The Davies-Bouldin Index in the scientific landscape

I feel like to have an idea on how it's used I needed an instrument to have a fast analysis of the articles that cite the index. For the approximative Meta-analysis I searched in the web of science database the articles that used the terms "Davies Bouldin" in the abstract. This resulted in roughly 530 articles. Then I followed the procedure as described here "https://www.vosviewer.com/getting-started" exporting the citation text file of all the articles found. I looked in the map resulting for the terms describing a discipline, these disciplines were cited:
 Genetics, Medicine, Applied math and statistics, Computer science & Informatics, Biology, Material sciences, Natural sciences, Biomedics, Cybernetics, Physics and Energy.
The most used terms which can be useful to cite for understanding in which fields the index is utilized are:
Signal, genetic algorithm, IEEE, Image, segmentation, CPCI S, Soft computing, Sources citation index, communication, electrical & electronic, health, applied math, biomed, bioinformatics, physics, chemistry, energy, environmental science, education, automation & control system, neuroimage, diagnosis, data mining.
On google scholar I inserted the terms: "Davies-Bouldin index" OR "Davies-Bouldin score" OR "Davies-Bouldin"

Database used: Google scholar
 Papers selected in base of the number of citations: n>=10.

Papers which analyze the Index

"Performance evaluation of some clustering algorithms and validity indices"
by U. Maulik; S. Bandyopadhyay
Publisher: IEEE Transactions on pattern analysis and machine intelligence, 2002•ieeexplore.ieee.org
(scimago evaluation is Q1 in all fields)
Concerning the validity measures the article describes the Davies-Bouldin Index, the Dunn Index, the Calinski Harabasz (CH) Index and the I Index, comparing them in the evaluation of the application of three algorithms in five well known data sets. The authors stated that "the index I is able to indicate the correct number of clusters for all the data sets" for all the algorithms, compared to it the Davies-Bouldin Index performs poorly getting right only two out of five clusterings.
A consideration I might add is that it seemed like a brutal confrontation to me, in fact I feel like an Index must be "adapted" by the way we decide to represent the dataset following the respective philosophy. Anyway surely it was interesting seeing an application of the I Index.

"Cluster validation techniques for genome expression data"
by N Bolshakova, F Azuaje
Publisher: Signal processing, 2003•Elsevier

(scimago evaluation was Q2 in almost all fields)
An analysis on how the use of different metrics (mathematical sense, i.e. distances) and different ways to look at intra/inter-cluster distance influences the Dunn, Silhouette and Davies-Bouldin's scoring. Here they have used Kohonen Self-organizing Maps (SOM) algorithm on two real data sets.
The use of different distances is useless since all norms are equivalent in finite-dimensional real vector spaces, ergo all they did was messing with the definition of the intra/inter-cluster distances, in fact the Silhouette method wasn't affected in its scoring.

"Cluster Validity Measurement techniques"
by Ferenc Kovács, Csaba Legány, Attila Babos
From: "Proceedings of the 5th WSEAS International Conference on Artificial Intelligence, Knowledge Engineering and Data Bases"
It's a recap of various cluster scores indexes with a couple of common tests.
It's useful since it does a nice framing of the problem and how the indexes try to address it

"Nonparametric genetic clustering: comparison of validity indices"
by S. Bandyopadhyay, U. Maulik
Publisher: IEEE Transactions on Systems, Man, and Cybernetics: Systems.
(Q1 on Scimago in 2001)
The authors are the same as the first paper analyzed and they did a similar work indeed, using five different data sets and comparing the Dunn and Davies-Bouldin index with their own introduced in the precedent article. This index seems accurate indeed.

"A comparison between the silhouette index and the Davies-Bouldin index in labeling ids clusters"
By S Petrovic
From: Proceedings of the 11th Nordic workshop of secure IT systems, 2006
The article proposes to use clustering labeling indexes to help with intrusion detection systems. I didn't really get most of the article. Yet one thing is clear, in this type of field time is key, so the fact that the davies-bouldin index is less costly in a computational sense makes it more useful in the field.

"Validation indices for graph clustering"
By Simon Gunter, Horst Bunke
Publisher: Pattern Recognition Letters, Elsevier
(Q2 on Scimago in almost all fields that year)
I haven't even started to read the article that I'm excited about it. This article touches an interesting argument which is the application of clustering on symbolical data, in fact in a mathematical sense the application of the Index gets tricky here since we are not in a finite real vector space but in a discrete one so the choice of the distance (math definition) is essential.
The symbolic data analyzed here are graphs. Fifteen letters and ten modified versions of each were the data set, both Indexes got the right amount of clusters needed.
Didn't add much to the understanding of Davies-Bouldin or Dunn index but was interesting seeing new distances applied

“A comparison of internal and external cluster validation indexes”
By Eréndira Rendón, Itzel M. Abundez, Citlali Gutierrez, Sergio Díaz Zagal, Alejandra Arizmendi, Elvia M. Quiroz, H. Elsa Arzate.
From: Proceedings of the 2011 American conference on applied mathematics and the 5th WSEAS international conference on Computer engineering and applications.

The article makes a comparison of nine different indexes with two clusterings of twelve different datasets, giving a “Right/Wrong” value at each evaluation. “Davies-Bouldin and Silhouette are the best” …. jokes aside is useful as it makes an overview of the scenery

“On Cluster Validity and the Information Need of Users”
By Benno Stein, Sven Meyer, Eissen Frank Wißbrock
Publisher: International Journal of Robotics and Automation, Acta press
(Mostly Q3 on Scimago that year)
This paper too applies the Davies-Bouldin and the Dunn Indexes on symbolic data, in particular to various datasets of documents. Other two indexes are applied which are thinked explicitly for graph data and perform better. This paper confirms that to apply Davies-Bouldin one needs to use an adequate distance to represent distance between symbolic data

“Investigation of Internal Validity Measures for K-Means Clustering“
By Jonathan Baarsch, M. Emre Celebi
From: Proceedings of the international multiconference of engineers and computer science subjects (IMECS), 2012
Compares a great variety of score indexes but in a context of artificial datasets, it’s interesting because it makes a good analysis of type of problems that can come with the type of data we are watching and with the type of clustering techniques.
It’s a good reminder that even though using a good index is useful it’s necessary to use multiple clustering techniques if one wants a good job done.
note: Here it says that Sum-of-Squares index performs better

“Estimation of the Number of Clusters Using Multiple Clustering Validity Indices”
By Krzysztof Kryszczuk, Paul Hurley
From: International Workshop on Multiple Classifier Systems (MCS), 2010
This article tries various ways of “fusing” a variety of indexes with good results.
Just like when Davide Chicco pitched me the idea i’m not a great fan of this approach.
Not cause it’s bad per se, but if it’s done it must be in a scrupulous way, here they fused three measures I wouldn’t have mixed for example. One thing they have done right is the decision-based techniques. Anyway by far this was the best attempt i found by now.

“Clustering and its validation in a symbolic framework”
By Kalyani Mali a, Sushmita Mitra
Publisher: Pattern Recognition Letters, Elsevier
(Q2 on Scimago in almost all fields that year)
How to approach clustering of symbolical data seems a niche and difficult subject.
Here the researchers try three different clustering techniques (conceptually different too) and some clustering score indexes: Davies-Bouldin, CI and Dunn’s, Hubert’s statistic.

