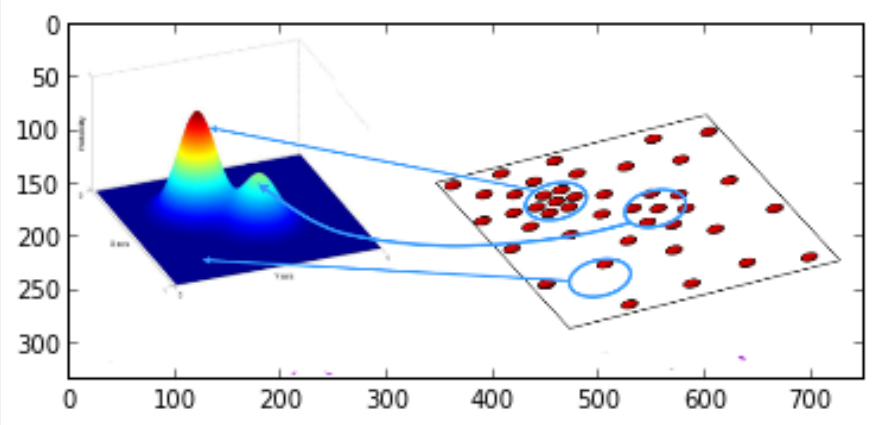
Ortalama Kaydirma ile Kumeleme (Mean Shift Clustering)

