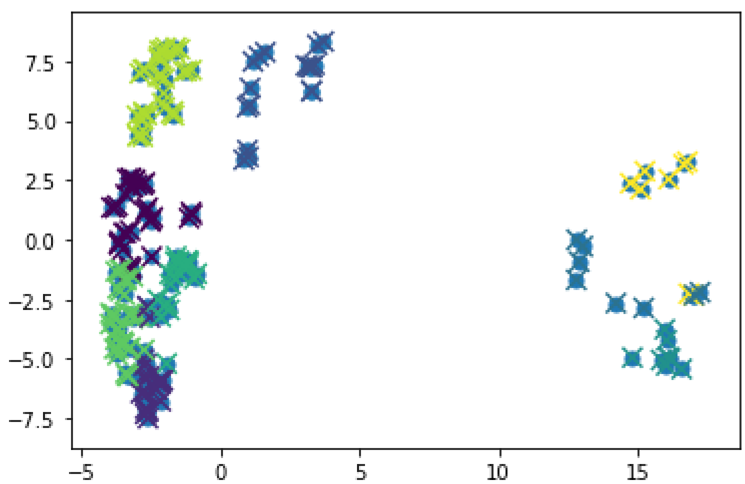
PCA for visualization

In [1]:
```
%matplotlib inline

import pandas as pd

# gene expression
nci60 = pd.read_csv('data/NCI60.txt',sep='\t', index_col=False)
# print(nci60.shape)
#display(nci60)
### pre-process
print(nci60.shape)
# expression data starts at column 5
expr = nci60.iloc[:,5:]
print(expr.shape)
```

```
(198, 389)
(198, 384)
```

In [2]:
```
# create coordiates for NCI60 dataset
from sklearn.decomposition import PCA
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans



Kmean = KMeans(n_clusters=9)
Kmean.fit(expr)

# pca = PCA(n_components=3)
# pca.fit(expr)
# print(pca.explained_variance_ratio_)
# coord = pca.transform(expr)

# plt.scatter(coord[ : , 1], coord[ : , 2], s = 50)

# plt.scatter(coord[ : , 1], coord[ : , 2], s = 100, marker='x', c=Kmean.label
s_)
# plt.show()

pca = PCA(n_components=2)
pca.fit(expr)
print(pca.explained_variance_ratio_)
coord = pca.transform(expr)

plt.scatter(coord[ : , 0], coord[ : , 1], s = 50)

plt.scatter(coord[ : , 0], coord[ : , 1], s = 100, marker='x', c=Kmean.labels_
)
plt.show()
```

```
[0.24630682 0.14342325]
```



PCA for unsupervised continuous analysis

[https://idyll.pub/post/dimensionality-reduction-293e465c2a3443e8941b016d/ (https://idyll.pub/post/dimensionality-reduction-293e465c2a3443e8941b016d/)](https://idyll.pub/post/dimensionality-reduction-293e465c2a3443e8941b016d/)

install libraries

1. pip install wurlitzer
2. pip install Pillow

Comment out:

1. from umap import UMAP
2. from MulticoreTSNE import MulticoreTSNE

Downloading data from the web

In [3]:

```
# scrape met website
import pandas as pd
import urllib.request as urllib2
import requests
import json

test = pd.read_csv('data/met/met.csv')
namelink = test[['Object Number','Object ID']]
metalink = 'https://collectionapi.metmuseum.org/public/collection/v1/objects/'
dest_dir = 'data/met/images/'
```

In [ ]:
```
#for i in range(len(namelink)):
for i in range(len(test)):
    # get the API metadate and retrieve the link for the actual image
    meta_id = namelink['Object ID'][i]
    response = urllib2.urlopen(metalink+str(meta_id))
    page_source = response.read().decode('utf-8')
    json_obj = json.loads(page_source)
    img_url = json_obj['primaryImage']
    # dowload the image
    print(meta_id,img_url)
    if img_url is not "":
        img_data = requests.get(img_url).content
        with open(dest_dir+str(meta_id)+'.jpg', 'wb') as handler:
            handler.write(img_data)
    #<meta property="og:image" content="https://collectionapi.metmuseum.org/api/collection/v1/iiif/200/33441/main-image" />

#static/images/met/
```

```
200 https://images.metmuseum.org/CRDImages/ad/original/DT163.jpg
237 https://images.metmuseum.org/CRDImages/ad/original/DT179.jpg
364 https://images.metmuseum.org/CRDImages/ad/original/DP228047.jpg
674 https://images.metmuseum.org/CRDImages/ad/original/DT11610.jpg
802 https://images.metmuseum.org/CRDImages/ad/original/DP104414.jpg
1029 https://images.metmuseum.org/CRDImages/ad/original/DP161659.jpg
1047 https://images.metmuseum.org/CRDImages/ad/original/DP108643.jpg
1083 https://images.metmuseum.org/CRDImages/ad/original/DT180.jpg
1084 https://images.metmuseum.org/CRDImages/ad/original/68.100.1.jpg
1503 https://images.metmuseum.org/CRDImages/ad/original/DT189.jpg
1524 https://images.metmuseum.org/CRDImages/ad/original/DP222293.jpg
```

