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Факультет «Информатика, искусственный и системы управления»

Кафедра «Системы обработки информации и управления»

Отчет по Лабораторной работе №6

«*Анализ и прогнозирование*

временного ряда»

по дисциплине «Технология машинного обучения»

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In [7]:
```
import numpy as np
import pandas as pd
from matplotlib import pyplot
import matplotlib.pyplot as plt
```

In [8]:
```
df = pd.read_csv('births.csv', index_col = "Date", parse_dates = True)
```

In [9]:
```
df.head()
```

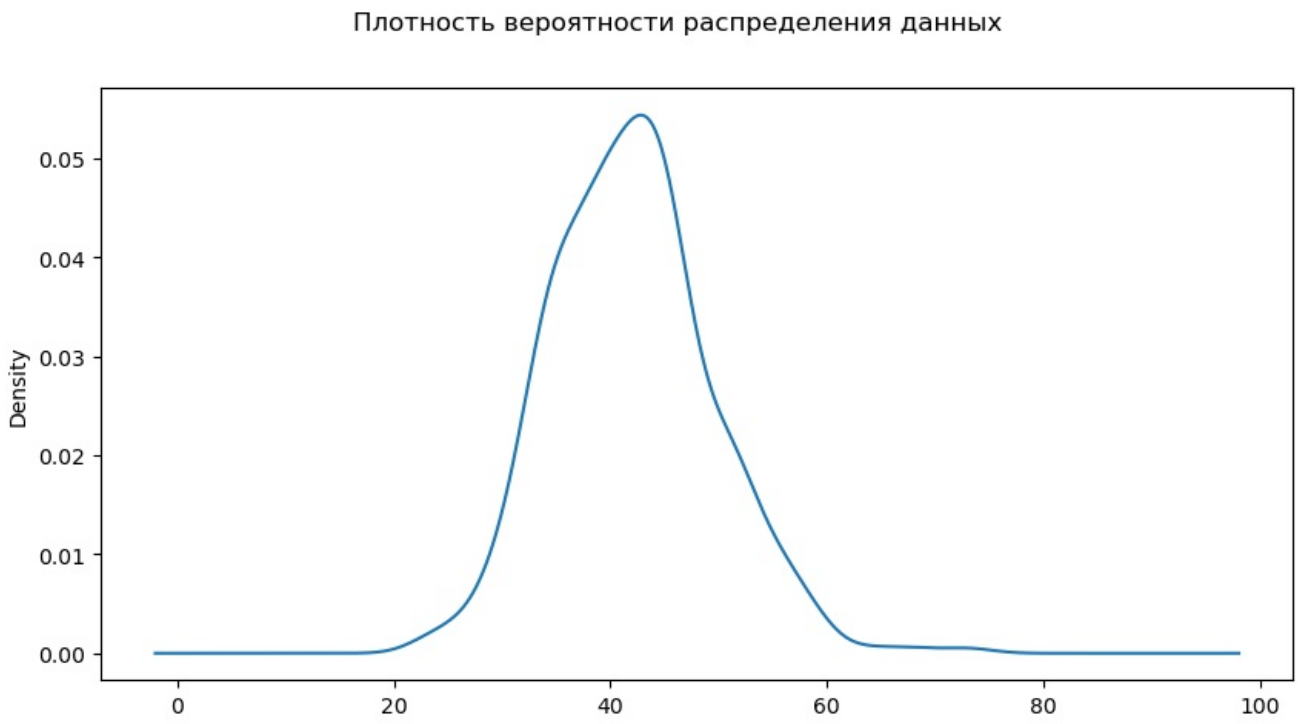
Out[9]:

Date	Births
1959-01-01	35
1959-01-02	32
1959-01-03	30
1959-01-04	31
1959-01-05	44

