

This is my adaptation of an article written by Baris Karaman on Towards Data Science.

I used his article as a way to get familiar with grouping customers based on their recency, frequency, and monetary value—an incredibly powerful way to understand your customers and how they fit within specific segments.

This understanding can be used to guide future decisions and give non-technical stakeholders a quick, reliable, and easy-to-digest view of their customer base.

Baris's article can be found here:

<https://towardsdatascience.com/data-driven-growth-with-python-part-2-customer-segmentation-5c019d150444>

RFM Segmentation

In this notebook, I'll be working through an orders dataset from a UK-based online retailer and creating different customer segments based on their R (recency), F (frequency), and M (monetary value).

Recency can be thought of in a few different ways; in today's notebook, it will be shown as the number of days since a customer's last purchase.

Frequency looks at how often a customer makes purchases within a specific time period.

Monetary value is a customer's total orders multiplied by their average order value, again within a specified time window. High-revenue customers usually go hand in hand with recency and frequency.

Theoretically, we'll end up with segments like...

1. Low Value

Customers who are not very frequent buyers and are less active. They generate very low, or maybe even negative, monetary value.

1. Medium Value

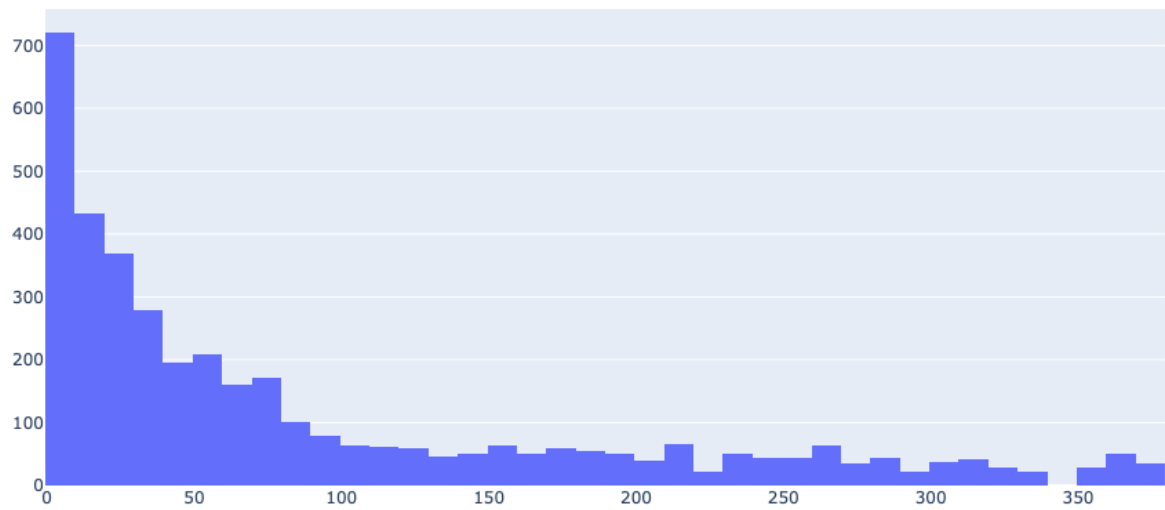
Medium-value customers tend to make purchases often and are fairly active. They generate solid revenue and are important to understand.

1. High Value

Frequent, high-order volume customers. They generate a ton of revenue and are a group you never want to lose.

Let's look at recency first. We'll examine a customer's most recent purchase and find how long it's been since they've made that purchase. (measure in days)