Loading image data (takes long time to execute)

In [4]:
```
artworks = pd.read_csv('data/met/met.csv')
print(artworks.shape)
artworks.loc[0]
```

```
(10, 43)
```

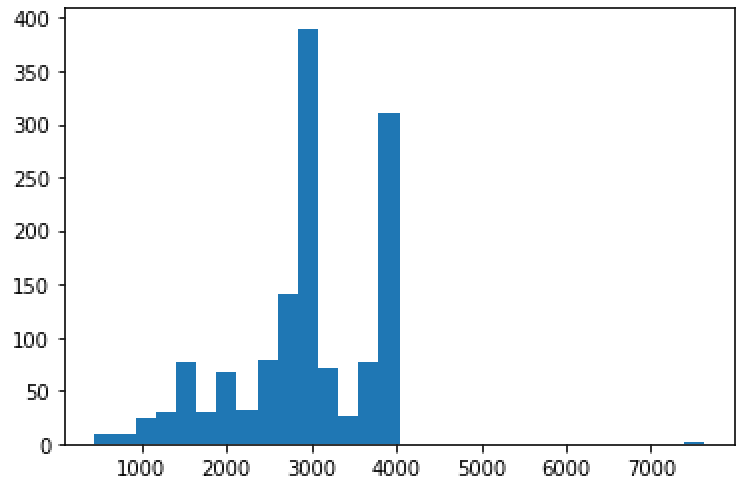
Out[4]:
```
Object Number                                                         51.12.2
Is Highlight                                                             True
Is Public Domain                                                         True
Object ID                                                                 200
Department                                           American Decorative Arts
Object Name                                                          Armchair
Title                                                   Spindle-back armchair
Culture                                                              American
Period                                                                    NaN
Dynasty                                                                   NaN
Reign                                                                     NaN
Portfolio                                                                 NaN
Artist Role                                                               NaN
Artist Prefix                                                             NaN
Artist Display Name                                                       NaN
Artist Display Bio                                                        NaN
Artist Suffix                                                             NaN
Artist Alpha Sort                                                         NaN
Artist Nationality                                                        NaN
Artist Begin Date                                                         NaN
Artist End Date                                                           NaN
Object Date                                                           1640-80
Object Begin Date                                                        1640
Object End Date                                                          1680
Medium                                                                    Ash
Dimensions                  44 3/4 x 23 1/2 x 15 3/4 in. (113.7 x 59.7 x 4...
Credit Line                                   Gift of Mrs. J. Insley Blair, 1951
Geography Type                                  Possibly made in Possibly made in
City                                                        Boston Charlestown
State                                                                     NaN
County                                                                    NaN
Country                                             United States United States
Region                                                                    NaN
Subregion                                                                 NaN
Locale                                                                    NaN
Locus                                                                     NaN
Excavation                                                                NaN
River                                                                     NaN
Classification                                                      Furniture
Rights and Reproduction                                                   NaN
Link Resource               http://www.metmuseum.org/art/collection/search...
Metadata Date                                                    6/25/18 8:00
Repository                              Metropolitan Museum of Art, New York, NY
Name: 0, dtype: object
```

