```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
         %matplotlib inline
         # Импортирование необходимых модулей и атрибутов
        from sklearn import linear model
        from sklearn.datasets import load digits
        from sklearn.model selection import train test split, GridSearchCV, KFold
        from sklearn.linear model import LogisticRegression
        from sklearn.discriminant analysis import LinearDiscriminantAnalysis
        from sklearn.neighbors import KNeighborsClassifier
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.naive bayes import GaussianNB
        from sklearn.svm import LinearSVC
        from sklearn.svm import SVC
        from sklearn.neural network import MLPClassifier
        from sklearn.ensemble import BaggingClassifier
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.ensemble import ExtraTreesClassifier
        from sklearn.ensemble import AdaBoostClassifier
        from sklearn.ensemble import GradientBoostingClassifier
        from sklearn.model selection import KFold
        from sklearn.model selection import cross val score
        from sklearn.pipeline import Pipeline
        from sklearn.preprocessing import StandardScaler
        from sklearn.preprocessing import MinMaxScaler
        from sklearn.preprocessing import Normalizer
        from matplotlib import pyplot
        from sklearn.neighbors import KNeighborsRegressor
        from sklearn.metrics import mean squared error, r2 score, mean absolute p
        from sklearn.pipeline import make pipeline, Pipeline
        from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegre
        from sklearn.linear model import LinearRegression, LogisticRegression, SG
        from sklearn.svm import SVR
        from sklearn.tree import DecisionTreeRegressor
        import warnings
        warnings.filterwarnings("ignore")
        import tensorflow as tf
        from tensorflow import keras
        from tensorflow.keras import layers
        print(tf.__version__)
        2.11.0
       data iqr new = pd.read excel(r'C:\Users\55944\Desktop\888/data iqr new.xl
In [2]:
        data_iqr_new.drop(['Unnamed: 0'], axis=1,inplace=True)
        data iqr new
In [3]:
Out[3]:
             Соотношение
                                       модуль
                                               Количество Содержание Температура По
                          Плотность.
                                    упругости, отвердителя, эпоксидных
                матрица-
                                                                        вспышки,
                              кг/м3
                                                                             C_2
             наполнитель
                                         ГПа
                                                      м.%
                                                            групп,%_2
                 1.857143 2030.000000 738.736842
                                                 50.000000
                                                             23.750000
                                                                       284.615385
```

1.857143 2030.000000 738.736842

129.000000

21.250000

300.000000

2	2.771331	2030.000000	753.000000	111.860000	22.267857	284.615385
3	2.767918	2000.000000	748.000000	111.860000	22.267857	284.615385
4	2.569620	1910.000000	807.000000	111.860000	22.267857	284.615385
915	2.271346	1952.087902	912.855545	86.992183	20.123249	324.774576
916	3.444022	2050.089171	444.732634	145.981978	19.599769	254.215401
917	3.280604	1972.372865	416.836524	110.533477	23.957502	248.423047
918	3.705351	2066.799773	741.475517	141.397963	19.246945	275.779840
919	3.808020	1890.413468	417.316232	129.183416	27.474763	300.952708

920 rows × 13 columns

In [4]: # посмотрим с каким типом переменных нам предстоит работать
для этого есть метод .info()
data_iqr_new.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 920 entries, 0 to 919
Data columns (total 13 columns):

#	Column	Non-Null Count	Dtype
0	Соотношение матрица-наполнитель	920 non-null	float64
1	Плотность, кг/м3	920 non-null	float64
2	модуль упругости, ГПа	920 non-null	float64
3	Количество отвердителя, м.%	920 non-null	float64
4	Содержание эпоксидных групп,%_2	920 non-null	float64
5	Температура вспышки, С_2	920 non-null	float64
6	Поверхностная плотность, г/м2	920 non-null	float64
7	Модуль упругости при растяжении, ГПа	920 non-null	float64
8	Прочность при растяжении, МПа	920 non-null	float64
9	Потребление смолы, г/м2	920 non-null	float64
10	Угол нашивки	920 non-null	int64
11	Шаг нашивки	920 non-null	float64
12	Плотность нашивки	920 non-null	float64

dtypes: float64(12), int64(1)
memory usage: 93.6 KB

In [5]: # посмотрим на основные статистические показатели (summary statistics)
с помощью метода .describe()
data iqr new.describe()

Out[5]:

	Соотношение матрица- наполнитель	Плотность, кг/м3	модуль упругости, ГПа	Количество отвердителя, м.%	Содержание эпоксидных групп,%_2	Температура вспышки, С_2
count	920.000000	920.000000	920.000000	920.000000	920.000000	920.000000
mean	2.926372	1974.155232	735.557925	111.153473	22.197906	286.208267
std	0.895102	71.066017	327.740846	26.778743	2.395341	39.453365
min	0.547391	1784.482245	2.436909	38.668500	15.695894	179.374391
25%	2.319283	1923.443748	498.438068	92.781590	20.555086	259.218101
50%	2.907832	1977.321002	734.464332	111.183627	22.166307	286.220763
75%	3.548025	2020.158764	956.411813	130.164272	23.955936	313.029126

max	5.314144	2161.565216	1628.000000	181.828448	28.955094	386.067992
-----	----------	-------------	-------------	------------	-----------	------------

```
In [6]: # проверим, есть ли пропущенные значения
        data_iqr_new.isnull().sum()
Out[6]: Соотношение матрица-наполнитель
                                                 0
        Плотность, кг/м3
                                                 0
        модуль упругости, ГПа
                                                 0
        Количество отвердителя, м.%
                                                 0
        Содержание эпоксидных групп,% 2
                                                 0
        Температура вспышки, С 2
                                                 0
        Поверхностная плотность, г/м2
                                                 0
        Модуль упругости при растяжении, ГПа
                                                0
        Прочность при растяжении, МПа
                                                 0
        Потребление смолы, г/м2
                                                 0
                                                 0
        Угол нашивки
                                                 0
        Шаг нашивки
        Плотность нашивки
                                                 0
        dtype: int64
```

In [7]: # посчитаем коэффициент корреляции для всего датафрейма и округлим значен
получается корреляционная матрица
corr_matrix=data_iqr_new.corr()
corr matrix

Out[7]:

