Kickstarter Analysis

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Introduction

Have you ever had an ambitious idea but did not have resources to pursue it? Kickstarter is a crowdfunding platform for creators who need support for their projects. Since launching in 2009, 19 million people have pledged to back up projects, and nearly 190,000 projects have been successfully funded.

However, many more projects failed to reach their goals, and our group is interested in analyzing what made projects succeed and fail. The dataset Kickstarter Projects comes from Kaggle, which contains Kickstarter projects up until January 2018.

We will be exploring which variables influence the success of a Kickstarter project by observing which types of projects are more likely to be funded. Our questions include:

- Does the amount of money a creator asks for influence it's chance of success?
- Does the category of project influence it's chance of success?

Our hypotheses include:

- The more money the project asks for, the less successful it will be in terms of getting funding.
- The project category is associated with the success rate.

The goal of the project is to give future Kickstarter creators insight into which projects failed and succeeded. This will give them the tools to perform better against their competition, by giving estimates for what has and has not worked based on this historical dataset. Modelling which categories will be most successful best will give creators insight into predicted category success, assuming that there exists a relationship between project categories and success rates.

Data Description

```
## Rows: 378,661
## Columns: 15
## $ ID               <dbl> 1000002330, 1000003930, 1000004038, 1000007540, 10...
## $ name             <chr> "The Songs of Adelaide & Abullah", "Greeting From ...
## $ category         <chr> "Poetry", "Narrative Film", "Narrative Film", "Mus...
## $ main_category    <chr> "Publishing", "Film & Video", "Film & Video", "Mus...
## $ currency         <chr> "GBP", "USD", "USD", "USD", "USD", "USD", "USD", "...
## $ deadline         <date> 2015-10-09, 2017-11-01, 2013-02-26, 2012-04-16, 2...
## $ goal             <dbl> 1000, 30000, 45000, 5000, 19500, 50000, 1000, 2500...
## $ launched         <dttm> 2015-08-11 12:12:28, 2017-09-02 04:43:57, 2013-01...
## $ pledged          <dbl> 0.00, 2421.00, 220.00, 1.00, 1283.00, 52375.00, 12...
```

```
## $ state            <chr> "failed", "failed", "failed", "failed", "canceled"...
## $ backers          <dbl> 0, 15, 3, 1, 14, 224, 16, 40, 58, 43, 0, 100, 0, 0...
## $ country          <chr> "GB", "US", "US", "US", "US", "US", "US", "US", "U...
## $ `usd pledged`    <dbl> 0.00, 100.00, 220.00, 1.00, 1283.00, 52375.00, 120...
## $ usd_pledged_real <dbl> 0.00, 2421.00, 220.00, 1.00, 1283.00, 52375.00, 12...
## $ usd_goal_real    <dbl> 1533.95, 30000.00, 45000.00, 5000.00, 19500.00, 50...
```

This data set contains 15 variables and 378,661 observations, where each observation is one kickstarter project.

The categorical variables include the name of each project, the category of each project (music, narrative film, restaurant, etc.), a broader category of each (food, film, publishing, etc.), the crowdsourcing currency, the state of each project (failed, successful, or cancelled), and the country of origin for each project.

