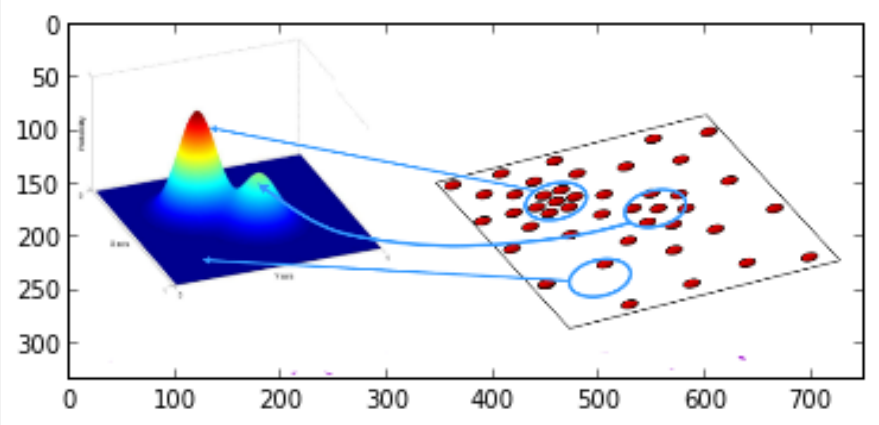
Ortalama Kaydirma ile Kumeleme (Mean Shift Clustering)

Kumeleme yapmak icin bir metot daha: Ortalama Kaydirma metotu. Bu metodun mesela K-Means'den farki kume sayisinin onceden belirtilmeye ihtiyaci ol**ma**masidir, kume sayisi otomatik olarak metot tarafindan saptanir.

"Kume" olarak saptanan aslinda veri icindeki tum yogunluk bolgelerinin merkezleridir, yani alttaki resmin sag kismindaki bolgeler.

```
im=imread("dist.png"); imshow(im)
```

```
<matplotlib.image.AxesImage at 0xa3f3c4c>
```



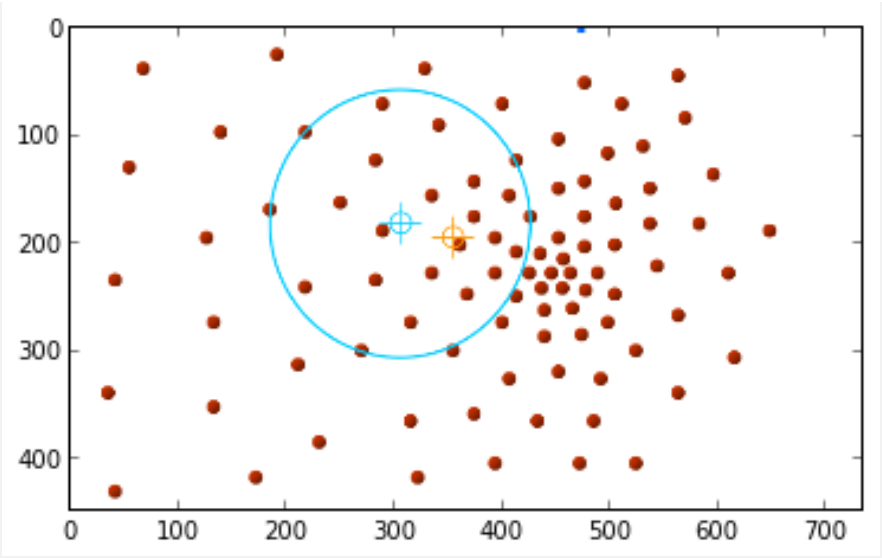
Baslangic neresidir? Baslangic tum noktalardir, yani her noktadan baslanarak

1. O nokta etrafinda (yeterince buyuk) bir pencere tanimla
2. Bu pencere icine dusen tum noktalari hesaba katarak bir ortalama yer hesapla
3. Pencereyi yeni ortalama noktayi merkezine alacak sekilde kaydir

Metotun ismi buradan geliyor, cunku pencere yeni ortalamaya dogru "kaydiriliyor". Altta bir noktadan baslanarak yapilan hareketi goruyoruz. Kaymanin saga dogru olmasi mantikli cunku tek pencere icinden bakinca bile yogunlugun "sag tarafa dogru" oldugu gorulmekte. Yontemin puf noktasi burada.

