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Transit Passenger Segmentation Based On The Travel Patterns Mined From Smart Card Data Using Optics Algorithm

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Abstract—.: **Smart card automated fare collection systems are becoming popular in public transportation systems, providing a large quantity of continuous and dynamic data on the boarding and alighting locations of transit passengers. These data helps the transit operators for the operation of transit system to the strategic long-term planning of the network. This paper proposes a comprehensive methodology for transit passenger segmentation based on the smart card data. By reconstructing the travel trip from individual transactions, a set of valid transactions performed by the passengers are obtained. The spatial information such as origins-destinations and temporal habitual travelling time of the users are mined by applying a density based algorithm such as ordering points to identify the clustering structure (OPTICS). The passengers are then segmented into identifiable groups according to an a priori market segmentation approach. A comparative study of density based algorithms such as DBSCAN and OPTICS used for mining spatial-temporal travel patterns of passenger's are done. Results shows that OPTICS give more accurate clustering results**.

Index terms –Reconstruction Algorithm, Density based Algorithm, DBSCAN, OPTICS, A priori Market Segmentation

I. INTRODUCTION

The Transit operators require a better knowledge of each user market segment for satisfying the needs and preferences of transit passengers[20]. Transit agencies have issued policies [15] in order to increase the use of public transportation by offering better services. Larger volumes of individual trip data which supports large-scale, economical, continuous, multi-day method to discover the multiday behaviors of transit passengers are collected using smart card automated fare collection systems. Previous works in public transit systems doesn't focus on understanding passenger segments and behaviors, because different segments of passengers would behave differently in a transit system and also majority of the studies are based on improving vehicle performance, passenger travelling time and obtaining the origin-destination (OD) information through smartcard transactions [20]. The traditional approach of obtaining travel patterns is done by conducting transit passenger surveys, but they are rather costly, time consuming and are only valid within a time period. Compared to this traditional survey approach, the data analyzed through smart cards are validated automatically and continuous data is available for longer periods of time. Moreover, the sample size is much bigger and access to larger sets of individual data is possible compared to a limited number of respondents in a traditional survey approach. Thus the manual data collection approaches are getting replaced by the low cost, disaggregated automated fare collection systems.

This paper proposes transit passenger characterization by passenger segmentation using the dynamic Smart Card data. The aim of segmentation is to classify passengers of similar travel pattern, i.e., with the same level of transit journeys at regular times and places. The basic need of mining passengers are required to find their travel trip, regularity of passengers, their engagement to the environment, and the total time spend by them in the travel. The market segmentation of transit passengers brings various helps to transit authorities to provide better services to their customers. Travel pattern mining helps in understanding the growth of passenger demands, providing incentives and personalized service to passengers of regular usage for encouraging them to use public transport [20]. The analysis of the travel pattern also helps operational strategies such as origin–destination (OD) demand management and transfer coordination by monitoring and inferring passenger movements through their travel customs.

For the study, the smartcard transactions made by the passengers for travelling are chosen in order to determine their day to day behavior. The authors have connected individual SC boarding/alighting records to reconstruct user itineraries using the smart card data. A number of studies have analyzed transit passenger travel patterns by different level of aggregation from whole aggregated dataset to each individual Smart Card user. Compared to this, (1) provides an in-depth temporal and spatial analysis for individual travel patterns, (2) An A priori Market Rule for Transit passenger segmentation 3) comparison of OPTICS and DBSCAN methods used for mining travel patterns of passengers are done.

II. RELATED WORK

Literature review of existing studies explored travel patterns of smart card users by different level of aggregation on passenger and stop level. Blythe [11] conducted studies to

manage the demand through the network and makes public transit more easier. Bagchi and white [10] in their work states that conducting strategic planning using smart cards are better than other data collection methods. They analyzed bus-to-bus interchanges of passengers based on a sample of their journeys collected in Bradford and Southport, UK. Advantage of this method is the user role in data collection done by the survey process is minimized and also disadvantage is that the user's ultimate destination is not provided, despite a method to deduce it.

