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Typology of carsharing members

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ABSTRACT

Carsharing systems are the focus of an increasing number of researches. In addition to gaining new members every week, new carsharing systems are being launched around the Globe. In Montreal, carsharing in now part of the transportation strategies to alleviate congestion and contribute to the reduction in dependency towards the individual car. Thanks to a continuous partnership with Communauto, the Quebec carsharing operator, it has been possible to provide quantitative assessment of various aspects of the system, both regarding supply and demand. This paper builds on these previous researches and concentrates on the systematic analysis of the behaviors of members, in terms of transactions and kilometers travelled. Data mining techniques are used to classify members according to various temporal units expressing their behaviors.

Results show that, with respect to frequency of use, there are two main types of carsharing members in Montreal, high frequency users (≈ 2.2 transactions per week) and low frequency users (≈ 0.4 transaction per week), the later gathering 86% of the members. Results also show, still based on frequency, that there are five types of weekly patterns and that members have a dominant weekly pattern that is, in average, representative of 62% of their weeks. This study shows that weekly patterns change namely during the holiday periods (summer months, December-January). With respect to weekly distance travelled by members, two clusters are also identified, one gathering 87% of the members with an average of 14.3 km travelled per week and the other ones related to higher averages (76.8 km per week). Other classifications are discussed.

INTRODUCTION

Carsharing is a mode of transportation that consists of sharing vehicles between members. Carsharing looks like automobile-rental service but vehicles are rented by the hour, and require minimal effort to check in and checkout *(1)*. It offers short-term vehicle access for the members. It permits to benefit from the flexibility of a car, without bearing the constraints of owning one. When a member plans to use a car, he needs to reserve it from a fleet. The member takes the car in a specific location and needs to bring it back to the same location when he is done. For each reservation, the member pays for its usage; rates may depend on different criteria (duration, distance).

Carsharing takes a specific position between the different existing modes; Britton *(2)* shows the place of carsharing considering distance and flexibility. Carsharing appears to be a complementary mode between high-density and private ones. Carsharing has lower fixed costs and higher variable costs than private-vehicle ownership. This makes occasional use of a vehicle affordable, even to low-income households.

Carsharing is growing rapidly, mainly in large urban area *(3)*. It offers many advantages for the members and the society *(4, 5, 6, 7, 8)*: reduces the number of cars in cities (members selling personal vehicle and those avoiding vehicle purchase), decreases traffic congestion, reduces parking demand, improves urban air quality (fewer motorized kilometers, higher efficiency vehicles and complementarity with public transit), and promotes the use of other transportation modes such as rail transit by reducing dependency upon privately-owned cars. Carsharing services are common in European countries and are increasingly common in North America *(1)*, they are growing at different levels all over the world *(9)*.

For multiple reasons (billing and traceability being preponderant) carsharing companies generate plenty of data. This data are rich in information about the service that is offered to the user as well as regarding the way that members use the system.

The purpose of this paper is to analyze a transaction dataset in order to create a typology of carsharing members. A typology is "*the systematic classification of the types of something according to their common characteristics*." *(10)*. Using Montreal's Communauto datasets, data mining techniques are used to identify the relevant common characteristics based on carsharing service use. The frequency of use and distribution of distance traveled will retain our attention. Three years of continuous data are processed which allows also assessing the temporal stability of use.

The structure of the paper is the following. First, a literature review presents relevant works on carsharing systems: their evolution, their impacts and key results on user behaviors. Then, the Montreal case study is presented as well as the dataset available and the way it was structured for the classification process. Details on data mining techniques chosen are provided. A section then proposes results of the various classification processes, based on usage (frequency, weekly patterns, daily temporal distribution) and distance travelled (by week, by type of day). The paper is then concluded.

LITERATURE REVIEW

Evolution of carsharing

After some difficulties related to the start of a new business, carsharing organizations seem to be stabilizing *(4)*. If most operators currently chose to be nonprofit organizations (cooperatives, public transit, and university research programs), a majority of vehicles (around 70% in North America) and members (around 80% in North America) are linked to profit organizations.

The Modus Operandi is simple: usually, members pay hourly and/or mile fares, in addition to an annual fee. Some companies also require one-time membership fee (for capitalization) that can be refund if someone drops out. Yearly costs include fuel and insurance. Carsharing is distinct from car rental, through which vehicles are borrowed under a negotiated contract with the customer for longer periods and from centralized, staffed locations *(11)*. Carsharing leads to small costs for occasional users and opens new markets for specific users (students, low incomes families, and citizens living in dense areas). Even though 11% of Japanese consider the automobile as a status symbol, over than 25% of the total sample expressed a high level of interest in carsharing if properly priced.

Some authors identify two types of carsharing systems: the one-way type and the round-trip type, depending on whether users have to return the vehicle in a specific station (round-trip) or not (one-way) *(5)*. The one-way type is harder to manage because travel patterns are often directional creating important unbalances in the availability of cars or parking spots; it is also costly because cars then need to be repositioned by employees to ensure adapted supply. The authors propose a method for optimizing vehicle assignment according to distribution balance of parked vehicles.

Impacts of carsharing

Some authors use cost benefit analysis techniques to show that carsharing could produce net benefits to society *(6)*. They used the example of the West Midlands area, UK. They proved that even with the most conservative estimates of car share participation, net benefits would be comparable to those produced by major road schemes. Slightly less conservative estimates of participation give net benefits in excess of road schemes.

