

# Mining Public Transport Usage For Personalised Intelligent Transport Systems

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**Abstract**—Traveller information, route planning, and service updates have become essential components of public transport systems: they help people navigate built environments by providing access to information regarding delays and service disruptions. However, one aspect that these systems lack is a way of tailoring the information they offer in order to provide personalised trip time estimates and relevant notifications to each traveller. Mining each user’s travel history, collected by automated ticketing systems, has the potential to address this gap. In this work, we analyse one such dataset of travel history on the London underground. We then propose and evaluate methods to (a) predict personalised trip times for the system users and (b) rank stations based on future mobility patterns, in order to identify the subset of stations that are of greatest interest to the user and thus provide useful travel updates.

## I. INTRODUCTION

Interactive maps, route planners, and real-time service alerts have become essential components of public transport systems. However, these systems notably lack an ability to dynamically tailor information to the individual needs of each traveller [1]. Most online transit tools, for example, have yet to incorporate an understanding of travellers’ preferences or mobility-related requirements. Personalisation offers a rich opportunity to match information to the appropriate individual traveler and reduces the need for manually searching for relevant transit notifications. In this paper, we explore automated methods to enable public transit personalisation; the goal here is to explore the viability of personalised travel information with little-to-no direct feedback from the travellers themselves.

A significant historical obstacle to personalising the public transport experience has been the lack of data about individual traveller preferences and routines. However, the introduction and widespread adoption of automated fare collection (AFC) systems offer a potential channel to this missing data. These new payment systems create a digital record every time a trip is made, which can be linked back to the individual traveller. Mining the travel data that is created as travellers enter and exit stations can give vast insight into the travellers themselves: their implicit preferences, travel times, and commuting habits.

In this work, we focus on what AFC data can reveal about individual traveller behaviour. We use data collected from the London Underground (tube) system, which implements electronic ticketing in the form of RFID-based contact-less

smart cards (Oyster cards). Indeed, recent work [2] states that, on average, only 46-62% of the time that users spend in the tube is actually spent riding the trains. The rest of the time is spent interchanging, walking, or waiting: thus, differences between users will strongly impact travel time and should be incorporated into transport route planning and notification services. We show how AFC systems can be used to uncover individual differences in travel patterns that, in turn, can be used to enable personalised transit services. We focus on two facets of personalisation, both of which can be formalised as prediction problems: (a) predicting personalised travel times between any origin and destination pairs to provide users with accurate estimates of *their* transit time, and (b) predicting and ranking the interest that individual travellers will have for alert notifications about particular stations based on their past travel histories.

In particular, this paper makes the following contributions. First, we perform an extensive analysis of a large corpus of anonymised per-person usage of the London underground (Section II). Although aggregate summaries of the data point toward a consistent use of the system, we highlight measurable differences in transit usage between travellers that more concretely motivate the need for personalisation. Second, we propose and evaluate a set of simple algorithms to personalise travel time estimation (Section III). In doing so, we aim to implicitly capture aspects of underground usage that affects travel time such as route choice, the ability to physically move about a station, and route familiarity. We also evaluate a means of combining the different methods that takes into account the varying amount of data available for each prediction. Finally, we design and evaluate (Sections IV) a set of ranking algorithms that aim to identify which stations will be of interest to each traveller in their future journeys. We believe that this paper not only highlights the potential value of AFC datasets to the data mining and personalisation research communities, but will also be of value to public transportation planners and operators.

## II. THE LONDON UNDERGROUND AFC DATASET

The London Underground consists of 11 interconnected underground lines, six fare regions (zones), and over 250 tube stations. In this analysis, we use two datasets of London’s tube usage from different 83-day periods (D1, May-July 2009 and D2, October 2009-January 2010). Each