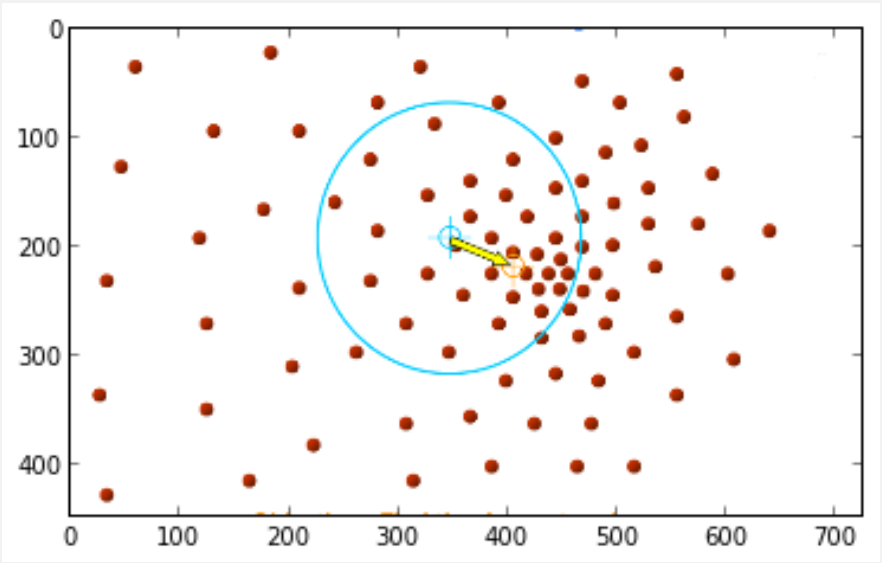
```
im=imread("mean_2.png"); imshow(im)
```

```
<matplotlib.image.AxesImage at 0x9b966ac>
```



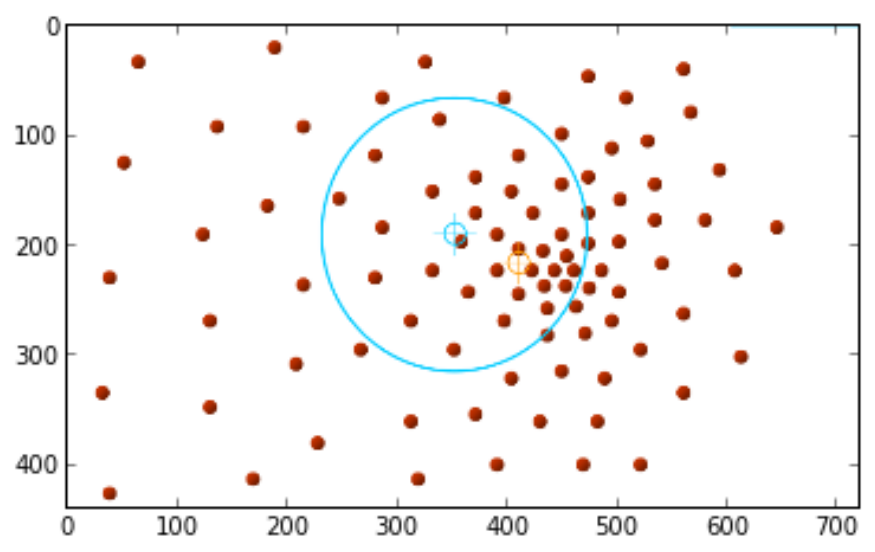

```
im=imread("mean_3.png"); imshow(im)
```

```
<matplotlib.image.AxesImage at 0x9cd99ec>
```



