A Multimodel Fusion Engine for Filtering Webpages

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\textbf{ABSTRACT} Fusing multiple existing models for filtering webpages can mitigate the shortcomings of individual filtering models. To provide an engine for such fusion, we propose a multimodel fusion engine for filtering webpages for the extraction of target webpages. This engine can handle large datasets of webpages crawled from websites and supports five individual filtering models and the fusion of any two of them. There are two possible fusion methods: one is to simultaneously satisfy the conditions of both individual models, and the other is to satisfy the conditions of one of the two individual models. We present the functions, architecture, and software design of the proposed engine. We use recall ratio (RR) and precision ratio (PR) as the evaluation indices of the filtering models and propose rules describing how PR and RR change when individual models are fused. We use 200,000 webpages collected by crawling the popular online shopping website “www.jd.com” as the experimental dataset to verify these rules. The experimental results show that two-model fusion can improve either PR or RR. Thus, the proposed engine has good practical value for engineering applications.

\textbf{INDEX TERMS} Multimodel, fusion, engine design, webpage filtering.

\section{I. INTRODUCTION}
An engine for filtering webpages is an important component of a search engine. Its purpose is to screen incoming webpages to determine which pages should be displayed to users. A good webpage filtering engine allows users to block pages from websites that are likely to include unwanted advertising, pornographic content, spyware, viruses, or other objectionable content. The academic and engineering communities have developed various webpage filtering engines that support one or more filtering models.

At present, most vertical web crawlers support only a single filtering model. Some researchers have fused 2–3 individual filtering models to obtain new filtering models [1]–[4], thereby proving that fusing existing filtering models is an effective way to mitigate the shortcomings of individual filtering models [1]–[3]. However, no engine that supports multiple individual filtering models and their fusion is available on the market. Therefore, to fill this gap, we developed a multimodel fusion engine for filtering webpages (MMFEFWP). MMFEFWP can handle large datasets from webpages crawled from websites and supports five individual filtering models and the fusion of any two of them.

\section{II. RELATED WORK}
Four categories of webpage filtering models have been proposed in existing research [4], [5]. The first category consists of filtering models based on the uniform resource identifiers (URIs) of webpages [6]. The second consists of filtering models based on the features of webpage tags. The third consists of filtering models based on autonomous learning. These existing models also aim to delete redundant tags from the webpages before filtering.

Filtering models based on the URIs of webpages are simple and easy to implement, but they are not suitable for the new mechanism of URI generation and mapping used by many
websites. For convenience, many websites map their URIs to shorter URIs. Using these shorter URIs alone, models of this kind cannot determine whether a given webpage is a target page [6].

Filtering models based on the features of webpage tags use several essential features to define the filtering conditions of webpages, including specific strings, specific tags [7], [8], specific tree nodes [9], specific tree structures in a webpage [10], and the link ratio of a webpage. These filtering models are applicable only to specific websites and require programmers to have a prior understanding of the content of these websites [11], [12].

Filtering models based on the structures of webpages can be divided into two subclasses. The models in one subclass filter webpages by calculating the similarities between two XML trees [10], [13]–[17]. The models in the other subclass judge the types of webpages according to their layouts [18]–[20].

Filtering models based on autonomous learning are first trained on a certain training set of webpages and then apply certain learning algorithms and statistics, including K-means clustering and term frequency-inverse document frequency (TF-IDF), to cluster the input webpages [21]–[23]. After the clustering process, such a model requires a supplementary algorithm to generate the target classification. It is difficult to determine a suitable threshold for the classification of webpages, and such programs are highly complex [24]–[27].

Certain scholars have fused multiple filtering models to form new filtering models. Some researchers have used the “fuzzy ontology + support vector machine (SVM) + blacklist” fusion approach to filter out websites with pornographic content [1], while others have used multistring matching to detect malicious web sites [1], [2] or “K-nearest neighbor + SVM” fusion to filter out pornographic websites [3]. The results of these studies show that the fusion of multiple filtering models can improve the precision ratio (PR) and recall ratio (RR) of the filtering results. Because these studies have used different experimental datasets and the source codes for the fused models are not provided in the literature, these fusion results are difficult to reproduce. However, we have implemented a multistring matching model as a single model for comparative analysis.

