Semantic Search for Context-Aware Learning

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Abstract—**The thirst for information in complex working environments calls for intelligent systems which optimally assist the user, i.e. which offer the user the most relevant information. The aim is to decrease the time the user has to spend on his hunt for information and to offer him the best fitting help and learning material in an on-demand manner. We present an approach for the semantic retrieval of help and learning material which takes the working context into account. Based on the semantic structure of an ontology with attached binding weights a context-aware ranking of help and learning material is generated. The semantic search results fit better to the learner's actual situation than e.g. a pure full-text search, because the underlying ontology-based retrieval is aware of relations in the search domain and uses this knowledge in a way aligned to the learning process as well as to the specific domain. The results of the semantic search are presented for an application scenario in radar-based image interpretation. The advantages of the semantic approach are shown by a comparison with a state-of-the-art full-text search engine.**

Keywords-semantic retrieval, e-learning, image interpretation, ontology, semantic spreading activation

I. Introduction

Lifelong learning enriches our knowledge base and our experience with new information and new processes. In our modern information society we have to keep up with the rapid development of technology and the steady increase of information. Although we apparently have to move along with the changes there are to come, most of the time this is a tedious task. We cannot succeed in knowing everything, especially everything which is new. Because of that people have to train themselves at their workplaces, and not only in school or only with specific qualifying training. This is especially true for people who work in complex working environments. They have to continuously update their knowledge according to the tasks at hand and incorporate that new knowledge into their own experience. Assistance and e-learning systems help the user with their on-the-job training.

In this paper we present an approach how to offer the learner the information which is most relevant to his current working context.

The application scenario of this paper is image interpretation. The work of an aerial image interpreter, perfectly fits the description of a complex working environment. The image interpreter must recognize objects (such as vehicles, buildings, site infrastructures etc.) and interpret their meaning based on aerial images. Different sensor and imaging parameters, a high variety in appearance of objects around the globe and time pressure create a challenging working environment. For critical scenarios (e.g. military) the information gathered by image interpreters can be crucial for the mission. An aggravation of the interpretation task is the use of different types of imaging sensors, for example radar-based sensors. One of the most demanding tasks is the analysis of complex facilities (such as airfields, harbors and industrial installations) based on *Synthetic Aperture Radar* (SAR) images. SAR is an imaging technology based on reflections of microwave pulses emitted by a radar sensor. It is used in a wide variety of application scenarios, e.g. pollution detection, cartography, ice layer and biomass monitoring as well as reconnaissance and surveillance. For the latter the radar images have some advantages over optical images, for instance no need for illumination (e.g. from the sun) and it is rather unaffected by weather effects like clouding, as for example Fig. 1. You can see an optical satellite image of downtown Karlsruhe, a city in the South of Germany. At some parts the area is clouded and the optical image is obviously affected by that. However, a radar sensor is able to penetrate the clouding and present the viewer with the area beneath the occluded area. Obviously this is of high interest for reconnaissance.

Nevertheless SAR has also some disadvantages. Though optical and radar images look alike at first glance in detail they differ substantially. Radar signatures contain certain effects which make them hard to interpret correctly. For an example see Fig. 2. You can see the optical image of the famous harbour bridge and its surrounding area in Sydney, Australia.

One example of a particular radar effect is the so called layover-effect which you can see in the flipped-down bridge or buildings (illumination is from the South). An additional curious effect is the wide white bar on top of the bridge arc which is actually the bridge's bottom.

