WEB ANALYTICS
Analysing, Classifying and Describing Web Metrics with Fuzzy Logic

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Abstract: In the Internet economy, it has become a crucial task of electronic business to monitor and optimize websites, their usage and online marketing success. Web analytics, which is defined as the measurement, collection, analysis and reporting of Internet data, is an effective instrument of website management. First, this paper describes the technical functionality and use of web analytics and discusses different web metrics. Second, a fuzzy web analytics approach is proposed, which makes it possible to classify metrics precisely into more than one class at the same time. Third, a fuzzy web metrics index has been developed for multidimensional, intelligent web analysis. Fuzzy logic enables computing with words and more intuitive, human-oriented queries, segmentation and descriptions of metrics in natural language. Finally, a web analytics framework is suggested to analyze and control key performance indicators in a web controlling loop.

1 INTRODUCTION

Since the development of the World Wide Web 20 years ago, company websites have become a crucial instrument of information, communication and electronic business. With the growing importance of the web, the *analysis*, *monitoring* and *optimization* of a website and online marketing, web analytics, is now an important issue for business practice and academic research. Web analytics (WA) enables better understanding of the *traffic* and *behavior* of users on websites, by analyzing different metrics and success factors, i.e. key performance indicators (KPIs).

Today, many companies are using *web analytics software* from providers like Google, Nedstad, WebTrends or Omniture to collect, store and analyze web data. These tools provide dashboards and *reports* with many metrics to web analysts and managers, responsible for planning and decision-making about website-related activities. One problem of measurement-based reports is that all values, e.g. the number of page views, visits, visitors or conversions, are often raw numbers and therefore *difficult to interpret*. Usually, they only make sense in comparison with past values, target values or external values, or if segmented by other metrics. Another problem is that web data and metrics are usually reported, classified and evaluated in a *sharp manner*.

This paper proposes a fuzzy logic approach making it possible to classify web data and metrics fuzzily and to analyze and express their values with meaningful *linguistic variables* (i.e. words or word combinations). After an initial presentation of the functionality and use of WA, different web metrics are introduced in *section 2*. *Section 3* explains and exemplifies the fuzzy logic approach, showing how it can be used for classifying, indexing, segmenting and computing with words. *Section 4* explains the web controlling loop and *section 5* offers a conclusion and outlines likely future developments.

2 WEB ANALYTICS

2.1 Definition

According to the Web Analytics Association (2009), *web analytics* is the measurement, collection, analysis and reporting of Internet data for the purposes of understanding and optimizing web usage.

Weischedel et al. (2005) define WA as the monitoring and reporting of website usage so that enterprises can better understand the complex interactions between website visitor actions and website offers, as well as leverage insight to optimize the site for increased customer loyalty and sales.

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However, it is not only web usage and online sales which can be monitored, but other goals of a web presence too. In this paper, therefore, web analytics is defined as the selection, definition, analysis and evaluation of key performance indicators (KPIs) and web metrics in order to verify the *achievement of website-based objectives*.

2.2 Functionality of Web Analytics

Technically, in web analytics a distinction can be made between five different approaches to collecting data: the analysis of log files (server-side data collection), page tagging (client-side data collection), the use of packet sniffing, web beacons and reverse proxies. The following paragraphs focus on log file analysis and page tagging, as other methods are not often used in research and business practice.

Server-side Data Collection. In this method, data from *log files* are extracted and analyzed. Each time a web page is loaded in a browser, data such as the user's IP address and the names of requested files is saved with a time stamp in the log file of a web server. The *advantage* of log file analysis is that all requests and file downloads (text, PDF, picture or video files) from a web server are logged. However, one *disadvantage* of log file analysis is that traffic on the site is not measured exactly because of the caching in browsers and proxy servers. Additionally, the requests from search engines, robots and crawlers distort the statistics. Moreover, visitors cannot be identified distinctly, and user actions like mouse clicks are not tracked either. Finally, the extraction, preparation and analysis of log files can be complex and time-consuming. Given these problems, log file analysis has lost ground in recent years. Today, most tools are using page tagging, or *hybrid methods* (using both server- and client-side data collection).

Client-side Data Collection. In this WA method, a piece of *JavaScript code* is inserted in each HTML page. If a page is loaded in the client's browser, the JavaScript is executed, a 1x1 pixel tag loaded, and all data regarding the page view and the visitor's actions is transmitted to an internal or external tracking server. Using *cookies*, data about each user and that user's sessions are recorded.

