Javier Palomares Homework 1 b

1. Correlations

- When given a data matrix, an easy way to tell if any two columns are correlated is to look at a scatter plot of each column against each other column. For a warm up, do this: Look at the data in DF1 in HW1b Data.zip.

In [21]:
```
df1FilePath="./DF1"
df2FilePath="./DF2"

import pandas as pd
df1 = pd.read_csv(df1FilePath,index_col=0)
df2 = pd.read_csv(df2FilePath,index_col=0)
df1.info()
df1.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 0 to 9999
Data columns (total 4 columns):
0    10000 non-null float64
1    10000 non-null float64
2    10000 non-null float64
3    10000 non-null float64
dtypes: float64(4)
memory usage: 390.6 KB
```

Out[21]:

	0	1	2	3
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	0.007704	0.009313	0.007586	-0.008455
std	1.000779	1.002686	1.000794	1.002581
min	-3.471566	-4.056024	-3.524182	-3.930215
25%	-0.663449	-0.663886	-0.666489	-0.697856
50%	0.017736	0.009027	0.012372	-0.007986
75%	0.667565	0.695943	0.672933	0.668582
max	3.854101	3.908736	3.608846	3.985592

Which columns are (pairwise) correlated? Figure out how to do this with Pandas, and also how to do this with Seaborn.

In [37]:
```
df1.corr()
```

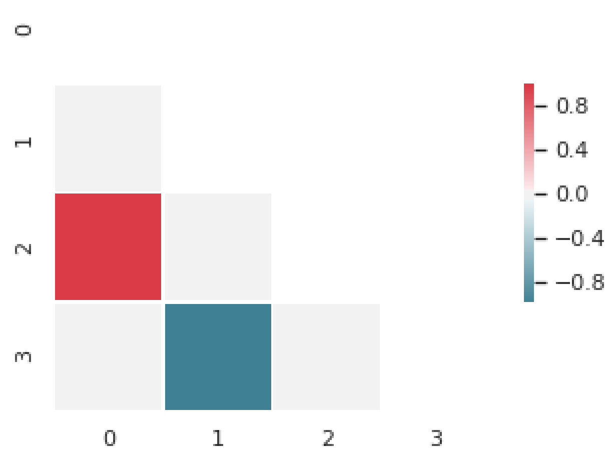
Out[37]:

	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

Using pandas, we see that columns at position 0 and position 2 are correlated, and columns at position 1 and 3 are negatively correlated

In [38]:
```
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
sns.set(style='white')
corr1 = df1.corr()

# Generate a mask for the upper triangle
mask = np.zeros_like(corr1, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
# Set up the matplotlib figure
f, ax = plt.subplots();

# Generate a custom diverging colorma# Generate a custom diverging co
lormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)
# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr1, mask=mask, cmap=cmap, vmax=1.0, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f64166a2a58>
```



Using seaborn, I can see the correlation between columns 0 and 2, and the negative correlation between columns 1 and 3

- Compute the covariance matrix of the data. Write the explicit expression for what this is, and then use any command you like (e.g., np.cov) to compute the 4 × 4 matrix. Explain why the numbers that you get fit with the plots you got.

Let DF1 have size $n \times n$. Let x_i be the i-th column of DF1 and $x_i[j]$ be the j-th component of x_i. Note that columns of DF1 have n components. Let μ_i be the mean of x_i and let σ^2 be the variance of x_i. Then the i, j entry of the covariance matrix is given by:

$$cov_{ij} = \frac{1}{n} \sum_{k=1}^{n} (x_i[k] - \mu_i)(x_j[k] - \mu_j)$$

In [39]:
```
df1.cov()
```

Out[39]:

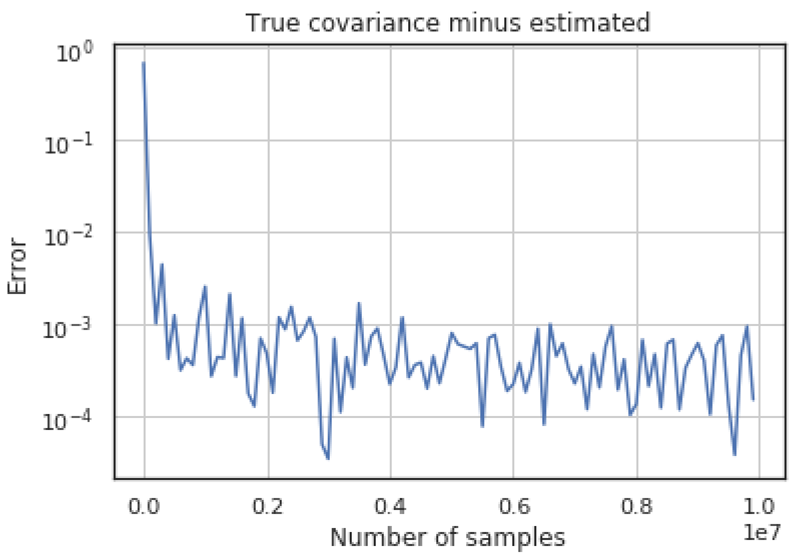
	0	1	2	3
0	1.001558	-0.004012	0.991624	0.004125
1	-0.004012	1.005378	-0.004099	-0.995457
2	0.991624	-0.004099	1.001589	0.004081
3	0.004125	-0.995457	0.004081	1.005168

The values in the covariance matrix are consistent with the values in the correlation as they differ by a normalization factor.

- The above problem in reverse. Generate a zero-mean multivariate Gaussian random variable in 3 dimensions, Z = (X1, X2, X3) so that (X1, X2) and (X1, X3) are uncorrelated, but (X2, X3) are correlated. Specifically: choose a covariance matrix that has the above correlations structure, and write this down. Then find a way to generate samples from this Gaussian. Choose one of the non-zero covariance terms (Cij , if C denotes your covariance matrix) and plot it vs the estimated covariance term, as the number of samples you use scales. The goal is to get a visual representation of how the empirical covariance converges to the true (or family) covariance.

In [79]:
```
def estimateGaussianCov(mean,cov,numSamples,i,j):
    x = np.random.multivariate_normal(mean, cov,numSamples).T
    estCov = np.cov(x)
    c_ij = estCov[i][j]
    error = c_ij - cov[i][j]
    return error

mean = [0,0,0]
cov = [[1,0,0],[0,1,.99],[0,.99,1]]
#c_1,2 is non zero
i = 1
j = 2
numSamples = list(range(10,10000000,100000))
err = np.zeros(len(numSamples))
for k in range(len(numSamples)):
    n = numSamples[k]
    err[k] = estimateGaussianCov(mean,cov,n,i,j)
```

In [85]:
```
err = abs(err)
plt.semilogy(numSamples,err)
plt.title("True covariance minus estimated")
plt.grid(True)
plt.xlabel("Number of samples")
plt.ylabel("Absolute value of error")
plt.show()
```



2. Outliers

Consider the two-dimensional data in DF2 in HW1b Data.zip. Look at a scatter plot of the data. It contains two points that look like potential outliers. Which one is “more” outlying? Propose a transformation of the data that makes it clear that the point at (−1, 1) is more outlying than the point at (5.5, 5), even though the latter point is“farther away” from the nearest points. Plot the data again after performing this transformation. Provide discussion as appropriate to justify your choice of transformation. Hint: if y comes from a standard Gaussian in two dimensions (i.e., with covariance equal to the two by two identity matrix), and

$$Q = \begin{pmatrix} 2 & \frac{1}{2} \\ \frac{1}{2} & 2 \end{pmatrix}$$

what is the covariance matrix of the random variable $\mathbf{z} = Q\mathbf{y}$?If you are given z, how would you create a random Gaussian vector with covariance equal to the identity, using z?

