Seminar_CoViD_tristate_comparison

January 16, 2022

1 Data Science 2 Seminar

1.1 Business/project evaluation stage

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1.1.1 Premise

Vacations/holidays have a visible effect on CoViD-19 infection rates in the tri-state area.

If that can be shown, I will try to form a prediction model for future holidays or give an idea what is possible in this model and what is not. We know that events changing the infection rate show their effect for the following 5-12 days. So a 14 day window will be used applied for the factors.

1.1.2 Python

Versions of the central libraries

- Python 3.9.4
- Pandas 1.2.4
- sklearn 0.24.2
- skforecast 0.4.1

1.2 Init

Settings can be modified the change some key parameters of the calculations

[ ]:
```
import pandas as pd
import numpy as np
from numpy import mean
from numpy import std

import matplotlib.pyplot as plt
from datetime import datetime as dt, timedelta

from helpers import *
# Some of the statics can be found in init.py
import init as util

from dataprep import  *
```

```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪RepeatedKFold, StratifiedKFold, GridSearchCV
from sklearn.svm import SVR
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler

# make the graphs actually viewable
plt.rcParams['figure.figsize'] = [6, 4]
plt.rcParams['figure.dpi'] = 100

class Settings(object):
    incident_window_size = 7 # days (used for N-Day rate)
    change_rate_window_size = 7 # days (sliding window size)
    off_day_relevance_window = 14 # days (used in the OffDayFactor)
    # timeframe used from the base data. Had some instances where data at the␣
↪start or end got sketchy, so a clear cut-off produced better results
    timeframe_start = dt.strptime('2020-03-15',"%Y-%m-%d")
    timeframe_end = dt.strptime('2021-12-31',"%Y-%m-%d")
    training_columns = ['NDRC_SW_Yesterday','OffDayFactor', 'OffDay'] # columns␣
↪used in training the algorithms

    # Data sources
    generate_data = False        # read data from original source
    save_generated_data = True   # write the data to the datapreparation cache␣
↪files
    load_pregenerated_data = True # load the data from the pregenerated cache␣
↪files (replaces data from original source in this ipynb)

    base_dir = "./"
    data_dir = base_dir + "datasets/"
    source_dir = data_dir + 'orig/'

    # all paths relative to this document
    original_be_data = source_dir + 'COVID19BE_CASES_AGESEX.csv'
    original_nl_data = source_dir + 'COVID-19_aantallen_gemeente_cumulatief.csv'
    original_de_data = source_dir + 'RKI_COVID19_Nordrhein-Westfalen.csv'

    # cache files
    emr_infection_data = data_dir + "EMR_prepared.csv"
    de_reference_data = data_dir + "de_ref_cal.csv"
    nl_reference_data = data_dir + "nl_ref_cal.csv"
    be_reference_data = data_dir + "be_ref_cal.csv"

settings = Settings()
```

1.3 Data preparation

The area of relevance is the EMR (Euregio Maas-Rhine region) as defined by the EU.

- The CoViD-19 data corresponding to that area is collected from
  - https://data.rivm.nl/covid-19/
  - https://epistat.sciensano.be/Data/COVID19BE_CASES_AGESEX.csv
  - https://npgeo-corona-npgeo-de.hub.arcgis.com/datasets/a99afefd4258435f8af660b6cbed9bf7_0/explore
- The original formats are all UTF-8 encoded CSV, whereas BE and DE data is comma separated and NL is semicolon separated
- German and belgian data contains daily cases. Dutch data contains total cases and needs to be converted
- Original data contains features describing
  - Date
  - Province reference
  - Daily total cases
- Additional derived fields are added
  - Daily cases per 100k inhabitants
  - A sliding window rate for N-Days (settled on N=7)
  - A change rate for the N-Day-Rate
  - A sliding window variant of the change rate
- The compiled dataset is saved/cached as CSV
- The holiday and school-holidays are compiled in separate datasets
- They contain the following features per day
  - Date
  - Province reference
  - Holiday
  - Vacation day
  - OffDay
  - OffDayFactor (a factor calculated as the sum of OffDays over a certain period)

1.3.1 Loading data and saving to cache files

[ ]:
```
if settings.generate_data:
    emr_df = prepareData(settings)
    be_ref_df, nl_ref_df, de_ref_df = prepareRefCals(settings)
```

1.3.2 Importing previously prepared data

Reloading generated data from cache to reduce run-times

[ ]:
```
if settings.load_pregenerated_data:
    emr_df = pd.read_csv(settings.emr_infection_data)
```

```
    emr_df = addDateTypeColumn(emr_df,'Date')

    be_ref_df, nl_ref_df, de_ref_df = loadRefData(settings)
```

Combining incident datasets with off-day datasets. Resulting datasets grouped by off-days

[ ]:
```
de_off_dfs = {}
nl_off_dfs = {}
be_off_dfs = {}

for i in [10,20,30,40]:
    de_off_dfs[i] = prepareDf(emr_df, i, de_ref_df)

for i in [10,20,30,40]:
    nl_off_dfs[i] = prepareDf(emr_df, i, nl_ref_df)

for i in [10,20,30,40]:
    be_off_dfs[i] = prepareDf(emr_df, i, be_ref_df)
```

1.3.3 Verify timeline completeness

Since certain data remained riddled with missing days, we verify that the timestretches we use are complete. Missing days are mostly the result of 0 incidence days or delay in registering the cases

