Kickstarter Campaign Success Prediction

January 31, 2019

1 Introduction: Kickstarter Success Prediction Project

In this notebook, I'm going to look at the different features of kickstarter campaigns and how they correspond to the likelihood that a campaign will succeed. The dataset can be found here: https://data.world/rdowns26/kickstarter-campaigns/workspace/data-dictionary

```
In [67]: # @hiden_cell
         #pandas and numpy for data manipulation
         import pandas as pd
         import numpy as np

         #visualization libraries for graphing
         import matplotlib.pyplot as plt
         import seaborn as sns
         sns.set(font_scale = 2)
         %matplotlib inline

         # No warnings about setting value on copy of slice
         pd.options.mode.chained_assignment = None

         # Display up to the total number of columns of this dataframe
         pd.set_option('display.max_columns', 67)

         # Internal ipython tool for setting figure size
         from IPython.core.pylabtools import figsize

         # Splitting data into training and testing
         from sklearn.model_selection import train_test_split
```

```
In [79]: df = pd.read_csv("kickstarter_data_full.csv", index_col=0);
```

```
C:\Users\riley\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:2785: DtypeWarning:
  interactivity=interactivity, compiler=compiler, result=result)
```

```
In [80]: df.shape
```

```
Out[80]: (20632, 67)
```

The dataset starts out with 20,632 observations of 67 features.

```
In [81]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20632 entries, 0 to 20631
Data columns (total 67 columns):
id                            20632 non-null int64
photo                         20632 non-null object
name                          20632 non-null object
blurb                         20627 non-null object
goal                          20632 non-null float64
pledged                       20632 non-null float64
state                         20632 non-null object
slug                          20632 non-null object
disable_communication         20632 non-null bool
country                       20632 non-null object
currency                      20632 non-null object
currency_symbol               20632 non-null object
currency_trailing_code        20632 non-null bool
deadline                      20632 non-null object
state_changed_at              20632 non-null object
created_at                    20632 non-null object
launched_at                   20632 non-null object
staff_pick                    20632 non-null bool
backers_count                 20632 non-null int64
static_usd_rate               20632 non-null float64
usd_pledged                   20632 non-null float64
creator                       20632 non-null object
location                      20587 non-null object
category                      18743 non-null object
profile                       20632 non-null object
spotlight                     20632 non-null bool
urls                          20632 non-null object
source_url                    20632 non-null object
friends                       60 non-null object
is_starred                    60 non-null object
is_backing                    60 non-null object
permissions                   60 non-null object
name_len                      20627 non-null float64
name_len_clean                20627 non-null float64
blurb_len                     20627 non-null float64
blurb_len_clean               20627 non-null float64
deadline_weekday              20632 non-null object
state_changed_at_weekday      20632 non-null object
created_at_weekday            20632 non-null object
launched_at_weekday           20632 non-null object
deadline_month                20632 non-null int64
```

```
deadline_day                 20632 non-null int64
deadline_yr                  20632 non-null int64
deadline_hr                  20632 non-null int64
state_changed_at_month       20632 non-null int64
state_changed_at_day         20632 non-null int64
state_changed_at_yr          20632 non-null int64
state_changed_at_hr          20632 non-null int64
created_at_month             20632 non-null int64
created_at_day               20632 non-null int64
created_at_yr                20632 non-null int64
created_at_hr                20632 non-null int64
launched_at_month            20632 non-null int64
launched_at_day              20632 non-null int64
launched_at_yr               20632 non-null int64
launched_at_hr               20632 non-null int64
create_to_launch             20632 non-null object
launch_to_deadline           20632 non-null object
launch_to_state_change       20632 non-null object
create_to_launch_days        20632 non-null int64
launch_to_deadline_days      20632 non-null int64
launch_to_state_change_days  20632 non-null int64
SuccessfulBool               20632 non-null int64
USorGB                       20632 non-null int64
TOPCOUNTRY                   20632 non-null int64
LaunchedTuesday              20632 non-null int64
DeadlineWeekend              20632 non-null int64
dtypes: bool(4), float64(8), int64(26), object(29)
memory usage: 10.2+ MB
```

2 Data Cleaning

The majority of the dataset contains integer variables, some floats, and some objects. There is a chunk with only 60 observations (friends, is_starred, is_backing, and permissions). These look weird, so I'm going to look closer.

```
In [82]: df['friends'].isnull().value_counts()
```

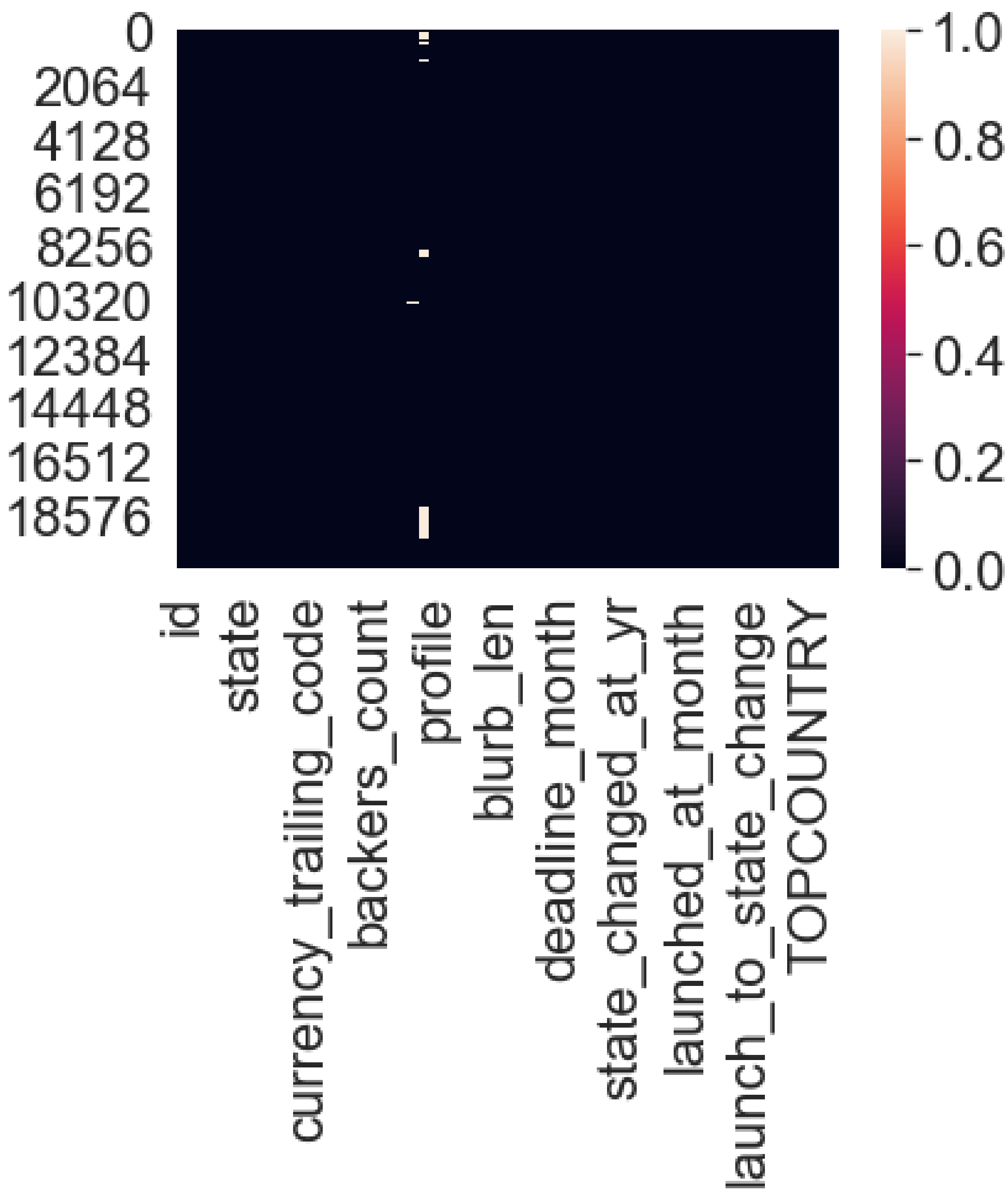
```
Out[82]: True     20572
         False       60
         Name: friends, dtype: int64
```

