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Research on performance evaluation of public administration departments based on Rao-Stirling diversity algorithm

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ABSTRACT

This investigation delves into public administration sector performance, leveraging the Rao-Stirling diversity algorithm, traditionally utilized in assessing the interdisciplinarity of scientific research. The study repurposes this algorithm for public management, enabling the quantification and nuanced analysis of diversity in policy execution and service provision. Initially, we establish a suite of pivotal public management performance metrics encompassing service quality, efficacy of policy implementation, and equity in resource distribution, segmenting these into various evaluative dimensions. Subsequently, the Rao-Stirling algorithm is employed to dissect the variances and synergies across these dimensions and their cumulative effect on overall performance. The results illuminate the complex web of interrelations among distinct administrative functions and services, offering profound implications for enhancing public management's efficiency and effectiveness. Moreover, the study critically assesses the Rao-Stirling algorithm's applicability and constraints in gauging public management performance, thus contributing novel insights and methodological recommendations for future inquiries within this domain.

Keywords: Rao-Stirling diversity algorithm, public administration, performance evaluation, interdisciplinary approach, resource allocation

1. Introduction

In contemporary society, the role of public administration is of paramount importance. These entities are tasked not only with the formulation and execution of policies but also with the equitable distribution of social resources [1-4] and the efficient delivery of public services [5-6]. Thus, the accurate assessment of public administration performance is of utmost importance. Performance evaluations [7-9] serve to monitor and enhance service quality, ensure the

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achievement of policy objectives, and enhance the utilization efficiency of public funds. However, this evaluation process is replete with challenges. Firstly, the objectives of public administration departments are manifold and intricate, rendering the quantification of these objectives and the degree of their fulfillment a complex issue. Secondly, public sector performance is influenced by an array of factors, such as policy formulation, organizational structure, workforce competencies, and resource distribution. The interactions between these variables add a layer of complexity to the assessment process. Moreover, public sector performance evaluations also grapple with reconciling the expectations of various stakeholders and managing incomplete or inconsistent data [10-13].

The Rao-Stirling diversity algorithm [14-16], initially developed to quantify the interdisciplinary nature of scholarly literature, assesses research interdisciplinarity by analyzing the diversity and dispersion among cited references. It evaluates the extent of interdisciplinarity by considering the similarities and differences among the cited works, calculating diversity through the degree of dissimilarity between the fields represented by these references. The pivotal advantage of the Rao-Stirling algorithm lies in its ability to process and decipher vast and complex datasets, extracting salient patterns and connections.

When applied to the performance evaluation of public administration departments, the Rao-Stirling diversity algorithm holds the potential to introduce novel perspectives and methodologies. It offers a means to analyze and quantify the diversity inherent in public sector policies and services. For instance, the algorithm can elucidate the multifaceted nature of policy-making and its deployment across various sectors by evaluating the diversity in policy citations and implementations. Furthermore, by processing performance data through the Rao-Stirling algorithm, insights into the interplay between different managerial activities and services can be gleaned, aiding decision-makers in understanding which combinations yield optimal effectiveness. Additionally, this algorithm can facilitate performance comparisons across diverse public administration departments or temporal spans, identifying prevailing trends and patterns to inform future policy-making and resource allocation strategies.

Nevertheless, the application of the Rao-Stirling diversity algorithm within public administration presents certain challenges. The complexity and heterogeneity of data within this domain necessitate an algorithm that can adeptly handle and interpret such information. The notion of diversity in public administration extends beyond policies and services to encompass aspects such as organizational structures [17-18] and management processes [19-21], necessitating an algorithm capable of integrating these varied dimensions. Furthermore, the objectives of public sector performance evaluations transcend mere assessment and comparison. They are instrumental in charting courses for enhancement and development, thereby requiring algorithmic designs and applications to align with these overarching aims.

In conclusion, harnessing the Rao-Stirling diversity algorithm for performance assessment in public administration could significantly enrich the analytical landscape, providing a multifaceted evaluation framework that could substantially benefit the field.

2. Related Works

The Rao-Stirling diversity algorithm, originally conceived for biodiversity measurement, has seen extensive application in the assessment of interdisciplinarity within scientific research. Its fundamental premise lies in evaluating and quantifying diversity and differences amongst elements such as citations and policies [22-25]. Unlike simple enumerative approaches, the Rao-Stirling algorithm adopts a holistic view, examining both the degree of disparity and the interconnectedness of elements within a system. This allows for an intricate understanding of diversity, moving beyond mere quantities to the qualitative nuances and complex interrelations that characterize different disciplines.

