Lab 6 - Wyatt Madden & Dan Crowley

March 25, 2020

1 Dan Crowley & Wyatt Madden - Lab 6

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.image as mpimg
import matplotlib.pyplot as plt
import seaborn as sns
from im2rgb import *
from rgb2im import *
from pointclouds import *
from pointrings import *
random.seed(1)
```

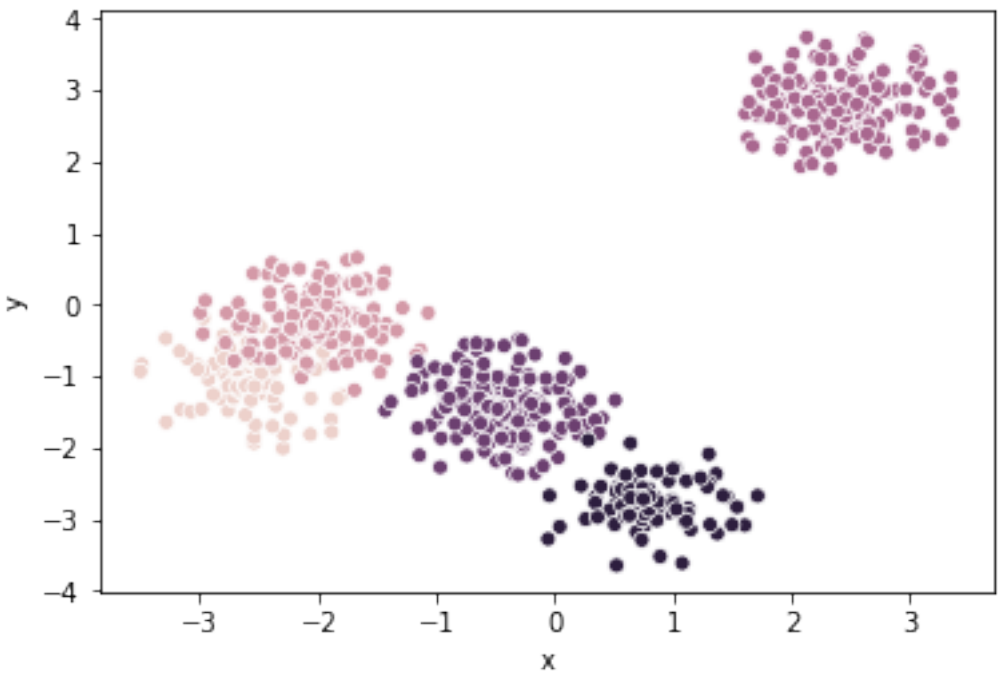
1.1 1

In [2]:
```
# K-Means
#  Separate data points into K clusters with no other information.
# Inputs:
#  X - D-by-N matrix of N points in D dimensions.
#  K - Integer number of clusters to detect.
# Outputs:
#  mu - D-by-K matrix with the learned cluster centroids.
#  labels - Length N vector with integer (1, 2, ..., K) class assignments.

import random
import numpy as np

def km(X, K):
    #set first K centroids at random data points
    centroids = X.loc[random.sample(range(0, X.shape[0]), K)]

    #calculate first set of assignments to nearest centroid
    centroid_dist = np.empty((X.shape[0], K))
    for i in range(0, K):
        dist_from_i_centroid = np.sqrt(np.sum((X.loc[:,("x", "y")] - centroids.iloc[i]
        centroid_dist[:, i] = dist_from_i_centroid
    X['centroid'] = np.argmin(centroid_dist, axis = 1)
```