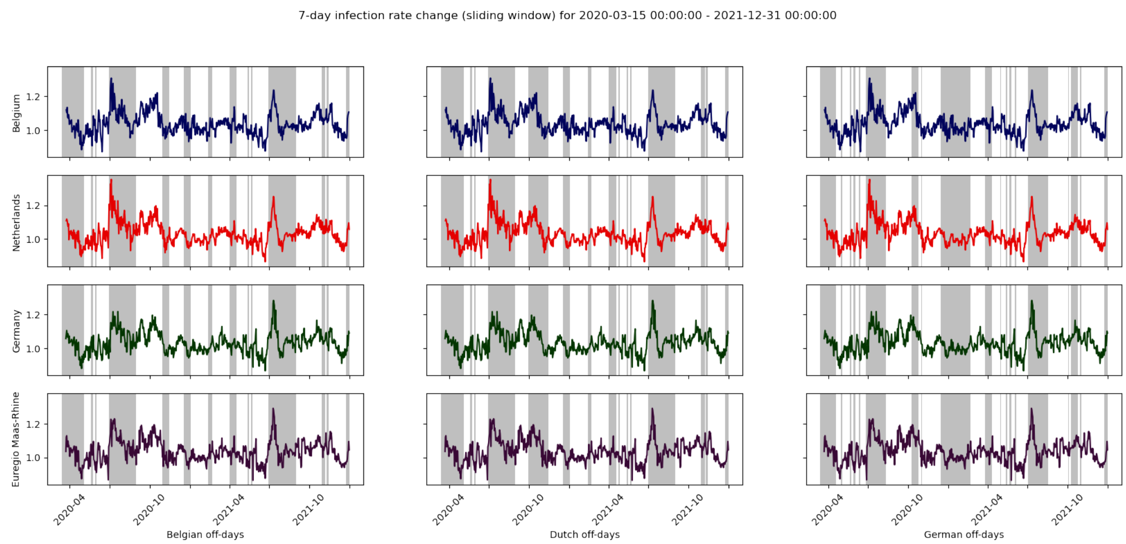
[ ]:
```
for name, df_dict in [('be',be_off_dfs), ('nl',nl_off_dfs), ('de',de_off_dfs)]:
    for k, df in df_dict.items():
        print('Off days: {od} provinceId: {pid} complete: {comp}'.
 ↪format(od=name, pid =k, comp=(df.index == pd.date_range(start=df.index.min(),
                                    end=df.index.max(),
                                    freq=df.index.freq)).all()))
```

```
Off days: be provinceId: 10 complete: True
Off days: be provinceId: 20 complete: True
Off days: be provinceId: 30 complete: True
Off days: be provinceId: 40 complete: True
Off days: nl provinceId: 10 complete: True
Off days: nl provinceId: 20 complete: True
Off days: nl provinceId: 30 complete: True
Off days: nl provinceId: 40 complete: True
Off days: de provinceId: 10 complete: True
Off days: de provinceId: 20 complete: True
Off days: de provinceId: 30 complete: True
Off days: de provinceId: 40 complete: True
```

1.4 Visual comparison

A scatter plot for visual comparison of the cross-border influence. It shows the respective countries infection rate changes as colored plots on a timeline with the set of Off-Days as grey bars.

```
[ ]: scatterInfectionComparison(emr_df, be_ref_df, nl_ref_df, de_ref_df, settings,␣
      ↪plotsize=[20,8])
```



Based on the fact that impacts are clearly visible, I went forward with training regression algorithms to get clearer numbers of the correlation and attempt forecasting

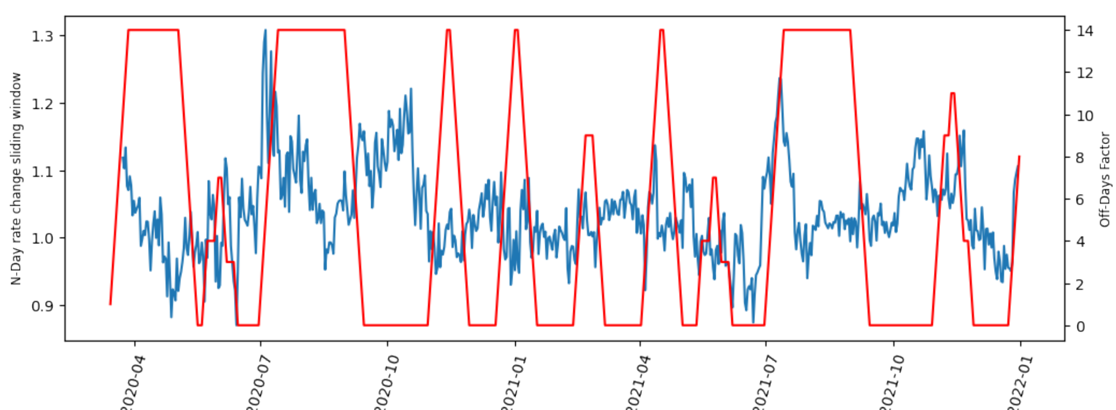
1.5 Regression

I initially compared diffrent regression models on my data to compare results. Ridge Regression, SVR and Gradient Boosting all yielded similar scoring results (after adding grid search) with the Boosted Tree being slightly ahead in performance.

As a derived feature an Off-Day-Factor has been added to the holiday reference data.

