Konecta Internship Task 4 (Customer Segmentation)

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Track: Artificial Intelligence & Machine Learning
Repository Link: https://github.com/AhmedAyman4/konecta-internship/tree/main/Task-4

Load & Explore

1. Import dataset, do summary stats & distributions.

In [1]:
```python
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
from sklearn.cluster import KMeans
from sklearn.cluster import AgglomerativeClustering
from sklearn.cluster import DBSCAN
from sklearn.metrics import silhouette_score
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from mpl_toolkits.mplot3d import Axes3D  # 3D plotting
import scipy.cluster.hierarchy as sch
from sklearn.cluster import MeanShift, estimate_bandwidth

# Ignore warnings
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```python
df = pd.read_csv('/content/Wholesale_customers_data.csv')
df.head()
```

Out[2]:

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	2	3	12669	9656	7561	214	2674	1338
1	2	3	7057	9810	9568	1762	3293	1776
2	2	3	6353	8808	7684	2405	3516	7844
3	1	3	13265	1196	4221	6404	507	1788
4	2	3	22615	5410	7198	3915	1777	5185

In [3]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 440 entries, 0 to 439
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Channel           440 non-null    int64
 1   Region            440 non-null    int64
 2   Fresh             440 non-null    int64
 3   Milk              440 non-null    int64
 4   Grocery           440 non-null    int64
 5   Frozen            440 non-null    int64
 6   Detergents_Paper  440 non-null    int64
 7   Delicassen        440 non-null    int64
dtypes: int64(8)
memory usage: 27.6 KB
```

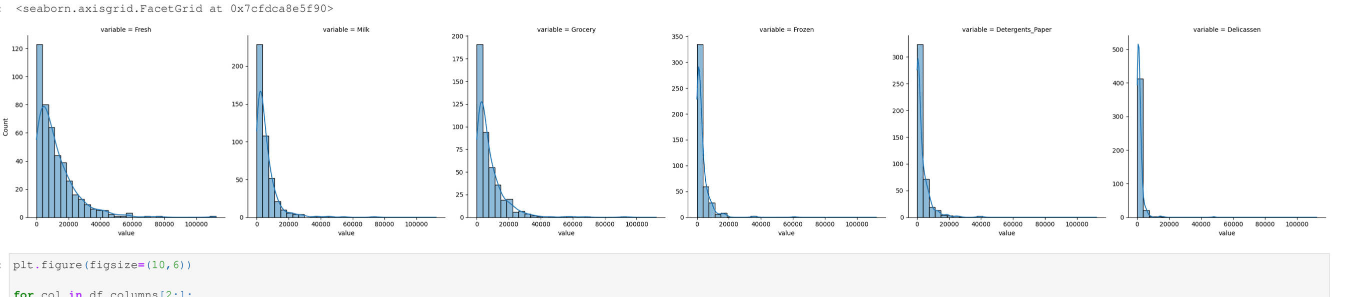
In [4]:
```python
df.describe()
```

Out[4]:

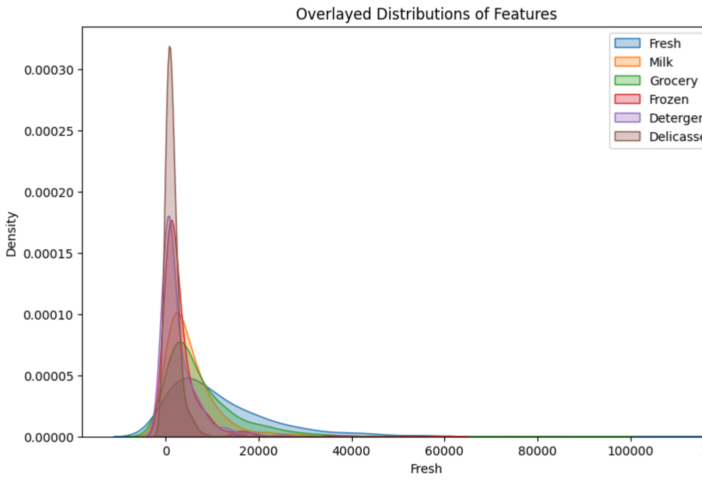
	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
count	440.000000	440.000000	440.000000	440.000000	440.000000	440.000000	440.000000	440.000000
mean	1.322727	2.543182	12000.297727	5796.265909	7951.277273	3071.931818	2881.493182	1524.870455
std	0.468052	0.774272	12647.328865	7380.377175	9503.162829	4854.673333	4767.854448	2820.105937
min	1.000000	1.000000	3.000000	55.000000	3.000000	25.000000	3.000000	3.000000
25%	1.000000	2.000000	3127.750000	1533.000000	2153.000000	742.250000	256.750000	408.250000
50%	1.000000	3.000000	8504.000000	3627.000000	4755.500000	1526.000000	816.500000	965.500000
75%	2.000000	3.000000	16933.750000	7190.250000	10655.750000	3554.250000	3922.000000	1820.250000
max	2.000000	3.000000	112151.000000	73498.000000	92780.000000	60869.000000	40827.000000	47943.000000

In [5]:
```python
sns.displot(
    df.melt(value_vars=df.columns[2:]),  # reshape to long format
    x="value", col="variable", kde=True,
    facet_kws={"sharex": False, "sharey": False}, bins=30
)
# Takes all columns starting from the 3rd one (ignoring Channel and Region which are categorical).
```

Out[5]: <seaborn.axisgrid.FacetGrid at 0x7cfdca8e5f90>



In [6]:
```python
plt.figure(figsize=(10,6))

