Documentation - PreDeCon Algorithm

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1 Introduction

In this paper the PreDeCon (subspace PREference weighted DEnsity and CONnected clustering) algorithm is explained. The algorithm was created by Böhm, Christian, et al.[BRKK04] in 2004. PreDeCon is a clustering algorithm that was developed to perform well in high-dimensional feature spaces. High-dimensional feature spaces cause many clustering algorithms to break down, due to the curse of dimensionality. In this case this refers to the phenomenon, that clustering algorithms which calculate distances in the full dimensional space deteriorate in performance, because the distances in such spaces lose their meaning. That's why specialized clustering algorithms were developed, which are based on the observation that clusters exist only in specific subspaces of the full feature space. There are several approaches to this problem, two of them will be explained here briefly. Subspace clustering tries to find all possible clusters in all axis-parallel subspaces in a bottom-up way, here it is possible for clusters to overlap, this means that points can be assigned to multiple clusters, see [AGGR98] and [KKK04]. In projected clustering all points are uniquely assigned to clusters or noise in a top-down approach, therefor clusters cannot overlap.

2 The PreDeCon Algorithm

PreDeCon belongs to the group of projected clustering algorithms. It follows an instance-based approach, which calculates for each point in the data base a subspace preference in the entire feature space and merges the points with similar preferences together to form a cluster. The rational behind this approach follows the locality assumption, which states that "the subspace preference can be learned from the local neighborhood in the d-dimensional space", as mentioned in the courses slides. PreDeCon is based on the density-based clustering algorithm DBSCAN [EKS+96] and can be seen as an extension of it for high-dimensional spaces. PreDeCon has the following features[BRKK04]:

- the clustering result is determinate
- it is robust against noise
- it has a worst-case time complexity of $O(dn^2)$

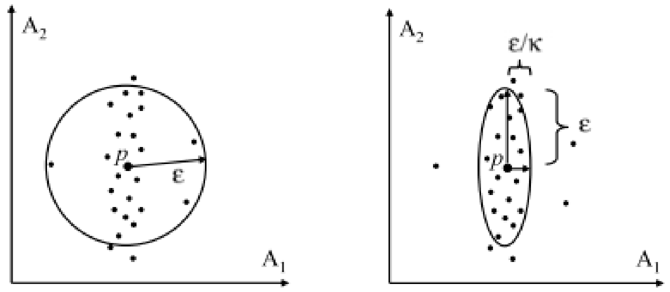
2.1 Underlying Ideas

The underlying idea of PreDecon is the "subspace preference cluster" [BRKK04], which expands the idea of density connected set of points by a subspace preference vector. Note, that from now on all points p, q are considered as elements of the data base. The subspace preference vector skews the ϵ-neighborhood of point p in the direction of the lowest attribute variance, where the attribute variance of a point p is given by:

$$VAR_{A_i}(N_\epsilon(p)) = \frac{\sum_{q\in(N_\epsilon(p))}(dist(\pi_{A_i}(p), \pi_{A_i}(q)))^2}{|N_\epsilon(p)|}$$

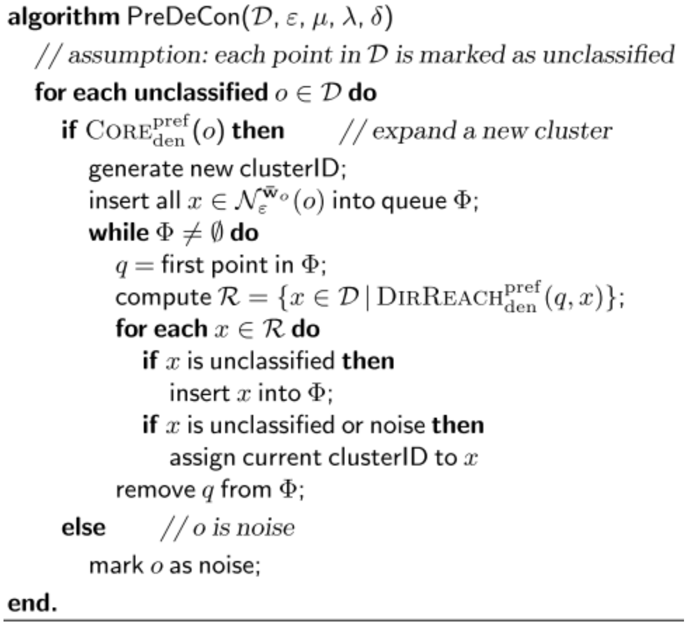
From the attribute variance the subspace preference vector of a point p is derived as

$$w_i = \begin{cases} 1 & \text{if } VAR_{A_i}(N_\epsilon(p)) > \delta \\ \kappa & \text{if } VAR_{A_i}(N_\epsilon(p)) \leq \delta \end{cases}$$