Our research team has developed a filtering engine that supports the processing of large sets of web data using multiple individual webpage filtering models and fusions thereof. We call this engine MMFEFWP. MMFEFWP currently supports the following functions:

1) **MMFEFWP supports five individual filtering models.** These models include a model for filtering pages by strings (MFPS), a model for filtering pages by tags and attributes (MFPTA), a model for filtering pages by trees (MFPT), a model for filtering pages by link ratios (MFPLR), and a model for filtering pages by similarity degree (MFPSD). Among them, MFPS, MFPTA, MFPT, and MFPLR are filtering models based on the features of webpage tags, while MFPSD is a filtering model based on the structures of webpages.

2) **MMFEFWP supports the fusion of any two of the five individual filtering models.** There are two possible fusion methods. One is to simultaneously satisfy the conditions of both individual models. The other is to satisfy the conditions of one of the two individual models. Such fusion can improve either PR or RR.

3) **MMFEFWP can process millions of webpages in a day.** In this study, we use 200,000 webpages collected by crawling the popular online shopping website “www.jd.com” as our experimental dataset.

### III. ENGINE DESIGN

To develop MMFEFWP, we followed the research route shown in Figure 1. First, we designed the engine functions, the engine architecture, and the engine software. Then, we conducted a performance analysis. We used open-source software such as Spring, jsoup, and HtmlUnit to develop MMFEFWP.

#### A. ENGINE FUNCTIONS

The functions of MMFEFWP are shown in Figure 2. First, the engine deletes redundant tags from the collected webpages. Then, the engine filters these webpages.

![FIGURE 1. Research route of MMFEFWP.](image)

![FIGURE 2. Functions of the proposed engine.](image)
When filtering webpages, the engine can use any one of the five individual filtering models or a fusion of any two of them. As our research continues to develop, our engine will support more filtering models and more complex fusions.

MMFEFWP requires a large dataset for experimental analysis. Our research team has developed a multimachine and multithread vertical crawler that can crawl tens of millions of webpages in a day.

B. ENGINE ARCHITECTURE

To realize the fusion function depicted in Figure 2 and to implement the filtering models, we designed MMFEFWP with the hierarchical architecture shown in Figure 3. The technical details of the architecture, including the data processing, filtering algorithms, and open-source software used, are fully described here.

The engine architecture consists of five layers: a data layer, a component encapsulation layer, a filtering component layer, a component combination layer and a data presentation layer. In the data layer and the component encapsulation layer, webpage queues are implemented as database tables using SQL Server, and jsoup is used as the tool for tree processing. All operations on the queues and all operations on the trees are encapsulated as JavaBeans.

In addition, to speed up data processing, we use a buffer for queue operations. The encapsulated JavaBeans are managed by a Spring container using the Inversion of Control (IoC) design concept. These JavaBeans are encapsulated using two bean types: singleton and prototype.

In the filtering component layer, the following algorithms are implemented in the form of JavaBeans: a tag deleting function, MFPS, MFPTA, MFPT, MFPLR, and MFPSD. In the component combination layer, these components are managed and combined using the aspect-oriented programming (AOP) characteristics of Spring. Spring configuration files are used to configure the pre-Advice and post-Advice parts of the Spring container to manage JavaBeans and form a combined filtering workflow.

In the data presentation layer, HTML and JFreeChart are used to visualize the results of data analysis and show the commodity price analysis curve. By using JavaScript Object Notation (JSON), we can access web services in a simple way to obtain the data for the engine.

C. ENGINE SOFTWARE

According to the architecture design shown in Figure 3, we need a buffer for quickly processing webpages. The design of the filtering function is shown in Figure 4. Based on the original design depicted in Figure 4, we further consider the following two factors.

1) QUEUE AND BUFFER STORAGE

The queues are stored as database tables using SQL Server. The queue of pages waiting to be filtered is mapped to one table. The queue of filtered pages is mapped to another table. The buffer size is calculated using the following formula:

\[
BS = k \times n \times (l + m)
\]
We set $k = 10$, $n = 10$, $l = 300$, and $m = 40,000$; then, the buffer size is:

$$BS = k \times n \times (l + m)$$
$$= 10 \times 10 \times (300 + 40,000)$$
$$= 4,030,000 \text{ bytes}$$

Therefore, the buffer occupies approximately 4 MB of memory space, which is acceptable for the current configurations of mainstream servers.