In [10]:
```
df.shape
```

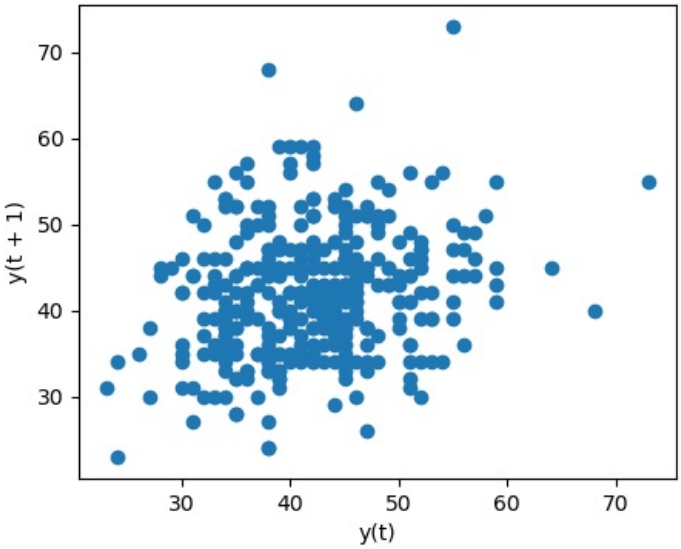
Out[10]:
```
(365, 1)
```

In [11]:
```
fig, ax = pyplot.subplots(1, 1, sharex='col', sharey='row', figsize=(10,5))
fig.suptitle('Плотность вероятности распределения данных')
df.plot(ax=ax, kind='kde', legend=False)
pyplot.show()
```

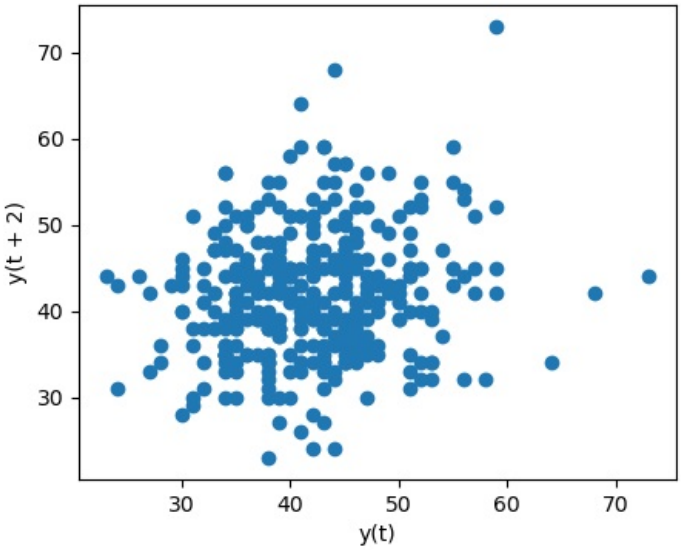


In [12]:
```
for i in range(1, 5):
    fig, ax = pyplot.subplots(1, 1, sharex='col', sharey='row', figsize=(5,4))
    fig.suptitle(f'Лаг порядка {i}')
    pd.plotting.lag_plot(df, lag=i, ax=ax)
    pyplot.show()
```