Client-side WA solutions are mostly provided as 'software as a service' (SaaS) by application service providers (ASP). They have many *advantages:* First, all of the actions of each website user are recorded in real time, i.e. all mouse clicks and all keyboard entries. Technical information about users is captured too: the size, resolution and colors of the monitor, type and language of the browser and operating system, and all plug-ins installed. Second, there is no caching in browsers or proxies, and the JavaScript is not read by search engine crawlers and robots. Finally, the tagging method can be implemented easily and no IT specialists are needed. Despite data privacy issues, the client-side data collection method has become the *standard method* in web analytics.

2.3 Use of Web Analytics

The *use of web analytics* depends on the objectives of a website. However, the main benefits are:

User and Customer Orientation. With WA the tracking system reveals the information (pages, content, files) and services (searches, forms, blogs, RSS) accessed by users. By analyzing *information demand*, a high degree of user and customer orientation can be guaranteed, which is valuable for CRM.

Website Optimization. Based on an analysis of each user's information accessing behaviour, websites can be adapted to their surfing, clicking, navigation and search characteristics. Moreover, *website quality* can be improved by testing and optimizing the navigation, structure, links, functionality, usability, design and content of the website.

Search Engine Optimization. WA is used to analyze and monitor *search engine optimization* (SEO) and *marketing* (SEM). The goal of SEO and SEM is to improve rankings in search engines, using certain techniques. Web analytics tools reveal where users are located (continent, country and place) and identify the *search words* used to find the web page.

Optimization of Online Marketing. Additionally, WA can help to measure the effects of *online marketing instruments* like banner advertisements, newsletters, surveys and online campaigns.

Finally, WA facilitates *rational decision-making*, and target- and performance-oriented *management* of websites in order to improve e-business success.

2.4 Web Metrics

For WA, a number of metrics have been reported. These are listed in Table 1 and appear in Figure 1.

The number of *page views*, *visits*, *visitors* and the *time on page* are the standard metrics measured by most tools and which have often been discussed in the literature (see e.g. Sterne 2002, Peterson 2005, Kaushik 2009). The main KPIs of web usage a

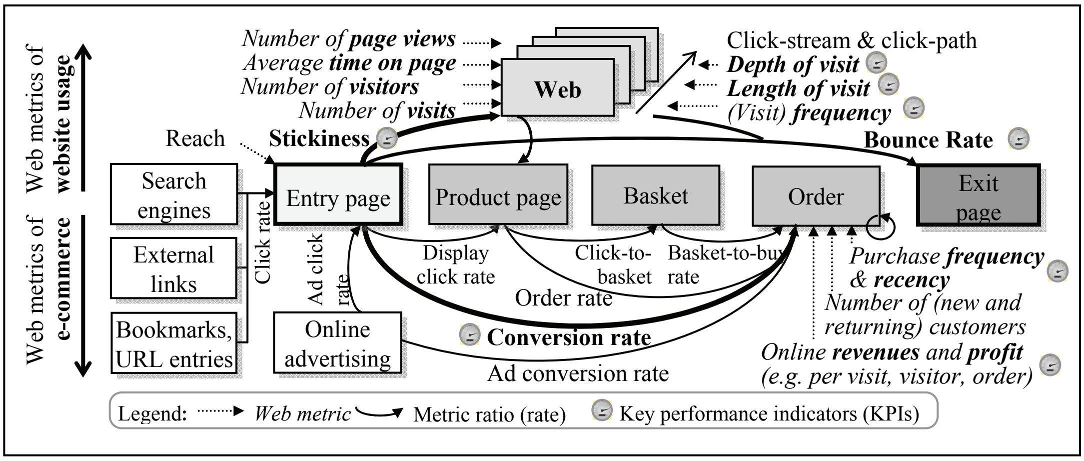

Figure 1: Relations between important web metrics.

Table 1: Definitions of various web metrics.

