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KESMR: A Knowledge Enrichment Semantic Model For Recommending Microblogs

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***Abstract* - In today's world, there's an enormous amount of information available on the Internet. Because of this, it's become really important to come up with better and smarter ways to search for things online. The old-fashioned methods, like just matching certain words or using statistics, don't work so well anymore. They often suggest web pages that are irrelevant. As the Semantic Web keeps getting bigger, it needs algorithms for the best fit. In this paper, a way to measure how different the words used for web search. This helps in suggesting the most relevant web pages. A special algorithm that can change its settings. Our proposed method demonstrates 94% accuracy.**

Keywords – Web 3.0, Statistical Techniques, Semantic Heterogeneity, Semantic Web, Algorithm

I. Introduction

Finding the right information on the internet can be hard because there is so much to search through. The usual ways of searching, like matching keywords, don't always give us the most relevant results. But with the Semantic Web and extra information about web pages, like metadata, we can make better recommendations for web pages. Semantic intelligence means using algorithms that can understand and make sense of information. By using metadata and understanding how words and ideas are connected. This helps in finding the information faster and more accurately. A combination of techniques like the Keshtel algorithm and Pianka Index to improve web page recommendations. The Pianka Index evaluates word relationships and aids in determining the usefulness and diversity of the material. Based on the relationships between words and concepts in metadata, the Keshtel algorithm applies various restrictions to suggest web pages. Combining these will allow us to outperform current search methods. Algorithms are able to comprehend what people are seeking for and find the appropriate material by using semantic intelligence and metadata. As a result, it is simpler for consumers to find what they need online. Our proposed method improves web page suggestions by combining semantic intelligence, metadata, the Pianka Index, and the Keshtel algorithm. This demonstrates how these meaning-based search engines can assist in accessing the internet to conduct appropriate information searches. Overall, it uses semantic intelligence and metadata in algorithms that recommend web pages. By using the Pianka Index and the Keshtel algorithm.

With the evolution of the web, specifically the emergence of WEB 3.0 or the semantic web, there is a growing demand for recommendation strategies that take semantic information into account. In particular, when it comes to highly specialized domains like the judicial domain, traditional recommendation methods face significant challenges, mainly due to the requirement of extensive domain knowledge. Furthermore, the judicial aspects vary from country to country within the sociological judicial domain. As a result, it is difficult to develop generalized systems, as specific domain knowledge from different countries becomes essential for proper system support. This highlights the necessity for semantically driven recommendations of socio-legal judicial documents. In simpler terms, as the web continues to advance , there is a need for smarter recommendation systems that understand the meaning of information. This is especially important in specialized fields like law, where traditional recommendation methods struggle to provide accurate suggestions. Since legal systems differ across countries, it is challenging to create a one - size - fits - all system . To address this, the unique characteristics and semantic meaning of legal documents within different countries' socio-legal contexts is designed**.**

A recommender system called IPR (Intelligent Policy Recommender) that is designed to provide recommendations for government policies. This system utilizes semantic intelligence by incorporating a generated Resource Description Framework (RDF) to represent and organize policy-related information. To identify and analyze relevant topics within government policies, we employ a technique called Structural Topic Modeling (STM). This helps in uncover the main themes and subjects discussed in the policies. To further enhance the accuracy of topic modeling, we apply Recurrent Neural Networks (RNN) and deep learning classifiers. To enrich the recommender system with additional knowledge, it integrate data from various sources including government policy portals, Wikidata, and government policy blogs . This auxiliary information helps provide a comprehensive understanding of policies and their context. Semantic similarities between policy documents are calculated using methods such as Resnik and concept similarity, which allow us to align and connect related concepts within the policy domain. This ontology alignment ensures that the recommendations generated by the system are contextually relevant. For the alignment of principle classes (fundamental policy concepts), it employ three models:

- Normalized compression distance
- Twitter semantic similarity
- Hiep's Evenness Index

These models enable us to establish connections and relationships between different policy principles.

