# Data Science Project 3

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- Student Pace: Flex / 40 weeks
- Scheduled Project Review Date / Time: Thurs, Sept 16 / 12pm
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## Setup, EDA, Preprocessing

In [439…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from datetime import datetime

from sklearn.model_selection import train_test_split, GridSearchCV, \
cross_val_score
from sklearn.impute import SimpleImputer
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier, \
BaggingClassifier, ExtraTreesClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, recall_score, \
precision_score, confusion_matrix, classification_report, roc_curve, auc, \
average_precision_score
from sklearn.preprocessing import StandardScaler, LabelEncoder, \
MinMaxScaler, OneHotEncoder
from sklearn.pipeline import Pipeline
from xgboost import XGBClassifier
from imblearn.over_sampling import SMOTE

import warnings
warnings.filterwarnings('ignore')
```

### Load in Data

In [440…
```
df = pd.read_csv('data/investments_VC.csv', encoding = "ISO-8859-1")
```

### Basic Cleaning

In [441…
```
# getting rid of extra spaces in market and funding_total_usd
df = df.rename(columns={' market ': 'market',
                        ' funding_total_usd ': 'funding_total_usd'})
```

Dropping irrelevant columns:

In [442…
```
df = df.drop(columns=['permalink', 'homepage_url', 'category_list',
                      'founded_quarter', 'post_ipo_equity',
                      'post_ipo_debt', 'secondary_market'],
             axis=1)
```

In [443…
```
# converting to float
df['funding_total_usd'][~df['funding_total_usd'].isnull()] = \
    [float(num.replace(" ", "0").replace(",", "0").replace("-", "0")) \
     for num in df['funding_total_usd'][~df['funding_total_usd'].isnull()]]
```

Dropping duplicates, if any:

In [444…
```
df = df.drop_duplicates()
```

In [445…
```
df['status'].value_counts()
```

Out[445]:
```
operating    41829
acquired      3692
closed        2603
Name: status, dtype: int64
```

## Exploratory Analysis - Full Dataset

In [446…
```
data = df
```

In [447…
```
print(data.info())
data.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 49439 entries, 0 to 49438
Data columns (total 32 columns):
 #   Column                 Non-Null Count  Dtype  
---  ------                 --------------  -----  
 0   name                   49437 non-null  object 
 1   market                 45470 non-null  object 
 2   funding_total_usd      49438 non-null  object 
 3   status                 48124 non-null  object 
 4   country_code           44165 non-null  object 
 5   state_code             30161 non-null  object 
 6   region                 44165 non-null  object 
 7   city                   43322 non-null  object 
 8   funding_rounds         49438 non-null  float64
 9   founded_at             38554 non-null  object 
 10  founded_month          38482 non-null  object 
 11  founded_year           38482 non-null  float64
 12  first_funding_at       49438 non-null  object 
 13  last_funding_at        49438 non-null  object 
 14  seed                   49438 non-null  float64
 15  venture                49438 non-null  float64
 16  equity_crowdfunding    49438 non-null  float64
 17  undisclosed            49438 non-null  float64
 18  convertible_note       49438 non-null  float64
 19  debt_financing         49438 non-null  float64
 20  angel                  49438 non-null  float64
 21  grant                  49438 non-null  float64
 22  private_equity         49438 non-null  float64
 23  product_crowdfunding   49438 non-null  float64
 24  round_A                49438 non-null  float64
 25  round_B                49438 non-null  float64
 26  round_C                49438 non-null  float64
 27  round_D                49438 non-null  float64
 28  round_E                49438 non-null  float64
 29  round_F                49438 non-null  float64
 30  round_G                49438 non-null  float64
 31  round_H                49438 non-null  float64
dtypes: float64(20), object(12)
memory usage: 12.4+ MB
None
```

Out[447]:

| | name | market | funding_total_usd | status | country_code | state_code | regio |
|---|---|---|---|---|---|---|---|
| **0** | #waywire | News | 1.705e+09 | acquired | USA | NY | Ne Yor Cit |
| **1** | &TV Communications | Games | 4e+09 | operating | USA | CA | Lo Angele |
| **2** | 'Rock' Your Paper | Publishing | 4e+06 | operating | EST | NaN | Tallin |
| **3** | (In)Touch Network | Electronics | 1.5e+09 | operating | GBR | NaN | Londo |
| **4** | -R- Ranch and Mine | Tourism | 6e+06 | operating | USA | TX | Dalla |

5 rows × 32 columns

In [448…
```
df.describe()
```

Out[448]:

| | funding_rounds | founded_year | seed | venture | equity_crowdfunding | u |
|---|---|---|---|---|---|---|
| count | 49438.000000 | 38482.000000 | 4.943800e+04 | 4.943800e+04 | 4.943800e+04 | 4.9 |
| mean | 1.696205 | 2007.359129 | 2.173215e+05 | 7.501051e+06 | 6.163322e+03 | 1.: |
| std | 1.294213 | 7.579203 | 1.056985e+06 | 2.847112e+07 | 1.999048e+05 | 2.9 |
| min | 1.000000 | 1902.000000 | 0.000000e+00 | 0.000000e+00 | 0.000000e+00 | 0.0 |
| 25% | 1.000000 | 2006.000000 | 0.000000e+00 | 0.000000e+00 | 0.000000e+00 | 0.0 |
| 50% | 1.000000 | 2010.000000 | 0.000000e+00 | 0.000000e+00 | 0.000000e+00 | 0.0 |
| 75% | 2.000000 | 2012.000000 | 2.500000e+04 | 5.000000e+06 | 0.000000e+00 | 0.0 |
| max | 18.000000 | 2014.000000 | 1.300000e+08 | 2.351000e+09 | 2.500000e+07 | 2.9 |

In [449…
```
data.isnull().sum()
```

Out[449]:
```
name                        2
market                   3969
funding_total_usd           1
status                   1315
country_code             5274
state_code              19278
region                   5274
city                     6117
funding_rounds              1
founded_at              10885
founded_month           10957
founded_year            10957
first_funding_at            1
last_funding_at             1
seed                        1
venture                     1
equity_crowdfunding         1
undisclosed                 1
convertible_note            1
debt_financing              1
angel                       1
grant                       1
private_equity              1
product_crowdfunding        1
round_A                     1
round_B                     1
round_C                     1
round_D                     1
round_E                     1
round_F                     1
round_G                     1
round_H                     1
dtype: int64
```

In [450…
```
data['founded_at'].head()
```

Out[450]:
```
0    2012-06-01
1           NaN
2    2012-10-26
3    2011-04-01
4    2014-01-01
Name: founded_at, dtype: object
```

In [451…
```
data['region'].value_counts()
```

Out[451]:
```
SF Bay Area      6804
New York City    2577
Boston           1837
London           1588
Los Angeles      1389
                 ... 
Carlisle            1
Hellerup            1
Tashkent            1
Paignton            1
TTO - Other         1
Name: region, Length: 1089, dtype: int64
```

In [452…
```
data['city'].value_counts()
```

Out[452]:
```
San Francisco        2615
New York             2334
London               1257
Palo Alto             597
Austin                583
                     ... 
Plouzané                1
West Chicago            1
North Kansas City       1
Marquette               1
Warrenville             1
Name: city, Length: 4188, dtype: int64
```

In [453…
```
data['state_code'].value_counts()
```

Out[453]:
```
CA    9917
NY    2914
MA    1969
TX    1466
WA     974
      ... 
MB      13
AK      12
NB       8
SK       4
PE       2
Name: state_code, Length: 61, dtype: int64
```

In [454…
```
data['country_code'].value_counts()
```

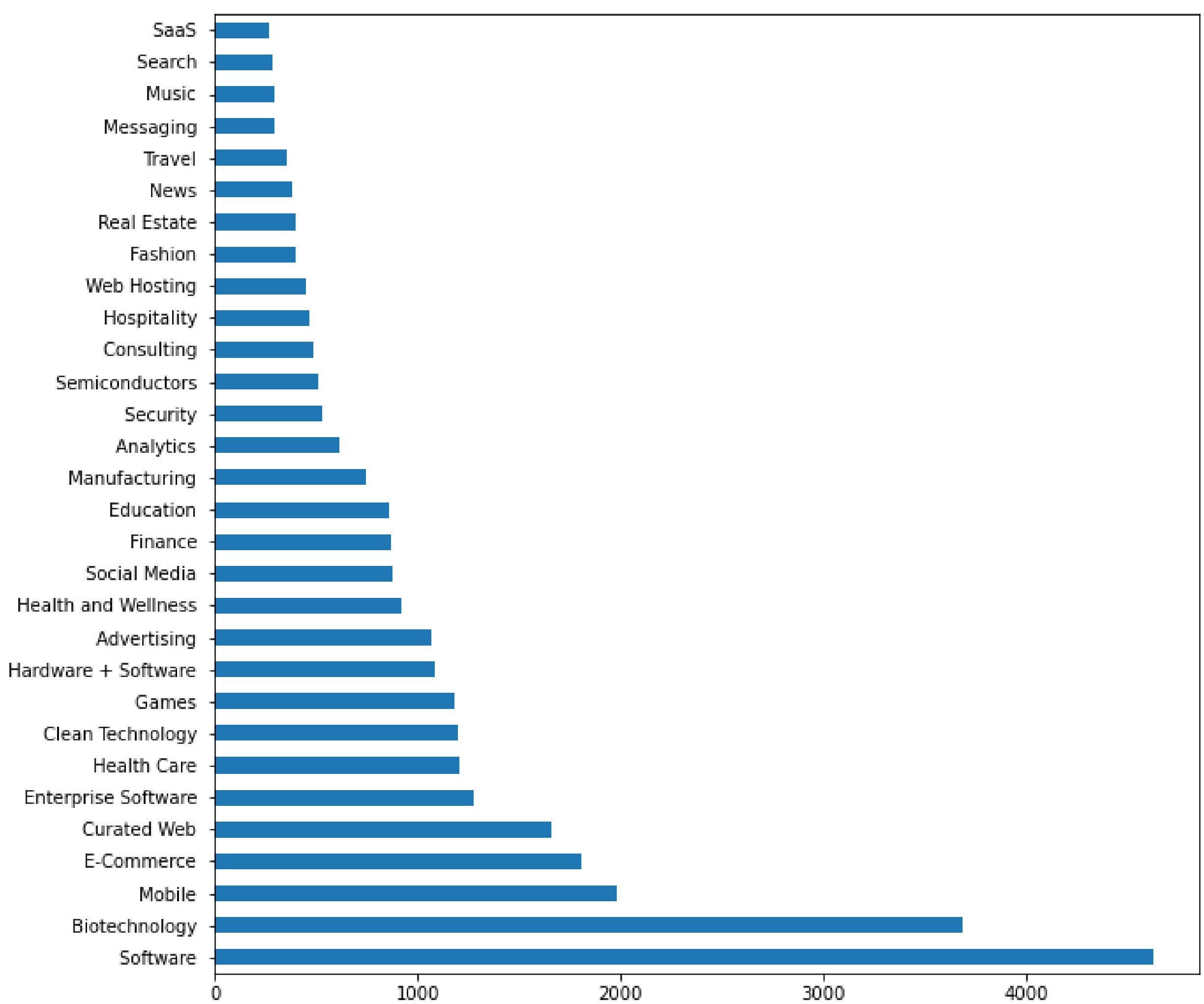
Out[454]:
```
USA     28793
GBR      2642
CAN      1405
CHN      1239
DEU       968
        ...
TTO         1
SYC         1
JEY         1
MAF         1
UZB         1
Name: country_code, Length: 115, dtype: int64
```

In [455…
```
# inspecting market feature - lots of catgories
print("Number of unique markets: ", len(set(data['market'])))
print("Markets with more than 200 companies: ",
      str(sum(data['market'].value_counts() >= 200)))
```

```
Number of unique markets:  754
Markets with more than 200 companies:  39
```

In [456…
```
fig, ax = plt.subplots(figsize = (10,10))
data['market'].value_counts()[:30].plot(kind='barh')
```

Out[456]: <AxesSubplot:>



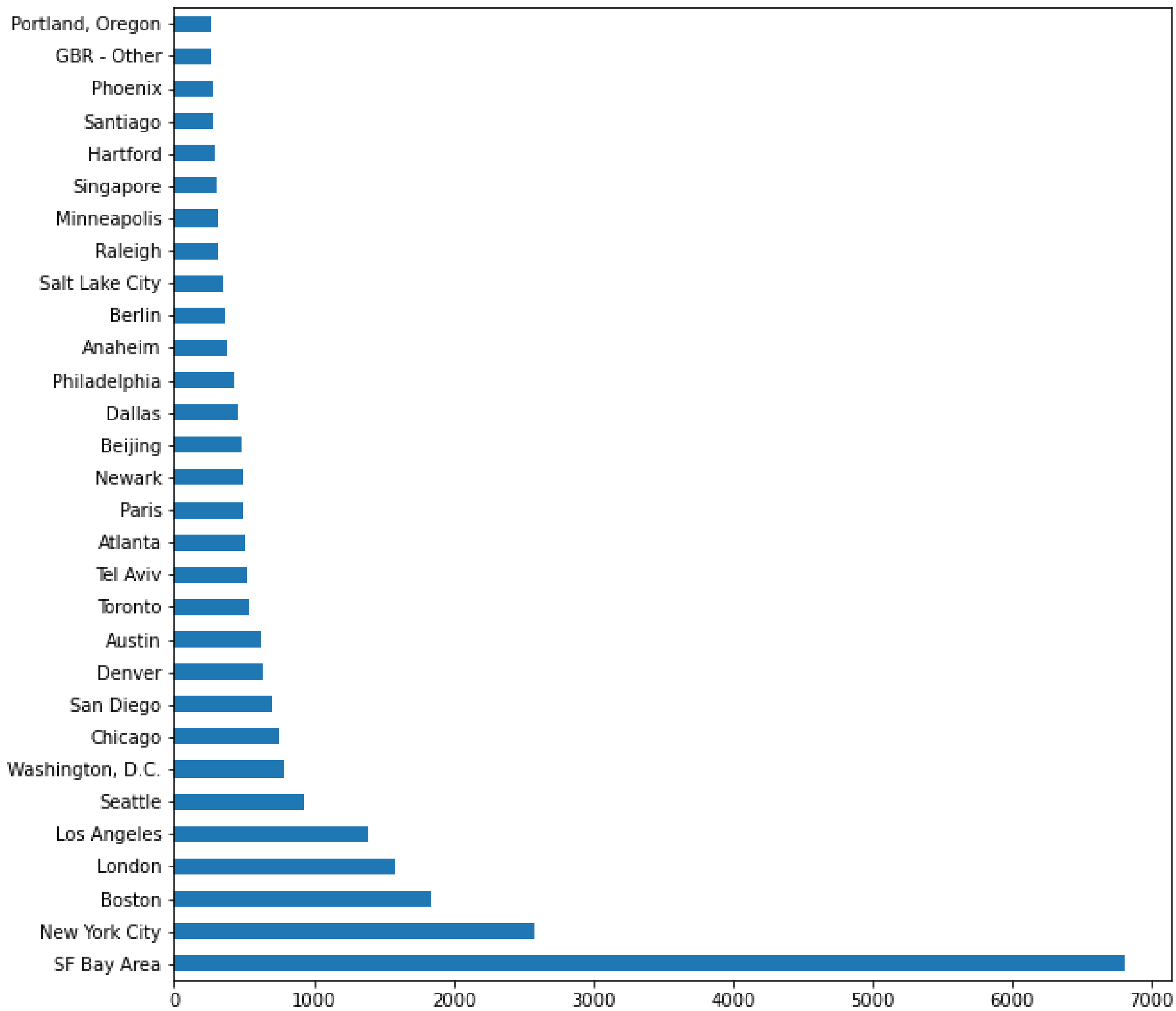

In [457…
```
# same deal with region
print("Number of unique regions: ", len(set(data['region'])))
```

```
print("Regions with more than 200 companies: ",
      str(sum(data['region'].value_counts() >= 200)))
```

