Taking Printed Books into Internet of Things

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***Abstract*—The aim of this paper is to describe a development process for bookAI, a system that takes printed books into the Internet of Things by applying smartphones, different identification methods, mobile internet, and cloud computing. BookAI connects the books into the Internet with NFC, RFID or barcode identifiers that are read by smart phones. The challenge in the book identification is recognizing the object from various coding sets and connect it to the existing metadata and content: In bookstores the EAN-13 barcodes are used, while in libraries there are several RFID standards as well as several barcode formats in use. Metadata and available digital content, related to the physical object, are read from different sources. The received data is not in a structured format, which means there are incomplete records and missing data that makes challenges for further computing. BookAI applies semantic computing to build a network of detailed relations between the books and personal reading interests. The personal reading interests are recorded as self-evaluations of the users, so bookAI requires several evaluations before it can make personalized suggestions. After the system has learned the user preferences, it enables searching interesting books from the libraries, bookstores or even from private book shelfs by optimizing the personal content and context map taught by the user. One of the challenges, in designing and end-user product, is user interface. The first version of the bookAI was evaluated complex to use, so the second revision is built based on end-user feedback. Computationally built semantics and ontologies save remarkably time when modeling big domains or big data like library collections. The future research is focusing in building methods to collect more complete datasets about books as well as designing the overall user experience of the system.**

Keywords; smartphones; mobile internet; books; libraries; cloud computing

I. Introduction

The Internet of Things (IoT) is the network of physical objects embedded with electronics, software, data and connectivity. In IoT, each thing is uniquely identifiable and is able to interoperate within the existing Internet infrastructure. This has been expected to extend the understanding of the physical world, leading to innovative services and increase in efficiency and productivity [1][2].

The relation between books and internet, as well as smart museums are widely studied [3]. However, in the discussions of IoT applications printed books are mentioned only in relatively small number of studies [4][5]. In fact, in terms of information retrieval, we can say there is no big difference between real-world pages or books compared to web pages or social media.

Social media services, such as YouTube and Flickr, contain enormous number of content related to each other. Search engines can list numerous pieces of content that matches more or less perfectly to keywords. A common method to increase information accessibility in social media applications is tagging. However, when tags are used only as single words, we easily end up to information overload.

Furthermore, in social media, we do not have standardized way to tag content. In fact, tagging the content in an optimal way is a difficult task for several reasons. Cultural background, educational background, community and its social behavior, as well as context where tagging is constructed affects enormously the selection of tags. The term ‘context’ can be understood in many ways. In this study, context is understood to cover all conditions, physical, social and mental, which can be considered as causes or consequences of activity.

The structure of the paper is following: in Section 2, related work and background information is presented. In Section 3, research objectives are described. In Section 4, the research results are presented and explained. In Section 5, conclusions are discussed.

II. Related Work

In this study, semantic networks based approach is used to model a user's personal interests in order to optimize the recommendations the user gets. In this approach, the originality and novelty is in getting a detailed understanding of what a users likes, prefers or needs to know in order to reorganize the content map and recommendations to meet the needs of the user. In other words, this is more related to user centric computing than information retrieval. Author’s previous studies on the subject has been made especially related to learning sciences [6] and information overload [7][8]. The fours on this section is on describing the known challenges from existing research: 1) Challenges in tagging the content, where also finding the most important words from the texts is considered as tagging, 2) challenges in adaptive media, 3) challenges in behavior modeling and 4) known work in connecting media objects to digital systems.

Tagging is very subjective and numerous research is done in order to improve user experiences and information retrieval in social media [9][10][11]. Unclear, or in worst case misleading, tagging leads to information loss in social media. Especially, constructing storytelling or narration between pieces of user generated content becomes impossible without socially constructed tagging semantics. Furthermore, tagging can be seen as a one key element when building platforms for personalized services, but understanding semantics brings new dimension to text analytics. Recently, Google had added semantics into its searches, but many educational subjects require more detailed conceptual models for successful content personalization. Furthermore, there are other personalization and adaptation solutions for media [12].