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>
```



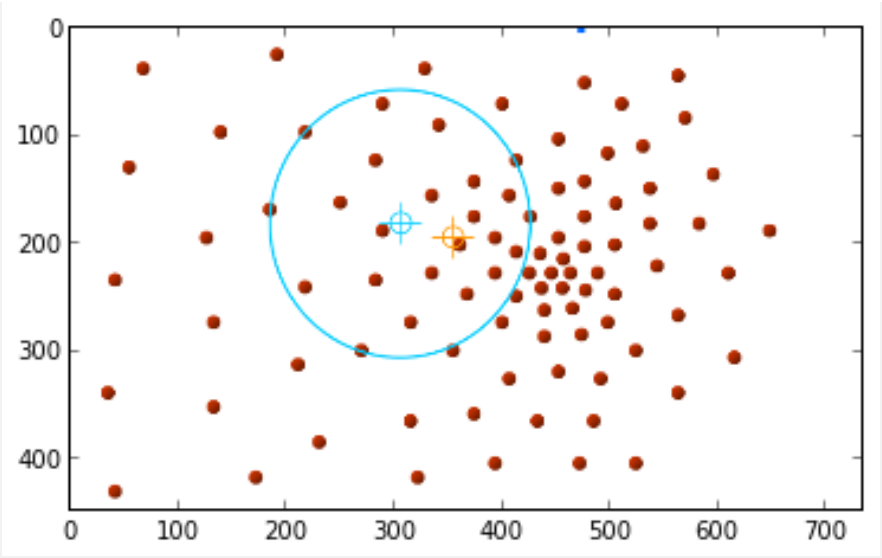
Baslangic neresidir? Baslangic tum noktalardir, yani her noktadan baslanarak

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.

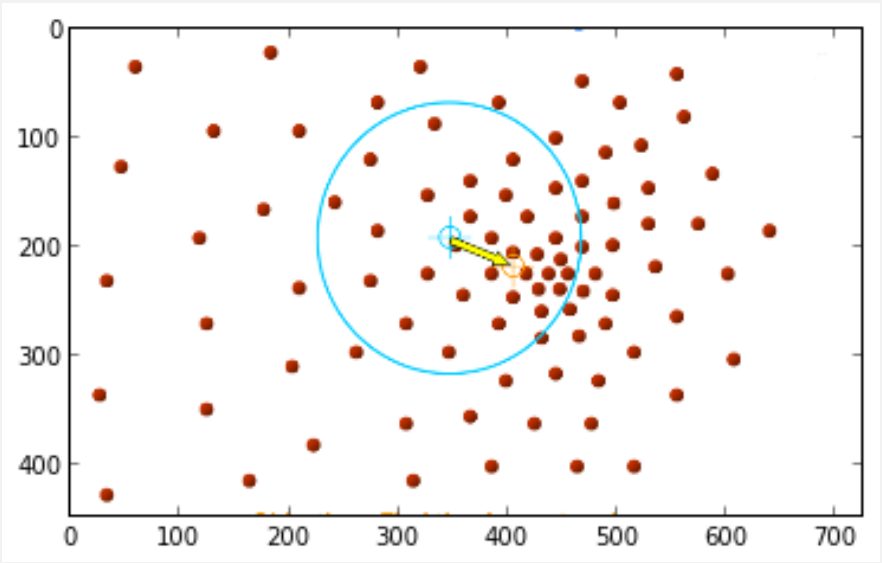
```
im=imread("mean_2.png"); imshow(im)
```

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



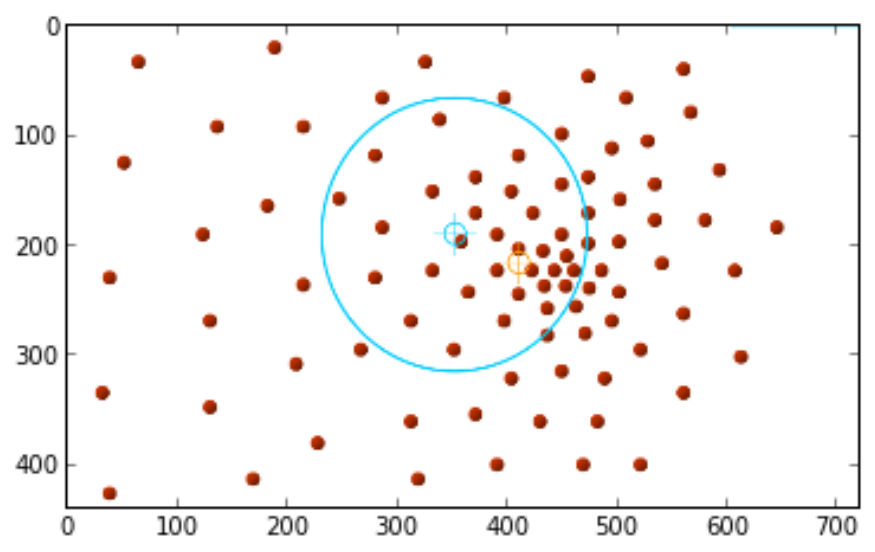

```
im=imread("mean_3.png"); imshow(im)
```

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



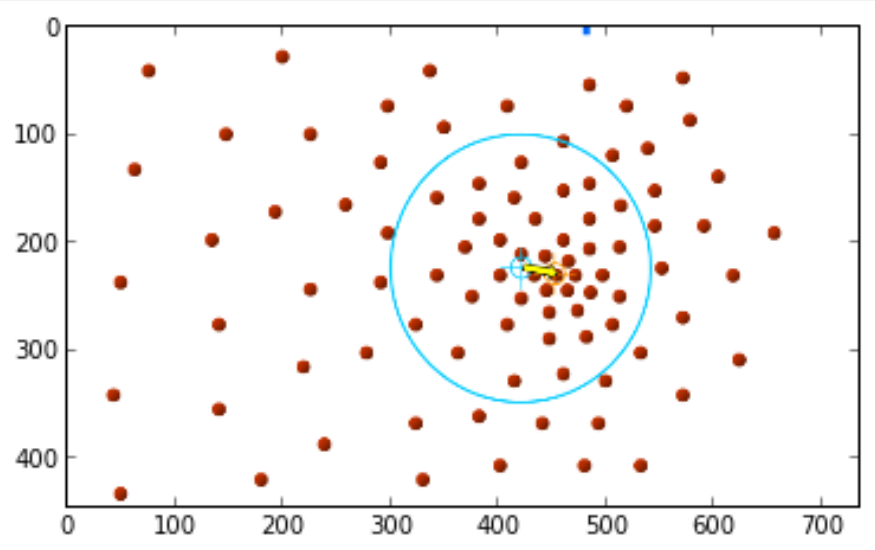