```
        #recalculate centroids and reassign until stable
        while True:
            centroids = X.groupby('centroid').agg({'x': 'mean', 'y': 'mean'})
            for i in range(0, K):
                dist_from_i_centroid = np.sqrt(np.sum((X.loc[:,("x", "y")] - centroids.iloc
                centroid_dist[:, i] = dist_from_i_centroid
            X['centroid_new'] = np.argmin(centroid_dist, axis = 1)
            #check if centroid assignments didn't change
            if sum(X['centroid_new'] == X['centroid']) == X.shape[0]:
                break
            X['centroid'] = X['centroid_new']

        mu = centroids
        labels = X['centroid']

        return mu, labels
```

1.2 2

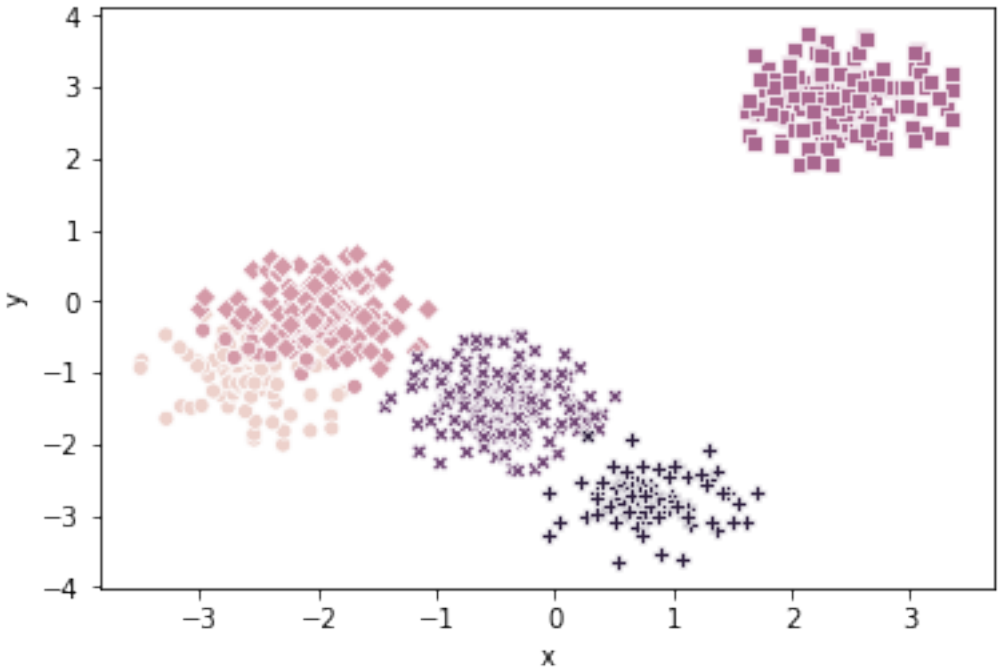
