Capstone Project 1: Predicting Success in Kickstarter Campaigns

Kickstarter is a funding platform for creative projects. When creative groups, companies, or individuals have an idea, a clear plan and a final funding goal, they can submit their projects to the Kickstarter platform in order to garner public support and funding. The Kickstarter platform provides a space where where campaigns can both ask for funding donations, and provide incentives and rewards to those who pledge funds to the project.

The Kickstarter platform is funded by fees collected from each donation, and from the overall funding amount when a campaign is successful. Kickstarter applies a 5% fee to any successful campaigns, and collects a 3-5% payment processing fee per donation, depending on the donation amount. If a campaign is not successful and does not reach their funding goal, Kickstarter does not collect the standard 5% fee. Therefore, in order for Kickstarter to continue their success, and increase their profits, they must host successful campaigns that reach or exceed their funding goal. Currently, successful Kickstarter campaigns are estimated at 35% of total campaigns, while failed campaigns are closer to 52%.

An analysis of successful Kickstarter campaigns will address metrics for campaigns that reach and exceed their funding goals. This includes the category of campaign, rewards/incentives offered, funding goal, funding time frame, and campaign description.

The ability to predict a successful Kickstarter campaign will be of great benefit to both Kickstarter as a company, and to companies and creators who launch campaigns on their website. Kickstarter has an inherent intrerest in running successful campaigns because of their fee structure, and their overall profits as a company. Additionally, competition from other crowdfunding platforms are gaining popularity and Kickstarter will need remain competitive in offering services and exposure to clients that will lead to succesful campaign outcomes.

Companies and creators who are launching campaigns also have an inherent interest in understanding the factors that create a successful campaign. Having a campaign or project reach or exceed funding status could alter the trajectory of a product or idea. Alternatively, campaigns and projects that end up failing to meet their funding goals could end up on life support.

By analyzing trends in successful campaigns, Kickstarter will be able to determine which campaigns are more likely to reach or exceed funded status. Armed with this data insight, Kickstarter will be able to make data driven, impactful decisions in regards to

```
- Services offered to clients
- Fees that are collected from clients and from contributors,
- Campaign guidelines and recommendations
```

5.4 Data Wrangling

The dataset that was used for analysis was provided in one .csv file, obtained from [Kaggle (https://www.kaggle.com/kemical/kickstarter-projects#ks-projects-201801.csv)](https://www.kaggle.com/kemical/kickstarter-projects#ks-projects-201801.csv). At first glance, the data is fairly clean containing 15 columns with 378,661 rows of data. Each Kickstarter campaign is represented by one row of data including the campaign name, the main category that the campaign falls under, the currency type that pledges are converted to, the campaign deadline, funding goal, the state of the campaign, how many backers supported the campaign, what country the campaign originated from, and then two columns that are conversions of the pledged amount column converted to USD.

To start off the data cleaning process, Python packages that will be utilized are imported and the data is read into a pandas data frame. The packages that I believe will be the most useful in the cleaning process are pandas and numPy.

Basic Data Exploration

In [1]:
```
#import packages
import pandas as pd
import numpy as np
import scipy
from scipy import stats
from scipy.stats.stats import pearsonr
from pandas_profiling import ProfileReport
import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import Image
from numpy.random import seed
from scipy.stats import t
from scipy.stats import ttest_ind
from wordcloud import WordCloud, STOPWORDS
from six.moves import range
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import CountVectorizer
from matplotlib import colors
from matplotlib.ticker import PercentFormatter
import itertools
import collections
import nltk
from scipy.stats import shapiro
from scipy.stats import wilcoxon
from statsmodels.graphics.gofplots import qqplot
from scipy.stats import chi2_contingency
from scipy.stats import kruskal
from scipy.stats import friedmanchisquare
import scipy.stats as st
```

In [2]:
```
#read in csv
df = pd.read_csv(r'/Users/kellipeluso/Desktop/Springboard/ks-projects-20
1801.csv', encoding = 'latin')
```

I began the cleaning process by determining whether any data was duplicated. Each Kickstarter campaign is assigned a campaign ID, and I proceeded to work on deduplication based off of this column. In order to check for duplicate rows, I created a new data frame that would contain any potential duplicates. I created this data frame using df.duplicated() and then printing the shape of the new data frame. There were no duplicate rows that needed to be removed in the original data frame.

In [3]:
```
#check out df shape
df.shape
```
Out[3]:
```
(378661, 15)
```

In [4]:
```
#check for any duplicate rows/campaigns
duplicate_rows_df = df[df.duplicated()]
print ("number of duplicate rows: ", duplicate_rows_df.shape)
```
```
number of duplicate rows:  (0, 15)
```

Dataframe Cleaning

In [5]:
```
#Take a look at the dataset
df.head()
```
Out[5]:

	ID	name	category	main_category	currency	deadline	goal	launched	p
0	1000002330	The Songs of Adelaide & Abullah	Poetry	Publishing	GBP	2015-10-09	1000.0	2015-08-11 12:12:28	
1	1000003930	Greeting From Earth: ZGAC Arts Capsule For ET	Narrative Film	Film & Video	USD	2017-11-01	30000.0	2017-09-02 04:43:57	
2	1000004038	Where is Hank?	Narrative Film	Film & Video	USD	2013-02-26	45000.0	2013-01-12 00:20:50	
3	1000007540	ToshiCapital Rekordz Needs Help to Complete Album	Music	Music	USD	2012-04-16	5000.0	2012-03-17 03:24:11	
4	1000011046	Community Film Project: The Art of Neighborhoo...	Film & Video	Film & Video	USD	2015-08-29	19500.0	2015-07-04 08:35:03	

In [6]:
```
#examine column names
print ("column names: ", df.columns.values)
```

```
column names:  ['ID' 'name' 'category' 'main_category' 'currency' 'dead
line' 'goal'
 'launched' 'pledged' 'state' 'backers' 'country' 'usd pledged'
 'usd_pledged_real' 'usd_goal_real']
```

In [7]:
```
#check for columns with null values
df.isnull().sum()
```

Out[7]:
```
ID                     0
name                   4
category               0
main_category          0
currency               0
deadline               0
goal                   0
launched               0
pledged                0
state                  0
backers                0
country                0
usd pledged         3797
usd_pledged_real       0
usd_goal_real          0
dtype: int64
```

In [8]:
```
df.dropna(inplace=True)
```

Add Columns

In [9]:
```
#number of characters in campaign name
df['name_cl'] = [len(str(i).strip(' ')) for i in df.name]
df.name_cl.head()
```

Out[9]:
```
0    31
1    45
2    14
3    49
4    58
Name: name_cl, dtype: int64
```

In [10]:
```
#number of words in campaign name
df['name_len'] = [len(str(i).split()) for i in df.name]
df.name_len.head()
```

Out[10]:
```
0    6
1    8
2    3
3    7
4    8
Name: name_len, dtype: int64
```

In [11]:
```
#encode categorical data from main_category column for future stats anal
ysis
df["main_category"] = df["main_category"].astype('category')
df["main_category_encode"] = df["main_category"].cat.codes
```

In [12]:
```
#bin backers
df['backers_binned'] = pd.qcut(df['backers'], q=5, duplicates = 'drop')
df['backers_binned'].value_counts()
```

Out[12]:
```
(-0.001, 1.0]       86679
(76.0, 219382.0]    74955
(24.0, 76.0]        72620
(6.0, 24.0]         71427
(1.0, 6.0]          69179
Name: backers_binned, dtype: int64
```

In [13]:
```
#bin the data for usd_goal_real
df['goal_binned'] = pd.qcut(df['usd_goal_real'], q=10, duplicates = 'dro
p')
df['goal_binned'].value_counts()
```

Out[13]:
```
(700.0, 1500.0]                     40842
(2500.0, 4000.0]                    38356
(0.009000000000000001, 700.0]       37955
(5500.0, 9000.0]                    37626
(46048.377, 166361390.71]           37486
(20459.66, 46048.377]               37484
(12500.0, 20459.66]                 37337
(4000.0, 5500.0]                    36997
(9000.0, 12500.0]                   36182
(1500.0, 2500.0]                    34595
Name: goal_binned, dtype: int64
```

In [14]:
```
#bin the data for usd_pledged_real
df['pledge_binned'] = pd.qcut(df['usd_pledged_real'], q=10, duplicates =
'drop')
df['pledge_binned'].value_counts()
```

Out[14]:
```
(-0.001, 11.0]              75820
(1408.286, 2900.0]          37511
(13873.2, 20338986.27]      37486
(624.495, 1408.286]         37486
(233.066, 624.495]          37486
(5687.0, 13873.2]           37479
(2900.0, 5687.0]            37468
(70.0, 233.066]             37207
(11.0, 70.0]                36917
Name: pledge_binned, dtype: int64
```

In [15]:
```
#add column for campaign duration
df['launched'] = pd.to_datetime(df['launched']).dt.date
df['deadline'] = pd.to_datetime(df['deadline']).dt.date
df['campaign_duration'] = df['deadline'] - df['launched']
```

Drop Columns/Remove Data

In [16]:
```
#we cannot determine a state of live or undefined campaigns, we will rem
ove these campaigns from the analysis
#drops a total of 6361 rows
df = df[df.state != 'live']
df = df[df.state != 'undefined']
df = df[df.state != 'canceled']
df = df[df.state != 'suspended']
df['state'].value_counts()
```

Out[16]:
```
failed        197611
successful    133851
Name: state, dtype: int64
```

In [17]:
```
binary = {'successful' : 1, 'failed': 0}
df['binary_state'] = df.state.map(binary)
df.binary_state.value_counts()
```

Out[17]:
```
0    197611
1    133851
Name: binary_state, dtype: int64
```

In [18]:
```
df.dropna(inplace=True)
```

In [19]:
```
#drop usd pledged column
clean_df = df.drop('usd pledged', axis = 1)
```

In [20]:
```
#re-examine column names after usd pledged is dropped and binary is adde
d
print ("column names: ", clean_df.columns.values)
```

```
column names:  ['ID' 'name' 'category' 'main_category' 'currency' 'dead
line' 'goal'
 'launched' 'pledged' 'state' 'backers' 'country' 'usd_pledged_real'
 'usd_goal_real' 'name_cl' 'name_len' 'main_category_encode'
 'backers_binned' 'goal_binned' 'pledge_binned' 'campaign_duration'
 'binary_state']
```

In [21]:
```
#examine shape of new cleaned dataset
clean_df.shape
```

Out[21]:
```
(331462, 22)
```

Clean Dataframe Exploration

In [22]:
```
clean_df.describe()
```

Out[22]:

	ID	goal	pledged	backers	usd_pledged_real	usd_goal_real
count	3.314620e+05	3.314620e+05	3.314620e+05	331462.000000	3.314620e+05	3.314620e+05
mean	1.074288e+09	4.426583e+04	1.058081e+04	116.456315	9.939989e+03	4.152286e+04
std	6.191996e+08	1.118269e+06	1.015117e+05	965.732911	9.664561e+04	1.109279e+06
min	5.971000e+03	1.000000e-02	0.000000e+00	0.000000	0.000000e+00	1.000000e-02
25%	5.371698e+08	2.000000e+03	5.000000e+01	2.000000	5.000000e+01	2.000000e+03
50%	1.074686e+09	5.000000e+03	7.820000e+02	15.000000	7.875000e+02	5.000000e+03
75%	1.609865e+09	1.500000e+04	4.658000e+03	63.000000	4.609000e+03	1.500000e+04
max	2.147476e+09	1.000000e+08	2.033899e+07	219382.000000	2.033899e+07	1.663614e+08

In [23]:
```
#examine the first 10 rows of the dataset
clean_df.head(10)
```

Out[23]:

	ID	name	category	main_category	currency	deadline	goal	launched
0	1000002330	The Songs of Adelaide & Abullah	Poetry	Publishing	GBP	2015-10-09	1000.0	2015-08-11
1	1000003930	Greeting From Earth: ZGAC Arts Capsule For ET	Narrative Film	Film & Video	USD	2017-11-01	30000.0	2017-09-02
2	1000004038	Where is Hank?	Narrative Film	Film & Video	USD	2013-02-26	45000.0	2013-01-12
3	1000007540	ToshiCapital Rekordz Needs Help to Complete Album	Music	Music	USD	2012-04-16	5000.0	2012-03-17
5	1000014025	Monarch Espresso Bar	Restaurants	Food	USD	2016-04-01	50000.0	2016-02-26
6	1000023410	Support Solar Roasted Coffee & Green Energy! ...	Food	Food	USD	2014-12-21	1000.0	2014-12-01
7	1000030581	Chaser Strips. Our Strips make Shots their B*tch!	Drinks	Food	USD	2016-03-17	25000.0	2016-02-01
10	100004721	Of Jesus and Madmen	Nonfiction	Publishing	CAD	2013-10-09	2500.0	2013-09-09
11	100005484	Lisa Lim New CD!	Indie Rock	Music	USD	2013-04-08	12500.0	2013-03-09
12	1000055792	The Cottage Market	Crafts	Crafts	USD	2014-10-02	5000.0	2014-09-02

10 rows × 22 columns

In [24]:
```
#examine information about column datatypes
clean_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 331462 entries, 0 to 378660
Data columns (total 22 columns):
ID                        331462 non-null int64
name                      331462 non-null object
category                  331462 non-null object
main_category             331462 non-null category
currency                  331462 non-null object
deadline                  331462 non-null object
goal                      331462 non-null float64
launched                  331462 non-null object
pledged                   331462 non-null float64
state                     331462 non-null object
backers                   331462 non-null int64
country                   331462 non-null object
usd_pledged_real          331462 non-null float64
usd_goal_real             331462 non-null float64
name_cl                   331462 non-null int64
name_len                  331462 non-null int64
main_category_encode      331462 non-null int8
backers_binned            331462 non-null category
goal_binned               331462 non-null category
pledge_binned             331462 non-null category
campaign_duration         331462 non-null timedelta64[ns]
binary_state              331462 non-null int64
dtypes: category(4), float64(4), int64(5), int8(1), object(7), timedelt
a64[ns](1)
memory usage: 47.1+ MB
```

Most of our columns are objects, and would not have an outlier associated with them. In order to identify outliers in the appropriate columns (goal, pledged, usd_pledged_real, usd_goal_real) the datatypes are examined once again in order to remove the object columns. After object columns are removed there are only 6 columns left. From these 6 columns, a zscore over 3 is calculated, and any outliers identified are rejected. After the outliers are rejected, the data frame is left with 375,784 rows in comparison to the original 378,661. This will be helpful to take into account when statistical analysis is completed.

Identify Outliers

In [25]:
```
#identify outliers
print ("data types: \n", clean_df.dtypes)
print ("shape before :", clean_df.shape)
clean_df_num = clean_df.select_dtypes(exclude=['object'])
print ("shape after excluding object columns: ", clean_df_num.shape)
```

```
data types:
 ID                                  int64
name                               object
category                           object
main_category                    category
currency                           object
deadline                           object
goal                              float64
launched                           object
pledged                           float64
state                              object
backers                             int64
country                            object
usd_pledged_real                  float64
usd_goal_real                     float64
name_cl                             int64
name_len                            int64
main_category_encode                 int8
backers_binned                   category
goal_binned                      category
pledge_binned                    category
campaign_duration         timedelta64[ns]
binary_state                        int64
dtype: object
shape before : (331462, 22)
shape after excluding object columns:  (331462, 15)
```

It is important to identify outliers in order to account for possible statistical errors in the future. Outliers can skew statistical measures such as means and medians, and will need to be further considered when designing the predictive model. For data exploration purposes, the outliers continue to remain in the dataset at this time.

7.2 Data Storytelling

Campaign Success & Failure: Descriptive Stats

The majority of Kickstarter campaigns end either in failure, or in success. Suprisingly, more Kickstarter campaigns fail than succeed. 197,719 Kickstarter campaigns failed, while 133,956 Kickstarter campaigns succeeded. Now that we've taken a broad look at the state of all Kickstarter campaigns within this dataset, we can zero in on attributes of successful campaigns.

In [26]:
```
clean_df['state'].value_counts()
```

Out[26]:
```
failed        197611
successful    133851
Name: state, dtype: int64
```

In [201]:

```
#campaign duration column
clean_df['launched'] = pd.to_datetime(clean_df['launched']).dt.date
clean_df['deadline'] = pd.to_datetime(clean_df['deadline']).dt.date
clean_df['campaign_duration'] = clean_df['deadline'] - clean_df['launche
d']
clean_df['camp_days'] = (clean_df['deadline'] - clean_df['launched']).dt
.days


#successful campaign descriptive stats
success = clean_df['state'] == 'successful'
total = clean_df['usd_pledged_real'] >= 0
success_df = clean_df[success & total]

#compare this to the overall backers stats
back_avg = success_df['backers'].mean()
back_min = success_df['backers'].min()
back_max = success_df['backers'].max()

#compare this to the overall campaign duration stats
duration_min = success_df['campaign_duration'].min()
duration_max = success_df['campaign_duration'].max()
duration_mean = success_df['campaign_duration'].mean()

success_min = success_df['usd_pledged_real'].min()
success_max = success_df['usd_pledged_real'].max()
success_mean = success_df['usd_pledged_real'].mean()

print(back_min)
print(back_max)
print(back_avg)

print(success_min)
print(success_max)
print(success_mean)
pd.options.mode.chained_assignment = None

success_df.sort_values(by=['usd_pledged_real'],ascending=False).head(10)
success_df.shape

success_df['main_category'].value_counts()
```

```
1
219382
264.12839650058646
0
20338986
22664.329411061553
```

Out[201]:

```
Music            24105
Film & Video     23612
Games            12518
Publishing       12300
Art              11510
Design           10549
Theater           6534
Technology        6433
Food              6085
Comics            5842
Fashion           5593
Photography       3305
Dance             2338
Crafts            2115
Journalism        1012
Name: main_category, dtype: int64
```

In [28]:

```
#successful campaign descriptive stats
success_df.state.describe()
```

Out[28]:

```
count         133851
unique             1
top       successful
freq          133851
Name: state, dtype: object
```

In [29]:

```
#failed campaign descriptive stats
failed = clean_df['state'] == 'failed'
total2 = clean_df['usd_pledged_real'] >= 0
fail_df = clean_df[failed & total2]

#compare this to the overall backers stats
fback_avg = fail_df['backers'].mean()
fback_min = fail_df['backers'].min()
fback_max = fail_df['backers'].max()

#compare this to the overall campaign duration stats
fduration_min = fail_df['campaign_duration'].min()
fduration_max = fail_df['campaign_duration'].max()
fduration_mean = fail_df['campaign_duration'].mean()

fail_min = fail_df['usd_pledged_real'].min()
fail_max = fail_df['usd_pledged_real'].max()
fail_mean = fail_df['usd_pledged_real'].mean()

print(fback_min)
print(fback_max)
print(fback_avg)

print(fail_min)
print(fail_max)
print(fail_mean)
pd.options.mode.chained_assignment = None

fail_df.sort_values(by=['usd_pledged_real'],ascending=False).head(10)
fail_df.shape

fail_df['main_category'].value_counts()
```

```
0
6550
16.431236115398434
0.0
757352.94
1321.102820642584
```

Out[29]:

```
Film & Video    32891
Publishing      23113
Music           21696
Technology      20613
Games           16002
Food            15969
Design          14814
Fashion         14181
Art             14130
Photography      6384
Crafts           5703
Comics           4036
Theater          3708
Journalism       3136
Dance            1235
Name: main_category, dtype: int64
```

In [30]:
```
#failed campaign descriptive stats
fail_df.state.describe()
```

Out[30]:
```
count     197611
unique         1
top       failed
freq      197611
Name: state, dtype: object
```

To further analyze attributes of a successful Kickstarter campaign, success_df and fail_df are created to house all successful or failed campaigns based off of the state column. An examination of successful campaigns reveals the following. Successful Kickstarter campaigns have:

- An average of 263 backers per campaign
- Run for an average campaign duration of 31 days
- Have raised an average of 22670 per campaign

The most successful Kickstarter campaign within this dataset is for **Pebble Time - Awesome Smartwatch, No Compromises**. Back in 2012, Pebble also had the highest grossing campaign in Kickstarter history with their first project - which ended up being the very first smart watch. **Pebble Time - Awesome Smartwatch, No Compromises** raised $20,338,986. in only 31 days, with 78471 backers. The original campaign goal was \$500,000. It's very inspiring to see that a company with multiple top campaigns was able to create a technology gadget that so many people now use on a daily basis. From additional research, it seems as though Pebble was able to set the ground work for the tech industry's creation of smart watches - a field now dominated by brands like Apple and Samsung.

Campaign Names

In [31]:
```
#generate word cloud for all campaigns
comment_words = ''
stopwords = set(STOPWORDS)

# iterate through the csv file
for val in df.name:

    # typecaste each val to string
    val = str(val)

    # split the value
    tokens = val.split()

    # Converts each token into lowercase
    for i in range(len(tokens)):
        tokens[i] = tokens[i].lower()

    comment_words += " ".join(tokens)+" "

wordcloud = WordCloud(width = 800, height = 800,
                background_color ='white',
                stopwords = stopwords,
                min_font_size = 10).generate(comment_words)

# plot the WordCloud image
plt.figure(figsize = (8, 8), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)
plt.show()
```


debut album
new album
project
music video
serie
film
world
new
help
one
album
movie
design
dream
short film
ep
time
kid
game
book
love
adventure
story
life
art
make
music
day
shirt
documentary
app
tour
first
heart
black
journey
collection
feature film
little
song
free
need
present
play
back
graphic novel
america
show
man
road
king
support
first album
record
light
novel
best
people
blue
food
comic
issue
city
playing card
production
american
space
go
dog
making
magazine
card game
season
house
bring
war
artist
musical
cd
apparel
ultimate
live
video
tale
dance
home
festival
women
print
community
girl
clothing
children
full length
mobile
storie
part
dream
school
system
kitchen
food truck

In [32]:
```
#wordcloud for successful campaigns
comment_words = ''
stopwords = set(STOPWORDS)

# iterate through the csv file
for val in success_df.name:

    # typecaste each val to string
    val = str(val)

    # split the value
    tokens = val.split()

    # Converts each token into lowercase
    for i in range(len(tokens)):
        tokens[i] = tokens[i].lower()

    comment_words += " ".join(tokens)+" "

wordcloud = WordCloud(width = 800, height = 800,
                background_color ='white',
                stopwords = stopwords,
                min_font_size = 10).generate(comment_words)

# plot the WordCloud image
plt.figure(figsize = (8, 8), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)
```


project
short film
new album
debut album
book
art
new
album
documentary
world
game
love
life
film
music
help
tour
make
one
full length
ep
first
adventure
record
playing card
collection
girl
story
comic
people
serie
enamel pin
dance
free
miniature
bring
feature film
magazine
present
recording
good
great
zombie
making
system
painting
king
home
blue
length album
fantasy
vinyl
red
big
city
novel
show
last
live
inspired
journey
part
anthology
ultimate
play
video
design
year
little
history
new york
work
music video
made
go
food
modern
dice
space
issue
back
festival
artist
house
women
time
star
day
launch
children
theatre
card game
smart
tale
kid
musical
man
future
best
wallet
american
season
children book
summer
band
farm
need
community
heart
cat
print
war
cd
shirt
production
volume
dark
studio album
song
movie
black
hand
monster
light
dream
calendar
debut ep
rpg
sound
sci fi
storie
board game
edition
support
dog
night
graphic novel
family
web serie
documentary film
performance

In [33]:
```
#wordcloud for failed campaigns
comment_words = ''
stopwords = set(STOPWORDS)

# iterate through the csv file
for val in fail_df.name:

    # typecaste each val to string
    val = str(val)

    # split the value
    tokens = val.split()

    # Converts each token into lowercase
    for i in range(len(tokens)):
        tokens[i] = tokens[i].lower()

    comment_words += " ".join(tokens)+" "

wordcloud = WordCloud(width = 800, height = 800,
                background_color ='white',
                stopwords = stopwords,
                min_font_size = 10).generate(comment_words)

# plot the WordCloud image
plt.figure(figsize = (8, 8), facecolor = None)
plt.imshow(wordcloud)
plt.axis("off")
plt.tight_layout(pad = 0)
```


book
project
life
art
love
app
new
world
game
documentary
music
short film
kid
shirt
one
magazine
day
novel
film
time
help
design
story
album
movie
serie
dream
first
adventure
make
music video
collection
video
people
feature film
journey
tour
apparel
debut album
clothing
light
food
mobile
free
system
show
city
artist
live
home
american
card game
children
online
ep
making
experience
fashion
community
new album
america
photography
best
man
ultimate
studio
custom
little
road
space
future
black
blue
girl
production
gaming
playing card
graphic novel
house
street
real
build
support
earth
original
dead
friend
history
farm
dance
night
king
boy
sound
star
modern
tale
kitchen
monster
dark
war
cafe
band
fund
festival
soul
want
bring
digital
photo
work
power
word
shop
back
eye
guide
handmade
bag
calendar
organic
urban
musical
natural
record
hope
creation
painting
good
start
two
kit
box
print
women
car
year
save
go
comic
part
family
storie
coffee
create
dog
song
baby
great
inspired
play
company
social
school
living
lost
rock
full length
sport
cd
big
heart
need
zombie
travel
launch
website
business
la
pet
cat
season
water
unique
children book
food truck
creative
made
building
web serie
garden
green
way
smart
style
last
red
god
magic
friend
fun
jewelry
hand
present
line
3d
cd
fake
take

In [34]:
```
#word frequency in campaigns
#split campaign names into lists and convert to lower case
clean_df['name']=clean_df['name'].apply(str)
cn = clean_df['name']
words_in_name = [word.lower().split() for word in cn]
words_in_name[:1]
# List of all words in campaign names
all_words = list(itertools.chain(*words_in_name))
# Create counter
word_counts = collections.Counter(all_words)
#most common words and their count
word_counts.most_common(15)
#set stop words
from nltk.corpus import stopwords
stop_words = set(stopwords.words('english'))
list(stop_words)[0:10]
#remove stop words from campaign names to focus in on meaningful words
words_new = [[word for word in words if not word in stop_words]
              for words in words_in_name]
#combine all words from campaign names into one list to gauge frequency
all_words_new = list(itertools.chain(*words_new))
counts_new = collections.Counter(all_words_new)
counts_new.most_common(15)
```

Out[34]:
```
[('-', 47101),
 ('&', 15673),
 ('new', 12156),
 ('album', 9351),
 ('film', 9319),
 ('project', 8948),
 ('book', 7722),
 ('art', 6682),
 ('game', 6637),
 ('music', 5973),
 ('first', 5553),
 ('help', 5474),
 ('short', 4656),
 ('debut', 4361),
 ('documentary', 3499)]
```

In [35]:
```
#word frequency in successful campaigns
#split campaign names into lists and convert to lower case
success_df['name']=success_df['name'].apply(str)
sn = success_df['name']
words_success = [word.lower().split() for word in cn]
words_success[:1]
#remove stop words from campaign names to focus in on meaningful words
stop_words = set(stopwords.words('english'))
s_words = [[word for word in words if not word in stop_words]
              for words in words_success]

#combine all words from campaign names into one list to gauge frequency
success_words_new = list(itertools.chain(*words_success))
success_counts_new = collections.Counter(success_words_new)
success_counts_new.most_common(15)
```

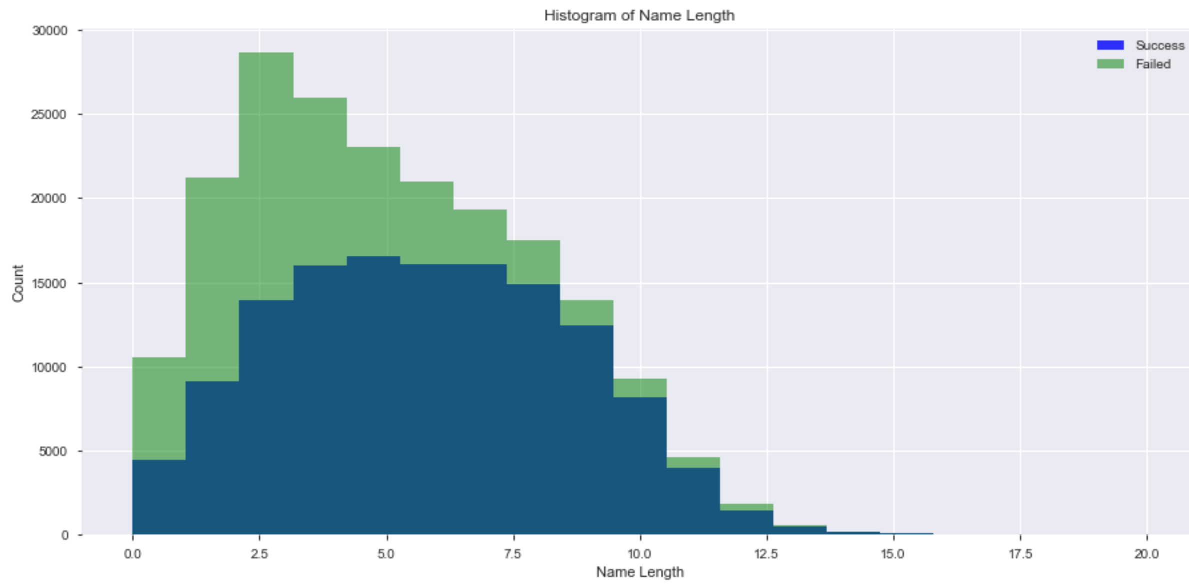
Out[35]:
```
[('the', 89822),
 ('-', 47101),
 ('a', 44200),
 ('of', 33071),
 ('and', 22309),
 ('for', 20821),
 ('to', 18199),
 ('&', 15673),
 ('in', 15593),
 ('new', 12156),
 ('album', 9351),
 ('film', 9319),
 ('project', 8948),
 ('by', 8858),
 ('your', 7989)]
```

In [36]:
```
#word frequency in failed campaigns
#split campaign names into lists and convert to lower case
fail_df['name']=fail_df['name'].apply(str)
fn = fail_df['name']
words_fail = [word.lower().split() for word in fn]
words_fail[:1]
#remove stop words from campaign names to focus in on meaningful words
stop_words = set(stopwords.words('english'))
f_words = [[word for word in words if not word in stop_words]
              for words in words_fail]

#combine all words from campaign names into one list to gauge frequency
fail_words_new = list(itertools.chain(*words_fail))
fail_words_new = collections.Counter(fail_words_new)
fail_words_new.most_common(15)
```

Out[36]:
```
[('the', 50593),
 ('-', 25293),
 ('a', 23643),
 ('of', 19055),
 ('and', 13446),
 ('for', 12677),
 ('to', 11009),
 ('in', 8891),
 ('&', 8453),
 ('new', 5477),
 ('project', 5366),
 ('your', 5031),
 ('with', 4505),
 ('book', 4289),
 ('film', 4137)]
```

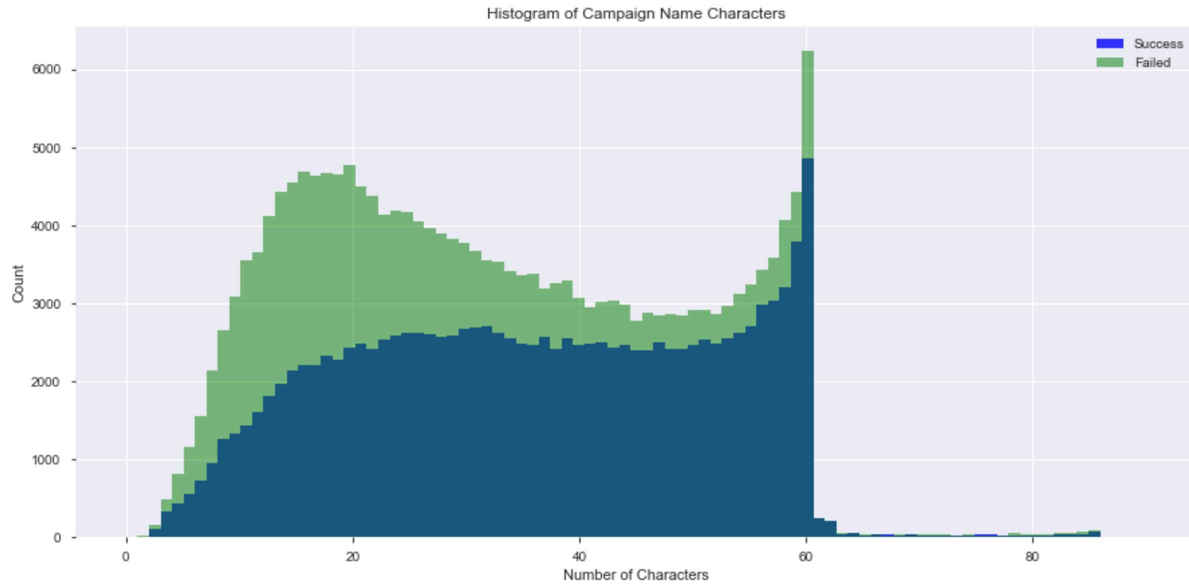
Many of the same words appear in word clouds for both successful campaigns and failed campaigns. It doesn't seem like there any particular words that will possibly predict success. Maybe shorter, concise titles help to predict success?

