

# Segmentação de clientes

Usar o algoritmo K-Means para agrupar clientes com base em seus comportamentos de compra. Descrever as características de cada grupo.

## Instalação de bibliotecas

```
In [1]: %pip install pandas matplotlib seaborn sklearn
```

```
Requirement already satisfied: pandas in c:\python312\lib\site-packages (2.2.2)
Requirement already satisfied: matplotlib in c:\python312\lib\site-packages (3.9.2)
Requirement already satisfied: seaborn in c:\python312\lib\site-packages (0.13.2)
Collecting sklearn
  Using cached sklearn-0.0.post12.tar.gz (2.6 kB)
  Installing build dependencies: started
  Installing build dependencies: finished with status 'done'
  Getting requirements to build wheel: started
  Getting requirements to build wheel: finished with status 'error'
Note: you may need to restart the kernel to use updated packages.
```

```
error: subprocess-exited-with-error
```

```
× Getting requirements to build wheel did not run successfully.
```

```
| exit code: 1
```

```
└─> [15 lines of output]
```

```
The 'sklearn' PyPI package is deprecated, use 'scikit-learn'
rather than 'sklearn' for pip commands.
```

Here is how to fix this error in the main use cases:

- use 'pip install scikit-learn' rather than 'pip install sklearn'
- replace 'sklearn' by 'scikit-learn' in your pip requirements files (requirements.txt, setup.py, setup.cfg, Pipfile, etc ...)
- if the 'sklearn' package is used by one of your dependencies, it would be great if you take some time to track which package uses 'sklearn' instead of 'scikit-learn' and report it to their issue tracker
- as a last resort, set the environment variable  
SKLEARN\_ALLOW\_DEPRECATED\_SKLEARN\_PACKAGE\_INSTALL=True to avoid this error

More information is available at

<https://github.com/scikit-learn/sklearn-pypi-package>

[end of output]

note: This error originates from a subprocess, and is likely not a problem with pip.

```
error: subprocess-exited-with-error
```

```
× Getting requirements to build wheel did not run successfully.
```

```
| exit code: 1
```

```
└─> See above for output.
```

note: This error originates from a subprocess, and is likely not a problem with pip.

```
[notice] A new release of pip is available: 24.0 -> 24.3.1
```

```
[notice] To update, run: python.exe -m pip install --upgrade pip
```

## Importação das tabelas

```
In [2]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans

# Carregar os datasets
customers = pd.read_csv("olist_customers_dataset.csv")
geolocation = pd.read_csv("olist_geolocation_dataset.csv")
order_items = pd.read_csv("olist_order_items_dataset.csv")
order_payments = pd.read_csv("olist_order_payments_dataset.csv")
order_reviews = pd.read_csv("olist_order_reviews_dataset.csv")
orders = pd.read_csv("olist_orders_dataset.csv")
products = pd.read_csv("olist_products_dataset.csv")
sellers = pd.read_csv("olist_sellers_dataset.csv")
product_category_translation = pd.read_csv("product_category_name_translation.csv")
```

## Preparação dos dados (RFV)

```
In [3]: # Calcula o valor total de cada pedido
order_items['total_value'] = order_items['price'] + order_items['freight_value']
order_totals = order_items.groupby('order_id')['total_value'].sum().reset_index()
orders = pd.merge(orders, order_totals, on='order_id', how='left')

# Converte a data de compra para datetime
orders['order_purchase_timestamp'] = pd.to_datetime(orders['order_purchase_times

# Define a data mais recente como um dia após a última compra
most_recent_date = orders['order_purchase_timestamp'].max() + pd.Timedelta(days=

# Calcula a Recência, Frequência e Valor Monetário (RFV)
rfv = orders.groupby('customer_id').agg({
    'order_purchase_timestamp': lambda x: (most_recent_date - x.max()).days, #
    'order_id': 'count', # Frequência
    'total_value': 'sum' # Valor Monetário
})

rfv.rename(columns={
    'order_purchase_timestamp': 'Recency',
    'order_id': 'Frequency',
    'total_value': 'MonetaryValue'
}, inplace=True)

print(rfv.head())

# Padroniza os dados (importante para o K-Means)
scaler = StandardScaler()
rfv_scaled = scaler.fit_transform(rfv)
```

customer_id	Recency	Frequency	MonetaryValue
00012a2ce6f8dcda20d059ce98491703	338	1	114.74
000161a058600d5901f007fab4c27140	459	1	67.41
0001fd6190edaaaf884bc3d49edf079	597	1	195.42
0002414f95344307404f0ace7a26f1d5	428	1	179.35
000379cdec625522490c315e70c7a9fb	199	1	107.01

