Google Merchandize Store

- REVENUE PREDICTION
- MARKETING STRATEGY

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AGENDA

1. Business Case
2. Feature Engineering
3. Modeling
4. Clustering
5. Strategy

Business Case

Problem & Objective

The 80/20 rule has proven true for many businesses–only a small percentage of customers produce most of the revenue. But major part of the revenue comes from only 20% of the customers.

MARKETING BUDGET ALLOCATION

Marketing budget can better be utilized If they target only those users who are most likely to purchase a product in the future.

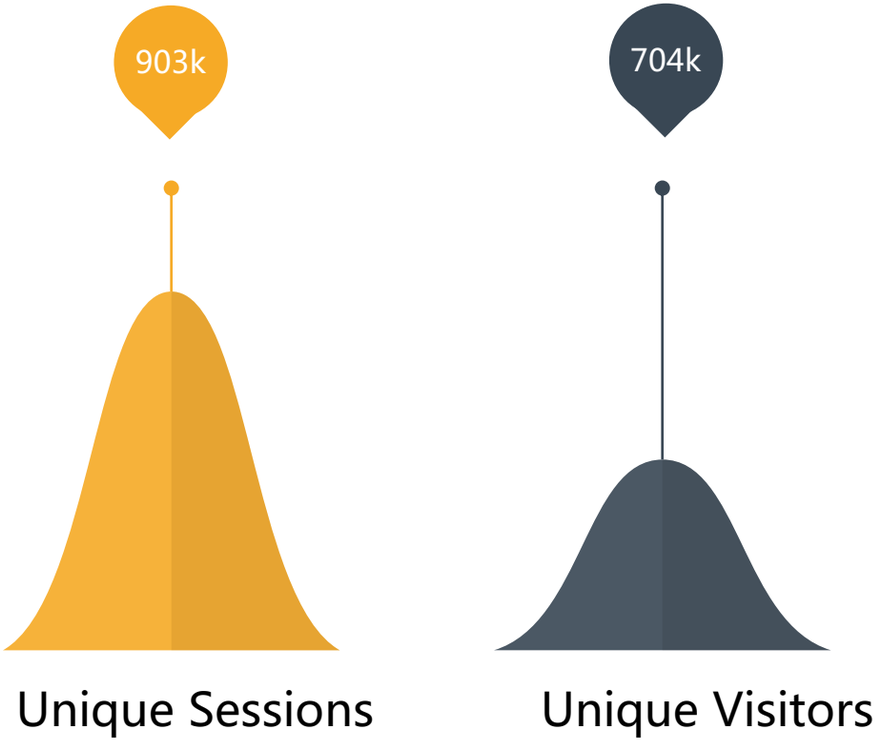
REVENUE PREDICTION

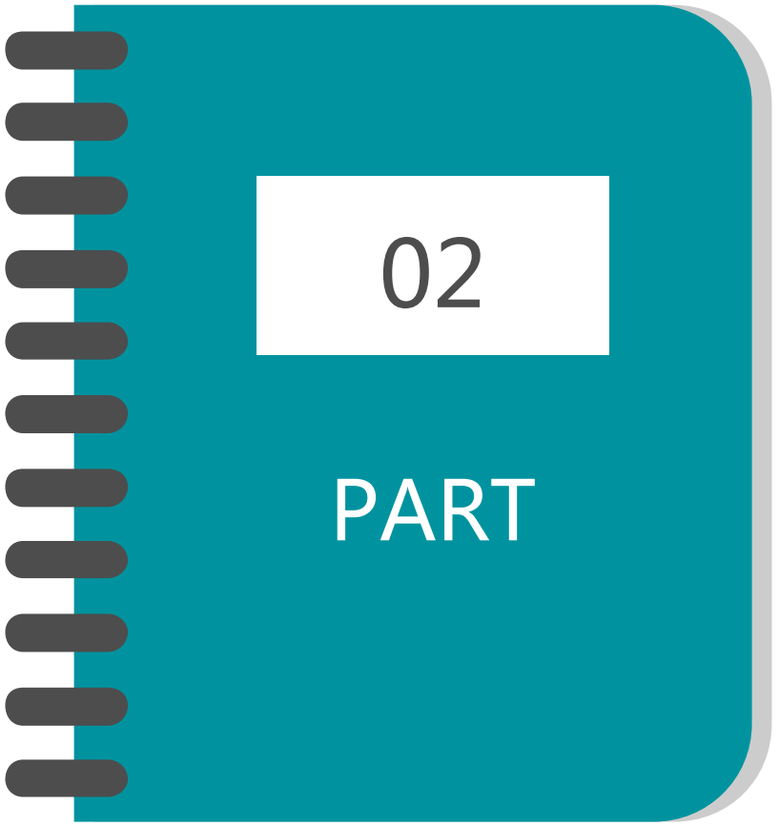
Analyze a Google Merchandise Store customer dataset to predict revenue per customer

Data Source

Our Data is from Google Analytics, GA is a tool for tracking online visitor behavior, such as their pageviews, how long do they stay and their transaction revenue.

The time spans of our data is from Aug 1, 2016 to Aug 1, 2017, it records 903,653 sessions, 704,353 unique visitors.



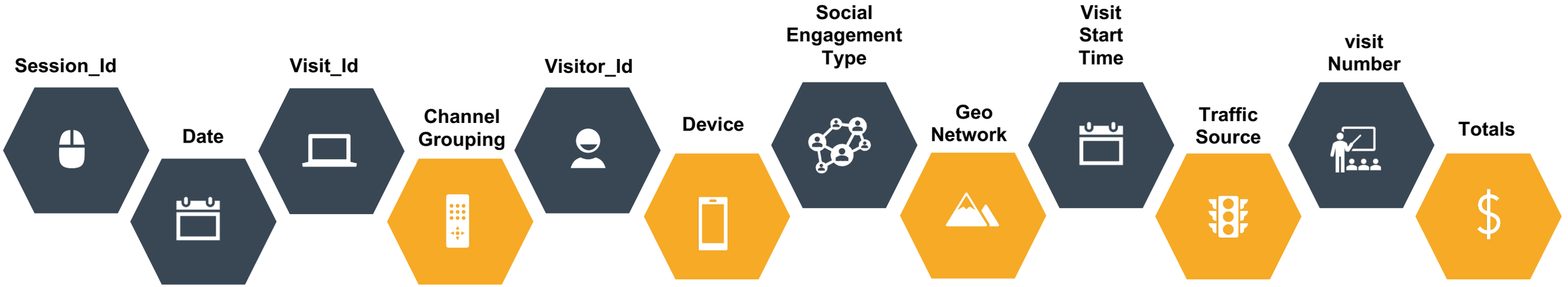


Feature Engineering

- Data Description
- Data Exploring
- Data Transformation
- EDA

Data Description

The raw data contains 12 columns, 5 of them are in the nested Json format.



- (Other)
- Affiliates
- Direct
- Display
- Organic Search
- Paid Search
- Referral
- Social

- Browser
- Operating system

- Continent
- Subcontinent
- Country
- City

- campaign
- source
- medium
- keyword

- Visits
- Hits
- Pageviews
- Bounces
- NewVisits

** full description is in the appendix*

EDA - Feature Engineering

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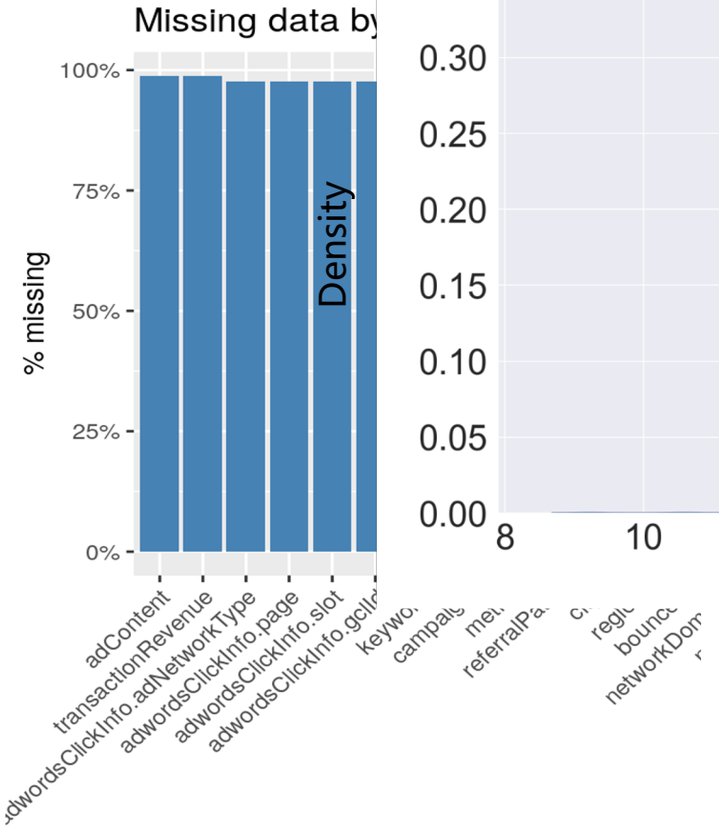

