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\textbf{Algorithm} \ PROCLUS\_SPMMP \ (No. of \ clusters: k, Average \ number \ of \ dimensions: l)
\{C_i \text{ is the } i^{th} \text{ cluster}\}
\{D_i \text{ is the set of dimension associated with cluster } C_i\}
\{M_{best} \text{ is the best set of medoids found so } far\}
{N is the final set of medoids with associated dimension}
{A, B are constant integers}
{D is the set of all dimension (all the process stages)}
{P is the set of all points (all the production paths)}
begin
     \{1. Initialization Phase\}
S = random \ sample \ of \ size \ A \cdot k
M = Greedy(S, B \cdot k)
     {2. Iterative Phase}
BestObjective = \infty
M_{current} = Random \ set \ of \ medoids \ \{m_1, m_2, \dots, m_k\} \subset M
repeat
     {approximate the optimal set of dimensions}
     (L_1, \dots, L_k) = FindLocality(S, M_{current})
     (D_1, D_2, ..., D_k) = FindDimensions(k, l, L)
     {form the clusters}
     (C_1,\dots,C_k) = AssignPoints(D_1,\dots,D_k)
     ObjectiveFunction = EvaluateClusters(C_1, \dots, C_k, D_1, \dots, D_k)
     if ObjectiveFunction < BestObjective then</pre>
     begin
          BestObjective = ObjectiveFunction
          M_{best} = M_{current}
     Compute M_{current} by replacing the bad medoids in M_{best} with random points from M
{\it until}~(termination\_criterion)
     {3. Refinement Phase}
L = \{C_1, \dots, C_k\}
(D_1, \dots, D_k) = FindDimensions(k, l, L)
(C_1, ..., C_k) = AssignPoints(D_1, ..., D_k)
N = (M_{best}, D_1, \dots, D_k)
return(N)
end
```

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Algorithm PROCLUS_SPMMP (No. of clusters: k, Average number of dimensions: l, number of agent T)
\{C_i \text{ is the } i^{th} \text{ cluster}\}
\{D_i \text{ is the set of dimension associated with cluster } C_i\}
\{M_{best} \text{ is the best set of medoids found so far}\}
{N is the final set of medoids with associated dimension}
{A, B are constant integers}
{D is the set of all dimension (all the process stages)}
{P is the set of all points (all the production paths)}
begin
     {1. Initialization Phase}
S = random \ sample \ of \ size \ A \cdot k
M = Greedy(S, B \cdot k)
BestObjective = \infty
for agent t \in T do
     begin
     t.\,M_{current} = Random\,set\,of\,\,medoids\,\{m_1,m_2,\ldots,m_k\} \subset M
     t.L = FindLocality(S, t.M_{current})
     t.D = FindDimensions(k, l, t.L)
     t.C = AssignPoints(t.D)
     t. \textit{ObjectiveFunction} = EvaluateClusters(t. \textit{C}, t. \textit{D})
     if ObjectiveFunction < BestObjective then</pre>
          begin
               BestObjective = t.ObjectiveFunction
               M_{best} = t.M_{current}
               C_{best}=t.\,C
          end
     end
     {2. Iterative Phase}
repeat
for agent t \in T do
     {find better solution with slightly change medoid}
     if rv \sim u(0,1) < 0.5 then
          begin
               if bad medoids in t. M<sub>current</sub> then
                    t.M_{current} = Change\ M_{best}'s\ bad\ medoid\ with\ random\ points\ from\ M
                    t.M_{current} = Change M_{best}'s one medoid with random points from M
     {find better solution from totally random medoids}
     \textbf{else then } t.M_{current} = Random\,set\,of\,\,medoids\,\{m_1,m_2,\ldots,m_k\} \subset M
