Capstone Project
Machine Learning Engineer Nanodegree

Demand prediction for a bike sharing systems

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1. Definition

1.1 Project Overview

I was looking for a problem that is solvable with machine learning in the field of transport and logistics because this is my area of expertise. I found a very promising dataset by the company called Capital Bike Share. It is a bike sharing system in Washington DC. I use this dataset to utilizing machine learning to forecast the demand for the bike sharing system.
I applied different types of regression to find an algorithm to predict the demand for bikes based on calendric and weather information. The information about weather, calendar and bike market is available in a dataset by the University of Porto at UCI ML Repository.
This project tries to create a forecasting function based on two years of historical data by utilizing the machine learning libraries scikit-learn and tensor-flow.

1.2 Problem Statement

The long-term goal of a corporation is to make a profit. To do so, the corporation has to make decisions regarding financing and investing that factor in the current and future situation of the organization. To quantify the future position of the business, forecasts and predictions of all important performance indicators are necessary.
For a bike sharing company, the future demand for its bikes is a key indicator to consider when making decisions. Predictions about the demand are vital when scheduling maintenance of the current bicycle fleet or when to acquiring additional vehicles.
The goal in this project is to forecast the demand for bikes in dependency of weather conditions like outside temperature and calendric informations e.g. holidays. These information and the demand structure is provided in a set with two years of daily historic data. The

demand is given as the total daily demand and as a split for registered users and casual users. To increase the quality of the prediction registered user demand and casual user demand will be predicted separately in step two.
To make predictions machine learning is used to train regressors. Scikit-Learn recommends a support vector regressor (SVR) for this kind of problem and data amount. In addition a deep neuronal network (DNN) regressor is trained for comparison. To find the hyper-parameters for these regressors grid search and randomized search are utilized. Due to the small dataset cross validation is applied.

1.3 Metrics

To measure the performance of the regressions two standard regression metrics are used: Mean squared error (MSE) and the coefficient of determination (R^2). Both metrics are calculated for both regressor types. For comparison and parameter tuning only R^2 is used due to the better readability.

2 Analysis

2.1 Data Exploration

- instant: record index

Feature column(s):
- dteday : date
- season : season (1:springer, 2:summer, 3:fall, 4:winter)
- yr : year (0: 2011, 1:2012)
- mnth : month (1 to 12)
- hr : hour (0 to 23)
- holiday : weather day is holiday or not (extracted from http://dchr.dc.gov/page/holiday-schedule)
- weekday : day of the week
- workingday : if day is neither weekend nor holiday is 1, otherwise is 0.
+ weathersit :
    - 1: Clear, Few clouds, Partly cloudy, Partly cloudy
    - 2: Mist + Cloudy, Mist + Broken clouds, Mist + Few clouds, Mist
    - 3: Light Snow, Light Rain + Thunderstorm + Scattered clouds,

Light Rain + Scattered clouds
- 4: Heavy Rain + Ice Pallets + Thunderstorm + Mist, Snow + Fog
- temp : Normalized temperature in Celsius. The values are divided to 41 (max)
- atemp: Normalized feeling temperature in Celsius. The values are divided to 50 (max)
- hum: Normalized humidity. The values are divided to 100 (max)
- windspeed: Normalized wind speed. The values are divided to 67 (max)

Target column:
- casual: count of casual users
- registered: count of registered users
- cnt: count of total rental bikes including both casual and registered

Data values:

instant	dteday	season	yr	mnth	holiday	weekday	workingday	weathersit
1	2011-01-01	1	0	1	0	6	0	2
2	2011-01-01	1	0	1	0	0	0	2
3	2011-01-03	1	0	1	0	1	1	1
4	2011-01-04	1	0	1	0	2	1	1
5	2011-01-05	1	0	1	0	3	1	1

instant	weathersit	temp	atemp	hum	windspeed	casual	registered	cnt
1	2	0.344	0.363	0.805	0.160	331	654	985
2	2	0.363	0.353	0.696	0.248	131	670	801
3	1	0.196	0.189	0.437	0.248	120	1229	1349
4	1	0.200	0.212	0.590	0.160	108	1454	1562
5	1	0.226	0.229	0.436	0.186	82	1518	1600

