KickStarter Project

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Part I. Report

Summary and Problem Statement

A description of the problem that is driving the project (comprehensible by an educated lay person).

In this project, we are predicting the success rate of Kickstarter campaigns. Kickstarter is the world's largest funding platform for creative projects, with projects ranging from technology to arts. Kickstarter's rule states that if a project falls short of meeting its minimum funding goal by its deadline, the project will not receive any fund. Thus very important to set a realistic goal. However, there is currently no practical suggestion or guidance, and the analytics dashboard is hard to set up. Therefore, we are interested in predicting the projects' success rate given a project's goal and other independent variables. Predicting the success rate increases the number of funding goals reached. Ultimately, it supports the entrepreneurs, and in the process support art, advocate for social causes, and bring innovation ideas and products to the world.

Data

A rationale for selecting the data collected used to investigate the problem.

The dataset we used is pre-scraped data stored in multiple csv files. It includes 7,574 projects from North America, Europe, Pacific countries, and Japan. Each project in our dataset has either failed, successful, live, suspended or canceled status. Since we are only interested in projects with status of either successful or failed, we filtered out projects whose status is not successful or failed. In addition we also dropped projects that have missing values.

Our selected dataset is complete and good for us to analyze the data and construct data predictive models. We payed attention to some specific parameters that are important for our analysis such as projects' goal, amount pledged, category, duration, region, etc. All those features are included, even though the data might be untidy or not in the best format for analysis. However, some unrelated parameters such as projects' description, urls, photo have nothing to do with success rate. Thus, we drop those columns and leave parameters that are closely related with project's success.

Cleaning, Visualization, and Prediction

Justification for the processes implemented, and the technical choices you made for your project.

For data cleaning, we chose to use tidyverse, lubridate packages with regular expression and some baseR functions. In order to extract useful information and get rid of irrelevant data, we used regular expression to extract category, location and tidy other parameters into standard format. Also we used lubridate package to create duration columns based on given information about launched date and end date.

In the process of data exploration and visualization analysis, we chose to use ggthemes and rworldmap packages for visualizing the data and dplyr packages to select relevant data. Ggthemes can help us make data more visualized in terms of colors of bars, lines, and points. For example, the higher proportion the category takes or the higher the success rate is, the darker the color of that category is. We also used rworldmap package because we want to present and acknowledge where our data is coming from. It is relatively wide-ranged, even though it does not cover Africa and South America.

For prediction, we used the following models: k-nearest neighbour, logistic regression, support vector machine, and naive bayes. K-nn model is commonly used in classification and regression predictive problems, but has a long calculation time. Simple logistic regression model is used because there are multiple independent variables. SVM is used for classification because if can find an optimal boundary between the classes. NB model takes less time to train, and requires less data. Thus, we choose to implement the above four models for our prediction/classification task.

Issues and Solution

A description of any issues you ran into and how you resolved them.

When we clean the dataset, one challenge we had is that some of columns' data are stored in JSON format and they actually compress a lot of relevant data. The approach we took to solve this problem is by using string extract and replace with regular expression to extract useful information and split them into several columns. In addition, the original data does not have the duration in format of number of days, instead we had launched date and end date, both in Unix time. We used r packages to convert them into readable year/month/day format, and computed two duration variables with the three given timestamp.

In the prediction process, we encounter the following problems:

First, the data frame contains a mix of independent variables and dependent variables. To solve this problem, we implemented a correlation plot of all the variables, and dropped those that are in fact dependent variables. For instance, we dropped "spotlight" (meaning if a Kickstarter project is featured on the homepage of the website), because it is highly correlated with the final state (successful or unsuccessful), and is in fact a dependent variable.

Second, some models (SVM) takes has a long calculation time in R. As a result, we choose to implement the models in python using jupyter notebook for shorter time and more suitable visualization tools (such as Matlibplot).

Please refer to Part II and Part III of this report for input code and session outputs.

Insigths and Potential Future Work

Insights on what you learned and potential future work.

Throughout this project, We have learned some things that we do not learn in lectures or homeworks. First, it is our first time to play around with such huge, untidy, and real data. We had some challenges for cleaning data but solved them eventually (refer to the issue section for more details). We realized that a fairly confident prediction can be generated based on our chosen variables. Thus, it is possible to predict the success, and potentially make modification to the project setup, in order to improve the success rate of Kickstarter crowdfunding projects.

In future, we are planning to do a multi-class/multinomial classification or prediction, instead of the binary classification process we are using. This would give more precise feedbacks to the project initiators.

We are also considering building interactive visualization tools (possibly chrome extension) to analyze a specific project's parameters, and give real-time feedback to the project initiators. The feedback could focus on variables such as project duration, pledged amount, areas of improvement on project description etc. Some examples of the suggestions are: "Use a longer time period of 100 days." "Reduce the pledged amount to 1000 dollars." "Replace the word 'must' with 'could'." "Set more pledging options with smaller amounts, such as $5."

Part II. Data Cleaning and Visualization

#1. **Data Acquisition and Integration

```
data_source_1 <- read.csv("./data/Kickstarter001.csv", header = TRUE, sep = ",")
data_source_2 <- read.csv("./data/Kickstarter002.csv", header = TRUE, sep = ",")

raw_data <- rbind(data_source_1, data_source_2)
```

#2. **Data Cleaning There are 3784 data totally and there are 3680 projects are completed.

```
live_data <- raw_data %>% filter(raw_data$state == "live")
```

To clean the “catagory” column

```
raw_data$category <- raw_data$category %>%
  str_extract("slug\":\".+\",\"") %>%
  str_replace_all("\",\"", "") %>%
  str_replace_all("slug\":\"", "") %>%
  str_replace("/.+", "")
```

To clean the “location” column

```
raw_data$location <- raw_data$location %>%
  str_extract("name\":\".+\",\"") %>%
  str_replace("\",\".+", "") %>%
  str_replace_all("name\":\"", "")
```

To get rid of creator,photo, slug, urls column

```
raw_data$creator <- NULL
raw_data$photo <- NULL
raw_data$slug <- NULL
raw_data$urls <- NULL
```

