Завершение кода

In [72]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import tensorflow as tf
import seaborn as sns
import plotly.express as px
import tensorflow as tf
import sklearn

from sklearn import linear_model
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.linear_model import LinearRegression, LogisticRegression, SGDRegres
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_percenta
from sklearn.model_selection import train_test_split, GridSearchCV, KFold, cross
from sklearn.neighbors import KNeighborsRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.pipeline import make_pipeline, Pipeline
from sklearn import preprocessing
from sklearn.preprocessing import Normalizer, LabelEncoder, MinMaxScaler, Standa
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor

from tensorflow import keras as keras
from tensorflow.keras import layers
from tensorflow.keras.layers import Dense, Flatten, Dropout, BatchNormalization,
from pandas import read_excel, DataFrame, Series
from keras.wrappers.scikit_learn import KerasClassifier, KerasRegressor
from tensorflow.keras.models import Sequential
from numpy.random import seed
from scipy import stats
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
#Загружаем первый датасет (базальтопластик) и посмотрим на названия столбцов
df = pd.read_excel(r"C:\Users\Avona\Desktop\Моя ВКР\Itog\itog.xlsx")
df.shape
```

Out[2]:
```
(922, 15)
```

Прогнозируем модуль упругости при растяжении, ГПа

In [3]:
```
#разбиваем на тестовую, тренировочную выборки, выделяя предикторы и целевые пере
normalizer = Normalizer()
res = normalizer.fit_transform(df)
df_norm_n = pd.DataFrame(res, columns = df.columns)
x_train_2, x_test_2, y_train_2, y_test_2 = train_test_split(
    df_norm_n.loc[:, df_norm_n.columns != 'Модуль упругости при растяжении, ГПа'
    df[['Модуль упругости при растяжении, ГПа']],
       test_size = 0.3,
    random_state = 42)
```

In [4]:
```
# Проверка правильности разбивки
```

```
df_norm_n.shape[0] - x_train_2.shape[0] - x_test_2.shape[0]
```

Out[4]: 0

In [5]:
```
x_train_2.head()
```

Out[5]:

	Unnamed: 0.1	Unnamed: 0	Соотношение матрица-наполнитель	Плотность, кг/м3	модуль упругости, ГПа	Количество отвердителя, м.%	Содержани эпоксидны групп,%_
481	0.156444	0.156444	0.000515	0.574468	0.128874	0.020477	0.0060
650	0.215475	0.215475	0.000410	0.587940	0.221451	0.025956	0.0069
483	0.159163	0.159163	0.000565	0.570410	0.166143	0.042288	0.0068
355	0.108012	0.108012	0.000901	0.539490	0.302537	0.024182	0.0065
850	0.280412	0.280412	0.000526	0.546876	0.242346	0.031364	0.0069

In [6]:
```
y_train_2
```

Out[6]:

	Модуль упругости при растяжении, ГПа
481	69.573625
650	80.691499
483	71.887367
355	68.314525
850	72.997468
...	...
106	74.519119
270	70.325533
860	77.995289
435	70.199234
102	72.625213

645 rows × 1 columns

In [7]:
```
y_train_2.shape
```

Out[7]: (645, 1)

In [8]:
```
# Функция для сравнения результатов предсказаний с моделью, выдающей среднее зна
def mean_model(y_test_2):
    return [np.mean(y_test_2) for _ in range(len(y_test_2))]
y_2_pred_mean = mean_model(y_test_2)
```

In [9]:
```
#Проверка различных моделей при стандартных параметрах
# Метод опорных векторов - 1
```

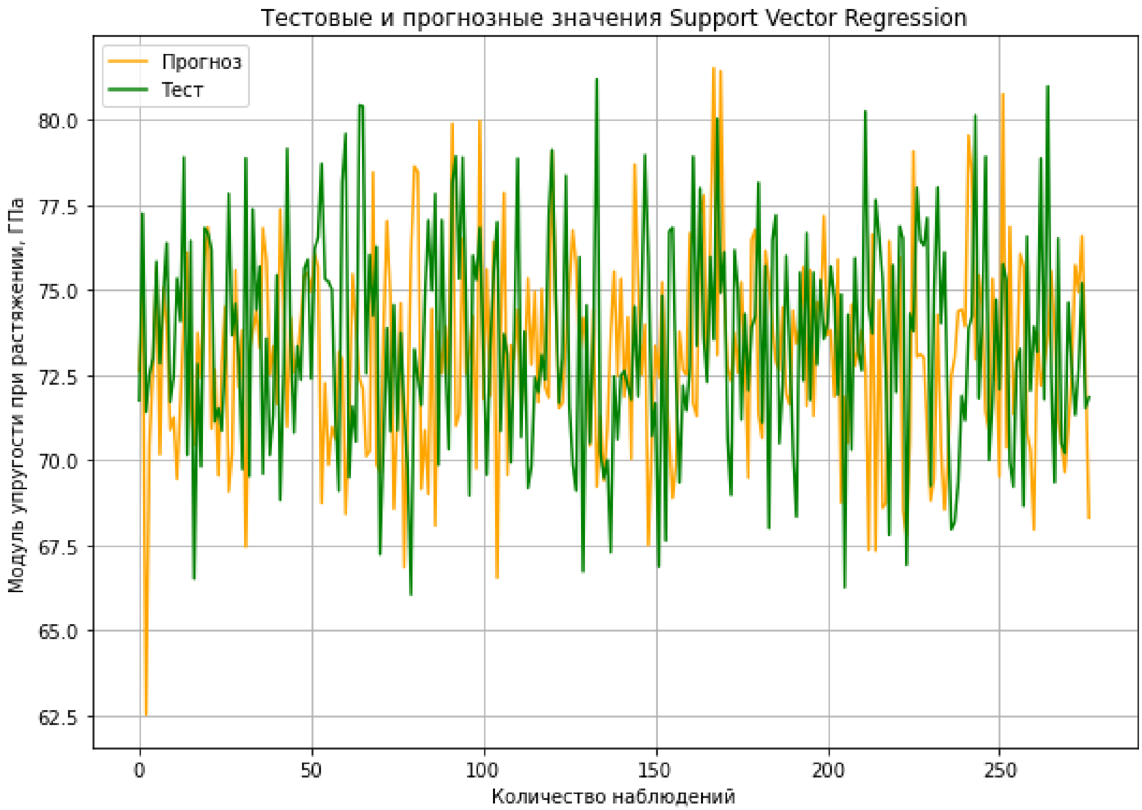
In [10]:
```
svr2 = make_pipeline(StandardScaler(), SVR(kernel = 'rbf', C = 500.0, epsilon =
#обучаем модель
svr2.fit(x_train_2, np.ravel(y_train_2))
#вычисляем коэффициент детерминации
y_pred_svr2 = svr2.predict(x_test_2)
mae_svr2 = mean_absolute_error(y_pred_svr2, y_test_2)
mse_svr_elast2 = mean_squared_error(y_test_2,y_pred_svr2)
print('Support Vector Regression Results Train:')
print("Test score: {:.2f}".format(svr2.score(x_train_2, y_train_2))) # Скор для
print('Support Vector Regression Results:')
print('SVR_MAE:', round(mean_absolute_error(y_test_2, y_pred_svr2)))
print('SVR_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test_2, y_pred_
print('SVR_MSE: {:.2f}'.format(mse_svr_elast2))
print("SVR_RMSE: {:.2f}".format (np.sqrt(mse_svr_elast2)))
print("Test score: {:.2f}".format(svr2.score(x_test_2, y_test_2))) # Скор для ме
```

```
Support Vector Regression Results Train:
Test score: 0.90
Support Vector Regression Results:
SVR_MAE: 3
SVR_MAPE: 0.05
SVR_MSE: 18.69
SVR_RMSE: 4.32
Test score: -0.89
```

In [11]:
```
#Результаты модели, выдающей среднее значение
mse_lin_elast2_mean = mean_squared_error(y_test_2, y_2_pred_mean)
print("MAE for mean target: ", mean_absolute_error(y_test_2, y_2_pred_mean))
print("MSE for mean target: ", mse_lin_elast2_mean)
print("RMSE for mean target: ", np.sqrt(mse_lin_elast2_mean))
```

```
MAE for mean target:  2.578499535756179
MSE for mean target:  9.910360742106828
RMSE for mean target:  3.148072543971442
```

In [12]:
```
plt.figure(figsize = (10, 7))
plt.title("Тестовые и прогнозные значения Support Vector Regression")
plt.plot(y_pred_svr2, label = "Прогноз", color = "orange")
plt.plot(y_test_2.values, label = "Тест", color = "green")
plt.xlabel("Количество наблюдений")
plt.ylabel("Модуль упругости при растяжении, ГПа")
plt.legend()
plt.grid(True);
```

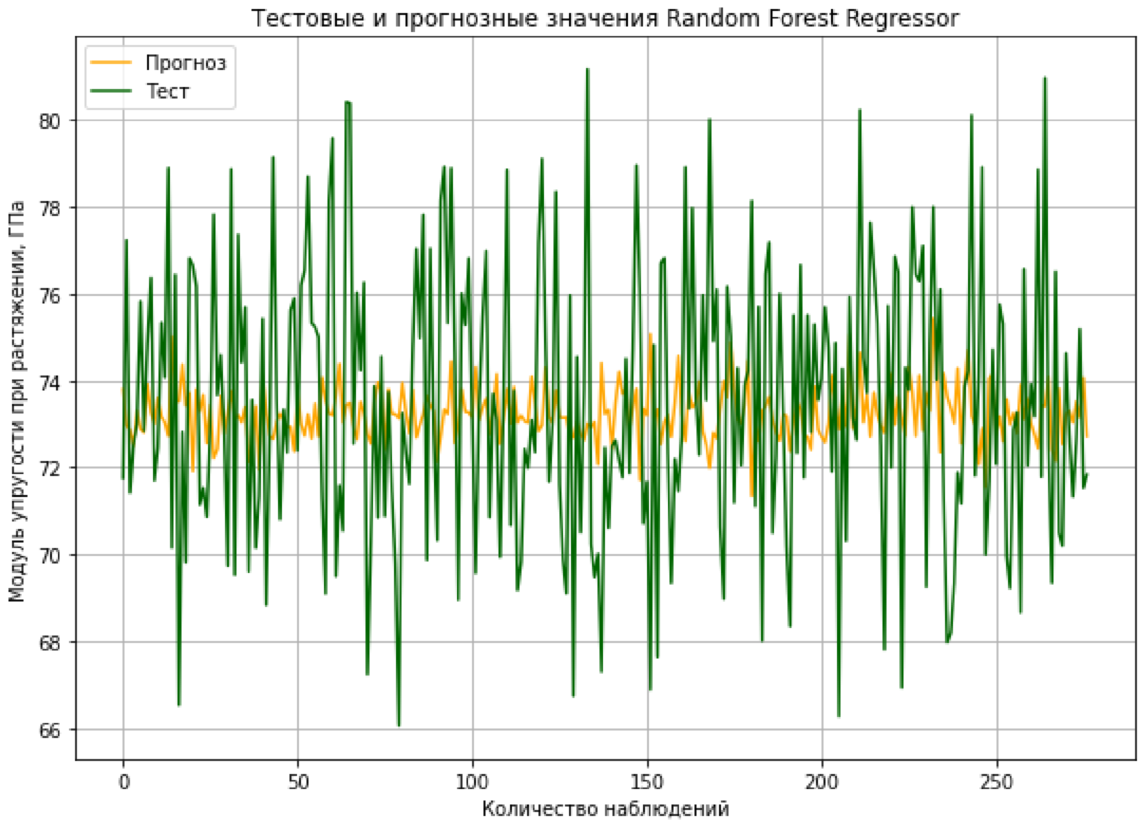


In [13]:
```
# Метод случайного леса - Random Forest Regressor - 2
```

In [14]:
```
#построение модели и вузуализация метода случайный лес
rfr2 = RandomForestRegressor(n_estimators = 15,max_depth = 7, random_state = 33)
rfr2.fit(x_train_2, y_train_2.values)
y2_pred_forest = rfr2.predict(x_test_2)
mae_rfr2 = mean_absolute_error(y2_pred_forest, y_test_2)
mse_rfr_elast2 = mean_squared_error(y_test_2,y2_pred_forest)
print('Random Forest Regressor Results Train:')
print("Test score: {:.2f}".format(rfr2.score(x_train_2, y_train_2))) # Скор для
print('Random Forest Regressor Results:')
print('RF_MAE: ', round(mean_absolute_error(y_test_2, y2_pred_forest)))
print('RF_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test_2, y2_pred_
print('RF_MSE: {:.2f}'.format(mse_rfr_elast2))
print("RF_RMSE: {:.2f}".format (np.sqrt(mse_rfr_elast2)))
print("Test score: {:.2f}".format(rfr2.score(x_test_2, y_test_2))) # Скор для ме
```

