rf_week_ahead

July 26, 2023

1 Week-ahead Prediction Accuracy

In this notebook I hope to illustrate the differences between week-ahead prediction accuracies for Random Forest models trained in the same way on 2021-2023 data.

[ ]:
```
from joblib import dump, load
import numpy as np
import pandas as pd
import seaborn as sns
from tscv import GapRollForward
from tqdm.notebook import tqdm
from sklearn.ensemble import RandomForestRegressor
```

[ ]:
```
df = pd.read_csv('../data/merged_interpolated.csv')
df.datetime = df.datetime.astype('datetime64')
df.head()
```

[ ]:
```
             datetime  tempc  cloud8  windk   wdir  humid  rainmm  radkjm2  \
0 2018-03-06 09:30:00  20.75     2.5   14.5  135.0   44.5     0.0   1915.0
1 2018-03-06 10:00:00  21.50     1.0   16.0  140.0   40.0     0.0   2340.0
2 2018-03-06 10:30:00  22.25     1.5   15.5  145.0   37.0     0.0   2570.0
3 2018-03-06 11:00:00  23.00     2.0   15.0  150.0   34.0     0.0   2800.0
4 2018-03-06 11:30:00  23.55     2.0   13.0  145.0   32.0     0.0   2945.0

    pv_est  net_load  total_load
0  318.991      1288     1136.79
1  375.231      1237     1054.87
2  430.909      1189     1002.35
3  485.129      1150      971.54
4  523.989      1122      943.68
```

Expand datetime feature to its various component parts, plus day of week and week of year.

[ ]:
```
dt = df['datetime'].astype('datetime64[ns]').dt
df['year'] = dt.year
df['month'] = dt.month
df['day'] = dt.day
df['hour'] = dt.hour
```

```
df['minute'] = dt.minute
df['day_of_week'] = dt.day_of_week
df['week'] = dt.isocalendar().week
df.dtypes
```

```
[ ]: datetime       datetime64[ns]
     tempc                 float64
     cloud8                float64
     windk                 float64
     wdir                  float64
     humid                 float64
     rainmm                float64
     radkjm2               float64
     pv_est                float64
     net_load                int64
     total_load            float64
     year                    int64
     month                   int64
     day                     int64
     hour                    int64
     minute                  int64
     day_of_week             int64
     week                   UInt32
     dtype: object
```

Select training features and extract training matrix X and response y.

```
[ ]: X_inds = list(range(1, 8)) + list(range(11, 18))
     y_ind = 9

     print(df.columns[X_inds].values)
     print(df.columns[y_ind])
```

```
['tempc' 'cloud8' 'windk' 'wdir' 'humid' 'rainmm' 'radkjm2' 'year' 'month'
 'day' 'hour' 'minute' 'day_of_week' 'week']
net_load
```

Cross-validation splits are done in an appropriate time-series fashion, with one observation-year (48 observations * 365 days) for each training set and test set. There should be a good number of splits with a roll size (gap between successive training set starting points) of 30 days.

```
[ ]: obs_year = 48*365
     obs_week = 48*7
     tscv = GapRollForward(min_train_size=obs_year, max_train_size=obs_year,
                           min_test_size=obs_week, max_test_size=obs_week,
                           roll_size=obs_week)

     df_2021 = df[df['year'] >= 2021]
     n_splits = sum(1 for i in tscv.split(df_2021)) # get length of a generator
```

```
print('Number of models to be trained:', n_splits)
```

```
Number of models to be trained: 61
```

Training of each forest is parallelised to save time, but even so the full training takes a few minutes. No hyperparameters are selected or tuned. Models and their last training observation's timestamps are saved.

Predictions are made on a full ensuing year per model and merged into a single dataframe, with calculated residuals and absolute percentage error.

