An Approach to Web Adaptation by Modelling User Interests Using TF-IDF: A Feature Selection and Multi-Criteria Approach Using AHP

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***Abstract*—User reviews provide a rich source of information regarding user interests. Many Web platforms allow or even encourage their visitors to leave their feedback regarding the products and services they have consumed. The Term Frequency (TF) and the Inverse Document Frequency (IDF) are two factors that have been used extensively in capturing users' preferences. This paper collects users' reviews from e-tourism Web platforms, calculates the TF and the IDF for each user and adopts a multi-criteria approach in order to quantify users' preferences and dynamically adapt the websites design accordingly. It utilizes the Analytic Hierarchy Process (AHP) and similarity methods in order to determine the relative importance of terms and Web pages and then rearranges them in a new website structure.**

Keywords-Web Adaptation; TF-IDF; AHP; Multi-Criteria Analysis.

I. INTRODUCTION

According to the Internet Web statistics, there are approximately 7,634,758,428 Web users around the globe [1]. Data also shows that more than 1.5 billion websites exist today, with more 200 million being active [2]. A great number of Web users often leave their feedback in the form of users' reviews, thus developing a very rich source of information regarding services and products, customers' needs and suppliers' quality. Thus, a huge amount of information becomes available to users for almost every single topic. Although this is a very promising development, at the same time searching through this vast ocean of data in order to identify the required information is quite of an endeavour. Within the context of Web personalisation, context personalisation aims at providing the right information to the right user, while presentation personalisation focuses on presenting the content with the most suitable media combination taking into account users' factors such as media limitations, users' media preferences, etc [3]. With respect to presentation personalisation, [3] suggest 5 groups of factors to be taken into consideration:

User-specific features pertain to users' media preferences. For example, a user would rather choose a graphical to text presentation. *Information features* refer to representational differences and capabilities of media since not all media are equally suitable for projecting the same piece of information. *Contextual information* refers to user environmental conditions, such as noise, light, weather, speed, etc. that may affect the presentation quality to the user. *Media constraints* imply the need to effectively combine the characteristics and capabilities of different media in order to improve the quality of presentation. *Limitations of technical resources* relate to device limitations such as screen size, bandwidth, etc. With respect to content personalisation, the analysis of User Generated Content (UGC) provides Web developers as well as service and product designers with valuable information regarding users' preferences as well as suppliers quality and potential [4]. The Term Frequency (TF) and the Inverse Document Frequency (IDF) are used extensively in capturing user preferences [5]. Several representational methodologies have been proposed for developing user profiles. Most frequently though are the three different formats namely: *keywords*, *semantic networks* and *concept-based* representations [5][6]. Keywords represent domains of users' preferences. They are associated with weights that indicate the strength of user interests for a particular topic. Polysemy and Synonymy are problems associated with keywords. Semantic networks, address these problems, by representing keywords with nodes on graphs that are connected with each other, including co-occurrences. Concept-based representations resemble semantic networks in structure but they differ in having nodes to represent abstract topics rather than keywords [5][6]. Filtering and clustering techniques are very useful in reducing the number of concepts that are found on the Web when attempting to formulate user profiles. However, [6] argues that these techniques lack effectiveness for they produce the same structure of user preferences for users with different needs, thus failing to produce highly refine, accurate and personalised representations of individual users. Research shows that while many approaches have been used in order to produce and use user profiles, e.g. in Web

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personalisation, recommender systems, etc., there exists no definite procedure for deriving user interests [6][7]. The AHP have been used in documents ranking [8]. However, the use of multi-criteria methods in analysing the TF-IDF is overlooked. This paper addresses the need for investigating alternative ways of developing user preferences models and suggests the analysis of the TF-IDF with the use of AHP.