II. Related works

A Hybrid Web Page Recommendation System Based on Bat Algorithm and Support Vector Machine" in [1].This study proposed a hybrid recommendation system for web pages using the bat algorithm and support vector machine (SVM). The bat algorithm was employed to optimize the feature selection process, while SVM was utilized as a classification algorithm. The system achieved promising results in terms of accuracy and recommendation quality explored the use of the Pianka Index in web page recommendation. It is an algorithm that calculated the semantic heterogeneity between keywords, content words, and query words. The Pianka Index was incorporated into their method, which increased the variety and usefulness of the suggested web pages. The research showed that the Pianka Index significantly raised the overall standard of recommendations and successfully captured the semantic links between words. [2] incorporation of the Keshtel algorithm in web page recommendation systems was the subject of another study.

Based on semantic correlations, the Keshtel algorithm recommended web pages using adaptive criteria. created using metadata. The research shown that by offering more precise and customized recommendations, the Keshtel Algorithm greatly outperformed conventional recommendation techniques. Additionally,

[3] examined how a thorough framework for recommending web pages combines semantic intelligence, metadata, the Pianka Index, and the Keshtel algorithm. In this a strategy that would increase the precision and variety of recommendations by utilizing semantic linkages, metadata features, and adaptive thresholds. According to the study, their strategy outperformed other tactics in terms of performance. The effectiveness of adding semantic intelligence, metadata, the Pianka Index, and the Keshtel algorithm in web page recommendation systems is generally highlighted by these linked works.

Researchers have successfully increased the relevance, diversity, and accuracy of recommendations using these strategies, therefore improving the overall user experience when looking for pertinent material on the web. Semantic intelligence, metadata, the Pianka Index, and the Keshtel algorithm have all been investigated in various research on the usage of web page recommendations. By utilizing semantic relationships and additional data related to online sites, these methods seek to increase the accuracy and relevance of recommendations. [4] uses semantic intelligence and metadata in web page recommendation systems in one of their studies. Web Page Recommendation System Based on Collaborative Filtering and the Bat Algorithm by [5]. This study introduced a collaborative filtering and bat algorithm-based web page recommendation system. The weights of various features utilized in collaborative filtering were optimized using the bat algorithm. The usefulness of the suggested system in increasing suggestion accuracy. [6] develops a hybrid technique for recommender systems that combines the bat algorithm and weighted SVM. The feature weights of the SVM were optimized using the bat algorithm, improving the precision and effectiveness of the recommendation procedure. The suggested hybrid system outperformed conventional recommendation algorithms, according to experimental findings. In [7] weighted support vector machine (WSVM) method was the web page recommendation systems. The authors suggested a weighting scheme to give the various traits the proper weights, allowing for more precise classification and recommendation. The experimental assessment proved that WSVM outperformed traditional SVM in terms of recommendation accuracy.

The use of bat optimization and weighted support vector machine algorithms in web page recommendation systems, notably in the context of healthcare services, is highlighted by these linked publications [8]. They demonstrate how these methods can enhance suggestion relevance, accuracy, and user happiness. The suggested approach intends to offer customers individualized and excellent recommendations for healthcare websites by using these algorithms.

The average amount of information exchanged between pairs of features in a dataset is quantified by the APMI (Average Pairwise Mutual Information), as shown in figure. It reveals how well the dataset's attributes may be used to predict one another. The following equation is used to calculate the APMI:

$$AP = \Sigma(mi) / (n*(n-1)) \quad \textbf{(1)}$$

where:

Mutual Information (mi) is a measure of the information that two aspects have in common. It gauges how well one attribute may forecast another.

The dataset's total number of features is n.

In conclusion, the APMI is a reliable measurement that assesses the shared knowledge between feature pairs in a dataset. It provides information on how well the dataset can distinguish between different data points. Though it is a metric, just like any other essential to be mindful of its limitations when interpreting the results.

