Predicting Kickstart Project State

March 11, 2018

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CSC 478 Final Project

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Introduction

The purpose of this document is to outline our approach in predicting the status of different projects presented to the public using the Kickstarter platform. The group leveraged many algorithms and functions available in the sklearn library to operationalize the defined machine learning workflow. This document will provide an overview of the dataset leveraged to complete the machine learning project, as well as an in-depth analysis of the methodologies implemented, the requisite results, and any conclusions, as well as constraints or blockers, the group was able to identify while completing the project.

Overview

The dataset used to complete the group's analysis can be found on the Kaggle website as a competition dataset.[1] There are two datasets listed under the competition page. After a comparison of both datasets, it was determined that both datasets contain the same information in terms of relevant data points. The most recent dataset, entitled "ks-projects-201801.csv", contains a "cleansed" dataset, where all of the misnomers and formatting issues have been removed and / or rectified. After conducting this analysis, the group determined that the only dataset required to complete the project was the ks-projects-201801.csv. All of the analysis presented throughout this document solely references this dataset. After settling on the ks-projects-201801.csv dataset, the group created a GitHub repository and uploaded the .csv file in question to said repository. The group used GitHub to build their analysis leveraging the same base dataset, and complete the necessary objectives independently, within a central repository.

[1] Kemical. "Kickstarter projects." Kaggle.com. https://www.kaggle.com/kemical/kickstarter-projects (accessed February 13, 2018).

Concerning an overview of the features of the dataset specifically, the table below contains relevant high-level statistics in terms of row count and number of columns below:

Statistic	Value
Number of Rows	378,661
Number of Columns	15

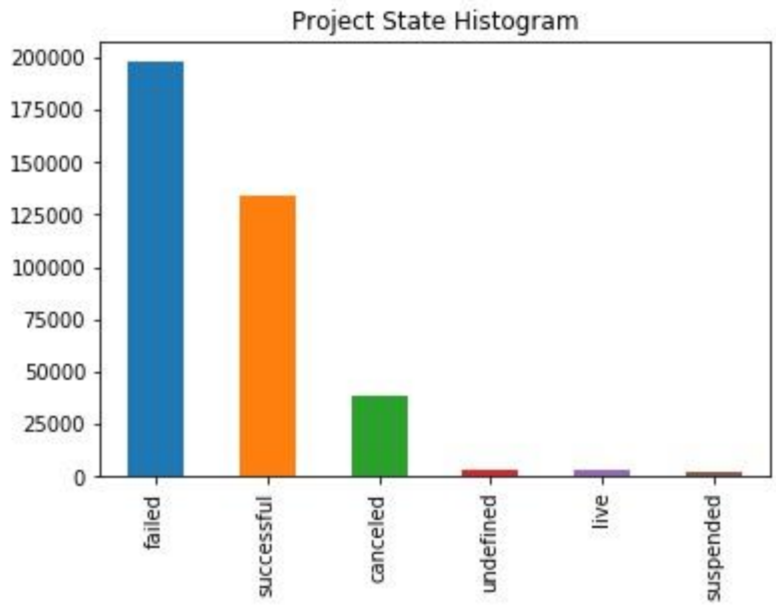
In addition to the number of rows and columns, the feature names and corresponding data types can be found below:

Sequence Number	Column Name	Data Type
1	ID	Numeric
2	name	String
3	category	String
4	main_category	String
5	currency	String
6	deadline	DateTime
7	goal	Numeric
8	launched	DateTime
9	pledged	Numeric
10	state	String
11	backers	Numeric
12	country	String
13	usd pledged	Numeric
14	usd_pledged_real	Numeric
15	usd_goal_real	Numeric

Once the dataset was identified, the group conducted a deeper dive of the data – analyzing features as well as observations.