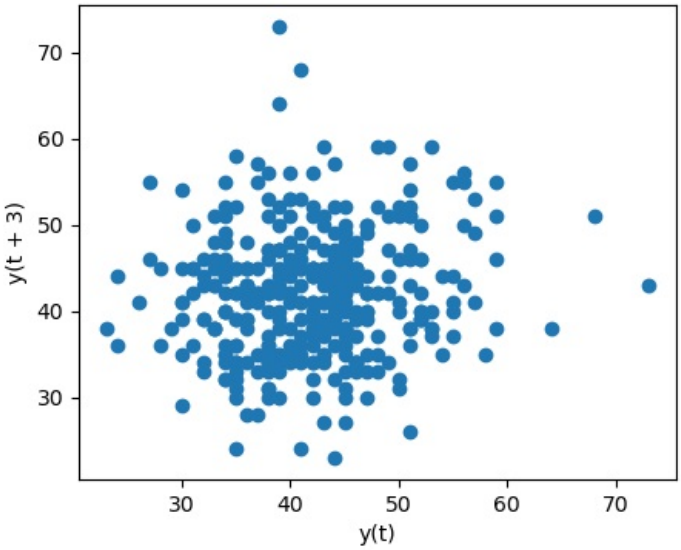
Лаг порядка 1



Лаг порядка 2

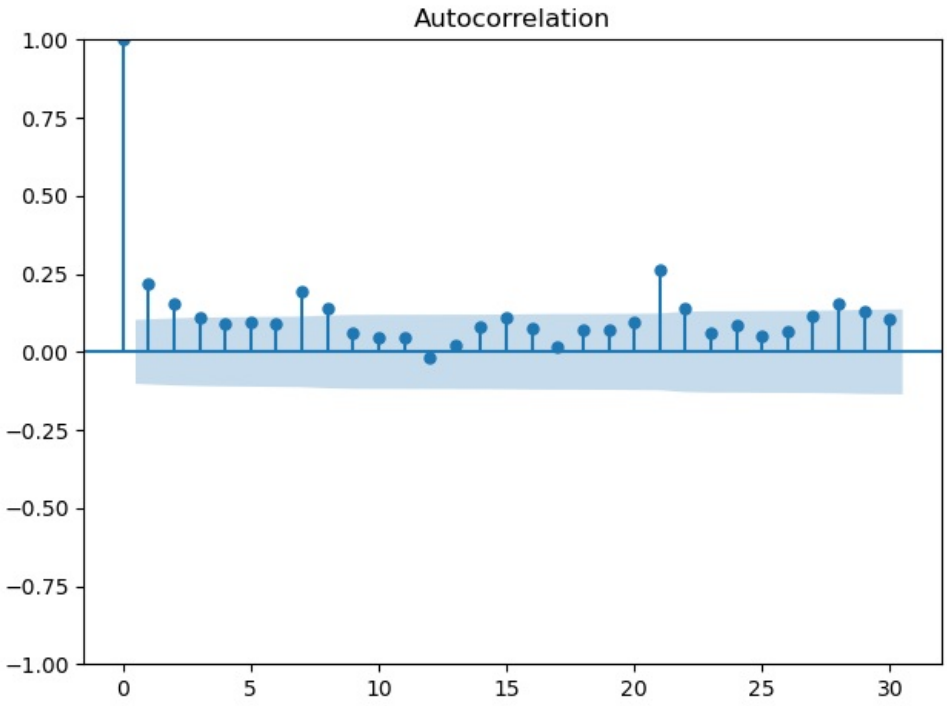


Лаг порядка 3



In [13]:
```
fig, ax = pyplot.subplots(1, 1, sharex='col', sharey='row', figsize=(10,5))
fig.suptitle('Автокорреляционная диаграмма')
