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The role of artificial intelligence in advancing the performance of information retrieval

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ABSTRACT

The motivation behind applying artificial intelligence (AI) in information retrieval (IR) is that the current methodologies include algorithms designed by researchers, leaving space for the applicability of genetic AI algorithms in IR. While different algorithms designed by developers rely on the originality or performance of the algorithm, precise results are achieved through integrating AI algorithms with traditional algorithms. The proposed methodology introduces document structure weighting with optimized performance. It is enabled by employing genetic algorithm and genetic programming for learning optimal weights in ranking document components. The Croft probabilistic ranking, vector space inner product models, and the BM25 standard were compared with each other after AI integration. Genetic algorithm and genetic programming were applied in the stemming and thesaurus forming processes of these models. Inducing genetic algorithm and genetic programming into the specified models increased the mean average precision of the Croft model and the vector space method by approximately 5% while there were no observable result improvements in BM25. It was found that applying genetic algorithm and genetic programming in learning synonyms and stemming rules, respectively, increased the overall performance of IR models, emphasizing the need for AI in IR.

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1. INTRODUCTION

The challenge of accurately representing documents and matching inaccurate applications of AI technology has been swiftly addressed by denotations (AI) approaches to information retrieval (IR). IR refers to search procedures where users select a portion of data from a large body of knowledge that is pertinent to their information needs. The person looking for information creates a query to try and express their information demand. A comparison is made between the query and representations based on documents that have been taken at the time of an index. A similarity function like the Cosine is generally used to match the representations of documents and queries. Users are shown the documents that are the most comparable so they may judge the relevance to their particular situation [1].

IR and artificial intelligence were developing together in the early days of computer science. They began working together in the 1980s, and the phrase "intelligence in information retrieval" (IIR) was created to describe AI applications in IR. They began working together in the 1980s, and the phrase "intelligence in information retrieval" (IR) was created to describe applications of AI in IR. In the year of 1990s, rating systems using probabilistic methods and the vector space model replaced set-based boolean retrieval models in IR. Figure 1 depicts components of the IR model. More intelligent value-added components were able to enter the market because of these approximate reasoning algorithms. There has been a lot of study done in this area due to the desire for intelligent text retrieval techniques and the large number of textual documents that are accessible online and in specialized repositories. To improve systems, better preprocessing is now crucial by the way to extract more knowledge from the data. The results of off-the-shelf methods are worse than those of systems tailored to users' domain-specific, and data needs. Currently, retrieval systems have successfully used the majority of AI-developed strategies. Systems frequently employ machine learning to optimize their outcomes when user data is available.

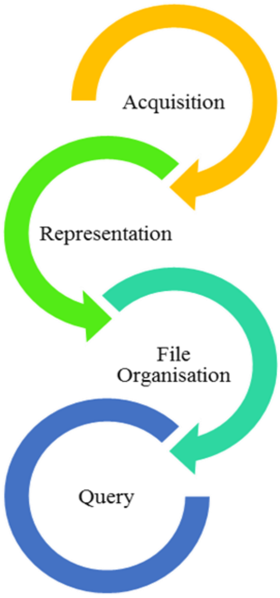

Figure 1. Components of information retrieval/IR model

IR systems integrate different classical methods for document representation and ranking. Figure 2 depicts the various processes in the IR system.

Indexing is related to the storage, portrayal, as well as retrieval of knowledge that is pertinent to a particular user problem. The person looking for information creates a query to try and express their data demand. Usually, the query is contrasted with representations of the documents. A correlation measure like the cosine and/or the dice-based coefficient is generally used to be consistent with how information and searches are represented. Users are shown the documents that are the most comparable so they can assess the relevance to their particular situation. Figure 3 depicts indexing process.