Utsunomiya et al[2]. is an example of aggregated dataset analysis. The authors described the data possessing and analysis methods to mine meaningful information from AFC data. Trepanier et al.[5] propose an algorithm to infer passengers' get-off site from smart card data . Sun *et al.* estimate the spatio-temporal density of passengers inside metro systems.Jang demonstrated the use of AFC data in travel time and transfer locations analysis. The method facilitates the comparison between different transit modes and the identification of passenger transfer choices. Hasan et al.[12] exploited AFC data to observe both spatial and temporal passenger travel pattern. The authors modeled two important passenger decisions: (a) which place to visit and (b) how long to stay.The whole dataset analysis explores general travel patterns from transit passengers.

Trepanier and Morency[5] used boarding transactions by card and starting and ending dates and calculated the life span of the card and the ratio of use of smart card users. Park and Kim analyzed future trend estimation and created a future demand matrix which helps for network extension and adaptation. Seaborn[14] et.al used a method for analyzing the complete journeys and identified a direct link for minimizing transfers. Hoffman et.al used iterative classification algorithm to obtain more information on transfer journeys.

Some other author's analysis are based on the aggregation of several similar characteristics of the passengers and their travel pattern. Morency et al. [5]aggregated the Smart Card users into five classes according to the card type and their route usage. Chu et al. [3] proposed a new framework to mine spatial-temporal distribution of transit demand by different aggregation level such as stop, route, link, node and card type. Lee and Hickman [4] developed a heuristic rules algorithm and a classification decision tree to group smart Card users into different classes and infer their trip purposes. Several studies identified spatial and temporal patterns by individually analyzing each Smart Card user. Chu & Chapleau [3] described a disaggregated travel pattern analysis framework for multi-day SC data. They analyzed Runtime estimation, Itinerary reconstruction, Spatial-temporal pattern of the network and concept of Driver Assisted Bus Interview (DABI). Travel pattern analysis often spatially breaks down to stop-to-stop repeated journeys. However, the limitation of this method has been identified by several authors like Ma et al.[13] and Kieu et al. (2014) [1] applied the DBSCAN algorithm for mining spatial and temporal travel patterns. DBSCAN provides flexibility in defining the group of stops that the passenger repeatedly choose and clusters stops of close proximity, and the travel pattern is defined according to the number of repeated journeys.

III. Objectives & Overview Of The Proposed MECHANISM

A. Objectives

This paper proposes transit passenger characterization by passenger segmentation using the dynamic Smart Card data. The idea is to mine the spatial and temporal travel pattern from the historical trip database.A density -based clustering algorithm called OPTICS [9] is used for the purpose because it solves the problem of parameter discovery and performs clustering with various parameters simultaneously and creates ordered clustering results. This enables to locate an optimal clustering result easily and helps to detect the daily changes in travel pattern. OPTICS algorithm[19] can't produce a clustering result explicitly but creates an augmented ordering of data set representing the density-based structures from which embedded and multi-density clusters can be identified.
The features of OPTICS algorithm in travel pattern mining include :

- It does not require the user to provide any density threshold.
- It can identify clusters of any shape and size. A travel pattern can be any shape and size due to its nature of human behavior.
- Doesn't require the predetermination of initial cores number of clusters. In travel pattern analysis the number of patterns from an individual passenger is unknown.
- Handle high dimensional data sets and clusters of varying densities .
- Sensitivity of density is removed.

B. Overview of the proposed Mechanism

The first step in travel pattern analysis is to reconstruct the travel itineraries of passengers using a reconstruction algorithm. By reconstructing travel itineraries a set of valid transactions are obtained. Then a density based algorithm called OPTICS is used to mine the spatial and temporal patterns of passengers.The spatial origin-destination stops are represented as geographical coordinates, and the alighting times are represented as timestamps. Density-based clustering algorithm is adopted because they can identify clusters of high density and noise of low density thus regular patterns can be identified and can be differentiated from anomaly pattern.