```
In [3]: temp_cloud = pointclouds()
        pc = pd.DataFrame(temp_cloud[0], columns = ("x", "y"))
        pc["cluster"] = temp_cloud[1]

In [4]: sns.scatterplot(x = "x", y = "y", hue = "cluster", data=pc, legend = False)

Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x1a087f8d68>
```



We see the five clusters, colored by the true centroid from which they were generated. We now cluster these with the K-means algorithm below, and plot the same points with shapes indicating which clusters the K-means assigned them to.

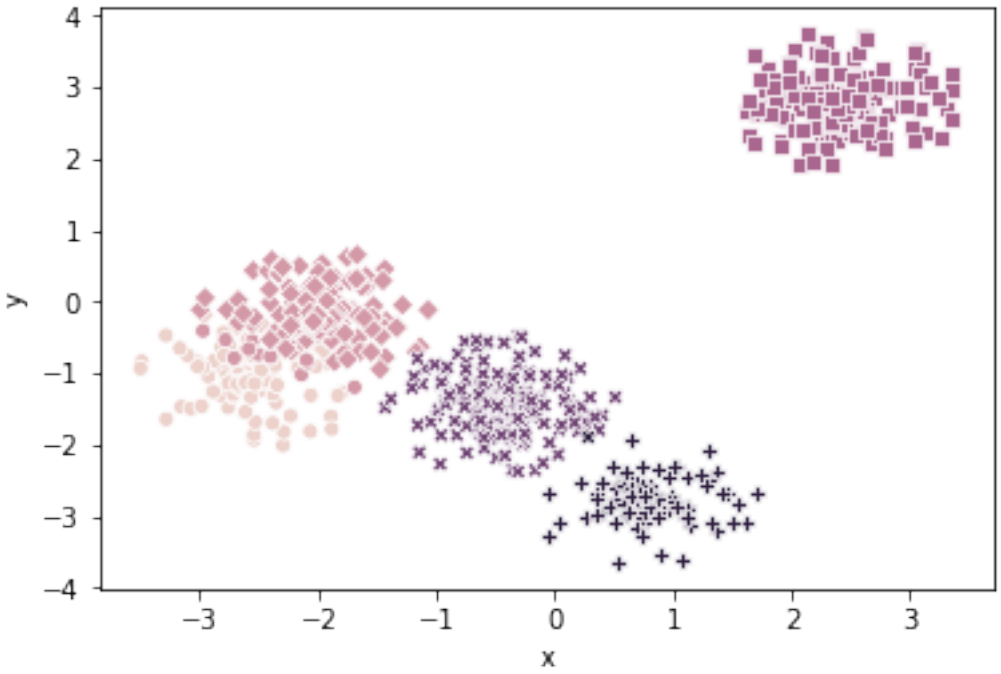
```
In [5]: temp_km = km(pc, 5)
        pc["label"] = temp_km[1]
        sns.scatterplot(x = "x", y = "y", hue = "cluster", style = "label", data=pc, legend = F
```