Adaptive and/or personalized media is always designed to produce optimized user experiences. In adaptation, the mechanics optimize the content with technologies that can be divided into two main groups: indirect (static) adaptation and direct (dynamic) adaptation. In indirect adaptation, the rules are fixed beforehand by developers. Indirect adaptation is based on statistical rules, decision trees, state machines, or the cumulative effects of several fixed functions. In dynamic adaptation, the mechanics track the user and optimize the content according to a user's behavior. In other words, dynamic adaptation is based on machine learning. Dynamic adaptation requires at the very least 1) a user model, 2) a context model and 3) artificial intelligence [13][14][15].

Semantic networks, also known as conceptual graphs, are knowledge representations constructed with directed or undirected graphs [16][17]. Semantic neural networks (SNN) are generally used for processing natural languages [18]. However, SNNs, as knowledge representations are relatively extensible and they have been used, for example, to model mental disturbances [19]. On the other hand SNN can be utilized to model the characteristics of users, profiles, patterns of behavior, and skill levels in order to support or challenge the performance of individuals.

Parallel methods, such as behavior recording [20][21] and behaviour mining [22][23] have been studied and used in the game industry for some time. Behavior recording refers to game development and behavior mining usually refers to intrusion detection in networks, etc. Because the idea of adaptive educational systems is to produce individual and optimized learning experiences [24][25], high end user models, as well as methods, are relatively complex. In the high end solutions intelligence is based on neural, semantic, or Bayesian networks, as well as genetic algorithms [26][27][28].

Applying NFC and RFID in end-user products has been studied e.g., in social mobile games with educational dimensions, with shared social experience and physical interaction between players [29][30][31]. Furthermore, location based NFC games and location aware NFC UIs allow users to play games in mixed reality in that they can interact with both real and virtual objects within that location [32][33][34][35]. In these environment NFC and RFID are used to extend mobile devices as media controllers, but not only because of the object. The key idea has been to connect the textual content of the physical objects into digital systems.

III. Research objectives

The aim of this paper is to describe a development process for bookAI. The technological challenge of this study is related to the complexity of the system: i) Recognizing a book with NFC, various RFID and barcode formats, 2) collecting unstructured and incomplete information from various sources, 3) modeling context maps as well as user's personalization maps based on incomplete data and 4) visualizing complex phenomena in a way that end-user can find it useful.

This is a design study including i) algorithm and system design, ii) experimental tests with real world big data and iii) piloting study with small number of real-world users.

The first version of the system was evaluated with small (n=10) end-user group that consist of Finnish librarians. The aim of the pilot study was to proof that the concept works. Test persons reported only bugs and challenges in usability. Furthermore, they were asked to give ideas and improvement comments for next prototype that should be piloted with library customers in Fall 2015. No survey data was collected after piloting.

When the content consists of millions of objects and billions of relations, compared to previous studies with only thousands of objects and hundred millions relations [25][36], the computational management of the relations between the objects becomes a challenge in terms of smooth user experience. When redefining the relations between content objects, this system can be managed through semantic networks in a computationally efficient way. The data-sample size is more than 2 million books from Satakunta regional libraries. This sample data contains with more than 500GB of descriptive data about the books, and the data enables to build more than 3 billion connections between books. This requires also system design from Big Data point of view.

The challenge in the book identification is recognizing the object from various coding sets and connect it to the available metadata and content: In bookstores the EAN-13 barcodes are used, while in libraries there are NFC, several RFID standards as well as several barcode formats in use. Metadata and available content (e.g., abstracts) are read from different sources. The received data is not is a structured format, which means there are incomplete records and missing data that makes challenges for computing.

IV. Results

Results section is presented in the order required to start to use the system: First the context model is explained, secondly how the system learns the user preferences and finally how it adopts to user's needs. The results and feedback from the pilot study is presented with the topic it belongs to.

Context model design starts with defining the dependencies (or proximity) between single objects (books). In this study, the proximity is defined by name of the book, keywords and other metadata given by book publisher/librarians and abstract text. All this information is not necessary available: metadata is subjective, It varies between different libraries and bookstores. Also, there are differences in abstract texts and surprisingly also with book names. The differences in book names is related to age of records. Some of the oldest records we use was form eighties, and so there were misspellings, additional info in name-record, etc.

The proximity is calculated by searching for similar words in similar sections (name, keywords, abstract) and weighting the findings according to frequencies of the words. An example of the idea is visualized in Figure 1.

