Bank Churn Customer Analysis: Customer Segmentation

|| Segmenting Bank Customers and Recommend Potential New Products or Services for each Segment ||

Objective 1: Preparing the Data for Modeling

Our First Objective is to Prepare the Data for Modeling by Selecting a Subset of Fields, making sure they are Numeric, looking at their Distributions, and Engineering a new feature.

In [1]:
```
# Importing the Required Libraries
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:
```
# First, make sure your Google Drive is mounted in Colab:
# from google.colab import drive
# drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [2]:
```
# churn_cust_info = pd.read_excel("Bank_Churn_Messy.xlsx")
# data = pd.read_csv("/content/drive/MyDrive/Data Analytics & BI Career Path/Batch 2/Python/Bank Churn Customer Project/Bank_Churn.csv")
data = pd.read_csv("Bank_Churn.csv")
data.head()
```

Out[2]:

	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
0	15634602	Hargrave	619	France	Female	42	2	0.00	1	1	1	101348.88	1
1	15647311	Hill	608	Spain	Female	41	1	83807.86	1	0	1	112542.58	0
2	15619304	Onio	502	France	Female	42	8	159660.80	3	1	0	113931.57	1
3	15701354	Boni	699	France	Female	39	1	0.00	2	0	0	93826.63	0
4	15737888	Mitchell	850	Spain	Female	43	2	125510.82	1	1	1	79084.10	0

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 13 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   CustomerId       10000 non-null  int64  
 1   Surname          10000 non-null  object 
 2   CreditScore      10000 non-null  int64  
 3   Geography        10000 non-null  object 
 4   Gender           10000 non-null  object 
 5   Age              10000 non-null  int64  
 6   Tenure           10000 non-null  int64  
 7   Balance          10000 non-null  float64
 8   NumOfProducts    10000 non-null  int64  
 9   HasCrCard        10000 non-null  int64  
 10  IsActiveMember   10000 non-null  int64  
 11  EstimatedSalary  10000 non-null  float64
 12  Exited           10000 non-null  int64  
dtypes: float64(2), int64(8), object(3)
memory usage: 1015.8+ KB
```

Let's keep a subset of the Data

Create a DataFrame containing all fields except "CustomerId", "Surname" and "Exited".

In [4]:
```
data_subset = data [['CreditScore', 'Geography', 'Gender',
                     'Age', 'Tenure', 'Balance', 'NumOfProducts',
                     'HasCrCard', 'IsActiveMember', 'EstimatedSalary']]

