A Distributed, Semiotic-Inductive, and Human-Oriented Approach to Web-Scale Knowledge Retrieval

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1. ABSTRACT
Web-scale knowledge retrieval can be enabled by distributed information retrieval, clustering Web clients to a large-scale computing infrastructure for knowledge discovery from Web documents. Based on this infrastructure, we propose to apply semiotic (i.e., sub-syntactical) and inductive (i.e., probabilistic) methods for inferring concept associations in human knowledge. These associations can be combined to form a fuzzy (i.e., gradual) semantic net representing a map of the knowledge in the Web. Thus, we propose to provide interactive visualizations of these cognitive concept maps to end users, who can browse and search the Web in a human-oriented, visual, and associative interface.

Categories and Subject Descriptors
H.3.4 [Information Storage and Retrieval]: Systems and Software - Distributed Systems
H.5.2 [Information Interfaces and Presentation]: User Interfaces - Graphical User Interfaces, Interaction Styles, Prototyping, User-Centered Design
I.2.6 [Artificial Intelligence]: Learning - Concept Learning, Induction, Knowledge Acquisition

General Terms
Algorithms, Performance, Design, Experimentation, Human Factors, Theory

Keywords
Distributed information retrieval, knowledge discovery from data, human-oriented computer interaction, human-computer information retrieval, inductive inference, computational semiotics, explorative search, Web-scale knowledge retrieval

1. INTRODUCTION

Globally the amount of information storage and communication capacity is growing exponentially [13], but because the amount of knowledge that the human brain can process is constant, the ratio between individual knowledge and available information (i.e., pooling of data or knowledge about a topic) is decreasing drastically. In order to help individuals cope with the information glut, we propose a framework for knowledge extraction from Web data that is presented to the user in a human-oriented, visual, and interactive way and concentrates on human-oriented computer interaction as a map of the emerging global knowledge landscape. The proposed approach is an extension of Kaufmann and Portmann’s notion with a distributed information retrieval approach for Web-scale capacity [16]. Figure 1 illustrates our Web-scale knowledge retrieval framework, achieved by “Web semantics analytics.” The framework, based on components of distributed information retrieval (DIR), knowledge discovery from data (KDD), and human-computer interaction (HCI), provides interactive, visual cognitive concept maps of the Web and enables human-computer information retrieval and collective intelligence amplification in the WEB (Web, End Users, and Behaviors; see Figure 1).

Because such an infrastructure needs massive scalability to process the exponentially increasing amount of information we propose a distributed information retrieval system architecture [6] in order to make our framework Web-scale capable.

Based on information retrieved from the distributed extracted Web data, we intend to apply knowledge discovery algorithms that create abstraction from input data (and information) in order to extract knowledge that can be presented to end users. Recently inductive reasoning has had a revival in linguistics [7] and neuropsychology [27], indicating that probabilistic inference is quite likely a fundamental cognitive ability for perceptual learning as well as language acquisition. Accordingly, our knowledge discovery algorithm clusters the knowledge space using a probabilistic similarity indicator based on a measure of likelihood.

The Web as a world-spanning information system, including the end users, computers (i.e., servers and clients), interconnections (i.e., the Internet) that constitute it, and the behaviors that emerge from it, can be seen as one object of study in information systems research. Hence, for the information system emerging from the interaction of a myriad of users with and on the Web, we use the
acronym “WEB,” which encompasses the Web, its End users, and emerging Behaviors. We think that the WEB, as a giant information system, is in an intelligence amplification feedback loop in which end users create augmented content (even programs) on the Web by accessing knowledge from the Web, which in turn augments future content creation of other users, and so on. This is identified as collective knowledge systems [8] mixed with intelligence amplification [25]. Our framework is intended to accelerate the rate of intelligence amplification by enabling end users not only to find information, but also to see and interact with emergent semantic knowledge structures and thus discover new associations while searching for information [5,14,16,18].

This paper is structured as follows: In section 2, we evaluate the presentation of knowledge in a human-oriented, visual, and interactive way, thus enabling a human-computer information retrieval process, as well as a knowledge discovery algorithm based on semiotics and inductive logic in order to discover knowledge from Web documents by extracting probabilistic semantic networks. In section 3, we design a Web-scalable distributed systems architecture for crawling the Web that enables knowledge discovery from Web documents. In section 4, which concludes the paper, we summarize our research proposal, discuss the approach, and give an outlook on further research.