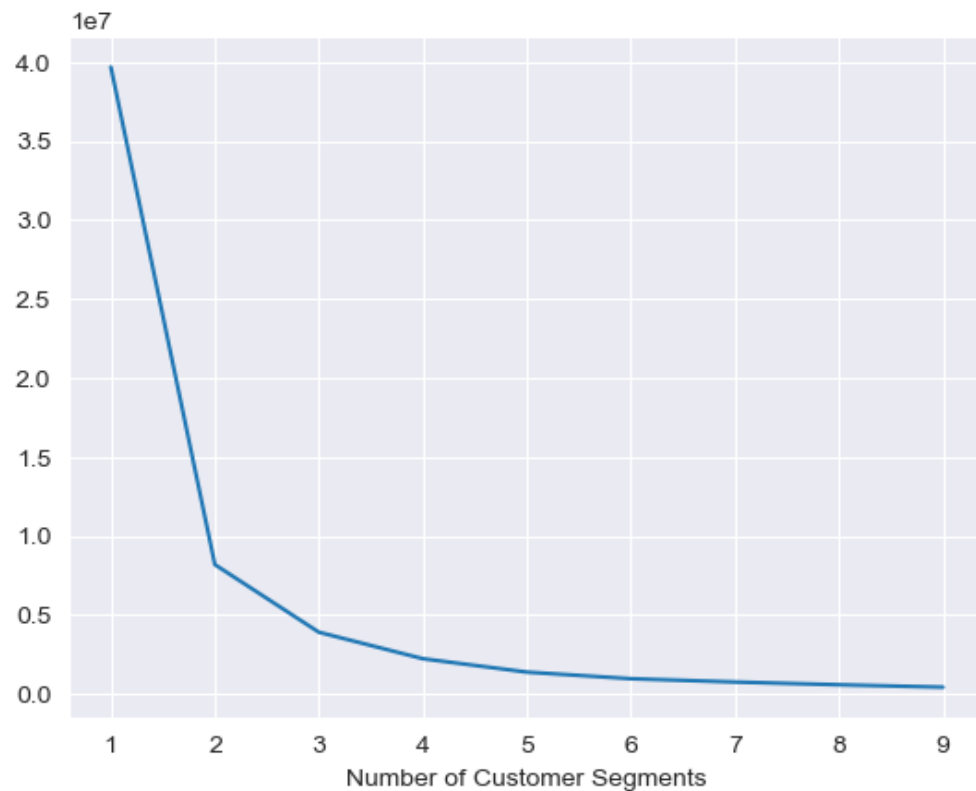
Recency



	CustomerID	Recency
count	3950.000000	3950.000000
mean	15562.029367	90.778481
std	1576.848325	100.230349
min	12346.000000	0.000000
25%	14208.250000	16.000000
50%	15571.500000	49.000000
75%	16913.750000	142.000000
max	18287.000000	373.000000

So, looking at our customers and their most recent purchase, the average recency (in days) is 90, and our median is 49 days. The longest it's been since a customer of ours made a purchase is 373 days. We have our highest distribution of recency within 0 - 9 days, meaning 720 customers have made a purchase within the last week and a half.

Now, we're going to use machine learning, specifically K-means clustering, to group our customers into specific groups based on their recency. Before we move forward, we need to determine how many clusters or segments we want to create. This is typically based on intuition and domain expertise, but since we don't have that right now, there are ways to ask our model what it thinks is best. Let's look.



It looks like 3 is the optimal number of segments here. When looking at an elbow graph like this, we can make our decision based on the elbow in the graph and its corresponding x-value. A case could be made for two or three, and any real decision would be based on end business requirements. I'm actually going to choose four, as four customer segments makes the most sense to me.

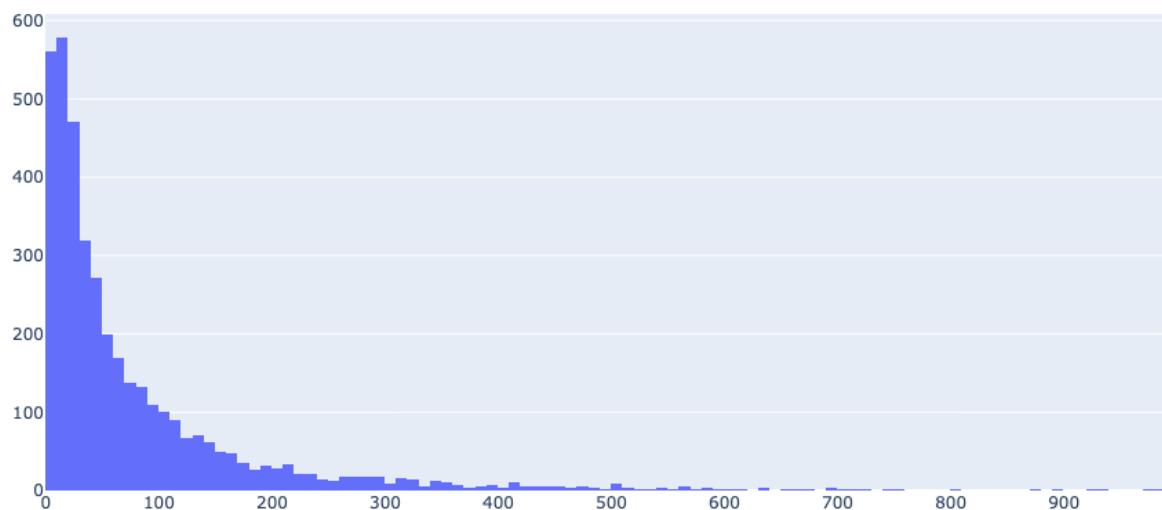
	count	mean	std	min	25%	50%	75%	max
RecencyCluster								
0	478.0	304.393305	41.183489	245.0	266.25	300.0	336.00	373.0
1	568.0	184.625000	31.753602	132.0	156.75	184.0	211.25	244.0
2	954.0	77.679245	22.850898	48.0	59.00	72.5	93.00	131.0
3	1950.0	17.488205	13.237058	0.0	6.00	16.0	28.00	47.0

