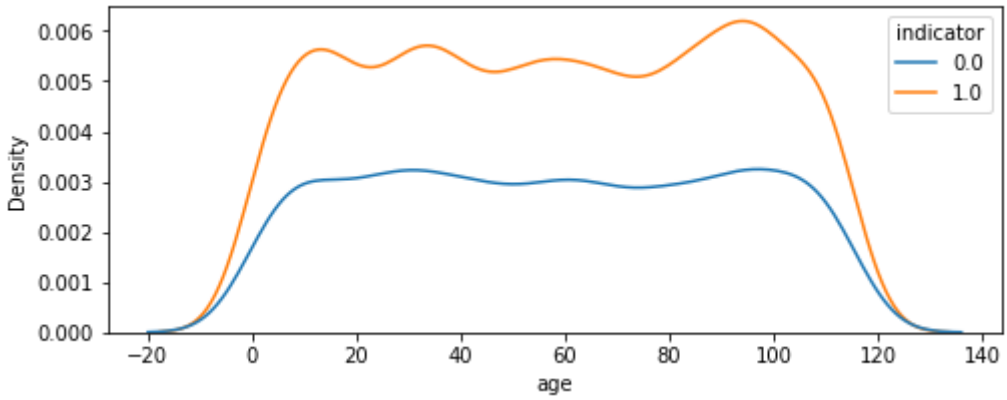

trombocyty
indicator


indicator
0.0
1.0
Density
trombocyty


state
indicator


indicator
0.0
1.0
Density
state


age
indicator



Dummy OneR

In [11]:
```
def rule1(row):
    if row['leukocyty'] > 8.1 and row['leukocyty'] < 9.5:
        return 0
    else:
        return 1

def oner(data):
    return data.apply(lambda row: rule1(row), axis=1)
```

In [12]:
```
pred = oner(X_train)
print(classification_report(y_train, pred))
```

```
              precision    recall  f1-score   support

         0.0       0.61      0.76      0.68      2294
         1.0       0.85      0.74      0.79      4186

    accuracy                           0.75      6480
   macro avg       0.73      0.75      0.73      6480
weighted avg       0.77      0.75      0.75      6480
```

In [13]:
```
pred = oner(X_test)
print(classification_report(y_test, pred))
```

```
              precision    recall  f1-score   support

         0.0       0.63      0.77      0.69      1179
         1.0       0.85      0.73      0.78      2013

    accuracy                           0.75      3192
   macro avg       0.74      0.75      0.74      3192
weighted avg       0.77      0.75      0.75      3192
```

Dummy OneR má napevno nastavené intervaly hodnôt pre ktoré má urobiť klasifikáciu. Keďže sme zvolili nastavovanie hodnôt pre atribút ktorý sa najviac líšil medzi 0 a 1, tak aj úspešnosť je pomerne dobrá, 75%.

OneR

In [14]:
```
class OneRClassifier():
    def __init__(self, number_of_breakpoints=2, silent=True):
```

```
        self.number_of_breakpoints = number_of_breakpoints
        self.silent = silent
        self.dict_of_intervals = {}
        self.list_attributes = []

    def oner(self, X_col, y_data):
        df = pd.concat([X_col, y_data], axis=1)
        df = df.sort_values(by=[X_col.name])
        part_def = len(df) // (self.number_of_breakpoints + 1)

        parts = []
        for i in range(self.number_of_breakpoints):
            parts.append(part_def*(i + 1))

        breakpoints = []
        start = 0
        end = len(df)
        ranges = []
        for index, part in enumerate(parts):
            breakpoints.append(df.iloc[part][X_col.name])
            if index == 0:
                ranges.append(range(start , part))
            elif index == (len(parts) - 1):
                ranges.append(range(parts[index-1], part))
                ranges.append(range(part, end))
            else:
                ranges.append(range(parts[index-1], part))

        values = []
        for r in ranges:
            subframe = df.iloc[r][y_data.name]
            ln = len(subframe)
            sm = subframe.sum()
            if sm/ln >= 0.5:
                values.append(1)
            else:
                values.append(0)

        return [breakpoints, values]

    def fit(self, X_data, y_data):
        self.list_attributes = list(X_data.columns)
        for att in self.list_attributes:
            self.dict_of_intervals[att] = self.oner(X_data[att], y_data)
            self.dict_of_intervals[att].append(self.calculate_error(X_data, y_data,
        return self

    def apply_rule_1_attr(self, row, attr):
        for index, value in enumerate(self.dict_of_intervals[attr][0]):
            if row[attr] < value:
                return self.dict_of_intervals[attr][1][index]
        return self.dict_of_intervals[attr][1][-1]

    def calculate_error(self, X_data, y_data, attr):
        pred = X_data.apply(lambda row: self.apply_rule_1_attr(row, attr), axis=1)
        return (1 - classification_report(y_data, pred, output_dict=True, zero_divis

    def apply_all_rules(self, row):
        count = 0
        sm = 0
        changed = False
        for rowid in row.index:
            if rowid not in self.list_attributes:
                continue
```

```
            count += 1
            for index, value in enumerate(self.dict_of_intervals[rowid][0]):
                if row[rowid] <= value:
                    sm += self.dict_of_intervals[rowid][1][index]
                    changed = True
                    break
            if not changed:
                sm += self.dict_of_intervals[rowid][1][-1]

        if sm / count >= 0.5:
            return 1
        else:
            return 0

    def rules_print(self, list_attributes):
        for attr in list_attributes:
#             print("Predicting on: {} with minimal error of {:.2f}%".format(attr, s
            if not self.silent:
                print("Predicting on: {} with minimal error of {:.2f}%".format(attr,
                print("Intervals for {} are:".format(attr))
                for index, point in enumerate(self.dict_of_intervals[attr][0]):
                    if index == 0:
                        print("-infinity, {} -> {}".format(point, self.dict_of_inter
                    elif index == (len(self.dict_of_intervals[attr][0]) - 1):
                        print("{}, {} -> {}".format(self.dict_of_intervals[attr][0][
                        print("{}, +infinity -> {}".format(point, self.dict_of_inter
                    else:
                        print("{}, {} -> {}".format(self.dict_of_intervals[attr][0][

    def predict_multiple(self, X_data, list_attributes=None):
        if list_attributes is not None:
            X_selected = X_data[list_attributes]
        else:
            X_selected = X_data
            list_attributes = list(X_selected.columns)
        self.rules_print(list_attributes)
        return X_selected.apply(lambda row: self.apply_all_rules(row), axis=1)

    def predict(self, X_data):
        minimum = min(self.dict_of_intervals, key=lambda x: self.dict_of_intervals[x
        return self.predict_multiple(X_data, [minimum])

    def __repr__(self):
         return "OneRClassifier()"

    def __str__(self):
         return "Member of OneRClassifier"
```