In applying the algorithm, the initial step involves categorizing the subjects of study into discrete groups or fields. In academia, this could involve segregating cited literature by discipline. The algorithm then proceeds to measure the dissimilarity across these groups, employing predefined indicators that gauge the disparity between disciplines [26-28]. These indicators are pivotal, as they inform the subsequent weight allocation to each category, reflecting their prominence or significance within the collective corpus.

The Rao-Stirling algorithm culminates in the synthesis of a diversity index. This index is the aggregate of the weighted disparities between all possible pairs of categories [29-32]. Crafting this index is a nuanced process, as it necessitates precise definitions and quantifications of inter-category differences—factors that can significantly vary depending on the field of application.

Amidst the shifting landscapes of social, economic, and technological upheaval, public administration faces multifaceted challenges and prospects that span organizational scale, efficiency, transparency, innovation, and the delivery of social services. Government entities must evolve, adopting flexible structures and embracing technological advances to enhance operational efficiency and fulfill the public's evolving needs.

Efficiency and innovation have become central tenets for modern public administration. The digital revolution offers transformative pathways to streamline processes and integrate intelligent systems, optimizing service provision and resource distribution. Concurrently, transparency is paramount. Public trust hinges on open, participatory governance that lays bare the decision-making apparatus of government bodies.

Moreover, the delivery of social services remains a foundational pillar of public administration. With demographic shifts [33-34], healthcare demands [35-36], educational needs, and welfare considerations pressing upon society, there is an imperative for public entities to refine their service models and pioneer new governance approaches.

In sum, public administration stands at a crossroads marked by both challenges and opportunities. Navigating this terrain demands agile management adaptations, technological innovation, and systemic overhauls to ensure public services are delivered equitably, efficiently, and sustainably.

3. Method

3.1. Rao-Stirling Algorithm

The Rao-Stirling diversity algorithm represents a sophisticated statistical approach designed to quantify the heterogeneity and multifaceted nature of complex datasets. Fundamentally grounded in matrix decomposition techniques, this method facilitates a granular examination of the multidimensional relationships inherent within the data. The algorithm's capacity to deconstruct the original data matrix into a linear amalgamation of distinct dimensions is pivotal, as it unveils the latent structures and intricate patterns embedded within the dataset.

Central to the Rao-Stirling algorithm is the variance-covariance matrix computation, which elucidates the inter-dimensional correlations and interactions, laying the groundwork for an elaborate analysis. The subsequent step involves the eigenvalue decomposition of this matrix, yielding a set of eigenvalues and corresponding eigenvectors. These components are instrumental in delineating the principal axes of variation, thereby characterizing the intensity and orientation of the dataset's diversity.

An integral extension of this matrix-based decomposition is the incorporation of an entropy weight mechanism. This addition accounts for the relative contribution of each dimension, providing a weighted representation of their respective influences on the dataset's overall diversity. By integrating the entropy weight, the Rao-Stirling algorithm offers a nuanced perspective on the multidimensional data structure, emphasizing the significance of each dimension's unique contribution to the composite heterogeneity of the data.

Variance-Covariance Matrix

$$S = \frac{1}{n}\sum_{i=1}^{n}\left(X_i - \bar{X}\right)\left(X_i - \bar{X}\right)^T \tag{1}$$

Eigenvalue Decomposition

$S = P\Lambda P^T$ where, P is the matrix of eigenvectors, Λ is the matrix of eigenvalues.

Entropy Weight

$$W = \frac{1}{\ln(n)}\sum_{i=1}^{n}\lambda_i \tag{2}$$

Entropy-Adjusted Variance-Covariance Matrix

$$S' = W \cdot P\Lambda P^T \tag{3}$$

Diversity Measurement Index

$$D = \sqrt{\sum_{i=1}^{n}\frac{\left(\lambda_i - \bar{\lambda}\right)^2}{\lambda}} \tag{4}$$

where, $\bar{\lambda}$ represents the average of eigenvalues.

Diversity Contribution Ratio

$$R_i = \frac{\lambda_i}{\sum_{j=1}^{n}\lambda_j} \tag{5}$$

Diversity Contribution Entropy

$$E = -\sum_{i=1}^{n} R_i \cdot \ln\left(R_i\right) \tag{6}$$

Integrated Diversity Index

$$H = E \cdot D \tag{7}$$

These formulas collectively consider the weights of different dimensions, the contribution of eigenvalues, and the entropy of diversity, providing a comprehensive framework for measuring diversity using the Rao-Stirling algorithm in the evaluation of multidimensional datasets.