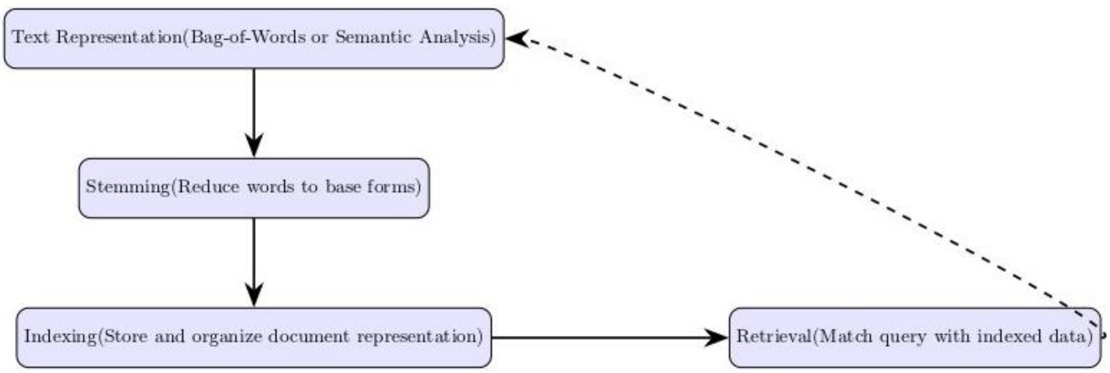

Figure 2. IR processes

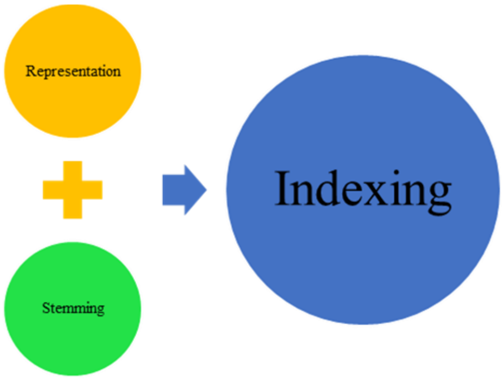

Figure 3. Indexing process

Stemming involves numerous stages. Stop words are eliminated after word segmentation. The document representation ignores common words like articles and prepositions because they have little meaning on their own. Second, word formations are reduced to their most fundamental component, the stem. For instance, homes would change into homes during the stemming phase. In most cases, differentials in word forms are not required for the document representation. A word's significance for a document might vary. Certain phrases more accurately convey a document's content than others. The frequency of a stem inside a document's text determines this weight [2]. The background is crucial to make the choice of each and every query type, as well as document selection in multimedia retrieval. It may be possible to compare various media depictions or decide that changes are necessary.

The majority of the time, natural language phrases without any syntactic or semantic background are used to represent text texts. The bag-of-words strategy is another name for this. Due to the fact that its background and connections to other phrases were obscured, these kinds of keywords or concepts could only inadequately depict an item/object. However, significant progress has been achieved, and semantic analysis systems are becoming more competitive. Computational linguistics has produced sophisticated semantic as well as syntactic parsing for the reliable processing only with large amounts of information [3]. Using understanding of the domain's principles enhances the representation scheme [4].

Indexing is the final process, which predominantly depends on stemming and the bag of words. Stemming is to ensure retrieval quality through preserving semantic meaning. Bag of words confirms semantic parsing.

2. LITERATURE REVIEW

In structured IR, authors distinguish between two basic groups of query reformulation approaches: Methods for reformulating queries that are (a) information-oriented [5]–[7] and (b) framework [8], [9]. Authors will concentrate on content-oriented query reformulation techniques in our study. These methods employ the same conventional IR technique while taking into account the terms derived from XML elements with various levels of granularity.

Mass and Mandelbrod were among the first to invest in this problem [10]. On an expanded vector model, they employed the Rocchio formula algorithm-based query new formulation [11]. Holland [12] bases the query extension on the idea of the ontology. It entails pulling terms (or rather, concepts) related to the original question from the ontology and adding them to the original query to create a new one.

