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Engineering

A PASSENGER PREFERENCE BASED QOS IMPROVING MODEL FOR AVIATION SYSTEM

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ABSTRACT Passenger services getting high priority and demanding effective QoS from Aerodrome authorities. Many approaches proposed by surveyors and analysts to improve the services provided to passengers within airport and during aviation. In this paper a machine learning model oriented analysis approach proposed tom support QoS, decision making systems, trend estimators effectively track the passenger preferences. The approach uses training data collected from various passenger related services offered by aircraft aviation systems subjected to learning tools analysis. Identifying the best services that can be offered to passengers based on portfolios analysis, categories analysis and past experience based data analysis. The results are examined with real time training samples for improvement factor estimation over traditional approaches followed for passenger service providence system. The model also supports customizable journeys according to passenger preferences as an auto preference analyzer tool.

KEYWORDS : Preferences, Data Mining, ARM, Correlation, Rule miners.

INTRODUCTION

The application of machine learning tools over statistical data samples increases the rate of knowledge discovery in multi dimensional views [2]. Large data sets like passenger reservation lists and flight booking portfolios maintain bulk data over heterogeneous databases which are distributed over networks [1]. The Data Warehouse technology helps to handle large blocks of data with various file system architectures converted into a scalable format as Data marts [3]. The increased web transactions need an interrogation with high end tools to retrieve meaningful data from voluminous web logs and web transactional data sheets [4]. The concepts of interesting topics have been polarizing by various domains of aircraft aviation systems [11]. The application of machine learning algorithms unites diverged knowledge patterns to bring better information for decision making systems improvement [5]. In this paper a set of machine learning techniques applied over training data sets to ameliorate facilitation services offered by airport authorities during aviation. The classification of journey, passenger and flight classes using decision tree algorithms generates new possible classification rules to train future training sets effectively. Many researchers proposed various models to understand the preferential bias of passengers using various criteria's for improving facilitation services [7][9]. A SERVQUAL methodology considering various dimensions of airport services and passenger experiences assessed for reliability based performance levels estimation done [6][14]. Many researchers focused on developing a conceptual model for estimating the correlation between customer expectations, customer satisfaction and airport profitability based on airport service quality [10]. The relevant airport facilities modernization based on customer expectations targeting the success of airport business becoming current issue of interest [12]. A rule based customization of services is also gaining more focus to develop service portfolios for diverged territorial based passengers [13][15].

PASSENGER SERVICES

There is an observation that substantial services provided by airlines for passengers are check-in desks, boarding gates, Identity verification, luggage conformity and issues related to passengers and their flight. The local authorities such as police, civil aviation institutions and flight management services assists passenger in their travel.

- Passengers reception at check-in desks
- Luggage and Ticket check-in
- Airline service management
- Delays and irregularities management
- Boarding and gate way truck bus services
- Management of passengers with specificities
- Escort service for unaccompanied minors

The services like medical, emergency, insurance and hospitality are integral part of Airline management system.

DATA PREPARATION

In this work we collected training data sets from some airports past passenger services databases. The raw data sets are subjected to data pre-processing and converted into .CSV, .XLS and .ARFF formats which can be loaded into ORANGE®, TANAGRA® and WEKA® data mining tools for our analysis process.

METHODOLOGY

In this paper an approach of Machine Learning to identify decision supportive factors to improve the quality of airport authority services provided to passengers. The correlation analysis is a process which identifies the similarity factor among two distributions statistically. This process with correlation matrix methodology applied over training data set of various passenger classes booking. The process of learning given as below algorithm

Correlation Algorithm
Input: Generalized Training Data set D
Output: Correlation matrix C_M, Thermal Graph of distribution D_G.