Seik *(12)* expresses that carsharing is a good solution to satisfy citizens' aspiration to use a car in cities where cars are largely unaffordable due to the imposition of restraints such as high taxes and vehicle quotas. He took the example of Singapore. Using survey data, he concludes that members still mainly used public transport for traveling to work after attaining membership but turned more often to the co-operative car rather than public transport for marginal uses such as leisure and social trips.

Nine months after the introduction of car sharing Cervero analyzed car transit in San Francisco, California *(13)*. He estimated 7% of members' trips and more than 20% of vehicle miles traveled were by shared-use vehicles. Evidence suggests that access to shared cars stimulated motorized travel. Car-share vehicles are used more for personal business and social-recreational travel than for nondiscretionary, routine travel such as to work or school. He reveals that shared cars are generally not used during peak periods or to dense settings well served by transit, such as downtown. This reflects a judicious use of car sharing and leads substantial travel-time and money savings for the members.

Celsor and Millard-Ball *(14)* show that neighborhood and transportation characteristics are more important indicators for carsharing success than the individual demographics of carsharing members. They outline that low vehicle ownership has the strongest, most consistent correlation to the amount of carsharing service in a neighborhood. From that information they determine the relevant place to develop a carsharing program. Stillwater et al. use multivariate regression to analyze the relationship between carsharing and environment (building, sidewalk, road characteristics, transit services and demographic factors) *(15)*. Data from an urban U.S. carsharing operator are used for 16 months period in 2006 and 2007. The study shows that neither density nor strictly demographic factors play an overt role in the success of carsharing locations. The study concludes that that high-density auto travel and carsharing act as economic complements. Using transaction data from the Montreal Company and results from a travel survey among members, (16) estimate that car share during a typical weekday is cut by half when comparing a high-frequency carsharing user with someone who owns a private car (single-person).

Behaviors of carsharing users

Morency et al. define an object model for a carsharing system *(17)*. They process administrative datasets from the Montreal carsharing system to estimate indicators regarding both demand and supply. They study the members (persistency, spatial dispersion) and their trip chains using the shared cars (typical use of cars). Members, trip chains (transactions), cars, and stations are analyzed using continuous data. In another work, they *(18)* use a transaction database covering a full year of operation to extract typical patterns of use of the car sharing system with data mining. The current research builds on this previous work.

CASE STUDY

Data for this study has been made available by Communauto, inc. Founded in 1994, Communauto is established in the four largest urban areas of the province of Quebec: Montreal, Quebec City, Gatineau and Sherbrooke. It was the first to bring carsharing in North America and has grown to be one of the most important carsharing company on the continent and is still growing at a fast pace. Communauto now has more than 20,000 members and operates about 1000 cars.

Information system

The dataset contains the record of the transactions made in the carsharing system between January 1st, 2005 and December 31st, 2007. Figure 1 presents the number of objects involved, according to the Transportation Object-Oriented Modeling (TOOM) *(17)*. On the figure, we see that 705 cars and 195 stations were used during the period. A little more than 500,000 transactions were reported as trips (other transactions involved cancelled, modified or non operated rentals).

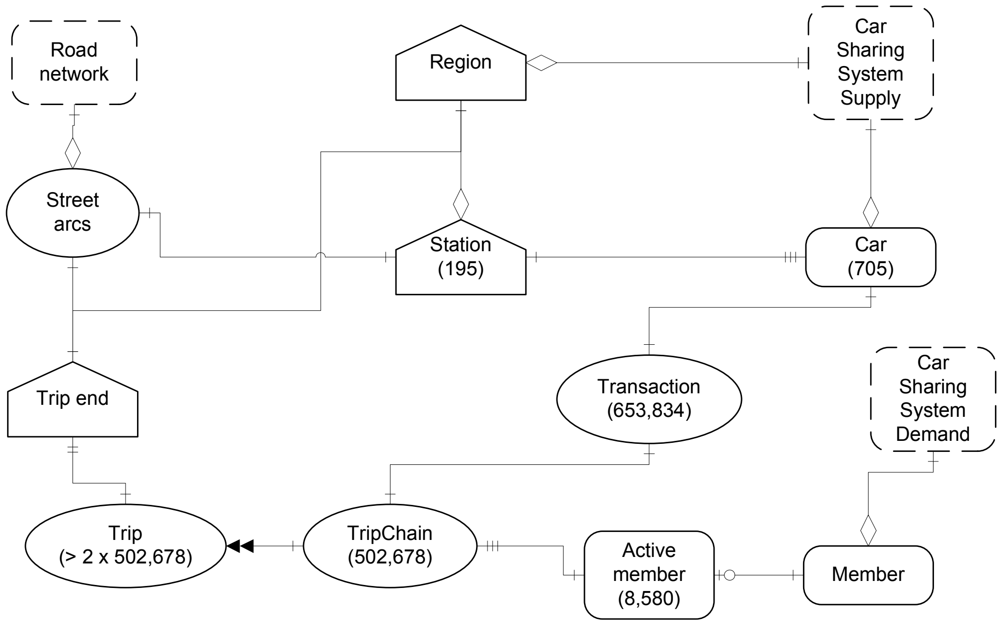

Figure 1: Number of object instances in dataset from 2005 to 2007

The following concepts were developed to facilitate the extraction and the analysis of transactional data. It also shapes out the interpretation of results presented in the next main section.

