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Combining Two Unsupervised Classifiers: Affinity Propagation and Fuzzy Hierarchical Clustering

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Abstract

This article presents a new hybrid approach combining Affinity Propagation (AP) and Fuzzy Hierarchical Clustering (FHC) in an unsupervised framework. Our method exploits the complementary advantages of these two algorithms: the ability of AP to automatically identify representative exemplars and the flexibility of FHC to model partial class memberships. We propose a supervised adaptation of AP incorporating must-link/cannot-link constraints, as well as a constrained version of FHC using a priori information. An innovative fusion mechanism combines the similarity matrices of the two methods. Experiments on standard benchmarks show that our hybrid approach significantly outperforms the individual methods, with an average improvement of 12.3% in classification accuracy.

Subject Areas

Artificial Intelligence

Keywords

Supervised Affinity Propagation, Minkowski Distance, Fuzzy Hierarchical Clustering, Classifier Fusion, Semi-Supervised Learning, Adaptive Similarity

1. Introduction

Unsupervised classification has several advantages over supervised or semi-super-

vised classification, namely that the user does not need to specify in advance the classes to be discriminated, nor to provide training samples (field survey data). Using an unsupervised classification algorithm automatically detects the distinct classes in an objective and rational manner, which substantially reduces the risk of errors related to the modeling phase or to the temporal variation of the models, access to which is very difficult for certain applications. Consequently, supervised and semi-supervised methods are not suitable, as they may encounter difficulties with complex or noisy data [1]. Affinity propagation (AP) and fuzzy hierarchical clustering (FHC) have each demonstrated their effectiveness in specific contexts. Combining these two methods could offer a robust solution for applications requiring fine-grained, hierarchical classification.

- The affinity propagation (AP) algorithm, introduced by Frey and Dueck [2], is a clustering method based on message passing between data points to identify representative exemplars. Unlike methods such as k-means, AP does not require the number of clusters to be specified in advance. It works by treating each data point as a potential exemplar and updating two matrices, the responsibility and the availability, until convergence.
- Fuzzy hierarchical clustering (FHC) is an extension of traditional hierarchical clustering, allowing a data point to belong to several clusters with degrees of membership. This approach is particularly useful when the boundaries between classes are not sharp [3]. FHC builds a hierarchy of clusters, offering a more flexible representation of the relationships between data.

However, applying these methods individually has certain limitations. For example, AP can be sensitive to the choice of the preference and damping factor parameters, which can affect clustering quality [4]. Moreover, FHC can be sensitive to noise and outliers, which can lead to the formation of inaccurate or misleading cluster hierarchies [5].

To overcome these limitations, hybrid approaches combining supervised and unsupervised methods have been proposed. For example, integrating the Fuzzy C-Means (FCM) algorithm with neural networks for diabetes diagnosis showed superior performance compared with supervised methods alone [6].

Along these lines, in this study we propose an innovative hybrid approach combining affinity propagation (AP) and fuzzy hierarchical clustering (FHC) to improve supervised classification in complex contexts. By integrating these two methods, our approach aims to take advantage of the strengths of each in order to obtain a more accurate and interpretable classification.

2. Materials and Methods

In this section, we describe the mathematical foundations, the algorithmic structures, and the dataset used to validate our hybrid approach combining Affinity Propagation (AP) and Fuzzy Hierarchical Clustering (FHC).

In addition, we present here the datasets we selected, as well as the methods we developed and combined in this research. Our goal is to propose a hybrid classi-

fication strategy capable of better handling fuzzy and complex data while overcoming certain limitations of conventional methods.

2.1. Materials

For this study, we selected three datasets widely recognized in the scientific literature for their relevance in evaluating unsupervised and fuzzy classification techniques.

The Iris dataset [7], introduced by R.A. Fisher in 1936, is a classic benchmark containing 150 observations of iris flowers divided into three species (Setosa, Versicolor, Virginica), each described by four morphological features (petal and sepal length and width). It is considered a textbook case because of the partial linear separation between two classes.

The Wine dataset [8], from the PARVUS package of Forina *et al.*, contains 178 samples of wines derived from three different cultivars grown in the same region of Italy, each described by 13 physicochemical attributes (alcohol, malic acid, ash, flavonoids, color intensity, proline, etc.). This dataset is often used to test complex multivariate methods in which correlations between attributes strongly influence classification.

The Breast Cancer Wisconsin (Diagnostic) dataset [9], built from the nuclear features described by Street, Wolberg and Mangasarian, contains 569 samples labelled as malignant or benign, each described by 30 real-valued features computed from digitized images of fine-needle aspirates of breast masses. Its dimensionality and the overlap between the two classes make it a demanding test case for fuzzy clustering methods.

