

▼ Modeling air pollution

Let us try to predict Beijing's air pollution, especially [PM2.5](#) values in advance!
Inspiration comes from [here](#).

Dataset

[Beijing PM2.5 Data Data Set](#)

Columns of the dataset:

- No: row number
- year: year of data in this row
- month: month of data in this row
- day: day of data in this row
- hour: hour of data in this row
- pm2.5: PM2.5 concentration
- DEWP: Dew Point
- TEMP: Temperature
- PRES: Pressure
- cbwd: Combined wind direction
- Iws: Cumulated wind speed
- Is: Cumulated hours of snow
- Ir: Cumulated hours of rain

```
1 !wget https://raw.githubusercontent.com/jbrownlee/Datasets/master/pollution.csv
显示隐藏的输出项

1 !pip install seglearn
显示隐藏的输出项

1 import pandas as pd
2 import csv
3 import numpy as np
4 import matplotlib.pyplot as plt
5
6 #import warnings
7 #warnings.filterwarnings("ignore")
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13
14 def sniff_format(location):
15     with open(location, newline='') as csvfile:
16         sniffer = csv.Sniffer()
17         sample = csvfile.read(1024)
18         dialect = sniffer.sniff(sample)
19         header = sniffer.has_header(sample)
20         if header:
21             header=0
22         else:
23             header=None
24     return ["dialect":dialect, "header":header]
25
26 def describe_full(df):
27     #pd.options.display.float_format = '{:.2f}'.format
28     dtypes_description=pd.DataFrame(dict(df.dtypes), ["dtypes"])
29     na_description = pd.DataFrame(dict(df.isna().sum()), ["NA-s"])
30     na_percent = ((pd.DataFrame(dict(df.isna().sum()), ["NA%"])/len(df))*100).round(decimals=2)
31     description = df.describe(include='all')
32     full_description = dtypes_description.append(na_description).append(na_percent).append(description).replace(np.nan, '', regex=True)
33
34     mask = full_description.loc["freq",:]==1
35     full_description.at[["top"],mask.index[mask]]=""
36     #1000: scientific notation - could be nicer
37
38     return full_description
39
40
41 csv_format = sniff_format("pollution.csv")
42
43 df = pd.read_csv("pollution.csv",header=csv_format["header"],dialect=csv_format["dialect"])
44
45 #There is a warning that would be worth investigation, but for now, let's ignore it
46 import warnings
47 warnings.filterwarnings("ignore")
48
49 describe_full(df)
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52      No      year      month      day      hour      pm2.5      DEWP      TEMP      PRES      cbwd      Iws      Is      Ir
53 dtypes  int64      int64      int64      int64      int64      float64      int64      float64      float64      object      float64      int64      int64
54 NA-s      0      0      0      0      0      2067      0      0      0      0      0      0      0
55 NA%      0      0      0      0      0      4.72      0      0      0      0      0      0      0
56 count  43824  43824  43824  43824  43824  41757  43824  43824  43824  43824  43824  43824  43824
57 unique
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60 mean  21912.5    2012    6.52355    15.7278      11.5    98.6132    1.81725    12.4485    1016.45      23.8891    0.0527337    0.194916
61 std   12651    1.41384    3.44857    6.92227    92.0504    14.4334    12.1986    10.2687      50.0106    0.760375    1.41587
62 min      1    2010      1      1      0      0      -40      -19    991      0.45      0      0      0
63 25%  10956.8    2011      4      8      5.75      29      -10      2    1008      1.79      0      0
64 50%  21912.5    2012      7     16     11.5      72      2     14    1016      5.37      0      0
65 75%  32868.2    2013     10     23     17.25     137     15     23    1025      21.91      0      0
66 max   43824    2014     12     31     23     994     28     42    1046      585.6      27     36
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```

	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	cbwd	Iws	Is	Ir
date												
2010-01-01 00:00:00	2010	1	1	0	NaN	-21	-11.0	1021.0	NW	1.79	0	0
2010-01-01 01:00:00	2010	1	1	1	NaN	-21	-12.0	1020.0	NW	4.92	0	0
2010-01-01 02:00:00	2010	1	1	2	NaN	-21	-11.0	1019.0	NW	6.71	0	0
2010-01-01 03:00:00	2010	1	1	3	NaN	-21	-14.0	1019.0	NW	9.84	0	0
2010-01-01 04:00:00	2010	1	1	4	NaN	-20	-12.0	1018.0	NW	12.97	0	0
2010-01-01 05:00:00	2010	1	1	5	NaN	-19	-10.0	1017.0	NW	16.10	0	0
2010-01-01 06:00:00	2010	1	1	6	NaN	-19	-9.0	1017.0	NW	19.23	0	0

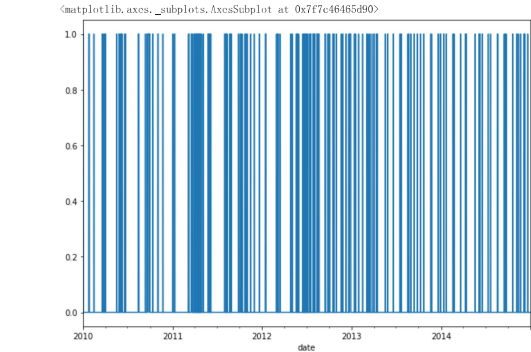
Encoding day of week

We explicitly encode the day of week, since we assume that weekends and workdays behave differently.

