

# Proceedings of the 1<sup>st</sup> Workshop on Semantic Personalized Information Management

**SPIM 2010**

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## **Preface**

Search engines have become an essential tool for the majority of users for finding information in the huge amount of documents contained in the Web. Even though, for most ad-hoc search tasks, they already provide a satisfying performance, certain fundamental properties still leave room for improvement. For example, if users perform general questions, they get frequently lost in navigating the huge amount of documents returned and typically stop their search after scanning a couple of result pages. Basically, results are ranked based on word frequencies and link structures, but other factors, such as sponsored links and ranking algorithms, are also taken into account.

Standard search engines do not consider semantic information that can help in recognizing the relevance of a document with respect to the meaning of a query, so that users have to analyze every document and decide which documents are relevant with respect to the meaning implied in their search. Therefore, they also struggle for matching the individualized information needs of a user.

Since users are different, and want to access information according to their experience and knowledge, different techniques for constructing user models, analyzing user profiles and deriving information about a user for the adaptation of content have been proposed. An emerging approach is to use Semantic Web and Web 2.0 technologies to model information about users.

## **Program Committee**

We would like to express our thanks to the members of the program committee that helped in putting the program together and enhancing the quality of the workshop

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# Program

**9:00 - 9:30** Opening and Greetings (Workshop organizers)

**9:30 - 10:00** Keynote (Organizer)

**10:00 - 10:30 ADAPTIVE USER-CENTRIC LAYOUT OF NEWS WITH AESTHETIC CONSTRAINTS**

*Thomas Strecker and Sahin Albayrak*

**10:30 – 11:00 Coffee Break**

**11:00 – 11:30 POPULATION AND ENRICHMENT OF EVENT ONTOLOGY USING TWITTER**

*Shashi Narayan, Srdjan Prodanovic, Zoë Bogart and Mohammad Fazleh Elahi*

**11:30 – 12:00 PERSONALIZED LEARNING TO RANK APPLIED TO SEARCH ENGINES**

*Christian Scheel, Ernesto William De Luca, Sahin Albayrak, Sascha Narr, Orlando Macone, Dennis Egert and Matthias Hohner*

**12:00 – 12:30 PERSONALIZED MULTI-DOCUMENT SUMMARIZATION USING N-GRAM TOPIC MODEL FUSION**

*Leonhard Hennig and Sahin Albayrak*

**12:30 – 13:00 SUMMARIZATION AND VISUALIZATION OF DIGITAL CONVERSATIONS**

*Vincenzo Pallotta, Rodolfo Delmonte and Marita Ailomaa*

**13:00 – 14:30 Lunch Break**

**14:30 – 15:00 SEMANTIC TV ENGINE: AN IPTV ENABLER FOR PERSONALIZED RECOMMENDATIONS**

*Juri Glass, Torsten Schmidt, Stefan Marx and Fikret Sivrikaya*

**15:00 – 15:30 A DESKTOP-INTEGRATED SEMANTIC PLATFORM FOR PERSONAL INFORMATION MANAGEMENT**

*Noemi Scarpato, Maria Teresa Pazienza, Armando Stellato and Andrea Turbati*

**15:30 – 16:00 Coffee Break**

**16:00 – 17:00 Open Discussion**

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# A Desktop-Integrated Semantic Platform for Personal Information Management

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## Abstract

The Semantic Web dream of a real world-wide graph of interconnected resources is – slowly but steadily – becoming a concrete reality. Still, the whole range of models and technologies which will change forever the way we interact with the web, seems to be missing from every-day technologies available on our personal computers. Ontologies, annotation facilities and semantic querying could (and should) bring new life to Personal Information Management, supporting users in contrasting the ever-growing information overload they are facing in these years, overwhelmed by plethora of communication channels and media.

In this paper we present our attempt in bringing the Semantic Web Knowledge Management paradigm at the availability of diverse personal desktop tools (Web Browser, Mail clients, Agenda etc...), by evolving Web Browser Semantic extension Semantic Turkey to an extensible framework providing RDF data access at different levels: java access through OSGi extensions, HTTP access or dedicated JavaScript API for the whole range of tools from the open source suite of Mozilla applications

## 1. Introduction

The Semantic Web is becoming ever and ever a concrete reality: with SPARQL reaching W3C recommendation early this year (Prud'hommeaux, 2008), languages for data representation and querying have finally reached standardization, while interests and research in Semantic Web technologies have definitely migrated from mere ontology development (which has now met industry standards) aspects to the discovery and devise of applications which can both show and exploit Semantic Web full potential.

Despite this encouraging trend of Semantic Web models and technologies, these seem to be missing from applications which we use every day on our personal desktop computers. Hopefully, they could surely contribute to improve the quality of personally managed data by supporting users with powerful vocabularies (ontologies) which can be extended (by adapting them to personal needs) and shared through different applications and with other people.

Recently, several efforts have been spent towards definition of applications and solutions for implementing the so called Semantic Desktop (Iturrioz, Díaz, Fernández Anzuola, & Azpeitia, 2003; Sauermaun, 2005; Groza, et al., 2007).

All the Semantic Desktop approaches cited above usually aim at centralizing an RDF Semantic Repository as a local information management resource, which can be accessed by diverse applications on the desktop sharing common data but providing different services over them.

In this work, we present our proposal for a Semantic Integrated Environment for the Mozilla suite (though it can be exploited also by other applications) of desktop utilities (Firefox, Sunbird, Thunderbird etc...). This project originated from our ontology tool Semantic Turkey (Griesi, Pazienza, & Stellato, 2007), which was originally thought as a Semantic extension for the Firefox Web Browser and lately evolved into a multi-layered extensible framework for Knowledge Management and Acquisition.

The current framework which still backbones Semantic Turkey, is two-fold in its offer: by first, being of interest for ontology developers and domain experts, since it aims at facilitating the process of knowledge acquisition and development, and, on the other side, providing an extensible infrastructure over which SW applications, needing and relying on rock-solid web browsing functionalities as well as on RDF management capacities, can be developed and deployed. In this paper we present the different service layers which are exposed by current version of Semantic Turkey, and how they can be accessed by Mozilla-based and other external applications to give life to a new multimodal Semantic Desktop.

## 2. Other works

Beside the main research stream which is conducted in this field, other researchers are focusing on finding new powerful and versatile ways of interaction with the user, which can exploit the advanced possibilities given by the Semantic Desktop. as in (Iturrioz, Díaz, & Fernández Anzuola, 2008) where the seMouse (Semantic Mouse) offers a Mouse extension (cabled at Operating System level) allowing for easy classification, authoring, retrieval etc... of files on the desktop and of their textual content. Since it is acting at OS level, this mouse extension is not limited to any specific working environment/application: no matter whether the user is working with Word, Power-Point, Netscape, etc, the semantic button is available for annotation/authoring and the user does not have to move to a new dedicated editor when annotating.

Though intuitions such as the one of seMouse centered the limitations of past approaches with respect to their concrete usability in real life, most recent trends tend to favor the centralization of core knowledge services, thus giving the possibility to all desktop applications to feature even very specific and advanced functionalities while interacting together with (and possibly be coordinated by) the central semantic repository.

