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Multi-Label Categorical Data using Orthogonal-Constrained Meta-Heuristic Adaptive Multi-View Clustering

Babu Karri[1], Suresh Babu Yalavarthi[2], Sk Althaf Hussain Basha[3]

1. Babu karri, Research scholar, Acharya Nagarjuna University , Guntur. E-mail karrribabu@gmail.com

2. Suresh Babu Yalavarthi, Professor and Director for MCA , Jagarlamudi Kuppuswamy Choudary College, Guntur ;E-mai;l yalavarthi_s@yahoo.com

3. SK Althaf Hussain Basha ,Principal and Professor of CSE, Rishi MS Institute of Engineering and Technology for Women, Hyderabad , Telangana, India. Email I.D. : althafbashacse@gmail.com

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Abstract:

Clustering is a fundamental concept in data mining for real-time data processing; nevertheless, assessing how well attributes are represented in clustering is a major challenge in AI-related fields. A popular idea in multi-labeled categorical data analysis, multi-labeled clustering provides a wealth of useful information for attribute assessment and representation. The objective of multi-dimensional clustering is to produce accurate clustering results under varied settings by combining complementing data from several dimensions.To visualize the data as a cluster with several categories, we offer a new method in this study called Orthogonal Constrained Meta Heuristic Adaptive Multi-View Clustering (OCMHAMVC). One method that has been suggested uses multi-labeled data to group comparable labeled samples into dimensional data concepts and then uses the optimal matrix factorization (OMF) method to assess low-dimensional data. Then, we use an adaptive heuristic to merge complimentary data from multiple dimensions and show the data in an orthonormality-constrained way. We also add complexity to the computational analysis of the data. Testing the suggested method on large datasets with many views yields efficient and scalable results when compared to more conventional clustering methods that are connected to various perspectives.

Key Words: Clustering, Data with multiple labels, Clustering , Several views, Meta heuristic, Document clustering.

Introduction

In multi-label classification (MLC), each label represents a different class or category and is applied to each instance in turn. Depending on whether the interactions between labels are complimentary, redundant, or even competing, MLC becomes complicated. When dealing with categorical data, existing methods frequently encounter difficulties caused by the lack of inherent numerical order. These intricacies are frequently too much for traditional machine learning algorithms to maintain.**[1].** The consensus principle aims to maximize agreement among competing viewpoints, while the complementary principle shows that each perspective contains unique knowledge. An ineffective approach to integrating multiple views in typical model-view-controller (MVC) systems involves merging features from different views into a single feature space and then using a single view clustering algorithm, such as spectral clustering, to achieve the desired clustering performance **[2].** The merging of multi-view data often overlooks valuable information. There are many advanced learning algorithms designed for maximum value convolution (MVC), with current MVC approaches generally falling into two categories: those that rely on representation learning [3]. This overview will cover MVC techniques related to representation learning, focusing on models that incorporate an inner layer for representation learning from input to output. There are two groups of models that incorporate many perspectives: the representation learning-based MVC family and the deep-representation learning-based MVC group **[4].** The new model-view-controller (MVC) that relies on deep representation learning can manage more complicated data structures thanks to its deep network architecture overall categorization in Fig1.