pd.plotting.autocorrelation_plot(df, ax=ax)
pyplot.show()
```

In [14]:
```
from statsmodels.graphics.tsaplots import plot_acf
plot_acf(df, lags=30)
plt.tight_layout()
```



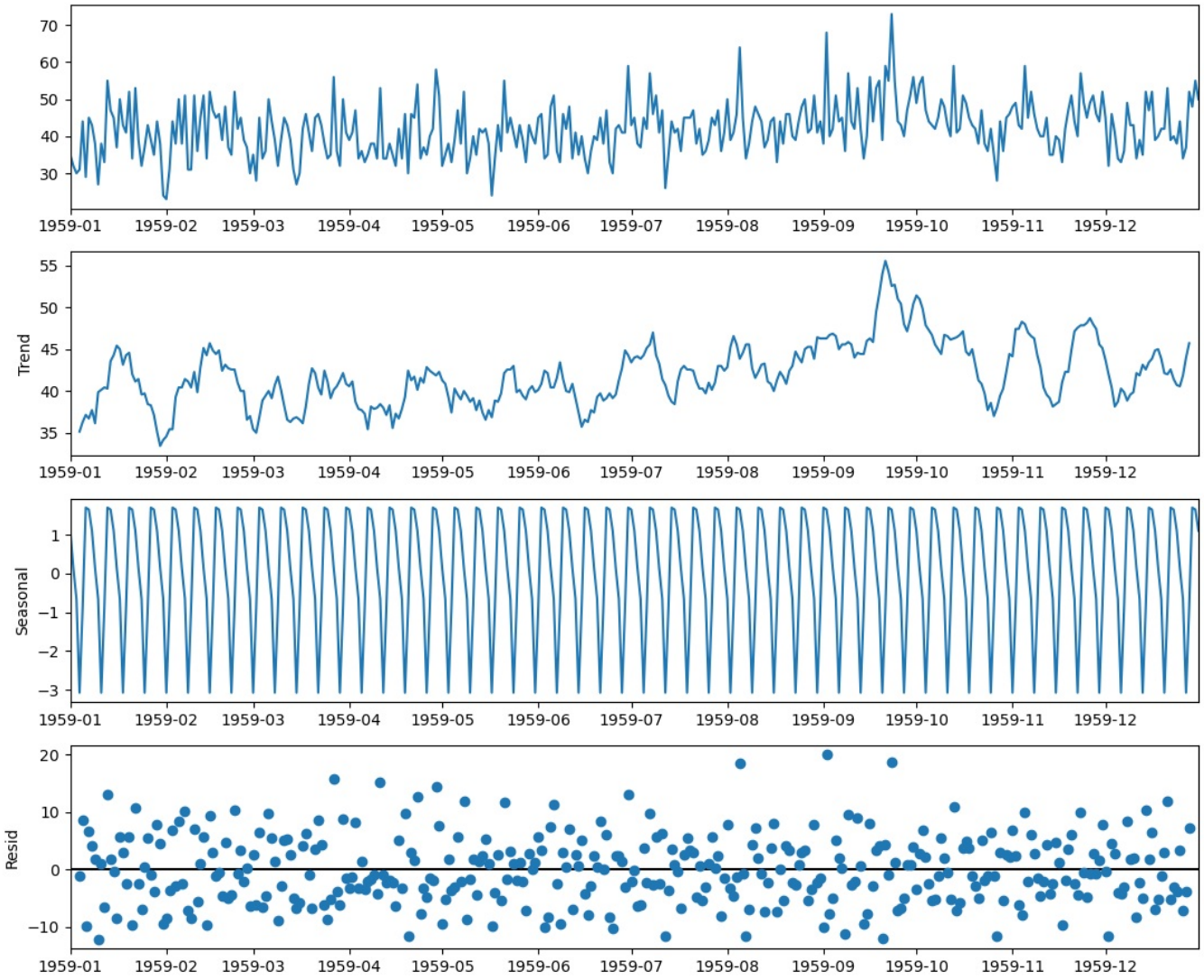
In [15]:
```
df.index = pd.to_datetime(df.index)
```

