ExampleE

March 27, 2024

1 Project enda : Example E

In this example we will set up a more complex dayahead power generation prediction, in order to test a backtesting operation of the dataset.

Note this example may take some time (up to 15 minutes) to run completly, and a fair amount of RAM (around 1.5GB) is required to load the historical data.

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


pd.options.display.max_columns = None
pd.options.display.max_colwidth = 30

import matplotlib.pyplot as plt
```

[2]:
```
DIR = '.'
generation_source = ["wind", "solar", "river"]
```

2 1. Read and prepare data

[3]:
```
def get_example_e_dataset(source):

    if source not in ["wind", "solar", "river"]:
            raise NotImplementedError("unknown source argument")

    # get station portfolio
    stations = enda.Contracts.read_contracts_from_file(os.path.join(
        DIR, source, "stations_" + source + ".csv")
    )

    # display it as a multiindex with day as second index
    stations = enda.PowerStations.get_stations_daily(
        stations,
```

```python
    station_col='station',
    date_start_col="date_start",
    date_end_exclusive_col="date_end_exclusive"
)

# between dates of interest
stations = enda.PortfolioTools.get_portfolio_between_dates(
    stations,
    start_datetime=pd.to_datetime('2017-01-01'),
    end_datetime_exclusive=pd.to_datetime('2022-01-01')
)

# on a 30-minutes scale
stations = enda.Resample.upsample_and_interpolate(
    stations,
    freq='30min',
    tz_info='Europe/Paris',
    index_name='time',
    forward_fill=True
)

# integrate outages
outages = enda.PowerStations.read_outages_from_file(
    os.path.join(DIR, "events.csv"),
    station_col='station',
    time_start_col="time_start",
    time_end_exclusive_col="time_end",
    pct_outages_col="impact_production_pct_kw",
    tzinfo="Europe/Paris"
)

stations = enda.PowerStations.integrate_outages(
    df_stations=stations,
    df_outages=outages,
    station_col='station',
    time_start_col="time_start",
    time_end_exclusive_col="time_end",
    installed_capacity_col="installed_capacity_kw",
    pct_outages_col="impact_production_pct_kw"
)

# get production
production = pd.read_csv(
    os.path.join(DIR, source, "production_" + source + ".csv"),
    parse_dates=["time"],
    date_parser=lambda col: pd.to_datetime(col, utc=True)
)
```

```
    production['time'] = enda.TimezoneUtils.
↪convert_dtype_from_object_to_tz_aware(production['time'], tz_info='Europe/
↪Paris')
    production.set_index(["station", "time"], inplace=True)

    production = enda.Resample.downsample(
        production,
        freq='30min',
        index_name='time'
    )

    dataset = pd.merge(stations, production, how='inner', left_index=True,␣
↪right_index=True)
    dataset = dataset.dropna()

    # get weather for wind and solar
    if source in ["wind", "solar"]:
        weather = pd.read_csv(
            os.path.join(DIR, source, "weather_forecast_" + source + ".csv"),
            parse_dates=["time"],
            date_parser=lambda col: pd.to_datetime(col, utc=True)
        )
        weather['time'] = enda.TimezoneUtils.
↪convert_dtype_from_object_to_tz_aware(weather['time'], tz_info='Europe/
↪Paris')
        weather.set_index(["station", "time"], inplace=True)

        weather = enda.Resample.upsample_and_interpolate(
            weather,
            freq='30min',
            tz_info='Europe/Paris',
            index_name='time',
            method="linear",
            forward_fill=True
        )

        dataset = pd.merge(dataset, weather, how='inner', left_index=True,␣
↪right_index=True)

    # featurize for solar
    if source == "solar":
        dataset = enda.DatetimeFeature.split_datetime(
            dataset, split_list=['minuteofday', 'dayofyear']
        )

        dataset = enda.DatetimeFeature.encode_cyclic_datetime_index(
            dataset, split_list=['minuteofday', 'dayofyear']
```

```
        )

    return dataset
```

[4]:
```
%%time
dataset_wind = get_example_e_dataset("wind")
```

```
CPU times: user 34.3 s, sys: 2.03 s, total: 36.4 s
Wall time: 36.7 s
```

[5]:
```
%%time
dataset_solar = get_example_e_dataset("solar")
```

```
CPU times: user 1min 34s, sys: 7.84 s, total: 1min 42s
Wall time: 1min 56s
```

[6]:
```
%%time
dataset_river = get_example_e_dataset("river")
```

```
CPU times: user 4min 20s, sys: 19.1 s, total: 4min 39s
Wall time: 6min 3s
```

[7]:
```
dataset = dict(zip(generation_source, [dataset_wind, dataset_solar,␣
 ↪dataset_river]))
```

[8]:
```
# Compute load factor
# We drop the power_kw information during that step, not to bias the IA␣
 ↪algorithm afterwards.
def wrapper_compute_load_factor(df):
    return enda.PowerStations.compute_load_factor(
                df,
                installed_capacity_kw='installed_capacity_kw',
                power_kw='power_kw',
                drop_power_kw=True
            )

dataset_final = {source: wrapper_compute_load_factor(d) for source, d in␣
 ↪dataset.items()}
```

3 2. Make a basic prediction

3.0.1 Separe between training and forecasting dataset to backtest the data

We have here the full datasets which have been built using the Enda utilities function, and some historical information gathered from the TSO, diverse meteo information suppliers, and contracts data.

We will now distinguish our full datasets in two, in order to obtain the training and forecasting datasets representative of what could be obtained in real life condition.

[9]:
```
# wrapper function around the
def separate_train_test_sets(df):