for col in df.columns[2:]:
    sns.kdeplot(df[col], label=col, fill=True, alpha=0.3)

plt.legend()
plt.title("Overlayed Distributions of Features")
plt.show()
```



Right-Skewed Distribution

Preprocessing

1. Scale features (StandardScaler/MinMax).

- StandardScaler → makes features have mean = 0 and standard deviation = 1 (like converting to z-scores).
- MinMaxScaler → squishes all values into a fixed range, usually 0 → 1.

2. Consider log-transform (if data is skewed).

- Apply a logarithm (log) to "compress" large values and make the distribution more balanced / closer to normal.

In short:

- Scaling = make all features comparable in size.
- Log-transform = reduce the effect of very large values so the data looks more balanced.

In [7]:
```python
# Keep a copy of the original dataframe
df_original = df.copy()

# Columns you want to log-transform
cols = ["Fresh", "Milk", "Grocery", "Frozen", "Detergents_Paper", "Delicassen"]

# Apply log1p (log(1 + x)) to avoid issues with 0 values
df[cols] = df[cols].apply(np.log1p)
```

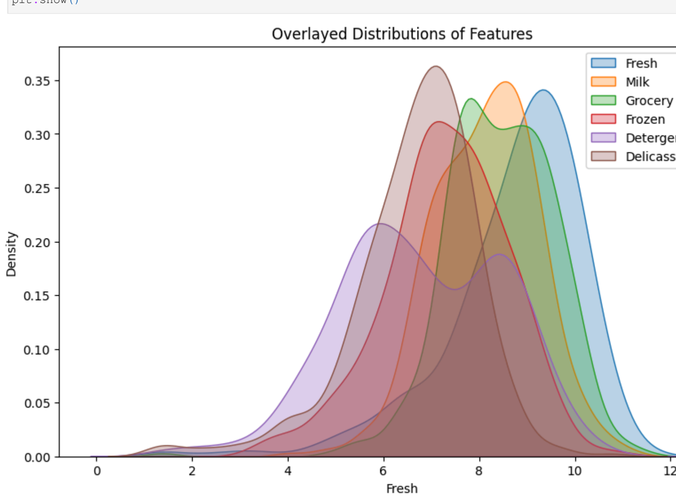
Since logs can't handle 0 values, we usually add 1 (np.log1p) to be safe.

In [8]:
```python
df.head()
```

Out[8]:

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	2	3	9.446992	9.175438	8.930891	5.370638	7.891705	7.199678
1	2	3	8.861917	9.191259	9.166284	7.474772	8.099858	7.482682
2	2	3	8.756840	9.083529	8.947026	7.785721	8.165364	8.967632
3	1	3	9.492960	7.087574	8.348064	8.764834	6.230481	7.489412
4	2	3	10.026413	8.596189	8.881697	8.272826	7.483244	8.553718

In [9]:
```python
plt.figure(figsize=(10,6))

for col in df.columns[2:]:
    sns.kdeplot(df[col], label=col, fill=True, alpha=0.3)

