Infotact Solutions

Customer Segmentation using K-Means

INTERNSHIP

Problem Statement

- Businesses struggle with generic marketing \rightarrow wasted ad spend.
- Customers have different spending behaviors.
- Goal: Segment customers into groups for personalized marketing.

Dataset Overview

Customer Segmentation using K-Means

- Source: customer_shopping_data.csv from Kaggle
- 143,622 transactions, 10 columns
- Key features: Age, Gender, Category, Quantity, Price, Payment method, Mall
- Granularity: Transaction-level \rightarrow aggregated to customer-level

☑ Dataset loaded successfully!
Shape: (143622, 10)

First 5 rows:

shopping_mall	invoice_date	payment_method	price	quantity	category	age	gender	customer_id	invoice_no	
Kanyon	5/8/2022	Credit Card	1500.4	5	Clothing	28.0	Female	C241288	1138884	0
Forum Istanbul	12/12/2021	Debit Card	1800.51	3	Shoes	21.0	Male	C111565	1317333	1
Metrocity	9/11/2021	Cash	300.08	1	Clothing	20.0	Male	C266599	1127801	2
Metropol AVM	16/05/2021	Credit Card	3000.85	5	Shoes	66.0	Female	C988172	1173702	3
Kanyon	24/10/2021	Cash	60.6	4	Books	53.0	Female	C189076	1337046	4

Data Cleaning (Week 1)

Customer Segmentation using K-Means

- Removed 31,000 duplicate rows
- Fixed missing values & datatypes
- Removed invalid values (negative prices, unrealistic ages)
- Final dataset: 112,002 clean records

Cleaned dataset shape: (112002, 10)

	invoice_no	customer_id	gender	age	category	quantity	price	payment_method	invoice_date	shopping_mall
0	1138884	C241288	Female	28.0	Clothing	5	1500.40	Credit Card	2022-08-05	Kanyon
1	1317333	C111565	Male	21.0	Shoes	3	1800.51	Debit Card	2021-12-12	Forum Istanbul
2	1127801	C266599	Male	20.0	Clothing	1	300.08	Cash	2021-11-09	Metrocity
3	1173702	C988172	Female	66.0	Shoes	5	3000.85	Credit Card	2021-05-16	Metropol AVM
4	1337046	C189076	Female	53.0	Books	4	60.60	Cash	2021-10-24	Kanyon

Handle Duplicates

We check for duplicate rows and remove them to avoid biased analysis.

```
dup_count = df.duplicated().sum()
print("Duplicate rows before:", dup_count)

# Remove duplicates
df = df.drop_duplicates()

print("Duplicate rows after:", df.duplicated().sum())
```