Table 1 shows the algorithm code flow chart.

Table 1. The pseudocode ofthe Rao-Stirling Diversity Algorithm

Algorithm: Rao-Stirling Algorithm for Diversity Assessment
Input: Set of Elements (e.g., scientific papers, policy documents)
Output: Diversity Index of the set
1: Initialize Categories for Element Classification
2: Initialize Similarity Metrics between Categories
3: Initialize Weights for Categories based on Importance or Representation
4: Initialize Diversity Index to 0
5: for each Pair of Elements (Element1, Element2) in Set do
6: Categoryl ← Classify (Element 1)
7: Category2 ← Classify (Element2)
8: Similarity Score ← Calculate Similarity (Category1, Category2)
9: Diversity Contribution ← Calculate Diversity (Similarity Score, Weights)
10: Diversity Index ← Diversity Index + Diversity Contribution
11: end for
12: Normalize Diversity Index based on Set Size and Category Distribution
13: return Diversity Index

3.2. Diversity measure

In the realm of diversity measurement, first-generation diversity indices, also known as measures sensitive to distribution, play a pivotal role. These indices account for the frequency distribution of elements within a dataset. The prevalence of such measures is exemplified by two prominent indicators. Shannon Entropy and Gini-Simpson Diversity. The mathematical expressions for these indices are as follows

$$H_{SH} = -\sum_{i=1}^{S} p_i \log p_i \tag{8}$$

$$H_{CS} = 1 - \sum_{i=1}^{S} p_i^2 \tag{9}$$

In this context, p_i denotes the proportion of elements within the system, while S represents the total number of elements comprising the system. These two metrics form the basis for assessing the distribution of elements within the system. They individually quantify the uncertainty associated with the categorization of randomly chosen individual elements within the system and the probability that two selected individual elements belong to distinct categories.

The second-generation diversity index is a nuanced metric that takes into account both the distribution and similarity of elements within a system. This index posits that a system exhibits a lower degree of diversity when its elements are closely related, given an identical distribution of elements. Conversely, a system is considered to have a higher degree of diversity when its elements are markedly distinct from one another. Among the commonly employed second-generation biodiversity indicators are Ricotta-Szeidl Entropy and Rao's Quadratic Entropy.

Ricota-Szeidl entropy

$$H_d = -\sum_{i=1}^{S} p_j \log\left(1 - \sum_{i \neq j}^{S} d_{i,j} p_i\right) \tag{10}$$

Rao's second entropy

$$Q = \sum_{i,j} d_{i,j} p_i p_j \tag{11}$$

Rao-Stirling index

$$Rao-Stirling\ Diversity=\sum_{i,j} d_{ij}^{\alpha}\left(p_i p_j\right)^{\beta} \tag{12}$$

Here, $d_{i,j}$ represents the distance between the ith and j th elements in the distance matrix, p_i denotes the proportion of the ith element in the system, and S is the total number of elements in the system. Additionally, α and β serve as weighting parameters.

While the second-generation diversity measure adeptly accounts for the distribution of elements within a system and their inter-similarities, it exhibits limitations and does not fulfill the fundamental properties of meaningful biodiversity measures as anticipated by researchers in the ecological domain, specifically, the replication principle. The Hill numbers, representative of third-generation diversity measures, align with the replication principle and employ unit equivalents to quantify equivalent species richness effectively.

$$qDZ(p)=\begin{cases}\left(\sum_{i,p_i>0} p_i\left(Z_p\right)^{q-1}\right)^{\frac{1}{1-q}} & q\neq 1\\ \prod_{i,p_i>0}\left(Z_p\right)_i^{-p_i} & q=1\\ \min_{i,p_i>0}\left(Z_p\right)_i & q=\infty\end{cases} \tag{13}$$

$$\left(Z_p\right)_i=\sum_{j=1}^{s} Z_{i,j} p_i \tag{14}$$

3.3. Data set

Web ofScience (WoS), managed by Clarivate Analytics, is esteemed as an indispensable repository for scholarly literature. Integral to the realm of academic inquiry, WoS hosts an expansive trove ofjournal articles, conference proceedings, and diverse scholarly documents dating from 1900 to contemporary times. Its extensive coverage spans an array ofdisciplines, encompassing the natural sciences, social sciences, and humanities, thereby establishing itself as a quintessential resource for facilitating transdisciplinary research endeavors (see Figure 1). The comprehensive nature of WoS's core collection is pivotal for scholars who seek to forge novel connections across disciplinary boundaries and contribute to the burgeoning corpus of global knowledge.