plt.legend()
plt.title("Overlayed Distributions of Features")
plt.show()
```

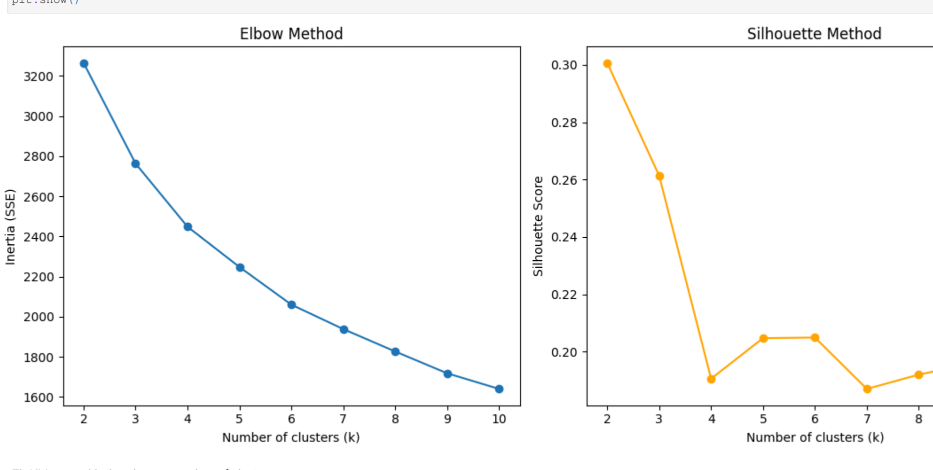


Clustering

1. K-Means → try different k, use Elbow/Silhouette.
2. Hierarchical → dendrograms, different linkage.
3. DBSCAN → tune eps, min_samples.
4. Meanshift Algorithm

KMeans

In [10]:
```python
# K-Means → try different k, use Elbow/Silhouette.
# Columns to use (numeric features only, after log-transform)
cols = ["Fresh", "Milk", "Grocery", "Frozen", "Detergents_Paper", "Delicassen"]
X = df[cols].values

# Range of k values to try
k_values = range(2, 11)  # from 2 to 10 clusters

inertia = []            # for Elbow method
silhouette_scores = []  # for Silhouette method

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
    labels = kmeans.fit_predict(X)

    inertia.append(kmeans.inertia_)
    silhouette_scores.append(silhouette_score(X, labels))

# --- Plot Elbow Curve ---
plt.figure(figsize=(12,5))

plt.subplot(1,2,1)
plt.plot(k_values, inertia, marker='o')
plt.xlabel("Number of clusters (k)")
plt.ylabel("Inertia (SSE)")
plt.title("Elbow Method")

# --- Plot Silhouette Scores ---
plt.subplot(1,2,2)
plt.plot(k_values, silhouette_scores, marker='o', color='orange')
plt.xlabel("Number of clusters (k)")
plt.ylabel("Silhouette Score")
plt.title("Silhouette Method")

