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1 Customer Segmentation for a Credit Card Company

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November 2020

1.1 Problem statement

This project is about customer segmentation for a credit card company. One way to reduce the costs associated with credit card signup incentives and offering successful marketing campaigns is to offer credit cards with carefully targeted benefits that will attract new cardholders. The goal of customer segmentation here is to get an idea of popular benefits to associate with each new card offering. To study the various kinds of users who use the company's products we are looking at the user data over a 6 month period. The data consists of 8950 rows (one for each cardholder) organized in columns with descriptive headers. The data has been provided by J. Patrick Weller. Currently this data is not publicly available.

Column label information:

- CUST_ID : Credit card holder ID
- BALANCE : Monthly average balance (based on daily balance averages)
- BALANCE_FREQUENCY : Ratio of last 12 months with balance
- PURCHASES : Total purchase amount spent during last 12 months
- ONEOFF_PURCHASES : Total amount of one-off purchases
- INSTALLMENTS_PURCHASES : Total amount of installment purchases
- CASH_ADVANCE : Total cash-advance amount
- PURCHASES_FREQUENCY : Frequency of purchases (percentage of months with at least one purchase)
- ONEOFF_PURCHASES_FREQUENCY : Frequency of one-off-purchases
- PURCHASES_INSTALLMENTS_FREQUENCY : Frequency of installment purchases
- CASH_ADVANCE_FREQUENCY : Cash-Advance frequency
- AVERAGE_PURCHASE_TRX : Average amount per purchase transaction
- CASH_ADVANCE_TRX : Average amount per cash-advance transaction
- PURCHASES_TRX : Average amount per purchase transaction

- PURCHASES_TRX : Average amount per purchase transaction
- CREDIT_LIMIT : Credit limit
- PAYMENTS : Total payments (due amount paid by the customer to decrease their statement balance) in the period

1.2 Summary of results

I used Kmeans and Hierarchical Clustering to segment customers. Both methods resulted in comparable outcomes. I identified 4 clusters with the following descriptions:

- Cluster 1: Low balance, infrequent users. Mostly use the card for one off purchases and cash advances. Rarely pay the balance in full. Low credit limit.
- Cluster 2: Low balance, frequent users. Don't spend too much money with this card but use it frequently for small purchases. Rarely do cash advance. Low credit limit.
- Cluster 3: High balance driven by frequent cash advance not purchases. Prefer to pay for everything in cash! Rarely pay the balance in full. High credit limit.
- Cluster 4: High balance driven by frequent purchases (both one-off purchases and installments), not so much by cash advances. Use credit to pay for everything!. High credit limit.

Reommendation:

Here I came up with some simple offer components that can be attractive to different customer segments. Tailoring these offers requires a lot of knowledge about the costs associated with each type of offer.

- Offer low APR for customers who rarely pay their balance in full (cluster # 1 and # 3)
- Offer low cash advance fee for customers who frequently take cash advances (cluster # 3)
- Offer sign up bonuses (e.g. $200 bonus if you spend $500 in the first 3 months) for customers with low balance, customers who use their cards frequently but for small purchases or do not use it often (cluster # 1 and # 2)
- Offer higher cash back for high spenders and frequent users (stay competitive in the credit card space) to retain customers (cluster # 1 and # 4)

2 Exploring the data

2.1 Import modules

In [1]:

```python
import datetime as dt
import numpy as np
import pandas as pd
import seaborn as sns
import warnings

import matplotlib.dates as mdates
import matplotlib.pyplot as plt

from sklearn.decomposition import PCA
from sklearn.cluster import KMeans, AgglomerativeClustering
from scipy.cluster.hierarchy import dendrogram

from sklearn.preprocessing import StandardScaler
from scipy.spatial.distance import cdist
from sklearn.metrics import davies_bouldin_score, silhouette_score


from patsy import dmatrices
from statsmodels.stats.outliers_influence import variance_inflation_factor

pd.set_option("display.max_columns", None)
sns.set_context("poster", font_scale=1.2)
# warnings.filterwarnings('ignore')
```

2.2 Helper functions

In [2]:

```python
def print_full(x):
    pd.set_option("display.max_rows", len(x))
    pd.set_option("display.max_columns", None)
    pd.set_option("display.width", 2000)
    pd.set_option("display.float_format", "{:20,.2f}".format)
    pd.set_option("display.max_colwidth", None)
    print(x)
    pd.reset_option("display.max_rows")
    pd.reset_option("display.max_columns")
    pd.reset_option("display.width")
    pd.reset_option("display.float_format")
    pd.reset_option("display.max_colwidth")


def col_name_cleaner(df):
    df.columns = [column.replace("(", "") for column in df.columns]
    df.columns = [column.replace(")", "") for column in df.columns]
    df.columns = [column.replace(" ", "_") for column in df.columns]
    df.columns = [column.replace("/", "_") for column in df.columns]
    df.columns = [column.lower() for column in df.columns]
```

2.3 Import data

In [3]:
```python
df = pd.read_csv("cc_info.csv")
df.head()
```

Out[3]:

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PU
0	C10001	40.900749	0.818182	95.40	0.00	
1	C10002	3202.467416	0.909091	0.00	0.00	
2	C10003	2495.148862	1.000000	773.17	773.17	
3	C10004	1666.670542	0.636364	1499.00	1499.00	
4	C10005	817.714335	1.000000	16.00	16.00	

In [4]:
```python
## Checking for data types and nulls and converting to lowercase the column names
col_name_cleaner(df)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8950 entries, 0 to 8949
Data columns (total 18 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   cust_id                           8950 non-null   object 
 1   balance                           8950 non-null   float64
 2   balance_frequency                 8950 non-null   float64
 3   purchases                         8950 non-null   float64
 4   oneoff_purchases                  8950 non-null   float64
 5   installments_purchases            8950 non-null   float64
 6   cash_advance                      8950 non-null   float64
 7   purchases_frequency               8950 non-null   float64
 8   oneoff_purchases_frequency        8950 non-null   float64
 9   purchases_installments_frequency  8950 non-null   float64
 10  cash_advance_frequency            8950 non-null   float64
 11  cash_advance_trx                  8950 non-null   int64  
 12  purchases_trx                     8950 non-null   int64  
 13  credit_limit                      8949 non-null   float64
 14  payments                          8950 non-null   float64
 15  minimum_payments                  8637 non-null   float64
 16  prc_full_payment                  8950 non-null   float64
 17  tenure                            8950 non-null   int64  
dtypes: float64(14), int64(3), object(1)
memory usage: 1.2+ MB
```

In [5]:
```
df.isnull().sum()
```

Out[5]:
```
cust_id                             0
balance                             0
balance_frequency                   0
purchases                           0
oneoff_purchases                    0
installments_purchases              0
cash_advance                        0
purchases_frequency                 0
oneoff_purchases_frequency          0
purchases_installments_frequency    0
cash_advance_frequency              0
cash_advance_trx                    0
purchases_trx                       0
credit_limit                        1
payments                            0
minimum_payments                  313
prc_full_payment                    0
tenure                              0
dtype: int64
```

In [6]:
```
df = df.dropna()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 8636 entries, 0 to 8949
Data columns (total 18 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   cust_id                           8636 non-null   object 
 1   balance                           8636 non-null   float64
 2   balance_frequency                 8636 non-null   float64
 3   purchases                         8636 non-null   float64
 4   oneoff_purchases                  8636 non-null   float64
 5   installments_purchases            8636 non-null   float64
 6   cash_advance                      8636 non-null   float64
 7   purchases_frequency               8636 non-null   float64
 8   oneoff_purchases_frequency        8636 non-null   float64
 9   purchases_installments_frequency  8636 non-null   float64
 10  cash_advance_frequency            8636 non-null   float64
 11  cash_advance_trx                  8636 non-null   int64  
 12  purchases_trx                     8636 non-null   int64  
 13  credit_limit                      8636 non-null   float64
 14  payments                          8636 non-null   float64
 15  minimum_payments                  8636 non-null   float64
 16  prc_full_payment                  8636 non-null   float64
 17  tenure                            8636 non-null   int64  
dtypes: float64(14), int64(3), object(1)
memory usage: 1.3+ MB
```