## Aplicando o K-Means

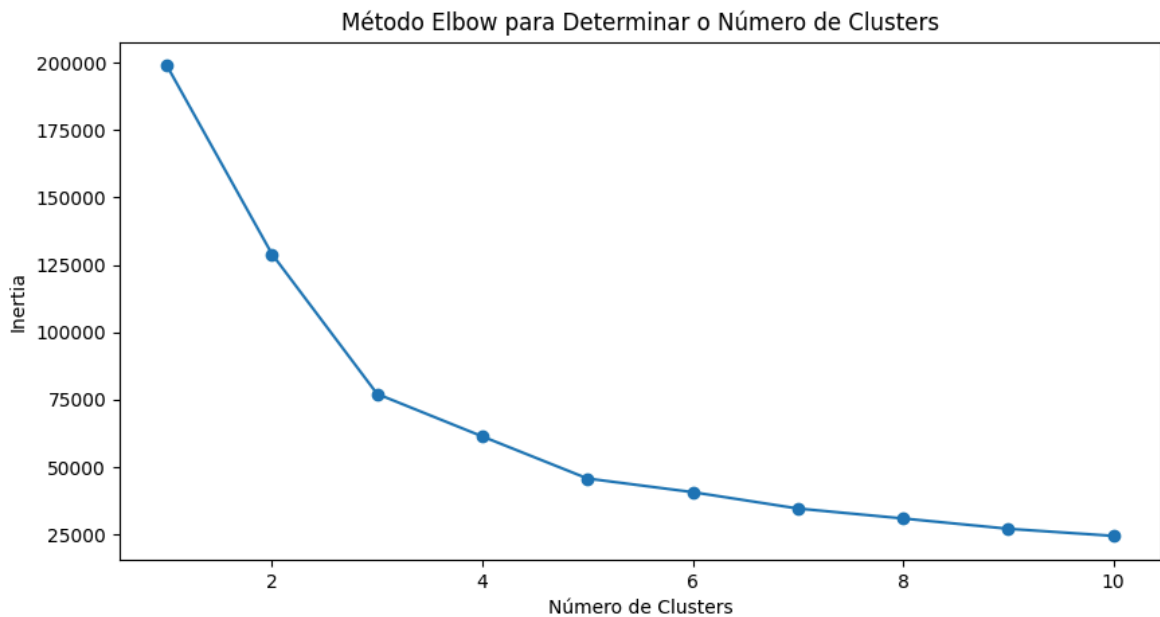
```
In [4]: # Determina o número ideal de clusters (método Elbow)
inertia = []
for n in range(1, 11):
    kmeans = KMeans(n_clusters=n, random_state=42)
    kmeans.fit(rfv_scaled)
    inertia.append(kmeans.inertia_)

plt.figure(figsize=(10, 5))
plt.plot(range(1, 11), inertia, marker='o')
plt.title('Método Elbow para Determinar o Número de Clusters')
plt.xlabel('Número de Clusters')
plt.ylabel('Inertia')
plt.show()
```

```
# Escolhe o número de clusters baseado no gráfico do Elbow (exemplo: 4 clusters)
n_clusters = 4 # modifique se o gráfico elbow indicar outro valor ideal

kmeans = KMeans(n_clusters=n_clusters, random_state=42)
rfv['Cluster'] = kmeans.fit_predict(rfv_scaled)

print(rfv.head())
```



customer_id	Recency	Frequency	MonetaryValue	Cluster
00012a2ce6f8dcda20d059ce98491703	338	1	114.74	1
000161a058600d5901f007fab4c27140	459	1	67.41	1
0001fd6190edaaaf884bc3d49edf079	597	1	195.42	1
0002414f95344307404f0ace7a26f1d5	428	1	179.35	1
000379cdec625522490c315e70c7a9fb	199	1	107.01	0