We've ran our clustering model specifying four segments and assigned each customer to their appropriate segment. Segment 0 belongs to our least recent customers, and segment 3 belongs to our most recent.

We're going to do the same thing for frequency and monetary value.

Remember, recency saw how many days it's been since a customers last purchase. Frequency will look at how many unique purchases were made within a time period.

Frequency



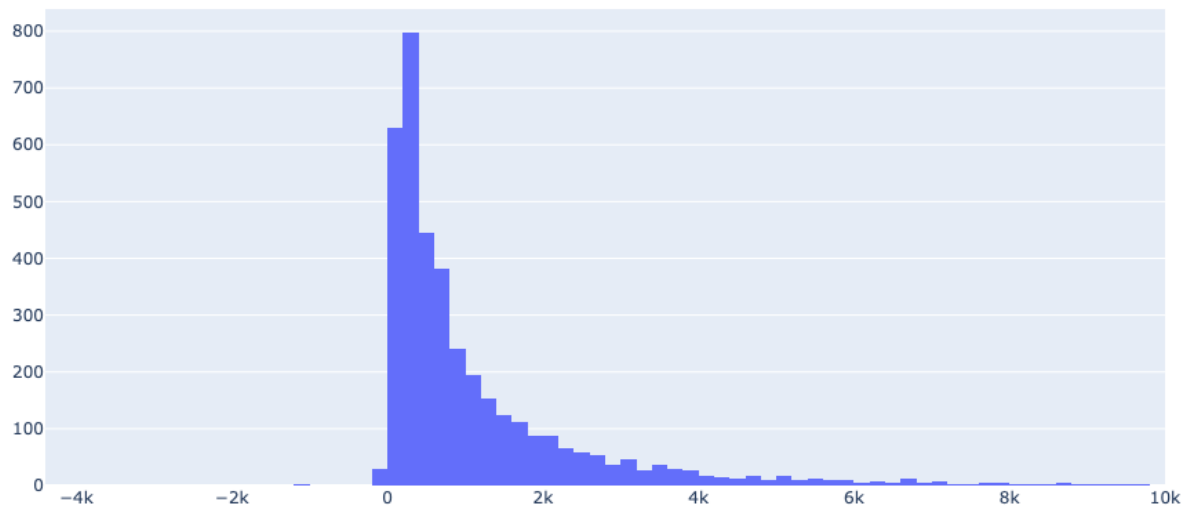
	count	mean	std	min	25%	50%	75%	max
FrequencyCluster								
0	3496.0	49.525744	44.954212	1.0	15.0	33.0	73.0	190.0
1	429.0	331.221445	133.856510	191.0	228.0	287.0	399.0	803.0
2	22.0	1313.136364	505.934524	872.0	988.5	1140.0	1452.0	2782.0
3	3.0	5917.666667	1805.062418	4642.0	4885.0	5128.0	6555.5	7983.0

Segment 0 represents our least frequent customers, and segment three represents our most frequent customers.

You can see how many customers are in each segment, and what their average number of purchases is. For segment 3, the average number of purchases is 5917 and there are only 3 customers in this segment.

Now we'll do the same thing for monetary value. We can call it revenue from now on.

Monetary Value



	count	mean	std	min	25%	50%	75%	max
RevenueCluster								
0	3696.0	915.727558	936.627600	-4287.63	264.2675	574.550	1262.0225	4435.79
1	226.0	7974.646062	3825.716457	4455.73	5308.3525	6662.095	9412.5725	25748.35
2	26.0	43736.679615	15866.891384	26626.80	29629.0950	38346.100	53859.2650	88125.38
3	2.0	221960.330000	48759.481478	187482.17	204721.2500	221960.330	239199.4100	256438.49

Same logic as before.