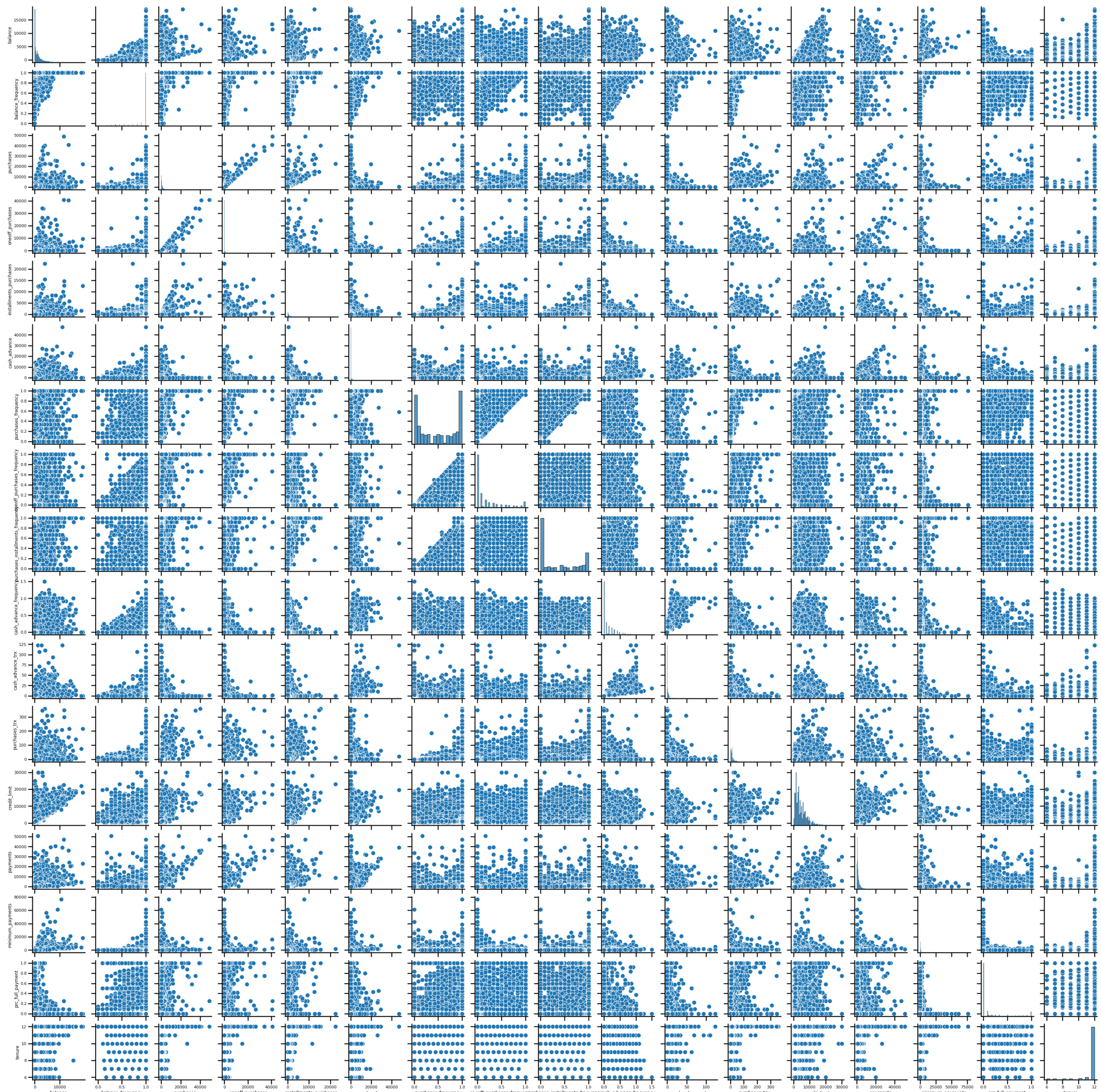
In [7]:
```
## Checking for duplicates in cust_id: all good
df.cust_id.nunique()
```

Out[7]:
```
8636
```

2.4 EDA

In [8]:
```python
## Pair plots, no obvious clusters stand out
sns.set_context("poster", font_scale=0.5)
sns.pairplot(df.iloc[:, 1:])
```

Out[8]: <seaborn.axisgrid.PairGrid at 0x1f62b83fa60>



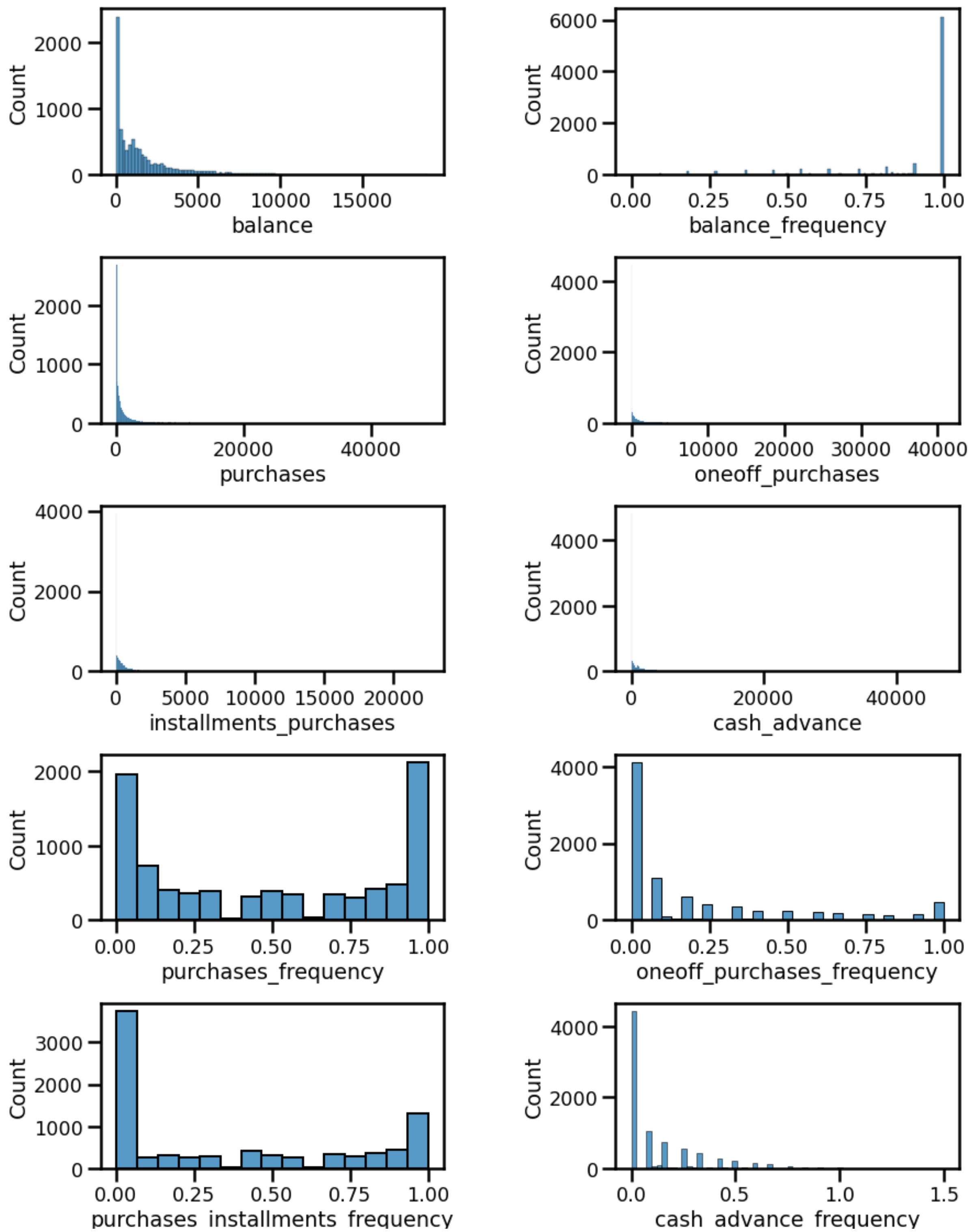
In [9]:

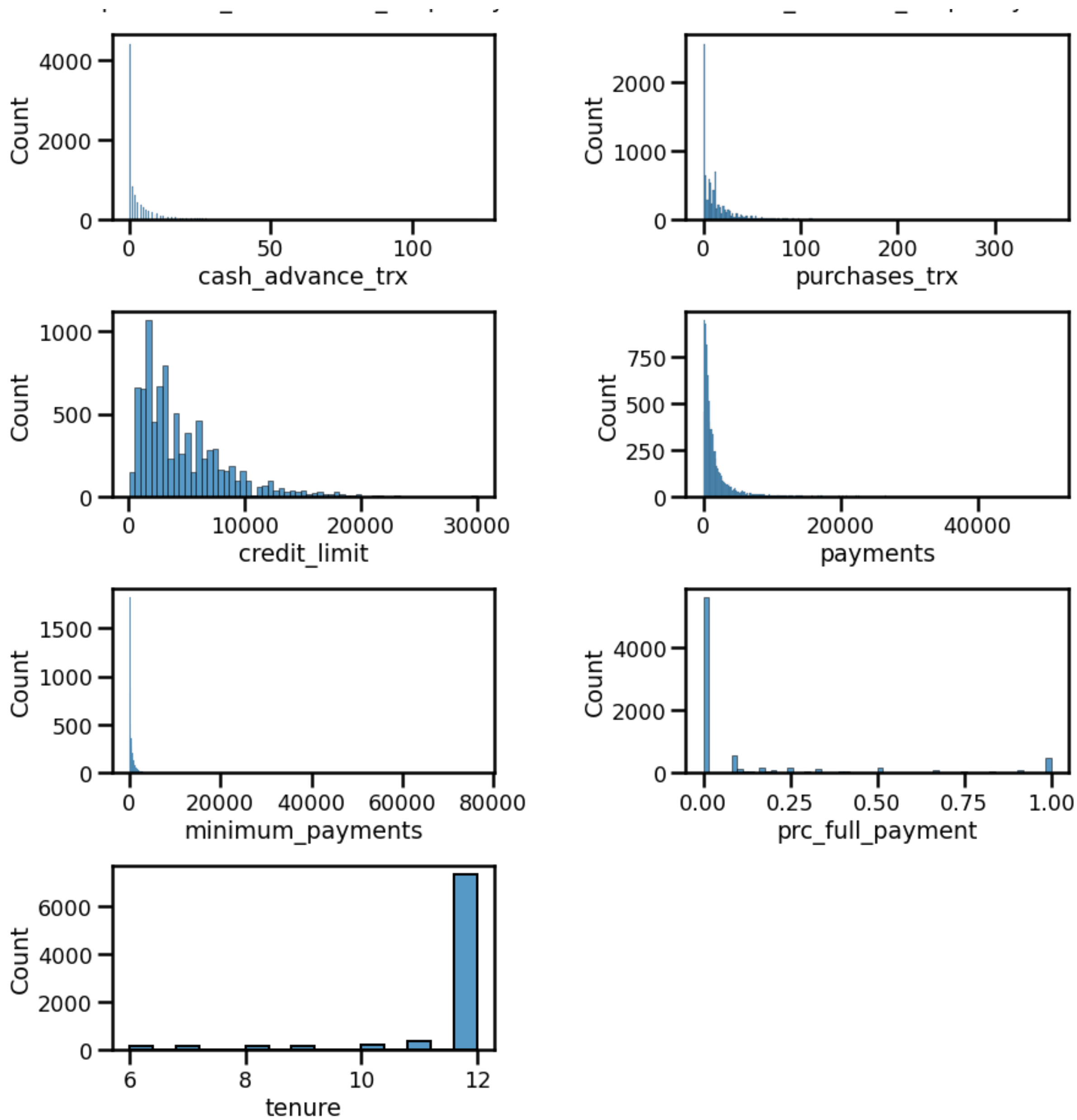
```
## Plot histograms
sns.set_context("poster", font_scale=0.8)
n_cols = len(df.columns)

fig, ax = plt.subplots((n_cols) // 2, 2, figsize=(14, 2 * (n_cols)))


for i in range(1, n_cols):
    sns.histplot(df.iloc[:, i], ax=ax[(i - 1) // 2][(i - 1) % 2])
    ax[(i - 1) // 2][(i - 1) % 2].set_xlabel(df.columns[i])

fig.subplots_adjust(hspace=0.5, wspace=0.5)
fig.delaxes(ax[8][1])
```