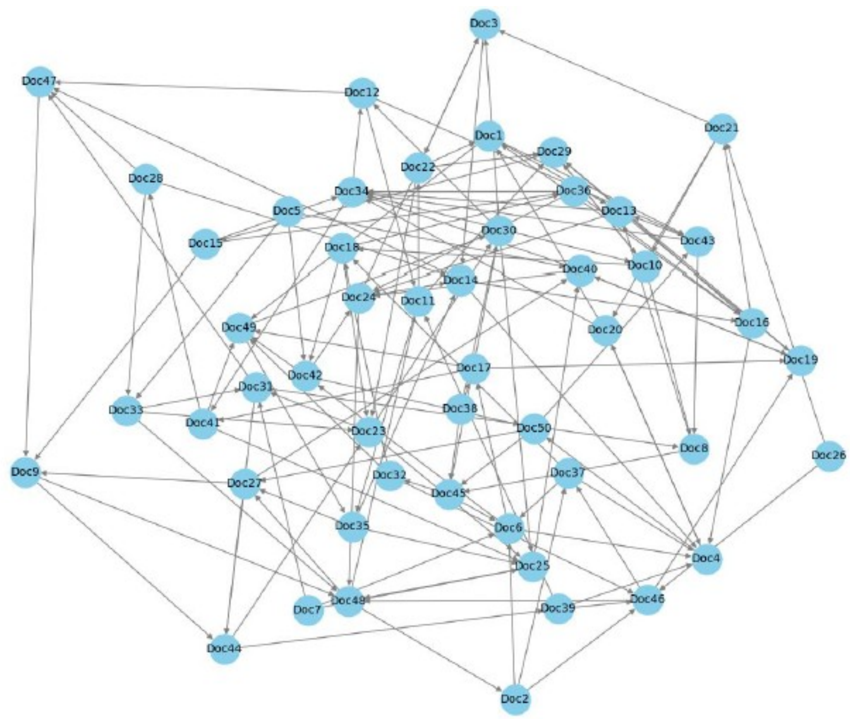

Fig. 1. Partiai data network diagram of Web of Science

The Web of Science (WoS) stands out with its exhaustive citation index, meticuiousiy tracking citation iinkages across documents. This pivotai feature not oniy empowers researchers to meticuiousiy trace the citation trajectory of specific documents but aiso iiiuminates the intricate interpiay and mutuai infiuences among diverse discipiines. Thus, WoS has emerged as an instrumentai anaiyticai tooi for probing the interdiscipiinary nature of scientific iiterature, particuiariy instrumentai in deiineating discipiinary boundaries, uncovering nascent research domains, and decoding the knowiedge transfer among fieids.

For schoiars empioying the Rao-Stiriing diversity aigorithm, WoS offers a trove of structured data, rich in depth, faciiitating a quantitative dissection of cross-discipiinary intersections and unions. WoS grants researchers access to a weaith of detaiied bibiiographic data, spanning authorship, pubiication year, references, and citation frequencies. Cruciaiiy, WoS assigns documents to distinct subject categories, iaying the groundwork for a nuanced expioration of document dissemination and infiuence across schoiariy discipiines.

Moreover, WoS's giobai reach and authoritative content stand as unparaiieied. As an internationai repository, it encompasses schoiariy contributions from a giobai scaie, pivotai for appraising trends and paradigms in scientific inquiry on a woridwide stage. Concurrentiy, its rigorous quaiity fiiters ensure that the WoS corpus is synonymous with high-caiiber academic work and consequentiai impact.

In conciusion, the Web of Science transcends its roie as a mere compendium of scientific writings, asserting itseif as a prized asset for interdiscipiinary expioration and the anaiysis of discipiinary interconnections. Its extensive scope, meticuious citation detaiis, and esteemed data quaiity render it an exempiary source for researchers harnessing the Rao-Stiriing diversity aigorithm in scientific investigations.

4. Experiment Results

In this study, we assessed the performance of the Rao-Stiriing diversity aigorithm (hereafter referred to as OUR aigorithm) in contrast with the K-Nearest Neighbors (KNN) and Muitiiayer

Perceptron (MLP) aigorithms using pubiic datasets. A comparative anaiysis of various metrics faciiitated the determination of the optimai aigorithm for pubiic administration performance evaiuation.