	Соотношение матрица- наполнитель	Плотность, кг/м3	модуль упругости, ГПа	Количество отвердителя, м.%	Содержание эпоксидных групп,%_2	Темпеј всп
Соотношение матрица- наполнитель	1.000000	0.009873	0.050317	0.002223	0.020305	-0.0
Плотность, кг/ м3	0.009873	1.000000	-0.000982	-0.049445	0.005589	-0.0
модуль упругости, ГПа	0.050317	-0.000982	1.000000	0.045107	-0.002341	0.0
Количество отвердителя, м.%	0.002223	-0.049445	0.045107	1.000000	0.011945	0.0
Содержание эпоксидных групп,%_2	0.020305	0.005589	-0.002341	0.011945	1.000000	-0.0
Температура вспышки, С_2	-0.010702	-0.020804	0.038188	0.070592	-0.025338	1.0
Поверхностная плотность, г/ м2	0.012439	0.062258	-0.006213	0.038464	-0.015443	0.0
Модуль упругости при растяжении, ГПа	-0.029204	-0.012335	0.018457	-0.055980	0.051470	0.0
Прочность при растяжении, МПа	0.019667	-0.081340	0.029136	-0.065738	-0.013156	-0.0
Потребление смолы, г/м2	0.076048	-0.009816	0.006692	-0.014363	0.010113	0.0
Угол нашивки	-0.030406	-0.053618	-0.029789	0.033480	0.035715	0.0

```
        Шаг нашивки
        0.043237
        -0.050780
        0.011725
        -0.018336
        0.009404
        0.0

        Плотность нашивки
        0.045075
        0.088828
        0.078131
        0.008752
        -0.036162
        -0.0
```

```
In [8]: data iqr new.columns
\mathsf{Out}[8]: Index(['Соотношение матрица-наполнитель', 'Плотность, кг/м3',
                 'модуль упругости, ГПа', 'Количество отвердителя, м.%',
                 'Содержание эпоксидных групп, % 2', 'Температура вспышки, С 2',
                 'Поверхностная плотность, г/м2', 'Модуль упругости при растяжении,
         ГПа',
                 'Прочность при растяжении, МПа', 'Потребление смолы, г/м2',
                 'Угол нашивки', 'Шаг нашивки', 'Плотность нашивки'],
               dtype='object')
        # отберем признаки и поместим их в переменную Х
 In [9]:
         x=data_iqr_new[['Плотность, кг/м3',
                 'модуль упругости, ГПа', 'Количество отвердителя, м.%',
                 'Содержание эпоксидных групп,\S_2', 'Температура вспышки, С_2',
                 'Поверхностная плотность, г/м2', 'Модуль упругости при растяжении,
                 'Прочность при растяжении, МПа', 'Потребление смолы, г/м2',
                 'Угол нашивки', 'Шаг нашивки', 'Плотность нашивки']]
In [10]: # целевую переменную поместим в переменную у
         y=data iqr new[['Соотношение матрица-наполнитель']]
In [11]: print(type(x), type(y))
         <class 'pandas.core.frame.DataFrame'> <class 'pandas.core.frame.DataFram</pre>
         e'>
In [12]: # разобьем данные на обучающую и тестовую выборку
          # размер тестовой выборки составит 30%
         # также зададим точку отсчета для воспроизводимости
         x train, x test, y train, y test = train test split(x, y,
                                                               test size = 0.3,
                                                               random state = 42)
In [13]: # посмотрим на новую размерность обучающей
         print(x train.shape, y train.shape)
         # и тестовой выборки
         print(x test.shape, y test.shape)
         (644, 12) (644, 1)
         (276, 12) (276, 1)
In [14]: normalizer = tf.keras.layers.Normalization(axis=-1)
         normalizer.adapt(np.array(x train))
         def build_and_compile_model(norm):
           model = keras.Sequential([
               layers.Dense(64, activation='relu'),
               layers.Dense(64, activation='relu'),
               layers.Dense(1)
           1)
           model.compile(loss='mean_squared_error',
                          optimizer=tf.keras.optimizers.Adam(0.001), metrics=['mae']
           return model
```

```
model = build_and_compile_model(normalizer)
model.summary()
```

Model: "sequential"

Epoch 12/100

```
Layer (type) Output Shape
                                    Param #
     ______
      normalization (Normalizatio (None, 12)
                                      2.5
      dense (Dense)
                      (None, 64)
                                      832
      dense 1 (Dense)
                      (None, 64)
                                      4160
      dense 2 (Dense)
                      (None, 1)
                                      65
     ______
     Total params: 5,082
     Trainable params: 5,057
     Non-trainable params: 25
In [15]: %%time
     history = model.fit(
       x train,
       y train,
       validation split=0.2,
        verbose=1, epochs=100)
     Epoch 1/100
     17/17 [=============== ] - 24s 13ms/step - loss: 6.9719 - m
     ae: 2.4424 - val loss: 3.2553 - val mae: 1.6097
     e: 1.2482 - val loss: 1.0167 - val mae: 0.8153
     Epoch 3/100
     17/17 [=======] - Os 3ms/step - loss: 1.2909 - ma
     e: 0.9181 - val loss: 1.0163 - val mae: 0.8129
     e: 0.8751 - val loss: 0.9344 - val mae: 0.7802
     Epoch 5/100
     e: 0.8486 - val_loss: 0.9283 - val_mae: 0.7747
     Epoch 6/100
     e: 0.8342 - val loss: 0.9329 - val mae: 0.7776
     Epoch 7/100
     e: 0.8227 - val loss: 0.9419 - val mae: 0.7837
     Epoch 8/100
     e: 0.8169 - val loss: 0.9391 - val mae: 0.7832
     Epoch 9/100
     17/17 [=======] - Os 3ms/step - loss: 0.9730 - ma
     e: 0.8044 - val loss: 0.9323 - val mae: 0.7797
     Epoch 10/100
     e: 0.7970 - val loss: 0.9460 - val mae: 0.7929
     Epoch 11/100
     e: 0.7841 - val loss: 0.9251 - val mae: 0.7815
```