- An **active member** is a user that did at least one transaction during the observation period, typically a day, a week or a month.
- A **trip chain** is created each time a member borrows a car. At this point, we do not have the tools to exactly know how many trips were made with the car, but it is at least twice the number of trip chains because there is at least a trip departing from the carsharing station, and another one to get the car back at the station.
- A **member-day** is the observation of a single member during one day. It exists only when the user did at least one transaction. Hence, for the 3-year period, a total of 702,016 member-days are reported. This is superior to the number of transactions because some transactions last more than one day. For each member-day we can derive the hourly profile of use (using dummy variables indicating if a car is borrowed for each hour of the day). This allows identifying the structure of typical days of use of the carsharing service.
- A **member-week** is the observation of a member during a week. There are 319,403 member-weeks in the dataset. For each member-week, we derive the number of transactions per day, the distance traveled and the duration of use.
- In the same perspective, the **member-month** is defined to represent the behavior of a member during a month. There are 128,014 member-months in the dataset. With these analysis units, we try to identify similar behaviors by summing the number of transactions, the distance traveled and the duration of use for each day of the week. As for member-week, a member-month exists only if the member did at least one transaction during this month.

Data mining techniques

Data mining techniques focus on extracting knowledge from large datasets. Data mining techniques are currently divided in supervised and unsupervised learning where the user chose or not which parameters may be focused. Different models then allow predicting a parameter depending on a set of explanatory factors or explaining relationships between parameters. Example of data mining applications in various domains can be found in (19) while (20) and (21) provide details regarding available methods and tools.

Among numerous tools, clustering techniques are the most common. Clustering divides a population in different subgroups. On one side, elements in the same group (cluster) must have similar characteristics (a short "distance" that depends on the metric used), while elements in different groups must be "different" (longer distance). One the other side, clusters may be disjoint (an element is in only one cluster), included one in another in a hierarchical structure (an element is in one cluster and in all upper clusters) or fuzzy (an element belongs to different clusters with more or less strength).

Clustering is useful in many ways since a heterogeneous population is subdivided in several, smaller, homogeneous clusters. It permits then to deal with each cluster independently and so learn characteristics of each subgroup that may have different patterns.

Depending of the nature and volume of the data to deal with, different clustering techniques are more or less efficient, adapted, pertinent and easy to configure. In the present case, we have only numerical data; the vector describing each element of the dataset has a constant dimension, providing various opportunities. Since the vectors describing each element are similar (same number of coordinate and comparable range of values) Euclidian distance is applied and pertinent for further analyses. Besides, considering the large volume of data, hierarchical methods do not apply; also fuzzy methods would not give relevant additional information and would be more complex. The clustering method considered in this study is the k-mean. K-means is an iterative method that selects cluster centers, affects each element to the closest center, and computes new centers and so on until stabilization.

K-mean needs the user to select the number of clusters (k*) to compute. In the present study, k* is defined using the following procedure: a k-mean segmentation is computed with a relatively large number of clusters (k=25). Using a hierarchical agglomerative clustering (HAC) method, a dendogram is built for the precedent k=25 cluster centers. The largest step of the dendogram gives k*.

Data mining techniques have already been used in the transportation field to increase the value of datasets; (22) provides example of applications for an urban transit network.

RESULTS

As can be seen on the TOOM, more than 8,500 different members were active over the period of analysis (3 years). During this period, members have done an average of 3.53 transactions per month (± 3.87 transactions per month), with some 6% using the system more than 10 times per month, on average. Also, monthly frequency of use seems to decrease with age.

For an average month, we can estimate that 20% of the members are responsible for more than 50% of the transactions. Actually, the 10% most frequent users do more than 35% of the monthly transactions.

With respect to distance travelled, members travel an average of 180 km per month (± 205 km). Again, a small proportion of the users are responsible for a high proportion of the monthly kilometers travelled. The high variability in the mean distance travelled per month suggests that spatial patterns differ a lot between members. Actually, patterns of distance travelled are directly linked to patterns of usage frequency with a small proportion of the members travelling a high proportion of the monthly kilometers.

Hence, there seems to be a wide range of frequency usage among the members and data mining methods will help to systematically identify the typical patterns of usage.

Two indicators will be examined to classify the members in typical classes of behaviors: 1) frequency of use (by week, period of the day, and type of day) and 2) distance travelled (by day or trip chain). Various datasets are developed for these purposes based on concepts of members, member-weeks and member-days. The choice of this unit of analysis that cuts individual behaviors into weeks or days of observations allows pooling all data without having a bias coming from the different lifespan of members within the carsharing system. Therefore, all member-weeks or member-days have the same weigh in the analysis.

Typology based on frequency of use

Transactions per week

Using observed transactions per week, we conclude that two main types of members use the carsharing services: low-frequency users and high-frequency users, the former gathering more than 86% of all users. Similar results were obtained by (18) for a 10-month period in 2005. Worth noticing is the fact that the number of transactions per week has been increasing in time for the high frequency users, from 2005 to 2007, at a mean rate of 0.01 per week until June 2007, where rates are stabilizing. An increase is also observed for the low-frequency users: between January 2005 and April 2007, the average number of transactions per day increased from 0.23 to 0.42 and then has more or less stabilized. There are no differences, with respect to age or gender, in the belonging of members in those two clusters. Seasonality of behaviors is also revealed in these data (Figure 2) where there is a decrease in the average number of transactions per week during the summer months because members usually take the cars for longer periods and travel longer distances in fewer trips.