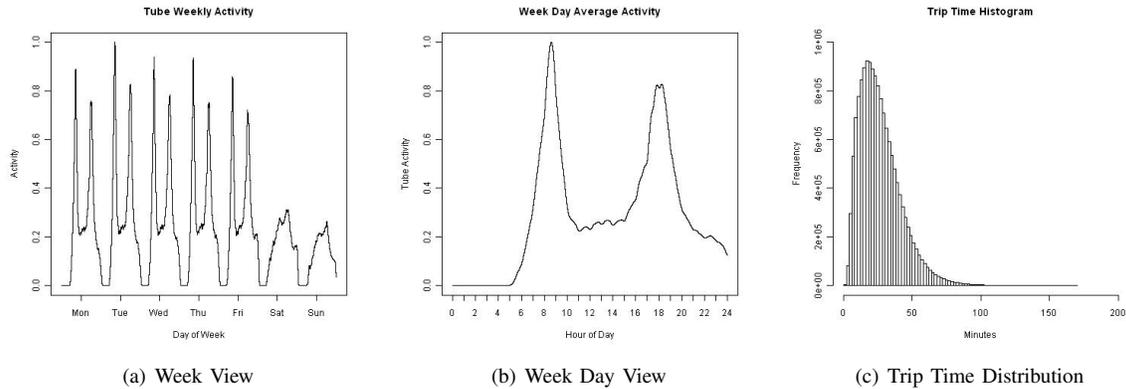


Figure 1. (a) An aggregate view of weekly/week day tube activity. Note how a two-spike temporal pattern corresponding to heavy commuting periods is visible on weekdays but not on weekends. (b) Trip time distribution

dataset is a 5% sub-sample of all users who were recorded during the two periods, with data points being tuples in the form  $\langle u, (o, d), t_o, t_d \rangle$ : the unique, persistent user id ( $u$ ), the trip (with origin ( $o$ ) and destination ( $d$ ) stations), the time stamp  $t_o$  when  $u$  entered the origin station and the time  $t_d$  when  $u$  exited from the destination station. These time stamps allow us to compute trip time in minutes. We first filtered inconsistent entries from the data: we removed trips with invalid or missing origin or destination stations (caused by users who did not touch their ticket to the reader when starting or ending a trip), trips with the same origin and destination, and trips whose arrival timestamp was prior or equal to the departure time. Approximately 7% of the raw data was discarded; we were left with 7,534,700 trips by 298,294 travellers in D1 and 7,702,713 trips by 309,588 travellers in D2. We begin by analysing the *aggregate* temporal usage patterns of the underground and the underlying differences that exist in *individual* traveller patterns.

**A. Aggregate Behaviour.** The primary focus here is to highlight systemic patterns that (a) give a broad perspective of the usage of the system and (b) may impact our ability to accurately predict travel times or stations of interest. This analysis also provides a necessary context within which to interpret our results.

**1. Temporal Patterns.** Figure 1 plots the cumulative number of ongoing trips over time: over the course of a week and weekday. The two distinct peaks in weekday activity (Figure 1(b)) reflect London’s dependence on the tube as a means of commuting: the largest proportion of trips occur within the morning commute, 6.30 to 9.30am (22.95%), and the longer spanning evening commute, 4.30 to 8pm (29.19%). Unsurprisingly, these temporal patterns are not shared by weekends or national holidays where the number of ongoing journeys steadily increases during the course of the day until approximately 7pm.

**2. Travel Time.** The global mean trip time for D1 is  $26.81 \pm 14.93$  minutes, while for D2 it is  $27.11 \pm 15.12$  minutes; the overall average trip time for the *entire system* is

roughly half an hour. Finer grained travel time estimates can be obtained by incorporating zoning information. London tube zones are used to demarcate the city and its surrounding area into pricing tiers. Inter-zonal average travel time increases proportionally to the number of traversed zones; the longest average trips tend to be those between Zones 1 and 6.

Lastly, we turned to the individual trips. Figure 1(c) is the overall trip time histogram: trip times in the tube network tend to follow a near-gaussian distribution with a long tail. From the data, we also computed trip time averages and standard deviations for each possible pair. Approximately 90% of the trips are within ten minutes of the average; in fact, about 40% of the trips are within 5 minutes of the respective average trip time. In summary, coarse view of London underground’s usage patterns points to two main results: (a) the tube is primarily used to commute to and from work, and (b) user travel times are very close to the mean travel times. This analysis would suggest the existence of a single *type* of traveller. In the following section, we demonstrate that this is not the case.

**B. Traveller Characteristics.** In this section, we highlight user-centric patterns of travel: repeat trips over time, usage similarities between different groups of users and relative travel times. The emerging differences in usage and travel time emphasise the potential that personalisation has to offer in this context.

**1. Repeat Trips.** In Figure 2(a) we show the temporal view of repeat trips: by the end of each dataset (83 days), approximately 60% of the user-trip pairs are repeat trips. The vertical plot lines represent weekends, where users tend to be less regular in their movements than during commuting weekdays. Commuting behaviour can be further illustrated by tracing the number of users per day whose last journey ends where their first journey began. We found that over 88% of the users per day form a loop with their travels. Note that this does not take into account multi-modal transport. In fact, over 55% of the users who *did not* form a circuit with their trips took only 1 tube trip in that respective day.

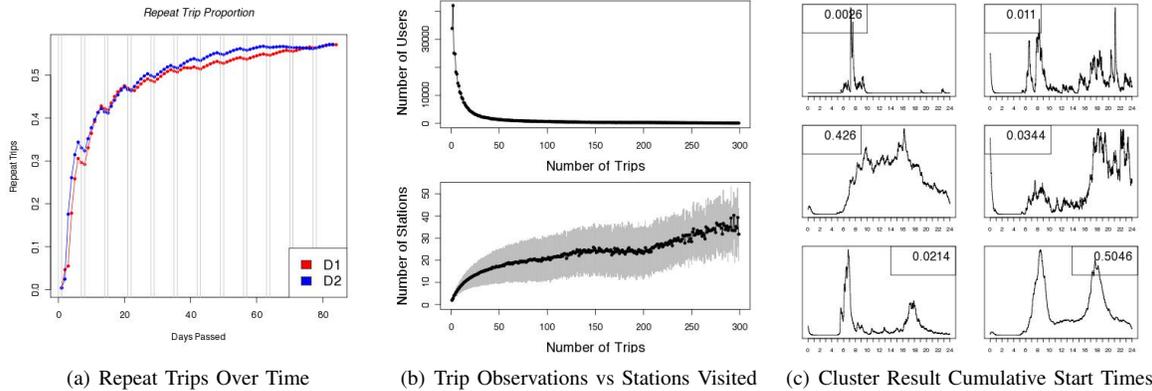


Figure 2. (a) Proportion of Repeat Trips Over Time for each Dataset (vertical lines are weekends), (b) Number of users (top), and average number of stations visited (bottom), as trip observations increase, (c) User activity of different clusters.

Figure 2(b) plots the number of trips that a user takes against the average number of stations that the user has visited. Note that as the number of trip observations increases, so does the breadth of stations that the user, on average, has visited. Interestingly, the graph appears to be segmented into two unique parts: it is composed of two point wise bounded parabolic growth functions with asymptotes corresponding roughly to 18 stations and 25 stations respectively. The pivot point between the two functions (at 110 trips) corresponds to roughly 2 trips/day on average in our dataset. The key here is that the number of stations visited differs between travellers along with their frequency of travel.

**2. User Activity Clustering.** The overall average trips per user (in each of the full 83-day datasets) is 25.26 for D1, and 24.88 for D2 (both medians are 9), with approximately 9% of each set composed of users who we only see once. On the broadest level, users can be split into groups based on *when* they travel; whether they use the system throughout the entire week, or only during weekdays or weekends. As summarised in Table I, the smallest group is the users who *only* travel on weekends (approximately 8% of each dataset), while the largest group includes users who travel throughout the entire week including both weekday and weekend travel (56%). A noteworthy proportion of users (35%) travels only on weekdays. We delved further into the differences that emerge in temporal usage patterns by clustering the users’ weekday travel. We applied *dendrogram* clustering [3], a form of agglomerative hierarchical clustering, on vectors of binned user trip start times. More formally, we split the 24-

hour day into 5 segments using Figure 1(b); each segment represents a particular time of day. For each user who has made more than a single trip, we construct a frequency vector denoting the number of trips started within each time segment. The similarity between the travel patterns of user  $a$  and  $b$ , who have respectively made a total of  $A$  and  $B$  trips, can then be computed as follows:

$$d_{a,b} = \frac{1}{5} \sum_i \left| \frac{a_i}{A} - \frac{b_i}{B} \right|$$

Each iteration of the clustering algorithm merges the two users who share the *smallest* value of  $d_{a,b}$ ; the resulting vector is the sum of the two users. Due to the high volume of users that each dataset contains, we clustered 10 uniformly-selected subsamples of 1,000 users and averaged the results. The iteration stops when a pre-defined number of clusters have been formed: we manually tuned and examined the results of varying cluster thresholds, and settled on 6 as this produced a variety of diverse user profiles.

**Cluster Results.** Based on the clusters found above, we plot the cumulative start times per profile in Figure 2(c). Note that these images are *not* plots of the cluster centroids themselves, but rather are the cumulative start times of all members of the given cluster. The six profiles that are produced are (reading from left to right): morning-only travellers, irregular travellers (with, for example, a peak immediately *after* the end of the evening rush hour), day-time-only travellers, users who travel most frequently in the evening, early-morning commuters (who go to work *before* the normal rush hour), and, lastly, the commuting majority. The clusters each vary in size, ranging from very few average users (0.26%) for the morning-only travellers to an average of 50.46% for the commuting majority. The overall cumulative view of the system as depicted in Figure 1(b) only reflects the largest of these groups. However, the second largest cluster (43%) is that of the day-time-only travellers; a significant portion of the population does *not* fit the two-spiked commuting pattern.

**3. Travel Time.** As above, we also explored the extent

	Users (%)		Avg Trips Per User	
	D1	D2	D1	D2
Week-End Only	7.71	7.61	2.33	2.32
Week-Day Only	35.40	35.81	10.73	10.45
Both Week/Weekend	56.89	56.58	37.41	37.05
Total	100	100	25.26	24.88

Table I  
GROUPS OF USERS AND AVERAGE TRIPS PER GROUP: A SMALL PROPORTION OF USERS ONLY TRAVEL ON WEEKENDS.

that travel time differences emerge between users. We first looked at the relation between trip *familiarity*, or the number of times that a user has taken a trip, and their trip time relative to the overall mean. Given a user  $u$  who, on average, completes a trip  $(o, d)$  in  $\bar{u}_{o,d}$  minutes (while the overall trip average time is  $\bar{m}_{o,d}$ ), we can compute the normalised residual  $r_{o,d}$  trip time. A positive residual indicates that the user tends to be *slower* than the overall mean, while a negative residual shows that the user’s average travel time is *faster* than the mean. We computed the residuals for all trip observations; the results show that trip residuals are positive, on average, when the trip frequency is small (less than 3); however, as trip frequency increases beyond 3, the residuals become, on average, negative. The overall results point to the fact that as users become more familiar with a trip, they also tend to be faster in completing it.

In the following sections, we build models that estimate trip time by incorporating each users travel history into the estimation algorithms. This perspective addresses many of the shortcomings of the above, such as accounting for trip familiarity and per-user transit speed differences, and aims at capturing the hidden variables that relate to the system users: their physical aptitude (i.e., their ability to move about the train station), their knowledge of the system, and their route choices.

### III. PERSONALISED TRIP TIME ESTIMATION

In this section, we describe our proposals for computing personalised estimates of trip time. None of our proposed models below incorporate information about the London underground network topology, historical train arrival/departure data, service disruption histories, geographic distances between stations, route transfer data, station size, or train schedule information. Access to any of these additional datasets may very well improve personalised trip time estimation.

**Baselines.** We have three available baseline estimates; two of these were discussed in the previous section. They include (a) the global mean trip time (roughly half an hour), (b) the inter-zone transit time  $\bar{z}_{o,d}$  and (c) the mean trip time between the station of origin and destination.