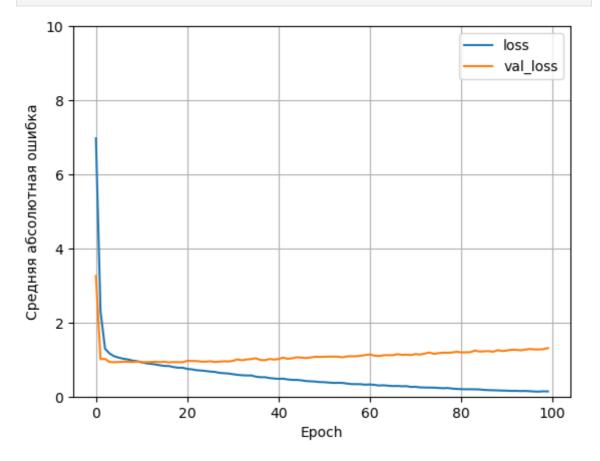
```
e: 0.7744 - val loss: 0.9318 - val mae: 0.7893
Epoch 13/100
e: 0.7679 - val loss: 0.9325 - val mae: 0.7893
Epoch 14/100
e: 0.7623 - val loss: 0.9415 - val mae: 0.7941
Epoch 15/100
e: 0.7521 - val loss: 0.9300 - val mae: 0.7898
Epoch 16/100
e: 0.7458 - val loss: 0.9413 - val mae: 0.8026
Epoch 17/100
e: 0.7456 - val loss: 0.9230 - val mae: 0.7929
Epoch 18/100
e: 0.7314 - val loss: 0.9318 - val_mae: 0.7962
Epoch 19/100
17/17 [============] - 0s 2ms/step - loss: 0.7801 - ma
e: 0.7253 - val loss: 0.9302 - val mae: 0.8009
Epoch 20/100
e: 0.7242 - val loss: 0.9269 - val mae: 0.7994
Epoch 21/100
e: 0.7081 - val_loss: 0.9652 - val_mae: 0.8137
Epoch 22/100
e: 0.6987 - val loss: 0.9611 - val mae: 0.8112
Epoch 23/100
e: 0.6901 - val loss: 0.9599 - val mae: 0.8119
Epoch 24/100
17/17 [======== ] - Os 3ms/step - loss: 0.7039 - ma
e: 0.6864 - val loss: 0.9456 - val mae: 0.8049
Epoch 25/100
e: 0.6811 - val loss: 0.9419 - val mae: 0.8048
Epoch 26/100
17/17 [======== ] - Os 3ms/step - loss: 0.6756 - ma
e: 0.6698 - val loss: 0.9544 - val mae: 0.8071
Epoch 27/100
e: 0.6649 - val_loss: 0.9341 - val_mae: 0.8003
Epoch 28/100
e: 0.6519 - val_loss: 0.9430 - val_mae: 0.8036
Epoch 29/100
17/17 [===========] - 0s 3ms/step - loss: 0.6318 - ma
e: 0.6476 - val loss: 0.9541 - val mae: 0.8079
Epoch 30/100
e: 0.6437 - val loss: 0.9481 - val mae: 0.8048
Epoch 31/100
17/17 [=======] - Os 3ms/step - loss: 0.6052 - ma
e: 0.6345 - val loss: 0.9671 - val mae: 0.8068
Epoch 32/100
17/17 [===========] - 0s 3ms/step - loss: 0.5877 - ma
e: 0.6204 - val loss: 1.0044 - val mae: 0.8261
Epoch 33/100
e: 0.6126 - val loss: 0.9810 - val mae: 0.8116
```

```
Epoch 34/100
17/17 [=========== ] - 0s 4ms/step - loss: 0.5701 - ma
e: 0.6096 - val loss: 1.0027 - val mae: 0.8228
Epoch 35/100
e: 0.6124 - val loss: 1.0143 - val mae: 0.8216
Epoch 36/100
e: 0.5935 - val loss: 1.0354 - val mae: 0.8340
Epoch 37/100
e: 0.5840 - val loss: 0.9891 - val mae: 0.8143
Epoch 38/100
17/17 [======== ] - Os 3ms/step - loss: 0.5235 - ma
e: 0.5825 - val loss: 0.9821 - val mae: 0.8098
Epoch 39/100
e: 0.5709 - val loss: 1.0160 - val mae: 0.8231
Epoch 40/100
e: 0.5643 - val loss: 0.9993 - val mae: 0.8198
Epoch 41/100
e: 0.5563 - val loss: 1.0154 - val mae: 0.8285
Epoch 42/100
e: 0.5610 - val_loss: 1.0524 - val_mae: 0.8373
Epoch 43/100
e: 0.5443 - val loss: 1.0198 - val mae: 0.8267
Epoch 44/100
e: 0.5362 - val loss: 1.0345 - val_mae: 0.8310
Epoch 45/100
e: 0.5395 - val loss: 1.0623 - val mae: 0.8344
Epoch 46/100
e: 0.5328 - val loss: 1.0518 - val mae: 0.8327
Epoch 47/100
e: 0.5153 - val loss: 1.0409 - val mae: 0.8345
Epoch 48/100
17/17 [======== ] - Os 3ms/step - loss: 0.4125 - ma
e: 0.5104 - val_loss: 1.0557 - val_mae: 0.8348
Epoch 49/100
e: 0.5107 - val loss: 1.0744 - val_mae: 0.8404
Epoch 50/100
e: 0.4980 - val loss: 1.0709 - val mae: 0.8487
Epoch 51/100
e: 0.4946 - val loss: 1.0756 - val mae: 0.8476
Epoch 52/100
e: 0.4910 - val loss: 1.0783 - val mae: 0.8393
Epoch 53/100
e: 0.4840 - val loss: 1.0791 - val mae: 0.8407
Epoch 54/100
e: 0.4861 - val loss: 1.0777 - val mae: 0.8521
Epoch 55/100
```

```
17/17 [=======] - Os 3ms/step - loss: 0.3694 - ma
e: 0.4905 - val loss: 1.0607 - val mae: 0.8282
Epoch 56/100
17/17 [=========== ] - 0s 2ms/step - loss: 0.3519 - ma
e: 0.4682 - val loss: 1.0852 - val mae: 0.8528
Epoch 57/100
e: 0.4592 - val loss: 1.0906 - val mae: 0.8524
Epoch 58/100
17/17 [=========== ] - 0s 6ms/step - loss: 0.3368 - ma
e: 0.4607 - val loss: 1.0895 - val mae: 0.8437
Epoch 59/100
e: 0.4559 - val loss: 1.1038 - val mae: 0.8688
Epoch 60/100
e: 0.4458 - val_loss: 1.1216 - val_mae: 0.8596
Epoch 61/100
e: 0.4516 - val loss: 1.1365 - val_mae: 0.8637
Epoch 62/100
e: 0.4404 - val loss: 1.1061 - val mae: 0.8646
Epoch 63/100
17/17 [======== ] - Os 3ms/step - loss: 0.2996 - ma
e: 0.4308 - val loss: 1.0959 - val mae: 0.8616
Epoch 64/100
e: 0.4356 - val loss: 1.1143 - val mae: 0.8597
Epoch 65/100
e: 0.4286 - val loss: 1.1191 - val mae: 0.8711
Epoch 66/100
e: 0.4209 - val loss: 1.1167 - val mae: 0.8731
Epoch 67/100
e: 0.4186 - val loss: 1.1447 - val mae: 0.8821
Epoch 68/100
e: 0.4134 - val loss: 1.1262 - val mae: 0.8810
Epoch 69/100
17/17 [=======] - Os 3ms/step - loss: 0.2823 - ma
e: 0.4218 - val loss: 1.1317 - val mae: 0.8787
Epoch 70/100
e: 0.4008 - val_loss: 1.1217 - val_mae: 0.8717
Epoch 71/100
e: 0.4046 - val loss: 1.1479 - val mae: 0.8740
Epoch 72/100
e: 0.3909 - val loss: 1.1355 - val mae: 0.8814
Epoch 73/100
e: 0.3855 - val loss: 1.1611 - val mae: 0.8897
Epoch 74/100
e: 0.3797 - val loss: 1.1893 - val mae: 0.9106
Epoch 75/100
17/17 [===========] - 0s 3ms/step - loss: 0.2412 - ma
e: 0.3807 - val loss: 1.1543 - val mae: 0.8916
Epoch 76/100
```

```
e: 0.3795 - val loss: 1.1719 - val mae: 0.9024
Epoch 77/100
e: 0.3707 - val loss: 1.1859 - val mae: 0.9040
Epoch 78/100
e: 0.3757 - val loss: 1.1842 - val mae: 0.8903
Epoch 79/100
e: 0.3600 - val loss: 1.1899 - val mae: 0.9032
Epoch 80/100
e: 0.3497 - val loss: 1.2103 - val mae: 0.9098
Epoch 81/100
e: 0.3506 - val loss: 1.1931 - val mae: 0.9071
Epoch 82/100
e: 0.3417 - val loss: 1.1960 - val_mae: 0.9115
Epoch 83/100
17/17 [======== ] - Os 2ms/step - loss: 0.1989 - ma
e: 0.3471 - val loss: 1.1977 - val_mae: 0.9144
Epoch 84/100
e: 0.3461 - val loss: 1.2446 - val mae: 0.9188
Epoch 85/100
e: 0.3342 - val_loss: 1.2163 - val_mae: 0.9170
Epoch 86/100
e: 0.3291 - val loss: 1.2235 - val mae: 0.9203
Epoch 87/100
e: 0.3187 - val loss: 1.2282 - val mae: 0.9240
Epoch 88/100
17/17 [======== ] - Os 3ms/step - loss: 0.1712 - ma
e: 0.3185 - val loss: 1.2115 - val mae: 0.9169
Epoch 89/100
e: 0.3131 - val loss: 1.2528 - val mae: 0.9358
Epoch 90/100
e: 0.3026 - val loss: 1.2298 - val mae: 0.9272
Epoch 91/100
e: 0.3089 - val loss: 1.2449 - val mae: 0.9360
Epoch 92/100
e: 0.2953 - val_loss: 1.2647 - val_mae: 0.9409
Epoch 93/100
e: 0.2977 - val loss: 1.2637 - val mae: 0.9360
Epoch 94/100
e: 0.2952 - val loss: 1.2491 - val mae: 0.9353
Epoch 95/100
17/17 [=======] - Os 3ms/step - loss: 0.1531 - ma
e: 0.2976 - val loss: 1.2682 - val mae: 0.9429
Epoch 96/100
e: 0.2853 - val loss: 1.2855 - val mae: 0.9514
Epoch 97/100
e: 0.2818 - val loss: 1.2747 - val mae: 0.9462
```

```
Epoch 98/100
      17/17 [=========== ] - 0s 3ms/step - loss: 0.1337 - ma
      e: 0.2752 - val loss: 1.2734 - val mae: 0.9437
      Epoch 99/100
      e: 0.2858 - val loss: 1.2785 - val mae: 0.9439
      Epoch 100/100
      e: 0.2840 - val loss: 1.3110 - val mae: 0.9551
      Wall time: 29.1 s
In [16]: mae=model.evaluate(x test, y test, verbose=1)
      0.9175
In [17]: def plot loss(history):
        plt.plot(history.history['loss'], label='loss')
        plt.plot(history.history['val loss'], label='val loss')
        plt.ylim([0, 10])
        plt.xlabel('Epoch')
        plt.ylabel('Средняя абсолютная ошибка')
        plt.legend()
        plt.grid(True)
In [18]: plot_loss(history)
```



```
Model Results:
Model_MAE: 1
Model_MAPE: 0.41
Test score: 1.31
```

```
In [20]: # 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'Tectoble и прогнозные значения: {model_name}')
    plt.plot(orig, label = 'Tect')
    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), 'C
```