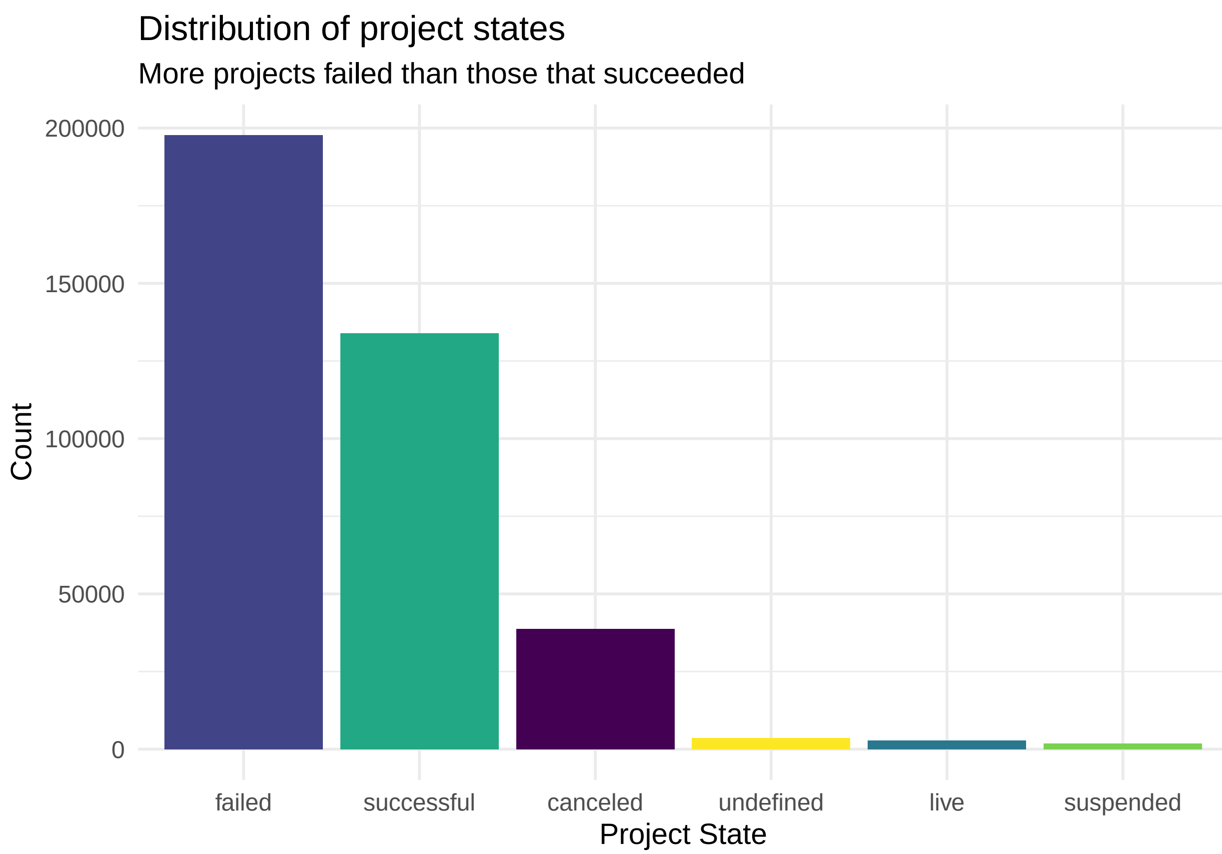
The numerical data are the project's ID number, the monetary goal for each, the money pledged to each project, how many backers of each project; there are three numerical variables that are not self-explanatory, usd_pledged: conversion in US dollars of the pledged column (conversion done by kickstarter), usd_pledge_real: conversion in US dollars of the pledged column (conversion from Fixer.io API), and usd_goal_real: conversion in US dollars of the goal column (conversion from Fixer.io API).

There are also two date columns, one for the project launch and the other for the crowdsourcing deadline.

The data were collected from Kickstarter Platform likely using web scraping methods on their own site, to be used by data scientists to model whether or not a project will be successful or not when it is launched.

Explorative Data Analysis

Overview of project state




```
## # A tibble: 6 x 2
## # Groups:   state [6]
##   state            n
##   <chr>        <int>
## 1 failed      197719
## 2 successful  133956
## 3 canceled     38779
## 4 undefined     3562
## 5 live          2799
## 6 suspended     1846
```

```
## # A tibble: 1 x 1
##   `project success rate`
##                    <dbl>
## 1                  0.354
```