We now have our customers in three distinct segments based on their recency, frequency, and monetary value. Now we're going to combine the three to create an overall score, i.e., how well does a customer fit within all three segments. Could a customer have high revenue but low frequency and recency? We'll be able to answer questions like this after we find our combined score.

	Recency	Frequency	Revenue
OverallScore			
0	304.584388	21.995781	303.339705
1	185.362989	32.596085	498.087546
2	78.972856	47.060803	871.842586
3	20.684941	68.787318	1097.999703
4	14.627517	272.835570	3607.121678
5	9.600000	374.103448	9382.324276
6	8.038462	901.307692	22663.667308
7	1.857143	1272.714286	103954.025714
8	1.333333	5917.666667	42177.930000

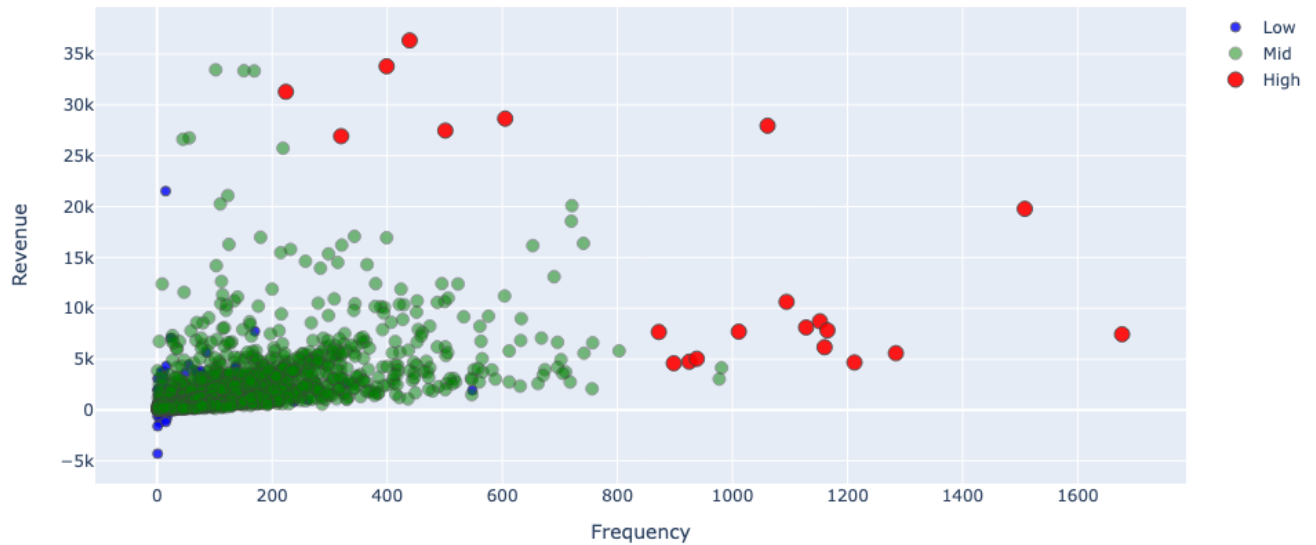
Remember that our highest segment was three for each group, so the maximum possible score is nine if they scored three across each cluster.

Eight seems to be the highest score here, with customers who scored eight being our most valuable customers. Curiously, though, the average revenue seems to be way higher for cluster seven. Perhaps a customer who spent a massive amount a while ago is causing that.