These scores seem to agree too much in the evaluation. Which I personally wouldn't take as a good sign in the way they represented the data.

"Analyzing the Role of Dimension Arrangement for Data Visualization in Radviz"
By Luigi Di Caro, Vanessa Frias-Martinez & Enrique Frias-Martinez
From: Pacific-Asia Conference on Knowledge Discovery and Data Mining
PAKDD 2010: Advances in Knowledge Discovery and Data Mining
In this article the Davies-Bouldin Index is used as an assessment tool to evaluate a visualization tool.

"Analysis of determining centroid clustering x-means algorithm with davies-bouldin index evaluation"
By M Mughnyanti, S Efendi and M Zarlis
From: IOP Conference Series: Materials Science and Engineering
Unsatisfactory…

"An Overview of Fairness in Clustering"
By Anshuman Chhabra; Karina Masalkovaitė; Prasant Mohapatra
Publisher: IEEE Access
(Q1 on Scimago)
This article shouldn't be here but I added it since it gives a nice view on how data are organized and in which context cluster indexes are utilized.

"Performance Evaluation of Some Symmetry-Based Cluster Validity Indexes"
By Sriparna Saha; Sanghamitra Bandyopadhyay
IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)
(Q1 on Scimago that year)
This is an almost scholastical article: introduces various cluster scoring indexes and uses them in the evaluation of the clustering of five different real life data sets.

"Comparison analysis of K-Means and K-Medoid with Ecluidience Distance Algorithm, Chanberra Distance, and Chebyshev Distance for Big Data Clustering"
By Syawal Gultom, S. Sriadhi, M. Martiano and Janner Simarmata
From: IOP Conference Series: Materials Science and Engineering
In this article the focus is on how the Davies-Bouldin evaluation changes on the change of the metric used. Something happens: using the Chanberra distance centroids are really close to each other giving an unreadable result with the index, which doesn't surprise me since the distance between clusters Davies-Bouldin's weak point.

"Comparison and Evaluation of Different Cluster Validity Measures Including Their Kernelization"
By Wataru Hashimoto, Tetsuya Nakamura, Sadaaki Miyamoto
From: SCIS & ISIS, 2008
As many other articles cited previously there's a comparison between different Indexes. No notable result emerges. Not even from the Kernelization of the index (which I personally don't see the need seeing the results)

"Minimization of the value of Davies-Bouldin index"
By I. Kärkkäinen, P. Fränti
From International Conference Signal Processing and Communications ER, 2000
They tried to improve the Davies-Bouldin Index by modifying the way the centroids are determined. Focusing on the Voronoi cells centroid and not a mediation of the data itself. This approach gave poor results, performing even slightly worse than the original one.

"Supervised application of internal validation measures to benchmark dimensionality reduction methods in scRNA-seq data"
By Forrest C. Koch, Gavin J. Sutton, Irina Voineagu and Fatemeh Vafaee
Publisher: Briefings in Bioinformatics - Oxford University Press
(Q1 on Scimago)
Looks at how the index evaluates the before and after of a dimensionality reduction of datasets. Davies-Bouldin performs as usual but this article is interesting as it shows a good application of the indexes

"Effectivity of Internal Validation Techniques for Gene Clustering"
By Chunmei Yang, Baikun Wan & Xiaofeng Gao
From: 7th International Symposium, ISBMDA 2006, Thessaloniki, Greece, December 7-8, 2006. Proceedings
In addition to the usual work of comparison of different indexes: Silhouette, FOM, Dunn, D-B the article underlines a "sympathy" of the D-B to Hierarchical clustering algorithms, which undermines it as a useful index in my opinion

"Cluster validation using graph theoretic concepts"
By N.R.Pal and J. Biswas
Publisher: Pattern Recognition Letters, Elsevier
(Q2 on scimago on those years)

The percentage refers to the appearances per article. (Ex. (6) means it appeared in 6 articles over 20).

Clustering algorithm	Indexes confronted	Datasets used	Intracluster measurement used
10% (2) Dim. reduc. 10% (2) C-Means 10% (2) DBSCAN 15% (3) SOM 40% (8) K-Means 45% (9) Others	10% (2) solo 15% (3) I 25% (5) CHI 30% (6) Sil 30% (6) DBI-variation 60% (12) others 65% (13) Dunn	25% (5) Mixed 35% (7) Artificial 40% (8) Real.	5% (1) Variance 20% (4) Not specified 75% (15) Centroids

Papers I sorted as an example of use of Davies-Bouldin Index in the medical field

"Classification of surface EMG signals using optimal wavelet packet method based on Davies-Bouldin criterion"
By Gang Wang, Zhizhong Wang, Weiting Chen, Jun Zhuang
Publisher: Medical & Biological Engineering & Computing
(Q2 on Scimago)

Pathology of the Patients:

The article does not mention any specific pathology of the patients whose data is being studied. Instead, it describes the experimental setup involving normally limbed subjects performing forearm and hand movements. Thus, the study seems to focus on healthy individuals rather than those with specific pathologies.

Type of Data Analyzed:

Surface electromyographic (SEMG) signals collected from the right forearm of subjects are analyzed. These signals are recorded during different types of movements such as forearm pronation, forearm supination, hand close, and hand open.

Biomedical Problem Addressed:

The main biomedical problem addressed in the study is the improvement of classification accuracy of SEMG signals for the control of powered prosthetic limbs. Accurate classification of SEMG signals is crucial for prosthetic control systems as inaccuracies can lead to dangerous situations for amputees.

Cluster Validation Indexes Used:

The Davies-Bouldin (DB) criterion is used as a cluster validation index to measure the classification ability of feature space. This index is applied to evaluate the effectiveness of the Optimal Wavelet Packet (OWP) method for feature extraction in SEMG signal classification.

Clustering Techniques Used:

The primary clustering technique used in the study is the Optimal Wavelet Packet (OWP) method for feature extraction. This method involves wavelet packet decomposition and selection of an optimal basis for classification problems based on the DB criterion. Additionally, the study employs Principle Components Analysis (PCA) for feature dimensionality reduction.

Purpose of Cluster Validation Indexes:

The cluster validation indexes, particularly the Davies-Bouldin (DB) criterion, are used to evaluate the classification ability of the feature space generated by the OWP method. The goal is to select the optimal wavelet packet basis that maximizes the class separability for SEMG signal classification. The effectiveness of the OWP method is assessed based on its performance in improving classification accuracy compared to other existing methods.

"EMG feature evaluation for movement control of upper extremity prostheses"
By M. Zardoshti-Kermani; B.C. Wheeler; K. Badie; R.M. Hashemi
Publisher: IEEE Transactions on Rehabilitation Engineering
(Q3 at the time I suppose)

Pathology of the patients whose data is being studied: The patients studied are amputees, specifically those with above-elbow amputations. The article mentions the recording of EMG signals from residual biceps and triceps muscles of an above-elbow amputee.

