KickStarterProject

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1.

**Data Acquisition and Integration

```
data_source_1 <- read.csv("Kickstarter001.csv", header = TRUE, sep = ",")
data_source_2 <- read.csv("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 - F
## 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

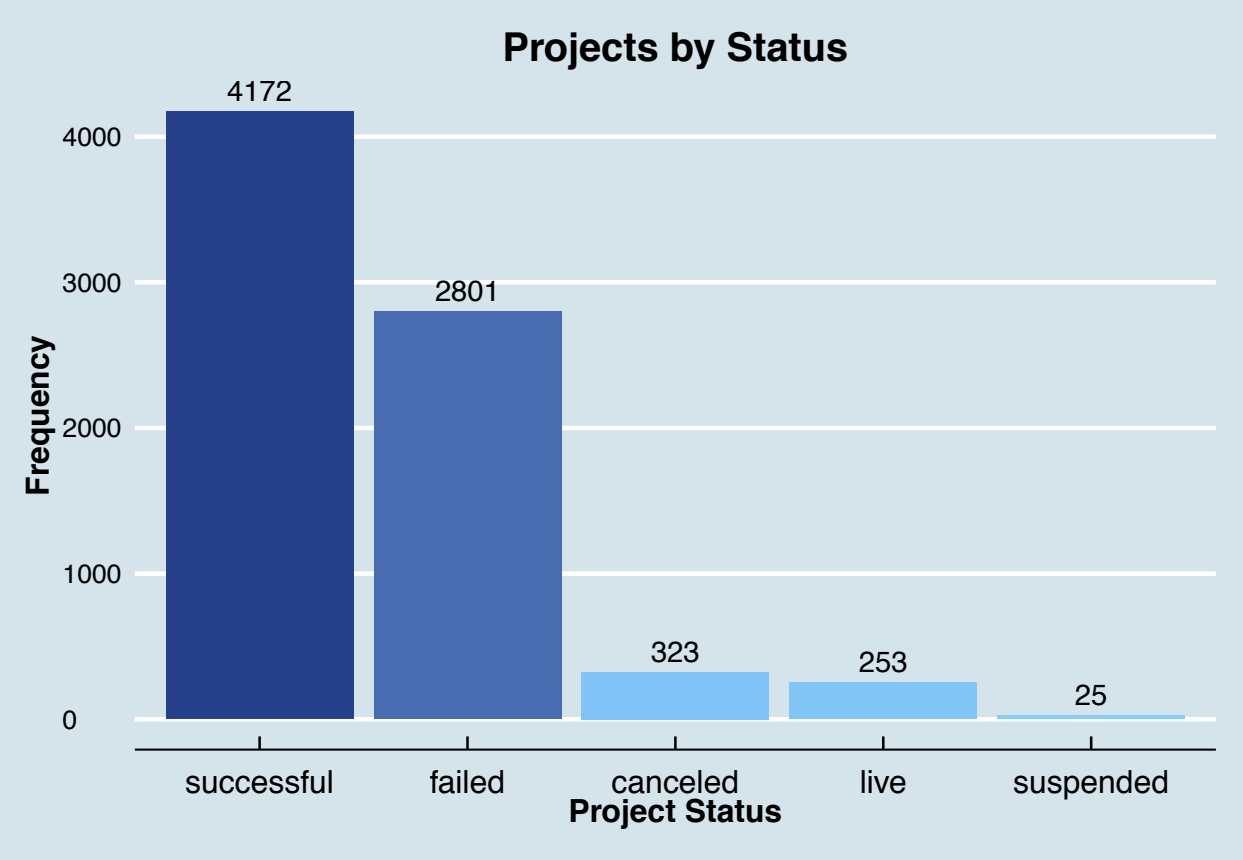
3.1 Summarise the number of projects for each status

```
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)) + ge
  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")
```



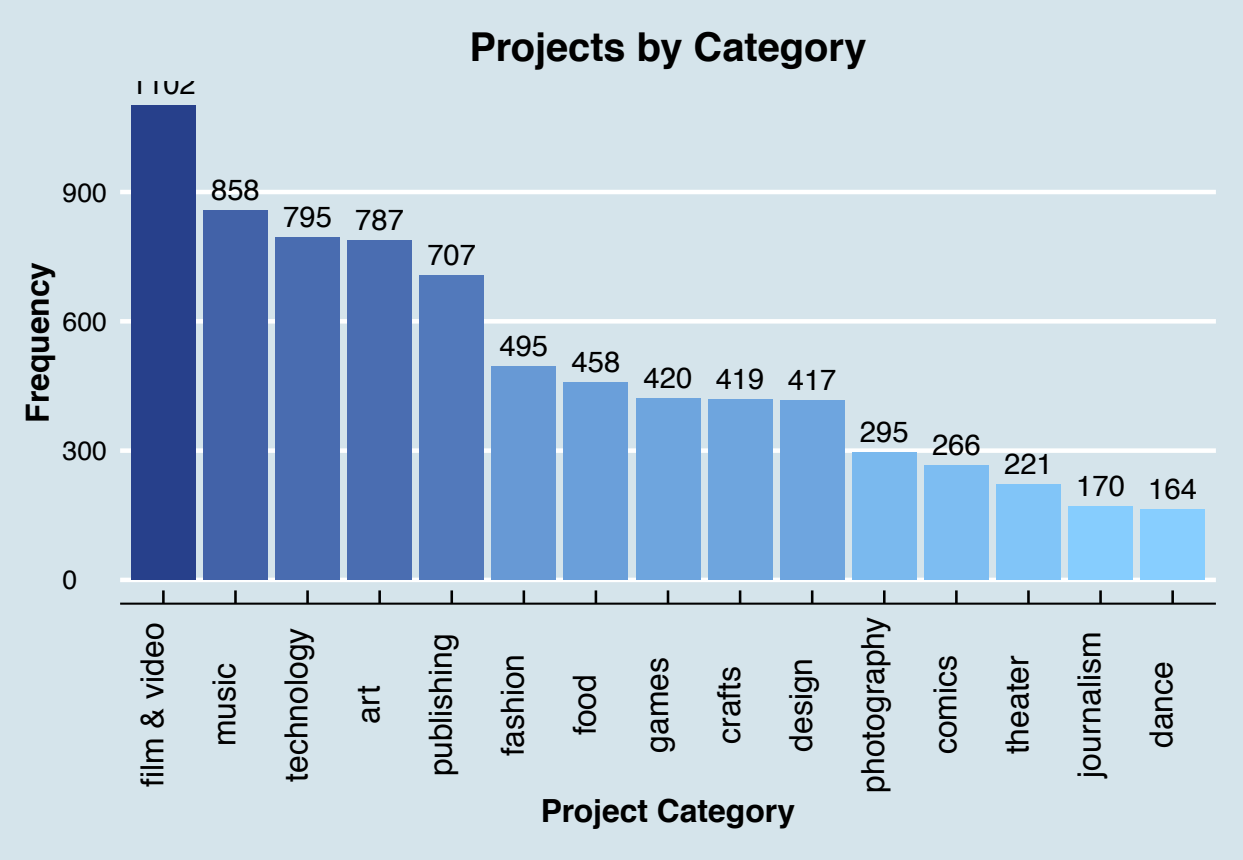
3.2 Summarise the number of projects for each catagory