plt.tight_layout()
plt.show()
```



Fit KMeans with the chosen number of clusters

In [11]:
```python
best_k = 6
final_kmeans = KMeans(n_clusters=best_k, random_state=42, n_init=10)
df["Cluster"] = final_kmeans.fit_predict(X)
```

In [12]:
```python
df.head()
```

Out[12]:

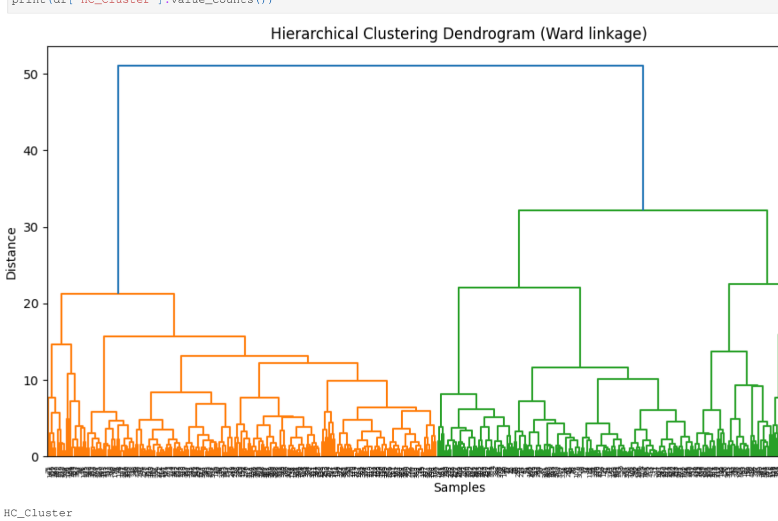
	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen	Cluster
0	2	3	9.446992	9.175438	8.930891	5.370638	7.891705	7.199678	3
1	2	3	8.861917	9.191259	9.166284	7.474772	8.099858	7.482682	1
2	2	3	8.756840	9.083529	8.947026	7.785721	8.165364	8.967632	1
3	1	3	9.492960	7.087574	8.348064	8.764834	6.230481	7.489412	0
4	2	3	10.026413	8.596189	8.881697	8.272826	7.483244	8.553718	0

Hierarchical Clustering

Dendrogram with different linkages

- The linkage method tells how to measure distance between clusters when merging:
- single → based on the closest pair of points (can cause "chaining").
- complete → based on the farthest pair of points (tighter clusters).
- average → based on average distance between points.
- ward → minimizes variance within clusters (most common).

In [13]:
```python
# Data (same features you used for KMeans)
X = df[["Fresh", "Milk", "Grocery", "Frozen", "Detergents_Paper", "Delicassen"]]

# --- Dendrogram ---
plt.figure(figsize=(12,6))
dendrogram = sch.dendrogram(sch.linkage(X, method='ward'))
plt.title("Hierarchical Clustering Dendrogram (Ward linkage)")
plt.xlabel("Samples")
plt.ylabel("Distance")
plt.show()

# --- Try Agglomerative Clustering with Ward linkage ---
hc = AgglomerativeClustering(n_clusters=3, metric='euclidean', linkage='ward')
df["HC_Cluster"] = hc.fit_predict(X)

print(df["HC_Cluster"].value_counts())
```



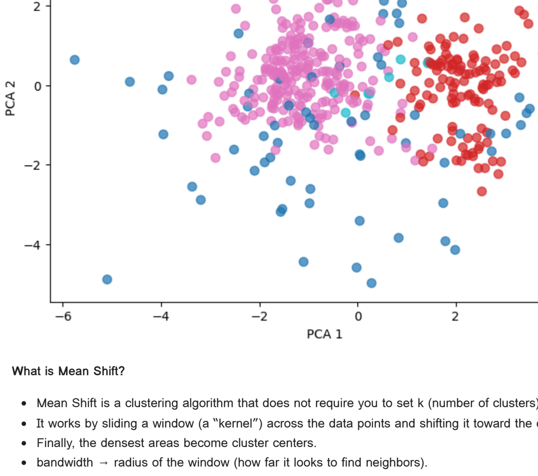

```
HC_Cluster
1    208
2    137
0     95
Name: count, dtype: int64
```

DBSCAN

- DBSCAN (Density-Based Spatial Clustering of Applications with Noise) groups points that are close together into clusters.
- Unlike K-Means, you don't need to choose k in advance.
- It also automatically detects outliers (noise points).
- eps → maximum distance between two points to be considered neighbors.
- min_samples → minimum number of points required to form a dense region (cluster).

In [14]:
```python
# Features for clustering
X = df[["Channel","Region","Fresh", "Milk", "Grocery", "Frozen", "Detergents_Paper", "Delicassen"]]

# Scale data (important for DBSCAN distance calculation)
X_scaled = StandardScaler().fit_transform(X)

# Try DBSCAN
dbscan = DBSCAN(eps=1.5, min_samples=5)  # tune eps & min_samples
labels = dbscan.fit_predict(X_scaled)

# Add cluster labels (note: -1 means noise/outliers)
df["DBSCAN_Cluster"] = labels

print(df["DBSCAN_Cluster"].value_counts())

# --- 2D PCA visualization ---
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

plt.figure(figsize=(8,6))
plt.scatter(
    X_pca[:,0], X_pca[:,1],
    c=labels, cmap="tab10", s=50, alpha=0.7
)
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.title("DBSCAN Clusters (with Noise)")
plt.show()
```

