Customer Segmentation Analysis

— By **Jiayi Jiang**

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Problem Identification

Given HP's **first hand data** of printer and ink customers,
how to **maximize customer lifetime value**?

Defining customer lifetime value as **revenue brought by each customer**:

Revenue =

Personal Printer 15%

+

Supplies 62%

Printer Purchase
- Number of Printers Purchased
- Purchase frequency

Supplies Consumption
- Pages printed/month
- Ink consumption/month

Revenue Drivers

x

Customer Loyalty

To be specific:

How to increase each customer's **printing volume and frequency**,
extend duration of customer engagement, and **boost repurchase rate**?

↓

With current data, our solution:

Use a **machine learning** model to cluster customers
with similar **purchase and usage habits,**
identify **distinct features**,
and provide different business recommendations accordingly

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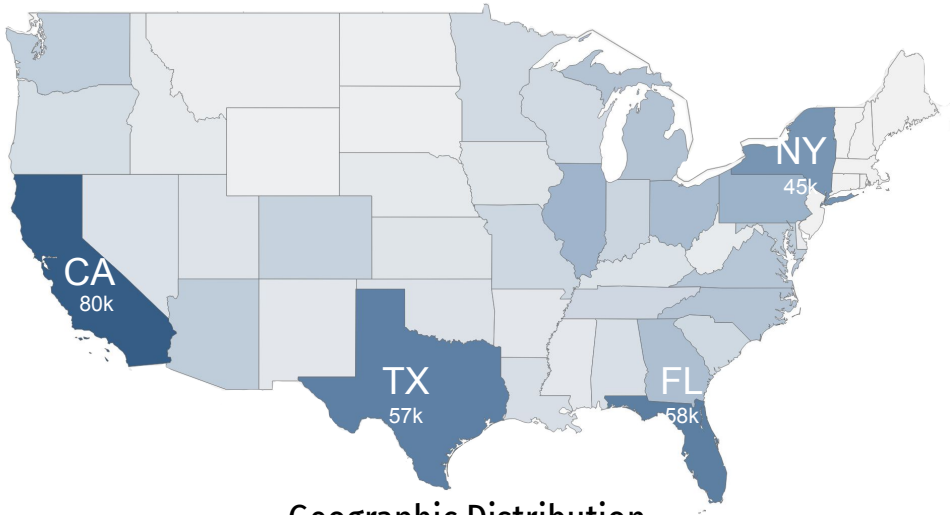
Exploratory Data Analysis

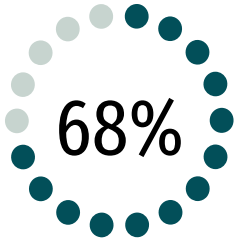
Diversified customer composition



Geographic Distribution

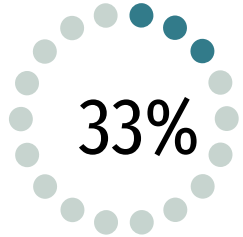
(According to counts of zip codes)

Major markets spread across different regions of the country



Devices for Home Usage

Max=Home-Personal Min=Office



Users with Household of 2

Min=9 Max=2

Exploratory Data Analysis

Printer

$113~$157	Price range of 50% of purchases; avg price $159.45
96%	Percentage of customers who purchased only once
4~5 months	Gap between first and last purchase for returning customers

Average annual ink consumption per customer per printer	**66 cc**
Percentage of Ink of total consumption	**94%**
Percentage of printers registered for Ink plans	**37%**

Ink

Contents

Key Definition & Assumption

Repurchased

Bought more than 2 products
on different dates
within 12 months

Shared account

1 registered account may
contain more than 1 user

Cluster

Segment customers into
distinct clusters

Feature Engineering

01

Outlier and Null Value Treatment

- Dropped outliers of each column
- Replaced nulls with column means, randomly assigned values based on original ratios

02

Calculation and Variable Pre-Selection

- Calculated '# of printers' and RFM (Recency, Frequency, Monetary) value for each customer
- Dropped variables unrelated to the current problem, Feature selection

03

Categorical Variable Encoding

- Transformed some of the categorical variables to dummy values

04

Scaling

- As we are using the k-means clustering model, which groups the customers according to the distance between them, we scaled the data to avoid the influence of units

Customer “RFM” Features

1

Recency

Time since the most recent purchase

2

Frequency

Average time between purchases (Intensity)