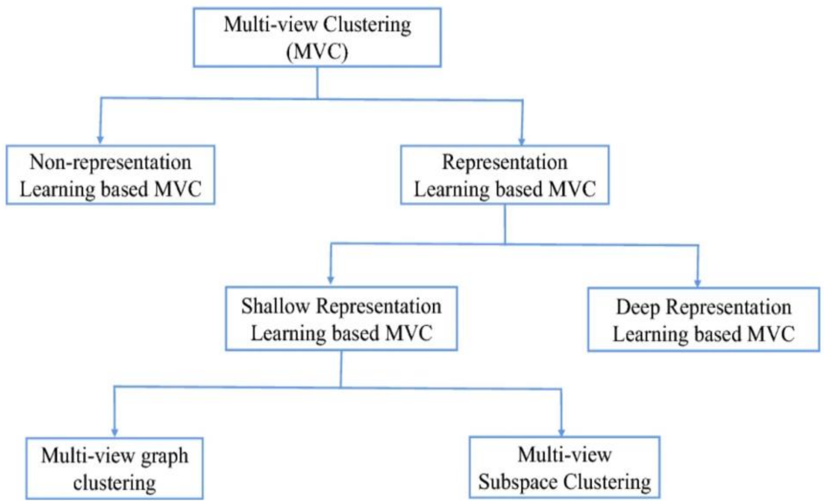

Fig 1:"Taxonomy of Model-View-Control (MVC) Methods

2. Literature Review

To verify obtaining data ready for classification, feature selection is an important first step. Problems with choosing features have been effectively addressed by optimization techniques that take into account many objectives. To introduce MOMFS, a two-particle swarm-based method for selecting features for multi-objective multi-label filters in **Wang et al., [5] Zhu et al., [6].** They have deployed mutual information to gauge what are theoretically two goals: feature redundancy and the relationship between feature and label sets. With the goal of preventing particle swarm optimization (PSO) from reaching local optima and producing a misleading Pareto front, two distinct objectives are maximized using PSO. Improved hybrid topology is offered according to particle fitness value. There is also a strategy for managing archives that will ensure their continued circulation **Liu et al., [7].** Nowadays, many apps utilize multi-label classification to categorize unknown patterns into multiple categories. Researchers frequently employ a feature selection strategy based on genetic algorithms to enhance the accuracy of multi-label classification. However, genetic algorithms can be time-consuming as they struggle to identify the best feature subsets. **Wang et al. [8]** proposed a memetic feature selection approach for multi-label classification. This approach aims to enhance multi-label classification by extracting feature subsets from genetic searches that have been optimized using memetic data. In a separate study, **Liu et al. [9]** introduced a new multi-population genetic algorithm specifically designed to tackle the feature selection issue in the context of multiple labels. Their experiments on 18 multi-label datasets demonstrated that this new approach outperformed other multi-population-based feature selection methods. Feature selection is a technological approach that can significantly reduce the dimensionality of data. In terms of global optimization, the feature selection study demonstrates the effectiveness of the multi-objective optimization approach. Using the Pareto relationship, conflicting objectives in multi-objective issues can be efficiently managed. **Zhou and Liu, [10]** As a result, SHAPFS-ML was created. It is a method for selecting features for multi-label learning that combines Shapley value. The mutation and crossover operators, proposed using the Shapley value, work well for identifying relevant, unnecessary, and excessive features. **Fakhri et al., [11]** Optimization goals that include several labels are considered by this approach **Xu et al., [12]** Utilizing a feature selection strategy that considers multiple objectives can enhance the accuracy of multi-label classification. A preliminary step in addressing multi-label classification challenges is feature selection, which aims to identify relevant attributes. To optimize classification efficiency and minimize computational expenses, it is feasible to select a small number of outstanding characteristics. The research emphasizes the need for an optimization strategy with multiple objectives. **Huang et al., [13]** When dealing with numerous labels, effectively managing feature selection involves identifying a subset of features within a complex, large-scale search space. This can be achieved by using a reference-based multi-objective optimization strategy designed for multi-label data to select features in **Qi et al., [14]** An evolutionary method can solve the issue of multi-label feature selection in parallel by dividing it into smaller, more manageable subproblems, similar to a decomposition-based multi-objective optimization approach.**Trigeorgis et al. [15]** To address new information concerns, a comprehensive two-dimensional representation was obtained using the grid premise. As a result, the results of the deep representation in low dimensions were directly affected by the basic architecture. This method explores a thorough two-dimensional depiction of the basic data structure., **Zhao et al. [16]** factorization in practice is associated with a deep premise framework, and it has been suggested that a deep premise picture learning-dependent NMF approach be implemented. **R. Zhang et al. [17]** Create the innate diagram and the punishment chart independently using the paired requirement data. **D.A. Spielman et al. [18]** created a progressive bipartite diagram by utilizing multi-layered pyramid-style structures. Finally, the gathering structure maximizes the use of SVM **D. Hidru et al. [19]**Presented here is a novel approach, OCMHAMCV, which stands for Orthogonal Constrained Meta Heuristic Adaptive Multi-View Cluster.**Yang, S., and Zhang, Y. [20]** . The original goal of the OMF method was to create low-dimensional data clusters from labelled samples of data that were comparable to one another. Applying adaptive heuristics to integrate complementary data in an appropriate orthonormality-constrained perspective increases computational analysis complexity along several dimensions.