**User Self-Similarity.** The first assumption that we incorporate is that of user *self-similarity*: when users repeatedly make the same trip, they will tend to follow the same path within the system and therefore have similar travel time performance. We thus define  $U_{o,d} \subset T_{o,d}$  as the set (of size  $M$ , with members  $x_{u,t}$ ) of user  $u$ ’s trips between  $o$  and  $d$ , and  $\bar{u}_{o,d}$  as the *user* mean time of these observations. In order to compensate for potential outliers in the user’s set of trip times, we define  $\bar{u}_{o,d}$  as the geometric mean of observed times:

$$\bar{u}_{o,d} = \left( \prod_{U_{o,d}} x_{u,t} \right)^{1/M} = \exp \left( \frac{1}{M} \sum_{U_{o,d}} \ln x_{u,t} \right)$$

If the user has not taken the given trip before, then the overall trip mean is returned. More generally, the reliability of the mean computed by the moving average will be proportional to the number of trip observations  $M$  that are available. We use  $M$  as a weight: the personalised prediction  $\hat{p}_{u,o,d}$  can thus be computed as a  $\frac{1}{M}$ -weighted combination of the baseline and the user mean.

**Trip Familiarity Model.** In the previous section, we discussed the relation between the number of times  $M$  we have observed a user taking a trip (which we use to quantify how *familiar* she is with it) and the average time it takes her to complete it: trip time is inversely proportional to familiarity. These observations translate into a predictive model as follows. Given a user  $u$  who has taken a trip between  $o$  and  $d$   $M$  times, we define  $F_{o,d}$  as the set of *user* mean times  $\bar{u}_{o,d}$  of all users who have familiarity  $f_u$  that is at least  $M$ . The weighted average of all members of this set forms the personalised prediction:

$$\hat{p}_{u,o,d} = \frac{\sum_{F_{o,d}} (\bar{u}_{o,d} \times f_u)}{\sum_{F_{o,d}} f_u}$$

The intuition behind this model is to partition, for each traveller, all other users into two groups and use the most relevant one, in terms of familiarity, to compute trip time.

**Trip Context Model.** The third method we examine aims to uncover any similarities between users based on the temporal context of their travel. In this model, we do not explicitly formulate or quantify the precise context, but instead assume that users who begin travelling at the *same time* implicitly experience similar contexts. Given a time interval of size  $w$ , we assume that all users who travel from  $o$  to  $d$ , starting their trip within a window of size  $2w$  centred on  $t$ , are similar to the user  $u$  who travels from  $o$  to  $d$  at time  $t$ . The user’s trip time is estimated with geometric mean of all trip times in this window. Broadly speaking, this method is a simple two sided moving average. However, given the sparsity of our underlying dataset, there may be a substantial number of travel windows for which we have little to no data for  $\bar{w}_{o,d}$ . To account for this, we implement a weighting scheme that is similar to that used in the self-similarity method above. Given a trip, for which we have  $M$  observations and  $N$  trips within the pre-defined window, personalised predictions are defined as a  $\frac{N}{M}$ -weighted linear combination of the baseline and window mean.

**Combined Model.** We adopt a *chaining* approach to combine methods. Each of the proposals above relies on a *baseline* to resort to when there is insufficient data. For example, if a user has taken a trip before, we can use the self-similarity method. In our combined approach, we iteratively replace the baseline of one method with the output of another. In our experiments, we chain the methods as follows: the zone transfer is combined with the trip mean  $(\bar{m}\bar{z}_{o,d})$ , which becomes the baseline for the trip context model, which is then fed into the user similarity approach.

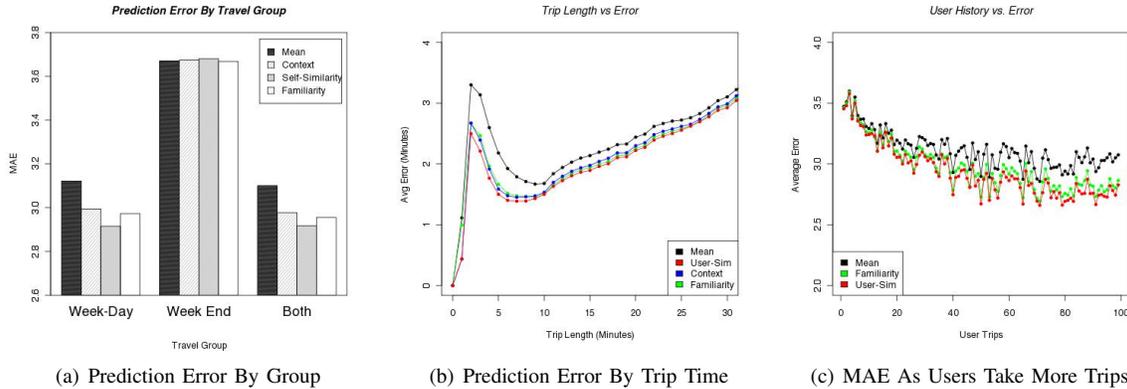


Figure 3. Decompositions of prediction error, by group (week-day only, week-end only, week-long travellers), by trip time, and by travel history size.

Method	MAE (Mins)		MAPE (%)	
	D1	D2	D1	D2
<b>Baselines</b>				
Global Mean	11.454	11.981	65.56	63.49
Zone Mean	8.561	9.215	46.88	47.36
<b>Trip Mean</b>	<b>3.109</b>	<b>3.650</b>	<b>13.31</b>	<b>14.02</b>
<b>Personalised Models</b>				
Trip Context	2.986	3.601	12.33	13.42
Familiarity Model	2.989	3.599	12.28	13.37
<b>Self-Similarity</b>	<b>2.924</b>	<b>3.556</b>	<b>11.97</b>	<b>13.17</b>
Combined Model	2.922	3.556	11.95	13.17

Table II  
PREDICTION MEAN AVERAGE ERROR AND MEAN AVERAGE PERCENTILE ERROR RESULTS

**Prediction Evaluation.** In order to test the predictive power of the models above, we split our data into training and test sets using the trip time stamps. We used the last 9 days of data for testing (approx. 90%/10% split). We pruned a small proportion of both users and origin-destination pairs from the test set that had not been seen before. We used the Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) to quantify trip prediction error [5].

The results for each model over the two datasets is shown in Table II. All of the proposed personalisation methods, while producing MAE results that lie between 2 and 3 minutes, outperform the best baseline; the self-similarity approach, when used alone, is the most accurate. The combined model produces the most accurate results overall, but with diminishing returns. We compare the predictive accuracy for weekday-only, weekend-only, or full-week travel in Figure 3(a). The error is not distributed evenly between the groups; those who only travel on weekends show consistently high MAE values. In fact, the personalised methods do not outstrip the baseline for these users. Figure 3(b) plots the relation between the actual time the trip took ( $t_d - t_o$ ) and the prediction error. It shows that the simple proposals that we put forward improve predictions from the baseline in all trips; moreover, the improvements are indeed greater for shorter trip lengths. In Figure 3(c), we plot the average error against the trip frequency: these results clearly establish the potential benefits of personalisation, since the divergence between the baseline and the personalised approaches grows

as travellers continue to use the system. Overall, we found that, while mean trip times already provide good estimates of travel time, simple personalisation techniques can produce more accurate results.

#### IV. STATION INTEREST RANKING

The second prediction problem relates to identifying the subset of the transport system that each user is interested in (i.e., stations they often visit). We view this context as a ranking problem: we would like to create, for each user, a personalised *ranking* of the stations  $s \in S$  that will reflect their future journeys. We describe three such methods:

**Baseline.** The baseline ( $b_s$ ) generates the same ranking for each user, by sorting the stations according to *popularity*: stations that are frequented the most are ranked higher than those that are visited less.

**User History.** The user history method augments the baseline to include higher weights for stations that the user  $u$  has visited in the past.

**Station Similarity Model.** Given our dataset, we can create a co-occurrence station matrix  $C$ , where each entry  $c_{i,j}$  is the frequency count of trips that have stations  $i$  and  $j$  as their endpoints. Higher values of  $c_{i,j}$  thus denote stations that are similar to each other, in that users frequently travel between them (this is *usage similarity* rather than *geographic proximity*). The  $c_{i,j}$  values are normalised with each row sum, to produce normalised matrix  $W$ , with entries  $w_{i,j}$ . This matrix can then be used to increase the score of stations that are similar to those that the user has previously visited. Given a station  $s$  in the set of stations  $S_u$  visited by user  $u$ , we increase the score of all of  $s$ 's neighbours  $n$  in  $N_s$  by  $w_{s,n}$ . The final weighting for each station is produced as follows:

$$\hat{r}_{u,s} = b_s + \beta h_{u,s} + \sum_{s \in S_u} \left( \sum_{n \in N_s} w_{s,n} \right)$$