The most recent (and sensible) effort following this trend has been represented by the FP6 EU funded project NEPOMUK (Groza, et al., 2007) where a massive range

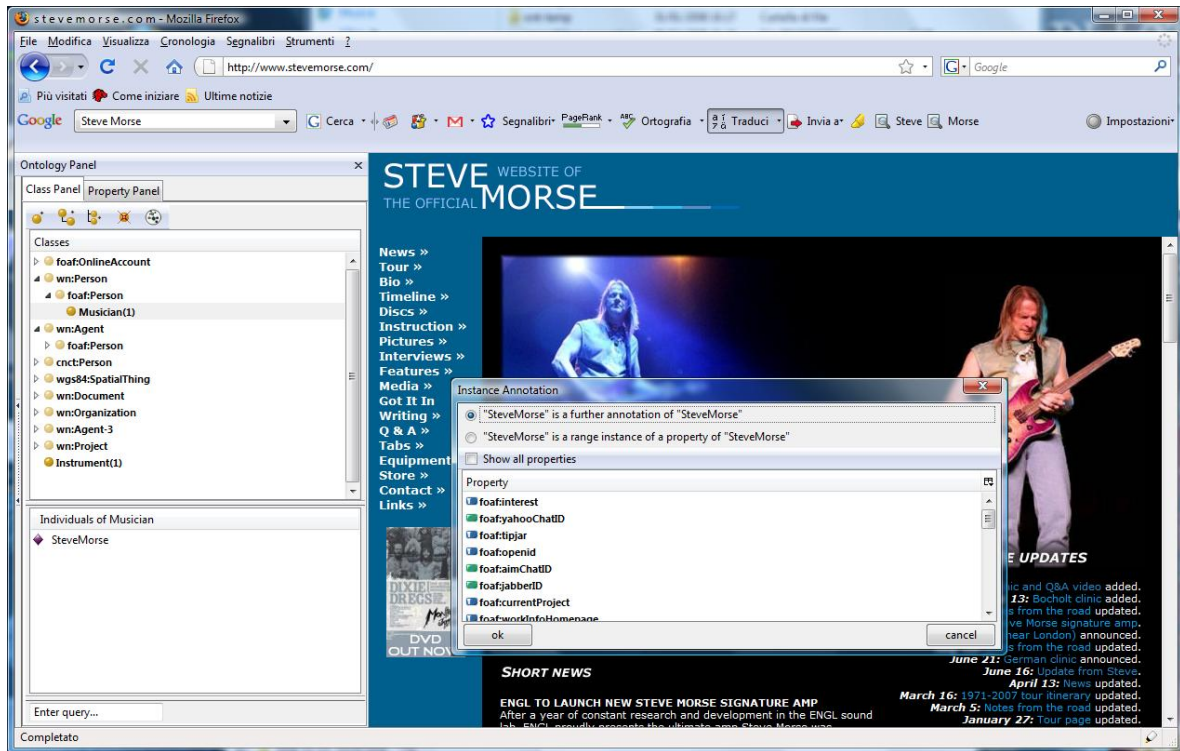


Fig. 1 Semantic Bookmarking with Semantic Turkey

of technologies comprehended several extensions for existing applications centered around an RDF Data server activated by the Operating System.

Eventually, a Semantic Desktop could probably rely on a combination of both approaches, which are not in contrast with each other.

Another important aspect of research is the definition of the metamodels which should contradistinguish such powerful organization systems: in PIMO (Sauermann, van Elst, & Dengel, 2007) a multilayered ontology model is presented. The PIMO (Personal Information Models) Ontology offer a first distinction between three conceptual categories: Native Resources (files, e-mails, contacts etc...), Native Structures (representing organizational schemas for the above, such as folders, bookmark folders, tags etc...) and lastly the Mental Model provides a cognitive representation of the knowledge a user is intended to manage, which is independent of (though may be linked to) the above.

PIMO is structured according to five layers which account for different levels of specification (such as for the first three levels: *PIMO-Basic*, *PIMO-Upper* and *PIMO-Mid*) as well as for the specific exigencies of the user (*PIMO-User*) and of the working/social environment where he acts (*Domain ontologies*).

The necessity for addressing different facets of knowledge in organization systems is also present (though in a less general perspective, which is specifically aimed at enterprise organizations) in (Apostolou, Mentzas, & Abecker, 2008), where a single Knowledge Object (KO) may be characterized according to descriptors which are provided by different facets of the whole ontology. These facets are: Business, Domain, Community, Context and Content, describing *where* a KO may be used, according

to *which conditions* its use is suggested, the *range of users* which may be interested in it, and the like.

### 3. From Semantic Bookmarking to Knowledge Management and Acquisition

Semantic Turkey was born inside a national project – funded by the FILAS agency (Finanziaria Laziale di Sviluppo) under contract C5748-2005 – focused on innovative solutions for browsing the web and for collecting and organizing the information observed during navigation.

The prototype for the project immediately took the form of a Web Browser extension allowing users to annotate information from visited web sites and organize it according to a personally defined domain model: Semantic Turkey paradigmatic innovation was in fact to “obtain a clear separation between (acquired) knowledge data (the WHAT) and web links (the WHERE)” pointing to it. That is, to be able, through very easy-to-use drag’n’drop gestures, to *select* textual information from web pages, *create* objects in a given domain and *annotate* their presence in the web by keeping track of the selected text and of its provenience (web page *url*, *title* etc...). We coined the expression “semantic bookmarking” for this kind of activity.

Due to its proverbial extensibility, the Firefox platform (<http://www.mozilla.com/en-US/firefox/>) had been chosen as the hosting browser for our application, while Semantic Web standards and technologies were the natural candidate for representing its knowledge model.

Semantic Turkey (Fig 1) was thus born. Standing on top of mature results from research on Semantic Web technologies, like Sesame (Broekstra, Kampman, & van Harmelen, 2002) and OWLim (Kiryakov, Ognyanov, &