Analysis of Features and Observations

To gain better insight into the data, the group produced a series of histograms to show distributions by different segments of the data. Please find a histogram, as well as a summary table, of project status below:



Project State	Observation Count
failed	197,719
successful	133,956
canceled	38,779
undefined	3,562
live	2,799
suspended	1,846

From the information presented in this histogram and corresponding summary table, one can easily determine that most projects fail, with projects succeeding being the second most frequent project state. Aside from projects succeeding, applicable statuses include '"canceled", "undefined", "live", and "suspended". The group decided to keep all statuses aside from undefined, due to the ambiguity associated with the undefined project state. Upon removal, a distribution of the project states used for analysis can be found below:

Removing the undefined status reduced the total dataset record count to 375,099. Aside from removing observations where the project state was equal to undefined, the group also removed features "goal", "pledged", and "usd pledged". The dataset contains Kickstarter campaigns from a number of different countries, with the stated goal and pledged values in the native currency.

The creator of the dataset converted the goal and pledged amounts to United States Dollars (usd). This conversion is represented in the dataset as "usd_pledged_real" and "usd_goal_real". Removal of the aforemtioned columns reduces the number of numeric variables to three – usd_pledged_real, usd_goal_real, and backers. Summary statistics for these variables can be found below:

Statistic	backers	usd_goal_real	usd_pledged_real
count	375099.000000	3.750990e+05	3.750990e+05
mean	106.620436	9.123935e+03	4.584708e+04
std	911.423593	9.140142e+04	1.158404e+06
min	0.000000	0.000000e+00	1.000000e-02
25%	2.000000	3.100000e+01	2.000000e+03
50%	12.000000	6.250000e+02	5.500000e+03
75%	57.000000	4.050180e+03	1.600000e+04

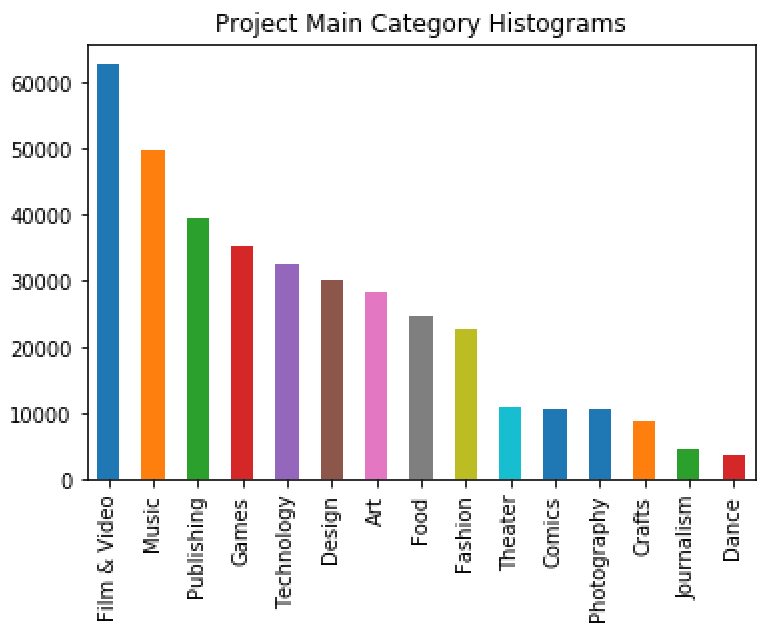
After producing high level summary statics for the numeric variables, the group produced a correlation matrix to view any weak or strong relationships within the data. A heatmap was also produced to present the relationships graphically. Please find the correlation matrix and corresponding heatmap below:

	ID	backers	usd_pledged_real	usd_goal_real
ID	1.000000	0.000676	-0.000016	0.001868
backers	0.000676	1.000000	0.752528	0.004478
usd_pledged_real	-0.000016	0.752528	1.000000	0.005571
usd_goal_real	0.001868	0.004478	0.005571	1.000000

The elicited results show strong relationships between all three of the numeric variables, with the relationship between usd_pledged_real and backers particularly strong with a value of 0.75. Based on the operational understanding of the data, this is to be expected. The number of backers positively drive the amount pledged for a given project.