To add a preparation_duration column

```
raw_data$preparation_duration <- raw_data$launched_at - raw_data$created_at
raw_data$preparation_duration_r <- seconds_to_period(raw_data$preparation_duration)
```

To add a launch_duration column

```
raw_data$launch_duration <- raw_data$deadline - raw_data$launched_at
raw_data$launch_duration_r <- seconds_to_period(raw_data$launch_duration)
raw_data$launch_duration_r <- day(raw_data$launch_duration_r)
```

To convert epoch seconds to readable time

```
raw_data$created_at_readable <- anytime(raw_data$created_at)
raw_data$deadline_readable <- anytime(raw_data$deadline)
raw_data$launched_at_readable <- anytime(raw_data$launched_at)
raw_data$preparation_duration_r <- NULL
```

Transfer raw data into a new variable

```
clean_data <- raw_data
write.csv(clean_data, "./data/data.csv")
head(clean_data)
```

```
##   backers_count
## 1           30
## 2            0
## 3          102
## 4           22
## 5            2
## 6            7
##
## 1 Experience tea and coffee as it should be in our handmade, fine bone china mugs. Made exclusively
## 2    Playing Roles Outside of Basic Education (P.R.O.B.E)\nThe magazine that highlights extracurricul
## 3                                                                                         A pilot for
## 4 A film about suicide. The struggles of our modern world taking people to their limit and how commo
## 5               Fusing the technical qualities and accuracy of photography with a digital process to
## 6                                         A digital, interactive magazine and online community fo
##      category converted_pledged_amount country created_at currency
## 1      crafts                     1547      GB 1515610761      GBP
## 2  publishing                        0      US 1426362805      USD
## 3 film & video                    8101      US 1525106061      USD
## 4 film & video                    1566      GB 1519854040      GBP
## 5          art                      11      US 1407346285      USD
## 6  publishing                      826      US 1411150798      USD
##   currency_symbol currency_trailing_code current_currency   deadline
## 1               £                  false              USD 1521190409
## 2               $                   true              USD 1429112946
## 3               $                   true              USD 1531713540
## 4               £                  false              USD 1522443600
## 5               $                   true              USD 1410484909
## 6               $                   true              USD 1414008752
##   disable_communication friends  fx_rate  goal         id is_backing
## 1                 false         1.308394  1000 1361161119
## 2                 false         1.000000  5000  746509287
## 3                 false         1.000000  6000 1402909261
## 4                 false         1.308394   400  311541751
## 5                 false         1.000000 11000  466957735
## 6                 false         1.000000  2000 1471254290
##   is_starrable is_starred launched_at       location
## 1        false             1517306009         London
## 2        false             1426520946       Columbus
## 3        false             1529070876 St. Petersburg
## 4        false             1519937886         Dorset
## 5        false             1407892909      Ypsilanti
## 6        false             1411416752  San Francisco
##                                        name permissions pledged
## 1 Fine Bone China Ceramic Mugs, Made in England           1111.0
## 2                          P.R.O.B.E. Magazine              0.0
## 3                       'Merican Wasteland Pilot          8101.0
## 4                          Cliff - Feature Film           1116.5
## 5                              Photo to Artwork             11.0
## 6   Lilah Magazine 1st issue launching Dec 2014            826.0
##
## 1
## 2
## 3
## 4 {"id":3322408,"project_id":3322408,"state":"active","state_changed_at":1523464237,"name":"CLIFF -
## 5
## 6
##                                                                source_url
## 1                 https://www.kickstarter.com/discover/categories/crafts
## 2 https://www.kickstarter.com/discover/categories/publishing/periodicals
## 3       https://www.kickstarter.com/discover/categories/film%20&%20video
## 4       https://www.kickstarter.com/discover/categories/film%20&%20video
## 5      https://www.kickstarter.com/discover/categories/art/digital%20art
## 6 https://www.kickstarter.com/discover/categories/publishing/periodicals
##   spotlight staff_pick      state state_changed_at static_usd_rate
## 1      true      false successful       1521190409        1.413819
## 2     false      false     failed       1429112947        1.000000
## 3      true      false successful       1531713540        1.000000
## 4      true      false successful       1522443600        1.390235
## 5     false      false     failed       1410484909        1.000000
## 6     false      false     failed       1414008752        1.000000
##   usd_pledged      usd_type preparation_duration launch_duration
## 1    1570.753 international              1695248         3884400
## 2       0.000 international               158141         2592000
## 3    8101.000 international              3964815         2642664
## 4    1552.197 international                83846         2505714
## 5      11.000      domestic               546624         2592000
## 6     826.000 international               265954         2592000
##   launch_duration_r created_at_readable   deadline_readable
## 1                44 2018-01-10 13:59:21 2018-03-16 04:53:29
## 2                30 2015-03-14 15:53:25 2015-04-15 11:49:06
## 3                30 2018-04-30 12:34:21 2018-07-15 23:59:00
## 4                29 2018-02-28 16:40:40 2018-03-30 17:00:00
## 5                30 2014-08-06 13:31:25 2014-09-11 21:21:49
## 6                30 2014-09-19 14:19:58 2014-10-22 16:12:32
##   launched_at_readable
## 1  2018-01-30 04:53:29
## 2  2015-03-16 11:49:06
## 3  2018-06-15 09:54:36
## 4  2018-03-01 15:58:06
## 5  2014-08-12 21:21:49
## 6  2014-09-22 16:12:32
```

