ASSESSING TRANSIT LOYALTY WITH SMART CARD DATA

Martin TRÉPANIER, P.Eng., Ph.D., Associate professor, École Polytechnique de Montréal, Department of Mathematics and Industrial Engineering

Catherine MORENCY, P.Eng., Ph.D., Associate professor, École Polytechnique de Montréal, Department of Civil, Geological and Mining Engineering

ABSTRACT

Smart card data systems have mainly been considered for their administrative function of collecting revenues and controlling access to the transit network. Smart card is a convenient way of collecting fares, especially when there are multiple modes and operators. But these systems also generate large amount of data regarding the daily use of the transit network. The aim of this study is to develop methods and models to characterize transit loyalty (rider retention) with the help of smart card fare collection system data. The paper characterizes loyalty in relation with some factors, such as "birth date", fare type, and home location.

INTRODUCTION

Transit loyalty is a concept that reflects the assiduity of a given individual in the usage of a public transportation network. The term "rider retention" is also used in the literature. Its knowledge is useful for several reasons. Transit operators can use transit loyalty rates to focus on specific customers in their marketing campaigns. They could also better preparea their fare packages offer. Planners can use loyalty measures to evaluate the impacts of network changes or disruptions. Loyalty can be used to calculate elasticity patterns related to different mode usage.

Loyalty is historically hard to estimate because of the anonymousness of the fare validation transactions. Nowadays, with the advent of smart cards, there is a possibility to follow the use of a transit network by looking at the transactions associated to a card. At this level of detail, loyalty can now be related to given dates, routes, fare categories and other derived attributes.

This paper proposes a method to calculate the transit loyalty based on timestamp transactions of a smart card automated fare collection system based in Gatineau, Canada. The application of a totally disaggregate and object-oriented approach in transportation permits the analysis of transactional data at high level of resolution. The paper is structured as follow: first, a literature review is proposed on transit loyalty concept and the processing of smart card data in public transportation. Then, the methodological elements are

presented, with a focus on the information system that was used in this work. Afterwards, we assess the loyalty indicators generally (over 5 years) and by fare type. As a first modelling attempt, A regression model is estimated using more than 150,000 observations to describe one variable related to loyalty: the number of month in the system (lifespan). Finally, there is a discussion on perspectives brought by this type of work.

BACKGROUND

Smart cards in public transit

The complex fare system that is used by many public transport authorities can be better managed with the help of a smart card automated fare collection system, because smart cards can store more than one transport document at a time and the card is validated automatically. Over the years, the need to integrate fare policies within large metropolitan areas will promote smart card usage (Bonneau and ed. 2002). As stated by Chira-Chavala and Coifman (1996), smart card "*could reduce passenger boarding times, vehicle downtime due to malfunctions of the fare system, and driver workload and stress*" and also "*enhance the collection and quality of transit data*".

However, privacy is an important issue that could limit smart card implementation. The French Council for Computer and Liberty recommends being careful with such data because one may reconstitute the personal movements of a specific person (CNIL 2003). But Clarke (2001) recalls that smart card data is not different from other individual data collection systems like credit card usage, road tolls, police corps database.

With technological and ethical problems resolved, several advantages arise from the analysis of SCAFC data (Bagchi and White 2004):

- Access to larger sets of individual data;
- Possibilities of links between user and card information;
- Continuous data available for long periods of time;
- Better knowledge of a large part of the transit users.

These authors conducted a study on the passenger transfer behaviours on the Bradford and Merseyside transit networks (UK). The absence of alighting location information was then identified as the main issue for further analysis. In another paper (Bagchi and White 2005), they propose different actions to avoid undermining data quality in SCAFC systems. They especially insist on the need of implementing complementary surveys to validate SCAFC data. They also propose that the organizations prepare a 2-year settling-in period to implement such systems.

There are also several technical problems addressed in the literature. In smart card, there could be missing values, incorrect references to the planned service and systematic erreors in the database. There is sometimes a need to complete existing dataset with additional information (Chu et al. 2009). Hofmann and O'Mahony presented an iterative classification algorithm to identify the transfer journey in the case of United Kingdom systems (Hofmann and O'Mahony 2005). In their study, Utsunomiya et al. (2006) pointed the difficulties of analyzing large dataset with possible malfunction errors and missing values. Achieving the

interoperability of smart card systems between transit authorities and with other smart card uses is also a quite difficult task (Yoh et al. 2006).

In the case of the Société de transport de l'Outaouais (STO), Trépanier et al. (2004) have shown the potentialities of using SCAFC data for public transport network planning with the help of a Transportation Object-Oriented Modelling. They also proposed a destination estimation algorithm for the system (Trepanier et al. 2007) and analyzed user travel behavior with the help of data mining techniques (Morency et al. 2007).

Transit loyalty and rider retention

Rider retention had been scarcely addressed in the scientific literature, but is often mentioned in the technical reports related to transit planning and development. In addition, it has been found that customer loyalty can be an important transit network performance measure (Foote et al. 2001). The literature can be classified in three topics: causes of service cessation, retention strategies and loyalty rate measurements.

In their technical report, Perk et al. (2008) identify the new ownership of a car as the major cause of cessation in transit use. Socio-demographic attributes also have an influence, especially in the younger age where people change their way of living, becoming workers after their studies.

In several studies the level of satisfaction of users is related to the transit loyalty. Retention strategies are then identified as specific programs that would increase satisfaction. Better service frequency, lower waiting and travel times, vehicle comfort and cleanliness are usually identified as key factors for retaining customers (Tyrinopoulos and Antoniou 2008). Evanschitzky et al. (2006) have found that the presence of loyalty cards can enhance the retention process.