2) FILTERING PROCESS

During the data preparation stage, the crawler pushes the crawled webpages into the queue of pages waiting to be filtered. The buffer maintenance thread is used to provide the datasets of the webpages to the filtering thread. The procedure executed by the buffer maintenance thread is provided in algorithm 1.

Algorithm 1 Buffer Maintenance Algorithm

```java
/* While the queue of pages waiting to be filtered is not empty */
1: While (QueueWaiting is not empty)
   // Traverse the buffer to find an empty block
2:    For i = 1 to 10 step 1
3:       If Blocki is empty Then
4:          /* Pop out n webpages from QueueWaiting into block */
5:             popup(QueueWaiting, block, n)
6:          End If
7:    End For
8: End While
```

According to algorithm 1, once the buffer maintenance thread discovers an empty block in the buffer, it pops out $n$ webpages from the queue of pages waiting to be filtered and then pushes these webpages into the empty block found.

The procedure executed by the filtering thread is given in algorithm 2.

Algorithm 2 Webpage Filtering Algorithm

```java
/* While the queue of pages waiting to be filtered is not empty and the buffer is not empty */
1: While (QueueWaiting is not empty and buffer is not empty)
   // Traverse the buffer to find a block that is not empty */
2:    For i = 1 to 10 step 1
3:       If Blocki is not empty Then
4:          // Pop out Blocki in buffer into block
5:             popup(buffer, Blocki, block)
6:          /* Filter the webpages using the filtering models */
7:             filterResult = filterWebPages(block)
8:          /* Push the filtering result into the filtered page queue */
9:             push(filterResult, QueueFiltered)
10:     End If
11: End For
12: End While
```

According to algorithm 1, once the buffer maintenance thread discovers an empty block in the buffer, it pops out $n$ webpages from the queue of pages waiting to be filtered and then pushes these webpages into the empty block found.

D. FUSION RULES

At present, MMFEFWP supports the fusion of two of the five individual filtering models. We derived the rules describing how the PR and RR change for two methods of fusion, which are given below:

1) Fusion rule 1. The conditions of both individual models are simultaneously satisfied. If we denote the individual filtering conditions of the two fused filtering models by filterModel1.conditions and filterModel2.conditions, respectively, then the conditions to be satisfied for this fusion method are expressed as follows:

$$RR \leq \text{Min}(RR_1, RR_2) \quad (2)$$

Second, the PR of the fused results should be greater than or equal to the larger of the PRs of the two individual filtering models. This rule is expressed as follows:

$$PR \geq \text{Max}(PR_1, PR_2) \quad (3)$$

Theoretically, we believe that the filtering performance after fusion should be described by the following two rules.

First, the $RR$ of the fused results should be less than or equal to the smaller of the $RR$s of the two individual filtering models. This rule is expressed as follows:

$$RR \leq \frac{TAF}{TUF} \times 100\% \quad (4)$$

where $TAF$ is the number of target pages obtained after filtering and $TUF$ is the number of target pages in the pages to be filtered.

Second, the $PR$ of the fused results should be greater than or equal to the larger of the $PR$s of the two individual filtering models. This rule is expressed as follows:

$$PR = \frac{TAF}{AF} \times 100\% \quad (5)$$

where $AF$ is the number of pages obtained after being filtered.

We derive the two rules above as follows. For $RR$, the number of target pages in the pages to be filtered is fixed, and the
number of target pages obtained after filtering should either decrease or remain unchanged. Therefore, the calculated $RR$ should also either decrease or remain unchanged.

For $PR$, the number of target pages obtained after filtering and the number of pages obtained after filtering should either be reduced or remain unchanged. The range of variation of the number of pages obtained after filtering is greater than the range of variation of the number of target pages obtained after filtering. Therefore, the calculated $PR$ should either increase or remain unchanged. Moreover, the change in $PR$ should be smaller than the change in $RR$. These rules will be shown to hold in the subsequent experimental analysis.