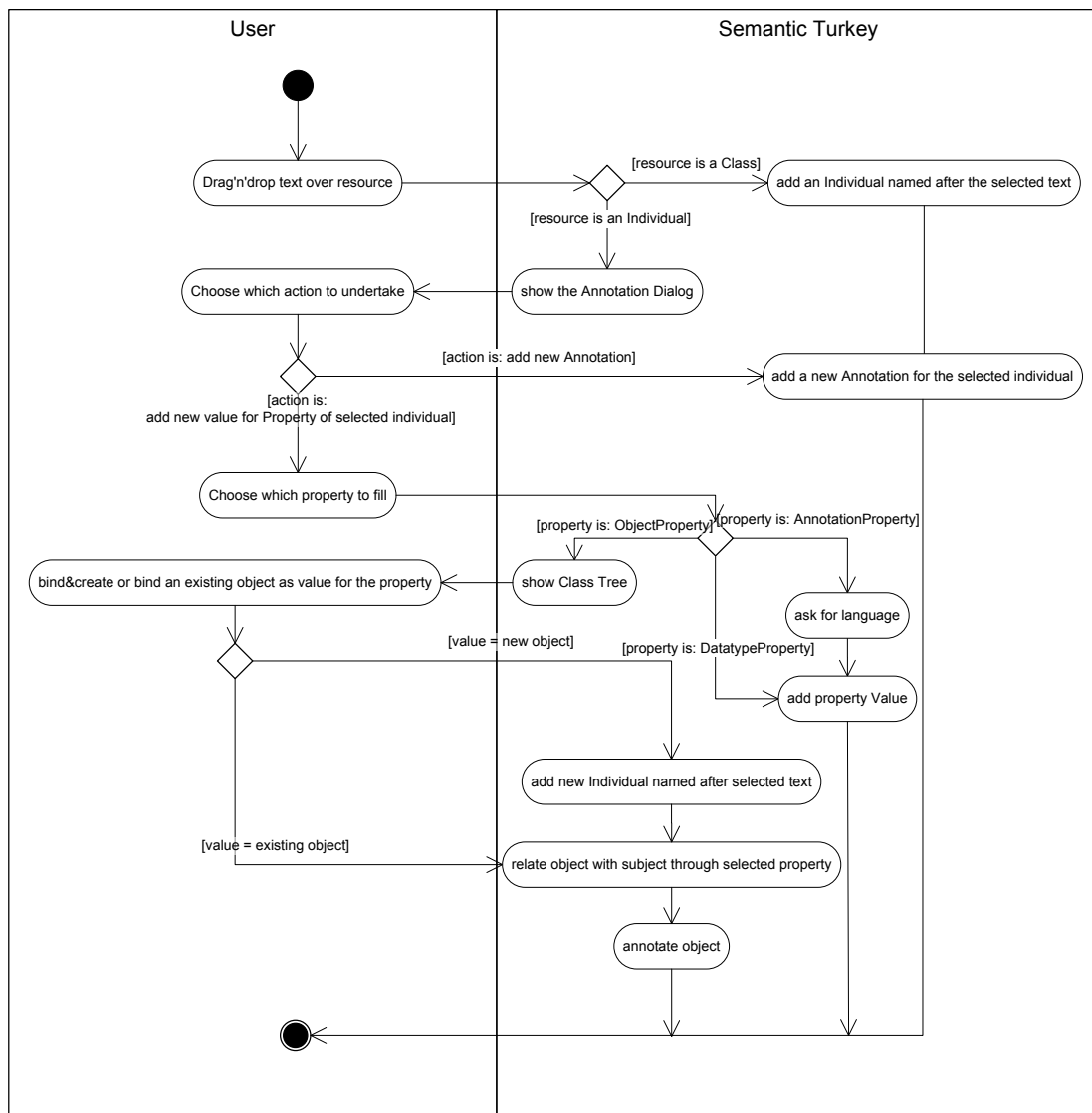


Fig. 2 Activity diagram for semantic bookmarking/annotation

Manov, 2005) as well as on a robust platform such as the Firefox web browser, ST (Semantic Turkey) differentiated from other existing approaches which are more specifically tailored respectively towards knowledge management and editing (Gennari, et al., 2003), semantic mashup and browsing (Dzbor, Domingue, & Motta, Magpie: Towards a Semantic Web Browser, 2003; Huynh, Mazzocchi, & Karger, 2005) and pure semantic annotation (Ciravegna, Dingli, Petrelli, & Wilks, 2002; Kahan & Koivunen, 2001), by introducing a new dimension which is unique to the process of building new knowledge while exploring the web to acquire it. By focusing on this aspect, we went beyond the original concept of Semantic Bookmarking and tried to amplify the potential of a new Knowledge Management and Acquisition System: we thus aimed at reducing the impedance mismatch between domain experts and knowledge investigators on the one side, and knowledge engineers on the other, providing them with a unifying platform for acquiring, building up, reorganizing and refining knowledge.

Fig. 2 shows the different annotation/knowledge acquisition possibilities offered by the functionalities based on interaction with the hosting web browser. In the new version of ST, support for all kind of properties has been introduced and reflected in the bookmarking facility: when a portion of text is selected from the page and dragged over an individual, the user may choose (as in the old version) to add a new annotation for the same individual or to use the annotation to fill one property slot for it. In the second case, the user can now choose from a list of properties (see small window in ) the one which will be filled: this list includes those properties having their `rdfs:domain` including one of the types of the selected instance, but may be extended to cover all properties (letting the inference engine do the rest). If the property selected for enrichment is an object property, the user is prompted with a class tree (rooted on the `rdfs:range` of the selected property) and is given the possibility of creating a new individual named after the text selected for the annotation or to choose an existing one: in both cases the selected individual is bound –

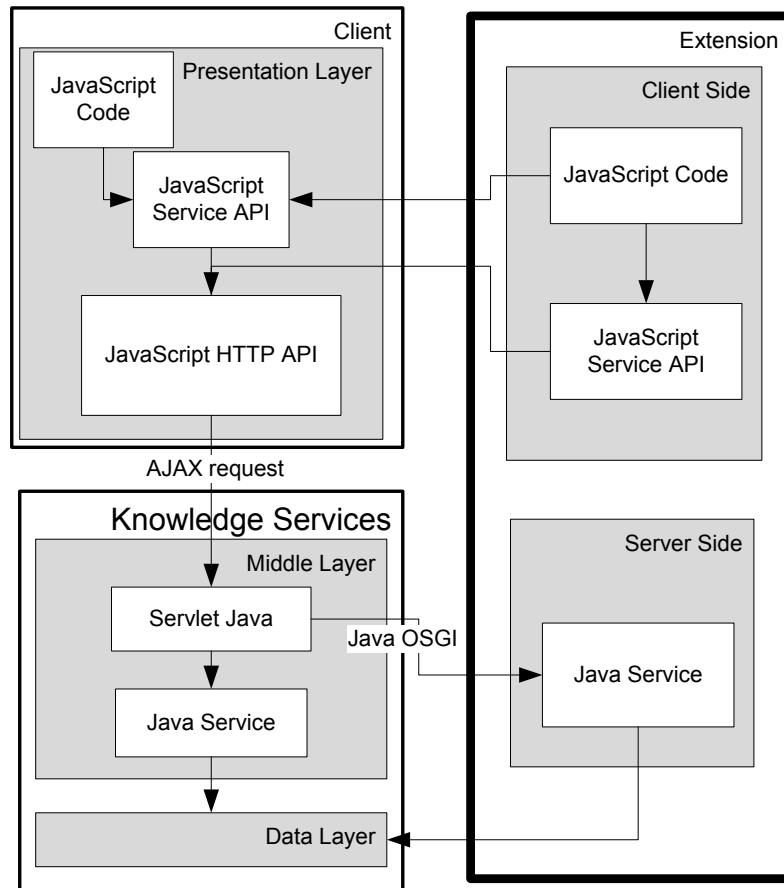


Fig. 3 Architecture of the different Access layers for Mozilla Semantic Desktop

through the chosen property – to the one where he originally dropped the text; a bookmark is also added for it, pointing to the page where the object has been observed. Even in this case, the user may choose to visualize the entire class tree and not the one dominated by the range of the property: the inference engine will automatically assign the pointed instance to that range.

The above interaction modalities for knowledge acquisition/annotation/bookmarking can be used in the main Ontology Editor tool, as well as be exported as *pluggable functional objects*, into other client applications willing to adopt them in simpler user-centered environments for Personal Data Management. The next sections describes the different service layers which are available through Semantic Turkey and how they can be used to propel Semantic based desktop applications.

#### 4. Service Layers for Applications

The main underlying application consists of an RDF framework made of an HTTP application server (which in Semantic Turkey is automatically started through Firefox) based on Java technologies and of a set of client layers facilitating access by users or third party applications.