Once correlations were identified, the group focused their analysis on the relationship between main_category and category. The main_category feature is a parent of the category feature, with 170 categories available and fifteen distinct main categories. A breakdown of observations by main_category can be found below:

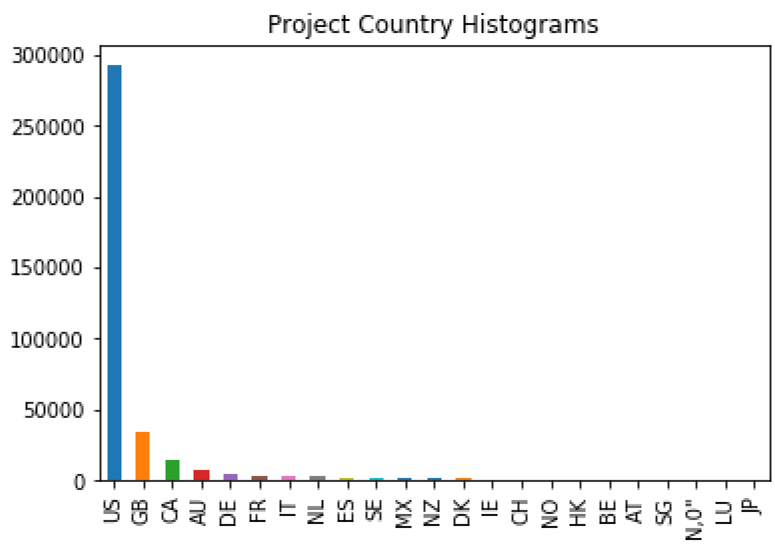
Main Category	Observation Count
Art	28,153
Comics	10,819
Crafts	8,809
Dance	3,767
Design	30,068
Fashion	22,813
Film & Video	62,731
Food	24,602
Games	35,230
Journalism	4,755
Music	49,684
Photography	10,778
Publishing	39,412
Technology	32,566
Theater	10,912



Based on this analysis, the top three categories in terms of observation count are "Film & Video", "Music", and "Publishing".

In addition to reviewing project status and category, the project group also reviewed the country of origin for each Kickstarter project. Please find a breakdown of projects by country, as well as a corresponding histogram, below:

Country	Observation Count
AT	597
AU	7,839
BE	617
CA	14,756
CH	761
DE	4,171
DK	1,113
ES	2,276
FR	2,939
GB	33,672
HK	618
IE	811
IT	2,878
JP	40
LU	62
MX	1,752
N,0"	235
NL	2,868
NO	708
NZ	1,447
SE	1,757
SG	555
US	292,627



The three most frequent countries in the Kickstarter dataset are the United States (US), Great Britain (GB), and Canada (CA). Completing this analysis brought to the group's attention a misnomer in the data – 235 observations with a country value of "N,0"", which is not a valid country code. These observations were removed from the dataset.

Transformations

In addition to the analysis completed on the categorical and numeric features found within the Kickstarter dataset, two transformations were completed before algorithm application. The first transformation addressed Kickstarter campaigns without names, or titles. This issue impacted four records, and the group converted the name to the value of "Unknown". The second transformation dealt with invalid data types for the dataset. The Pandas library applied the wrong data type to a few of the features. The impacted features included "deadline", "launched", "usd_goal_real", and "usd_pledged_real". The "deadline" and "launched" features were converted to dates, removing time from the observations. The "usd_goal_real" and "usd_pledged_real" features were converted to integer data types. Transformations were applied in an attempt to align the working dataset with the data types presented on the project's Kaggle site.