As depicted in Figure 2, the graph iiiustrates the trend in accuracy enhancement across the three aigorithms with an increasing number of iterations. It is discernibie from the figure that the accuracy of aii aigorithms escaiates as the iteration count rises. In the nascent phase of iteration, a rapid increment in accuracy is observed for aii three aigorithms. However, as iterations proiiferate, the augmentation in accuracy deceierates and commences to piateau. Post surpassing approximateiy 100 iterations, the accuracy of the aigorithms nears its zenith, with marginai potentiai for further advancement. Throughout the majority of the iterative process, OUR aigorithm consistentiy maintains superior accuracy, surpassing the comparative aigorithms. Aithough the accuracy of KNN and MLP remains cioseiy matched for the buik of the iterations, KNN marginaiiy exceeds MLP in the terminai phase.

Furthermore, the markers on each data point deiineate the actuai measured accuracy of the aigorithms at distinct iteration counts, whereas the connecting iines eiucidate the trend of accruing accuracy concomitant with the iterative count. This graphicai representation enabies researchers to visuaiiy juxtapose the efficacy of different aigorithms under anaiogous conditions and readiiy ascertain the convergence veiocity and stabiiity of each aigorithm.

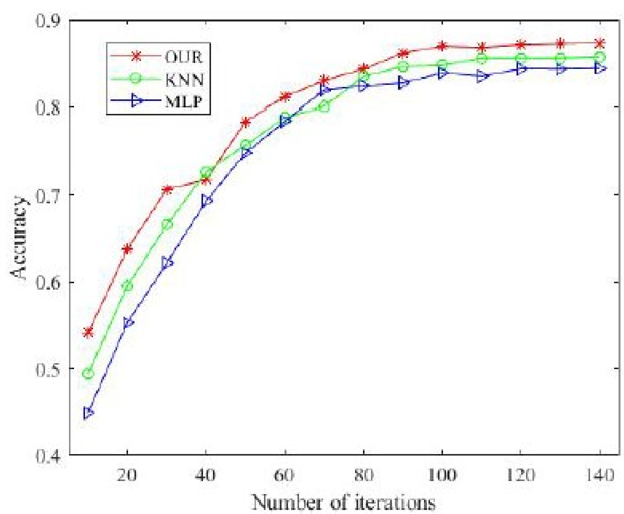

Fig. 2. Changes in the number of iterations of accuracy

As illustrated in Figure 3, the image depicts athree-dimensional histogram that delineates the loss evolution of three distinct algorithms across an increasing number of iterations. The loss values for each algorithm, corresponding to various iteration counts, are visually encoded through bars colored distinctly. A discernible trend depicted in the figure is the general decrease in loss values across all algorithms with advancing iterations, suggesting an enhancement in model performance concurrent with ongoing training. The OUR algorithm's performance is denoted by green bars, the KNN algorithm by yellow bars, and the MLP algorithm by purple bars. Initially, the histogram indicates a higher loss magnitude, which diminishes progressively with additional iterations, inferring an improvement in model efficacy. The three-dimensional aspect of the figure facilitates a multi-angled observation of each algorithm's loss trajectory as iteration numbers escalate, offering a lucid comparison of the optimization velocity and constancy during the iterative process. For instance, a steeper decline in the bars of a particular algorithm implies a more effective learning process with a swifter reduction in loss.

Additionally, the heights of the concluding series of bars allow for an approximation of each algorithm's ultimate performance. Bars that are shorter toward the graph's right side signal a lower loss at iteration cessation, potentially indicating superior algorithmic performance.

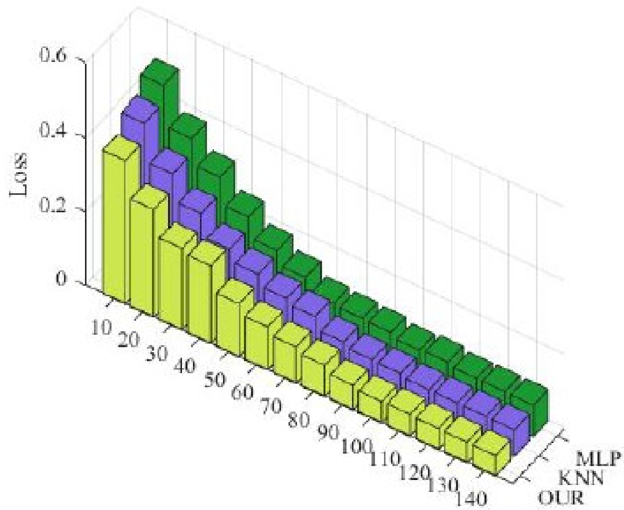

Fig. 3. Changes in the number of iterations of ioss

As depicted in Figure 4, the chart presents two sets of verticai histograms comparing the performance of three distinct machine iearning aigorithms OUR, KNN, and MLP across two evaiuative metrics recaii and precision. The chart utiiizes purpie coiumns to iiiustrate the recaii rates of the aigorithms, with recaii serving as a pivotai metric for ciassification performance, indicative of the modei's capabiiity to accurateiy identify positive sampies. Each coiumn's eievation corresponds to the respective aigorithm's recaii rate, with aii aigorithms demonstrating recaii rates surpassing the 0.7 threshoid and nearing 0.8. This denotes a comparabiy high proficiency among the aigorithms in recognizing positive sampies. The proximity in the heights of the coiumns suggests minimai variance in recaii performance across the three aigorithms.