## Analizando os Clusters

```
In [5]: # Analisa as características de cada cluster
print("\nCaracterísticas dos Clusters:")
print(rfv.groupby('Cluster').agg({
    'Recency': ['mean', 'median'],
    'Frequency': ['mean', 'median'],
    'MonetaryValue': ['mean', 'median']
})))

# Visualizando os clusters (exemplo com Recency x Frequency)

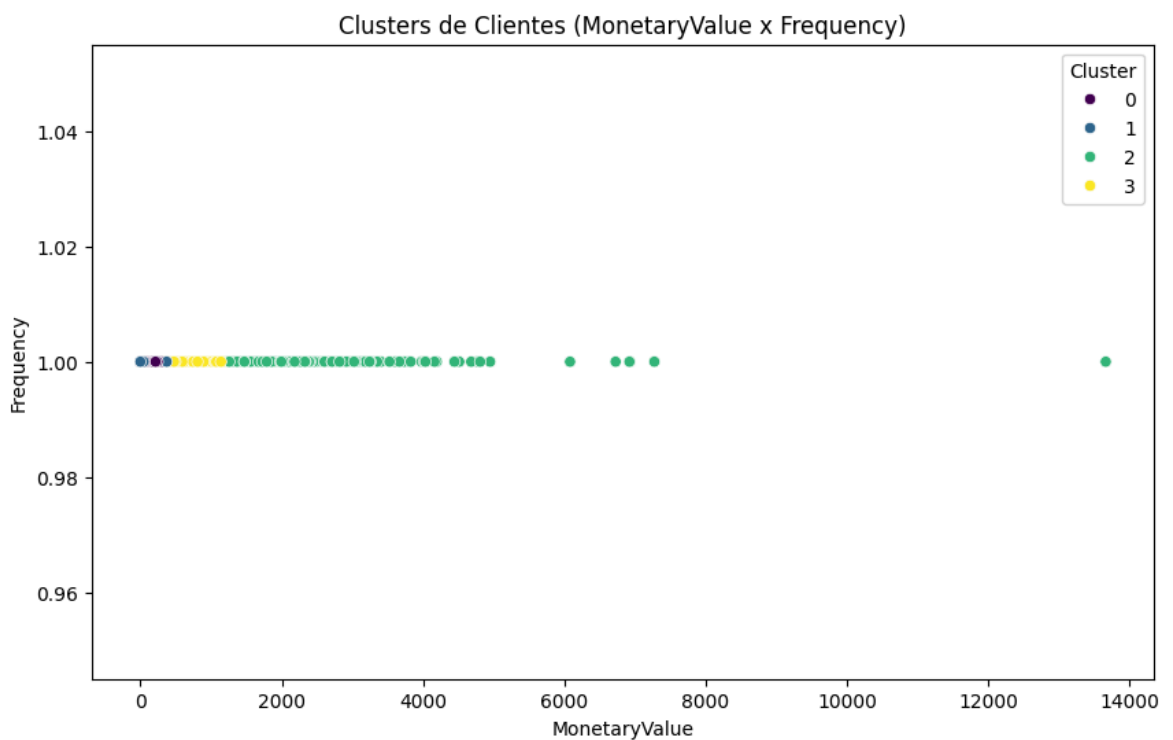
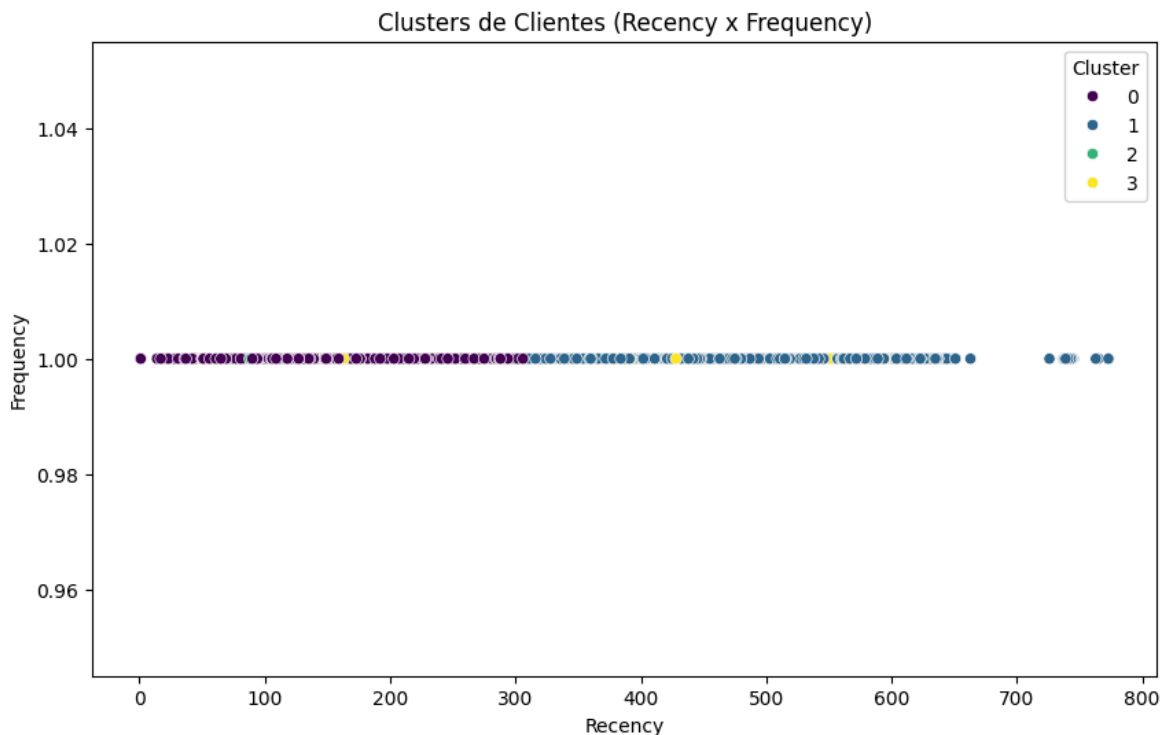
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Recency', y='Frequency', hue='Cluster', data=rfv, palette='vi')
plt.title('Clusters de Clientes (Recency x Frequency)')