Retention measurement is usually done through customer satisfaction studies. Liu (2009) has found a high retention rates related to the implementation of a new light rail service. Perk et al. (2008) also conducted this kind of study where users are surveyed on their level of satisfaction, their use of the service and their concurrent choices. But transit loyalty rate is rarely estimated at the individual level, with revealed preference data coming from sources independent from satisfaction surveys. This process has long been used in other fields, like retail (Mauri 2003). Bagchi and White (2005) have described the potentialities of using smart card data to measure user turnover rates according to time, space and transit network infrastructures. This is the key element on which our work is founded.

METHODOLOGY

In this section, we define the case study and the smart card object model. Some attributes of the dataset are also presented.

Case study

The examined network is operated by the "Société de transport de l'Outaouais" (STO), Gatineau, Quebec. The STO is a medium-size public transport authority operating 200

buses and servicing 240,000 inhabitants. The STO operates its smart card system since 2001. Today, more than 80% of all STO passengers hold a smart card.

Moreover, every STO bus is equipped with GPS reader. At each boarding event of a user, stop location and bus route are stored in the database along with a timestamp. Since the STO uses a high-level secured procedure to ensure the privacy of the data, smart card data are completely anonymous. No nominal information on user can be found in the database. Fortunately, STO users have personalized cards with picture and the user number is made available to us for adults; this allows to follow an adult user even though he has changed his card through the years. But this cannot be applied to all users, because some of them had new user numbers reassigned. Later, we will explain a procedure that we have developed and applied to identify them and to impute the database.

The Gatineau region is located across the River from Ottawa, Ontario. The city is quite extended (about 50 km from west to east). The transit network is composed of regular routes (mostly located in central areas), of express routes (aimed to bring users to the CBD and to Ottawa) and interzone routes (which service the outer bounds of the region). In the morning peak hour, most routes bring people to downtown and to the core center of Ottawa, but there are also routes servicing the college, the university, and some high schools of the area.

A special information system has been developed at the STO to manage SCAFC data. The following describe the general process. Smart cards are first bought by travelers at emission locations and can be recharged at further locations. Then, when the user boards the buses, the smart card's fare gets validated. The validation is done following those steps: the bus system contains the planned runs for the day (a run is a sequence of stops to be deserved; it usually represents one direction of a route). The Global Positioning System (GPS) reader on the bus identifies the stop where the boarding is made. The system validates the run (correct route) at this location. Card number, date, time, validation status and stop number are stored at each boarding. This information is downloaded to the central server at each end of day, when buses get back to the depot (infrared transmission).

Object model

From the smart card information system, we can identify several objects which can be described and related to the database tables. The method used for this task is Transportation Object-Oriented Modeling (TOOM). TOOM classifies data into four metaclasses of objects: static (supporting transportation), kinetic (describing movements), dynamic (transportation actors) and systemic (networks, systems). This method is a natural extension of the Totally Dissagregate Approach, because it involves analysis of individual elements of the system and uses the same basic procedures (Trepanier and Chapleau 2001). The method involves four major groups of objects:
   A. Network objects are the user-interfaced elements of the STO transit network (drivers, buses, routes, route-stops);
   B. Operations objects are related to STO bus operations (drivers, buses, workpieces, garage);
   C. Administrative objects are defined for the purposes of the smart card system itself;
   D. Trips, tripchains and users are composing the demand.

The experiments cover the period between January 1st, 2004 and September 30th, 2009. This 69 months period is used to better evaluate the loyalty under different levels: years, months, seasons, weeks and weekdays. A dedicated dataset has been extracted from the universe of transactions. It contains the user number, the fare type, the month of observation and the number of transactions. A more detailed dataset has been extracted for the school year 2008-2009, containing in addition the week number and the route identification.

In TOOM, object models help to explain the relationships among the elements of data available. Figure 1 illustrates the object model of the smart card system of the STO. The number of instances is shown for the period. The dataset contains almost 53 millions boarding transactions for the whole period, related to 43.8 million trips (the rest of the boardings are related to invalidation, refusal or transfer).
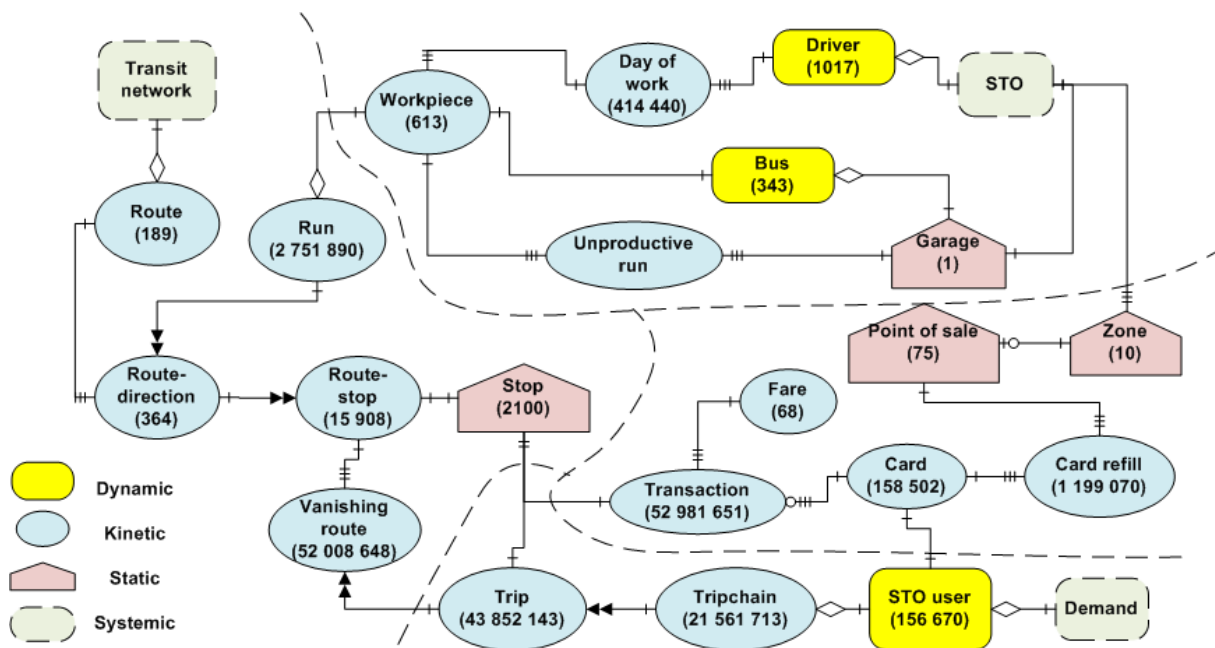