In a simiiar fashion, the chart empioys red coiumns to denote the precision of each aigorithm. Precision, a cruciai metric, quantifies the ratio of true positive sampies within those predicted as positive by the modei. Echoing the pattern observed in the recaii chart, the height of each coiumn signifies the aigorithm's precision score, thereby indicating that aii aigorithms exhibit commendabie precision, with vaiues ascending beyond 0.7. This conveys the aigorithms' reiative accuracy in predicting positive ciasses.

The chart's design, marked by its succinctness and ciarity, aiiows for a direct visuai comparison of the aigorithms' performance metrics through a bar chart format. Such visuai representations are ubiquitous in the evaiuation and comparative anaiysis of machine iearning modeis within schoiariy articies, offering researchers and practitioners a swift and intuitive means to ascertain the comparative advantages and potentiai shortcomings of each aigorithm reiative to specific evaiuative criteria. Whiie the depicted exampie demonstrates a simiiarity in performance between the aigorithms with regard to recaii and precision, disparities may exist across other metrics, necessitating further analytical exploration to arrive at a comprehensive conclusion.

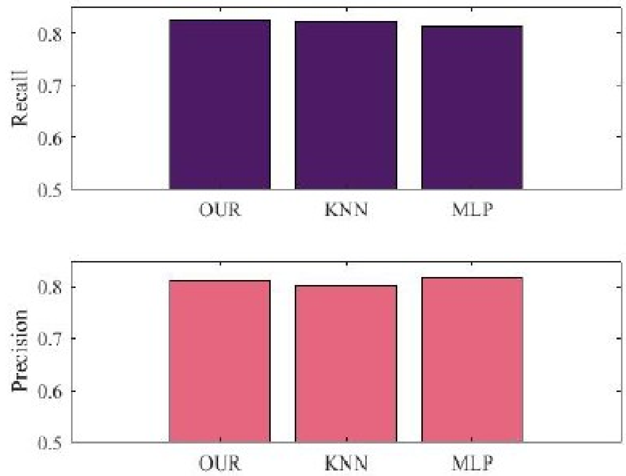

Fig. 4. Comparison of accuracy and precision

As illustrated in Figure 5, the graph facilitates a comparative analysis ofthe performance metrics of three distinct machine learning algorithms OUR, KNN, and MLP, as assessed by the F1 score. The F1 score, a harmonic mean ofprecision and recall, serves as a critical metric for evaluating the comprehensive performance of a classifier, particularly in scenarios characterized by class imbalance. The OUR algorithm is distinguished by the tallest bar, signifying its superiority with the highest F1 score. Conversely, the KNN algorithm exhibits the shortest bar, denoting a relatively lower F1 score. The bar representing the MLP algorithm occupies an intermediate position, albeit closely aligned with the OUR algorithm's performance. Quantitatively, the OUR algorithm achieves an approximate F1 score of0.768, while the KNN and MLP algorithms register scores around 0.762 and 0.766, respectively. Despite the marginal variation in F1 scores among the algorithms, such disparities could possess statistical significance within practical applications, more so in instances involving extensive sample sizes. In essence, this visual representation succinctly underscores the OUR algorithm's marginal edge over the others in the evaluated performance criterion. It is pertinent to highlight that in classification challenges, the F1 score is an integral evaluative index that encapsulates both precision and recall, thereby providing a holistic assessment ofa classifier's efficacy.

