t-SNE

December 22, 2017

1 t-Distributed Stochastic Neighbor Embedding Visualization

```
In [3]: from __future__ import print_function, division
        from builtins import range, input
        import numpy as np
        import matplotlib.pyplot as plt
        from mpl_toolkits.mplot3d import Axes3D
        from sklearn.manifold import TSNE
```

1.1 Define the centers of each Gaussian cloud

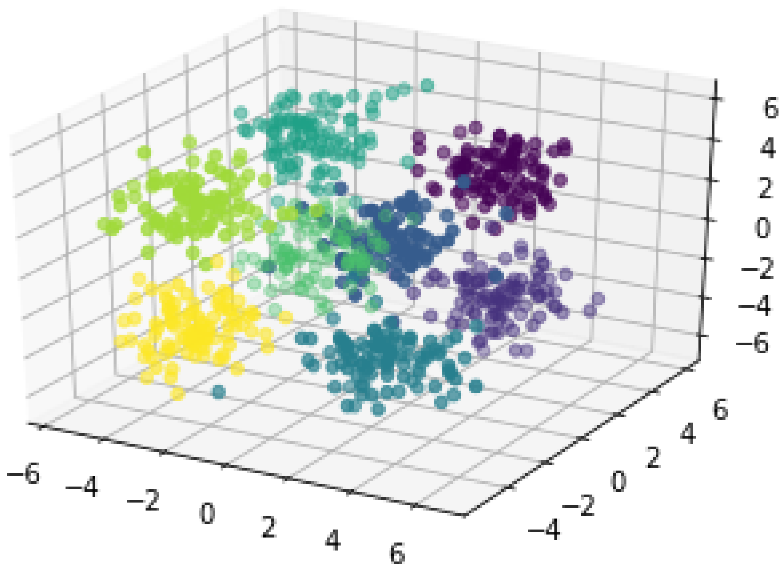
```
In [4]: centers = np.array([
                        [ 1,  1,  1],
                        [ 1,  1, -1],
                        [ 1, -1,  1],
                        [ 1, -1, -1],
                        [-1,  1,  1],
                        [-1,  1, -1],
                        [-1, -1,  1],
                        [-1, -1, -1]])*3
```

1.2 Create the clouds, Gaussian samples centered at each of the centers we just made

```
In [9]: data = []
        pts_per_cloud = 100
        for c in centers:
            cloud = np.random.randn(pts_per_cloud, 3) + c
            data.append(cloud)
        data = np.concatenate(data)
```

1.3 Visualize the clouds in 3-D add colors / labels so we can track where the points go

```
In [10]: colors = np.array([[i]*pts_per_cloud for i in range(len(centers))]).flatten()
         fig = plt.figure()
         ax = fig.add_subplot(111, projection='3d')
         ax.scatter(data[:,0], data[:,1], data[:,2], c=colors)
         plt.show()
```

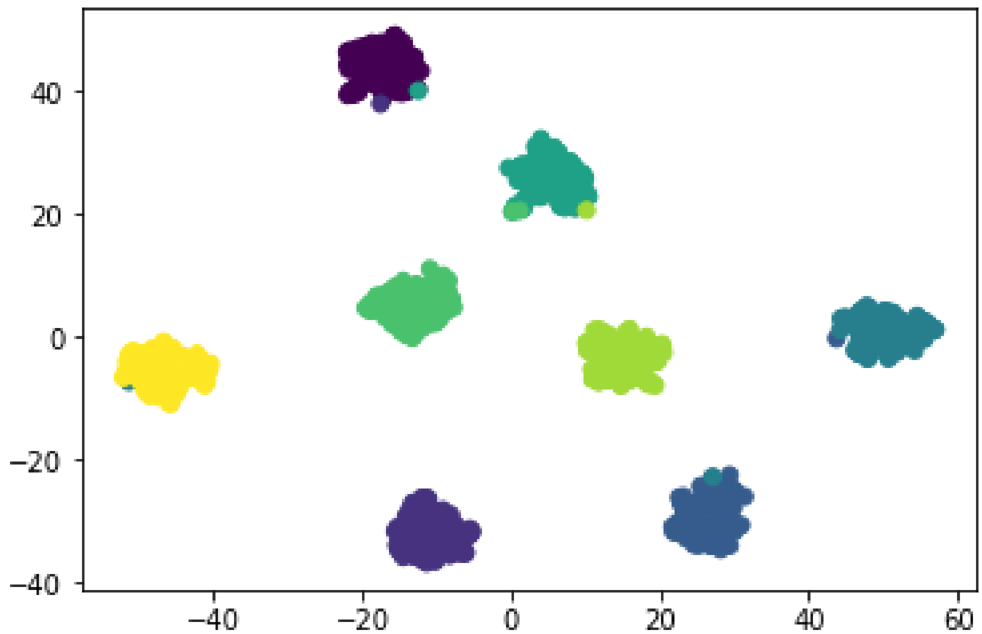


1.4 Perform dimensionality reduction

```
In [11]: tsne = TSNE()
         transformed = tsne.fit_transform(data)
```

1.5 Visualize the clouds in 2-D

```
In [12]: plt.scatter(transformed[:,0], transformed[:,1], c=colors)
         plt.show()
```



So here we've reduced a 3-D plot into 2-D.