```
1 df["dayofweek"] = df.index.dayofweek + 1
```

Decision about NaN-s

```
1 fig = plt.gcf()
2 fig.set_size_inches(10,7)
3 df["pm2.5"].isnull().astype(float).plot()
```



```
1 def isnullsum(df):
2     return df.isnull().sum()
3 print("1-----")
4 print("% NaN datapoints per year:", (df.groupby(df.index.year)["pm2.5"].apply(isnullsum)/df.groupby(df.index.year)["pm2.5"].count())*100.0)
5
6 print("2-----")
7
8
9 print("% NaN datapoints per month:", (df.groupby(df.index.month)["pm2.5"].apply(isnullsum)/df.groupby(df.index.month)["pm2.5"].count())*100.0)
10
11 print("3-----")
12
13 print("% NaN datapoints per dayofweek:", (df.groupby(df.index.dayofweek)["pm2.5"].apply(isnullsum)/df.groupby(df.index.dayofweek)["pm2.5"].count())*100)
14
15 print("4-----")
16 print("% NaN datapoints per hour:", (df.groupby(df.index.hour)["pm2.5"].apply(isnullsum)/df.groupby(df.index.hour)["pm2.5"].count())*100.0)
17
```

显示隐藏的输出项

After examining the NaN values in pm2.5, we see no obvious temporal pattern. This is cause for worry, since by simply dropping the rows with NaN values, we can destroy the temporal coherence of the data, hence **data imputation is desirable**.

The autocorrelation charts below imply, that it is not unreasonable to take the previous value to fill NaN-s (high autocorrelation with the previous timestep).

```
1
2 df.fillna(method='ffill', inplace=True)
3
4 print(df.isnull().sum())
5
6 df.dropna(inplace=True)
7
8 print(df.isnull().sum())
9
```

显示隐藏的输出项

Examining autocorrelations

```
1 from statsmodels.graphics.tsaplots import plot_pacf
2
3 #column = [] #use this for speedup
4 columns = ["pm2.5", "DEWP", "TEMP", "PRES", "Iws", "Is", "Ir"]
5
6 for col in columns:
7     plt.figure()
8     plot_pacf(df[col].dropna(), lags=200, zero=False)
9
10 plt.show()
11
```

显示隐藏的输出项

What do we see?

Well, the fact, that we don't see.

Or more precisely: smog (and weather) is slow to move, it is extremely strongly autocorrelated with itself one-two hours before, so in order to at least be able to see some autocorrelation structure beyond this, we need to filter out the first some hours from our autocorrelation analysis. (By the way, that's why we don't stick to the prediction of the next hour as in the original 'inspiration' blogpost. Would not be too relevant...)