(a) (b)

Figure 1: ϵ-neighborhood of p according to (a) simple Euclidean and (b) preference weighted Euclidean distance.(Figure taken from [BRKK04])



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algorithm PreDeCon($\mathcal{D}$, $\varepsilon$, $\mu$, $\lambda$, $\delta$)
  // assumption: each point in $\mathcal{D}$ is marked as unclassified
  for each unclassified $o \in \mathcal{D}$ do
    if $\text{CORE}^{\text{pref}}_{\text{den}}(o)$ then        // expand a new cluster
      generate new clusterID;
      insert all $x \in \mathcal{N}^{\bar{\mathbf{w}}_o}_{\varepsilon}(o)$ into queue $\Phi$;
      while $\Phi \neq \emptyset$ do
        $q$ = first point in $\Phi$;
        compute $\mathcal{R} = \{x \in \mathcal{D} \mid \text{DIRREACH}^{\text{pref}}_{\text{den}}(q, x)\}$;
        for each $x \in \mathcal{R}$ do
          if $x$ is unclassified then
            insert $x$ into $\Phi$;
          if $x$ is unclassified or noise then
            assign current clusterID to $x$
        remove $q$ from $\Phi$;
    else        // $o$ is noise
      mark $o$ as noise;
end.
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Figure 2: Pseudo code of the PreDeCon algorithm.(Figure taken from [BRKK04])

and the preference weighted similarity measure associated with a point p can then be calculated as a simple weighted Euclidean distance [BRKK04]. Here the parameter δ specifies the threshold for a low variance. Due to the weighting factor this similarity measure is asymmetric, this means that $dist_p(p,q) = dist_p(q,p)$ does not hold anymore. This can be corrected by using the maximum of the two distances, see [BRKK04]. Look at figure 1, to see the consequences of the preference weighted Euclidean distance. With this new weighted distance function the preference weighted ϵ-neighborhood for each point can be calculated. Another important concept which has been adapted from DBSCAN are the preference weighted core points. Similar to the definition of core points in DBSCAN a preference weighted core point needs to have a minimum number of points in its preference weighted ϵ-neighborhood, denoted by the parameter μ. The PreDeCon algorithm allows the user to specify additionally a maximum preference dimensionality of the ϵ-neighbourhood of a point, denoted as λ. The last notion in order for PreDeCon to work is the direct preference weighted reachability. It states that a point p is direct preference weighted reachable from a point q if q is a preference weighted core point, the preference weighted dimensionality of the ϵ-neighborhood of point p is smaller or equal to λ and p is in the preference weighted epsilon neighborhood of q. For a more detailed explanation of these concepts refer to [BRKK04].

2.2 The Algorithm

PreDeCon needs the following user specified parameters[BRKK04]:

- μ: Minimal number of points in ϵ-neighborhood
- ϵ: Distance parameter for neighborhood calculation
- δ: Variance threshold for subspace preference clusters
- λ: Threshold for dimensionality of ϵ-neighbourhood of a point
- κ: Weight for subspace preference vectors

In figure 2 the pseudo code of the original paper is shown. The inner workings of this algorithm are explained in the next section, when the implementation of PreDeCon are discussed.

3 The Pseudocode of our implementation

Enter pseudocode of our implementation as soon as finished.

References

[AGGR98] Rakesh Agrawal, Johannes Gehrke, Dimitrios Gunopulos, and Prabhakar Raghavan. *Automatic subspace clustering of high dimensional data for data mining applications*, volume 27. ACM, 1998.

[BRKK04] Christian Bohm, K Railing, H-P Kriegel, and Peer Kroger. Density connected clustering with local subspace preferences. In *Data Mining, 2004. ICDM'04. Fourth IEEE International Conference on*, pages 27–34. IEEE, 2004.

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