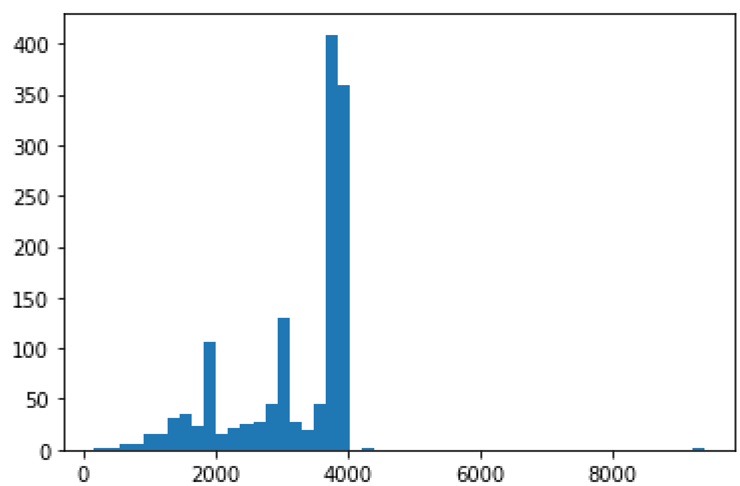
In [5]:
```
from os import path
from PIL import Image, ImageStat
import numpy as np
import pickle

X = []
w = []
h = []
l = []

for index, artwork in artworks.iterrows():
    #     print(artwork['Object ID'])
    nm = 'data/met/images/' + str(artwork['Object ID']) + '.jpg'
    if not path.exists(nm):
        continue
    im = Image.open(nm)
    w.append(im.size[0])
    h.append(im.size[1])
    im = im.resize((250, 250), Image.ANTIALIAS)
    sz = np.array(im).flatten().shape[0]
    if sz == 187500:
        l.append(artwork['Object ID'])
        X.append(np.expand_dims(np.array(im).flatten(),axis=0))
    #print(X[-1].shape)
# pickle.dump(X, open("met_pickle.pkl", "wb" ))
# pickle.dump(w, open("w.pkl", "wb" ))
# pickle.dump(h, open("h.pkl", "wb" ))
# pickle.dump(l, open("l.pkl", "wb" ))
```

Start here (faster)

In [6]:
```
# read pickles
import pickle
import matplotlib.pyplot as plt
import numpy as np
from sklearn.decomposition import PCA
import pandas as pd


X = pickle.load( open( "met_pickle.pkl", "rb" ) )
w = pickle.load( open( "w.pkl", "rb" ) )
h = pickle.load( open( "h.pkl", "rb" ) )
l = pickle.load( open( "l.pkl", "rb" ) )
```

In [7]:
```
%matplotlib inline
plt.hist(w, bins=30)
plt.show()

plt.hist(h, bins=50)
plt.show()
```





In [8]:
```
print(len(X), X[0].shape)
Xdata = np.vstack( X )
print(Xdata)
print(Xdata.shape)

# pd.DataFrame(Xdata).to_csv("met_data_orange2.csv", index=False)
# print("done")
```

```
1372 (1, 187500)
[[169 169 165 ... 198 197 195]
 [166 166 166 ... 198 197 198]
 [156 156 154 ... 219 219 219]
 ...
 [145 144 141 ... 149 145 143]
 [184 174 168 ... 182 177 173]
 [191 176 162 ... 184 177 174]]
(1372, 187500)
```

Running PCA to arrange by brightness

In [9]:
```
pca = PCA(n_components=2)
X_pca = pca.fit_transform(Xdata)
print(np.sum(pca.explained_variance_ratio_), '% variance captured')
print(X_pca.shape)
```

```
0.566234443254128 % variance captured
(1372, 2)
```

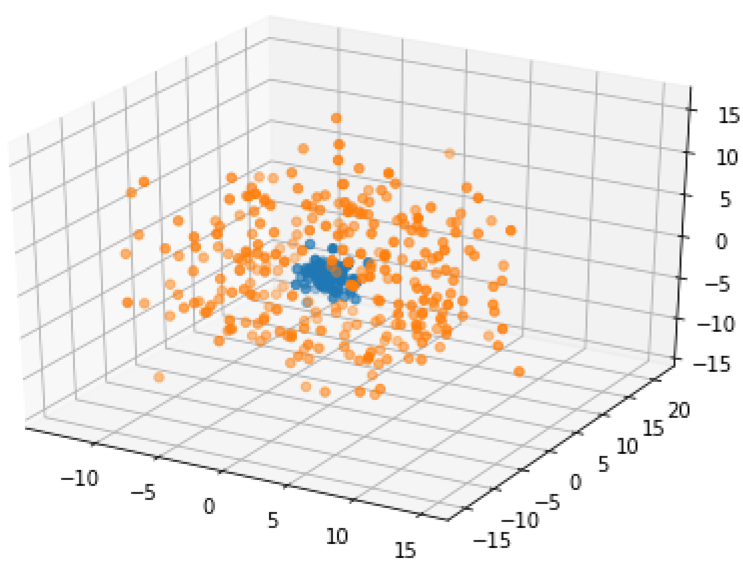
In [10]:
```
plt.figure(figsize=((12,12)))
plt.scatter(x=X_pca[:,0], y=X_pca[:,1], alpha=0.6, s=15)
for i, txt in enumerate(l):
    if i % 10 == 0:
        plt.annotate(txt, (X_pca[i,0], X_pca[i,1]))
plt.show()
```

