```
!pip install --upgrade sktime[all_extras]
!pip install tsai
!pip install adtk
```

```
Collecting sktime[all_extras]
  Downloading sktime-0.24.1-py3-none-any.whl (20.7 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 20.7/20.7 MB 27.3 MB/s eta
0:00:00
ent already satisfied: numpy<1.27,>=1.21 in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(1.23.5)
Requirement already satisfied: packaging in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(23.2)
Requirement already satisfied: pandas<2.2.0,>=1.1 in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(1.5.3)
Collecting scikit-base<0.7.0 (from sktime[all_extras])
  Downloading scikit_base-0.6.1-py3-none-any.whl (122 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 122.4/122.4 kB 16.0 MB/s eta
0:00:00
ent already satisfied: scikit-learn<1.4.0,>=0.24 in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(1.2.2)
Requirement already satisfied: scipy<2.0.0,>=1.2 in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(1.11.3)
Collecting arch<6.3.0,>=5.6 (from sktime[all_extras])
  Downloading arch-6.2.0-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (981 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 981.7/981.7 kB 31.3 MB/s eta
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ent already satisfied: cloudpickle in /usr/local/lib/python3.10/dist-
packages (from sktime[all_extras]) (2.2.1)
Collecting dash!=2.9.0 (from sktime[all_extras])
  Downloading dash-2.14.1-py3-none-any.whl (10.4 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 10.4/10.4 MB 54.2 MB/s eta
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ent already satisfied: dask in /usr/local/lib/python3.10/dist-packages
(from sktime[all_extras]) (2023.8.1)
Collecting dtw-python (from sktime[all_extras])
  Downloading dtw_python-1.3.0-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (645 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 645.5/645.5 kB 42.4 MB/s eta
0:00:00
 sktime[all_extras])
  Downloading gluonts-0.14.1-py3-none-any.whl (1.5 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.5/1.5 MB 31.6 MB/s eta
0:00:00
ent already satisfied: holidays in /usr/local/lib/python3.10/dist-
```

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packages (from sktime[all_extras]) (0.36)
Collecting kotsu>=0.3.1 (from sktime[all_extras])
  Downloading kotsu-0.3.3-py3-none-any.whl (14 kB)
Requirement already satisfied: matplotlib>=3.3.2 in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(3.7.1)
Collecting mne (from sktime[all_extras])
  Downloading mne-1.6.0-py3-none-any.whl (8.3 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 8.3/8.3 MB 60.2 MB/s eta
0:00:00
 sktime[all_extras])
  Downloading pycatch22-0.4.2.tar.gz (49 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 49.0/49.0 kB 3.0 MB/s eta
0:00:00
ents to build wheel ... etadata (pyproject.toml) ... an-
bardo<0.10,>=0.9.7 (from sktime[all_extras])
  Downloading pykalman_bardo-0.9.7-py2.py3-none-any.whl (244 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 244.3/244.3 kB 31.3 MB/s eta
0:00:00
ize (from sktime[all_extras])
  Downloading scikit_optimize-0.9.0-py2.py3-none-any.whl (100 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 100.3/100.3 kB 16.3 MB/s eta
0:00:00
 sktime[all_extras])
  Downloading scikit_posthocs-0.8.0-py3-none-any.whl (32 kB)
Requirement already satisfied: seaborn>=0.11 in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(0.12.2)
Collecting seasonal (from sktime[all_extras])
  Downloading seasonal-0.3.1-py2.py3-none-any.whl (18 kB)
Collecting skpro<2.2.0,>=2 (from sktime[all_extras])
  Downloading skpro-2.1.1-py3-none-any.whl (196 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 196.1/196.1 kB 29.1 MB/s eta
0:00:00
ent already satisfied: statsmodels>=0.12.1 in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(0.14.0)
Requirement already satisfied: xarray in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(2023.7.0)
Collecting filterpy>=1.4.5 (from sktime[all_extras])
  Downloading filterpy-1.4.5.zip (177 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 178.0/178.0 kB 22.3 MB/s eta
0:00:00
etadata (setup.py) ... mlearn>=0.2.7 (from sktime[all_extras])
  Downloading hmmlearn-0.3.0-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.whl (160 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 160.4/160.4 kB 23.0 MB/s eta
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 sktime[all_extras])
  Downloading keras-self-attention-0.51.0.tar.gz (11 kB)
  Preparing metadata (setup.py) ...  sktime[all_extras])
  Downloading pyod-1.1.2.tar.gz (160 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 160.5/160.5 kB 25.6 MB/s eta
0:00:00
etadata (setup.py) ... py>=1.5.1 (from sktime[all_extras])
  Downloading stumpy-1.12.0-py3-none-any.whl (169 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 169.1/169.1 kB 26.8 MB/s eta
0:00:00
 sktime[all_extras])
  Downloading tslearn-0.5.3.2-py3-none-any.whl (358 kB)
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0:00:00
ent already satisfied: h5py in /usr/local/lib/python3.10/dist-packages
(from sktime[all_extras]) (3.9.0)
Requirement already satisfied: numba<0.59,>=0.53 in
/usr/local/lib/python3.10/dist-packages (from sktime[all_extras])
(0.58.1)
Collecting pmdarima!=1.8.1,<3.0.0,>=1.8 (from sktime[all_extras])
  Downloading pmdarima-2.0.4-cp310-cp310-
manylinux_2_17_x86_64.manylinux2014_x86_64.manylinux_2_28_x86_64.whl
(2.1 MB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 2.1/2.1 MB 76.3 MB/s eta
0:00:00
ent already satisfied: prophet>=1.1 in /usr/local/lib/python3.10/dist-
packages (from sktime[all_extras]) (1.1.5)
Collecting statsforecast<1.7.0,>=0.5.2 (from sktime[all_extras])
  Downloading statsforecast-1.6.0-py3-none-any.whl (110 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 110.9/110.9 kB 15.3 MB/s eta
0:00:00
 sktime[all_extras])
  Downloading tbats-1.1.3-py3-none-any.whl (44 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 44.0/44.0 kB 7.2 MB/s eta
0:00:00
ent already satisfied: tensorflow in /usr/local/lib/python3.10/dist-
packages (from sktime[all_extras]) (2.14.0)
Collecting tsfresh>=0.17 (from sktime[all_extras])
  Downloading tsfresh-0.20.1-py2.py3-none-any.whl (95 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 95.3/95.3 kB 15.8 MB/s eta
0:00:00
ent already satisfied: Flask<3.1,>=1.0.4 in
/usr/local/lib/python3.10/dist-packages (from dash!=2.9.0-
>sktime[all_extras]) (2.2.5)
Requirement already satisfied: Werkzeug<3.1 in
/usr/local/lib/python3.10/dist-packages (from dash!=2.9.0-
>sktime[all_extras]) (3.0.1)
Requirement already satisfied: plotly>=5.0.0 in
/usr/local/lib/python3.10/dist-packages (from dash!=2.9.0-
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>sktime[all_extras]) (5.15.0)
Collecting dash-html-components==2.0.0 (from dash!=2.9.0-
>sktime[all_extras])
  Downloading dash_html_components-2.0.0-py3-none-any.whl (4.1 kB)
Collecting dash-core-components==2.0.0 (from dash!=2.9.0-
>sktime[all_extras])
  Downloading dash_core_components-2.0.0-py3-none-any.whl (3.8 kB)
Collecting dash-table==5.0.0 (from dash!=2.9.0->sktime[all_extras])
  Downloading dash_table-5.0.0-py3-none-any.whl (3.9 kB)
Requirement already satisfied: typing-extensions>=4.1.1 in
/usr/local/lib/python3.10/dist-packages (from dash!=2.9.0-
>sktime[all_extras]) (4.5.0)
Requirement already satisfied: requests in
/usr/local/lib/python3.10/dist-packages (from dash!=2.9.0-
>sktime[all_extras]) (2.31.0)
Collecting retrying (from dash!=2.9.0->sktime[all_extras])
  Downloading retrying-1.3.4-py3-none-any.whl (11 kB)
Collecting ansi2html (from dash!=2.9.0->sktime[all_extras])
  Downloading ansi2html-1.8.0-py3-none-any.whl (16 kB)
Requirement already satisfied: nest-asyncio in
/usr/local/lib/python3.10/dist-packages (from dash!=2.9.0-
>sktime[all_extras]) (1.5.8)
Requirement already satisfied: setuptools in
/usr/local/lib/python3.10/dist-packages (from dash!=2.9.0-
>sktime[all_extras]) (67.7.2)
Requirement already satisfied: importlib-metadata in
/usr/local/lib/python3.10/dist-packages (from dash!=2.9.0-
>sktime[all_extras]) (6.8.0)
Requirement already satisfied: pydantic<3,>=1.7 in
/usr/local/lib/python3.10/dist-packages (from gluonts>=0.9-
>sktime[all_extras]) (1.10.13)
Requirement already satisfied: tqdm~=4.23 in
/usr/local/lib/python3.10/dist-packages (from gluonts>=0.9-
>sktime[all_extras]) (4.66.1)
Requirement already satisfied: toolz~=0.10 in
/usr/local/lib/python3.10/dist-packages (from gluonts>=0.9-
>sktime[all_extras]) (0.12.0)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.3.2-
>sktime[all_extras]) (1.2.0)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.3.2-
>sktime[all_extras]) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.3.2-
>sktime[all_extras]) (4.44.3)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.3.2-
>sktime[all_extras]) (1.4.5)
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Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.3.2-
>sktime[all_extras]) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.3.2-
>sktime[all_extras]) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.10/dist-packages (from matplotlib>=3.3.2-
>sktime[all_extras]) (2.8.2)
Requirement already satisfied: llvmlite<0.42,>=0.41.0dev0 in
/usr/local/lib/python3.10/dist-packages (from numba<0.59,>=0.53-
>sktime[all_extras]) (0.41.1)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas<2.2.0,>=1.1-
>sktime[all_extras]) (2023.3.post1)
Requirement already satisfied: joblib>=0.11 in
/usr/local/lib/python3.10/dist-packages (from pmdarima!
=1.8.1,<3.0.0,>=1.8->sktime[all_extras]) (1.3.2)
Requirement already satisfied: Cython!=0.29.18,!=0.29.31,>=0.29 in
/usr/local/lib/python3.10/dist-packages (from pmdarima!
=1.8.1,<3.0.0,>=1.8->sktime[all_extras]) (3.0.5)
Requirement already satisfied: urllib3 in
/usr/local/lib/python3.10/dist-packages (from pmdarima!
=1.8.1,<3.0.0,>=1.8->sktime[all_extras]) (2.0.7)
Requirement already satisfied: cmdstanpy>=1.0.4 in
/usr/local/lib/python3.10/dist-packages (from prophet>=1.1-
>sktime[all_extras]) (1.2.0)
Requirement already satisfied: importlib-resources in
/usr/local/lib/python3.10/dist-packages (from prophet>=1.1-
>sktime[all_extras]) (6.1.1)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-
packages (from pyod>=0.8->sktime[all_extras]) (1.16.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-
learn<1.4.0,>=0.24->sktime[all_extras]) (3.2.0)
Requirement already satisfied: polars in
/usr/local/lib/python3.10/dist-packages (from
statsforecast<1.7.0,>=0.5.2->sktime[all_extras]) (0.17.3)
Collecting fugue>=0.8.1 (from statsforecast<1.7.0,>=0.5.2-
>sktime[all_extras])
  Downloading fugue-0.8.7-py3-none-any.whl (279 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 279.8/279.8 kB 38.8 MB/s eta
0:00:00
ent already satisfied: patsy>=0.5.2 in /usr/local/lib/python3.10/dist-
packages (from statsmodels>=0.12.1->sktime[all_extras]) (0.5.3)
Requirement already satisfied: distributed>=2.11.0 in
/usr/local/lib/python3.10/dist-packages (from tsfresh>=0.17-
>sktime[all_extras]) (2023.8.1)
Requirement already satisfied: click>=8.0 in
```

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/usr/local/lib/python3.10/dist-packages (from dask-
>sktime[all_extras]) (8.1.7)
Requirement already satisfied: fsspec>=2021.09.0 in
/usr/local/lib/python3.10/dist-packages (from dask-
>sktime[all_extras]) (2023.6.0)
Requirement already satisfied: partd>=1.2.0 in
/usr/local/lib/python3.10/dist-packages (from dask-
>sktime[all_extras]) (1.4.1)
Requirement already satisfied: pyyaml>=5.3.1 in
/usr/local/lib/python3.10/dist-packages (from dask-
>sktime[all_extras]) (6.0.1)
Requirement already satisfied: pooch>=1.5 in
/usr/local/lib/python3.10/dist-packages (from mne->sktime[all_extras])
(1.8.0)
Requirement already satisfied: decorator in
/usr/local/lib/python3.10/dist-packages (from mne->sktime[all_extras])
(4.4.2)
Requirement already satisfied: jinja2 in
/usr/local/lib/python3.10/dist-packages (from mne->sktime[all_extras])
(3.1.2)
Requirement already satisfied: lazy-loader>=0.3 in
/usr/local/lib/python3.10/dist-packages (from mne->sktime[all_extras])
(0.3)
Requirement already satisfied: defusedxml in
/usr/local/lib/python3.10/dist-packages (from mne->sktime[all_extras])
(0.7.1)
Collecting pyaml>=16.9 (from scikit-optimize->sktime[all_extras])
  Downloading pyaml-23.9.7-py3-none-any.whl (23 kB)
Requirement already satisfied: absl-py>=1.0.0 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (1.6.3)
Requirement already satisfied: flatbuffers>=23.5.26 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (23.5.26)
Requirement already satisfied: gast!=0.5.0,!=0.5.1,!=0.5.2,>=0.2.1
in /usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (0.5.4)
Requirement already satisfied: google-pasta>=0.1.1 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (0.2.0)
Requirement already satisfied: libclang>=13.0.0 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (16.0.6)
Requirement already satisfied: ml-dtypes==0.2.0 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (0.2.0)
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Requirement already satisfied: opt-einsum>=2.3.2 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (3.3.0)
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!
=4.21.3,!=4.21.4,!=4.21.5,<5.0.0dev,>=3.20.3 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (3.20.3)
Requirement already satisfied: termcolor>=1.1.0 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (2.3.0)
Requirement already satisfied: wrapt<1.15,>=1.11.0 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (1.14.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (0.34.0)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (1.59.2)
Requirement already satisfied: tensorboard<2.15,>=2.14 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (2.14.1)
Requirement already satisfied: tensorflow-estimator<2.15,>=2.14.0
in /usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (2.14.0)
Requirement already satisfied: keras<2.15,>=2.14.0 in
/usr/local/lib/python3.10/dist-packages (from tensorflow-
>sktime[all_extras]) (2.14.0)
Requirement already satisfied: wheel<1.0,>=0.23.0 in
/usr/local/lib/python3.10/dist-packages (from astunparse>=1.6.0-
>tensorflow->sktime[all_extras]) (0.41.3)
Requirement already satisfied: stanio~=0.3.0 in
/usr/local/lib/python3.10/dist-packages (from cmdstanpy>=1.0.4-
>prophet>=1.1->sktime[all_extras]) (0.3.0)
Requirement already satisfied: locket>=1.0.0 in
/usr/local/lib/python3.10/dist-packages (from distributed>=2.11.0-
>tsfresh>=0.17->sktime[all_extras]) (1.0.0)
Requirement already satisfied: msgpack>=1.0.0 in
/usr/local/lib/python3.10/dist-packages (from distributed>=2.11.0-
>tsfresh>=0.17->sktime[all_extras]) (1.0.7)
Requirement already satisfied: psutil>=5.7.2 in
/usr/local/lib/python3.10/dist-packages (from distributed>=2.11.0-
>tsfresh>=0.17->sktime[all_extras]) (5.9.5)
Requirement already satisfied: sortedcontainers>=2.0.5 in
/usr/local/lib/python3.10/dist-packages (from distributed>=2.11.0-
>tsfresh>=0.17->sktime[all_extras]) (2.4.0)
Requirement already satisfied: tblib>=1.6.0 in
/usr/local/lib/python3.10/dist-packages (from distributed>=2.11.0-
>tsfresh>=0.17->sktime[all_extras]) (3.0.0)
```

```
Requirement already satisfied: tornado>=6.0.4 in
/usr/local/lib/python3.10/dist-packages (from distributed>=2.11.0-
>tsfresh>=0.17->sktime[all_extras]) (6.3.2)
Requirement already satisfied: zict>=2.2.0 in
/usr/local/lib/python3.10/dist-packages (from distributed>=2.11.0-
>tsfresh>=0.17->sktime[all_extras]) (3.0.0)
Requirement already satisfied: itsdangerous>=2.0 in
/usr/local/lib/python3.10/dist-packages (from Flask<3.1,>=1.0.4->dash!
=2.9.0->sktime[all_extras]) (2.1.2)
Collecting triad>=0.9.3 (from fugue>=0.8.1-
>statsforecast<1.7.0,>=0.5.2->sktime[all_extras])
  Downloading triad-0.9.3-py3-none-any.whl (60 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 60.4/60.4 kB 9.2 MB/s eta
0:00:00
 fugue>=0.8.1->statsforecast<1.7.0,>=0.5.2->sktime[all_extras])
  Downloading adagio-0.2.4-py3-none-any.whl (26 kB)
Collecting qpd>=0.4.4 (from fugue>=0.8.1->statsforecast<1.7.0,>=0.5.2-
>sktime[all_extras])
  Downloading qpd-0.4.4-py3-none-any.whl (169 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 169.2/169.2 kB 24.5 MB/s eta
0:00:00
 fugue>=0.8.1->statsforecast<1.7.0,>=0.5.2->sktime[all_extras])
  Downloading fugue-sql-antlr-0.1.8.tar.gz (154 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 154.7/154.7 kB 24.9 MB/s eta
0:00:00
etadata (setup.py) ... ent already satisfied: sqlglot in
/usr/local/lib/python3.10/dist-packages (from fugue>=0.8.1-
>statsforecast<1.7.0,>=0.5.2->sktime[all_extras]) (17.16.2)
Requirement already satisfied: zipp>=0.5 in
/usr/local/lib/python3.10/dist-packages (from importlib-metadata-
>dash!=2.9.0->sktime[all_extras]) (3.17.0)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2->mne-
>sktime[all_extras]) (2.1.3)
Requirement already satisfied: tenacity>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from plotly>=5.0.0->dash!
=2.9.0->sktime[all_extras]) (8.2.3)
Requirement already satisfied: platformdirs>=2.5.0 in
/usr/local/lib/python3.10/dist-packages (from pooch>=1.5->mne-
>sktime[all_extras]) (4.0.0)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->dash!=2.9.0-
>sktime[all_extras]) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in
/usr/local/lib/python3.10/dist-packages (from requests->dash!=2.9.0-
>sktime[all_extras]) (3.4)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->dash!=2.9.0-
>sktime[all_extras]) (2023.7.22)
```

```
Requirement already satisfied: google-auth<3,>=1.6.3 in
/usr/local/lib/python3.10/dist-packages (from tensorboard<2.15,>=2.14-
>tensorflow->sktime[all_extras]) (2.17.3)
Requirement already satisfied: google-auth-oauthlib<1.1,>=0.5 in
/usr/local/lib/python3.10/dist-packages (from tensorboard<2.15,>=2.14-
>tensorflow->sktime[all_extras]) (1.0.0)
Requirement already satisfied: markdown>=2.6.8 in
/usr/local/lib/python3.10/dist-packages (from tensorboard<2.15,>=2.14-
>tensorflow->sktime[all_extras]) (3.5.1)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0
in /usr/local/lib/python3.10/dist-packages (from
tensorboard<2.15,>=2.14->tensorflow->sktime[all_extras]) (0.7.2)
Collecting antlr4-python3-runtime<4.12 (from fugue-sql-antlr>=0.1.6-
>fugue>=0.8.1->statsforecast<1.7.0,>=0.5.2->sktime[all_extras])
  Downloading antlr4_python3_runtime-4.11.1-py3-none-any.whl (144 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 144.2/144.2 kB 19.0 MB/s eta
0:00:00
ent already satisfied: cachetools<6.0,>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.15,>=2.14->tensorflow->sktime[all_extras]) (5.3.2)
Requirement already satisfied: pyasn1-modules>=0.2.1 in
/usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.15,>=2.14->tensorflow->sktime[all_extras]) (0.3.0)
Requirement already satisfied: rsa<5,>=3.1.4 in
/usr/local/lib/python3.10/dist-packages (from google-auth<3,>=1.6.3-
>tensorboard<2.15,>=2.14->tensorflow->sktime[all_extras]) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in
/usr/local/lib/python3.10/dist-packages (from google-auth-
oauthlib<1.1,>=0.5->tensorboard<2.15,>=2.14->tensorflow-
>sktime[all_extras]) (1.3.1)
Requirement already satisfied: pyarrow>=6.0.1 in
/usr/local/lib/python3.10/dist-packages (from triad>=0.9.3-
>fugue>=0.8.1->statsforecast<1.7.0,>=0.5.2->sktime[all_extras])
(9.0.0)
Collecting fs (from triad>=0.9.3->fugue>=0.8.1-
>statsforecast<1.7.0,>=0.5.2->sktime[all_extras])
  Downloading fs-2.4.16-py2.py3-none-any.whl (135 kB)
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 135.3/135.3 kB 20.5 MB/s eta
0:00:00
ent already satisfied: pyasn1<0.6.0,>=0.4.6 in
/usr/local/lib/python3.10/dist-packages (from pyasn1-modules>=0.2.1-
>google-auth<3,>=1.6.3->tensorboard<2.15,>=2.14->tensorflow-
>sktime[all_extras]) (0.5.0)
Requirement already satisfied: oauthlib>=3.0.0 in
/usr/local/lib/python3.10/dist-packages (from requests-
oauthlib>=0.7.0->google-auth-oauthlib<1.1,>=0.5-
>tensorboard<2.15,>=2.14->tensorflow->sktime[all_extras]) (3.2.2)
Requirement already satisfied: appdirs~=1.4.3 in
/usr/local/lib/python3.10/dist-packages (from fs->triad>=0.9.3-
```

```
>fugue>=0.8.1->statsforecast<1.7.0,>=0.5.2->sktime[all_extras])
(1.4.4)
Building wheels for collected packages: filterpy, pycatch22, pyod,
keras-self-attention, fugue-sql-antlr
  Building wheel for filterpy (setup.py) ... e=filterpy-1.4.5-py3-
none-any.whl size=110458
sha256=12d2abaed57fa0d3f90365f430795777b74d0943e26787a8ee76927f69a0725
f
  Stored in directory:
/root/.cache/pip/wheels/0f/0c/ea/218f266af4ad626897562199fbbcba521b849
7303200186102
  Building wheel for pycatch22 (pyproject.toml) ... e=pycatch22-0.4.2-
cp310-cp310-linux_x86_64.whl size=112981
sha256=b1f208ae9063e9a2271965e39b40fcef9699b63229ccac267bcf2240e272bad
3
  Stored in directory:
/root/.cache/pip/wheels/d1/05/8c/0077a885e7ab81e51339f35e4b91eb1ad86d6
b9898cab53dfd
  Building wheel for pyod (setup.py) ... e=pyod-1.1.2-py3-none-any.whl
size=190289
sha256=b6e9cd788c44049bafb40b8e09ca2e0d18cea9a8e42a7220aee6919b9f5b57e
3
  Stored in directory:
/root/.cache/pip/wheels/81/1b/61/aa85b78c3c0c8871f4231e3f4a03bb23cecb7
db829498380ee
  Building wheel for keras-self-attention (setup.py) ...
e=keras_self_attention-0.51.0-py3-none-any.whl size=18895
sha256=c339c59e3d243c7236150bd141d59c3a28af14ee6179fbe24f4d62ee41c9170
5
  Stored in directory:
/root/.cache/pip/wheels/b8/f7/24/607b483144fb9c47b4ba2c5fba6b68e54aeee
2d5bf6c05302e
  Building wheel for fugue-sql-antlr (setup.py) ... e=fugue_sql_antlr-
0.1.8-py3-none-any.whl size=158200
sha256=242bb82bcbf013400f120f6721a23d9af47892b7ec3b47464377f5fe729094d
4
  Stored in directory:
/root/.cache/pip/wheels/a4/2b/3e/8ac985ad100a8f27de940864344fe14f47bc3
d2fed7f29bf70
Successfully built filterpy pycatch22 pyod keras-self-attention fugue-
sql-antlr
Installing collected packages: pycatch22, dash-table, dash-html-
components, dash-core-components, antlr4-python3-runtime, scikit-base,
retrying, pyaml, keras-self-attention, fs, ansi2html, stumpy,
seasonal, pykalman-bardo, dtw-python, tslearn, triad, sktime, skpro,
scikit-optimize, pyod, mne, kotsu, hmmlearn, gluonts, filterpy, dash,
scikit-posthocs, pmdarima, fugue-sql-antlr, arch, adagio, tsfresh,
tbats, qpd, fugue, statsforecast
Successfully installed adagio-0.2.4 ansi2html-1.8.0 antlr4-python3-
runtime-4.11.1 arch-6.2.0 dash-2.14.1 dash-core-components-2.0.0 dash-
```

```
html-components-2.0.0 dash-table-5.0.0 dtw-python-1.3.0 filterpy-1.4.5
fs-2.4.16 fugue-0.8.7 fugue-sql-antlr-0.1.8 gluonts-0.14.1 hmmlearn-
0.3.0 keras-self-attention-0.51.0 kotsu-0.3.3 mne-1.6.0 pmdarima-2.0.4
pyaml-23.9.7 pycatch22-0.4.2 pykalman-bardo-0.9.7 pyod-1.1.2 qpd-0.4.4
retrying-1.3.4 scikit-base-0.6.1 scikit-optimize-0.9.0 scikit-
posthocs-0.8.0 seasonal-0.3.1 skpro-2.1.1 sktime-0.24.1 statsforecast-
1.6.0 stumpy-1.12.0 tbats-1.1.3 triad-0.9.3 tsfresh-0.20.1 tslearn-
0.5.3.2
```