```
Number of unique regions:  1090
Regions with more than 200 companies:  44
```

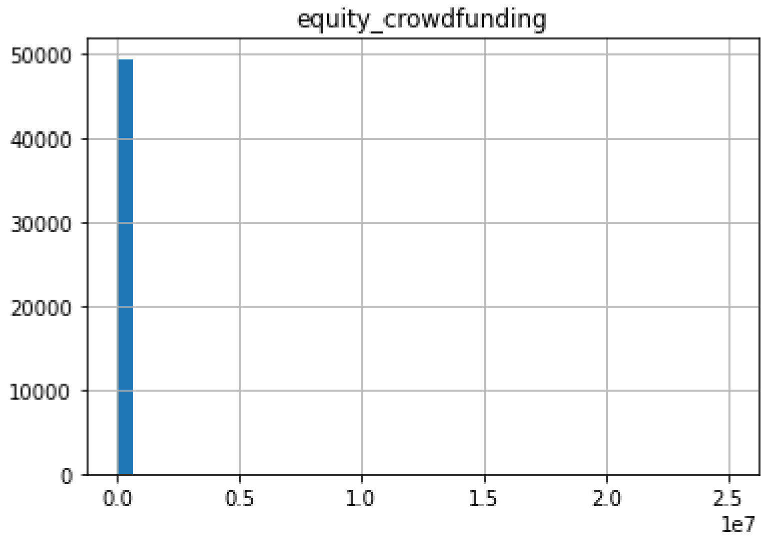
In [458…
```
fig, ax = plt.subplots(figsize = (10,10))
data['region'].value_counts()[:30].plot(kind='barh')
```

Out[458]: <AxesSubplot:>




In [459…
```
data.hist('equity_crowdfunding', bins=40)
# there are some very skewed columns in the funding area
```

Out[459]:
```
array([[<AxesSubplot:title={'center':'equity_crowdfunding'}>]],
      dtype=object)
```




## Preprocessing & Feature Engineering

In [460…
```
data.columns
```

Out[460]:
```
Index(['name', 'market', 'funding_total_usd', 'status', 'country_code',
       'state_code', 'region', 'city', 'funding_rounds', 'founded_at',
       'founded_month', 'founded_year', 'first_funding_at', 'last_funding_a
t',
       'seed', 'venture', 'equity_crowdfunding', 'undisclosed',
       'convertible_note', 'debt_financing', 'angel', 'grant',
       'private_equity', 'product_crowdfunding', 'round_A', 'round_B',
       'round_C', 'round_D', 'round_E', 'round_F', 'round_G', 'round_H'],
      dtype='object')
```

### Missing Values

- I am removing rows with missing status or company name.
- I am also dropping rows with a missing founded_year because this feature has high importance in many of the models & thus would prefer not to impute at risk of skewing the model. I tried both dropping and keeping the missing founded_years (imputed). The proportion of companies in each status category & model results are fairly similar with & without imputing the median of year so I am comfortable dropping these rows.

In [461…
```
data = data.dropna(subset=['status', 'name', 'founded_year'])
data.isnull().sum()
```

Out[461]:
```
name                         0
market                    1801
funding_total_usd            0
status                       0
country_code              2936
state_code               13332
region                    2936
city                      3357
funding_rounds               0
founded_at                   0
founded_month                0
founded_year                 0
first_funding_at             0
last_funding_at              0
seed                         0
venture                      0
equity_crowdfunding          0
undisclosed                  0
convertible_note             0
debt_financing               0
angel                        0
grant                        0
private_equity               0
product_crowdfunding         0
round_A                      0
round_B                      0
round_C                      0
round_D                      0
round_E                      0
round_F                      0
round_G                      0
round_H                      0
dtype: int64
```

In [462…
```
len(data)
```

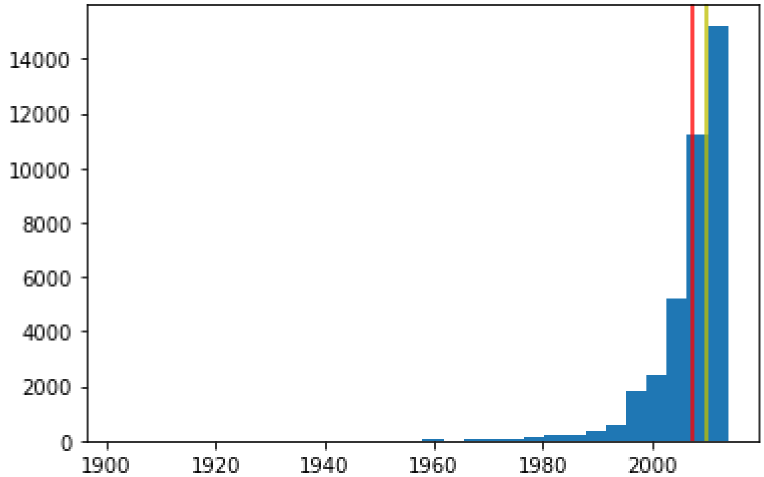
Out[462]:
```
37563
```

In [463…
```
# filling categoricals
data = data.fillna(value={'market': 'other', 'country_code': 'other',
                          'region': 'other', 'city': 'other',
                          'state_code': 'other'})
```

In [464…
```
# distribution of non NA years
plt.hist(data['founded_year'][~data['founded_year'].isnull()], bins=30)
plt.axvline(x=np.nanmean(data['founded_year']), color='r')
plt.axvline(x=np.nanmedian(data['founded_year']), color='y')

p10 = np.percentile(data['founded_year'][~data['founded_year'].isnull()], 10)
print("10th percentile of founded_year: ", p10)

#10th percentile year is 2000, we will subset for startups founded on or after
print("Num Rows before 2000: ", len(data[data['founded_year'] < 2000]))
data = data[data['founded_year'] >= 2000].reset_index(drop=True)
len(data)
```

```
10th percentile of founded_year:  2000.0
Num Rows before 2000:  3518
```

Out[464]:
```
34045
```




In [465…

```
len(df[(df['founded_year'] < 2000) & (df['status'] != 'operating')])
```

Out[465]: 838

Date data - convert to datetime:

In [466…

```
data['founded_at'] = [datetime.strptime(day, '%Y-%m-%d') for day \
                      in data['founded_at'][~data['founded_at'].isnull()]]
data['first_funding_at'] = [datetime.strptime(day, '%Y-%m-%d').date() for day \
                            in data['first_funding_at']]
data['last_funding_at'] = [datetime.strptime(day, '%Y-%m-%d').date() for day \
                            in data['last_funding_at']]
data['founded_month'] = [datetime.strptime(mth, "%Y-%m").month for mth in data[
```

Fill year & founded_at with simple imputer (only if not removing NaN rows). Since the data is skewed (see plot above), we will use median rather than mean.

In [467…

```
# uncomment the below to impute founded_year with mean, only if we are not
# dropping nans for this feature

#imp_median = SimpleImputer(missing_values=np.nan, strategy='median')

#data['founded_year'] = imp_median.fit_transform(data[['founded_year']])
#data['founded_at'] = imp_median.fit_transform(data[['founded_at']])
```

In [468…

```
data['founded_at'] = pd.to_datetime(data['founded_at'])
data['founded_year'] = [day.year for day in data['founded_at']]
```

In [469…

```
data['founded_at'].value_counts()
```

Out[469]:
```
2012-01-01    2100
2011-01-01    2096
2010-01-01    1810
2009-01-01    1561
2013-01-01    1535
              ...
2004-04-25       1
2009-08-12       1
2014-08-04       1
2002-08-02       1
2010-11-06       1
Name: founded_at, Length: 2935, dtype: int64
```

In [470…
```
data.isna().sum()
```

Out[470]:
```
name                    0
market                  0
funding_total_usd       0
status                  0
country_code            0
state_code              0
region                  0
city                    0
funding_rounds          0
founded_at              0
founded_month           0
founded_year            0
first_funding_at        0
last_funding_at         0
seed                    0
venture                 0
equity_crowdfunding     0
undisclosed             0
convertible_note        0
debt_financing          0
angel                   0
grant                   0
private_equity          0
product_crowdfunding    0
round_A                 0
round_B                 0
round_C                 0
round_D                 0
round_E                 0
round_F                 0
round_G                 0
round_H                 0
dtype: int64
```

Basic data cleaning:

In [471…
```
# getting rid of extra spaces in market, city, state code, region
data['market'] = [x.strip() for x in data['market']]
data['country_code'] = [x.strip() for x in data['country_code']]
data['state_code'] = [x.strip() for x in data['state_code']]
data['region'] = [x.strip() for x in data['region']]
data['city'] = [x.strip() for x in data['city']]
```

In [472…
```
data.dtypes
```

Out[472]:
```
name                              object
market                            object
funding_total_usd                 object
status                            object
country_code                      object
state_code                        object
region                            object
city                              object
funding_rounds                   float64
founded_at                datetime64[ns]
founded_month                      int64
founded_year                       int64
first_funding_at                  object
last_funding_at                   object
seed                             float64
venture                          float64
equity_crowdfunding              float64
undisclosed                      float64
convertible_note                 float64
debt_financing                   float64
angel                            float64
grant                            float64
private_equity                   float64
product_crowdfunding             float64
round_A                          float64
round_B                          float64
round_C                          float64
round_D                          float64
round_E                          float64
round_F                          float64
round_G                          float64
round_H                          float64
dtype: object
```

In [473…
```
# need to convert this data type to integer
data['funding_total_usd'].value_counts()
```

Out[473]:
```
0.000000e+00    5632
1.000000e+09     627
1.000000e+08     582
5.000000e+08     573
4.000000e+06     466
                ...
3.012099e+11       1
1.045077e+08       1
1.000108e+12       1
1.609205e+09       1
2.068042e+11       1
Name: funding_total_usd, Length: 10560, dtype: int64
```

In [475…
```
# data['funding_total_usd'] = [float(num.replace(" ", "0").replace(",", "0").\
#                                     replace("-", "0"))
#                               for num in data['funding_total_usd']]
# data['funding_total_usd'].dtypes
```

## Feature Engineering

In [476…
```
# creating column that labels country as domestic or international
data['international'] = [0 if country=='USA' else 1 for country in data['countr
```

In [477…
```
# creating temporary columns to aid in calculation of time to first funding

data['founded_at_temp'] = [day.date() for day in data['founded_at']]
data['founded_at_temp'] = pd.to_datetime(data['founded_at_temp'],
                                         format = '%Y-%m-%d')

data['first_funding_at_temp'] = pd.to_datetime(data['first_funding_at'],
                                               format = '%Y-%m-%d',
                                               errors='coerce')
data['last_funding_at_temp'] = pd.to_datetime(data['last_funding_at'],
                                              format = '%Y-%m-%d',
                                              errors='coerce')

data['time_to_first_funding'] = (data['first_funding_at_temp'] - \
                                 data['founded_at_temp']) / pd.Timedelta(days=3

data['time_first_to_last_funding'] = (data['last_funding_at_temp'] - \
                                      data['first_funding_at_temp']) / pd.Timed
```

In [478…
```
# checking for nulls
print(data['first_funding_at'][data['time_to_first_funding'].isnull()])
print(data['last_funding_at'][data['time_first_to_last_funding'].isnull()])
```

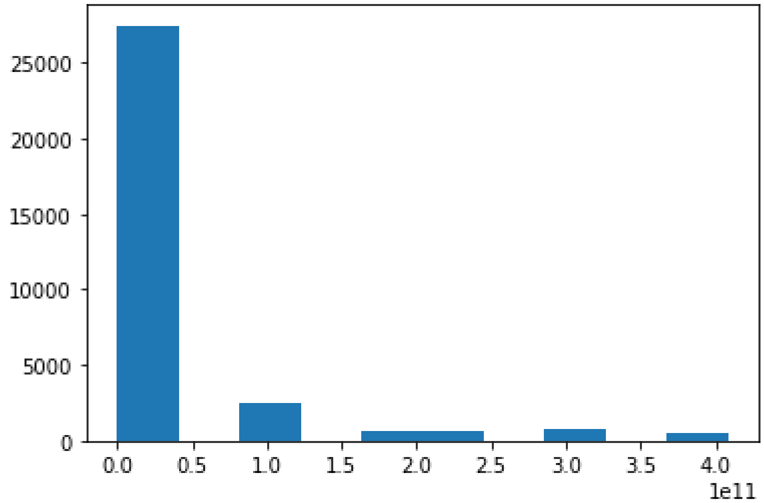
```
1030     0020-06-14
4514     0019-11-20
9863     0201-01-01
20287    0007-05-13
21784    0001-05-14
Name: first_funding_at, dtype: object
1030     2013-06-01
4514     2013-04-01
9863     0201-01-01
20287    2014-09-25
21784    0001-05-14
Name: last_funding_at, dtype: object
```

In [479…
```
# dropping these
data = data.dropna(subset=['time_to_first_funding'])
```

## OPTIONAL - Outliers

In [480…
```
# Funding total USD
print(np.percentile(data['funding_total_usd'], 95))

plt.hist(data['funding_total_usd'][data['funding_total_usd'] < 408206869399.0])
print(len(data[data['funding_total_usd'] < 408206869399.0]))
print(len(data))
```

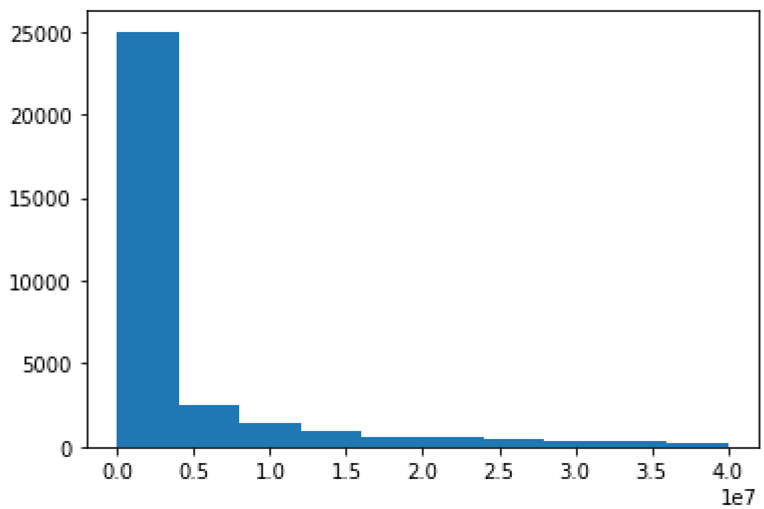
```
408206869399.0
32338
34040
```




In [481…

```
np.percentile(data['venture'], 95)

plt.hist(data['venture'][data['venture'] < 40000000.0])
print(len(data[data['venture'] < 40000000.0]))
print(len(data[(data['venture'] < 40000000.0) &
               (data['funding_total_usd'] < 408206869399.0)]))
print(len(data))
```

```
32301
31990
34040
```




In [482…

```
### THIS DOESN'T HELP THE MODELS, SO I COMMENTED THIS OUT
```

In [483…

```
# uncomment to remove outliers

#data = data[(data['venture'] < 40000000.0) &
#              (data['funding_total_usd'] < 408206869399.0)].reset_index(drop=Tru
#len(data)
```

## Correlations

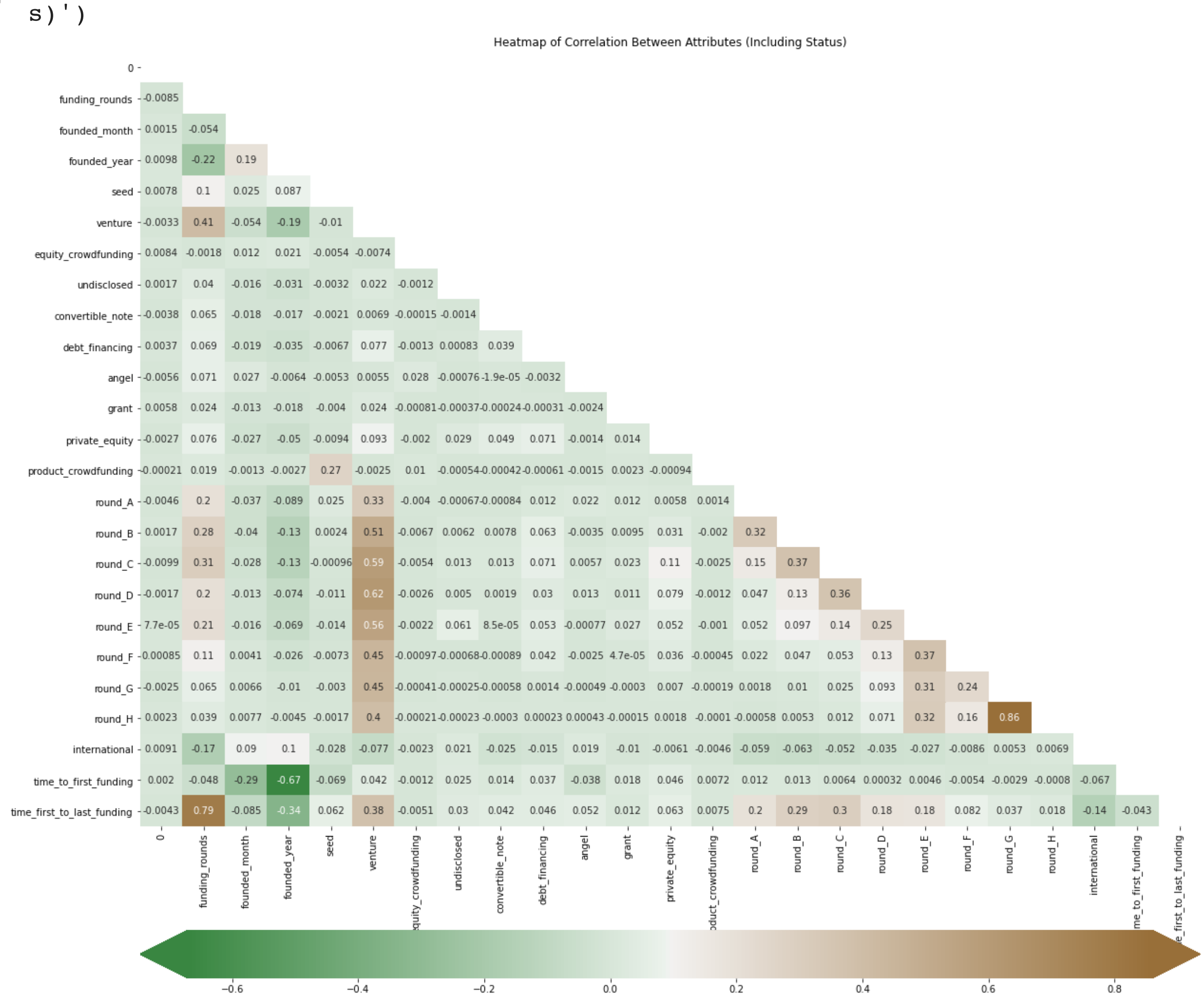
Based on the below, the strongest correlations occur between debt_financing and funding_total_usd, round_H and round_G, followed by venture and all of the rounds of funding

In [484…

```python
# with status
encoder = LabelEncoder()
heatmap_data = pd.concat([pd.Series(encoder.fit_transform(data['status'])),
                          data.drop('status', axis=1)], axis=1)