The whole extension mechanism of the framework is implemented through a proper combination of the Mozilla extension framework (which is used to extend the user interface, drive user interaction, add/modify application functionalities and provide javascript API for the whole

set of Mozilla desktop utilities) and the OSGi java extension framework (OSGi RFC0112, 2005) which provides extension capabilities for the service and data layers of the architecture. A comprehensive description of Semantic Turkey architecture can be found in (Griesi, Pazienza, & Stellato, 2007) and in (Pazienza, Scarpato, Stellato, & Turbati, 2008). In this section we focus instead on the different layers (see Fig. 3 above) and extension points which characterize Semantic Turkey as an open RDF framework with specialized functionalities for Personal Information Management.

##### 4.1. Javascript extensibility

Thanks to javascript dynamic programming paradigm, where functions are first-class citizens of the language, functionalities such as the annotation resolver described in section 3, can be dynamically imported and associated to logically coherent events in different client applications of the Mozilla suite. The *pluggable functional objects* mentioned in section 3 can thus be considered independent components which can be exported and be reused in web browser as well as in email clients. For example, highlighting text in a web page within Firefox, and dropping it over a class, could invoke the same behavior when selecting text in emails from within Thunderbird. Conversely, reacting to changes in the underlying knowledge could produce different effects depending on the client platform which is connected to the



Semantic Desktop: finding RDFa (Adida & Birbeck, 2007) data on a web page from within the web browser, detailing scheduled events, could lead to the import of that data inside the semantic desktop's ontology, and the consequent export of this data inside other desktop applications for calendar management such as Lightning or Sunbird<sup>1</sup>.

## 4.2. OSGi extensibility

OSGi compliance is obtained through the OSGi implementation developed inside the Apache Software Foundation, called Felix (felix.apache.org/).

Two main extension points have been introduced: an *OntologyManager Extension* and a *Service extension*.

The *OntologyManager Extension* point allows different triple-store technologies implementing low level RDF data storage, to be plugged to the system. Current implementations provide support for Sesame2, OWLIM and Jena (McBride, 2001) – through its NG4J extension (Bizer, Cyganiak, & Hartig) supporting named graphs – technologies.

The *service extension* point allows new java services to be plugged to the system, this way further desktop applications can automatically deploy and add their functionalities to the main service.

The set of services offered by the Knowledge Server provide high-level, macro operations, other than standard ontology management ones. The pure triple-level RDF data layer is not obfuscated by macro-operations, and is directly accessible through java API as well as replicated in a set of basic knowledge services for RDF manipulation.

A third extension point allows for the registration of plug-ins: these act as collectors for set of services sharing a common logical ratio. While standard service extensions are sort of add-ons to the main application and are always available unless deactivated or removed, extensions bound to plug-ins are activated/deactivated according to the status of the plug-in. Plug-ins are assigned to projects and their status and persistent information is stored with the metadata for each project.

The project-based behavior of the platform comes from its ontology-editor ancestry, while when it is being used as Semantic Desktop Server, a single project (called *main-project*), is always active and automatically started at system initialization. Each application based on the Semantic Desktop and needing customized services thus registers itself as a plug-in and installs all of its required services via OSGi.

Finally, a data extension point allows for the declaration of *support* and *application* ontologies which are loaded by the system to drive its behavior and the one of its extensions and connected applications. These ontologies are not treated the same way as imported domain/user ontologies and are explicitly registered for their role. Registering an ontology through this extension point has a variety of consequences: these are loaded automatically at system startup even if they are not explicitly imported by the edited domain ontologies and application ontologies' content (and content classified after application ontologies' concepts) is not shown explicitly but only

managed and exposed indirectly through applications' services.

We enabled this classification of ontologies since all the data which is available through the Mozilla Semantic Desktop (MSD from now on) is available as RDF triples: it was thus mandatory to separate the knowledge which is being managed by the user, from the one which is being used by the Semantic Desktop to coordinate its activities. Despite this "conceptual separation" – ontology spaces are managed through the use of *named graphs* (Carroll, Bizer, Hayes, & Stickler, 2005) – having a single RDF cauldron where all triples are being stored allows for more tight connection between these spaces, so that, for example, data in the application space could be used to organize the domain information according to different *facets*, or add annotations which should not be available as domain ontology. As an example of application ontology, the basic version (i.e. no extensions installed) of MSD declares an *application ontology* called *Annotation*<sup>2</sup> describing the textual occurrences from which entities submitted by the user have been annotated, together with details about the document (type of document, url for web pages, title etc...) where these annotations have been taken. An example of *support ontology* is instead provided by the Sesame2 implementation of the *OntologyManager* extension point: Sesame2 library does not support OWL reasoning nor includes the OWL vocabulary; since Mozilla Semantic Desktop relies on the OWL vocabulary, this is being declared as a support ontology and dynamically added to the core knowledge.

Data defined upon vocabulary from the Annotation ontology (since it is an application ontology) is thus not shown by default in all ontology editing interfaces, and its content is made available to the user through MSD's functionalities (such as those for retrieving documents associated to ontology resources, or for highlighting all the annotations taken in a document), while resources from the OWL vocabulary (being it a support ontology) are shown but are kept separate from user data (owl vocabulary is not saved together with user data nor it is explicitly imported by user ontology).

## 4.3. HTTP Access

All of OSGi services are available via AJAX through HTTP request. The response to these requests is codified in XML or (in some cases) in JSON, depending on request type, available standards and compactness of the content. Due to its complete platform/technology independence, this is the layer which can be exploited by any application which has no direct connection with the service layer and is not compatible with Mozilla technology.

## 4.4. Mozilla JavaScript API

Upon the above layer, a set of JavaScript API, completely hiding the HTTP request/response interaction, has been built by using Mozilla technology. These are the API which are currently used inside Semantic Turkey Semantic Web Browser.

These API are coded as exportable functions into Mozilla modules, a proprietary Mozilla solution for JavaScript allowing for persistence (JavaScript objects inside a module persist upon different imports of the same

<sup>1</sup> <http://www.mozilla.org/projects/calendar/>

<sup>2</sup> <http://art.uniroma2.it/ontologies/annotation>

module) and hiding/encapsulation (a module's developer must choose which objects/functions are exported by users of the module and which ones just serve as hidden internal machinery).

These JavaScript Modules (roughly paired with their service counterparts in the service layer) can thus easily be imported into any sheet of a Mozilla based application (or extension). In the following example:

```
Components.utils.import(
  "resource://stservices/SERVICE_Cls.jsm",semanticturkey
)
```

all the objects and functions exposed by the SERVICE\_Cls module are imported into the variable semanticturkey: this is a good practice to prevent variable clashing, as Mozilla extensions share a common space where all script code (from main application and all of its extension) is pooled.

Once the above statement is explicated in a script document, API methods contained in SERVICE\_Cls can be used in the same sheet, like in the following:

```
semanticturkey.STRequests.Cls.getInstanceList(clsName)
```

where all instances of class identified by clsName are retrieved and returned by the method.

HTTP masking is handled by a common module:

```
resource://stmodules/SemTurkeyHTTP.jsm
```

which is shared by all API methods. The SemTurkeyHTTP.jsm module contains convenience methods for composing GET and POST requests, for unmarshalling received XML/JSON over HTTP responses and recomposing them in terms of dedicated JavaScript objects.