Type of data being analyzed: Electromyography (EMG) signals are being analyzed. EMG signals are recordings of electrical activity produced by skeletal muscles. In this context, the EMG signals are collected from residual muscles of amputees.

Biomedical problem being addressed: The biomedical problem being addressed is the control of upper extremity prostheses using EMG signals from residual muscles of amputees. The aim is to find effective features within the EMG signals that can accurately estimate the volitional muscle control and map it to desired prosthetic movements.

Cluster validation indexes (score indexes) being used: Two cluster validation indexes are being used:

1. K-Nearest Neighborhood (KNN) misclassification rate estimation: This is a nonparametric approach that evaluates the performance of a classifier on experimental data. It calculates the misclassification rate and is useful for assessing the quality of the feature space.
2. Davies-Bouldin (DB) cluster separation measure: This is a parametric approach that directly addresses the issue of cluster separability in the feature space. It quantifies how well-separated the clusters are from each other.

Clustering techniques (dimension reduction techniques or techniques whose clustering is being evaluated) used: The article discusses various features extracted from EMG signals, such as Integral of Absolute Value (IAV), Zero Crossing (ZC), Variance (VAR), Willison Amplitude (WAMP), v-Order detector (V), log detector (LOG), and EMG Histogram (HIST). These features are used to create a feature space with lower dimensionality. Additionally, the article mentions the use of the K-Nearest Neighbor (KNN) method as a clustering technique to classify feature vectors.

Cluster validation indexes used for: The cluster validation indexes are used to evaluate the quality of the feature space derived from EMG signals. They assess how well-separated the clusters are within the feature space, which is crucial for accurate classification and control of prosthetic movements. The KNN misclassification rate estimation helps to quantify the performance of the classifier on experimental data, while the Davies-Bouldin (DB) cluster separation measure directly measures the cluster separability in the feature space, providing insights into the effectiveness of the features for prosthetic control.

“GA-based Feature Subset Selection for Myoelectric Classification”
By Mohammadreza Asghari Oskoei, Huosheng Hu
From: 2006 IEEE International Conference on Robotics and Biomimetics
Pathology of the patients whose data is being studied: The article does not explicitly mention the pathology of the patients whose data is being studied. However, it focuses on upper limb activities and myoelectric signals (MES) collected from muscles during these activities. Therefore, it can be inferred that the patients likely have conditions affecting upper limb mobility or function.

The type of data that is being analyzed: Myoelectric signals (MES) collected from surface electrodes placed on the user's muscles during upper limb activities.

The biomedical problem that's being addressed: The biomedical problem being addressed is the challenge of accurately interpreting MES data and classifying its features to control assistive devices and robots based on user intention. Specifically, the article discusses the difficulty in achieving high accuracy and stability in multi-function controls using current myoelectric control systems.

What cluster validation indexes (score indexes) are being used: Davies-Bouldin index (DBI) and Fisher's Linear Discriminant Index (FLDI) are employed as filter objective functions to evaluate subsets of features. Additionally, linear discriminant analysis (LDA) and artificial neural networks (ANN) are used as classifier evaluation metrics.

What clustering techniques (dimension reduction techniques or techniques whose clustering is being evaluated) are used: The article discusses various dimensionality reduction techniques and feature selection methods applied to MES data, such as Principle Component Analysis (PCA), Wavelets Transform (WT), Wavelet Pocket Transform (WPT), Self-Organizing Feature Map (SOFM), and Linear Discriminate Analysis (LDA).

What are the cluster validation indexes used for: The cluster validation indexes (DBI and FLDI) are used to assess the quality of feature subsets selected for classification tasks. These indexes help to evaluate the effectiveness of the selected features in separating classes or clusters in the feature space. Lower values of DBI and FLDI indicate better class separability and discrimination provided by the selected features, which is crucial for accurate classification and control in myoelectric systems. Additionally, LDA and ANN are used to evaluate the generalization capabilities of the features when applied by classifiers.

In general the three articles are similar in all the points of classification:

- Pathology: Patients with amputated limbs.
- Biomedical problem addressed: Physical and functional consequences of limb amputation. Specifically, they seek to improve the interpretation of EMG signals to enhance the quality of life of patients using prostheses.
- Type of data: SEMG data acquired from the residual biceps and triceps muscle of an above-elbow amputee in the first two articles. EMG in the third
- Application of the metric: Measuring the classification ability of the feature space for SEMG/EMG signals classification, with satisfactory results

In these articles one can observe what is a general appreciation of the feedback given by the index in terms of overall precision and computability. In the third they compared it to a few other indexes which is comforting

"The Emotion Recognition System Based on Autoregressive Model and Sequential Forward Feature Selection of Electroencephalogram Signals"
By Sepideh Hatamikia, Keivan Maghooli, Ali Motie Nasrabadi
Publisher: Journal of Medical Signals and Sensors
(Q3 on Scimago)

- Pathology: The patients in this study don't appear to have a specific pathology mentioned. They are 32 participants from a publicly available dataset (DEAP) for emotion analysis using physiological signals. The EEG signals were recorded during emotional audio-visual inductions.
- Biomedical problem addressed: IThe biomedical problem being addressed is the classification of emotional states using EEG signals. The study aims to investigate the performance of autoregressive (AR) features in the classification of emotional states, particularly valence and arousal levels.
- Type of data: The data being analyzed consists of EEG signals recorded from 32 participants during emotional audio-visual inductions. Additionally, self-assessment manikins (SAM) questionnaire ratings for valence and arousal dimensions are used to categorize emotional states into two and three classes.
- Application of the metric: Measuring the classification ability of the feature space for EEG signals in order to recognize emotional states.
- The article doesn't mention any specific cluster validation indexes being used. However, it evaluates the performance of the proposed method by comparing classification accuracies obtained using different feature selection methods (Davies–Bouldin index and sequential forward feature selection) and different classifiers (K-nearest neighbor, quadratic discriminant analysis, and linear discriminant analysis).
- The primary technique used in the study is not clustering but rather classification. However, the article mentions the use of autoregressive (AR) modeling for feature extraction from EEG signals. AR coefficients are extracted as feature vectors. Additionally, two different feature selection methods (Davies–Bouldin index and sequential forward feature selection) are employed to reduce complexity and redundancy of features. Finally, three classifiers (K-nearest neighbor, quadratic discriminant analysis, and linear discriminant analysis) are used for discriminating between two and three different classes of valence and arousal levels.
- Since the study primarily focuses on classification rather than clustering, there's no explicit use of cluster validation indexes. However, the evaluation metrics used (such as classification accuracies) serve a similar purpose by assessing the performance of the proposed method in accurately classifying emotional states based on EEG signals. These metrics help validate the effectiveness of the feature extraction, feature selection, and classification techniques employed in the study.