#3. **Data exploration and Visualization

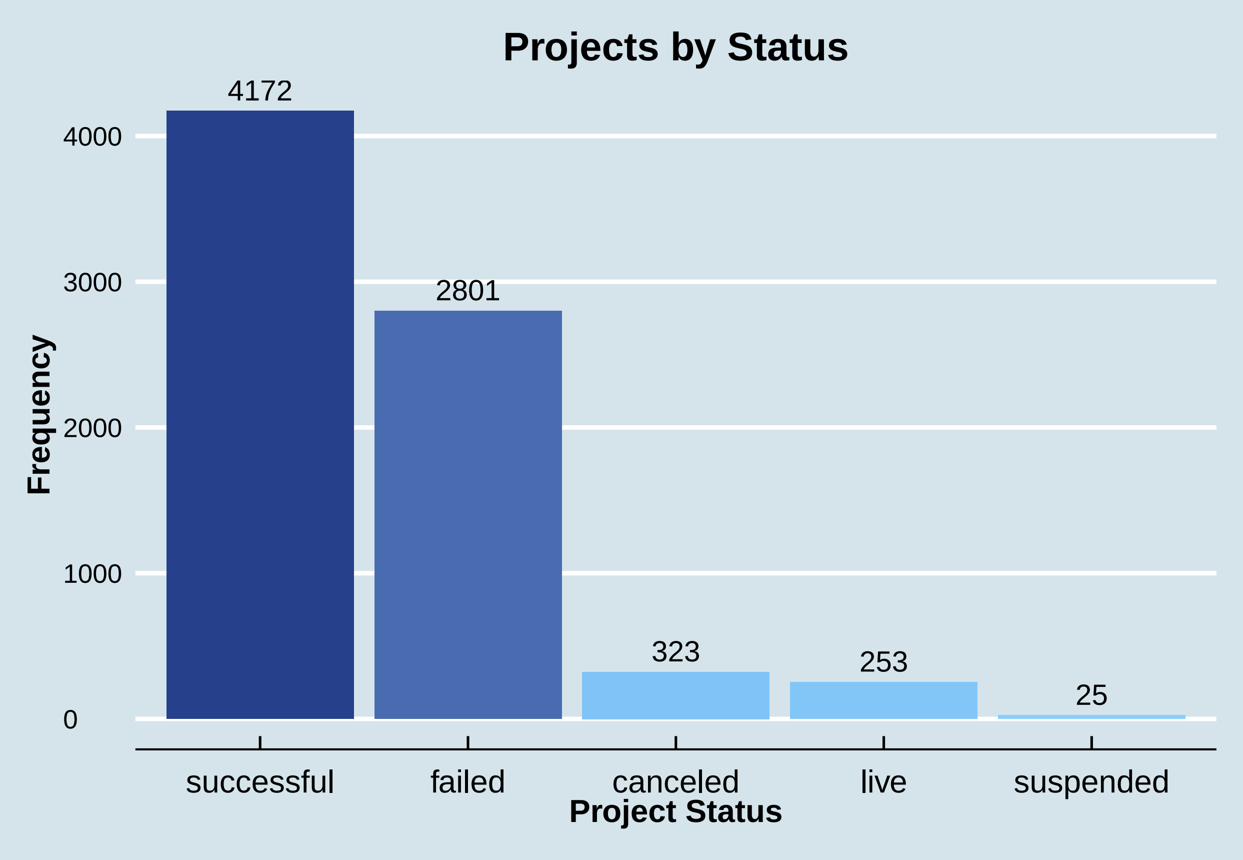
3.1 Summarise the number of projects for each status

```r
status_prjects <- clean_data %>%
  group_by(clean_data$state) %>%
  summarise(count = n()) %>%
  arrange(desc(count))
head(status_prjects)
```

```
## # A tibble: 5 x 2
##   `clean_data$state` count
##   <fct>              <int>
## 1 successful          4172
## 2 failed              2801
## 3 canceled             323
## 4 live                 253
## 5 suspended             25
```

Plot the number of projects for each status

```
ggplot(status_prjects, aes(reorder(status_prjects$`clean_data$state`, -count), count, fill=count)) + geo
  ggtitle("Projects by Status") + xlab("Project Status") + ylab("Frequency") +
  geom_text(aes(label=count), vjust=-0.5) + theme_economist() +
  theme(plot.title=element_text(hjust=0.5), axis.title=element_text(size=12, face="bold"),
        axis.text.x=element_text(size=12), legend.position="null") +
  scale_fill_gradient(low="skyblue1", high="royalblue4")
```



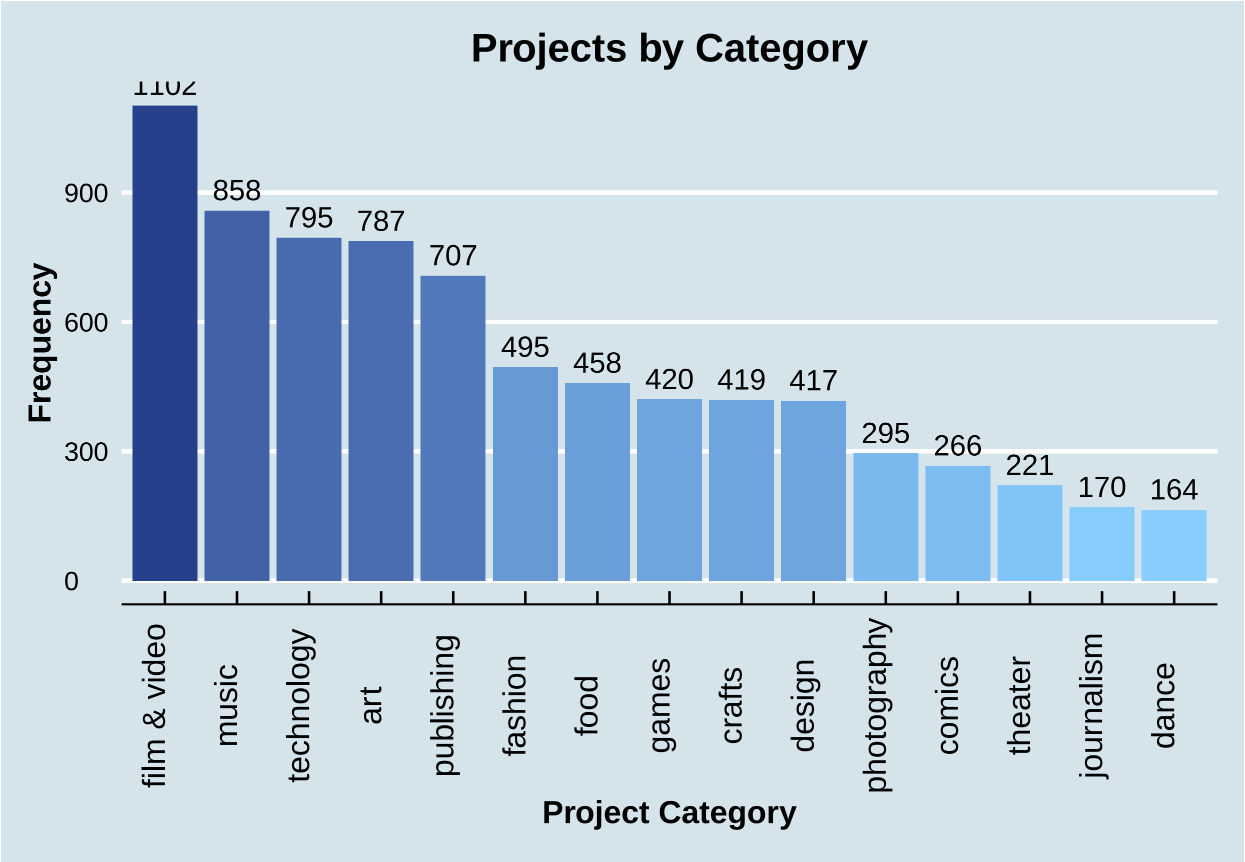
3.2 Summarise the number of projects for each catagory

```
catagory_projects <- clean_data %>%
  group_by(clean_data$category) %>%
  summarise(count = n()) %>%
  arrange(desc(count))
head(catagory_projects)
```

```
## # A tibble: 6 x 2
##   `clean_data$category` count
##   <chr>                 <int>
## 1 film & video           1102
## 2 music                   858
## 3 technology              795
## 4 art                     787
## 5 publishing              707
## 6 fashion                 495
```

