Aalto Data Science Hackathon — Final Report

ViBE: Visual Bus Data Exploration Tool

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1 Introduction

This project was done as part of Aalto Data Science Hackathon[2] during April 24 – April 26, 2015. The hackathon offered three tracks of which we chose the Smart Cities track. Helsinki Regional Transport Authority (HSL) had prepared a dataset of all bus traffic from Helsinki region from the past year for this track.

The HSL dataset could be used to address various interesting questions, such as: *Where are delays formed? What kind of daily/weekly patterns the bus traffic follows? Can we observe cascade effects caused by unexpected events?* Nevertheless, we decided that before diving deep into complex analyses, a tool for visualizing the results should be developed. This lead us to design and implement a tool called Visual Bus Data Exploration Tool (ViBE), which is available online at:

`http://asolin.github.io/aalto-data-science-hackathon/`

First, we present the HSL dataset in Section 2. Second, in Section 3, we briefly introduce the technologies used in ViBE, and third, we present the results and draw conclusions in Sections 4 and 5.

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[2]`http://datasciencehackathon.cs.hut.fi/`

2 Data

The HSL dataset[3], provided by the Helsinki Regional Transport Authority contains all bus traffic from the Helsinki region between January 1, 2014 and April 5, 2015. The data follows a CSV format where each row represents a stop made by a single bus and the 53 columns in a row contain various information, including:

- bus number
- stop ID
- arrival time
- departure time
- scheduled departure time

In total, there are 211 million rows in the data and they occupy 46 GB when stored in an SQLite database.

3 Methods

3.1 Front-end

The front-end of ViBE is implemented using JavaScript and Google Maps API. The website design was inspired by the `http://www.auratkartalla.com/` web page.

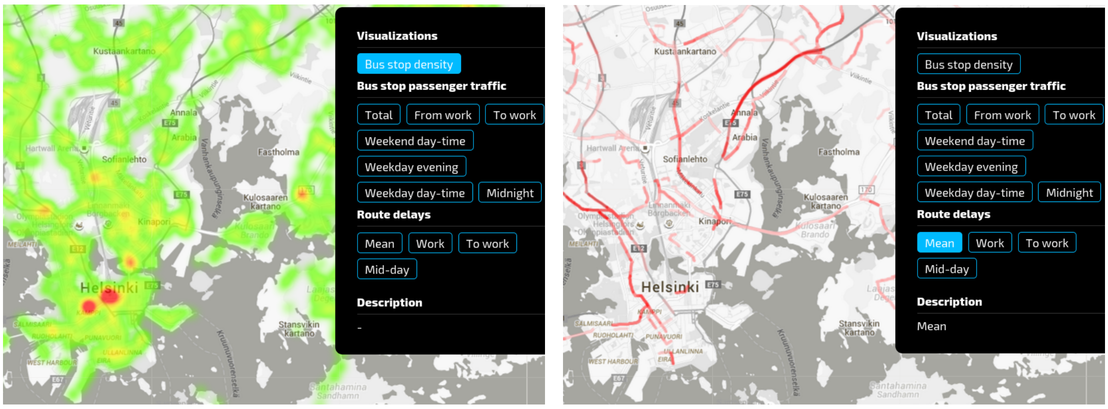
ViBE features two different visualization modes, both having a map in the background. The first mode shows a heat map of bus stops associated with some quantities. By setting the quantities to one, we obtain simply the density of bus stops, whereas by setting them to the cumulative time different buses have spent at the stop, we can estimate the passenger volumes in different parts of the Helsinki region (direct passenger information is not included in the HSL dataset due to privacy issues). The second mode colors the routes between consecutive stops based on some associated quantities, for example, the average delays at the end of the routes with respect to the scheduled passing times. These two modes are illustrated in Figure 1.

A Git repository for the project can be found at:

`https://github.com/asolin/aalto-data-science-hackathon`

which contains the front-end code under the `site` directory.

[3]Data is available at: `http://dev.hsl.fi/ajoaika_gps/`



(a) Bus stop density. (b) Average route delay.