```
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")
```



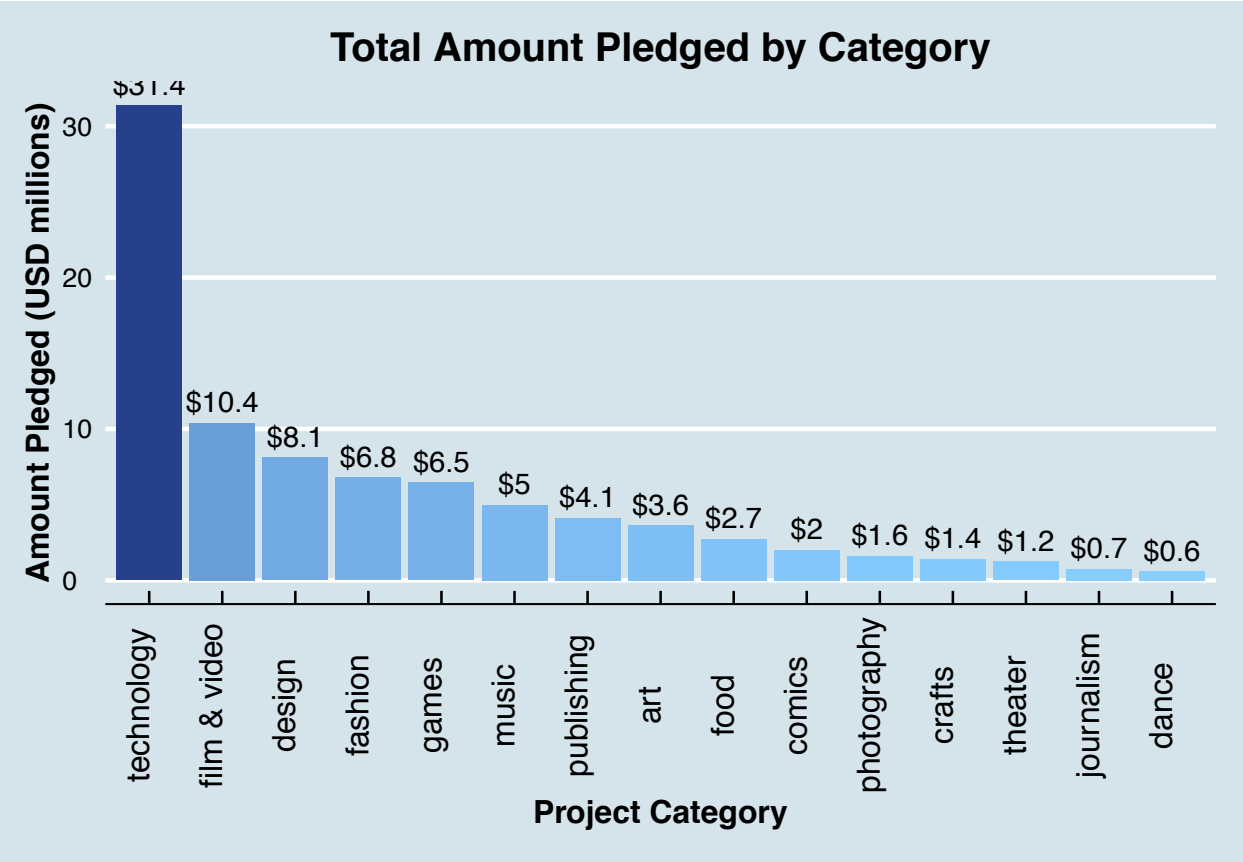
3.3 What types of projects are being funded?

