Facilitating information exchange in assembly assistance by recommending contextualized annotations

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ABSTRACT

To maintain an equally high quality and efficiency in production processes despite the increased flexibility, information and knowledge are the company's strategically most important resources today. At the same time the intellectual resources are difficult to capture and manage, thus requiring intelligent assistance systems that support the individuals by providing suitable means for interacting with information. Therefore, it is of great importance to find an easy and fast way to record and store "new" information, as well as to provide a sensible mechanism to provide the information when needed.

We propose to use annotations in combination with a formalized knowledge base that represents the work domain to enable an intuitive (semi-)automatic information contextualization. This pre-condition enables a context-based annotation recommendation allowing for the annotations to be provided automatically for a better information communication. We propose a framework to integrate different factors to measure the relevance of an annotation according to a given situation and illustrate the results of our work using the example of an assembly assistance system.

CCS Concepts

•**Information systems** → *Ontologies;* **Data exchange;**
•**Applied computing** → **Enterprise applications;**

1. INTRODUCTION

In production, former rigid product processes are substituted by more flexible yet also more specialized processes to cope with the increasing mass customization. To maintain an equally high quality and efficiency despite the increased flexibility "information and knowledge are the firm's strategically most important resources today" [26]. Especially the knowledge an experienced worker has acquired over time is in this regard very valuable.

Even as the importance of information sharing is widely accepted [16, 24], motivation and communication barriers are still a great obstacle to sharing knowledge [9]. Hereby, it is of great importance to find an easy and fast way to record and store "new" information, as well as to provide a sensible mechanism to access the information.

We propose to use content annotations as an intuitive interaction means to digitally communicate context-related information. We understand annotations as content objects (e.g. text snippets, photos) containing additional information about a related entity.

To enable further contextualization and re-usability of the annotations, we propose to formalize the (information) domain by an ontology enabling its concepts and instances in turn to be annotated with additional content. The unstructured annotation data is contextualized by linking it to the concepts and instances of the ontology modelling the domain context. The ontology in turn enables context-based recommendation of interesting annotations, that is the information is not only automatically provided in the exact context that it was created in, but also in another similar or related context.

In [4] we proposed the usage of ontology-based annotations as missing link between the tacit knowledge of a worker and an intelligent assistance system. We showed the deeper integration of conceptual knowledge modeled in ontology-based annotations with procedural knowledge in cognitive architectures. This paper considers further contextual factors that influence the information's relevance and can be used to automatically recommend interesting annotations. We examine how annotations can be utilized as intuitive and easy means to contextualize content in an intelligent information system and propose measurements to quantify an information's relevance to a given situation. After introducing annotations as means for information communication in general, we present related work, before getting in detail for our use case of the work domain. We explain the architecture enabling the presented features briefly and explain details of our information selection framework integrating different contextual factors.

2. ANNOTATIONS

Regarding the demand for a simpler means of communication, basic forms of knowledge sharing using annotations has been performed by diverse groups of people for a long time [6]. When books were a common good that was frequently exchanged between people, annotations were written in margins to communicate thoughts and further information about the text. Since most people today own their own copy of a book, this annotation activity for communication purposes has been weakened. However, annotations can still be found anywhere where people want to communicate a missing or new information, e.g. on notice boards or as placard on a wall [8]. With the rise of the Internet and digital connectivity, information resources are shared again in groups. This opens digital possibilities for collectively discussing and enriching these documents by digital annotations.

A digital annotation is in this context an additional content that relates to an already existing content, increasing this existing content by providing an additional layer of explanation [2]. The annotation approach supports both communication sides in an intuitive way: annotations are easily created as well as accessed. Where complicated and strict forms or input masks confuse and demotivate, the annotation approach scores with the freedom to comment a content quickly and easily.

3. RELATED WORK

Besides looking at "traditional" collaborative annotation systems, we take a look at relevant technologies from other areas that tackle challenges of information communication. As communication consists of two parts, recipient and transmitter, relevant technologies address on the one hand context-aware information provision, while on the other hand the transmitting side addresses technologies to integrate and contextualize the information.

