ExampleB

March 26, 2021

1 Project enda : Example B

If you haven't already, read Example A first, it is not long. Download `example_b.zip` and run this notebook in the correct python environment.

Install all the required packages in your python virtualenv:

```
pip install numexpr bottleneck pandas enda jupyter h2o scikit-learn statsmodels matplotlib jobl
pip install jours-feries-france vacances-scolaires-france Unidecode # used for feature enginee
```

In this example we will go more in depth, with realistic data and more historical data (~4-5 years). This example is divided in 7 parts: 1. Read and prepare data, check for missing values and gaps 2. Visualize data 3. Feature engineering : datetime and calendar features 4. Portfolio forecast & basic prediction 5. Benchmark with simple evaluation 6. Benchmark with Backtesting 7. Make the prediction

We set ourselves in a setup as if we were **exactly on 2020-11-30**. We want to predict the total consumption of customers for the next few days starting 2020-12-01 at a 30min time-step. We have: - our customer contracts until 2020-11-30 included. - historical load data from 2015-01-01 until 2020-11-15 included. There is a ~15 day time-gap between the last moment for which we have an actual load measure and 'today' (2020-11-30). - weather forecast until 2020-12-11 (11 days). - our TSO's network load forecast until 2020-12-7 (7 days).

In here (example B), we will put all our customers in only 1 group and forecast the next 7 days. We will first construct the dataset and the forecast input data and test it with a basic linear regressor. We will then try various algorithms and compare them. Finally we will give an example of backtesting on the data.

[1]:
```
import enda
import pandas as pd
import os
```

1.1 1. Read and prepare data, check for missing values and gaps

[2]:
```
# Replace this with the path to your example_b directory.
# You should have ExampleB.ipynb opened in jupyter, so you can run each step
DIR = '/Users/emmanuel.charon/Documents/CodeProjects/enercoop/enda/data/
↪example_b'
```

[3]:
```python
# Get the 30min time-step data just like in Example A
# (columns are a bit different and there is more data)
# Here we consider all customers in one big group.
def read_data():
    contracts = enda.Contracts.read_contracts_from_file(os.path.join(DIR,␣
 ↪"contracts.csv"))
    contracts["contracts_count"] = 1
    portfolio_by_day = enda.Contracts.compute_portfolio_by_day(
        contracts,
        columns_to_sum = ["contracts_count", "kva"],
        date_start_col="date_start",
        date_end_exclusive_col="date_end_exclusive",
    )
    portfolio = enda.TimeSeries.interpolate_daily_to_sub_daily_data(
        portfolio_by_day,
        freq='30min',
        tz='Europe/Paris'
    )

    historic_load_measured = pd.read_csv(os.path.join(DIR,␣
 ↪"historic_load_measured.csv"))
    weather_and_tso_forecasts = pd.read_csv(os.path.join(DIR,␣
 ↪"weather_and_tso_forecasts.csv"))
    # correctly format 'time' as a pandas.DatetimeIndex of dtype: datetime[ns,␣
 ↪tzinfo]
    for df in [historic_load_measured, weather_and_tso_forecasts]:
        df['time'] = pd.to_datetime(df['time'])
        df['time'] = enda.TimeSeries.align_timezone(df['time'], tzinfo =␣
 ↪'Europe/Paris')
        df.set_index('time', inplace=True)

    # keep only where both loads are known
    historic_load_measured = historic_load_measured.dropna()
    historic_load_measured["load_kw"] =␣
 ↪historic_load_measured["smart_metered_kw"] + historic_load_measured["slp_kw"]
    # keep only the full load
    historic_load_measured = historic_load_measured[["load_kw"]]


    return contracts, portfolio, historic_load_measured,␣
 ↪weather_and_tso_forecasts
```

[4]:
```python
contracts, portfolio, historic_load_measured, weather_and_tso_forecasts =␣
 ↪read_data()
# remove data where tso is not available
```

```
weather_and_tso_forecasts = weather_and_tso_forecasts.
 ↪dropna(subset=["tso_forecast_load_mw"])
```

[5]:
```
contracts
```

[5]:
```
        date_start date_end_exclusive   kva meter_reading_type  contracts_count
0       2006-08-09                NaT  12.0            PROFILE                1
1       2006-09-01         2006-11-23   6.0            PROFILE                1
2       2006-09-01         2007-11-01   3.0            PROFILE                1
3       2006-09-01         2007-12-19  12.0            PROFILE                1
4       2006-09-01         2008-06-28  12.0            PROFILE                1
…              …                 …    …                  …              …
162598  2020-11-30                NaT   6.0            PROFILE                1
162599  2020-11-30                NaT   6.0            PROFILE                1
162600  2020-11-30                NaT   6.0            PROFILE                1
162601  2020-11-30                NaT   6.0            PROFILE                1
162602  2020-11-30                NaT   6.0            PROFILE                1

[162603 rows x 5 columns]
```

[6]:
```
portfolio
```

[6]:
```
                           contracts_count       kva
time
2006-08-09 00:00:00+02:00              1.0      12.0
2006-08-09 00:30:00+02:00              1.0      12.0
2006-08-09 01:00:00+02:00              1.0      12.0
2006-08-09 01:30:00+02:00              1.0      12.0
2006-08-09 02:00:00+02:00              1.0      12.0
…                                       …        …
2020-11-30 21:30:00+01:00          96134.0  820005.7
2020-11-30 22:00:00+01:00          96134.0  820005.7
2020-11-30 22:30:00+01:00          96134.0  820005.7
2020-11-30 23:00:00+01:00          96134.0  820005.7
2020-11-30 23:30:00+01:00          96134.0  820005.7

[250946 rows x 2 columns]
```

[7]:
```
historic_load_measured
```

[7]:
```
                               load_kw
time
2015-01-01 00:00:00+01:00  2490.925806
2015-01-01 00:30:00+01:00  2412.623113
2015-01-01 01:00:00+01:00  2365.611276
2015-01-01 01:30:00+01:00  2336.141065
2015-01-01 02:00:00+01:00  2300.935642
```

```
…                                        …
2020-11-15 21:30:00+01:00  7657.293444
2020-11-15 22:00:00+01:00  7317.540759
2020-11-15 22:30:00+01:00  7580.051439
2020-11-15 23:00:00+01:00  7496.273993
2020-11-15 23:30:00+01:00  7376.005701

[97198 rows x 1 columns]
```

[8]:

```python
# t_weighted is the average french temperature weighted by population density
# t_smooth is a smoothing computed over t_weighted to take into account␣
 ↪building calorific inertia
# (t_smooth is computed out of enda here)
weather_and_tso_forecasts
```

[8]:

```
                           tso_forecast_load_mw  t_weighted  t_smooth
time
2015-01-01 00:00:00+01:00               72900.0       -0.41      1.17
2015-01-01 00:30:00+01:00               71600.0       -0.48      1.17
2015-01-01 01:00:00+01:00               69900.0       -0.55      1.15
2015-01-01 01:30:00+01:00               70600.0       -0.66      1.14
2015-01-01 02:00:00+01:00               70500.0       -0.78      1.11
…                                             …           …         …
2020-12-07 21:30:00+01:00               68400.0        4.20      4.13
2020-12-07 22:00:00+01:00               66900.0        4.12      4.10
2020-12-07 22:30:00+01:00               67600.0        4.03      4.08
2020-12-07 23:00:00+01:00               70200.0        3.94      4.07
2020-12-07 23:30:00+01:00               69600.0        3.94      4.07

[104064 rows x 3 columns]
```

[9]:

```python
# lets create the train set with historical data
historic = pd.merge(
    portfolio,
    historic_load_measured, # here we select only the load of the desired group
    how='inner', left_index=True, right_index=True
)

historic = pd.merge(
    historic,
    weather_and_tso_forecasts,
    how='inner', left_index=True, right_index=True
)
```

[10]:

```python
historic
```

[10]:
```
                           contracts_count       kva      load_kw  \
time
2015-01-01 00:00:00+01:00          21261.0  167416.4  2490.925806
2015-01-01 00:30:00+01:00          21261.0  167416.4  2412.623113
2015-01-01 01:00:00+01:00          21261.0  167416.4  2365.611276
2015-01-01 01:30:00+01:00          21261.0  167416.4  2336.141065
2015-01-01 02:00:00+01:00          21261.0  167416.4  2300.935642
…                                      …         …          …
2020-11-15 21:30:00+01:00          95475.0  813328.8  7657.293444
2020-11-15 22:00:00+01:00          95475.0  813328.8  7317.540759
2020-11-15 22:30:00+01:00          95475.0  813328.8  7580.051439
2020-11-15 23:00:00+01:00          95475.0  813328.8  7496.273993
2020-11-15 23:30:00+01:00          95475.0  813328.8  7376.005701

                           tso_forecast_load_mw  t_weighted  t_smooth
time
2015-01-01 00:00:00+01:00               72900.0       -0.41      1.17
2015-01-01 00:30:00+01:00               71600.0       -0.48      1.17
2015-01-01 01:00:00+01:00               69900.0       -0.55      1.15
2015-01-01 01:30:00+01:00               70600.0       -0.66      1.14
2015-01-01 02:00:00+01:00               70500.0       -0.78      1.11
…                                           …          …         …
2020-11-15 21:30:00+01:00               46200.0       12.05     12.01
2020-11-15 22:00:00+01:00               45200.0       11.92     11.97
2020-11-15 22:30:00+01:00               46400.0       11.84     11.96
2020-11-15 23:00:00+01:00               48600.0       11.75     11.94
2020-11-15 23:30:00+01:00               49400.0       11.64     11.92

[97198 rows x 6 columns]
```

[11]:
```python
# check that there is no NaN value
historic.isna().sum()
```

[11]:
```
contracts_count         0
kva                     0
load_kw                 0
tso_forecast_load_mw    0
t_weighted              0
t_smooth                0
dtype: int64
```

[12]:
```python
# note that the type of the index is precise
historic.index.dtype, type(historic.index)
```

[12]:
```
(datetime64[ns, Europe/Paris], pandas.core.indexes.datetimes.DatetimeIndex)
```

[13]:
```
# check missing data in the timeseries (based on the time index only)
freq, missing_periods, extra_points = enda.TimeSeries.
↪find_missing_and_extra_periods(
    dti=historic.index,
    expected_freq = '30min',
    expected_start_datetime = pd.to_datetime('2015-01-01 00:00:00+01:00').
↪astimezone('Europe/Paris'),
    expected_end_datetime = pd.to_datetime('2020-11-30 23:30:00+01:00').
↪astimezone('Europe/Paris')
)
for missing_period in missing_periods:
    print("Missing data from {} to {}.".format(missing_period[0],␣
↪missing_period[1]))
if len(extra_points) > 0 :
    print("Extra points found: {}".format(extra_points))
```

```
Missing data from 2015-09-01 00:00:00+02:00 to 2015-11-30 23:30:00+01:00.
Missing data from 2018-06-01 00:00:00+02:00 to 2018-06-30 23:30:00+02:00.
Missing data from 2020-11-16 00:00:00+01:00 to 2020-11-30 23:30:00+01:00.
```

We expected the missing data from 2020-11-16 to 2020-11-30, but not from the rest.