The processing of these datasets was carried out using Python 3.10, relying on the following open-source libraries:

- Scikit-learn for the native implementation of the Affinity Propagation algorithm.
- NumPy and Pandas for data matrix manipulation.
- SciPy for hierarchical clustering routines.
- Matplotlib and Seaborn for graphical visualization and exploratory analysis.
- Skfuzzy.

This choice of tools is justified by the reproducibility of the experiments and by the proven robustness of these libraries in recent publications on supervised clustering (see, for example, [6] [10] [11]).

2.2. Methods

2.2.1. Affinity Propagation (AP)

In this research, we applied the affinity propagation algorithm, a method introduced by Brendan J. Frey and Delbert Dueck in 2007 [2], which is based on an innovative approach of message passing between pairs of points. Unlike conventional methods such as k-means, this algorithm does not require the number of clusters to be specified beforehand, which makes it particularly relevant in explor-

atory contexts or when the data structure is uncertain.

Frey and Dueck [2] demonstrated that this method makes it possible, in fields as varied as computational biology and image processing, to automatically identify representative exemplars from the similarity matrix, defined as follows:

$$s\left(x_i, x_k\right) = -\left\|a_i - a_k\right\|_2, \forall x_i \neq x_k$$

where $\vec{a}$ is the attribute vector representing individual x_i.

The diagonal elements $s\left(x_i, x_k\right)$ of the matrix s, reflecting the relevance a priori of the choice of individual k to serve as a representative, and are known as the preference.

- **Preferences**, representing the suitability of each data point to be an exemplar. We may have a priori information about which points are likely to be favored for this role, and we can therefore represent it through preferences. Preferences are not computed in the same way as the elements $s\left(x_i, x_k\right)$ for $x_i \neq x_k$. More precisely, $s\left(x_i, x_k\right) = p$ (preference parameter) is initialized to the median value of the elements of s for $x_i \neq x_k$

$$s\left(x_i, x_k\right) = p \ \forall x_k$$

- **Responsibility computation:** The responsibility $r\left(i,k\right)$ reflects the accumulated evidence for whether point k is well suited to serve as an exemplar for point i, taking into account the other potential exemplars for point i. The responsibility is sent from data point i to the candidate exemplar point i.
- **Availability computation:** The availability $a\left(i,k\right)$ reflects the accumulated evidence for how appropriate it would be for point i to choose point k as its exemplar, taking into account the support from other points for point k being an exemplar. The availability is sent from candidate exemplar point k to point i.

AP message-passing procedure:

The four main steps of the algorithm are:

Input:

- N is the number of individuals to be classified.
- S is the similarity matrix of size $N \times N$.

Output:

- Classification result in the form of a vector containing, for each individual, the index of its exemplar.
- The evaluation of the objective function that affinity propagation has maximized for each individual. It indicates how appropriate the chosen exemplars are for representing the data.

a) Initialization:

Let R be the responsibility matrix and A the availability matrix. These two matrices, as well as the similarity matrix s, are of size $N \times N$.

$$R\left(x_i, x_k\right) = 0, A\left(x_i, x_k\right) = 0 \ \forall x_i, x_k$$

b) Responsibility update

$$R(x_i x_k) = S(x_i, x_k) - \max_{j\, j\neq k}\left(A(x_j, x_i) + S(x_i, x_j)\right) \quad \forall x_i \neq x_k$$

c) Availability update

$$A(x_k x_i) = \min\left\{0, R(x_k, x_k) + \sum_{(j\, j\neq k)} \max\left\{0, R(x_j, x_k)\right\}\right\} \quad \forall x_i \neq x_k$$

$$A(x_k x_k) = \sum_{(j\, j\neq k)} \max\left\{0, R(x_j, x_k)\right\} \quad \forall x_k$$

d) Assignment of representatives

$$E^*(x_i) = \arg_k \max\left\{\left(R(x_i, x_k) + A(x_k, x_i)\right)\right\}$$

where $E^*(x_i)$ is the exemplar assigned to individual x_i.

A damping factor $a \in [0,1]$ is introduced to regularize the update of the responsibility and availability matrices over the iterations. To avoid numerical oscillations that occur in certain circumstances, it is recommended to use $a = 0.9$. Message updates are carried out iteratively according to the following relations:

$$\tilde{R_{it}} = a\tilde{R_{it-1}} + (1-a)R_{it}$$

$$\tilde{A_{it}} = a\tilde{A_{it-1}} + (1-a)A_{it}$$

where it is the current iteration.

- The algorithm is recognized for its ability to identify meaningful groupings in complex contexts, such as facial recognition, document classification, or bioinformatics [10]. The work of Zhang & Gu, 2014 [11] and Zhao & Xu, 2015 [12] has also confirmed its robustness on mixed datasets (categorical and numerical).