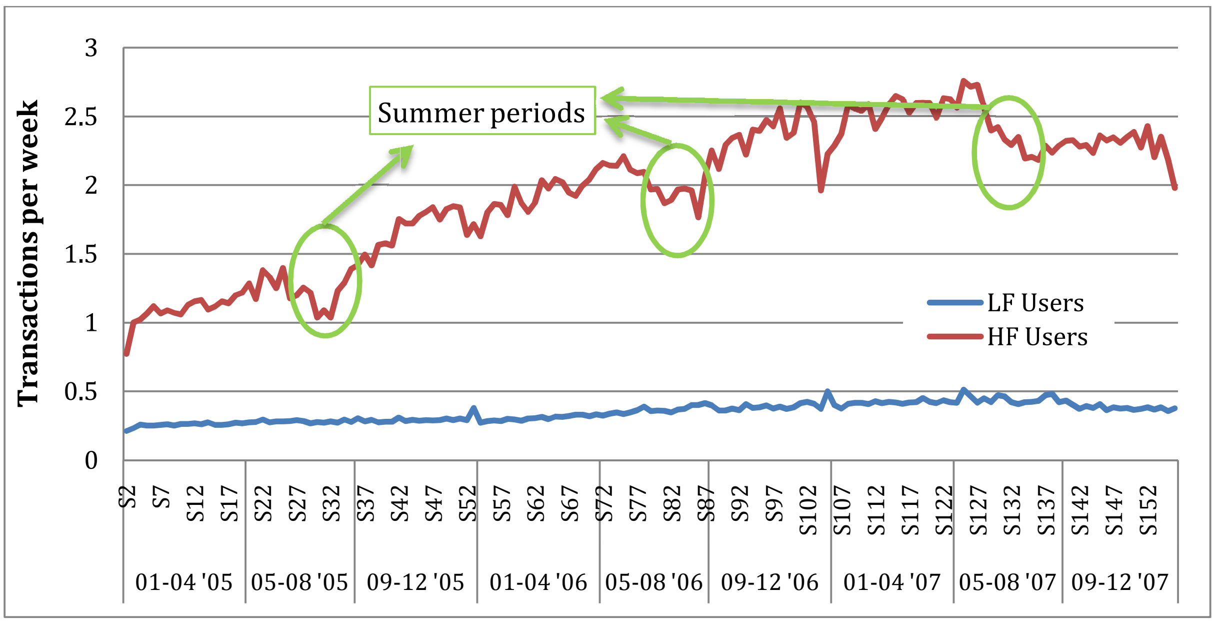

Figure 2: Evolution of the number of transactions per week for the two main types of users, over a 3 years period (LF=low frequency, HF=high frequency)

Weekly patterns of transactions

For this second analysis, the member-week file is used. This file indicates, with dummy variables, if there was at least one transaction for each day of the week (Monday to Sunday), for each active week of every member. The data mining process outputs 5 distinctive clusters of weekly behaviors (only for active weeks i.e. weeks where members did at least one transaction). The mean attributes of the clusters are illustrated in the next figure that also provides some key figures on the clusters.

First, we observe that **C3** gathers half of the observed weeks of behaviors and that this cluster mainly relates to low-frequency usage and week-end activity patterns: 28% of the weeks having a transaction on Fridays, 40% on Saturdays and 37% on Sundays. The other clusters have the following attributes:

- **C1** (9.5% of the weeks): weekday usage with more than 50% of the weeks belonging to this cluster having a transaction every weekday and with higher proportions in the mid-week as well as low proportion of transactions during the week-ends;

- **C2** (10.4% of the weeks): usage throughout the week but in higher proportions during the week-ends;
- **C4** (16.0% of the weeks): 100% usage on Thursdays and sometimes any other day;
- **C5** (13.4% of the weeks): 100% usage on Tuesdays and sometimes any other day.

