

Algorithm AS 136: A K-Means Clustering Algorithm<br>Author(s): J. A. Hartigan and M. A. Wong<br>Reviewed work(s):<br>Source: Journal of the Royal Statistical Society. Series C (Applied Statistics), Vol. 28, No. 1 (1979), pp. 100-108<br>Published by: Wiley-Blackwell for the Royal Statistical Society<br>Stable URL: http://www.jstor.org/stable/2346830<br>Accessed: 22/10/2012 06:29

Your use of the JSTOR archive indicates your acceptance of the Terms \& Conditions of Use, available at http://www.jstor.org/page/info/about/policies/terms.jsp

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.

```
C FIND MAXIMUM ENTRY
    60 PIVOT = ACU
    KK=0
            DO 70 I = II, M
            K = INDEX(I)
            IF (ABS(IU\K, II)) .IE. PIVOT) GOTO 7O
            PIVOT = ABS(IUJ(K, II))
            KK = I
        70 CONTINUS
            IF (KK .ER. 0) GOYTO 10
C
            SWITCH ORDER
            ISAVE = INDEX(KK)
            INDEX(KK) = INDEX(II)
            INDEX(II) = ISAVE
C
                    pUT IN cOLUMNs OF LU ONE AT A TIME
            IF (INTL) IBASE(II) = IROW
            IF (II .EQ. M) GOTO gO
            J=II + 1
            DO $O I = J,M
            K = INDEX(I)
            LU(K,II) = UU(K,II) / WU(ISAVE,II)
        8O CONTINUE
        9O CONTINUE
            KKK = IROW
            RETURN
            END
```


## Algorithm AS 136

# A $K$-Means Clustering Algorithm 

By J. A. Hartigan and M. A. Wong

Yale University, New Haven, Connecticut, U.S.A.
Keywords: K-means clustering algorithm; transfer algorithm

## Language

ISO Fortran

## Description and Purpose

The $K$-means clustering algorithm is described in detail by Hartigan (1975). An efficient version of the algorithm is presented here.

The aim of the $K$-means algorithm is to divide $M$ points in $N$ dimensions into $K$ clusters so that the within-cluster sum of squares is minimized. It is not practical to require that the solution has minimal sum of squares against all partitions, except when $M, N$ are small and $K=2$. We seek instead "local" optima, solutions such that no movement of a point from one cluster to another will reduce the within-cluster sum of squares.

## Method

The algorithm requires as input a matrix of $M$ points in $N$ dimensions and a matrix of $K$ initial cluster centres in $N$ dimensions. The number of points in cluster $L$ is denoted by $N C(L) . D(I, L)$ is the Euclidean distance between point $I$ and cluster $L$. The general procedure is to search for a $K$-partition with locally optimal within-cluster sum of squares by moving points from one cluster to another.

Step 1. For each point $I(I=1,2, \ldots, M)$, find its closest and second closest cluster centres, $I C 1(I)$ and $I C 2(I)$ respectively. Assign point $I$ to cluster $I C 1(I)$.

Step 2. Update the cluster centres to be the averages of points contained within them.
Step 3. Initially, all clusters belong to the live set.
Step 4. This is the optimal-transfer (OPTRA) stage:
Consider each point $I(I=1,2, \ldots, M)$ in turn. If cluster $L(L=1,2, \ldots, K)$ is updated in the last quick-transfer ( $Q T R A N$ ) stage, then it belongs to the live set throughout this stage. Otherwise, at each step, it is not in the live set if it has not been updated in the last $M$ optimaltransfer steps. Let point $I$ be in cluster L1. If $L 1$ is in the live set, do Step 4a; otherwise, do Step 4b.