Thus, this research aims to propose a multi-criteria approach based on the AHP and the TF-IDF for adapting websites design according to users' preferences relative importance. The relative importance of users' interests has not been considered in the literature. When it comes to personalisation though, it is the relative importance of terms for each individual user that would rank and distinguish users' interests and subsequently decide how to structure websites. Web adaptation is a decision making process where users would pairwise compare terms and decide which ones they mostly prefer to know about. Their choices influence the Web design, which needs to adapt to users' preferences. The rest of the paper is structured as follows. Section II presents the proposed methodology and the methods used for data analysis. In Section III, the paper discusses the empirical study and the data analysis. Finally, the paper presents its conclusions in Section IV.

II. METHODOLOGY AND METHODS

This paper aims to dynamically rearrange the structure of websites, according to user interests. By capturing and modelling user preferences, this paper proposes an approach to reallocate Web pages based on their importance. Web pages' importance is calculated based on user priorities. Data is collected from platforms such as TripAdvisor.com and Booking.com. User reviews, regarding users' stay in Greece and Italy hotels, were collected by using the Scrapy Web crawler tool. The reviews were then analysed by utilizing the Knime text mining tool. Next, the importance of each term was calculated and analysed by utilizing the Analytic Hierarchy Process (AHP) multicriteria analysis method. In recent years, many researchers adopted Multi-Criteria Decision Making (MCDM) approaches to problem solving such assessing alternative solutions, to selection problems, strategic analysis [9] etc. The steps of the proposed methodology adopted follow.

A. Methodology for evaluating business strategy based on Web analytics.

Step 1: Collect documents published by users.

A total of 5453 reviews were collected, from hotels ranging from 3 to 5 stars. The data size is more than sufficient for calculating user preferences with AHP. Reviews were analysed in order to calculate the Term Frequency (TF) and the Inverse Document Frequency (IDF) factors.

Step 2: Calculate the importance W_{tk} for each term (t_k) and formulate User-Interests Vector (UIV). Calculate the importance of each term (t_k), using the following formula:

$$W_{tk} = TF_{tk} * IDF_{tk} \qquad (1)$$

where, W_{tk}, represents the weight of term (t_k), TF_{tk}, is the term frequency for term (t_k), $IDF_{tk} = \log(\frac{N_u}{d_{tk}})$, N_u, is the total number of documents published by user (u) and d_{tk}, represents the number of documents that contain term (t_k). The UIV shows the importance that each user perceives for each term. The UIV takes the following from: $UIV_u^n = \{w_{(u,1)}, w_{(u,2)}, ..., w_{(u,k)}\}$. Thus, $UIV = \{w_{(u,t)}\}$, where $w_{(u,t)}$ indicates the weight, i.e. the importance of term ($t = 1,..k$) for user ($u = 1,..n$). By combining all users' preferences, the UIM matrix is formed.

$$UIM_u^n = \begin{matrix} w_{(1,1)} & w_{(1,2)} & w_{(1,3)} & \dots & w_{(1,k)} \\ w_{(2,1)} & w_{(2,2)} & w_{(2,3)} & \dots & w_{(2,k)} \\ w_{(3,1)} & w_{(3,2)} & w_{(3,3)} & \dots & w_{(3,k)} \\ \dots & \dots & \dots & \dots & \dots \\ w_{(n,1)} & w_{(n,2)} & w_{(n,3)} & \dots & w_{(n,k)} \end{matrix}$$

Each row of the *UIM* matrix represents the preferences of the user associated with the corresponding. The UIM will later be used to calculate the interests' similarities among users and recommend users items to see.

Step 3: Evaluate the relative importance of each Web page for every user using AHP.

Each Web page is assessed in terms of the importance of the terms it contains. Drawing on each user's UIV, the AHP pairwise comparison matrix is calculated. The pairwise comparison matrix that shows terms' perceived importance for each user takes the following form.

$$A^u = \begin{array}{c|cccc} & t_1 & t_2 & \dots & t_k \\ t_1 & 1 & a^u{}_{(1,2)} & \dots & a^u{}_{(1,k)} \\ t_2 & 1/a^u{}_{(1,2)} & 1 & \dots & a^u{}_{(2,k)} \\ \dots & \dots & \dots & 1 & \dots \\ t_k & 1/a^u{}_{(1,k)} & 1/a^u{}_{(2,k)} & \dots & 1 \end{array},$$

where $a^u{}_{(i,j)} = w_{(u,i)} / w_{(u,j)}$, $\forall i, j = \{1,..., k\}$ with i and j indicating the terms and $and \forall u = \{1,...n\}$, where u, indicates the users. If $i = j$ then $a^u{}_{(i,j)} = 1$.