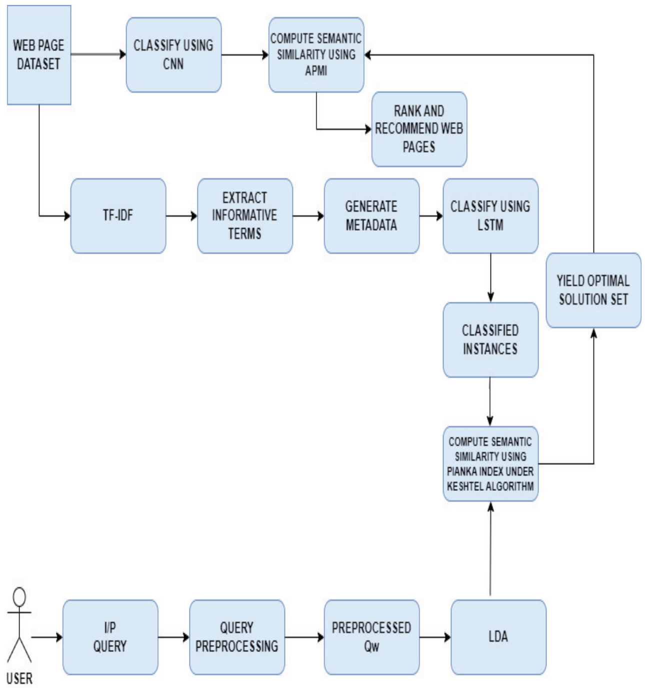

Fig. 1. Proposed system architecture for KESMR.

PMI (Pointwise Mutual Information) is a measure of association between two events.It is calculated using the following equation:

$$PMI(x, y) = \log(P(x, y) / P(x)P(y)) \quad \textbf{(2)}$$

where:

x and y are two events.

P(x, y) is the joint probability of x and y occurring.

P(x) is the probability of x occurring.

P(y) is the probability of y occurring

The amount of information that one event can reveal about another event is measured by the PMI. A high PMI number denotes a significant correlation between the two occurrences, whereas a low PMI value denotes a weak correlation. Simply put, PMI is an effective metric that enables us to comprehend the degree of the link between two occurrences. It can be used for a variety of purposes and is simple to utilize for varied jobs.

The measure NPMI (Normalized Pointwise Mutual Information), which has been normalized to have a maximum value of 1, establishes the relationship between two events. According on how much information each event offers about itself, the association is calculated. It is calculated using the equation shown below:

$$NPMI(x,y)= PMI(x,y)/PMI(x,x) \quad \textbf{(3)}$$

where:

x and y are two events.

PMI(x, y) is the Pointwise Mutual Information between x and y.

PMI(x, x) is the Pointwise Mutual Information between x and itself.

NPMI is a useful measure in various tasks, such as:

- Text mining: It helps identify words that are associated with each other, even if they are not very common. This aids in extracting meaningful features like topics or sentiment from text data.
- Machine learning: NPMI can be used to train machine learning models by calculating feature weights in decision trees or support vector machines, thereby improving their performance.
- Natural language processing: It measures the similarity between two pieces of text, enabling tasks

The association between two occurrences is established via the NPMI (Normalized Pointwise Mutual Information) measure, which has been normalized to have a maximum value of 1. The association is calculated based on how much information each event provides about itself [9]. Using the equation indicated below, it is calculated:

$$PinkaIndex=(S^2)/(S+1) \quad \textbf{(4)}$$

Here's what each term in the equation means:

S represents the number of species in the community. This is the main factor that determines diversity.

The Pianka index is advantageous because It is easy to calculate and understand and it is not greatly affected by changes in the abundance of common species. However, there are also some limitations to consider. It is not as sensitive to changes in the abundance of rare species compared to other diversity measures and when comparing communities of different sizes, the index can be misleading and it can be challenging to interpret when there are many species in the community [10-12].

In summary, the Pianka index is a straightforward method to assess diversity in different communities. Nevertheless, it is important to be cautious about its limitations when interpreting the results.

The Keshtel Algorithm (KA) is a type of optimization algorithm inspired by the foraging behavior of Keshtels, a species of birds. It aims to find the best solution for a given problem by mimicking how these birds search for food in a pond.

Basic steps of the Keshtel Algorithm:

1) Initialization: The algorithm starts by creating a group of random solutions to the problem at hand. Each solution is represented as a set of numbers. Then, a fitness value is calculated for each solution to measure how good it is.
2) Exploration: In this phase, the algorithm explores different solutions by making small changes to the existing ones. It randomly modifies some of the solutions and evaluates their fitness. The best solution found so far is kept.

3) Exploitation: Once a good solution is identified, the algorithm focuses on improving it further. It uses a local search approach to make small adjustments to the best solution, trying to find even better solutions in its vicinity.