3.1 Collaborative Annotation Systems

Collaborative annotation systems usually enable users to enrich documents with additional content, such as comments. The user can browse the document's content while getting additional information created by others as marginal notes or similar to sticky notes on top of the original content. Famous examples are the collaboration features of MS Word or Adobe Acrobat Reader allowing the user to annotate documents. The user does not have to search for information, the annotation is usually visible where it belongs to or at least a marker is seen to point out the presence of an annotation. Web-based collaborative visual analysis systems, such as sens.us [11] and Many Eyes [23], support collaboration by allowing analysts to link text comments and graphic annotations to specific views or states of an interactive visualization. Other approaches mimic a board with post-it notes for brainstorming purposes, e.g. Wright et al.'s Sandbox [27].

All those systems have in common, that they do not handle a large number of annotations well. The visibility of the annotations or the original content as well as the "cognitive load" can be impaired, as the annotations are usually not filtered. Furthermore, the regarded "context" is very limited to the annotated content.

3.2 Context-aware information provision

Traditional knowledge management systems rely on the user to explicitly search for additional information by himself due to a demand regarding his current task [24]. The field of information retrieval researches methods to find information according to requested search terms. However, as the users require a more easy and intuitive means that minimizes this additional effort to get to the information, we are focusing on ways that automatically provide relevant information.

Recommender systems are a subclass of the information filtering systems that attempt to predict a "rating" or "preference" that a user would assign to an item. Based on this rating, a recommender system provides information to the user. Popular domains of research are movie, shopping, document and book recommendations [17]. Recommender systems usually produce a list of recommendations by collaborative or content-based filtering analysing the users' behavior in the past or the similarity of items. The traditional recommender systems usually disregard the notion of "situated actions" [20], the fact that users interact with the system within a particular "context" and that preferences for items within one context may be different from those in another context. Context-aware recommender systems [1] define a context in order to create more intelligent and useful recommendations. Here, contextual factors such as time, location, purchasing purpose are also taken into account. Cantador and Castells [7] for example propose semantic contextualization for their news recommender system news@hand.

Appropriate recommendations facilitate the discovery of relevant and interesting objects for the user. Yet, recommender systems rarely provide intuitive and simple ways to create and integrate new information. For our work, we make use of the simplicity of the annotations, but enrich them with ranking mechanisms to enable our system to recommend contextual relevant information to the user.

3.3 Integration and contextualization of information

Content annotations get some form of "context" by their reference to the annotated content, but there is usually no further contextualization. Thus, the annotations are well integrated in the annotated object, but the lack of indexing and further contextualizing results in a lack of possibilities for re-use or retrieval of the annotation's content [14]. There are more aspects for contextualization, such as coherencies, person, situation, time and environment.

A popular approach for contextualization of information is the enriching of documents with meta-data by associating ontology-concepts. Research in this field is summarized as "semantic annotation" [21]. The information's context is in many research approaches formalized in an ontology. Context-driven ontology engineering in turn researches how to model the context ontology [10]. The greatest challenge of semantic annotation is the (semi-)automatic (and right) annotation of the information object as manual contextualization is seen as too time-consuming [19].

Our work uses on the one hand content annotations for integration of additional information and on the other hand a domain ontology for further contextualization of the information similar to the functionality of semantic annotation.

4. INFORMATION COMMUNICATION USING ANNOTATIONS

Our objective is to provide the user with a quick and easy interaction means to access and capture additional information. The digitization of the annotation activity enables several new possibilities and benefits for utilizing them as information communication means. Since the annotations represent an own content, it is conceivable that they are not only of interest in reference to a single object. Their content can describe more than one object or give enriching information about groups of objects.