The upper book (Birds of Europe) do have tags/keywords (Europe, biology, geography,…) and an abstract text. The centre book (Capital cities Europe) do have a same word in the name (Europe), two same keywords (Europe, geography) and two same words in the abstract. When summarizing the total proximity value, keywords are as valuable as name and abstract together. So the total score in this example is 7 hits. In the final algorithm, the words are also weighted based on their reversed frequency, which means words like “news” or “sports” do have less weight than words like “Oslo” or “Owl”, so this also effects the final scoring, but is excluded from this example in order to keep this simple.

The book in the bottom (Capital in the twenty-first century) has one same word in name that Capital cities Europe (Capital) and the same word (capital) in abstract. The total proximity score for the book is two, even though we know there is relatively little common between capital cities and money. That’s why there is always a minimum value for proximity that has to be passed before the proximity has been validated. In this case (without word weighting) it would be 4 or 5 hit points. In other words, couple of common words is not enough to show proximity in this algorithm.

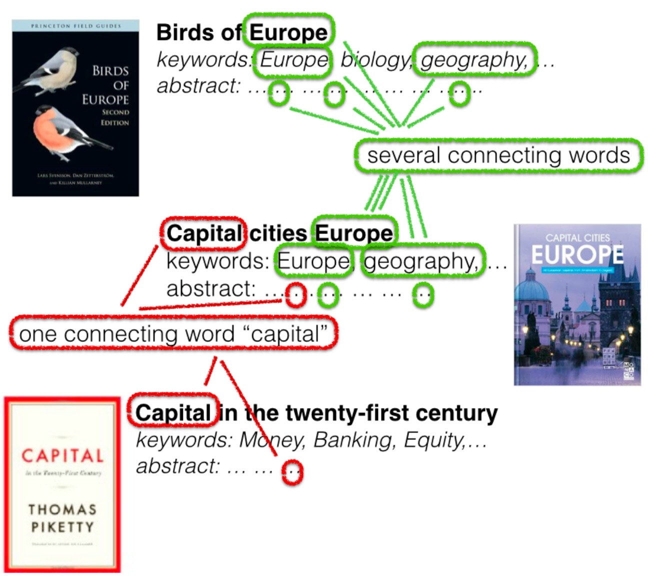

Figure 1. Calculating the distance between the objects

In the example, there is no common words between “Birds of Europe” and “Capital in the twenty-first century”, which is relatively obvious. Naturally, pronouns, numerals, participles, etc. are excluded from the meaningful word set. The biggest difference in this study is that the non-meaningful words are excluded computationally. If a word occurs frequently in texts, the word is useless from text prediction point of view. Rare words, however, are useful but alone they might be misleading, like previous example on word “capital”. That’s why weighting the words as well as requiring several common words seems to give reasonable results as a full computational approach.

The biggest challenge in building proximity map between the books is in the total number of relations between the books. For example (Figure 2, in Finnish) the 10 nearest book to “Birds of Europe” forms a network of 46 relations when maximum is 50 relations between 10 books. In other words, the biggest challenge is not to find proximate books, but rank the nature of the proximity and manage the big data.

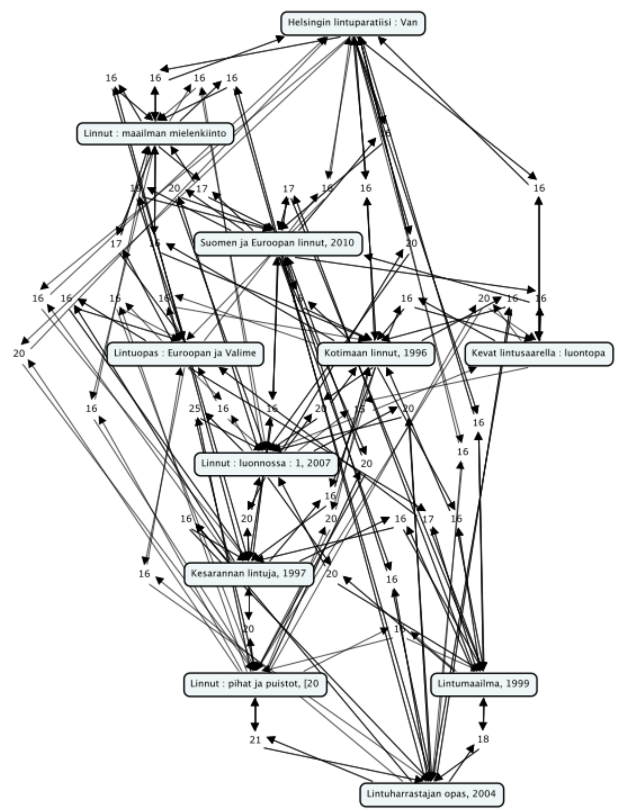

Figure 2. Example on sub-network of books in neighborhood of “Birds of Europe”