```
Random Forest Regressor Results Train:
Test score: 0.40
Random Forest Regressor Results:
RF_MAE:  3
RF_MAPE: 0.04
RF_MSE: 10.47
RF_RMSE: 3.24
Test score: -0.06
```

In [15]:
```
plt.figure(figsize=(10, 7))
plt.title("Тестовые и прогнозные значения Random Forest Regressor")
plt.plot(y2_pred_forest, label = "Прогноз", color = "orange")
plt.plot(y_test_2.values, label = "Тест", color = 'darkgreen')
plt.xlabel("Количество наблюдений")
plt.ylabel("Модуль упругости при растяжении, ГПа")
plt.legend()
plt.grid(True);
```

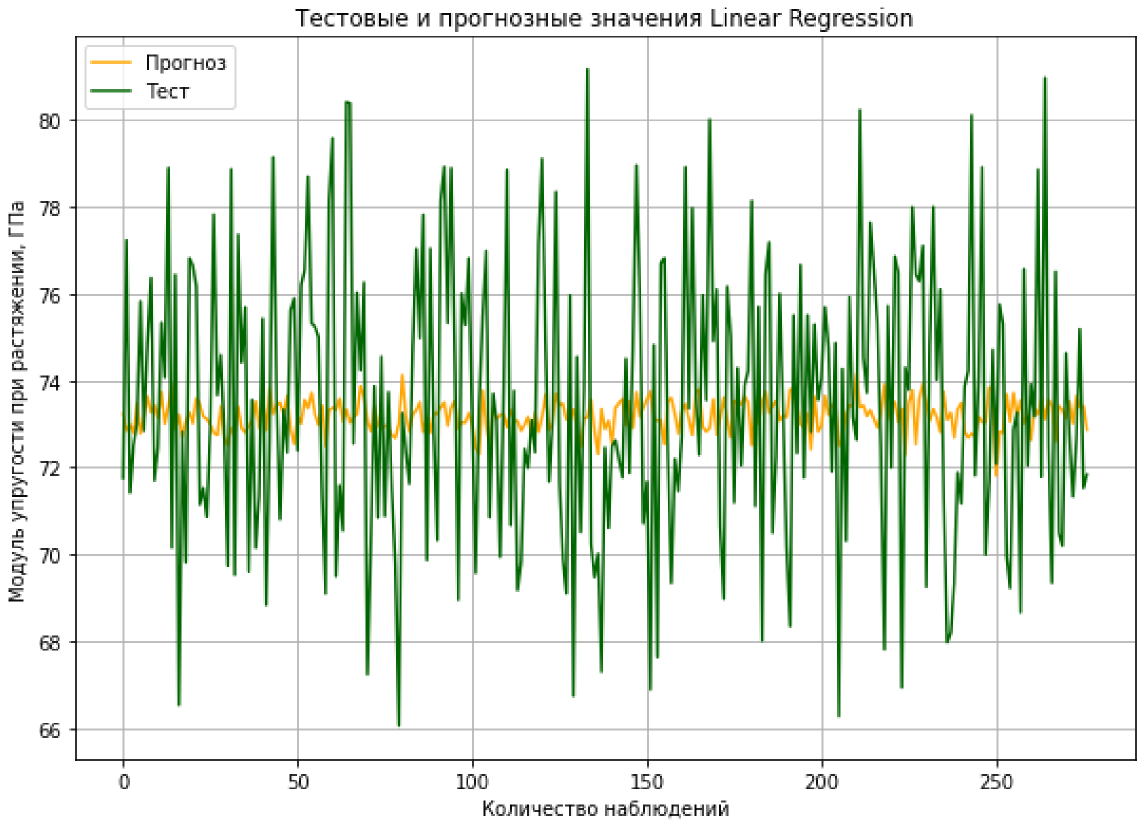


In [16]:
```
#Метод линейной регрессии - Linear Regression - 3
```

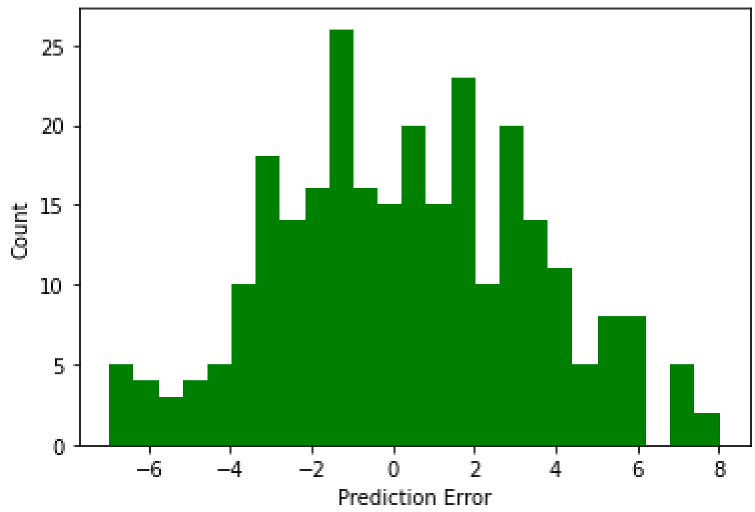
In [17]:
```
#построение модели и вузуализация Линейной регрессии
lr2 = LinearRegression()
lr2.fit(x_train_2, y_train_2)
y_pred_lr2 = lr2.predict(x_test_2)
mae_lr2 = mean_absolute_error(y_pred_lr2, y_test_2)
mse_lin_elast2 = mean_squared_error(y_test_2, y_pred_lr2)
print('Linear Regression Results Train:') # Скор для тренировочной выборки
print("Test score: {:.2f}".format(lr2.score(x_train_2, y_train_2)))
print('Linear Regression Results:')
print('lr_MAE: ', round(mean_absolute_error(y_test_2, y_pred_lr2)))
print('lr_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test_2, y_pred_l
print('lr_MSE: {:.2f}'.format(mse_lin_elast2))
print("lr_RMSE: {:.2f}".format (np.sqrt(mse_lin_elast2)))
print("Test score: {:.2f}".format(lr2.score(x_test_2, y_test_2))) # Скор для тес
```

```
Linear Regression Results Train:
Test score: 0.02
Linear Regression Results:
lr_MAE:  3
lr_MAPE: 0.04
lr_MSE: 10.18
lr_RMSE: 3.19
Test score: -0.03
```

In [18]:
```
plt.figure(figsize = (10, 7))
plt.title("Тестовые и прогнозные значения Linear Regression")
plt.plot(y_pred_lr2, label = "Прогноз", color = 'orange')
plt.plot(y_test_2.values, label = "Тест", color = 'darkgreen')
plt.xlabel("Количество наблюдений")
plt.ylabel("Модуль упругости при растяжении, ГПа")
plt.legend()
plt.grid(True);
```



In [19]:
```
error = y_test_2 - y_pred_lr2
plt.hist(error, bins = 25, color = "g")
plt.xlabel('Prediction Error')
_ = plt.ylabel('Count')
```

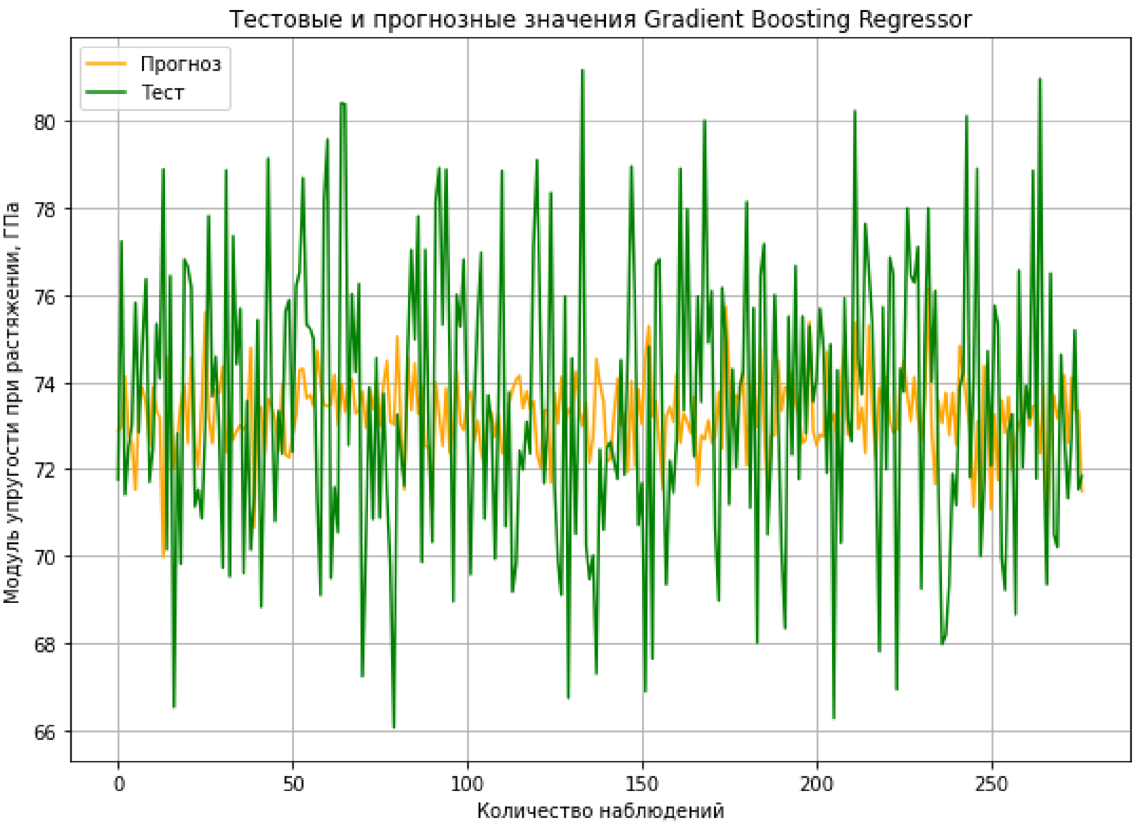


In [20]:
```
gbr2 = make_pipeline(StandardScaler(), GradientBoostingRegressor())
gbr2.fit(x_train_2, np.ravel(y_train_2))
y_pred_gbr2 = gbr2.predict(x_test_2)
mae_gbr2 = mean_absolute_error(y_pred_gbr2, y_test_2)
mse_gbr_elast2 = mean_squared_error(y_test_2,y_pred_gbr2)
print('Gradient Boosting Regressor Results Train:')
print("Test score: {:.2f}".format(gbr2.score(x_train_2, y_train_2))) # Скор для
print('Gradient Boosting Regressor Results:')
print('GBR_MAE: ', round(mean_absolute_error(y_test_2, y_pred_gbr2)))
print('GBR_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test_2, y_pred_
print('GBR_MSE: {:.2f}'.format(mse_gbr_elast2))
```

```
print("GBR_RMSE: {:.2f}".format (np.sqrt(mse_gbr_elast2)))
print("Test score: {:.2f}".format(gbr2.score(x_test_2, y_test_2)))# Скор для тес
```

```
Gradient Boosting Regressor Results Train:
Test score: 0.53
Gradient Boosting Regressor Results:
GBR_MAE:  3
GBR_MAPE: 0.04
GBR_MSE: 10.81
GBR_RMSE: 3.29
Test score: -0.09
```

In [21]:
```
plt.figure(figsize = (10, 7))
plt.title("Тестовые и прогнозные значения Gradient Boosting Regressor")
plt.plot(y_pred_gbr2, label = "Прогноз", color = "orange")
plt.plot(y_test_2.values, label = "Тест", color = "green")
plt.xlabel("Количество наблюдений")
plt.ylabel("Модуль упругости при растяжении, ГПа")
plt.legend()
plt.grid(True);
```

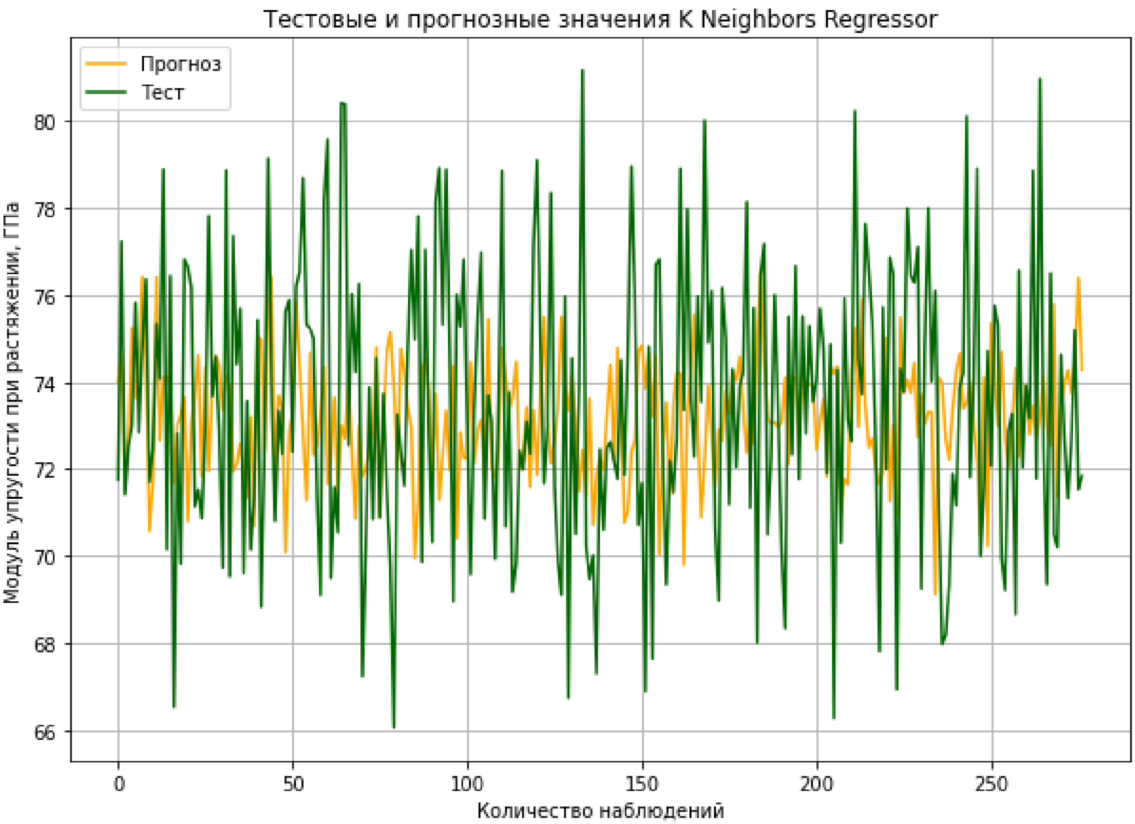


In [22]:
```
# Метод K ближайших соседей - K Neighbors Regressor - 5
knn2 = KNeighborsRegressor(n_neighbors=5)
knn2.fit(x_train_2, y_train_2)
y_pred_knn2 = knn2.predict(x_test_2)
mae_knr2 = mean_absolute_error(y_pred_knn2, y_test_2)
mse_knn_elast2 = mean_squared_error(y_test_2,y_pred_knn2)
print('K Neighbors Regressor  Results Train:')
print("Test score: {:.2f}".format(knn2.score(x_train_2, y_train_2)))# Скор для т
print('K Neighbors Regressor  Results:')
print('KNN_MAE: ', round(mean_absolute_error(y_test_2, y_pred_knn2)))
print('KNN_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test_2, y_pred_
print('KNN_MSE: {:.2f}'.format(mse_knn_elast2))
```

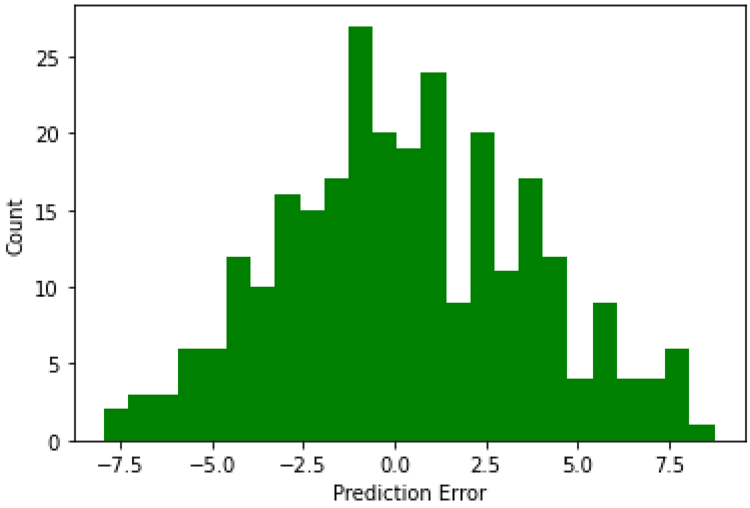
```
print("KNN_RMSE: {:.2f}".format (np.sqrt(mse_knn_elast2)))
print("Test score: {:.2f}".format(knn2.score(x_test_2, y_test_2)))# Скор для тес
```

```
K Neighbors Regressor  Results Train:
Test score: 0.24
K Neighbors Regressor  Results:
KNN_MAE:  3
KNN_MAPE: 0.04
KNN_MSE: 11.88
KNN_RMSE: 3.45
Test score: -0.20
```

In [23]:
```
plt.figure(figsize = (10, 7))
plt.title("Тестовые и прогнозные значения K Neighbors Regressor")
plt.plot(y_pred_knn2, label = "Прогноз", color = 'orange')
plt.plot(y_test_2.values, label = "Тест", color = 'darkgreen')
plt.xlabel("Количество наблюдений")
plt.ylabel("Модуль упругости при растяжении, ГПа")
plt.legend()
plt.grid(True);
```



In [24]:
```
#Визуализация гистограммы распределения ошибки
error = y_test_2 - y_pred_knn2
plt.hist(error, bins = 25, color = "g")
plt.xlabel('Prediction Error')
_ = plt.ylabel('Count')
```



In [25]:
```
#Деревья решений - Decision Tree Regressor - 6

dtr2 = DecisionTreeRegressor()
dtr2.fit(x_train_2, y_train_2.values)
y_pred_dtr2 = dtr2.predict(x_test_2)
mae_dtr2 = mean_absolute_error(y_pred_dtr2, y_test_2)
mse_dtr_elast2 = mean_squared_error(y_test_2,y_pred_dtr2)
print('Decision Tree Regressor Results Train:')
print("Test score: {:.2f}".format(dtr2.score(x_train_2, y_train_2)))# Скор для т
print('Decision Tree Regressor Results:')
print('DTR_MAE: ', round(mean_absolute_error(y_test_2, y_pred_dtr2)))
print('DTR_MSE: {:.2f}'.format(mse_dtr_elast2))
print("DTR_RMSE: {:.2f}".format (np.sqrt(mse_dtr_elast2)))
print('DTR_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test_2, y_pred_
print("Test score: {:.2f}".format(dtr2.score(x_test_2, y_test_2)))# Скор для тес
```