    # let's create the input train dataset
    train_set = df[df.index.get_level_values(1) < pd.to_datetime('2021-12-01 00:
 ↪00:00+01:00')]

    # let's create the input data for our forecast
    forecast_set = df[df.index.get_level_values(1) >= pd.
 ↪to_datetime('2021-12-01 00:00:00+01:00')]
    forecast_set = forecast_set.drop(columns="load_factor")

    # and let us keep the information of the real power generation for testing␣
 ↪purposes
    future_set = df[df.index.get_level_values(1) >= pd.to_datetime('2021-12-01␣
 ↪00:00:00+01:00')]

    return train_set, forecast_set, future_set

train_test_future_sets = {source: separate_train_test_sets(data) for source,␣
 ↪data in dataset_final.items()}

train_set = {source: train_test_future_sets[source][0] for source in␣
 ↪generation_source}
forecast_set = {source: train_test_future_sets[source][1] for source in␣
 ↪generation_source}
future_set = {source: train_test_future_sets[source][2] for source in␣
 ↪generation_source}
```

[10]:
```
train_set["wind"].shape
```

[10]:
```
(634176, 4)
```

Let's use the enda algorithms to make a simple power prediction.

3.0.2 Run of river prediction

[11]:
```
# import a dummy ML backend for river
from enda.estimators import EndaEstimatorRecopy

# build a PowerPredictor object
river_predictor = enda.PowerPredictor(standard_plant=False)

# use PowerPredictor to train the estimator from the run of river data,
# and from a naive recopy estimator
river_predictor.train(train_set["river"],␣
 ↪estimator=EndaEstimatorRecopy(period='1D'), target_col="load_factor")
```

[12]:
```
train_set["river"]
```

[12]:
```
                                           installed_capacity_kw  load_factor
station time
hy_0    2019-12-22 00:00:00+01:00                          595.0     0.375294
        2019-12-22 00:30:00+01:00                          595.0     0.396471
        2019-12-22 01:00:00+01:00                          595.0     0.429412
        2019-12-22 01:30:00+01:00                          595.0     0.434118
        2019-12-22 02:00:00+01:00                          595.0     0.432941
…                                                            …          …
hy_99   2021-11-30 21:30:00+01:00                           80.5     1.040580
        2021-11-30 22:00:00+01:00                           80.5     1.023188
        2021-11-30 22:30:00+01:00                           80.5     0.994203
        2021-11-30 23:00:00+01:00                           80.5     0.901449
        2021-11-30 23:30:00+01:00                           80.5     0.837681

[3936142 rows x 2 columns]
```

[13]:
```
# Once it has been trained, we can predict the power for each power plant␣
↪individually, calling predict()
# from PowerPredictor()
pred_river = river_predictor.predict(forecast_set["river"],␣
↪target_col="load_factor")
```

[14]:
```
pred_river
```

[14]:
```
                                   load_factor
station time
hy_0    2021-12-01 00:00:00+01:00     0.000000
        2021-12-01 00:30:00+01:00     0.000000
        2021-12-01 01:00:00+01:00     0.000000
        2021-12-01 01:30:00+01:00     0.000000
        2021-12-01 02:00:00+01:00     0.000000
…                                         …
hy_99   2021-12-31 21:30:00+01:00     0.457669
        2021-12-31 22:00:00+01:00     0.457669
        2021-12-31 22:30:00+01:00     0.457669
        2021-12-31 23:00:00+01:00     0.457669
        2021-12-31 23:30:00+01:00     0.457669

[123504 rows x 1 columns]
```

3.0.3 Wind prediction

[15]:
```
# boot up an H20 server
import h2o
h2o.init(nthreads=-1)
```

```
h2o.no_progress()
```

```
Checking whether there is an H2O instance running at http://localhost:54321.
connected.

--------------------------  ----------------------------------------
H2O_cluster_uptime:         7 mins 43 secs
H2O_cluster_timezone:       Europe/Paris
H2O_data_parsing_timezone:  UTC
H2O_cluster_version:        3.46.0.1
H2O_cluster_version_age:    13 days
H2O_cluster_name:           H2O_from_python_clement_jeannesson_xqjnib
H2O_cluster_total_nodes:    1
H2O_cluster_free_memory:    3.978 Gb
H2O_cluster_total_cores:    8
H2O_cluster_allowed_cores:  8
H2O_cluster_status:         locked, healthy
H2O_connection_url:         http://localhost:54321
H2O_connection_proxy:       {"http": null, "https": null}
H2O_internal_security:      False
Python_version:             3.9.10 final
--------------------------  ----------------------------------------
```

[16]:
```
# enda's wrapper around H2O models
from enda.ml_backends.h2o_estimator import EndaH2OEstimator
from h2o.estimators import H2OGradientBoostingEstimator
from h2o.estimators import H2OGeneralizedLinearEstimator