Hlaoua and Boughanem [6] employ a method based on the Rocchio formula to broaden the query with new terms, giving significance to terms that are frequently repeated in the XML components deemed important. The result terms are weighted according to how frequently they appear in the XML components that are deemed important. Unfortunately, there are two issues with this approach. The starting issue is considered as an overlapping issue with the obtained elements of XML that need to be evaluated. The addition of unnecessary XML components in the process of choosing phrases is the second issue. The next part will go into more detail about these two issues.

The upcoming sections will elaborate on integrating AI in the IR Methodology. Compare traditional methods with AI-based methods, with their shortcomings and advantages. Conclude with future enhancements and applications of IR.

3. ARTIFICIAL INTELLIGENCE IDEAS AND MODELS FOR INFORMATION RETRIEVAL

The usage of AI will increase precision. This study has used standard test batteries and evaluations for learning and assessment. The strategies will be investigated for ad hoc retrieval of entire XML documents, but they can also be used for relevance feedback. Figure 4 depicts the AI integrated IR models.

3.1. Precision improvement ideas

Three strategies will be investigated: first, using the structures of the document to increase precision; next was ranking based on the generic-purpose techniques; as well as third will be the combination of above said methods.

3.1.1. Ranking based on structured wight's

Each document structure weight can have its own element in an array that contains the weights. The genetic algorithm is the obvious choice of learning algorithm for this encoding [12]. An assortment of persons is initially selected based on randomized weight(s). For each generation, the mean average precision of each person is determined. The selection of individuals for the following generation subsequently occurs via reproduction, mutation, and crossover. So, over a large set of queries, loaded recovery ability (with ideal weights) can always be at least as excellent as un-weighted detection accuracy. Furthermore, as GAs are a tried-and-true optimization approach, an upper constraint on performance should be possible.

3.1.2. Ranking based on general purpose

A careful review of the earlier findings reveals why the new ones are unexpected. A combination of operators and evidence utilized in the baseline function at a minimum should be employed in the learnt ranking function. Learning of the baseline could not be done unless this, and the same considered as reasonable, suppose that it will not be improved [13], [14]. To put it another way, if a ranking function f () that already exists combines evidence () and operators (), it cannot outperform a genetic programming taught function that combines evidence () and operators () if it is a subset of and is a subset of. This is so that the genetic programming might understand f (). Moreover, the learning process can be imposed with the f (), which ensures that at least f ().

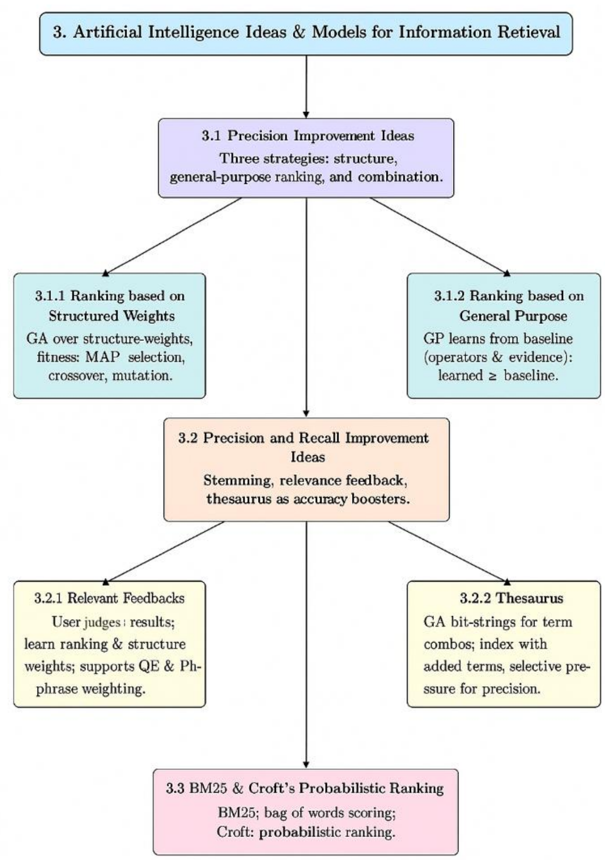

Figure 4. AI integrated IR models

3.2. Precision and recall improvement ideas

There are already many methods for enhancing recollection; some examples are stemming, relevance feedback, and thesaurus. Instead, these methods might be seen as pure accuracy boosters. Every newly discovered pertinent document receives a prevision score greater than 0, even though its accuracy score was zero when it was undiscovered. By finding more pertinent documents, this improves precision.