t-SNE for visualization

[https://mlexplained.com/2018/09/14/paper-dissected-visualizing-data-using-t-sne-explained/ (https://mlexplained.com/2018/09/14/paper-dissected-visualizing-data-using-t-sne-explained/)](https://mlexplained.com/2018/09/14/paper-dissected-visualizing-data-using-t-sne-explained/)

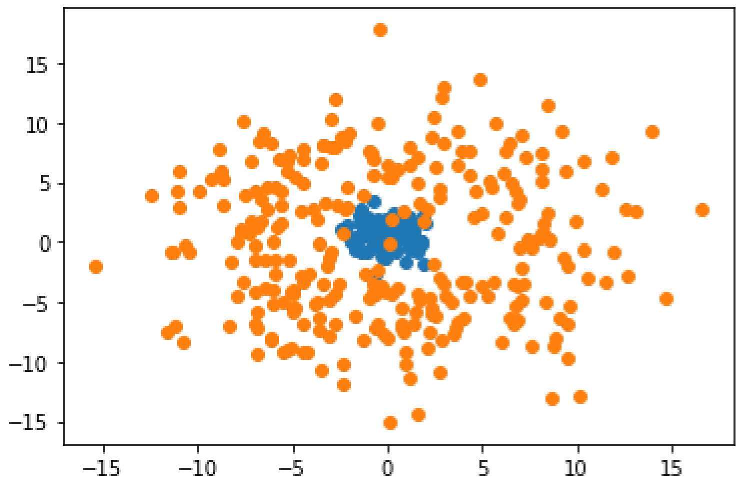
In [2]:
```
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
# import importlib
# importlib.import_module('mpl_toolkits').__path__

A = np.random.normal(scale=1, size=(100,3))
B = np.array([x for x in np.random.normal(scale=5, size=(500,3)) if np.linalg.
norm(x) > 7])

from mpl_toolkits.mplot3d import Axes3D

fig = plt.figure()
ax = Axes3D(fig)

ax.scatter(A[:, 0],A[:, 1],A[:, 2])
ax.scatter(B[:, 0],B[:, 1],B[:, 2])
```