Key goals of the suggested method are as follows:

a) To introduce an unsupervised multi-labeled clustering algorithm that utilizes orthogonal matrix factorization a combination of normalization and orthogonal constraints to ensure consistent representation of regularities across different data perspectives.
b) In order to implement an objective model, this serves as the baseline for the proposed model.
c) To effectively assess the suggested strategy's performance and compare it with traditional approaches, it should be tested on various real-time datasets, including multi-labeled cluster data.

Preliminaries

The suggested method and its suitable procedures are introduced in this part, which details the fundamental preliminary steps.

1. **Optimized Matrix Factorization (OMF) :** Consider the multi-labeled data shown i$A = \{a_0, a_1, \dots\dots\dots a_n\} \in M_+^{nxd}$, In this context, n is the sample size and d is the feature vector dimension.

$a_j(1 \le q \le n)$ This results in consistency when expressed with sample n. One specific application of OMF is the identification of reduced rank-based matrices in non-negative relationships.$H = \{h_1, h_2, \dots\dots\dots h_d\} \in Q_+^d$ & $W = \{w_1, w_2, \dots\dots\dots w_d\}\, Q_+^d(K \propto\propto n\&d \propto D)$ that are represented. After investigating matrix relations (H&W), the next step is to investigate input data. as $A_j = \sum_{i=1}^{d} \quad h_i, w_{ij}$ It is defined by a mix of linear matrix architecture $w = \{w_1, w_2, \dots\dots\dots w_d\}$ and impact factor w_j so Described below is the desired function of negative matrix development as eq (1),

$$min_{H.W} |A - HW|_F^2 \;\; w.r.I \qquad H \ge 0, W \ge 0 \text{ .... (1)}$$

The Karush-Kuhn-Tucker (KKT) ruling requirement with correlated parameters and the W&H variables are illustrated in Eqn. (2).

$$W_{ij} = W_{ij} \frac{(H^T\, A)_{ij}}{(W^T\, HW)_{ij}} \text{...................................(2)}$$

Deep learning factorisation, as shown in Eqn. (3),

$$W^m \simeq H_1^m H_2^m H_1^m \simeq H_2^m W_2^m \dots\dots\dots H_{1-2}^m \simeq H_{l-1}^m H_{l-1}^m H_{l-1}^m \simeq H_1^m W_1^m \text{ .... (3)}$$

$H_1^m H_2^m, \dots\dots\dots H_{1-1}^m H_1^m$ &W_1^m,$W_2^m \dots W_{1-1}^m W_1^m$Characterized by matrices and coefficients in m-dimensional basis. A combination of the following variables is denoted as Equation (4).

$$min_{w_i^m.H_i^m} \sum_{m-1}^{m} \quad |A^m - H_l^m w_l^m w_{1-l}^m \dots\dots\dots W_2^m W_l^m.|_F^2 \;\; w.r.I \qquad H_l^m \ge 0, W_l^m \ge 0 \text{................ (4)}$$

Equation (5) describes the objective functionality using several variables.

$$min_{H_l^m W_l^m} |A^m - H_l^m w_l^m w_{1-l}^m \dots\dots\dots W_2^m W_l^m.|_F^2 \;\; w.r.I \qquad H_l^m \ge 0, W_l^m \ge 0 \text{............................ (5)}$$

3.1Deep matrix indices factorized in depth

"Deep matrix index factorization with significant depth. The goal is to eliminate irrelevant data from matrix A by using associative flexibility when describing or investigating the structure of complex processes. The equation shows that optimal matrix functionality can be learned through deep learning."

$$A \simeq Z_1 W_1 A \simeq Z_1 Z_2 W_2 \dots A \simeq Z_1 Z_2 W_2 \dots Z_m W_m \text{ ....(7)}$$

$Z_i \in Q^{K_{t-1} * k_t}$ be the $l - th(l - \le m)$ matrix relates to basis $W_l \in R^{K_{i*}n}$ is The representation of the matrix at the lth layer involves using m-dimensional layers in matrix factorization. This can be done in a grouped or individually recognized form. This approach allows for using the same grouping processes on different datasets to capture various perspectives on multi-labeled data.For multi-labeled clustering with different attribute relations, the deep matrix factorisation approach can be utilised. In view of these preliminary findings, we present a novel heuristic method for studying multi-labeled data clustering using augmented matrix construction.

