Thesis Draft

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Background

The Data: City of Melbourne Pedestrian Data

The City of Melbourne provides an open data platform to access council datasets, with the intention "to increase transparency, improve public services and support new economic and social initiatives"[1]. This paper will focus primarily on the pedestrian data collected from pedestrian sensors placed throughout Melbourne's CBD. In particular, we want to be able to model the pedestrian traffic at different locations in the CBD, and forecast the traffic. In addition, we aim to have an interactive, dynamic data visualisation of the model to help us to understand how Melbourne operates.

The dataset being investigated can be obtained from the official City of Melbourne's open data[2]. The pedestrian data is in the form of hourly pedestrian counts for 43 sensor locations. In total, there is 1409712 observations in the dataset, representing 26293 hours of data. It is available in `.csv` format, allowing for easy data import into R. We can also access the pedestrian data using the the `rwalkr` package by Earo Wang[3]. This package allows R to import the data from `data.melbourne.vic.gov.au` which is updated monthly, or from the data source which is used by `pedestrian.melbourne.vic.gov.au` which is updated daily.

Not even an single sensor location has complete data for the period between between 1/1/2014 and 12/10/2017.

Imputation Literature Review Notes

Reviewing current research on imputation of missing values in traffic data, a paper on imputation of missing classified traffic data during winter season (Imputation of Missing Classified Traffic Data During Winter Season - *Hyuk-Jae Roh, Satish Sharma, Prasanta K. Sahu*) stated some methods which were found to be poor for imputation. The data they were attempting imputation for were traffic counters located on the highway network in Alberta, Canada with between 40% and 60% missing data.

Replacement with "good" historical values, or using historical average values was found to have resulted in very poor fit with high MARE/MARD (mean absolute relative error/difference). They did find that using a moving average worked the best out of all the heuristic methods used. The largest problem with heuristic methods, however, is the inherent inability to reflect sudden fluctuations/shocks during abnormal periods. With such a large proportion of missing values, pattern matching methods were investigated. This involves comparing the *study curve*, the pattern at the counter which is to be imputed, to candidate patterns (patterns at other locations).

For the purposes of that paper, it was found to be inappropriate with the data being analysed. However, unlike *Roh et al.* where patterns were compared to traffic volumes in different jurisdictions (large geographical distance), the geographic distances between the sensor locations in the Melbourne CBD pedestrian data are much smaller. Another difference is the randomness of the missing values, where the periods of missing data run longer in the Melbourne CBD pedestrian data compared to that in the Alberta traffic data. They proposed using non-parametric estimation methods with k-Nearest Neighbours for their imputation, although this is unlikely to work well with the lack of data at certain sensor locations in the Melbourne CBD Pedestrian data.

[1] from *'About Melbourne Data'* page at https://data.melbourne.vic.gov.au/about

[2] the specific pedestrian data is available at https://data.melbourne.vic.gov.au/Transport-Movement/Pedestrian-volume-updated-monthly-/b2ak-trbp

[3] https://github.com/earowang/rwalkr/

Methodology: Imputation of Missing Values

Basic GLM Approach

The first method used to impute missing values is to fit generalised linear models (GLMs) at each sensor location. Estimating a GLM with a Quasi-Poisson error distribution, where specify the model as:

$$E\left[\text{HourlyCounts}|\text{Sensor}, \text{HDay}, \text{Time}\right] = \exp(\mu_{\text{Sensor,HDay,Time}})$$

$$\text{where} \quad \mu_{\text{Sensor,HDay,Time}} \sim \text{Time} \times \text{HDay} \tag{1}$$

`Time` is the time of the day, while `HDay` is the day of the week, with an additional factor level for public holidays. Both these variables are categorical/factors. We cannot treat time of the day as an integer or numeric because it does not have a linear relationship with counts.s

We use the Quasi-Poisson error distribution as opposed to normal/Gaussian errors due to the response variables being count data. The Poisson distribution allows for only non-negative integer values, while estimating a Quasi-Poisson model estimates an additional parameter for overdispersion. This allows more flexibility in the model by allowing the assumption that $E[Y] = Var[Y] = \mu$ to be relaxed. Instead, the Quasi-Poisson distribution allows for $Var[Y] = \theta\mu$.