In [82]:
```
df2FilePath="./DF2"

import pandas as pd
df2 = pd.read_csv(df2FilePath,index_col=0)
df2.info()
df2.describe()
```

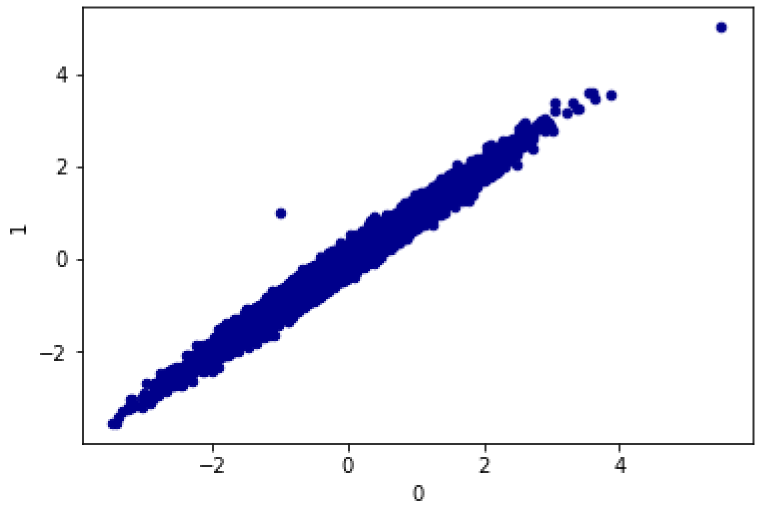
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10000 entries, 0 to 9999
Data columns (total 2 columns):
0    10000 non-null float64
1    10000 non-null float64
dtypes: float64(2)
memory usage: 234.4 KB
```

Out[82]:

	0	1
count	10000.000000	10000.000000
mean	0.008139	0.008169
std	1.002321	1.002078
min	-3.471566	-3.524182
25%	-0.663686	-0.666489
50%	0.017736	0.012527
75%	0.667909	0.673805
max	5.500000	5.000000

In [83]:
```
df2.plot.scatter(x=0,y=1,c='DarkBlue')
```

Out[83]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fd108216da0>
```



if $\mathbf{z} = Q\mathbf{y}$, then
$Covar(\mathbf{z}) = Q^T Covar(\mathbf{y}) Q$
and since $Covar(\mathbf{y}) = 1$ (identity matrix) then $Covar(\mathbf{z}) = Q^T Q$.
So by finding the covariance of $\mathbf{z}$, we have $Q^T Q$.
Q can then be found using Cholesky decomposition. Finally, we can get $\mathbf{y}$ by
$\mathbf{y} = Q^{-1}\mathbf{z}$

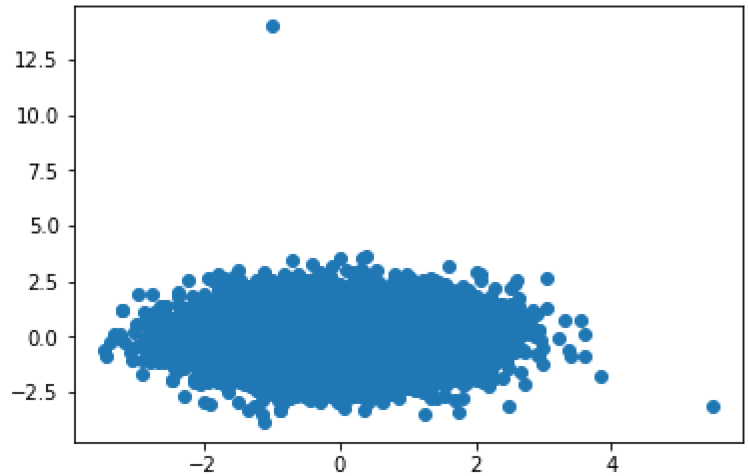
In [93]:
```
covariance = df2.cov()
Q = np.linalg.cholesky(covariance)
Q_inv = np.linalg.inv(Q)
print(Q_inv)
```

```
[[ 0.99768418  0.        ]
 [-6.96054618  7.03339266]]
```

In [113]:
```
outlier1 = np.array([-1,1])
outlier2 = np.array([5.5,5])
print(np.dot(Q_inv,outlier1.T).T)
print(np.dot(Q_inv,outlier2.T).T)
```

```
[-0.99768418 13.99393883]
[ 5.48726302 -3.1160407 ]
```

In [114]:
```
# the transformed data
z = np.dot(Q_inv,df2.T)
z = z.T
plt.scatter(z[:,0],z[:,1])
plt.show()
```



We can see that the point at (-1,1) has been mapped to a point further from the origin than (5.5,5) was mapped to.

3. Even More Standard Error

(This is to be completed only after you've completed the last written exercise below). In one of the written exercises below, you derive an expression 1for what is called the Standard Error: where β denotes the "truth," $\hat{\beta}$ denotes the value we compute using least squares linear regression, and Z and e are as in the exercise below, you find: $\hat{\beta} - \beta = Ze$. If we know the distribution of the noise (the distribution generating the noise vectors, e i), then we know the distribution for the error, ($\hat{\beta} - \beta$). This allows us to answer the question given in class: if we solve a regression and obtain value $\hat{\beta}$, how can we tell if it is statistically significant? The answer is: we compare the size of β̂ to the spread introduced by the noise (i.e., the standard error), and we ask: what is the likelihood that the true $\beta = 0$, and what we observed was purely due to the noise. If the noise is Gaussian (normal), i.e., $e_i \sim N(0, \sigma^2)$, and if the values of the x_i are normalized, then we expect error of the size $\frac{\sigma}{\sqrt{n}}$, as this is roughly the standard deviation of the expression for the error that you derive above. This means: if you have twice the data points, you should expect the error to be reduced by about 1.4 (the formula says that the standard deviation of the error would decrease by a factor of $1/\sqrt{2}$).

Compute this empirically, as follows: We will generate data for a regression problem, solve it, and see what the error is: Generate data as I did in the example from class: $x_i \sim N(0,1), ei \sim N(0,1)$. Generate y by $y_i = \beta_0 + x_i\beta + e_i$, where $\beta_0 = -3$ and $\beta = 0$. Note that since $\beta = 0$, this means that y and x are unrelated! The question we are exploring here is as follows: when we solve a regression problem, we are not going to find $\hat{\beta} = 0$ - we will find that $\hat{\beta}$ takes some other values, hopefully close to zero. How do we know if the value of $\hat{\beta}$ we get is statistically meaningful?

In [118]:
```
beta0 = -3
beta = 0
meanX = 0
varX = 1
meanE = 0
varE = 1
```

- By creating fresh data and each time computing $\hat{\beta}$ and recording $\hat{\beta} - \beta$, compute the empirical standard deviation of the error for n = 150 (the number we used in class). In class, in the exercise where I tried to find a linear regression of y vs. noise, we found $\hat{\beta} = -0.15$. Given your empirical computation of the standard deviation of the error, how significant is the value −0.15?

