In [329]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

In [330]:

```
# Importing the dataset
df = pd.read_csv('Lutsenko_data.csv')
```

In [331]:

```
df
```

Out[331]:

	Age	Sex	ALB	ALT	AST	CHOL	CREA	GGT	PROT	Category
0	32	m	38.5	7.7	22.1	3.23	106.0	12.1	69.0	0
1	32	m	38.5	18.0	24.7	4.80	74.0	15.6	76.5	0
2	32	m	46.9	36.2	52.6	5.20	86.0	33.2	79.3	0
3	32	m	43.2	30.6	22.6	4.74	80.0	33.8	75.7	0
4	32	m	39.2	32.6	24.8	4.32	76.0	29.9	68.7	0
...	...	...	...	...	...	...	...	...	...	...
610	62	f	32.0	5.9	110.3	6.30	55.7	650.9	68.5	1
611	64	f	24.0	2.9	44.4	3.02	63.0	35.9	71.3	1
612	64	f	29.0	3.5	99.0	3.63	66.7	64.2	82.0	1
613	46	f	33.0	39.0	62.0	4.20	52.0	50.0	71.0	1
614	59	f	36.0	100.0	80.0	5.30	67.0	34.0	68.0	1

615 rows × 10 columns

Как мы видим, переменную Sex необходимо отформатировать к 0 и 1.

In [332]:

```
# Function Encoding
def encoding_char(x):
    char_var = list(set(x.columns) - set(x._get_numeric_data().columns))
    for col_names in char_var:
        f = pd.factorize(x[col_names])
        x[col_names] = pd.factorize(x[col_names])[0]
    return(x)


# Encoding categorical data
df = encoding_char(df)
df
```

Out[332]:

	Age	Sex	ALB	ALT	AST	CHOL	CREA	GGT	PROT	Category
0	32	0	38.5	7.7	22.1	3.23	106.0	12.1	69.0	0
1	32	0	38.5	18.0	24.7	4.80	74.0	15.6	76.5	0
2	32	0	46.9	36.2	52.6	5.20	86.0	33.2	79.3	0
3	32	0	43.2	30.6	22.6	4.74	80.0	33.8	75.7	0
4	32	0	39.2	32.6	24.8	4.32	76.0	29.9	68.7	0
...	...	...	...	...	...	...	...	...	...	...
610	62	1	32.0	5.9	110.3	6.30	55.7	650.9	68.5	1
611	64	1	24.0	2.9	44.4	3.02	63.0	35.9	71.3	1
612	64	1	29.0	3.5	99.0	3.63	66.7	64.2	82.0	1
613	46	1	33.0	39.0	62.0	4.20	52.0	50.0	71.0	1
614	59	1	36.0	100.0	80.0	5.30	67.0	34.0	68.0	1

615 rows × 10 columns

Наши данные нужно подготовить, т.е. проверить наличие выбросов и пропусков.

In [333]:

```
# Для начала определим, есть ли выбросы
mean_Age = np.mean(df['Age'], axis=0)
sd_Age = np.std(df['Age'], axis=0)

mean_ALB = np.mean(df['ALB'], axis=0)
sd_ALB = np.std(df['ALB'], axis=0)

mean_ALT = np.mean(df['ALT'], axis=0)
sd_ALT = np.std(df['ALT'], axis=0)

mean_AST = np.mean(df['AST'], axis=0)
sd_AST = np.std(df['AST'], axis=0)

mean_CHOL = np.mean(df['CHOL'], axis=0)
sd_CHOL = np.std(df['CHOL'], axis=0)

mean_CREA = np.mean(df['CREA'], axis=0)
sd_CREA = np.std(df['CREA'], axis=0)

mean_GGT = np.mean(df['GGT'], axis=0)
sd_GGT = np.std(df['GGT'], axis=0)

mean_PROT = np.mean(df['PROT'], axis=0)
sd_PROT = np.std(df['PROT'], axis=0)

counter_Age = 0
counter_ALB = 0
counter_ALT = 0
counter_AST = 0
counter_CHOL = 0
counter_CREA = 0
counter_GGT = 0
counter_PROT = 0

for Age, ALB, ALT, AST, CHOL, CREA, GGT, PROT in zip(df['Age'], df['ALB'], df['ALT'], d
f['AST'], df['CHOL'], df['CREA'], df['GGT'], df['PROT']):
    if not mean_Age - 3*sd_Age <= Age <= mean_Age + 3*sd_Age:
        counter_Age += 1
    if not mean_ALB - 3*sd_ALB <= ALB <= mean_ALB + 3*sd_ALB:
        counter_ALB += 1
    if not mean_ALT - 3*sd_ALT <= counter_ALT <= mean_ALT + 3*sd_ALT:
        counter_ALT += 1
    if not mean_AST - 3*sd_AST <= counter_AST <= mean_AST + 3*sd_AST:
        counter_AST += 1
    if not mean_CHOL - 3*sd_CHOL <= counter_CHOL <= mean_CHOL + 3*sd_CHOL:
        counter_CHOL += 1
    if not mean_CREA - 3*sd_CREA <= counter_CREA <= mean_CREA + 3*sd_CREA:
        counter_CREA += 1
    if not mean_GGT - 3*sd_GGT <= counter_GGT <= mean_GGT + 3*sd_GGT:
            counter_GGT += 1
    if not mean_PROT - 3*sd_PROT <= counter_PROT <= mean_PROT + 3*sd_PROT:
        counter_PROT += 1

counter_dicts = {'counter_Age': counter_Age,
                'counter_ALB': counter_ALB,
                'counter_ALT': counter_ALT,
                'counter_AST': counter_AST,
                'counter_CHOL': counter_CHOL,
                'counter_CREA': counter_CREA,
```

```
                'counter_GGT': counter_GGT,
                'counter_PROT': counter_PROT}
print(counter_dicts)
```

```
{'counter_Age': 0, 'counter_ALB': 14, 'counter_ALT': 0, 'counter_AST': 0,
'counter_CHOL': 2, 'counter_CREA': 0, 'counter_GGT': 0, 'counter_PROT': 5
6}
```

Избавляемся от выбоpoсов# Function Outliers

def outliers(df): num_var = list(df._get_numeric_data().columns) for col_names in num_var: df[col_names] = df[col_names].apply(lambda y: df[col_names].mean()-3*df[col_names].std() if y < df[col_names].mean()-3*df[col_names].std() else y) df[col_names] = df[col_names].apply(lambda y: df[col_names].mean()+3*df[col_names].std() if y > df[col_names].mean()+3*df[col_names].std() else y) return(df)

In [334]:

```
# Function Outliers
def outliers(df):
    num_var = list(df._get_numeric_data().columns)
    for col_names in num_var:
        df[col_names] = df[col_names].apply(lambda y: df[col_names].mean()-3*df[col_nam
es].std()
                                   if y < df[col_names].mean()-3*df[col_names].std() else y)
        df[col_names] = df[col_names].apply(lambda y: df[col_names].mean()+3*df[col_nam
es].std()
                                   if y > df[col_names].mean()+3*df[col_names].std() else y)
    return(df)


# Outliers
df = outliers(df)
df.describe()
```

Out[334]:

	Age	Sex	ALB	ALT	AST	CHOL	CREA
count	615.000000	615.000000	614.000000	614.000000	615.000000	605.000000	615.000000
mean	47.408130	0.386992	41.619034	27.374917	33.139378	5.365605	79.023852
std	10.055105	0.487458	5.368663	18.312519	23.652140	1.118583	19.472858
min	19.000000	0.000000	24.278307	0.900000	10.600000	1.969914	8.000000
25%	39.000000	0.000000	38.800000	16.400000	21.600000	4.610000	67.000000
50%	47.000000	0.000000	41.950000	23.000000	25.900000	5.300000	77.000000
75%	54.000000	1.000000	45.200000	33.075000	32.900000	6.060000	88.000000
max	77.000000	1.000000	58.495497	104.859881	134.058412	8.758481	230.556303