```
DBSCAN_Cluster
 1    242
 0    124
-1     67
 2      7
Name: count, dtype: int64
```

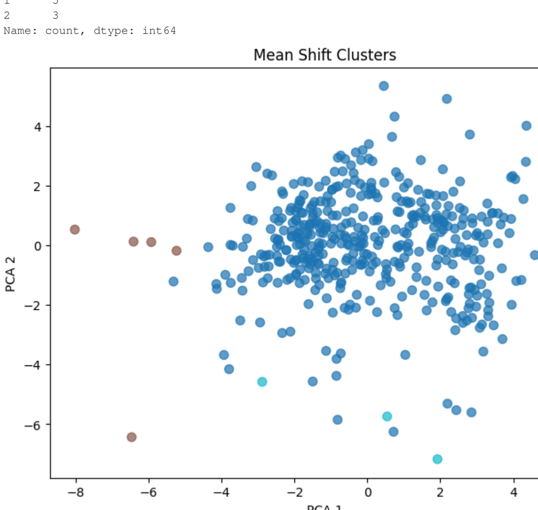


What is Mean Shift?

- Mean Shift is a clustering algorithm that does not require you to set k (number of clusters).
- It works by sliding a window (a "kernel") across the data points and shifting it toward the densest region.
- Finally, the densest areas become cluster centers.
- bandwidth → radius of the window (how far it looks to find neighbors).

In [15]:
```python
# Columns already log-transformed
cols = ["Fresh", "Milk", "Grocery", "Frozen", "Detergents_Paper", "Delicassen"]

X = df[cols]  # use data as-is

# Estimate good bandwidth
bandwidth = estimate_bandwidth(X, quantile=0.5, n_samples=200)

# Apply MeanShift
ms = MeanShift(bandwidth=bandwidth, bin_seeding=True)
labels = ms.fit_predict(X)

# Add cluster labels to dataframe
df["MeanShift_Cluster"] = labels

print(df["MeanShift_Cluster"].value_counts())

# 2D PCA visualization
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)

plt.figure(figsize=(8,6))
plt.scatter(
    X_pca[:,0], X_pca[:,1],
    c=labels, cmap="tab10", s=50, alpha=0.7
)
plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.title("Mean Shift Clusters")
plt.show()
```

```
MeanShift_Cluster
0    432
1      5
2      3
Name: count, dtype: int64
```



Evaluation

1. Silhouette, Davies–Bouldin, Calinski–Harabasz.
2. Compare between methods.

Silhouette Score

Measures how similar a point is to its own cluster vs. other clusters.

- Range: -1 to 1
- 1 → perfectly clustered
- 0 → overlapping clusters
- Negative → probably misclassified
- Higher is better.

In [16]:
```python
from sklearn.metrics import silhouette_score

sil_score = silhouette_score(X, df["Cluster"])
print("Silhouette Score:", sil_score)
```

```
Silhouette Score: 0.2049017339759311
```

Davies–Bouldin Index

- Measures the average similarity between each cluster and its most similar cluster.
- Lower is better → means clusters are well-separated.

In [17]:
```python
from sklearn.metrics import davies_bouldin_score

db_score = davies_bouldin_score(X, df["Cluster"])
print("Davies-Bouldin Index:", db_score)
```

```
Davies-Bouldin Index: 1.3615455691621807
```

Calinski–Harabasz Index

- Measures variance ratio between clusters vs. within clusters.
- Higher is better → clusters are dense and well-separated.

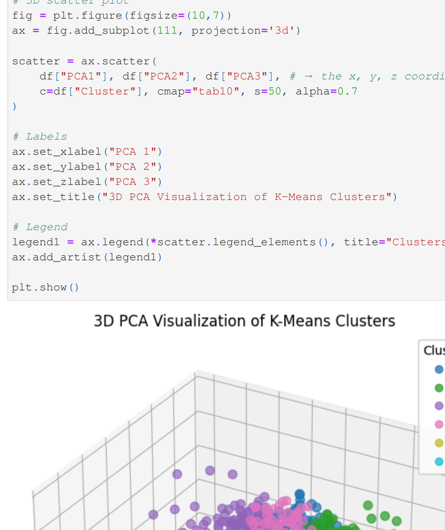
In [18]:
```python
from sklearn.metrics import calinski_harabasz_score

ch_score = calinski_harabasz_score(X, df["Cluster"])
print("Calinski-Harabasz Index:", ch_score)
```