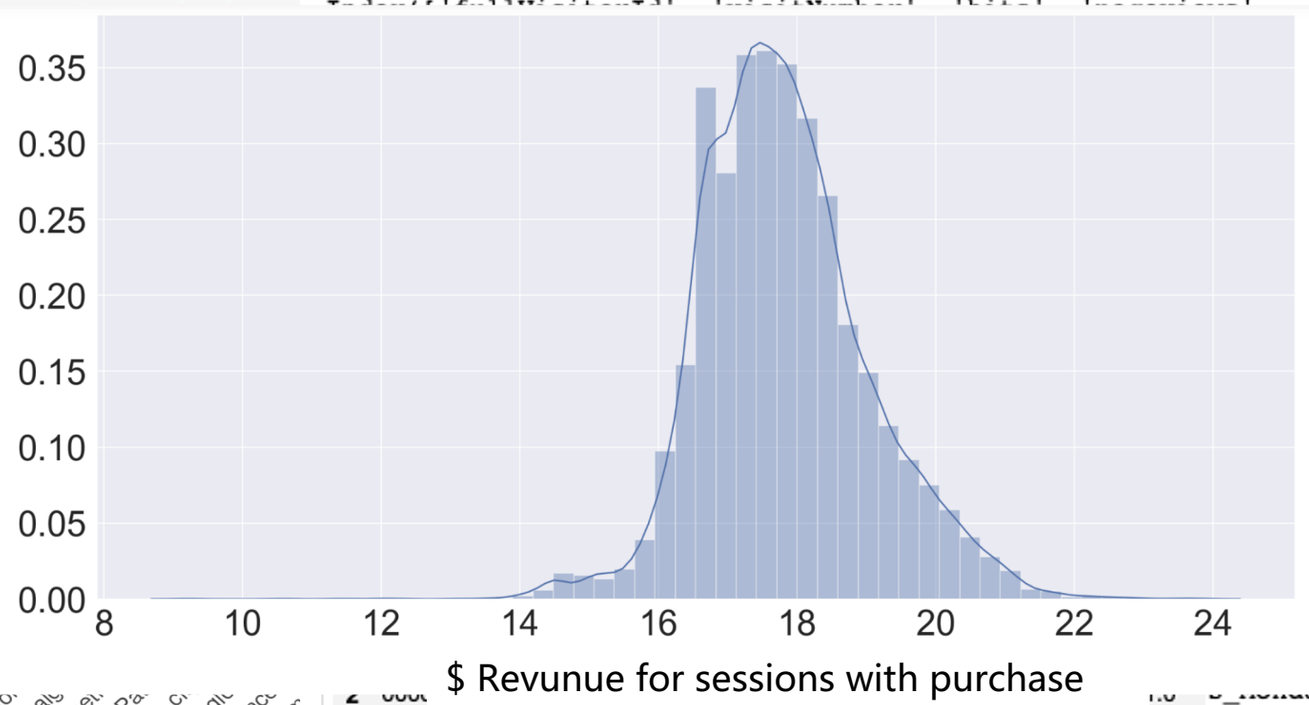


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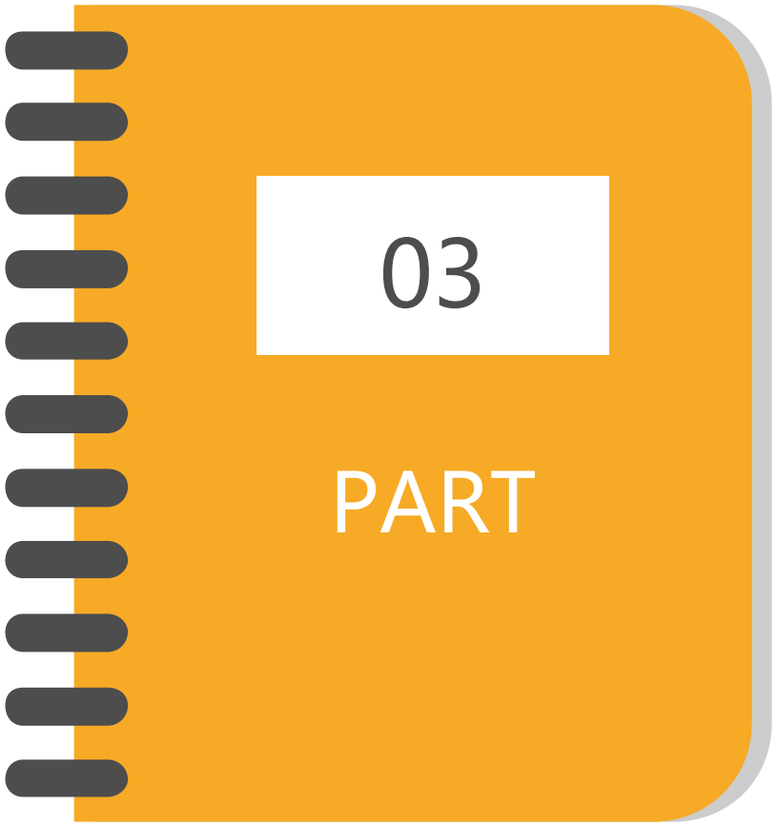
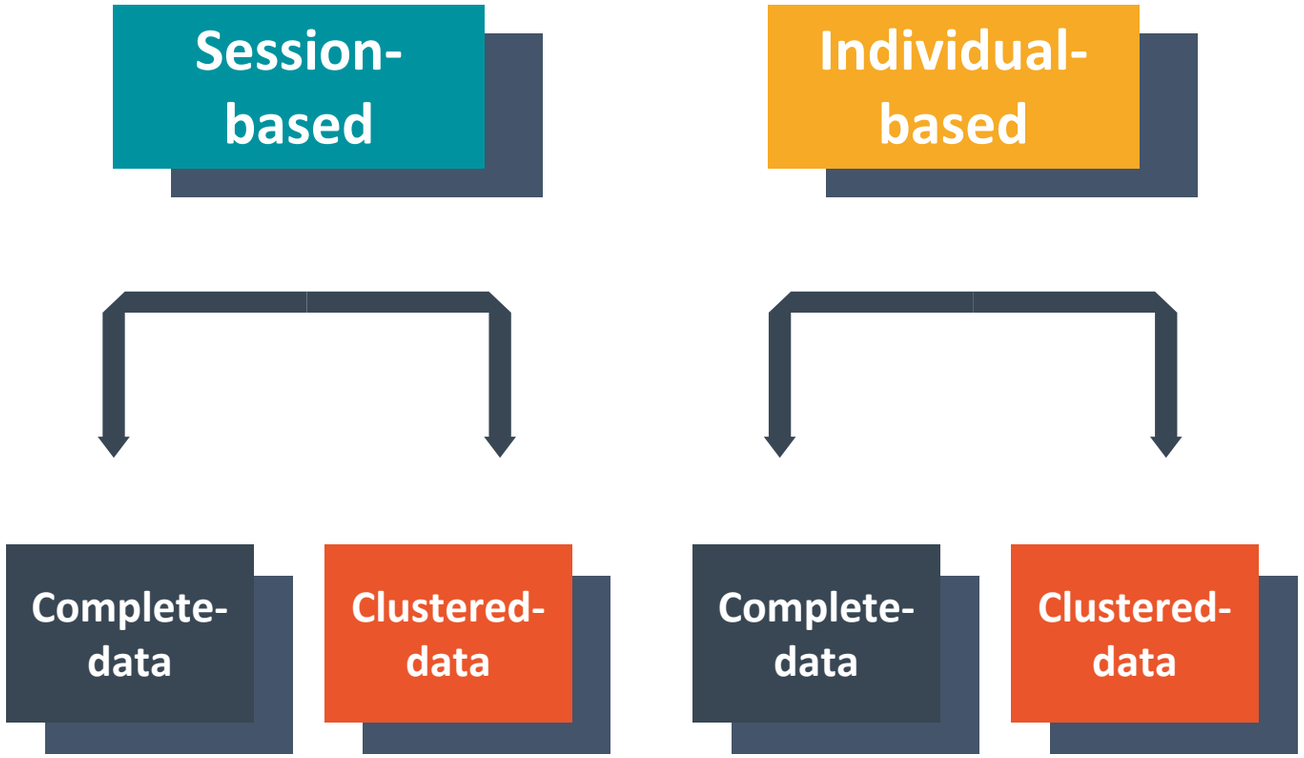


Modeling

- ML Models
- Clustered
- Session/Individual
- Balanced

Hierarchical Modeling Approaches



Approach-1:
Session-based vs. Individual-based Modeling

To serve for different purposes

Approach-2:
Complete-data vs. Clustered-data Modeling

To improve models' performances

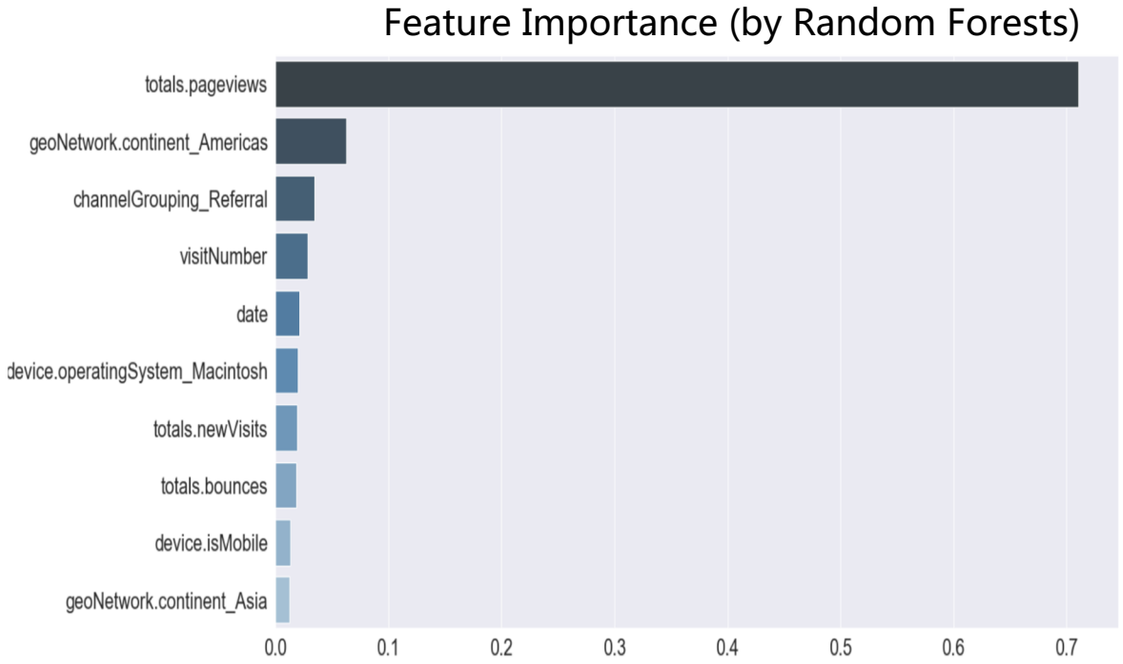
Approach-1: Session-based vs. Individual-based Modeling

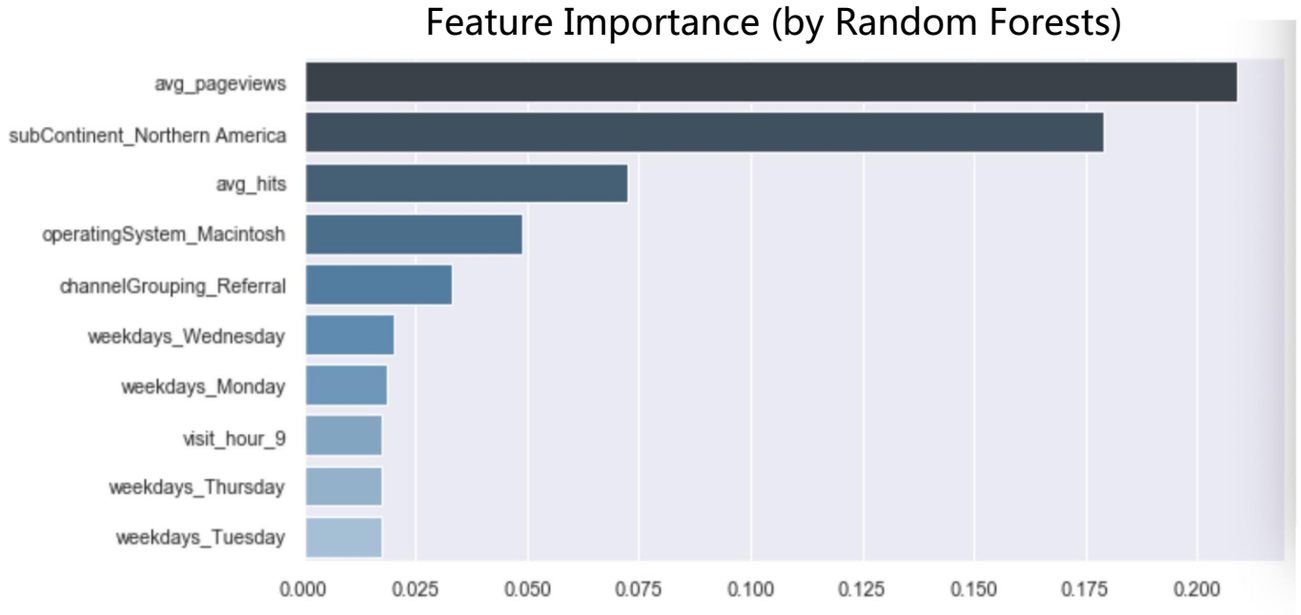
Session-based Modeling

- Original dataset to predict revenue for each session

Individual-based Modeling

- Aggregated features based on unique Individual ID (e.g. sum transaction level, average pageview)
- Most new created features' weights swell compared to original features that they are derived from





Candidate Models

	Pro	Con
Random Forest	Average result resulting in unbiasede result	Took time to tune the parameters
Gradient Boosting	Corrected errors made by each sample to enhance results	May result in over-fitting
XGB Boosting	Resolved over-fitting by puting a penalized terms	Time-consuming to deliver the result
Ridge Regression	Less time to finalize result and remove multicollinearity	Results are, most of time, not as good as Machine Learning Model
Lasso Regression	Less time to finalize result and remove multicollinearity	Like Ridge Regression, is parametric method and has assumption of residual
Linear Regression	Good interpretability	Several assumptions about linear regressions should be met

Models Performance Assessment

Session-based Models Performances

	GradientBoosting	LinearRegression	RandomForest	Ridge	XGBRegressor
All_Customer (RMSE)	1.82	2.01	1.82	2.01	1.92

Individula-based Models Performances

	GradientBoosting	Lasso	RandomForest	Ridge	XGBRegressor
All_Customer (RMSE)	2.022375	2.370443	2.253886	2.263846	2.027313

- Comparison Between Session-based and Individual-based Models
  - Session-based models generally outperform Individual-based models, but the differences are tiny
  - It means a little amount of bias may be introduced with the creation of aggregated features
- Comparison Within Session-based or Individual-based Models
  - Tree models outperform GLM models
  - Boosting result outperforms Random Forest

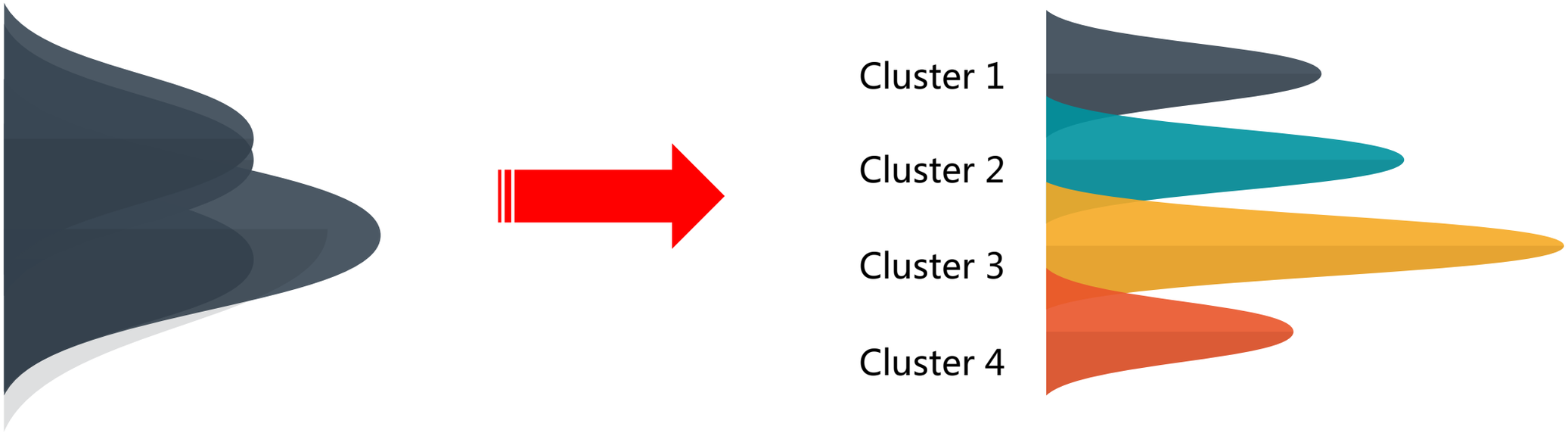
Approach-2: Complete vs. Clustered Modeling