Figure 1: Object model for case study

A total of 156,760 users have been examined. As said before, this does not represent all different individuals because user ID can be issued several times to a same person:

- The students have new cards reissued each September and their user ID is reinitialized at this time. We will have to omit students from our multiyear analysis.
- Users that subscribe to the authorized bank (AP) payment program also get a new user ID and a new card. We developed a method to retrieve them in order to correct the database.

The procedure is intuitive. For each user that stops using the transit service, we try to find another user who begins using the service at about the same time (maximum interval of 10 days). The assumption is that the other user will need to have the same behaviour than the user it "replaces". Due to the size of the database and the time of calculation, we use simple indicators like the average time of departure and the most frequent route numbers and stop numbers to find a similar user. We only consider users with similar fares (for example, switching from regular express to AP express). We acknowledge the limits of this approach, because a lot of mismatches could be done, but we think that the method for the moment is acceptable at such an aggregate level.

In order to analyse the data, we define the concept of "birth date". The "birth date" of a user is the first month where he is using the service, whenever the issue date of the first smart card in his possession. The concept of "lifespan" is related to the period of time for which the user will use the service. The lifespan is then the period between the first and the last transaction date made in the system. Is could differ from the number of active months, that are months where the user effectively made at least a transaction in the network. We define the "utilization rate" as the ratio between the number of active months and the lifespan. The temporal unit of analysis is mostly the month, but some analysis are based on weeks.

RIDERSHIP

This section and the following are based on the smart card ridership, which do not represent all users of the STO. In addition to cash and tickets payments, there are several transit users from the Ottawa Carleton Transportation Commission (OC Transpo), located across the Ottawa River. Smart card riders are estimated at 80% of all passengers.

Monthly evolution

In the Gatineau region, ridership has slightly increased in the 2004-2009 period. Of course, smart card data can be used to show the evolution of the number of transactions. Figure 2 shows the number of transactions by fare type and month. We can see the cycles in the ridership demand, with an important decrease in summertime except for seniors where the demand remains stable. We also see the constant increase through the years: about +13% over 5 years for the regular adult fare. Before the school year 2008-2009, college and university student less than 21 y.o. were admissible to student fare. In 2008-2009, the limit has been changed to 18 y.o.. This caused an important transfer from student to college and university fare, as visible on the figure.
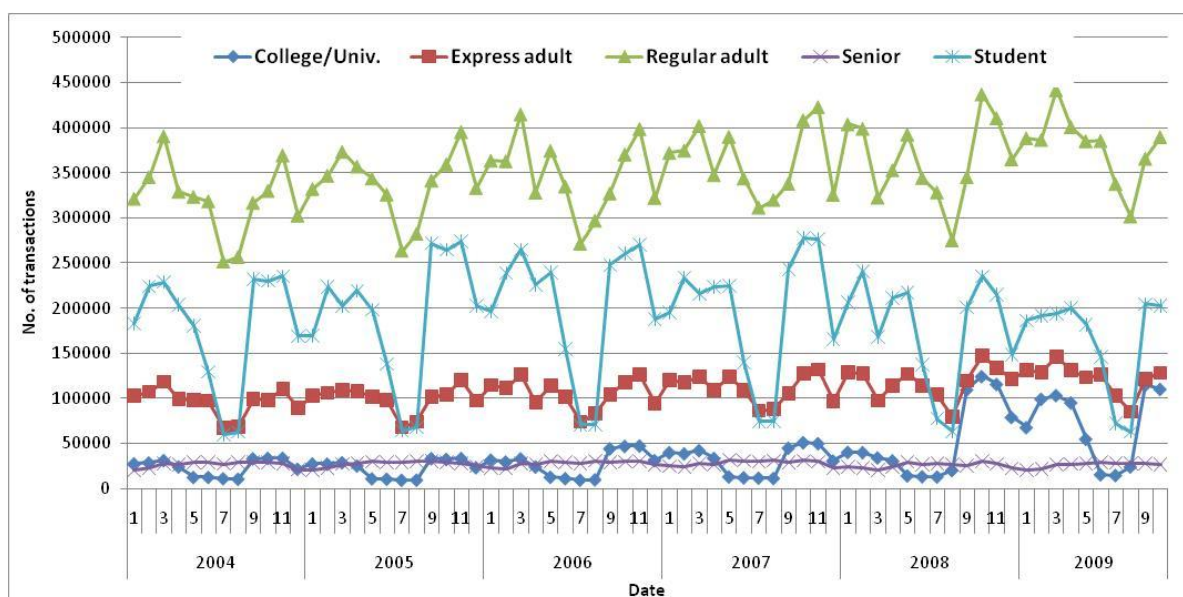

