Towards the Modelling of Public Transport Route Choice under Disruption

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Introduction

Public transport disruption may force travellers to switch from habitual travel behaviour, requiring them to choose alternative routes with which they may be less familiar. In London, the transportation system is under some serious threat due to its aging infrastructures (Willams et al., 2004), and vulnerability brought by the network's high complexity and industrial disputes (Darlington, 2009).

Besides some incident response work (e.g. Jespersen-Groth et al.'s, 2007; Zhu and Levinson, 2010; Freemark, 2013), it is of great importance to understand public transport users' route choice under disruption. However, existing research focuses predominantly on analysing decision-making on public transport under normally functioning conditions (e.g. Raveau et al., 2011, Brands et al., 2014), and adopts approaches under economically rational premises, assuming human can always maximize their benefit through selecting the best one from a range of choices. Serious questions have been raised on the adaptiveness of such presumptions under the uncertainty brought by the disruption. Within recent years, behavioural theories such as Prospect Theory (Kahneman and Tversky, 1979) and heuristic decision-making (Gigerenzer and Todd, 1999) have demonstrated a great potential to be practiced with traditional Random Utility Models (RUM) and Game Theory in transportation (Manley, et al, 2015).

Our research aims to construct a comprehensive framework to understand people's decision-making under disruption, exploring whether transport users choose routes as economic models suggested, rationally, or bounded by their ability, relying on some simple rules. This paper addresses the necessary work towards constructing such a framework, particularly on the first rational discrete choice model. Proposed methodology will be applied to London's public transport system, focusing underground

passengers' commuting trips. It covers a range of topics, including smart card data analysis, integrated transport network building, discrete route choice modelling and beyond.

Methodology

Overall, three models are intended to be examined that 1) a base model utilizing most prevalent discrete choice methods, 2) another one embedded with Prospect Theory features, 3) a non-compensatory heuristic model falls into bounded rationality paradigm i.e. Take-The-Best (Gigerenzer and Todd, 1999).

It also aims to demonstrate the viability of conducting route choice models on a large-scale urban area with multiple transport modes (underground, bus and train), looking into the revealed preference captured in the smart card, and mapping out each individual's choice to support the above decision-making models.

Present work

Several constituent elements have been developed towards constructing the base discrete choice model.

Integrated public transport network

A within-city scaled public transport network is built to support the route choice decision-making, incorporating a frequency-based structure for short-interval underground and bus services and a time-expanded network for long-interval train service. It gives great detailed representation of London's public transport system, with desired travel time attributes embedded (e.g. in-vehicle, waiting and walking time), different transport modes connecting through walking links, serving as physical walking time between access points. The data come from a variety of sources, including Transport for London (TfL) and Google Transit Data.

Route choice generation method

A customized route choice set generation method, *service elimination,* has specifically designed for the network, based on traditional link elimination/penalty method (De La Barra et al., 1993). It iterates through underground and bus services, eliminating services in turn, to find different path combinations while delivering a high computational performance. At the same, by keeping station and bus stop nodes intact, it avoids any potential travel path break caused by the traditional elimination method.

Bayesian inference on route selection

A Bayesian inference approach has been adopted to characterize individuals' route choices in the underground where passengers' choices cannot be explicitly identified. Specifically, one's route choice is

modelled through Bayesian inference on the mixture of the alternatives' travel time distributions between smart card taps at the two ends of underground (Marin et al., 2005; Fu, 2014; Sun et al., 2015).

The posterior distribution of an individual's choice, given travel time t, can be inferred through maximizing the sum of each weighted alternative's travel time distribution ($f(t_i|\theta_r)$) over the whole population (n).

$$\pi(\theta, p|t) \propto (\prod_{i=1}^{n} \sum_{r}^{R} p_r f(t_i|\theta_r))\pi(\theta, p)$$

By applying a Markov Chain Monte Carlo (MCMC) algorithm (Metropolis-Hasting), we then obtain all the parameters (θ and p) and can further decide which individual passenger tends to choose which route. Expectation-Maximization (EM) algorithm works in a similar fashion, with less computational stress, could be used for future application.

Case Studies

Case study 1: A one-to-many ODs route choice experiment

This case study demonstrates a discrete choice model implemented between one origin and multiple destinations during an underground strike in London. During the morning peak, passengers have experienced a longer commuting time and showed a more spread out public transportation system using, comparing to the well-operated day before (Figure 1).

