Detecting Activity Patterns from Smart Card Data

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Abstract

During the past decades, the modelling of transport demand by activity based methods has gained considerable attention from the scientific community. Such demand models offer a greater modelling flexibility than traditional models, by modelling transport demand as a phenomenon which emerges from the desire to perform activities at different locations, as opposed to more traditional models where an origin destination demand matrix of trips is distributed over different routes and modes.

One of the drawbacks of the activity based paradigm is that data related to activities is more difficult to collect than traffic counts. Modern technologies, such as smart card ticketing systems and smart phones, allow us to collect more detailed accounts of the movements of individual passengers. This gives us the possibility to analyse consecutive journeys and therefore the time a passenger spends in a certain location. This information can be very useful from an activity based modelling perspective.

In this paper we take an exploratory approach to derive important activity time intervals from smart card data. We apply a clustering algorithm on the intervals observed at individual stations to detect which time intervals capture enough activities. We then construct a tree-based labelling algorithm that allows us to label the activities and analyse activity chains of individual passengers. We count pairs of consecutive activity labels, visualise the results as a network and calculate which triplets of consecutive activities occur most often. Using this approach, we are able to identify activity patterns that differ from the typical time windows associated with home-work activities.

1 Introduction

One of the most valuable pieces of information during the development and operational planning of passenger transportation systems is passenger demand. Understanding how demand develops allows governments and public transport operators to assess the profitability of infrastructure investments. It also serves as input for decisions on service frequencies, the choice of vehicle types and rolling stock allocation.

Traditional demand models typically estimate an origin-destination matrix of trips and use a traffic assignment model to map routes to OD-pairs in the transportation network. One of the drawbacks of this approach is that it is not very straightforward to make the matrix time dependent, introduce heterogeneous groups of travellers or to include the change in demand resulting from interaction between passengers and the network, such as for example due to crowding.

Activity Based Models [3] provide an improvement in this regard. The main idea of this paradigm is that transport demand emerges from many individual desires to perform certain activities at different locations at certain times. An example implementation of such a model is the open source agent-based transport simulation package MATSim [4], that has been applied at different locations around the world. The input required for such models consists of individual day plans that define a chain of activities. Since this input data cannot be directly deducted from an OD-matrix, random plans generated from economic and geographical data are often combined with travel diaries collected through surveys.

In this paper we develop a method to deduce and analyse activity patterns and activity sequence patterns within the time dimension. We define an activity as a combination of a time interval and a location. These activities are reconstructed from the set of trips stored in the data for a specific person. Using both clustering and labelling methods, we identify important activity time intervals and analyse common activity chains. We consider a time interval to be important if it represents at least 10% of the activities at a station in the network. We are not only able to identify home-work patterns, but also identify shorter activities. Moreover, the activity chains provide information on the order of different activities. We aim to extend our method to include spatial dimensions in the future, by labelling stations into groups based on the temporal patterns outputted. We believe that the results obtained using our method can provide public transport operators insight into how their network is being used and give valuable input for activity based models.

2 Smart Card Data

The Dutch smart card system, called "OV-Chipkaart" is a nation wide smart card for payment of public transport journeys across modes and operators. The system is operated by the common smart card authority "Trans Link Systems", which collects the transactions and provides the operators with the data of their customers. This is raw transactional data where each record contains at least the following fields: a unique media ID of the smart card, date and time of the transaction, an ID specifying the station or stop where the transaction took place and the type of the transaction (i.e. check in or check out). One of the important features of the Dutch implementation is that passengers both need to check in when they start their journey and check out at the end. As a result, we do not need to estimate alighting points.

In order to analyse the intervals corresponding to activities in the network, we have extended our implementation discussed [6] in order to extract the activities from the raw smart card data.