# define an estimator
gradboost_estimator = EndaH2OEstimator(H2OGradientBoostingEstimator(
    ntrees=500,
    max_depth=5,
    sample_rate=0.5,
    min_rows=5,
    seed=17
))
```

[17]:
```
# build a PowerPredictor object
wind_predictor = enda.PowerPredictor(standard_plant=True)
```

[18]:
```
# train the estimator
wind_predictor.train(train_set["wind"], estimator=gradboost_estimator,␣
 ↪target_col="load_factor")
```

[19]:
```
# predict
pred_wind = wind_predictor.predict(forecast_set['wind'],␣
 ↪target_col="load_factor", is_normally_clamped=True)
```

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

[20]:
```
pred_wind
```

[20]:
```
                                    load_factor
station time
eo_0    2021-12-01 00:00:00+01:00      0.000000
        2021-12-01 00:30:00+01:00      0.000000
        2021-12-01 01:00:00+01:00      0.000000
        2021-12-01 01:30:00+01:00      0.000000
        2021-12-01 02:00:00+01:00      0.000000
…                                         …
eo_9    2021-12-31 21:30:00+01:00      0.044654
        2021-12-31 22:00:00+01:00      0.044654
        2021-12-31 22:30:00+01:00      0.044654
        2021-12-31 23:00:00+01:00      0.044654
        2021-12-31 23:30:00+01:00      0.044654

[29760 rows x 1 columns]
```

3.0.4 Solar prediction

[21]:
```
# keep the best estimator from h2o

# build a PowerPredictor object
solar_predictor = enda.PowerPredictor(standard_plant=True)

# use the same good estimator
gradboost_estimator = EndaH2OEstimator(H2OGradientBoostingEstimator(
    ntrees=500,
    max_depth=5,
    sample_rate=0.5,
    min_rows=5,
    seed=17
))

# train the estimator
solar_predictor.train(train_set["solar"], estimator=gradboost_estimator,␣
 ↪target_col="load_factor")

# predict
pred_solar= solar_predictor.predict(forecast_set["solar"],␣
 ↪target_col="load_factor", is_normally_clamped=True)
```

[22]:
```
pred_solar
```

[22]:
```
                                    load_factor
station time
pv_0    2021-12-01 00:00:00+01:00      0.000442
```

```
        2021-12-01 00:30:00+01:00     0.000442
        2021-12-01 01:00:00+01:00     0.000603
        2021-12-01 01:30:00+01:00     0.001096
        2021-12-01 02:00:00+01:00     0.000666
…                                          …
pv_9    2021-12-31 21:30:00+01:00     0.000000
        2021-12-31 22:00:00+01:00     0.000000
        2021-12-31 22:30:00+01:00     0.000000
        2021-12-31 23:00:00+01:00     0.000000
        2021-12-31 23:30:00+01:00     0.000000

[65376 rows x 1 columns]
```

[23]:

```
# shutdown your h2o local server
h2o.cluster().shutdown()
# wait for h2o to really finish shutting down
time.sleep(5)
```

```
H2O session _sid_a3cd closed.
```

3.0.5 Getting back to power prediction

To get back to power prediction, we simply need to use the installed capacity field and multiply it by the load factor to find again the power (kw)

[24]:

```
# we start by merging again the installed_capacity (kw) field

def merge_stations_and_features(df1, df2):
    df = pd.merge(df1, df2, how='inner', left_index=True, right_index=True)
    return df.dropna()

pred = dict(zip(generation_source, [pred_wind, pred_solar, pred_river]))
prediction = {source: merge_stations_and_features(
                          forecast_set[source].loc[:,␣
 ↪["installed_capacity_kw"]],
                          pred[source])
              for source in generation_source
             }
```

[25]:

```
# We drop the load_factor information during that step.
def wrapper_compute_power_kw_from_load_factor(df):
    return enda.PowerStations.compute_power_kw_from_load_factor(
               df,
               installed_capacity_kw='installed_capacity_kw',
               load_factor='load_factor',
               drop_load_factor=True
           )
```