```
Out[5]: <matplotlib.axes._subplots.AxesSubplot at 0x1a140f8470>
```




```
In [6]: sns.scatterplot(x = "x", y = "y", hue = "cluster", style = "label", data=pc, legend = F
```

```
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x1a14152c18>
```

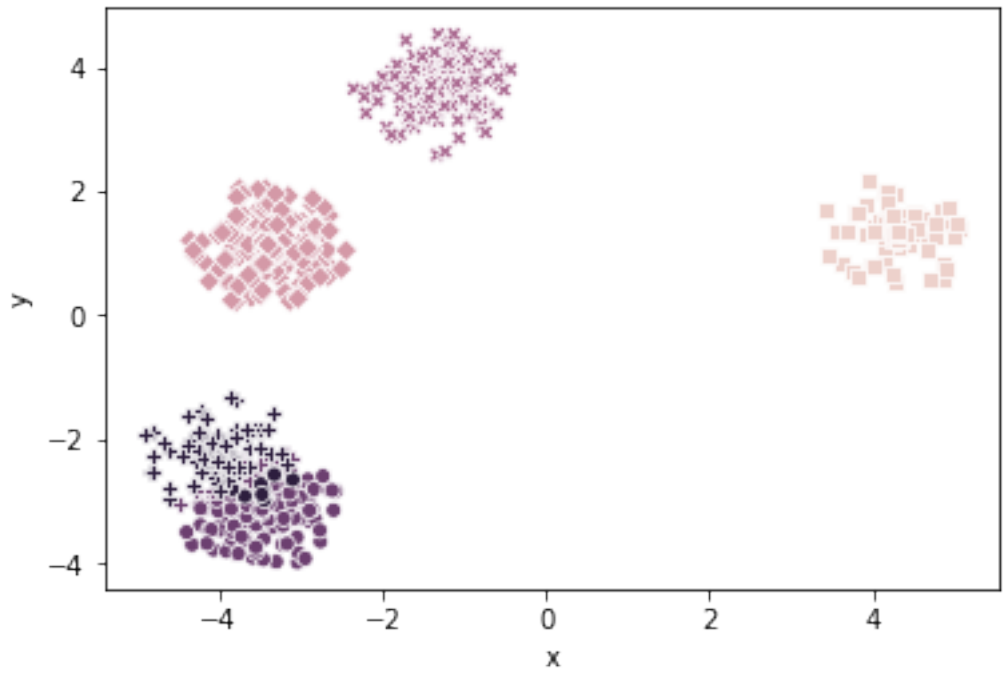


We see that except for where there is some overlap in groups, the k-means perform very well.

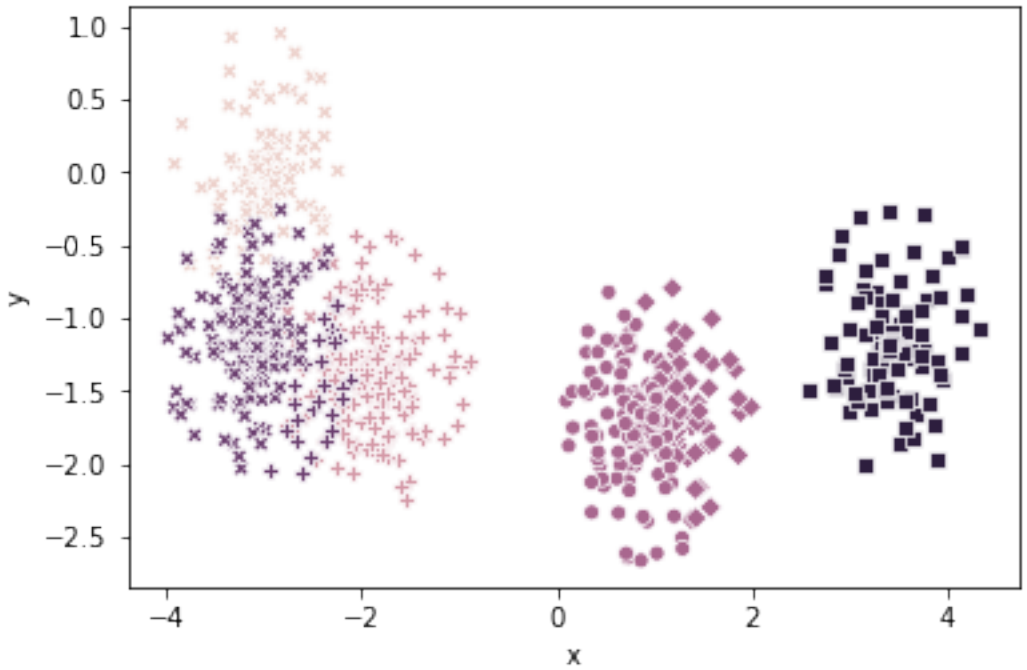
2 3