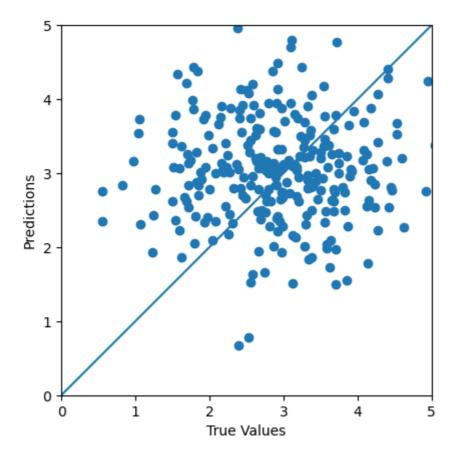
```
9/9 [======] - 0s 2ms/step
```



```
In [21]: test_predictions = model.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



In [22]: pip install scikeras

Requirement already satisfied: scikeras in c:\users\55944\anaconda\lib\si te-packages (0.10.0)

Requirement already satisfied: scikit-learn>=1.0.0 in c:\users\55944\anac onda\lib\site-packages (from scikeras) (1.0.2)

Requirement already satisfied: packaging>=0.21 in c:\users\55944\anaconda \lib\site-packages (from scikeras) (21.3)

Requirement already satisfied: pyparsing!=3.0.5,>=2.0.2 in c:\users\55944 \anaconda\lib\site-packages (from packaging>=0.21->scikeras) (3.0.9)

Requirement already satisfied: numpy>=1.14.6 in c:\users\55944\anaconda\l ib\site-packages (from scikit-learn>=1.0.0->scikeras) (1.21.5)

Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\55944\ana conda\lib\site-packages (from scikit-learn>=1.0.0->scikeras) (2.2.0)

Requirement already satisfied: joblib>=0.11 in c:\users\55944\anaconda\lib\site-packages (from scikit-learn>=1.0.0->scikeras) (1.1.0)

Requirement already satisfied: scipy>=1.1.0 in c:\users\55944\anaconda\lib\site-packages (from scikit-learn>=1.0.0->scikeras) (1.9.1)

Note: you may need to restart the kernel to use updated packages.

```
In [23]: from keras.wrappers.scikit_learn import KerasRegressor
import numpy as np
import tensorflow as tf
from sklearn.model_selection import GridSearchCV
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
```

```
In [24]: from tensorflow.keras.layers import Dropout
```

```
In [25]: def create_model_1(lyrs=[32], act='softmax', optimizer='adam', dr=0.1):
    seed = 7
    np.random.seed(seed)
    tf.random.set_seed(seed)
```

```
model_1 = Sequential()
model_1.add(Dense(lyrs[0], input_dim=x_train.shape[1], activation=act
for i in range(1,len(lyrs)):
    model_1.add(Dense(lyrs[i], activation=act))

model_1.add(Dropout(dr))
model_1.add(Dense(1)) # выходной слой

model_1.compile(loss='mean_squared_error', optimizer='adam', metrics=
return model_1
```

WARNING:tensorflow:5 out of the last 14 calls to <function Model.make_tes t_function.<locals>.test_function at 0x0000015E74DE8B80> triggered tf.fun ction retracing. Tracing is expensive and the excessive number of tracing s could be due to (1) creating @tf.function repeatedly in a loop, (2) pas sing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. Fo r (2), @tf.function has reduce_retracing=True option that can avoid unnec essary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_doc s/python/tf/function for more details.

WARNING:tensorflow:5 out of the last 13 calls to <function Model.make_test_function.<locals>.test_function at 0x0000015E72814F70> triggered tf.function retracing. Tracing is expensive and the excessive number of tracing s could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnected essary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.

```
Best: -0.808694 using {'batch_size': 10, 'epochs': 100}
-3.535093 (0.521314) with: {'batch_size': 10, 'epochs': 10}
-0.821332 (0.153429) with: {'batch_size': 10, 'epochs': 50}
-0.808694 (0.160369) with: {'batch_size': 10, 'epochs': 100}
-5.811971 (1.550652) with: {'batch_size': 20, 'epochs': 10}
-1.264936 (0.368176) with: {'batch_size': 20, 'epochs': 50}
-0.823463 (0.156108) with: {'batch_size': 20, 'epochs': 100}
-6.063465 (0.749669) with: {'batch_size': 20, 'epochs': 10}
-2.107765 (0.460876) with: {'batch_size': 30, 'epochs': 50}
-0.884638 (0.170303) with: {'batch_size': 30, 'epochs': 100}
-6.888370 (1.225409) with: {'batch_size': 40, 'epochs': 50}
-3.311201 (0.985067) with: {'batch_size': 40, 'epochs': 50}
-1.228713 (0.412477) with: {'batch_size': 40, 'epochs': 50}
```