```
Decision Tree Regressor Results Train:
Test score: 1.00
Decision Tree Regressor Results:
DTR_MAE:  4
DTR_MSE: 19.90
DTR_RMSE: 4.46
DTR_MAPE: 0.05
Test score: -1.01
```

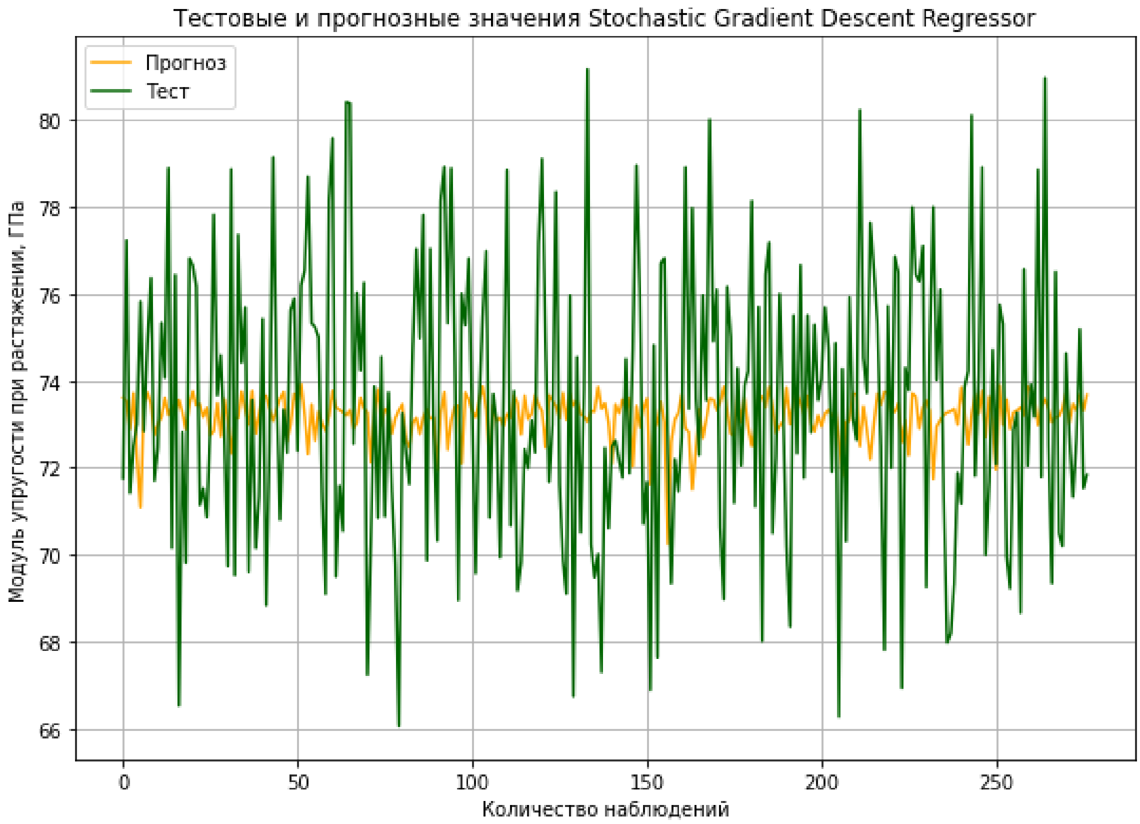
In [26]:
```
plt.figure(figsize = (10, 7))
plt.title("Тестовые и прогнозные значения Decision Tree Regressor")
plt.plot(y_pred_dtr2, label = "Прогноз", color = 'orange')
plt.plot(y_test_2.values, label = "Тест", color = 'darkgreen')
plt.xlabel("Количество наблюдений")
plt.ylabel("Модуль упругости при растяжении, ГПа")
plt.legend()
plt.grid(True);
```

In [27]:
```
# Смохастический градиентный спуск (SGD) - Stochastic Gradient Descent Regressor

sdg2 = SGDRegressor()
sdg2.fit(x_train_2, y_train_2)
y_pred_sdg2 = sdg2.predict(x_test_2)
mae_sdg2 = mean_absolute_error(y_pred_sdg2, y_test_2)
mse_sdg_elast2 = mean_squared_error(y_test_2,y_pred_sdg2)
print('Stochastic Gradient Descent Regressor Results Train:')
print("Test score: {:.2f}".format(sdg2.score(x_train_2, y_train_2)))# Скор для м
print('Stochastic Gradient Descent Regressor Results:')
print('SGD_MAE: ', round(mean_absolute_error(y_test_2, y_pred_sdg2)))
print('SGD_MSE: {:.2f}'.format(mse_sdg_elast2))
print("SGD_RMSE: {:.2f}".format (np.sqrt(mse_sdg_elast2)))
print('SGD_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test_2, y_pred_
print("Test score: {:.2f}".format(sdg2.score(x_test_2, y_test_2)))# Скор для мес
```

```
Stochastic Gradient Descent Regressor Results Train:
Test score: -0.01
Stochastic Gradient Descent Regressor Results:
SGD_MAE:  3
SGD_MSE: 10.27
SGD_RMSE: 3.20
SGD_MAPE: 0.04
Test score: -0.04
```

In [28]:
```
plt.figure(figsize = (10, 7))
plt.title("Тестовые и прогнозные значения Stochastic Gradient Descent Regressor"
plt.plot(y_pred_sdg2, label = "Прогноз", color = 'orange')
plt.plot(y_test_2.values, label = "Тест", color = 'darkgreen')
plt.xlabel("Количество наблюдений")
plt.ylabel("Модуль упругости при растяжении, ГПа")
plt.legend()
plt.grid(True);
```

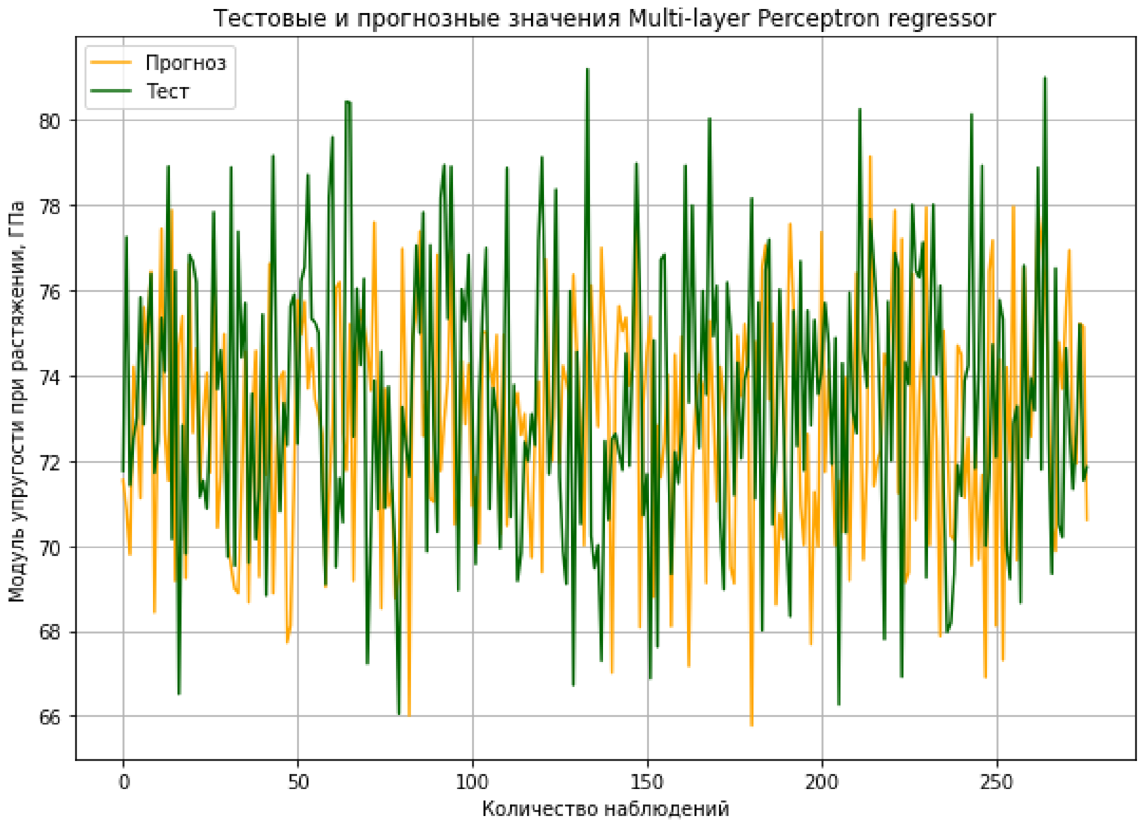


In [29]:
```
# Многослойный перцептрон - Multi-layer Perceptron regressor - 8

mlp2 = MLPRegressor(random_state = 1, max_iter = 500)
mlp2.fit(x_train_2, y_train_2)
y_pred_mlp2 = mlp2.predict(x_test_2)
mae_mlp2 = mean_absolute_error(y_pred_mlp2, y_test_2)
mse_mlp_elast2 = mean_squared_error(y_test_2,y_pred_mlp2)
print('Multi-layer Perceptron regressor Results Train:')
print("Test score: {:.2f}".format(mlp2.score(x_train_2, y_train_2)))# Скор для м
print('Multi-layer Perceptron regressor Results:')
print('SGD_MAE: ', round(mean_absolute_error(y_test_2, y_pred_mlp2)))
print('SGD_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test_2, y_pred_
print('SGD_MSE: {:.2f}'.format(mse_mlp_elast2))
print("SGD_RMSE: {:.2f}".format (np.sqrt(mse_mlp_elast2)))
print("Test score: {:.2f}".format(mlp2.score(x_test_2, y_test_2)))# Скор для мес
```

```
Multi-layer Perceptron regressor Results Train:
Test score: -0.77
Multi-layer Perceptron regressor Results:
SGD_MAE:  3
SGD_MAPE: 0.05
SGD_MSE: 17.30
SGD_RMSE: 4.16
Test score: -0.75
```

In [30]:
```
plt.figure(figsize = (10, 7))
plt.title("Тестовые и прогнозные значения Multi-layer Perceptron regressor")
plt.plot(y_pred_mlp2, label = "Прогноз", color = 'orange')
plt.plot(y_test_2.values, label = "Тест", color = 'darkgreen')
plt.xlabel("Количество наблюдений")
plt.ylabel("Модуль упругости при растяжении, ГПа")
plt.legend()
plt.grid(True);
```

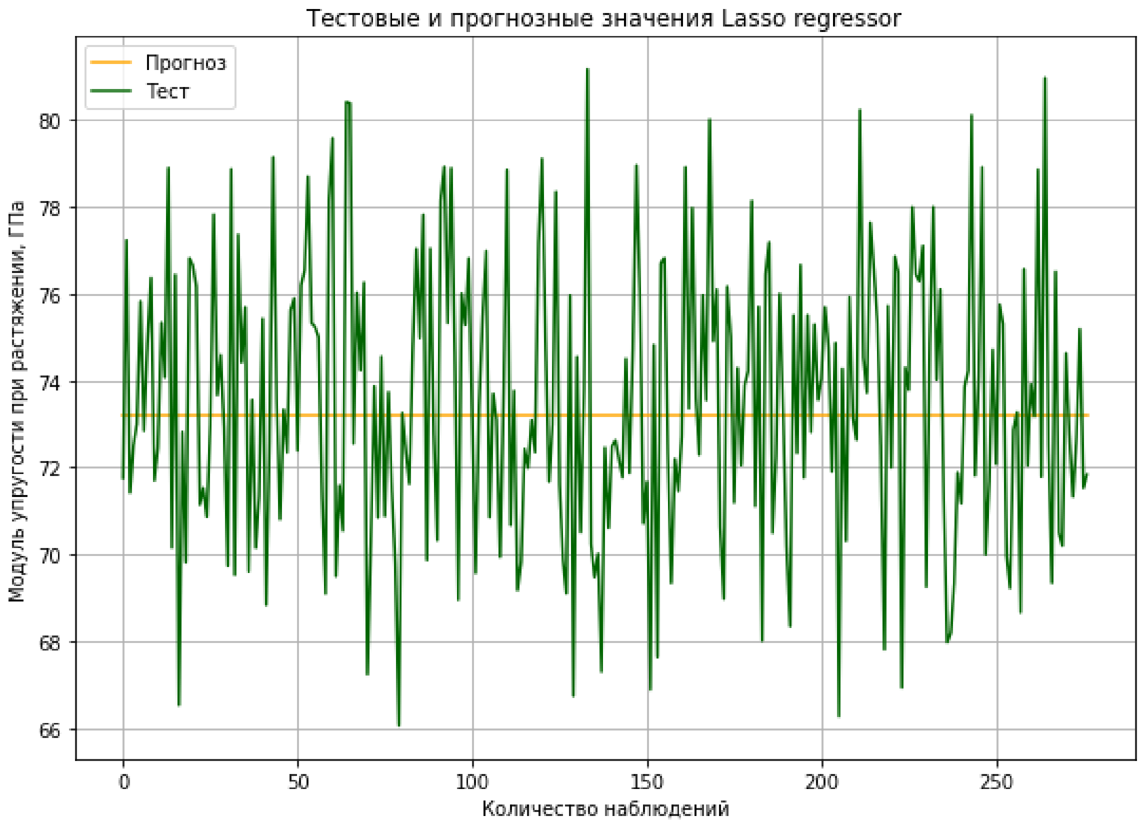


In [31]:
```
# Лассо регрессия - the Lasso - 9

clf2 = linear_model.Lasso(alpha = 0.1)
clf2.fit(x_train_2, y_train_2)
y_pred_clf2 = clf2.predict(x_test_2)
mae_clf2 = mean_absolute_error(y_pred_clf2, y_test_2)
mse_clf_elast2 = mean_squared_error(y_test_2,y_pred_clf2)
print('Lasso regressor Results Train:')
print("Test score: {:.2f}".format(clf2.score(x_train_2, y_train_2)))# Скор для м
print('Lasso regressor Results:')
print('SGD_MAE: ', round(mean_absolute_error(y_test_2, y_pred_clf2)))
print('SGD_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test_2, y_pred_
print('SGD_MSE: {:.2f}'.format(mse_clf_elast2))
print("SGD_RMSE: {:.2f}".format (np.sqrt(mse_clf_elast2)))
print("Test score: {:.2f}".format(clf2.score(x_test_2, y_test_2)))# Скор для тес
```

```
Lasso regressor Results Train:
Test score: 0.00
Lasso regressor Results:
SGD_MAE:  3
SGD_MAPE: 0.04
SGD_MSE: 10.00
SGD_RMSE: 3.16
Test score: -0.01
```

In [32]:
```
plt.figure(figsize = (10, 7))
plt.title("Тестовые и прогнозные значения Lasso regressor")
plt.plot(y_pred_clf2, label = "Прогноз", color = 'orange')
plt.plot(y_test_2.values, label = "Тест", color = 'darkgreen')
plt.xlabel("Количество наблюдений")
plt.ylabel("Модуль упругости при растяжении, ГПа")
plt.legend()
plt.grid(True);
```



In [33]:
```
#сравним наши модели по метрике MAE
mae_df2 = {'Регрессор': ['Support Vector', 'RandomForest', 'Linear Regression',
mae_df2 = pd.DataFrame(mae_df2)
```

In [34]:
```
# Проведем поиск  по сетке гиперпараметров с перекрестной проверкой, количество
# модели случайного леса - Random Forest Regressor - 2

parametrs = { 'n_estimators': [200, 300],
              'max_depth': [9, 15],
              'max_features': ['auto'],
              'criterion': ['mse'] }
grid21 = GridSearchCV(estimator = rfr2, param_grid  = parametrs, cv=10)
grid21.fit(x_train_2, y_train_2)
```

Out[34]:
```
GridSearchCV(cv=10,
             estimator=RandomForestRegressor(max_depth=7, n_estimators=15,
                                             random_state=33),
             param_grid={'criterion': ['mse'], 'max_depth': [9, 15],
                         'max_features': ['auto'], 'n_estimators': [200, 300]})
```

In [35]:
```
grid21.best_params_
```

Out[35]:
```
{'criterion': 'mse',
 'max_depth': 9,
 'max_features': 'auto',
 'n_estimators': 200}
```

In [36]:
```
#Выводим гиперпараметры для оптимальной модели
print(grid21.best_estimator_)
knr_u = grid21.best_estimator_
print(f'R2-score RFR для модуля упругости при растяжении: {knr_u.score(x_test_2,
```