It is calculated as the sum of off-days over the past N days.

```
[ ]: plotOffDaysFactor(emr_df.loc[emr_df.Province_Id == 10], be_ref_df)
```



1.5.1 Ridge Regression

RR yields a similar score (R2) as Gradient Boosting does

[ ]:
```
from sklearn.datasets import make_regression
from sklearn.kernel_ridge import KernelRidge
from sklearn.model_selection import train_test_split

pt_gbtr_df = de_off_dfs[30].copy()
X, y = pt_gbtr_df.loc[:, settings.training_columns], pt_gbtr_df.
↪NDRC_Sliding_Window

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=1)

gbtReg = KernelRidge()
gbtReg.fit(X_train, y_train)
gbtReg.score(X_test, y_test) # R2
```

[ ]:
```
0.6849798878983979
```

1.5.2 Support Vector Regression

During initial tryouts SVM yielded significantly worse R2-scored compared to both RR and Gradient Boosting. After running a grid search the results aren't as far off anymore, but still worse compared to Gradient Boosting. Aside from that the parameters for the results differed more widely which would make a comparison weaker.

[ ]:
```
gbtr_df = de_off_dfs[30].copy()
X, y = gbtr_df.loc[:, settings.training_columns], gbtr_df.NDRC_Sliding_Window

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
↪random_state=1)

regr = make_pipeline(StandardScaler(), SVR(kernel='rbf',C=1.0, epsilon=0.2))
regr.fit(X_train, y_train)
regr.score(X_test, y_test) # R2
```

[ ]:
```
-0.2514353561051441
```

Applying a grid search to the SVR to improve scores.

[ ]:
```
def doGridSearchForSVM():
    param_grid = {
        'kernel': ['rbf', 'linear', 'poly'],
```

```
        'C': [1, 10, 100],
        'gamma': [1e-3, 1e-4],
        'epsilon': [0.2],
    }

    svr = SVR()
    cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
    grid_search = GridSearchCV(estimator = svr, param_grid = param_grid,
                              cv = cv, n_jobs = -1, verbose = 0,␣
↪scoring='neg_mean_absolute_error')
    results = pd.DataFrame(columns={'region','offdays','score'})

    for name, df_dict in [('be',be_off_dfs), ('nl',nl_off_dfs),␣
↪('de',de_off_dfs)]:
        for k, df in df_dict.items():
            X = df.loc[:,['NDRC_SW_Yesterday','OffDayFactor']]
            y = df.NDRC_Sliding_Window
            grid_search.fit(X, y)
            res = grid_search.best_params_.copy()
            res['offdays'] = name
            res['region'] = util.class_labels[k]
            res['score'] = grid_search.best_score_
            results = results.append(res, ignore_index=True)
    return results
```

[ ]:
```
scores = doGridSearchForSVM()
scores.loc[:,['region','offdays','score']]
```

[ ]:

	region	offdays	score
0	Belgium	be	-0.065336
1	Netherlands	be	-0.067136
2	Germany	be	-0.061060
3	Euregio Maas-Rhine	be	-0.055512
4	Belgium	nl	-0.065431
5	Netherlands	nl	-0.067538
6	Germany	nl	-0.061199
7	Euregio Maas-Rhine	nl	-0.055094
8	Belgium	de	-0.065536
9	Netherlands	de	-0.071629
10	Germany	de	-0.062333
11	Euregio Maas-Rhine	de	-0.053652

1.5.3 Gradient Boosting Regressor

Applying the parameters from the grid search below I got a R2-score to have a comparison to the other models

[ ]:
```
pt_gbtr_df = de_off_dfs[30].copy()
X, y = pt_gbtr_df.loc[:,settings.training_columns], pt_gbtr_df.
 ↪NDRC_Sliding_Window

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=0)

# From Gridsearch
params = {'learning_rate': 0.075,
 'max_depth': 3,
 'min_samples_leaf': 10,
 'min_samples_split': 2,
 'n_estimators': 80,
 'subsample': 0.85
 }

gbtReg = GradientBoostingRegressor( random_state=0, **params)

gbtReg.fit(X_train, y_train)
gbtReg.score(X_test, y_test) # R2
```

[ ]: 0.6888012453547856

I applied grid search to find the best overall parameters and to have a comparison/measure of the stability/impacts of the off days on their respective countries, the neighbouring countries and the EMR as a whole.

(The original grid params are commented out to have it run in reasonable time.)

[ ]:
```
def doGridSearchForGradientBoostingRegressor():
    # param_grid = {
    #     'max_depth': [2, 3, 5, 10],
    #     'subsample': [0.05, 0.1, 0.2, 0.5, 0.8, 0.85, 0.9],
    #     'n_estimators': [10, 50, 80, 90, 100, 200, 500],
    #     'learning_rate': [0.01, 0.02, 0.05,0.075, 0.1, 0.5],
    #     'min_samples_split': [2, 5, 10],
    #     'min_samples_leaf': [2, 5, 10]
    # }

    param_grid = {
        'max_depth': [3],
        'subsample': [0.85],
        'n_estimators': [80],
        'learning_rate': [0.075],
        'min_samples_split':[2],
        'min_samples_leaf':[10]
    }
```

```
    gbr = GradientBoostingRegressor(random_state=1)
    cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)
    grid_search = GridSearchCV(estimator = gbr, param_grid = param_grid,
                               cv = cv, n_jobs = -1, verbose = 0,␣
↪scoring='neg_mean_absolute_error')
    results = pd.DataFrame(columns={'region','offdays','score'})

    for name, df_dict in [('be',be_off_dfs), ('nl',nl_off_dfs),␣
↪('de',de_off_dfs)]:
        for k, df in df_dict.items():
            X = df.loc[:,['NDRC_SW_Yesterday','OffDayFactor']]
            y = df.NDRC_Sliding_Window
            grid_search.fit(X, y)
            res = grid_search.best_params_.copy()
            res['offdays'] = name
            res['region'] = util.class_labels[k]
            res['score'] = grid_search.best_score_
            results = results.append(res, ignore_index=True)
    return results
```

The resulting scores show that on very similar parameters the predictions of incident changes for off-days corresponding to their own country are reasonably stable. Across borders and spanning the whole EMR are roughly equally well. The scores as such seem to be in a range where they give predictions in the right ball park for a next-day prediction but aren't suitable/stable enough for forecasts over longer stretches. This stems from each prediction being based on a true value of the previous day.