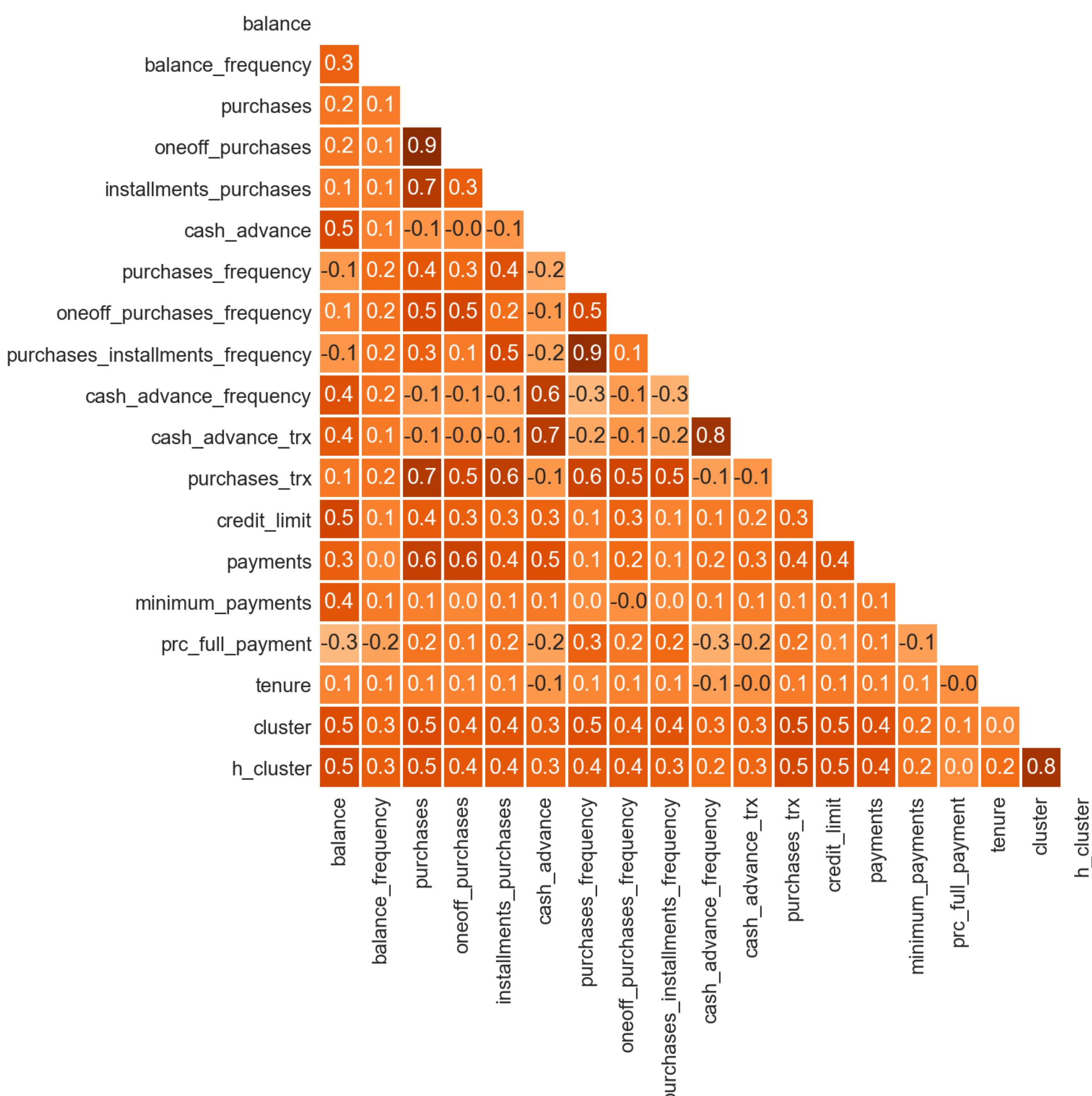



Count
cash_advance_trx
Count
purchases_trx
Count
credit_limit
Count
payments
Count
minimum_payments
Count
prc_full_payment
Count
tenure

In [34]:

```python
## Correlation matrix
plt.figure(figsize=(20, 20))
sns.set(font_scale=2.5, style="whitegrid")
correlation_matrix = df.corr()
# sns.heatmap(df.corr())


matrix = np.triu(df.corr())
sns.heatmap(
    correlation_matrix,
    mask=matrix,
    vmax=1,
    vmin=-1,
    square=True,
    cmap="Oranges",
    annot=True,
    fmt=".1f",
    linewidth=3,
    linecolor="white",
    cbar=False,
)
plt.xticks(rotation=90);
```



3 PCA

The purpose of the PCA study here is to understand if there are a limited number of features which can explain most of the variations in the feature space. If we could determine only 2 or 3 features are important we can use those features for 2D/3D plotting and visualizing the clusters. It is important to do standardization before PCA to avoid having outliers determine the structure of PCA. Here 80% of the variance can be explained by the first 7 components. Therefore, PCA cannot help us much with making 2D/3D plots after clustering. Therefore I won't use it.

In [11]:
```
## Scaling the features
scaler = StandardScaler()
X_std = scaler.fit_transform(df.iloc[:, 1:])
```

In [12]:
```
## How much variance we can capture with only two principal components
pca = PCA(n_components=2)
pca_fitted = pca.fit_transform(X_std)
principalDf = pd.DataFrame(
    data=pca_fitted, columns=["principal component 0", "principal component 1"]
)

print(
    "Explained variation per principal component: {}".format(
        pca.explained_variance_ratio_
    )
)
```

```
Explained variation per principal component: [0.27231177 0.20374308]
```

In [13]:

```
## Structure of these two components based on the original features
print("pca components:\n", pca.components_)
```

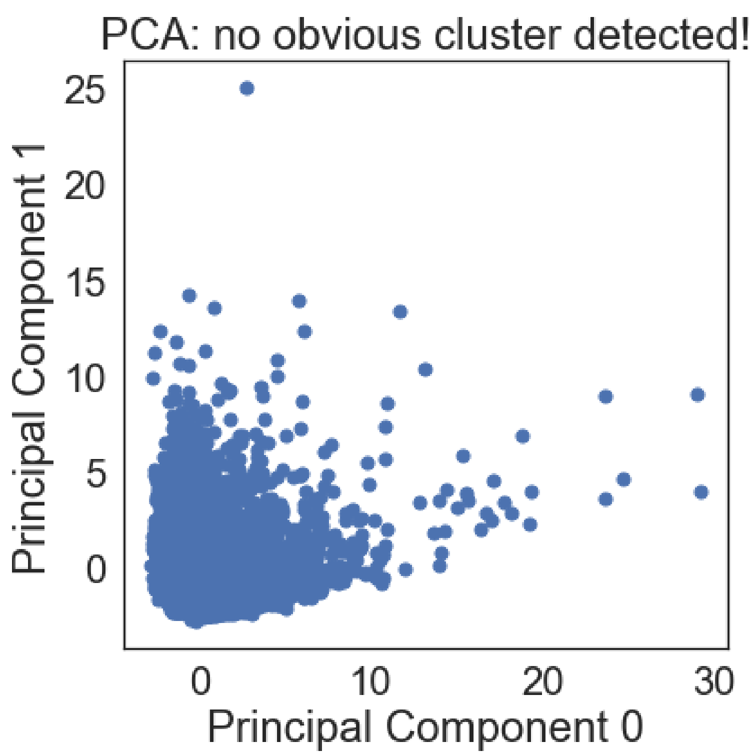
```
pca components:
 [[ 0.09198554  0.10981227  0.41215118  0.34677532  0.33705558 -0.03058773
   0.32366483  0.2947613   0.27722627 -0.09914536 -0.05696032  0.39106662
   0.2100521   0.26372558  0.05932642  0.13056491  0.07791863]
 [ 0.40597942  0.12773854  0.04953037  0.06992969 -0.01148122  0.43724697
  -0.18658162 -0.01474647 -0.17357694  0.42999685  0.41641174 -0.01194676
   0.24382257  0.26418161  0.17041556 -0.19570867 -0.00456549]]
```