4.1 Use Case: Assembly Assistance

In production, there is an increasing demand for individual products, so that small batch sizes and flexible work processes are required. To ensure the quality of the work, the manual assembly should be supported by digital means. An assistance system can display information on the work process to optimize and control the process. User-authored annotations complement the work instructions. This may be

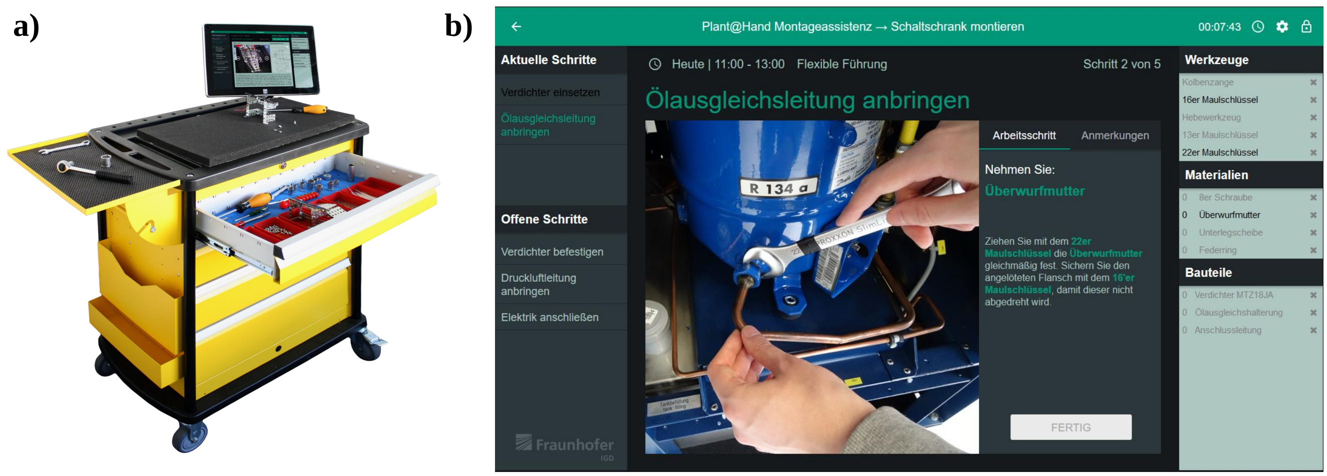

Figure 1: The Plant@Hand assembly assistant by Fraunhofer IGD: a) An assembly trolley is equipped with an information provision system that is supported by a cognitive architecture [4]. b) The display at the (mobile) work station shows information supporting the current work task step.

necessary because the work instructions themselves are not extensive enough so that they cannot be implemented without further assistance. Particularly newer employees do not have the experience to assess vague instructions. We want to offer the opportunity to explicate the implicit knowledge of more experienced workers. Workers gather in the course of their work experiences that are useful when implementing tasks. In this particular case of the assembly, this includes especially the experience with special tasks, materials and tools. If a person generates annotations explaining something noteworthy, everyone using the annotation system can benefit from the information. Hereby, the digitization of the annotation activity facilitates the re-usability of annotations and allows for mechanisms enabling their (context-based) retrieval.

For a better understanding we want to give the following example: A worker is supported in his assembly task by a system that provides them with information regarding the current work task such as by step-by-step instructions and manuals. An example of such an system is the Plant@Hand Assembly Assistant shown in Figure 1. As the worker is experienced with a specific material used in the current work task, we consider it very desirable that they explicit their knowledge regarding specifics of this material (e.g. be careful with tools as the surface of this material scratches very easily). The additional information is swiftly and easily added as annotation into the assistance system. As the material is used in different tasks, the information regarding this material is also of interest to different tasks than the one that resulted in the creation of the annotation. Therefore, this added information should be provided in the context of each task which is using the same material. As the user does not know of the existence of an interesting annotation, it cannot be assumed that he will search for it. So we automatically recommend relevant and interesting annotations to the user. This way, the user is well informed and additionally can discover new and interesting information provided by colleagues.

We utilize user-authored annotations and the "sticky-note" metaphor as fast and intuitive means to explicate tacit knowledge. As a consequence we encounter the challenge to (semi-) automatically contextualize the annotations to re-use them in different contexts. Furthermore, we have to find a way to measure the "relevance" of an annotation regarding a specific context to determine if it should be recommended.