In [335]:

```
# проверка пропущенных значений
df.isnull().sum()
```

Out[335]:

```
Age          0
Sex          0
ALB          1
ALT          1
AST          0
CHOL        10
CREA         0
GGT          0
PROT         1
Category     0
dtype: int64
```

Избавимся от пропущенных значений, заменив их на средние в колонках

In [336]:

```
#Deal with missing data
from sklearn.impute import SimpleImputer
df[['ALB']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_transform(df[[
'ALB']]).round()
df[['ALT']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_transform(df[[
'ALT']]).round()
df[['CHOL']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_transform(df[[
'CHOL']]).round()
df[['PROT']] = SimpleImputer(missing_values=np.nan, strategy='mean').fit_transform(df[[
'PROT']]).round()

df.isnull().sum()
```

Out[336]:

```
Age         0
Sex         0
ALB         0
ALT         0
AST         0
CHOL        0
CREA        0
GGT         0
PROT        0
Category    0
dtype: int64
```

Logistic Regression

In [337]:

```
# Splitting the dataset into the Training set and Test set
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1
3)
```

Прошкалируем данные

In [338]:

```
# Feature Scaling
from sklearn.preprocessing import StandardScaler
sc_X = StandardScaler().fit(X_train)
X_train = sc_X.transform(X_train)
X_test = sc_X.transform(X_test)
```

Далее нам необходимо определиться, какие именно переменные использовать для модели

In [339]:

```
# Baseline model
import statsmodels.api as sm
lr = sm.Logit(y_train, X_train).fit()
print(lr.summary2())
```

```
Optimization terminated successfully.
         Current function value: 0.320513
         Iterations 8
                         Results: Logit
=================================================================
Model:              Logit            Pseudo R-squared: 0.195
Dependent Variable: y                AIC:              333.3844
Date:               2020-10-30 00:16 BIC:              371.1707
No. Observations:   492              Log-Likelihood:   -157.69
Df Model:           8                LL-Null:          -195.80
Df Residuals:       483              LLR p-value:      2.8171e-13
Converged:          1.0000           Scale:            1.0000
No. Iterations:     8.0000
--------------------------------------------------------------------
       Coef.     Std.Err.        z       P>|z|      [0.025     0.975]
--------------------------------------------------------------------
x1    -0.1169      0.1550    -0.7545    0.4506    -0.4206     0.1868
x2    -0.0125      0.1697    -0.0734    0.9415    -0.3450     0.3201
x3    -0.4582      0.2079    -2.2043    0.0275    -0.8656    -0.0508
x4    -1.8240      0.2561    -7.1225    0.0000    -2.3259    -1.3221
x5     5.5425      0.4986    11.1151    0.0000     4.5652     6.5199
x6    -0.3669      0.1656    -2.2162    0.0267    -0.6914    -0.0424
x7    -0.1720      0.2007    -0.8570    0.3914    -0.5653     0.2213
x8     0.9895      0.2305     4.2930    0.0000     0.5378     1.4413
x9     0.2533      0.1925     1.3160    0.1882    -0.1240     0.6305
=================================================================
```

Имееем:исходя из P целесообразнее всего использовать x4, x5, x8. Это соответствует ALT,AST,GGT

In [307]:

```
# Features selection
X_train = X_train[:,[3,4,7]]
X_test = X_test[:,[3,4,7]]
```

In [340]:

```
# Fitting Logistic Regression to the Training set
from sklearn.linear_model import LogisticRegression
slr = LogisticRegression(random_state = 13).fit(X_train, y_train)
```

In [341]:

```
# Predicting the Test set results
y_pred = slr.predict(X_test)
slr.score(X_test,y_test)
```

Out[341]:

```
0.9512195121951219
```

In [342]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[107   1]
 [  5  10]]
```

Как мы видим, исходя из параметра accuracy, что равен 0,93, модель отлично справилась со своей задачей. Так же мы имеем 8 ложных предсказаний.

k-Nearest Neighbors

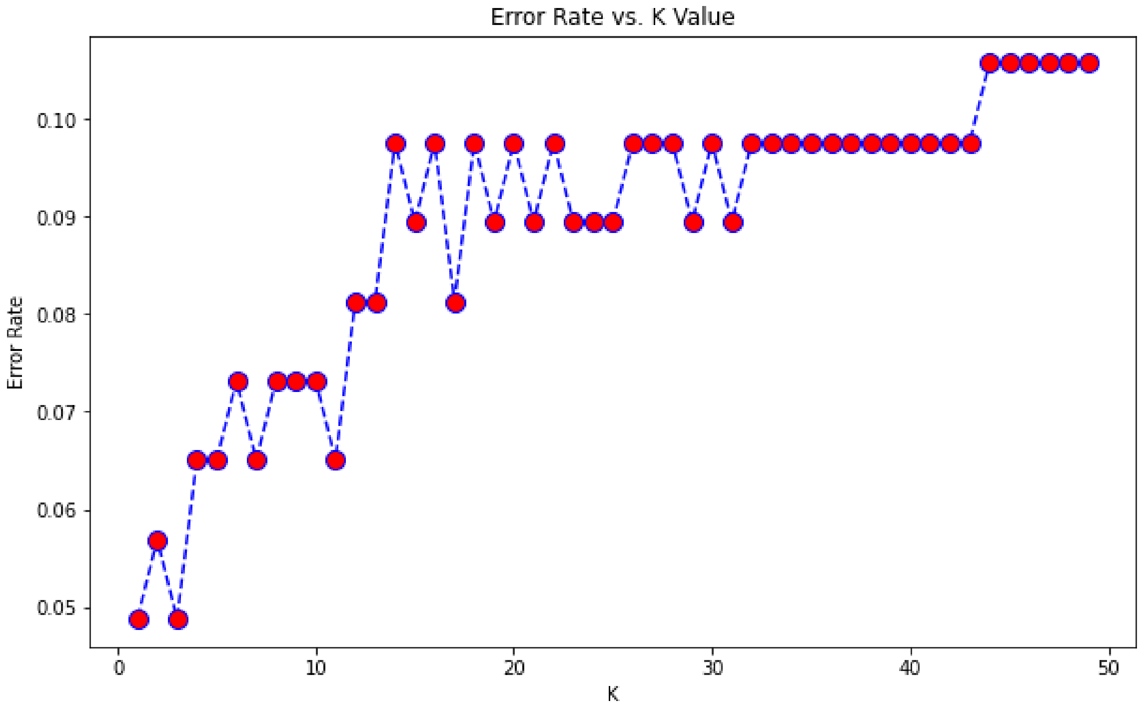
Для построения этой модели нам первостепенно важно определить k.

In [343]:

```
# Optimal K
from sklearn.neighbors import KNeighborsClassifier
error_rate = []
for i in range(1,50):
     knn = KNeighborsClassifier(n_neighbors=i)
     knn.fit(X_train,y_train)
     pred_i = knn.predict(X_test)
     error_rate.append(np.mean(pred_i != y_test))

plt.figure(figsize=(10,6))
plt.plot(range(1,50),error_rate,color='blue', linestyle='dashed',
         marker='o',markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
print("Minimum error:-",min(error_rate),"at K =",error_rate.index(min(error_rate)))
```

```
Minimum error:- 0.04878048780487805 at K = 0
```



Выберем значение k = 5

In [344]:

```
# Fitting K-NN to the Training set
knn = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2).fit(X_train, y
_train)

y_pred = knn.predict(X_test)
knn.score(X_test,y_test)
```

Out[344]:

```
0.9349593495934959
```

In [345]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[108   0]
 [  8   7]]
```

Как мы видим, исходя из параметра accuracy, что равен 0,976, модель отлично справилась со своей задачей. Так же мы имеем 3 ложных предсказаний.