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
from matplotlib.pyplot import figure
import warnings
import sktime
from datetime import datetime


sns.set_style('white')
sns.set(rc={'figure.figsize':(11, 4)})

warnings.simplefilter("ignore", FutureWarning)
%matplotlib inline

from sktime.forecasting.model_selection import
temporal_train_test_split
from sktime.forecasting.base import ForecastingHorizon
from sktime.forecasting.compose import (
    EnsembleForecaster,
    MultiplexForecaster,
    TransformedTargetForecaster,
    make_reduction,
)
from sktime.forecasting.model_evaluation import evaluate
from sktime.forecasting.model_selection import (
    ExpandingWindowSplitter,
    ForecastingGridSearchCV,
    SlidingWindowSplitter,
    temporal_train_test_split,
)
from sktime.forecasting.exp_smoothing import ExponentialSmoothing
from sktime.forecasting.naive import NaiveForecaster
from sktime.forecasting.theta import ThetaForecaster
from sktime.forecasting.trend import PolynomialTrendForecaster
from sktime.performance_metrics.forecasting import
MeanAbsolutePercentageError, MeanSquaredError
from sktime.transformations.series.detrend import Deseasonalizer,
Detrender
```

```python
from sktime.utils.plotting import plot_series
from sktime.forecasting.compose import TransformedTargetForecaster
from sktime.forecasting.trend import PolynomialTrendForecaster
from sktime.transformations.panel.tsfresh import
TSFreshFeatureExtractor
from sktime.forecasting.fbprophet import Prophet
from sktime.forecasting.tbats import TBATS
smape = MeanAbsolutePercentageError(symmetric = True)
rmse  = MeanSquaredError(square_root=True)
from sktime.forecasting.sarimax import SARIMAX
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import LabelEncoder

from sklearn.pipeline import make_pipeline
from statsmodels.tsa.stattools import adfuller
from sklearn.metrics import r2_score
from sklearn.ensemble import RandomForestClassifier
import pmdarima as pm


r2_score = lambda y_pred, y_test: 1-np.sum(np.square(y_pred -
y_test))/np.sum(np.square(y_test - np.mean(y_test)))

try:
    df =
pd.read_csv('https://raw.githubusercontent.com/numenta/NAB/master/
data/realKnownCause/nyc_taxi.csv')

except FileNotFoundError:
    print("File not found.")
except pd.errors.EmptyDataError:
    print("No data")
except pd.errors.ParserError:
    print("Parse error")
except Exception:
    print("Some other exception")
```

DEF

```python
def adf_test(series,title=''):
    """
    Pass in a time series and an optional title, returns an ADF report
    """
    print(f'Augmented Dickey-Fuller Test: {title}')
    result = adfuller(series.dropna(),autolag='AIC') # .dropna()
handles differenced data
```

```
    labels = ['ADF test statistic','p-value','# lags used','#
observations']
    out = pd.Series(result[0:4],index=labels)

    for key,val in result[4].items():
        out[f'critical value ({key})']=val

    print(out.to_string())          # .to_string() removes the line
"dtype: float64"

    if result[1] <= 0.05:
        print("Strong evidence against the null hypothesis")
        print("Reject the null hypothesis")
        print("Data has no unit root and is stationary")
    else:
        print("Weak evidence against the null hypothesis")
        print("Fail to reject the null hypothesis")
        print("Data has a unit root and is non-stationary")

def checkDuplicates(df):
    '''
    Checks for duplicates in the entire DataFrame.
    Returns a DataFrame with the duplicates.
    '''

    duplicate_mask = df.duplicated()

    duplicate_df = df[duplicate_mask]

    return duplicate_df

def split_by_month(df, months):
    df_ = pd.DataFrame()
    for month in np.atleast_1d(months):
        df_ = df_.append(df.loc[df.index.month == month])
    return df_

def to_segments(df, column, size = 24):
    df.index.hour[0]
    start_idx = 24-df.index.hour[0]
    df = df.iloc[start_idx:]
    val = df[[column]].values
    return val[:size*(val.size//size)].reshape(-1,size)

def extract_country(df_all, country_code, year_min=None,
year_max=None):
    # List of columns to extract
    columns = [col for col in df_all.columns if
col.startswith(country_code)]
    # Extract columns and remove country codes from column labels
    columns_map = {col : col[3:] for col in columns}
```