```
In [7]: def gen_km(dat):
            pc = pd.DataFrame(dat[0], columns = ("x", "y"))
            pc["cluster"] = dat[1]
            temp_km = km(pc, 5)
            pc["label"] = temp_km[1]
            sns.scatterplot(x = "x", y = "y", hue = "cluster", style = "label", data=pc, legend
```

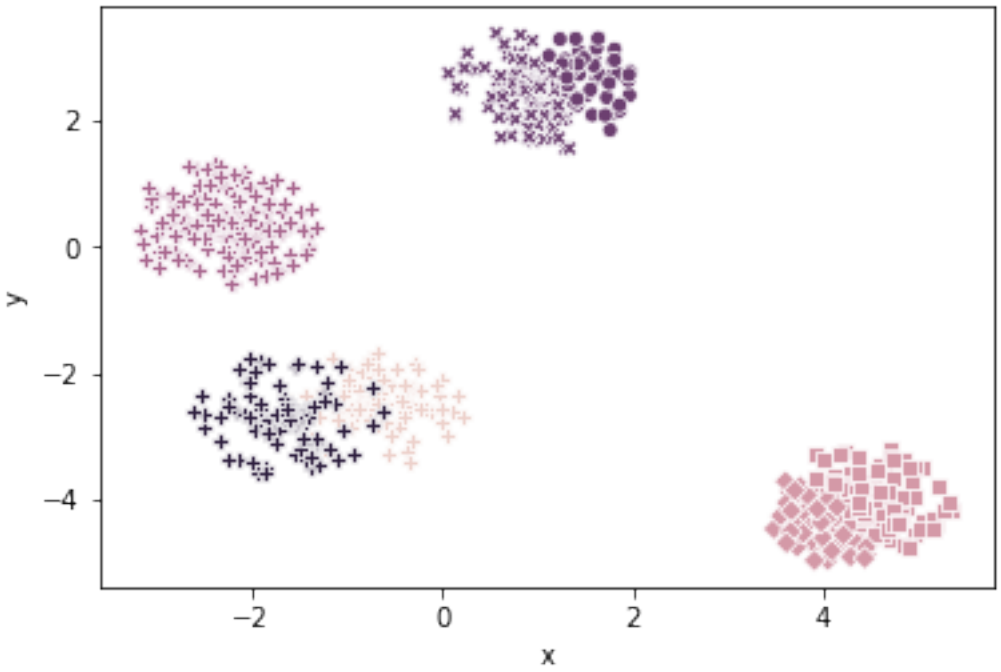
