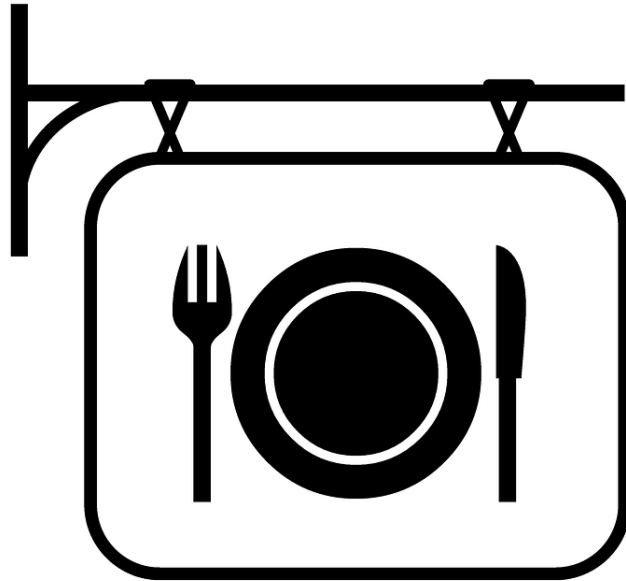


Food Establishment Recommender



CKMEI36 - Capstone report on food establishment dataset predictive
and recommendation with supervised machine learning algorithm

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Certificate in big data and predictive analytics

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1. Introduction

In the digital world we live in, humans' daily life is integrated to a digital technology in many different forms such as communication, entertainment, shopping, travel, social media etc. The common theme among technology base service providers is the reliance of a historical user data or/and product attributes in order to predict & recommend products and services to customers that are similar to the one that they are currently purchased. Recommender systems primary advantage is filtering a large set of data, item and/or product in order to provide much relevant and personal service customers in order to enhance their experience.

For the capstone project a city of Toronto Dinesafe food hygiene dataset in combination of yelp and travel advisor websites food premises customer review & rating data to create a predictive and recommender system.

2. Literature Review

In the information age we live in, the creation of data grows exponentially and not all the data is in a structured format. For individuals to shift through this large data in order to retrieve a relevant information that is suitable for their consumption is time consuming and tedious.

Information scientist developed a technique using statistics, machine learning and sentiment analysis to identify a relationship between items in order to provide a richer experience for users by providing only relevant information.

The primary articles that was reviewed in preparation of the capstone are

- I. An Introduction to Recommendation Systems in Software Engineering by Martin P. Robillard and Robert J. Walker
- II. Amazon.com recommendation, Item to Item collaborative filtering by Greg Linden, Brent Smith & Jeremy York
- III. A Literature Survey on Recommendation System Based on Sentimental Analysis by Achin Jain, Vanita Jain and Nidhi Kapoor
- IV. Incorporating popularity in a personalized news recommender system by Nirmal Jonnalagedda, Susan Gauch, Kevin Labille and Sultan Alfarhood
- V. Algorithms and Methods in Recommender Systems by Daniar Asanov
- VI. Basic Approaches in Recommendation Systems by Alexander Felfernig, Michael Jeran, Gerald Ninaus, Florian Reinfrank, Stefan Reiterer, and Martin Stettinger

There are three main techniques recommender systems are implemented on

1. **Collaborative Filtering:** This is a domain independent technique that analysis users profile attribute against item attributes to generate a recommendation. Recommendation is provided based on a similarity of user profiles and item profile using historical preference data.

Collaborative filtering is considered as the most basic and easiest recommender system technique. The disadvantage of this technique is with a cold start, this refers to lack of user profile data when users are new with no existing profile in the recommender system.

2. **Content Based Filtering:** This is a domain dependent technique that analysis attributes of items in order to generate a recommendation. This technique is used when there is a cold start, where the user has no profile. The recommendation depends on attribute similarities between items with no user profile input; therefore it is capable of recommending items to users that are new or has no historic data.

The second advantage of content based filtering is that, the technique is good in handling data sparsity, data sparsity refers to a lack of user rating or reviews on items. The disadvantage of this technique is when there is no enough item attributes, it fails to recommend the item to a user.

3. **Hybrid Filtering:** This technique is a combination multiple techniques such as collaborative, content based & context based techniques to take the strength of both techniques and improve the performance of the recommendation.

3. Dataset Review

As part of City of Toronto Open Data Initiative, the Toronto Public Health food safety inspection DineSafe data is available online for public use and this dataset will be used in this exercise.

<http://www.toronto.ca/health/dinesafe/index.htm>

In this project a subset of the **dinesafe** dataset has over 16,199 rows of historical inspection result, with 2,715 food premises for the year 2015 and 2016. The data attributes and description are provided below.

ATTRIBUTE NAME	DESCRIPTION
ROW_ID	Represents the Row Number
ESTABLISHMENT_ID	Unique identifier for an establishment
INSPECTION_ID	Unique identifier for each Inspection
ESTABLISHMENT_NAME	Business name of the establishment
ESTABLISHMENTTYPE	Establishment type ie restaurant, mobile cart
ESTABLISHMENT_ADDRESS	Municipal address of the establishment
ESTABLISHMENT_STATUS	Pass, Conditional Pass, Closed
MINIMUM_INSPECTIONS_PERYEAR	Every eating and drinking establishment in the City of Toronto receives a minimum of 1, 2, or 3 inspections each year depending on the specific type of establishment, the food preparation processes, volume and type of food served and other related criteria
INFRACTION_DETAILS	Description of the Infraction
INSPECTION_DATE	Calendar date the inspection was conducted
SEVERITY	Level of the infraction, i.e. S - Significant, M - Minor, C - Crucial
ACTION	Enforcement activity based on the infractions noted during a food safety inspection
COURT_OUTCOME	The registered court decision resulting from the issuance of a ticket or summons for outstanding infractions to the Health Protection and Promotion Act
AMOUNT_FINED	Fine determined in a court outcome

Dataset Adaptation

Dinesafe dataset is suitable for a predictive analytics, however it doesn't contain any customer oriented attributes such as user profile, rating, postal code and other attributes that are necessary for recommender system.

In order to adopt the data for an enhanced analytics & recommender system, customer rating, dollar value and cuisine type information was added to the dataset manually based on yelp and travel adviser customer rating. Also zip code and district information was extracted from google geocode for all the premises based on their street address.

ATTRIBUTE NAME	DESCRIPTION
ROW_ID	Represents the Row Number
ESTABLISHMENT_ID	Unique identifier for an establishment
INSPECTION_ID	Unique identifier for each Inspection
ESTABLISHMENT_NAME	Business name of the establishment
REVIEW	Customer satisfaction rating (1-5), 1 low, 5 high
VALUE	Value for money (1 - 5), 1 cheap , 5 expensive
CUISINE TYPE	Cuisine Type such as North American, European, African, Latin American, South Asian, Far Eastern etc...
ESTABLISHMENTTYPE	Establishment type ie restaurant, mobile cart
ESTABLISHMENT_ADDRESS	Municipal address of the establishment
ESTABLISHMENT_STATUS	Pass, Conditional Pass, Closed
MINIMUM_INSPECTIONS_PERYEAR	Every eating and drinking establishment in the City of Toronto receives a minimum of 1, 2, or 3 inspections each year depending on the specific type of establishment, the food preparation processes, volume and type of food served and other related criteria
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COURT_OUTCOME	The registered court decision resulting from the issuance of a ticket or summons for outstanding infractions to the Health Protection and Promotion Act
AMOUNT_FINED	Fine determined in a court outcome
ADDRESS	Full premises address
DISTRICT	Toronto district (Metro Toronto, York, North York, East York,

	Etobicoke, Scarborough)
CITY	Toronto
POSTAL CODE	Toronto postal codes

4. Methodology

In this project R language on RStudio was used in the implementation of project. The procedure that was followed in the analysis and development of a proof of concept is outlined below

Step 1: Define Objective

- The objective of this investigation is to produce an efficient mechanism to predict & recommend food premises such as restaurants, coffee shops, deli, bakery across Toronto based on Toronto Public Health historical DineSafe inspection dataset.

Step 2: Prepare & Explore Data

- Collect and explore dataset
- Clean dataset by removing institutions, convenience stores, groceries, schools etc
- Create data consistency by removing typo errors, missing
- Identify missing attributes & retrieved from yelp, traveladvisor & google
- Merge missing attributes with the dinesafe dataset

Step 3: Explorative Analyze Data

- Analyze data structure, missingness, dimension & description
- Perform univariant data analysis
- Perform bivariant data analysis
- Perform multivariant data analysis

Step 4: Transform Data

- Define dataset as supervised or non-supervised algorithm
- Analyze predictive & recommender algorithms to use
- Remove duplicate premises data
- Select labels from subset of the dataset
- Transform nominal categorical data into a numerical nominal value
- Normalize the data