data_subset.head()
```

Out[4]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	Female	42	2	0.00	1	1	1	101348.88
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	699	France	Female	39	1	0.00	2	0	0	93826.63
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

Making Text Fields Numeric

In [5]:
```
data_clean = data_subset.copy()
data_clean.head()
```

Out[5]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	Female	42	2	0.00	1	1	1	101348.88
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	699	France	Female	39	1	0.00	2	0	0	93826.63
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

In [6]:
```
data_clean.Geography.value_counts()
```

Out[6]:

	count
Geography	
France	5014
Germany	2509
Spain	2477

dtype: int64

In [7]:
```
data_clean.Gender.value_counts()
```

Out[7]:

	count
Gender	
Male	5457
Female	4543

dtype: int64

In [8]:
```
data_clean.Gender = np.where(data_clean.Gender == 'Female', 1, 0)
data_clean.head()
```

Out[8]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	1	42	2	0.00	1	1	1	101348.88
1	608	Spain	1	41	1	83807.86	1	0	1	112542.58
2	502	France	1	42	8	159660.80	3	1	0	113931.57
3	699	France	1	39	1	0.00	2	0	0	93826.63
4	850	Spain	1	43	2	125510.82	1	1	1	79084.10

In [12]:
```
data_clean = pd.get_dummies(data_clean, columns = ['Geography'], dtype = 'int', prefix = '', prefix_sep = '')
data_clean.head()
```

Out[12]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain
0	619	1	42	2	0.00	1	1	1	101348.88	1	0	0
1	608	1	41	1	83807.86	1	0	1	112542.58	0	0	1
2	502	1	42	8	159660.80	3	1	0	113931.57	1	0	0
3	699	1	39	1	0.00	2	0	0	93826.63	1	0	0
4	850	1	43	2	125510.82	1	1	1	79084.10	0	0	1

Exploring the Data

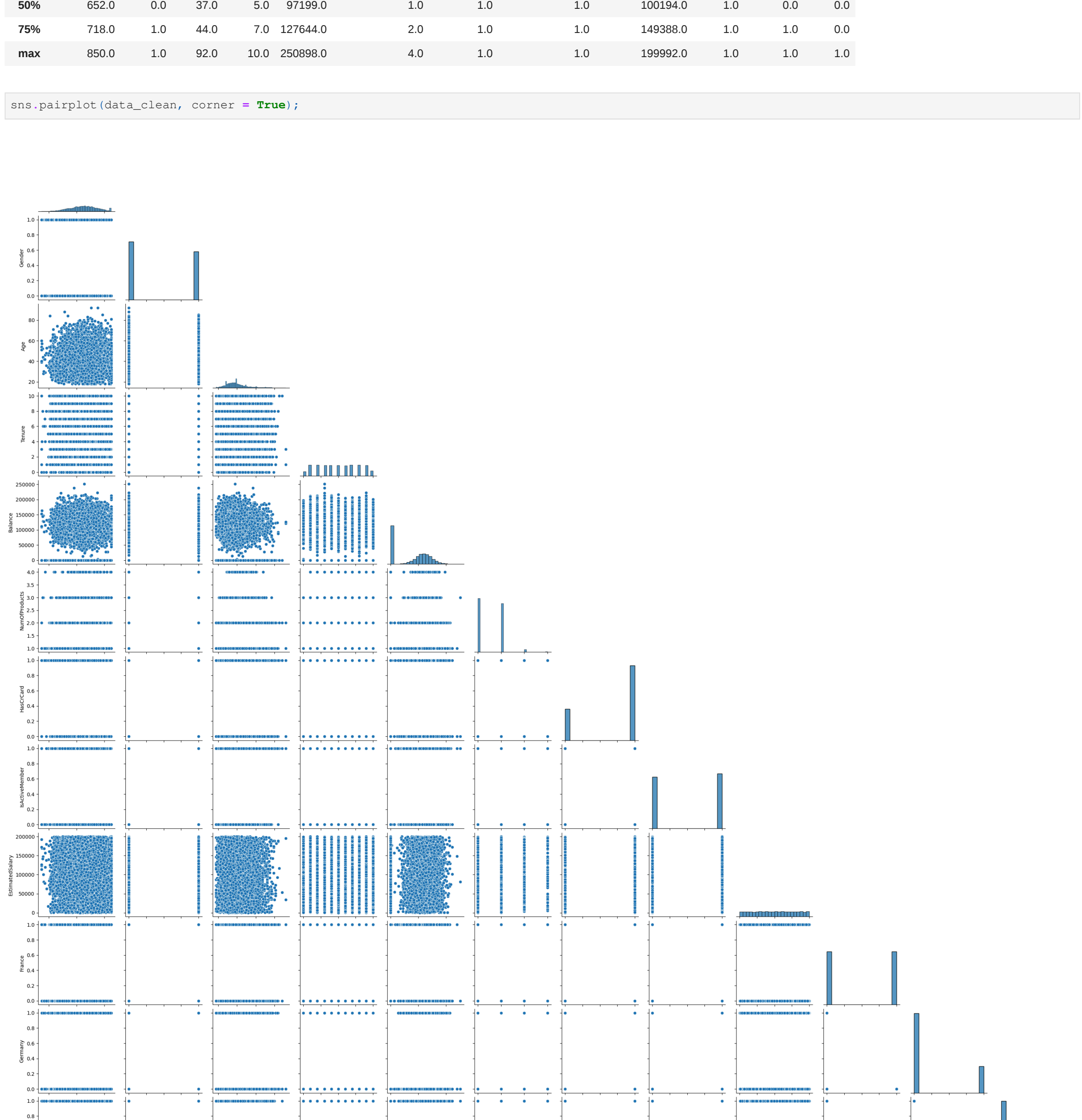
Exploring the Data by looking at the Min/Max values and the Distribution of each Column.

In [13]:
```
data_clean.describe().round()
```

Out[13]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain
count	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0
mean	651.0	0.0	39.0	5.0	76486.0	2.0	1.0	1.0	100090.0	1.0	0.0	0.0
std	97.0	0.0	10.0	3.0	62397.0	1.0	0.0	0.0	57510.0	1.0	0.0	0.0
min	350.0	0.0	18.0	0.0	0.0	1.0	0.0	0.0	12.0	0.0	0.0	0.0
25%	584.0	0.0	32.0	3.0	0.0	1.0	0.0	0.0	51002.0	0.0	0.0	0.0
50%	652.0	0.0	37.0	5.0	97199.0	1.0	1.0	1.0	100194.0	1.0	0.0	0.0
75%	718.0	1.0	44.0	7.0	127644.0	2.0	1.0	1.0	149388.0	1.0	1.0	0.0
max	850.0	1.0	92.0	10.0	250898.0	4.0	1.0	1.0	199992.0	1.0	1.0	1.0

In [14]:
```
sns.pairplot(data_clean, corner = True);
```



Let's Engineer a New Feature

Engineer a new feature called "ProductsPerYear".

In [15]:
```
data_clean['ProductsPerYear'] = np.where(data_clean.Tenure == 0, data_clean.NumOfProducts, data_clean.NumOfProducts / data_clean.Tenure)
data_clean.head()
```

Out[15]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain	ProductsPerYear
0	619	1	42	2	0.00	1	1	1	101348.88	1	0	0	0.500
1	608	1	41	1	83807.86	1	0	1	112542.58	0	0	1	1.000
2	502	1	42	8	159660.80	3	1	0	113931.57	1	0	0	0.375
3	699	1	39	1	0.00	2	0	0	93826.63	1	0	0	2.000
4	850	1	43	2	125510.82	1	1	1	79084.10	0	0	1	0.500

In [16]:
```
data_clean.describe().round()
```

Out[16]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain	ProductsPerYear
count	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0
mean	651.0	0.0	39.0	5.0	76486.0	2.0	1.0	1.0	100090.0	1.0	0.0	0.0	1.0
std	97.0	0.0	10.0	3.0	62397.0	1.0	0.0	0.0	57510.0	1.0	0.0	0.0	1.0
min	350.0	0.0	18.0	0.0	0.0	1.0	0.0	0.0	12.0	0.0	0.0	0.0	0.0
25%	584.0	0.0	32.0	3.0	0.0	1.0	0.0	0.0	51002.0	0.0	0.0	0.0	0.0
50%	652.0	0.0	37.0	5.0	97199.0	1.0	1.0	1.0	100194.0	1.0	0.0	0.0	0.0
75%	718.0	1.0	44.0	7.0	127644.0	2.0	1.0	1.0	149388.0	1.0	1.0	0.0	1.0
max	850.0	1.0	92.0	10.0	250898.0	4.0	1.0	1.0	199992.0	1.0	1.0	1.0	4.0

Objective 2: Cluster the Customers (Round 1)

Our Second Objective is to Segment the Customers using K-Means Clustering, including Standardizing the Data, Creating an Inertia Plot, and Interpreting the Clusters.

Scale the Data using Stardardization

Standardize the data so that each column has a Mean of 0 and Standard Deviation of 1.

In [19]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
df_scaled = pd.DataFrame(scaler.fit_transform(data_clean), columns = data_clean.columns)
df_scaled.head()
```