```
RandomForestRegressor(criterion='mse', max_depth=9, n_estimators=200,
                      random_state=33)
R2-score RFR для модуля упругости при растяжении: -0.035
```

In [37]:
```
#подставим оптимальные гиперпараметры в нашу модель случайного леса
rfr21_grid = RandomForestRegressor(n_estimators=200, criterion='mse', max_depth=
#Обучаем модель
rfr21_grid.fit(x_train_2, y_train_2)

predictions_rfr21_grid = rfr21_grid.predict(x_test_2)
#Оцениваем точность на тестовом наборе
mae_rfr21_grid = mean_absolute_error(predictions_rfr21_grid, y_test_2)
mae_rfr21_grid
```

Out[37]:
```
2.6288324927708726
```

In [38]:
```
new_row_in_mae_df = {'Регрессор': 'RandomForest1_GridSearchCV', 'MAE': mae_rfr21

mae_df = mae_df2.append(new_row_in_mae_df, ignore_index = True)
```

In [39]:
```
mae_df
```

Out[39]:

	Регрессор	MAE
0	Support Vector	3.467880
1	RandomForest	2.621567
2	Linear Regression	2.612273
3	GradientBoosting	2.649635
4	KNeighbors	2.789287
5	DecisionTree	3.628268
6	SGD	2.613983
7	MLP	3.338349
8	Lasso	2.580193
9	RandomForest1_GridSearchCV	2.628832

In [40]:
```
# Проведем поиск  по сетке гиперпараметров с перекрестной проверкой, количество
# Метода К ближайших соседей - K Neighbors Regressor - 5
knn21 = KNeighborsRegressor()
knn21_params = {'n_neighbors' : range(1, 301, 2),
          'weights' : ['uniform', 'distance'],
          'algorithm' : ['auto', 'ball_tree', 'kd_tree', 'brute']
          }
#Запустим обучение модели. В качестве оценки модели будем использовать коэффицие
# Если R2<0, это значит, что разработанная модель даёт прогноз даже хуже, чем пр
gs21 = GridSearchCV(knn21, knn21_params, cv = 10, verbose = 1, n_jobs=-1, scorin
gs21.fit(x_train_2, y_train_2)
knn_21 = gs21.best_estimator_
gs21.best_params_
```

```
Fitting 10 folds for each of 1200 candidates, totalling 12000 fits
```

Out[40]:
```
{'algorithm': 'auto', 'n_neighbors': 269, 'weights': 'uniform'}
```

In [41]:
```
#Выводим гиперпараметры для оптимальной модели
print(gs21.best_estimator_)
gs121 = gs21.best_estimator_
print(f'R2-score KNR для модуля упругости при растяжении: {gs121.score(x_test_2,
```

```
KNeighborsRegressor(n_neighbors=269)
R2-score KNR для модуля упругости при растяжении: -0.013
```

In [42]:
```
#подставим оптимальные гиперпараметры в нашу модель метода к ближайших соседей
knn21_grid = KNeighborsRegressor(algorithm = 'brute', n_neighbors = 7, weights =
#Обучаем модель
knn21_grid.fit(x_train_2, y_train_2)

predictions_knn21_grid = knn21_grid.predict(x_test_2)
#Оцениваем точность на тестовом наборе
mae_knn21_grid = mean_absolute_error(predictions_knn21_grid, y_test_2)
mae_knn21_grid
```

Out[42]: 2.745343552900663

In [43]:
```
new_row_in_mae_df = {'Регрессор': 'KNeighbors1_GridSearchCV', 'MAE': mae_knn21_g

mae_df = mae_df.append(new_row_in_mae_df, ignore_index=True)
mae_df
```

Out[43]:

	Регрессор	MAE
0	Support Vector	3.467880
1	RandomForest	2.621567
2	Linear Regression	2.612273
3	GradientBoosting	2.649635
4	KNeighbors	2.789287
5	DecisionTree	3.628268
6	SGD	2.613983
7	MLP	3.338349
8	Lasso	2.580193
9	RandomForest1_GridSearchCV	2.628832
10	KNeighbors1_GridSearchCV	2.745344

In [44]:
```
# Проведем поиск  по сетке гиперпараметров с перекрестной проверкой, количество
#деревья решений - Decision Tree Regressor - 6
criterion21 = ['squared_error', 'friedman_mse', 'absolute_error', 'poisson']
splitter21 = ['best', 'random']
max_depth21 = [3,5,7,9,11]
min_samples_leaf21 = [100,150,200]
min_samples_split21 = [200,250,300]
max_features21 = ['auto', 'sqrt', 'log2']
param_grid21 = {'criterion': criterion21,
               'splitter': splitter21,
               'max_depth': max_depth21,
               'min_samples_split': min_samples_split21,
               'min_samples_leaf': min_samples_leaf21,
```

```
                'max_features': max_features21}
#Запустим обучение модели. В качестве оценки модели будем использовать коэффицие
# Если R2<0, это значит, что разработанная модель даёт прогноз даже хуже, чем пр
gs21 = GridSearchCV(dtr2, param_grid21, cv = 10, verbose = 1, n_jobs=-1, scoring
gs21.fit(x_train_2, y_train_2)
dtr_21 = gs21.best_estimator_
gs21.best_params_
```

```
Fitting 10 folds for each of 1080 candidates, totalling 10800 fits
```

Out[44]:
```
{'criterion': 'friedman_mse',
 'max_depth': 7,
 'max_features': 'log2',
 'min_samples_leaf': 200,
 'min_samples_split': 250,
 'splitter': 'best'}
```

In [45]:
```
#Выводим гиперпараметры для оптимальной модели
print(gs21.best_estimator_)
gs21 = gs21.best_estimator_
print(f'R2-score DTR для модуля упругости при растяжении: {gs21.score(x_test_2,
```

```
DecisionTreeRegressor(criterion='friedman_mse', max_depth=7,
                      max_features='log2', min_samples_leaf=200,
                      min_samples_split=250)
R2-score DTR для модуля упругости при растяжении: -0.019
```

In [46]:
```
#подставим оптимальные гиперпараметры в нашу модель метода деревья решений
dtr21_grid = DecisionTreeRegressor(criterion='poisson', max_depth=7, max_feature
                      min_samples_leaf=100, min_samples_split=250)
#Обучаем модель
dtr21_grid.fit(x_train_2, y_train_2)

predictions_dtr21_grid = dtr21_grid.predict(x_test_2)
#Оцениваем точность на тестовом наборе
mae_dtr21_grid = mean_absolute_error(predictions_dtr21_grid, y_test_2)
mae_dtr21_grid
```

Out[46]:
```
2.606181669247976
```

In [47]:
```
new_row_in_mae_df = {'Регрессор': 'DecisionTree1_GridSearchCV', 'MAE': mae_dtr21

mae_df = mae_df.append(new_row_in_mae_df, ignore_index=True)
mae_df
```

Out[47]:

	Регрессор	MAE
0	Support Vector	3.467880
1	RandomForest	2.621567
2	Linear Regression	2.612273
3	GradientBoosting	2.649635
4	KNeighbors	2.789287
5	DecisionTree	3.628268
6	SGD	2.613983
7	MLP	3.338349
8	Lasso	2.580193
9	RandomForest1_GridSearchCV	2.628832
10	KNeighbors1_GridSearchCV	2.745344
11	DecisionTree1_GridSearchCV	2.606182

In [49]:

```
pipe2 = Pipeline([('preprocessing', StandardScaler()), ('regressor', SVR())])
param_grid2 = [
{'regressor': [SVR()], 'preprocessing': [StandardScaler(), MinMaxScaler(), None]
'regressor__gamma': [0.001, 0.01, 0.1, 1, 10, 100],
'regressor__C': [0.001, 0.01, 0.1, 1, 10, 100]},
{'regressor': [RandomForestRegressor(n_estimators=100)],
'preprocessing':  [StandardScaler(), MinMaxScaler(), None]},
{'regressor': [LinearRegression()], 'preprocessing':  [StandardScaler(), MinMaxS
{'regressor': [GradientBoostingRegressor()], 'preprocessing':  [StandardScaler()
{'regressor': [KNeighborsRegressor()], 'preprocessing':  [StandardScaler(), MinM
{'regressor': [DecisionTreeRegressor()], 'preprocessing':  [StandardScaler(), Mi
{'regressor': [SGDRegressor()], 'preprocessing':  [StandardScaler(), MinMaxScale
{'regressor': [MLPRegressor(random_state=1, max_iter=500)], 'preprocessing':  [S
{'regressor': [linear_model.Lasso(alpha=0.1)], 'preprocessing':  [StandardScaler
grid2 = GridSearchCV(pipe2, param_grid2, cv=10)
grid2.fit(x_train_2, np.ravel(y_train_2))
print("Наилучшие параметры:\n{}\n".format(grid2.best_params_))
print("Наилучшее значение правильности перекрестной проверки: {:.2f}".format(gri
print("Правильность на тестовом наборе: {:.2f}".format(grid2.score(x_test_2, y_t
```

```
Наилучшие параметры:
{'preprocessing': MinMaxScaler(), 'regressor': SVR(C=10, gamma=100), 'regressor
__C': 10, 'regressor__gamma': 100}

Наилучшее значение правильности перекрестной проверки: -0.01
Правильность на тестовом наборе: -0.01
```

In [50]:

```
print("Наилучшая модель:\n{}".format(grid2.best_estimator_))
```

```
Наилучшая модель:
Pipeline(steps=[('preprocessing', MinMaxScaler()),
                ('regressor', SVR(C=10, gamma=100))])
```

После обучения моделей была проведена оценка точности этих моделей на обучающей и тестовых выборках. В качестве параметра оценки модели использовалась средняя абсолютная ошибка (MAE). Обе модели даже на тренировочном датасете не смогли обучиться и приблизиться к исходным данным. Поэтому ошибка на тестовом датасете выше.

Написать нейронную сеть, которая будет рекомендовать соотношение матрица-наполнитель.

In [51]:
```
# Сформируем входы и выход для модели

tv = df['Соотношение матрица-наполнитель']
tr_v = df.loc[:, df.columns != 'Соотношение матрица-наполнитель']

# Разбиваем выборки на обучающую и тестовую
x_train, x_test, y_train, y_test = train_test_split(tr_v, tv, test_size = 0.3, r
```

In [52]:
```
# Нормализуем данные

x_train_n = tf.keras.layers.Normalization(axis =-1)
x_train_n.adapt(np.array(x_train))
```

In [53]:
```
def create_model(lyrs=[32], act='softmax', opt='SGD', dr=0.1):

    seed = 7
    np.random.seed(seed)
    tf.random.set_seed(seed)

    model = Sequential()
    model.add(Dense(lyrs[0], input_dim=x_train.shape[1], activation=act))
    for i in range(1,len(lyrs)):
        model.add(Dense(lyrs[i], activation=act))

    model.add(Dropout(dr))
    model.add(Dense(3, activation='tanh'))  # выходной слой

    model.compile(loss='binary_crossentropy', optimizer=opt, metrics=['mae', 'ac

    return model
```

In [54]:
```
# строим модель
model = KerasClassifier(build_fn=create_model, verbose=0)

# определяем параметры
batch_size = [4, 10, 20, 50, 100]
epochs = [10, 50, 100, 200, 300]
param_grid = dict(batch_size=batch_size, epochs=epochs)

# поиск оптимальных параметров
grid = GridSearchCV(estimator=model,
                    param_grid=param_grid,
                    cv=10,
                    verbose=1, n_jobs=-1)

grid_result = grid.fit(x_train, y_train)
```

```
Fitting 10 folds for each of 25 candidates, totalling 250 fits
```

In [55]:
```
# результаты
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
```

```python
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.001538 using {'batch_size': 4, 'epochs': 10}
0.001538 (0.004615) with: {'batch_size': 4, 'epochs': 10}
0.001538 (0.004615) with: {'batch_size': 4, 'epochs': 50}
0.001538 (0.004615) with: {'batch_size': 4, 'epochs': 100}
0.001538 (0.004615) with: {'batch_size': 4, 'epochs': 200}
0.001538 (0.004615) with: {'batch_size': 4, 'epochs': 300}
0.001538 (0.004615) with: {'batch_size': 10, 'epochs': 10}
0.001538 (0.004615) with: {'batch_size': 10, 'epochs': 50}
0.001538 (0.004615) with: {'batch_size': 10, 'epochs': 100}
0.001538 (0.004615) with: {'batch_size': 10, 'epochs': 200}
0.001538 (0.004615) with: {'batch_size': 10, 'epochs': 300}
0.001538 (0.004615) with: {'batch_size': 20, 'epochs': 10}
0.001538 (0.004615) with: {'batch_size': 20, 'epochs': 50}
0.001538 (0.004615) with: {'batch_size': 20, 'epochs': 100}
0.001538 (0.004615) with: {'batch_size': 20, 'epochs': 200}
0.001538 (0.004615) with: {'batch_size': 20, 'epochs': 300}
0.001538 (0.004615) with: {'batch_size': 50, 'epochs': 10}
0.001538 (0.004615) with: {'batch_size': 50, 'epochs': 50}
0.001538 (0.004615) with: {'batch_size': 50, 'epochs': 100}
0.001538 (0.004615) with: {'batch_size': 50, 'epochs': 200}
0.001538 (0.004615) with: {'batch_size': 50, 'epochs': 300}
0.001538 (0.004615) with: {'batch_size': 100, 'epochs': 10}
0.001538 (0.004615) with: {'batch_size': 100, 'epochs': 50}
0.001538 (0.004615) with: {'batch_size': 100, 'epochs': 100}
0.001538 (0.004615) with: {'batch_size': 100, 'epochs': 200}
0.001538 (0.004615) with: {'batch_size': 100, 'epochs': 300}
```

In [56]:

```python
model = KerasClassifier(build_fn=create_model, epochs=50, batch_size=4, verbose=

optimizer = ['SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Nadam']
param_grid = dict(opt=optimizer)

grid = GridSearchCV(estimator=model, param_grid=param_grid, cv=10, verbose=2)
grid_result = grid.fit(x_train, y_train)
```