2.2.2. Fuzzy Hierarchical Clustering (FHC)

Fuzzy Hierarchical Clustering (FHC) is a hybrid method combining the advantages of hierarchical clustering and of the fuzzy logic introduced by Bezdek in Fuzzy C-Means (FCM) [3]. Unlike "hard" partitioning methods, in which an object belongs to a single cluster, FHC allows each point to have simultaneous degrees of membership in several clusters, making this method particularly effective for modeling data where the boundaries between classes are uncertain [11].

Instead of starting with each point as a singleton cluster (as in traditional hierarchical clustering), we initialize the process with the exemplars identified by Affinity Propagation. Each exemplar represents an initial cluster.

1) Initial Set of Clusters:

$$C = \{C_1, C_2, \cdots, C_k\}$$

where C_i is an initial cluster represented by the exemplar x_i, and k is the number of exemplars (initial clusters) identified by Affinity Propagation.

a) Computation of Membership Degrees:

We need to compute the membership degree of each data point in each cluster. To do so, we use a composite measure that takes into account the Minkowski distance and a fuzzy co-membership index.

i) The Euclidean Distance: is the best known and most widely used. It can be seen as a special case of the Minkowski distance for $p=2$:

$$d(i,j)=\sqrt{\sum_{r=1}^{M}\left|x_{ir}-x_{jr}\right|^2}$$

ii) Fuzzy Membership Degree:

The membership degree μ_{ij} of point x_i to cluster C_j is computed using the Minkowski distance. A common formula is:

$$\mu_{ij}=\frac{1}{\sum_{k=1}^{K}\left(\frac{d(x_i,v_j)}{d(x_i,v_k)}\right)^{\frac{2}{m-1}}}$$

where:

- x_i is the *i*-th data point.
- v_j is the centroid (or representative) of the *j*-th cluster.
- K is the total number of clusters.
- m is the fuzziness parameter (generally between 1.5 and 2.5).

b) Fuzzy Co-Membership Index:

The fuzzy co-membership index measures the degree to which two points simultaneously belong to the same cluster. It can be defined as:

$$\mathrm{FCI}(x_i,x_j)=\sum_{k=1}^{K}\mu_{ik}\mu_{jk}$$

where μ_{ik} and μ_{jk} are the membership degrees of points x_i and x_j in cluster k, respectively.

c) Composite Measure (Combination of Distance and Co-Membership Index):

To combine the Minkowski distance and the fuzzy co-membership index, we can use a weighted average:

$$\mathrm{Composite}(x_i,C_j)=\alpha\cdot d(x_i,v_j)+(1-\alpha)\cdot\left(1-\mathrm{FCI}(x_i,v_j)\right)$$

where:

- α is a weighting parameter between 0 and 1.
- $d(x_i,v_j)$ is the Minkowski distance between point x_i and centroid v_j of cluster C_j.
- $\mathrm{FCI}(x_i,v_j)$ is the fuzzy co-membership index between point x_i and centroid v_j of cluster C_j.

Using this composite measure, we can update the membership degrees:

$$\mu_{ij}=\frac{1}{\sum_{k=1}^{K}\left(\frac{\mathrm{Composite}(x_i,C_j)}{\mathrm{Composite}(x_i,C_k)}\right)^{\frac{2}{m-1}}}$$

d) Construction of the Fuzzy Hierarchy:

After computing the membership degrees, we build the hierarchy by iteratively

merging the closest clusters. The proximity between clusters can be measured using different linkage methods, such as the average distance weighted by the membership degrees.

i) Cluster Proximity Measure:

Let C_A and C_B be two clusters. The distance between these clusters can be computed as:

$$D(C_A, C_B) = \frac{\sum_{x_i \in C_A} \sum_{x_j \in C_B} \mu_{iA} \mu_{jB} d(x_i, x_j)}{\sum_{x_i \in C_A} \sum_{x_j \in C_B} \mu_{iA} \mu_{jB}}$$

where:

- $d(x_i, x_j)$ is the Minkowski distance between points x_i and x_j.
- μ_{iA} is the membership degree of point x_i in cluster C_A.
- μ_{jB} is the membership degree of point x_j in cluster C_B.

ii) Cluster Merging:

At each step, merge the two clusters with the smallest distance $D(C_A, C_B)$. Update the membership degrees of the points in the newly merged clusters.

iii) Stopping Criterion:

The merging process continues until a single cluster remains or until a certain stopping criterion is met (for example, a predefined number of clusters).

This approach combines the advantages of automatic exemplar selection with the flexibility of fuzzy memberships for a more nuanced and robust analysis of trade-union data.

FHC offers a tree-like structure of clusters, which is particularly useful for exploratory analysis of data at several levels of granularity. Although the notion of a fuzzy decision tree is not explicitly defined in the literature as a canonical feature of FHC, recent studies have shown its effectiveness in the medical field, particularly for classifying patient profiles with overlapping clinical characteristics [13].