```
1 from statsmodels.graphics.tsaplots import _prepare_data_corr_plot, _plot_corr
2 import statsmodels.graphics.utils as utils
3 from statsmodels.tsa.stattools import pacf
4
5 def plot_pacf_drop(x, ax=None, lags=None, alpha=.05, method='ywunbiased',
6                   use_vlines=True, title='Partial Autocorrelation', zero=True,
7                   vlines_kwargs=None, drop_no=0, **kwargs):
8
9     lags_orig=lags
10    fig, ax = utils.create_mpl_ax(ax)
11    vlines_kwargs = {} if vlines_kwargs is None else vlines_kwargs
```

```

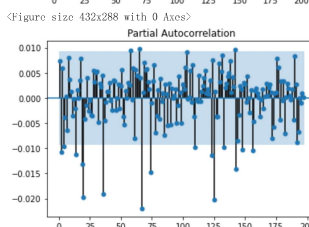
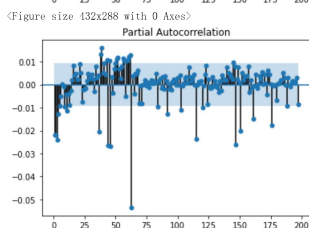
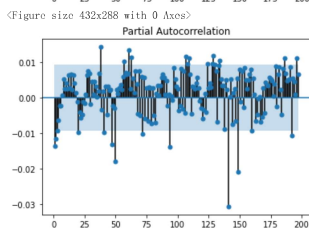
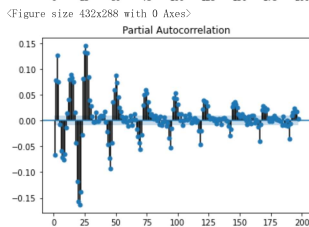
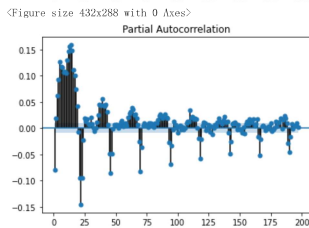
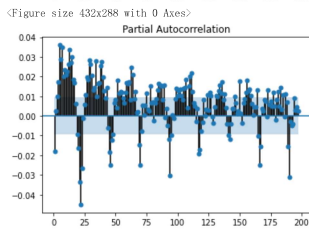
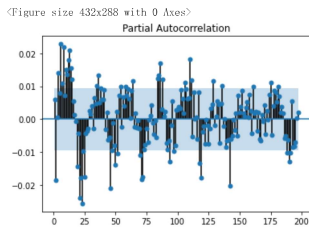
12     lags, nlags, irregular = _prepare_data_corr_plot(x, lags, zero)
13     confint = None
14     if alpha is None:
15         acf_x = pacf(x, nlags=nlags, alpha=alpha, method=method)
16     else:
17         acf_x, confint = pacf(x, nlags=nlags, alpha=alpha, method=method)
18
19     if drop_no:
20         acf_x = acf_x[drop_no+1:]
21         confint = confint[drop_no+1:]
22         lags, nlags, irregular = _prepare_data_corr_plot(x, lags_orig=drop_no, zero)
23
24     _plot_corr(ax, title, acf_x, confint, lags, False, use_vlines,
25               vlines_kwargs, **kwargs)
26
27     return fig

```

```

1 import matplotlib.pyplot as plt
2
3 #columns = [] #use this for speedup
4 columns = ["pm2.5", "DEWP", "TEMP", "PRES", "Iws", "Is", "Ir"]
5
6 for col in columns:
7     plt.figure()
8     plot_pacf_drop(df[col].dropna(), lags=200, drop_no=3, zero=False)
9
10 plt.show()
11

```



Studying even the filtered charts leaves us in doubt about the possible window for modeling (in case of the classical models), so we will keep 100 as the modeling window (nearly two weeks). This is a parameter that is worth empirically studying later on.

It is worth mentioning, that the pacf charts would definitely change drastically if we would use some differencing. Since down below we decide

Seasonal decomposition and the question of trends

```
1 from statsmodels.tsa.seasonal import seasonal_decompose
2 from statsmodels.tsa.tsautils import freq_to_period
3 import matplotlib.pyplot as plt
4
5 analysis = seasonal_decompose(df["pm2.5"], freq=freq_to_period(df.index.inferred_freq))
6
7 analysis.plot()
8 plt.show()
```

显示隐藏的输出项

Well, the default setting (infer periods - hourly) is rather uninformative, so it is maybe worth using some domain knowledge here, and use yearly frequency.