Page views	Number of page views (impressions of a web page) accessed by a human visitor
Visits	A sequence of page views (sessions) requests of a visitor without interruption
Visitors	Number of unique visitors (users) on a website (excluding crawlers, robots, spiders)
Time on page	Average length of time spent on a web page by all visitors
Stickiness	Ability of a web page to keep a visitor on the website
Bounce rate	% of single page view visits (users quit the page immediately without further action)
Frequency	# of visits a user has made to the website
Visit recency	Number of days since a visitor's last visit to the site
Visit length	Length of visit, the time visitors spend on the website (in seconds)
Visit depth	# of pages accessed by a visitor on a visit
Conversion rate	Proportion of visitors (users, surfers) becoming online customers (buyers)
Ad conversion rate	Proportion of visitors clicking on a banner and then making a purchase on the website
Display click rate	Proportion of visitors viewing one or more product/service pages
Click-to-basket rate	Proportion of visitors putting one (or more) product(s) in the shopping basket
Basket-to-buy rate	Proportion of visitors paying for a product after placing it in the shopping basket
Order rate	Proportion of visitors ordering a product after viewing the product page
Repurchase rate	Proportion of online customers making repeat purchases on the website
Purchase recency	Length of time since the online customer's last purchase on the website
Purchase frequency	Number of purchases made by an online customer on the website for a certain period
Monetary value	Monetary value, e.g. revenues, from an online customer for a certain period

considered to be *stickiness, visit frequency*, *length of visit* and *depth of visit*. If products or services are offered in an online shop, additional metrics and numbers of transaction are useful to analyze and control electronic business and electronic commerce.

Which product pages were visited? Which products were put in the electronic shopping cart and which were actually purchased? In order to optimize pages, processes, e-shops or product mixes it is important to have the answers to these questions.

Finally, *conversion* and *order rates*, *purchase frequency* and *recency*, *revenues* and *profits* are also all KPIs of electronic commerce.

3 FUZZY WEB ANALYTICS

3.1 Fuzzy Classification of Metrics

The theory of fuzzy logic and fuzzy sets goes back to Lofti A. Zadeh in 1965. It takes the subjectivity, imprecision, uncertainty and vagueness of human thinking and language into account, and expresses it with mathematical functions.

A fuzzy set can be defined formally as follows (1; Zimmermann 1992, Meier et al. 2008): if X is a set, then a fuzzy set A in X ($A \subset X$) is defined as

$$A = \left\{ \left(x_i, \mu_A \left(x_i \right) \right) \right\} \qquad (1)$$

where $x_i \in X$, $\mu_A : X \rightarrow [0, 1]$ is the *membership function* of A and $\mu_A(x) \in [0, 1]$ is the *membership degree* of x in A. In what follows, an illustration of fuzzy web analytics is provided. In a sharp set (see Figure 2a), the *terms* “few”, “medium” or “many” of the *linguistic variable* (web metric) “page views” can be either true (1) or false (0). A value of 1 of the *membership function* μ (Y-axis in Figure 2a) means that the number of page views (on the X-axis) corresponds to one set. A value of 0 indicates that a number of page views does not belong to one of the sets. In the illustration, the number of page views is defined as “few” between 0 and 32, while 33 to 65 is “medium” and more than 66 is classified as “many”. If page 1 is visited 65 times, it is classified in the “medium” class, while web page 2, with 69, has “many” views. Although the two pages have been visited nearly the *same* number of times, they are assigned to two *different sets*. In contrast, when defining *fuzzy sets* (Figure 2b) by membership functions, there are *continuous transitions* between the terms “few”, “medium” and “many”. In a fuzzy approach, the number of page views for page 1 is classified both as “medium” (0.55 or 55%) and as “many” (45%).

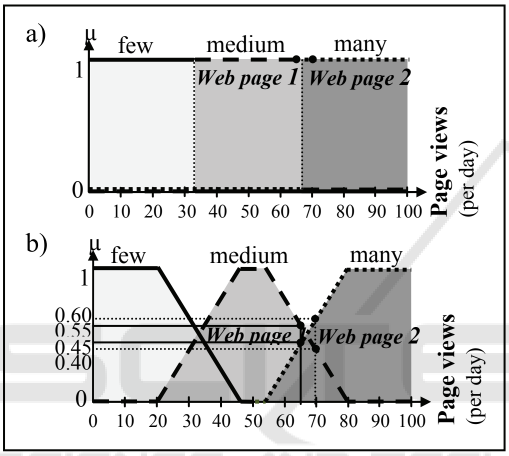

Figure 2: One-dimensional sharp (a) and fuzzy (b) classification of the web metric page views.

Page 2 also has part membership in two classes *at the same time* (60% for “many” and 40% for “medium”).