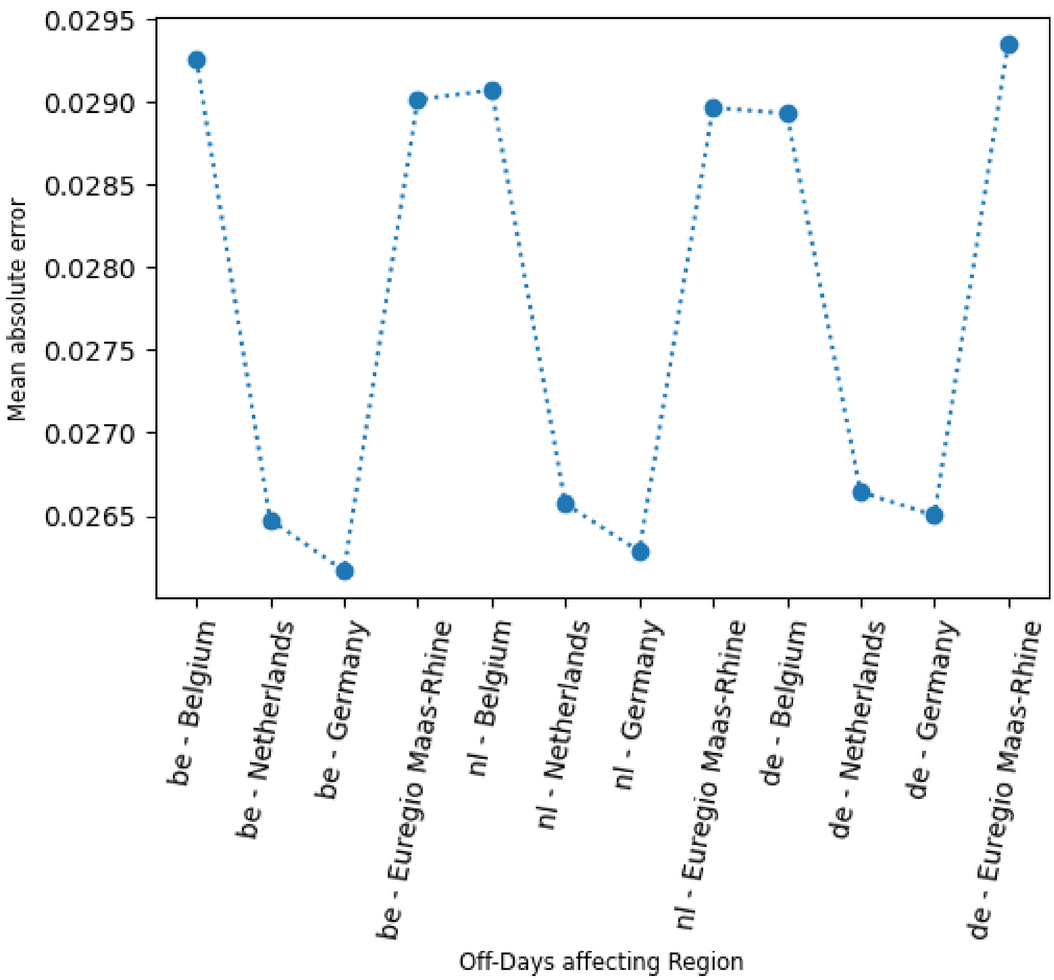
[ ]:
```
scores = doGridSearchForGradientBoostingRegressor()
scores.loc[:,['region','offdays','score']]
```

[ ]:

	region	offdays	score
0	Belgium	be	-0.029262
1	Netherlands	be	-0.026476
2	Germany	be	-0.026168
3	Euregio Maas-Rhine	be	-0.029013
4	Belgium	nl	-0.029071
5	Netherlands	nl	-0.026572
6	Germany	nl	-0.026284
7	Euregio Maas-Rhine	nl	-0.028965
8	Belgium	de	-0.028930
9	Netherlands	de	-0.026643
10	Germany	de	-0.026501
11	Euregio Maas-Rhine	de	-0.029355

The results are split between the impact of everything onto Germany and the Netherlands and on the weaker side onto Belgium and the EMR as a whole. The difference is not large (~10%), but clearly visible. Some conclusions I would draw from this, which could be verified in a diffrent context. * Belgium makes up roughly 45% of the EMR population, so its numbers have a bigger impact on the EMR as a whole * The belgian EMR-parts because of its size have a diffrent incidence-inertia * The reporting-lag is diffrent or perhaps less stable in Belgium, so the change rates are less crisp in their reaction * The dutch and german numbers have a bigger impact on the belgian incidence numbers than the other way around and as such produce a blurrier result

[ ]:
```
plotCrossBorderScores(scores)
```



1.6 Forecasting

I attempted two diffrent methods of forecasting. One with the skforecast library and one coded iteratively by hand. Both led me to the conclusion that a near time forecast is pretty accurate, but any forecasts surpassing 1-2-3 days become too unstable to be relevant.

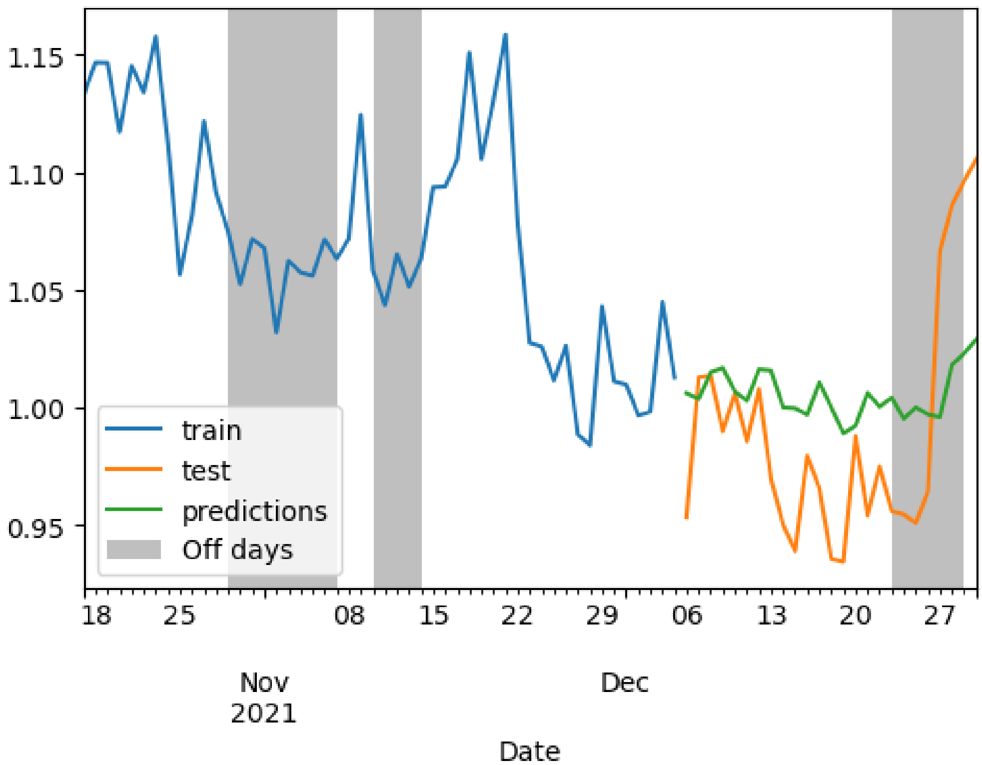
1.6.1 skforecast

The skforecast is classically trained on the available data and adds/predicts a future time-window from there.

```
[ ]: import matplotlib.pyplot as plt

     from sklearn.linear_model import LinearRegression
     from sklearn.linear_model import Lasso
     from sklearn.ensemble import RandomForestRegressor
     from sklearn.metrics import mean_squared_error
     from sklearn.preprocessing import StandardScaler
     from sklearn.pipeline import make_pipeline

     from skforecast.ForecasterAutoreg import ForecasterAutoreg
     from skforecast.ForecasterAutoregCustom import ForecasterAutoregCustom
     from skforecast.ForecasterAutoregMultiOutput import ForecasterAutoregMultiOutput

     from joblib import dump, load

     def doRunSkForecaster(df, test_range, training_columns, refDf = None):
         fk_df = df.copy()

         data_train = fk_df[:-test_range]
         data_test = fk_df[-test_range:]

         regr = GradientBoostingRegressor(random_state=1, **params)
         forecaster = ForecasterAutoreg( regressor = regr, lags = 100 )
         forecaster.fit(y=data_train.NDRC_Sliding_Window, exog=data_train.loc[:,␣
      ↪training_columns])
         predictions = forecaster.predict(steps=test_range, exog=data_test.loc[:,␣
      ↪training_columns])

         fig, ax = plt.subplots()
         if refDf is not None:
             mask = (refDf.Date > data_train.index.min()) & (refDf.Date < data_test.
      ↪index.max())
             addDayOffStreaks(refDf.loc[mask], ax = ax, streakLabel='Off days')
         data_train[-test_range*2:].NDRC_Sliding_Window.plot(ax=ax, label='train')
         data_test.NDRC_Sliding_Window.plot(ax=ax, label='test')
         predictions.plot(ax=ax, label='predictions')
         ax.legend()
         return predictions
```

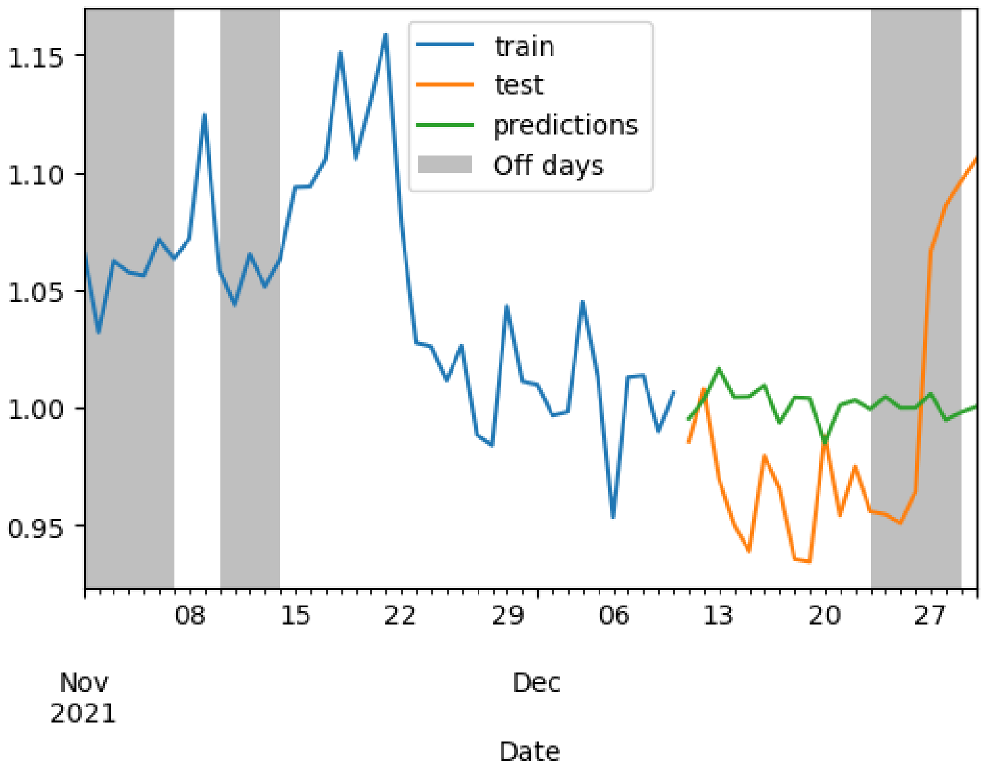
The forecast works reasonably well if we use the true value of yesterdays change rate as supporting data for the prediction. The tendencies for each day or spike respectively are learned and can be displayed well.

```
[ ]: _ = doRunSkForecaster(nl_off_dfs[10], 25, settings.training_columns, refDf =␣
      ↪nl_ref_df)
```



The forecast becomes quickly unstable and very inaccurate when based solely on vacation days and recursively calculated change values

[ ]:
```
_ = doRunSkForecaster(nl_off_dfs[10], 20, ['OffDay','OffDayFactor'], refDf =␣
↪nl_ref_df)
```

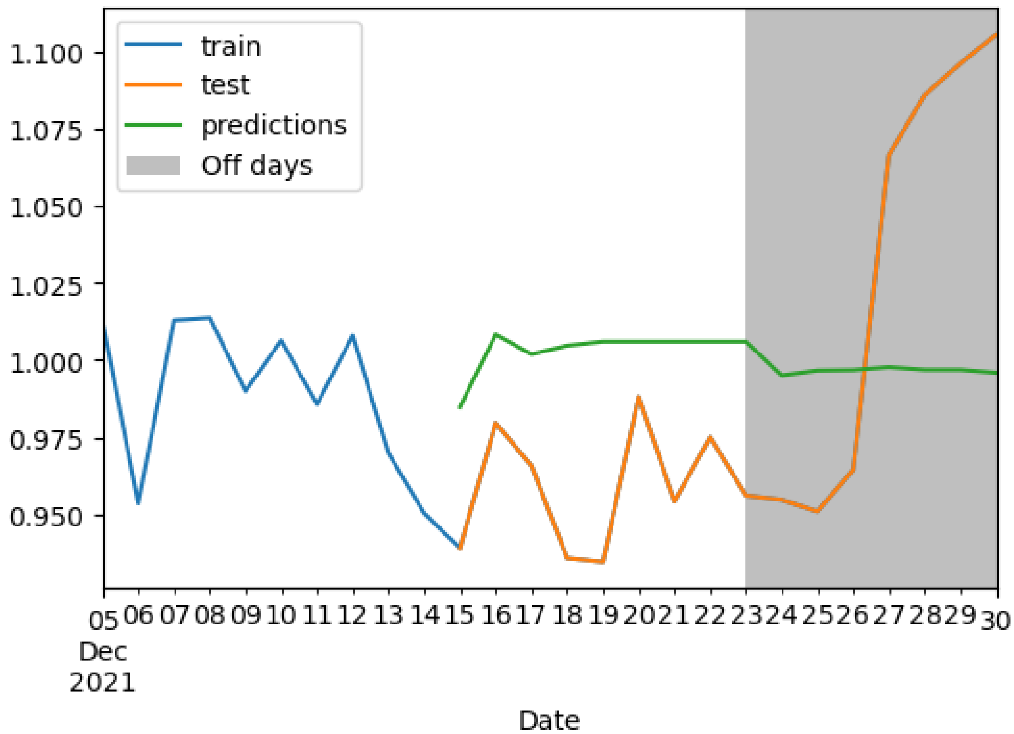


1.6.2 Recursive forecasting

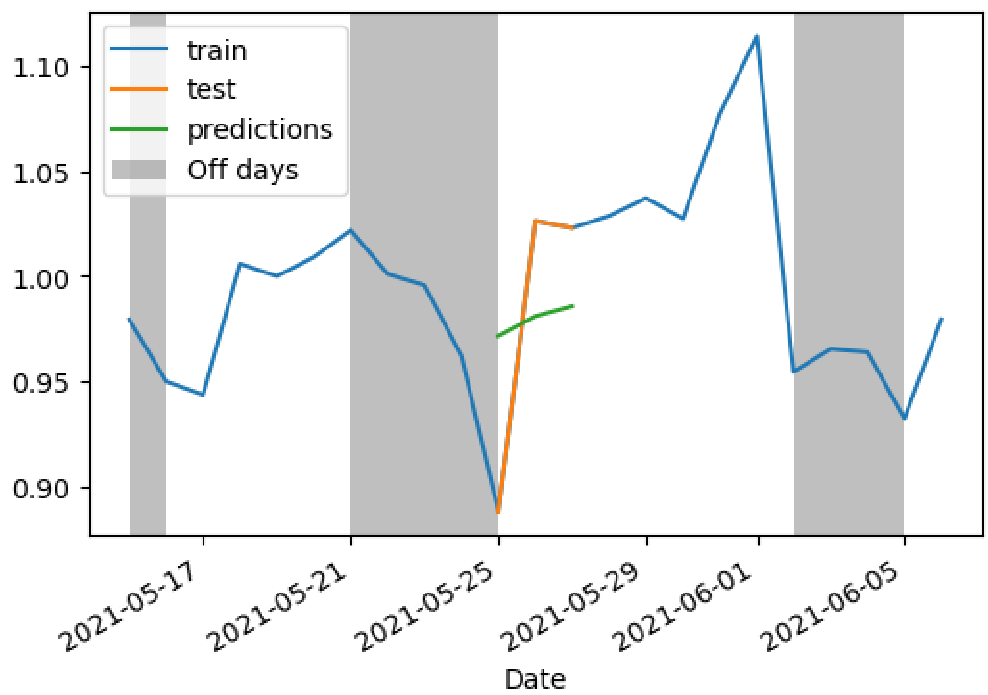
On the handmade forecasting I sketched windows within the data range, to be able to compare multiple scenarios that differ widely. This algorithm forwards solely yesterdays value of prediction.

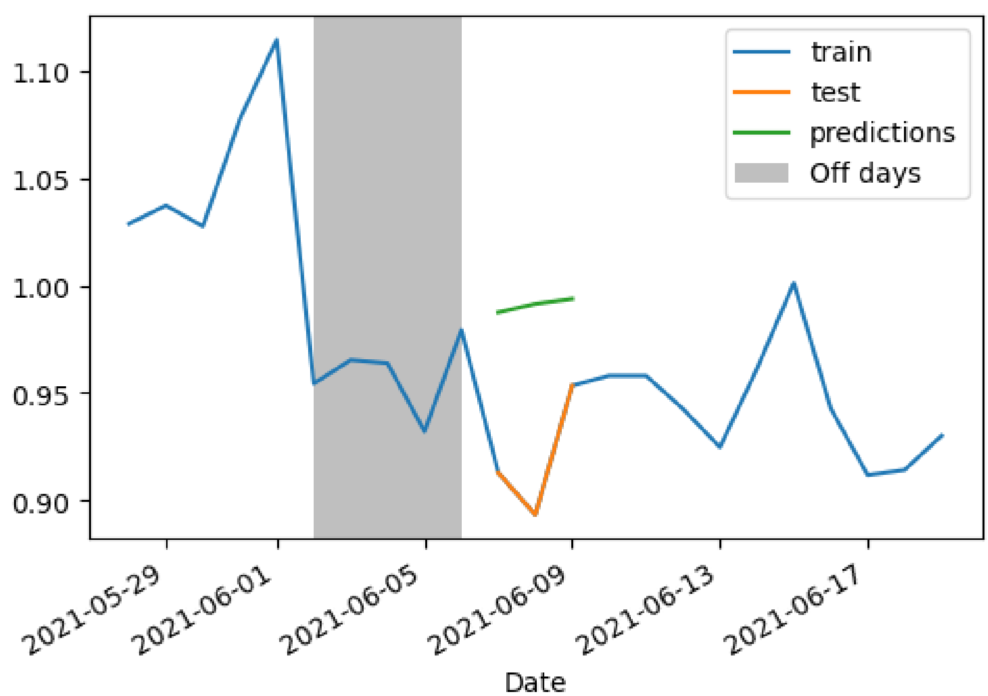
As a comparison I will plot a similar window as above and some other examples showing the growing inaccuracy.

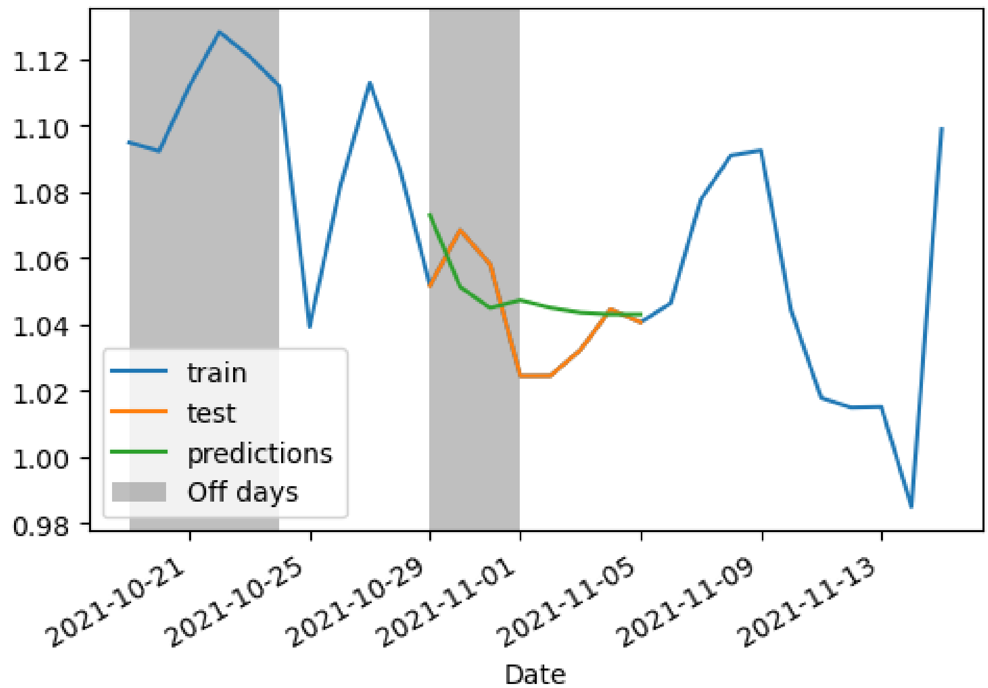
[ ]:
```
_ = recursiveWindowForecast(nl_off_dfs[10],'2021-12-15','2021-12-31', settings,␣
↪params=params, refDf=nl_ref_df, visualWindow=10)
```

