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First, we consider the fraction of attrition by card holder type (over all cardholders belonging to that type). We see that the Silver type cardholders have higher attrition rate than other card holders where the typical attrition rate is less than 20% (see upper left). It might also be a sign of attrition if the card is unutilized, customers could be notified if their card has never been used (see upper right).
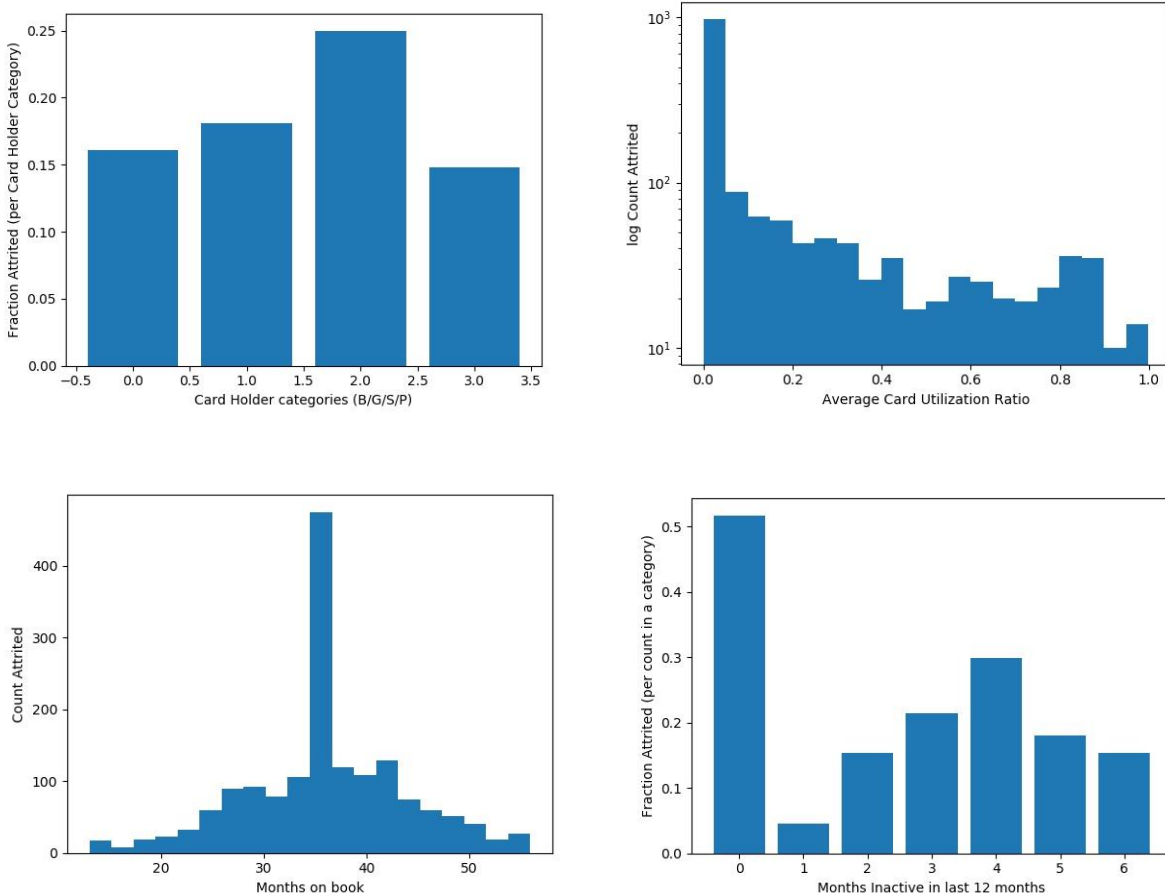

Figure 1. Trends of some features of the data and their individual effects on attrition.

