# EE379K: Lab 2

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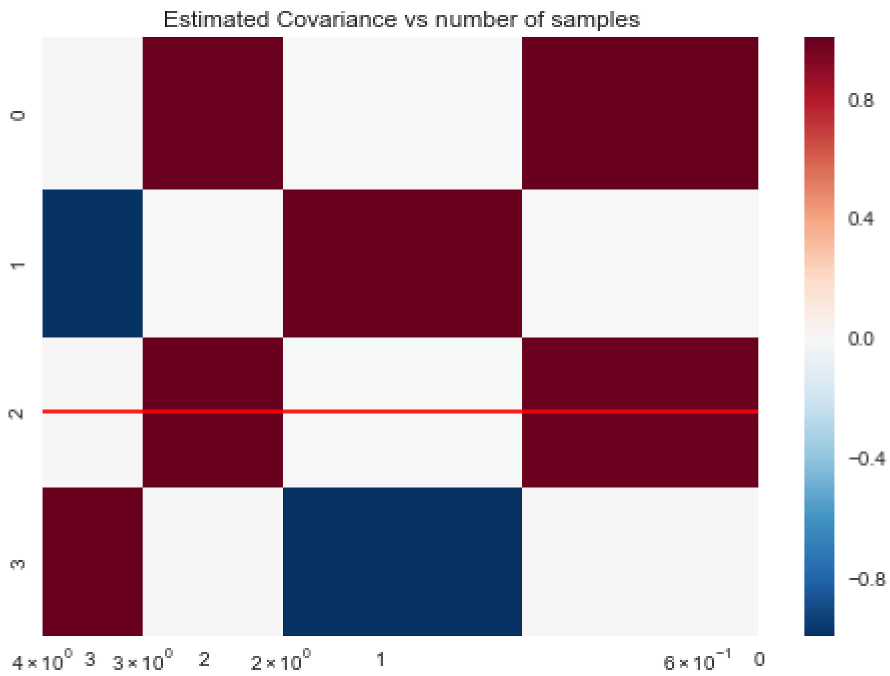
## Question 1

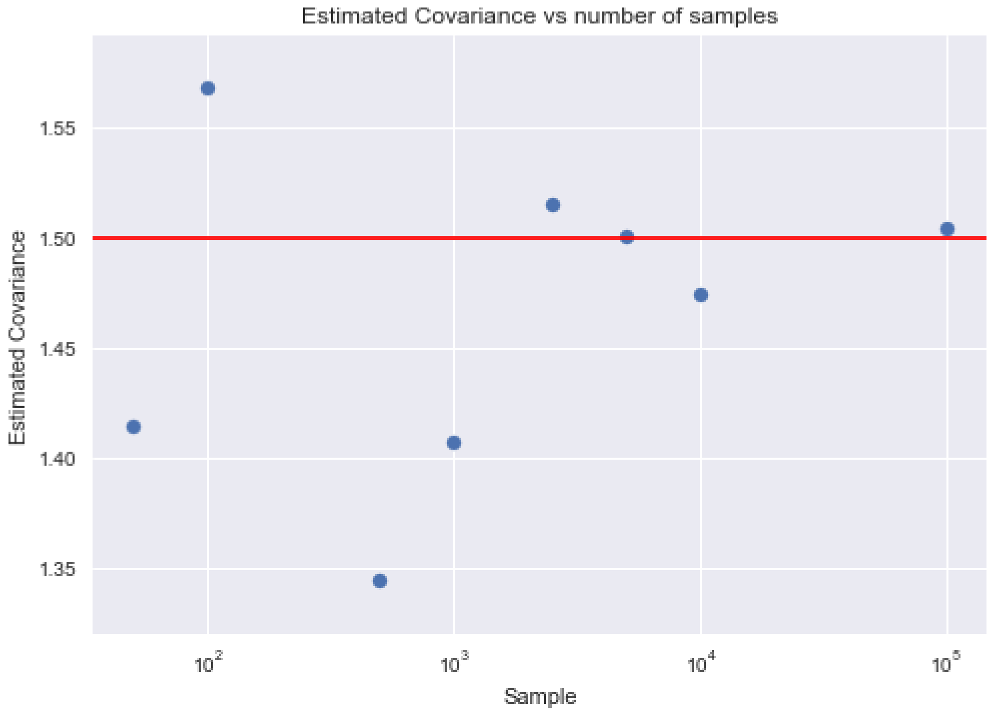
In [34]:
```
import pandas as pd
import seaborn as sns
import numpy as np
from pandas.plotting import scatter_matrix
import matplotlib.pyplot as plt

df = pd.read_csv('Lab2_Data/DF1')
df = df.drop(df.columns[[0]], axis=1)
corr = df.corr()
print("-------------1a--------------")
print("-----Correlation coefficients from pandas-----\n")
print(corr)

print("\n------ Heatmap from Seaborn -------\n")
sns.heatmap(corr)
plt.show()

print("\nFrom the data it can be seen that the following columns are correla
print("(0,2), (1,3)\n")

print("--------- 1b ----------")
print("Covariance matrix is the pairwise covariance between all the columns
print(df.cov())
print("The covariance matrix reflects the results seen in the plots. Specifi

print("\n--------- 1c ----------")
cov = [[3, 0, 0], [0, 1.5, 0.5], [0, 0.5, 6]]
print('Choosen covariance:\n{}\n'.format(np.matrix(cov)))
samples = [50, 100, 500, 1000, 2500, 5000, 10000, 100000]
res = []

for n in samples:
    sample = np.random.multivariate_normal([0,0,0], cov, n)
    estimated_cov = np.cov(sample, rowvar=False)
    res.append(estimated_cov[1][1])

fig = plt.figure()
ax = plt.gca()
ax.scatter(samples, res)
ax.set_xscale('log')
ax.set_title('Estimated Covariance vs number of samples')
plt.axhline(y=1.5, c='r')
plt.xlabel('Sample')
plt.ylabel('Estimated Covariance')
plt.show()
```

```
-------------1a--------------
-----Correlation coefficients from pandas-----

          0         1         2         3
0  1.000000 -0.003998  0.990066  0.004111
1 -0.003998  1.000000 -0.004085 -0.990235
2  0.990066 -0.004085  1.000000  0.004067
3  0.004111 -0.990235  0.004067  1.000000
```

```
------ Heatmap from Seaborn -------
```