3.2.1. Relevant feedbacks

A user performs a search, the results are returned for review, the search is then reevaluated with the knowledge of the evaluations, and the new results are acquired. This process is known as relevance feedback. One can use the techniques already discussed to get input on relevance. After the initial round of judging, the initial question and a set of judgements are known, making it simple to learn a ranking function and structure weights. Using this learning method with pre-existing relevance feedback methods [15] such query expansion and phrase weighting is an option. Term weights have already been learned using genetic algorithm [16].

3.2.2. Stemming

It has been determined through research that stemming is unsuccessful [17]. This may be because a stemming algorithm's "stemming quality" is determined by the “stemming error rate”, whereas the "Information retrieval quality" is determined by the means of average precision, are the two separate measurements. This unfavorable result might be improved in case stemming algorithms are created with the single goal of raising means of average precision.

3.2.3. Thesaurus

A conventional genetic algorithm is used to learn effective combinations after an individual seeds a population, who has random bits set. Regardless of how it affects recall, selective pressure is used to boost precision. The document collection would first be indexed to include these terms, after which specific content bearing phrases would be found using pre-existing approaches [18]. The bit-string thesaurus learning would then be used.

3.3. BM25 and croft’s probabilistic ranking models

A bag-of-words retrieval algorithm called BM25 scores a bundle of documents based on the query keywords that exist in each one, regardless of where in the text they appear. It is a group of scoring functions with marginally unique elements and constraints.

4. RESULTS AND DISCUSSION

Learned ranking functions should be portable as soon as no evidence linking the function to the individual document collection. Moreover, you can assess the portability by evaluating any trained function's performance on a variety of document collections. Whether these functions are portable via statistical comparison to other portable ranking systems, it's going to be identified as BM25.

Using inner product, probabilistic, and Okapi BM25 ranking, a preliminary examination towards learning document structural weights was conducted [19].

The BM25 function, according to Okapi, is given below.

Were,

The Croft’s probabilistic ranking function, that based on Harman [6], is given below

Were,

Where the values of C and K are 1 and 0.3, respectively.

According to Robertson et analysis, the BM25 implementation was accurate. [19]

N was always the total number of documents, not the total number of documents containing the word, and tftd was the total number of times the word appeared in document d. (Likewise, tftq in the query). Based on the training content covering items 151-200, it served as the training set. Less than five assessments on a topic were disregarded. There were 50 people in the population, and numerous tests were conducted for 25 generations. Results of the evaluation against subjects 101–150 are displayed in Table 1. The Model Performance results and statistical analysis for 50×25 is given in Table 2 and Table 3, respectively.

Table 1. Comparison of different ranking functions

S. No	Function	Improvement	Improvement in (%)
1	BM25	-0.0008	-0.35
2	Croft’s probabilistic ranking	0.0112	6.69

Table 2. Performance of model for 50×25

Model used	Mean average precision	Precision for 10 generations	Recall for 100 generations	Analysis
BM25	0.41 ± 0.02	0.45 ± 0.02	0.60 ± 0.03	Performs in baseline
BM25 and AI	0.44 ± 0.02	0.46 ± 0.02	0.61 ± 0.03	Slight increase (~2%); not significant
Croft	0.48 ± 0.02	0.52 ± 0.02	0.66 ± 0.03	Baseline in probabilistic ranking
Croft and AI	0.54 ± 0.02	0.58 ± 0.02	0.74 ± 0.03	~13% MAP gain; highly significant (p < 0.001)