```
1 analysis = seasonal_decompose(df["pm2.5"], freq=24*365)
2
3 analysis.plot()
4 plt.show()
```

显示隐藏的输出项

We do get the first impression, that there is no overarching simple trend, as well as there are non-trivial seasonal patterns. At a later stage we should investigate differencing regimes, but for now, we leave the data as is.

Train, valid, test split - before normalization

Contamination by the normalization values is a distant possibility, but let's stick to paranoid practices.

```
1 VALID_AND_TEST_SIZE=0.1

1 from sklearn.model_selection import train_test_split
2
3 X_train, X_else, y_train, y_else = train_test_split(df, df["pm2.5"], test_size=VALID_AND_TEST_SIZE*2, shuffle=False)
4 X_valid, X_test, y_valid, y_test = train_test_split(X_else, y_else, test_size=0.5, shuffle=False)
5
```

We could have used `temporal_split` from `seglearn`, but that would have cast everything to numpy, so it was more convenient this way for now. Using `seglearn` is encouraged - if we would like to go into classical modeling.

Data normalization

Our default assumption is to use Scikit's minmax scaler for easier learning by neural models.

But there are some exceptions:

How to normalize dates?

For the year it is more tricky, it is basically an ordinal. Subtracting the first year is nice, but how to handle the normalization to 0,1?

We could use 2018 as a max, but **WE WOULD HAVE TO WRITE A BIG CAVEAT MESSAGE FOR DEPLOY PEOPLE!**

So it should be something like $(df.year - (df.year.min() - 1)) / ((df.year.max() - df.year.min()) * 2)$ (-1 is for avoiding zero, making the life of the network more easy...)

For now we stick to the minmax scaler (living risky... :-)

For month, day, hour default assumption is, scikit's minmax scaler could work, but we will choose a more elaborate solution from [here](#). This capitalizes on the circular nature of these quasi ordinals.

```
1 from sklearn.preprocessing import MinMaxScaler
2 import warnings
3 from sklearn.exceptions import DataConversionWarning
4 warnings.filterwarnings(action='ignore', category=DataConversionWarning)
5 # I literally hate when a standard Scikit function throws big bunches of warnings
6 # - though suppressing them is a dangerous practice. Hence this comment.
7
8 def minmax_scale(df_x, series_y, normalizers=None):
9     features_to_minmax = ["year", "pm2.5", "DEWP", "TEMP", "PRES", "lws", "ls", "lr"]
10
11     if not normalizers:
12         normalizers = {}
13
14     for feat in features_to_minmax:
15         if feat not in normalizers:
16             normalizers[feat] = MinMaxScaler()
17             normalizers[feat].fit(df_x[feat].values.reshape(-1, 1))
18
19     df_x[feat] = normalizers[feat].transform(df_x[feat].values.reshape(-1, 1))
20
21     series_y = normalizers["pm2.5"].transform(series_y.values.reshape(-1, 1))
22
23     return df_x, series_y, normalizers
```

```
1
2 X_train_norm, y_train_norm, normalizers = minmax_scale(X_train, y_train)
3 X_valid_norm, y_valid_norm, _ = minmax_scale(X_valid, y_valid, normalizers=normalizers)
4 X_test_norm, y_test_norm, _ = minmax_scale(X_test, y_test, normalizers=normalizers)
5
```

```
1 normalizers

{'DEWP': MinMaxScaler(copy=True, feature_range=(0, 1)),
 'lr': MinMaxScaler(copy=True, feature_range=(0, 1)),
 'ls': MinMaxScaler(copy=True, feature_range=(0, 1)),
 'lws': MinMaxScaler(copy=True, feature_range=(0, 1)),
 'PRES': MinMaxScaler(copy=True, feature_range=(0, 1)),
 'TEMP': MinMaxScaler(copy=True, feature_range=(0, 1)),
 'pm2.5': MinMaxScaler(copy=True, feature_range=(0, 1)),
 'year': MinMaxScaler(copy=True, feature_range=(0, 1))}
```