```
prediction = {source: wrapper_compute_power_kw_from_load_factor(p)
              for source, p in prediction.items()}
```

[26]:
```
prediction["river"]
```

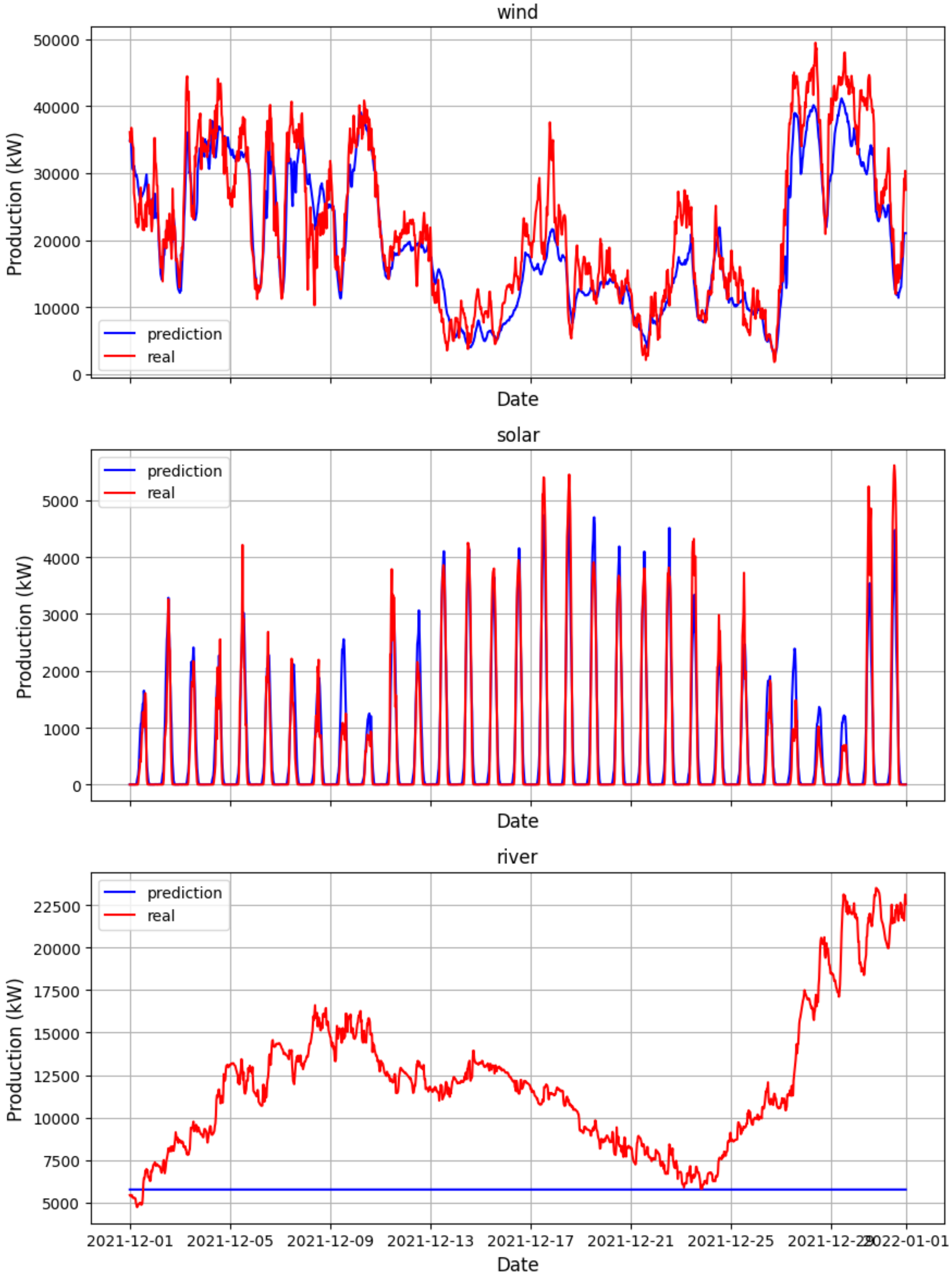
[26]:
```
                                    installed_capacity_kw   power_kw
station time
hy_0    2021-12-01 00:00:00+01:00                   595.0   0.000000
        2021-12-01 00:30:00+01:00                   595.0   0.000000
        2021-12-01 01:00:00+01:00                   595.0   0.000000
        2021-12-01 01:30:00+01:00                   595.0   0.000000
        2021-12-01 02:00:00+01:00                   595.0   0.000000
…                                                   …         …
hy_99   2021-12-31 21:30:00+01:00                    80.5  36.842361
        2021-12-31 22:00:00+01:00                    80.5  36.842361
        2021-12-31 22:30:00+01:00                    80.5  36.842361
        2021-12-31 23:00:00+01:00                    80.5  36.842361
        2021-12-31 23:30:00+01:00                    80.5  36.842361

[123504 rows x 2 columns]
```

4 3. Plots and KPI

4.0.1 Plot predicted data along with the real production

[27]:
```
# Get back to the power_kw
real = {source: wrapper_compute_power_kw_from_load_factor(r)
             for source, r in future_set.items()}


fig, axis = plt.subplots(3, 1, figsize=(9, 12), sharex=True, sharey=False)

i = 0
for source, data in prediction.items():
    axis[i].grid(True)
    axis[i].plot(data["power_kw"].groupby(level=1).agg("sum"),␣
 ↪label="prediction", c="blue")
    axis[i].set_xlabel('Date', fontsize=12)
    axis[i].set_ylabel('Production (kW)', fontsize=12)
    axis[i].set_title(source)
    i+=1

i = 0
for source, data in real.items():
    axis[i].plot(data["power_kw"].groupby(level=1).agg("sum"), label="real",␣
 ↪c="red")
    axis[i].set_xlabel('Date', fontsize=12)
```

```
    axis[i].set_ylabel('Production (kW)', fontsize=12)
    axis[i].legend()
    i +=1

fig.tight_layout()
```



4.0.2 Compute the nMAPE

[28]:
```
# create the benchmark dataframe for wind power plant