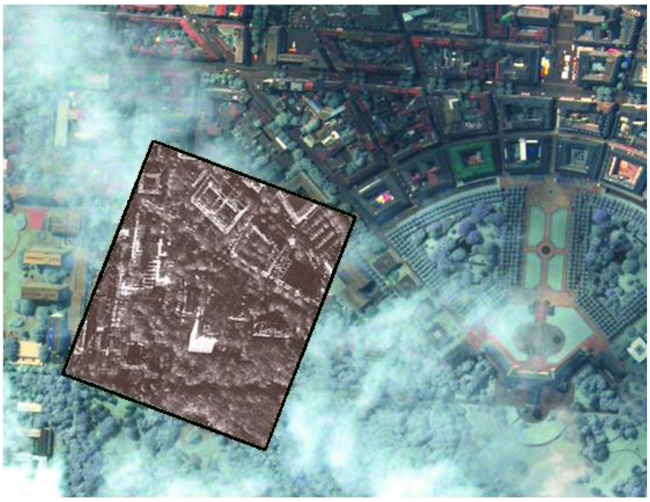


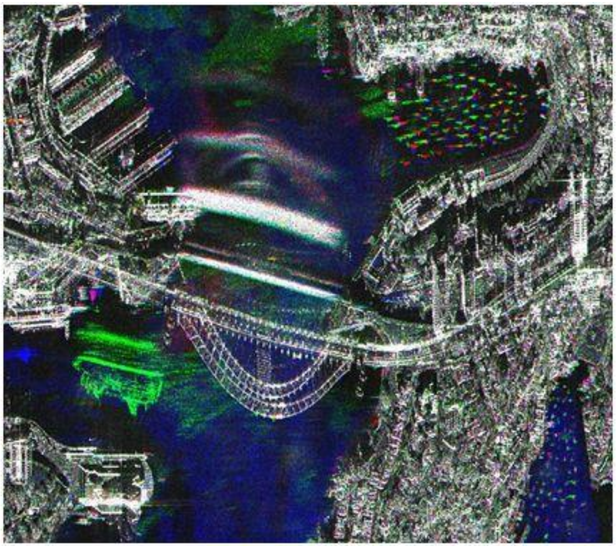
Figure 1. Radar vs. optical image: penetration of clouding (copyright by Cassidian, radar, and Eurimage, optical)

This is because the radar beam is being reflected by the water (layback effect). There are a lot more of these and other effects which have various kinds of manifestations for different surroundings [7].

To help the image interpreters assistance systems are being developed which provide a variety of tools, e.g. for image processing, image annotations or automatic classification [8]. However, the human-factor in the interpretation process still is seen as the essential element of correct and sound interpretation.

During an interpretation task the user constantly interacts with an assistance system. The system is then well aware of the progress, e.g. it knows which objects have already been identified or which have most probably been missed. This knowledge about the current progress can be used to provide the user with tailored and useful help and learning material, e.g. learning units of an e-learning system.

(a) Optical image (copyright by Google Inc.)



(b) Radar signature (copyright by Infoterra GmbH)

Figure 2. Optical image and radar signature of the harbor area of Sydney, Australia

We present an approach for semantic retrieval of learning units depending on the current working context. Our approach is based on an ontology with attached binding weights and semantic spreading activation [9]. It provides the user with qualified learning material which is intelligently retrieved based on the current working situation. This is in contrast to previous systems where the retrieval of information is solely based on text retrieval methods, thus considering a limited search space only.

The preliminary results of our work are shown in a prototype implementation of an assistance and learning system for SAR image interpretation. The aim is to optimally assist the image interpreter in his work by offering appropriate learning units for search objects in an image.

II. RELATED WORK

This paper presents an ontology-based retrieval algorithm which retrieves learning units relevant to the user's context by exploiting the structure of the underlying semantic network using the spreading activation principle. This enables the e-learning system to find learning material tailored to the user model.

Using ontologies in e-learning systems and linking assistance systems is a growing field of research [1], [11]. Without loss of generality ontologies can be used to model teaching knowledge [4] as well as to exploit Semantic Web techniques to enable for instance reasoning [13] and semantic search [12]. However, in the context of true information retrieval pure semantic search lacks the ability to rank the results. This renders the search process as plain data retrieval only. Combined with weights in the semantic network a mechanism based on the spreading activation principle [6] is able to produce scores for each accounted concept to enable a ranking of the results. Spreading activation in information retrieval can be seen in [5] and [9]. An approach similar to ours but without reference to context-aware e-learning is shown in [16] in which a search architecture is presented that combines classical search techniques with spreading activation techniques to execute semantic searches in websites.

Rather than using keywords as user input for the semantic search it is possible to provide the search terms automatically by a preceding system, e.g. by an assistance system. This can be seen as intelligently interlinking multiple assistance systems. Interlinking of assistance systems and e-learning systems has been presented by [11] and [14]. They give a description of how to interlink an assistance system [3] for use in image interpretation of SAR images with an e-learning application.

III. ONTOLOGY-BASED SEARCH MODEL

The search space for the presented semantic retrieval is spanned using an ontology which is based the *Simple Knowledge Organization System (SKOS)* [15] principle which provides an elementary vocabulary to describe basic structures of concept schemes. Because of its simplicity a SKOS-based ontology facilitates interoperability (e.g. ontology alignment) because only a limited set of ontology concepts and properties must be considered. Moreover the logic background of the ontology allows semantic reasoning [10]. As an example for reasoning see Fig. 3.