```
im=imread("mean_4.png"); imshow(im)
```

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



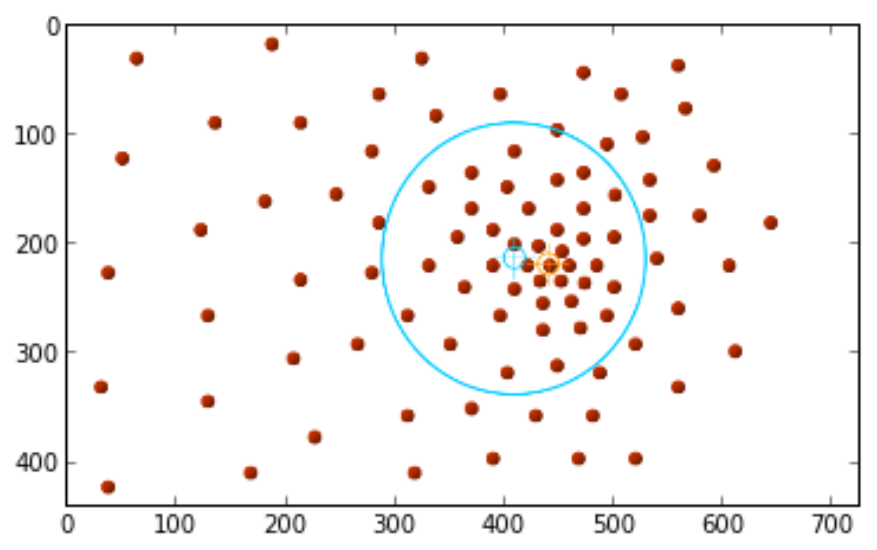

```
im=imread("mean_5.png"); imshow(im)
```

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



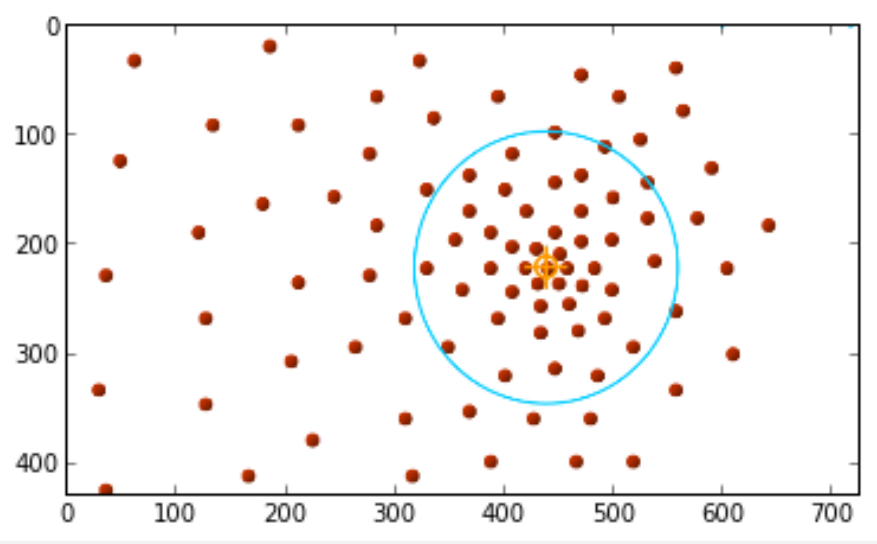