# we keep the active capacity, the actual power injection, and the power␣
↪prediction
def build_becnhmark(source):
    benchmark = pd.merge(real[source][["installed_capacity_kw", "power_kw"]],
                         prediction[source]["power_kw"].to_frame(),
                         how="inner", left_index=True, right_index=True)
    benchmark = benchmark.rename({"power_kw_x": "actual",
                                  "power_kw_y": "enda",
                                 },
                                 axis=1)
    return benchmark

benchmark = {source: build_becnhmark(source)for source in generation_source}

benchmark['wind']
```

[28]:
```
                                  installed_capacity_kw  actual       enda
station time
eo_0    2021-12-01 00:00:00+01:00                  28.0     0.0   0.000000
        2021-12-01 00:30:00+01:00                  28.0     0.0   0.000000
        2021-12-01 01:00:00+01:00                  28.0     0.0   0.000000
        2021-12-01 01:30:00+01:00                  28.0     0.0   0.000000
        2021-12-01 02:00:00+01:00                  28.0     0.0   0.000000
…                                                     …       …          …
eo_9    2021-12-31 21:30:00+01:00                1190.0     0.0  53.137871
        2021-12-31 22:00:00+01:00                1190.0     0.0  53.137871
        2021-12-31 22:30:00+01:00                1190.0     0.0  53.137871
        2021-12-31 23:00:00+01:00                1190.0     0.0  53.137871
        2021-12-31 23:30:00+01:00                1190.0     0.0  53.137871

[29760 rows x 3 columns]
```

[29]:
```
# sum over all power plants
benchmark_portfolio = {source: benchmark[source].groupby(level="time").sum()␣
↪for source in generation_source}
```

[30]:
```
# define a scoring
scoring_benchmark = {source: enda.Scoring(benchmark_portfolio[source],
                                          target="actual",
```

```
↪normalizing_col="installed_capacity_kw") for source in generation_source}
```

[31]:
```
# compute the nAE
nAE = {source: scoring_benchmark[source].normalized_absolute_error() for source␣
 ↪in generation_source}
nAE['wind']
```

[31]:
```
                                  enda
time
2021-12-01 00:00:00+01:00  0.020446
2021-12-01 00:30:00+01:00  0.012919
2021-12-01 01:00:00+01:00  0.004236
2021-12-01 01:30:00+01:00  0.049716
2021-12-01 02:00:00+01:00  0.060889
…                               …
2021-12-31 21:30:00+01:00  0.089449
2021-12-31 22:00:00+01:00  0.120188
2021-12-31 22:30:00+01:00  0.096930
2021-12-31 23:00:00+01:00  0.137204
2021-12-31 23:30:00+01:00  0.095328

[1488 rows x 1 columns]
```

[32]:
```
nMAPE = {source: nAE[source].mean() for source in generation_source}
nMAPE
```

[32]:
```
{'wind': enda    0.052819
 dtype: float64,
 'solar': enda    0.015574
 dtype: float64,
 'river': enda    0.103418
 dtype: float64}
```

It is a 5% difference (not exactly a percentage) for wind, 1% for solar, and 10% for run of river.

5 4. Perform a benchmark with backtesting

As in example B_load, we will perform a backtesting of the data we gathered, week after week. With the given dataset, this means : - for each week w from early 2020 until the end of the dataset : train using data from the beginning of the dataset (early 2018) until a few days before week w, then eval on w. - the first iteration will train an algorithm using data from 2018 to 2019, then eval on the first week of 2020 - the second iteration will train using data from 2018 to a bit before the first week of 2020, then eval on the second week of 2020 - and so on… - keep the predictions of each time-step using this method, from early 2020 to december 2021.
- 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.

We'll just perform it for wind turbines

[33]:
```
# boot up an H2O server
import h2o
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: openjdk version "21.0.1" 2023-10-17 LTS; OpenJDK Runtime
Environment Zulu21.30+15-CA (build 21.0.1+12-LTS); OpenJDK 64-Bit Server VM
Zulu21.30+15-CA (build 21.0.1+12-LTS, mixed mode, sharing)
  Starting server from /Users/clement.jeannesson/.pyenv/versions/3.9.10/envs/end
a_1.0.0_dev/lib/python3.9/site-packages/h2o/backend/bin/h2o.jar
  Ice root: /var/folders/pp/kyc80_js50g283hj0_c4yrhc0000gp/T/tmp6duu00fs
  JVM stdout: /var/folders/pp/kyc80_js50g283hj0_c4yrhc0000gp/T/tmp6duu00fs/h2o_c
lement_jeannesson_started_from_python.out
  JVM stderr: /var/folders/pp/kyc80_js50g283hj0_c4yrhc0000gp/T/tmp6duu00fs/h2o_c
lement_jeannesson_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:         01 secs
H2O_cluster_timezone:       Europe/Paris
H2O_data_parsing_timezone:  UTC
H2O_cluster_version:        3.46.0.1
H2O_cluster_version_age:    13 days
H2O_cluster_name:           H2O_from_python_clement_jeannesson_18495p
H2O_cluster_total_nodes:    1
H2O_cluster_free_memory:    3.984 Gb
H2O_cluster_total_cores:    8
H2O_cluster_allowed_cores:  8
H2O_cluster_status:         locked, healthy
H2O_connection_url:         http://127.0.0.1:54321
H2O_connection_proxy:       {"http": null, "https": null}
H2O_internal_security:      False
Python_version:             3.9.10 final
--------------------------  -----------------------------------------
```

[34]:
```
# we'll test simple estimators from Sklearn we haven't tried yet, for␣
↪demonstration purposes.
from enda.ml_backends.sklearn_estimator import EndaSklearnEstimator
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression, SGDRegressor
```

