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Information Retrieval Systems using an Associative Conceptual Space

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Abstract

An AI-based retrieval system inspired by the WEBSOM-algorithm is proposed. Contrary to the WEBSOM however, we introduce a system using only the *index* of every document. The knowledge extraction process results into a so-called *Associative Conceptual Space* where the words as found in the documents are organised using a Hebbian-type of (un)learning. Next, 'concepts' (i.e.word-clusters) are identified using the SOM-algorithm. Thereupon, each document is characterised by comparing the concepts found in it, to those present in the concept space. Applying the characterisations, all documents can be clustered such that semantically similar documents lie close together on a Self-Organising Map.

1. Introduction

The availability of huge collections of books, CD-ROMs, video movies, articles etc. in modern libraries or their respective depositories has prompted the creation of many intelligent search systems. These Information Retrieval[1] systems (IR-systems) apply different levels of Artificial Intelligence (AI). Every IR-system needs a type of query to do its job. In the classical 'boolean retrieval systems' [1], the user can specify a query by summing up the words that should occur in the title or body of the documents[2]. By comparing the words of the query to the data[3] collected from the individual books, the search result is found and shown to the user. These systems show a well-known trade-off between precision and recall (see footnote 1): using more keywords in the query usually results into a higher precision and a lower recall, and

[1] Comparing IR-systems is not easy because performance is a complicated notion. Besides inspecting issues like the degree to which the collection of items is covered and their user friendliness, IR-systems are mostly evaluated with respect to their *recall* (the part of the relevant information available that has actually been found) and to their *precision* (the part of the information found that is really relevant to the user) [1]. The notion of *relevance* is quite personal however, and therefore not unique which strongly complicates the evaluation.

[2] Logic operators like 'not', 'and', and 'or' can sometimes be used to improve the query.

[3] Data on the books are usually stored in an *inverted index*, containing the most important words with references to the documents in which they appear.

vice versa. Analysing this performance, we notice that boolean retrieval systems only use individual keywords. They lack knowledge about the *semantic relations* between these words and between the common underlying notions.

An approach to improve IR-systems is the ‘vector-space model’ [2] where documents and queries are represented by vectors, each component of which corresponds to a word. Every component’s value represents the number of times the word appears in the text. Comparison of the query-vector to the document-vectors results in a set of documents presented to the user. Another development is the use of ‘relevance feedback’ [1] where the user can report to the system whether the documents found are relevant to the user. The system can then try to find documents similar to these relevant documents. However, still very little semantics is taken into account. Using a ‘thesaurus’ (a vocabulary where synonymous, semantically covering, or otherwise related words are being collected) can solve this problem: the user’s query can be augmented with words related by the thesaurus. The thesaurus is usually created manually and their construction is therefore time-consuming.

Attempts have already been made to use automatically constructed domain-knowledge. Two such systems, the WEBSOM [4] and the Aqua-browser [5], will be described in the next section. Using these descriptions, a general architecture for an IR-system will be derived. Thereupon, we introduce our ACR-WEBSOM IR-system.

2. Knowledge based IR-systems

The original WEBSOM-algorithm uses full-text documents as input. After having removed all non-alphabetical characters and less frequent words, each remaining word is represented by a unique *n*-dimensional real vector x_i with random-number components, where *i* denotes the *i*-th word in the text. The relation between words is determined using the average *short context* $X(i)= [\mathrm{E}\ \{ x_{i-1}\ |x_i\ \},\ \varepsilon x_i\ ,\ \mathrm{E}\ \{ x_{i+1}\ |x_i\ \}]^{\mathrm{T}}$, where E denotes the estimated expectation value evaluated over the text corpus, and ε is a small scalar number (e.g., $\varepsilon = 0.2$). The $X(i) \in \Re^{3n}$ constitute the input vectors to a Self-Organising Map (SOM)[6] called the *word category map*. Using this map, a ‘fingerprint’ of every book can be constructed consisting of a cluster histogram. These histograms are used as input for a second SOM called the *document map* where documents addressing similar topics are generally mapped close together.