It looks like there are only 60 rows in which friends is not null, so I went ahead and looked at the other three variables and saw that that was the case. I decided to drop all four of those variables.

```
In [83]: cols_to_drop = ['friends', 'is_starred', 'is_backing', 'permissions']


         df.drop(labels=cols_to_drop, axis=1, inplace=True)
```

```
In [84]: sns.heatmap(df.isnull()) #looking here we can see that 'is_backing' and 'profile' conta
```

```
Out[84]: <matplotlib.axes._subplots.AxesSubplot at 0x25d28735940>
```



I can see that the only other column with missing values is the profile column. Looking at the first item of this we can learn a bit of what kind of data that involves and whether or not it is valuable.

```
In [85]: df['profile'][0]
```

```
Out[85]: '{"background_image_opacity":0.8,"should_show_feature_image_section":true,"link_text_co
```

It looks like it is mostly metadata and some of the information is captured by other columns like state, blurb, and so on. The dataset is heavily featured in general so I'm going to drop this one too.

```
In [86]: df.drop(labels='profile', axis=1, inplace=True)
```

I was going to look at the state variable but since that includes values like inactive and cancelled, it has too many levels. There's one better in this dataset: SuccessfulBool, 0=failed and 1=succeeded. We will use that for our dependent variable. Let's take a look at the distribution below.

```
In [87]: #there are a lot of unnecessary features, I will give a short explanation comment inlin
         second_col_drop = ['id', #useful as a private key but we aren't joining tables, so it's
                            'photo', #I'm not going to go into image recognition in this project
                            'state', #we already have SuccessfulBool, the cleaned version of sta
                            'slug', #the legal characterization of the name column so it's redun
                            'currency_symbol', #already have currency code (USD)
                            'currency_trailing_code', #honestly, I don't know what this is, but
                            'static_usd_rate', #I think this has to do with instances where the
                            'usd_pledged', #see above
                            'creator', #looked at this and while name could be captured among so
                            'location', #redundant. I already have the country and would like to
                            'urls', #just URLs, not using them
                            'source_url', #similar reason
                            'name_len', #there is a cleaned version
                            'blurb_len', #same as above
                            'create_to_launch', #calculated but an object, there exists an int c
                            'launch_to_deadline', #same as above
                            'launch_to_state_change',#same as above
                            'USorGB', #probably for GDPR, don't need it for my purposes
                            'TOPCOUNTRY', #probably indicates top country, again not part of my
                            'LaunchedTuesday', #probably someone else's analysis, I'll see what
                            'DeadlineWeekend', #same as above
                            'deadline_month', 'deadline_day', 'deadline_yr', 'deadline_hr', #the
                            'state_changed_at_month', 'state_changed_at_day', 'state_changed_at_
                            'created_at_month', 'created_at_day', 'created_at_yr', 'created_at_h
                            'launched_at_month', 'launched_at_day', 'launched_at_yr', 'launched_

         df.drop(labels=second_col_drop, axis=1, inplace=True)

In [88]: df.shape

Out[88]: (20632, 25)
```

We reduced dimensionality from 67 to 25! Now we are getting close to thinking about doing exploratory data analysis.

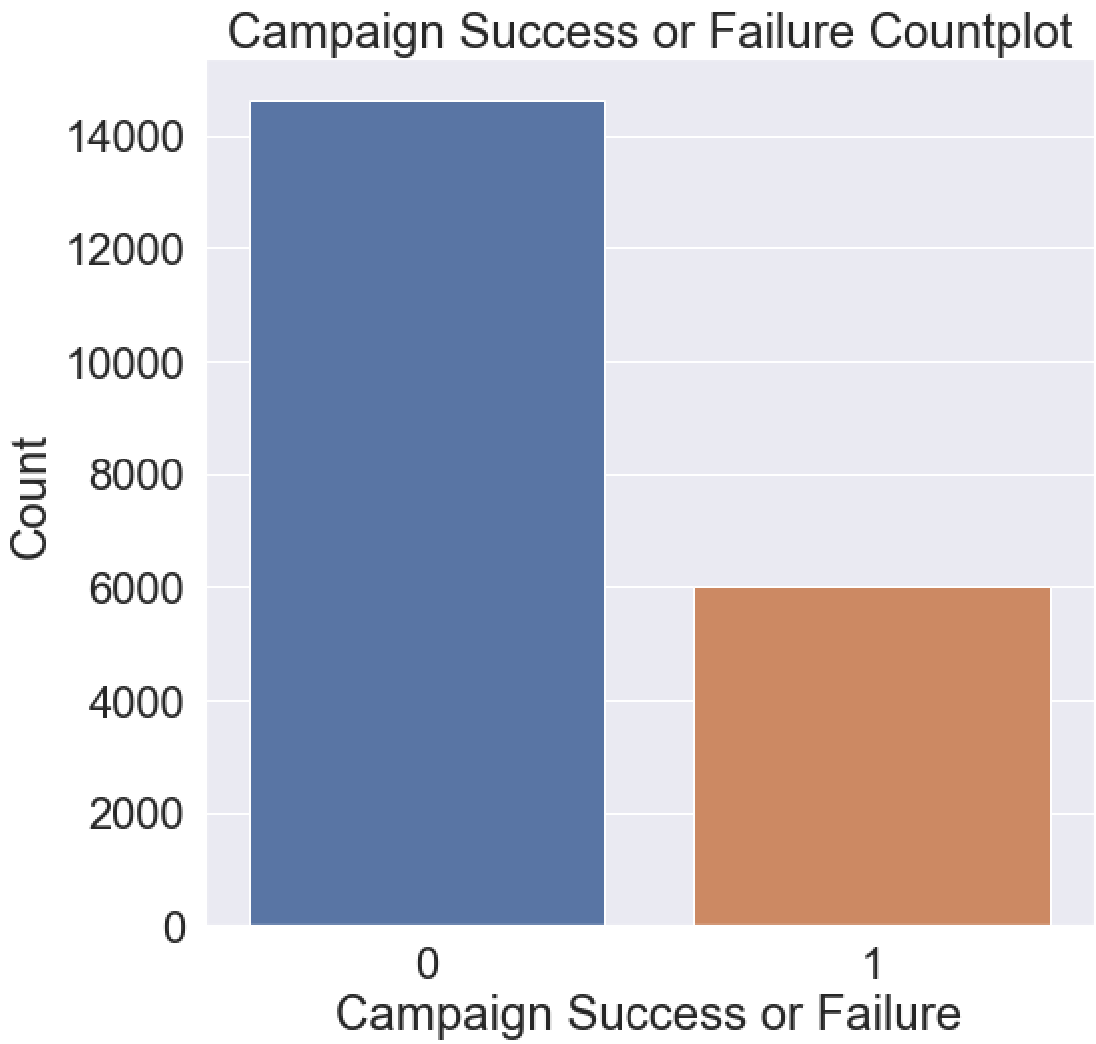
```
In [89]: df['disable_communication'] = df['disable_communication'] * 1 #converts type bool to 0
```

```
In [90]: df['staff_pick'] = df['staff_pick'] * 1 #doing the same for these two as well. If there

         df['spotlight'] = df['spotlight'] * 1
```