Out[19]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain	ProductsPerYear
0	-0.326221	1.095988	0.293517	-1.041760	-1.225848	-0.911583	0.646092	0.970243	0.021886	0.997204	-0.578736	-0.573809	-0.016781
1	-0.440036	1.095988	0.198164	-1.387538	0.117350	-0.911583	-1.547768	0.970243	0.216534	-1.002804	-0.578736	1.742740	0.967674
2	-1.536794	1.095988	0.293517	1.032908	1.333053	2.527057	0.646092	-1.030670	0.240687	0.997204	-0.578736	-0.573809	-0.262894
3	0.501521	1.095988	0.007457	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	-0.108918	0.997204	-0.578736	-0.573809	2.936584
4	2.063884	1.095988	0.388871	-1.041760	0.785728	-0.911583	0.646092	0.970243	-0.365276	-1.002804	-0.578736	1.742740	-0.016781

In [ ]:
```
df_scaled.describe().round()
```

Out[ ]:

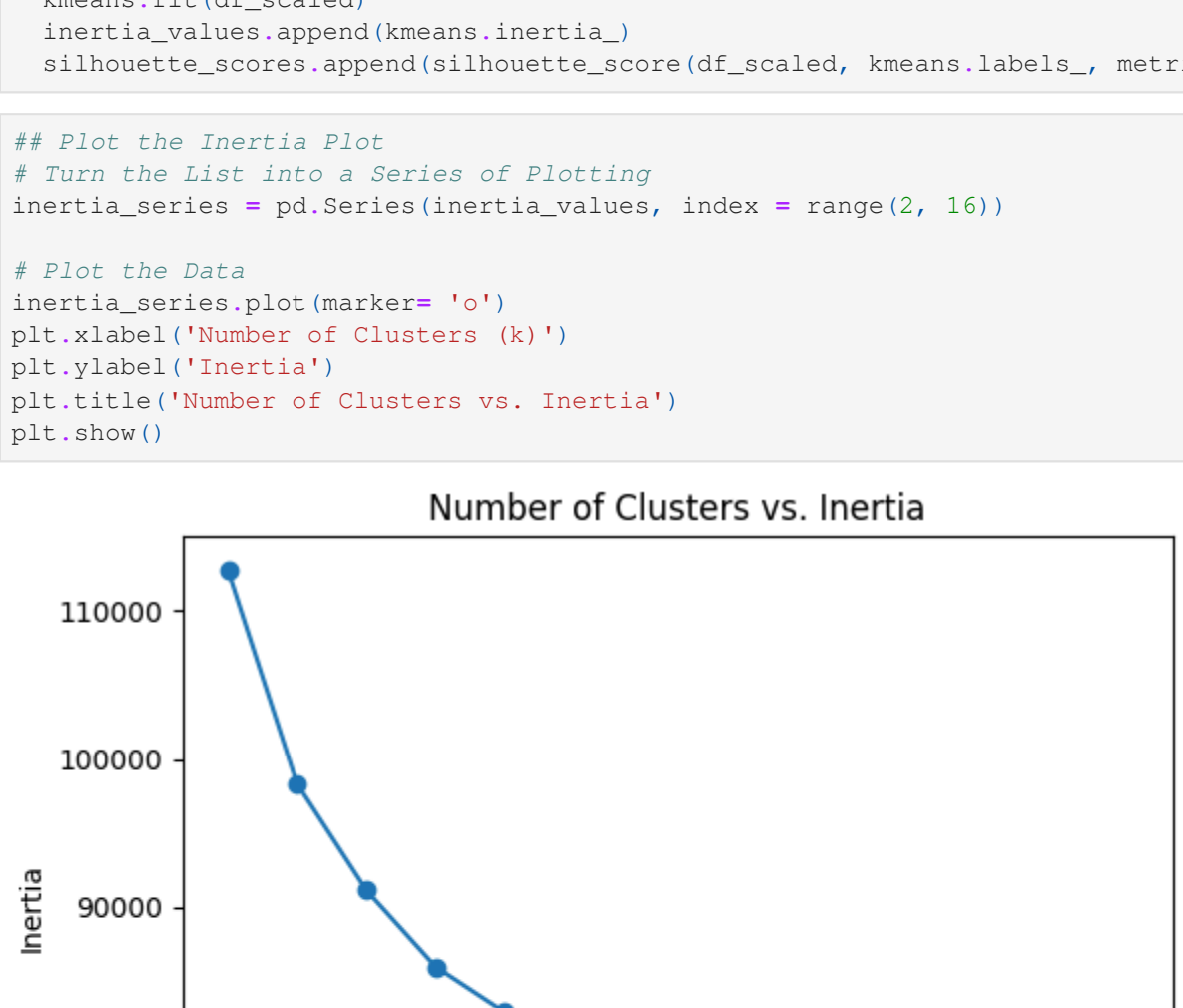
	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain	ProductsPerYear
count	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0	10000.0
mean	-0.0	-0.0	0.0	-0.0	-0.0	0.0	-0.0	-0.0	-0.0	0.0	-0.0	-0.0	0.0
std	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
min	-3.0	-1.0	-2.0	-2.0	-1.0	-1.0	-2.0	-1.0	-2.0	-1.0	-1.0	-1.0	-1.0
25%	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-2.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0
50%	0.0	-1.0	-0.0	-0.0	0.0	-1.0	1.0	1.0	0.0	1.0	-1.0	-1.0	-0.0
75%	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	2.0	-1.0	0.0
max	2.0	1.0	5.0	2.0	3.0	4.0	1.0	1.0	2.0	1.0	2.0	2.0	7.0

