Modelling Cellphone Trace Travel Mode with Neural Networks Using Transit SmartCard and Home Interview Survey Data

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ABSTRACT

Problem Statement

Cellphone trace data are increasingly being used to identify trips within urban regions. The obvious advantage of these data is the potentially very large size of revealed preference data on trip-making, as well as the potential to observe the same trip-maker (or, more precisely, the same cellphone) over extended periods of time. Cellphone trace data are also of interest since they are ubiquitously available in urban regions worldwide, typically with very high market penetration rates across a wide range of socio-economic strata (as opposed to smartphones, which still possess significant socio-economic biases in many urban regions). Key limitations with respect to these data, however, include the generally complete lack of information concerning trip-makers' socio-economic attributes, as well as the mode and purpose of the observed trips. Mode and purpose imputation is further complicated by technical limits to the spatial and temporal precision of the traces that can generally be achieved. To date, the question of mode imputation has often been ignored, with researchers focussing on auto-based travel. If cellphone data are to be of widespread use in multi-modal travel analysis and modelling, new, robust methods for imputing travel mode are required.

Also to date, few attempts have been made to exploit other major travel-related datasets that might be used to help impute cellphone trace travel modes. These include public transit smartcard transaction data and traditional household-interview travel survey data. Smartcard data provide massive amounts of transit trip data, but no information about other travel modes, while household-interview surveys provide very detailed information concerning trip mode, purpose and trip-maker attributes, but generally are static (cross-sectional one-day surveys) and very small sample. The question arises as to whether alternative datasets such as these can be used to help identify cellphone trace travel mode.

Research Objectives

The objective of the research reported in this paper is to investigate the use of deep neural networks as a means for exploiting public transit smartcard transaction data and household survey data to impute cellphone trace travel modes.

The empirical case study region for this research is Montevideo, Uruguay, for which high-quality data for all three types of data (cellphone traces, transit smartcard transactions and household travel survey records) are available. The City of Montevideo, the regional transit authority and the largest Uruguayan telecom company all supported this project given its potential to support transportation planning analysis and modelling within the greater Montevideo urban region.

Data

Primary data sources for this project include:

- A 40% sample of all cellphone traces for the month of May, 2018 were provided by the largest telecom in Uruguay, Antel. This consisted of 117,862,000 cellphone traces for about 948,600 unique cellphones. The data were aggregated to a 135 traffic zone system for the region.
- A 100% sample of all smartcard transactions (representing 82.5% of all transit trips within the Montevideo region) were provide by the Intendencia de Montevideo for the same May, 2018 time period and traffic zone system. These consisted of 29,868,716 recorded transactions, 734,569 unique smartcards.
- An August, 2016 one-day household travel survey, the Montevideo Household Mobility Survey (MHMS). This is a very high-quality, but small sample (0.34%) survey consisting of 2,230 households and 5,946 individuals interviews, reporting 12,546 trips for a single weekday.
- Emme road and transit networks were constructed by the study team from open source information concerning the Montevideo road and transit netowrks.
- 2011 Uruguay census data.

Methodological Approach

A deep neural network approach was adopted in this study as a logical approach to imputing cellphone trace travel modes for the large datasets being used. The key concern in developing any neural network is the availability of a "labelled" dataset containing observed outcomes (in this case, travel mode) which can be used to train and validate the neural network before it as applied to an application dataset. Given that cellphone traces by definition do not provide travel mode information, the key methodological question was how to construct a labelled training set in this application.

Figure 1 displays the overall approach developed in this study to imputing trip mode for the cellphone traces. The first, key (and novel) step in this procedure is to convert MHMS (and/or smartcard) O-D trips into pseudo cellphone traces; i.e., for each trip, convert it into a "trace" at the same level of spatial and temporal aggregation as the actual Antel traces. These MHMS pseudo-traces were then used as labelled input data to train the neural network model.

In order to construct these traces, the MHMS O-D trips must first be assigned to paths (routes) through the road and transit networks (depending on each trip's chosen mode). To do this, road and transit networks for Montevideo where constructed within the Emme network modelling software system. Maximum utility paths through the road and transit networks were found for auto (drive, passenger, taxi, motorcycle) and public transit trips, respectively. Active mode traces were constructed by taking the shortest distance paths through the road network at an assumed speed of 4 kph. Since it was not possible to calibrate Montevideo-specific assignment model parameters within this study, parameters from Toronto's GTAModel V4.0 were used.

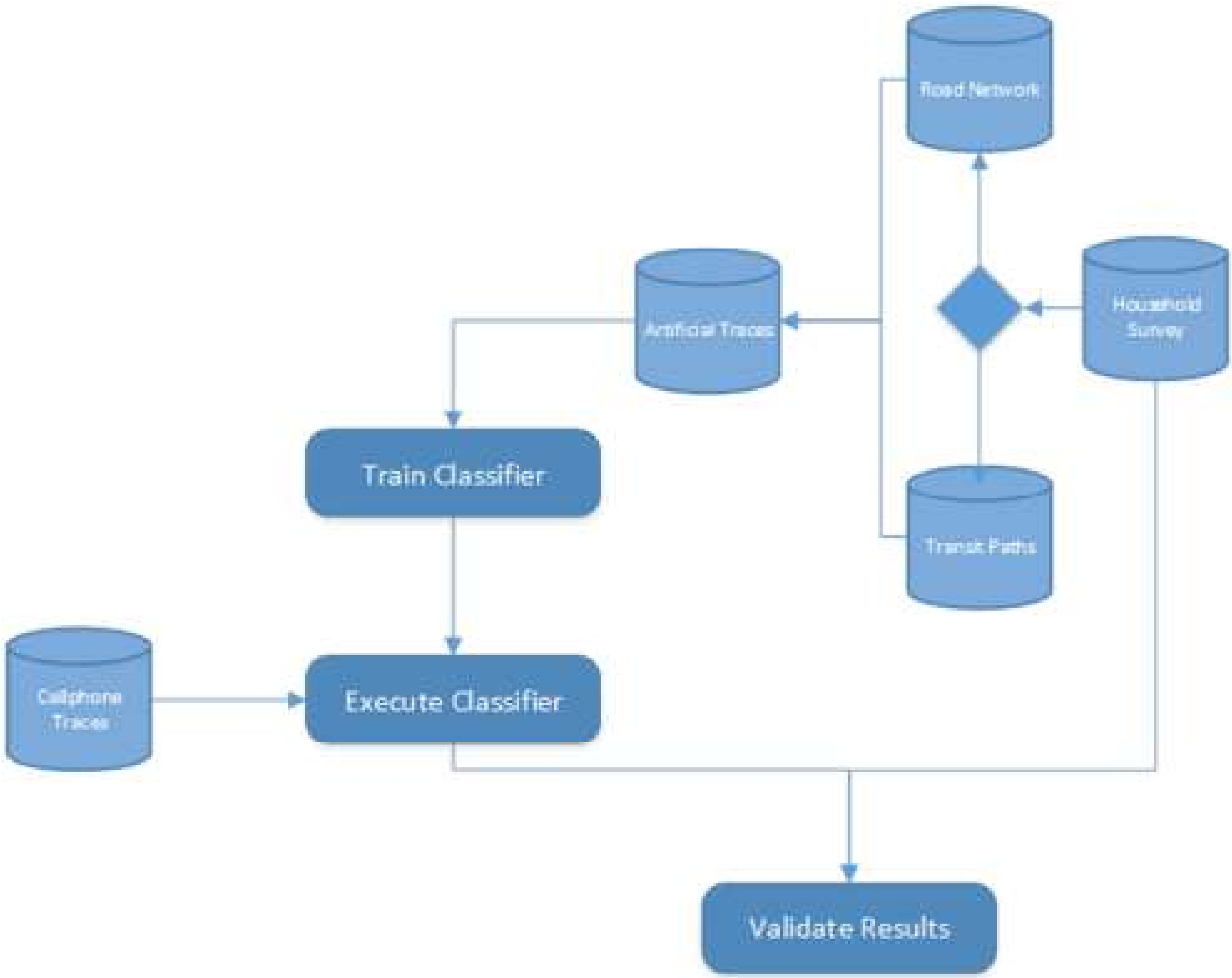

Figure 1: Analysis Approach

In this model, the day is divided into five-minute segments. A trip is defined by:

1. Whether it is occurring during a given five-minute segment (=1) or not (=0); i.e., whether the person is moving during this time segment.
2. The distance travelled during the five-minute segment.

The job of the neural net model is to determine that probability of each trip being made by the auto, transit or active modes, given the time of day, trip length (in time and distance) and distances travelled per time segment (approximate speed) for the trip.

The neural net classifier model developed in this study consisted of three hidden layers, with 400 neurons per layer. Weights were randomly initialized from a normal distribution. Backpropagation combined with stochastic gradient descent (SGD) was used to update the weights in each iteration of the training session. Weights were chosen to maximize a cross-entropy (effectively a log-likelihood) function. A linear rectifier activation function was used for the hidden layer neurons. A softmax activation function was used for the output layer, in order to generate probabilities to assign to the three modes. Note that the softmax activation function is effectively a logit model which assigns for each trace a probability for each travel mode.

Results

To date, only the MHMS data have been used to train the neural network classifier. Results obtained have been very promising, with 98% correct predictions being achieved by the trained model on its training set, and 86.9% correct predictions being achieved with the validation set. Comparison of predicted cellphone trace travel modes with MHMS observed data yields generally good results, although there appears to be an under-prediction of morning peak-period trips. The causes of this apparent under-prediction is still being investigated at the time of this abstract's submission.

Also at time of this abstract's submission the authors are working on incorporating the smartcard transaction data into the neural network's construction using the same methods as described above for the MHMS data. Results of the updated modelling using the combination of household survey and smartcard transaction data will be included in the paper's presentation at the mobil.TUM conference.