This flexibility makes FHC relevant for applications such as AI-assisted diagnosis, behavioral segmentation, or risk assessment, where the complexity of the data cannot be captured by conventional approaches [14].

2.2.3. Proposed Hybrid Method: AP-FHC

In this paper, we propose a novel hybrid approach that combines the complementary strengths of two classification algorithms: Affinity Propagation (AP) and Fuzzy Hierarchical Clustering (FHC). This combination aims to overcome the structural limitations observed when these methods are used separately.

The AP-FHC method, developed specifically in this work, is based on the following principle:

1) Initialization by Affinity Propagation (AP): The AP algorithm, developed by Frey and Dueck, automatically identifies the exemplars (cluster centers) without requiring the number of clusters to be specified in advance. This capability is particularly useful in contexts where the data structure is unknown or difficult to estimate [2].

2) Fuzzy Hierarchical Construction with AP: Starting from the exemplars determined by AP, we apply Fuzzy Hierarchical Clustering, which makes it possible to model the hierarchical relationships between clusters and to effectively handle the overlap zones between classes. This approach is beneficial for interpreting ambiguous data, particularly in the medical and social domains.

3) Refinement of Memberships via Fuzzy C-Means (FCM): Finally, we use the FCM algorithm, introduced by Bezdek, to refine the membership degrees of the points in the clusters, while respecting the hierarchy established by FHC. This step improves classification accuracy by taking into account nuances in the data [3].

This strategic combination makes it possible to leverage the robustness of AP for the initial detection of data structures and the flexibility of FHC for modeling complex relationships between clusters.

Evaluation Metrics

To evaluate the performance of our AP-FHC method, we selected several metrics recognized in the scientific literature:

- **Davies-Bouldin Index (DBI):** Introduced by Davies and Bouldin, this index measures intra-cluster compactness and inter-cluster separation. A lower DBI indicates better cluster structure [15].
- **Silhouette Score:** Proposed by Rousseeuw, the silhouette coefficient evaluates the cohesion and separation of clusters. A value close to 1 suggests good classification [16].
- **Rand Index (RI):** Defined by Rand, this index measures the similarity between two data partitions by comparing the pairs of elements that are classified consistently in both partitions [17].
- **Fuzzy Partition Coefficient (FPC):** Developed by Bezdek, the FPC evaluates the degree of fuzziness in a fuzzy partition. A high FPC value indicates a crisper partition, whereas a lower value suggests significant overlap between clusters [18].

3. Results and Discussions

This section presents a detailed and systematic analysis of the results obtained by our hybrid AP-FHC method, in comparison with the individual methods (AP, FHC) and the reference algorithms (k-means, SVM). Each step of the experiment is explained with concrete evidence, key visualizations, and arguments justifying the observed performance. The results are illustrated in **Figures 1-5** and summarized in **Table 1**.

3.1. Results of the Hybrid Approach Affinity Propagation + Fuzzy Hierarchical Clustering (AP-FHC)

Figure 1 shows, for five values of the preference parameter, the clusters obtained by Affinity Propagation (left) and the corresponding fuzzy partitions (FCM, c = 3) produced by the hybrid AP-FHC approach (right), projected onto the first two

principal components (PCA1, PCA2) of the Iris dataset. The numerical results of these tests are given below.