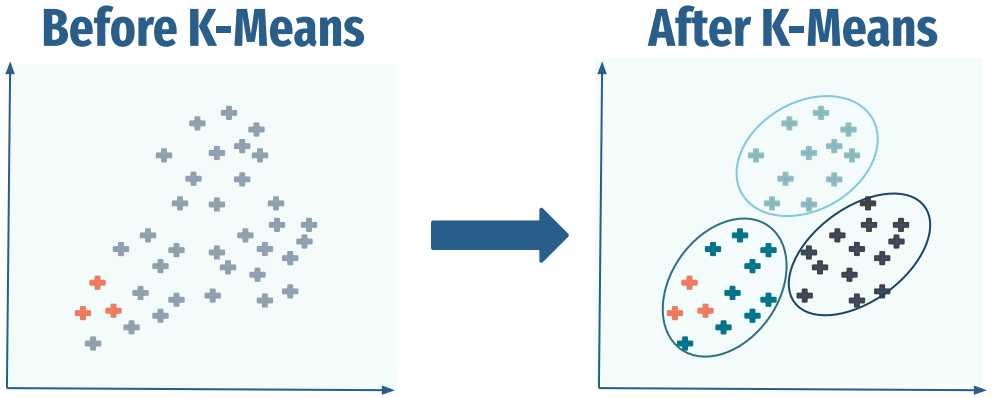
3

Monetary

Total and average purchase values

Model Introduction K-means Clustering

- Customer RFM
- Customer Geographics
- Customer Interests
- Customer Usage



K-Means clustering will group together customers with similar characteristics

Has the clustering worked ?

To validate the clustering algorithm, we checked for significant differences in **proportions of repurchase customers** among the groups.

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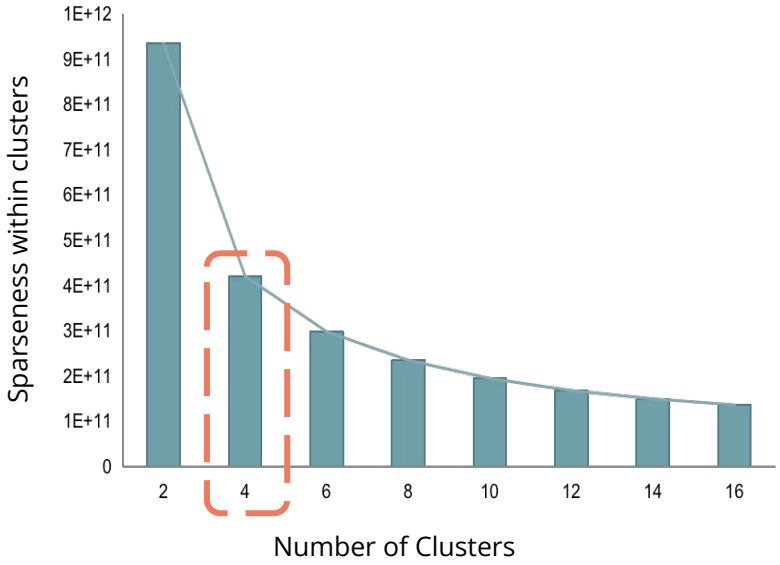
Model Result & Evaluation

Choosing the number of clusters



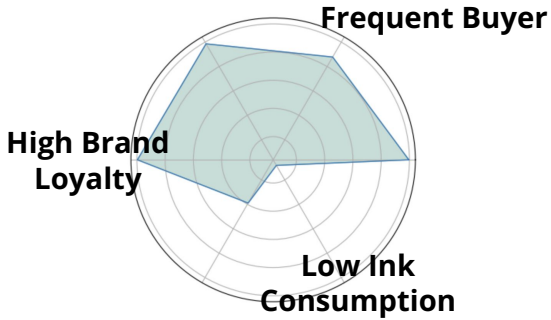
Optimal Number of Clusters = 4

Data of each cluster

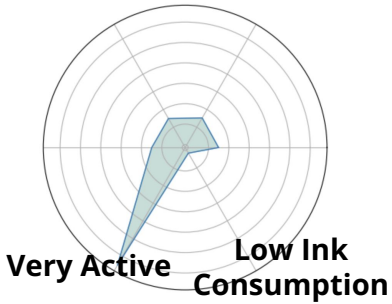
Cluster	Repurchased	# of Printers	Ink/Mo	Active Days
1	No	1	7 cc	455
2	No	1	7 cc	541
3	No	1	11 cc	584
4	Yes	2	11 cc	451