Appendix

```
# coding: utf-8


# # Kickstarter Projects

# ### CSC 478 Final Project

# #### Synopsis:

# * The purpose of this project is to predict whether a kickstarter campaign will fail, succeed, or cancel based on the available information available [here](https://raw.githubusercontent.com/stfox13/CSC478FinalProject/master/Data/ks-projects-201801.csv).

# * We will use an array of machine learning algorithms, including KNN, Linear Regression, Logistic Regression, and / or SVM to find the most accurate model.

#

# #### Contributors:

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# * [Sidney Fox (1524992)](https://github.com/stfox13)

#

# ## Libraries used through the project:


get_ipython().magic(u'matplotlib inline')

import matplotlib.pyplot as plt

import numpy as np

import pandas as pd

import seaborn as sns

import os

import math

import requests

import datetime as dt

import matplotlib as mpl
```

```
import io
from pandas import Series, DataFrame
from sklearn.pipeline import Pipeline
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.ensemble import ExtraTreesClassifier
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler, Imputer, LabelEncoder
from sklearn import svm
from sklearn.metrics import f1_score, confusion_matrix, accuracy_score, classification_report
import itertools
from sklearn.feature_selection import RFE
from collections import defaultdict
import pylab

#Environment settings
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
mpl.rcParams['figure.figsize'] = (10,10)
np.set_printoptions(suppress=True)

# ## Load raw data as Pandas DataFrame:
url = 'https://raw.githubusercontent.com/stfox13/CSC478FinalProject/master/Data/ks-projects-201801.csv'
kickproj_org= pd.read_csv(url)
print "Total rows in dataset:",len(kickproj_org)

# ## Define Useful Functions
```

```
#Roundup function
def roundup(x, y):
  return int(math.ceil(x / y) * y)


#Define a fuction to print and plot confusin matrix
def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
  """
  This function prints and plots the confusion matrix.
  Normalization can be applied by setting `normalize=True`.
  """
  if normalize:
    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
  else:
    pass

  plt.imshow(cm, interpolation='nearest', cmap=cmap)
  plt.title(title)
  plt.colorbar()
  tick_marks = np.arange(len(classes))
  plt.xticks(tick_marks, classes, rotation=45)
  plt.yticks(tick_marks, classes)

  fmt = '.2f' if normalize else 'd'
  thresh = cm.max() / 2.
  for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, format(cm[i, j], fmt),
```

```
            horizontalalignment="center",
            color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')

#Define a fuction to calculate and print TP, TN, FP, and FN for each category
def show_statistics(test_y, y_pred, matrix):
    TP = np.diag(matrix)
    FP = np.sum(matrix, axis=0) - TP
    FN = np.sum(matrix, axis=1) - TP
    TN = []
    for i in range(len(matrix)):
        temp = np.delete(matrix, i, 0)    # delete ith row
        temp = np.delete(temp, i, 1)  # delete ith column
        TN.append(sum(sum(temp)))
    temp_dic = {'TP': TP, 'FP' : FP,
                'TN' : TN, 'FN' : FN}
    scoreMatrix = DataFrame.from_dict(temp_dic)
    return scoreMatrix

# Define a fuction to print F1 Score for each class and global (micro)
def formatResult(preResult, columnNames):
    resultDF = DataFrame(preResult.values(), columns=columnNames, index=preResult.keys())
    resultDF.loc['sum'] = np.sum(preResult.values(), axis=0)
    resultDF['Sum of Class F1'] = np.append(np.sum(preResult.values(), axis=1), np.NaN)
    return resultDF
```

```
#Define a function to run KNeighborsClassifier with different n_neighbors and store f1 score
def runKNN(trainX, trainY, testX, testY, number, f1_only = False, trainSetName = '', dic_result_knn = {}):
    i = 3
    cls = KNeighborsClassifier(n_neighbors=i)
    while i <= number:
        cls = KNeighborsClassifier(n_neighbors=i)
        cls.fit(trainX, trainY)
        predY = cls.predict(testX)
        result = f1_score(testY, predY, average=None).round(2)
        result = np.append(result, f1_score(testY, predY, average='micro').round(2))