2) Fusion rule 2. The conditions of only one of the two individual models must be satisfied. The conditions to be satisfied for this fusion method are expressed as follows:

$\text{filterModel1} \cdot \text{conditions} \lor \text{filterModel2} \cdot \text{conditions}$

Theoretically, we believe that the filtering performance after fusion should be described by the two following rules. First, the $RR$ of the fused results should be greater than or equal to the larger of the $RR$s of the two individual filtering models. This rule is expressed as follows:

$$RR \geq \text{Max}(RR_1, RR_2)$$ (6)

Second, the $PR$ of the fused results should be less than or equal to the smaller of the $PR$s of the two individual filtering models. This rule is expressed as follows:

$$PR \leq \text{Min}(PR_1, PR_2)$$ (7)

The derivation of these rules is similar to that for fusion method 1, and so it is not repeated here. To determine which fusion method should be used in practice, we proposed the following selection principles. If the $RR$s of the two individual filtering models are both acceptable and the $PR$s are unacceptable, $PR$ needs to be improved. Thus, we suggest choosing fusion rule 1. If the $PR$s of the two individual filtering models are both unacceptable and the $RR$s are also unacceptable, $RR$ needs to be improved. Thus, we suggest choosing fusion rule 2. To enable this determination, an acceptance threshold can be set for $RR$ and $PR$ (e.g., 85%).

IV. PERFORMANCE ANALYSIS

To verify the functions of MMFEFWP and the rules described above, we used 200,000 webpages crawled from the popular online shopping website “www.jd.com” as our experimental dataset. The dataset contains 57,570 pages with detailed information. The filtering goal is to find these detailed information pages. The filtering results were assessed in terms of the processing time per thousand pages and the cumulative processing time. The accuracies of the filtering models were assessed in terms of $RR$ and $PR$. The number of detailed information pages obtained after being filtered is considered as $TAF$ and the number of target pages in the pages to be filtered is considered as $TUF$.

B. EXPERIMENTAL ANALYSIS OF THE INDIVIDUAL FILTERING MODELS

The effects of the individual filtering models were experimentally analyzed. The main configuration of MMFEFWP for each model is listed in Table 2. In each experiment, the same 200,000 pages were filtered. The experimental results are shown in Figure 6 and Figure 7. The performances of the filtering models were assessed in terms of the processing time per thousand pages and the cumulative processing time. The accuracies of the filtering models were assessed in terms of $RR$ and $PR$. For effective calculation in real experiments, the number of detailed information pages obtained after being filtered is considered as $TAF$ and the number of target pages in the pages to be filtered is considered as $TUF$.

In Figure 6 and Figure 7, the abscissa represents the number of webpages filtered, whereas the ordinate is the $RR$ or $PR$ value. Because the trends in the $RR$ and $PR$ values can be clearly seen in Figure 6, detailed explanations are not given below.

C. FUSED APPLICATION OF THE FIVE FILTERING MODELS

The purpose of combining individual filtering models is to improve the $RR$ and $PR$ of the filtering results. As seen in
TABLE 2. Main configurations of MMFEFWP.

<table>
<thead>
<tr>
<th>Filtering model</th>
<th>Main configuration</th>
</tr>
</thead>
</table>
| **MFPS**        | The following conditions must be satisfied at the same time.  
|                 | **Condition 1.** Each webpage obtained after filtering must include one of the following strings:  
|                 | "price", "flash purchase price", "Jingdong price", "exclusive price", or "price spike". This condition is expressed as follows:  
|                 | `page.containsString("price") or page.containsString("flash purchase price") or page.containsString("Jingdong price") or page.containsString("exclusive price") or page.containsString("price spike")`  
|                 | **Condition 2.** Each webpage obtained after filtering must include the string "distribution". This condition is expressed as follows:  
|                 | `page.containsString("distribution")`  
| **MFPTA**       | **Condition 1.** Each webpage obtained after filtering must include the tag `<div>`, and the value of the "class" attribute of the tag `<div>` must be "crumb-wrap". This condition is expressed as follows:  
|                 | `page.containsTag(divTag) and page.divTags.containsAttribute(classAttribute)`  
| **MFPT**        | **Condition 1.** Each webpage obtained after filtering must have a structure tree such as that shown in Figure 5. This condition is expressed as follows:  
|                 | `page.containsTree(treeFigure5)`  
| **MFPLR**       | **Condition 1.** The link ratio threshold is set to 0.25. This condition is expressed as follows:  
|                 | `page.linkRatioOut(0.25)`  
| **MFPSD**       | **Condition 2.** The similarity between each webpage and a template webpage is calculated as the ratio of the number of identical nodes between the trees to the total number of nodes in the smaller of the two trees. The condition for two nodes to be identical is that the node name and the class attribute must have the same values. The similarity threshold is set to 0.5. This condition is expressed as follows:  
|                 | `page.similarityOut(0.5)`

from the above analysis, the \(RR\)s of the five filtering models are acceptable, but their \(PR\)s are not ideal. Therefore, we adopt the following approaches in our fusion analysis.