Step 4a. Compute the minimum of the quantity, $R 2=\left[N C(L) * D(I, L)^{2}\right] /[N C(L)+1]$, over all clusters $L(L \neq L 1, L=1,2, \ldots, K)$. Let $L 2$ be the cluster with the smallest $R 2$. If this value is greater than or equal to $\left[N C(L 1) * D(I, L 1)^{2}\right] /[N C(L 1)-1]$, no reallocation is necessary and $L 2$ is the new $I C 2(I)$. (Note that the value $\left[N C(L 1) * D(I, L 1)^{2}\right] /[N C(L 1)-1]$ is remembered and will remain the same for point $I$ until cluster $L 1$ is updated.) Otherwise, point $I$ is allocated to cluster $L 2$ and $L 1$ is the new $I C 2(I)$. Cluster centres are updated to be the means of points assigned to them if reallocation has taken place. The two clusters that are involved in the transfer of point $I$ at this particular step are now in the live set.

Step 4b. This step is the same as Step 4a, except that the minimum $R 2$ is computed only over clusters in the live set.

Step 5. Stop if the live set is empty. Otherwise, go to Step 6 after one pass through the data set.

Step 6. This is the quick-transfer (QTRAN) stage:
Consider each point $I(I=1,2, \ldots, M)$ in turn. Let $L 1=I C 1(I)$ and $L 2=I C 2(I)$. It is not necessary to check the point $I$ if both the clusters $L 1$ and $L 2$ have not changed in the last $M$ steps. Compute the values

$$
R 1=\left[N C(L 1) * D(I, L 1)^{2}\right] /[N C(\mathrm{~L} 1)-1] \quad \text { and } \quad R 2=\left[N C(L 2) * D(I, L 2)^{2}\right] /[N C(L 2)+1]
$$

(As noted earlier, $R 1$ is remembered and will remain the same until cluster $L 1$ is updated.) If $R 1$ is less than $R 2$, point $I$ remains in cluster $L 1$. Otherwise, switch $I C 1(I)$ and $I C 2(I)$ and update the centres of clusters $L 1$ and $L 2$. The two clusters are also noted for their involvement in a transfer at this step.

Step 7. If no transfer took place in the last $M$ steps, go to Step 4. Otherwise, go to Step 6.
STRUCTURE
SUBROUTINE KMNS ( $A, M, N, C, K, I C 1, I C 2, N C, A N 1, A N 2, N C P, D, I T R A N, L I V E$, ITER, WSS, IFAULT)

## Formal parameters

| A | Real array ( $M, N$ ) | input: | the data matrix |
| :---: | :---: | :---: | :---: |
| M | Integer | input: | the number of points |
| $N$ | Integer | input: | the number of dimensions |
| C | Real array ( $K, N$ ) | input: | the matrix of initial cluster centres |
|  |  | output: | the matrix of final cluster centres |
| K | Integer | input: | the number of clusters |
| IC1 | Integer array ( $M$ ) | output: | the cluster each point belongs to |
| IC2 | Integer array ( $M$ ) | workspace: | this array is used to remember the cluster which each point is most likely to be transferred to at each step |
| $N C$ | Integer array ( $K$ ) | output: | the number of points in each cluster |
| AN1 | Real array ( $K$ ) | workspace: |  |
| AN2 | Real array ( $K$ ) | workspace: |  |


| NCP | Integer array $(K)$ |
| :--- | :--- |
| $D$ | Real array $(M)$ |
| ITRAN | Integer array $(K)$ |
| LIVE | Integer array $(K)$ |
| ITER | Integer |
| WSS | Real array $(K)$ |
| IFAULT | Integer |

workspace:
workspace:
workspace:
workspace:
input: the maximum number of iterations allowed
output: the within-cluster sum of squares of each cluster output: see Fault Diagnostics below

## Fault Diagnostics

$I F A U L T=0 \quad$ No fault
$I F A U L T=1$ At least one cluster is empty after the initial assignment. (A better set of initial cluster centres is called for)
$I F A U L T=2$ The allowed maximum number of iterations is exceeded
$I F A U L T=3 K$ is less than or equal to 1 or greater than or equal to $M$

## Auxiliary algorithms

The following auxiliary algorithms are called: SUBROUTINE OPTRA $(A, M, N, C, K$, IC1, IC2, NC, AN1, AN2, NCP, D, ITRAN, LIVE, INDEX) and SUBROUTINE QTRAN $(A, M, N, C, K, I C 1, I C 2, N C, A N 1, A N 2, N C P, D, I T R A N, I N D E X)$ which are included.

