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Research Article

Enhanced Reinforcement Algorithm for Topic Categorization Using Machine Learning Method

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ABSTRACT

Information seekers rely heavily on search engines to extract relevant information because of the Internet's exponential development in users and traffic. The availability of a vast amount of textual, audio, video, and other content has expanded search engines' duty. Users of the Internet can obtain pertinent information about their query from the search engine by using factors like content and link structure. It does not, however, imply that the information is accurate. The link structure of web sites is analyzed using Web Structure Mining (WSM), and their content is analyzed using Web Content Mining (WCM), which determines how well the ranking module performs.A multitude of content-based recommender systems are currently in use, and they are well-researched in both text acquisition and filtering. These systems recommend documents based on text analysis. The management information system can benefit from Web Content Ming technology. Web content mining is the process of extracting or mining knowledge or useful information from web pages. The purpose of this work is to investigate web content extraction technology enhanced Reinforcement algorithm which anticipates user interest by analyzing the page according to user view related topic.This ERIM procedure involves locating web sites linked to user queries and using hyperlinks to locate a collection of related web pages and find the topic categorization using machine learning method.

Keywords: Content Based Document Similarity, Topic similarity, Web Content Extraction, Topic Categorizing, Enhanced Reinforcement

I. INTRODUCTION

The Internet has grown to be the primary source of information for individuals nowadays. Web pages are the smallest and most unbreakable units according to the majority of information retrieval tools on the Web; yet, a web page taken as a whole might not be suitable to represent a single semantic. This doctoral study proposes a visual representation-based examination of web content structure.This doctoral study proposes a visual representation-based examination of web content structure. This structure can be useful for a variety of web applications, including information extraction, information retrieval, and automatic page modification. Moreover, a web page frequently includes a number of themes that are not all related to one another. As a result, identifying a web page's semantic content structure may help with web information retrieval efficiency. The World Wide Web (WWW) is a widely used interactive platform for information dissemination in the modern day. When a person asks a search engine, it typically provides a vast array of pages in response.Several relevant and irrelevant pages are included in this result list based on the user's query. As users add more irrelevant pages to the search result list, different ranking algorithms are applied to the search results to make it easier for users to navigate the result list. Finding pertinent information resources from a collection of information resources is the process of information retrieval.

Figure 1.1 illustrates why it is challenging to automatically find Web-based information due to the absence of information sources' structures on the Internet. Conventional search engines like Google, Lycos, Alta Vista, or WebCrawler are helpful while looking for information. However, the issue lies in the fact that they don't offer structural information through document classification, filtering, or interpretation.There are two different viewpoints on web content mining: the database view and the information retrieval view. Enhancing users' ability to filter and locate information is the primary objective of the information retrieval perspective. The field of web content mining employs two different methodologies.

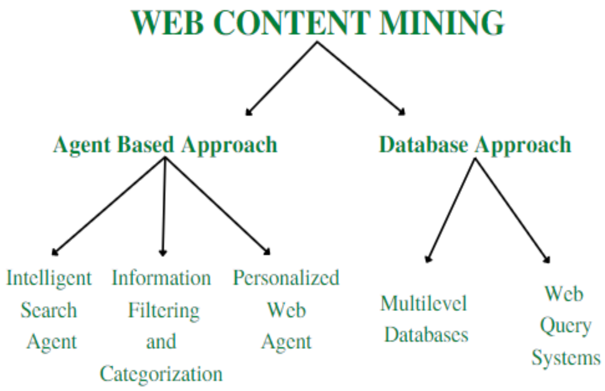

Fig.1.1 Web Content Mining

The database approach and the agent-based approach are the two methods. Semi-structured data from web documents can be retrieved with the use of the database technique. The agent-based method facilitates the organization of the information gathered by doing pertinent searches. More sophisticated information retrieval techniques, like multilevel databases and intelligent web agents, have been created by researchers.

(i) Agent-based Methodology: The agent strategy gathers pertinent data from the World Wide Web by using what are known as Web agents.

(ii) Agent-based Approach: This method gathers pertinent data from the World Wide Web by using what are known as "Web agents." An application known as a Web agent browses a website and selects the content the user is interested in viewing. Three kinds of the agent-based technique exist: Intelligent Search Agents, Information Filtering/Categorization, and Personalized Web Agents.Personalized Web Agents, Information Filtering/Categorization, and Intelligent Search Agents.