Step 1: Apply Data Mining Tool on D with ideal parameters to generate Correlation metrics

Step 2: Generate Correlation Matrix using tool

Step 3: Identification of Correlation data points within limits of [0.8 to 1] as best factors

Step 4: Generate Correlation factors to identify Countries having similarity in passengers

The next approach proposed deals with training data related to passenger's services provided by authorities subjected to association rule mining to identify the utilization rate of services by passengers. Various interesting measures generated by machine learning algorithm improve the airport services quality and also helps to identify the rate of service requirement.

Rule Mining Algorithm
Input: Generalized Training Data set D
Output: Frequent Patterns FP, Support rate S, Confidence rate C.

Step 1: Apply Data Mining Tool on D with ideal parameters to generate frequent patterns.

Step 2: Let Support and Lift values chosen according to requirements.

Step 3: Generation of Association rules for service combinations and their Passenger preferences.

Step 4: Generate Decision supportive service patterns for various passenger demands for future trend estimation of service preferences.

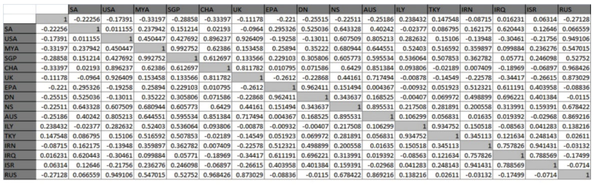
The algorithms identify interesting patterns to improve the QoS of airport authority services. The impact of proposed methodologies over passenger training data over Airport Aviation System observed through analysis performed below.

RESULT ANALYSIS

Passenger Correlation Analysis

The various types of passengers and their journey to various countries/Cities considered as training data to perform knowledge engineering techniques for identification of correlations among countries. This approach helps to estimate the future passenger classes booking rates as well as preferred visiting purpose rates of passengers to a certain country.

Fig-1 represents the correlation ship among countries which having bookings to flights with various passenger types. The country sets {UK, USA} in studies, {USA, Singapore} in Tourists and Visitors, {USA, China, Australia} in Delegates, {Saudi Arabia, Ethiopia, Durban} in Contract, {USA, UK, Australia, China} in Political, {USA, Malaysia, Singapore, Italy} in Cinematography and {USA, UK, Australia} in Business having high rate passengers bookings of flights with best correlation factor between[0.8962 to 1].