Fit K-Means Models with 2-15 Clusters

Fit K-Means Clustering Models on the Standardized Data with 2-15 Clusters to create an Inertia Plot.

In [20]:
```
# Import kmeans and write a loop to fit models with 2 to 15 clusters
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Create an empty list to hold many Inertia and Silhouette Values
inertia_values = []
silhouette_scores = []

# Creat 2-15 clusters, and add the Intertia Scores and Silhouette Scores to the Lists

for k in range(2, 16):
  kmeans = KMeans(n_clusters = k, n_init= 10, random_state = 42) #changed from auto to 10
  kmeans.fit(df_scaled)
  inertia_values.append(kmeans.inertia_)
  silhouette_scores.append(silhouette_score(df_scaled, kmeans.labels_, metric= 'euclidean', sample_size= None))
```

In [23]:
```
## Plot the Inertia Plot
# Turn the List into a Series of Plotting
inertia_series = pd.Series(inertia_values, index = range(2, 16))

# Plot the Data
inertia_series.plot(marker= 'o')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.title('Number of Clusters vs. Inertia')
plt.show()
```



So, looking at this we need to find the Elbow of this Inertia Plot.

The Inertia drops significantly at K=5. So, we choose k=5 for our KMeans Clustering.

Plot the Intertia Values and Find the Elbow

Identify the Elbow of the Inertia Plot and Fit a K-Means Model using that value of k.

In [24]:
```
kmeans5 = KMeans(n_clusters= 5, n_init= 10, random_state= 42)
kmeans5.fit(df_scaled)
```

Out[24]:
```
KMeans
KMeans(n_clusters=5, n_init=10, random_state=42)
```

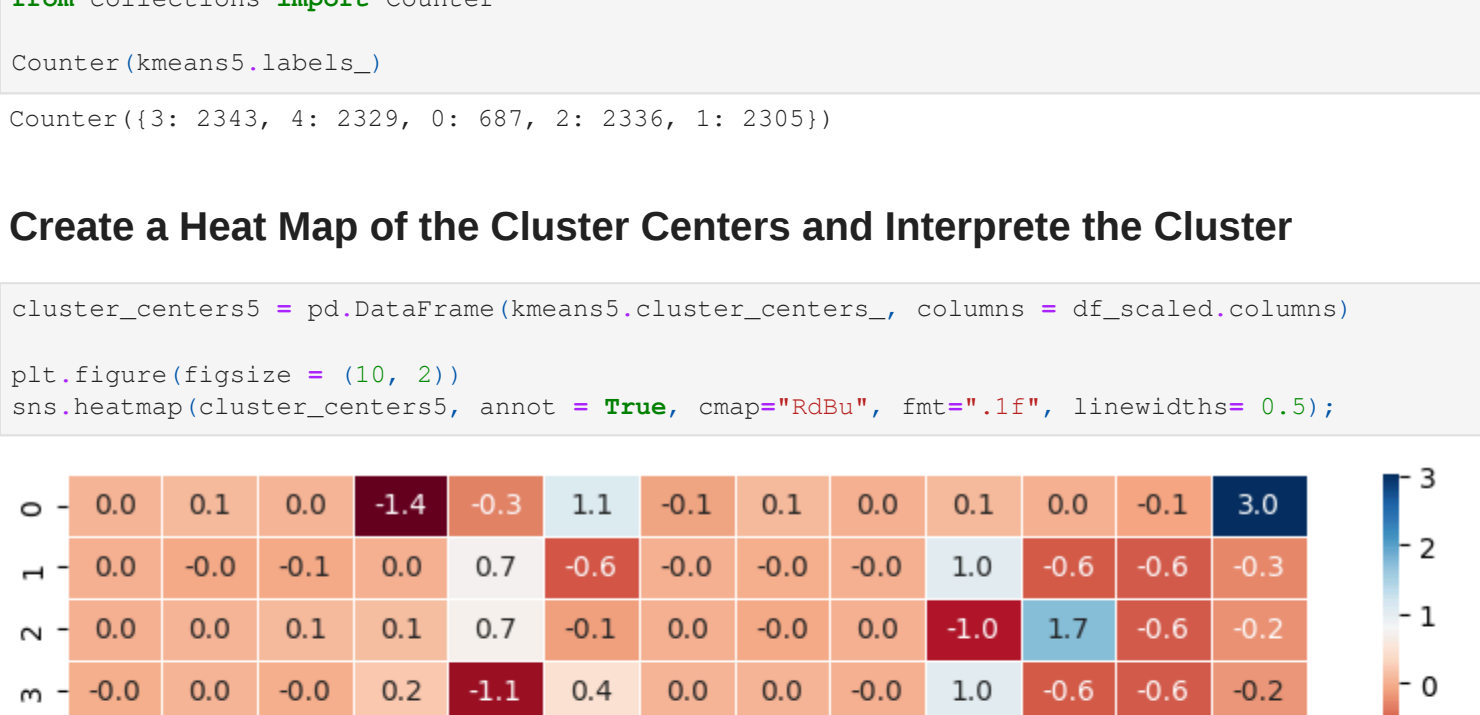
Check the Number of Customers in each Cluster

