This jupyter notebook is prepared by “Joseph Torres”.

1. Run the block below to upload the dataset. (Note that the file list gets refreshed every time your runtime is disconnected. Simply run this when you return to upload the file again using the files API. Once you run, it should wait for you to upload the file. (1pt)

```
from google.colab import files
uploaded = files.upload()
```

Choose Files startup_info_.csv

- **startup_info_.csv**(text/csv) - 168764 bytes, last modified: 2/8/2023 - 100% done

```
Saving startup_info_.csv to startup_info_.csv
```

2. Import numpy, pandas, matplotlib.pyplot and seaborn packages. (2pt)

If you need additional packages, you can import it on the go in any code-block below.

```
#TODO
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

3. Import the dataset into a pandas dataframe. Then report how many rows and columns are present in the dataset. (2pt)

```
#TODO
df = pd.read_csv(r'startup_info_.csv')
print("Number of Rows:", len(df.axes[0]))
print("Number of Columns:",len(df.axes[1]))
```

```
Number of Rows: 923
Number of Columns: 28
```

4. Call the describe method to see summary statistics of the numerical attribute columns. (1pt)

```
#TODO
df.describe()
```

	Unnamed: 0	latitude	longitude	labels	age_first_funding_year	age_last_funding_year	age_first_milestone_year	ag
count	923.000000	923.000000	923.000000	923.000000	923.000000	923.000000	771.000000	
mean	572.297941	38.517442	-103.539212	0.646804	2.235630	3.931456	3.055353	
std	333.585431	3.741497	22.394167	0.478222	2.510449	2.967910	2.977057	
min	1.000000	25.752358	-122.756956	0.000000	-9.046600	-9.046600	-14.169900	
25%	283.500000	37.388869	-122.198732	0.000000	0.576700	1.669850	1.000000	
50%	577.000000	37.779281	-118.374037	1.000000	1.446600	3.528800	2.520500	
75%	866.500000	40.730646	-77.214731	1.000000	3.575350	5.560250	4.686300	
max	1153.000000	59.335232	18.057121	1.000000	21.895900	21.895900	24.684900	

5.1 List all attribute columns (1pt)