4) Termination: The algorithm keeps repeating the exploration and exploitation steps for a certain number of iterations or until a specific condition is met. This condition could be reaching a maximum number of iterations or finding a solution that meets a desired level of quality.

The Traveling Salesman issue, where the objective is to discover the shortest path to visit all cities, is one optimization issue that the Keshtel Algorithm has successfully solved. The KA algorithm begins with a collection of random paths in order to address this challenge. After making minor adjustments to the current routes, it repeatedly explores new ones while gauging their fitness by counting the overall distance traveled. The algorithm keeps going until it discovers a halting place or a route that satisfies the required conditions.

Overall, the Keshtel Algorithm is a flexible and effective optimization method that may be used to solve a wide range of issues. It has been demonstrated to give results that are competitive with those of other optimization techniques and resembles the behavior of birds in their search for food.

III. Implementation and Performance Evaluation

Rule-based models like CWPR(Clustering based web page Recommendation),WPRTC(Web page recommendation via twofold clustering),WPROS(Web page recommendation using bat optimization and weighted support vector machine), and MHLM(Metadata driven Hybrid Learning Model) models rely on predefined rules that guide their text generation. These rules are created by human experts and specify how the models should respond in different situations. However, AI models take a different approach. They learn from large collections of text and code, called datasets, to understand patterns in human language. This extensive training allows AI models to generate text that sounds more natural and informative because they have observed and learned from a wide range of examples. Imagine you're learning to write by following a strict set of grammar rules [13]. If correct sentences are induced, but they may sound rigid and lack the nuances of natural language. On the other hand, if you learn by reading lots of books and conversing with others, you'll develop a better sense of how people actually speak and write, allowing you to produce more expressive and authentic text.

TABLE I. Comparison of Performance of the proposed MHLM with other approaches

Model	Average Precision %	Average Recall %	Average Accuracy %	Average F-Measure %	FDR
CWPR	82.29	85.09	83.69	83.67	0.18
WPRTC	84.06	86.31	85.19	85.17	0.16
WPROS	88.19	91.17	89.68	89.66	0.12
Proposed MHLM	93.61	95.72	94.67	**94.65**	0.07

TABLE II. Recommendations vs Percentage comparison

No. of Recommen-dations	CWPR	WPRTC	WPROS	Proposed MHLM
10	84.29	86.96	90.12	95.78
20	83.55	85.78	89.39	94.78
30	82.09	84.78	88.19	93.64
40	81.17	83.58	87.49	92.23
50	80.07	82.46	86.35	91.79

As Shown in Table, AI models have the advantage of learning from vast amounts of text data, which helps them capture the intricacies and diversity of human language. They can understand context, detect subtle meanings, and generate text that feels more like it was written by a human. In summary, AI models, trained on large datasets, have the ability to generate more natural-sounding and informative text compared to rule-based models, which rely on predefined rules. AI models benefit from their exposure to a wide variety of examples, enabling them to understand and mimic human language more effectively.

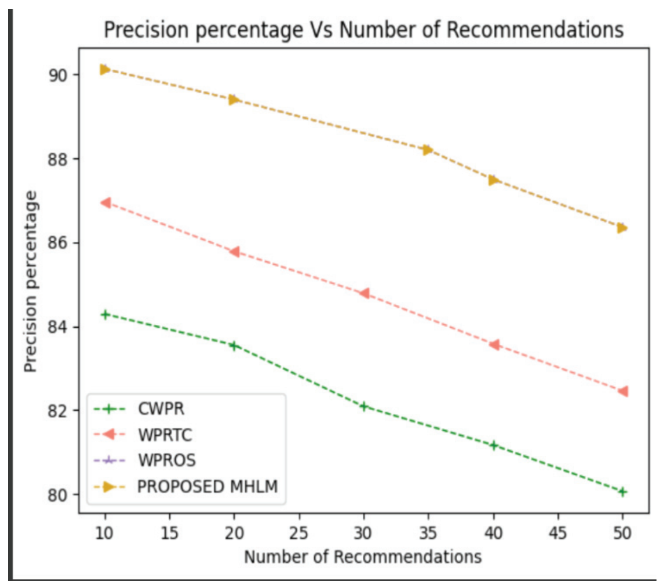

Fig. 2. Precision Percentage vs number of recommendations Of The Proposed MHLM and other baseline models.