4.2 Architecture solution

To achieve the explained features, we developed an architecture for easy and intuitive contextualization of information. A first design draft of our architecture was presented in [3]. The information has to be put in its right context to make it versatilely reusable. For this purpose we use a domain ontology modeling real-world objects and their relationships to formalize the information context. Real-world objects are in this context not necessarily only physical objects, but also abstract concepts such as a work task and its steps. From this ontology only that information has to be extracted that is actually relevant for a user's current situation. We utilize information retrieval mechanisms working on the structure of the ontology and the annotations attributes for this context-based information extraction. Figure 2 shows an overview of the conceptual structure. In summary, the following three steps have to be performed:

- Create knowledge base: Formalize domain and context knowledge as an *ontology*.
- Annotating: *Capture additional information* as annotations and match them with corresponding ontology concept(s) and instances.
- Providing information: Recommend *contextually relevant* information for a given situation by selecting and ranking the annotations.

We demonstrated, how the annotation activity can help to easily and intuitively insert information into the system. In the following we want to explain, how to get the relevant information out of the system.

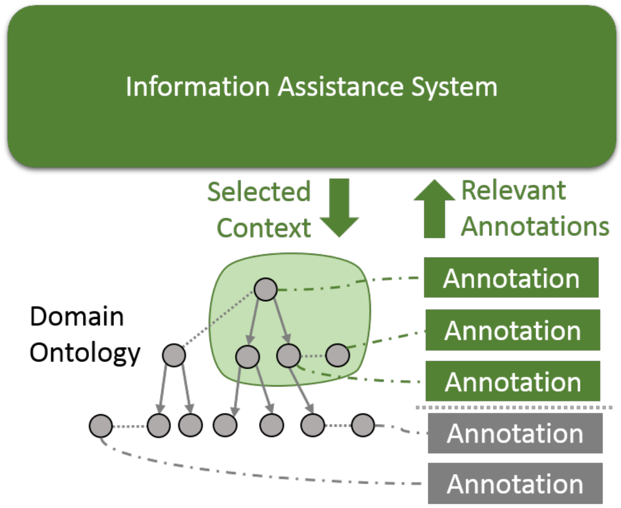

Figure 2: Concept of supporting an information assistance system by contextualized annotations. An ontology graph represents the information domain. Each annotation connects to at least one ontology concept to give an anchor to the information. The information assistance system requests additional information that is relevant to a given context regarding e.g. a specific task or object (green area). Relevant annotations (green) are selected in respect to the corresponding ontology concepts.

4.3 Information selection and ranking by contextual factors

If unimportant or too much information is shown to a person, they are challenged again to search for the relevant information themselves. The necessary additional effort causes the user to be fatigued and generally demotivated to browse the information. We use different contextual factors to measure the information's relevance to a given situation. We utilize a number of measures and combine them to an aggregated information selection measure.

4.3.1 Contextual factors

Ontology distance. Our first measure quantifies the relevance of the annotated ontology concepts to our current situation utilizing the ontology's graph structure. The ontology formalizes tasks and related things of a specific domain. Based on the concept c_1 of the ontology representing the current task, a concept c_2 of the ontology is considered to suggest relevant information if it is "near" the concept c_1, i.e. the measured distance between c_1 and c_2 is below a limiting value.

A $path(c_1, c_2)$ consists of a starting concept c_1 following different kind of relations to an ending concept c_2. The edges of a single relationship path $path_X(c_1, c_2)$ are all of the same type X. To measure the distance between c_1 and c_2 we have to differentiate between paths containing upwards and downwards directed (hierarchical) relationships ($X \in \{isA, partOf, ...\}$), paths containing horizontal (non-hierarchical) relationships ($X \in \{uses, ...\}$), and paths containing hierarchical and non-hierarchical (mixed) relationships. For **hierarchical** paths we use Resnik's [18] notion of a concept's information content IC. Being derived of the probability p it implicitly contains path length and depth enabling the weighting of upwards and downwards directed paths between two concepts c_1 and c_2. We utilize the method that Mazuel and Sabouret [15] derived from the Jiang and Conrath measure [13]:

$$W(path_{X\in\{isA,partOf,...\}}(c_1, c_2)) = |IC(c_1) - IC(c_2)|$$

For the **non-hierarchical** relationships a different weighting approach is needed. Mazuel and Sabouret [15] associate an individual weight TC_X for each relationship type X that is non-hierarchical:

$$W(path_{X\in\{uses,...\}}(c_1, c_2)) = TC_X \times \frac{|path_X(c_1, c_2)|}{|path_X(c_1, c_2)| + 1}$$