In [25]:
```
from collections import Counter

Counter(kmeans5.labels_)
```

Out[25]:
```
Counter({3: 2343, 4: 2329, 0: 687, 2: 2336, 1: 2305})
```

Create a Heat Map of the Cluster Centers and Interprete the Cluster

In [27]:
```
cluster_centers5 = pd.DataFrame(kmeans5.cluster_centers_, columns = df_scaled.columns)

plt.figure(figsize = (10, 2))
sns.heatmap(cluster_centers5, annot = True, cmap="RdBu", fmt=".1f", linewidths= 0.5);
```



- 0: Many Products in a Short Time
- 1: French Customers with Few Products and High Balance
- 2: German Customers with a High Balance
- 3:French Customers with More Products and Low Balance
- 4: Spanish Customers

Objective 3: Cluster the Customers (Round 2)

Our Third Objective is to Segment the Customers using K-Means Clustering using a different Subset of Fields and Compare the Model Results.

Updating the Model Dataset

We will look at the Summary Stats by Country, and Exclude the Country Field as currently the clusters are dominated by the Country Field. Then we use the updated dataset for KMeans Clustering same way as the previous steps.

In [28]:
```
data_subset.head()
```

Out[28]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	Female	42	2	0.00	1	1	1	101348.88
1	608	Spain	Female	41	1	83807.86	1	0	1	112542.58
2	502	France	Female	42	8	159660.80	3	1	0	113931.57
3	699	France	Female	39	1	0.00	2	0	0	93826.63
4	850	Spain	Female	43	2	125510.82	1	1	1	79084.10

In [29]:
```
data_geo = data_subset.copy()
data_geo.Gender = np.where(data_geo.Gender == 'Female', 1, 0)
data_geo.head()
```

Out[29]:

	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
0	619	France	1	42	2	0.00	1	1	1	101348.88
1	608	Spain	1	41	1	83807.86	1	0	1	112542.58
2	502	France	1	42	8	159660.80	3	1	0	113931.57
3	699	France	1	39	1	0.00	2	0	0	93826.63
4	850	Spain	1	43	2	125510.82	1	1	1	79084.10

In [30]:
```
data_geo.groupby('Geography').mean().round()
```

Out[30]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary
Geography									
France	650.0	0.0	39.0	5.0	62093.0	2.0	1.0	1.0	99899.0
Germany	651.0	0.0	40.0	5.0	119730.0	2.0	1.0	0.0	101113.0
Spain	651.0	0.0	39.0	5.0	61818.0	2.0	1.0	1.0	99441.0

In [31]:
```
data_geo[data_geo.Geography == 'France'].Balance.round(-5).value_counts()
```

Out[31]:

	count
Balance	
0.0	2459
100000.0	2123
200000.0	432

dtype: int64

In [ ]:
```
data_geo[data_geo.Geography == 'Spain'].Balance.round(-5).value_counts()
```

Out[ ]:

	count
Balance	
0.0	1214
100000.0	1040
200000.0	222
300000.0	1

dtype: int64

In [ ]:
```
data_geo[data_geo.Geography == 'Germany'].Balance.round(-5).value_counts()
```

Out[ ]:

	count
Balance	
100000.0	2176
200000.0	314
0.0	19

dtype: int64

Customers from French, Spain and Germany have pretty similar attributes except in Balance. German customoers have higher Balance than the other two countries.

So, we will exclude the Country Field.