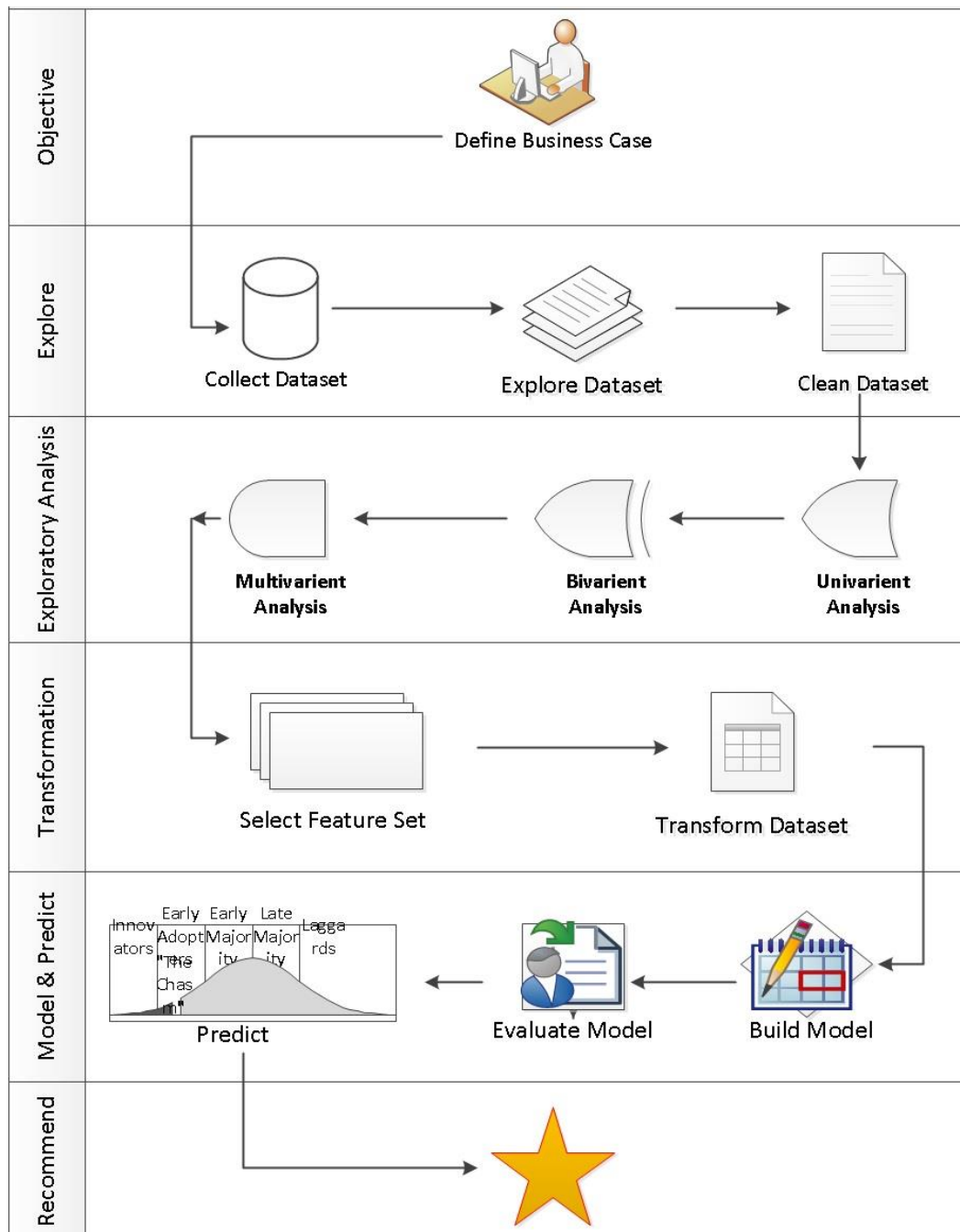
Step 5: Develop Predictive Model & Outcome

- Select machine learning algorithm
- Split data into training and testing
- Cross validation dataset
- Build a model
- Evaluate & validate the model
- Calculate model accuracy
- Improve accuracy
- Apply model on test dataset & observe outcome

Step 5: Create Recommendation

- Build a recommender model

- Apply data set on a recommender model and validate the prediction result.



5. Data Exploration

5.1 Initial dataset description

- Dinesafe dataset

[1] "ROW_ID"	"ESTABLISHMENT_ID"	"INSPECTION_ID"
[4] "ESTABLISHMENT_NAME"	"REVIEW"	"VALUE"
[7] "CUISINE_TYPE"	"ESTABLISHMENT_TYPE"	"ESTABLISHMENT_ADDRESS"
[10] "ESTABLISHMENT_STATUS"	"MINIMUM_INSPECTIONS_PERYEAR"	"INFRACTION_DETAILS"
[13] "INSPECTION_DATE"	"SEVERITY"	"ACTION"
[16] "COURT_OUTCOME"	"AMOUNT_FINED"	

- Address dataset

[1] "ESTABLISHMENT_ID"	"ESTABLISHMENT_NAME"	"LONG_ADDRESS"	"SHORT_ADDRESS"	"DISTRICT"
[6] "CITY"	"POSTAL_CODE"			

5.2 Dataset Summary

- Dinesafe dataset Summary

ROW_ID	ESTABLISHMENT_ID	INSPECTION_ID	ESTABLISHMENT_NAME	REVIEW	VALUE
Min. : 1	Min. : 1222579	Min. : 103179834	TIM HORTONS: 1135	Min. : 1.000	Min. : 1.000
1st Qu.: 22014	1st Qu.: 10198651	1st Qu.: 103542961	SUBWAY : 919	1st Qu.: 3.000	1st Qu.: 1.000
Median : 42690	Median : 10393868	Median : 103666608	PIZZA PIZZA: 428	Median : 3.000	Median : 1.000
Mean : 42345	Mean : 10107910	Mean : 103658272	MCDONALD'S : 383	Mean : 3.236	Mean : 1.526
3rd Qu.: 62202	3rd Qu.: 10488300	3rd Qu.: 103785830	SECOND CUP : 234	3rd Qu.: 3.500	3rd Qu.: 2.000
Max. : 86941	Max. : 10584261	Max. : 103890691	FRESHII : 222	Max. : 5.000	Max. : 4.000
			(Other) : 12878	NA's : 11	NA's : 452
CUISINE_TYPE	ESTABLISHMENT_TYPE	ESTABLISHMENT_ADDRESS			
Cafe : 3194	Restaurant : 10870	300 BOROUGH DR : 147			
North American: 2898	Food Take Out : 2991	2300 YONGE ST : 119			
Deli : 2353	Food Court Vendor : 1672	1 DUNDAS ST W : 103			
European : 2137	Bakery : 307	1800 SHEPPARD AVE E: 99			
Far Eastern : 1962	Bake Shop : 174	3401 DUFFERIN ST : 98			
Mediterranean : 876	Ice Cream / Yogurt Vendors: 74	40 KING ST W : 95			
(Other) : 2779	(Other) : 111	(Other) : 15538			
ESTABLISHMENT_STATUS	MINIMUM_INSPECTIONS_PERYEAR				
Closed : 101	Min. : 1.000				
Conditional Pass: 2973	1st Qu.: 2.000				
Pass : 13125	Median : 2.000				
	Mean : 2.255				
	3rd Qu.: 3.000				
	Max. : 3.000				

Operator fail to properly wash surfaces in rooms :1619
 Operator fail to properly maintain rooms :1299
 Operator fail to properly wash equipment :1114
 Operator fail to properly maintain equipment(NON-FOOD) : 523
 Fail to ensure the presence of the holder of a valid food handler's certificate - Municipal Code Chapter 545 Sec. 5G(17)(a): 389
 (Other) :5607
 NA's :5648

INSPECTION_DATE	SEVERITY	ACTION
25-10-2016: 72	C - Crucial : 430	Notice to Comply :8031
04-10-2016: 64	M - Minor :5560	Corrected During Inspection :2190
17-05-2016: 62	NA - Not Applicable: 904	Ticket : 245
18-05-2016: 58	S - Significant :3657	Summons : 48
24-10-2016: 58	NA's :5648	Summons and Health Hazard Order: 19
19-01-2015: 57		(Other) : 18
(Other) :15828		NA's :5648

COURT_OUTCOME	AMOUNT_FINED
Pending : 135	Min. : 0.0
Conviction - Fined: 122	1st Qu.: 60.0
Charges Withdrawn : 25	Median : 120.0
Cancelled : 6	Mean : 208.1
Charges Quashed : 2	3rd Qu.: 305.0
(Other) : 2	Max. :1875.0
NA's :15907	NA's :16063

Address dataset Summary

ESTABLISHMENT_ID	ESTABLISHMENT_NAME	LONG_ADDRESS
Min. : 1222579	TIM HORTONS : 272	2 STRACHAN AVE, TORONTO, ON M6K 3C3, CANADA : 112
1st Qu.:10197086	SUBWAY : 232	100 PRINCES' BLVD, TORONTO, ON M6K 3C3, CANADA : 76
Median :10411080	PIZZA PIZZA : 102	1 BLUE JAYS WAY, TORONTO, ON M5V 1J3, CANADA : 59
Mean :10113602	SHOPPERS DRUG MART: 76	300 BOROUGH DR, SCARBOROUGH, ON M1P 4P5, CANADA : 54
3rd Qu.:10515149	STARBUCKS : 71	3401 DUFFERIN ST, NORTH YORK, ON M6A 2T9, CANADA: 43
Max. :10584261	MCDONALD'S : 70	(Other) :15056
	(Other) :14730	NA's : 153

SHORT_ADDRESS	DISTRICT	CITY	POSTAL_CODE
2 STRACHAN AVE : 112	METRO TORONTO:7387	RICHMOND HILL: 1	M6K 3C3: 247
100 PRINCES BLVD: 76	NORTH YORK :2696	TORONTO :15549	M9W : 97
1 BLUE JAYS WAY : 59	SCARBOROUGH :2492	VAUGHAN : 3	M5J : 89
300 BOROUGH DR : 54	ETOBICOKE :1770		M2N : 80
3401 DUFFERIN ST: 43	YORK : 748		M1B : 64
40 BAY ST : 43	EAST YORK : 441		M5V : 63
(Other) :15166	(Other) : 19		(Other):14913

5.3 Dataset Structure

Data structure of Dinesafe and Address datasets which has numeric and factor values

Dinesafe dataset Structure

```
'data.frame': 16199 obs. of 17 variables:
 $ ROW_ID      : int  68185 50462 50463 50464 50465 30104 30105 30106 30107 44731 ...
 $ ESTABLISHMENT_ID : int  10510325 10435255 10435255 10435255 10435255 10300086 10300086 10300086 10405624 ...
 $ INSPECTION_ID  : int  103505421 103490016 103550463 103750018 103824680 103490223 103551664 103750021 103824682 103522023 ...
 $ ESTABLISHMENT_NAME : factor w/ 864 levels "0109 Dessert + Chocolate",... 1 2 2 2 2 3 3 3 4 ...
 $ REVIEW         : num  3.5 3 3 3 3 3.5 3.5 3.5 3.5 3 ...
 $ VALUE          : num  2 1 1 1 1 1 1 1 1 ...
 $ CUISINE_TYPE    : factor w/ 17 levels "African","Bakeries",... 15 4 4 4 4 8 8 8 8 5 ...
 $ ESTABLISHMENT_TYPE : factor w/ 12 levels "Bake Shop","Bakery",... 12 9 9 9 9 9 9 9 12 ...
 $ ESTABLISHMENT_ADDRESS : factor w/ 1986 levels "1 ADELAIDE ST E",... 668 4 4 4 4 4 4 4 4 1191 ...
 $ ESTABLISHMENT_STATUS : factor w/ 3 levels "Closed","Conditional Pass",... 3 3 3 3 3 3 3 3 ...
 $ MINIMUM_INSPECTIONS_PERYEAR: int  1 2 2 2 2 2 2 2 2 ...
 $ INFRACTION_DETAILS : factor w/ 226 levels "Altering number of washbasins in facility without inspector's approval 0. Reg 562/90 Sec. 69",... NA NA
 NA NA NA NA NA NA NA ...
 $ INSPECTION_DATE : factor w/ 523 levels "01-02-2016","01-03-2016",... 55 207 214 227 60 207 214 227 60 386 ...
 $ SEVERITY         : factor w/ 4 levels "C - Crucial",... NA NA NA NA NA NA NA ...
 $ ACTION           : factor w/ 8 levels "Corrected During Inspection",... NA NA NA NA NA NA NA ...
 $ COURT_OUTCOME    : factor w/ 7 levels "Cancelled","Charges Quashed",... NA NA NA NA NA NA NA ...
 $ AMOUNT_FINED     : int  NA NA NA NA NA NA NA NA NA ...
```