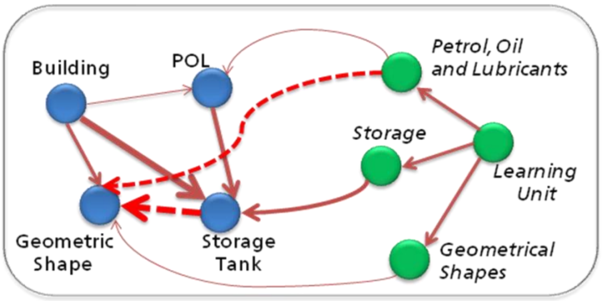


Figure 3. Simple example for reasoning in a semantic network. Solid lines are defined relations, dashed lines indicate relations automatically infered by a reasoner engine

Initially the concepts "Geometric Shape" and "Storage Tank" are not defined as to be related to each other. The relations between "Building" and "Storage Tank" and "Geometric Shape" are defined to be transitive. Because of that it can be inferred that "Geometric Shape" is transitively related to "Storage Tank". The actual type of relationship is then defined by the underlying logic in the ontology. A similar reasoning can be done for the learning unit "Petrol, Oil and Lubricants" which can be inferred as to be related to "Geometric Shape".

Basis for the search process is a domain ontology that describes the topic of the learning units. In the example case of SAR image interpretation it is an ontology of airfields enriched with simple geometrical aspects. The domain ontology only consists of the one concept *skos:Concept*; all other items are instances of this concept. The relations between instances are defined by the SKOS-relations *broader*, *narrower* (inverse to *broader*) and *related* extended with the self-defined relation *hasPart* to construct a partonomy.

Furthermore an identification label as well as synonyms and translations are introduced to offer a broader search space and to provide internationalization.

The second part of the ontology model describes the learning units. Each learning unit is an instance of the concept *Document*. The main annotation relations are *hasPrimarySubject*, *hasSubjectTags* and *hasKeyword(integer)*. The connection to exactly one concept of the domain ontology is established by the relation *hasPrimarySubject*. The relation *hasSubjectTags* assigns further topics and may link to several concepts – the number is not limited. The relation *hasKeyword(integer)* is not explicitly defined a priori, it is inferred during the reasoning process. The assigned integer value is the calculated binding weight for any concept accessible through relations starting from the learning unit by spreading activation. There may be further relations defined by a didactic ontology describing the educational dependencies to other units as well as properties like media type. These relations may be used for the visualization of search results but are not essential for retrieval.

IV. Semantic Retrieval

The primary objective of the semantic retrieval in the current context of retrieving learning units is to intelligently find those learning units which fit best to the user's needs. To find semantically relevant concepts the search process makes use of the ontologies' semantic net structure and applies the technique of spreading activation.

A. Semantic Spreading Activation

The spreading activation mechanism originates in cognitive psychology [6] to model spontaneous associations when the brain recognizes a word and activates other concepts linked to that term. In information retrieval spreading activation can be applied to expand the search space [2] [9].

The spreading activation process is applied to networks for labeled nodes and weighted edges. When activated, the weight, or "activation energy", of each activated node is propagated through the network to their linked nodes. In our semantic net we use real valued weights $w \in \Re$, where $0 \le w \le 1.0$. The weights can be discounted by multi-plication as the activation spreads through the network rendering the neighboring nodes most important and the most distant ones as irrelevant.

In a recursive fashion the propagation of the binding weights is computed for a node n_i and the linked node n_{i+1} as

$$O(n_{i+1}) = O(n_i) \cdot w[r(n_i, n_{i+1})]$$

$O(n_{i+1})$ denotes the output $O : N \to \Re$ of the linked node n_{i+1} and $O(n_i)$ the output of the preceding node n_i. Let N be the set of all nodes in the network and R the set of all relations between the nodes. An edge between two connected nodes $n_i, n_{i+1} \in N, i \ge 0$ is defined as a relation $r : N \times N \to R$. The function $w : R \to \Re$ yields the binding weight for a single relation $r \in \Re$. The base case for the starting node n_0 is defined as $O(n_0) = 1$.