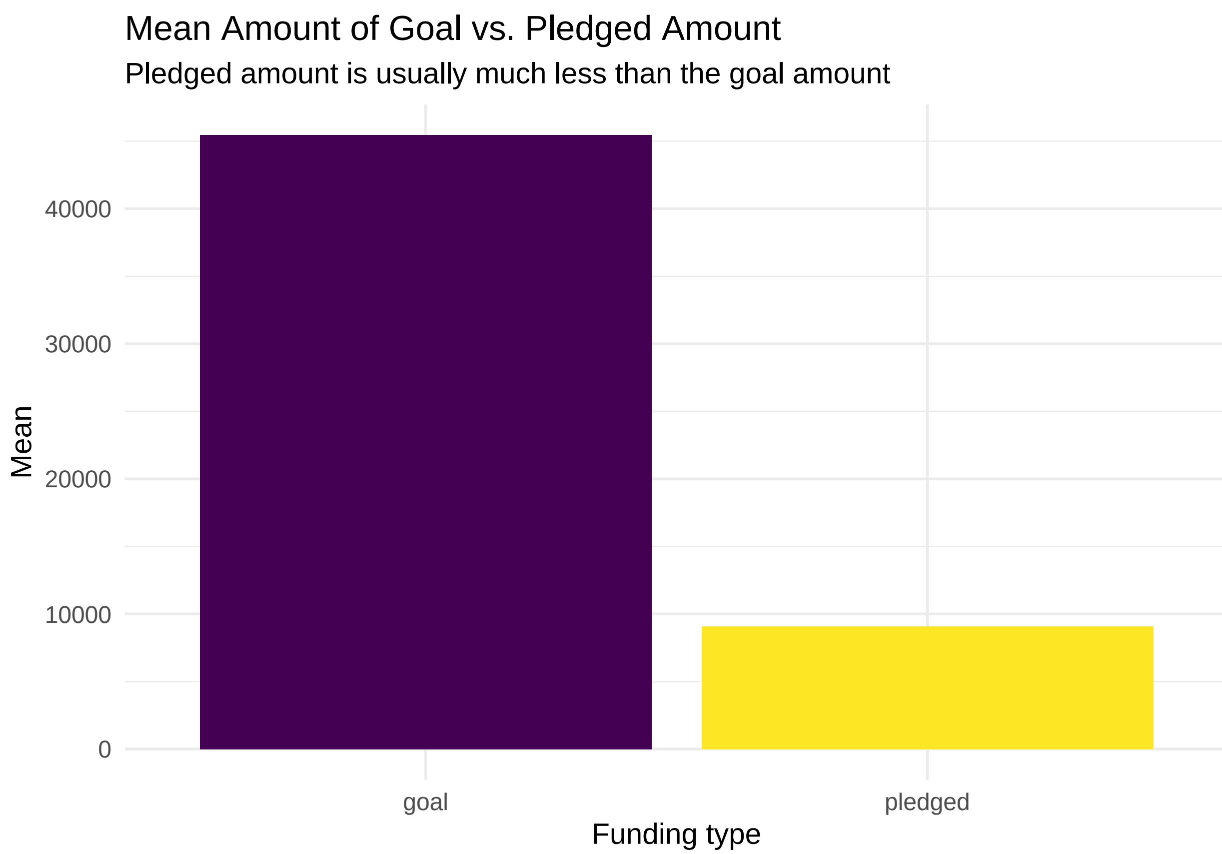
More projects failed than those that succeeded, with an average success rate of 35.4%.

Overview of pledged and goal amount in USD:

```
## # A tibble: 1 x 4
```

```
##    mean median     sd type
##   <dbl>  <dbl>  <dbl> <chr>
## 1 9059.   624. 90973. pledged
```

```
## # A tibble: 1 x 4
##     mean median      sd type
##    <dbl>  <dbl>   <dbl> <chr>
## 1 45454.   5500 1152950. goal
```



The average funding pledged was 9058.92, with a standard deviation of 90,973.34. In comparison, the average funding goal was 45,454 with a standard deviation of 1,152,950. The observed differences between both groups is tremendous.

Methodology

In this analysis, we conducted two central limit thereom (CLT)-based tests. Due to the sheer size of this dataset, using a simulation based method for analysis is not appropriate. We removed all projects that were "Live" and currently asking for funding, so that any discrepencies seen would be negated. If we had included "Live" projects, each project category may not have been representative of the population and project goal amounts may be skewed. Thereforein the first section of the analysis, we overwrote the Kickstarter dataframe with observations that are not "Live". To analyze success, rather than using the given variable "success", we created our own. The original variable "success" contained cancelled, suspended, and undefined states along with successful and failed states. We had no indication if those projects that were cancelled, suspended, or undefined met their goals and cancelled prematurely or if they cancelled due to no funding at all, which may skew our data. To analyze our data, we created an indicator for success: 1 being successful and 0 being unsuccessful (failed, cancelled, suspended, or undefined).