In [16]:
```
# импортируем функцию seasonal_decompose из statsmodels
from statsmodels.tsa.seasonal import seasonal_decompose

# задаем размер графика
from pylab import rcParams
rcParams['figure.figsize'] = 11, 9

# применяем функцию к данным
decompose = seasonal_decompose(df)
decompose.plot()

plt.show()
```



In [17]:

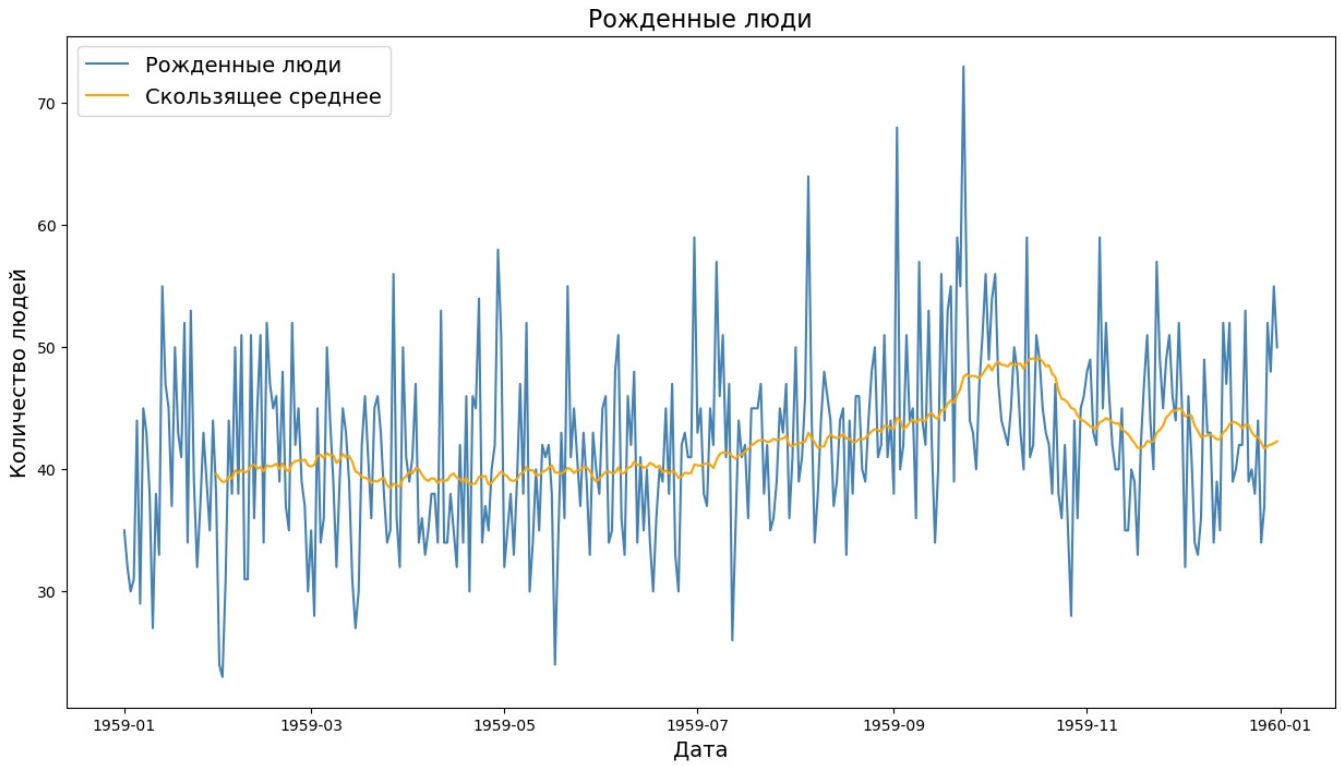
```
# зададим размер графика
plt.figure(figsize = (15,8))

# поочередно зададим кривые (перевозки и скользящее среднее) с подписями и цветом
plt.plot(df, label = 'Рожденные люди', color = 'steelblue')
plt.plot(df.rolling(window = 30).mean(), label = 'Скользящее среднее', color = 'orange')

# добавим легенду, ее положение на графике и размер шрифта
plt.legend(title = '', loc = 'upper left', fontsize = 14)

# добавим подписи к осям и заголовки
plt.xlabel('Дата', fontsize = 14)
plt.ylabel('Количество людей', fontsize = 14)
plt.title('Рожденные люди', fontsize = 16)

# выведем обе кривые на одном графике
plt.show()
```