4.Implementation of Proposed Framework

This section discusses the orthogonal and combined framework with co-regularization requirements, and introduces a suggested method using an unsupervised learning clustering technique called OCMHAMVC. Initially, the objective functions propose an optimal method for clustering multi-labeled data, and then examine the computational analysis of the proposed approach, taking into account efficiency.

Multi objective functions of AMVCOCMH

The Optimal Control Method for Hybrid Automata with Multiple Variables (OCMHAMVC) is a mathematical optimization technique designed to solve control problems for hybrid systems. Hybrid systems are systems that exhibit both continuous and discrete dynamics, such as those found in robotics, autonomous vehicles, and power systems.Equation (7) represents labelled constraints in multi perspectives; for instance 1 samples make up labelled data and l-1 samples make up unlabelled data depending on attribute data.

$$X= [C_{c*l}\ 0\ 0\ I_{n-1}]\text{..........................}(7)$$

C_{ij} be the attribute data with i[th] and j[th] classes $C_{ij} = 0$ it labelled information with l samples I_{n-1} defines $(n-1)$ $(n-l)$ an unlabelled sample is defined as one that is associated with the creation of an identity matrix. Using the investigate the labelled constraint data from the unknown labelled data if the samples of unlabelled data are more than the threshold cluster data. Eqn. (8) describes the development of clusters using labelled matrix data.

$$X = [C_{c*l}\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ I_{n-l-1}] = [C_{c*l}\ 0\ 0\ I_{n-1}]\text{.................................}(8)$$

With respect to the auxiliary matrix Z, the following are the various goal functions for orthogonal matrix formation

$$MO_F = \sum_{u=1}^{n_u} \theta_u \| A^u - V^u (Z^u)^T X^T \|_F^2 + \lambda \sum_{u=1}^{n_u} \| Fo(Z^u (Z^u)^T) - I \|_F^2 + \sum_{u=1}^{n_u} \sum_{s=1}^{n_u} \frac{1}{2} \theta_{us} \| Z^u - Z^s \|_F^2$$

Investigate dimension-free feature representations for run-time sample data with this multi-objective function. Determine the best possible representation of each dimension for each desirable feature. The two most important characteristics of a good feature representation are scalability and the presence of an efficient discriminating factor in the attributes used to compare classes. In multi-labeled clustering, utilise orthogonal restrictions to meet the representation of intended feature presentation.

$F_{ij}\ \{1\ j = i\ 1 \leq j, i \leq c\ 0\ otherwise\ 0$ .... (9)

Then orthogonal constraint framework described as $\lambda \sum_{u=1}^{n_u} \quad ||FO(Z^u(Z^u)^T - I||_F^2$

In this case, we may determine the control ability of the orthogonal constraint relation by representing the multiplication operator with distinct notations. This is a representation of various forms in various dimensions that may hold unity data according to the clustering specification's structure.

B) Convex Feature Optimization:

According to the global minimum relations-based objective function, which investigates many variables $V^u \& Z^u$ The optimization process is adjusted to accommodate additional constraints, such as connecting one attribute to other attributes provided as constants, along with non-convex functions. When employing convex optimization with non-negative attribute relations and Lagrange multipliers, the non-negative matrix relations described by the equation can be used in Lagrange matrices.

$$La\_r = \sum_{u=1}^{n_u} \theta_u \| A^u - V^u (Z^u)^T X^T \|_F^2 + \lambda \sum_{u=1}^{n_u} \| Fo(Z^u (Z^u)^T) - I \|_F^2 + \sum_{u=1}^{n_u} \sum_{s=1}^{n_u} \frac{1}{2} \theta_{us} \| Z^u - Z^s \|_F^2$$
$$+ \sum_{u=1}^{n_u} tr(\beta^u (V^u)^T) + \sum_{u=1}^{n_u} tr(\alpha^u (Z^u)^T)$$

The qualities labeled by Eqn (11) are subject to KKT conditions during implementation.