Hereby, TC_X represents the semantic cost of the relationship type X. For $TC_X = 1$ the cost is similar to a hierarchical relation. If $TC_X < 1$ the relation is assumed to be informative which is why the cost of the edge is reduced while a $TC_X > 1$ indicates a more costly relation.

To weight the distance between the ontology concepts c_1 and c_2 connected by **mixed relationships** the $path(c_1, c_2)$ has to be factorized into an ordered set $F(path(c_1, c_2))$ of n single-relation sub-paths where

$$path(c_1, c_2) = path_{X_1}(c_1, z_1) \oplus path_{X_2}(z_1, z_2) \oplus ... \\ \oplus\, path_{X_n}(z_{n-1}, c_2).$$

We call $path_{X_i}$ sub-path. The distance between c_1 and c_2 is the sum of the weights of the sub-paths of the factorization $F(path(c_1, c_2))$:

$$W(path(c_1, c_2)) = \sum\nolimits_{subpath \in F(path(c_1,c_2))} W(subpath)$$

If there are multiple factorizations possible, the factorization resulting in the lowest W is preferred. In a previous work [5] we focused on this relevance algorithm working a distance measure on the ontology. However, this path weight measure only gives a first ranking of which annotations are fitting for a given task. We found that additionally to this relevance measure, it is sensible to consider other factors for further ranking and filtering of the annotations. Therefore we consider further criteria to evaluate the quality of the annotations especially regarding their being helpful in supporting and educating the worker during his task.

Time. Hereby, time is an interesting factor, as an "old" annotation can be out-of-date while a "new" one has great potential to be more interesting. However, older annotations can also still be useful if their content is time independent. Therefore the "age" alone of the annotation is no reliable indicator of the annotations quality. Jan et al. [12] propose that useful annotations are reread. Therefore, an annotation that has been frequently read may be of more quality than an annotation that is infrequently read. They define two quantity factors T_1 and T_2 where T_1 indicates the duration since the annotation was last visited and T_2 describes the average time between successive readings of an annotation. We assume that an annotation has been read j times thus far. The current time is t and t_j represents the time of the j^{th} time that the annotation was read, T_1 and T_2 are defined as follows:

$$T_1 = t - t_j$$

$$T_2 = \frac{t_j - t_1}{j - 1}$$

T_1 and T_2 accept values greater than 0, where a smaller value of T_1 and T_2 respectively indicates a higher quality of the annotation regarding their helpfulness.

Viewer feedback. Furthermore, annotations can be rated by a viewer's feedback fb as helpful or useless. The feedback can be given explicitly by the user, giving him some option to vote. The feedback could also be derived automatically, where e.g. reading an annotation is regarded as positive feedback while ignoring an annotation is regarded as negative feedback. To use the individual reviews as a metric, the number of positive reviews and the number of negative reviews concerning a specific annotation are put in relation to each other:

$$fb = \frac{|fb_{positive}| - |fb_{negative}|}{|fb_{total}| + 1}$$

fb accepts values between -1 and 1 where a value close to 1 indicates a very positive regarded annotation while a value close to -1 indicates a very negative assessment of the annotation. A value close to 0 indicates that the number of positive and negative reviews is balanced.