```
# define a dict of estimators
all_estimators= dict()

all_estimators['sklearn_lin_reg'] = EndaSklearnEstimator(LinearRegression())

all_estimators['sklearn_sgd'] = EndaSklearnEstimator(
    Pipeline([('standard_scaler', StandardScaler()),
              ('sgd', SGDRegressor())
             ]
            )
)

all_estimators['h2o_gboost'] = EndaH2OEstimator(H2OGradientBoostingEstimator(
    ntrees=500,
    max_depth=5,
    sample_rate=0.5,
    min_rows=5,
    seed=17
))
```

[35]:

```
# create a PowerPredictor
predictor = enda.PowerPredictor(standard_plant=True)
```

[36]:

```
# run the backtesting and fill a benchmark_wind dataframe with the results from␣
↪the different algorithms

start_backtesting_dt = pd.to_datetime('2020-01-01 00:00:00+01:00').
↪tz_convert('Europe/Paris')
benchmark_wind = dataset_final['wind'][dataset_final['wind'].index.
↪get_level_values('time') \
                                       >= start_backtesting_dt]["load_factor"].
↪to_frame("actual_load_factor")

days_in_each_iteration = 28

for estimator_name, estimator in all_estimators.items():

    count_iterations = 0

    estimator_predictions = []

    for train_set, test_set in enda.BackTesting.yield_train_test(
        dataset_final['wind'],
        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(
                estimator_name, count_iterations,
                train_set.index.get_level_values('time').min(),
                train_set.index.get_level_values('time').max(),
                test_set.index.get_level_values('time').min(),
                test_set.index.get_level_values('time').max()))

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

        # train and predict
        predictor.train(train_set, estimator=estimator,␣
↪target_col='load_factor')
        estimator_predictions.append(predictor.predict(test_set,␣
↪target_col='load_factor', is_normally_clamped=True))

    benchmark_wind[estimator_name] = pd.concat(estimator_predictions)
```

```
Model sklearn_lin_reg, backtesting iteration 1, train set 2018-12-22
00:00:00+01:00->2019-12-17 23:30:00+01:00, test set 2020-01-01
00:00:00+01:00->2020-01-28 23:30:00+01:00

Model sklearn_lin_reg, backtesting iteration 2, train set 2018-12-22
00:00:00+01:00->2020-01-14 23:30:00+01:00, test set 2020-01-29
00:00:00+01:00->2020-02-25 23:30:00+01:00

Model sklearn_lin_reg, backtesting iteration 10, train set 2018-12-22
00:00:00+01:00->2020-08-25 23:30:00+02:00, test set 2020-09-09
00:00:00+02:00->2020-10-06 23:30:00+02:00

Model sklearn_lin_reg, backtesting iteration 20, train set 2018-12-22
00:00:00+01:00->2021-06-01 23:30:00+02:00, test set 2021-06-16
00:00:00+02:00->2021-07-13 23:30:00+02:00

Model sklearn_sgd, backtesting iteration 1, train set 2018-12-22
00:00:00+01:00->2019-12-17 23:30:00+01:00, test set 2020-01-01
00:00:00+01:00->2020-01-28 23:30:00+01:00

Model sklearn_sgd, backtesting iteration 2, train set 2018-12-22
00:00:00+01:00->2020-01-14 23:30:00+01:00, test set 2020-01-29
00:00:00+01:00->2020-02-25 23:30:00+01:00

Model sklearn_sgd, backtesting iteration 10, train set 2018-12-22
```

```
00:00:00+01:00->2020-08-25 23:30:00+02:00, test set 2020-09-09
00:00:00+02:00->2020-10-06 23:30:00+02:00

Model sklearn_sgd, backtesting iteration 20, train set 2018-12-22
00:00:00+01:00->2021-06-01 23:30:00+02:00, test set 2021-06-16
00:00:00+02:00->2021-07-13 23:30:00+02:00

Model h2o_gboost, backtesting iteration 1, train set 2018-12-22
00:00:00+01:00->2019-12-17 23:30:00+01:00, test set 2020-01-01
00:00:00+01:00->2020-01-28 23:30:00+01:00

Model h2o_gboost, backtesting iteration 2, train set 2018-12-22
00:00:00+01:00->2020-01-14 23:30:00+01:00, test set 2020-01-29
00:00:00+01:00->2020-02-25 23:30:00+01:00

Model h2o_gboost, backtesting iteration 10, train set 2018-12-22
00:00:00+01:00->2020-08-25 23:30:00+02:00, test set 2020-09-09
00:00:00+02:00->2020-10-06 23:30:00+02:00

Model h2o_gboost, backtesting iteration 20, train set 2018-12-22
00:00:00+01:00->2021-06-01 23:30:00+02:00, test set 2021-06-16
00:00:00+02:00->2021-07-13 23:30:00+02:00
```

[37]:
```
# 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_a004 closed.
```

[38]:
```
benchmark_wind
```

[38]:
```
                                        actual_load_factor  sklearn_lin_reg  \
station time
eo_0    2020-01-01 00:00:00+01:00                      0.0         0.000847
        2020-01-01 00:30:00+01:00                      0.0         0.001620
        2020-01-01 01:00:00+01:00                      0.0         0.002394
        2020-01-01 01:30:00+01:00                      0.0         0.000575
        2020-01-01 02:00:00+01:00                      0.0         0.000000
…                                                      …               …
eo_9    2021-12-31 21:30:00+01:00                      0.0         0.136792
        2021-12-31 22:00:00+01:00                      0.0         0.137046
        2021-12-31 22:30:00+01:00                      0.0         0.137046
        2021-12-31 23:00:00+01:00                      0.0         0.137046
        2021-12-31 23:30:00+01:00                      0.0         0.137046