Address dataset Structure

```
'data.frame': 15553 obs. of 7 variables:
 $ ESTABLISHMENT_ID : int  9337616 10384957 10390332 10492908 10233710 10480531 10527234 10550136 10580268 10412094 ...
 $ ESTABLISHMENT_NAME : Factor w/ 12154 levels "*-SUNNYLEA COOP NURSERY SCHOOL",...: 9652 11211 4855 1802 9669 7984 6717 895 3154 9662 ...
 $ LONG_ADDRESS : Factor w/ 10741 levels "1 ADELAIDE ST E, TORONTO, ON M5C 2V9, CANADA",...: 1 1 1 2 3 3 4 5 6 7 ...
 $ SHORT_ADDRESS : Factor w/ 10885 levels "1 ADELAIDE ST E",...: 1 1 1 2 3 3 4 5 6 7 ...
 $ DISTRICT : Factor w/ 8 levels "EAST YORK","Etobicoke",...: 4 4 4 4 5 5 4 4 4 4 ...
 $ CITY : Factor w/ 3 levels "RICHMOND HILL",...: 2 2 2 2 2 2 2 2 2 ...
 $ POSTAL_CODE : Factor w/ 5139 levels "L3T","L4J","L4J 8J8",...: 2571 2571 2571 2876 1006 1006 3070 2173 2200 2891 ...
```

5.4 Dataset Sample

A sample of the two datasets using a head function

- Dinesafe dataset sample

ESTABLISHMENT_ID	ROW_ID	INSPECTION_ID	ESTABLISHMENT_NAME.x	REVIEW	VALUE	CUISINE_TYPE	ESTABLISHMENT_TYPE	ESTABLISHMENT_ADDRESS
10584093	86928	103889233	PIZZAIOLO	3.5	1	European	Restaurant	123 SPADINA AVE
10584149	86932	103889610	Thai Express	3.0	1	South East Asian	Food Take Out	320 FRONT ST W
10584240	86939	103890492	Starbucks Coffee	3.7	2	Cafe	Food Take Out	621 KING ST W
10584261	86940	103890691	GLAD DAY	4.5	2	Cafe	Restaurant	499 CHURCH ST
10584261	86941	103890691	GLAD DAY	4.5	2	Cafe	Restaurant	499 CHURCH ST

ESTABLISHMENT_STATUS	MINIMUM_INSPECTIONS_PERYEAR	INFRACTION_DETAILS	INSPECTION_DATE
Pass	2	NA	10-01-2017
Pass	2	NA	11-01-2017
Pass	2	NA	12-01-2017
Pass	2	FAIL TO PROVIDE THERMOMETER IN STORAGE COMPARTMENT O. REG 562/90 SEC. 21	12-01-2017
Pass	2	Operator fail to properly maintain rooms	12-01-2017

- Address dataset sample

ESTABLISHMENT_NAME	LONG_ADDRESS	SHORT_ADDRESS	DISTRICT	CITY	POSTAL_CODE
LIPSTICK & DYNAMITE	992 QUEEN ST W, TORONTO, ON M6J 1H1, CANADA	992 QUEEN ST W	METRO TORONTO	TORON...	M6J 1H1
FRANKIES BAR & CAFE	994 QUEEN ST W, TORONTO, ON M6J 1H1, CANADA	994 QUEEN ST W	METRO TORONTO	TORON...	M6J 1H1
PROGRESS PORTUGUESE BAKERY AND PASTRY	996 DOVERCOURT RD, TORONTO, ON M6H 2X5, CANADA	996 DOVERCOURT RD	METRO TORONTO	TORON...	M6H 2X5
MACELLERIA SAN GABRIELE BUTCHER & GRILL	998 ST CLAIR AVE W, TORONTO, ON M6E 1A2, CANADA	998 ST CLAIR AVE W	YORK	TORON...	M6E 1A2
FRIDA RESTAURANT & BAR	999 EGLINTON AVE W, YORK, ON M6C 2C7, CANADA	999 EGLINTON AVE W	YORK	TORON...	M6C 2C7

5.5 Merged Dataset Summary

The dinesafe and address datasets were merged based on establishment id. The new dataset structure includes establishment information, inspection outcome and geographical location.

```
'data.frame': 16199 obs. of 23 variables:
 $ ESTABLISHMENT_ID : int  1222579 1222807 1222807 1222807 1222807 1222807 1222807 1222807 1223056 1223056 ...
 $ ROW_ID : int  1 4 5 6 7 8 9 10 11 12 ...
 $ INSPECTION_ID : int  103868579 103472815 103537032 103537032 103616870 103702528 103732221 103874297 103541411 103647049 ...
 $ ESTABLISHMENT_NAME.x : Factor w/ 864 levels "0109 Dessert + Chocolate",...: 683 645 645 645 645 645 645 645 658 658 ...
 $ REVIEW : num  5 3.5 3.5 3.5 3.5 3.5 3.5 3.5 3 ...
 $ VALUE : num  1 1 1 1 1 1 1 1 2 2 ...
 $ CUISINE_TYPE : Factor w/ 17 levels "African","Bakeries",...: 16 9 9 9 9 9 9 9 8 8 ...
 $ ESTABLISHMENT_TYPE : Factor w/ 12 levels "Bake Shop","Bakery",...: 9 12 12 12 12 12 12 12 12 ...
 $ ESTABLISHMENT_ADDRESS : Factor w/ 1986 levels "1 ADELAIDE ST E",...: 1903 417 417 417 417 417 417 417 1623 1623 ...
 $ ESTABLISHMENT_STATUS : Factor w/ 3 levels "Closed","Conditional Pass",...: 3 3 3 3 3 3 3 3 3 3 ...
 $ MINIMUM_INSPECTIONS_PERYEAR : int  2 3 3 3 3 3 3 3 2 2 ...
 $ INFRACTION_DETAILS : Factor w/ 226 levels "Altering number of washbasins in facility without inspector's approval O. Reg 562/90 Sec. 69",...: 159 159 120 150 NA NA NA NA NA ...
 $ INSPECTION_DATE : Factor w/ 523 levels "01-02-2016","01-03-2016",...: 360 385 370 370 447 69 299 499 491 98 ...
 $ SEVERITY : Factor w/ 4 levels "c - Crucial",...: 2 2 4 2 NA NA NA NA NA ...
 $ ACTION : Factor w/ 8 levels "Corrected During Inspection",...: 3 3 1 3 NA NA NA NA NA ...
 $ COURT_OUTCOME : Factor w/ 7 levels "Cancelled","Charges Quashed",...: NA NA NA NA NA NA NA NA ...
 $ AMOUNT_FINED : int  NA NA NA NA NA NA NA NA ...
 $ ESTABLISHMENT_NAME.y : Factor w/ 12154 levels "*-SUNNYLEA COOP NURSERY SCHOOL",...: 8793 7838 7838 7838 7838 7838 7838 7993 7993 ...
 $ LONG_ADDRESS : Factor w/ 10741 levels "1 ADELAIDE ST E, TORONTO, ON M5C 2V9, CANADA",...: 10207 2397 2397 2397 2397 2397 2397 8874 8874 ...
 $ SHORT_ADDRESS : Factor w/ 10885 levels "1 ADELAIDE ST E",...: 10354 2403 2403 2403 2403 2403 2403 8884 8884 ...
 $ DISTRICT : Factor w/ 8 levels "EAST YORK","Etobicoke",...: 6 5 5 5 5 5 5 3 3 ...
 $ CITY : Factor w/ 3 levels "RICHMOND HILL",...: 2 2 2 2 2 2 2 2 2 ...
 $ POSTAL_CODE : Factor w/ 5139 levels "L3T","L4J","L4J 8J8",...: 172 4019 4019 4019 4019 4019 4019 4526 4526 ...
```

Explore cuisine type, inspection outcome & its severity and establishment location.

African	Bakeries	Bar	Cafe	Caribbean
72	53	461	3194	234
Deli	Dessert	European	Far Eastern	Juicery & Smoothies
2353	187	2137	1962	335
Latin American	Mediterranean	Middle Eastern	North American	Pastries
213	876	115	2898	218
South Asian	South East Asian	<NA>		
318	573	0		
Closed	Conditional	Pass	<NA>	
101	2973	13125	0	
EAST YORK	Etobicoke	ETOBICOKE	METRO TORONTO	NORTH YORK
364	0	1387	8290	3097
YORK	<NA>			SCARBOROUGH
534	0			2517
				TORONTO ISLAND
				10
C - Crucial	M - Minor	NA - Not Applicable	S - Significant	
430	5560	904	3657	

6. Data Munging

6.1 Remove duplicates

- Remove duplicate columns from the two dataset merger such as “establishment name” & “establishment address”

```
Dinesafe <- subset(Dinesafe, select = -c(ESTABLISHMENT_NAME.y, ESTABLISHMENT_ADDRESS) )
```

- Remove data columns that are not relevant to the analysis such as “court outcome”, “amount fined” and “infraction detail”

```
Dinesafe <- subset(Dinesafe, select = -c(ROW_ID, COURT_OUTCOME, AMOUNT_FINED, LONG_ADDRESS, INFRACTION_DETAILS) )
```