Prioritization. Additionally, a prioritization can be assigned to the annotation at creation time. The annotation's creator can state, if the annotation contains information that is necessary to prevent errors (high priority) or information to help improve the work process (normal priority). The priority $prio$ can be quantified by one value per annotation:

$$prio = \begin{cases} 1 & \text{high priority (error prevention)} \\ 0 & \text{normal priority (process optimization)} \end{cases}$$

Expertise. The expertise of the annotation's creator affects the annotation's quality. If an expert has worked in the field for a long time, it is reasonable to assume that the knowledge they posses is valuable. Consequently, the annotations created by experts can be assumed to be especially valuable. As we presume that the elders will teach the younger employees and that the youngers will create corresponding annotations, the length of service is not necessarily a reliable factor. The annotation's quality improves if the annotation's creator has more experience with the annotation activity [12]. While the working expertise exp_w could be measured by the time a person has worked in the domain and can be taken from a personal profile, the annotation expertise exp_a of a $person$ could be measured by the number of annotations created and read by this $person$. Hereby, the creation of an annotation gives more experience than reading an annotation, e.g.:

$$exp_a(person) = |created(person)| + 0.2 * |read(person)|$$

Alternatively or additionally a self-assessment of the annotator regarding their expertise could be included. Both measures exp_w and exp_a give values greater than 0 where a value near 0 marks a lack of experience. A higher value of $exp_{w/a}$ corresponds with a greater experience of the annotation's creator and thus indicates a "better" annotation.

4.3.2 Rank aggregation

The different measures (W, T_1, T_2, fb, $prio$, exp_w, exp_a) quantify the annotations in different ways, so it is difficult to integrate them into a single measure. Rank fusion or aggregation is in information retrieval defined as the problem of combining a set of ranking lists in such a way to optimize the performance of the combination [25]. The traditional approach to integrate multiple ranking results from different individual rankers is to combine the ranking results (e.g., scores or ranks) produced by the individual rankers through certain rank aggregation techniques. Existing approaches fall into the categories (semi-)supervised and unsupervised. For the (semi-)supervised approaches it is expensive to acquire supervised ranked data. Therefore, we aim for an unsupervised approach.

For combining our contextual factors, we first pre-select topically relevant annotations by the ontology distance W. Subsequently, we compile a set of several rankings

$$M = \{m_W, m_{T_1}, m_{T_2}, m_{fb}, m_{prio}, m_{exp_w}, m_{exp_a}\}$$

of this pre-selected set of annotations $A = \{a_1, ..., a_n\}$ using the presented measures. The resulting rankings are combined utilizing an easy and powerful approach from voting theory: the Borda count [22]. The Borda count is an election method in which voters rank options in order of preference. The winner of an election is determined by giving each option, for each ballot, a number of points corresponding to the number of candidates ranked lower. Once all votes have been counted the option with the most points is the winner. In our case, the different rankings are the voters that sort the annotation options by preference according to the applied measurement. A ranking $m \in M$ of an annotation a determines the place of this annotation in the ranking $m(a) = m : a \mapsto r$ where $a \in A$ and $r \in \{1, ..., n\}$. We assign Borda points to the annotations according to their places in a ranking following the formula $1/place$, i.e. the first ranked annotation gets one point, the second ranked gets $1/2$ point, the third ranked gets $1/3$ point and the last place of n annotations gets $1/n$ points. The Borda points $bc_m(a)$ assigned to each annotation $a \in A$ for each ranking $m \in M$ can be defined as:

$$bc_m(a) = \frac{1}{m(a)}$$

The total Borda count score of each annotation a is then the sum of the Borda points of this annotation for all rankings. The original Borda count treats all classifiers/voters equal. To indicate a different "importance" of the measures, we propose to use a multiplier TX_m to weight each measurement before summing the individual Borda count values:

$$BC_a = \sum\nolimits_{m \in M} TX_m bc_m(a)$$

For instance, the feedback measure can get a parameter of $TX_{fb} = 2$ to balance that the time and experience measures are already very influential because there are two measures representing time and experience values. A higher Borda count BC_a indicates a higher relevance of an annotation a