```
    df_out = df_all[columns].rename(columns=columns_map)
    # Exclude years outside of specified range, if any
    if year_min is not None:
        df_out = df_out[df_out.index.year >= year_min]
    if year_max is not None:
        df_out = df_out[df_out.index.year <= year_max]
    return df_out

def transform_dataframe(df, cols_map):
    # Rename columns for convenience
    df = df[list(cols_map.keys())].rename(columns=cols_map)
    df = df / 1000 # Convert from MW to GW
    df = df.rename_axis('Date')
    return df

def split_by_month(df, months):
    df_ = pd.DataFrame()
    for month in np.atleast_1d(months):
        df_ = df_.append(df.loc[df.index.month == month])
    return df_

def to_segments(df, column, size = 24):
    df.index.hour[0]
    start_idx = 24-df.index.hour[0]
    df = df.iloc[start_idx:]
    val = df[[column]].values
    return val[:size*(val.size//size)].reshape(-1,size)
```

Результаты предварительного анализа выбранного одноперeменного ВР

```
df.head()
```

	timestamp	value
0	2014-07-01 00:00:00	10844
1	2014-07-01 00:30:00	8127
2	2014-07-01 01:00:00	6210
3	2014-07-01 01:30:00	4656
4	2014-07-01 02:00:00	3820

```
df['timestamp'] = pd.to_datetime(df['timestamp'])
print(f"Минимальная дата: {df['timestamp'].min().strftime('%Y-%m-
%d')}, Максимальная дата: {df['timestamp'].max().strftime('%Y-%m-
%d')}")
```

```
date_difference= df['timestamp'].max() - df['timestamp'].min()
print(f"Количество дней в промежутке: {date_difference.days} дней")
```

```
Минимальная дата: 2014-07-01, Максимальная дата: 2015-01-31
Количество дней в промежутке: 214 дней
```

```
df.set_index('timestamp', inplace=True)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 10320 entries, 2014-07-01 00:00:00 to 2015-01-31
23:30:00
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   value   10320 non-null  int64
dtypes: int64(1)
memory usage: 161.2 KB
```

Теперь набор представляет собой запросы такси:

- timestamp — дата в формате гггг-мм-дд ч-м-с;
- value — Общее число запросов;

Проведем анализ сформированного набора данных

```
# Проверим дубликаты и пропуски в df
checkDuplicates(df)
```

```
                     value
timestamp
2014-07-03 11:30:00  16778
2014-07-03 14:30:00  19078
2014-07-05 01:30:00  12535
2014-07-06 00:30:00  14615
2014-07-06 11:00:00  11595
...                    ...
2015-01-31 17:00:00  20715
2015-01-31 17:30:00  23595
2015-01-31 20:00:00  24985
2015-01-31 21:00:00  23719
2015-01-31 22:00:00  25721

[2231 rows x 1 columns]
```

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

```
value    0
dtype: int64
```

```
print('Размерность набора данных:', df.shape)
```

```
Размерность набора данных: (10320, 1)
```

```
print(df.index.day)
print(df.index.weekday)
print(df.index.year)
```

```
Int64Index([ 1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
            ...
            31, 31, 31, 31, 31, 31, 31, 31, 31, 31],
           dtype='int64', name='timestamp', length=10320)
Int64Index([1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
            ...
            5, 5, 5, 5, 5, 5, 5, 5, 5, 5],
           dtype='int64', name='timestamp', length=10320)
Int64Index([2014, 2014, 2014, 2014, 2014, 2014, 2014, 2014, 2014,
2014,
            ...
            2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015, 2015,
2015],
           dtype='int64', name='timestamp', length=10320)
```

```
df.describe()
```

```
              value
count  10320.000000
mean   15137.569380
std     6939.495808
min        8.000000
25%    10262.000000
50%    16778.000000
75%    19838.750000
max    39197.000000
```

- Теперь посмотрим на распределение запросов такси по неделям и месяцам;

```
df[['value']].loc['2014-07-01':'2014-12-31'].asfreq('W')
```

```
            value
timestamp
2014-07-06  15427
2014-07-13  25792
2014-07-20  25137
2014-07-27  25659
2014-08-03  24613
2014-08-10  23701
2014-08-17  23263
2014-08-24  22666
2014-08-31  19205
2014-09-07  25818
```

```
2014-09-14  27320
2014-09-21  26477
2014-09-28  27269
2014-10-05  25224
2014-10-12  26610
2014-10-19  28093
2014-10-26  26866
2014-11-02  25110
2014-11-09  26931
2014-11-16  26651
2014-11-23  27424
2014-11-30  20149
2014-12-07  26695
2014-12-14  26065
2014-12-21  25530
2014-12-28  16514
```

```python
df[['value']].asfreq('M')
```

```
            value
timestamp
2014-07-31  15486
2014-08-31  19205
2014-09-30   9459
2014-10-31  19957
2014-11-30  20149
2014-12-31  14294
2015-01-31  25778
```

```python
df.resample('1m').median()
```

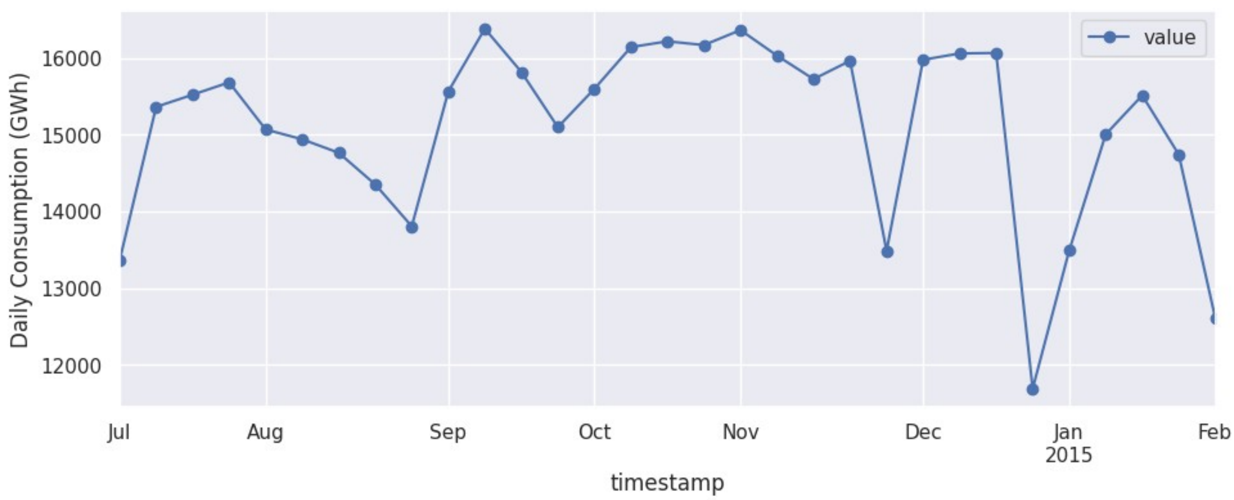
```
              value
timestamp
2014-07-31  16625.5
2014-08-31  16184.0
2014-09-30  17244.5
2014-10-31  17767.5
2014-11-30  17287.0
2014-12-31  16587.0
2015-01-31  16061.0
```

```python
# linewidth=0.5 - толищина
df['value'].plot(linewidth=0.5)

plt.xlabel('Временной промежуток')
plt.ylabel('Число запросов такси')

plt.show();
```

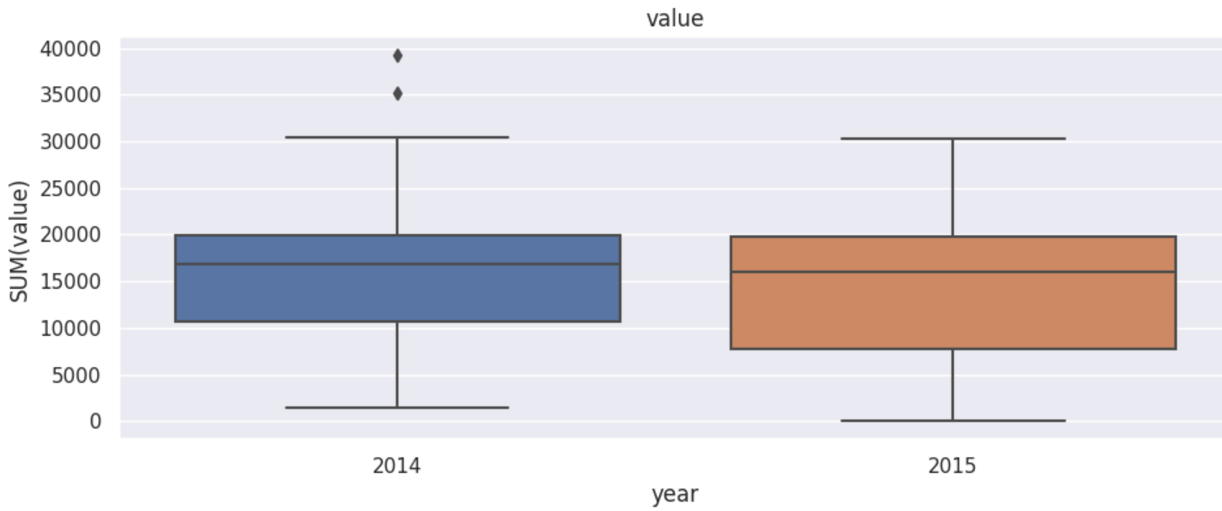

```python
import matplotlib.pyplot as plt
import matplotlib.dates as mdates

df_monthly = df.resample('M').sum(min_count=7)

# Получение осей
ax = plt.gca()

# График
ax.plot(df_monthly['value'], color='blue', linewidth=2, label='Total
Value')  # Изменяем цвет и толщину линии

ax.xaxis.set_major_locator(mdates.YearLocator())  # Устанавливаем
локатор для года
ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y'))  #
Форматируем метки года

# Добавляем сетку
ax.grid(True, linestyle='--', alpha=0.7)

# Добавляем заголовок и метку оси Y
ax.set_title('Monthly Number of Taxi Requests')
ax.set_ylabel('Monthly Number of Requests')

# Поворачиваем метки по оси X для лучшей читаемости
plt.setp(ax.xaxis.get_majorticklabels(), rotation=45)

# Отображаем график
#plt.tight_layout()  # Решаем проблемы с наложением элементов
plt.show()
```

- Посмотрим также распределение по неделям, для более наглядного графика.

```
ax = df.resample('W').mean().plot(marker='o',
linestyle='-',linewidth=1.5)
ax.set_ylabel('Daily Consumption (GWh)')
plt.show();
```

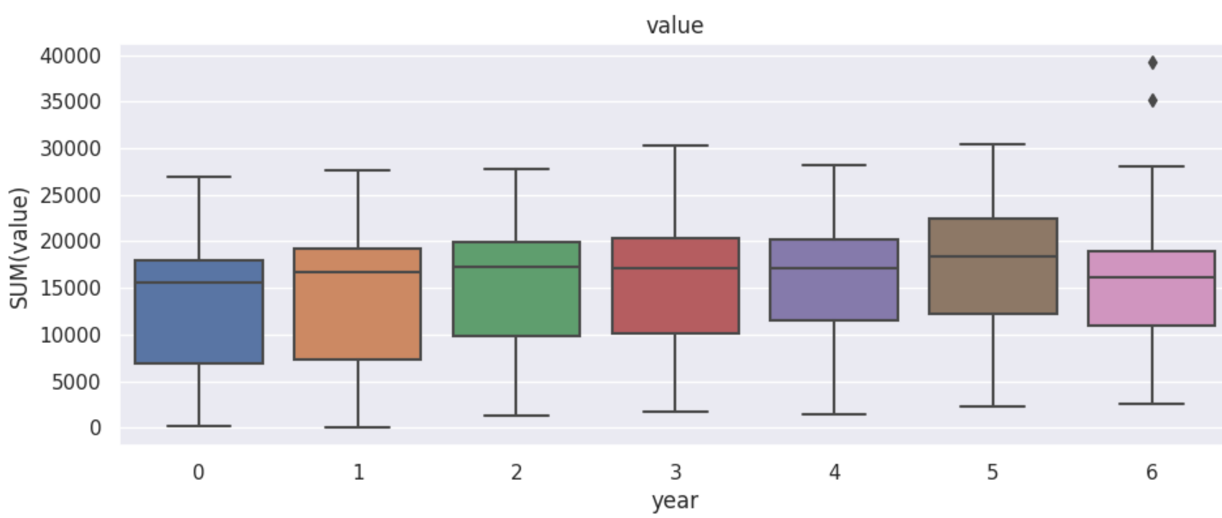



```
#BBox

ax = sns.boxplot(data=df, x=df.index.year, y='value')
ax.set_ylabel('SUM(value)')
ax.set_xlabel('year')
ax.set_title('value')
plt.show();
```



- Сезонность дней недели
  - можно заметить что к выходным спрос повышается, но ничего не обычного нет

```
ax = sns.boxplot(data=df, x=df.index.weekday, y='value');
ax.set_ylabel('SUM(value)')
ax.set_xlabel('year')
ax.set_title('value')
plt.show()
```



- Анализ полученных графиков показывает следующее:
  - Графики показывают, что присутствует сезонность, с приходом холодов (Конец Августа - частота запросов такси находятся на пике)
  - Также можно заметить - большой спад, в конце года спрос падает на минимальный уровень(К праздникам подготовились, все находятся дома)
  - В 2014 году видны выбросы, 2015 год можно не учитывать, слишком мало данных за год

Сравнение не менее 3-х методов предсказаний значений ВР по выбранной метрике точности и визуально. Соответственно рекомендации по выбору метода.

TRAIN_TEST_SPLIT

```
# Сразу определим оценку модели
r2_score = lambda y_pred, y_test: 1-np.sum(np.square(y_pred - y_test))/np.sum(np.square(y_test - np.mean(y_test)))

df.info()

<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 10320 entries, 2014-07-01 00:00:00 to 2015-01-31 23:30:00
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   value   10320 non-null  int64
dtypes: int64(1)
memory usage: 419.3 KB

y = df.value.asfreq('7d')
# y.index = pd.PeriodIndex(y.index) # pd.to_datetime(y.index)
y.head()

timestamp
2014-07-01    10844
2014-07-08     9292
2014-07-15    10089
2014-07-22    10611
2014-07-29    10468
Freq: 7D, Name: value, dtype: int64
```

- Сгруппируем по дням и просуммируем значения
  - Без четкого определения данных сложно сказать что конкретнно подразумевается под запросами такси. Пусть счетчик подсчитывал каждые 30 минут количество "запросов", тогда можно будет с уверенность просуммировать данные по дням и начать сравнение 3-х методов предсказания значений.