```
#TODO
df.columns
```

```
Index(['Unnamed: 0', 'state_code', 'latitude', 'longitude', 'zip_code', 'id',
       'city', 'Unnamed: 6', 'name', 'labels', 'founded_at', 'closed_at',
       'first_funding_at', 'last_funding_at', 'age_first_funding_year',
       'age_last_funding_year', 'age_first_milestone_year',
       'age_last_milestone_year', 'relationships', 'funding_rounds',
       'funding_total_usd', 'milestones', 'state_code.1', 'category_code',
       'object_id', 'avg_participants', 'is_top500', 'status'],
      dtype='object')
```

5.2 The "Unnamed: 0","Unnamed: 6", "state_code.1" and "object_id" feature columns are not useful. Drop them in-place. (1pt)

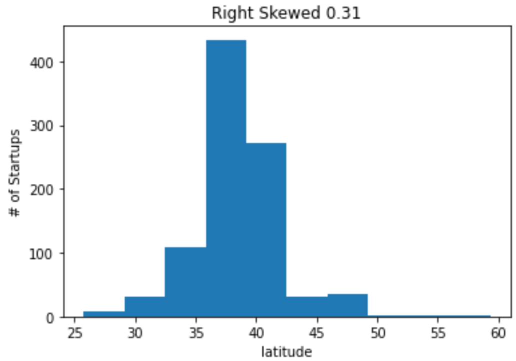
```
#TODO
df = df.drop(columns = ["Unnamed: 0", "Unnamed: 6", "state_code.1", "object_id"])
```

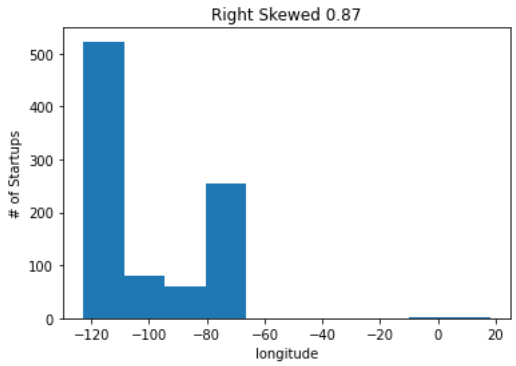
6.1 Show all the numeric columns and save it to a new dataframe. (2pt)

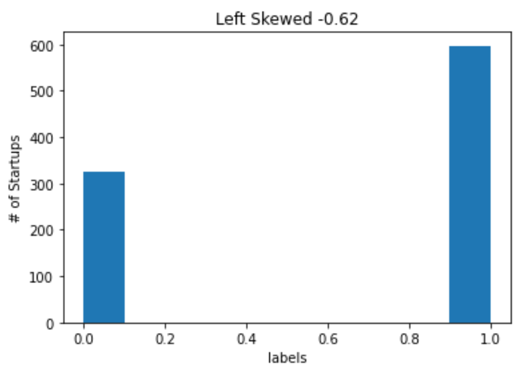
```
#TODO
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
newdf = df.select_dtypes(include=numerics)
```

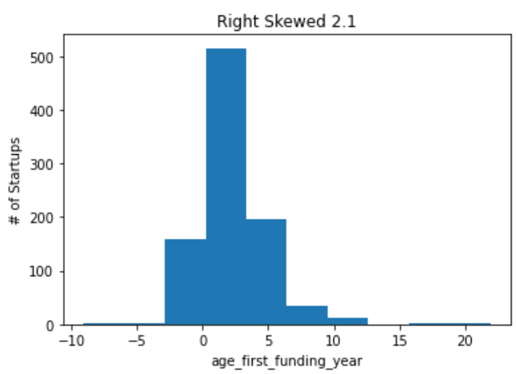
6.2 Plot distributions of the numeric columns using histogram and record the skew of each distribution. (Note: positive value = right skewed, negative value = left skewed) (4pt)

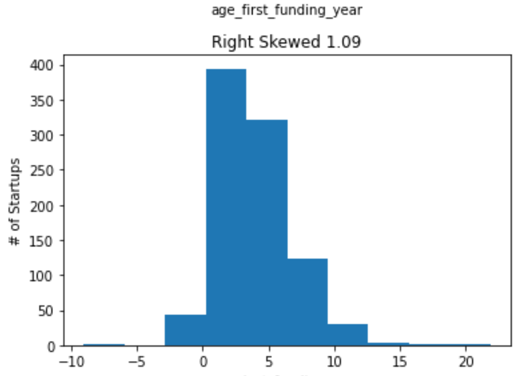
```
#TODO
def skew_lr(num):
  num = float("{:.2f}".format(num))
  if num > 0:
    return "Right Skewed " + str(num)
  else:
    return "Left Skewed " + str(num)

def createHist(strCol, num):
  plt.hist(newdf[strCol], bins = 10)
  plt.xlabel(strCol)
  plt.ylabel("# of Startups")
  plt.title(skew_lr(num))
  plt.show()

arr = newdf.skew()
for k, v in arr.items():
  createHist(k, v)
```

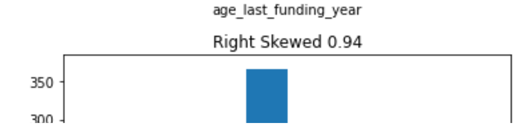

Right Skewed 0.31
# of Startups
latitude


Right Skewed 0.87
# of Startups
longitude


Left Skewed -0.62
# of Startups
labels


Right Skewed 2.1
# of Startups
age_first_funding_year


Right Skewed 1.09
# of Startups
age_last_funding_year


Right Skewed 0.94

7. Show all the categorical columns and save it to a new dataframe. (2pt)

```
#TODO
catDf = df.select_dtypes(exclude=["number"])
catDf.head()
```

	state_code	zip_code	id	city	name	founded_at	closed_at	first_funding_at	last_funding_at	categor
0	CA	92101	c:6669	San Diego	Bandsintown	1/1/2007	NaN	4/1/2009	1/1/2010	
1	CA	95032	c:16283	Los Gatos	TriCipher	1/1/2000	NaN	2/14/2005	12/28/2009	en
2	CA	92121	c:65620	San Diego	Plixi	3/18/2009	NaN	3/30/2010	3/30/2010	
3	CA	95014	c:42668	Cupertino	Solidcore Systems	1/1/2002	NaN	2/17/2005	4/25/2007	s
4	CA	94105	c:65806	San Francisco	Inhale Digital	8/1/2010	10/1/2012	8/1/2010	4/1/2012	games

8. Examine missing values (2+2+3=7pt)

8.1 Show a list with column wise count of missing values and display the list in count wise descending order.