		SA	USA	MYA	SGP	CHA	UK	EPA	DN	NS	AUS	ILY	TKY	IRN	IRQ	ISR	RUS
	1	-0.22256	-0.17391	-0.33197	-0.28858	-0.33397	-0.11178	-0.221	-0.25515	-0.22511	-0.25186	0.238432	0.147548	-0.08715	0.016231	0.06314	-0.27128
SA	-0.22256	1	0.011155	0.237942	0.151214	0.02193	-0.0964	0.295326	0.525036	0.643328	0.40242	-0.02377	0.086795	0.162175	0.620443	0.12646	0.066559
USA	-0.17391	0.011155	1	0.450447	0.427692	0.896237	0.926409	-0.19258	-0.13011	0.607509	0.805213	0.282632	0.15106	-0.13948	-0.30461	-0.21756	0.949106
MYA	-0.33197	0.237942	0.450447	1	0.992752	0.62386	0.153458	0.25894	0.35222	0.680944	0.644551	0.52403	0.516592	0.359897	0.099884	0.236276	0.547015
SGP	-0.28858	0.151214	0.427692	0.992752	1	0.612697	0.133566	0.229103	0.305806	0.605773	0.595534	0.536064	0.507853	0.362782	0.05771	0.246098	0.52752
CHA	-0.33397	0.02193	0.896237	0.62386	0.612697	1	0.811782	0.010795	0.071586	0.6429	0.851384	0.093806	-0.02189	0.007409	-0.18969	-0.06897	0.968426
UK	-0.11178	-0.0964	0.926409	0.153458	0.133566	0.811782	1	-0.2612	-0.22868	0.44161	0.717494	-0.00878	-0.14549	-0.22578	-0.34417	-0.26615	0.873029
EPA	-0.221	0.295326	-0.19258	0.25894	0.229103	0.010795	-0.2612	1	0.962411	0.151494	0.004367	-0.00932	0.051923	0.512321	0.611191	0.403958	-0.08836
DN	-0.25515	0.525036	-0.13011	0.35222	0.305806	0.071586	-0.22868	0.962411	1	0.343637	0.168525	-0.00407	0.069972	0.498899	0.696221	0.401384	-0.0115
NS	-0.22511	0.643328	0.607509	0.680944	0.605773	0.6429	0.44161	0.151494	0.343637	1	0.895531	0.217508	0.281891	0.200558	0.313991	0.159391	0.678422
AUS	-0.25186	0.40242	0.805213	0.644551	0.595534	0.851384	0.717494	0.004367	0.168525	0.895531	1	0.106299	0.056831	0.01635	0.019392	-0.02968	0.869216
ILY	0.238432	-0.02377	0.282632	0.52403	0.536064	0.093806	-0.00878	-0.00932	-0.00407	0.217508	0.106299	1	0.934752	0.150518	-0.08563	0.041283	0.138216
TKY	0.147548	0.086795	0.15106	0.516592	0.507853	-0.02189	-0.14549	0.051923	0.069972	0.281891	0.056831	0.934752	1	0.345113	0.121634	0.248143	0.02611
IRN	-0.08715	0.162175	-0.13948	0.359897	0.362782	0.007409	-0.22578	0.512321	0.498899	0.200558	0.01635	0.150518	0.345113	1	0.757826	0.941431	-0.03132
IRQ	0.016231	0.620443	-0.30461	0.099884	0.05771	-0.18969	-0.34417	0.611191	0.696221	0.313991	0.019392	-0.08563	0.121634	0.757826	1	0.788569	-0.17499
ISR	0.06314	0.12646	-0.21756	0.236276	0.246098	-0.06897	-0.26615	0.403958	0.401384	0.159391	-0.02968	0.041283	0.248143	0.941431	0.788569	1	-0.0714
RUS	-0.27128	0.066559	0.949106	0.547015	0.52752	0.968426	0.873029	-0.08836	-0.0115	0.678422	0.869216	0.138216	0.02611	-0.03132	-0.17499	-0.0714	1