In [14]:

```
## Visualizing the data on the first and second PCs: no obvious clusters using the first
sns.set(font_scale=2, style="white")
plt.figure(figsize=(6, 6))
plt.xlabel("Principal Component 0")
plt.ylabel("Principal Component 1")
plt.title("PCA: no obvious cluster detected!")


plt.scatter(
    principalDf.loc[:, "principal component 0"],
    principalDf.loc[:, "principal component 1"],
    s=50,
)
```

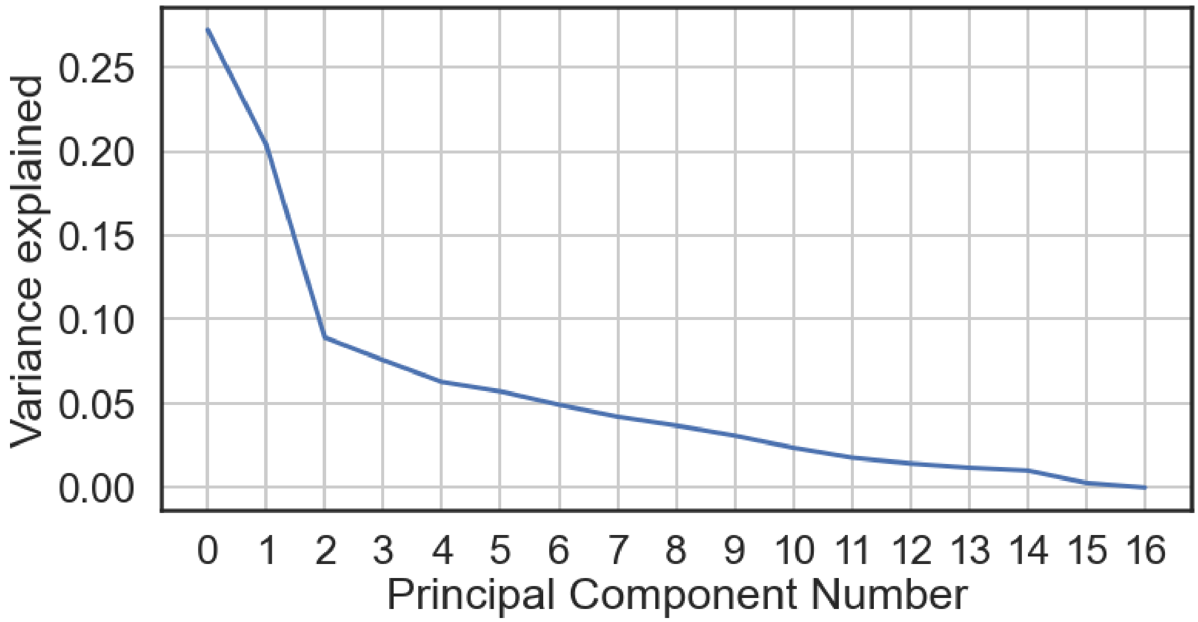
Out[14]: <matplotlib.collections.PathCollection at 0x1f644843880>



In [15]:

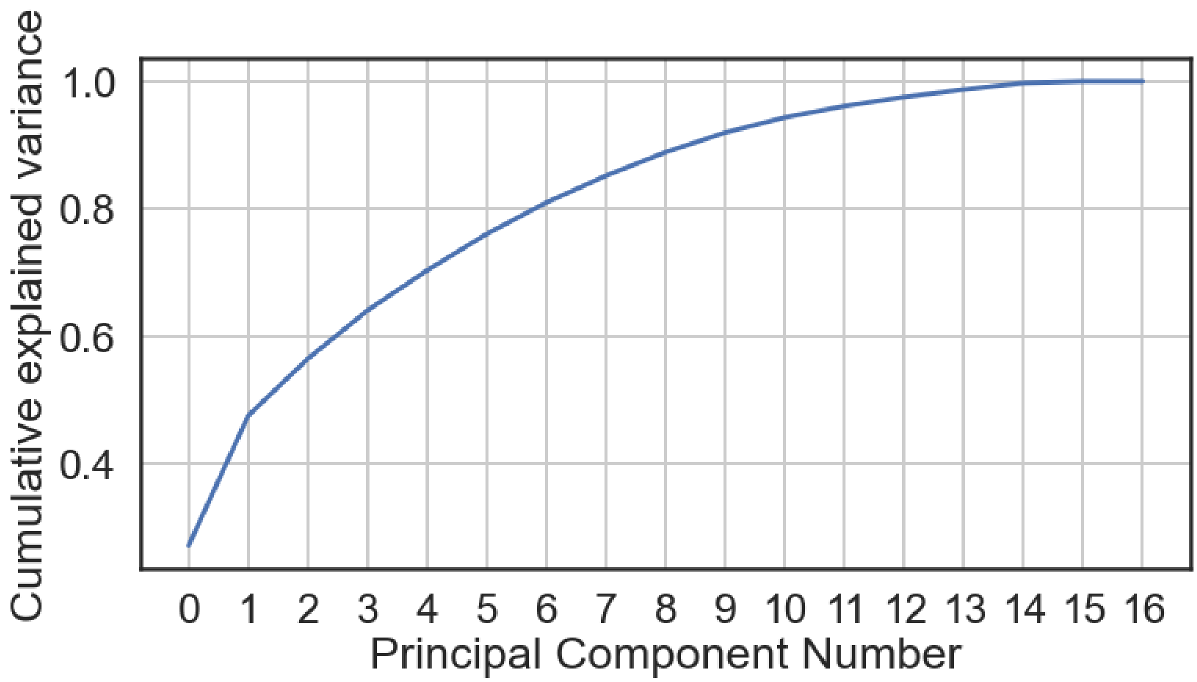
```python
## PCA without specifying n_components to get all of them
sns.set_context("poster", font_scale=1.2)
fig, ax = plt.subplots(figsize=(12, 6))

pca = PCA()
pca.fit(X_std)
# plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.plot(pca.explained_variance_ratio_)
ax.set_xlabel("Principal Component Number")
ax.set_ylabel("Variance explained")
ax.set_xticks([x for x in range(len(pca.explained_variance_ratio_))])
ax.grid()
```



In [16]:

```
## Cumulative variance explained by components
## 80% of variance was explained by first 7 PCs
fig, ax = plt.subplots(figsize=(12, 6))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
ax.set_xlabel("Principal Component Number")
ax.set_ylabel("Cumulative explained variance")
ax.set_xticks([x for x in range(len(pca.explained_variance_ratio_))])
ax.grid()
```



4 Kmeans

K-Means is one of the most popular "clustering" algorithms. K-means stores k centroids that it uses to define clusters. A point is considered to be in a particular cluster if it is closer to that cluster's centroid than any other centroid.

K-Means finds the best centroids by alternating between (1) assigning data points to clusters based on the current centroids (2) choosing centroids (points which are the center of a cluster) based on the current assignment of data points to clusters.

4.1 Selecting K

The Elbow Method is one of the most popular methods to determine this optimal value of k. The idea behind the elbow method is to identify the value of k where the score begins to decrease most rapidly before the Inertia curve reaches a plateau. Inertia is the sum of squared distances of samples to their closest cluster center.

Another method is using the Silhouette score. The silhouette value for every data point is a measure of how similar an object is to its own cluster compared to other clusters. The silhouette ranges from −1 to +1, where a high value indicates that the object is well matched to its own cluster and poorly matched to neighboring clusters. The cluster number with the maximum average Silhouette score would be the optimum one. In this problem, Silhouette scores for clusters between 2 to 13 are all close and vary between 0.2 to 0.24, so there is no real winner.

I selected k=4 based on the elbow method and observing a decrease in the Inertia slope after 4 clusters. However, the elbow does not have a sharp bend that we would like to see in the inertia plots. Therefore, I plan to use another clustering algorithm later that could work better for this data.