Figure 2: No. of transactions by fare type and month, 2004-2009

Trip rate

Smart card data can be used to show the differences in trip rate between the users (characterized through fare type). Figure 3 gives the specific trip rate by fare type on a week-to-week basis. It is said specific because it only involves the users that have made at least one transaction in the given week. On the figure, we clearly see the Christmas period (week 2008-52, 2008-53 and 2009-01) and other Holidays. We also see that College and University Students are the most frequent users of the service. This is particularly true during summertime, where the number of fare holders drops, but the one remaining in the system increase their use of the network.
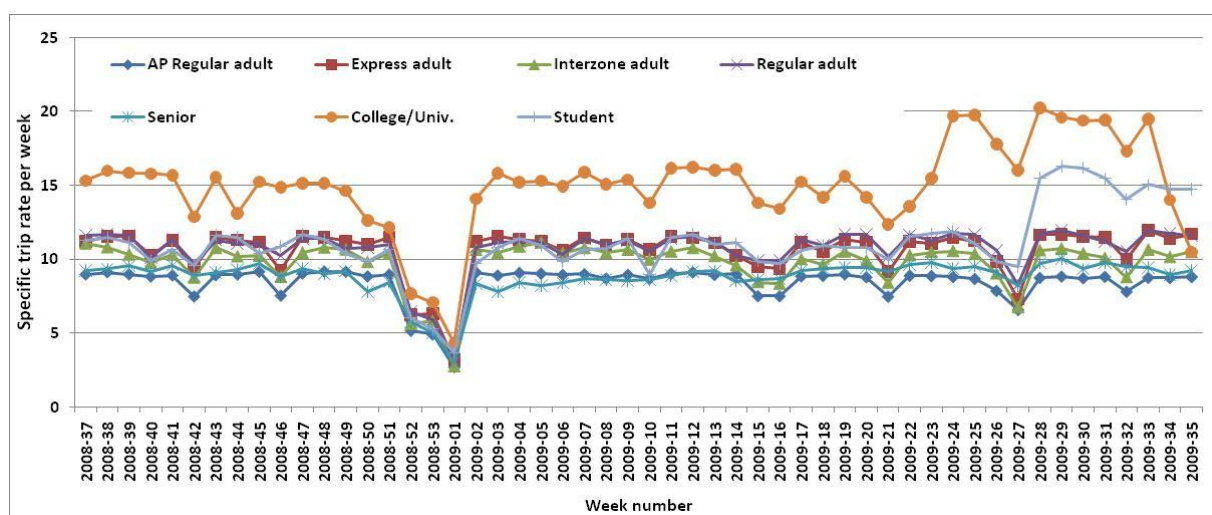

Figure 3: Specific trip rate by fare type, school year 2008-09

RETENTION RATE

In this section, we try to qualify the retention rate of the system, which is the proportion of the users that is still active in the network after a certain amount of time. The analysis is firstly done by fare type, and then examined with regard to "birth date". The retention rate by fare type is estimated from the lifespan of users in the system. The lifespan is calculated for each user by subtracting the "birth date" from the last date where a transaction was recorded. During this period, the user may not be active or not, but he is for at least the beginning and the ending months. Lifespan indicators are sorted to produce the cumulative charts.

Fare type

Figure 4 shows the retention rate of users that have "birth date" in 2004 and 2005. Since the transactions database rolls until 2009, we are able to get 4-year lifespan in the chart. Results shows that authorized payment (AP) members are more loyal and will be more retained in the system, at a level of 60% after 4 years for the holders of the AP Express fare. Express fare holders have better retention rates than regular users. In this case, seniors have surprisingly good retention rate, showing that they may be captive users in the system. Because of the card renewal rules (let us remind that some users change id every year),

students have much lower retention rates. The clientele of College and University students have an interesting retention curve pattern. After 12 and 24 months, there are steep decrease in the chart, reflecting the turnovers in student population of college (2 or 3 year terms in Quebec) and universities.
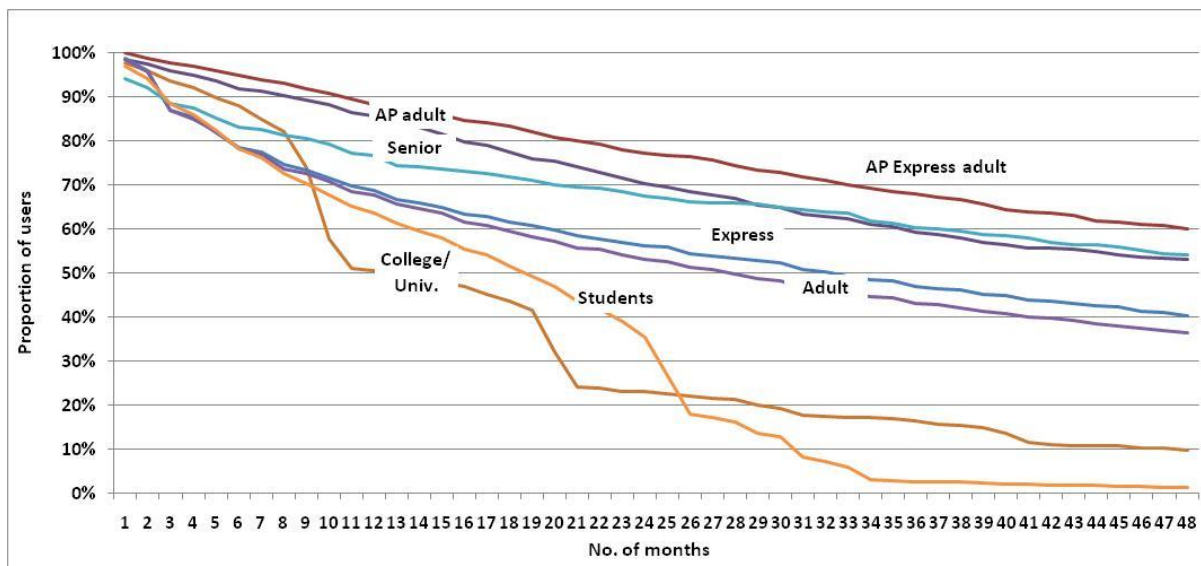

Figure 4: retention rate of users with "birth date" in 2004 and 2005, by fare

Birth date

We can also examine the retention rate curve patterns according to the "birth date" of the users, without fare discrepancy. We choose the September and the January groups for four years to see if there are differences between month of birth and over the years. At first sight, Figure 5 shows a clear discrepancy between the September group (upper curves) and the January group (lower curves). Part of the people that begin to use the service in January will leave it during next summer, so their lifespan is shorter than those that started in September. On another hand, users with older "birth year" have a higher retention rate than the one that started in 2006 and 2007. This "decrease" i transit loyalty through the year is somewhat not that much significant.
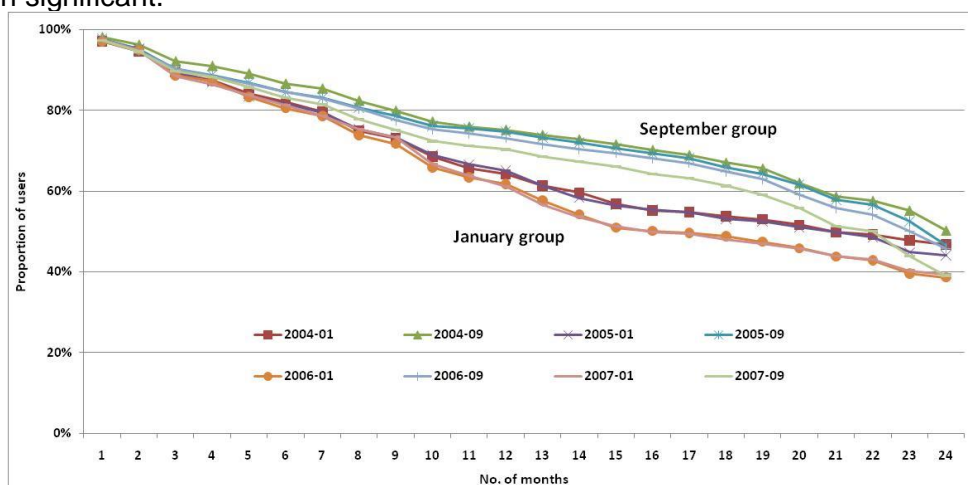

Figure 5: retention rate of users with specific "birth dates", all fare

SURVIVAL PROFILES

Survival profiles are created by looking at individual "birth date" and by analysing the individual use of the network. The user that is "born" at a specific month will remain in his cohort through the analysis.

Regular adult fare

The survival profile of transactions for regular adult fare (not AP) is shown at Figure 6. For each of the series, the reader can follow the number of transactions made by the cohort until the end of the period. The figure shows the seasonal decrease in transactions during summer period and the month of December during Holiday season. The figure also reflects the slight increase of ridership through the years for this fare type.
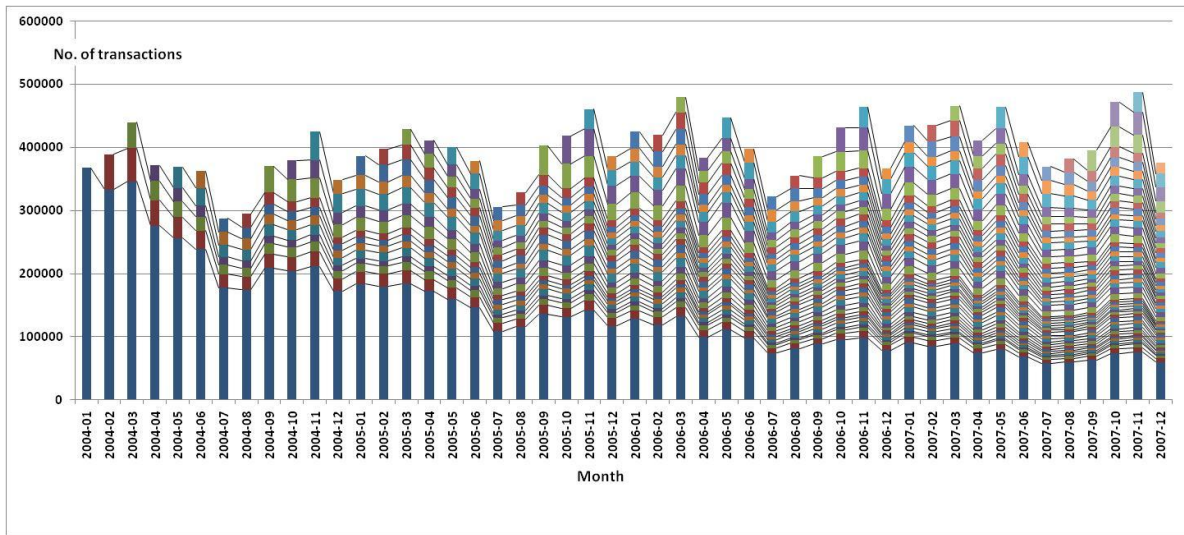

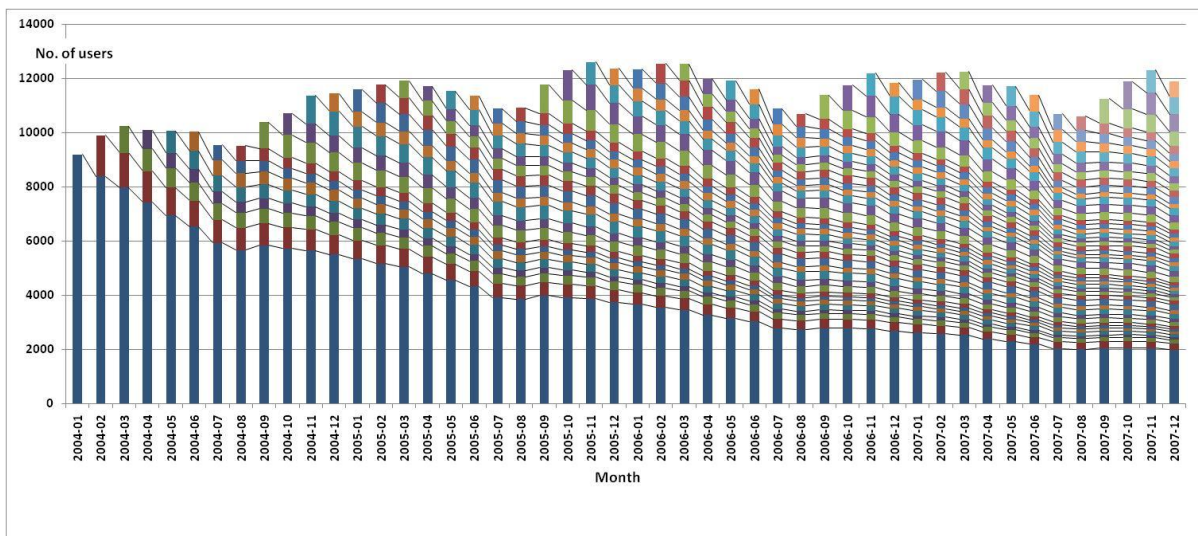**Figure 6: Survival profile of transactions for regular adult fare**

Figure 7: Survival profile of users for regular adult fare

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Figure 7 relates to the same period, this time in terms of number of users that remains in the system. The survival is established here with the lifespan, thus some users may be not active at certain months. Let us remark the slight decrease of users in summertime, and the importance of September periods (-09), even for adults.

AP adult fare

The picture for AP adult fare is quite different (Figure 8). In Fall 2004, there has been at major boom in the number of adhesion, due to an important marketing campaign. Afterwards, the number of users remains stable. When we follow the series, we can see that the retention rate is higher at the end than the adult non-AP fare.
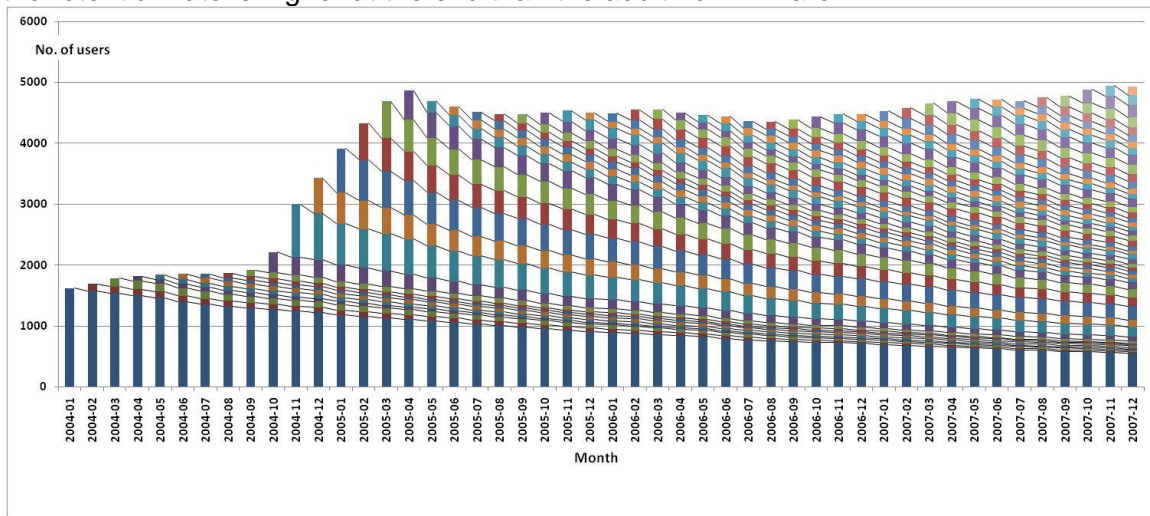

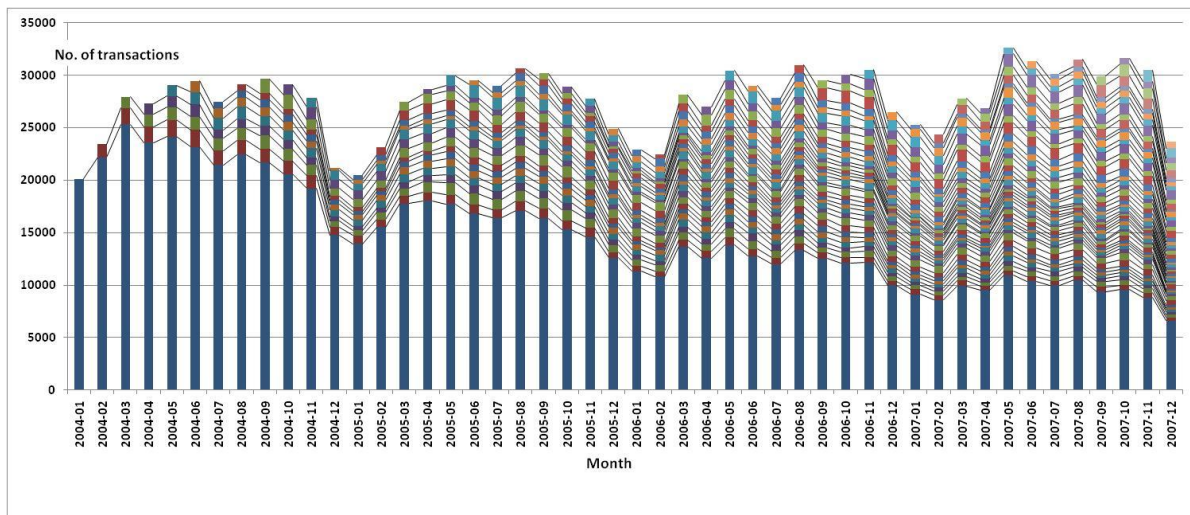
Figure 8: Survival profile of users for AP adult fare

Figure 9: Survival profile of transactions for senior fare

Senior fare

The senior fare is also exposed here to see the differences of behaviour compared with regular adult users (Figure 9). The figure shows that the number of transactions has increased through the years. In the case of seniors, the winter months are the low season

because of the very cold weather that affects this area during this time, while ridership remains high in summertime.

Utilization rate

In Figure 10, we show that utilization rate of the network depends on the "birth date" and the fare type. Utilization rate is calculated by dividing the number of active months by the lifespan. Users that were "born" in the first quarter of 2008 have a utilization rate of about 60% for all fare types except student. As stated before, users that begin to use the service in the last quarter of the year are most likely to use the service intensively. In the case of student and, to a lesser level, the college and university students, the use of the transit service is also higher. AP fare holders have a slightly higher utilization rate.
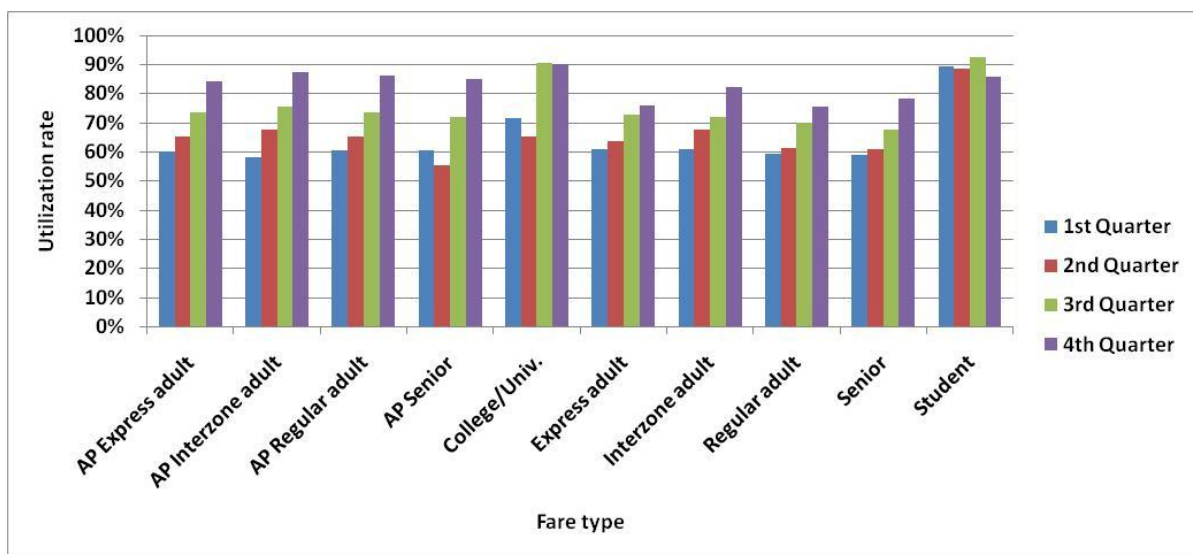

Figure 10: Utilization rate by fare type for users with "birth date" in 2008

EXPLICATIVE MODEL

To better interpret the descriptive results presented in the preceding sections, we propose a multiple regression analysis to identify the variables that would best explain the phenomenon of loyalty (lifespan). A dataset of 150,752 observations has been introduced in a multiple linear regression model for the period 2004-2009. Each observation represents the life of a smartcard; therefore it can be associated to a user except for those who changed their card and their fare during the period. Results are presented in

Table 1 and the map in Figure 11 helps to locate the different regions involved.

Table 1: Results of the regression model

Variable (x_i)	Description	Coefficient (β_i)	t*	Proportion of group
*Y = No. of months (Lifespan) R^2 = 0,2254, No of obs. = 150752*			
$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n + \varepsilon$ all x_i 0 or 1			
Group: Month of "birth"				
Ref group	*January (7,43%) and August (12,02%)*			*19,45%*
mnais_02	February	-0,929	-7,64	5,79%
mnais_03	March	-1,160	-8,89	4,85%
mnais_04	April	-1,831	-13,98	4,80%
mnais_05	May	-2,146	-17,16	5,38%
mnais_06	June	-2,346	-19,03	5,58%
mnais_07	July	-3,453	-30,85	7,20%
mnais_09	September	-0,581	-7,50	24,98%
mnais_10	October	-1,766	-18,35	11,30%
mnais_11	November	-2,133	-18,28	6,58%
mnais_12	December	-2,442	-17,45	4,08%
Group: Year of "birth"				
Ref group	*Year 2009*			*16,02%*
anais_2004	Year 2004	9,820	106,33	15,57%
anais_2005	Year 2005	8,802	97,45	16,44%
anais_2006	Year 2006	7,619	84,84	16,59%
anais_2007	Year 2007	6,169	69,20	17,18%
anais_2008	Year 2008	3,973	45,28	18,21%
Group: Home location region				
Ref group	*Central districts*			*36,14%*
d_plateau	Plateau	1,331	14,17	9,19%
d_pte_gat	Pointe-Gatineau	-0,574	-8,02	21,30%
d_aylmer	Aylmer	1,443	19,44	17,45%
d_gat_est	Gatineau-East	-0,598	-6,44	10,72%
d_ott	Ottawa	-2,607	-13,86	1,92%
d_mas_ang	Masson-Angers	1,455	9,90	3,28%
Group: Fare type				
Ref group	*Adults***			*30,75%*
f_ap_ad	AP Adult	6,486	47,79	3,97%
f_ap_ex	AP Adult Express	8,192	45,15	2,22%
f_ap_sen	AP Senior	9,005	13,30	6,58%
f_ex	Adult Express	1,741	15,13	0,14%
f_stud	Students	-7,081	-114,70	47,37%
f_colluniv	College & Univ.	-4,127	-38,86	8,19%
f_other	Others	1,199	4,09	0,78%
_cons	Constant	7,618	77,70	