In [15]:

```
def report_generator(pred_train, pred_test, y_train, y_test, driver_silent):
    if not driver_silent:
        print("Predicting for train dataset:")
        print(classification_report(y_train, pred_train))

        print("Predicting for test dataset:")
        print(classification_report(y_test, pred_test))

    report_train = classification_report(y_train, pred_train, output_dict=True)
    report_test = classification_report(y_test, pred_test, output_dict=True)

    return report_train, report_test
```

In [16]:

```
def onerDriver(X_train, X_test, y_train, y_test, driver_silent=True, number_of_break
    oner1 = OneRClassifier(number_of_breakpoints=number_of_breakpoints, silent=silen
    oner1.fit(X_train, y_train)

    pred_train = oner1.predict(X_train)
    pred_test = oner1.predict(X_test)

    return oner1, *report_generator(pred_train, pred_test, y_train, y_test, driver_s
```

In [17]:

```
oner1, train1, test1 = onerDriver(X_train, X_test, y_train, y_test, driver_silent=Fa
```

```
Predicting on: leukocyty with minimal error of 27.87%
Intervals for leukocyty are:
-infinity, 6.94453 -> 1
6.94453, 8.38503 -> 1
8.38503, 9.06224 -> 0
9.06224, +infinity -> 1
Predicting on: leukocyty with minimal error of 27.87%
Intervals for leukocyty are:
-infinity, 6.94453 -> 1
6.94453, 8.38503 -> 1
8.38503, 9.06224 -> 0
9.06224, +infinity -> 1
Predicting for train dataset:
              precision    recall  f1-score   support

         0.0       0.65      0.46      0.54      2294
         1.0       0.75      0.87      0.80      4186

    accuracy                           0.72      6480
   macro avg       0.70      0.66      0.67      6480
weighted avg       0.71      0.72      0.71      6480

Predicting for test dataset:
              precision    recall  f1-score   support

         0.0       0.67      0.48      0.56      1179
         1.0       0.74      0.86      0.80      2013

    accuracy                           0.72      3192
   macro avg       0.71      0.67      0.68      3192
weighted avg       0.71      0.72      0.71      3192
```

In [18]:

```
oner2, train2, test2 = onerDriver(X_train, X_test, y_train, y_test, driver_silent=Fa
```

```
Predicting on: leukocyty with minimal error of 25.42%
Intervals for leukocyty are:
-infinity, 6.21581 -> 1
6.21581, 7.19198 -> 1
7.19198, 8.08076 -> 1
8.08076, 8.58285 -> 0
8.58285, 8.9527 -> 0
8.9527, 9.42163 -> 0
9.42163, +infinity -> 1
Predicting on: leukocyty with minimal error of 25.42%
Intervals for leukocyty are:
-infinity, 6.21581 -> 1
6.21581, 7.19198 -> 1
7.19198, 8.08076 -> 1
8.08076, 8.58285 -> 0
8.58285, 8.9527 -> 0
```

```
8.9527, 9.42163 -> 0
9.42163, +infinity -> 1
Predicting for train dataset:
              precision    recall  f1-score   support

         0.0       0.62      0.75      0.68      2294
         1.0       0.84      0.75      0.79      4186

    accuracy                           0.75      6480
   macro avg       0.73      0.75      0.73      6480
weighted avg       0.76      0.75      0.75      6480

Predicting for test dataset:
              precision    recall  f1-score   support

         0.0       0.63      0.76      0.69      1179
         1.0       0.84      0.74      0.79      2013

    accuracy                           0.75      3192
   macro avg       0.74      0.75      0.74      3192
weighted avg       0.76      0.75      0.75      3192
```

OneR vytvorený v tejto fáze funguje tak, že pre zadaný dataset rozdelí všetky jeho atribúty na intervaly a priradí im klasifikačnú triedu. Následne skontroluje, ktorý atribút má najmenšiu chybovosť klasifikácie. Ten vyberie a podľa neho klasifikuje nové dáta. Algoritmus má jeden hyperparameter, number_of_breakpoints, ktorý určuje počet zlomov intervalov. Experimentálne sme zistili, že pre naše zadané dáta dosahuje náš algoritmus najlepšie výsledky, ak je number_of_breakpoints nastavený na 6. V tom prípade je teda pre atribút vytvorených 7 intervalov. Najvyššia úspešnosť, akú sme pre náš OneR dosiahli na testovacej množine je 75%.

2. Natrénovanie a vyhodnotenie klasifikátora strojového učenia (5b)

- Na trénovanie využite minimálne jeden stromový algoritm strojového učenia v scikit-learn.
- Vizualizujte natrénované pravidlá.
- Vyhodnoťte natrénovaný model pomocou metrík accuracy, precision a recall
- Porovnajte natrénovaný klasifikátor s Vašimi manuálne vytvorenými pravidlami z prvého kroku.

Algoritmy:

1. Decision tree

In [19]:
```
def decisionTreeDriver(X_train, X_test, y_train, y_test, driver_silent=True, max_dep
    cls = DecisionTreeClassifier(max_depth=max_depth, random_state=1)
    cls.fit(X_train, y_train)

    pred_train = cls.predict(X_train)
    pred_test = cls.predict(X_test)

    return cls, *report_generator(pred_train, pred_test, y_train, y_test, driver_sil
```

In [20]:
```
cls1, train_report1, test_report1 = decisionTreeDriver(X_train, X_test, y_train, y_t
```

```
Predicting for train dataset:
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2294
         1.0       1.00      1.00      1.00      4186

    accuracy                           1.00      6480
   macro avg       1.00      1.00      1.00      6480
weighted avg       1.00      1.00      1.00      6480

Predicting for test dataset:
              precision    recall  f1-score   support

         0.0       0.83      0.82      0.83      1179
         1.0       0.90      0.90      0.90      2013

    accuracy                           0.87      3192
   macro avg       0.86      0.86      0.86      3192
weighted avg       0.87      0.87      0.87      3192
```

Vyhodnotenie Decision tree podľa natrénovaných pravidiel pomocou metrík

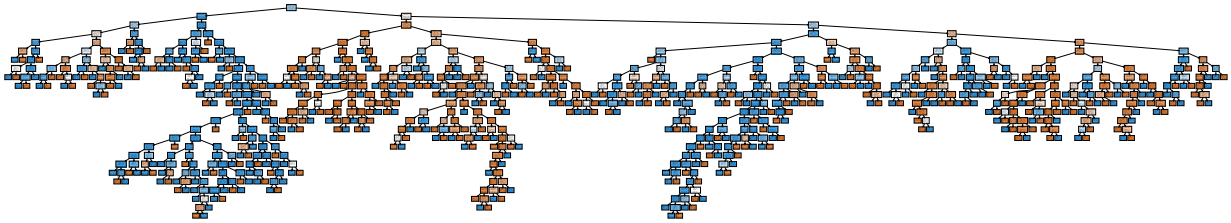
Podľa tohto výsledku je zjavné, že nastal overfitting.