```
#TODO
print("Missing values in each column", df.isnull().sum().sort_values(ascending = False), sep = '\n')
```

```
Missing values in each column
closed_at                  588
age_last_milestone_year    152
age_first_milestone_year   152
state_code                   0
age_last_funding_year        0
is_top500                    0
avg_participants             0
category_code                0
milestones                   0
funding_total_usd            0
funding_rounds               0
relationships                0
age_first_funding_year       0
latitude                     0
last_funding_at              0
first_funding_at             0
founded_at                   0
labels                       0
name                         0
city                         0
id                           0
zip_code                     0
longitude                    0
status                       0
dtype: int64
```

8.2 Show columnwise percentage of missing values.

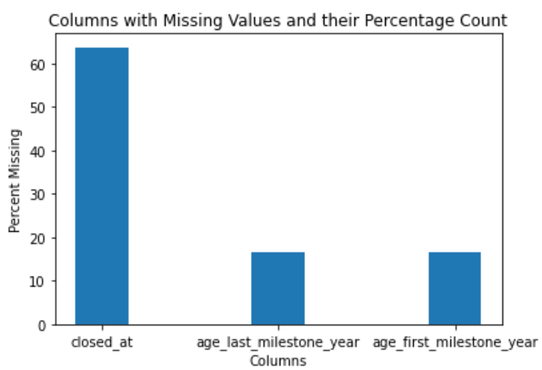
```
#TODO
print("Missing value percentage in each column", df.isnull().sum().sort_values(ascending = False) / 923 * 100, sep = '\n')
```

```
Missing value percentage in each column
closed_at                  63.705309
age_last_milestone_year    16.468039
age_first_milestone_year   16.468039
state_code                  0.000000
age_last_funding_year       0.000000
is_top500                   0.000000
avg_participants            0.000000
category_code               0.000000
milestones                  0.000000
funding_total_usd           0.000000
funding_rounds              0.000000
relationships               0.000000
age_first_funding_year      0.000000
latitude                    0.000000
```

```
last_funding_at            0.000000
first_funding_at           0.000000
founded_at                 0.000000
labels                     0.000000
name                       0.000000
city                       0.000000
id                         0.000000
zip_code                   0.000000
longitude                  0.000000
status                     0.000000
dtype: float64
```

8.3 Display a bar plot to visualize only the columns with missing values and their percentage count.

```
#TODO
missingArr = df.isnull().sum().sort_values(ascending = False) / 923 * 100
labels = []
values = []
for k, v in missingArr.items():
  if v != 0.0:
    labels.append(k)
    values.append(v)

plt.bar(labels, values, width = 0.3)
plt.xlabel("Columns")
plt.ylabel("Percent Missing")
plt.title("Columns with Missing Values and their Percentage Count")
plt.show()
```



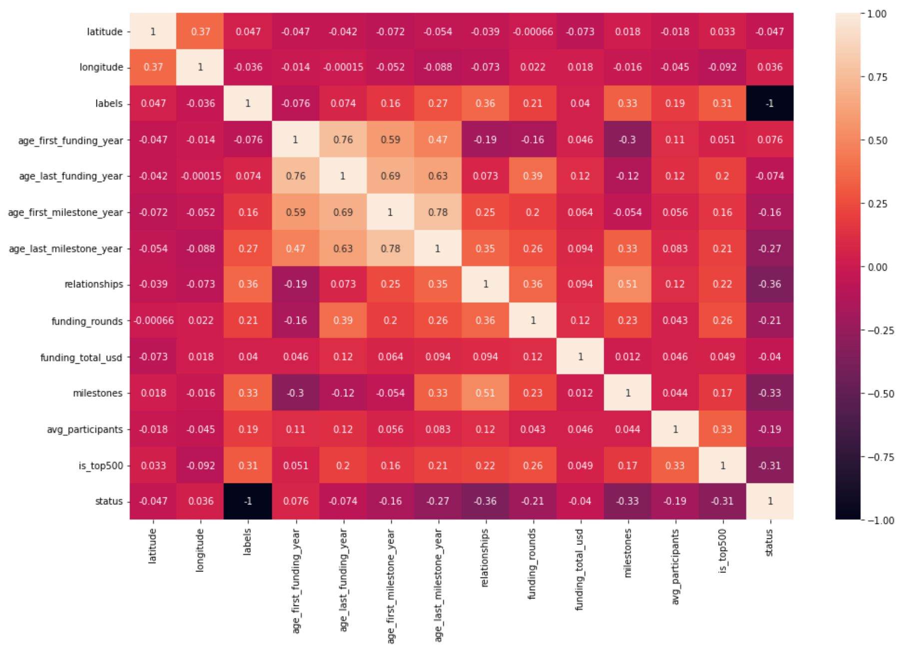
9. Label Encoding : Copy the dataframe to a new one. Then using scikitlearn's Label Encoder, transform the "status" column to 0-1. (5pt)