```
Calinski-Harabasz Index: 113.09769471584652
```

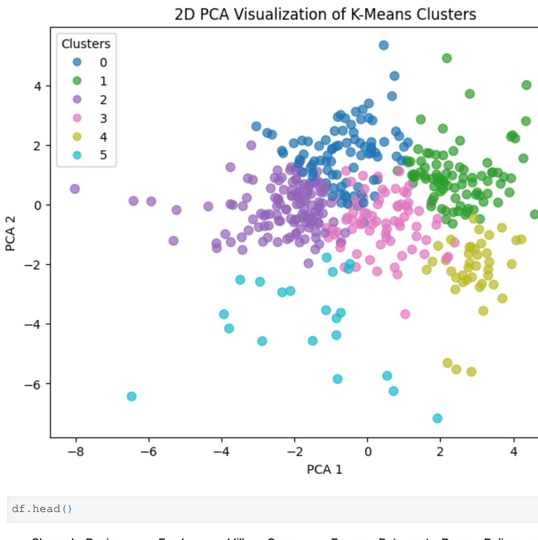
Visualization

1. PCA / t-SNE for 2D plots.
2. Show how clusters separate.

In [19]:
```python
# Reduce dimensions to 3D with PCA
pca = PCA(n_components=3)
X_pca = pca.fit_transform(df[cols])

# Add PCA results to DataFrame (optional)
# We save them in df so we can plot them easily.

df["PCA1"] = X_pca[:,0] # means first column (PCA1)
df["PCA2"] = X_pca[:,1] # second column (PCA2)
df["PCA3"] = X_pca[:,2] # third column (PCA3)

# 3D scatter plot
fig = plt.figure(figsize=(10,7))
ax = fig.add_subplot(111, projection='3d')

scatter = ax.scatter(
    df["PCA1"], df["PCA2"], df["PCA3"], # → the x, y, z coordinates
    c=df["Cluster"], cmap="tab10", s=50, alpha=0.7
)

# Labels
ax.set_xlabel("PCA 1")
ax.set_ylabel("PCA 2")
ax.set_zlabel("PCA 3")
ax.set_title("3D PCA Visualization of K-Means Clusters")

# Legend
legend1 = ax.legend(*scatter.legend_elements(), title="Clusters")
ax.add_artist(legend1)

plt.show()
```



In [20]:
```python
# 2D scatter plot using PCA1 and PCA2
plt.figure(figsize=(8,6))
plt.scatter(
    df["PCA1"], df["PCA2"],
    c=df["Cluster"], cmap="tab10", s=50, alpha=0.7
)

plt.xlabel("PCA 1")
plt.ylabel("PCA 2")
plt.title("2D PCA Visualization of K-Means Clusters")