In [124]:
```
import numpy as np
import math
def computeBetaHat(meanX,varX,meanE,varE,n):
    # get x and e from an normal distribution
    x = np.random.normal(meanX,math.sqrt(varX),n)
    e = np.random.normal(meanE,math.sqrt(varE),n)
    # compute y from x and e
    y = beta0 + beta*x + e
    # expression computed from last problem of homework
    betaHat = np.dot(x,y) / np.dot(x,x)
    return betaHat

n = 150
betaHat = computeBetaHat(meanX,varX,meanE,varE,n)
print("The computed value of beta (betaHat) is {} for n={}".format(be
taHat,n))
```

```
The computed value of beta (betaHat) is -0.2548654898775995 for n=150
```

In [125]:
```
def meanStdDevBeta(numTrials,meanX,varX,meanE,varE,n):
    betaSamples = np.zeros(numTrials)
    for i in range(numTrials):
        betaSamples[i] = computeBetaHat(meanX,varX,meanE,varE,n)
    meanBeta = np.mean(betaSamples)
    stdBeta = np.std(betaSamples)
    return meanBeta,stdBeta
```

In [126]:
```
# compute the standard deviation for the computed value of beta^ when
n = 150
numTrials = 1000;
meanBeta,stdBeta = meanStdDevBeta(numTrials,meanX,varX,meanE,varE,n)
print("After {} trials, betaHat has a mean of {} with a standard devi
ation of {}".format(numTrials,meanBeta,stdBeta))
```

```
After 1000 trials, betaHat has a mean of -0.0009606705594536155 with
a standard deviation of 0.2516646103140726
```

Finding a value for $\hat{\beta} = -0.15$ is about half a standard deviation away from the mean (using the empirical values)

- Now repeat the above experiment for different values of n. Plot these values, and on the same plot, plot $1/\sqrt{n}$. How is the fit?

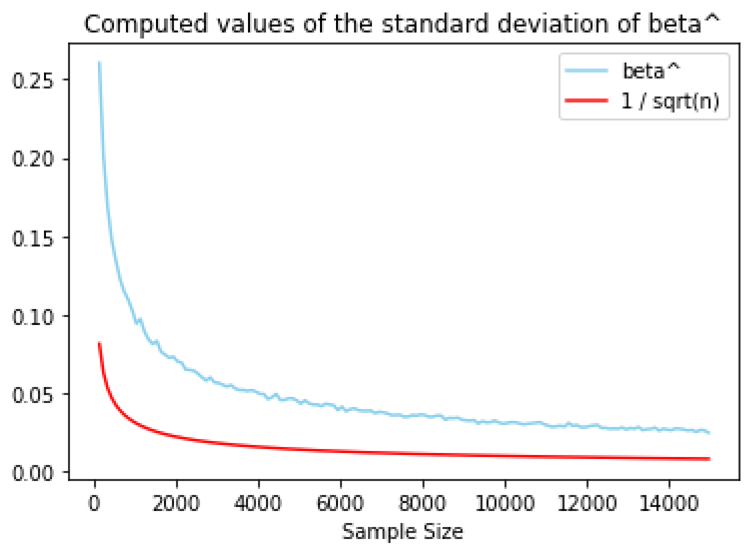
In [129]:

```
sampleSizes = np.arange(150, 15000,100)
betaHatMean = np.zeros(len(sampleSizes))
betaHatStd = np.zeros(len(sampleSizes))
# compute the mean and stdDev for betaHat for different values of n
for i in range(len(sampleSizes)):
    betaHatMean[i],betaHatStd[i] = meanStdDevBeta(numTrials,meanX,var
X,meanE,varE,sampleSizes[i])
```

In [130]:

```
import matplotlib.pyplot as plt
plt.plot(sampleSizes,betaHatStd,color='skyblue',label = "beta^")
plt.plot(sampleSizes,1.0/np.sqrt(sampleSizes),color='red',label = '1
 / sqrt(n)')
plt.title("Computed values of the standard deviation of beta^")
plt.xlabel("Sample Size")
plt.legend()
```

Out[130]: <matplotlib.legend.Legend at 0x7fd106103208>

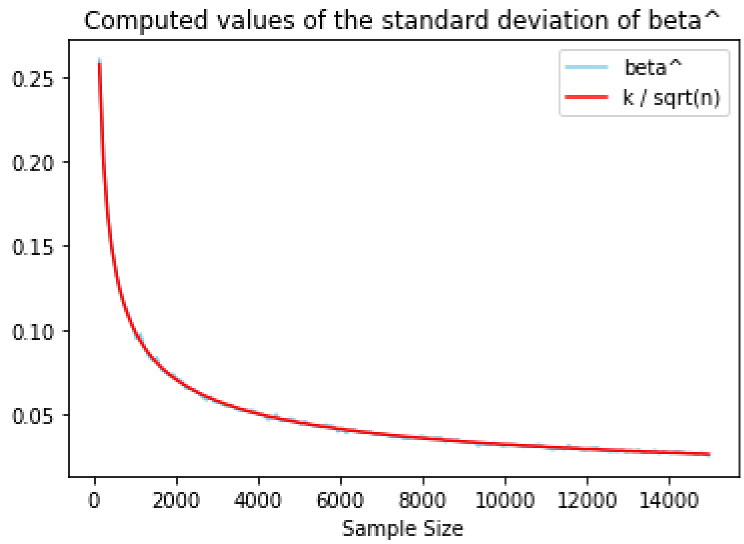


In [134]:

```
sigma = np.divide(betaHatStd,1.0/np.sqrt(sampleSizes))
k = np.mean(sigma)
```

In [136]:
```
import matplotlib.pyplot as plt
plt.plot(sampleSizes,betaHatStd,color='skyblue',label = "beta^")
plt.plot(sampleSizes,k/np.sqrt(sampleSizes),color='red',label = 'k /
 sqrt(n)')
plt.title("Computed values of the standard deviation of beta^")
plt.xlabel("Sample Size")
plt.legend()
```

Out[136]: <matplotlib.legend.Legend at 0x7fd10eff77f0>



$\frac{1}{\sqrt{n}}$ is off from the empirical value of the standard deviation of $\hat{\beta}$ by a constant multiple. If I instead plot $\frac{k}{\sqrt{n}}$ where k is the mean of $\frac{std(\hat{\beta})}{1.0/\sqrt{n}}$, then the 2 lines are almost on top of each other.

Names and Frequencies

The goal of this exercise is for you to get more experience with Pandas, and to get a chance to explore a cool data set. Download the file Names.zip from Canvas. This contains the frequency of all names that appeared more than 5 times on a social security application from 1880 through 2015

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

In [1]:
```
import pandas as pd
def topKNames(k,year):
    # read the file containing the name frequency for the year
    filepath = "./Names/yob{}.txt".format(year)
    df = pd.read_csv(filepath,header=None)
    # first column of the dataframe is the name, followed by the gend
er and last by the frequency
    df.columns = ['name','gender','frequency']
    # sort the dataframe by the frequency in descending order
    df= df.sort_values(by='frequency',ascending=False)
    # return the name of the  first k rows of the data
    topKNames = df.iloc[0:k,0]
    return topKNames.to_list()
```

In [62]:
```
print(topKNames(7,1990))
```

```
['Michael', 'Christopher', 'Jessica', 'Ashley', 'Matthew', 'Joshua',
'Brittany']
```

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

In [101]:
```
# find the frequency of a name in a year for men and women
def freqMFNameByYear(name,year):
    # read the file containing the name frequency for the year
    filepath = "./Names/yob{}.txt".format(year)
    df = pd.read_csv(filepath,header=None)
    # first column of the dataframe is the name, followed by the gend
er and last by the frequency
    df.columns = ['name','gender','frequency']
    # find the rows for the give name using case insensitive comparis
on
    rows = df.loc[df['name'].str.lower() == name.lower()]
    # iterate over the rows
    menFrequency = 0
    womenFrequency = 0
    for index,row in rows.iterrows():
        if(row['gender'].lower() == 'm'):
            menFrequency += row['frequency']
        elif(row['gender'].lower() == 'f'):
            womenFrequency += row['frequency']
    return menFrequency,womenFrequency
```

In [105]:
```
men,women = freqMFNameByYear("Ashley",1990)
print("{} men were named Ashley in 1990. {} women were named Ashley i
n 1990".format(men,women))
```

```
239 men were named Ashley in 1990. 45553 women were named Ashley in 1
990
```

- It could be that names are more diverse now than they were in 1880, so that a name may be relatively the most popular, though its frequency may have been decreasing over the years. Modify the above to return the relative frequency. Note that in the next coming lectures we will learn how to quantify diversity using entropy.