        dic_result_knn['N=' + str(i) +'-' + trainSetName] = result
        i = i + 2
    return dic_result_knn

# Define a function to run LogisticRegression with different class_weight settings and store f1 score
def runLogistic(trainX, trainY, testX, testY, f1_only = False, trainSetName = '', dic_result_log = {}):
    cls = LogisticRegression()
    cls.fit(trainX, trainY)
    predY = cls.predict(testX)
    result = f1_score(testY, predY, average=None).round(2)
    result = np.append(result, f1_score(testY, predY, average='micro').round(2))
    dic_result_log['CWeight = None - ' + trainSetName] = result

    cls = LogisticRegression(class_weight='balanced')
    cls.fit(trainX, trainY)
    predY = cls.predict(testX)
    result = f1_score(testY, predY, average=None).round(2)
    result = np.append(result, f1_score(testY, predY, average='micro').round(2))
    dic_result_log['CWeight = balanced - ' + trainSetName] = result
```

```
    return dic_result_log

# Define a function to run SVM with different kernel settings and store f1 score
def runSVM(trainX, trainY, testX, testY, f1_only = False, trainSetName = '', dic_result_log = {}):

    C = 1.0 # SVM regularization parameter
    svc = svm.SVC(kernel='linear', C=C, decision_function_shape='ovr').fit(trainX, trainY)
    predY = svc.predict(X_plot)
    result = f1_score(testY, predY, average=None).round(2)
    result = np.append(result, f1_score(testY, predY, average='micro').round(2))
    print results
    dic_result_log['SVCKernel = linear - ' + trainSetName] = result

    svc = svm.SVC(kernel='rbf', C=C, decision_function_shape='ovr').fit(trainX, trainY)
    predY = svc.predict(X_plot)
    result = f1_score(testY, predY, average=None).round(2)
    result = np.append(result, f1_score(testY, predY, average='micro').round(2))
    print results
    dic_result_log['SVCKernel = rbf - ' + trainSetName] = result

    return dic_result_log



# ## Check the Y data:


#Plot histogram
kickproj_org['state'].value_counts()
kickproj_org['state'].value_counts().plot(kind='bar', title='Project State Histogram')
```

```
# ### Drop projects when the state is equal to "undefined":

# Remove state = 'undefined'

kickproj = kickproj_org[kickproj_org['state'] != 'undefined']

len(kickproj)


#Plot histogram

kickproj['state'].value_counts().plot(kind='bar', title='Project State Histogram (without undefined)')


#Review first five records:

kickproj.head(5)



# #### Since we have the goal and pledge amounts converted to US dollars (usd), we will drop the original goal and pledged columns:

kickproj = kickproj.drop(['goal','pledged','usd pledged'], axis=1)

len(kickproj)

kickproj.head(5)



# ## Check the X data:

#High level descriptive stats and correlation:

kickproj.describe()

kickproj.corr()


print('Heat Map of Correlation Coefficients:')

sns.heatmap(kickproj.corr(), cmap="BuGn_r", linewidths=0.5, annot=True)


#Review different categories in dataset:

categoryDF = kickproj.groupby(['category']).size().reset_index(name='counts')
```

```
len(categoryDF)

categoryDF.sort(['counts']).head(5)


#Review main categories in dataset:

kickproj.groupby(['main_category']).size().reset_index(name='counts')

kickproj['main_category'].value_counts().plot(kind='bar', title='Project Main Category Histograms')


#Review relationship of categories to main_categories (parent-child)

cateDF = kickproj.groupby(['main_category', 'category']).size().reset_index(name='counts')

len(cateDF)

cateDF.head(40)


#Distribution by country:

kickproj.groupby(['country']).size().reset_index(name='counts')

kickproj['country'].value_counts().plot(kind='bar', title='Project Country Histograms')



# ### Remove country with invalid value, N,0"

kickproj = kickproj[kickproj['country'] != 'N,0"']

kickproj.groupby(['country']).size().reset_index(name='counts')

kickproj['country'].value_counts().plot(kind='bar', title='Project Country Histograms')



# ### Check null value

null_columns=kickproj.columns[kickproj.isnull().any()]

null_columns

kickproj[null_columns].isnull().sum()

kickproj[kickproj["name"].isnull()][null_columns]
```

```