```
#df.index = pd.to_datetime(df.index)
df_grouped = df.resample('D').sum()
```

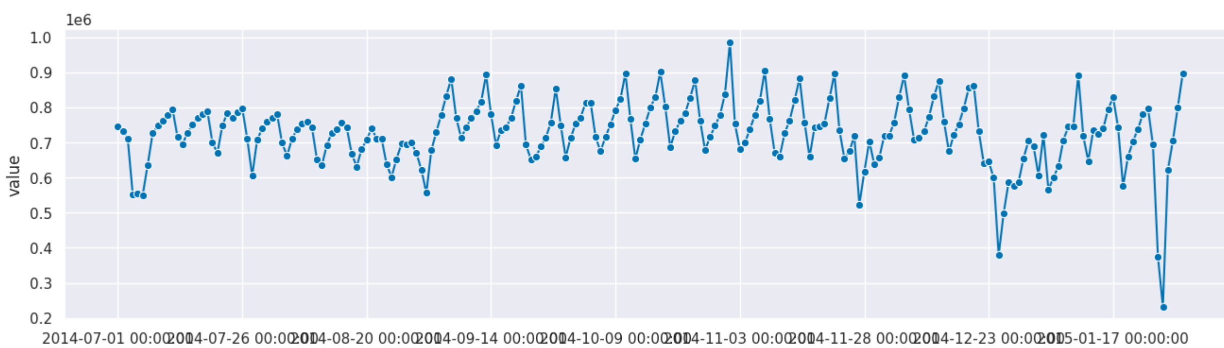
```
df_grouped.head()
```

```
                 value
timestamp
2014-07-01  745967
2014-07-02  733640
2014-07-03  710142
2014-07-04  552565
2014-07-05  555470
```

```
y = df_grouped.value.asfreq('1d')
# y.index = pd.PeriodIndex(y.index) # pd.to_datetime(y.index)
y.tail()
```

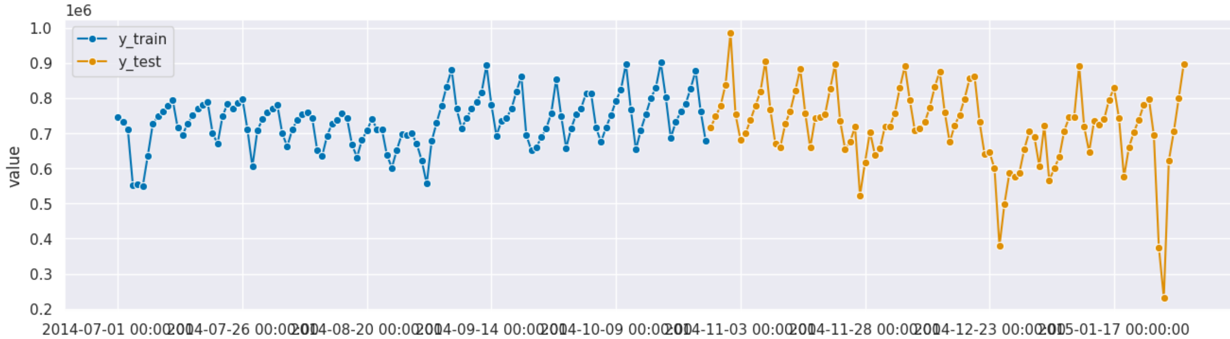
```
timestamp
2015-01-27    232058
2015-01-28    621483
2015-01-29    704935
2015-01-30    800478
2015-01-31    897719
Freq: D, Name: value, dtype: int64
```

```
sktime.utils.plotting.plot_series(y);
```



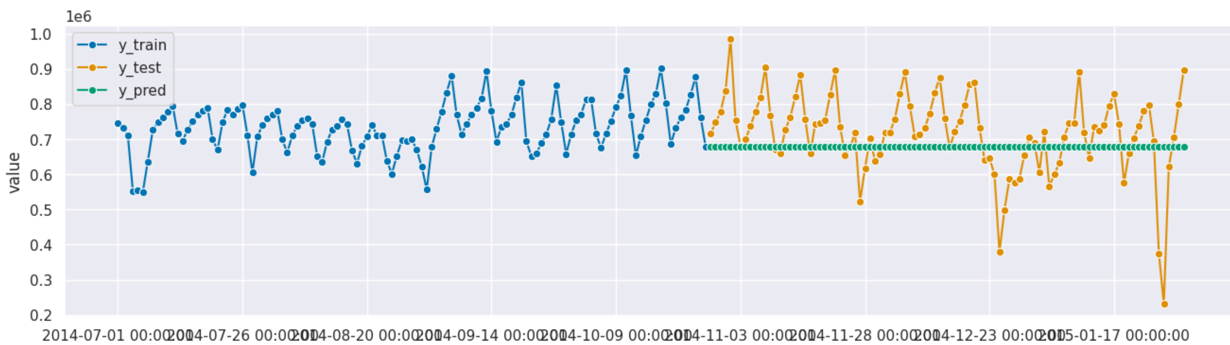

```
TEST_SIZE = int(0.45*y.size)

y_train, y_test = temporal_train_test_split(y, test_size=TEST_SIZE)

print(f'Check splitted data size: Train: {y_train.shape[0]}, Test: {y_test.shape[0]}')

sktime.utils.plotting.plot_series(y_train, y_test, labels=["y_train", "y_test"]);
```

```
Check splitted data size: Train: 119, Test: 96
```




```python
# ГОРИЗОНТ

#fh = np.arange(y_test.size) + 1
fh = ForecastingHorizon(y_test.index, is_relative=False)

# ПРЕДСКАЗАТЕЛЬ
forecaster = NaiveForecaster(strategy="last")
forecaster.fit(y_train)

# ПРЕДСКАЗАНИЕ
y_pred = forecaster.predict(fh)
plot_series(y_train, y_test, y_pred, labels=["y_train", "y_test",
"y_pred"])

# ОШИБКА
print(f'sMAPE = {smape(y_pred.values, y_test.values):.3f}')
```

```
sMAPE = 0.134
```

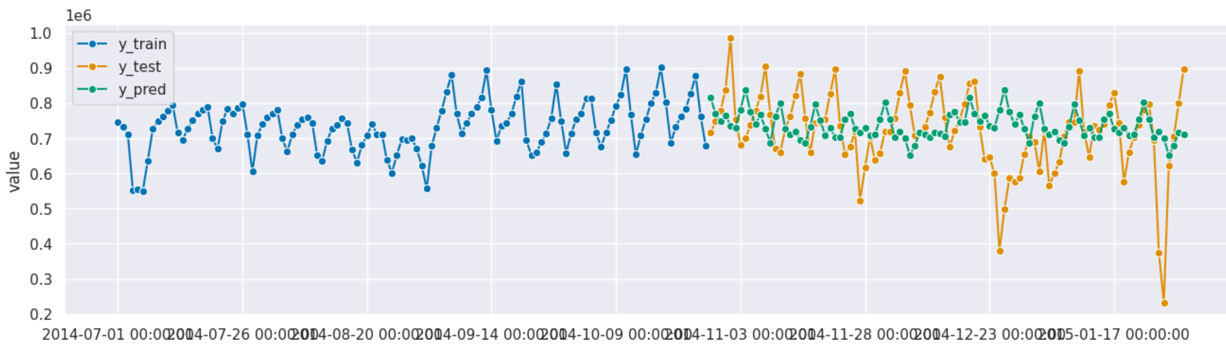


Наивное сезонное предсказание

```python
SEASON = 52

forecaster = NaiveForecaster(strategy="mean", sp=SEASON)
forecaster.fit(y_train)

y_pred = forecaster.predict(fh)
```

```
plot_series(y_train, y_test, y_pred, labels=["y_train", "y_test",
"y_pred"])

print(f'sMAPE = {smape(y_pred.values, y_test.values):.3f}')
```

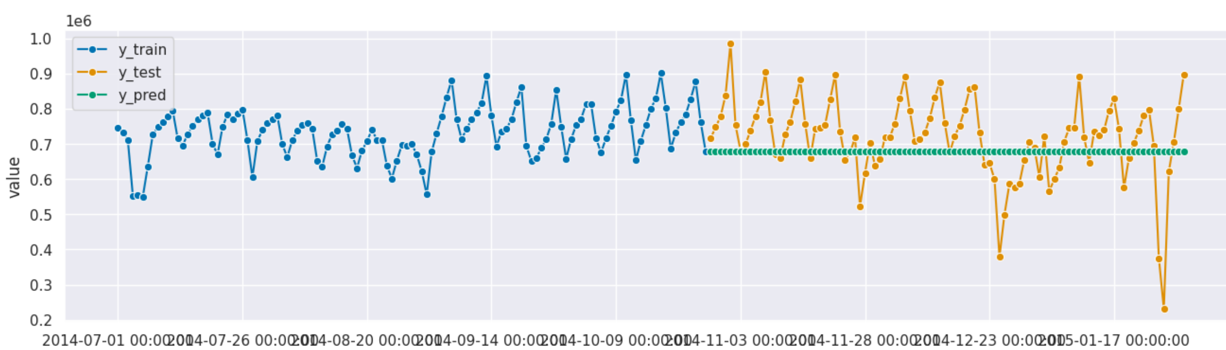
```
sMAPE = 0.130
```



Simple Exponential Smoothing

```
forecaster = ExponentialSmoothing()
forecaster.fit(y_train)
y_pred = forecaster.predict(fh)
plot_series(y_train, y_test, y_pred, labels=["y_train", "y_test",
"y_pred"])

print(f'sMAPE = {smape(y_pred.values, y_test.values):.3f}')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/holtwinters/
model.py:917: ConvergenceWarning: Optimization failed to converge.
Check mle_retvals.
  warnings.warn(

sMAPE = 0.134
```

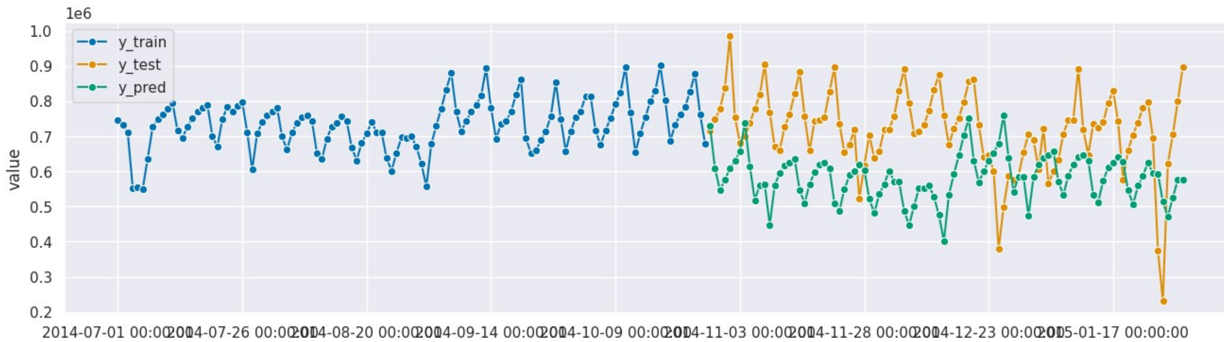



```
SEASON = 52

# МЕТОДЫ
ses          = ExponentialSmoothing(sp=SEASON)
```

```
holt        = ExponentialSmoothing(trend="add", damped_trend=False, 
sp=SEASON)
damped_holt = ExponentialSmoothing(trend="add", damped_trend=True, 
sp=SEASON)
holt_winter = ExponentialSmoothing(trend="add", seasonal="additive", 
sp=SEASON)
holt_winter_add_boxcox  = ExponentialSmoothing(trend="add", 
seasonal="additive", use_boxcox =True, sp=SEASON)
holt_winter_mul_boxcox  = ExponentialSmoothing(trend="mul", 
seasonal="additive", use_boxcox =True, sp=SEASON)
holt_winter_sadd_boxcox = ExponentialSmoothing(trend="add", 
seasonal="mul", use_boxcox =True, sp=SEASON)
holt_winter_smul_boxcox = ExponentialSmoothing(trend="mul", 
seasonal="mul", use_boxcox =True, sp=SEASON)

# ПРЕДСКАЗАТЕЛЬ
forecaster = EnsembleForecaster(
    [
#          ("ses", ses),
#          ("holt", holt),
#          ("damped", damped_holt),
        ("holt-winter",holt_winter),
#          ("holt-winter, additive trend, box-cox", 
holt_winter_add_boxcox),
        ("holt-winter, multiplicative trend, box-cox", 
holt_winter_mul_boxcox),
#          ("holt-winter, multiplicative season, box-cox", 
holt_winter_sadd_boxcox),
#          ("holt-winter, multiplicative both,   box-cox", 
holt_winter_smul_boxcox)
    ]
)
forecaster.fit(y_train)

# ПРЕДСКАЗАНИЕ
y_pred = forecaster.predict(fh)
plot_series(y_train, y_test, y_pred, labels=["y_train", "y_test", 
"y_pred"])

# РЕЗУЛЬТАТ
print(f'sMAPE = {smape(y_pred.values, y_test.values):.3f}')
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/holtwinters/
model.py:917: ConvergenceWarning: Optimization failed to converge. 
Check mle_retvals.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/holtwinters/
model.py:917: ConvergenceWarning: Optimization failed to converge. 
Check mle_retvals.
  warnings.warn(
```

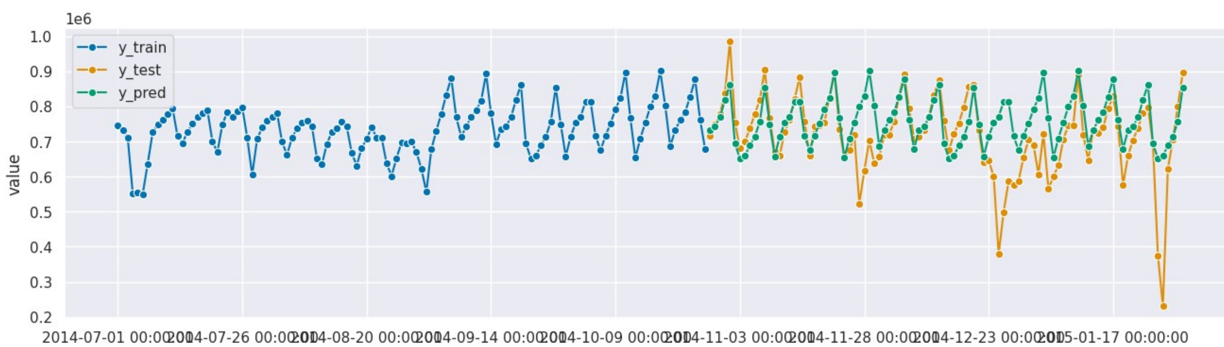
```
sMAPE = 0.257
```



KNeighborsRegressor

