



ITMO UNIVERSITY

Saint Petersburg, Russia

Using the FEDOT framework functionality to fill in the gaps in time series

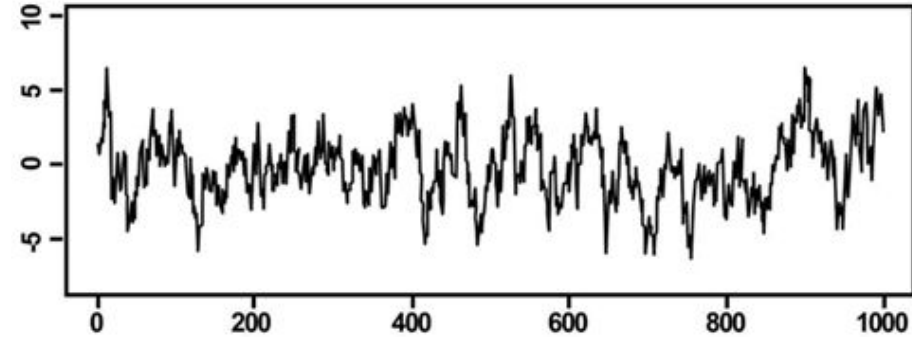
NSS-Lab ITMO

tutorial

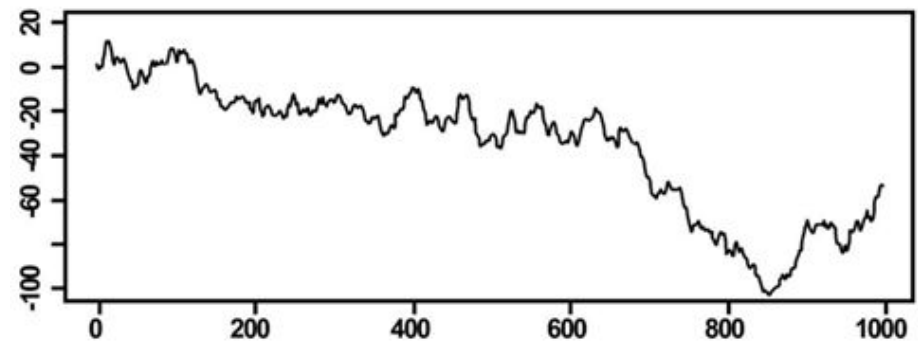
Time series

A time series is a series of data points indexed (or listed or graphed) in time order. Most commonly, a time series is a sequence taken at successive equally spaced points in time