```
Fitting 10 folds for each of 6 candidates, totalling 60 fits
[CV] END ............................................opt=SGD; total time=  17.3
s
[CV] END ............................................opt=SGD; total time=  12.7
s
[CV] END ............................................opt=SGD; total time=  13.7
s
[CV] END ............................................opt=SGD; total time=  10.8
s
[CV] END ............................................opt=SGD; total time=  10.6
s
[CV] END ............................................opt=SGD; total time=  11.9
s
[CV] END ............................................opt=SGD; total time=  11.9
s
[CV] END ............................................opt=SGD; total time=  12.0
s
[CV] END ............................................opt=SGD; total time=  13.2
s
[CV] END ............................................opt=SGD; total time=  12.2
s
[CV] END ........................................opt=RMSprop; total time=  10.9
s
[CV] END ........................................opt=RMSprop; total time=  10.9
s
[CV] END ........................................opt=RMSprop; total time=  10.4
s
[CV] END ........................................opt=RMSprop; total time=  11.1
s
[CV] END ........................................opt=RMSprop; total time=  11.2
s
[CV] END ........................................opt=RMSprop; total time=  23.7
s
[CV] END ........................................opt=RMSprop; total time=  24.2
s
[CV] END ........................................opt=RMSprop; total time=  23.9
s
[CV] END ........................................opt=RMSprop; total time=  24.8
s
[CV] END ........................................opt=RMSprop; total time=  26.1
s
[CV] END ........................................opt=Adagrad; total time=  16.2
s
[CV] END ........................................opt=Adagrad; total time=  10.8
s
[CV] END ........................................opt=Adagrad; total time=  11.1
s
[CV] END ........................................opt=Adagrad; total time=  10.1
s
[CV] END ........................................opt=Adagrad; total time=  10.3
s
[CV] END ........................................opt=Adagrad; total time=  11.6
s
[CV] END ........................................opt=Adagrad; total time=  11.8
s
[CV] END ........................................opt=Adagrad; total time=  11.3
s
[CV] END ........................................opt=Adagrad; total time=  12.0
s
[CV] END ........................................opt=Adagrad; total time=  14.6
```

```
s
[CV] END ......................................opt=Adadelta; total time=  13.1
s
[CV] END ......................................opt=Adadelta; total time=  13.5
s
[CV] END ......................................opt=Adadelta; total time=  13.4
s
[CV] END ......................................opt=Adadelta; total time=  11.1
s
[CV] END ......................................opt=Adadelta; total time=  10.1
s
[CV] END ......................................opt=Adadelta; total time=  12.0
s
[CV] END ......................................opt=Adadelta; total time=  14.1
s
[CV] END ......................................opt=Adadelta; total time=  15.4
s
[CV] END ......................................opt=Adadelta; total time=  13.6
s
[CV] END ......................................opt=Adadelta; total time=  15.8
s
[CV] END ..........................................opt=Adam; total time=  12.9
s
[CV] END ..........................................opt=Adam; total time=  13.6
s
[CV] END ..........................................opt=Adam; total time=  12.6
s
[CV] END ..........................................opt=Adam; total time=  11.2
s
[CV] END ..........................................opt=Adam; total time=  12.4
s
[CV] END ..........................................opt=Adam; total time=  12.6
s
[CV] END ..........................................opt=Adam; total time=  14.6
s
[CV] END ..........................................opt=Adam; total time=  17.1
s
[CV] END ..........................................opt=Adam; total time=  13.4
s
[CV] END ..........................................opt=Adam; total time=  14.0
s
[CV] END .........................................opt=Nadam; total time=  12.6
s
[CV] END .........................................opt=Nadam; total time=  11.2
s
[CV] END .........................................opt=Nadam; total time=  11.9
s
[CV] END .........................................opt=Nadam; total time=  14.4
s
[CV] END .........................................opt=Nadam; total time=  16.4
s
[CV] END .........................................opt=Nadam; total time=  20.5
s
[CV] END .........................................opt=Nadam; total time=  15.3
s
[CV] END .........................................opt=Nadam; total time=  17.3
s
[CV] END .........................................opt=Nadam; total time=  15.8
s
```

```
[CV] END ........................................opt=Nadam; total time=  12.5
s
```

In [57]:

```python
# результаты
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.001538 using {'opt': 'SGD'}
0.001538 (0.004615) with: {'opt': 'SGD'}
0.001538 (0.004615) with: {'opt': 'RMSprop'}
0.001538 (0.004615) with: {'opt': 'Adagrad'}
0.001538 (0.004615) with: {'opt': 'Adadelta'}
0.001538 (0.004615) with: {'opt': 'Adam'}
0.000000 (0.000000) with: {'opt': 'Nadam'}
```

In [58]:

```python
model = KerasClassifier(build_fn=create_model, epochs=50, batch_size=4, verbose=

layers = [[8],[16, 4],[32, 8, 3],[12, 6, 3], [64, 64, 3], [128, 64, 16, 3]]
param_grid = dict(lyrs=layers)

grid = GridSearchCV(estimator=model, param_grid=param_grid, cv=10, verbose=2)
grid_result = grid.fit(x_train, y_train)
```

```
Fitting 10 folds for each of 6 candidates, totalling 60 fits
[CV] END ............................................lyrs=[8]; total time=  11.4
s
[CV] END ............................................lyrs=[8]; total time=  11.4
s
[CV] END ............................................lyrs=[8]; total time=  10.5
s
[CV] END ............................................lyrs=[8]; total time=  11.7
s
[CV] END ............................................lyrs=[8]; total time=  11.2
s
[CV] END ............................................lyrs=[8]; total time=  12.3
s
[CV] END ............................................lyrs=[8]; total time=  11.9
s
[CV] END ............................................lyrs=[8]; total time=  14.0
s
[CV] END ............................................lyrs=[8]; total time=  12.0
s
[CV] END ............................................lyrs=[8]; total time=  11.2
s
[CV] END ........................................lyrs=[16, 4]; total time=  11.5
s
[CV] END ........................................lyrs=[16, 4]; total time=  11.8
s
[CV] END ........................................lyrs=[16, 4]; total time=  11.2
s
[CV] END ........................................lyrs=[16, 4]; total time=  10.5
s
[CV] END ........................................lyrs=[16, 4]; total time=  12.0
s
[CV] END ........................................lyrs=[16, 4]; total time=  13.6
s
[CV] END ........................................lyrs=[16, 4]; total time=  16.3
s
[CV] END ........................................lyrs=[16, 4]; total time=  16.0
s
[CV] END ........................................lyrs=[16, 4]; total time=  13.3
s
[CV] END ........................................lyrs=[16, 4]; total time=  12.8
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  12.0
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  11.8
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  11.1
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  12.5
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  15.3
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  14.4
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  14.7
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  12.6
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  14.1
s
[CV] END .....................................lyrs=[32, 8, 3]; total time=  15.2
```

```
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  11.1
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  10.8
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  13.5
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  11.5
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  12.4
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  15.1
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  13.9
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  12.3
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  11.8
s
[CV] END ....................................lyrs=[12, 6, 3]; total time=  12.3
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  11.5
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  12.2
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  13.6
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  14.0
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  12.8
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  14.7
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  13.3
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  14.9
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  14.7
s
[CV] END ...................................lyrs=[64, 64, 3]; total time=  14.1
s
[CV] END ..............................lyrs=[128, 64, 16, 3]; total time=  12.2
s
[CV] END ..............................lyrs=[128, 64, 16, 3]; total time=  12.1
s
[CV] END ..............................lyrs=[128, 64, 16, 3]; total time=  14.1
s
[CV] END ..............................lyrs=[128, 64, 16, 3]; total time=  15.4
s
[CV] END ..............................lyrs=[128, 64, 16, 3]; total time=  12.7
s
[CV] END ..............................lyrs=[128, 64, 16, 3]; total time=  14.0
s
[CV] END ..............................lyrs=[128, 64, 16, 3]; total time=  13.6
s
[CV] END ..............................lyrs=[128, 64, 16, 3]; total time=  13.7
s
[CV] END ..............................lyrs=[128, 64, 16, 3]; total time=  14.7
s
```

```
[CV] END .............................lyrs=[128, 64, 16, 3]; total time=  14.7
s
```

In [59]:

```python
# результаты
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.004639 using {'lyrs': [128, 64, 16, 3]}
0.000000 (0.000000) with: {'lyrs': [8]}
0.001538 (0.004615) with: {'lyrs': [16, 4]}
0.001538 (0.004615) with: {'lyrs': [32, 8, 3]}
0.001538 (0.004615) with: {'lyrs': [12, 6, 3]}
0.001538 (0.004615) with: {'lyrs': [64, 64, 3]}
0.004639 (0.009877) with: {'lyrs': [128, 64, 16, 3]}
```

In [60]:

```python
model = KerasClassifier(build_fn=create_model, epochs=50, batch_size=4, verbose=

activation = ['softmax', 'softplus', 'softsign', 'relu', 'tanh', 'sigmoid', 'har
param_grid = dict(act=activation)

grid = GridSearchCV(estimator=model, param_grid=param_grid, n_jobs=-1, cv=10)
grid_result = grid.fit(x_train, y_train)
```

In [61]:

```python
# результаты
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.001538 using {'act': 'softmax'}
0.001538 (0.004615) with: {'act': 'softmax'}
0.001538 (0.004615) with: {'act': 'softplus'}
0.001538 (0.004615) with: {'act': 'softsign'}
0.001538 (0.004615) with: {'act': 'relu'}
0.001538 (0.004615) with: {'act': 'tanh'}
0.001538 (0.004615) with: {'act': 'sigmoid'}
0.001538 (0.004615) with: {'act': 'hard_sigmoid'}
0.001538 (0.004615) with: {'act': 'linear'}
```

In [62]:

```python
model = KerasClassifier(build_fn=create_model, epochs=50, batch_size=4, verbose=

drops = [0.0, 0.01, 0.05, 0.1, 0.2, 0.3, 0.5]
param_grid = dict(dr=drops)

grid = GridSearchCV(estimator=model, param_grid=param_grid, cv=10, verbose=2)
grid_result = grid.fit(x_train, y_train)
```

```
Fitting 10 folds for each of 7 candidates, totalling 70 fits
[CV] END ..............................................dr=0.0; total time=  10.3
s
[CV] END ..............................................dr=0.0; total time=  11.7
s
[CV] END ..............................................dr=0.0; total time=  11.2
s
[CV] END ..............................................dr=0.0; total time=  10.9
s
[CV] END ..............................................dr=0.0; total time=  11.8
s
[CV] END ..............................................dr=0.0; total time=  14.8
s
[CV] END ..............................................dr=0.0; total time=  11.9
s
[CV] END ..............................................dr=0.0; total time=  13.4
s
[CV] END ..............................................dr=0.0; total time=  12.7
s
[CV] END ..............................................dr=0.0; total time=  12.0
s
[CV] END .............................................dr=0.01; total time=  10.6
s
[CV] END .............................................dr=0.01; total time=  11.3
s
[CV] END .............................................dr=0.01; total time=  10.2
s
[CV] END .............................................dr=0.01; total time=  11.0
s
[CV] END .............................................dr=0.01; total time=  12.5
s
[CV] END .............................................dr=0.01; total time=  19.9
s
[CV] END .............................................dr=0.01; total time=  12.9
s
[CV] END .............................................dr=0.01; total time=  12.9
s
[CV] END .............................................dr=0.01; total time=  11.7
s
[CV] END .............................................dr=0.01; total time=  13.6
s
[CV] END .............................................dr=0.05; total time=  15.9
s
[CV] END .............................................dr=0.05; total time=  12.2
s
[CV] END .............................................dr=0.05; total time=  10.6
s
[CV] END .............................................dr=0.05; total time=  11.4
s
[CV] END .............................................dr=0.05; total time=  12.1
s
[CV] END .............................................dr=0.05; total time=  14.8
s
[CV] END .............................................dr=0.05; total time=  15.2
s
[CV] END .............................................dr=0.05; total time=  15.4
s
[CV] END .............................................dr=0.05; total time=  13.1
s
[CV] END .............................................dr=0.05; total time=  13.5
```

```
s
[CV] END ............................................dr=0.1; total time=  10.8
s
[CV] END ............................................dr=0.1; total time=  11.6
s
[CV] END ............................................dr=0.1; total time=  11.8
s
[CV] END ............................................dr=0.1; total time=  16.1
s
[CV] END ............................................dr=0.1; total time=  14.9
s
[CV] END ............................................dr=0.1; total time=  13.2
s
[CV] END ............................................dr=0.1; total time=  12.0
s
[CV] END ............................................dr=0.1; total time=  12.5
s
[CV] END ............................................dr=0.1; total time=  11.7
s
[CV] END ............................................dr=0.1; total time=  11.9
s
[CV] END ............................................dr=0.2; total time=  10.5
s
[CV] END ............................................dr=0.2; total time=  11.6
s
[CV] END ............................................dr=0.2; total time=  13.3
s
[CV] END ............................................dr=0.2; total time=  12.1
s
[CV] END ............................................dr=0.2; total time=  13.7
s
[CV] END ............................................dr=0.2; total time=  17.3
s
[CV] END ............................................dr=0.2; total time=  14.2
s
[CV] END ............................................dr=0.2; total time=  12.2
s
[CV] END ............................................dr=0.2; total time=  12.9
s
[CV] END ............................................dr=0.2; total time=  13.2
s
[CV] END ............................................dr=0.3; total time=  14.5
s
[CV] END ............................................dr=0.3; total time=  11.9
s
[CV] END ............................................dr=0.3; total time=  12.8
s
[CV] END ............................................dr=0.3; total time=  10.2
s
[CV] END ............................................dr=0.3; total time=  10.3
s
[CV] END ............................................dr=0.3; total time=  11.7
s
[CV] END ............................................dr=0.3; total time=  11.2
s
[CV] END ............................................dr=0.3; total time=  11.4
s
[CV] END ............................................dr=0.3; total time=  12.3
s
[CV] END ............................................dr=0.3; total time=  11.7
```

```
s
[CV] END ............................................dr=0.5; total time=   9.8
s
[CV] END ............................................dr=0.5; total time=  10.0
s
[CV] END ............................................dr=0.5; total time=   9.9
s
[CV] END ............................................dr=0.5; total time=  10.1
s
[CV] END ............................................dr=0.5; total time=  10.2
s
[CV] END ............................................dr=0.5; total time=  11.5
s
[CV] END ............................................dr=0.5; total time=  11.4
s
[CV] END ............................................dr=0.5; total time=  12.1
s
[CV] END ............................................dr=0.5; total time=  11.4
s
[CV] END ............................................dr=0.5; total time=  11.2
s
```

In [63]:

```
# результаты
print("Best: %f using %s" % (grid_result.best_score_, grid_result.best_params_))
means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print("%f (%f) with: %r" % (mean, stdev, param))
```

```
Best: 0.001538 using {'dr': 0.0}
0.001538 (0.004615) with: {'dr': 0.0}
0.001538 (0.004615) with: {'dr': 0.01}
0.001538 (0.004615) with: {'dr': 0.05}
0.001538 (0.004615) with: {'dr': 0.1}
0.001538 (0.004615) with: {'dr': 0.2}
0.001538 (0.004615) with: {'dr': 0.3}
0.001538 (0.004615) with: {'dr': 0.5}
```

In [64]:

```
# построение окончательной модели
model = create_model(lyrs=[128, 64, 16, 3], dr=0.05)

print(model.summary())
```

```
Model: "sequential_195"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense_493 (Dense)           (None, 128)               1920      
                                                                 
 dense_494 (Dense)           (None, 64)                8256      
                                                                 
 dense_495 (Dense)           (None, 16)                1040      
                                                                 
 dense_496 (Dense)           (None, 3)                 51        
                                                                 
 dropout_195 (Dropout)       (None, 3)                 0         
                                                                 
 dense_497 (Dense)           (None, 3)                 12        
                                                                 
=================================================================
Total params: 11,279
Trainable params: 11,279
Non-trainable params: 0
_________________________________________________________________
None
```

In [65]:

```
# обучаем нейросеть, 80/20 CV
model_hist = model.fit(x_train,
    y_train,
    epochs = 100,
    verbose = 1,
    validation_split = 0.2)
```