[14]:
```
# Zoom on a daylight savings time change to double-check that it was handled␣
↪correctly
historic[(historic.index >= '2019-10-27 01:00:00+02:00') & (historic.index <␣
↪'2019-10-27 03:30:00+01:00')]
```

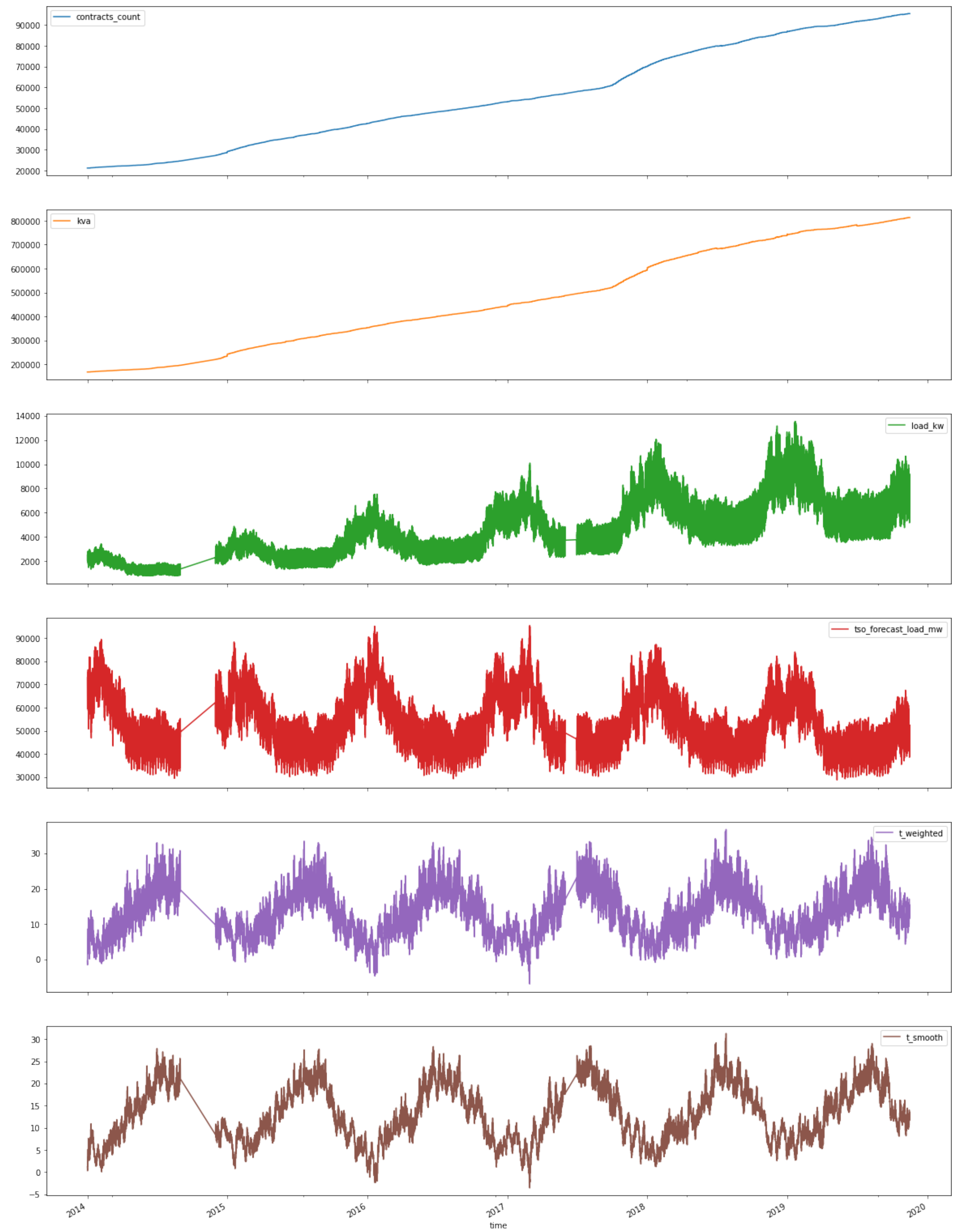
[14]:
```
                           contracts_count       kva      load_kw  \
time
2019-10-27 01:00:00+02:00          84131.0  716816.4  5179.955556
2019-10-27 01:30:00+02:00          84131.0  716816.4  5087.111111
2019-10-27 02:00:00+02:00          84131.0  716816.4  4898.400000
2019-10-27 02:30:00+02:00          84131.0  716816.4  4616.533333
2019-10-27 02:00:00+01:00          84131.0  716816.4  4259.822222
2019-10-27 02:30:00+01:00          84131.0  716816.4  4208.888889
2019-10-27 03:00:00+01:00          84131.0  716816.4  4137.955556

                           tso_forecast_load_mw  t_weighted  t_smooth
time
2019-10-27 01:00:00+02:00               41300.0       13.65     13.49
2019-10-27 01:30:00+02:00               40700.0       13.52     13.47
2019-10-27 02:00:00+02:00               36700.0       13.40     13.46
2019-10-27 02:30:00+02:00               36700.0       13.26     13.44
2019-10-27 02:00:00+01:00               36700.0       13.12     13.42
2019-10-27 02:30:00+01:00               36700.0       12.91     13.39
2019-10-27 03:00:00+01:00               36700.0       12.70     13.37
```

1.2 2. Visualize data

In order to visualise using pandas, we use the `matplotlib` backend.

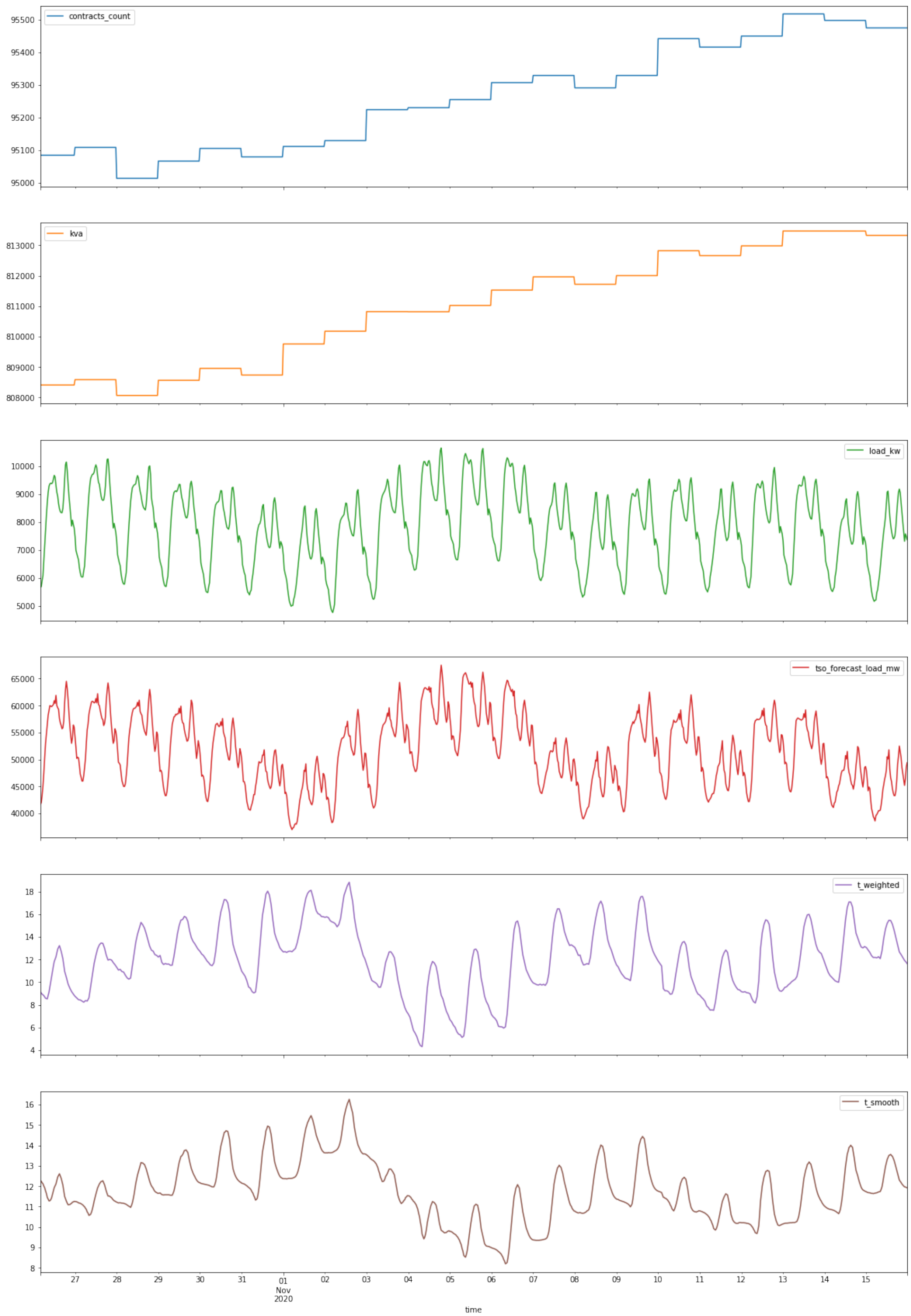
[15]:
```
# Show full data set
historic.plot(figsize=(20, 30), subplots=True)
```

[15]:
```
array([<AxesSubplot:xlabel='time'>, <AxesSubplot:xlabel='time'>,
       <AxesSubplot:xlabel='time'>, <AxesSubplot:xlabel='time'>,
       <AxesSubplot:xlabel='time'>, <AxesSubplot:xlabel='time'>],
      dtype=object)
```



[16]:
```
# Show recent data
historic[-1000:].plot(figsize=(20, 30), subplots=True)
```

[16]:
```
array([<AxesSubplot:xlabel='time'>, <AxesSubplot:xlabel='time'>,
       <AxesSubplot:xlabel='time'>, <AxesSubplot:xlabel='time'>,
       <AxesSubplot:xlabel='time'>, <AxesSubplot:xlabel='time'>],
      dtype=object)
```


contracts_count
kva
load_kw
tso_forecast_load_mw
t_weighted
t_smooth
time
Nov
2020

Don't hesitate to add your own visualisations!

