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Прогнозирование заказов такси

Описание процесса

Компания агрегатор такси собрала исторические данные о заказах такси в аэропортах. Чтобы привлекать больше водителей в период пиковой нагрузки, нужно спрогнозировать количество заказов такси на следующий час. Постройте модель для такого предсказания.

Цель

Построить модель для предсказания. Значение метрики *RMSE* на тестовой выборке должно быть не больше 48.

Задачи

1. Загрузить данные и проанализировать данные.
2. Выполнить их ресемплирование по одному часу и дополнить признаки.
3. Обучить разные модели с различными гиперпараметрами. Сделать тестовую выборку размером 10% от исходных данных.
4. Проверить данные на тестовой выборке и сделать выводы.

Выбранный подход к решению

1. Для анализа временного ряда буду использовать автокорреляцию, анализ трендов и сезонности, проверку на стационарность ряда.
2. Исходя из анализа получу информацию о сезонности в данных, которую буду использовать для создания дополнительных признаков (лаг и скользящее среднее).
3. Обучу множество различных моделей - в основном линейная регрессия (с регуляризацией и без), а так же модели градиентного бустинга (Catboost и LGBM).
4. В процессе обучения лучшие гиперпараметры и метрики моделей сохраню в отдельную переменную и получу таблицу с результатами.
5. Для итогового теста выберу лучшую модель градиентного бустинга и линейную модель, и найду улучшения метрики RMSE по сравнению с dummy моделью.

Описание данных

Данные лежат в файле `taxi.csv`. Количество заказов находится в столбце `num_orders` (от англ. *number of orders*, «число заказов»).

Импорт библиотек и данных, первичный осмотр

```
!pip install catboost
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting catboost
  Downloading catboost-1.2-cp310-cp310-manylinux2014_x86_64.whl (98.6 MB)
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ent already satisfied: graphviz in /usr/local/lib/python3.10/dist-packages (from catboost) (0.20.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from catboost) (3.7.1)
```

```
Requirement already satisfied: numpy>=1.16.0 in
/usr/local/lib/python3.10/dist-packages (from catboost) (1.22.4)
Requirement already satisfied: pandas>=0.24 in
/usr/local/lib/python3.10/dist-packages (from catboost) (1.5.3)
Requirement already satisfied: scipy in
/usr/local/lib/python3.10/dist-packages (from catboost) (1.10.1)
Requirement already satisfied: plotly in
/usr/local/lib/python3.10/dist-packages (from catboost) (5.13.1)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-
packages (from catboost) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost)
(2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas>=0.24->catboost)
(2022.7.1)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost)
(1.0.7)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost)
(0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost)
(4.39.3)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost)
(1.4.4)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost)
(23.1)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost)
(8.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib->catboost)
(3.0.9)
Requirement already satisfied: tenacity>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from plotly->catboost)
(8.2.2)
Installing collected packages: catboost
Successfully installed catboost-1.2
```

Импорт библиотек

```python
# Pandas
import pandas as pd

# Seaborn
import seaborn as sns
```

```python
# Numpy
import numpy as np

# Matplotlib
import matplotlib.pyplot as plt

# Scipy
from scipy import stats as st

# Scikit-learn
from sklearn.model_selection import train_test_split, GridSearchCV,
TimeSeriesSplit
from sklearn.linear_model import (
    LinearRegression,
    Lasso,
    ElasticNet,
    Ridge
)
from sklearn.tree import DecisionTreeRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.dummy import DummyRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error,
r2_score
from sklearn.svm import LinearSVR, SVR
from sklearn.ensemble import RandomForestRegressor

# LightGMB
from lightgbm import LGBMRegressor

# Catboost
from catboost import CatBoostRegressor

# Time
import time

# Statmodels
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics import tsaplots
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.arima.model import ARIMA
```

Импорт данных

```python
data = pd.read_csv('https://code.s3.yandex.net/datasets/taxi.csv',
                   index_col=[0], parse_dates=[0])
```