While this works well with a small proportion of missing values, it also requires a large number of observations. Specifically, with this paramaterisation, we have $23 + 7 + (23 \times 7) + 1 = 192$ coefficients to estimate. Another disadvantage of using this model is the lack of robustness to outliers due to the sensitivity of some parameters. This becomes particularly problematic at sensor locations which have been recently installed, where there is a lack of historical data.

Small-Large Split Approach

The proposed alternative approach to imputing the missing values in the data focuses on improving the models used at locations with a large proportion of missing values. A potential threshold value which could be used to class a sensor as having a "large" proportion of missing values vs a "small" proportion of missing values is 10%. At locations with a "small" proportion of missings, we can continue to use the GLM quasi-possion regression specified in (1). At the locations with a large proportion of missing values, we need to use information from neighbouring sensors.

The first issue which needs to be addressed is the potential of values which are actually missing due to sensor failure or malfunction having a zero count. This issue will cause bias in the estimates, as well as affect the classification of a sensor. Of course, we cannot simply classify all zero counts as `NA`, as true zero values are possible.

Table 1: Summary statistics of the sequence lengths of repeated values

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
2	2	2	16.98	2	19967

Instead, a simple check we can implement is to look for long sequences of zero counts. For example, we may want to classify any sequence of `Hourly_Counts = 0` running for longer than 24 hours as being considered `NA`. From the summary of lengths of repeated values (which are repeated at least once), we see that the distribution of the lengths are very positively skewed with a mean length of 16.98 hours of missing data. Classifying any sequence of repeated values, typically 0, which has a length greater than 6 as `NA` should allow true zero counts to avoid being misclassified as `NA`. We select the length of 6 hours as it would be unreasonable to assume any sensor location to have the exact same number of pedestrian counts over such a long period.

After we have replaced questionable zero values with the value `NA`, we can calculate the proportion of missing values for each sensor location. From these calculated proportion, we can classify sensors as either having a "large" or "small" proportion of missing values, where large is defined as $\texttt{NAprop}_{sensor} > \texttt{threshold}$ and `threshold = 0.1`.

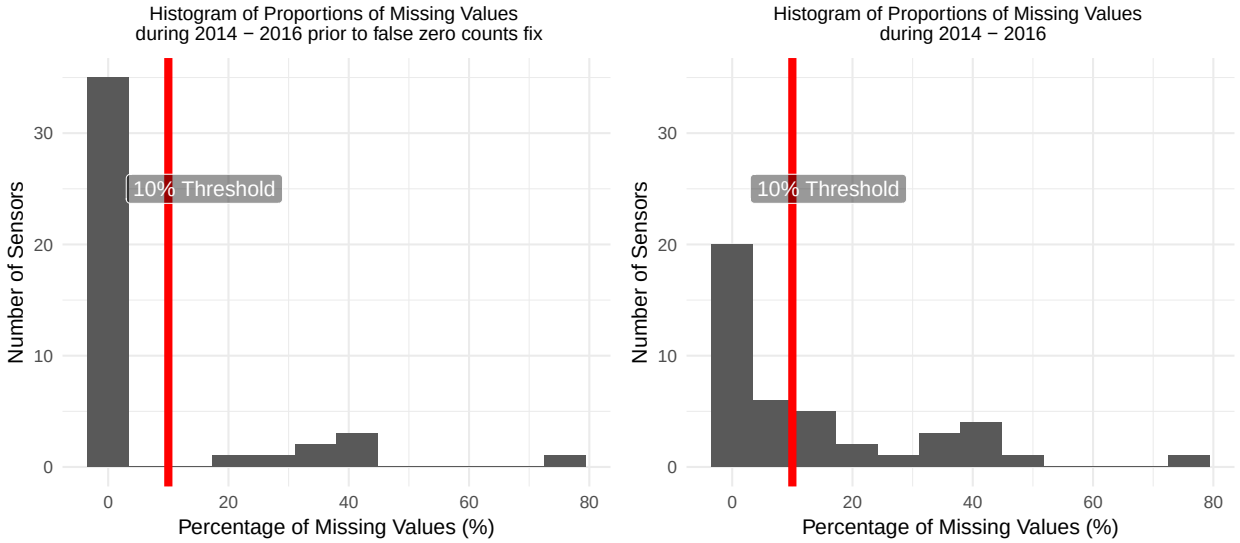


Figure 1: Comparison of distribution of proportion of missing values at each sensor is significantly different after correcting for false zero counts in the data