Support Vector Machine

In [346]:

```
from sklearn.svm import SVC
svm = SVC(kernel = 'rbf', random_state = 10).fit(X_train, y_train)


# Predicting the Test set results
y_pred = svm.predict(X_test)
svm.score(X_test,y_test)
```

Out[346]:

```
0.975609756097561
```

In [347]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[108   0]
 [  3  12]]
```

Как мы видим, исходя из параметра accuracy, что равен 0,976, модель отлично справилась со своей задачей. Так же мы имеем 3 ложных предсказаний.

Naive Bayes

In [348]:

```
# Fitting Naive Bayes to the Training set (2 variables)
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB().fit(X_train, y_train)

y_pred = nb.predict(X_test)
nb.score(X_test,y_test)
```

Out[348]:

```
0.9349593495934959
```

In [349]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[103   5]
 [  3  12]]
```

Как мы видим, исходя из параметра accuracy, что равен 0,935, модель отлично справилась со своей задачей. Так же мы имеем 8 ложных предсказаний.

Classification Tree

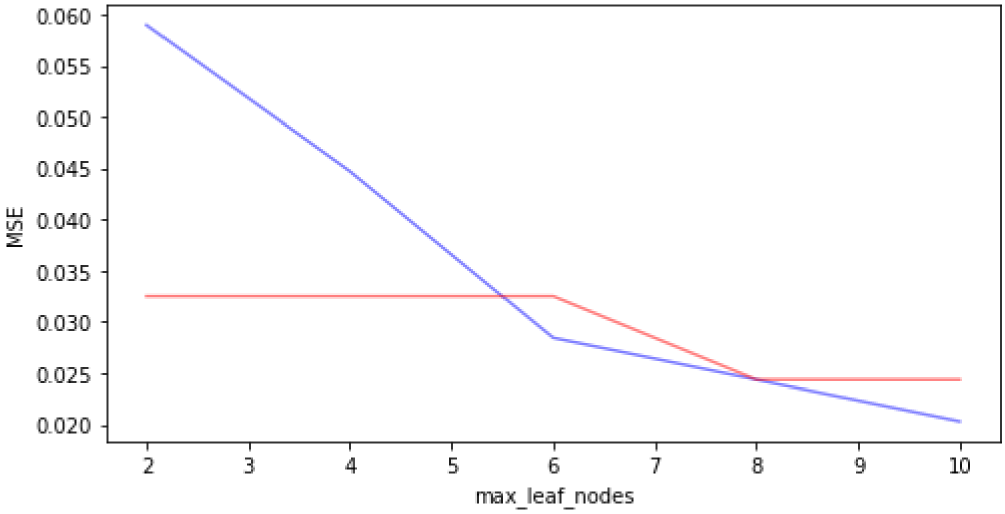
Во избежание переобучения, необходимо определить размер дерева

In [350]:

```
def max_leaf_nodes(X_train, X_test, y_train, y_test, n):
    mse_train = []
    mse_test = []
    for i in n:
        rf = DecisionTreeClassifier(max_leaf_nodes = i, random_state=10).fit(X_train, y
_train)
        mse_train.append(mean_squared_error(y_train, rf.predict(X_train)))
        mse_test.append(mean_squared_error(y_test, rf.predict(X_test)))
    fig, ax = plt.subplots(figsize=(8, 4))
    ax.plot(n, mse_train, alpha=0.5, color='blue', label='train')
    ax.plot(n, mse_test, alpha=0.5, color='red', label='test')
    ax.set_ylabel("MSE")
    ax.set_xlabel("max_leaf_nodes")
```

In [351]:

```
# The optimal number of max_leaf_nodes
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import mean_squared_error
max_leaf_nodes(X_train, X_test, y_train, y_test, [2, 4, 6, 8, 10])
```



Теперь нам нужно выбрать оптимальную точку. Как мы видим, качество результатов тренировочной выборки растет нестремительно до 8, далее резко падает. Качество результатов тестовой выборки резко падает все время. Выбираем размер дерева = 6.

In [352]:

```
# Fitting Classification Tree to the Training set
ct = DecisionTreeClassifier(max_leaf_nodes = 6, criterion = 'entropy', random_state = 1
0).fit(X_train, y_train)

# Predicting the Test set results
y_pred = ct.predict(X_test)
ct.score(X_test,y_test)
```

Out[352]:

```
0.975609756097561
```

In [353]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[108   0]
 [  3  12]]
```

Как мы видим, исходя из параметра accuracy, что равен 0,976, модель отлично справилась со своей задачей. Так же мы имеем 3 ложных предсказаний.

NN Classification

In [354]:

```
import keras
from keras.models import Sequential
from keras.layers import Dense
```

In [358]:

```
X_train = X_train[:,[3,4,7]]
X_test = X_test[:,[3,4,7]]
```

In [359]:

```
# Initialising the ANN 3-2-1
cnn1 = Sequential()

# Adding the input layer and the first hidden layer
cnn1.add(Dense(units = 2, kernel_initializer = 'uniform', activation = 'relu', input_di
m = 3))

# Adding the output layer
cnn1.add(Dense(units = 1, kernel_initializer = 'uniform', activation = 'sigmoid'))

# Compiling the ANN
cnn1.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
```

In [360]:

```
# Fitting the ANN to the Training set
cnn1.fit(X_train, y_train, batch_size = 10, epochs = 100)
```

```
Epoch 1/100
50/50 [==============================] - 0s 936us/step - loss: 0.6827 - ac
curacy: 0.8638
Epoch 2/100
50/50 [==============================] - 0s 1ms/step - loss: 0.6547 - accu
racy: 0.8638
Epoch 3/100
50/50 [==============================] - 0s 1ms/step - loss: 0.6147 - accu
racy: 0.8638
Epoch 4/100
50/50 [==============================] - 0s 1ms/step - loss: 0.5671 - accu
racy: 0.8638
Epoch 5/100
50/50 [==============================] - 0s 1ms/step - loss: 0.5152 - accu
racy: 0.8638
Epoch 6/100
50/50 [==============================] - 0s 1ms/step - loss: 0.4656 - accu
racy: 0.8638
Epoch 7/100
50/50 [==============================] - 0s 1ms/step - loss: 0.4207 - accu
racy: 0.8638
Epoch 8/100
50/50 [==============================] - 0s 1ms/step - loss: 0.3826 - accu
racy: 0.8638
Epoch 9/100
50/50 [==============================] - 0s 1ms/step - loss: 0.3516 - accu
racy: 0.8638
Epoch 10/100
50/50 [==============================] - 0s 1ms/step - loss: 0.3262 - accu
racy: 0.8638
Epoch 11/100
50/50 [==============================] - 0s 1ms/step - loss: 0.3061 - accu
racy: 0.8638
Epoch 12/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2895 - accu
racy: 0.8638
Epoch 13/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2762 - accu
racy: 0.8638
Epoch 14/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2652 - accu
racy: 0.8638
Epoch 15/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2563 - accu
racy: 0.8638
Epoch 16/100
50/50 [==============================] - 0s 992us/step - loss: 0.2488 - ac
curacy: 0.8638
Epoch 17/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2429 - accu
racy: 0.8638
Epoch 18/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2378 - accu
racy: 0.8638
Epoch 19/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2334 - accu
racy: 0.8638
Epoch 20/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2296 - accu
racy: 0.8638
Epoch 21/100
```