[ ]:

```

```

1.3 3. Feature engineering

Before we train, we will add some features based on the `datetime`, and some calendar features related to national holidays or school holydays.

We use some packages for the holidays, which are used in **enda.feature_engineering.calendar** :

```
pip install jours-feries-france vacances-scolaires-france Unidecode
```

[17]:

```python
import enda.feature_engineering.calendar
```

[18]:

```python
# define the features we want to add before training/predicting
def featurize(df):
    # put datetime features to capture the data frequencies: daily, weekly and␣
↪yearly periods.
    df = enda.DatetimeFeature.split_datetime(
        df, split_list = ['minuteofday', 'dayofweek', 'month']
    )
    df = enda.DatetimeFeature.encode_cyclic_datetime_index(
        df, split_list = ['minuteofday', 'dayofweek', 'dayofyear']
    )

    # add features about national holidays and school holidays (French holidays␣
↪here)
    special_days = enda.feature_engineering.calendar.Calendar().
↪get_french_special_days()
    df = pd.merge(
        df, special_days,
        how='left', left_index=True, right_index=True
    )
    return df
```

[19]:

```python
full_train_set = featurize(historic)
```

[20]:

```python
full_train_set
```

[20]:

```
                           contracts_count       kva      load_kw  \
time
2015-01-01 00:00:00+01:00          21261.0  167416.4  2490.925806
2015-01-01 00:30:00+01:00          21261.0  167416.4  2412.623113
2015-01-01 01:00:00+01:00          21261.0  167416.4  2365.611276
2015-01-01 01:30:00+01:00          21261.0  167416.4  2336.141065
```

```
2015-01-01 02:00:00+01:00          21261.0  167416.4  2300.935642
…                                    …        …          …
2020-11-15 21:30:00+01:00          95475.0  813328.8  7657.293444
2020-11-15 22:00:00+01:00          95475.0  813328.8  7317.540759
2020-11-15 22:30:00+01:00          95475.0  813328.8  7580.051439
2020-11-15 23:00:00+01:00          95475.0  813328.8  7496.273993
2020-11-15 23:30:00+01:00          95475.0  813328.8  7376.005701

                           tso_forecast_load_mw  t_weighted  t_smooth  \
time
2015-01-01 00:00:00+01:00               72900.0       -0.41      1.17
2015-01-01 00:30:00+01:00               71600.0       -0.48      1.17
2015-01-01 01:00:00+01:00               69900.0       -0.55      1.15
2015-01-01 01:30:00+01:00               70600.0       -0.66      1.14
2015-01-01 02:00:00+01:00               70500.0       -0.78      1.11
…                                         …          …        …
2020-11-15 21:30:00+01:00               46200.0       12.05     12.01
2020-11-15 22:00:00+01:00               45200.0       11.92     11.97
2020-11-15 22:30:00+01:00               46400.0       11.84     11.96
2020-11-15 23:00:00+01:00               48600.0       11.75     11.94
2020-11-15 23:30:00+01:00               49400.0       11.64     11.92

                           minuteofday  dayofweek  month  minuteofday_cos  \
time
2015-01-01 00:00:00+01:00            0          3      1         1.000000
2015-01-01 00:30:00+01:00           30          3      1         0.991445
2015-01-01 01:00:00+01:00           60          3      1         0.965926
2015-01-01 01:30:00+01:00           90          3      1         0.923880
2015-01-01 02:00:00+01:00          120          3      1         0.866025
…                                  …          …    …             …
2020-11-15 21:30:00+01:00         1290          6     11         0.793353
2020-11-15 22:00:00+01:00         1320          6     11         0.866025
2020-11-15 22:30:00+01:00         1350          6     11         0.923880
2020-11-15 23:00:00+01:00         1380          6     11         0.965926
2020-11-15 23:30:00+01:00         1410          6     11         0.991445

                           minuteofday_sin  dayofweek_cos  dayofweek_sin  \
time
2015-01-01 00:00:00+01:00         0.000000      -0.900969       0.433884
2015-01-01 00:30:00+01:00         0.130526      -0.900969       0.433884
2015-01-01 01:00:00+01:00         0.258819      -0.900969       0.433884
2015-01-01 01:30:00+01:00         0.382683      -0.900969       0.433884
2015-01-01 02:00:00+01:00         0.500000      -0.900969       0.433884
…                                    …              …             …
2020-11-15 21:30:00+01:00        -0.608761       0.623490      -0.781831
2020-11-15 22:00:00+01:00        -0.500000       0.623490      -0.781831
2020-11-15 22:30:00+01:00        -0.382683       0.623490      -0.781831
```

```
2020-11-15 23:00:00+01:00        -0.258819       0.623490      -0.781831
2020-11-15 23:30:00+01:00        -0.130526       0.623490      -0.781831

                           dayofyear_cos  dayofyear_sin  lockdown  \
time
2015-01-01 00:00:00+01:00       1.000000       0.000000       0.0
2015-01-01 00:30:00+01:00       1.000000       0.000000       0.0
2015-01-01 01:00:00+01:00       1.000000       0.000000       0.0
2015-01-01 01:30:00+01:00       1.000000       0.000000       0.0
2015-01-01 02:00:00+01:00       1.000000       0.000000       0.0
…                                    …            …        …
2020-11-15 21:30:00+01:00       0.691771      -0.722117       0.0
2020-11-15 22:00:00+01:00       0.691771      -0.722117       0.0
2020-11-15 22:30:00+01:00       0.691771      -0.722117       0.0
2020-11-15 23:00:00+01:00       0.691771      -0.722117       0.0
2020-11-15 23:30:00+01:00       0.691771      -0.722117       0.0

                           public_holiday  nb_school_areas_off  \
time
2015-01-01 00:00:00+01:00             1.0                  3.0
2015-01-01 00:30:00+01:00             1.0                  3.0
2015-01-01 01:00:00+01:00             1.0                  3.0
2015-01-01 01:30:00+01:00             1.0                  3.0
2015-01-01 02:00:00+01:00             1.0                  3.0
…                                      …                   …
2020-11-15 21:30:00+01:00             0.0                  0.0
2020-11-15 22:00:00+01:00             0.0                  0.0
2020-11-15 22:30:00+01:00             0.0                  0.0
2020-11-15 23:00:00+01:00             0.0                  0.0
2020-11-15 23:30:00+01:00             0.0                  0.0

                           extra_long_weekend
time
2015-01-01 00:00:00+01:00                 0.0
2015-01-01 00:30:00+01:00                 0.0
2015-01-01 01:00:00+01:00                 0.0
2015-01-01 01:30:00+01:00                 0.0
2015-01-01 02:00:00+01:00                 0.0
…                                        …
2020-11-15 21:30:00+01:00                 0.0
2020-11-15 22:00:00+01:00                 0.0
2020-11-15 22:30:00+01:00                 0.0
2020-11-15 23:00:00+01:00                 0.0
2020-11-15 23:30:00+01:00                 0.0

[97198 rows x 19 columns]
```

[21]:
```
# train a basic SKLearnLinearRegression
from enda.ml_backends.sklearn_estimator import SklearnEstimator
from sklearn.linear_model import LinearRegression

lin_reg = SklearnEstimator(LinearRegression())
lin_reg.train(full_train_set, target_col='load_kw')
```

1.4 4. Portfolio forecast & basic prediction

We need an estimate of our portfolio in the next few days, the tso_load and weather forecasts.

In order to get our portfolio in the next few days, here we will just consider the latest trends in our portfolio.

In another setup, you might want to connect to your sales software or ERP and take into account contracts that will end or start soon.