2.1 From raw transactions to journeys

The first step in preparing our data for analysis is to derive a data set of journeys from the raw smart card data. In order to do this, we sort the raw smart card data based on the media ID and the time stamps, such that we can easily process consecutive transactions card by card. Every time we detect a check in followed by a check out while passing through the data, we generate a trip containing a departure time, departure location, arrival time and arrival location. For some modes (bus and tram) a journey may consist of several trips. After the trip-construction we merge all trips that take place within the operator specified allowed transfer time. If we end up with journeys that start and end at the same station, we remove them from the final set of journeys.

2.2 From journeys to activities and time intervals

After our first step of the process we have obtained a sequence of journeys $j_1, j_2, \ldots, j_n$ for each smart card, ordered by time. If journey j_i's arrival location is equal to journey j_{i+1}'s departure location, we create an activity at the common location from the arrival time of journey j_i until the departure time of journey j_{i+1}.

As it is possible that our activities span multiple days, we simplify them by projecting them onto a modular ring. Let us first pick a number of time slots U. Throughout this paper we will work with hourly time slots, so $U = 24$. All calculation involving the intervals will now be done on the modular ring $\mathbb{Z}_U$. Under the assumption that $\mathbb{Z}_U$ represents a day, the begin time of the activity is projected onto the ring, rounding the final time slot down after scaling, while the end time of the activity is rounded up after scaling. This gives us an interval $x = (x_b, x_e)$ which starts at a time slot $x_b \in 0, 1, \ldots, U-1$ and ends at time slot $x_e \in 0, 1, \ldots, U-1$. As a result, a time slot can be an "overnight" time slot in case $x_b > x_e$. For such time slots, it is not correct to take the difference $x_b - x_e$ to calculate the duration of the time slot, as time moves forward. To overcome this fact we define the duration x_d of an interval x as follows:

$$x_d = \begin{cases} x_e - x_b & \text{if } x_e \geq x_b \\ x_e + U - x_b & \text{otherwise} \end{cases}$$

Input : Distance measure parameters θ, the number of clusters k, a random seed σ, a threshold t
Output: A set of relevant intervals R, a weight map w

Method *runExperiment(I, θ, k, σ, t)* **:**
  foreach *station* $s \in S$ **do**
    $R \leftarrow \emptyset$;
    $C_1, \ldots, C_k \leftarrow k$-means++ applied on I_s with distance measure d_θ and random seed σ;
    for $i \in 1, \ldots, k$ **do**
      if $\frac{|C_i|}{|I_s|} \geq t$ **then**
        $x \leftarrow$ centroid of C_i;
        $R \leftarrow R \cup \{x\}$;
        $w(x) \leftarrow w(x) + \frac{|C_i|}{|I_s||S|}$;
      end
    end
  end
  return (R,w)
end

Algorithm 1: Iterative loop used to calculate relevant time intervals in the network

3 Extracting Frequent Time Intervals by Clustering

As the number of different intervals observed at each station is likely to be too large for regular interpretation, we will apply a clustering algorithm in order to obtain a compact description of the types of intervals observed at the station. As the dissimilarity of two time intervals may depend of the context of the activities, we introduce a parameterised distance measure. As an example of such differences, consider that activities at an office will likely have high similarity in the starting time of the activity, while shopping or entertainment activities are more likely to have similarity in the duration.

After processing the raw smart card data, we end up with a set of stations S and a multiset I_s of observed intervals at a each station $s \in S$. We then apply[1] the k-means++ algorithm [2] on each multiset I_s. The advantage of the k-means++ over the traditional k-means algorithm is that it is $O(\log k)$ competitive due to a sampling method for the initial clustering that favours centroids that are far away from each other. Since there are many stations in the network, we also propose a method to aggregate the cluster outputs to a full network level. The reason we do not apply the clustering algorithm on the union of all I_s multisets is that we are also interested in time intervals that occur frequently at a station that does not serve a large part of the total demand.

Finally, as the results of the clustering algorithm may vary with the random initial configuration, the parametrization of the distance measure and the choice for k, we run our clustering and aggregation method multiple times in order to get a feeling for the robustness of the cluster centroids.