Stationary Time Series



Non-stationary Time Series

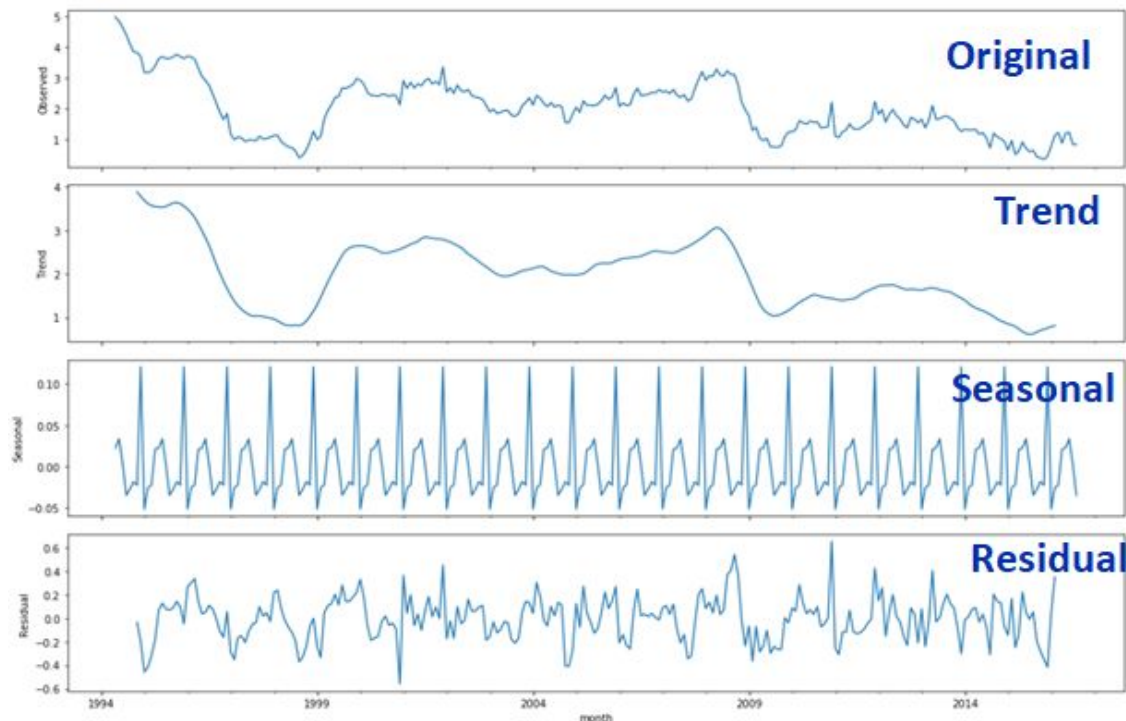


Stationarity – the constant of mean and variance over time

Time series decomposition

Components:

- **Trend** - long-term time series change;
- **Seasonality** – time series changes with constant period;
- **Cyclic** - time series changes with variable period;
- **Residuals** — a component that is left after other components have been calculated and removed from time series data.



Additional factors

Example:

SARIMAX Model: Daily & 6-Month Forecast Price of West Texas Intermediate (WTI) Crude Oil Futures from 2016



Variables:

1. Date - Daily based on Business Days
2. Price - Daily Closing Price – predictor
3. Open - Daily Opening Price
4. High - Intraday Maximum Price
5. Low - Intraday Minimum Price
6. Volume - # of futures traded
7. % Change - Percent change from previous day's closing price

```
def predict_arima(trained_model, predict_data: InputData) -> OutputData:
    start, end = trained_model.nobs, \
        trained_model.nobs + len(predict_data.target) - 1
    exog = predict_data.features

    if trained_model.data.endog is predict_data.target:
        # if train sample used
        start, end = 0, len(predict_data.target)

    prediction = trained_model.predict(start=start, end=end,
                                       exog=exog)

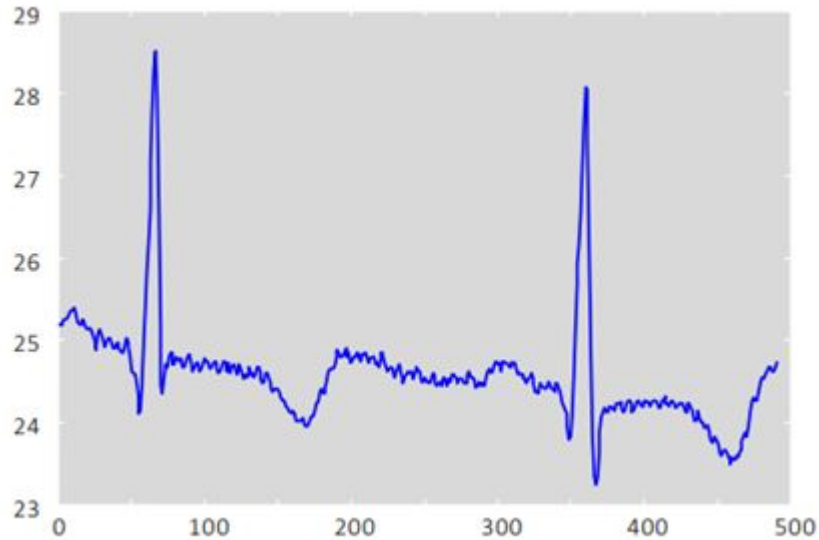
    return prediction[0:len(predict_data.target)]

def fit_arima(train_data: InputData, params):
    return ARIMA(train_data.target, **params,
                 exog=train_data.features).fit(dispatch=0)
```