In order to proceed with the AHP, assume the following hierarchy:

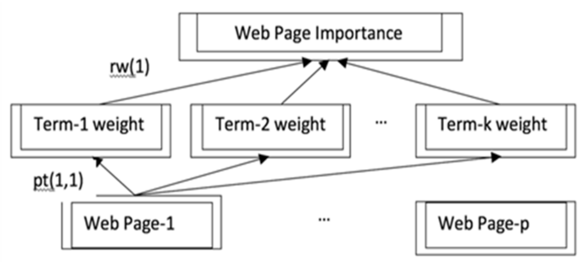

Figure 1: The AHP hierarchy for the evaluation of Web pages relative importance

The terms relative importance for each user reflects Web pages importance for each user, since a Web page is a collection of terms. Thus, the AHP analysis returns the relative importance of each term; therefore, the relative weight of each Web page for each user. A Web page is modelled as a vector which elements are the relative importance $rw_{(t)}$ of each term as resulted from the AHP, weighted by the normalised frequency ($pt_{wp,tk}$) that term t_k appears on the corresponding Web page ($wp=1,...p$). Time related factors can also be used in measuring Web pages importance. Thus, drawing on the AHP theory, the importance of every Web page is represented by the *User Page Vector* (UPV) as follows:

$$UPV^p_{wp} = \{rw_{(t1)} * pt_{(wp,t1)}, rw_{(t2)} * pt_{(wp,t2)},..., rw_{(tk)} * pt_{wp,tk}\} = \{upv^p{}_{t1}, upv^p{}_{t2},...upv^p{}_{tk}\} \quad (2)$$

where, $\sum_{tk=1}^{k} pt_{wp,tk} = 1$ since frequencies are normalised and $upv^p{}_{tk} = rw_{(ti)} * pt_{(wp,ti)}$ Indicating the importance of term t_k in page wp. If a term does not appear on a Web page (i.e. $pt_{wp,tk} = 0$) then the term's importance for the corresponding page is zero.

Step 4: website Modelling. By considering the UPV^p_{wp} of all Web pages in a website, the *User Site Matrix* (USM) is formed. Thus, $USM = \{UPV_{(p)}\}$ .The USM matrix takes the following form:

$$USM^u = \begin{matrix} UPV^u{}_1 \\ UPV^u{}_2 \\ ... \\ UPV^u{}_{wp} \end{matrix}, \ \forall wp = 1,...p, \text{ where } wp$$

indicates the Web pages, $\forall u = \{1,...n\}$, and u indicating the users.

Step 5: Calculate the Similarity of Web Pages. Drawing on the USM matrix, the similarity between Web pages is calculated by using the following formula of the cosine similarity method.

$$s_{i,j} = \frac{\left| \sum_{i,j=1,u=1}^{p,n} upv_{iu} * upv_{ju} \right|}{\sqrt{\left(\sum_{i,j=1,u=1}^{p,n} upv_{iu}^2\right) * \left(\sum_{i,j=1,u=1}^{p,n} upv_{ju}^2\right)}} \quad (3)$$

where $u = 1,..n$ and $i, j = 1,2,..., p$ representing users and Web pages respectively. Web pages with high similarity values are re-grouped in website layers.

Step 6: Rearrange Web pages into website layers (L). The total number of Web pages (P) in a website is calculated by using the following formula:

$$P = \frac{T}{tpp}, \quad (4)$$

where *P*, is the total number of Web pages in a website; *T* indicates the total number of terms identified and *tpp*, is the number of terms allowed per page. The resulting number *P* is round up to the next integer if needed.

