# Practical 7: Data Stream Mining (cont) - solved

### I. Evaluation of data stream clustering

Internal evaluation measures:

- "average.between" Average distance between clusters
- "average.within" Average distance within clusters
- "max.diameter" Maximum cluster diameter
- "entropy" entropy of the distribution of cluster memberships

#### External evaluation measures:

- "precision" and "recall":
  - Precision=TP/(TP+FP)
  - Recall=TP/(TP+FN)
- "purity": Average purity of clusters. The purity of each cluster is the proportion of the points of the majority true group assigned to it.
- "Euclidean": Euclidean dissimilarity of the memberships

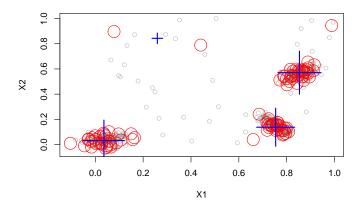
See the stream package for more measures

```
library("stream")
stream <- DSD_Gaussians(k = 3, d = 2, noise = .05)</pre>
```

1. Use Reservoir sampling to generate 100 data points and use K-means to generate 4 clusters.

```
Reservoir_Kmeans =
  DSC_TwoStage(micro = DSC_Sample(k = 100), macro = DSC_Kmeans(k = 4))
update(Reservoir_Kmeans, stream, n=500)
Reservoir_Kmeans
```

```
## Reservoir sampling + k-Means (weighted)
## Class: DSC_TwoStage, DSC_Macro, DSC
## Number of micro-clusters: 100
## Number of macro-clusters: 4
```



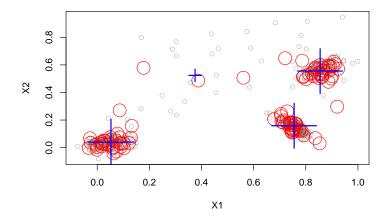
```
## Evaluation results for macro-clusters.
## Points were assigned to micro-clusters.
##
## average.between precision recall
## 0.7095732 0.9450260 0.9965974
## attr(,"type")
## [1] "macro"
## attr(,"assign")
## [1] "micro"
```

2. Use sliding window method rather than Reservoir sampling in the above example. Compare the precision and recall of the two methods.

 $Hint: Window\_Kmeans = DSC\_TwoStage(micro = DSC\_Window(horizon = 100), macro = DSC\_Kmeans(k = 4)).$ 

```
Window_Kmeans = DSC_TwoStage(micro = DSC_Window(horizon = 100)
, macro = DSC_Kmeans(k = 4))
update(Window_Kmeans, stream, n=500)
Window_Kmeans
```

```
## Sliding window + k-Means (weighted)
## Class: DSC_TwoStage, DSC_Macro, DSC
## Number of micro-clusters: 100
## Number of macro-clusters: 4
```



```
evaluate static(Window Kmeans, stream
,measure = c("average.between"
,"precision","recall")
n = 500
## Evaluation results for macro-clusters.
## Points were assigned to micro-clusters.
##
                                             recall
## average.between
                         precision
##
         0.7144800
                         0.9630804
                                          0.9960112
## attr(,"type")
## [1] "macro"
## attr(,"assign")
## [1] "micro"
```

# **II. Concept Drift**

Concept drift means the changes of the data generating process over time. It implies that the statistical properties of the data also change when time passes. A good data mining algorithm should be able to deal with concept drift. In the stream package, DSD\_Benchmark(1) is an example data stream which contains concept drift. To show the concept drift we request four times 250 data points from the stream and plot them. To fast-forward in the stream we request 1400 points in between the plots and ignore them. The codes below will show 4 figures of the data at different time points.

```
stream <- DSD_Benchmark(1)</pre>
stream
## Benchmark 1: Two clusters moving diagonally from left to right, meeting
## in the center (d = 2, k = 2, 5\% noise).Class: DSD_MG, DSD_R, DSD
## With 3 clusters in 2 dimensions. Time is 1
for(i in 1:4) {
plot(stream, 250, xlim = c(0, 1), ylim = c(0, 1))
tmp <- get_points(stream, n = 1400)</pre>
}
   0.8
                                                  0.8
   9.0
                                                  9.0
   0.4
                                                  0.4
                                                  0.2
   0.2
             0.2
                                  0.8
                                         1.0
                                                     0.0
                                                            0.2
                                                                   0.4
                                                                                 0.8
                                                                                        1.0
      0.0
                    0.4
                           0.6
                                                                          0.6
                        X1
                                                                       X1
   1.0
                                                  0.8
   9.0
                                                  9.0
                                               X
   0.4
                                                  0.4
```

We can use animation package to demonstrate this:

X1

0.6

0.8

1.0

0.4

0.2

0.0

0.2

0.0 0.2

0.0

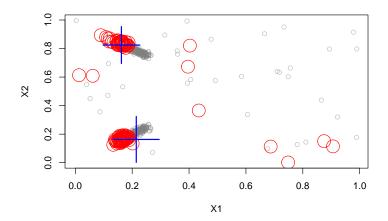
0.2

0.4

X1

## III. Evaluation of data stream clustering with concept drift

1. Using Reservoir sampling and K-means



```
evaluate_stream(Reservoir_Kmeans, stream
, measure = c( "precision", "recall"), n =5000, horizon=100)
```

```
##
      points precision
                          recall
## 1
           0 0.8166259 0.9876787
## 2
         100 0.8506122 0.9928537
## 3
         200 0.8781175 0.9954400
## 4
         300 0.7689487 0.9792423
## 5
         400 0.8482813 0.9930620
         500 0.7690738 0.9782045
## 6
## 7
         600 0.7250608 0.9659643
## 8
         700 0.8335334 0.9904898
## 9
         800 0.8164015 0.9881481
         900 0.8341483 0.9932072
## 10
## 11
        1000 0.8261734 0.9885769
## 12
        1100 0.8000816 0.9849322
## 13
        1200 0.8215686 0.9868111
## 14
        1300 0.7381818 0.9712919
## 15
        1400 0.4264864 0.9880656
```

```
## 16
        1500 0.4397939 0.9912917
## 17
        1600 0.4565357 0.9943899
## 18
        1700 0.4175431 0.9910135
## 19
        1800 0.4697097 0.9973202
## 20
        1900 0.4096063 0.9949925
## 21
        2000 0.4675325 0.9986790
## 22
        2100 0.7979798 0.9909684
## 23
        2200 0.4776610 0.9945280
## 24
        2300 0.4411462 0.9967396
## 25
        2400 0.9022526 0.9973321
## 26
        2500 0.8169988 0.9877089
## 27
        2600 0.8374083 0.9913169
## 28
        2700 0.8020408 0.9859508
## 29
        2800 0.8503457 0.9924063
## 30
        2900 0.8865648 0.9959331
## 31
        3000 0.9216327 0.9982317
## 32
        3100 0.9391408 0.9991536
## 33
        3200 0.8161141 0.9860270
## 34
        3300 0.8316389 0.9912748
## 35
        3400 0.8357664 0.9903892
## 36
        3500 0.8497959 0.9923737
        3600 0.8791517 0.9977293
## 37
## 38
        3700 0.8605028 0.9943768
## 39
        3800 0.8341483 0.9903241
## 40
        3900 0.7984590 0.9859790
## 41
        4000 0.7937574 0.9881948
## 42
        4100 0.8671469 0.9944929
## 43
        4200 0.8357664 0.9903892
## 44
        4300 0.7845777 0.9816233
## 45
        4400 0.9062626 0.9973321
## 46
        4500 0.8479392 0.9929709
## 47
        4600 0.7671068 0.9795606
## 48
        4700 0.8519723 0.9961959
## 49
        4800 0.8464646 0.9943047
## 50
        4900 0.8731192 0.9953639
```

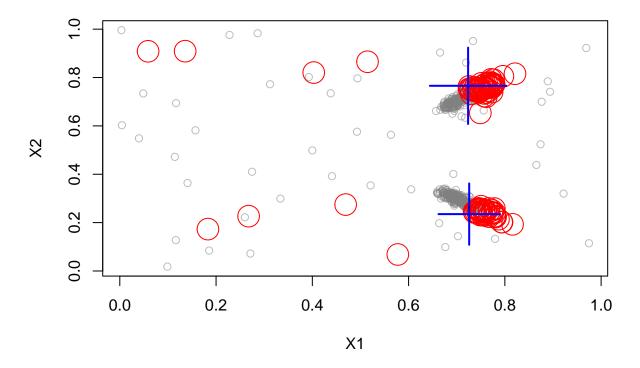
### 2. Evaluate the Sliding window + K-means clustering

```
#2. Sliding window + K-means clustering
Window_Kmeans = DSC_TwoStage(micro = DSC_Sample(k = 100, biased = TRUE)
, macro = DSC_Kmeans(k = 2))
update(Window_Kmeans, stream, n=500)
Window_Kmeans
```

```
## Reservoir sampling (biased) + k-Means (weighted)
```

```
## Class: DSC_TwoStage, DSC_Macro, DSC
## Number of micro-clusters: 100
## Number of macro-clusters: 2
```

### plot(Window\_Kmeans, stream)



```
evaluate_static(Window_Kmeans, stream
, measure = c("precision"
, "recall")
, n =5000, horizon=100)

## Evaluation results for macro-clusters.
## Points were assigned to micro-clusters.
##
## precision recall
## 0.5207447 0.6257415
## attr(,"type")
## [1] "macro"
## attr(,"assign")
## [1] "micro"
```