For successful campaigns only upper 17% of data for count of backers is more than the value of mean 851.1, whereas median itself is 201. Given these circumstances, and the fact that some more than 33% of data is more than double or even greater than median value, it seems as mean gives kind of a better understanding of what number of backers did campaigns receive, for the ones that were in the top of data set in terms of being able to collect the biggest capital. Whereas, median gives a better understanding in case of looking at actual number of backers received for all the campaigns, disregarding how much capital they obtained. It states that half of the data, or number of backers received by successful campaigns was 201 or less. Nevertheless, given the fact that half of the data set falls within 4th of the value of the mean, when thinking about conducting analysis for the number of successful campaigns as a whole and thinking about how many backers all of them received, median seems more acceptable value.  
Similar tendency can be seen for unsuccessful or failed campaigns. Mean is way greater than standard deviation nearly double of the value of the mean. In these inputs, we see that median is 114, which once again is far better indicator for total number of backers for failed campaigns, compared to mean. Given that 61% of the data inputs has value of less than half that of the mean, this assumption can be supported.   
In terms of Variability of the data, there are several summaries to take into account. Firstly, variance for unsuccessful campaigns seems to be less than that of successful ones. This makes sense on various levels. For instance, the number of unsuccessful campaigns was less than number of successful ones. This does not necessarily mean that all data sets that are greater than another will have greater variance, however it is definitely one of the possibilities, as number of entries increase, deviation between the values of those entries may increase as well. This is another characteristic of data entries for successful campaigns to be mentioned. As we know only 17% of top is more than or equal to the value of the mean and in fact first entry is more than 450 times less than last entry for number of backers for successful campaigns. For these reasons, we are getting variance and standard deviation, which are in very large numbers especially compared to mode, median or mean. Mode in fact, is 80 for successful campaigns, and 1 for unsuccessful ones. It is clear, that when looking into the data that successful outcome or failure was not dependent on the number of backers, given the fact that successful campaigns were achievable even with mere 16 backers, and the fact that projects with 6080 backers could not still attain successful outcome, what comes to mind is the fact that surely there should be another factor involved in the process, which determines either failure or success of those campaigns. On the other hand, it is highly notable that failed campaigns usually had higher goal expectations, even though there were some successful ones in the top end of the data entries who have capitalized on far more than what either their expectation was or goal. In addition, it is also notable that average donations have similar characteristics of mean and variable as do backers count for both successful and unsuccessful campaigns. Meaning, actual amount of donation per individual/backer would be very hard to predict or assume. Ass most of the data, is not situated around the mean. Nevertheless, it is also notable that lowest size of donations was mostly falling under successful campaigns, whereas failed campaigns were able to receive higher amount of donation per backer. One more observation that can be made about this data, is that campaigns that required little capital between 1000 and 4999, have enjoyed most success nominally (that is most successful campaigns produced in terms of a goal), however it is important to note that campaigns that had much higher goals of around 30-35 thousand, have achieved 100% success rate. Moreover, it is also noteworthy that most of cancelled campaigns were ones with 50K goal or more. Furthermore, it when looking at success or failure of campaigns according to date launched, we get a very differently sorted data compared to one with backers count or average donations. Here we see a clear pattern that certain number of projects always very close to the mean with standard deviation of 4 or 5 will either fail or succeed respectively, for that given number of campaigns. The dataset also suggests that, more than half of the campaigns are usually successful. Nevertheless, as this pattern is only suggestable from looking at data through launch dates, it will be of little use to predict, which campaigns will actually be successful or failed. In addition, we have already determined above that data is highly skewed, given this fact statistical assumptions made upon inputs for backers count or average donations, will be highly limited in its predicting ability. Whilst looking through launch date outcomes Pivot Table, parent category was applied to filters, we can easily identify which categories seem to have more normally distributed inputs rather than skewness, which in turn would help us identify, which of the categories of campaigns were on average constant in terms of failures and successes. We could also add goal category column to initial crowdfunding sheet, this would enable us to apply in pivot table filter for goal category in addition to Category of campaign itself, which in turn would tell us more in detail what kind of campaigns in what Parent category and in what goal bracket falls mostly to failure or achieves success. Lastly, once again it is important to note that various entries in dataset are highly skewed and thus pose risk at prediction.