```
1 X_train_norm
2 y_train_norm
```

	year	month	day	hour	pm2.5	DEWP	TEMP	PRES	cbwd	Iws	Is	Ir	dayofweek
date													
2010-01-02 00:00:00	0.0	1	2	0	0.129779	0.278689	0.250000	0.527273	SE	0.002290	0.000000	0.0	6
2010-01-02 01:00:00	0.0	1	2	1	0.148893	0.295082	0.250000	0.527273	SE	0.003811	0.000000	0.0	6
2010-01-02 02:00:00	0.0	1	2	2	0.159960	0.360656	0.233333	0.545455	SE	0.005332	0.000000	0.0	6
2010-01-02 03:00:00	0.0	1	2	3	0.182093	0.426230	0.233333	0.563636	SE	0.008391	0.037037	0.0	6

▼ Encoding of ordinals

The encoding of `cbwd` is interesting, since it is an ordinal again, or better to say not even that, it has a nice circular topology, so we will use the same `sin-cos` solution.

Problem is, that there is a valid "zero" value, marked 'cv' in there. We are tempted to replace that with 0.

```
1
2 def encode_cyclicals(df_x):
3     # "month", "day", "hour", "cbwd", "dayofweek"
4
5     DIRECTIONS = {'N':1.0, "NE":2.0, "E":3.0, "SE":4.0, "S":5.0, "SW":6.0, "W":7.0, "NW":8.0, "cv":np.nan}
6
7     df_x['month_sin'] = np.sin(2*np.pi*df_x.month/12)
8     df_x['month_cos'] = np.cos(2*np.pi*df_x.month/12)
9     df_x.drop('month', axis=1, inplace=True)
10
11     df_x['day_sin'] = np.sin(2*np.pi*df_x.day/31)
12     df_x['day_cos'] = np.cos(2*np.pi*df_x.day/31)
13     df_x.drop('day', axis=1, inplace=True)
14
15     df_x['dayofweek_sin'] = np.sin(2*np.pi*df_x.dayofweek/7)
16     df_x['dayofweek_cos'] = np.cos(2*np.pi*df_x.dayofweek/7)
17     df_x.drop('dayofweek', axis=1, inplace=True)
18
19     df_x['hour_sin'] = np.sin(2*np.pi*df_x.hour/24)
20     df_x['hour_cos'] = np.cos(2*np.pi*df_x.hour/24)
21     df_x.drop('hour', axis=1, inplace=True)
22
23     df_x.replace({'cbwd': DIRECTIONS}, inplace=True)
24     df_x['cbwd'] = df_x['cbwd'].astype(np.float64)
25
26     df_x['cbwd_sin'] = np.sin(2.0*np.pi*df_x.cbwd/8.0)
27     df_x['cbwd_sin'].replace(np.nan, 0.0, inplace=True) #Let's handle the case with no wind specially
28     df_x['cbwd_cos'] = np.cos(2.0*np.pi*df_x.cbwd/8.0)
29     df_x['cbwd_cos'].replace(np.nan, 0.0, inplace=True) #Let's handle the case with no wind specially
30     df_x.drop('cbwd', axis=1, inplace=True)
31
32     return df_x
33
34
35 X_train_norm = encode_cyclicals(X_train_norm)
36 X_valid_norm = encode_cyclicals(X_valid_norm)
37 X_test_norm = encode_cyclicals(X_test_norm)
38
39
40 X_train_norm
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```
1 X_train_rolled[:1]