Plot the popularity of each category, which is dertermined by the number of projects

```
ggplot(catagory_projects, aes(reorder(catagory_projects$`clean_data$category`, -count), count, fill=cou
  ggtitle("Projects by Category") + xlab("Project Category") + ylab("Frequency") +
  geom_text(aes(label=count), vjust=-0.5) + theme_economist() +
  theme(plot.title=element_text(hjust=0.5), axis.title=element_text(size=12, face="bold"),
        axis.text.x=element_text(size=12, angle=90), legend.position="null") +
  scale_fill_gradient(low="skyblue1", high="royalblue4")
```



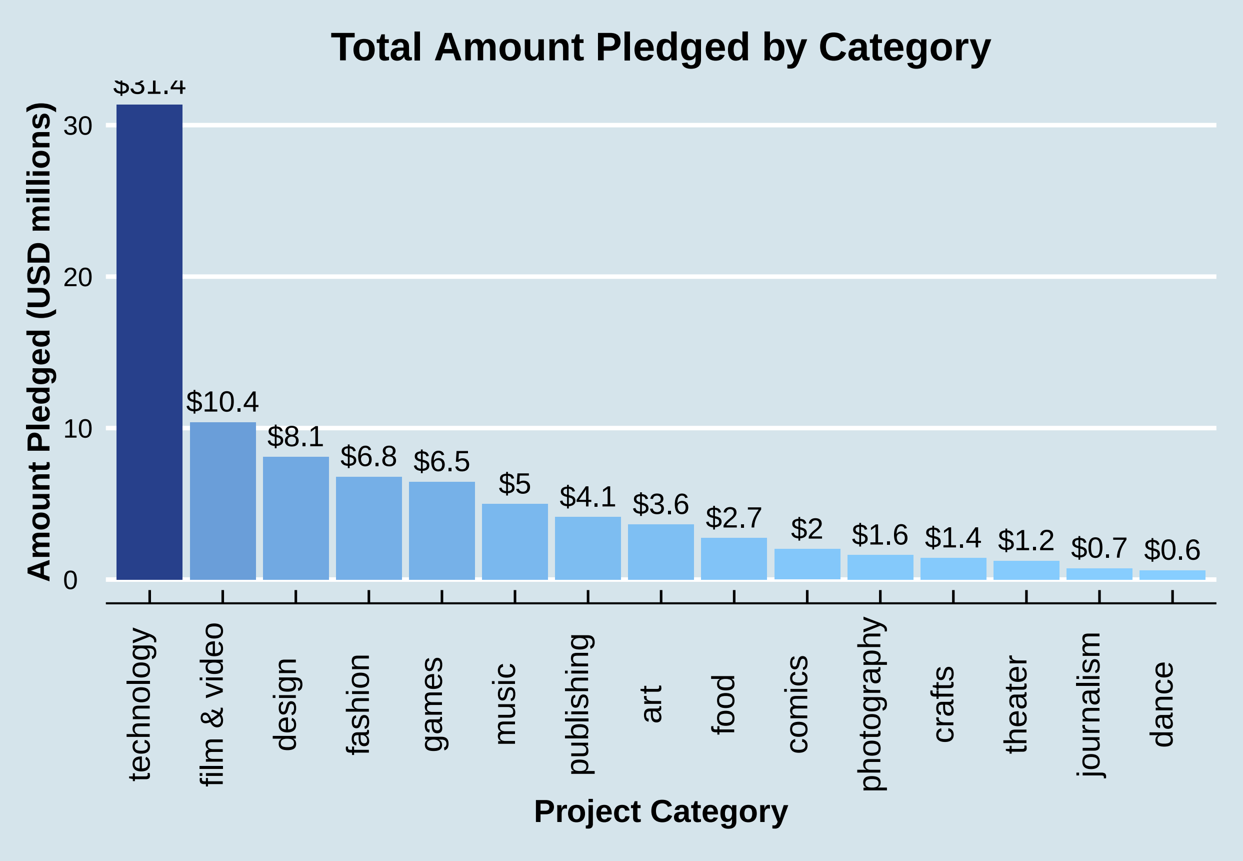
3.3 What types of projects are being funded?

```
pledged_category <- clean_data %>%
  group_by(clean_data$category) %>%
  summarise(total = sum(usd_pledged)) %>%
  arrange(desc(total))
head(pledged_category)
```

```
## # A tibble: 6 x 2
##   `clean_data$category`     total
##   <chr>                     <dbl>
## 1 technology            31373736.
## 2 film & video          10398557.
## 3 design                 8108525.
## 4 fashion                6797765.
## 5 games                  6465490.
## 6 music                  4988363.
```