Based on the data from bookAI, there are approximately 3 000 000 000 two-way relations between 2 000 000 books, which means, on average, that each book does have approximately 750 single relations to other books. Naturally, when just looking for the most proximate books, we don’t need two-way relations for all these thousands of books: rank

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ordered index is enough for defining the data and at the same time, performance is fast.

In other words, when building a end-user version of this solution, we won't use the full computational model for all the calculations. Most of the information presented in end-user user interface is pre-computed indexes which ensures the smooth performance of the system even with high number of users.

Another challenge is visualize complex data. N-dimensional networks are not interesting for most of the users, so the information should be presented in more understandable form.

In our prototype application, we have transformed n-dimensional network into 2-dimensional grid/heatmap (Figure 3, in Finnish). The idea of the grid is that in the the most proximate books are always neighboring and the heat (from red to yellow) shows the proximity to the requested books (Birds of Europe in this case). In other words, we flatten the information in some sense, but increase the instant readability of the data.

Figure 3. Example visualization on two-dimensional network neighborhood of "Birds of Europe" (names in Finnish).

The texts in Figure 3 are in Finnish, including the name of the book, author of the book, ISBN and language and location of the book. The heatmap behind the text is the most important factor when visualizing how proximate the books are. What closer to red the background is, that proximate the books are. If the background is white (no heat) there is not much common between the book in whit background and the center book (the book we are focusing now).

One major challenge with this data visualization is, that we loose some books: if a book is 9th proximate to starting book and also 9th proximate (or less) to it's successors, it will be dropped to the grid even though there will be books on the grid that has very little to do with the starting book. This challenge will be fixed in future studies, when we'll bring different type of visualizations into end-user testing and so we can empirically find what kind of visualizations users really like.

The context model is a general model about the context we're dealing with, it is built with unsupervised machine learning model, where the learning is based on given dataset. The personalization / adaptive model, described next, is built over context model by applying supervised learning -type of methods, where learning is based on input given by the user.

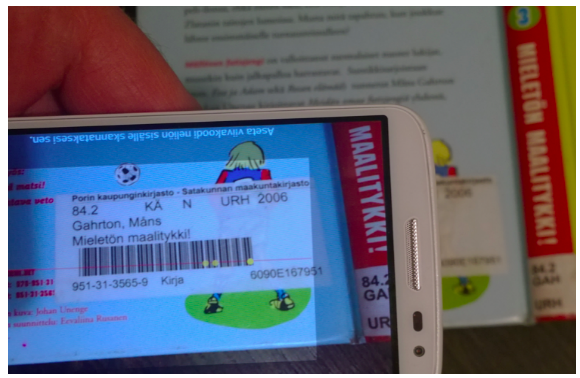

Figure 4. Scanning a book with mobile phone.

In end-user application, the process starts by recognizing the book (Figure 4) we are working with. The recognition of the book is done by scanning the barcode behind the book (either library dependent identifier or global EAN barcode) with which we can find the ISBN of the book. The scanning is done with mobile device's camera. The mobile device is the connecting object between books and the internet.

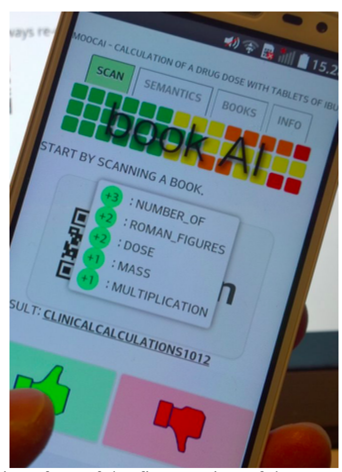

Figure 5. Main interface of the first version of the system and evaluation of a scanned book.

ISBN number is the key element of the context model, while in user model side words are the key elements. This is crucial in order to e.g., deal with multiple ISBNs related to same book. In fact, is is common that there are tens of different ISBNs related to the same specific book because of e.g., new editions, which automatically get a ISBN number.