# ### Replace nan with Unknown for name

kickproj["name"].fillna('Unknown', inplace=True)

null_columns=kickproj.columns[kickproj.isnull().any()]

null_columns


# ### Apply correct data types to DataFrame:

print 'Data types do not align with the data types defined in the data dictionary:\n\n', kickproj.dtypes


# Columns that are of date data type:

datecols = ['deadline','launched']


# Columns that are of int data type:

intcols = ['usd_pledged_real','usd_goal_real']


# Convert date columns to date data type:

for col in datecols:

    kickproj[col] = pd.to_datetime(kickproj[col]).dt.date

    kickproj[col] = pd.to_datetime(kickproj[col])


# Convert int columns to int data type:

kickproj[intcols] = kickproj[intcols].fillna(0).astype(np.int64)


print 'Review converted data types:\n\n', kickproj.dtypes


#Review dataset after conversion:

kickproj.head(5)


# ### Model Classification Using All Features (Start)
```

```
#Encode non-numeric variables - needed to run most of the models, understand anything feature importance:

le = preprocessing.LabelEncoder

d = defaultdict(le)

le_df = kickproj.apply(lambda x: d[x.name].fit_transform(x))


#Split data into two subsets - features and target - looking to predict state of the project:

features = le_df[le_df.columns.drop('state')]

target = le_df['state']



# #### Feature Selection Method One: Recursive Feature Elimination


#Look at recursive feature elimination (RFE) with logistic regression and select three features:

LogReg_RFE = RFE(LogisticRegression(), 3).fit(features, target)


print('The three most important features according to Logistic Regression:\n'),(np.array(features.columns)[LogReg_RFE.support_])


#Look at recursive feature elimination (RFE) with linear regression and select three features:

LinReg_RFE = RFE(LinearRegression(), 3).fit(features, target)


print('The three most important features according to Linear Regression:\n'),(np.array(features.columns)[LinReg_RFE.support_])


#We'll use extra trees classifier to calculate feature importance:

ETC = ExtraTreesClassifier().fit(features, target)

feat_imp_df = pd.DataFrame({'Columns':pd.Series(features.columns)})

feat_imp_df['Feature Importance'] = pd.Series(ETC.feature_importances_)
```

```
feat_imp_df.set_index(['Columns'],inplace=True)



# #### Feature Selection Method Two: Feature Importance

print('Column Names and Associated Feature Importance:')

feat_imp_df

feat_imp_df.plot(kind="bar", title="Feature Importance Results", legend = False)


# Observation: according to the extra trees classifier, the most important features
are:<br>usd_pledged_real, usd_goal_real, backers<br><br>Let's split the data into test and train and
compare approaches.


# ### Model Execution

#split the dataset in two parts [:n] for training and [n:] for testing (n = 50%)

le_len = int(math.floor(len(le_df)/2))

le_train, le_test = le_df.iloc[:le_len], le_df.iloc[le_len:]


#Create x and y train and test data sets, where x contains features and y contains target

x_train, y_train = le_train[le_train.columns.drop('state')], le_train['state']

x_test, y_test = le_test[le_test.columns.drop('state')],le_test['state']



# #### Run battery of algorithms: KNN, Logistic Regression, SVM

#Initialize le_result_Dic:

le_result_Dic = {}


#Algorithm 1: KNN

le_result_Dic = runKNN(x_train, y_train.values.ravel(), x_test, y_test.values.ravel(), 18, trainSetName =
'LE KNN', dic_result_knn = le_result_Dic)
```

```
#Algorithm 2: Logistic Regression

le_result_Dic = runLogistic(x_train, y_train.values.ravel(), x_test, y_test.values.ravel(), trainSetName =
'LE LR', dic_result_log = le_result_Dic)


#Algorithm 3: (Attempt) SVM

most_important_cols = ['backers','usd_pledged_real','usd_goal_real']

svm_x_train, svm_y_train = le_train[most_important_cols], le_train['state']

svm_x_test, svm_y_test = le_test[most_important_cols], le_test['state']


svm.SVC(kernel='linear', C=1.0, decision_function_shape='ovr').fit(svm_x_train, svm_y_train)


#View results:

le_result_Dic


# ### Find out correlation among all variables:

kickproj.apply(lambda x : pd.factorize(x)[0]).corr(method='pearson', min_periods=1)

print('Heat Map of Correlation Coefficients:')