```
from sklearn.neighbors import KNeighborsRegressor

REGRESSION_WINDOW = 15

regressor  = KNeighborsRegressor(n_neighbors=1)
forecaster = make_reduction(regressor,
window_length=REGRESSION_WINDOW, strategy="recursive")

forecaster.fit(y_train)

y_pred = forecaster.predict(fh)

plot_series(y_train, y_test, y_pred, labels=["y_train", "y_test",
"y_pred"])

print(f'sMAPE = {smape(y_pred.values, y_test.values):.3f}')
```

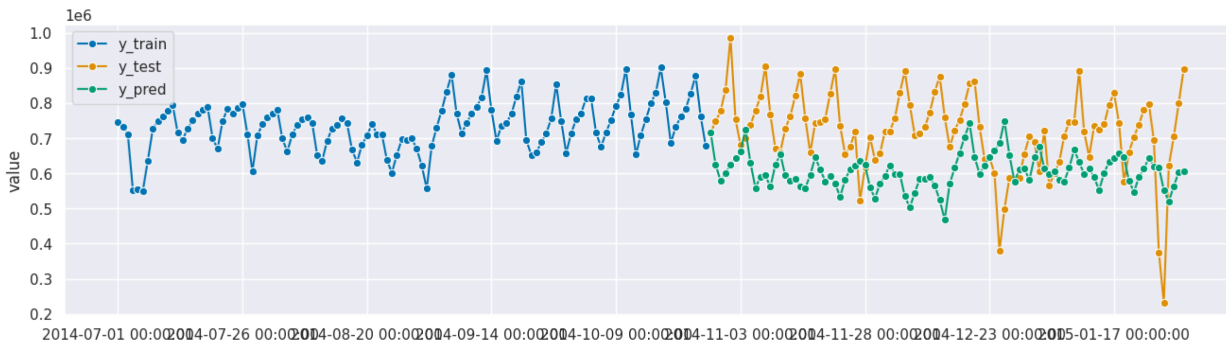
```
sMAPE = 0.101
```



ThetaForecaster

```
forecaster = ThetaForecaster(sp=SEASON)
forecaster.fit(y_train, fh=fh)
y_pred = forecaster.predict(fh)
```

```
plot_series(y_train, y_test, y_pred, labels=["y_train", "y_test",
"y_pred"])
print(f'sMAPE = {smape(y_pred.values, y_test.values):.3f}')

/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/holtwinters/
model.py:917: ConvergenceWarning: Optimization failed to converge.
Check mle_retvals.
  warnings.warn(

sMAPE = 0.219
```



Отчет о выборе параметров модели SARIMA (можно в режиме автовыбора или ручном режиме, возможна их комбинация). Отчет также должен включать описание остаточной части предсказания.

Проверка стационарности

```
P_THRESHOLD = 0.05
def check_ADF(y, p_threshold = P_THRESHOLD):
    result = adfuller(y)
    adf_value = result[0]
    p_value   = result[1]
    print('ADF Statistic: {:.4f}'.format(adf_value))
    print('p-value: {:.4f}'.format(p_value))
    print('Critical Values:')
    for key, value in result[4].items():
        print('\t{}: {:.4f}, {}'.format(key, value, 'outperformed' if
adf_value>value else ""))
    print(f'Result: The series is {"not " if p_value < p_threshold
```

```
else ""}stationary')
    return result

check_ADF(y_train, p_threshold = P_THRESHOLD);
```

```
ADF Statistic: -3.4141
p-value: 0.0105
Critical Values:
     1%: -3.4912, outperformed
     5%: -2.8882,
     10%: -2.5810,
Result: The series is not stationary
```

```
y_sdif = y_train[:].diff(1).diff(SEASON).dropna()
results = check_ADF(y_sdif);
```

```
ADF Statistic: -3.8985
p-value: 0.0020
Critical Values:
     1%: -3.5507,
     5%: -2.9138,
     10%: -2.5946,
Result: The series is not stationary
```

```
y_sdif = y_train[:].diff(2).diff(SEASON).dropna()
results = check_ADF(y_sdif);
```

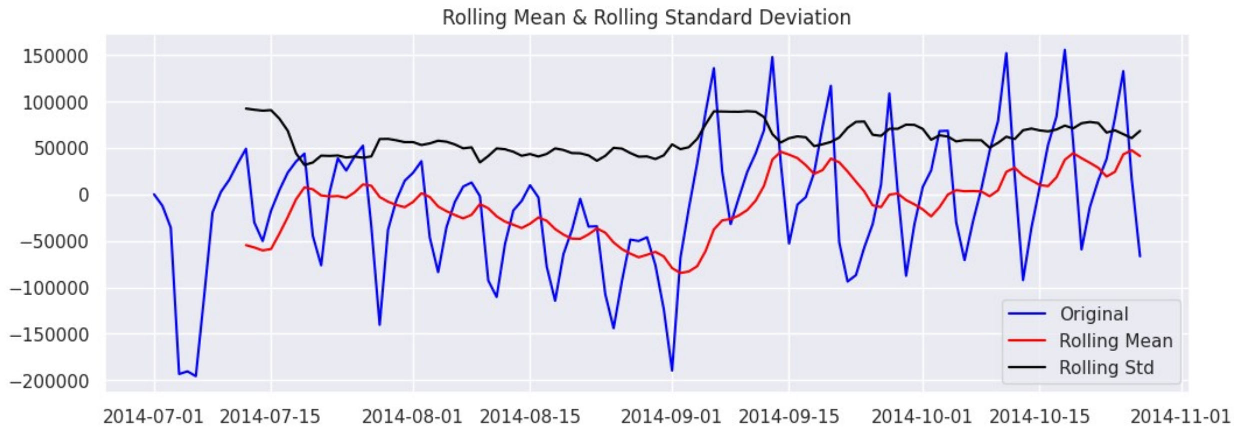
```
ADF Statistic: -4.2100
p-value: 0.0006
Critical Values:
     1%: -3.5507,
     5%: -2.9138,
     10%: -2.5946,
Result: The series is not stationary
```

```
y_sdif = y_train[:].diff(3).diff(SEASON).dropna()
results = check_ADF(y_sdif);
```

```
ADF Statistic: -1.7962
p-value: 0.3823
Critical Values:
     1%: -3.5629, outperformed
     5%: -2.9190, outperformed
     10%: -2.5974, outperformed
Result: The series is stationary
```

```
rolling_mean = y_train.rolling(window = 12).mean()
rolling_std  = y_train.rolling(window = 12).std()

plt.figure(figsize=(12,4), dpi=100)
```

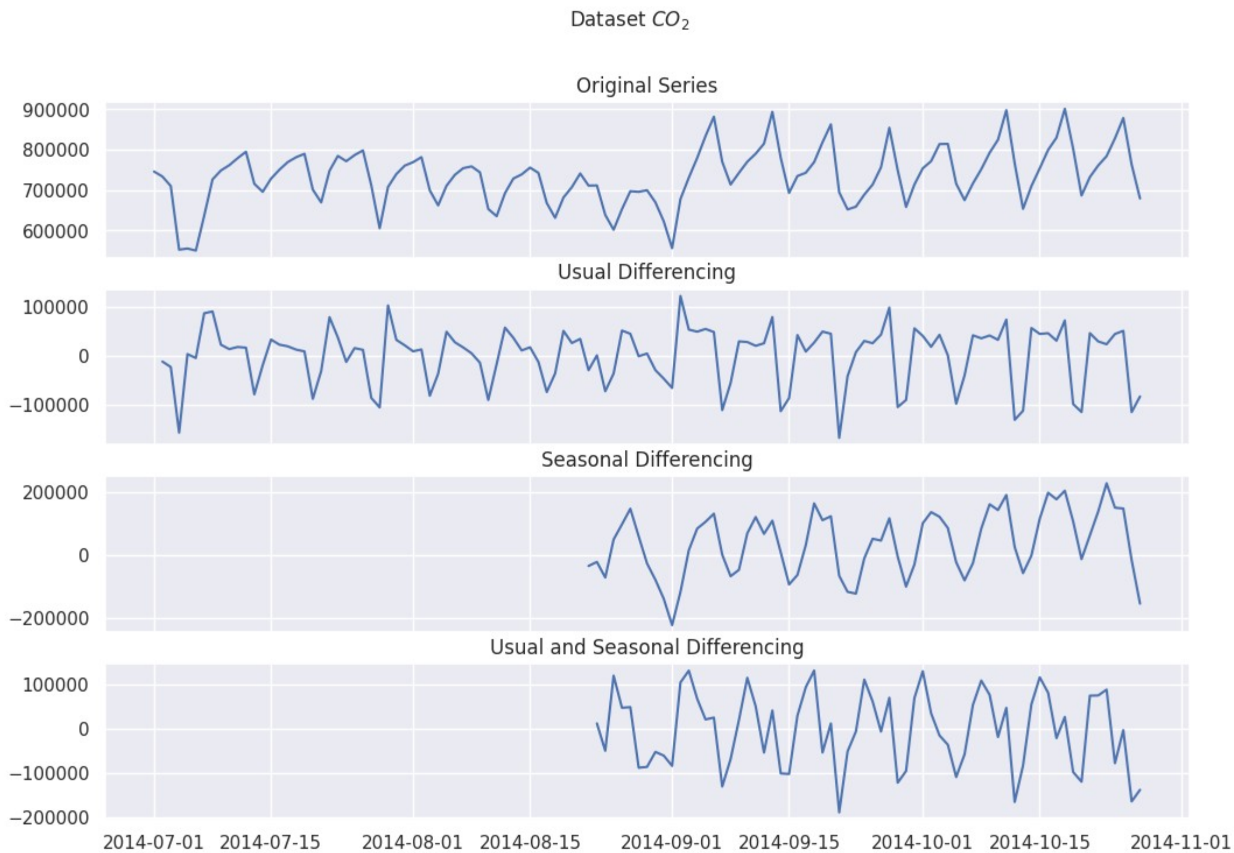
```
plt.plot(y_train-y_train[0],       color = 'blue',  label = 'Original')
plt.plot(rolling_mean-y_train[0], color = 'red',   label = 'Rolling
Mean')
plt.plot(rolling_std,              color = 'black', label = 'Rolling
Std')

plt.legend(loc = 'best')
plt.title('Rolling Mean & Rolling Standard Deviation')
plt.show();
```



- Сделали проверку на стационарность временного ряда с использованием теста на наличие единичного корня (ADF-тест). Вывод:
  - value равно 0.0105, что меньше порога в 0.05. Таким образом данные не соответствуют критерию стационарности, поскольку p-value меньше уровня значимости.

```
SEASON = 52

fig, axes = plt.subplots(4, 1, figsize=(12,8), dpi=100, sharex=True)

# Original Series
axes[0].plot(y_train[:])
axes[0].set_title('Original Series')

# Usual Differencing
axes[1].plot(y_train[:].diff(1))
axes[1].set_title('Usual Differencing')

# Seasinal Differencing
axes[2].plot(y_train[:].diff(SEASON))
axes[2].set_title('Seasonal Differencing')

# Seasinal and Usual Differencing
axes[3].plot(y_train[:].diff(1).diff(SEASON))
```

```
axes[3].set_title('Usual and Seasonal Differencing')

plt.suptitle('Dataset $CO_2$', fontsize=12)
plt.show();
```



Model

```
from sktime.forecasting.arima import AutoARIMA

model = AutoARIMA(start_p=1,  # начальный порядок AR
                  d=1,        # Порядок производной
                  start_q=0,  # начальный порядок MA
                  max_p=5,    # конечный порядок AR
                  max_q=5,    # конечный порядок MA
                  seasonal=True,  # Использовать SARIMA
                  start_P=0,  # начальный порядок SAR
                  start_Q=0,  # начальный порядок SMA
                  D=1,        # Порядок сезонной производной
                  sp=52,      # Период сезонности
                  max_order = 7, # Максимальный порядок p+q+P+Q
                  trace  = True,   # отчет он-лайн
                  stepwise = True, # метод ускоренного выбора
параметров.
```

```
                  n_jobs = 1,      # для stepwise парралелизм не 
доступен.
                  error_action='ignore',
                  suppress_warnings=True)

model.fit(y_train)

model.summary()

Performing stepwise search to minimize aic
 ARIMA(1,1,0)(0,1,0)[52] intercept   : AIC=1689.955, Time=0.67 sec
 ARIMA(0,1,0)(0,1,0)[52] intercept   : AIC=1690.001, Time=0.38 sec
 ARIMA(1,1,0)(1,1,0)[52] intercept   : AIC=1690.123, Time=9.15 sec
 ARIMA(0,1,1)(0,1,1)[52] intercept   : AIC=1688.205, Time=7.53 sec
 ARIMA(0,1,0)(0,1,0)[52]             : AIC=1702.126, Time=0.53 sec
 ARIMA(0,1,1)(0,1,0)[52] intercept   : AIC=1689.950, Time=1.27 sec
 ARIMA(0,1,1)(1,1,1)[52] intercept   : AIC=inf, Time=17.24 sec
 ARIMA(0,1,1)(0,1,2)[52] intercept   : AIC=inf, Time=18.07 sec
 ARIMA(0,1,1)(1,1,0)[52] intercept   : AIC=1690.049, Time=1.86 sec
 ARIMA(0,1,1)(1,1,2)[52] intercept   : AIC=inf, Time=19.78 sec
 ARIMA(0,1,0)(0,1,1)[52] intercept   : AIC=1689.267, Time=2.87 sec
 ARIMA(1,1,1)(0,1,1)[52] intercept   : AIC=1690.139, Time=7.08 sec
 ARIMA(0,1,2)(0,1,1)[52] intercept   : AIC=1690.172, Time=6.61 sec
 ARIMA(1,1,0)(0,1,1)[52] intercept   : AIC=1688.427, Time=2.56 sec
 ARIMA(1,1,2)(0,1,1)[52] intercept   : AIC=inf, Time=15.20 sec
 ARIMA(0,1,1)(0,1,1)[52]             : AIC=1686.267, Time=2.26 sec
 ARIMA(0,1,1)(0,1,0)[52]             : AIC=1687.893, Time=0.32 sec
 ARIMA(0,1,1)(1,1,1)[52]             : AIC=inf, Time=4.65 sec
 ARIMA(0,1,1)(0,1,2)[52]             : AIC=inf, Time=13.49 sec
 ARIMA(0,1,1)(1,1,0)[52]             : AIC=1688.058, Time=1.56 sec
 ARIMA(0,1,1)(1,1,2)[52]             : AIC=inf, Time=20.90 sec
 ARIMA(0,1,0)(0,1,1)[52]             : AIC=1687.348, Time=2.60 sec
 ARIMA(1,1,1)(0,1,1)[52]             : AIC=1688.198, Time=5.07 sec
 ARIMA(0,1,2)(0,1,1)[52]             : AIC=1688.236, Time=6.85 sec
 ARIMA(1,1,0)(0,1,1)[52]             : AIC=1686.486, Time=2.15 sec
 ARIMA(1,1,2)(0,1,1)[52]             : AIC=inf, Time=10.49 sec