Because the models for the sensors with a large proportion of missing values rely on having neighbouring sensors having complete cases (no missing values), we want to impute these values first. This will then allow us to have as much information to be available for the models which use neighbouring sensors to to train on.

For sensors with a small proportion of missing values, we use a GLM quasipoisson model. To improve on the previous model used, we use the model:

$$E\left[\text{HourlyCounts}|\text{Sensor}, \text{Month}, \text{DayType}, \text{Time}\right] = \exp(\mu_{\text{Sensor},\text{Month},\text{DayType},\text{Time}})$$

$$\text{where} \quad \mu_{\text{Sensor},\text{Month},\text{DayType},\text{Time}} \sim \text{Month} + \text{Time} \times \text{DayType} \tag{2}$$

Instead of `HDay`, we use `DayType` which classifies Tuesday, Wednesday and Thursday as a single factor level, Midweek. We do this as the daily patterns on these weekdays are similar. This reduces the number of parameters to estimate by 46. A result of this is we also have more robust estimates for the midweek days, being less sensitive to outliers. Because this model will be estimated for sensor locations with few missing values, we have enough data to add in month as an additive effect. This will help capture the annual seasonality.

Using these estimated models, we impute the missing values to produce complete data at all these sensor locations. For the locations with high proportions of missing values can be predicted using the now complete data from all the locations which had a small proportion of missing values. Using a threshold of 10%, this gives us 25 sensor locations to use.

For each of the sensor locations with high proportions of missings, we need to decide which sensor to use for prediction. A simple method of finding a geographical closest neighbour is to take the haversine/great-circle distance between the sensor to be imputed and all the possible candidates.

Using the two geographically closest sensors with complete cases, we use another GLM specified as:

$$E\left[\text{HourlyCounts}_{\text{sensor}}|\text{Time}, \text{HourlyCounts}_{\text{neighbours}}\right] = \mu_{\text{Time},\text{HourlyCounts}_{\text{neighbours}}}$$