Various strategies have been proposed when to stop the propagation process [16], e.g. stop when a specific concept is hit (concept type constraint) or when the output's lower limit is hit (distance constraint). Latter is used in this work. The spreading stops when the node output drops below a given threshold T, i.e. $I < T$.

Here, an ontology is used as the semantic network. The concepts are the nodes of the network whereas the properties or relations are the edges. Semantic spreading activation takes into account the meaning of the relations. Thus, in combination with a reasoner, the weights are semantically supplemented by means of their logical correlation. Inference in the ontology can yield to new relations between the nodes and therefore enhancing the search space drastically.

B. Semantic Retrieval

For each relation in the SKOS-based ontology weights are introduced which influence the rank of the found documents in the retrieval result (Table I). These weights were initially chosen due to the following considerations:

The primary subject is what the learning content is about and usually part of the document's heading, thus *hasPrimarySubject* gets the highest binding weight. The subject tags (relation *hasSubjectTags*) are equally directly associated to the unit and should therefore be considered more relevant than any other concept reached by the spreading activation process. Hence the relations between the domain ontology concepts are weighed less than the content ontology relations.

TABLE I. SEMANTIC SPREADING ACTIVATION WEIGHTS

Relation r	Origin	Weight w
domain:hasPrimary-Subject	content ontology	1.0
domain:hasSubjectTags	content ontology	0.9
domain:hasPart	domain ontology	0.8
skos:broader	domain ontology	0.8
skos:narrower	domain ontology	0.7
skos:related	domain ontology	0.75

Regarding the domain ontology the relations *broader* and *hasPart* are the ones with the highest weight. Both of them have a close correlation to the origin term.

For a specific relevant concept it is often helpful to take the more general concept (relation *broader*) into consideration, too, to get a more complete overview. And, for *hasPart*, if something as a whole is in focus, the parts of it may help to understand it better. Whereas *narrower* – although similar to *hasPart* and inverse to *broader* – may lead to a more specific term that is less helpful to solve the learner's actual problem. For example if the topic of interest is a cat it may be interesting that a cat has something to do with pets (*broader*) as well as the fact that a cat typically has four pads, a tail and long whiskers (*hasPart*). But one cannot automatically assume that the learner needs information exactly about the Norwegian Forrest Cat (*narrower*). The relation *related* can be seen as in between. Relation is not such a strong binding as a partonomy but may be much more helpful than the more specific concept. The initial weights were tested on an excerpt of a learning course and led to the expected results, so that only little modifications were necessary. Table 1 shows the experimentally determined weights.

The primary objective of the presented retrieval is to find relevant learning units and to rank the results based on their relevance regarding the current working situation. The algorithm calculates a binding weight for attached concepts for each learning unit depending on how the concepts are related to each other using the weights defined in Table 1. According to the spreading activation principle the terms in the ontology are activated and the activation energy is passed through the network degenerating in accordance with the weights of the relations. The result is a list of learning documents (learning units) where the most semantically relevant documents are ranked first.

Knowing the learning context it is possible to expand the search space by using a collection of search keywords given by the assistance system. $C = \{c_1,\ldots,c_m\}$ is the set of concepts of the domain ontology, $S = \{s_1,\ldots,s_n\}$ is the set of all search keywords and a subset of C $(S \subseteq C)$. $LU = \{LU_1,\ldots,LU_m\}$ are the learning units and R is the set of relations. The set of paths $Paths_{LU_j c_i} = \{P_1,\ldots,P_l\}$ are all possible connections from learning unit LU_j to concept c_i regarding the associated relations. The binding weight sum $B(LU_j, S)$ of a learning unit is calculated as

$$B(LU_j, S) = \sum_{i=1}^{n} b_{LU_j}(s_i)$$

with $s_i \in S$, and $b_{LU_j}(s_i)$ is the factor of each conducted spreading activation run regarding every search keyword. Further mathematical details about the algorithm see [14]. In essence the retrieved learning units are ranked by the binding weight sum $B(LU_j, S)$.

V. APPLICATION

The described retrieval process is implemented in a prototype for SAR image interpretation (see also section I).

A. Involved Systems

In our application scenario the image interpreters interact with an assistance system for infrastructure image interpretation and with an e-learning system which provides help and learning content.