In [136]:
```
def getTotalMWFreqByYear(year):
    filepath = "./Names/yob{}.txt".format(year)
    df = pd.read_csv(filepath,header=None)
     # first column of the dataframe is the name, followed by the gen
der and last by the frequency
    df.columns = ['name','gender','frequency']
    # find the total frequency for men and women
    menTotal = df.loc[df['gender'].str.lower() == "m"]['frequency'].s
um()
    womenTotal = df.loc[df['gender'].str.lower() == "f"]['frequency']
.sum()
    return menTotal,womenTotal

# find the relative frequency of a name in a year for men and women
def relFreqMFNameByYear(name,year):
    # get the frequency of a name in a year for men and women
    men,women = freqMFNameByYear(name,year)
    menTotal,womenTotal = getTotalMWFreqByYear(year)
    return men/menTotal,women/womenTotal
```

In [137]:
```
men,women = relFreqMFNameByYear("Ashley",1990)
print("{}% of men were named Ashley in 1990. {}% of women were named
 Ashley in 1990".format(men*100,women*100))
```

```
0.011643417182176121% of men were named Ashley in 1990. 2.40029676358
028% of women were named Ashley in 1990
```

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

In [4]:
```
startYear = 1880
endYear = 2015
years = np.arange(startYear,endYear+1)
# initialize a dictionary for men and women to hold the count of a na
me per year
namesM = {}
namesW = {}
columns = ['name','gender','frequency']
for year in years:
    filepath = "./Names/yob{}.txt".format(year)
    df = pd.read_csv(filepath,header=None)
     # first column of the dataframe is the name, followed by the gen
der and last by the frequency
    df.columns = columns
    for index,row in df.iterrows():
        name = row['name']
        isFemale = row['gender'].lower() == 'f'
        frequency = row['frequency']
        if isFemale:
            names = namesW
        else:
            names = namesM
        counts = names.get(name,{})
        # store the frequency in the counts
        counts[year] = frequency
        names[name] = counts
```

In [6]:
```
import numpy as np
# Note: there are thousands of names who flip. For pdf purposes, I'll
only show 20 flips for men and women.
numLines = 20;
i = 0;
# now iterate over all the names and find if a name becomes more popu
lar for one gender vs the other
for name,countsM in namesM.items():
    countsW = namesW.get(name,{})
    if len(countsW) == 0:
        # no women are named name
        continue
    # there are women with the name
    sign = None
    for year in years:
        numMen = countsM.get(year,0)
        numWomen = countsW.get(year,0)
        diff = numMen - numWomen
        s = np.sign(diff)
        if not sign:
            sign = s
            continue
        if (s != sign):
            i+=1
            sign = s
            if(s > 0):
                if(i < numLines):
                    print("{} become more popular for men({}) that wo
men({}) in {}".format(name,numMen,numWomen,year))
            elif(s < 0):
                if( i < numLines):
                    print("{} become more popular for women({}) that
 men({}) in {}".format(name,numWomen,numMen,year))
            else:
                if( i < numLines):
                    print("{} became as popular for men({}) and women
({}) in {}".format(name,numMen,numWomen,year))

i=0
# do the same for women's name
for name,countsW in namesW.items():
    countsM = namesM.get(name,{})
    if len(countsM) == 0:
        # no men are named name
        continue
    # there are men with the name
    sign = None
    for year in years:
        numMen = countsM.get(year,0)
        numWomen = countsW.get(year,0)
        diff = numMen - numWomen
        s = np.sign(diff)
        if not sign:
            sign = s
            continue
        if (s != sign):
```

```
            sign = s
            i=i+1
            if (s > 0):
                if( i < numLines):
                    print("{} become more popular for men({}) that wo
men({}) in {}".format(name,numMen,numWomen,year))
            elif(s < 0):
                if( i< numLines):
                    print("{} become more popular for women({}) that
 men({}) in {}".format(name,numWomen,numMen,year))
            else:
                if(i < numLines):
                    print("{} became as popular for men({}) and women
({}) in {}".format(name,numMen,numWomen,year))
```

```
Ed became as popular for men(0) and women(0) in 2012
Charley become more popular for women(63) that men(61) in 1987
Charley became as popular for men(56) and women(56) in 1990
Marion become more popular for women(184) that men(163) in 1883
Marion become more popular for men(184) that women(181) in 1884
Marion become more popular for women(198) that men(141) in 1885
Marion become more popular for men(299) that women(293) in 1972
Marion became as popular for men(229) and women(229) in 1977
Marion become more popular for women(211) that men(187) in 1981
Marion become more popular for men(169) that women(165) in 1984
Marion become more popular for women(168) that men(154) in 1985
Marion become more popular for men(164) that women(162) in 1986
Marion become more popular for women(150) that men(137) in 1987
Marion become more popular for men(117) that women(115) in 1996
Marion become more popular for women(141) that men(102) in 2000
Marion become more popular for men(158) that women(119) in 2003
Marion become more popular for women(111) that men(102) in 2011
Marion became as popular for men(109) and women(109) in 2012
Jessie become more popular for men(1094) that women(1070) in 1948
Jessie become more popular for men(1094) that women(1070) in 1948
Jessie become more popular for women(1031) that men(1023) in 1949
Jessie become more popular for men(1019) that women(937) in 1950
Jessie become more popular for women(1276) that men(1117) in 1986
Jessie become more popular for men(1255) that women(1116) in 1990
Jessie become more popular for women(1096) that men(1048) in 1992
Jessie become more popular for men(627) that women(618) in 2003
Jessie become more popular for women(607) that men(570) in 2004
Jessie become more popular for men(590) that women(507) in 2005
Jessie become more popular for women(493) that men(488) in 2008
Jessie become more popular for men(459) that women(421) in 2009
Jessie become more popular for women(419) that men(406) in 2010
Myrtle became as popular for men(0) and women(0) in 1998
Myrtle became as popular for men(0) and women(0) in 2006
Myrtle became as popular for men(0) and women(0) in 2015
Blanche became as popular for men(0) and women(0) in 2015
Maud became as popular for men(0) and women(0) in 1963
Maud became as popular for men(0) and women(0) in 1971
Maud became as popular for men(0) and women(0) in 1975
```

Visualization Tools and Missing/Hidden Values

Visualization is important both for exploring the data, as well as for explaining what you have done. There are a huge number of such tools now available. This exercise walks through various functionalities of matplotlib and pandas.