2. CONCEPT AND COMPONENTS

For better understanding, this section first clarifies the fundamentals of this paper. In subsection 2.1, searching and learning by example are outlined. Subsection 2.2 describes inductive fuzzy grassroots ontology as means for computers to collect meaning. We then demonstrate the use of visual interactive search and learning by fuzzy semantic nets in subsection 2.3. At the end of this section, our approach to semiotic inductive knowledge discovery is explained (subsection 2.4). Each of these fundamentals will be briefly demonstrated and related academic work provided as well.

2.1 Searching and Learning by Example

Maslow’s hierarchy of needs exemplifies humans’ motivation to fulfill basic needs before moving on to other, more advanced needs [19]. The concept implies observations of our inborn curiosity that puts humans in a perpetual search loop. Therefore, search is considered as a vital life activity because all living organisms seek sustenance and propagation [18].

In today’s Web, however, searching to learn becomes increasingly important as more and more data can be found online. In fact, the social Web (which supports and fosters social interaction) provides encouraging applications to ease online publication, thereby increasing the possibility of publishing additional relevant information. Based on this information, third parties can learn and by making the learned available they allow yet others to learn. This online collaboration loop allows the origin of a collective intelligence that represents an emergent characteristic quality between humans and ways of processing information through the Web [8].

Searching the Web has become a daily activity for everyone. Again, learning searches involve multiple iterations and return sets of objects that require cognitive processing and interpretation. These objects may be instantiated in various media and often require an information seeker to spend time scanning, viewing, comparing, and making qualitative judgments [18]. That is, we often follow a learning-by-example approach. Simply put, this is learning by watching; in contrast to deductive learning, where someone explains (i.e. top-down) what to do, inductive learning shows (i.e. bottom-up) what to do.

To team up human and computers better, both need the ability to learn from each other, thus allowing the augmentation of human intelligence. This may progress quite naturally because every time our ability to process information and communicate it to others improves, yielding an increased intelligence over a natural one [25]. For example, through dynamic query interfaces [28] humans are able to adapt to computers, and through machine learning computers can (better) adapt to humans. To support average people in their searches, dynamic query interfaces should fit into the single user’s knowledge. To do this, the computer should rely on machine learning to defer to the average user, who uses language in a natural way. Through dynamic interfaces that integrate digital content into a human’s life in seamless ways, a computer should even become adaptable to each individual user. Because of this, fuzzy set theory (see subsection 2.2) is also suitable for personalization purposes (see for example Portmann et al. [21]).

With an automatically built in ontology, computers may, for example, become (more) responsive to humans. With this in mind, subsection 2.2 illustrates Kaufmann and Portmann’s inductive fuzzy grassroots ontology, which can be used to bring together human and computers [16].

2.2 Inductive Fuzzy Grassroots Ontology

In computing with words, the objects of computation are words, phrases, and propositions drawn from natural language [34]. Computing with words is based on fuzzy set theory that is problem-adequately to handle imprecise, vague, and uncertain data. With fuzzy set theory a computer becomes able to handle today’s challenges of inconsistency, uncertainty, and relevance in Web users’ natural language.

To capture humans’ worldview on a grand scale, which results from meaning negotiation in Web content [24], our aspiration is to build an ontology that represents knowledge as a set of concepts and relationships. In order to compile ontologies, we build on distributed Web agents that constantly crawls the Web and, in a computational semiotic sense (see subsection 2.4), look for signs and their connections to other signs. In this way, a distance \( d \) (i.e., distinguishability, similarity, proximity, or functionality), can be elicited by using a metric function that provides a way of describing what it means for signs to be “close to” or “far away from” each other. In the end, a computed sign distance \((x, y)\) between signs \(x\) and \(y\) permit a fuzzy gradation of the sign relationships. To allow computing with information [16], we now have to aggregate the crawled signs to clusters. For that purpose, fuzzy clustering algorithms, which permit a classification of the normalized signs into different sign clusters, can be used. Here normalized means “modifying the signs to make them consistent in some way.”