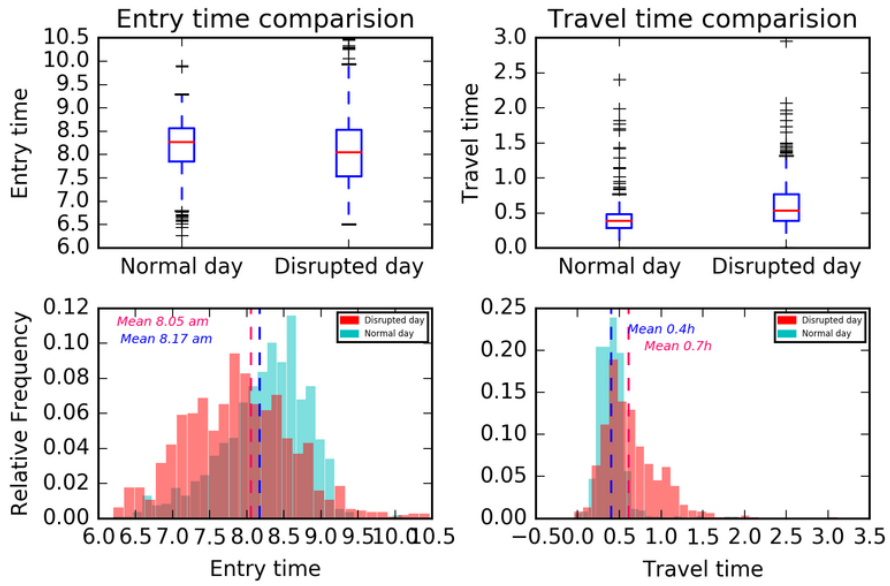

Figure 1 Descriptive statistics comparing a disrupted and non-disrupted day

A Multinomial Logit (MNL) model was developed based on their route choice with the specification:

$$V = \beta_{ivt} * ivt + \beta_{waiting\ time} * waiting\ time + \beta_{walking\ time} * walking\ time + \beta_{transfer} * transfer + \beta_{bus\ leg\ ratio} * bus\ leg\ ratio + \beta_{first\ leg\ ratio} * first\ leg\ ratio$$

Where a journey's in-vehicle travel time, waiting time, walking time, transfer times, bus and first public transport leg's proportion were extracted. This model was estimated in PythonBiogeme 2.5, giving a result (Table 1).

Table 1 MNL model result

β_{ivt}	-0.634
$\beta_{waiting\_time}$	-0.611
$\beta_{walking\_time}$	-0.942
$\beta_{transfer}$	2.30
$\beta_{bus\_leg\_ratio}$	-0.984
$\beta_{first\_leg\_ratio}$	5.06
Initial Log-Likelihood/Final Log-Likelihood	-1497.885/-965.993

The signs associated with most of these parameters are as expected. However, we find that the transfer times one is positive, contradicting to the common sense. This may be largely due to the fact that route selection is based purely on shortest paths between tap in and out stations, which assumes least travel time path even if the passenger must make more transfers. To fix this problem, we introduce our Bayesian inference approach towards route selection.

Case study 2: Bayesian inference on route selection in the underground

Passengers' route choices between two London underground stations have been deduced through a Bayesian Gaussian mixture model. A series of parameters have been estimated using Metropolis-Hasting algorithm regarding passengers' travel time extracted from a normal workday morning. Specifications can be seen in Table 2.

$$\pi(\theta_s, p|t) \propto \left(\prod_{i=1}^{n=383} \sum_{r}^{R=2} p_r f(t_i|\theta_{rs}) \right) \pi(\theta_s)\pi(p)$$