IR-systems based on Connectionist Semantic Networks (CSN) [13] also start out removing less frequent words. The remaining words are placed in a network where each node represents a word and where the connection weights represent the strength of the relations between words. Normally, these weights are based on *word-co-occurrence*: words that often appear close to each other are more strongly connected. This CSN can then be made accessible to the user by means of a graphical interface where words can be selected using mouse-clicks.

Both systems just briefly reviewed, show a new development in IR-systems: instead of matching documents on a word-by-word basis using the words of the query, the documents are analysed to find underlying concepts to which these words are related. So, these systems attempt to compare the documents and the query given on *a higher level of abstraction*.

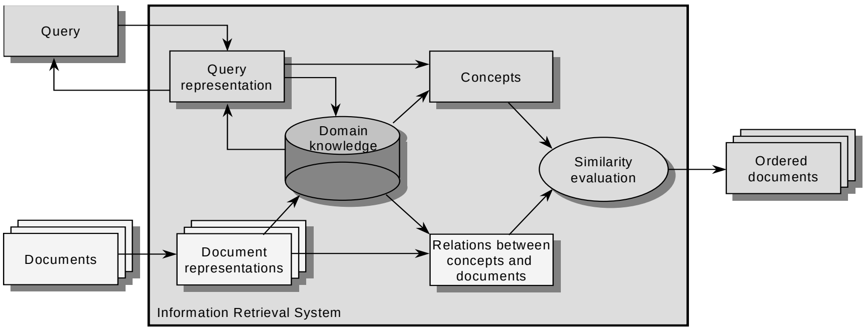
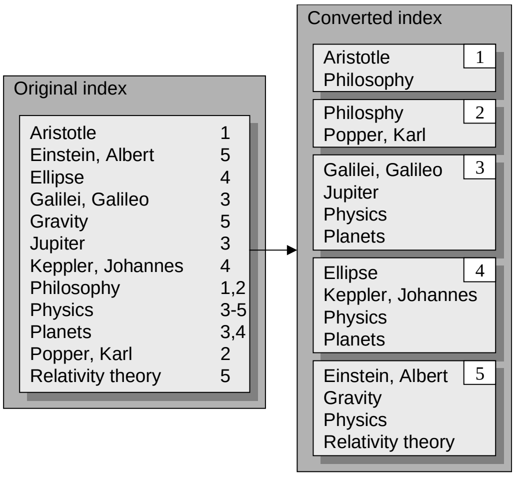


Figure 1: Architecture of an IR-system that uses domain-knowledge to match documents and a query on a higher level of abstraction. This knowledge base can also be used to aid the user in formulating the query through an interactive, usually graphical interface.

In both approaches, it is assumed that *full-text* representations of all documents are available and small enough to be handled within a realistic timeframe. This is not always the case. In libraries for instance, there are usually many books of several hundred pages, not available in electronic format. To characterise each book, it would be preferable to use only a small part of the entire book such as the *index*.

3. ACS-WEBSOM

At first sight, an index may seem to hold little information on the meaning of the words occurring in the document. Otherwise, the words present in the index have been found significant enough to be mentioned. Moreover, part of the order in which they appear in the text can be reconstructed as depicted in figure 2. We could hereby make the assumption that *if words occur on the same page they most likely are related*. For the *word-co-occurrence*–method used by CSN-based IR-systems, the information available in the ‘converted index’ may suffice. However, books often contain a long array of concepts, so we suppose that the holistic coupling of documents to *concept*s as used by the WEBSOM performs better in describing the contents of the documents. We can use the WEBSOM (which demands vectors as input) by creating a conceptual space using word-co-occurrence, the so-dubbed *Associative Conceptual Space* (*ACS*). This space contains a set X of n vectors, $X = \{x_1, x_2, x_3, \ldots, x_{n-1}, x_n\}$, each vector x_i consisting of d components. Each such vector is one-to-one related to a word w_i of the collection $W = \{w_1, w_2, w_3, \ldots, w_{n-1}, w_n\}$ of index words. We further apply the convention that *the*



Original index

Aristotle	1
Einstein, Albert	5
Ellipse	4
Galilei, Galileo	3
Gravity	5
Jupiter	3
Keppler, Johannes	4
Philosophy	1,2
Physics	3-5
Planets	3,4
Popper, Karl	2
Relativity theory	5