"Machine Learning Clustering for Blood Pressure Variability Applied to Systolic Blood Pressure Intervention Trial (SPRINT) and the Hong Kong Community Cohort"

By Kelvin K.F. Tsoi, Nicholas B. Chan, Karen K.L. Yiu, Simon K.S. Poon, Bryant Lin and Kendall Ho
Publisher: Hypertension
(Q1 on Scimago)

- Pathology: The study involves patients with hypertension from two cohorts: the SPRINT study conducted in the United States and the eHealth cohort in Hong Kong. The patients in these cohorts are hypertensive individuals who are at risk of cardiovascular diseases such as myocardial infarction, stroke, and heart failure.
- Biomedical problem addressed: The biomedical problem being addressed is the classification of BPV levels and its association with cardiovascular diseases. The study aims to classify BPV levels using different machine learning algorithms and evaluate their effectiveness in predicting cardiovascular events such as myocardial infarction, stroke, and heart failure.
- Type of data: The data being analyzed is visit-to-visit blood pressure variability (BPV) data. This includes systolic blood pressure (SBP) and diastolic blood pressure (DBP) readings over time, which are used to assess the variability in blood pressure levels.
- Application of the metric: These cluster validation indexes are used to assess the performance of the clustering methods in classifying BPV levels. The Stability Index evaluates the stability of clustering methods, while the Davies-Bouldin Index and Silhouette Index assess the similarity of clusters and dispersion of data within and across clusters. Additionally, Cox proportional hazard regression models are used to evaluate the association between different clustering methods and the risk of myocardial infarction, stroke, and heart failure, serving as an external validation of clustering performance.
- The study uses three cluster validation indexes:

  Stability Index: This index measures the stability of clustering methods by assessing the accuracy of clustering on validation datasets from the training datasets.

  Davies-Bouldin Index (DBI): This index describes the data dispersion within clusters and across clusters. Lower values indicate better clustering with less similarity.

  Silhouette Index (SI): This index computes the ratio of similarity of the original data from the clusters. Higher values indicate better clustering with less similarity.

  - The study employs both traditional quantile clustering and five machine learning algorithms for clustering BPV levels:

1. K-means Clustering
2. Partitioning Around Medoids (PAM)
3. Spectral Clustering
4. Ward's Method
5. Expectation Maximization (EM)

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"Fast Automatic Template Matching for Spike Sorting Based on Davies-Bouldin Validation Indices"
By Takashi Sato; Takafumi Suzuki; Kunihiko Mabuchi

From: 2007 29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society
I haven't fully understood the article but it seems they used the Davies-Bouldin Index to accelerate the template matching of a set of data. So rather than dividing the data in clusters and then evaluate these clusters, they used the index to set a threshold by which distinguish the templates that were more similar to the structure of the found data (I may have said some stupid stuff caused by my ignorance)

- Pathology: The article does not explicitly mention the pathology of the patients whose data is being studied. However, it describes recording signals from the hippocampus region of a Wistar rat, which suggests that the study involves animal models rather than human patients
- Biomedical problem addressed: The biomedical problem being addressed is spike sorting, which is the process of detecting and classifying extracellular action potentials of neurons. Accurate spike sorting is crucial for various neuroscience studies and applications, such as understanding neuronal activity patterns and developing brain-machine interfaces (BMIs).
- Type of data: The data being analyzed consists of extracellular waveforms of neurons, specifically spikes. These spikes are recorded from the hippocampus region of a Wistar rat using an electrode.
- Application of the metric:DBVIs are used to determine the order of windowing pairs for template matching and to optimize the clustering process. By minimizing the DBVI value, the appropriate number of clusters for template construction is chosen. Additionally, DBVIs are used to prioritize the order of windowing pairs for template matching in order to reduce computational cost without compromising sorting quality.
- Davies-Bouldin validation indices (DBVIs) are used as cluster validation indices. DBVIs are utilized to prioritize point-by-point calculation in the spike sorting process.
- The clustering techniques used in the study include:
- Principle Component Analysis (PCA): Used for rapid peak-to-peak spike detection and to characterize spike waveforms.
- K-means clustering: Utilized in conjunction with PCA to cluster spike waveforms and automatically generate templates.
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"Harmonization of radiomic features of breast lesions across international DCE-MRI datasets"
By Heather M. Whitney, Hui Li, Yu Ji, Peifang Liu, Maryellen L. Giger
Publisher: Journal of Medical Imaging
(Q2 on Scimago)
The index here was used in a counterintuitive way, a bad value here was looked for since the objective of the harmonization is to "merge" the two datasets (our clusters). So one desires to have lower values before the harmonization and higher after

- Pathology: The data analyzed consists of dynamic contrast-enhanced magnetic resonance (DCE-MR) breast imaging studies of benign lesions and cancers. The benign lesions and cancers are collected from international datasets, specifically from patients in the United States and China.
- Biomedical problem addressed: The Davies–Bouldin index is used to evaluate the degree of clustering between populations for both benign lesions and cancers. This

index assesses the similarity of clusters, with a lower value indicating better clustering.

- Type of data: Radiomic features extracted from DCE-MR breast imaging studies. These radiomic features cover various categories including size, shape, morphology, texture, and kinetics of contrast dynamics.
- The ComBat method is employed for harmonization of radiomic features. This method is based on additive and multiplicative batch effects using empirical Bayes estimates to transform features.
  K-means clustering is utilized after dimensionality reduction with t-distributed stochastic neighbor embedding (t-SNE) to assess inter- and intra-cluster agreement across the two populations.
- Application of the metric: the Davies–Bouldin index is used to evaluate the impact of harmonization on the clustering of radiomic features between populations. A higher index value post-harmonization suggests that the features are more similar between populations, indicating successful harmonization.
  Additionally, the Davies–Bouldin index is employed to assess inter- and intra-cluster agreement across populations after clustering of the t-SNE values, providing insights into the effectiveness of harmonization in reducing differences between populations.
- The Davies–Bouldin index is used to evaluate the degree of clustering between populations for both benign lesions and cancers. This index assesses the similarity of clusters, with a lower value indicating better clustering.

"A note on relevance of diagnostic classification and rating scales used in psychiatry"[*]
By Yiqun Gana, Tamar Kakiashvili b, Waldemar W. Koczkodaj, Feng Li
Publisher: Computer Methods and Programs in Biomedicine - Elsevier
(Q2 on Scimago that year)
There's a confused use of the Davies-Bouldin's and Dunn's Indexes.
The authors limit themselves to calculate them but don't explain the use they make of these observations. There's also the never ending question of "how do we express distance between symbolic data?" . Nevertheless it was useful to read how this type of problems can be approached.

- Pathology: The patients in this study are faculty members from a university in Mainland China. Their pathology is not explicitly mentioned, but the study focuses on measuring burnout and depression using the Maslach Burnout Inventory (MBI) and Beck Depression Inventory (BDI), respectively.
- Biomedical problem addressed: The biomedical problem being addressed is the difficulty in accurately diagnosing and distinguishing between burnout and depression using rating scales due to their overlapping symptoms and lack of tangible medical evidence.
- Type of data:The data being analyzed consist of responses from the MBI and BDI questionnaires completed by 413 faculty members. These questionnaires measure burnout and depression, respectively, using rating scales.
- Application of the metric:The cluster validation indexes (Dunn index and Davies–Bouldin index) are used to assess the quality of the clusters formed by the K-means algorithm. Specifically, they help evaluate how well the clusters separate individuals with burnout from those with depression, providing a measure of the effectiveness of the clustering technique in distinguishing between the two conditions.