```
-7.086890 (1.509289) with: {'batch size': 50, 'epochs': 10}
      -3.150868 (0.657717) with: {'batch size': 50, 'epochs': 50}
      -1.566316 (0.340155) with: {'batch size': 50, 'epochs': 100}
In [27]: model 1 = KerasRegressor(build fn=create model 1, epochs=100, batch size=
      optimizer = ['SGD', 'RMSprop', 'Adagrad', 'Adadelta', 'Adam', 'Nadam']
      param grid = dict(optimizer=optimizer)
      grid = GridSearchCV(estimator=model 1, param grid=param grid, cv=10, verb
      grid result = grid.fit(x train, y train)
      Fitting 10 folds for each of 6 candidates, totalling 60 fits
      [CV] END ......optimizer=SGD; total time=
      6.2s
      [CV] END .....optimizer=SGD; total time=
      [CV] END .....optimizer=SGD; total time=
      6.2s
      [CV] END .....optimizer=SGD; total time=
      [CV] END ......optimizer=SGD; total time=
      5.8s
      [CV] END .....optimizer=SGD; total time=
      5.9s
      [CV] END .....optimizer=SGD; total time=
      [CV] END .....optimizer=SGD; total time=
      [CV] END .....optimizer=SGD; total time=
      [CV] END ......optimizer=SGD; total time=
      5.8s
      [CV] END ......optimizer=RMSprop; total time=
      [CV] END ......optimizer=RMSprop; total time=
      6.3s
      [CV] END .....optimizer=RMSprop; total time=
      6.2s
      [CV] END ......optimizer=RMSprop; total time=
      6.2s
      [CV] END ......optimizer=RMSprop; total time=
      [CV] END ......optimizer=RMSprop; total time=
      5.8s
      [CV] END ......optimizer=RMSprop; total time=
      6.5s
      [CV] END .....optimizer=RMSprop; total time=
      5.8s
      [CV] END ......optimizer=RMSprop; total time=
      6.3s
      [CV] END ......optimizer=RMSprop; total time=
      6.0s
      [CV] END ......optimizer=Adagrad; total time=
      6.25
      [CV] END ......optimizer=Adagrad; total time=
      [CV] END .....optimizer=Adagrad; total time=
      6.2s
      [CV] END ......optimizer=Adagrad; total time=
      6.3s
      [CV] END .....optimizer=Adagrad; total time=
      [CV] END .....optimizer=Adagrad; total time=
```

5.9s				
[CV]	END	optimizer=Adagrad;	total	time=
	END	optimizer=Adagrad;	total	time=
5.8s [CV]	END	optimizer=Adagrad;	total	time=
5.8s [CV]	END	optimizer=Adagrad;	total	time=
6.0s	END	optimizer=Adadelta;	total	time=
6.3s		optimizer=Adadelta;		
6.2s		-		
6.2s		optimizer=Adadelta;		
[CV] 6.0s	END	optimizer=Adadelta;	total	time=
[CV] 5.9s	END	optimizer=Adadelta;	total	time=
[CV] 5.8s	END	optimizer=Adadelta;	total	time=
	END	optimizer=Adadelta;	total	time=
[CV]	END	optimizer=Adadelta;	total	time=
	END	optimizer=Adadelta;	total	time=
	END	optimizer=Adadelta;	total	time=
6.0s [CV]	END	optimizer=Adam;	total	time=
6.2s [CV]	END	optimizer=Adam;	total	time=
6.3s [CV]	END	optimizer=Adam;	total	time=
6.6s				
6.1s		optimizer=Adam;		
6.0s		optimizer=Adam;		
6.0s				
6.0s		optimizer=Adam;		
[CV] 6.4s	END	optimizer=Adam;	total	time=
[CV] 5.9s	END	optimizer=Adam;	total	time=
[CV] 5.8s	END	optimizer=Adam;	total	time=
[CV]	END	optimizer=Nadam;	total	time=
	END	optimizer=Nadam;	total	time=
[CV]		optimizer=Nadam;	total	time=
		optimizer=Nadam;	total	time=
	END	optimizer=Nadam;	total	time=
5.9s [CV]	END	optimizer=Nadam;	total	time=
5.8s [CV]	END	optimizer=Nadam;	total	time=
5.9s				
				-

```
5.98
       [CV] END .....optimizer=Nadam; total time=
       [CV] END ......optimizer=Nadam; total time=
       5.9s
In [28]: # результаты
       print("Best: %f using %s" % (grid result.best score , grid result.best pa
       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: -0.807970 using {'optimizer': 'Adagrad'}
       -0.808197 (0.160460) with: {'optimizer': 'SGD'}
       -0.809522 (0.160431) with: {'optimizer': 'RMSprop'}
       -0.807970 (0.159451) with: {'optimizer': 'Adagrad'}
       -0.808436 (0.159496) with: {'optimizer': 'Adadelta'}
       -0.808260 (0.159257) with: {'optimizer': 'Adam'}
       -0.808976 (0.159796) with: {'optimizer': 'Nadam'}
In [29]: model 1 = KerasRegressor(build fn=create model 1, epochs=100, batch size=
       layers = [[8],[16, 2],[32, 8, 2],[12, 6, 1], [64, 64, 3], [128, 64, 16, 3
       param grid = dict(lyrs=layers)
       grid = GridSearchCV(estimator=model_1, param_grid=param_grid, cv=10, verb
       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=
       [CV] END .....lyrs=[8]; total time=
       6.1s
       [CV] END ......lyrs=[8]; total time=
       6.1s
       [CV] END .....lyrs=[8]; total time=
       [CV] END ......lyrs=[8]; total time=
       5.8s
       [CV] END .....lyrs=[8]; total time=
       5.8s
       [CV] END ......lyrs=[8]; total time=
       6.2s
       [CV] END ......lyrs=[8]; total time=
       [CV] END ......lyrs=[8]; total time=
       5.8s
       [CV] END ......lyrs=[8]; total time=
       5.8s
       [CV] END .....lyrs=[16, 2]; total time=
       [CV] END ......lyrs=[16, 2]; total time=
       6.7s
       [CV] END .....lyrs=[16, 2]; total time=
       [CV] END ......lyrs=[16, 2]; total time=
       [CV] END .....lyrs=[16, 2]; total time=
       [CV] END .....lyrs=[16, 2]; total time=
       [CV] END .....lyrs=[16, 2]; total time=
```

6.20			
6.2s [CV] ENDlyrs=[16, 2	2];	total	time=
6.2s [CV] ENDlyrs=[16, 2	2];	total	time=
6.4s [CV] ENDlyrs=[16, 2	2];	total	time=
6.6s [CV] ENDlyrs=[32, 8, 2	2];	total	time=
7.2s [CV] ENDlyrs=[32, 8, 2	2];	total	time=
7.0s [CV] ENDlyrs=[32, 8, 2	2];	total	time=
7.2s [CV] ENDlyrs=[32, 8, 2	2];	total	time=
7.1s [CV] ENDlyrs=[32, 8, 2	2];	total	time=
6.8s [CV] ENDlyrs=[32, 8, 2	2];	total	time=
6.9s [CV] ENDlyrs=[32, 8, 2			
6.7s [CV] ENDlyrs=[32, 8, 2			
6.9s [CV] ENDlyrs=[32, 8, 2			
6.8s [CV] ENDlyrs=[32, 8, 2			
6.8s [CV] ENDlyrs=[12, 6, 1			
7.6s			
[CV] ENDlyrs=[12, 6, 17.0s			
[CV] ENDlyrs=[12, 6, 17.0s			
[CV] ENDlyrs=[12, 6, 1 6.9s			
[CV] ENDlyrs=[12, 6, 1 6.8s			
[CV] ENDlyrs=[12, 6, 1 6.7s	l];	total	time=
[CV] ENDlyrs=[12, 6, 1 6.8s	l];	total	time=
[CV] ENDlyrs=[12, 6, 1 6.6s	l];	total	time=
[CV] ENDlyrs=[12, 6, 16.7s	L];	total	time=
[CV] ENDlyrs=[12, 6, 16.7s	L];	total	time=
[CV] ENDlyrs=[64, 64, 3	3];	total	time=
[CV] ENDlyrs=[64, 64, 3	3];	total	time=
7.8s [CV] ENDlyrs=[64, 64, 3	3];	total	time=
7.3s [CV] ENDlyrs=[64, 64, 3	3];	total	time=
7.6s [CV] ENDlyrs=[64, 64, 3	3];	total	time=
7.2s [CV] ENDlyrs=[64, 64, 3	3];	total	time=
7.3s [CV] ENDlyrs=[64, 64, 3	3];	total	time=
7.1s [CV] ENDlyrs=[64, 64, 3	3];	total	time=
7.2s [CV] ENDlyrs=[64, 64, 3	3];	total	time=