Duplicate rows before: 31615
Duplicate rows after: 0

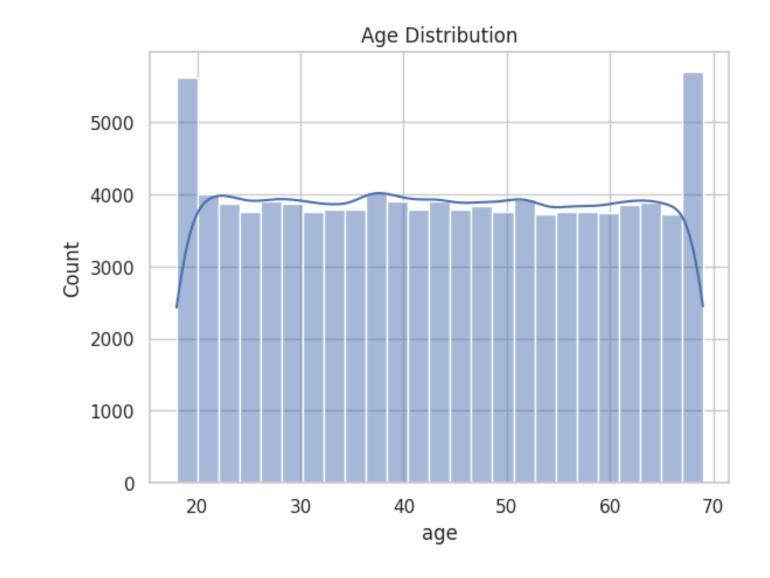
Feature Engineering

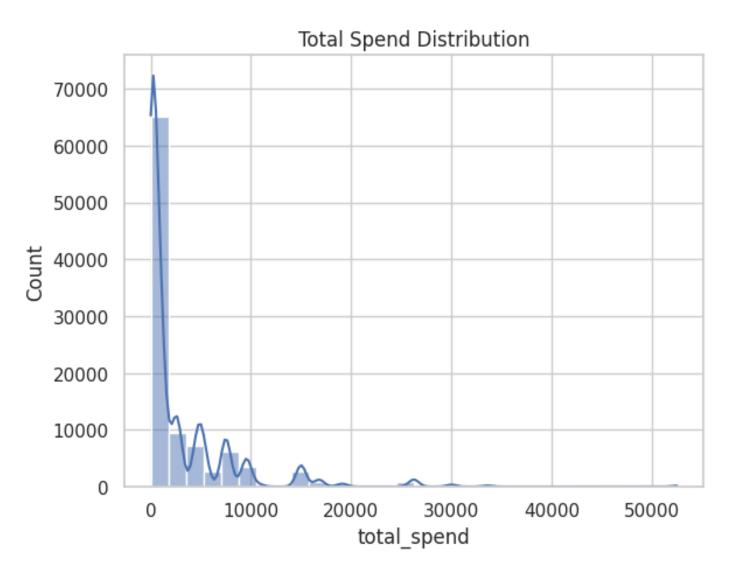
- Aggregated features per customer:
- Total spend
- Total quantity
- #Unique categories, malls
- Recency (days since last purchase)
- Invoice count
- Added line_amount = quantity × price

	customer_id	gender	age	total_spend	total_quantity	unique_categories	unique_malls	first_purchase	last_purchase	num_
0	C100004	Male	61.0	7502.00	5	1	1	2021-11-26	2021-11-26	
1	C100005	Male	34.0	2400.68	2	1	1	2023-03-03	2023-03-03	
2	C100006	Male	44.0	322.56	3	1	1	2022-12-01	2022-12-01	
3	C100012	Male	25.0	130.75	5	1	1	2021-08-15	2021-08-15	
4	C100019	Female	21.0	35.84	1	1	1	2021-07-25	2021-07-25	

Exploratory Data Analysis (EDA)

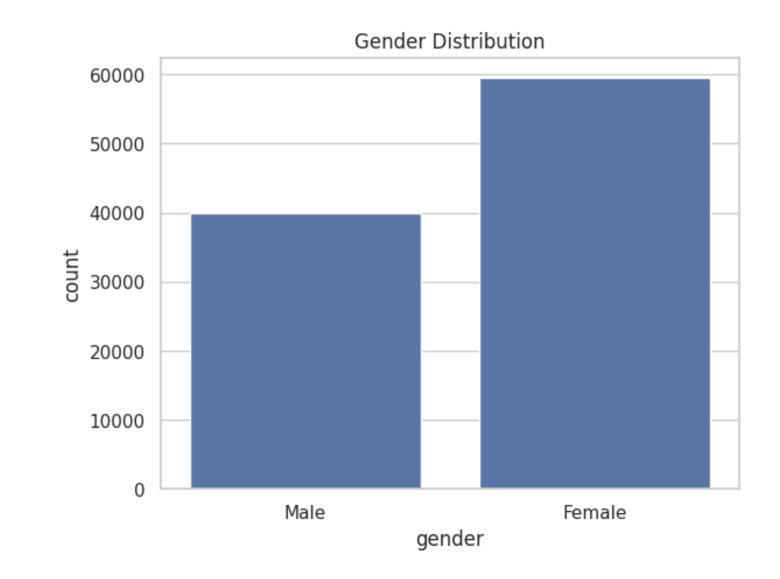
- Age Distribution: 20–60 dominates
- Spend Distribution: Skewed, few high spenders
- Gender: Balanced
- Recency: Many inactive
- Correlations: Spend ↔ Quantity strong