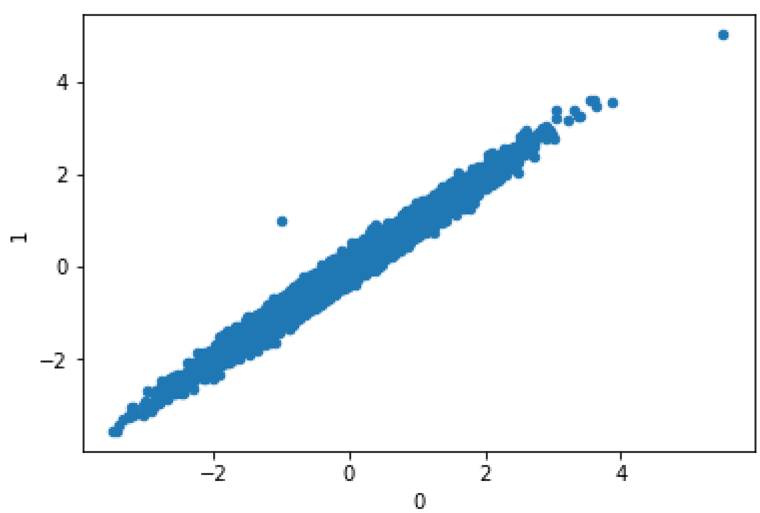

```
From the data it can be seen that the following columns are correlated:
(0,2), (1,3)

--------- 1b ----------
Covariance matrix is the pairwise covariance between all the columns in t
he dataset

          0         1         2         3
0  1.001558 -0.004012  0.991624  0.004125
1 -0.004012  1.005378 -0.004099 -0.995457
2  0.991624 -0.004099  1.001589  0.004081
3  0.004125 -0.995457  0.004081  1.005168
The covariance matrix reflects the results seen in the plots. Specificall
y we can see that columns 0 and 2 and 1 and 3 have the highest covarianc
e.


--------- 1c ----------
Choosen covariance:
[[ 3.   0.   0. ]
 [ 0.   1.5  0.5]
 [ 0.   0.5  6. ]]
```


Estimated Covariance vs number of samples
Estimated Covariance
1.55
1.50
1.45
1.40
1.35
$10^2$
$10^3$
$10^4$
$10^5$
Sample

# Question 2

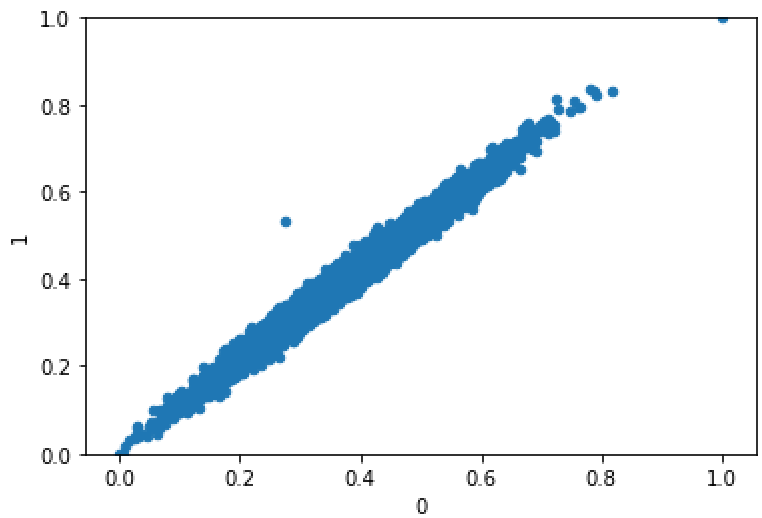
In [22]:
```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
%matplotlib inline

print('------ Original plot ------\n')
df2 = pd.read_csv('Lab2_Data/DF2')
df2 = df2.ix[:, 1:]
df2.plot.scatter(x='0', y='1')
plt.show()

scaler = MinMaxScaler()
df2_scale = scaler.fit_transform(df2)
df2_scaled = pd.DataFrame(data=df2_scale)

print('\nWe used the MinMaxScaler as it would shrink the x and y axises to a
print('We believe shrinking the x-axis especially will reveal the outlier wh
print('\n----- Transformed plot ------\n')
g = df2_scaled.plot.scatter(x=0, y=1)
g.set_ylim([0, 1])
plt.show()
```

```
------ Original plot ------


/Users/irfanhasan/anaconda/lib/python3.6/site-packages/ipykernel_launche
r.py:7: DeprecationWarning:
.ix is deprecated. Please use
.loc for label based indexing or
.iloc for positional indexing

See the documentation here:
http://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate_ix (h
ttp://pandas.pydata.org/pandas-docs/stable/indexing.html#deprecate_ix)
  import sys
```




```
We used the MinMaxScaler as it would shrink the x and y axises to a range
from 0 to 1.
We believe shrinking the x-axis especially will reveal the outlier which
is more prominent on the y-axis.
```

```
----- Transformed plot ------
```