To begin our analysis after removing "Live" projects, we assessed whether there is a relationship between the amount of money a creator asks for and its success. We categorized projects by tiers, on a scale of 1-7, with Tier 1 asking for the least amount of funding and Tier 7 the most. We grouped Tiers 1-4 and 5-7 together when we ran our CLT-based test, placing the lower and higher groups in the same category when running this test. We had to first determine a relationship between tiers and success, so we used a χ^2 test. After determining this relationship, we used a linear model to show the differences in success between Tiers. It would make intuitive sense if the projects that require less funding then they will be more successful. These projects that ask for less funding should require a lower volume of money funded and meet their goal and on average meet more of their goals before project funding deadlines. Furthermore, we believed that these projects would require less backers donating money, assuming each backer donates an equal amount, and thus be dependent on a lower amount of people for funding.

After establishing a relationship between project success and the intial funding goal and modelling the predicted success based on each Tier, we used a CLT-based test to determine if there was a relationship between project categories and their success. We used the variable "main_category" instead of "category" because the latter was far too specific for our purposes. "Main_category" was composed of 15 distinct categories, each for a unique industry. We felt that 15 categories allowed our analyss to be broader and therefore each could encompass many more projects as not to pigeon hole a creator when using our analysis for their purposes. There may be possible crossover between main categories that we were unable to screen for, however, but we assumed this to be a neglible amount of projects, if it existed at all, and thus continued with "main_category" over "category" for analysis.

Following these analyses, we modelled each project's log-odds of success based on "main_category". Success here was a boolean value, with 1 representing successful funding and 0 representing unsuccessful funding. This model enables future creators to think about their project in the larger scheme of a category and base their opinions off these values. Technology was used as the reference level for our model, so each value is based off success relative to the technology category. We used a proportionality level of 0.50 to determine if a project category was worth pursuing. A level greater than 0.50 meant that the category was predicted to have more successful projects than unsuccessful ones.

Results

As explained in the Methodology section, we first overwrited the initial kickstarter dataframe with projects that are not "Live".

Project Goal Amount and Success

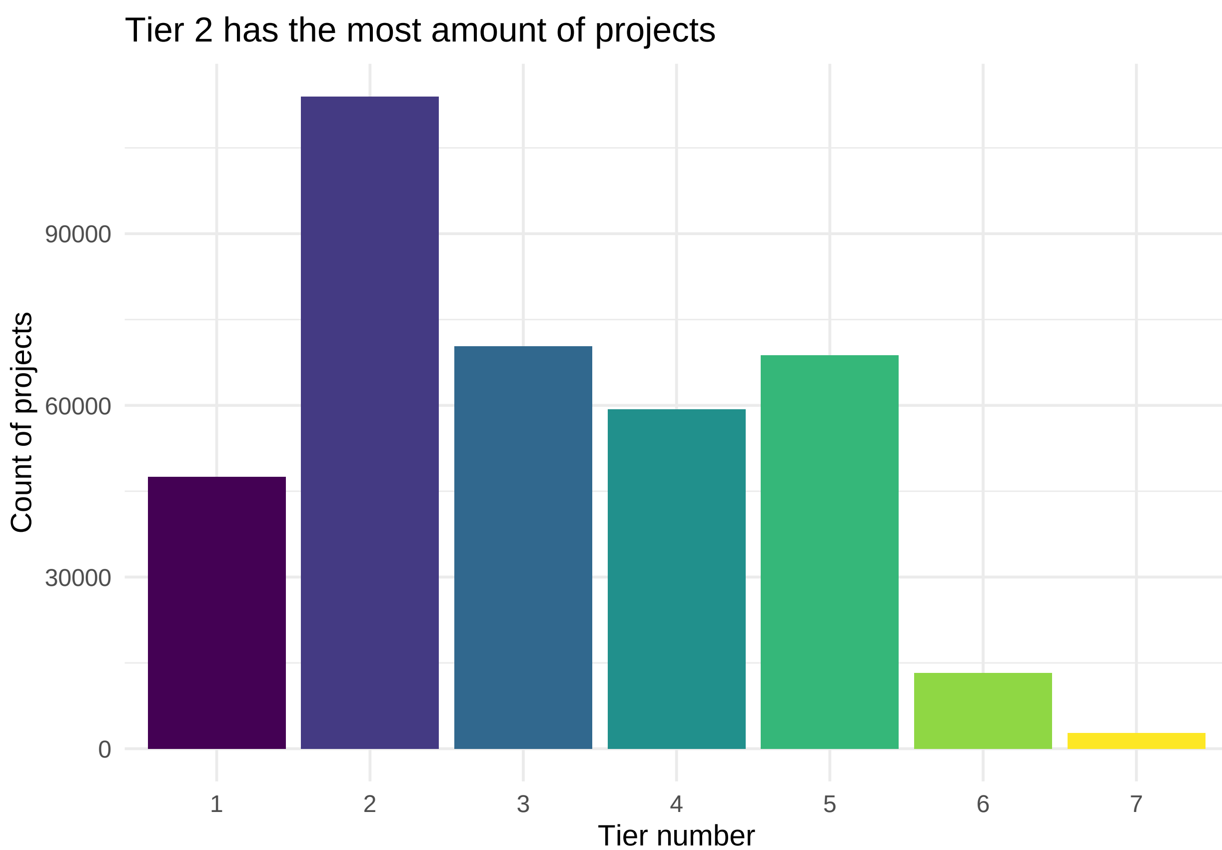
In the Explorative Data Analysis section, the first visualization gave an overview of project states, and the second revealed the large difference between the amount of money asked for and raised. However, from those two plots, we could neither see the goal and pledge amount of each successful and failed projects, nor could we know if whether or not there is a relationship between the goal and pledge amount. In lieu of this, we decided to examine the association between projects' success and their goal amount. To do so, we first came up with a claim that states our assumed association.