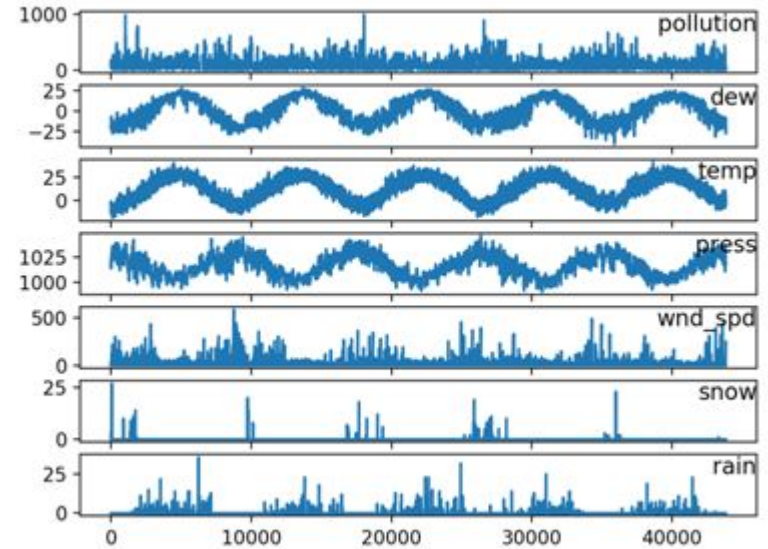
SARIMAX - Seasonal AutoRegressive
Integrated Moving Average with eXogenous
regressors

Univariate and multivariate time series

Univariate time series



Multivariate time series



R^2 – explained variance

```
1 from sklearn.metrics import r2_score
2
3 print("Linear Regression R^2:", round(r2_score(y, y_pred_lr), 3))
4 print("SMA R^2:", round(r2_score(y, y_sma), 3))
```

Linear Regression R^2: 0.942
SMA R^2: 0.822

Mean squared error /
Root Mean Square Error

```
1 from sklearn.metrics import mean_squared_error
2
3 print("Linear Regression MSE:", round(mean_squared_error(y, y_pred_lr), 3))
4 print("SMA MSE:", round(mean_squared_error(y, y_sma), 3))
```

Linear Regression MSE: 1882343.713
SMA MSE: 5774211.042

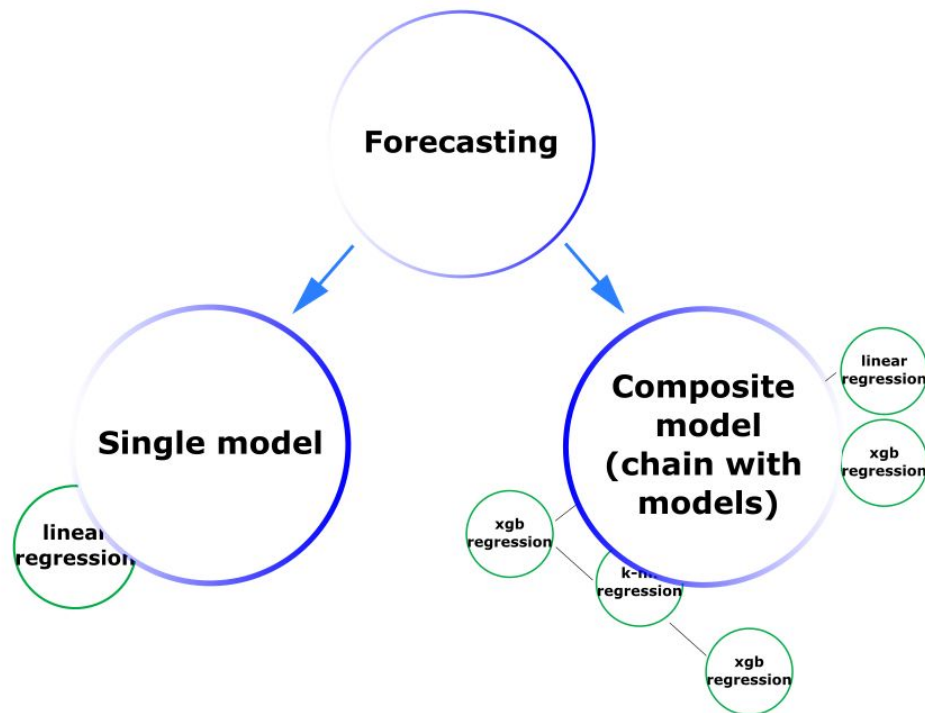
Mean absolute percentage
error

```
1 def mean_absolute_percentage_error(y_true, y_pred):
2     return round(np.mean(np.abs((y_true - y_pred) / y_true)) * 100, 3)
3
4 print("Linear Regression MAPE:", mean_absolute_percentage_error(y, y_pred_lr))
5 print("SMA MAPE:", mean_absolute_percentage_error(y, y_sma))
6
```