Table 2 Bayesian mixture model descriptive data

Parameters	Descriptions	Distributions	Data sources	Estimates	Validation
$i \in n$	Individual passenger i of total population n (383).	-	Smart Card	-	-
t_i	Travel time of individual i	-	Smart Card	-	-
$r \in R$	Victoria – Holborn (Route 1 via Oxford Circus, Route 2 via Green Park)	-	2012 TfL Rolling Origin Destination Survey (RODS)	**82% – Route 1, 18% – Route 2**	**78% – Route 1, 22% – Route 2 (RODS)**
$\theta^1_{ivt-mean}$	Average in-vehicle travel time of Route 1.	$N \sim(10.08, 1)$	Integrated public transport network model	9.4511	-
$\theta^1_{ivt-std}$	Standard deviation of in-vehicle travel time of Route 1.	$Gamma \sim(2.3, 1.67)$	-	0.8860	
$\theta^1_{ovt-mean}$	Average out-vehicle travel time of Route 1.	$N \sim(7.6750, 2)$	Integrated public transport network model	6.9563	
$\theta^1_{ovt-std}$	Standard deviation of out-vehicle travel time of Route 1.	$Gamma \sim(4, 1.25)$	-	1.6516	
$\theta^2_{ivt-mean}$	Average in-vehicle travel time of Route 2.	$N \sim(10.29, 1.1)$	Integrated public transport network model	10.3381	
$\theta^2_{ivt-std}$	Standard deviation of in-vehicle travel time of Route 2.	$Gamma \sim(2.3, 1.43)$	-	1.0223	
$\theta^2_{ovt-mean}$	Average out-vehicle travel time of Route 2.	$N \sim(8.8250, 2.2)$	Integrated public transport network model	8.9187	
$\theta^2_{ovt-std}$	Standard deviation of out-vehicle travel time of Route 2.	$Gamma \sim(5, 1)$	-	2.1433	
$p_{r=1}$	Component distribution weight	$u \sim(0, 1)$	-	0.6949	
$f(t_i \mid \theta_{rs})$	Component distribution of travel time on route R, given descriptive parameters	$N \sim((\sum_{r=1}^{R} \theta_{mean}), (\sqrt[R]{\sum_{r=1}^{R} {\theta_{std}}^2}))$	-	-	
$\pi_r(\theta_s, p_r \mid t)$	Posterior probability of selection route r, given travel time t	$p_r f(t_i \mid \theta_{rs}) / \sum_{r}^{R=2} p_r f(t_i \mid \theta_{rs})$	-	-	

It shows a very positive result, the estimation being very close to the local official's surveying data. The mixture model plot can be seen in Figure 2.

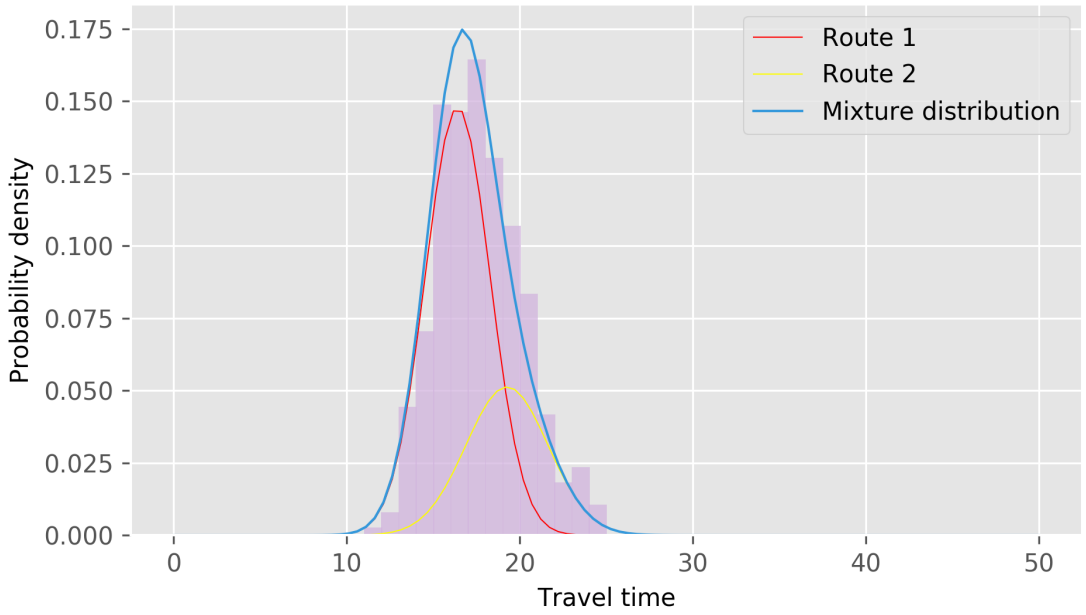

Figure 2 Mixture travel time distribution

Discussion

The present work contributes to the base model in this project, also offering a platform for the two remaining models. The results demonstrate the necessity to integrate these separate elements together to give a comprehensive representation of people's route choice. Given the uncertain nature under disruptions, we believe that the rationally assumed discrete choice model may not provide enough explanation for passengers' choices, with behavioural models providing a plausible alternative theory of decision-making.

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