In [17]:

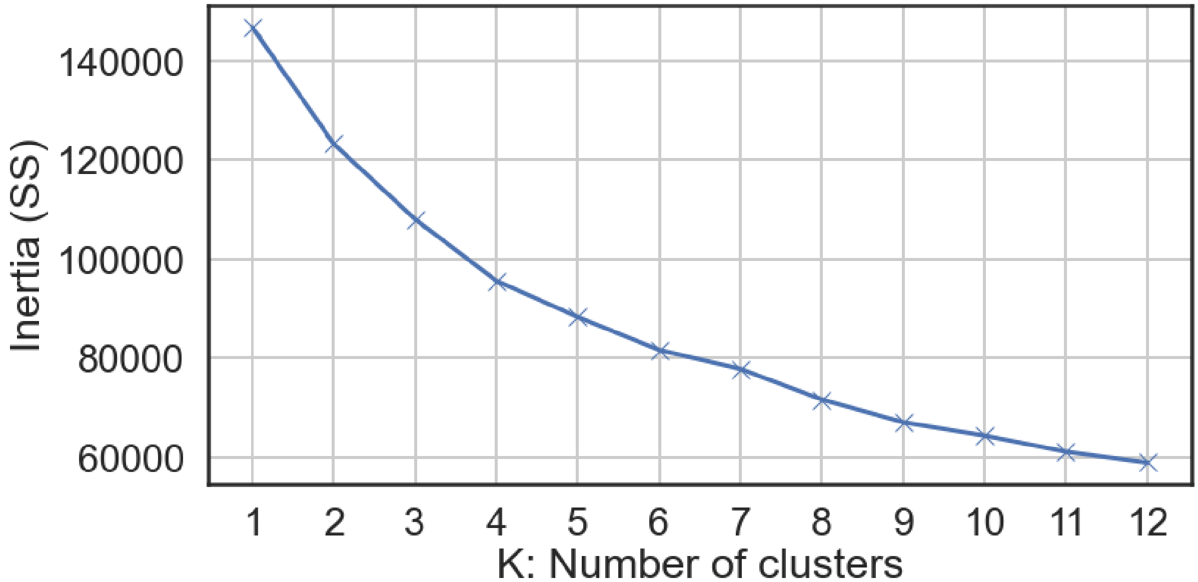
```
## Calculating Inertia (sum of squared distances from the cluster centers) as a functior

SS = []
D = []
DB = []
SIL = []
for k in range(1, 13):
    model = KMeans(n_clusters=k, init="random", random_state=0)
    model.fit(X_std)
    clusters = model.labels_

    SS.append(model.inertia_)
    D.append(
        sum(np.min(cdist(X_std, model.cluster_centers_, "euclidean"), axis=1))
        / X_std.shape[0]
    )
    if k >= 2:
        SIL.append(silhouette_score(X_std, clusters))
```

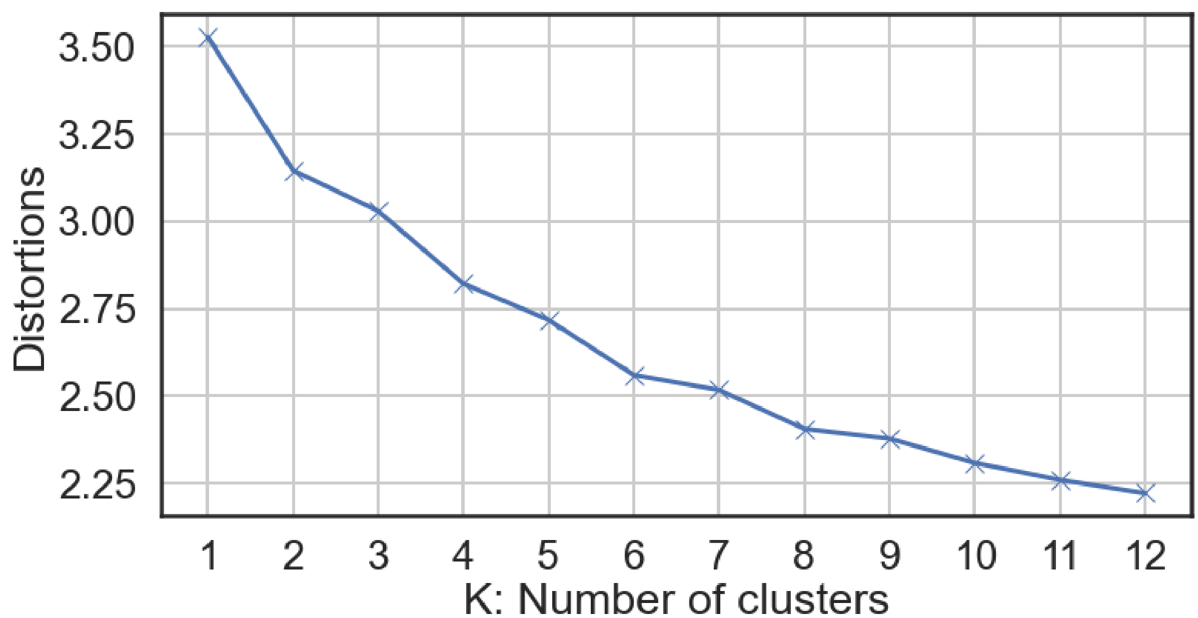
In [18]:

```
## Plotting Inertia vs number of clusters
fig, ax = plt.subplots(figsize=(12, 6))
plt.plot(range(1, 13), SS, "bx-")
plt.xlabel("K: Number of clusters")
plt.xticks(range(1, 13))
plt.ylabel("Inertia (SS)")
plt.grid()
```



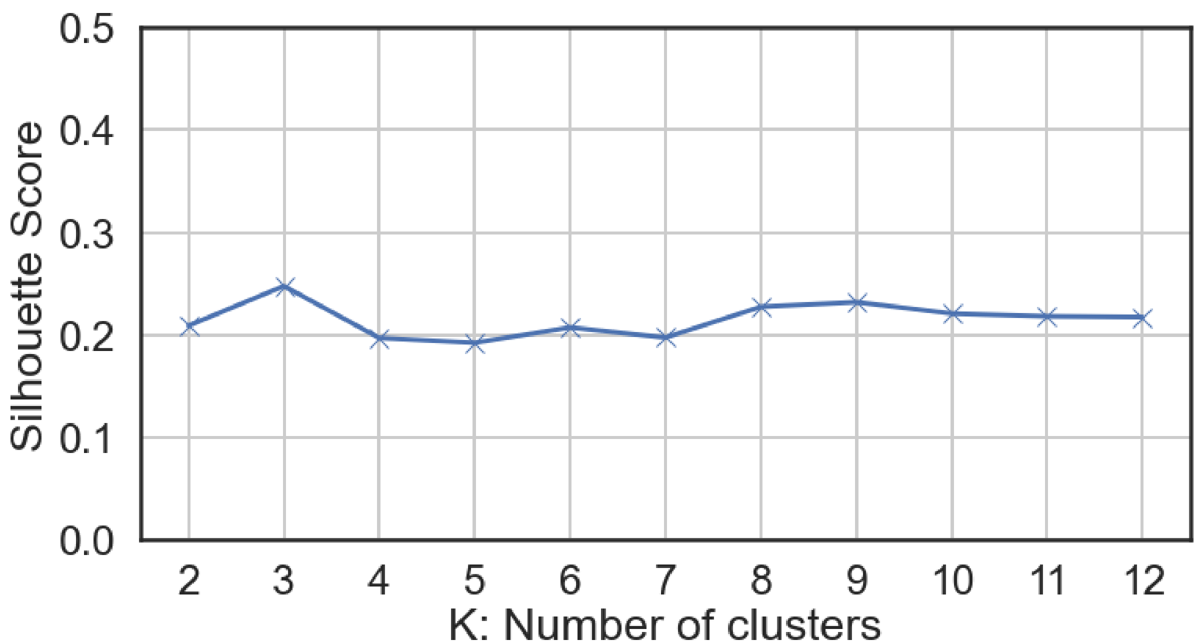
In [19]:

```
## Plotting Distortion vs number of clusters
## Distortion: It is calculated as the average of the squared distances from the cluster
fig, ax = plt.subplots(figsize=(12, 6))
plt.plot(range(1, 13), D, "bx-")
plt.xlabel("K: Number of clusters")
plt.xticks(range(1, 13))
plt.ylabel("Distortions")
plt.grid()
```



In [20]:

```python
## Plotting Silhouette Score vs number of clusters
fig, ax = plt.subplots(figsize=(12, 6))
plt.plot(range(2, 13), SIL, "bx-")
plt.xlabel("K: Number of clusters")
plt.xticks(range(2, 13))
plt.ylabel("Silhouette Score")
plt.ylim((0, 0.5))
plt.grid()
```



In [21]:

```python
## I have selected k=4 based on the elbow method
## Cluster sizes
k = 4
model = KMeans(n_clusters=k, random_state=1)
model.fit(X_std)

## Counting the number of units in each cluster
# labels = model.predict(X_std)
# counter = {}

# for label in labels:  # or use scipy.stats.itemfreq
#     if label not in counter:
#         counter[label] = 1
#     else:
#         counter[label] += 1

# fig, ax = plt.subplots(figsize=(8, 5))
# plt.bar(counter.keys(), counter.values())
# plt.xlabel("Cluster Number")
# plt.ylabel("Cluster Size")
# plt.xticks(range(0, k));
```