Complete Modeling

- Complete dataset for all models
- **Pro**: Can be compared among candidate models directly using a single RMSE
- **Con**: Patterns of different sections of data may be hard to capture by a single model

Clustered Modeling

- Clustered datasets using the selected features
- **Pro**: Respectively modeling for different clusters to choose the best fit for each
- **Con**: Time-consuming and Heavily relying on how fit the data is clustered



Models Performance Assessment

Complete Modeling

- (Same as the previous page)

- **Session-based models**

	GradientBoosting	LinearRegression	RandomForest	Ridge	XGBRegressor
All_Customer (RMSE)	1.82	2.01	1.82	2.01	1.92

- **Individual-based models**

	GradientBoosting	Lasso	RandomForest	Ridge	XGBRegressor
All_Customer (RMSE)	2.022375	2.370443	2.253886	2.263846	2.027313

Clustered Modeling

- RMSE varies a lot among clusters but changes litte within a single cluster for different models
- Individual-based Clustering improves model fitting results except for Cluster_4
- In Cluster_4, Standard Deviation of response is much higher than other clusters due to the small sample size of this cluster
- **Session-based models**

	Linear Regressor	Random Forest Regressor	Ridege Regressor	XGBRegressor	GradientBoostingRegressor
Cluster1(RMSE)	2.173270	2.001115	2.173344	2.116877	2.011489
Cluster2(RMSE)	1.035442	0.990795	1.035533	1.010749	0.984474
Cluster3(RMSE)	3.944547	3.680210	3.944839	3.811918	3.657345
Cluster4(RMSE)	13.468780	8.968768	13.355924	13.633525	10.950509

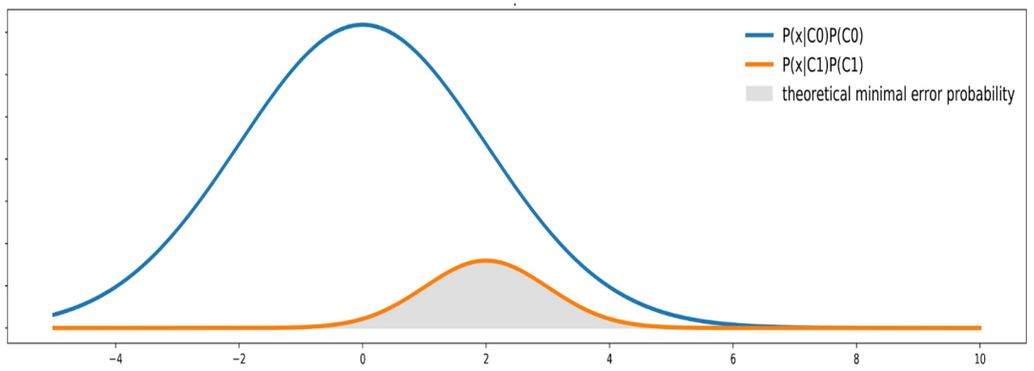
- **Individual-based models**

	GradientBoosting	Lasso	RandomForest	Ridge	XGBRegressor
Cluster1 (RMSE)	1.899737	1.939845	1.939845	1.900526	1.766069
Cluster2 (RMSE)	0.069714	0.137477	0.091165	0.000181	0.076158
Cluster3 (RMSE)	1.351296	1.458767	1.417745	1.422674	1.350185
Cluster4 (RMSE)	16.370706	15.842980	16.278821	16.031220	16.852300

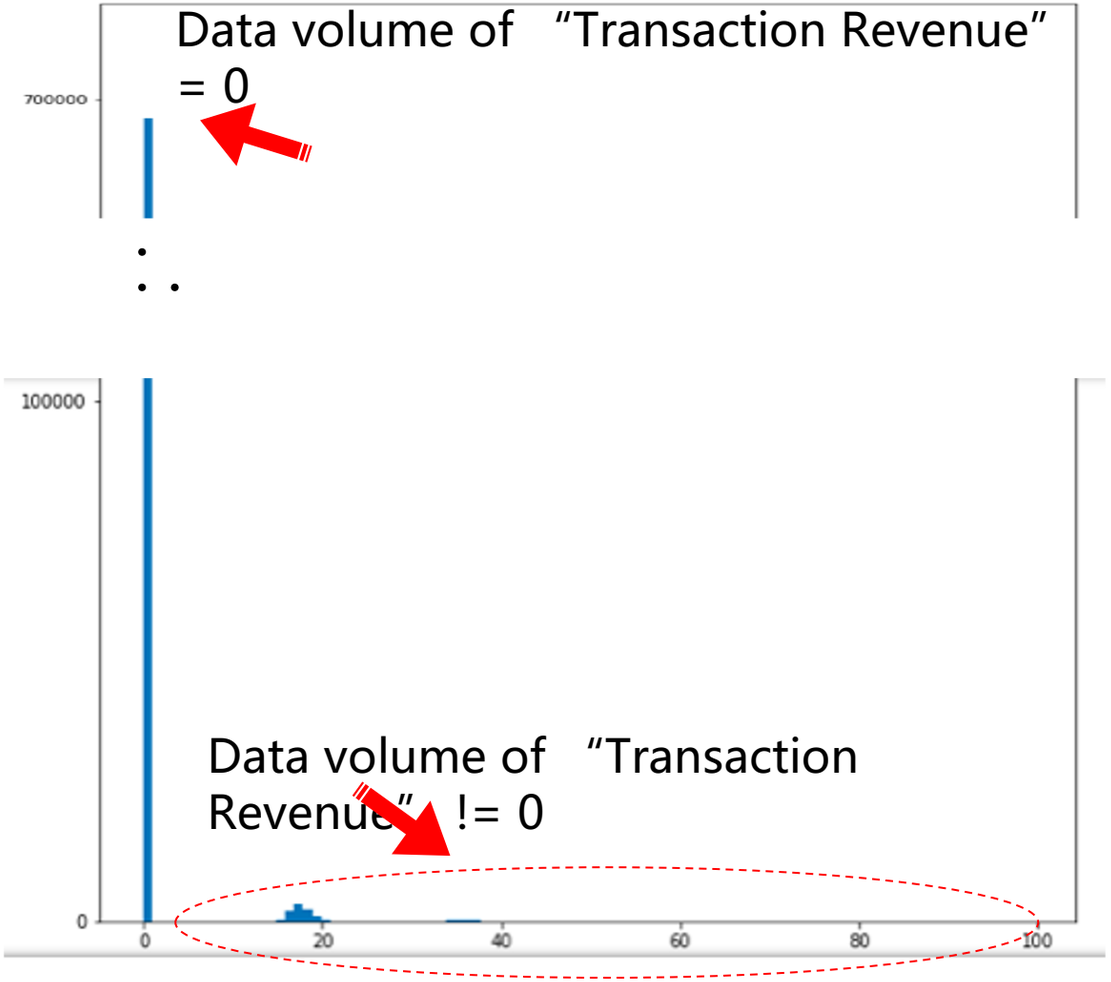
Unsolved Challenge: Data Imbalance

Problems caused by Data Imbalance

- Except the long tails, observations close to the Majority's mean are inclined to fall into its SD range
- Too small theoretical minimum error probability (area under the minority curve) to teach machines



	Zero	Non-Zero
Target Variable "Transaction Revenue"	**98.6%**	**1.4%**



Approach-3: Two-steps Modeling with Balanced Re-sampling

Step-1: Classification for Transaction

- To predict individuals who will have transactions
- Models trained with full dataset
- Given the extreme imbalance between Majority ("TR" = 0) and Minority ("TR" != 0), probability of prediction as Majority overweighs too much
- **Balanced Re-sampling is needed**

Step-2: Regression for Transaction Revenue

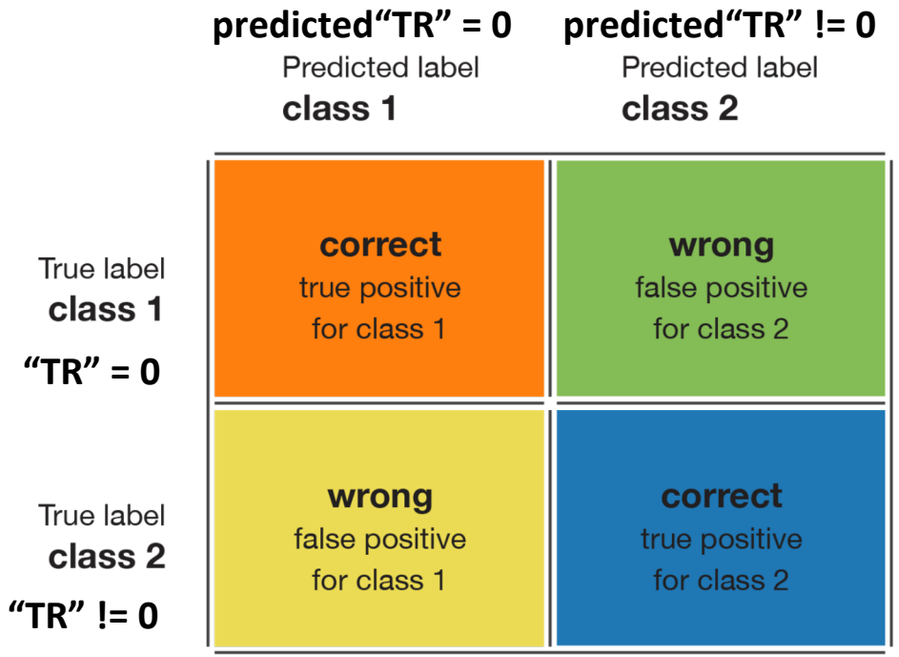
- To predict how much the transactions will be
- Models trained with sub-dataset of Minority ("TR" != 0)
- Process similar to the previous regression models

Comparison between Models

- Under-sampling better benefits model fitting than Over-sampling, but the diff is tiny
- LR and SVM overperform Tree models, although the diffs are not significant
- Overfitting is the root cause

	Over-sampling	Under-sampling
Random Forest	☑	☑
Decision Tree	☑	☑
SVM	☑	☑
Logistic Regression	☑	☑

Models' Performance Assessment



Model Interpretation

- **CONSERVATIVE for "TR = 0"**

  low Recall + high Precision : the model misses some real values, but those recognized values are highly reliable

- **LIBERAL for "TR != 0"**

  high Recall + low Precision : most (if not all) real values are recognized, but counterfeits are mixed inside