Plot the amount pledged by each category

```r
ggplot(pledged_category, aes(reorder(pledged_category$`clean_data$category`, -total), total/1000000, fil
  ggtitle("Total Amount Pledged by Category") + xlab("Project Category") +
  ylab("Amount Pledged (USD millions)") +
  geom_text(aes(label=paste0("$", round(total/1000000,1))), vjust=-0.5) + theme_economist() +
  theme(plot.title=element_text(hjust=0.5), axis.title=element_text(size=12, face="bold"),
        axis.text.x=element_text(size=12, angle=90), legend.position="null") +
  scale_fill_gradient(low="skyblue1", high="royalblue4")
```



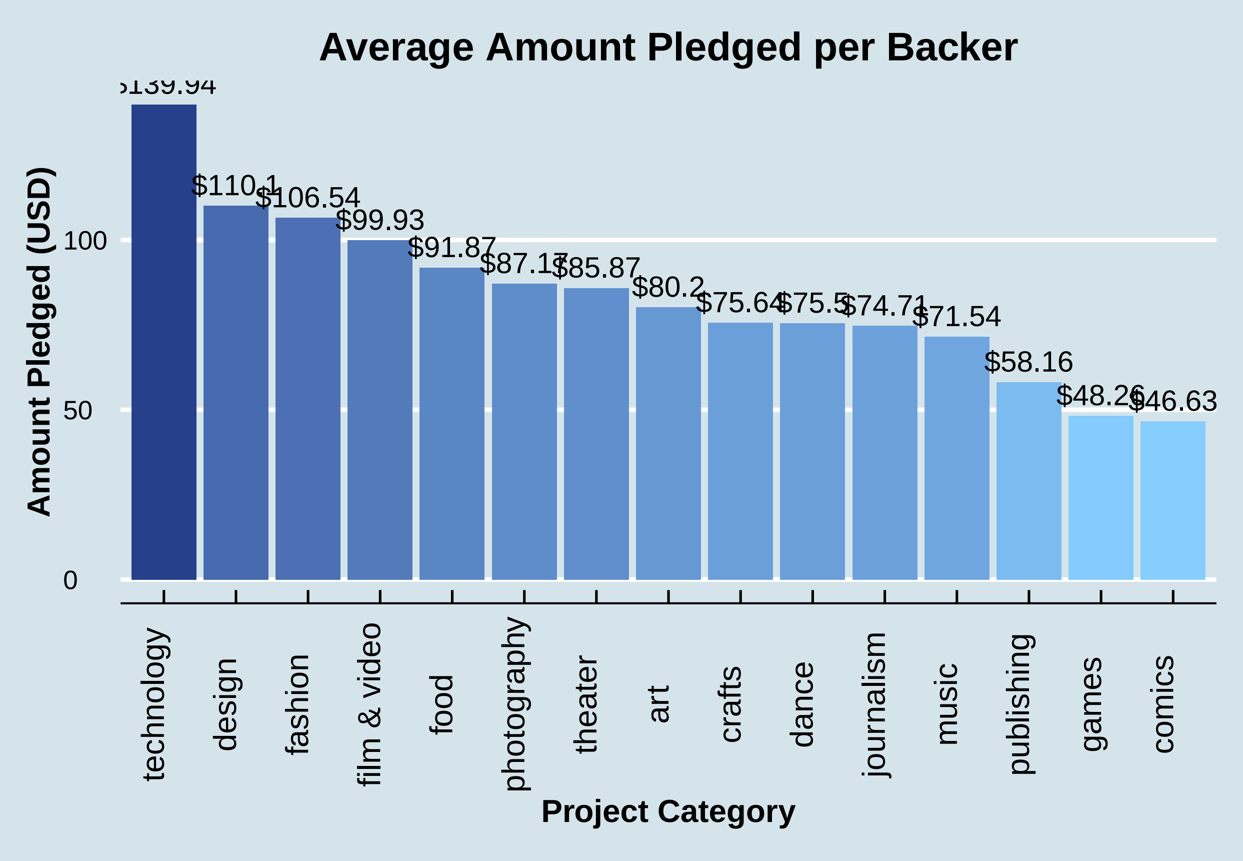
3.4 How much is pledged per backer for each category?

```r
pledged_avg_category <- clean_data %>%
  group_by(clean_data$category) %>%
  summarise(pledged = sum(usd_pledged), backers=sum(backers_count)) %>%
  mutate(avg = pledged/backers) %>%
  arrange(desc(avg))
head(pledged_avg_category)
```

```
## # A tibble: 6 x 4
##   `clean_data$category`   pledged backers   avg
##   <chr>                     <dbl>   <int> <dbl>
## 1 technology            31373736.  224188 140. 
## 2 design                 8108525.   73647 110. 
## 3 fashion                6797765.   63802 107. 
## 4 film & video          10398557.  104058  99.9
## 5 food                   2745202.   29880  91.9
## 6 photography            1620027.   18585  87.2
```

Plot the amount pledged per backer for each category

```
ggplot(pledged_avg_category, aes(reorder(pledged_avg_category$`clean_data$category`, -avg), avg, fill=a
  ggtitle("Average Amount Pledged per Backer") + xlab("Project Category") +
  ylab("Amount Pledged (USD)") +
  geom_text(aes(label=paste0("$", round(avg,2))), vjust=-0.5) + theme_economist() +
  theme(plot.title=element_text(hjust=0.5), axis.title=element_text(size=12, face="bold"),
        axis.text.x=element_text(size=12, angle=90), legend.position="null") +
  scale_fill_gradient(low="skyblue1", high="royalblue4")
```



