

Understanding the Function of Web Elements for Mobile Content Delivery Using Random Walk Models

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ABSTRACT

In this paper, we describe a method for understanding the function of web elements. It classifies web elements into five functional categories: Content (C), Related Links (R), Navigation and Support (N), Advertisement (A) and Form (F). We construct five graphs for a web page, and each graph is designed such that most of the probability mass of the stationary distribution is concentrated in nodes belong to its corresponding category. We perform random walks on these graphs until convergence and classify based on its rank value in different graphs. Our experiment shows that the new method performed very well comparing to basic machine learning methods.

Categories & Subject Descriptors

H.4.3 [Communications Applications]: Communications Applications - *Information browsers*; H.5.2 [User Interfaces]: User Interfaces - *Graphical user interfaces (GUI)*.

General Terms

Documentation, Design.

Keywords

HTML, WWW (World Wide Web), Classification.

1. INTRODUCTION

A web page is made up of hundreds of basic elements. The functional role of each element is different. For example, an image can be the banner of a website, an advertisement, or a picture for a news article. This paper aims to solve the problem of accurately understanding the functional role of each element. We will classify the content into six categories:

- Content (C): The main content of a web page, including main article, title, author, date, supporting picture etc
- Related Link (R): links to web pages that tell the related story and help a reader to further explore a topic.
- Form (F): Forms can be used to enable the reader to interact with the webpage.

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- Advertisement (A): Web page is filled with internal or external advertisements.
- Navigation and Support (N): The links that helps a reader to navigate or content like the banner, and the logos.

We propose automatically categorizing the web elements. It is based on random walks on specially designed graphs. For each web page we build five graphs, one for each functional category, with the basic elements in the web page as vertices. Each graph is specifically designed such that most of the probability mass of the stationary distribution of a random walk on it is concentrated in nodes that belong to its corresponding category. The score of each element in the graph after random walk is called CategoryRank. We compare an element's CategoryRank in the five graphs and classify the element into the category where it has maximum value.

2. BUILDING CATEGORY GRAPHS

Many different methods have been proposed to partition an HTML page into blocks. For example [3] [6] [7]. We use the algorithm similar to [6] that uses the DOM interface provided by the web browser to divide the web page into non-overlapping visible elements. Figure 1 shows how a CNN web page will be divided.



Figure 1. Homepage of www.cnn.com.

We construct directed graphs for each functional category based on the elements such that the sum of the weights coming out of each node to 1. The weight of edge (i, j) is the probability of a random walker at node i moving to node j at the next time instance.

Based on the features of two basic elements, we will connect them with a weight that increases with the likelihood that the two nodes belong to the same object. We take the following features into consideration:

1. Match(P_m): The cosine similarity between elements.
2. Distance(P_d): The pixel distance between elements
3. Neighborhood(N_b): if positioned next to each other

4. Same Edge(Eg): with same left, right top or bottom edge.
5. Same Tag(Tg): two elements have same tag
6. Same Parent(Pr): children of the same parent node in the HTML hierarchy tree.

The weight from the element i to element j is calculated by the function $W(i, j)$ where

$$W(i, j) = I(i, j) / \sum_{j=1}^N I(S, j)$$

$$I(i, j) = Pm(i, j) + Pd(i, j) + Nb(i, j) + Pr(i, j) + Eg(i, j) + Tg(i, j)$$

For each of all the edges in the basic graph we will add category dependent weight to generate category graphs. For Content (C) graph, we will consider features including the size of the element, the location of the element, the element tag type (tag like “<P>” or “” is normally used for main content), and the text length of the two. For Advertisement (A) graph, we use the tag features. (Animated Flash is mainly used for advertisements). We also collect a collection of words that are often be used in advertisement, for example “advertisement”, “sponsor”, “sale”, “classified”, further more, if an element contains links to an advertisement website like “doubleclick.com” or the URL structure is under a folder “/ads/” or “ad=” etc, we will increase its weight. For Relate (R) Graph, we use features including Tag information (“”, “<a>”) the length of anchor text and link category (internal or external). For Navigation and Support Graph (N), we will use the tag category, location, anchor text length. For Form Graph (F) the tag category information is a very important indicator, together with the appearance of words like “search”, “submit”, “form”, “login” etc. In this manner each category graph is constructed

We propose the idea of “CategoryRank” (CR) to calculate the likelihood that an element in a web page belongs to certain category. “CategoryRank” can be thought of as a model of user behavior similar to “PageRank” proposed by [4], where random walking separately takes place in five graphs. Each element will get five “CategoryRank” from the five graphs. We then compare the element’s “CategoryRank” in five graphs and classify an element to a category with the maximum “CategoryRank”. The formula for updating the rank in each round is:

$$CR^t(i) = (1-d)CR^{t-1}(i) + d \sum_{(j,i) \in E} W(j,i) * CR^{t-1}(j)$$

Each round the CategoryRank of node i will be updated with the contribution from itself and all linking vertices in the graph. We set d as 0.85, We set a threshold to check whether the probability distribution has converged in each round of iteration. This is done by summing up all the changes in the CategoryRank of every element and stopping the iterations if the sum is smaller than 0.0001. Normally it takes about 10 rounds before the scores stabilize.

3. EXPERIMENT RESULT

We implemented the system to validate our ideas and evaluate the performance of this approach. To compare with simple machine learning approaches, we used the off-the-shelf system WEKA [6] for this experiment. Precision (P), recall (R) and F-measure as the evaluation

We manually labeled 12,134 elements from 150 websites into one of the five categories. We set aside the first 10,009 as the training set and the rest 2,125 as the test set. The corresponding results on the test set are showed in Table 1.

Table 1, Experiment result with test set

Class	Precision	Recall	F-Measure
Content	0.92	0.93	0.93
Advertisement	0.75	0.90	0.82
Relate	0.58	0.66	0.62
Navigation	0.76	0.56	0.64
Form	0.93	0.74	0.82

To compare the experiment result, we use the WEKA package J48 classifier. The results are listed in table 2:

Table 2, Experiment result on test sets

Class	Precision	Recall	F-Measure
Content	0.85	0.77	0.80
Advertisement	0.40	0.60	0.48
Related Link	0.12	0.58	0.20
Navigation	0.85	0.68	0.76
Form	0.47	0.75	0.58

The result on the training and test set shows that the multi-graph random walk method is an effective and practical for method for classifying web elements. As we can see from the Table 1 and Table 2, the performance of our approach is better than the machine learning approach for all categories except for the navigation.

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