Converted index

Aristotle Philosophy	1
Philosphy Popper, Karl	2
Galilei, Galileo Jupiter Physics Planets	3
Ellipse Keppler, Johannes Physics Planets	4
Einstein, Albert Gravity Physics Relativity theory	5

Figure 2: Conversion of an index

(*euclidian*) *distance* $\| x_i - x_j \|$ *between the reference-vectors* x_i *and* x_j *should indicate the strength of the association between the corresponding words*. To find the correct associations, we use the *Hebbian* rule of learning [9]. If two words *i* and *j* are simultaneously activated, the strength of the their connection is increased:

$$x_i(t+1) = x_i(t) + \eta(t)\frac{x_j(t) - x_i(t)}{|| x_j(t) - x_i(t) ||}$$

($\eta(t)$ is the current *learning-rate*)

However, simply applying the given association-rule alone may easily lead to false associations where a related word that is moved closer, is also brought closer to an unrelated word. To counter this effect, an *active forgetting* rule is introduced:

$$x_i(t+1) = x_i(t) - \lambda\,(delta)\,\frac{x_j(t) - x_i(t)}{delta}$$

where $delta = || x_j(t) – x_i(t) ||$. If the effect of the active forgetting is made mostly local, correct orderings in more remote parts of the conceptual space will remain intact. Therefore, $\lambda(delta)$ should be decreasing over *delta*. Some of the dynamics we could expect from a *combination* of learning through association and active forgetting, is shown in fig 3 (for more details, we refer to [10], [11]).

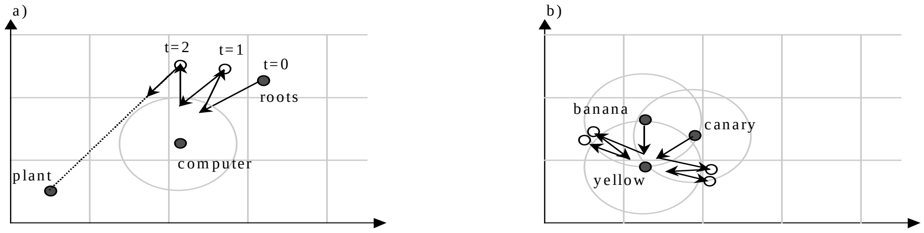


Figure 3: Active forgetting: the circles represent the repulse-behaviour.

We can form an ACS from book indices if these indices are converted as described earlier. To do so, the words in each converted index are concatenated into a text-string T_i of index-terms $t_{i\,j}$, $T_i = \{t_{i\,1}, t_{i\,2}, t_{i\,3}, \dots, t_{i\,m-1}, t_{i\,m}\}$ where *i* denotes the *i*-th book in the collection of *k* books. These strings in turn, are concatenated into one long string $T_* = \{T_1, T_2, T_3, \dots, T_{k-1}, T_{k.}\}$. We define the *vocabulary W* as the set of (unique) words occurring in T_*. For each word t_{*c} in T_* , we define a neighbourhood N_c with radius *r*. Each element of the neighbourhood is activated in combination with t_{*c}.

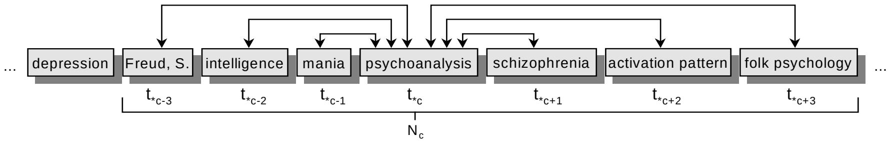


Figure 4: Example of a neighbourhood with *r*=*3* and the activation combinations made.