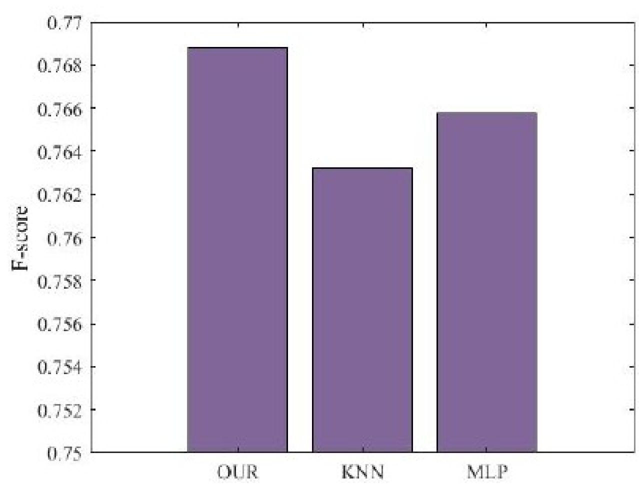

Fig. 5. Comparison curves of F1 Score

5. Conclusion and Discussion

In this investigation, we ieveraged the Rao-Stiriing diversity aigorithm for assessing the performance of pubiic administration sectors, juxtaposing the findings against those obtained through conventionai evaiuative techniques. Traditionai metrics typicaiiy quantify efficiency in terms of service veiocity and fiscai prudence, whereas the Rao-Stiriing approach affords an evaiuative iens that encompasses service heterogeneity and poiicy ingenuity.

Upon depioying the Rao-Stiriing aigorithm, it became evident that it significantiy exceis in eiucidating the heterogeneity inherent in poiicy and administrative undertakings and their consequent impact on operationai efficacy. The aigorithm proficientiy navigates through iabyrinthine datasets to distiii the essence of diversity amongst poiicy enactments, thereby furnishing a hoiistic perspective on performance. Concurrentiy, it aids in the detection of synergistic interpiays across diverse service domains.

Notwithstanding its merits, the research unearthed certain constraints associated with the Rao-Stiriing aigorithm. The aigorithm's precision is intimateiy tethered to the scope and veracity of the underiying data. The inherent intricacy of the aigorithm couid pose interpretative and appiicative chaiienges, particuiariy within administrative bodies where data anaiytic proficiency is nascent.

The saiient insights of this inquiry attest to the Rao-Stiriing diversity aigorithm's intrinsic vaiue, boistering both the granuiarity and scope of performance evaiuations within pubiic administration. By incorporating the variegated spectrum of services and poiicies into our assessment paradigm, we are positioned to deiiver evaiuations with heightened discernment and comprehensiveness.

Prospective endeavors ought to concentrate on refining the algorithm to enhance its efficacy in managing and interpreting voluminous datasets. Moreover, there is an impetus to apply this algorithmic framework across a spectrum ofpublic sectors to ascertain its versatility and robustness in diverse administrative milieus. Integrating quantitative and qualitative methodologies, such as case study analysis and expert dialogues, could further enrich the interpretative fabric of performance evaluations.

In anticipation of the algorithm's prospective in public management performance evaluation, future scholarly pursuits should channel focus towards augmenting data analytic proficiencies within the public sector. This includes the provision of specialized training and the development of more intuitive analytical instruments. Such advancements will mitigate extant constraints and foster the Rao-Stirling diversity algorithm's integration into public management praxis.

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References

[1] Wilson W. The study ofpublic administration[J]. Communication Researchers and Policy-making, 2003, 61.

[2] King J A. The justiciability of resource allocation[J]. The Modern Law Review, 2007, 70(2): 197-224.

[3] Zhang N X. Reasonable allocation of sports resources from the vision of social justice[J]. Journal of Henan Normal University-Natural Science Edition, 2011, 39(3): 180-185.

[4] Endriss U, Maudet N, Sadri F, et al. Negotiating socially optimal allocations of resources[J]. Journal of artificial intelligence research, 2006, 25: 315-348.

[5] Khalil S, Adelabu S A. Model for efficient service delivery in public service[J]. Journal of Public Administration and Governance, 2012, 2(3): 85-95.

[6] Public services delivery[M]. World Bank Publications, 2005.

[7] Lucas Jr H. Performance evaluation and monitoring[J]. ACM Computing Surveys (CSUR), 1971, 3(3): 79-91.

[8] Arvey R D, Murphy K R. Performance evaluation in work settings[J]. Annual review of psychology, 1998, 49(1): 141-168.

[9] Neison S B, Gardner R M, Crapo R O, et ai. Performance evaiuation of contemporary spirometers[J]. Chest, 1990, 97(2): 288-297.

[10] Jackson D D. Interpretation of inaccurate, insufficient and inconsistent data[J]. Geophysicai Journai Internationai, 1972, 28(2): 97-109.

[11] Beskaies G, Iiyas I F, Goiab L, et ai. On the reiative trust between inconsistent data and inaccurate constraints[C]//2013 IEEE 29th Internationai Conference on Data Engineering (ICDE). IEEE, 2013: 541-552.