## Related Algorithms

A related algorithm is AS 113 (A transfer algorithm for non-hierarchial classification) given by Banfield and Bassill (1977). This algorithm uses swops as well as transfers to try to overcome the problem of local optima; that is, for all pairs of points, a test is made whether exchanging the clusters to which the points belong will improve the criterion. It will be substantially more expensive than the present algorithm for large $M$.

The present algorithm is similar to Algorithm AS 58 (Euclidean cluster analysis) given by Sparks (1973). Both algorithms aim at finding a $K$-partition of the sample, with within-cluster sum of squares which cannot be reduced by moving points from one cluster to the other. However, the implementation of Algorithm AS 58 does not satisfy this condition. At the stage where each point is examined in turn to see if it should be reassigned to a different cluster, only the closest centre is used to check for possible reallocation of the given point; a cluster centre other than the closest one may have the smallest value of the quantity $\left\{n_{l} /\left(n_{l}+1\right)\right\} d_{l}^{2}$, where $n_{l}$ is the number of points in cluster $l$ and $d_{l}$ is the distance from cluster $l$ to the given point. Hence, in general, Algorithm AS 58 does not provide a locally optimal solution.

The two algorithms are tested on various generated data sets. The time consumed on the IBM 370/158 and the within-cluster sum of squares of the resulting $K$-partitions are given in Table 1. While comparing the entries of the table, note that AS 58 does not give locally optimal solutions and so should be expected to take less time. The WSS are different for the two algorithms because they arrive at different partitions of the sets of points. A saving of about 50 per cent in time occurs in $K M N S$ due to using "live" sets and due to using a quicktransfer stage which reduces the number of optimal transfer iterations by a factor of 4 . Thus, $K M N S$ compared to $A S 58$ is locally optimal and takes less time, especially when the number of clusters is large.

## Time and Accuracy

The time is approximately equal to $C M N K I$ where $I$ is the number of iterations. For an IBM 370/158, $C=2 \cdot 1 \times 10^{-5} \mathrm{sec}$. However, different data structures require quite different numbers of iterations; and a careful selection of initial cluster centres will also lead to a considerable saving in time.

Storage requirement: $M(N+3)+K(N+7)$.

Table 1

|  |  | Time（sec） | WSS |
| :--- | :--- | :---: | :---: |
| 1．$M=1000, N=10, K=10$ | AS 58 | $63 \cdot 86$ | $7056 \cdot 71$ |
| （random spherical normal） | KMNS | $36 \cdot 66$ | $7065 \cdot 59$ |
| 2．$M=1000, N=10, K=10$ | AS 58 | $43 \cdot 49$ | $7779 \cdot 70$ |
| （two widely separated random normals） | KMNS | $19 \cdot 11$ | $7822 \cdot 01$ |
| 3．$M=1000, N=10, K=50$ | AS 58 | $135 \cdot 71$ | $4543 \cdot 82$ |
| （random spherical normal） | KMNS | 76.00 | $4561 \cdot 48$ |
| 4．$M=1000, N=10, K=50$ | AS 58 | $95 \cdot 51$ | $5131 \cdot 04$ |
| （two widely separated random normals） | KMNS | $57 \cdot 96$ | $5096 \cdot 23$ |
| 5．$M=50, N=2, K=8$ | AS 58 | 0.17 | $21 \cdot 03$ |
| （two widely separated random normals） | $K M N S$ | $0 \cdot 18$ | 21.03 |

Missing variate values cannot be handled by this algorithm．
The algorithm produces a clustering which is only locally optimal；the within－cluster sum of squares may not be decreased by transferring a point from one cluster to another，but different partitions may have the same or smaller within cluster sum of squares．

The number of iterations required to attain local optimality is usually less than 10.