```
[CV] END .....lyrs=[64, 64, 3]; total time=
      7.3s
      [CV] END ......lyrs=[128, 64, 16, 3]; total time=
      8.1s
      [CV] END ......lyrs=[128, 64, 16, 3]; total time=
      8.1s
      [CV] END ......lyrs=[128, 64, 16, 3]; total time=
      [CV] END .....lyrs=[128, 64, 16, 3]; total time=
      8.7s
      [CV] END ......lyrs=[128, 64, 16, 3]; total time=
      8.3s
      [CV] END .....lyrs=[128, 64, 16, 3]; total time=
      8.2s
      [CV] END .....lyrs=[128, 64, 16, 3]; total time=
      8.0s
      [CV] END ......lyrs=[128, 64, 16, 3]; total time=
      [CV] END ......lyrs=[128, 64, 16, 3]; total time=
      7.9s
      [CV] END ......lyrs=[128, 64, 16, 3]; total time=
In [30]: # результаты
      print("Best: %f using %s" % (grid result.best score , grid result.best pa
      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: -0.807429 using {'lyrs': [8]}
      -0.807429 (0.160722) with: {'lyrs': [8]}
      -0.808426 (0.158461) with: {'lyrs': [16, 2]}
      -0.808542 (0.161404) with: {'lyrs': [32, 8, 2]}
      -0.807575 (0.159281) with: {'lyrs': [12, 6, 1]}
      -0.808248 (0.160392) with: {'lyrs': [64, 64, 3]}
      -0.809074 (0.163147) with: {'lyrs': [128, 64, 16, 3]}
In [31]: model_1 = KerasRegressor(build_fn=create_model_1, epochs=100, batch size
      drops = [0.0, 0.01, 0.05, 0.1, 0.2, 0.3, 0.5]
      param grid = dict(dr=drops)
      grid = GridSearchCV(estimator=model 1, param grid=param grid, cv=10, verb
      grid_result = grid.fit(x_train, y_train)
      Fitting 10 folds for each of 7 candidates, totalling 70 fits
      6.0s
      5.8s
      6.1s
      [CV] END .......dr=0.0; total time=
      6.0s
      6.0s
      5.98
      [CV] END ......dr=0.0; total time=
```

7.28

5.8s				
	END	dr=0.0;	total	time=
5.8s [CV]	END	dr=0.0;	total	time=
5.8s	END	dr=0.01;	total	time=
6.2s				
[CV] 6.2s	END	dr=0.01;	total	time=
[CV]	END	dr=0.01;	total	time=
	END	dr=0.01;	total	time=
	END	dr=0.01;	total	time=
	END	dr=0.01;	total	time=
[CV]	END	dr=0.01;	total	time=
	END	dr=0.01;	total	time=
5.9s [CV]	END	dr=0.01;	total	time=
5.8s	END	dr=0.01;	total	time=
6.2s		dr=0.05;		
6.1s				
[CV] 6.2s	END	dr=0.05;	total	time=
[CV] 6.1s	END	dr=0.05;	total	time=
	END	dr=0.05;	total	time=
	END	dr=0.05;	total	time=
	END	dr=0.05;	total	time=
[CV]	END	dr=0.05;	total	time=
	END	dr=0.05;	total	time=
5.9s [CV]	END	dr=0.05;	total	time=
5.8s	END	dr=0.05;	total	time=
5.9s				
6.1s		dr=0.1;		
[CV] 6.1s	END	dr=0.1;	total	time=
[CV] 6.1s	END	dr=0.1;	total	time=
[CV]	END	dr=0.1;	total	time=
	END	dr=0.1;	total	time=
[CV]	END	dr=0.1;	total	time=
	END	dr=0.1;	total	time=
5.8s [CV]	END	dr=0.1;	total	time=
5.9s [CV]	END	dr=0.1;	total	time=
5.9s		dr=0.1;		
[C v]	עווים		cocar	CINC

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5.98
6.25
6.2s
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5.8s
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6.2s
5.8s
5.9s
5.9s
5.8s
5.9s
6.1s
6.2s
6.2s
6.0s
6.1s
[CV] END ......dr=0.5; total time=
5.8s
6.1s
```

```
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: -0.804978 using {'dr': 0.01}
       -0.809019 (0.164376) with: {'dr': 0.0}
       -0.804978 (0.163927) with: {'dr': 0.01}
       -0.805363 (0.161511) with: {'dr': 0.05}
       -0.824838 (0.174830) with: {'dr': 0.1}
       -0.810791 (0.158583) with: {'dr': 0.2}
       -0.809039 (0.159315) with: {'dr': 0.3}
       -0.810640 (0.159274) with: {'dr': 0.5}
In [45]: # построение окончательной модели
       model 1 = create model 1(lyrs=[12,8,4], dr=0.01)
       print(model 1.summary())
       Model: "sequential 347"
        Layer (type)
                              Output Shape
                                                    Param #
       ______
        dense 797 (Dense)
                               (None, 12)
                                                     156
        dense 798 (Dense)
                               (None, 8)
                                                     104
        dense 799 (Dense)
                                (None, 4)
                                                     36
        dropout 346 (Dropout)
                                                     \cap
                                (None, 4)
        dense 800 (Dense)
                               (None, 1)
       ______
       Total params: 301
       Trainable params: 301
       Non-trainable params: 0
       None
In [46]: # обучаем нейросеть, 80/20 CV
       model 1 hist = model 1.fit(x train,
          y_train,
           epochs = 100,
           verbose = 1,
           validation split = 0.2)
       Epoch 1/100
       17/17 [=========== ] - 1s 10ms/step - loss: 8.6813 - ma
       e: 2.8024 - val loss: 8.9237 - val mae: 2.8663
       17/17 [======== ] - Os 3ms/step - loss: 8.3863 - ma
       e: 2.7501 - val loss: 8.6337 - val mae: 2.8153
       Epoch 3/100
       17/17 [========] - Os 4ms/step - loss: 8.1075 - ma
       e: 2.6994 - val loss: 8.3523 - val mae: 2.7648
       Epoch 4/100
       e: 2.6509 - val loss: 8.0760 - val mae: 2.7144
       Epoch 5/100
       17/17 [=========== ] - Os 3ms/step - loss: 7.5735 - ma
       e: 2.5980 - val loss: 7.8098 - val mae: 2.6649
       Epoch 6/100
```

```
e: 2.5496 - val loss: 7.5459 - val mae: 2.6149
Epoch 7/100
e: 2.4981 - val loss: 7.2905 - val mae: 2.5656
Epoch 8/100
e: 2.4518 - val loss: 7.0409 - val mae: 2.5165
Epoch 9/100
e: 2.4008 - val loss: 6.7920 - val mae: 2.4666
Epoch 10/100
e: 2.3520 - val loss: 6.5526 - val mae: 2.4175
Epoch 11/100
e: 2.3025 - val loss: 6.3189 - val mae: 2.3687
Epoch 12/100
e: 2.2532 - val loss: 6.0873 - val_mae: 2.3193
Epoch 13/100
17/17 [======== ] - Os 3ms/step - loss: 5.6718 - ma
e: 2.2024 - val loss: 5.8616 - val mae: 2.2701
Epoch 14/100
e: 2.1509 - val loss: 5.6368 - val mae: 2.2201
Epoch 15/100
e: 2.1030 - val_loss: 5.4218 - val_mae: 2.1711
Epoch 16/100
e: 2.0551 - val loss: 5.2089 - val_mae: 2.1219
Epoch 17/100
e: 2.0043 - val loss: 4.9934 - val mae: 2.0713
Epoch 18/100
17/17 [======== ] - Os 3ms/step - loss: 4.6374 - ma
e: 1.9547 - val loss: 4.7886 - val mae: 2.0220
Epoch 19/100
e: 1.9097 - val loss: 4.5893 - val mae: 1.9734
Epoch 20/100
17/17 [======== ] - Os 4ms/step - loss: 4.2584 - ma
e: 1.8597 - val loss: 4.3932 - val mae: 1.9245
Epoch 21/100
e: 1.8100 - val_loss: 4.2029 - val_mae: 1.8759
Epoch 22/100
e: 1.7588 - val_loss: 4.0201 - val_mae: 1.8278
Epoch 23/100
17/17 [===========] - 0s 3ms/step - loss: 3.7383 - ma
e: 1.7159 - val loss: 3.8446 - val mae: 1.7805
Epoch 24/100
e: 1.6730 - val loss: 3.6808 - val mae: 1.7351
Epoch 25/100
17/17 [=======] - Os 3ms/step - loss: 3.4071 - ma
e: 1.6238 - val loss: 3.5143 - val mae: 1.6880
Epoch 26/100
17/17 [===========] - 0s 3ms/step - loss: 3.2807 - ma
e: 1.5849 - val loss: 3.3589 - val mae: 1.6433
Epoch 27/100
e: 1.5382 - val loss: 3.2086 - val mae: 1.5993
```