plt.show()

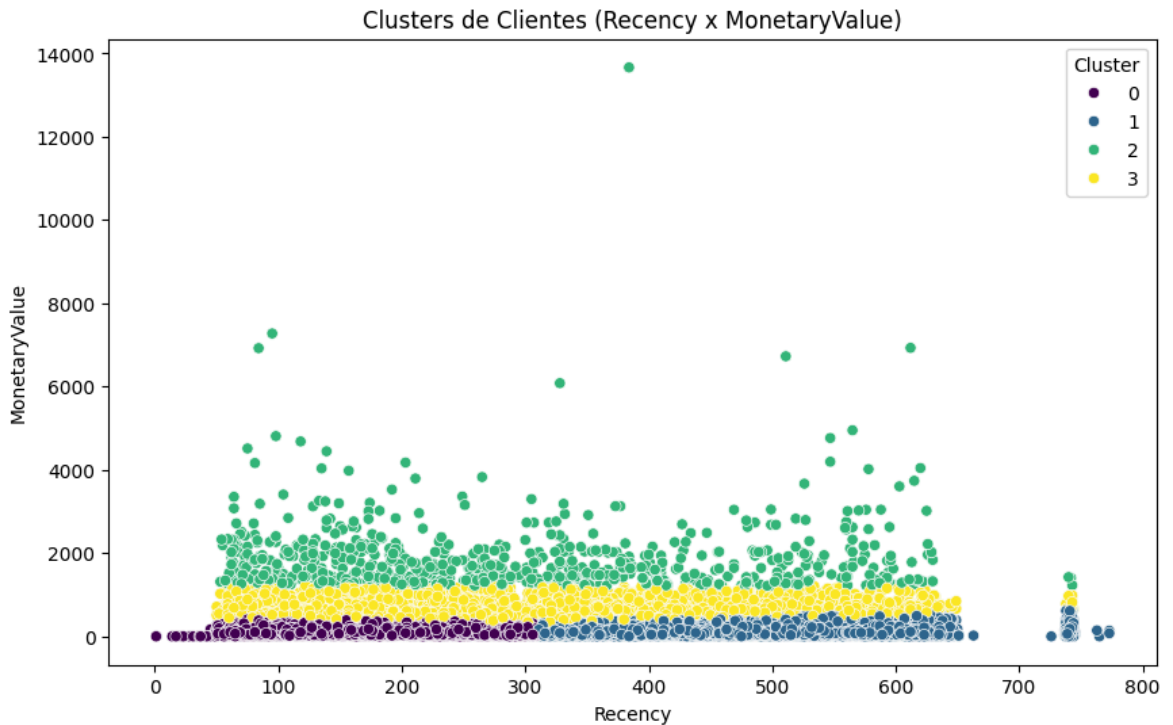
# Visualizando os clusters (exemplo com MonetaryValue x Frequency)
plt.figure(figsize=(10, 6))
sns.scatterplot(x='MonetaryValue', y='Frequency', hue='Cluster', data=rfv, palet
plt.title('Clusters de Clientes (MonetaryValue x Frequency)')
plt.show()
```

```
# Visualizando os clusters (exemplo com Recency x MonetaryValue)
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Recency', y='MonetaryValue', hue='Cluster', data=rfv, palette
plt.title('Clusters de Clientes (Recency x MonetaryValue)')
plt.show()
```