Through fuzzy clustering algorithms, a fuzzy cluster of signs is represented through an archetypical sign (i.e., the cluster center). The degree of membership of a related sign to the cluster decreases with increasing distance \(d\) to the cluster center; signs with a short distance to the cluster are assigned high membership, whereas signs with larger distances are assigned low membership. In order to do that, a clustering algorithm begins with a random initialization and updates the memberships and the archetypical clusters iteratively.
navigation process starts. Because of that, in the first place a clever mix of Web browsing and Web searching can be used to obtain a first shot of intelligence amplification with users. Therefore, in the near future, a search engine should provide possibilities for searching and browsing not only the retrieved Web documents, but also their underlying structural semantics. Consider as example a user searching the Web. Now, in addition to browsing only from a found Web document (e.g., through a Web search engine) via a link to another document, his search is extended by the possibility to follow a link into visualized structural semantics. The user navigates the net structures for some period of time and then returns to a link to a different Web document, as Bizer et al. illustrates [5].

$$\forall x, y \in X$$

\[ \mu_{relevant}(x, y) \]

\[ H_{relevant}(y, x) \]

Figure 2. Schema of Inductive Fuzzy Cognitive Maps

Our proposed inductive fuzzy grassroots ontology is a structural semantic net, which may be interactively visualized as inductive fuzzy cognitive maps [17] to allow a Web user to navigate both forward and backward, thereby changing the focal point of a search. Fuzzy cognitive maps are knowledge-processing tools with fuzzy signed graphs, which can be presented as an associative single-layer neuronal network (i.e., imitating human neurons; see next subsection). They describe particular domains using nodes (i.e., fuzzy clusters C) and signed fuzzy relationships between them. The fuzzy component allows having fuzzy taxonomy relations T between the clusters C. So as to interactively visualize the semantic structures inherent in the inductive fuzzy grassroots ontology, we propose inductive fuzzy cognitive maps as visualized diagrammatic presentations used as fuzzy inductive relevance representations between signs. These are directed labeled graphs representing an inductive structural semantic net to the Web user (see Figure 2). Accordingly, as stated above, this directed labeled graph is defined by edges S ∈ X, and inductive sequencing membership degrees as vertices $\mu_{relevant} : X \times X \rightarrow [0,1]$. An edge $\mu_{relevant}(x, y)$ represents the likelihood that after sign x follows sign y.

Subsection 2.4 introduces the indicated semiotic and inductive approach to semantic analysis of the Web.

2.4 Semiotic Knowledge Discovery

We are proposing a semiotic and inductive approach to Web semantics analytics. A semiotic approach [3] asserts that the WEB (see section 1) can be described by a semiosis, a sign process involving end users, computers, and interconnections, as well as the way these signs are processed and interpreted. Accordingly, the signs of the Web can be, for example, words, phrases, hyperlinks, images, tags, and semantic annotations. Thus, our algorithm processes the Web’s data on a sub-syntactical level. Furthermore, an inductive approach [10] applies uncertain, non-deductive methods for inference with a certain degree of support by a likelihood metric L (see subsection 2.2).
Accordingly, our knowledge discovery algorithm evaluates likelihoods in sign sequences on the Web $W$, consisting of resources $R \in W$, with URI’s $U$. A resource $R$ is an ordered set of atomic signals (i.e., characters and byte streams) $s \in R$ that are aggregated to signs $S \in R$. The set of all signs considered forms the sign space $\mathcal{X}$. The goal of the algorithm is to extract knowledge in the form of a probabilistic semantic network as a directed labeled graph $G$, with edges $S \in \mathcal{X}$, and vertices $\mu_{\text{relevant}}: X \times X \to [0,1]$, which is an indicator of degree of membership in the fuzzy set [31] of likely sign sequences. Thus, it relies on a likelihood metric. As early as 1948, Shannon [26] proposed this kind of probabilistic sequencing for text analysis. However, according to Griffiths [7], it has only recently received new attention in natural language processing. Since we intend to bring humans and computers closer together, we implement computers’ human neuropsychological processes (i.e., through machine learning).