Figure 1: Two visualization modes illustrated. **(a)** Bus stop density. **(b)** Average delay at the end of the route when comparing the actual and the scheduled passing time.

3.2 Back-end

We have stored the HSL dataset into an SQLite database in order to be able to compute the required quantities efficiently. Summary statistics, such as the cumulative time spent per bus stop, can be computed by executing simple SQL queries. However, one such query for the whole dataset takes about 10 minutes to complete.

The back-end is implemented in Python, and the database is accessed from the code using the SQLAlchemy package. The code is available in file `bus_queries.py` under `src` directory.

The website is static and it reads precomputed quantity data from a file in JSON format. It should be relatively easy to make the website dynamic using some Python web framework, like Flask, but due to the relatively long querying times, we implemented a simple static website as it would not have been real-time in any case. If one wanted to make a dynamic website which loads the data without too much lag, one could limit the time frame so that not each row of the database would need to be aggregated.

3.3 Spatio–temporal analysis with matrix factorization

Instead of merely analyzing spatial patterns, we also want to visualize spatio–temporal patterns found in the data. One solution would be to animate maps over time, but we chose to use matrix factorization techniques as the results are easy to visualize using the static visualization tools we have already presented.

First, we build a stop time matrix whose values correspond to the cumula-

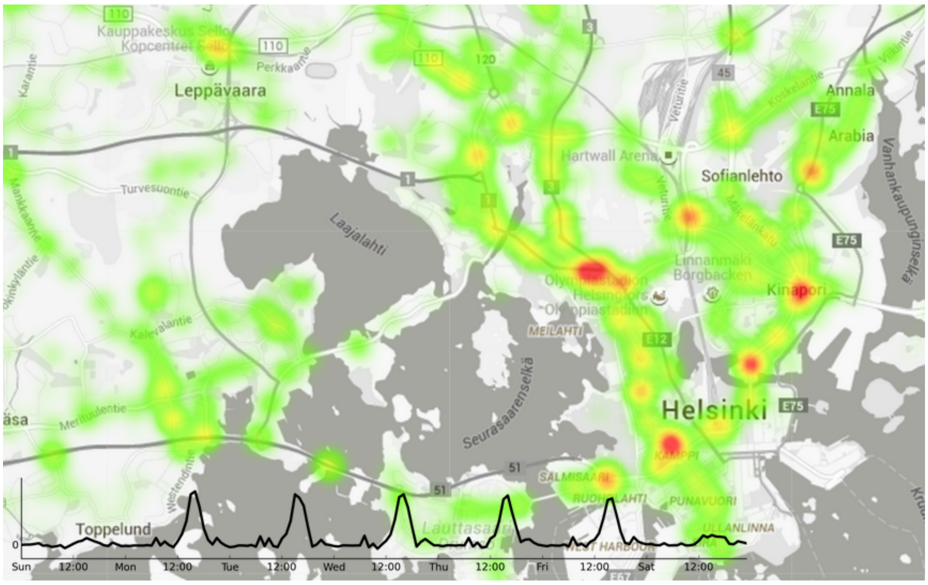


Figure 2: The first NMF component visualized as a heatmap and its strength at different hours of the week. The component corresponds to the time when people return from work.

tive time spent at a given stop (column) and at a given week of the hour (row). This gives us a 168×6490 matrix. Since the values of the matrix are always non-negative, we factorize the matrix using non-negative matrix factorization (NMF). This allows us to summarize the matrix by taking k leading components, which represent distributions over different bus stops, and the strengths of these components at different hours. The first NMF component is visualized in Figure 2.

Similarly, we compute a route delay matrix which contains the average delay at the end of a route between two bus stops. The delays can also be negative if the bus is ahead of its schedule. Therefore, we conduct the matrix factorization using the principal component analysis (PCA).

The matrix factorization related code is available in file `pca.py` under `src` directory.

4 Results

4.1 Spatio–temporal analyses

By visualizing the stop times, we were able to approximate relative passenger volumes stepping in or stepping out of the bus at different parts of the Helsinki region. The results were not too surprising; large terminal points, such as the city centre, Leppävaara station, and Herttoniemi metro station, have large volumes, probably partly because of the multitude of nearby stops located in these areas.

The first NMF components were also easy to interpret; they correspond to the traffic from/to work on weekdays, weekend traffic, midnight traffic, etc. The midnight traffic is heavily concentrated to the city centre, whereas the other components spread more evenly.

The analysis of route delays also revealed clear weekly patterns. The first principal component corresponds to the morning and afternoon hours when people travel to/from work. The largest delays were exhibited in Paciuksenkatu and route E75 when going from the centre towards Viikki. The fact that the largest delays occur at peak hours in the morning and afternoon suggests that even though the bus time schedules try to take into account traffic volumes, the peak hours are not adequately accounted for.

All of these components are shown in the online demo.

4.2 Bus waiting time

The results of the visual analysis are probably most interesting to HSL and urban planners, but we also wanted to provide something for a regular passenger. One relevant question for the people who have troubles leaving for the bus stop on time is the following: *What is the probability that I have already missed the bus?*, when the person arrives to bus stop x minutes before/after the scheduled departure.

To address this question, we computed the cumulative bus missing probability given x, and averaged it over all bus stops. The resulting plot is shown in Figure 3. The plot shows that if you arrive to the stop exactly when the bus is scheduled to leave, in 26 % of the cases, the bus has already passed the stop, whereas by arriving one minute before, the bus missing probability is only 10 %.

5 Conclusions and Discussion

We have introduced a Visual Bus Data Exploration Tool (ViBE), which can be used to visualize and discover spatio–temporal patterns in the bus traffic data released by HSL. Several intuitive patterns, e.g., corresponding to people going to work, were discovered from the data. The results suggest that even though the peak hours are accounted for in the bus time schedules, the buses are still delayed at these hours.

ViBE comes with at least two limitations which the user should be aware of and which we did not have time to fix during the hackathon. First, the heatmap visualization is not suitable for all types of bus stop specific data since it "sums" the values of nearby stops. When computing cumulative stop time in order to estimate passenger volumes, as we have done in the online demo, the summation is justifiable, but in some other cases, if the user wanted to, e.g., analyze delays

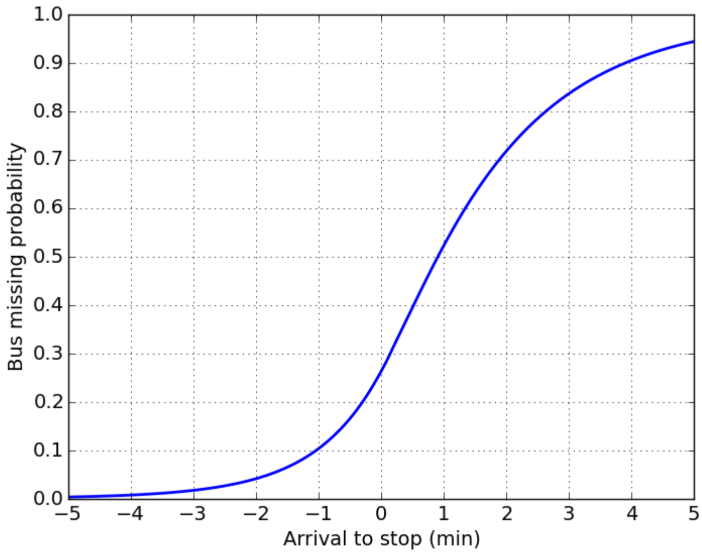


Figure 3: Bus missing probability curve.

per stop, the summation would not be meaningful, since the highest delays would be shown in areas with high bus stop concentrations.

The second limitation is that when we visualize route delays, it is not guaranteed that the delay has occurred exactly between the two stops where the colorbar is shown, since the delay is cumulative and it could have occurred already in the beginning of the bus line. To fix this, we should have computed the delay at bus stop $i + 1$ and subtracted the delay at bus stop i. However, this was not trivial to compute efficiently with our database schema.

In future, ViBE could be used for analyzing individual days. It would be interesting to see, what kind of cascade effects are caused by special events, such as accidents or events attracting large crowds which can cause significant delay spikes at a certain part of the traffic network.