```
#TODO
from sklearn import preprocessing
encDf = df
encode_column = 'status'
labelEncoder = preprocessing.LabelEncoder()
labelEncoder.fit(encDf[encode_column])
encDf[encode_column] = labelEncoder.transform(encDf[encode_column])

encDf.head()
```

	state_code	latitude	longitude	zip_code	id	city	name	labels	founded_at	closed_at	...	age_first_milesto
0	CA	42.358880	-71.056820	92101	c:6669	San Diego	Bandsintown	1	1/1/2007	NaN	...	

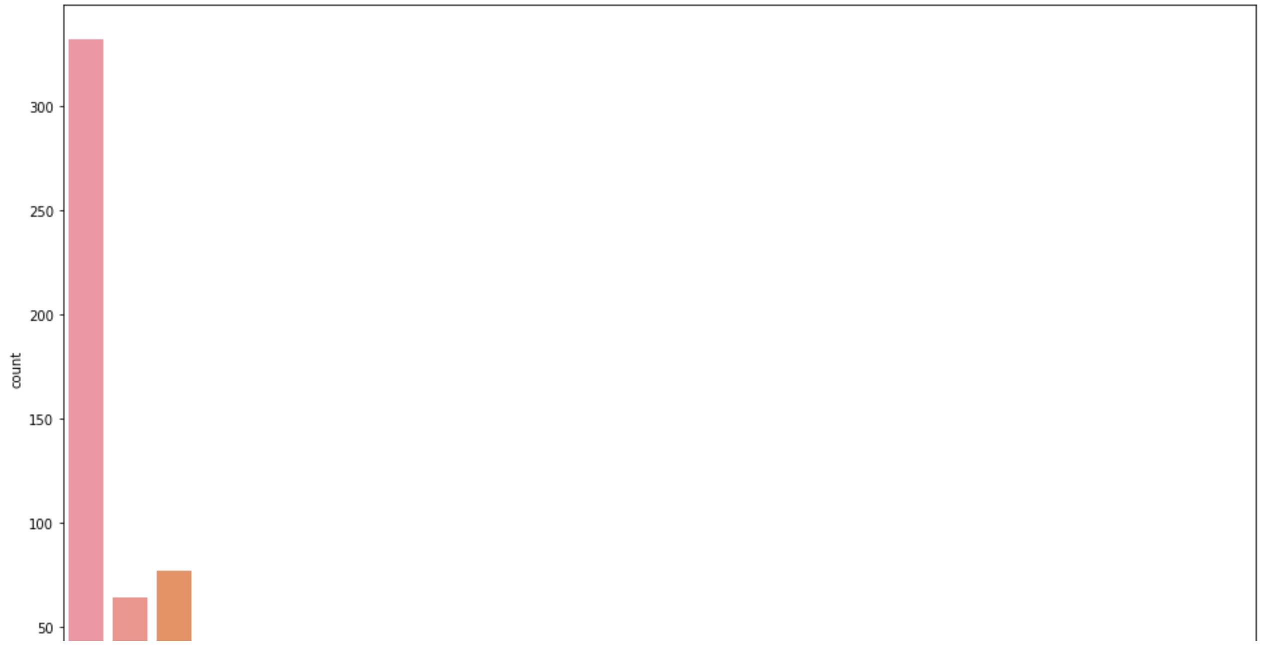
10. Correlation: Use seaborn's heatmap to visualize the correlation between numeric features. (3pt)

```
#TODO
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
corrDf = encDf.select_dtypes(include=numerics)
corr = corrDf.corr()

plt.figure(figsize = (16, 10))
sns.heatmap(corr,vmin = -1, vmax = 1, annot = True)
plt.show()
```



11.1 Use seaborn's countplot to visualize relationship between "*state_code*" and "*labels*". Comment on which state produced majority of successful startups (3pt)