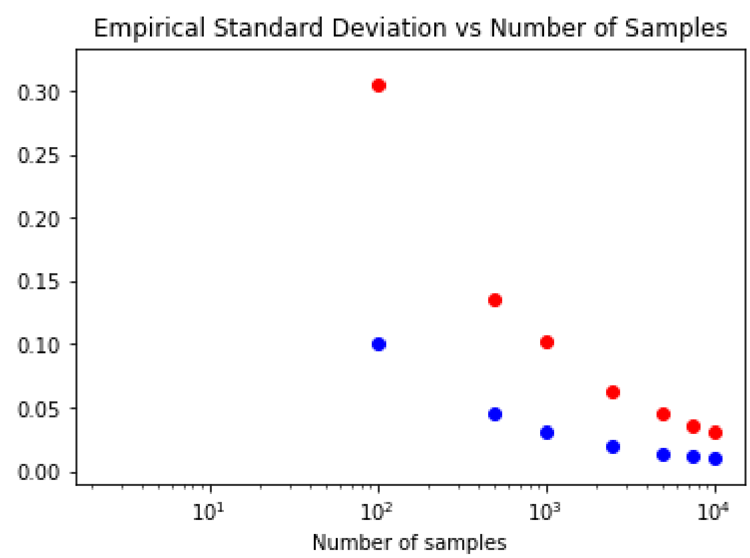

# Question 3

In [1]:
```python
import numpy as np

def calc_std_dev(n):
    deltas = []
    for i in range(n):
        X = np.random.randn(n)
        E = np.random.randn(n)
        y = -3 + np.dot(X, 0) + E
        beta_h = np.dot(X,y) / np.dot(X,X)
        deltas.append(beta_h)
    return np.std(deltas)

calc_std_dev(150)
```

Out[1]:
```
0.24904452509546193
```

We can see that B_hat = -0.15 is not as significant since the empirical standard deviation of the error is much larger than 0.15, so the error accounts for all of it.

In [5]:
```
import math
import numpy as np
import matplotlib.pyplot as plt

def calc_std_dev(n):
    deltas = []
    for i in range(n):
        X = np.random.randn(n)
        E = np.random.randn(n)
        y = -3 + np.dot(X, 0) + E
        beta_h = np.dot(X,y) / np.dot(X,X)
        deltas.append(beta_h)
    return np.std(deltas)

samples =  [100, 500, 1000, 2500, 5000, 7500, 10000]
std_devs = []
one_over = []
for n in samples:
    std_dev = calc_std_dev(n)
    std_devs.append(std_dev)
    one_over.append(1/math.sqrt(n))

fig = plt.figure()
ax = plt.gca()
ax.scatter(samples, std_devs, c='r')
ax.scatter(samples, one_over, c='b')
ax.set_xscale('log')
ax.set_title('Empirical Standard Deviation vs Number of Samples')
plt.xlabel('Number of samples')
plt.show()
print('The fit is good.')
```




The fit is good.

## Question 4

In [33]:
```
import sys
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

class Question4:
    def get_k_names(self, k, year):
        filename = "Names/yob" + str(year) + ".txt"
        data = pd.read_csv(filename, sep=",", header=None)
        print data.head(k)

    def name_frequency(self, name):
        m = 0
        f = 0
        for year in range(1880, 2016):
            filename = "Names/yob" + str(year) + ".txt"
            data = pd.read_csv(filename, sep=",", header=None)
            data = data[data[0] == name]
            for row in data.itertuples():
                if row[2] == 'M':
                    m += row[3]
                else:
                    f += row[3]

        print "For name " + name
        print "Male: "  + str(m)
        print "Female: " + str(f)

    def relative_frequency(self, name, year):
        filename = "Names/yob" + str(year) + ".txt"
        data = pd.read_csv(filename, sep=",", header=None)
        total = data[2].sum()
        data = data[data[0] == name]

        print "For year " + str(year)
        for row in data.itertuples():
            print "{0} {1} {2:.9f}".format(row[1], row[2], float(row[3])/tot

    def change_in_pop(self):
        result = set()
        names = dict(dict())  # {name : []}

        for year in range(1880, 2016):
            filename = "Names/yob" + str(year) + ".txt"
            data = pd.read_csv(filename, sep=",", header=None)

            for row in data.itertuples():
                if row[1] not in names:
                    names[row[1]] = {}
                if year not in names[row[1]]:
                    names[row[1]][year] = 0

                if row[2] == 'M':
                    names[row[1]][year] += row[3]
                else:
                    names[row[1]][year] -= row[3]
```

```
        for name, entries in names.iteritems():
            pos = neg = False
            for y in sorted(entries.iterkeys()):
                if entries[y] > 0 and neg:
                    result.add(name)
                    break
                elif entries[y] < 0 and pos:
                    result.add(name)
                    break
                elif entries[y] > 0:
                    pos = True
                elif entries[y]:
                    neg = True

        for n in result:
            print n

q4 = Question4()
```

Write a program that on input k and XXXX, returns the top k names from year XXXX

In [5]:
```
q4.get_k_names(5, 1996)
```

|   | 0 | 1 | 2 |
|---|---|---|---|
| 0 | Emily | F | 25150 |
| 1 | Jessica | F | 24192 |
| 2 | Ashley | F | 23676 |
| 3 | Sarah | F | 21029 |
| 4 | Samantha | F | 20545 |

Write a program that on input Name returns the frequency for men and women of the name Name

In [9]:
```
q4.name_frequency('Bailey')
```

```
For name Bailey
Male: 20457
Female: 91648
```

Modify the above program to return relative frequency.