In [32]:
```
df_scaled.head()
```

Out[32]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain	ProductsPerYear
0	-0.326221	1.095988	0.293517	-1.041760	-1.225848	-0.911583	0.646092	0.970243	0.021886	0.997204	-0.578736	-0.573809	-0.016781
1	-0.440036	1.095988	0.198164	-1.387538	0.117350	-0.911583	-1.547768	0.970243	0.216534	-1.002804	-0.578736	1.742740	0.967674
2	-1.536794	1.095988	0.293517	1.032908	1.333053	2.527057	0.646092	-1.030670	0.240687	0.997204	-0.578736	-0.573809	-0.262894
3	0.501521	1.095988	0.007457	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	-0.108918	0.997204	-0.578736	-0.573809	2.936584
4	2.063884	1.095988	0.388871	-1.041760	0.785728	-0.911583	0.646092	0.970243	-0.365276	-1.002804	-0.578736	1.742740	-0.016781

In [33]:
```
df_scaled_no_geo = df_scaled.drop(columns = ['France', 'Germany', 'Spain'])
df_scaled_no_geo.head()
```

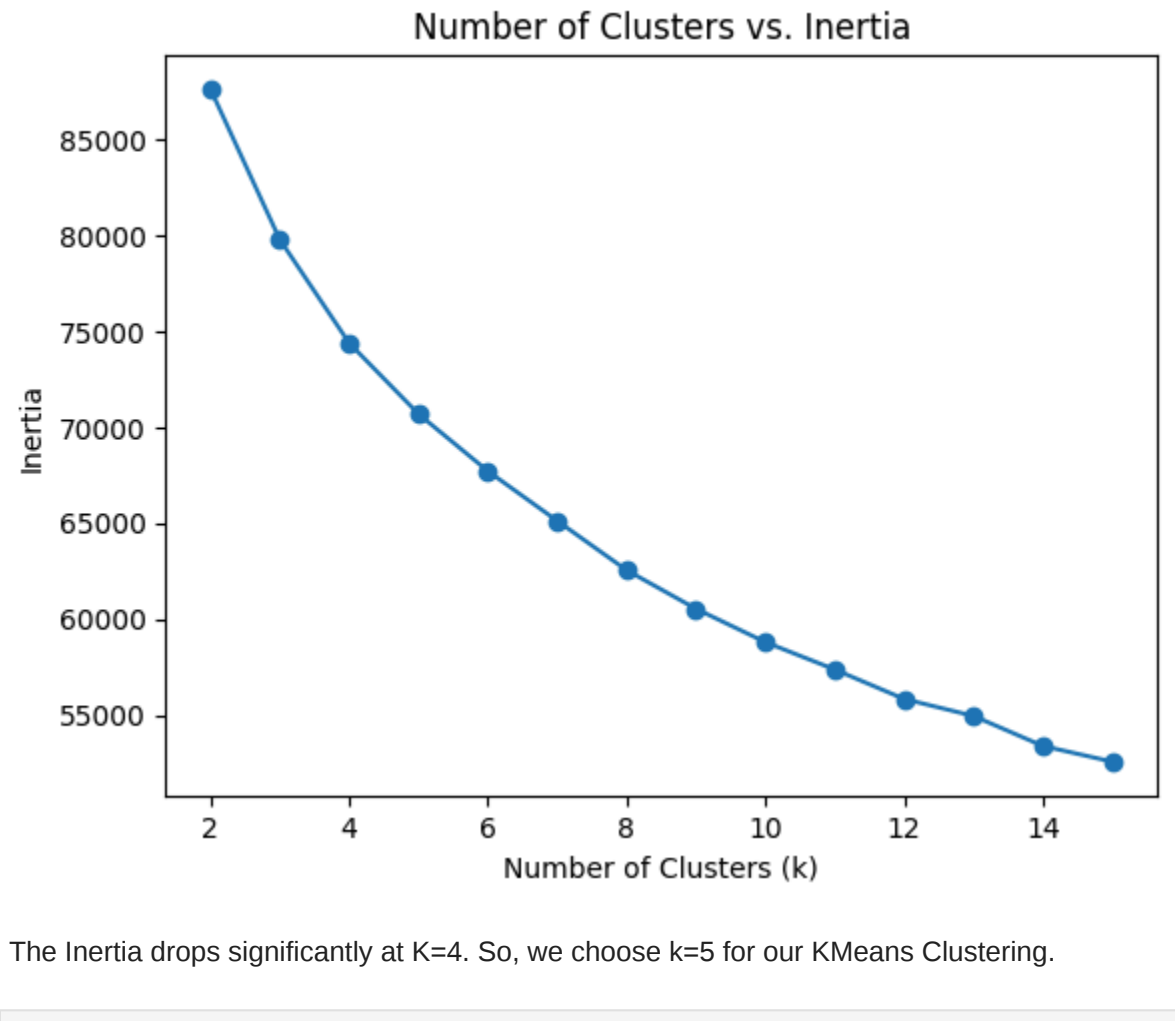
Out[33]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	ProductsPerYear
0	-0.326221	1.095988	0.293517	-1.041760	-1.225848	-0.911583	0.646092	0.970243	0.021886	-0.016781
1	-0.440036	1.095988	0.198164	-1.387538	0.117350	-0.911583	-1.547768	0.970243	0.216534	0.967674
2	-1.536794	1.095988	0.293517	1.032908	1.333053	2.527057	0.646092	-1.030670	0.240687	-0.262894
3	0.501521	1.095988	0.007457	-1.387538	-1.225848	0.807737	-1.547768	-1.030670	-0.108918	2.936584
4	2.063884	1.095988	0.388871	-1.041760	0.785728	-0.911583	0.646092	0.970243	-0.365276	-0.016781