```
im=imread("mean_6.png"); imshow(im)
```

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




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

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



Fakat metodu anlatan kaynaklarda pek bahsedilmeyen bir konu var, o da pencere icindeki diger noktalarin kume aidiyeti ve pencere ilerlerken o pencerenin altinda olan ve olmus tum noktalarin "bakilmis" yani "islenmis" olarak addedilmesi ve bir daha ele alinmamasi. Mesela alttaki resimde sol ust kisimdaki herhangi bir noktadan baslamissak, o bolgedeki diger noktalar da herhalde benzer pencerelerin altina dusecekler, ve yavas yavas, yeni ortalamalar sayesinde o pencereyi asagi dogru itecekler, ve soldaki yogunluk merkezini bulacagiz. Ayni sey sag tarafa da olacak. O sebeple pencere altina dusen nokta artik ayri bir sekilde baslangic olarak islenmiyor.

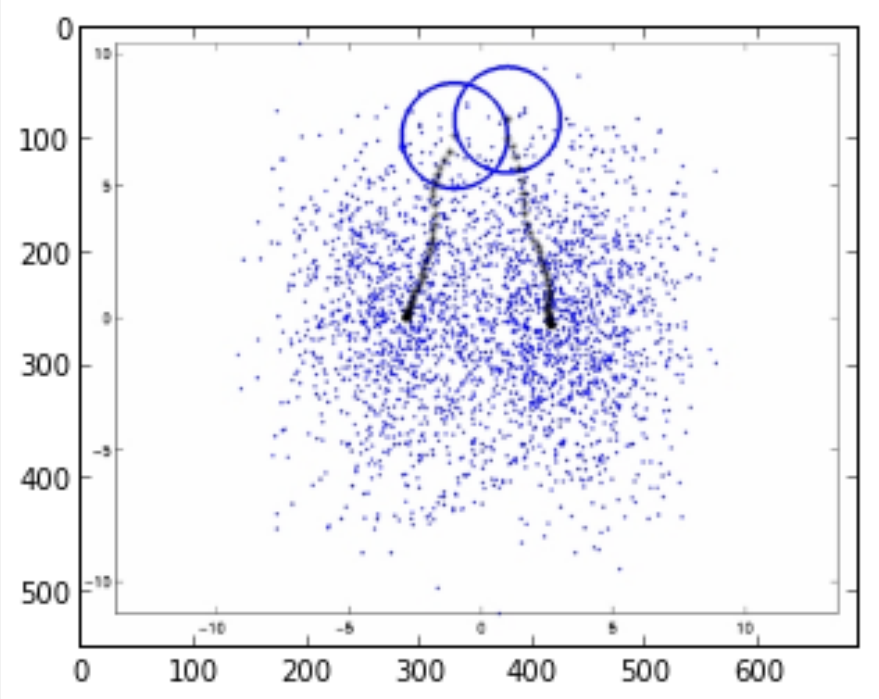
Bir diger konu: ya yogunluk merkezine cok yakin bir noktadan / noktalardan baslamissak?

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. Fakat bu secimin cok "hassas" bir ayar olmadigini gorduk (ki bu iyi bir sey), yani pencere buyuklugunde yapilan ufak degisimlerin bulunan kume sayisi, ve kalitesinde buyuk degisimler yaratmiyor.

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

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



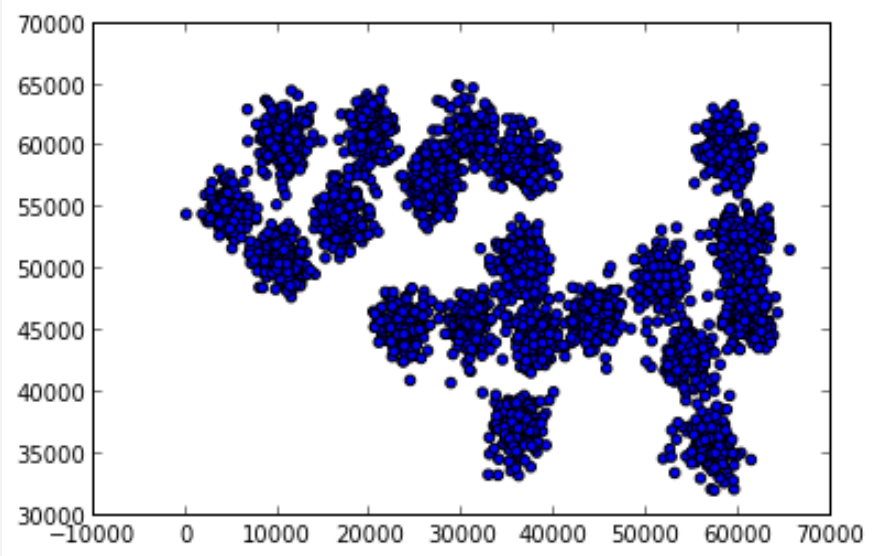
Altta ornek veri ve kodu bulabilirsiniz. Metot kume sayisi 17'yi otomatik olarak buluyor.