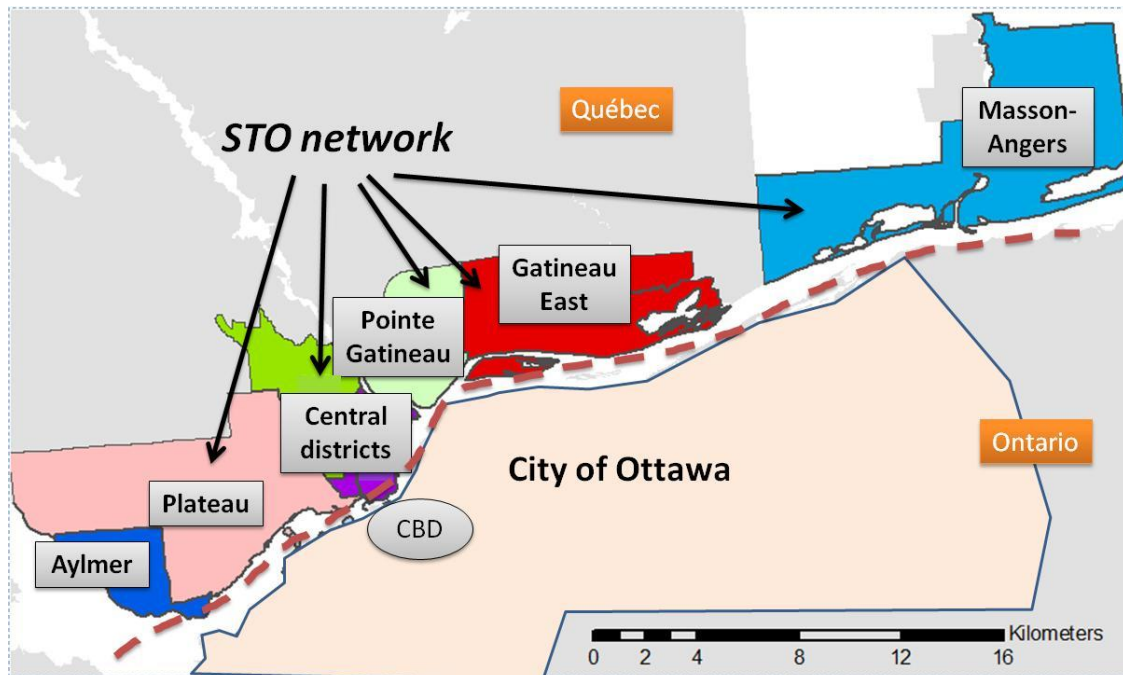*** t values at 95%   * including interzone fares (AP and non-AP)*

Figure 11: map of the study region

The model relating lifespan and various spatial-temporal variables explains 22,54% of the intrinsic variability of transif user lifespan. This is satisfying since the model is estimated at the card level and that the sample is very large. All explanatory variables were converted into dummies to facilitate interpretation and identification of significant features. Hence, interpretation must always be in relation to the reference group (Ref group). If we look at the first group of variables, we see that all month of "birth" have a negative effect of duration, compared to the reference group composed of January and August. People that began to use the service in June, July or in December will be less loyal to the service than the others. The effect is less for September and February, two months that follow the reference months. As expected, the year of "birth" is correlated with the lifespan. A card born in 2004 will have a lifespan 9 months longer than one born in 2009. The study area was exploded in 8 zones of home location. The central districts were retained as the reference group. We see that the group of users from Ottawa will have shorter lifespans; this could be explained by the burden of having to use two transit networks. Also, in most suburb districts like Plateau, Aylmer and Masson-Angers, the vast majority of trips are home-based (pendular) and use express routes. This seems to have a positive impact on lifespan. The effect is negative for Pointe-Gatineau and Gatineau-East, where trips are more mixed. As seen in the previous sections, fare type has an important impact on lifespan. We see in the results that users of the automated bank payment system will have longer lifespan. It is the same for express fare compared to regular. Students have the shortest lifespan due to the one-year fare policy; college and university students will remain in the system only for the duration of their studies. Let us take an example to better illustrate the model: an AP adult regular user, with a birth date in May 2008, living in Aylmer. Since all variables are dummy-like, his projected lifespan will be 7,618 (constant) + 6,486 (AP adult fare) + 1,443 (Aylmer) + 3,973 (Year 2008) -2,146 (May) = 17,364 months. Estimation is hence easy for various types of cards.

DISCUSSION AND CONCLUSIONS

This paper has presented new concepts and calculation methods for estimating the transit loyalty (rider retention) with the help of smart card data. A 6-year dataset was used to provide key figures like survival profiles, retention profile by fare type and utilization rate. The explicative model gives us insight on what could influence the strength of the retention of transit users: month of "birth" (higher duration if August or January), year of "birth" (gradually correlated), place of living (pendular trips have higher loyalty) and fare type (automated bank payment and Express fares have higher retention).

The perspectives brought by this work are manifold. First, there is an interest to continue applying the explicative model if more individual characteristics were made available to us. There could also be separate models for some fare types. A detailed analysis of the trip paths of the users can be used to derive additional indicators like travel time and distance and the purpose of the trip (by looking at the type of destination). But this would involve the use of the destination estimation algorithm and the robustness of the model needs to be evaluated. On another hand, a dynamic ordered probability model could be applied to the dataset to evaluate the influence of the behaviour of each month on the preceding one. This model has been used in the case of carsharing membership, with a similar dataset (Morency et al. 2009). The current work done on a longitudinal analysis of this dataset reveals external factors that could be related to loyalty, like weather conditions, network reconfiguration and major events.

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