Vizualizácia natrénovaných pravidiel:

Výsledný strom sa uloží ako png súbor

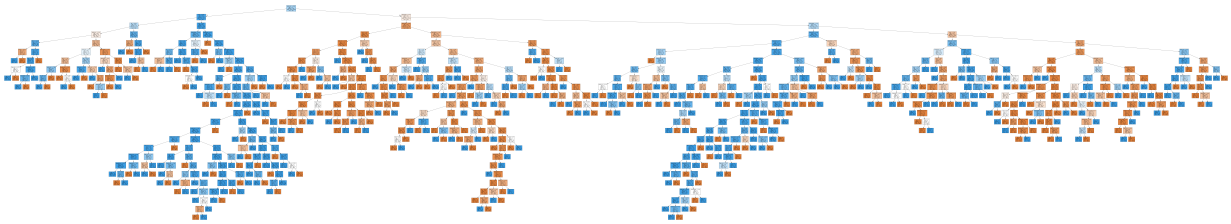
In [21]:
```
clf = cls1
graph = Source(export_graphviz(clf, feature_names=X_train.columns, class_names=['fal
graph
```

Out[21]:



In [22]:
```
graph.render('decision_tree')
Image(filename='decision_tree.png')
```

Out[22]:



2. Random forest

In [23]:
```
def randomForestDriver(X_train, X_test, y_train, y_test, driver_silent=True, max_dep
                       criterion='gini', max_features='auto', min_samples_leaf=1, n_
    cls = RandomForestClassifier(random_state=1, criterion=criterion, max_depth=max_
                                 max_features=max_features, min_samples_leaf=min_sam
    cls.fit(X_train, y_train)

    pred_train = cls.predict(X_train)
    pred_test = cls.predict(X_test)
```

```
    return cls, *report_generator(pred_train, pred_test, y_train, y_test, driver_sil
```

In [24]:
```
cls2, train_report2, test_report2 = randomForestDriver(X_train, X_test, y_train, y_t
```

```
Predicting for train dataset:
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2294
         1.0       1.00      1.00      1.00      4186

    accuracy                           1.00      6480
   macro avg       1.00      1.00      1.00      6480
weighted avg       1.00      1.00      1.00      6480

Predicting for test dataset:
              precision    recall  f1-score   support

         0.0       0.90      0.87      0.88      1179
         1.0       0.92      0.94      0.93      2013

    accuracy                           0.91      3192
   macro avg       0.91      0.90      0.91      3192
weighted avg       0.91      0.91      0.91      3192
```

Vyhodnotenie Random forest podľa natrénovaných pravidiel pomocou metrík

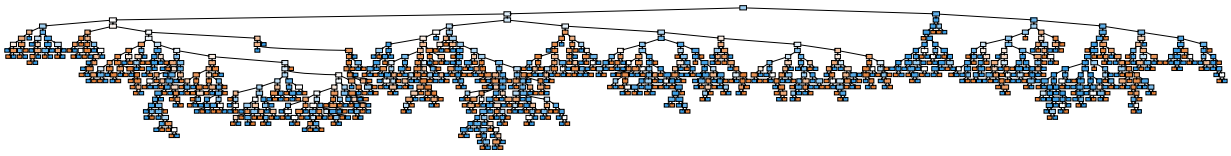
Podľa tohto výsledku je zjavné, že nastal overfitting.

Vizualizácia natrénovaných pravidiel:

Výsledný strom sa uloží ako png súbor

In [25]:
```
clf = cls2
graph = Source(export_graphviz(clf.estimators_[0], feature_names=X_train.columns, cl
graph
```

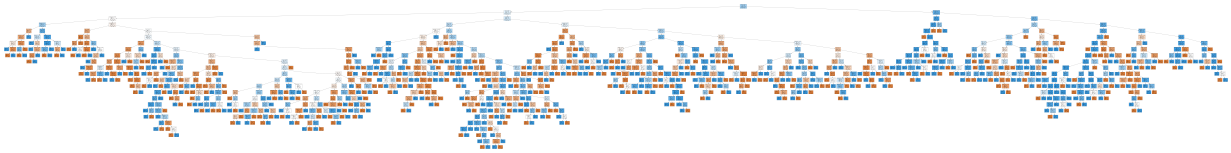
Out[25]:



Model RandomForest na vizualizáciu obsahuje v našom prípade prvý Decision tree v celom RandomForest. (clf.estimators_[0])

In [26]:
```
graph.render('rf')
Image(filename='rf.png')
```

Out[26]:



Porovnanie a záver bodu 2

Ako môžeme vidieť, DecisionTreeClassifier dosahuje na testovacom datasete úspešnosť 87%. Môžeme však vidieť, že nastal výrazný overfit, keďže na trénovacej množine má úspešnosť klasifikácie až 100%.

RandomForestClassifier dosiahol úspešnosť na testovacom datasete 91%, čo je lepšie ako DecisionTreeClassifier. Avšak, rovnako ako pri DecisionTreeClassifier, aj tu nastal výrazný overfit.

Rozhodli sme sa ďalej pracovať s RandomForest algoritmom. Hoci aj ten nám vytvoril overfitting, vo všeobecnosti dosahuje lepšie výsledky.

OneR z predchádzajúceho bodu dosiahol najvyššiu úspešnosť 75%. RandomForestClassifier dosiahol najvyššiu úspešnosť 91%. Z toho je zjavné, že RandomForestClassifier je oveľa lepší algoritmus pre klasifikáciu dát, pretože na rozdiel od OneR, ktorý zohľadňuje len jeden atribút, RandomForest zohľadňuje vzťahy všetkých atribútov.