Tradeoff

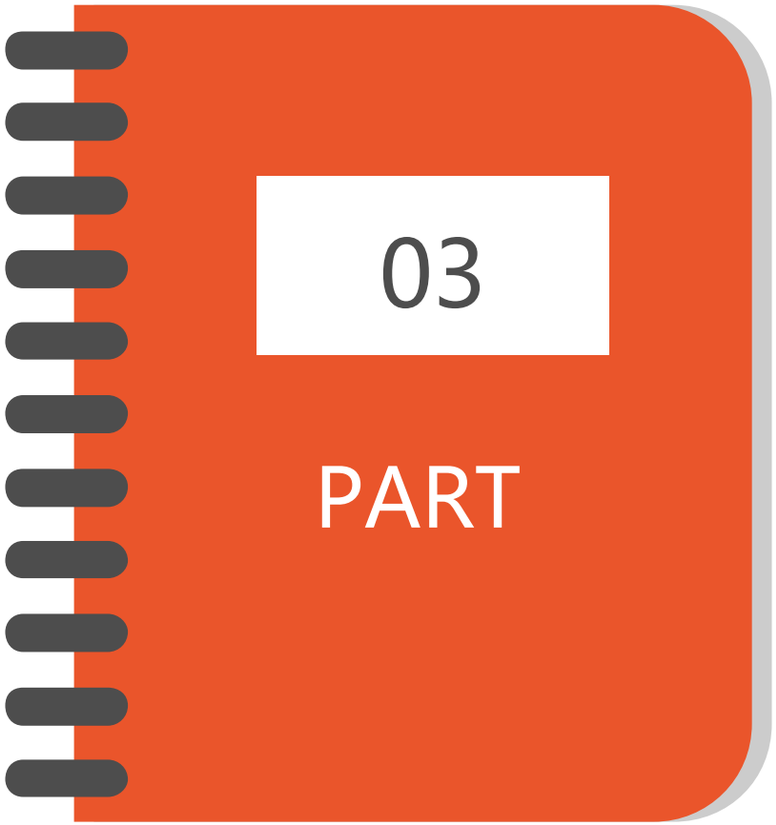
- **Targetted Customers : "TR != 0"**

$$\text{accuracy} = \frac{\blacksquare + \blacksquare}{\blacksquare + \blacksquare + \blacksquare + \blacksquare}$$

$$\text{class 1 precision} = \frac{\blacksquare}{\blacksquare + \blacksquare} \qquad \text{class 2 precision} = \frac{\blacksquare}{\blacksquare + \blacksquare}$$

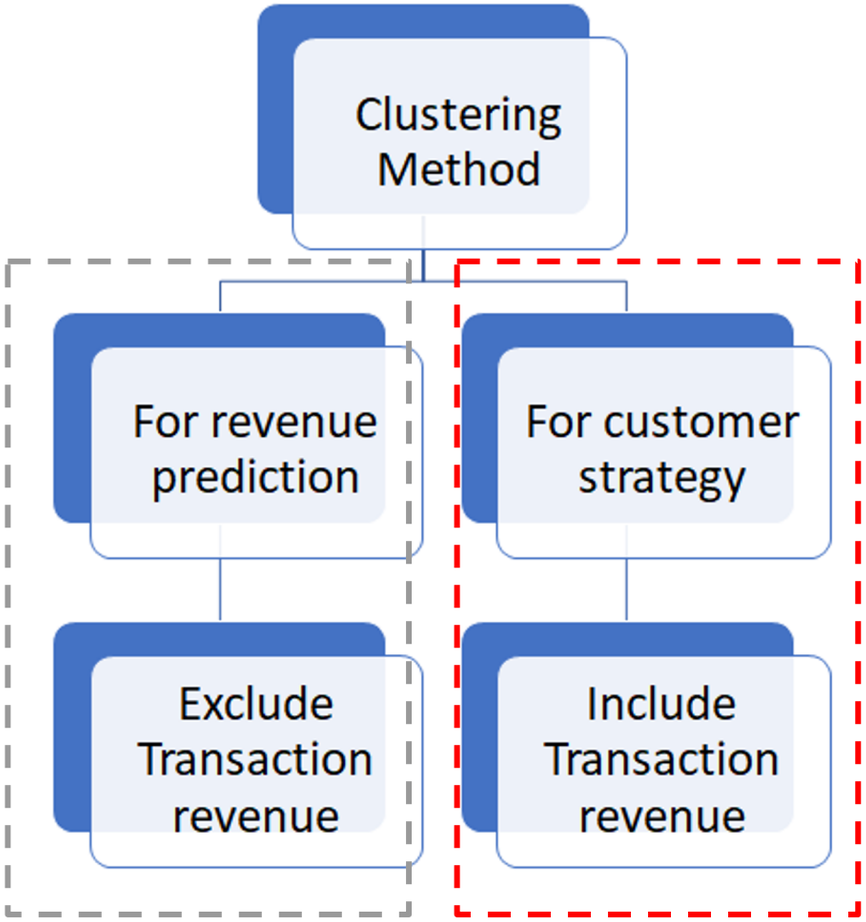
$$\text{class 1 recall} = \frac{\blacksquare}{\blacksquare + \blacksquare} \qquad \text{class 2 recall} = \frac{\blacksquare}{\blacksquare + \blacksquare}$$

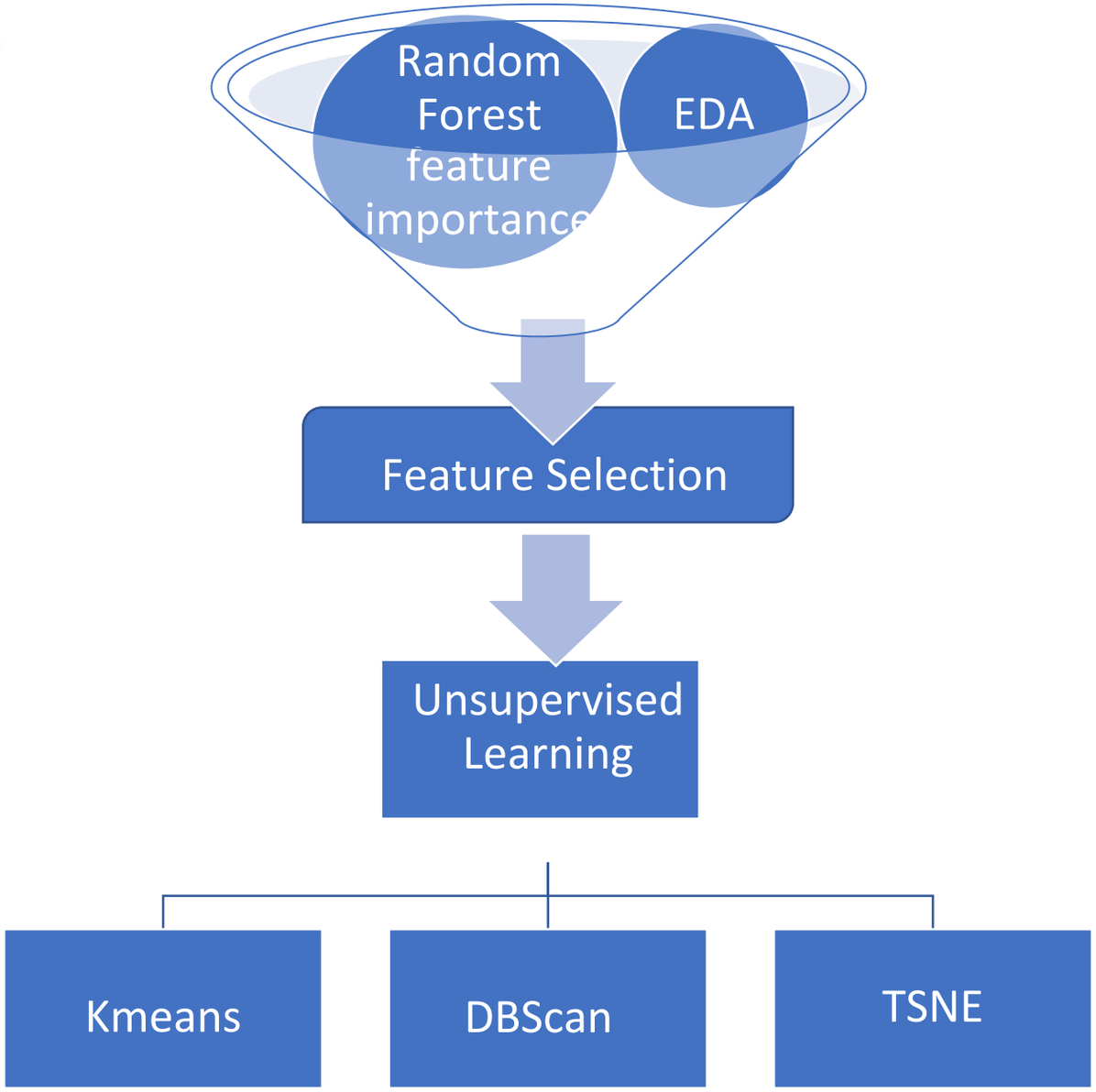
	precision	recall	f1-score
0	1.00	0.93	0.96
1	0.16	0.98	0.28
accuracy			0.93
macro avg	0.58	0.95	0.62
weighted avg	0.99	0.93	0.95



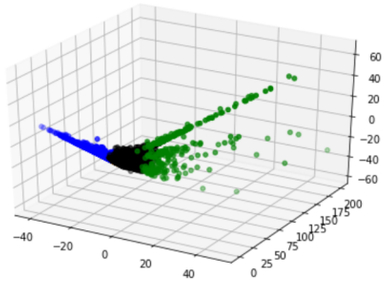
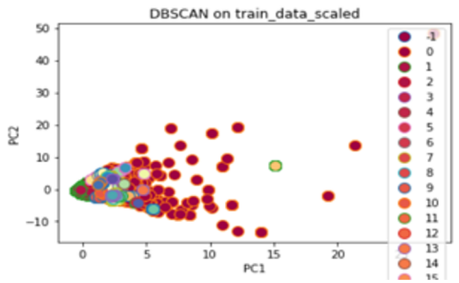
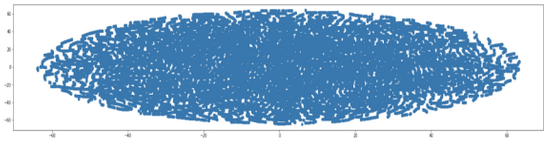
Clustering

Customer Clustering for Two Purposes



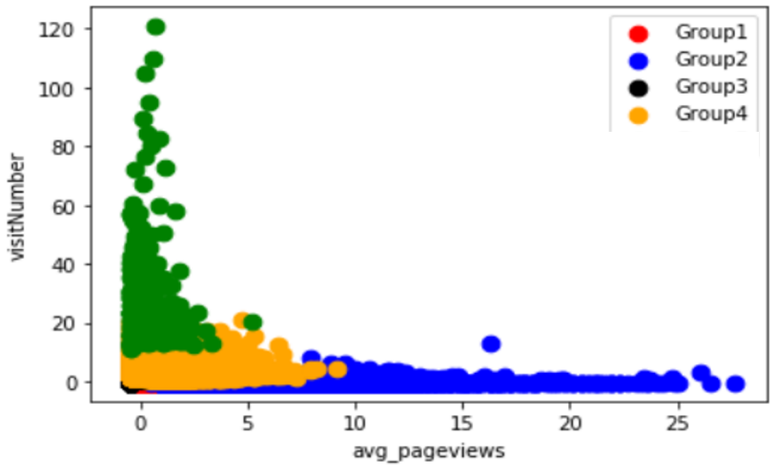


Clustering Method - Models Comparison

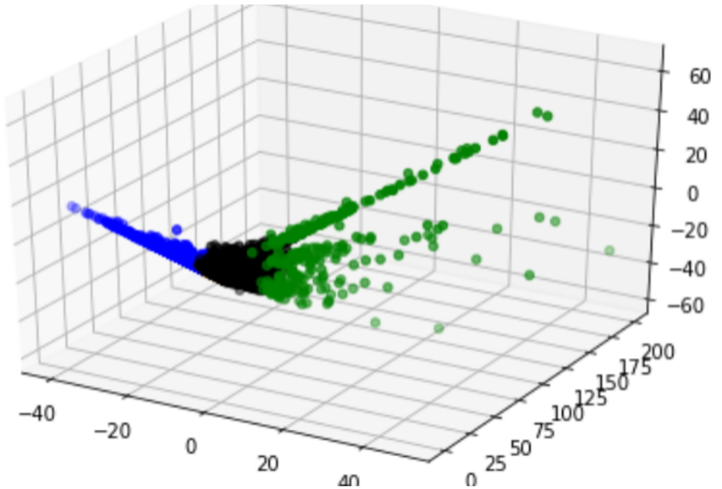
Metrics	Kmeans	DBSCAN	TSNE
Number of clusters:	4 clusters	> 20 clusters	1 cluster
Visualization:			
Conclusion:	Pro: - Clear clustering - Easy implementation Con: - need of determination of number of cluster initially - Curse of Dimensionality	Pro: - No need to determine the number of cluster initially Con: - Works better with non-round shape - Curse of Dimensionality - Too sensitive to the model parameters	Pro: - Dimension reduction - Good for exploration purpose Con: - No clear pattern - Points are relative to each other without easy interpretation.