```
50/50 [==============================] - 0s 886us/step - loss: 0.2266 - ac
curacy: 0.8638
Epoch 22/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2235 - accu
racy: 0.8638
Epoch 23/100
50/50 [==============================] - 0s 2ms/step - loss: 0.2204 - accu
racy: 0.8638
Epoch 24/100
50/50 [==============================] - 0s 2ms/step - loss: 0.2179 - accu
racy: 0.8638
Epoch 25/100
50/50 [==============================] - 0s 913us/step - loss: 0.2157 - ac
curacy: 0.8638
Epoch 26/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2136 - accu
racy: 0.8638
Epoch 27/100
50/50 [==============================] - 0s 858us/step - loss: 0.2118 - ac
curacy: 0.8638
Epoch 28/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2099 - accu
racy: 0.8638
Epoch 29/100
50/50 [==============================] - 0s 930us/step - loss: 0.2084 - ac
curacy: 0.8638
Epoch 30/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2068 - accu
racy: 0.8638
Epoch 31/100
50/50 [==============================] - 0s 917us/step - loss: 0.2052 - ac
curacy: 0.8638
Epoch 32/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2039 - accu
racy: 0.8638
Epoch 33/100
50/50 [==============================] - 0s 1ms/step - loss: 0.2023 - accu
racy: 0.8638
Epoch 34/100
50/50 [==============================] - 0s 958us/step - loss: 0.2010 - ac
curacy: 0.8638
Epoch 35/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1998 - accu
racy: 0.8638
Epoch 36/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1987 - accu
racy: 0.8638
Epoch 37/100
50/50 [==============================] - 0s 860us/step - loss: 0.1972 - ac
curacy: 0.8638
Epoch 38/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1960 - accu
racy: 0.8638
Epoch 39/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1946 - accu
racy: 0.8638
Epoch 40/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1934 - accu
racy: 0.8638
Epoch 41/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1922 - accu
```

```
racy: 0.8638
Epoch 42/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1908 - accu
racy: 0.8638
Epoch 43/100
50/50 [==============================] - 0s 816us/step - loss: 0.1897 - ac
curacy: 0.8638
Epoch 44/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1885 - accu
racy: 0.8638
Epoch 45/100
50/50 [==============================] - 0s 973us/step - loss: 0.1873 - ac
curacy: 0.8659
Epoch 46/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1860 - accu
racy: 0.9533
Epoch 47/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1849 - accu
racy: 0.9533
Epoch 48/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1836 - accu
racy: 0.9533
Epoch 49/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1823 - accu
racy: 0.9533
Epoch 50/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1812 - accu
racy: 0.9533
Epoch 51/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1801 - accu
racy: 0.9533
Epoch 52/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1790 - accu
racy: 0.9533
Epoch 53/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1781 - accu
racy: 0.9533
Epoch 54/100
50/50 [==============================] - 0s 3ms/step - loss: 0.1771 - accu
racy: 0.9533
Epoch 55/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1763 - accu
racy: 0.9533
Epoch 56/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1754 - accu
racy: 0.9533
Epoch 57/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1743 - accu
racy: 0.9533
Epoch 58/100
50/50 [==============================] - 0s 940us/step - loss: 0.1734 - ac
curacy: 0.9533
Epoch 59/100
50/50 [==============================] - 0s 3ms/step - loss: 0.1727 - accu
racy: 0.9533
Epoch 60/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1718 - accu
racy: 0.9553
Epoch 61/100
50/50 [==============================] - 0s 878us/step - loss: 0.1711 - ac
curacy: 0.9533
```

```
Epoch 62/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1701 - accu
racy: 0.9553
Epoch 63/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1693 - accu
racy: 0.9553
Epoch 64/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1685 - accu
racy: 0.9573
Epoch 65/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1679 - accu
racy: 0.9553
Epoch 66/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1672 - accu
racy: 0.9553
Epoch 67/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1667 - accu
racy: 0.9553
Epoch 68/100
50/50 [==============================] - 0s 949us/step - loss: 0.1660 - ac
curacy: 0.9553
Epoch 69/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1653 - accu
racy: 0.9533
Epoch 70/100
50/50 [==============================] - 0s 882us/step - loss: 0.1648 - ac
curacy: 0.9512
Epoch 71/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1641 - accu
racy: 0.9512
Epoch 72/100
50/50 [==============================] - 0s 900us/step - loss: 0.1637 - ac
curacy: 0.9512
Epoch 73/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1631 - accu
racy: 0.9512
Epoch 74/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1626 - accu
racy: 0.9512
Epoch 75/100
50/50 [==============================] - 0s 839us/step - loss: 0.1620 - ac
curacy: 0.9512
Epoch 76/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1615 - accu
racy: 0.9533
Epoch 77/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1610 - accu
racy: 0.9533
Epoch 78/100
50/50 [==============================] - 0s 3ms/step - loss: 0.1607 - accu
racy: 0.9533
Epoch 79/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1600 - accu
racy: 0.9533
Epoch 80/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1597 - accu
racy: 0.9533
Epoch 81/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1592 - accu
racy: 0.9553
Epoch 82/100
```

```
50/50 [==============================] - 0s 1ms/step - loss: 0.1589 - accu
racy: 0.9533
Epoch 83/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1584 - accu
racy: 0.9553
Epoch 84/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1581 - accu
racy: 0.9553
Epoch 85/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1576 - accu
racy: 0.9553
Epoch 86/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1572 - accu
racy: 0.9553
Epoch 87/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1569 - accu
racy: 0.9553
Epoch 88/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1564 - accu
racy: 0.9553
Epoch 89/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1563 - accu
racy: 0.9553
Epoch 90/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1557 - accu
racy: 0.9553
Epoch 91/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1554 - accu
racy: 0.9553
Epoch 92/100
50/50 [==============================] - 0s 3ms/step - loss: 0.1550 - accu
racy: 0.9553
Epoch 93/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1548 - accu
racy: 0.9553
Epoch 94/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1544 - accu
racy: 0.9553
Epoch 95/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1542 - accu
racy: 0.9553
Epoch 96/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1540 - accu
racy: 0.9553
Epoch 97/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1536 - accu
racy: 0.9553
Epoch 98/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1532 - accu
racy: 0.9553
Epoch 99/100
50/50 [==============================] - 0s 1ms/step - loss: 0.1531 - accu
racy: 0.9533
Epoch 100/100
50/50 [==============================] - 0s 2ms/step - loss: 0.1526 - accu
racy: 0.9533
```

Out[360]:

```
<tensorflow.python.keras.callbacks.History at 0x7fec6c37c390>
```

In [361]:

```
# Predicting the Test set results
y_pred = cnn1.predict(X_test)
y_pred = (y_pred > 0.5)
```

In [362]:

```
# Making the Confusion Matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

```
[[107   1]
 [  4  11]]
```

Как мы видим, исходя из параметра accuracy, что равен 0,959, модель отлично справилась со своей задачей. Так же мы имеем 5 ложных предсказаний.

Абсолютно все модели классификации показали результаты, что больше 90% точности. Методы k-Nearest Neighbors, Support Vector Machine, Classification Tree справились с задачей приблизительно с одинаковой точностью, что равна 0,976 и имея всего 3 ложных предсказания.Немного менее качественный результат дала нейронная сеть (0,959 точности). Модели Naive Bayes, Logistic Regression показали себя незначительно хуже - accuracy = 0,93.

