

# Transportation Mode Classification from Smartphone Sensors via a Long-Short-Term-Memory Network

**Björn Friedrich\***

Carl von Ossietzky University  
Oldenburg, Germany

**Andreas Hein**

Carl von Ossietzky University  
Oldenburg, Germany

**Benjamin Cauchi\***

OFFIS e.V.  
Institute for Information Technology  
Oldenburg, Germany

**Sebastian Fudickar**

Carl von Ossietzky University  
Oldenburg, Germany

## ABSTRACT

This article introduces the architecture of a Long-Short-Term-Memory network for classifying transportation-modes via smartphone data and evaluates its accuracy. By using a Long-Short-Term-Memory with common preprocessing steps such as normalisation for classification tasks an F1-Score accuracy of 63.68 % was achieved with an internal test dataset.

We participated as team "GanbareAMT" in the "SHL recognition challenge".

## KEYWORDS

Supervised Machine Learning; LSTM; Mode of Transportation; Classification; Inertial; IMU; Phones

## 1 INTRODUCTION

Knowledge about the specific modes of transportation in urban areas are very important. More and more people are moving to urban areas and stress traffic infrastructure and especially the means of mass transportation. Knowledge about the mode of transportation and the flow of people inside a traffic system is important for optimising the traffic system, traffic control, travel behaviour research and the recommendation of travelling routes and means of transportation for people themselves.

Such information is typically collected via questionnaires and phone-surveys. However, these methods are time consuming and expensive - since requiring manual labor. Since smartphones are omnipresent it is reasonable to use the data collected by smartphone-sensors to identify mode of transportation.

Thus, the recognition of transportation modes is a relevant step to enhance the contextual knowledge of user, as required for behavioural investigations and characterisation of the users physical activity level, among others. With over 700 hours of annotated data covering 8 transportation modes, which have been recorded by 3 participants, the "Sussex-Huawei Locomotion- Transportation (SHL) dataset"

[2, 7] represents a milestone for the development and training of algorithms for locomotion analysis via mobile devices. Due to its coverage of multiple sensor-types (such as inertial sensors, magnetometer and GPS) and wearing positions it is well suited to compare the accuracy among algorithms transportation mode classifiers and sensor-modalities.

By setting up the Sussex-Huawei locomotion machine learning/data science challenge 2019, Roggen and colleagues challenge define a venue to compare the efficiency of various approaches to classify 8 modes of locomotion and transportation via inertial data from smartphone-integrated sensory. Thereby, the variation of sensor placement on various body-parts among training-set and test-set is foreseen as the main challenge. Since previously studies have indicated that the classification of movements via inertial data is mainly dependent on sensor-placement [5].

The article at hand introduces one training network, that has been proposed for the challenge we participated in as team "GanbareAMT".

## 2 RELATED WORK

Large scale datasets for working with mode of transportation tasks are rare. One of the largest ones is the Microsoft Asia Geolife Trajectory dataset. The data has been collected over four years with 178 users [9]. With a variety of sensor models being used, the dataset only contains GPS data and therefore it is not comparable to the dataset for the challenge. As pointed out in [7] various sensor-types, features, signal-preprocessing methodologies and machine learning (ML) methods have been shown to be suitable for transportation mode and human activity recognition. The comprehensive summary shows that besides the classic algorithms like Support-Vector-Machines and k-Nearest-Neighbours deep learning techniques have been used as well. Even though the suitability to classify human activity recognition on IMU data via Recurrent Neural Networks and Long-Short-Term-Memory (LSTM) networks are confirmed [8], they have not been considered in the review.

\*Both authors contributed equally to this research.

E.g. Zebin et al. acquired 92 % accuracy by classifying eight different human activities via LSTM for IMU data [8]. Since, the accuracy of such classifier networks be most meaningful evaluated on a common dataset, the article at hand aims to evaluate the suitability of LSTM-based network on the Sussex-Huawei Locomotion-Transportation (SHL) dataset.