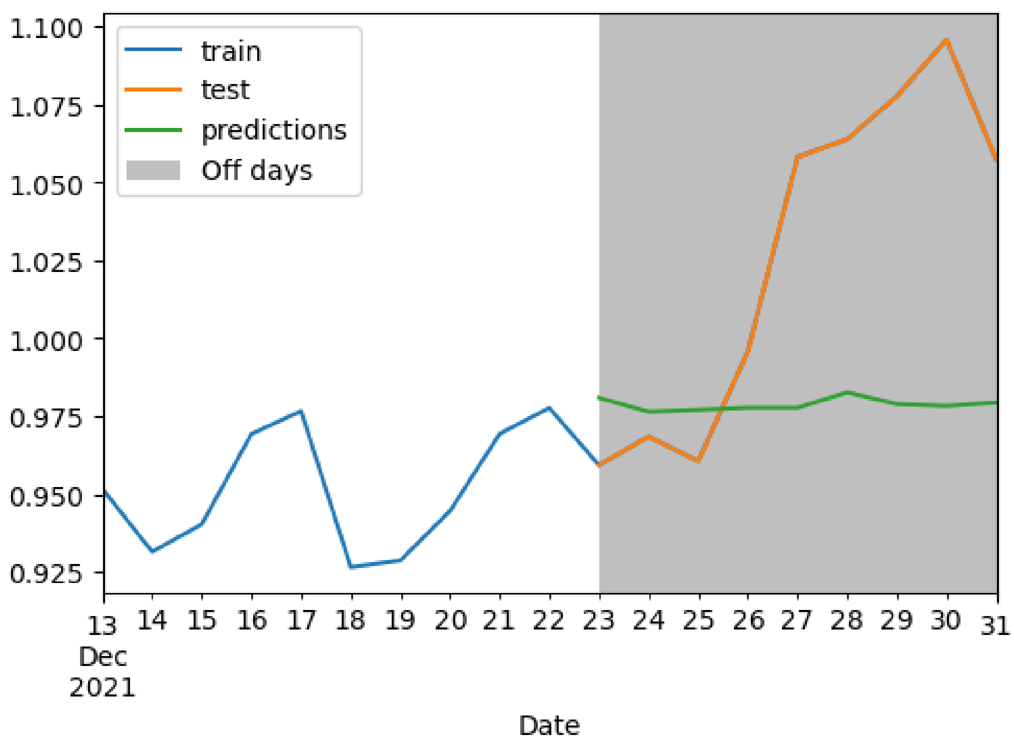



```
[ ]: # even small windows show a similar tendency, but are imprecise
_ = recursiveWindowForecast(de_off_dfs[30],'2021-05-25','2021-05-27', settings,␣
↪params=params, refDf=de_ref_df, visualWindow=10)
_ = recursiveWindowForecast(de_off_dfs[30],'2021-06-07','2021-06-09', settings,␣
↪params=params, refDf=de_ref_df, visualWindow=10)
_ = recursiveWindowForecast(de_off_dfs[30],'2021-10-29','2021-11-05', settings,␣
↪params=params, refDf=de_ref_df, visualWindow=10)
_ = recursiveWindowForecast(be_off_dfs[20],'2021-12-23','2021-12-31', settings,␣
↪params=params, refDf=be_ref_df, visualWindow=10)
```


train
test
predictions
Off days
1.10
1.05
1.00
0.95
0.90
2021-05-17
2021-05-21
2021-05-25
2021-05-29
2021-06-01
2021-06-05
Date


train
test
predictions
Off days
1.10
1.05
1.00
0.95
0.90
2021-05-29
2021-06-01
2021-06-05
2021-06-09
2021-06-13
2021-06-17
Date


1.12
1.10
1.08
1.06
1.04
1.02
1.00
0.98
2021-10-21
2021-10-25
2021-10-29
2021-11-01
2021-11-05
2021-11-09
2021-11-13
Date
train
test
predictions
Off days


1.100
1.075
1.050
1.025
1.000
0.975
0.950
0.925
13 Dec 2021
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
Date
train
test
predictions
Off days

1.7 Conclusion

On a day to day basis an effect as a tendency of holidays/vacationdays/off-days can be seen reasonably well. As a sole factor for any sort of longer forecasting it is not feasible, though it should be considered and included in any combined attempt at case or incidence forecasting