(iii) Database-based Approach: The goal of the database approach to Web mining is to create methods for grouping semi-structured material that is online into more structured information resource collections [3]. These collections can be analyzed using data mining methods and standard database querying procedures.

Web content mining is made possible by a combination of text mining, data mining, information retrieval, and machine learning. Its main goals are to enhance information retrieval, filter information, and integrate data on the web to enable the execution of increasingly complex online searches. In a nutshell, mining is the process of extracting and combining useful information, expertise, and data from Web pages.Because data mining techniques are applied to virtually free text found on the web, it is related to both text mining and data mining. The information that content data relates to is what the website was intended to tell users.

II. RELATED WORK

According to Alduaiji et al., an SLR [1] concentrates on social networks and makes recommendations in line with those findings. Additionally, it has extracted data using five digital libraries: Web of Science, IEEEXplore, Springer, ScienceDirect, ACM, and Scopus. It also claims that very accurate hybrid models produce recommender systems. Deep learning is utilized for developing social recommendation systems. This article does not specifically address data mining techniques like association, clustering, and anomaly analysis for storing and handling the massive amounts of data generated by social media platforms. Instead, it concentrates solely on deep learning approaches utilized for recommendation. Furthermore, possible problems or restrictions that could help the system get better are not addressed.

A survey paper by Javed et al. 2021 [7] examines context- and content-based reinforcement learning while taking into account hybrid, CBF, and CF models. It examines publications published between 2000 and 2015. It displays the distribution of RS-related articles by year. It also displays how RS has categorized its approaches. Rather than concentrating on social networks and data mining strategies, this article primarily discusses methodologies and tactics employed by RS.

Social network data suggest systems are employed on a broad basis [5]. A survey showcasing various recommendation techniques is conducted using extensive social network data. It also emphasizes on issues like data volume, volatility, and variation that large-scale RS must deal with. Additionally, it talks about articles from special issues in this field. Simple item RS and context awareness are highlighted. However, this does not address neural network-based session-based regression or any other data mining technique that can handle massive amounts of data.

A recommendation system is a crucial component of any contemporary social media or e-commerce platform, according to Dhelim et al. 2020 [4]. The product recommendation system, which is a classic example of a legacy recommendation system, has two significant flaws: it makes redundant recommendations and is unpredictable when it comes to new products (cold start). Thus, we provide Meta-Interest in this paper, a personality-aware system for product selection based on metapath identification and user interest mining.

According to Ge et al. [6], microblogging, a well-liked social media platform, has developed into a new information channel where users may share and receive the most recent information on events happening in the world. As a result, it is an essential platform for optimizing community influence with numerous application opportunities in advertising, recommendation systems, and other domains. Communities play a significant role in online social networks, which are becoming more and more integrated into our everyday lives due to the increasing growth of mobile Internet usage. Furthermore, the majority of current approaches ignore other aspects of event propagation in favor of concentrating just on event propagation. It is difficult to keep track of significant events promptly because users' interests vary and they are not always monolithic. Additionally, the topic of the event and the user's interests will shift over time.

A technique for extracting material from web pages was presented by YesuRaju et al. [9] and includes four stages: selecting web documents, creating web cubes, pre-processing web documents, and presenting them. They mainly concentrate on extracting valuable information from the online content data in their article. They specifically take into account the problems associated with web content mining in the context of online information repositories. This is due to the fact that data in relational databases are organized and categorized into tables using a set of characteristics and rows.Web documents are unstructured when it comes to web repositories. Applying a data mining system to directly search the complete World Wide Web in order to find the necessary information based on user query is not that simple. A list of online documents is chosen from the WWW in web content mining in order to extract pertinent data. They mine using key terms found in the papers according to their methodology.

III. METHODOLOGY

3.1 TREC Dataset

There are 5500 labeled questions in the training set and an additional 500 in the test set of the Text REtrieval Conference (TREC) Question Classification dataset. The dataset contains 6 coarse class labels and 50 fine class labels. Each phrase has an average length of ten and a vocabulary size of 8700. The TREC dataset is a question categorization dataset made up of fact-based, open-domain questions categorized into wide semantic groups. There are two versions of it: TREC-6 for six classes and TREC-50 for fifty classes. TREC-50, which comprises 500 test cases and 5,452 training samples, has more accurate labeling than the other model. Among the benchmark datasets used to assess text classification skills are AGNews and GLUE. Deep learning methods such as XLNet and RoBERTa have achieved some of the largest performance gains in recent years for text classification tasks.

