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Distinguishing transfer from activity using public transport fare data [1]

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Abstract

Transport smart cards offer transit planners access to a tremendous source of spatial–temporal data, offering opportunities to infer a passenger's mobility pattern and path choices. To estimate travel demand, the origin–destination matrix is required, which must be estimated from commuters' trajectories in multi-leg journeys. To infer a destination from alighting stops requires the ability to distinguish between transfer and activity and to improve the accuracy of detecting short or hidden activities. In this paper, a new heuristic method has been developed using SQL software based on the trip chain model for bus passengers in Adelaide, using smart card information. This study uses some assumptions and develops a technique to differentiate a transfer from an activity. By this method, it is assumed that 'if a passenger alights, then later boards another bus on the same or a parallel route, it is assumed that the passenger was not transferring but was undertaking some activity between the trip legs. Analysis of a week's data for bus users validated based on a survey. The result is useful in estimating the Origin–Destination (OD) matrix and assists in reaching an accurate estimation of public transport demand; the OD matrix will help public agencies to rationalise routes, leading to higher public transport patronage.

Keywords: Origin–Destination matrix, public transport, trip chain model, smart card

1. Introduction

As public transport agencies increasingly adopt the use of automatic data collection systems, a significant amount of boarding data becomes available, providing an excellent opportunity for transit planners to access spatial–temporal data (Rahbar et al. 2017; Tao 2018) which can be used for a better understanding of human mobility and the performance of a transit system (El Mahrsi et al. 2017). Smart card data can be used to examine a whole network regularly, and to make practical estimates of passenger origin–destination (OD) patterns. To estimate the OD matrix, it is essential to infer a passenger's destination, and as an alighting stop may be a transfer point or a destination, distinguishing a transfer from an activity is necessary to be able to estimate a destination. A new methodology is developed, using SQL software based on the trip chain model, to distinguish between bus users' transfer and activity.

2. Transfer identification and activity detection

Developing a methodology that enables planners to distinguish between whether a passenger has alighted to make a transfer or to perform an activity is the main aim of this paper.

[1] This is an abridged version of the paper originally presented at ATRF 2018. For further information about this research please contact the authors.

Various rules have been suggested to distinguish a transfer from an activity, most of them time- or distance-based (Table 1).

Table 1. Activity detection and transfer identification

Criteria	Value/Description	Reference
Time threshold	30-minute interval between separate boarding transactions	Bagchi and White (2005)
	18-minute maximum gap from alighting to next boarding	Barry, Freimer and Slavin (2009)
	15-25 minutes for subway to bus, 30-50 minutes for bus to subway, 40-60 minutes for bus to bus	Seaborn, Attanucci and Wilson (2009)
	30 to 60 minutes	Ma et al. (2013)
	Less than 10 minutes for 80% of journeys	Jang (2010)
	30-minute interval	Munizaga and Palma (2012)
	Maximum 35 minutes	Yap, Nijënstein and van Oort (2018)
Distance	Walking distance is 400 Euclidean metres	Yap et al. (2017)
	750-metre walking distance to the next boarding point	Gordon, J et al. (2013)
	Destination is less than 400 metres from the origin of the journey	(Gordon, J et al. 2013; Nassir, Hickman & Ma 2015)
Other	The last transaction of a day is considered an activity	Gordon, JB (2012)
	The ratio of gap to the total travel time should be considered	Nassir, Hickman and Ma (2015)
	If the commuter uses the same route as the previous alighting, it is an activity	Nassir, Hickman and Ma (2015)

3. Structure of Data

The data used in this paper is from the MetroCard database of Adelaide, for May 2017 and contains spatial and temporal information (see Table 2).

Table 2. Individual MetroCard information

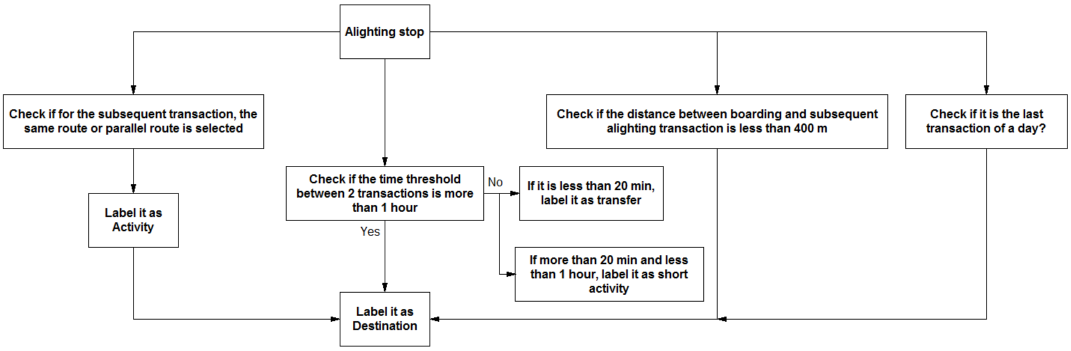
Media code	Fare type	Transport mode	Date & time	Stop code	Latitude	Longitude	Route code	Direction
807*CB**	SV	Tram	2017-05-01 09:49:35	8089	-34.979759	138.525912	Tram	1
6AD*07**	28DAY	Bus	2017-05-01 10:02:20	2658	-34.890404	138.585119	235	1
94E*FB**	TICKETS	Bus	2017-05-01 10:39:15	3351	-34.924343	138.598468	271	1
584*97**	OTHER	Train	2017-05-08 11:06:36	1852	-34.860916	138.650472	GAW	1

There are some deviations from the one-swipe rule: the railway stations operate under a closed system and swiping is required for both boarding and alighting; and various systemic and user issues mean that transfers between the train and other modes cannot be estimated directly from the smart card. Also, there is a free tram zone in Adelaide where passengers do not need to swipe their cards; this means that the tram boarding point is not available. Given these limitations, this study focuses on bus users.