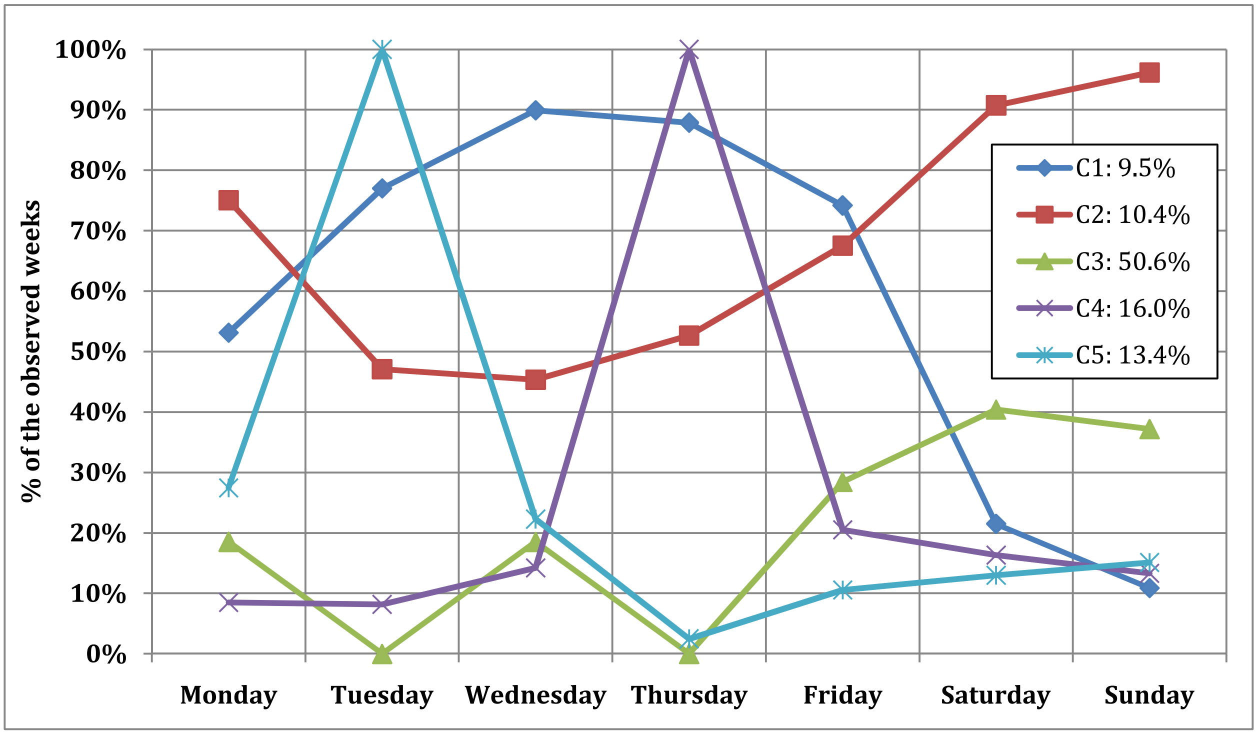

Figure 3: Mean features (centers) of the 5 types of member-weeks (with proportions of each class)

Using these previous results, it is possible to assess the regularity of the member's weekly patterns (only considering active weeks) because every week of activity is now linked to a specific cluster. Various facts are outputted using the dominant cluster of the member, the proportion of their active week in the dominant cluster, and the total number of clusters describing their behaviors across the observation period.

- *Dominant cluster:* every member is associated to a dominant cluster that reflects the group of behaviors for which its number of active weeks is the highest. This concept reveals the following distribution, confirming the importance of low-frequency weekly patterns more concentrated on week-end days' usage. On average, members have 62% of their observed weeks associated to their dominant cluster, suggesting they will have similar weekly patterns two thirds of the time. These proportions are quite different according to the dominant cluster.
    - **C1**: 2.11% of the members with, on average, 72% of the observed weeks in this dominant cluster;
    - **C2**: 4.13% of the members with, on average, 52% of the observed weeks in this dominant cluster;
    - **C3**: 80.59% of the members with, on average, 63% of the observed weeks in this dominant cluster;
    - **C4**: 5.05% of the members with, on average, 56% of the observed weeks in this dominant cluster;

- ○ **C5**: 8.12% of the members with, on average, 55% of the observed weeks in this dominant cluster.

- *Total number of clusters by member:* using all the active weeks of every member, it is possible to assess the regularity of behaviors by estimating the number of different clusters required to describe the usage. Such indicator reveals that 7.73%, 10.65%, 19.04%, 24.34% and 38.24% are respectively linked to one, two, three, four and five clusters. The study of the various combinations of clusters reveals that there are numerous (up to 443) different combinations (taking into account the order by importance) of clusters to represent the overall weekly patterns of users.

Finally, it is worth noticing that these weekly patterns also have seasonality. The following figure shows the distribution, in proportion, of weeks in the 5 clusters throughout the year. It shows that weekly patterns during the summer months and during holiday periods are different from the rest of the year with lower importance of C3 (low frequency weekend patterns) and higher importance of namely C2 patterns (week long transactions with concentration during week-ends).