Attrited cardholders had a relationship with the bank for up to 50 months, but it seems that attrition is less if you are a relatively new cardholder or have been a cardholder for a long time (see lower left). There is unusually high attrition at around 35 months of relationship with the bank; probably incentives could be given for cardholders holding on to the card for that amount of time. It is, however, counterintuitive that active cards (inactive for 0 months) has the higher percentage of attrition (see lower right). It is possible that the total count of all attrited cards inactive for 0 months is small. Aside from that, cardholders with cards inactive for four months could also be notified, however four months is short compared to the typical timescale of attrition (which is roughly 35 months).
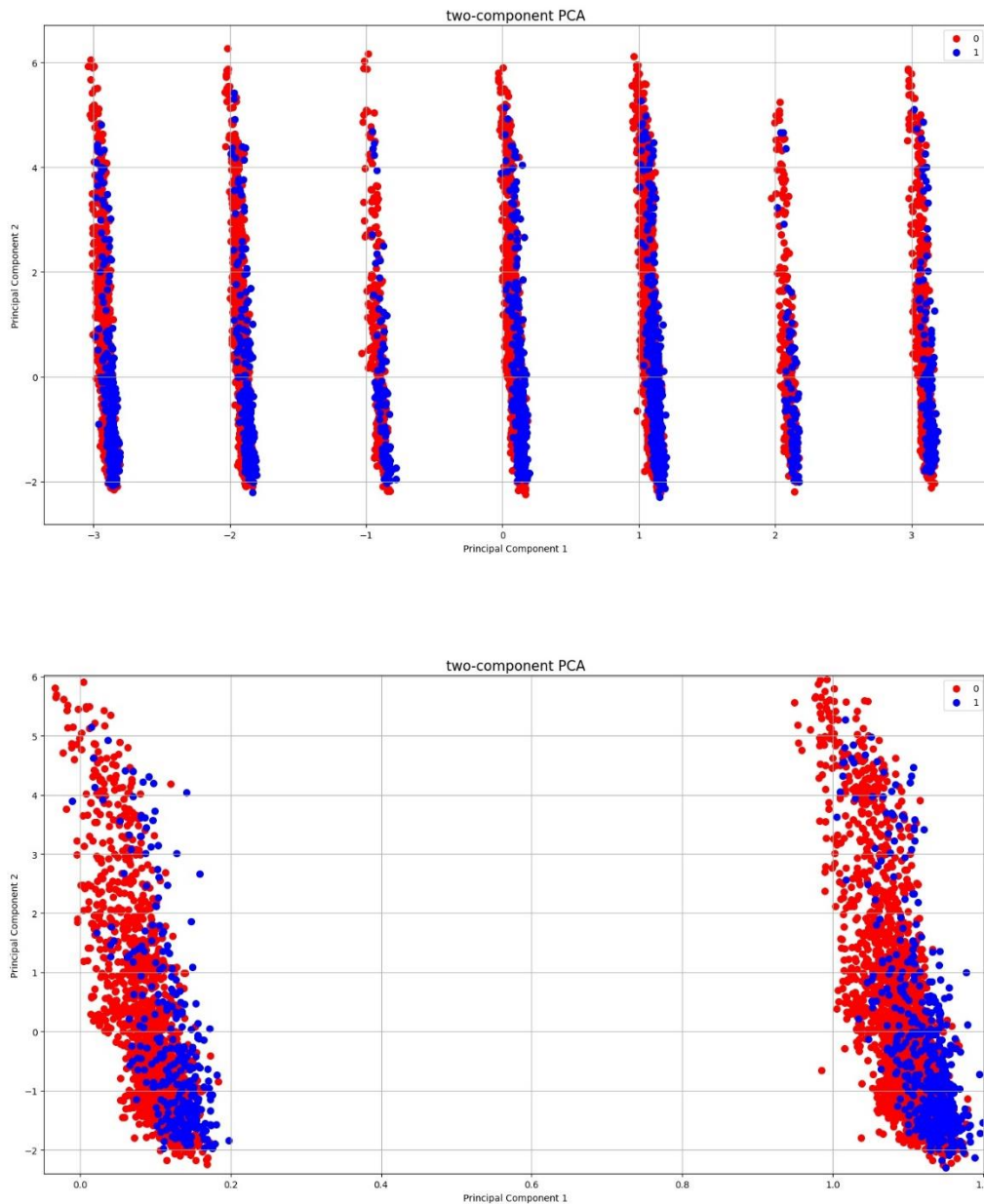
Figure 2. Mapping of 20 features into a 2-dimensional subspace with attrited (1) Customers in blue and existing (0) customers in red.

For the 2-dimensional visualization of a 20-dimensional data, we see that there are seven distinct blobs in the PCA plot corresponding to each Education level (labeled 0 to 6). Zooming in, we see a common behavior of the '1' (blue) examples wherein relative to those blobs, the blue examples cluster in such a way that they have a larger first principal component and smaller second principal component. Interpretation of these principal components is difficult since each feature contribute to each principal component.