Now, fit the Clustering Model with the Updated Data

In [34]:
```
# Import kmeans and write a loop to fit models with 2 to 15 clusters
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Create an empty list to hold many Inertia and Silhouette Values
inertia_values = []
silhouette_scores = []

# Creat 2-15 clusters, and add the Intertia Scores and Silhouette Scores to the Lists

for k in range(2, 16):
  kmeans = KMeans(n_clusters = k, n_init= 10, random_state = 42) #changed from auto to 10
  kmeans.fit(df_scaled_no_geo)
  inertia_values.append(kmeans.inertia_)
  silhouette_scores.append(silhouette_score(df_scaled_no_geo, kmeans.labels_, metric= 'euclidean', sample_size= None))
```

In [35]:
```
## Plot the Inertia Plot
# Turn the List into a Series of Plotting
inertia_series = pd.Series(inertia_values, index = range(2, 16))

# Plot the Data
inertia_series.plot(marker= 'o')
plt.xlabel('Number of Clusters (k)')
plt.ylabel('Inertia')
plt.title('Number of Clusters vs. Inertia')
plt.show()
```



The Inertia drops significantly at K=4. So, we choose k=5 for our KMeans Clustering.

In [36]:
```
kmeans4 = KMeans(n_clusters= 4, n_init= 10, random_state= 42)
kmeans4.fit(df_scaled_no_geo)
```

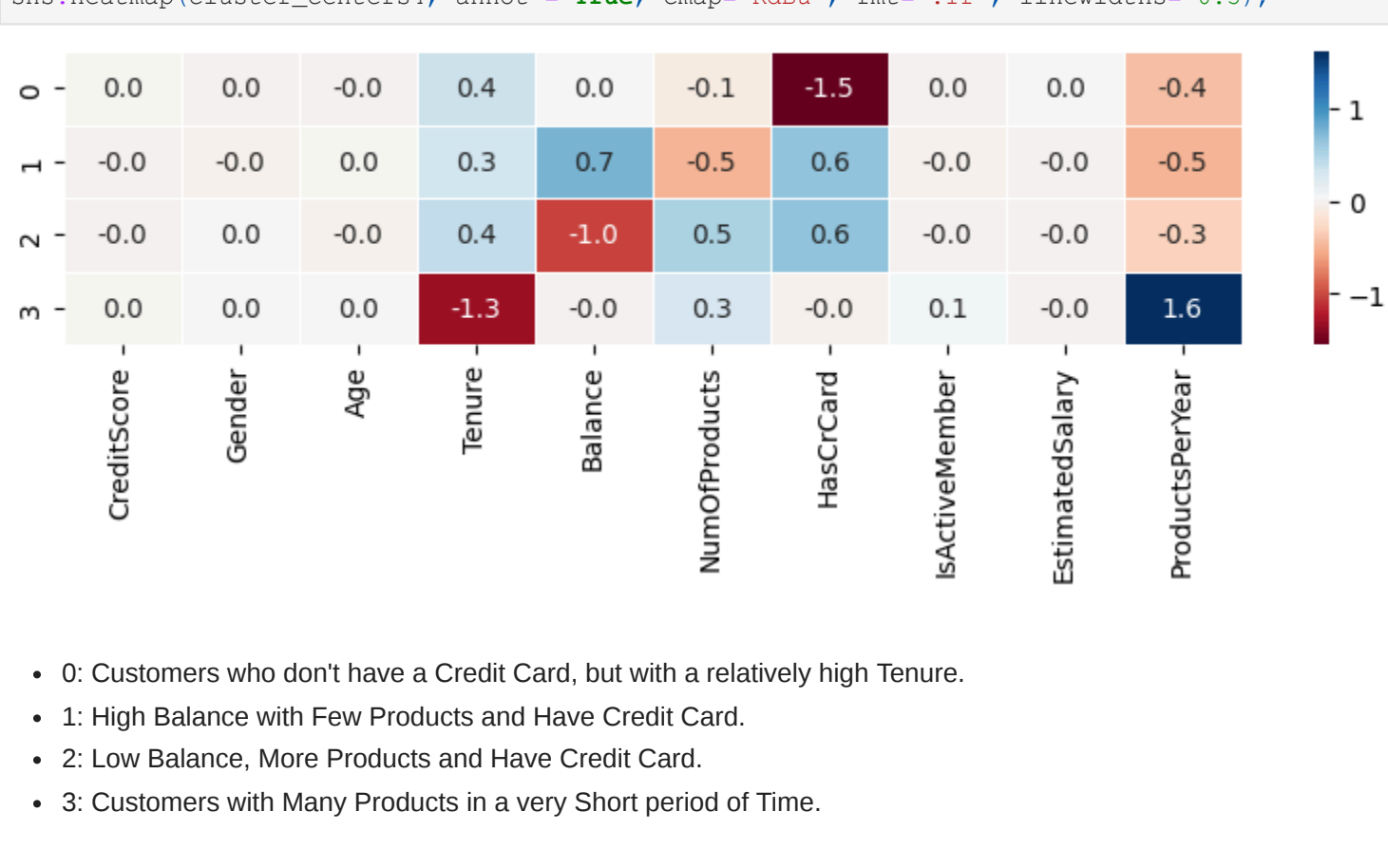
Out[36]:
```
KMeans
KMeans(n_clusters=4, n_init=10, random_state=42)
```

