

Agenda



1. Introduction and Problem Statement

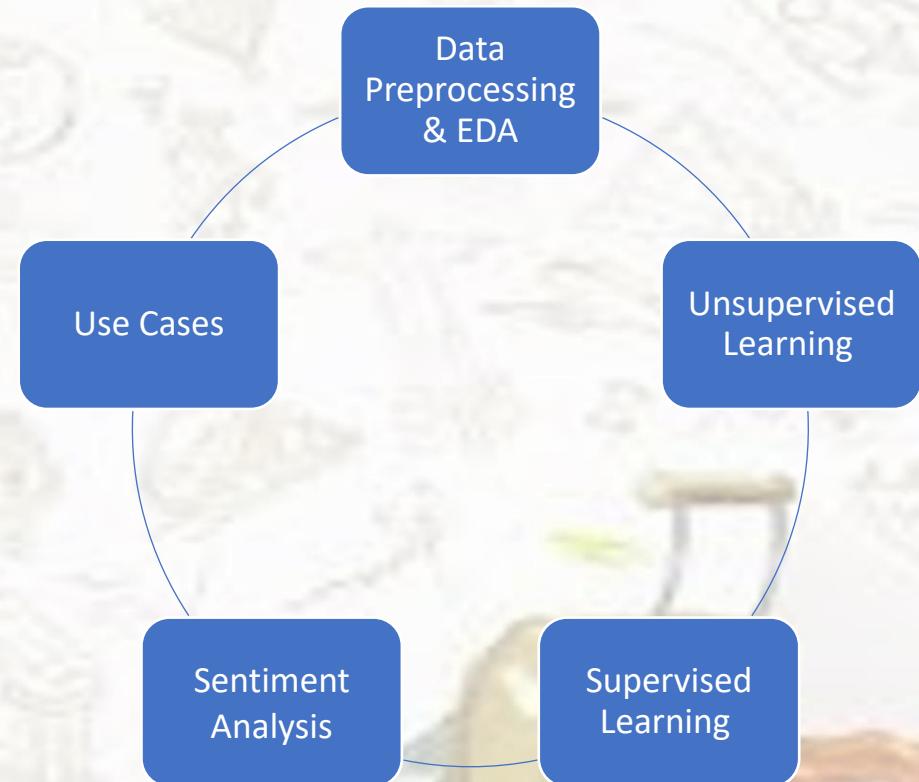
2. Data Pre-processing & EDA

3. Unsupervised

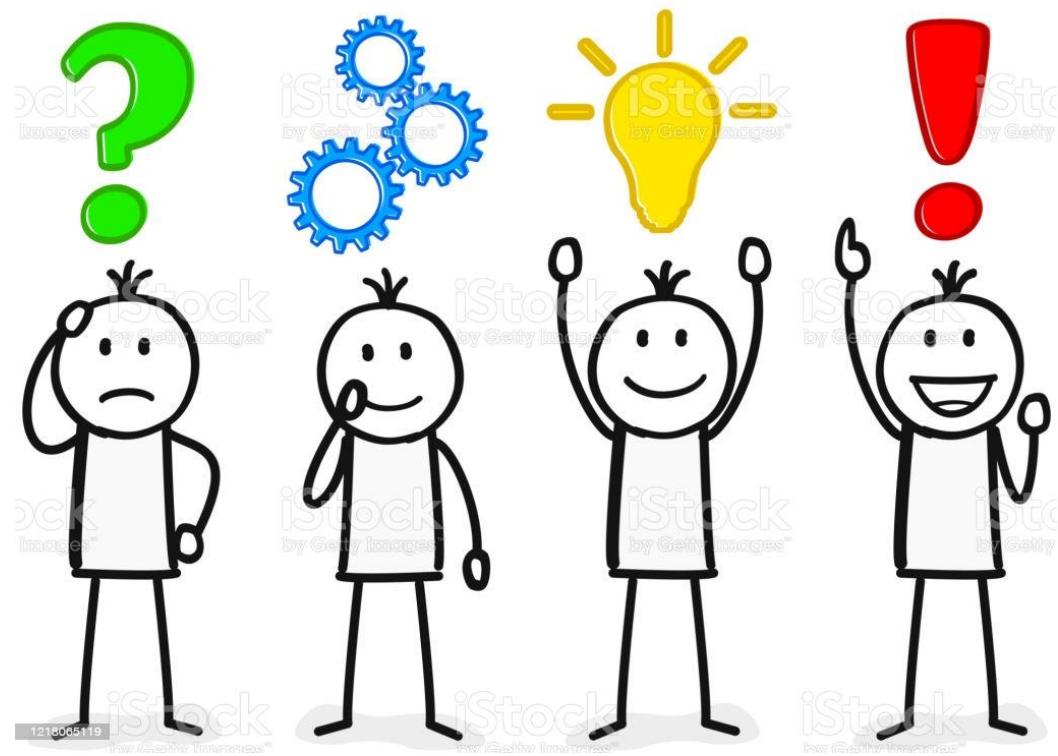
4. Supervised

5. Sentiment analysis

6. Use case and deployment



1. Introduction & Problem Statement



Introduction

- **Analyst Group presenting to Europe Tourism Board**
- **Data set is from Google Review & Trip Advisor**
- **24 Attractions are being reviewed**
- **Costumer's feedback review on hotels**
- **Rating is an average from a scale from 0 to 5 (5 being the best)**



Introduction

- **Goal is to boost tourism across Europe**
- **Provide content to advertise & attract different customer profiles**
- **Analyze feedback to target improvement**



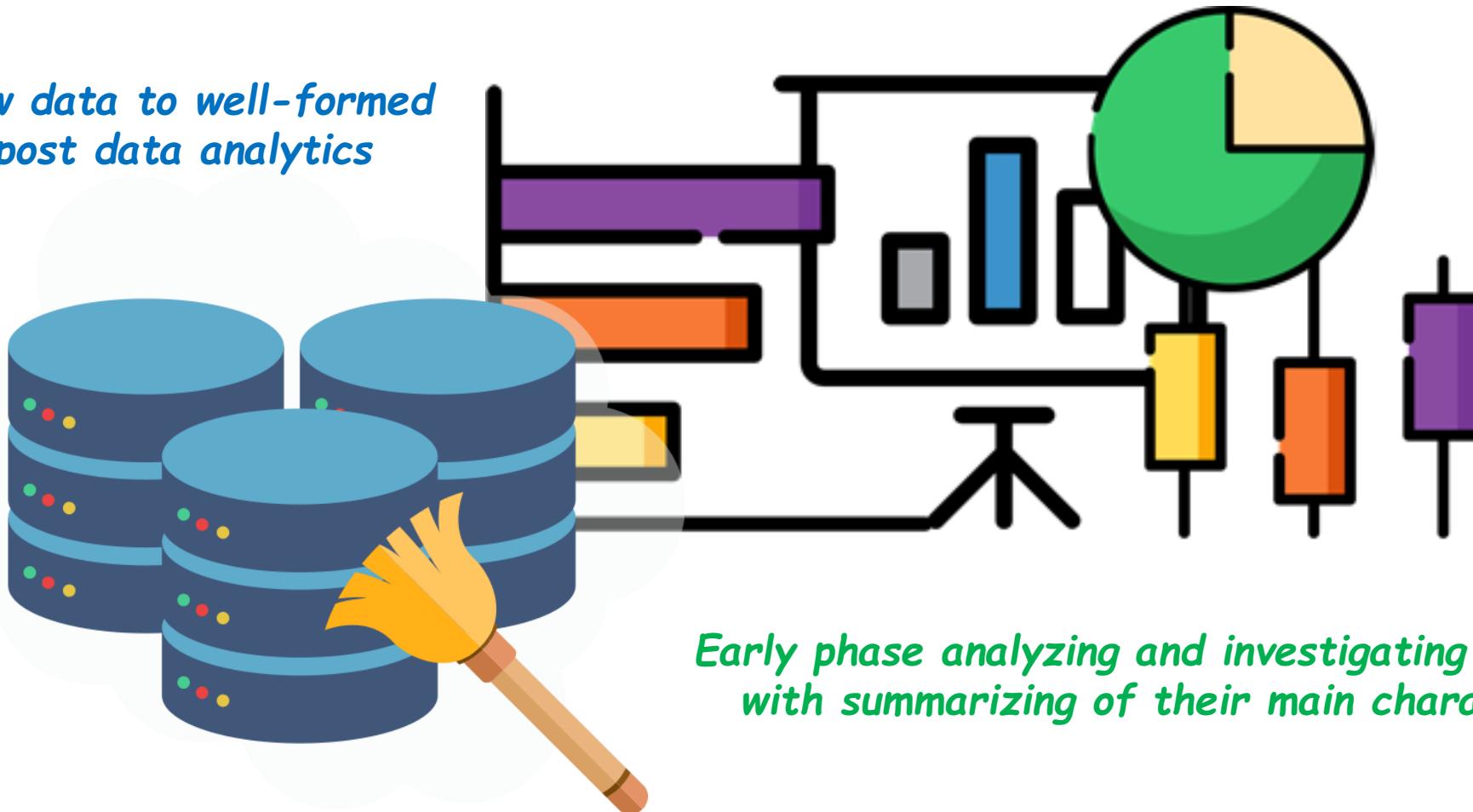


Problem Statement

- **Understanding & identifying costumer profile.**
- **Characteristic of each attraction.**
- **Correlation between customers & attraction.**
- **Improve service quality & hospitality experience.**

2. Data Preprocessing & EDA

Transforming raw data to well-formed datasets for post data analytics



Early phase analyzing and investigating of datasets with summarizing of their main characteristics

Raw Data Understanding

In [2]: `# read the raw datasets from Google Travel Ratings .csv file on Kaggle`
`travel_review = pd.read_csv("../mining/google_review_ratings.csv")`

In [3]: `# preview the raw datasets from Google Travel Ratings .csv file on Kaggle`
`travel_review.head()`

Out[3]:

User	Category 1	Category 2	Category 3	Category 4	Category 5	Category 6	Category 7	Category 8	Category 9	...	Category 16	Category 17	Category 18	Category 19	Category 20
0 User 1	0.0	0.0	3.63	3.65	5.0	2.92	5.0	2.35	2.33	...	0.59	0.5	0.0	0.5	0
1 User 2	0.0	0.0	3.63	3.65	5.0	2.92	5.0	2.64	2.33	...	0.59	0.5	0.0	0.5	0
2 User 3	0.0	0.0	3.63	3.63	5.0	2.92	5.0	2.64	2.33	...	0.59	0.5	0.0	0.5	0
3 User 4	0.0	0.5	3.63	3.63	5.0	2.92	5.0	2.35	2.33	...	0.59	0.5	0.0	0.5	0
4 User 5	0.0	0.0	3.63	3.63	5.0	2.92	5.0	2.64	2.33	...	0.59	0.5	0.0	0.5	0

5 rows × 26 columns

In [4]: `# understand the original shape of the datasets`
`# total of 5456 observations and 26 variables`
`travel_review.shape`

Out[4]: (5456, 26)