Now, an additional web metric, the *bounce rate*, can be considered. Web page X has a “low” bounce rate (and is therefore "sticky") if visitors view at least one other page (Y) after visiting page X. Page X has a “high” bounce rate if visitors leave the website immediately after viewing page X (e.g. by closing the browser window). As can be seen in Figure 3, the two metrics ‘page views’ and bounce rate’ define a *two-dimensional matrix* with four classes: Class 1 (C1) is defined by a high bounce rate and many page views, while the pages in C2 - "leaky flop pages" - have high bounce rates and few views. C3 represents “sticky top pages”, and pages in C4 are also sticky, but have few page views. Here too, the sharp classification of web pages is problematic: although web page C has almost the *same* values as B, C is classified as a “leaky flop page”, and B falls into the *opposite* group as a “sticky top page”.

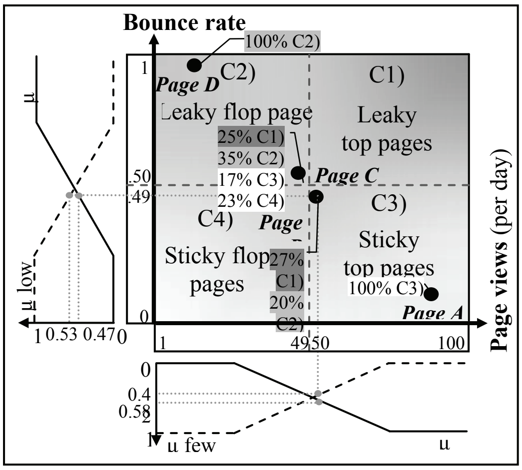

Figure 3: Two-dimensional fuzzy classification of the web metrics ‘page views’ and ‘bounce rate’.

If a web analyst wants to identify all pages in C3, a sharp query will return page B and A, but not page C, although B & C are in very similar positions. In a *fuzzy classification*, sharp boundaries disappear and pages can belong to more than one class. In a fuzzy approach, pages like B and C in the middle of the matrix, belong to *four classes at the same time*.

The basis for calculating the values for each class is the *γ-operator* in equation (2). This algebraic product operator, known as the “compensatory and”, has been empirically tested by Zimmermann (1992).

$$\mu_{Ai}(x) = \left(\prod_{i=1}^{m} \mu_i(x)\right)^{1-\gamma} \cdot \left(1 - \prod_{i=1}^{m} \left(1 - \mu_i(x)\right)\right)^{\gamma} \qquad (2)$$

where $x \in X$, $\gamma \in [0, 1]$ and μ_i is the membership degree between 0 and 1 in a class (x); m is the number of fuzzy sets $A_1, \ldots, A_m$ defined over the reference set X with membership functions $\mu_1, \ldots, \mu_m$; γ is a constant used to influence the degree of membership in the classes. Here, γ is defined as 0.5. The product is calculated with the membership degrees of each class and their inverted values $(1 - \mu_i(x))$.

For example, the membership degree of page B (in Figure 3) in class 1 is calculated as follows (3):

$$C1 = (.58 \cdot .47)^{(1-.5)} \cdot \left(\left(1 - (1 - .58)\right) \cdot (1 - .47)\right)^{.5} = .2726 \qquad (3)$$

Obviously, the definition of fuzzy sets allows *gradual ranking* within classes, and as a result, more *precise classifications* of web metric values. In addition, data can be classified without loss of information. Fuzzy classifications of KPIs like revenues and conversion rates are especially important, since their values have far-reaching consequences for business.