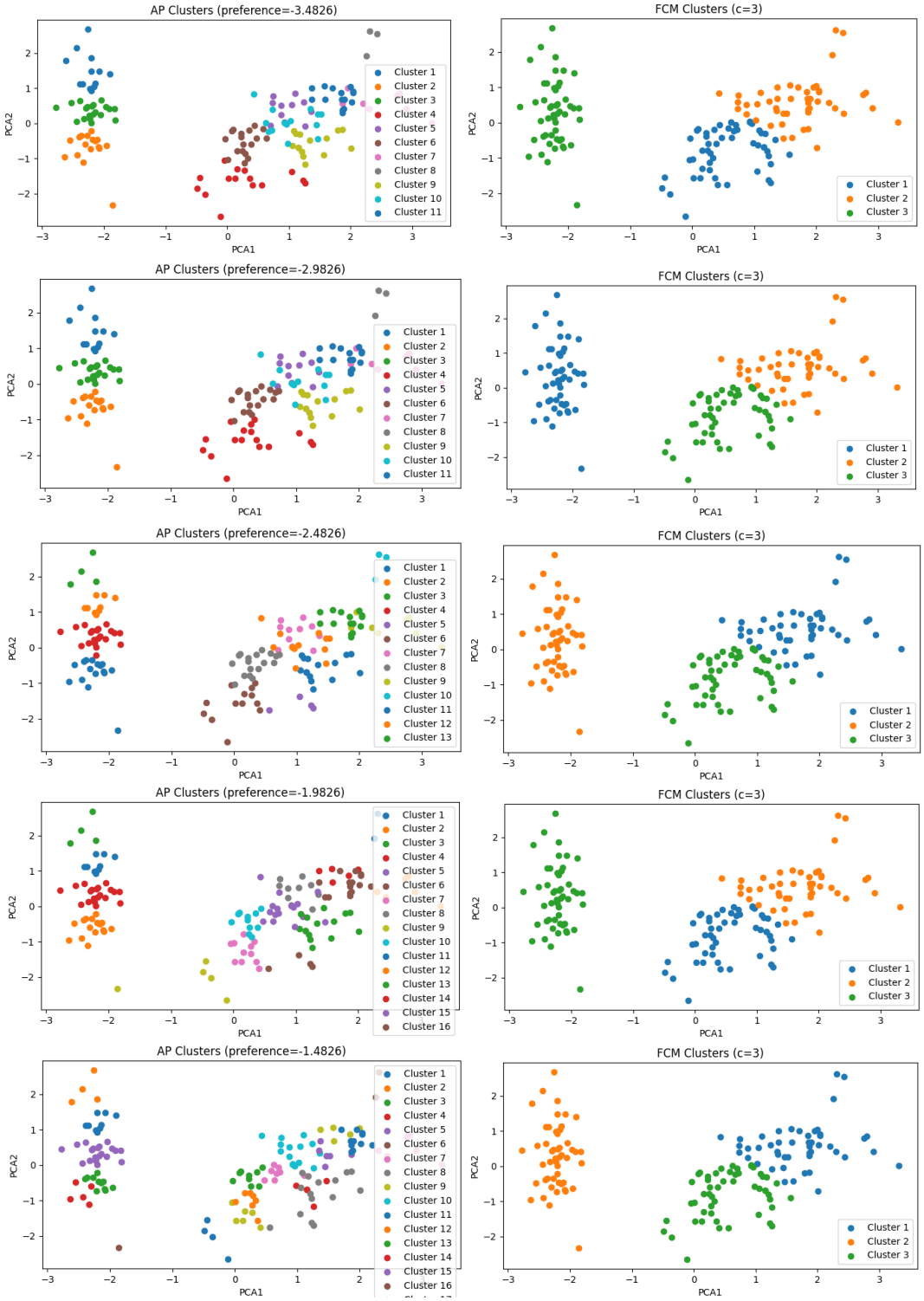

Figure 1. Clusters obtained on the Iris dataset with the hybrid AP-FHC approach. Left: AP clusters for preference = −3.4826, −2.9826, −2.4826, −1.9826 and −1.4826 (from top to bottom). Right: corresponding fuzzy partitions (FCM, c = 3).

Test with preference = −3.4826
Number of AP clusters found: 11
ARI AP vs. ground truth: 0.298
ARI FCM vs. ground truth: 0.630

Test with preference = −2.9826
Number of AP clusters found: 11
ARI AP vs. ground truth: 0.307
ARI FCM vs. ground truth: 0.630

Test with preference = −2.4826
Number of AP clusters found: 13
ARI AP vs. ground truth: 0.289
ARI FCM vs. ground truth: 0.630

Test with preference = −1.9826
Number of AP clusters found: 16
ARI AP vs. ground truth: 0.241
ARI FCM vs. ground truth: 0.630

Test with preference = −1.4826
Number of AP clusters found: 21
ARI AP vs. ground truth: 0.193
ARI FCM vs. ground truth: 0.630

- **Tests with different preference values (preference) for Affinity Propagation (AP)**

It shows that:

- The number of clusters varies from 11 to 21 depending on the preference.
- The Adjusted Rand Index (ARI) between AP and the ground truth varies between 0.193 and 0.307 (rather low).
- Fuzzy clustering (FCM) maintains a stable ARI of 0.630, clearly higher than AP alone.

Interpretation:

The hybrid approach significantly improves clustering quality compared with AP alone, with a higher ARI, which indicates a better match with the ground truth. However, AP alone appears sensitive to the preference parameter, which affects the number of clusters and their quality.

3.2. Results of the Affinity Propagation Algorithm Alone

Figure 2 shows the clusters of the Iris dataset obtained by Affinity Propagation alone, with the exemplars (cluster centers) marked by crosses, and Figure 3 presents the corresponding program output with the evaluation metrics.