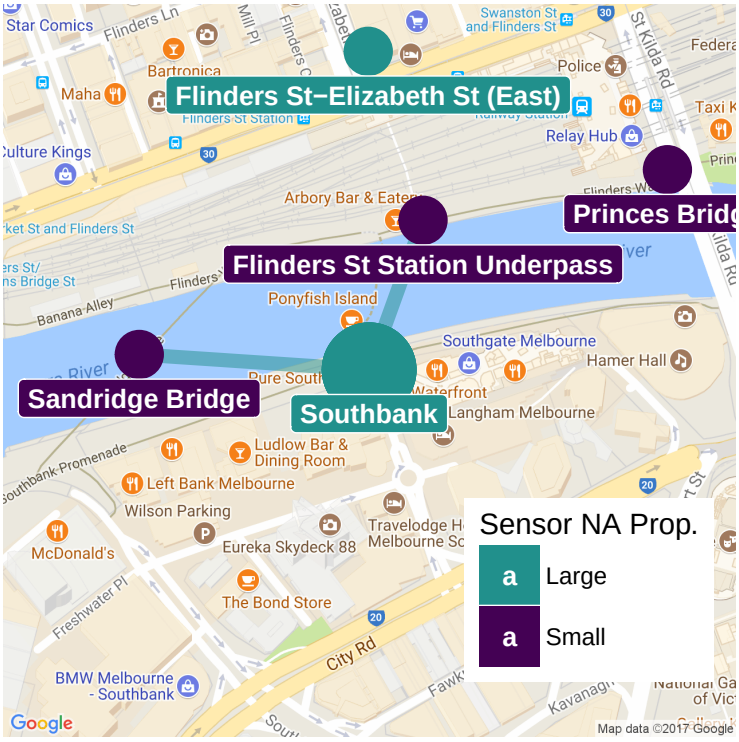
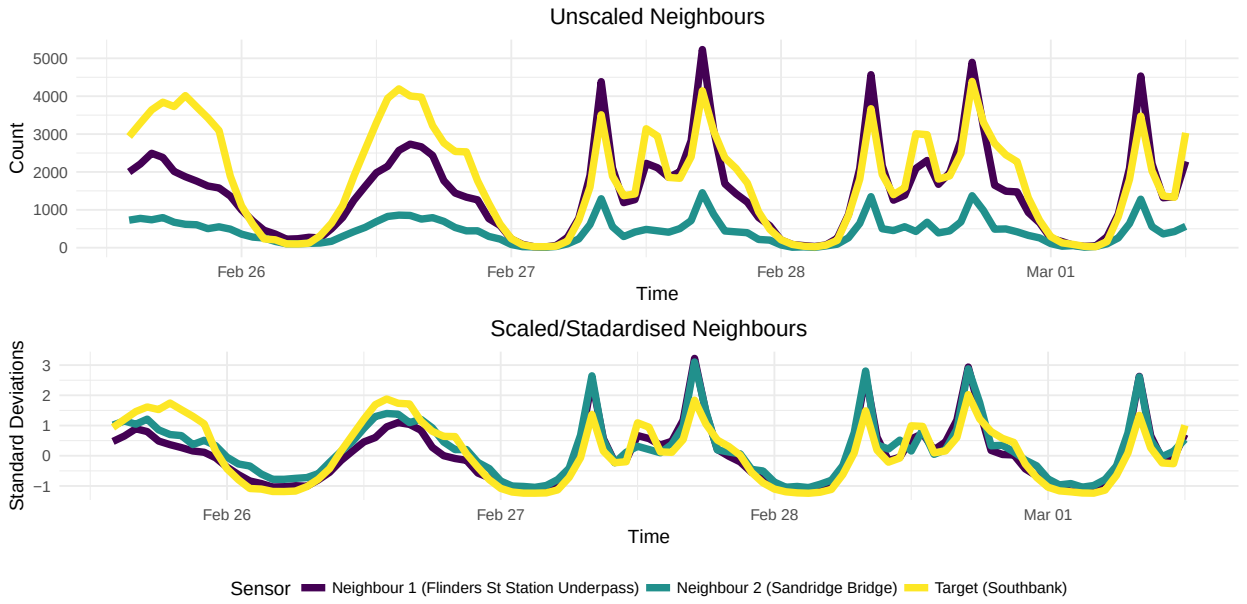


Figure 2: Map showing the algorithm selecting Flinders St Station Underpass and Sandridge Bridge as neighbours to be used to predict the pedestrian counts at Southbank

$$\text{where} \quad \mu_{\text{Time,HourlyCounts}_{\text{neighbours}}} \sim \text{Time} \times \text{HourlyCounts}^{SC}_{\text{neighbour 1}} + \text{Time} \times \text{HourlyCounts}^{SC}_{\text{neighbour 2}}$$

We would expect that the amount of people passing through the neighbouring sensors will be a strong predictor of the pedestrian counts as they are likely to also pass through. Using geographical neighbours, we can capture rare events effectively. Any large shocks to the counts at the neighbouring sensors will have an effect on the counts to be imputed.



In order to use a mixture of the patterns from two different sensors, we need to use the scaled counts at the neighbouring sensors to avoid the magnitude of the counts having an effect on the predicted counts. We scale the counts by standardising to $\mu = 0, \sigma^2 = 1$. Because the covariance with neighbouring sensors may vary over time, we also add an interaction term between the neighbouring sensor counts and the time of the day.

Imputation Results

Firstly, we evaluate the initial model used to impute:

$$\text{where} \quad \mu_{\text{Sensor,HDay,Time}} \sim \text{Time} \times \text{HDay} \tag{1}$$

Note, this is also after the adjustments made to treat suspiciously long sequences of 0 values as `NA` in the actual counts. The simple GLM model is trained before this correction, while the improved model is trained on the adjusted data.