2 t-SNE on the Donut

2.1 Function to gather data for the 'donut' distribution

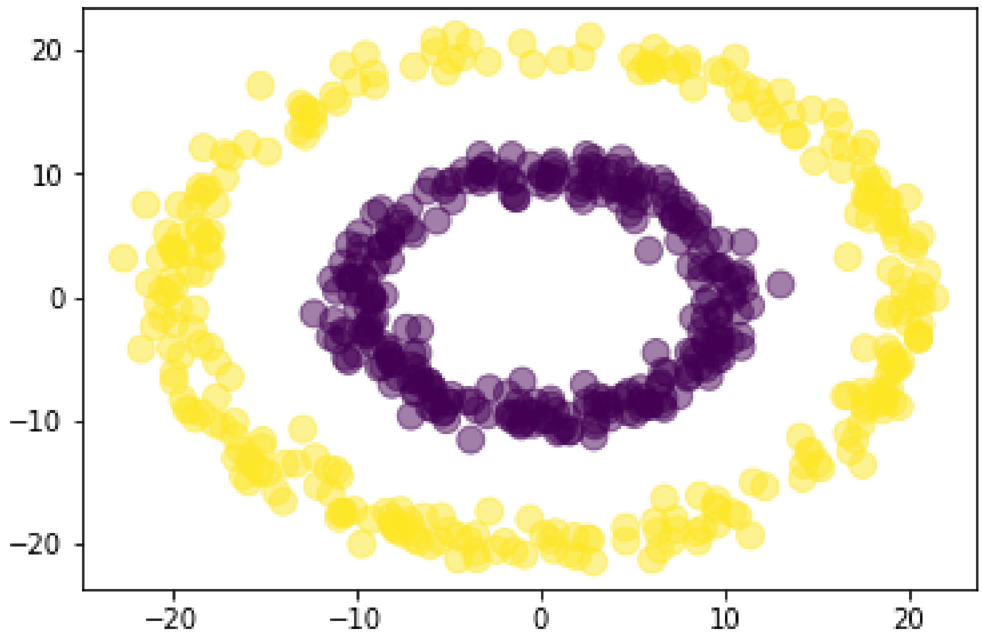
```
In [23]: def get_donut_data():
             N = 600
             R_inner = 10
             R_outer = 20

             # distance from origin is radius + random normal
             # angle theta is uniformly distributed between (0, 2pi)
             R1 = np.random.randn(300) + R_inner
             theta = 2*np.pi*np.random.random(300)
             X_inner = np.concatenate([[R1 * np.cos(theta)], [R1 * np.sin(theta)]]).T
             #300 comes from N/2
             R2 = np.random.randn(300) + R_outer
             theta = 2*np.pi*np.random.random(300)
             X_outer = np.concatenate([[R2 * np.cos(theta)], [R2 * np.sin(theta)]]).T

             X = np.concatenate([ X_inner, X_outer ])
             Y = np.array([0]*(300) + [1]*(300))
             return X, Y
```