In [37]:
```
#name length analysis - number of words in a campaign
f, ax =plt.subplots(figsize=(15,7))
x = clean_df['name_len'].loc[clean_df['state'] == 'successful']
y = clean_df['name_len'].loc[clean_df['state'] == 'failed']
bins = np.linspace(0, 20, 20)

plt.hist(x, bins=bins, alpha=0.8, label='Success', color = 'blue')
plt.hist(y, bins=bins, alpha=0.5, label='Failed', color = 'green')
plt.legend(loc='upper right')
ax.set(ylabel="Count", xlabel = "Name Length", title = 'Histogram of Nam
e Length')
plt.show()

#name length descriptive stats
print('\033[1m' + "Success Descriptive Statistics" + '\033[0m')
print(x.describe())
print('')
print('\033[1m' + "Failed Descriptive Statistics" + '\033[0m')
print(y.describe())
```




```
Success Descriptive Statistics
count    133851.000000
mean          6.013059
std           2.704427
min           1.000000
25%           4.000000
50%           6.000000
75%           8.000000
max          27.000000
Name: name_len, dtype: float64

Failed Descriptive Statistics
count    197611.000000
mean          5.372479
std           2.763098
min           1.000000
25%           3.000000
50%           5.000000
75%           7.000000
max          29.000000
Name: name_len, dtype: float64
```

In [38]:
```
#plot the number of campaign name characters compairing successful campa
igns and failed campaigns
f, ax =plt.subplots(figsize=(15,7))
n = clean_df['name_cl'].loc[clean_df['state'] == 'successful']
q = clean_df['name_cl'].loc[clean_df['state'] == 'failed']
bins = np.linspace(0, 90, 90)

plt.hist(n, bins=bins, alpha=0.8, label='Success', color = 'blue')
plt.hist(q, bins=bins, alpha=0.5, label='Failed', color = 'green')
plt.legend(loc='upper right')
ax.set(ylabel="Count", xlabel = "Number of Characters", title = 'Histogr
am of Campaign Name Characters')
plt.show()

#descriptive stats of campaign character numbers
print('\033[1m' + "Success Descriptive Statistics" + '\033[0m')
print(n.describe())
print('')
print('\033[1m' + "Failed Descriptive Statistics" + '\033[0m')
print(q.describe())
```




```
Success Descriptive Statistics
count    133851.000000
mean         36.290442
std          15.651188
min           1.000000
25%          23.000000
50%          36.000000
75%          50.000000
max          87.000000
Name: name_cl, dtype: float64

Failed Descriptive Statistics
count    197611.000000
mean         32.886727
std          16.069067
min           1.000000
25%          19.000000
50%          31.000000
75%          47.000000
max          87.000000
Name: name_cl, dtype: float64
```

Based on the two histograms above, it appears that successful campaigns tend to have fewer words in a campaign name and fewer characters in a campaign name then campaigns that end in failure.

Research Question, Hypothesis and Statistics

Research Question: Is there a statistically significant relationship between the number of words in a campaign name and the campaign outcome?

H0: The distributions of number of words in a successful campaign is the same as the distribution of number of words in a failed campaign.

In [39]:
```
#normality test
data_nl = clean_df.name_len
print('\033[1m' + "Descriptive Stats" + '\033[0m')
print(data_nl.describe())
#calculate sem & ci
print('\033[1m' + "Standard Error of Mean" + '\033[0m')
print(st.sem(data_nl))
print('\033[1m' + "Confidence Intervals" + '\033[0m')
print(st.t.interval(0.95, len(data_nl)-1, loc=np.mean(data_nl), scale=st
.sem(data_nl)))
# normality test
stat, p = shapiro(data_nl)
print('\033[1m' + "Shapiro Test" + '\033[0m')
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
```

```
Descriptive Stats
count    331462.000000
mean          5.631158
std           2.757524
min           1.000000
25%           3.000000
50%           5.000000
75%           8.000000
max          29.000000
Name: name_len, dtype: float64
Standard Error of Mean
0.004789635505313476
Confidence Intervals
(5.621770775455233, 5.6405458701934394)
Shapiro Test
Statistics=0.966, p=0.000
Sample does not look Gaussian (reject H0)

/Users/kellipeluso/opt/anaconda3/lib/python3.7/site-packages/scipy/stat
s/morestats.py:1660: UserWarning: p-value may not be accurate for N > 5
000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [40]:
```
# Kruskal-Wallis H-test
# compare distributions
stat, p = kruskal(x, y)
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Same distributions (fail to reject H0)')
else:
    print('Different distributions (reject H0)')
```

```
Statistics=4704.860, p=0.000
Different distributions (reject H0)
```

In [41]:
```
#bootstrap analysis on the mean of number of words in campaign name
x = clean_df['name_len'].loc[clean_df['state'] == 'successful']
y = clean_df['name_len'].loc[clean_df['state'] == 'failed']
N_rep = 5000
success_nl_mean = np.empty(N_rep)
failed_nl_mean = np.empty(N_rep)

for i in range(N_rep):
    success_nl_mean[i] = np.mean(np.random.choice(x, size=len(x)))
    failed_nl_mean[i] = np.mean(np.random.choice(y, size=len(y)))

mean_diff_nl = failed_nl_mean - success_nl_mean
```

In [42]:
```
p_value = np.sum(mean_diff_nl < 0) / N_rep
print(p_value)
```

```
1.0
```

The H0 is rejected because there does appear to be differences in the distribution of successful campaign name length and failed campaign name length. Based on the bootstrap analysis comparing the means of these two groups it appears that the means of successful campaign name length and failed campaign name length are different.

Research Question: Is there a statistically significant relationship between the number of characters in a campaign name and the campaign outcome?

H0: The distribution of number of characters in a successful campaign name is the same as the distribution of numbers of characters in a failed campaign.

In [43]:
```
#normality test
# generate univariate observations
data_cl = clean_df['name_cl']
print('\033[1m' + "Descriptive Stats" + '\033[0m')
print(data_cl.describe())
#calculate sem & ci
print('\033[1m' + "Standard Error of Mean" + '\033[0m')
print(st.sem(data_cl))
print('\033[1m' + "Confidence Intervals" + '\033[0m')
print(st.t.interval(0.95, len(data_cl)-1, loc=np.mean(data_cl), scale=st
.sem(data_cl)))
# normality test
stat, p = shapiro(data_cl)
print('\033[1m' + "Shapiro Test" + '\033[0m')
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
```

```
Descriptive Stats
count    331462.000000
mean         34.261215
std          15.989077
min           1.000000
25%          21.000000
50%          33.000000
75%          48.000000
max          87.000000
Name: name_cl, dtype: float64
Standard Error of Mean
0.02777196002530174
Confidence Intervals
(34.20678322341801, 34.315647703807436)
Shapiro Test
Statistics=0.963, p=0.000
Sample does not look Gaussian (reject H0)
```

In [44]:
```
# Kruskal-Wallis H-test
# compare distributions
stat, p = kruskal(n, q)
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Same distributions (fail to reject H0)')
else:
    print('Different distributions (reject H0)')
```

```
Statistics=3755.170, p=0.000
Different distributions (reject H0)
```

In [45]:
```
#bootstrap analysis on the mean of number of characters in campaign name
n = clean_df['name_cl'].loc[clean_df['state'] == 'successful']
q = clean_df['name_cl'].loc[clean_df['state'] == 'failed']
N_rep = 5000
success_cl_mean = np.empty(N_rep)
failed_cl_mean = np.empty(N_rep)

for i in range(N_rep):
    success_cl_mean[i] = np.mean(np.random.choice(n, size=len(n)))
    failed_cl_mean[i] = np.mean(np.random.choice(q, size=len(q)))

mean_diff_cl = failed_cl_mean - success_cl_mean
```

In [46]:
```
p_value = np.sum(mean_diff_cl < 0) / N_rep
print(p_value)
```

```
1.0
```

The H0 is rejected because there does appear to be differences in the distribution of successful campaign character length and failed campaign character length. Based on the bootstrap analysis comparing the means of these two groups it appears that the means of successful campaign character length and failed campaign character length are different.

Main Categories

As previously stated, the ability to predict a successful Kickstarter campaign will be of huge benefit to both Kickstarter and to companies and groups who use their services to raise funds for their projects. The success of Kickstarter campaigns means continued success and profitability for the Kickstarter platform, and successful campaigns are given the opportunity to launch their innovative products and ideas - which at times maybe didn't seem possible through traditional funding. It's important to begin looking at any potential relationships between the characteristics of successful campaigns and unsuccessful campaigns. What differentiates them? Is it enough to just put a project on Kickstarter and see what happens, or are there outside factors that need to be taken into account or at least discussed?

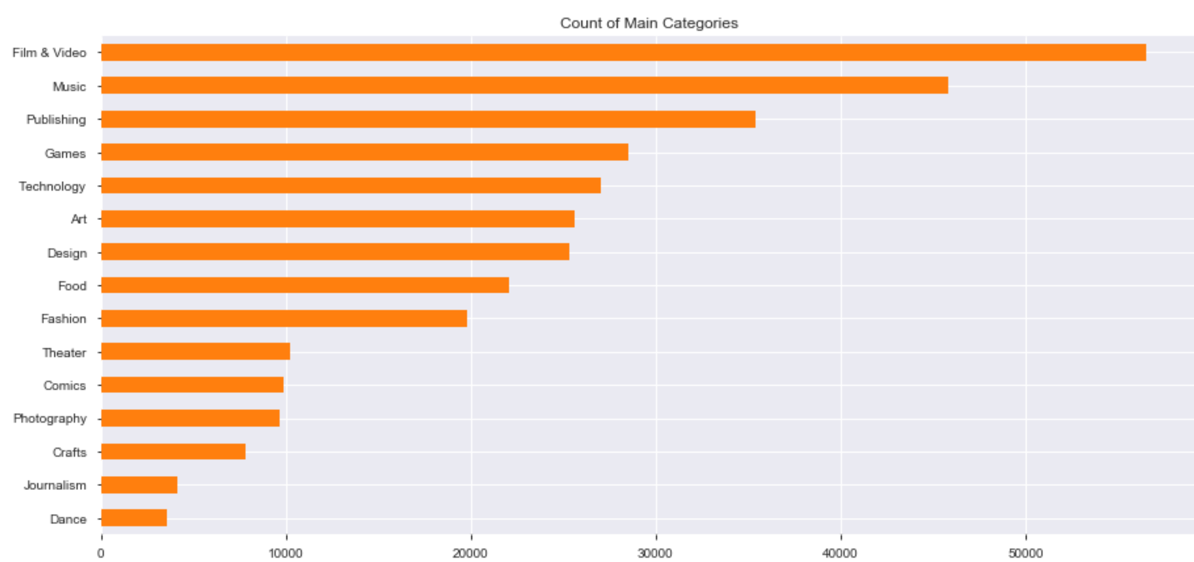
In [47]:
```
#Identify the top ten main campaign categories
clean_df['main_category'].value_counts().head(30)
```

Out[47]:
```
Film & Video     56503
Music            45801
Publishing       35413
Games            28520
Technology       27046
Art              25640
Design           25363
Food             22054
Fashion          19774
Theater          10242
Comics            9878
Photography       9689
Crafts            7818
Journalism        4148
Dance             3573
Name: main_category, dtype: int64
```

Visually, this chart represents what we know to be true about the data at first glance. This ranking is based off of the number of campaigns in each category. The top 10 main categories do not increase drastically between Fashion and Games, however there is an identified steep increase from Theater to Fashion, and from Publishing to both Music and Film & Video. The top ten main categories are calculated from the sum of campaigns that fall under each category.

In [48]:
```
#Visualize the top ten main kickstarter campaign categories, based on co
unt of campaigns in each category
clean_df.main_category.value_counts()[:30].sort_values().plot(kind='bar
h', title='Count of Main Categories', color = 'tab:orange',figsize=(15,
7))
```

Out[48]: <matplotlib.axes._subplots.AxesSubplot at 0x1a652c4a10>



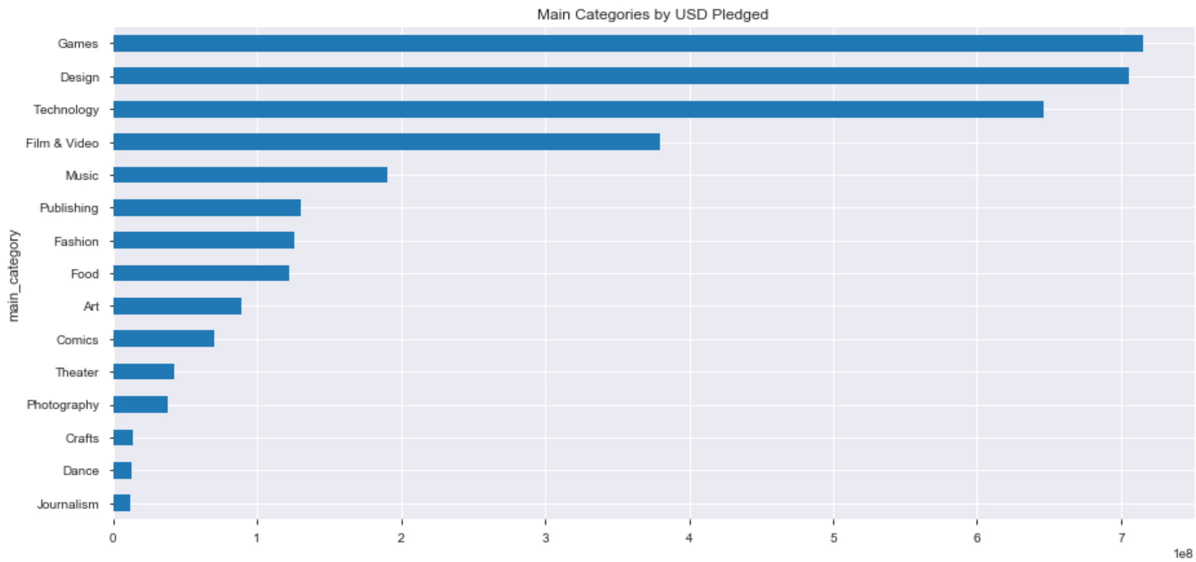
Intrestingly, when we look at the top 10 main categories based on the sum of pledged USD, the data provides interesting insight. Although games are the 4th ranked main category in terms of number of campaigns, it far out paces Film & Video. Campaigns with the main category games brought in $741,321,067 in pledges alone from 35,231 campaigns. For Kickstarter, this accounts to a \$37,066,053.35 profit from the successful Game campaigns, not accounting for additional fees collected at the time of each pledge - that's a lot of money! Design is not far behind Games, bringing in $734,215,606 in pledges for 30,070 games. This seems to be related to the amount of money needed to fund campaigns for categories such as Games and Technology.

In [49]:
```
clean_df.usd_pledged_real = clean_df.usd_pledged_real.astype(int)
usd_main = clean_df.groupby('main_category')['usd_pledged_real'].sum().s
ort_values(ascending = False)
print(usd_main)
```

```
main_category
Games           715062392
Design          705221712
Technology      645802498
Film & Video    379513169
Music           190777264
Publishing      130755927
Fashion         125676176
Food            122779551
Art              89075714
Comics           70598884
Theater          42660798
Photography      37708728
Crafts           13952984
Dance            12907799
Journalism       12194691
Name: usd_pledged_real, dtype: int64
```

In [50]:
```
#top 10 campaign categories by total sum of money pledged
clean_df.usd_pledged_real = clean_df.usd_pledged_real.astype(int)
clean_df.groupby('main_category')['usd_pledged_real'].sum().sort_values(
ascending = True).plot(kind='barh', title='Main Categories by USD Pledge
d', color = 'tab:blue',figsize=(15, 7))
```

Out[50]: <matplotlib.axes._subplots.AxesSubplot at 0x1a459f9110>



It is not surprising to see that for each category, successful campaigns were the most lucrative. Failed campaigns appear to be the second most lucrative campaign state, while live, suspended and undefined have the lowest pledge amounts.

In [51]:
```
#top 10 campaign categories by total sum of money pledged for each campa
ign state
clean_df.usd_pledged_real = clean_df.usd_pledged_real.astype(int)
camp_df = clean_df.groupby(['main_category','state'])['usd_pledged_real'
].sum().sort_index(ascending = False).reset_index()
camp_df
```

Out[51]:

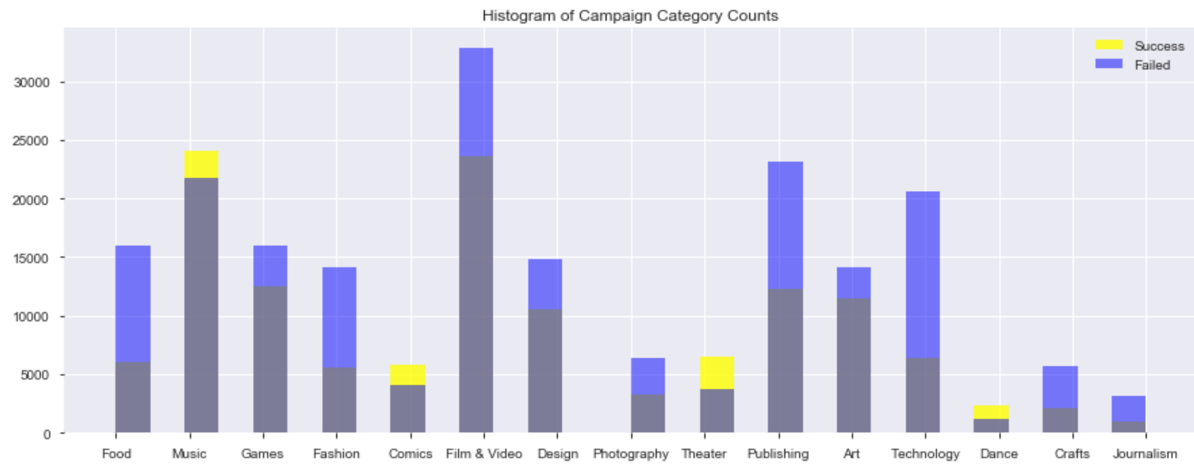
	main_category	state	usd_pledged_real
0	Theater	successful	39027485
1	Theater	failed	3633313
2	Technology	successful	596149844
3	Technology	failed	49652654
4	Publishing	successful	116072212
5	Publishing	failed	14683715
6	Photography	successful	33418618
7	Photography	failed	4290110
8	Music	successful	177143132
9	Music	failed	13634132
10	Journalism	successful	10468921
11	Journalism	failed	1725770
12	Games	successful	678832833
13	Games	failed	36229559
14	Food	successful	105570318
15	Food	failed	17209233
16	Film & Video	successful	329545180
17	Film & Video	failed	49967989
18	Fashion	successful	113461777
19	Fashion	failed	12214399
20	Design	successful	663143933
21	Design	failed	42077779
22	Dance	successful	12143392
23	Dance	failed	764407
24	Crafts	successful	11906517
25	Crafts	failed	2046467
26	Comics	successful	66514085
27	Comics	failed	4084799
28	Art	successful	80244909
29	Art	failed	8830805

After determining breaking down the main categories by the campaign state, we were able to find both the pledge amount by campaign state in each main category (as shown above), and the total number of campaigns by state in each main category. In the future, we will compare the success and failure rates of each campaign main category to help determine main categories at a higher financial risk.

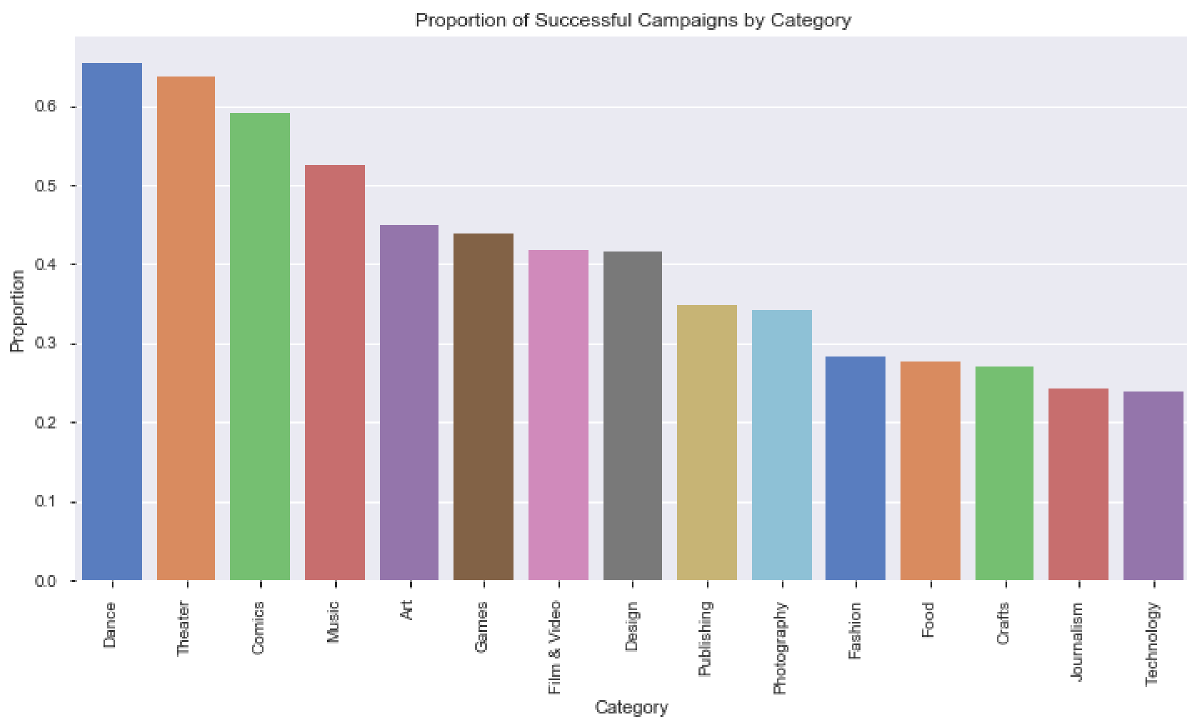
In [52]:
```
# a look at the status of campaigns based on their main category
# do certain campaign categories have a higher failure rate than others?
main_state = clean_df.groupby('main_category')['state'].value_counts()
print(main_state)
```

```
main_category  state     
Art            failed        14130
               successful    11510
Comics         successful     5842
               failed         4036
Crafts         failed         5703
               successful     2115
Dance          successful     2338
               failed         1235
Design         failed        14814
               successful    10549
Fashion        failed        14181
               successful     5593
Film & Video   failed        32891
               successful    23612
Food           failed        15969
               successful     6085
Games          failed        16002
               successful    12518
Journalism     failed         3136
               successful     1012
Music          successful    24105
               failed        21696
Photography    failed         6384
               successful     3305
Publishing     failed        23113
               successful    12300
Technology     failed        20613
               successful     6433
Theater        successful     6534
               failed         3708
Name: state, dtype: int64
```

In [53]:
```
#campaign category counts by campaign state
x = clean_df['main_category'].loc[clean_df['state'] == 'successful']
y = clean_df['main_category'].loc[clean_df['state'] == 'failed']
fig =plt.figure(figsize=(15,5.5))

plt.hist(x, bins = 30, alpha=0.8, label='Success', color = 'yellow')
plt.hist(y, bins = 30, alpha=0.5, label='Failed', color = 'blue')
plt.legend(loc='upper right')
plt.title('Histogram of Campaign Category Counts')
plt.show()
```



In [54]:
```
#portion successful campaign categories
y = (clean_df['main_category'].loc[clean_df['state'] == 'successful'].va
lue_counts())/(clean_df['main_category'].value_counts())
y = y.sort_values(ascending = False)
fig=plt.figure(figsize=(12, 6))
locs,labels = plt.xticks()
plt.setp(labels, rotation=90)
ax = sns.barplot(x = y.index, y = y, order = y.index, palette = 'muted')
plt.xlabel('Category')
plt.ylabel('Proportion')
plt.title('Proportion of Successful Campaigns by Category')
plt.show()
print(y)
```




```
Dance           0.654352
Theater         0.637961
Comics          0.591415
Music           0.526299
Art             0.448908
Games           0.438920
Film & Video    0.417889
Design          0.415921
Publishing      0.347330
Photography     0.341108
Fashion         0.282846
Food            0.275914
Crafts          0.270530
Journalism      0.243973
Technology      0.237854
Name: main_category, dtype: float64
```

Research Question, Hypothesis and Statistics

Research Question: Is there a statistically significant relationship between the campaign category and campaign outcomes?

H0: There is a no difference in successful campaign category distributions and failed campaign category distributions.

The variables being investigated are both categorical. Because of this, we use a stacked histogram and chi-square to determine whether there is any significant relationship between campaign category and campaign success.

In [55]:
```
test = clean_df.groupby(['main_category','state']).mean().sort_index(asc
ending = False).reset_index()
test.mean()
```

Out[55]:
```
ID                     1.073398e+09
goal                   3.282699e+04
pledged                1.255880e+04
backers                1.332252e+02
usd_pledged_real       1.169342e+04
usd_goal_real          3.084706e+04
name_cl                3.496199e+01
name_len               5.691177e+00
main_category_encode   7.000000e+00
binary_state           5.000000e-01
dtype: float64
```

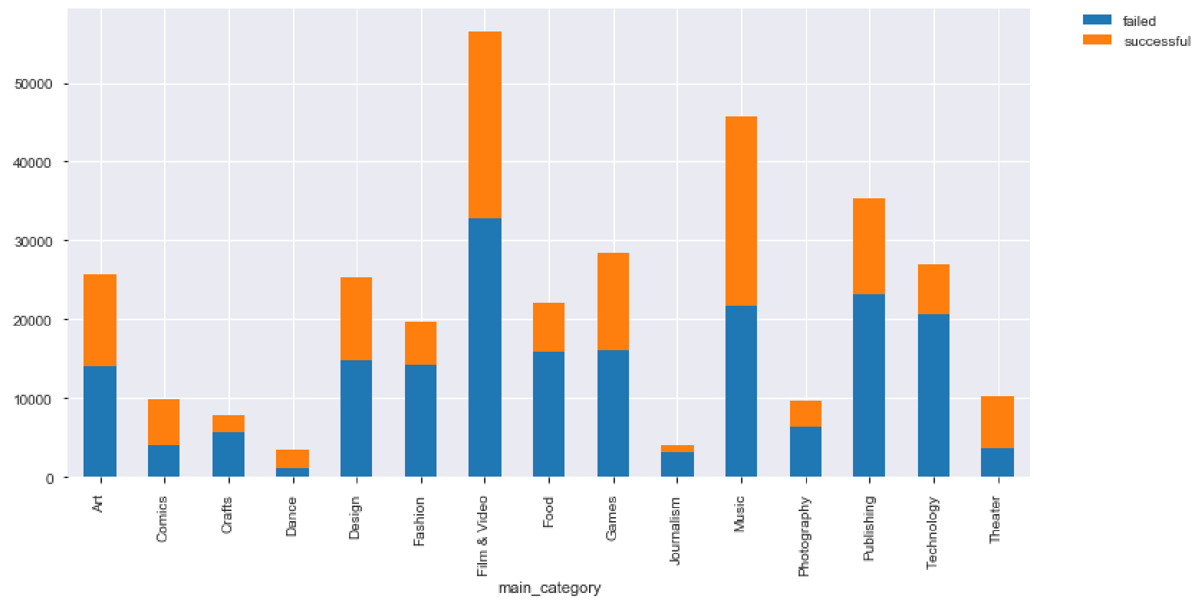
In [56]:
```
cat_state_table = pd.crosstab(index=clean_df["main_category"],
                              columns=clean_df["state"])

cat_state_table
```

Out[56]:

state main_category	failed	successful
Art	14130	11510
Comics	4036	5842
Crafts	5703	2115
Dance	1235	2338
Design	14814	10549
Fashion	14181	5593
Film & Video	32891	23612
Food	15969	6085
Games	16002	12518
Journalism	3136	1012
Music	21696	24105
Photography	6384	3305
Publishing	23113	12300
Technology	20613	6433
Theater	3708	6534

In [57]:
```
#campaign outcomes by main category
cat_state_table.plot(kind="bar",
                     figsize=(12,6),
                     stacked=True)
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

Out[57]: <matplotlib.legend.Legend at 0x1a5ab55990>



In [58]:
```
#normality test
data_cat = cat_state_table
print('\033[1m' + "Descriptive Stats" + '\033[0m')
print(data_cat.describe())
#calculate sem & ci
print('\033[1m' + "Standard Error of Mean" + '\033[0m')
print(st.sem(data_cat))
print('\033[1m' + "Confidence Intervals" + '\033[0m')
print(st.t.interval(0.95, len(data_cat)-1, loc=np.mean(data_cat), scale=
st.sem(data_cat)))
# normality test
stat, p = shapiro(data_cat)
print('\033[1m' + "Shapiro Test" + '\033[0m')
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
```

```
Descriptive Stats
state          failed    successful
count       15.000000     15.000000
mean     13174.066667   8923.400000
std       9080.054731   7092.876213
min       1235.000000   1012.000000
25%       4869.500000   4449.000000
50%      14181.000000   6433.000000
75%      18307.500000  11905.000000
max      32891.000000  24105.000000
Standard Error of Mean
[2344.46005047 1831.37276328]
Confidence Intervals
(array([8145.69996006, 4995.4960767 ]), array([18202.43337327, 12851.30
39233 ]))
Shapiro Test
Statistics=0.911, p=0.015
Sample does not look Gaussian (reject H0)
```

In [59]:
```
#Chi-Squared Test
table = cat_state_table
stat, p, dof, expected = chi2_contingency(table)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Probably independent')
else:
    print('Probably dependent')
```

```
stat=15425.822, p=0.000
Probably dependent
```

This p-value is <.001 - due to the size of the chi square statistic and p-value, it appears that the campaign category does have a significant relationship with the outcome of a campaign.

Campaign Goals

An overview of the Kickstarter campaign campaigns seek funding ranging anywhere from $0 to \$20,000,000, however the average campaign goal is $49080. With conversions for different currencies already taken into account, total pledges for campaigns range anywhere from
0toahighof$20, 338, 986.Onaverage, campaignsendupraising9058 total funding regardless of their

eventual success or failure.

In [60]:
```
#explore the campaign goal data by identifying min/max/mean
goal_max = clean_df['goal'].max()
goal_min = clean_df['goal'].min()
goal_mean = clean_df['goal'].mean()
print('Campaign goal amounts range from $', goal_min, ' to $', goal_max,
'.', 'The average campaign goal is $', goal_mean)
#explore the campaign goal data by identifying min/max/mean
pledge_max = clean_df['usd_pledged_real'].max()
pledge_min = clean_df['usd_pledged_real'].min()
pledge_mean = clean_df['usd_pledged_real'].mean()
print('Campaign pledge amounts range from $', pledge_min, ' to $', pledg
e_max,'.', 'The average pledge amount is $', pledge_mean)
```

```
Campaign goal amounts range from $ 0.01  to $ 100000000.0 . The average
campaign goal is $ 44265.8254486185
Campaign pledge amounts range from $ 0  to $ 20338986 . The average ple
dge amount is $ 9939.867275886829
```

In [61]:
```
#create a new column to show the proportion of final campaign pledged to
the original campaign goal
clean_df['goal_prop'] = clean_df['usd_pledged_real'] / clean_df['usd_goa
l_real']
clean_df.goal_prop.head()
```

Out[61]:
```
0    0.000000
1    0.080700
2    0.004889
3    0.000200
5    1.047500
Name: goal_prop, dtype: float64
```

Research Question, Hypothesis and Statistics

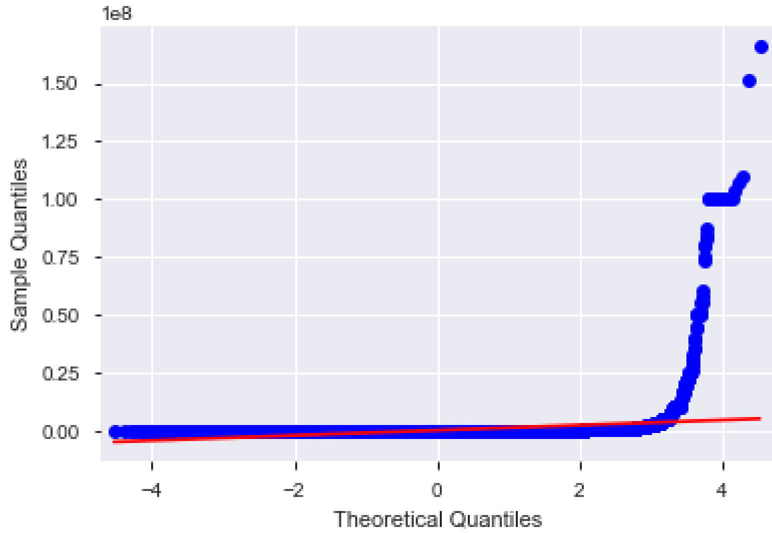
Research Question: Is there is a statistically significant relationship between campaign goals and the outcome of a campaign?

H0: The distribution of campaign goals for failed campaigns is different than the distribution of campaign goals for successful campaigns.

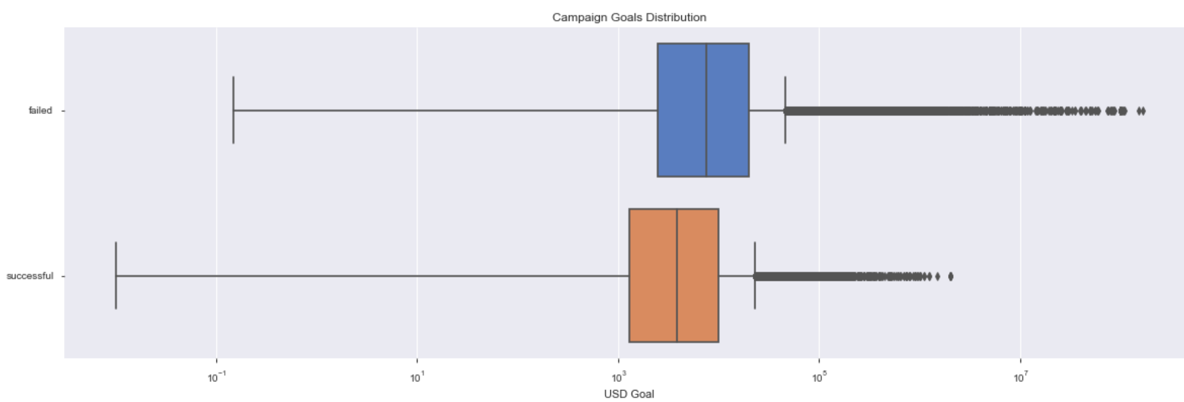
In [62]:
```
#test for normal distribution
# generate univariate observations
data_goal = clean_df['usd_goal_real']
print('\033[1m' + "Descriptive Stats" + '\033[0m')
print(data_goal.describe())
#calculate sem & ci
print('\033[1m' + "Standard Error of Mean" + '\033[0m')
print(st.sem(data_goal))
print('\033[1m' + "Confidence Intervals" + '\033[0m')
print(st.t.interval(0.95, len(data_goal)-1, loc=np.mean(data_goal), scal
e=st.sem(data_goal)))
# normality test
stat, p = shapiro(data_goal)
print('\033[1m' + "Shapiro Test" + '\033[0m')
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
```

```
Descriptive Stats
count    3.314620e+05
mean     4.152286e+04
std      1.109279e+06
min      1.000000e-02
25%      2.000000e+03
50%      5.000000e+03
75%      1.500000e+04
max      1.663614e+08
Name: usd_goal_real, dtype: float64
Standard Error of Mean
1926.7430780662376
Confidence Intervals
(37746.49455398775, 45299.216214486936)
Shapiro Test
Statistics=0.010, p=0.000
Sample does not look Gaussian (reject H0)

/Users/kellipeluso/opt/anaconda3/lib/python3.7/site-packages/scipy/stat
s/morestats.py:1660: UserWarning: p-value may not be accurate for N > 5
000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [63]:
```
#use quantile-quantile plot to test for normal distribution
qqplot(clean_df.usd_goal_real, line='s')
plt.show()
```



In [64]:
```
#use a box plot to test for normal distribution of campaign goals across
campaign states
f, ax = plt.subplots(figsize=(20, 6))
ax.set_xscale("log")
sns.boxplot(x="usd_goal_real", y = 'state', data=clean_df, palette = 'mu
ted')
ax.xaxis.grid(True)
ax.set(ylabel="", xlabel = "USD Goal", title = 'Campaign Goals Distribut
ion')
plt.show()
```



In [65]:
```
# Kruskal-Wallis H-test
# compare samples
goal_s= clean_df['usd_goal_real'].loc[clean_df['state'] == 'successful']
goal_f = clean_df['usd_goal_real'].loc[clean_df['state'] == 'failed']
stat, p = kruskal(goal_s, goal_f)
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Same distributions (fail to reject H0)')
else:
    print('Different distributions (reject H0)')
```

```
Statistics=16315.582, p=0.000
Different distributions (reject H0)
```

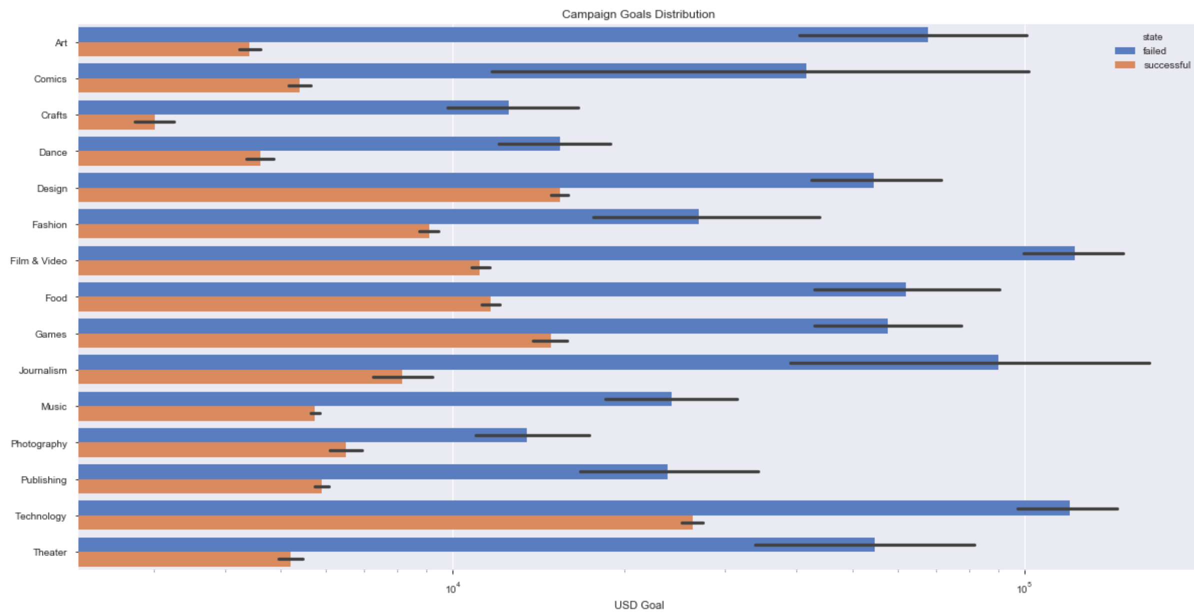
In [66]:
```
#bootstrap analysis on campaign goals
N_rep = 5000
success_goal_mean = np.empty(N_rep)
failed_goal_mean = np.empty(N_rep)

for i in range(N_rep):
    success_goal_mean[i] = np.mean(np.random.choice(goal_s, size=len(goa
l_s)))
    failed_goal_mean[i] = np.mean(np.random.choice(goal_f, size=len(goal
_f)))

mean_diff_goal = failed_goal_mean - success_goal_mean
```

In [67]:
```
p_value = np.sum(mean_diff_goal < 0) / N_rep
print(p_value)
```

```
0.0
```

The H0 is rejected because the distributions of failed campaign goals is different than the distribution of successful campaign goals. However, a bootstrap analysis compares the means and finds a p-value of <.001 - it's possible that the means of the distributions are similar.

In [68]:
```
#use a histogram to examine distribution of campaign goals by main categ
ory, by campaign state
f, ax = plt.subplots(figsize=(20, 10))
ax.set_xscale("log")
sns.barplot(x="usd_goal_real", y = 'main_category', hue = 'state', data=
clean_df, palette = 'muted')
ax.xaxis.grid(True)
ax.set(ylabel="", xlabel = "USD Goal", title = 'Campaign Goals Distribut
ion')
plt.show()
```



Campaign Duration

After exploring some of the campaign data, it is important to add a column that shows the duration of a campaign to contextualize how much time it has taken for successful campaigns to reach or surpass their funding goal, or for determining the average length of time of a failed campaign. In order to create a campaign duration column, both the launched and deadline columns are converted to datetime. From there, the campaign_duration column is created and added to clean_df by calculating the difference between launched and deadline. Exploration of this new column shows that the minimum campaign duration is only 7 hours and 17 minutes, while the longest campaign duration was 16738 days. Campaigns typically run for an average length of time of 33 days.

In [69]:
```
#convert the launched date and deadline date to datetime, solve for the
 duration between the launch date and
#deadline - drop the hr:mm:ss from the analysis
print(clean_df['campaign_duration'].head(10))
dur_min=clean_df['campaign_duration'].min()
dur_max=clean_df['campaign_duration'].max()
dur_mean=clean_df['campaign_duration'].mean()
print('The shortest campaign duration was',dur_min, ',',' the longest ca
mpaign duration was',dur_max,
      '.          The average campaign duration was ',dur_mean)
```

```
0     59 days
1     60 days
2     45 days
3     30 days
5     35 days
6     20 days
7     45 days
10    30 days
11    30 days
12    30 days
Name: campaign_duration, dtype: timedelta64[ns]
The shortest campaign duration was 1 days 00:00:00 ,  the longest campa
ign duration was 92 days 00:00:00 .          The average campaign durat
ion was  33 days 22:56:30.665596
```

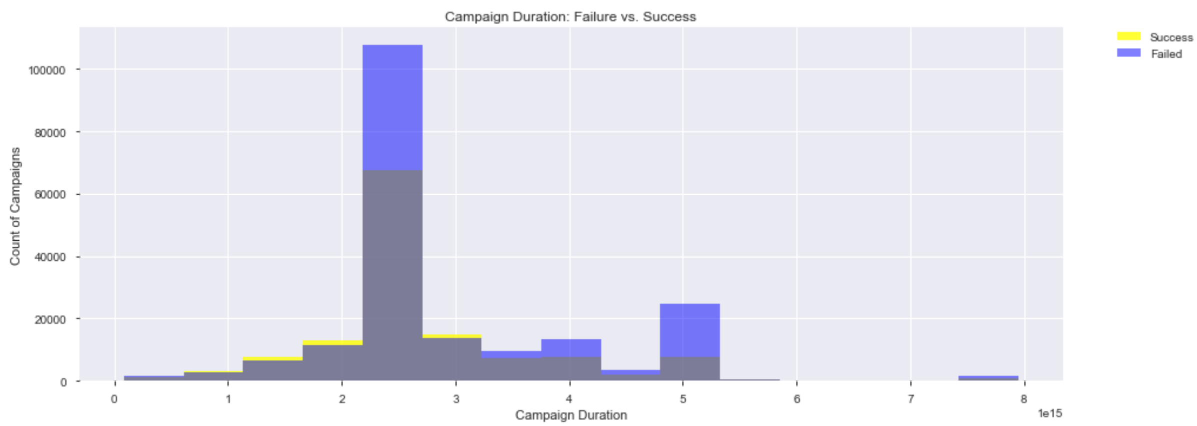
In [70]:
```
#successful campaign duration
#redo datetime for success_df
success_df['launched'] = pd.to_datetime(success_df['launched']).dt.date
success_df['deadline'] = pd.to_datetime(success_df['deadline']).dt.date
success_df['campaign_duration'] = success_df['deadline'] - success_df['l
aunched']
duration_min = success_df['campaign_duration'].min()
duration_max = success_df['campaign_duration'].max()
duration_mean = success_df['campaign_duration'].mean()
print(duration_min, duration_max, duration_mean)
```

```
1 days 00:00:00 92 days 00:00:00 32 days 03:45:40.524912
```

In [71]:
```
#failed campaign duration
#redo datetime for success_df
fail_df['launched'] = pd.to_datetime(fail_df['launched']).dt.date
fail_df['deadline'] = pd.to_datetime(fail_df['deadline']).dt.date
fail_df['campaign_duration'] = fail_df['deadline'] - fail_df['launched']
fduration_min = fail_df['campaign_duration'].min()
fduration_max = fail_df['campaign_duration'].max()
fduration_mean = fail_df['campaign_duration'].mean()
print(fduration_min, fduration_max, fduration_mean)
```

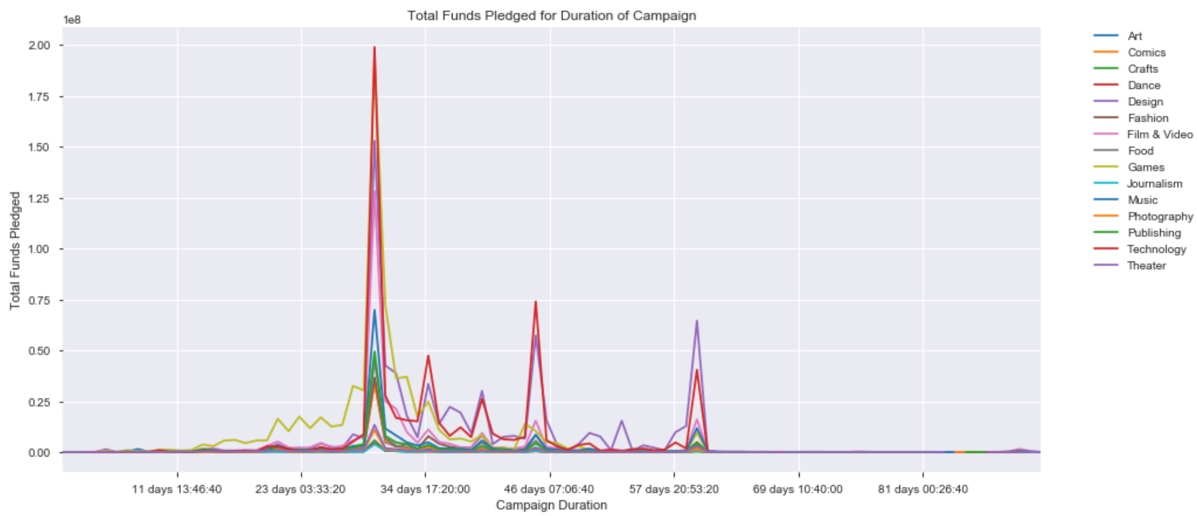
```
1 days 00:00:00 92 days 00:00:00 35 days 04:11:24.180536
```

In [72]:
```
#campaign duration by campaign state
clean_df['campaign_duration'] = pd.to_numeric(clean_df['campaign_duratio
n'], errors='coerce')
x = clean_df['campaign_duration'].loc[clean_df['state'] == 'successful']
y = clean_df['campaign_duration'].loc[clean_df['state'] == 'failed']
fig =plt.figure(figsize=(15,5.5))

plt.hist(x, bins = 15, alpha=0.8, label='Success', color = 'yellow')
plt.hist(y, bins = 15, alpha=0.5, label='Failed', color = 'blue')
plt.legend(loc='upper right')
plt.title('Campaign Duration: Failure vs. Success')
plt.xlabel('Campaign Duration')
plt.ylabel('Count of Campaigns')
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
plt.show()
```



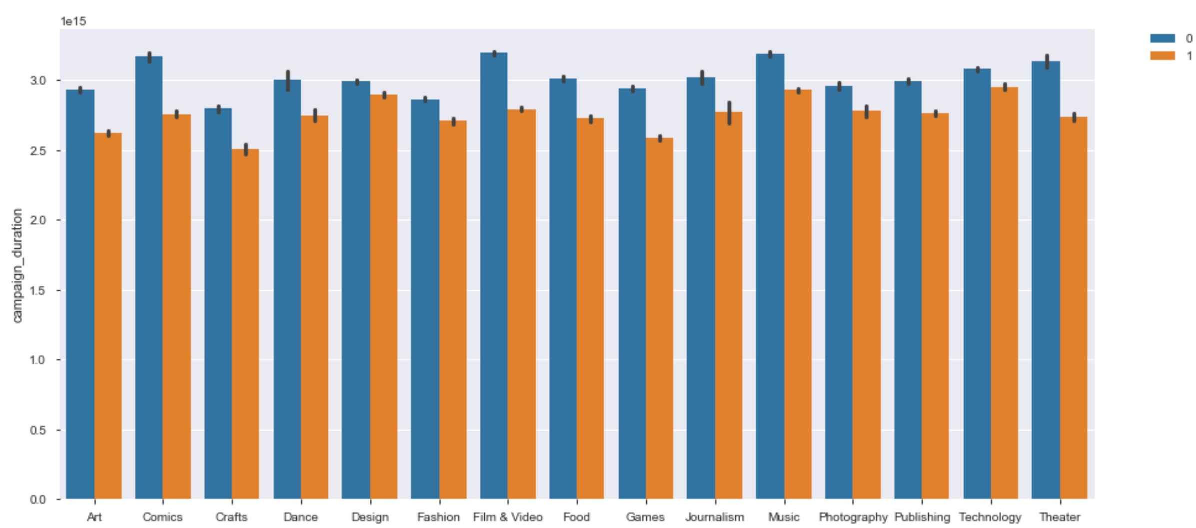
In [73]:
```
# plot data
fig, ax = plt.subplots(figsize=(15,7))
# use unstack()
success_df.groupby(['campaign_duration','main_category']).sum()['usd_ple
dged_real'].unstack().plot(ax=ax)
plt.xlabel('Campaign Duration')
plt.ylabel('Total Funds Pledged')
plt.title('Total Funds Pledged for Duration of Campaign')
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

Out[73]: <matplotlib.legend.Legend at 0x1a5b7d7a50>



In [74]:
```
#a look at campaign duration of failed and successful campaigns
fig, ax = plt.subplots(figsize=(15,7))
sns.barplot(x='main_category', y='campaign_duration', hue ="binary_stat
e",  data = clean_df, ax=ax)
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

Out[74]: <matplotlib.legend.Legend at 0x1a65946c90>



In [ ]:

Research Question, Hypothesis and Statistics

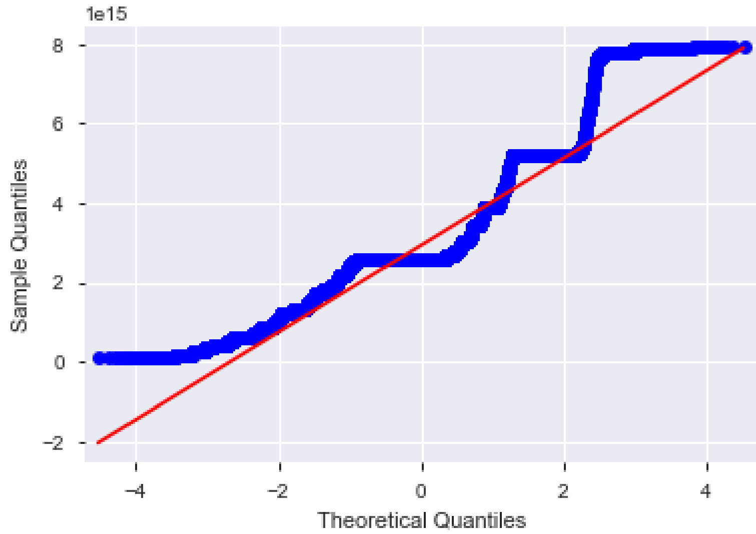
Research Question: Is there a statistically significant relationship between the duration of a campaign and campaign outcome?

H0: The distribution of successful campaign durations is the same as the distribution of failed campaign durations.

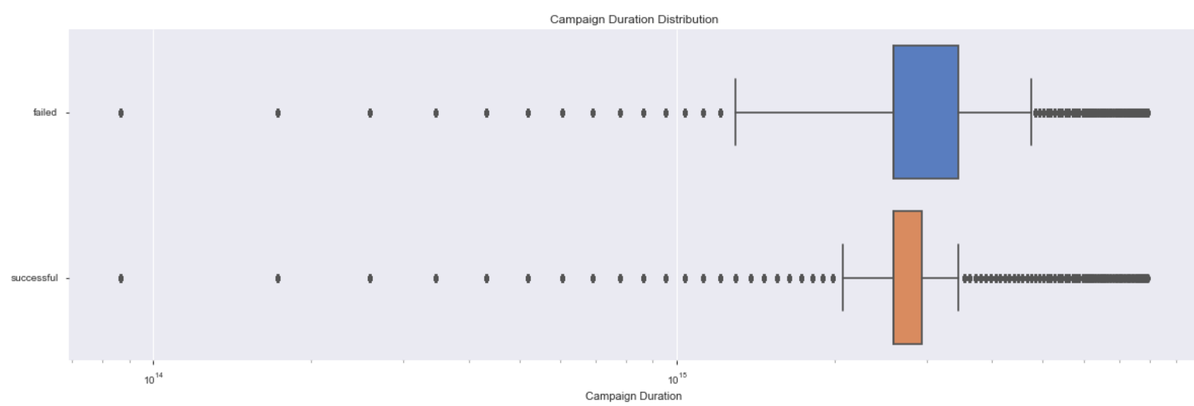
In [75]:
```
# generate univariate observations
data_camp = clean_df['campaign_duration']
print('\033[1m' + "Descriptive Stats" + '\033[0m')
print(data_camp.describe())
#calculate sem & ci
print('\033[1m' + "Standard Error of Mean" + '\033[0m')
print(st.sem(data_camp))
print('\033[1m' + "Confidence Intervals" + '\033[0m')
print(st.t.interval(0.95, len(data_camp)-1, loc=np.mean(data_camp), scal
e=st.sem(data_camp)))
# normality test
stat, p = shapiro(data_camp)
print('\033[1m' + "Shapiro Test" + '\033[0m')
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
```

```
Descriptive Stats
count    3.314620e+05
mean     2.933791e+15
std      1.098495e+15
min      8.640000e+13
25%      2.592000e+15
50%      2.592000e+15
75%      3.110400e+15
max      7.948800e+15
Name: campaign_duration, dtype: float64
Standard Error of Mean
1908013116787.4346
Confidence Intervals
(2930051014950076.0, 2937530316243396.0)
Shapiro Test
Statistics=0.831, p=0.000
Sample does not look Gaussian (reject H0)

/Users/kellipeluso/opt/anaconda3/lib/python3.7/site-packages/scipy/stat
s/morestats.py:1660: UserWarning: p-value may not be accurate for N > 5
000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [76]:
```
#use quantile-quantile plot to test for normal distribution
qqplot(clean_df.campaign_duration, line='s')
plt.show()
```



In [77]:
```
#use box whisker plot to test for normal distribution of campaign goals
 across all campaign states
f, ax = plt.subplots(figsize=(20, 6))
ax.set_xscale("log")
sns.boxplot(x="campaign_duration", y = 'state', data=clean_df, palette =
'muted')
ax.xaxis.grid(True)
ax.set(ylabel="", xlabel = "Campaign Duration", title = 'Campaign Durati
on Distribution')
plt.show()
```



In [78]:
```
#kruskal-Wallis test non-parametric equivalent of 2 way anova
camp_s= clean_df['campaign_duration'].loc[clean_df['state'] == 'successf
ul']
camp_f = clean_df['campaign_duration'].loc[clean_df['state'] == 'failed'
]
stat, p = kruskal(camp_s, camp_f)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Probably the same distribution')
else:
    print('Probably different distributions')
```

```
stat=3046.714, p=0.000
Probably different distributions
```

In [79]:
```
#bootstrap analysis on campaign goals
N_rep = 5000
success_camp_mean = np.empty(N_rep)
failed_camp_mean = np.empty(N_rep)

for i in range(N_rep):
    success_camp_mean[i] = np.mean(np.random.choice(camp_s, size=len(cam
p_s)))
    failed_camp_mean[i] = np.mean(np.random.choice(camp_f, size=len(camp
_f)))

mean_diff_camp = failed_camp_mean - success_camp_mean
```

In [80]:
```
p_value = np.sum(mean_diff_goal < 0) / N_rep
print(p_value)
```

```
0.0
```

The H0 is rejected. The distributions of successful campaign durations and failed campaign durations are both different, and both have different means.

Campaign Countries of Origin

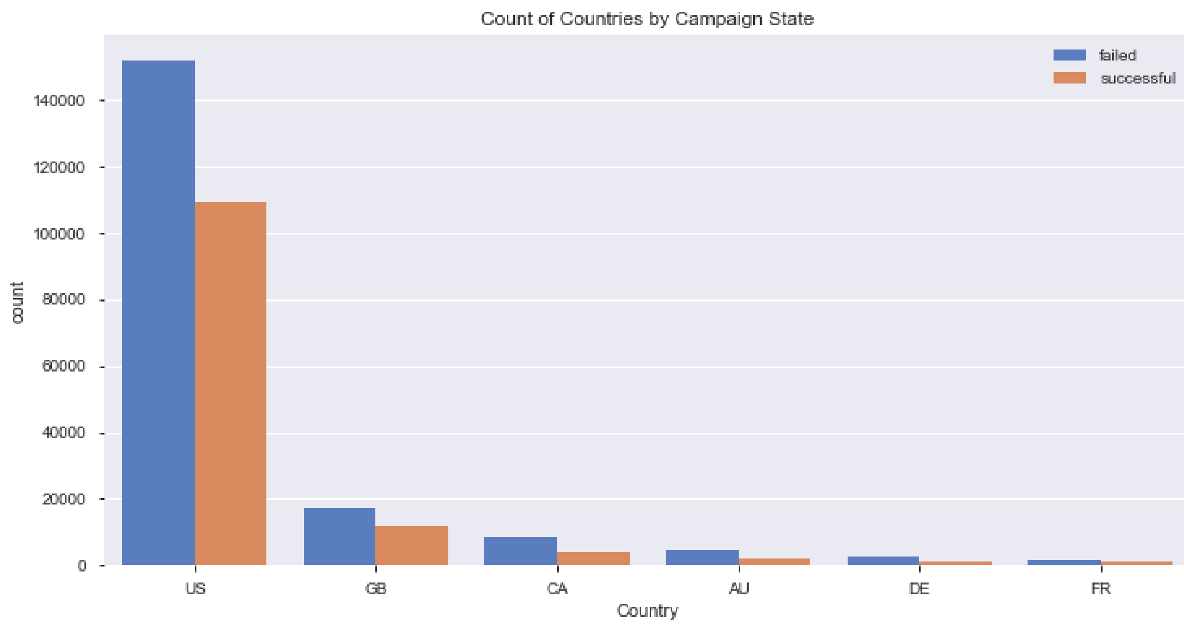
In [81]:
```
#count of successful campaigns per category
success_country = success_df['country'].value_counts()
print(success_country)
```

```
US    109299
GB     12067
CA      4134
AU      2010
DE       937
FR       908
NL       617
SE       509
ES       492
NZ       448
IT       439
MX       396
DK       360
HK       216
IE       207
CH       187
SG       178
NO       162
BE       152
AT       107
LU        19
JP         7
Name: country, dtype: int64
```

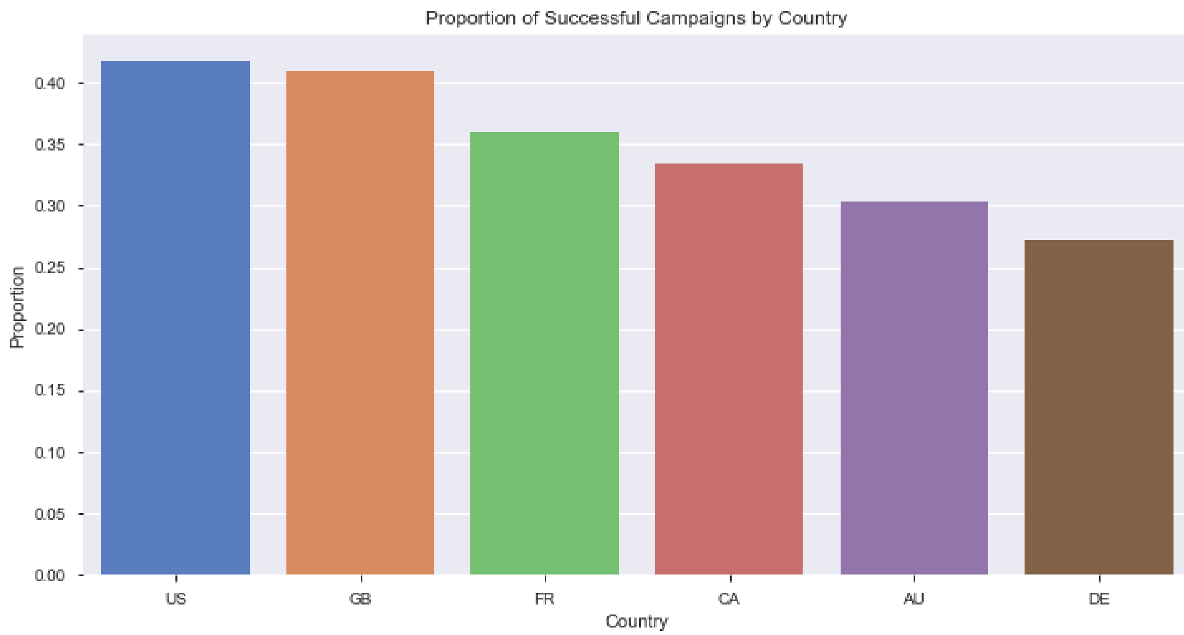
In [82]:
```
#count of failed campaigns per country
fail_country = fail_df['country'].value_counts()
print(fail_country)
```

```
US    152059
GB     17386
CA      8236
AU      4606
DE      2499
IT      1930
NL      1794
FR      1612
ES      1381
MX      1015
SE      1000
NZ       826
DK       566
IE       476
CH       465
NO       420
AT       378
BE       371
SG       276
HK       261
LU        38
JP        16
Name: country, dtype: int64
```

In [83]:
```
#count of campaigns by country and campaign state
fig = plt.figure(figsize = (12, 6))
sns.countplot(x = 'country', hue = 'state', palette = 'muted',
              data = clean_df[clean_df.country.isin(['US', 'GB', 'CA',
'AU', 'DE', 'FR'])],
              order = clean_df.country.loc[clean_df.country.isin(['US',
'GB', 'CA', 'AU', 'DE', 'FR'])].value_counts().index)
plt.legend(title ='')
plt.xlabel('Country')
plt.title('Count of Countries by Campaign State')
plt.show()
```



In [84]:
```
#what portion of campaigns in each country were successful?
y = (clean_df['country'].loc[clean_df['country'].isin(['US', 'GB', 'CA',
'AU', 'DE', 'FR',])].loc[clean_df['state'] == 'successful'].value_counts
())/(clean_df['country'].loc[clean_df['country'].isin(['US', 'GB', 'CA',
'AU', 'DE', 'FR'])].value_counts())
y = y.sort_values(ascending = False)
fig=plt.figure(figsize=(12,6))
ax = sns.barplot(x = y.index, y = y, order = y.index, palette = 'muted')
plt.xlabel('Country')
plt.ylabel('Proportion')
plt.title('Proportion of Successful Campaigns by Country')
plt.show()
print(y)
```




```
US    0.418196
GB    0.409704
FR    0.360317
CA    0.334196
AU    0.303809
DE    0.272701
Name: country, dtype: float64
```

In [85]:
```
#group categories by main category and campaign state
grouped = clean_df.groupby(['country','state'])
grouped.size()
```

Out[85]:
```
country  state
AT       failed           378
         successful       107
AU       failed          4606
         successful      2010
BE       failed           371
         successful       152
CA       failed          8236
         successful      4134
CH       failed           465
         successful       187
DE       failed          2499
         successful       937
DK       failed           566
         successful       360
ES       failed          1381
         successful       492
FR       failed          1612
         successful       908
GB       failed         17386
         successful     12067
HK       failed           261
         successful       216
IE       failed           476
         successful       207
IT       failed          1930
         successful       439
JP       failed            16
         successful         7
LU       failed            38
         successful        19
MX       failed          1015
         successful       396
NL       failed          1794
         successful       617
NO       failed           420
         successful       162
NZ       failed           826
         successful       448
SE       failed          1000
         successful       509
SG       failed           276
         successful       178
US       failed        152059
         successful    109299
dtype: int64
```

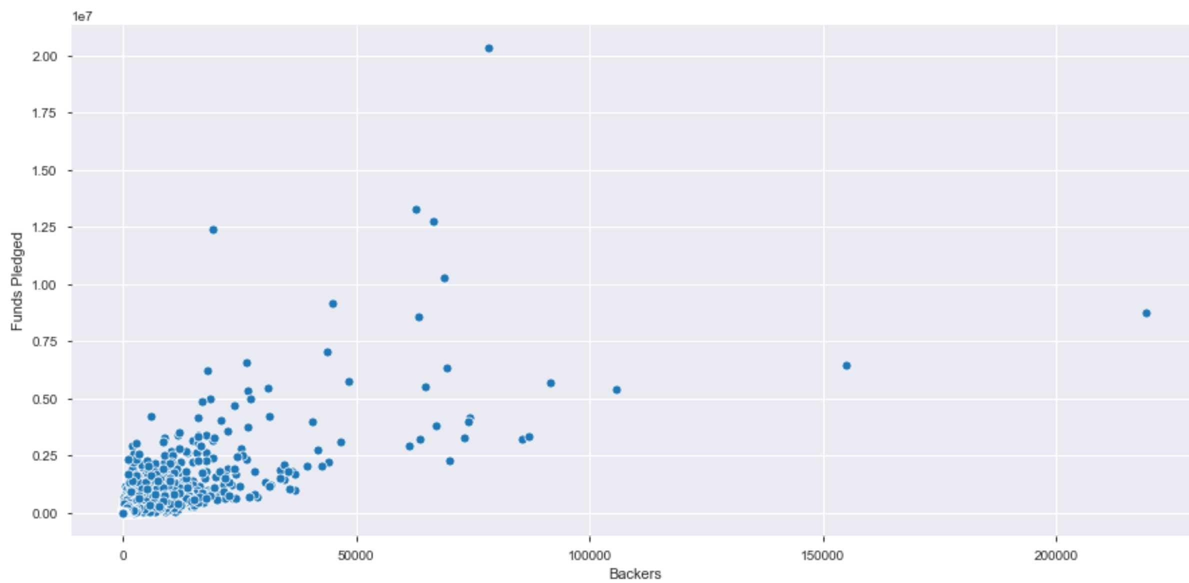
Campaign Backers

All campaigns have an average of 106 backers per campaign. Successful campaigns have an average of 263 backers per campaign. Failed campaigns have an average of 16 backers per campaign.

In [86]:
```
#average backers per campaign
cbackers = clean_df.backers.mean()
sbackers = success_df.backers.mean()
fbackers = fail_df.backers.mean()
print(cbackers, sbackers, fbackers)
```

```
116.45631475101219 264.12839650058646 16.431236115398434
```

In [87]:
```
#number of backers and campaign pledge amounts
cam = pd.to_numeric(clean_df['backers'])
num = pd.to_numeric(clean_df['usd_pledged_real'])
fig, ax = plt.subplots(figsize=(15,7)) # define the axes so we can modif
y them
sns.scatterplot(cam, num,data=success_df,ax = ax) # tell sns to use ax
ax.set_xlabel('') # turn off title
ax.set_ylabel('') # turn off title
plt.xlabel('Backers')
plt.ylabel('Funds Pledged')
plt.show()
```



Research Question, Hypothesis and Statistics

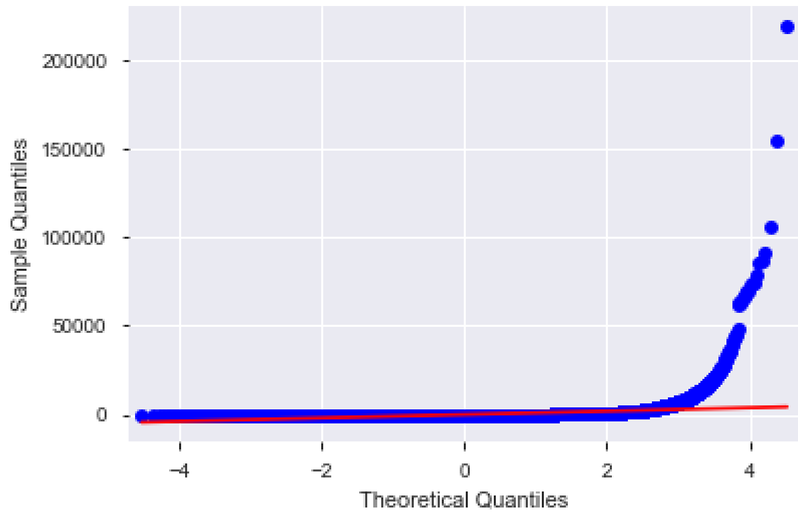
Research Question : Is there a relationship between the number of backers per campaign and campaign success?

H0: The distribution of failed campaign backers is the same as the distribution of successful campaign backers.

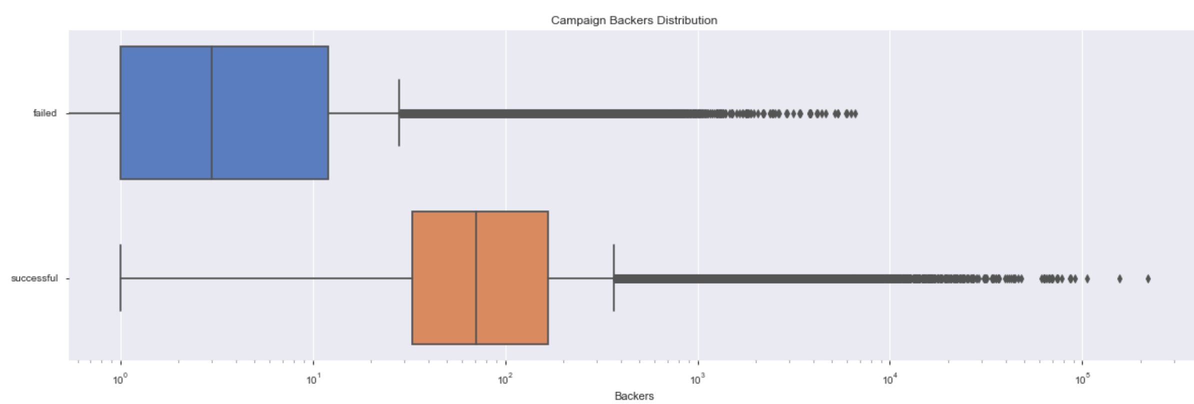
In [88]:
```
# generate univariate observations
data_back = clean_df['backers']
print('\033[1m' + "Descriptive Stats" + '\033[0m')
print(data_back.describe())
#calculate sem & ci
print('\033[1m' + "Standard Error of Mean" + '\033[0m')
print(st.sem(data_back))
print('\033[1m' + "Confidence Intervals" + '\033[0m')
print(st.t.interval(0.95, len(data_back)-1, loc=np.mean(data_back), scal
e=st.sem(data_back)))
# normality test
stat, p = shapiro(data_back)
print('\033[1m' + "Shapiro Test" + '\033[0m')
print('Statistics=%.3f, p=%.3f' % (stat, p))
# interpret
alpha = 0.05
if p > alpha:
    print('Sample looks Gaussian (fail to reject H0)')
else:
    print('Sample does not look Gaussian (reject H0)')
```

```
Descriptive Stats
count    331462.000000
mean        116.456315
std         965.732911
min           0.000000
25%           2.000000
50%          15.000000
75%          63.000000
max      219382.000000
Name: backers, dtype: float64
Standard Error of Mean
1.6774135955830822
Confidence Intervals
(113.16863251117475, 119.74399699084962)
Shapiro Test
Statistics=0.063, p=0.000
Sample does not look Gaussian (reject H0)

/Users/kellipeluso/opt/anaconda3/lib/python3.7/site-packages/scipy/stat
s/morestats.py:1660: UserWarning: p-value may not be accurate for N > 5
000.
  warnings.warn("p-value may not be accurate for N > 5000.")
```

In [89]:
```
#use quantile-quantile plot to test for normal distribution
qqplot(clean_df.backers, line='s')
plt.show()
```



In [90]:
```
#box whisker plot to test for normal distribution for campaign backers
f, ax = plt.subplots(figsize=(20, 6))
ax.set_xscale("log")
sns.boxplot(x="backers", y = 'state', data=clean_df, palette = 'muted')
ax.xaxis.grid(True)
ax.set(ylabel="", xlabel = "Backers", title = 'Campaign Backers Distribu
tion')
plt.show()
```



In [91]:
```
#kruskal-Wallis test non-parametric equivalent of 2 way anova
back_s= clean_df['backers'].loc[clean_df['state'] == 'successful']
back_f = clean_df['backers'].loc[clean_df['state'] == 'failed']
stat, p = kruskal(back_s, back_f)
print('stat=%.3f, p=%.3f' % (stat, p))
if p > 0.05:
    print('Probably the same distribution')
else:
    print('Probably different distributions')
```

```
stat=169378.627, p=0.000
Probably different distributions
```

In [92]:
```
#bootstrap analysis on campaign backers
N_rep = 5000
success_back_mean = np.empty(N_rep)
failed_back_mean = np.empty(N_rep)

for i in range(N_rep):
    success_back_mean[i] = np.mean(np.random.choice(back_s, size=len(bac
k_s)))
    failed_back_mean[i] = np.mean(np.random.choice(back_f, size=len(back
_f)))

mean_diff_back = failed_back_mean - success_back_mean
```

In [93]:
```
p_value = np.sum(mean_diff_back < 0) / N_rep
print(p_value)
```

```
1.0
```

The H0 is rejected because the distribution of successful campaign backers and failed campaign backers is different. The means of the two distributions appear to also be different.

Correlations Matrix

In [203]:
```
clean_df.head()
```

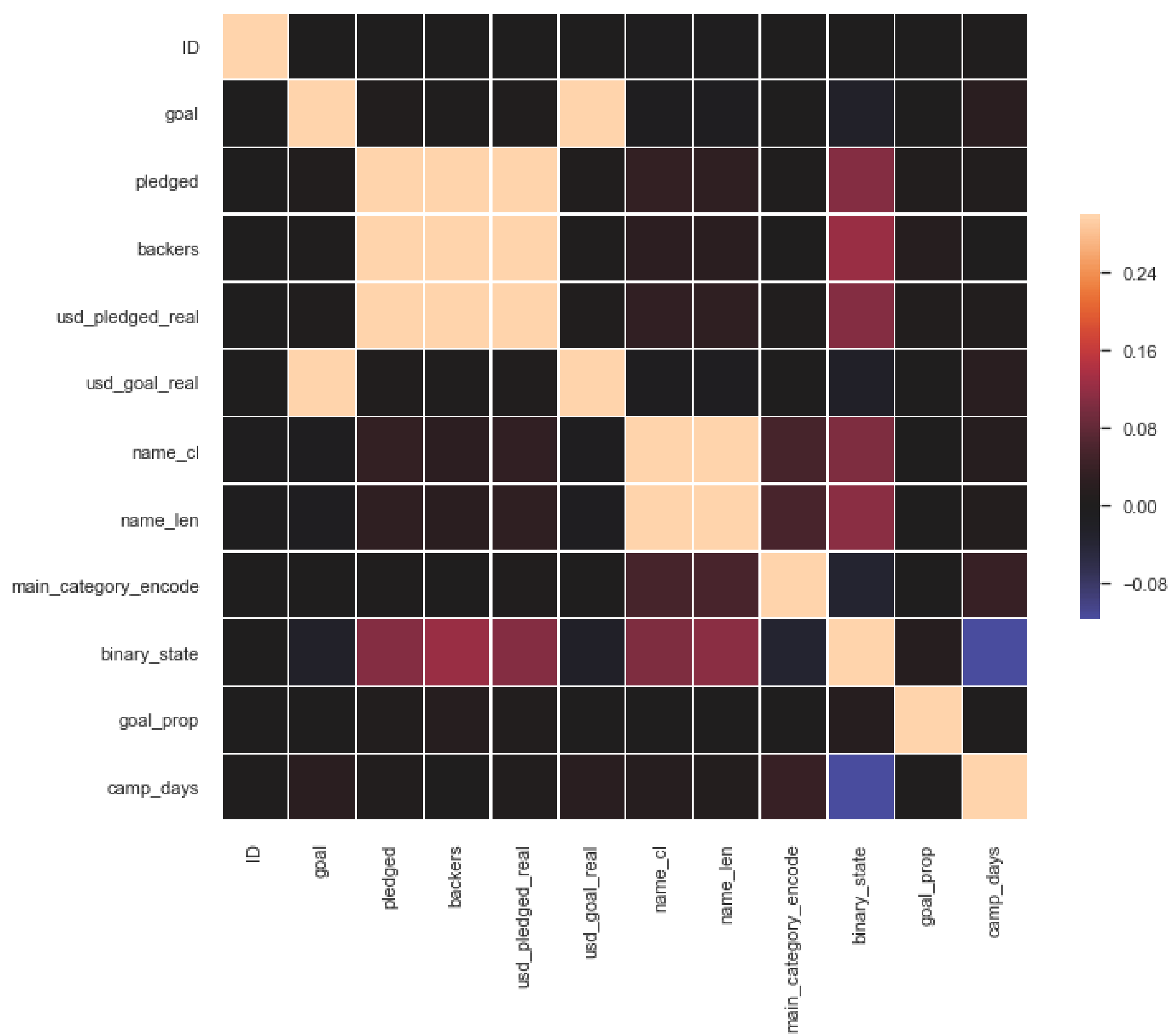
Out[203]:

	ID	name	category	main_category	currency	deadline	goal	launched	p
0	1000002330	The Songs of Adelaide & Abullah	Poetry	Publishing	GBP	2015-10-09	1000.0	2015-08-11	
1	1000003930	Greeting From Earth: ZGAC Arts Capsule For ET	Narrative Film	Film & Video	USD	2017-11-01	30000.0	2017-09-02	
2	1000004038	Where is Hank?	Narrative Film	Film & Video	USD	2013-02-26	45000.0	2013-01-12	
3	1000007540	ToshiCapital Rekordz Needs Help to Complete Album	Music	Music	USD	2012-04-16	5000.0	2012-03-17	
5	1000014025	Monarch Espresso Bar	Restaurants	Food	USD	2016-04-01	50000.0	2016-02-26	5

5 rows × 24 columns

In [202]:
```
#plot correlation matrix
sns.set(style="white")

# Compute the correlation matrix
corr = clean_df.corr()

# Generate a mask for the upper triangle
mask = np.triu(np.ones_like(corr, dtype=np.bool))

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(11, 9))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[202]: <matplotlib.axes._subplots.AxesSubplot at 0x1a800e8190>



In [192]:
```
clean_df.campaign_duration.head()
```

Out[192]:
```
0    5097600000000000
1    5184000000000000
2    3888000000000000
3    2592000000000000
5    3024000000000000
Name: campaign_duration, dtype: int64
```

Modeling

Random Forest

In [267]:
```
from sklearn.metrics import confusion_matrix
model = clean_df[[ 'backers', 'binary_state', 'name_cl', 'name_len', 'ca
mp_days', 'usd_goal_real', 'main_category_encode']]
model = pd.DataFrame(model)
```

In [268]:
```
model.head()
```

Out[268]:

	backers	binary_state	name_cl	name_len	camp_days	usd_goal_real	main_category_encode
0	0	0	31	6	59	1533.95	12
1	15	0	45	8	60	30000.00	6
2	3	0	14	3	45	45000.00	6
3	1	0	49	7	30	5000.00	10
5	224	1	20	3	35	50000.00	7

In [269]:
```
#import train test split
from sklearn.model_selection import train_test_split
#create baseline accuracy model using dummy classifiers
X = model.drop('binary_state',axis=1)
y = model['binary_state']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30
)
#determine baseline accuracy
#Dummy Classifier
from sklearn.dummy import DummyClassifier
clf = DummyClassifier(strategy= 'most_frequent').fit(X_train,y_train)
y_pred = clf.predict(X_test)
#distribution of y test
print('y actual : \n' +  str(y_test.value_counts()))
#distribution of y predicted
print('y predicted : \n' + str(pd.Series(y_pred).value_counts()))
```

```
y actual :
0    59354
1    40085
Name: binary_state, dtype: int64
y predicted :
0    99439
dtype: int64
```

In [270]:
```
#baseline model accuracy scores
from sklearn.metrics import accuracy_score,recall_score,precision_score,
f1_score, roc_auc_score, log_loss
print('Accuracy Score : ' + str(accuracy_score(y_test,y_pred)))
print('Precision Score : ' + str(precision_score(y_test,y_pred)))
print('Recall Score : ' + str(recall_score(y_test,y_pred)))
print('F1 Score : ' + str(f1_score(y_test,y_pred)))
print('ROC_AUC : ' + str(roc_auc_score(y_test,y_pred)))
print('Confusion Matrix : \n' + str(confusion_matrix(y_test,y_pred)))
```

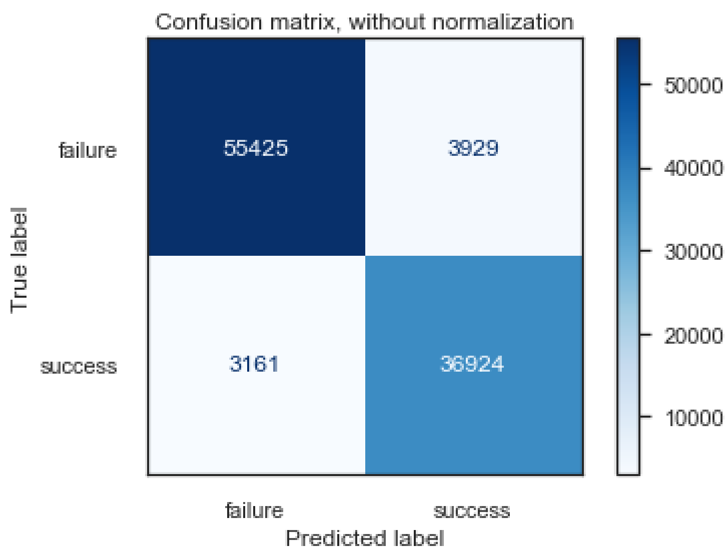
```
Accuracy Score : 0.5968885447359688
Precision Score : 0.0
Recall Score : 0.0
F1 Score : 0.0
ROC_AUC : 0.5
Confusion Matrix :
[[59354     0]
 [40085     0]]
```

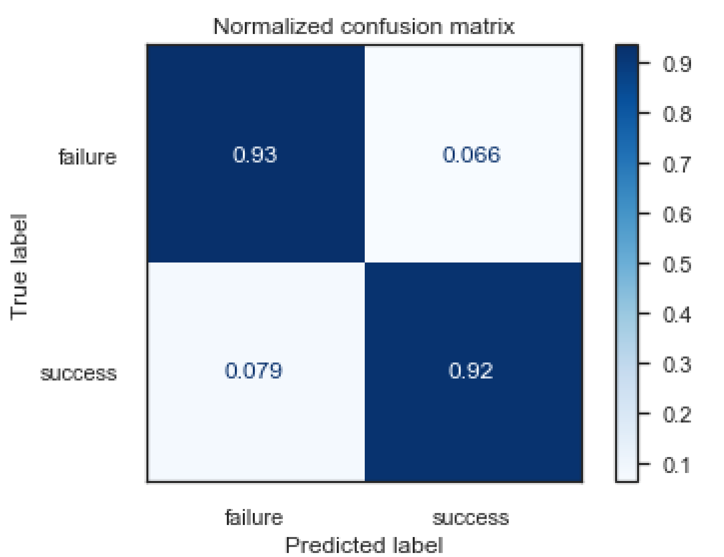
In [271]:
```
#build random forest classifier with default parameters
from sklearn.ensemble import RandomForestClassifier
rfc = RandomForestClassifier().fit(X_train,y_train)
y_pred = rfc.predict(X_test)
# metrics to evaluate model
print('Accuracy Score : ' + str(accuracy_score(y_test,y_pred)))
print('Precision Score : ' + str(precision_score(y_test,y_pred)))
print('Recall Score : ' + str(recall_score(y_test,y_pred)))
print('F1 Score : ' + str(f1_score(y_test,y_pred)))
print('ROC_AUC : ' + str(roc_auc_score(y_test,y_pred)))
print('Confusion Matrix : \n' + str(confusion_matrix(y_test,y_pred)))
```

```
Accuracy Score : 0.9287000070394915
Precision Score : 0.9038259124176927
Recall Score : 0.9211425720344268
F1 Score : 0.9124020855469619
ROC_AUC : 0.9274732639799456
Confusion Matrix :
[[55425  3929]
 [ 3161 36924]]
```

In [272]:
```
# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
class_names = ['failure','success']
for title, normalize in titles_options:
    disp = plot_confusion_matrix(rfc, X_test, y_test,
                                 display_labels=class_names,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)

plt.show()
```

```
Confusion matrix, without normalization
[[55425  3929]
 [ 3161 36924]]
Normalized confusion matrix
[[0.93380396 0.06619604]
 [0.07885743 0.92114257]]
```





In [273]:
```
#evaluate model with default parameters
n_nodes = []
max_depths = []
for ind_tree in rfc.estimators_:
    n_nodes.append(ind_tree.tree_.node_count)
    max_depths.append(ind_tree.tree_.max_depth)
print(f'Average number of nodes {int(np.mean(n_nodes))}')
print(f'Average maximum depth {int(np.mean(max_depths))}')
```

```
Average number of nodes 34681
Average maximum depth 34
```

In [274]:
```
#hyperparameter tuning using randomized search
from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
#create grid to be searched
param_grid = {
    'n_estimators': np.linspace(10, 200).astype(int),
    'max_depth': [None] + list(np.linspace(3, 20).astype(int)),
    'max_features': ['auto', 'sqrt', None] + list(np.arange(0.5, 1, 0.1
)),
    'max_leaf_nodes': [None] + list(np.linspace(10, 50, 500).astype(int
)),
    'min_samples_split': [2, 5, 10],
    'bootstrap': [True, False]
}

estimator = RandomForestClassifier(random_state = 42)
rs = RandomizedSearchCV(estimator, param_grid, n_jobs = -1,
                        scoring = 'roc_auc', cv = 5,
                        n_iter = 10, verbose = 1, random_state=42)
rs.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent work
ers.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed: 10.4min
[Parallel(n_jobs=-1)]: Done  50 out of  50 | elapsed: 13.4min finished
```

Out[274]:

```
RandomizedSearchCV(cv=5, estimator=RandomForestClassifier(random_state=
42),
                   n_jobs=-1,
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [None, 3, 3, 3, 4,
4, 4, 5,
                                                      5, 5, 6, 6, 6, 7,
7, 7, 8,
                                                      8, 8, 9, 9, 9, 1
0, 10, 10,
                                                      11, 11, 12, 12, 1
2, ...],
                                        'max_features': ['auto', 'sqr
t', None,
                                                         0.5, 0.6, 0.7,
                                                         0.799999999999
9999,
                                                         0.899999999999
9999],
                                        'max_leaf_nodes': [None, 10, 1
0, 10, 10,
                                                           10, 10, 10,
10, 10,
                                                           10, 10, 10,
10, 11,
                                                           11, 11, 11,
11, 11,
                                                           11, 11, 11,
11, 11,
                                                           11, 12, 12,
12, 12, ...],
                                        'min_samples_split': [2, 5, 1
0],
                                        'n_estimators': array([ 10,  1
3,  17,  21,  25,  29,  33,  37,  41,  44,  48,  52,  56,
        60,  64,  68,  72,  75,  79,  83,  87,  91,  95,  99, 103, 106,
       110, 114, 118, 122, 126, 130, 134, 137, 141, 145, 149, 153, 157,
       161, 165, 168, 172, 176, 180, 184, 188, 192, 196, 200])},
                   random_state=42, scoring='roc_auc', verbose=1)
```

In [276]:

```python
#what are the best params from the randomized search
print(rs.best_params_)
best_model = rs.best_estimator_
```

```
{'n_estimators': 196, 'min_samples_split': 10, 'max_leaf_nodes': 49, 'm
ax_features': 0.7, 'max_depth': 17, 'bootstrap': True}
```

In [277]:
```
#evaluate model with best parameters
n_nodes = []
max_depths = []
for ind_tree in best_model.estimators_:
    n_nodes.append(ind_tree.tree_.node_count)
    max_depths.append(ind_tree.tree_.max_depth)
print(f'Average number of nodes {int(np.mean(n_nodes))}')
print(f'Average maximum depth {int(np.mean(max_depths))}')
```

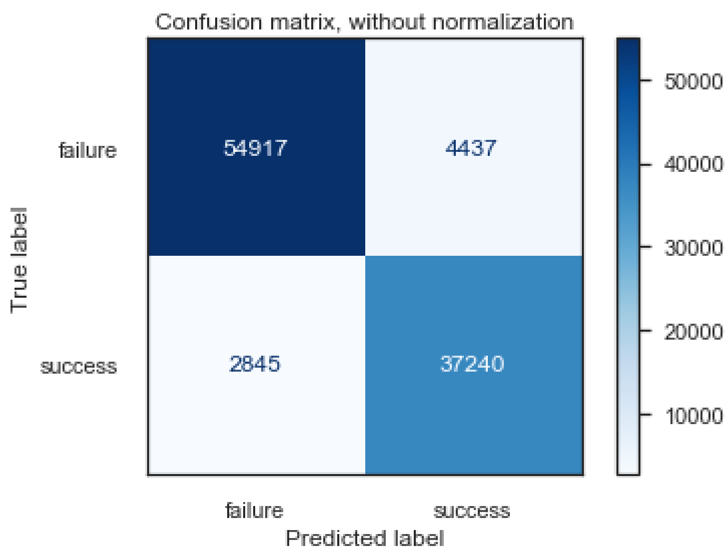
```
Average number of nodes 97
Average maximum depth 7
```

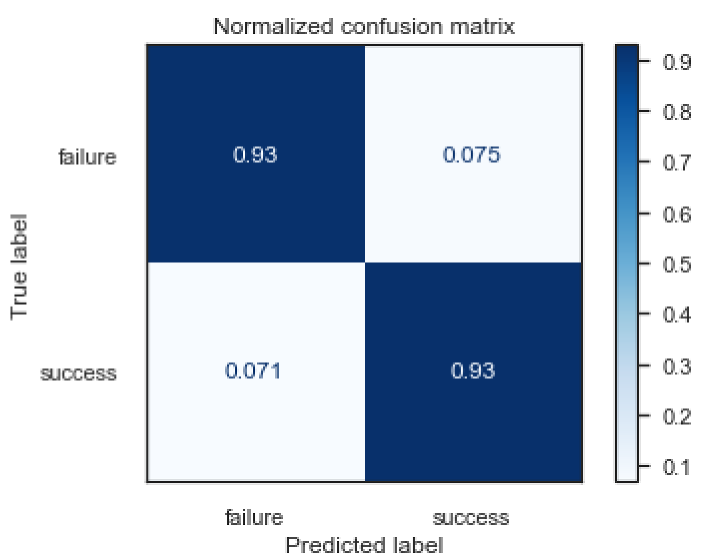
In [278]:
```
#run model with best fit parameters added
rf = RandomForestClassifier(n_estimators = 196,
 min_samples_split = 10,
 max_leaf_nodes = 49,
 max_features = 0.7,
 max_depth = 17,
 bootstrap = True).fit(X_train,y_train)
y_pred = rf.predict(X_test)
# metrics to evaluate model
print('Accuracy Score : ' + str(accuracy_score(y_test,y_pred)))
print('Precision Score : ' + str(precision_score(y_test,y_pred)))
print('Recall Score : ' + str(recall_score(y_test,y_pred)))
print('F1 Score : ' + str(f1_score(y_test,y_pred)))
print('ROC_AUC : ' + str(roc_auc_score(y_test,y_pred)))
print('Confusion Matrix : \n' + str(confusion_matrix(y_test,y_pred)))
```

```
Accuracy Score : 0.9267691750721548
Precision Score : 0.8935384024761859
Recall Score : 0.929025820132219
F1 Score : 0.9109366209241456
ROC_AUC : 0.9271354797328549
Confusion Matrix :
[[54917  4437]
 [ 2845 37240]]
```

In [279]:
```
# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
class_names = ['failure','success']
for title, normalize in titles_options:
    disp = plot_confusion_matrix(rf, X_test, y_test,
                                 display_labels=class_names,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)

plt.show()
```

```
Confusion matrix, without normalization
[[54917  4437]
 [ 2845 37240]]
Normalized confusion matrix
[[0.92524514 0.07475486]
 [0.07097418 0.92902582]]
```

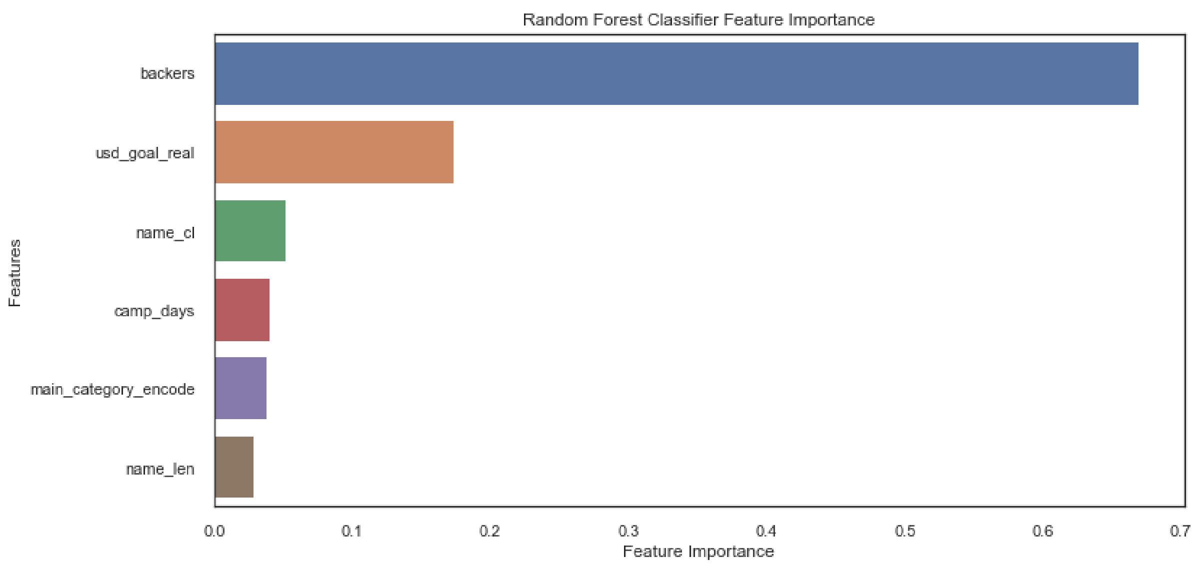




In [280]:
```
#evaluate nodes and leaves of best params to ensure that best parameters
were appropriately applied
n_nodes = []
max_depths = []
for ind_tree in rf.estimators_:
    n_nodes.append(ind_tree.tree_.node_count)
    max_depths.append(ind_tree.tree_.max_depth)
print(f'Average number of nodes {int(np.mean(n_nodes))}')
print(f'Average maximum depth {int(np.mean(max_depths))}')
```

```
Average number of nodes 97
Average maximum depth 8
```

In [281]:
```
#most important features
features = list(X.columns)
rfc_feats = pd.DataFrame({'Feature': features,
                   'Importance': rfc.feature_importances_}).\
                    sort_values('Importance', ascending = False)
fig=plt.figure(figsize=(12,6))
ax = sns.barplot(x = 'Importance', y = 'Feature', data = rfc_feats)
plt.xlabel('Feature Importance')
plt.ylabel('Features')
plt.title('Random Forest Classifier Feature Importance')
plt.show()
print('\033[1m' + "Feature Importance" + '\033[0m')
print(rfc_feats)
```



Feature Importance

	Feature	Importance
0	backers	0.668820
4	usd_goal_real	0.173350
1	name_cl	0.051161
3	camp_days	0.039767
5	main_category_encode	0.038042
2	name_len	0.028859

Logistic Regression

In [287]:
```
#train test split data
#create baseline accuracy model using dummy classifiers
A = model.drop('binary_state',axis=1)
b = model['binary_state']
A_train, A_test, b_train, b_test = train_test_split(A, b, test_size=0.30
)
#determine baseline accuracy
clf = DummyClassifier(strategy= 'most_frequent').fit(A_train,b_train)
b_pred = clf.predict(A_test)
#Distribution of y test
print('y actual : \n' +  str(b_test.value_counts()))
#Distribution of y predicted
print('y predicted : \n' + str(pd.Series(b_pred).value_counts()))
```

```
y actual :
0    59330
1    40109
Name: binary_state, dtype: int64
y predicted :
0    99439
dtype: int64
```

In [288]:
```
#baseline model accuracy scores
print('Accuracy Score : ' + str(accuracy_score(b_test,b_pred)))
print('Precision Score : ' + str(precision_score(b_test,b_pred)))
print('Recall Score : ' + str(recall_score(b_test,b_pred)))
print('F1 Score : ' + str(f1_score(b_test,b_pred)))
print('ROC_AUC : ' + str(roc_auc_score(b_test,b_pred)))
print('Confusion Matrix : \n' + str(confusion_matrix(b_test,b_pred)))
```

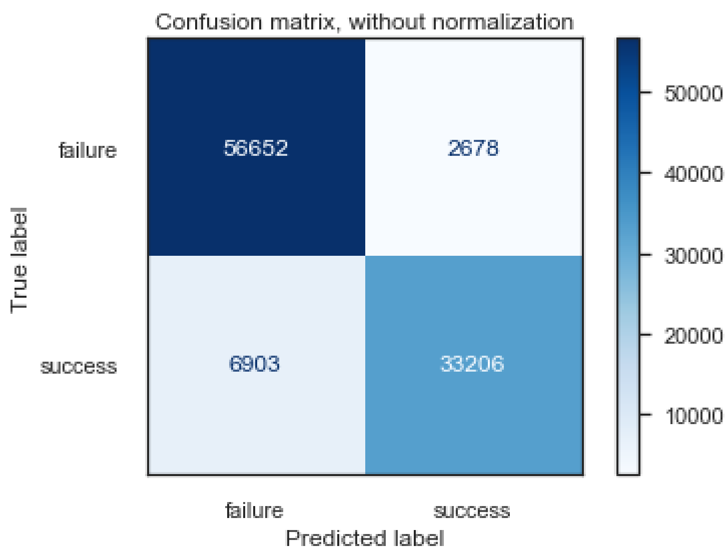
```
Accuracy Score : 0.5966471907400517
Precision Score : 0.0
Recall Score : 0.0
F1 Score : 0.0
ROC_AUC : 0.5
Confusion Matrix :
[[59330     0]
 [40109     0]]
```

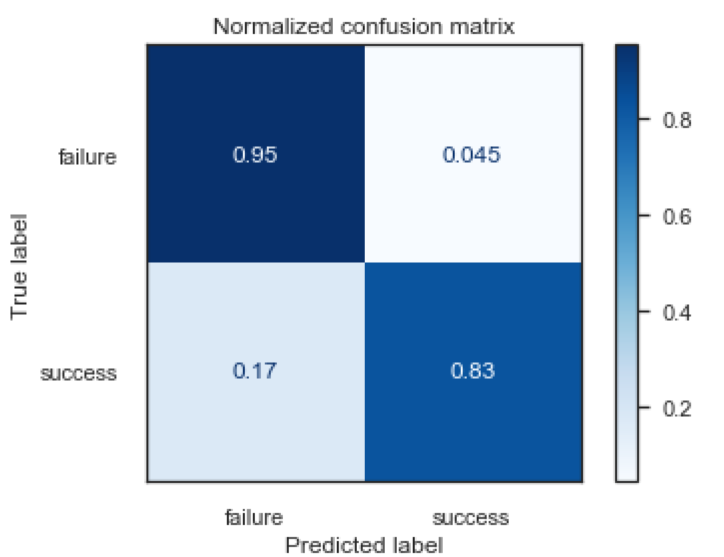
In [289]:
```
#logistic regression with default parameters
from sklearn.linear_model import LogisticRegression
clf = LogisticRegression().fit(A_train,b_train)
b_pred = clf.predict(A_test)
# metrics to evaluate model
scoring = 'neg_log_loss'
print('Accuracy Score : ' + str(accuracy_score(b_test,b_pred)))
print('Precision Score : ' + str(precision_score(b_test,b_pred)))
print('Recall Score : ' + str(recall_score(b_test,b_pred)))
print('F1 Score : ' + str(f1_score(y_test,b_pred)))
print('ROC_AUC : ' + str(roc_auc_score(b_test,b_pred)))
print('Confusion Matrix : \n' + str(confusion_matrix(b_test,b_pred)))
```

```
Accuracy Score : 0.9036494735465964
Precision Score : 0.9253706387247799
Recall Score : 0.8278939888803012
F1 Score : 0.3825771038186629
ROC_AUC : 0.8913783108062385
Confusion Matrix :
[[56652  2678]
 [ 6903 33206]]
```

In [290]:
```
# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
class_names = ['failure','success']
for title, normalize in titles_options:
    disp = plot_confusion_matrix(clf, A_test, b_test,
                                 display_labels=class_names,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)

plt.show()
```

```
Confusion matrix, without normalization
[[56652  2678]
 [ 6903 33206]]
Normalized confusion matrix
[[0.95486263 0.04513737]
 [0.17210601 0.82789399]]
```





In [292]:

```
logistic = LogisticRegression()
# Create regularization penalty space
penalty = ['l1', 'l2']

# Create regularization hyperparameter space
C = np.logspace(0, 4, 10)

# Create hyperparameter options
hyperparameters = dict(C=C, penalty=penalty)
# Create grid search using 5-fold cross validation
clf_ = GridSearchCV(logistic, hyperparameters, cv=5, verbose=0)
# Fit grid search
best_model_ = clf_.fit(A_train, b_train)
# View best hyperparameters
print('Best Penalty:', best_model_.best_estimator_.get_params()['penalt
y'])
print('Best C:', best_model_.best_estimator_.get_params()['C'])
```

```
Best Penalty: l2
Best C: 21.544346900318832
```

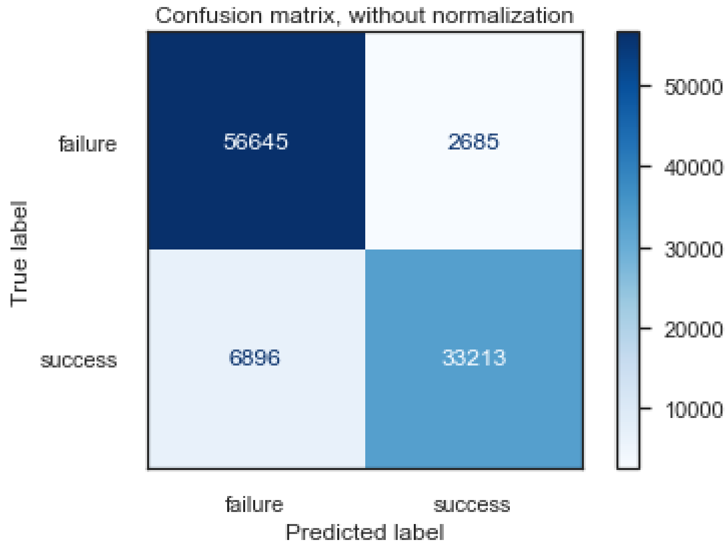
In [293]:

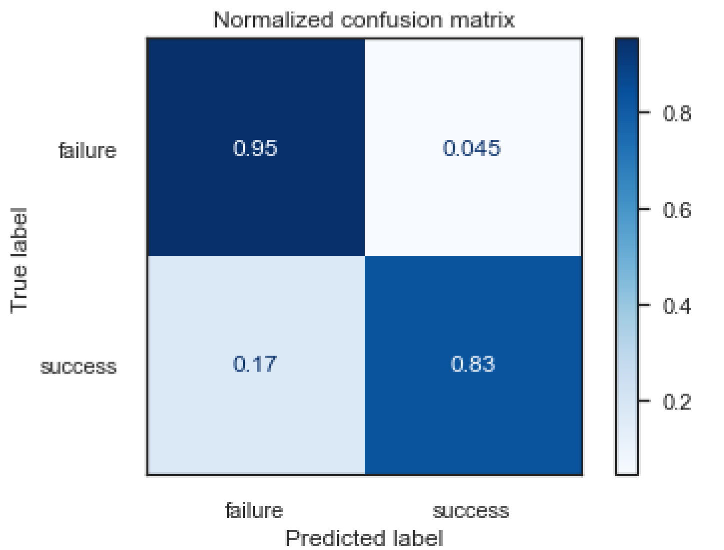
```
#logistic regression with optimized parameters
from sklearn.linear_model import LogisticRegression
_clf = LogisticRegression(C=21.544346900318832, penalty='l2').fit(A_trai
n,b_train)
b_pred_ = clf_.predict(A_test)
# metrics to evaluate model
scoring = 'neg_log_loss'
print('Accuracy Score : ' + str(accuracy_score(b_test,b_pred_)))
print('Precision Score : ' + str(precision_score(b_test,b_pred_)))
print('Recall Score : ' + str(recall_score(b_test,b_pred_)))
print('F1 Score : ' + str(f1_score(y_test,b_pred_)))
print('ROC_AUC : ' + str(roc_auc_score(b_test,b_pred_)))
print('Confusion Matrix : \n' + str(confusion_matrix(b_test,b_pred_)))
```

```
Accuracy Score : 0.9036494735465964
Precision Score : 0.9252047467825506
Recall Score : 0.8280685133012541
F1 Score : 0.3825855783530526
ROC_AUC : 0.8914065809385083
Confusion Matrix :
[[56645  2685]
 [ 6896 33213]]
```

In [294]:
```
# Plot non-normalized confusion matrix
titles_options = [("Confusion matrix, without normalization", None),
                  ("Normalized confusion matrix", 'true')]
class_names = ['failure','success']
for title, normalize in titles_options:
    disp = plot_confusion_matrix(_clf, A_test, b_test,
                                 display_labels=class_names,
                                 cmap=plt.cm.Blues,
                                 normalize=normalize)
    disp.ax_.set_title(title)

    print(title)
    print(disp.confusion_matrix)

plt.show()
```

```
Confusion matrix, without normalization
[[56645  2685]
 [ 6896 33213]]
Normalized confusion matrix
[[0.95474465 0.04525535]
 [0.17193149 0.82806851]]
```

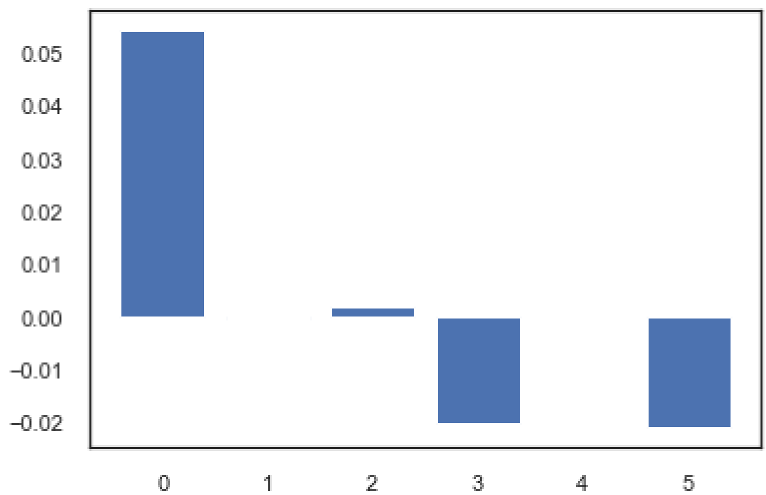




In [298]:
```
# logistic regression for feature importance
from sklearn.datasets import make_classification
from matplotlib import pyplot
importance = _clf.coef_[0]
# summarize feature importance
for i,v in enumerate(importance):
        print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance

pyplot.bar([x for x in range(len(importance))], importance)
```

```
Feature: 0, Score: 0.05413
Feature: 1, Score: -0.00030
Feature: 2, Score: 0.00182
Feature: 3, Score: -0.02009
Feature: 4, Score: -0.00023
Feature: 5, Score: -0.02089
```

Out[298]: <BarContainer object of 6 artists>



In [ ]:

Capstone 1: Predicting Kickstarter Success

The Problem: Kickstarter is a funding platform for creative projects. When creative groups, companies, or individuals have an idea, a clear plan and a final funding goal, they can submit their projects to the Kickstarter platform in order to garner public support and funding. The Kickstarter platform provides a space where campaigns can both ask for funding donations, and provide incentives and rewards to those who pledge funds to the project.

The Kickstarter platform is funded by fees collected from each donation, and from the overall funding amount when a campaign is successful. Kickstarter applies a 5% fee to any successful campaigns, and collects a 3-5% payment processing fee per donation, depending on the donation amount. If a campaign is not successful and does not reach their funding goal, Kickstarter does not collect the standard 5% fee. Therefore, in order for Kickstarter to continue their success, and increase their profits, they must host successful campaigns that reach or exceed their funding goal. Currently, successful Kickstarter campaigns are estimated at 35% of total campaigns, while failed campaigns are closer to 52%.

The Client: The ability to predict a successful Kickstarter campaign will be of great benefit to both Kickstarter as a company, and to companies and creators who launch campaigns on their website. Kickstarter has an inherent interest in running successful campaigns because of their fee structure, and their overall profits as a company. Additionally, competition from other crowdfunding platforms are gaining popularity and Kickstarter will need to remain competitive in offering services and exposure to clients that will lead to successful campaign outcomes.

The Approach: An analysis of successful Kickstarter campaigns will address metrics for campaigns that reach and exceed their funding goals. This includes the category of campaign, rewards/incentives offered, funding goal, funding time frame, and campaign description. Companies and creators who are launching campaigns also have an inherent interest in understanding the factors that create a successful campaign. Having a campaign or project reach or exceed funding status could alter the trajectory of a product or idea. Alternatively, campaigns and projects that end up failing to meet their funding goals could end up on life support.

By analyzing trends in successful campaigns, Kickstarter will be able to determine which campaigns are more likely to reach or exceed funded status. Armed with this data insight, Kickstarter will be able to make data driven, impactful decisions in regards to:

- Services offered to clients
- Fees that are collected from clients and from contributors,
- Campaign guidelines and recommendations

Data Wrangling

Overview:

The dataset that was used for analysis was provided in one .csv file, obtained from [Kaggle]. At first glance, the data is fairly clean containing 15 columns with 378,661 rows of data. Each Kickstarter campaign is represented by one row of data including the campaign name, the main category that the campaign falls under, the currency type that pledges are converted to, the campaign deadline, funding goal, the state of the campaign, how many backers supported the campaign, what country the campaign originated from, and then two columns that are conversions of the pledged amount column converted to USD.

Duplicate Data: I began the cleaning process by determining whether any data was duplicated. Each Kickstarter campaign is assigned a campaign ID, and I proceeded to work on deduplication based off of this column. In order to check for duplicate rows, I created a new data frame that would contain any potential duplicates. I created this data frame using df.duplicated() and then printing the shape of the new data frame. There were no duplicate rows that needed to be removed in the original data frame.

Null Values: Next, I determined whether there were any null values that needed to be addressed. To get a broad overview of all of the column names, I printed the column values, and examined whether there were any null values in each column. There were 4 null values in the **name** column, and 3797 null values in the **usd_pledged** column. The 4 null names are for campaigns that were cancelled or potentially created in error without a campaign name.

Column Adjustments:
Upon further inspection and research, the **usd_pledged** column and **usd_pledged_real** column are similar in that their existence had a common goal. The two columns were meant to convert the pledged entirely to USD, as some campaign pledges were in other countries' currency. The first column, **usd_pledged**, was created by Kickstarter, and looks as though it did not completely convert all pledges successfully. Alternatively, the **usd_pledged_real** column contains all correctly converted values. Because of this, I decided to remove the usd pledged column from the data frame, and create a new data frame called **clean_df,** using df.drop on the usd pledged column. To double check that everything went correctly, the column names and data frame shape are reprinted confirming that **usd_pledged** has been removed.
The campaign state column was examined to look at the total campaigns for each campaign state. There are 6 different campaign state categories: successful, failed, live, suspended, cancelled and undefined. We cannot possibly determine the campaign state of live, undefined, suspended, or canceled campaigns. Rows containing these campaign states are removed from the analysis.
For future statistical analysis, a new column - binary_state - is created that includes failure: 0, success: 1. Campaign outcomes are defined as a campaign that reaches its campaign duration and either met or exceeds its campaign goal amount, or failed to meet its campaign goal amount.

Outliers: Due to the nature of this dataset, it can be expected that some columns will contain outliers. For example, ambitious campaigns who set a very high campaign goal or campaigns that exceeded expectations and raised thousands of dollars more than expected. Most columns in the Kickstarter data set are objects, and would not have an outlier associated with them because they are categorical. In order to identify outliers in the appropriate columns (goal, pledged, usd_pledged_real, usd_goal_real) the datatypes are re-examined in order to remove the object columns. After object columns are removed there are only 6 columns left. From these 6 columns, a zscore over 3 is calculated, and any outliers identified are rejected. After the outliers are rejected, the data frame is left with 375,784 rows in comparison to the original 378,661. This will be helpful to take into account when statistical analysis is completed. It is important to identify outliers in order to account for possible statistical errors in the future. Outliers can skew statistical measures such as means and medians, and will need to be further considered when designing the predictive model. For data exploration purposes, the outliers continue to remain in the dataset at this time.

Data Storytelling & Statistics

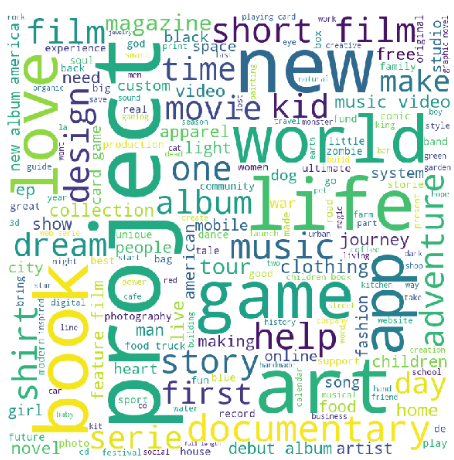
Campaign Names

Exploring the names of campaigns and whether they had any impact on the success or failure of a campaign was something I found very interesting. In order to analyze campaign names, I created three word clouds to get a visual understanding of what words were coming up in failed and successful campaigns.

All Campaigns:

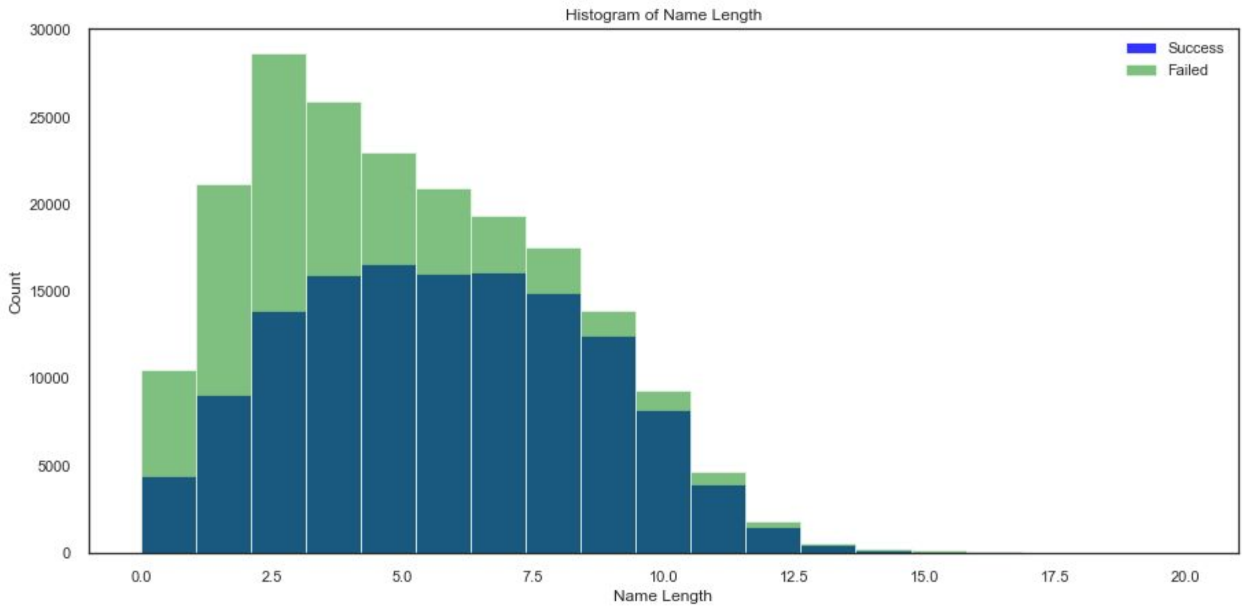
Successful Campaigns:

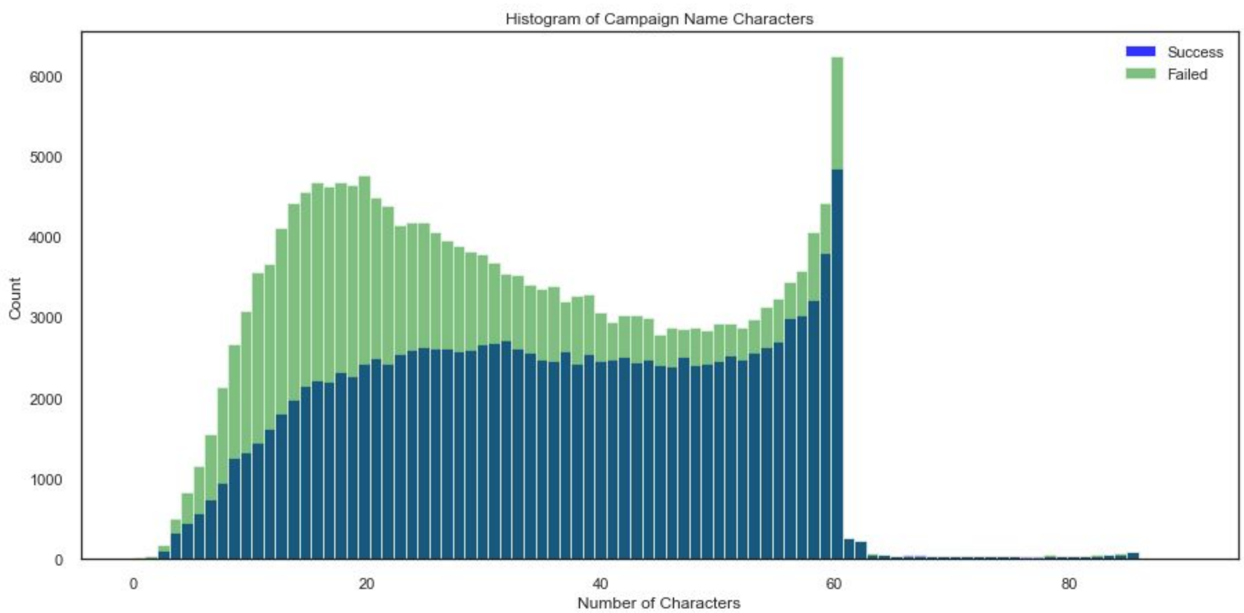
Failed Campaigns:



As you can see from the word clouds, many campaigns share similar words regardless of their success or failure. To dig into this a bit deeper I created two new columns: one for the number of characters in a campaign name (name_cl) and one for the number of words in a campaign name (name_len).

When plotted in a histogram, it appears as though campaign names with more characters are more likely to fail than campaigns with less characters in their name. Similarly, campaign names that have less words in them are more likely to succeed than campaigns with more words in them. Even though the campaign name itself doesn't seem to have an impact on success or failure, the number of characters and the number of words in a campaign name seems it may have an effect on the campaign outcome.

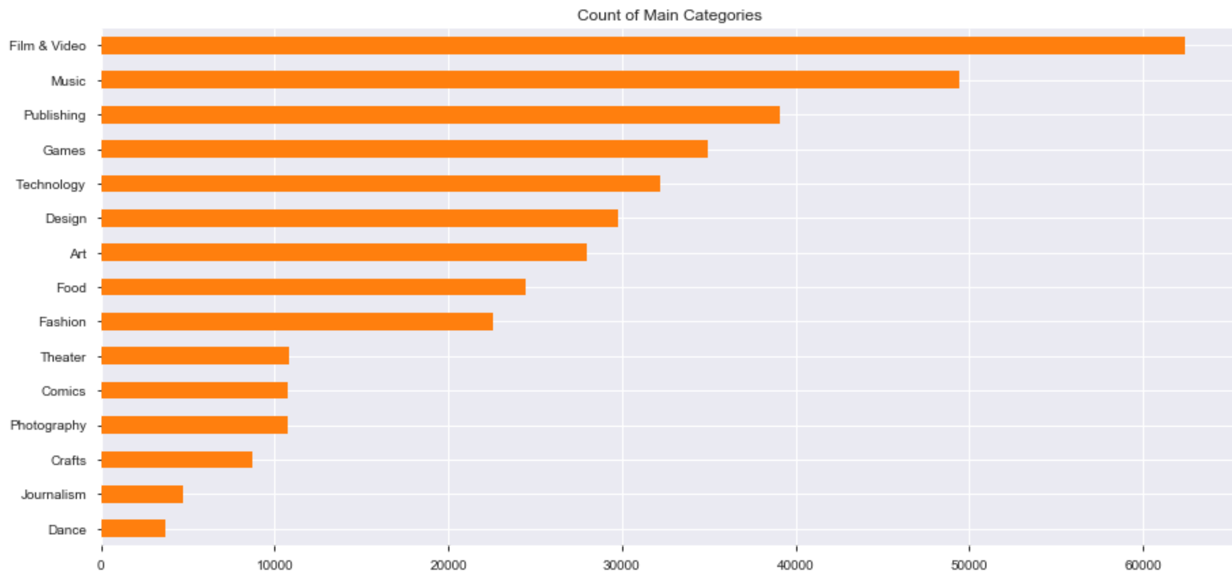




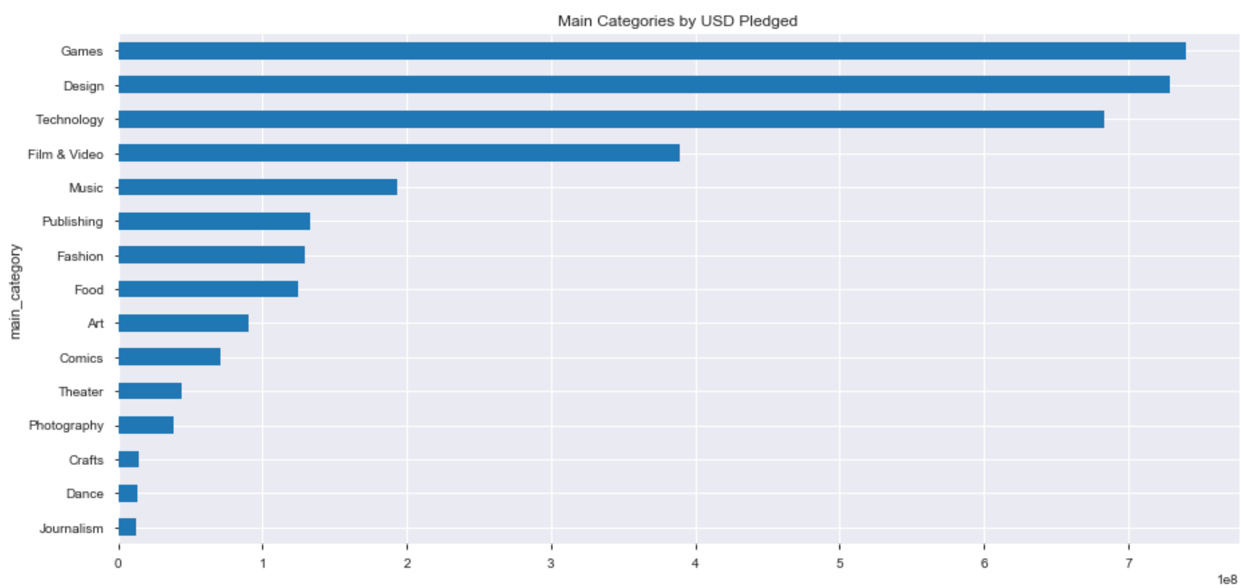
To test whether the length of the campaign name or the number of characters in a campaign name had an impact on the campaign outcome, I first tested the normality of the distributions using the Shapiro-Wilks test. I followed the normality test with the Kruskal-Wallis H-Test to determine whether the medians of the two groups were different. The Kruskal-Wallis test determined that the population medians were unequal. A bootstrap analysis was completed to compare the means of the two groups and found that there was a statistically significant difference. My analysis for both the number of characters in a campaign name and the length of the campaign name were very similar, finding that there was a statistically significant difference between the two outcome groups.

Campaign Categories

It's important to begin this analysis by looking at any potential relationships between the campaign category and it's rate of success. Are there campaign categories that are simply more popular than others? Or are there categories that are overflowing with campaigns, not all of which are worth investing into? This chart represents a count of Kickstarter campaigns by category:

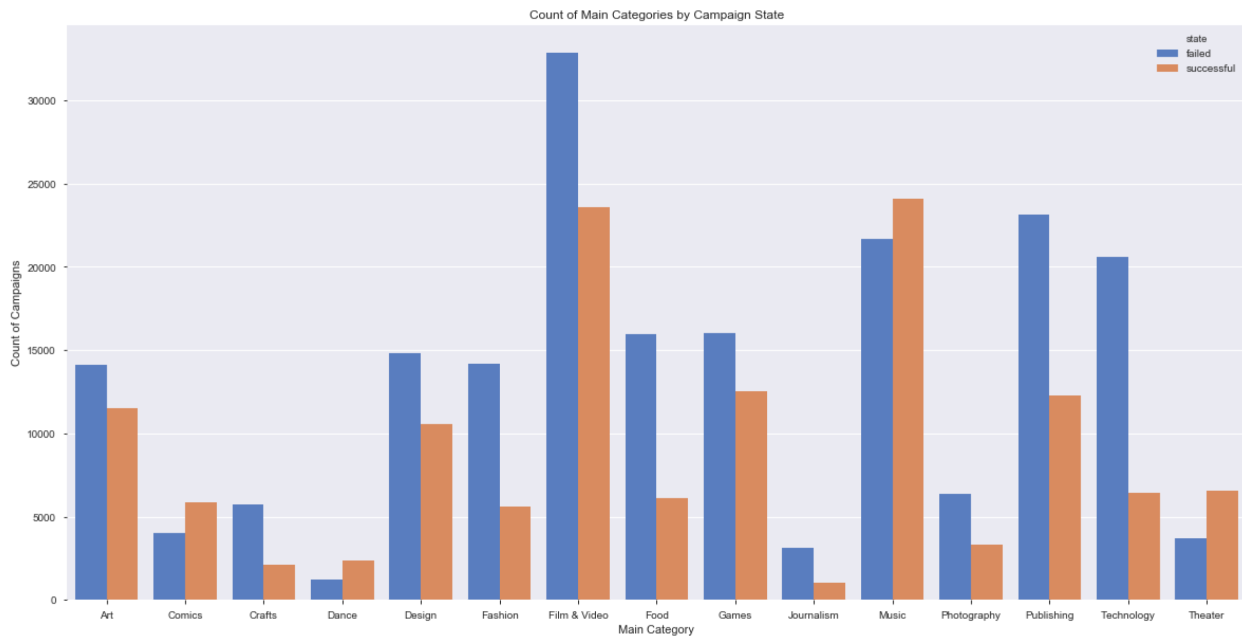


Next, I want to look at the campaigns based off of the total sum of usd_pledged_real per campaign category. When this is applied, we get the following:

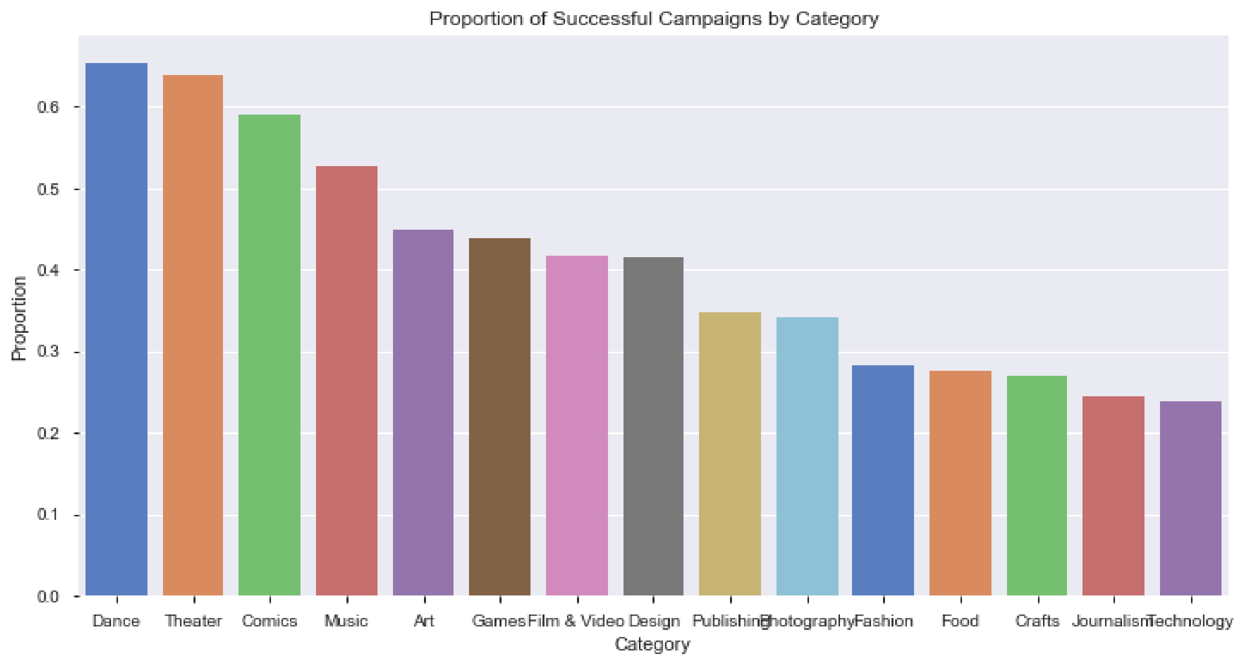


Interestingly, the main categories based on the sum of pledged USD does not line up with which campaign categories produce the most campaigns. Although games are the 4th ranked main category in terms of number of campaigns, it far outpaces Film & Video. Campaigns with the main category games brought in $739,853,563 in pledges alone from 34,943 campaigns. For Kickstarter, this accounts to a $678,832,833 profit from the successful Game campaigns, not accounting for additional fees collected at the time of each pledge - that's a lot of money!

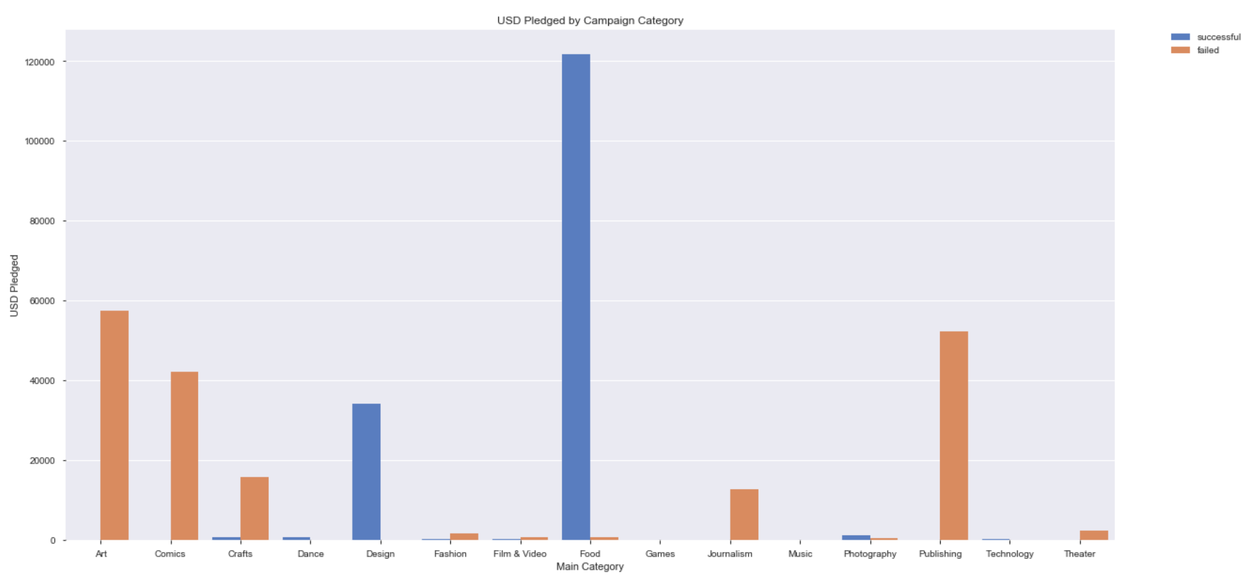
From here, I broke down each category by campaign outcome to begin to look at the success rate within a campaign category. This chart is based off of the count of each campaign state within each campaign category:



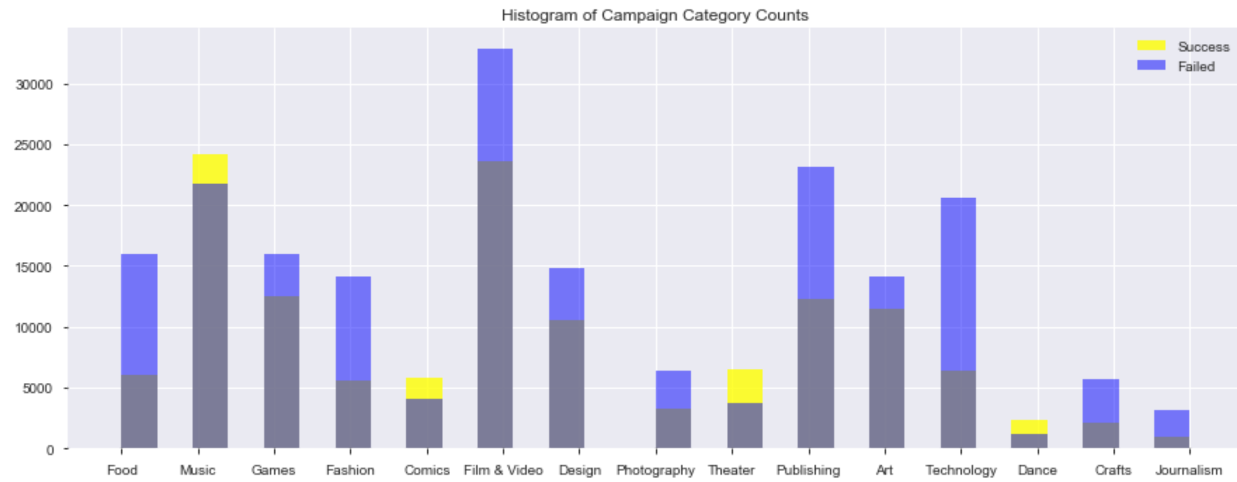
What proportion of these categories were successful? Proportion of success was determined for each main category and displayed in the chart below. Dance has the highest proportionality of success, while technology has the lowest proportionality of success. Based on what we know about the campaign categories, Dance has a total of 3,749 campaigns, pulling in a total of $112,997,480 across all campaign states. Technology has a total of 32,189 campaigns, pulling in a total of $683,918,915 across campaign states. This graphic is helpful in showing the proportionality of campaign success, but it should also be noted that some campaign categories have many more campaigns than others, leading to a higher chance of failure.



Next, I broke this down further by looking at the total sum of usd_pledged_real by the campaign state, per campaign category:



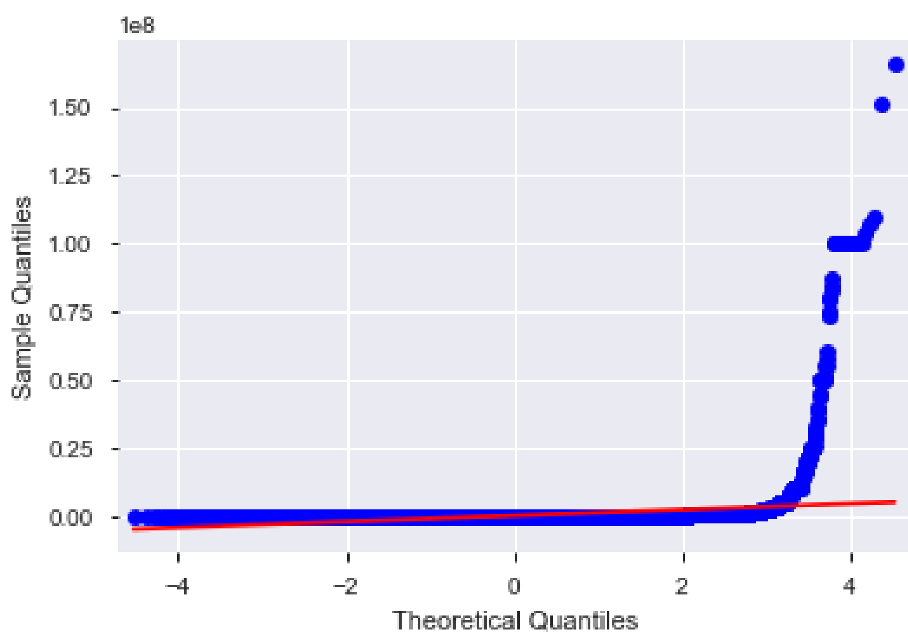
Because this is categorical data, I created a cross tab and histogram to visualize any relationship between campaign category and campaign outcome:

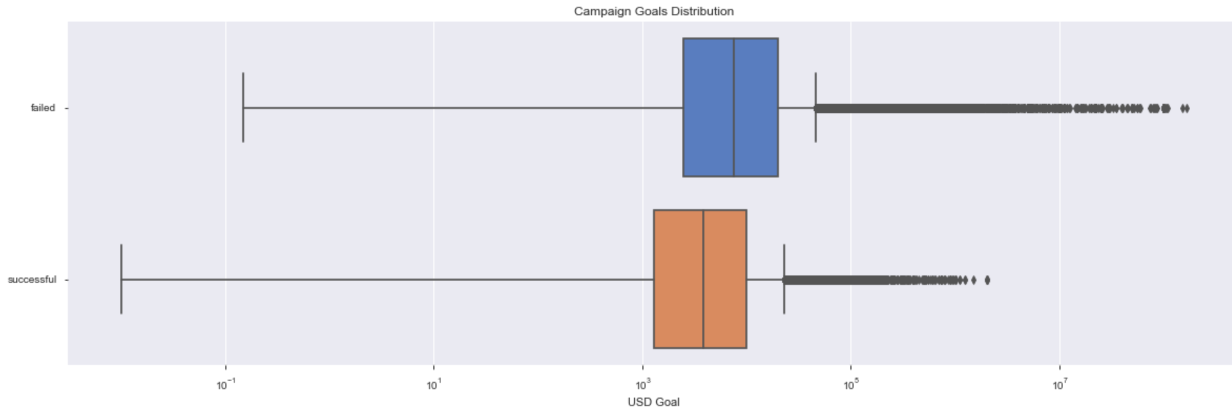


Campaign Goals

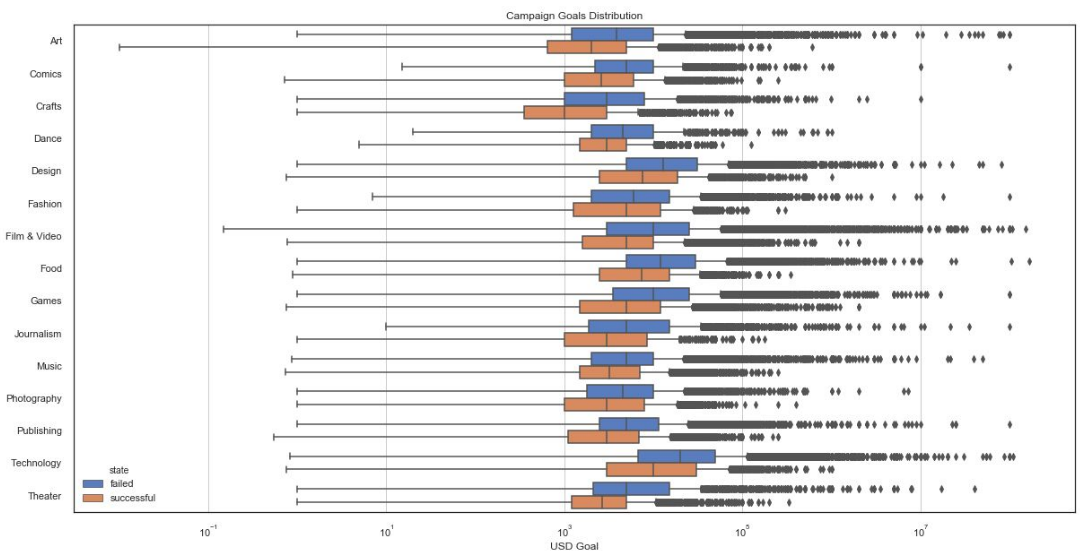
Kickstarter campaigns seek funding that ranges anywhere from $0 to $ 100,000,000, however the average campaign goal is $49300. With conversions for different currencies already taken into account, total pledges for campaigns range anywhere from $0 to a high of $20,338,986. On average, campaigns end up raising $9148 total funding regardless of their eventual success or failure.

In order to test the hypothesis, I first had to check whether or not the campaign goal data follows a normal distribution. I used three different tests to determine the normality of the distribution: Shapiro-Wilkes Test, qqplot, and a box-whisker plot. The Shapiro-Wilkes test loses p value reliability when there are over 5k data points, so the additional visualizations are helpful to validate the Shapiro-Wilkes finding of non-gaussian:





Not only does this distribution appear to be abnormal, it looks as though the campaign goal alone would not determine a campaign outcome. However, for some campaign categories, this may not be the case:



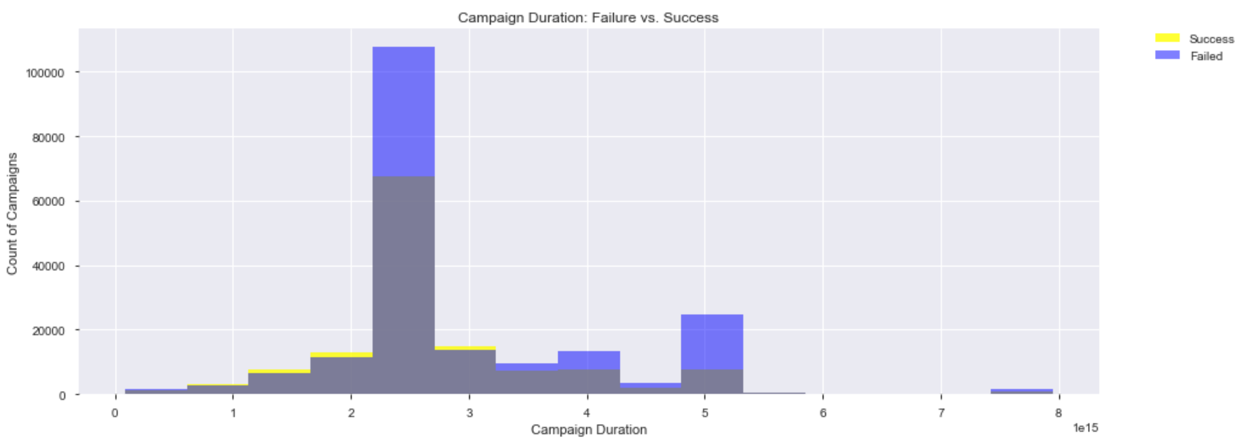
Campaign Duration

Research Question: Is there a statistically significant relationship between the duration of a campaign and campaign outcome?
Hypothesis: There is no statistically significant relationship between the duration of a campaign and the campaign outcome.

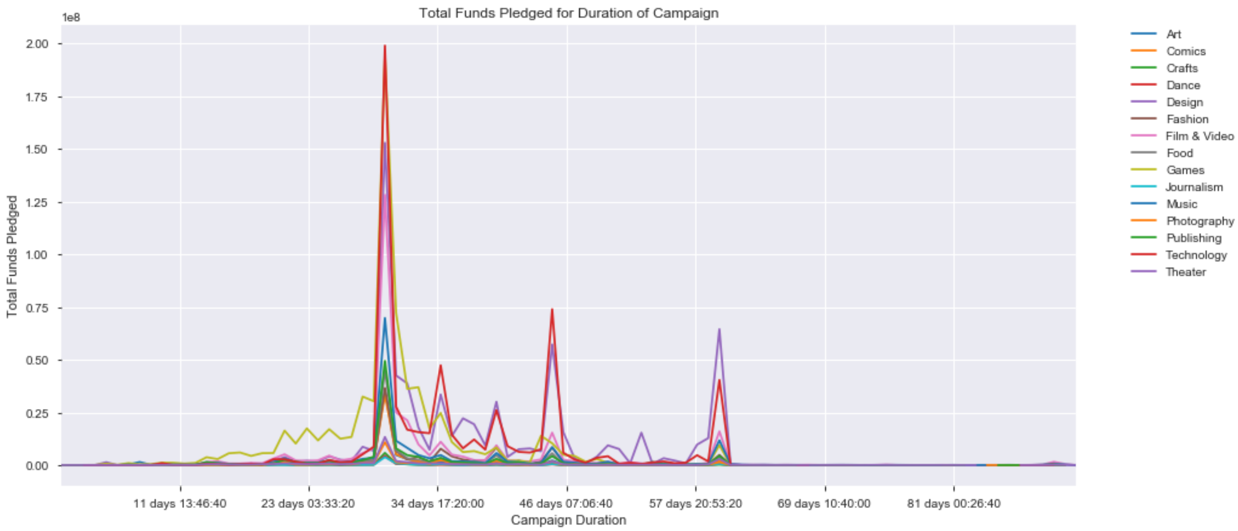
After exploring the campaign data, it is important to add a column that shows the duration of a campaign to contextualize how much time it has taken for successful campaigns to reach or surpass their funding goal, or for determining the average length of time of a failed campaign. In order to create a campaign duration column, both the launched and deadline columns are converted to datetime. From there, the campaign_duration and camp_days columns are created and added to clean_df by calculating the difference between launched and deadline. Exploration of this new column shows that the minimum campaign duration is 1 day, while the longest campaign duration was 16739 days (cancelled or suspended campaign). Successful campaigns typically run for an average length of time of 32 days, while failed campaigns typically run for an average length of 35 days.

According to Kickstarter.com: “Projects on Kickstarter can last anywhere from 1 - 60 days. We've done some research, and found that projects lasting any longer are rarely successful. We recommend setting your campaign at 30 days or less. Campaigns with shorter durations have higher success rates, and create a helpful sense of urgency around your project.” We do have some outliers in both the failed data frame and successful data frame (duration of 92 days). These outliers could be potentially explained by previous Kickstarter policy.

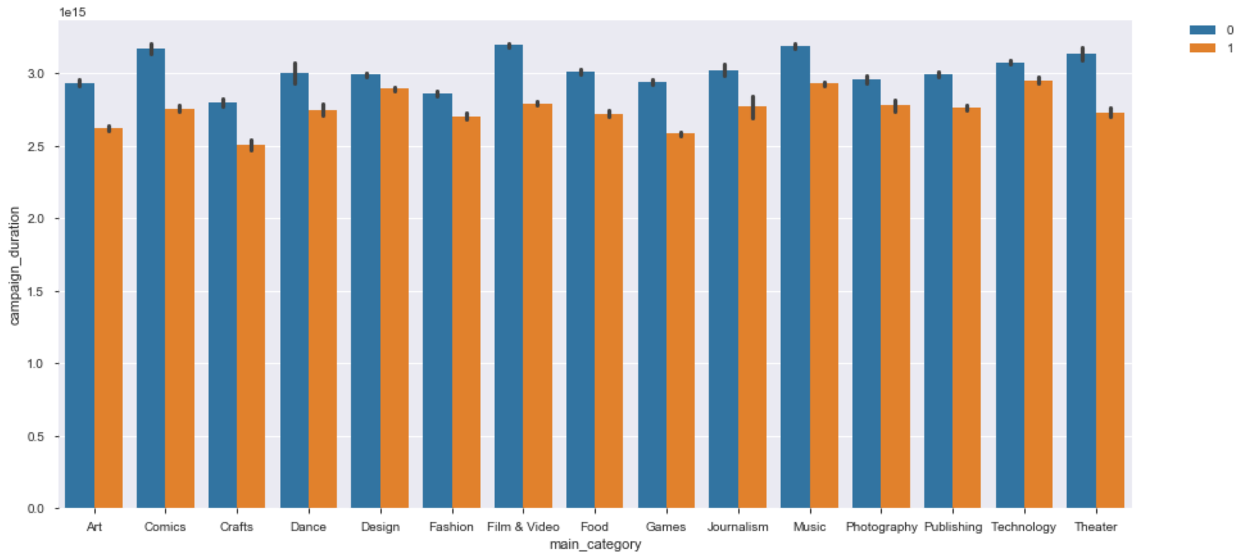
Around the 30 day mark on this chart, we see the highest number of campaigns in their successful or failed state. This supports the analysis that the majority of campaigns end around the 30 day mark, and that more campaigns are failing around this campaign duration than succeeding. Here we see the count of campaign success and failure by campaign duration:



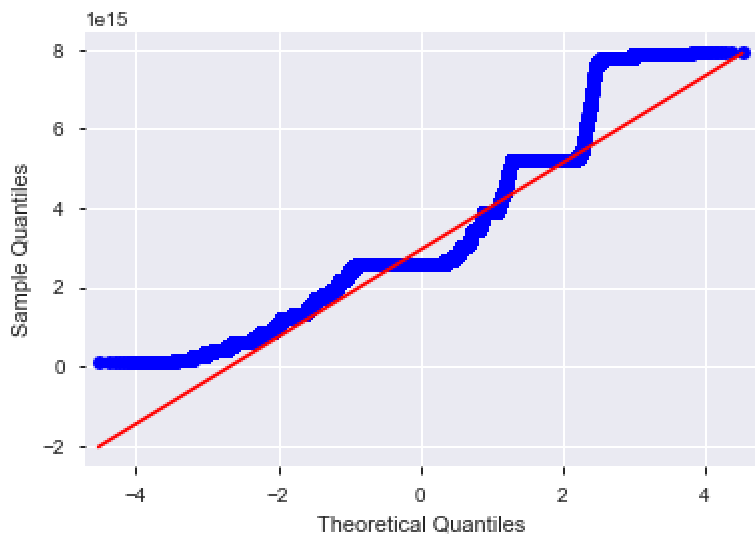
Does the duration have any correlation with USD pledged? Following the same patterns as our previous duration analysis, the campaigns with the highest USD pledged by category occur around the 30 day mark of a campaign:

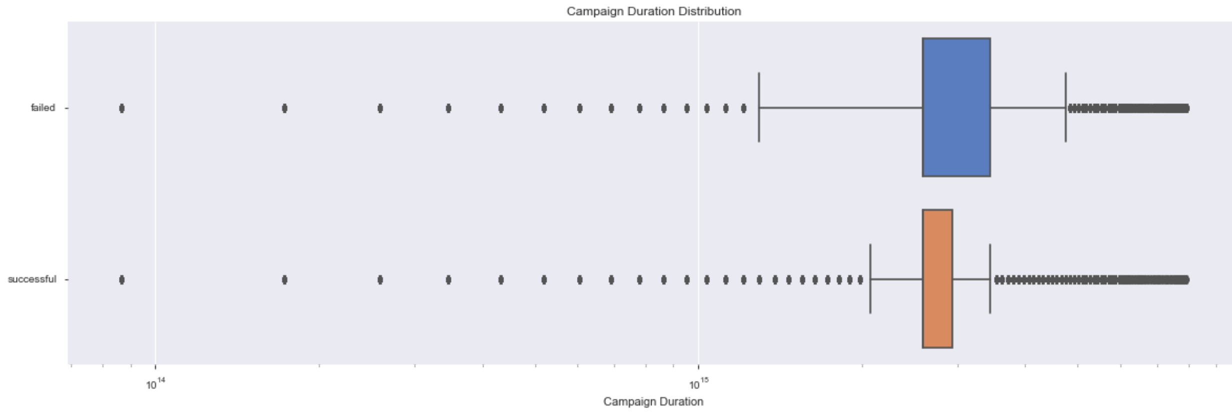


Total Funds Pledged for Duration of Campaign
1e8
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Total Funds Pledged
11 days 13:46:40
23 days 03:33:20
34 days 17:20:00
46 days 07:06:40
57 days 20:53:20
69 days 10:40:00
81 days 00:26:40
Campaign Duration
Art
Comics
Crafts
Dance
Design
Fashion
Film & Video
Food
Games
Journalism
Music
Photography
Publishing
Technology
Theater



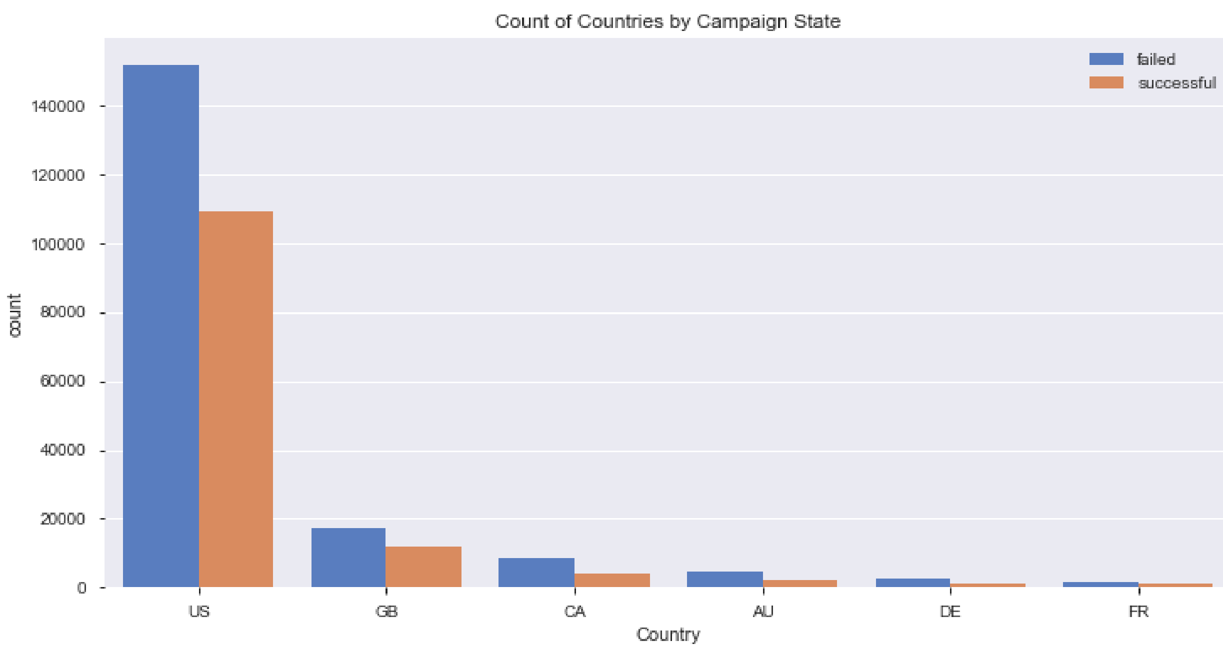
To test null hypothesis, I conducted the Shapiro-Wilkes test, qqplot and box-whisker plot to test the normality of the distribution of campaign durations:



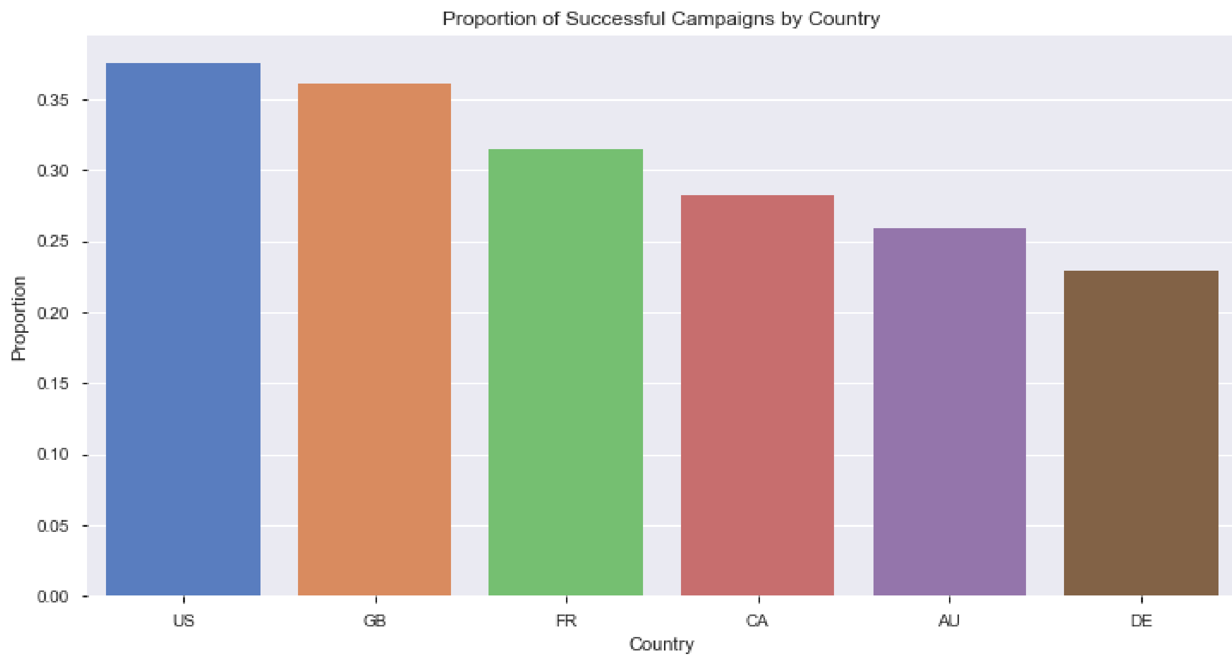


Campaign Country

Kickstarter was launched in the United States and is head-quartered in Brooklyn, NY. It seems unsurprising that campaigns in the US are more successful than campaigns outside of the US, by exposure alone. The US far exceeds any other country with their overall count of campaigns:



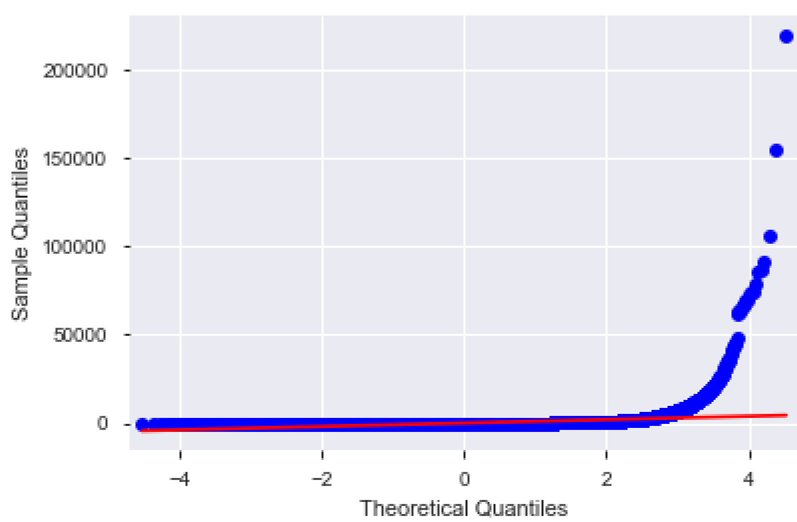
While the US has 109,299 successful campaigns, they have 152061 failures accounting for a 0.375744% success rate. Great Britain - while far behind in campaign volume - has 12067 successful campaigns and 17387 failed campaigns, accounting for a 0.361363% success rate. These two success rates are very similar to one another:

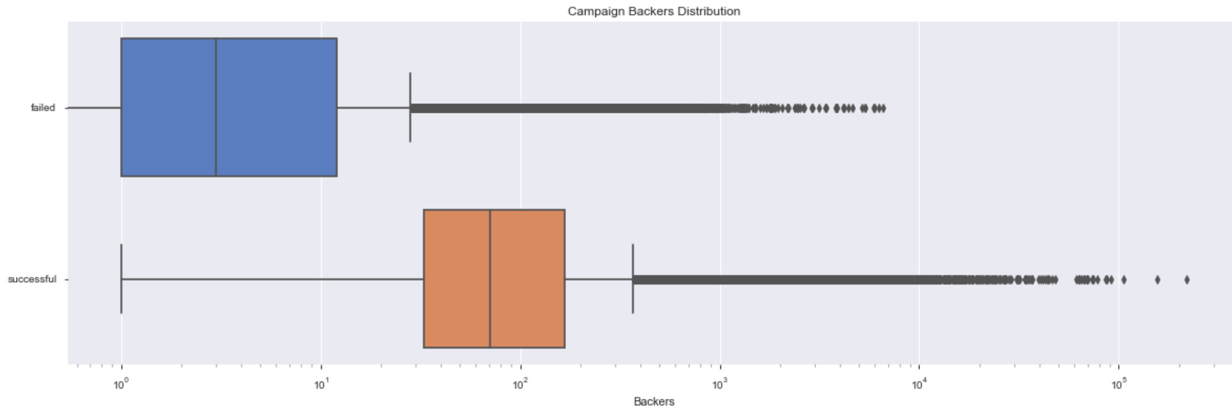


Campaign Backers

Research Question: Is there a statistically significant relationship between the number of backers per campaign and campaign outcome?
Hypothesis: There is no statistically significant relationship between the number of backers per campaign and campaign outcome.

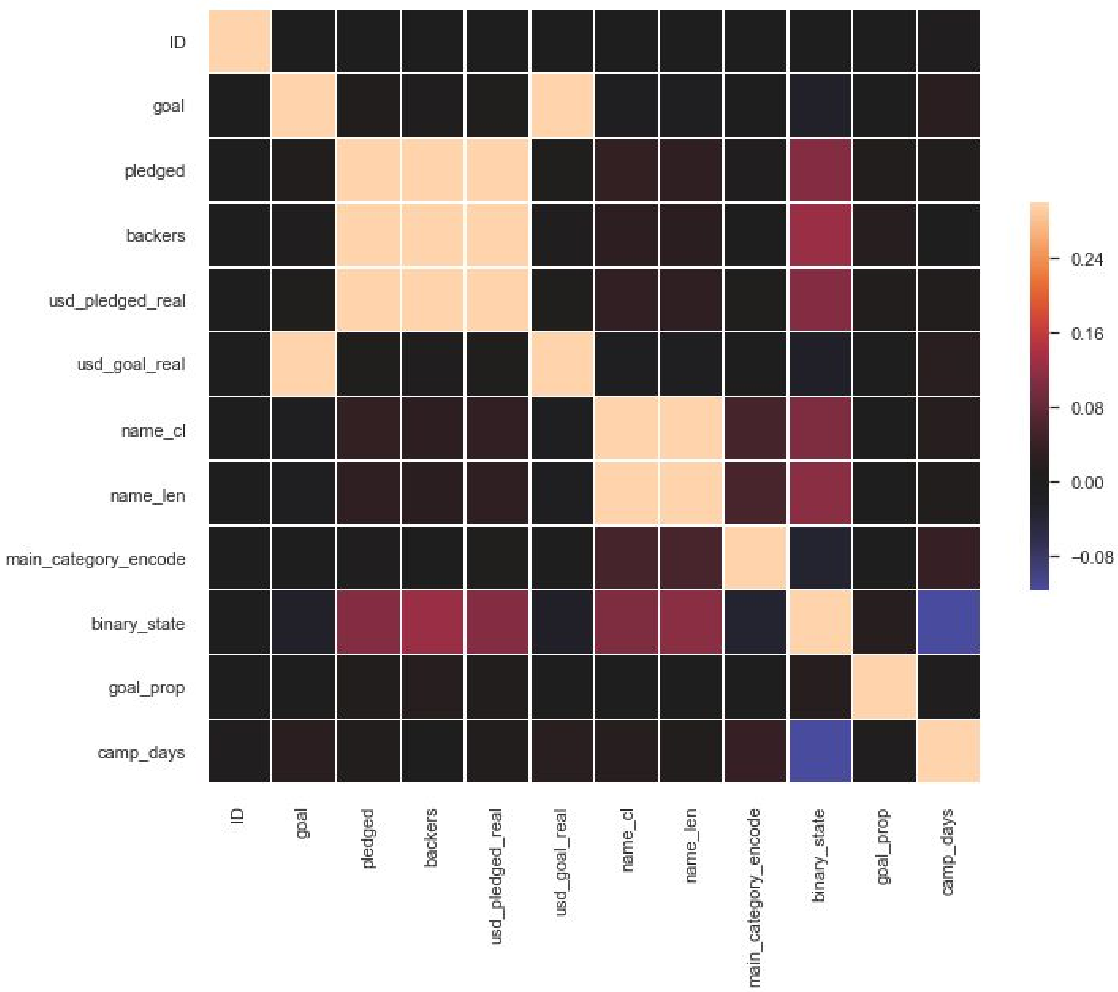
All campaigns have an average of 106 backers per campaign. Successful campaigns have an average of 263 backers per campaign. Failed campaigns have an average of 16 backers per campaign.





Correlations Matrix

A correlation matrix was created to provide an overview of possible relationships between variables from the Kickstarter dataset:



Observations from Data Storytelling and Statistics

From visualizing the dataset and exploring the relationships between features and campaign outcomes, there are several observations that I feel are worth exploring further in the machine learning models.
A challenge with this data set is that all feature distributions appear to be abnormal in some way. Using inferential statistics I examined features separated by the campaign outcomes. In doing so, I believe that features such as campaign_category, usd_pledged_real, campaign_duration, and backers will be particularly important to test in creating a classification model.

Modeling

Data Preparation

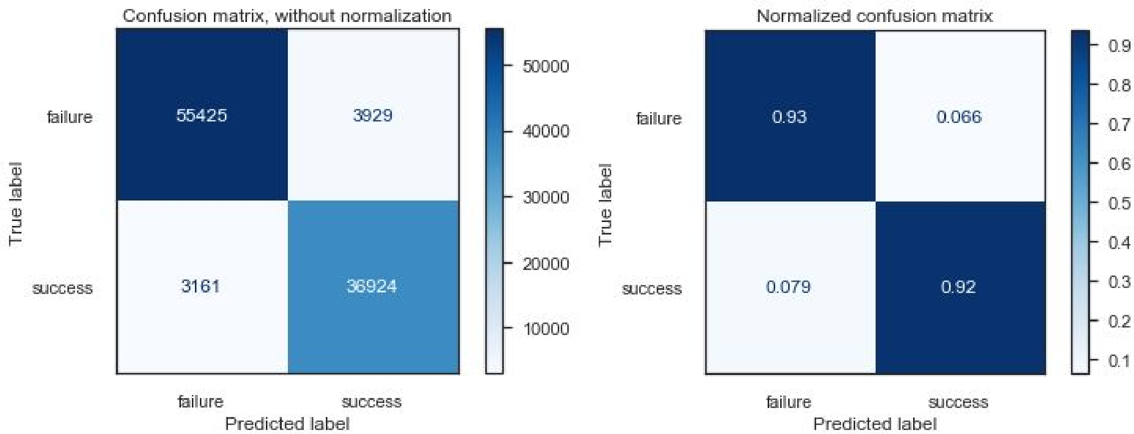
Because I had been prepping data as I went, not much needed to be adjusted with my data set in order to get it cleaned up for testing classification models. The main category's had already been encoded, a binary_state column was created for campaign outcomes, the name_len and name_cl columns had previously been created as well. The remainder of features i'd like to test out were numeric from the original data set.
To begin testing out classification models I created a new dataframe - model. The target label for this model is 0 - failure, 1 - success from the binary_state column.

Random Forest

The first classification model that I chose to explore is the Random Forest Classifier. I chose this model due to the abnormality of most of the Kickstarter data. Random forest reduces the chance of overfitting by analyzing random sub samples of data. This felt like a good model to try due to the abnormality of the Kickstarter dataset.
To test the Random Forest model, I created a baseline model using dummy classifiers to show what the baseline performance of the model would be if someone was simply guessing. Using the dummy classifier predicts the majority class to give better insight into parameters of the model.

The Kickstarter data is a total of 99,439 campaigns. 59,421(59%) of the campaign outcomes are 0 - failure, 40,018(41%) are 1-success. Using dummy classifiers the baseline model predicted all 99,439 campaign outcomes as 0-failure, because it is the majority class. The baseline classification accuracy of the baseline model is 59.6%.
Next, I ran the model with default parameters to compare accuracy to the baseline model:

Random Forest Classifier with Default Parameters:

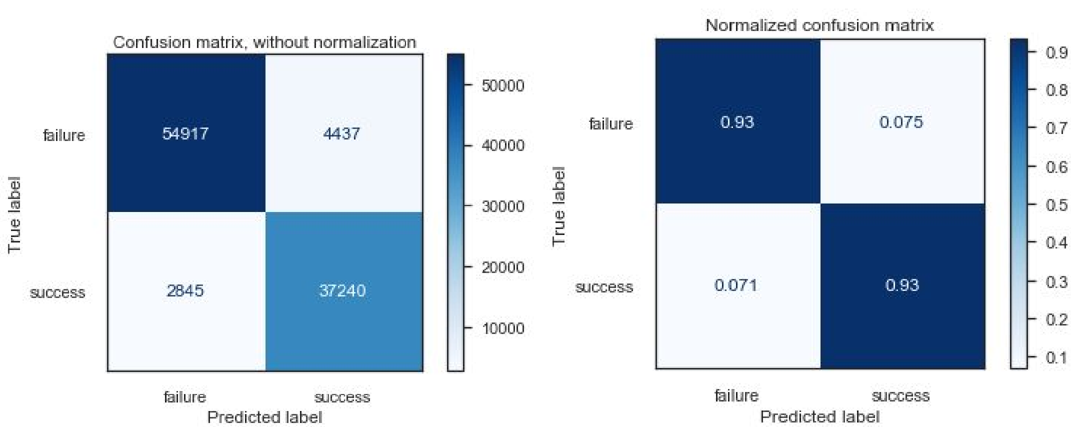


To optimize the Random Forest Model, I began tuning parameters with RandomSearchCV. I chose RandomSearchCV for hyperparameter tuning because RandomSearchCV because it is efficient, reliable and quick. RandomSearchCV was a good fit because I already had an understanding of which hyperparameters in particular we could look at tuning.
I used a 5 fold cross validation, and roc_auc scoring. RandomSearchCV determined the best parameters would be:

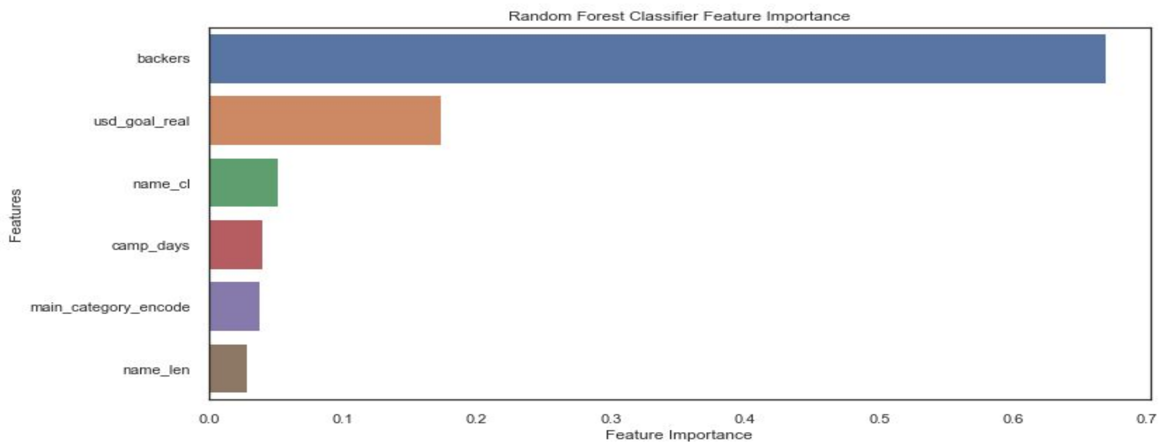
{'n_estimators': 196, 'min_samples_split': 10, 'max_leaf_nodes': 49, 'max_features': 0.7, 'max_depth': 17, 'bootstrap': True}

The most notable change from the Random Forest Classifier that was built using default parameters, and the best parameters identified by RandomSearch CV was the average number of nodes. With the default parameters, the average number of nodes was 35000 while the average maximum depth was 35. The best parameters estimate an average of 97 nodes and an average maximum depth of 8.

Random Forest Classifier with Optimal Parameters:



While using the best parameters set forth from RandomizedSearchCV, the Random Forest Classifier's F1 score rose from 90.49% to 90.8%. While the boost is relatively small, it accounts for a decrease in both false positives and false negatives. I chose to focus primarily on ROC_AUC scores, as they are better indicators of the models ability to distinguish between features. When the model was run with optimal parameters the ROC_AUC score dipped by 0.04% while the recall score rose from 92.1% to 92.9%. It appears that the efforts to improve the recall value effectively lowered the accuracy of other metrics.



I was surprised to find that the most important feature to the model was overwhelmingly backers at 66.88%.

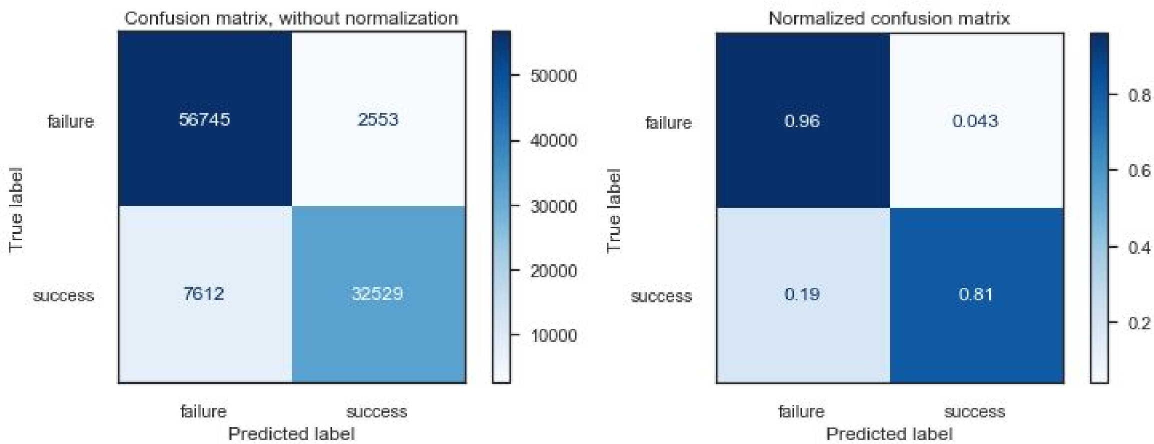
Feature	Importance
backers	66.88%
usd_goal_real	17.34%
name_cl	5.12%
camp_days	3.98%
main_category_encode	3.80%
name_len	2.89%

Logistic Regression

I chose to use Logistic Regression for an additional classifier model, because it can provide additional insight into the relevance of predictive features and as well as their direction of association.

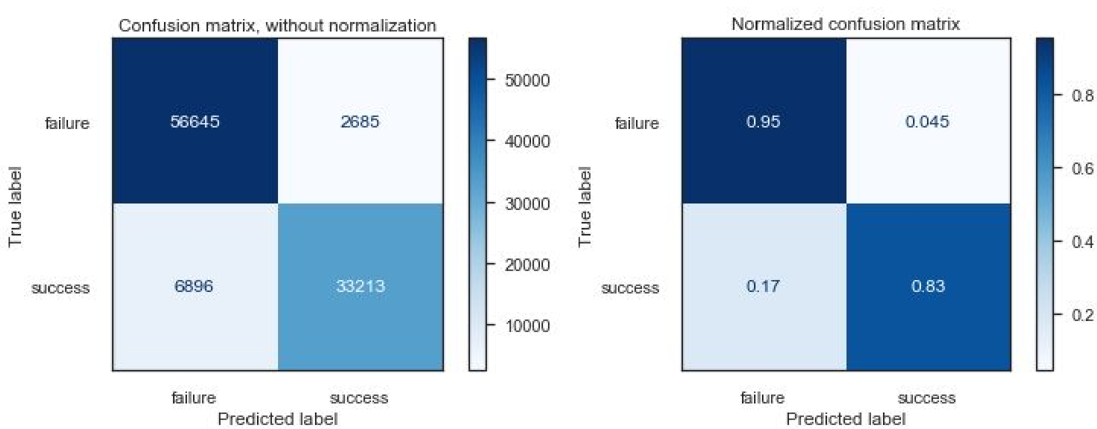
In order to build my Logistic Regression model I took the same steps to set up a baseline accuracy score as I did with the Random Forest classifier. As with the Random Forest Classifier, the Logistic Regression baseline predicted all 0-failures, the majority class, accounting for a 59.6% accuracy score.
After determining the baseline classification accuracy, I ran the Logistic Regression model with default parameters:

Logistic Regression Model with Default Parameters:

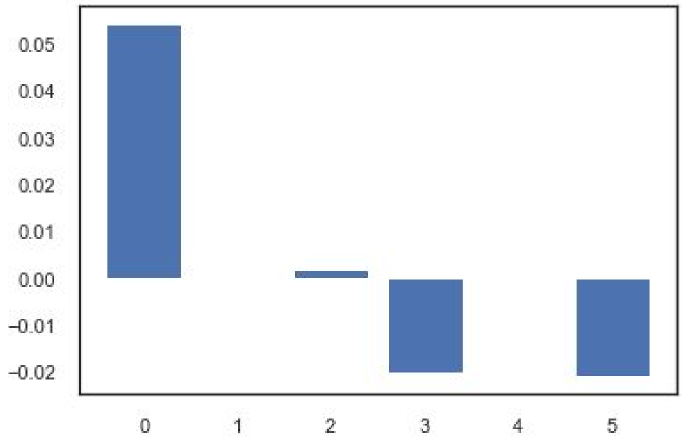


To best improve it's accuracy, I chose GridSearchCV to tune the hyperparameters for the Logistic Regression model. I chose GridSearchCV because it is an exhaustive search option when determining the optimal hyperparameters.
GridSearchCV found that the optimal parameters would be:
Best Penalty: l2
Best C: 21.544346900318832

Logistic Regression with Optimal Parameters



When the Logistic Regression model was run with optimal parameters, it came to the same accuracy as using default parameters. This will require further exploration to determine whether any features could be fine tuned in order to improve model accuracy, or if any additional parameters could be adjusted.



Feature	Importance
0 - backers	0.05413
1 - name_cl	-0.0003
2 - name_len	0.00182
3 - camp_days	0.00182
4 - usd_goal_real	-0.00023
5 - main_category_encode	-0.02089

Feature importance followed a similar pattern as it did with the Random Forest classifier, with Backers making the biggest impact.

Conclusion & Recommendations

After spending time exploring, manipulating and visualizing the Kickstarter dataset, I believe I can draw several conclusions that could help Kickstarter improve their business model for themselves and for their clients.

First, campaign categories do matter. The majority of campaign categories had higher failure rates than success rates, from examining the data this could possibly be attributed to their high goals, making it more difficult for these campaigns to reach or exceed their funding. Campaign categories such as comics, music, theater and dance tend to have lower goals on average in comparison to categories like film & video, publishing, and technology.

That leads me to the second conclusion - the goal of the campaign matters! If a campaign starts out with an incredibly ambitious goal, it will be much more difficult to reach and exceed said goal. The initial goal amount, coupled with the number of campaign backers, makes a big impact on the likelihood that a campaign will succeed.

While the length of the name and the number of characters in a name did not make a particularly large impact in the Random Forest classifier, it does appear to correlate some with campaign outcomes. The fewer number of characters in a campaign name and the fewer words in a campaign name lead to higher successful outcomes than more characters in a campaign name or more words in a campaign name. Campaign names often make the first impression of a campaign, and lengthier names appear to turn donors off.

The Kickstarter dataset that I have been working with did not include some data points that are generated from campaigns such as the campaign description, and further exploration of these additional features would be very interesting. Moving forward, i’m interested in exploring additional features and the possibilities of Natural Language Processing for the campaign names and the campaign descriptions.

Predicting Success in Kickstarter Campaigns

Kelli Peluso
Capstone 1
Springboard Data Science Career Track

Table of Contents

Background

Kickstarter Campaigns

The Data: obtained from Kaggle, this dataset includes 378,661 rows of data. Each Kickstarter campaign is represented by one row of data spanning 15 features.

The Problem: The success of Kickstarter campaigns benefits both the companies and creators who launch campaigns, and Kickstarter itself.

The Approach: An analysis of both failed and successful Kickstarter campaigns will address potential features that are predictive of the campaign outcome of future campaigns.

The Goal: Provide Kickstarter with the ability to make data-driven, impactful decisions in regards to: the services they offer, fees that they charge, and future campaign guidelines and recommendations

Data Wrangling

Data Wrangling

- Duplicate Values: The data obtained was fairly clean, and did not require the removal of any duplicate campaigns.
- Null Values: Two features had null values - ‘name’ (4) and ‘usd_pledged’ (3797). The 4 null values from ‘name’ were dropped, and the entire ‘usd_pledged’ feature was dropped, as there is an additional feature (usd_pledged_real) that is complete and more reliable.
- Feature Manipulation:
    - campaign_state > binary_state
        - Removal of ‘live’, ‘undefined’, ‘suspended’,
        - Creation of binary feature for campaign outcomes (target classifier)
    - name_len, name_cl, main_category_encode, goal_binned, pledge_binned, backers_binned, campaign_duration, camp_days

Data Storytelling

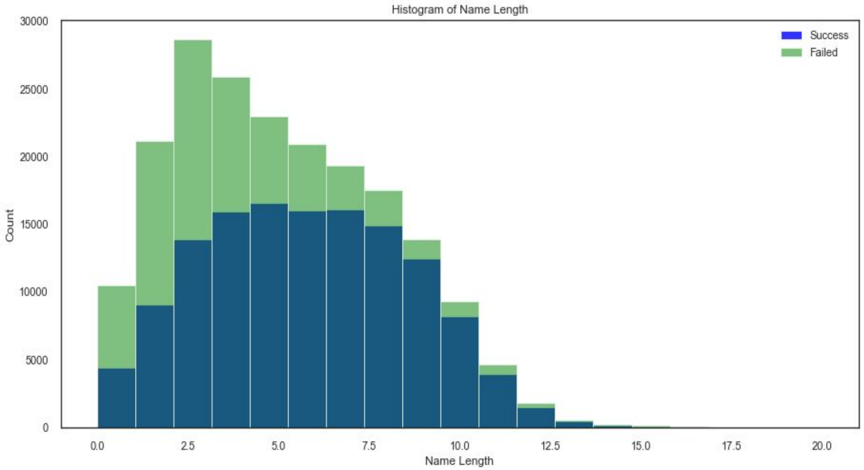
Campaign Name

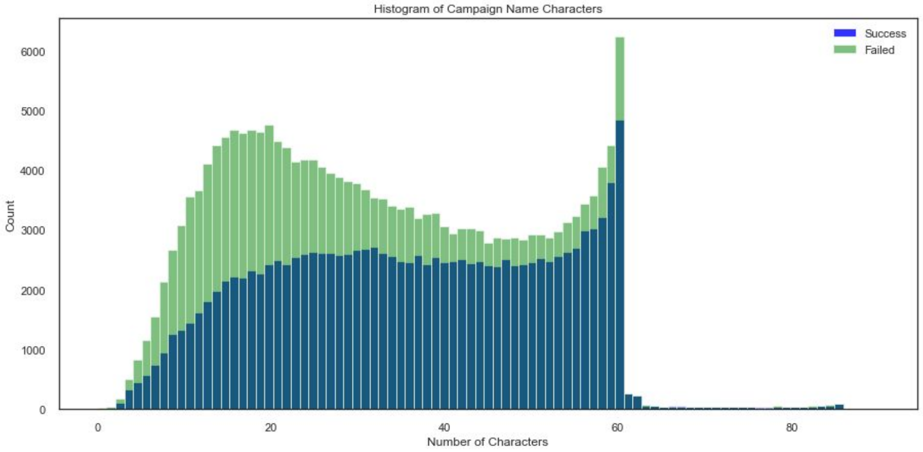
All Campaigns

Successful Campaigns

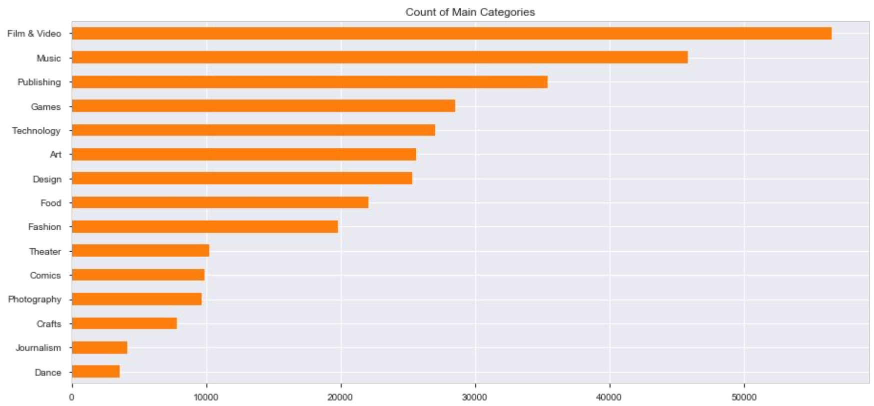
Failed Campaigns

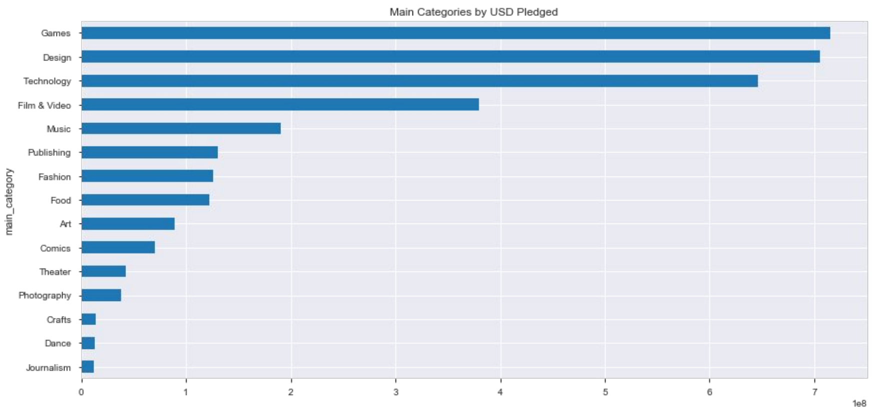
Campaign Names





Main Categories

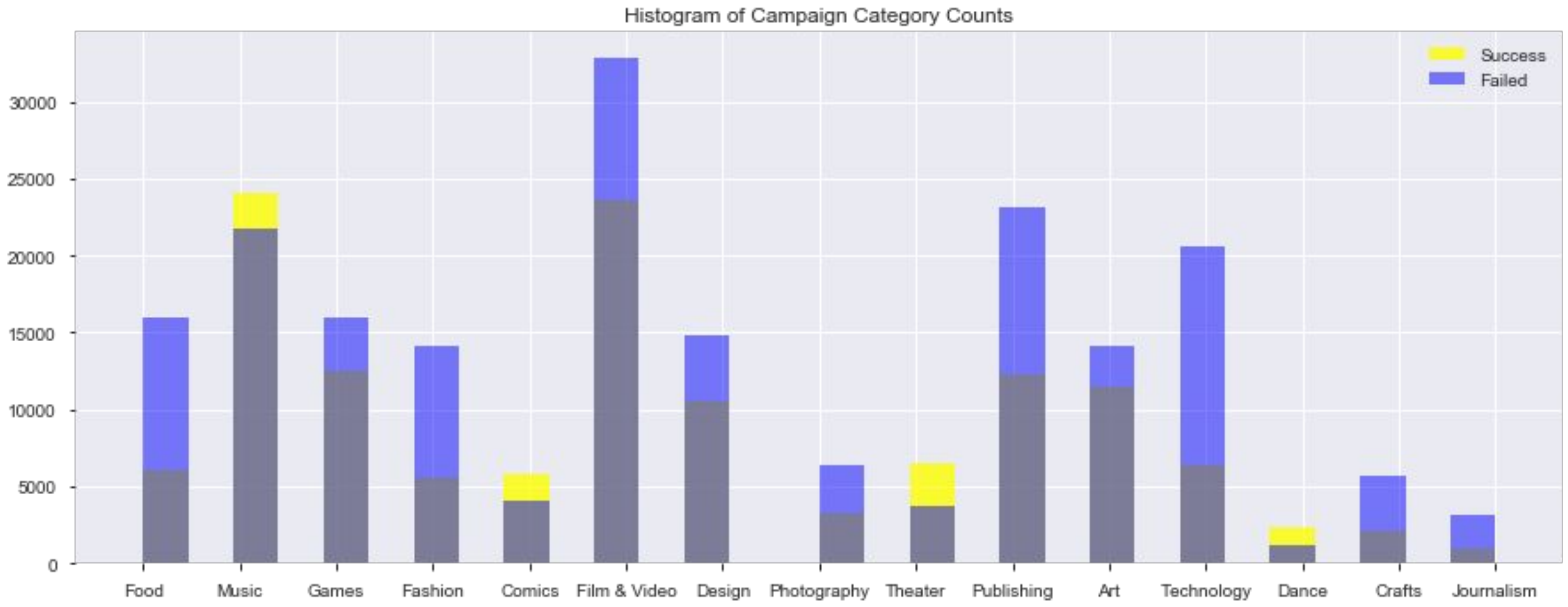




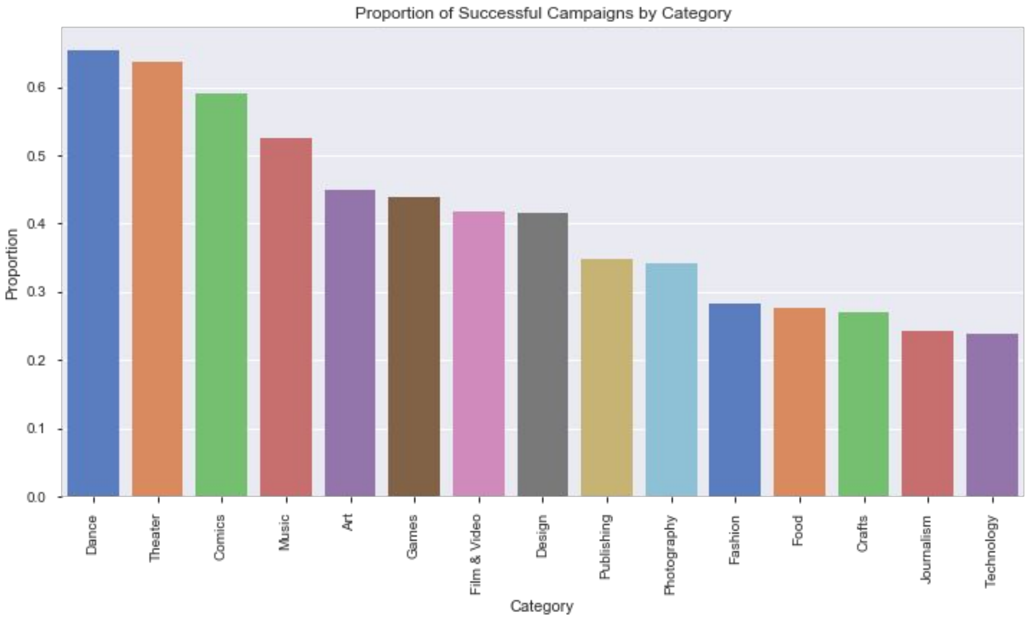
Main Categories by Count

Main Categories by USD Pledged

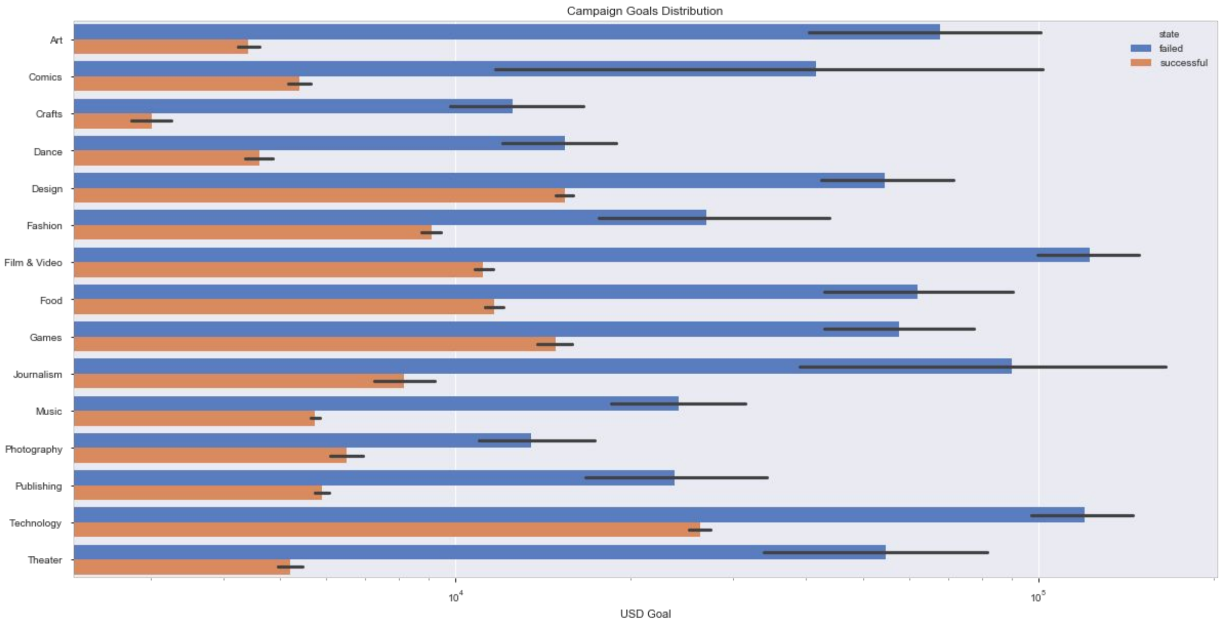
Main Categories



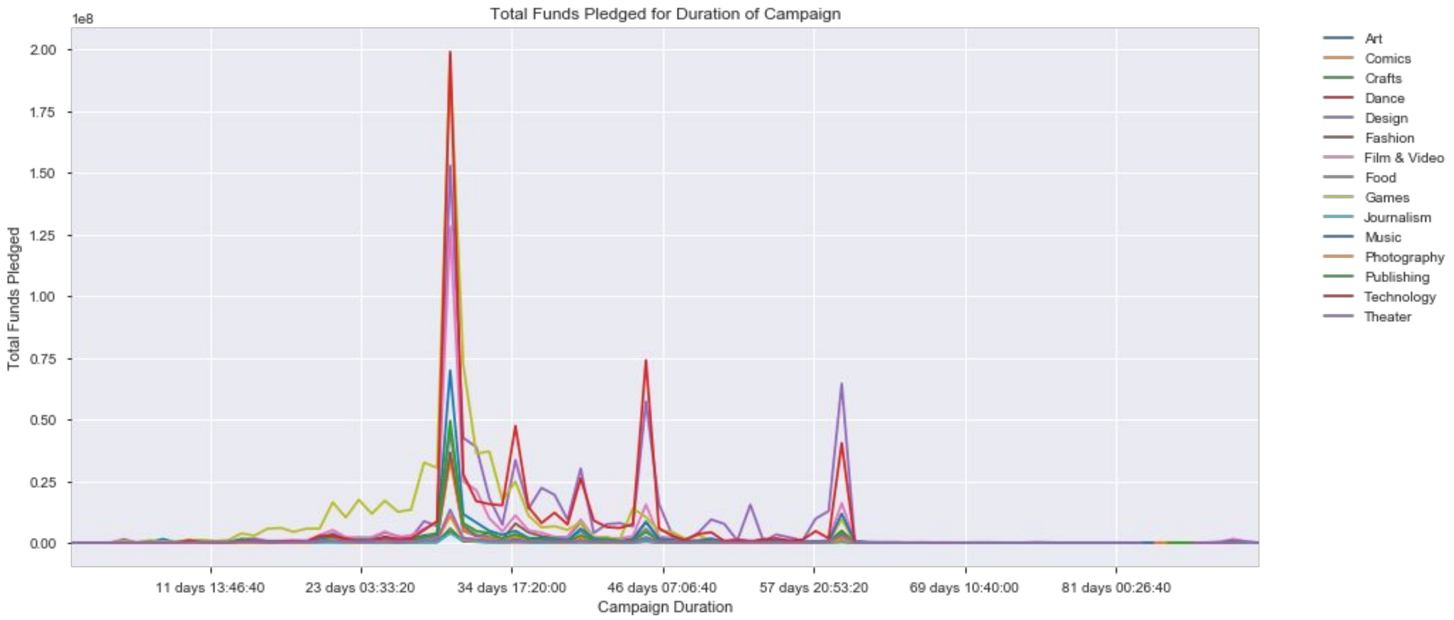
Main Categories



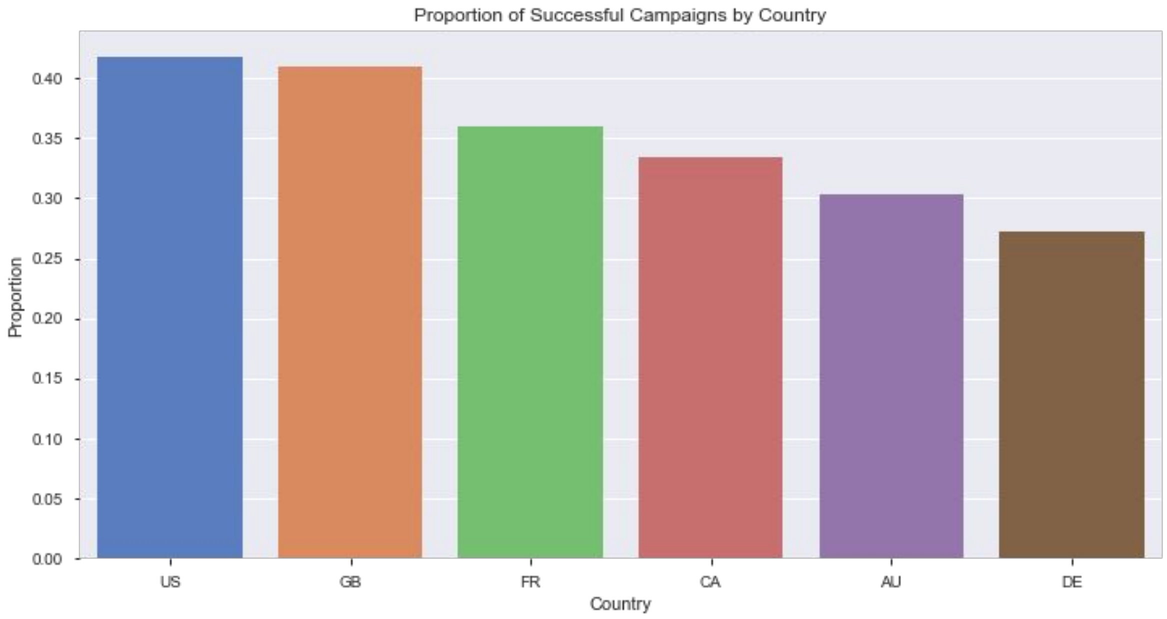
Campaign Goals



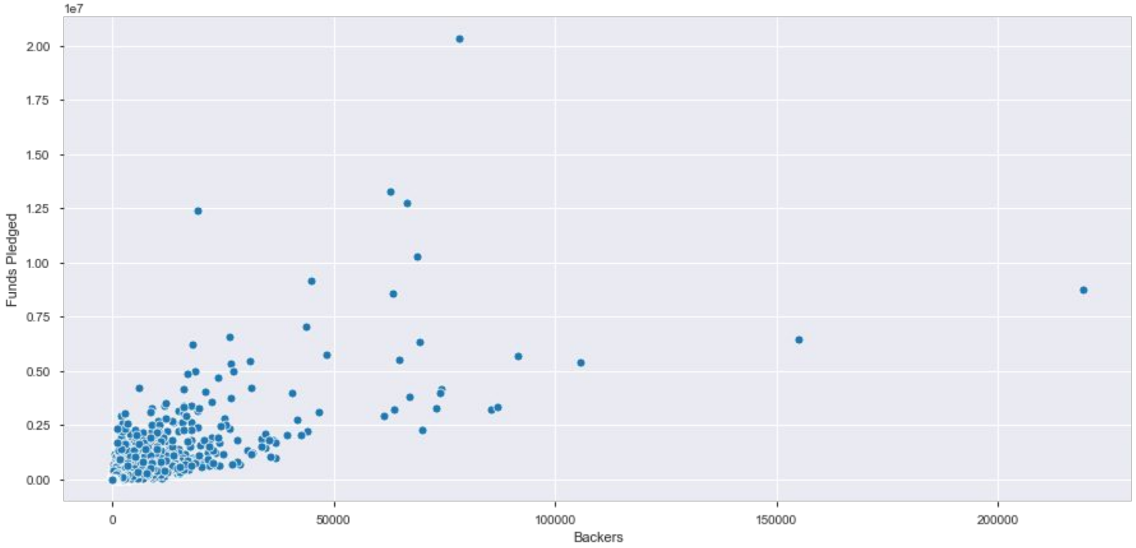
Campaign Duration



Campaign Countries of Origin



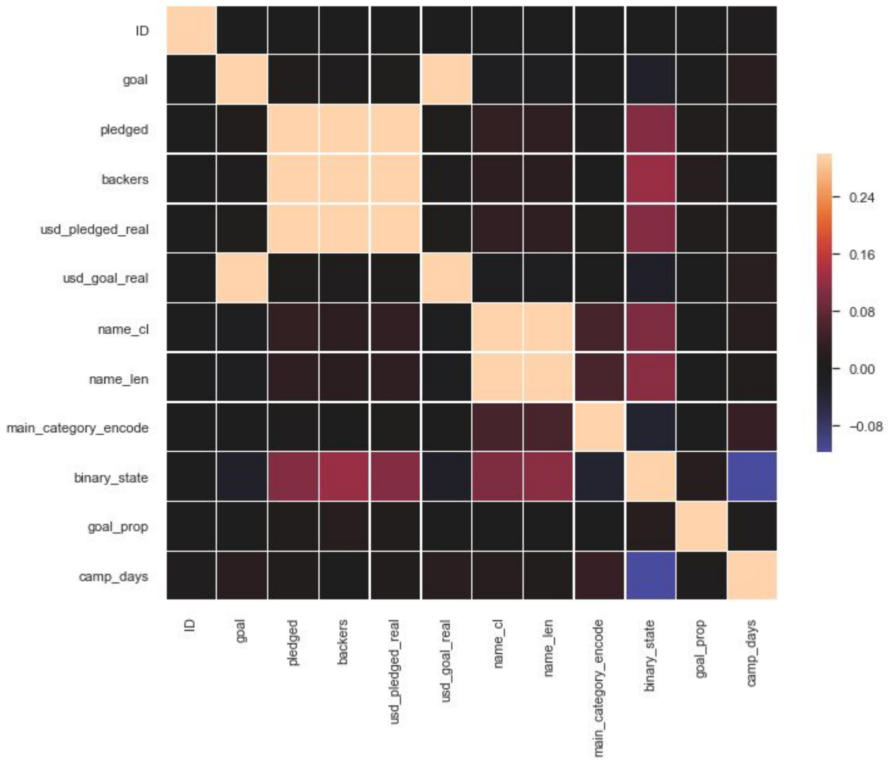
Campaign Backers



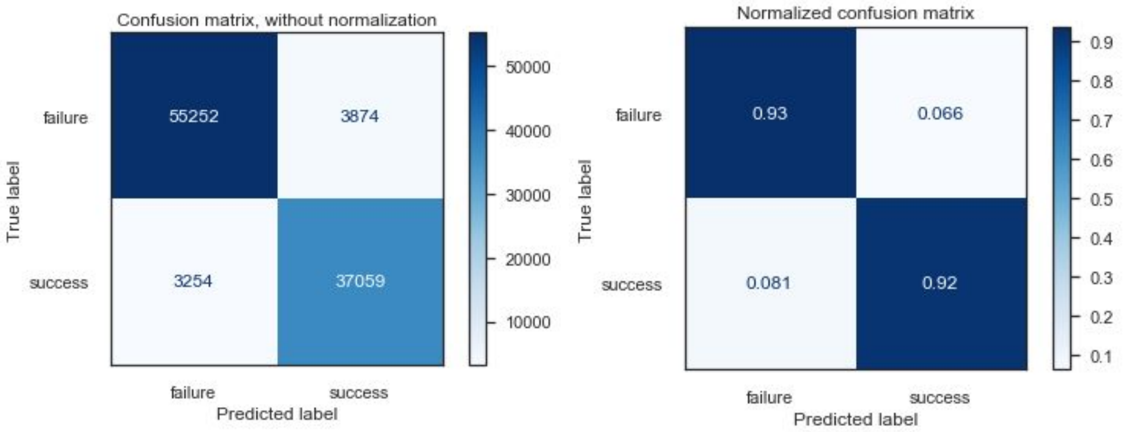
Relationship between Funds Pledged and Campaign Backers

Modeling & Statistics

Correlations



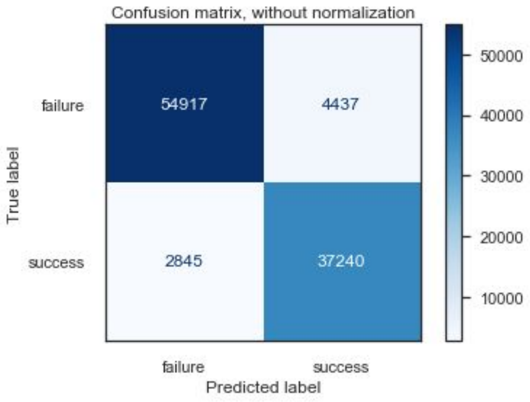
Random Forest Classifier

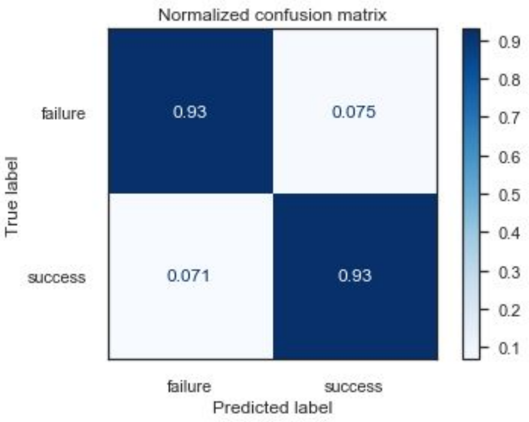


Metric	Result
Accuracy Score	92.87%
Precision Score	90.38%
Recall Score	92.11%
F1 Score	91.24%
ROC_AUC	92.75%

Default Parameters

Random Forest Classifier



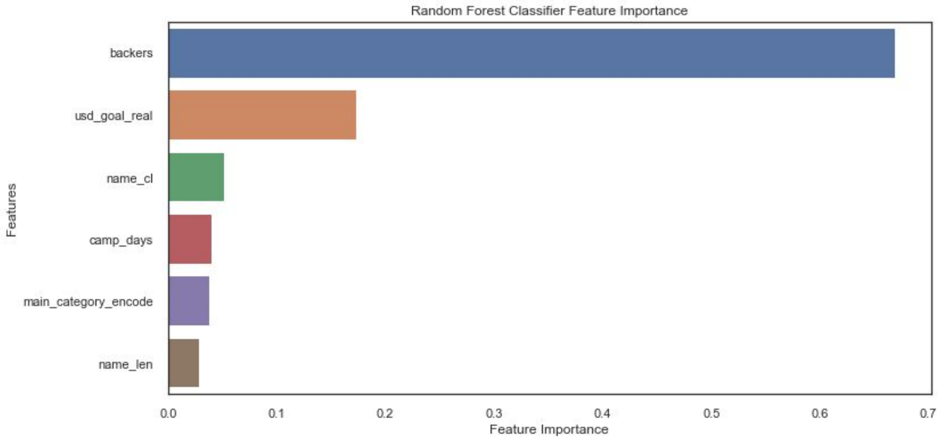


Metric	Result
Accuracy Score	92.68%
Precision Score	89.35%
Recall Score	92.90%
F1 Score	91.09%
ROC_AUC	92.71%

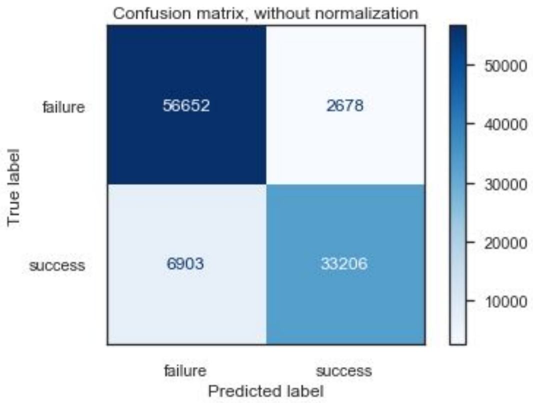
Optimized Parameters

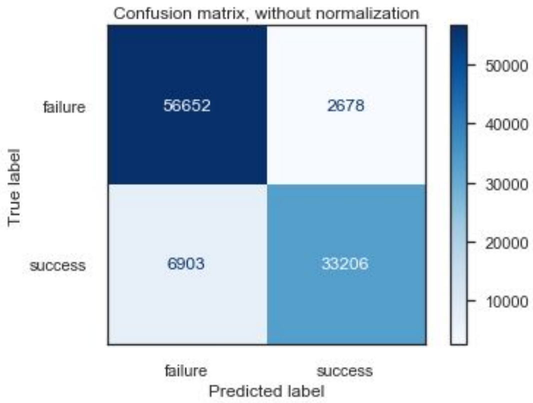
Random Forest Classifier

Metric	Default	Optimized	+/-
Accuracy Score	92.87%	92.68%	-0.21%
Precision Score	90.38%	89.35%	-1.14%
Recall Score	92.11%	92.90%	0.86%
F1 Score	91.24%	91.09%	-0.16%
ROC_AUC	92.75%	92.71%	-0.04%



Logistic Regression





Metric	Result
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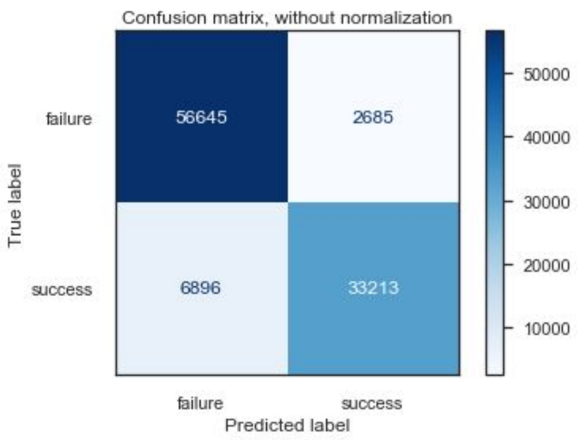
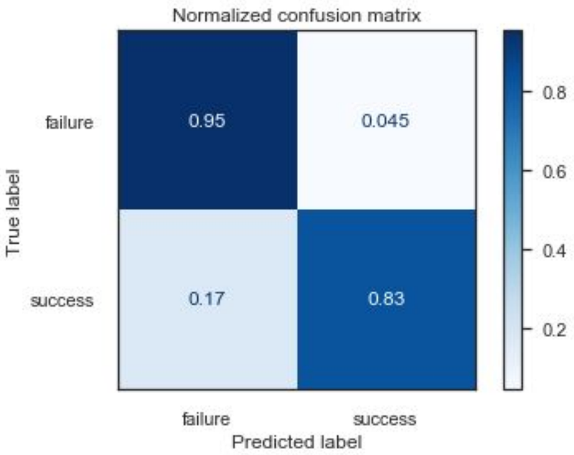
Logistic Regression

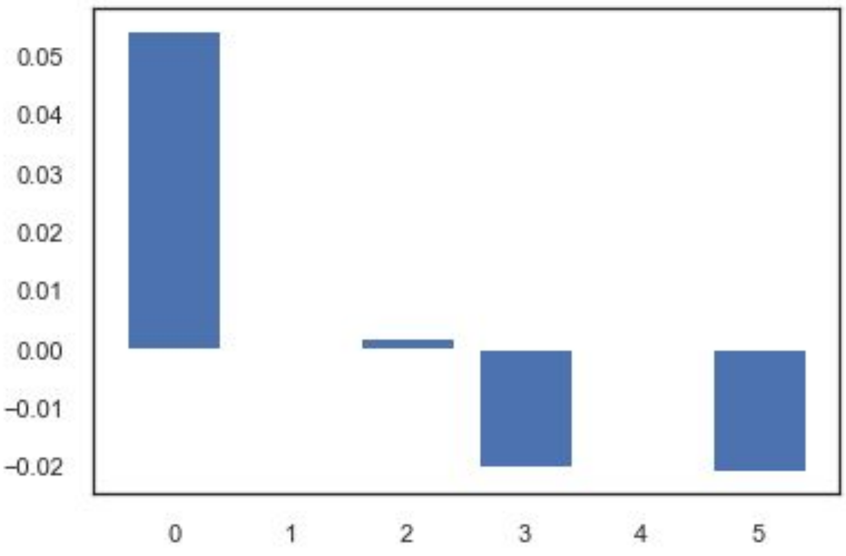




Metric	Result
Accuracy Score	90.36%
Precision Score	92.52%
Recall Score	82.81%
F1 Score	38.26%
ROC_AUC	89.14%

Logistic Regression

Feature Importance



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3 - camp_days	0.00182
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5 - main_category_encode	-0.02089

Conclusions

Thoughts and Recommendations

After examining the data, and fine-tuning the random forest classifier, I believe that I can make several recommendations to Kickstarter. These recommendations should assist in their development of campaign services, campaign recommendations and guidelines, and their fee structure.

1. Campaigns with smaller, less ambitious goals tend to be more successful
2. The number of campaign backers will help determine whether or not a campaign will succeed or fail
3. Main categories of campaigns do matter, with some seeing much higher rates of success (Music, Comics, Theater, Dance) than others (Film & Video, Food, Technology, Publishing)