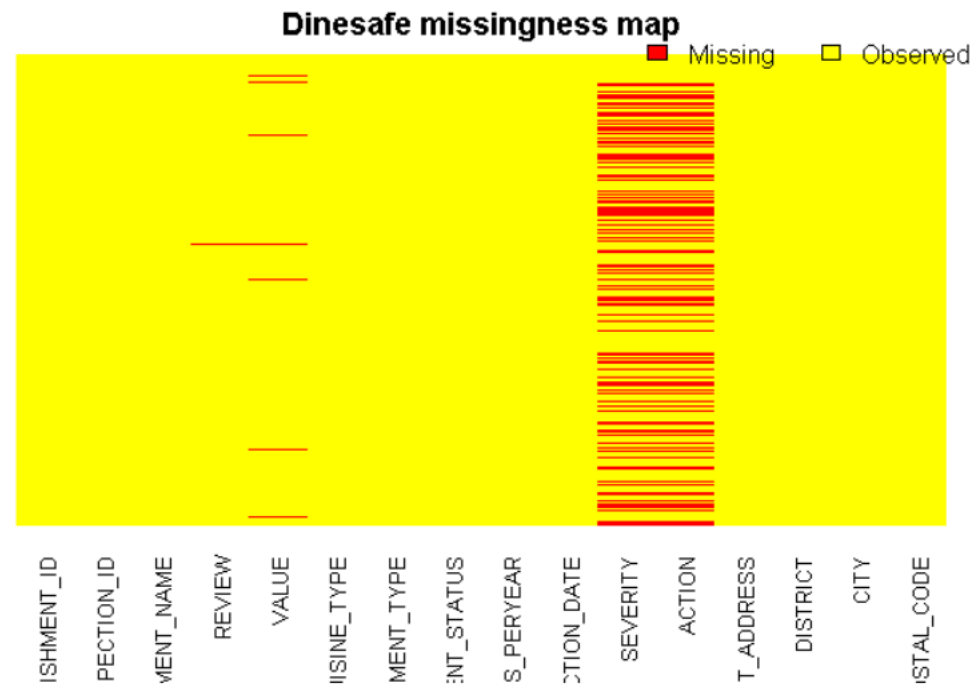
- Rename “establishment_name.x” to “establishment_name”

```
colnames(Dinesafe)[colnames(Dinesafe) == 'ESTABLISHMENT_NAME.x'] <- 'ESTABLISHMENT_NAME'
```

6.2 Missingness

- Identify & quantify missingness in the dataset, the “review”, “value”, “action” and “severity” columns has missing values that need to be imputed. This is represented in the missmap graph shown below in red using the Amelia package.

REVIEW	ESTABLISHMENT_ID	INSPECTION_ID	ESTABLISHMENT_NAME
11	0	0	0
ESTABLISHMENT_STATUS	VALUE	CUISINE_TYPE	ESTABLISHMENT_TYPE
0	452	0	0
MINIMUM_INSPECTIONS_PERYEAR	INSPECTION_DATE	SEVERITY	
ACTION	0	0	5648
POSTAL_CODE	SHORT_ADDRESS	DISTRICT	CITY
0	0	0	0



6.3 Format Data Types

- Convert Action column from factor to character type to avoid error during data imputation

```
Dinesafe$ACTION = as.character(Dinesafe$ACTION)
```

- Set Categorical Data Type Level for Establishment Status column

```
Dinesafe$ESTABLISHMENT_STATUS =  
factor(Dinesafe$ESTABLISHMENT_STATUS, levels=c("Closed", "Conditional Pass", "Pass"))
```

- Set Categorical Data Type Level for Severity column

```
Dinesafe$SEVERITY <- factor(Dinesafe$SEVERITY, levels = c("NA - Not Applicable", "N - No  
Action", "M - Minor", "S - Significant", "C - Crucial"))
```

6.4 Describe Dataset

- Describe quantitative values in “Review” and “Value” columns using HMISC library

```
Dinesafe$REVIEW
  n missing distinct    Info    Mean    Gmd    .05    .10    .25    .50    .75    .90    .95
16188      11      22  0.921  3.236  0.6238  2.5    2.5    3.0    3.0    3.5    4.0    4.0

lowest : 1.0 1.5 2.0 2.5 2.8, highest: 4.2 4.3 4.5 4.6 5.0

Dinesafe$VALUE
  n missing distinct    Info    Mean    Gmd
15747      452      5  0.768  1.526  0.5575

Value      1.0    2.0    2.5    3.0    4.0
Frequency  7932  7398    4   364   49
Proportion 0.504 0.470 0.000 0.023 0.003
```


Identify complete rows with no missing (NA) value using complete case function returning 10195 rows.

- `Complete_Dinesafe <- Dinesafe[complete.cases(Dinesafe),]`
- `nrow(Complete_Dinesafe)`

6.5 Impute Missing Values

Impute missing values in “review”, “value”, “severity” & “action” columns

- Impute “Review” column using the mean review value for the specific cuisine type, the below script demonstrates this for an “African” cuisine type
`Dinesafe$REVIEW[is.na(Dinesafe$REVIEW) & Dinesafe$CUISINE_TYPE=="African"] = mean(Dinesafe$REVIEW[Dinesafe$CUISINE_TYPE=="African"], na.rm=TRUE)`
- Impute “Value” column using the mean value for the specific cuisine type, the below script demonstrates this for an “African” cuisine type
`Dinesafe$VALUE[is.na(Dinesafe$VALUE) & Dinesafe$CUISINE_TYPE=="African"] = mean(Dinesafe$VALUE[Dinesafe$CUISINE_TYPE=="African"], na.rm=TRUE)`
- In Severity column, the only missing values were for “Pass” establishment status, therefore the missing value in severity column was imputed with “Not applicable”
`Dinesafe$SEVERITY[is.na(Dinesafe$SEVERITY) & Dinesafe$ESTABLISHMENT_STATUS == "Pass"] = "NA - Not Applicable"`
- In Action column, the only missing values were for “Pass” establishment status,
`Dinesafe$ACTION[is.na(Dinesafe$ACTION) & Dinesafe$ESTABLISHMENT_STATUS == "Pass" & Dinesafe$SEVERITY == "NA - Not Applicable"] = "No Action Required"`

Finally checking for incompleteness it returns zero value confirming there is no missing data.

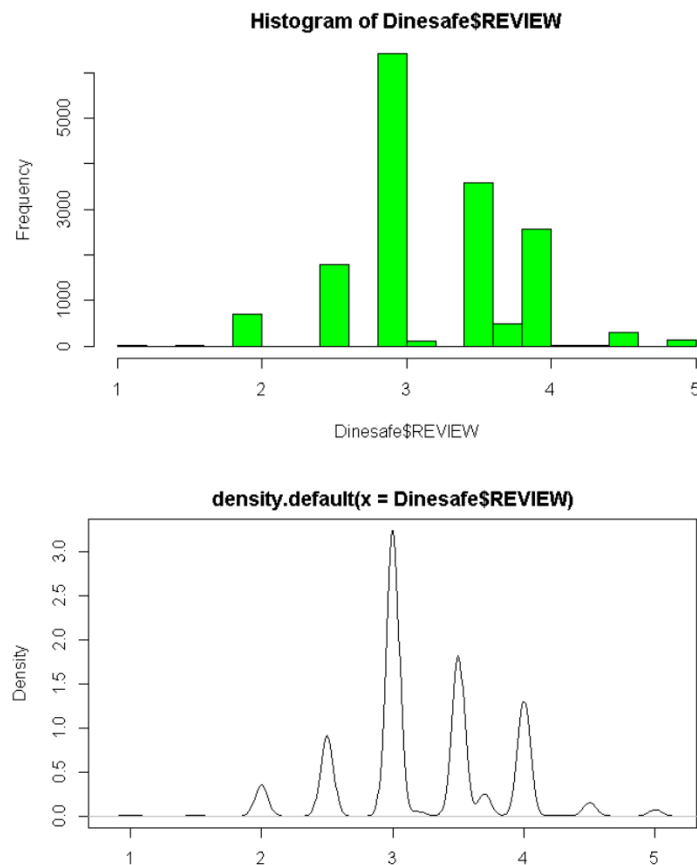
- `Dinesafe_NA <- Dinesafe[!complete.cases(Dinesafe),]`
- `nrow(Dinesafe_NA)`

7. Data Exploratory Analysis & Visualization

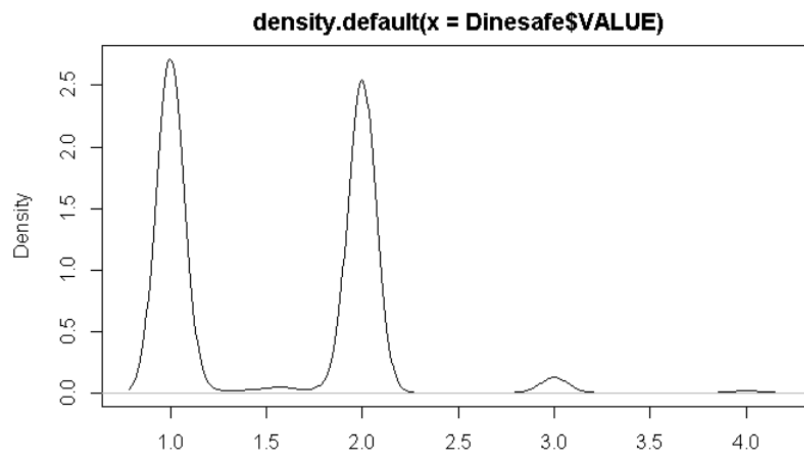
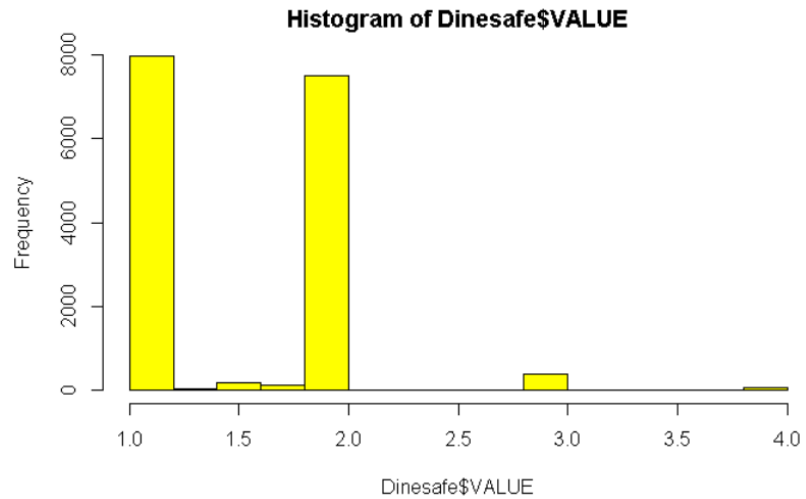
7.1 Univariate Data Analysis

In this section a single variable from the dataset was analyzed to understand the data using histogram and density graphical representation