```
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 0x9fb632c>
```




```
from numpy import *
from numpy import linalg as la

def mean_shift(dataPts, bandWidth):
    dataPts = asarray( dataPts )
    bandWidth = float( bandWidth )
    plotFlag = False

    numDim, numPts = dataPts.shape
    numClust = 0
    bandSq = bandWidth**2
    initPtInds = arange( numPts )
    #biggest size in each dimension
    maxPos = dataPts.max(0)
    #smallest size in each dimension
    minPos = dataPts.min(0)
    #bounding box size
    boundBox = maxPos-minPos
    #indicator of size of data space
    sizeSpace = la.norm(boundBox)
    #when mean has converged
    stopThresh = 1e-3*bandWidth
    #center of clust
    clustCent = []
    #track if a points been seen already
    beenVisitedFlag = zeros( numPts, dtype = uint8 )
    #number of points to possibly use as initilization points
```

```
    numInitPts = numPts
    #used to resolve conflicts on cluster membership
    clusterVotes = []

    while numInitPts:

        rand = random.rand()
        #pick a random seed point
        tempInd = int(floor( (numInitPts-1e-6)*rand ))
        #use this point as start of mean
        stInd = initPtInds[ tempInd ]
        # intilize mean to this points location
        myMean = dataPts[ :, stInd ]
        # points that will get added to this cluster
        myMembers = []
        #used to resolve conflicts on cluster membership
        thisClusterVotes = zeros( numPts, dtype = uint16 )

        while True:
            #dist squared from mean to all points still active
            sqDistToAll = (( myMean[:,newaxis] - dataPts )**2).sum(0)
            #points within bandWidth
            inInds = where(sqDistToAll < bandSq)
            #add a vote for all the in points belonging to this cluster
            thisClusterVotes[ inInds ] = thisClusterVotes[ inInds ]+1

            #save the old mean
            myOldMean = myMean
            #compute the new mean
            myMean = mean( dataPts[ :, inInds[0] ], 1 )
            #add any point within bandWidth to the cluster
            myMembers.extend( inInds[0] )
            #mark that these points have been visited
            beenVisitedFlag[myMembers] = 1

            if la.norm(myMean-myOldMean) < stopThresh:
                #check for merge posibilities
                mergeWith = None
                for cN in xrange( numClust ):
                    #distance from possible new clust max to old clust max
                    distToOther = la.norm( myMean - clustCent[ cN ] )
                    #if its within bandwidth/2 merge new and old
                    if distToOther < bandWidth/2:
                        mergeWith = cN
                        break

                # something to merge
                if mergeWith is not None:
                    #record the max as the mean of the two merged (I know biased twoards
                        new ones)
                    clustCent[ mergeWith ] = 0.5*( myMean + clustCent[ mergeWith ] )
```