# without status
#heatmap_data = data.drop('status', axis=1)

h_corr = heatmap_data.corr()
fig, ax = plt.subplots(figsize=(20, 20))
mask = np.triu(np.ones_like(h_corr, dtype=bool))
cmap = sns.diverging_palette(130, 50, as_cmap=True)
cbar_kws = {'label': 'Correlation', 'orientation': 'horizontal',
            'pad': .1, 'extend': 'both'}
sns.heatmap(data=h_corr, mask=mask, ax=ax, annot=True, cbar_kws=cbar_kws, cmap=
ax.set_title('Heatmap of Correlation Between Attributes (Including Status)')
```

Out[484]:

```
Text(0.5, 1.0, 'Heatmap of Correlation Between Attributes (Including Statu
s)')
```




In [485…

```python
#data_corr=data.drop(columns=['status'], axis=1).corr()
corr = h_corr.abs().stack().reset_index().sort_values(0, ascending=False)
corr['pairs'] = list(zip(corr.level_0, corr.level_1))
corr.set_index(['pairs'], inplace = True)
corr.drop(columns=['level_1', 'level_0'], inplace = True)
```

```
# cc for correlation coefficient
corr.columns = ['cc']
corr.drop_duplicates(inplace=True)

corr[(corr['cc'] > 0.7) & (corr['cc'] < 1)]
```

Out[485]:

| pairs | cc |
|---|---|
| (round_H, round_G) | 0.859849 |
| (funding_rounds, time_first_to_last_funding) | 0.793787 |

In [486…

```
# dropping temp columns
data = data.drop(columns=['founded_at', 'first_funding_at', 'last_funding_at',
                          'first_funding_at_temp', 'last_funding_at_temp',
                          'founded_at_temp'], axis=1).reset_index(drop=True)

# creating csv file to work from
data.to_csv('data/final_working_data.csv')
```

In [487…

```
# dropping columns with correlation coefficient greater than 0.7
data_uncorr = data.drop(columns=['round_H', 'time_first_to_last_funding'],
                        axis=1).reset_index(drop=True)

#renaming full dataset
data_full = data
```

### OPTIONAL - Binary Representation of Funding Rounds

In [488…

```
# data['had_round_A'] = [0 if x==0 else 1 for x in data['round_A']]
# data['had_round_B'] = [0 if x==0 else 1 for x in data['round_B']]
# data['had_round_C'] = [0 if x==0 else 1 for x in data['round_C']]
# data['had_round_D'] = [0 if x==0 else 1 for x in data['round_D']]
# data['had_round_E'] = [0 if x==0 else 1 for x in data['round_E']]
# data['had_round_F'] = [0 if x==0 else 1 for x in data['round_F']]
# data['had_round_G'] = [0 if x==0 else 1 for x in data['round_G']]
# data['had_venture'] = [0 if x==0 else 1 for x in data['venture']]
# data['had_seed'] = [0 if x==0 else 1 for x in data['seed']]
# data['had_eq_crowdfunding'] = [0 if x==0 else 1 for x in data['equity_crowdfu
# data['had_pd_crowdfunding'] = [0 if x==0 else 1 for x in data['product_crowdi
# data['had_angel'] = [0 if x==0 else 1 for x in data['angel']]
# data['had_grant'] = [0 if x==0 else 1 for x in data['grant']]
# data['had_pe'] = [0 if x==0 else 1 for x in data['private_equity']]
# data['had_convert'] = [0 if x==0 else 1 for x in data['convertible_note']]
```

# Functions

### train_test_preprocess

In [489…

```
'''
Function to perform train_test_split and necessary preprocessing / scaling
'''

def train_test_preprocess(X, y):
```

```
    X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=42)

    # check that there are the same number of rows in X as values in y
    assert X_train.shape[0] == y_train.shape[0]

    # Categorizing features in preparation for scaling / encoding
    X_train_cat_eng = X_train.select_dtypes(include=['int64']).reset_index(drop
    X_test_cat_eng = X_test.select_dtypes(include=['int64']).reset_index(drop=T

    X_train_cont = X_train.select_dtypes(exclude=['object','int64']).reset_inde
    X_test_cont = X_test.select_dtypes(exclude=['object','int64']).reset_index(

    cat_columns = ['market', 'region']
    cat_train = X_train[cat_columns].reset_index(drop=True)
    cat_test = X_test[cat_columns].reset_index(drop=True)

    # Scale continuous variables using Min Max Scaler:
    scaler = MinMaxScaler() # instantiate MinMaxScaler

    ## TRAIN
    # Fit and transform X_train
    X_train_cont_scaled = scaler.fit_transform(X_train_cont)
    X_train_cont_scaled = pd.DataFrame(X_train_cont_scaled, columns=X_train_con

    # One hot encode categoricals
    ohe = OneHotEncoder(handle_unknown = 'ignore')
    encoded_train = ohe.fit_transform(cat_train).toarray()
    X_train_cat = pd.DataFrame(encoded_train, columns=ohe.get_feature_names(cat

    # Putting it all together:
    X_train_processed = pd.concat([X_train_cat, X_train_cont, X_train_cat_eng],
    X_train_scaled = pd.concat([X_train_cat, X_train_cont_scaled, X_train_cat_e

    ## TEST
    # Scale continuous features
    X_test_cont_scaled = scaler.transform(X_test_cont)
    X_test_cont_scaled = pd.DataFrame(X_test_cont_scaled, columns=X_test_cont.c

    # One hot encoding categoricals
    encoded_test = ohe.transform(cat_test).toarray()
    X_test_cat = pd.DataFrame(encoded_test, columns=ohe.get_feature_names(cat_t

    # Putting it all together
    X_test_scaled = pd.concat([X_test_cat, X_test_cont_scaled, X_test_cat_eng],
    X_test_processed = pd.concat([X_test_cat, X_test_cont, X_test_cat_eng], axi

    return X_train_processed, X_train_scaled, X_test_processed, X_test_scaled,
```

## print_scores

In [490…

```
'''
Function to print relevant scoring metrics
'''

def print_scores(y_train, y_hat_train, y_test, y_hat_test, binary=True):
    if binary:
        print('Training Recall: ',
              recall_score(y_train, y_hat_train))
        print('Testing Recall: ',
```

```
            recall_score(y_test, y_hat_test))
        print('\n')
        print('Training F1: ',
            f1_score(y_train, y_hat_train))
        print('Testing F1: ',
            f1_score(y_test, y_hat_test))
        print('\n')
        false_positive_rate, true_positive_rate, thresholds = \
        roc_curve(y_test, y_hat_test)
        roc_auc = auc(false_positive_rate, true_positive_rate)
        print('ROC AUC: ', roc_auc)
        print('PR AUC: ', average_precision_score(y_test, y_hat_test))
        print('\n')

    else:
        print('Training Recall (weighted avg): ',
            recall_score(y_train, y_hat_train, average='weighted'))
        print('Testing Recall (weighted avg): ',
            recall_score(y_test, y_hat_test, average='weighted'))
        print('\n')
        print('Training Recall (macro avg): ',
            recall_score(y_train, y_hat_train, average='macro'))
        print('Testing Recall (macro avg): ',
            recall_score(y_test, y_hat_test, average='macro'))
        print('\n')
        print('Training F1-Score (weighted avg): ',
            f1_score(y_train, y_hat_train, average='weighted'))
        print('Testing F1-Score (weighted avg): ',
            f1_score(y_test, y_hat_test, average='weighted'))
        print('\n')
        print('Training F1-Score (macro avg): ',
            f1_score(y_train, y_hat_train, average='macro'))
        print('Testing F1-Score (macro avg): ',
            f1_score(y_test, y_hat_test, average='macro'))
        print('\n')
        print('Testing Recall (failure class): ',
            recall_score(y_test, y_hat_test, average=None, labels=[1]))
        print('\n')

    print('Training Accuracy: ', accuracy_score(y_train, y_hat_train))
    print('Testing Accuracy: ', accuracy_score(y_test, y_hat_test))
```

## return_scores

In [491…

```
'''
Function that stores relevant scoring metrics
'''

def return_scores(y_train, y_hat_train, y_test, y_hat_test):
    r_train = recall_score(y_train, y_hat_train)
    r_test = recall_score(y_test, y_hat_test)

    f1_train = f1_score(y_train, y_hat_train)
    f1_test = f1_score(y_test, y_hat_test)

    false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_h
    roc_auc = auc(false_positive_rate, true_positive_rate)

    pr_auc = average_precision_score(y_test, y_hat_test)
```

```
    ac_train = accuracy_score(y_train, y_hat_train)
    ac_test = accuracy_score(y_test, y_hat_test)

    return r_train, r_test, f1_train, f1_test, ac_train, ac_test, roc_auc, pr_a
```

## train_test_check

In [492…

```
'''
Function that checks new train & test splits for proper shape
'''

def train_test_check(X_train_processed, X_train_scaled, X_test_processed,
                     X_test_scaled, y_train, y_test):

    assert X_train_processed.shape[0] == y_train.shape[0]
    assert X_train_scaled.shape[0] == y_train.shape[0]

    assert X_test_processed.shape[0] == y_test.shape[0]
    assert X_test_scaled.shape[0] == y_test.shape[0]

    print("There are {} features in train set".format(len(X_train_processed.col
    print("There are {} features in test set".format(len(X_test_processed.colum
    print('\n')

    print("There are {} features in train set (scaled)".format(len(X_train_scal
    print("There are {} features in test set (scaled)".format(len(X_test_scalec
    print('\n')

    print(f"y_train is a Series with {y_train.shape[0]} values")
    print('\n')
    print("target breakdown: ", y_train.value_counts(normalize=True))

    display(X_train_processed.head())
    display(X_train_scaled.head())
```

## correlation_check

In [493…

```
'''
Function that checks for excessive correlations across features
'''
def correlation_check(X_train_processed):

    df_corr=X_train_processed.corr()

    df = df_corr.abs().stack().reset_index().sort_values(0, ascending=False)
    df['pairs'] = list(zip(df.level_0, df.level_1))
    df.set_index(['pairs'], inplace = True)
    df.drop(columns=['level_1', 'level_0'], inplace = True)

    # cc for correlation coefficient
    df.columns = ['cc']
    df.drop_duplicates(inplace=True)

    display(df[(df.cc>.5) & (df.cc<1)])
```

# Acquired or Closed Dataset

In [494…
```
data_ac = df[df['status'] != 'operating']
```

# EDA / Preprocessing

In [495…
```
data_ac.isnull().sum()
```

Out[495]:
```
name                      2
market                  611
funding_total_usd         1
status                 1315
country_code            835
state_code             2582
region                  835
city                    951
funding_rounds            1
founded_at             1720
founded_month          1725
founded_year           1725
first_funding_at          1
last_funding_at           1
seed                      1
venture                   1
equity_crowdfunding       1
undisclosed               1
convertible_note          1
debt_financing            1
angel                     1
grant                     1
private_equity            1
product_crowdfunding      1
round_A                   1
round_B                   1
round_C                   1
round_D                   1
round_E                   1
round_F                   1
round_G                   1
round_H                   1
dtype: int64
```

In [496…
```
len(data_ac)
```

Out[496]:
```
7610
```

In [497…
```
data_ac = data_ac.dropna(subset=['status', 'name'])
len(data_ac)
```

Out[497]:
```
6294
```

In [498…
```
data_ac.dtypes
```

Out[498]:
```
name                        object
market                      object
funding_total_usd           object
status                      object
country_code                object
state_code                  object
region                      object
city                        object
funding_rounds             float64
founded_at                  object
founded_month               object
founded_year               float64
first_funding_at            object
last_funding_at             object
seed                       float64
venture                    float64
equity_crowdfunding        float64
undisclosed                float64
convertible_note           float64
debt_financing             float64
angel                      float64
grant                      float64
private_equity             float64
product_crowdfunding       float64
round_A                    float64
round_B                    float64
round_C                    float64
round_D                    float64
round_E                    float64
round_F                    float64
round_G                    float64
round_H                    float64
dtype: object
```

In [499…
```
# converting to float
data_ac['funding_total_usd'] = [float(num) for num in data_ac['funding_total_us
```

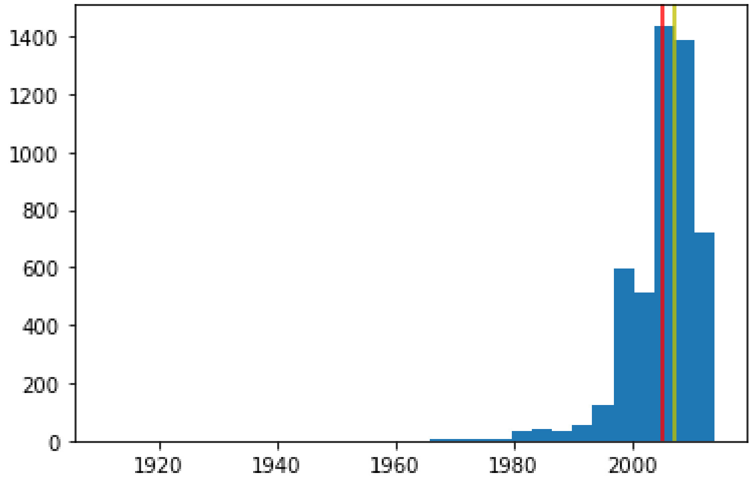
In [500…
```
data_ac['status'].value_counts(normalize=True)
```

Out[500]:
```
acquired    0.58659
closed      0.41341
Name: status, dtype: float64
```

In [501…
```
# filling categoricals
data_ac = data_ac.fillna(value={'market': 'other', 'country_code': 'other',
                                'region': 'other', 'city': 'other',
                                'state_code': 'other'})
```

In [502…
```
# distribution of non NA years
plt.hist(data_ac['founded_year'][~data_ac['founded_year'].isnull()], bins=30)
plt.axvline(x=np.nanmean(data_ac['founded_year']), color='r')
plt.axvline(x=np.nanmedian(data_ac['founded_year']), color='y')

p1 = np.percentile(data_ac['founded_year'][~data_ac['founded_year'].isnull()],
print("1st percentile of founded_year: ", p1)

#1980 looks like a good cutoff point
print("Num Rows before 1980: ", len(data_ac[data_ac['founded_year'] < 1980]))
data_ac = data_ac[data_ac['founded_year'] >= 1980].reset_index(drop=True)
```

```
1st percentile of founded_year:  1982.0
Num Rows before 1980:  35
```




In [503…

```
data_ac['founded_at'] = [datetime.strptime(day, '%Y-%m-%d') for day \
                          in data_ac['founded_at'][~data_ac['founded_at'].isnull
data_ac['first_funding_at'] = [datetime.strptime(day, '%Y-%m-%d').date() for da
                                in data_ac['first_funding_at']]
data_ac['last_funding_at'] = [datetime.strptime(day, '%Y-%m-%d').date() for day
                               in data_ac['last_funding_at']]
data_ac['founded_month'] = [datetime.strptime(mth, "%Y-%m").month for mth in da
```

In [504…

```
# imputing median for day, then pulling founded year and month from that
imp_median = SimpleImputer(missing_values=np.nan, strategy='median')

data_ac['founded_at'] = imp_median.fit_transform(data_ac[['founded_at']])

data_ac['founded_at'] = pd.to_datetime(data_ac['founded_at'])
data_ac['founded_year'] = [day.year for day in data_ac['founded_at']]
data_ac['founded_month'] = [day.month for day in data_ac['founded_at']]
```

In [505…

```
# creating column that labels country as domestic or international
data_ac['international'] = [0 if country=='USA' else 1 for country in data_ac['
```

In [506…

```
# creating temporary columns to aid in calcuation of time to first funding

data_ac['founded_at_temp'] = [day.date() for day in data_ac['founded_at']]
data_ac['founded_at_temp'] = pd.to_datetime(data_ac['founded_at_temp'],
                                            format = '%Y-%m-%d')

data_ac['first_funding_at_temp'] = pd.to_datetime(data_ac['first_funding_at'],
                                                  format = '%Y-%m-%d',
                                                  errors='coerce')
data_ac['last_funding_at_temp'] = pd.to_datetime(data_ac['last_funding_at'],
                                                 format = '%Y-%m-%d',
                                                 errors='coerce')

data_ac['time_to_first_funding'] = (data_ac['first_funding_at_temp'] - \
                                    data_ac['founded_at_temp']) / pd.Timedelta(

data_ac['time_first_to_last_funding'] = (data_ac['last_funding_at_temp'] - \
                                         data_ac['first_funding_at_temp']) / pd
```

In [507…

```
# checking for nulls
```

```
print(data_ac['first_funding_at'][data_ac['time_to_first_funding'].isnull()])
print(data_ac['last_funding_at'][data_ac['time_first_to_last_funding'].isnull()
```

```
3697    0011-11-14
Name: first_funding_at, dtype: object
3697    2012-07-24
Name: last_funding_at, dtype: object
```

In [508…