3.2 Enhanced Reinforcement Method (ERIM)

Through trial and error and the use of feedback from its own actions and experiences, an agent can learn in an interactive environment through the use of the Enhanced Reinforcement Learning Method (ERIM), a sort of machine learning technique. Through interaction with its surroundings, an agent gains decision-making skills in order to optimize a reward signal. The agent learns the best course of action to follow in various circumstances by receiving feedback for its activities in the form of incentives or penalties. The agent's goal is to acquire a policy that maximizes its cumulative reward over time by mapping states to actions. When employing Reinforcement Learning, an agent typically acts in response to receive a reward signal, bases its decisions on the state of the environment at the time, and then adjusts its decision-making process in response to the reward. By assigning states to actions, the agent aims to learn a policy that maximizes its cumulative reward over time. RL can also be used to train models that prioritize and condense content by identifying key phrases or sentences. The model produces a summary that is compared to a reward signal, and the model's parameters are adjusted to optimize the reward. By training a model to predict a text's sentiment based on a reward signal, reinforcement learning (RL) can be applied to sentiment analysis. Based on how well it predicts, the model engages with a task environment, such as a dataset of labeled instances, and is rewarded with an output.Metrics reflecting the quality of the model's predictions, like as accuracy, F1-score, or AUC-ROC, might serve as the basis for the reward signal. Over time, the RL algorithm learns to fine-tune the model's parameters in order to enhance the sentiment analysis's quality. As the model learns to recognize pertinent elements and patterns that are helpful for predicting the sentiment of a text, this method may lead to more reliable and accurate sentiment analysis models. Nevertheless, RL-based sentiment analysis can also be difficult since it has to address the problem of class imbalance, which occurs when one sentiment class is more common than the others, and create an appropriate reward function that matches the model's intended performance.

3.3Preprocessing

3.3.1 N-Gram Stemmer

Stemming is the process of reducing words to their most basic form; stemmers and stemming algorithms make this process easier. For instance, "retrieval" becomes "retrieve," and "chocolates" becomes "chocolate." This is important because natural language processing pipelines require tokenized words that are obtained from the initial step of breaking down a document into its individual words. N-Gram Stemmer.

The process referred to as "n-grams," in which n is often two or three, divides words into n-length pieces. Statistical analysis is then used to find patterns in the segments. A group of n consecutive characters taken from a word is called an n-gram, and words that are related will share a large number of n-grams. It depends on the language and is based on string comparisons.

3.3.2 NLTK Stopwords

Stop words are frequently occurring words in a Words that are commonly used in a language but are rarely included in natural language processing (NLP) tasks are known as stopwords since they are not very important for understanding the meaning of a document. The specific stopword list may vary depending on the circumstance and language under study. A comprehensive list of stopword categories is provided below:During text preprocessing, these words which are the most common in a language—are commonly eliminated.More words might be regarded as stopwords, depending on the particular task or domain. These may be terminology specialized to a certain domain that add little to the broader meaning. In the medical field, terms such as "patient" and "treatment" could be regarded asas custom stop words.

In some situations, numbers and numeric characters may be regarded as stopwords, particularly if the analysis is more concerned with the text's meaning than with particular numerical values.Stopwords can be single characters such as "a," "I," "s," or "x," particularly if they don't mean anything on their own. Words that make sense in one context but are stopwords in another are known as contextual stopwords. The word "will" might be a stopword in the context of general language processing, but it might be essential for future prediction.

3.4Feature Weighing

3.4.1 Explicit Semantic Analysis (ESA)

Rather of searching for latent patterns, ESA makes advantage of explicit traits found in an already-existing knowledge base. ESA is mostly used as a feature extraction approach for explicit topic modeling and for determining the semantic similarity of text documents. Text document categorization is the main application of ESA as a classification algorithm. Both categorical and numerical input data can be used with the feature extraction and classification versions of ESA.