In [37]:
```
Counter(kmeans4.labels_)
```

Out[37]:
```
Counter({2: 2366, 3: 2135, 1: 3223, 0: 2276})
```

Create the Heatmap again to Find the Cluster Centers

In [38]:
```
cluster_centers4 = pd.DataFrame(kmeans4.cluster_centers_, columns = df_scaled_no_geo.columns)

plt.figure(figsize = (10, 2))
sns.heatmap(cluster_centers4, annot = True, cmap="RdBu", fmt=".1f", linewidths= 0.5);
```



- 0: Customers who don't have a Credit Card, but with a relatively high Tenure.
- 1: High Balance with Few Products and Have Credit Card.
- 2: Low Balance, More Products and Have Credit Card.
- 3: Customers with Many Products in a very Short period of Time.

Objective 4: Explore the Clusters and Make Recommendations

Our Final Objective is to further Explore Our K-Means Clusters by looking at their Churn Rate and Country Breakdown, then make Recommendations for how to Cater to each Customer Segment.

Let's create a DataFrame that combines the data set from the end of Objective 1, the "Exited" field, and the cluster labels.

In [39]:
```
data_clean.head()
```

Out[39]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain	ProductsPerYear
0	619	1	42	2	0.00	1	1	1	101348.88	1	0	0	0.500
1	608	1	41	1	83807.86	1	0	1	112542.58	0	0	1	1.000
2	502	1	42	8	159660.80	3	1	0	113931.57	1	0	0	0.375
3	699	1	39	1	0.00	2	0	0	93826.63	1	0	0	2.000
4	850	1	43	2	125510.82	1	1	1	79084.10	0	0	1	0.500

In [40]:
```
data.Exited.head()
```

Out[40]:

	Exited
0	1
1	0
2	1
3	0
4	0

dtype: int64

In [ ]:
```
kmeans4.labels_
```

Out[ ]:
```
array([2, 3, 2, ..., 0, 2, 1], dtype=int32)
```

Let's merge those together:

In [41]:
```
data_final = pd.concat([data_clean, data.Exited, pd.Series(kmeans4.labels_, name = 'Cluster')], axis = 1)
data_final.head()
```

Out[41]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain	ProductsPerYear	Exited	Cluster
0	619	1	42	2	0.00	1	1	1	101348.88	1	0	0	0.500	1	2
1	608	1	41	1	83807.86	1	0	1	112542.58	0	0	1	1.000	0	3
2	502	1	42	8	159660.80	3	1	0	113931.57	1	0	0	0.375	1	2
3	699	1	39	1	0.00	2	0	0	93826.63	1	0	0	2.000	0	3
4	850	1	43	2	125510.82	1	1	1	79084.10	0	0	1	0.500	0	1

View the Exited Percent for Each Cluster

In [42]:
```
data_final.groupby('Cluster').mean().round(2)
```

Out[42]:

	CreditScore	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	France	Germany	Spain	ProductsPerYear	Exited
Cluster														
0	651.20	0.46	38.92	6.03	78730.20	1.48	0.00	0.52	101285.72	0.50	0.24	0.26	0.29	0.21
1	649.38	0.43	39.04	5.98	123236.38	1.24	1.00	0.50	99856.40	0.42	0.38	0.20	0.25	0.23
2	650.24	0.46	38.52	6.17	11731.06	1.83	1.00	0.51	99487.18	0.62	0.07	0.31	0.34	0.16
3	651.88	0.47	39.19	1.18	75279.81	1.69	0.69	0.55	99837.12	0.49	0.27	0.24	1.32	0.21

So, cluster 1 has the highest churn rate (23%) and cluster 2 has the lowest churn rate (16%)

View the Geography Breakdown for Each Cluster

For Cluster 2 there are many French Customers and very few German Customers.

Making Recommendations

We have to make recommendations for how to Cater to each Customer Segments.

These are the characteristics of the Clusters we found earlier:

- 0: Customers who don't have a Credit Card.
- 1: High Balance with Few Products and Have Credit Card.
- 2: Low Balance, More Products and Have Credit Card.
- 3: Customers with Many Products in a very Short period of Time.

Recommendations:

- **Clsuter 0:** Create an Entry-level Credit Card; Also, do some research on their Demographic Information.
- **Cluster 1:** They have very high Balance, but likely to leave. So, try to keep them by offering them financial seminars or advisors or, maybe suggest investment opportunities.
- **Cluster 2:** They are less likely to leave. We can reward them (French and Spanish Customers) for staying. We can introduce reward programs to encourage them to invest in more products.
- **Cluster 3:** They have many products in a very short time. Churn rate is also relatively high. Since, they like products we may offer them products with higher tenure.