```
data_ac = data_ac.dropna(subset=['time_to_first_funding']).reset_index(drop=Tru
```

In [509…

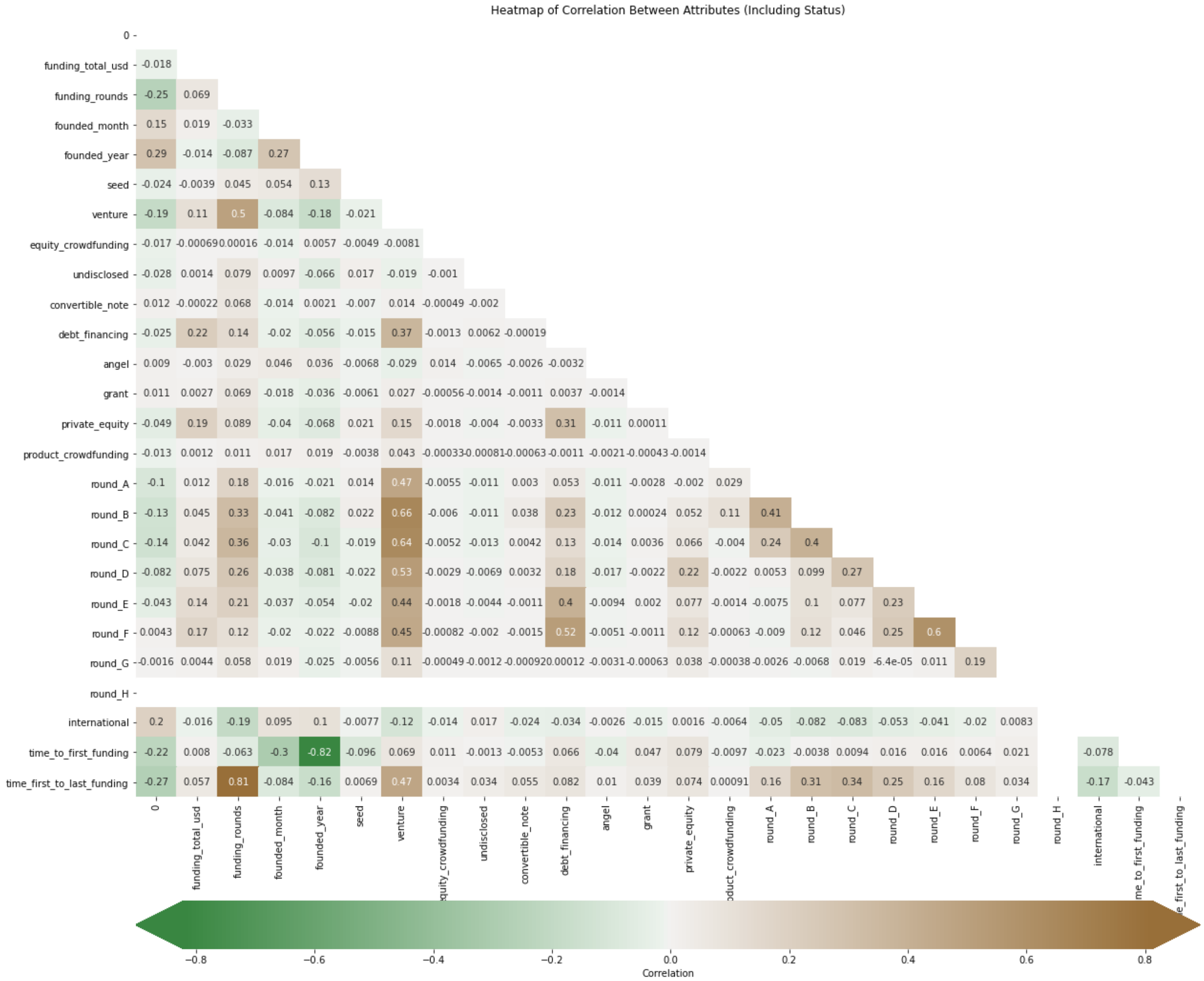
```
# getting rid of extra spaces

data_ac['market'] = [x.strip() for x in data_ac['market']]
data_ac['country_code'] = [x.strip() for x in data_ac['country_code']]
data_ac['state_code'] = [x.strip() for x in data_ac['state_code']]
data_ac['region'] = [x.strip() for x in data_ac['region']]
data_ac['city'] = [x.strip() for x in data_ac['city']]
```

In [510…

```
# correlation check
# with status
encoder = LabelEncoder()
heatmap_data = pd.concat([pd.Series(encoder.fit_transform(data_ac['status'])),
                          data_ac.drop('status', axis=1)], axis=1)

# without status
#heatmap_data = data.drop('status', axis=1)

h_corr = heatmap_data.corr()
fig, ax = plt.subplots(figsize=(20, 20))
mask = np.triu(np.ones_like(h_corr, dtype=bool))
cmap = sns.diverging_palette(130, 50, as_cmap=True)
cbar_kws = {'label': 'Correlation', 'orientation': 'horizontal',
            'pad': .1, 'extend': 'both'}
sns.heatmap(data=h_corr, mask=mask, ax=ax, annot=True, cbar_kws=cbar_kws, cmap=
ax.set_title('Heatmap of Correlation Between Attributes (Including Status)')
```

Out[510]:

```
Text(0.5, 1.0, 'Heatmap of Correlation Between Attributes (Including Statu
s)')
```




In [511…

```
corr = h_corr.abs().stack().reset_index().sort_values(0, ascending=False)
corr['pairs'] = list(zip(corr.level_0, corr.level_1))
corr.set_index(['pairs'], inplace = True)
corr.drop(columns=['level_1', 'level_0'], inplace = True)

# cc for correlation coefficient
corr.columns = ['cc']
corr.drop_duplicates(inplace=True)

corr[(corr['cc'] > 0.7) & (corr['cc'] < 1)]
```

Out[511]:

| | cc |
|---|---|
| **pairs** | |
| **(time_to_first_funding, founded_year)** | 0.819908 |
| **(funding_rounds, time_first_to_last_funding)** | 0.812019 |

In [512…

```
# reducing number of categories in market & region

print(sum(data_ac['market'].value_counts() >= 15))
data_ac['market'][data_ac['market'].map(data_ac['market'].value_counts()) < 15]
print(data_ac['market'].value_counts())

print(sum(data_ac['region'].value_counts() >= 60))
```

```
data_ac['region'][data_ac['region'].map(data_ac['region'].value_counts()) < 60]
print(data_ac['region'].value_counts())
```

```
48
other                   1162
Software                 569
Curated Web              347
Mobile                   281
Enterprise Software      200
Biotechnology            189
Advertising              173
Games                    172
E-Commerce               164
Social Media             136
Hardware + Software      100
Semiconductors            96
Security                  92
Web Hosting               84
Clean Technology          78
Health Care               75
Finance                   71
Analytics                 59
Messaging                 55
Search                    54
News                      47
Music                     45
Education                 43
Public Relations          42
Video                     41
Travel                    40
Networking                38
Photography               36
Social Network Media      34
Consulting                33
Health and Wellness       32
SaaS                      29
Sports                    25
Sales and Marketing       23
Web Development           23
Internet                  23
Manufacturing             21
Cloud Computing           20
Android                   20
iPhone                    19
Fashion                   19
Apps                      18
Facebook Applications     18
Marketplaces              18
Automotive                17
Shopping                  17
Hospitality               17
Real Estate               15
Name: market, dtype: int64
13
other              2128
SF Bay Area        1250
New York City       338
Boston              260
Los Angeles         186
London              146
Seattle             143
Washington, D.C.     85
Chicago              85
```

```
Austin                84
San Diego             77
Denver                75
Tel Aviv              73
Name: region, dtype: int64
```

In [513…
```
# dropping correlated columns for logistic regression, which can be
# sensitive to correlated features
data_final = data_ac.drop(columns=['founded_at', 'first_funding_at', 'last_func
                                  'first_funding_at_temp', 'last_funding_at_te
                                  'founded_at_temp', 'round_H', 'founded_year'
                                  'time_first_to_last_funding'],
                       axis=1)
# all inclusive
data_final2 = data_ac.drop(columns=['founded_at', 'first_funding_at', 'last_fur
                                   'first_funding_at_temp', 'last_funding_at_t
                                   'founded_at_temp', 'round_H'],
                       axis=1)
```

In [514…
```
data_final.columns
```

Out[514]:
```
Index(['name', 'market', 'funding_total_usd', 'status', 'country_code',
       'state_code', 'region', 'city', 'funding_rounds', 'founded_month',
       'seed', 'venture', 'equity_crowdfunding', 'undisclosed',
       'convertible_note', 'debt_financing', 'angel', 'grant',
       'private_equity', 'product_crowdfunding', 'round_A', 'round_B',
       'round_C', 'round_D', 'round_E', 'round_F', 'round_G', 'internationa
l',
       'time_to_first_funding'],
      dtype='object')
```

In [515…
```
data_final2.columns
```

Out[515]:
```
Index(['name', 'market', 'funding_total_usd', 'status', 'country_code',
       'state_code', 'region', 'city', 'funding_rounds', 'founded_month',
       'founded_year', 'seed', 'venture', 'equity_crowdfunding', 'undisclose
d',
       'convertible_note', 'debt_financing', 'angel', 'grant',
       'private_equity', 'product_crowdfunding', 'round_A', 'round_B',
       'round_C', 'round_D', 'round_E', 'round_F', 'round_G', 'internationa
l',
       'time_to_first_funding', 'time_first_to_last_funding'],
      dtype='object')
```

In [516…
```
data_final2['funding_total_usd'].dtypes
```

Out[516]:
```
dtype('float64')
```

# X/Y Split

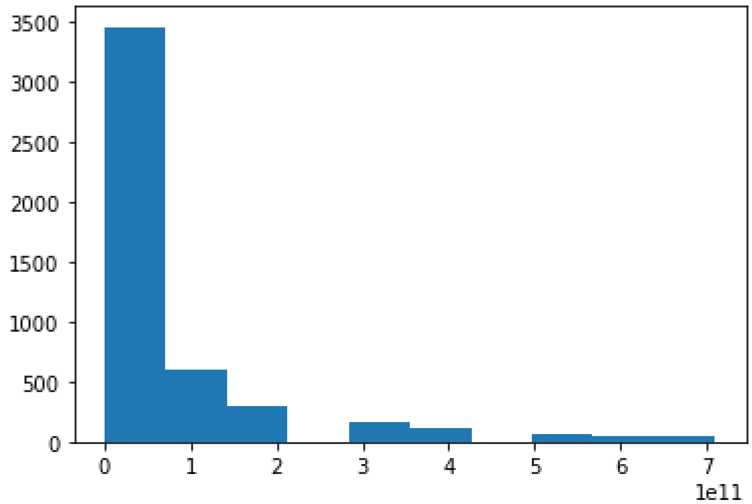
In [517…
```
X_ac = data_final2.drop(columns=['status', 'name', 'country_code', 'state_code'
                             'city'], axis=1)

encoder = LabelEncoder()
y_ac = pd.Series(encoder.fit_transform(data_final2['status']))
# acquired is 0, closed is 1

y_ac.value_counts(normalize=True)
```

Out[517]:
```
0    0.59716
1    0.40284
dtype: float64
```

For the logistic regression model, we'll get rid of some extre outliers and exclude highly correlated features

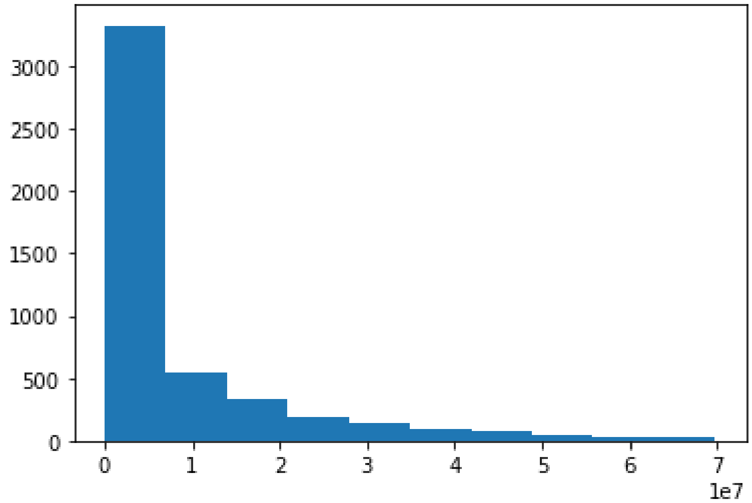
In [518…
```
# Funding total USD
print(np.percentile(data_final['funding_total_usd'], 97.5))

plt.hist(data_final['funding_total_usd'][data_final['funding_total_usd'] < 800(
print(len(data_final[data_final['funding_total_usd'] >= 800000000000.0]))
print(len(data_final))
```

```
807015451469.2499
147
4930
```




In [519…
```
print(np.percentile(data_final['venture'], 97.5))

plt.hist(data_final['venture'][data_final['venture'] < 70000000.0])
print(len(data_final[data_final['venture'] > 70000000.0]))
print(len(data_final[(data_final['venture'] > 70000000.0) &
               (data_final['funding_total_usd'] > 800000000000.0)]))
print(len(data_final))
```

```
69561028.64999995
119
96
4930
```




In [520…
```
data_lr = data_final[(data_final['venture'] < 70000000.0) &
                     (data_final['funding_total_usd'] < 800000000000.0)].reset_
```

In [521…
```
X_ac_lr = data_lr.drop(columns=['status', 'name', 'country_code',
                                'state_code', 'city'], axis=1)

encoder = LabelEncoder()
y_ac_lr = pd.Series(encoder.fit_transform(data_lr['status']))
# acquired is 0, closed is 1

y_ac_lr.value_counts(normalize=True)
```

Out[521]:
```
0    0.588742
1    0.411258
dtype: float64
```

# Baseline Model

In [522…
```
X_train_processed, X_train_scaled, X_test_processed, \
X_test_scaled, y_train, y_test = train_test_preprocess(X_ac_lr, y_ac_lr)
```

In [523…
```
train_test_check(X_train_processed, X_train_scaled, X_test_processed,
                 X_test_scaled, y_train, y_test)
```

```
There are 83 features in train set
There are 83 features in test set


There are 83 features in train set (scaled)
There are 83 features in test set (scaled)


y_train is a Series with 3570 values


target breakdown:  0    0.581793
1    0.418207
dtype: float64
```

| | market_Advertising | market_Analytics | market_Android | market_Apps | market_Automotive | n |
|---|---|---|---|---|---|---|
| **0** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **1** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **2** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **3** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **4** | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | |

5 rows × 83 columns

| | market_Advertising | market_Analytics | market_Android | market_Apps | market_Automotive | n |
|---|---|---|---|---|---|---|
| **0** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **1** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **2** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **3** | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | |
| **4** | 1.0 | 0.0 | 0.0 | 0.0 | 0.0 | |

5 rows × 83 columns

In [524…

```
correlation_check(X_train_processed)
```

| pairs | cc |
|---|---|
| **(funding_total_usd, venture)** | 0.914405 |
| **(venture, round_B)** | 0.611358 |
| **(venture, round_C)** | 0.604260 |
| **(region_other, international)** | 0.567555 |
| **(funding_total_usd, round_C)** | 0.562303 |
| **(round_B, funding_total_usd)** | 0.554304 |
| **(funding_rounds, venture)** | 0.552203 |
| **(funding_total_usd, funding_rounds)** | 0.517989 |
| **(region_other, region_SF Bay Area)** | 0.504931 |

In [525…

```
baseline_model = LogisticRegression(random_state=42)
baseline_model.fit(X_train_scaled, y_train)
```

Out[525]:

```
LogisticRegression(random_state=42)
```

In [526…

```
y_hat_train = baseline_model.predict(X_train_scaled)
y_hat_test = baseline_model.predict(X_test_scaled)

print_scores(y_train, y_hat_train, y_test, y_hat_test)
```

```
Training Recall:  0.6269256530475552
Testing Recall:  0.5956989247311828


Training F1:  0.6582278481012658
Testing F1:  0.604143947655398


ROC AUC:  0.6773260463876298
PR AUC:  0.5229138248539754


Training Accuracy:  0.7277310924369748
Testing Accuracy:  0.6952141057934509
```

## Baseline Analysis

- point A
- point B
- point C

## Grid Search on Baseline**

In [527…

```
param_grid = {'penalty':['l2', None],
              'solver':['lbfgs', 'sag'],
              'C': [1.0, 1e12],
              'class_weight': [None, 'balanced']
             }
```

In [528…

```
grid_logreg = GridSearchCV(baseline_model, param_grid, cv = 5,
                           scoring='recall') # macro or weighted
grid_logreg.fit(X_train_scaled, y_train)
grid_logreg.best_params_
```

Out[528]:

```
{'C': 1000000000000.0,
 'class_weight': 'balanced',
 'penalty': 'l2',
 'solver': 'lbfgs'}
```

In [529…

```
y_preds_grid_lr_train = grid_logreg.predict(X_train_scaled)
y_preds_grid_lr = grid_logreg.predict(X_test_scaled)

print_scores(y_train, y_preds_grid_lr_train, y_test, y_preds_grid_lr)
```

```
Training Recall:  0.7675820495646349
Testing Recall:  0.7526881720430108


Training F1:  0.7009174311926605
Testing F1:  0.6616257088846881


ROC AUC:  0.708988714120679
PR AUC:  0.5408085437239796


Training Accuracy:  0.7260504201680672
Testing Accuracy:  0.6994122586062133
```

In [530…

```
## Top coefficients
lr = LogisticRegression(random_state=42, class_weight='balanced',
                        solver='lbfgs', C=1e12, penalty='l2')
lr.fit(X_train_scaled, y_train)

coef_df = pd.DataFrame(lr.coef_, columns=X_train_scaled.columns).transpose()
coef_df.to_csv('coef_logreg.csv')

coef_df.columns=['coef']
coef_df['coef_abs'] = abs(coef_df['coef'])

coef_df.sort_values(by='coef_abs', ascending=False)[:20]
```

Out[530]:

| | coef | coef_abs |
|---|---|---|
| **time_to_first_funding** | -14.647481 | 14.647481 |
| **private_equity** | -3.980899 | 3.980899 |
| **venture** | -3.631479 | 3.631479 |
| **funding_rounds** | -3.303331 | 3.303331 |
| **seed** | -3.140217 | 3.140217 |
| **undisclosed** | -3.132247 | 3.132247 |
| **convertible_note** | 2.843864 | 2.843864 |
| **funding_total_usd** | 2.159750 | 2.159750 |
| **market_Clean Technology** | 2.135076 | 2.135076 |
| **debt_financing** | -1.698484 | 1.698484 |
| **round_A** | -1.609651 | 1.609651 |
| **market_Consulting** | 1.605654 | 1.605654 |
| **market_Sports** | 1.435275 | 1.435275 |
| **market_Biotechnology** | 1.235120 | 1.235120 |
| **region_other** | 1.198366 | 1.198366 |
| **market_Analytics** | -1.192643 | 1.192643 |
| **region_Denver** | 1.006539 | 1.006539 |
| **market_Apps** | -0.943704 | 0.943704 |
| **grant** | -0.843960 | 0.843960 |
| **market_Health Care** | 0.840521 | 0.840521 |

In [531…