Next, assume the allowed number of Web Pages per Layer (WPL) in the website and calculate the number of required website layers (L), by using the following formula:

$$L = \frac{P}{wpl}, \quad (5)$$

where *L* is the total number of layers in a website; *P*, is the total number of Web pages in a website and *wpl* is the allowed number of Web pages per layer. The resulting number *L* is round up to the next integer if needed.

Web pages of similar importance are grouped together into the layers. Therefore, a layer $L_{WL} = \{WP_i, WP_j,...WP_p\}$, where L_{WL} is the WL-th website layer, which consists of a group of Web pages

$WP_i, WP_j, ...WP_p$, where $i, j, p = 1,2,..., p$. The Web pages are grouped upon their importance similarity degree.

B. The Analytic Hierarchy Process (AHP) Method.

The AHP method was developed by [10]–[13]. It considers a hierarchy of criteria and possibly sub-criteria that contribute towards the realisation of the goal. The AHP calculates the relative weight of each criterion, i.e. the importance of each criterion with respect to the goal. Upon the criteria hierarchy and their relative importance, the AHP evaluates and ranks a set of alternatives. The AHP and its fuzzy extension [14] have been extensively used in multi-criteria decision making problems [15], such as in selection [16]–[18], strategic management [19], in determining the critical factors of success for information service industry [14], etc. The steps of the AHP are discussed below:

AHP Step 1: Assume a set of criteria which are evaluated in a pairwise manner using a nine point scale [13]. The criteria are represented by the comparison matrix A.

$$A = \begin{matrix} 1 & a_{(1,2)} & a_{(1,3)} & \dots & a_{(1,n)} \\ 1/a_{(1,2)} & 1 & a_{(2,3)} & \dots & a_{(2,n)} \\ 1/a_{(1,3)} & 1/a_{(2,3)} & 1 & \dots & a_{(3,n)} \\ \dots & \dots & \dots & \dots & \dots \\ 1/a_{(1,n)} & 1/a_{(2,2n} & 1/a_{(3,n)} & \dots & 1 \end{matrix}$$

AHP Step 2: The criteria relative weights are calculated by using the formula (6):

$$A * w = \lambda_{\max} * w \qquad (6)$$

where w represents the eigenvector of the matrix A comparison matrix, and $\lambda_{\max}$ is the largest eigenvalue of the matrix A.

AHP Step 3: Calculate the consistency rate.

The consistency of the matrix and subsequently the consistency of the weights is calculated by examining the reliability of judgments in the pairwise comparison. The Consistency Index (CI) and the Consistency Ratio (CR) are defined by using the following formulas:

$$CI - \frac{\lambda_{\max} - n}{n-1} \quad (7) \quad \text{and} \quad CR = \frac{CI}{RI} \quad (8)$$

where n is the number of criteria used in comparison matrix A, and RI is the Random Index. The RI values for a number of criteria (n) are shown in Table 1.

TABLE I. THE RANDOM INDEX (RI)

n	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

AHP Step 4: Synthesise and Calculate the Alternatives' Evaluation

The evaluation of each alternative is calculated by taking the sum of products of weights by using the following formula:

$$Eal_i = \sum_{i=1}^{m} \prod_{j=1}^{n} w_{i,j} * w_j \qquad (9)$$

where Eal_i indicates the evaluation of alternative (I) is, $i = 1,..m$ indicates the alternatives, $j = 1,..n$ represents the criteria, $w_{i,j}$ is the weight of alternative (i) with respect to criterion (j) and w_j is the weight of the criterion (j).

III. EMPIRICAL STUDY AND DATA ANALYSIS

Assume that for User-1 the total number of documents (N_{u1} =15) and the total number of terms identified in the documents are ($T = 13$). Assume the data shown in Table 2 is collected by analysing User-1 documents. Similar analysis is performed for all users.