2.2 Define the X and y variables.

In [24]:
```
X, Y = get_donut_data()
```

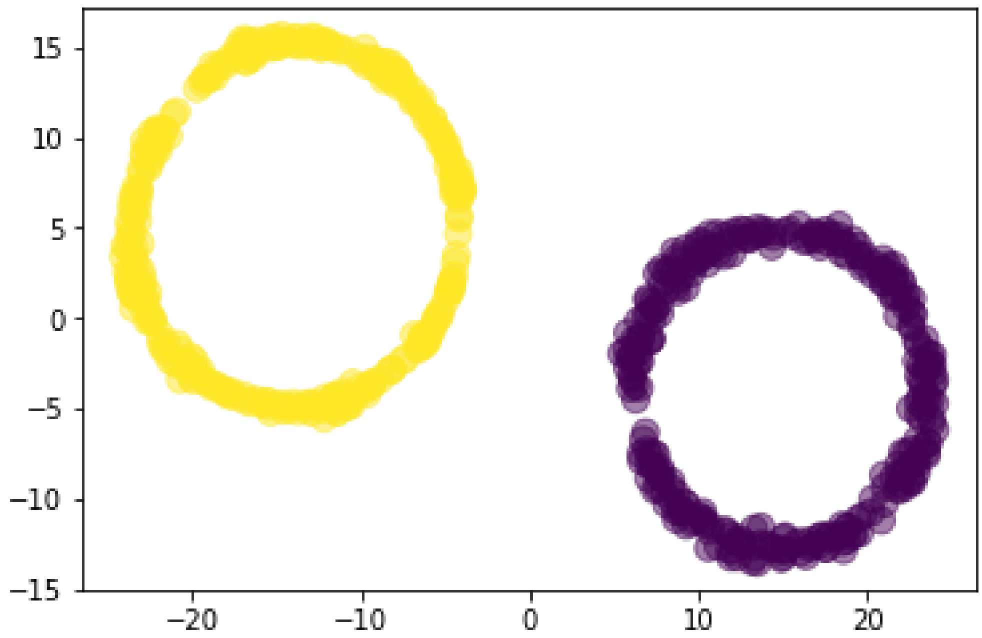
2.3 Display the data

In [25]:
```
plt.scatter(X[:,0], X[:,1], s=100, c=Y, alpha=0.5)
plt.show()
```



2.4 Dimensionality reduction

In [26]:
```
tsne = TSNE(perplexity=40)
Z = tsne.fit_transform(X)
plt.scatter(Z[:,0], Z[:,1], s=100, c=Y, alpha=0.5)
plt.show()
```



3 t-SNE on XOR

3.1 Function to get the XOR dataset

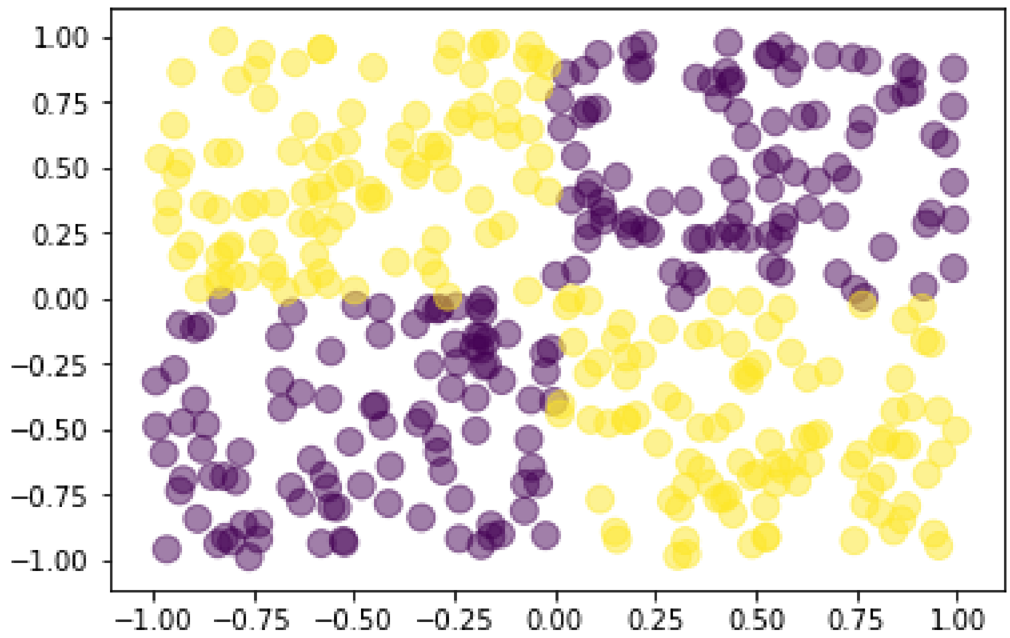
```
In [27]: def get_xor_data():
             X1 = np.random.random((100, 2))
             X2 = np.random.random((100, 2)) - np.array([1, 1])
             X3 = np.random.random((100, 2)) - np.array([1, 0])
             X4 = np.random.random((100, 2)) - np.array([0, 1])
             X = np.vstack((X1, X2, X3, X4))
             Y = np.array([0]*200 + [1]*200)
             return X, Y
```