An a priori market segmentation approach groups the passengers into identifiable groups. It is based on the assumption that there are different stereotypes about different classes. In this method the cluster defining descriptions are already selected by the researcher, thereby conducting study of them will not influence these predefined segments. A comparative study of the density based clustering methods called DBSCAN and OPTICS for mining travel patterns are done.

IV. MINING OF SPATIAL AND TEMPORAL PATTERNS

A. Data description

The smart card data used for this study comes from Translink, the transit authority of South East Queensland (SEQ), Australia. The dataset is a compilation of approximately 20000 transactions made by a million Smart Cards over different transit stops. Each transaction contains the following fields:

CardID: Unique Smart Card ID
T_on: Timestamp for touch on (boarding)
T_off: Time stamp for touch off (alighting)
S_on: Station ID at touch on
S_off: Station ID at touch off
ValidIndicator: A binary indicator for differentiating valid from invalid transactions. It has been used by the operator for ticketing purpose. Valid transaction is the combination of a touch on and a touch off from the same transit line, within a 2 hours limit.
Route Used: The transit line that the passenger has used.
Direction: Direction of travel (Inbound/Outbound).
Fare : The fare paid for the transaction in Australian dollars.

B. Reconstruction of travel itineraries

The Reconstruction of Travel trips from the individual transaction is the first step in travel pattern mining. The Reconstruction algorithm [1] is to connect individual transactions of each user on each working day into completed journeys from first origin stop to the destination stop. The algorithm is built on a binary "ReconstructingIndicator" to identify on-going/new journey and a "TripID" to distinguish the completed journeys. A connected transaction are decided using a fixed threshold of 60 min. "origin stop" is defined as the first boarding stop of a completed trip and "destination stop" is defined as the last alighting stop of a completed trip.. The transferring time is defined as the interval between the alighting time of a transaction and the boarding time of the next transaction of the same.

Reconstruction of Travel Itineraries [1] process involves the following steps:

Step1: A variable called binary ReconstructingIndicator is defined and initialized as 0.
Step2: Then the variable ValidIndicator is checked. If this is equal to 0 the transaction is invalid and the corresponding trips will be discarded.
Step 3: Then check If the ReconstructingIndicator is 0, then a variable OriginLocation is defined and set as equal to the current T_on. A new unique TripID is assigned and the ReconstructingIndicator is changed to 1, save the current transaction, and move to the next transaction.If the ReconstructingIndicator is 1 and the time gap between the current T_on and the last T_off is less than 1 hour, we move to Step4. If the time gap is more than 1 hour, the transaction with the previous TripID is connected into a completed trip. A new TripID and a new OriginLocation are assigned.The ReconstructingIndicator is set as 1.
Step4: If the current S_off is different to the Origin- Location, the transaction is connected to the trip as a continuation journey. If it is also the last transaction of the day, the trip reconstruction process for the study passenger is finished; otherwise, move to the next transaction.

