Machine Learning Engineer Nanodegree

Capstone Project

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July 29, 2017

Dependence of the soiling rate of solar concentrators on weather parameters

Content

1. Definition

1.1. Project Overview and domain background

Concentrating Solar Power plants (CSP plants) capture and concentrate sunlight and transfer its energy to a heat transfer fluid. Currently there are installed about 5000 MW of CSP power worldwide (source: cspplaza.com). It is predicted that due to the rapid development of emerging markets including Morocco, South Africa and China the CSP capacity will have a huge increase in the next years.

Figure 1: Solar Through Collector, source: www.dlr.de

Soiling (= "getting dirty") of these solar concentrators (= back-coated glass mirrors) is an important issue that significantly reduces plant efficiency and causes high cleaning costs for the plant operators. For a lot of potential plant sites there is no soiling data available. Also, in state-of-the-art cost-effectiveness studies during the planning phase of a CSP plant the soiling issue is not considered in sufficient detail: the soiling rate is assumed as a constant factor independent from plant location, without variation during the year and constant during the entire plant life. A recent study by (Wolfertsstetter, 2016) does an in-depth analysis on the effects of soiling on CSP plants. Soiling is dependent on several environmental factors like wind speed and direction, condensation and aerosol particle concentration. All of these parameters vary during the time of a year and strongly depend on the location of the plant. In the work of (Wolfertsstetter, 2016), a new measurement device is designed, that measures the cleanliness of solar concentrator (mirror) probe. During 3 years the cleanliness of the mirror has been logged together with the above-mentioned weather factors. The soiling rate is then found as the time derivative of the cleanliness.

Dr. Wolfertstetter and DLR e.V. (German Aerospace Center) kindly agreed to provide the measurement data and domain information and thus make this capstone project possible.

1.2. Problem- and Solution Statement

1.2.1. Problem description

In the work of (Wolfertsstetter, 2016) a prediction model for the soiling rate is built. The model is based on linear regression. The independent parameters (features) are the

weather parameters like temperature, humidity, windspeed, mirror orientation and others. The dependent variable (label) is the soiling rate. As a result of the regression analysis it was found that the Pearson correlation coefficient (PCC) was > 0.3 for none of the features. None of the features shows strong linear correlation with the dependent variable. Only 4 of 43 input features showed a PCC > 0.2 with the labels, and all the other features showed a PCC < 0.2 with the labels. It is estimated that the model can make reliable predictions for a maximum of 2 months only. The aim of this work is to find a better prediction model.

1.2.2. Solution description

As the soiling rate consists of floating point values and requires no classification, the problem to solve is a regression problem. Solving the problem means to provide a model that accurately predicts the soiling rate dependent on the meteorological features.

The following steps are taken to solve the problem and create an accurate model:

- First, a label to be used with supervised learning is created. The label should be free of trends, or seasonalities, in order to avoid time series problems. While the cleanliness could be used as label available in 1-min resolution, it shows a strong decreasing trend, as shown Figure 4. To remove the trend, the time derivative of the cleanliness (soiling rate) has to be used.

- Data preparation of the data set

- An appropriate splitting method is chosen to divide the data set in test and validation data and optionally perform cross validation.

- Regression algorithms are to be applied, like Linear Regression, SVM, Decision Trees, AdaBoost and XgBoost, and MLP Regression NN. If available, the feature importance functionality of the algorithm should be used to gather information on the importance of the weather parameters.

- Create Learning curves in order to understand the behavior of the learner.

- Parameter optimization for the algorithm that is best suited, aiming to minimize the prediction errors

- Perform a PCA with the best-performing algorithm in order to reduce feature dimensions while capturing as much variance as possible. The hope here is that regression algorithms might work better on the PCA-transformed data set than with the original features.

- If no results are obtained with the above algorithms, a LSTM NN can be used

1.3. Metrics

The Pearson coefficient reveals only linear dependencies and thus cannot be used as an indicator for non-linear dependencies. The R2 score is more appropriate for this analysis, as well as the mean squared error.

1.3.1. Mean squared error

The mean square error or MSE is a risk metric corresponding to the expected value of the quadratic error or loss (sckit-learn.org - mean squared error, 2017). The MSE incorporates both the variance and the bias of the learner. For an unbiased estimator, the MSE is the variance of the estimator (Wikipedia - mean squared error, 2017)

1.3.2. R2 score

The R2 score function computes R^2, the coefficient of determination. In terms of machine learning the R2 score compares a model to the simplest possible model, the mean:

$$R^2 = 1 - \frac{MSE(model)}{MSE(mean)}$$

MSE(model) and MSE(mean) being the mean squared errors of the performing model and of the mean, respectively. The MSE(mean) can also be seen as the variance of the data.

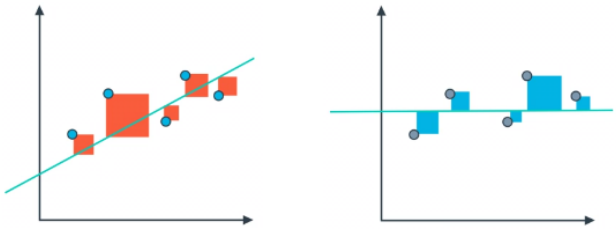


Figure 2: MSE(model) on the left and MSE(mean) on the right, assuming a linear regression model in this example, images kindly provided by (Udacity, 2017)

Thus, the R2 score gets close to 1 either if the MSE of the model gets very small or the variance of the labeled data is very big.

When comparing R2 scores from train/validation- and test data sets, it is important to consider the variance of both data sets.

In more general terms the R2 shows the amount of variance in the labels, or dependent variable, that is predictable from the features. A R2 score of 1 indicates a perfect fit of model and data. A score of 0 indicates that the model is just as good as one that predicted always the mean of the data. Negative R2 scores indicate that the model performs worse than one that would just be predicting the mean. For non-linear models and/or data with underlying non-linear models the R2 score can become arbitrarily negative.

2. Analysis

2.1. Data Exploration

The main data set provides 1-min time resolution for all 43 measurement channels (features). It contains 874k raw-data points. The measurements were performed over approximately 1.5 years. Figure 3 shows the number of NaN values for each feature. The data set contains a huge number of NaN values that have to be processed in the data preparation step.

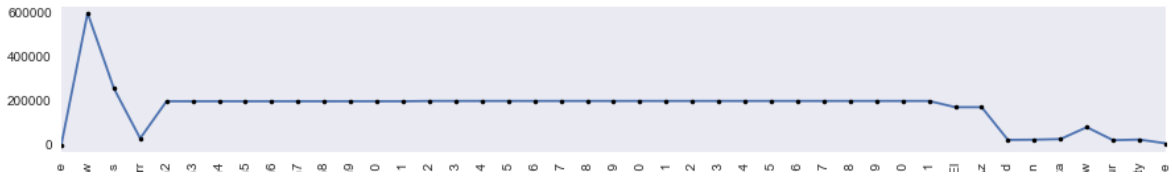


Figure 3: number of NaN values for each feature

There is a second data set available with 1-day resolution and 544 data points. Due to its small size and some negative pre-tests it is not considered for the supervised learning task anymore.

2.1.1. Understanding cleanliness and soiling rate

The cleanliness is measured in minute resolution and could be used as label. However, the measured raw data of the cleanliness is heavy bias and variance due to several optical and atmospheric effects (see Figure 4).

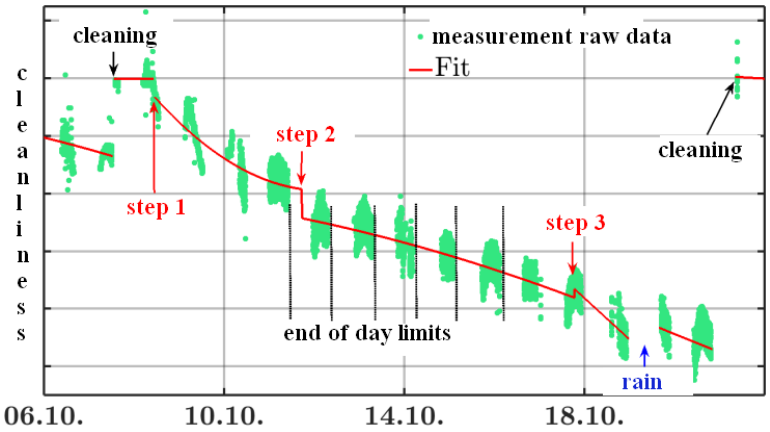


Figure 4: 1-min resolution data set cleanliness measurements (green dots) and the data fit (red curve) in order to create the 1-day resolution soiling-rate dataset. The figure includes 3 cleaning events that cause steps in the fitted curves. Rain effects the cleanliness, too.

Also, the cleanliness is affected by "cleaning events", when the mirrors are cleaned. In this case a step appears in the data after the cleaning. These steps depend on the applied cleaning schedule and cannot be predicted. And, most importantly, the cleanliness shows a time trend. The soiling rate is the time derivative of the cleanliness and independent of the applied experimental protocol. It does not show an obvious trend.

In Figure 4 the soiling rate can be seen as the slope of the fitted (red) line. In order to calculate the soiling rate, a corrected version of the cleanliness is used. The correction includes removing the steps and fitting splines rather to use the original data. The whole process is done by domain experts at DLR and its steps are explained in (Wolfertsstetter, 2016). The correction is not scope of this work.

The corrected cleanliness is chosen as base feature for the creation of the soiling rate.

2.2. Exploratory Visualization

2.2.1. Feature and label distributions

In order to work well, most machine learning algorithms need the features as well as the labels to be distributed normally. Figure 5 shows some of the features' distributions after being preprocessed. The preprocessing steps are explained in section 3.1. As can be seen, some of the distributions are close to normal, while some others are not at all normally distributed.

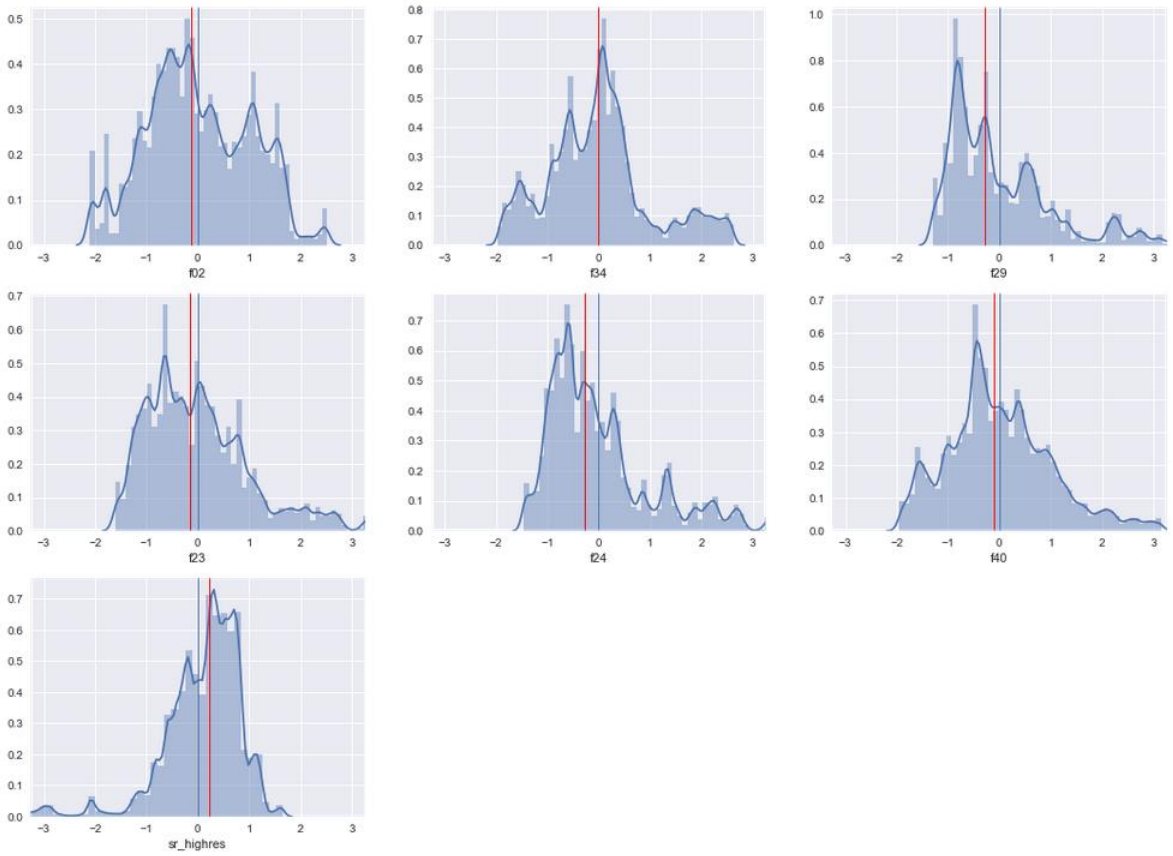


Figure 5: distribution plots for some of the input features and the label (soiling rate, "sr_highres")

The data distribution depends heavily on the data preprocessing like outlier removal, moving average and standardization- and normalization techniques. With the present data set, none of these techniques lead to a very good normal distribution, however. Also, advanced methods like log-transformations or Box-Cox transformations where not able to transform these distributions to normal. It is assumed that with more future measurement data the feature distributions will automatically get closer to a normal distribution.

2.2.2. Cleanliness and soiling rate

The corrected cleanliness provides the base for the creation of the label, the soiling rate. Figure 6 shows both the corrected cleanliness and the calculated soiling rate. The corrected cleanliness is a curve "patched together" by experts, based on domain knowledge and raw cleanliness data, as described in section 2.1.1. The raw cleanliness data is only available for a few hours during the day. For this time, the correction is done by removing measurement biases and fitting a spline to the raw data. During the night and morning hours no raw data is available and the corrected cleanliness is created by intra- and extrapolation.

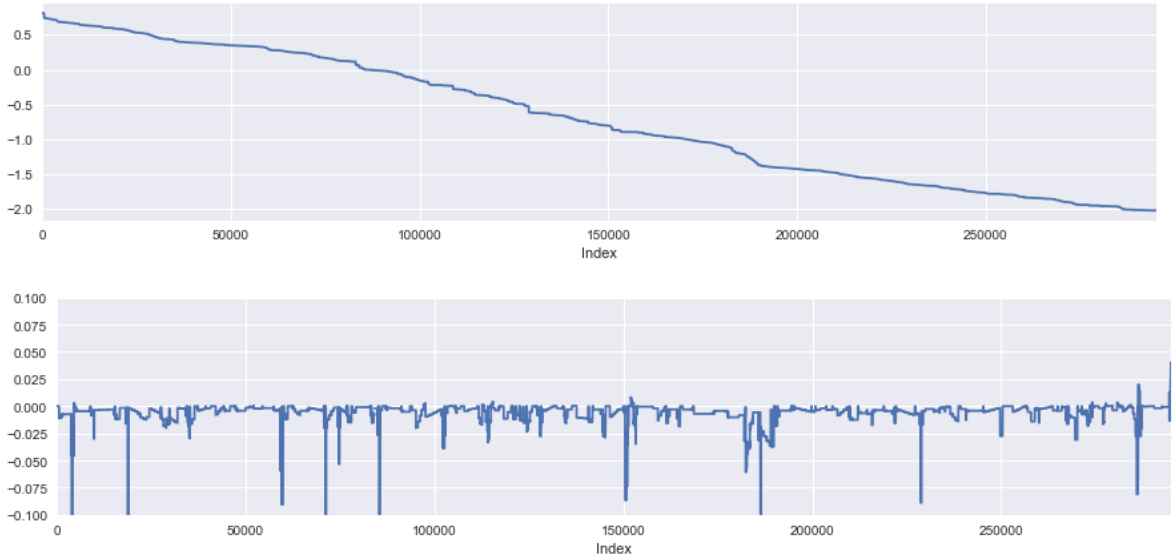


Figure 6: corrected cleanliness and calculated soiling rate, shown for the day time hours with DNI >200W/m², whole data set, recorded between 06/2013 and 08/2014

As the corrected cleanliness is a patched curve, the soiling rate shows a lot of what looks like strange artefacts. Moving average, as described in section 2.3.4 is used to smoothen the soiling rate and remove the artifacts.

2.3. Algorithms and techniques

2.3.1. Supervised learning algorithms

In this section, some of the used learning algorithms that performed well on the data, are presented in general terms.

2.3.1.1. SVM

Support Vector Machines (SVM) are based on the maximum margin algorithm. The working principle can be best explained for classification, but is also valid for regression. A linear SVM for binary classification (linear SVC) is a linear separator that will find a "maximum-margin" line - this is the line "in the middle" between 2 different classes. In the middle because it has the maximum distance to the points of both classes. This separator line is found during training by taking only the closest points of each category into consideration. These points are called support vectors, hence the name of the SVM.

The intuition behind this approach of taking only the closest points into consideration, is that if a classifier is good at the most challenging comparisons (the points closest to each other) then the classifier will be even better at the easy comparisons (comparing points are farer away from each other).

In the case that the classes cannot be separated by a line, but by a curve, SVM uses the so-called Kernel-Trick. Instead of fitting a curve on the data, SVM lifts the observed features into higher dimensions and thus is able to separate them by so-called hyperplanes (higher-dimensional planes). These hyperplanes, in the original data, show up as the desired curves that separate the data (Quora - SVM in layman's terms, 2014). Hyperparameters are, amongst others: 1. The penal parameter C on the error term. 2. ε in the ε-SVR specifies the epsilon-tube within which no penalty is associated in the training loss function model. 3. The kernel itself, that can be of type 'linear', 'poly', 'rbf', 'sigmoid', 'precomputed' or a callable (scikit-learn.org - SVR, 2017).

2.3.2. Decision Trees and Gradient Boosting algorithms

Decision Trees are basically rule sets that indicate how to best split data into groups recursively. The best split consists of picking the attribute that has the most information gain or the attribute that most reduces the entropy in the newly split groups.

> *A decision tree is a tree-like structure in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes). The paths from root to leaf represent classification rules. (Wikipedia - Decision Trees, 2017)*

Decision trees can be used as weak learners (weak learner = slightly better than random guessing), if only few decisions are allowed (i.e. decision tree with a depth of 3). Gradient boosting- or gradient tree boosting algorithms use weak learners in a stage-wise, additive model. This additive model adds tens or hundreds of decision trees to minimize a loss function. In stage-wise additive models, only one learner is added at time and once a weak learner is added, it remains unchanged (Brownlee, XGBoost with Python - Gradient Boosted Trees with XGBoost and scikit-learn, 2017). The loss function must be differentiable and could be – for regression tasks - the (mean) squared error, for example. The first algorithm of this kind was AdaBoost.

> *The weak learners in AdaBoost are decision trees with a single split, called decision stumps for their shortness. AdaBoost works by weighting the observations, putting more weight on difficult to classify instances and less on those already handled well. New weak learners are added sequentially that focus their training on the more difficult patterns. (Brownlee, XGBoost with Python - Gradient Boosted Trees with XGBoost and scikit-learn, 2017)*

XGBoost is an implementation of gradient boosting created originally by Tianqi Chen. The algorithm is specially designed for speed, as it can perform parallel tree constructions on multiple CPU cores. It can automatically handle missing values, what can be of great help with incomplete data sets. Also, the algorithm allows for continued training

which makes it possible to train and fit an existing model on new data. Adjustable hyperparameters are, amongst others, the learning rate and the number of estimators (number of trees). The learning rate gives control over the weighting of each tree and thus control over the contribution of each tree to the summary prediction. A smaller learning rate requires more estimators (trees) to be added to the model, which can be done using the mentioned hyperparameter.

2.3.3. Day-based soiling rate creation

As explained in the last section, the soiling rate is calculated from the corrected cleanliness curve that is contained in the data set. The corrected cleanliness curve is provided for both moments with actual cleanliness raw data (during day time with sufficient solar radiation) and moments without cleanliness raw data (see Figure 4). However, tests showed that the corrected cleanliness should only be used for training when actual cleanliness raw data was available (about 30% of all data). When all of the corrected cleanliness data is used, the learner performance drops significantly. This seems caused by the fact that if no raw cleanliness data is available, the corrected cleanliness was inter- or extrapolated, and thus not accurate. In order to extract these subsets of data of corrected cleanliness, an algorithm was created. Its pseudocode is shown in Figure 7.

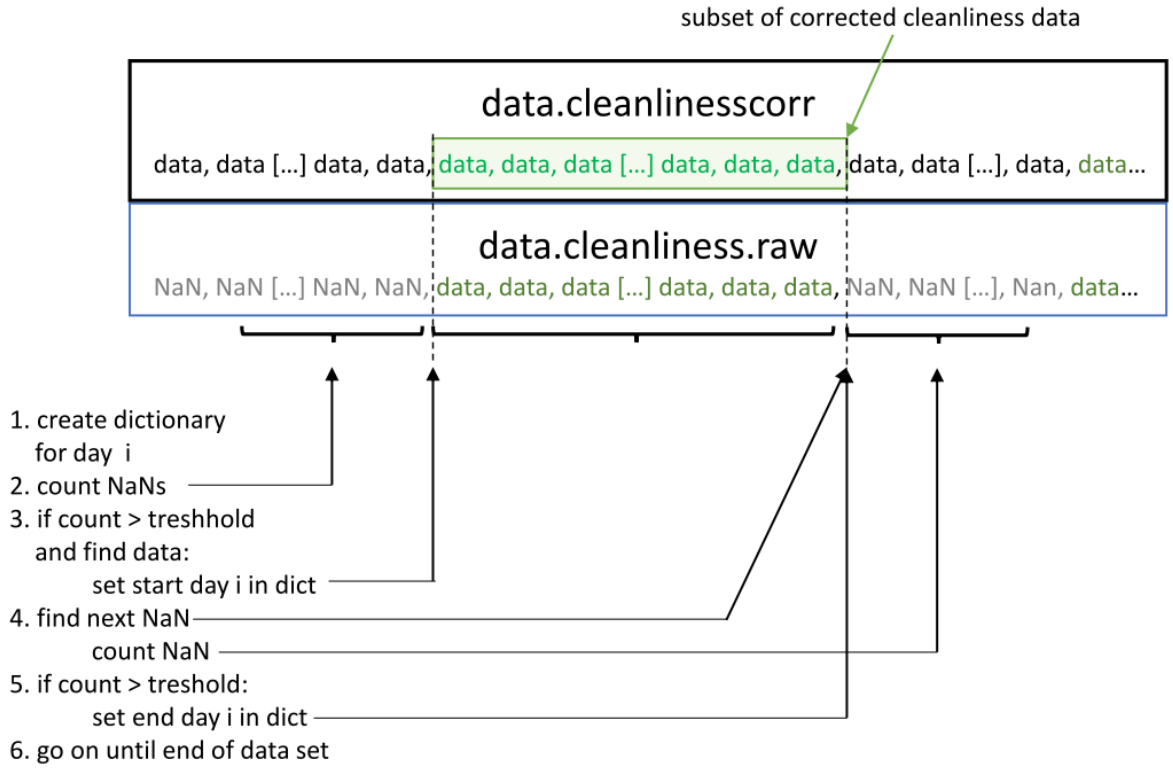


Figure 7: pseudo code for the algorithm that creates a dictionary for the extraction of daily subsets from the corrected cleanliness

While it might seem easier to just drop all data rows that contain NaN in the raw cleanliness in order to create the new data frame, in this case the soiling rate would contain artefact values at the transition from one day to the next. These would have to be deleted, making it necessary again to know the positions of all day-to-day transitions. Also, the calculation of the daily mean values, used to fill the gaps, would be more

complicated. The method presented here makes it easy to perform any desired soiling rate operation on a daily base, not on the whole data set.

2.3.4. Moving Average

The moving average is used to reduce the effect of noise and outliers. Soiling is a slow process and thus the data should be characterized through slow changes in the features. The moving average creates this type of data.

2.3.5. Outlier removal

Outliers are removed using the Tukey-Method feature-wise. All data points, that are smaller than the first quartile – 1.5 * inter-quartile-range and bigger than the third quartile + 1.5 * inter-quartile-range are considered outliers. However, when this method was applied onto all features, it removed so many outliers, that the dataset shrinked to about 25% of its original size. In the end, only 2 features were processed with outlier removal: f39 and f40. These features had only a few but huge outlier that could easily be removed.

2.3.6. Standardization

Feature standardization was performed on the whole dataset, including the test data set. Train/validation and test- dataset have different means and thus separate standardizations would have introduced an offset into the predictions of the test set. It is assumed, that with time there will be more measurement data available and mean and variance of the data will repeat cyclically. In that case the train/valid. and test data sets can be chosen such that means are closer to each other, and standardization can be done separately for each subset.

2.4. Benchmarks

In (Musango, 2016) a "multilayer feed forward neural network" is proposed to estimate the cleanliness of CSP reflectors and an R2 score of 0.95 for the independent test data set is reported. The model used 10 hidden layers with 10 neurons each and hyperbolic activation functions.

The work of (Musango, 2016) provides a useful base, as it tries to prove that MLP NNs (and thus other machine learning algorithms) can be used to solve this type of problems.

3. Methodology

3.1. Data Preprocessing

Several steps are to be performed before the supervised learning tasks can be implemented. They can be divided into general preprocessing steps and steps to prepare the supervised learning. Figure 8 shows the general preprocessing steps. These steps can be adjusted. The size off the moving average window, is set to 1 week, centered, moving

average. The value was chosen because the cleaning interval of the solar mirrors uses to be 1 to 2 weeks and so the moving average and the average cleanliness of the solar collectors are in the same range.

Figure 8: first part of the preprocessing steps

Table 1: Preprocessing parameter

property	parameter(s)
data set start / stop	2013/06/11
removed features	time, cleanlinesscorr, cleanlinessraw, cleanliness, f32, f33, f36, f38
used features	35 features total
daily soiling rate calculation: - fill NaN values method:	 fill with daily mean

- moving average	10min, centered
fill NaN values method (all features and labels)	padding 1 value to the right, then fill all remaining gaps with the mean
Outlier removal	Tukey method, performed on f39, f40
moving average on whole data set including soiling rate	10080min, centered

After that the data set is ready and its basic statistic properties can be displayed, as shown in Table 2.

Table 2: basic statistics for the data set with the raw data

count	740,002.0000	740,002.0000	740,002.0000	740,002.0000	740,002.0000
mean	0.0000	0.0000	0.0000	0.0000	0.0000
std	1.0000	1.0000	1.0000	1.0000	1.0000
min	-1.8018	-1.5846	-1.4563	-1.2886	-1.1573
25%	-0.8502	-0.8322	-0.7874	-0.7381	-0.7043
50%	-0.1250	-0.1782	-0.2646	-0.2995	-0.2612
75%	0.8761	0.8085	0.7693	0.5476	0.3499
max	2.8775	3.5902	3.6348	3.8251	4.0072

In Table 2 some features and their summary statistics are shown. It is seen that the data set contains 740000 standardized data points. In a next step, the data set is prepared for the supervised learning task. To do so the data is first splitted into train-/validation data and test data.

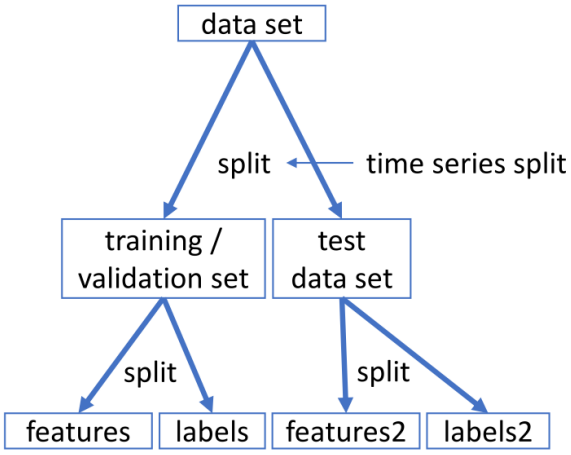


Figure 9: data splitting to prepare the supervised learning task

As shown in Figure 9 the data set is first splitted into the train-/validation set and the test set. The learning algorithm trains and validates using k-Fold cross validation, shuffle split or a similar technique. Here, shuffle split is used. After the training is complete, the test set is used in order to see how well the algorithm generalizes to new, unseen data. In order to improve by training, the learning algorithm needs the features (independent, input data) and the labels (dependent, output data) to perform the regression.

Table 3: key data of the splitted data sets

	Train / Validation data set		**test data set**
	training set	**validation set**	
start date	2013-06-26		2014-08-04
stop date	2014-08-04		2014-11-24
Variance	1.003		0.282
number of data points	157500	52500	60082

Table 3 shows the key data of the splitted data sets. Note the even though the train/validation set comprises 6 times more days than the test set, it has just twice the number of data points.

3.2. Implementation

3.2.1. Shuffle split cross validation

One basic implementation of the supervised learning task in this work is shown in Figure 10. The partition of the data set, that is assigned for training and validation, is used to create a number of distinct - training and assigned validation - sets. In this work, this number is usually set to 10, meaning we perform 10-fold cross validation or shuffled split cross validation with 10 splits.

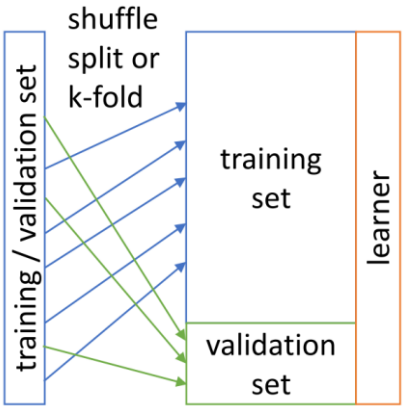


Figure 10: basic supervised learning task using k-fold cross validation

The only difference between shuffled splits and k-fold is that k-fold does use every data point only once while shuffled splits can use data points repeatedly in training- and validation sets. This makes learners using shuffled splits a little bit more prone to over-fitting, while on the upside shuffled splits provides some more data points in each split. In this work both split methods where tested and shuffled splits often provided slightly better results and hence is preferred to k-fold.

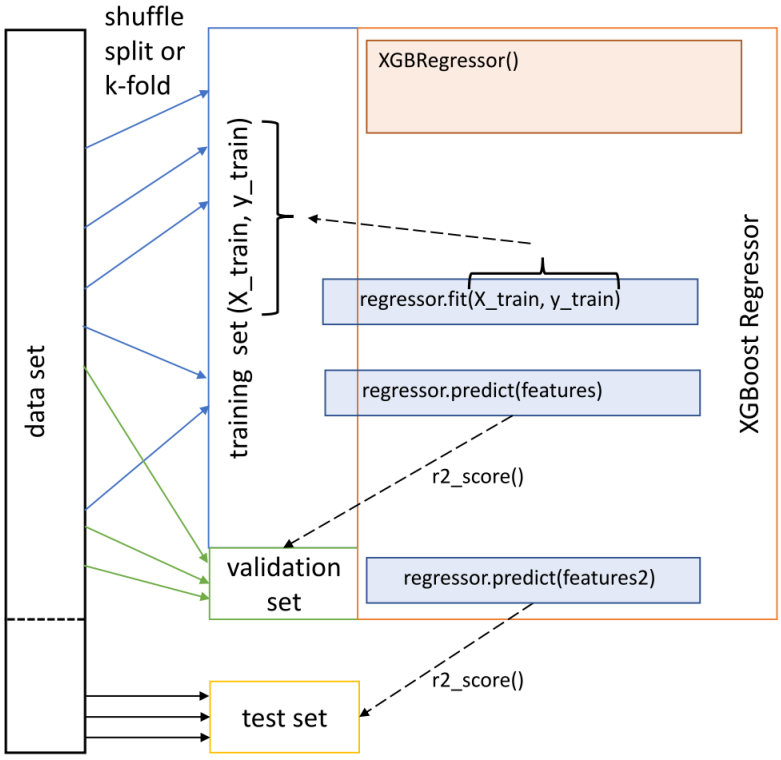


Figure 11: extended supervised learning task using train/validation data and an independent test set

In a next step, the chosen model's generalization ability on new data has to be checked. Thus, an independent data set is introduced, the test data set. While the algorithms use

parts of the validation sets for training during cross validation, the test set is truly independent and first shown to the learner after training and cross validation is finished. Figure 11 shows the implementation. The introduction of the test set revealed strong overfitting behavior of the spot-checked algorithms:

3.2.2. Early Stopping functionality

The XGBoost algorithm provides a very practical functionality called early stopping.

> *(Early stopping) … avoids overfitting by attempting to automatically select the inflection point where performance on the test dataset starts to decrease while performance on the training dataset continues to improve as the model starts to overfit." (Brownlee, XGBoost with Python - Gradient Boosted Trees with XGBoost and scikit-learn, 2017)*

When using early stopping, the algorithms stops fitting more trees, if the chosen evaluation metric on the test set stops to improve for a number of steps. Figure 12 shows the root mean squared error on both validation and test sets during the fit process, using early stopping.

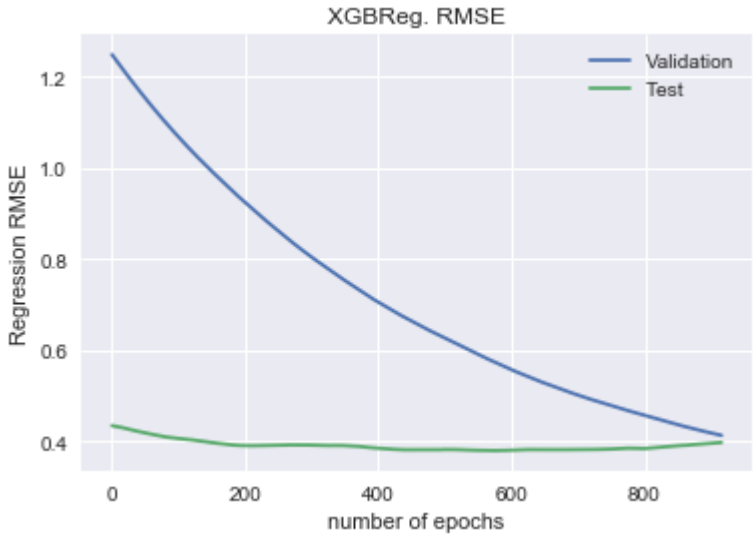


Figure 12: learning curves of the XGBoost algorithm on validation and test set

These curves are called learning curves. In the example shown in Figure 12, after finding the lowest RMSE on the test data set, the algorithm continues for 350 steps (early stopping rounds) before stopping the fit. It can also be seen that the lowest RMSE on the test set is reached after about 550 epochs (550 fitted trees), while the error on the validation set still decreases strongly. The early stopping rounds parameter was chosen like this to achieve the same MSE for train/validation- and test set.

3.2.3. Principal Component Analysis

The Principal Component Analysis or PCA is used to reduce the feature dimensionality. It is assumed that – because of the "curse of dimensionality" – higher number of features require higher numbers of data points for the learner to reach the same accuracy.

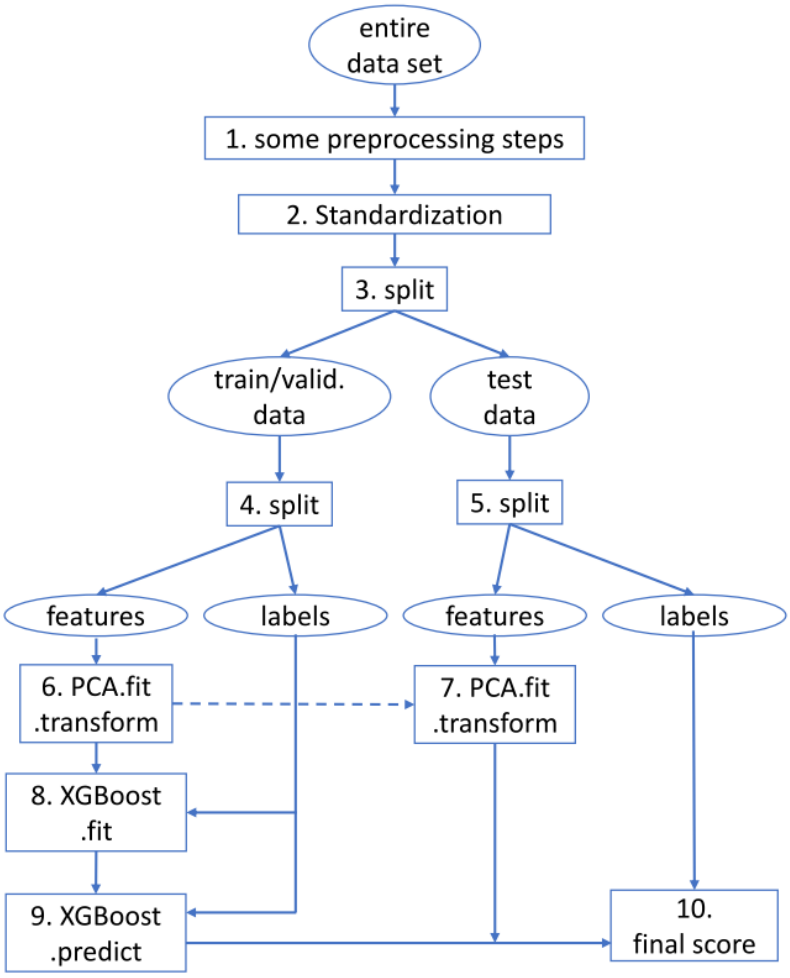


Figure 13: PCA implementation

The PCA will reduce the number of features by examining the interrelations among the features and determining "independent" features. Independent means "orthogonal to each other in the n-dimensional feature space (Udacity, 2017). The PCA's implementation is shown in Figure 13.

3.3. Refinement

Several hyperparameters of the XGBoost algorithm were adjusted to achieve better results (Brownlee, XGBoost Tuning, 2017). The learning rate was reduced from 0.1 to 0.002 and the maximum number of estimators (number of trees) was increased from 100 to 1200. This combination usually increases the generalization performance at the cost of increased runtime (Note that due to early stopping the fit might stop i.e. after 900 trees, even if the number of trees is set to 1200). The early stopping rounds parameter was set to 320. Next, depth of the trees was reduced from 4 to 3, also to reduce overfitting and improve generalization capabilities. No further tuning was done.

4. Results

4.1. Model Evaluation and Validation

The learning algorithms used with the basic implementation are shown in Figure 14.

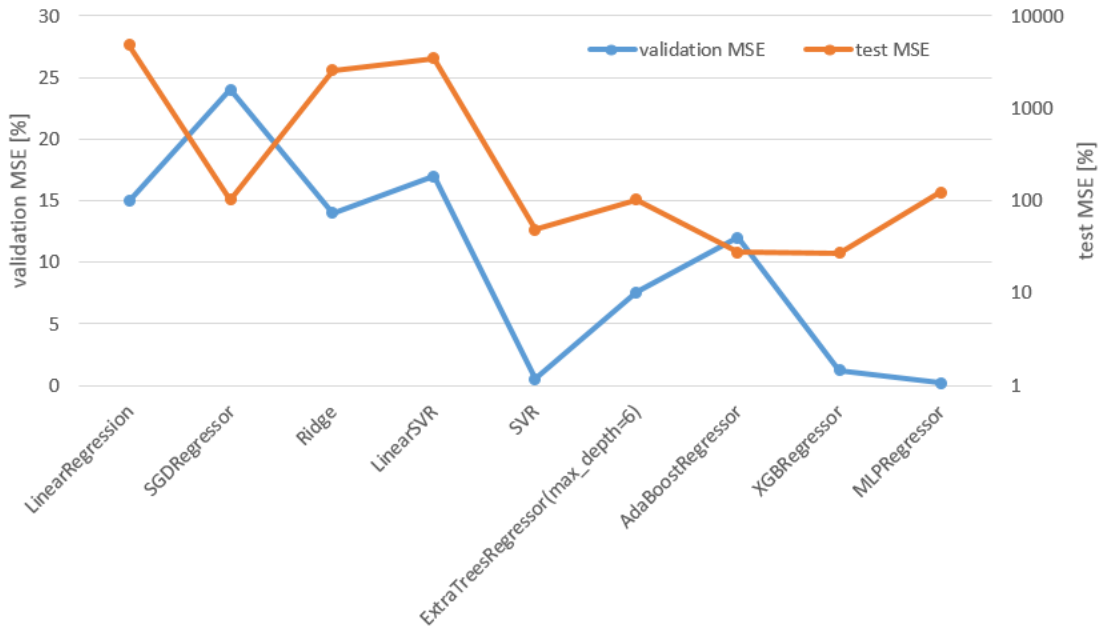


Figure 14: spot check, validation and test mean squared error of several supervised learning algorithms

Out of these algorithms XGBoost (Extreme Gradient Boosting), Support vector machines (SV, or Support Vector Regressor, SVR) and the MLP regressor (Multilayer Perceptron Neural Network) reached the lowest MSE on the train/validation set, around 1.25% for XGBoost, 0.5% for SVR and 0.18% for the MLPR. As just stated, more important is the performance on the independent test set. There, AdaBoost and XGBoost got the lowest MSE with about 27%. The SVR and MLPR performed worse with 49% and 124% respectively. Thus, AdBoost und XGBoost seem to generalize better to unseen data than the MLP regressor, for example.

It seems that boosted trees algorithms in general perform well on this type of problems, as the ExtraTrees regressor also got a relatively low MSE of 100% on the test set. Linear algorithms like Linear regression or Linear SVR on the contrary were not able to capture the underlying model of the data and got high MSE up to 4800% on the test set.

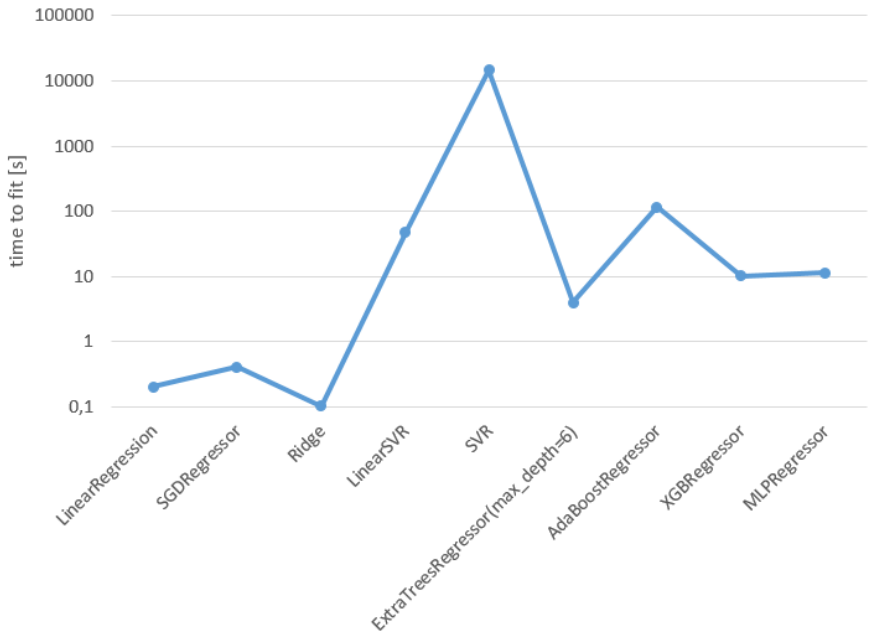


Figure 15: spot check, time to fit needed for the training data, for 1 split, 157500 data points, 35 features

As AdaBoost and XG Bost are the best performing algorithms on this data set, the time to fit, shown in Figure 15, is compared. It results that the XGBoost regressor is a lot faster in fitting the model, with 11.4s compared to 117s of the AdaBoost regressor. This is possible due to the parallelization of tree construction using all available CPU cores (multithreading).

Other advantages of XGBoost over other learners are, that, like AdaBoost, XGBoost provide feature importance functionality and XGBoost alone accepts sparse data (NaN values), which is a big advantage when working with the present meteorology data. Thus, XGBoost is chosen as the algorithm to work with.

4.1.1. Short- mid- and long-term prediction models

The learning tasks are divided into 3 learning tasks: long-term, mid-term and short-term prediction. The following table characterizes these terms in detail:

Table 4: soiling rate learning task classification

	training / validation time span data	**test time span data**
long-term prediction	> 2 years	6 months to several years
mid-term prediction	< 2 years	< 6 months
short term prediction	< 4 months	< 1 month

4.1.1.1. Long-term model performance

Long-term training brings the advantage of lots of available data. It is supposed that the features and thus the soiling rate will show cycles with one-year periodicity. Maybe there are even more cycles hidden in the data. Also, there could be a global trend hidden in the data. These occurrences of seasonality and trends reduce the performance of the regression learners and thus have to be identified and removed before training the model. At the moment of writing this work, no long-term data sets where available and with the available data no seasonality or trend could be identified. The long-term prediction performance of the learner could not be evaluated.

4.1.1.2. Mid-term model performance

The train/validation test set comprises 13 months of data and the test set 3.5 months of data. As can be seen in Table 3 and Figure 17, one clue of these data subsets is, that the variance of the train/validation set is 3.5 times higher than the variance of the test set.

Figure 16 shows the parameters that can be adjusted in XGBoost. Parameters found to work well on this data set and where changed from its standard are:

- learning_rate = 0.002 (standard = 0.1)
- max_depth = 3 (standard = 4)
- n_estimators = 1200 (standard = 100)
- earlyStopRounds = 320

```
--------------------------------------------------------------------------------
XGBRegressor(base_score=0.5, colsample_bylevel=1, colsample_bytree=1, gamma=0,
       learning_rate=0.002, max_delta_step=0, max_depth=3,
       min_child_weight=1, missing=None, n_estimators=1200, nthread=-1,
       objective='reg:linear', reg_alpha=0, reg_lambda=1,
       scale_pos_weight=1, seed=0, silent=True, subsample=1)
--------------------------------------------------------------------------------
```

Figure 16: final model parameters as shown in Python

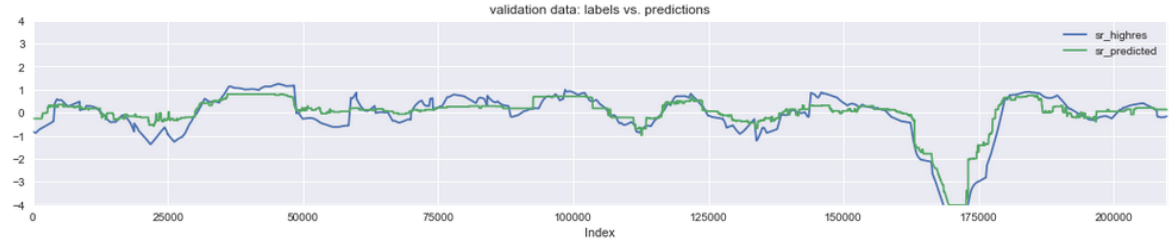
Lowering of the learning rate combined with increasing the number of estimators (the number of trees) usually reduces overfitting at the cost of longer algorithm runtimes. As described in section 3.2 and Figure 11, the early stopping functionality can be used to stop the fitting process as soon as the lowest error von the test set is reached.

Table 5: Results for the learning task

	Train / Validation data set	test data set
MSE [%]	17.7	15.6
r2 score	0.848	0.16
soiling rate mean	-0.122	0.428
predicted mean	-0.017	0.219

deviation predicted / soiling rate [%]	-86.8	-48

The mean squared error (MSE) for both train/validation and test sets are 17% and 16% respectively. The r2 score for the train/valid. set is 0.13 and 0.85 for the train/valid. set. As a next quality measure, the mean of the soiling rate introduced. When predicting the soiling rate over a period of time, it is important that the average soiling rate is accurately predicted, because the total soiling of the power plant's solar concentrators over a period of time is very important. In this test, it can be seen, that the deviation of the soiling rate for the train/valid. set deviates -80% (the predicted soiling rate is 80% below the actual soiling rate) and for the test set the deviation is -52%.




```
('validation set r2 score:', 0.84820547688330328)
validation set mean squared error: 17.70%
sr mean: -0.122379074689 | predicted mean: -0.0169649347663 | pred. deviation from sr: -86.1373892478%
```


```
('test set r2 score:', 0.15552652201571771)
test set mean squared error: 15.55%
sr mean: 0.427742180433 | predicted mean: 0.219372272491 | pred. deviation from sr: -48.7139023162%
```

Figure 17: result plot for the mid-term learning task, using the advanced model

Figure 17 shows the result of the training and testing process. In the upper plot the train/validation run and below the test run is shown. Looking at the plots in Figure 17 it can be seen, that the model's prediction sticks closer to 0 than the actual values. It can be said that the model underestimates the deviation of the soiling rate from the mean. This is also an important point in (Musango, 2016) where it is stated:

> *"The neural network underestimated soiling measurements with maximum percentage difference between the measured and estimated cleanliness of about 5.4%."*

Even though (Musango, 2016) used the cleanliness as label and not the soiling rate, the reason for this underestimation in both works could be caused by the data distribution of the features and labels, as discussed in section 2.2.1 and Figure 5. The soiling rate, for example, is not very normally distributed. There are several peaks far from the

mean, that could lead to bias in the model's predictions. Also, the features that are important for the prediction, do deviate from a normal distribution. Figure 18 shows the feature importance for the above created mid-term model. Lots of the important features in Figure 18 are not normally distributed.

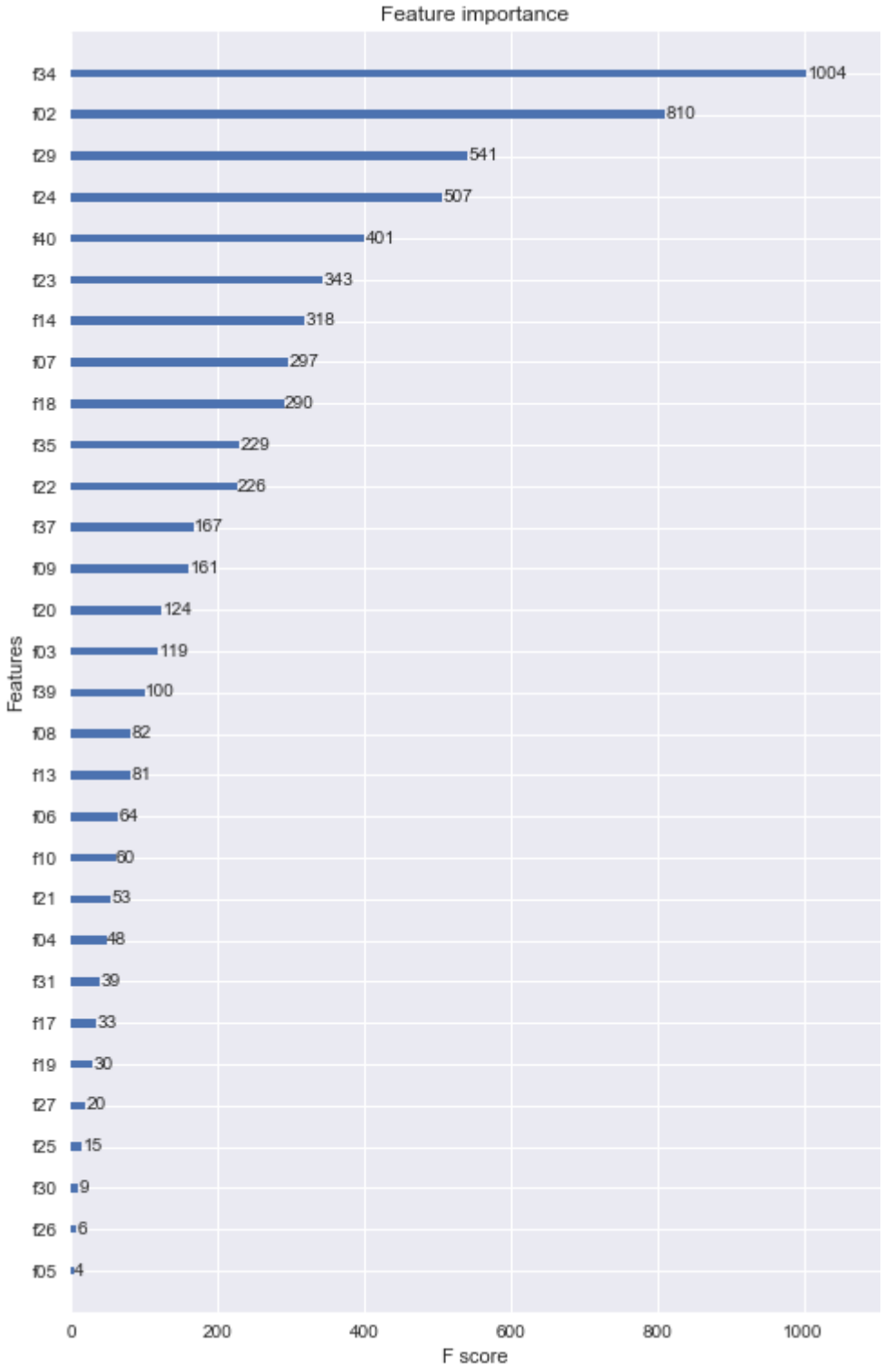


Figure 18: feature importance

The less important features seem to be randomly distributed over the importance ranks. Thus, it is expected that their influence on the predictions can be neglected (see next section).

Tests were performed using the PCA to reduce feature dimensionality. The tested configurations were from 6 to 12 components, where 6 components already showed an explained variance of 98,6%. However, using the PCA the MSE from Table 5 dropped from 17% to 50% for the train/valid. set and from 15.6% to 18.5% for the test set. Hence the PCA optimizations was note pursued any further.

4.1.1.3. Short-term model performance

No tests were done for short-term model performance. It is estimated that the short-term model performance is equal or better than the mid-term performance. A very interesting application of the short-term model is presented in section 0.

4.2. Justification

The high R2 score reported in (Musango, 2016) could not be reached in the present work. This is assumed to be due to two main factors: First, the features used in the benchmark are different to the features used here (see Table 6). Second, one of the features used by (Musango, 2016), is the direct normal irradiation of the sun (DNI). In this work and in (Wolfertsstetter, 2016) the assumption is made, that the DNI helps explaining the high variance in the cleanliness raw data. Due to the measurement device working principle the raw data spread (shown in Figure 4) is indeed caused be the DNI. Thus, the DNI feature rather helps to explain the measurement device variance (high) than actual cleanliness variance (low, compared to the measurement variance).

Table 6: comparison of the (Musango, 2016) setup and the present setup

	Musango data set	**this data set**
Data set size:	n/a	270082 data points (used data)
preprocessing procedures	n/a	see section 3.1
splitting technique	n/a	see section 3.1
feature distributions	n/a	see section 2.2.1
number of features	5	35
features directly related to cleanliness / soiling	0	29 particle channels
features indirectly related to cleanliness / soiling	3	4
R2 score (test set)	0.95	0.16
MSE (test set)	n/a	16 %

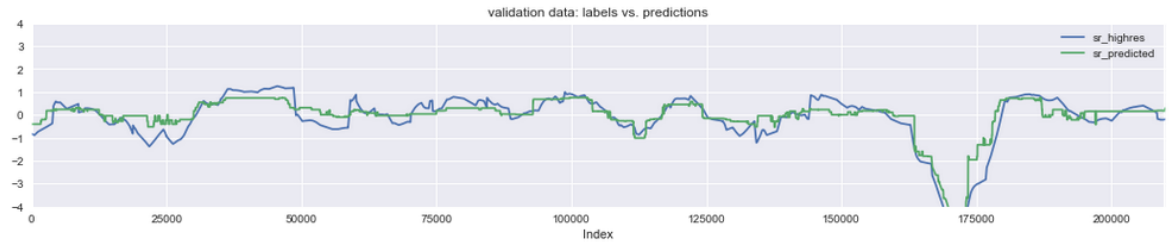
In order to compare the benchmark results with the ones presented here, the following aspects from Table 5 have to be taken into consideration: The number of data points used for the benchmark training and testing is not reported. The data preprocessing is

not detailed: No information on the data spitting- and cross validation technique is given, noise reduction is mentioned, but not explained (use of moving average, etc.) and no information on the feature distributions is given. The benchmark high-score of 0.95 on the test set seems very high.

5. Conclusion

5.1. Free-Form Visualization

After training on a relatively small data set of 13 months of weather data, the XGBoost learning algorithm is capable of making predictions for 3.5 months of data with an MSE of less the 20%. If the number of features is reduced from 35 to the most important 6 features, the MSE for both train/valid. and test data sets stays below this threshold of 20% as can be seen in Figure 19.




```
('validation set r2 score:', 0.83195009435545719)
validation set mean squared error: 19.64%
sr mean: -0.122281275742 | predicted mean: -0.0312911383808 | pred. deviation from sr: -74.4105234501%
```


```
('test set r2 score:', 0.1571287895169925)
test set mean squared error: 15.68%
sr mean: 0.422672875954 | predicted mean: 0.44134619832 | pred. deviation from sr: 4.41791357538
```

Figure 19: result plot for the mid-term learning task, using the advanced model and 6 input features only

Figure 20 shows the feature importance of the 6 features. Interestingly, compared to Figure 18, the first two positions are swapped. As in Figure 18, of the two most important features f02 and f34, f02 is directly related to soiling processes and f34 is indirectly related.

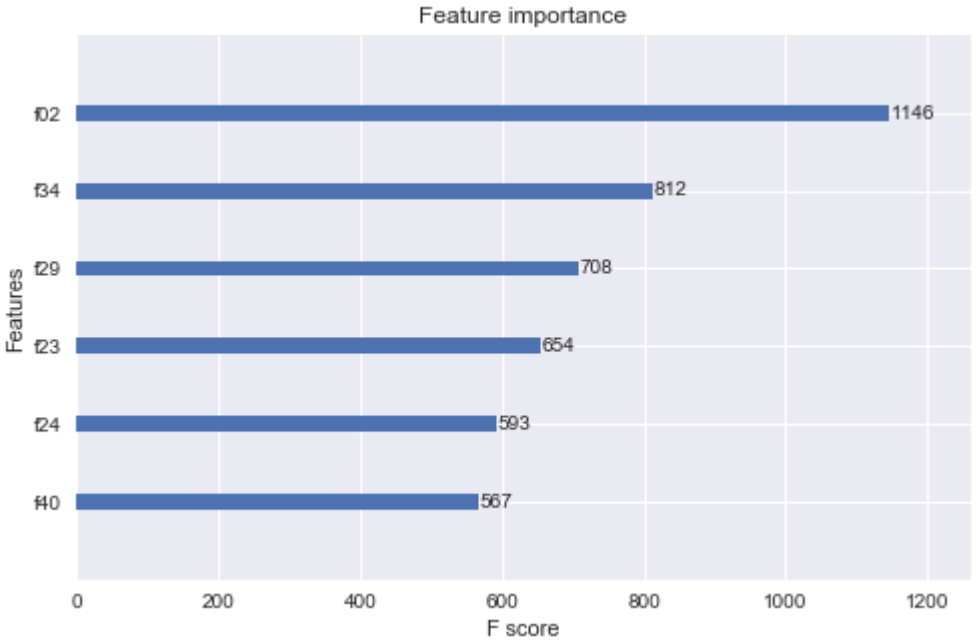


Figure 20: feature importance, XGBoost uses only 6 features

5.2. Reflection

The aim of this project was to train a supervised learning algorithm such that it is able to predict to soiling of solar concentrating mirrors, given the weather conditions. The DLR e.V. provided a 16.5-month data set that could be used for training, validation and testing. A seasonality check (python statsmodels.tsa) on the data did not reveal any seasonalities, although given the fact, that meteorological data is used, there definitely have to be seasonalities in the data. Once more data is available (more than 2 years) the seasonality check should be repeated.

After creating the necessary pre-processing steps and performing all necessary splits, several supervised learning algorithms where tested. Some of these, like AdaBoost and XGBoost showed good results. In the end XGBoost was picked as algorithm-of-choice. The idea of creating a LSTM-NN was discarded. After optimization of the XGBoost algorithm, the prediction MSE on the test data set dropped below 20%. Given the inhomogeneity and incompleteness of the data set, this error rate is considered to be quite low. At the same time overfitting in the train/validation set could be reduced using the Early Stopping functionality provided by XGBoost.

Interestingly, a part of the information contained in the 35 features seems to be redundant, as the MSE does not increase notably when the features are reduced from 35 to 6. Nevertheless, at the same time the PCA was not able to improve the prediction quality by combining the 35 features into 6 main components.

In order to use this project in a real-world setting, a couple of improvements should be made. They are described in the next section.

5.3. Improvement

There are a number of improvements that can be made to take this project from its experimental stage to a real application:

As a first step, the preprocessing has to be modified so that XGBoost can work with NaN values. The advantage of this is: Real world meteorology data usually contains lots of NaN values and NaN processing is time-consuming. Also, deleting a whole data row just because of one feature having a NaN entry, deletes lots of valid data unnecessarily.

As a next step, for the features and labels, better normally shaped distributions have to be achieved. It is assumed that with more measurement data over time the distributions automatically will get closer to normal distributions. Thus, the learning algorithm's assumption on feature distributions will be met and prediction results will get better. Using several years of data will also reveal more information to the learner. Seasonality tests, performed on several years of data, will eventually reveal periodic characteristics and trends, that can be modeled and removed, again improving learning and prediction.

The outlier detection performed here, removed too many data points and had to be limited on features with only few outliers. A more intelligent method could be created and applied on all features and then reduce biases.

The creation of the day dictionary could be made more stable and include more exceptional states when the cleanliness data is not recoded very well (too many NaNs for example). Also, the daily-based soiling rate calculation could be further improved, maybe be adding more processing steps than just filling-in missing values and performing a moving average.

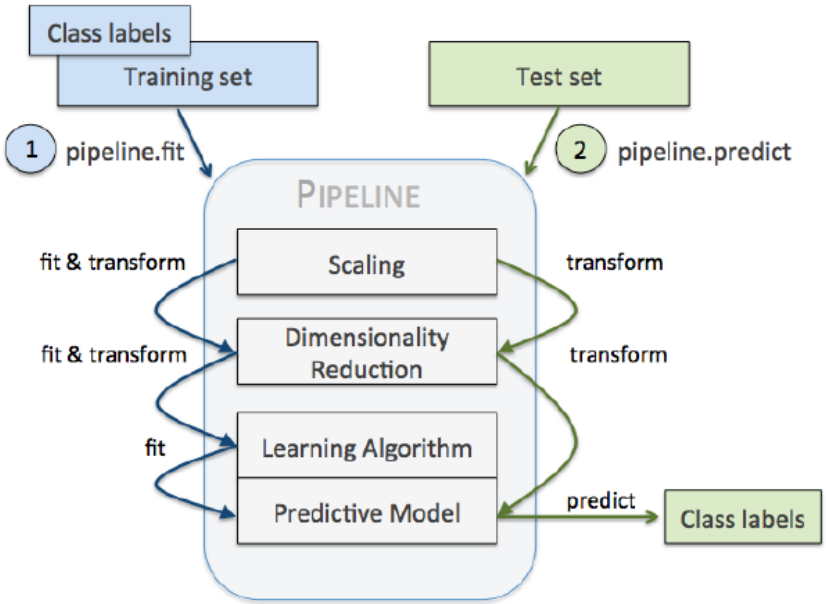


Figure 21: pipeline concept, picture kindly provided by (Raschka, 2015)

The use of the pipeline class from (scikit-learn - Pipeline, 2017) could achieve a better structure of the code by applying all data transforms in a pipeline and then cross-validate them all together, see Figure 21. In that manner, data leakage from one data set into the other can be avoided.

With all above steps done, a Meteo Data Management System (MDMS, (N. Geuder, 2015)) implementation could be done, were most of the work, that is now done manually, could be automated. Figure 22 shows the implementation in theory.

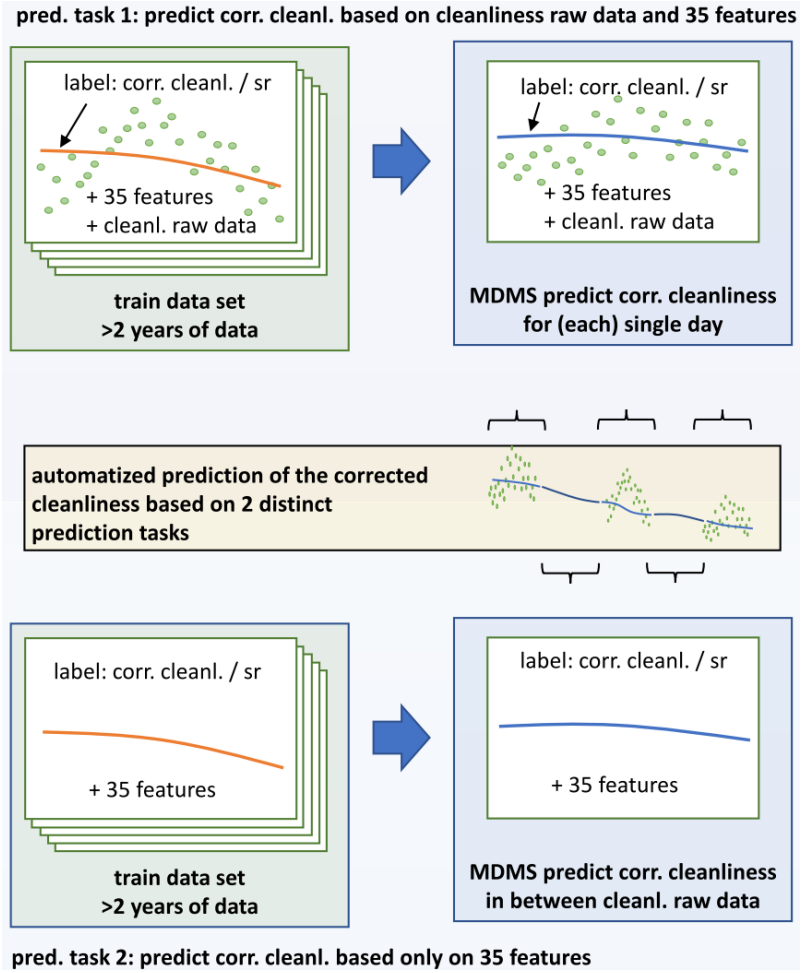


Figure 22: automatization of MDMS creation of corrected cleanliness

In a first task XGBoost learns to predict the cleanliness (or soiling rate) based on the cleanliness raw data and the 35 meteorology features. This task normally needs to be done manually. After a few hundred or better a few thousand learning examples, the learner should be able to predict the cleanliness with a high accuracy.

The second task is the one presented in this capstone project: The cleanliness raw data is now discarded and the algorithm is trained to predict the soiling rate based only on the 35 meteorology features. After enough training data is available, the error rate will go down and the predictions will be accurate. Then these predictions can be used to fill in the soiling rate (or cleanliness) for the periods of time where no cleanliness raw data is available.

Another approach to remove NaNs from the data set, an LSTM-NN could be trained to fill in time series prediction values into NaN values. This LSTM-NN could also be used to do short-term or mid-term forcasts on cleanliness or soiling, or just on the features.

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