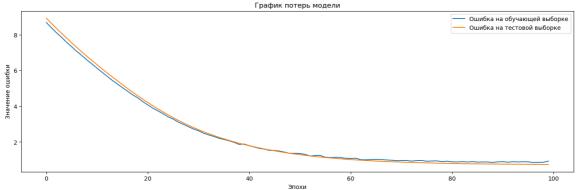
```
Epoch 28/100
17/17 [=========== ] - 0s 3ms/step - loss: 2.9877 - ma
e: 1.4974 - val loss: 3.0707 - val mae: 1.5580
Epoch 29/100
e: 1.4539 - val loss: 2.9359 - val mae: 1.5170
Epoch 30/100
e: 1.4168 - val loss: 2.8061 - val mae: 1.4770
Epoch 31/100
e: 1.3849 - val loss: 2.6869 - val mae: 1.4400
Epoch 32/100
17/17 [======== ] - Os 3ms/step - loss: 2.4897 - ma
e: 1.3411 - val loss: 2.5714 - val mae: 1.4035
Epoch 33/100
e: 1.3109 - val loss: 2.4639 - val mae: 1.3685
Epoch 34/100
e: 1.2767 - val loss: 2.3622 - val mae: 1.3345
Epoch 35/100
e: 1.2456 - val loss: 2.2670 - val mae: 1.3025
Epoch 36/100
e: 1.2177 - val_loss: 2.1767 - val_mae: 1.2715
Epoch 37/100
e: 1.1975 - val loss: 2.0895 - val mae: 1.2410
Epoch 38/100
e: 1.1644 - val loss: 2.0078 - val_mae: 1.2118
Epoch 39/100
e: 1.1271 - val loss: 1.9289 - val mae: 1.1832
Epoch 40/100
e: 1.1234 - val loss: 1.8565 - val mae: 1.1562
Epoch 41/100
e: 1.0920 - val loss: 1.7897 - val mae: 1.1304
Epoch 42/100
e: 1.0691 - val_loss: 1.7250 - val_mae: 1.1049
Epoch 43/100
e: 1.0418 - val loss: 1.6650 - val mae: 1.0812
Epoch 44/100
e: 1.0278 - val loss: 1.6072 - val mae: 1.0587
Epoch 45/100
e: 1.0030 - val loss: 1.5543 - val mae: 1.0385
Epoch 46/100
e: 0.9950 - val loss: 1.5024 - val mae: 1.0185
Epoch 47/100
e: 0.9798 - val loss: 1.4532 - val mae: 0.9991
Epoch 48/100
e: 0.9600 - val loss: 1.4072 - val mae: 0.9808
Epoch 49/100
```

```
e: 0.9400 - val loss: 1.3615 - val mae: 0.9622
Epoch 50/100
17/17 [===========] - 0s 3ms/step - loss: 1.3643 - ma
e: 0.9324 - val loss: 1.3212 - val mae: 0.9463
Epoch 51/100
17/17 [=======] - Os 3ms/step - loss: 1.3543 - ma
e: 0.9265 - val loss: 1.2872 - val mae: 0.9328
Epoch 52/100
17/17 [=========== ] - 0s 3ms/step - loss: 1.3045 - ma
e: 0.9152 - val loss: 1.2514 - val mae: 0.9185
Epoch 53/100
e: 0.8802 - val loss: 1.2166 - val mae: 0.9043
Epoch 54/100
e: 0.8819 - val_loss: 1.1854 - val_mae: 0.8917
Epoch 55/100
e: 0.8776 - val loss: 1.1552 - val_mae: 0.8795
Epoch 56/100
e: 0.8504 - val loss: 1.1281 - val mae: 0.8681
Epoch 57/100
17/17 [======== ] - Os 3ms/step - loss: 1.1230 - ma
e: 0.8428 - val loss: 1.1022 - val mae: 0.8574
Epoch 58/100
e: 0.8459 - val loss: 1.0781 - val mae: 0.8472
Epoch 59/100
e: 0.8446 - val loss: 1.0553 - val mae: 0.8374
Epoch 60/100
e: 0.8260 - val loss: 1.0336 - val mae: 0.8278
Epoch 61/100
e: 0.8206 - val loss: 1.0137 - val mae: 0.8190
Epoch 62/100
e: 0.8265 - val loss: 0.9951 - val mae: 0.8108
Epoch 63/100
17/17 [======== ] - Os 3ms/step - loss: 1.0106 - ma
e: 0.8004 - val loss: 0.9773 - val mae: 0.8030
Epoch 64/100
e: 0.7948 - val loss: 0.9617 - val mae: 0.7960
Epoch 65/100
e: 0.7967 - val loss: 0.9454 - val mae: 0.7890
Epoch 66/100
e: 0.7994 - val loss: 0.9304 - val mae: 0.7825
Epoch 67/100
e: 0.7930 - val loss: 0.9169 - val mae: 0.7769
Epoch 68/100
e: 0.7888 - val loss: 0.9049 - val mae: 0.7723
Epoch 69/100
17/17 [==========] - 0s 3ms/step - loss: 0.9782 - ma
e: 0.7816 - val loss: 0.8939 - val mae: 0.7681
Epoch 70/100
```

```
e: 0.7754 - val loss: 0.8823 - val mae: 0.7636
Epoch 71/100
e: 0.7729 - val loss: 0.8716 - val mae: 0.7594
Epoch 72/100
e: 0.7692 - val loss: 0.8611 - val mae: 0.7555
Epoch 73/100
e: 0.7647 - val loss: 0.8527 - val mae: 0.7523
Epoch 74/100
e: 0.7740 - val loss: 0.8447 - val mae: 0.7493
Epoch 75/100
e: 0.7685 - val loss: 0.8367 - val mae: 0.7461
Epoch 76/100
e: 0.7584 - val loss: 0.8283 - val mae: 0.7427
Epoch 77/100
17/17 [=======] - Os 3ms/step - loss: 0.9333 - ma
e: 0.7608 - val loss: 0.8204 - val mae: 0.7394
Epoch 78/100
e: 0.7606 - val loss: 0.8137 - val mae: 0.7364
Epoch 79/100
e: 0.7533 - val_loss: 0.8067 - val_mae: 0.7336
Epoch 80/100
e: 0.7591 - val loss: 0.8005 - val_mae: 0.7312
Epoch 81/100
e: 0.7479 - val loss: 0.7941 - val mae: 0.7287
Epoch 82/100
17/17 [=======] - Os 3ms/step - loss: 0.8785 - ma
e: 0.7452 - val loss: 0.7893 - val mae: 0.7267
Epoch 83/100
e: 0.7529 - val loss: 0.7851 - val mae: 0.7249
Epoch 84/100
e: 0.7432 - val loss: 0.7804 - val mae: 0.7229
Epoch 85/100
e: 0.7469 - val_loss: 0.7759 - val_mae: 0.7210
Epoch 86/100
e: 0.7390 - val_loss: 0.7720 - val_mae: 0.7193
Epoch 87/100
e: 0.7450 - val loss: 0.7704 - val mae: 0.7186
Epoch 88/100
e: 0.7461 - val loss: 0.7680 - val mae: 0.7175
Epoch 89/100
17/17 [=======] - Os 3ms/step - loss: 0.8523 - ma
e: 0.7390 - val loss: 0.7642 - val mae: 0.7157
Epoch 90/100
17/17 [===========] - 0s 3ms/step - loss: 0.8831 - ma
e: 0.7485 - val loss: 0.7613 - val mae: 0.7144
Epoch 91/100
e: 0.7470 - val loss: 0.7581 - val mae: 0.7129
```

```
Epoch 92/100
       17/17 [=========== ] - Os 2ms/step - loss: 0.8648 - ma
       e: 0.7427 - val loss: 0.7561 - val mae: 0.7120
       Epoch 93/100
       e: 0.7448 - val loss: 0.7538 - val mae: 0.7109
       Epoch 94/100
       e: 0.7425 - val loss: 0.7529 - val mae: 0.7104
       Epoch 95/100
       e: 0.7478 - val loss: 0.7515 - val mae: 0.7097
       Epoch 96/100
       e: 0.7480 - val loss: 0.7491 - val mae: 0.7085
       Epoch 97/100
       17/17 [==========] - 0s 3ms/step - loss: 0.8505 - ma
       e: 0.7348 - val loss: 0.7470 - val mae: 0.7074
       Epoch 98/100
       e: 0.7400 - val loss: 0.7456 - val mae: 0.7068
       Epoch 99/100
       e: 0.7415 - val loss: 0.7432 - val mae: 0.7055
       Epoch 100/100
       e: 0.7598 - val_loss: 0.7415 - val_mae: 0.7048
In [47]: # оценим модель
       scores = model 1.evaluate(x test, y test)
       print("\n%s: %.2f%%" % (model 1.metrics names[1], scores[1]*100))
       9/9 [======== ] - 0s 3ms/step - loss: 0.8063 - mae:
       0.7136
       mae: 71.36%
In [48]:
      # Посмотрим на график потерь на тренировочной и тестовой выборках
       def model_1_loss_plot(model_1_hist):
         plt.figure(figsize = (17,5))
         plt.plot(model 1 hist.history['loss'],
                label = 'ошибка на обучающей выборке')
         plt.plot(model 1 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 выборк
         plt.show()
       model_1_loss_plot(model_1_hist)
                              График потерь модели
                                                  Ошибка на обучающей выборке

    Ошибка на тестовой выборке
```



```
In [49]: # 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'Tecтовые и прогнозные значения: {model_name}')
    plt.plot(orig, label = 'Tect')
    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_1.predict(x_test.values),
```

