The current dataset contains data related to crowdfunding campaigns. There are some conclusions that can be drawn about crowdfunding campaigns from this data set. The crowdfunding campaign types were divided into several categories with theatre being the most frequent project category, followed by film & video and music. The theatre category was made up of only one subcategory - plays. For the film & video category, most projects were under the documentary subcategory and rock was the most popular subcategory for the music category. A graphical visualization of this can be found in Sheet 1 and Sheet 2’s column graphs. Theatre and plays also had the highest number of successful campaigns. Thus, we can conclude that the most frequent types of crowdfunding projects in this dataset are those that fall into the theatre category and are also more likely to be successful.

Across all categories and years, July was the month where the highest number of successful outcomes occurred. For the theatre category, the highest number of successful campaigns were observed during the month of June.

Lastly, we can also deduce that there was a difference in the number of backers between successful and unsuccessful campaigns. Successful campaigns had a higher number of backers compared to the unsuccessful campaigns. Successful campaigns had a median number of 201 backers and the unsuccessful campaigns had a median number of 115 backers.

However, these conclusions cannot be generally applied to all crowdfunding data but only to the crowdfunding data from this dataset because one of the limitations of this dataset is its sample size. 1000 samples might not be enough to draw robust conclusions and generalize them to other data. Another glaring drawback of the dataset is that the funding data is not in a uniform currency which can make it difficult to compare the data from across countries due to varying currency exchange rates.

In terms of possible expansions to this analysis, we can create additional tables and graphs to extract more value from the data. One such expansion can be to focus on one specific category of interest such as film & video and conduct a more thorough analysis where we see if a particular subcategory was more successful from country to country. For this, we can make a pivot table that is filtered by outcome and parent category and contains the subcategory, country and count of outcome. This can help determine if there is any sort of geographic variability among the projects and where they are common and successful. We can also compare the average goal set by each category for projects that were successful and for those that failed to see whether the outcome was associated with the initial goal. Another addition that can be made is to explore whether there is a link between the average lifetime of each project and its likelihood of success. For this, we can make another column in the original spreadsheet named average lifetime where we calculate the number of days between the project was created and when it ended and then to compare the average lifetime of successful vs. unsuccessful projects. This can provide insight into whether the number of days a project is live matters. Lastly can also look at the average amount pledged to successful vs. unsuccessful projects as opposed to only looking at the number of backers because the number of backers might not be reflective of the amount of money that was pledged.