Due to the masking of HTTP details by Mozilla JavaScript Semantic API, all of their methods return explicit JavaScript exceptions. These are classified as:

- *errors*: error JavaScript exceptions mask HTTP communication errors as well as exceptions thrown at run time by the invoked service and caught by the HTTP Server. Usually it is not easy for the common user to discover the problem which has been generated, and these kind of exceptions are considered as severe application faults
- *exceptions*: JavaScript exceptions marked as application exceptions are due to predictable java exceptions which occurred at server level. Usually they contain understandable messages which may be explicitly communicated to the user. Also, specific management of these exceptions depending on their type and the context where these occurred can be performed by the application invoking the method which threw them.

Developers of new applications based on the Mozilla framework can thus invoke the underlying services and handle exceptions depending on the context of invocation, thus following a traditional structured programming approach and producing readable “narrative scripting” code, instead of writing complex code for client-server interaction.

Application Developers willing to add further APIs for interfacing with their software, can extend the service layer through OSGi and then build new modules for the

JavaScript API, relying on the common SemTurkeyHTTP.jsm infrastructure.

#### 4.5. Reusable widgets for Semantic Applications based on this Mozilla Semantic Desktop

Applications exploiting the Mozilla Semantic Desktop which are based on the same Mozilla technology, can benefit of exportable widgets expressly dedicated to Ontology Management. We are currently expanding this aspect, which is currently limited to reusable widgets for class and property trees, and for resource editors (class, property, instance and ontology resource editor widgets) to cover a whole range of widgets for ontology maintenance and editing.

Also, to satisfy the more complex needs of end-user applications, which should hide the ontology editing aspects and show custom widgets more close to their specific nature, we are considering the addition of a dedicated UI generator based on the Fresnel model (Pietriga, Bizer, Karger, & Lee, 2006) for browser independent visualization of RDF graphs. Our UI generator will provide a Fresnel parser and UI generation facilities based on the XML User Interface Language XUL, which is adopted by the suite of Mozilla tools.

## 5. Conclusions

We have presented here our ongoing work for a fully-extensible RDF based platform realizing the Semantic Desktop paradigm.

The strength of Mozilla Semantic Desktop is not in the whole range of end-user services (which are currently limited to the Semantic Bookmarking services offered by its originating platform Semantic Turkey), but in the wide spectrum of connections that are exposed to future applications willing to interact with it.

A second point is on the depth and completeness of its ontology management capabilities, providing a solid platform with convenience methods for ontology editing, disburdening the application developer from the non-trivial effort of maintaining the underlying ontology. Keeping the RDF graph clean (free from potential redundancies and from dangling triples, i.e. triples out of the reachability of any application insisting on them) is in fact a non-trivial aspect from which applications should abstract and which is not supported by default triple-store systems. Advanced layers for RDF management should consider the kind of triple-store they are using, the level of reasoning which is supported (and, where necessary, the “trivial reasoning” which should be computed by them to present data in a readable way) etc.. to provide an homogeneous interaction layer for the application developer.

These “advanced management” requirements are not limited to pure graph maintenance. RDF/OWL pushed forward concepts such as explicit semantics, shareability and interconnectivity: platforms supporting shared knowledge for cooperation of RDF-based applications, should be able to provide powerful tools for meta-management: modularization, multi-faceted perspectives, visualization, are all fundamental aspects which should contradistinguish the layering of future RDF based frameworks, and in special case for Semantic Desktop Platforms.

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# Adaptive User-Centric Layout of News with Aesthetic Constraints

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## Abstract

Traditional newspapers are laid out by professionals and require a lot of manual effort which multiplies with every reuse of content. In contrast, the personalized news lists of a user are mostly just that: lists with pointers to content which is laid out in a wide range of styles. Electronic Paper proposes to bridge the gap between the traditional newspaper and the personalized news each user collects for their own use by allowing for adaptivity of content and layout.

In order to fill the gap, this work proposes an approach which incorporates the knowledge traditional newspaper design, reuses existing contents and provides means to personalize the selection of information which is presented. The result of this approach is a newspapers-like layout of information which is relevant for the specific user, presented in a pleasing way and potentially ready to be deployed on ePaper devices.

## 1. Introduction

The process of identifying relevant and discarding irrelevant information and duplicates in the current information universe is only one step in dealing with the “information overload”. The other step is the consumption which typically inherits the heterogeneous nature of the information sources, i.e. the user has to log in to the different systems and consume the information in the form the system defines. In contrast, traditional printed newspapers, magazines and journals provide relevant and well-researched information in a clean, readable and structured format, which has been exercised and refined for hundreds of years and provides superior consumability. However, to have every newspaper carefully prepared by a set of editors has at a price: every reader gets the same information no matter what her specific interests are, i.e. they do not adapt to the user at all.

The increasing amount of divergent and heterogeneous information published on the Internet and the consolidated and integrated style of newspapers are obviously the two extremes of the current situation. With the new ePaper devices, however, a third option emerges: personalized information presented in the traditional form of a newspaper.

In order to implement this option a number of tasks have to be solved, including the collection and consolidation of news from heterogeneous sources, the computation of relevance of any piece of information for the user, the adaptation of the information to resemble a newspaper and the delivery of the results to the user which could employ optimized clients in order to provide interactive elements, thus combining the presented information with exploration, retrieval and management mechanisms. Last but not least, the interaction of the user with a client can be used to obtain feedback which can be used to adapt the user’s preferences. This paper presents a system which addresses all of the aforementioned tasks, of which the focus is the layout process, however. Chapter 2. presents the general overview of the system, detailing on the content preprocessing, preparation and delivery. Chapter 3. describes the theoretical foundation of the layout algorithm, while Chapter 4. describes

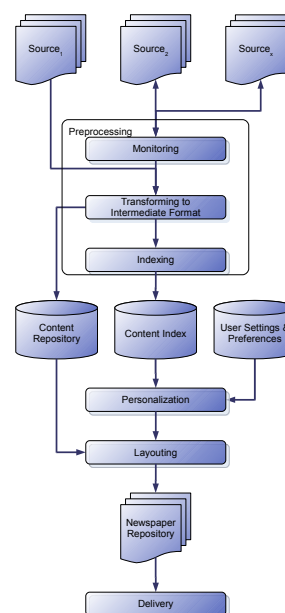


Figure 1: Abstract Architecture of the System

the actual implementation and Chapter 5. presents the results obtained in the experiments we conducted. The last Chapter concludes the paper by summarizing the results and giving an outlook of further research.

## 2. The Information Management System

A system which addresses all of the tasks listed in the introduction, must essentially consist of a number of dedicated sub-systems which are interacting to produce the desired results. Figure 1 provides an overview of the system which we designed for our experiments. For the sake of simplicity we will, however, only address in detail the sub-systems which are especially relevant to the tasks of information management and personalization, which are Preprocessing, Delivering and Personalized Retrieval.

## 2.1. Preprocessing

The preprocessing of contents consists of two steps. The first takes the incoming contents and transforms it into the format which is used for storage. The second step consists of updating the content repository and index with the new information.

Because the system deals with news contents, the input format of choice was NITF<sup>1</sup> an industry standard by the IPTC<sup>2</sup>. NITF is a XML-based format which provides meta-information about the news, e.g. subjects, urgency, keywords, revision history, etc, and the actual news item in a single document. It does not, however, contain information about the style of the news item. Therefore, anyone wishing to present the news to a user has the freedom to create their own presentation. Any content not compliant with this standard may be transformed to NITF with the proper tools. The implemented preprocessing component separates actual contents from meta data by discarding everything that is inside the NITF header element, except for the identifier and the source information, and retaining only the headlines, paragraphs and media references of the body element. All other data and meta data is not needed in the layout process. However, some of the meta data is used in the index in order to improve the retrieval functions. News items are indexed using Apache Lucene<sup>3</sup>, a high-performance full-text search engine. The obvious advantage of Lucene is its built-in extensible set of Natural Language Processing (NLP) functions, i.e. it is possible to perform language-dependent stop word elimination and stemming both on incoming news items and for subsequent queries by users.