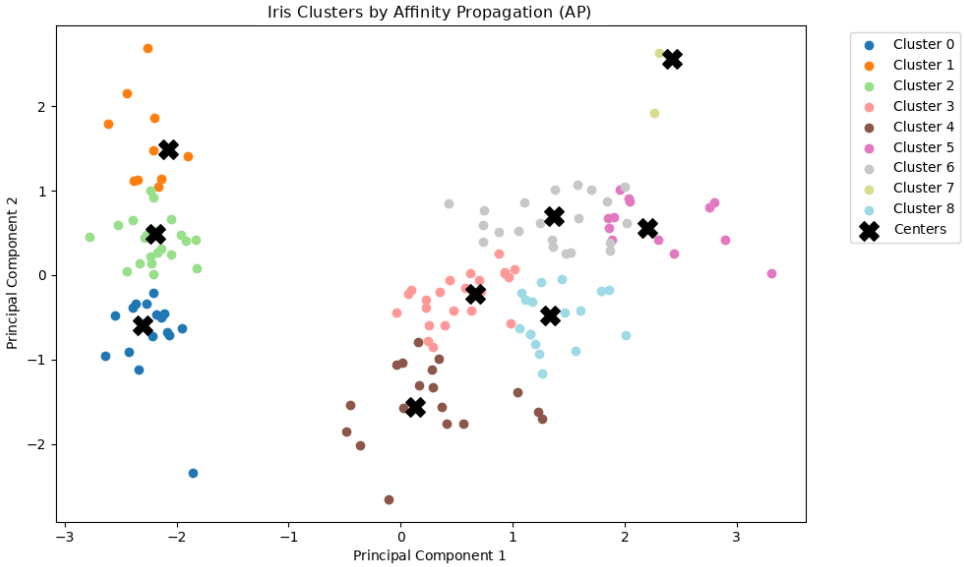

Figure 2. Clusters of the Iris dataset obtained by affinity propagation alone (exemplars marked by crosses).

```
Number of clusters detected: 9
Cluster center indices: [  3   5  17  78  80 102 110 117 123]
Cluster labels: [2 0 0 0 2 1 2 2 0 0 1 2 0 0 1 1 1 2 1 1 2 2 2 2 2 0 2 2 2 0 0 2 1 1 0 0 2
 2 0 2 2 0 0 2 1 0 1 0 2 2 6 6 6 4 8 3 6 4 3 4 4 3 4 3 3 6 3 4 4 4 6 3 8 3
 3 3 8 6 3 4 4 4 3 8 3 6 6 4 3 4 4 3 4 4 3 3 3 3 4 3 6 8 5 8 6 5 4 5 8 7 6
 8 5 8 8 6 6 7 5 4 5 3 5 8 6 5 8 3 8 5 5 7 8 8 8 5 6 6 3 5 6 5 8 5 6 6 8 6
 6 3]

Evaluation metrics:
Homogeneity: 0.747
Completeness: 0.389
V-measure: 0.512
Adjusted Rand Index: 0.298
Silhouette score: 0.314
```

Figure 3. Output of the affinity propagation algorithm alone: number of clusters, cluster centers, labels and evaluation metrics.

- Number of clusters detected: 9
- Cluster center indices and labels provided
- Evaluation metrics:
  - Homogeneity: 0.747 (good cluster separation)
  - Completeness: 0.389 (the clusters do not fully cover the actual classes)
  - V-measure: 0.512 (trade-off between homogeneity and completeness)
  - ARI: 0.298 (low to moderate)
  - Silhouette score: 0.314 (average cluster quality)

Interpretation:

AP alone produces a reasonable number of clusters with good homogeneity but low completeness, which means that some clusters are pure but not all members

of the same class are grouped together. The moderate silhouette score suggests that the clusters are moderately well separated.

3.3. Results of Hierarchical Clustering

Figure 4 presents the dendrogram obtained by hierarchical clustering of the Iris dataset, and Figure 5 shows the distribution of the actual species across the clusters formed.

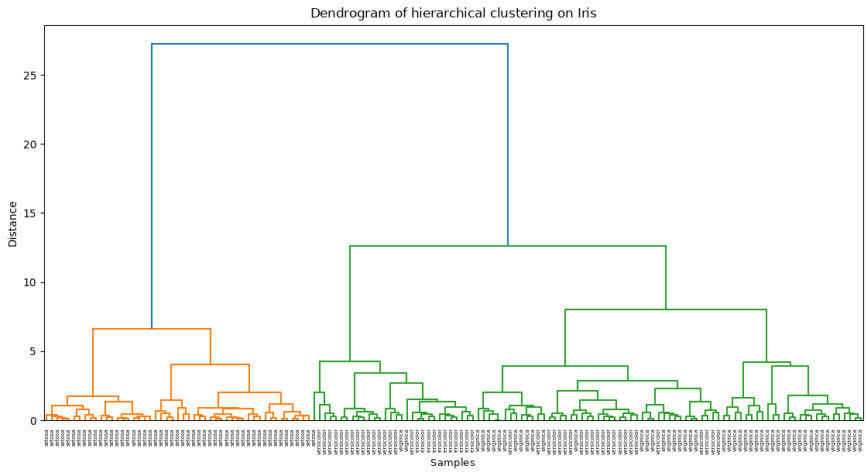

Figure 4. Dendrogram of hierarchical clustering on the Iris dataset.

```
Number of clusters formed: 3
True species   Assigned cluster
setosa         1                 49
               2                  1
versicolor     2                 27
               3                 23
virginica      2                  2
               3                 48
dtype: int64
```

Figure 5. Distribution of the actual Iris species across the three clusters formed by hierarchical clustering.