After the book and ISBN is recognized user can evaluate the book by giving thumbs up or thumbs down for a book (Figure 5). In this example we are evaluating a book about medical treatment, so when giving thumbs up (user likes the book or get the information he/she wanted), the application shows the words that get additional positive weight from the user.

Each evaluation (thumbs up / thumbs down) increases the information about user's preferences. In other words, algorithm learns user preferences case by case and improves the explanative power of user model case by case.

In the first version of the bookAI, the scanning button and evaluation was placed in the front of the main screen. Users were expected to either scan a new book, evaluate a previous one or open a new tab. The proximity maps was placed on the next tabs, which user should open in order to see the scanned maps and personalizations. The user interface was found too complex to use and test users reported that is was difficult to recognize which book they are evaluating or what proximity map they were following.

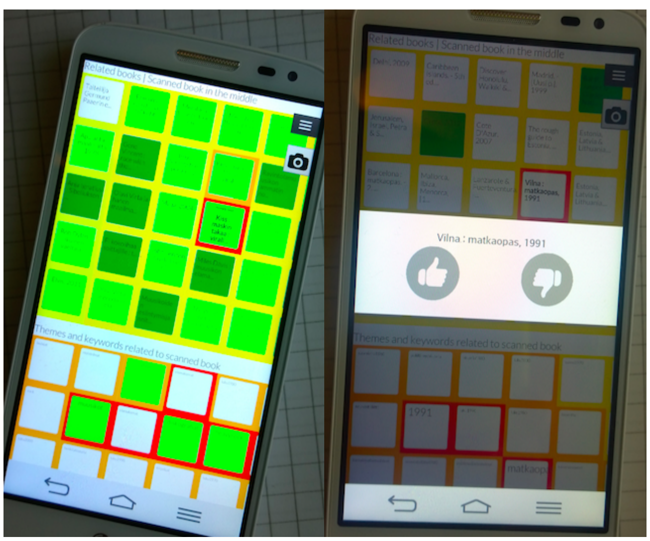

Figure 6. Main interface (left), evaluation (left) in the revised bookAI user interface.

This map can be seen as personalized reading assistant showing always new books to read. From user experience point of view, it is important to show also books that user may not like. If showing only books that are probably liked, user will sooner or later miss all the interesting new books that are close to liked books but with vocabulary not exactly the same.

In the revised version of the bookAI (Figure 6) the user interface was rebuilt in order to override all these reported challenges. The main screen in the heat map with smaller grid, consisting only 30 most proximate books, followed by semantic heat map, showing the words and themes connected to scanned book. In the top-right corner of UI there is two icons: upper icon is for menu, from which user can see the list of canned books. The list is ordered from newest to oldest, so user can immediately see what heatmap he/she is following. The camera button takes to scanner and evaluation is immediate action after scan. User can override the evaluation any time, but in this we we ensure user knows for sure what book he/she is evaluating.

In Figure 7, an example about fictive reader's opinions about bird-books: User has evaluated altogether 10 bird books, from which 4 can be seen in Figure 6. Books covering natural environments (or environment is not mentioned) are thumbed up and books related to built environment are thumbed down.

In Figure 7, the background heat map (context map) and the texts are the same as in Figure 3. The personal layer consist of a) books with blue background, representing the probability that user don't like the book, b) green backgrounds representing that user most probably like the books (what lighter green that higher probability) and c) grey backgrounds showing that user data about the book is noisy.

About the personalized map user can immediately see which books he/she likes and how the books are related to centre book.

Figure 7. Example on two-dimensional personalized network neighborhood of "Birds of Europe" (names in Finnish)

From machine learning point of view it is crucial to give extensive evaluations. If the system starts to get only positive evaluations from very narrow context and the context would get even narrower all the time, there is soon nothing to learn any more. From information theory point of view the system needs entropy in order to learn more.

The recommendation system can be used outside the library e.g., in online education (Figure 8) as well as for presenting additional information already online (Figure 9).

When the online content is added into bookAI as a 'book', we can connect physical books in the library into the digital course (Figure 8). The idea in case of online learning is that user thumbs up content that he/she understands and thumbs down the content he/she don't understand. The application, in this case, shows the books related to online content and also predicts if user understands the specific topic of the book.