Data stats:

	instant	season	yr	mnth	holiday	weekday	workingday	weathersit
count	731	731	731	731	731	731	731	731
mean	366	2.49	0.50	6.51	0.02	2.99	0.68	1.39
std	211	1.11	0.50	3.45	0.16	2.00	0.46	0.54
min	1.00	1.00	0.00	1.00	0.00	0.00	0.00	1.00
25%	183.5	2.00	0.00	4.00	0.00	1.00	0.00	1.00

50%	366	3.00	1.00	7.00	0.00	3.00	1.00	1.00
75%	548	3.00	1.00	10.0	0.00	5.00	1.00	2.00
max	731	4.00	1.00	12.0	1.00	6.00	1.00	3.00

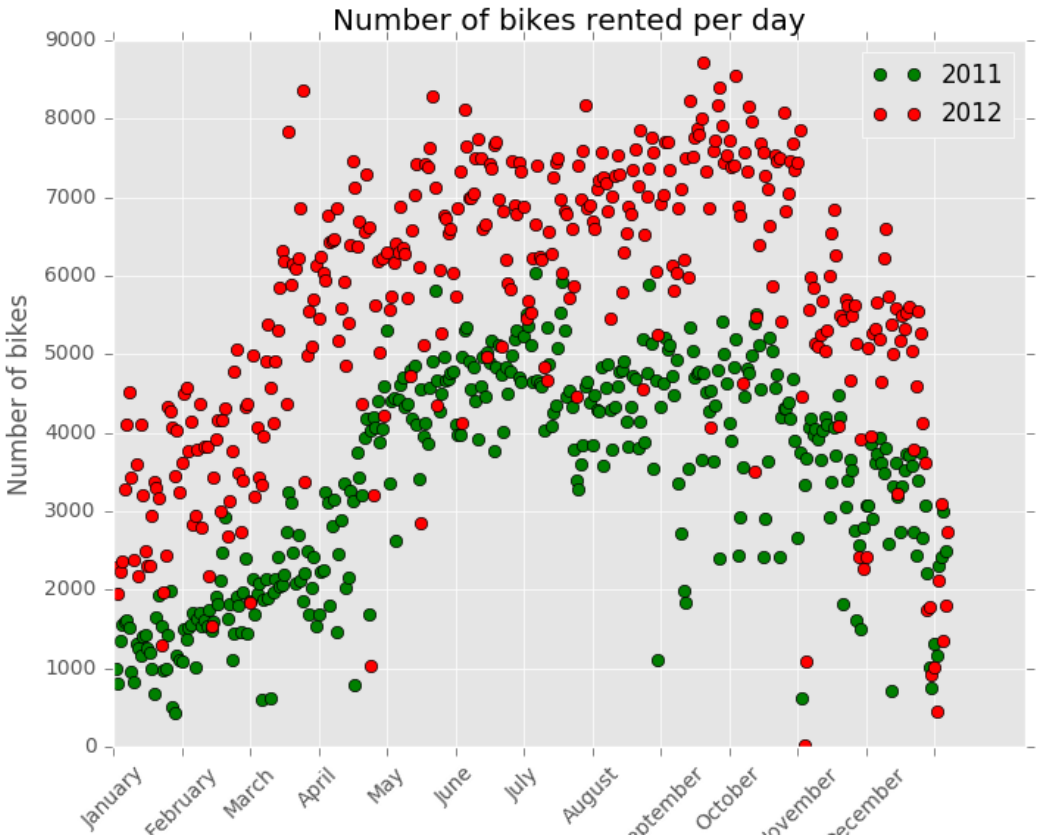
	temp	atemp	hum	windspeed	casual	registered	cnt
count	731	731	731	731	731	731	731
mean	0.49	0.47	0.62	0.19	848	3656	4504
std	0.18	0.16	0.14	0.07	686	1560	1937
min	0.05	0.07	0.00	0.02	2.00	20.0	22.0
25%	0.33	0.33	0.52	0.13	315	2497	3152
50%	0.49	0.48	0.62	0.18	713	3662	4548
75%	0.65	0.60	0.73	0.23	1096	4776	5956
max	0.86	0.84	0.97	0.50	3410	6946	8714

Characteristics

The characteristics of the dataset are very favorable because it was already processed. It is very concise, and missing values are not a problem. Also, most of the data is already normalized or binary. Other categorical data like 'weekday' or 'working day'/'holiday' were processed.

2.2 Exploratory Visualization

The visualization shows a classic seasonal pattern with an up trend year over year. There are some outliers. These are left in the dataset because they are not due to measurement errors, but to extreme weather conditions. Because extreme weather conditions are part of the problem, so the data is not excluded.



2.3 Data Preprocessing (Methodology)

Dates get dropped because the regressor can not read this datatype and the order information is already stored in the index. The instant variable replicates this information also.

2.4 Algorithms and Techniques

Two types of regressors are trained. An SVR and a DNN-Regressor. Both are first used off-the-shelf with default parameters to create a benchmark.

2.5 Benchmark

Both "benchmarks" for the coefficient of determination are very low. Parameter tuning is mandatory.

Score SVR:
`-0.031042`

Score DNN:
-0.082288

3 Methodology

3.1 Implementation

The regressors are trained using randomized search and cross-validation to identify the area of the best parameters. Then a grid search is used to tune parameter values of the regressor functions.

SVR tuned with GridSearch and RandomizesSearch

```
Score SVR: -0.031042
Score SVR tuned GS: 0.798317
Score SVR tuned RS: 0.802120
```

The tuning works for the SVR.

DNN-Regressor tuned with GridSearch and RandomizesSearch

```
DNN: -0.082288
DNN tuned GS: 0.138676
DNN tuned RS: 0.143749
```

Same picture with the DNN Regressor. The tuning helps, but the results are still underwhelming. Also, the best DNN result is no match for the tuned SVR.

Results

```
SVR tuned RS: 0.802120
DNN tuned RS: 0.143749
```

SVR works much better than the DNN Regressor.

3.2 Refinement

The count of rented bikes (cnt) is just the sum of the features casual and registered. Two separate models are trained to predict these features. And add up afterward. This split should improve the projection.

SVR with GridSearch - for casual users

```
Best parameter from grid search: {'kernel': 'linear',
'C': 1000}
```

SVR with RandomizesSearch - for casual users

```
best CV score from grid search: 0.645292
```

SVR with GridSearch - for registered users

Best parameter from grid search:
```
{'kernel': 'linear', 'C': 1000}
```

SVR with RandomizesSearch - for registered users

```
best CV score from grid search: 0.645292
```

4 Results

4.1 Model Evaluation and Validation

```
SVR untuned: -0.031042
SVR tuned grid search: 0.798317
SVR tuned random search: 0.802120

DNN untuned: -0.082288
DNN tuned grid search: 0.138676
DNN tuned random search: 0.143749

SVR tuned cas: 0.619215
SVR tuned  reg: 0.774632
SVR tuned  sum: 0.802635
```

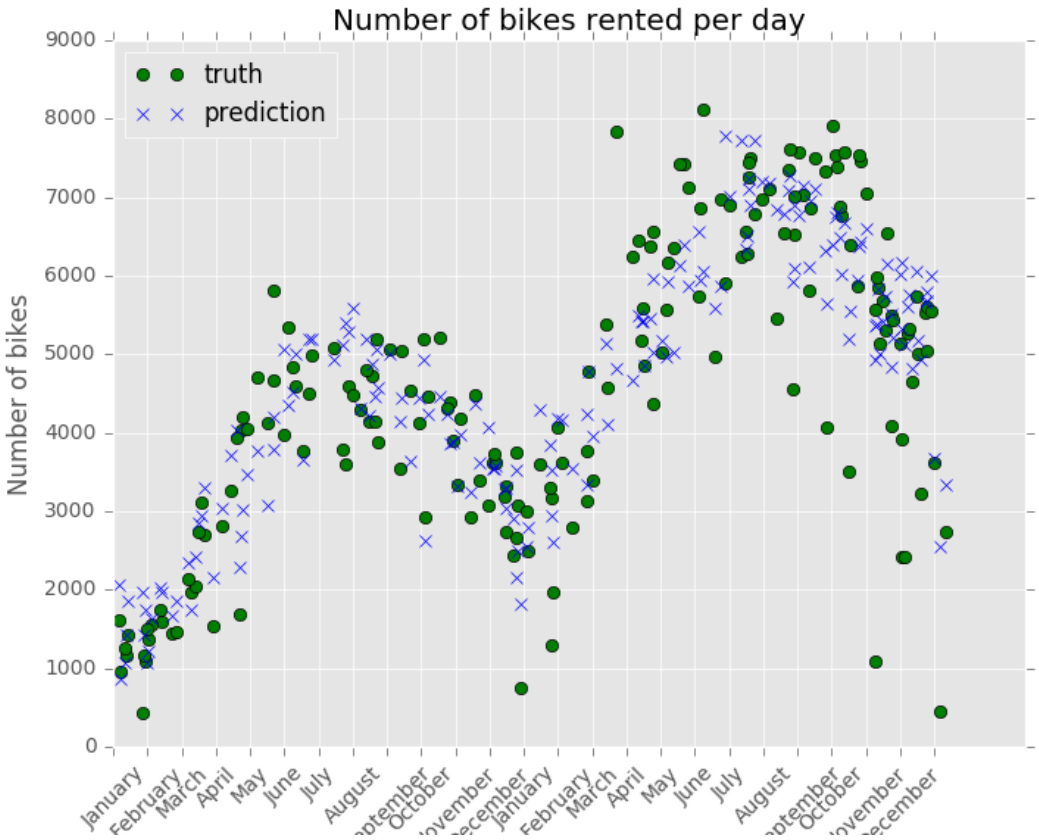
4.2 Justification

As expected the tuning of the parameters of the regressors improves the performance. Both regressors make much better predictions after tuning. Parameter tuning with random search can improve the performance even further after the right interval was identified by grid search. Despite the tuning, the SVR beats the DNN Regressor by far. The

predictions by the SVR are more than five times as good as the DNN Regressors.
Splitting the dataset and predicting casual and registered customers separately increase the R^2 score also slightly.
A coefficient of determination of more than 80% is a decent result for the SVR regressor. The DNN Regressor predictions are disappointing. Maybe the size of the dataset is insufficient to train the DNN Regressor properly.

5 Conclusion

5.1 Free-Form Visualization



The predictions on the test set are reasonably good, without overfitting.

5.2 Reflection

I had high hopes for the DNN Regressor. It was kind of disappointing that it does not even come close to the SVR results. Maybe my tuning was not right, or it needs a larger dataset or computational power. Utilizing grid and randomize search in a way that makes sense was a little tricky. At first, the results of the parameter tuning seemed random.

This behavior might be caused by local minima in the solution space. Parameter tuning results became more stable when I switched the order of the search methods . It makes more sense to start with a broad grid search and then use randomized search on the given interval, instead of visa verse. It is also computational more efficient.

5.3 Improvement

The coefficient of determination of the regressors could be increased by additional iterations in training and the number of folds in the cross-validation, at the expense of computing time. More iterations might be particularly useful with the performance of DNN Regressor.
The performance of the DNN Regressor might also increase with the amount of data available. Of course, there are also other regressors available that might perform better on this specific dataset.

Reference

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> http://archive.ics.uci.edu/ml/datasets/Bike+Sharing+Dataset
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sklearn.svm.SVR.html#sklearn.svm.SVR
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