Claim: The amount of money a project asks for is related to its success in getting enough funding.

In order to perform a hypothesis testing on this claim, we need to quantify the goal amount into only a few levels rather than using the original discrete data (amount in USD). Otherwise, sample tests wouldn't work well because of too many data points. We decided that using a tiering system would better suit our purposes of determining a relationship between success and how much money a project asks for. Furthermore, visualizing the project tier can give insight to how many projects fall in each range. Therefore, we decided to categorize the goal amount using the following metric and to create new variable named “usd_goal_real_tier” to classify “usd_goal_real” into tiers.

The tiers are as follows: Tier 1 $<$ 1,000 in goal USD, Tier 2 $\geq$ 1,000 and $<$ 5,000, Tier 3 $\geq$ 5,000 and $<$ 10,000, Tier 4 $\geq$ 10,000 and $<$ 20,000, Tier 5 $\geq$ 20,000 and $<$ 100,000, Tier 6 $\geq$ 100,000 and $<$ 500,000, and Tier 7 $\geq$ 500,000.

```
## # A tibble: 7 x 2
##   usd_goal_real_tier numbers
##                <dbl>   <int>
## 1                  1   47494
## 2                  2  113993
## 3                  3   70338
## 4                  4   59285
## 5                  5   68727
## 6                  6   13231
## 7                  7    2794
```



Then, we created a new binary variable named success_state to represent whether a project was successful or not. If a project is not successful (“failed”, “undefined”, “suspended”, or “canceled”), then it could carry a value of 0. Creating this binary variable gets rid of unnecessary project states so that we could focus only on successful projects.

Now we test our first claim using a CLT-based approach:

Hypotheses:

At the $\alpha = 0.05$ level:

H_0: $project_{tiers}$ are independent of $project_{success}$

H_1: $project_{tiers}$ are not independent of $project_{success}$, where $project_{tiers}$ is the variable "usd_goal_real_tiers" and $project_{success}$ the variable "success_state".

Our following CLT approach is testing whether or not there is a relationship between how much money a project attempts to raise and its success.

```
##
##  Pearson's Chi-squared test
##
## data:  table(kickstarter$usd_goal_real_tier, kickstarter$success_state)
## X-squared = 19624, df = 6, p-value < 2.2e-16
```

Analysis of Results:

At the previously stated α level of 0.05, our χ^2 value is 19624 with 6 degrees of freedom and a p-value of less than 2.2e-16. Since our p-value is less than our α value, we have enough evidence to reject our null hypothesis that the Tier a project is independent of its success. There is enough evidence to suggest that a project's Tier is related to its success rate.

Logistic Model for Success based on Project Tiers

Here we used a logistic regression model to predict category success based on the project tier.