## 2.2. Personalization

So far, the process described is the same for all users. The question therefore is, how the newspaper will be personalized. For this task three options are implemented. The first is the incorporation of interests; the second is the desired media ratio of the newspaper; the last option is the total number of pages to create.

The restriction on the total number of pages is important because not all articles may be placed on the resulting pages. If more pages are available articles have more opportunities to be placed even if the number of their layouts are limited. A small number of pages require more articles to be discarded, thus enforcing each article to be of high importance and, therefore, the need to ensure that highly relevant articles can be placed on a page in at least one way by providing a great number of layout options for each article.

The media ratio personalization allows the users to select a type of newspaper to generate. The implemented options are a choice between mostly textual contents, mostly media contents or a balanced version. The idea behind these options is the typical media-driven layout of the yellow press in contrast to serious newspapers such as *New York Times*, *Frankfurter Allgemeine Zeitung* and others, while the third option allows for a type of newspaper between the extremes.

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<sup>1</sup>News Industry Text Format, see <http://www.nitf.org/>

<sup>2</sup>International Press Telecommunications Council

<sup>3</sup>See <http://lucene.apache.org/>

A user's interest is expressed by setting preferences for specific topics, potentially associated with specific providers. In the implemented system, this consists of the possibility to select from the available information sources and the information topics they offer. For this purpose the IPTC subject codes<sup>4</sup> are used. They define a taxonomy of about 1.400 subjects in three levels. However, users may only select from the first level which contains 17 subjects. The second and third levels are reserved for the use in implicit topic selection where a system may refine the user-specified topics with details learned from the interaction of the user with the system, e.g. preferences concerning specific kinds of sports, cultural events or social matters.

Before the layout process starts a relevance score is computed for every active article which has been provided by or updates any of the user-selected news providers. Additional personal preferences, e.g. letting the user define the desired number of pages per category or the weighting of topics are not considered as part of the personal preferences for the layout process. This is no restriction, though, because these preferences can be simulated by adjusting the relevance of articles accordingly: articles belonging to topics more relevant to a user should receive a higher relevance score. Because one goal of the optimization process is to produce pages with high relevance, it will lead to pages containing more of the articles with boosted relevance.

## 2.3. Delivery and Interaction

In addition to merely displaying the generated newspaper, a client can be used to monitor the user to obtain explicit as well as implicit feedback which can be used to further refine the initially defined preferences: for each action the client allows the user to perform the attributes are stored and sent back to the system at regular intervals. Examples of such actions are:

- Marking an article
- Discarding an article
- Searching for a keyword
- Searching for articles related to a given article
- Requesting additional articles for a topic
- Requesting a detail view of an article
- Skipping a topic or page

Each of these actions is translated into an adaptation of the user's profile, e.g. marking an article results in an increase in the relevance of the article's topics and terms, while discarding an article will result in a decrease. In addition, the actions can be used to compute user-user similarities for collaborative filtering and recommendation/exploration. For the current system, however, this was out of scope.

The Figures 2, 3, 4, and 5 depict the client at various states of interaction with the user.

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<sup>4</sup>See <http://cv.iptc.org/newscodes/subjectcode/>



Figure 2: Main View on an Exemplary Device



Figure 3: Alternative View for Navigation

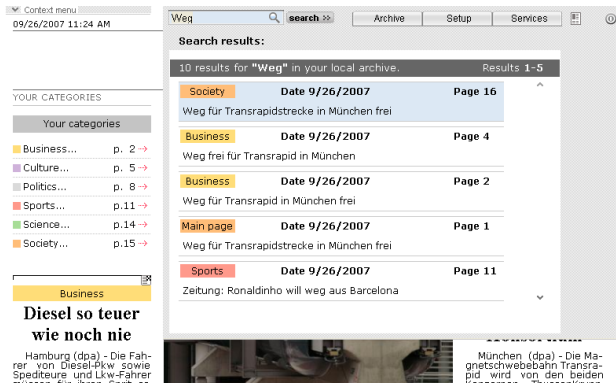


Figure 4: Search for News

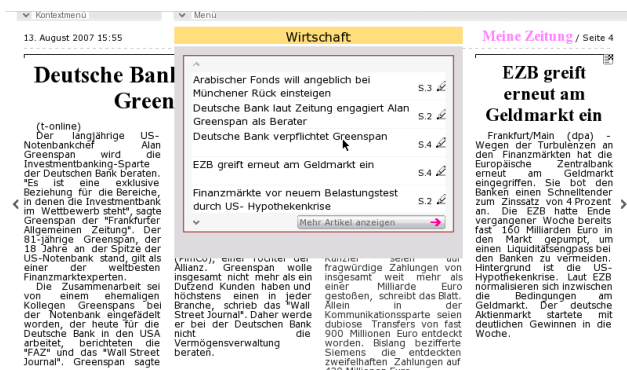


Figure 5: Overview of Content for a Category

### 3. A Short Theory of Automatic Layout and Aesthetics

The goal of the proposed system is to provide a substitute for the layout process performed by the editors and the familiar reading experience of a newspaper. Therefore, the questions which must be addressed are "What makes up a good newspaper?" and "How can this be automated?"

The history of aesthetics reaches as far back as Plato and Aristoteles, maybe even further. However, aesthetics were considered impossible to formalize and therefore typically taught/learned by giving rules which the designer was to follow, modern examples here are (Rehe, 1985) and (Collier, 1990). Until today, most editors use a mixture of intuition and style guides to achieve the unique look of their newspaper.

At the beginning of the last century, however, the first formal theories started to emerge, which claimed that the aesthetic quality of a design could be computed mathematically. The starting point was Birkhoff's "Aesthetic Measures" (Birkhoff, 1933) which was further refined by Bense (Bense, 1965a; Bense, 1965b; Bense, 1969), Greenfield (Greenfield, 2005) and others.

Most of these theories, however, started with some more or less intuitive notion of aesthetics, and therefore consistently failed to capture some of the important aspects. The change came towards the end of the last century when empirical user studies (Streveler and Wasserman, 1984; Sears, 1993; Ngo, 1994; Tullis, 1997; Ngo and Byrne, 1998) evaluated the influence of aesthetics and thus eliminated some of the subjectivity of the approaches, and established mathematical theories of interface aesthetics. Of these theories Ngo et al (Ngo et al., 2003) and Harrington et al (Harrington et al., 2004) can be considered as unifying the others and providing a comprehensive set of measures which serve to define the aesthetic quality of any interface.

Most of the measures proposed by the two papers have corresponding measures in the other, although they may have a different name or a slightly different computation. They can be roughly divided into two groups: measures which consider the basic optical aspects of the layout and measures which consider cognitive aspects. Examples of the first group are balance, equilibrium, density, white-space fraction and free-flow, which compute the optical density (or weight) of the elements on the page and their distribution. The second group, containing for example alignment, regularity, homogeneity, cohesion, proportion and economy, consists of measures which take into account aspects which deal with the overall perception and reading guidance.