3 Exploratory Data Analysis

Let's start this process by examing in the target feature: success of the campaigns.

```
In [91]: figsize(8, 8)
         sns.countplot(df['SuccessfulBool']);
         plt.xlabel('Campaign Success or Failure');
         plt.ylabel('Count'); plt.title('Campaign Success or Failure Countplot');

         #sns.countplot('SuccessfulBool', data=df)
```



```
In [92]: print("Only "
               + str(np.round(df['SuccessfulBool'].value_counts()[1] / len(df) * 100, decimals=2
               + "% of campaigns were successful across the whole dataset.")
```

```
Only 29.17% of campaigns were successful across the whole dataset.
```

So we can see that there were more failed campaigns than successful campaigns. Sadly, this is expected and understandable.

3.1 Outlier data

```
In [93]: df.describe().transpose()
```

```
Out[93]:                              count          mean           std  min     25%  \
         goal                        20632.0  94104.965285  1.335511e+06  1.0  4000.0
         pledged                     20632.0  21392.675739  1.204973e+05  0.0    25.0
         disable_communication       20632.0      0.011148  1.049952e-01  0.0     0.0
         staff_pick                  20632.0      0.105903  3.077215e-01  0.0     0.0
         backers_count               20632.0    183.675843  1.222013e+03  0.0     2.0
         spotlight                   20632.0      0.291683  4.545481e-01  0.0     0.0
         name_len_clean              20627.0      5.292578  2.418168e+00  1.0     3.0
         blurb_len_clean             20627.0     13.081204  3.283547e+00  1.0    11.0
         create_to_launch_days       20632.0     49.577598  1.110946e+02  0.0     3.0
         launch_to_deadline_days     20632.0     34.716896  1.187314e+01  1.0    30.0
         launch_to_state_change_days 20632.0     31.169397  1.427971e+01  0.0    28.0
         SuccessfulBool              20632.0      0.291683  4.545481e-01  0.0     0.0

                                         50%       75%           max
         goal                        14000.0  50000.00  1.000000e+08
         pledged                       695.0   5954.25  6.225355e+06
         disable_communication           0.0      0.00  1.000000e+00
         staff_pick                      0.0      0.00  1.000000e+00
         backers_count                  12.0     63.00  1.058570e+05
         spotlight                       0.0      1.00  1.000000e+00
         name_len_clean                  5.0      7.00  1.400000e+01
         blurb_len_clean                13.0     15.00  3.000000e+01
         create_to_launch_days          14.0     45.00  1.754000e+03
         launch_to_deadline_days        30.0     40.00  9.100000e+01
         launch_to_state_change_days    30.0     35.00  9.100000e+01
         SuccessfulBool                  0.0      1.00  1.000000e+00
```

It looks like the goal variable has a huge spread. I'll take a look at the tail of sorted values below.

```
In [94]: df['goal'].sort_values().tail()
```

```
Out[94]: 3487     40000000.0
         11043    55000000.0
```

```
8678      60000000.0
4801     100000000.0
8696     100000000.0
Name: goal, dtype: float64
```

Looking at the goal value, we can see that the last two are 100 million dollars! These are some serious outliers!

```
In [95]: df['pledged'].sort_values().tail()
```

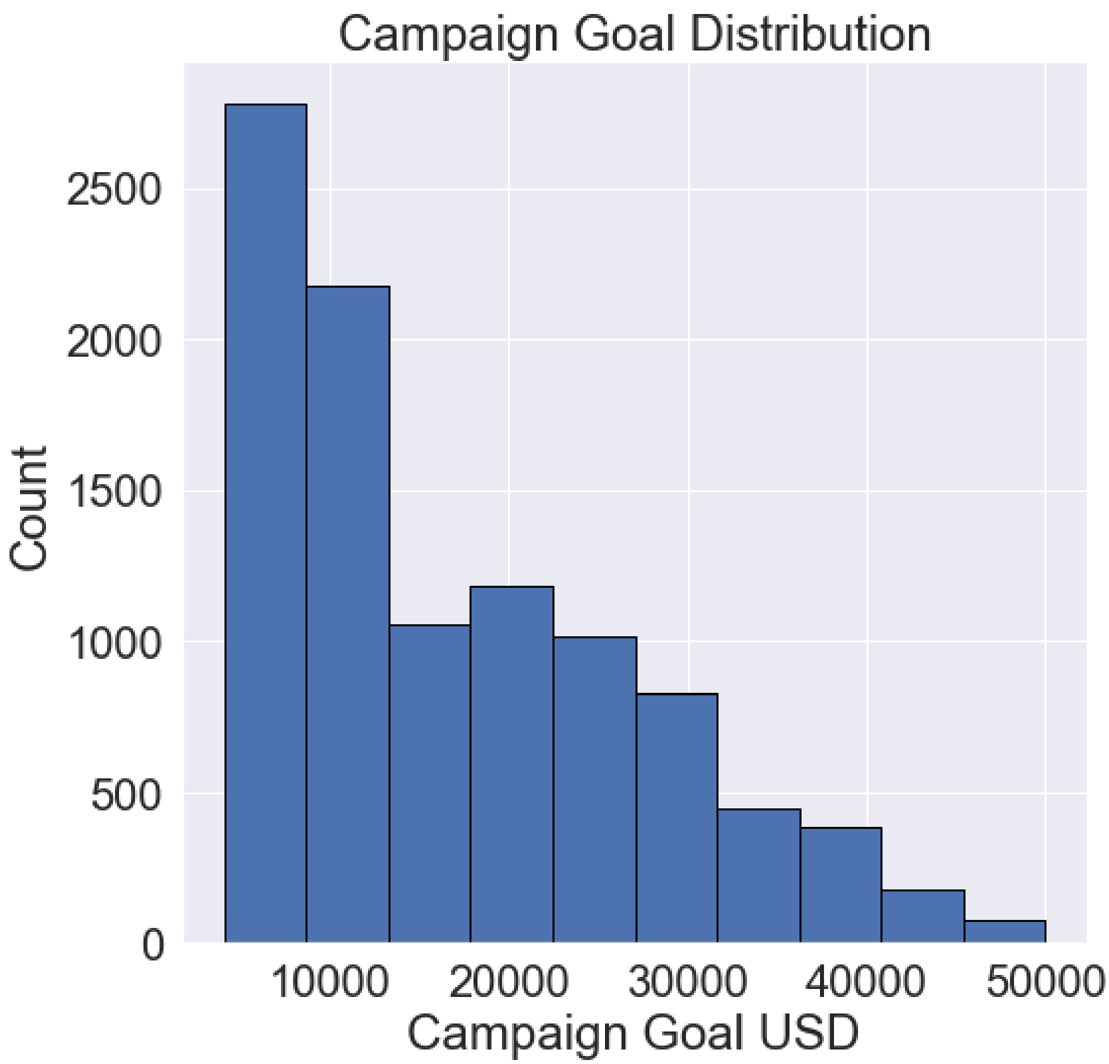
```
Out[95]: 8763     2708472.39
         12829    2952508.59
         12911    4961032.74
         4363     5408916.95
         8805     6225354.98
         Name: pledged, dtype: float64
```

Understandably, the pledged amount is more reasonable because this represents real money that people decided to give. Simmer down there, project managers!

I will use the definition of extreme outlier, which is that the value is outside the bounds of the first and third quartile, or the interquartile range. Let's define that here and then plot the goal with just interquartile range included.

```
In [96]: first_quartile = df['goal'].describe()['25%']

         third_quartile = df['goal'].describe()['75%']

         iqr = third_quartile - first_quartile

         df_goal_iqr = df[(df['goal'] > first_quartile) & (df['goal'] < third_quartile)]
```

```
In [97]: # Histogram Plot of Site EUI
         figsize(8, 8)
         plt.hist(df_goal_iqr['goal'], edgecolor = 'black');
         plt.xlabel('Campaign Goal USD');
         plt.ylabel('Count'); plt.title('Campaign Goal Distribution');
```



3.1.1 More outliers

A box and whisker plot is a good way to look at different variables and their spread and see if there are any more outliers to deal with using the previously used methods. First lets re-examine the spread of the variables using .describe().transpose() to see which ones have high spread (for example a min of 0 and a max of 2,344,000 with a standard deviation of 67,000!).

```
In [99]: df_goal_iqr.describe().transpose()
```

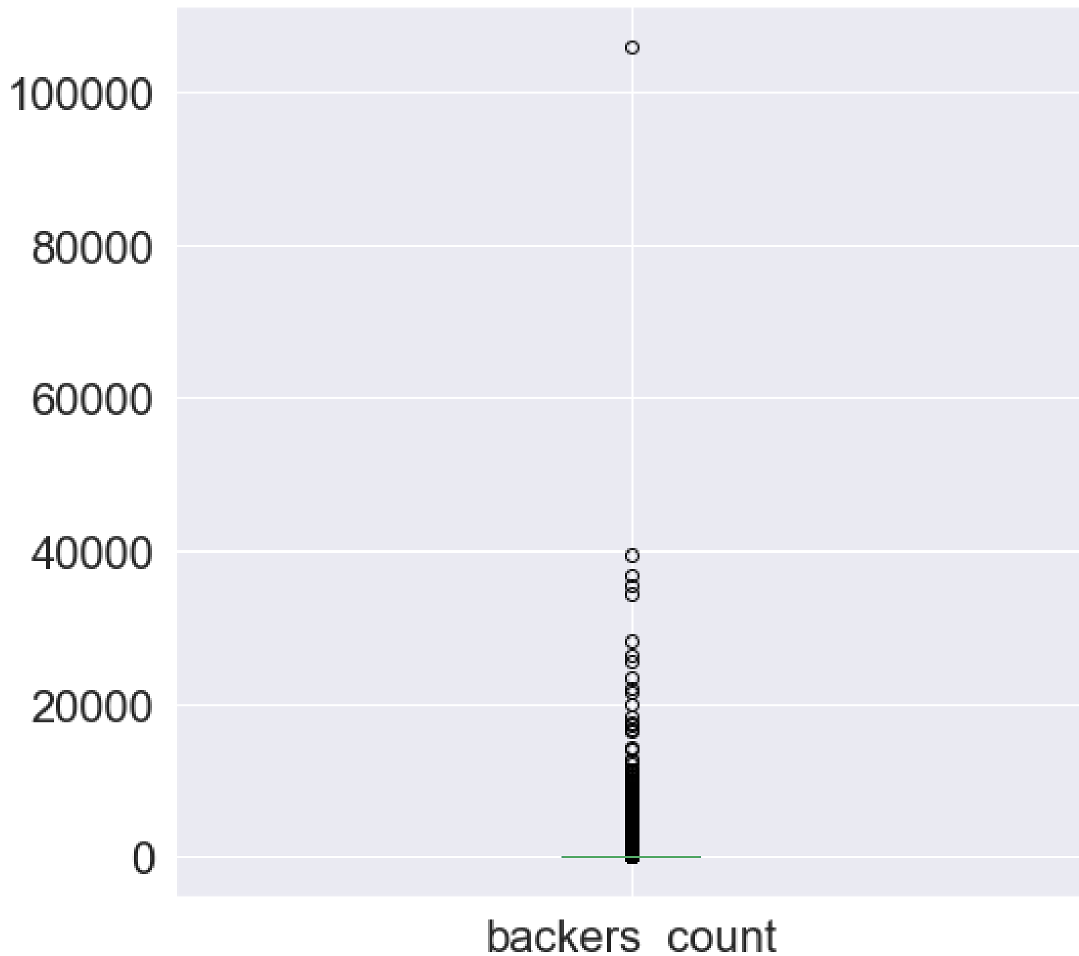
```
Out[99]:                           count          mean           std     min  \
         goal                    10107.0  16841.510237  10887.732017  4059.0
         pledged                 10107.0  14891.312073  67578.044235     0.0
         disable_communication   10107.0      0.011477      0.106520     0.0
         staff_pick              10107.0      0.109330      0.312068     0.0
         backers_count           10107.0    173.063125    907.532746     0.0
```

```
spotlight                     10107.0    0.266053    0.441914    0.0
name_len_clean                10105.0    5.366452    2.431118    1.0
blurb_len_clean               10105.0   13.073726    3.285475    1.0
create_to_launch_days         10107.0   53.305036  113.766666    0.0
launch_to_deadline_days       10107.0   34.896309   11.219802    1.0
launch_to_state_change_days   10107.0   31.493915   13.800788    0.0
SuccessfulBool                10107.0    0.266053    0.441914    0.0

                                 25%      50%      75%         max
goal                          8000.0  15000.0  25000.0    49999.00
pledged                         28.0    840.0   8489.0  2344134.67
disable_communication            0.0      0.0      0.0        1.00
staff_pick                       0.0      0.0      0.0        1.00
backers_count                    2.0     13.0     82.0    36781.00
spotlight                        0.0      0.0      1.0        1.00
name_len_clean                   3.0      6.0      7.0       14.00
blurb_len_clean                 11.0     13.0     15.0       30.00
create_to_launch_days            4.0     16.0     50.0     1692.00
launch_to_deadline_days         30.0     30.0     40.0       91.00
launch_to_state_change_days     29.0     30.0     35.0       91.00
SuccessfulBool                   0.0      0.0      1.0        1.00
```

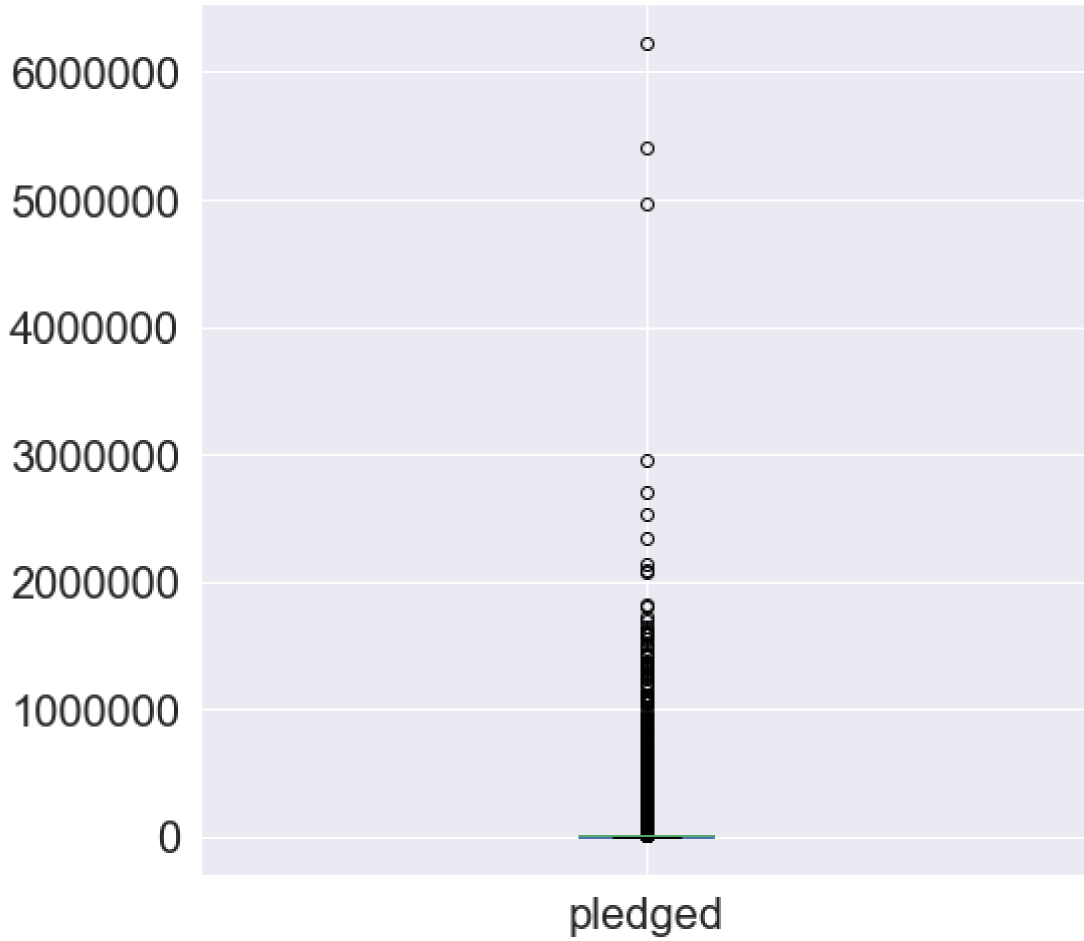
I can see I definitely want to do something to tame backers_count, and create_to_launch_days, and pledged due to the high spread. Let's confirm with a box and whisker for each.

```
In [101]: df.boxplot(['backers_count'])
```

```
Out[101]: <matplotlib.axes._subplots.AxesSubplot at 0x25d27ba05f8>
```

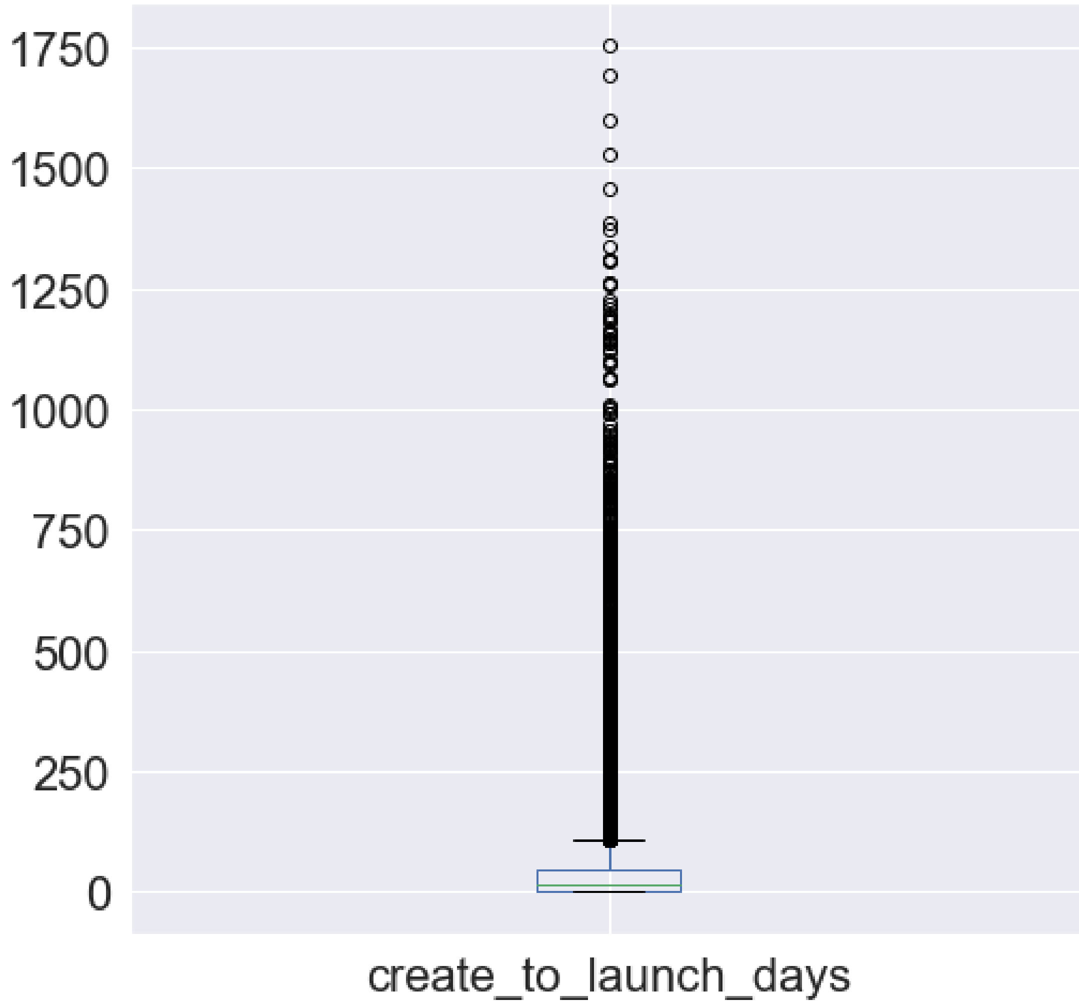



```
In [102]: df.boxplot(['pledged'])

Out[102]: <matplotlib.axes._subplots.AxesSubplot at 0x25d28017400>
```




```
In [103]: df.boxplot(['create_to_launch_days'])
```

```
Out[103]: <matplotlib.axes._subplots.AxesSubplot at 0x25d28734828>
```



Yeah, let's definitely trim all three of those and create a new IQR dataframe with these truncated values.

```
In [104]: df_iqr_trimmed = df_goal_iqr

          first_quartile = df['create_to_launch_days'].describe()['25%']
          third_quartile = df['create_to_launch_days'].describe()['75%']

          iqr = third_quartile - first_quartile

          df_iqr_trimmed = df[(df['create_to_launch_days'] > first_quartile) & (df['create_to_la

          #-----------------------------------------------------------------

          first_quartile = df['pledged'].describe()['25%']
          third_quartile = df['pledged'].describe()['75%']
```

```
iqr = third_quartile - first_quartile

df_iqr_trimmed = df[(df['pledged'] > first_quartile) & (df['pledged'] < third_quartile

#-------------------------------------------------------------------

first_quartile = df['backers_count'].describe()['25%']
third_quartile = df['backers_count'].describe()['75%']

iqr = third_quartile - first_quartile

df_iqr_trimmed = df[(df['backers_count'] > first_quartile) & (df['backers_count'] < th
```

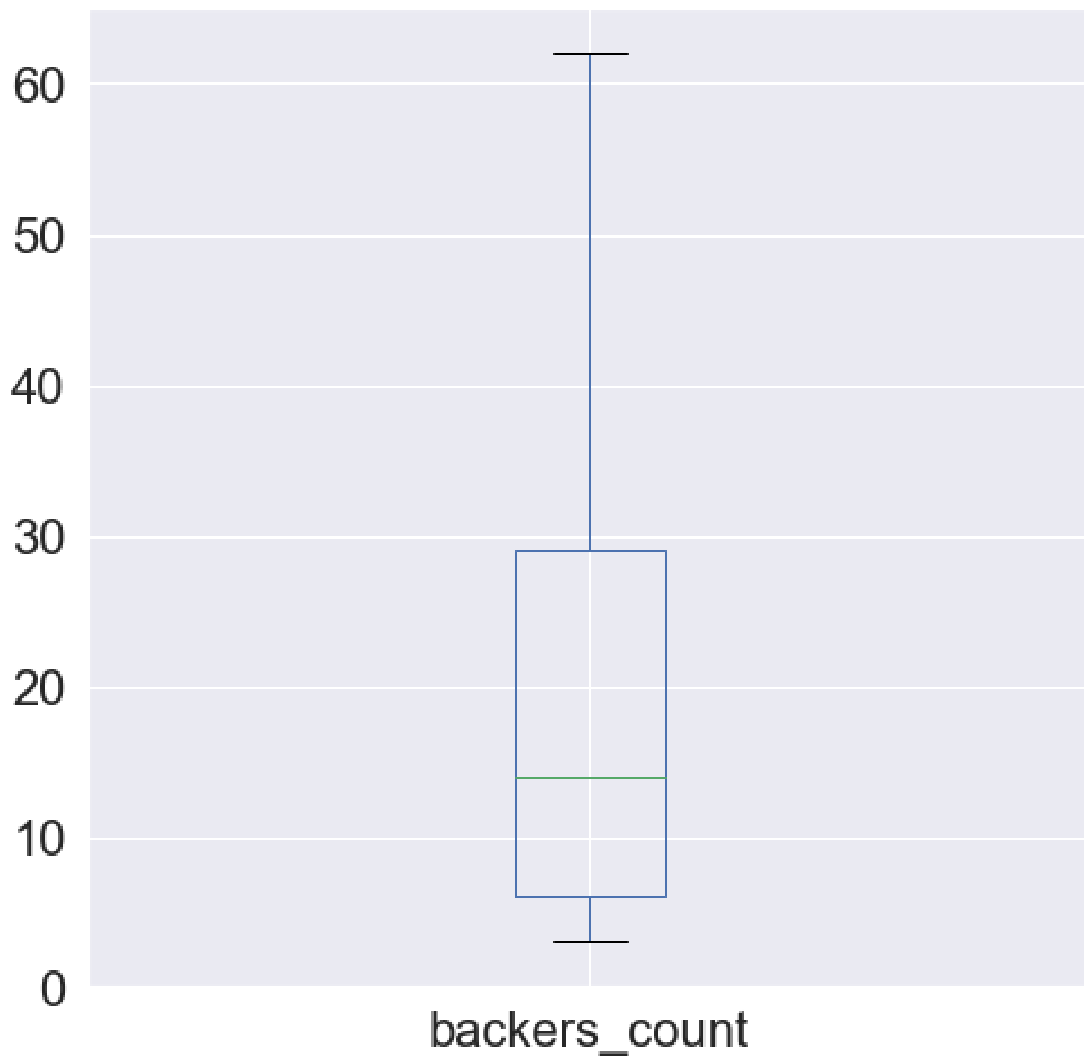
```
In [105]: len(df_iqr_trimmed)
```

```
Out[105]: 9308
```

This reduction resulted in a dataframe where there are 9308 instances, with only the IQR for the variables in question remaining.

```
In [106]: df_iqr_trimmed.boxplot(['backers_count']) #for example, this looks a bit more reasonab
```

```
Out[106]: <matplotlib.axes._subplots.AxesSubplot at 0x25d277d0ac8>
```



3.1.2 Correlations

Next up let's look at the correlations between each variable against SuccessfulBool, which remember, is a binary value where 0=failed and 1=succeeded.

```
In [107]: df_iqr_trimmed.corr()['SuccessfulBool'].sort_values()
```

```
Out[107]: launch_to_deadline_days       -0.184938
          create_to_launch_days         -0.085983
          disable_communication         -0.053091
          launch_to_state_change_days   -0.047071
          goal                          -0.033484
          name_len_clean                -0.027807
          blurb_len_clean                0.058825
```

```
staff_pick                    0.109232
pledged                       0.133948
backers_count                 0.404936
spotlight                     1.000000
SuccessfulBool                1.000000
Name: SuccessfulBool, dtype: float64
```

Looking at the correlations above we can see that nothing is too strongly correlated except spotlight, backers_count, pledged, and staff_pick. But really the only significant ones are backers_count and spotlight. It's crazy that spotlight has a correlation of 1. I'm going to look at that one real quick.

```
In [108]: len(df_iqr_trimmed[df_iqr_trimmed['spotlight'] == 1])
```

```
Out[108]: 2200
```

```
In [110]: len(df_iqr_trimmed[df_iqr_trimmed['SuccessfulBool'] == 1])
```

```
Out[110]: 2200
```

As we can see, there are exactly 2200 that are in the spotlight and were successful. And taken together with the spotlight variable's correlation to SuccessfulBool, we can conclude that all spotlighted campaigns were successful, at least in this dataset, taking into account the fact that it is reduced to IQR values only.

I'm going to pool together these strongly correlated features for feature selection later to see if restricting the model's training on just these features will improve, detract from, or keep performance neutral.

```
In [111]: reduced_x_features = df_iqr_trimmed[['launch_to_deadline_days', 'staff_pick', 'pledged
          reduced_y = df_iqr_trimmed['SuccessfulBool']
```

Because of the original format of the variables, we need to take the log and sqrt transformations of them and check correlation with those as well to account for non-linear relationships.

```
In [112]: # Select the numeric columns
          numeric_subset = df_iqr_trimmed.select_dtypes('number')

          # Create columns with square root and log of numeric columns
          for col in numeric_subset.columns:
              # Skip the Energy Star Score column
              if col == 'SuccessfulBool':
                  next
              else:
                  numeric_subset['sqrt_' + col] = np.sqrt(numeric_subset[col])
                  numeric_subset['log_' + col] = np.log(numeric_subset[col])

          # Select the categorical columns
          categorical_subset = df_iqr_trimmed['category']
```

```
# One hot encode
categorical_subset = pd.get_dummies(categorical_subset)

# Join the two dataframes using concat
# Make sure to use axis = 1 to perform a column bind
features = pd.concat([numeric_subset, categorical_subset], axis = 1)

# Drop buildings without an energy star score
features = features.dropna(subset = ['SuccessfulBool'])

# Find correlations with the score
correlations = features.corr()['SuccessfulBool'].dropna().sort_values()
correlations.head()
```

```
C:\Users\riley\Anaconda3\lib\site-packages\ipykernel_launcher.py:11: RuntimeWarning: divide by z
  # This is added back by InteractiveShellApp.init_path()
C:\Users\riley\Anaconda3\lib\site-packages\ipykernel_launcher.py:11: RuntimeWarning: invalid val
  # This is added back by InteractiveShellApp.init_path()
```

```
Out[112]: log_goal                         -0.554957
          sqrt_goal                        -0.272015
          log_launch_to_deadline_days      -0.219717
          sqrt_launch_to_deadline_days     -0.205036
          launch_to_deadline_days          -0.184938
          Name: SuccessfulBool, dtype: float64
```

So we saw in the previous step that goal got a boost in correlation what you take its log, so I will add log_goal into the reduced_x_features dataframe. We also saw log_pledged show a significant boost as well, so that will be included.

```
In [115]: reduced_x_features['log_goal'] = features['log_goal']
          reduced_x_features['log_pledged'] = features['log_pledged']
          reduced_x_features.drop('pledged', axis=1, inplace=True)
```

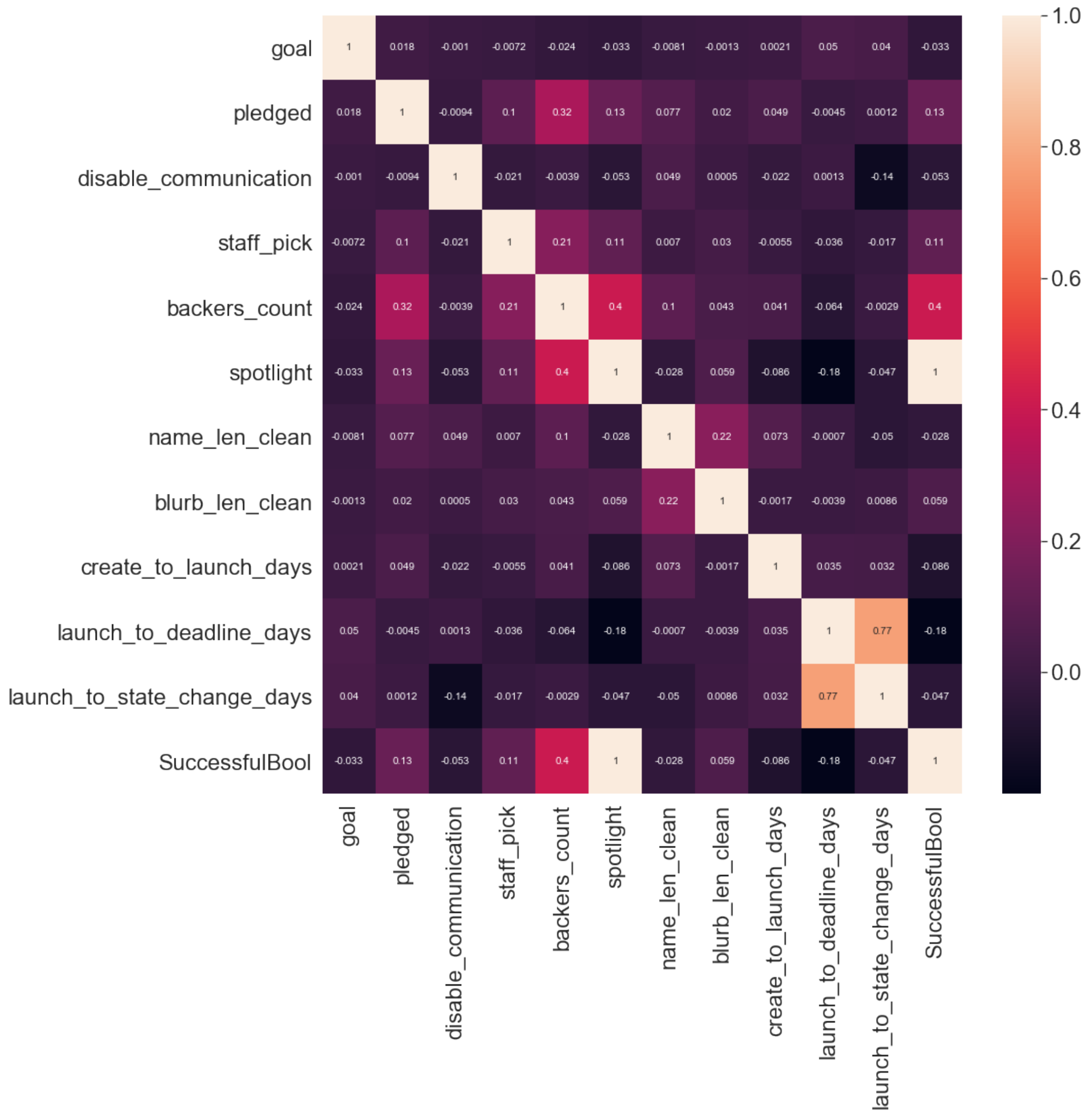
```
---------------------------------------------------------------------------

KeyError                                  Traceback (most recent call last)

<ipython-input-115-c9c84d862de4> in <module>()
  1 reduced_x_features['log_goal'] = features['log_goal']
  2 reduced_x_features['log_pledged'] = features['log_pledged']
----> 3 reduced_x_features.drop('pledged', axis=1, inplace=True)


~\Anaconda3\lib\site-packages\pandas\core\frame.py in drop(self, labels, axis, index, co
3695                                           index=index, columns=columns,
3696                                           level=level, inplace=inplace,
```

```
-> 3697                                         errors=errors)
   3698
   3699     @rewrite_axis_style_signature('mapper', [('copy', True),


    ~\Anaconda3\lib\site-packages\pandas\core\generic.py in drop(self, labels, axis, index,
   3109         for axis, labels in axes.items():
   3110             if labels is not None:
-> 3111                 obj = obj._drop_axis(labels, axis, level=level, errors=errors)
   3112
   3113         if inplace:


    ~\Anaconda3\lib\site-packages\pandas\core\generic.py in _drop_axis(self, labels, axis, l
   3141                 new_axis = axis.drop(labels, level=level, errors=errors)
   3142             else:
-> 3143                 new_axis = axis.drop(labels, errors=errors)
   3144             result = self.reindex(**{axis_name: new_axis})
   3145


    ~\Anaconda3\lib\site-packages\pandas\core\indexes\base.py in drop(self, labels, errors)
   4402             if errors != 'ignore':
   4403                 raise KeyError(
-> 4404                     '{} not found in axis'.format(labels[mask]))
   4405             indexer = indexer[~mask]
   4406         return self.delete(indexer)


    KeyError: "['pledged'] not found in axis"
```