```
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

```
ggplot(pledged_category, aes(reorder(pledged_category$`clean_data$category`, -total), total/1000000, fi
  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?

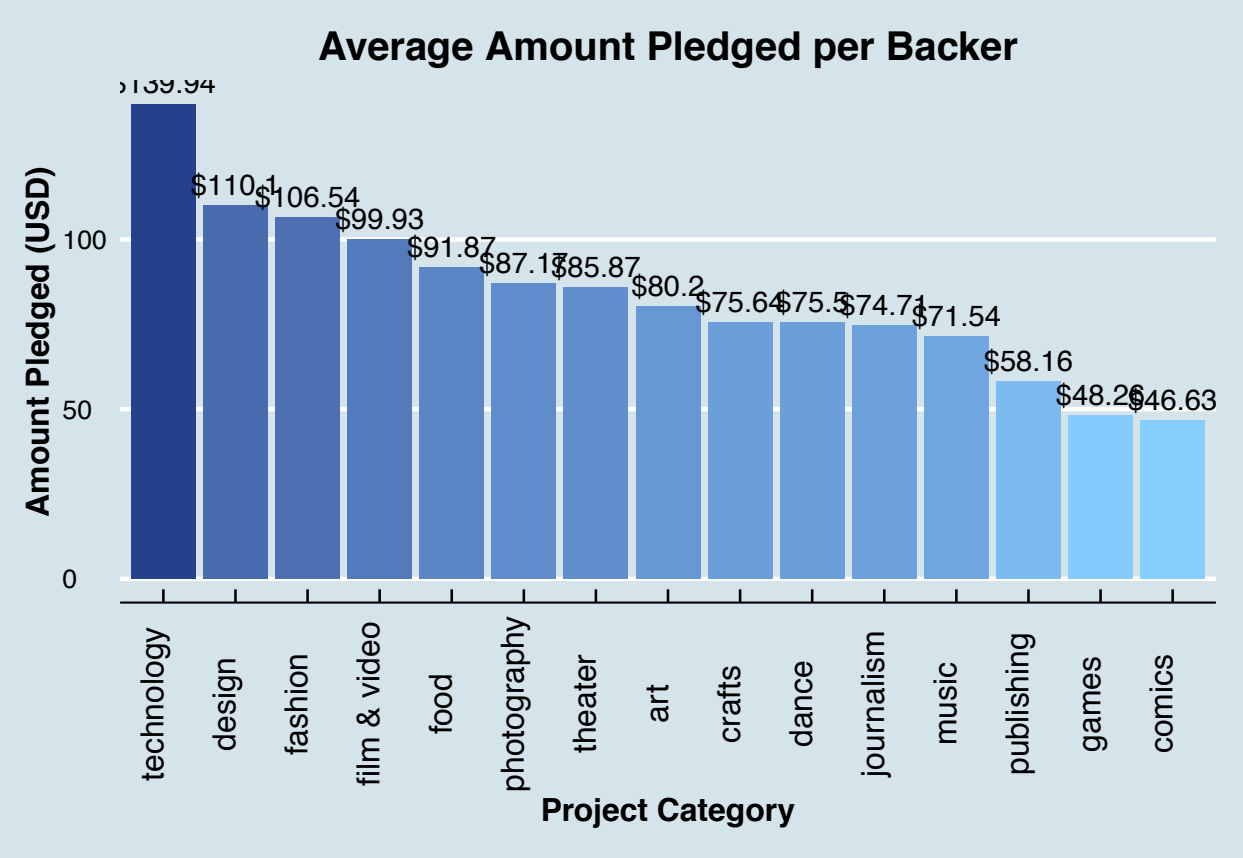
```
pledged_avg_category <- clean_data %>%
  group_by(clean_data$category) %>%
  summarise(pledged = sum(usd_pledged), backers=sum(backers_count)) %>%
  mutate(avg = pledged/backers) %>%
  arrange(desc(avg))
head(pledged_avg_category)
```

```
## # 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=av
  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

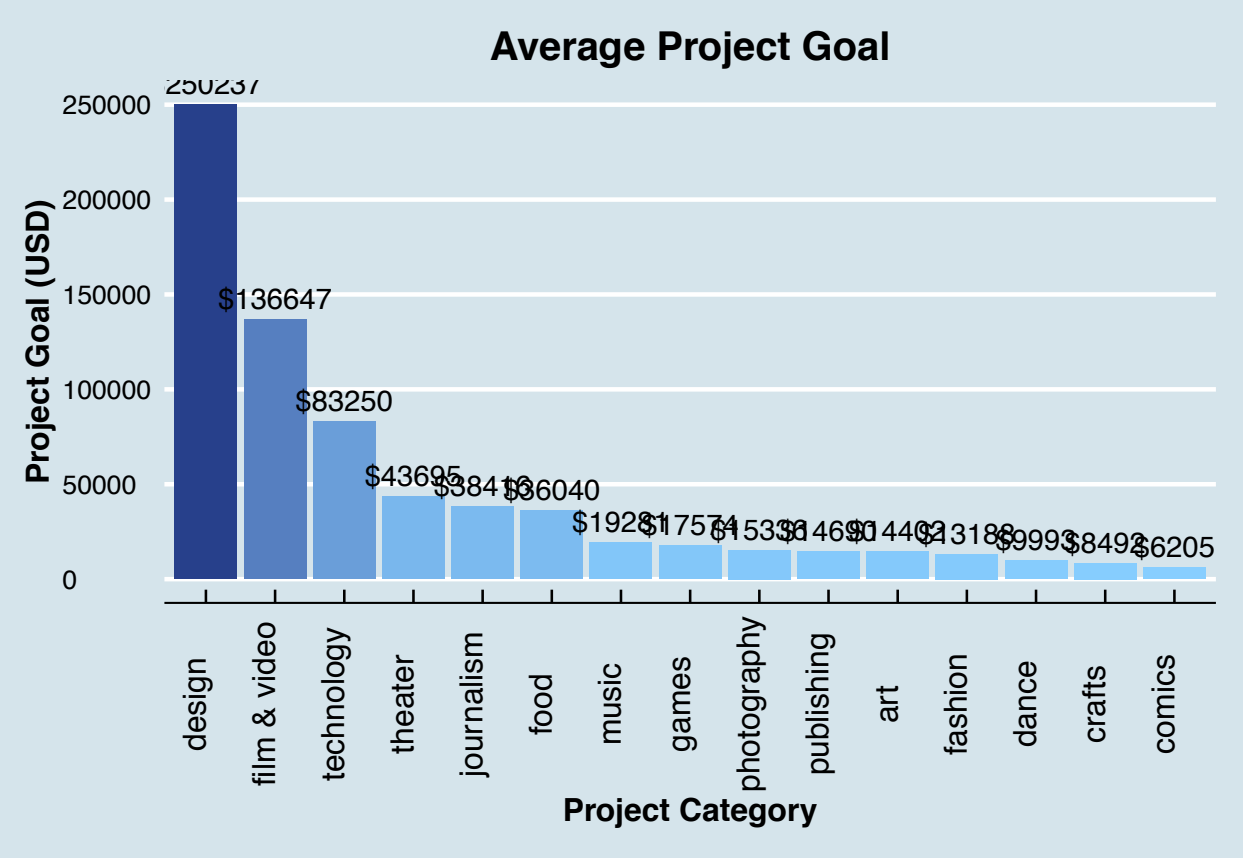
```
goal_avg <- clean_data %>%
  group_by(category) %>%
  summarise(goals = sum(goal), projects = n()) %>%
```

```
  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")
```