In [15]:
```
q4.relative_frequency('Bailey', 1996)
```

```
For year 1996
Bailey F 0.001149507
Bailey M 0.000425134
```

Find all names that used to be more popular for one gender, but then became more popular for another gender.

In [ ]:
```
q4.change_in_pop() # names are not printed due to there are too many of ther
```

# Question 5

Tutorial by Dataquest

In [2]:
```
import pandas as pd

tweets = pd.read_csv("tweets.csv")
tweets.head()
```

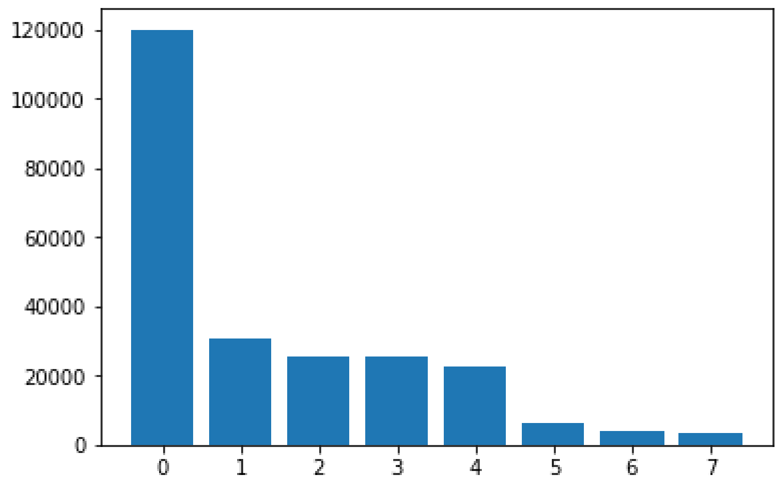
Out[2]:

| | id | id_str | user_location | user_bg_color | retweet_count | user_name | polarity | |
|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 729828033092149248 | Wheeling WV | 022330 | 0 | Jaybo26003 | 0.00 | 10 |
| **1** | 2 | 729828033092161537 | NaN | C0DEED | 0 | britttttany_ns | 0.15 | 10 |
| **2** | 3 | 729828033566224384 | NaN | C0DEED | 0 | JeffriesLori | 0.00 | 10 |
| **3** | 4 | 729828033893302272 | global | C0DEED | 0 | WhorunsGOVs | 0.00 | 10 |
| **4** | 5 | 729828034178482177 | California, USA | 131516 | 0 | BJCG0830 | 0.00 | 10 |

In [3]:
```
def get_candidate(row):
    candidates = []
    text = row["text"].lower()
    if "clinton" in text or "hillary" in text:
        candidates.append("clinton")
    if "trump" in text or "donald" in text:
        candidates.append("trump")
    if "sanders" in text or "bernie" in text:
        candidates.append("sanders")
    return ",".join(candidates)

tweets["candidate"] = tweets.apply(get_candidate,axis=1)
```

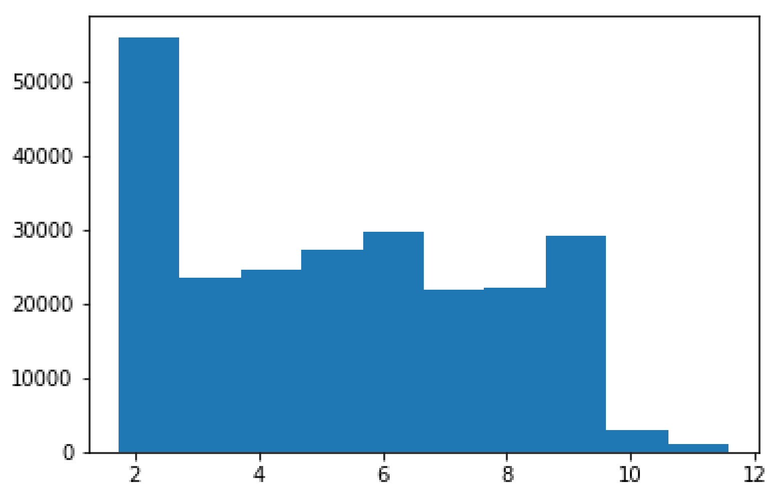
In [5]:
```
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline
```

In [6]:
```
counts = tweets["candidate"].value_counts()
plt.bar(range(len(counts)), counts)
plt.show()

print(counts)
```

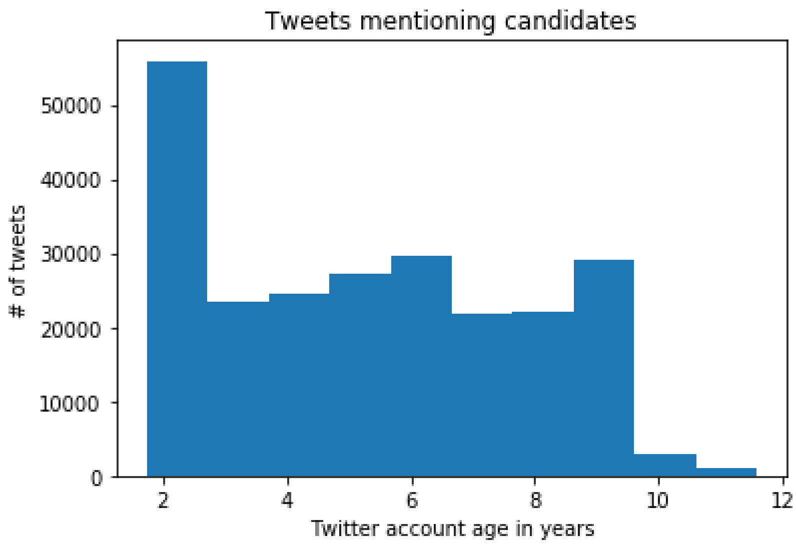



```
trump                      119998
clinton,trump               30521
                            25429
sanders                     25351
clinton                     22746
clinton,sanders              6044
clinton,trump,sanders        4219
trump,sanders                3172
Name: candidate, dtype: int64
```