Data Cleaning Process

User	Category 1	Category 2	Category 3	Category 4	Category 5	Category 6	Category 7	Category 8	Category 9	...	Category 16	Category 17	Category 18	Category 19
0 User 1	0.00	0.00	3.63	3.65	5.00	2.92	5.00	2.35	2.33	...	0.59	0.50	0.00	0.50
1 User 2	0.00	0.00	3.63	3.65	5.00	2.92	5.00	2.64	2.33	...	0.59	0.50	0.00	0.50
2 User 3	0.00	0.00	3.63	3.63	5.00	2.92	5.00	2.64	2.33	...	0.59	0.50	0.00	0.50
3 User 4	0.00	0.50	3.63	3.63	5.00	2.92	5.00	2.35	2.33	...	0.59	0.50	0.00	0.50
4 User 5	0.00	0.00	3.63	3.63	5.00	2.92	5.00	2.64	2.33	...	0.59	0.50	0.00	0.50
...
5451 User 5452	0.91	5.00	4.00	2.79	2.77	2.57	2.43	1.09	1.77	...	0.66	0.65	0.66	0.69
5452 User 5453	0.93	5.00	4.02	2.79	2.78	2.57	1.77	1.07	1.76	...	0.65	0.64	0.65	1.56
5453 User 5454	0.94	5.00	4.03	2.80	2.78	2.57	1.75	1.05	1.75	...	0.65	0.63	0.64	0.74
5454 User 5455	0.95	4.05	4.05	2.81	2.79	2.44	1.76	1.03	1.74	...	0.64	0.63	0.64	0.75
5455 User 5456	0.95	4.07	5.00	2.82	2.80	2.57	2.42	1.02	1.74	...	0.64	0.62	0.63	0.78

5456 rows × 26 columns

Incorrect Type

```
In [7]: # Data Pre-processing step 2 - removal or replace missing data or invalid variables (columns)
# Based on observation, there is a unnamed column as "Unnamed: 25"
# Delete this invalid column
del travel_review['Unnamed: 25']
```

```
[9]: # Data Pre-processing step 2 - removal or replace missing data or invalid variables (columns)
# Based on observation, categories 12 & 24 which is the rating score is less than 5% which can be removed.
travel_review = travel_review.dropna()
```

Missing Data

Unclear Variables

	user_id	churches	resorts	beaches	parks	theatres	museums	malls	zoo	restaurants	...	art_galleries	dance_clubs	swimming_pools	gyms	ba
0	User 1	0.00	0.00	3.63	3.65	5.00	2.92	5.00	2.35	2.33	...	1.74	0.59	0.50	0.00	
1	User 2	0.00	0.00	3.63	3.65	5.00	2.92	5.00	2.64	2.33	...	1.74	0.59	0.50	0.00	
2	User 3	0.00	0.00	3.63	3.63	5.00	2.92	5.00	2.64	2.33	...	1.74	0.59	0.50	0.00	
3	User 4	0.00	0.50	3.63	3.63	5.00	2.92	5.00	2.35	2.33	...	1.74	0.59	0.50	0.00	
4	User 5	0.00	0.00	3.63	3.63	5.00	2.92	5.00	2.64	2.33	...	1.74	0.59	0.50	0.00	
...	
5451	User 5452	0.91	5.00	4.00	2.79	2.77	2.57	2.43	1.09	1.77	...	5.00	0.66	0.65	0.66	
5452	User 5453	0.93	5.00	4.02	2.78	2.78	2.57	1.77	1.07	1.76	...	0.89	0.65	0.64	0.65	
5453	User 5454	0.94	5.00	4.03	2.80	2.78	2.57	1.75	1.05	1.75	...	0.87	0.65	0.63	0.64	
5454	User 5455	0.95	4.05	4.05	2.81	2.79	2.44	1.76	1.03	1.74	...	5.00	0.64	0.63	0.64	
5455	User 5456	0.95	4.07	5.00	2.82	2.80	2.57	2.42	1.02	1.74	...	0.85	0.64	0.62	0.63	

5454 rows × 25 columns

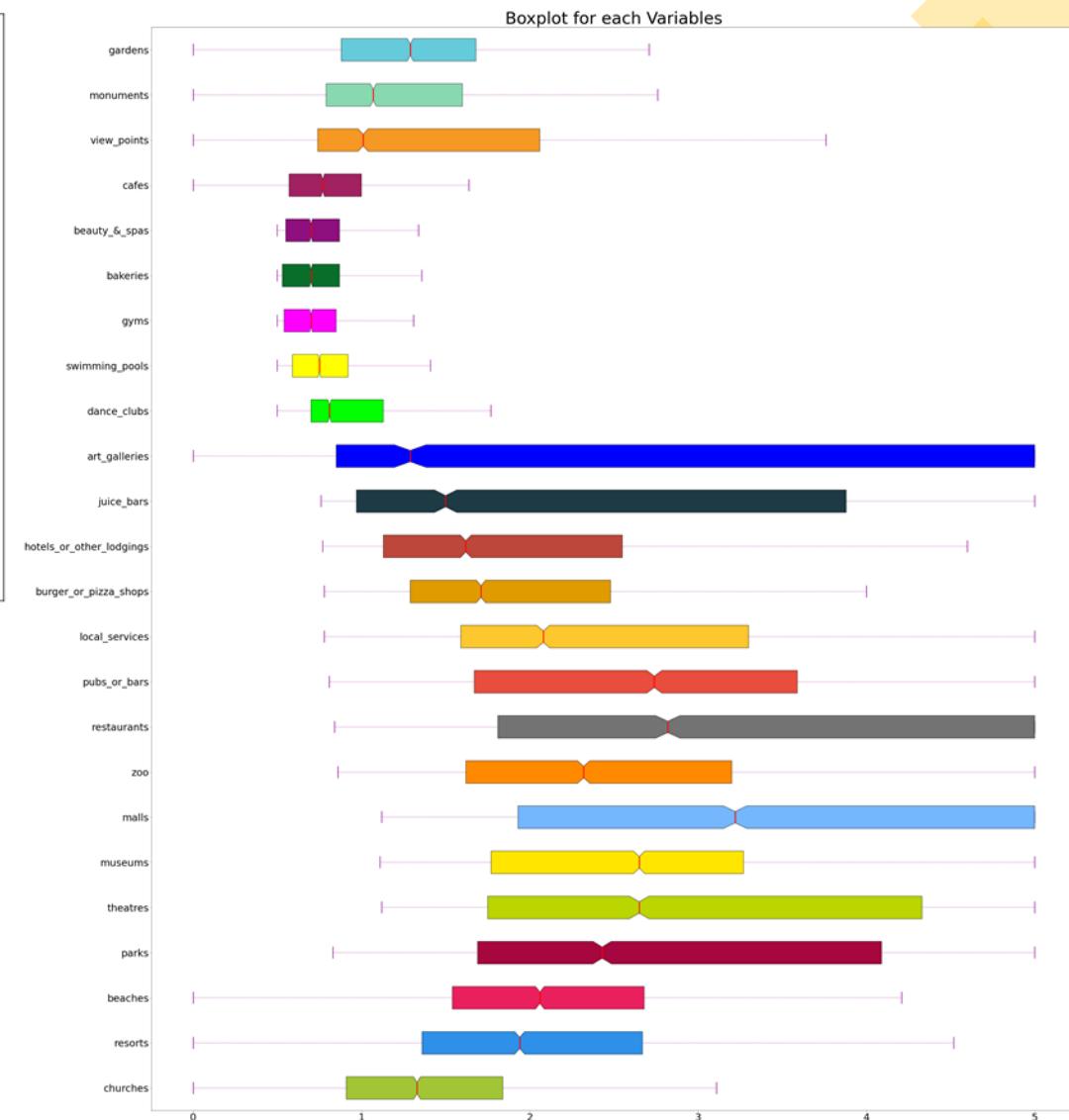
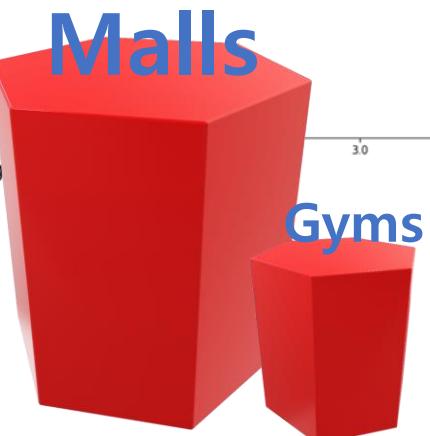
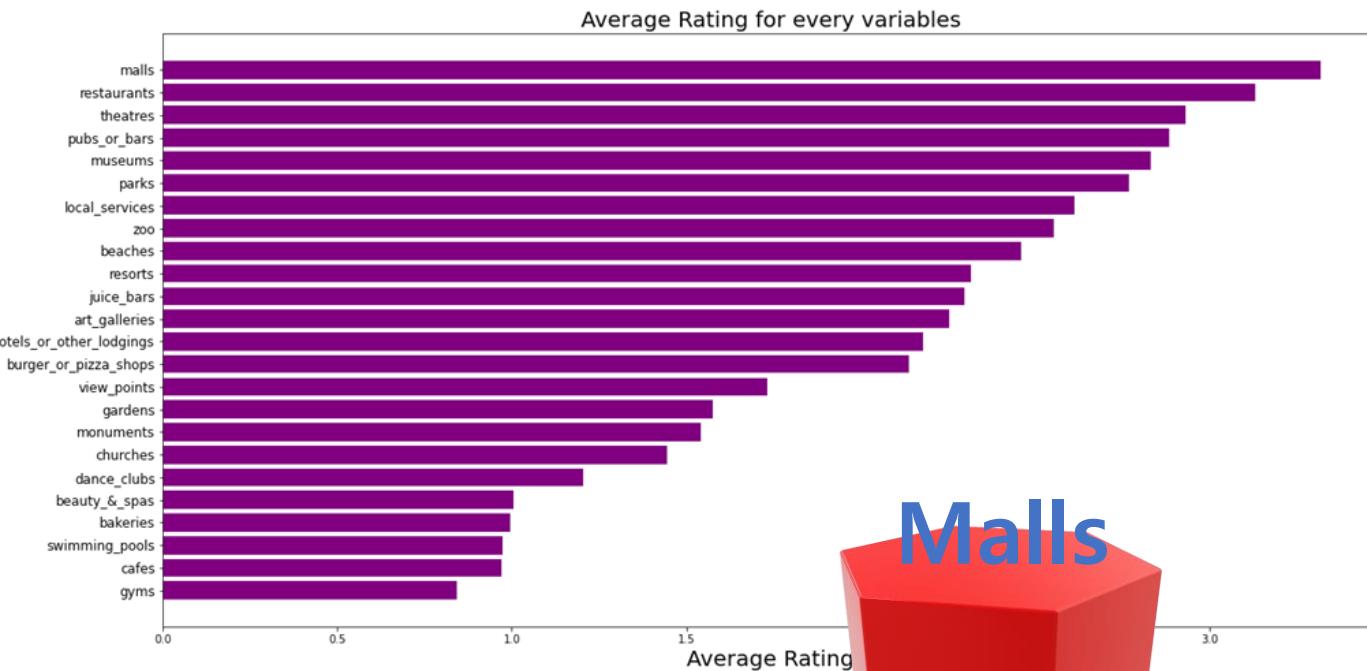
```
In [15]: # Data Pre-processing step 5 - Renaming the variables to description for easy representation
description = ['user_id', 'churches', 'resorts', 'beaches', 'parks', 'theatres', 'museums', 'malls', 'zoo', 'restaurants',
travel_review.columns = description
travel_review.head()
```

```
In [13]: # Data Pre-processing step 4 - Perform conversion of the data-type to Category 11 into numerical
travel_review['Category 11'] = pd.to_numeric(travel_review['Category 11'], errors='coerce')
```