Customer Clustering - Using the Cluster Centroids

Actual Features Graph -2D



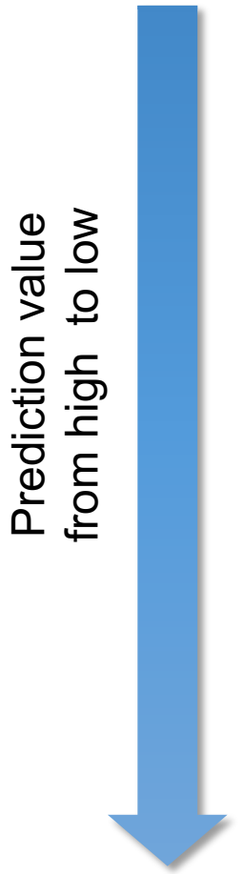
Principle Components Graph - 3D



Customer Type	ColorCode	TransRevenue	Pageview	VisitNumber	Bounces	Referral
One-time buyer	Red/Blue	Low	Low	Low	Low	Low
Easy-be-influenced	Orange	High	Low	High	High	High
Budget buyer	Black	Medium	High	Low	Low	Low
Technophile	Green	High	Medium	Medium	Medium	Medium

Strategy

Segmented Marketing Strategy



Customer Segmentation

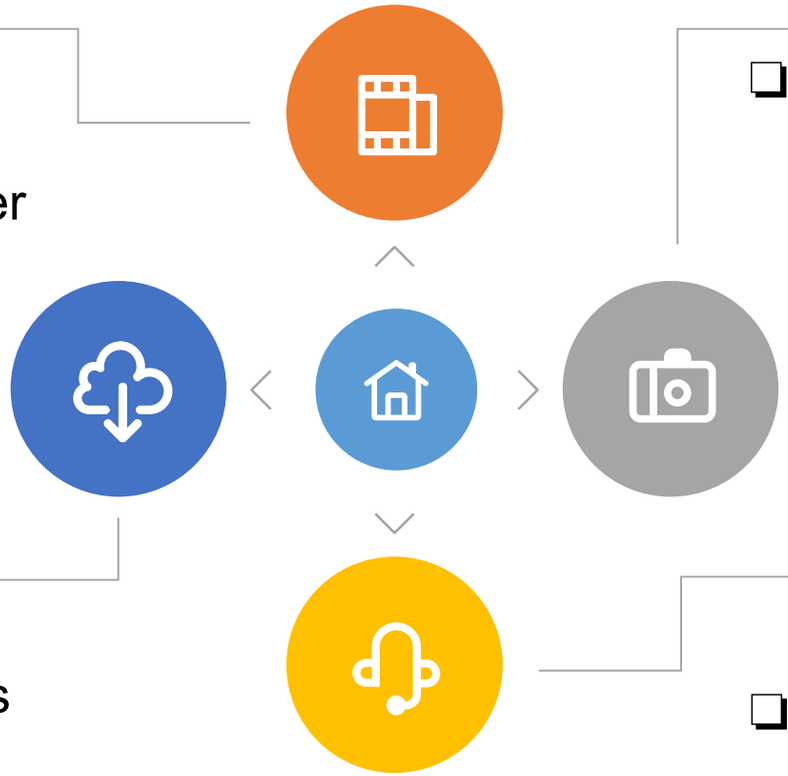
- Technophile: generate a large amount of revenue with relatively low pageviews or hits
- Easy-be-influenced: this group of people is mainly attracted by referrals
- Budget buyer: they browse the website a lot before making a purchase decision
- One-time buyer: this group of people is the least interested in the product of our store. They wander in our store occasionally and rarely buy anything

Strategy

- Enhance their loyalty and encourage them to influence other customers
- e.g., Start a membership program
- Content driven. Establish the brand that google products are cool
- Let them have more exposure to the brand
- Price driven. Sending promotions and coupons
- Boost awareness. Promote our store at special occasions

With Machine Learning techniques, Google Merchandise Store can

- Identify *likely* high-value *customers* by analyzing *existing* high-value customer purchasing behavior



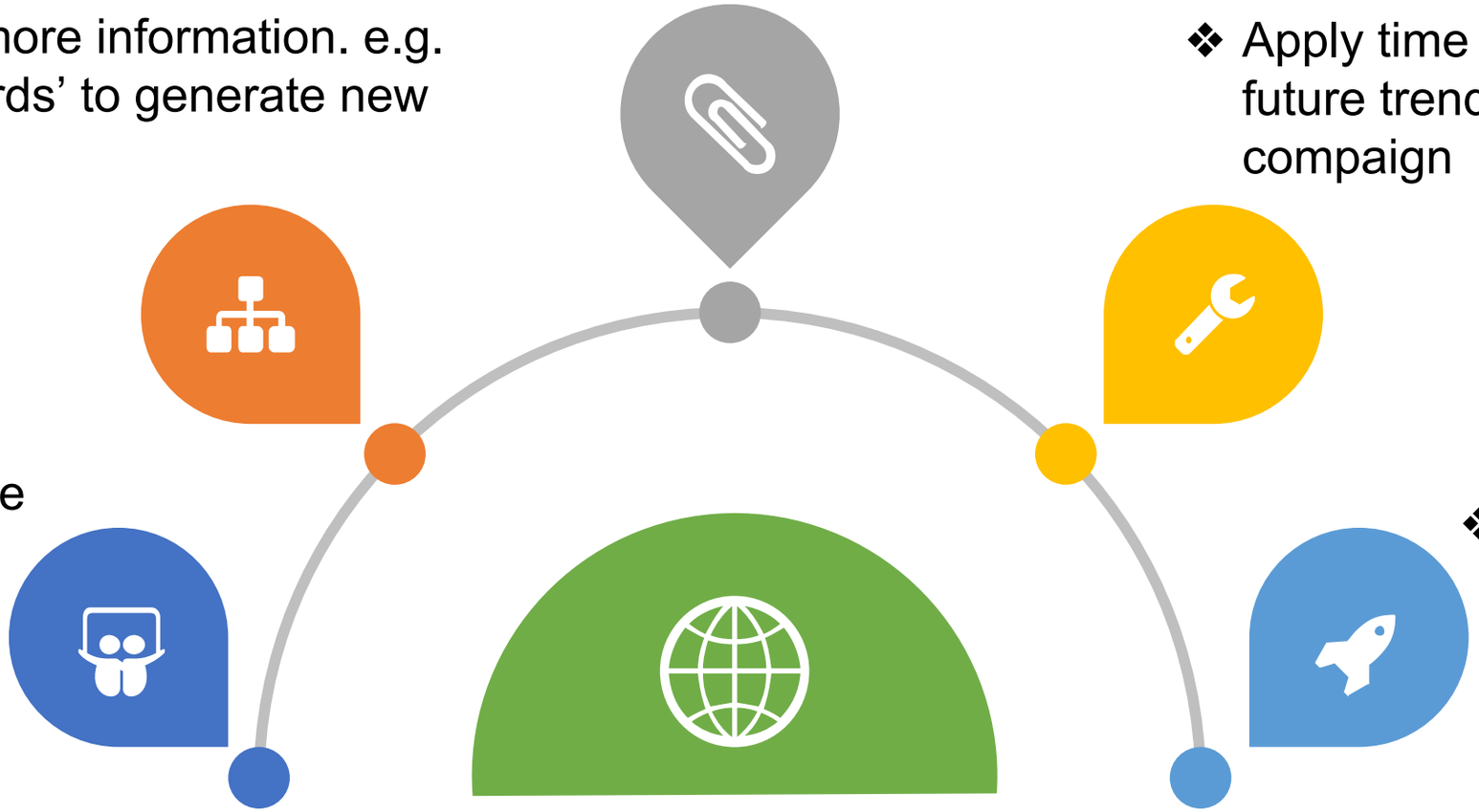
- Predict revenue based on customer purchasing history
- Retain high-value customers by different marketing strategies
- Focus product development on high-value customer products

Future Plans

- Add in more features. e.g. customer demographic from CRM

- NLP analysis for more information. e.g. ‘Campaign keywords’ to generate new features

- Apply time series model to predict future trend to design holiday compaign



- A/B test to increase pageviews

- Handle imbalanced datasets

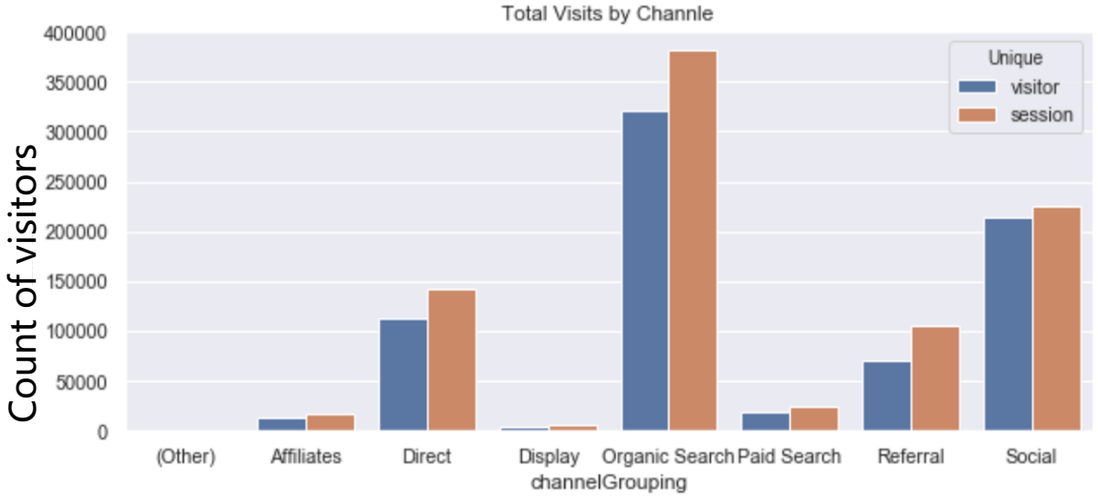
THANK YOU

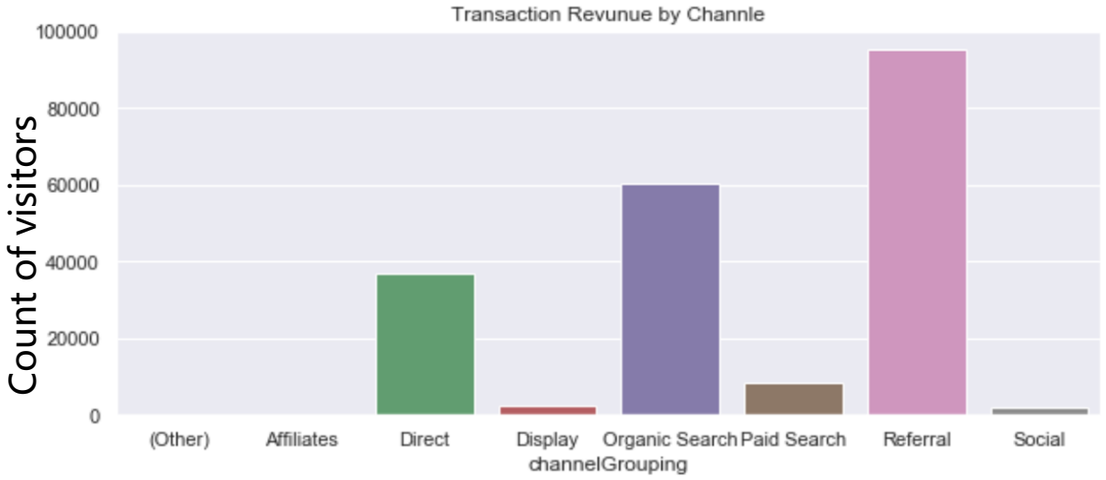
Appendix

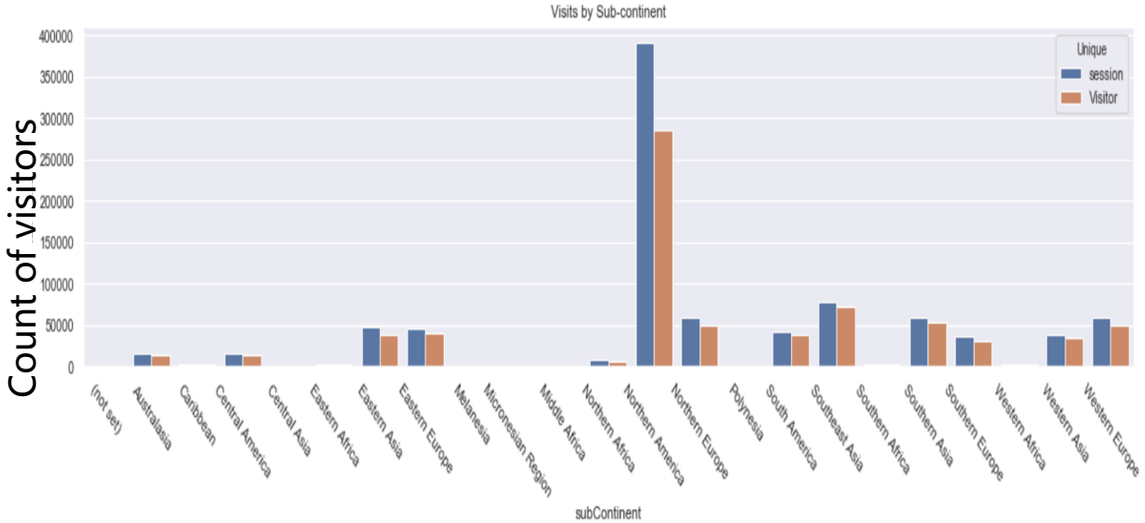
Google Analytics Channel Grouping definition:

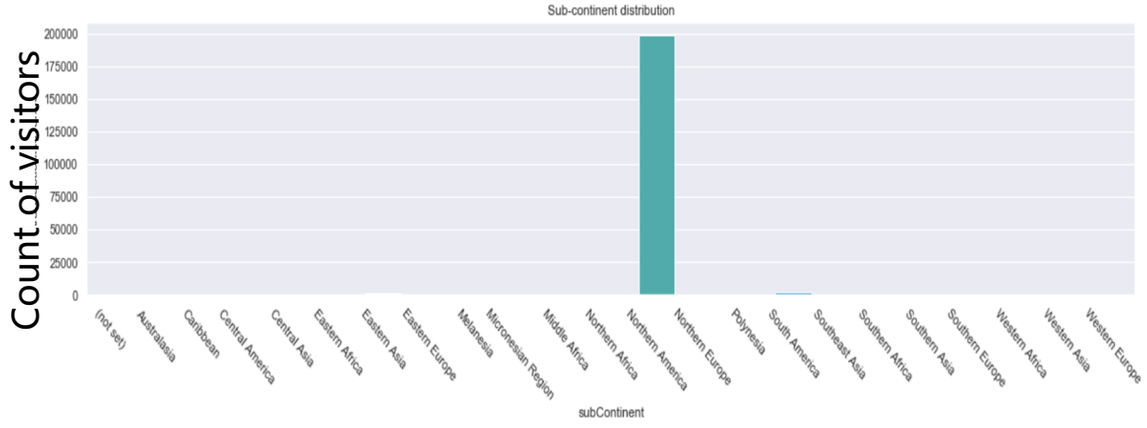
Channel	Definition
Direct	Source exactly matches direct AND Medium exactly matches (not set) OR Medium exactly matches (none)
Organic Search	Medium exactly matches organic
Social	Social Source Referral exactly matches Yes OR Medium matches regex ^(social|social-network|social-media|sm|social network|social media)$
Email	Medium exactly matches email
Affiliates	Medium exactly matches affiliate
Referral	Medium exactly matches referral
Paid Search	Medium matches regex ^(cpc|ppc|paidsearch)$ AND Ad Distribution Network does not exactly match Content
Other Advertising	Medium matches regex ^(cpv|cpa|cpp|content-text)$
Display	Medium matches regex ^(display|cpm|banner)$ OR Ad Distribution Network exactly matches Content
(unavailable) or (other)	Sessions don't match any channel description.

EDA - Where do the traffics come from?

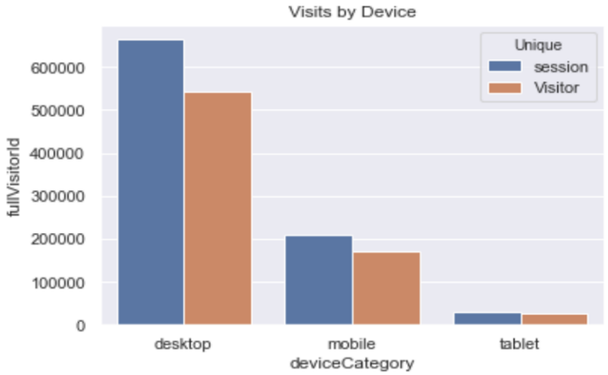


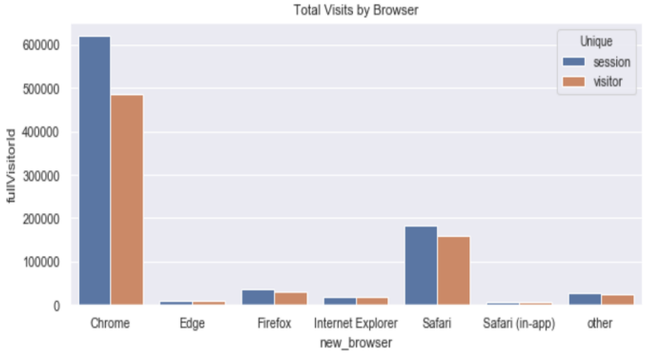


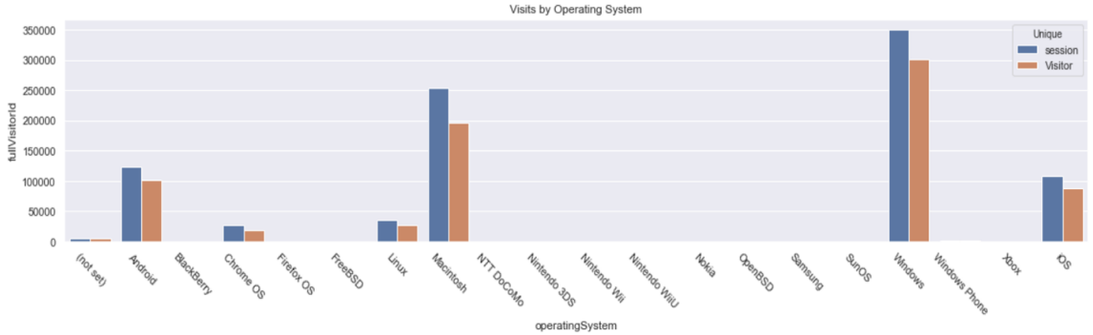


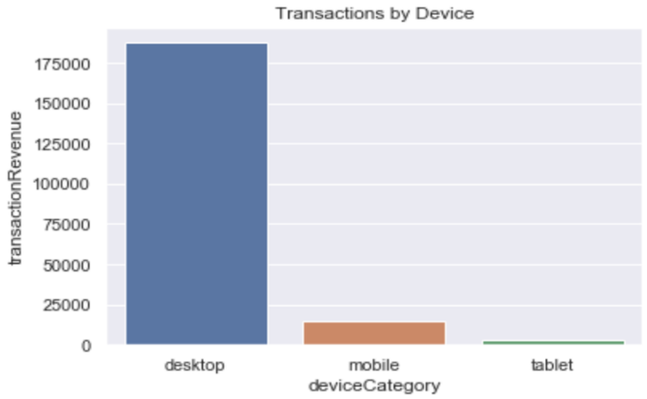


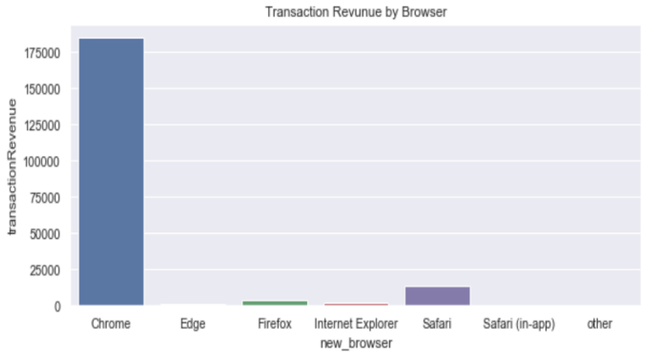
EDA - What devices, OS do people use?

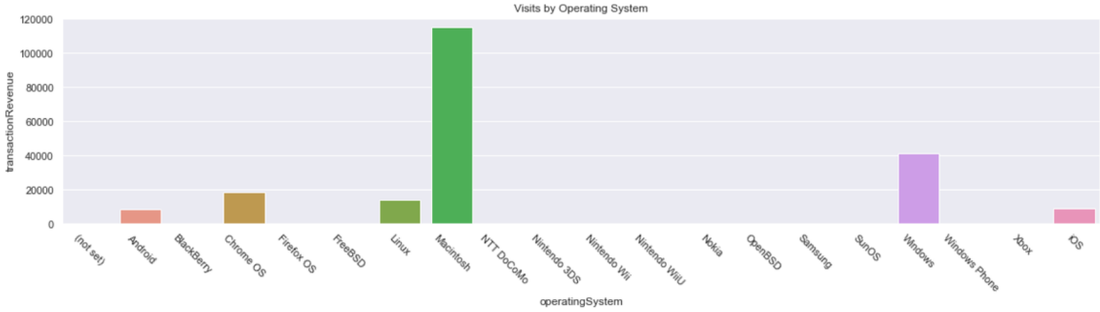




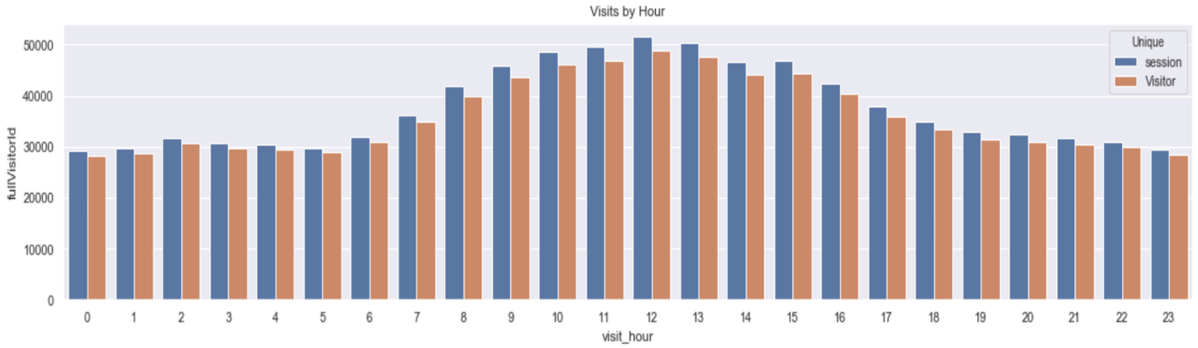


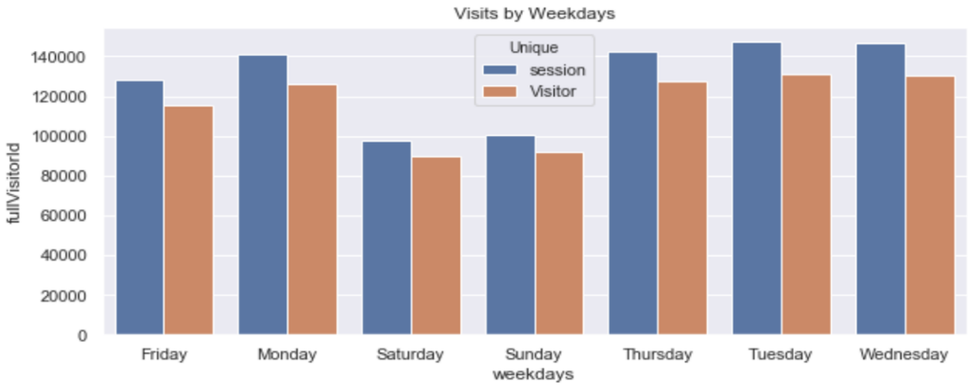


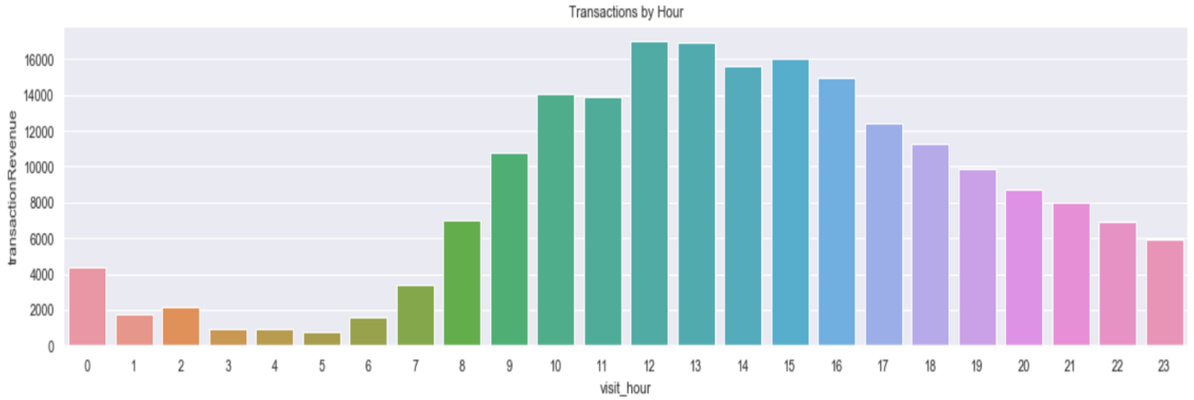


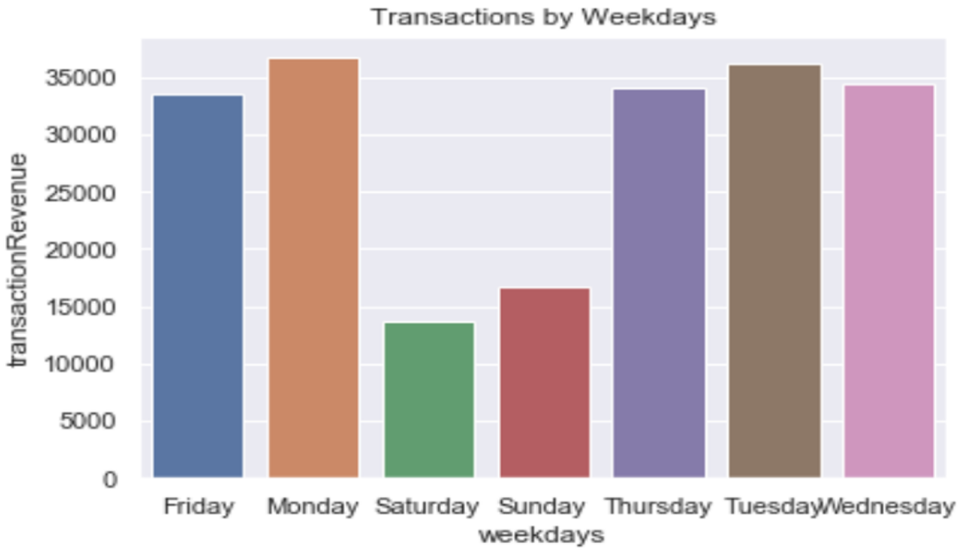


EDA - When do people visit?