We used Tier 1 as our reference level.

```
## # A tibble: 7 x 5
##   term                estimate std.error statistic   p.value
##   <chr>                  <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)           0.505    0.00214     236.  0.
## 2 usd_goal_real_tier2  -0.0675   0.00255     -26.5 1.56e-154
## 3 usd_goal_real_tier3  -0.147    0.00277     -53.2 0.
## 4 usd_goal_real_tier4  -0.188    0.00287     -65.5 0.
## 5 usd_goal_real_tier5  -0.289    0.00278    -104.  0.
## 6 usd_goal_real_tier6  -0.416    0.00458     -90.7 0.
## 7 usd_goal_real_tier7  -0.479    0.00908     -52.8 0.
```

Project Category and Success

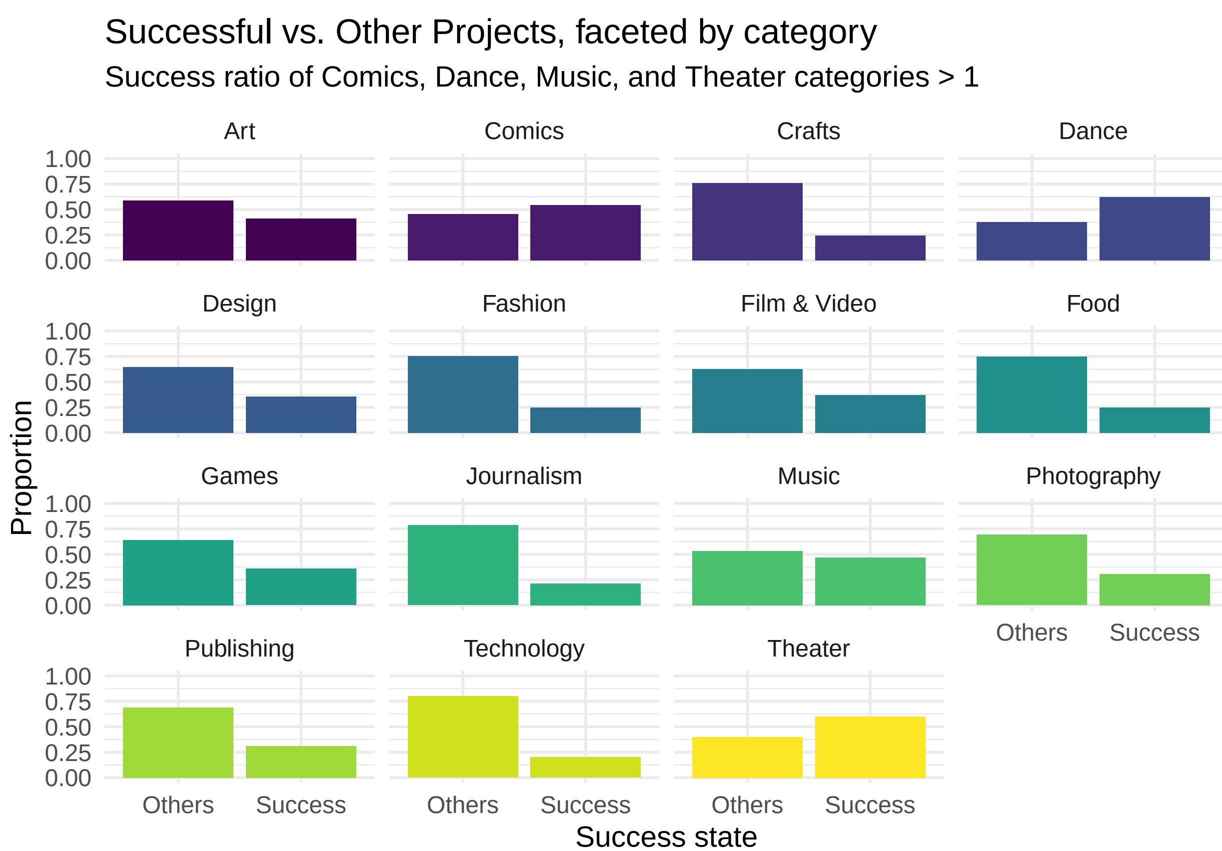
Olivia TODO:

- We probably need to explain why we're studying this question just to provide some context for readers. And for each step, we will need some explanations about why we do what we do. (similar to section 1 of Data Analysis)
- Clean up and explain the bullet point below that says "limitations: . . . "

Question: Does the category of project influence it's chance of success?