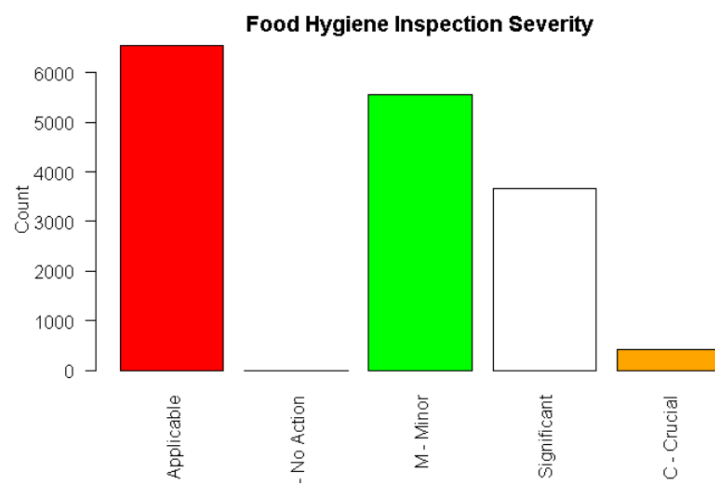
7.1.1 Review Variable : The data is normally distrusted



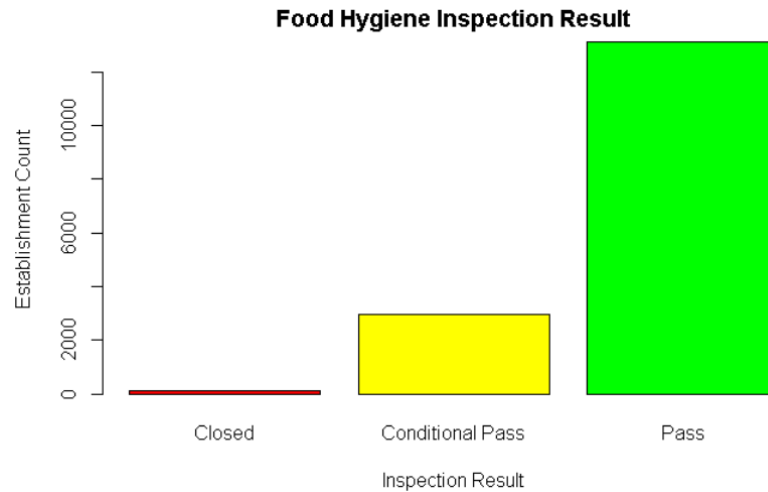
7.1.2 Value Variable : The data is skewed to the right



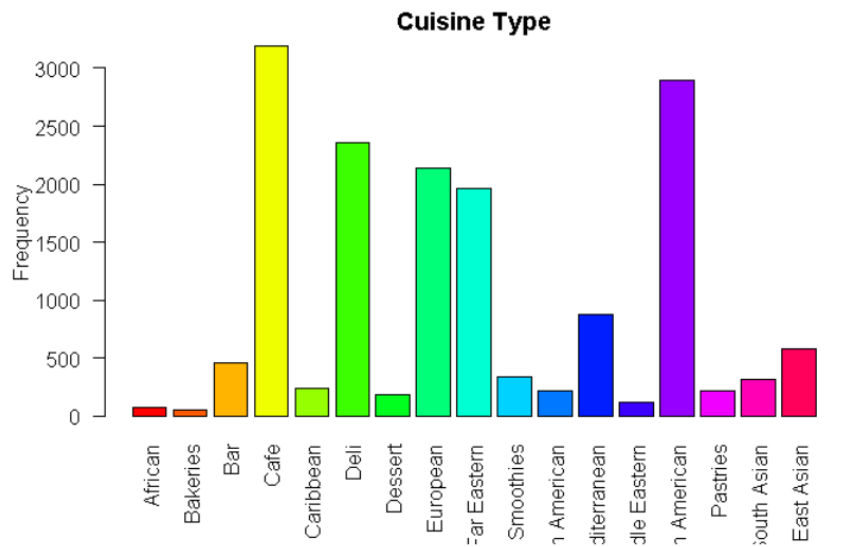
7.1.3 Food inspection severity graph



7.1.4 Food Hygiene Inspection Result

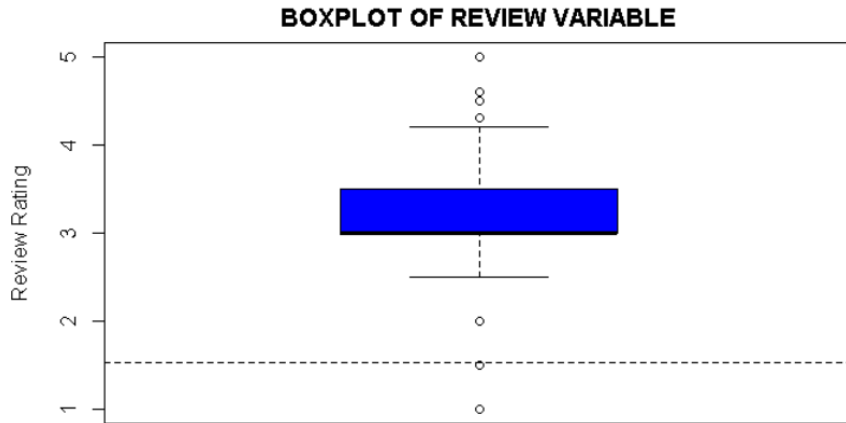


7.1.5 Establishment Cuisine Type



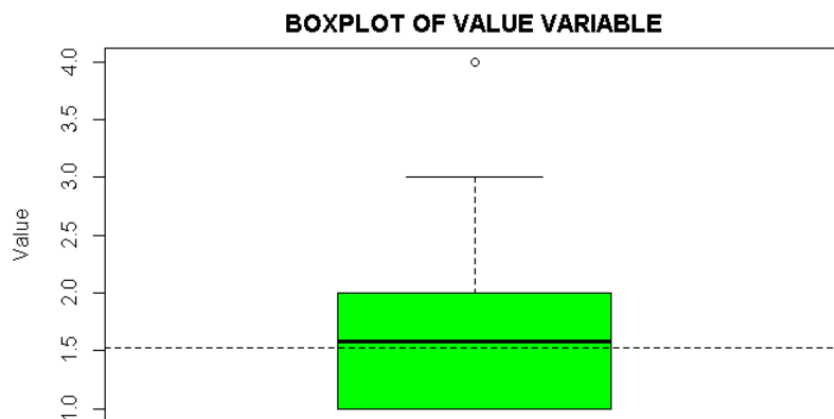
7.1.6 Boxplot of Review Variable

The data graph shows that the mean and median values (Horizontal dot line) are far apart and most of the values are lying between 3 and 3.5 with outlier value below 2.5 and above 3.5



7.1.7 Boxplot of Value Variable

The data graph shows that the mean and median values (Horizontal dot line) are close to each other at 1.5 and most of the values are lying between 1 and 2 with outlier value at 4.