We will use `enda.Contracts.forecast_using_trend`which requires the `statsmodel` package :

`pip install statsmodels`

[22]:
```
# we will forecast the portfolio using holt method
forecast_portfolio =  enda.Contracts.forecast_using_trend(
    portfolio_df=portfolio,
    start_forecast_date=pd.to_datetime("2020-12-01 00:00:00+01:00"),
    nb_days=7,
    past_days=150  # only use recent portfolio trend to forecast the next few␣
 ↪days
)
forecast_portfolio
```

```
/Users/emmanuel.charon/Documents/CodeProjects/enercoop/enda/venv/lib/python3.7/s
ite-packages/statsmodels/tsa/holtwinters/model.py:922: ConvergenceWarning:
Optimization failed to converge. Check mle_retvals.
  ConvergenceWarning,
```

[22]:

	contracts_count	kva
time		
2020-12-01 00:00:00+01:00	96134.6	820008.8
2020-12-01 00:30:00+01:00	96135.3	820011.8
2020-12-01 01:00:00+01:00	96135.9	820014.9
2020-12-01 01:30:00+01:00	96136.5	820017.9
2020-12-01 02:00:00+01:00	96137.1	820021.0
…	…	…
2020-12-07 21:30:00+01:00	96341.2	821020.6
2020-12-07 22:00:00+01:00	96341.8	821023.7
2020-12-07 22:30:00+01:00	96342.4	821026.7
2020-12-07 23:00:00+01:00	96343.1	821029.8
2020-12-07 23:30:00+01:00	96343.7	821032.8

```
[336 rows x 2 columns]
```

[23]:
```python
# add weather_and_tso_forecasts
forecast_input_data = pd.merge(
    forecast_portfolio,
    weather_and_tso_forecasts,
    how='inner', left_index=True, right_index=True
)
# add feature engineering
forecast_input_data = featurize(forecast_input_data)
forecast_input_data
```

[23]:
```
                           contracts_count       kva  tso_forecast_load_mw  \
time
2020-12-01 00:00:00+01:00          96134.6  820008.8               66100.0
2020-12-01 00:30:00+01:00          96135.3  820011.8               64200.0
2020-12-01 01:00:00+01:00          96135.9  820014.9               61900.0
2020-12-01 01:30:00+01:00          96136.5  820017.9               62800.0
2020-12-01 02:00:00+01:00          96137.1  820021.0               62300.0
…                                        …         …                    …
2020-12-07 21:30:00+01:00          96341.2  821020.6               68400.0
2020-12-07 22:00:00+01:00          96341.8  821023.7               66900.0
2020-12-07 22:30:00+01:00          96342.4  821026.7               67600.0
2020-12-07 23:00:00+01:00          96343.1  821029.8               70200.0
2020-12-07 23:30:00+01:00          96343.7  821032.8               69600.0

                           t_weighted  t_smooth  minuteofday  dayofweek  \
time
2020-12-01 00:00:00+01:00        4.69      5.08            0          1
2020-12-01 00:30:00+01:00        4.82      5.10           30          1
2020-12-01 01:00:00+01:00        4.96      5.12           60          1
2020-12-01 01:30:00+01:00        5.04      5.13           90          1
2020-12-01 02:00:00+01:00        5.13      5.14          120          1
…                                   …         …            …          …
2020-12-07 21:30:00+01:00        4.20      4.13         1290          0
2020-12-07 22:00:00+01:00        4.12      4.10         1320          0
2020-12-07 22:30:00+01:00        4.03      4.08         1350          0
2020-12-07 23:00:00+01:00        3.94      4.07         1380          0
2020-12-07 23:30:00+01:00        3.94      4.07         1410          0

                           month  minuteofday_cos  minuteofday_sin  \
time
2020-12-01 00:00:00+01:00     12         1.000000         0.000000
2020-12-01 00:30:00+01:00     12         0.991445         0.130526
2020-12-01 01:00:00+01:00     12         0.965926         0.258819
2020-12-01 01:30:00+01:00     12         0.923880         0.382683
```

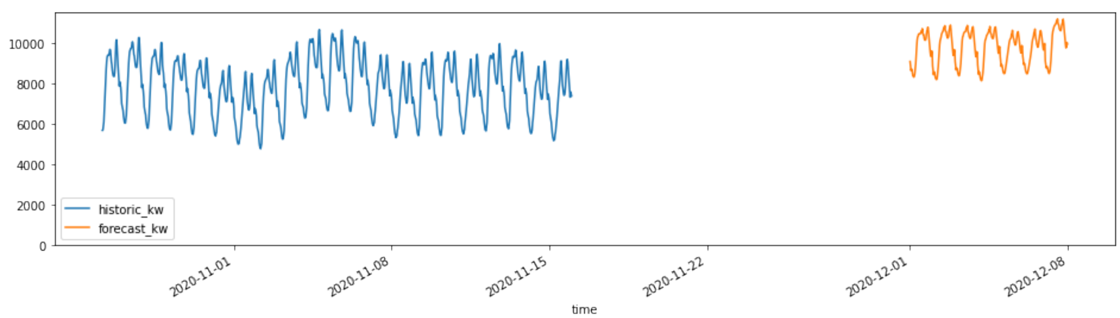
```
2020-12-01 02:00:00+01:00     12         0.866025         0.500000
…                            …              …                …
2020-12-07 21:30:00+01:00     12         0.793353        -0.608761
2020-12-07 22:00:00+01:00     12         0.866025        -0.500000
2020-12-07 22:30:00+01:00     12         0.923880        -0.382683
2020-12-07 23:00:00+01:00     12         0.965926        -0.258819
2020-12-07 23:30:00+01:00     12         0.991445        -0.130526

                           dayofweek_cos  dayofweek_sin  dayofyear_cos  \
time
2020-12-01 00:00:00+01:00        0.62349       0.781831       0.861702
2020-12-01 00:30:00+01:00        0.62349       0.781831       0.861702
2020-12-01 01:00:00+01:00        0.62349       0.781831       0.861702
2020-12-01 01:30:00+01:00        0.62349       0.781831       0.861702
2020-12-01 02:00:00+01:00        0.62349       0.781831       0.861702
…                                  …             …             …
2020-12-07 21:30:00+01:00        1.00000       0.000000       0.909308
2020-12-07 22:00:00+01:00        1.00000       0.000000       0.909308
2020-12-07 22:30:00+01:00        1.00000       0.000000       0.909308
2020-12-07 23:00:00+01:00        1.00000       0.000000       0.909308
2020-12-07 23:30:00+01:00        1.00000       0.000000       0.909308

                           dayofyear_sin  lockdown  public_holiday  \
time
2020-12-01 00:00:00+01:00      -0.507415       0.0             0.0
2020-12-01 00:30:00+01:00      -0.507415       0.0             0.0
2020-12-01 01:00:00+01:00      -0.507415       0.0             0.0
2020-12-01 01:30:00+01:00      -0.507415       0.0             0.0
2020-12-01 02:00:00+01:00      -0.507415       0.0             0.0
…                                  …        …             …
2020-12-07 21:30:00+01:00      -0.416125       0.0             0.0
2020-12-07 22:00:00+01:00      -0.416125       0.0             0.0
2020-12-07 22:30:00+01:00      -0.416125       0.0             0.0
2020-12-07 23:00:00+01:00      -0.416125       0.0             0.0
2020-12-07 23:30:00+01:00      -0.416125       0.0             0.0

                           nb_school_areas_off  extra_long_weekend
time
2020-12-01 00:00:00+01:00                  0.0                 0.0
2020-12-01 00:30:00+01:00                  0.0                 0.0
2020-12-01 01:00:00+01:00                  0.0                 0.0
2020-12-01 01:30:00+01:00                  0.0                 0.0
2020-12-01 02:00:00+01:00                  0.0                 0.0
…                                        …                 …
2020-12-07 21:30:00+01:00                  0.0                 0.0
2020-12-07 22:00:00+01:00                  0.0                 0.0
2020-12-07 22:30:00+01:00                  0.0                 0.0
```

```
2020-12-07 23:00:00+01:00                    0.0                   0.0
2020-12-07 23:30:00+01:00                    0.0                   0.0

[336 rows x 18 columns]
```

[24]:
```
# do the prediction
lin_reg_prediction = lin_reg.predict(forecast_input_data, target_col="load_kw")
```

[25]:
```
# visualize recent load along with our forecast; remember we don't have recent␣
↪actual load so there is a time-gap.
to_plot = pd.merge(
    historic["load_kw"][-1000:].to_frame("historic_kw"),
    lin_reg_prediction.rename(columns={"load_kw": "forecast_kw"}),
    how='outer', left_index=True, right_index=True
)
to_plot.plot(ylim=0, figsize=(16, 4))
```

[25]: <AxesSubplot:xlabel='time'>



1.5 5. Benchmark with simple evaluation

The previous forecast based on linear regression is very limited. Let's try and use a better algorithm !

We will define some algorithms using `scikit-klearn` as a machine learning backend and others using `h2o`.

For that we need the `h2o` package:

`pip install h2o`

[26]:
```
# here we do a benchmark, we want to compare with actual data,
# lets say from 2020-11-01 to 2020-11-15
benchmark_train = full_train_set[full_train_set.index < '2020-11-01']
benchmark_test = full_train_set[full_train_set.index >= '2020-11-01']

benchmark = benchmark_test["load_kw"].to_frame("actual_load_kw")
```

```
benchmark_test = benchmark_test.drop(columns=["load_kw"])
```

[27]:
```
# some parts give ConvergenceWarnings here and we'll ignore them.
import warnings
warnings.filterwarnings('ignore')
```

[28]:
```
# use the same method as before to predict a portfolio for 2020-11-01 ->␣
↪2020-11-15
benchmark_test_portfolio = enda.Contracts.forecast_using_trend(
    portfolio_df=portfolio[portfolio.index < '2020-11-01'],
    start_forecast_date=pd.to_datetime("2020-11-01 00:00:00+01:00"),
    nb_days=15,
    past_days=150  # only use recent portfolio trend to forecast the next few␣
↪days
)
benchmark_test['kva'] = benchmark_test_portfolio['kva']
benchmark_test['contracts_count'] = benchmark_test_portfolio['contracts_count']
benchmark_test
```