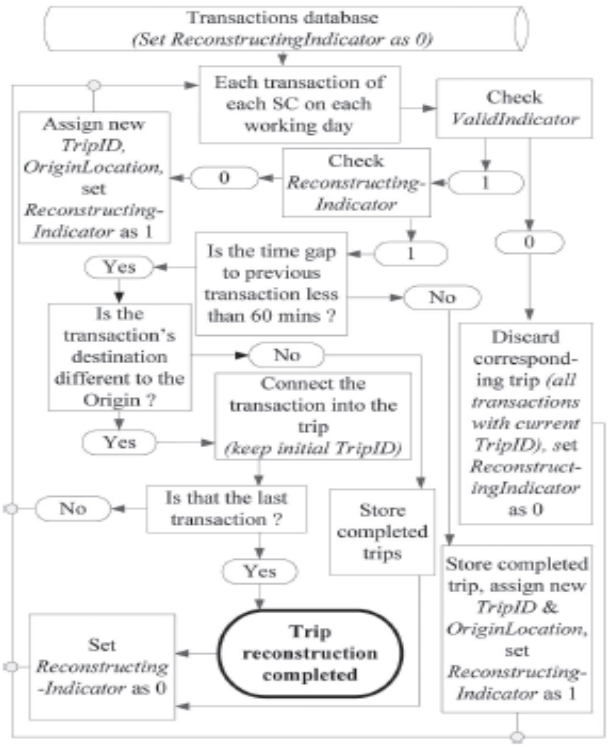

Figure 1: Trip Reconstruction Flowchart

C. Mining spatial and Temporal patterns using Optics algorithm[9]

Optics require two input parameters from the user such as ε and the Minpts. Like density based algorithms such as DBSCAN , the basic idea of OPTICS[9] is to find the groups for each point of which the number of points that has to be contained by the neighborhood of a given radius ε should be no less than a minimum MinPts.A point p is called core point such that there are atleast minpts points in its ε neighbourhood Nε (p). In density models the two parameters ε and Minpts determine the density of points that a group should contain. But this will cause a problem that a denser point set is contained in more than one group. To solve this optics

introduce two distance concepts , core distance and reachability distance to assign cluster memberships[17].
The Core-distance[9] of a point *p* is the distance to its MinPts-th point,

$$\text{Core distance } \varepsilon,\text{Minpts(p)} = \begin{cases} UNDEFINED \mid (\text{N}\varepsilon(\text{p}) \mid < MinPts \\ \text{MinPts} - \text{distance(p)}, \text{Otherwise} \end{cases} \quad (9)$$

And the Reachability-distance[9] of a point *p* from another point *o* is the larger of the distance between them and the core-distance of point *o*, defined as

$$\text{Reachability distance}_{\varepsilon,\text{Minpts(p,o)}} = \begin{cases} UNDEFINED \ \ (\text{N}\varepsilon(\text{O}) \mid < MinPts| \\ \max(\text{core} - \text{distance(o)}, \text{distance(p. o)}), \text{otherwise} \end{cases} \quad (9)$$

OPTICS Algorithm steps [17]
Step 1. Specify ε and MinPts.
Step 2. Mark all the points in the dataset as unprocessed.
Step 3. For each unprocessed point, find its neighbors w.r.t parameters ε and MinPts. Mark the point p as processed.
Step 4. Set the core-distance for the point.
Step 5. Add the point to the order file.
Step 6. If the core distance is undefined return to step 3, else go to step 7.
Step 7. Find the reachability distance for all neighbors and update the order seed depending on the new values.
Step 8. For all data in the order seed find the neighbor of the point.
Step 9. Mark the point as processed.
Step 10. Set the core-distance for the point.
Step 11. Add the point to the order file.
Step 12. If the core distance is undefined return to step 8, else go to step 13.
Step 13. Find the reachability distance for all neighbors and update the order seed depending on the new values.
End

A two-level procedure[1] is applied to separately mine the regular last alighting and first boarding stops of each SC user. Origin and destination of the travelling purpose of passengers's are obtained as clusters. In level 1 optics algorithm is used to separately mine the boarding stops of each passengers. ε , which describes the maximum distance of the passengers from one to another stop of the same boarding pattern. MinPts is equal to the minimum number of journeys made to be considered "regular." Minpts is the value of the minimum number of transactions taken place within the travel distance. If both origin stop and destination stop are not anomaly pattern, the corresponding OD is identified as a regular spatial travel pattern.The result after level 1 and level 2 is clusters representing the S_on and S_off (Origin-destination pairs) of each passenger's travelling pattern.

After identifying the spatial travel pattern , next step is to mine the temporal travel pattern of each user. It is the time at which a smart card user habitually boards a transit vehicle. Each trip of the passengers are recorded as time stamps. A passenger having two journeys at 8:00 A.M., three journeys at 8:05 A.M., and one trip at 7:55 A.M. were grouped into a temporal pattern. ε is denoted as the variability of boarding times within the same travel pattern. The value of Minpts can be find out by how the transit operators define the travel pattern. Minpts is the value of minimum boarding considered "regular". Any repeated boarding will be considered regular if the value of Minpts equals to 2. The result is clusters representing the t_on and t_off of each passenger's travelling time.

E. A priori Market Segmentation for Transit passenger segmentation.

An a priori market segmentation approach [1] is used where passenger classes are selected based on the proportion of regular OD/habitual time trips in the total transit usage. The segmentation approach[16] used in this paper could be classified as a physiological segmentation, where passenger travel characteristics, i.e., spatial and temporal travel patterns, define the type of passenger. During the passenger segmentation process each SC user itinerary is revisited. The travel patterns of passengers which are identified, during the study period follows regular origin-destination (OD),habitual time pattern, or not following any pattern. Three segments of passengers can be identified based on the following heuristic rules. Only passengers with no recognizable pattern are segmented into the irregular passenger type. The other passengers could be grouped into two identifiable classes.

Rule 1: If no temporal or spatial travel pattern is identified, the passenger is classified as an irregular passenger.
Rule 2: If more than 50% of the journeys were made within habitual times and between regular ODs, the SC user is classified as a transit commuter.
Rule 3: The remaining passengers are segmented into regular OD passengers if the proportion of the regular OD journeys is more than the habitual time journeys, and vice versa for the habitual time passengers

V. PERFORMANCE EVALUATION

Density based algorithms such as DBSCAN[8] and OPTICS[9] are used to mine the spatial and temporal travel pattern of passengers. After applying DBSCAN , 8 spatial clusters and 3 temporal clusters are found .while using the proposed method , 31 spatial clusters and 36 temporal clusters are found. The input parameters ε and Minpts to DBSCAN for spatial clustering is taken as 150m and 8 respectively and for temporal clustering it is 1300 and 6. The input parameters ε and Minpts to the proposed method for spatial clustering is taken as 300m and 18 respectively and for habitual clustering it is 1300 and 15.

A. Performance Metrics

We evaluate mainly the performance according to the following metrics.The accuracy of methods were compared using calculating the F-measure (F1-score).

F1-Score : **F_1 score** (also **F-score** or **F-measure**) is a measure of a test's accuracy. It considers both the precision and the recall of the test to compute the score.

Precision : is the number of correct positive results divided by the number of all positive results.

Recall: is the number of correct positive results divided by the number of positive results that should have been returned. The F_1 score can be interpreted as a weighted average of the precision and recall where an F_1 score reaches its best value at 1 and worst at 0.

$$\text{F1} - \text{Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (17)$$

where precision and recall can be defined as

$$\text{Precision} = \frac{True\ positive\ (TP)}{True\ positive\ (TP) + False\ positive\ (FP)} \quad (17)$$

$$\text{Recall} = \frac{True\ positive\ (TP)}{True\ positive\ (TP) + False\ negative\ (FN)} \quad (17)$$

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B. Results

Experimental result shows that the proposed method OPTICS has more F1-Score than the method DBSCAN . Thus it is having more clustering accuracy.

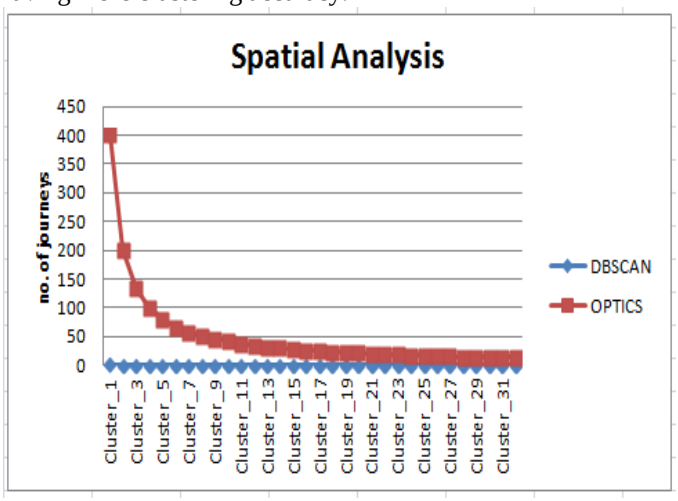

Figure 2: Comparison of F measure of spatial analysis of DBSCAN and OPTICS method