3. Optimalizácia - hyperparameter tuning (5b)

- Preskúmajte hyperparametre Vášho zvoleného klasifikačného algoritmu v druhom kroku a vyskúšajte ich rôzne nastavenie tak, aby ste minimalizovali overfitting (preučenie) a optimalizovali výsledok.
- Vysvetlite, čo jednotlivé hyperparametre robia. Pri nastavovaní hyperparametrov algoritmu využite krížovú validáciu (cross validation) na trénovacej množine.

Klasifikačný algoritmus RandomForest má dokopy 18 parametrov, z toho 7 je kľučových:

- max_depth
- min_sample_split
- max_leaf_nodes
- min_samples_leaf
- n_estimators
- max_sample (bootstrap sample)
- max_features

Aby sme optimalizovali parametre, a tak vylepšili úspešnosť, pričom príliš nezaťažili naše výpočtové zdroje, rozhodli sme sa použiť tieto:

- max_depth: maximálna hĺbka stromu (10, 20, 30, 40)
- criterion: funkcia na meranie kvality rozdelenia (gini, entropy)
- max_features: maximálny počet atribútov, ktorý je potrebné zvážiť počas každého delenia (log2, 2, 4, 5, 6, 8, 10)
- n_estimators: počet stromov pred priemerovaním predikcií (5, 10, 50, 100, 200)
- min_sample_leaf: minimálny počet vzoriek, ktoré majú pripadnúť na jeden leaf node (2, 5, 10, 20, 50)

Na zvýšenie rýchlosti vykonávania sme sa rozhodli pridať parameter random_state a neobmedzili sme počet procesorov, na ktorých pôjde výpočet (n_jobs).

Parameter verbose slúži na to, koľko výpisov má zobraziť. My sme použili verbose=1, aby sme základé výpisy videli, ako napr. počet kandidátov a počet fits.

In [27]:
```
params = {
    'max_depth': [10, 20, 30, 40],
    'criterion': ['gini', 'entropy'],
    'max_features': ['log2', 2, 4, 5, 6, 8, 10],
    'min_samples_leaf': [5,10,20,50],
```

```
    'n_estimators': [10,25,30,50]
}
```

In [28]:
```
cls = RandomForestClassifier(random_state=1)
```

GridSearch Cross Validation

In [29]:
```
gridCV = GridSearchCV(cls, params, cv=3, verbose=1, n_jobs=-1)
```

Trvá pomerne dlho

In [30]:
```
gridCV.fit(X_train, y_train)
```

Out[30]:
```
Fitting 3 folds for each of 896 candidates, totalling 2688 fits
GridSearchCV(cv=3, estimator=RandomForestClassifier(random_state=1), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [10, 20, 30, 40],
                         'max_features': ['log2', 2, 4, 5, 6, 8, 10],
                         'min_samples_leaf': [5, 10, 20, 50],
                         'n_estimators': [10, 25, 30, 50]},
             verbose=1)
```

In [31]:
```
gridCV.best_score_
```

Out[31]:
```
0.9299382716049384
```

In [32]:
```
bestGrid = gridCV.best_estimator_
bestGrid
```

Out[32]:
```
RandomForestClassifier(criterion='entropy', max_depth=20, max_features=10,
                       min_samples_leaf=5, n_estimators=30, random_state=1)
```

In [33]:
```
gridPred_train = bestGrid.predict(X_train)
gridPred = bestGrid.predict(X_test)
```

In [34]:
```
print(classification_report(y_train, gridPred_train))
```

```
              precision    recall  f1-score   support

         0.0       0.97      0.95      0.96      2294
         1.0       0.97      0.99      0.98      4186

    accuracy                           0.97      6480
   macro avg       0.97      0.97      0.97      6480
weighted avg       0.97      0.97      0.97      6480
```

In [35]:
```
print(classification_report(y_test, gridPred))
```

```
              precision    recall  f1-score   support

         0.0       0.91      0.90      0.90      1179
         1.0       0.94      0.95      0.94      2013

    accuracy                           0.93      3192
```

```
   macro avg       0.93      0.92      0.92      3192
weighted avg       0.93      0.93      0.93      3192
```

RandomizedSearch Cross Validation

In [36]:
```
randomCV = RandomizedSearchCV(cls, params, cv=7, verbose=1, n_jobs=-1, random_state=
```

In [37]:
```
randomCV.fit(X_train,y_train)
```

Out[37]:
```
Fitting 7 folds for each of 10 candidates, totalling 70 fits
RandomizedSearchCV(cv=7, estimator=RandomForestClassifier(random_state=1),
                   n_jobs=-1,
                   param_distributions={'criterion': ['gini', 'entropy'],
                                        'max_depth': [10, 20, 30, 40],
                                        'max_features': ['log2', 2, 4, 5, 6, 8,
                                                         10],
                                        'min_samples_leaf': [5, 10, 20, 50],
                                        'n_estimators': [10, 25, 30, 50]},
                   random_state=1, verbose=1)
```

In [38]:
```
randomCV.best_score_
```

Out[38]:
```
0.9217557143691053
```

In [39]:
```
bestRandom = randomCV.best_estimator_
bestRandom
```

Out[39]:
```
RandomForestClassifier(max_depth=30, max_features=10, min_samples_leaf=5,
                       n_estimators=10, random_state=1)
```

In [40]:
```
randomPred_train = bestRandom.predict(X_train)
randomPred = bestRandom.predict(X_test)
```

In [41]:
```
print(classification_report(y_train, randomPred_train))
```

```
              precision    recall  f1-score   support

         0.0       0.96      0.94      0.95      2294
         1.0       0.97      0.98      0.97      4186

    accuracy                           0.96      6480
   macro avg       0.96      0.96      0.96      6480
weighted avg       0.96      0.96      0.96      6480
```

In [42]:
```
print(classification_report(y_test, randomPred))
```

```
              precision    recall  f1-score   support

         0.0       0.90      0.89      0.89      1179
         1.0       0.94      0.94      0.94      2013

    accuracy                           0.92      3192
   macro avg       0.92      0.91      0.91      3192
weighted avg       0.92      0.92      0.92      3192
```

Aplikovanie zvolených najlepších hodnôt hyperparametrov do driver funkcie

In [43]:
```
cls3, train_report3, test_report3 = randomForestDriver(X_train, X_test, y_train, y_t
                  criterion='entropy', max_depth=20, max_features=10, min_samples_l
```

```
Predicting for train dataset:
              precision    recall  f1-score   support

         0.0       0.97      0.95      0.96      2294
         1.0       0.97      0.99      0.98      4186

    accuracy                           0.97      6480
   macro avg       0.97      0.97      0.97      6480
weighted avg       0.97      0.97      0.97      6480

Predicting for test dataset:
              precision    recall  f1-score   support

         0.0       0.91      0.90      0.90      1179
         1.0       0.94      0.95      0.94      2013

    accuracy                           0.93      3192
   macro avg       0.93      0.92      0.92      3192
weighted avg       0.93      0.93      0.93      3192
```