4 Feature Engineering and Selection

I selected variables based on their correlations with the target variable, either positive or negative. This is feature selection, or rather deselection, because there were many that I was ignoring and not selecting. Feature engineering is the process of creating new features from existing ones in a sense, so when I transformed goal and pledged to log_goal and log_pledged, I found that these had a stronger correlation than their original forms, so these new features were added to reduced_x_features.

```
In [116]: figsize(14,14)
          sns.heatmap(df_iqr_trimmed.corr(), annot=True)

Out[116]: <matplotlib.axes._subplots.AxesSubplot at 0x25d27cc7048>
```



5 Modeling

```
In [117]: from sklearn.model_selection import train_test_split

          # Split into 70% training and 30% testing set
          X, X_test, y, y_test = train_test_split(reduced_x_features, reduced_y, test_size = 0.2

          print(X.shape)
          print(X_test.shape)
          print(y.shape)
          print(y_test.shape)
```

```
(7446, 7)
(1862, 7)
(7446,)
(1862,)
```

```
In [118]: # Imputing missing values and scaling values
          from sklearn.preprocessing import MinMaxScaler

          # Machine Learning Models
          from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
          from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
          from sklearn.svm import SVC
          from sklearn.neighbors import KNeighborsClassifier

          # Hyperparameter tuning
          from sklearn.model_selection import RandomizedSearchCV, GridSearchCV
```

If I use scalers, the values that are non-binary come to be mapped relative to their original values in a range between 0 and 1. Since this is a classification problem, this boosts the correlation between variables against the target variable too much and leads to perfect performance across all machine learning algorithms. Because of this I will not scale.

```
In [119]: from sklearn.metrics import classification_report, confusion_matrix

          # Takes in a model, trains the model, and evaluates the model on the test set
          def fit_and_evaluate(model):

              # Train the model
              model.fit(X, y)

              # Make predictions and evalute
              predictions = model.predict(X_test)

              # Return the performance metric
              return print(classification_report(y_test, predictions), '\n', confusion_matrix(y_
```

```
In [120]: lr = LogisticRegression()

          fit_and_evaluate(lr)
```

```
             precision    recall  f1-score   support

          0       0.93      0.94      0.94      1411
          1       0.82      0.77      0.79       451

avg / total       0.90      0.90      0.90      1862

 [[1333   78]
```

```
 [ 102  349]]
```

In [121]:
```
svm = SVC(C = 1000, gamma = 0.1)

fit_and_evaluate(svm)
```

```
             precision    recall  f1-score   support

          0       0.87      0.97      0.92      1411
          1       0.87      0.56      0.68       451

avg / total       0.87      0.87      0.86      1862

 [[1374   37]
 [ 198  253]]
```

In [122]:
```
random_forest = RandomForestClassifier(random_state=101)

fit_and_evaluate(random_forest)
```

```
             precision    recall  f1-score   support

          0       1.00      1.00      1.00      1411
          1       1.00      1.00      1.00       451

avg / total       1.00      1.00      1.00      1862

 [[1411    0]
 [   0  451]]
```

In [124]:
```
knn = KNeighborsClassifier(n_neighbors=5)

fit_and_evaluate(knn)
```

```
             precision    recall  f1-score   support

          0       0.93      0.94      0.94      1411
          1       0.82      0.79      0.81       451

avg / total       0.91      0.91      0.91      1862

 [[1332   79]
 [  93  358]]
```

In [176]:
```
gradient_boosted = GradientBoostingClassifier(random_state=60)

fit_and_evaluate(gradient_boosted)
```

```
             precision    recall  f1-score   support

          0       1.00      1.00      1.00      1411
          1       1.00      1.00      1.00       451

avg / total       1.00      1.00      1.00      1862

 [[1411    0]
 [   0  451]]
```

This one has perfect performance so we will use that to predict a new campaign:

```
In [190]: reduced_x_features

          #log of 14000 is 9.6, which means the goal is 1000 and the pledged is 14000, and it st
          gradient_boosted.predict_proba([[45, 0, 6, 1, 15000, 9.62, 6.91]])

Out[190]: array([[5.44896131e-04, 9.99455104e-01]])
```

A campaign with 45 days until the deadline, that was not staff picked, backed by 6 backers, is in the spotlight, has a goal of 15000 USD, which is a log_goal of 9.62, and a log_pledged of 6.91 (equal to 1000 USD) has a 99.9% chance of succeeding!

6 Interpretation

```
In [185]: importances = gradient_boosted.feature_importances_

          feature_list = list(X.columns)

          feature_results = pd.DataFrame({'feature': feature_list,
                                          'importance': importances})

          feature_results

Out[185]:                  feature  importance
          0  launch_to_deadline_days        0.00
          1               staff_pick        0.00
          2            backers_count        0.00
          3                spotlight        0.72
          4                     goal        0.00
          5                 log_goal        0.00
          6               log_pledged       0.00
```

According to our gradient boosting classifier algorithm's calculations, the most important feature in determining the outcome of a Kickstarter campaign is whether or not it is in the spotlight. That makes sense!

7 Conclusions

With this dataset, it is possible to predict the success or failure of a kickstarter campaign with just 7 variables describing it, and with the gradient_boosted.predict_proba() method, we can know the probability of either failure or success, given a new input of unseen features. Project by Riley Predum. To see more projects/coding, visit my github!