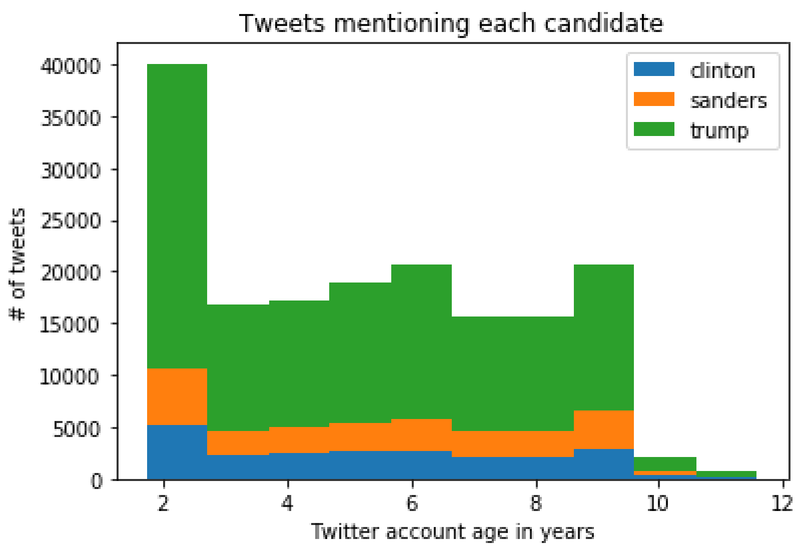
In [7]:
```
from datetime import datetime

tweets["created"] = pd.to_datetime(tweets["created"])
tweets["user_created"] = pd.to_datetime(tweets["user_created"])

tweets["user_age"] = tweets["user_created"].apply(lambda x: (datetime.now()
plt.hist(tweets["user_age"])
plt.show()
```



In [8]:
```
plt.hist(tweets["user_age"])
plt.title("Tweets mentioning candidates")
plt.xlabel("Twitter account age in years")
plt.ylabel("# of tweets")
plt.show()
```

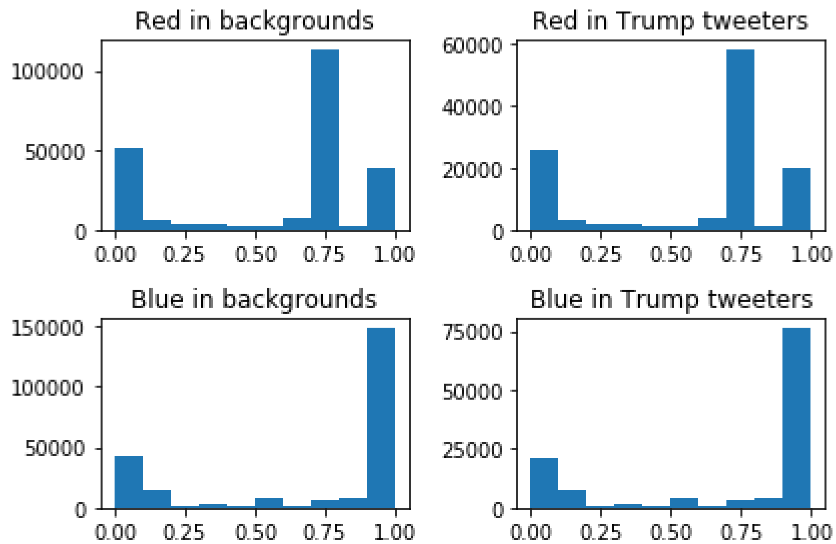


In [14]:
```
cl_tweets = tweets["user_age"][tweets["candidate"] == "clinton"]
sa_tweets = tweets["user_age"][tweets["candidate"] == "sanders"]
tr_tweets = tweets["user_age"][tweets["candidate"] == "trump"]
plt.hist([
        cl_tweets,
        sa_tweets,
        tr_tweets
    ],
    stacked=True,
    label=["clinton", "sanders", "trump"]
)
plt.legend()
plt.title("Tweets mentioning each candidate")
plt.xlabel("Twitter account age in years")
plt.ylabel("# of tweets")
plt.show()
```




In [30]:
```
import matplotlib.colors as colors

tweets["red"] = tweets["user_bg_color"].apply(lambda x: colors.hex2color('#
tweets["blue"] = tweets["user_bg_color"].apply(lambda x: colors.hex2color('#
```

In [31]:
```
fig, axes = plt.subplots(nrows=2, ncols=2)
ax0, ax1, ax2, ax3 = axes.flat

ax0.hist(tweets["red"])
ax0.set_title('Red in backgrounds')

ax1.hist(tweets["red"][tweets["candidate"] == "trump"].values)
ax1.set_title('Red in Trump tweeters')

ax2.hist(tweets["blue"])
ax2.set_title('Blue in backgrounds')

ax3.hist(tweets["blue"][tweets["candidate"] == "trump"].values)
ax3.set_title('Blue in Trump tweeters')

plt.tight_layout()
plt.show()
```