                                        sklearn_sgd  h2o_gboost
```

```
station time
eo_0    2020-01-01 00:00:00+01:00     0.001637    0.000000
        2020-01-01 00:30:00+01:00     0.002426    0.000000
        2020-01-01 01:00:00+01:00     0.003215    0.000000
        2020-01-01 01:30:00+01:00     0.001347    0.000000
        2020-01-01 02:00:00+01:00     0.000000    0.000000
…                                          …           …
eo_9    2021-12-31 21:30:00+01:00     0.139112    0.043632
        2021-12-31 22:00:00+01:00     0.139297    0.043632
        2021-12-31 22:30:00+01:00     0.139297    0.043632
        2021-12-31 23:00:00+01:00     0.139297    0.043632
        2021-12-31 23:30:00+01:00     0.139297    0.043632

[635664 rows x 4 columns]
```

[39]:

```
# add the installed_capacity
benchmark_wind_kw = pd.merge(benchmark_wind,␣
 ↪dataset_final['wind']["installed_capacity_kw"],
                          how='inner', left_index=True, right_index=True)

benchmark_wind_kw = (benchmark_wind_kw.
 ↪multiply(benchmark_wind_kw["installed_capacity_kw"], axis=0)
                                       .drop(columns="installed_capacity_kw")
                                       .rename({"actual_load_factor":␣
 ↪"actual_power_kw"}, axis=1)
        )

benchmark_wind_kw = pd.merge(benchmark_wind_kw,␣
 ↪dataset_final['wind']["installed_capacity_kw"],
                          how='inner', left_index=True, right_index=True)
benchmark_wind_kw
```

[39]:

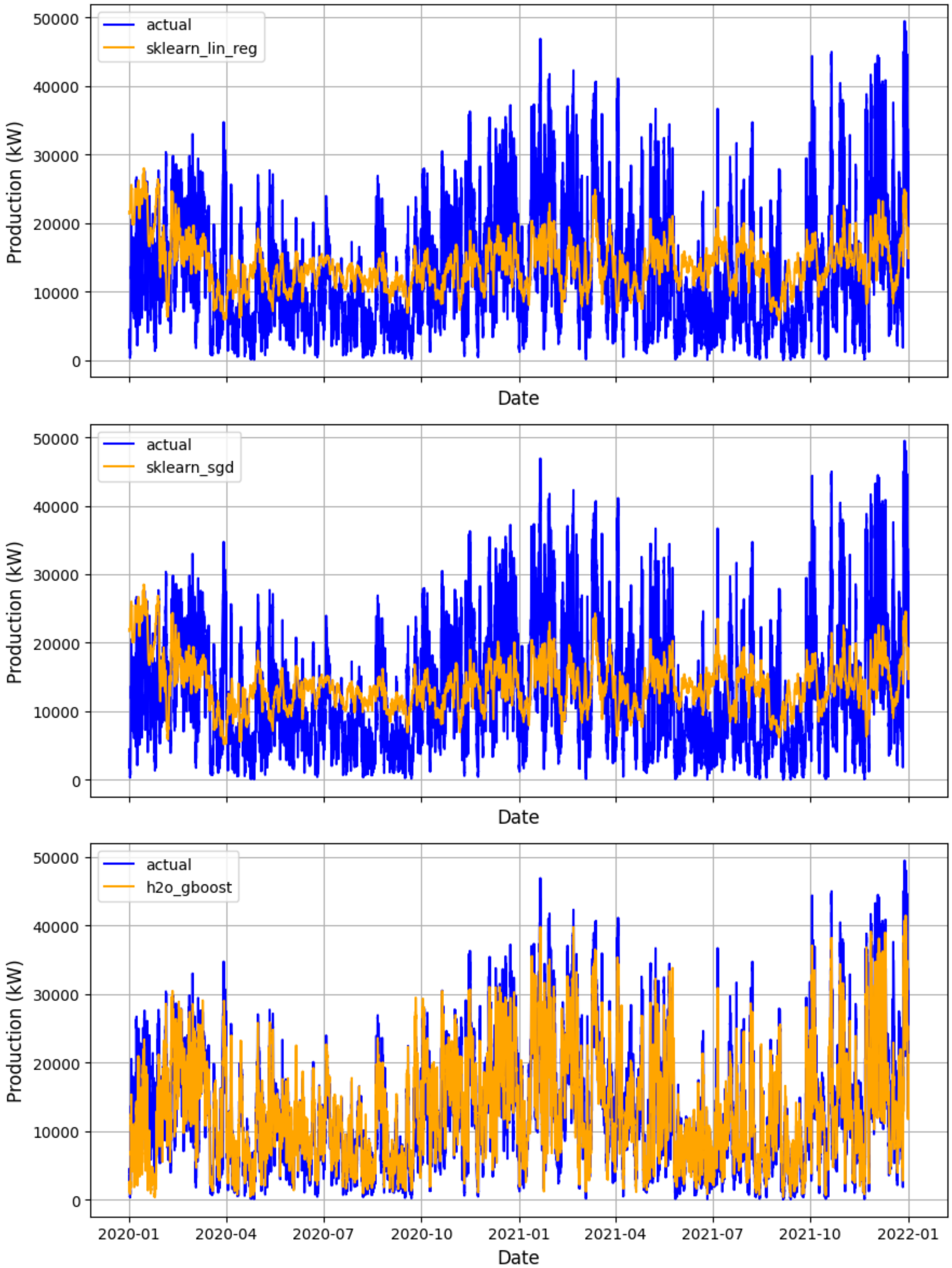
```
                                   actual_power_kw  sklearn_lin_reg  \
station time
eo_0    2020-01-01 00:00:00+01:00              0.0         0.023703
        2020-01-01 00:30:00+01:00              0.0         0.045373
        2020-01-01 01:00:00+01:00              0.0         0.067043
        2020-01-01 01:30:00+01:00              0.0         0.016094
        2020-01-01 02:00:00+01:00              0.0         0.000000
…                                                …                …
eo_9    2021-12-31 21:30:00+01:00              0.0       162.783013
        2021-12-31 22:00:00+01:00              0.0       163.084212
        2021-12-31 22:30:00+01:00              0.0       163.084212
        2021-12-31 23:00:00+01:00              0.0       163.084212
        2021-12-31 23:30:00+01:00              0.0       163.084212