For the purposes of evaluating the imputation method at a location with a small proportion of missing values, we will first look at the counts from Southern Cross Station. At this sensor, the proportion of missing values (adjusted) is 0.02Firstly, we evaluate the goodness of fit of the predictions made within the training period (01/01/2014 to 31/12/2016).

Visually, we can see that the fitted values are good estimates as the relationship between the actuals vs fitted is very close to 1:1. This is seen when we perform a least squares estimate of $\widehat{Fitted}_t = \hat{\beta}_0 + \hat{\beta}_1 Actual_t$, and the estimated $\hat{\beta}_0$ is close to 0 and $\hat{\beta}_1$ is close to 1.

Here we see that the GLM model with only time and date based variables work well for fitting small periods of missing data.

However, if we try to use this same model specification at sensor locations with large proportions of missing values, the fit is poor. We use the sensor at Australia on Collins, where the proportion of missing values is 41.96%.

We can see that the simple model has bias caused by the false zero counts, resulting in the predicted values to be underestimated. This is shown by the slope of the fitted line on the actual counts against predicted counts being < 1, emphasising the importance of the first step taken in the algorithm of the improved model to class the false zero counts as missing values.

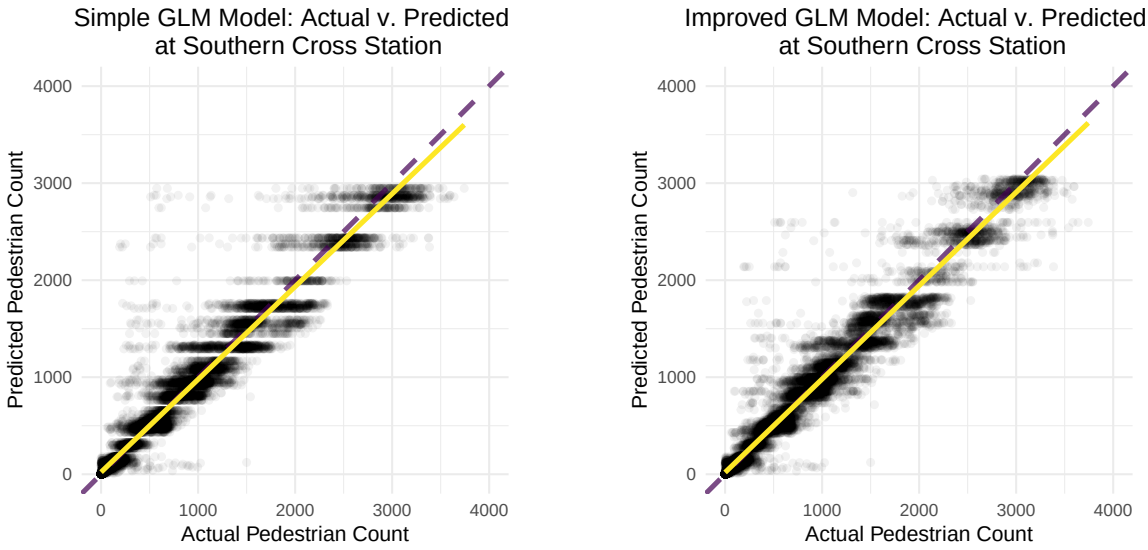


Figure 3: A plot of the in-sample Actual vs Predicted pedestrian counts at Southern Cross Station (sensor location with small proportion of missing values) for the simple GLM model and the improved GLM model. The dashed line is $x = y$, representing a reference for perfect fit, while solid line is the linear fit of the points.