In [44]:
```
cls4, train_report4, test_report4 = randomForestDriver(X_train, X_test, y_train, y_t
                  max_depth=30, max_features=10, min_samples_leaf=5, n_estimators=1
```

```
Predicting for train dataset:
              precision    recall  f1-score   support

         0.0       0.96      0.94      0.95      2294
         1.0       0.97      0.98      0.97      4186

    accuracy                           0.96      6480
   macro avg       0.96      0.96      0.96      6480
weighted avg       0.96      0.96      0.96      6480

Predicting for test dataset:
              precision    recall  f1-score   support

         0.0       0.90      0.89      0.89      1179
         1.0       0.94      0.94      0.94      2013

    accuracy                           0.92      3192
   macro avg       0.92      0.91      0.91      3192
weighted avg       0.92      0.92      0.92      3192
```

Nastavenie hyperparametrov pre RandomForestClassifier sme robili 2 metódami, GridSearchCV a RandomizedSearchCV. GridSearchCV vrátil ako najlepšie nastavenie hyperparametrov RandomForestClassifier(criterion='entropy', max_depth=20, max_features=10, min_samples_leaf=5, n_estimators=30, random_state=1). RandomizedSearchCV vrátil ako najlepšie nastavenie hyperparametrov RandomForestClassifier(max_depth=30, max_features=10, min_samples_leaf=5, n_estimators=10, random_state=1).

Hyperparametre nájedené pomocou GridSearchCV aj RandomizedSearchCV minimalizujú overfit. Hyperparametre nájdené pomocou GridSearchCV dosahujú o 1% vyššiu úspešnosť, preto ich použijeme v nasledujúcej fáze.

4. Vyhodnotenie vplyvu zvolenej stratégie riešenia na klasifikáciu (5b)

Vyhodnotíte Vami zvolené stratégie riešenia projektu z hľadiska classification accuracy:

- Stratégie riešenia chýbajúcich hodnôt a outlierov;
- Scaling resp. transformer či zlepší accuracy klasifikácie;
- Výber atribútov a výber algoritmov;
- Hyperparameter tuning resp. ensemble learning.

Ktorý spôsob z každého hore-uvedených bodov sa ukázal ako vhodnejší pre daný problém? Vyhodnotenie podložíte dôkazmi.

In [45]:
```
original_data = phase1()
```

In [46]:
```
def process_data(pipeline, original_data):
    preprocessed_data = pipeline.fit_transform(original_data)
    X_train, X_test, y_train, y_test = train_test_split(preprocessed_data.drop(['ind
                                                        preprocessed_data['indicator'],
    return X_train, X_test, y_train, y_test
```

In [47]:
```
def generate_pipelines():
    na = [['nothing', None], ['remove', None], ['replace', 'mean'], ['replace', 'med
    out = ['nothing', 'remove', 'replace']
    tran = ['nothing', 'power', 'quan', 'minmax', 'standard']
    attr = ['all', ['leukocyty', 'etytr', 'hematokrit','alp', 'ast', 'indicator']]

    pipelines = []
    settings = []

    for a in na:
        for b in out:
            for c in tran:
                for d in attr:
                    p1 = pipelineGenerator(na_method=a[0], na_strategy=a[1], outlier
                                           select_attributes=d)
                    pipelines.append(p1)
                    settings.append([a, b, c, d])

    return pipelines, settings
```

In [48]:
```
pipelines, settings = generate_pipelines()
```

In [49]:
```
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

def try_algo(algo):
    accuracies = []
```

```
    for count, pipeline in enumerate(pipelines):

        try:
            X_train, X_test, y_train, y_test = process_data(pipeline, original_data)
        except:
            print("Pipeline", count, "processing error")
            continue

        try:
            cls, train_report, test_report = algo(X_train, X_test, y_train, y_test,
        except:
            print("Pipeline", count, "algorithm error")
            continue

        accuracies.append([count, test_report['accuracy']])
        print("Pipeline", count, "finished")

    return accuracies
```

In [50]:

```
def evaluate_algo(accuracies):
    nas = [['nothing', None], ['remove', None], ['replace', 'mean'], ['replace', 'me
    outs = ['nothing', 'remove', 'replace']
    trans = ['nothing', 'power', 'quan', 'minmax', 'standard']
    attrs = ['all', ['leukocyty', 'etytr', 'hematokrit','alp', 'ast', 'indicator']]


    for na in nas:
        maxna = 0
        maxsettings = []
        for acc in accuracies:
            if settings[acc[0]][0] == na and acc[1] > maxna:
                maxna = acc[1]
                maxsettings = settings[acc[0]]
        print("For NA strategy {} is max accuracy {} with settings {}".format(na, ma

    for out in outs:
        maxout = 0
        maxsettings = []
        for acc in accuracies:
            if settings[acc[0]][1] == out and acc[1] > maxout:
                maxout = acc[1]
                maxsettings = settings[acc[0]]
        print("For OUT strategy {} is max accuracy {} with settings {}".format(out,

    for tran in trans:
        maxtran = 0
        maxsettings = []
        for acc in accuracies:
            if settings[acc[0]][2] == tran and acc[1] > maxtran:
                maxtran = acc[1]
                maxsettings = settings[acc[0]]
        print("For TRANS strategy {} is max accuracy {} with settings {}".format(tra

    for attr in attrs:
        maxattr = 0
        maxsettings = []
        for acc in accuracies:
            if settings[acc[0]][3] == attr and acc[1] > maxattr:
                maxattr = acc[1]
                maxsettings = settings[acc[0]]
        print("For ATTR strategy {} is max accuracy {} with settings {}".format(attr

    maxacc = 0
```

```
    maxcount = 0
    for acc in accuracies:
        if acc[1] > maxacc:
            maxacc = acc[1]
            maxcount = acc[0]

    print('''\nNajlepšiu accuracy {} pre zvolený algoritmus dosiahla kombinácia para
          na_method={}, na_strategy={}, outliers_method={}, tranformation_method={},
          '''.format(maxacc, maxcount, settings[maxcount][0][0], settings[maxcount][

    pipeline = pipelineGenerator(na_method=settings[maxcount][0][0], na_strategy=set
                    outliers_method=settings[maxcount][1],
                      tranformation_method=settings[maxcount][2], select_attributes=
    return pipeline
```