$(A^n\, XZ^n - V^n\, (z^u)^T\, X^T\, XZ^n)_{ij}\;\; V_{ij}^u = 0 \quad \theta_u\, X^T\;\; (A^u)^T V^u\;\; -2\lambda (FO(Z^u (Z^u)^T) Z^u + 2\lambda Z^u - 4\lambda F(Z^u . Z^u . Z^u) +$
$4\lambda F(Z^u . Z^u . Z^u) - \sum_{s=1}^{n_u} \quad \theta_{us}, Z_{ji}{}^{s}\; Z_{ji}^{U} = 0$ .... (11)

As shown in Eqn. (12), the final multi-objective function is

$$v_{ji}^u \leftarrow v_{ji}^u \, \frac{(A^u\, XZ^u)_{ji}}{\left(V^u (Z^u)^T\, X^T\, XZ^u\right)_{ji}}$$

$$Z_{ji}^u \leftarrow Z_{ji}^u \, \frac{(\theta_u\, X^T\;\; (A^u)^T V^u + 2\lambda Z^u + 4\lambda F(Z^u . Z^u . Z^u) + \sum_{s=1}^{n_u} \quad \theta_{us} Z^s)_{ij}}{(\theta_u\, X^T\, XZ(V^u)^u + 2\lambda FO(Z^u (Z^u)^T) Z^u + 4\lambda F(Z^u . Z^u . Z^u) + \sum_{s=1}^{n_u} \quad \theta_{us} Z^s)_{ij}} \text{........................(12)}$$

The following is an objective algorithm description based on the above:

Algorithm 1: A method for optimising multi-labeled clustering is proposed.

I/p: Multi labeled data set $\{A^1, A^2 \ldots\ldots A^{nu}\}$ no. of clusters, no. of samples, different parameters θ_v, θ_{vs}
Produced X-matrix with constraints and labels
Developed a restricted matrix with optimal constraints F
for u=1-n then
factors with normalization i.e.$A^u(\lvert A^u(:,j \rvert^2)$
update initialize parameters $V^u \& Z^u$ in ploted range [1,0]
E-for
For for u=1 n_u then
a. Develop iterative matrix structures <T

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b. Constant V^u then update Z^u
c. Constant Z^uthen update V^u
E-for
Assess the low-dimensional data representation i.e.U^v =XZ^u
Review the completed low-dimensional data representation. $U^* = \frac{\sum_{u=1}^{n_u} U^u}{n_v}$
o/p: Final multi labeled cluster result

4.1 Multi labeled Dimensional Clustering

Hierarchical Clustering with Multiple Labels In order to create multi-label clustering using basic cluster functions, we first determine the similarity measure between input articles in the same cluster and use it to calculate an average similarity weight. Framework for investigating figure-depicted multi-dimensional document clustering

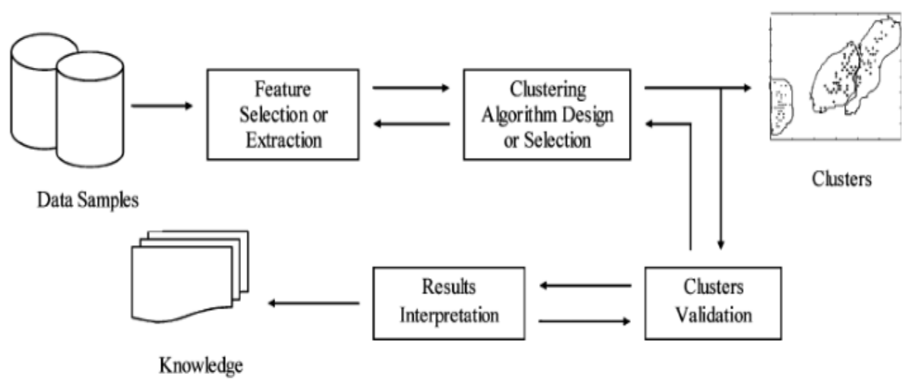

Fig 2: Architecture of proposed approach

Figure 1 The overall, step-by-step process for gathering multi-dimensional cluster findings is illustrated in This method yielded the weighted similarity expression, which is given by Eqn (13)