7.2 Bivariate Data Analysis

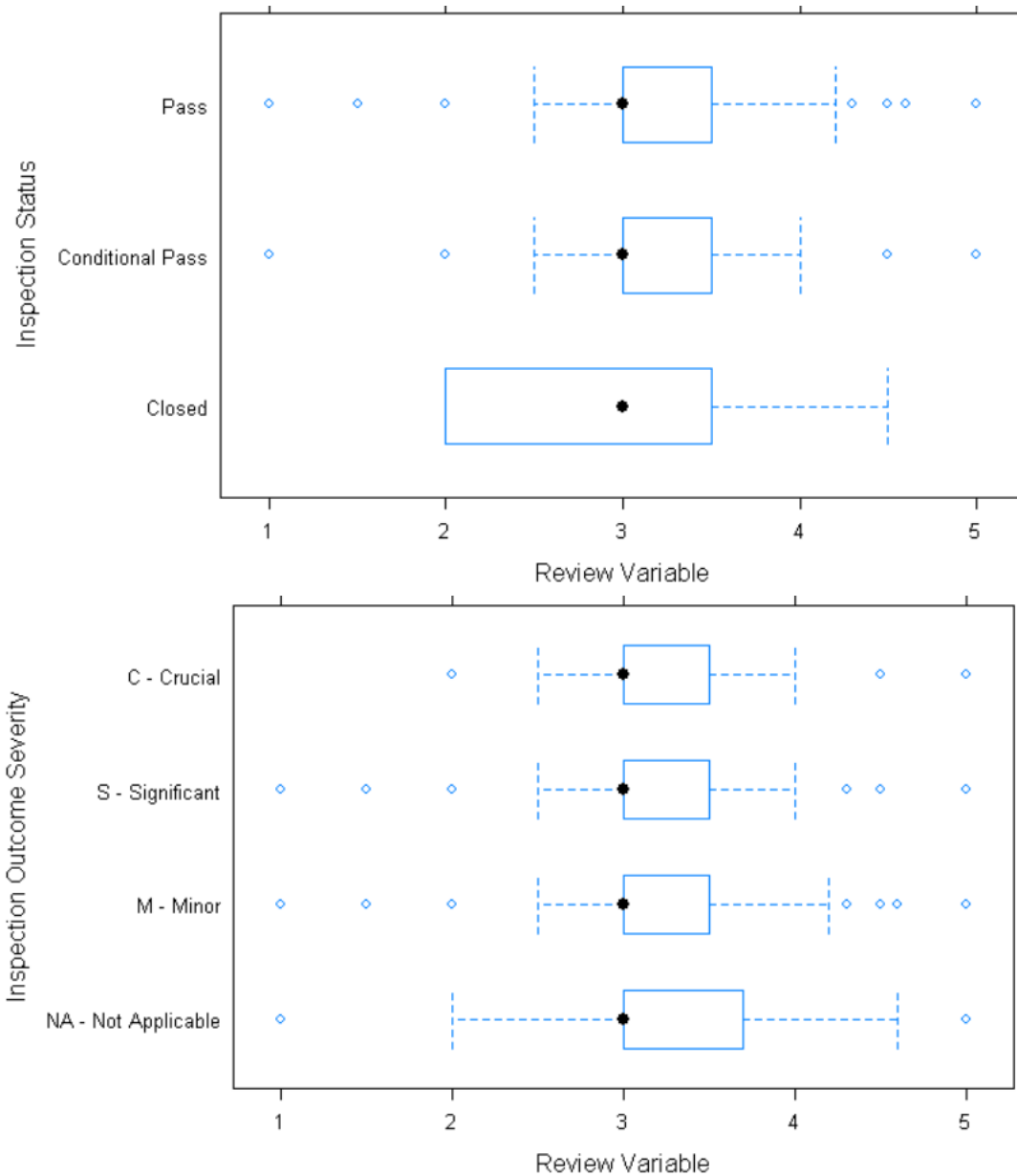
7.2.1 Mean and Standard Deviation

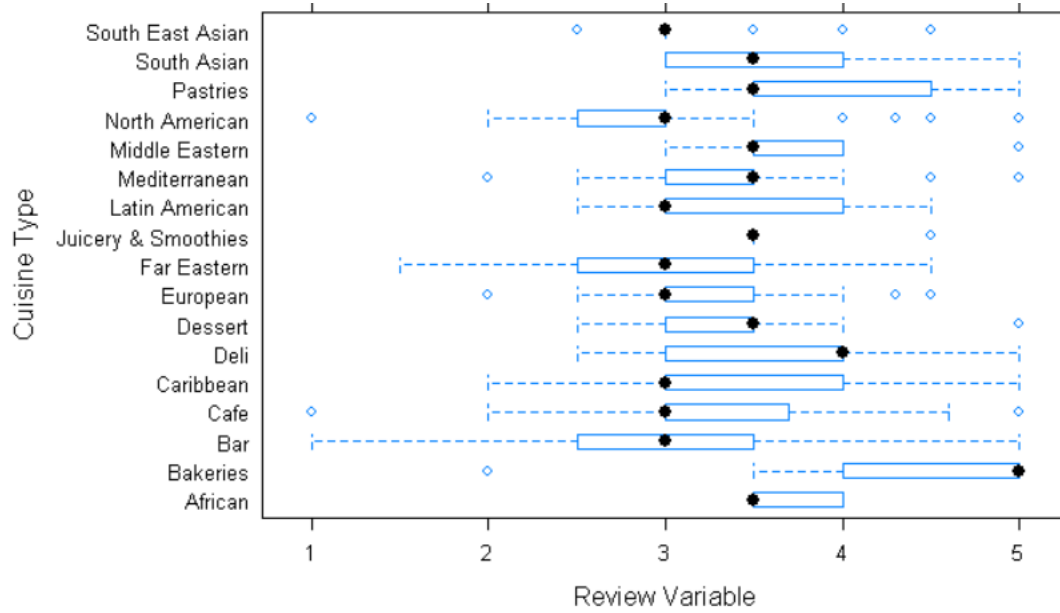
The mean and standard deviation value of food premises that failed inspection had a mean review value below those that passed inspection. Also failed food premises had a higher standard deviation value as compared to those who passed.

On the other hand the relationship between mean/standard deviation value and inspection outcome is not observed due to consistent result across all three values.

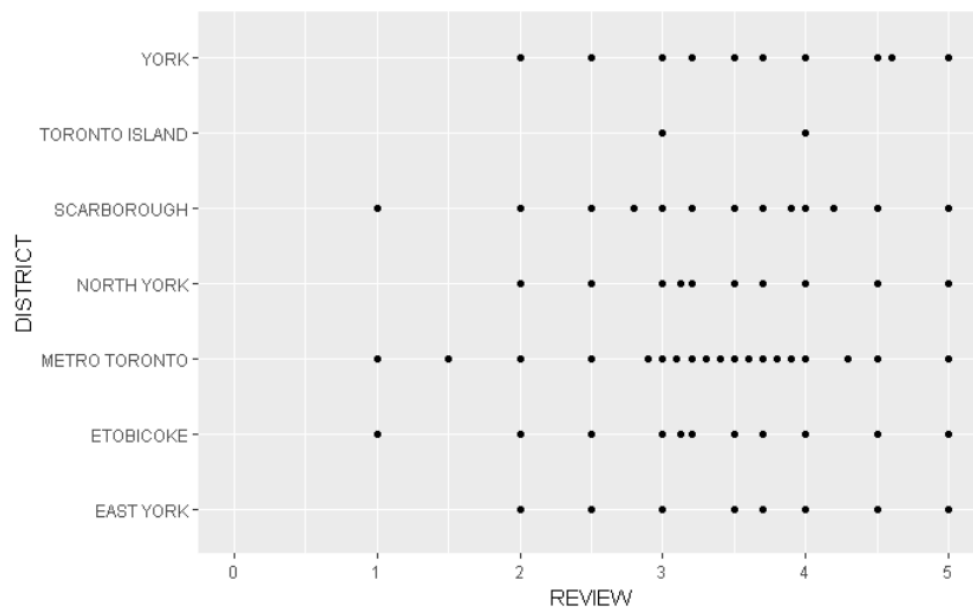
Mean Review data against establishment inspection status	Closed 2.871287	Conditional Pass 3.176495	Pass 3.252679
Standard Deviation of Review data against establishment inspection status	Closed 0.7471729	Conditional Pass 0.5964501	Pass 0.5700371
Mean value data against establishment inspection status	Closed 1.536582	Conditional Pass 1.580754	Pass 1.516429
Standard Deviation of Value data against establishment inspection status	Closed 0.4915077	Conditional Pass 0.5203282	Pass 0.5617093

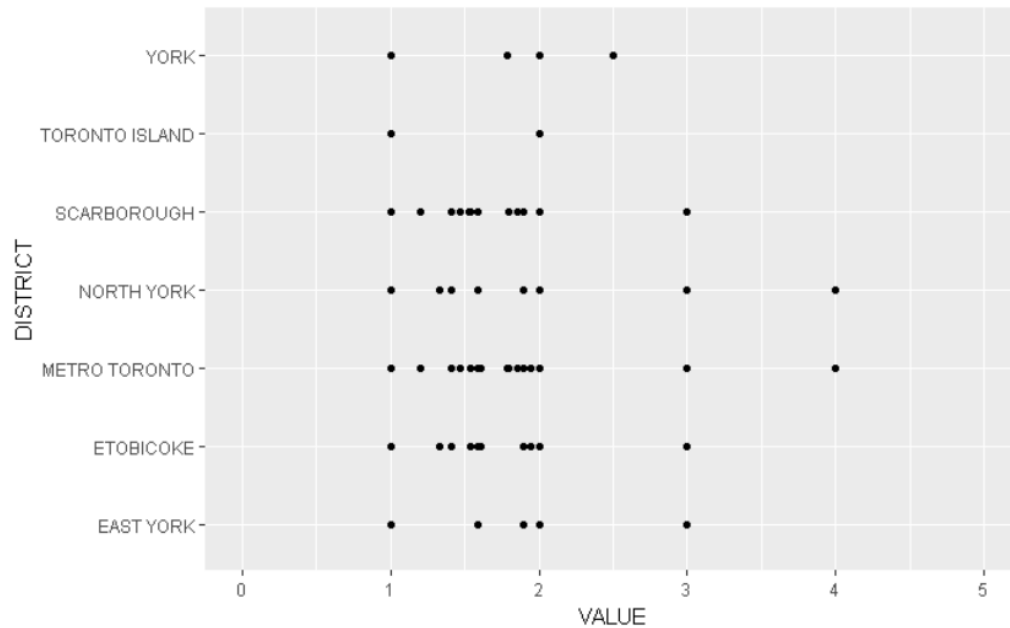
7.2.2 Categorical vs Numerical data analysis using lattice package





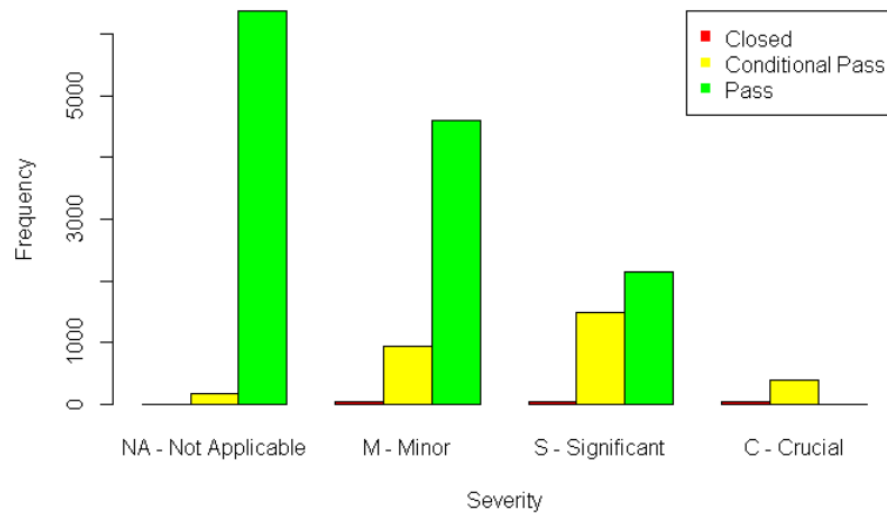
7.2.3 Categorical vs Numerical data analysis using ggplot2 package





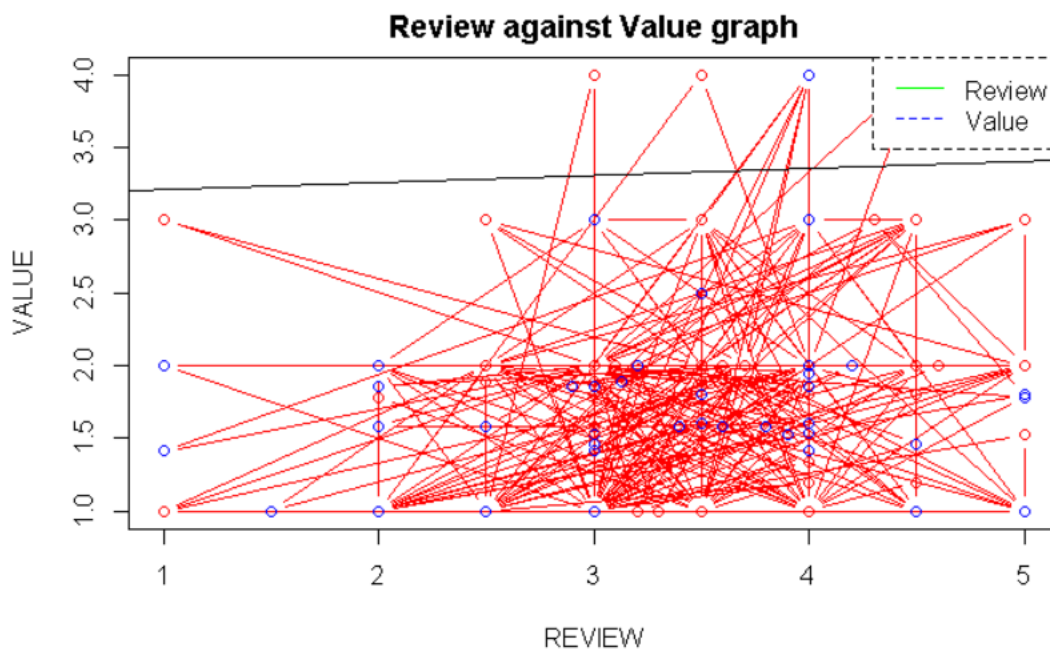
7.2.4 Crosstab analysis of “Severity” and “Inspection Status” analysis with Crosstab & barplot