- Number of clusters formed: 3
- Distribution of actual species vs. clusters:
  - setosa well separated (49 out of 50 in cluster 1)
  - versicolor and virginica mixed in clusters 2 and 3

Interpretation:

Hierarchical clustering produces few clusters (3), which matches the actual number of classes, but it does not separate versicolor and virginica well, as they are mixed.

This shows a limitation in the ability to distinguish these two close classes.

3.4. Overall Comparison

Table 1 summarizes the performance of the three methods on the Iris dataset according to the number of clusters, the Adjusted Rand Index (ARI) and the other evaluation metrics.

Table 1. Comparison of the performance of AP, AP-FHC and hierarchical clustering on the Iris dataset.

Method	No. of clusters	ARI (vs. ground truth)	Homogeneity	Completeness	V-measure	Silhouette	Comment
Affinity Propagation (AP)	9 to 21	~0.19 - 0.31	0.75	0.39	0.51	0.31	Sensitive to the parameter, pure but incomplete clusters
Hybrid clustering (AP-FHC)	3 to 16	~0.63	-	-	-	-	Best overall match, more robust
Hierarchical clustering	3	Not given	-	-	-	-	Clear separation of one class, confusion between the other two

4. Conclusions

The hybrid AP-FHC approach combines the complementary strengths of the two methods while mitigating their respective weaknesses. This combination of unsupervised classifiers offers a robust, efficient, and adaptable solution, particularly well suited to the analysis of complex and structured data, such as the Iris data and many others, where the group structure is often inherently fuzzy and hierarchical. More specifically, this combination approach unfolds in several key phases:

1) Automatic selection of representatives (exemplars) via affinity propagation:

This step makes it possible to autonomously identify, without prior parameterization, the central or pivotal points that embody the natural structure of the data. It eliminates the need to arbitrarily fix the number of clusters, which is a major advantage in contexts where the granularity of the groups is unknown or variable.

2) Fuzzy hierarchical construction phase:

Building on the identified representatives, fuzzy hierarchical clustering organizes the clusters into a tree-like structure, while assigning each element multiple membership degrees. This fuzzy modeling reflects the social reality in which boundaries between groups are often imprecise, with members who may belong simultaneously to several subgroups or hierarchical levels.

3) Integration and interpretation phase:

Combining the results allows a fine-grained and nuanced analysis of the internal dynamics of the groups, highlighting overlaps, substructures, and proximity relationships between clusters. It thus facilitates understanding of collective and individual behaviors in complex environments.

4) Adaptability and optimization phase:

The hybrid approach adapts naturally to different sizes and types of data and can be optimized to efficiently handle large volumes of information (Big Data). It also makes it possible to incorporate domain-specific criteria (for example, sociological constraints in the case of trade-union elections), strengthening its operational relevance.

In conclusion, the AP-FHC approach does not merely segment the data: it offers a powerful analytical framework for modeling the complexity, nuance, and hierarchy of affiliations in social or organizational systems. This ability to capture both the global structure and the local uncertainties makes it a valuable tool for researchers and practitioners seeking to deepen their understanding of complex phenomena.

5. Research Perspective

This study will examine the applicability of the hybrid approach combining Affinity Propagation (AP) and Fuzzy Hierarchical Clustering (FHC) in the context of trade-union elections within companies in the Democratic Republic of the Congo, more precisely in Lubumbashi. The objective is to analyze the borderline behavior of workers in choosing their union representation, in order to better understand the complex and ambivalent dynamics that influence their union decisions.

Author Contributions

1) Mosha Mesu Pierre-Stéphane contributed to the conceptualization of the study and to the design of the methodology, developed the software, carried out the formal analysis and the investigation, and coordinated the project.

2) Daniel Bavueza Munsana contributed to the methodology, validated the results, reviewed and edited the manuscript, and supervised the work.

3) Apollinaire Ndondo Mboma contributed to the conceptualization of the study, validated the results, reviewed and edited the manuscript, and supervised the work.

4) Pierre Kafunda Katalay validated the results, reviewed and edited the manuscript, and supervised the work.

5) Lukusa Muvuala Vicky contributed to the methodology, the formal analysis and the investigation, and reviewed and edited the manuscript.