Exploratory Data Analysis

Variables (Attractions)



Exploratory Data Analysis



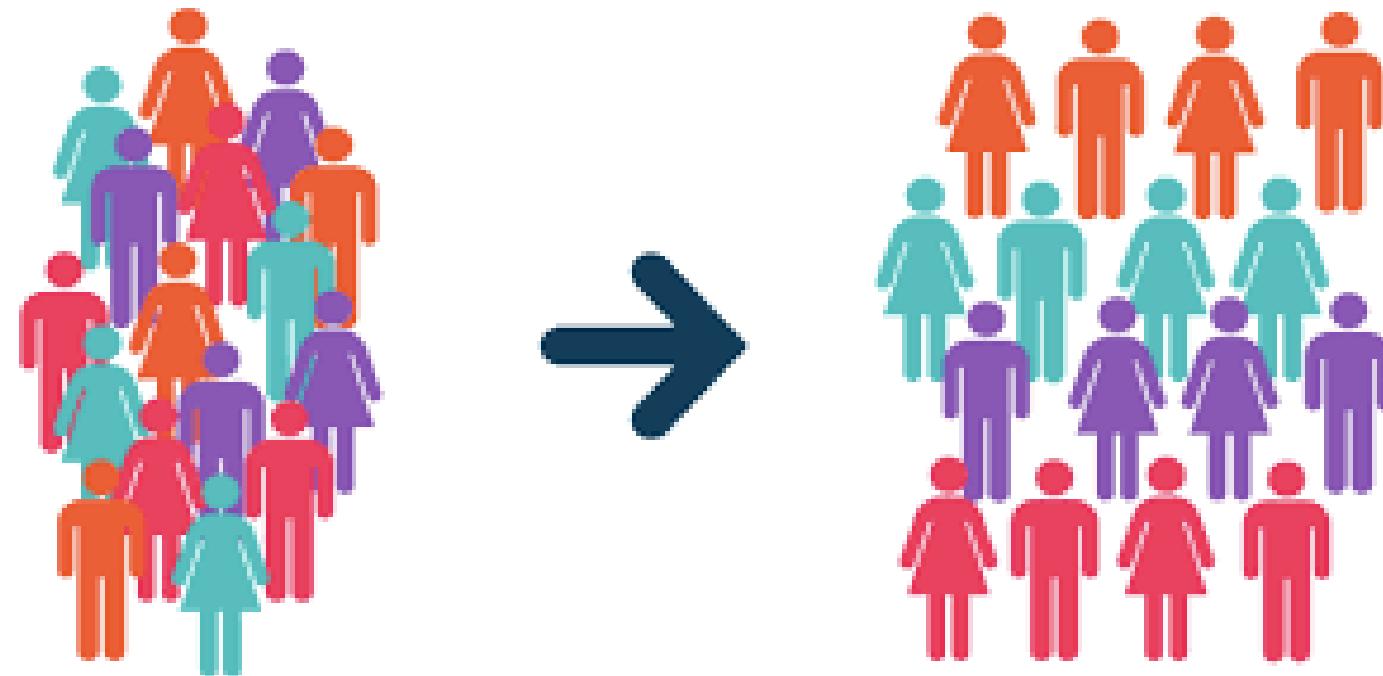
Representation of how each variable relates to others

E.g. Theatres has a high correlation to Amusement Parks and moderately to Museums and Beaches

Correlation matrix visualization:

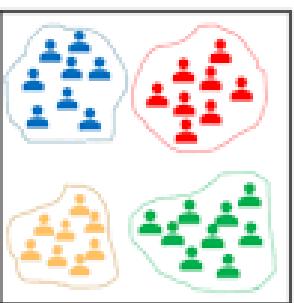
	churches	resorts	beaches	parks	theatres	museums	malls	zoos	restaurants	pubs_or_bars	local_services	burger_or_pizza_shops	hotels_or_other_lodgings	juice_bars	art_galleries	dance_clubs	swimming_pools	gyms	bakeries	beauty_&_spas	cafes	view_points	monuments	gardens
churches	1	0.25	0.15	0.071	0.036	-0.093	-0.26	-0.18	-0.29	-0.27	-0.21	-0.26	-0.18	-0.24	-0.14	0.067	0.13	0.16	0.18	0.2	0.31	0.36	0.41	0.49
resorts	0.25	1	0.33	0.17	0.15	0.054	-0.05	-0.0047	-0.051	-0.092	-0.22	-0.16	-0.21	-0.13	-0.067	-0.033	-0.077	-0.026	0.033	0.097	0.089	0.019	0.078	0.13
beaches	0.15	0.33	1	0.4	0.33	0.16	-0.073	-0.19	-0.22	-0.18	-0.16	-0.24	-0.18	-0.16	-0.13	-0.022	-0.084	-0.12	-0.075	-0.0085	0.0021	0.13	0.12	0.083
parks	0.071	0.17	0.4	1	0.63	0.32	-0.068	-0.13	-0.17	-0.12	-0.12	-0.17	-0.15	-0.31	-0.27	0.018	-0.13	-0.18	-0.19	-0.092	-0.055	0.28	0.17	0.091
theatres	0.036	0.15	0.33	0.63	1	0.49	0.077	-0.0027	-0.17	-0.1	-0.12	-0.1	-0.091	-0.28	-0.32	-0.057	-0.18	-0.24	-0.26	-0.19	-0.13	0.12	0.13	0.099
museums	-0.093	0.054	0.16	0.32	0.49	1	0.38	0.2	0.11	-0.02	-0.15	-0.16	-0.14	-0.15	-0.19	-0.15	-0.23	-0.27	-0.27	-0.23	-0.2	-0.091	-0.08	-0.066
malls	-0.26	-0.05	-0.073	-0.068	0.077	0.38	1	0.41	0.43	0.26	0.098	0.031	0.025	0.09	0.093	-0.14	-0.21	-0.23	-0.27	-0.23	-0.26	0.36	-0.22	-0.25
zoos	-0.18	-0.0047	-0.19	-0.13	-0.0027	0.2	0.41	1	0.54	0.55	0.29	0.0032	-0.011	-0.021	-0.064	-0.12	0.2	-0.24	-0.28	-0.25	-0.27	-0.26	-0.17	-0.14
restaurants	-0.29	-0.051	-0.22	-0.17	-0.17	0.11	0.43	0.54	1	0.56	0.26	-0.013	0.019	0.033	0.13	-0.12	-0.23	-0.27	-0.27	-0.16	-0.19	0.27	0.27	-0.33
pubs_or_bars	-0.27	-0.092	-0.18	-0.12	-0.1	-0.02	0.26	0.55	0.56	1	0.47	0.13	0.066	-0.0012	0.039	-0.032	-0.21	-0.27	-0.32	-0.25	-0.23	-0.18	-0.21	-0.26
local_services	-0.21	-0.22	-0.16	-0.12	-0.12	-0.15	0.098	0.29	0.26	0.47	1	0.32	0.26	0.057	-0.027	-0.0015	-0.047	-0.11	-0.19	-0.29	-0.33	-0.098	-0.13	-0.18
burger_or_pizza_shops	-0.26	-0.16	-0.24	-0.17	-0.1	-0.16	0.031	0.0032	-0.013	0.13	0.32	1	0.47	0.35	0.15	-0.047	0.028	0.063	0.02	-0.13	-0.28	0.32	-0.21	-0.18
hotels_or_other_lodgings	-0.18	-0.21	-0.18	-0.15	-0.091	-0.14	0.025	-0.011	0.019	0.066	0.26	0.47	1	0.51	0.2	-0.049	0.024	0.075	0.064	-0.057	-0.21	-0.2	-0.16	-0.13
juice_bars	-0.24	-0.13	-0.16	-0.31	-0.28	-0.15	0.09	-0.021	0.033	-0.0012	0.057	0.35	0.51	1	0.37	-0.0063	0.076	0.1	0.12	0.032	-0.1	-0.29	-0.29	-0.21
art_galleries	-0.14	-0.067	-0.13	-0.27	-0.32	-0.19	0.093	-0.064	0.13	0.039	-0.027	0.15	0.2	0.37	1	0.099	0.063	0.078	0.064	0.07	0.058	-0.18	-0.16	-0.21
dance_clubs	0.067	-0.033	-0.022	0.018	-0.057	-0.15	-0.14	-0.12	-0.12	-0.032	-0.0015	-0.047	-0.049	-0.0063	0.099	1	0.37	0.22	0.02	0.062	0.16	0.099	0.051	0.028
swimming_pools	0.13	-0.077	-0.084	-0.13	-0.18	-0.23	-0.21	-0.2	-0.23	-0.21	-0.047	0.028	0.024	0.076	0.063	0.37	1	0.51	0.28	0.083	0.17	0.11	0.13	0.15
gyms	0.16	-0.026	-0.12	-0.18	-0.24	-0.27	-0.23	-0.24	-0.27	-0.27	-0.11	0.063	0.075	0.1	0.078	0.22	0.51	1	0.43	0.2	0.19	0.09	0.14	0.17
bakeries	0.18	0.033	-0.075	-0.19	-0.26	-0.27	-0.27	-0.28	-0.27	-0.32	-0.19	0.02	0.064	0.12	0.064	0.02	0.28	0.43	1	0.32	0.19	0.069	0.088	0.13
beauty_&_spas	0.2	0.097	-0.0085	-0.092	-0.19	-0.23	-0.23	-0.25	-0.16	-0.25	-0.29	-0.13	-0.057	0.032	0.07	0.062	0.083	0.2	0.32	1	0.3	0.19	0.14	0.12
cafes	0.31	0.089	0.0021	-0.055	-0.13	-0.2	-0.26	-0.27	-0.19	-0.23	-0.33	-0.28	-0.21	-0.1	0.058	0.16	0.17	0.19	0.19	0.3	1	0.37	0.35	0.3
view_points	0.36	0.019	0.13	0.28	0.12	-0.091	-0.36	-0.26	-0.27	-0.18	-0.098	-0.32	-0.2	-0.29	-0.18	0.099	0.11	0.09	0.069	0.19	0.37	1	0.47	0.32
monuments	0.41	0.078	0.12	0.17	0.13	-0.08	-0.22	-0.17	-0.27	-0.21	-0.13	-0.21	-0.16	-0.29	-0.16	0.051	0.13	0.14	0.088	0.14	0.35	0.47	1	0.46
gardens	0.49	0.13	0.083	0.091	0.099	-0.066	-0.25	-0.14	-0.33	-0.26	-0.18	-0.18	-0.13	-0.21	-0.21	0.028	0.15	0.17	0.13	0.12	0.3	0.32	0.46	1

3. Unsupervised Learning



Purpose:

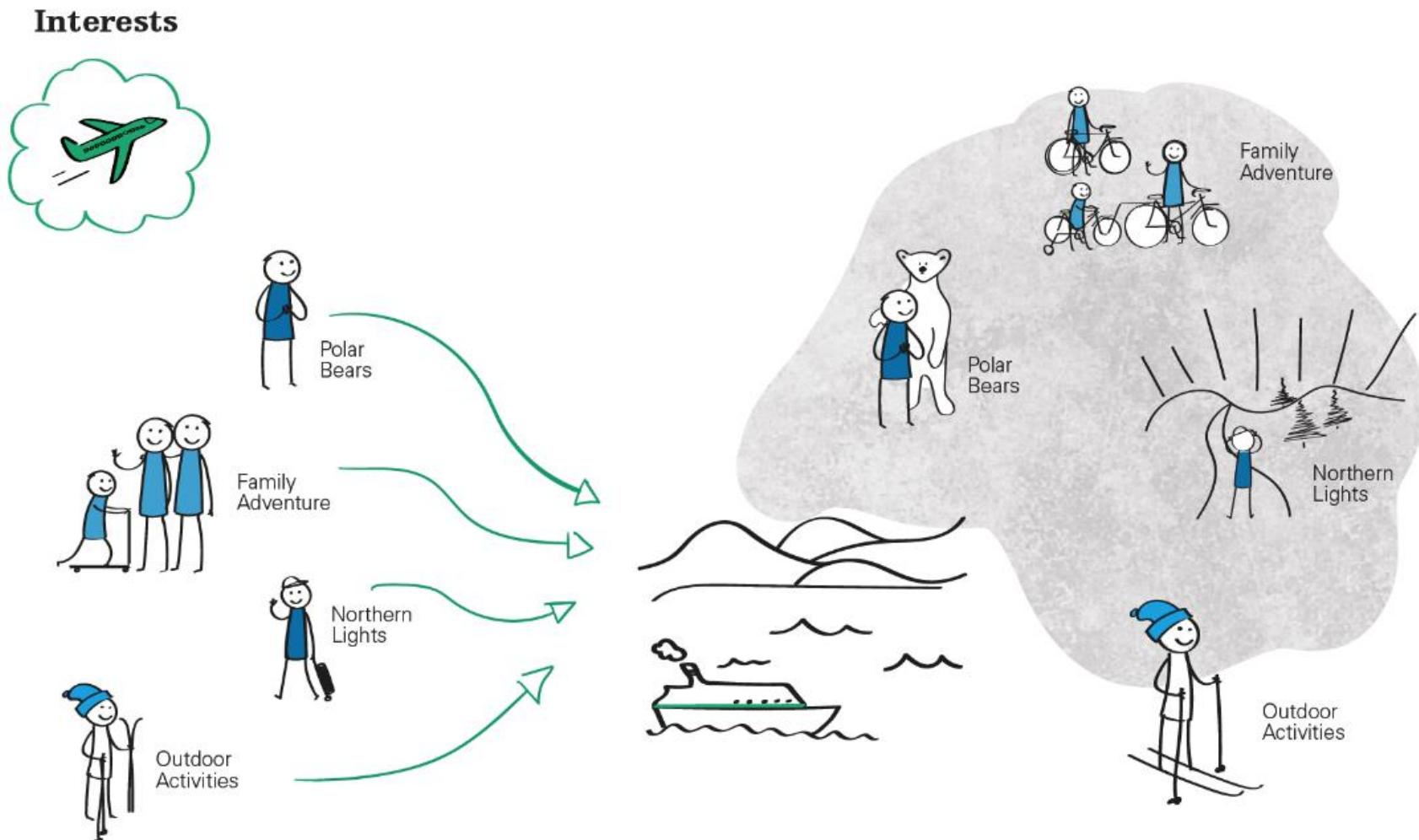
- Divide the Google review user into different clusters with similar interest.
- Allow tourists to get to preferred venues quickly.



Trying to determine the appropriate audience for the product

Using clustering algorithms on the customer base

Selling the product to the targeted audience



Model Selection----K-Means

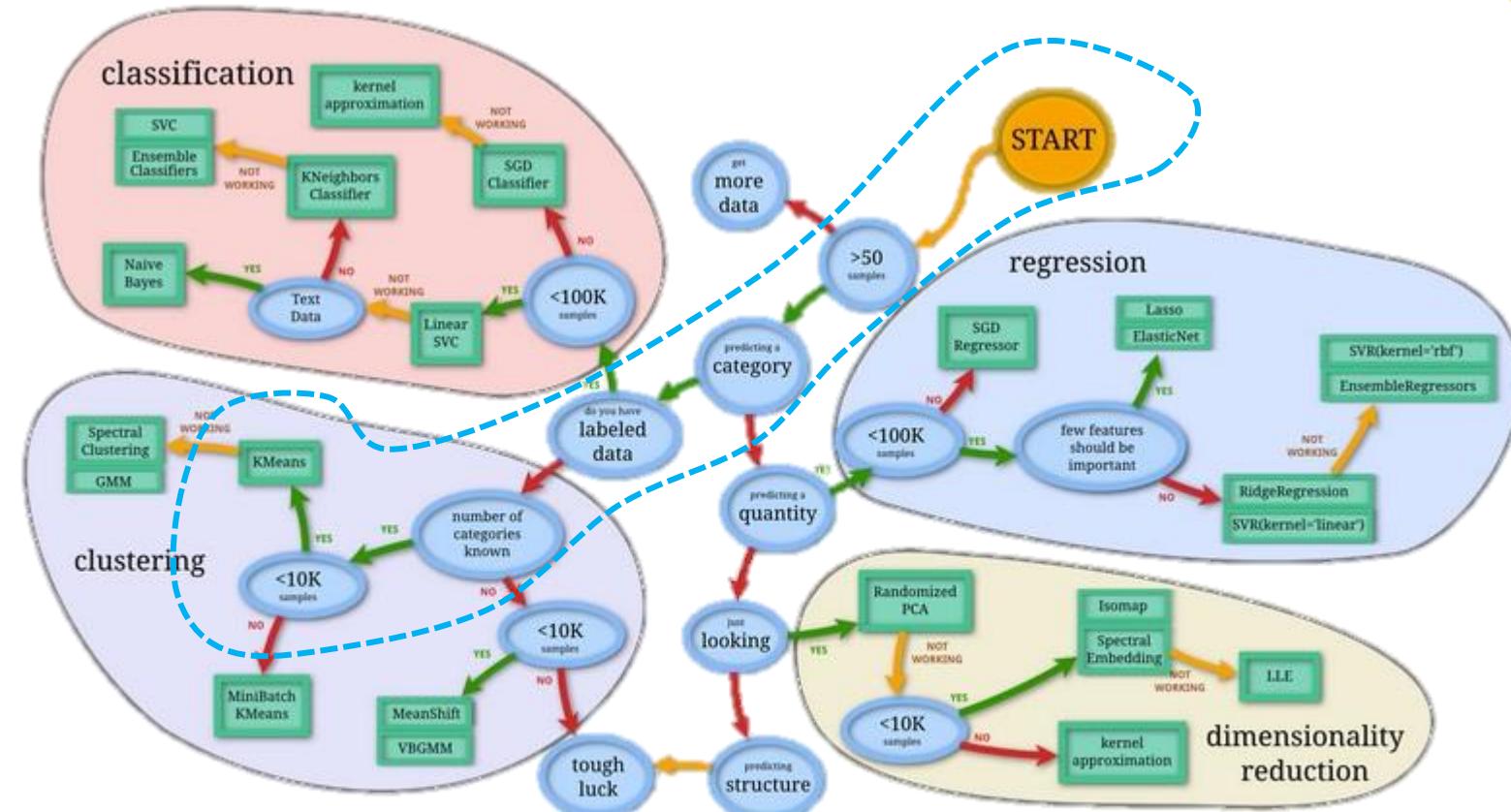
- Algorithm:

K-Means Clustering & Hierarchical Clustering

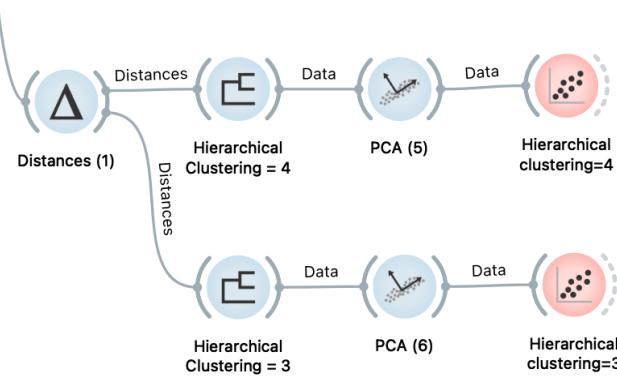
- Try different algorithm on 2 scenarios and compared its result:

Hierarchical Clustering on original data (Cluster = 3/ Cluster = 4)

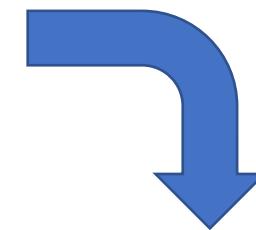
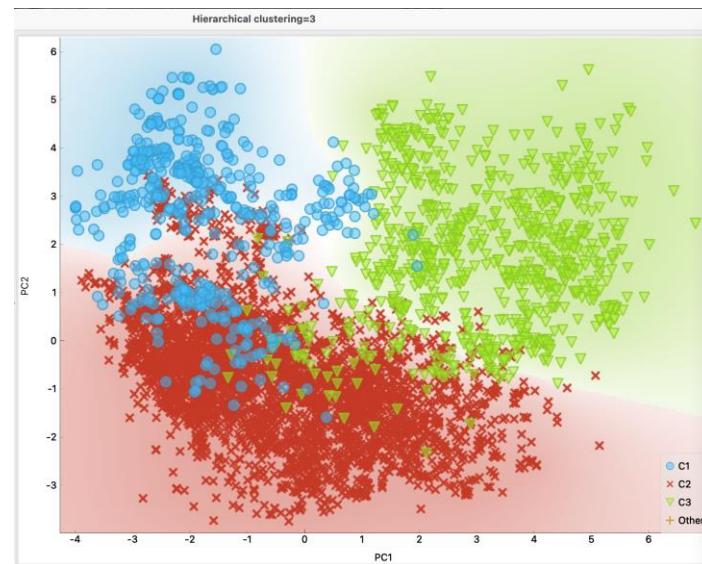
K-Means Clustering on scaled original data (Cluster = 3/ Cluster = 4)