Cluster 4 contains the most of the repurchasing customers

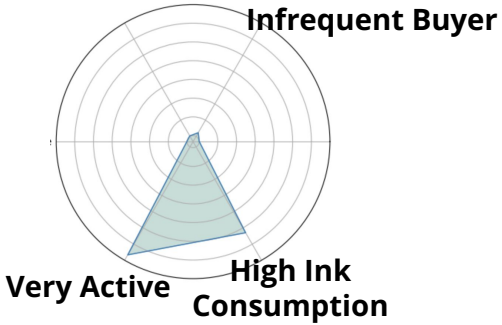
Cluster 1
Fans who don't print much



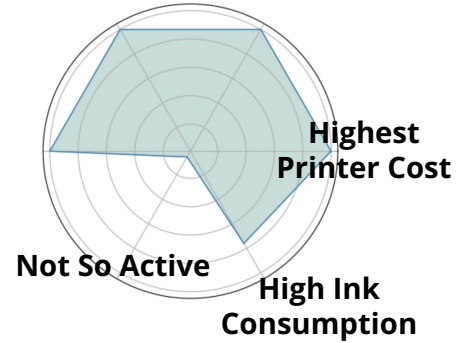
Cluster 2
Print a bit every day



Cluster 3
Heavy users



Cluster 4
MVP users



Note: Graphs created with Google Cloud products

Recommendations

Different Clusters, Different Strategies

01 Purchase

- Frequent buyers: promote either cheaper or more pricey products

- Infrequent buyers: promote medium-priced products

02 Printing

- Diversified printing habits require more flexible ink plans

- Leverage Smart data that captures usage patterns to design more ink subscription options

03 Retention

- Improve activeness might not improve loyalty

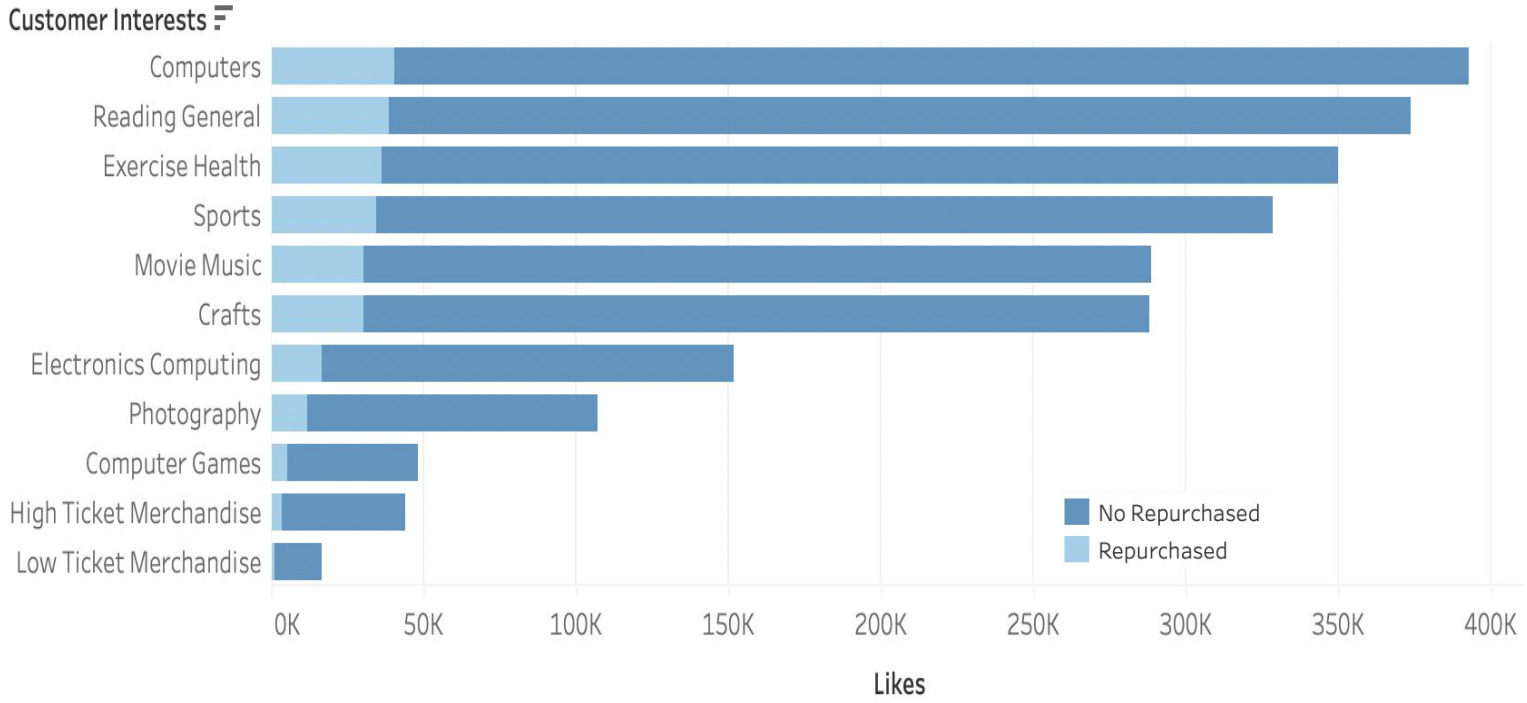
- Ink plan subscription increases stickiness while bringing stable revenue

Thank you!