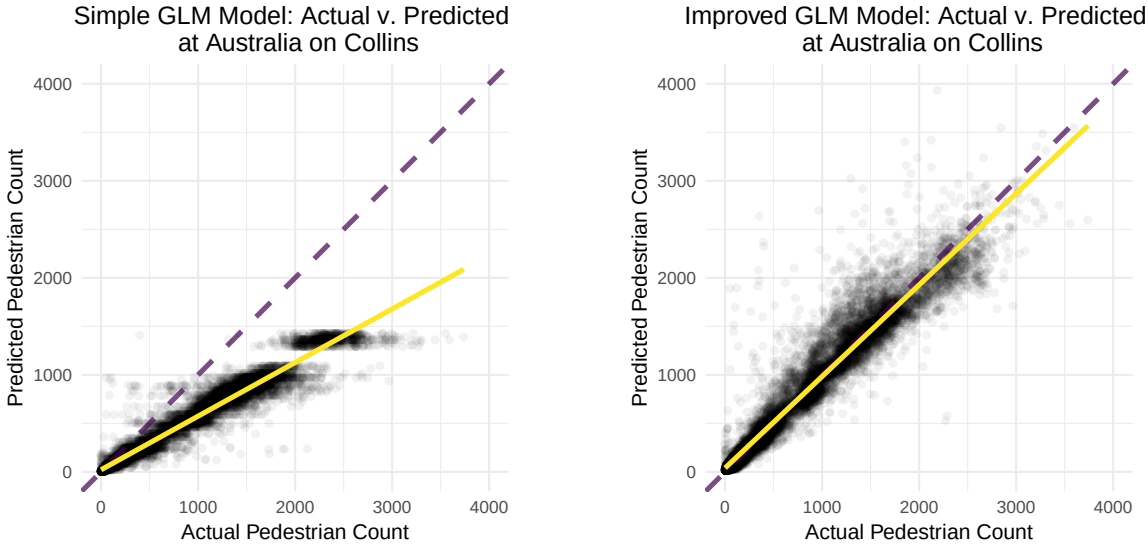


Figure 4: A plot of the in-sample Actual vs Predicted pedestrian counts at Australia on Collins (sensor location with large proportion of missing values) for the simple GLM model and the improved GLM model. The dashed line is $x = y$, representing a reference for perfect fit, while solid line is the linear fit of the points.

The criterion we will use to measure goodness of fit is MARE. It is calculated by:

$$MARE_{sensor} = \frac{1}{T^2} \frac{\sum_{t=1}^{T} |\widehat{\text{HourlyCounts}}_{sensor,t} - \text{HourlyCounts}_{sensor,t}|}{\sum_{t=1}^{T} \text{HourlyCounts}_{sensor,t}}$$

We calculate a seperate MARE for predictions in-sample (in the training set) and the predictions out of sample (test set of 2017 data). This will help to identify overfitting of the data. We use MARE as it will be a comparable measure between sensor locations as well as comparable between models.

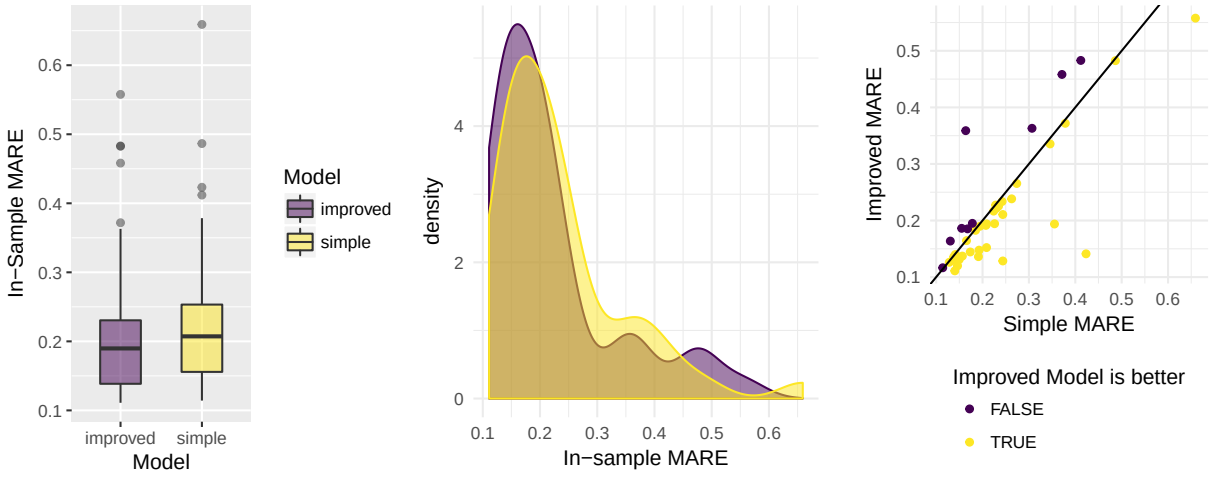


Figure 5: Distribution of in-sample (2014-2016 data) MARE by imputation model

Focusing on the date 04/07/2014, which has 3 hours of missing data:

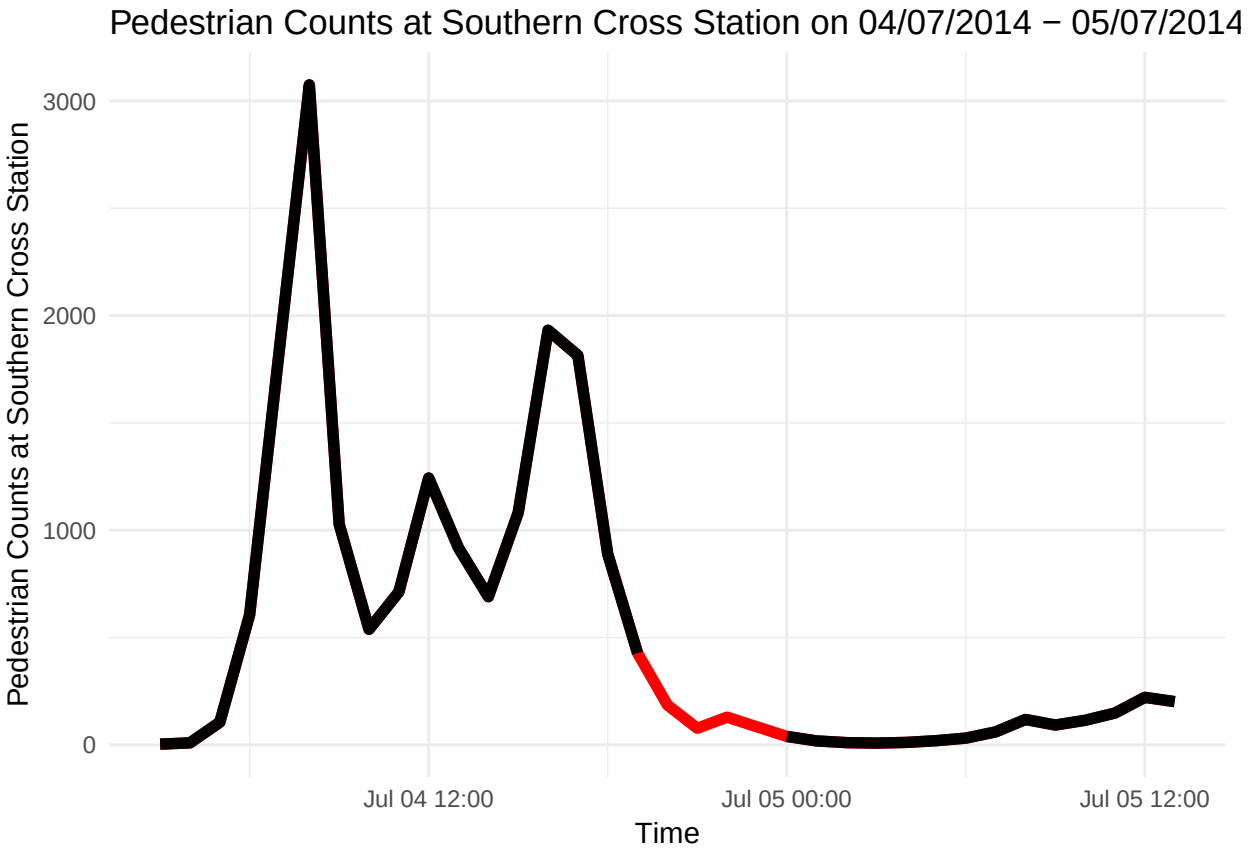


Figure 6: A plot of the pedestrian counts at Southern Cross Station. The black line is the observed counts, where the red line is the imputed counts.