## Additional Comments

One way of obtaining the initial cluster centres is suggested here．The points are first ordered by their distances to the overall mean of the sample．Then，for cluster $L(L=1,2, \ldots, K)$ ，the $\{1+(L-1) *[M / K]\}$ th point is chosen to be its initial cluster centre． In effect，some $K$ sample points are chosen as the initial cluster centres．Using this initialization process，it is guaranteed that no cluster will be empty after the initial assignment in the subroutine．A quick initialization，which is dependent on the input order of the points，takes the first $K$ points as the initial centres．

## Acknowledgements

This research is supported by National Science Foundation Grant MCS75－08374．

## References

Banfield，C．F．and Bassill，L．C．（1977）．Algorithm AS113．A transfer algorithm for non－hierarchical classification．Appl．Statist．，26，206－210．
Hartigan，J．A．（1975）．Clustering Algorithms．New York：Wiley．
Sparks，D．N．（1973）．Algorithm AS 58．Euclidean cluster analysis．Appl．Statist．，22，126－130．

```
SUBROUTINE KMNS(A, M, N, C, K, IC1, IC2, NC, AN1, AN2, NCP,
* D, ITRAR, LIVE, ITJR, WSS, IFAULT)
    ALGORITHM AS 136 APPL. STATIST. (1979) VOL.28, NO.1
        dIVIDE M POINTS IN N-DIMENSIONAL SPACE INTO K CLUSTERS
        SO that the WITHIN CLUSTER SUM IF SQUARES IS MINIMIZED.
    DIMENSION A(M, N), IC1(M), IC2(M), D(M)
    dIMENSION C(K,N), NC(K), AN1(K), AN2(K), NCP(K)
    DIMENSION ITRAN(K), LIVE(K), WSS!K), DT(2)
        define big to be a very Large positive Number
        DATA BIG/1.OE10/
```

のロロ

IFAULT $=3$
IF (K . INE. 1 .OR. K 。GE. M) RETURN

FOR EACH POINT I, FIND ITS TWO CLOSEST CENTRES, IC1 (I) AND IC2(I). ASSIGN IT TO IC1 (I).

Do $50 \mathrm{I}=1$, M
IC1 (I) $=1$
$\mathrm{IC} 2(\mathrm{I})=2$
DO 10 IL $=1,2$
$\operatorname{Dr}(I L)=0.0$
DO $10 \mathrm{~J}=1$, N
$D A=A(I, J)-C(I L, J)$
$\mathrm{DT}(\mathrm{IL})=\mathrm{DT}(\mathrm{IL})+\mathrm{DA} * \mathrm{DA}$
10 Continue
IF (DT(1) . LE. DT(2)) GOTO 20
$\mathrm{IC} 1(\mathrm{I})=2$
IC2 $(\mathrm{I})=1$
$\operatorname{TEMP}=\mathrm{DT}(1)$
$\mathrm{DT}(1)=\mathrm{DT}(2)$
$\operatorname{DT}(2)=$ TEMP
$20 \mathrm{DO} 50 \mathrm{~L}=3, \mathrm{~K}$
$\mathrm{DB}=0.0$
DO $30 \mathrm{~J}=1$, N
$D C=A(I, J)-C(L, J)$
$\mathrm{DB}=\mathrm{DB}+\mathrm{DC} * \mathrm{DC}$
IF (DB .GE. DT(2)) GOTO 50
30 CONTINUE
IF (DB . ET. DT(1)) GOTO 40
$\mathrm{DT}(2)=\mathrm{DB}$

Goros 50
$40 \operatorname{DT}(2)=\operatorname{Dr}(1)$
$\mathrm{IC2}(\mathrm{I})=\mathrm{IC1}(\mathrm{I})$
$\mathrm{DT}(1)=\mathrm{DB}$
IC1 $(\mathrm{I})=\mathrm{L}$
50 continue