Since a particular subset of stations are popular destinations, then these neighbours may appear in more than one of  $u$ 's station's neighbourhoods: its weights may be increased more than once. In order to accommodate for this, we give a

Method	Percentile-Ranking	
	D1	D2
Baseline	0.2467	0.2561
User History	0.0642	0.0611
<b>Station Similarity</b>	<b>0.0591</b>	<b>0.0555</b>

Table III  
STATION INTEREST RANKING RESULTS

higher weight  $\beta$  to the history weights  $h_{u,s}$  when computing the final score. This model is a similarity thresholded nearest neighbour approach, where distance is based on usage similarity. The choice of a station neighbourhood model, rather than a user neighbourhood model, has the benefit of being highly scalable.

**Interest Ranking Evaluation.** We adopt a measure that has previously been used to evaluate ranking on the web: the average percentile ranking [4]. We define the *interest* that a user  $u$  has in station  $s$  as the proportion of times that the user starts or ends a journey at the station throughout the test period. We also restrict our test set to those users who have appeared at least once in the training period. We define  $rank_{u,s}$  as the percentile ranking of station  $s$  for user  $u$  in the ranked list of stations; if  $rank_{u,s} = 0$ , then the station appears first in the list, while  $rank_{u,s} = 1$  implies that the station was the last in the list. We combine these with each user’s interest in the station  $interest_{u,s}$  and average the results:

$$\overline{rank} = \frac{\sum_{u,s} interest_{u,s} \times rank_{u,s}}{\sum_{u,s} interest_{u,s}}$$

This measure produces values between 0 and 1. Lower values are inherently better; they reflect the case where stations that will be frequently visited (high interest) are ranked higher.

**Results.** The percentile-ranking results, for each dataset, are shown in Table III. Both personalised methods provide a large improvement over the baseline by reducing the percentile ranking to less than 0.07. These figures tell us that using the above techniques to rank station notifications would significantly improve the relevance of information residing in the top-ranked places: by using AFC data, we can give users important notification updates without any further input from them.

## V. RELATED WORK

There is a broad literature on predicting travel time [6]; however, current solutions either do not have access to per-user data or explicitly focus on the aggregate usage [2]. We take a personalised perspective: we mine public transport usage data to uncover individual characteristics of travel behaviour and leverage it to build user-tailored travel time estimates. Our data prevents us from building trajectory or sub-route-based models (e.g., [5] or [3]) since the *actual* route that a user undertakes between any origin and destination is unknown to us; in many cases, there are a wide variety of candidate routes. An important area of future

work will be to incorporate additional contextual information such as the London underground network topology, train scheduling information, and service disruption history in order to further bound our estimates and assist in identifying anomalies. Personalisation has been a key component of collaborative filtering-based recommender systems [7]. A noteworthy point of these methods is that they use measured similarities across items (in our case: between two *different* trips), in order to formulate predictions. Our methods, instead, focus on inter-user similarity within a single trip. Preliminary analysis of the data shows that relative transit speed is *not* consistent: just because a user travels quickly between an origin and destination, does not mean that s/he will be faster than others on a different trip.

## VI. CONCLUSION

This paper is the first to explore the potential opportunities that AFC datasets provide for personalisation services. Our analysis of two large datasets of London’s tube usage demonstrated that there are substantial differences between travellers that emerge from this usage data. Based on these insights, we proposed three simple personalised prediction methods. We showed that not only do these methods outperform the baseline, but tend to improve over time as travellers continue to use the system. We also proposed a means of *ranking* stations to match traveller’s interests; we showed that by tracking where users have been, systems that anticipate where they will go can be built. Ultimately, the key prediction—whether it be trip time or station interest—will be application-specific. The key conclusion remains: there are a variety of benefits and uses for incorporating data about system users into intelligent transport systems.

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