
Usage Patterns of Bicycle Counting Stations in Heidelberg and the Influence of External Factors

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Abstract

- Describe topic
- Data source (just heidelberg) and external Factors
- sentence in one method
- Results briefly

1. Introduction

- Short introduction, but more motivational, bicycle traffic more important over the years...
- Name what is interesting and why it matters
- Shortly introduce the data, and the main method

2. Data

Begin describing each dataset, DO NOT REPEAT WHAT THIS SECTION IS about.

- Cyclist data
- Describe shortly what it is and how it is physically collected, what information does it contain?
- Describe the fetching process and SOURCE AS HYPERLINK OR FOOTNOTE?
- Link to figure showing the placement in Heidelberg, evaluate the placement, describe geography, flat, etc.
- Data Sanity, show a plot for a few (or only one) station, maybe also show failures and give more information about it? PLOT: SRTATION

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- Weather data,
- Why we need this, Station data is bad, describing fetching, here we name the source
- OPTIONAL: Give comparison plot between temperatures and bad metrics as rain PLOT: WEATHERDATA
- Accident data? Not used, but need to include it
- Holiday data,
- We we need it, describe source, also name that there were some errors in the dataset, we have to be careful, ...

3. Method

Previous works often rely on predefined rules to categorize bicycle traffic (Miranda-Moreno et al., 2013). However, such an approach may fail to capture hybrid usage patterns. We propose a more data-driven, implicit approach. By extracting features that quantify the ‘shape’ of daily, weekly, and seasonal profiles, we map each station into a multi-dimensional feature space. This allows us to use unsupervised k-means clustering (Lloyd, 1982) to discover different station types.

In a subsequent step in chapter 4, we assign one of the following labels to each cluster (cf. Fig.):

- *Utilitarian*: Traffic showing strong commuting patterns, with two distinct peaks in traffic volume during the morning and afternoon hours.
- *Recreational*: Traffic dominated by leisure activities. These locations exhibit a single peak in traffic volume around midday or early afternoon.
- *Mixed*: Locations that serve a dual purpose, showing characteristics of both utilitarian and recreational usage.

To characterise the counting stations, we derive three distinct features that capture traffic patterns across different timescales: daily, weekly and seasonal to exploit the distinct pattern visible in Figure xyz .

Figure Patterns, Indices

Figure pattern

Double Peak Index (DPI)

Weekday hourly profiles of some stations exhibit a double-peak structure, typically associated with morning and evening commuting. The DPI quantifies this behaviour by identifying dominant morning (5–10 h) and evening (14–20 h) peaks and relating their magnitudes to the average midday level (8–14 h). Stations with clear, balanced commuting peaks yield high DPI values, whereas flat or single-peak profiles result in low scores.

Formally, let p_m and p_e denote the magnitudes of the morning and evening peaks at hours h_m and h_e , and let m be the average midday traffic level. The DPI is defined as

$$\text{DPI} = \max(S \cdot Y \cdot D, 0)$$

where S , Y and D models strength, symmetry and distance, respectively:

$$S = \frac{(p_m - m) + (p_e - m)}{2}$$
$$Y = 1 - \frac{|p_m - p_e|}{\max(p_m, p_e)}$$
$$D = \min\left(\frac{|h_e - h_m|}{10}, 1\right)$$

Weekend Shape Difference (WSD)

Differences between weekday and weekend hourly traffic patterns provide an additional discriminator between usage types. To capture this effect, we compare the shape of the weekday and weekend hourly profiles. Let \mathbf{p}^{wd} and \mathbf{p}^{we} denote the weekday and weekend hourly profiles, normalised to sum to one.

$$\text{WSD} = \left\| \frac{\mathbf{p}^{wd}}{\sum_h p_h^{wd}} - \frac{\mathbf{p}^{we}}{\sum_h p_h^{we}} \right\|_2$$

Seasonal Drop Index (SDI)

Finally, we consider long-term patterns. Seasonality provides a discriminator between leisure and utilitarian-oriented stations. The SDI quantifies the relative decline between high and low-usage months. Let I_m denote the monthly index values of a station. Using upper and lower quantiles to ensure robustness against outliers

$$q_{90} = \text{quantile}_{0.9}(I_m)$$
$$q_{10} = \text{quantile}_{0.1}(I_m)$$

the SDI is defined as

$$\text{SDI} = \frac{q_{90} - q_{10}}{q_{90}}$$

High values indicate strong seasonal variation, whereas low values correspond to relatively stable, year-round usage.

4. Results

- describe temporal shift, describe why this is expected and why, PLOT: city,
- describe holidays impact, describe behaviour (similar as weekend) PLOT: show shift
- include also plot of different public holidays (my own one), this is just to have a funny fact (Vater Tag) PLOT: funny plot, na werden zu viele plots
- describe weather impact, obvious PLOT: weather

5. Conclusion

- summarize
- limitations
- problems
- statements that can be made

Contribution Statement

Add this, see original template

References

Lloyd, S. Least squares quantization in pcm. *IEEE Transactions on Information Theory*, 28(2):129–137, 1982. doi: 10.1109/TIT.1982.1056489.

Miranda-Moreno, L. F., Nosal, T., Schneider, R. J., and Proulx, F. Classification of bicycle traffic patterns in five north american cities. *Transportation Research Record*, 2339(1):68–79, 2013. doi: 10.3141/2339-08. URL <https://doi.org/10.3141/2339-08>.