```
X_train_scaled['private_equity'].value_counts()
# vast majority of observations are 0, so coefficient probably isn't
# as important as its ranking implies
```

Out[531]:
```
0.000000    3529
0.026667       2
0.932000       1
0.006667       1
0.800000       1
0.133333       1
0.126667       1
0.933333       1
0.011106       1
0.840000       1
0.046667       1
0.033333       1
0.123335       1
0.022267       1
0.160000       1
0.533333       1
0.960000       1
0.000173       1
1.000000       1
0.408116       1
0.148482       1
0.529627       1
0.042667       1
0.248854       1
0.186667       1
0.252775       1
0.019813       1
0.053333       1
0.074248       1
0.060000       1
0.154667       1
0.240000       1
0.087976       1
0.066667       1
0.005051       1
0.081411       1
0.244853       1
0.624849       1
0.724281       1
0.006000       1
0.120000       1
Name: private_equity, dtype: int64
```

## Custom Pipeline

In [532…
```
scores = pd.DataFrame(columns = ['recall_train', 'recall_test', 'f1_train',
                                 'f1_test', 'accuracy_train', 'accuracy_test',
                                 'roc_auc', 'pr_auc', 'params'])
```

In [533…
```
# creates a data frame with various scores for each model
def customPipe(model, model_name, X, y):
    X_train_processed, X_train_scaled, X_test_processed, X_test_scaled, \
    y_train, y_test = train_test_preprocess(X, y)

    if ('lr' in model_name) | ('knn' in model_name):
        model.fit(X_train_scaled, y_train)
        y_hat_train = model.predict(X_train_scaled)
        y_hat_test = model.predict(X_test_scaled)
```

```
    else:
        model.fit(X_train_processed, y_train)
        y_hat_train = model.predict(X_train_processed)
        y_hat_test = model.predict(X_test_processed)

    r_train, r_test, f1_train, f1_test, ac_train, ac_test, roc_auc, pr_auc = \
    return_scores(y_train, y_hat_train, y_test, y_hat_test)

    score_list = []
    score_list.extend((r_train, r_test, f1_train, f1_test,
                       ac_train, ac_test, roc_auc, pr_auc, str(model)))

    scores.loc[model_name] = score_list
    return scores
```

In [534…

```
# model inputs
lr = LogisticRegression(random_state=42, class_weight='balanced',
                        solver='lbfgs', C=1e12, penalty='l2')
rf = RandomForestClassifier(random_state=42)
dtc = DecisionTreeClassifier(random_state=42)
ext = ExtraTreesClassifier(random_state=42)
xgb = XGBClassifier(random_state=42)
knn = KNeighborsClassifier()
```

In [535…

```
# running the function
customPipe(lr, 'lr', X_ac_lr, y_ac_lr)
customPipe(rf, 'rf', X_ac, y_ac)
customPipe(dtc, 'dtc', X_ac, y_ac)
customPipe(ext, 'ext', X_ac, y_ac)
customPipe(xgb, 'xgb', X_ac, y_ac)
customPipe(knn, 'knn', X_ac, y_ac)
```

Out[535]:

| | recall_train | recall_test | f1_train | f1_test | accuracy_train | accuracy_test | roc_auc | |
|---|---|---|---|---|---|---|---|---|
| **lr** | 0.767582 | 0.752688 | 0.700917 | 0.661626 | 0.726050 | 0.699412 | 0.708989 | 0. |
| **rf** | 1.000000 | 0.589178 | 1.000000 | 0.643326 | 1.000000 | 0.735604 | 0.712164 | 0. |
| **dtc** | 1.000000 | 0.577154 | 1.000000 | 0.588957 | 1.000000 | 0.673966 | 0.658468 | 0 |
| **ext** | 1.000000 | 0.571142 | 1.000000 | 0.617551 | 1.000000 | 0.713706 | 0.690884 | 0. |
| **xgb** | 0.933423 | 0.607214 | 0.927188 | 0.641949 | 0.941033 | 0.725872 | 0.706877 | 0 |
| **knn** | 0.709482 | 0.577154 | 0.714528 | 0.576577 | 0.771977 | 0.656934 | 0.644163 | 0. |

Looking at recall and accuracy, the Random Forest and XGBoost models seem to yield the best scores. Will hyper tune each of these models.

In [536…

```
# storing dataframe for easy access
scores_base = scores # models pre hyper parameter tuning
```

# Other Models - Hypertuning

## Random Forest

In [537…

```
rf = RandomForestClassifier(random_state=42)

# Initial search
rf_param_grid = {
    'criterion':['gini','entropy','log_loss'],
    'max_depth':[8,12,20],
    'min_samples_leaf': [5,10],
    'class_weight': [None, 'balanced']
}

# Fine tuning
rf_param_grid2 = {
    'criterion':['gini'],
    'max_depth':[20,25],
    'min_samples_leaf': [10,15,20],
    'class_weight': ['balanced'],
    'n_estimators': [100, 200]
}

grid_rfc = GridSearchCV(rf, rf_param_grid2, cv = 5, scoring='recall')
grid_rfc.fit(X_train_processed, y_train)

grid_rfc.best_params_
```

Out[537]:

```
{'class_weight': 'balanced',
 'criterion': 'gini',
 'max_depth': 20,
 'min_samples_leaf': 20,
 'n_estimators': 200}
```

In [538…

```
rf_best = RandomForestClassifier(random_state = 42, class_weight='balanced',
                                 criterion='gini', max_depth=20, #12
                                 min_samples_leaf=15, n_estimators=100) #100
customPipe(rf_best, 'rf_best', X_ac, y_ac)
```

Out[538]:

| | recall_train | recall_test | f1_train | f1_test | accuracy_train | accuracy_test | roc_auc |
|---|---|---|---|---|---|---|---|
| **lr** | 0.767582 | 0.752688 | 0.700917 | 0.661626 | 0.726050 | 0.699412 | 0.708989 |
| **rf** | 1.000000 | 0.589178 | 1.000000 | 0.643326 | 1.000000 | 0.735604 | 0.712164 |
| **dtc** | 1.000000 | 0.577154 | 1.000000 | 0.588957 | 1.000000 | 0.673966 | 0.658468 |
| **ext** | 1.000000 | 0.571142 | 1.000000 | 0.617551 | 1.000000 | 0.713706 | 0.690884 |
| **xgb** | 0.933423 | 0.607214 | 0.927188 | 0.641949 | 0.941033 | 0.725872 | 0.706877 |
| **knn** | 0.709482 | 0.577154 | 0.714528 | 0.576577 | 0.771977 | 0.656934 | 0.644163 |
| **rf_best** | 0.726967 | 0.703407 | 0.712591 | 0.690945 | 0.764133 | 0.745337 | 0.738624 |

## Feature Importance

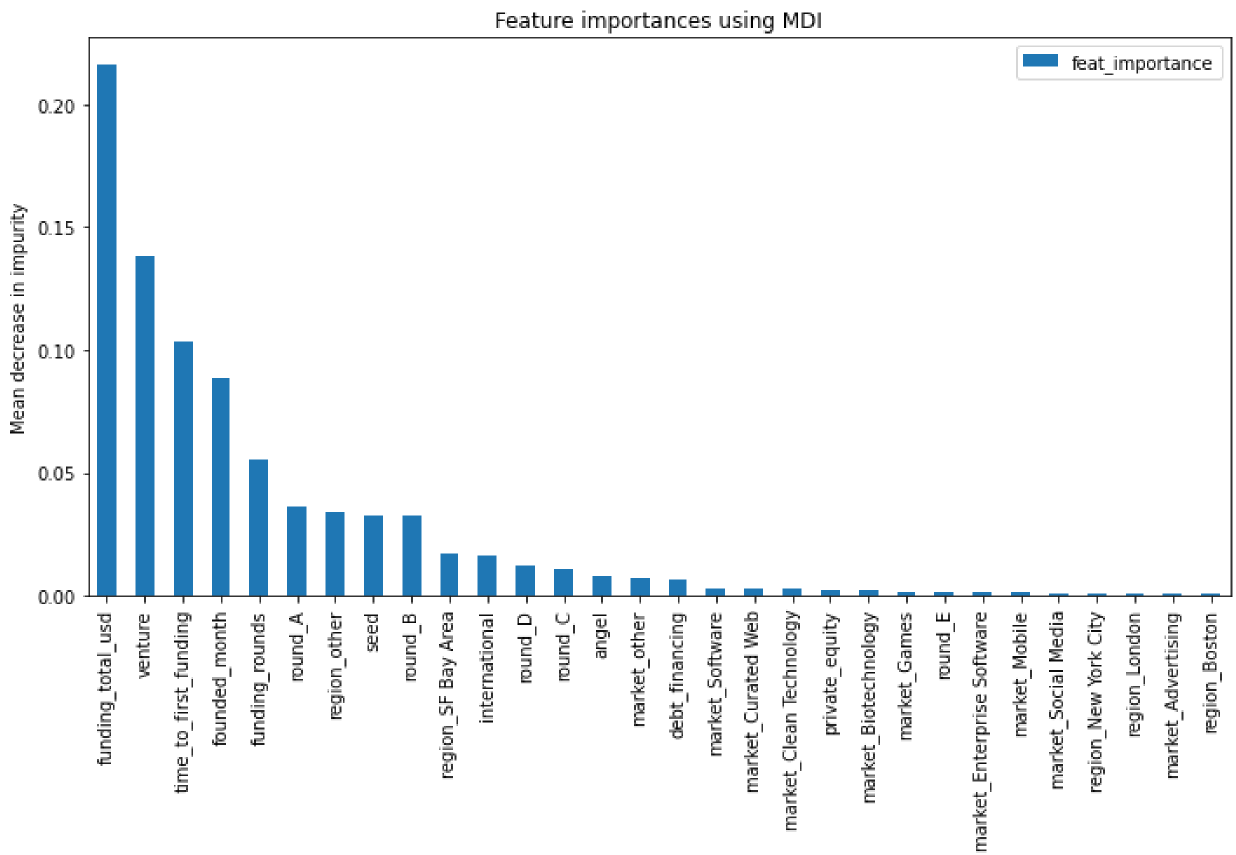
In [539…

```
feats = {} # a dict to hold feature_name: feature_importance
for feature, importance in zip(X_train_processed.columns, rf_best.feature_impor
    feats[feature] = importance #add the name/value pair
```

```
feats_rf = pd.DataFrame(feats.items())

feats_rf.columns = ['col', 'feat_importance']
feats_rf = feats_rf.sort_values(by=['feat_importance'], ascending=False)
feats_rf_20 = feats_rf[:20]
feats_rf_30 = feats_rf[:30]
```

In [540…

```
fig, ax = plt.subplots(figsize = (10,7))
feats_rf_30.plot.bar(ax=ax) # yerr=std,
ax.set_title("Feature importances using MDI")
ax.set_ylabel("Mean decrease in impurity")
ax.set_xticklabels(feats_rf_30['col'])
fig.tight_layout()
```




In [541…

```
list(feats_rf['col'][:10])
```

Out[541]:

```
['funding_total_usd',
 'venture',
 'time_to_first_funding',
 'founded_month',
 'funding_rounds',
 'round_A',
 'region_other',
 'seed',
 'round_B',
 'region_SF Bay Area']
```

## XG Boost*

In [542…

```
# 45+ runtime
xgb = XGBClassifier(random_state=42)
```

```
# initial grid search
xgb_param_grid = {
    'learning_rate': [0.1, 0.2],
    'max_depth': [4,6,8],
    'min_child_weight': [3,5,7],
    'subsample': [0.5, 0.7],
    'scale_pos_weight':[1.5,2]
}

# fine tuning
xgb_param_grid2 = {
    'learning_rate': [0.1],
    'max_depth': [1,2,4],
    'min_child_weight': [1,5,10],
    'subsample': [0.7, 0.9],
    'scale_pos_weight':[2]
}

grid_xgb = GridSearchCV(xgb, xgb_param_grid2, cv = 5, scoring='recall')
grid_xgb.fit(X_train_processed, y_train)

grid_xgb.best_params_
```

Out[542]:

```
{'learning_rate': 0.1,
 'max_depth': 1,
 'min_child_weight': 10,
 'scale_pos_weight': 2,
 'subsample': 0.7}
```

In [543…

```
xgb_best = XGBClassifier(random_state=42, max_depth=1, min_child_weight=10,
                         subsample=0.7, learning_rate=0.2, scale_pos_weight=2)

customPipe(xgb_best, 'xgb_best', X_ac, y_ac)
```

Out[543]:

| | recall_train | recall_test | f1_train | f1_test | accuracy_train | accuracy_test | roc_au |
|---|---|---|---|---|---|---|---|
| **lr** | 0.767582 | 0.752688 | 0.700917 | 0.661626 | 0.726050 | 0.699412 | 0.70898 |
| **rf** | 1.000000 | 0.589178 | 1.000000 | 0.643326 | 1.000000 | 0.735604 | 0.71216 |
| **dtc** | 1.000000 | 0.577154 | 1.000000 | 0.588957 | 1.000000 | 0.673966 | 0.65846 |
| **ext** | 1.000000 | 0.571142 | 1.000000 | 0.617551 | 1.000000 | 0.713706 | 0.69088 |
| **xgb** | 0.933423 | 0.607214 | 0.927188 | 0.641949 | 0.941033 | 0.725872 | 0.70687 |
| **knn** | 0.709482 | 0.577154 | 0.714528 | 0.576577 | 0.771977 | 0.656934 | 0.64416 |
| **rf_best** | 0.726967 | 0.703407 | 0.712591 | 0.690945 | 0.764133 | 0.745337 | 0.73862 |
| **xgb_best** | 0.806994 | 0.797595 | 0.710059 | 0.695197 | 0.734920 | 0.716951 | 0.72986 |

## Feature Importance

In [544…

```
xgb_best.fit(X_train_processed, y_train)
```

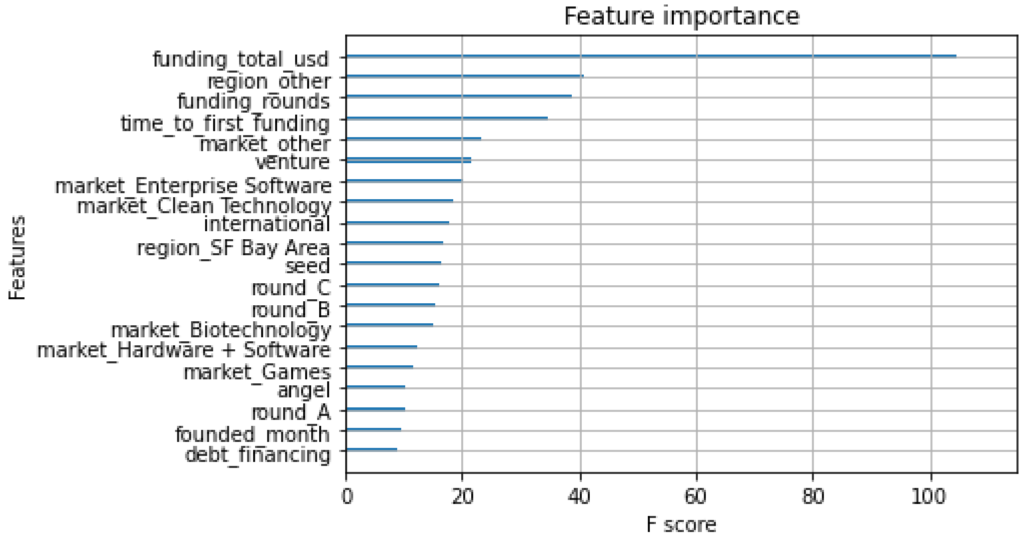
Out[544]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.2, max_delta_step=0, max_depth=1,
              min_child_weight=10, missing=nan, monotone_constraints='()',
              n_estimators=100, n_jobs=0, num_parallel_tree=1, random_state=4
2,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=2, subsample=0.7,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

In [545…
```
f = 'gain' # importance type
feat_imp = xgb_best.get_booster().get_score(importance_type= f)
feats_xg = pd.DataFrame(sorted(feat_imp.items(), key=lambda item: item[1],
                              reverse=True))
feats_xg.columns = ['col', 'feat_importance']
feats_xg[:15]
```

Out[545]:

| | col | feat_importance |
|---|---|---|
| **0** | funding_total_usd | 104.421405 |
| **1** | region_other | 40.776967 |
| **2** | funding_rounds | 38.640555 |
| **3** | time_to_first_funding | 34.493131 |
| **4** | market_other | 23.375635 |
| **5** | venture | 21.451009 |
| **6** | market_Enterprise Software | 20.053893 |
| **7** | market_Clean Technology | 18.556825 |
| **8** | international | 17.840616 |
| **9** | region_SF Bay Area | 16.663320 |
| **10** | seed | 16.484204 |
| **11** | round_C | 16.219026 |
| **12** | round_B | 15.510055 |
| **13** | market_Biotechnology | 14.875709 |
| **14** | market_Hardware + Software | 12.360651 |

In [546…
```
from xgboost import plot_importance
plot_importance(xgb_best, max_num_features=20, importance_type=f,
                show_values=False)
plt.show()
```




## ExtraTrees

In [547…