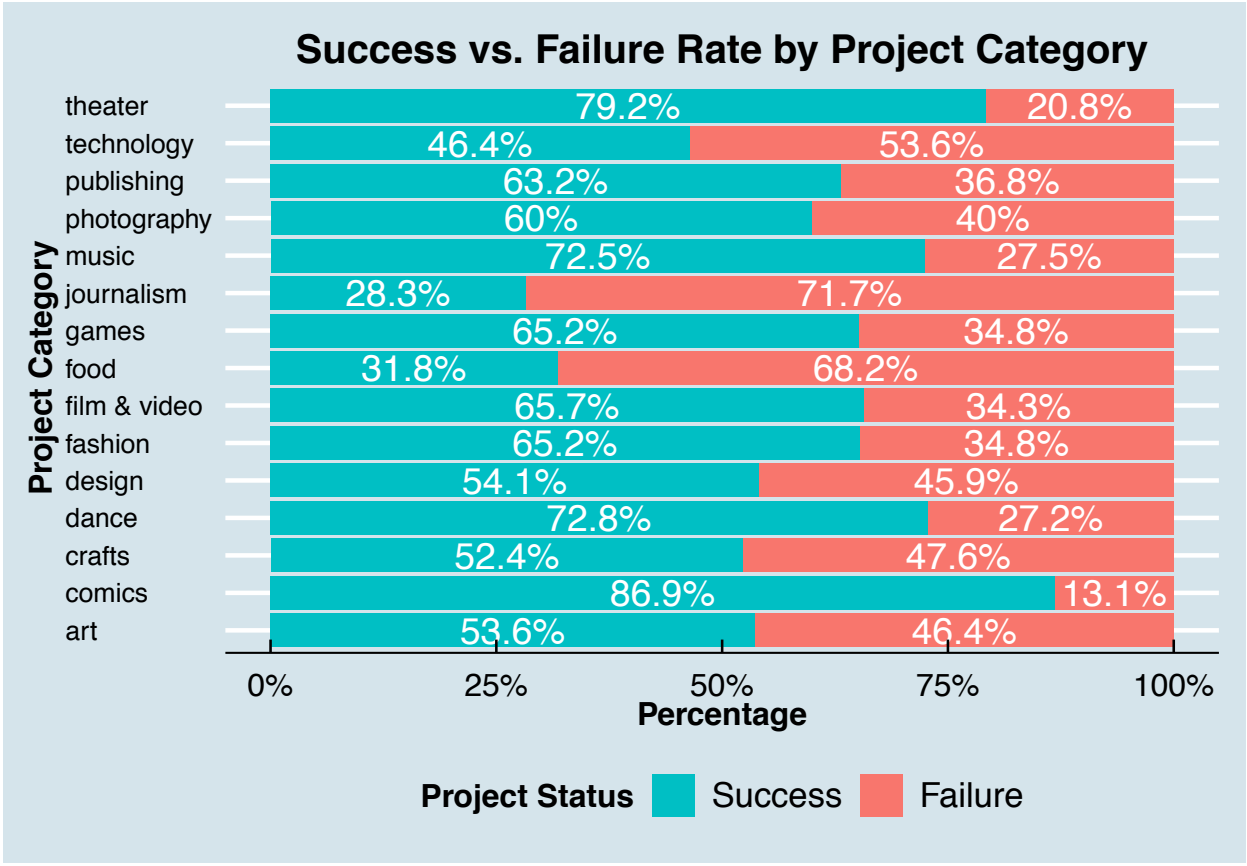
3.7 percentage for projects in each category

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

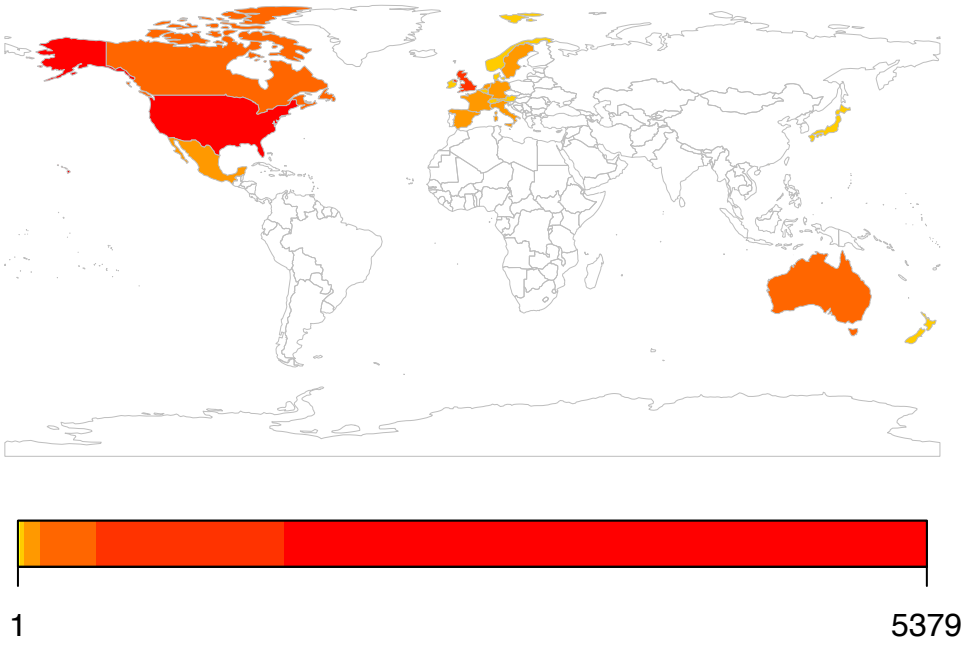
3.9 Where it is coming form?

```
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



Data Model Construction and Prediction

April 17, 2019

1 Predicting Crowdfunding Success

Using kNN, logistic regression model, support vector machine, naive bayes to predict success rate of crowdfunding.