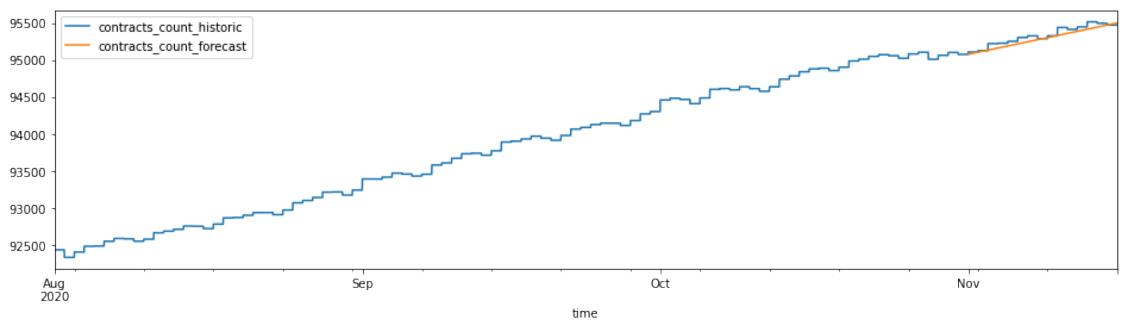
[28]:
```
                           contracts_count       kva  tso_forecast_load_mw  \
time
2020-11-01 00:00:00+01:00          95079.6  808742.3               47900.0
2020-11-01 00:30:00+01:00          95080.2  808744.8               45800.0
2020-11-01 01:00:00+01:00          95080.8  808747.2               43700.0
2020-11-01 01:30:00+01:00          95081.4  808749.7               43900.0
2020-11-01 02:00:00+01:00          95081.9  808752.2               43200.0
…                                      …         …                   …
2020-11-15 21:30:00+01:00          95500.0  810510.5               46200.0
2020-11-15 22:00:00+01:00          95500.6  810512.9               45200.0
2020-11-15 22:30:00+01:00          95501.2  810515.4               46400.0
2020-11-15 23:00:00+01:00          95501.8  810517.9               48600.0
2020-11-15 23:30:00+01:00          95502.4  810520.4               49400.0

                           t_weighted  t_smooth  minuteofday  dayofweek  \
time
2020-11-01 00:00:00+01:00       12.67     12.37            0          6
2020-11-01 00:30:00+01:00       12.68     12.37           30          6
2020-11-01 01:00:00+01:00       12.70     12.37           60          6
2020-11-01 01:30:00+01:00       12.66     12.37           90          6
2020-11-01 02:00:00+01:00       12.63     12.36          120          6
…                                   …         …            …          …
2020-11-15 21:30:00+01:00       12.05     12.01         1290          6
2020-11-15 22:00:00+01:00       11.92     11.97         1320          6
2020-11-15 22:30:00+01:00       11.84     11.96         1350          6
2020-11-15 23:00:00+01:00       11.75     11.94         1380          6
2020-11-15 23:30:00+01:00       11.64     11.92         1410          6
```

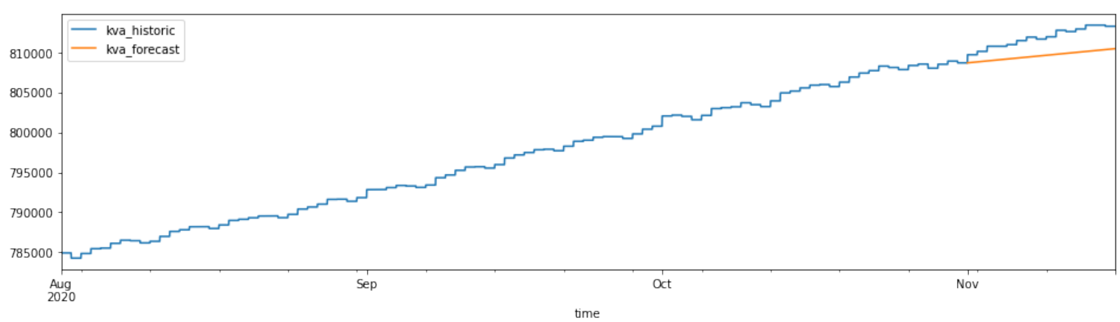
```
                           month  minuteofday_cos  minuteofday_sin  \
time
2020-11-01 00:00:00+01:00     11         1.000000         0.000000
2020-11-01 00:30:00+01:00     11         0.991445         0.130526
2020-11-01 01:00:00+01:00     11         0.965926         0.258819
2020-11-01 01:30:00+01:00     11         0.923880         0.382683
2020-11-01 02:00:00+01:00     11         0.866025         0.500000
…                            …                …                …
2020-11-15 21:30:00+01:00     11         0.793353        -0.608761
2020-11-15 22:00:00+01:00     11         0.866025        -0.500000
2020-11-15 22:30:00+01:00     11         0.923880        -0.382683
2020-11-15 23:00:00+01:00     11         0.965926        -0.258819
2020-11-15 23:30:00+01:00     11         0.991445        -0.130526

                           dayofweek_cos  dayofweek_sin  dayofyear_cos  \
time
2020-11-01 00:00:00+01:00        0.62349      -0.781831       0.500000
2020-11-01 00:30:00+01:00        0.62349      -0.781831       0.500000
2020-11-01 01:00:00+01:00        0.62349      -0.781831       0.500000
2020-11-01 01:30:00+01:00        0.62349      -0.781831       0.500000
2020-11-01 02:00:00+01:00        0.62349      -0.781831       0.500000
…                                    …              …             …
2020-11-15 21:30:00+01:00        0.62349      -0.781831       0.691771
2020-11-15 22:00:00+01:00        0.62349      -0.781831       0.691771
2020-11-15 22:30:00+01:00        0.62349      -0.781831       0.691771
2020-11-15 23:00:00+01:00        0.62349      -0.781831       0.691771
2020-11-15 23:30:00+01:00        0.62349      -0.781831       0.691771

                           dayofyear_sin  lockdown  public_holiday  \
time
2020-11-01 00:00:00+01:00      -0.866025       0.0             1.0
2020-11-01 00:30:00+01:00      -0.866025       0.0             1.0
2020-11-01 01:00:00+01:00      -0.866025       0.0             1.0
2020-11-01 01:30:00+01:00      -0.866025       0.0             1.0
2020-11-01 02:00:00+01:00      -0.866025       0.0             1.0
…                                    …        …              …
2020-11-15 21:30:00+01:00      -0.722117       0.0             0.0
2020-11-15 22:00:00+01:00      -0.722117       0.0             0.0
2020-11-15 22:30:00+01:00      -0.722117       0.0             0.0
2020-11-15 23:00:00+01:00      -0.722117       0.0             0.0
2020-11-15 23:30:00+01:00      -0.722117       0.0             0.0

                           nb_school_areas_off  extra_long_weekend
time
2020-11-01 00:00:00+01:00                  3.0                 0.0
2020-11-01 00:30:00+01:00                  3.0                 0.0
```

```
2020-11-01 01:00:00+01:00                   3.0                0.0
2020-11-01 01:30:00+01:00                   3.0                0.0
2020-11-01 02:00:00+01:00                   3.0                0.0
…                                         …                 …
2020-11-15 21:30:00+01:00                   0.0                0.0
2020-11-15 22:00:00+01:00                   0.0                0.0
2020-11-15 22:30:00+01:00                   0.0                0.0
2020-11-15 23:00:00+01:00                   0.0                0.0
2020-11-15 23:30:00+01:00                   0.0                0.0

[720 rows x 18 columns]
```

[29]:

```python
# compare portfolio forecast to reality
for c in ["contracts_count", "kva"]:
    to_plot = pd.merge(
        portfolio[(portfolio.index >= '2020-08-01') & (portfolio.index <␣
 ↪'2020-11-16')][c].to_frame(c+"_historic"),
        benchmark_test[c].to_frame(c+"_forecast"),
        how='outer', left_index=True, right_index=True
    )

    to_plot.plot(figsize=(16, 4))
```





[30]:
```
# Lets define some algorithms then train and predict with them
# All the models we define implement the enda.models.ModelInterface (see the␣
↪docs)
# Enda comes with wrappers around scikit-learn and H2O models:
#  sklearn: enda.ml_backends.sklearn_estimator.SklearnEstimator
#  H2O: enda.ml_backends.h2o_estimator.H2OEstimator

import time
import h2o
import random
import numpy

from sklearn.linear_model import LinearRegression, SGDRegressor
from sklearn.neural_network import MLPRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler

from enda.ml_backends.h2o_estimator import H2OEstimator  # enda's wrapper␣
↪around H2O models
from h2o.estimators import H2OGeneralizedLinearEstimator
from h2o.estimators import H2OXGBoostEstimator
from h2o.estimators import H2OGradientBoostingEstimator
from h2o.estimators import H2ORandomForestEstimator
from h2o.estimators import H2ODeepLearningEstimator
```

[31]:
```
random.seed(17)  # set random seed for reproducibility
numpy.random.seed(17) # for sklearn
# for h2o we will define it in each model
```

[32]:
```
all_models = dict()
```

[33]:
```
# Some models with the sklearn machine learning backend

all_models['sklearn_lin_reg'] = SklearnEstimator(LinearRegression())

all_models['sklearn_sgd'] = SklearnEstimator(
    Pipeline([('standard_scaler', StandardScaler()),
              ('sgd', SGDRegressor())
             ]
            )
)

all_models['sklearn_ada_boost'] = SklearnEstimator(AdaBoostRegressor(
    n_estimators=500,
    loss='linear', # 'square'
    learning_rate=0.8)
```

```
)

all_models['sklearn_nn'] = SklearnEstimator(
    Pipeline([('standard_scaler', StandardScaler()),
              ('mlp', MLPRegressor(
                  solver='adam',
                  activation='relu',
                  hidden_layer_sizes=[48, 48, 24],
                  max_iter=150
              ))
             ]
            )
)
```

[34]:

```
# Some models with the h2o machine learning backend

all_models['h2o_glm'] = H2OEstimator(H2OGeneralizedLinearEstimator(
    standardize=False,
    intercept=True,
    seed=17)
)

all_models['h2o_rf'] = H2OEstimator(H2ORandomForestEstimator(
    ntrees=300,
    max_depth=15,
    sample_rate=0.8,
    min_rows=10,
    nbins=52,
    mtries=3,
    seed=17
))

all_models['h2o_gbm'] = H2OEstimator(H2OGradientBoostingEstimator(
    ntrees=500,
    max_depth=5,
    sample_rate=0.5,
    min_rows=5,
    seed=17
))

all_models['h2o_xgboost'] = H2OEstimator(H2OXGBoostEstimator(
    **{
        "ntrees": 500,
        "max_depth": 5,
        "sample_rate": 0.8,
        "min_rows": 10,
        "seed": 17
```

```
    }
))

all_models['h2o_nn'] = H2OEstimator(H2ODeepLearningEstimator(
    **{
        "activation": "Tanh",
        "hidden": [48, 48, 24],
        "distribution": "gaussian",
        "epochs": 20,
        "seed": 17
    }
))
```