Best model:  ARIMA(0,1,1)(0,1,1)[52]
Total fit time: 181.311 seconds

<class 'statsmodels.iolib.summary.Summary'>
"""
                                     SARIMAX Results                                      

======================================================================
====================
Dep. Variable:                                  y   No. Observations:
119
Model:             SARIMAX(0, 1, 1)x(0, 1, 1, 52)   Log Likelihood
-840.133
```

```
Date:                             Mon, 27 Nov 2023   AIC
1686.267
Time:                                     05:42:20   BIC
1692.836
Sample:                                 07-01-2014   HQIC
1688.863
                                      - 10-27-2014

Covariance Type:                               opg

======================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------
--------
ma.L1          0.1660      0.091      1.821      0.069      -0.013
0.345
ma.S.L52      -0.3238      0.086     -3.754      0.000      -0.493
-0.155
sigma2      6.931e+09   3.67e-12   1.89e+21      0.000    6.93e+09
6.93e+09
======================================================================
=============
Ljung-Box (L1) (Q):                   1.04   Jarque-Bera (JB):
5.64
Prob(Q):                              0.31   Prob(JB):
0.06
Heteroskedasticity (H):               2.03   Skew:
-0.70
Prob(H) (two-sided):                  0.11   Kurtosis:
2.73
======================================================================
=============

Warnings:
[1] Covariance matrix calculated using the outer product of gradients
(complex-step).
[2] Covariance matrix is singular or near-singular, with condition
number    inf. Standard errors may be unstable.
"""
```

```
smape_value = smape(y_test, y_pred)
print(f"sMAPE: {smape_value}")
```

```
sMAPE: 0.2187027360998355
```

```
forecaster = SARIMAX(order=(3, 1, 0), seasonal_order=(0, 1, 0, 52))
forecaster.fit(y_sdif)
print(forecaster.summary())
```

```
/usr/local/lib/python3.10/dist-packages/statsmodels/tsa/statespace/
sarimax.py:966: UserWarning: Non-stationary starting autoregressive
parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'

                                     SARIMAX Results

======================================================================
====================
Dep. Variable:                             value   No. Observations:
64
Model:             SARIMAX(3, 1, 0)x(0, 1, 0, 52)   Log Likelihood
-145.608
Date:                         Mon, 27 Nov 2023   AIC
301.216
Time:                                 05:42:22   BIC
303.205
Sample:                             08-25-2014   HQIC
299.961
                                  - 10-27-2014

Covariance Type:                           opg

======================================================================
========
                 coef    std err          z      P>|z|      [0.025
0.975]
----------------------------------------------------------------------
--------
intercept  -3.074e+04   5.27e+04     -0.583      0.560   -1.34e+05
7.26e+04
ar.L1          0.3465      0.334      1.039      0.299      -0.307
1.000
ar.L2          0.0323      0.391      0.083      0.934      -0.735
0.800
ar.L3         -0.7714      0.401     -1.924      0.054      -1.557
0.015
sigma2       1.42e+10      0.250   5.68e+10      0.000    1.42e+10
1.42e+10
======================================================================
=============
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):
0.36
Prob(Q):                              0.95   Prob(JB):
0.84
Heteroskedasticity (H):               1.23   Skew:
-0.10
Prob(H) (two-sided):                  0.85   Kurtosis:
2.14
======================================================================
```

```
=============

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 4.01e+26. Standard errors may be unstable.

Параметры модели:
```

- Выбранная модель SARIMA имеет параметры (3, 1, 0) без сезонных компонент (p, d, q) и (0, 1, 0, 52) для сезонной составляющей (P, D, Q, s).
- Данная спецификация указывает, что в модели применено первое разностное преобразование временного ряда, авторегрессионные компоненты ar.L1, ar.L2 и ar.L3, и отсутствуют скользящие средние.
- Сезонная составляющая также предполагает первое сезонное разностное преобразование.

```
Метрики качества модели:
```

- Логарифмическое правдоподобие (Log Likelihood) составляет -145.608.
- Значение AIC равно 301.216, что является критерием информативности модели. * * Меньшие значения AIC сигнализируют о лучшей подгонке модели.

```
Коэффициент дисперсии (sigma2):
```

- Коэффициент дисперсии (sigma2) равен 1.42e+10, что предоставляет оценку дисперсии остатков модели.

```
Диагностические тесты:
```

- Ljung-Box тест (Q) на первом лаге (L1) имеет p-значение 0.95, что свидетельствует о автокорреляции в остатках отсутствует на первом лаге.
- Jarque-Bera тест (JB) на нормальность остатков имеет p-значение 0.84, что не отвергает гипотезу о нормальности остатков. В этом случае, остатки подчиняются нормальному распределению.

```
Гетероскедастичность:
```

- Тест на гетероскедастичность (H) имеет p-значение 0.85, что не достаточно низкое для отвержения гипотезы о гетероскедастичности в остатках. Коэффициенты модели:

- Intercept имеет значение -3.074e+04 со стандартной ошибкой 5.27e+04. P-значение равно 0.560, что не позволяет отвергнуть гипотезу о том, что коэффициент не отличается от нуля.

- Коэффициенты авторегрессии (ar.L1, ar.L2, ar.L3) не являются статистически значимыми при уровне значимости 0.05, что может указывать на их несущественность в модели.

```
Выводы:
```

- Модель SARIMA с параметрами (3, 1, 0)x(0, 1, 0, 52) имеет низкое значение AIC, что указывает на хорошее качество подгонки к данным. Диагностические тесты не выявили автокорреляцию в остатках, но не исключают возможности гетероскедастичности.
- Важно также обратить внимание на нестатистически значимые коэффициенты авторегрессии и наличие предупреждений относительно возможных проблем с оценкой коэффициентов (условие номер [1] и [2]). Дополнительные исследования и коррекции могут быть необходимы для улучшения модели.

Сравнение выбранных методов предсказаний и результатов работы настроенной модели SARIMA.

```
Простое экспоненциальное сглаживание:
   - sMAPE: 0.134.

 KNeighborsRegressor:
   - sMAPE: 0.101.

 ThetaForecaster:
   - sMAPE: 0.219.

 Модель SARIMA:
   - sMAPE: 0.1304.
```

- **KNeighborsRegressor** демонстрирует наименьшее значение sMAPE (0.101), что указывает на лучшую точность прогнозирования среди представленных методов.

- **SARIMA** также показывает хороший результат с sMAPE 0.1304, приближаясь к точности простого экспоненциального сглаживания.

- **Простое экспоненциальное сглаживание** имеет sMAPE 0.134, что также является конкурентоспособным результатом.

- **ThetaForecaster** имеет более высокое значение sMAPE (0.219), что указывает на менее точные прогнозы по сравнению с другими методами.

С основным критерием оценик sMAPE, то **KNeighborsRegressor** показывает наилучшие результаты, за ним следует **SARIMA**, и затем **Простое экспоненциальное сглаживание**. **ThetaForecaster** показывает наименьшую точность среди представленных методов.

Аналогично примерам (классификация временных рядов) анализ выбранного одноперременного ряда на предмет классификации его сегментов. Задачу можно сформулировать самостоятельно, например, как синтетическую для того же набора данных, который использовался для предсказания. Можно выбрать и новый набор данных. Результатом анализа должна быть таблица не менее чем из 3-х методов, которые сравнены по точности.

Предобработка

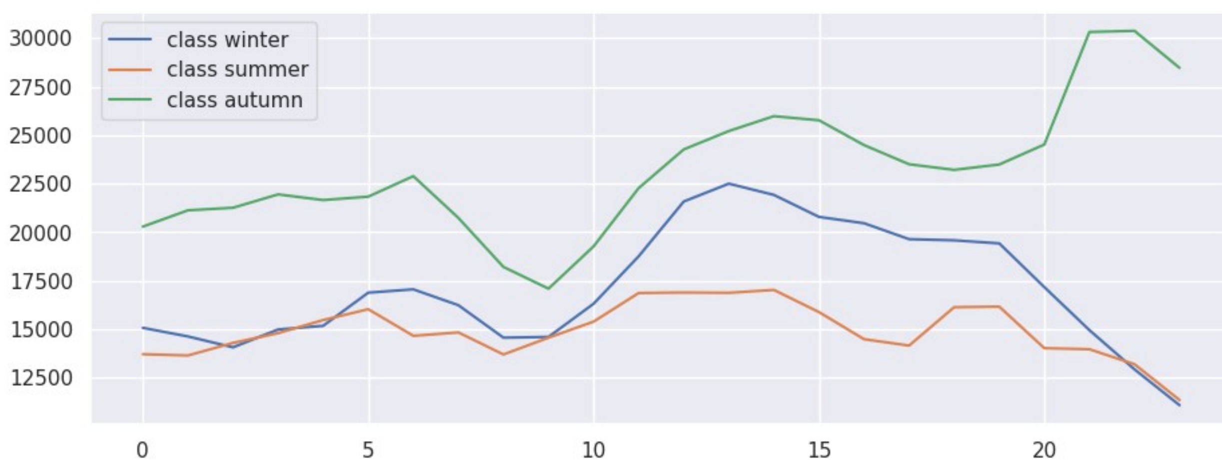
```
try:
    df = 
pd.read_csv('https://raw.githubusercontent.com/numenta/NAB/master/
data/realKnownCause/nyc_taxi.csv', index_col='timestamp', 
parse_dates=True)

except FileNotFoundError:
    print("File not found.")
except pd.errors.EmptyDataError:
    print("No data")
except pd.errors.ParserError:
    print("Parse error")
except Exception:
    print("Some other exception")

df.info()

<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 10320 entries, 2014-07-01 00:00:00 to 2015-01-31 
23:30:00
```

```
Data columns (total 1 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   value   10320 non-null  int64
dtypes: int64(1)
memory usage: 161.2 KB
```

```
df['day_of_the_week'] = pd.to_datetime(df.index).weekday

winter = to_segments(split_by_month(df, [1, 2, 12]), 'value', size=24)
summer = to_segments(split_by_month(df, [6, 7, 8]), 'value', size=24)
autumn = to_segments(split_by_month(df, [9, 10, 11]), 'value',
size=24)

print(winter.shape, summer.shape, autumn.shape)
```

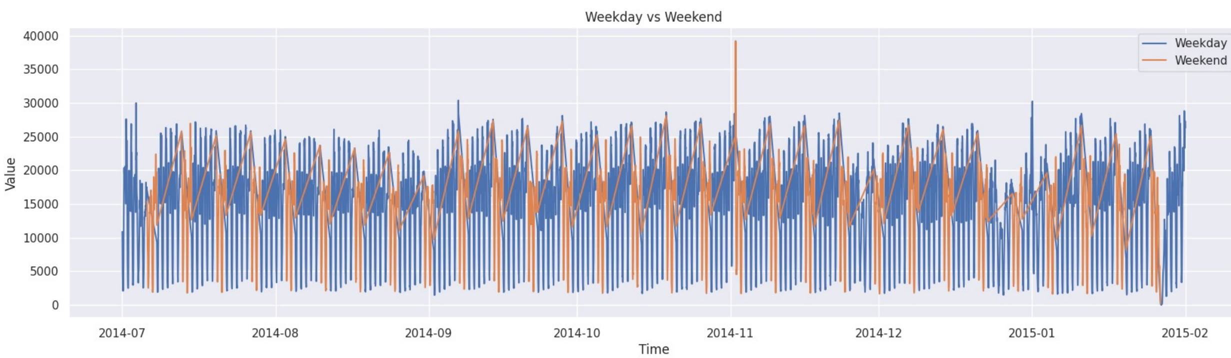
```
(123, 24) (123, 24) (181, 24)
```

```
plt.figure()
day = 10
for i,(c,d) in enumerate(zip([winter,summer,autumn],
['winter','summer','autumn'])):
    plt.plot(c[day], label="class " + str(d))
plt.legend(loc="best")
plt.show()
plt.close()
```




```
# weekday - будние дни (пн-пт)
weekday = df[(df['day_of_the_week'] >= 1) & (df['day_of_the_week'] <=
5)]

# weekend - выходные (сб-вс)
weekend = df[(df['day_of_the_week'] == 0) | (df['day_of_the_week'] ==
6)]
```

```
print(weekday.shape, weekend.shape)

(7440, 2) (2880, 2)

# Постройте графики для будних и выходных
plt.figure(figsize=(20, 5))

plt.plot(weekday['value'], label='Weekday')
plt.plot(weekend['value'], label='Weekend')

plt.xlabel('Time')
plt.ylabel('Value')
plt.title('Weekday vs Weekend')
plt.legend(loc='best')

plt.show()
```



Классификация

```
from sklearn.model_selection import train_test_split


X = np.concatenate((
                    weekday,
                    weekend))


y = np.concatenate((
                    0*np.ones(weekday.shape[0]),
                    1*np.ones(weekend.shape[0])
                   ))


X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)
print(X_train.shape, y_train.shape, X_test.shape, y_test.shape)

(7224, 2) (7224,) (3096, 2) (3096,)
```

Модели

TimeSeriesForestClassifier

```
from sktime.classification.interval_based import
TimeSeriesForestClassifier

clf = TimeSeriesForestClassifier(n_estimators=100,random_state=47)
clf.fit(X_train, y_train)
tsf_score = clf.score(X_test, y_test)

print(f' Score {clf.score(X_test, y_test):.3f}')
```

```
 Score 0.663
```

RidgeClassifierCV

```
from sklearn.linear_model import RidgeClassifierCV

# Assuming X_train, X_test, y_train, y_test are defined

# RidgeClassifierCV
ridge_clf = RidgeClassifierCV()
ridge_clf.fit(X_train, y_train)

# Evaluate the model on the test set
ridge_score = ridge_clf.score(X_test, y_test)
print(f'Test score with RidgeClassifierCV: {ridge_score:.3f}')
```

```
Test score with RidgeClassifierCV: 0.728
```

KNeighborsTimeSeries

```
from sktime.classification.distance_based import
KNeighborsTimeSeriesClassifier

knn_clf = KNeighborsTimeSeriesClassifier(n_neighbors=5)
knn_clf.fit(X_train, y_train)
knn_score = knn_clf.score(X_test, y_test)

print(f'Score with K-nearest neighbors: {knn_clf.score(X_test,
y_test):.3f}')
```

```
Score with K-nearest neighbors: 0.688
```

Сравнение

```
results = pd.DataFrame({
    'Model': ['TimeSeriesForest', 'RidgeClassifier',
'KNeighborsTimeSeries'],
    'Score': [tsf_score, ridge_score, knn_score]
```

```
})
results
```

```
                    Model     Score
0      TimeSeriesForest  0.662791
1       RidgeClassifier  0.728036
2  KNeighborsTimeSeries  0.687984
```

- TimeSeriesForest (0.662791): Эта модель использует алгоритм леса решений для временных рядов.
- RidgeClassifier (0.728036): Эта модель использует линейный классификатор Ridge.
- KNeighborsTimeSeries (0.687984): Эта модель использует метод k-ближайших соседей для временных рядов.