```
ext_param_grid = {'criterion':['entropy','gini'],
                 'max_depth':[15,20,25],
                 'min_samples_leaf': [1,5],
                 'class_weight': ['balanced'],
                 'max_features': ['auto']
                }

ext = ExtraTreesClassifier(random_state=42)

grid_ext = GridSearchCV(ext, ext_param_grid, cv = 5, scoring='recall')
grid_ext.fit(X_train_processed, y_train)

grid_ext.best_params_
```

Out[547]:

```
{'class_weight': 'balanced',
 'criterion': 'entropy',
 'max_depth': 20,
 'max_features': 'auto',
 'min_samples_leaf': 5}
```

In [548…

```
ext_grid = ExtraTreesClassifier(random_state=42, class_weight='balanced',
                                criterion='gini', max_depth= 25,
                                max_features='auto', min_samples_leaf= 5)
customPipe(ext_grid, 'ext_best', X_ac, y_ac)
```

Out[548]:

| | recall_train | recall_test | f1_train | f1_test | accuracy_train | accuracy_test | roc_au |
|---|---|---|---|---|---|---|---|
| lr | 0.767582 | 0.752688 | 0.700917 | 0.661626 | 0.726050 | 0.699412 | 0.70898 |
| rf | 1.000000 | 0.589178 | 1.000000 | 0.643326 | 1.000000 | 0.735604 | 0.71216 |
| dtc | 1.000000 | 0.577154 | 1.000000 | 0.588957 | 1.000000 | 0.673966 | 0.65846 |
| ext | 1.000000 | 0.571142 | 1.000000 | 0.617551 | 1.000000 | 0.713706 | 0.69088 |
| xgb | 0.933423 | 0.607214 | 0.927188 | 0.641949 | 0.941033 | 0.725872 | 0.70687 |
| knn | 0.709482 | 0.577154 | 0.714528 | 0.576577 | 0.771977 | 0.656934 | 0.64416 |
| rf_best | 0.726967 | 0.703407 | 0.712591 | 0.690945 | 0.764133 | 0.745337 | 0.73862 |
| xgb_best | 0.806994 | 0.797595 | 0.710059 | 0.695197 | 0.734920 | 0.716951 | 0.72986 |
| ext_best | 0.781439 | 0.711423 | 0.729212 | 0.664172 | 0.766567 | 0.708840 | 0.70925 |

## Decision Tree***

In [549…

```
dtc_param_grid = {'criterion':['gini','entropy'],
                  'max_depth':[5,10,15],
                  'min_samples_leaf': [15,20,25],
                  'class_weight': [None, 'balanced']
             }

dtc = DecisionTreeClassifier(random_state=42)

grid_dtc = GridSearchCV(dtc, dtc_param_grid, cv = 5, scoring='recall')
grid_dtc.fit(X_train_processed, y_train)

grid_dtc.best_params_
```

Out[549]:

```
{'class_weight': 'balanced',
 'criterion': 'gini',
 'max_depth': 15,
 'min_samples_leaf': 25}
```

In [550…

```
dtc_best = DecisionTreeClassifier(random_state=42, class_weight='balanced',
                                  criterion='gini', max_depth= 5,
                                  min_samples_leaf= 20)

dtc_best.fit(X_train_processed, y_train)
customPipe(dtc_best, 'dtc_best', X_ac, y_ac)
```

Out[550]:

| | recall_train | recall_test | f1_train | f1_test | accuracy_train | accuracy_test | roc_au |
|---|---|---|---|---|---|---|---|
| lr | 0.767582 | 0.752688 | 0.700917 | 0.661626 | 0.726050 | 0.699412 | 0.70898 |
| rf | 1.000000 | 0.589178 | 1.000000 | 0.643326 | 1.000000 | 0.735604 | 0.71216 |
| dtc | 1.000000 | 0.577154 | 1.000000 | 0.588957 | 1.000000 | 0.673966 | 0.65846 |
| ext | 1.000000 | 0.571142 | 1.000000 | 0.617551 | 1.000000 | 0.713706 | 0.69088 |
| xgb | 0.933423 | 0.607214 | 0.927188 | 0.641949 | 0.941033 | 0.725872 | 0.70687 |
| knn | 0.709482 | 0.577154 | 0.714528 | 0.576577 | 0.771977 | 0.656934 | 0.64416 |
| rf_best | 0.726967 | 0.703407 | 0.712591 | 0.690945 | 0.764133 | 0.745337 | 0.73862 |
| xgb_best | 0.806994 | 0.797595 | 0.710059 | 0.695197 | 0.734920 | 0.716951 | 0.72986 |
| ext_best | 0.781439 | 0.711423 | 0.729212 | 0.664172 | 0.766567 | 0.708840 | 0.70925 |
| dtc_best | 0.797579 | 0.773547 | 0.707637 | 0.683791 | 0.734920 | 0.710462 | 0.72050 |

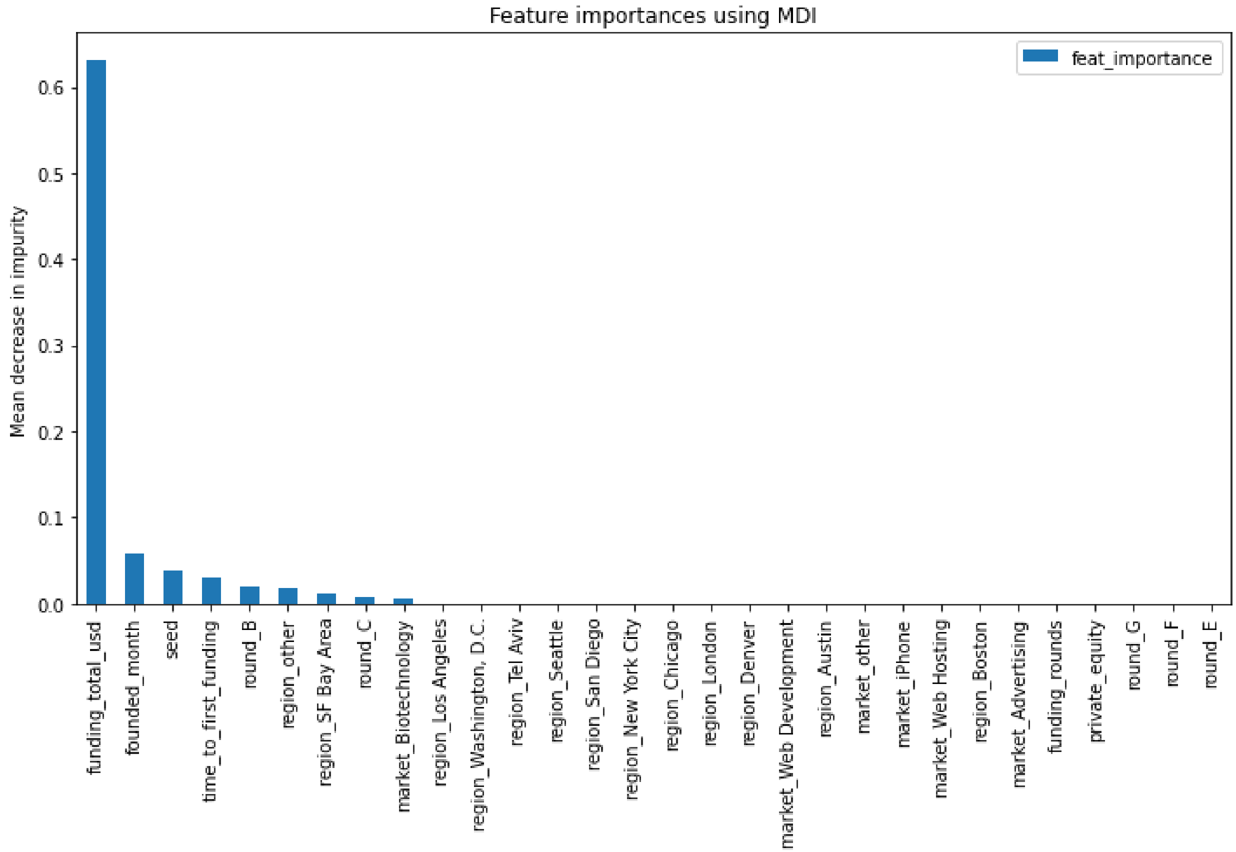
## Feature Importance

In [551…

```
feats = {} # a dict to hold feature_name: feature_importance
for feature, importance in zip(X_train_processed.columns, dtc_best.feature_impo
    feats[feature] = importance #add the name/value pair

feats_dtc = pd.DataFrame(feats.items())

feats_dtc.columns = ['col', 'feat_importance']
feats_dtc = feats_dtc.sort_values(by=['feat_importance'], ascending=False)
feats_dtc_30 = feats_dtc[:30]
```

In [552…

```
fig, ax = plt.subplots(figsize = (10,7))
feats_dtc_30.plot.bar(ax=ax) # yerr=std,
ax.set_title("Feature importances using MDI")
ax.set_ylabel("Mean decrease in impurity")
ax.set_xticklabels(feats_dtc_30['col'])
fig.tight_layout()
```




# Final Model

- XG Boost is the best model, with ~81% recall, 71% accuracy and 73% AUC
- Now that we have narrowed down the best models, we will run then with reduced features & SMOTE to see if that generates any improvement

In [553…
```
X_train_processed, X_train_scaled, X_test_processed, \
X_test_scaled, y_train, y_test = train_test_preprocess(X_ac, y_ac)
```

## Feature Reduction

In [554…
```
# top 20 features
X_train_xg = X_train_processed[list(feats_xg['col'][:20])]
X_train_dtc = X_train_processed[list(feats_dtc['col'][:20])]

X_test_xg = X_test_processed[list(feats_xg['col'][:20])]
X_test_dtc = X_test_processed[list(feats_dtc['col'][:20])]
```

In [555…
```
# XG Boost
final_model = XGBClassifier(random_state=42, max_depth=1, min_child_weight=10,
                            subsample=0.7, learning_rate=0.2, scale_pos_weight=

final_model.fit(X_train_xg, y_train)

y_hat_train = final_model.predict(X_train_xg)
y_hat_test = final_model.predict(X_test_xg)
```

```
print_scores(y_train, y_hat_train, y_test, y_hat_test)
```

```
Training Recall:  0.7794216543375925
Testing Recall:  0.7775551102204409


Training F1:  0.6909090909090909
Testing F1:  0.6867256637168141


ROC AUC:  0.7232462199603567
PR AUC:  0.5681406268836522


Training Accuracy:  0.7195022991614822
Testing Accuracy:  0.7128953771289538
```

In [556…

```
# Decision Trees - 2nd place
final_model = dtc_best
final_model.fit(X_train_dtc, y_train)

y_hat_train = final_model.predict(X_train_dtc)
y_hat_test = final_model.predict(X_test_dtc)

print_scores(y_train, y_hat_train, y_test, y_hat_test)
```

```
Training Recall:  0.6778749159381304
Testing Recall:  0.6533066132264529


Training F1:  0.6845500848896435
Testing F1:  0.6612576064908722


ROC AUC:  0.7169802820900657
PR AUC:  0.5776345895793111


Training Accuracy:  0.7487151744657831
Testing Accuracy:  0.7291159772911597
```

Feature reduction doesn't improve the models.

## SMOTE

In [557…

```
#Using SMOTE to further reduce class imbalance
smote = SMOTE(random_state=42)
X_train_resampled, y_train_resampled = smote.fit_sample(X_train_processed, y_tr
```

In [558…

```
final_model_smote = XGBClassifier(random_state=42, max_depth=1, min_child_weigh
                                  subsample=0.7, learning_rate=0.2)

final_model_smote.fit(X_train_resampled, y_train_resampled)

y_hat_train = final_model_smote.predict(X_train_resampled)
y_hat_test = final_model_smote.predict(X_test_processed)

print_scores(y_train_resampled, y_hat_train, y_test, y_hat_test)
```

```
Training Recall:  0.7737556561085973
Testing Recall:  0.7474949899799599


Training F1:  0.7687120701281187
Testing F1:  0.7037735849056603


ROC AUC:  0.7456820998946121
PR AUC:  0.5991873412046519


Training Accuracy:  0.7671945701357467
Testing Accuracy:  0.7453365774533658
```

## Model Selection

In [559…

```
final_model = XGBClassifier(random_state=42, max_depth=1, min_child_weight=10,
                            subsample=0.7, learning_rate=0.2, scale_pos_weight=

customPipe(final_model, 'final_model', X_ac, y_ac)
```

Out[559]:

| | recall_train | recall_test | f1_train | f1_test | accuracy_train | accuracy_test | roc_ |
|---|---|---|---|---|---|---|---|
| **lr** | 0.767582 | 0.752688 | 0.700917 | 0.661626 | 0.726050 | 0.699412 | 0.708 |
| **rf** | 1.000000 | 0.589178 | 1.000000 | 0.643326 | 1.000000 | 0.735604 | 0.71 |
| **dtc** | 1.000000 | 0.577154 | 1.000000 | 0.588957 | 1.000000 | 0.673966 | 0.658 |
| **ext** | 1.000000 | 0.571142 | 1.000000 | 0.617551 | 1.000000 | 0.713706 | 0.690 |
| **xgb** | 0.933423 | 0.607214 | 0.927188 | 0.641949 | 0.941033 | 0.725872 | 0.706 |
| **knn** | 0.709482 | 0.577154 | 0.714528 | 0.576577 | 0.771977 | 0.656934 | 0.64 |
| **rf_best** | 0.726967 | 0.703407 | 0.712591 | 0.690945 | 0.764133 | 0.745337 | 0.738 |
| **xgb_best** | 0.806994 | 0.797595 | 0.710059 | 0.695197 | 0.734920 | 0.716951 | 0.729 |
| **ext_best** | 0.781439 | 0.711423 | 0.729212 | 0.664172 | 0.766567 | 0.708840 | 0.709 |
| **dtc_best** | 0.797579 | 0.773547 | 0.707637 | 0.683791 | 0.734920 | 0.710462 | 0.720 |
| **final_model** | 0.806994 | 0.797595 | 0.710059 | 0.695197 | 0.734920 | 0.716951 | 0.729 |

In [560…

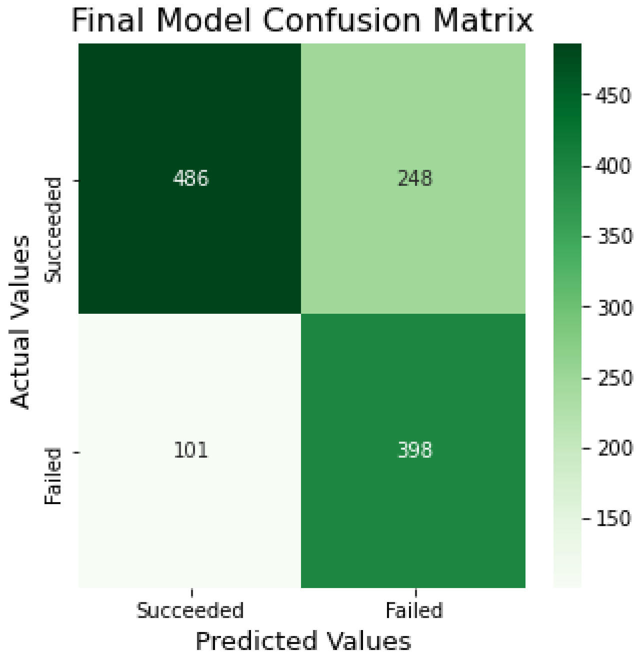
```
# storing dataframe for easy access
scores_final = scores
scores_final.to_csv('final_scores.csv')
scores_final.sort_values(by=['recall_test'], ascending=False)[1:]
```

Out[560]:

| | recall_train | recall_test | f1_train | f1_test | accuracy_train | accuracy_test | roc_ |
|---|---|---|---|---|---|---|---|
| **final_model** | 0.806994 | 0.797595 | 0.710059 | 0.695197 | 0.734920 | 0.716951 | 0.729 |
| **dtc_best** | 0.797579 | 0.773547 | 0.707637 | 0.683791 | 0.734920 | 0.710462 | 0.720 |
| **lr** | 0.767582 | 0.752688 | 0.700917 | 0.661626 | 0.726050 | 0.699412 | 0.708 |
| **ext_best** | 0.781439 | 0.711423 | 0.729212 | 0.664172 | 0.766567 | 0.708840 | 0.709 |
| **rf_best** | 0.726967 | 0.703407 | 0.712591 | 0.690945 | 0.764133 | 0.745337 | 0.738 |
| **xgb** | 0.933423 | 0.607214 | 0.927188 | 0.641949 | 0.941033 | 0.725872 | 0.706 |
| **rf** | 1.000000 | 0.589178 | 1.000000 | 0.643326 | 1.000000 | 0.735604 | 0.71 |
| **dtc** | 1.000000 | 0.577154 | 1.000000 | 0.588957 | 1.000000 | 0.673966 | 0.658 |
| **knn** | 0.709482 | 0.577154 | 0.714528 | 0.576577 | 0.771977 | 0.656934 | 0.64 |
| **ext** | 1.000000 | 0.571142 | 1.000000 | 0.617551 | 1.000000 | 0.713706 | 0.690 |

In [561…

```
# visualizing predictions

y_hat_test = final_model.predict(X_test_processed)

conf_matrix = confusion_matrix(y_test, y_hat_test)

fig, ax = plt.subplots(figsize=(5,5))

ax = sns.heatmap(conf_matrix, annot=True, cmap='Greens', fmt='d')

ax.set_title('Final Model Confusion Matrix', fontsize=16);
ax.set_xlabel('Predicted Values',fontsize=13)
ax.set_ylabel('Actual Values ', fontsize=13);

## Ticket labels - List must be in alphabetical order
ax.xaxis.set_ticklabels(['Succeeded','Failed'])
ax.yaxis.set_ticklabels(['Succeeded','Failed'])