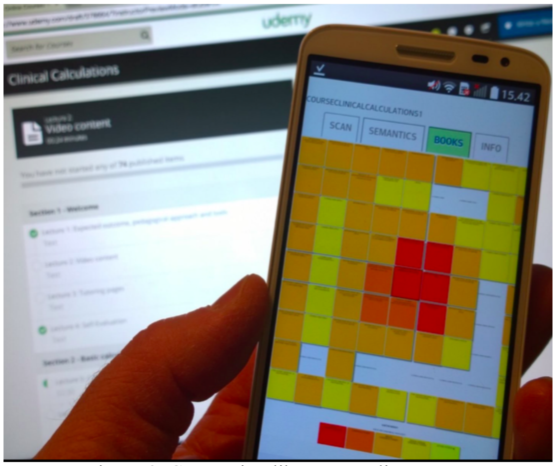

Figure 8. Connecting library to online course

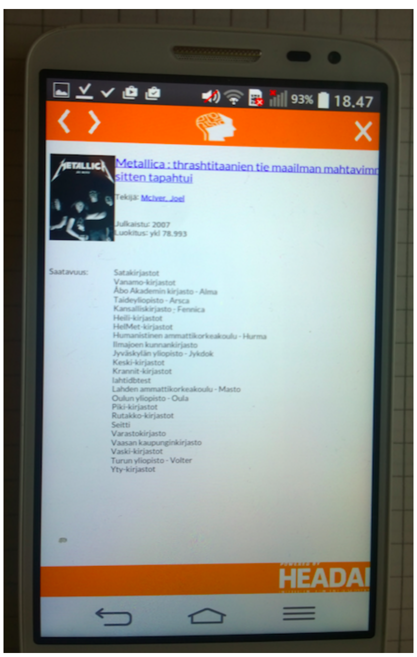
Figure 9. Connecting libraries existing online content to books.

The same goes with e.g., household appliances: When scanning the barcode of microwave oven, a user will get a heat map about books related to cooking, microwave technology and ovens. The personal layer depends on user's personal preferences (cooking or technology or both). In all cases, the books will be connected to other objects via user's personal mobile device.

Furthermore, existing online content about the books, can be connected to bookAI. With this feature, user can immediately find additional information about the book without logging into library's information system. The additional content is can be accessed directly from heatmaps.

V. Conclusions

The aim of this paper was to describe the production and design challenges of bookAI. The bookAI maps the content automatically, algorithm based, which means no manually designed semantics or ontologies are needed. Computationally built semantics and ontologies save remarkably time when modeling big domains or big data like library collections. This kind of non-supervised learning requires, however, a large learning data and the idea is not applicable for small or medium size learning data. For example, single web page is far to small on content in order to be mapped, but conference proceedings with hundreds of papers may be enough.

When comparing bookAI to more known literature recommendation systems, such as e.g., Amazon Bookstore's crowd sourced 'the buyers of this book also bought the following books' -type of recommendation systems, we can immediately point out two major benefits.

First of all, when crowd sourcing recommendations, we need a big user data in advance. Without big user data, we can give suggestions for only a small number of book. The minimum requirement for such data would be equal to the number of books and in that case there should be exactly two bought books per user and no overlapping at all. Naturally this never exists in real world and the required data would be remarkably bigger. With bookAI we can start recommendations immediately and the recommendations get more exact during the use of the system.

Secondly, when recommendations are based on previous buys, the first buys starts to control the next buys and finally there is no room for real, empirically grounded, recommendations. In other words, the crowd sourced recommendation data is corrupted by the meas how it was collected. BookAI can bring recommendations based on the semantic proximity of the books and empirically collected user preferences. This gives the user better understanding on what is available without limitations of somewhat misleading way to use empirical data.

BookAI learn user skills and competences based on self-evaluations (thumbs up / down) and connects preferences to general context map. Using machine learning for personalization enables developer to bring any content to system. Pre-fixed preference lists, defined by users, are always to restricted and out of date. The downside on using supervised machine learning is that it requires tens of evaluations before the system has learned something about the user. When the user has spent some time to do evaluations (teaching the system), the user model is transferrable to other contexts as well, so in long run, the time it takes to start teaching the system pays off.

The visualization of the data is designed to be easily understandable. This, however, requires more research. According to user feedback received from librarians, the data is readable but maybe still a bit too complex for average library user. This indicates that more research has to be done in visualization side in order to build a successful consumer platform.

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