```
In [1]: import re
        import pandas as pd
        import numpy as np
        import seaborn as sns
        import datetime
        import matplotlib.pyplot as plt
        from sklearn.pipeline import Pipeline, FeatureUnion
        from sklearn.pipeline import make_pipeline
        from sklearn.model_selection import train_test_split

        from sklearn.metrics import make_scorer, accuracy_score
        from sklearn.model_selection import cross_val_score
        from sklearn.model_selection import GridSearchCV
        from sklearn.preprocessing import StandardScaler
        from sklearn.linear_model import LogisticRegression
        from sklearn.neighbors import KNeighborsClassifier

        from sklearn.svm import SVC
        from sklearn.metrics import classification_report, confusion_matrix

        from sklearn.naive_bayes import GaussianNB

        %matplotlib inline
```

1.1 Data Cleaning & Processing

```
In [2]: df = pd.read_csv('./data/data.csv')
        df.head(1)
```

```
Out[2]:    Unnamed: 0  backers_count  \
        0           1             21

                                                    blurb category  \
```

```
0  2006 was almost 7 years ago... Can you believ...     Rock

   converted_pledged_amount country  created_at currency currency_symbol  \
0                       802      US  1387659690      USD               $

   currency_trailing_code         ...          static_usd_rate  usd_pledged  \
0                    True         ...                      1.0        802.0

        usd_type preparation_duration  preparation_duration_r  \
0  international               351356           4d 1H 35M 56S

   launch_duration  launch_duration_r  created_at_readable  \
0          3888000       45d 0H 0M 0S  2013-12-21 16:01:30

     deadline_readable launched_at_readable
0  2014-02-08 17:37:26  2013-12-25 17:37:26

[1 rows x 41 columns]
```

```
In [3]: df.shape
```

```
Out[3]: (3779, 41)
```

```
In [4]: df.state.value_counts()
```

```
Out[4]: successful    2224
        failed        1276
        canceled       149
        live           120
        suspended       10
        Name: state, dtype: int64
```

```
In [5]: # drop status rows labeled as live, canceled, suspended.
        df = df[~df['state'].isin(['live', 'canceled', 'suspended'])]
        df.shape
```

```
Out[5]: (3500, 41)
```

```
In [6]: # drop irrelevant or independent variables
        df.drop(['Unnamed: 0', 'blurb', 'created_at', 'currency_symbol', 'currency_trailing_co
                 'deadline', 'disable_communication', 'friends', 'id',
                 'is_backing', 'is_starred', 'launched_at', 'state_changed_at',
                 'name', 'permissions', 'profile', 'source_url', 'staff_pick',
                 'preparation_duration_r', 'launch_duration_r',
                 'created_at_readable', 'deadline_readable', 'launched_at_readable',
                 'location', 'usd_type'], axis = 1, inplace = True)
        df.head()
```

```
Out[6]:    backers_count     category  converted_pledged_amount country currency  \
        0             21         Rock                       802      US      USD
```

```
1             97  Mixed Media                     2259      US      USD
2             88   Photobooks                    29638      US      USD
3            193     Footwear                    49158      IT      EUR
4             20     Software                      549      US      USD

    fx_rate     goal  is_starrable  pledged  spotlight       state  \
0  1.000000    200.0         False    802.0       True  successful
1  1.000000    400.0         False   2259.0       True  successful
2  1.000000  27224.0         False  29638.0       True  successful
3  1.128433  40000.0         False  43180.0       True  successful
4  1.000000   1000.0         False    549.0      False      failed

   static_usd_rate   usd_pledged  preparation_duration  launch_duration
0         1.000000    802.000000                351356          3888000
1         1.000000   2259.000000                413843          1728000
2         1.000000  29638.000000                769946          2595600
3         1.136525  49075.152523                314662          3625358
4         1.000000    549.000000                212500          2592000
```

In [7]:
```
df['state'] = df.state.str.contains('successful').astype(int)
```

In [8]:
```
# add column representing continent
def classifier(row):
    if row.country in ['US', 'CA', 'GT', 'MX', 'PR', 'NI', 'SV', 'PA', 'BO', 'GU']:
        return 'America'
    elif row.country in ['NG', 'GH', 'ZA', 'KE', 'ET', 'CD', 'MA', 'TZ', 'ZM', 'LR', 'I
        return 'Africa'
    elif row.country in ['GB', 'NO', 'DE', 'SE', 'BA', 'IS', 'HU', 'IT', 'NL','FR', 'UI
       'TR','FI', 'CZ','AM', 'PT','DK','CH', 'SJ', 'RU', 'UA', 'BG','ES','PL', 'GE','I
        return 'Europe'
    elif row.country in ['JM', 'HT','BS','DO','LC', 'DO', 'TT']:
        return 'Carribean'
    elif row.country in ['CN', 'TW', 'HK', 'NP', 'ID', 'SG', 'IN', 'JP', 'LB', 'KZ', 'I
        return 'Asia'
    elif row.country in ['IL','QA', 'AF','KZ','AE','PS','SY','SA', 'IQ','IR','TJ',]:
        return 'Arab'
    else:
        return "Oceania"
df["continent"] = df.apply(classifier, axis=1)
```

In [9]:
```
df.head()
```

Out[9]:
```
   backers_count     category  converted_pledged_amount country currency  \
0             21         Rock                       802      US      USD
1             97  Mixed Media                      2259      US      USD
2             88   Photobooks                     29638      US      USD
3            193     Footwear                     49158      IT      EUR
4             20     Software                       549      US      USD
```