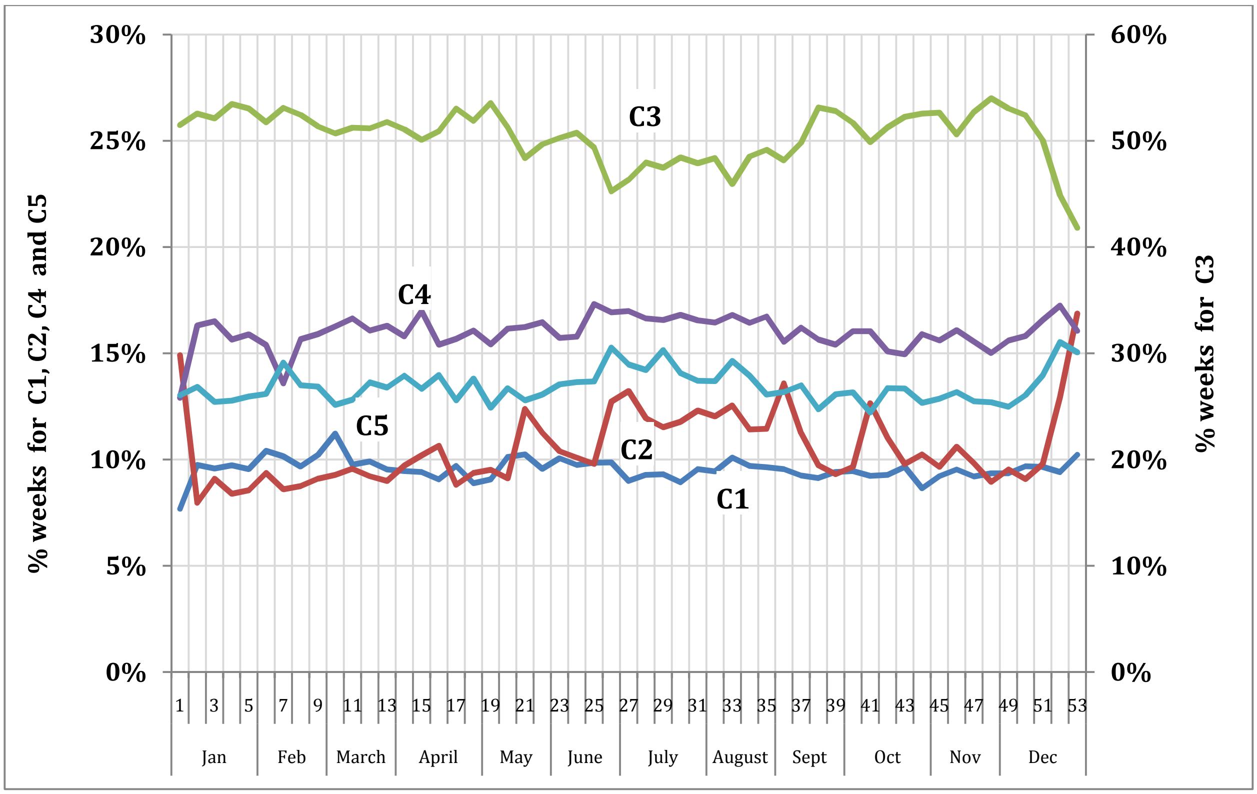

Figure 4: Variability of the distribution of weeks in the five clusters throughout the year

Temporal distribution of daily transactions

Two main types of behaviors are observed with respect to the daily temporal distribution of transactions, all types of day pooled. The 702,016 member-days are used for this analysis, each day being characterized by the temporal distribution of the transactions coded as dummy variables for each hour of the day (a 1 meaning that the member is currently holding a shared car):

- **C1** (69.3% of the days) relates to low-frequency usage with higher proportion of transaction in the late afternoon;
- **C2** (30.7% of the days) relates to higher-frequency usage with transactions occurring during the midday period (11h to 17h).

The distribution of days in these two clusters changes with the type of days, proportions in C1 being lower for week-end days. There are no significant differences observed according to gender or age.

Typology based on distance travelled

Kilometers travelled per week

The second set of classification relies on distance travelled. The same first segmentation in two main groups is obtained when kilometers travelled weekly is examined, with a dominant cluster gathering 87.0% of the members. Globally, members belonging to this cluster will travel an average of 14.3 km per week while the other members, belonging to the second cluster, will travel, on average, some 76.8 km per week. Of course, there is a direct relation between the fact of being a high-frequency user and travelling more kilometers. Actually, 93.5% of the members belonging to the high frequency cluster also belong to the cluster of those travelling longer distances. However, when average distances travelled per week are estimated using only the active weeks (where a member used a shared car), differences becomes almost insignificant with low-frequency users travelling some 129.1 km and high-frequency users travelling 123.5 km. Frequency hence seems to be the determinant feature.

Frequency distribution of weekly distance travelled

For this second clustering based on distances, frequency distributions of distance travelled weekly are examined. Each member is described with respect to the proportion of its weeks belonging to one of eleven classes of distance. The classification process outputs three distinctive classes (see Figure 5). The three clusters relate to very distinctive behaviors:

- **C1** (one third of the members): gathers members that travel short distances at least 50% of the time (less than 10 kilometers travelled per week) and very few long distance trip chains.
- **C3** (17% of the members): gathers members mainly travelling long distances with the shared cars with more than 40% of their observed weeks involving more than 100 km travelled. Actually, these members either travel very short distances (less than 10 km 25% of the time) or very long distances (more than 40% of the time).
- **C2** (almost half of the members): spread distribution with more than 40% of the weeks involving some 20 km or less but also more than 10% with 80 km or more. This cluster reflects the variability of usage that carsharing can have for members.

There is no significant difference between genders regarding to their belonging to these clusters. Some differences are notable with respect to age: younger (less than 24 years old) and older (65 years and older) members are in higher proportions linked to C1 (shorter distances) while the 35-44 years old are in higher proportions in C3 (longer distances).