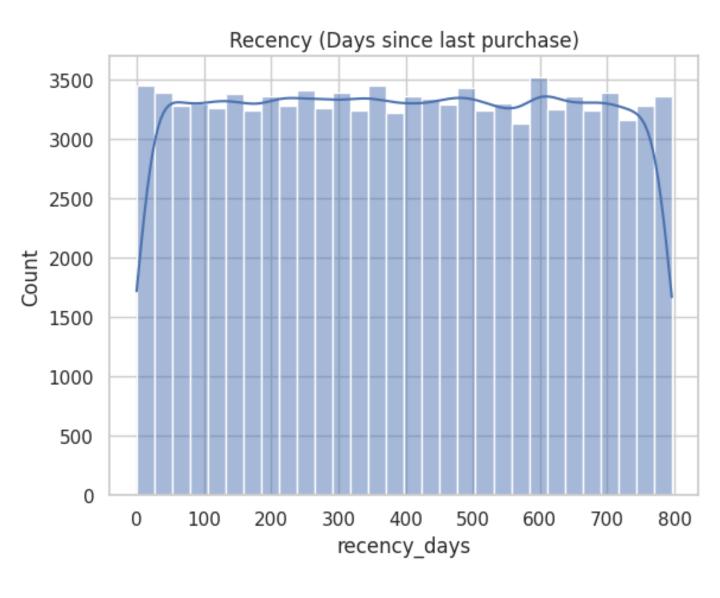




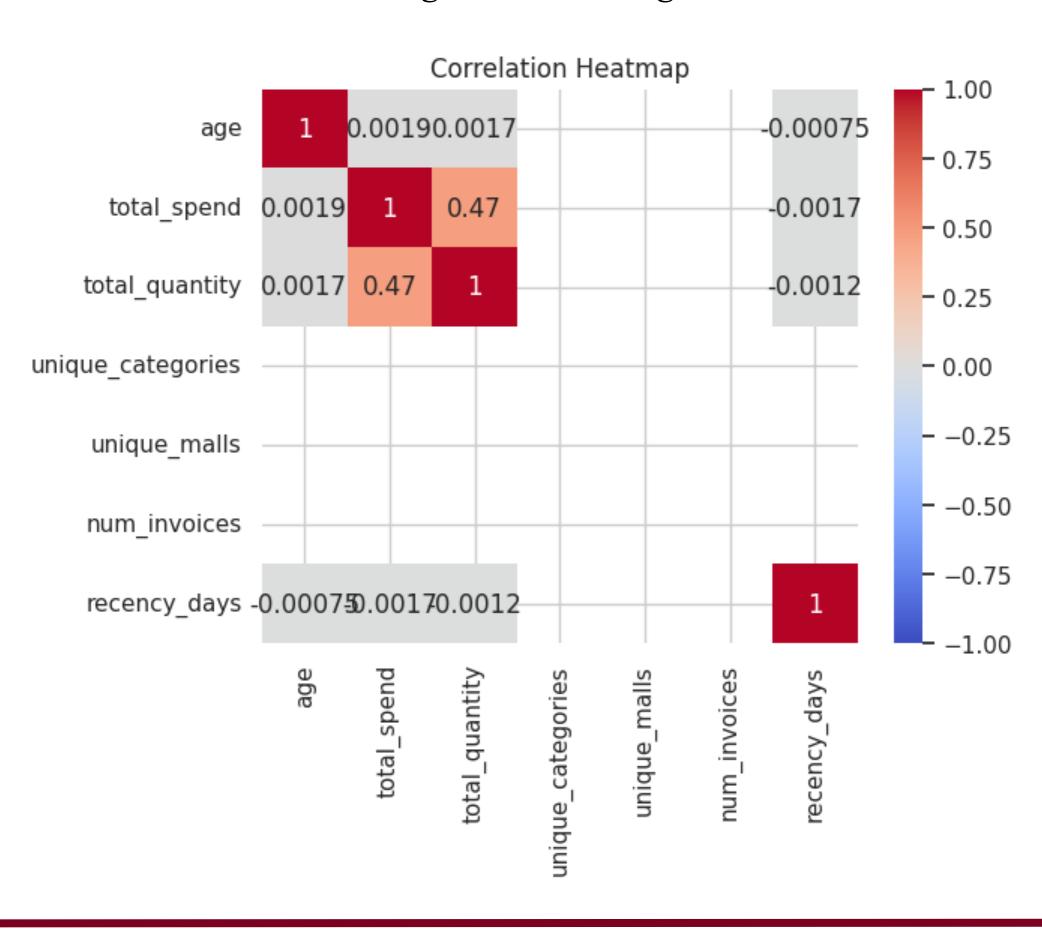
Exploratory Data Analysis (EDA)

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Exploratory Data Analysis (EDA)



Scaling

Customer Segmentation using K-Means

- Features on different scales (spend vs quantity vs recency).
- Applied StandardScaler to normalize.
- Saved: X_scaled.npy, scaler.pkl

Scaling complete. Files saved:

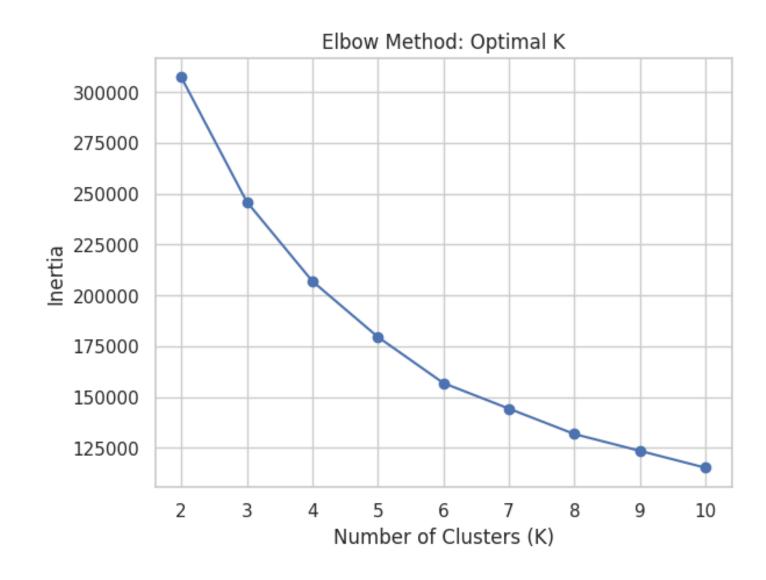
- customer_level_week1.csv
- X_scaled.npy
- scaler.pkl