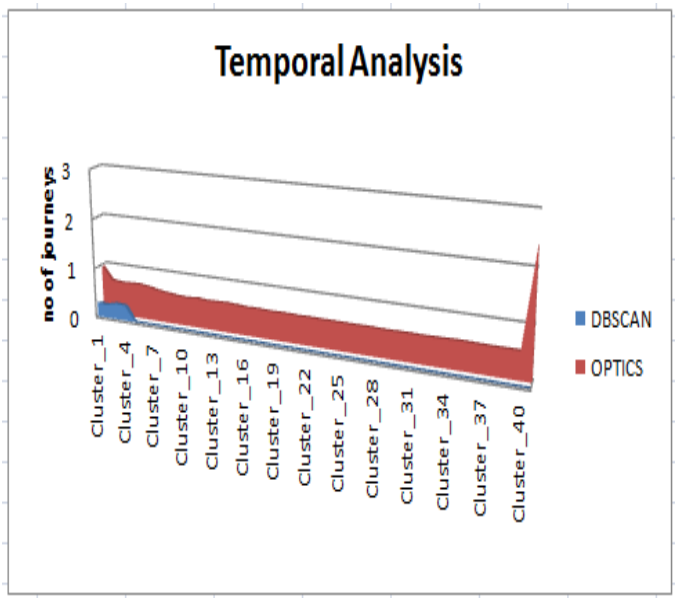

Figure 3: Comparison of F measure of temporal analysis of OPTICS and DBSCAN method

The F-measure analysis shows that OPTICS algorithm have better accuracy. The ratio of Transit commuters, Regular OD passengers,Irregular passengers obtained by applying OPTICS and DBSCAN algorithm is shown. The results show that OPTICS give more accurate clustering results .

Ratio of Transit commuters	Ratio of Regular OD	Ratio of Irregular
762:76	790:79	790:79
767:76	822:82	822:82
786:78	798:79	786:78
785:78	831:83	785:78
764:76	825:82	749:74
749:74	795:79	798:79
780:78	792:79	831:83
-	832:83	825:82
-	806:80	795:79
-	803:80	793:79
-	812:81	792:79
-	840:84	762:76
-	-	832:83
-	-	806:80
-	-	767:76
-	-	764:76
-	-	803:80
-	-	812:81
-	-	840:84
-	-	780:78

Table1: Ratio of passengers in clusters.

The ratio of transit commuters, Regular OD's , and Irregular passengers obtained by applying OPTICS Algorithm is given below.

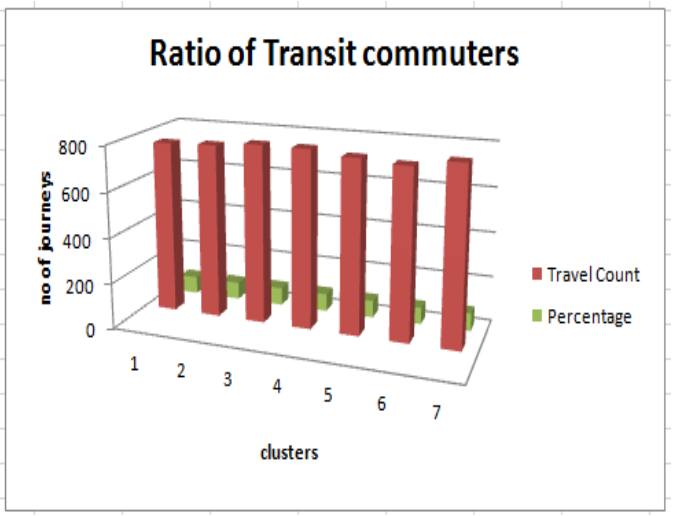

Figure 4 Graph shows the ratio of transit commuters after applying OPTICS algorithm