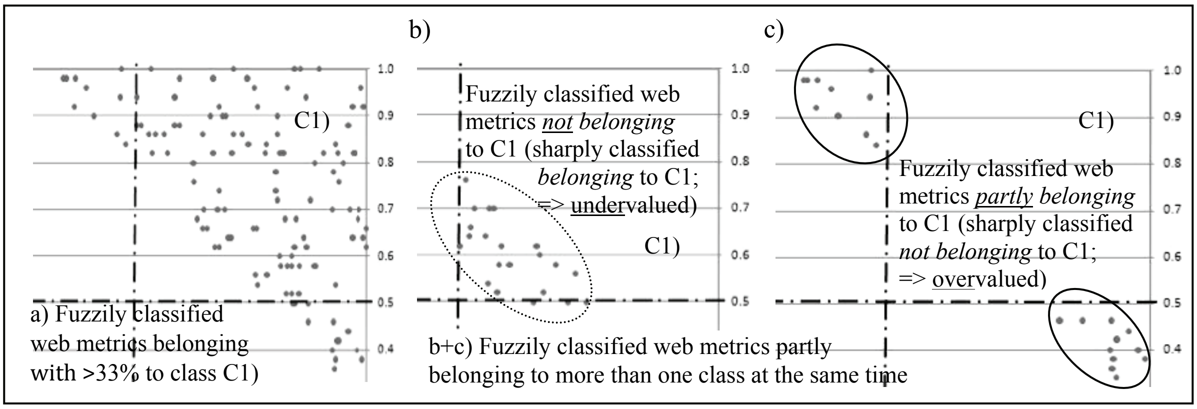

Figure 4: Example of fuzzily classified web metrics.

3.2 Comparison of Sharp and Fuzzy

In what follows a specific example of fuzzily classified metrics is presented, focusing on class 1 (C1 in Figure 3 or 4). In a sharp classification, metrics of pages belong strictly to one class only (e.g. to C1; note that the data in Figure 4 is normalized in values between 0 and 1).

In a fuzzy classification, we can select metrics which belong to C1 with a *certain degree* of membership (for C1 in Figure 4a it is 33%). Figure 4b shows that in comparison to a sharp classification: Some data in the corner of the class 1 is *no longer considered* as in that class when we use a fuzzy classification. That is, this data is *undervalued* in a sharp classification. In contrast, other fuzzily classified data do belong *partially* to C1 (Figure 4c), while in a sharp classification they are excluded.

This comparison shows the differences between a sharp and fuzzy classification of metrics. While in a sharp classification web data belongs strictly to one class, in a fuzzy classification data can be classified more appropriately and handled more flexibly. In a fuzzy classification, the *risks of misclassification* (under- or overvaluations) of data near the class border are *reduced*.

3.3 Fuzzy Web Metrics Index

Classifications are not bound to one dimension (in Figure 2) or two dimensions (in Figure 3 and 4). In an *index*, for instance, any number of web metrics (dimensions) can be modelled simultaneously.

If an *index* (I) is the aggregation of a number of *weighted* (w) *web metrics* (wm) values of a website with a number of different *web pages* (g) in *period* (p), equation (1) in section 3.1 is adapted as follows (4):

$$I_p^g = \sum_1^{wm} \left(w_{wm} \left(x_i, \mu_{wm}(x_i) \right) \right) \tag{4}$$

Eight metrics of table 1 are considered in the index (5): *page views* (PV), *visitors* (VS), *visits* (VI), average *time on page* (TP), *length of visit* (LV), *depth of visit* (DV), *visit frequency* (VF) and *stickiness* (ST).

$$\begin{aligned} I_p^g &= w_{PV}\left(x_i, \mu_{PV}(x_i)\right) + w_{VS}\left(x_i, \mu_{VS}(x_i)\right) \\ &+ w_{VI}\left(x_i, \mu_{VI}(x_i)\right) + w_{TP}\left(x_i, \mu_{TP}(x_i)\right) + w_{LV}\left(x_i, \mu_{LV}(x_i)\right) \\ &+ w_{DV}\left(x_i, \mu_{DV}(x_i)\right) + w_{VF}\left(x_i, \mu_{VF}(x_i)\right) + w_{ST}\left(x_i, \mu_{ST}(x_i)\right) \end{aligned} \tag{5}$$

Assuming that all metrics have the same weight (w =1), equation (4) can be defined, in which the value $\mu_{wm}(x_i)$ of a *single web metric* (wm) is assigned to a *linguistic term* (class) “low”, “medium” or “high”:

$$wm_p^g = \left\{ \begin{array}{l} \left(x_{low}, \mu_{wm}(x_{low})\right) \\ \left(x_{medium}, \mu_{wm}(x_{medium})\right) \\ \left(x_{high}, \mu_{wm}(x_{high})\right) \end{array} \right\} \tag{6}$$

In the example of equation 7, a *page 1* (g = 1) has the following normalized values in *period 1* (p = 1):

$$wm_1^1 = \left\{ \begin{array}{l} (\text{PV}, 0.752), (\text{VS}, 0.389), (\text{VI}, 0.324), \\ (\text{TP}, 0.141), (\text{LV}, 0.108), (\text{DV}, 0.907), \\ (\text{FR}, 0.789), (\text{ST}, 0.945) \end{array} \right\} \tag{7}$$