Decision Tree

In [51]:
```
accuracies_decision = try_algo(decisionTreeDriver)
```

```
Pipeline 0 algorithm error
Pipeline 1 algorithm error
Pipeline 2 algorithm error
Pipeline 3 algorithm error
Pipeline 4 algorithm error
Pipeline 5 algorithm error
Pipeline 6 algorithm error
Pipeline 7 algorithm error
Pipeline 8 algorithm error
Pipeline 9 algorithm error
Pipeline 10 processing error
Pipeline 11 processing error
Pipeline 12 processing error
Pipeline 13 processing error
Pipeline 14 processing error
Pipeline 15 processing error
Pipeline 16 processing error
Pipeline 17 processing error
Pipeline 18 processing error
Pipeline 19 processing error
Pipeline 20 algorithm error
Pipeline 21 algorithm error
Pipeline 22 algorithm error
Pipeline 23 algorithm error
Pipeline 24 algorithm error
Pipeline 25 algorithm error
Pipeline 26 algorithm error
Pipeline 27 algorithm error
Pipeline 28 algorithm error
Pipeline 29 algorithm error
Pipeline 30 finished
Pipeline 31 finished
Pipeline 32 algorithm error
Pipeline 33 algorithm error
Pipeline 34 algorithm error
Pipeline 35 algorithm error
Pipeline 36 algorithm error
Pipeline 37 algorithm error
Pipeline 38 algorithm error
Pipeline 39 algorithm error
Pipeline 40 finished
Pipeline 41 finished
```

```
Pipeline 42 algorithm error
Pipeline 43 algorithm error
Pipeline 44 algorithm error
Pipeline 45 algorithm error
Pipeline 46 algorithm error
Pipeline 47 algorithm error
Pipeline 48 algorithm error
Pipeline 49 algorithm error
Pipeline 50 finished
Pipeline 51 finished
Pipeline 52 algorithm error
Pipeline 53 algorithm error
Pipeline 54 algorithm error
Pipeline 55 algorithm error
Pipeline 56 algorithm error
Pipeline 57 algorithm error
Pipeline 58 algorithm error
Pipeline 59 algorithm error
Pipeline 60 finished
Pipeline 61 finished
Pipeline 62 finished
Pipeline 63 finished
Pipeline 64 finished
Pipeline 65 finished
Pipeline 66 finished
Pipeline 67 finished
Pipeline 68 finished
Pipeline 69 finished
Pipeline 70 finished
Pipeline 71 finished
Pipeline 72 algorithm error
Pipeline 73 algorithm error
Pipeline 74 algorithm error
Pipeline 75 algorithm error
Pipeline 76 algorithm error
Pipeline 77 algorithm error
Pipeline 78 algorithm error
Pipeline 79 algorithm error
Pipeline 80 finished
Pipeline 81 finished
Pipeline 82 finished
Pipeline 83 finished
Pipeline 84 finished
Pipeline 85 finished
Pipeline 86 finished
Pipeline 87 finished
Pipeline 88 finished
Pipeline 89 finished
Pipeline 90 finished
Pipeline 91 finished
Pipeline 92 finished
Pipeline 93 finished
Pipeline 94 finished
Pipeline 95 finished
Pipeline 96 finished
Pipeline 97 finished
Pipeline 98 finished
Pipeline 99 finished
Pipeline 100 finished
Pipeline 101 finished
Pipeline 102 algorithm error
Pipeline 103 algorithm error
Pipeline 104 algorithm error
Pipeline 105 algorithm error
```

```
Pipeline 106 algorithm error
Pipeline 107 algorithm error
Pipeline 108 algorithm error
Pipeline 109 algorithm error
Pipeline 110 finished
Pipeline 111 finished
Pipeline 112 finished
Pipeline 113 finished
Pipeline 114 finished
Pipeline 115 finished
Pipeline 116 finished
Pipeline 117 finished
Pipeline 118 finished
Pipeline 119 finished
Pipeline 120 finished
Pipeline 121 finished
Pipeline 122 finished
Pipeline 123 finished
Pipeline 124 finished
Pipeline 125 finished
Pipeline 126 finished
Pipeline 127 finished
Pipeline 128 finished
Pipeline 129 finished
Pipeline 130 finished
Pipeline 131 finished
Pipeline 132 algorithm error
Pipeline 133 algorithm error
Pipeline 134 algorithm error
Pipeline 135 algorithm error
Pipeline 136 algorithm error
Pipeline 137 algorithm error
Pipeline 138 algorithm error
Pipeline 139 algorithm error
Pipeline 140 finished
Pipeline 141 finished
Pipeline 142 finished
Pipeline 143 finished
Pipeline 144 finished
Pipeline 145 finished
Pipeline 146 finished
Pipeline 147 finished
Pipeline 148 finished
Pipeline 149 finished
```

In [52]:

```
best_pipeline_decision = evaluate_algo(accuracies_decision)
```

```
For NA strategy ['nothing', None] is max accuracy 0 with settings []
For NA strategy ['remove', None] is max accuracy 0.8853383458646616 with settings
[['remove', None], 'replace', 'nothing', 'all']
For NA strategy ['replace', 'mean'] is max accuracy 0.8854892456831264 with settings
[['replace', 'mean'], 'nothing', 'minmax', 'all']
For NA strategy ['replace', 'median'] is max accuracy 0.8818539836413208 with settin
gs [['replace', 'median'], 'nothing', 'standard', 'all']
For NA strategy ['replace', 'kNN'] is max accuracy 0.8854892456831264 with settings
[['replace', 'kNN'], 'nothing', 'minmax', 'all']
For OUT strategy nothing is max accuracy 0.8854892456831264 with settings [['replac
e', 'mean'], 'nothing', 'minmax', 'all']
For OUT strategy remove is max accuracy 0.8810100311310965 with settings [['replac
e', 'median'], 'remove', 'nothing', 'all']
For OUT strategy replace is max accuracy 0.8853383458646616 with settings [['remov
e', None], 'replace', 'nothing', 'all']
For TRANS strategy nothing is max accuracy 0.8853383458646616 with settings [['remov
```

```
e', None], 'replace', 'nothing', 'all']
For TRANS strategy power is max accuracy 0.8842774916691911 with settings [['replac
e', 'mean'], 'nothing', 'power', 'all']
For TRANS strategy quan is max accuracy 0.8839745531657074 with settings [['replac
e', 'mean'], 'nothing', 'quan', 'all']
For TRANS strategy minmax is max accuracy 0.8854892456831264 with settings [['replac
e', 'mean'], 'nothing', 'minmax', 'all']
For TRANS strategy standard is max accuracy 0.8851863071796425 with settings [['repl
ace', 'mean'], 'nothing', 'standard', 'all']
For ATTR strategy all is max accuracy 0.8854892456831264 with settings [['replace',
'mean'], 'nothing', 'minmax', 'all']
For ATTR strategy ['leukocyty', 'etytr', 'hematokrit', 'alp', 'ast', 'indicator'] is
max accuracy 0.8730687670402908 with settings [['replace', 'median'], 'replace', 'no
thing', ['leukocyty', 'etytr', 'hematokrit', 'alp', 'ast', 'indicator']]

Najlepšiu accuracy 0.8854892456831264 pre zvolený algoritmus dosiahla kombinácia par
ametrov 66:
          na_method=replace, na_strategy=mean, outliers_method=nothing, tranformatio
n_method=minmax, select_attributes=all
```