Características dos Clusters:

Cluster	Recency		Frequency		MonetaryValue	
	mean	median	mean	median	mean	median
0	179.519870	181.0	1.0	1.0	118.238119	99.14
1	442.008264	430.0	1.0	1.0	118.952898	96.12
2	297.415816	283.0	1.0	1.0	1819.093431	1589.91
3	275.690562	263.5	1.0	1.0	608.856138	558.52





Cluster 0: Recency baixa, Frequency alta, Monetary Value alto. Este cluster pode representar os clientes mais valiosos, que compram frequentemente e recentemente. Devem ser recompensados com ofertas exclusivas e programas de fidelidade.

Cluster 1: Recency alta, Frequency baixa, Monetary Value baixo. Este cluster pode representar clientes em risco de churn, que não compram há muito tempo e gastam pouco. Campanhas de reativação e ofertas personalizadas podem ser eficazes.

Cluster 2: Recency média, Frequency média, Monetary Value médio. Este cluster pode representar os clientes "típicos", que compram ocasionalmente. Campanhas de up-selling e cross-selling podem ser interessantes.

Cluster 3: Recency baixa, Frequency baixa, Monetary Value baixo. Este cluster pode representar clientes novos ou esporádicos. É importante incentivá-los a comprar novamente e aumentar seu valor monetário.

## Considerando outra variável

```
In [6]: # Merge para obter customer_unique_id em order_items
order_items_with_customer = pd.merge(order_items, orders[['order_id', 'customer_id']], on='order_id')
order_items_with_customer = pd.merge(order_items_with_customer, customers[['customer_id', 'customer_unique_id']], on='customer_id')

# Merge para obter as categorias dos produtos
order_items_with_category = pd.merge(order_items_with_customer, products[['product_id', 'product_category']], on='product_id')

# Encontra a categoria mais comprada por cliente (agora com customer_unique_id)
most_frequent_category = order_items_with_category.groupby(['customer_unique_id', 'product_category']).count().reset_index()
most_frequent_category = most_frequent_category.groupby('customer_unique_id').apply(lambda x: x['product_category'].idxmax())
most_frequent_category.reset_index(drop=True, inplace=True)
most_frequent_category = most_frequent_category[['customer_unique_id', 'product_category']]
most_frequent_category = most_frequent_category.rename(columns={'product_category': 'most_frequent_category'})
```

```

most_frequent_category.head()

# Adiciona a categoria mais frequente ao dataframe RFV (usando customer_unique_id)
rfv = pd.merge(rfv, most_frequent_category, on='customer_unique_id', how='left')

# Criar uma cópia do RFV somente com as variáveis numéricas para o K-Means
rfv_kmeans = rfv.drop(columns=['MostFrequentCategory']) # Remove a coluna categ

# Padroniza os dados (importante para o K-Means)
# Aplicar o scaler APÓS adicionar a categoria mais frequente e criar rfv_kmeans
scaler = StandardScaler()
rfv_scaled = scaler.fit_transform(rfv_kmeans)

# Determina o número ideal de clusters (método Elbow)
inertia = []
for n in range(1, 11):
    kmeans = KMeans(n_clusters=n, random_state=42)
    kmeans.fit(rfv_scaled)
    inertia.append(kmeans.inertia_)

plt.figure(figsize=(10, 5))
plt.plot(range(1, 11), inertia, marker='o')
plt.title('Método Elbow para Determinar o Número de Clusters')
plt.xlabel('Número de Clusters')
plt.ylabel('Inertia')
plt.show()

# Escolhe o número de clusters baseado no gráfico do Elbow (exemplo: 4 clusters)
n_clusters = 4 # modifique se o gráfico elbow indicar outro valor ideal

kmeans = KMeans(n_clusters=n_clusters, random_state=42)
rfv['Cluster'] = kmeans.fit_predict(rfv_scaled)

print(rfv.head())

# Analisando os clusters, incluindo a categoria mais frequente:
print(rfv.groupby('Cluster').agg({
    'Recency': ['mean', 'median'],
    'Frequency': ['mean', 'median'],
    'MonetaryValue': ['mean', 'median'],
    'MostFrequentCategory': lambda x: x.value_counts().index[0] # Categoria mai
})))