Hierarchical Clustering

In [187]:

```
df = df.drop(['Category'], axis=1)
```

In [188]:

```
df
```

Out[188]:

	Age	Sex	ALB	ALT	AST	CHOL	CREA	GGT	PROT
0	32	0	38.0	8.0	22.1	3.0	106.0	12.100000	69.0
1	32	0	38.0	18.0	24.7	5.0	74.0	15.600000	76.0
2	32	0	47.0	36.0	52.6	5.0	86.0	33.200000	79.0
3	32	0	43.0	31.0	22.6	5.0	80.0	33.800000	76.0
4	32	0	39.0	33.0	24.8	4.0	76.0	29.900000	69.0
...	...	...	...	...	...	...	...	...	...
610	62	1	32.0	6.0	110.3	6.0	55.7	203.516384	68.0
611	64	1	24.0	3.0	44.4	3.0	63.0	35.900000	71.0
612	64	1	29.0	4.0	99.0	4.0	66.7	64.200000	82.0
613	46	1	33.0	39.0	62.0	4.0	52.0	50.000000	71.0
614	59	1	36.0	100.0	80.0	5.0	67.0	34.000000	68.0

615 rows × 9 columns

Для того что бы уровнять наши переменные и ни один из параметров не перетягивал все на себя, проведет шкалирование.

In [189]:

```
# Feature Scaling
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler().fit(df)
df = sc.transform(df)
df = pd.DataFrame(df, columns = ['Age','sex','ALB','ALT','AST','CHOL','CREA','GGT', 'PR
OT']).round(4)
```

In [190]:

```
df
```

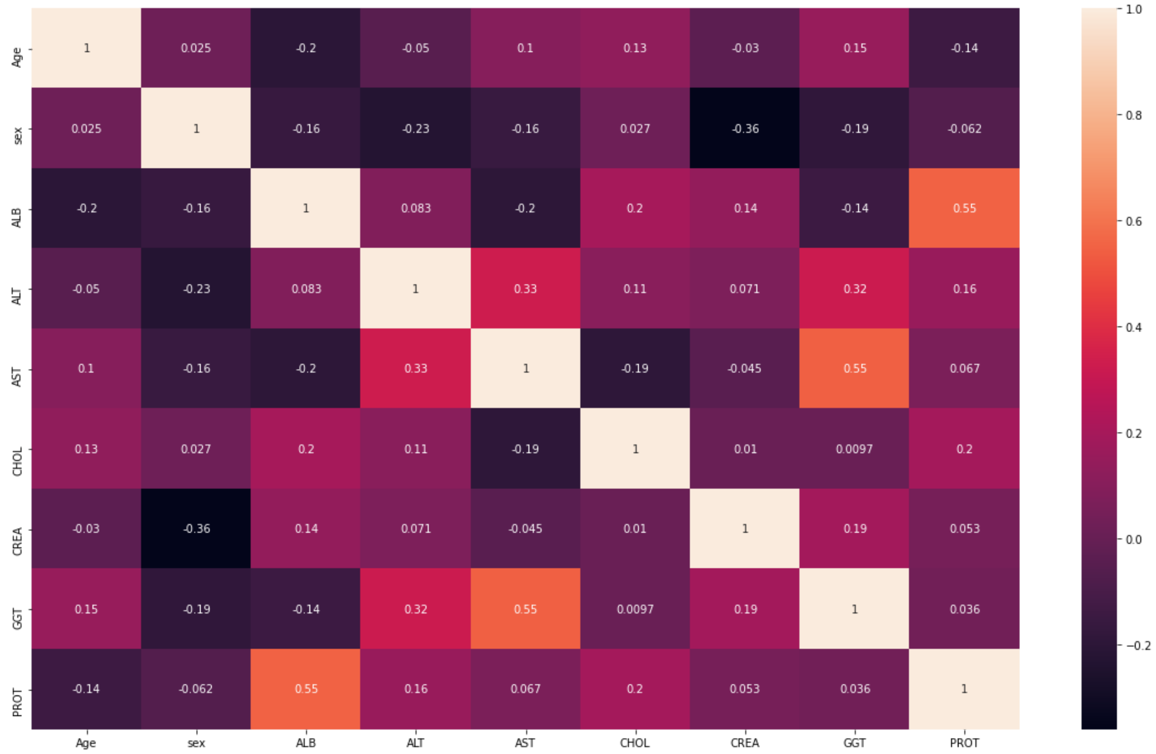
Out[190]:

	Age	sex	ALB	ALT	AST	CHOL	CREA	GGT	PROT
0	0.2241	0.0	0.4118	0.0673	0.0931	0.1429	0.4403	0.0382	0.4194
1	0.2241	0.0	0.4118	0.1635	0.1142	0.4286	0.2966	0.0558	0.6452
2	0.2241	0.0	0.6765	0.3365	0.3402	0.4286	0.3505	0.1442	0.7419
3	0.2241	0.0	0.5588	0.2885	0.0972	0.4286	0.3235	0.1472	0.6452
4	0.2241	0.0	0.4412	0.3077	0.1150	0.2857	0.3055	0.1276	0.4194
...	...	...	...	...	...	...	...	...	...
610	0.7414	1.0	0.2353	0.0481	0.8076	0.5714	0.2143	1.0000	0.3871
611	0.7759	1.0	0.0000	0.0192	0.2738	0.1429	0.2471	0.1578	0.4839
612	0.7759	1.0	0.1471	0.0288	0.7160	0.2857	0.2638	0.3000	0.8387
613	0.4655	1.0	0.2647	0.3654	0.4163	0.2857	0.1977	0.2286	0.4839
614	0.6897	1.0	0.3529	0.9519	0.5621	0.4286	0.2651	0.1482	0.3871

615 rows × 9 columns

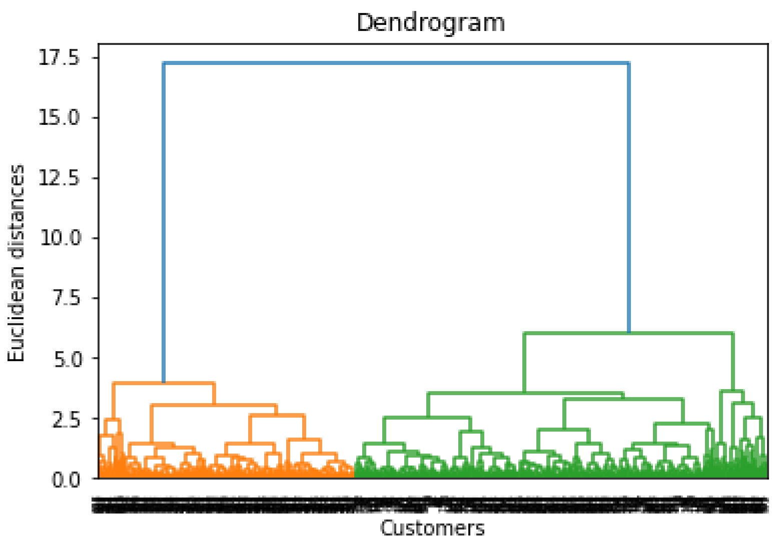
In [191]:

```
# Cheking correlations
import seaborn as sns
cormat = df.corr()
f, ax = plt.subplots(figsize=(20, 12))
sns.heatmap(cormat, annot=True)
plt.show()
```



In [192]:

```
# Using the dendrogram to find the optimal number of clusters
import scipy.cluster.hierarchy as sch
dendrogram = sch.dendrogram(sch.linkage(df, method = 'ward'))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean distances')
plt.show()
```



Исходя из длины полученных веток, имеем: оптимальнее всего рассматривать 9 кластеров. Но стоит заметить, что такое кол-во тяжело в интерпретации.

In [193]:

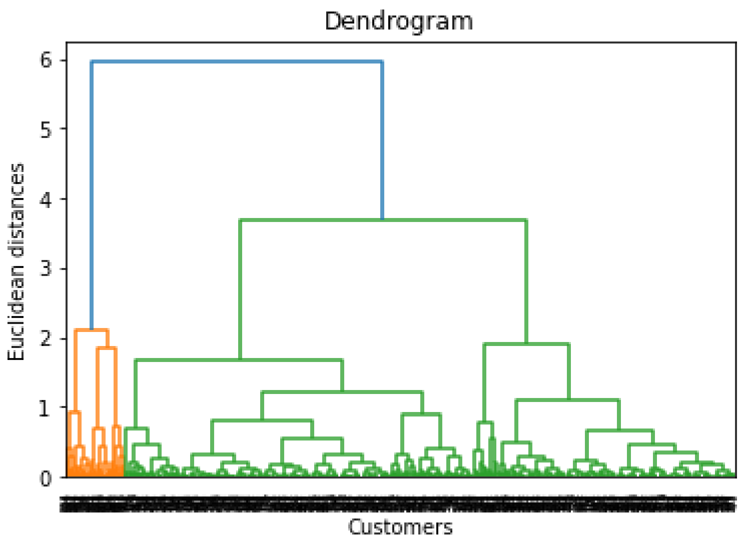
```
# Fitting Hierarchical Clustering to the dataset
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n_clusters = 9, affinity = 'euclidean', linkage = 'ward').
fit_predict(df)
```

Попробуем отобрать меньшее число переменных, выбрав ALB, AST

In [194]:

```
# Less features
X = df.iloc[:, [2, 4]]

# Using the dendrogram to find the optimal number of clusters
import scipy.cluster.hierarchy as sch
dendrogram = sch.dendrogram(sch.linkage(X, method = 'ward'))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean distances')
plt.show()
```



In [225]:

```
# Fitting Hierarchical Clustering to the dataset
from sklearn.cluster import AgglomerativeClustering
hc_opt = AgglomerativeClustering(n_clusters = 2, affinity = 'euclidean', linkage = 'war
d').fit_predict(df)
```

In [226]:

```
hc_opt
```

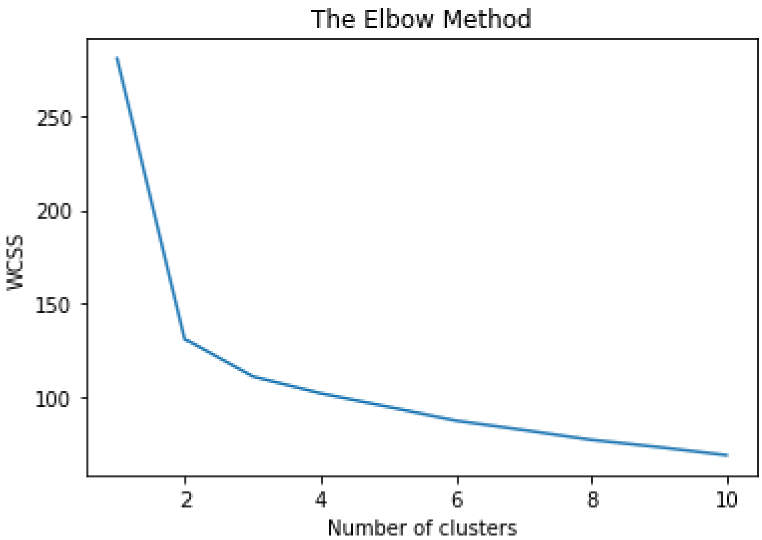
Out[226]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0])
```

K-Means Clustering

In [197]:

```
# Using the elbow method to find the optimal number of clusters
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 0)
    kmeans.fit(df)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```



Исходя из графика выше, резко уходить вниз прямая начинает с 2. Но на всякий случай попробуем посмотреть подробнее диапазон от 2 до 4 используя другой метод.

In [198]:

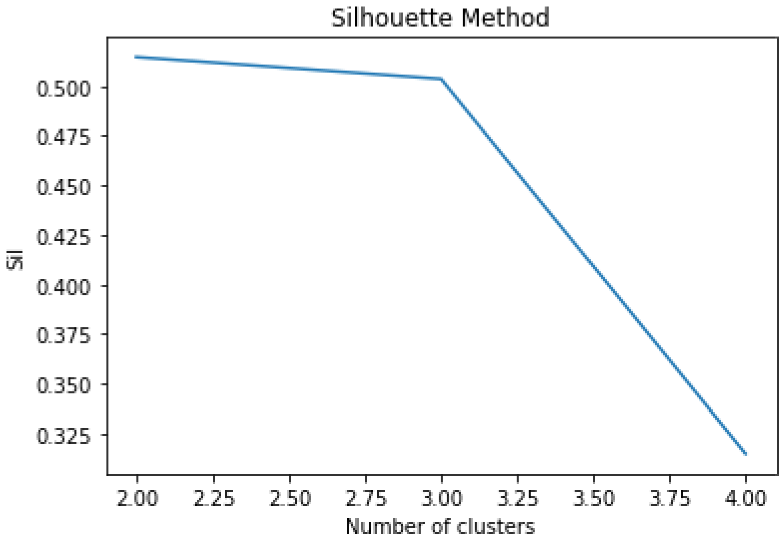
```
# Using the silhouette method to find the optimal number of clusters
from sklearn.metrics import silhouette_score

sil = []

for k in range(2, 5):
  kmeans = KMeans(n_clusters = k).fit(df)
  preds = kmeans.fit_predict(df)
  sil.append(silhouette_score(df, preds, metric = 'euclidean'))


plt.plot(range(2, 5), sil)
plt.title('Silhouette Method')
plt.xlabel('Number of clusters')
plt.ylabel('Sil')
plt.show()

for i in range(len(sil)):
 print(str(i+2) +":"+ str(sil[i]))
```




```
2:0.5146613686173553
3:0.5036152250024468
4:0.3149365150653946
```

Оставим значение 4.

In [199]:

```
# Fitting K-Means to the dataset
km = KMeans(n_clusters = 4, init = 'k-means++', random_state = 0).fit_predict(df)
kms = KMeans(n_clusters = 4, random_state = 0).fit(df)
pd.DataFrame(kms.cluster_centers_, columns = ['Age','sex','ALB','ALT','AST','CHOL','CRE
A','GGT', 'PROT']).round(decimals=4)
```

Out[199]:

	Age	sex	ALB	ALT	AST	CHOL	CREA	GGT	PROT
0	0.3948	-0.0000	0.6054	0.3070	0.1604	0.5017	0.3474	0.1431	0.5927
1	0.4903	1.0000	0.4889	0.1959	0.1319	0.4866	0.2810	0.1048	0.5068
2	0.6258	0.0000	0.4595	0.2096	0.1388	0.4571	0.3446	0.1373	0.4080
3	0.5552	0.0889	0.4196	0.4256	0.6717	0.4159	0.3140	0.6219	0.5455

In [200]:

```
# Fitting K-Means to the dataset
km = KMeans(n_clusters = 4, init = 'k-means++', random_state = 0).fit_predict(df)
kms = KMeans(n_clusters = 4, random_state = 0).fit(df)
pd.DataFrame(kms.cluster_centers_, columns = ['Age','sex','ALB','ALT','AST','CHOL','CRE
A','GGT', 'PROT']).round(decimals=1)
```