3.5 Get the 10 highest goal successful projects

```
top_ten_success <- clean_data[clean_data$state == "successful",] %>%
  select("category", "goal", "state") %>%
  arrange(desc(goal))
head(top_ten_success)
```

```
##      category    goal      state
## 1  technology 1500000 successful
## 2  technology  800000 successful
## 3  technology  800000 successful
## 4 photography  700000 successful
## 5  technology  500000 successful
## 6      design  500000 successful
```

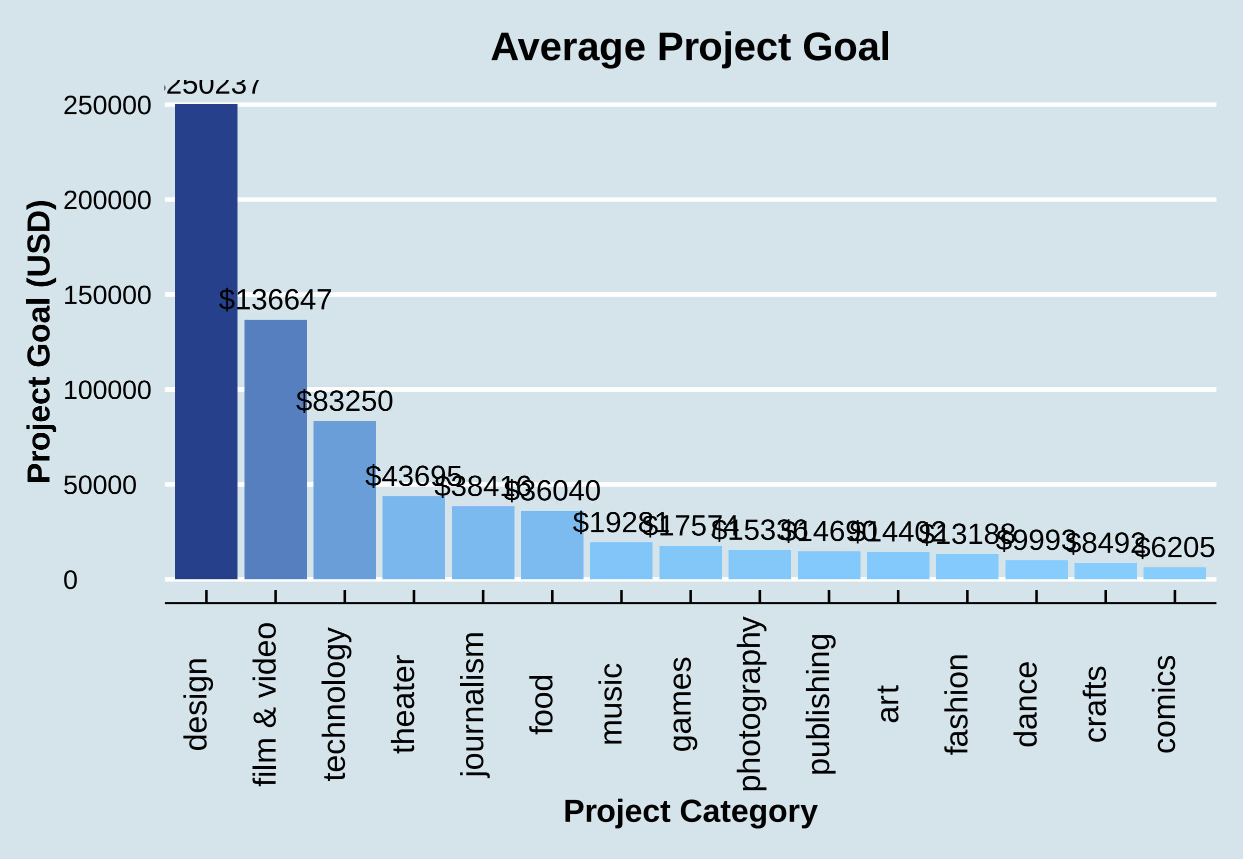
3.6 Get the average project goal

```
goal_avg <- clean_data %>%
  group_by(category) %>%
  summarise(goals = sum(goal), projects = n()) %>%
  mutate(avg = goals/projects) %>%
  arrange(desc(avg))
head(goal_avg)
```

```
## # A tibble: 6 x 4
##   category          goals projects     avg
##   <chr>             <dbl>    <int>   <dbl>
## 1 design        104348985       417 250237.
## 2 film & video 150585489.     1102 136647.
## 3 technology     66183820       795  83250.
## 4 theater         9656489       221  43695.
## 5 journalism      6530680       170  38416.
## 6 food           16506111       458  36040.
```

Plot the average project goal.

```
ggplot(goal_avg, aes(reorder(goal_avg$category, -avg), avg, fill=avg)) + geom_bar(stat="identity") +
  ggtitle("Average Project Goal") + xlab("Project Category") + ylab("Project Goal (USD)") +
  geom_text(aes(label=paste0("$", round(avg,0))), vjust=-0.5) + theme_economist() +
  theme(plot.title=element_text(hjust=0.5), axis.title=element_text(size=12, face="bold"),
        axis.text.x=element_text(size=12, angle=90), legend.position="null") +
  scale_fill_gradient(low="skyblue1", high="royalblue4")
```