In [18]:
```
# импортируем необходимую функцию
from statsmodels.tsa.stattools import adfuller

# передадим ей столбец с данными о перевозках и поместим результат в adf_test
adf_test = adfuller(df['Births'])

# выведем p-value
print('p-value = ' + str(adf_test[1]))
```

```
p-value = 5.243412990149949e-05
```

In [19]:
```
from statsmodels.tsa.holtwinters import ExponentialSmoothing
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.arima.model import ARIMA
```

In [20]:
```
xnum = list(range(df.shape[0]))
Y = df['Births'].values
train_size = int(len(Y) * 0.7)
xnum_train, xnum_test = xnum[0:train_size], xnum[train_size:]
train, test = Y[0:train_size], Y[train_size:]
```

In [21]:
```
history_arima = [x for x in train]
history_es = [x for x in train]
```

In [22]:
```
arima_order = (6,1,0)
```

In [23]:
```
predictions_arima = list()
for t in range(len(test)):
    model_arima = ARIMA(history_arima, order=arima_order)
    model_arima_fit = model_arima.fit()
    yhat_arima = model_arima_fit.forecast()[0]
    predictions_arima.append(yhat_arima)
    history_arima.append(test[t])
```

In [24]:
```
error_arima = mean_squared_error(test, predictions_arima, squared=False)
```

In [25]:
```
predictions_es = list()
for t in range(len(test)):
    model_es = ExponentialSmoothing(history_es)
    model_es_fit = model_es.fit()
    yhat_es = model_es_fit.forecast()[0]
    predictions_es.append(yhat_es)
    history_es.append(test[t])
```

In [26]:
```
error_es = mean_squared_error(test, predictions_es, squared=False)
```