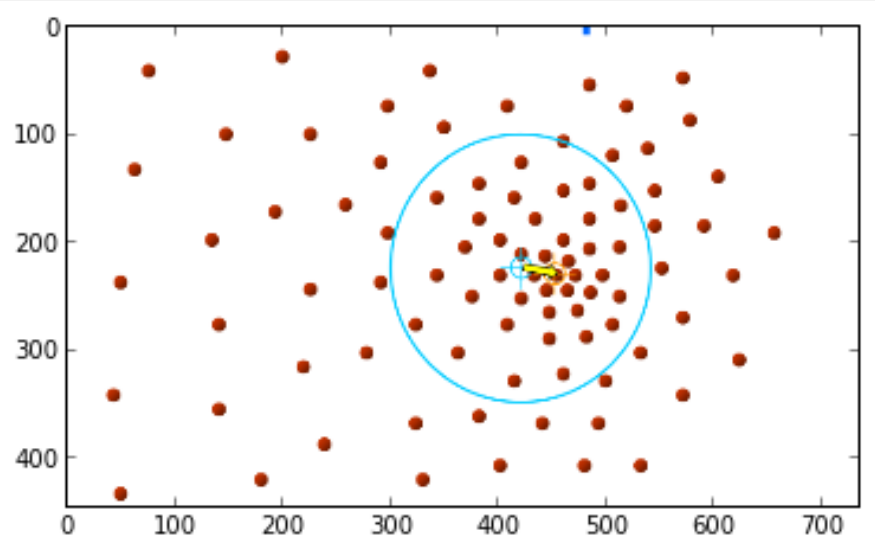

```
im=imread("mean_4.png"); imshow(im)
```

```
<matplotlib.image.AxesImage at 0x9e3cfac>
```



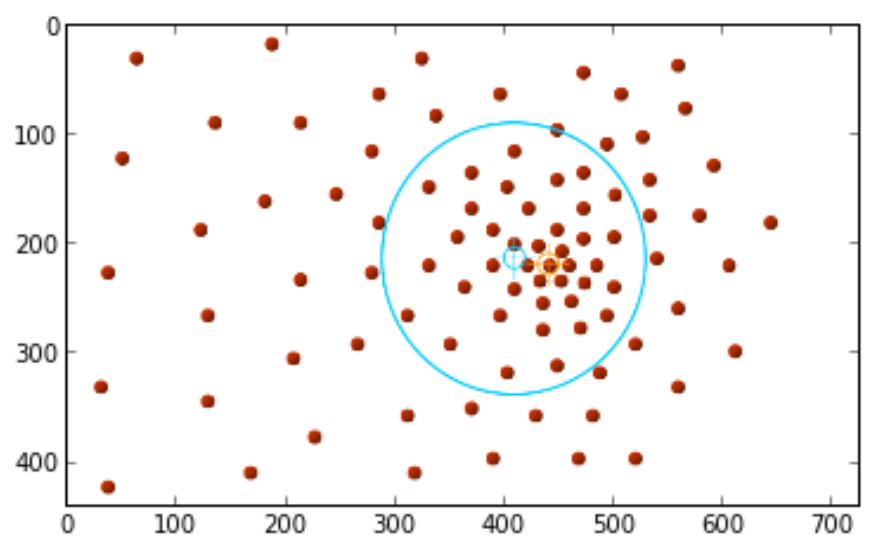

```
im=imread("mean_5.png"); imshow(im)
```

```
<matplotlib.image.AxesImage at 0x9f9b5ec>
```



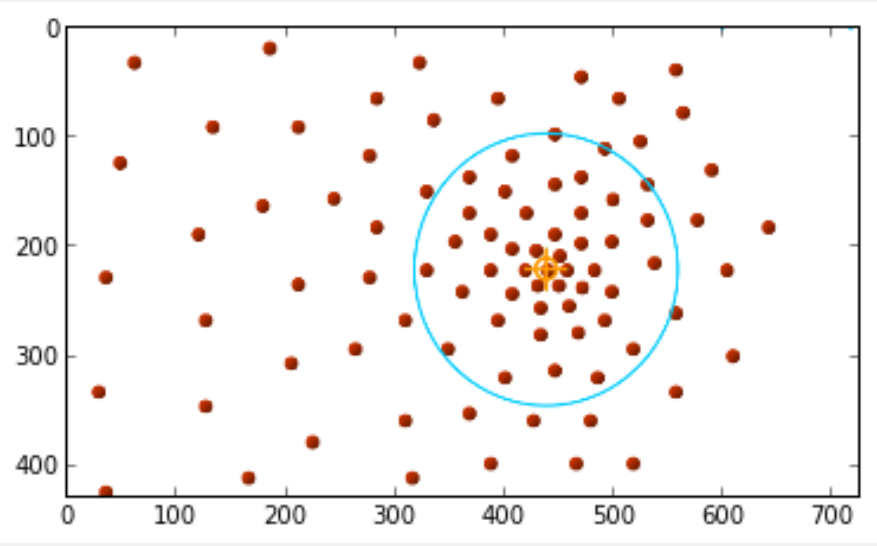

```
im=imread("mean_6.png"); imshow(im)
```

```
<matplotlib.image.AxesImage at 0xa13cd0c>
```




```
im=imread("mean_7.png"); imshow(im)
```

```
<matplotlib.image.AxesImage at 0xa2a132c>
```



Eger yogunluk merkezine cok yakin bir noktadan / noktalardan baslamissak ne olur?