```
                    #add these votes to the merged cluster
                    clusterVotes[ mergeWith ] += thisClusterVotes
                else:
                    #increment clusters
                    numClust = numClust+1
                    #record the mean
                    clustCent.append( myMean )
                    clusterVotes.append( thisClusterVotes )

                break

        initPtInds = where(beenVisitedFlag == 0)[0]
        numInitPts = len(initPtInds)

    data2cluster = asarray( clusterVotes ).argmax(0)

    return clustCent, data2cluster
```

```
dataPts = asarray([[1,1],[2,2],[3,3],[9,9],[9,9],[9,9],[10,10]]).T
print dataPts
print dataPts.shape
bandwidth = 2
print 'data points:', dataPts
print 'bandwidth:', bandwidth
clustCent, data2cluster = mean_shift(dataPts, 2)
print 'cluster centers:', sorted( asarray( clustCent ).squeeze().tolist() )
print 'data2cluster:', data2cluster
print len( clustCent )
print sorted( asarray( clustCent ).squeeze().tolist() )
```

```
[[ 1  2  3  9  9  9 10]
 [ 1  2  3  9  9  9 10]]
(2, 7)
data points: [[ 1  2  3  9  9  9 10]
 [ 1  2  3  9  9  9 10]]
bandwidth: 2
cluster centers: [[2.0, 2.0], [9.25, 9.25]]
data2cluster: [1 1 1 0 0 0 0]
2
[[2.0, 2.0], [9.25, 9.25]]
```

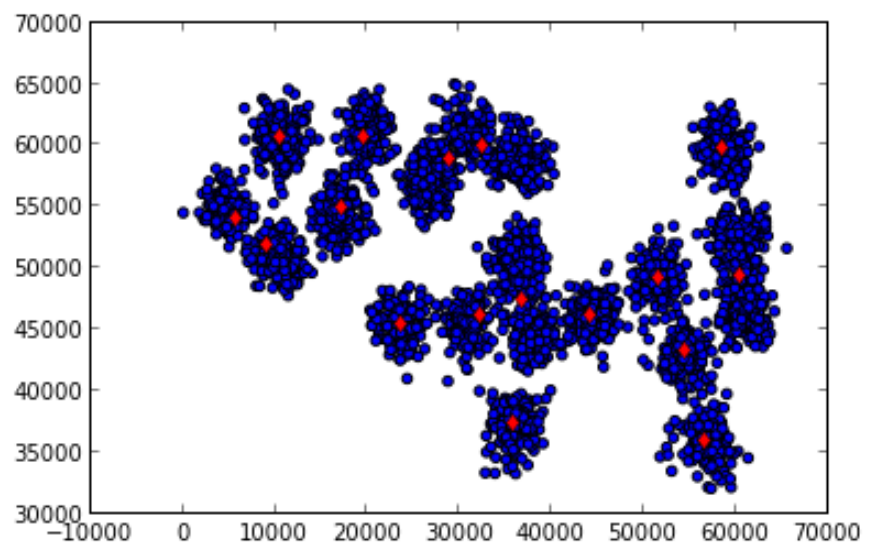
```
print asarray(data.T)[:30]
clustCent, data2cluster = mean_shift(asarray(data.T), 5000)
```

```
[[54620 52694 53253 ...,  8828  8879 10002]
 [43523 42750 43024 ..., 59102 59244 61399]]
```

```
print asarray(clustCent)[:6]
print asarray(clustCent).shape
```

```
[[ 23699.95483871  45459.8       ]
 [ 51577.72222222  49152.9691358 ]
 [ 36875.68540055  47307.43779413]
 [ 10569.30463576  60602.27152318]
 [ 19721.95906433  60651.1871345 ]
 [ 32502.45283019  59820.74339623]]
(17, 2)
```

```
scatter(data[:,0],data[:,1])
plt.hold(True)
for x in asarray(clustCent): 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

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