```
In [8]: gen_km(pointclouds())
```



In [9]: `gen_km(pointclouds())`

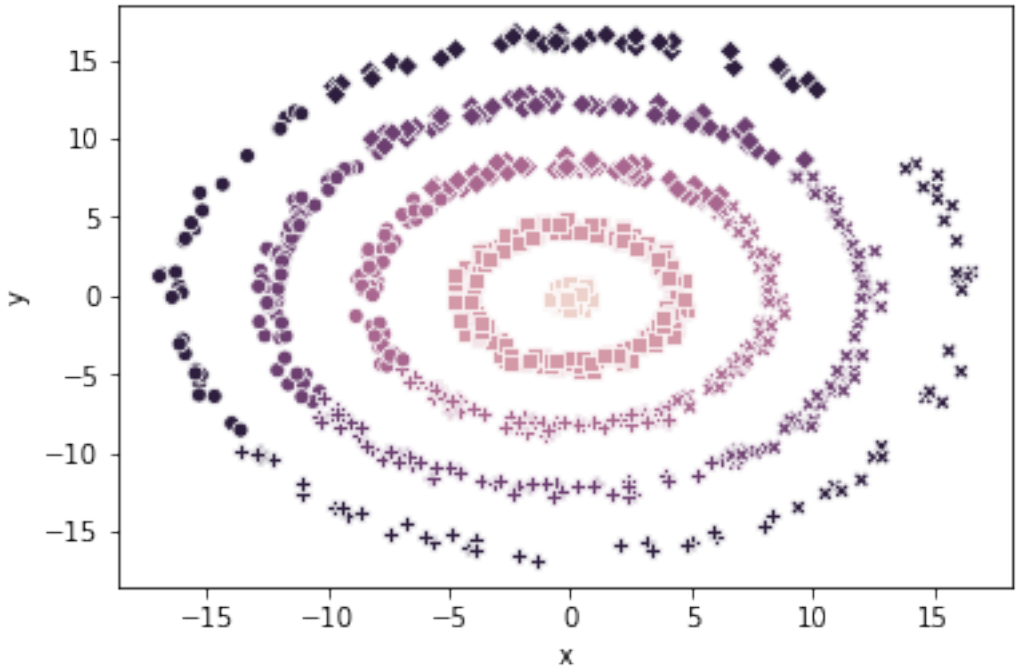


In [10]: gen_km(pointclouds())

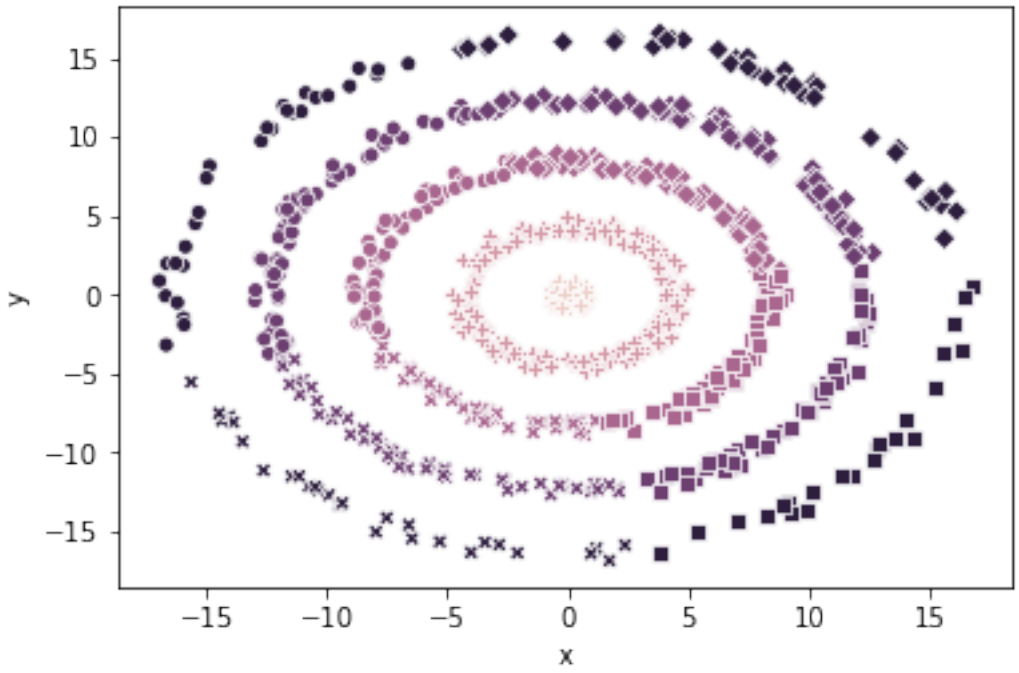


3 4

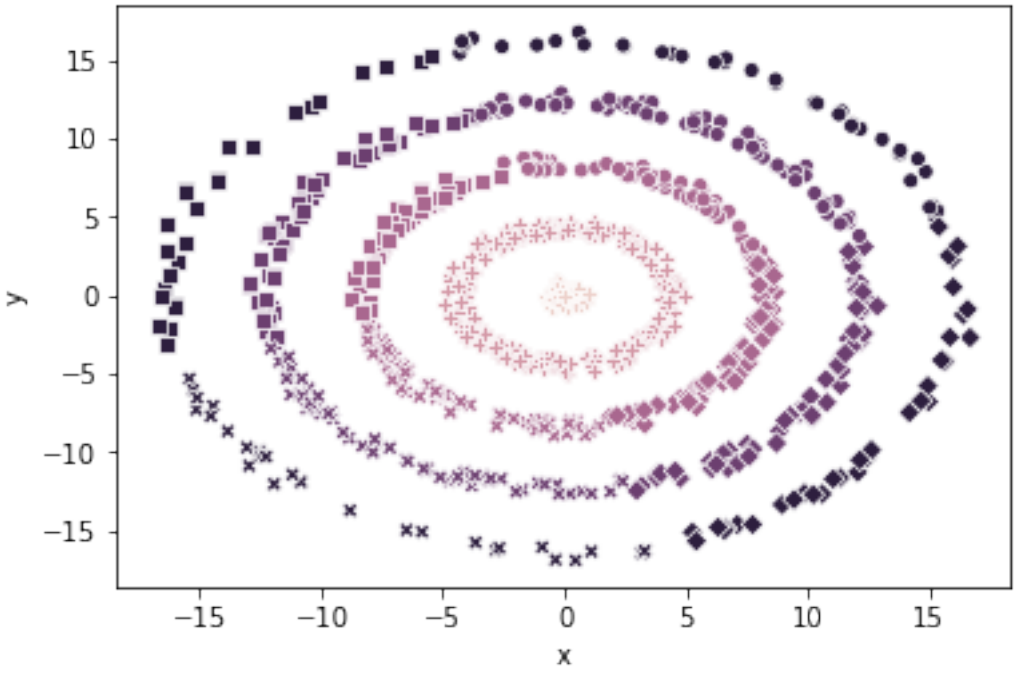
In [11]: gen_km(pointrings())



In [12]: `gen_km(pointrings())`