Out[21]:

```
KMeans(n_clusters=4, random_state=1)
```

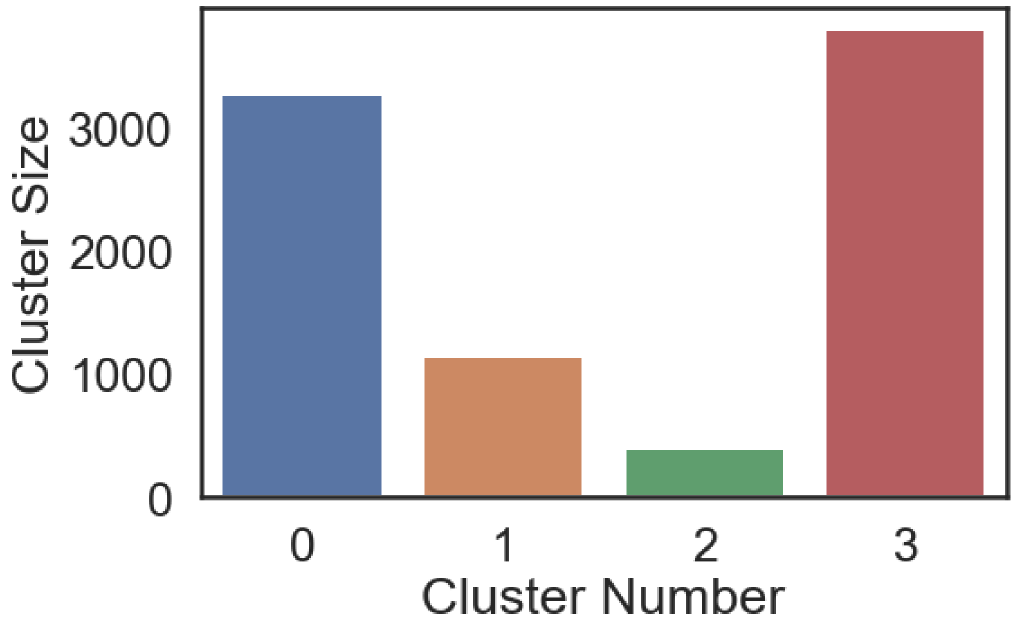
4.2 Comparing Clusters

In [22]:

```
## Labeling the rows with cluster numbers
kmeans = KMeans(n_clusters=4, init="random", random_state=0).fit(X_std)
df["cluster"] = kmeans.labels_
```

In [23]:

```
## Counting the number of units in each cluster
fig, ax = plt.subplots(figsize=(8, 5))
sns.countplot(x='cluster', data=df)
plt.xlabel("Cluster Number")
plt.ylabel("Cluster Size");
```



In [24]:

```
## Rename the clusters to make comparison easier, start the numbering from one not zero
def cluster_name_changer(x):
    dic = {0: 2, 3: 1, 1: 3, 2: 4}
    return dic[x]


df["cluster"] = df["cluster"].apply(lambda x: cluster_name_changer(x))
```

In [25]:

```
## Compare the mean of the clusters
df.groupby("cluster").mean().transpose()
```

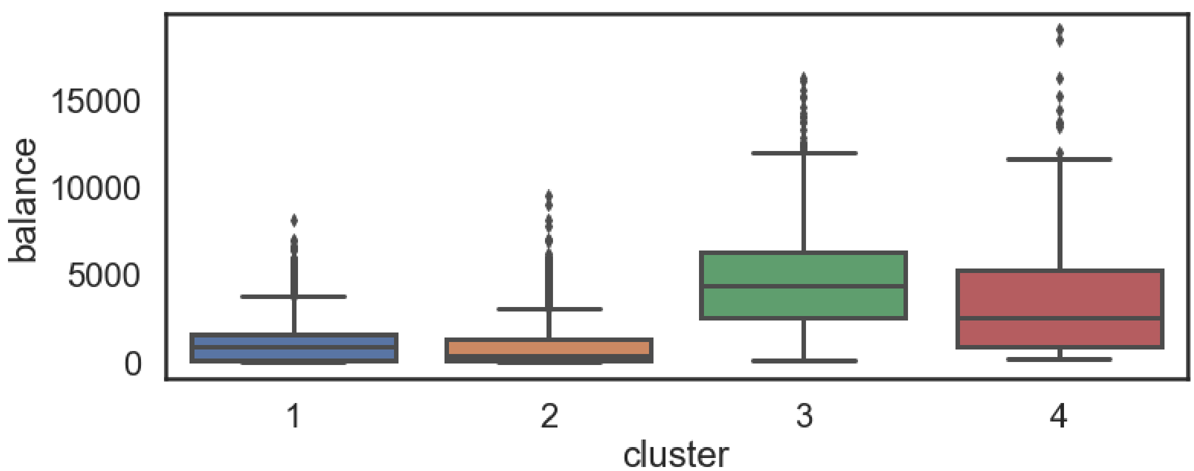
Out[25]:

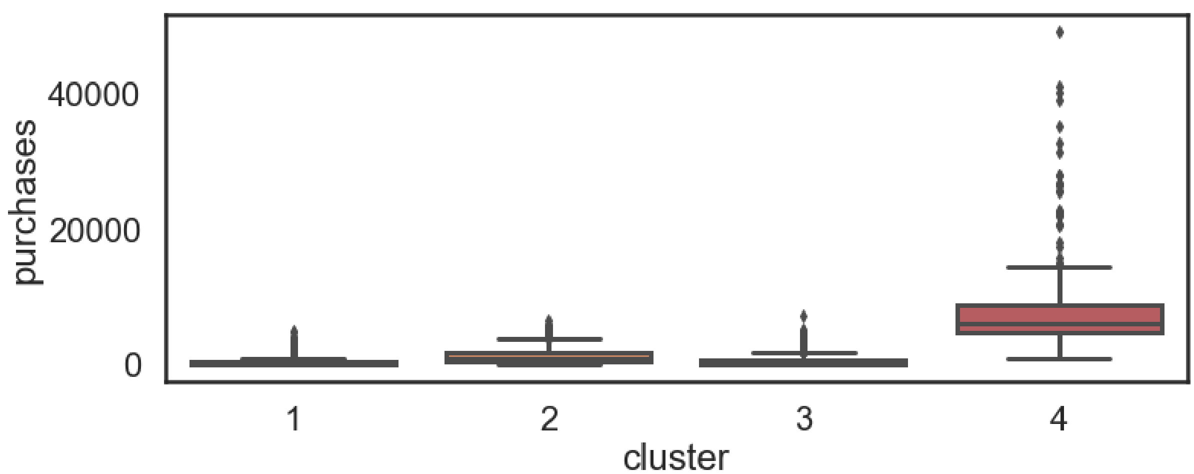
cluster	1	2	3	4
balance	1061.245064	914.398598	4654.668634	3586.147809
balance_frequency	0.818901	0.946186	0.969185	0.986840
purchases	273.943703	1264.766249	504.585671	7816.070736
oneoff_purchases	210.942878	611.185037	319.242797	5194.559518
installments_purchases	63.279848	653.862529	185.430900	2623.034061
cash_advance	606.661232	218.782441	4588.716197	658.230083
purchases_frequency	0.174488	0.887337	0.290148	0.944589
oneoff_purchases_frequency	0.087724	0.302426	0.139707	0.737344
purchases_installments_frequency	0.083122	0.713626	0.187588	0.786971
cash_advance_frequency	0.119162	0.043855	0.487532	0.070831
cash_advance_trx	2.211038	0.816880	14.457143	2.098985
purchases_trx	2.997898	22.507313	7.752381	90.347716
credit_limit	3259.159877	4255.521101	7648.099174	9775.380711
payments	1013.575184	1373.920198	3556.710634	7454.041676
minimum_payments	573.842255	649.503571	2038.647135	2016.140976
prc_full_payment	0.084056	0.274251	0.035357	0.291842
tenure	11.479106	11.601158	11.385281	11.949239

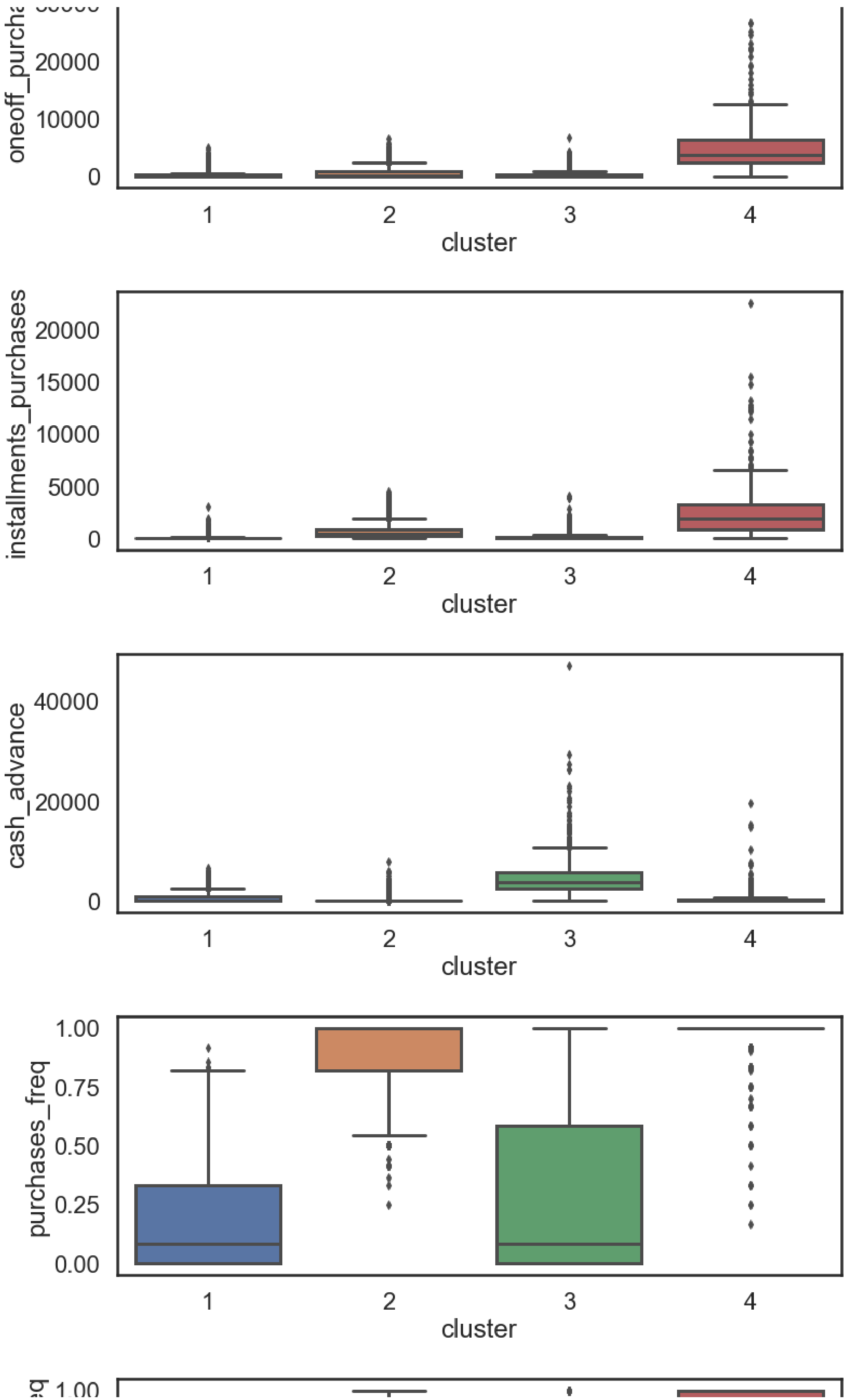
In [26]:

```python
## boxplots
sns.set_context("poster", font_scale=1)
cols_to_plot = [
    "balance",
    "purchases",
    "oneoff_purchases",
    "installments_purchases",
    "cash_advance",
    "purchases_frequency",
    "oneoff_purchases_frequency",
    "purchases_installments_frequency",
    "cash_advance_frequency",
    "credit_limit",
    "prc_full_payment",
]
n = len(cols_to_plot)

fig, ax = plt.subplots(n, 1, figsize=(12, 6 * n))
for i in range(n):
    sns.boxplot(x="cluster", y=cols_to_plot[i], data=df, ax=ax[i])
    ## shorten the ylabels
    if cols_to_plot[i][-9:] == "frequency":
        y_label = cols_to_plot[i][:-9] + "freq"
        ax[i].set_ylabel(y_label)
fig.subplots_adjust(hspace=0.4)
```