# Legend for clusters
plt.legend(*plt.gca().collections[0].legend_elements(), title="Clusters")

plt.show()
```



In [21]:
```python
df.head()
```

Out[21]:

	Channel	Region	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen	Cluster	HC_Cluster	DBSCAN_Cluster	MeanShift_Cluster	PCA1	PCA2	PCA3
0	2	3	9.446992	9.175438	8.930891	5.370638	7.891705	7.199678	3	2	0	0	1.746904	0.062700	0.975606
1	2	3	8.861917	9.191259	9.166284	7.474772	8.099858	7.482682	1	2	0	0	1.793552	0.869707	-0.212709
2	2	3	8.756840	9.083529	8.947026	7.785721	8.165364	8.967632	1	2	0	0	1.884226	1.669358	-1.297679
3	1	3	9.492960	7.087574	8.348064	8.764834	6.230481	7.489412	0	1	1	0	-1.137087	1.449765	-0.539310
4	2	3	10.026413	8.596189	8.881697	8.272826	7.483244	8.553718	0	2	0	0	0.784600	2.453600	-0.459114

Interpretation

1. Describe customer segments in plain words (e.g. high Grocery & Milk = retailers).

In [22]:
```python
# the average spending per product category for each cluster.
cluster_summary_log = df.groupby("Cluster")[["Fresh", "Milk", "Grocery", "Frozen", "Detergents_Paper", "Delicassen"]].mean()
cluster_summary_log
```

Out[22]:

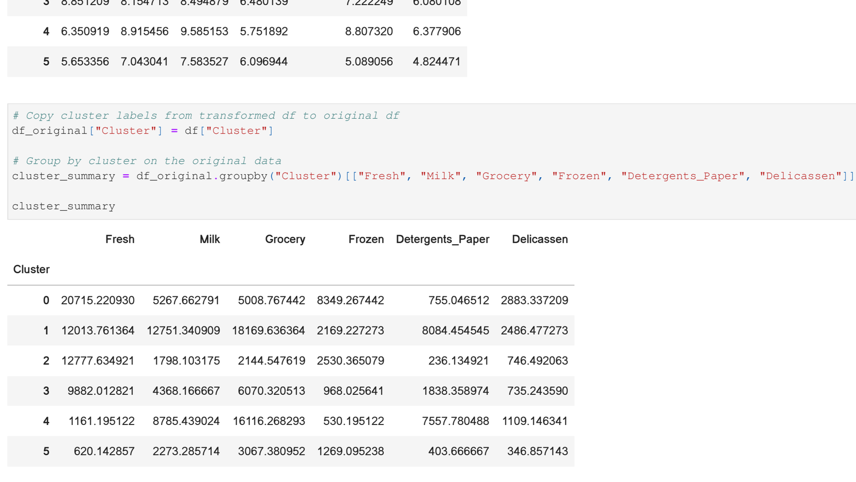
Cluster	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	9.576697	8.216473	8.321770	8.739390	6.348646	7.524453
1	9.010294	9.211809	9.626438	7.333320	8.746333	7.515059
2	9.178045	7.196427	7.435917	7.517002	5.090613	6.268230
3	8.851209	8.154713	8.494879	6.480139	7.222249	6.080108
4	6.350919	8.915456	9.585153	5.751892	8.807320	6.377906
5	5.653356	7.043041	7.583527	6.096944	5.089056	4.824471

In [23]:
```python
# Copy cluster labels from transformed df to original df
df_original["Cluster"] = df["Cluster"]

# Group by cluster on the original data
cluster_summary = df_original.groupby("Cluster")[["Fresh", "Milk", "Grocery", "Frozen", "Detergents_Paper", "Delicassen"]].mean()

cluster_summary
```

Out[23]:

Cluster	Fresh	Milk	Grocery	Frozen	Detergents_Paper	Delicassen
0	20715.220930	5267.662791	5008.767442	8349.267442	755.046512	2883.337209
1	12013.761364	12751.340909	18169.636364	2169.227273	8084.454545	2486.477273
2	12777.634921	1798.103175	2144.547619	2530.365079	236.134921	746.492063
3	9882.012821	4368.166667	6070.320513	968.025641	1838.358974	735.243590
4	1161.195122	8785.439024	16116.268293	530.195122	7557.780488	1109.146341
5	620.142857	2273.285714	3067.380952	1269.095238	403.666667	346.857143

In [24]:
```python
plt.figure(figsize=(12,6))
sns.heatmap(cluster_summary, annot=True, fmt=".0f", cmap="YlGnBu")
plt.title("Average Spending per Cluster")
plt.show()
```



This heatmap makes it clear which features are dominant in each cluster.

Customer Segments (Heatmap: Avg Spending per Cluster)

- **Cluster 0: "Fresh & Frozen"** 🍎

High spend on **Fresh** and **Frozen**, low elsewhere — likely meal preppers or small food businesses.

- **Cluster 1: "Bulk Buyers / Retailers"** 🛒

High spending on **Fresh**, **Milk**, **Grocery**, and **Detergents_Paper** — likely retailers, restaurants, or large families.

- **Cluster 2: "Fresh-First Shoppers"** 🥕

Focused almost entirely on **Fresh** — may buy other items elsewhere or run a produce-focused business.

- **Cluster 3: "Household Essentials"** 🧼

Moderate on groceries, highest on **Detergents_Paper** — typical household prioritizing cleaning supplies.

- **Cluster 4: "Grocery & Milk"** 🥛

High on **Grocery** and **Milk**, low on Fresh — possibly small stores or families favoring packaged/dairy goods.

- **Cluster 5: "Low-Volume Shoppers"** 🤏

Low spending across all categories — infrequent shoppers, singles, or supplemental customers.