Table 3. Statistical analysis of model for 50×25

Evaluation metric used	Model comparison	Test	Statistic	p-Value	Interpretation
MAP	BM25 and BM25+AI	Paired t-test	-2.53	0.0172	Not significant
MAP	Croft and Croft+AI	Paired t-test	-11.30	0.000	Significant
Precision for 10 generations	Croft and Croft+AI	t-test	-25.68	0.000	Significant
Recall for 100 generations	Croft and Croft+AI	t-test	-18.67	0.000	Significant
Overall	All models	ANOVA	F (3,116) = 166.96	6.3×10^{-42}	Significant differences

With the same training set, this study conducted trials to learn a general-purpose ranking function., 9 Topics 151-200. There were several runs of 100 people for 100 generations. Learning was exclusive and BM25 and other ranking functions were seeded into it. The model performance results and statistical analysis for 100×100 is given in Table 4 and Table 5, respectively.

Table 4. Performance of model for 100×100

Model Used	Mean Average Precision	Precision for 10 generations	Recall for 100 generations	Analysis
BM25	0.411 ± 0.020	0.461 ± 0.021	0.614 ± 0.030	Performs at baseline with moderate recall and precision.
BM25 with AI	0.442 ± 0.019	0.471 ± 0.020	0.617 ± 0.031	Not statistically significant
Croft	0.481 ± 0.021	0.522 ± 0.019	0.670 ± 0.029	Steady retrieval performance.
Croft with AI	0.550 ± 0.018	0.60 ± 0.020	0.781 ± 0.028	Showing strong AI–GA synergy.

Table 5. Statistical analysis of model for 100×100

Model Comparison	Evaluation Metric	t-statistic	p-value	Interpretation
BM25 and BM25 with AI	MAP	-0.56	0.5780	Not significant
BM25 and BM25 with AI	Precision for 10 generations	-2.51	0.0180	Not significant
BM25 and BM25 with AI	Recall for 100 generations	-0.71	0.48	Not significant
Croft and Croft with AI	MAP	-16.6	0.000	significant
Croft and Croft with AI	Precision for 10 generations	-178.2	0.0000	significant
Croft and Croft with AI	Recall for 100 generations	-173.93	0.0000	significant

The 5% improvement in the performance of Croft's probabilistic model and vector space method integrated with AI proves that it outperforms the fixed weight strategies and adopts a novel dynamic weighting through AI. Also, BM25 did not show significant results, implying that the term-frequency normalization and inverse document frequency are already effective, requiring less tuning.

The integration of AI with IR gives flexibility and scalability to the IR algorithms. But they are not global across all the algorithms, giving space for further research. The models can also be combined with hybrid approaches for sentiment analysis using different datasets [20]-[24]. Still AI methods such as particle swarm optimization [25] will not better match this problem domain.

5. CONCLUSION AND FUTURE FOCUS

This study focuses on how artificial intelligence methods can be applied to enhance information retrieval. Precision can be increased with Genetic Algorithms and Genetic Programming, as has already been demonstrated. The symbolic outcomes are what set these algorithms apart from others (like neural networks). You can check out the ranking function. Thesaurus-style printing is available for the thesaurus results. More significantly, it is possible to transfer the results from one document collection to another and expect them to keep working well. Examining recall and precision is a subjective decision that may not be the ideal one. With AI, classification can undoubtedly be improved. How might it be applied in a question-and-answer format? How may these methods be applied to enhance a user's interactive experience? Could index compression be applied to Genetic Programming? Maybe a clever caching system might increase throughput? AI is undoubtedly crucial for clustering, but might genetic methods also be used?

What more effective encodings besides those suggested here exist? Has anyone used these methods before? What efficiency concerns need to be looked at? What future paths and this strategy should be pursued is the most crucial unresolved issue.

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Abdullah Ahmad Alhaj		✓	✓			✓		✓	✓	✓	✓	✓		
A. V. Senthil Kumar	✓	✓	✓	✓			✓			✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability does not apply to this paper as no new data were created or analyzed in this study.

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