- The cluster validation indexes used in this study are the Dunn index and Davies–Bouldin index. These indexes are used to evaluate the effectiveness of the clustering algorithms in distinguishing between burnout and depression.
- The primary clustering technique used in the study is the K-means cluster analysis. This technique is applied to partition the data into two clusters based on similarities in responses to the MBI and BDI questionnaires.

"Prediction of dyslexia severity levels from fixation and saccadic eye movement using machine learning"
By A. JothiPrabha, R. Bhargavi, B.V Deepa Rani
Publisher: Biomedical Signal Processing and Control
(Q1 on Scimago)
In this article the Davis-Bouldin Index is used in the classic way paired with Silhouette, Elbow and Manova methods. As usual Silhouette and Davies-Bouldin were the best performing Indexes

- Pathology: The study focuses on dyslexic individuals, particularly children around 9-10 years old. Dyslexia is described as a neurological disorder affecting reading and comprehension skills. Symptoms include difficulty in reading, writing, spelling, and poor vocabulary. Dyslexics exhibit erratic eye movements while reading, characterized by longer fixations, shorter saccades, and more regressions compared to non-dyslexic individuals.
- Biomedical problem addressed: The study aims to identify severity levels of dyslexia based on eye movement patterns, specifically fixations and saccades. By clustering dyslexic patients into high and low severity groups using unsupervised learning techniques, the researchers seek to understand and quantify differences in eye movement characteristics between these subgroups. This can potentially aid in early screening and intervention programs for dyslexia.
- The cluster validation indexes used in this study are Silhouette analysis, Elbow Method, and Davies Bouldin Index. These indexes help in determining the optimal number of clusters (k) and assessing the quality of the clusters formed by the K-Means clustering algorithm.
- Type of data: Eye movement data, specifically fixations and saccades, are being analyzed. Fixations are pauses in eye movement during reading, while saccades are rapid eye movements between fixations. Various features related to fixations and saccades, such as fixation duration, number of fixations, saccade duration, and number of saccades, are extracted from the eye gaze points recorded by an eye tracker.
- The primary clustering technique employed is K-Means clustering, a popular unsupervised learning algorithm used for partitioning data into distinct clusters based on similarity. K-Means clustering is applied to group dyslexic patients into high and low severity clusters based on features extracted from their eye movement data.
-
- Application of the metric: Evaluation of optimal number of severity levels of dyslexia based on data

"Intelligent Kernel K-Means for Clustering Gene Expression"
By Teny Handhayani, Lely Hiryanto
From Procedia Computer Science
The authors compare the results given by two different clustering techniques using the Global Silhouette's and the Davies-Bouldin's Indexes with satisfactory results.

- Pathology: The data being studied pertains to gene expression of human colorectal carcinoma. The article mentions using a dataset consisting of 1536 genes of human colorectal carcinoma, each gene consisting of 111 tissues (100 cancer tissues and 11 normal tissues). After preprocessing, 341 representative genes were used.
-
- Biomedical problem addressed: The biomedical problem being addressed is the need for efficient analysis of gene expression data to identify genes potentially contributing to cancer diseases like colorectal carcinoma. The study aims to develop and evaluate a clustering algorithm, Intelligent Kernel K-Means (IKKM), to cluster gene expression data and analyze its relationship with clinical data (phenotypes).
- Global silhouette value and Davies-Bouldin index are being used as cluster validation indexes. These indexes are employed to assess the quality of the resulting clusters in terms of their compactness and separation.
- Type of data: Gene expression data is being analyzed. This includes the expression levels of various genes associated with human colorectal carcinoma
- Application of the metric: The cluster validation indexes, global silhouette value, and Davies-Bouldin index, are used to assess the quality of the clusters produced by the IKKM algorithm. They help in determining how well-separated and compact the clusters are, providing insight into the reliability and effectiveness of the clustering process.
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- The primary clustering technique used is Intelligent Kernel K-Means (IKKM). IKKM is a fully unsupervised clustering algorithm based on kernel. It combines Intelligent K-Means and Kernel K-Means and is capable of clustering kernel matrices without prior knowledge of the number of required clusters. Anomalous pattern algorithm and Iterative Kernel Anomalous Pattern are also mentioned as steps within the IKKM algorithm.

Longitudinal K-means approaches to clustering and analyzing EHR opioid use trajectories for clinical subtypes
By Sarah Mullin, Jaroslaw Zola, Robert Lee, Jinwei Hu, Brianne MacKenzie, Arlen Brickman, Gabriel Anaya, Shyamashree Sinha, Angie Li, Peter L. Elkin
Publisher: Journal of Biomedical Informatics
(Q1 on Scimago)

- Pathology: The patients under study are those who have been prescribed opioids, particularly prescription opioids. The cohort consists of individuals from an inpatient hospital and an outpatient practice in Buffalo, NY. Patients included in the study are aged between 12 to 90 years old and have been prescribed opioids for seven or more days during the study period. The study excluded patients diagnosed with cancer, with the exception of non-melanoma skin cancers, due to differing guidelines for opioid use in cancer pain treatment. The final cohort comprises 3,997 individuals.

- Three main clustering techniques are employed:

● Longitudinal k-means with imputation (kml)
● Longitudinal k-means with B-splines
● K-means on Variational Recurrent Autoencoders (VRAE)

-
- Biomedical problem addressed: The study aims to identify patient subtypes within the population prescribed opioids, particularly prescription opioids. The objective is to analyze opioid prescription trajectories to identify patterns and subtypes of opioid use, with the ultimate goal of designing personalized treatment regimens for opioid patients. This is important due to the increase in opioid-related adverse effects and the need for more effective treatment strategies.

The study employs several cluster validation indexes:

● For the k-means clustering method with imputation (kml), the Calinski and Harabasz criterion is used for choosing the optimal number of clusters. Davies-Bouldin, and Ray and Turi
● For the longitudinal k-means with B-splines, the Bayesian Information Criterion (BIC) is used for selecting the optimal number of clusters.
● For the k-means on Variational Recurrent Autoencoders (VRAE), the silhouette score combined with the elbow method is used to determine the number of clusters.

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- Type of data: The data being analyzed is electronic health record (EHR) data, specifically focusing on prescription dosage information of opioids. This includes details such as prescription quantities, types of opioids prescribed, prescription duration, and morphine milligram equivalent (MME) conversion data.

- Application of the metric:These cluster validation indexes are used to determine the optimal number of clusters for each clustering method. They help in assessing the quality and appropriateness of the clustering solutions by evaluating the compactness of clusters and the separation between clusters, ultimately aiding in the selection of the most suitable number of clusters for the data.

Deep learning of pharmacogenomics resources: moving towards precision oncology
By Yu-Chiao Chiu, Hung-I Harry Chen†, Aparna Gorthi, Milad Mostavi, Siyuan Zheng, Yufei Huang and Yidong Chen
Publisher: Briefings in Bioinformatics
(Q1 on Scimago)

- Pathology: The study primarily focuses on cancer patients, including both adult and pediatric cancers. It mentions data from various sources, such as the National Cancer Institute (NCI) Molecular Analysis for Therapy Choice (NCI-MATCH) trial, the Cancer Genome Atlas (TCGA), the Cancer Cell Line Encyclopedia (CCLE), the MET500 cohort, the Therapeutically Applicable Research to Generate Effective Treatments (TARGET) project, and the Pediatric Pan-Cancer (PedPanCan) study.