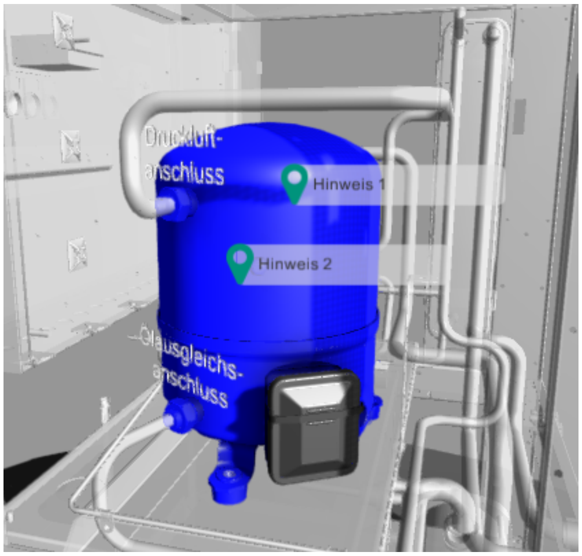

Figure 3: Annotations located at a 3D object of a compressor.

to a given context. Accordingly, we sort and provide the annotations beginning with the one scoring the highest BC.

4.4 Implementation Example

The practical implementation of the assistance system is carried out in a smart assembly trolley as seen in Figure 1. The Plant@Hand assembly trolley of Fraunhofer IGD is equipped with an information provision system that is supported by a cognitive architecture. A monitor displays information that supports the current work process. The annotations complement the work instructions as (side) notes. There are two modes for annotating. The user can locate an annotation directly on a 3D model e.g. of an assembly part and write their comments (see Figure 3). Secondly, you can create the annotation besides the work instructions to enrich the existent information.

Our example ontology models (amongst other tasks) the assembly of a compressor. Figure 4 gives an overview of this part of the ontology. It is defined what steps are part of the work task and especially what kind of materials (such as screws and nuts of different sizes) and tools (such as wrenches of different sizes) are needed for each work task step. Annotations are linked to the ontology concepts that represent the task and/or things that are annotated.

When a worker is supported by our information system during the work task step of attaching a compressor, our recommendation tool selects interesting annotations that have a low weighted ontology distance to the "Verdichter befestigen" concept of the ontology in Figure 4. For the filtering we choose empirically a limiting value of $W < 3$ where the horizontal *uses* relation has a semantic cost of $TC_{uses} = 1$. There are 12 annotations in our example to fit this limit. The IDs of these selected annotations are summarized in the following list sorted by their value of W:

- W = 1 (1 horizontal link):

  76, 78, 83, 84, 85, 86, 93, 94, 95, 96
- W = 1.79 (1 hierarchical link): 75
- W = 2.58 (1 horizontal + 1 hierarchical link): 101

Already with a limited number of annotations we see that there are many annotations with the same value of W as they have the same kind of relationship to the focused ontology concept. Some of them even annotate the same ontology concept. To still accomplish a sensible ranking of the annotations we apply some of the other introduced measures (W, T_1, T_2, fb, exp_w, exp_a) and rank them according to their aggregated Border Count BC. We applied a weight $TX_{fb} = 2$ for the feedback value while we left all other $TX = 1$ as we perceived the feedback measure as not influencing enough otherwise. The ranks each of the 12 annotations receives for the measures W, T_1, T_2, exp_a, exp_w, and fb, as well as the resulting BC score is summarized in the following Table 1.

ID	W	m_W	m_{T_1}	m_{T_2}	m_{exp_a}	m_{exp_w}	m_{fb}	BC
95	1	1	6	9	10	3	1	3.71
96	1	1	7	1	6	5	10	2.71
76	1	1	5	8	1	7	9	2.69
93	1	1	4	3	3	12	3	2.67
84	1	1	12	12	3	9	2	2.61
83	1	1	9	2	9	2	8	2.47
78	1	1	11	11	11	1	12	2.44
86	1	1	8	4	5	4	6	2.16
94	1	1	2	10	8	10	7	2.11
101	2.6	12	1	5	6	8	4	2.07
85	1	1	3	6	12	6	10	1.95
75	1.8	11	10	7	2	11	5	1.32

Table 1: The ranks each of the 12 pre-selected annotations receives for the different measures, sorted by the resulting BC score.