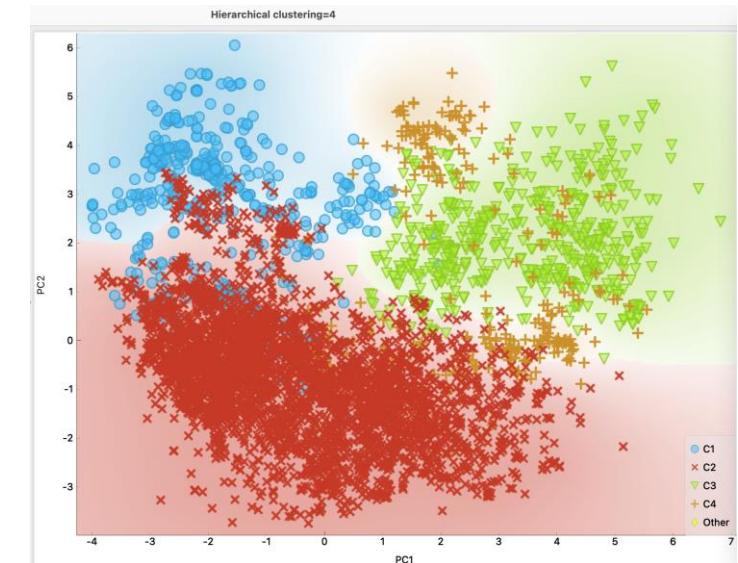
Hierarchical Clustering



Cluster = 3

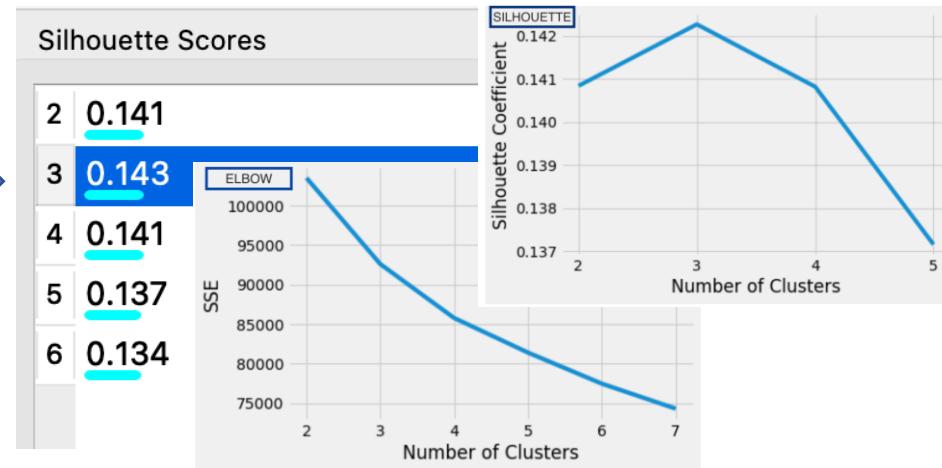
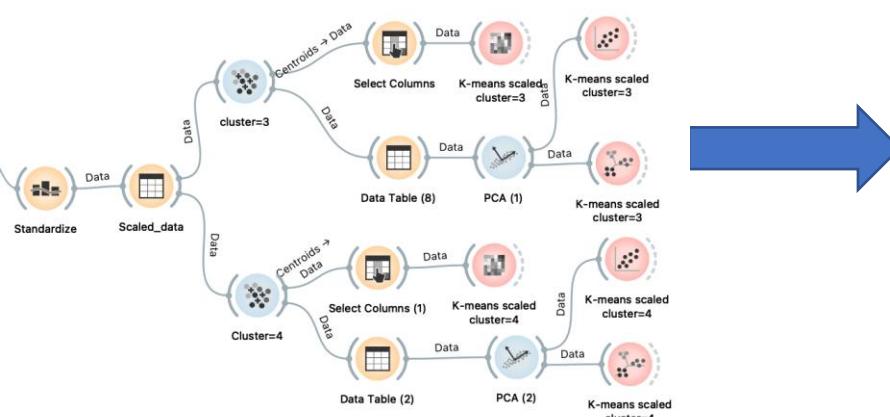


How about
Cluster = 4 ?



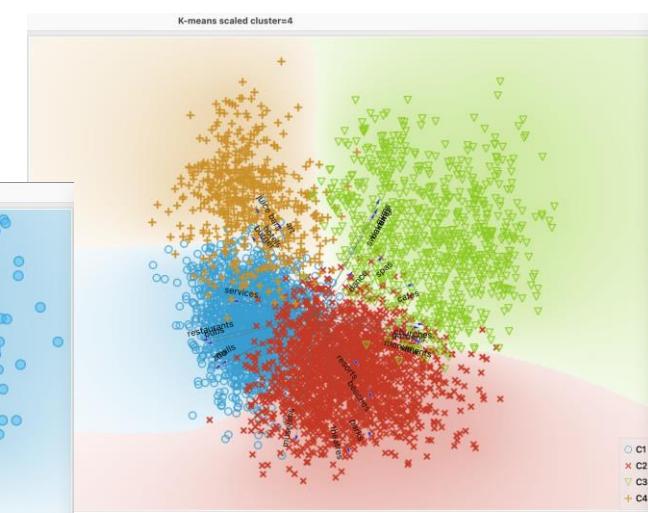
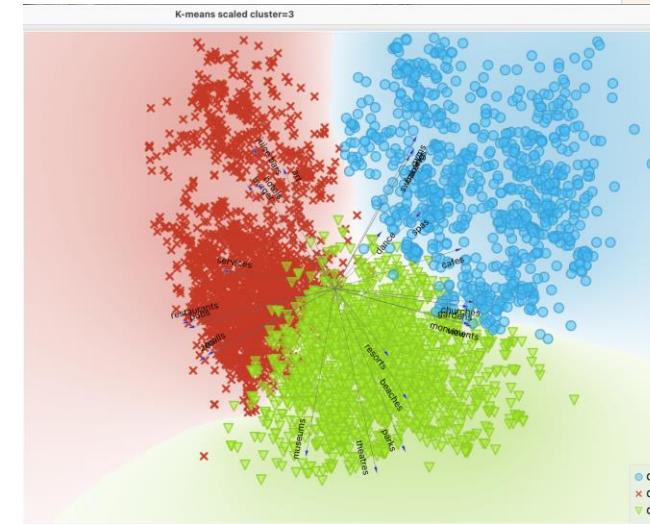
Let's have a try on
k-means

K-Means Clustering on scaled original data



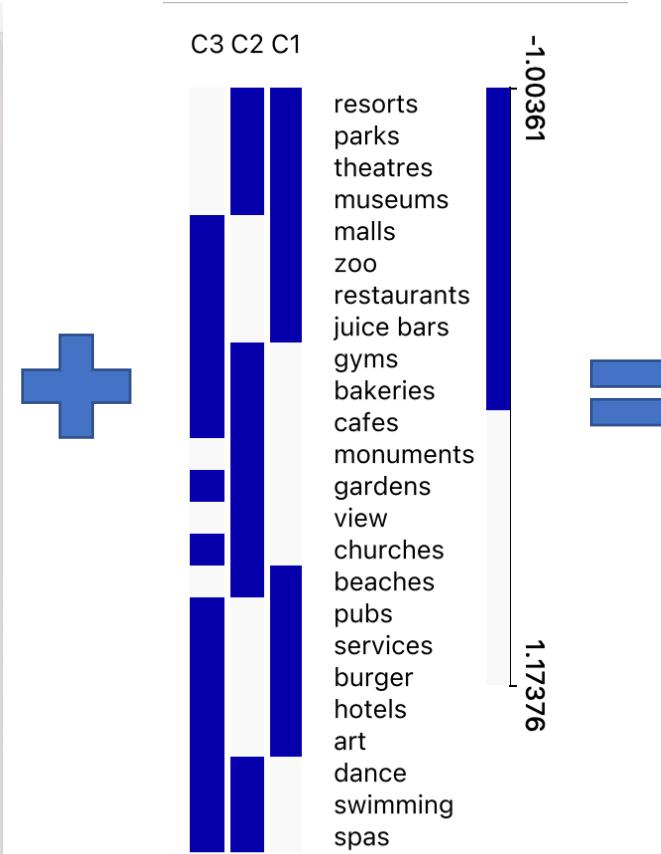
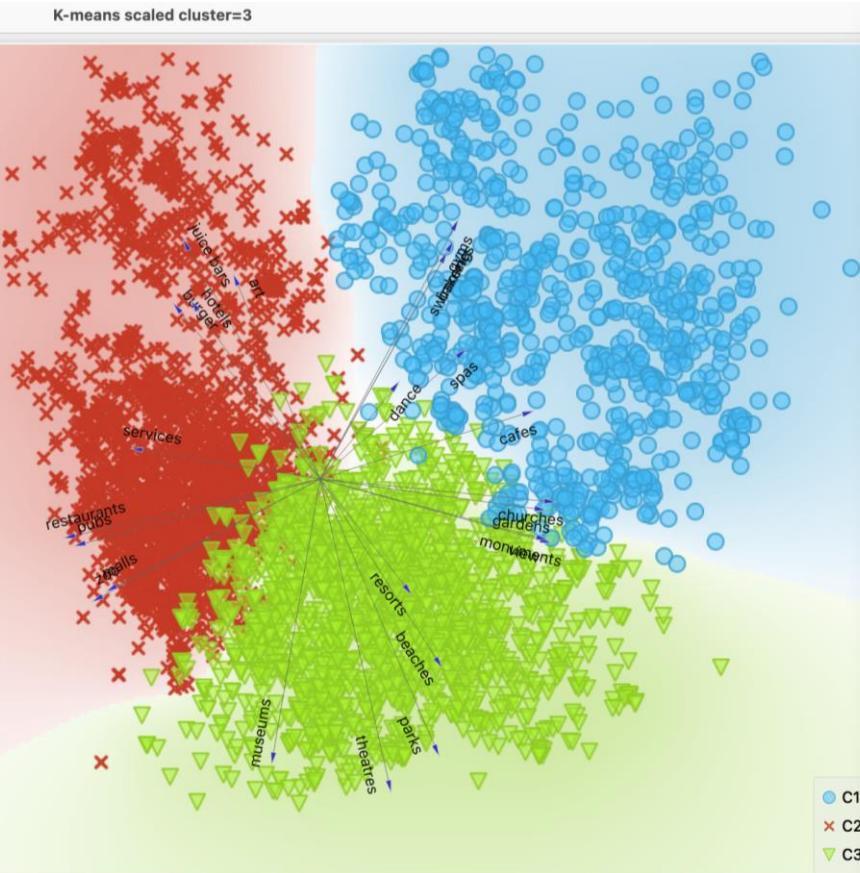
**It's hard to
choose!**

Similar > <



The scores
are similar.
Cluster = 3 ? Or 4 ?

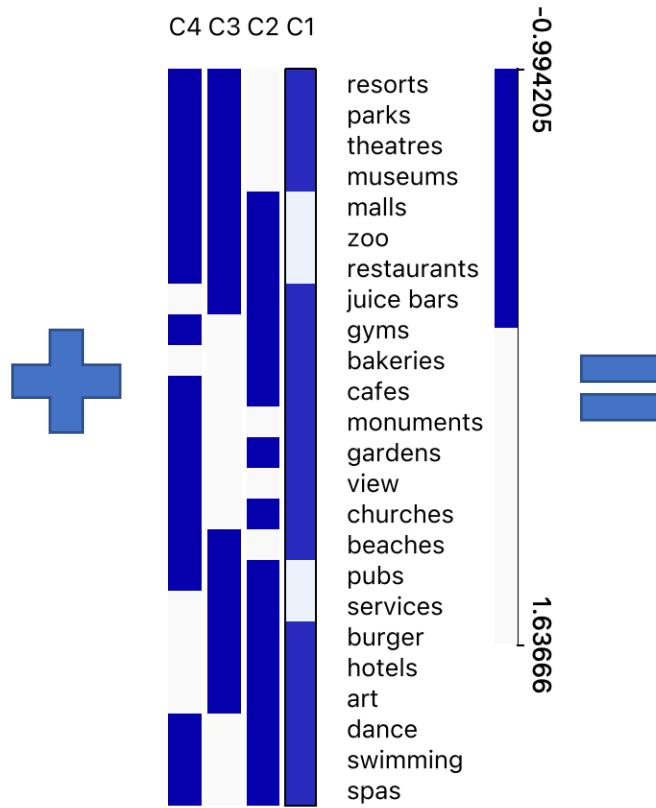
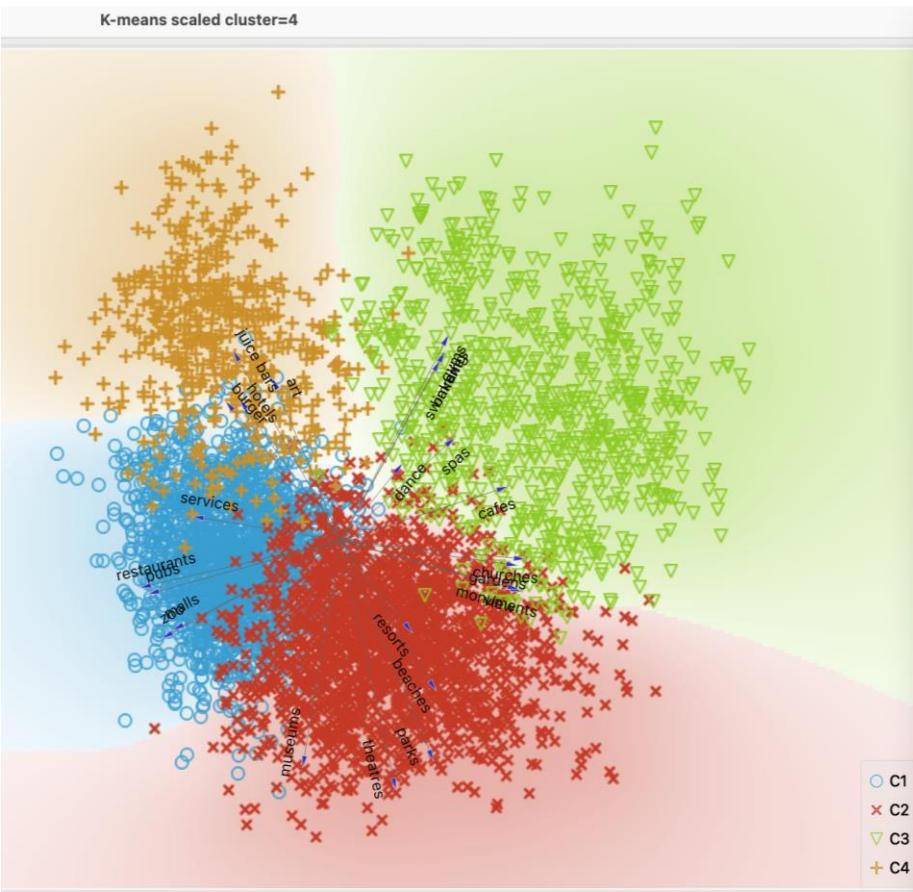
Result of K-Means Cluster=3