Linear Regression MAPE: 4.0
SMA MAPE: 22.493

Two ways to build models using FEDOT

- Based on the framework's functionality it is possible to build time series forecasting systems from a single model and then select the optimal hyperparameters for it;
- Or you can build chains of models that are harder to train, but will be more accurate.

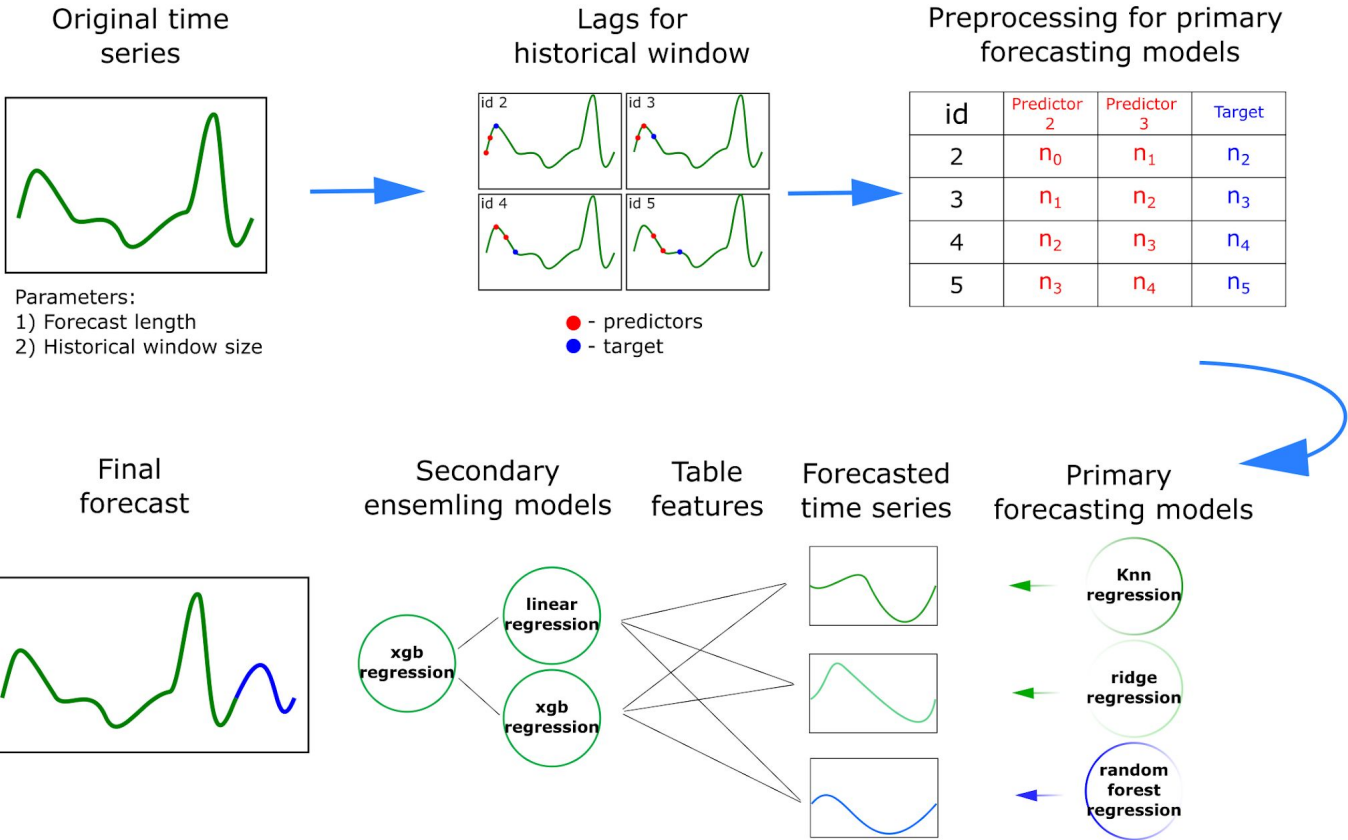


Fast train

A shorter time series
length is required

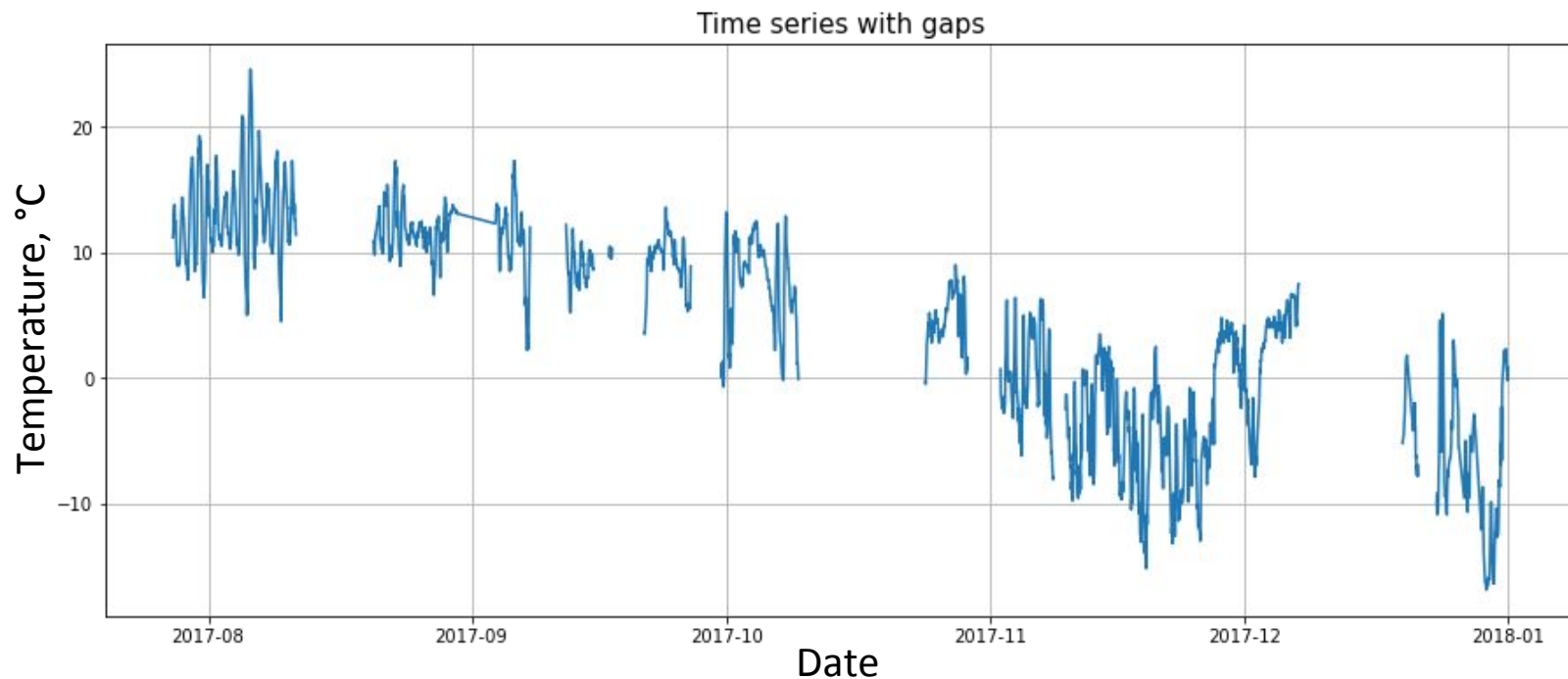
More accurate

Time series forecasting with FEDOT

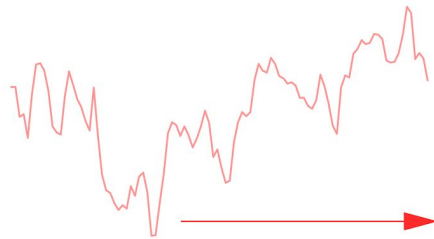
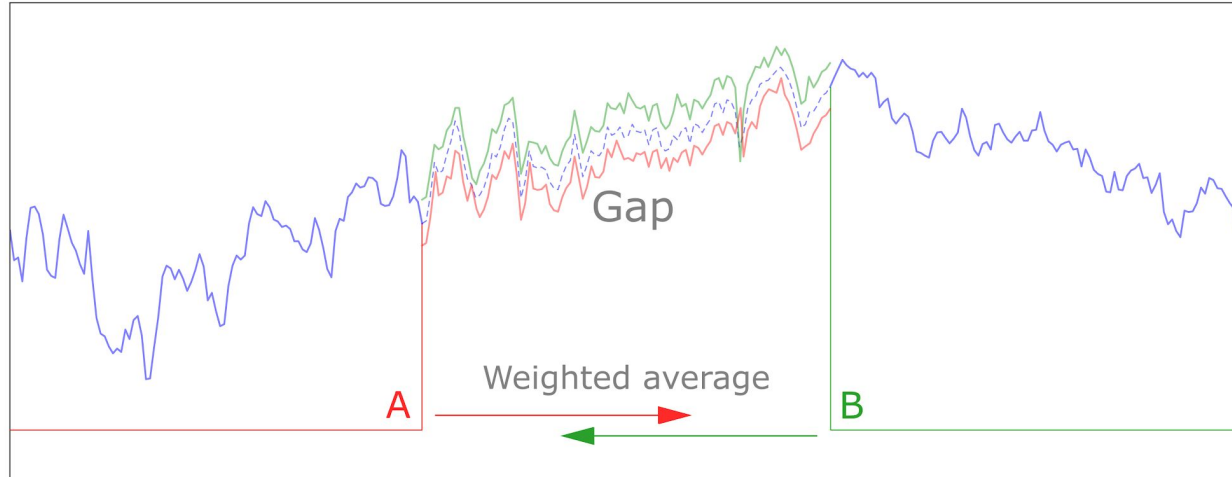


Gaps in time series

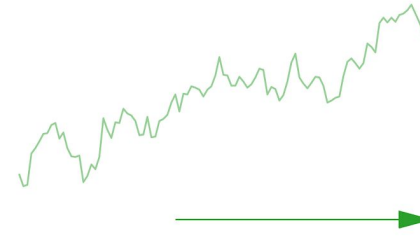
- Gap filling task \geq time series forecasting;
- For the gap filling task, to predict values, information can be used not only before the gap, but also the section of the time series after the omitted values.