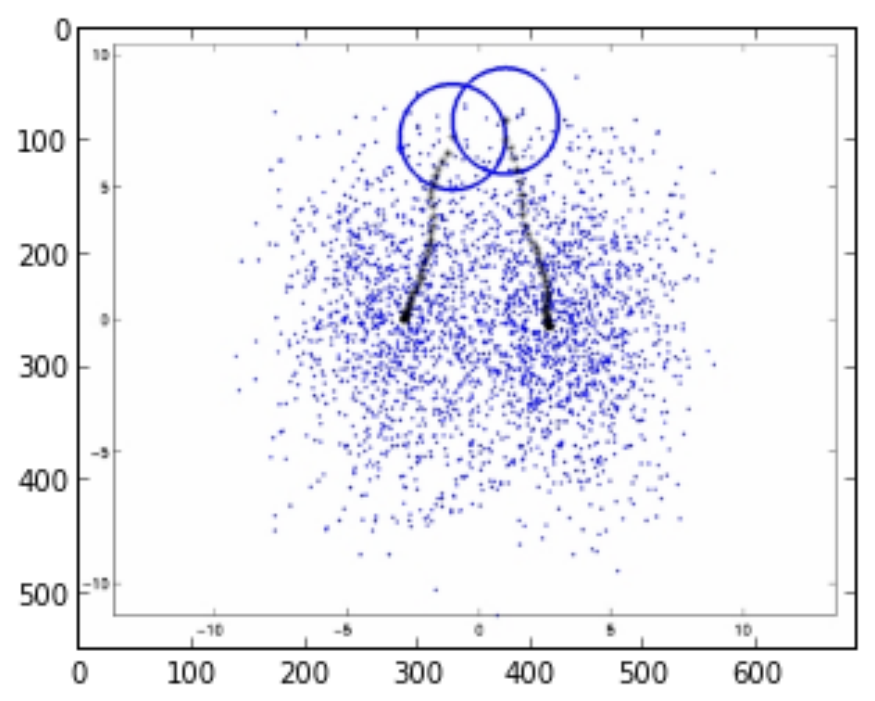
O zaman ilerleme o baslangic noktasi icin aninda bitecek, cunku hemen yogunluk merkezine gelmis olacagiz. Diger yonlerden gelen pencereler de ayni yere gelecekler tabii, o zaman ayni / yakin yogunluk merkezlerini ayni kume olarak kabul etmemiz gerekir. Bu "ayni kume irdelemesi" sayisal hesaplama acisindan ufak farklar gosterebilir tabii, ve bu ufak farki gozonune alarak "kume birlestirme" mantigini da eklemek gerekiyor.

Ortalama Kaydirma sisteminde pencere buyuklugu kullanici tarafindan tanimlanir. Optimal

pencere buyuklugunu nasil buluruz? Deneme yanilma yontemi, verinin tarifsel istatistiklerine kestirme bir hesap (estimate) etmek, ya da kullanicinin ayni istatistiklere bakarak tahminde bulunmasi. Birkac farkli pencere buyuklugu de denenebilir. Bu konu literaturde (Ing. bandwidth selection) adi atlinda uzun uzadiya tartisilmaktadir. Fakat evet, kullanici tarafindan tanimli bu parametrenin bir anlamda bu metotun bir zayifligi oldugu soylenebilir. KMeans kume sayisini istiyordu, bu metot ta pencere buyuklugunu istiyor. Hangi metotun ne zaman uygun oldugunu anlamak tecrube gerektiriyor.

```
im=imread("start.png"); imshow(im)
```

```
<matplotlib.image.AxesImage at 0x9af0f2c>
```