3.2 Define the X and y variables

```
In [28]: X, Y = get_xor_data()
```

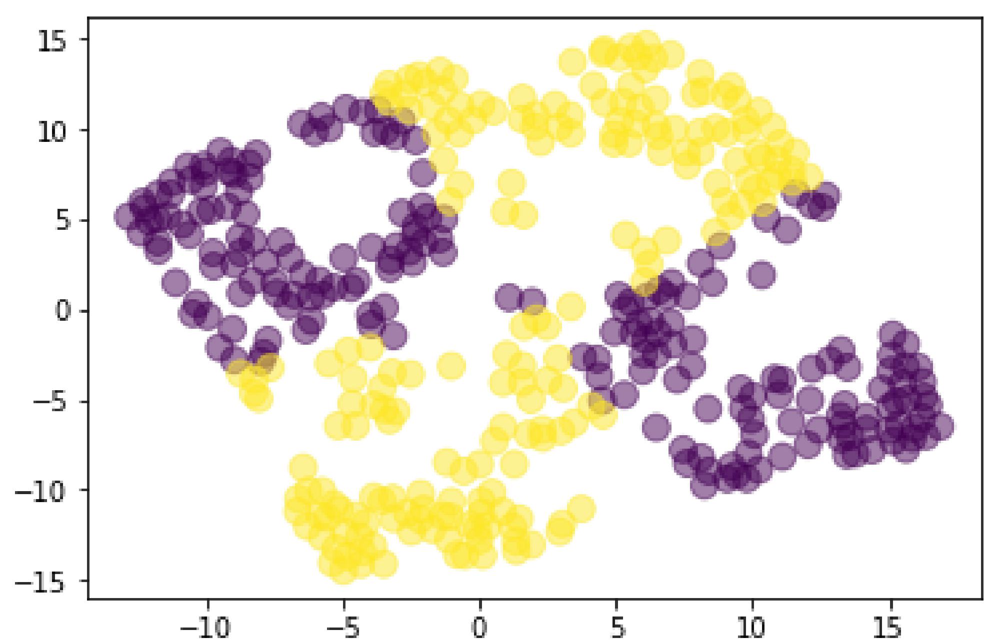
3.3 View the 2D 'Checkerboard' Plot

```
In [29]: plt.scatter(X[:,0], X[:,1], s=100, c=Y, alpha=0.5)
         plt.show()
```



3.4 Dimensionality reduction

```
In [38]: tsne = TSNE(perplexity=40)
         Z = tsne.fit_transform(X)
         plt.scatter(Z[:,0], Z[:,1], s=100, c=Y, alpha=0.5)
         plt.show()
```



It doesn't look like much has happened here, but to t-SNE, the data was unlabeled and uncategorized, and the distances were uniformly distributed. The fact that the result is similar is demonstration of the abilities of the t-SNE method.

4 t-SNE on MNIST

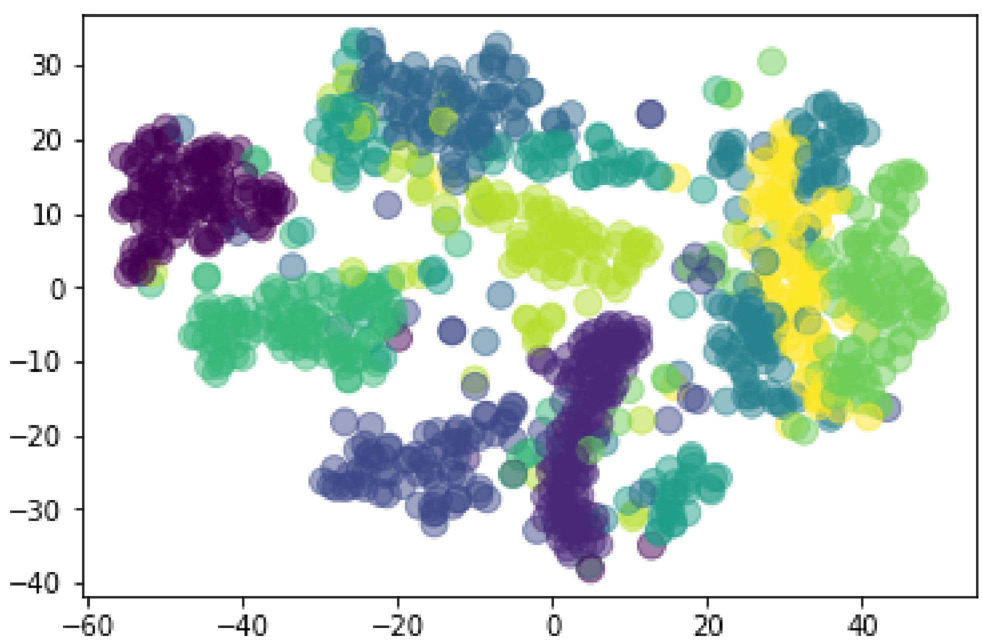
Import the dataset, assign the appropriate variables, and view the plot.

```
In [8]: import numpy as np
        import matplotlib.pyplot as plt
        from sklearn.manifold import TSNE
        from util import getKaggleMNIST
        import os
        import sys
```

```
In [2]: Xtrain, Ytrain, _, _ = getKaggleMNIST()
```

```
In [3]: sample_size = 1000
        X = Xtrain[:sample_size]
        Y = Ytrain[:sample_size]
```

```
In [4]: tsne = TSNE()
        Z = tsne.fit_transform(X)
        plt.scatter(Z[:,0], Z[:,1], s=100, c=Y, alpha=0.5)
        plt.show()
```



Here we see that the data has been categorized and is easier to view when compared to the the PCA. Although this model can't be applied to new data, it is still a great classification using a completely unsupervised method.