Out[200]:

	Age	sex	ALB	ALT	AST	CHOL	CREA	GGT	PROT
0	0.4	-0.0	0.6	0.3	0.2	0.5	0.3	0.1	0.6
1	0.5	1.0	0.5	0.2	0.1	0.5	0.3	0.1	0.5
2	0.6	0.0	0.5	0.2	0.1	0.5	0.3	0.1	0.4
3	0.6	0.1	0.4	0.4	0.7	0.4	0.3	0.6	0.5

In [202]:

```
df
```

Out[202]:

	Age	sex	ALB	ALT	AST	CHOL	CREA	GGT	PROT
0	0.2241	0.0	0.4118	0.0673	0.0931	0.1429	0.4403	0.0382	0.4194
1	0.2241	0.0	0.4118	0.1635	0.1142	0.4286	0.2966	0.0558	0.6452
2	0.2241	0.0	0.6765	0.3365	0.3402	0.4286	0.3505	0.1442	0.7419
3	0.2241	0.0	0.5588	0.2885	0.0972	0.4286	0.3235	0.1472	0.6452
4	0.2241	0.0	0.4412	0.3077	0.1150	0.2857	0.3055	0.1276	0.4194
...	...	...	...	...	...	...	...	...	...
610	0.7414	1.0	0.2353	0.0481	0.8076	0.5714	0.2143	1.0000	0.3871
611	0.7759	1.0	0.0000	0.0192	0.2738	0.1429	0.2471	0.1578	0.4839
612	0.7759	1.0	0.1471	0.0288	0.7160	0.2857	0.2638	0.3000	0.8387
613	0.4655	1.0	0.2647	0.3654	0.4163	0.2857	0.1977	0.2286	0.4839
614	0.6897	1.0	0.3529	0.9519	0.5621	0.4286	0.2651	0.1482	0.3871

615 rows × 9 columns

Как мы видим исходя из результатов, переменные Age, ALB, ALT, CHOL, CREA, PROT особо не влияют на результат -> перестроим модель без них.

In [201]:

```
# Less features
X = df[:, [1, 4, 7]]
```

```
---------------------------------------------------------------------------
-
TypeError                                 Traceback (most recent call las
t)
<ipython-input-201-aba6ae783ba6> in <module>
      1 # Less features
----> 2 X = df[:, [1, 4, 7]]

~/venvs/jupyter/lib64/python3.7/site-packages/pandas/core/frame.py in __ge
titem__(self, key)
   2798             if self.columns.nlevels > 1:
   2799                 return self._getitem_multilevel(key)
-> 2800             indexer = self.columns.get_loc(key)
   2801             if is_integer(indexer):
   2802                 indexer = [indexer]

~/venvs/jupyter/lib64/python3.7/site-packages/pandas/core/indexes/base.py
 in get_loc(self, key, method, tolerance)
   2644                 )
   2645             try:
-> 2646                 return self._engine.get_loc(key)
   2647             except KeyError:
   2648                 return self._engine.get_loc(self._maybe_cast_index
er(key))

pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas/_libs/index.pyx in pandas._libs.index.IndexEngine.get_loc()

TypeError: '(slice(None, None, None), [1, 4, 7])' is an invalid key
```

In [228]:

```
# Fitting K-Means to the dataset
km = KMeans(n_clusters = 2, init = 'k-means++', random_state = 0).fit_predict(X)
kms_opt = KMeans(n_clusters = 2, random_state = 0).fit(X)
pd.DataFrame(kms.cluster_centers_, columns = ['sex','AST','GGT']).round(1)
```

Out[228]:

	sex	AST	GGT
0	0.0	-0.2	-0.2
1	-0.4	2.4	2.3

In [222]:

```
# Comparing Clustering Algorithms
from sklearn.metrics.cluster import adjusted_rand_score
adjusted_rand_score(hc,km)
```

Out[222]:

```
-0.022884086849087697
```

In [ ]:

```
##### Итого: методы практически не пересекаются.
```

SOM

In [207]:

```
# Feature Scaling
import SimpSOM as sps
from sklearn.preprocessing import StandardScaler
sc = StandardScaler().fit(df)
df = sc.transform(df)
```

In [208]:

```
X = df[:, [1, 4, 7]]
```

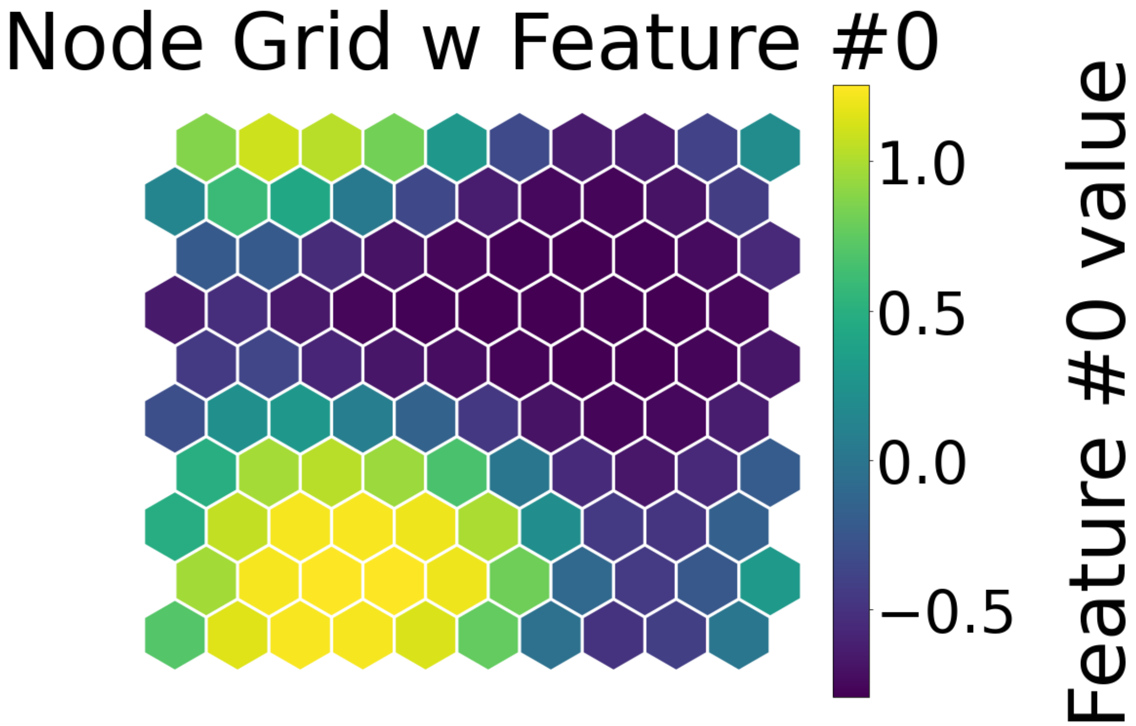
In [214]:

```
np.random.seed(605891282)
net = sps.somNet(10, 10, X, PBC=True)
net.train(0.01, 20000)
#net.save('filename_weights')
```

```
Periodic Boundary Conditions active.
The weights will be initialised randomly.
Training SOM... done!
```