GROUP	CATEGORY
Cluster_1	Active and Healthy Leisure
Cluster_2	City Recreation
Cluster_3	Amusement Park

We can use it go for
Supervised learning
later! (cluster=3)

Result of K-Means Cluster=4



GROUP	CATEGORY
Cluster_1	City Recreation
Cluster_2	Amusement Park
Cluster_3	Active & Healthy Leisure
Cluster_4	Staycation

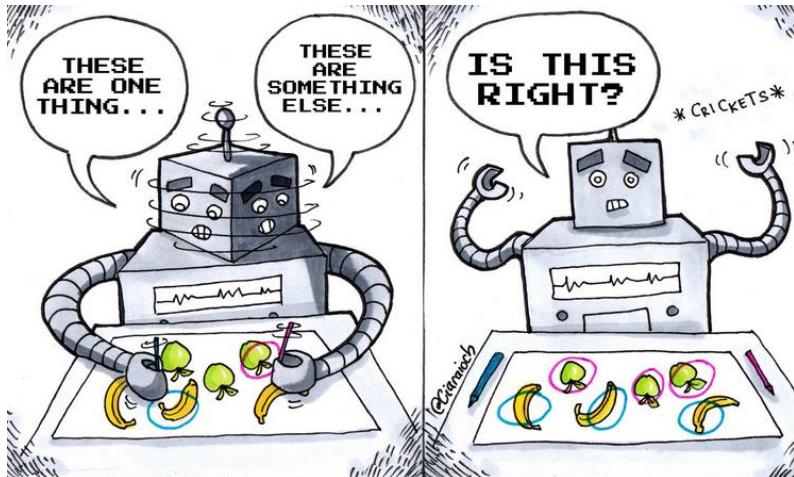


4. Supervised Learning



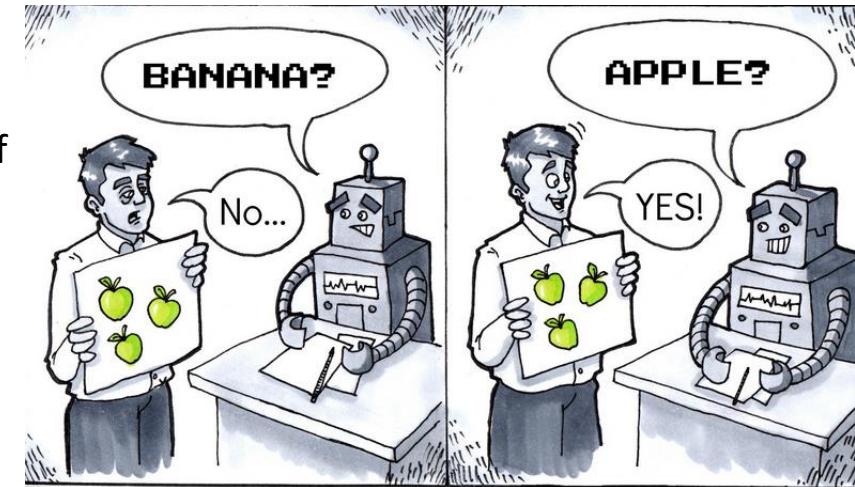
Predicting A Customer Travel Preference

- Use the clusters from unsupervised learning as label for the supervised model.
- Classification models are used to determine the customer preference by classify the customer to the cluster characteristic.



Unsupervised Learning

This group of object with similar features is Apple



Supervised Learning

Supervised Model Selection

- **Model selection based on the use case to :**

i) understand the customer group profiling

ii) use of the input features is important

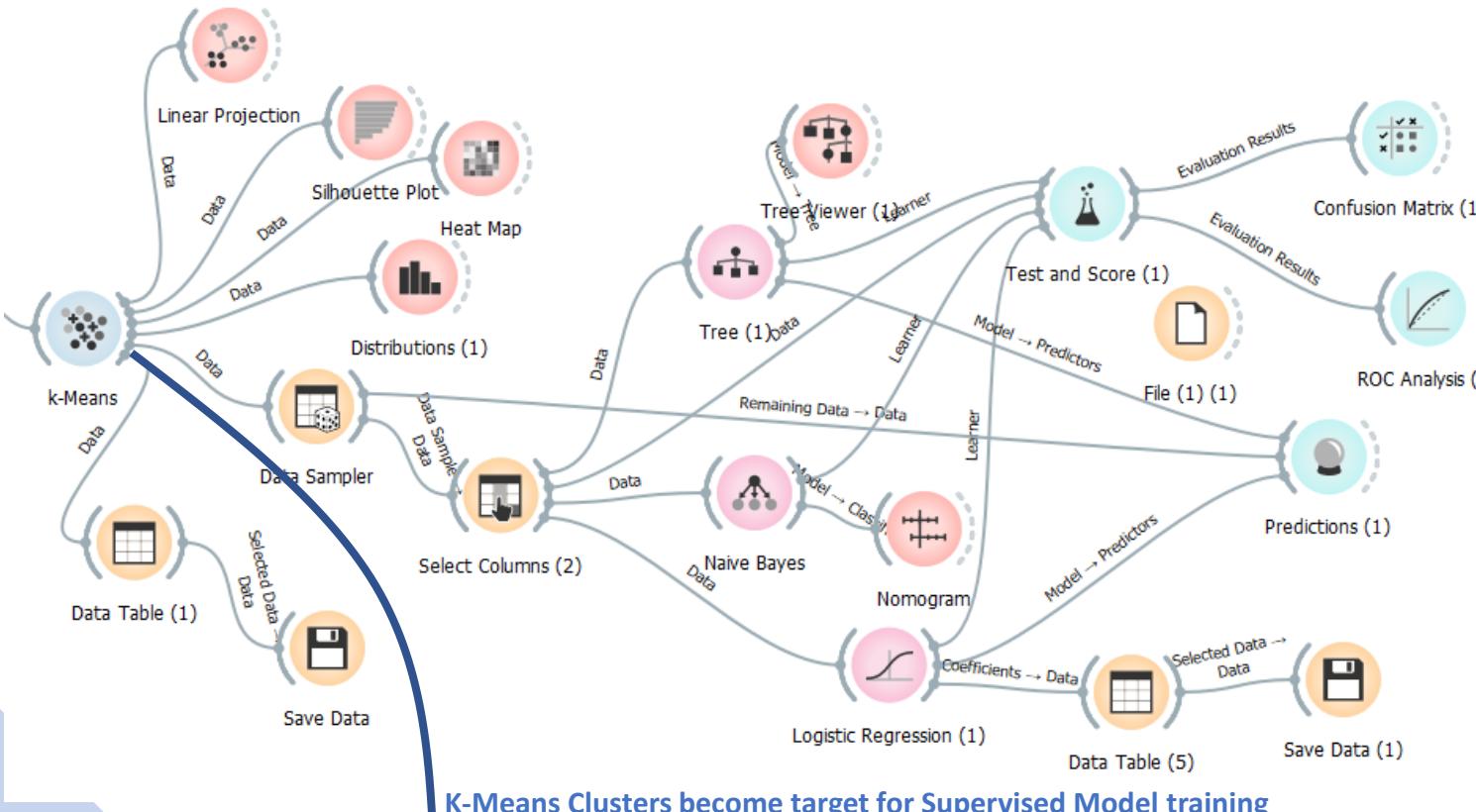
iii) precision or type 2 error not vital

Hence high interpretability for decision classification models will be priority.

Classification Models	Interpretability	Performance
Decision Tree	High	Low
Random Forest	Low	High
Support Vector Machine	Low	High
K Nearest Neighbor	Low	High
Naive Bayes	High	Low
Logistic Regression	High	Moderate

Supervised Model Evaluation

- Cluster from K-Means become the label/target for Supervised Model.**
- As expected the Logistic Regression is a better model among the 3.**



	User	Cluster	Silhouette	resorts	parks	theatres	museums	malls	zoo	restaurants
1	User 1	C2	0.510679	0.00	3.65	5.00	2.92	5.00	2.35	2.
2	User 2	C2	0.508844	0.00	3.65	5.00	2.92	5.00	2.64	2.
3	User 3	C2	0.508721	0.00	3.63	5.00	2.92	5.00	2.64	2.
4	User 4	C2	0.512292	0.50	3.63	5.00	2.92	5.00	2.35	2.
...

Evaluation with 10-fold Cross Validation.