```
Epoch 1/100
17/17 [==============================] - 1s 18ms/step - loss: 45.4418 - mae: 3.
3252 - accuracy: 0.0000e+00 - val_loss: 42.8621 - val_mae: 3.1117 - val_accurac
y: 0.0000e+00
Epoch 2/100
17/17 [==============================] - 0s 5ms/step - loss: 40.2136 - mae: 3.2
242 - accuracy: 0.0000e+00 - val_loss: 28.3176 - val_mae: 2.8310 - val_accurac
y: 0.0000e+00
Epoch 3/100
17/17 [==============================] - 0s 4ms/step - loss: 30.0003 - mae: 3.0
047 - accuracy: 0.0000e+00 - val_loss: 27.6395 - val_mae: 2.7770 - val_accurac
y: 0.0000e+00
Epoch 4/100
17/17 [==============================] - 0s 4ms/step - loss: 29.3570 - mae: 2.9
674 - accuracy: 0.0000e+00 - val_loss: 27.1260 - val_mae: 2.7562 - val_accurac
y: 0.0000e+00
Epoch 5/100
17/17 [==============================] - 0s 4ms/step - loss: 28.7412 - mae: 2.9
550 - accuracy: 0.0000e+00 - val_loss: 26.6705 - val_mae: 2.7449 - val_accurac
y: 0.0000e+00
Epoch 6/100
17/17 [==============================] - 0s 4ms/step - loss: 28.2981 - mae: 2.9
462 - accuracy: 0.0000e+00 - val_loss: 26.2300 - val_mae: 2.7450 - val_accurac
y: 0.0000e+00
Epoch 7/100
17/17 [==============================] - 0s 4ms/step - loss: 27.8005 - mae: 2.9
491 - accuracy: 0.0000e+00 - val_loss: 25.8002 - val_mae: 2.7484 - val_accurac
y: 0.0000e+00
Epoch 8/100
17/17 [==============================] - 0s 6ms/step - loss: 27.3542 - mae: 2.9
540 - accuracy: 0.0000e+00 - val_loss: 25.3727 - val_mae: 2.7547 - val_accurac
y: 0.0000e+00
Epoch 9/100
17/17 [==============================] - 0s 4ms/step - loss: 18.9556 - mae: 2.7
619 - accuracy: 0.0000e+00 - val_loss: 9.7200 - val_mae: 2.3389 - val_accuracy:
0.0000e+00
Epoch 10/100
17/17 [==============================] - 0s 3ms/step - loss: 9.7895 - mae: 2.53
13 - accuracy: 0.0000e+00 - val_loss: 8.8560 - val_mae: 2.3176 - val_accuracy:
0.0000e+00
Epoch 11/100
17/17 [==============================] - 0s 4ms/step - loss: 8.8622 - mae: 2.51
49 - accuracy: 0.0000e+00 - val_loss: 8.0307 - val_mae: 2.3078 - val_accuracy:
0.0000e+00
Epoch 12/100
17/17 [==============================] - 0s 3ms/step - loss: 7.9078 - mae: 2.51
01 - accuracy: 0.0000e+00 - val_loss: 7.1886 - val_mae: 2.3041 - val_accuracy:
0.0000e+00
Epoch 13/100
17/17 [==============================] - 0s 4ms/step - loss: 6.9894 - mae: 2.50
87 - accuracy: 0.0000e+00 - val_loss: 6.3418 - val_mae: 2.3037 - val_accuracy:
0.0000e+00
Epoch 14/100
17/17 [==============================] - 0s 3ms/step - loss: 6.0750 - mae: 2.50
59 - accuracy: 0.0000e+00 - val_loss: 5.4653 - val_mae: 2.3051 - val_accuracy:
0.0000e+00
Epoch 15/100
17/17 [==============================] - 0s 5ms/step - loss: 5.1011 - mae: 2.50
87 - accuracy: 0.0000e+00 - val_loss: 4.5913 - val_mae: 2.3075 - val_accuracy:
0.0000e+00
```

```
Epoch 16/100
17/17 [==============================] - 0s 5ms/step - loss: 4.0804 - mae: 2.51
25 - accuracy: 0.0000e+00 - val_loss: 3.6970 - val_mae: 2.3103 - val_accuracy:
0.0000e+00
Epoch 17/100
17/17 [==============================] - 0s 4ms/step - loss: 3.1810 - mae: 2.51
04 - accuracy: 0.0000e+00 - val_loss: 2.7768 - val_mae: 2.3131 - val_accuracy:
0.0000e+00
Epoch 18/100
17/17 [==============================] - 0s 4ms/step - loss: 2.0161 - mae: 2.51
87 - accuracy: 0.0000e+00 - val_loss: 1.8144 - val_mae: 2.3159 - val_accuracy:
0.0000e+00
Epoch 19/100
17/17 [==============================] - 0s 3ms/step - loss: 1.1421 - mae: 2.51
51 - accuracy: 0.0000e+00 - val_loss: 0.9175 - val_mae: 2.3183 - val_accuracy:
0.0000e+00
Epoch 20/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0363 - mae: 2.52
08 - accuracy: 0.0000e+00 - val_loss: 0.1350 - val_mae: 2.3205 - val_accuracy:
0.0000e+00
Epoch 21/100
17/17 [==============================] - 0s 4ms/step - loss: -0.9634 - mae: 2.5
215 - accuracy: 0.0000e+00 - val_loss: -0.5890 - val_mae: 2.3216 - val_accurac
y: 0.0000e+00
Epoch 22/100
17/17 [==============================] - 0s 4ms/step - loss: -1.6298 - mae: 2.5
228 - accuracy: 0.0000e+00 - val_loss: -1.0732 - val_mae: 2.3223 - val_accurac
y: 0.0000e+00
Epoch 23/100
17/17 [==============================] - 0s 4ms/step - loss: -2.2286 - mae: 2.5
261 - accuracy: 0.0000e+00 - val_loss: -1.3935 - val_mae: 2.3229 - val_accurac
y: 0.0000e+00
Epoch 24/100
17/17 [==============================] - 0s 4ms/step - loss: -2.7391 - mae: 2.5
257 - accuracy: 0.0000e+00 - val_loss: -2.0796 - val_mae: 2.3236 - val_accurac
y: 0.0000e+00
Epoch 25/100
17/17 [==============================] - 0s 6ms/step - loss: -3.1726 - mae: 2.5
258 - accuracy: 0.0000e+00 - val_loss: -2.7100 - val_mae: 2.3242 - val_accurac
y: 0.0000e+00
Epoch 26/100
17/17 [==============================] - 0s 4ms/step - loss: -3.5435 - mae: 2.5
241 - accuracy: 0.0000e+00 - val_loss: -3.1445 - val_mae: 2.3248 - val_accurac
y: 0.0000e+00
Epoch 27/100
17/17 [==============================] - 0s 4ms/step - loss: -4.1473 - mae: 2.5
309 - accuracy: 0.0000e+00 - val_loss: -3.3916 - val_mae: 2.3254 - val_accurac
y: 0.0000e+00
Epoch 28/100
17/17 [==============================] - 0s 6ms/step - loss: -4.5222 - mae: 2.5
289 - accuracy: 0.0000e+00 - val_loss: -3.4078 - val_mae: 2.3254 - val_accurac
y: 0.0000e+00
Epoch 29/100
17/17 [==============================] - 0s 5ms/step - loss: -4.5934 - mae: 2.5
313 - accuracy: 0.0000e+00 - val_loss: -3.4510 - val_mae: 2.3254 - val_accurac
y: 0.0000e+00
Epoch 30/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4666 - mae: 2.5
261 - accuracy: 0.0000e+00 - val_loss: -3.4013 - val_mae: 2.3255 - val_accurac
y: 0.0000e+00
```

```
Epoch 31/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4969 - mae: 2.5
286 - accuracy: 0.0000e+00 - val_loss: -3.6364 - val_mae: 2.3254 - val_accurac
y: 0.0000e+00
Epoch 32/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4613 - mae: 2.5
286 - accuracy: 0.0000e+00 - val_loss: -3.4672 - val_mae: 2.3254 - val_accurac
y: 0.0000e+00
Epoch 33/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4839 - mae: 2.5
288 - accuracy: 0.0000e+00 - val_loss: -3.6557 - val_mae: 2.3254 - val_accurac
y: 0.0000e+00
Epoch 34/100
17/17 [==============================] - 0s 6ms/step - loss: -4.5917 - mae: 2.5
309 - accuracy: 0.0000e+00 - val_loss: -3.5606 - val_mae: 2.3254 - val_accurac
y: 0.0000e+00
Epoch 35/100
17/17 [==============================] - 0s 5ms/step - loss: -4.4238 - mae: 2.5
260 - accuracy: 0.0000e+00 - val_loss: -3.6552 - val_mae: 2.3253 - val_accurac
y: 0.0000e+00
Epoch 36/100
17/17 [==============================] - 0s 5ms/step - loss: -4.4447 - mae: 2.5
257 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3253 - val_accurac
y: 0.0000e+00
Epoch 37/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4976 - mae: 2.5
280 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3253 - val_accurac
y: 0.0000e+00
Epoch 38/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5840 - mae: 2.5
291 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3253 - val_accurac
y: 0.0000e+00
Epoch 39/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4384 - mae: 2.5
268 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3252 - val_accurac
y: 0.0000e+00
Epoch 40/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4387 - mae: 2.5
267 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3252 - val_accurac
y: 0.0000e+00
Epoch 41/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4095 - mae: 2.5
243 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3252 - val_accurac
y: 0.0000e+00
Epoch 42/100
17/17 [==============================] - 0s 3ms/step - loss: -4.4817 - mae: 2.5
266 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3251 - val_accurac
y: 0.0000e+00
Epoch 43/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4434 - mae: 2.5
250 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3251 - val_accurac
y: 0.0000e+00
Epoch 44/100
17/17 [==============================] - 0s 4ms/step - loss: -4.2355 - mae: 2.5
210 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3250 - val_accurac
y: 0.0000e+00
Epoch 45/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4462 - mae: 2.5
248 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3250 - val_accurac
y: 0.0000e+00
```

```
Epoch 46/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4937 - mae: 2.5
285 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3250 - val_accurac
y: 0.0000e+00
Epoch 47/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5392 - mae: 2.5
289 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3250 - val_accurac
y: 0.0000e+00
Epoch 48/100
17/17 [==============================] - 0s 5ms/step - loss: -4.4782 - mae: 2.5
269 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3249 - val_accurac
y: 0.0000e+00
Epoch 49/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4217 - mae: 2.5
240 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3249 - val_accurac
y: 0.0000e+00
Epoch 50/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5188 - mae: 2.5
276 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3249 - val_accurac
y: 0.0000e+00
Epoch 51/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5914 - mae: 2.5
280 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3248 - val_accurac
y: 0.0000e+00
Epoch 52/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4291 - mae: 2.5
251 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3248 - val_accurac
y: 0.0000e+00
Epoch 53/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4513 - mae: 2.5
262 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3248 - val_accurac
y: 0.0000e+00
Epoch 54/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4026 - mae: 2.5
255 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3247 - val_accurac
y: 0.0000e+00
Epoch 55/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4794 - mae: 2.5
275 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3247 - val_accurac
y: 0.0000e+00
Epoch 56/100
17/17 [==============================] - 0s 4ms/step - loss: -4.6031 - mae: 2.5
306 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3247 - val_accurac
y: 0.0000e+00
Epoch 57/100
17/17 [==============================] - 0s 4ms/step - loss: -4.3214 - mae: 2.5
223 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3246 - val_accurac
y: 0.0000e+00
Epoch 58/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4316 - mae: 2.5
238 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3246 - val_accurac
y: 0.0000e+00
Epoch 59/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5925 - mae: 2.5
285 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3246 - val_accurac
y: 0.0000e+00
Epoch 60/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5084 - mae: 2.5
273 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3245 - val_accurac
y: 0.0000e+00
```

```
Epoch 61/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5451 - mae: 2.5
269 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3245 - val_accurac
y: 0.0000e+00
Epoch 62/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4552 - mae: 2.5
248 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3245 - val_accurac
y: 0.0000e+00
Epoch 63/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4916 - mae: 2.5
259 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3244 - val_accurac
y: 0.0000e+00
Epoch 64/100
17/17 [==============================] - 0s 5ms/step - loss: -4.4805 - mae: 2.5
251 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3244 - val_accurac
y: 0.0000e+00
Epoch 65/100
17/17 [==============================] - 0s 5ms/step - loss: -4.6268 - mae: 2.5
294 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3244 - val_accurac
y: 0.0000e+00
Epoch 66/100
17/17 [==============================] - 0s 5ms/step - loss: -4.4414 - mae: 2.5
250 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3243 - val_accurac
y: 0.0000e+00
Epoch 67/100
17/17 [==============================] - 0s 5ms/step - loss: -4.5781 - mae: 2.5
275 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3243 - val_accurac
y: 0.0000e+00
Epoch 68/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5457 - mae: 2.5
279 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3243 - val_accurac
y: 0.0000e+00
Epoch 69/100
17/17 [==============================] - 0s 5ms/step - loss: -4.4725 - mae: 2.5
246 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3242 - val_accurac
y: 0.0000e+00
Epoch 70/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4543 - mae: 2.5
236 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3242 - val_accurac
y: 0.0000e+00
Epoch 71/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4883 - mae: 2.5
254 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3241 - val_accurac
y: 0.0000e+00
Epoch 72/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5511 - mae: 2.5
265 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3241 - val_accurac
y: 0.0000e+00
Epoch 73/100
17/17 [==============================] - 0s 5ms/step - loss: -4.5925 - mae: 2.5
281 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3241 - val_accurac
y: 0.0000e+00
Epoch 74/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4217 - mae: 2.5
223 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3240 - val_accurac
y: 0.0000e+00
Epoch 75/100
17/17 [==============================] - 0s 5ms/step - loss: -4.4099 - mae: 2.5
207 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3240 - val_accurac
y: 0.0000e+00
```

```
Epoch 76/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4323 - mae: 2.5
224 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3239 - val_accurac
y: 0.0000e+00
Epoch 77/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5303 - mae: 2.5
258 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3239 - val_accurac
y: 0.0000e+00
Epoch 78/100
17/17 [==============================] - 0s 4ms/step - loss: -4.3928 - mae: 2.5
202 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3238 - val_accurac
y: 0.0000e+00
Epoch 79/100
17/17 [==============================] - 0s 5ms/step - loss: -4.5268 - mae: 2.5
238 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3238 - val_accurac
y: 0.0000e+00
Epoch 80/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4799 - mae: 2.5
240 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3237 - val_accurac
y: 0.0000e+00
Epoch 81/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5491 - mae: 2.5
260 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3237 - val_accurac
y: 0.0000e+00
Epoch 82/100
17/17 [==============================] - 0s 5ms/step - loss: -4.5622 - mae: 2.5
272 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3236 - val_accurac
y: 0.0000e+00
Epoch 83/100
17/17 [==============================] - 0s 5ms/step - loss: -4.4865 - mae: 2.5
232 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3236 - val_accurac
y: 0.0000e+00
Epoch 84/100
17/17 [==============================] - 0s 5ms/step - loss: -4.5589 - mae: 2.5
267 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3236 - val_accurac
y: 0.0000e+00
Epoch 85/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5464 - mae: 2.5
256 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3235 - val_accurac
y: 0.0000e+00
Epoch 86/100
17/17 [==============================] - 0s 5ms/step - loss: -4.5924 - mae: 2.5
275 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3235 - val_accurac
y: 0.0000e+00
Epoch 87/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5796 - mae: 2.5
251 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3235 - val_accurac
y: 0.0000e+00
Epoch 88/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5413 - mae: 2.5
254 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3234 - val_accurac
y: 0.0000e+00
Epoch 89/100
17/17 [==============================] - 0s 4ms/step - loss: -4.6143 - mae: 2.5
266 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3234 - val_accurac
y: 0.0000e+00
Epoch 90/100
17/17 [==============================] - 0s 5ms/step - loss: -4.6117 - mae: 2.5
274 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3234 - val_accurac
y: 0.0000e+00
```