[35]:
```
# You can add more models to the benchmark here if you like
```

[36]:
```
# to train or predict with H2O models, we boot up a local h2o server
h2o.init(nthreads=-1)
h2o.no_progress()
```

```
Checking whether there is an H2O instance running at http://localhost:54321
… not found.
Attempting to start a local H2O server…
  Java Version: java version "12.0.1" 2019-04-16; Java(TM) SE Runtime
Environment (build 12.0.1+12); Java HotSpot(TM) 64-Bit Server VM (build
12.0.1+12, mixed mode, sharing)
  Starting server from /Users/emmanuel.charon/Documents/CodeProjects/enercoop/en
da/venv/lib/python3.7/site-packages/h2o/backend/bin/h2o.jar
  Ice root: /var/folders/5x/409ks2012xxch_pmbs6qpzfh0000gp/T/tmpx3_pia1b
  JVM stdout: /var/folders/5x/409ks2012xxch_pmbs6qpzfh0000gp/T/tmpx3_pia1b/h2o_e
mmanuel_charon_started_from_python.out
  JVM stderr: /var/folders/5x/409ks2012xxch_pmbs6qpzfh0000gp/T/tmpx3_pia1b/h2o_e
mmanuel_charon_started_from_python.err
  Server is running at http://127.0.0.1:54321
Connecting to H2O server at http://127.0.0.1:54321 … successful.

-------------------------- ␣
↪-----------------------------------------------------------------
H2O_cluster_uptime:         02 secs
H2O_cluster_timezone:       Europe/Paris
H2O_data_parsing_timezone:  UTC
H2O_cluster_version:        3.32.0.4
H2O_cluster_version_age:    1 month and 23 days
H2O_cluster_name:           H2O_from_python_emmanuel_charon_xqjnib
H2O_cluster_total_nodes:    1
H2O_cluster_free_memory:    4 Gb
H2O_cluster_total_cores:    4
H2O_cluster_allowed_cores:  4
H2O_cluster_status:         accepting new members, healthy
```

```
H2O_connection_url:         http://127.0.0.1:54321
H2O_connection_proxy:       {"http": null, "https": null}
H2O_internal_security:      False
H2O_API_Extensions:         Amazon S3, XGBoost, Algos, AutoML, Core V3,␣
↪TargetEncoder, Core V4
Python_version:             3.7.6 final
-------------------------- ␣
↪------------------------------------------------------------------
```

[37]:
```
# this should take between 5 and 15 minutes to run (in function of your␣
↪hardware)
print("Benchmark with {} models : {}\n".format(len(all_models), list(all_models.
↪keys())))
for model_name, model in all_models.items():
    model_start_time = time.time()
    print("Training {} before predicting with it..".format(model_name))
    model.train(benchmark_train, target_col='load_kw')
    model_prediction = model.predict(benchmark_test, target_col='load_kw')
    benchmark[model_name] = model_prediction
    print("{} took {:.1f} seconds.\n".format(model_name, time.
↪time()-model_start_time))
```

```
Benchmark with 9 models : ['sklearn_lin_reg', 'sklearn_sgd',
'sklearn_ada_boost', 'sklearn_nn', 'h2o_glm', 'h2o_rf', 'h2o_gbm',
'h2o_xgboost', 'h2o_nn']

Training sklearn_lin_reg before predicting with it..
sklearn_lin_reg took 0.1 seconds.

Training sklearn_sgd before predicting with it..
sklearn_sgd took 1.3 seconds.

Training sklearn_ada_boost before predicting with it..
sklearn_ada_boost took 62.1 seconds.

Training sklearn_nn before predicting with it..
sklearn_nn took 59.4 seconds.

Training h2o_glm before predicting with it..
h2o_glm took 5.4 seconds.

Training h2o_rf before predicting with it..
h2o_rf took 33.2 seconds.

Training h2o_gbm before predicting with it..
h2o_gbm took 22.7 seconds.
```

```
Training h2o_xgboost before predicting with it..
h2o_xgboost took 64.1 seconds.

Training h2o_nn before predicting with it..
h2o_nn took 80.2 seconds.
```

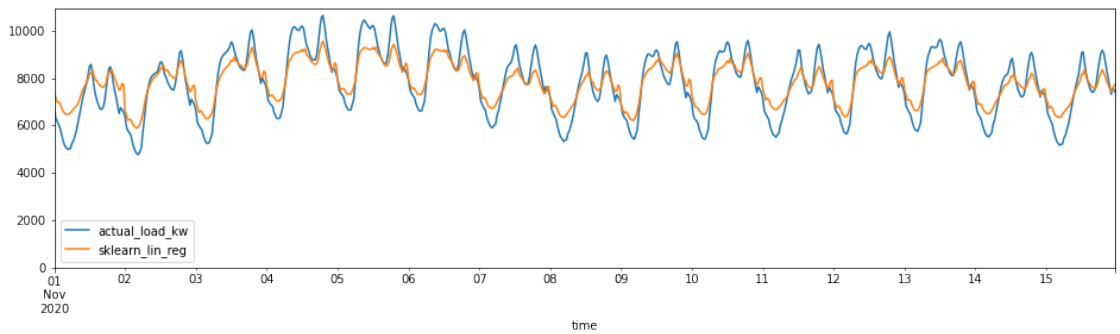
[38]:
```
benchmark
```

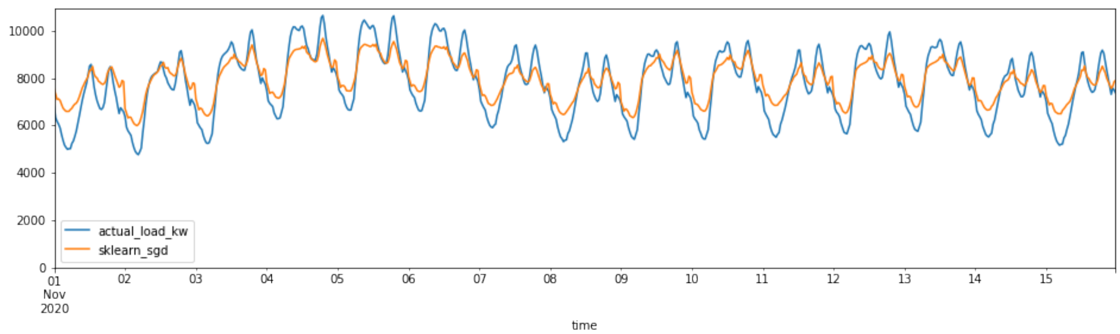
[38]:
```
                           actual_load_kw  sklearn_lin_reg  sklearn_sgd  \
time
2020-11-01 00:00:00+01:00     6817.332090      7416.477529  7542.312564
2020-11-01 00:30:00+01:00     6326.667322      7192.916989  7319.436451
2020-11-01 01:00:00+01:00     6172.223671      6974.931684  7102.126243
2020-11-01 01:30:00+01:00     6050.575318      6993.462928  7122.302861
2020-11-01 02:00:00+01:00     5898.881230      6928.525322  7058.529345
…                                     …                …            …
2020-11-15 21:30:00+01:00     7657.293444      7554.874780  7696.545257
2020-11-15 22:00:00+01:00     7317.540759      7422.568321  7565.035767
2020-11-15 22:30:00+01:00     7580.051439      7510.802466  7655.102382
2020-11-15 23:00:00+01:00     7496.273993      7702.238171  7848.835422
2020-11-15 23:30:00+01:00     7376.005701      7759.626894  7908.068267

                           sklearn_ada_boost   sklearn_nn      h2o_glm  \
time
2020-11-01 00:00:00+01:00        6822.188092  7351.172908  7402.432609
2020-11-01 00:30:00+01:00        6414.531562  7008.480631  7164.175176
2020-11-01 01:00:00+01:00        6260.174000  6668.162284  6925.916729
2020-11-01 01:30:00+01:00        6260.174000  6546.138912  6948.635651
2020-11-01 02:00:00+01:00        6162.218857  6329.058216  6869.233390
…                                        …            …            …
2020-11-15 21:30:00+01:00        7679.641519  8075.749892  7227.449423
2020-11-15 22:00:00+01:00        7632.927837  7831.622914  7114.005755
2020-11-15 22:30:00+01:00        7726.430994  7792.580825  7250.192657
2020-11-15 23:00:00+01:00        7823.412347  7839.531977  7499.847540
2020-11-15 23:30:00+01:00        7823.412347  7739.108252  7590.647251

                                h2o_rf      h2o_gbm  h2o_xgboost       h2o_nn
time
2020-11-01 00:00:00+01:00  6537.198906  7010.410149  7032.040527  7400.976455
2020-11-01 00:30:00+01:00  6228.407756  6408.337175  6492.153809  6841.493779
2020-11-01 01:00:00+01:00  6058.203420  6207.136015  6351.727051  6353.977698
2020-11-01 01:30:00+01:00  6019.727900  6059.606349  6259.075684  6178.509022
2020-11-01 02:00:00+01:00  5838.660528  5967.455171  6184.107422  5974.518119
…                                  …            …            …            …
2020-11-15 21:30:00+01:00  7483.921108  7272.697440  7436.578125  8017.731406
2020-11-15 22:00:00+01:00  7369.696343  7050.622522  7187.884766  7788.172288
```

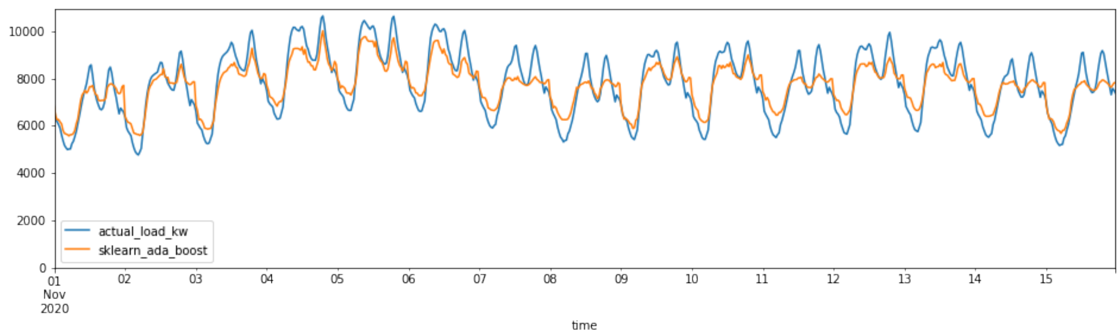
```
2020-11-15 22:30:00+01:00  7411.223903  7247.823333  7486.856934  7715.353810
2020-11-15 23:00:00+01:00  7425.497777  7294.028407  7286.999512  7702.300630
2020-11-15 23:30:00+01:00  7458.976123  7117.461922  7210.519043  7612.710499

[720 rows x 10 columns]
```

