ABSTRACT
Web content quality measurement is crucial to various web content processing applications. This paper will explore multi-scale features which may affect the quality of a host, and develop automatic statistical methods to evaluate the Web content quality. The extracted properties include statistical content features, page and host level link features and TFIDF features. The experiments on ECML/PKDD 2010 Discovery Challenge data set show that the algorithm is effective and feasible for the quality tasks of multiple languages, and the multi-scale features have different identification ability and provide good complement to each other for most tasks.

Categories and Subject Descriptors
H.5.4 [Information Interfaces and Presentation]: Hypertext/Hypermedia; K.4.m [Computer and Society]: Miscellaneous; H.4.m [Information Systems]: Miscellaneous

General Terms
Measurement, Experimentation, Algorithms

Keywords
Web Spam, Web Content Quality, Quality Assessment

1. INTRODUCTION
The evaluation of Web content quality plays an important role for various Web content processing applications, such as search engine, Web archiving service and Internet directory, etc; but how to evaluate the quality of the Web content? In the past, most data quality measures were developed on an ad hoc basis to solve specific problems, and fundamental principles necessary for developing stable metrics in practice were insufficient [4]. In the research of Web content quality assessment, computational models that can automatically predict the Web content quality should be focused on.

Web spam can significantly deteriorate the quality of search engine results, but high quality is more than just the opposite of Web spam. ECML/PKDD 2010 Discovery Challenge (DC2010) aims at more aspects of the Web sites. DC2010 wants to develop site-level classification for the genre of the Web sites (editorial, news, commercial, educational, “deep Web” or Web spam and more) as well as their readability, authoritativeness, trustworthiness and neutrality [2].

Statistical learning methods have demonstrated their effectiveness for many classification problems, such as Web spam detection, text categorization and anti-phishing [1] [3] [5] [6] [13] [19], which inspires us to evaluate Web content quality with statistical learning algorithms. In this paper, we will explore a series of features from multiple views, and compare their effectiveness for Web content quality assessment.

The rest of this paper is organized as follows. Section 2 first introduces the multi-scale features extraction, among which the description of TFIDF and host level link features extracting are our focus. Then it discusses the feature fusion strategy. Section 3 gives the Web content quality assessment method. Section 4 presents our experiment results. Finally, section 5 draws the conclusion and discusses the future work on Web content quality assessment.

2. FEATURES EXTRACTION
In this section, we will describe multi-scale features extracted from four different views, including content statistics features, page level link related features, host level link related features and text features(TFIDF) [5], and give the feature fusion strategy.

2.1 Content, Link and TFIDF Features
The content features and page level link features used here are provided by the ECML/PKDD 2010 Discovery Challenge organization committee, i.e. content-based features and link-based features [2].

We compute the TFIDF [5] features with term frequencies and document frequencies provided by DC2010 [2]:

\[
\sigma_{ik} = f_{ik} \times \log \frac{N}{n_i} \quad (1)
\]
where $a_{ik}$ is the weight of word $i$ in document $k$, $f_{ik}$ the frequency of word $i$ in document $k$, $N$ the number of documents in the collection, and $n_i$ the total number of the word $i$ occurs in the whole collection.

After computing $a_{ik}$, feature selection is performed. Feature selection attempts to remove non-informative terms in order to improve the classification performance and reduce the computation complexity. In this paper, we select information gain (IG) for feature selection. IG measures the number of bits of information obtained for the category prediction by knowing the presence or absence of a word in the document. Information gain has been proved to be one of the most effective feature selection methods for text categorization [5], statistical spam filtering [9] and information retrieval [16], etc.

### 2.2 Host Level Link Related Features

PageRank [11] is one of the most famous link analysis algorithms, which reflects the importance of Web pages. With the growing prevalence of link spam, PageRank scores become unreliable as a quality measure. Considering the hypotheses which benign nodes tend to link to other high quality nodes and malicious nodes are mainly linked by low quality nodes, we will extract a series of host link analysis features and attempt to mine the quality relations from the topology dependency.