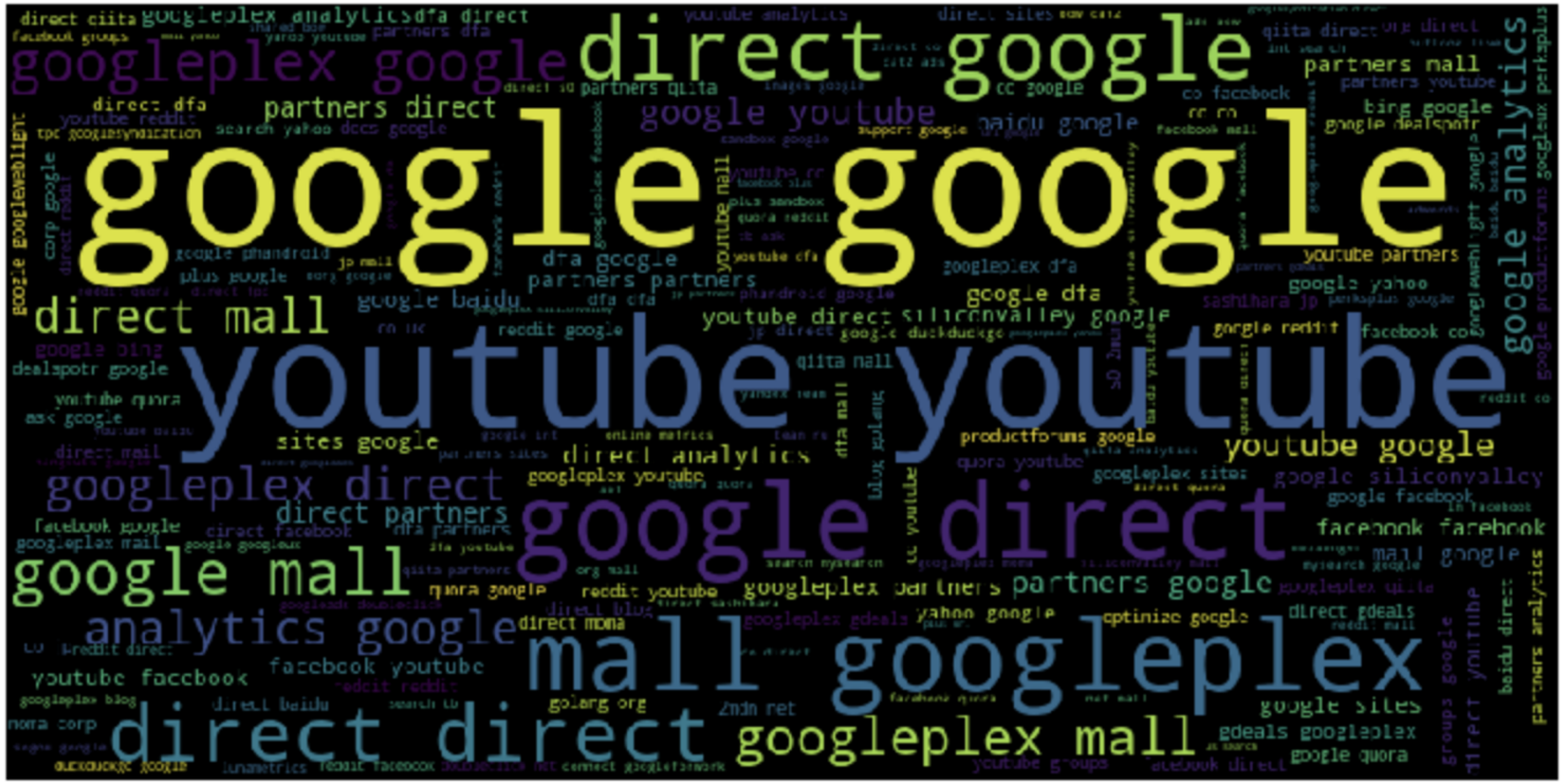




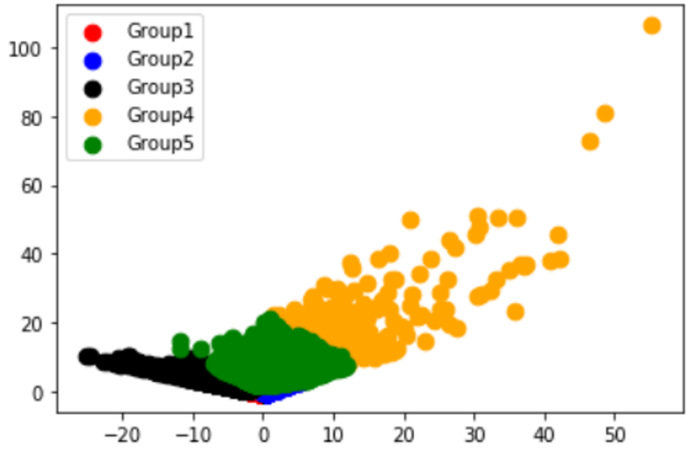


Word Cloud - Source Insights

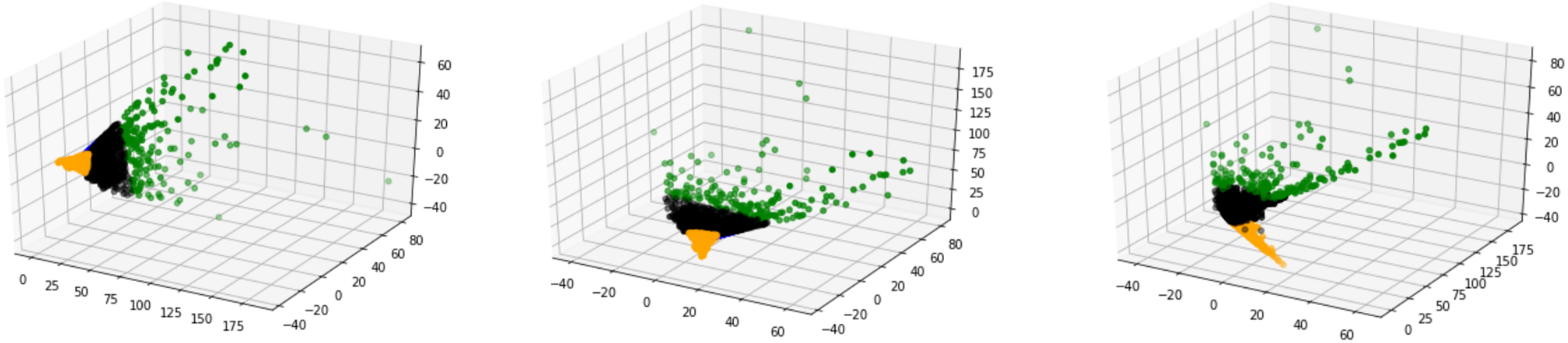
We leveraged word cloud in order to select a feature from the “source” column. Selecting features was a balance between quantitative and qualitative analysis. As per below, we considered visuals and even intuition for feature selection.



Clustering - PCA 2D and 3D cluster graphs



PCA 2D



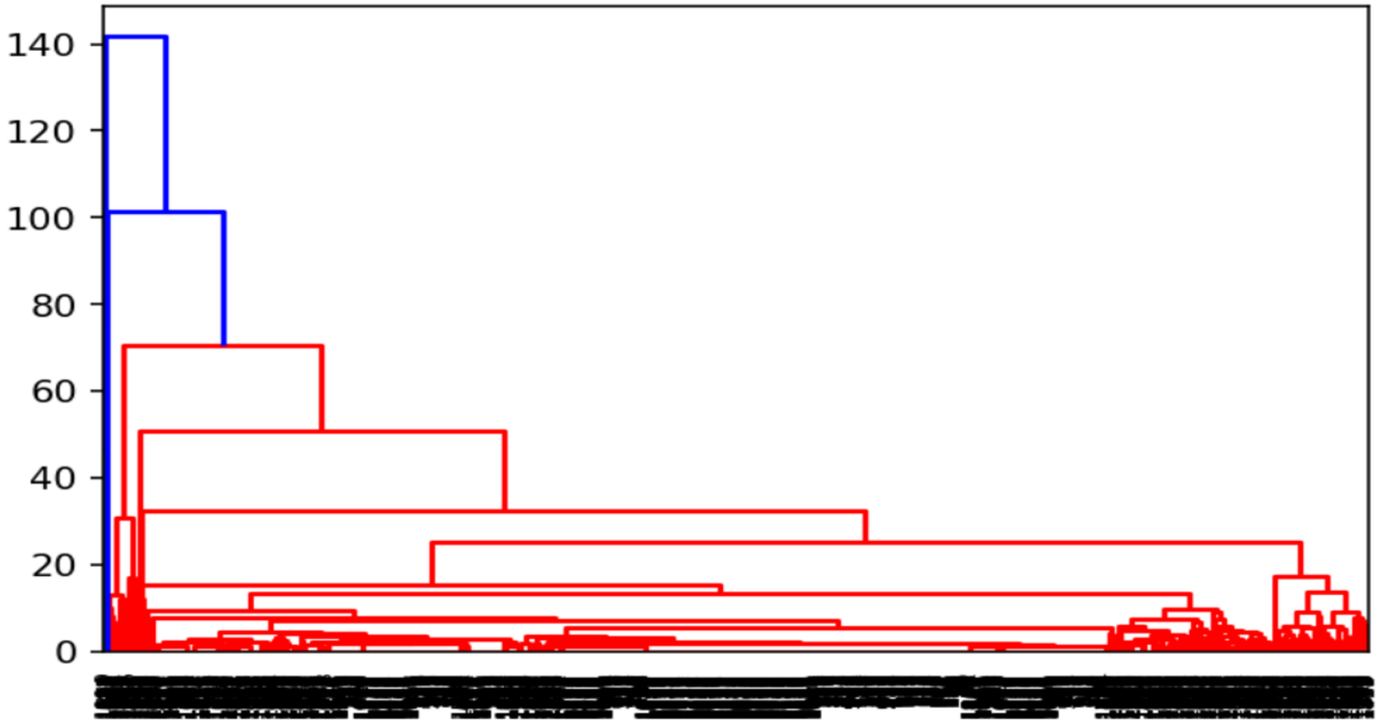
DIfferent angles of the 3D graph

Clustering - Centroid

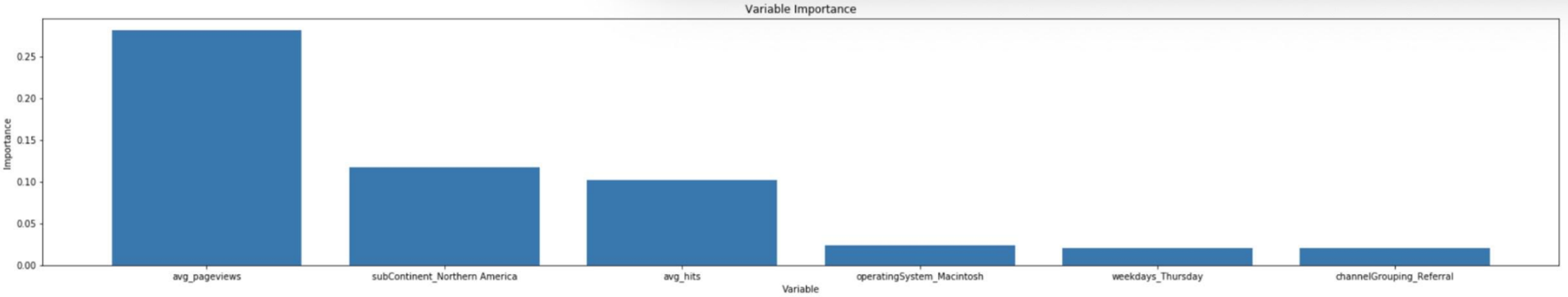
	TransactionRevenue	avg_hits	avg_pageviews	visitNumber	bounces	subContinent_Northern America	channelGrouping_Referral	operatingSystem_Macintosh
0	-0.110441	-0.393288	-0.428811	-0.057135	0.563936	-0.164687	-0.138419	-0.097527
1	1.790688	4.131920	4.134419	0.110488	-0.694717	0.399958	0.245629	0.142676
2	3.751890	0.320003	0.313998	28.197042	20.225843	23.089617	12.757502	16.358559
3	3.311221	0.895065	0.929444	3.952471	1.358732	3.830821	4.213349	3.546220
4	-0.108356	0.173239	0.217487	-0.099808	-0.740459	0.026308	-0.000229	-0.025073