```
    fx_rate     goal  is_starrable  pledged  spotlight  state  \
0  1.000000    200.0         False    802.0       True      1
1  1.000000    400.0         False   2259.0       True      1
2  1.000000  27224.0         False  29638.0       True      1
3  1.128433  40000.0         False  43180.0       True      1
4  1.000000   1000.0         False    549.0      False      0

   static_usd_rate   usd_pledged  preparation_duration  launch_duration  \
0         1.000000    802.000000                351356          3888000
1         1.000000   2259.000000                413843          1728000
2         1.000000  29638.000000                769946          2595600
3         1.136525  49075.152523                314662          3625358
4         1.000000    549.000000                212500          2592000

  continent
0   America
1   America
2   America
3    Europe
4   America
```

```
In [10]: from sklearn import preprocessing
         def encode_features(df):
             features = ['category', 'country', 'currency', 'is_starrable', 'continent', 'spotl
             df_combined = pd.concat([df])

             for feature in features:
                 le = preprocessing.LabelEncoder()
                 le = le.fit(df_combined[feature])
                 df[feature] = le.transform(df[feature])
             return df

         data = encode_features(df)
         data.head()
```

```
Out[10]:    backers_count  category  converted_pledged_amount  country  currency  \
         0             21       120                       802       20        13
         1             97        83                      2259       20        13
         2             88        99                     29638       20        13
         3            193        59                     49158       12         4
         4             20       126                       549       20        13

             fx_rate     goal  is_starrable  pledged  spotlight  state  \
         0  1.000000    200.0             0    802.0          1      1
         1  1.000000    400.0             0   2259.0          1      1
         2  1.000000  27224.0             0  29638.0          1      1
         3  1.128433  40000.0             0  43180.0          1      1
         4  1.000000   1000.0             0    549.0          0      0
```

```
   static_usd_rate   usd_pledged  preparation_duration  launch_duration  \
0         1.000000    802.000000                351356          3888000
1         1.000000   2259.000000                413843          1728000
2         1.000000  29638.000000                769946          2595600
3         1.136525  49075.152523                314662          3625358
4         1.000000    549.000000                212500          2592000

   continent
0          0
1          0
2          0
3          2
4          0
```

```
In [11]: df.continent.value_counts()
```

```
Out[11]: 0    2677
         2     689
         3      98
         1      36
         Name: continent, dtype: int64
```

```
In [12]: X = df.drop(['preparation_duration', 'launch_duration', 'state', 'backers_count', 'sp
         y = df['state']
```

```
In [13]: from sklearn.preprocessing import Imputer
         X = Imputer().fit_transform(X)
```

1.2 kNN Model

```
In [14]: k_range = range(1,200)
         k_scores = []
         for k in k_range:
             knn = KNeighborsClassifier(n_neighbors=k)
             scores = cross_val_score(knn, X, y, cv=10, scoring = 'accuracy')
             k_scores.append(scores.mean())
         print('Computed k_scores for k value in range 1 to 200.')
```

```
Computed k_scores for k value in range 1 to 200.
```

```
In [15]: scores.mean()
```

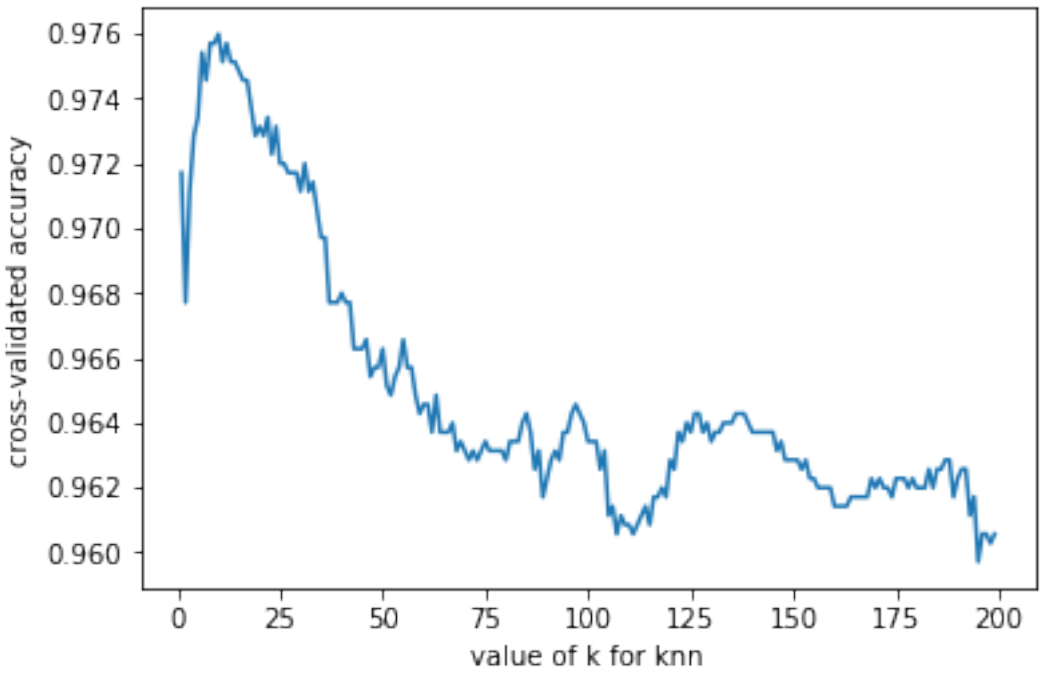
```
Out[15]: 0.9605670786816919
```

```
In [16]: scores.max()
```

```
Out[16]: 0.9885386819484241
```

```
In [16]: plt.plot(k_range, k_scores)
         plt.xlabel('value of k for knn')
         plt.ylabel('cross-validated accuracy')
```

```
Out[16]: Text(0,0.5,'cross-validated accuracy')
```



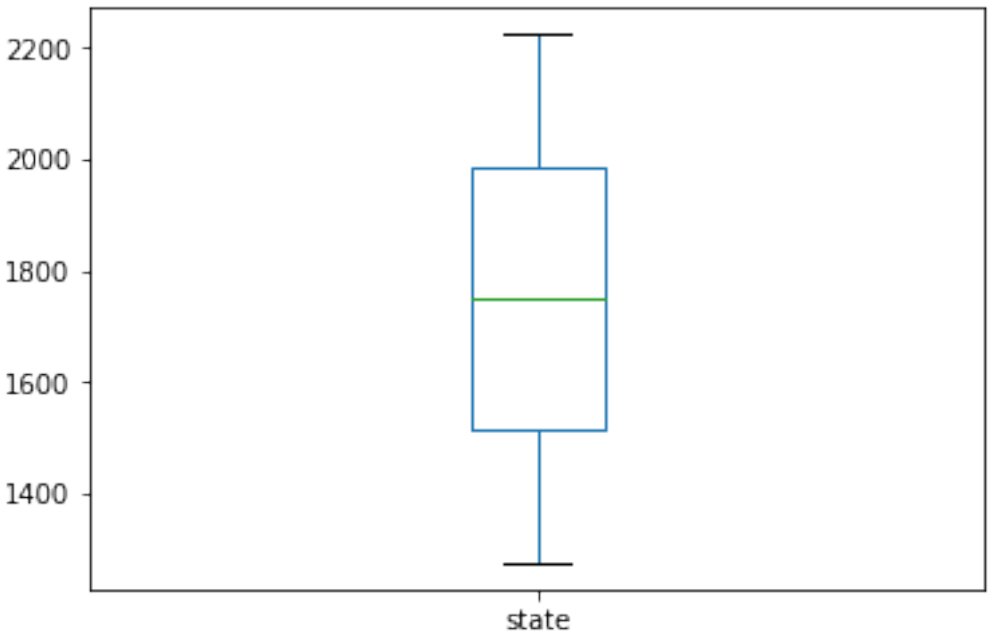