These datasets cover a wide range of cancer types and subtypes, providing a comprehensive view of cancer genomics.

- Biomedical problem addressed: The biomedical problem being addressed is the classification of cancer types and subtypes using genomic profiles, as well as the prediction of drug response and synergy based on cancer genomic data. The article aims to leverage machine learning (ML) approaches, particularly deep learning (DL), to extract meaningful patterns from high-dimensional genomic data and improve our understanding of cancer heterogeneity, treatment response, and drug discovery.
- Type of data: The data being analyzed includes various types of omics data related to cancer, such as tumor mutations, transcriptomes, methylomes, proteomes, and microbiomes. The article mentions high-dimensional genomics data, including DNA- and RNA-derived genomics data from TCGA, as well as data from other projects like CCLE, MET500, TARGET, and PedPanCan. The focus is on gene expression profiles, genetic variations, and regulatory effects across different cancer types.
- Application of the metric:The cluster validation indexes, such as the DB index and the DR index, are used to evaluate the effectiveness of dimension reduction methods in capturing cancer type-specific information from high-dimensional gene expression profiles. Lower values of these indexes indicate higher intra-cancer similarity, suggesting better performance in preserving inter-cancer differences and capturing relevant information for cancer classification and subtype identification.
- The article mentions the use of the Davies-Bouldin index (DB index) and the average ratio between mean intra-cluster distances to mean inter-cluster distances across cancer classes (distance ratio, DR index) for quantifying the richness of information captured by dimension reduction methods. These indexes are utilized to compare the performance of different dimension reduction techniques, such as autoencoders (AEs), in capturing cancer type-specific information from high-dimensional expression profiles.
- The article primarily focuses on dimension reduction techniques, particularly autoencoders (AEs), and their variants. It discusses the use of fully connected AEs (FC-AE) and gene-set regularized AEs (GSAE) for dimension reduction of gene expression profiles in cancer genomics data. Additionally, the article mentions the use of dimension reduction methods like t-distributed stochastic neighbor embedding (t-SNE) and principal component analysis (PCA) for visualization and clustering of high-dimensional genomic data.

[Statistical models for brain signals with properties that evolve across trials]
By Hernando Ombao, Mark Fiecas, Chee-Ming Ting, Yin Fen Low
Publisher: Neuroimage
([Q1] on Scimago)

- Pathology: The article doesn't explicitly mention any specific pathology of the patients whose data is being studied. However, it's implied that the study involves healthy subjects as it refers to "8 healthy subjects" and mentions data collection protocols approved by a research ethics committee.
- Biomedical problem addressed: The study aims to model dynamic brain connectivity using EEG data recorded across multiple trials in an experiment. Specifically, it focuses on changes in brain responses to stimuli (frequent and target tones) over the

course of the experiment, with a particular interest in understanding the evolution of brain connectivity patterns during selective attention tasks.

- Type of data: Electroencephalograms (EEGs) recorded across replicated trials in an experiment.
- Application of the metric: Comparing two statistical modeling frameworks along with silhouette. which can indirectly be seen as assessing the effectiveness of the clustering techniques in capturing the underlying dynamics of the EEG data.
- Markovian regime-switching vector autoregressive model (MS-VAR): This model treats EEGs as realizations of an underlying brain process that switches between different states both within a trial and across trials in the entire experiment.
  Slowly evolutionary locally stationary process (SEv-LSP): This model characterizes observed EEGs as a mixture of oscillatory activities at various frequency bands, capturing the dynamic nature of band-oscillations and cross-correlations between them.
  Novel Phenotyping for Acute Heart Failure-Unsupervised Machine Learning-Based Approach

By Szymon Urban, Mikołaj Błaziak, Maksym Jura, Gracjan Iwanek, Agata Zdanowicz, Mateusz Guzik, Artur Borkowski, Piotr Gajewski, Jan Biegus, Agnieszka Siennicka, Maciej Pondel, Petr Berka, Piotr Ponikowski and Robert Zymli ´nski
Publisher: Biomedicines
(Q1 on Scimago)

- Pathology: The study focuses on patients with Acute Heart Failure (AHF), a condition characterized by sudden onset or worsening of symptoms of heart failure, leading to urgent medical attention. The patients included in the study exhibited a range of clinical presentations and comorbidities associated with AHF, such as hypertension, diabetes, chronic obstructive pulmonary disease (COPD), history of stroke, coronary artery disease (CAD), valvular heart disease, and chronic intoxication.
- Biomedical problem addressed:The biomedical problem addressed in the study is the natural phenotypic heterogeneity of the AHF population. The goal is to identify distinct phenotypes within the AHF patient population using clustering techniques and to evaluate the associations between these phenotypes and clinical outcomes, including mortality.
- The study uses the Davies-Bouldin index as the main criterion for optimizing the clustering algorithm. This index evaluates the clustering quality by measuring the average similarity between each cluster and its most similar cluster, relative to the cluster's size. A lower Davies-Bouldin index indicates better clustering quality.
- The study employs the k-medoids algorithm for clustering, which is a partitioning algorithm that divides the dataset into a predetermined number of clusters based on similarity measures. Unlike k-means clustering, k-medoids uses actual data points as cluster representatives (centroids), making it more interpretable. The study also utilizes various distance/similarity measures for clustering, such as Correlation Similarity.
- Type of data: The study analyzes clinical and biochemical data of AHF patients, including 63 variables such as demographic information, clinical signs and symptoms, laboratory parameters, and lifestyle factors. These variables were evaluated at the time of admission to the hospital.

- Application of the metric: The cluster validation indexes, particularly the Davies-Bouldin index, are used to optimize the clustering process by determining the optimal number of clusters and the most suitable distance/similarity measure. These indexes help ensure that the resulting clusters are meaningful and reflect the underlying structure of the data, allowing for accurate characterization of distinct phenotypes within the AHF patient population.

[KISL: knowledge-injected semi-supervised learning for biological co-expression network modules]

By Gangyi Xiao, Renchu Guan, Yangkun Cao, Zhenyu Huang and Ying Xu
Publisher: Frontiers in Genetics
([Q2] on Scimago)

- Pathology: The article focuses on cancer samples from eight different types of tumors: BLCA (bladder urothelial carcinoma), BRCA (breast invasive carcinoma), COAD (colon adenocarcinoma), KIRC (kidney renal clear cell carcinoma), LUAD (lung adenocarcinoma), LUSC (lung squamous cell carcinoma), PAAD (pancreatic adenocarcinoma), and STAD (stomach adenocarcinoma).
- Biomedical problem addressed: The main problem being addressed is the identification of gene modules (clusters of highly co-expressed genes) in co-expression networks. These gene modules can provide insights into the functional relationships between genes, which are crucial for understanding cancer development, designing therapeutic interventions, and predicting prognoses.
- The main clustering technique used in the article is weighted gene co-expression network analysis (WGCNA), which utilizes hierarchical clustering to identify gene modules. Additionally, a new method called knowledge-injected semi-supervised learning approach (KISL) is proposed for module identification in co-expression networks. KISL combines semi-supervised clustering methods with prior biological knowledge to address limitations of existing unsupervised clustering methods.
- Type of data: The data being analyzed is gene expression data obtained from RNA-seq datasets of cancer samples. This gene expression data is used to construct co-expression networks, which represent the relationships between genes based on statistical correlations among their expressions.
- The article mentions three common internal measures to evaluate the validity of clustering: the silhouette coefficient, the Calinski-Harabasz index, and the Davies-Bouldin index.
- The cluster validation indexes are used to compare the performance of the KISL algorithm with the standard WGCNA method. Specifically, they are used to evaluate the quality of the clusters generated by each method based on different evaluation metrics such as silhouette coefficient, Calinski-Harabasz index, and Davies-Bouldin index. The higher values of these indexes indicate better clustering quality, which implies that the KISL algorithm outperformed WGCNA in terms of cluster evaluation values and gene module aggregation.