$$CS = \sum_{r=1}^{n} m_r \left[\frac{1}{m_t^2} \sum_{t_i,t_j,S_r} S(t_i,t_j)\right] \ldots\ldots\ldots\ldots\ldots (13)$$

$$\sum_{t_i,t_j,\in,S_r} S(t_i,t_j) = \sum_{t_i,t_j,\in,S_r} S(t_i^d,t_j) - \frac{2m_r}{m-m_r} \sum_{t_i,\in,S_r} t_i^t, \sum_{t_m,\in,S/S_r} t_h + n_r^2$$

$$= T_r^d T_r - \frac{2m_r}{m-m_r} T_r^d (\mathrm{T}-T_r) + m_r^2 \frac{m+m_r}{m-m_r} |T_r|^2 - \frac{2m_r}{m-m_r} T_r^d \mathrm{T} + m_r^2$$

Filtering documents based on their degree of similarity using weighted cluster functions, as shown in Eq(14).

$$CF = \sum_{r=1}^{n} \quad \frac{1}{m_r}\left[\frac{m+m_r}{m-m_r}|T_r|^2 - \left(\frac{m+m_r}{m-m_r} - 1\right) T_r^d T\right] \ldots\ldots\ldots\ldots\ldots\ldots(14)$$

The optimal weighted attribute is the foundation of the assessment, which contrasts the min-max functionality between two words in the input texts with optimal weighted cluster functions T_r^d T It is possible to represent the integration of cluster-related document functionality as Eqn (15)

$$\underline{CF} = \sum_{r=1}^{K} \quad \frac{\lambda_r}{m_r}\left[\frac{m+m_r}{m-m_r}|T_r|^2 - \left(\frac{m+m_r}{m-m_r} - 1\right) T_r^d T\right] \ldots\ldots\ldots\ldots\ldots(15)$$

For related document clustering, the optimised functionality (Y) is assessed using Eqn. (18),

$$Y = \sum_{r=1}^{k} \quad \sum_{t_i, t_j, \in, S_r} \quad \frac{1}{m-m_r} \sum_{t_h, \in, S/S_r} \quad S\left(t_i - t_h \, \frac{C_r}{||C_r||} - t_h\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(16)$$

Cluster functionality, to be assessed using Eqn, is the primary determinant of multi-labeled clustering optimisation using weighted cluster functions. It is based on the same principle as cluster creation with multiple multi-label functionalities.

$$MLC_{opt} \sum_{r=1}^{K} \quad I_r\,(m_r T_r) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(17)$$

Optimal multi-label clustering involves iteratively applying several label data sets to a set of inputs in order to get optimised cluster results, which are then used to update the relations in the convergence cluster matrix using a similarity measure.

5. Experimental Evaluation of AMVCOCMH

In this section, we will compare OCMHAMVC's performance with that of more conventional methods across various parameters. We will test the effectiveness of the suggested method by using real document data. OCMHAMVC clusters multi-labeled documents using a similarity measure that relies on weighted cluster functions based on cosine and relative Jaccard scores, as well as on the standard geometric distance.

a) Input clustering data

In this experiment, we combine new benchmark data sets from comprehensive and efficient sources for multi-labeled document clustering; in prior tests, we used k1b and Reuter's 8-10 versions of this data for document clustering. Incorporate cloud-related data sources and downloaded data sets into real-time clustering processes by considering their quantitative commonalities. The BBC Series dataset, Reuter's dataset, Series 3 sources dataset, and MSRC dataset are the main datasets utilized in our proposed way. These databases include massive volumes of data presented in HTML documents gathered from a wide range of sources, such as those associated with entertainment, politics, sports, medicine, and commerce. Many traditional multi-dimensional clustering techniques are compared to the proposed method before it is evaluated on all of these datasets. Here are some of the ways that are currently being used: MultiNMF, GMNMF, CoNMF-P, and MVCC.