Implemented approach



Prediction based on the source part
of the time series



Prediction based on the inverted part
of the time series

- Necessary imports

```
import numpy as np
from core.composer.node import PrimaryNode, SecondaryNode
from core.composer.ts_chain import TsForecastingChain
from core.models.data import InputData
from core.repository.dataset_types import DataTypesEnum
from core.repository.tasks import Task, TaskTypesEnum, TsForecastingParams
```

- Declaring a chain of one model

```
chain = TsForecastingChain(PrimaryNode( 'ridge' ))
```

- Declaring a time series forecasting task and preparing input data

```
task = Task(TaskTypesEnum.ts_forecasting,
            TsForecastingParams( forecast_length=forecast_length,
                                max_window_size=max_window_size,
                                return_all_steps=True,
                                make_future_prediction=True))

input_data = InputData( idx=np.arange(0, len(timeseries_train_part)),
                        features=None,
                        target=timeseries_train_part,
                        task=task,
                        data_type=DataTypesEnum.ts)
```

- Train model

```
chain.fit_from_scratch(input_data)
```

- Preparing data for the forecast

```
test_data = InputData( idx=np.arange(0, len_gap),  
                        features=None,  
                        target=None,  
                        task=task,  
                        data_type=DataTypesEnum.ts)
```

- Make prediction

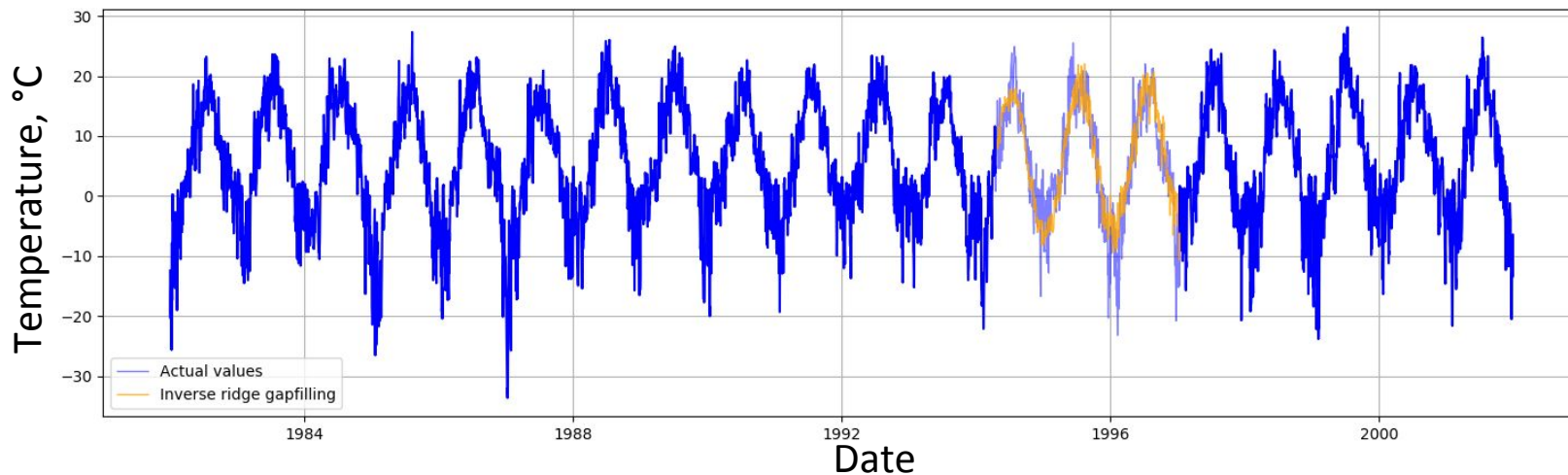
```
predicted_values = chain.forecast( initial_data=input_data,  
supplementary_data=test_data).predict
```

- Repeat the procedure for the inverted “right” part of the time series, weigh the forecasts and combine.