- The first part of this exercise was created by Dataquest. Run through the commands given in this tutorial: [https://www.dataquest.io/blog/matplotlib-tutorial/ (https://www.dataquest.io/blog/matplotlib-tutorial/)](https://www.dataquest.io/blog/matplotlib-tutorial/) and understand the code.

Exploring tweets with Pandas

- Import the Pandas library.
- Read tweets.csv into a Pandas DataFrame.
- Print the first 5 rows of the DataFrame

In [44]:
```
import pandas as pd
tweets = pd.read_csv("tweets.csv")
tweets.head()
```

Out[44]:

	id	id_str	user_location	user_bg_color	retweet_count	user_name	polarity
0	1	729828033092149248	Wheeling WV	022330	0	Jaybo26003	0.0(
1	2	729828033092161537	NaN	C0DEED	0	britttany_ns	0.1!
2	3	729828033566224384	NaN	C0DEED	0	JeffriesLori	0.0(
3	4	729828033893302272	global	C0DEED	0	WhorunsGOVs	0.0(
4	5	729828034178482177	California, USA	131516	0	BJCG0830	0.0(

Generating a candidates column

- Create a function that finds what candidate names occur in a piece of text.
- Use the apply method on DataFrames to generate a new column called candidate that contains what candidate(s) the tweet mentions.

In [140]:
```
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)
```

Making the first plot

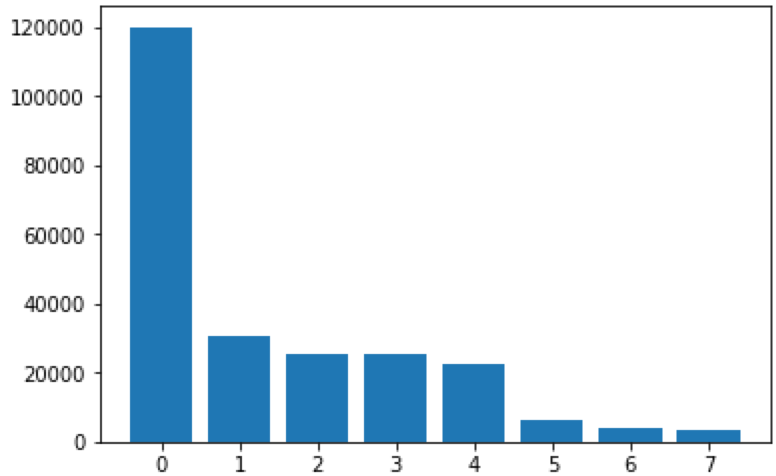
Importing matplotlib

In [141]:
```
import matplotlib.pyplot as plt
import numpy as np
%matplotlib inline
```

Making a bar plot

- Use the value_counts method on Pandas Series to count up how many tweets mention each candidate.
- Use plt.bar to create a bar plot. We'll pass in a list of numbers from 0 to the number of unique values in the candidate column as the x-axis input, and the counts as the y-axis input.
- Display the counts so we have more context about what each bar represents.

In [142]:
```
counts = tweets["candidate"].value_counts()
plt.bar(range(len(counts)), counts)
plt.show()

print(counts)
```

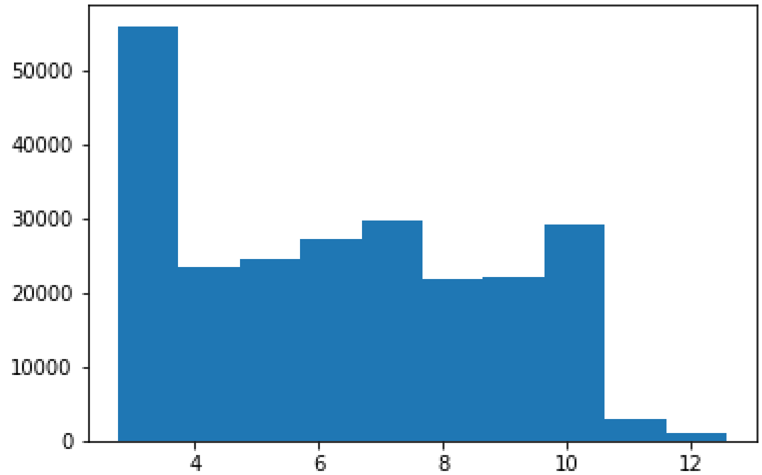



```
trump                     119998
clinton,trump              30521
                           25429
sanders                    25351
clinton                    22746
clinton,sanders             6044
clinton,trump,sanders       4219
trump,sanders               3172
Name: candidate, dtype: int64
```

Customizing plots

- Convert the created and user_created columns to the Pandas datetime type.
- Create a user_age column that is the number of days since the account was created.
- Create a histogram of user ages.
- Show the histogram.

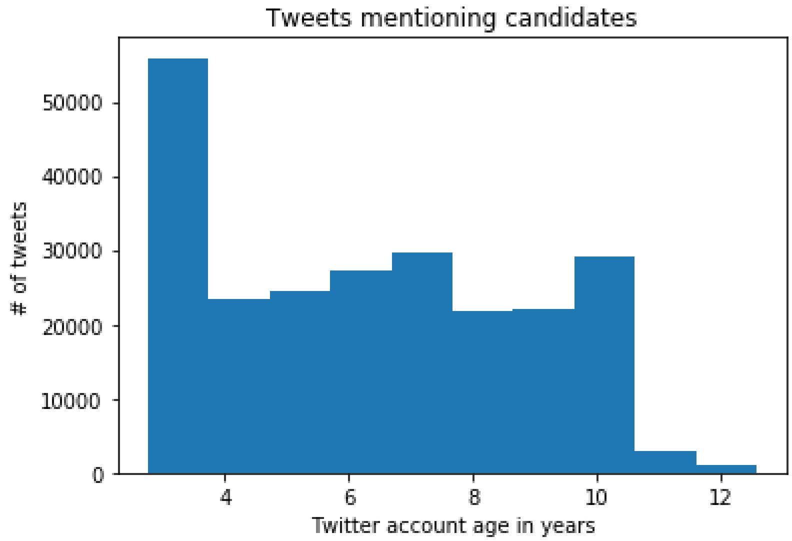
In [143]:
```
from datetime import datetime

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() - x).total_seconds() / 3600 / 24 / 365)
plt.hist(tweets["user_age"])
plt.show()
```



Adding labels

- Generate the same histogram we did before.
- Draw a title onto the histogram.
- Draw an x axis label onto the histogram.
- Draw a y axis label onto the histogram.
- Show the plot.