DO $70 \mathrm{~L}=1$, K
$\mathrm{NC}(\mathrm{L})=0$
Do $60 \mathrm{~J}=1$, N
$60 \mathrm{c}(\mathrm{L}, \mathrm{J})=0.0$
70 CONTINUS:
DO $90 I=1, M$
$\mathrm{L}=\mathrm{IC1}(\mathrm{I})$
$\mathrm{NC}(\mathrm{L})=\mathrm{NC}(\mathrm{L})+1$
Do $80 \mathrm{~J}=\mathrm{R}$, N
$80 \mathrm{C}(\mathrm{L}, \mathrm{J})=\mathrm{C}(\mathrm{L}, \mathrm{J})+\mathrm{A}(\mathrm{I}, \mathrm{J})$
90 CONTINUR
check to see if there is any empty cluster at this stage
TFAULT $=1$
DO $100 \mathrm{~L}=1, \mathrm{~K}$
IF (NC(L) .ER, ol RETURN
100 continue
IFAULT $=0$
DO $120 \mathrm{~L}=1, \mathrm{~K}$
$\mathrm{AA}=\mathrm{NC}(\mathrm{L})$
D $110 \mathrm{~J}=1$, N
AN2 ( $L$ ) IS EQUAL TO NC' $L$ ) / (NC (L) +1$)$
$\operatorname{ITRAN}(E)=1$ IF CJUSTER L IS UPDATED IN THE QUICK-THANSFER STAGE
ITRAN $(L)=0$ OTHERWISE
IN THE OPTIMAI-TRANSFER STAGE, NCP(L) INDICATES THE STEP AT ${ }^{\circ}$
WHICH CENSTER L IS LAST UPDATED

C
c
C
in the quick-transfer stage, ncp(L) is equal to the step at WhICH Cluster \& is dast updated plus m
$\operatorname{AN2}(L)=A A /(A A+1.0)$
$\mathrm{AN} 1(\mathrm{~L})=\mathrm{BIG}$
IF (AA . GT. 1.0) ANI (L) $=A A /(A A-1.0)$
$\operatorname{ITRAN}(L)=1$
$\operatorname{NCP}(L)=-1$
120 Contraus
INDEX $=0$
DO $140 \mathrm{IJ}=1$, ITER
in this stage, there is only one pass through the data. each ponft is reallocated, if necessary, to the cluster that will induce the maximum reduction in within-Cluster SUM OF SQUARES

CALL OPTRA(A, M, N, C, K, IC1, IC2, NC, AN1, AN2, NCP,

* D, itran, live, index)

STOP If NO TRANSFER TOOK place in the last m OPTIMAL-TRANSFER STEPS

IF (INDEX .FQ. M) GOTOU 150
EACH point is tested in turn to see if it should be reallucated to the cluster wifich it is most likely to be transferred to (IC2(I)) frdm its present cluster (iC1(I)). Loop tirgugi the data until no further change is to take place

CALL QTran (A, M, N, C, K, IC1, IC2, NC, AN1, AN2,

* NCP, D, ITRAN, index)
if there are only two clusters, NO NEED TO RE-ENTER OPTMMAL-TRANSFER STAGE

IF (K .EQ. 2) GOTO 150
NCP HAS TI BE SET TO O BEFORS ENTERING OPTRA
DO $130 \mathrm{~L}=1, \mathrm{~K}$
$130 \mathrm{NCP}(\mathrm{L})=0$
140 CONTINUS

```
    IFAult = 2
```

COMPUTE WITHIN CLUSTER SUM OF SQUARES FIJR EACH CLUSTER
150 DO $160 \mathrm{~L}=1, \mathrm{~K}$ $\operatorname{VISS}(L)=0.0$
$\mathrm{Ji} 160 \mathrm{~J}=1$, N
$C(L, J)=0.0$
160 CONTINUE
DO $170 \mathrm{I}=1, \mathrm{M}$
II = IC1 (I)
ma $170 \mathrm{~J}=1$, N
$C(I I, J)=C(I I, J)+\Lambda(I, J)$
170 CONTINUE
DO $100 \mathrm{~J}=1$, N
DO $180 \mathrm{~L}=1$, K
$180 \mathrm{C}(\mathrm{L}, \mathrm{J})=\mathrm{C}(L, J) / \operatorname{FLOAT}(\operatorname{NC}(L))$
DO $190 \mathrm{I}=1, \mathrm{M}$
II = IC1 (I)
$D A=A(I, J)-C(I I, J)$
WSS(II) $=$ YSS(II) $+\mathrm{DA} * \mathrm{DA}$
190 comtinue
return
END