oneoff_purcha
20000
10000
0
1
2
3
4
cluster
installments_purchases
20000
15000
10000
5000
0
1
2
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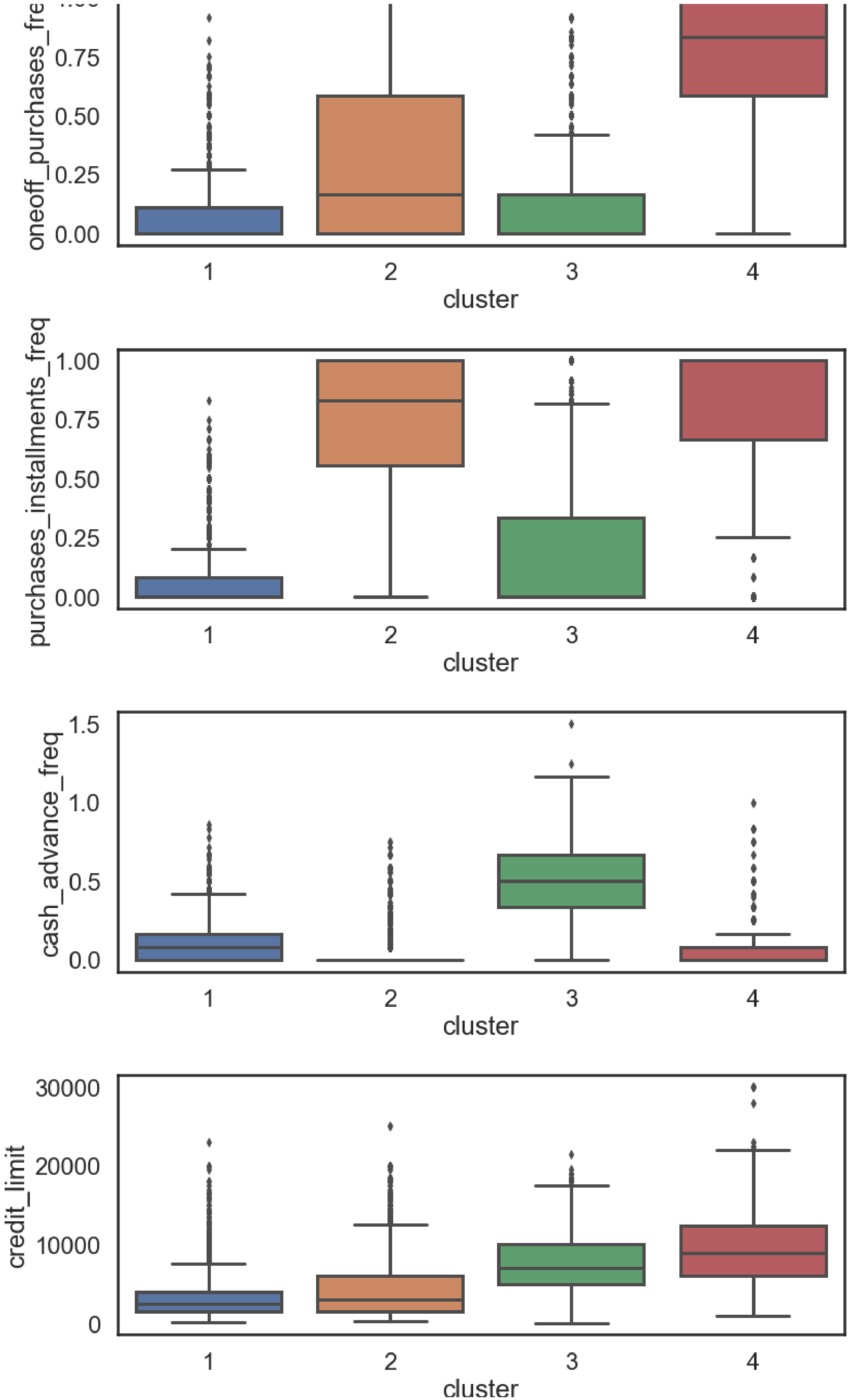
4
cluster
cash_advance
40000
20000
0
1
2
3
4
cluster
purchases_freq
1.00
0.75
0.50
0.25
0.00
1
2
3
4
cluster
1.00


oneoff_purchases_fre
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purchases_installments_freq
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3
4
cluster
cash_advance_freq
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0.5
1.0
1.5
1
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3
4
cluster
credit_limit
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10000
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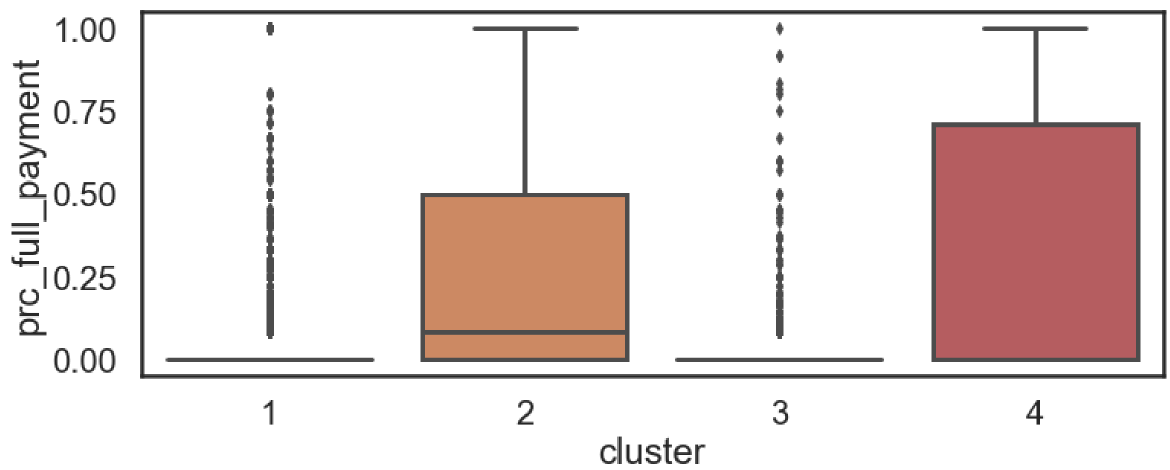
30000
1
2
3
4
cluster



5 Hierarchical Clustering

There are two types of Hierarchical clustering techniques:

1. Agglomerative clustering which is a bottom-up approach. Each data point is assumed to be a separate cluster at first. Then the similar clusters are iteratively combined.
2. Divisive clustering which is a top down approach. We start with one giant cluster including all data points. Then the data points are separated into different clusters. This method is less popular.

How do the algorithms identify closest clusters? There are a few methods to measure the similarity. Ward's linkage is one of the popular ones. In general "linkage" specifies how the distance between two clusters is calculated. Ward's linkage minimizes the within variance of the clusters being merged. Least increase in total variance around cluster centroids is aimed. In K-means we were trying to minimize the sum of squared distances from the cluster centers (inertia) to plot our elbow method chart, here it's almost the same; however, instead of minimizing inertia we are minimizing the within-cluster variance.

Here I will use Agglomerative clustering with Ward's linkage.