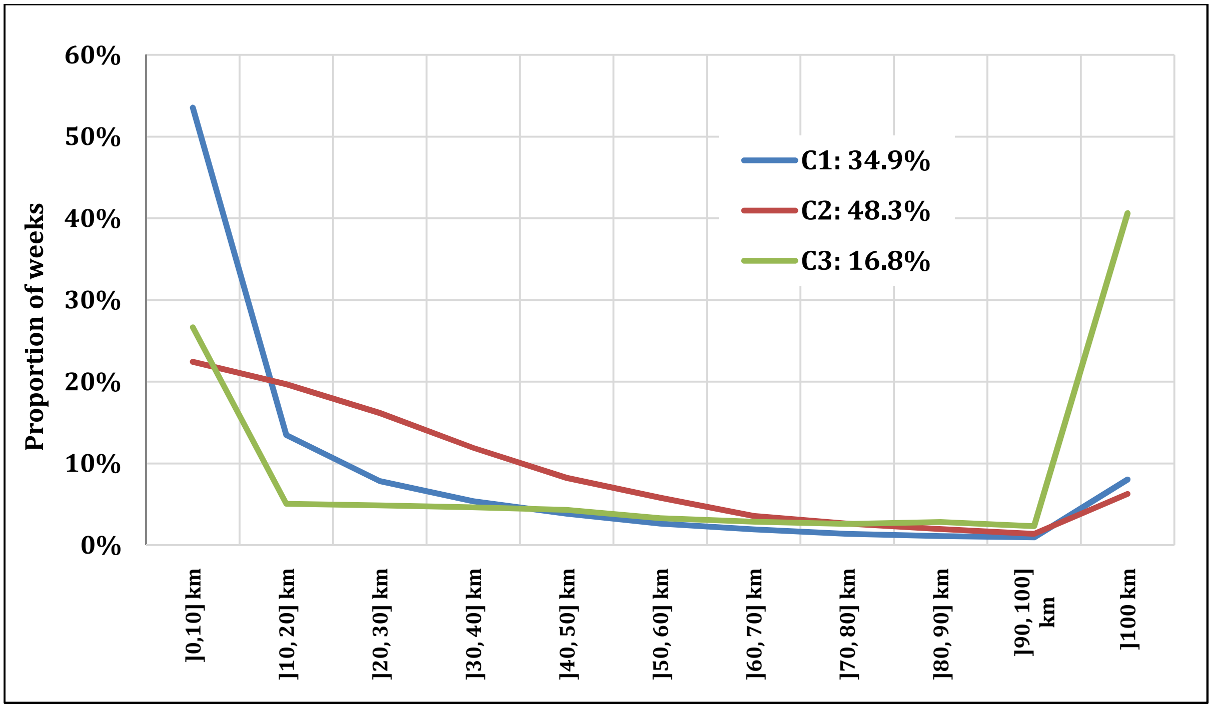

Figure 5: Central distributions of the three clusters regarding frequency distribution of distance travelled weekly by the members

Weekly patterns of distance travelled

The distribution of distances across days of the week is finally examined to see when members travel longer or shorter distances. For this analysis, a member-week file is processed. For each active week of every member, the record provides the number of kilometers travelled on each day. For transactions lasting more than a day, it was decided to split the overall distance uniformly over the days.

The classification process outputs five distinctive clusters but there are really two dominant behaviors: normal weeks (91.4% of the observed weeks) and weeks involving long distances. Still, these clusters confirm that carsharing plays different role in the mobility of members, both typical urban trips and long-distance, holiday-related, trips. The centers of the five clusters are illustrated in Figure 6 (points for C5 are linked to the secondary y axes, at the right):

- **C5** (91.4% of the member-weeks) is the dominant cluster and shows that typical daily distance travelled are between 7 and 10 kilometers, with a slight increase on Saturdays;
- **C1** (3.0% of the member-weeks) relates to distance of around 100 kilometers every weekdays and urban trips (7-8 km) on week-end days;
- **C2** (0.4% of the member-weeks) relates to extraordinary weeks with long distances travelled on Mondays (around 700 km) and considerably long distances on Fridays (around 300 km). This is typical of weeks where either Fridays or Mondays are holidays and that members make trips outside of the urban area;
- **C3** (1.1% of the member-weeks) is also linked to inter-urban travels performed mainly on Saturdays (≈ 350 km), the rest of the days having more regular average distances (<100 km);
- **C4** (4.0% of the member-weeks) contains higher trip distances during Fridays and Saturdays days but still in the range of urban trips (some 50 km), longer trips on Sundays (210 km) and regular urban distance during the week-days (10-20 km).