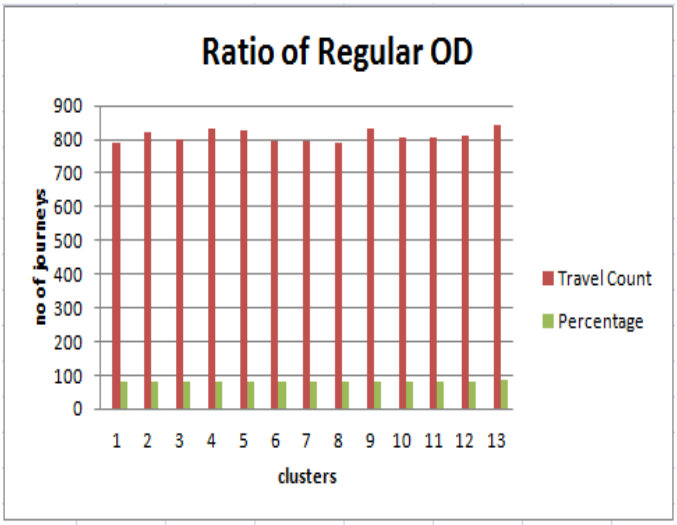

Figure 5 Graph shows the ratio of Regular OD's after applying OPTICS algorithm.

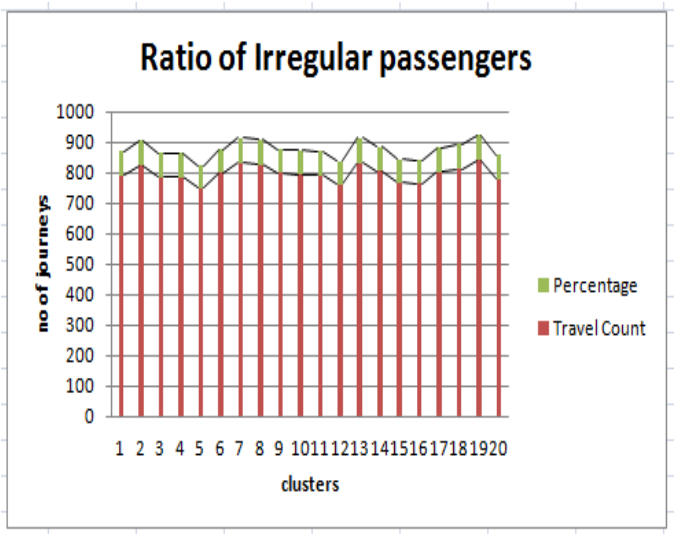

Figure 6 Graph shows the ratio of Irregular passengers after applying OPTICS algorithm

The ratio of transit commuters, Regular OD's , and Irregular passengers obtained by applying OPTICS Algorithm is given below

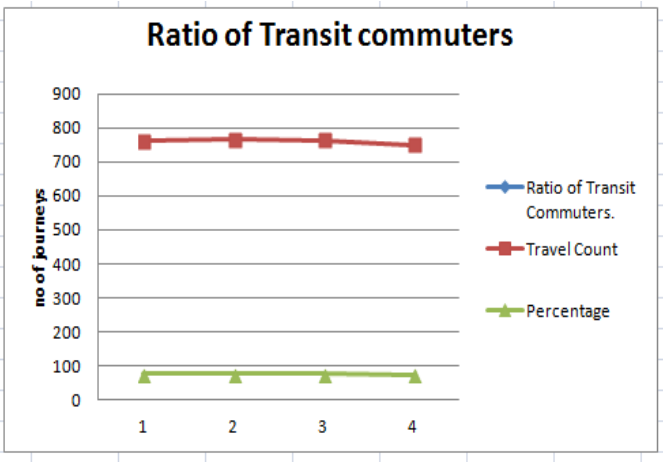

Figure 7 Graph shows the ratio of Transit commuters after applying DBSCAN algorithm