According to the law of likelihood [10], observed evidence $E$ supports a hypothesis $H$ over a different, incompatible hypothesis $H'$ if (and only if) $L(H|E) > L(H'|E)$. The epistemic problem of induction [30] is to find a suitable method for computing $L$. As described by Hawthorne, Kaufmann applied a normalized likelihood ratio of a hypothesis and its opposite as a likelihood metric for measuring the strength of evidence and showed that this is equivalent to a Bayesian posterior conditional probability if (and only if) the prior probabilities are assumed to be equal [15]. However, this likelihood ratio raises the raven paradox [11]: Consider the hypothesis ravens ($E$) are black ($H$). Now, should the observation of numerous white clouds (i.e., non-black, non-ravens) support this hypothesis? Using the classical likelihood ratio, it does so; because a large number of observations of instances of $\neg H \land \neg E$ (e.g., white clouds) increase the likelihood ratio of $H$ by decreasing $p(E|\neg H)$. In order to resolve this paradox, the epistemic problem of induction is reevaluated, attempting the development of a likelihood measure based on recent results from neuropsychological research.

For instance, a result published by Rao [23] “suggests a new interpretation of the spiking probability of a neuron in terms of the posterior probability of the preferred state encoded by the neuron, given past inputs” (p.6). Shi and Griffiths support this interpretation and provide results that indicate that routing of stimuli in the visual cortex can be sufficiently accurately modeled by a reverse Bayesian inference [27]: “The brain then has to reverse the generative model to recover the latent variables expressed in the data. The direction of inference is thus the opposite of the direction in which the data are generated.” (p.4). In their model, neural representation of Bayesian inference is an instance of importance sampling. The synaptic weights are modeled by the posterior probability of activation of a neuron $x$, given a stimulus $S_x$. The neuron $x$ represents a (hidden) state that possibly generates the stimulus, called a latent variable. Accordingly, as stated by Formula 1, the activation $act(x|S_x)$ is defined as a ratio of the probability of $S_x$ conditional to $x$, divided by the sum of probabilities of $S_x$, conditional to alternate latent variables $x'$:

$$act(x|S_x) := \frac{p(S_x|x)}{\sum_{x'} p(S_x|x')}$$  

(1)

In fact, this kind of likelihood measure resolves the raven paradox, because observation of instances of the opposites, $\neg S_x$ and $\neg x$, does not affect $act(x|S_x)$ directly. The activation is determined only by the conditional probability of the stimulus given $x$ in comparison to the probability conditional to affirmative alternate explanations $x'$ in the inverse inference.

Analogically, we will evaluate an application of this reverse Bayesian inference as a form of a neuropsychologically inspired likelihood measure for knowledge extraction in our algorithm. For two signs $x, y \in X$, the sequential association likelihood $\mu_{\text{relevant}}(x, y)$, constituting a labeled directed edge of the semantic network, is defined accordingly in Formula 2, where the relevance is defined as the sequence likelihood, weighted by the joint probability of occurrence. Note that by applying the insights of Rao [23] as well as Shi and Griffiths [27], the direction of inference of $y$ from $x$ is reversed.

$$\mu_{\text{relevant}}(x, y) := p(x, y) \frac{p(y|x)}{\sum_{y'} p(y'|x')}$$  

(2)

The sampled conditional probabilities $p$ are computed by counting the fuzzy events [33] that two signs occur “near” to each other within the same range, where $near(y_i, x_i) \in [0,1]$ is a fuzzy proposition [32] indicating how closely two terms $y, x \in S^*$ are located in an occurrence $i$. The frequency counts $\varphi$ are defined as follows:

- The frequency of $x \cap y$ is defined as $\varphi_{x,y} := \sum_i \mu_{\text{near}}(y_i, x_i)$.
- The frequency of $x$ is defined as $\varphi_x := \sum_i \varphi_{x,y}$.
- The frequency of $y$ is defined as $\varphi_y := \sum_i \varphi_{x,y}$.

In total, the number of fuzzy events is defined as $\varphi := \sum_i \varphi_y = \sum_i \varphi_x$.

Accordingly, counting the relative frequencies of these fuzzy events, the conditional probabilities can be estimated by applying Formula 3.

$$p(y|x) = \frac{p(x,y)}{p(x)} = \frac{\varphi_{x,y}}{\varphi_x}$$  

(3)

The fuzzy term near is precisiated [35] by Formula 4, where $i \in \mathbb{N}$ is the index of the particular measurement $a_i \in \mathbb{N}$ is the sequential position index of a term in the document $\cdot$ is the absolute amount; $r \in \mathbb{N}$ is the sign observation radius parameter, which determines the maximal distance between signs to be considered somewhat near (i.e., $\mu_{\text{near}} > 0$); and $x_i, y_i \in X$ are terms found in the same range.

$$\mu_{\text{near}}(y_i, x_i) := 1 - \left( |(i(y_i) - i(x_i))| - 1 \right) / r$$  

(4)

Algorithmically, the fuzzy frequency counts can be extracted, as shown in Algorithm 1. This processing is of linear complexity as a function of the number of terms, weighted by the (constant) radius size $r$.