[ ]:
```
models, train_ends = [], []
prdfs = []

for i, (train_ind, test_ind) in tqdm(enumerate(tscv.split(df_2021))):
    X_train, X_test = df_2021.iloc[train_ind, X_inds], df_2021.iloc[test_ind,␣
 ↪X_inds]
    y_train, y_test = df_2021.iloc[train_ind, y_ind], df_2021.iloc[test_ind,␣
 ↪y_ind]

    # train or load
    begin, end = df_2021.iloc[[train_ind[0], train_ind[-1]], 0].dt.date
    model_filename = f'../models/sa/rf/{begin}_{end}.joblib'
    try:
        rf = load(model_filename)
    except FileNotFoundError:
        rf = RandomForestRegressor(n_jobs=8)
        rf.fit(X_train, y_train)
        dump(rf, model_filename)

    models.append(rf)
    train_ends.append(df_2021.iloc[train_ind[-1], 0])

    # predict
    prd = rf.predict(X_test)
    prdf = pd.DataFrame({'datetime': df_2021.iloc[test_ind, 0],
                         'model': i,
                         'train_end': end,
                         'obs_ahead': np.arange(len(prd)) + 1,
                         'predicted': prd,
                         'net_load': y_test})
    prdfs.append(prdf)
predictions = pd.concat(prdfs)
predictions['residual'] = predictions['net_load'] - predictions['predicted']
predictions['pe'] = predictions['residual'] / predictions['net_load']
predictions['ape'] = predictions['pe'].abs()
predictions
```