- limitations: possible crossover in the main_categories that we cannot screen for

```
## # A tibble: 30 x 5
## # Groups:   main_category [15]
##    main_category success_state     n  prop plot_success
##    <chr>                 <dbl> <int> <dbl> <chr>
##  1 Art                       0 16449 0.588 Others
##  2 Art                       1 11510 0.412 Success
##  3 Comics                    0  4901 0.456 Others
##  4 Comics                    1  5842 0.544 Success
##  5 Crafts                    0  6618 0.758 Others
##  6 Crafts                    1  2115 0.242 Success
##  7 Dance                     0  1412 0.377 Others
##  8 Dance                     1  2338 0.623 Success
##  9 Design                    0 19215 0.646 Others
## 10 Design                    1 10550 0.354 Success
## # ... with 20 more rows
```



We created another variable called "plot_success" which enabled us to plot the results while excluding the 1's and 0's.

We plotted histograms to show the ratio of successes to failures ("other") of the projects, faceted by category. By using a ratio of successes to failures, we were able to visualize the relative success of each category.

Interestingly, the visualization shows that most categories had more failures than successes in raising enough money to meet their goals.

Only the categories of Comics, Dance, and Theatre had more successess than failures according to our visualizations.

Hypotheses:

- H_0: There is no relationship between main_category and success.
- H_1: There is a relationship between main_category and success.

We will perform a CLT simulation at the $\alpha = 0.05$.

```
##
##  Pearson's Chi-squared test
##
## data:  table(kickstarter$main_category, kickstarter$success_state)
## X-squared = 16137, df = 14, p-value < 2.2e-16
```

Analysis of Results:

The Chi-squared test compares observed vs. the expected counts that we would expect if the null hypothesis were true.

We used a Chi-squared test because we want to see if the variables main_category and success_rate are independent of one another in this data set. In other words, running a Chi-squared test helps us evaluate our hypothesis; that there is an association between project category and project success rate.

From our Chi-squared test, we calculate the p-value to be < 2.2e-16. Our test statistic was 16137, which has a Chi-square distribution with 14 degrees of freedom under the null hypothesis. This corresponds to a p-value less than 2.2e-16. Thus, our decision is to reject the null hypothesis. Moreover, there is sufficient evidence to claim that the alternative hypothesis, that there is an an association between main category and success, is true.

Logistic Regression Model to Predict Category Success

Here we used a logistic regression model to predict category success. Specifically, we wanted to see how the project's main category leads to differences in the odds of success.

We used Technology as our reference level.

```
## # A tibble: 15 x 2
##    term                       estimate
##    <chr>                         <dbl>
##  1 (Intercept)                 -1.39
##  2 main_categoryArt             1.03
##  3 main_categoryComics          1.56
##  4 main_categoryCrafts          0.246
##  5 main_categoryDance           1.89
##  6 main_categoryDesign          0.788
##  7 main_categoryFashion         0.277
##  8 main_categoryFilm & Video    0.870
##  9 main_categoryFood            0.284
## 10 main_categoryGames           0.804
## 11 main_categoryJournalism      0.0875
## 12 main_categoryMusic           1.26
## 13 main_categoryPhotography     0.578
## 14 main_categoryPublishing      0.591
## 15 main_categoryTheater         1.80
```

Relative to Technology, the most likely funded project category is Dance. The odds of success for Dance are 6.374285 times the odds of success for Technology. Furthermore, all else being equal, the estimated probability of success for the Dance category is 0.62, whereas for Technology the probability of success is 0.21. There is sufficient evidence based on our model to suggest that Dance may be the most readily successful project type and is likely worth spending time looking into this category for project creators.

Discussion

TODO: Furthermore, the entire discussion section is missing, as there is no overall summary of what all of the hypothesis tests have shown in the context of the research question, along with the specific p-values that support these conclusions. To make your results and conclusions stronger, you should also critique your own methods and provide suggestions for improving your analysis, as showing possible faults in reliability and validity of your data and the appropriateness of the statistical analyses helps support your positions as researchers and knowledge of the data. To add onto conclusions that you write, you should also discuss what you would do next if you were going to continue work on the project to show where your analyses could have gone farther.