**Algorithm 1. Fuzzy Frequency Count of sign sequences**

```java
// Initialize the sequential term list
\forall R \in W
\forall S \subseteq R
S^*_i := S;
R^*_i := R; // Count the fuzzy events of near terms
\forall k \leq r \land R^*_i \implies R^*_{i+k}
x := S^*_i;
y := S^*_i+k;
```
In order to evaluate the conceptual framework on real-world data, a prototype implementation was developed that presented a small proof of concept for the basic idea of inductive fuzzy grassroots ontologies [16]. The relevance degrees were computed using Algorithm 1 and Formula 2 for a subset of frequent terms in a small sample of 5000 Wikipedia documents. The resulting inductive fuzzy cognitive map for the term “Australia” and the five most relevant child and grandchild terms are presented in Figure 3.

Figure 3. Inductive Fuzzy Grassroots Ontology Prototype

Section 3 illustrates our Web-scalable distributed information retrieval framework, which is of utmost importance to the realization of a practicable, robust and stable WEB for augmenting human intelligence.

3. DISTRIBUTED INFORMATION RETRIEVAL FRAMEWORK

In the following, important aspects of this research are presented in more detail. To establish a common vocabulary, the scope of this research is specified in subsection 3.1. Subsequently, each layer of the proposed architecture is presented in the following subsections 3.2 to 3.6.

3.1 Search Engine Architecture

Knowledge retrieval enhances the synergy of Web user and enables emotional and intellectual knowledge exchange between them. Through chaotic growth of information, in the near future knowledge-based search engines will become essential. It will require immense amounts of memory and computational power that will take up high planning, maintenance, infrastructure, and development resources. Based on this, an attempt should be made to allow producers and consumers (i.e., so-called prosumers; see for example Portmann et al. [22]) of Web content to collaborate on the memory and computational costs created by their needs. Such software should comply with the following criteria:

- Memory and computational power of the Web user should be harnessed. A distributed system could achieve this.
- User approval is intended by a focus on usability of the software. For example, an installation system like NSIS should guarantee the ease of the software deployment. Acceptance can be achieved by intuitive user interfaces.
- Open-source and free software are used to enable cost efficiency and encourage further software development.

Figure 4: Distributed Knowledge Retrieval Architecture

In the following subsections, an attempt to comply with these requirements will be presented. A search engine based on the work of Kaufmann and Portmann is presented here [16]. The software architecture presented in Figure 4 is inspired by the distributed software architecture of Anderson et al. [2] a central host issues computing tasks to clients, using their available computational power to send calculated results back to the host for further processing.

Our search engine is realized in a five-layered architecture (see figure 4) composed of a peer-to-peer (P2P) layer (introduced in subsection 3.2), a data access layer (subsection 3.3), a middleware layer (subsection 3.4), a Web application layer (subsection 3.5) and a presentation layer (subsection 3.6). Our P2P layer (see subsection 3.2) has a role similar to that of the clients in the distributed software architecture of Anderson et al.[2].

3.2 P2P Layer

The P2P layer has three components: It needs a Web crawler to be able to extract raw HTML pages from the Internet; a resource broker to coordinate the crawling task over the different clients; and a data-mining component to distribute the computational power of the knowledge retrieval algorithm. In the end, our P2P client is proposed as a download to Web users.

The Web crawler plays a central part; it aims at recovering Web content for the purpose of knowledge retrieval. Because of the immense number of documents available on the Web, its task is central, but also intensive in computational power and bandwidth. Based on this, a huge payload can be adopted by our P2P clients. Following a law of parsimony, the crawling mechanism is initially kept quite simple: Web pages are acquired by HTTP requests, and the page is then parsed to extract content and hyperlinks. Hyperlinks pointing to other domains are separated from a domain’s internal hyperlinks. By focusing on a single domain, we can observe the hyperlink structure as paths in tree form with the restriction of cyclic paths. This enables us to traverse them in

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1 http://ifgo.cwsurf.de/poc.html

2 http://nsis.sourceforge.net/download
level order, keeping a restriction stack to avoid cyclic crawling. To emphasize the claim of polite crawling by Heydon and Najork [12], each crawler should inspect three domains alternatively, which permits delaying requests on the same domain.