### 3 DATASET

The "Sussex-Huawei Locomotion-Transportation (SHL) dataset"[2, 7] features a great amount labeled data. The data has been collected by 3 participants each carrying in parallel HUAWEI Mate 9 smartphones at 4 different body-positions (hips, bag, torso and hand). The resulting 2800 hours of annotated data. The data of the accelerometer, gyroscope, magnetometer and an ambient pressure sensor included in the smartphone, as well as the orientation in quaternions, the gravity and the linear acceleration were provided for this challenge. The IMU sensors' sampling rates is around 100 Hz.

The challenge-dataset represents a selected subset of the SHL dataset. Herein, the data was divided into 5 second blocks (each consequently covering 500 data points). For the training and development set, the activities within the 500 labels might alter per sample-block, while in the test-set each block seams to contain labels for only one activity.

Among the datasets made available in the session, the following speciality of the included sensor position, is relevant - representing the fact, that the challenge wants to evaluate the transferability of trained samples for other conditions. The challenge dataset features the accelerometer, gyroscope, magnetometer, orientation, gravity, linear acceleration and ambient pressure. The training set contains data of the smartphones located at the bag, torso and hips. The validation set contains not only data of the bag, torso and hip, but also from the phone carried in the hand. In contrast, the test set comprises data of the hand only - the intended evaluation position.

While the general dataset holds various labels, for the given challenge only eight labels considering the transportation mode (namely "Still", "Walking", "Run", "Bike", "Car", "Bus", "Train" and "Subway") are relevant, and thus, considered.

The label-distribution in the given dataset (considering training and validation dataset) is imbalanced as shown in Figure 1. Herein sample-blocks in which labels varied, the label for the sample-block was determined per majority decision - an approach which appears appropriate since for the considered dataset - in this rare condition of varying activities, typically over 90% belonged to one label type.



Figure 1: This figure shows the distribution of the labels in the dataset. The validation set contains data of the hand only.

### 4 DATA PROCESSING PIPELINE

Since the challenge aimed at training on the phones placed at bag, torso and hip, while predicting on the data of the phone in the hand we combined the corresponding data in the training and validation set. Therefore, our training set comprises of the data of the 3 phones and our validation of the data of the phone carried in the hand as summarized in Table 1.

In order to overcome the dataset's imbalance, the dataset was balanced among the classes by under-sampling (that is by excluding samples for over-represented classes until a balance is achieved). The combined use of under-sampling and oversampling (via duplication of "Ru" class samples) for the training- and validation-set was as well considered but did not show convincing results.

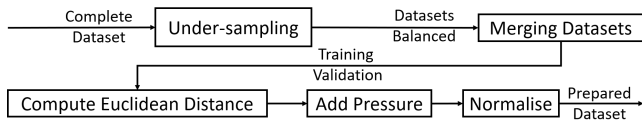
We are using all raw-data features provided in the dataset except for gravity and orientation, resulting in acceleration  $(x, y, z)$ , gyroscope  $(x, y, z)$ , magnetometer  $(x, y, z)$ , "linear acceleration" and pressure. We are calculating the activation as a single input feature over sensors as the sum of the Euclidean distance over all three axis per sensor by equation

$$\sum_{i=0}^4 \sqrt{x_i^2 + y_i^2 + z_i^2} + p$$

where  $i$  denotes the sensor. Thereby, each datum in a sequence is composed of all sensor data available for that specific measurement time. The data in the validation and test set are not consecutive in time. Hence, the window size is limited to 5 seconds. We are using a window size of 1 second, so that one sample is of shape  $5 \times 100$ . In terms of a LSTM input we have 100 features and 5 time steps. Before fed to the

**Table 1: Sample distribution for the sensor-placement among training, development and test-data set: An equal distribution among the considered classes of transportation-mode has been assured via under-sampling.**

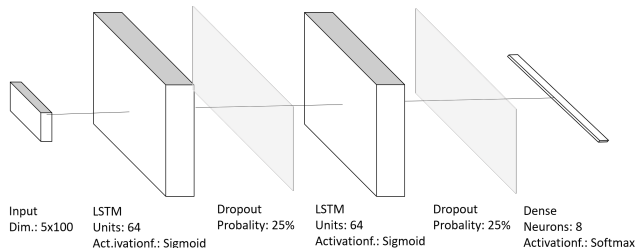
| Type       | Total samples | Sample distribution among placement |              |              |               |
|------------|---------------|-------------------------------------|--------------|--------------|---------------|
|            |               | Hip                                 | Bag          | Torso        | Hand          |
| Training   | 209280        | 69760 (33 %)                        | 69760 (33 %) | 69760 (33 %) | -             |
| Validation | 2136          | -                                   | -            | -            | 2136 (100 %)  |
| Test       | 55811         | -                                   | -            | -            | 55811 (100 %) |



**Figure 2: Our preprocessing pipeline is composed of 5 steps. The superficial samples have been removed and the data was merged from the different positions. Afterwards, the Euclidean distance is computed per sensor and pressure is added. Finally, the summarised datum is normalised.**

network, the dataset is normalised within a range of  $(-1, 1)$ . Figure 2 depicts the resulting 5 steps of our preprocessing pipeline.

## 5 NETWORK ARCHITECTURE



**Figure 3: This figure shows the architecture of our two layer LSTM network. Due to the basic principle of LSTMs even this small network has 51720 trainable parameters.**

A LSTM network has been used, due to its shown suitability for temporal data. LSTMs are not prone to the vanishing gradient or exploding gradient problem compared to common recurrent neural networks [1, 3].

Our architecture is composed of two LSTM layers and two dropout layers. On top a classification layer with eight neurons for the eight classes was added. Both LSTM layers consist of 64 neurons each and are activated by a Sigmoid activation function. The dropout layers have a probability of 25 % for dropping a neuron. The classification layer uses the Softmax function. The resulting network has overall 51720

trainable parameters and its architecture is shown in Figure 3.

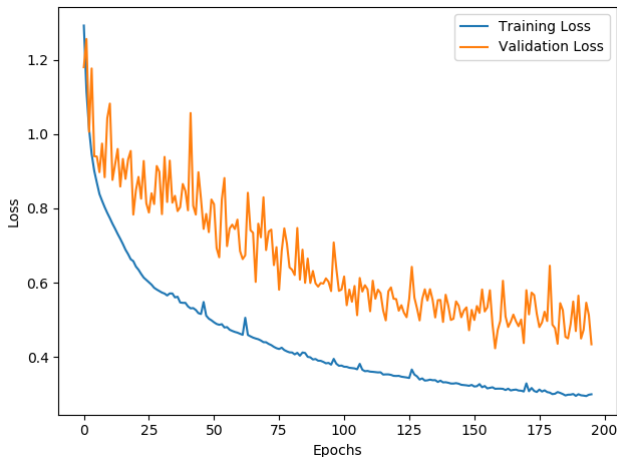
## 6 TRAINING

The resulting LSTM was trained for 197 epochs with the checkpoint saving condition to best, so that a checkpoint is saved, if there is an improvement in the validation accuracy. Finally, the most accurate configuration among all epochs is used. The ADAM optimizer [4] is used with the categorical-crossentropy loss function and the corresponding Categorical Accuracy metric, due to the classification task with eight classes. We performed the experiments on a NVIDIA TITAN V GPU with 12GB of VRAM as external GPU which was connected via a 40 GBit/s Thunderbolt3 connection - with each training epoch takes approximately 32 minutes. The final training was conducted on a NVIDIA Tesla P-100 with 16GB of VRAM where each training epoch takes approximately 40 minutes. The graphics card is in a node of a high-performance computing facility. We reserved 120GB of RAM and one Intel Xeon CPU with 12 cores at 2.2GHz as well.

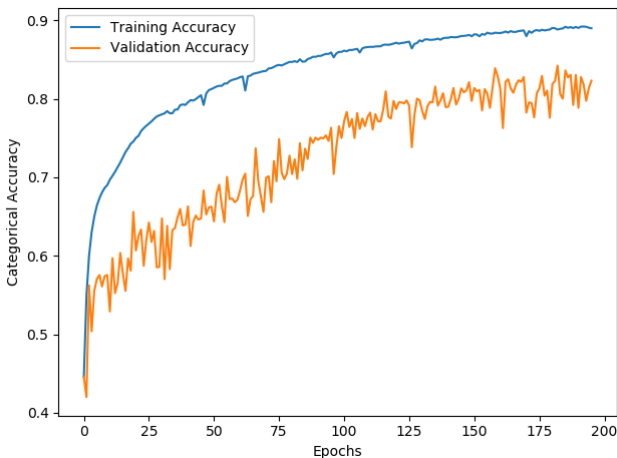
## 7 RESULTS

Figure 4 shows the progress of the loss over training time or epochs. The training loss shows a steep decrease over the first 125 epochs. After epoch 125 the loss is still decreasing, but much slower. The training loss is steadily decreasing except for a few epochs where we can see some small outliers. The loss on the validation set is steadily decreasing as well, but shows much more fluctuations. The progress of the accuracy goes with the progress of the loss. We see some small outliers at the same epochs. The training accuracy is steadily increasing, where the validation accuracy shows fluctuations while increasing over all.

For our prediction on the test set we used the epoch 183 with the best validation accuracy. At this epoch the training and validation loss were 0.3058 and 0.4357 and the accuracy 88.82 % for training and 84.22 % for validation. The predictions on the test set took about 143 seconds on the high-performance computing cluster. The 197 epochs for training took about 4



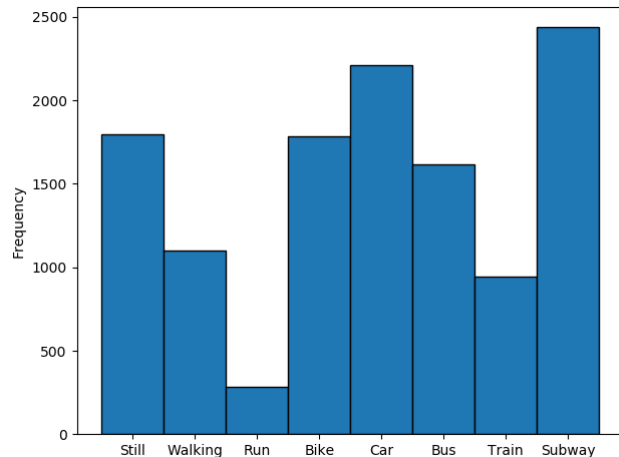
**Figure 4:** This figure shows the progress of the loss over training time. We see an asymptotic behaviour after epoch 175.



**Figure 5:** This figure shows the progress of the Categorical Accuracy over training time. In compliance with the loss there is an asymptotic behaviour after 175 as well.

days 4 hours 26 minutes 30 seconds on the cluster. The classification time of the test set was about 143 seconds. Figure 6 shows the distribution of the labels on the classified test set. There are only a few similarities to the distribution in the training and validation set. We can see, that the class "Run" seems to be under-represented as in the other sets and the difference between "Bike" and "Bus" is nearly the same as in the training set. The class "Subway" seems to be over-represented.

The confusion matrix (table 2) is computed on the unbalanced hand data of the validation set. Most false classification



**Figure 6:** This figure shows the distribution of the labels on the classified test dataset. We can see some similarities between the class "Run" of the distributions in the training and validation set. It seems there are too many samples in the "Subway" class.

occurred for "Train" being classified as "Subway". On the one hand this seems reasonable, because the movement characteristics of these activity-pairs are similar and thus challenging the differentiation of the activities based on the considered input features. On the other hand, the amount of samples of "Subway" classified as "Train" is very small. Moreover, we see a few false classifications as "Still" in all classes except for "Bike". This might happen, because all other means of transportation are frequently pausing for some time (e.g. on traffic lights or subway stations) and might switch over to a Still movement pattern during these times.

## 8 CONCLUSIONS

The article introduces the submission of the team "GanbareAMT" for the SHL challenge 2019. In order to classify the mode of transportation (differentiating eight transportation modes) using smartphone-sensors, an LSTM network was trained via data-samples recorded on the hip, in a backpack and at the torso. Regarding the sensitivity, the network achieved an F1-Score accuracy of 63.68 % on the hand data of the validation set. The recognition result for the testing dataset will be presented in the summary paper of the challenge [6].

## ACKNOWLEDGMENTS

This work has been conducted as part of the projects AudioPSS and Safety4Bikes funded by the Federal Ministry of Education and Research under grant number 02K16C201 and 16SV7668.

Moreover, we gratefully acknowledge the support of NVIDIA

**Table 2: Confusion matrix summarising the performance on the unbalanced hand data of the validation set.**

|         | Still | Walking | Run | Bike | Car  | Bus  | Train | Subway |
|---------|-------|---------|-----|------|------|------|-------|--------|
| Still   | 1339  | 12      | 0   | 171  | 56   | 33   | 45    | 81     |
| Walking | 15    | 1057    | 16  | 477  | 19   | 14   | 3     | 8      |
| Run     | 0     | 2       | 262 | 2    | 0    | 1    | 0     | 0      |
| Bike    | 61    | 6       | 1   | 683  | 205  | 32   | 1     | 4      |
| Car     | 93    | 2       | 1   | 209  | 1292 | 289  | 38    | 62     |
| Bus     | 86    | 16      | 2   | 176  | 420  | 1168 | 62    | 37     |
| Train   | 100   | 2       | 0   | 31   | 65   | 48   | 628   | 920    |
| Subway  | 105   | 4       | 0   | 38   | 153  | 31   | 167   | 1326   |

Corporation with the donation of the TITAN V GPU used for this research.

## REFERENCES

- [1] F. A. Gers, J. Schmidhuber, and F. Cummins. 1999. Learning to forget: continual prediction with LSTM. In *1999 Ninth International Conference on Artificial Neural Networks ICANN 99. (Conf. Publ. No. 470)*, Vol. 2. 850–855 vol.2. <https://doi.org/10.1049/cp:19991218>
- [2] Hristijan Gjoreski, Mathias Ciliberto, Lin Wang, Francisco Javier Ordonez Morales, Sami Mekki, Stefan Valentin, and Daniel Roggen. 2018. The university of sussex-huawei locomotion and transportation dataset for multimodal analytics with mobile devices,. *IEEE Access* 6 (23 July 2018), 42592–42604.
- [3] Sepp Hochreiter and Jürgen Schmidhuber. 1997. Long Short-Term Memory. *Neural Computation* 9, 8 (1997), 1735–1780. <https://doi.org/10.1162/neco.1997.9.8.1735> arXiv:<https://doi.org/10.1162/neco.1997.9.8.1735>
- [4] Diederik P. Kingma and Jimmy Ba. 2015. Adam: A Method for Stochastic Optimization. *CoRR* abs/1412.6980 (2015).
- [5] K. Kunze and P. Lukowicz. 2014. Sensor Placement Variations in Wearable Activity Recognition. *IEEE Pervasive Computing* 13, 4 (Oct 2014), 32–41. <https://doi.org/10.1109/MPRV.2014.73>
- [6] L. Wang, H. Gjoreski, M. Ciliberto, P. Lago, K. Murao, T. Okita, and D. Roggen. 2019. Summary of the Sussex-Huawei locomotion-transportation recognition challenge 2019. *Proc. HASCA 2019*.
- [7] L. Wang, H. Gjoreski, M. Ciliberto, S. Mekki, S. Valentin, and D. Roggen. 2019. Enabling Reproducible Research in Sensor-Based Transportation Mode Recognition With the Sussex-Huawei Dataset. *IEEE Access* 7 (2019), 10870–10891. <https://doi.org/10.1109/ACCESS.2019.2890793>
- [8] Tahmina Zebin, Matthew Sperrin, Niels Peek, and Alex Casson. 2018. Human activity recognition from inertial sensor time-series using batch normalized deep LSTM recurrent networks. In *IEEE EMBC*. <https://doi.org/10.1109/embc.2018.8513115>
- [9] Yu Zheng, Hao Fu, Xing Xie, Wei-Ying Ma, and Quannan Li. 2011. *Geolife GPS trajectory dataset - User Guide* (geolife gps trajectories 1.1 ed.). <https://www.microsoft.com/en-us/research/publication/geolife-gps-trajectory-dataset-user-guide/> Geolife GPS trajectories 1.1.