     t.\,M_{current} = Random\,set\,of\,\,medoids\,\{m_1,m_2,\ldots,m_k\} \subset M
     t.\,L = FindLocality(S,t.\,M)
     t.D = FindDimensions(k, l, t. L)
     t.C = AssignPoints(t.D)
     t.ObjectiveFunction = EvaluateClusters(t.C,t.D)
     if ObjectiveFunction < BestObjective then</pre>
                BestObjective = t.ObjectiveFunction
                M_{best} = t.M_{current}
          end
     end
until (termination_criterion)
     {3. Refinement Phase}
(D_1, ..., D_k) = FindDimensions(k, l, L)
(C_1, \dots, C_k) = AssignPoints(D_1, \dots, D_k)
N = (M_{best}, D_1, \dots, D_k)
return(N)
end
```

```
begin
for each medoid m_i \in M do
     begin
     \delta_i = \min\{Distance(m_i, m_j, D) | i \neq j\}
     L_i = \{x | x \in S \ and \ Distance(x, m_i, D) < \delta_i \, \}
     end
return((L_1, ..., L_k))
Algorithm Greedy(Set of points S, Number of medoids: k)
begin
M = \{m_1\}, \{m_1 \text{ is a random point of } S\}
for each x \in S \setminus M do dist(x) = Distance(x, m_1, D)
for i = 2 to k do
     begin
           let m_i \in S \setminus M be s.t. dist(m_i) = max\{dist(x) | x \in S \setminus M\}
           \textit{for each } x \in \textit{S} \backslash \textit{M do } \textit{dist}(x) = \min\{\textit{dist}(x), \textit{Distance}(x, m_i)\}
     end
return M
end
Algorithm Distance(point x_1, point x_2, dimension set D_x)
begin
CountNun=0
for dimension d \in D_x do
     begin
     if x_1(d) = x_2(d)
           CountNum = CountNum + 1
return (CountNum/|D_x|)
end
Algorithm FindDimensions(k, l, L)
\{X_{i,j} \text{ is the average distance from the points in } L_i \text{ to medoid } m_i, \text{ along dimension } j\}
for each medoid i do
     begin
     Y_{i} = \frac{\sum_{j=1}^{|D|} X_{i,j}}{|D|}
D_{i} = \emptyset
     \sigma_i = \sqrt{\frac{\sum_{j=1}^{|D|} (X_{i,j} - Y_i)^2}{d-1}}
     for each dimension j do Z_{i,j} = (X_{i,j} - Y_i)/\sigma_i
Pick the k·l numbers with the least (most negative) values of Z_{i,j}
subject to the constraint that there are at least 2 dimensions for each clusters
if Z_{i,j} is picked then add dimension j to D_i
return (D_1, D_2, ..., D_k)
end
```

Algorithm FindLocality(Set of points S, Set of medoids M)

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\textbf{Algorithm} \ AssignPoints(D_1, D_2, \dots, D_k)
begin
for each i \in \{1,..,k\} do C_i = \emptyset
for each p \in P
      Find i with the lowest value of Distance (p, m_i, D_i) and add p to C_i
\boldsymbol{return}\left(\mathcal{C}_{1},\ldots,\mathcal{C}_{k}\right)
end
Algorithm EvaluateClusters(C_1, ..., C_k, D_1, ..., D_k)
begin
for each C_i do
      begin
      for each dimension j \in D_i do
             begin
             Y_{i,j} = CentroidDistance(C_i, d_j)
             end
      w_i = \frac{\sum_{j} Y_{i,j}}{|D_i|}
return\left(rac{\sum_{i=1}^{k} |\mathcal{C}_i| \cdot w_i}{|\mathcal{P}|}\right)
Algorithm CentroidDistance(C_i, d_j)
\{d_j \text{ is a dimension in } D_i\}
\textit{Centroid}(\textit{C}_i, d_j) \text{ is an average vector of OneHotEncoding}(\textit{p}, d_j) \ \forall \textit{p} \in \textit{C}_i
for each p \in C_i dist(p) = \|OneHotEncoding(p, d_j) - Centroid(C_i, d_j)\|_1/2
return \left(\frac{\sum_{p \in C_i} dist(p)}{|C_i|}\right)
```