4. Methodology

For distinguishing transfer from activity, three assumptions are considered (see Figure 1). In this paper, the alighting stop and alighting time are estimated based on a trip chain model by calculating Euclidean distance.

Figure 1 Distinguishing transfer from activity



4.1. Subsequent route

One method of deciding whether a passenger has undertaken an activity between successive boardings is to see if that person used the next leg of the same route the second time, or used a different route to the same destination. In such cases it can be concluded that this is an activity, as there is no need to alight from a direct route and then take the same or a parallel route. If several bus routes exist between the boarding stop (A) and alighting stop (B), they are considered parallel routes. For investigating a parallel route, based on the algorithm the routes which have service between the boarding stop and alighting one are specified and labelled as parallel.

4.2. Time threshold

Another assumption for distinguishing a transfer from an activity is comparing the time difference between alighting and reboarding. In Adelaide, bus headway is 15 minutes; so taking five minutes as the maximum delay, 20 minutes can be considered transfer time. Based on the data analysis and the validation result from the survey (see Section 6), a time threshold of fewer than 20 minutes is treated as a transfer. This means a commuter who boards a bus less than 20 minutes after alighting from a previous one is assumed to have transferred; anything longer than 20 minutes is treated as an activity.

4.3. The distance between boarding and subsequent alighting

The distance between two trip legs can also be used as a criterion for distinguishing a transfer from an activity. If the distance between alighting and a second reboarding is less than 400 metres, then the alighting point is considered a destination, which means some activity occurred in between (Nassir, Hickman & Ma 2015).

5. Results

The results indicate that all the transfer points are the same for both weekdays and weekends, although destinations may change. Most transfers during weekdays occurred in three suburbs: Adelaide (CBD), Paradise, and Modbury (see Figure 2). Most passengers travelled to Adelaide during the morning peak to start a daily activity. Modbury and Paradise are busy interchanges, and it is evident that most commuters use these locations for transfer.

Figure 2 Suburbs with high numbers of destinations (a.m. peak, weekdays)

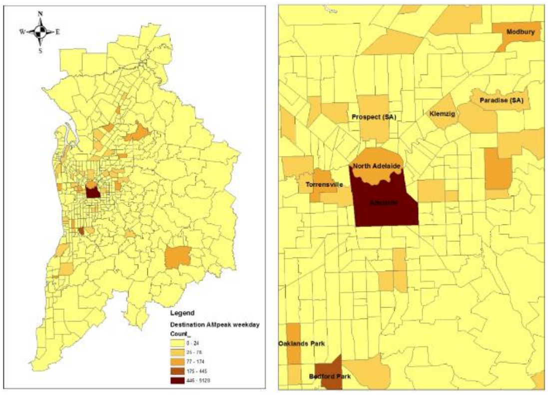
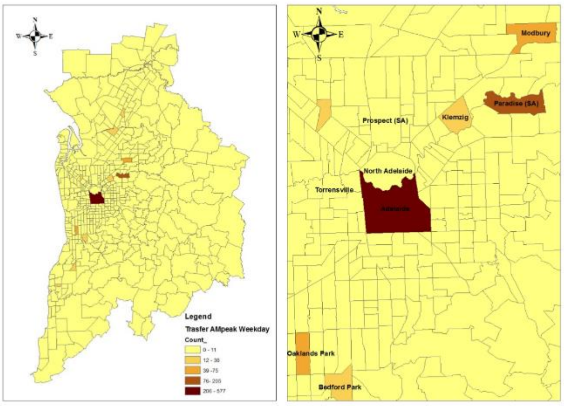


Figure 3 Suburbs with a high number of transfers (a.m. peak, weekdays)



Travel patterns change during the weekend as fewer work and educational trips occur, and this affects the behavioural attributes of trips. The transfer locations are the same as during weekdays because, as mentioned before, these locations are interchanges. The weekday afternoon peak analysis shows similar trends to those of the morning peak: most commuters are returning home during this time.

6. Validation

In this study, a survey was conducted by recruiting volunteers who usually used bus services. Fifteen volunteers were randomly identified, and For these participants over a five-month period, 1633 transactions were collected, but only 407 were considered for validation once trips using other modes of public transport and duplicated records of trips were filtered out. The new dataset was analysed based on the trip chain model and its assumptions, and validated through interviews with the volunteers. There were no discernible differences between the travel patterns derived from the trip chain model and the actual travel patterns of the volunteers, and the results were 98% accurate.

7. Conclusion

The result indicates that transfer locations are usually the same during morning and afternoon peak hours, on both weekdays and weekends. While the destination may change, the Central Business District (CBD) attracts maximum trips during morning and evening peaks.
The estimated travel patterns established after analysing a week's data for bus users in Adelaide were validated through primary survey data, which confirmed that the method of

pattern modelling was 98% accurate. This result is useful in estimating the OD matrix and assists in the understanding of the demand for public transport. Future analyses of trip purposes can be estimated from smart cards if the additional data related to the smart card is made available.

Acknowledgements

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