## Display the visualization of the Confusion Matrix.
plt.show()
```



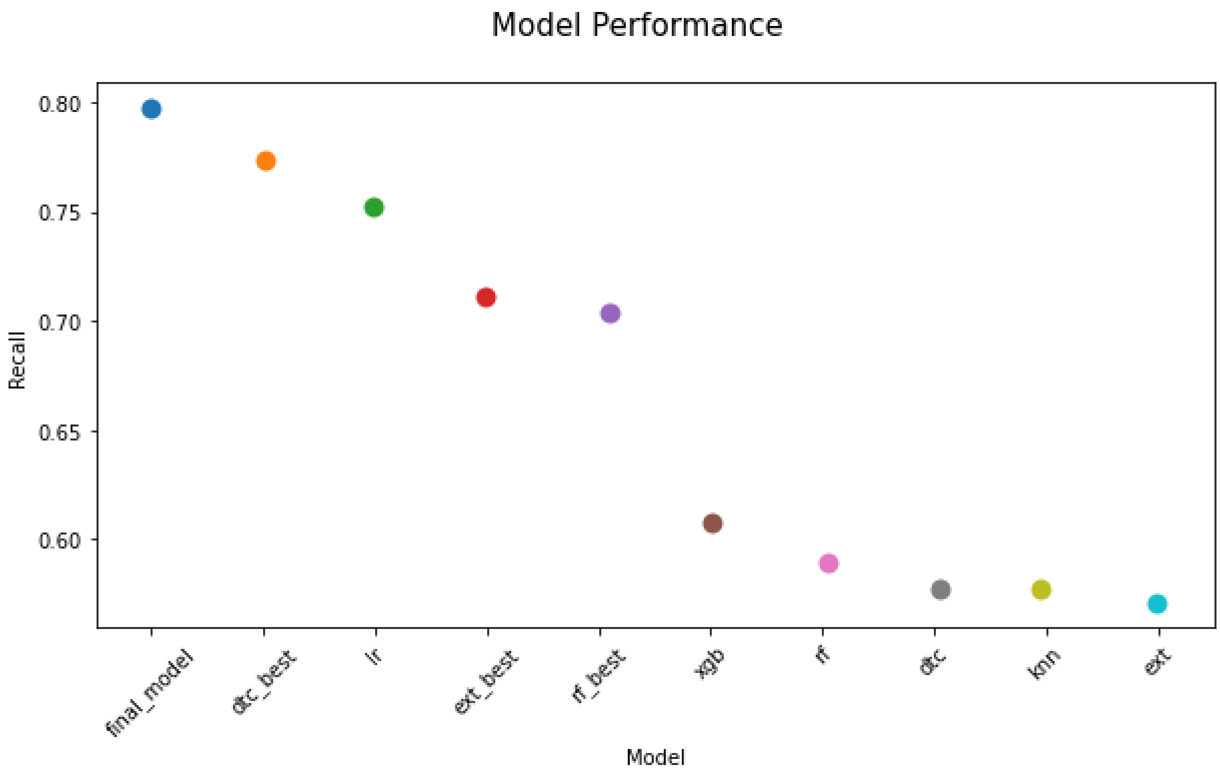

# Final Analysis & Visualizations

In [562…

```
## Model Comparison
scores_viz = scores_final.sort_values(by=['recall_test'], ascending=False)[1:].

fig, ax = plt.subplots(figsize=(10, 5))
sns.stripplot(x="index", y="recall_test", data=scores_viz, size=10)
plt.xticks(rotation = 45)
ax.set_xlabel("Model", fontsize=10)
ax.set_ylabel("Recall", fontsize=10)
fig.suptitle("Model Performance", fontsize=15)
```

Out[562]:

```
Text(0.5, 0.98, 'Model Performance')
```




In [563…

```
## Visualizing Important Features
```

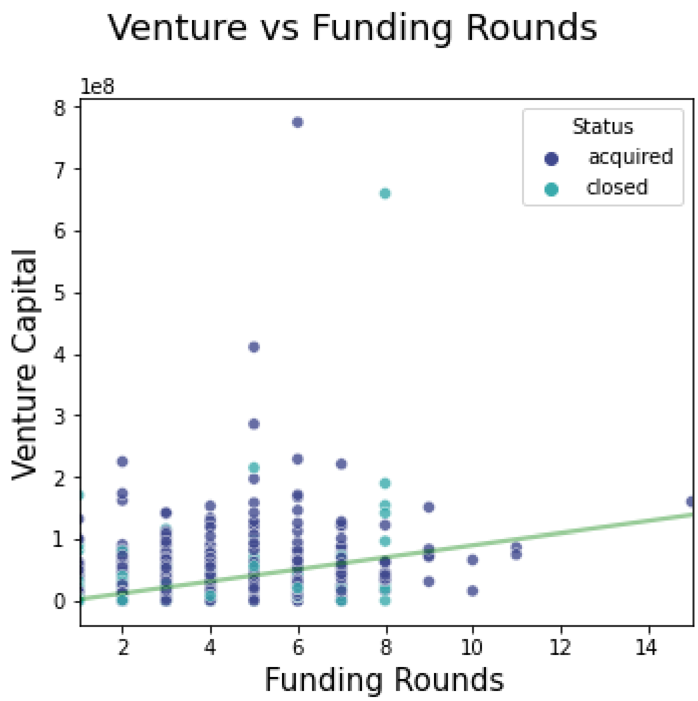
In [564…

```
df = data_final2
df['int_category'] = ['international' if x==1 else 'U.S.' for x in df['internat
df['one_funding_round'] = ['one' if x==1 else 'multiple' for x in df['funding_r

df_box = df[(df['venture'] < 40000000.0)]

cmap = sns.diverging_palette(130, 50, as_cmap=True)
```

In [565…

```
# setting up the figure with a single subplot
fig = plt.figure(figsize=(5, 5))
fig, ax = plt.subplots(figsize=(5, 5))
# scatterplot using seaborn
plot = sns.scatterplot(x='funding_rounds', y='venture', data=df,
hue=df.status, legend='full', alpha = 0.8, palette='mako')
# adding regression line using seaborn regplot
sns.regplot(data=df, x='funding_rounds', y='venture', scatter=False,
            ax=ax, ci=False, color='g', line_kws={'alpha':0.4})

# updating figure title, adding labels for x- and y-axis
fig.suptitle("Venture vs Funding Rounds", fontsize=18)
ax.set_xlabel("Funding Rounds", fontsize=15)
ax.set_ylabel("Venture Capital", fontsize=15)
# setting legend title
ax.get_legend().set_title("Status")
# getting everything to fit nicely on the plot
plt.tight_layout()
```

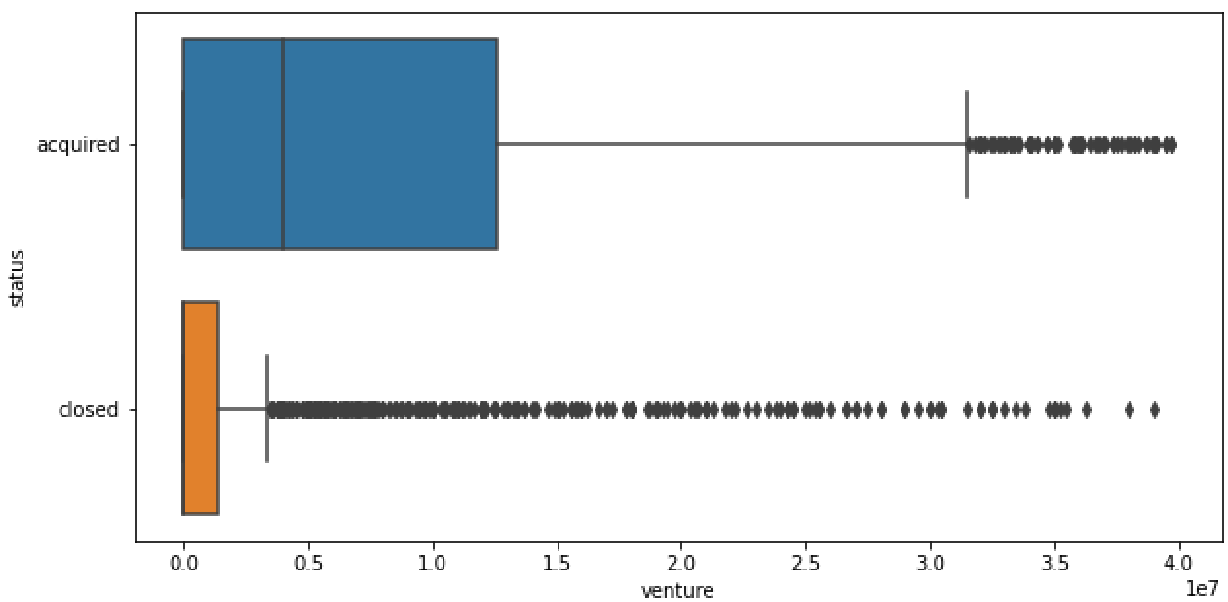
```
<Figure size 360x360 with 0 Axes>
```




In [566…

```
df_box = df[(df['venture'] < 40000000.0)]
#df_box = df[(df['funding_total_usd'] < 1000000.0)]

plt.figure(figsize=(10,5))
sns.boxplot(x=df_box['venture'], y=df_box['status'])
```

Out[566]: <AxesSubplot:xlabel='venture', ylabel='status'>

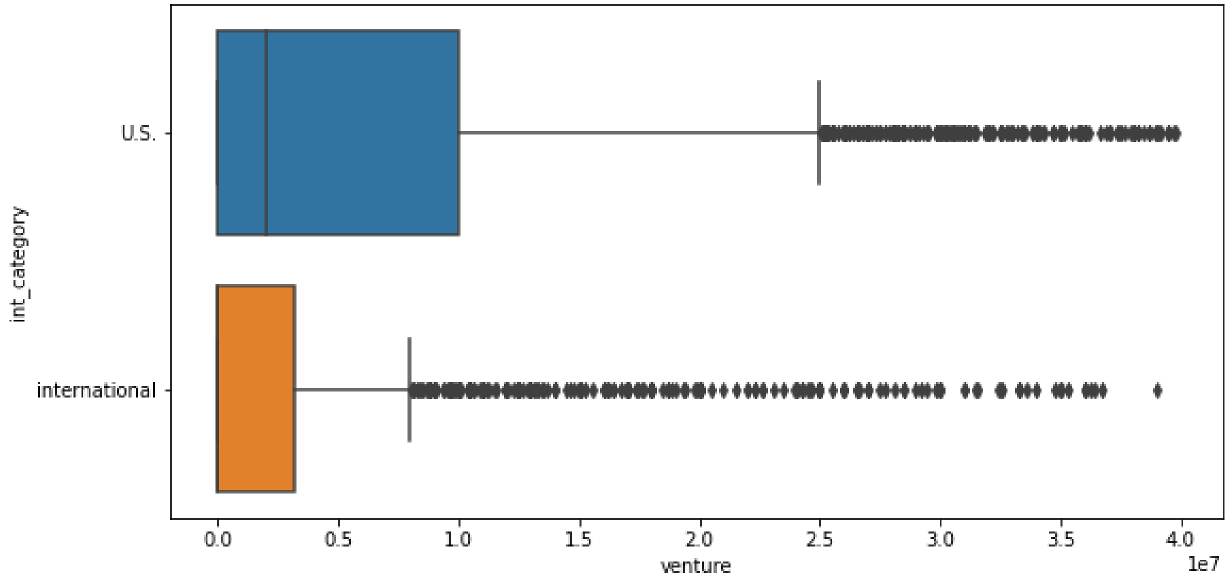



In [567…

```
plt.figure(figsize=(10,5))

sns.boxplot(x=df_box['venture'], y=df_box['int_category'])

df_box['int_category'].value_counts()
```

Out[567]:

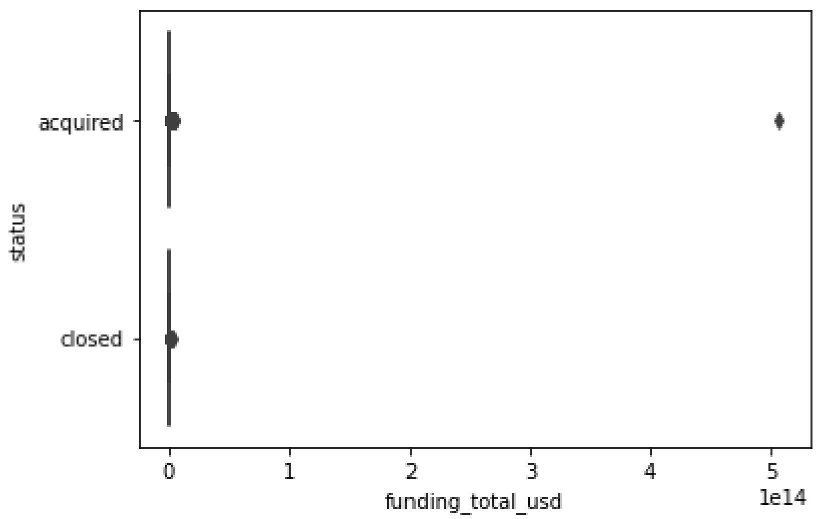
```
U.S.             3143
international    1443
Name: int_category, dtype: int64
```




In [568…

```
sns.boxplot(x=df_box['funding_total_usd'], y=df_box['status'])
```

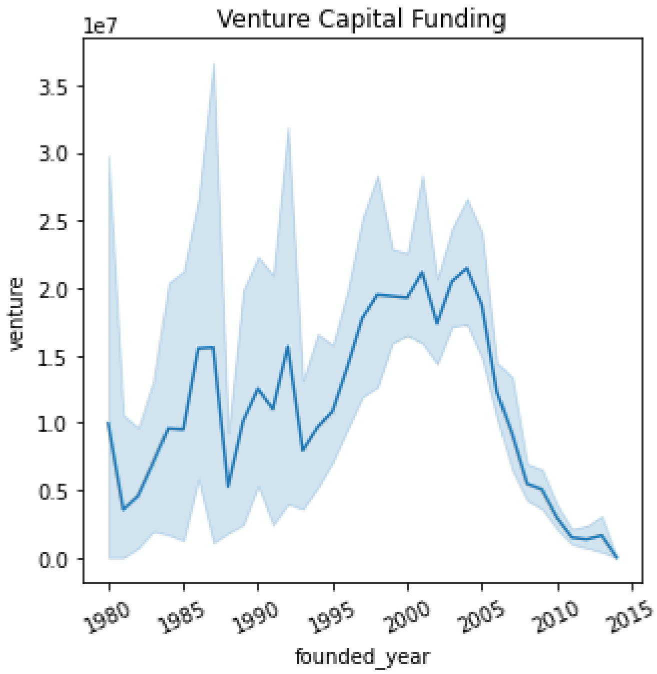
Out[568]: <AxesSubplot:xlabel='funding_total_usd', ylabel='status'>

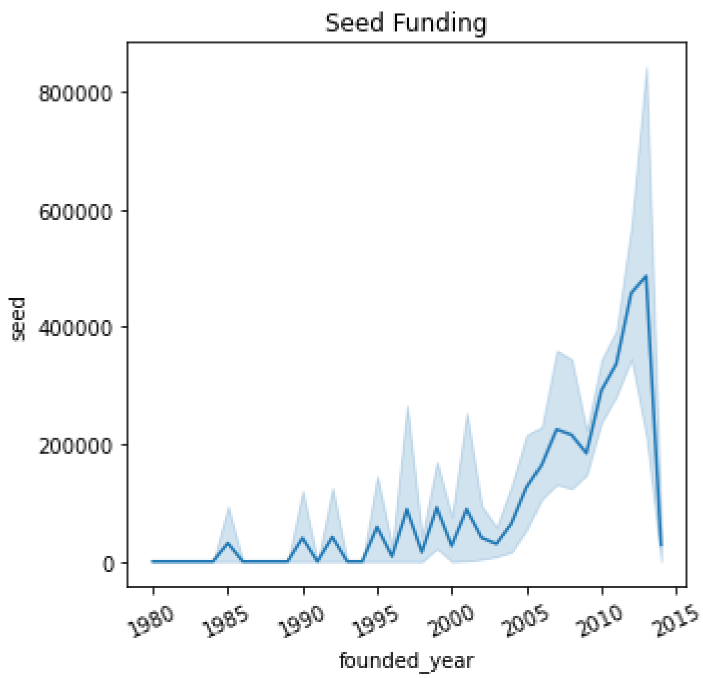



In [569…