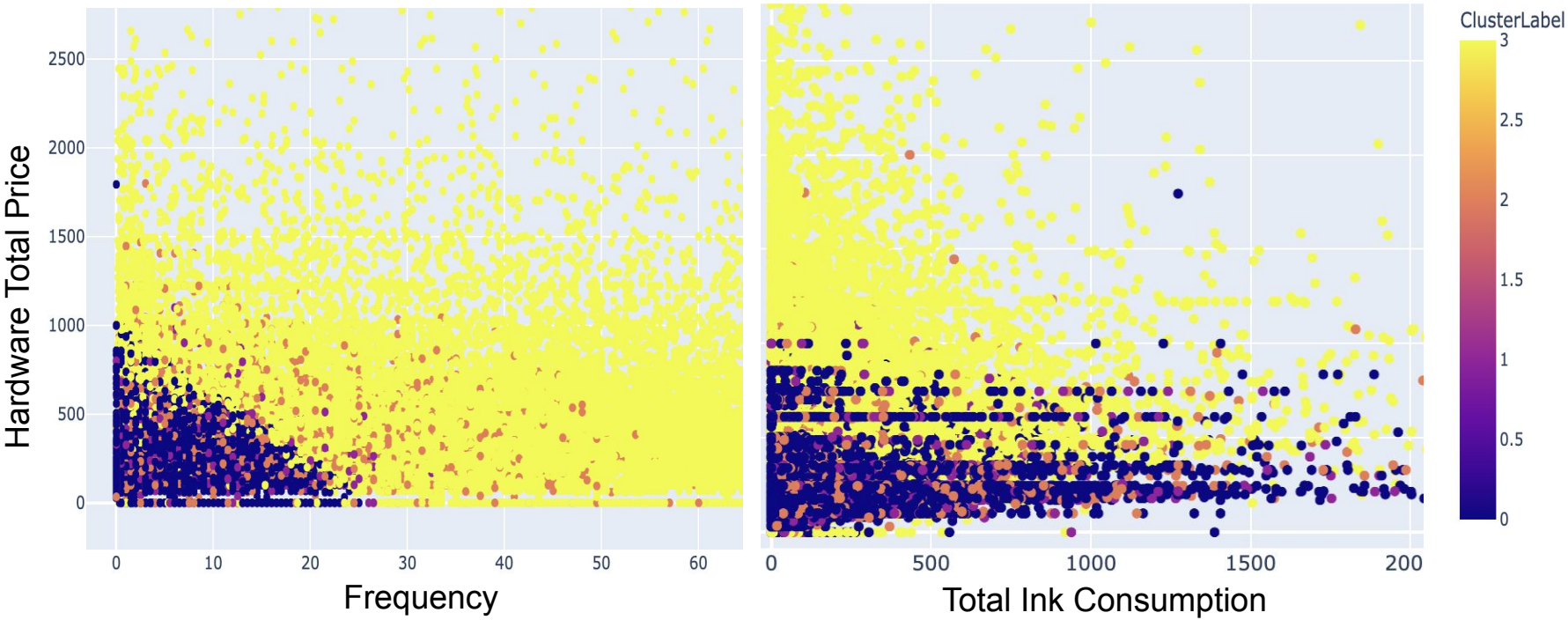
Welcome all the questions and feedback!

Appendix

Customer Interests — Repurchased VS. No Repurchase



Frequency / Ink Consumption vs Hardware Total Price



Model Evaluation

Metrics

We used the elbow method to determine the optimal number of clusters (k) for our clustering algorithm.

Result

The “elbow curve” describes the “inertia”, which is the sum of squared distances between each data point and its nearest centroid, against the number of clusters (k).

Decision

Our evaluation result indicates the optimal k = 4 after which the WCSS (Within Cluster Sum of Square) decreases slowly.

Model Evaluation - ARI Metric

Metrics

We used the Adjusted Rand Index is clustering evaluation metric that measures the similarity between the true labels and the predicted cluster labels.

Result

We get Adjusted Rand Index = 0.05900098600331566

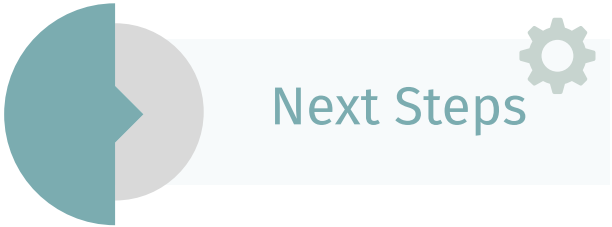
Decision

The value of ARI is close to zero, which indicates that the true labels and the predicted cluster labels is no better than what would be expected by chance

Discussion

Limitation and next steps

1. Detailed **product data** and **customer preference data** not available
2. No **synergy between PC and printers** is considered
3. K-Means clustering may **has less prediction power for future new data**



Predict the repurchase **propensity score** for each customer to better quantify the clustering results