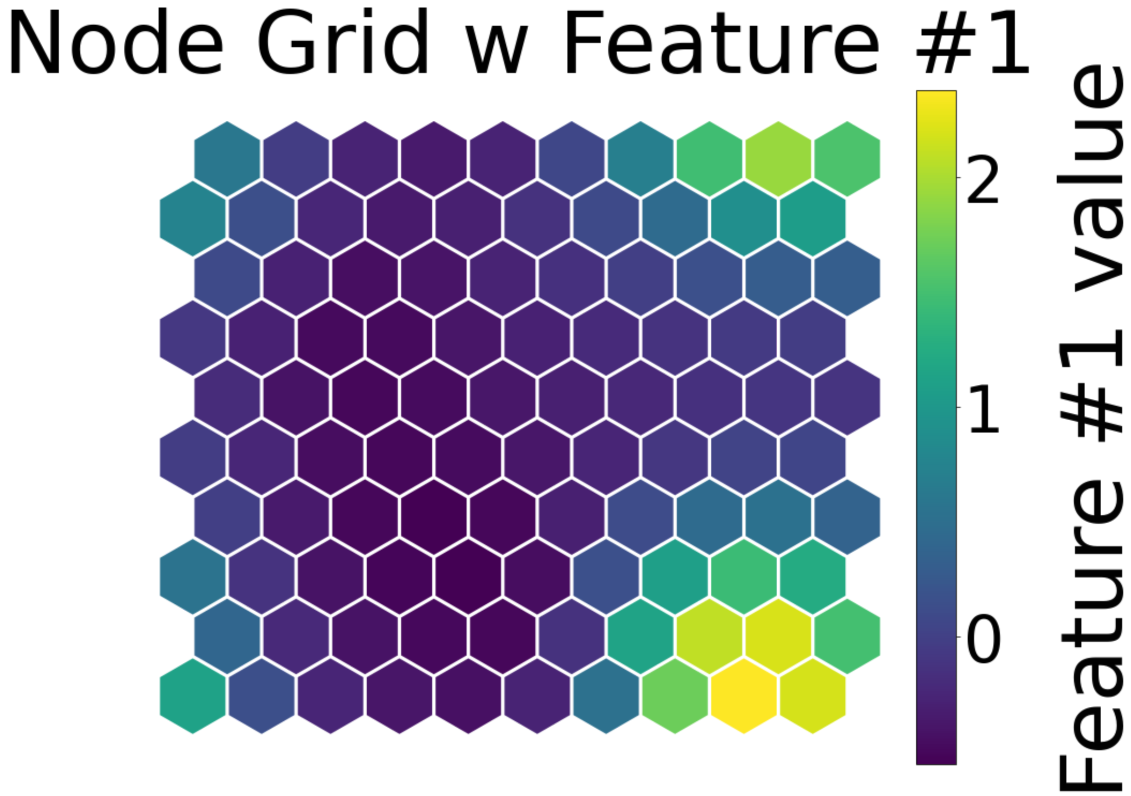
In [215]:

```
net.nodes_graph(colnum=0)
```



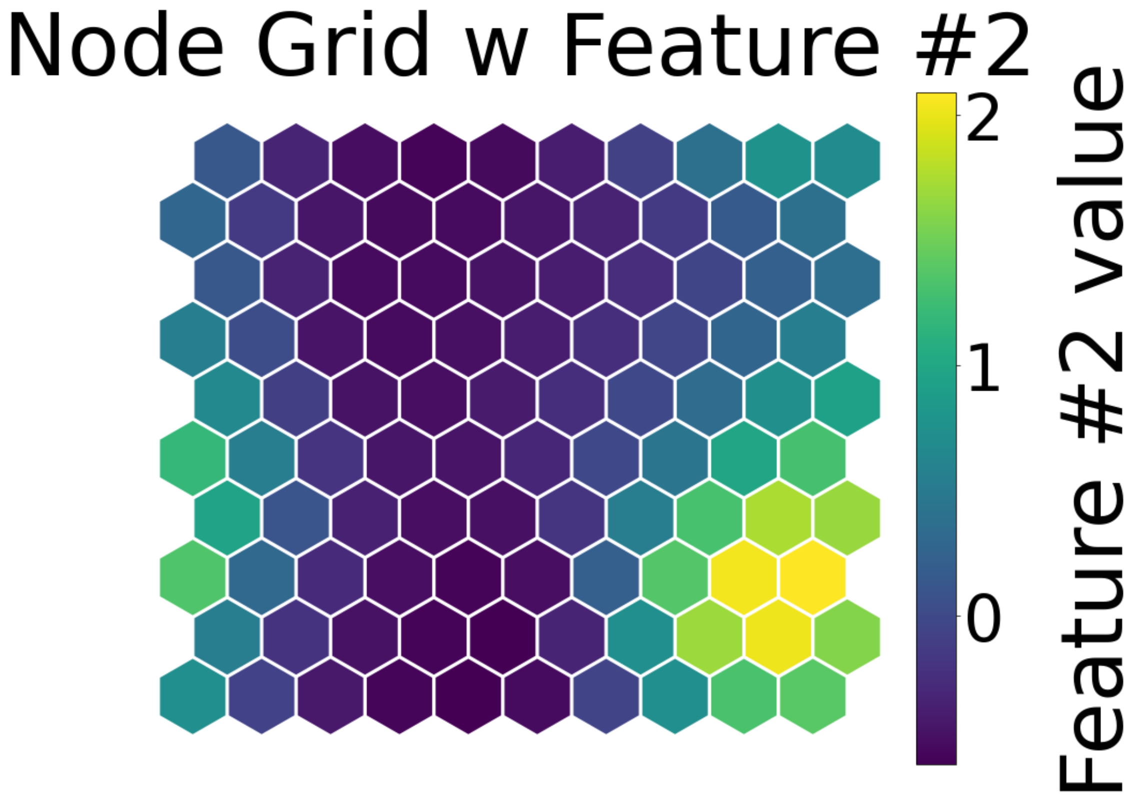
In [216]:

```
net.nodes_graph(colnum=1)
```



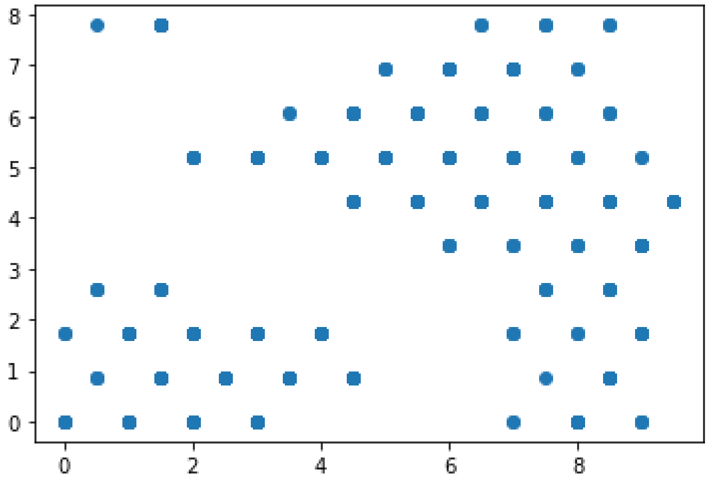
In [217]:

```
net.nodes_graph(colnum=2)
```



In [218]:

```
prj=np.array(net.project(X))
plt.scatter(prj.T[0],prj.T[1])
plt.show()
```



Очевидно выделяются 3 кластера

In [219]:

```
# Fitting kmeans to SOM
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=3, random_state=0).fit(prj)
```

In [227]:

```
# Comparing Clustering Algorithms
from sklearn.metrics.cluster import adjusted_rand_score
adjusted_rand_score(hc_opt,kmeans.labels_)
```

Out[227]:

```
0.5032101314210345
```

Методы пересекаются на 50%.

In [ ]:

```

```