-----		-----		-----	
	Pass		6383		4601
2139	2		13125		
			217.419		2.050
229.166	344.413				
			0.486		0.351
0.163	0.000		0.810		
			0.974		0.828
0.585	0.005				
			0.394		0.284
0.132	0.000				
-----		-----		-----	
	Column Total		6552		5560
3657	430		16199		
			0.404		0.343
0.226	0.027				
-----		-----		-----	
y NA - Not Applicable M - Minor S - Significant C - Crucial					
x					
Closed		1	28	41	31
Conditional Pass		168	931	1477	397
Pass		6383	4601	2139	2



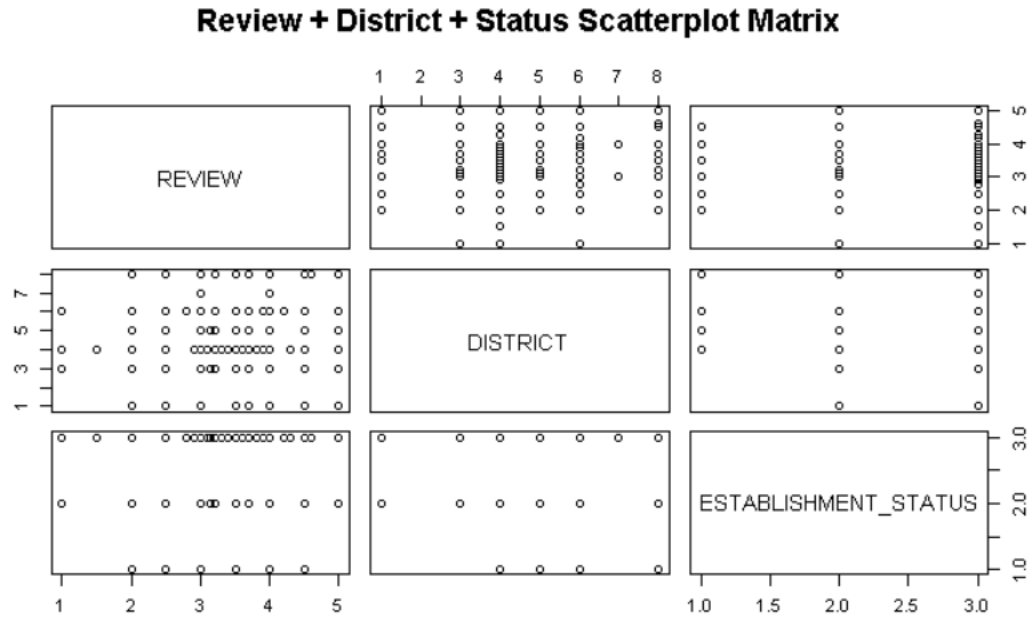
7.2.5 Relationship between “Review” and “Value” using scatter plot

As shown on the graph below there is no linear relationship between a restaurant review and value for money variables. The values are scattered all over the box and doesn't follow the simple linear regression model line.

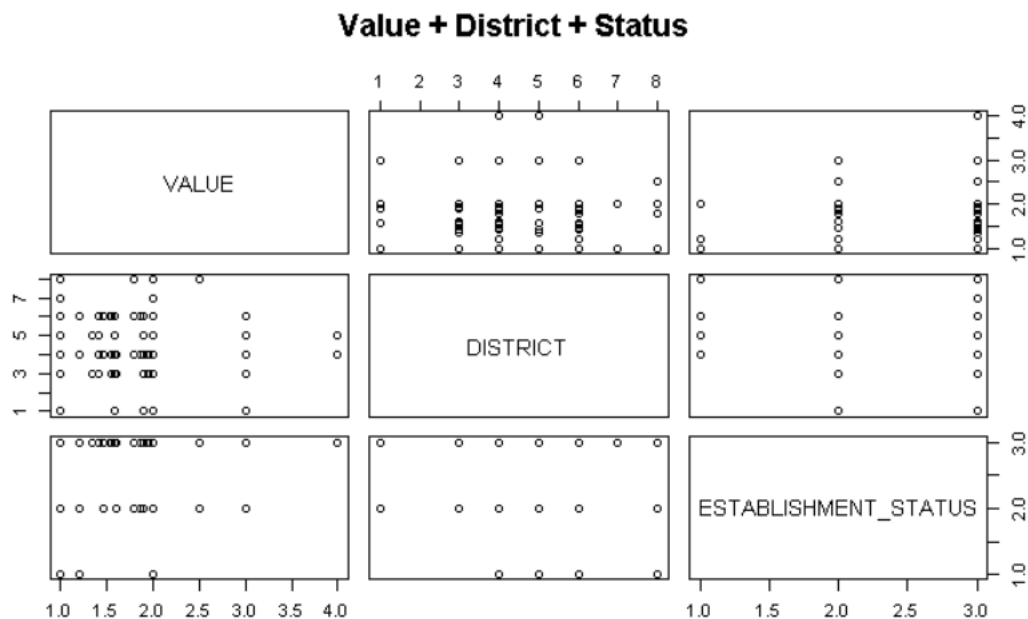


7.3 Multivariate Data Analysis

7.3.1 Simple Scatter Matrix on the relationship between Review, District and Status variables



7.3.2 Simple Scatter Matrix on the relationship between Value, District and Status variables



7.3.3 Aggregation of “Review” against “Status”, “Cuisine Type” and “District as categorical and numerical values.

```
head(aggregate(Dinesafe$REVIEW ~ Dinesafe$ESTABLISHMENT_STATUS + Dinesafe$CUISINE_TYPE +
Dinesafe$DISTRICT, FUN=mean),10)
```

	Dinesafe\$ESTABLISHMENT_STATUS <fctr>	Dinesafe\$CUISINE_TYPE <fctr>	Dinesafe\$DISTRICT <fctr>	Dinesafe\$REVIEW <dbl>
1	Pass	African	EAST YORK	3.500000
2	Pass	Bakeries	EAST YORK	5.000000
3	Conditional Pass	Cafe	EAST YORK	3.000000
4	Pass	Cafe	EAST YORK	3.217978
5	Conditional Pass	Deli	EAST YORK	4.000000
6	Pass	Deli	EAST YORK	3.771429
7	Pass	European	EAST YORK	3.010638
8	Pass	Far Eastern	EAST YORK	2.500000
9	Pass	Juicery & Smoothies	EAST YORK	3.500000
10	Pass	Latin American	EAST YORK	3.000000

1-10 of 10 rows

7.3.4 Aggregation of “Review” against “Status” and “Cuisine Type” values as categorical and numerical values.

```
head(aggregate(Dinesafe$REVIEW ~ Dinesafe$ESTABLISHMENT_STATUS + Dinesafe$CUISINE_TYPE,
FUN=length),10)
```

	Dinesafe\$ESTABLISHMENT_STATUS <fctr>	Dinesafe\$CUISINE_TYPE <fctr>	Dinesafe\$REVIEW <int>
1	Conditional Pass	African	7
2	Pass	African	65
3	Conditional Pass	Bakeries	5
4	Pass	Bakeries	48
5	Conditional Pass	Bar	60
6	Pass	Bar	401
7	Conditional Pass	Cafe	381
8	Pass	Cafe	2813
9	Closed	Caribbean	5
10	Conditional Pass	Caribbean	48

1-10 of 10 rows

8. Data Transformation

Following data exploration and analysis, the next step will be to perform data transformation in preparation for prediction and recommendation. The transformation processes are

- I. Selected appropriate variables to create a feature
The labels we are important for prediction and recommendation are “Establishment ID”, “Establishment Name”, “Review”, “Value” and “Cuisine Type”. The rest of the labels are not relevant in creating an attribute of the establishment.
- II. Created a unique rows based on the selected features. This reduces the number of rows from 16,199 to 2723
- III. Using “if else” function changed the “Cuisine Type” label from qualitative nominal value to quantitative nominal value Transform labels to the appropriate data type ranging from 1 to 17. These values are not ordinal and are treated as an index and it will be used an input to a predictive algorithm since only numeric values are accepted.

ESTABLISHMENT_ID <int>	ESTABLISHMENT_NAME <ctr>	REVIEW <dbl>	VALUE <dbl>	CUISINE_TYPE <ctr>	CUISINE_IDX <chr>
1222579	SAI-LILA KHAMAN DHOKLA HOUSE	5.0	1	South Asian	15
1222807	PHO BO TO	3.5	1	Far Eastern	9
1223056	PIZZA PIZZA	3.0	2	European	8
9000004	PAPINO'S PIZZA	4.0	1	European	8
9000026	2-4-1 PIZZA	2.5	2	European	8
9000029	2-4-1 PIZZA	2.5	2	European	8

- IV. Changed CUISINE_TYPE from factor to numerical value
`Dinesafe2$CUISINE_IDX <- as.numeric(Dinesafe2$CUISINE_TYPE)`

- V. Created binary values for the “Cuisine Type” in order to create a binary attributes

`Dinesafe2$African <- ifelse(Dinesafe2$CUISINE_TYPE == "African",1,0)`

ESTABLISHMENT_ID	ESTABLISHMENT_NAME	REVIEW	VALUE	CUISINE_TYPE	CUISINE_IDX	African	Bakeries	Bar	Cafe	Caribbean	Deli	Dessert	European	FarEastern	Mediterranean	MidEastern	NAmerican	Juice
1222579	SAI-LILA KHAMAN DHOKLA HOUSE	5.0	1.000000	South Asian	15	0	0	0	0	0	0	0	0	0	0	0	0	0
1222807	PHO BO TO	3.5	1.000000	Far Eastern	9	0	0	0	0	0	0	0	0	1	0	0	0	0
1223056	PIZZA PIZZA	3.0	2.000000	European	8	0	0	0	0	0	0	0	1	0	0	0	0	0
9000004	PAPINO'S PIZZA	4.0	1.000000	European	8	0	0	0	0	0	0	0	1	0	0	0	0	0
9000026	2-4-1 PIZZA	2.5	2.000000	European	8	0	0	0	0	0	0	0	1	0	0	0	0	0
9000029	2-4-1 PIZZA	2.5	2.000000	European	8	0	0	0	0	0	0	0	1	0	0	0	0	0

```

'data.frame': 2723 obs. of 22 variables:
 $ ESTABLISHMENT_ID: int 1222579 1222807 1223056 9000004 9000026 9000029 9000031 9000046 9000109 9000116 ...
 $ REVIEW          : num 5 3.5 3 4 2.5 2.5 2.5 2.5 3 2 ...
 $ VALUE           : num 1 1 2 1 2 2 2 2 2 2 ...
 $ CUISINE_TYPE    : Factor w/ 17 levels "African","Bakeries",...: 16 9 8 8 8 8 8 8 3 4 ...
 $ CUISINE_IDX     : num 15 9 8 8 8 8 8 8 3 4 ...
 $ African         : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Bakeries        : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Bar             : num 0 0 0 0 0 0 0 0 1 0 ...
 $ Cafe            : num 0 0 0 0 0 0 0 0 0 1 ...
 $ Caribbean       : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Deli            : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Dessert         : num 0 0 0 0 0 0 0 0 0 0 ...
 $ European        : num 0 0 1 1 1 1 1 1 0 0 ...
 $ FarEastern      : num 0 1 0 0 0 0 0 0 0 0 ...
 $ Mediterranean   : num 0 0 0 0 0 0 0 0 0 0 ...
 $ MidEastern      : num 0 0 0 0 0 0 0 0 0 0 ...
 $ NAmerican       : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Juicery         : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Pastries        : num 0 0 0 0 0 0 0 0 0 0 ...
 $ SouthAsian      : num 1 0 0 0 0 0 0 0 0 0 ...
 $ SEastAsian      : num 0 0 0 0 0 0 0 0 0 0 ...
 $ LAmerican       : num 0 0 0 0 0 0 0 0 0 0 ...