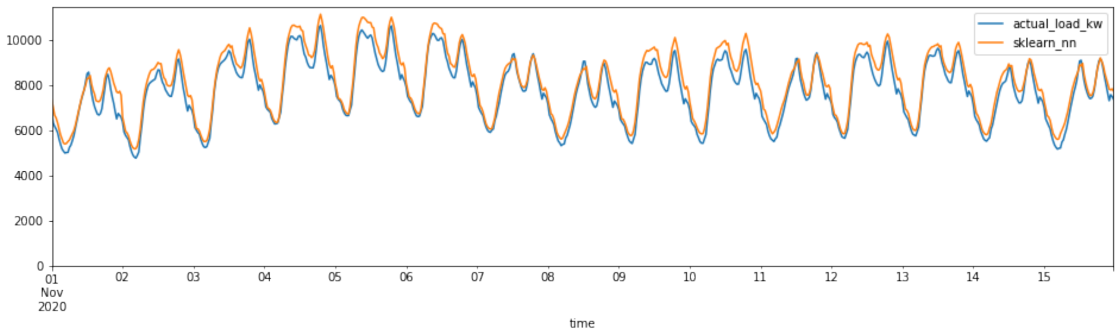
[39]:

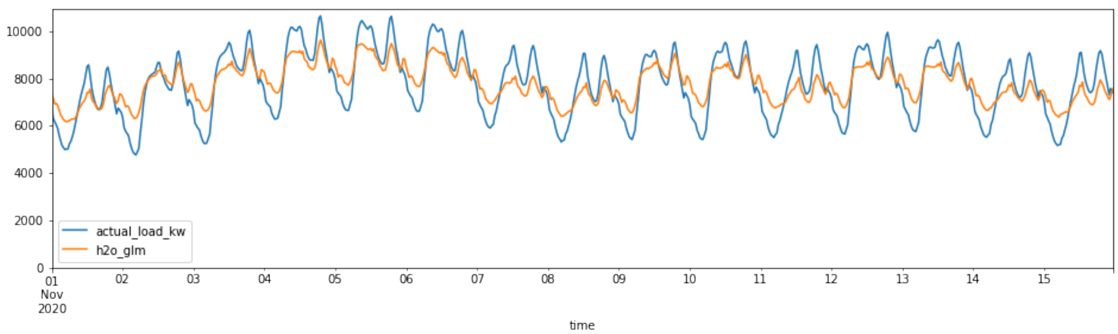
```python
# visualize predictions
for c in benchmark.columns:
    if c != "actual_load_kw":
        to_plot = benchmark[["actual_load_kw", c]]
        to_plot.plot(ylim=0, figsize=(16, 4))
```

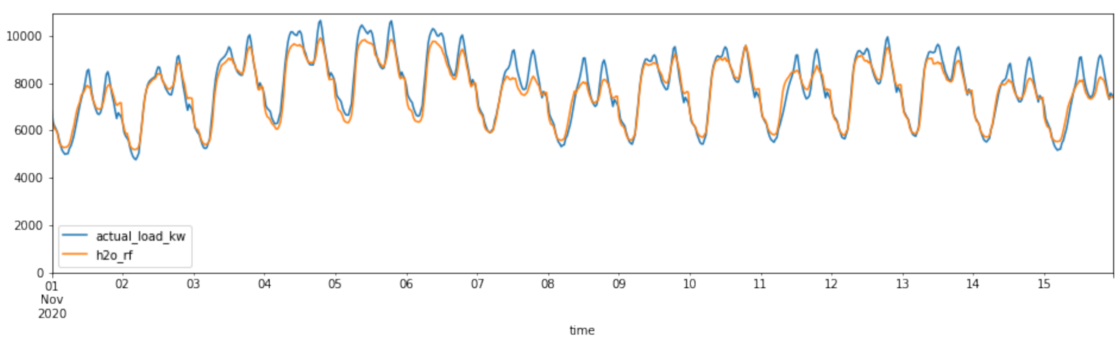


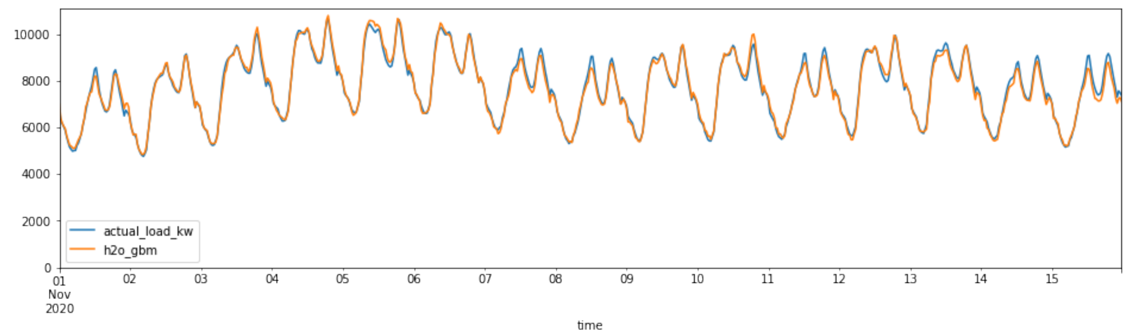


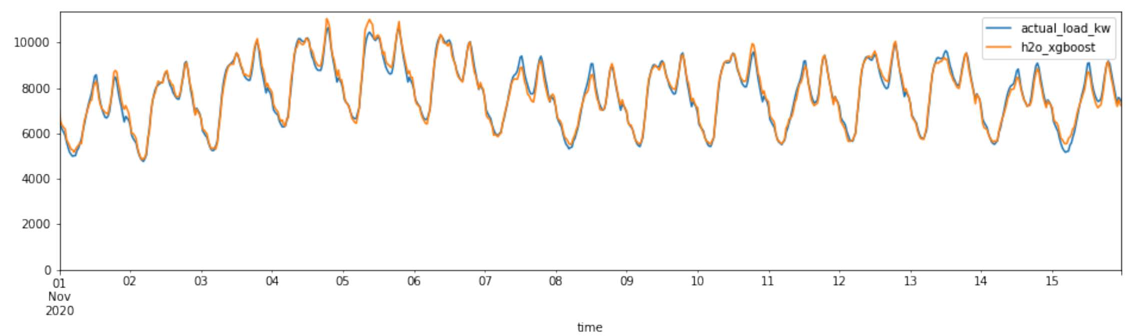


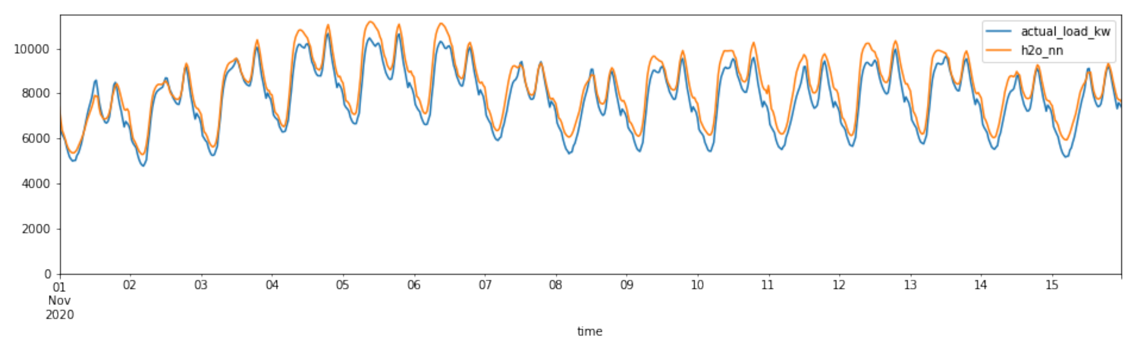

actual_load_kw
sklearn_nn
0
2000
4000
6000
8000
10000
01
Nov
2020
02
03
04
05
06
07
08
09
10
11
12
13
14
15
time


actual_load_kw
h2o_glm
0
2000
4000
6000
8000
10000
01
Nov
2020
02
03
04
05
06
07
08
09
10
11
12
13
14
15
time


actual_load_kw
h2o_rf
0
2000
4000
6000
8000
10000
01
Nov
2020
02
03
04
05
06
07
08
09
10
11
12
13
14
15
time







[40]:

```
# compute the mean absolute percentage error
benchmark_ape = benchmark.copy(deep=True).drop(columns=["actual_load_kw"])
for c in benchmark_ape.columns:
    benchmark_ape[c] = (benchmark_ape[c] - benchmark["actual_load_kw"]).abs()/
 ↪benchmark["actual_load_kw"]*100
benchmark_ape.mean().to_frame("mape")
```

[40]:

	mape
sklearn_lin_reg	7.055730

```
sklearn_sgd        7.513167
sklearn_ada_boost  6.347616
sklearn_nn         5.091200
h2o_glm            9.057864
h2o_rf             3.424008
h2o_gbm            1.721648
h2o_xgboost        1.995853
h2o_nn             6.338839
```

1.6 6. Benchmark with Backtesting

In traditional machine learning, we need more than just 1 evaluation to test an algorithm. We typically use cross-validation to see if the algorithm is not biased and if it can be expected to work well in most cases. For time-series predictions we cannot do a regular cross-validation because it is not realistic : we always want to train using historical data that happened before the prediction.

Here we will do **backtesting** week after week. With the given dataset, this means : - for each week w from early 2019 until the end of the dataset : train using data from the beginning of the dataset (early 2015) until a few days before week w, then eval on w. - the first iteration will train an algorithm using data from 2015 to 2018, then eval on the first week of 2019 - the second iteration will train using data from 2015 to a bit before the first week of 2019, then eval on the second week of 2019 - and so on… - keep the predictions of each time-step using this method, from early 2019 to november 2020.
- then compare these predictions to the historic data to evaluate the quality of each algorithm.

This makes most sense if in your production environment, you plan to retrain the algorithm regularly with recent data.