[Machine Learning Approach to Understand Worsening Renal Function in Acute Heart Failure]

By Szymon Urban, Mikołaj Błaziak, Maksym Jura, Gracjan Iwanek, Barbara Ponikowska, Jolanta Horudko, Agnieszka Siennicka, Petr Berka, Jan Biegus, Piotr Ponikowski and Robert Zymli ´nski
Publisher: Biomolecules
(Q1/Q2 on Scimago)

- Pathology: The patients studied suffer from acute heart failure (AHF), which is a complex condition involving the cardiovascular system. Additionally, the study focuses on the occurrence and impact of worsening renal function (WRF), a complication frequently overlapping AHF, especially in intensive cardiac care units. The simultaneous dysfunction of the kidneys and heart, known as cardiorenal syndrome, is also addressed.
- Biomedical problem addressed: The study aims to analyze the heterogeneity of the AHF population and describe different risk groups of WRF, along with its impact on prognosis. This addresses the challenge of understanding the complex interplay between cardiovascular and renal systems in AHF patients, particularly regarding the occurrence and significance of WRF.
- The Davies–Bouldin index is utilized to assess the quality of clustering. This index evaluates the quality of clustering considering intra-cluster distance (which should be low) and inter-cluster distance (which should be high). A lower Davies–Bouldin index value indicates better clustering quality.
- The study employs the k-medoids algorithm, a partitional clustering method, to segment the AHF patient population into internally similar subgroups. K-medoids creates non-overlapping clusters, and the number of resulting groups must be specified in advance. Unlike k-means clustering, where cluster centroids are computed by averaging values, each cluster in k-medoids clustering is represented using an existing, most representative example.
- The Davies–Bouldin index is used to evaluate the quality of clustering results. It helps in determining how well the patients within each cluster resemble each other (intra-cluster similarity) while being dissimilar to patients in other clusters (inter-cluster dissimilarity). This aids in identifying meaningful and distinct subgroups within the AHF patient population based on their clinical characteristics and outcomes.
- Type of data: The data analyzed includes clinical parameters routinely assessed during AHF patient monitoring. These parameters cover a wide range of aspects including HF subtype, etiology, comorbidities, symptomatology, biochemical presentation, and laboratory measurements such as serum creatinine levels.

A benchmark study of deep learning-based multi-omics data fusion methods for cancer
By Dongjin Leng, Linyi Zheng, Yuqi Wen, Yunhao Zhang, Lianlian Wu, Jing Wang, Meihong Wang, Zhongnan Zhang, Song He and Xiaochen Bo
Publisher: Genome Biology
(Q1 on Scimago)

- Pathology: The article evaluates DL-based multi-omics data fusion methods on three different types of datasets: simulated multi-omics datasets, single-cell multi-omics datasets, and cancer multi-omics datasets. For the cancer datasets, five types of cancer are considered: breast cancer (BRCA), glioblastoma (GBM), sarcoma (SARC), lung adenocarcinoma (LUAD), and stomach cancer (STAD). The evaluation involves ground-truth cancer subtypes obtained from The Cancer Genome Atlas (TCGA) data.

- Biomedical problem addressed: The biomedical problems being addressed include:

1. Personalized complex disease therapy
2. Drug discovery
3. Cancer drug target discovery These problems are tackled by leveraging multi-omics data to gain comprehensive insights into biological systems and improve understanding of diseases and their treatments.

The cluster validation indexes used in the evaluation include:

1. Jaccard index (JI)
2. C-index
3. Silhouette score
4. Davies Bouldin score These indexes are used to evaluate the performance of clustering methods by measuring aspects such as similarity, consistency, and quality of clusters.

Various DL-based data fusion methods are evaluated, including:

1. Fully connected neural network (FCNN)
2. Convolutional neural network (CNN)
3. Autoencoder (AE)
4. Graph neural network (GNN)
5. Capsule network (CapsNet)
6. Generative adversarial network (GAN)
7. Mixture DL-based models These methods are applied for multi-omics data fusion and downstream tasks such as classification and clustering.

- Type of data: The data being analyzed includes multi-omics data, which encompasses various types of omics data such as DNA methylation, mRNA gene expression, protein expression, chromatin accessibility data, and miRNA expression data. These omics data types are utilized across different datasets, including simulated data, single-cell data, and cancer data.
- The cluster validation indexes are used to assess the quality and performance of clustering algorithms. Specifically, they are utilized to measure the consistency between multi-omics data fusion-based clusters and ground-truth clusters, as well as the goodness of clustering structure without external information. This allows for the evaluation of clustering methods in terms of their ability to accurately group similar samples together and separate dissimilar samples.

A multi-step approach for tongue image classification in patients with diabetes

By Jun Li, Jingbin Huang, Tao Jiang, Liping Tu, Longtao Cui, Ji Cui, Xuxiang Ma, Xinghua Yao, Yulin Shi, Sihan Wang, Yu Wang, Jiayi Liu, Yongzhi Li, Changle Zhou, Xiaojuan Hu, Jiatuo Xu
Publisher: Computers in Biology and Medicine
([Q1] on Scimago)

- Pathology: The study focuses on patients with diabetes, specifically aiming to classify their tongue images into different categories. It mentions that diabetes is a heterogeneous disease with various complications, including cardiovascular issues, chronic kidney disease, diabetic retinopathy, diabetic foot, and increased risk of malignant tumors.
- Biomedical problem addressed: IThe biomedical problem addressed in the study is the precise classification of diabetic patients based on their tongue images. The goal is to provide a basis for formulating individualized treatment plans in Traditional Chinese Medicine (TCM) and to promote the standardization of TCM diagnosis.
- Type of data: The data being analyzed primarily consists of tongue images of diabetic patients. These images are processed to extract features related to color, texture, tongue coating, etc. Additionally, the study incorporates biomedical features extracted by the Tongue Diagnosis Analysis System (TDAS) and features extracted by the Vector Quantized Variational Autoencoder (VQ-VAE).
- The study utilizes several cluster validation indexes to evaluate the clustering results, including the silhouette score, the Calinski-Harabasz score, and the Davies-Bouldin score. These indexes assess the quality and consistency of clusters formed by the K-means algorithm.
- The primary clustering technique employed is K-means clustering. This technique is used to cluster the extracted features from tongue images, including features obtained from VQ-VAE and TDAS. The study also mentions the evaluation of other clustering algorithms like Agglomerative Clustering and Gaussian Mixture Model, although K-means yielded the best results.
- the cluster validation indexes are used to assess the effectiveness of the clustering process in categorizing the tongue images of diabetic patients. They help evaluate the quality of clusters formed by different clustering algorithms, providing insights into the separation and distinctiveness of the identified clusters.