```
In [13]: gen_km(pointrings())
```



4 5

Clearly the data sets generated from pointclouds are classified much better than the data sets generated from pointrings. This makes sense, as k-means learns centroids, and each of the rings generated from pointrings have identical centroid. Therefore they are not separable according to centroids. If we extended k-means to instead learn distance from centroid, it may perform better on the pointrings data set.

5 6

```
In [14]: temp_im = im2rgb('mountains_small.png')

In [15]: pc = pd.DataFrame(np.transpose(temp_im[0]), columns = ("x", "y", "z"))

In [16]: # K-Means
         #  Separate data points into K clusters with no other information.
         # Inputs:
         #  X - D-by-N matrix of N points in D dimensions.
         #  K - Integer number of clusters to detect.
         # Outputs:
         #  mu - D-by-K matrix with the learned cluster centroids.
         #  labels - Length N vector with integer (1, 2, ..., K) class assignments.
```

```
import random
import numpy as np

def km_3dim(X, K):
    #set first K centroids at random data points
    centroids = X.loc[random.sample(range(0, X.shape[0]), K)]

    #calculate first set of assignments to nearest centroid
    centroid_dist = np.empty((X.shape[0], K))
    for i in range(0, K):
        dist_from_i_centroid = np.sqrt(np.sum((X.loc[:,("x", "y", "z")] - centroids.il
        centroid_dist[:, i] = dist_from_i_centroid
    X['centroid'] = np.argmin(centroid_dist, axis = 1)

    #recalculate centroids and reassign until stable
    while True:
        centroids = X.groupby('centroid').agg({'x': 'mean', 'y': 'mean', 'z': 'mean'})
        for i in range(0, K):
            dist_from_i_centroid = np.sqrt(np.sum((X.loc[:,("x", "y", "z")] - centroid
            centroid_dist[:, i] = dist_from_i_centroid
        X['centroid_new'] = np.argmin(centroid_dist, axis = 1)
        #check if centroid assignments didn't change
        if sum(X['centroid_new'] == X['centroid']) == X.shape[0]:
            break
        X['centroid'] = X['centroid_new']

    mu = centroids
    labels = X['centroid']

    return mu, labels
```

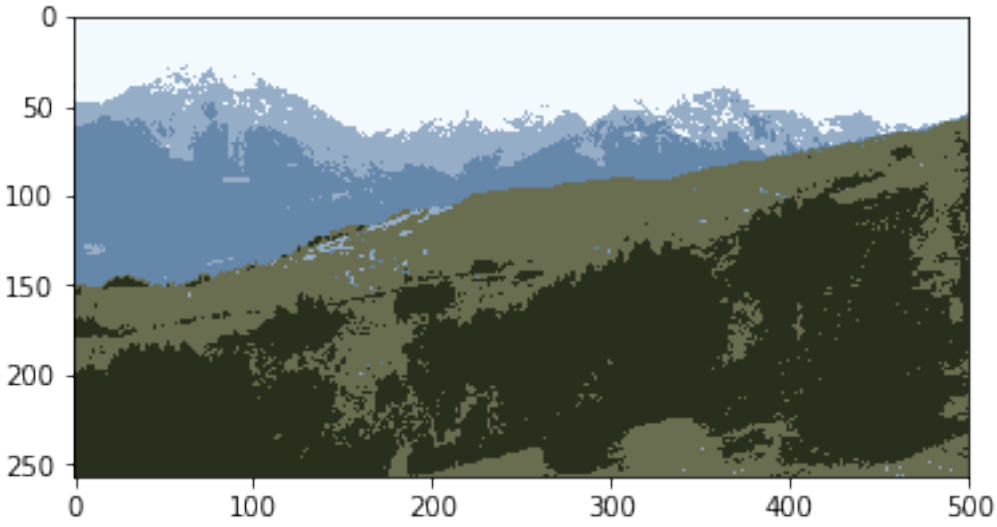
In [17]:
```
im_km = km_3dim(pc, 5)
```

```
/Users/wyattmadden/anaconda3/lib/python3.6/site-packages/ipykernel_launcher.py:20: RuntimeWarni
```

6 7

In [18]:
```
X = im_km[0].loc[im_km[1], ]

dims = temp_im[2]

I = 255.0 * np.reshape(np.array(X), [dims[0], dims[1], 3])

plt.imshow(I)
```

Out[18]:
```
<matplotlib.image.AxesImage at 0x1a14910c50>
```



Not bad!

7 Extra