```
plt.figure(figsize=(5,5))
plt.title('Venture Capital Funding')
sns.lineplot(x = "founded_year", y = "venture", data = df)
plt.xticks(rotation = 25)

plt.figure(figsize=(5,5))
sns.lineplot(x = "founded_year", y = "seed", data = df)
plt.xticks(rotation = 25)
plt.title('Seed Funding')
```

Out[569]: Text(0.5, 1.0, 'Seed Funding')

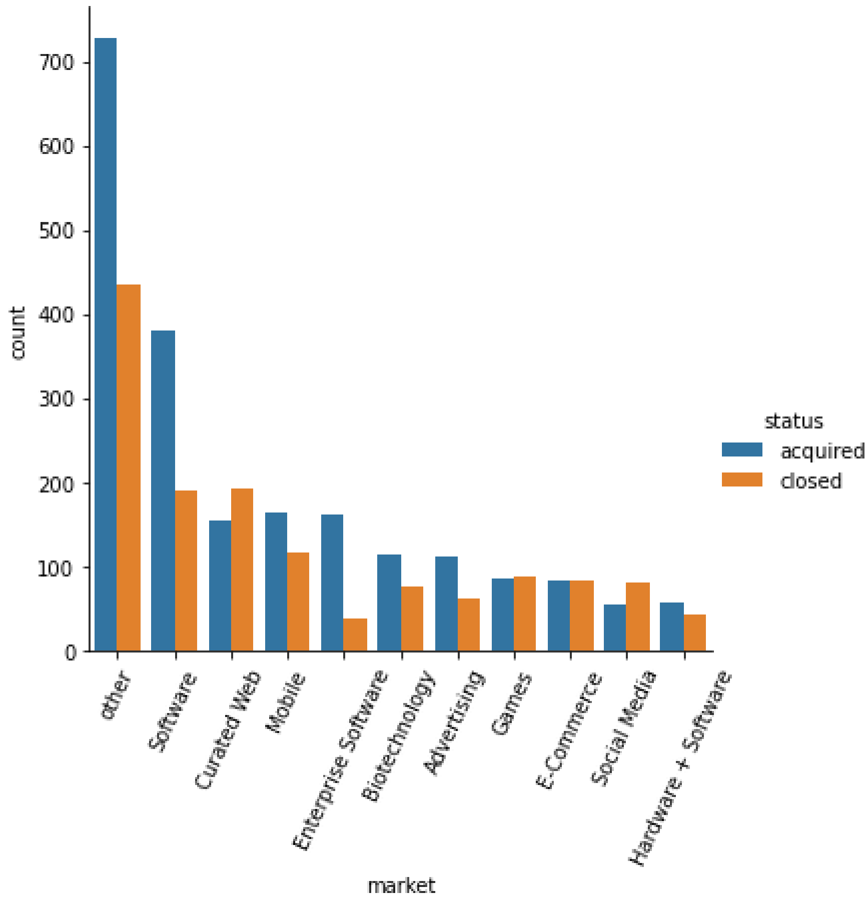



In [570…

```
# top 10 markets

#print(set(df['market'][df['market'].map(df['market'].value_counts()) >= 100]),
df['market'].value_counts()[1:11]
top10_mkt = list(set(df['market'][df['market'].map(df['market'].value_counts())
top10_mkt

plt.figure(figsize=(10,10))
sns.catplot(x='market',hue='status',data=df[df['market'].isin(top10_mkt)],
            kind="count",
            order = df['market'][df['market'].isin(top10_mkt)].value_counts().i
plt.xticks(rotation = 65)
```

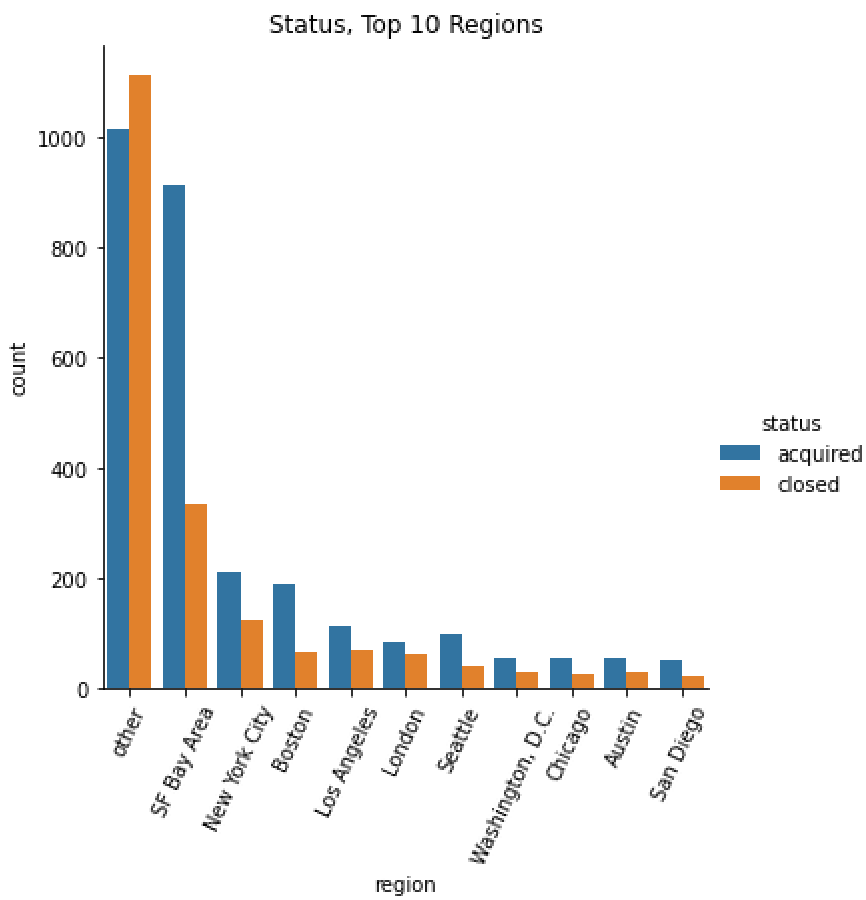
Out[570]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10]),
 [Text(0, 0, 'other'),
  Text(1, 0, 'Software'),
  Text(2, 0, 'Curated Web'),
  Text(3, 0, 'Mobile'),
  Text(4, 0, 'Enterprise Software'),
  Text(5, 0, 'Biotechnology'),
  Text(6, 0, 'Advertising'),
  Text(7, 0, 'Games'),
  Text(8, 0, 'E-Commerce'),
  Text(9, 0, 'Social Media'),
  Text(10, 0, 'Hardware + Software')])
<Figure size 720x720 with 0 Axes>
```




In [571…
```
print(df['region'].value_counts()[1:11])
top10_reg = list(set(df['region'][df['region'].map(df['region'].value_counts())
top10_reg

# fig= plt.figure(figsize=(10,5))
# fig, ax = plt.subplots(figsize=(10, 5))
# ax.set_xlabel("Region", fontsize=10)
# ax.set_ylabel("Count", fontsize=10)
# fig.suptitle("Status, Top 10 Regions", fontsize=15)

sns.catplot(x='region',hue='status',data=df[df['region'].isin(top10_reg)],
            kind="count",
            order = df['region'][df['region'].isin(top10_reg)].value_counts().i
plt.title('Status, Top 10 Regions')
plt.xticks(rotation = 65)
```

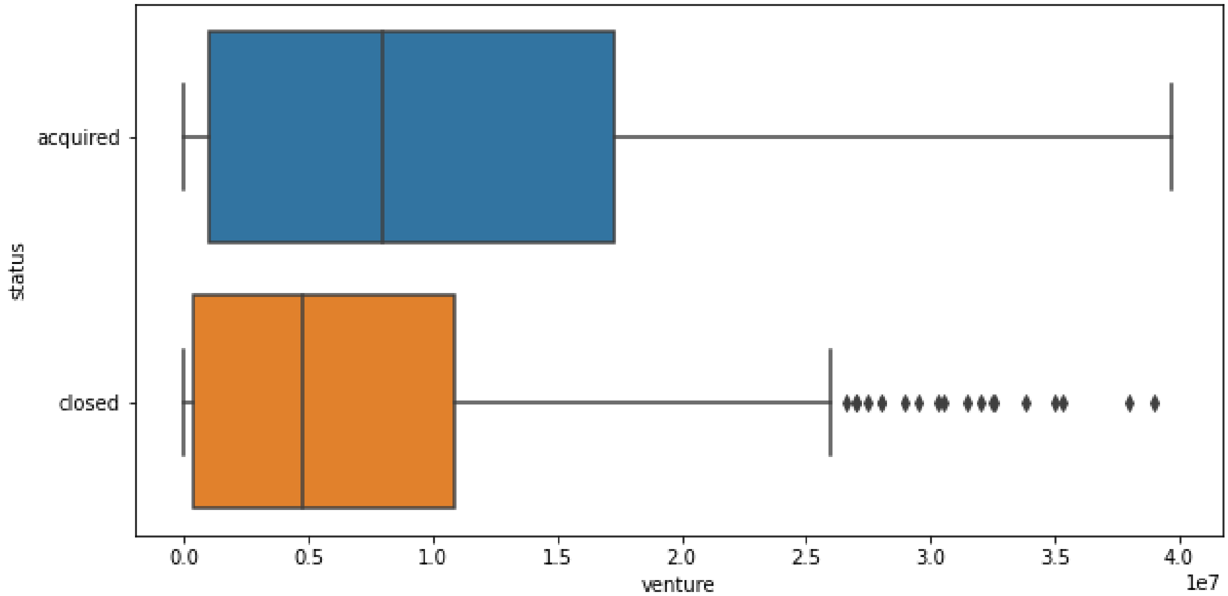
```
SF Bay Area           1250
New York City          338
Boston                 260
Los Angeles            186
London                 146
Seattle                143
Washington, D.C.        85
Chicago                 85
Austin                  84
San Diego               77
Name: region, dtype: int64
```

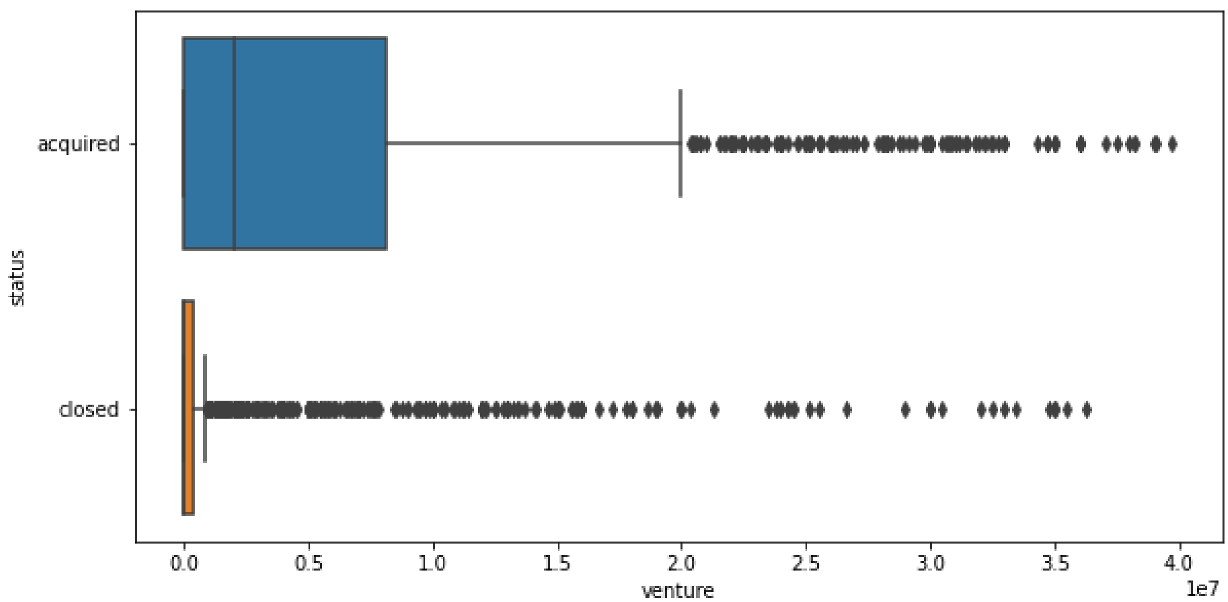
Out[571]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10]),
 [Text(0, 0, 'other'),
  Text(1, 0, 'SF Bay Area'),
  Text(2, 0, 'New York City'),
  Text(3, 0, 'Boston'),
  Text(4, 0, 'Los Angeles'),
  Text(5, 0, 'London'),
  Text(6, 0, 'Seattle'),
  Text(7, 0, 'Washington, D.C.'),
  Text(8, 0, 'Chicago'),
  Text(9, 0, 'Austin'),
  Text(10, 0, 'San Diego')])
```




In [572…
```
plt.figure(figsize=(10,5))
sns.boxplot(x=df_box['venture'][df_box['founded_year'] < 2005],
            y=df_box['status'][df_box['founded_year'] < 2005])

plt.figure(figsize=(10,5))
sns.boxplot(x=df_box['venture'][df_box['founded_year'] >= 2005],
            y=df_box['status'][df_box['founded_year'] >= 2005])
```

Out[572]: <AxesSubplot:xlabel='venture', ylabel='status'>

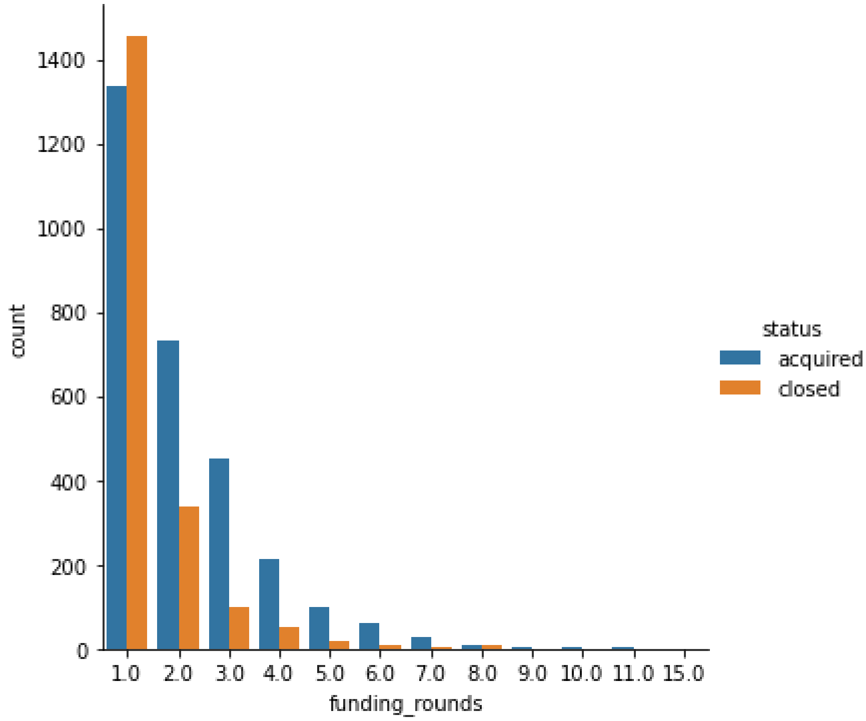



In [573…

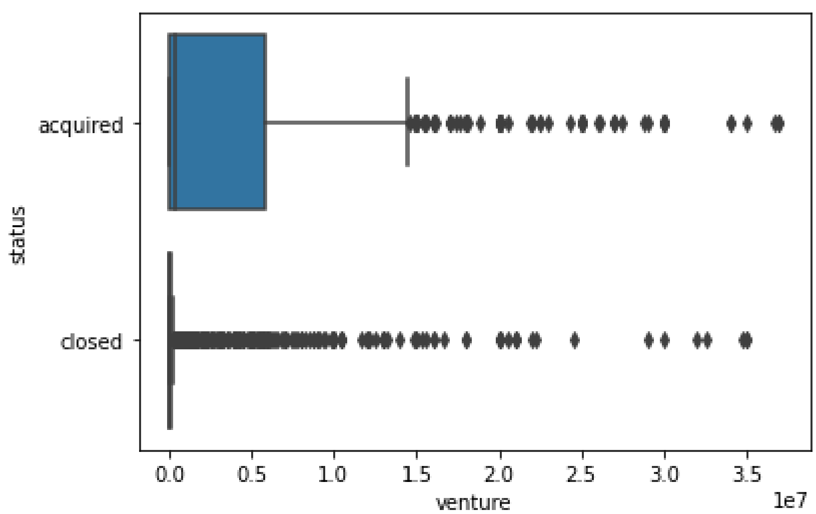
```
# number of funding rounds
df['funding_rounds'].value_counts()

# acquired or closed by number of funding rounds

sns.catplot(x='funding_rounds',hue='status', data=df, kind="count")
```

Out[573]: <seaborn.axisgrid.FacetGrid at 0x7fe27450fb20>



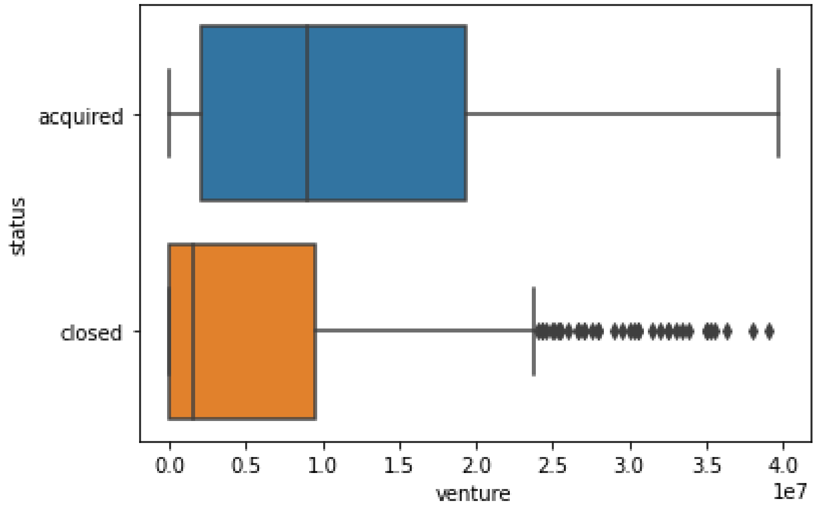

In [574…
```
# more than one funding round
df_ofr = df_box[df_box['one_funding_round']=='one']
df_mfr = df_box[df_box['one_funding_round']=='multiple']
sns.boxplot(x='venture', y='status', data=df_ofr)
```

Out[574]: <AxesSubplot:xlabel='venture', ylabel='status'>




In [575…
```
sns.boxplot(x='venture', y='status', data=df_mfr)
```

Out[575]: <AxesSubplot:xlabel='venture', ylabel='status'>




In [576…
```
sns.countplot(x='one_funding_round',hue='status', data=df, orient='v')
```

Out[576]: <AxesSubplot:xlabel='one_funding_round', ylabel='count'>