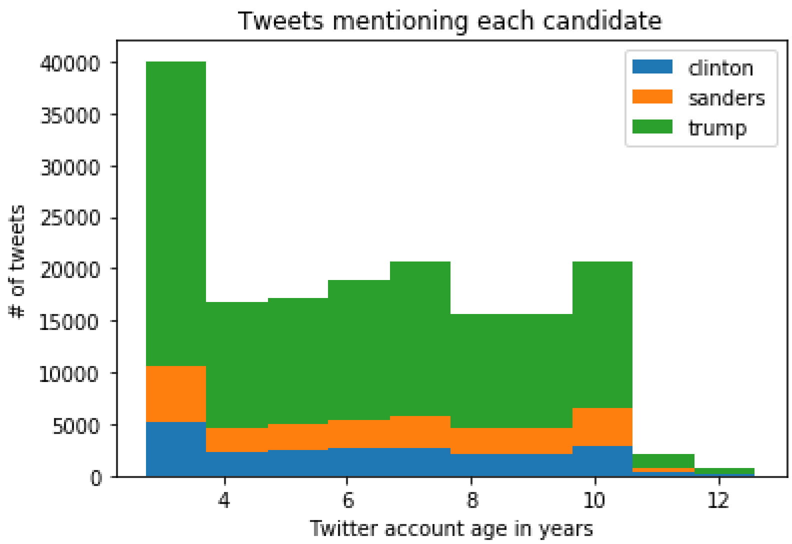
In [144]:
```
plt.hist(tweets["user_age"])
plt.title("Tweets mentioning candidates")
plt.xlabel("Twitter account age in years")
plt.ylabel("# of tweets")
plt.show()
```



Making a stacked histogram

- Generate three Pandas series, each containing the user_age data only for tweets about a certain candidate.
- Make a stacked histogram by calling the hist method with additional options.
    - Specifying a list as the input will plot three sets of histogram bars.
    - Specifying stacked=True will stack the three sets of bars.
    - Adding the label option will generate the correct labels for the legend.
- Call the plt.legend method to draw a legend in the top right corner.
- Add a title, x axis, and y axis labels.
- Show the plot.

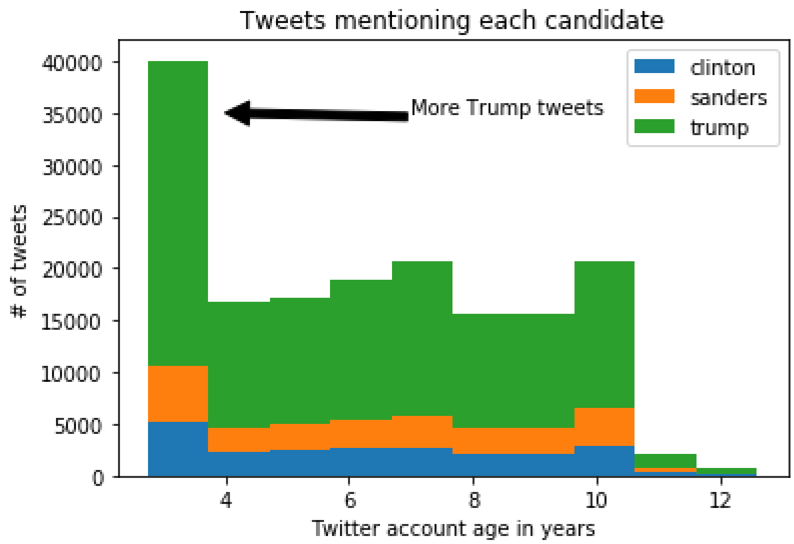
In [146]:
```
cl_tweets = tweets["user_age"][tweets["candidate"] == "clinton"]
sa_tweets = tweets["user_age"][tweets["candidate"] == "sanders"]
tr_tweets = tweets["user_age"][tweets["candidate"] == "trump"]
plt.hist([
        cl_tweets,
        sa_tweets,
        tr_tweets
    ],
    stacked=True,
    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()
```



Annotating the histogram

In the code below, we'll make the same histogram as we did above, but we'll call the plt.annotate method to add an annotation to the plot.

In [167]:
```
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.annotate('More Trump tweets', xy=(4, 35000), xytext=(7, 35000),
            arrowprops=dict(facecolor='black'))
plt.show()
```



Multiple subplots

Extracting colors

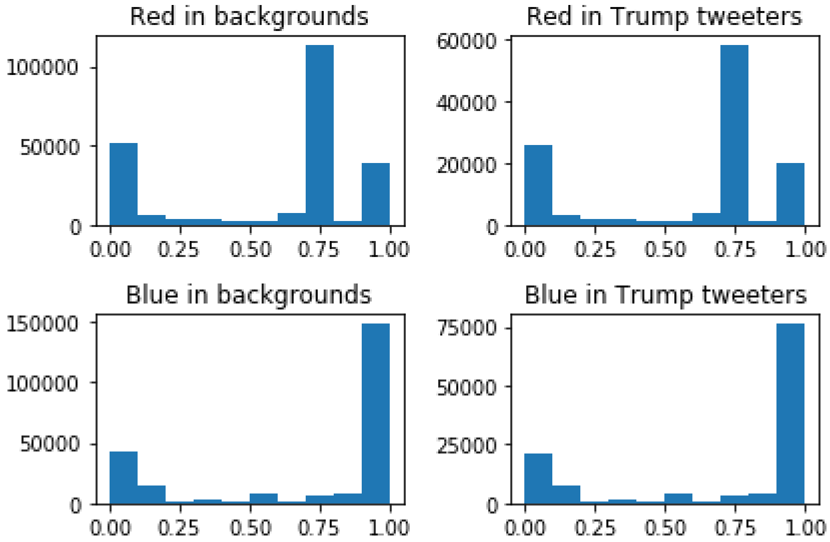
- Use the apply method to go through each row in the user_bg_color column, and extract how much red is in it.
- Use the apply method to go through each row in the user_bg_color column, and extract how much blue is in it.

In [168]:
```
import matplotlib.colors as colors

tweets["red"] = tweets["user_bg_color"].apply(lambda x: colors.hex2co
lor('#{0}'.format(x))[0])
tweets["blue"] = tweets["user_bg_color"].apply(lambda x: colors.hex2c
olor('#{0}'.format(x))[2])
```

Creating the plot

- Generate a Figure and multiple Axes with the subplots method. The axes will be returned as an array.
- The axes are returned in a 2x2 NumPy array. We extract each individual Axes object by using the flat property of arrays. This gives us 4 Axes objects we can work with.
- Plot a histogram in the first Axes using the hist method.
- Set the title of the first Axes to Red in all backgrounds using the set_title method. This performs the same function as plt.title.
- Plot a histogram in the second Axes using the hist method.
- Set the title of the second Axes to Red in Trump tweeters using the set_title method.
- Plot a histogram in the third Axes using the hist method.
- Set the title of the third Axes to Blue in all backgrounds using the set_title method. This performs the same function as plt.title.
- Plot a histogram in the fourth Axes using the hist method.
- Set the title of the fourth Axes to Blue in Trump tweeters using the set_title method.
- Call the plt.tight_layout method to reduce padding in the graphs and fit all the elements.
- Show the plot.