The additional measures enable a ranking of the annotations with identical values of W. Furthermore, the annotations are assessed based on more than only one of their attributes. Because of this, the annotations "95" and "96" are favored even as they score badly in one aspect. Interestingly the annotation with the id "101" is even favored above annotation "85" which is nearer to the topic, but scores worse in the entirety of its attributes. This can be sensible to achieve a recommendation of high quality annotations that score good in more than one aspect. The beforehand filtering of the annotations by their W value ensures that only topic relevant annotations are chosen as initial set. For the further sorting we consider the other contextual parameters to be equally important to find interesting and high quality annotations. If the distance to the topic is seen as much more important the method can be adapted to weight the distance more by using a $TX_W > 1$ or use the BC value only to sort annotations of the same W value.

5. SUMMARY

In this paper we introduced an approach for using annotations as an easy and intuitive means to capture new information and to recommend interesting annotations according to a given context. We enable a broader re-usability of the annotations by automatically recommending them to a user according to his current situation. Our recommendation mechanism includes a selection by a relatedness measurement of the annotations to the current context as well as a ranking of the annotations according to our assessment

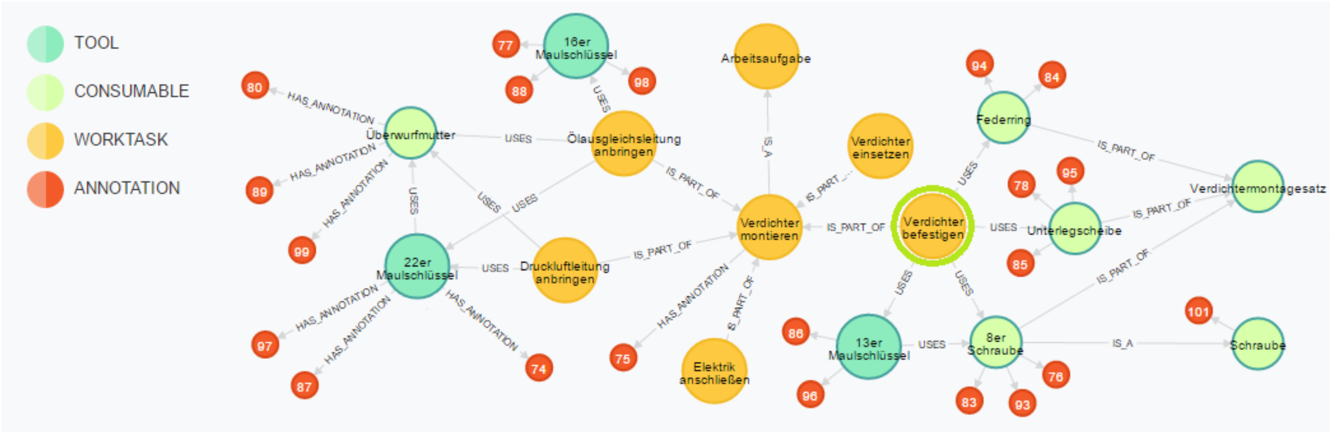

Figure 4: Part of our assembly domain ontology consisting especially of work task concepts and materials and tools. Annotations contain additional information describing the real life counter parts of those ontology concepts. The concept used in our sample calculation is circled green.

of several attributes. We showed how our method enabled a helpful information provision to an assembly work task. The approach is easily adaptable to other domains. Where human tasks are supported by an information system it is sensible to give the possibility to add missing or new information by annotations. The automatic recommendation of interesting annotations is also generally beneficial as users usually do not know what information to look for or are not motivated to search themselves for lack of time. Recommended annotations not only help to keep the user well informed, they support the further education of the users by providing diverse information and especially by encouraging the exchange of experiences.

In the near future we intent to perform experiments to explore which measures, parameters and weights are reasonable for specific use cases. Especially the scaling of the area of interest has to be researched in a real environment, i.e. which value of W is the limit. It can also be considered to enable the user to adjust this parameter to fit his information demand. Workers in training for example could be interested to get more annotations to enhance their learning process.

6. ACKNOWLEDGMENTS

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