TABLE II. TERMS IDENTIFIED FROM USER-1 DOCUMENTS AND ASSOCIATED WEIGHTS

row ID	USER-1 Terms	TF	Term Weight (Wt) Formula (1)
Row2	Hotel furnishing	0.041666667	0.02912375
Row6	Restaurant quality	0.069767442	0.061050786
Row10	bathroom	0.023255814	0.011095843
Row65	Timeliness of service	0.048780488	0.057370305
Row88	terrace	0.037037037	0.032409676
Row91	food	0.037037037	0.025887778
Row700	design	0.037037037	0.017671158
Row42	Quality of coffee	0.00990099	0.003277161
Row951	balcony	0.022222222	0.004929972
Row967	sea	0.022222222	0.010602695
Row995	fruits	0.022222222	0.007355405
Row997	sleep	0.014925373	0.004940197
Row1023	Understanding of staff	0.014925373	0.004940197

The application of the AHP returns the relative weights for each term. The AHP weights are shown in Table 3.

TABLE III. AHP TERMS' RELATIVE WEIGHTS

Terms	AHP Terms weights
furnish	0.106724446
restaurant	0.223721576
bathroom	0.04884162
timeliness	0.210234397
terrace	0.118765775
food	0.094866174
design	0.064756238
coffee	0.012009207
balcony	0.018065962
sea	0.038853743
fruits	0.026953998
sleep	0.018103432
understanding	0.018103432

Next, assume a subset of the terms' frequencies, as shown in Table 4, for each web page. This data is collected by counting the number each term appears on each Web page. For example, the term "furnish" appears 3 times in Web page-1, 5 times in Web page-2, etc.

TABLE IV. THE FREQUENCIES FOR EACH TERM PER WEB PAGE

Terms	Frequencies per Web page				
	Wp-1	*Wp-2*	*Wp-3*	*Wp-4*	*Wp-5*
furnish	3	5	1	0	3
restaurant	1	1	0	1	3
bathroom	3	5	2	1	7

Table 5 shows the normalised frequencies for each term per every page. The normalised frequencies are calculated by dividing each term's frequency of appearance on a web page by the sum of all terms frequencies of appearance on that web page.

TABLE V. TERMS' RELATIVE FREQUENCIES

Terms	Relative Normalised Frequencies per Web page				
	Wp-1	*Wp-2*	*Wp-3*	*Wp-4*	*Wp-5*
furnish	0.1034482 76	0.1515 15	0.0344 83	0	0.1034482 76
restaura nt	0.0344827 59	0.0303 03	0	0.0454 55	0.1034482 76
bathroo m	0.1034482 76	0.1515 15	0.0689 66	0.0454 55	0.2413793 1

Next, the importance of each Web page is calculated drawing on the terms' relative normalised frequencies and the terms AHP weights by using formulas (2) and (9). The results are shown in Table 6.

TABLE VI. THE WEB PAGES' IMPORTANCE BASED ON TERMS' RELATIVE IMPORTANCE

	Wp-1	*Wp-2*	*Wp-3*	**Wp-4**	**Wp-5**
furnish	0.0110 4046	0.0161 70371	0.0036 8	0	0.0110 4046
restaurant	0.0077 14537	0.0067 79442	0	0.0101 69	0.0231 43611
bathroom	0.0050 52581	0.0074 00245	0.0033 68	0.0022 2	0.0117 89357
timeliness	0.0362 4731	0.0063 70739	0.0072 49	0.0095 56	0.0072 49462
terrace	0.0040 95372	0.0071 97926	0.0040 95	0.0053 98	0.0040 95372
food	0.0098 13742	0.0201 23128	0.0098 14	0.0086 24	0.0032 71247
design	0.0022 32974	0.0039 2462	0.0089 32	0.0147 17	0.0022 32974
coffee	0.0004 14111	0.0010 91746	0.0012 42	0.0016 38	0.0020 70553
balcony	0.0018 68893	0.0005 47453	0.0031 15	0.0008 21	0.0006 22964
sea	0.0040 19353	0.0035 32158	0.0066 99	0.0052 98	0.0040 19353
fruits	0.0027 88345	0.0008 16788	0.0009 29	0.0012 25	0.0009 29448
sleep	0.0006 24256	0.0005 48589	0.0012 49	0.0016 46	0.0006 24256
understanding	0.0006 24256	0.0005 48589	0.0006 24	0.0008 23	0.0006 24256
Web pages' importance using formula (9), i.e. sum of terms' weights	**0.0865 36189**	**0.0750 51795**	**0.0509 97**	**0.0621 36**	**0.0717 13313**