Parkinson’s disease severity clustering based on tapping activity on mobile device
By Decho Surangsrirat, Panyawut Sri-iesaranusorn, Attawit Chaiyaroj, PeeraponVateekul & Roongroj Bhidayasiri
Publisher: Scientific Reports
([Q1] on Scimago)

- Pathology: The patients whose data is being studied suffer from Parkinson's disease (PD). Parkinson's disease is a neurodegenerative disorder that primarily affects motor functions, causing symptoms such as tremors, bradykinesia (slowness of movement), rigidity, and postural instability.
- The K-means clustering algorithm is utilized in the study for participant clustering based on features extracted from tapping tasks recorded on smartphones. K-means clustering is an unsupervised learning algorithm commonly used for partitioning data into distinct clusters based on similarity.

- Biomedical problem addressed: The biomedical problem being addressed is the assessment of the severity and progression of Parkinson's disease. Traditional clinical observation-based methods have limitations in comprehensively capturing the various motor and non-motor symptoms of PD. Therefore, there is a need for objective measurements to quantify disease severity accurately. The study aims to explore the feasibility of using instrumental measurements, specifically tapping activity on smartphones, to assess PD severity remotely and anonymously.
- Type of data: The data being analyzed includes clinical rating scales, questionnaires, and instrumental measurements. Clinical rating scales such as the Hoehn and Yahr rating scale (HY) and the Movement Disorder Society's Unified Parkinson's Disease Rating Scale (MDS-UPDRS) are used to assess disease severity. Questionnaires like the Parkinson's Disease Questionnaire (PDQ-8) are used to evaluate health-related quality of life. Instrumental measurements involve the use of sensor systems, accelerometers, and other devices to capture physical characteristics of PD symptoms, such as tremor, rigidity, and bradykinesia.
- The cluster validation indexes used in the study are the elbow method, Silhouette score, and Davies–Bouldin index. These indexes are applied to determine the optimal number of clusters in the data obtained from tapping activities recorded on smartphones.
- Application of the metric:The cluster validation indexes are used to determine the optimal number of clusters in the dataset. The elbow method, Silhouette score, and Davies–Bouldin index help assess the quality and coherence of clusters formed by the K-means algorithm. They assist in selecting the appropriate number of clusters that provide meaningful insights into the data without overfitting or underfitting.

[Feature-Level Fusion of Surface Electromyography for Activity Monitoring]
By Xugang Xi, Minyan Tang and Zhizeng Luo
Publisher: Sensors
([Q2] on Scimago)
- Pathology: The study involves healthy, able-bodied subjects without any specific pathology mentioned. The focus seems to be on capturing activities of daily living (ADLs) rather than pathology.
- Biomedical problem addressed: The biomedical problem being addressed is the development of a feature-level fusion technique (Weighting Genetic Algorithm for GCCA - WGA-GCCA) to improve the classification of activities based on EMG signals. The goal is to create a more effective feature space for distinguishing between different activities, which could be useful in various applications such as rehabilitation, human-computer interaction, and prosthetic control.
- Type of data: The data being analyzed are electromyography (EMG) signals obtained from sensors placed on various muscles of the lower limbs of the participants. These signals are used to monitor muscle activity during different activities.
- The Davies–Bouldin Index (DBI) is used as a cluster validation index to evaluate the performance of the feature space obtained from the proposed method. The DBI measures the degree of discrepancy between clusters and the degree of data of objects located in the same class.
- The main clustering technique used is the Weighting Genetic Algorithm for GCCA (WGA-GCCA), which is a feature-level fusion technique for EMG signal fusion. This method involves several steps including feature extraction, global canonical

correlation analysis (GCCA), and a genetic algorithm (GA) for feature selection. Additionally, fuzzy c-means clustering (FCM) is employed to evaluate the feature space using the DBI.

- Application of the metric: The DBI is used to evaluate the performance of the feature space obtained through the proposed method. A smaller DBI indicates a better feature space, which implies that the clusters are well-separated and the data points within each cluster are tightly packed. This evaluation helps assess the effectiveness of the proposed feature fusion technique in distinguishing between different activities based on EMG signals.

Pathologies	Biomed problem	Type
20%(4) Healthy 15%(3) Wide range of cancer types and subtypes 10%(2) Amputees/Upperlimb debilitated 10%(2) Acute heart failure and comorbidities 5%(1) Hypertension 5%(1) Breast cancer 5%(1) Burnout/Depression 5%(1) Dyslexia 5%(1) Colorectal carcinoma 5%(1) Chronic pain 5%(1) Diabetes and comorbidities 5%(1) Parkinson disease 5%(1) Data from a lab rat	30%(6) Improve SEMG/EMG/MES (including spike sorting) signal classification 30%(6) Improve diagnostics in respective field 15%(3) Gene analysis for cancer correlation 15%(3) Finding patterns in anamnesis to foresee outcome 10%(2) Others	25%(5) SEMG/EMG 25%(5) Lab measurements of phenotypic expressions or symptom expressions 20%(4) Omic and Genomic data 15%(3) Questionnaires (symbolic) 10%(2) Radiomic features 5%(1) Extracellular action potential (EAP) 5%(1) Myoelectric signals (MES) 5%(1) Blood pressure features (Some articles use mixed data from these categories)
Techniques analyzed (per appear.)	Cluster Scores (per appear.)	Use made of the indexes
50% (10) K-means and variants 20% (4) Autoencoders and fully connected autoencoders 20%(4) Principle Component Analysis (PCA) 10%(2) K-nearest 2 (KNN) K-medoids Fuzzy Convolutional Neural Networks (FCNN) Graph neural network (GNN) Convolutional neural network (CNN)	45%(9) Solo 40%(8) Silhouette (SI) 15%(3) Elbow method 15%(3) Calinski-Harabasz (CHI) 5%(1) Jaccard index (JI) C-index (Hubert) Distance ratio (DRI) Bayesian Information Criterion (BIC) Dunn Index Stability Index Fisher's Linear Discriminant Index (FLDI)	60%(12) Clustering evaluation 25%(5) Feature space performance 5%(1) Dim reduction 5%(1) Harmonization 5%(1) Template construction

Generative adversarial network(GAN) (Many other techniques were cited) 1. Partitioning Around Medoids (PAM) 2 2. linear discriminant analysis(LDA) 2		

Papers which use the Index

The following is a collection of doi's unchecked, every result with more than 10 reviews I found in google scholar for as far as I could.

https://doi.org/*10.1109/FUZZ-IEEE.2018.8491581*
https://doi.org/10.1016/j.neucom.2023.01.043
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