```

VI. Normalize the “Review”, “Value” & “Cuisine_idx” labels

```

'data.frame': 2723 obs. of 20 variables:
 $ African         : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Bakeries        : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Bar             : num 0 0 0 0 0 0 0 0 1 0 ...
 $ Cafe            : num 0 0 0 0 0 0 0 0 0 1 ...
 $ Caribbean       : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Deli            : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Dessert         : num 0 0 0 0 0 0 0 0 0 0 ...
 $ European        : num 0 0 1 1 1 1 1 1 1 0 ...
 $ FarEastern      : num 0 1 0 0 0 0 0 0 0 0 ...
 $ Mediterranean   : num 0 0 0 0 0 0 0 0 0 0 ...
 $ MidEastern      : num 0 0 0 0 0 0 0 0 0 0 ...
 $ NAmerican       : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Juicery         : num 0 0 0 0 0 0 0 0 0 0 ...
 $ Pastries        : num 0 0 0 0 0 0 0 0 0 0 ...
 $ SouthAsian      : num 1 0 0 0 0 0 0 0 0 0 ...
 $ SEastAsian      : num 0 0 0 0 0 0 0 0 0 0 ...
 $ LAmerican       : num 0 0 0 0 0 0 0 0 0 0 ...
 $ REVIEW          : num 1 0.625 0.5 0.75 0.375 0.375 0.375 0.5 0.25 ...
 $ VALUE           : num 0 0 0.333 0 0.333 ...
 $ CUISINE_IDX     : num 0.882 0.529 0.471 0.471 0.471 ...

```

VII. Randomly split the dataset into two for training and testing to be used in predictive analysis

9. Predictive Analysis

Predictive analysis is a process of making prediction of an outcome based on existing features using historical data. The data analysis, cleansing and transformation steps that were applied in the earlier steps are used in this predictive step

9.1 Algorithm selection

The primary objective in this task is to classify the food premises into a number of classes based on its attributes such as the cuisine type. This scenario is a good example of a supervised learning algorithm since the outcome value is provided during the training phase.

9.2 Model Building

The first phase of building the KNN model is to perform a cross validation to determine the optimum K value for the given dataset in order to create a more accurate outcome. 10 fold cross validation with three repeats and the outcome was plotted.

Caret and Class package were used to build the model

The smallest RMSE value indicates the most optimized K values to use and as shown below K = 5 was selected

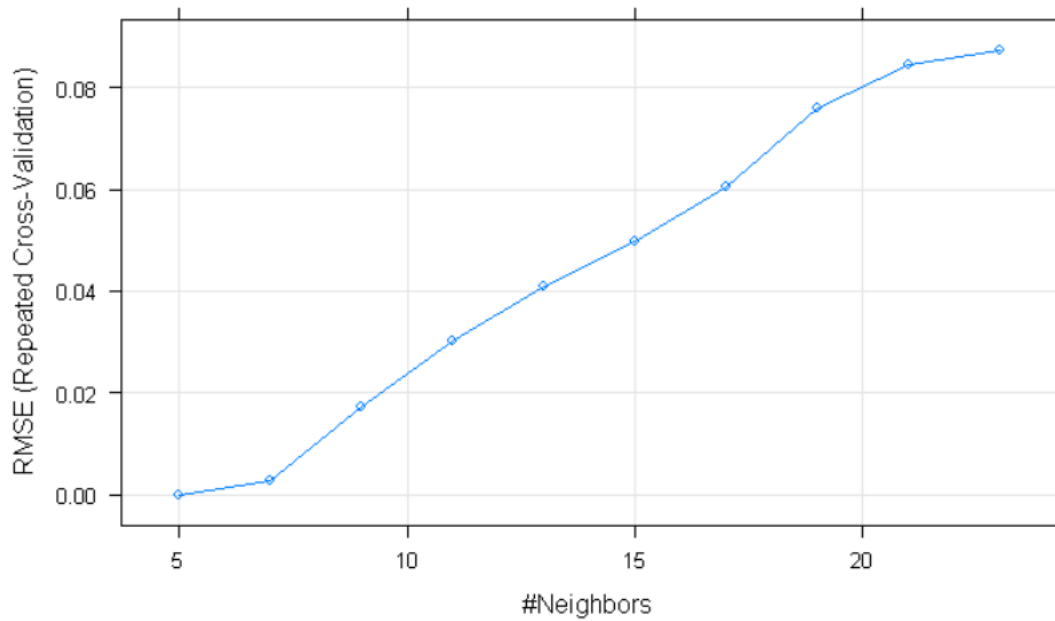
```
<truncated>k-Nearest Neighbors
```

```
2000 samples
 19 predictor
```

```
Pre-processing: centered (19), scaled (19)
Resampling: Cross-Validated (10 fold, repeated 3 times)
Summary of sample sizes: 1800, 1800, 1799, 1800, 1800, ...
Resampling results across tuning parameters:
```

k	RMSE	Rsquared
5	5.834634e-16	1.0000000
7	2.668497e-03	0.9996632
9	1.729579e-02	0.9857054
11	3.022194e-02	0.9692707
13	4.094209e-02	0.9503906
15	4.964589e-02	0.9374691
17	6.042854e-02	0.9077873
19	7.599317e-02	0.8641550
21	8.439008e-02	0.8395811
23	8.720328e-02	0.8307749

RMSE was used to select the optimal model using the smallest value.
The final value used for the model was k = 5.



9.3 Prediction

Confusion Matrix and Statistics

Prediction	Reference														
	African	Bakeries	Bar	Cafe	Caribbean	Deli	Dessert	European	Far Eastern	juicery	Latin American	Mediterranean	Middle Eastern	North American	Pastries
African	5	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Bakeries	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0
Bar	0	0	9	0	0	0	0	0	0	0	0	0	0	0	0
Cafe	0	0	0	203	0	0	0	0	0	0	0	0	0	0	0
Caribbean	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0
Deli	0	0	0	0	0	125	0	0	0	0	0	0	0	0	0
Dessert	0	0	0	0	0	0	12	0	0	0	0	0	0	0	0
European	0	0	0	0	0	0	0	96	0	0	0	0	0	0	0
Far Eastern	0	0	0	0	0	0	0	0	60	0	0	0	0	0	0
Juicery	0	0	0	0	0	0	0	0	0	21	0	0	0	0	0
Latin American	0	0	0	0	0	0	0	0	0	0	18	0	0	0	0
Mediterranean	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0
Middle Eastern	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0
North American	0	0	0	0	0	0	0	0	0	0	0	0	0	91	0
Pastries	0	0	0	0	0	0	0	0	0	0	0	0	0	0	13
South Asian	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
South East Asian	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Classification accuracy in KNN is a ratio of correct prediction to a total prediction made. To measure the accuracy of our result “confusion matrix” is applied in order to summarize the prediction result.

Prediction result is 100%

Overall Statistics

Accuracy : 1
 95% CI : (0.9949, 1)
 No Information Rate : 0.2808
 P-Value [Acc > NIR] : < 2.2e-16

Kappa : 1
 McNemar's Test P-Value : NA

10. Recommender System

The most common technique used in a recommender system to identify similarity between two items feature vectors.

The most common technique used in a recommender system is identifying similarity between two items feature vectors based on how close it is distance. The smaller the distance implies a higher similarity.

The distance between two items is calculated using the euclidean distance formula

$$\text{Euclidean Distance} = \sqrt{(x_1 - y_1)^2 + \dots + (x_N - y_N)^2}$$

```
distances <- as.matrix(dist(recommender , method="euclidean"))
```

	12661	12672	12689	12694	12698	12701
12661	0.0000000	0.4166667	1.487697	1.4923399	1.487697	1.4552881
12672	0.4166667	0.0000000	1.449872	1.5372669	1.449872	1.4718948
12689	1.4876966	1.4498725	0.0000000	1.4644975	0.0000000	1.4595192
12694	1.4923399	1.5372669	1.464498	0.0000000	1.464498	1.4442951
12698	1.4876966	1.4498725	0.0000000	1.4644975	0.0000000	1.4595192
12701	1.4552881	1.4718948	1.459519	1.4442951	1.459519	0.0000000
12705	1.4952186	1.4788737	1.420945	1.4596496	1.420945	1.4790037
12710	1.5475996	1.4904541	1.430653	0.3764786	1.430653	1.4718948
12712	1.4552881	1.4718948	1.459519	1.4442951	1.459519	0.0000000

Recommend three restaurants with African cuisine based on the recommender matrix and Euclidian distance between each items. The recommender output is restaurant id “12970”, “12996” & “13057”

```

{r}
cuisine <- "African"
listing <- most.probable.recommend(cuisine, recommender, distances)
rownames(recommender)[listing[1:3]]

```

```
[1] "12970" "12996" "13057"
```

This is a good example of content based recommender system where similarities are defined by item attributes in the absence of user profile. This recommender types is used to overcome cold start.

11. Conclusion

In this exercise the following tasks were accomplished

- Data exploration & preparation
- Data analysis
- Predictive analytics
- Implementation of recommendation system

Next Step

- Improve the recommendation accuracy
- Implement alternative supervised algorithm for recommender system

12. Reference

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