SUBRIUTINF OPTRA (A, M, N, C, K, IC1, IC2, NC, AN1, * AN2, NCP, D, ITRAN, LIVE, INDEX)
DO $40 \mathrm{~J}=1$, 3
$D B=A(I, J)-C(I 2, J)$
$D A=D A+D B * D B$
40 CONTINUS
$\mathrm{R} 2=\mathrm{DA} * \mathrm{AN} 2(12)$
DO $60 \mathrm{~L}=1$, K
if i is graater than or equal to live: Li), then in is nof in the live set. if this is true, we only need to consider clasters that are in the live set for possible trangrer of point I. otherwise, we need to consider all possible clusters

IF (I .GB. LIVE(LI) .AND. I .GF. LIVE(L) .OR.

* L .ER. HL .OR. L .ER. LL) GOTO 60
$\mathrm{RR}=\mathrm{R} 2 / \mathrm{AN} 2(\mathrm{~L})$
$D C=0.0$
DO $50 \mathrm{~J}=1$, H
$D D=A(I, J)-C \cdot L, J)$
$\mathrm{DC}=\mathrm{DC}+\mathrm{DD} * \mathrm{DD}$
IF (DC .GE. RR) GMOD 60

```
    50 CONTINUS
    R2 = DC* AN2(L)
    L2 = L
    60 continus
    IF (R2 .lT. D!IN) GOTO 70
c
    70 Index = 0
    LIVE(LI) = M + I
    LIVE(T\Omega)}=M+
    NCP(LI) = I
    NCP(12) = I
    ALI = NC(IN )
    ALN = ALH - 1.0
    AL2 = NC(12)
    ALT = AX2 + 1.0
    do 80 J=1, N
    C(LI, J) = (C(LI, J) * ALI - A(I, J)) / ALN
    C(L2,J)=(C(L2, J) % AL2 + A(I, J)) / Alr
    80 CONTINUS
    NC(L1) = NC(LI) - 1
    NC(L2) = NC(12) +1
    AN2(L1) = ALW / ALI
    AN1(LI) = BIG
    IF (ALW .GT. 1.0) AN1(LI) = ANY ! (ALW - 1.0)
    AN1(L2) = ALT / AL2
    AN2(L2) = ALT / (ALT + 1.0)
    IC1(I) = L2
    IC2(I) = LI
90 continuse
    IF (INDEX .ER. M) RETURN
    100 continue
    DiN 110 J_= 1, K
        ITRNN(J) IS SET TO ZERO BEFORE ENTERING QTRAN.
        ALSO, LIVE(J) HAS TO BE DECREASED BY M BEFORE
        RE-FNTERING OPTRA
    ITRAN(L) = 0
    LIVE(L) = LIVE(L) - M
    110 ConTINUE
    RETURN
    END
    SUBROUTINE QTRAN(A, M, N, C, K, IC1, IC2, NC, AN1,
    * aN2, NCP, D, ITRAN, Index)
        ALGORITHM AS 13(5.2 APPL. STATIST. (17%()) VOL.2%, NO.1
        this IS the quICK transfer stage.
        IC1(I) Is THE CLISTER WHICH POJNT I bELJNGS TO.
        IC2(x) Is the cuister which point I IS mOST
        LIKELY TO bE TRANSFERRED TO.
        FOR EACH POINT I, IC1(I) and IC2(I) are SwITCIED, IF
        NEGESSARY, TO REDUCE WITHIN CLUSTER SUM OF SQUARES.
        the cmaster centres are updated after each step
    DIMENSION A(Y, N), IC1(M), IC2(M), D(M)
    DIMENSIDN C{K, W), NC(K), AN1(K), AN2(K), NCP(K), ITRAN(K)
        dEFIRE big to be a very large positive number
    DATA BIG /1.0E10/
```

c
C
c
C

## APPLIED STATISTICS