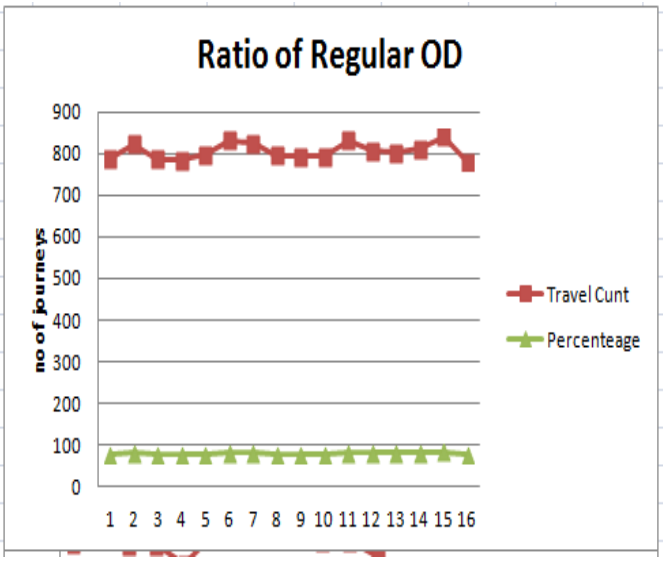

Figure 8 Graph shows the ratio of Regular OD after applying DBSCAN algorithm

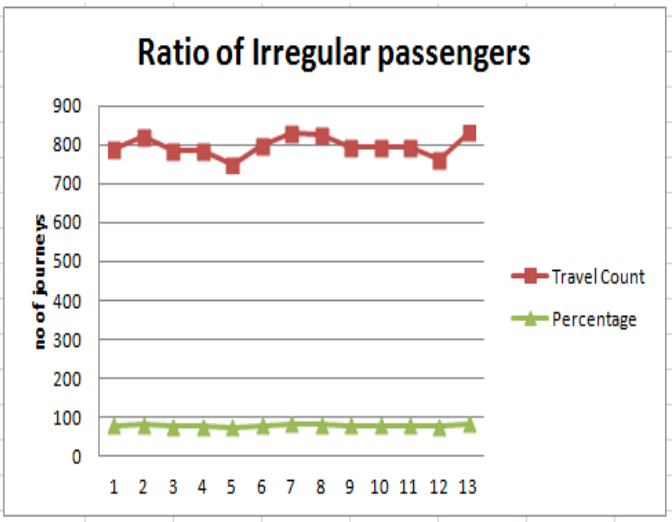

Figure 9 Graph shows the ratio of irregular passengers after applying DBSCAN Algorithm

The segmentation is obtained by finding the percentage of their total number of journeys and if their travel count in clusters are more than (50%) percenatage of journeys they are regarded as transit commuters. If the travel count in clusters is less than (50%)percentage of journeys they are regarded as regular OD's. Irregular passengers are one that doesn't follow any travel pattern. The ratio of passengers obtained by applying OPTICS algorithm give accurate results.The execution time of DBSCAN algorithm for both spatial and temporal clustering are 343ms and 436ms respectively and for OPTICS algorithm they are 3791ms and 1466 ms respectively. Experimental results shows that the performance of OPTICS is better than DBSCAN algorithm which is used for passenger segmentation analysis.OPTICS finds the spatial and temporal travel patterns in an effective way and give accurate results.

VI. Conclusion

Different clustering techniques with varying attributes are chosen for mining temporal and spatial travel patterns of users according to the requirement of data. This paper has proposed a systematic approach to mine the travel pattern using OPTICS algorithm and segment the passengers based on a priori market segmentation approach. OPTICS (ordering points to identify clustering structure) algorithm work well for large datasets and overcome the limitations of DBSCAN . DBSCAN has a weakness that it is difficult to discover parameters for obtaining optimal clustering result and take much time to discover them. OPTICS is an extension of DBSCAN that solves the problem of parameter discovery and performs clustering with various parameters simultaneously and creates ordered clustering results. A comparison of the accuracy and performance of both the algorithms are evaluated and find out that OPTICS provide better clustering results. As a Future work of this paper, an analysis of travel patterns through Optimized Optics algorithm is used which will reduce the selection of parameters manually .

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