3.1 The parameterised distance measure

In order to assign different penalties to the distance between start time, duration and end time of the activities, we introduce a vector $\theta = (\theta_1, \theta_2, \theta_3)$. Here, θ_1 and θ_2 control the penalties if either the duration, start time or end time is equal, while θ_3 controls the penalty if these values are all different. Our distance measure is calculated as follows:

$$d_\theta(x, y) = \begin{cases} \theta_1(x_d - y_d)^2 & \text{if } x_b = y_b \vee x_e = y_e \\ \theta_2(x_b - y_b)^2 & \text{if } x_d = y_d \\ \theta_3(|x_b - y_b| + |x_d - y_d|)^2 & \text{otherwise} \end{cases}$$

[1] We applied the implementation offered by the Apache Math Commons library, version 3.0. It is available at `http://commons.apache.org`

Input : A set $\mathcal{C}$ of configuration parameters for runExperiment, a cutoff number m
Output: A table with for each (x_b, x_e) interval the robustness fraction

Method *calcRobustness($\mathcal{C}$)* **:**
    $r \leftarrow$ new table of dimension $U \times U$ filled with 0-values;
    foreach $(\theta, k, \sigma, t) \in \mathcal{C}$ **do**
        $(J, w) \leftarrow$runExperiment(θ, k, σ, t);
        foreach $(x_b, x_e) \in J$ **do**
            if $w((x_b, x_e)) \geq$ *the mth highest value in* $\{w(x) : x \in J\}$ **then**
                $r[x_b][x_e] \leftarrow r[x_b][x_e] + \frac{100}{|\mathcal{C}|}$;
            end
        end
    end
    return r
end

Algorithm 2: Iterative loop used to calculate the robustness fraction.

In addition to the distance measure, we also need a way to calculate the centroid of a cluster. Since we work with $\mathbb{Z}_U$, the set of all intervals is given by $\mathbb{Z}_U^2$. In case of $U = 24$ this gives us 576 intervals. As a result, the best cluster center within a cluster of size n can be brute forced in $576 \cdot n$ calls to the distance measure.

3.2 Calculating the relevant cluster centroids and their robustness

In order to aggregate the clustering output of the individual stations, we decided to work with a threshold-based rule. This rule works as follows: given a threshold t, an interval (x_b, x_e) is relevant if there exists a station $s \in S$ such that (x_b, x_e) occurs as a centroid in the cluster output of the multiset I_s and that cluster contains more than $t|I_s|$ elements of I_s. The set of all intervals that adhere to this criterion can be calculated using Algorithm 1. We also keep track of a weight map w, which registers the fraction of the population covered by the interval in the cases where it exceeds the threshold.

Since the output of the clustering algorithm, and therefore the output of the *runExperiment* method can vary for different configurations of the parameters, we decided to apply it multiple times, keeping track of how often each interval shows up. Since the number of intervals in a single result set can still be quite large, we truncate the result set to the m highest scoring intervals according to the weight map w. We then count the number of times an interval is in a truncated result set and report this as the fraction of the total number of experiments as the "*robustness fraction*". The loop we use to calculate the *robustness fractions* is presented in Algorithm 2.

4 Labelling and Activity Chain Analysis

After we have applied the clustering algorithm to learn important time intervals in the network, we want to learn something about the relationship between the activities that take place during these intervals. Utilising the output of the clustering algorithm, we can propose a labelling algorithm that assigns a label to each interval. This algorithm then allows us to transform the chains of activities observed in the data of the separate passengers into chains of activity labels.