3.7 percentage for projects in each category

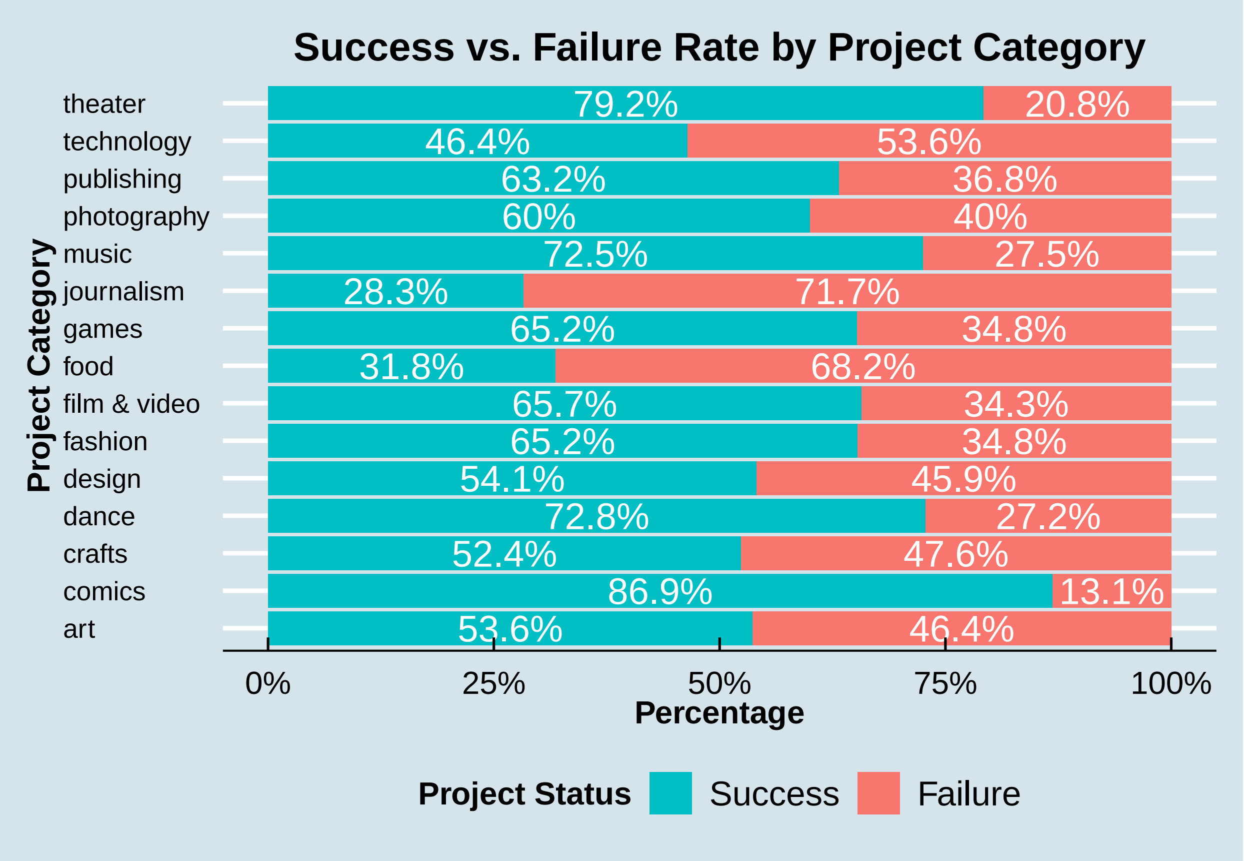
```
perc_projects <- clean_data %>%
  filter(state %in% c("successful", "failed")) %>%
  group_by(category, state) %>%
```

```r
  summarize(count=n()) %>%
  mutate(pct=count/sum(count)) %>%
  arrange(desc(state), pct)
head(perc_projects)
```

```
## # A tibble: 6 x 4
## # Groups:   category [6]
##   category   state      count   pct
##   <chr>      <fct>      <int> <dbl>
## 1 journalism successful    43 0.283
## 2 food       successful   132 0.318
## 3 technology successful   344 0.464
## 4 crafts     successful   199 0.524
## 5 art        successful   390 0.536
## 6 design     successful   198 0.541
```

Plot the percentage for each category

```r
ggplot(perc_projects, aes(perc_projects$category, pct, fill=state)) + geom_bar(stat="identity") +
  ggtitle("Success vs. Failure Rate by Project Category") +
  xlab("Project Category") + ylab("Percentage") + scale_y_continuous(labels=scales::percent) +
  scale_fill_discrete(name="Project Status", breaks=c("successful", "failed"),
                      labels=c("Success", "Failure")) +
  geom_text(aes(label=paste0(round(pct*100,1),"%")), position=position_stack(vjust=0.5),
            colour="white", size=5) + theme_economist() +
  theme(plot.title=element_text(hjust=0.5), axis.title=element_text(size=12, face="bold"),
        axis.text.x=element_text(size=12), legend.position="bottom",
        legend.title=element_text(size=12, face="bold")) + coord_flip()
```