Test and Score (1)					
Evaluation Results					
Model	AUC	CA	F1	Precision	Recall
Tree	0.953	0.933	0.933	0.933	0.933
Naive Bayes	0.988	0.925	0.925	0.926	0.925
Logistic Regression	0.997	0.965	0.965	0.966	0.965

Supervised Model Optimization

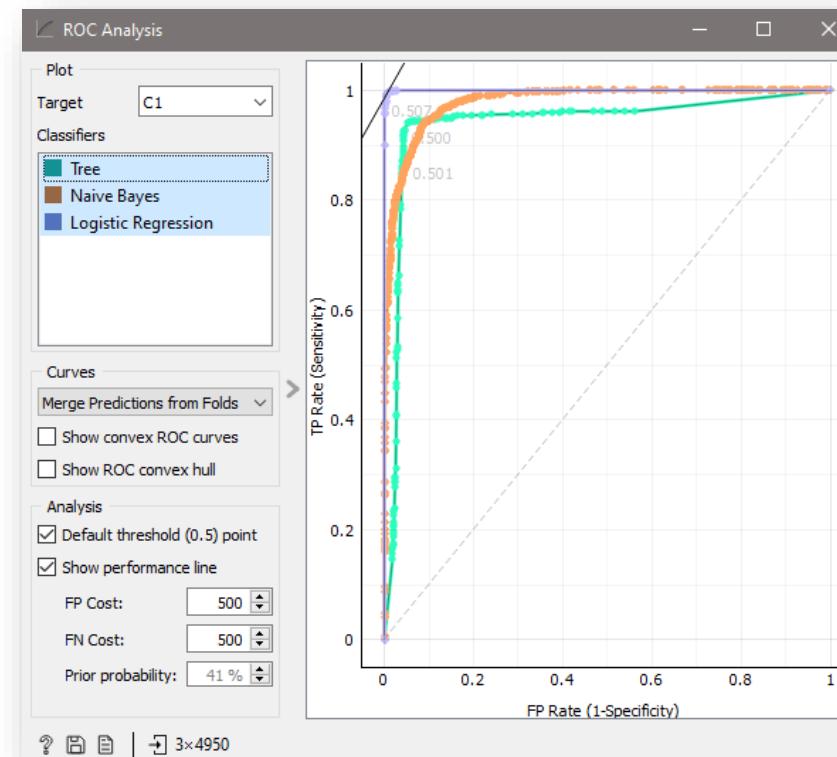
- Accuracy Logistic Regression can easily improve with reducing the penalizes the sum of square weightage by using Ridge Regularisation instead of Lasso.
- Prediction use a hidden data proved that the Tree and Naïve Bayes models does not yield as high accuracy compared to Logistic Regression.

Logistic Regression accuracy improved with Ridge regularisation.

Test and Score (1)					
Evaluation Results					
Model	AUC	CA	F1	Precision	Recall
Tree	0.953	0.933	0.933	0.933	0.933
Naive Bayes	0.988	0.925	0.925	0.926	0.925
Logistic Regression	0.997	0.965	0.965	0.966	0.965

Test and Score (1)					
Evaluation Results					
Model	AUC	CA	F1	Precision	Recall
Tree	0.953	0.933	0.933	0.933	0.933
Naive Bayes	0.988	0.925	0.925	0.926	0.925
Logistic Regression	1.000	0.991	0.991	0.991	0.991

+3.6%



Logistic Regression has better accuracy

	Logistic Regression	Tree	Naive Bayes	Cluster
30	C1	C1	C1	C1
31	C3	C3	C1	C3
32	C2	C2	C2	C2
33	C2	C2	C2	C2
34	C4	C4	C4	C4
35	C2	C1	C1	C2
36	C2	C2	C2	C2
37	C3	C3	C3	C3
38	C4	C4	C4	C4
39	C1	C1	C1	C1
40	C2	C2	C2	C2
41	C1	C1	C1	C1
42	C2	C2	C2	C2

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	0.999	0.959	0.960	0.963	0.959
Tree	0.943	0.918	0.918	0.918	0.918
Naive Bayes	0.986	0.939	0.938	0.941	0.939

Validation of Features Using Logistic Regression Odds Ratio

- Using 95% confidence interval, odds ratio > 1.96.

- Select the features related to each cluster.

- Compare to K-Means clusters features. Result comparable with K-Means Clusters.

Logistic Regression Model:

$$\ln(\text{odds ratio}) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_k X_{ki} + \varepsilon_i$$

Where k = number of independent variables in the model

ε_i = random error in observation i

3-Classes Logistic Regression

Odds Ratio

Feature Name	Cluster_1	Cluster_2	Cluster_3
restaurants	11.258	0.699	0.127
zoo	7.857	0.692	0.184
pubs	5.647	0.554	0.320
services	4.461	0.861	0.260
malls	3.102	0.996	0.324
juice bars	2.741	0.423	0.863
burger	2.696	0.764	0.486
art	2.481	0.495	0.815
hotels	1.989	0.727	0.692
museums	0.544	3.370	0.545
resorts	0.458	1.486	1.469
theatres	0.221	9.815	0.462
beaches	0.195	4.149	1.238
Amusement parks	0.168	7.959	0.748
spas	0.534	0.511	3.660
gyms	0.517	0.214	9.043
bakeries	0.490	0.406	5.025
dance	0.462	0.605	3.573
view	0.337	1.403	2.113
cafes	0.327	0.452	6.761
monuments	0.242	1.671	2.474
Botanic gardens	0.237	0.942	4.480
swimming	0.198	0.436	11.571
churches	0.104	0.964	9.993

K-Means 3 Clusters



4-Classes Logistic Regression

Odds Ratio

Feature Name	Cluster_1	Cluster_2	Cluster_3	Cluster_4
monuments	2.642	0.511	0.167	1.488
view	1.903	0.603	0.390	0.804
resorts	1.784	1.043	0.320	0.520
beaches	4.575	0.520	0.268	0.449
Amusement parks	10.299	0.416	0.187	0.225
theatres	9.994	0.535	0.234	-0.223
museums	3.652	1.400	0.299	-0.424
malls	1.025	4.080	0.708	-1.086
pubs	0.412	5.893	1.347	-1.185
restaurants	0.629	10.274	0.987	-1.852
zoo	0.902	15.066	0.518	-1.951
bakeries	0.388	0.218	2.300	1.638
art	0.379	0.998	3.786	-0.359
juice bars	0.289	0.629	8.383	-0.422
hotels	0.397	0.447	10.978	-0.669
services	0.522	1.879	3.067	-1.101
burger	0.350	0.515	23.062	-1.424
churches	1.767	0.372	0.073	3.041
swimming	0.476	0.259	0.480	2.828
gyms	0.244	0.464	1.006	2.174
cafes	0.687	0.558	0.322	2.092
Botanic gardens	1.666	0.374	0.305	1.663
spas	0.532	0.431	1.137	1.345
dance	0.637	0.524	0.951	1.149

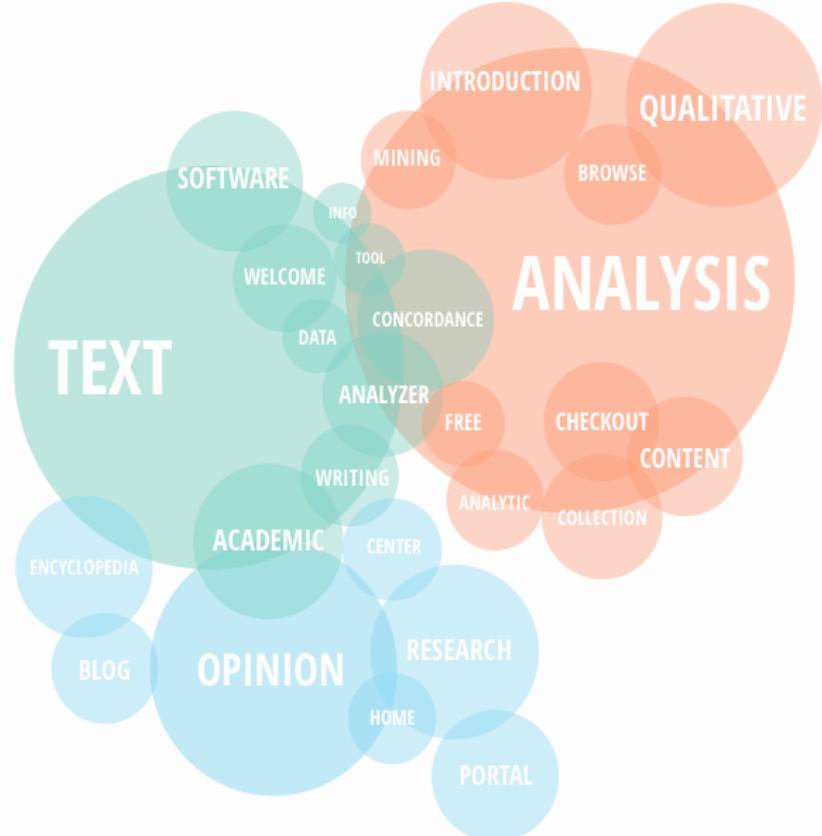
As the 3 or 4 classes are possible groupings of tourists. Both will be proposed to the tourism board who has the expertise to decide which is better to improve sales and tourist experiences.

5. Sentiment Analysis

good place clean *nice room* comfortable
what our customers say
nice! quiet close poor



Hotel Rating Review



Objective:

To improve customer's satisfaction on the overall travelling experiences and hence boost the tourism industry

How:

User reviews were extracted from website and the rating score is ranging from 1 to 5.

Rate 1 is the lowest score which gave us a hint that the chance of visitor not coming back again is high.