ESA uses a set of attribute vectors as its input. Every attribute vector has a concept associated with it. The concept is a feature or a target class in the context of feature extraction or classification. In the context of feature extraction or classification, the idea is a feature or a target class. In feature extraction, each feature can only have a single attribute vector associated with it.The training set may include more than one attribute vector linked to a particular target class for classification purposes.

A vast collection of text documents can be used to build an explicit semantic analysis (ESA) model, which produces a model with numerous attributes or titles. System Global Area (SGA) receives the model data for scoring as a shared (shared pool size) library cache object.The text method referenceable by several SQL predictive queries. If the SGA is too small, it may need to be reloaded each time the model is referenced, which will likely negatively impact performance.It is common to find explicit knowledge in writing form. Knowledge bases consist of various collections of text documents.There are numerous text document collections that make up knowledge bases.

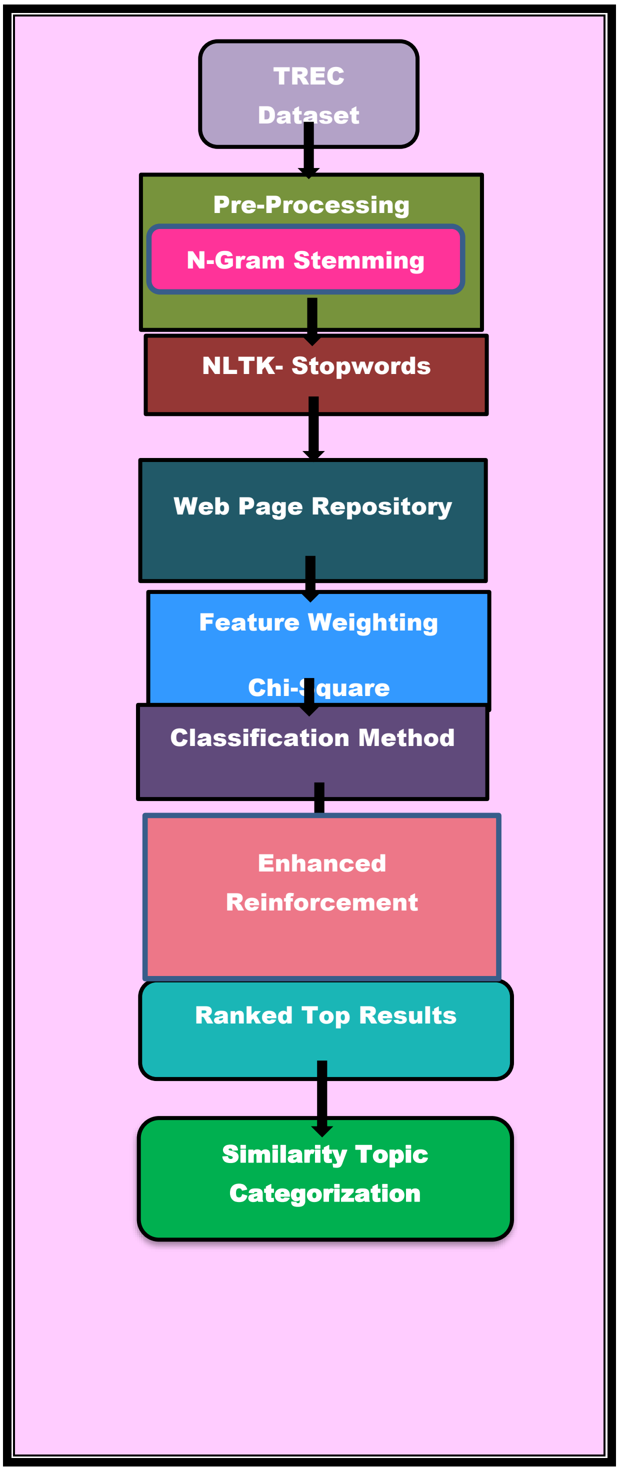

Fig.1.2Classification using ERIMMethod

3.4.2 Web Page Repository

A Web repository stores and maintains a vast collection of data "objects," in this example Web pages.It is essentially similar to other systems like file systems, database management systems, and information retrieval systems that store data objects. However, many of the features offered by the other systems, such transactions and a common directory naming scheme, are not necessary for a Web repository to have. As a result, the Web repository can be configured to deliver only the most necessary services in a scalable and effective manner.