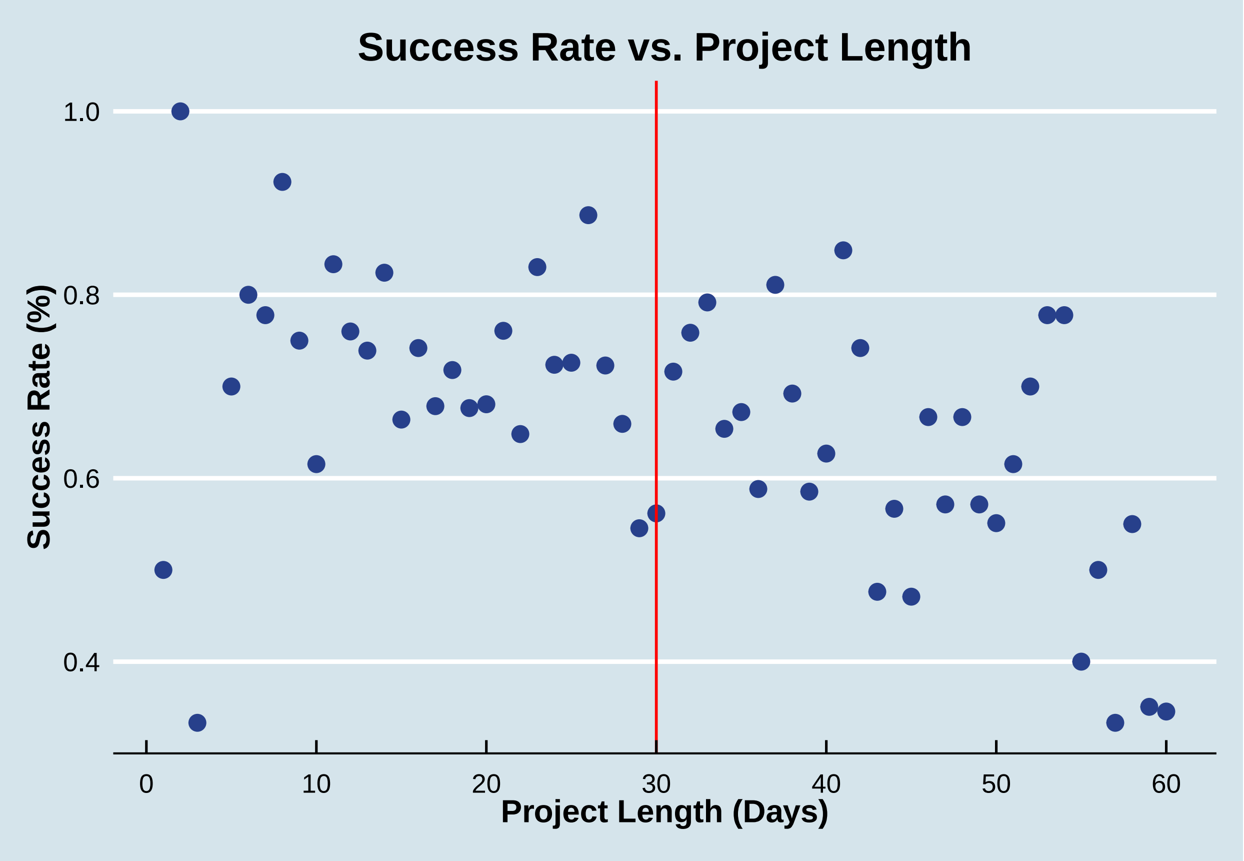


3.8 Does project length affect success rate?

```
perc_length <- clean_data %>%
  filter(state %in% c("successful", "failed"), launch_duration_r < 61) %>%
  group_by(launch_duration_r, state) %>%
  summarize(count=n()) %>%
  mutate(pct=count/sum(count))
head(perc_length)
```

```
## # A tibble: 6 x 4
## # Groups:   launch_duration_r [4]
##   launch_duration_r state      count   pct
##               <dbl> <fct>      <int> <dbl>
## 1                 1 failed         1 0.5
## 2                 1 successful     1 0.5
## 3                 2 successful     1 1
## 4                 3 failed         6 0.667
## 5                 3 successful     3 0.333
## 6                 4 failed         2 1
```

```
ggplot(perc_length[perc_length$state=="successful",], aes(launch_duration_r, pct)) +
  geom_point(colour="royalblue4", size=2.5) + ggtitle("Success Rate vs. Project Length") +
  xlab("Project Length (Days)") + ylab("Success Rate (%)") +
  scale_x_continuous(breaks=c(0,10,20,30,40,50,60)) + geom_vline(xintercept=30, colour="red") +
  theme_economist() +
  theme(plot.title=element_text(hjust=0.5), axis.title=element_text(size=12, face="bold"))
```



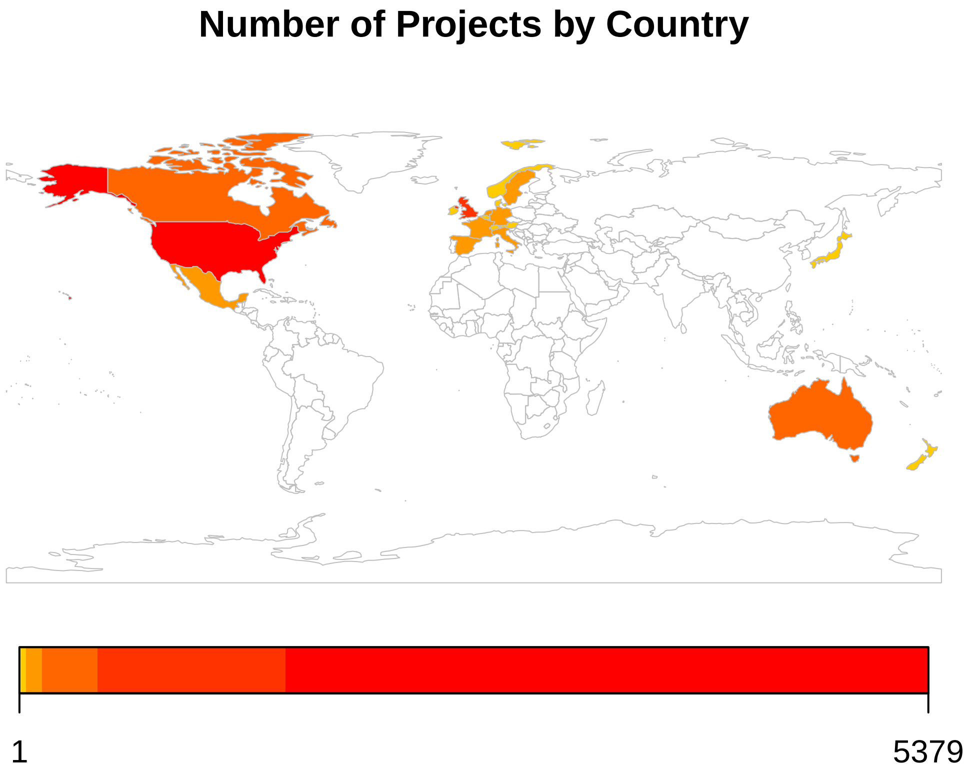
3.9 Where it is coming form?

```
countries_freq <- clean_data %>%
  group_by(country) %>%
  summarize(count=n())

countries.match <- joinCountryData2Map(countries_freq, joinCode="ISO2", nameJoinColumn="country")
```

```
## 22 codes from your data successfully matched countries in the map
## 0 codes from your data failed to match with a country code in the map
## 220 codes from the map weren't represented in your data
```

```
mapCountryData(countries.match, nameColumnToPlot="count",
               mapTitle="Number of Projects by Country", catMethod="logFixedWidth",
               colourPalette="heat")
```



Number of Projects by Country