Осмотр данных

```
print('Размер', data.shape)
print('Пропуски', data.isna().sum())
print('Дубликаты', data.duplicated().sum())
print('Тип', data.dtypes)
print('Монотонность', data.index.is_monotonic_increasing)
```

```
Размер (26496, 1)
Пропуски num_orders    0
dtype: int64
Дубликаты 26415
Тип num_orders    int64
dtype: object
Монотонность True
```

```
display(data.head(3))
```

```
                     num_orders
datetime
2018-03-01 00:00:00           9
2018-03-01 00:10:00          14
2018-03-01 00:20:00          28
```

Осмотр данных: вывод

- 26.5k объектов
- 1 столбец
- Пропусков нет
- Дубликаты есть
- Частота изменения - 10 минут
- Монотонные

Анализ временного ряда

- Проведу ресемплирование данных перед анализом в частоту измерения - 1 час

Ресемплирование

```
data.sort_index(inplace=True)
data = data.resample('1H').sum()
```

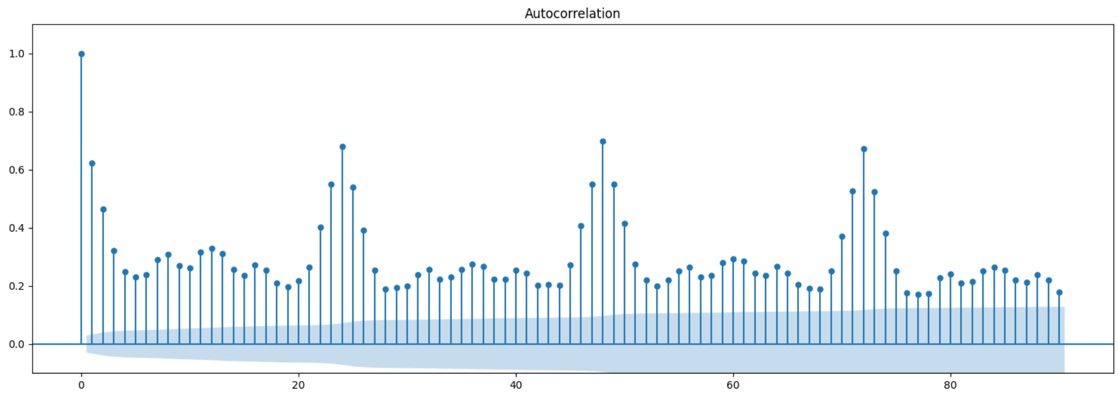
Временной период

```
print(data.index.max())
print(data.index.min())
```

```
2018-08-31 23:00:00
2018-03-01 00:00:00
```

Автокорреляция

```
fig = tsaplots.plot_acf(data['num_orders'], lags=90)
fig.set_size_inches(18.5, 6)
plt.ylim(-.1, 1.1)
plt.show()
```