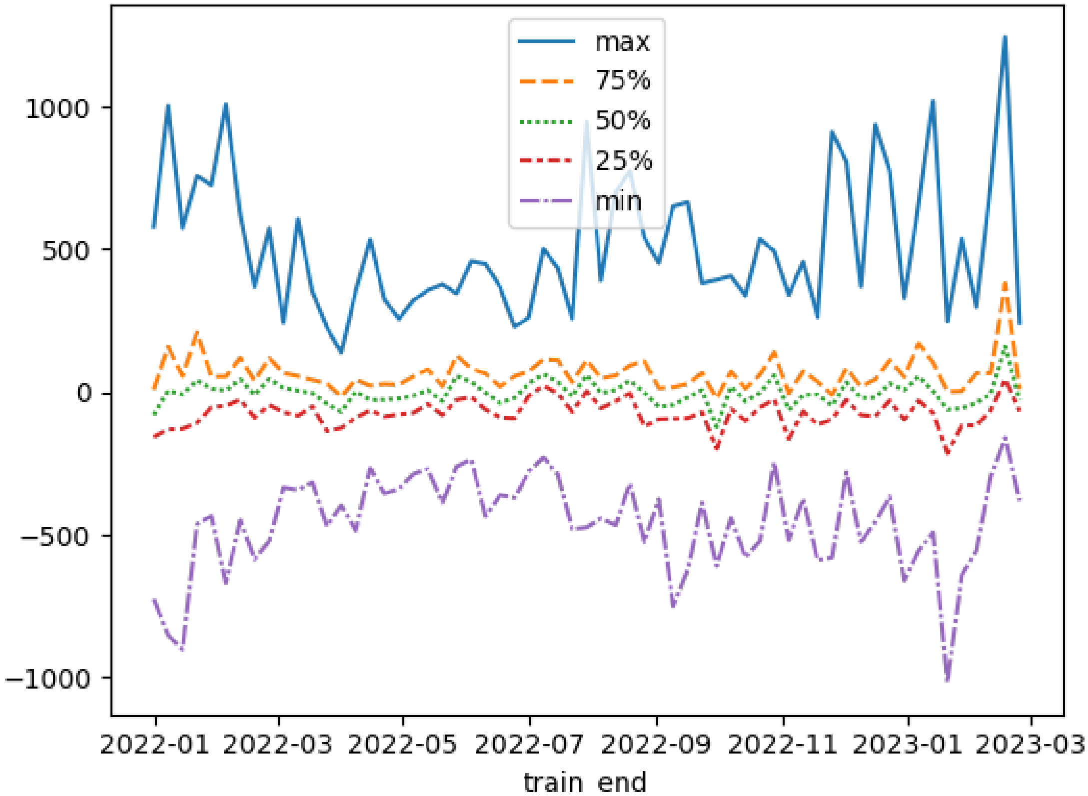
```
0it [00:00, ?it/s]
```

[ ]:
```
                 datetime  model  train_end  obs_ahead  predicted  net_load  \
67037 2022-01-01 00:00:00      0 2021-12-31          1    1496.59      1844
67038 2022-01-01 00:30:00      0 2021-12-31          2    1515.15      1769
67039 2022-01-01 01:00:00      0 2021-12-31          3    1582.54      1732
67040 2022-01-01 01:30:00      0 2021-12-31          4    1523.13      1626
67041 2022-01-01 02:00:00      0 2021-12-31          5    1318.30      1548
…                       …    …          …        …         …       …
87528 2023-03-03 21:30:00     60 2023-02-24        332    1464.29      1434
87529 2023-03-03 22:00:00     60 2023-02-24        333    1403.06      1401
87530 2023-03-03 22:30:00     60 2023-02-24        334    1368.80      1350
87531 2023-03-03 23:00:00     60 2023-02-24        335    1340.38      1324
87532 2023-03-03 23:30:00     60 2023-02-24        336    1336.10      1307

       residual        pe       ape
67037    347.41  0.188400  0.188400
67038    253.85  0.143499  0.143499
67039    149.46  0.086293  0.086293
67040    102.87  0.063266  0.063266
67041    229.70  0.148385  0.148385
…           …        …        …
87528    -30.29 -0.021123  0.021123
87529     -2.06 -0.001470  0.001470
87530    -18.80 -0.013926  0.013926
87531    -16.38 -0.012372  0.012372
87532    -29.10 -0.022265  0.022265

[20496 rows x 9 columns]
```

Plot residual quantiles over time/models.

[ ]:
```python
sns.lineplot(predictions.groupby('train_end').describe()['residual'][['max',␣
↪'75%', '50%', '25%', 'min']])
```