We now construct a conceptual space C_s by going through the entire text-string T_* several times whilst also applying the forget-rule. Words that often occur have a lower informative value. This can also be taken into account yielding the association-rule:

$$x_i(t+1) = x_i(t) + \eta(t) \frac{x_j(t) - x_i(t)}{|| x_j(t) - x_i(t) ||} \cdot \alpha(i,j) \qquad x_j(t+1) = x_j(t) - \eta(t) \frac{x_j(t) - x_i(t)}{|| x_j(t) - x_i(t) ||} \cdot \alpha(i,j)$$

$$\alpha(i,j) = \frac{2.freq_*}{freq_i + freq_j} \qquad freq_i = \text{frequency of word } i$$

$$freq_* = \frac{|T_*|}{|W|} \qquad |\,.\,| \text{ returns the number of elements in a collection}$$

Having applied the ACS-algorithm, the concept space C_s contains a multidimensional[4] knowledge structure. To use it, we can apply the WEBSOM-algorithm. First, we simply use the reference vectors of C_s as training vectors for a SOM. This results in a two-dimensional map of the knowledge structure (figure 5). Similar to the original WEBSOM, this word category map is used to create a document map (figure 6).

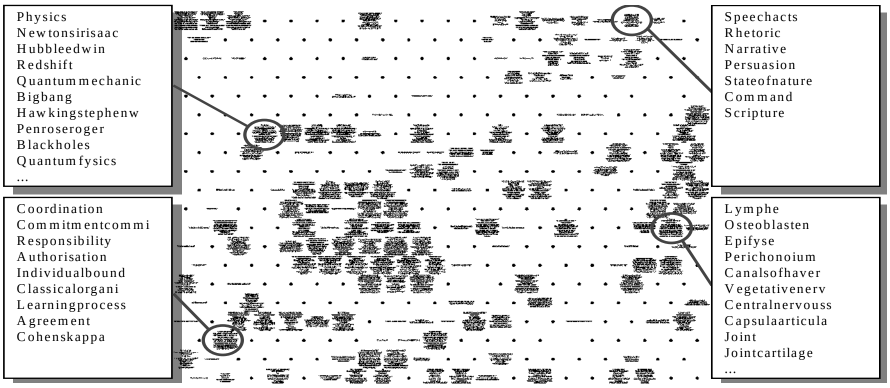


Figure 5: Examples of some clear categories in a word category map.

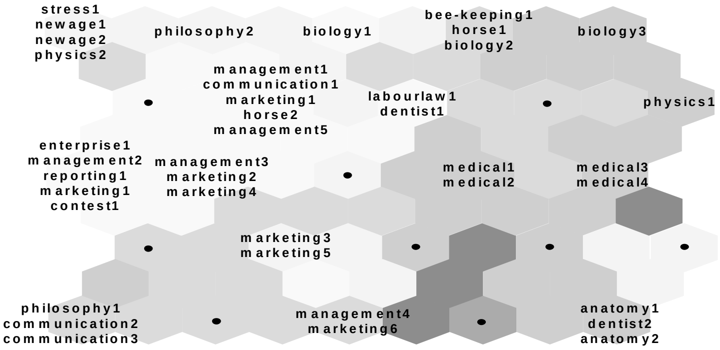


Figure 6: Document map based on the word category map of figure 5, where documents have been manually labelled using a crude categorisation. Note that documents from the same category tend to be found in each other's vicinity on the map.

[4] In our experiments, a five-dimensional space tended to give the best ordering.

4. Conclusions and outlook

Experiments show that the ACS-algorithm is able to create an ordering recognisable by and acceptable to humans. Further evidence shows that the algorithm will create very similar orderings independent of the initial values for the reference vectors. The ACS-WEBSOM-algorithm compares documents based on *concepts constructed from word-clusters* instead of on individual words. It is expected to achieve a higher precision and recall than traditional IR-systems. The biggest problem at this moment is the time-complexity of the learning process. This is mainly due to the application of the forget rule, which takes up approximately 95% of the processing time[5].

Further research should first of all be focused on reducing the time-complexity of the algorithm. The possibility of using the ACS-WEBSOM-algorithm on full-text documents should also be investigated. A CSN-based IR-system using the converted index as mentioned in section 3, is another interesting approach to consider.

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[5] Processing a document-set of 40 indices with a vocabulary of 2.439 words and a text-string of 20.621 words, took 8 hours and 10 minutes on a pentium-133 system.