Let $weight = f(n)$ be a weighting function, where $n$ is the number of links between any host pair $(h, v) \in V \times V$ and $E$ be the set of edges with $weight \geq W$, then the host graph $G$ can be defined as $G = (V, E, weight)$. Considering the topological dependencies of low and high quality nodes, the following features related to host graph can be extracted:

$$
F_1(h) = \frac{Measure(h)}{weight(h, v)}
$$

(2)

$$
F_2(h) = \frac{\sum_{v \in Inlink(h)} Measure(v) \times weight(h, v)}{\sum_{v \in Inlink(h)} weight(h, v)}
$$

(3)

$$
F_3(h) = \frac{\sum_{v \in Outlink(h)} Measure(v) \times weight(h, v)}{\sum_{v \in Outlink(h)} weight(h, v)}
$$

(4)

where $Measure \in \{\text{HostRank} (\text{Host Level PageRank}), \text{Domain PR}, \text{Truncated PageRank} (T = 1, 2, \cdots), \text{Adaptive Estimation of Supporters} (d = 1, 2, \cdots)\}$ [10]. HostRank is computed based on the host graph $G$, and DomainPR is the rank value of a host corresponding domain, which is queried from http://toolbarqueries.google.com, for example, the DomainPR of impressum.dukemaster.eu is the same as that of dukemaster.eu. \{h, v\} $\subseteq V$. $Inlink(h)$ is the inlink set of $h$ and $Outlink(h)$ is the outlink set of $h$. $weight(h, v)$ is the weight of host $h$ and $v$, $weight(h, v) \in \{1, \log(n), n\}$, where $n$ is the number of hyperlinks between $h$ and $v$.

In our experiments, $W = 1$, $T \in \{1, 2, 3, 4\}$, $d \in \{1, 2, 3, 4\}$ and $weight(h, v) \in \{1, n\}$. Finally, we extract 50 host level link features.

### 2.3 Feature Fusion Strategy

To analyze the effectiveness of features of different scales, we train classifiers with the fusion of different features. Fig. 1 shows the flow chart of fusion strategy with all the above-mentioned features.

![Figure 1: Flow Chart of Web Content Quality Assessment via Multi-scale Features.](image-url)

### 3. WEB CONTENT QUALITY ASSESSMENT

#### 3.1 Quality Assessment Strategy

Web content quality assessment is in fact a quality prediction problem. In ECML/PKDD 2010 Discovery Challenge, the quality value is defined based on genre, trust, factuality and bias. Typically, DC2010 gives the discrete value empirically: The Spam host has quality 0; News/Editorial and Educational sites are worth 5; Discussion hosts are worth 4 while others are worth 3. DC2010 also gives 2 bonus scores for Facts or Trust, but subtracts 2 for Bias hosts.

In general, we can first classify the Web sites according to the categories: Web Spam, News/Editorial, Commercial, Educational/Research, Discussion, Personal/Leisure, Neutrality, Bias and Trustiness. Then we further compute the Web content quality with the criteria given by DC2010. However, the state of art classification methods may be inappropriate for the ranking:

- Most given classes are imbalanced. Therefore, training an effective model is difficult.
- The predicted probability for every class cannot be fully used to rank the Web content quality.
- The discrete predictions are unfavorable to ranking the hosts.

Considering the Web content quality values are discrete values, we first treat the Web content quality assessment as a multi-class classification problem, thus the aforementioned shortcomings will be overcome in great degree. Then based on the predicted probabilities of samples belonging to each classes, the quality values of the Web sites are computed as follows:

$$
Quality(h) = \sum_{i=0}^{N-1} P_i(h) \times Q(i)
$$

(5)

where $N$ is the number of classes, $Quality(h)$ is the quality of host $h$, $P_i(h)$ is the predicted probability that the host $h$ belongs to class $i$, $\sum_{i=0}^{N-1} P_i(h) = 1$. $Q(i)$ is the quality value of class $i$ for ECML/PKDD 2010 Discovery Challenge quality tasks (Task2 and Task3), $Q(i) = i$, $N = 10$, i.e. $i \in \{0, 1, \cdots, 9\}$.

#### 3.2 Learning Algorithms

For the above-mentioned Web content quality assessment strategy, the most important is to predict the posterior probability of examples belonging to each class effectively. Then,
how to estimate the posterior probability as accurate as possible? Fan et al. [17] argue that randomized decision tree methods effectively approximate the true probability distribution using the decision tree hypothesis space. When bagging[7] is applied to C4.5[12], each random tree is computed based on a bootstrap of the training samples, which further optimizes the posterior probability predictions.

4. EXPERIMENTS

4.1 Data Collection

We realize our algorithms on ECML/PKDD 2010 Discovery Challenge dataset [2]. In the experiments, we use all the labeled samples of English host as the training samples set for Task1 and Task2. DC2010 only provides few labeled samples for French and German Tasks. We put all the labeled examples including English, French and German into training set for the multilingual quality tasks(Task3). The test set which we use in this paper is the test set for DC2000 contest.

In our experiments, we assume that the host with www and the www-less version have the same quality. After removing the duplicated samples, we obtain the English training set with 2114 samples, French training set with 2400 samples, and German training set with 2400 samples.