```
In [17]: MSE = [1 - x for x in k_scores]
         optimal_k = k_range[MSE.index(min(MSE))]
         print("The optimal number of neighbors is %d" % optimal_k)
```

```
The optimal number of neighbors is 10
```

1.3 Logistic Regression Model

```
In [18]: df.state.value_counts().plot(kind = 'box')
```

```
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x1a187ffd30>
```




```
In [19]: ss = StandardScaler()
         lr = LogisticRegression()
         lr_pipe = Pipeline([('sscale', ss), ('logreg', lr)])

In [20]: lr_pipe.fit(X, y)

Out[20]: Pipeline(memory=None,
              steps=[('sscale', StandardScaler(copy=True, with_mean=True, with_std=True)), ('lo
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=0, warm_start=False))])

In [21]: lr_pipe.score(X,y)

Out[21]: 0.838

In [22]: # divide the dataset into
         #  - 70% training data
         #  - 30% test data
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.30)

In [23]: lr_pipe.fit(X_train, y_train)

Out[23]: Pipeline(memory=None,
              steps=[('sscale', StandardScaler(copy=True, with_mean=True, with_std=True)), ('lo
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=0, warm_start=False))])
```

```
In [24]: lr_pipe.score(X_test, y_test)

Out[24]: 0.8133333333333334

In [25]: y_pred = lr_pipe.predict(X_test)

In [26]: from sklearn.metrics import accuracy_score, f1_score, precision_score, recall_score, c

In [27]: print(f1_score(y_test, y_pred, average="macro"))
         print(precision_score(y_test, y_pred, average="macro"))
         print(recall_score(y_test, y_pred, average="macro"))
         print(confusion_matrix(y_test,y_pred))
         print(classification_report(y_test,y_pred))

0.7979183032207384
0.802507012622721
0.794344333478072
[[282 110]
 [ 86 572]]
             precision    recall  f1-score   support

          0       0.77      0.72      0.74       392
          1       0.84      0.87      0.85       658

avg / total       0.81      0.81      0.81      1050
```

1.4 Support Vector Machine

```
In [ ]: svclassifier = SVC(kernel='linear')
        svclassifier.fit(X_train, y_train)

In [31]: y_pred = svclassifier.predict(X_test)

In [32]: print(confusion_matrix(y_test,y_pred))
         print(classification_report(y_test,y_pred))

[[386   0]
 [  0 664]]
             precision    recall  f1-score   support

          0       1.00      1.00      1.00       386
          1       1.00      1.00      1.00       664

avg / total       1.00      1.00      1.00      1050
```

1.5 Naive Bayes

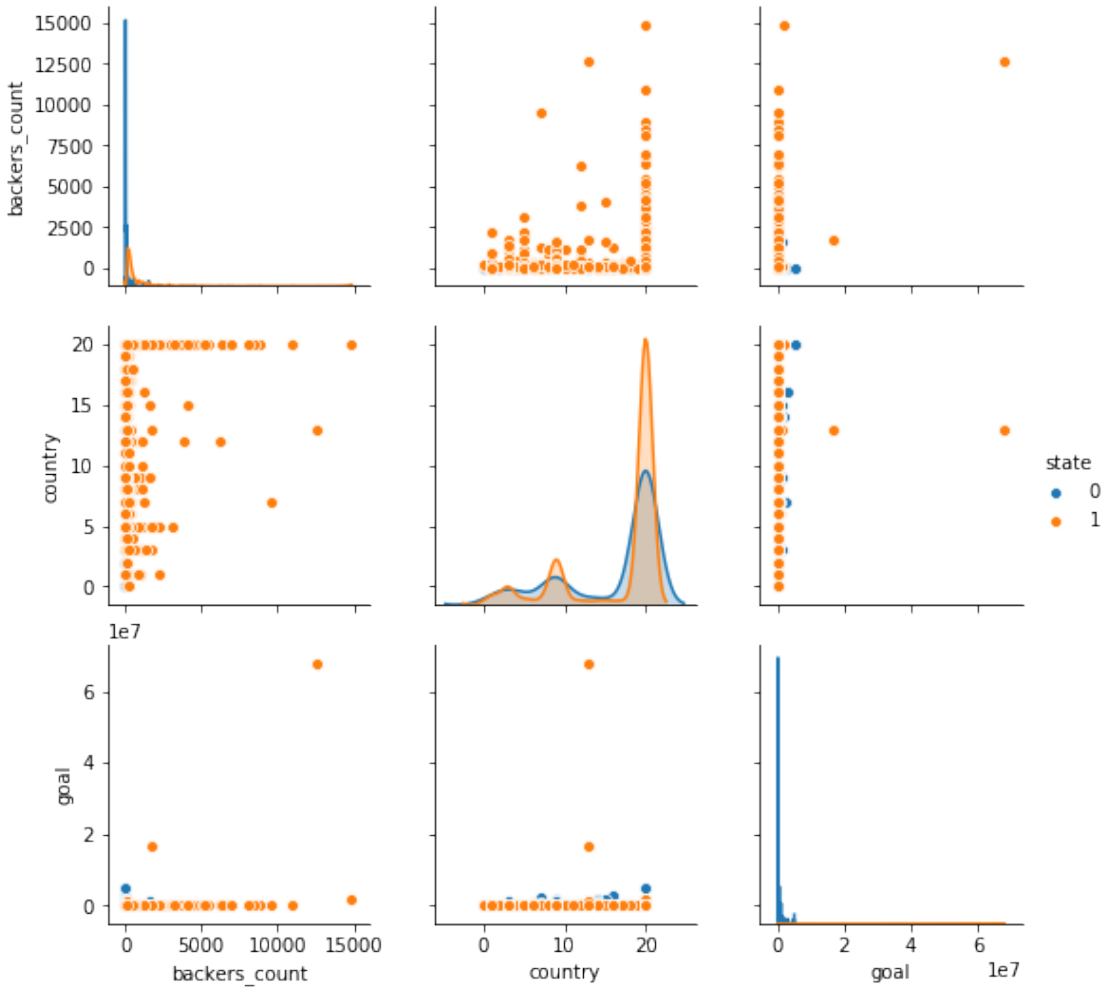
```
In [28]: gnb = GaussianNB()
         y_pred = gnb.fit(X_train, y_train).predict(X_test)