In [169]:
```
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()
```



Removing common background colors

Here's how to find the most common colors in background colors:

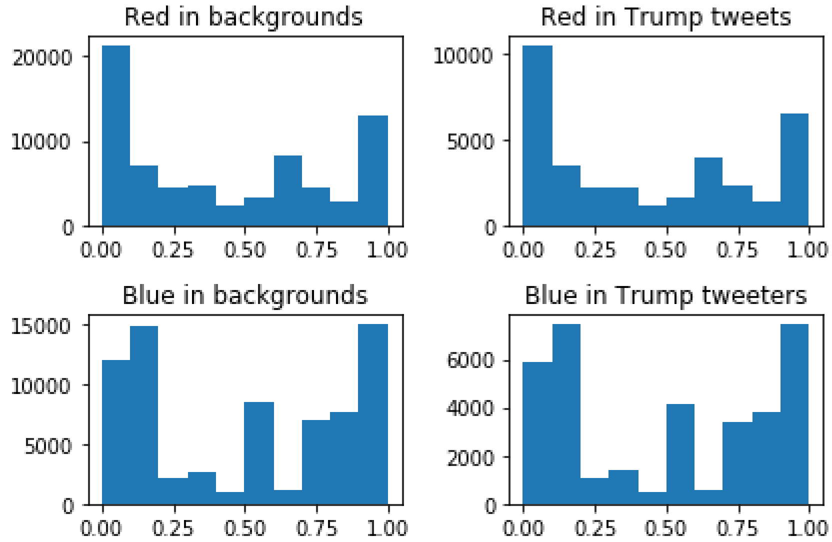
In [171]:
```
tweets["user_bg_color"].value_counts()
```

Out[171]:
```
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
           ...
BAE0F5         1
FBFBFB         1
F0488B         1
D0DBE0         1
878287         1
13BEED         1
233B47         1
8A2D5F         1
AA86B1         1
C2CC31         1
2028BD         1
332524         1
E50E06         1
8A868A         1
EAEBED         1
FCA9FC         1
993893         1
C20E0E         1
BF6F9C         1
FF7105         1
2288CC         1
F38630         1
09090A         1
1F1A1E         1
D9007E         1
5590AD         1
```

```
300030         1
0B4C5F         1
CCD6D6         1
8F0E8F         1
Name: user_bg_color, Length: 6970, dtype: int64
```

- Remove C0DEED, 000000, and F5F8FA from user_bg_color.
- Create a function with out plotting logic from the last chart inside.
- Plot the same 4 plots from before without the most common colors in user_bg_color.

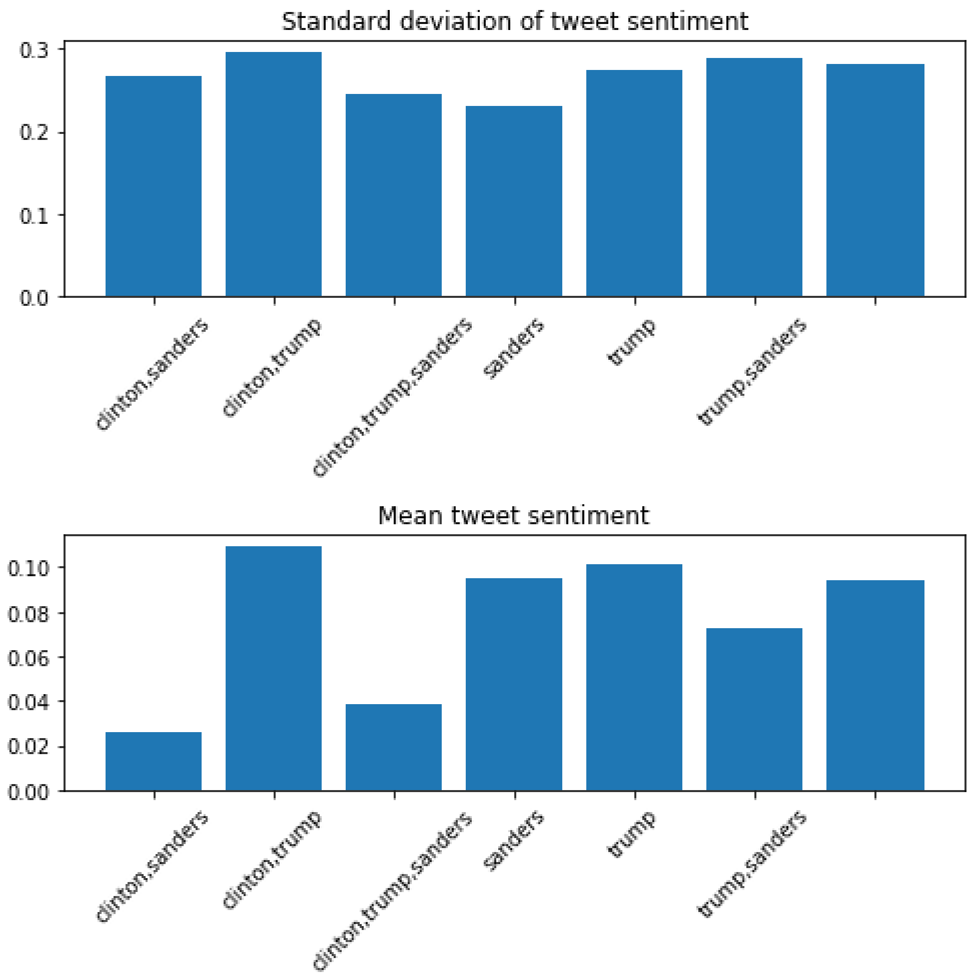
In [172]:
```
tc = tweets[~tweets["user_bg_color"].isin(["C0DEED", "000000", "F5F8F
A"])]

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)
```



Plotting sentiment

- Group tweets by candidate, and compute the mean and standard deviation for each numerical column (including polarity).
- Create a Figure that's 7 inches by 7 inches, with 2 Axes objects, arranged vertically.
- Create a bar plot of the standard deviation the first Axes object.
    - Set the tick labels using the set_xticklabels method, and rotate the labels 45 degrees using the rotation argument.
    - Set the title.
- Create a bar plot of the mean on the second Axes object.
    - Set the tick labels.
    - Set the title.
- Show the plot.

In [173]:
```
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()
```



Generating a side by side bar plot

Generating tweet lengths

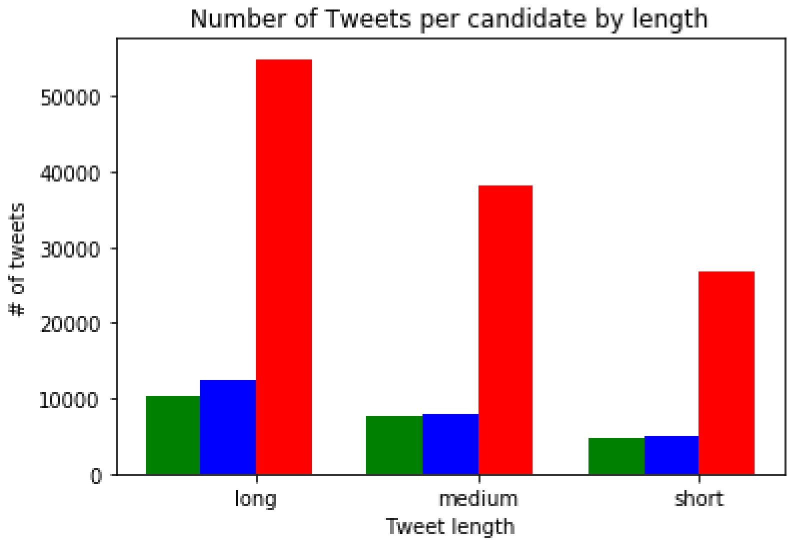
- Define a function to mark a tweet as short if it's less than 100 characters, medium if it's 100 to 135 characters, and long if it's over 135 characters.
- Use apply to generate a new column tweet_length.
- Figure out how many tweets by each candidate fall into each group.

In [175]:
```
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"] == can
didate].value_counts()
```

Plotting

- Create a Figure and a single Axes object.
- Define the width for each bar, .5.
- Generate a sequence of values, x, that is 0, 2, 4. Each value is the start of a category, such as short, medium, and long. We put a distance of 2 between each category so we have space for multiple bars.
- Plot clinton tweets on the Axes object, with the bars at the positions defined by x.
- Plot sanders tweets on the Axes object, but add width to x to move the bars to the right.
- Plot trump tweets on the Axes object, but add width * 2 to x to move the bars to the far right.
- Set the axis labels and title.
- Use set_xticks to move the tick labels to the center of each category area.
- Set tick labels.