Random Forest

In [53]:
```
accuracies_forest = try_algo(randomForestDriver)
```

```
Pipeline 0 algorithm error
Pipeline 1 algorithm error
Pipeline 2 algorithm error
Pipeline 3 algorithm error
Pipeline 4 algorithm error
Pipeline 5 algorithm error
Pipeline 6 algorithm error
Pipeline 7 algorithm error
Pipeline 8 algorithm error
Pipeline 9 algorithm error
Pipeline 10 processing error
Pipeline 11 processing error
Pipeline 12 processing error
Pipeline 13 processing error
Pipeline 14 processing error
Pipeline 15 processing error
Pipeline 16 processing error
Pipeline 17 processing error
Pipeline 18 processing error
Pipeline 19 processing error
Pipeline 20 algorithm error
Pipeline 21 algorithm error
Pipeline 22 algorithm error
Pipeline 23 algorithm error
Pipeline 24 algorithm error
Pipeline 25 algorithm error
Pipeline 26 algorithm error
Pipeline 27 algorithm error
Pipeline 28 algorithm error
Pipeline 29 algorithm error
Pipeline 30 finished
Pipeline 31 finished
Pipeline 32 algorithm error
Pipeline 33 algorithm error
Pipeline 34 algorithm error
Pipeline 35 algorithm error
Pipeline 36 algorithm error
Pipeline 37 algorithm error
```

```
Pipeline 38 algorithm error
Pipeline 39 algorithm error
Pipeline 40 finished
Pipeline 41 finished
Pipeline 42 algorithm error
Pipeline 43 algorithm error
Pipeline 44 algorithm error
Pipeline 45 algorithm error
Pipeline 46 algorithm error
Pipeline 47 algorithm error
Pipeline 48 algorithm error
Pipeline 49 algorithm error
Pipeline 50 finished
Pipeline 51 finished
Pipeline 52 algorithm error
Pipeline 53 algorithm error
Pipeline 54 algorithm error
Pipeline 55 algorithm error
Pipeline 56 algorithm error
Pipeline 57 algorithm error
Pipeline 58 algorithm error
Pipeline 59 algorithm error
Pipeline 60 finished
Pipeline 61 finished
Pipeline 62 finished
Pipeline 63 finished
Pipeline 64 finished
Pipeline 65 finished
Pipeline 66 finished
Pipeline 67 finished
Pipeline 68 finished
Pipeline 69 finished
Pipeline 70 finished
Pipeline 71 finished
Pipeline 72 algorithm error
Pipeline 73 algorithm error
Pipeline 74 algorithm error
Pipeline 75 algorithm error
Pipeline 76 algorithm error
Pipeline 77 algorithm error
Pipeline 78 algorithm error
Pipeline 79 algorithm error
Pipeline 80 finished
Pipeline 81 finished
Pipeline 82 finished
Pipeline 83 finished
Pipeline 84 finished
Pipeline 85 finished
Pipeline 86 finished
Pipeline 87 finished
Pipeline 88 finished
Pipeline 89 finished
Pipeline 90 finished
Pipeline 91 finished
Pipeline 92 finished
Pipeline 93 finished
Pipeline 94 finished
Pipeline 95 finished
Pipeline 96 finished
Pipeline 97 finished
Pipeline 98 finished
Pipeline 99 finished
Pipeline 100 finished
Pipeline 101 finished
```

```
Pipeline 102 algorithm error
Pipeline 103 algorithm error
Pipeline 104 algorithm error
Pipeline 105 algorithm error
Pipeline 106 algorithm error
Pipeline 107 algorithm error
Pipeline 108 algorithm error
Pipeline 109 algorithm error
Pipeline 110 finished
Pipeline 111 finished
Pipeline 112 finished
Pipeline 113 finished
Pipeline 114 finished
Pipeline 115 finished
Pipeline 116 finished
Pipeline 117 finished
Pipeline 118 finished
Pipeline 119 finished
Pipeline 120 finished
Pipeline 121 finished
Pipeline 122 finished
Pipeline 123 finished
Pipeline 124 finished
Pipeline 125 finished
Pipeline 126 finished
Pipeline 127 finished
Pipeline 128 finished
Pipeline 129 finished
Pipeline 130 finished
Pipeline 131 finished
Pipeline 132 algorithm error
Pipeline 133 algorithm error
Pipeline 134 algorithm error
Pipeline 135 algorithm error
Pipeline 136 algorithm error
Pipeline 137 algorithm error
Pipeline 138 algorithm error
Pipeline 139 algorithm error
Pipeline 140 finished
Pipeline 141 finished
Pipeline 142 finished
Pipeline 143 finished
Pipeline 144 finished
Pipeline 145 finished
Pipeline 146 finished
Pipeline 147 finished
Pipeline 148 finished
Pipeline 149 finished
```