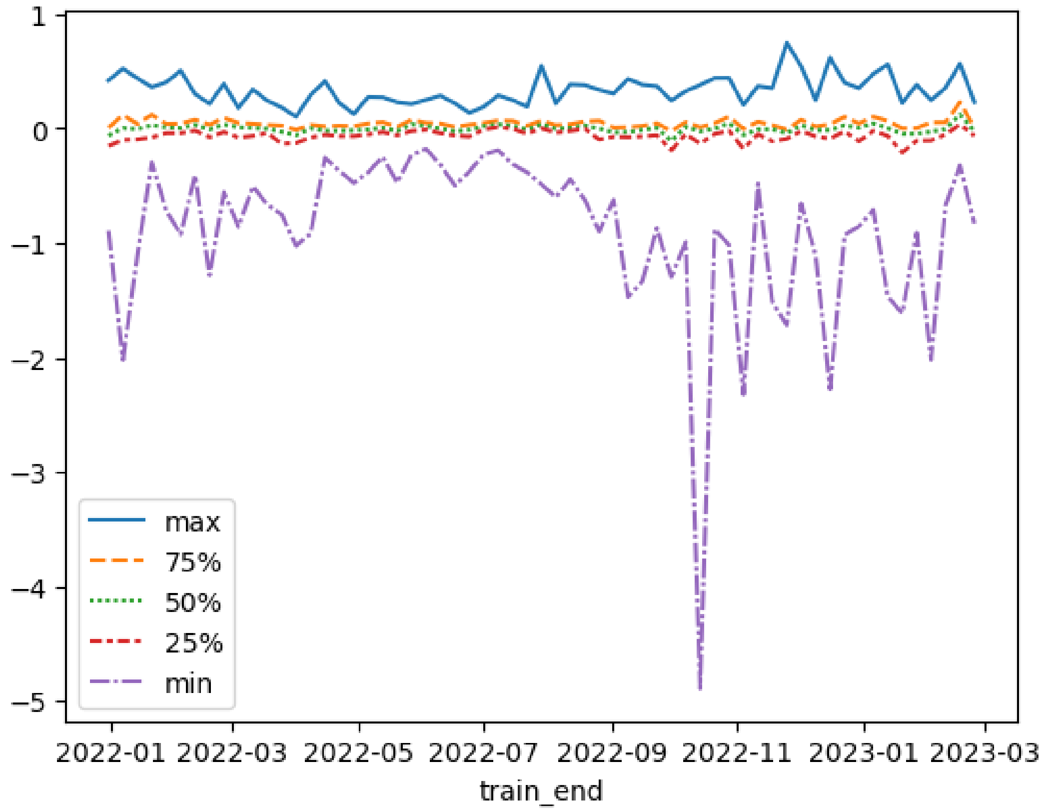
[ ]:
```
<Axes: xlabel='train_end'>
```



Plot percentage errors (relative error) quantiles.

```
[ ]: sns.lineplot(predictions.groupby('train_end').describe()['pe'][['max', '75%',␣
     ↪'50%', '25%', 'min']])
```

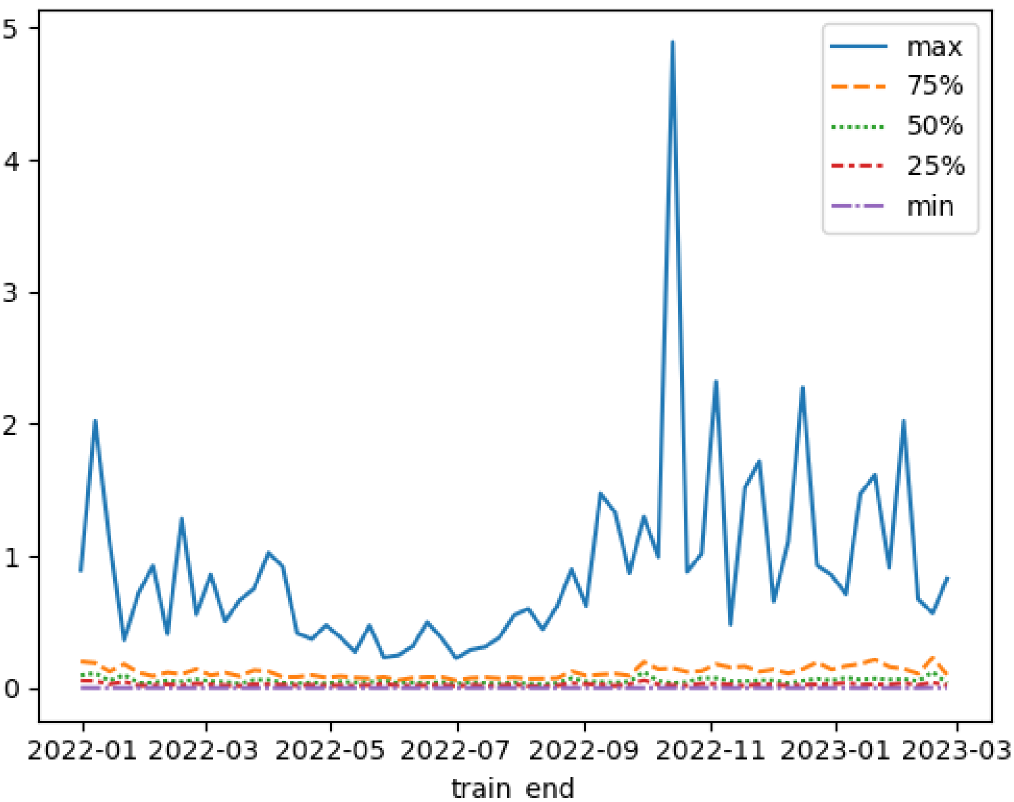
```
[ ]: <Axes: xlabel='train_end'>
```



Plot absolute percentage error quartiles over time/models.

```
[ ]: sns.lineplot(predictions.groupby('train_end').describe()['ape'][['max', '75%',␣
     ↪'50%', '25%', 'min']])
```

```
[ ]: <Axes: xlabel='train_end'>
```


max
75%
50%
25%
min
0
1
2
3
4
5
2022-01
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01
2023-03
train_end