As reliable algorithms for automated object recognition in aerial images are hardly available, these systems are often based on interactive approaches [3]. Such an assistance system supports image interpreters to perform a full analysis of a complex object arrangement, for example it helps to decide whether a radar image shows a civilian or military airfield. Singular objects (buildings, roads etc.) are marked by the user in the image and the system makes use of a probabilistic scene model to classify the function of the singular objects as well as the type of the overall facility. The classification results are presented to the user as recommendations.

The customized e-learning system [17] includes a comprehensive course about image interpretation in the domain of radar images for reconnaissance. It covers the very basics starting with physical principles of radar waves and continues to specific content like the actual radar signatures of buildings and vehicles. The e-learning application has been developed for education and information transfer in military image interpretation. It provides courses and training content as well as background information for SAR image interpretation.

Both systems go hand in hand in the education and knowledge transfer of image interpreters, and linking these two systems seems natural.

An intelligent retrieval enables the image interpretation system to provide the learner with context-sensitive learning material. Our implemented prototype interlinks an assistance system with an e-learning application. The data structures of the described systems were used to populate the domain ontology. The instances were amongst others collected from several existing data sources, e.g. from the taxonomic data structure of the involved assistance system and from already existing ontologies.

B. Intelligent Interlinking with Semantic Retrieval

The aim is to provide the image interpreter with context-sensitive help and learning material in an on-demand fashion when he is at a loss with his knowledge. For this the semantic retrieval algorithm finds the most relevant learning and help material. The result of the semantic retrieval is a list of learning units sorted by their relevance according to the spreading activation algorithm as explained before. Fig. 4 outlines how the user typically interacts with the involved systems.

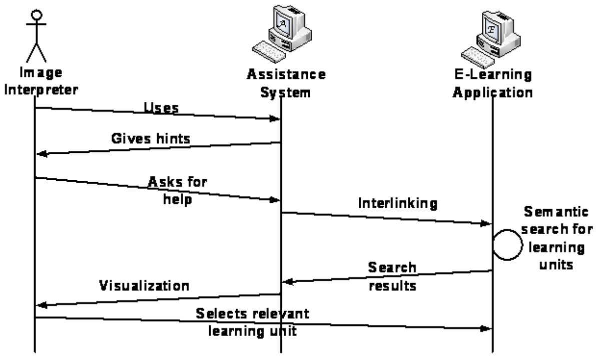
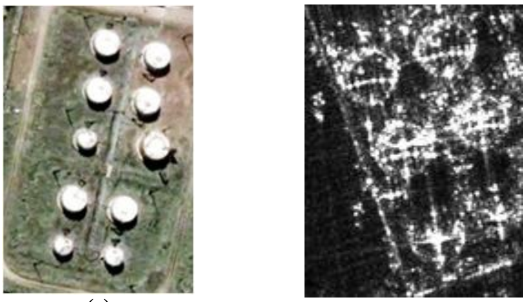


Figure 4. Interaction process. The image interpreter works with the assistance system and asks for help. The assistance system transfers the collected data to the learning system where the context-aware search is performed



(a) (b)

Figure 5. Storage tanks for petrol, oil and lubricants (POL). (a) optical image, (b) radar signature

The concept which has been selected by the user in the assistance system is assigned a higher initial weight to boost it to the top of the result list. However, based on the other concepts and their cumulated binding weights this boosted entry can actually be topped by concepts which are semantically more relevant. More semantic relevance means that they share higher weighted relations to a lot of other concepts which in turn results in higher binding weights.

C. Scenario & Use Case

As an example scenario the image interpreter has to analyze a site infrastructure of an airport. So far he has identified the runway, some barriers and some taxiways, but he is unsure about the other infrastructure components. The identification of some storage tanks for petrol, oil and lubricants (POL) would help him a lot to continue his task. This building is crucial for further interpretation because of its distinct characteristics to distinguish the airport type between civilian or military. For a civil airport the storage tanks are typically built above ground in contrast to the military case where they are hidden underground covered with soil. Fig. 5 gives an impression how storage tanks can appear from an aerial image.

D. Results

To offer the user quick and direct access to the help and learning material a sorted list of hyperlinks with direct access to the learning material is presented (Fig. 6) The entry “Permanent POL” is at the top of the list because on the one hand it is the primary search keyword and on the other hand it has a high semantic binding weight for the current context. The following entries represent learning material for different kinds of airfields where storage tanks are needed as well.