Parallel crawling on different clients could lead to multiple extraction of same content on given domains. To prevent a collision, a resource broker is implemented in the clients. Its operating mode is allowed through the sharing of collected external hyperlinks in a distributed file. The crawler can acquire a new domain to crawl by inspecting this file, informing the other peers of their acquired new crawling domain, and removing it from the list. Finally, to avoid content extraction on a visited domain, a second distributed file archives visited domains.

Another component of the P2P client is the data-mining component. An inverted file (i.e., a word-level index, as described in Baeza-Yates and Ribeiro-Neto [4]) and fuzzy frequency counts based on a limited sign-observation radius r (as introduced by Kaufmann and Portmann [16]) are implemented. The local file database is then transmitted to the global database middleware via the data access layer.

To reach cost efficiency, we intend to implement the P2P clients with JXSE framework, available as an Apache 1.1 license. JXSE implements the JXTA protocol published by Sun Microsystems Inc. [29]. The JXTA protocols allow the use of super-peer ID, the exchange of messages, the creation of peer groups, security services, advertising service, the pipe service, and file sharing service as an efficient implementation of the P2P clients. Since it is based on the HTTP protocol, it also enables a simple configuration of firewalls. Under Windows, for instance, the NSIS open-source installer makes installation easy.

3.3 Data Access Layer
Having a distributed RDBMS and different peers, we need a layer to connect them. However, the main task of this layer is to link the P2P clients with the RDBMS middleware. To connect to the P2P clients, the layer is composed of a peer group with access rights to this database. This peer group gives the scalability absolutely necessary for future expansion of the system.

At regular intervals, the data access peers ask clients to send them their data over a file service given by JXSE. These files are then saved in the RDBMS middleware by applying a time stamp. To balance the data load, the P2P layer has the ability to send messages to the data access layer; these will prioritize the file exchange between data access layer peers and a chosen client of the P2P layer.

The data access layer checks the document’s links, saved in the RDBMS for accessibility, with help of HTTP requests. If their accessibility has changed, it asks the client to crawl the given domain again. This procedure helps us to keep the database up to date. At given time intervals, the time stamps of the database are validated to determine the need of the P2P layer to crawl certain domains again.

Finally, we need a data access management terminal. For reasons of usability, this is a graphical user interface providing access to traffic statistics for decisions about the scalability extension of the layer. This user interface also provides the possible integration of proxies. However, this layer, in interaction with the database middleware (see subsection 3.4), also helps cope with security issues.

3.4 Database Middleware Layer
Thus far we have described distributed clients containing locally extracted data. In order to compute global likelihoods, we need a data container covering all frequency counts contained in the P2P clients. First, this data container should comply with Web scalability. This is most important because the amount of data of the Web is constantly growing (see also section 1). Also, the amount of data storage capacity provided by the clients will grow with their number. Second, balancing computational power is a requirement for scalability in distributed data management systems. Third, security should be provided to block harmful attacks, and last but not least, data integrity applying the ACID concept should also be guaranteed.

To meet these criteria, a distributed RDBMS system will furnish the necessary functionality for the algorithm in mind. The HadoopDB3 [1] project from the Yale University is a promising candidate for distributed relational database middleware. It is extremely scalable and allows for building private cloud databases using cutting-edge map-reduce technology. Thus, the immense amount of data and computation required for the computation of the likelihood metrics as vertices of our semantic network are distributed to the HadoopDB clients, whereas a unified interface is provided for global data access.

3.5 Web Application Layer
The web application layer provides an interface between the clustered RDBMS and the presentation layer. It provides the same encapsulation as the data access layer. Its main tasks are accepting and rooting of search queries, returning search results to the application layer, choosing a search algorithm, and allowing management of the server through a graphical user interface.

