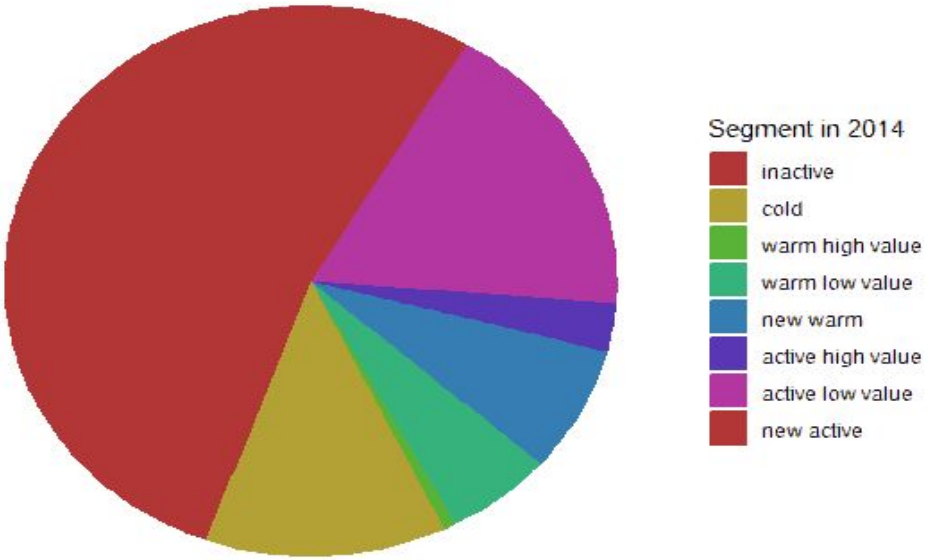
Finding Profitable and Less Profitable Segments 2014

	Group.1	recency	first_purchase	frequency	amount
1	inactive	2178.36083	2546.41838	1.814479	48.11277
2	cold	858.03140	1432.36718	2.303205	51.73989
3	warm high value	455.37605	2015.60294	4.714286	327.40746
4	warm low value	474.62736	2063.88929	4.531632	38.59193
5	new warm	509.55490	516.87260	1.044776	66.59903
6	active high value	89.07024	1986.15925	5.888307	240.04574
7	active low value	108.61100	2004.05199	5.935406	40.72452
8	new active	85.24074	90.26389	1.045635	77.13385

This table uses an aggregation formula that takes 51k customer observations (rows) and interpret the data so that customers are segmented into 8 groups using calculated mean “averages. This data is filtered so that customer who haven’t visited a store in over 3 years or (1095 days) should be put in the group inactive.

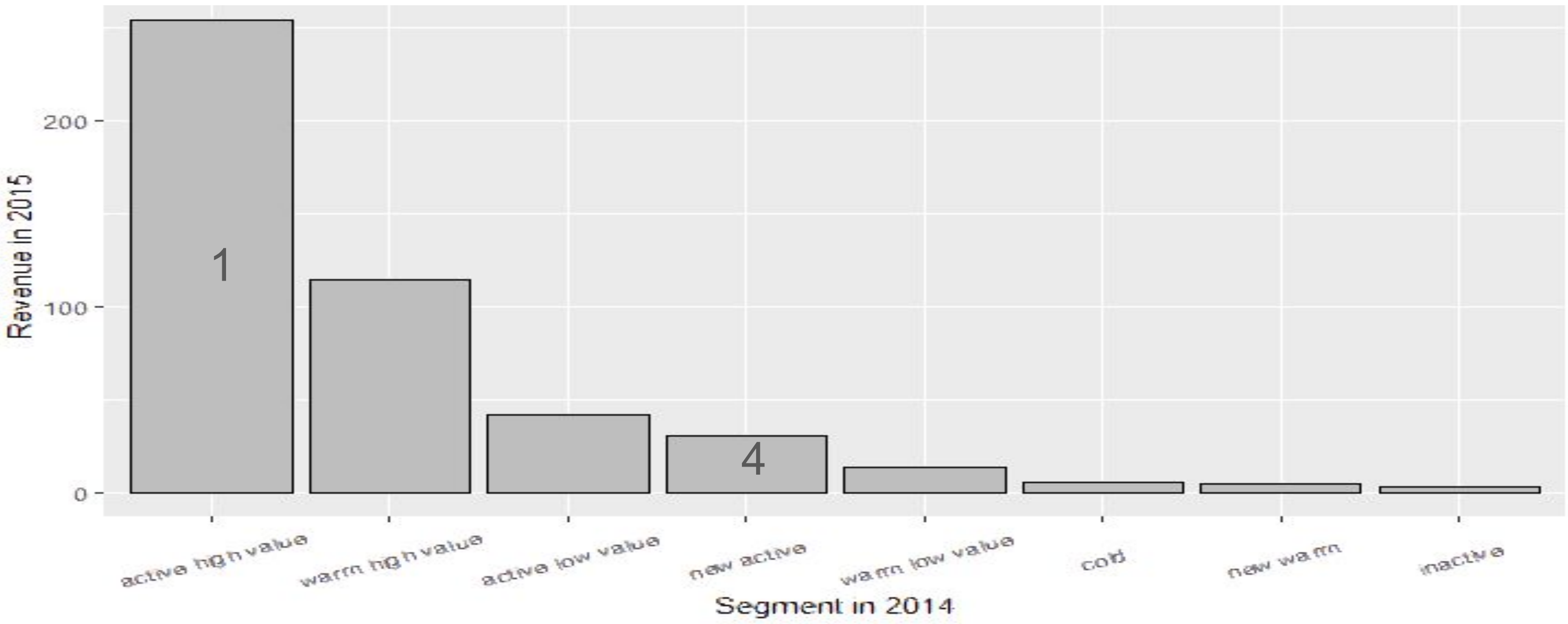
Distribution of Customers Per Segment in 2014



This table uses an aggregation formula that takes 51k customer observations (rows) and interpret the data so that customers are segmented into 8 groups using calculated mean “averages. This pie chart shows us a representation of customers. Here the conclusion can be made that most customer in 2014 are made up of people that have no visited our store in 3 years.

(reference the first table for numbers)

Revenue Forecasting of 2015, using customer segments from 2014



This table uses an aggregation formula that takes 51k customer observations (rows) and interpret the data so that customers are segmented into 8 groups using calculated mean “averages. 2014 customer purchases are grouped and used to predict 2015 revenue. This graph outputs the predicted revenue per 1 customer in a group for 2015. Here, we can predict that in 2015 losing 1 customer in bar 1, is like losing 6 customer in bar 4. Letting us know who to prioritize.

<u>(reference the first table for numbers)</u>