In a sharp multidimensional classification (in Figure 5a), values between 0 and 0.333 belong to “low”, 0.334 to 0.666 to “medium” and 0.667 to 1 to “high”. For instance, the metric *visits* (VI) with the value 0.324 belongs to *one class* (“low” in 8) only:

$$VIsharp_1^1 = \left\{ \left(x_i, \mu_{PV}(x_i)\right) \right\} = \left\{ \left(x_{low}, 1\right) \right\} \tag{8}$$

Applying (2), in a fuzzy classification (Figure 5b) the value of visits belongs to *two classes* in (9).

$$VIfuzzy_1^1 = \{(x_i, \mu_{PV}(x_i))\} = \{(x_{low}, 0.57), (x_{medium}, 0.43)\} \quad (9)$$

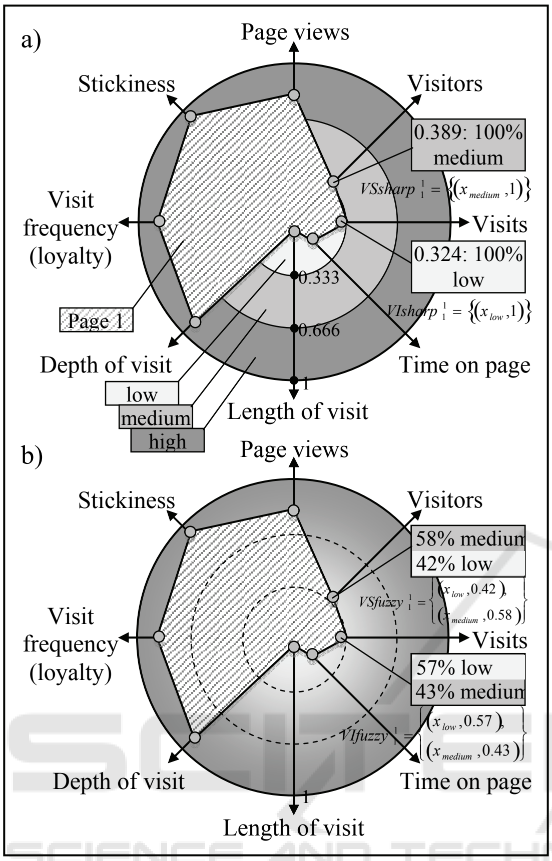

Figure 5: Multi-dimensional sharp (a) and fuzzy (b) classification of an index with eight web metrics.

A fuzzy index, represented in graphic form in Figure 5b, is an *intelligent web analytics system* which can model and measure a website's most important KPIs and web metrics. On an aggregated level, it makes it possible to display and analyze the performance of web usage and e-business, and to *compare* different web pages and users (segments). Moreover, it *monitors* changing values over time.

As the following sections will show, with a fuzzy index both quantitative data and qualitative criteria can be modelled with linguistic words.

Peterson proposes a sharp index to measure user interactivity and *engagement* (Peterson 2006):

$$I_{Engagement} = (C_i + R_i + D_i + L_i + B_i + F_i + I_i + S_i) \quad (10)$$

C_i stands for intensive visits, R_i for visit recency, D_i for engaged visits, B_i for brand index, F_i for feedback index, L_i for loyalty and S_i for subscription index. If users are more interactive and engaged, one or more metric(s) increase and so does the index.

However, index values are abstract and difficult to interpret. For this reason, WA needs a language-based approach to reading and analyzing web data.

3.4 Web Analytics with Words

Sections 3.1 and 3.2 explained that linguistic terms are used to describe membership functions of fuzzy sets in order to classify metrics more exactly.

Moreover, the fuzzy logic approach makes it possible to *describe, analyze* and *evaluate* results and changes in web analytics using human language. In soft computing, this is called *computing with words* (Zadeh 1996, 1999) and the consideration of *perception-based information* (Zadeh 2004).

For instance, a tool reported 1,718 page views in June (see left of Figure 6). What does this measurement-based information say to the analyst? Nothing, as long as the analyst cannot compare this absolute number with an internal or external benchmark. If in July 5,897 page views were recorded, the analyst knows from experience that this is *"much more"* than the month before. If the number of visitors increased by 2.3% in 2009, the analyst might state that the number of visitors *"increased slightly"* in 2009. Many other examples of analysis show that humans have a *perception-based* rather than a measurement-based approach to interpreting, describing and communicating web data and information.

WA tools report oodles of numbers, but web analysts often have difficulty interpreting web data, recognizing trends and deriving useful conclusions. In future intelligent web analytics systems will analyze and interpret data in a (semi or fully) automatic system. They will give meaningful answers to relevant business questions, which can be selected or formulated in natural language. For instance, an analyst may ask a *fuzzy web analytics system*:

- Which web or product pages have "many pages views" and "low bounce rates" (C1 in Figure 3)?
- Which product pages have "high order rates"?
- Which products or buyers have "high revenues"?
- Which visitors are "very loyal" and have "high engagement"?

3.5 Definition of Fuzzy Concepts

The fuzzy logic approach makes it possible to work with *quantitative metrics* (hard facts like revenues) and *qualitative variables* (soft criteria like engagement or loyalty) at the same time.

In fact, the strength of the fuzzy logic approach is the possibility to define and use qualitative, linguistic variables besides quantitative ones, which is not possible in binary computing.

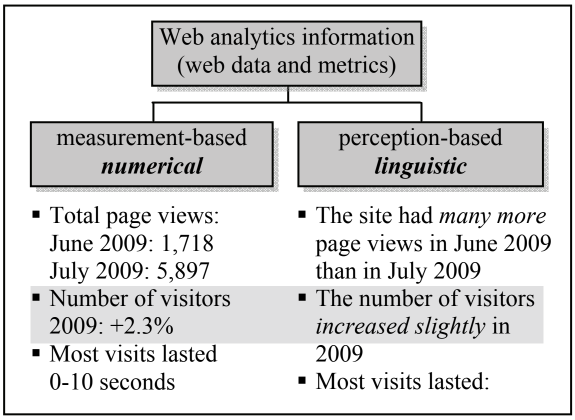

Figure 6: Measurement-based and perception-based information about website traffic.

For example, a analyst may define the following *fuzzy concepts* (Fasel & Zumstein 2009):

- “high traffic period”,
- “above-average conversion rates”,
- “strong online customer loyalty”,
- “attractive web pages” or
- “high visitor value”.

Time is an example of a dimension which benefits significantly from the use of *fuzzy constructs*. It does not suddenly become *evening* at 6 pm, or *night* at 10 pm. Human beings perceive a fluent transition between afternoon, evening and night (see Figure 7a). Similarly, different seasons such as spring, summer, autumn and winter do not start and end abruptly, and neither do seasonal variations, like the *high season* in summer (in Figure 7b).

In a *sharp classification* of the construct ‘evening’, only page views between 6 pm and 8 pm are displayed (but arbitrarily not those at 5.59 or 8.01). Within a *fuzzy logic* approach, page views after 4 and up until 10 pm are considered to have a certain membership degree (at 5 pm this is 50% afternoon and 50% evening in Figure 7a). Moreover, *uncertainty* and *imprecision* can be taken into account. For instance, warm summertime is “most” between June and August, but “sometimes”, summers already start in May and end later in September (Figure 7b).

Fuzzy time concepts are promising for web analytics, since they allow new types of deeper analysis. For example, the web analyst can query: “give me…

- all web pages with many page views and low bounces rates *in the evening*.”
- all web pages with high conversion rates in the *high season*.”
- the *most* loyal customers with high purchase frequency and high online revenues.”

The more metrics are considered in web analytics, the more difficult it is to draw conclusions from the web data. Qualitative statements in human language, which are transformed into computer language by fuzzy logic, reduce complexity and help to analyze and interpret web usage data.

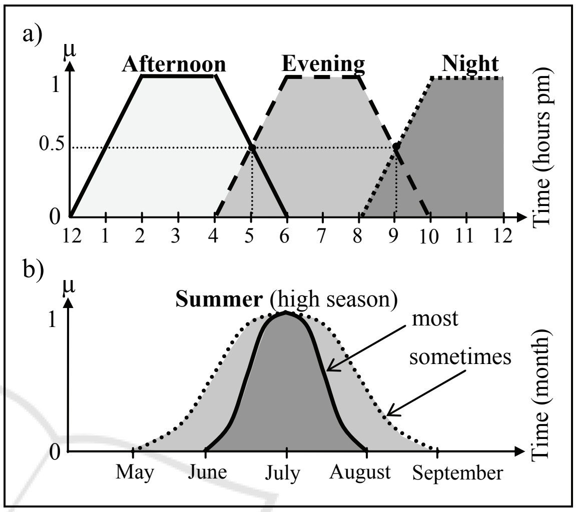

Figure 7: Fuzzy time constructs: afternoon, evening and night (a), and summer (b).