```
- RidgeClassifier продемонстрировал наилучшую производительность
среди трех моделей с точностью в 72.8% - набор данных имеет
линейные зависимости.
```

Отчет об исследовании выбранной задачи классификации при помощи глубоких нейронных сетей в пакете tsai. Исследование может быть проведено аналогично примеру. Результат анализа — рекомендованная архитектура нейронной сети. Архитектура должна быть сравнена с методами классификации из пункта выше.

Загрузка данных

```
from tsai.all import *
import warnings
from sklearn.model_selection import train_test_split
import torch
from torch import nn

computer_setup()
```

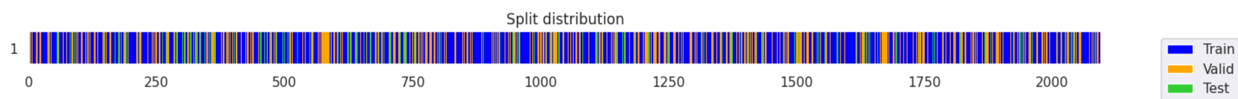
```
os               : Linux-5.15.120+-x86_64-with-glibc2.35
python           : 3.10.12
tsai             : 0.3.8
fastai           : 2.7.13
fastcore         : 1.5.29
torch            : 2.1.0+cu118
device           : cpu
cpu cores        : 1
threads per cpu  : 2
RAM              : 12.68 GB
GPU memory       : N/A

try:
    df = pd.read_csv('https://raw.githubusercontent.com/v-onuphrienko/Project.Study/main/14.%20HW1_ML_base/time_series_60.csv', sep=';')

except FileNotFoundError:
    print("File not found.")
except pd.errors.EmptyDataError:
    print("No data")
except pd.errors.ParserError:
    print("Parse error")
except Exception:
    print("Some other exception")

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 50398 entries, 0 to 50397
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   datetime  50398 non-null  object
 1   entsoe    50398 non-null  float64
dtypes: float64(1), object(1)
memory usage: 787.6+ KB

df['datetime'] = pd.to_datetime(df['datetime'])
df.set_index('datetime', inplace=True)

df

                            entsoe
datetime
2015-01-01 01:00:00+00:00  1794.96
2015-01-01 02:00:00+00:00  1744.76
2015-01-01 03:00:00+00:00  1743.17
2015-01-01 04:00:00+00:00  1751.47
2015-01-01 05:00:00+00:00  1767.16
...                            ...
```

```
2020-09-30 18:00:00+00:00  2801.24
2020-09-30 19:00:00+00:00  2615.98
2020-09-30 20:00:00+00:00  2219.68
2020-09-30 21:00:00+00:00  1940.76
2020-09-30 22:00:00+00:00  1826.01

[50398 rows x 1 columns]
```

Преобразование

```
winter = to_segments(split_by_month(df, [1,2, 12]), 'entsoe', size =
24)
summer = to_segments(split_by_month(df, [6, 7, 8]), 'entsoe', size =
24)
autumn = to_segments(split_by_month(df, [9,10,11]), 'entsoe', size =
24)
spring = to_segments(split_by_month(df, [3, 4, 5]), 'entsoe', size =
24)
print(winter.shape, summer.shape, autumn.shape, spring.shape)

X = np.concatenate((
                    winter,
                    summer,
                    autumn,
                    spring))
y = np.concatenate((
                    1*np.ones(winter.shape[0]),
                    2*np.ones(summer.shape[0]),
                    3*np.ones(autumn.shape[0]),
                    4*np.ones(spring.shape[0])
                   ))


X = np.atleast_3d(X).transpose(0,2,1)
y.astype(int)

(510, 24) (551, 24) (483, 24) (551, 24)

array([1, 1, 1, ..., 4, 4, 4])

class_map = {
    1:'winter',
    2:'summer',
    3:'autumn',
    4:'spring',
    }
class_map

labeler = ReLabeler(class_map)
y = labeler(y)
```

```
splits = get_splits(y,
                    n_splits=1,
                    valid_size=0.3,
                    test_size=0.1,
                    shuffle=True,
                    balance=False,
                    stratify=True,
                    random_state=42,
                    show_plot=True,
                    verbose=True)
splits
```




```
((#1258) [1276,1208,1046,1274,1487,631,1389,1166,1974,86...],
 (#628) [678,1677,1547,1846,1399,398,1267,1672,648,1031...],
 (#209) [1163,335,1275,113,80,950,288,493,470,548...])
```

- n_splits=1: - разделение
- valid_size=0.3: доля данных, включаемых в валидационный набор.
- test_size=0.1: доля данных, включаемых в тестовый набор.
- shuffle=True: перемешивание данных перед разделением.
- balance=False: отсутствие балансировки данных.
- stratify=True: стратификация разделения, что означает сохранение распределения классов в каждом разделении.
- random_state=42: задание случайного семени для воспроизводимости.
- show_plot=True: отображение графика разделения.
- verbose=True: отображение дополнительной информации о разделении.
- Создадим набор данных класса TSDatasets. В наборе данных зададим разделение данных и необходимые преобразования tfms.
- *Также* сконфигурируем загрузчик батчей TSDataLoaders. Загрузим тренировочный и валидационный наборы данных.

```
tfms  = [None, [Categorize()]]
dsets = TSDatasets(X, y, tfms=tfms, splits=splits)

bs = 4
dls   = TSDataLoaders.from_dsets(dsets.train, dsets.valid, bs=[bs,
bs*2])
```

- bs - размер батча
- TSDataLoaders.from_dsets - метод, используемый для создания загрузчиков данных для обучающего и валидационного наборов.
- dsets.train и dsets.valid - это обучающий и валидационный наборы данных.

- bs=[bs, bs*2] - размер пакета для обучающего и валидационного загрузчиков данных.

```
archs = [
         (RNNPlus, {'n_layers':3, 'bidirectional': True} ),
         (LSTMPlus,{'n_layers':3, 'bidirectional': True} ),
         (GRUPlus, {'n_layers':3, 'bidirectional': True} ),
         (RNNPlus, {'n_layers':4, 'bidirectional': True} ),
         (RNNPlus, {'n_layers':4, 'bidirectional': False}),
         (LSTM,    {'n_layers':3, 'bidirectional': False}),
         (RNN,     {'n_layers':3, 'bidirectional': True} ),
         (LSTM,    {'n_layers':3, 'bidirectional': True} ),
         (GRU,     {'n_layers':3, 'bidirectional': True} ),
         (ResNet, {}),
         (InceptionTime, {}),
         (XceptionTime,  {}),
         (TCN, {}),
         (LSTM_FCN, {}),
         (TST, {}),
         (FCN, {}),
        ]
```

Model

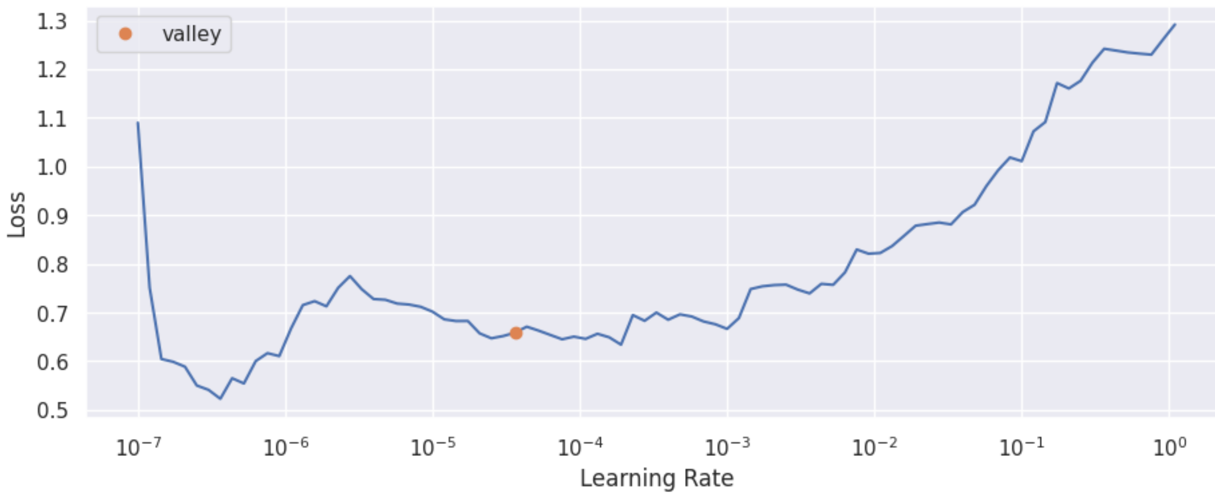
```
from IPython.display import clear_output



results = pd.DataFrame(columns=['arch', 'hyperparams', 'total params',
'train loss', 'valid loss', 'accuracy', 'time'])

for i, (arch, k) in enumerate(archs):

    model = create_model(arch, dls=dls, **k)

    print(model.__class__.__name__)

    learn = Learner(dls, model,  metrics=accuracy)
    start = time.time()
    learn.fit_one_cycle(5, 1e-3)
    elapsed = time.time() - start
    vals = learn.recorder.values[-1]
    results.loc[i] = [arch.__name__, k, count_parameters(model),
vals[0], vals[1], vals[2], int(elapsed)]
    results.sort_values(by='accuracy', ascending=False,
ignore_index=True, inplace=True)
    clear_output()
    display(results)

             arch                              hyperparams  total
params  \
```

```
0             FCN                                       {}
285188
1        LSTM_FCN                                       {}
326788
2   InceptionTime                                       {}
459780
3    XceptionTime                                       {}
403160
4          ResNet                                       {}
490500
5             TST                                       {}
399748
6         RNNPlus   {'n_layers': 4, 'bidirectional': True}
207204
7         RNNPlus  {'n_layers': 4, 'bidirectional': False}
73604
8             RNN   {'n_layers': 3, 'bidirectional': True}
146804
9         RNNPlus   {'n_layers': 3, 'bidirectional': True}
146804
10       LSTMPlus   {'n_layers': 3, 'bidirectional': True}
584804
11        GRUPlus   {'n_layers': 3, 'bidirectional': True}
438804
12           LSTM  {'n_layers': 3, 'bidirectional': False}
212404
13           LSTM   {'n_layers': 3, 'bidirectional': True}
584804
14            GRU   {'n_layers': 3, 'bidirectional': True}
438804
15            TCN                                       {}
71354

    train loss  valid loss  accuracy  time
0     0.690505    0.549458  0.840764    23
1     0.693379    0.562783  0.835987    37
2     0.690827    0.526885  0.826433    58
3     0.987582    0.684259  0.807325    90
4     0.855130    0.754525  0.765924    54
5     0.857263    0.934935  0.743631    38
6     1.287557    1.278174  0.385350    24
7     1.348353    1.329404  0.385350    14
8     1.374537    1.373512  0.269108    22
9     1.386506    1.385016  0.262739    27
10    1.383964    1.384864  0.262739    36
11    1.381867    1.383514  0.262739    28
12    1.386527    1.384841  0.262739    19
13    1.385887    1.384831  0.262739    43
```

```
14    1.385860    1.384938  0.262739    28
15    1.383779    1.384912  0.262739    74
```

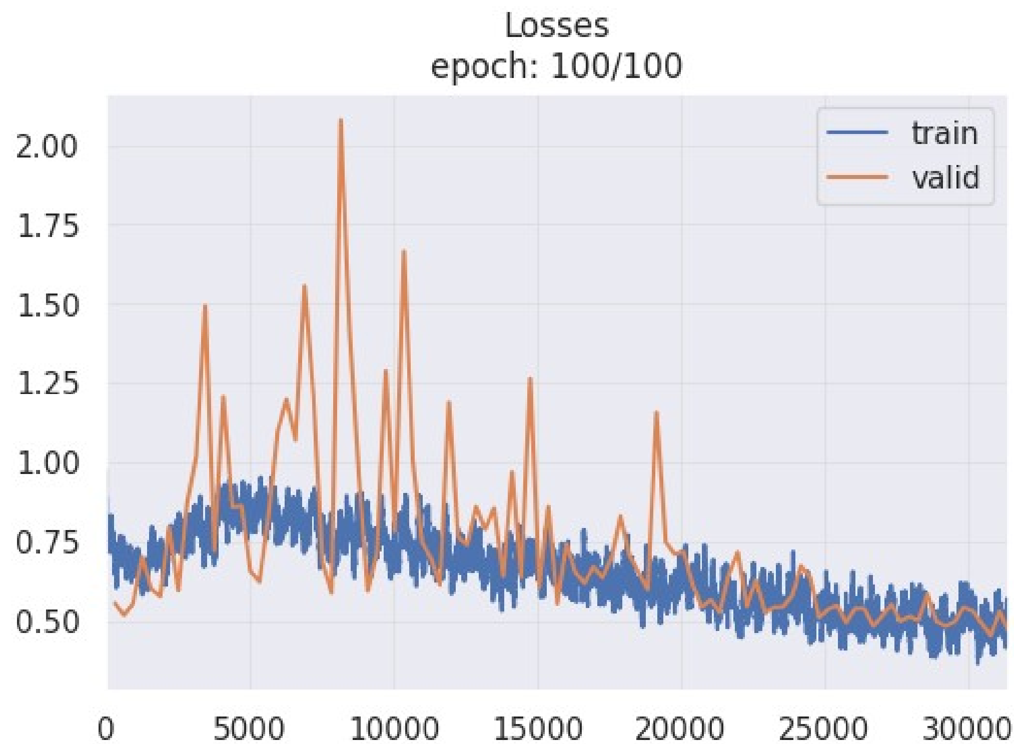
```
learn = ts_learner(dls, arch=model, metrics=accuracy)
learn.lr_find()
```

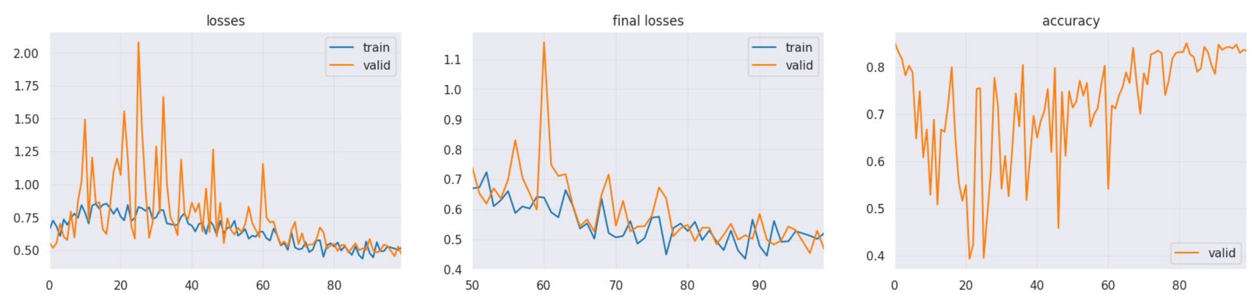
```
<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