- Or you can use the implemented functionality of the framework - class `ModelGapFiller`;
- To do this, declare an instance of the `ModelGapFiller` class and give it an input to the `inverse_ridge` function, where the ridge regression is used as the main model, your array with skips:

```
gapfiller = ModelGapFiller(gap_value=-100.0)
without_gap_arr_ridge = gapfiller.inverse_ridge(gap_array, max_window_size=250)
```

- Get output



- Instead of declaring a chain with a single model, you can put multiple models in the chain using code as example:

```
node_first = PrimaryNode( 'trend_data_model')
node_second = PrimaryNode( 'residual_data_model')
node_trend_model = SecondaryNode( 'linear', nodes_from=[node_first])
node_residual_model = SecondaryNode( 'linear', nodes_from=[node_second])

node_final = SecondaryNode( 'additive_data_model', nodes_from=[node_trend_model,
node_residual_model])
chain = TsForecastingChain(node_final)
```

- In this case, a chain of 5 models is declared, where there are two input nodes ('trend_data_model', 'residual_data_model'), two intermediate nodes ('linear', 'linear'), and one final node ('additive_data_model');

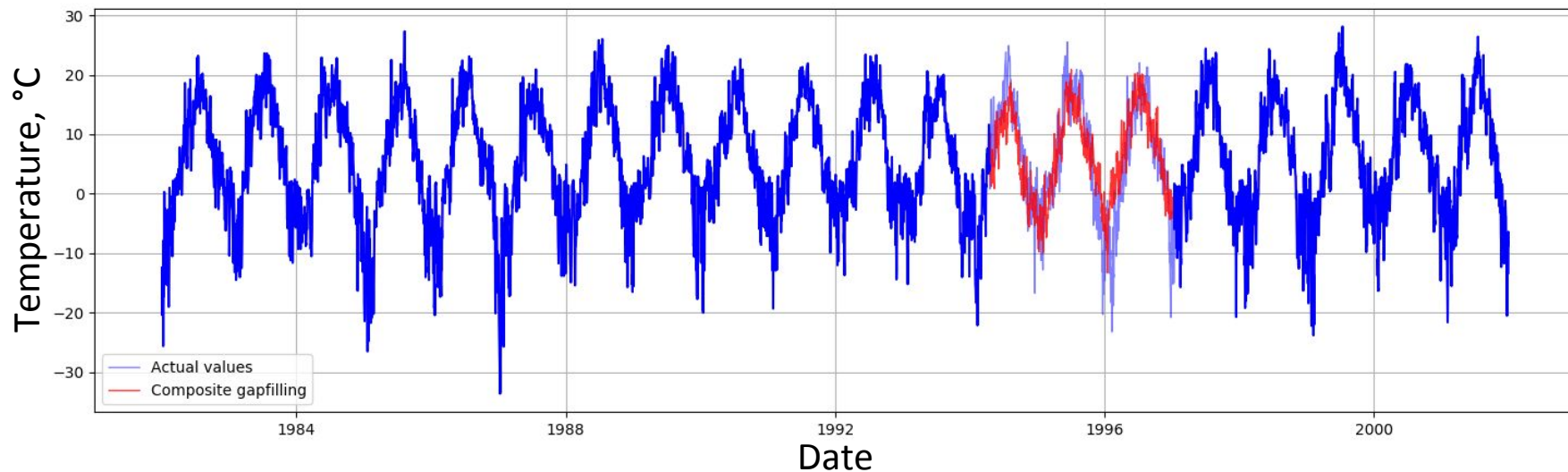
- Repeat all the same steps that we did from the chain with the same model.

FEDOT composite model example

- Or you can use a function from the class ModelGapFiller - `composite_fill_gaps`

```
gapfiller = ModelGapFiller( gap_value=-100.0)
without_gap_arr_composite = gapfiller.composite_fill_gaps(gap_array, max_window_size=1000)
```

- Get output



- As part of the development of the FEDOT automatic machine learning framework, the time series prediction functionality was implemented;
- Based on time series forecasting methods, algorithms for efficient gap recovery in time series have been developed;
- Two functions for restoring omissions in one-dimensional arrays based on a single model (`inverse_ridge`) and a chain with multiple models (`composite_fill_gaps`) were implemented;
- Based on high-level commands, it is now possible to restore gaps in one-dimensional arrays with only 2 lines of code using FEDOT.

Thank you for attention!

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