4.1 Developing the labelling algorithm

In [7] it was observed that there are differences in the extend to which different time intervals show up in different public transport networks. Since our intervals are described by two time slots, it is straightforward to visualise the robustness fractions in a grid containing all possible intervals. Such a plot gives great insight

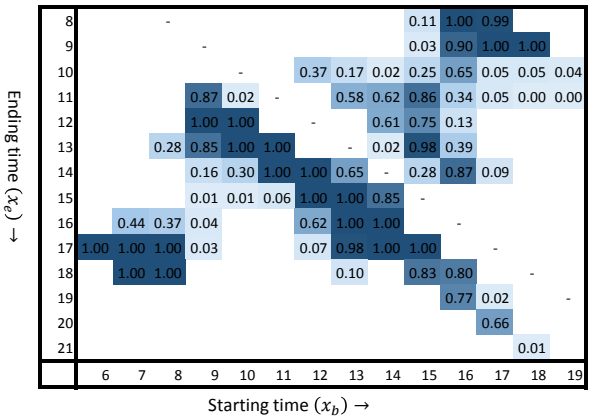


Figure 1: The table of the robustness fractions of the intervals as calculated by our clustering and aggregation algorithm.

in the extend to which time intervals are important. We can use the plot to construct a tree-based labelling rule by checking proposed rules against the robust intervals in the plot.

An important aspect to take into account during the development of the labelling rule is the interpretability of the chosen labels. As our focus is currently mostly exploratory, we decided to focus on labels that are easy to interpret, such as long, short, early, late and overnight.

4.2 Analysing consecutive activities

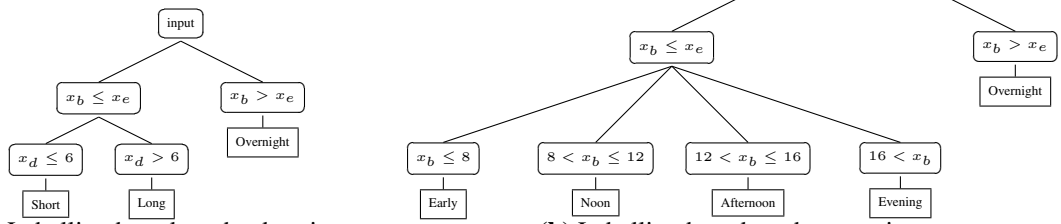
Utilising the labelling procedure developed in the previous section we can now analyse chains of activity labels. We count all consecutive pairs of activities that are performed by the same person and are connected by a single journey. The resulting table of counts can then be interpreted as the adjacency matrix of a weighted directed graph, where the nodes represent the activity labels and the arcs represent the "followed by" relationship as observed in the data. There are many software packages available that allow us to visualise and analyse such networks. During our analysis, we have worked with Gephi [5].

We can count activity chains of an arbitrary length in a similar fashion. We believe that counting chains that are very long will not give a lot of insight, as passengers are not likely to perform many activities within a single day. However, smaller chain lengths, such as three or four activities, could be interesting as these patterns are likely to represent behaviour over one or two days. For this reason we added a triplet counting routine to our implementation of the processing algorithm for the adjacency matrix generation.

5 Experiments and Results

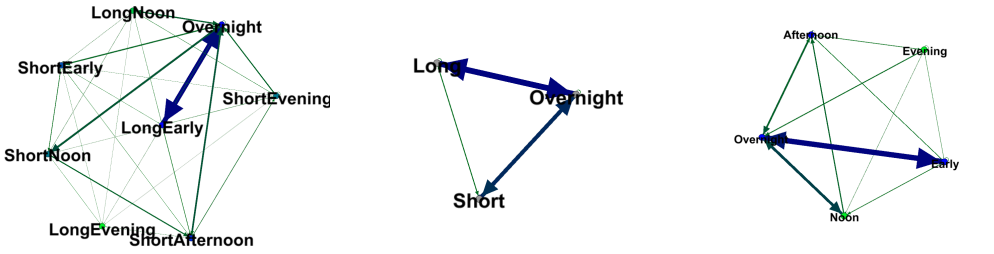
We have applied our clustering method on urban smart card data set from a Dutch network, containing four months of transactions. The data set contains roughly $22 \cdot 10^6$ journeys and $12 \cdot 10^6$ activities. We calculated the *robustness fractions* using the method described in Section 3.2. Our set of configurations contained all combinations of the following: for k one of $\{6, 8, 10, 20\}$, $\theta \in \{1, 2, 4\}^3$ with the constraint that $\theta_3 \geq \theta_1 \wedge \theta_3 \geq \theta_2$, one of two random seeds, $m = 40$ and $t = 0.1$. The total number of configurations is 112. The resulting table is visualised in Table 1.

Many of the highly robust intervals in Figure 1 are typically associated with commuting patterns. However, many shorter intervals that start after 9 are quite robust as well. Additionally, intervals with a duration of precisely 6 or 7 hours are very infrequent. This tells us 6 hours is a natural boundary to distinguish between short and long activities. The proposed labelling on the duration is presented in Figure 2a. Distinguishing between starting times appears to be more complicated. Before 9:00 short activities rarely begin,



(a) Labelling based on the duration **(b)** Labelling based on the start time

Figure 2: Labelling trees for the labels of an interval



(a) Combined labelling (b) Duration based labelling (c) Start time based labelling

Figure 3: Network visualisation of the adjacency matrices based on the different labellings

so 8:00 seems to be a good boundary for early activities. At 13:00 it seems that among the shorter activities, the intervals that are one hour longer than those starting before 13:00 become robust as well. As a result, we pick the second boundary at 12:00. Finally, after 16:00 the intervals or not very robust, so this gives us the final boundary. As it would be hard to interpret different labels for overnight activities, we introduce a single label "Overnight" for activities that have $x_b > x_e$. The resulting tree is presented in Figure 2b.

We visualised the trees for labelling on duration and start time based labelling separately, but they can be combined into one large tree. We can now apply the different trees to count the pairs of sequentially occurring activity labels. We visualised the pairs observed this way as a network in Figure 3

Some interesting patterns can be observed in Figure 3. First, the most prominent pairs of activities are those between an overnight interval and intervals that are early and long. These are typically time intervals associated with home-work and home-study patterns and are thus within expectation high ranking. A more interesting pattern occurs between overnight and noon activities. There is less interaction between early activities and noon activities than between overnight and noon activities.

Let us now consider the top ten of triplets occurring in the activity label chains. The most dominant triplets are typically associated with home - work - home like chains. The fourth and fifth triplet in the full labelling describe a single activity during noon. Here we might be a bit careful in labelling the overnight activity as home: maybe some people travel to their work by car and use the public transport system during lunch time to visit a nearby location. The 10th triplet shows a pattern where two activities are started within the noon window. There is also evidence of people performing a long activity one day and a short activity the next day, and vice versa, as witnessed by triplets eight and nine in the duration based labelling.

When we compare these results to the analysis of the "other" activity label considered during the analysis of Gautineau data by [7], we see that our the third triplet in the start time based labelling suggest a possible peak around 12:00. However, they also found a peak around 16:00, which would be the afternoon label in our case. However, if we consider labels in the start time table, only the sixth and ninth triplets represent evening activities and both are not as strong as the single noon triplet.

Full labelling				Duration based labelling				Start time based labelling			
Overnight	LongEarly	Overnight	19%	Overnight	Long	Overnight	23%	Overnight	Early	Overnight	20%
LongEarly	Overnight	LongEarly	16%	Long	Overnight	Long	20%	Early	Overnight	Early	19%
Overnight	LongNoon	Overnight	4%	Short	Overnight	Short	10%	Overnight	Noon	Overnight	7%
Overnight	ShortNoon	Overnight	3%	Short	Short	Short	9%	Noon	Overnight	Noon	5%
ShortNoon	Overnight	ShortNoon	2%	Overnight	Short	Overnight	7%	Noon	Overnight	Early	4%
ShortAfternoon	Overnight	ShortNoon	2%	Short	Short	Overnight	6%	Afternoon	Overnight	Noon	3%
Overnight	ShortEarly	Overnight	2%	Overnight	Short	Short	6%	Early	Overnight	Noon	2%
LongNoon	Overnight	LongNoon	2%	Short	Overnight	Long	6%	Afternoon	Overnight	Early	2%
ShortAfternoon	ShortAfternoon	Overnight	2%	Long	Overnight	Short	4%	Overnight	Afternoon	Overnight	2%
Overnight	ShortNoon	ShortNoon	2%	Overnight	Long	Short	2%	Overnight	Early	Noon	2%

Table 1: The most frequent triplets for each labelling method and the percentage with which they occurs among all triplets detected

6 Related Work

Pelletier et al. [10] present an excellent general review of smart card data research in public transport during the years 2000-2010. As this is an extensive literature review, we only present a short overview of research focused on activity analysis based on smart card data.

Agard et al. [1] analyse a binary vector indicating smart card activity during four fixed time slots, defined by the public transport operator. They find four main travel patterns using hierarchical clustering, the top two of which correspond to a home-work-home pattern and a home-study-home pattern. Morency et al. [9] focus on the variation in temporal patterns using a k-means clustering algorithm. They also consider vectors of 24 binary values indicating whether a passenger has boarded a vehicle during the corresponding hour of the day. Using clustering with the Hamming distance measure and the component wise median to derive cluster centroids, they are able to derive regularity indicators from the raw data. Devillaine et al. [7] present an analysis focused on the temporal distribution of activities based on smart card data from both Santiago, Chile and Gautineau, Canada. Their classification is based on both temporal aspects as well as card type. The assigned classes are work, study, home and other. They find that the temporal distribution of activities in Santiago differs from Gautineau. Activities classified as other have peaks at their starting times when they start more often around noon or four in the afternoon in the Gautineau network, while they are more evenly distributed in the Santiago network.

A different methodology to analyse spatio-temporal patterns is to calculate eigenbehaviors [8]. The general idea of the method is to apply Principal Components Analysis on vectors of binary variables representing time slot/location combinations. While this method is usually able to reduce a matrix of vectors to a few dominant eigenvectors, the fractional nature of the eigenvectors makes them complicated to interpret, especially if the goal is to create input for activity based models.

7 Conclusions and Future Work

We have developed an approach to cluster temporal intervals derived from activity data at a station level using a parameterised distance measure and to aggregate the results, such that we obtain the most interesting time intervals in the data. We repeat this process to obtain robustness fractions. Based on the robustness fractions, we constructed a tree-based labelling procedure. The labels allow us to find the most frequent pairs and triplets of activity types observed in individual activity chains. While the typical intervals associated with home and work activities are dominant, we are able to identify shorter activities as well and provide some insight on their relation to other activities within the activity chains of individual passengers.

Our current approach still has some drawbacks. The modular ring $\mathbb{Z}_U$ with $U = 24$ is a quite rigorous simplification, as we cannot distinguish between an activity that takes one hour and an activity that takes 25 hours. While this simplification allows us to get a general idea of what is happening within the system without having to look at too many numbers, it is likely more caution is necessary if we want to construct the input for activity based models. Another thing that we ignore is the distinction between weekdays and weekends, which has a very significant impact on travel behaviour. For the implementation of a valid simulation, it will be necessary to make this distinction. If we would introduce these detailed descriptions of the activity intervals, it would also be necessary to reconsider the proposed distance measured. Finally,

we constructed our labelling algorithm by hand. An interesting question is whether we can use automatic classification algorithms instead of our manually constructed labelling procedures.

Aside from further refinements of our methods, such as reducing the number of parameters to set and varying distance measures, there are two main topics for future research. First, we would like to use either the clustering output at the station level or the complete distribution of intervals observed at the stations to identify similar classes of stations. If we are able to reduce our stations to a small number of important classes, we could include some spatial aspects in the analysis of the activity chains. We would also like to include use our findings in order to generate input for an activity based agent simulation, such as MATSim has implemented. It would be interesting to see how accurate the observed traffic counts in the smart card data can be replicated using only a small set of typical activities.

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