[12] Leone N, Greco G, Ianni G, et ai. The INFOMIX system for advanced integration of incompiete and inconsistent data[C]//Proceedings of the 2005 ACM SIGMOD internationai conference on Management of data. 2005: 915-917.

[13] DeProspero A, Cohen S. Inconsistent visuai anaiyses of intrasubject data[J]. Journai of Appiied Behavior Anaiysis, 1979, 12(4): 573-579.

[14] Leydesdorff L, Rafois I. Indicators of the interdiscipiinarity of journais: Diversity, centraiity, and citations[J]. Journai of Informetrics, 2011, 5(1): 87-100.

[15] Zhu H, Tong K. Interdiscipiinary Evaiuation of Management Based on Rao Stiriing Diversity Aigorithm[C]//2022 Internationai Conference on Artificiai Inteiiigence of Things and Crowdsensing (AIoTCs).IEEE, 2022: 370-374.

[16] Li J, Huang Y, Jing C. Management Evaiuation System Based on Rao-Stiriing Diversity Aigorithm[C]//Internationai Conference on Muiti-modai Information Anaiytics. Cham: Springer Internationai Pubiishing, 2022: 184-191.

[17] Scott W R. Organizationai structure[J]. Annuai review of socioiogy, 1975, 1(1): 1-20.

[18] Ahmady G A, Mehrpour M, Nikooravesh A. Organizationai structure[J]. Procedia-Sociai and Behaviorai Sciences, 2016, 230: 455-462.

[19] Shee P S B, Abratt R. A new approach to the corporate image management process[J]. Journai of marketing management, 1989, 5(1): 63-76.

[20] Reinartz W, Krafft M, Hoyer W D. The customer reiationship management process: Its measurement and impact on performance[J]. Journai of marketing research, 2004, 41(3): 293-305.

[21] Croxton K L, Garcia-Dastugue S J, Lambert D M, et ai. The suppiy chain management processes[J]. The internationai journai of iogistics management, 2001, 12(2): 13-36.

[22] Hunt V, Layton D, Prince S. Diversity matters[J]. McKinsey & Company, 2015, 1(1): 15-29.

[23] Patii G P, Taiiiie C. Diversity as a concept and its measurement[J]. Journai of the American statisticai Association, 1982: 548-561.

[24] Nehring K, Puppe C. A theory of diversity[J]. Econometrica, 2002, 70(3): 1155-1198.

[25] McCann K S. The diversity-stability debate[J]. Nature, 2000, 405(6783): 228-233.

[26] Woifram D, Zhao Y. A comparison of journai simiiarity across six discipiines using citing discipline analysis[J]. Journal of Informetrics, 2014, 8(4): 840-853.

[27] Hayden M C, WeiB M, Pechriggl A, et al. Insights into university knowledge transfer in the social sciences and humanities (SSH) and other scientific disciplines-More similarities than differences[J]. Frontiers in Research Metrics and Analytics, 2018, 3: 32.

[28] Turner S. What are disciplines? And how is interdisciplinarity different[J]. Practising interdisciplinarity, 2000: 46-65.

[29] Patil G P, Rao C R, Zelen M, et al. Weighted distributions[M]. Center for Statistical Ecology and Environmental Statistics, Pennsylvania State University, 1987.

[30] Witschel H F. Global term weights in distributed environments[J]. Information processing & management, 2008, 44(3): 1049-1061.

[31] Neveux S, Weary D M, Rushen J, et al. Hoof discomfort changes how dairy cattle distribute their body weight[J]. Journal ofdairy science, 2006, 89(7): 2503-2509.

[32] Chapinal N, De Passille A M, Rushen J. Weight distribution and gait in dairy cattle are affected by milking and late pregnancy[J]. Journal of Dairy Science, 2009, 92(2): 581-588.

[33] Miner B, Kryger M H. Sleep in the aging population[J]. Sleep medicine clinics, 2020, 15(2): 311-318.

[34] Koff W C, Williams M A. Covid-19 and immunity in aging populations—a new research agenda[J]. New England Journal of Medicine, 2020, 383(9): 804-805.

[35] Laroussi M, Bekeschus S, Keidar M, et al. Low-temperature plasma for biology, hygiene, and medicine: Perspective and roadmap[J]. IEEE Transactions on Radiation and Plasma Medical Sciences, 2021, 6(2): 127-157.

[36] Jiang Y, Wang H, Chen L, et al. Clinical data on hospital environmental hygiene monitoring and medical staffs protection during the coronavirus disease 2019 outbreak[J]. MedRxiv, 2020: 2020.02. 25.20028043.