In [29]: print(confusion_matrix(y_test,y_pred))
         print(classification_report(y_test,y_pred))
```

```
[[383   9]
 [479 179]]
             precision    recall  f1-score   support

          0       0.44      0.98      0.61       392
          1       0.95      0.27      0.42       658

avg / total       0.76      0.54      0.49      1050
```

1.6 Data Visualization

```
In [33]: plots = sns.pairplot(df, vars = ['backers_count', 'country', 'goal'],
                               hue="state")
```

```
/anaconda3/lib/python3.7/site-packages/scipy/stats/stats.py:1713: FutureWarning: Using a non-tu
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```



In [34]:
```
df = df.drop(['is_starrable'], axis=1)
corr = df.corr()
corr
```

Out[34]:

	backers_count	category	converted_pledged_amount	\
backers_count	1.000000	0.074279	0.855609	
category	0.074279	1.000000	0.056564	
converted_pledged_amount	0.855609	0.056564	1.000000	
country	0.031723	-0.007631	0.031882	
currency	0.027896	-0.011621	0.027261	
fx_rate	-0.023226	-0.007235	-0.008231	
goal	0.330618	0.039287	0.198685	
pledged	0.357206	0.034792	0.229725	
spotlight	0.174372	-0.062161	0.140590	
state	0.174372	-0.062161	0.140590	
static_usd_rate	-0.031860	-0.006960	-0.015069	

```
usd_pledged                    0.855154  0.056879                  0.999866
preparation_duration           0.051476 -0.007718                  0.061744
launch_duration                0.043758  0.028363                  0.051582
continent                     -0.023403  0.023315                 -0.015755

                            country  currency   fx_rate      goal   pledged  \
backers_count              0.031723  0.027896 -0.023226  0.330618  0.357206
category                  -0.007631 -0.011621 -0.007235  0.039287  0.034792
converted_pledged_amount   0.031882  0.027261 -0.008231  0.198685  0.229725
country                    1.000000  0.984185  0.005072 -0.015072 -0.011316
currency                   0.984185  1.000000  0.001718 -0.020479 -0.016289
fx_rate                    0.005072  0.001718  1.000000 -0.111385 -0.107551
goal                      -0.015072 -0.020479 -0.111385  1.000000  0.991735
pledged                   -0.011316 -0.016289 -0.107551  0.991735  1.000000
spotlight                  0.047634  0.048726  0.002059 -0.000156  0.023665
state                      0.047634  0.048726  0.002059 -0.000156  0.023665
static_usd_rate           -0.102557 -0.106477  0.963558 -0.102855 -0.099714
usd_pledged                0.031217  0.026642 -0.008874  0.204915  0.235897
preparation_duration       0.026465  0.028097 -0.002326  0.009646  0.010948
launch_duration           -0.016174 -0.018033 -0.025344  0.020797  0.011791
continent                 -0.746953 -0.773095  0.195684  0.015929  0.012159

                           spotlight     state  static_usd_rate  usd_pledged  \
backers_count               0.174372  0.174372        -0.031860     0.855154
category                   -0.062161 -0.062161        -0.006960     0.056879
converted_pledged_amount    0.140590  0.140590        -0.015069     0.999866
country                     0.047634  0.047634        -0.102557     0.031217
currency                    0.048726  0.048726        -0.106477     0.026642
fx_rate                     0.002059  0.002059         0.963558    -0.008874
goal                       -0.000156 -0.000156        -0.102855     0.204915
pledged                     0.023665  0.023665        -0.099714     0.235897
spotlight                   1.000000  1.000000        -0.004343     0.140219
state                       1.000000  1.000000        -0.004343     0.140219
static_usd_rate            -0.004343 -0.004343         1.000000    -0.015418
usd_pledged                 0.140219  0.140219        -0.015418     1.000000
preparation_duration        0.012206  0.012206        -0.008198     0.061616
launch_duration            -0.144859 -0.144859        -0.025125     0.051350
continent                  -0.043037 -0.043037         0.285074    -0.015234

                           preparation_duration  launch_duration  continent
backers_count                          0.051476         0.043758  -0.023403
category                              -0.007718         0.028363   0.023315
converted_pledged_amount               0.061744         0.051582  -0.015755
country                                0.026465        -0.016174  -0.746953
currency                               0.028097        -0.018033  -0.773095
fx_rate                               -0.002326        -0.025344   0.195684
goal                                   0.009646         0.020797   0.015929
pledged                                0.010948         0.011791   0.012159
```

```
spotlight                0.012206        -0.144859  -0.043037
state                    0.012206        -0.144859  -0.043037
static_usd_rate         -0.008198        -0.025125   0.285074
usd_pledged              0.061616         0.051350  -0.015234
preparation_duration     1.000000         0.029690  -0.026049
launch_duration          0.029690         1.000000  -0.006020
continent               -0.026049        -0.006020   1.000000
```

In [35]:
```
sns.heatmap(corr, xticklabels=corr.columns, yticklabels=corr.columns)
```

Out[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1b3e6358>
```