                                   sklearn_sgd  h2o_gboost  \
```

```
station time
eo_0    2020-01-01 00:00:00+01:00     0.045843    0.000000
        2020-01-01 00:30:00+01:00     0.067934    0.000000
        2020-01-01 01:00:00+01:00     0.090025    0.000000
        2020-01-01 01:30:00+01:00     0.037725    0.000000
        2020-01-01 02:00:00+01:00     0.000000    0.000000
…                                          …          …
eo_9    2021-12-31 21:30:00+01:00   165.543803   51.921531
        2021-12-31 22:00:00+01:00   165.763577   51.921531
        2021-12-31 22:30:00+01:00   165.763577   51.921531
        2021-12-31 23:00:00+01:00   165.763577   51.921531
        2021-12-31 23:30:00+01:00   165.763577   51.921531

                                   installed_capacity_kw
station time
eo_0    2020-01-01 00:00:00+01:00                   28.0
        2020-01-01 00:30:00+01:00                   28.0
        2020-01-01 01:00:00+01:00                   28.0
        2020-01-01 01:30:00+01:00                   28.0
        2020-01-01 02:00:00+01:00                   28.0
…                                                     …
eo_9    2021-12-31 21:30:00+01:00                 1190.0
        2021-12-31 22:00:00+01:00                 1190.0
        2021-12-31 22:30:00+01:00                 1190.0
        2021-12-31 23:00:00+01:00                 1190.0
        2021-12-31 23:30:00+01:00                 1190.0

[635664 rows x 5 columns]
```

[40]:

```
# visualize predictions

n_estimators = len(all_estimators) # = len(benchmark_wind.columns)-1

fig, axis = plt.subplots(n_estimators , 1, figsize=(9, 4 * n_estimators),␣
↪sharex=True, sharey=False)

i = 0
for c in benchmark_wind.columns:
    if c != "actual_load_factor":
        axis[i].grid(True)
        axis[i].plot(benchmark_wind_kw["actual_power_kw"].groupby(level=1).
↪agg("sum"), label="actual", c="blue")
        axis[i].plot(benchmark_wind_kw[c].groupby(level=1).agg("sum"), label=c,␣
↪c="orange")
        axis[i].set_xlabel('Date', fontsize=12)
        axis[i].set_ylabel('Production (kW)', fontsize=12)
        #axis[i].set_title(source)
```

```
        axis[i].legend()
        i+=1

fig.tight_layout()
```



[41]:
```python
# sum over all power plants
benchmark_wind_portfolio = benchmark_wind_kw.groupby(level="time").sum()
```

[42]:
```python
# define a scoring
scoring_benchmark = enda.Scoring(benchmark_wind_portfolio ,␣
↪target="actual_power_kw", normalizing_col="installed_capacity_kw")
```

[43]:
```python
# compute the nAE
nAE = scoring_benchmark.normalized_absolute_error()
nAE
```

[43]:
```
                           sklearn_lin_reg  sklearn_sgd  h2o_gboost
time
2020-01-01 00:00:00+01:00         0.348391     0.354976    0.034527
2020-01-01 00:30:00+01:00         0.348430     0.355022    0.035228
2020-01-01 01:00:00+01:00         0.339901     0.346501    0.038276
2020-01-01 01:30:00+01:00         0.352671     0.359272    0.028830
2020-01-01 02:00:00+01:00         0.370592     0.377195    0.020328
…                                      …           …          …
2021-12-31 21:30:00+01:00         0.161710     0.163614    0.099381
2021-12-31 22:00:00+01:00         0.210789     0.213067    0.118962
2021-12-31 22:30:00+01:00         0.187531     0.189809    0.095704
2021-12-31 23:00:00+01:00         0.227805     0.230082    0.135978
2021-12-31 23:30:00+01:00         0.185929     0.188207    0.094102

[35088 rows x 3 columns]
```

[44]:
```python
nMAPE = nAE.mean()
nMAPE
```

[44]:
```
sklearn_lin_reg    0.118488
sklearn_sgd        0.118417
h2o_gboost         0.041353
dtype: float64
```

6 Conclusion

Do it with solar or run of river !