In [29]:
```
print("MSE ARIMA: ", error_arima)
print("MSE HWES: ", error_es)
```

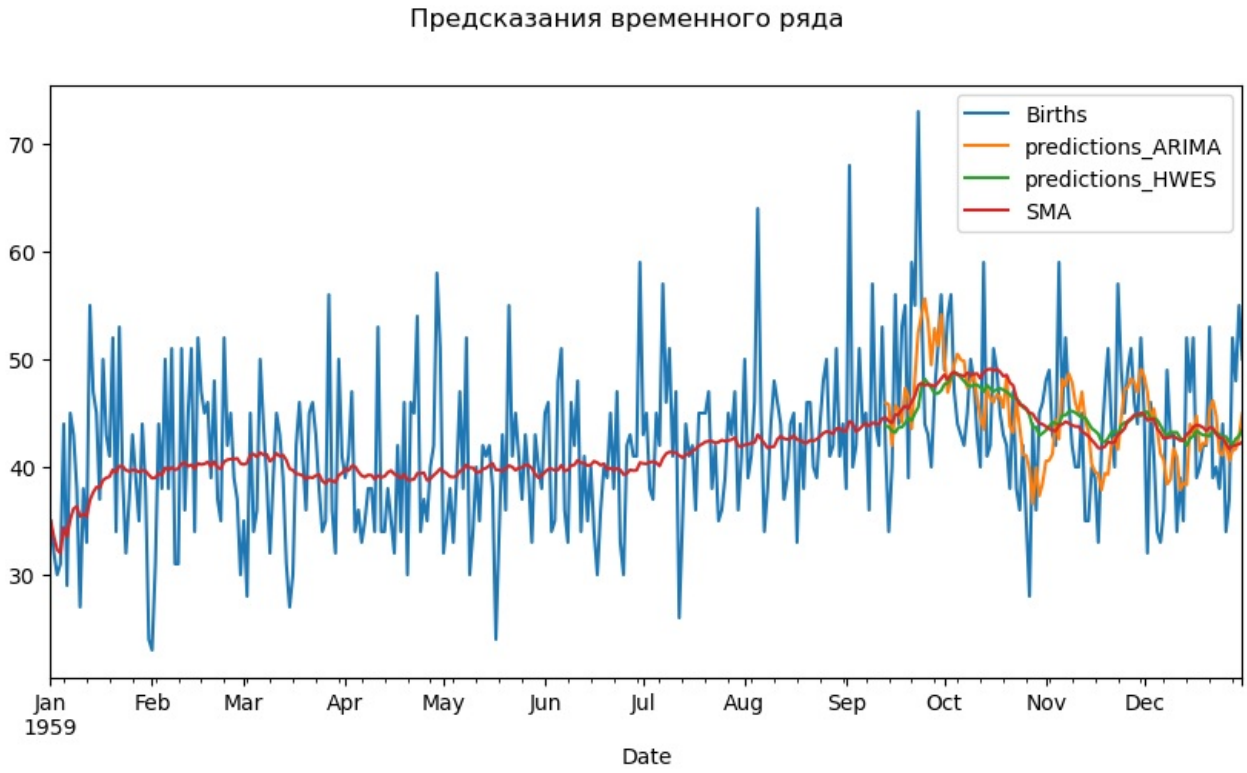
```
MSE ARIMA:  7.082306329654917
MSE HWES:  7.217016868586756
```

In [37]:
```
df['predictions_ARIMA'] = (train_size * [np.NAN]) + list(predictions_arima)
```

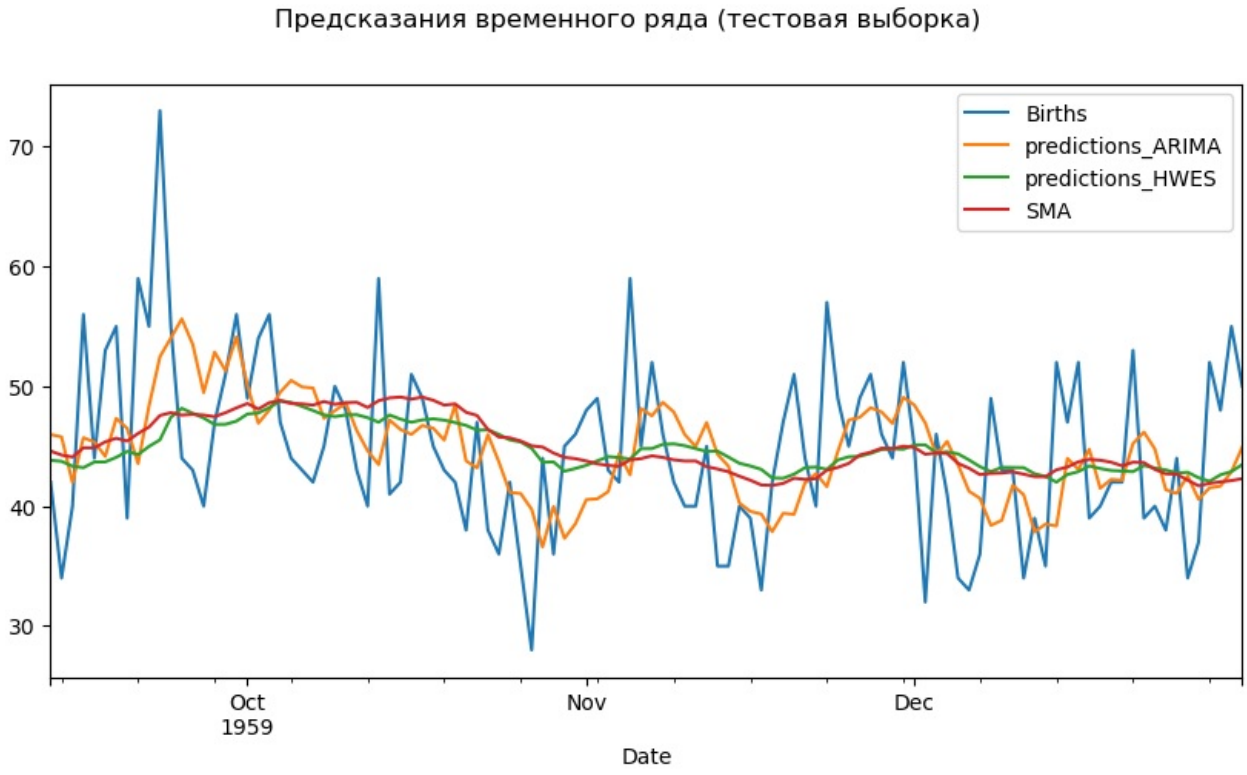
```
df['predictions_HWES'] = (train_size * [np.NAN]) + list(predictions_es)
```