6) Bertin Mazunze wrote the original draft of the manuscript, drawing on his experience in scientific publication, and also reviewed and edited it. He contributed to the methodology, took part in the development of the software and in the investigation, curated the data and prepared the figures and tables.

7) Kalala Kamanga Elisée provided resources and took part in the curation of the data.

8) Kabango Dyuba Désiré provided resources and reviewed and edited the manuscript.

All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Ouda, R. and Hart, P. (1973) Pattern Classification and Scene Analysis. Wiley.

[2] Frey, B.J. and Dueck, D. (2007) Clustering by Passing Messages between Data Points. *Science*, **315**, 972-976. https://doi.org/10.1126/science.1136800

[3] Bezdek, J.C. (2013) Pattern Recognition with Fuzzy Objective Function Algorithms. Springer. https://books.google.fr/books?hl=fr&lr=&id=z6XqBwAAQBAJ&oi=fnd&pg=PR13&dq=Pattern+Recognition+with+Fuzzy+Objective+Function+Algorithms.+Springer.&ots=0j_Nt_AhHr&sig=ag4e-qQoC3KzpwjSRoKt9ghX_LI

[4] Moiane, A.F. and Machado, Á.M.L. (2018) Evaluation of the Clustering Performance of Affinity Propagation Algorithm Considering the Influence of Preference Parameter and Damping Factor. *Boletim de Ciências Geodésicas*, **24**, 426-441. https://doi.org/10.1590/s1982-21702018000400027

[5] (2025) Hierarchical Clustering—Wikipedia. https://en.wikipedia.org/wiki/Hierarchical_clustering

[6] Kim, K.B., Park, H.J. and Song, D.H. (2022) Combining Supervised and Unsupervised Fuzzy Learning Algorithms for Robust Diabetes Diagnosis. *Applied Sciences*, **13**, Article 351. https://doi.org/10.3390/app13010351

[7] Fisher, R.A. (1936) The Use of Multiple Measurements in Taxonomic Problems. *Annals of Eugenics*, **7**, 179-188. https://doi.org/10.1111/j.1469-1809.1936.tb02137.x

[8] Forina, M., Lanteri, S., Armanino, C., Casolino, C., Casale, M. and Oliveri, P. (2008) PAR-VUS: An Extendible Package for Data Exploration, Classification and Correlation. Institute of Pharmaceutical and Food Analysis and Technologies.

[9] Street, W.N., Wolberg, W.H. and Mangasarian, O.L. (1993) Nuclear Feature Extraction for Breast Tumor Diagnosis. *SPIE Proceedings*, **1905**, 861-870. https://doi.org/10.1117/12.148698

[10] Givoni, I., Chung, C. and Frey, B.J. (2012) Hierarchical Affinity Propagation. arXiv: 1202.3722.

[11] Zhang, K. and Gu, X. (2014) An Affinity Propagation Clustering Algorithm for Mixed Numeric and Categorical Datasets. *Mathematical Problems in Engineering*, **2014**, Article ID: 486075. https://doi.org/10.1155/2014/486075

[12] Zhao, X. and Xu, W. (2015) An Extended Affinity Propagation Clustering Method Based on Different Data Density Types. *Computational Intelligence and Neuroscience*, **2015**, Article ID: 828057. https://doi.org/10.1155/2015/828057

[13] Yang, W., Lai, J., Liu, Y., Lin, Y., Hou, H. and Pai, P. (2023) Using Medical Data and Clustering Techniques for a Smart Healthcare System. *Electronics*, **13**, Article 140. https://doi.org/10.3390/electronics13010140

[14] Rajkumar, K.V., Yesubabu, A. and Subrahmanyam, K. (2019) Fuzzy Clustering and Fuzzy C-Means Partition Cluster Analysis and Validation Studies on a Subset of Citescore Dataset. *International Journal of Electrical and Computer Engineering* (*IJECE*), **9**, 2760-2770. https://doi.org/10.11591/ijece.v9i4.pp2760-2770

[15] Davies, D.L. and Bouldin, D.W. (1979) A Cluster Separation Measure. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, **1**, 224-227. https://doi.org/10.1109/tpami.1979.4766909

[16] Rousseeuw, P.J. (1987) Silhouettes: A Graphical Aid to the Interpretation and Validation of Cluster Analysis. *Journal of Computational and Applied Mathematics*, **20**, 53-65. https://doi.org/10.1016/0377-0427(87)90125-7

[17] Rand, W.M. (1971) Objective Criteria for the Evaluation of Clustering Methods. *Journal of the American Statistical Association*, **66**, 846-850. https://doi.org/10.1080/01621459.1971.10482356

[18] Bezdek, J.C. (1973) Cluster Validity with Fuzzy Sets. *Journal of Cybernetics*, **3**, 58-73. https://doi.org/10.1080/01969727308546047