A JBoss application server4 builds the bare bones of this layer and, through its service-tier logic, extensions are even possible. JBoss provides cost efficiency through its GNU lesser general public license. In the case of our algorithms, the data tier is used to accept search queries and execute them in the clustered RDBMS with help of JDBC to enhance query performance.

Clustering search results, as described by Kaufmann and Portmann [16], can be cast to an appropriate format for the presentation layer. The application tier of the server will support this. As container for the presentation layer, JBoss’RichFaces5 seems to be strong candidate. The service tier of the server can be used to implement logical extension of the algorithm, which can be switched for experimental purposes. A server management GUI provides the user a simple backup mechanism as well as statistics to analyze user behavior and monitor necessary extension of the system.

3.6 User Interface Layer
The presentation layer implements the graphical aspect of the search engine. In this layer a preponderant weight on usability should be given. This should enhance the approval of the Web user for inductive fuzzy concept maps (see subsection 2.3f) presented by Kaufmann and Portmann [16]. An AJAX client that assures a fluent user experience accomplishes the implementation. It provides a graphical representation of the extracted semantic network and a search interface for keyword search. It enables the presented vision of searching by browsing semantic net structures.

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3 http://sourceforge.net/projects/hadoopdb/
4 http://www.jboss.org/jbossas/downloads/
5 http://www.jboss.org/richfaces/download/
It may be that the main advantage of this approach, from a user standpoint, is the provision of integrated access to knowledge, information, and data from distributed and heterogeneous Web sources [5]. Just as hypertext browsing provided mechanisms for navigating forward and backward, in a document-centric information space, similar navigation controls are presented in our conceptual section 2. They enable users to move forward and backward between entities in a dynamic user interface using inductive fuzzy cognitive maps. These maps stem from inductive fuzzy grassroots ontologies that are rooted in semiotic inductive knowledge discovery and allow likewise such navigation in visualized structural semantic nets.

4. CONCLUSION

To summarize, we have presented a conceptual design for Web-scale knowledge retrieval. Its Web-scalability is based on a distributed, crowd-sourced P2P approach for distributed and human-oriented information retrieval. Based on this computing infrastructure, knowledge discovery from data methods are applied in order to extract knowledge from Web-content, in a semiotic (i.e., sub-linguistic) and inductive (i.e., probabilistic) way. This knowledge is provided to users as a visual, interactive graph, a concept map of the Web, a semantic net (i.e., a directed, labeled graph).

Our interactive, visual, human-oriented approach to knowledge presentation should help an information seeker understand, or get to know, and (thus) express information needs, formulate queries straightforwardly, select from available information, understand results by browsing not only the retrieved Web documents but also the semantic relations of the document’s content, and keep track of the progress of a search. The quality of the user interface depends strongly on how Web users react to it. Its preferences may be given through different factors, such as speed of the underlying framework or familiarity and aesthetic realization of the inductive fuzzy cognitive maps, and so on. All these points are to be evaluated in a further step; for example, using discount usability methods, as suggested in [4].

Neural and semiotic approaches to knowledge discovery go hand in hand. We can assume that semiotic signs are represented in the brain by neurons. In fact, our brain cannot observe and process reality directly. It receives stimuli from sensory neurons (e.g., through our five senses). Recent results from neuropsychological research indicate that our brain learns meanings by importance sampling of correlated stimuli within the information space of neural activation. Thus, the symbol-grounding problem [9] can be resolved (and it obviously has been, as exemplified by evolution of human cognition). Instead of grounding the meanings of symbols by their relationship to their real objects of reference, as asserted by traditional AI, the meanings of signs can be grounded by their co-relatedness on a semiotic level [24].

Our distributed architecture will enable scaling up the infrastructure needed for Web-scale knowledge retrieval. At the moment we are implementing first prototypes and conducting tests and evaluations of different types of configurations. At a later time, technical data analysis (e.g., network allocation and computational power measurements) should give us insight for further improvements and development of the infrastructure. Furthermore, we plan also to evaluate different likelihood metrics and user interfaces and to evaluate them using qualitative user surveys [4]. Furthermore, we will investigate possibilities of building n-grams; for example, by connecting edges to hyperedges, and we will provide methods for automated extraction of taxonomies from the available semantic networks. With this approach, we expect to open up new means of human-computer interaction without losing the technical scope of its feasibility.

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6. REFERENCES