Out[2]:
```
<mpl_toolkits.mplot3d.art3d.Path3DCollection at 0x12f0c12e588>
```

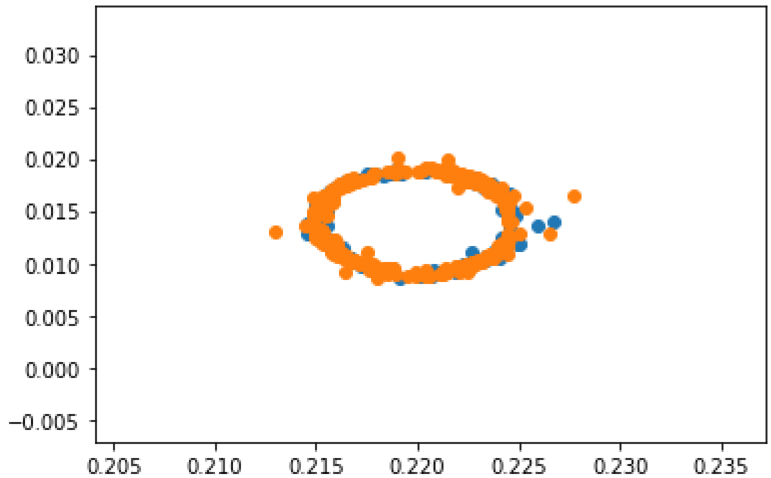


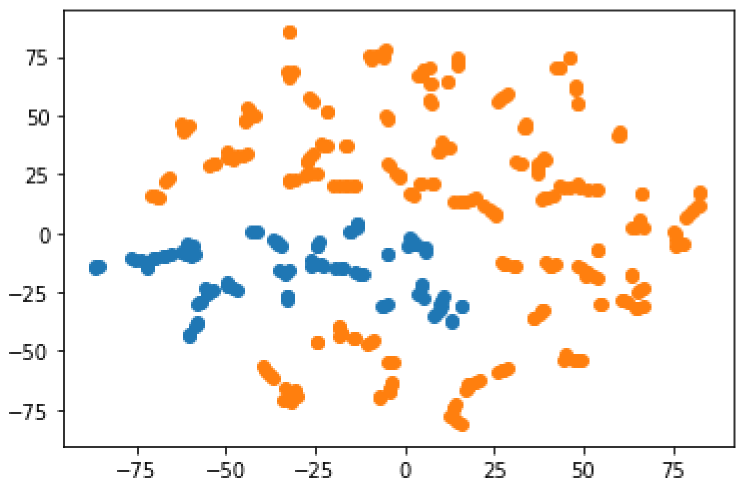
In [3]:
```
from sklearn.decomposition import PCA

X = np.r_[A,B]
X2 = PCA(n_components=2).fit_transform(X)

A2 = X2[:A.shape[0], :]
B2 = X2[A.shape[0]:, :]

plt.scatter(A2[:,0], A2[:, 1])
plt.scatter(B2[:,0], B2[:, 1])
```

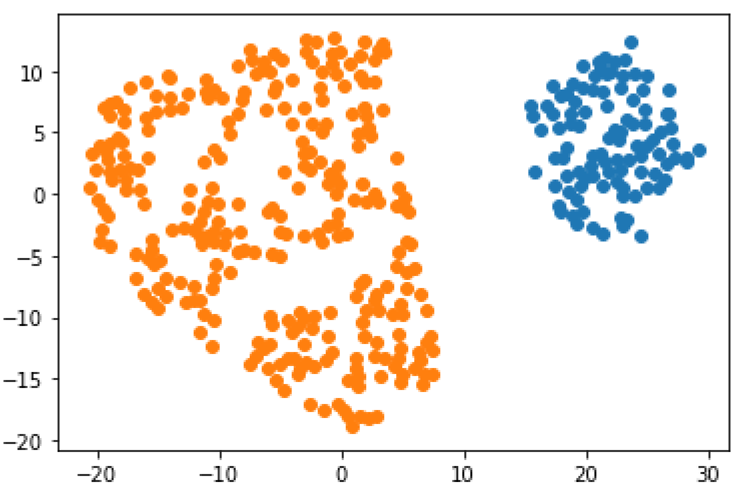
Out[3]: <matplotlib.collections.PathCollection at 0x12f0d646908>



In [7]:
```
from sklearn.manifold import TSNE

X3 = TSNE(n_components=2, perplexity=400).fit_transform(X)

A3 = X3[:A.shape[0], :]
B3 = X3[A.shape[0]:, :]

plt.scatter(A3[:,0], A3[:, 1])
plt.scatter(B3[:,0], B3[:, 1])
plt.show()

X3 = TSNE(n_components=2, perplexity=2).fit_transform(X)

A3 = X3[:A.shape[0], :]
B3 = X3[A.shape[0]:, :]

plt.scatter(A3[:,0], A3[:, 1])
plt.scatter(B3[:,0], B3[:, 1])
plt.show()

X3 = TSNE(n_components=2).fit_transform(X)

A3 = X3[:A.shape[0], :]
B3 = X3[A.shape[0]:, :]

plt.scatter(A3[:,0], A3[:, 1])
plt.scatter(B3[:,0], B3[:, 1])
plt.show()
```


0.030
0.025
0.020
0.015
0.010
0.005
0.000
−0.005
0.205
0.210
0.215
0.220
0.225
0.230
0.235


75
50
25
0
−25
−50
−75
−75
−50
−25
0
25
50
75


10
5
0
−5
−10
−15
−20
−20
−10
0
10
20
30

on your own

1. Execute above code multiple times (get different clustering, but still fairly similar)
2. Add hypterparameter perplexity=1 (or 400)

We can see that in the case of perplexity 1, all the points are scattered with no structure. This makes sense, since setting perplexity to 1 essentially means you only look at one neighbor, which makes it difficult to find local structure. Perplexity 400, on the other hand, clusters all the points into one blob. This is because perplexity 400, in this case, means all the points are your neighbors.

Lab 3 - Dimensionality reduction on nci60

Data: use nci60.csv

Optinal: Add hierarchical clustering

alt text

In [ ]:

```
```