Анализ трендов, сезонности

```
decomposed = seasonal_decompose(data['num_orders'])

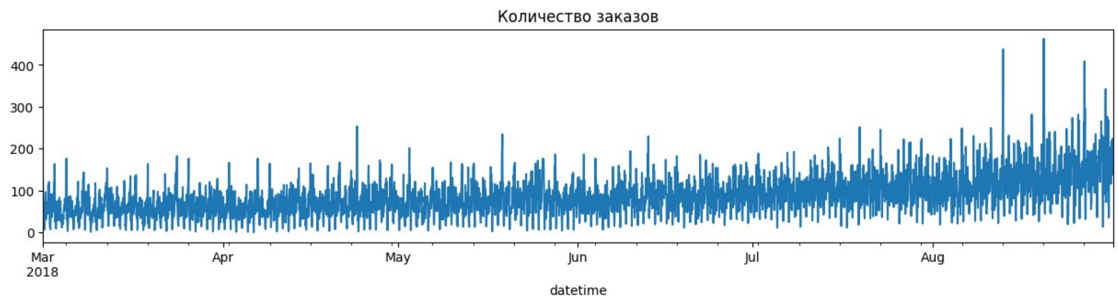
plt.figure(figsize=(15, 3))
plt.title('Количество заказов')
data['num_orders'].plot()
plt.show()

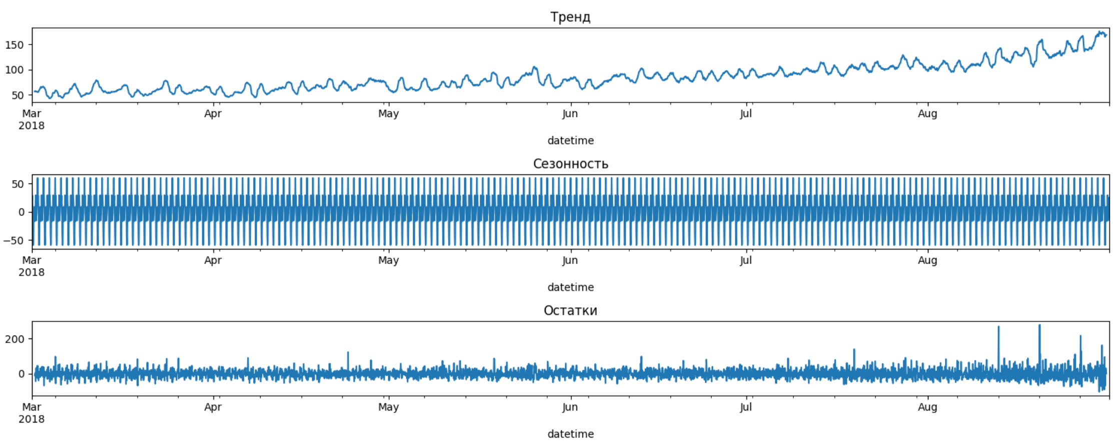
plt.figure(figsize=(15, 6))

plt.subplot(311)
decomposed.trend.plot(ax=plt.gca())
plt.title('Тренд')

plt.subplot(312)
decomposed.seasonal.plot(ax=plt.gca())
plt.title('Сезонность')

plt.subplot(313)
decomposed.resid.plot(ax=plt.gca())
plt.title('Остатки')
plt.tight_layout()
```



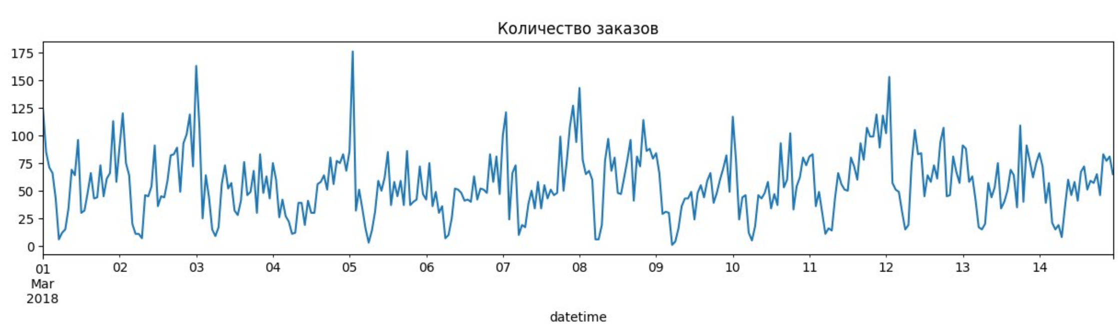


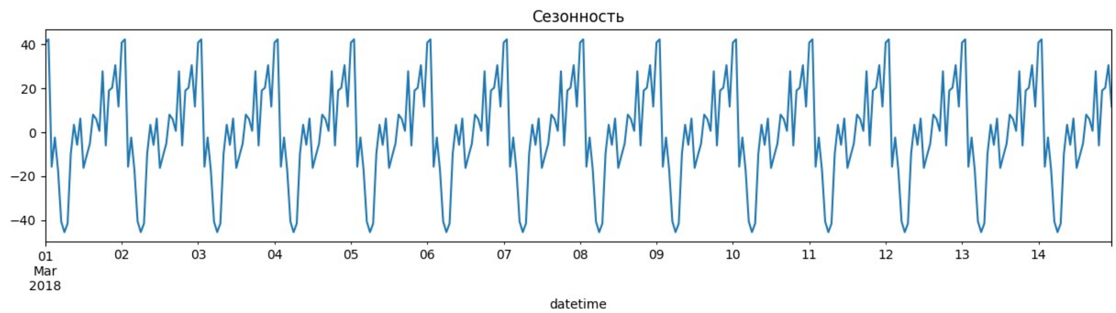
Анализ трендов, сезонности - посмотрим ближе

```
decomposed = seasonal_decompose(data['num_orders']['2018-03-01':'2018-
03-14'])

plt.figure(figsize=(15, 3))
plt.title('Количество заказов')
data['num_orders']['2018-03-01':'2018-03-14'].plot()
plt.show()

plt.figure(figsize=(15, 3))
decomposed.seasonal.plot(ax=plt.gca())
plt.title('Сезонность')
plt.show()
```





Проверка на стационарность

```
ts = data['num_orders']
st_test = adfuller(ts, regression='ctt')

print('Если значение с индексом 1 меньше P-Value, заданное нами
(обычно берут 0.05), то ряд стационарный')
if st_test[1] < 0.05:
    print('Наш ряд стационарный')
else:
    print('Ряд нестационарный')
```

```
Если значение с индексом 1 меньше P-Value, заданное нами (обычно берут
0.05), то ряд стационарный
Наш ряд стационарный
```

Анализ: вывод

- Существует тренд (количество заказов постепенно растёт), в строгом смысле данные не стационарные (хотя по тесту Дики-Фуллера являются стационарыми)
- Также существует квадратичный тренд ближе к концу данных
- Прослеживается сезонность в данных, в течении дня
- Необходимо делать минимум 24 лага для захвата интервала в сезонности, но сделаю 168 лагов, за всю неделю

Подготовка признаков

Создание признаков

Добавляю признаки:

- Связанные с датой (год, месяц, день, день недели, час)
- Лаг
- Скользящее среднее

```
# Создание функции
def make_features(data, max_lag, rolling_mean_size):
    # Date
    data['year'] = data.index.year
```

```
    data['month'] = data.index.month
    data['day'] = data.index.day
    data['day_of_week'] = data.index.dayofweek
    data['hour'] = data.index.hour
    # Lag
    for lag in range(1, max_lag + 1):
        data['lag_{}'.format(lag)] = data['num_orders'].shift(lag)
    # Rolling mean
    data['rolling_mean'] = data['num_orders'].shift().rolling(
        rolling_mean_size).mean()

# Создание признаков
make_features(data, 168, 10)
```

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highly fragmented.  This is usually the result of calling
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de-fragmented frame, use `newframe = frame.copy()`
  data['rolling_mean'] = data['num_orders'].shift().rolling(
```

Деление на трейн/тест

```
train, test = train_test_split(data, shuffle=False, test_size=0.1)
train = train.dropna()

X = train.drop('num_orders', axis=1)
y = train['num_orders']
X_test = test.drop('num_orders', axis=1)
y_test = test['num_orders']
```

Осмотр после изменения

```
display(data.head(3))
```

```
                     num_orders  year  month  day  day_of_week  hour
lag_1  \
datetime

2018-03-01 00:00:00         124  2018      3    1            3     0
NaN
2018-03-01 01:00:00          85  2018      3    1            3     1
124.0
2018-03-01 02:00:00          71  2018      3    1            3     2
85.0

                     lag_2  lag_3  lag_4  ...  lag_160  lag_161
lag_162  \
datetime                                  ...

2018-03-01 00:00:00    NaN    NaN    NaN  ...      NaN      NaN
NaN
2018-03-01 01:00:00    NaN    NaN    NaN  ...      NaN      NaN
NaN
2018-03-01 02:00:00  124.0    NaN    NaN  ...      NaN      NaN
NaN

                     lag_163  lag_164  lag_165  lag_166  lag_167
```

```
lag_168  \
datetime

2018-03-01 00:00:00      NaN      NaN      NaN      NaN      NaN
NaN
2018-03-01 01:00:00      NaN      NaN      NaN      NaN      NaN
NaN
2018-03-01 02:00:00      NaN      NaN      NaN      NaN      NaN
NaN

                     rolling_mean
datetime
2018-03-01 00:00:00           NaN
2018-03-01 01:00:00           NaN
2018-03-01 02:00:00           NaN

[3 rows x 175 columns]
```

Обучение

```
# Словарь для составления итоговой таблицы результатов
results = {}
best_parameters = {}
```

Функция для гридсерча и оценки моделей

- В этой функции использую TimeSeriesSplit

```
def model_eval_TSS(model_name, model, parameters):

    # Параметры для скоринга и кросс-валидации
    scoring = {'RMSE':'neg_root_mean_squared_error', "R2" : "r2",
'MAE' : 'neg_mean_absolute_error'}
    tscv = TimeSeriesSplit(4)

    # Гридсерч
    grid_search_model = GridSearchCV(model, parameters, cv=tscv,
scoring=scoring, n_jobs=-1, refit="RMSE")
    grid_search_model.fit(X, y)
    # Сохраняю метрики лучшей модели

    RMSE = -grid_search_model.best_score_
    MAE = -grid_search_model.cv_results_['mean_test_MAE']
[grid_search_model.best_index_]
    R2 = grid_search_model.cv_results_['mean_test_R2']
[grid_search_model.best_index_]

    # Вывод на экран метрик
    print('Метрики для модели', model_name)
    print('RMSE =', RMSE)
```

```python
    print('MAE =', MAE)
    print('R2 =', R2)
    print('Best parameters', grid_search_model.best_params_)

    # Время предсказания
    start_time = time.time()
    grid_search_model.predict(X)
    predict_time = time.time() - start_time

    # Сохраняю в общую таблицу метрики для модели
    results[model_name] = [RMSE, MAE, R2, predict_time]
    best_parameters[model_name] = grid_search_model.best_params_
    return None
```

Dummy + Arima

Dummy модель

- Создам dummy модель по предыдущему дню
- Она будет использована для сравнения с ML моделями

```python
print("Среднее количество заказов в час:",
      test['num_orders'].mean())

# Предсказания для dummy
pred_previous = test['num_orders'].shift()
pred_previous.iloc[0] = train['num_orders'].iloc[-1]

# Метрики для dummy
RMSE_d = mean_squared_error(pred_previous, test['num_orders'])**0.5
MAE_d = mean_absolute_error(pred_previous, test['num_orders'])
R2_d = r2_score(pred_previous, test['num_orders'])

# Вывожу
print("RMSE =", RMSE_d)
print('MAE =', MAE_d)
print('R2 =', R2_d)

# Сохраняю в общие результаты
results['dummy'] = [RMSE_d, MAE_d, R2_d, None]
```

```
Среднее количество заказов в час: 139.55656108597285
RMSE = 58.856486242815066
MAE = 44.97285067873303
R2 = -0.013102364208386286
```

ARIMA модель

```python
# Модель и предсказания
arima = ARIMA(data['num_orders'][:3806])
model_a = arima.fit()
```

```
y_pred = pd.Series(model_a.forecast(
    442)[0], index=data['num_orders'][3806:4416].index)
y_true = data['num_orders'][3806:4416]

# Метрики
RMSE_a = mean_squared_error(y_pred, y_true)**0.5
MAE_a = mean_absolute_error(y_pred, y_true)
R2_a = r2_score(y_pred, y_true)

# Вывожу
print("RMSE =", RMSE_a)
print('MAE =', MAE_a)
print('R2 =', R2_a)

# Сохраняю в общие результаты
results['arima'] = [RMSE_a, MAE_a, R2_a, None]
```

```
RMSE = 80.3642097404836
MAE = 63.06756286679472
R2 = 0.0
```

Линейные модели

Модель ElasticNet

```
parameters = {"alpha": [0.0001, 0.001, 0.01, 0.1, 1, 10, 100]}
model_eval_TSS('ElasticNet', ElasticNet(random_state=12345),
parameters)
```

```
Метрики для модели ElasticNet
RMSE = 22.129444434560195
MAE = 16.57932117353865
R2 = 0.6131862268326196
Best parameters {'alpha': 10}
```

Модель Lasso

```
parameters = {"alpha": [0.0001, 0.001, 0.01, 0.1, 1, 10, 100]}
model_eval_TSS('Lasso', Lasso(random_state=12345), parameters)
```

```
Метрики для модели Lasso
RMSE = 21.96109530502224
MAE = 16.425409658370967
R2 = 0.6196845683639057
Best parameters {'alpha': 10}
```

Модель Ridge

```
parameters = {"alpha": [0.0001, 0.001, 0.01, 0.1, 1, 10, 100]}
model_eval_TSS('Ridge', Ridge(random_state=12345), parameters)
```

```
Метрики для модели Ridge
RMSE = 22.859123006116082
MAE = 17.257669031425813
R2 = 0.5855943826143886
Best parameters {'alpha': 100}
```

Дерево, случайный лес, SVM

Модель решающего дерева

```
parameters = {"splitter": ["best", "random"],
              "max_depth": [1, 3, 5, 7, 9, 11, 12],
              "min_samples_leaf": [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
              "min_weight_fraction_leaf": [0.1, 0.2, 0.3, 0.4, 0.5],
              "max_features": ["auto", "log2", "sqrt", None]}
model_eval_TSS('Решающее дерево',
               DecisionTreeRegressor(random_state=12345), parameters)
```

```
Метрики для модели Решающее дерево
RMSE = 27.50896891613334
MAE = 20.26481478027594
R2 = 0.4073904165670297
Best parameters {'max_depth': 5, 'max_features': 'auto',
'min_samples_leaf': 1, 'min_weight_fraction_leaf': 0.1, 'splitter':
'best'}
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/tree/_classes.py:277:
FutureWarning: `max_features='auto'` has been deprecated in 1.1 and
will be removed in 1.3. To keep the past behaviour, explicitly set
`max_features=1.0'`.
  warnings.warn(
```

Модель случайного леса

```
parameters = {"n_estimators": [1, 10, 100, 500],
              "max_depth": [2, 4, 6, 8, 10]}
model_eval_TSS('Случайный лес',
               RandomForestRegressor(random_state=12345), parameters)
```

```
Метрики для модели Случайный лес
RMSE = 22.87200381632204
MAE = 16.801915275326667
R2 = 0.5897396476649712
Best parameters {'max_depth': 10, 'n_estimators': 500}
```

Модель SVM

```
parameters = {'kernel': ('linear', 'rbf', 'poly')}
model_eval_TSS('SVM', SVR(), parameters)
```

```
Метрики для модели SVM
RMSE = 31.301267390558685
```

```
MAE = 23.283655021610798
R2 = 0.20501983598915377
Best parameters {'kernel': 'poly'}
```

Градиентный бустинг

Модель LGBM

```
parameters = {'learning_rate': [0.01, 0.05, 0.1, 0.25, 0.5]}
model_eval_TSS('LGBMRegressor', LGBMRegressor(), parameters)
```

```
Метрики для модели LGBMRegressor
RMSE = 23.040256507744942
MAE = 16.973777479187905
R2 = 0.5831259433945055
Best parameters {'learning_rate': 0.05}
```

Модель Catboost

```
parameters = {'learning_rate': [0.01, 0.05, 0.1, 0.25, 0.5]}
model_eval_TSS('Catboost', CatBoostRegressor(
    logging_level='Silent'), parameters)
```

```
Метрики для модели Catboost
RMSE = 22.595848233043686
MAE = 16.551958739835996
R2 = 0.5994098100567953
Best parameters {'learning_rate': 0.01}
```

Модель линейной регрессии

```
model = LinearRegression()
model.fit(X[:3000], y[:3000])
y_pred = model.predict(X[3000:])
y_true = y[3000:]

# Метрики
RMSE_l = mean_squared_error(y_pred, y_true)**0.5
MAE_l = mean_absolute_error(y_pred, y_true)
R2_l = r2_score(y_pred, y_true)

# Время предсказания
start_time = time.time()
model.predict(X)
predict_time = time.time() - start_time

print("RMSE =", RMSE_l)
print('MAE =', MAE_l)
print('R2 =', R2_l)
# Сохраняю в общие результаты
results['LinearRegression'] = [RMSE_l, MAE_l, R2_l, predict_time]
```

```
RMSE = 27.091946897105835
MAE = 19.592714679134144
R2 = 0.2645719901414154
```

Тестирование

Результаты моделей получены

```
results_df = pd.DataFrame(results, index=['RMSE', 'MAE', 'R2',
'Predict_time'])

display(results_df.transpose().sort_values(by='RMSE'))
```

	RMSE	MAE	R2	Predict_time
Lasso	21.961095	16.425410	0.619685	0.014451
ElasticNet	22.129444	16.579321	0.613186	0.007385
Catboost	22.595848	16.551959	0.599410	0.013309
Ridge	22.859123	17.257669	0.585594	0.017787
Случайный лес	22.872004	16.801915	0.589740	0.205106
LGBMRegressor	23.040257	16.973777	0.583126	0.021238
LinearRegression	27.091947	19.592715	0.264572	0.027417
Решающее дерево	27.508969	20.264815	0.407390	0.003621
SVM	31.301267	23.283655	0.205020	0.713152
dummy	58.856486	44.972851	-0.013102	NaN
arima	80.364210	63.067563	0.000000	NaN

Выбираю LGBMRegressor для тестирования

```
results_df_test = pd.DataFrame(None, index=['RMSE', 'MAE', 'R2'])

best_parameters['LGBMRegressor']

{'learning_rate': 0.05}

model = LGBMRegressor(learning_rate=0.05)
model.fit(X, y)
y_pred = model.predict(X_test)

results_df_test['LGBM_test'] = [mean_squared_error(y_pred,
test['num_orders'])**0.5,
                           mean_absolute_error(y_pred,
test['num_orders']),
                           r2_score(y_pred, test['num_orders'])]
```

А также модель Lasso для тестирования

```
best_parameters['Lasso']

{'alpha': 10}

model = Lasso(alpha=10)
model.fit(X, y)
```

```
y_pred = model.predict(X_test)

results_df_test['Lasso_test'] = [mean_squared_error(y_pred, 
test['num_orders'])**0.5,
                            mean_absolute_error(y_pred, 
test['num_orders']),
                            r2_score(y_pred, test['num_orders'])]
```

Итоговый тест

```
results_df_test['LGBM_vs_dummy'] = abs(
    results_df_test['LGBM_test'] / results_df['dummy'][:3] - 1) * 100
results_df_test['Lasso_vs_dummy'] = abs(
    results_df_test['Lasso_test'] / results_df['dummy'][:3] - 1) * 100
display(results_df_test)
print('model_vs_Dummy столбец - Насколько процентов итоговая модель 
лучше Dummy')
```

	LGBM_test	Lasso_test	LGBM_vs_dummy	Lasso_vs_dummy
RMSE	36.976479	34.487655	37.175185	41.403815
MAE	26.421094	25.403447	41.251014	43.513816
R2	0.188138	0.420243	1535.910675	3307.383563

```
model_vs_Dummy столбец - Насколько процентов итоговая модель лучше 
Dummy
```

Общий вывод

- И модель Лассо и градиентный бустинг дают примерно одинаковый результат, лучше константной модели на 37-41% в метрике RMSE
- Некоторые линейные модели предсказывают быстрее чем градиентный бустинг, и в тесте они немного лучше
- Линейные модели с регуляризацией работают лучше, чем простая линейная регрессия (вероятно из-за коллинеарных признаков)