In [177]:
```
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()
```



- Suppose that you would now like to plot some of the results by state. As you will see, the state information is sometimes missing, and other times it comes in varying forms. Figure out how to aggregate the results by state. The challenge here: how many of the tweets can you (correctly) assign to a state? Note: depending on how well you want to do (i.e., how many tweets you want to correctly assign to their state), this is not an easy problem!

In [64]:
```
states = {
        'AK': 'Alaska',
        'AL': 'Alabama',
        'AR': 'Arkansas',
        'AS': 'American Samoa',
        'AZ': 'Arizona',
        'CA': 'California',
        'CO': 'Colorado',
        'CT': 'Connecticut',
        'DC': 'District of Columbia',
        'DE': 'Delaware',
        'FL': 'Florida',
        'GA': 'Georgia',
        'GU': 'Guam',
        'HI': 'Hawaii',
        'IA': 'Iowa',
        'ID': 'Idaho',
        'IL': 'Illinois',
        'IN': 'Indiana',
        'KS': 'Kansas',
        'KY': 'Kentucky',
        'LA': 'Louisiana',
        'MA': 'Massachusetts',
        'MD': 'Maryland',
        'ME': 'Maine',
        'MI': 'Michigan',
        'MN': 'Minnesota',
        'MO': 'Missouri',
        'MP': 'Northern Mariana Islands',
        'MS': 'Mississippi',
        'MT': 'Montana',
        'NA': 'National',
        'NC': 'North Carolina',
        'ND': 'North Dakota',
        'NE': 'Nebraska',
        'NH': 'New Hampshire',
        'NJ': 'New Jersey',
        'NM': 'New Mexico',
        'NV': 'Nevada',
        'NY': 'New York',
        'OH': 'Ohio',
        'OK': 'Oklahoma',
        'OR': 'Oregon',
        'PA': 'Pennsylvania',
        'PR': 'Puerto Rico',
        'RI': 'Rhode Island',
        'SC': 'South Carolina',
        'SD': 'South Dakota',
        'TN': 'Tennessee',
        'TX': 'Texas',
        'UT': 'Utah',
        'VA': 'Virginia',
        'VI': 'Virgin Islands',
        'VT': 'Vermont',
        'WA': 'Washington',
        'WI': 'Wisconsin',
```

```
        'WV': 'West Virginia',
        'WY': 'Wyoming'
}
import re
def getStateFromLocation(location):
    # search for the state abbreviation or full name in the string
    for key,value in states.items():
        if re.search(r'\b' + key + r'\b',location):
            return value
        elif re.search(r'\b' + value + r'\b',location):
            return value
    # found no state
    return np.nan
```

In [42]:
```
import json
import reverse_geocode as rg
import geocoder
import numpy as np

# the coordinates are given as a json string
# parse the string into a dictionary
def getCoordinates(geo):
    g = json.loads(geo)
    return g["coordinates"]

def getStateFromCoord(coord):
    if not coord:
        return np.nan
    location = rg.search(coord)
    state = np.nan
    if location:
        state = location[0]['admin1']
    return state

def getStateFromLoc(loc):
    location = geocoder.arcgis(loc)
    state = np.nan
    if location:
        coord = [location.json['lat'],location.json['lng']]
        state = getStateFromCoord(coord)
    return state

def getState(row):
    state = np.nan
    # try to get the state from a geolocation
    # or from the user's location
    geo = row["geo"]
    loc = row["user_location"]
    # map the geolocation to a state
    if(pd.isna(geo) == False):
        try:
            coord = getCoordinates(geo)
            state = getStateFromCoord(coord)
        except:
            return np.nan
    # map the location to a state
    elif(pd.isna(loc) == False):
        try:
            state = getStateFromLocation(loc)
        except:
            return np.nan
    return state
```

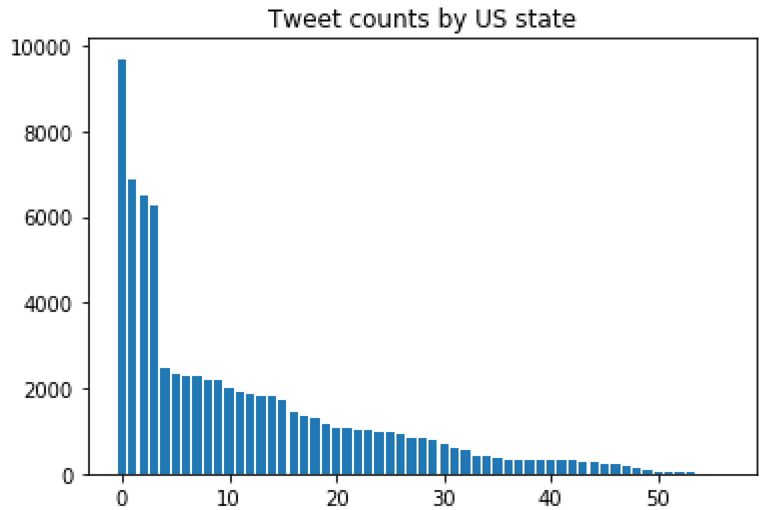
In [65]:
```
tweets["state"] = tweets.apply(getState,axis=1)
```

In [66]:
```
tweets.head()
```

Out[66]:

	id	id_str	user_location	user_bg_color	retweet_count	user_name	polarity
0	1	729828033092149248	Wheeling WV	022330	0	Jaybo26003	0.0(
1	2	729828033092161537	NaN	C0DEED	0	britttttany_ns	0.1!
2	3	729828033566224384	NaN	C0DEED	0	JeffriesLori	0.0(
3	4	729828033893302272	global	C0DEED	0	WhorunsGOVs	0.0(
4	5	729828034178482177	California, USA	131516	0	BJCG0830	0.0(

In [71]:
```
counts = tweets["state"].value_counts()
plt.bar(range(len(counts)), counts)
plt.title('Tweet counts by US state')
plt.show()

print(counts)
```


Tweet counts by US state
10000
8000
6000
4000
2000
0
0
10
20
30
40
50

```
California                9690
Texas                     6868
New York                  6511
Florida                   6257
Washington                2472
North Carolina            2344
Pennsylvania              2303
District of Columbia      2278
New Jersey                2213
Georgia                   2191
Arizona                   2023
Ohio                      1906
Virginia                  1856
Illinois                  1837
Tennessee                 1828
Michigan                  1715
Colorado                  1461
Massachusetts             1337
Oregon                    1324
Indiana                   1164
Minnesota                 1089
South Carolina            1071
Alabama                   1026
Maryland                  1004
Louisiana                  991
Wisconsin                  990
Nevada                     935
Missouri                   832
Connecticut                812
Oklahoma                   806
Kentucky                   680
Kansas                     611
Iowa                       538
Arkansas                   434
New Hampshire              405
Utah                       353
Nebraska                   340
West Virginia              332
Vermont                    322
Mississippi                320
Delaware                   311
Maine                      309
Idaho                      295
New Mexico                 291
Hawaii                     276
Alaska                     244
Montana                    219
Rhode Island               200
Puerto Rico                125
Wyoming                     64
South Dakota                55
North Dakota                54
National                    36
Virgin Islands              36
Guam                        14
Northern Mariana Islands     5
```

```
American Samoa                  3
Name: state, dtype: int64
```

In [ ]: