Pricing Products

for profit maximization

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Objective

Provide new business owners a starting point to price products based on the existing market

Framework

Data Cleaning → Exploratory Data Analysis (EDA) → Clustering → Multivariate Regression → Conclusion & Recommendation

Framework

- Dataset
- Process

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Framework

Data Cleaning → Exploratory Data Analysis (EDA) → Clustering → Multivariate Regression → Conclusion & Recommendation

Exploratory Data Analysis (EDA):

- Feature Engineering
- Insights

Framework

- Scope: **Phones** product sub-category
- Unsupervised clustering algorithms (KMeans, DBSCAN, Agglomerative Clustering)
- Evaluation metric: Distortion score to determine elbow and silhouette score

Data Cleaning → Exploratory Data Analysis (EDA) → **Clustering** → Multivariate Regression → Conclusion & Recommendation

Framework

Data Cleaning → Exploratory Data Analysis (EDA) → Clustering → **Multivariate Regression** → Conclusion & Recommendation

- Multivariate regression to view a good unit price range for each cluster
- Supervised regression algorithms (LassoCV, ElasticNet CV, Random Forest Regressor, Support Vector Regressor, XG Boost Regressor)
- Evaluation metric: R2 score

Framework

Data Cleaning → Exploratory Data Analysis (EDA) → Clustering → Multivariate Regression → Conclusion & Recommendation

- Conclusion
- Further development
- Limitations and challenges

Data Cleaning

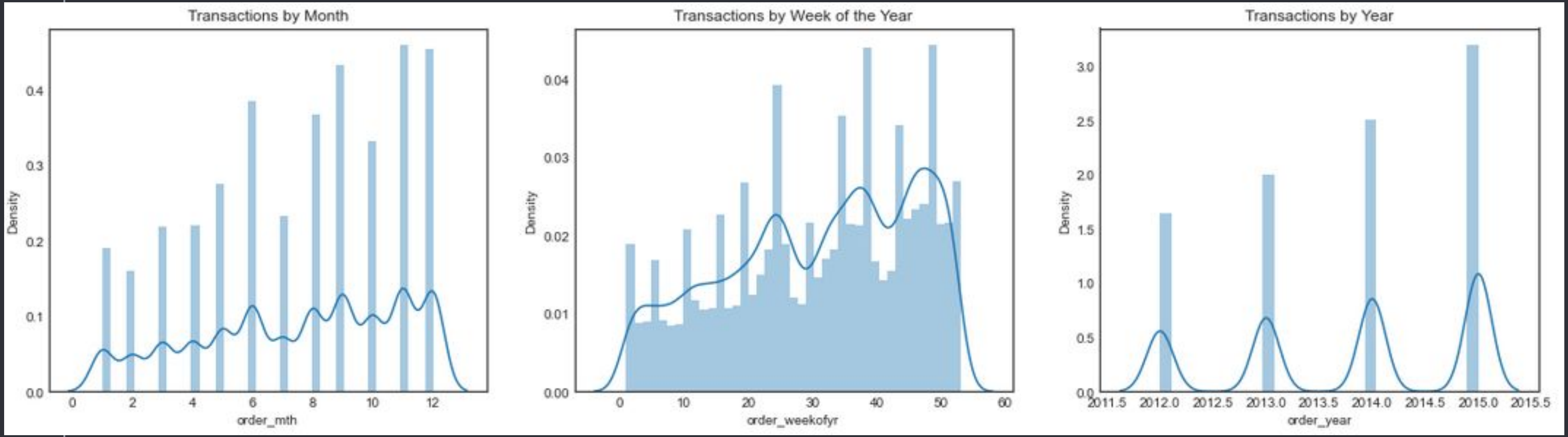
Dataset

- Global superstore data
- Compilation of transactions from retailers worldwide
- 2012 to 2015
- >50,000 rows of data
- 51 features
- Product categories : Technology, Furniture and Office Supplies

Cleaning process

- Removed features with substantial (>70%) missing values
- Removed those that do not provide added value eg. Product ID is unique to every product but would not help with clustering.
- Removed outliers

Exploratory Data Analysis (EDA)



Transaction count on a monthly, weekly and yearly basis

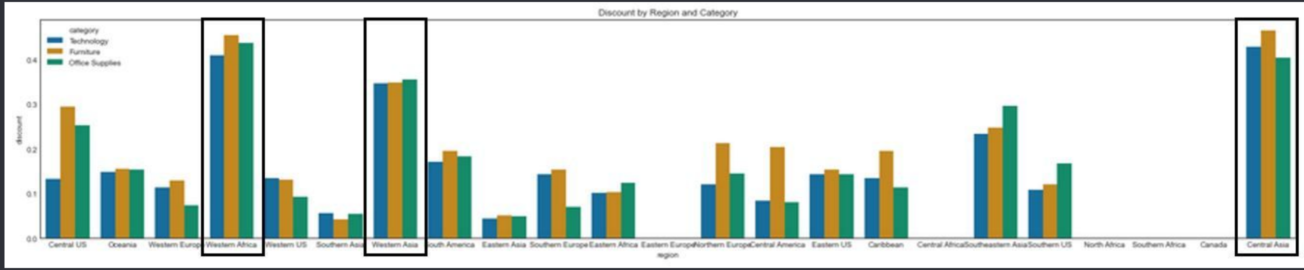
- Growing affluence over the years
- Seasonality in sales (more sales towards the end of the year - Christmas/ bonus payouts)

Exploratory Data Analysis (EDA)

Profit, sales and shipping cost of transactions by region and category

- Unprofitable regions : Western Africa, Western Asia and Central Asia
- Generally have lower sales and shipping cost
- Shipping cost across regions follow the same trend as sales

Exploratory Data Analysis (EDA)



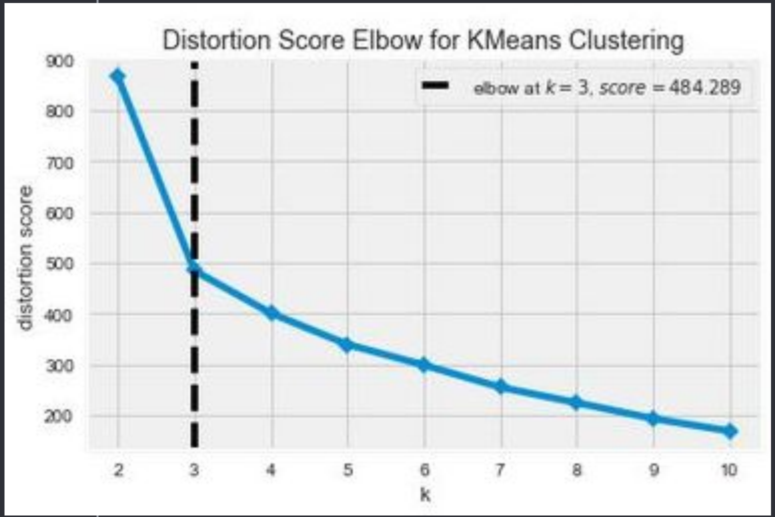
Transactions discount by region and category

- Unprofitable regions : Western Africa, Western Asia and Central Asia
- Generally have much higher discounts than other regions

Feature Engineer

- Heavily discounted (>0.3%) regions
- Non-profitable regions

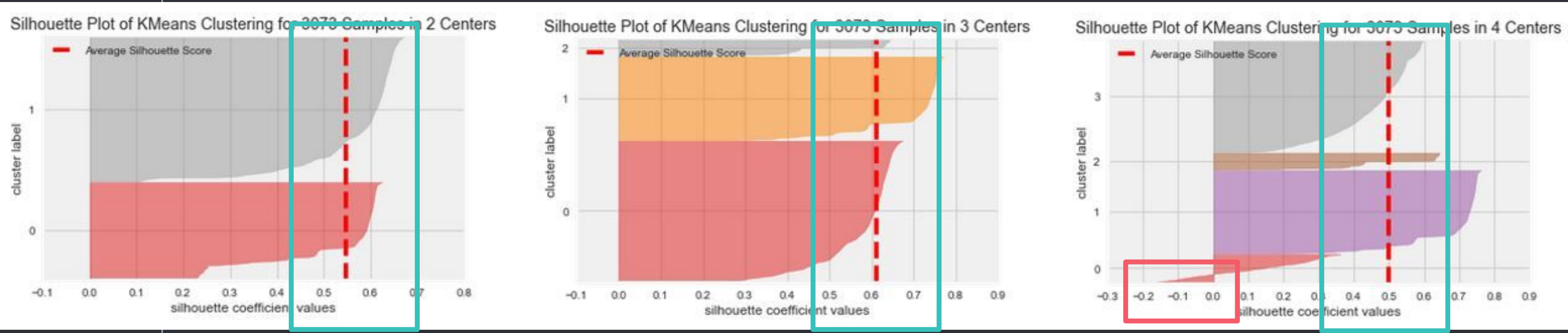
Clustering - KMeans



Distortion score :
Sum of squared errors from each point to its assigned centre

- **Phones** subcategory
- Determine optimal number of clusters using the elbow method
- Range of 2 to 10 clusters
- Identify a point as number of clusters increase, where the distortion score start to flatten, forming an elbow.
- Optimal number of clusters : **3**

Clustering - KMeans



Silhouette score :

Considers both the average intra-cluster distance and average inter-cluster distance. A score close to 1 means that clusters are well apart from each other and clearly distinguished.

- Positive silhouette coefficient values
- Each individual cluster having silhouette scores above the average
- **3** centers/clusters have the highest silhouette score of **~0.61**

Clustering - DBSCAN

- Well-suited for discovering data with arbitrary shapes

Silhouette Score on parameters and clusters		
Number Of Clusters	Param - Minimum Samples	Silhouette Score
35	3	0.282
13	10	0.271
6	100	0.121

- Silhouette score is significantly lower than KMeans
- Suggests that dataset comprise data points with varying density, resulting in very high number of clusters, with very low silhouette score.

Clustering - Agglomerative Clustering

- Works in a “bottom-up” manner whereby each object is initially considered as a single element cluster (leaf)
- At each step of the algorithm, two clusters that are most similar are combined into a bigger cluster (nodes)
- Process is repeated until all points are a member of a single big cluster

Silhouette Score on Clusters

Number Of Clusters	Silhouette Score
2	0.5429
3	0.61
4	0.4698
5	0.4746
6	0.481
7	0.4279
8	0.4399
9	0.4418
10	0.4637

- **3** clusters are optimal with silhouette score of **0.61**
- Results are similar to KMeans

Clustering - Conclusion

KMeans

- 3 clusters with 0.61 silhouette score
- Neighbouring clusters (2 clusters and 4 clusters) have higher silhouette scores than Agglomerative

DBSCAN

- 35 clusters with 0.282 silhouette score

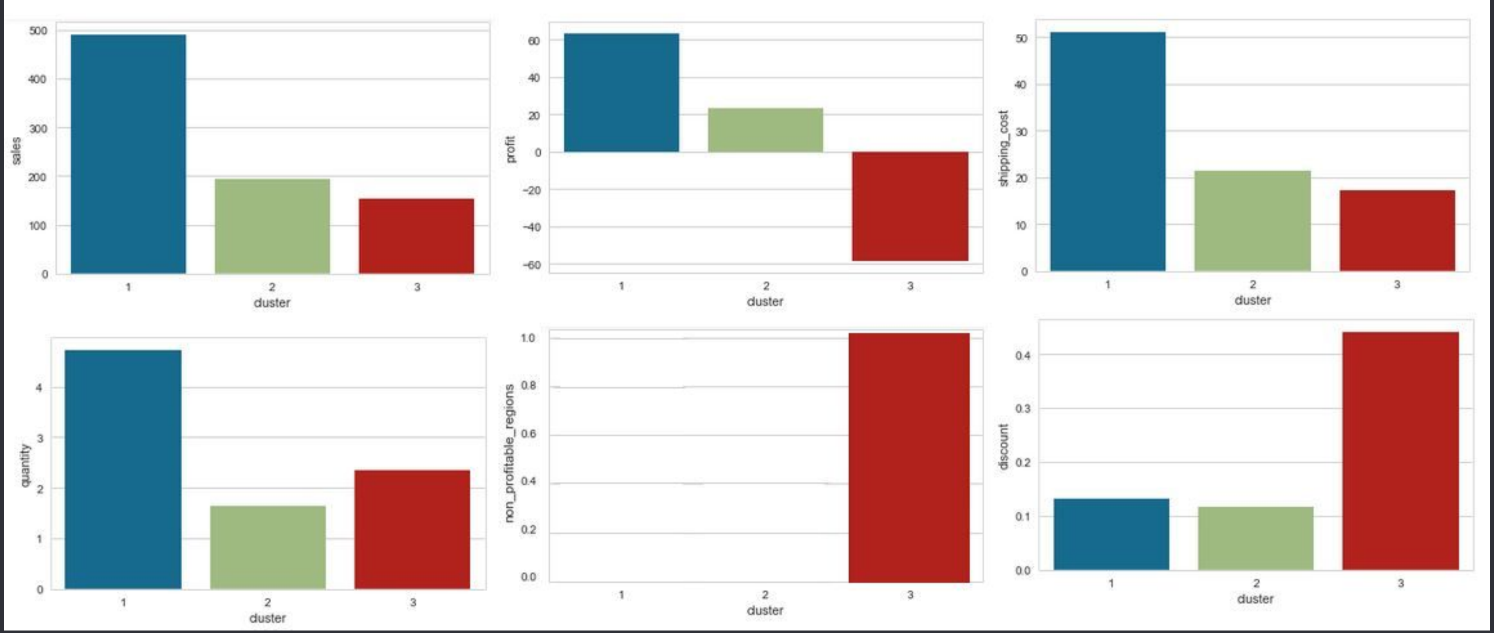
Agglomerative

- 3 clusters with 0.61 silhouette score

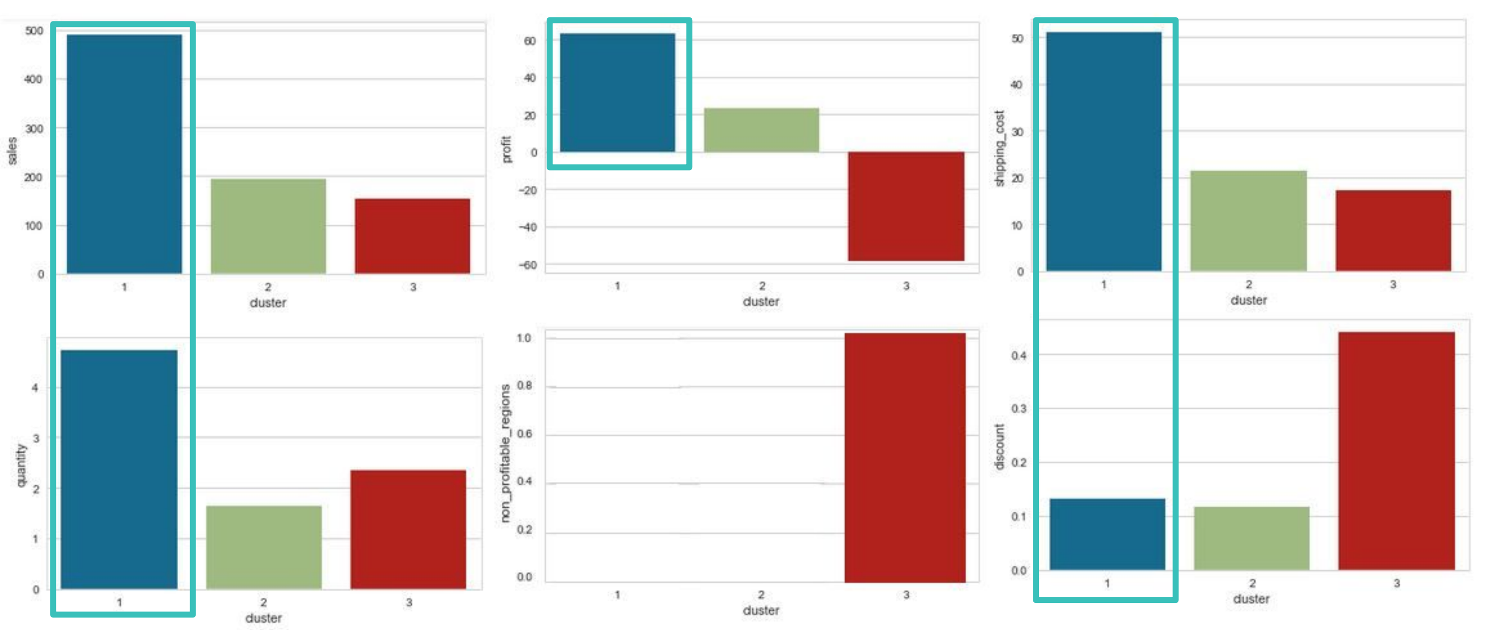
Selected Model : KMeans

Clustering - Characteristics

- Apply cluster labels from KMeans on dataset
- Identify characteristics



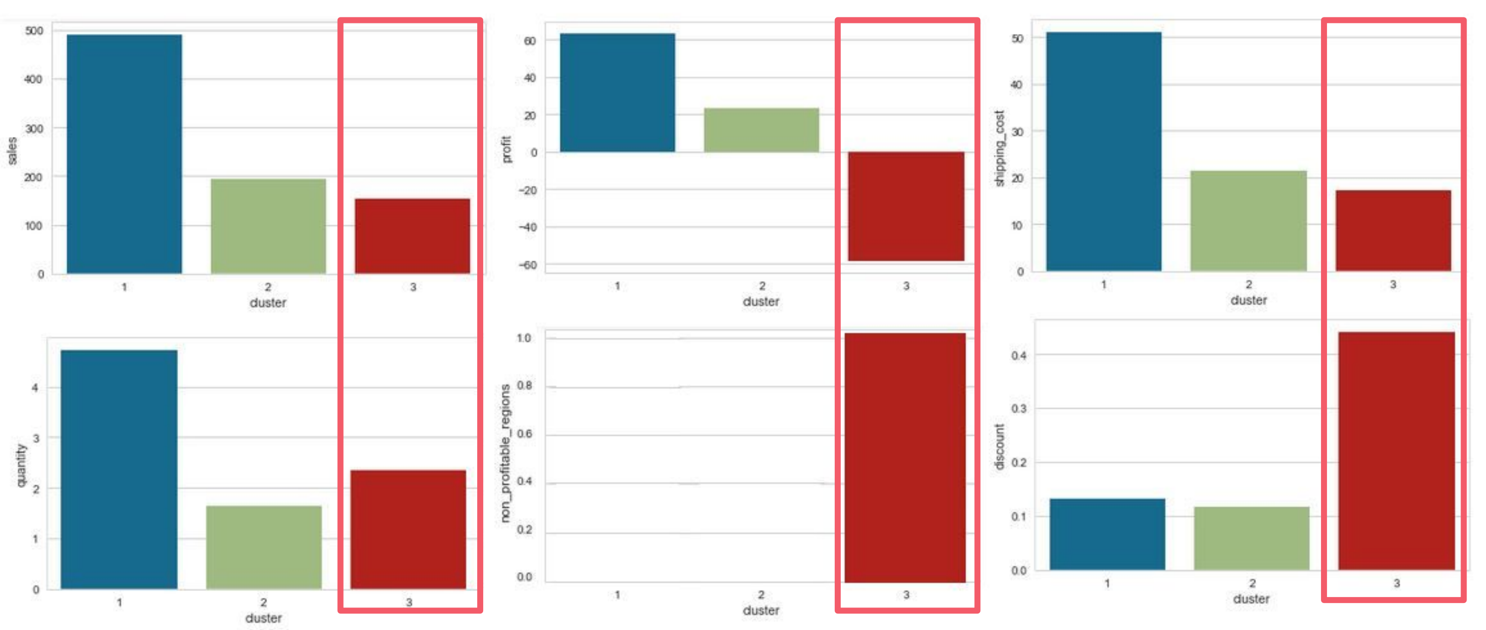
Clustering - Characteristics



Cluster 1

- Highest sales and most profitable
- Most quantity purchased (>3)
- Relatively low discounts (~0.1%)
- Excludes transactions from unprofitable regions

Clustering - Characteristics



Cluster 1

- Highest sales and most profitable
- Most quantity purchased (>3)
- Relatively low discounts (~0.1%)
- Excludes transactions from unprofitable regions

Cluster 2

- Moderate sales and profit
- Lower quantities (<3) purchased
- Relatively low discounts (~0.1%)
- Excludes transactions from unprofitable regions