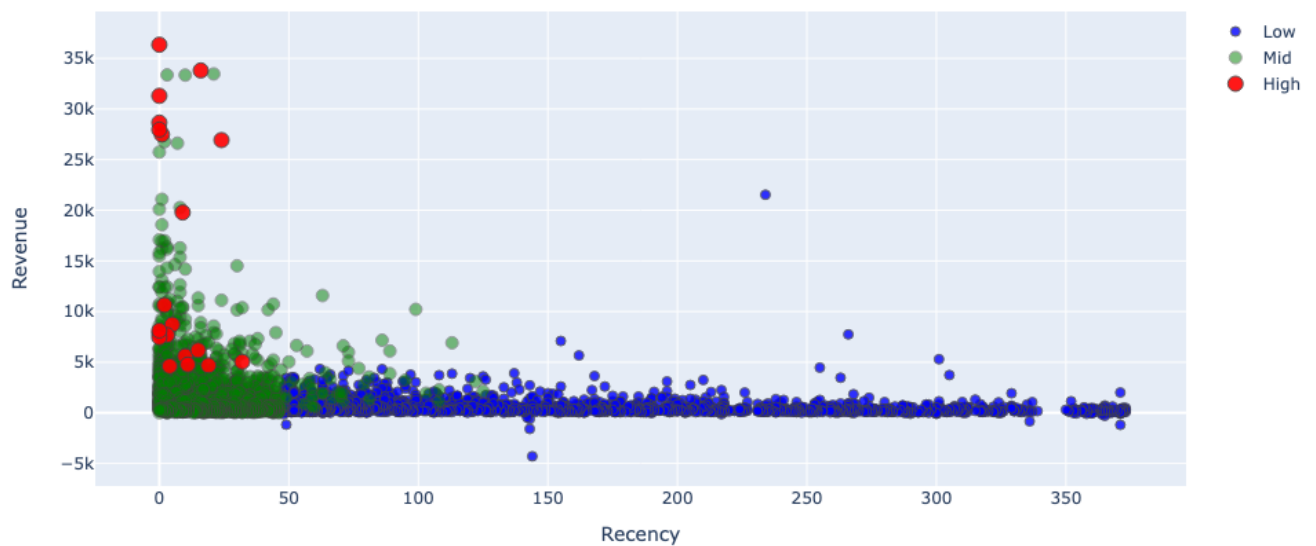
Let's make things easier to understand by throwing our customers into three segments:

1. Low value: corresponding to a score of 0 - 2.
2. Medium value: corresponding to a score of 3 - 5.
3. High value: corresponding to a score of 6+

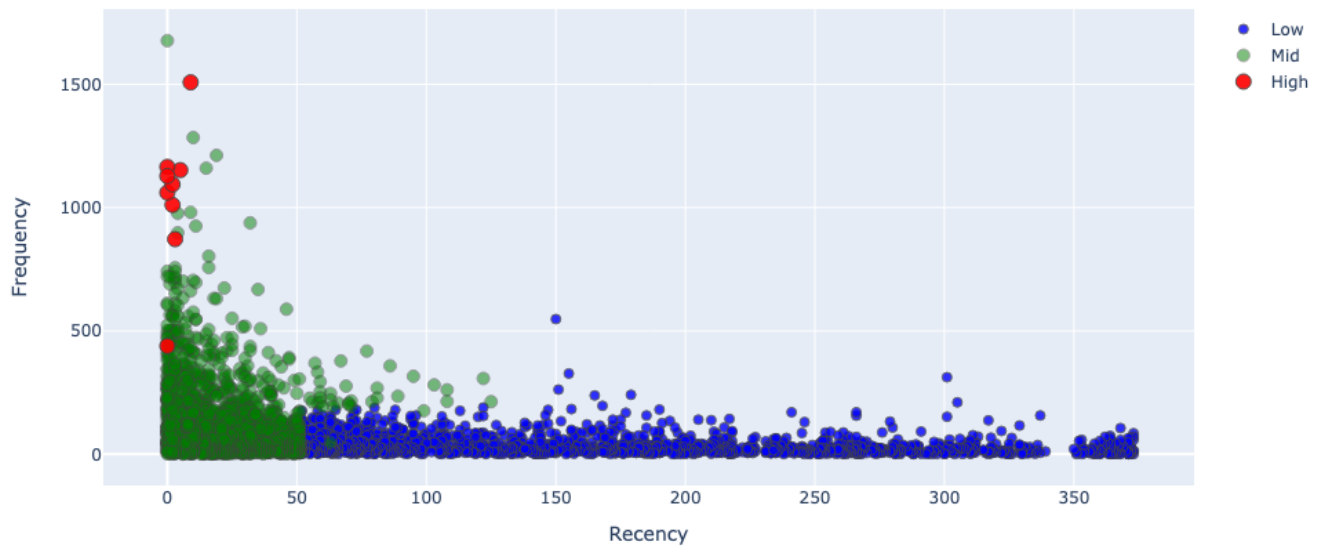
Revenue Segments Compared with Frequency Segments



Revenue Segments Compared with Recency Segments



Frequency Segments Compared with Recency Segments



The takeaways here are fairly intuitive:

1. You can see high-value customers tend to make more purchases and drive more revenue. (graph 1)
2. You can see high-value customers tend to be the most recent buyers and have higher revenue. (graph 2)
3. You can see high-value customers tend to be the most recent and most frequent. (graph 3)

Using these segments, we can begin to take action. We can create strategies to optimize our high value customers, and strategies to improve RFM among mid and low value customers.