Particularly interesting is the learning unit “Geometrical Shapes”. This is listed because of a relation between the concept “storage tank” and “cylinder”. As one can easily understand from Fig. 5 the storage tanks have a cylindrical shape in an aerial image (both in optical and radar images).

E. Comparison to Simple Full-Text Search

To assess the quality of the results of the semantic retrieval approach a comparison with a full-text search engine has been carried out. To guarantee objectiveness only the retrieval part has been exchanged, everything else of the algorithm stays the same (search space pre-processing, presentation of the results etc.).

Apache Lucene[1] has been used as the full-text search engine. This engine allows for weighting of the query’s input terms which is also done in a similar fashion by our approach. Because full-text search engines only work on the syntactic level the results include only those entries for which there are text-hits in the underlying documents. For the described scenario an example output is shown in Fig. 6, right side. The entry “Permanent POL” gets a high score, because it has been found multiply times in the underlying document for the learning unit in the e-learning system. This is as expected. But yet in comparison to the semantic retrieval approach (Fig. 6, left side) no other semantic relevant content is found. The relevance of the other entries is much lower compared to the semantic retrieval result (compare the relevance indicator bars in Fig. 6 and the comparison diagram in Fig. 7).

The entries “Geometrical Shapes” or the different types of Airfields couldn’t be found because they don’t contain the term “Permanent POL” neither do they contain parts of it nor its word-stems. For a numeric comparison the relevance scores $s_i \in [0;1], i = 1,\ldots 10$ of the Top 10 results of both approaches are summed up. The semantic approach achieves a cumulated relevance score of $s = 6.6$ whereas the full-text approach gives only $s = 3.5$ (*cf.* Table II). The semantic approach outperforms the This shows the advantage of the semantic retrieval approach. Related information is found as well and, most importantly, can be ranked by their semantic relevance.

Figure 6. Results of semantic retrieval (left) and full-text search (right). The filled bars on the left indicate the relevance of an entry

[1] Apache Lucene search engine: http://lucene.apache.org

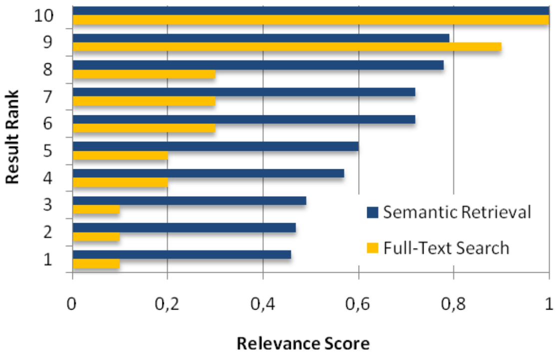


Figure 7. Comparison of relevance scores of the Top 10 results of the semantic retrieval and the full-text search

TABLE II. COMPARISON OF TOP 10 SUMED-UP SCORES (MIN SCORE 0, MAX SCORE 10)

Approach	Relevance Score Sum
Semantic Search	6.6
Full-Text Search	3.5

VI. CONCLUSION AND OUTLOOK

In this paper we presented a approach for semantic retrieval using the user's current working context. The semantic search is executed with a semantic spreading activation algorithm which uses an ontology as semantic network. Relevant help and learning material can be offered to the user. This content is tailored to the user's needs because the underlying ontology-based retrieval is aware of relations in the search domain and uses this knowledge in a way aligned to the learning process as well as to the specific domain. As the ontology is SKOS-based this allows for interoperability to other domains, direct reusability and feasible maintenance.

Still an open question is how to optimally determine the definite binding weights for the semantic spreading activation algorithm. Further work has to investigate how these weights can be automatically determined. Moreover experiments will be executed how to replace the manual ontology engineering process with a semi-automatic ontology learning process. The challenge in modeling the domain ontology is not simply to copy the content of a learning unit but to provide an overall view on the domain. Ideally the domain ontology already exists before learning material is developed.

For a truly objective comparison of both semantic search and full-text search, we plan to develop a ground truth data set (validation set). The definition of this validation set will be part of the next cooperation with the target user group, i.e. the image interpreters. Though the system has been already presented several times to the target user group – with promising positive resonance – a formal evaluation is still in the planning stage.

Crucial for the acceptance of the semantic search results is a simple and intuitive visualization of the search results. Only when the reasons for the ranking of the retrieval results can be made transparent to the users they will more likely accept this adaptive proposal and eventually – to some degree – trust the system.

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