Cluster 3

- Unprofitable, lowest sales
- Lower quantity (<3)
- High discounts (>0.3%)
- Non-profitable regions : Western Africa, Western Asia and Central Asia

Multivariate Regression

- Perform multivariate regression on each cluster
- Nested cross-validated R2 score to select best algorithm

Cluster 1

Cross-validated R2 score		
Algorithms	R2 Score	Standard Deviation
Elastic Net CV	88.3%	+/- 2.1%
Lasso	88.4%	+/- 2.1%
Random Forest Regressor	96.0%	+/- 1.2%
Support Vector Regressor	88.2%	+/- 2.4%
XGBoost Regressor	99.0%	+/- 0.4%

Cluster 2

Cross-validated R2 score		
Algorithms	R2 Score	Standard Deviation
Elastic Net CV	92.4%	+/- 2.7%
Lasso	92.5%	+/- 2.7%
Random Forest Regressor	94.8%	+/- 0.6%
Support Vector Regressor	92.4%	+/- 2.4%
XGBoost Regressor	97.39999999999999%	+/- 1.2%

Cluster 3

Cross-validated R2 score		
Algorithms	R2 Score	Standard Deviation
Elastic Net CV	71.6%	+/- 10.5%
Lasso	70.89999999999999%	+/- 11.1%
Random Forest Regressor	90.5%	+/- 2.5%
Support Vector Regressor	72.7%	+/- 9.6%
XGBoost Regressor	92.80000000000001%	+/- 1.3%

- Generally tree-based algorithms and support vector regressor work better

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- Generally tree-based algorithms and support vector regressor work better
- For interpretive value, I select the better of regularised regression model for each of the clusters
  - Cluster 1 : Lasso
  - Cluster 2 : Lasso
  - Cluster 3 : Elastic Net
- Obtain the coefficients and y-intercepts, to plot the regression line

Conclusion and Recommendation

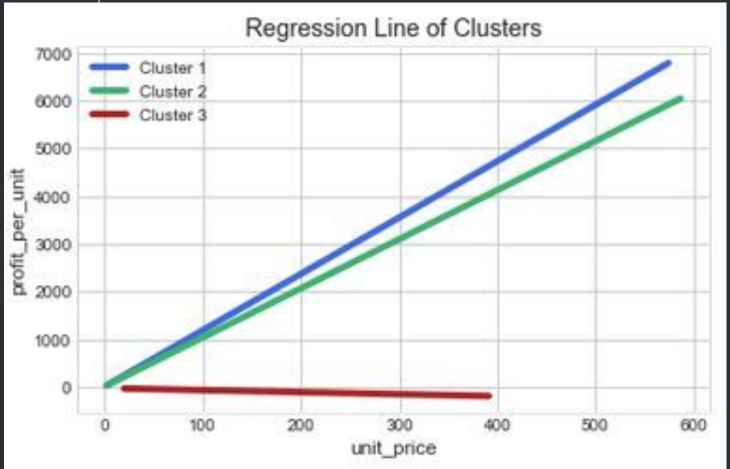
- How profit per unit changes with unit price

- Avoid selling phones at Western Africa, Western Asia, or Central Asia as all phone sales here are not profitable at any unit price

- Focus on selling phones in other regions

Conclusion and Recommendation

- How profit per unit changes with unit price



- Between Cluster 1 and Cluster 2, Cluster 1 comprise transactions with more quantities purchased than Cluster 2. These are probably corporate consumers.

- Target corporate consumers and consider providing bulk discounts or include free phone accessories if more phones are purchased.

Further Development

Customer Segmentation

- With customer details (eg. propensity to spend, age, income), can consider grouping by customers to provide more insights into consumer purchase behaviour
- Targeted marketing to each customer cluster

Breadth and/or Depth

- Analyse deeper within the product subcategory (eg. into specific phone brands, or specific phone models)
- Analyse other categories outside of phones

Limitations and Challenges

Nature of setting prices

- Attempted to price a product based purely on historical transactional data but pricing is as much art as it is science
- Several other external factors that influence prices eg. branding, marketing and advertising.

Scaling and Monitoring

- Consumer purchase behaviour changes over time and so there has to be consistent monitoring
- Scaling may be an issue as more consumers are added to the database, much more processing power is needed to handle huge amounts of data.

Thank You

Q&A