```
Epoch 91/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4731 - mae: 2.5
228 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3233 - val_accurac
y: 0.0000e+00
Epoch 92/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5588 - mae: 2.5
258 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3233 - val_accurac
y: 0.0000e+00
Epoch 93/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5822 - mae: 2.5
255 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3232 - val_accurac
y: 0.0000e+00
Epoch 94/100
17/17 [==============================] - 0s 4ms/step - loss: -4.4890 - mae: 2.5
215 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3232 - val_accurac
y: 0.0000e+00
Epoch 95/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5709 - mae: 2.5
269 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3231 - val_accurac
y: 0.0000e+00
Epoch 96/100
17/17 [==============================] - 0s 5ms/step - loss: -4.6278 - mae: 2.5
264 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3231 - val_accurac
y: 0.0000e+00
Epoch 97/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5016 - mae: 2.5
227 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3230 - val_accurac
y: 0.0000e+00
Epoch 98/100
17/17 [==============================] - 0s 4ms/step - loss: -4.5471 - mae: 2.5
243 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3230 - val_accurac
y: 0.0000e+00
Epoch 99/100
17/17 [==============================] - 0s 3ms/step - loss: -4.4532 - mae: 2.5
222 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3229 - val_accurac
y: 0.0000e+00
Epoch 100/100
17/17 [==============================] - 0s 4ms/step - loss: -4.6221 - mae: 2.5
246 - accuracy: 0.0000e+00 - val_loss: -3.7957 - val_mae: 2.3229 - val_accurac
y: 0.0000e+00
```

In [66]:

```
# оценим модель
scores = model.evaluate(x_test, y_test)
print("\n%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

```
9/9 [==============================] - 0s 4ms/step - loss: -4.3965 - mae: 2.446
9 - accuracy: 0.0000e+00

mae: 244.69%
```

In [67]:

```
# Посмотрим на потери модели

model_hist.history
```

Out[67]:
```
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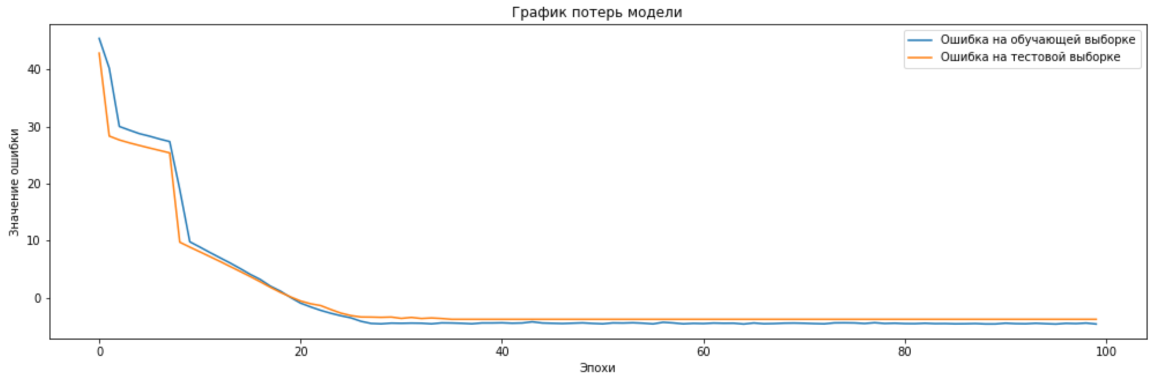
In [68]:
```python
# Посмотрим на график потерь на тренировочной и тестовой выборках
def model_loss_plot(model_hist):
    plt.figure(figsize = (17,5))
    plt.plot(model_hist.history['loss'],
             label = 'ошибка на обучающей выборке')
    plt.plot(model_hist.history['val_loss'],
            label = 'ошибка на тестовой выборке')
    plt.title('График потерь модели')
    plt.ylabel('Значение ошибки')
    plt.xlabel('Эпохи')
    plt.legend(['Ошибка на обучающей выборке', 'Ошибка на тестовой выборке'], lo
    plt.show()
model_loss_plot(model_hist)
```



In [69]:
```python
# Зададим функцию для визуализации факт/прогноз для результатов моделей
# Посмотрим на график результата работы модели
def actual_and_predicted_plot(orig, predict, var, model_name):
    plt.figure(figsize=(17,5))
    plt.title(f'Тестовые и прогнозные значения: {model_name}')
    plt.plot(orig, label = 'Тест')
    plt.plot(predict, label = 'Прогноз')
    plt.legend(loc = 'best')
    plt.ylabel(var)
    plt.xlabel('Количество наблюдений')
    plt.show()
actual_and_predicted_plot(y_test.values, model.predict(x_test.values), 'Соотноше
```

```
9/9 [==============================] - 0s 2ms/step
```

In [73]:
```python
# Сконфигурируем другую модель, зададим слои
from tensorflow.keras.layers import Dense
model1 = tf.keras.Sequential([x_train_n, layers.Dense(128, activation='relu'),
                                                 layers.Dense(128, activation='r
```

```
                                          layers.Dense(128, activation='r
                                          layers.Dense(64, activation='re
                                          layers.Dense(64, activation='re
                                          layers.Dense(32, activation='re
                                          layers.Dense(16, activation='re
                                          layers.Dense(1)
                              ])

model1.compile(optimizer = tf.keras.optimizers.Adam(0.001), loss = 'mean_squarec
# Посмотрим на архитектуру модели

model1.summary()
```

```
Model: "sequential_196"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 normalization (Normalizatio  (None, 14)               29
 n)

 dense_498 (Dense)           (None, 128)               1920

 dense_499 (Dense)           (None, 128)               16512

 dense_500 (Dense)           (None, 128)               16512

 dense_501 (Dense)           (None, 64)                8256

 dense_502 (Dense)           (None, 64)                4160

 dense_503 (Dense)           (None, 32)                2080

 dense_504 (Dense)           (None, 16)                528

 dense_505 (Dense)           (None, 1)                 17

=================================================================
Total params: 50,014
Trainable params: 49,985
Non-trainable params: 29
_________________________________________________________________
```

In [74]:
```
# Обучим модель

model_hist1 = model1.fit(
    x_train,
    y_train,
    epochs = 100,
    verbose = 1,
    validation_split = 0.2)
```

```
Epoch 1/100
17/17 [==============================] - 2s 24ms/step - loss: 6.9116 - root_mea
n_squared_error: 2.6290 - val_loss: 1.3523 - val_root_mean_squared_error: 1.162
9
Epoch 2/100
17/17 [==============================] - 0s 5ms/step - loss: 1.4837 - root_mean
_squared_error: 1.2181 - val_loss: 1.3695 - val_root_mean_squared_error: 1.1703
Epoch 3/100
17/17 [==============================] - 0s 5ms/step - loss: 1.1125 - root_mean
_squared_error: 1.0547 - val_loss: 1.1390 - val_root_mean_squared_error: 1.0672
Epoch 4/100
17/17 [==============================] - 0s 5ms/step - loss: 0.9776 - root_mean
_squared_error: 0.9888 - val_loss: 1.4329 - val_root_mean_squared_error: 1.1970
Epoch 5/100
17/17 [==============================] - 0s 4ms/step - loss: 0.8868 - root_mean
_squared_error: 0.9417 - val_loss: 1.2451 - val_root_mean_squared_error: 1.1158
Epoch 6/100
17/17 [==============================] - 0s 5ms/step - loss: 0.8349 - root_mean
_squared_error: 0.9137 - val_loss: 1.1285 - val_root_mean_squared_error: 1.0623
Epoch 7/100
17/17 [==============================] - 0s 5ms/step - loss: 0.7899 - root_mean
_squared_error: 0.8888 - val_loss: 1.1436 - val_root_mean_squared_error: 1.0694
Epoch 8/100
17/17 [==============================] - 0s 5ms/step - loss: 0.7581 - root_mean
_squared_error: 0.8707 - val_loss: 1.1829 - val_root_mean_squared_error: 1.0876
Epoch 9/100
17/17 [==============================] - 0s 5ms/step - loss: 0.7434 - root_mean
_squared_error: 0.8622 - val_loss: 1.1236 - val_root_mean_squared_error: 1.0600
Epoch 10/100
17/17 [==============================] - 0s 7ms/step - loss: 0.6999 - root_mean
_squared_error: 0.8366 - val_loss: 1.0859 - val_root_mean_squared_error: 1.0421
Epoch 11/100
17/17 [==============================] - 0s 6ms/step - loss: 0.6497 - root_mean
_squared_error: 0.8060 - val_loss: 1.0566 - val_root_mean_squared_error: 1.0279
Epoch 12/100
17/17 [==============================] - 0s 5ms/step - loss: 0.6521 - root_mean
_squared_error: 0.8075 - val_loss: 1.0468 - val_root_mean_squared_error: 1.0232
Epoch 13/100
17/17 [==============================] - 0s 5ms/step - loss: 0.5999 - root_mean
_squared_error: 0.7746 - val_loss: 1.0707 - val_root_mean_squared_error: 1.0347
Epoch 14/100
17/17 [==============================] - 0s 6ms/step - loss: 0.5687 - root_mean
_squared_error: 0.7541 - val_loss: 1.2484 - val_root_mean_squared_error: 1.1173
Epoch 15/100
17/17 [==============================] - 0s 6ms/step - loss: 0.5462 - root_mean
_squared_error: 0.7390 - val_loss: 1.1708 - val_root_mean_squared_error: 1.0820
Epoch 16/100
17/17 [==============================] - 0s 5ms/step - loss: 0.4648 - root_mean
_squared_error: 0.6818 - val_loss: 1.2609 - val_root_mean_squared_error: 1.1229
Epoch 17/100
17/17 [==============================] - 0s 5ms/step - loss: 0.4242 - root_mean
_squared_error: 0.6513 - val_loss: 1.1172 - val_root_mean_squared_error: 1.0570
Epoch 18/100
17/17 [==============================] - 0s 5ms/step - loss: 0.4339 - root_mean
_squared_error: 0.6587 - val_loss: 1.2005 - val_root_mean_squared_error: 1.0957
Epoch 19/100
17/17 [==============================] - 0s 6ms/step - loss: 0.3918 - root_mean
_squared_error: 0.6259 - val_loss: 1.2835 - val_root_mean_squared_error: 1.1329
Epoch 20/100
17/17 [==============================] - 0s 4ms/step - loss: 0.3164 - root_mean
```

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_squared_error: 0.5625 - val_loss: 1.2995 - val_root_mean_squared_error: 1.1400
Epoch 21/100
17/17 [==============================] - 0s 5ms/step - loss: 0.2615 - root_mean
_squared_error: 0.5113 - val_loss: 1.2745 - val_root_mean_squared_error: 1.1289
Epoch 22/100
17/17 [==============================] - 0s 5ms/step - loss: 0.2269 - root_mean
_squared_error: 0.4763 - val_loss: 1.2452 - val_root_mean_squared_error: 1.1159
Epoch 23/100
17/17 [==============================] - 0s 6ms/step - loss: 0.2309 - root_mean
_squared_error: 0.4806 - val_loss: 1.4742 - val_root_mean_squared_error: 1.2142
Epoch 24/100
17/17 [==============================] - 0s 5ms/step - loss: 0.2030 - root_mean
_squared_error: 0.4506 - val_loss: 1.2805 - val_root_mean_squared_error: 1.1316
Epoch 25/100
17/17 [==============================] - 0s 5ms/step - loss: 0.1656 - root_mean
_squared_error: 0.4070 - val_loss: 1.3946 - val_root_mean_squared_error: 1.1809
Epoch 26/100
17/17 [==============================] - 0s 5ms/step - loss: 0.1254 - root_mean
_squared_error: 0.3541 - val_loss: 1.4239 - val_root_mean_squared_error: 1.1933
Epoch 27/100
17/17 [==============================] - 0s 6ms/step - loss: 0.1145 - root_mean
_squared_error: 0.3384 - val_loss: 1.4365 - val_root_mean_squared_error: 1.1985
Epoch 28/100
17/17 [==============================] - 0s 5ms/step - loss: 0.1228 - root_mean
_squared_error: 0.3504 - val_loss: 1.4626 - val_root_mean_squared_error: 1.2094
Epoch 29/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0951 - root_mean
_squared_error: 0.3083 - val_loss: 1.6037 - val_root_mean_squared_error: 1.2664
Epoch 30/100
17/17 [==============================] - 0s 8ms/step - loss: 0.0855 - root_mean
_squared_error: 0.2923 - val_loss: 1.5551 - val_root_mean_squared_error: 1.2470
Epoch 31/100
17/17 [==============================] - 0s 7ms/step - loss: 0.0772 - root_mean
_squared_error: 0.2778 - val_loss: 1.6726 - val_root_mean_squared_error: 1.2933
Epoch 32/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0986 - root_mean
_squared_error: 0.3139 - val_loss: 1.4547 - val_root_mean_squared_error: 1.2061
Epoch 33/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0612 - root_mean
_squared_error: 0.2473 - val_loss: 1.5642 - val_root_mean_squared_error: 1.2507
Epoch 34/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0525 - root_mean
_squared_error: 0.2292 - val_loss: 1.5199 - val_root_mean_squared_error: 1.2329
Epoch 35/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0716 - root_mean
_squared_error: 0.2677 - val_loss: 1.3483 - val_root_mean_squared_error: 1.1612
Epoch 36/100
17/17 [==============================] - 0s 7ms/step - loss: 0.0802 - root_mean
_squared_error: 0.2833 - val_loss: 1.5039 - val_root_mean_squared_error: 1.2263
Epoch 37/100
17/17 [==============================] - 0s 7ms/step - loss: 0.0471 - root_mean
_squared_error: 0.2171 - val_loss: 1.6250 - val_root_mean_squared_error: 1.2748
Epoch 38/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0353 - root_mean
_squared_error: 0.1878 - val_loss: 1.4969 - val_root_mean_squared_error: 1.2235
Epoch 39/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0211 - root_mean
_squared_error: 0.1454 - val_loss: 1.5514 - val_root_mean_squared_error: 1.2456
Epoch 40/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0158 - root_mean
```

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_squared_error: 0.1257 - val_loss: 1.5651 - val_root_mean_squared_error: 1.2511
Epoch 41/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0152 - root_mean
_squared_error: 0.1234 - val_loss: 1.5103 - val_root_mean_squared_error: 1.2290
Epoch 42/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0122 - root_mean
_squared_error: 0.1103 - val_loss: 1.5152 - val_root_mean_squared_error: 1.2309
Epoch 43/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0182 - root_mean
_squared_error: 0.1348 - val_loss: 1.4904 - val_root_mean_squared_error: 1.2208
Epoch 44/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0170 - root_mean
_squared_error: 0.1302 - val_loss: 1.5196 - val_root_mean_squared_error: 1.2327
Epoch 45/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0119 - root_mean
_squared_error: 0.1091 - val_loss: 1.5081 - val_root_mean_squared_error: 1.2280
Epoch 46/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0118 - root_mean
_squared_error: 0.1088 - val_loss: 1.5411 - val_root_mean_squared_error: 1.2414
Epoch 47/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0092 - root_mean
_squared_error: 0.0961 - val_loss: 1.5360 - val_root_mean_squared_error: 1.2393
Epoch 48/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0055 - root_mean
_squared_error: 0.0744 - val_loss: 1.5291 - val_root_mean_squared_error: 1.2366
Epoch 49/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0056 - root_mean
_squared_error: 0.0750 - val_loss: 1.5413 - val_root_mean_squared_error: 1.2415
Epoch 50/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0087 - root_mean
_squared_error: 0.0931 - val_loss: 1.5389 - val_root_mean_squared_error: 1.2405
Epoch 51/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0128 - root_mean
_squared_error: 0.1130 - val_loss: 1.5877 - val_root_mean_squared_error: 1.2600
Epoch 52/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0109 - root_mean
_squared_error: 0.1043 - val_loss: 1.5732 - val_root_mean_squared_error: 1.2543
Epoch 53/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0089 - root_mean
_squared_error: 0.0944 - val_loss: 1.5175 - val_root_mean_squared_error: 1.2319
Epoch 54/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0076 - root_mean
_squared_error: 0.0874 - val_loss: 1.5326 - val_root_mean_squared_error: 1.2380
Epoch 55/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0076 - root_mean
_squared_error: 0.0872 - val_loss: 1.5608 - val_root_mean_squared_error: 1.2493
Epoch 56/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0099 - root_mean
_squared_error: 0.0993 - val_loss: 1.5859 - val_root_mean_squared_error: 1.2593
Epoch 57/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0074 - root_mean
_squared_error: 0.0862 - val_loss: 1.5621 - val_root_mean_squared_error: 1.2499
Epoch 58/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0075 - root_mean
_squared_error: 0.0865 - val_loss: 1.5689 - val_root_mean_squared_error: 1.2526
Epoch 59/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0058 - root_mean
_squared_error: 0.0763 - val_loss: 1.5171 - val_root_mean_squared_error: 1.2317
Epoch 60/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0053 - root_mean
```