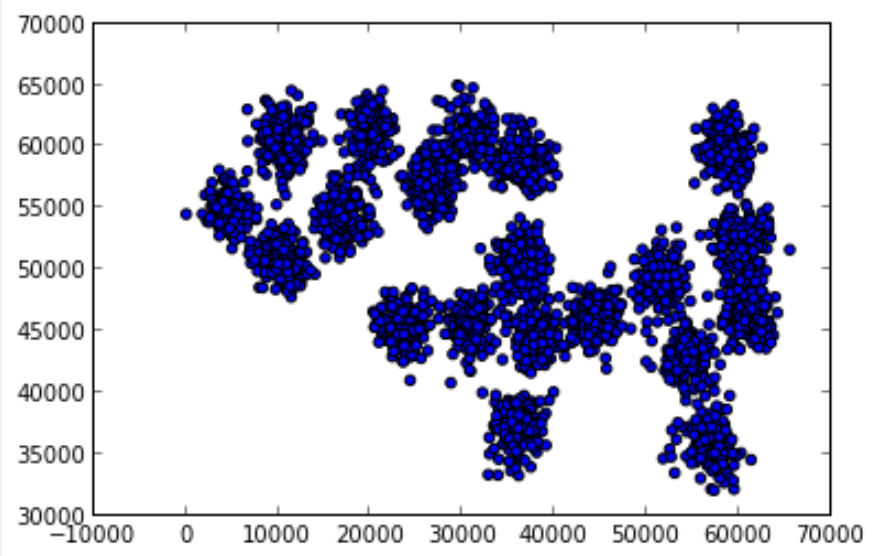
Altta ornek veri ve kodu bulabilirsiniz (kod scikit-learn adli kutuphaneden alinmistir). Metot kume sayisi 17'yi otomatik olarak buluyor. Alternatif bir kod meanshift_alternative.py dosyasinda bulunabilir.

```
from pandas import *
data = read_csv("synthetic.txt",header=None,sep=" ")
print data.shape
data = np.array(data)
```

```
(3000, 2)
```

```
scatter(data[:,0],data[:,1])
```

```
<matplotlib.collections.PathCollection at 0xa0b7e0c>
```




```
import numpy as np
from sklearn.neighbors import NearestNeighbors
from sklearn.utils import extmath

def mean_shift(X, bandwidth=None, max_iterations=300):

    seeds = X
    n_samples, n_features = X.shape
    stop_thresh = 1e-3 * bandwidth # when mean has converged
    center_intensity_dict = {}
    nbrs = NearestNeighbors(radius=bandwidth).fit(X)

    # For each seed, climb gradient until convergence or max_iterations
    for my_mean in seeds:
        completed_iterations = 0
        while True:
            # Find mean of points within bandwidth
            i_nbrs = nbrs.radius_neighbors([my_mean], bandwidth,
                                           return_distance=False)[0]
            points_within = X[i_nbrs]
            if len(points_within) == 0:
                break # Depending on seeding strategy this condition may occur
            my_old_mean = my_mean # save the old mean
            my_mean = np.mean(points_within, axis=0)
            # If converged or at max_iterations, addS the cluster
            if (extmath.norm(my_mean - my_old_mean) < stop_thresh or
                   completed_iterations == max_iterations):
```