array([[ 0. 0.0000000e+00,  1.29778672e-01,  2.78688325e-01, ...,
         1.00000000e+00,  1.22464680e-16, -1.00000000e+00],
       [ 0. 0.0000000e+00,  1.48893360e-01,  2.95081967e-01, ...,
         9.63925826e-01,  1.22464680e-16, -1.00000000e+00],
       [ 0. 0.0000000e+00,  1.59959759e-01,  3.60653738e-01, ...,
         8.66025404e-01,  1.22464680e-16, -1.00000000e+00],
       ...,
       [ 0. 0.0000000e+00,  7.74647887e-02,  1.31147511e-01, ...,
         9.63925826e-01,  1.00000000e+00,  6.12323400e-17],
       [ 0. 0.0000000e+00,  5.03018109e-02,  1.11751098e-01, ...,
         8.66025404e-01,  1.00000000e+00,  6.12323400e-17],
       [ 0. 0.0000000e+00,  4.42655936e-02,  1.14754098e-01, ...,
         7.07106781e-01,  1.00000000e+00,  6.12323400e-17]])
```

For non-sequence models

We have to “flatten” the data to be able to use classical, non-sequence regression models from Scikit.

We only need to do this for X, any transformation of y is unnecessary.

```
1 X_train_rolled.shape

(34917, 100, 18)

1 shape = X_train_rolled.shape
2 X_train_flattened = X_train_rolled.reshape(shape[0],shape[1]*shape[2])
3 X_train_flattened.shape

(34917, 1800)

1 X_valid_rolled, y_valid_rolled, _=segmenter.fit_transform([X_valid_norm.values], [y_valid_norm.flatten()])
2
3 shape = X_valid_rolled.shape
4 X_valid_flattened = X_valid_rolled.reshape(shape[0],shape[1]*shape[2])
```

Evaluation helper

Use this function to evaluate your models on validation data.

This assumes that your model has the `predict()` function, which is true for **Scikit-learn**, **XGBoost** and **Keras**, so you can hand over any of those.

A special issue by models optimized by iterative methods is to **get the final model**. **Early stopping** and / or **model save and reload** can help there.

WARNING: This is just a basic evaluation scheme, more thorough investigation needed in the future!

```
1 from sklearn.metrics import mean_squared_error
2 from math import sqrt
3
4 def evaluate_model(model, X_valid, y_valid_true):
5     predictions = model.predict(X_valid)
6     rms = sqrt(mean_squared_error(y_valid_true, predictions))
7     print('Root mean squared error on valid:',rms)
8     normalized_rms = normalizers['pm2.5'].inverse_transform(np.array([rms]).reshape(1, -1))[0][0]
9     print('Root mean squared error on valid inverse transformed from normalization:',normalized_rms)
10    return normalized_rms
```

Classical modeling

In “classical” modeling we assume a multiple regression case, so we **DO NOT USE** time series as such, but the “flat” versions of the data as input. Output is the same.

Baseline - DummyPredictor

TASK Create a dummy predictor as a baseline. Use Scikit-learn's builtin capability to do dummy models in regression case. Use the default setting, that is the prediction of the mean value.

```
1 from sklearn.dummy import DummyRegressor
2 dummy_model = DummyRegressor(strategy='mean')
3
4 dummy_model.fit(X_train_flattened,y_train_rolled)

DummyRegressor(constant=None, quantile=None, strategy='mean')
```

Evaluation

```
1 result = evaluate_model(dummy_model,X_valid_flattened,y_valid_rolled)

Root mean squared error on valid: 0.0986950073704243
Root mean squared error on valid inverse transformed from normalization: 98.10283732620175
```

Fitting a RandomForest on raw data

TASK: Fit a RandomForest from Scikit. Please be aware, that the number of trees in the model is having a strong influence on training time.

Suggestion: use couple of tens of trees, definitely << 100 to be able to wait it out...

Pro tip: To utilize all the CPU cores, use the right setting of `n_jobs`. That speeds things up.

```
1 #from sklearn...
2 from sklearn.ensemble import RandomForestRegressor
3 N_ESTIMATORS = 5
4 RANDOM_STATE = 452543634

1 RF_base_model = RandomForestRegressor(n_estimators=N_ESTIMATORS,random_state=RANDOM_STATE,n_jobs=-1)
2
3 RF_base_model.fit(X_train_flattened,y_train_rolled)

RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                        max_depth=None, max_features='auto', max_leaf_nodes=None,
                        max_samples=None, min_impurity_decrease=0.0,
                        min_impurity_split=None, min_samples_leaf=1,
                        min_samples_split=2, min_weight_fraction_leaf=0.0,
                        n_estimators=5, n_jobs=-1, oob_score=False,
                        random_state=452543634, verbose=0, warm_start=False)
```

Evaluation