```

C:\Users\salom\AppData\Local\Temp\ipykernel\_16412\430456860.py:10: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior is deprecated, and in a future version of pandas the grouping columns will be excluded from the operation. Either pass `include\_groups=False` to exclude the groupings or explicitly select the grouping columns after groupby to silence this warning.

```

most_frequent_category = most_frequent_category.groupby('customer_unique_id').apply(lambda x: x.nlargest(1, 'order_id'))

```

```

-----
KeyError                                Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_16412\430456860.py in ?()
    15 most_frequent_category.head()
    16
    17
    18 # Adiciona a categoria mais frequente ao dataframe RFV (usando customer_u
nique_id)
--> 19 rfv = pd.merge(rfv, most_frequent_category, on='customer_unique_id', how
='left')
    20
    21 # Criar uma cópia do RFV somente com as variáveis numéricas para o K-Mean
s
    22 rfv_kmeans = rfv.drop(columns=['MostFrequentCategory']) # Remove a colun
a categórica

c:\Python312\Lib\site-packages\pandas\core\reshape\merge.py in ?(left, right, ho
w, on, left_on, right_on, left_index, right_index, sort, suffixes, copy, indicato
r, validate)
    166         validate=validate,
    167         copy=copy,
    168     )
    169     else:
--> 170         op = _MergeOperation(
    171             left_df,
    172             right_df,
    173             how=how,

c:\Python312\Lib\site-packages\pandas\core\reshape\merge.py in ?(self, left, righ
t, how, on, left_on, right_on, left_index, right_index, sort, suffixes, indicato
r, validate)
    790         self.right_join_keys,
    791         self.join_names,
    792         left_drop,
    793         right_drop,
--> 794     ) = self._get_merge_keys()
    795
    796     if left_drop:
    797         self.left = self.left._drop_labels_or_levels(left_drop)

c:\Python312\Lib\site-packages\pandas\core\reshape\merge.py in ?(self)
   1306         if lk is not None:
   1307             # Then we're either Hashable or a wrong-length ar
raylike,
   1308             # the latter of which will raise
   1309             lk = cast(Hashable, lk)
-> 1310             left_keys.append(left._get_label_or_level_values
(lk))
   1311             join_names.append(lk)
   1312         else:
   1313             # work-around for merge_asof(left_index=True)

c:\Python312\Lib\site-packages\pandas\core\generic.py in ?(self, key, axis)
   1907         values = self.xs(key, axis=other_axes[0])._values
   1908     elif self._is_level_reference(key, axis=axis):
   1909         values = self.axes[axis].get_level_values(key)._values
   1910     else:
-> 1911         raise KeyError(key)
   1912
   1913     # Check for duplicates

```



```
1914         if values.ndim > 1:
```

```
KeyError: 'customer_unique_id'
```