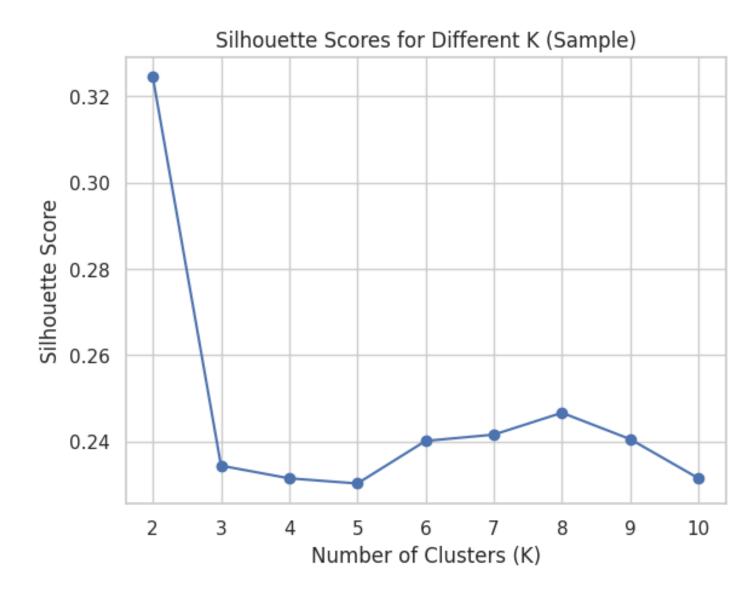
customer_level_week1

customer_id	gender	age	total_spend	total_quantity	unique_categories	unique_malls	first_purchase	last_purchase	num_invoices	recency_days
C100004	Male	61.0	7502.0	5	1	1	2021-11-26	2021-11-26	1	467
C100005	Male	34.0	2400.68	2	1	1	2023-03-03	2023-03-03	1	5
C100006	Male	44.0	322.56	3	1	1	2022-12-01	2022-12-01	1	97
C100012	Male	25.0	130.75	5	1	1	2021-08-15	2021-08-15	1	570
C100019	Female	21.0	35.84	1	1	1	2021-07-25	2021-07-25	1	591
C100025	Male	55.0	143.36	2	1	1	2021-06-03	2021-06-03	1	643
C100028	Female	21.0	15.15	1	1	1	2021-11-25	2021-11-25	1	468
C100030	Male	46.0	4801.28	4	1	1	2022-10-13	2022-10-13	1	146
C100034	Male	60.0	1200.32	2	1	1	2021-08-06	2021-08-06	1	579
C100041	Female	50.0	2700.7200000000000	3	1	1	2021-04-23	2021-04-23	1	684
C100042	Female	28.0	650.56	4	1	1	2022-01-04	2022-01-04	1	428
C100045	Male	48.0	5.23	1	1	1	2022-01-10	2022-01-10	1	422
C100066	Female	46.0	322.56	3	1	1	2022-08-02	2022-08-02	1	218
C100067	Female	62.0	600.17	1	1	1	2021-01-06	2021-01-06	1	791
C100078	Male	64.0	60.6	2	1	1	2022-12-01	2022-12-01	1	97
C100088	Female	30.0	5.23	1	1	1	2021-03-05	2021-03-05	1	733
C100090	Female	62.0	162.64	2	1	1	2022-03-07	2022-03-07	1	366
C100095	Female	31.0	130.75	5	1	1	2022-10-09	2022-10-09	1	150
C100096	Male	40.0	2700.7200000000000	3	1	1	2021-10-03	2021-10-03	1	521
C100099	Male	64.0	136.35000000000000	3	1	1	2022-03-23	2022-03-23	1	350

K-Means Clustering

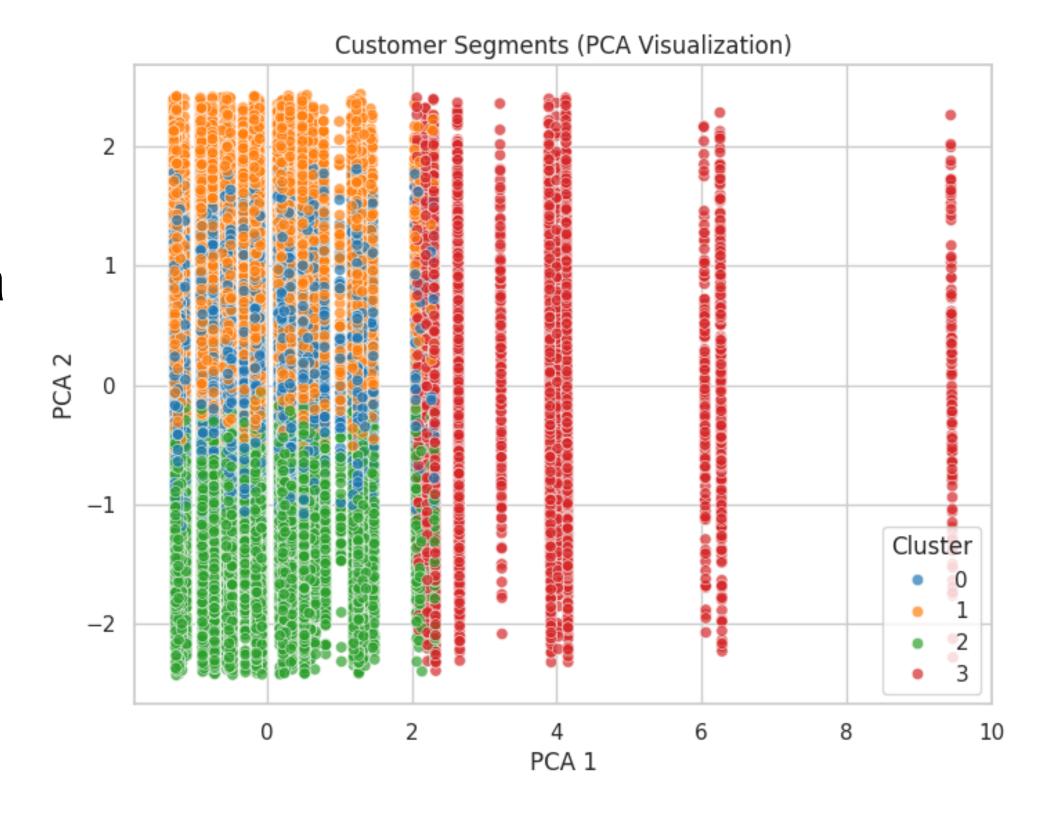
- Tested K=2 to 10
- Elbow Method → Optimal K=4
- Silhouette Score → Highest at 4 clusters
- Final model: **K**=**4**





PCA Visualization

- PCA reduced 7 features → 2 dimensions
- Clear separation of clusters observed
- Cluster boundaries show good segmentation



Cluster Profiles

- Cluster o: Young, moderate spend → Growth segment
- Cluster 1: Middle-aged, medium spend → Regulars
- Cluster 2: Older, low spend → Occasional shoppers
- Cluster 3: High-spending → VIP/Premium

<pre> Clustered dataset loaded cluster 1 34949 0 29324 2 28753 3 6427 Name: count, dtype: int64</pre>										
	customer_id	gender	age	total_spend	total_quantity	unique_categories	unique_malls	first_purchase	last_purchase	num_
0	C100004	Male	61.0	7502.00	5	1	1	2021-11-26	2021-11-26	
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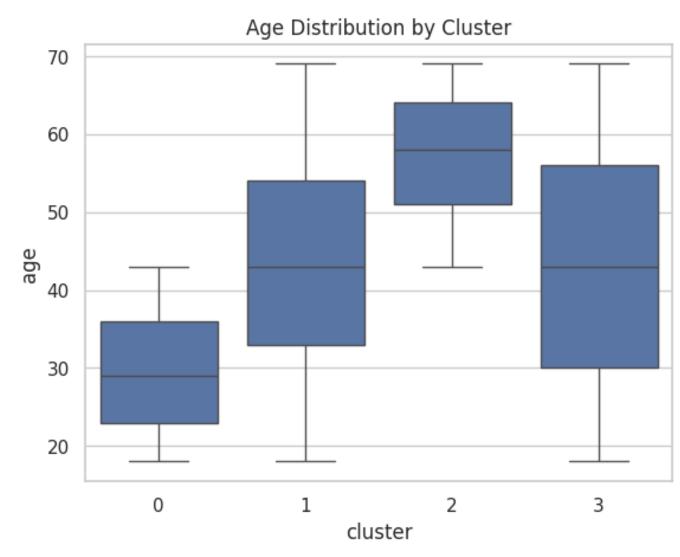
	age	total_spend	total_quantity	unique_categories	unique_malls	num_invoices	recency_days
cluster							
0	29.5	1790.5	3.2	1.0	1.0	1.0	252.9
1	43.5	1822.6	3.2	1.0	1.0	1.0	638.8
2	57.5	1834.8	3.2	1.0	1.0	1.0	249.8
3	43.4	17689.7	6.5	1.0	1.0	1.0	396.2

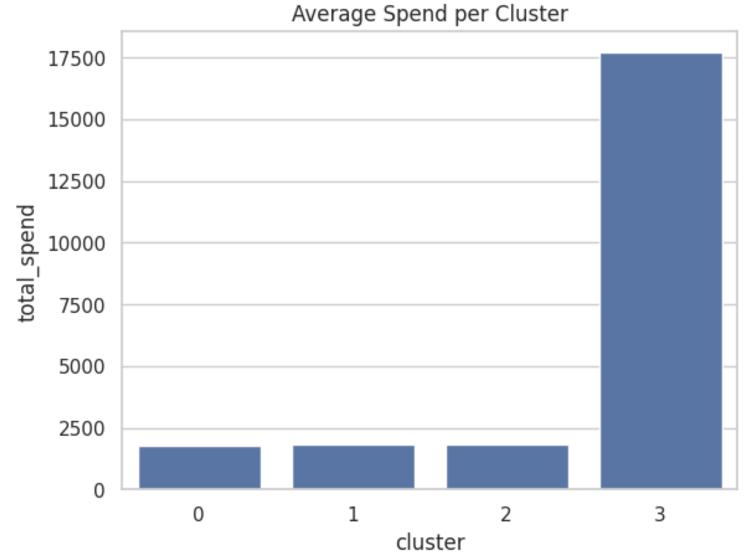
Cluster Distribution Visualizations

Customer Segmentation using K-Means

We plot visualizations to better understand cluster profiles:

- Bar Plot → Avg spend per cluster
- Box Plot \rightarrow Age distribution by cluster



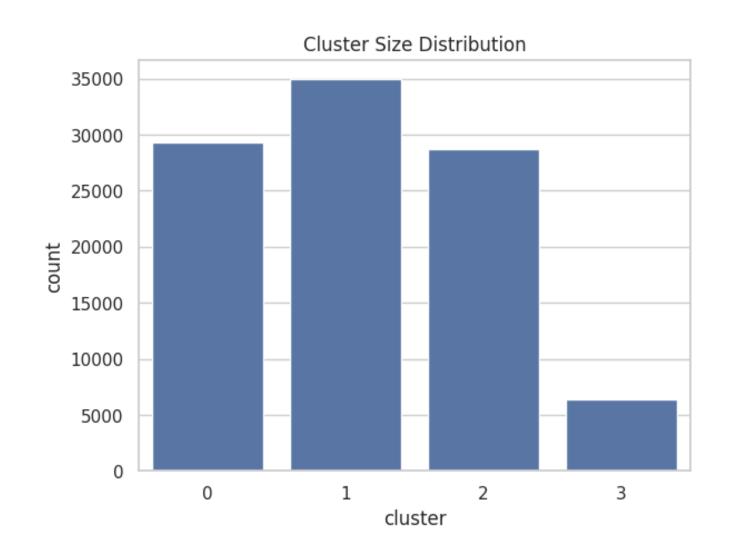


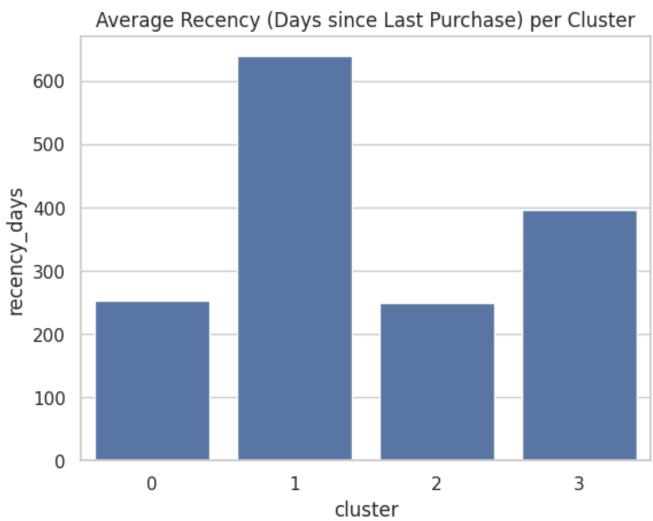
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We plot visualizations to better understand cluster profiles:

- Bar Plot → Avg spend per cluster
- Box Plot \rightarrow Age distribution by cluster
- Bar Plot → Recency by cluster
- Count Plot \rightarrow Cluster sizes





Marketing Strategies

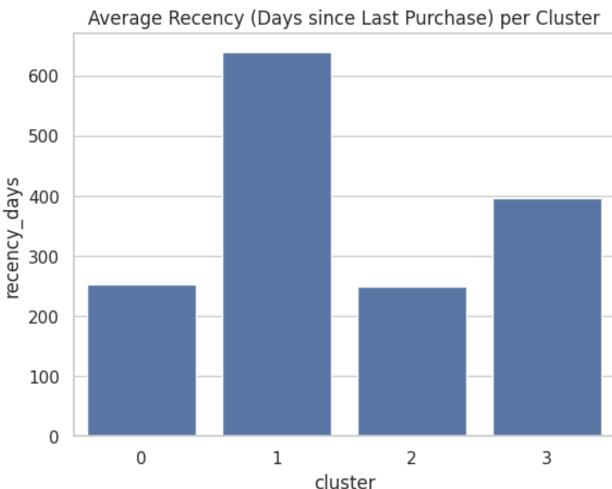
Customer Segmentation using K-Means

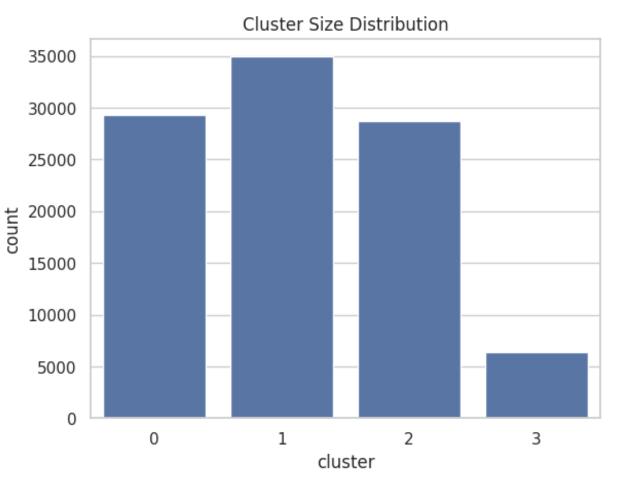
We plot visualizations to better understand cluster profiles:

- Bar Plot → Recency by cluster
- **Count Plot** → Cluster sizes

From the summary and visualizations, we can profile clusters like this (example):

- Cluster o: Young, high-spending, frequent buyers → Premium customers
- Cluster 1: Middle-aged, medium spend, moderate frequency → Regulars
- Cluster 2: Older, low spend, infrequent purchases → Occasional shoppers
- Cluster 3: Young but low recency (haven't purchased recently) → At-risk customers



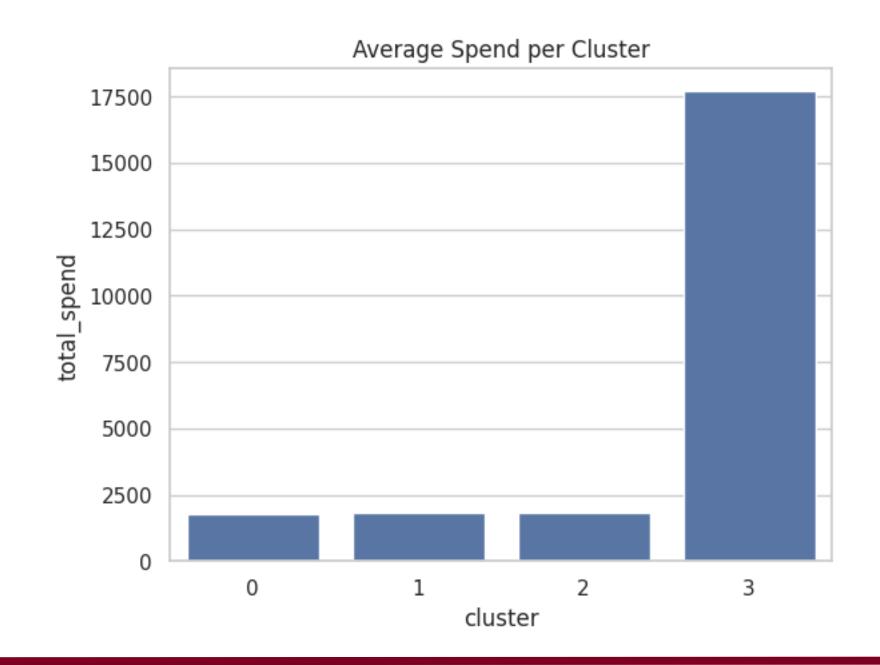


Visualizations for Report

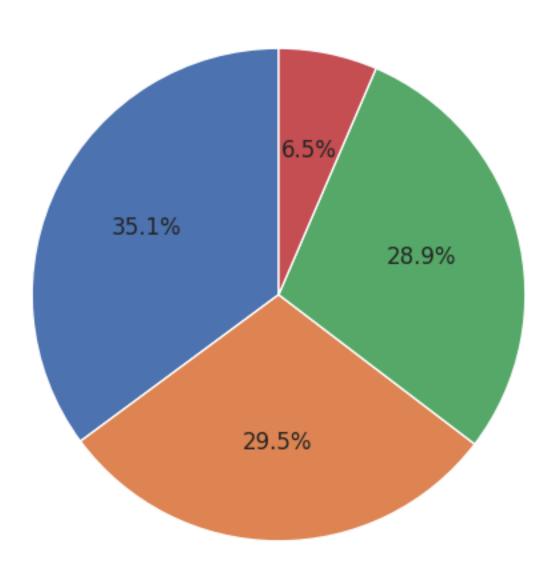
Customer Segmentation using K-Means

We now create professional visuals:

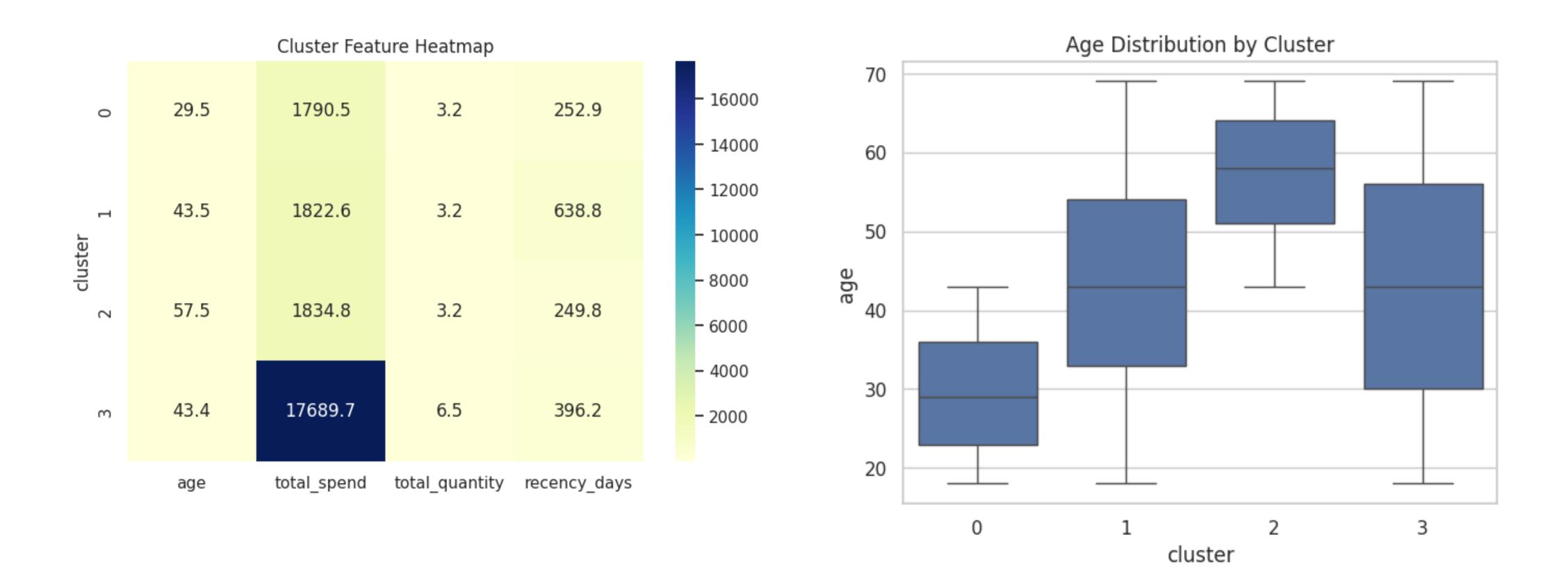
- Donut chart \rightarrow % customers per cluster
- Bar chart → Avg Spend by cluster
- Box plot → Age distribution per cluster
- Heatmap → Correlation of features within clusters



Customer Distribution by Cluster



Visualizations for Report



Final Results

Customer Segmentation using K-Means

- Segmented 99,453 customers into 4 clusters
- Generated final_customer_clusters.csv
- Ready for CRM integration

Key Findings:

- Cluster $o \rightarrow Young$, high-spending, frequent \rightarrow Premium segment
- Cluster 1 \rightarrow Middle-aged, moderate spending \rightarrow Regular customers
- Cluster $2 \rightarrow$ Older, low-spending \rightarrow Occasional shoppers
- Cluster $3 \rightarrow$ At-risk, low recency \rightarrow Need re-engagement

Marketing Recommendations:

- Premium → Loyalty rewards, VIP access
- Regular → Product bundles, upselling campaigns
- Occasional → Discount offers, seasonal promotions
- At-risk → Win-back campaigns, festive deals

This segmentation enables targeted marketing strategies to increase revenue & engagement.

Customer Distribution by Cluster

