Report Pervasive Computing Assignment 4

1) Data collection

Measurement tool: I downloaded the app "Sensor Logger" because it is able to track the acceleration in a 3-dimensional space and the sampling rate can be accurately chosen. Furthermore, the recorded tracks can be simply exported as csv-files. I used it for both devices.

Sampling rate for the recording: According to [2], 100 % of human movements shall lay below 20 Hz, 99 % below 15 Hz, and 98 % below 10 Hz. Beyond that, there is lot of human activity recognition research, which also tracks human body movements, which applies sampling rates in a range of 1 to 20 Hz [3]. Therefore, the sampling rate was set to **20 Hz** for both devices.

Data recording: I used two smartphones as devices. One I fixated on the wrist of the right arm where the screen pointed towards the body, the other one came into my right front trousers' pocket with the screen pointing in body movement direction. Both devices had were set upright. As it turned out, synchronizing the two devices can be quite struggling. I tried to hit the start buttons of the two devices simultaneously but of course this wasn't easily doable. The synchronization will be done in the pre-processing step.

I successfully collected data for a time frame of 65 minutes at once. The street was part-wise iced such that I walked carefully sometimes. The right arm on which the device was fixed swung freely. To be sure that the second device registers the leg movements, I wore this time tight trousers.

To avoid data loss, I split the data collecting process into several recordings which follow chronological on each other. Because one time point represents one sample, I ended up with a **final dataset of 65825 samples after pre-processing.**

2) Pre-processing

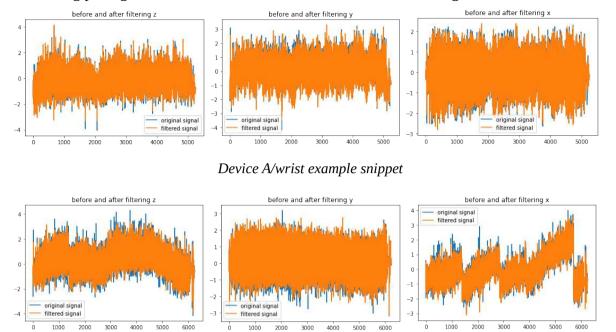
Cutting: For each signal I cut the first and last 10 seconds away to be sure that only the process of walking was recorded. It always took some time to position the devices. Moreover, it is important to synchronize the devices. The csv accelerometer files' first column represents the device's timestamps. In the lecture was mentioned that it is impossible that two devices have the exactly same current point in time. However, as I activated the recording buttons circa at the same time and we can assume that we don't need the point in time very precisely, I came to the conclusion to compare the first 11 digits of each timestamp of the recordings of the two devices. For instance, having the timestamp 1705060351195432700, only 17050603511 mattered for file comparison. To guarantee that the two devices record the same time interval, I had a look the first timestamps (after the 10 second cut-off) of the two simulatneously recordings and took the one which is later in time. This later in time timestamp marked the start of the two recordings.

Same line of thought accounts for the end of the accelerometer files. In this case the ending timestamp, which is earlier in time, marks the end of both device csv-files.

Through that cutting process and the usage of the same sample frequency the accelerometer files of the devices have the same amount of datapoints and are therefore suitable for the regression task.

Filtering: The low-pass filter enables the removal of noise and gravity acceleration [1]. I had a closer look at the low-pass **Butterworth filter**. As mentioned in the sampling rate choice, 99 % of human movenments shall be covered by 20 Hz [2]. Therefore, the filter threshold was set to that value. Besides that, [4] outlines that strong phase distortions might happen when an unsuitable filter order and frequency are selected. [3] also mentions that the filtering for each of the 3 dimensions shall happen separately.

I experimented with the filter setting. The order of the filter should be as high as possible, else I can observe strong shifts in the signal. Therefore, I ended up with an **order of 9 and a frequency of 20**. The following plots give an outlook of the filtered z-score normalized signal for one time recording.



Device B/right trousers' front pocket example snippet

It can be observed that the Butterworth filter doesn't lead to a drastic distortion in time domain. Furthermore, clear differences in the signals between the two devices can be observed for all recorded time snippets. Device B tends to build a wave like structure whereas device A doesn't do so.

Sample forumulation: To use the pre-processed data in WEKA, it was stored as arff-file. One sample/line was defined as (z-axis device A, y-axis device A, x-axis device A, z-axis device B, y-axis device B, x-axis device B) or when putting in the used feature names (Z1, Y1, X1, Z2, Y2, X2). In WEKA it is possible to remove all features which aren't of interest currently.

Train-test-split: For this task a train-test-split is needed. In the exercise slides was the request to apply an 80-20-split. This was done by loading the created arff-file. For the linear regression and multi-layer perceptron the time order doesn't matter. Therefore, for these two methods the dataset samples were shuffled to assure diversity in the train and test set. In contrast, gaussion process regression makes use of auto-correlation and thus it is important to keep the natural signal sequence. The dataset was for this case only split. Even further, WEKA had troubles when working with a huge dataset by using gaussian process. It simply stopped the process without feedback or raised the error message that the dataset would be too big. Therefore, I only used 1/10 of the whole dataset for it. The other two methods worked with the full dataset. The splitted dataset is then stored as train and test arff-files.

3) Regression

MAE = Mean Absolute Error; it is the reported measure

MAE scores in thick letters indicate that the current hyper-parameter modification is kept for further experiments.

Linear Regression

initial default tests: The outputs are sorted from condition 1 (first WEKA output) to condition 12 (last WEKA output). Each row is read from left to right.



Considering the almost not exsting correlations, the signals of the two devices doesn't seem to be linearly related. Besides that, it doesn't make sense to have a closer look at both conditions using the two same variables but with switched input and output. For instance Y1 = w*Y2 + b can be rewritten as Y2 = (Y1 - b)/w. Therefore, it seems to be redundant to always consider both versions. Even further, the hyper-parameter modification has no impact on the MAE. Most likely that's because linear regression is a very simple algorithm for which nothing needs to be changed.

best performing configurations:

The configurations 1, 2, 5, 6, 7, 11, and 12 have MAE scores of lower than 0.8 but always higher than 0.78. They almost not differ from the worse configurations.

worst performing configurations:

The worst performing configurations are the negative of the best performing ones, namely **configurations 3, 4, 8, 9, and 10. Their MAE lays between 0.801 and 0.8202**. They are only slightly worse than the best performing configurations. It turns out that linear regression isn't able to handle this type of task. Also computing linear regression with a signal correctly ordered in time doesn't lead to a better performing MAE. There doesn't seem to be a linear connection between the signals of devices A and B.

Gaussian Process Regression

initial default tests: The outputs are sorted from condition 1 (first WEKA output) to condition 12 (last WEKA output). Each row is read from left to right.

_					
Time taken to build model: 337.12 seconds		Time taken to build model: 406.35 seconds		Time taken to build model: 308.82 seconds	
Evaluation on test set		Evaluation on test set		=== Evaluation on test set ===	
Time taken to test model on supplied test set: 0.39 seconds		Time taken to test model on supplied test set: 0.33 seconds		Time taken to test model on supplied test set: 0.2 seconds	
Summary		Summary		=== Summary ===	
Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0051 0.8313 1.034 100.2965 % 100.3228 % 2194	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	-0.0087 0.6464 0.7994 100.6238 % 100.5098 % 1317	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	-0.0003 0.8411 0.9825 100.09 % 100.0152 %
Time taken to build model: 265.01 s	econds	Time taken to build model: 298.78	seconds	Time taken to build model: 415 se	econds
=== Evaluation on test set ===		Evaluation on test set		=== Evaluation on test set ===	
Time taken to test model on supplied test set: 0.16 seconds		Time taken to test model on supplied test set: 0.2 seconds		Time taken to test model on supplied test set: 0.38 seconds	
Summary		=== Summary ===		=== Summary ===	
Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	-0.0174 0.8405 0.9828 100.0113 % 100.054 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0005 0.8021 1.0696 100.1726 % 100.1813 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0285 0.7994 1.0646 99.83 % 99.8058 %
Time taken to build model: 365.52	a seconda	Time taken to build model: 321.63	eaconde	Time taken to build model: 299.03	seconds
=== Evaluation on test set ===		=== Evaluation on test set ===		=== Evaluation on test set ===	
Time taken to test model on supplied test set: 0.23 seconds		Time taken to test model on supplied test set: 0.22 seconds		Time taken to test model on supplied test set: 0.21 seconds	
Summary		=== Summary ===		=== Summary ===	
Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	-0.0094 0.8672 1.0291 100.0388 % 100.0224 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0325 0.8655 1.0278 99.8415 % 99.8949 % 1317	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	-0.0003 0.7306 0.9417 99.9656 % 99.9498 %
Time taken to build model: 287.31 seconds		Time taken to build model: 294.84 seconds		Time taken to build model: 521.31 seconds	
=== Evaluation on test set ===		=== Evaluation on test set ===		=== Evaluation on test set ===	
Time taken to test model on supplied test set: 0.22 seconds		Time taken to test model on supplied test set: 0.21 seconds		Time taken to test model on supplied test set: 0.44 seconds	
Summary		=== Summary ===		Summary	
Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	-0.0062 0.7309 0.9413 100.0288 % 99.9138 % 1317	Correlation coefficient Mean absolute error Reot mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0005 0.6831 0.855 99.9307 % 100.0097 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	-0.0152 0.6874 0.8611 100.554 % 100.7254 %

There is no correlation which would be worth to mention, all of them are very close to 0. Looking at the MAE some configurations seem to do a little bit better than others. These are **configuration 2, 11, and 12**. Each of them has a MAE **of smaller than 0.7**. However, considering that the values are z-score normalized where the majority lays between -3 and 3, this is still a huge error score, measuring the mean distance between the prediction and ground truth. For further hyper-parameter modifications the configurations with a MAE lower than 0.7 are considered.

```
<u>configuration 2:</u> MAE = 0.6464 | <u>configuration 11:</u> MAE = 0.6831 | <u>configuration 12:</u> MAE = 0.6874
```

```
kernel:
```

Puk → 0.667 **0.683** 0.6892

RBFKernel \rightarrow **0.646** 0.6831 **0.6856**

noise:

 $0.5 \rightarrow 0.6502 \ 0.6837 \ 0.6874$

 $1.5 \rightarrow 0.644 \quad 0.6826 \quad 0.6864$

 $2.0 \rightarrow 0.6433 \ 0.6825 \ 0.6841$

 $3.0 \rightarrow 0.6428 \ 0.6825 \ 0.6837$

 $4.0 \rightarrow 0.6426 \ 0.6826 \ \textbf{0.6836}$

 $5.0 \rightarrow 0.6425 \ 0.6827 \ 0.6836$

debug = True $\rightarrow 0.6425 \ 0.6825 \ 0.6836$

Final MAE: 0.6425 0.6825 0.6836

best performing configurations:

There is a slight decrease of MAE in all three investigated configurations observable. However, this improvement only takes place with the beginning of the third decimal place. The total gain of this examination seems to be limited. **Configuration 2** still outperforms the other ones. Here all axes of device A are taken to predict the x-axis of device B.

worst performing configurations:

The worst performing configurations reach a MAE score of at least 0.85. Namely, these are **configurations 7, MAE of 0.8672, and 8, MAE of 0.8655**. Those are worse than for linear regression. This shows that a simple model doesn't always underperform more complex models. It is striking that configuration 7 and 8 both try to predict the x-axis of device A.



Looking at the figure 1 above and knowing about the fact that device A was fixed at the wrist, it becomes clear that the arm swung along the x-axis. However, device B at the upper leg didn't swung in the same tact as the arm. It was more like that the leg moved almost twice times slower than the arm. Therefore, analyzing the signal curve device B (X2, Y2, Z2) could give only little information about the x-axis of device A.

Multilayer Perceptron Regression (MLP)

initial default tests: The outputs are sorted from condition 1 (first WEKA output) to condition 12 (last WEKA output). Each row is read from left to right.

`	1 /		U		
Time taken to build model: 3.66 seconds		Time taken to build model: 7.09 seconds		Time taken to build model: 3.8 seconds	
=== Evaluation on test set ===		=== Evaluation on test set ===		=== Evaluation on test set ===	
Time taken to test model on supplied test set: 0.07 seconds		Time taken to test model on supplied test set: 0.04 seconds		Time taken to test model on supplied test set: 0.04 seconds	
Sunnary		Summary		=== Summary ===	
•					
Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0079 0.7848 0.9891 100.3773 % 100.0634 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0457 0.7801 0.9875 99.779 % 99.8989 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	-0.0015 1.0376 1.2042 127.0679 % 122.136 %
Time taken to build model: 6.88 seconds		Time taken to build model: 3.74 seconds		Time taken to build model: 6.84 seconds	
=== Evaluation on test set ===		=== Evaluation on test set ===		=== Evaluation on test set ===	
Time taken to test model on supplied test set: 0.04 seconds		Time taken to test model on supplied test set: 0.05 seconds		Time taken to test model on supplied test set: 0.04 seconds	
Summary		Sunnary		=== Summary ===	
Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error	0.0132 1.0397 1.2066 127.3196 % 122.3803 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0057 0.8207 1.0128 104.3681 % 102.5487 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0161 0.8164 1.0089 103.8266 % 102.155 %
Total Number of Instances Time taken to build model: 3.5 se	13165		13165	Time taken to build model: 3.85	
=== Evaluation on test set ===		Time taken to build model: 6.92 seconds			
		=== Evaluation on test set ===		=== Evaluation on test set ===	
Time taken to test model on supplied test set: 0.06 seconds		Time taken to test model on supplied test set: 0.06 seconds		Time taken to test model on supplied test set: 0.06 seconds	
Summary		Summary		Summary	
Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0139 0.8905 1.1242 108.5577 % 112.9492 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.011 6.8917 1.1258 108.6956 % 113.1116 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	-0.0053 1.2522 1.4862 156.3339 % 148.9437 %
Time taken to build model: 6.92 seconds		Time taken to build model: 3.83 seconds		Time taken to build model: 6.79 seconds	
=== Evaluation on test set ===		=== Evaluation on test set ===		Evaluation on test set	
Time taken to test model on supplied test set: 0.03 seconds		Time taken to test model on supplied test set: 0.04 seconds		Time taken to test model on supplied test set: 0.06 second	
Sunnary		=== Summary ===		Sunmary	
Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0115 1.2486 1.4827 155.8938 % 148.5917 %	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0052 0.9172 1.1074 115.8729 % 112.3649 % 13165	Correlation coefficient Mean absolute error Root mean squared error Relative absolute error Root relative squared error Total Number of Instances	0.0359 0.916 1.106 115.7271 % 112.2161 %

The correlations almost don't exist as they not even reach a value of 0.1. Interestingly, the MAE is even higher than for the linear regression. This is obviously the case for **configurations 3, 4, 9, 10, 11, 12** which reach all at least a MAE of 0.9. Because the signal values are z-score normalized, most of the values range from -3 to 3. Therefore, a MAE of 0.9 is relatively high as it describes the mean distance between prediction and ground truth. For these the y-axis of both devices or the z-axis of the device A should be predicted. The MLP seems to struggle with this even harder. For further hyper-parameter modifications the configurations with a MAE lower than 0.8 are considered.

configuration 1: MAE = 0.7848 | configuration 2: MAE = 0.7801

learningRate:

 $0.1 \rightarrow 0.798 \quad 0.8059$

 $0.2 \rightarrow 0.7986 \ 0.7915$

 $0.4 \rightarrow 0.7831 \, 0.7774$

 $0.5 \rightarrow 0.7784 \ 0.7781$

 $0.6 \rightarrow 0.7793 \ 0.7781$

momentum:

 $0.0 \rightarrow 0.7809 \ 0.7825$

 $0.1 \rightarrow 0.7794 \ 0.7789$

 $0.3 \rightarrow 0.7781 \ 0.7795$

 $0.4 \rightarrow 0.7781 \ 0.7865$

 $0.5 \rightarrow 0.7782 \ 0.7968$

hiddenLayers:

 $1 \rightarrow 0.7781 \ 0.7777$

 $3 \rightarrow 0.7781 \ 0.7774$

 $6 \rightarrow 0.7781 \ 0.7774$

 $12 \rightarrow 0.7781 \, 0.7773$

trainingTime:

 $10 \rightarrow 0.7781 \ 0.7776$

 $100 \rightarrow 0.7781 \ 0.7773$

 $600 \rightarrow 0.7781 \ 0.7774$

decay = True \rightarrow 0.7806 0.7812

Final MAE: **0.7781 0.7773**

best performing configurations:

After hyper-parameter modification **configuration 1**'s MAE improves by 0.0067 and **configuration 2**'s MAE enhances by 0.0028. Also here it becomes clear that this is only a minimal improvement. The strength of MLP is it to learn by combining features. However, this task doesn't really seem to be suited for it as configuration 2 with its three feature inputs is minimally better than configuration 1 which only has X1 as variable input.

worst performing configurations:

Configurations 3, 4, 9, and 10 all reached a MAE of higher than 1.0. Therefore, these are the worst performing method-configuration combinations of the whole report. The z-score normalized values have a standard deviation of 1. These configurations have a mean distances between prediction and ground truth of even higher than one standard deviation. They are also the worst performing configurations of linear regression. They all have in common that they try to predict the y-axis. Figure 1 tells that the y-axis represents the distance to the ground for the set upright devices. During walking the height change to the ground could be relatively small. The acceleration along the y-axis could be minimal. Therefore it can be difficult to predict the small changes. That could

become even harder as the arm and leg don't move synchronized like it was explained in the gaussian process section.

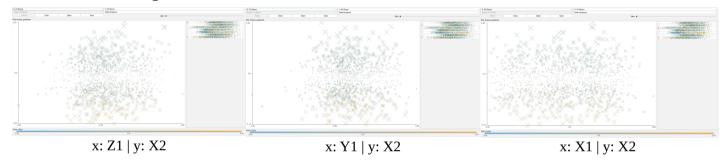
Visualizations

In this section the three different models are compared for configuration 2.

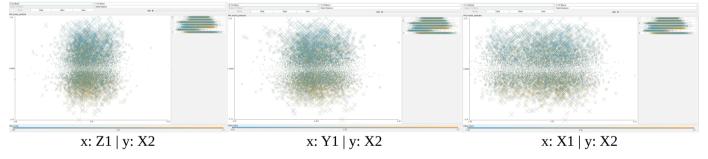


 $x: Z1 \mid y: X2 \\ x: Y1 \mid y: X2 \\ x: X1 \mid y: X2$

Gaussian Process Regression



MLP



All the plots show that one signal axis of device A is not enough to split the x-axis of device B into several intervals and therefore successful prediction on point cannot work.

Summary

The overall **best performing** configuration is achieved by the **gaussian process regression** method with the usage of **configuration 2 with a MAE of 0.6425**. The **worst** case happens for **MLP configuration 9 with a MAE of 1.2522**. Both MAE score aren't impressive in their performance. However, they differentiate by 0.6097 which is a massive gap for z-score normalized values. It follows that the configuration and method choice has a huge impact on the prediction performance.

References

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