Backtesting can take a significant amount of time. We backtest only 2 linear regressions below in order to have an example that runs fast. Don't hesitate to add other algorithms.

[41]:
```
all_models = dict()

all_models['sklearn_lin_reg'] = SklearnEstimator(LinearRegression())

all_models['h2o_glm'] =␣
 ↪H2OEstimator(H2OGeneralizedLinearEstimator(standardize=False,␣
 ↪intercept=True))
```

[42]:
```
start_backtesting_dt = pd.to_datetime('2019-01-01 00:00:00+01:00').
 ↪tz_convert('Europe/Paris')
benchmark = historic[historic.index>=start_backtesting_dt]["load_kw"].
 ↪to_frame("actual_load_kw")
days_in_each_iteration = 28


for model_name, model in all_models.items():
```

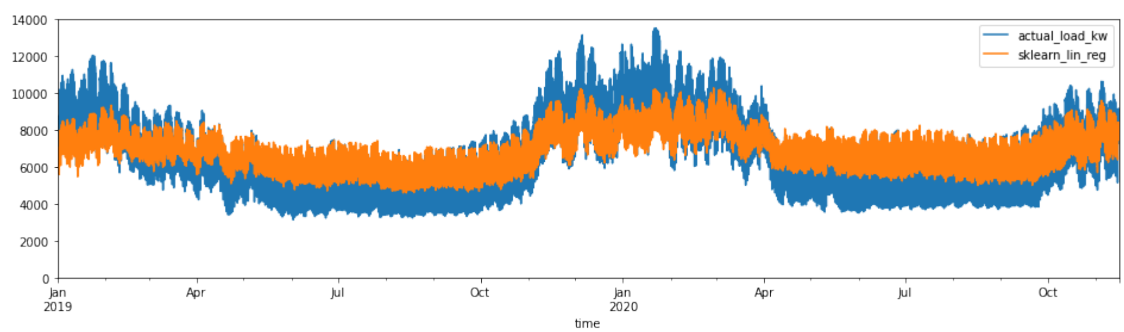
```python
count_iterations = 0

model_predictions = []

for train_set, test_set in enda.BackTesting.yield_train_test(
    historic,
    start_eval_datetime=start_backtesting_dt,
    days_between_trains=days_in_each_iteration,
    gap_days_between_train_and_eval=14
):
    count_iterations += 1
    if count_iterations <= 2 or count_iterations % 10 == 0:
        print("Model {}, backtesting iteration {}, train set {}->{}, test␣
↪set {}->{}\n".format(
                  model_name, count_iterations,
                  train_set.index.min(), train_set.index.max(),
                  test_set.index.min(), test_set.index.max()))

    # featurize
    train_set = featurize(train_set)
    test_set = test_set.drop(columns=["load_kw"])
    test_set = featurize(test_set)

    # use forecast porfolio in test_set
    forecast_portfolio = enda.Contracts.forecast_using_trend(
        portfolio_df=portfolio[portfolio.index<test_set.index.min()],
        start_forecast_date=test_set.index.min(),
        nb_days=days_in_each_iteration,
        past_days=150)  # recent portfolio trend

    test_set['kva'] = forecast_portfolio['kva']
    test_set['contracts_count'] = forecast_portfolio['contracts_count']

    # train and predict
    model.train(train_set, target_col='load_kw')
    model_predictions.append(model.predict(test_set, target_col='load_kw'))

benchmark[model_name] = pd.concat(model_predictions)
```

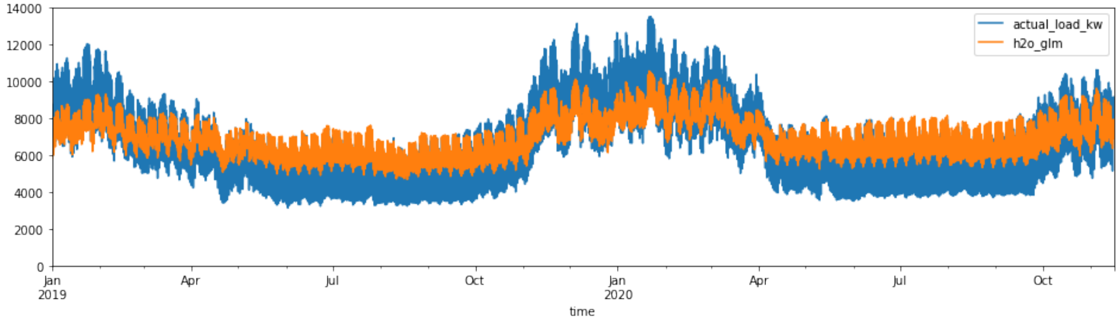
```
Model sklearn_lin_reg, backtesting iteration 1, train set 2015-01-01
00:00:00+01:00->2018-12-17 23:30:00+01:00, test set 2019-01-01
00:00:00+01:00->2019-01-28 23:30:00+01:00

Model sklearn_lin_reg, backtesting iteration 2, train set 2015-01-01
00:00:00+01:00->2019-01-14 23:30:00+01:00, test set 2019-01-29
00:00:00+01:00->2019-02-25 23:30:00+01:00
```

```
Model sklearn_lin_reg, backtesting iteration 10, train set 2015-01-01
00:00:00+01:00->2019-08-26 23:30:00+02:00, test set 2019-09-10
00:00:00+02:00->2019-10-07 23:30:00+02:00

Model sklearn_lin_reg, backtesting iteration 20, train set 2015-01-01
00:00:00+01:00->2020-06-01 23:30:00+02:00, test set 2020-06-16
00:00:00+02:00->2020-07-13 23:30:00+02:00

Model h2o_glm, backtesting iteration 1, train set 2015-01-01
00:00:00+01:00->2018-12-17 23:30:00+01:00, test set 2019-01-01
00:00:00+01:00->2019-01-28 23:30:00+01:00

Model h2o_glm, backtesting iteration 2, train set 2015-01-01
00:00:00+01:00->2019-01-14 23:30:00+01:00, test set 2019-01-29
00:00:00+01:00->2019-02-25 23:30:00+01:00

Model h2o_glm, backtesting iteration 10, train set 2015-01-01
00:00:00+01:00->2019-08-26 23:30:00+02:00, test set 2019-09-10
00:00:00+02:00->2019-10-07 23:30:00+02:00

Model h2o_glm, backtesting iteration 20, train set 2015-01-01
00:00:00+01:00->2020-06-01 23:30:00+02:00, test set 2020-06-16
00:00:00+02:00->2020-07-13 23:30:00+02:00
```

[43]:

```
# visualize predictions
for c in benchmark.columns:
    if c != "actual_load_kw":
        to_plot = benchmark[["actual_load_kw", c]]
        to_plot.plot(ylim=0, figsize=(16, 4))
```





[44]:
```
# compute absolute percentage error
benchmark_ape = benchmark.copy(deep=True).drop(columns=["actual_load_kw"])
for c in benchmark_ape.columns:
    benchmark_ape[c] = (benchmark_ape[c] - benchmark["actual_load_kw"]).abs()/
 ↪benchmark["actual_load_kw"]*100
benchmark_ape.mean().to_frame("mape")
```

[44]:

	mape
sklearn_lin_reg	13.164438
h2o_glm	14.279924

If you have time/computing power: - try more algorithms in the backtesting benchmark, this is longer but more reliable than a simple benchmark (think of it as crossval versus single eval in a non-time-series setup). - reduce the "days_in_each_iteration" down to 7 if you think you can have a weekly training in your production environment.

1.7 7. Make the prediction

Seeing the results from just the basic benchmark, we here decide to predict using h2o's gbm. We now need to train it on the full dataset and make the prediction.

[45]:
```
gbm = H2OEstimator(H2OGradientBoostingEstimator(
    ntrees=500,
    max_depth=5,
    sample_rate=0.5,
    min_rows=5
))
```

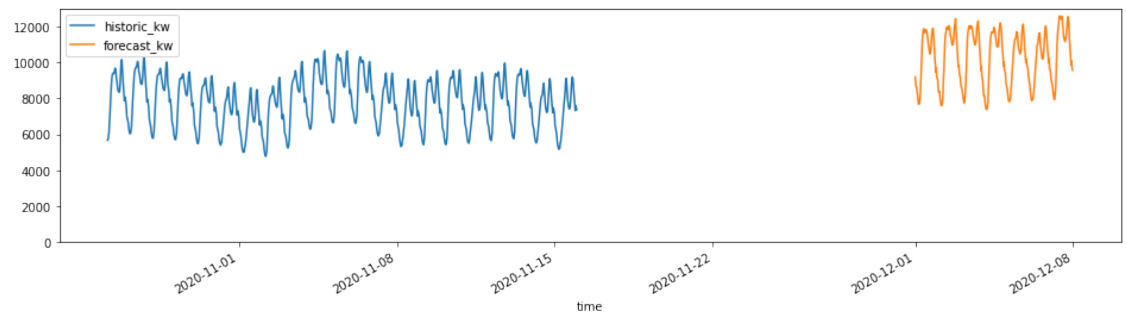
[46]:
```
gbm.train(full_train_set, target_col='load_kw')
```

[47]:
```
gbm_prediction = gbm.predict(forecast_input_data, target_col="load_kw")
```

[48]:
```
```

```
# visualize recent load along with our forecast; remember we don't have recent␣
↪actual load so there is a time-gap.
# (remember that the prediction takes weather forecast and more information␣
↪into account)
to_plot = pd.merge(
    historic["load_kw"][-1000:].to_frame("historic_kw"),
    gbm_prediction.rename(columns={"load_kw": "forecast_kw"}),
    how='outer', left_index=True, right_index=True
)
to_plot.plot(ylim=0, figsize=(16, 4))
```

[48]: <AxesSubplot:xlabel='time'>



[49]:
```
# don't forget to shutdown your h2o local server
h2o.cluster().shutdown()
# wait for h2o to really finish shutting down
time.sleep(5)
```

H2O session _sid_88cb closed.

1.8 Conclusion

Thats all for Example B. Check out Example C next. Thanks for reading and don't hesitate to send feeback at: emmanuel.charon@enercoop.org !