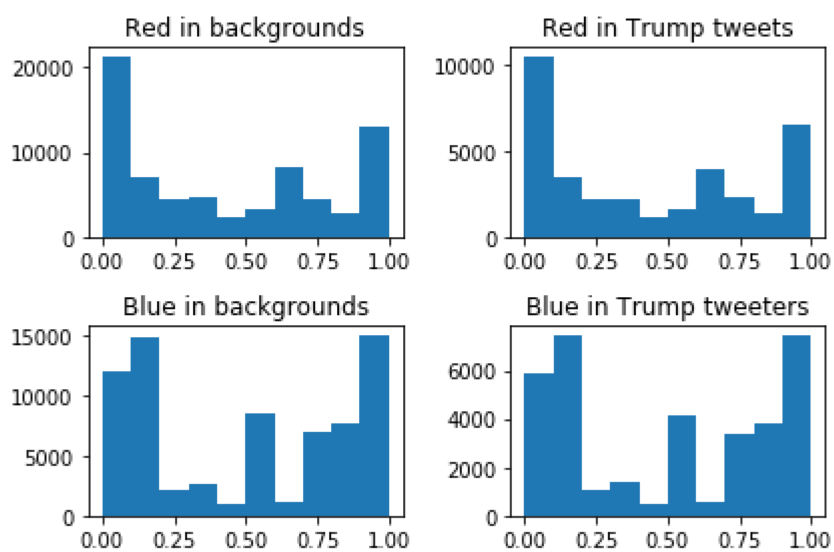


In [32]:
```
tweets["user_bg_color"].value_counts()
```

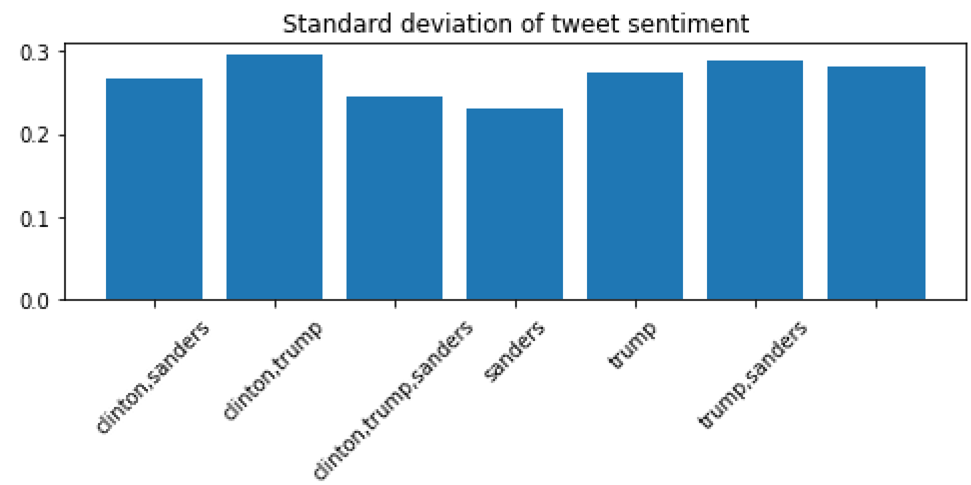
Out[32]:
```
C0DEED    108977
000000     31119
F5F8FA     25597
131516      7731
1A1B1F      5059
022330      4300
0099B9      3958
642D8B      3767
FFFFFF      3101
9AE4E8      2651
ACDED6      2383
352726      2338
C6E2EE      1978
709397      1518
EBEBEB      1475
FF6699      1370
BADFCD      1336
FFF04D      1300
EDECE9      1225
B2DFDA      1218
DBE9ED      1113
ABB8C2      1101
8B542B      1073
3B94D9       623
89C9FA       414
DD2E44       351
94D487       318
4A913C       300
9266CC       287
F5ABB5       267
           ...
5470A8         1
00AEFF         1
C49C4B         1
778877         1
09380E         1
09536E         1
3D3C3D         1
48394D         1
3D3C3A         1
140C0E         1
AE1BCF         1
EBE39B         1
056785         1
FCF3EA         1
2E332F         1
FCF7F8         1
FCF7F7         1
0F6B2C         1
1D1F1B         1
180018         1
2686B3         1
8F0E8F         1
CCD4E8         1
FFEF42         1
```

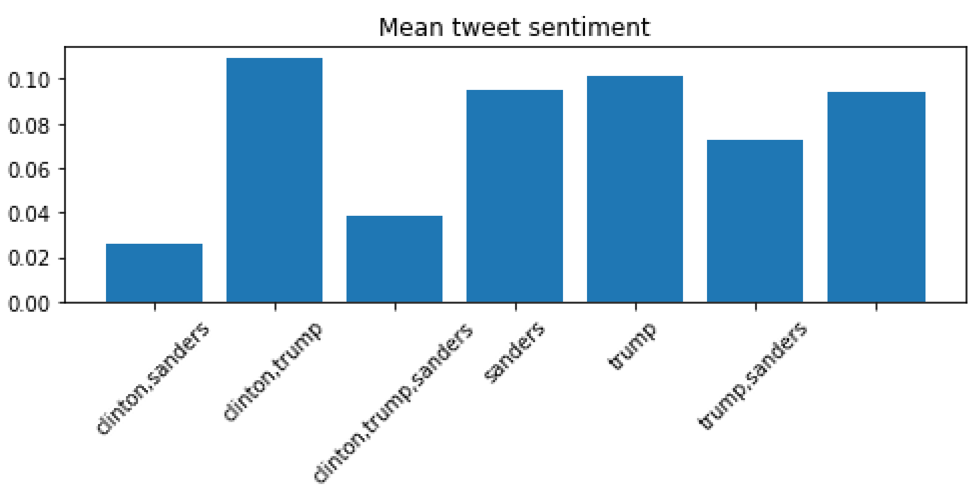
```
08F5F5         1
4E5254         1
42373E         1
272D29         1
F00CC2         1
A3004D         1
Name: user_bg_color, Length: 6970, dtype: int64
```