In [40]:
```
df['SMA'] = df['Births'].rolling(30, min_periods=1).mean()
```

In [41]:
```
fig, ax = pyplot.subplots(1, 1, sharex='col', sharey='row', figsize=(10,5))
fig.suptitle('Предсказания временного ряда')
df.plot(ax=ax, legend=True)
pyplot.show()
```



In [42]:
```
fig, ax = pyplot.subplots(1, 1, sharex='col', sharey='row', figsize=(10,5))
fig.suptitle('Предсказания временного ряда (тестовая выборка)')
df[train_size:].plot(ax=ax, legend=True)
pyplot.show()
```



ARIMA и HWES близки к скользящему среднему

In [45]:
```
from gplearn.genetic import SymbolicRegressor
```

%pip install gplearn

In [46]:
```
function_set = ['add', 'sub', 'mul', 'div', 'sin']
```

```
est_gp = SymbolicRegressor(population_size=500, metric='mse',
                           generations=70, stopping_criteria=0.01,
                           init_depth=(4, 10), verbose=1, function_set=function_set,
                           const_range=(-100, 100), random_state=0)
```

In [47]:
```
est_gp.fit(np.array(xnum_train).reshape(-1, 1), train.reshape(-1, 1))
```

```
C:\anaconda3\lib\site-packages\sklearn\utils\validation.py:993: DataConversionWarning: A column-vector y was pa
ssed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
    |   Population Average    |             Best Individual              |
---- ------------------------- ------------------------------------------ ----------
 Gen   Length          Fitness   Length          Fitness      OOB Fitness  Time Left
   0   263.65      7.25395e+55       26           368.24              N/A      1.93m
   1   168.80      3.08763e+11      190          137.664              N/A     57.31s
   2   187.17      1.23463e+10      190           137.64              N/A     54.87s
   3   126.69      3.36087e+22       14          63.3652              N/A     42.64s
   4   178.60      6.78824e+13       14          63.3685              N/A     53.37s
   5   123.38      1.01443e+14       10          58.1649              N/A     41.21s
   6    16.83        3.043e+14       25          57.1643              N/A     18.65s
   7    13.11      4.06308e+14        9          50.0916              N/A     19.34s
   8    15.99      4.05734e+14       22          50.0506              N/A     18.61s
   9    15.88      4.87469e+15       10          49.9905              N/A     20.16s
  10    15.11      2.53812e+15       41          49.8642              N/A     19.47s
  11    23.48      1.18829e+16       61          49.5823              N/A     19.32s
  12    26.29      2.84417e+15       19          49.2251              N/A     21.55s
  13    41.60      2.85776e+15       18          48.5365              N/A     22.46s
  14    52.15      7.12366e+15       29          48.4612              N/A     24.42s
  15    44.79      1.81606e+11      137          48.1081              N/A     22.79s
  16    38.99          37707.7      150          48.0293              N/A     21.36s
  17    57.33      5.89249e+06       59          47.2986              N/A     24.49s
  18   101.51      3.40558e+06       40          47.1072              N/A     34.02s
  19    97.39        1.701e+06       64          46.9361              N/A     28.80s
  20    67.71          30533.4      150          46.8244              N/A     24.79s
  21    73.77          59189.6       79          46.2824              N/A     25.28s
  22    85.94          37425.4      113          46.2358              N/A     26.47s
  23    97.07      1.30434e+06       61          45.8434              N/A     28.83s
  24    96.01      1.79859e+06      142          45.1803              N/A     26.86s
  25   108.38           686066      142          45.1803              N/A     28.56s
  26   130.18      1.06313e+06      154          44.8865              N/A     30.53s
  27   151.34           362193      152          44.7084              N/A     32.17s
  28   173.31          12847.7      256           44.563              N/A     37.23s
  29   170.85           708637      131          43.4877              N/A     34.96s
  30   164.65          18007.3      131          43.4877              N/A     32.21s
  31   159.97      7.12214e+06      204          43.0844              N/A     39.60s
  32   152.48           912883      204          43.0844              N/A     30.01s
  33   157.81           841393      296           42.874              N/A     32.40s
  34   202.25      2.11938e+06      321           42.627              N/A     33.46s
  35   247.06           951483      518          42.5981              N/A     36.35s
  36   252.69          22821.2      421          42.2247              N/A     36.23s
  37   276.74           245656      420          42.1337              N/A     39.97s
  38   347.55          11894.9      294           41.951              N/A     45.67s
  39   390.84       1.3304e+06      720          41.7752              N/A     48.72s
  40   410.14          254.802      762          41.7562              N/A     48.69s
  41   331.65          6379.31      466          41.0082              N/A     38.65s
  42   298.96           828984      552          40.4083              N/A     36.15s
  43   368.48           818223      551          39.8089              N/A     41.11s
  44   461.59           348617      692          39.3182              N/A     45.53s
  45   575.49          23406.9      626          39.2141              N/A     53.69s
  46   603.84          74068.7      693          38.3947              N/A     53.13s
  47   678.43          17712.6      716          38.1826              N/A     54.47s
  48   684.47          1933.23      755          37.9086              N/A     51.28s
  49   699.80           535678      755          37.7096              N/A     51.12s
  50   716.31          34874.9      741          37.7048              N/A     54.51s
  51   748.82          18785.5      808          37.4716              N/A     48.94s
  52   759.12          5933.17     1274          37.3378              N/A     47.11s
  53   747.69          34420.9     1193          36.9635              N/A     41.78s
  54   788.61           229922     1216          35.4431              N/A     40.50s
  55   845.38          11874.9     1236          35.4172              N/A     41.69s
  56  1159.01          11922.7     1216           34.917              N/A     52.82s
  57  1224.57          28908.2     1271          34.5268              N/A     51.30s
  58  1236.54           529802     1270           34.416              N/A     49.79s
  59  1233.49          214.684     1160          34.3678              N/A     41.83s
  60  1234.42           287984     1249          34.2335              N/A     39.51s
  61  1228.73          5863.85     1343          33.9161              N/A     35.58s
  62  1236.84          17811.7     1363          33.9147              N/A     31.66s
  63  1261.26          23379.8     1346           33.748              N/A     27.21s
  64  1277.07          16949.9     1346          33.2909              N/A     24.65s
  65  1274.63          17486.8     1335          33.2896              N/A     18.72s
  66  1289.95          119.186     1371          33.1259              N/A     13.63s
  67  1319.21          17531.2     2614          32.9963              N/A      9.42s
  68  1322.92          222.319     1437          33.0886              N/A      4.86s
  69  1329.79          295.903     1271          32.8986              N/A      0.00s
```

Out[47]:
```
SymbolicRegressor(const_range=(-100, 100),
                  function_set=['add', 'sub', 'mul', 'div', 'sin'],
                  generations=70, init_depth=(4, 10), metric='mse',
                  population_size=500, random_state=0, stopping_criteria=0.01,
                  verbose=1)
```

In [48]:
```
# Предсказания
y_gp = est_gp.predict(np.array(xnum_test).reshape(-1, 1))
y_gp[:10]
```

Out[48]:
```
array([40.28938386, 36.55290694, 44.0910671 , 42.43899561, 47.00219962,
       45.03593076, 39.69664985, 46.57498875, 44.92532119, 43.89997191])
```

In [49]:
```
df['predictions_GPLEARN'] = (train_size * [np.NAN]) + list(y_gp)
```

In [51]:
```
fig, ax = pyplot.subplots(1, 1, sharex='col', sharey='row', figsize=(10,5))
fig.suptitle('Предсказания временного ряда (тестовая выборка)')
df[train_size:].plot(ax=ax, legend=True)
pyplot.show()
```