5.1 Setting of Experiments

Study the to compare conventional and proposed methodologies based on various parameters. Draw random samples from multiple data sources, remove labeled data from the input, and search for the weight of each parameter using all input data. The multi-labeled dimensional clustering method is based on evaluating similarity using weights and metrics derived from geometric distances. Utilizing these measures in our suggested method will assess how well every cluster dataset performs in evaluating several measures, including precision, accuracy, recall, f-score, normalization factor, computational cost, memory consumption, and the Jaccard coefficient, accuracy, and normalization."

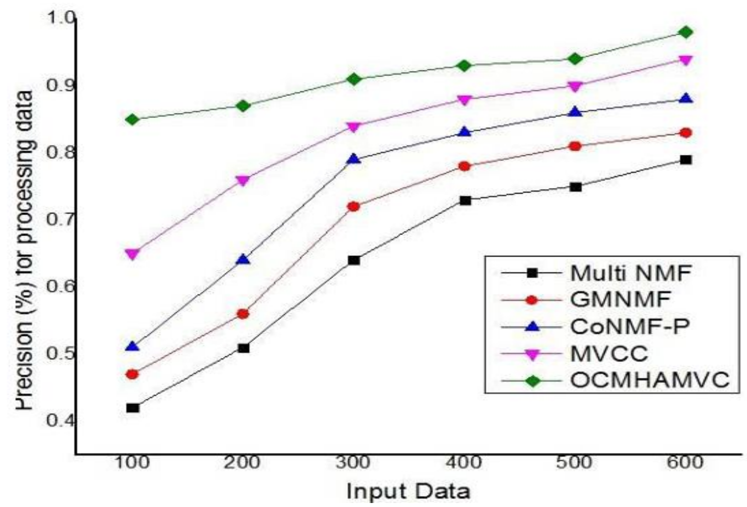

Fig 3: Accuracy as measured by parameters for multi-class labels.

Figure 2 shows the results of an analysis of five different clustering approaches based on the accuracy of 100–500 HTML text documents collected using multi-labeled data For every data set in the row, the bolded value is the best result from each method, while the remaining values are the second best.

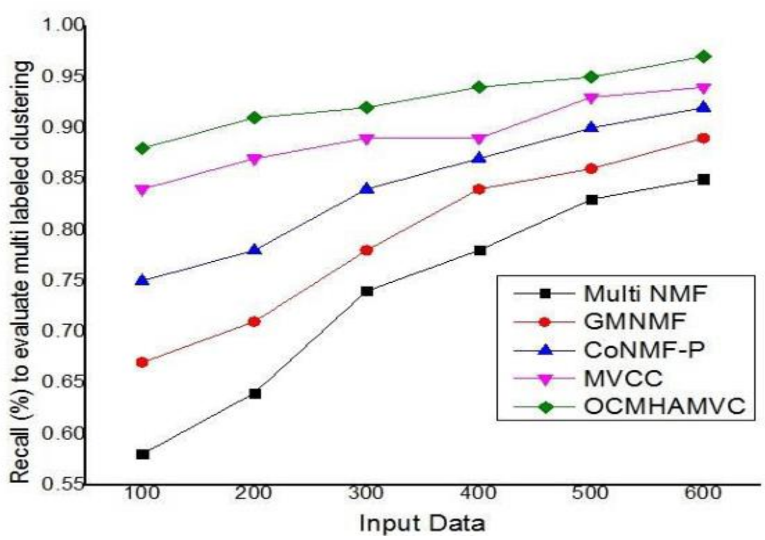

Fig4: Performance of clustering results in recall.

In Figure 4, we can observe the outcomes of f-score matching between HTML text documents and multi-dimensional documents. it demonstrates that AMVCOCMH outperforms traditional methods when the number of documents increases, and that it efficiently clusters documents with multiple attributes