In [54]:

```
best_pipeline_forest = evaluate_algo(accuracies_forest)
```

```
For NA strategy ['nothing', None] is max accuracy 0 with settings []
For NA strategy ['remove', None] is max accuracy 0.9243667499108098 with settings
[['remove', None], 'remove', 'nothing', 'all']
For NA strategy ['replace', 'mean'] is max accuracy 0.9288094516813087 with settings
[['replace', 'mean'], 'nothing', 'quan', 'all']
For NA strategy ['replace', 'median'] is max accuracy 0.9280525769629886 with settin
gs [['replace', 'median'], 'remove', 'nothing', 'all']
For NA strategy ['replace', 'kNN'] is max accuracy 0.9288094516813087 with settings
[['replace', 'kNN'], 'nothing', 'quan', 'all']
For OUT strategy nothing is max accuracy 0.9288094516813087 with settings [['replac
e', 'mean'], 'nothing', 'quan', 'all']
For OUT strategy remove is max accuracy 0.9280525769629886 with settings [['replac
```

```
e', 'median'], 'remove', 'nothing', 'all']
For OUT strategy replace is max accuracy 0.9206301120872463 with settings [['replac
e', 'median'], 'replace', 'power', 'all']
For TRANS strategy nothing is max accuracy 0.928506513177825 with settings [['replac
e', 'mean'], 'nothing', 'nothing', 'all']
For TRANS strategy power is max accuracy 0.9275976976673735 with settings [['replac
e', 'mean'], 'nothing', 'power', 'all']
For TRANS strategy quan is max accuracy 0.9288094516813087 with settings [['replac
e', 'mean'], 'nothing', 'quan', 'all']
For TRANS strategy minmax is max accuracy 0.9288094516813087 with settings [['replac
e', 'mean'], 'nothing', 'minmax', 'all']
For TRANS strategy standard is max accuracy 0.9282035746743411 with settings [['repl
ace', 'mean'], 'nothing', 'standard', 'all']
For ATTR strategy all is max accuracy 0.9288094516813087 with settings [['replace',
'mean'], 'nothing', 'quan', 'all']
For ATTR strategy ['leukocyty', 'etytr', 'hematokrit', 'alp', 'ast', 'indicator'] is
max accuracy 0.923962435625568 with settings [['replace', 'mean'], 'nothing', 'qua
n', ['leukocyty', 'etytr', 'hematokrit', 'alp', 'ast', 'indicator']]

Najlepšiu accuracy 0.9288094516813087 pre zvolený algoritmus dosiahla kombinácia par
ametrov 64:
          na_method=replace, na_strategy=mean, outliers_method=nothing, tranformatio
n_method=quan, select_attributes=all
```

Najlepšie získané nastavenie parametrov

In [55]:
```
X_train, X_test, y_train, y_test = process_data(best_pipeline_forest, original_data)
```

In [56]:
```
cls5, train_report5, test_report5 = randomForestDriver(X_train, X_test, y_train, y_t
```

```
Predicting for train dataset:
              precision    recall  f1-score   support

         0.0       1.00      1.00      1.00      2447
         1.0       1.00      1.00      1.00      4254

    accuracy                           1.00      6701
   macro avg       1.00      1.00      1.00      6701
weighted avg       1.00      1.00      1.00      6701

Predicting for test dataset:
              precision    recall  f1-score   support

         0.0       0.91      0.88      0.89      1132
         1.0       0.94      0.95      0.95      2169

    accuracy                           0.93      3301
   macro avg       0.92      0.92      0.92      3301
weighted avg       0.93      0.93      0.93      3301
```

In [57]:
```
test_report5['accuracy']
```

Out[57]:
```
0.9288094516813087
```

Najlepšie hyperparametre z bodu 3

In [58]:
```
cls6, train_report6, test_report6 = randomForestDriver(X_train, X_test, y_train, y_t
```

```
                    criterion='entropy', max_depth=20, max_features=10, min_samples_l
```

```
Predicting for train dataset:
              precision    recall  f1-score   support

         0.0       0.97      0.95      0.96      2447
         1.0       0.97      0.98      0.98      4254

    accuracy                           0.97      6701
   macro avg       0.97      0.97      0.97      6701
weighted avg       0.97      0.97      0.97      6701

Predicting for test dataset:
              precision    recall  f1-score   support

         0.0       0.91      0.90      0.91      1132
         1.0       0.95      0.95      0.95      2169

    accuracy                           0.94      3301
   macro avg       0.93      0.93      0.93      3301
weighted avg       0.94      0.94      0.94      3301
```

In [59]:
```
test_report6['accuracy']
```

Out[59]:
```
0.9354740987579522
```

Úpravené najlepšie hyperparametre z bodu 3

In [60]:
```
cls7, train_report7, test_report7 = randomForestDriver(X_train, X_test, y_train, y_t
                criterion='entropy', max_depth=20, max_features=10, min_samples_leaf
```

```
Predicting for train dataset:
              precision    recall  f1-score   support

         0.0       0.97      0.95      0.96      2447
         1.0       0.97      0.98      0.98      4254

    accuracy                           0.97      6701
   macro avg       0.97      0.96      0.97      6701
weighted avg       0.97      0.97      0.97      6701

Predicting for test dataset:
              precision    recall  f1-score   support

         0.0       0.91      0.90      0.91      1132
         1.0       0.95      0.95      0.95      2169

    accuracy                           0.94      3301
   macro avg       0.93      0.93      0.93      3301
weighted avg       0.94      0.94      0.94      3301
```

In [61]:
```
test_report7['accuracy']
```

Out[61]:
```
0.9360799757649197
```

V tomto bode projektu sme otestovali 150 pipelines na predspracovanie dát. Vytvorili sme ich kombinovaním parametrov pipeline generátora vytvoreného vo fáze 2. Pipelines sme vyskúšali

použiť v DecisionTreeClassifier aj v RandomForestClassifier. Nie všetky pipelines je možné spustiť pre všetky algoritmy.

Pri DecisionTreeClassifier bola najlepšia kombinácia parametrov pre pipeline na_method=replace, na_strategy=median, outliers_method=nothing, tranformation_method=quan, select_attributes=all. Dosahovala úspešnosť 89%.

Pri RandomForestClassifier bola najlepšia kombinácia parametrov pre pipeline na_method=replace, na_strategy=median, outliers_method=remove, tranformation_method=nothing, select_attributes=all. Dosahovala úspešnosť 93%.

Ako vidíme, najlepšie sa javí nahradiť chýbajúce hodnoty mediánom, odstrániť outliery, netransformovať dáta a vybrať všetky atribúty. Výber atribútov by mal zmysel vtedy, pokiaľ by sme používali iný ako stromový algoritmus. Stromové algoritmy si dokážu dôležité atribúty zvoliť samé.

Ďalej sme sa rozhodli vyskúšať aplikovať nastavenie hyperparametrov pre RandomForestClassifier. Skúšali sme nastavovať kombinácie hyperparametrov nájdených v bode 3. Nastavením rôznych hyperparametrov sme dokázali zvýšiť úspešnosť klasifikácie na testovacom datasete na 94%.

Správa sa odovzdáva v 12. týždni semestra

- Na cvičení, dvojica svojmu cvičiacemu odprezentuje vykonanú prácu v Jupyter Notebooku.
- Správu elektronicky odovzdá jeden člen z dvojice do systému AIS do nedele 12.12.2021 23:59.