Figure 1: Passengers Types Correlation Matrix

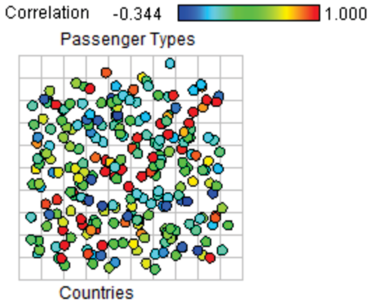


Figure 2: Correlation Distribution

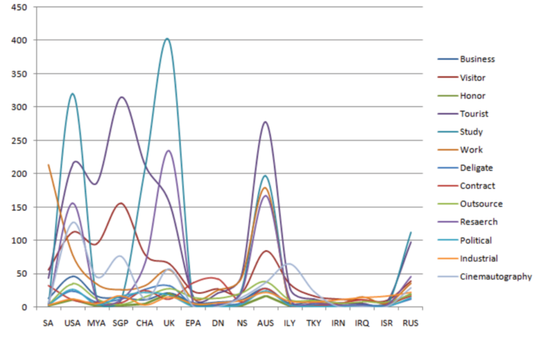
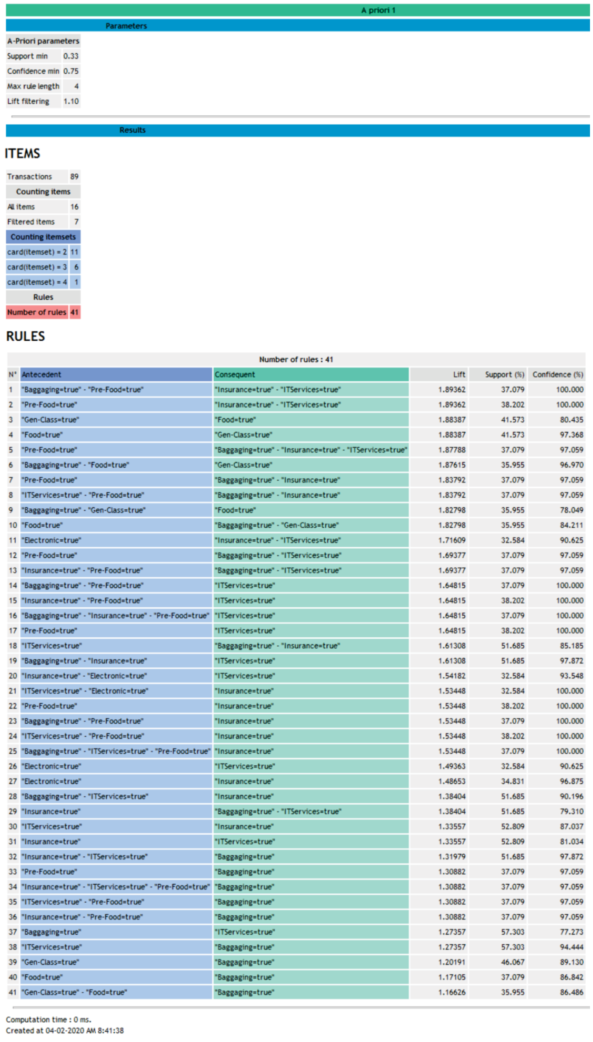


Figure 3: Rate Distribution of Passengers

Fig-2 and Fig-3 represents the rate of distribution of passengers booking of flights for mentioned types with correlated countries.

Identification of Airport Services preferences

The training data sets of airport aviation services and port services are considered for this analysis. The application of association rule mining over the training data set generates various interesting measures such as *Combination of Services with rating*, *Frequently used service patterns*, *low frequently used service patterns* etc.,. Using this machine learning analysis authorities can improve the service rates along with reduction of unnecessary expenditures over least preference services.



A priori 1

Parameters

A-Priori parameters	
Support min	0.33
Confidence min	0.75
Max rule length	4
Lift filtering	1.10

Results

ITEMS

Transactions	89
Counting items	
All items	16
Filtered items	7
Counting itemsets	
card(itemset) = 2	11
card(itemset) = 3	6
card(itemset) = 4	1
Rules	
Number of rules	41