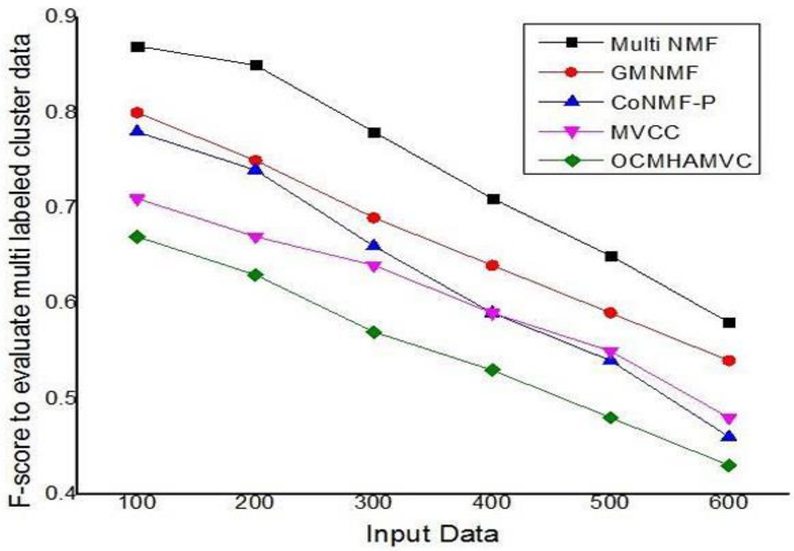

Fig5: Performance of multi-dimensional clustering results in F-score.

Figure 5 shows how five different clustering methods, with a significant bias towards collecting multi-labeled data, performed in terms of accuracy when applied to 100-500 HTML text pages.

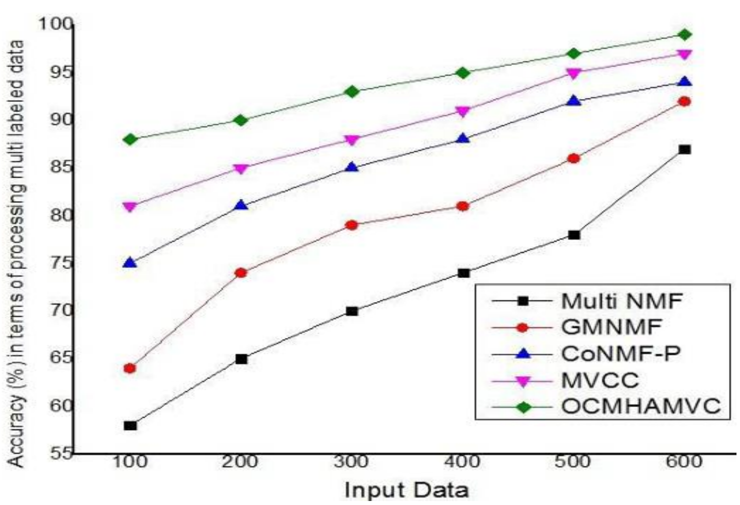

Fig 6: Performance of accuracy in multi –dimensional cluster results.

The results shown in the tables and figures above are based on the experimental setup of the suggested method as well as other methods. When applied to text-oriented documents containing various domains, it meets both the text data connected to curves and the basic convergence of AMVCOCMH. Using iterative functions to explore documents, AMVCOCMH finds efficient multi-dimensional clustering solutions with fewer iterations applied to various text-oriented materials. Time, accuracy, precision, memory usage, and CPU computational cost are the metrics used by AMVCOCMH to measure computational performance when processing multi-dimensional documents.

6. **Conclusion**

In this paper, a propose novel approach Orthogonal Constrained Meta Heuristic Adaptive Multi-View Clustering (OCMHAMVC) to group similar items using multi-labeled dimensional data. To handle the increasing amount of labeled data, this method clusters comparable label data relevant to cluster prototypes. Comparable classes are linked with unaltered, comparable labels and attribute relations of the cluster prototype. The method uses cooperative regularization to explore associative dimensions that are appealing from multiple perspectives to form equivalent cluster prototypes. It groups comparable labeled sample data into prototype dimensional data clusters and then employs the optimized matrix factorization (OMF) method to analyze low-dimensional data. A comprehensive performance evaluation, comparing it with state-of-the-art methodologies, is presented. The proposed method is applied to various real-time datasets. Furthermore, the performance of multi-labeled dimensions is compared with that of sampled class-labeled clusters with border relations. There is an intention to apply advanced machine learning multidimensional clustering to different data stream environments to further enhance the suggested technique.

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