4.2 Features

We use all the content-based features and link-based features provided by DC2010[2]. For TFIDF features, we select 500 dimensions with the top information gain values. We have also done experiments by selecting 1000, 1500 and 2000 TFIDF features and find there is no obvious difference for the performance. Besides, we extract 50 host level link features as mentioned in section 2.2.

4.3 Learning Algorithm and Evaluation

As described in section 3, the machine learning algorithm we use is bagging, with C4.5 decision tree as the weak classifier. In the experiments, the iterations of C4.5 in bagging are 90.

Normalized Discounted Cumulative Gain(NDCG)[14] is a measure of effectiveness of a Web search engine algorithm or related applications, which is often used in information retrieval. NDCG is also employed for evaluating the submissions for ECML/PKDD 2010 Discovery Challenge [2]. As for the detailed evaluation, please refer to DC2010 evaluation [15].

4.4 Experiment Results

Table 1 describes the NDCG performance with different features on Discovery Challenge 2010 Task1. In line 1, L denotes the page level link related features; H denotes the host level link features; C denotes content statistical features; T denotes the TFIDF features, HCT denotes the fusion of host level link features, content features and TFIDF features; and LHCT denotes the fusion of all the above-mentioned different scale features. The first column of the tables shows the subtask in Task1. The column 2 to 7 are the performances of the quality assessment method with different features on all the subtasks.

In table 1, the bold figures show the best values achieved for corresponding subtasks. We can see that fusion features are more effective for most subtasks. According to the average values, we achieve the best result with fusing all the features(LHCT), which indicates that the features extracted from different views can be complementary for the DC2010 classification task.

Table 2 shows the comparison of Web content quality assessment performance with different scale features for English task. The features used here is the same as that on Task1.

In table 2, we can see that link features gives the least effective result, and TFIDF features show the highest score. The fused features, such as HCT and LHCT, improve the performance slightly.

Table 3 gives the comparison of Web content quality assessment performance with different scale features for French and German task. In view of all the labeled hosts are used for the multilingual quality task, we only employ the page level link features and host level link features to avoid the semantic influence of different languages.

| Task | L | H | C | T | HCT | LHCT |
|------|---|---|---|---|-----|-----|
| Spam | 0.628 | 0.789 | 0.784 | 0.756 | 0.830 | 0.807 |
| News | 0.549 | 0.589 | 0.625 | 0.743 | 0.740 | 0.748 |
| Commercial | 0.715 | 0.741 | 0.753 | 0.88 | 0.883 | 0.883 |
| Educational | 0.726 | 0.808 | 0.805 | 0.872 | 0.885 | 0.884 |
| Discussion | 0.638 | 0.573 | 0.768 | 0.822 | 0.784 | 0.79 |
| Personal | 0.594 | 0.728 | 0.768 | 0.804 | 0.828 | 0.827 |
| Neutrality | 0.605 | 0.511 | 0.426 | 0.438 | 0.465 | 0.495 |
| Bias | 0.525 | 0.606 | 0.518 | 0.525 | 0.51 | 0.549 |
| Trustiness | 0.526 | 0.506 | 0.472 | 0.358 | 0.485 | 0.441 |
| Average | 0.612 | 0.65 | 0.658 | 0.689 | 0.712 | 0.714 |

In table 3, we can see that host level link features are more effective for the cross-linguistic quality tasks. The host level link features and page level link features we use are not complementary.

According to the previous description of NDCG performance on all the tasks, we can see that the host level link features are robust for most tasks. We can also find that multi-scale features fusion are necessary for statistical Web content quality assessment.
5. CONCLUSIONS

In this paper, we explore multi-scale features that may determine the quality of a host and develop automatic statistical methods to estimate Web content quality.

The effectiveness of the multi-scale features is analyzed on DC2010 benchmark. The experiments show that the features from different perspectives have different identification ability and can complement each other in some degree. For most tasks, we achieve the best evaluation results with fused features. The experiments also illustrate the feasibility of the proposed Web content quality assessment strategy.

Compared with our previous work on Web spam detection[6], this paper has the following differences: (a). In the aspect of targets, [6] is a detection question, but this paper aims at a ranking problem. (b). In respect of methods, [6] focus on improving the AUC performance of binary classification, but this paper draws support from the posterior probability of multiple classification to rank the Web content quality. (c). In terms of features, we use more features here, for example TFIDF features and DomainPR related features, etc.

Future work involves: (a). Extract more features, such as natural language processing features. (b). Explore effective feature fusion strategy. (c). Study new quality assessment algorithms, such as learning the idea of RankBoost[18].

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