1) **Choose a fusion method.** To improve \(RR\), fusion rule 1 should be chosen.

2) **Merge two filtering models.** Considering that the effects of the MFPTA and MFPT models are very similar,
FIGURE 7. RRs of the individual filtering models and fusion models.

TABLE 3. RRs and PRs of the models when filtering nearly 200,000 webpages.

<table>
<thead>
<tr>
<th>Filtering model</th>
<th>TUF</th>
<th>AF</th>
<th>TAF</th>
<th>RR</th>
<th>PR</th>
</tr>
</thead>
<tbody>
<tr>
<td>MFPS</td>
<td>57570</td>
<td>72643</td>
<td>52175</td>
<td>90.6%</td>
<td>71.8%</td>
</tr>
<tr>
<td>MFPTA</td>
<td>57570</td>
<td>76441</td>
<td>55725</td>
<td>96.8%</td>
<td>72.9%</td>
</tr>
<tr>
<td>MFPLR</td>
<td>57570</td>
<td>172694</td>
<td>56734</td>
<td>98.5%</td>
<td>32.9%</td>
</tr>
<tr>
<td>MFPT</td>
<td>57570</td>
<td>76407</td>
<td>55692</td>
<td>96.7%</td>
<td>72.9%</td>
</tr>
<tr>
<td>MFPSD</td>
<td>57570</td>
<td>70643</td>
<td>49843</td>
<td>86.6%</td>
<td>70.6%</td>
</tr>
<tr>
<td>TagAndLinks</td>
<td>57570</td>
<td>76423</td>
<td>55728</td>
<td>96.8%</td>
<td>72.9%</td>
</tr>
<tr>
<td>TagAndString</td>
<td>57570</td>
<td>71098</td>
<td>51987</td>
<td>90.3%</td>
<td>73.1%</td>
</tr>
<tr>
<td>LinksAndString</td>
<td>57570</td>
<td>67899</td>
<td>49858</td>
<td>86.6%</td>
<td>73.4%</td>
</tr>
<tr>
<td>LinksAndSim</td>
<td>57570</td>
<td>72547</td>
<td>52176</td>
<td>90.6%</td>
<td>71.9%</td>
</tr>
<tr>
<td>StringAndSim</td>
<td>57570</td>
<td>70632</td>
<td>49873</td>
<td>86.6%</td>
<td>70.6%</td>
</tr>
</tbody>
</table>

with MFPTA having a higher efficiency and a slightly higher RR, the MFPTA filtering model is considered representative of both these models for the remainder of the experimental analysis. Accordingly, we consider the following six fused filtering models.

1) The fusion of the MFPTA and MFPLR filtering models, denoted by TagAndLinks. The filtering conditions of TagAndLinks are that the conditions of MFPTA and MFPLR are all satisfied.

2) The fusion of the MFPTA and MFPS filtering models, denoted by TagAndString. The filtering conditions of TagAndString are that the conditions of MFPTA and MFPS are all satisfied.

3) The fusion of the MFPTA and MFPSD filtering models, denoted by TagAndSim. The filtering conditions of TagAndSim are that the conditions of MFPTA and MFPSD are all satisfied.

4) The fusion of the MFPLR and MFPS filtering models, denoted by LinksAndString. The filtering conditions of LinksAndString are that the conditions of MFPLR and MFPS are all satisfied.

5) The fusion of the MFPLR and MFPSD filtering models, denoted by LinksAndSim. The filtering conditions of LinksAndSim are that the conditions of MFPLR and MFPSD are all satisfied.

6) The fusion of the MFPS and MFPSD filtering models, denoted by StringAndSim. The filtering conditions of StringAndSim are that the conditions of MFPS and MFPSD are all satisfied.

The RRs and PRs of the six fused models above are shown in Figure 6 and Figure 7.

D. DISCUSSION

To facilitate a comparative analysis, Table 3 lists the RRs and PRs achieved by the models when the number of filtered webpages is nearly 200,000. The curve for the fused TagAndLinks model in Figure 6 and Figure 7 is similar to that for the individual MFPTA model. When the number of webpages filtered is nearly 200,000, the RR and PR of the fused TagAndLinks model are the same as those of the MFPTA model, whereas the RR and PR of the fused TagAndString model are 90.3% and 73.1%, respectively. We abstain
from reiterating the RR and PR of the other four fused filtering models here.

The curve for MFPTA is similar to that for MFPT. The similarity in the RR and PR of these two filtering models can be explained by considering the conditions applied in these models. As seen from Table 2, the conditions “page.containsTag(divTag) and page.divTags.containsAttribute(classAttribute)” are included in Condition 1 of MFPTA and Condition 1 of MFPT.

The execution efficiencies of the filtering models are shown in Figure 8 and Figure 9. In Figure 8, the ordinate is the average processing time in seconds for every thousand pages. In Figure 9, the ordinate is the cumulative processing time for all pages in seconds.
In general, the MFPTA model has the highest speed. This model takes only 1802.4 seconds, or approximately 30 minutes, to process 200,000 pages. The TagAndSim model is the slowest, taking 10447.4 seconds, or approximately 174.1 minutes, to process 200,000 pages; this is approximately six times slower than the MFPTA model.

From Figures 6–9 and Table 3, we can infer the following rules.

1) Among the six fused models, if the fused model was obtained by fusing MFPLR with another filtering model, then the graph for the fused model is biased towards that for the other model. For example, the graph for the fused TagAndLinks model is biased towards that for the individual MFPTA model. According to our analysis, the reason for this behavior is that the set of results produced by MFPLR is too large. When the number of filtered webpages is nearly 200,000, the number of MFPLR results is approximately 173,000, indicating that the MFPLR model has no obvious filtering effect.

2) The correctness of formula 2 and formula 3 is verified. RR decreases significantly with the fusions considered here, while PR does not markedly increase. For example, when the number of filtered webpages is nearly 200,000, the RR and PR of the fused StringAndSim model are 80.9% and 72.7%, respectively. The RR of this fused model is decreased by 9.7 percentage points and 5.7 percentage points compared with those of the individual MFPS and MFPSD models, respectively, while PR is correspondingly increased by only 0.9 percentage points and 2.1 percentage points, respectively.

We abstain here from describing fused models obtained using fusion rule 2 and from demonstrating the correctness of formula 6 and formula 7. As discussed above, the developed MMFEFWP supports five individual filtering models and their fusion, but the following three problems still remain.

1) We could not find a filtering model with both high RR and high PR. MMFEFWP supports several individual filtering models with high RRs, the lowest value of RR being 86.6%. However, the PRs of these individual models are not ideal, with the highest being only 72.9%. Even when two individual filtering models are fused, the highest PR is increased to only 73.4%. One possible way to solve this problem is to use an artificial intelligence algorithm, such as a deep neural network.

2) The number of individual filtering models supported by the engine is low. At present, MMFEFWP supports only five individual filtering models, and the PRs of these models are not high. More individual filtering models need to be supported.

3) The fusion capability supported by the engine is limited. Currently, MMFEFWP supports the fusion of only two individual filtering models. In the future, the fusion of three or more filtering models should be supported by the engine. It will also be necessary to study the rules governing how the PRs and RRs change with such complex fusions.

Our research team will address these three problems in our future work.

V. CONCLUSION

We have proposed the MMFEFWP architecture for the filtering of large datasets of webpages crawled from websites. Our proposed multimodel fusion engine for webpage filtering can extract target webpages using multiple models, including models based on strings, trees, link ratios, similarity degrees, and tags and attributes. We downloaded 200,000 pages from the popular online shopping website “www.jd.com” for use in experimental analysis. Our results show that fused filtering models achieve better PR values than the individual models; for example, the PR of the TagAndLinks model is 72.9%, which is considerably higher than the PR of 32.9% achieved by the individual MFPLR model. Although the PRs of the fused models are still not high, it is obvious that two-model fusion results in improved performance compared with the individual filtering models. Through fusion, the PR of an individual filtering model can be improved if its RR is acceptable, or the RR can be improved if the PR is acceptable.

In summary, our proposed MMFEFWP engine can filter a large number of webpages. This engine can be profitably used in engineering practice. In the future, in addition to solving the three problems mentioned in the previous section, we will integrate MMFEFWP with a crawler and a web system for displaying data.

REFERENCES


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