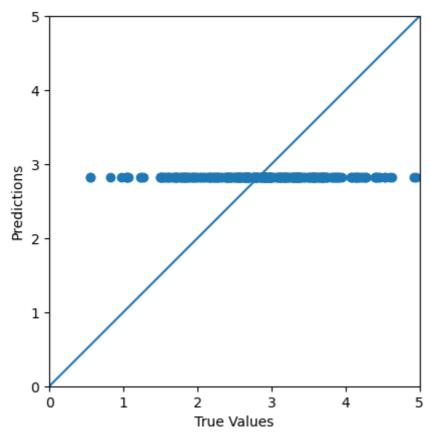
```
9/9 [=======] - 0s 0s/step
```



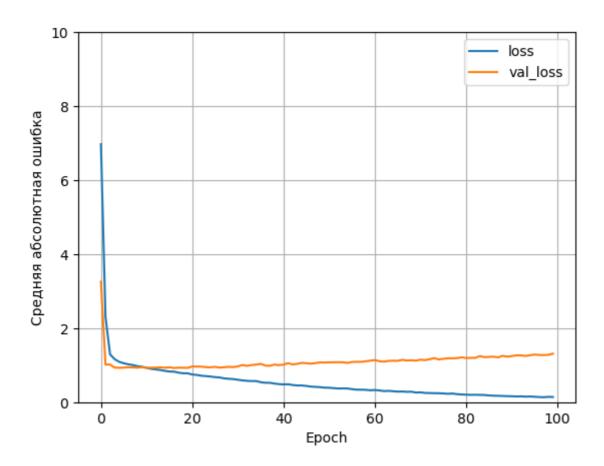
```
In [50]: test_predictions = model_1.predict(x_test).flatten()

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 0s/step



```
In [1]: #Сохраним первый вариант нейросети и проверим ее загрузку
In [51]: model.save('App/model/NEIRO')
         WARNING:absl:Found untraced functions such as _update_step_xla while savi
         ng (showing 1 of 1). These functions will not be directly callable after
         loading.
         INFO:tensorflow:Assets written to: App/model/NEIRO\assets
         INFO:tensorflow:Assets written to: App/model/NEIRO\assets
In [52]: model_loaded = keras.models.load_model('App/model/NEIRO')
In [53]: model_loaded.evaluate(x_test, y_test)
         9/9 [=======] - Os 813us/step - loss: 1.3124 - ma
         e: 0.9175
         [1.3124141693115234, 0.9174538850784302]
Out[53]:
In [54]: def plot loss(history):
           plt.plot(history.history['loss'], label='loss')
           plt.plot(history.history['val_loss'], label='val_loss')
           plt.ylim([0, 10])
           plt.xlabel('Epoch')
           plt.ylabel('Средняя абсолютная ошибка')
           plt.legend()
           plt.grid(True)
In [55]: plot_loss(history)
```



In []: