## Travel time prediction for trams in Warsaw

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## Motivation

- use big data from urban infrastructure to improve quality of citizens’ life in big cities
- improve passenger travel experience
- tell passengers precisely how long their travel will take and at what time vehicle arrives
- travel time depends on many factors difficult to predict


## Warsaw trams infrastructure

| Parameter | Value |
| ---: | :--- |
| Stop groups in Warsaw | 2204 |
| Stops in Warsaw | 6296 |
| Stops groups with trams | 237 |
| Stops with trams | 568 |
| Tram lines | 26 |
| Average number of stops per line | 31.84 |
| Maximal number of stops per line | 47 (line 11) |
| Minimal number of stops per line | 9 (line 2) |
| Average line route length | 12.999 km |
| Longest line route length | 20.007 km (line 11) |
| Shortest line route length | 5.600 km (line 2) |
| Average distance between two stops on route | 447.2 m |
| Maximal distance between two stops on route | 2203.1 m |
| Minimal distance between two stops on route | 42.5 m |
| Earliest planned tram departure | $03: 32$ (line 9 on Woronicza) |
| Latest planned tram on stop arrival | $01: 31$ (line 9 on Zajezdnia Wola) |

## Data sources

- information about the official planned schedules (stops locations, routes and lines on stop planned times)
- real trams' positions from GPS transmitters (coordinates of current position sent every 15 seconds)


## GPS data source

| Parameter | Value |
| ---: | :--- |
| All logs | 993263 |
| Unique logs (unique triples [time, line, brigade]) | $861054(86.7 \%)$ |
| Logs from Warsaw territory | $991639(99.84 \%)$ <br> Average time between logs from the same tram |
| 18.2 s |  |
| Average distance traveled between logs | 71.12 m |
| Unique pairs: [line, brigade] | 305 <br> Unique pairs: [line, brigade] in schedule |
| Un5 |  |

## Travel time vs hour



Comparison between average time between all stops pairs by hour of the days for the official schedule and real travels

## Prediction methods

- current delay propagation
- historical average time travel
- artificial neural network model

Available data: historical data from previous days about trams positions and all data from current day until prediction time and current tram position

## 1. current delay propagation

- finding current vehicle delay and propagate it to next stops on planned route
- does not use any historical data
- weakness: not able to predict future problems or delay changes


## 2. historical average time travel

- use average time travel from previous couple of days as an estimator for current day times
- take into consideration historical time travels or usual road fraction traffic conditions


## 3. artificial neural network model

- multilayer perceptron with backpropagation learning method
- output value: predicted tram's time travel from stop $\mathrm{s}_{\mathrm{i}}$ to another stop $\mathrm{s}_{\mathrm{j}}$
- input:
- order number of stop $s_{i}$ in route,
- order number of destination stop $\mathrm{s}_{\mathrm{j}}$ in route,
- travel time from route's start to stop $\mathrm{s}_{\mathrm{i}}$
- time of the day.


## 3. artificial neural network model



Learning data set contains intormation from all travels on given route in last 30 days

## Experimental setup

- simulates passenger view: how long trip form particular stop to another chosen stop takes
- 1000 random tram stop pairs
- four different hours: 8:00, 12:00, 16:00 and 20:00
- measure: difference between the real travel time and predicted travel time


## Experimental results

|  | $08: 00$ |  | $12: 00$ |  | $16: 00$ |  | $20: 00$ |  | All |  |
| ---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Diff | Best | Diff | Best | Diff | Best | Diff | Best | Diff | Best |
| Official timetables | 180.53 | $36 \%$ | 172.30 | $29 \%$ | 203.61 | $25 \%$ | 166.75 | $29 \%$ | 180.79 | $30 \%$ |
| Current delay prop | $\mathbf{1 7 8 . 4 1}$ | $30 \%$ | 118.94 | $34 \%$ | 172.99 | $27 \%$ | 98.33 | $33 \%$ | 142.17 | $31 \%$ |
| Historical avg travel | $\mathbf{1 5 9 . 7 0}$ | $\mathbf{3 7 \%}$ | $\mathbf{1 0 4 . 8 0}$ | $\mathbf{4 1 \%}$ | $\mathbf{1 3 7 . 8 3}$ | $\mathbf{4 0 \%}$ | $\mathbf{8 9 . 2 5}$ | $\mathbf{4 9 \%}$ | $\mathbf{1 2 2 . 8 9}$ | $\mathbf{4 2 \%}$ |
| Neural network | 161.70 | $\mathbf{4 2 \%}$ | 138.40 | $38 \%$ | 149.92 | $\mathbf{4 4 \%}$ | 143.01 | $40 \%$ | 148.25 | $41 \%$ |

- average planned time travel was 45 minutes
- average absolute prediction error: ~2 minutes
- official timetables error: 3 minutes
- worst results were obtained in rush hours


## Experimental results

|  | Shorter | Longer |
| :--- | ---: | ---: |
| Official timetables | $57.9 \%$ | $31.1 \%$ |
| Current delay prop | $57,7 \%$ | $30.1 \%$ |
| Historical avg travel | $48.5 \%$ | $39.1 \%$ |
| Neural network | $41.0 \%$ | $38.7 \%$ |

## Conclusions

- all proposed methods outperform prediction based on the official timetables
- the best method - historical average time travel reduced prediction error from 3 minutes (for the official schedule) to 2 minutes
- time travels are longer in rush hours and more difficult to predict


## Future work

- make similar researches for buses and compare them with trams
- do comparison between delays and prediction methods during holiday week and normal week
- apply results to mobile application for passengers or improve official schedules

Thank you