In order to compute the quality of a layout, the different measures are computed and combined to a final score which is higher the better the layout is.

An alternative approach to achieve a high aesthetic quality consists of learning from samples of good (and bad) layouts. Buhr et al (Buhr, 1996) used Artificial Neural Networks to learn the optimal distribution of optical weight, but yielded only poor results, most likely because of the relative simplicity of the network used. Soon after, Bernard et al (Bernard and Lirsia, 1998) proposed an inductive con-

straint logic to learn rules which create visually pleasing layouts. While the claim is that their algorithms could learn a constraint which would place a given set of articles (of a given size) on the page, they give no examples of the resulting layouts, thus making the evaluation difficult. In general, approaches which learn what defines a good layout, require a lot of training samples. This reduces their applicability to cases where such training data is available, which is seldom the case.

Another alternative for generating high quality layouts is the use of templates. Each template describes ways of arranging the elements of a page to obtain an appealing layout and typically consists of interdependent constraints which generate the typical look. Jacobs et al (Jacobs et al., 2003; Jacobs et al., 2004) use a set of templates which describe adaptive page layouts of which the system then selects the best sequence, given a particular document. The goodness of a chosen sequence is measured in terms of constraint satisfaction, while the specific values for all parameters were computed with the help of constraint solvers. Similarly, Lin (Lin, 2006) proposes an algorithm which is restricted to single pages, but allows for the placement of multiple elements on the page. Schrier et al (Schrier et al., 2008) proposed an XML-based layout language which allows the recursive definition of templates, conditional elements and grouping of elements, which is based on the approach of Jacobs et al. Templates are chosen based on preconditions and scores and subsequently finalized with a constraint solver. The major drawback of all template-based approaches, however, is their need of an extensive set of templates which the system can choose from and a deep understanding of the constraint definition language and the constraint solving mechanisms in order to achieve high quality results.

Apart from the pure scientific applications of automatic newspaper layout, a set of real-world application has come to life in the recent years, e.g. Tabbloid, FeedJournal, PersonalNews and niuu (Tabbloid, 2009; Martinsson, 2009; Syntops GmbH, 2009; InterTi GmbH, 2010). In general, they achieve only unpleasing results because they are too inflexible or do not impose suitable constraints. The exception are the PersonalNews and niuu systems, which compose a personal newspaper of whole pages taken from original newspapers, thus avoiding the layout problem at the cost of not providing a consistent look across the complete newspaper.

## 4. The Layout Algorithm

Based on the observations made in the previous Section, we decided to implement the layout algorithm as filling a page with a selection of articles from a content base and optimizing the aesthetic quality. This can be further refined to the sub-tasks of coming up with possible arrangements of article contents and the consequent selection which of the arrangements of articles to choose and where to place them. The selection should reflect the user's preferences and the relevance of the articles for the user and the arrangement and placement should result in a newspaper-like look and feel while simultaneously maximizing the aesthetic quality. This description is very similar to the family of Cutting & Packing (C&P) problems which are addressed in the field of

Operations Research (cf. (Wäscher et al., 2007; Kellerer et al., 2004)). C&P problems arise in many practical situations, e.g. loading containers, cutting stock, scheduling tasks, assigning courses, or VLSI wiring, but are  $\mathcal{NP}$ -hard in general (Garey and Johnson, 1979). Exact solutions for these problems are impractical, therefore. Approximation algorithms try to find solutions close to the optimum at greatly improved computational complexity (Sahni, 1975; Beasley, 2004; Julstrom, 2005; Hiley and Julstrom, 2006; Saraç and Sipahioglu, 2007; Singh and Baghel, 2007).

In order to achieve the desired amount of flexibility in the layout and of aesthetic quality, the proposed algorithm for the layout combines two concepts which were identified during the research on traditional layout and aesthetics. The first, is the use of a style guide for defining valid variations for the layout of each article. The second concept is the employment of an objective function which combines the applicable aesthetic measures and a score which reflects the similarity to the personal preferences of a user. The task for an algorithm which automates the layout process then is to find an arrangement of articles which maximize the objective function of the generated layout. These concepts are described in the next sections.

### 4.1. Style Guide

The style guide which was developed, is based on the concept of a grid as the underlying structure of each page, i.e. each page is into  $w$  columns and  $h$  rows resulting in  $w * h$  identical cells (cf. Figure 6). Any article on the page may occupy a rectangle of an arbitrary but integer number of cells. In addition, rules for text and page margins, the style of article headlines and the size and placement of media elements were defined. This very simple set of rules automatically optimizes some of the aesthetic measures and provides consistency among the laid out articles. How this is achieved, is shown in reference to the aesthetic measures of Ngo and Harrington (Ngo et al., 2003; Harrington et al., 2004). Cohesion, unity, simplicity and regularity are measures based on the number of alignment points and available forms. With the grid structure the number of different aspect ratios is effectively limited and the aspect ratios themselves are related because every dimension is a multiple of the basic underlying grid dimension, thus supporting the cohesion of the appearance. In addition, the grid reduces the alignment points between the articles, while the alignment of text lines in neighboring cells further minimizes the alignment points, thus achieving a high simplicity. Regularity, i.e. the similarity of the distances between alignment points, is also achieved by the aforementioned grid and text alignments.

Because of the gap between columns and the margins introduced at the top (above the headline) and bottom (below the last text lines or images), which separate the article contents from the rest, related information is grouped. This corresponds to the unity of the layout.

The number of design elements which are produced by the application of the style guide, is rather limited: only a single font is used for the text and the headlines differ only in the size of the font; all media elements are rectangular. Colors other than the default text color are used only



Figure 6: The basic grid with margins and sample contents

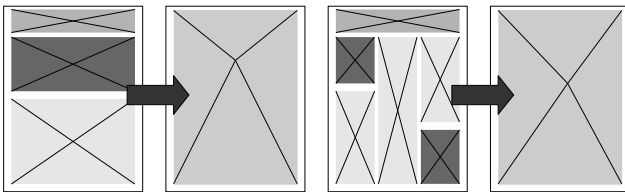


Figure 7: Computation of optical weight for an article from its parts. The level of gray denotes the optical weight.

to highlight important information and placed outside the main text areas. Therefore, the resulting layouts are very economic in their use of colors, fonts and forms.

The measure of rhythm is rather hard to grasp. The structure of the grid and the contained articles, which consist of a headline, text and optional images, introduce a systematic change in the arrangement of elements on the page. This can be considered as the style guide’s contribution to rhythm.