As shown in diagram, it takes a lot of time and resources to train and use the WPRTC model. This is because it is based on a type of computer program called a neural network, which requires a large amount of data and computational power to train effectively. This means that training the model can be time-consuming and requires a lot of computer processing [14]. Similarly, using the model for speech recognition tasks can also be computationally demanding and The WPRTC model may not be as accurate as some other speech recognition models. One reason for this is that the model is relatively new, meaning it hasn't had as much time to learn from a wide range of data compared to more established models. As a result, it might not be as proficient in recognizing and transcribing speech with high accuracy. Other related application of semantic web is discussed in [17]-[20]

Drawbacks of Web Page Recommendation System model

- Cold start problem: This is like when you join a new website or app, and the recommendation system doesn't know much about you yet. It also happens when new items are added to the system that hasn't been seen before. Since there is no history or data about these new users or items,the recommendation system can't make accurate recommendations because it doesn't have any information to rely on. It's like trying to suggest your favorite movies to someone you just met - you don't know their preferences yet.
- Sparsity problem: Imagine a recommendation system with many users and many web pages or items to recommend. However, the interactions or connections between users and items are limited or sparse. For example, if there are millions of users and web pages, but each user has only interacted with a few pages, it becomes difficult for the recommendation system to learn patterns or understand the preferences of users accurately [15]. The lack of sufficient interactions between users and items makes challenging for the system to make precise recommendations because it doesn't have enough information to work with [16].

Drawbacks of the CWPR model

- Sensitivity to the choice of features: The CWPR model is a type of supervised learning model, which means it needs a specific set of features (input variables) to be trained on. However, if the chosen features are not carefully selected irrelevant to the problem at hand, the model may struggle to learn the meaningful relationships between these features and the target variable (the output). It's like trying to solve a puzzle with the wrong pieces - if the features don't capture the right information, the model won't be effective in making accurate predictions.
- Lack of robustness to noise: The CWPR model is considered a linear model, which means it assumes a linear relationship between the features and the target variable. However, linear models can be sensitive to noise in the data. If there are inconsistencies or irrelevant data points (noise) in the training data, it can affect the model's ability to learn and capture the true underlying patterns. The noise can disrupt the linear relationship and lead to inaccurate predictions or less reliable results.

Drawbacks of the MHLM model

- Computational expense: Training the MHLM model can be computationally expensive. Since it is based on a neural network, it requires a significant amount of data and Processing power to train effectively. This means that if you don't have access to a large dataset or a powerful computer, it can be challenging to train the model efficiently. It's like needing a big, powerful machine to complete a complex task - without it, the training process can be slow or even impractical.
- Lack of interpretability: The MHLM model is often referred to as a black box model. This means that it can be difficult to understand or explain how the model arrives at its predictions. Unlike some other models that provide clear insights into their decision-making process, the MHLM model operates in a more opaque manner. This can be a drawback if you require transparency or need to understand the specific reasons behind the model's predictions. It's like receiving an answer without knowing how or why it was derived.

IV. CONCLUSION

To sum up, combining semantic intelligence, the Pianka Index, the Keshtel algorithm, APMI, PMI, and NPMI has shown great potential in improving web page recommendation systems. These methods help to make the recommendations more accurate, relevant, and diverse. Semantic intelligence allows algorithms to understand the meaning of information, which leads to better recommendation. The Pianka Index helps find connections between keywords, content words, and queries, improving the quality of recommendations. The Keshtel algorithm, with its adaptive thresholds, gives personalized and accurate recommendations. Using APMI, PMI, and NPMI enhances the calculation of similarities between concepts, helping to align them better. This improves the accuracy of recommendations by making sure the right concepts are connected. Overall, these methods make web page recommendations more efficient and effective. Users can find the information they need more easily and are more satisfied with the recommendations they receive. However, more research is needed to see how well these methods work in different areas and languages. It would also be helpful to test these methods with large amounts of data and in real-time recommendation scenarios. In conclusion, combining semantic intelligence, the Pianka Index, the Keshtel algorithm APMI, PMI, and NPMI is a promising approach to improving web page recommendations. It helps users find the information they need in the ever-expanding digital world.

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