```
_squared_error: 0.0727 - val_loss: 1.5943 - val_root_mean_squared_error: 1.2627
Epoch 61/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0051 - root_mean
_squared_error: 0.0718 - val_loss: 1.5700 - val_root_mean_squared_error: 1.2530
Epoch 62/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0056 - root_mean
_squared_error: 0.0751 - val_loss: 1.5749 - val_root_mean_squared_error: 1.2549
Epoch 63/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0049 - root_mean
_squared_error: 0.0700 - val_loss: 1.5446 - val_root_mean_squared_error: 1.2428
Epoch 64/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0044 - root_mean
_squared_error: 0.0667 - val_loss: 1.5586 - val_root_mean_squared_error: 1.2484
Epoch 65/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0045 - root_mean
_squared_error: 0.0673 - val_loss: 1.5272 - val_root_mean_squared_error: 1.2358
Epoch 66/100
17/17 [==============================] - 0s 8ms/step - loss: 0.0032 - root_mean
_squared_error: 0.0570 - val_loss: 1.5267 - val_root_mean_squared_error: 1.2356
Epoch 67/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0044 - root_mean
_squared_error: 0.0662 - val_loss: 1.5345 - val_root_mean_squared_error: 1.2388
Epoch 68/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0076 - root_mean
_squared_error: 0.0872 - val_loss: 1.4946 - val_root_mean_squared_error: 1.2226
Epoch 69/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0083 - root_mean
_squared_error: 0.0912 - val_loss: 1.5901 - val_root_mean_squared_error: 1.2610
Epoch 70/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0066 - root_mean
_squared_error: 0.0809 - val_loss: 1.5288 - val_root_mean_squared_error: 1.2364
Epoch 71/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0037 - root_mean
_squared_error: 0.0610 - val_loss: 1.5119 - val_root_mean_squared_error: 1.2296
Epoch 72/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0041 - root_mean
_squared_error: 0.0638 - val_loss: 1.4940 - val_root_mean_squared_error: 1.2223
Epoch 73/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0041 - root_mean
_squared_error: 0.0643 - val_loss: 1.5363 - val_root_mean_squared_error: 1.2395
Epoch 74/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0052 - root_mean
_squared_error: 0.0720 - val_loss: 1.5375 - val_root_mean_squared_error: 1.2400
Epoch 75/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0048 - root_mean
_squared_error: 0.0695 - val_loss: 1.5240 - val_root_mean_squared_error: 1.2345
Epoch 76/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0070 - root_mean
_squared_error: 0.0838 - val_loss: 1.5013 - val_root_mean_squared_error: 1.2253
Epoch 77/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0099 - root_mean
_squared_error: 0.0996 - val_loss: 1.5502 - val_root_mean_squared_error: 1.2451
Epoch 78/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0171 - root_mean
_squared_error: 0.1309 - val_loss: 1.5146 - val_root_mean_squared_error: 1.2307
Epoch 79/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0220 - root_mean
_squared_error: 0.1483 - val_loss: 1.5284 - val_root_mean_squared_error: 1.2363
Epoch 80/100
17/17 [==============================] - 0s 3ms/step - loss: 0.0236 - root_mean
```

```
_squared_error: 0.1537 - val_loss: 1.5162 - val_root_mean_squared_error: 1.2313
Epoch 81/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0651 - root_mean
_squared_error: 0.2551 - val_loss: 1.5771 - val_root_mean_squared_error: 1.2558
Epoch 82/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0634 - root_mean
_squared_error: 0.2519 - val_loss: 1.4032 - val_root_mean_squared_error: 1.1846
Epoch 83/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0595 - root_mean
_squared_error: 0.2440 - val_loss: 1.4747 - val_root_mean_squared_error: 1.2144
Epoch 84/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0729 - root_mean
_squared_error: 0.2700 - val_loss: 1.4150 - val_root_mean_squared_error: 1.1895
Epoch 85/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0766 - root_mean
_squared_error: 0.2767 - val_loss: 1.6155 - val_root_mean_squared_error: 1.2710
Epoch 86/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0534 - root_mean
_squared_error: 0.2311 - val_loss: 1.5398 - val_root_mean_squared_error: 1.2409
Epoch 87/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0289 - root_mean
_squared_error: 0.1699 - val_loss: 1.4532 - val_root_mean_squared_error: 1.2055
Epoch 88/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0186 - root_mean
_squared_error: 0.1363 - val_loss: 1.4613 - val_root_mean_squared_error: 1.2088
Epoch 89/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0122 - root_mean
_squared_error: 0.1104 - val_loss: 1.5166 - val_root_mean_squared_error: 1.2315
Epoch 90/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0086 - root_mean
_squared_error: 0.0925 - val_loss: 1.5206 - val_root_mean_squared_error: 1.2331
Epoch 91/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0074 - root_mean
_squared_error: 0.0858 - val_loss: 1.5245 - val_root_mean_squared_error: 1.2347
Epoch 92/100
17/17 [==============================] - 0s 6ms/step - loss: 0.0049 - root_mean
_squared_error: 0.0699 - val_loss: 1.5279 - val_root_mean_squared_error: 1.2361
Epoch 93/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0038 - root_mean
_squared_error: 0.0618 - val_loss: 1.4940 - val_root_mean_squared_error: 1.2223
Epoch 94/100
17/17 [==============================] - 0s 5ms/step - loss: 0.0022 - root_mean
_squared_error: 0.0470 - val_loss: 1.5091 - val_root_mean_squared_error: 1.2284
Epoch 95/100
17/17 [==============================] - 0s 4ms/step - loss: 0.0015 - root_mean
_squared_error: 0.0383 - val_loss: 1.5007 - val_root_mean_squared_error: 1.2250
Epoch 96/100
17/17 [==============================] - 0s 4ms/step - loss: 9.5466e-04 - root_
mean_squared_error: 0.0309 - val_loss: 1.4951 - val_root_mean_squared_error: 1.
2227
Epoch 97/100
17/17 [==============================] - 0s 5ms/step - loss: 7.6219e-04 - root_
mean_squared_error: 0.0276 - val_loss: 1.4798 - val_root_mean_squared_error: 1.
2165
Epoch 98/100
17/17 [==============================] - 0s 5ms/step - loss: 8.5690e-04 - root_
mean_squared_error: 0.0293 - val_loss: 1.4941 - val_root_mean_squared_error: 1.
2223
Epoch 99/100
17/17 [==============================] - 0s 5ms/step - loss: 7.1959e-04 - root_
```

```
mean_squared_error: 0.0268 - val_loss: 1.4963 - val_root_mean_squared_error: 1.
2232
Epoch 100/100
17/17 [==============================] - 0s 5ms/step - loss: 4.2799e-04 - root_
mean_squared_error: 0.0207 - val_loss: 1.4880 - val_root_mean_squared_error: 1.
2198
```

In [75]:
```
model1.evaluate(x_test, y_test)
```

```
9/9 [==============================] - 0s 2ms/step - loss: 1.2427 - root_mean_s
quared_error: 1.1147
```

Out[75]:
```
[1.2426555156707764, 1.1147445440292358]
```

In [76]:
```
y_pred_model = model1.predict(x_test)

print('Model Results:')
print('Model_MAE: ', round(mean_absolute_error(y_test, y_pred_model)))
print('Model_MAPE: {:.2f}'.format(mean_absolute_percentage_error(y_test, y_pred_
print("Test score: {:.2f}".format(mean_squared_error(y_test, y_pred_model)))
```

```
9/9 [==============================] - 0s 2ms/step
Model Results:
Model_MAE:  1
Model_MAPE: 0.37
Test score: 1.24
```

In [77]:
```
# Посмотрим на потери модели

model_hist1.history
```

```
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 1.237990379333496,
 1.2493128776550293,
 1.2593368291854858,
 1.2498514652252197,
 1.2525720596313477,
 1.2317216396331787,

```
 1.2626701593399048,
 1.252977967262268,
 1.25494384765625,
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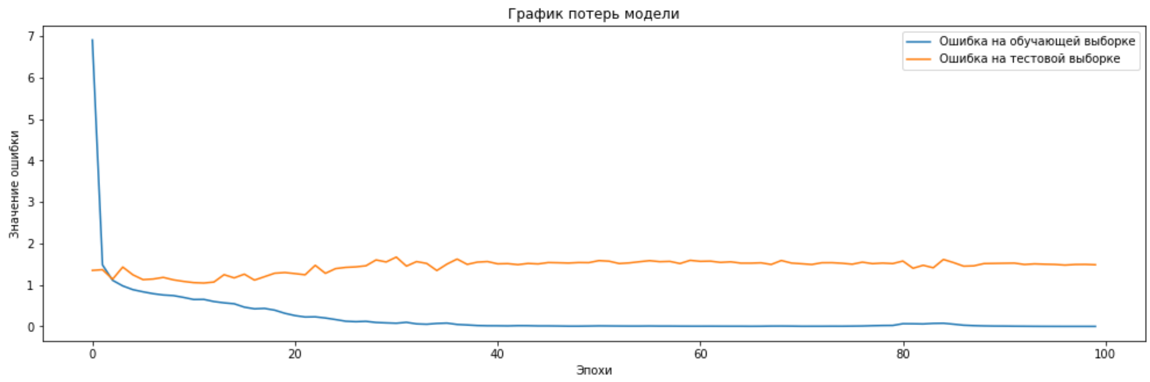
 1.2227294445037842,
 1.216477394104004,
 1.2223225831985474,
 1.2232319116592407,
 1.2198195457458496]}
```

In [81]:

```
# Посмотрим на график потерь на тренировочной и тестовой выборках
def model_loss_plot(model_hist1):
    plt.figure(figsize = (17,5))
    plt.plot(model_hist1.history['loss'],
             label = 'ошибка на обучающей выборке')
    plt.plot(model_hist1.history['val_loss'],
            label = 'ошибка на тестовой выборке')
    plt.title('График потерь модели')
    plt.ylabel('Значение ошибки')
    plt.xlabel('Эпохи')
    plt.legend(['Ошибка на обучающей выборке', 'Ошибка на тестовой выборке'], lo
    plt.show()
model_loss_plot(model_hist1)
```



In [78]:
```
# Зададим функцию для визуализации факт/прогноз для результатов моделей
# Посмотрим на график результата работы модели
def actual_and_predicted_plot(orig, predict, var, model_name):
    plt.figure(figsize=(17,5))
    plt.title(f'Тестовые и прогнозные значения: {model_name}')
    plt.plot(orig, label = 'Тест')
    plt.plot(predict, label = 'Прогноз')
    plt.legend(loc = 'best')
    plt.ylabel(var)
    plt.xlabel('Количество наблюдений')
    plt.show()
actual_and_predicted_plot(y_test.values, model1.predict(x_test.values), 'Соотнош
```

```
9/9 [==============================] - 0s 2ms/step
```

In [79]:
```
# оценка модели MSE
model1.evaluate(x_test, y_test, verbose = 1)
```

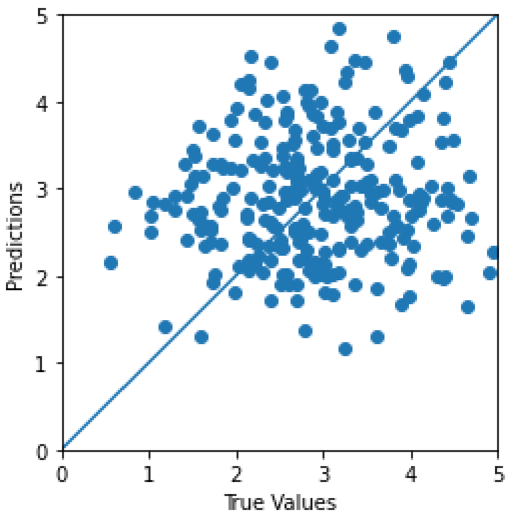
```
9/9 [==============================] - 0s 2ms/step - loss: 1.2427 - root_mean_s
quared_error: 1.1147
```

Out[79]:
```
[1.2426555156707764, 1.1147445440292358]
```

In [80]:
```
test_predictions = model1.predict(x_test).flatten()

a = plt.axes(aspect = 'equal')
plt.scatter(y_test, test_predictions)
plt.xlabel('True Values')
plt.ylabel('Predictions')
lims = [0, 5]
plt.xlim(lims)
plt.ylim(lims)
_ = plt.plot(lims, lims)
```

```
9/9 [==============================] - 0s 2ms/step
```



Заключение.

Подводя итоги, стоит сказать, что машинное обучение в задачах моделей прогнозирования – довольно сложный процесс, требующий не только навыков программирования, но и профессионального подхода к сфере самих композитных материалов. Необходимо понимать, на какие атрибуты нужно в первую очередь обратить внимание, чтобы суметь впоследствии грамотно и чётко спрогнозировать тот или иной признак. И, естественно, обладать всеми необходимыми знаниями, умениями и навыками для прогнозов и расчетов. В ходе работы был задействован дата-сет с реальными данными, произведена его подробная опись и сопутствующий анализ; построено множество разнообразных графиков; осуществлено разбиение данных на обучающую и тестовую выборки с использованием множества вспомогательных модулей из библиотеки SkLearn, которая во многом облегчила процесс машинного обучения и в целом была очень полезным инструментом в ходе работы над выпускной квалификационной работой. В рамках машинного обучения и поиска гиперпараметров были задействованы несколько алгоритмов: линейная регрессия, градиентный бустинг, К ближайших соседей, деревья решений, стохастический градиентный спуск, многослойный перцептрон, лассо регрессия, а также опорные вектора и случайный лес. Поиск гиперпараметров осуществлялся при помощи таких методов, как «GridSearch». Для каждой из выборок были составлены классификационные отчёты, содержащие в себе основополагающие метрики, оценивающие качество проводимого обучения. В конечном итоге было представлено сравнение результатов оценок работы алгоритмов, а также различные графики и диаграммы, позволяющие наглядно оценить итоги проведенного обучения. Обучена нейронная сеть и разработано пользовательское приложение, предсказывающе вероятный прогноз по заданным параметрам. Что касается перспектив решения данной проблемы композитных материалов, то я думаю, что в таких случаях необходимо уделить больше внимания изучению самой проблемы композитных материалов, углубить знания по статистике и регрессиям, поискать иные варианты решений с данным датасетом, создать плодтворную команду программистов и сотрудников, работающих с природными материалами, способную к совместной работе над усовершенствованием уже существующих разработок и поддержанием их качественного и бесперебойного функционирования.

```
In [ ]:
```