```
1 result = evaluate_model(RF_base_model,X_valid_flattened,y_valid_rolled)

Root mean squared error on valid: 0.09564886485904463
Root mean squared error on valid inverse transformed from normalization: 95.07497166989035
```

Fitting a RandomForest on feature transformed data

TASK: Since we use `seglearn`, we can try to capitalize on it's functionality to calculate features from the time time series. Use `FeatureRep` from `seglearn` to transform features, fit a RandomForest and hope for the best!

Evaluation

```
1 result = evaluate_model(RF_feature_model, feature_converter.fit_transform(X_valid_flattened), y_valid_rolled)

Root mean squared error on valid: 0.10491616432748488
Root mean squared error on valid inverse transformed from normalization: 104.28666734151996
```

Use the XGBoost library to fit gradient boosted trees to the problem. They are usually way quicker to learn and many times at least on par with RandomForests, or better. Let's see!

- Building an LSTM model

TASK: We believe, that the time dependent structure of this dataset is complex, so we try to use LSTM models from Keras. We are not explicitly utilizing **statefulness**, that is a **major area to be investigated later on**.

More information on statefulness can be found [here](#).

Fit an LSTM model on the time series - non-flat - data!

Use:

1. At least 1 LSTM layer
2. A dense layer for output - think about activation! This is a regression case!

Very advisable - but optional - to use Dropout. You can not use it everywhere, though... Experiment!

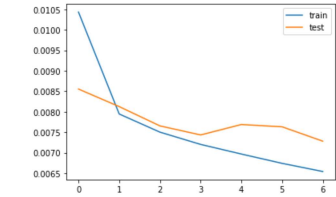
You are allowed to use functional API, but for this **Sequential API** is sufficient.

You can use `LeraningRateScheduler` if you like.

<https://colab.research.google.com/drive/1k7RT0-IN9Qcw8X1NIPUSsIF1tmXDXFDI#scrollTo=i0Q2PbKAKnBD&printMode=true>

```
Epoch 3/7
140/140 [=====] - 25s 176ms/step - loss: 0.0075 - val_loss: 0.0077
Epoch 4/7
140/140 [=====] - 25s 175ms/step - loss: 0.0072 - val_loss: 0.0074
Epoch 5/7
140/140 [=====] - 24s 174ms/step - loss: 0.0070 - val_loss: 0.0077
Epoch 6/7
140/140 [=====] - 25s 177ms/step - loss: 0.0067 - val_loss: 0.0076
Epoch 7/7
140/140 [=====] - 25s 175ms/step - loss: 0.0065 - val_loss: 0.0073

1 plt.plot(history.history['loss'], label='train')
2 plt.plot(history.history['val_loss'], label='test')
3 plt.legend()
4 plt.show()
```



```
1 # You can use the early stopped model OR load it.
2 # For that you have to import the load function...
3 # IF AND ONLY IF loading, it is good practice to throw out the trash from the graph...
4 %b0.clear_session()
5
6
7 result = evaluate_model(model,X_valid_rolled,y_valid_rolled)

Root mean squared error on valid: 0.08532426707552125
Root mean squared error on valid inverse transformed from normalization: 84.81232147306811

1 assert result < 86.0
```

Things that should be improved

- More conclusive investigation of PACF for better time window estimate
 - It can well be, that long windows do not add that much to the performance
- More interesting features for XGBoost (like from [tsfresh](#)), since present features are a disaster
- MOST IMPORTANT: **More thorough error / prediction analysis!!!**
- LSTM with **Custom iterator with stateful model**
- Investigation of different loss function (eg. MAE) for training. (And with it, think about the importance of extreme values: do we think they are outliers? Are they interesting to predict?)
- Investigation of "teacher forcing" for LSTM-s in Keras (if it makes sense)

Conclusion

Even with decent amount of struggle, the "dummy" of always using the mean is very appealing, so it seems, this is not that easy of a task 24 hours in advance. Further investigation of classical as well as neural models remains open!

Final test

We did not use the final test, since our investigations are not concluded yet. Remember: using it once before project "go live" is a good practice!