In [33]:
```python
tc = tweets[~tweets["user_bg_color"].isin(["C0DEED", "000000", "F5F8FA"])]

def create_plot(data):
    fig, axes = plt.subplots(nrows=2, ncols=2)
    ax0, ax1, ax2, ax3 = axes.flat

    ax0.hist(data["red"])
    ax0.set_title('Red in backgrounds')

    ax1.hist(data["red"][data["candidate"] == "trump"].values)
    ax1.set_title('Red in Trump tweets')

    ax2.hist(data["blue"])
    ax2.set_title('Blue in backgrounds')

    ax3.hist(data["blue"][data["candidate"] == "trump"].values)
    ax3.set_title('Blue in Trump tweeters')

    plt.tight_layout()
    plt.show()

create_plot(tc)
```



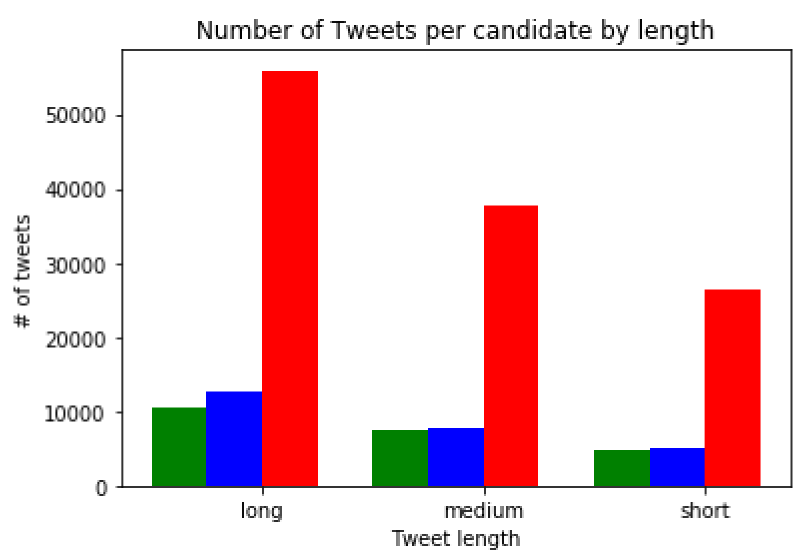
In [34]:
```
gr = tweets.groupby("candidate").agg([np.mean, np.std])

fig, axes = plt.subplots(nrows=2, ncols=1, figsize=(7, 7))
ax0, ax1 = axes.flat

std = gr["polarity"]["std"].iloc[1:]
mean = gr["polarity"]["mean"].iloc[1:]
ax0.bar(range(len(std)), std)
ax0.set_xticklabels(std.index, rotation=45)
ax0.set_title('Standard deviation of tweet sentiment')

ax1.bar(range(len(mean)), mean)
ax1.set_xticklabels(mean.index, rotation=45)
ax1.set_title('Mean tweet sentiment')

plt.tight_layout()
plt.show()
```



In [38]:
```
def tweet_lengths(text):
    if len(text) < 100:
        return "short"
    elif 100 <= len(text) <= 135:
        return "medium"
    else:
        return "long"

tweets["tweet_length"] = tweets["text"].apply(tweet_lengths)

tl = {}
for candidate in ["clinton", "sanders", "trump"]:
    tl[candidate] = tweets["tweet_length"][tweets["candidate"] == candidate]
```

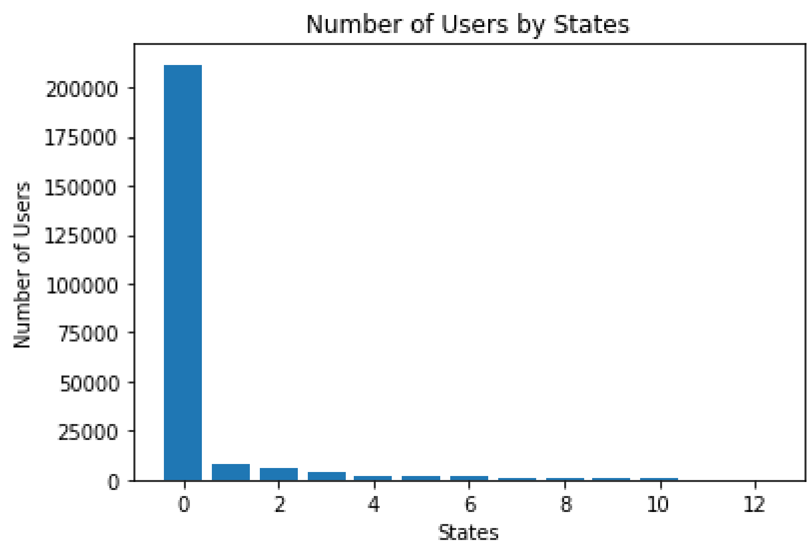
In [39]:
```
fig, ax = plt.subplots()
width = .5
x = np.array(range(0, 6, 2))
ax.bar(x, tl["clinton"], width, color='g')
ax.bar(x + width, tl["sanders"], width, color='b')
ax.bar(x + (width * 2), tl["trump"], width, color='r')

ax.set_ylabel('# of tweets')
ax.set_title('Number of Tweets per candidate by length')
ax.set_xticks(x + (width * 1.5))
ax.set_xticklabels(('long', 'medium', 'short'))
ax.set_xlabel('Tweet length')
plt.show()
```




Aggregate the results by state.