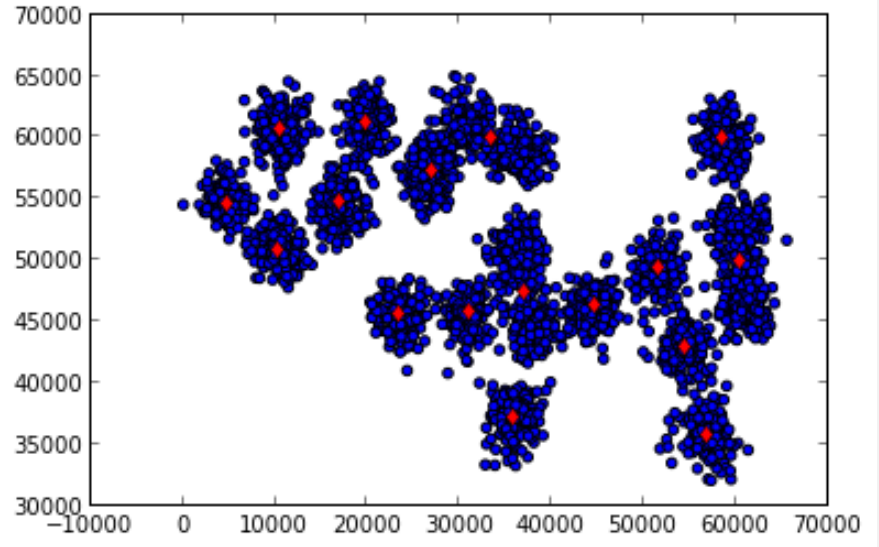
```
                center_intensity_dict[tuple(my_mean)] = len(points_within)
                break
            completed_iterations += 1

    # POST PROCESSING: remove near duplicate points
    # If the distance between two kernels is less than the bandwidth,
    # then we have to remove one because it is a duplicate. Remove the
    # one with fewer points.
    sorted_by_intensity = sorted(center_intensity_dict.items(),
                                 key=lambda tup: tup[1], reverse=True)
    sorted_centers = np.array([tup[0] for tup in sorted_by_intensity])
    unique = np.ones(len(sorted_centers), dtype=np.bool)
    nbrs = NearestNeighbors(radius=bandwidth).fit(sorted_centers)
    for i, center in enumerate(sorted_centers):
        if unique[i]:
            neighbor_idxs = nbrs.radius_neighbors([center],
                                                  return_distance=False)[0]
            unique[neighbor_idxs] = 0
            unique[i] = 1 # leave the current point as unique
    cluster_centers = sorted_centers[unique]

    # ASSIGN LABELS: a point belongs to the cluster that it is closest to
    nbrs = NearestNeighbors(n_neighbors=1).fit(cluster_centers)
    labels = np.zeros(n_samples, dtype=np.int)
    distances, idxs = nbrs.kneighbors(X)
    labels = idxs.flatten()

    return cluster_centers, labels
```

```
cluster_centers, labels = mean_shift(np.array(data), 4000)
```

```
print len(cluster_centers)
```

```
17
```

```
scatter(data[:,0],data[:,1])
plt.hold(True)
for x in asarray(cluster_centers): plot(x[0],x[1],'rd')
```



Teorik Konular

Bu metotu teorik bir yapiya oturtmak icin onu yazinin ilk basindaki resimde oldugu gibi gormek gerekiyor, yani mesela o ilk resmin sagindaki 2 boyuttaki veri dagilimi (ki ayriksal, sayisal), 3 boyuttaki surekli (continuous) bir baska dagilimin yansimasi sanki, ki o zaman 2 boyuttaki yogunluk bolgeleri surekli dagilimdaki tepe noktalarini temsil ediyorlar, ve biz o surekli versiyondaki tepe noktalarini bulmaliyiz. Fakat kumeleme isleminin elinde sadece 2 boyuttaki veriler var, o zaman surekli dagilimi bir sekilde yaratmak lazim.

Bunu yapmak icin problem / veri once bir Cekirdek Yogunluk Kestirimi (Kernel Density Estimation -KDE-) problemi gibi goruluyor, ki her nokta uzerine bir cekirdek fonksiyonu koyularak ve onlarin toplamim alinarak sayisal dagilim puruzsuz bir hale getiriliyor. Ortalama Kaydirma icin gerekli kayma "yonu" ise iste bu yeni surekli fonksiyonun gradyanidir deniyor, ve gradyan yerel tepe noktasini gosterdigi icin o yone yapilan hareket bizi yavas yavas tepeye goturecektir. Bu hareketin yerel tepeleri bulacagi, ve tum yontemin nihai olarak sonuca yaklasacagi (convergence) matematiksel olarak ispat edilebilir.

Tum dagilim fonksiyonunun icbukey olup olmadigi onemli degil (ki mesela lojistik regresyonda bu onemliydi), cunku nihai tepe noktasini degil, birkac yerel tepe noktasindan birini (hatta hepsini) bulmakla ilgileniyoruz. Gradyan bizi bu noktaya tasiyacaktir.

Kaynaklar

http://www.serc.iisc.ernet.in/∼venky/SE263/slides/Mean-Shift-Theory.pdf

http://saravananthirumuruganathan.wordpress.com/2010/04/01/introduction-to-mean-shift-algorithm/

http://www.cse.yorku.ca/∼kosta/CompVis_Notes/mean_shift.pdf

http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/TUZEL1/MeanShift.pdf

Scikit-Learn Kodlari

http://yotamgingold.com/code/MeanShiftCluster.py