```
#TODO
plt.figure(figsize = (16, 10))
suc = df.loc[df['labels'] > 0, ['state_code']]
unsuc = df.loc[df['labels'] < 0, ['state_code']]
sns.countplot(x = suc['state_code'])
plt.show()
#California
```

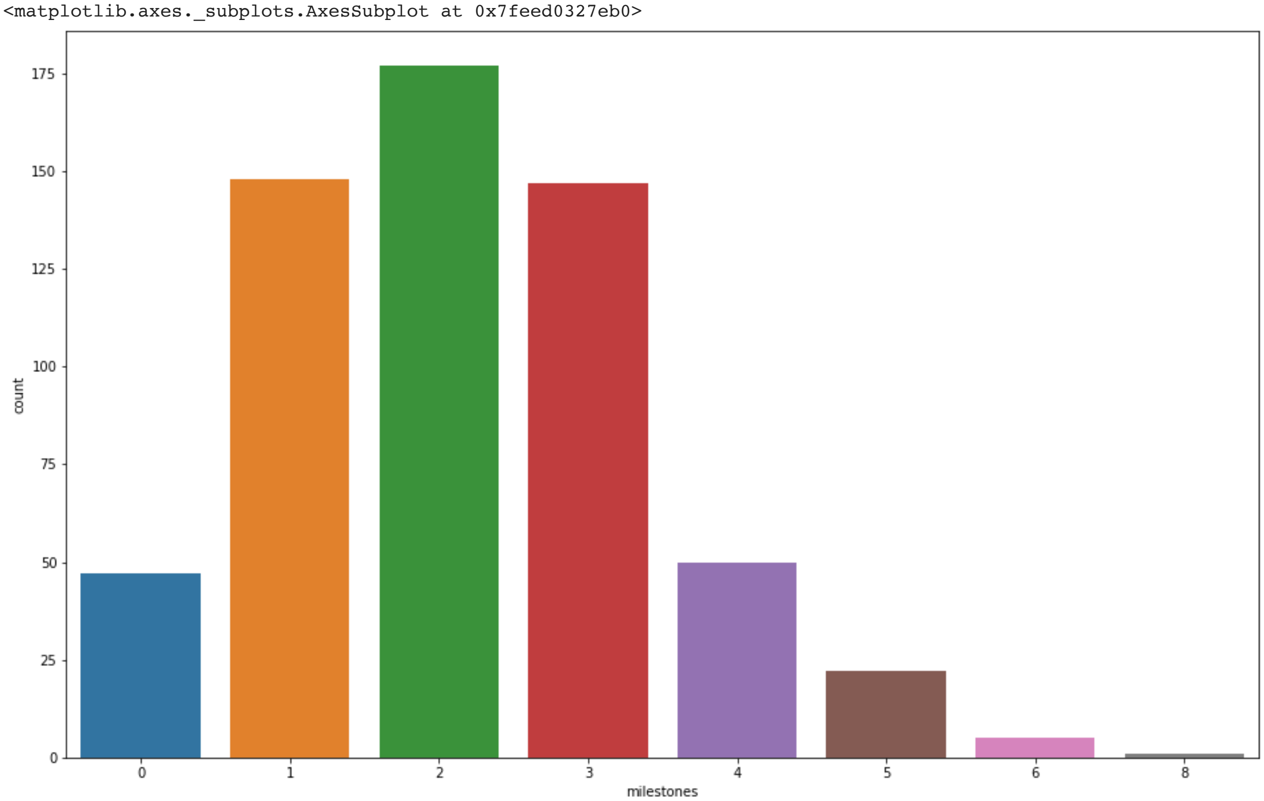


11.2 Use seaborn's countplot to visualize relationship between "*milestones*" and "*labels*". Comment on which milestone made the statistically highest number of successful startups (3pt)

Double-click (or enter) to edit

```
#TODO
plt.figure(figsize = (16, 10))
suc = df.loc[df['labels'] > 0, ['milestones']]
sns.countplot(x = suc['milestones'])