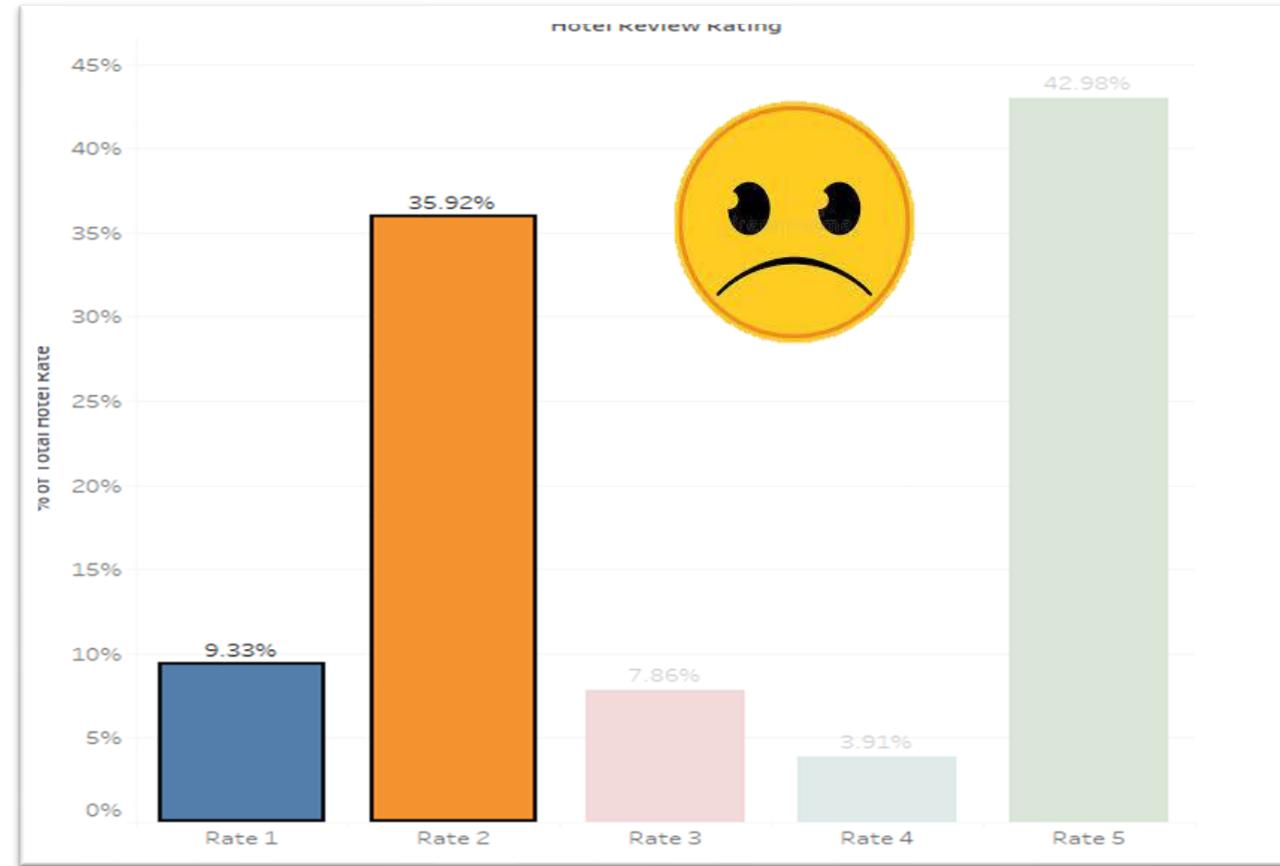
Hotel Rating Review

Total **45.25%** of hotel reviews were at Rate 1 & 2

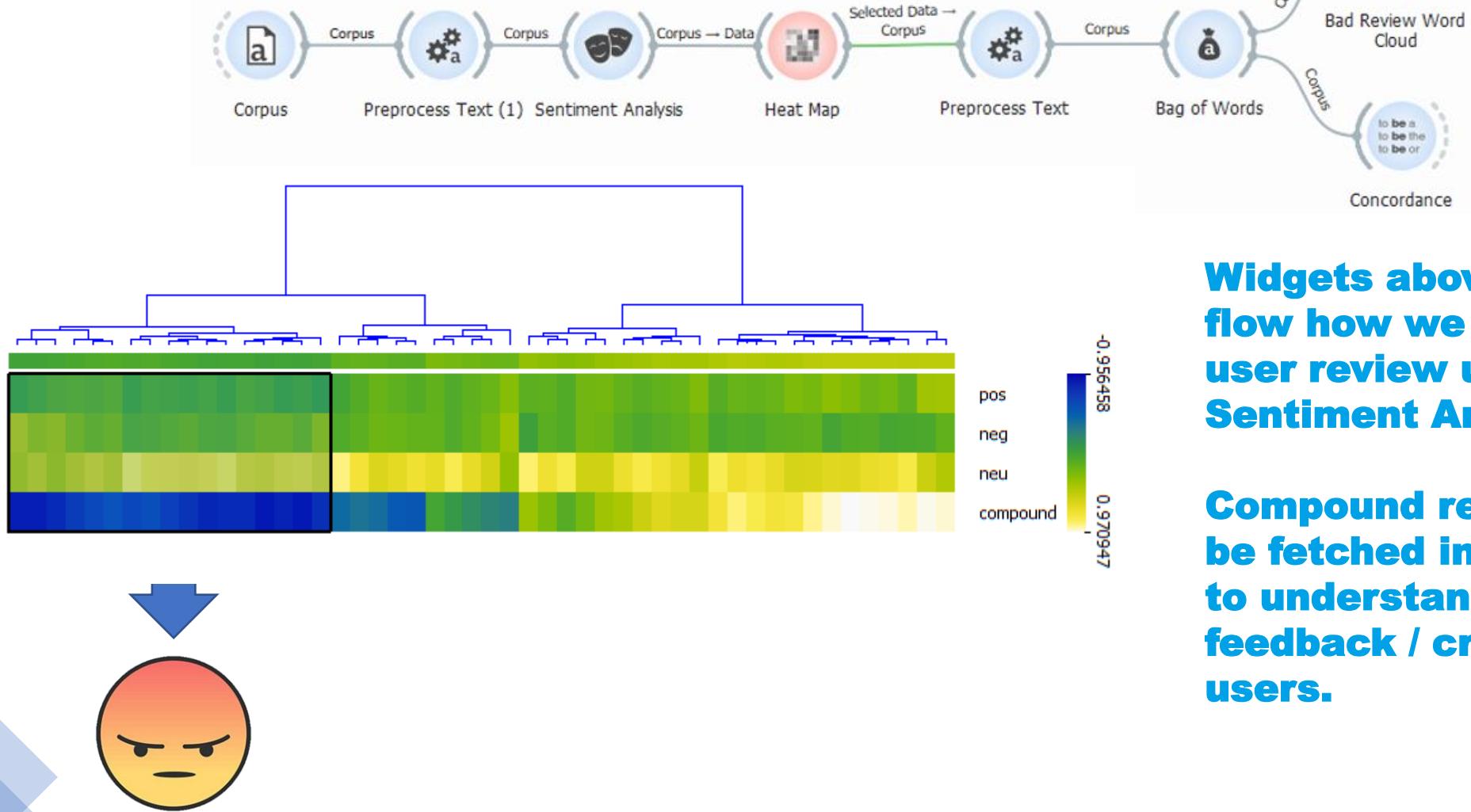
To improve customer's satisfaction, we would like to raise the rating from 1, 2 to at least Rate 3.

By using the Sentiment Analysis, we would like to understand what is the main most concern factor or expectation for visitor during their stay in hotel.

Data sampling for Sentiment Analysis will be only focus on rate 1 & rate 2 and total 500 data will be used for analysis (limitation on computing power)



Sentiment Analysis Result



Widgets above shows the flow how we extract the user review using Sentiment Analysis.

Compound result <0.5 will be fetched into Word Cloud to understand the negative feedback / criticism from users.

Sentiment Analysis Result

From the Word Cloud result, we can observe that most of the negative feedback are focus on customer service as well as the cleanliness of the room.

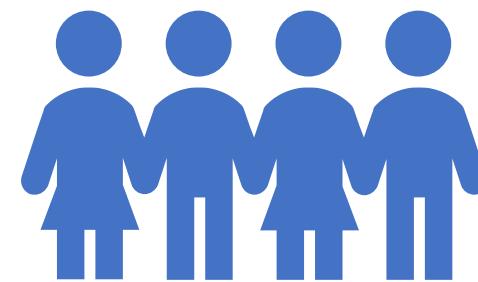
As a result, these should be the improvement areas in to order to delight customer and achieving better review score.



6. Use Case and Deployment



Mass Marketing



Niche Marketing

Use cases and deployment

Use Case 1: Improve marketing efficiency and effectiveness

- Advertise places within clusters

- E.g. Tourists like zoo also like pub

- Form business partnership to boost sales

- E.g. 1 ticket for multiple attraction places, Zoo, pub.

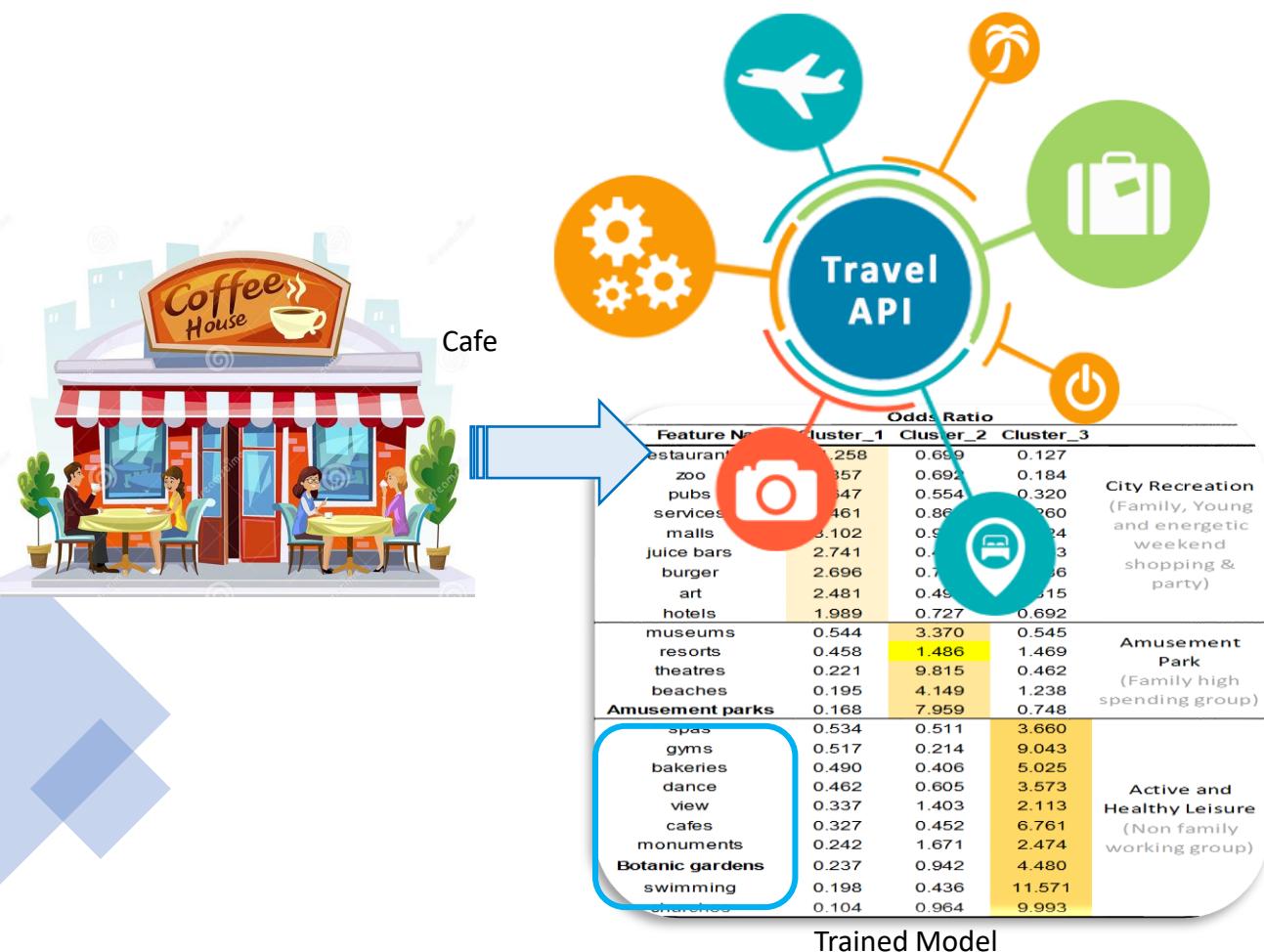
Multi-Park	Adult/Youth^	Child (Ages 3 to 12)
ParkHopper Plus		
Includes • Admission to Jurong Bird Park, Night Safari, River Wonders and Singapore Zoo. • Tram rides at Jurong Bird Park, Night Safari and Singapore Zoo. • Wild Animal Carousel ride at Singapore Zoo (child ticket only). • Amazon River Quest ride at River Wonders. • Valid for 14 days from your first visit and for one-time entry to each park.	\$\\$ 90	\$\\$ 69
4-Park Admission - save \$70!	\$\\$ 83.60 (U.P. \$88.00)	\$\\$ 61.75 (U.P. \$65.00)
2-Park Admission	\$\\$ 50	\$\\$ 40
2-Park Admission	\$\\$ 74.10 (U.P. \$78.00)	\$\\$ 52.25 (U.P. \$55.00)
Any 2 Parks		



Use cases and deployment

Use Case 1: Improve marketing efficiency and effectiveness

- Predict package that suit tourist's preference
 - Input to Model: Tourist's Profile (via Survey, spending trend)
 - Output from Model: Recommend Package



Use cases and deployment

Use Case 2: Improve hospitality service to enhance customer's experience

- **Process customers' feedback using text mining technique to identify problems**
 - E.g. poor customer services and house keeping
 - **Develop plan to address the problems**
 - Retrain employees to improve skills
 - Increase employee engagement
 - Hire professions with the right skillsets
 - **Implement plan and process new feedback**
 - **Measure performance, learn and refine plan**