SuggestedLRs(valley=3.630780702224001e-05)
```




```
learn = Learner(dls, model,  metrics=accuracy)
start = time.time()
learn.fit_one_cycle(n_epoch = 100, lr_max = 0.0036, cbs=ShowGraph())
```

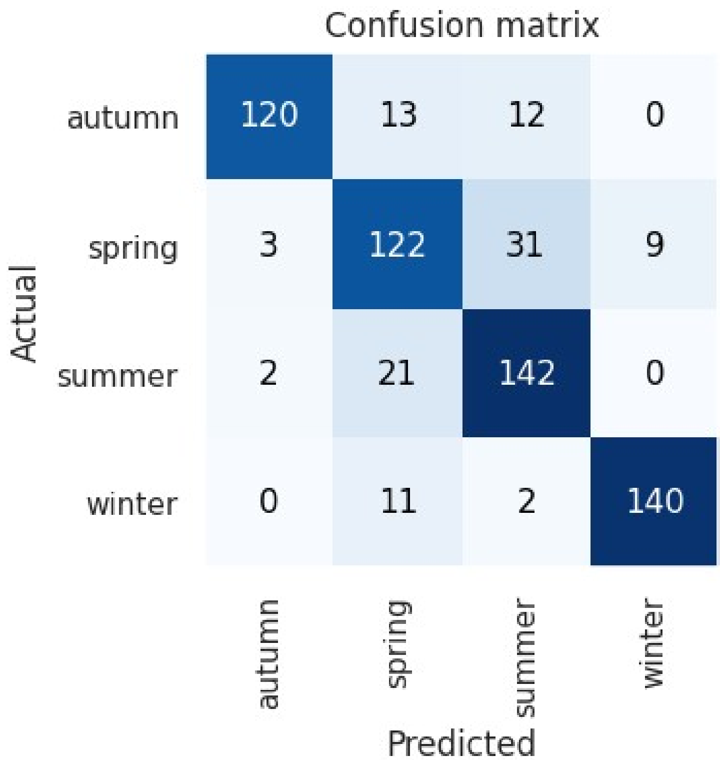
```
<IPython.core.display.HTML object>

<IPython.core.display.HTML object>
```






```
interp = ClassificationInterpretation.from_learner(learn)
interp.plot_confusion_matrix()
```

```
<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>
```



- Осень-Зима достаточно не плохо определена, Лето-Весна чуть хуже отрабатывает

```
# Выведем наиболее ошибочные случаи из матрицы
interp.most_confused(min_val=3)

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

[('spring', 'summer', 31),
 ('summer', 'spring', 21),
 ('autumn', 'spring', 13),
 ('autumn', 'summer', 12),
 ('winter', 'spring', 11),
 ('spring', 'winter', 9),
 ('spring', 'autumn', 3)]

probas, _, preds = learn.get_X_preds(X[splits[2][:5]])
preds, y[splits[2][:5]]

<IPython.core.display.HTML object>

<IPython.core.display.HTML object>

("['autumn', 'winter', 'autumn', 'winter', 'winter']",
 array(['autumn', 'winter', 'autumn', 'winter', 'winter'],
dtype='<U6'))
```

```
probas, _, preds = learn.get_X_preds(X[splits[2]])

class_map = {
    'winter':3,
    'summer':2,
    'autumn':0,
    'spring':1,
    }
class_map

labeler = ReLabeler(class_map)

from sklearn.metrics import accuracy_score

accuracy_score(np.argmax(probas,axis=-1), labeler(y[splits[2]]))

0.861244019138756

# Преобразование строковых меток в числовые
label_encoder = LabelEncoder()
numeric_labels = label_encoder.fit_transform(labeler(y[splits[2]]))

# Вычисление точности
acc_tsai = accuracy_score(np.argmax(probas, axis=-1), numeric_labels)
print(f"Accuracy: {accuracy}")

Accuracy: 0.861244019138756

acc_tsai

0.861244019138756
```

Сравнение

```
results = pd.DataFrame({
    'Model': ['TimeSeriesForest', 'RidgeClassifier',
'KNeighborsTimeSeries', 'tsai_result'],
    'Score': [tsf_score, ridge_score, knn_score, acc_tsai]
})
results

                  Model     Score
0      TimeSeriesForest  0.662791
1       RidgeClassifier  0.728036
2  KNeighborsTimeSeries  0.687984
3           tsai_result  0.861244
```

- Как мы видим, новая модель работает на порядок лучше TimeSeriesForest, RidgeClassifier, KNeighborsTimeSeries

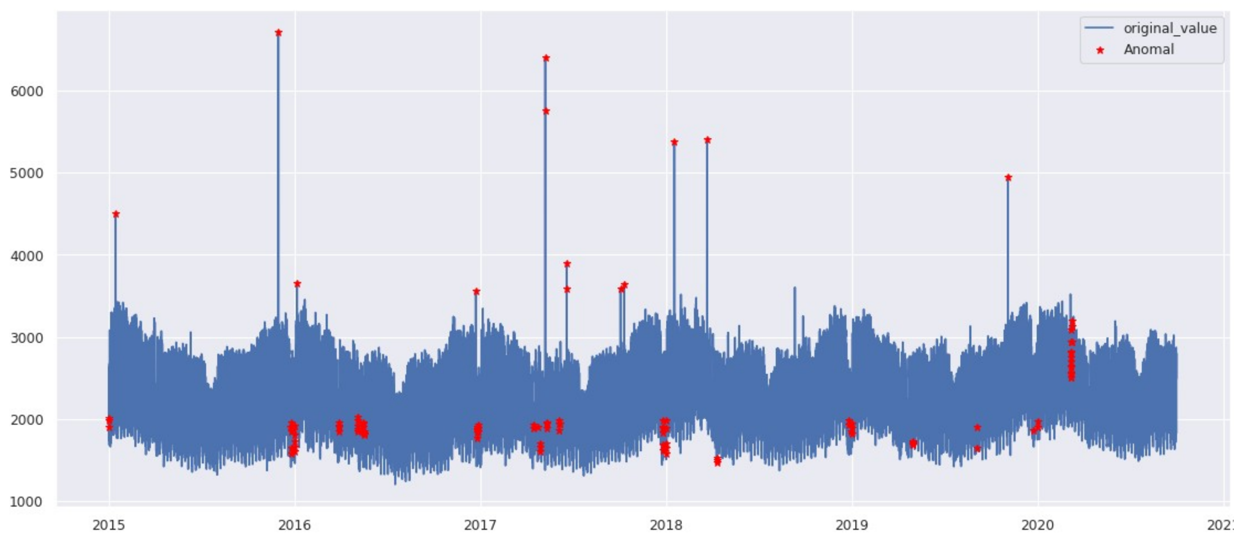
Отчет о выявлении аномалий во временном ряду. Может быть выбран ВР, использованный ранее. Отчет должен включать результаты анализа не менее чем 3-х методов аналогичных тем, что в примерах. Отчет может быть произведен в текстовом виде, например, как наиболее частые типы аномалий или гипотезы о причинах их появления. Также в отчет можно включить рекомендации по выбору и настройке методов выявления аномалий.

QuantileAD

- QuantileAD - метод использования квантилей.
  - Выставим минимальные пороги квантилей

```
from adtk.detector import QuantileAD
quantile_ad = QuantileAD(high=0.99, low=0.01)
anomalies = quantile_ad.fit_detect(df)
print('Число аномальных выбросов:', anomalies.values.sum())

Число аномальных выбросов: 1008

df.head

<bound method NDFrame.head of                            entsoe
datetime
2015-01-01 01:00:00+00:00  1794.96
2015-01-01 02:00:00+00:00  1744.76
2015-01-01 03:00:00+00:00  1743.17
2015-01-01 04:00:00+00:00  1751.47
2015-01-01 05:00:00+00:00  1767.16
...                            ...
2020-09-30 18:00:00+00:00  2801.24
2020-09-30 19:00:00+00:00  2615.98
2020-09-30 20:00:00+00:00  2219.68
2020-09-30 21:00:00+00:00  1940.76
2020-09-30 22:00:00+00:00  1826.01
```

```
[50398 rows x 1 columns]>

df2 = df.copy()
df2['a'] = anomalies['entsoe']
df_all = df2[df2['a'] == True].copy()

figure(figsize=(14, 6), dpi=80, layout='constrained')
plt.plot(df['entsoe'], label='original_value')
plt.plot(df_all['entsoe'], color='red', marker='*', linestyle='',
label='Anomal')
plt.legend()
plt.show();
```

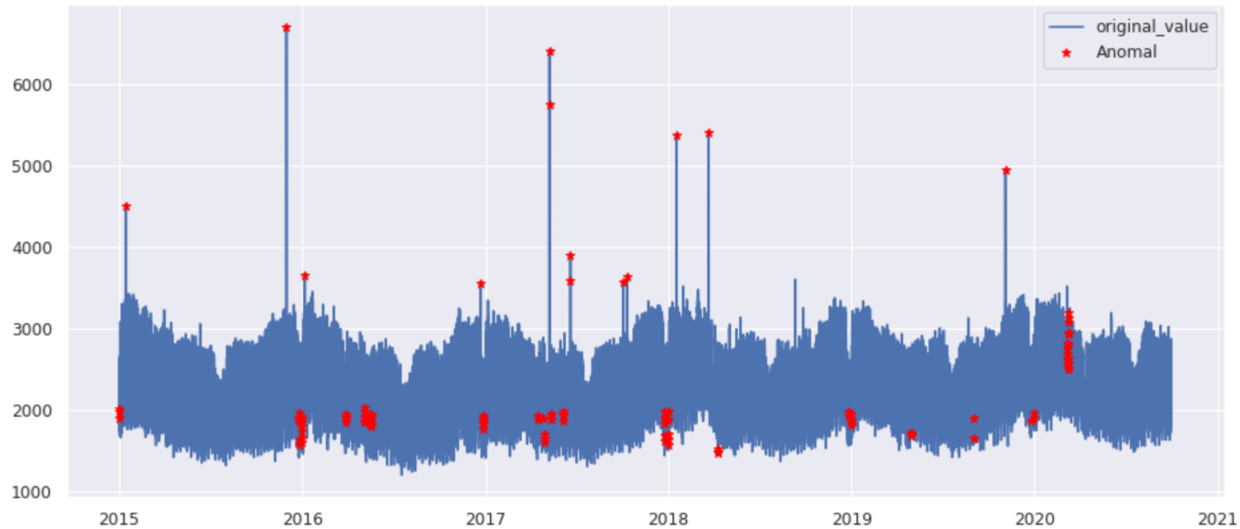


SeasonalAD

- SeasonalAD - сезонная адаптивная декомпозиция.

```
from adtk.detector import SeasonalAD
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure

seasonal_vol = SeasonalAD()
anomalies = seasonal_vol.fit_detect(df[['entsoe']])

df2 = df.copy()
df2['a'] = anomalies['entsoe']
df_all = df2[df2['a'] == True].copy()

figure(figsize=(14, 6), dpi=80)
plt.plot(df['entsoe'], label='original_value')
plt.plot(df_all['entsoe'], color='red', marker='*', linestyle='',
label='Anomal')
```

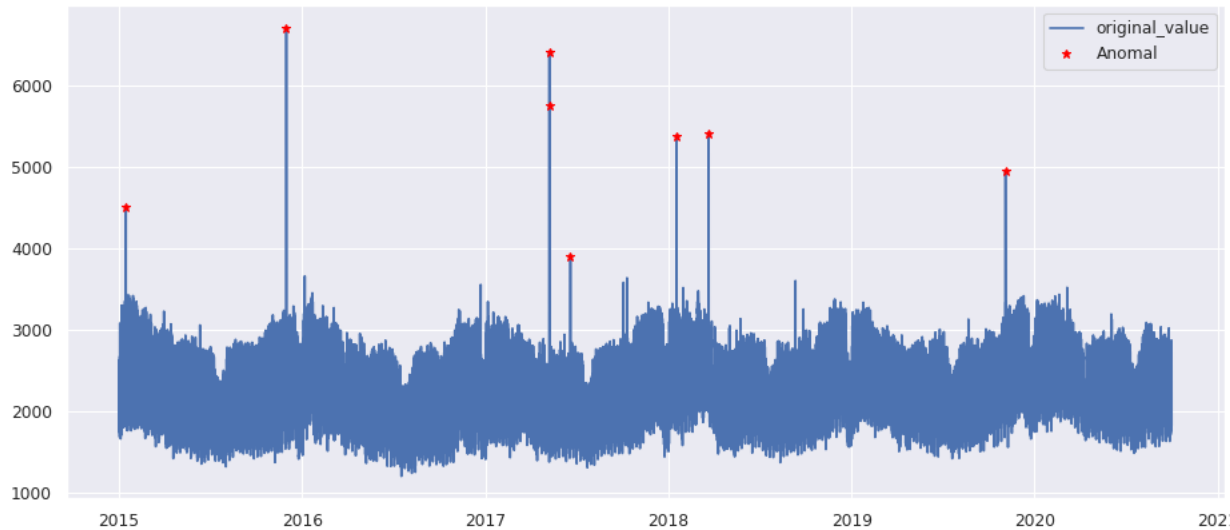
```
plt.legend()
plt.show();
```



InterQuartileRangeAD

InterQuartileRangeAD (детектор аномалий на основе интерквартильного диапазона) - это метод обнаружения аномалий во временных рядах, основанный на интерквартильном диапазоне (IQR).

```
from adtk.detector import InterQuartileRangeAD

iqr_ad = InterQuartileRangeAD(c=1.5)
anomalies_iqr = iqr_ad.fit_detect(df[['entsoe']])

df_iqr = df.copy()
df_iqr['anomalies'] = anomalies_iqr['entsoe']
df_all_iqr = df_iqr[df_iqr['anomalies'] == True].copy()

figure(figsize=(14, 6), dpi=80)
plt.plot(df['entsoe'], label='original_value')
plt.plot(df_all_iqr['entsoe'], color='red', marker='*', linestyle='',
label='Anomal')
plt.legend()
plt.show()
```



Вывод

- QuantileAD:
  - QuantileAD основан на использовании квантилей для выявления аномалий. Высокие и низкие квантили устанавливают верхний и нижний пороги, и точки данных за пределами этих порогов считаются аномалиями.
  - QuantileAD подходит для обнаружения общих аномалий, не зависящих от времени.
- SeasonalAD:
  - SeasonalAD предназначен для обнаружения сезонных аномалий, которые повторяются в определенные периоды времени. Метод использует характерные сезонные паттерны для выявления отклонений.
  - Полезен при поиске аномалий, связанных с сезонными колебаниями.
- InterQuartileRangeAD:
  - InterQuartileRangeAD использует межквартильный размах (IQR) для определения аномалий. Он опирается на разницу между первым и третьим квартилями данных.
  - Подходит для выявления аномалий, не вписывающихся в типичные распределения данных.
- Можно заметить что в начале каждого из годов видны аномально низкие показатели, наверное это сезонность, высокие показатели могут быть из-за тех. проблем, сбои в работе, либо аномально большая нагрузка.