# Milestone 2 has the most successful startups.
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7feed0327eb0>
```



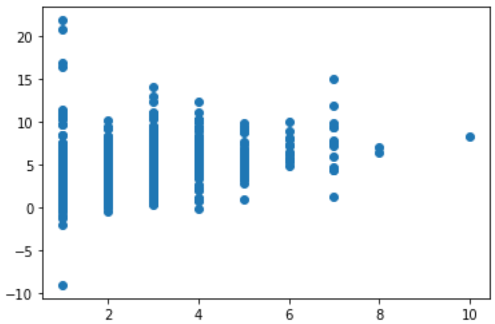
12. Drop features with duplicate values in-place, then show dataframe's new shape. (1pt)

```
#TODO
droppedDups = df
droppedDups.drop_duplicates()
print(droppedDups.shape)
```

```
(923, 24)
```

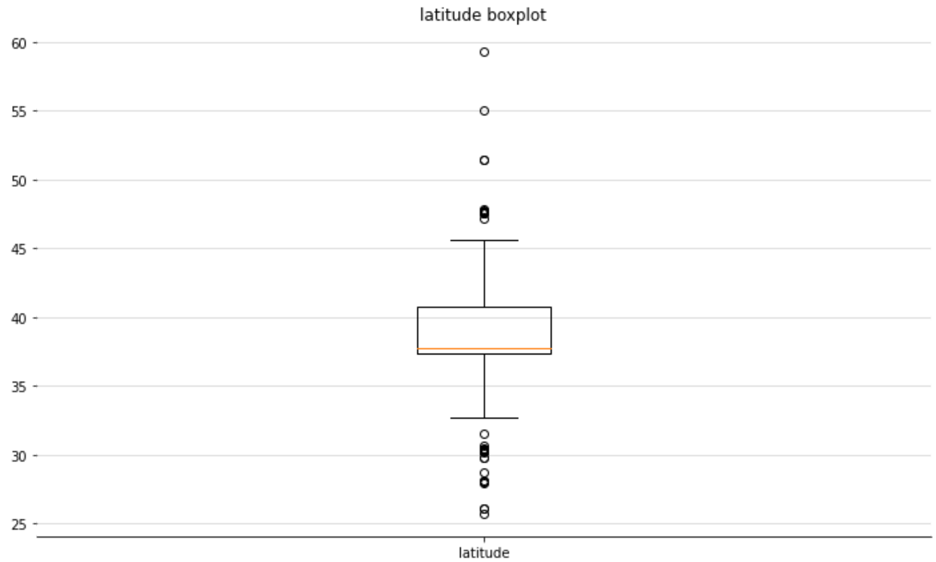
13. From correlation heatmap above, comment on which feature has the highest correlation with "*funding_rounds*". Visualize a scatterplot with that and "*funding_rounds*". (3+3 = 6pt)

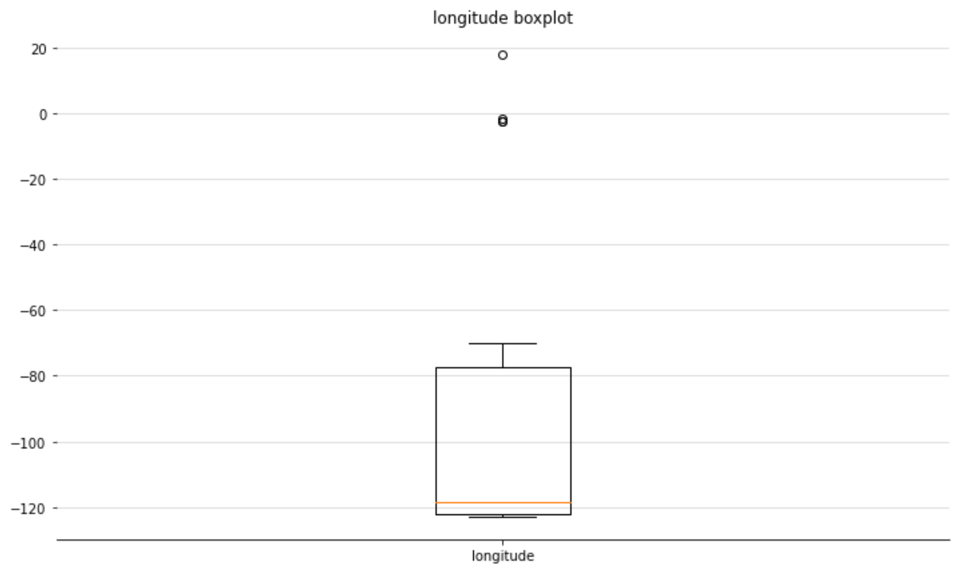
```
#TODO
plt.scatter(corrDf['funding_rounds'], corrDf['age_last_funding_year'])
plt.show()
```

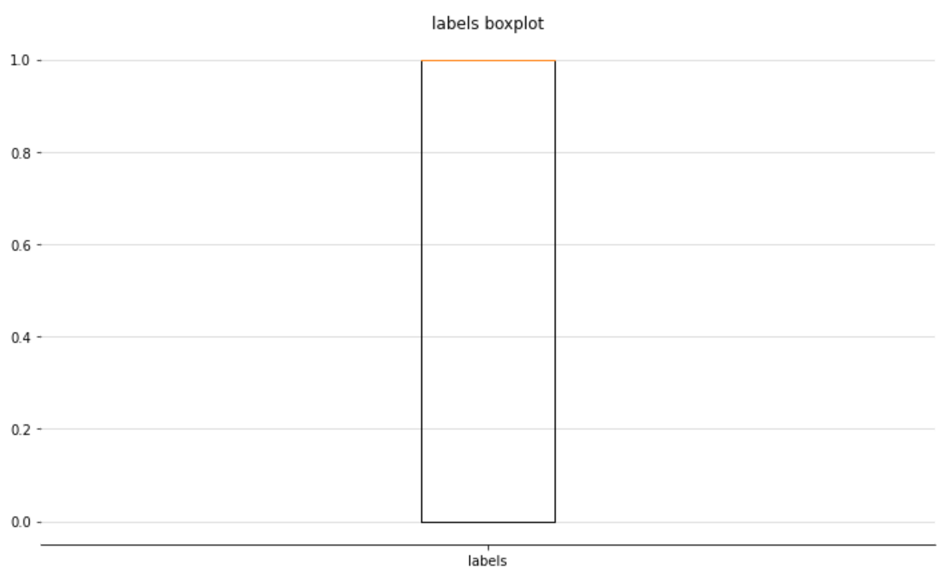


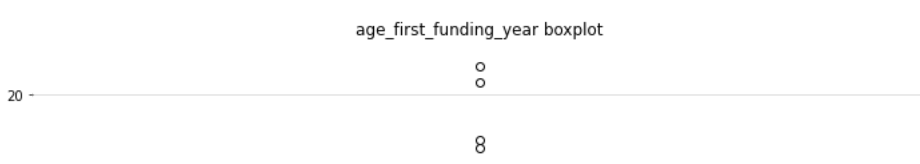
14. Show boxplots for the numeric features to detect outliers. (4pt)