sns.heatmap(kickproj.apply(lambda x : pd.factorize(x)[0]).corr(method='pearson', min_periods=1),
cmap="BuGn_r", linewidths=0.5, annot=True)


#Define binrange

binrange = range(1, roundup(max(kickproj['usd_pledged_real']),100000), 5000000)

binrange


#Review minimum and maximum values for usd_goal_real

min(kickproj['usd_goal_real'])

max(kickproj['usd_goal_real'])


# All successful records have usd_pledged_real >= 0
```

```
min(kickproj['usd_pledged_real'])
max(kickproj['usd_pledged_real'])

kickproj[(kickproj['usd_pledged_real']==0) & (kickproj['state']=='successful')]

#Shuffle dataset
shffled_kickproj = kickproj.sample(frac=1)

shffled_kickproj['state_cd'] = shffled_kickproj['state'].apply(lambda a: True if a == 'successful' else False)
shffled_kickproj.head(5)

le = preprocessing.LabelEncoder()
le.fit(shffled_kickproj['country'])
shffled_kickproj['country_cd'] = le.transform(shffled_kickproj['country'])
shffled_kickproj.head(5)

num = shffled_kickproj.shape[0]/2

train_x, train_y = shffled_kickproj.iloc[0:num, [5,6,8,9,10,11,13]], shffled_kickproj.iloc[0:num, 12]
test_x, test_y = shffled_kickproj.iloc[num:, [5,6,8,9,10,11,13]], shffled_kickproj.iloc[num:, 12]
train_x.head(2)
train_x.shape
train_y.head(2)
train_y.shape
test_x.head(2)
test_x.shape
test_y.head(2)
test_y.shape
```

```
# ### Train training set

temp_features_train = train_x['country_cd'].reshape(-1, 1) # Needs to be the correct shape

temp_features_test = test_x['country_cd'].reshape(-1, 1) # Needs to be the correct shape


ohe = preprocessing.OneHotEncoder(sparse=False) #Easier to read


#fit on training set only

ohe.fit(temp_features_train)

countryDF_train = DataFrame(ohe.transform(temp_features_train), columns = ohe.active_features_,
index = train_x.index)

countryDF_test = DataFrame(ohe.transform(temp_features_test), columns = ohe.active_features_,
index = test_x.index)

countryDF_train.head(10)

countryDF_test.head(10)


train_x.shape

countryDF_train.shape

test_x.shape

countryDF_test.shape


train_X1 = pd.merge(train_x.drop(['country','country_cd'], axis=1), countryDF_train, left_index=True,
right_index=True)

train_X1.head(10)

train_X1.shape


test_X1 = pd.merge(test_x.drop(['country','country_cd'], axis=1), countryDF_test, left_index=True,
right_index=True)

test_X1.head(10)

test_X1.shape
```

```
result_Dic = {}

#Call function to run KNeighborsClassifier with different n_neighbors settings (up to 20) and store the f1 score results

result_Dic = runKNN(train_X1, train_y.values.ravel(), test_X1, test_y.values.ravel(), 18, trainSetName = 'Basic&Country', dic_result_knn = result_Dic)

#Call function to run LogisticRegression with different class_weight settings (None or Balance)  and store the f1 score results

result_Dic = runLogistic(train_X1, train_y.values.ravel(), test_X1, test_y.values.ravel(), trainSetName = 'Basic&Country', dic_result_log = result_Dic)

#Store number of classes

n_classes = np.unique(shffled_kickproj['state_cd'])

n_classes

resultDF = formatResult(result_Dic, np.append(n_classes, 'micro'))

resultDF.head(10)

# Print out the top 10 Micro (overall) F1 score from all settings

resultDF.drop('sum').nlargest(5, 'micro')

resultDF.drop('sum').nlargest(5, 'Sum of Class F1')

knnClr = KNeighborsClassifier(n_neighbors=5)

knnClr.fit(train_X1, train_y.values.ravel())

final_y_pred = knnClr.predict(test_X1)

# Compute confusion matrix

cnf_matrix = confusion_matrix(test_y, final_y_pred)

np.set_printoptions(precision=2)
```

```
# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=[False,True],
                      normalize=False,
                      title='Confusion matrix, without normalization (True = successful; False = Other)')
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=[False,True],
                      normalize=True,
                      title='Confusion matrix, with normalization (True = successful; False = Other)')


stats = show_statistics(test_y, final_y_pred, cnf_matrix)
strName = map((lambda a: 'successful' if a == True else 'Failed/Cancelled/Live/Suspended'),  [False,
True])
print "Classificaiton Report:"
print classification_report(test_y, final_y_pred, target_names=strName, digits=2)
```