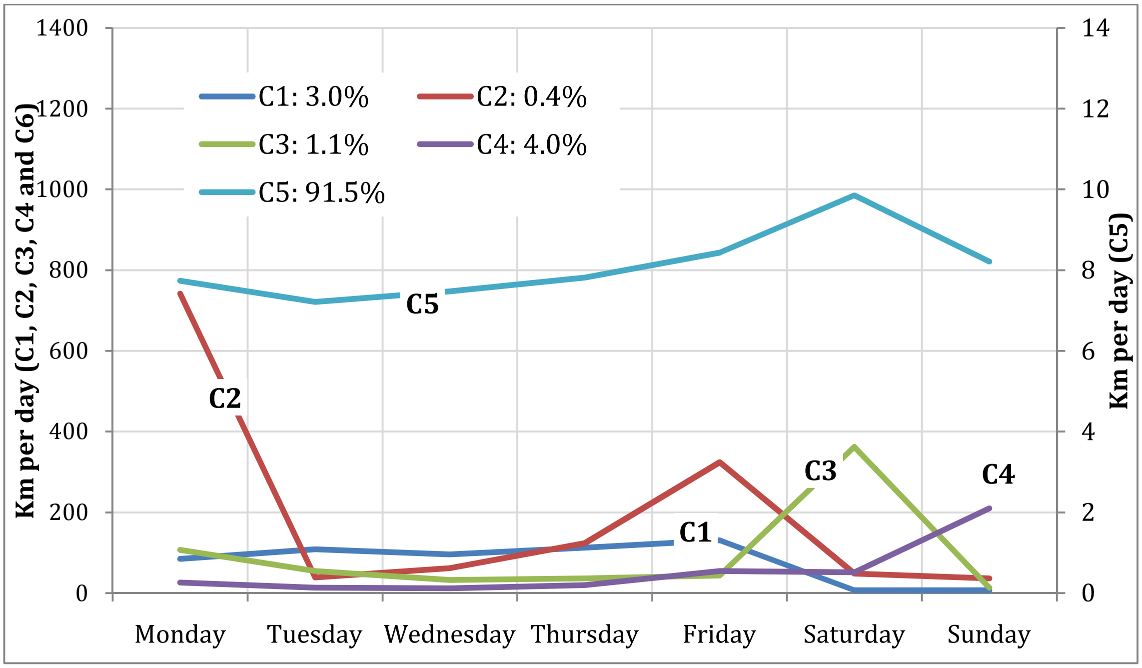

Figure 6: Central distributions of the five clusters regarding mean distance travelled during each day of the week, for member-weeks

When examined across a year, the proportion of weeks belonging to each cluster changes, also confirming that some periods are more typical of longer distance usage than others. Figure 7 shows the mean distribution per month. It confirms that during summer (July and August), proportions change with an increasing proportion of weeks linked to C1 to C4 to the expense of C5.

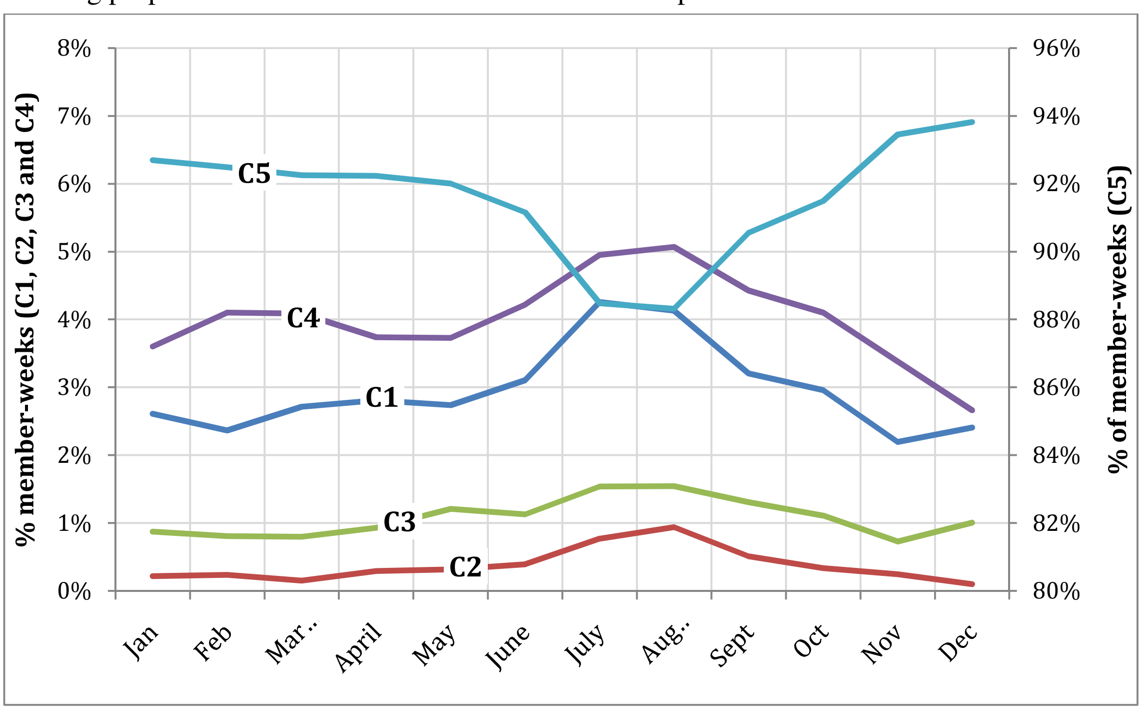

Figure 7: Evolution of the proportion of weeks belonging to each cluster throughout the year

CONCLUSION

This paper has proposed a typology of carsharing members using data mining techniques, namely k-means algorithm. Using three years of continuous data from the Montreal carsharing company, behaviors were examined with respect to two indicators: number of transactions and distance travelled. These indicators were used to look at lifetime behaviors using the week as unit of analysis (number of transactions per week, kilometers travelled per week) and observe if these behaviors were stable throughout the years and for members.

With respect to weekly usage, results show that there are two main types of users, the high-frequency users (with some 2.2 transactions per week, on average), gathering around 14% of the members and the low-frequency users doing around 0.4 transactions per week. Regularity of weekly patterns was also assessed at the member level using the member-week concept. Systematic classification resulted in five types of weeks, the most important cluster gathering around 50% of the observed weeks of activity. Using the dominant cluster concept, we were able to estimate regularity of active weeks of members at 62%, meaning that almost two-thirds of the times, members will have similar weeks of usage.

With respect to distance travelled weekly, the classification process also outputs two main types of weekly usage, highly correlated to the two clusters based on frequency. Also, three clusters are derived from the classification process relying on frequency of trips belonging to 11 classes of distances. Finally, the member-weeks were also examined with respect to distance travelled daily and resulted in the creation of five main clusters but really two distinctive behaviors: either urban distances throughout the week or long distances on one of the days.

Other researches are currently conducted using transaction datasets but also with GPS traces from the shared cars. These data will help estimated the number of trips that are really involved in the trip chains of members and enhance our understanding of the travel behaviors of members.

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