```
#TODO
def createBox(strCol):
  fig, ax = plt.subplots(figsize=(12, 7))


  ax.spines['top'].set_visible(False)
  ax.spines['right'].set_visible(False)
  ax.spines['left'].set_visible(False)

  ax.grid(color='grey', axis='y', linestyle='-', linewidth=0.5, alpha=0.5)
  ax.set_title(strCol + " boxplot")
  plt.boxplot(df[strCol], labels = [strCol])
  plt.show()

for k, v in corrDf.items():
  createBox(k)
  print("")
```


latitude boxplot
60
55
50
45
40
35
30
25
latitude


longitude boxplot
20
0
−20
−40
−60
−80
−100
−120
longitude


labels boxplot
1.0
0.8
0.6
0.4
0.2
0.0
labels


age_first_funding_year boxplot
20
15

15. Summary and Discussion: Mention what additional steps are required to use this dataset in a binary classifier. Eg: any column to remove, any record to remove, any distribution to rebalance, any features to be joined together to generate new feature etc. (2pt)

TODO

```
'''
The data we would want to train on should be all in a numerical sense. The state that the startup originates from can be put as ar
to then use a means of correlation, so can all other categorical data, this is assuming we want to work with all the data given. W
to remove latitude, longitude, and zip code and get a geographical sense of each startup with city and state only, maybe even just
run the case of overfitting. We then fit a logistic regression model and calculate a confusion matrix to be able to calculate an a
'''
```

```
'\nThe data we would want to train on should be all in a numerical sense. The state that the startup originates from can be p
\nto then use a means of correlation, so can all other categorical data, this is assuming we want to work with all the data g
ble\nto remove latitude, longitude, and zip code and get a geographical sense of each startup with city and state only, maybe
ght potentially\nrun the case of overfitting. We then fit a logistic regression model and calculate a confusion matrix to be
rary score.\n'
```