Document scalability is the repository must be able to handle a very large number of objects due to the Web's size and growth. It is imperative that the repository can be distributed over a cluster of disks and machines with ease. We find it particularly interesting that the repository is being stored on network disks [14]. A disk with a CPU and a network interface that enables direct network connection is called a network disk. Network disks might be a particularly suitable option for Web repositories since they offer a low-cost and easy method of building big data storage arrays.Network disks might be a particularly suitable option for Web repositories since they offer a low-cost and easy method of building big data storage arrays.***Streams:*** Although access to individual Web pages must be allowed by the repository, bulk access to big groups of pages for data mining or indexing purposes will be the most demanding. Hence, stream access—in which the complete collection is scanned and sent to a client for analysis—must be supported by the repository. The repository might eventually need to handle ordered streams, which allow pages to be quickly returned in a specific sequence.

Expunging pages: When an object is no longer required, it is usually explicitly destroyed in file or data systems. On the other hand, the repository is not informed when a webpage is taken down from a website. As a result, the repository needs a system in place for identifying and eliminating outdated pages. This is similar to "garbage collection," except it doesn't rely on reference counts.

3.5 Enhanced Reinforcement Algorithm for Topic Similarity

The goal of the value-based method is to identify the maximum Ivalue at a state under any policy, or the optimal value function. As a result, the agent anticipates the long-term return under policy π at any state or states. The goal of the policy-based method is to determine, without the use of the value function, the best policy for the maximum future benefits. With this method, the agent attempts to implement a policy in such a way that each step's activity contributes to maximizing the reward in the future. Two primary types of policies are used in the policy-based approach:

Every state's policy (π) produces the same action, making it deterministic.Deterministic means that the identical action is produced by the policy (π) at any state. Stochastic helps to generated action in this strategy is determined by probability.In the model-based approach, the environment is represented by a virtual model that the agent investigates and learns about. Since the model representation varies depending on the environment, there is no set solution or algorithm for this technique.

$$V(s) = \max [R(s,a) + \gamma V(s`)] \quad \text{--------(1)}$$

V(s)= value calculated at a particular point.

R(s,a) = Reward by carrying out an action at a specific condition.

γ = Discount factor

V(s`) = the value at the previous state.

An agent's behaviour at a specific moment in time is referred to as its policy. It links the actions performed in relation to the perceived situations of the environment. The fundamental component of RL is a policy since it is the only thing that can specify an agent's behaviour. A straightforward function or lookup table may be used in certain situations, whereas general calculation acting as a search procedure may be required in others. The policy may be stochastic or deterministic:

$$\text{for deterministic policy: } a = \pi(s)$$
$$\text{for stochastic policy: } \pi(a \mid s) = P[At = a \mid St = s] \text{----(2)}$$

The reward signal determines the objective of reinforcement learning. A reward signal is an instantaneous signal that the environment gives to the learning agent at each state. These incentives are granted based on the agent's good and negative deeds. Maximizing the overall amount of rewards for good deeds is the agent's primary goal. If an agent's action selection yields a poor reward, the reward signal may alter the policy to select a different course of action in the future.

A number of metrics are used to quantify the performance, including percentage error, accuracy, F-measure, geometric mean (G-mean), precision, sensitivity, and specificity. The total number of forecasts needed to guarantee that the system operates as intended is known as accuracy. It is estimated as the ratio of the total number of correct forecasts to the total number of predictions.

Algorithm of ERIMMethod

Step 1:	***Start TREC Document DataSet***
Step 2:	***Σ = {0, 1, #} is a finite set, disjoint of containing terminal symbols***
Step 3:	***Tokenize and stemming the Document***

Step 4:	***Initialize the state u(t)***
Step 5:	***Sort all the document in order***
Step 6:	***N-gram stemming Remove grammatical word B x S x BH x N***
Step 7:	***Combine all TREC document and thenremove duplicated terms usir stopwords using NLTK***
Step 8:	***ReDim SW(1 To StopWords.Count) For I = 1 To StopWords.Count SW(I) = StopWords(I) Next I CleanStopWords = .Replace(S, "")***
Step 9:	$\chi^2 = \sum(O_i - E_i)^2/E_i$ ***Expected Value and observed value***
Step 10:	$ft = \sigma(Wxfxt + Whfht{-}1 + Wcfct{-}1 + bf)$
Step 11:	***Determine the Z-score using the Normal Distribution***
Step 12:	***End***