5.1 Building a agglomerative clustering model

In [27]:

```
## Building the Agglomerative model
## distinace threshold = 0 means can fill out entire dendrogram
hc = AgglomerativeClustering(
    distance_threshold=0, n_clusters=None, affinity="euclidean", linkage="ward"
)
## Fit the model
hc.fit(X_std)
```

Out[27]:

```
AgglomerativeClustering(distance_threshold=0, n_clusters=None)
```

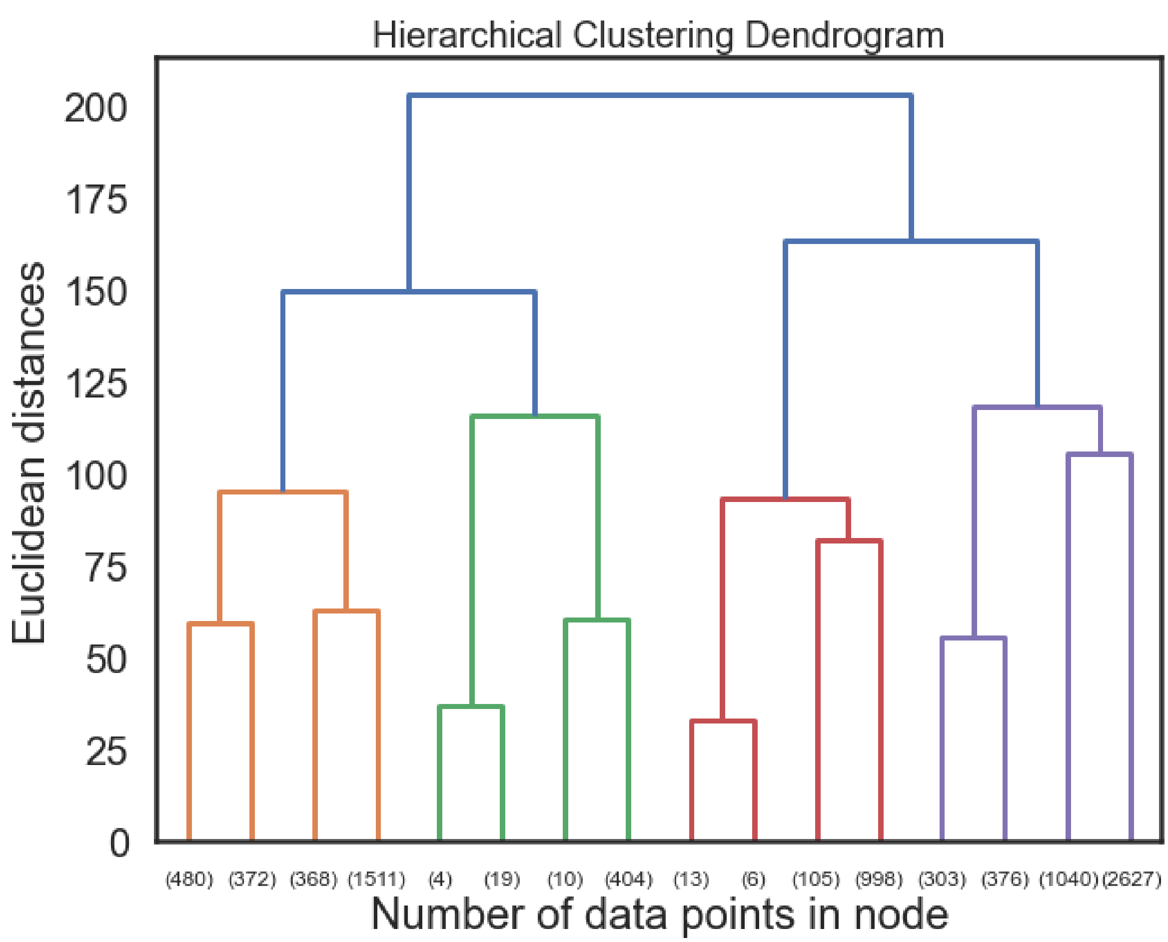
In [28]:

```
## A Dendrogram is a tree-like diagram that records the sequences of merges or splits.
## Create linkage matrix and then plot the dendrogram

def plot_dendrogram(model, **kwargs):
    # create the counts of samples under each node
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count

    linkage_matrix = np.column_stack([model.children_, model.distances_,
                                      counts]).astype(float)
    # Plot the corresponding dendrogram
    dendrogram(linkage_matrix, **kwargs)


## Plot the top 3 levels of the dendrogram
plt.figure(figsize = (10,8))
plot_dendrogram(hc, truncate_mode='level', p=3)
plt.title('Hierarchical Clustering Dendrogram', size = 20)
plt.xlabel("Number of data points in node") # (or index of point if no parenthesis)
plt.ylabel('Euclidean distances');
```



5.2 Selecting the number of clusters and comparison

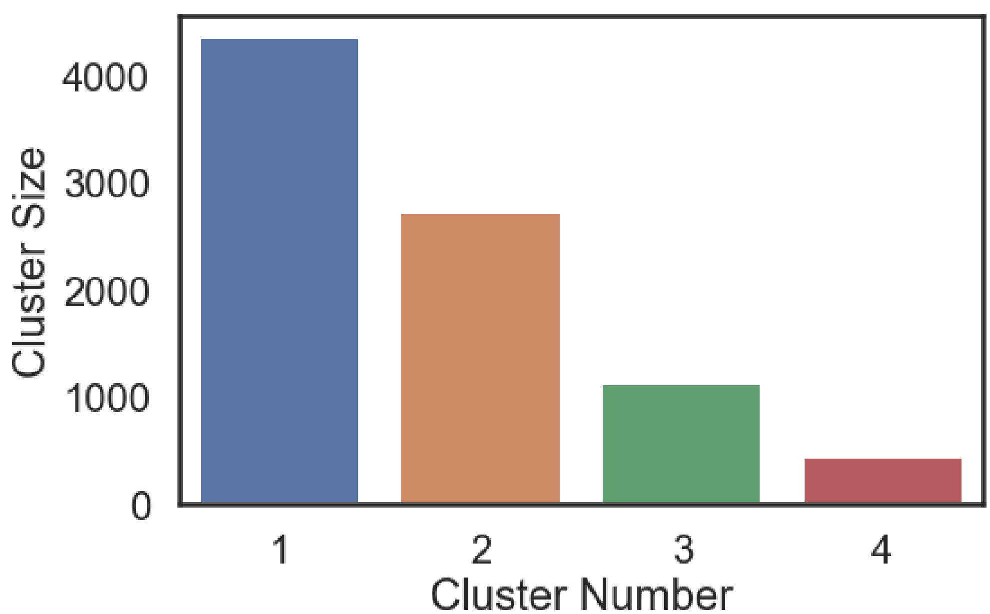
Dendrograms helps in showing progressions as clusters are merged. It also demonestrates how each cluster is composed of its child nodes. From the dendrogram we can realize that a good candidate for the number of clusters is four and that two of the clusters (red and orange) have better seperation from the rest compared to the other two. In general the separation between the four clusters is not as much as we would like since the amount of the jump in the Euclidean distances by merging the lower level clusters is not very large.

In [29]:
```
## Selecting 4 clusters
hc4 = AgglomerativeClustering(n_clusters=4,
                                  affinity='euclidean',
                                  linkage='ward')
hc4.fit_predict(X_std)
df['h_cluster'] = hc4.labels_
```

In [30]:
```
## Rename the clusters to make comparison easier, start the numbering from one not zero
def cluster_name_changer(x):
    dic = {0: 1, 3: 2, 1: 4, 2: 3}
    return dic[x]

df['h_cluster'] = df['h_cluster'].apply(lambda x: cluster_name_changer(x))
```

In [31]:
```
## Size of the clusters
fig, ax = plt.subplots(figsize=(8, 5))
sns.countplot(x='h_cluster', data=df)
plt.xlabel("Cluster Number")
plt.ylabel("Cluster Size");
```



In [32]:

```
## Compare the mean of the clusters
## One quick dirty way to compare these results with Kmeans labels is to look at the las
## which is the avg of previously assigned Kmeans labels for the points inside these new
df.groupby('h_cluster').mean().transpose()
```

Out[32]:

h_cluster	1	2	3	4
balance	979.609234	954.735370	4695.246244	3879.514557
balance_frequency	0.813965	0.975482	0.976833	0.988517
purchases	338.900152	1385.719044	516.485713	6908.217849
oneoff_purchases	209.611742	709.145632	333.451417	4581.572037
installments_purchases	129.627200	676.753047	183.144519	2328.018810
cash_advance	651.253000	286.676850	4167.246654	679.151156
purchases_frequency	0.261787	0.893277	0.259272	0.950319
oneoff_purchases_frequency	0.090834	0.333145	0.141404	0.720803
purchases_installments_frequency	0.169404	0.700948	0.161969	0.807517
cash_advance_frequency	0.119777	0.050301	0.442056	0.078805
cash_advance_trx	2.293833	1.007689	13.413547	1.940503
purchases_trx	4.463185	23.716221	7.625668	84.908467
credit_limit	3234.823232	4430.276955	7805.748663	9467.048055
payments	946.141268	1577.517889	3759.561600	6344.149755
minimum_payments	625.426832	539.832131	2217.096414	1794.436496
prc_full_payment	0.112638	0.283814	0.037234	0.158697
tenure	11.169351	11.939216	11.795009	11.965675
cluster	1.230557	2.036250	2.667558	3.450801

In [33]:

```
sns.pairplot(df[['balance', 'cash_advance', 'purchases', 'h_cluster']], hue='h_cluster')
```