Drawing on the Web pages relative importance, their similarity is calculated, using formula (3). The similarity degrees are shown in Table 7.

TABLE VII. WEB PAGES IMPORTANCE SIMILARITIES

Similarity Degrees	Wp-1	Wp-2	Wp-3	Wp-4	Wp-5
Wp-1	1	0.618507 331	0.662001 567	0.627411 733	0.568 705
Wp-2	0.6185 07331	1	0.777926 514	0.624975 126	0.659 007
Wp-3	0.6620 01567	0.777926 514	1	0.568704 978	0.431 098
Wp-4	0.6274 11733	0.624975 126	0.568704 978	1	0.623 204
Wp-5	0.5687 04978	0.659006 777	0.431097 94	0.623203 947	1

Drawing on the importance and similarities degrees shown in Tables 6 and 7, respectively, Web pages are grouped into layers. Assuming that the allowed number of terms per page (tpp=2) and total number of terms (T=13), then the maximum number of Web pages is 13/2=6.5 round up to 7, by applying formula (4). By applying formula (5), assuming wpl=2 pages per layer, the maximum number of layers is 7/2, which rounded returns maximum 4 layers in the website. Results show that Web page-1 is the most important followed by Web page-2 and Web page-5. However, Web page-5 is the least important of the three, thus it is arranged in a hierarchical level below in the website, since the maximum number of pages per layer (*wpl*) is set at two (2). Web page-3 is grouped with Web page-2 since the two are more similar than with the other pages. Thus, Web page-3 is linked to Web page-2 but in a layer below, due to (*wpl*) limitation. Similarly, Web page-4 is linked with Web page-1 but following in a layer below. Thus, the resulting website structure is shown in Figure 2.

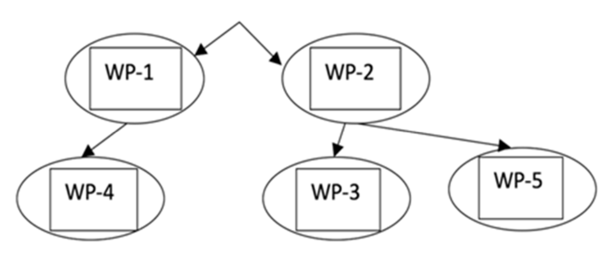

Figure 2: The resulting Web structure

In the same way, similarities among terms are calculated so that terms are re-arranged accordingly, i.e. to be removed from one page and linked with another. By calculating the similarities between terms and among Web pages, terms can be grouped dynamically and re-grouped so that the content of Web pages changes, thus manipulating the page's importance in a flexible way and produce alternative websites' designs.

IV. CONCLUSIONS

UGC provides a rich source of information regarding user preferences. Content personalisation and presentation personalisation rely on understanding and modelling users' interests. This paper suggests that the use of multi-criteria approaches can be used in conjunction with similarity methods to analyse text indices such as the TF-IDF, etc. The proposed approach utilises the AHP in order to calculate the relative importance of terms and subsequently of the associated Web pages. Upon their importance and similarities terms and Web pages can be re-arranged, thus producing Web structures that dynamically adapt to user preferences following. As soon as user interests' change and these changes can be traced in UGC, the proposed approach recalculates importance and similarity degrees and adapts the Web design. Future research can focus on calculating similarities of users and adopting recommender systems technologies and methods in the Web design domain.

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