4 WEB CONTROLLING LOOP

To implement fuzzy web analytics effectively, management first has to define the *goals* of a web offer at a strategic level (number 1 in the WA architecture of Figure 8). Websites have many objectives, such as informing, communicating, branding, advertising, lead generating, selling, supporting, entertaining or community-building. Consequently, website success is linked to the achievement of specific goals (Bélanger et al. 2006). *KPIs* and metrics are derived and defined according to the goals of the website (2). After collecting data on the website and data layer, metrics are analyzed and controlled regularly in an ongoing process of web controlling (4 to 5).

The *web controlling loop* (6) makes it possible to monitor the achievement of website objectives and plans (3), and to *(re)act* on an operational level (7).

Finally, the controlling loop enables *the ongoing optimization* of website quality, electronic marketing and CRM in a dedicated manner. This permits web managers to allocate resources more effectively.

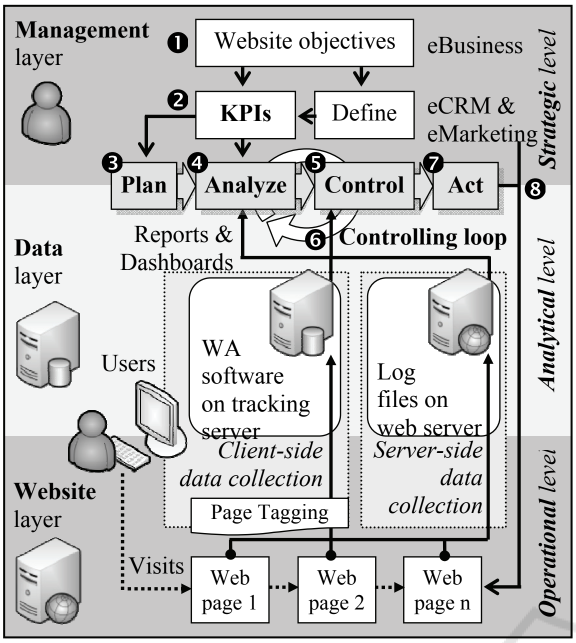

Figure 8: Web analytics architecture with different layers and the web controlling loop.

5 CONCLUSIONS

This paper has introduced a fuzzy logic approach to web analytics and discussed a number of indicators and metrics in web analytics.

Fuzzy web analytics has several *advantages:*

- *precise classification* of elements (e.g. web data and metrics) in classes and a gradual ranking within classes
- *reduction of complexity* (of web data and information overload) without loss of information
- use of *quantitative variables* (numerical values) and *qualitative variables* (non-numerical values)
- use of *linguistic variables* or terms for queries and *computing with words*
- *human-oriented*, perception-based and intuitive processing of web data, metrics and information
- *dynamic* and *multidimensional analysis* considering different metrics, and the
- consideration and mapping of *concepts* and *constructs* which are intrinsically fuzzy, i.e. vague, uncertain or subjective per definition.

Nevertheless, fuzzy logic is confronted with certain *problems:*

- Sharp classification is usually clear, simple and straightforward for everyone. In contrast, fuzzy classification is *more complicated*, not as easy to understand, to communicate and to implement.
- Fuzzy classifications can be *confusing* or even *contradictory*, if an object can belong to different, conflicting classes at the same time.
- In practice, some *decisions* have to be "sharp". In these situations, fuzzy classifications may not be adequate.

Moreover, the theoretical approach of this paper has to be tested with *real web data* from e-business in future studies. In fact, *case studies* with firms are already planned to show the advantages and limitations of the fuzzy logic method in web analytics.

The *research center Fuzzy Marketing Methods* (www.FMsquare.org) is engaged with applications of fuzziness to different domains in information systems. FMsquare provides a number of open source prototypes, including the fCQL (fuzzy classification query language) toolkit, which enables fuzzy queries and the calculation of membership degrees of data stored in MySQL or in PostgreSQL databases.

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