Clustering - Hierarchical Clustering - with only 10k data. Memory error with entire data set

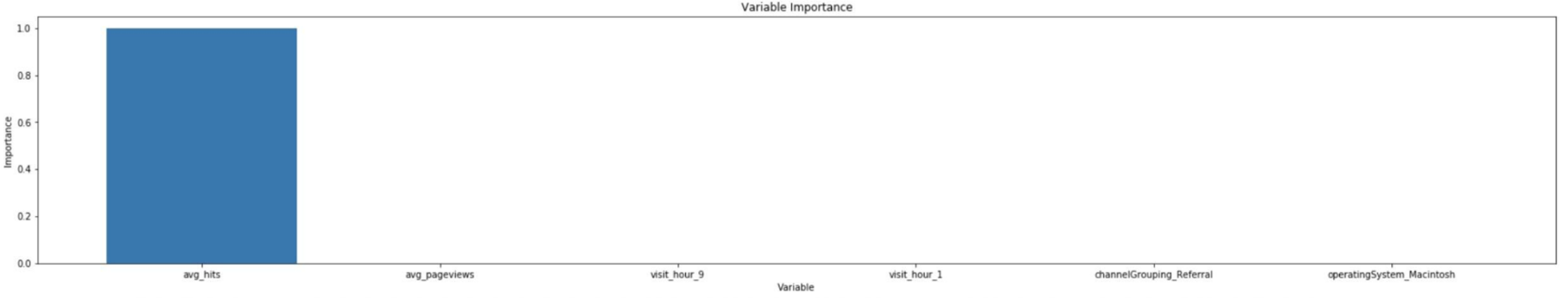
In [32]:
```
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import linkage, dendrogram

plt.rcParams['figure.dpi'] = 150

customer = split_data.index.values
customer_type = list(customer)
mergings = linkage(split_data, method='complete')

dendrogram(mergings,
           labels= customer_type,
           leaf_rotation=90,
           leaf_font_size=6)
plt.show()
```



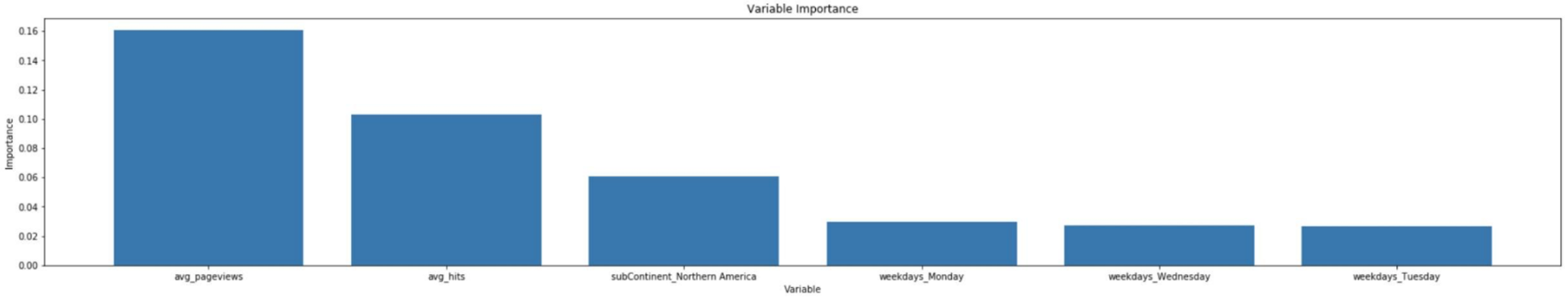
Cluster 1 Feature Importances



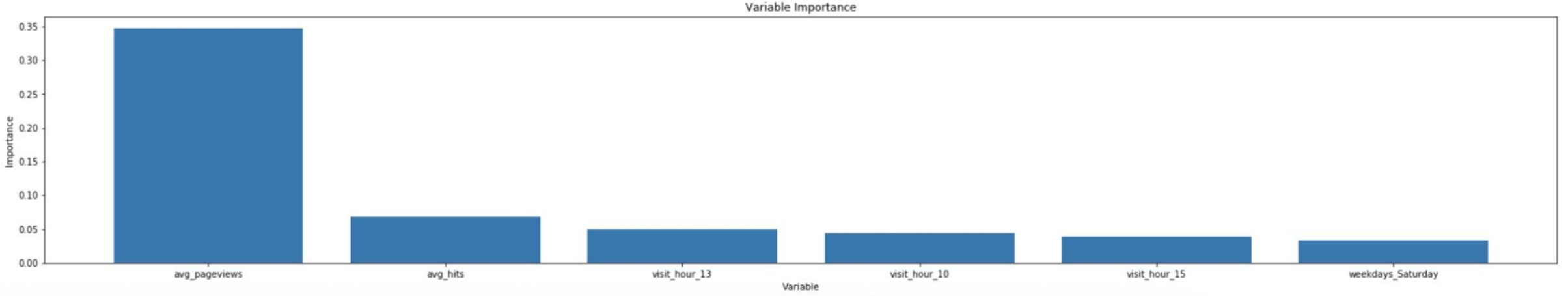
Cluster 2 Feature Importances



Cluster 3 Feature Importances



Cluster 4 Feature Importances

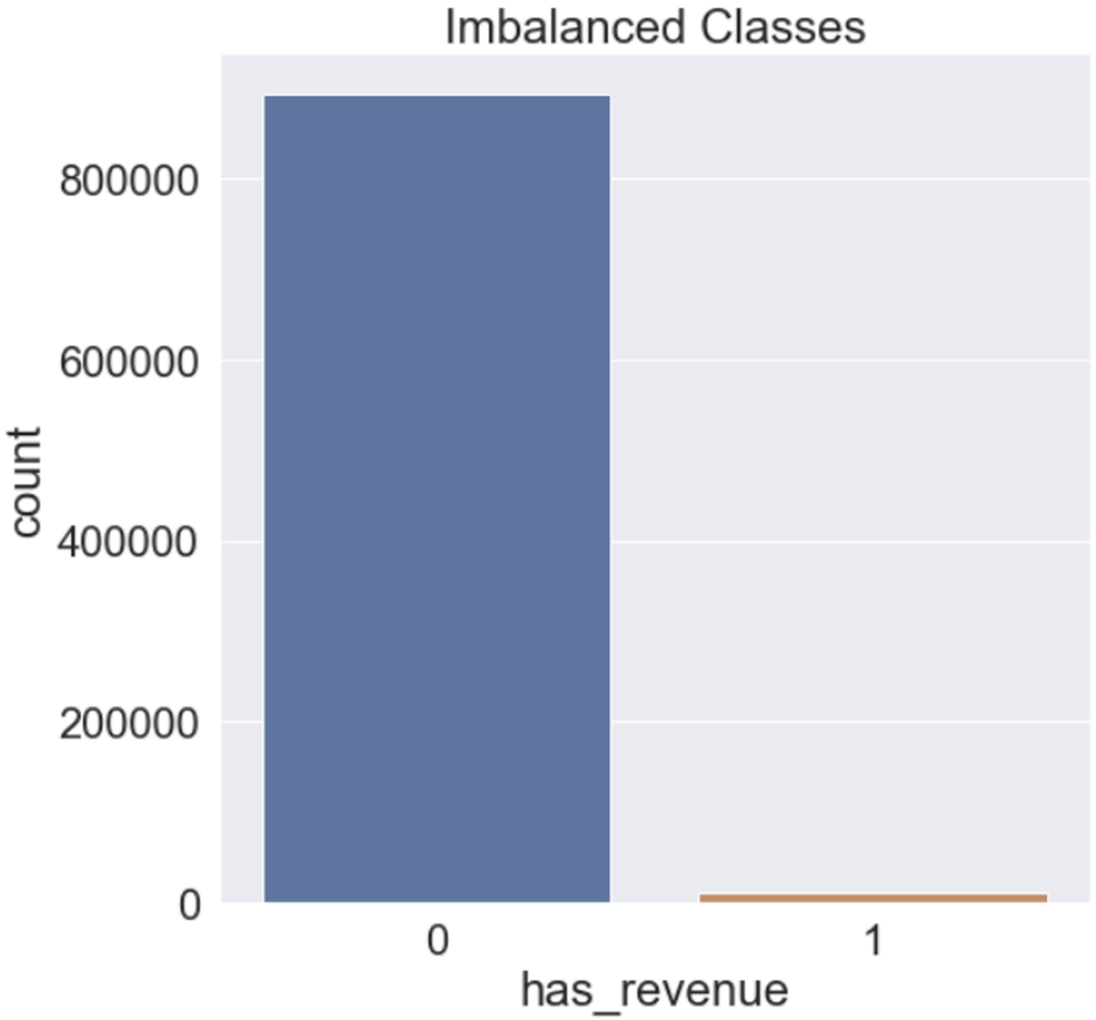


Bayesian Optimization

- Used for tuning the numerical hyperparameters
- Faster for hyperparameters to converge
- Assume a prior for objective function and update with data to convert it into posterior distribution

iter	target	learni...	max_depth	max_fe...	min_rows	ntrees
1	-4.102	0.3754	15.8	2.01	16.05	232.1
2	-4.098	0.0832	7.794	32.41	17.94	584.9
3	-4.099	0.3773	15.28	19.99	27.56	124.6
4	-4.101	0.6035	11.26	51.16	12.81	278.3
5	-4.097	0.7207	19.52	29.58	23.85	888.8
6	-4.1	0.8052	6.276	5.437	13.4	890.3
7	-4.102	0.0886	11.32	86.29	20.66	722.7
8	-4.099	0.284	15.3	75.45	10.37	775.1
9	-4.101	0.89	16.22	26.68	25.79	192.9
10	-4.103	0.4032	18.63	27.84	15.76	217.0
11	-4.101	0.1725	18.62	2.509	27.92	994.1
12	-4.099	0.01242	5.495	89.85	24.65	998.3
13	-4.098	0.146	16.86	88.16	28.31	999.6
14	-4.104	0.75	18.39	89.42	27.65	999.9

Imbalanced datasets to balanded datasets throgh undersampling



Data Fields

- *fullVisitorId*- A unique identifier for each user of the Google Merchandise Store.
- *channelGrouping* - The channel via which the user came to the Store.
- *date* - The date on which the user visited the Store.
- *device* - The specifications for the device used to access the Store.
- *geoNetwork* - This section contains information about the geography of the user.
- *socialEngagementType* - Engagement type, either "Socially Engaged" or "Not Socially Engaged".
- *totals* - This section contains aggregate values across the session.
- *trafficSource* - This section contains information about the Traffic Source from which the session originated.
- *visitId* - An identifier for this session. This is part of the value usually stored as the _utmb cookie. This is only unique to the user. For a completely unique ID, you should use a combination of fullVisitorId and visitId.
- *visitNumber* - The session number for this user. If this is the first session, then this is set to 1.
- *visitStartTime* - The timestamp (expressed as POSIX time).
- *hits* - This row and nested fields are populated for any and all types of hits. Provides a record of all page visits.
- *customDimensions* - This section contains any user-level or session-level custom dimensions that are set for a session. This is a repeated field and has an entry for each dimension that is set.
- *totals* - This set of columns mostly includes high-level aggregate data.