The value function provides information on the relative merits of the action and the situation, as well as the expected payoff for the agent. A reward indicates the signal for each good and bad action immediately, but a value function defines the favourable condition and action for the future. Since there could be no value without a reward, the value function is dependent on the reward. Estimating values is done in an effort to maximize rewards. The last part of reinforcement learning is the model, which mimics behaviour found in the environment. One can draw conclusions about the behaviour of the environment with the aid of the model. Such as, if a state and an action are given, then a model can forecast the next state and reward given a state and an action.

IV. RESULTS AND DISCUSSIONS

When the question is represented as a vector with a similar measurement to the routes that represent the other documents, the abnormality of angles among all document vectors, aside from the creative query vector, can be associated to calculate the rankings of documents based on the keyword search using the expectations of document similarities theory. A significance of the difference between term frequency-inverse document frequency approaches and Boolean document gathering illustration's compactness. Any document's boolean weights are located at a vertex in an n-dimensional hypercube.

The region delineated by the vertices of the hypercube becomes denser and more populated as documents are added to the collection. In contrast to Boolean, the inverse document frequencies of the terms in the novel document increase while those of the outstanding terms fall when a document is added utilizing term frequency-inverse document frequency weights. Typically, as more papers are added, the area in which they are located becomes more flexible, hence increasing the overall compactness of the assortment picture.

Certain class documents or themes, such as research articles and text mining, yield less useful recall findings. in order for the recall and precision values' f1 score to still yield an average result above 80%. The accuracy findings for the full ERIM Method used. The average values were obtained by applying the text document supports to the accuracy outcomes of the complete ERIM Method.

Table 1.1. The Comparison Table of Enhanced Reinforcement Method

Methods	Precision	Recall	F1-Score	Accuracy
SVM	85.76	87.81	86.04	86.41
ANBM	91.45	92.45	92.87	94.19
APMLDS	92.34	92.31	93.79	94.23
ERIM	93.67	94.45	94.23	94.15

The split results in Table 1.3 were acquired with random state = 1. Test results with ERIM values are applied to Fedweb, Dynamic Domain Track, Knowledge Base Acceleration (KBA), Microblog, Tasks Track.

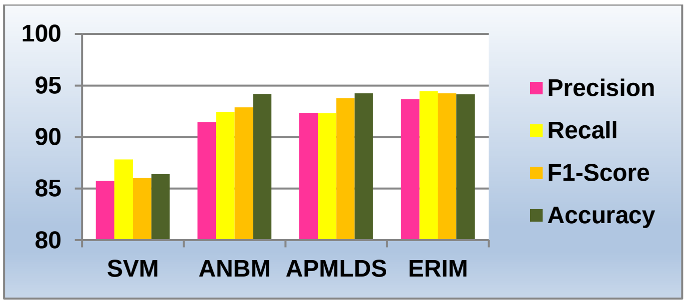

Fig 1.2 TheComparison chart of Enhanced Reinforcement Machine Learning Method

The categorization of content-based document similarity mining using the Enhanced Reinforcement Machine learning Topic Document Similarity Method is explained in Fig. 1.2. When compared to other existing approach and proposed methods such support vector machine Advanced Naïve Bayes, APMLDS, and ERIM, the suggested method ERIM yields superior results in terms of accuracy, precision, recall, and the F1-Score measure.

V. CONCLUSION

As a result of chi-square feature selection topic related document frequency finding techniques and Boolean approaches having different densities for their document collection representations. The document collection and the region specified by the vertices of the hypercube become increasingly populated when the maximum Euclidean distance and the potential document representations are added. The term frequency-inverse document frequency method is used to add a document; as a result, the weights of some terms in the document increase while those of the other terms decrease. When new documents are added, the region in which they are located expands, controlling the density of the collection representation as a whole to find the topic categorization related articles from the TREC database. This is done using the ERIM method. This study compares the precision, recall, F1-score, and accuracy numbers obtained from the Reuter's dataset with those obtained from other approaches. When compared to current methods, the suggested ERIM efficiently determines the similarity of Topic categorization related articles for all metrics taken into consideration.

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