In [14]:
```
'''
Adding to the filters for each state will increaes the number of captures
'''

filters = [
    ['al', 'alabama'],
    ['ak', 'alska'],
    ['az', 'arizona'],
    ['ar', 'arkansas'],
    ['ca', 'cali', 'california'],
    ['co', 'colorado'],
    ['ny'],
    ['pa', 'pittsburgh'],
    ['tx', 'texas', 'austin', 'houstin'],
    ['va', 'virginia'],
    ['wv'],
    ['wy']]

def get_state(row):
    result = []
    location = str(row).lower().split(' ')

    found = False
    for word in location:
        found = False
        for f in filters:
            for addr in f:
                if addr == word:
                    found = True
                    result.append(f[0])
                    break
            if found:
                break
        if found:
            break

    if found == False:
        result.append('N/A')

    return ",".join(result)

tweets["state"] = tweets['user_location'].apply(get_state)
```

In [15]:
```
counts = tweets['state'].value_counts()
plt.bar(range(len(counts)), counts)
plt.title("Number of Users by States")
plt.xlabel("States")
plt.ylabel("Number of Users")
plt.show()

print (counts)
```




```
N/A     211669
ca        8394
```

## Written Questions

1.

a. $Z_{avg} = \sum_{i=1}^{n} \frac{z_i}{n}$

when $n = 10{,}000$

$\mu_{avg} = 0 \quad \sigma_{avg} = \frac{1}{\sqrt{10{,}000}} = 0.01$

Thus $Z_{avg} \sim N(0, 0.01^2)$

Using normal table

$P(Z_{avg} > 0.1) \approx 0$

$P(Z_{avg} > 0.01) = 0.1587$

$P(Z_{avg} > 0.001) \approx 0.4602$

b. $Z \sim N(\mu, \sigma^2)$

$\mu_{avg} = \mu$

$\sigma_{avg} = \frac{\sigma}{\sqrt{n}}$

$Z_{avg} \sim N(\mu, \frac{\sigma^2}{n})$

$Z_{avg} - \mu$ shifts $Z_{avg}$'s mean to 0.

i. Thus $z = \frac{n^{-\frac{1}{3}}}{\sigma}$

$P(Z_{avg} - \mu > n^{-1/3}) = \int_{\frac{n^{-1/3}}{\sigma}}^{\infty} \frac{1}{\sqrt{2\sigma^2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

ii. $P(Z_{avg} - \mu > n^{-1/2}) = \int_{\frac{n^{-1/2}}{\sigma}}^{\infty} \frac{1}{\sqrt{2\sigma^2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

iii. $P(Z_{avg} - \mu > n^{-2/3}) = \int_{\frac{n^{-2/3}}{\sigma}}^{\infty} \frac{1}{\sqrt{2\sigma^2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

EE379K HW #2

Question #2

$$x_i^2\beta^2 - 2x_iy_i\beta + y_i^2$$

a) $\frac{1}{n}\sum_{i=1}^{n}(x_i\beta - y_i)^2$

$$\frac{1}{n}\left[(x_1\beta - y_1)^2 + (x_2\beta - y_2)^2 + \cdots (x_n\beta - y_n)^2\right]$$

$$\frac{1}{n}\left[\beta^2(x_1^2 + x_2^2 + \cdots x_n^2) - 2\beta(x_1y_1 + x_2y_2 + \cdots x_ny_n) + (y_1^2 + \cdots y_n^2)\right]$$

$$\frac{1}{n}\left[\beta^2\sum_{i=1}^{n}x_i^2 - 2\beta\sum_{i=1}^{n}x_iy_i + \sum_{i=1}^{n}y_i^2\right]$$

$$A = \frac{1}{n}\sum_{i=1}^{n}x_i^2 \quad B = -\frac{2}{n}\sum_{i=1}^{n}x_iy_i \quad C = \sum_{i=1}^{n}y_i^2$$

$A \geq 0$ because the value is squared and any number squared is non-negative.

b) $\frac{d}{d\beta}\min_{\beta} = \frac{2}{n}\beta\sum_{i=1}^{n}x_i^2 - \frac{2}{n}\sum_{i=1}^{n}x_iy_i$

$$\beta\sum_{i=1}^{n}x_i^2 = \sum_{i=1}^{n}x_iy_i$$

$$\hat{\beta} = \frac{\sum_{i=1}^{n}x_iy_i}{\sum_{i=1}^{n}x_i^2}$$

c) $\hat{\beta} = \frac{\sum x_i(x_i\beta + e_i)}{\sum x_i^2}$ $\quad \hat{\beta} = \beta + \frac{\sum x_ie_i}{\sum x_i^2}$

$$\hat{\beta} = \frac{\sum x_i^2\beta + x_ie_i}{\sum x_i^2} \qquad Ze = \frac{\sum x_ie_i}{\sum x_i^2}$$

$$\hat{\beta} = \frac{\sum x_i^2\beta}{\sum x_i^2} + \frac{\sum x_ie_i}{\sum x_i^2} \qquad Z = \frac{\vec{x}}{\|\vec{x}\|^2}$$