RULES

Number of rules : 41

N°	Antecedent	Consequent	Lift	Support (%)	Confidence (%)
1	"Baggaging=true" - "Pre-Food=true"	"Insurance=true" - "ITServices=true"	1.89362	37.079	100.000
2	"Pre-Food=true"	"Insurance=true" - "ITServices=true"	1.89362	38.202	100.000
3	"Gen-Class=true"	"Food=true"	1.88387	41.573	80.435
4	"Food=true"	"Gen-Class=true"	1.88387	41.573	97.368
5	"Pre-Food=true"	"Baggaging=true" - "Insurance=true" - "ITServices=true"	1.87788	37.079	97.059
6	"Baggaging=true" - "Food=true"	"Gen-Class=true"	1.87615	35.955	96.970
7	"Pre-Food=true"	"Baggaging=true" - "Insurance=true"	1.83792	37.079	97.059
8	"ITServices=true" - "Pre-Food=true"	"Baggaging=true" - "Insurance=true"	1.83792	37.079	97.059
9	"Baggaging=true" - "Gen-Class=true"	"Food=true"	1.82798	35.955	78.049
10	"Food=true"	"Baggaging=true" - "Gen-Class=true"	1.82798	35.955	84.211
11	"Electronic=true"	"Insurance=true" - "ITServices=true"	1.71609	32.584	90.625
12	"Pre-Food=true"	"Baggaging=true" - "ITServices=true"	1.69377	37.079	97.059
13	"Insurance=true" - "Pre-Food=true"	"Baggaging=true" - "ITServices=true"	1.69377	37.079	97.059
14	"Baggaging=true" - "Pre-Food=true"	"ITServices=true"	1.64815	37.079	100.000
15	"Insurance=true" - "Pre-Food=true"	"ITServices=true"	1.64815	38.202	100.000
16	"Baggaging=true" - "Insurance=true" - "Pre-Food=true"	"ITServices=true"	1.64815	37.079	100.000
17	"Pre-Food=true"	"ITServices=true"	1.64815	38.202	100.000
18	"ITServices=true"	"Baggaging=true" - "Insurance=true"	1.61308	51.685	85.185
19	"Baggaging=true" - "Insurance=true"	"ITServices=true"	1.61308	51.685	97.872
20	"Insurance=true" - "Electronic=true"	"ITServices=true"	1.54182	32.584	93.548
21	"ITServices=true" - "Electronic=true"	"Insurance=true"	1.53448	32.584	100.000
22	"Pre-Food=true"	"Insurance=true"	1.53448	38.202	100.000
23	"Baggaging=true" - "Pre-Food=true"	"Insurance=true"	1.53448	37.079	100.000
24	"ITServices=true" - "Pre-Food=true"	"Insurance=true"	1.53448	38.202	100.000
25	"Baggaging=true" - "ITServices=true" - "Pre-Food=true"	"Insurance=true"	1.53448	37.079	100.000
26	"Electronic=true"	"ITServices=true"	1.49363	32.584	90.625
27	"Electronic=true"	"Insurance=true"	1.48653	34.831	96.875
28	"Baggaging=true" - "ITServices=true"	"Insurance=true"	1.38404	51.685	90.196
29	"Insurance=true"	"Baggaging=true" - "ITServices=true"	1.38404	51.685	79.310
30	"ITServices=true"	"Insurance=true"	1.33557	52.809	87.037
31	"Insurance=true"	"ITServices=true"	1.33557	52.809	81.034
32	"Insurance=true" - "ITServices=true"	"Baggaging=true"	1.31979	51.685	97.872
33	"Pre-Food=true"	"Baggaging=true"	1.30882	37.079	97.059
34	"Insurance=true" - "ITServices=true" - "Pre-Food=true"	"Baggaging=true"	1.30882	37.079	97.059
35	"ITServices=true" - "Pre-Food=true"	"Baggaging=true"	1.30882	37.079	97.059
36	"Insurance=true" - "Pre-Food=true"	"Baggaging=true"	1.30882	37.079	97.059
37	"Baggaging=true"	"ITServices=true"	1.27357	57.303	77.273
38	"ITServices=true"	"Baggaging=true"	1.27357	57.303	94.444
39	"Gen-Class=true"	"Baggaging=true"	1.20191	46.067	89.130
40	"Food=true"	"Baggaging=true"	1.17105	37.079	86.842
41	"Gen-Class=true" - "Food=true"	"Baggaging=true"	1.16626	35.955	86.486

Computation time : 0 ms.
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Figure 4: ARM generation Frequent Patterns

Table 1: Rule Based Decision Support

Service Combinations (Frequent Sets)	Confidence (%)
[Bagging, Food, IT-Services, Insurance]	100%
[Electronic, Entertainment, Luxury Class]	25%
[Premium food, General Class, IT-Services]	52%
[General Class, Food]	43%
[Physically Disabled Services, Insurance, IT-Services]	24%
[Electronic, Entertainment]	74%
[Premium Food, Executive Class, IT-Service]	62.4%

From the Table-1 we can have highly confidence based rules for service preferences. With these methodologies authority can predict passenger preference trends with score.

CONCLUSIONS

The proposed methods using machine learning techniques proved to identify best interesting measures with passenger preferences. The benefit of this approach identifies rate of service requirement along with service combinations. This estimation based approach useful to analysis future trends with airport economical improvement direction. Also our research work is helpful to identify the passenger preferences and supports preference based servicing capability. This methodology can be adoptable to any civil transportation systems under government sectors.

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