## 4.2. Objective Function

The objective function must be designed to capture both the aesthetic quality of the generated layout and the closeness of the selected content and layout to the user’s preferences. The goodness of the content selection can be measured by the relevance score of each article (cf. Section 2.2.). The layout’s quality and relation to the user defined media aspect ratio, requires the computation of a measure closely related to the formal theories of aesthetic: the optical density ( $M_c$ ) and center ( $x_c, y_c$ ). For each generated variation of an article layout, is computed as a weighed sum of the parts (cf. Figure 7):

$$x_c = \frac{\sum_i x_i * M_i * a_i}{\sum_i M_i * a_i}$$

$$y_c = \frac{\sum_i y_i * M_i * a_i}{\sum_i M_i * a_i}$$

$$M_c = \frac{\sum_i M_i * a_i}{a_i}$$

where  $i$  iterates over all elements of the article (headline, text parts and, if available, images) and  $x_i, y_i, M_i$  and  $a_i$  the optical center and weight, and the area of the part, respectively. For each part the center is assumed to be identical to the center of the rectangular area it occupies, and the density is fixed and computed as  $M_i = 1.0 - \text{brightness}^5$ . Based on these properties for each article layout, the different aesthetic measures (cf. Section 3.) can be computed, as well as the overall relevance of a page for a user:

- Relevance, i.e. topical and term-based correlation with user preferences ( $r_i$ : relevance of article  $i$ ,  $a_i$  area of article  $i$ ):  $RM = \sum_i r_i * a_i$
- Balance ( $(x_c, y_c)$ : desired center of gravity,  $x_m = \frac{\sum_i x_i * M_i}{\sum_i M_i}$ ,  $y_m = \frac{\sum_i y_i * M_i}{\sum_i M_i}$ : optical center of the page):  $BM = 1 - \sqrt{\frac{(x_m - x_c)^2 + (y_m - y_c)^2}{2}}$
- Sequence, i.e. “Relevance Order” ( $x_r = \frac{\sum_i x_i * r_i}{\sum_i r_i}$ ,  $y_r = \frac{\sum_i y_i * r_i}{\sum_i r_i}$ : “relevance center” of the page):  $SM = 1 - \sqrt{\frac{(x_r - x_c)^2 + (y_r - y_c)^2}{2}}$
- Density:  $DM = \frac{D_{target} - \sum_i a_i * M_i}{D_{scale}}$  where  $D_{scale} = \max(M_i) - \min(M_i)$
- Fullness, i.e. minimization of Whitespace:  $WM = \frac{\sum_i a_i * c_i}{W * H}$
- Page score (weighted sum of scores):  $f = \frac{1}{\alpha + \beta + \gamma + \delta + \epsilon} * (\alpha * RM + \beta * BM + \gamma * SM + \delta * DM + \epsilon * WM)$

Because the system collects news contents from multiple sources, the issue of redundant news must be addressed, too. The objective function can be extended to contain a term which imposes a penalty for the redundancy of the included items. This can be done by computing the cosine similarity of the content (as a term frequency vector) of any pair of items and including the measure into the objective function:

- Diversity ( $sim_{ij}$ : similarity of article  $i$  and  $j$ ,  $n$ : number of articles on page):  $DivM = 1 - \frac{\sum_{i \neq j} sim_{ij}}{n^2}$

## 5. Experimental Results

Based on the objective function presented in Section 4.2., different optimization algorithms were used. As Strecker et al showed in (Strecker and Hennig, 2009), relatively simple approximation algorithms could be used for simple objective functions. Using these algorithms in combination with the present objective function yielded only poor results, which we mainly attribute to the huge problem space

<sup>5</sup>The brightness of an element is computed by converting its content from RGB to HSB color space and averaging the brightness values.



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### Energieeffiziente IT: Öffentliche Hand soll Vorbildrolle wahrnehmen

Die Deutsche Energie-Agentur GmbH (dena) bietet im Rahmen der Initiative Energieeffizienz-Schulungen zur Beschaffung energieeffizienter Informations- und Kommunikationstechnik an. Das Angebot richtet sich vor allem an die 30.000 Beschäftigten in öffentlichen Einrichtungen, da diese bei der Umsetzung der Ziele der Bundesregierung zur Steigerung der Energieeffizienz mit gutem Beispiel vorangehen sollen. Bundesbehörden sind durch eine entsprechende Verwaltungsvorschrift bereits dazu verpflichtet. Für Landes- und Kommunalverwaltungen bestehen teilweise

teausstattung spart beispielsweise 50 Prozent der Stromkosten gegenüber einer ineffizienten. Voraussetzung für die dauerhafte Erschließung dieser Potenziale ist, dass Energieeffizienz standardmäßig im Beschaffungsprozess berücksichtigt wird. Das ist nach Erfahrungen der dena zwar von den Beteiligten in der öffentlichen Beschaffung oft gewollt, jedoch zumeist noch nicht entsprechend institutionalisiert. Als Hemmnis wird vielfach die Unsicherheit empfunden, Kriterien für Energieeffizienz zu bestimmen und rechtskonform in Ausschreibungen einzubinden.

Wie das geht, zeigt die neue Schulung der Initiative Energieeffizienz. Beschaffer lernen anhand praktischer Beispiele Schritt für Schritt, wie sie die wirtschaftlichsten Geräte beschaffen können. Die dena bietet die Schulungen in Kooperation mit regionalen Partnern deutschlandweit an. Dies ist ein wichtiger Schritt, um die Energieeffizienz der Bundesregierung zu erreichen und die öffentlichen Haushalte zu entlasten. Die Schulungstermine sowie weitere Informationen und Serviceangebote zu dem Thema sind zu finden unter: [www.office-topten.de](http://www.office-topten.de).

Die Initiative Energieeffizienz ist eine bundesweite Aktionsplattform zur effizienten Stromnutzung, die von der dena und den Unternehmen E.ON Energie AG, EnBW AG, RWE Energie AG sowie Vattenfall Europe AG getragen und durch das Bundesministerium für Wirtschaft und Technologie gefördert wird.

Weitere Informationen unter [www.berliner-energietage.de](http://www.berliner-energietage.de)

### co2online auf den Berliner Energietagen 2009

Bereits zum zehnten Mal finden dieses Jahr die Berliner Energieitage statt. Vom 4. bis zum 6. Mai treffen sich wieder Fachleute und Interessierte in Berlin, um unter dem Motto "Energieeffizienz in Deutschland" über Konzepte, Initiativen und Maßnahmen zum Klimaschutz zu diskutieren.

co2online darf auf diesem wichtigen Branchentreff natürlich nicht fehlen und wird mit drei Vorträgen auf der Tagung vertreten sein. Die Themen der Vorträge bilden die Bandbreite der Arbeit von co2online ab und lauten im Einzelnen "Energieparknote und Smart Metering".

Mehr als 4.500 Teilnehmer werden für die rund 40 Fachveranstaltungen erwartet, die sich in sechs Themenschwerpunkten gliedern. Außerdem wird es an den drei Tagen eine begleitende Fachmesse "Energie-Impuls 2009" geben, auf der Informationen über neueste Produkte und Dienstleistungen im Bereich Energieeffizienz ausgetauscht werden können. Die vom Berliner Impuls-E-Programm veranstalteten EnergieTage, die sich mittlerweile im Themenfeld Energieeffizienz zur Leitveranstaltung in Deutschland entwickelt haben, werden gefördert durch die Berliner Senatsverwaltung für Gesundheit, Umwelt und Verbraucherschutz, das Bundesumweltministerium sowie das Bundeswirtschaftsministerium.

### Merke! Will Wirtschaft vor Finanzmärkten schützen

Berlin (dpa) - Nach den Turbulenzen auf den Finanzmärkten ruft die Bundeskanzlerin Angela Merkel (CDU) eindringlich zu Überlegungen auf die Wirtschaft zu verlagern.

Es müsse jetzt alles dringender gemacht werden, als zu einer Klage zwischen der Situation auf den Finanzmärkten vor Realwirtschaft komme, sagte Merkel am Dienstag auf dem Ministerkongress der Industrie in Berlin. Bei der steigenden Ertragsbelastung müsse die Wirtschaft verlagert werden.

In der Finanzmarkt-Debatte müsse sich die Politik anstrengen und für mehr Transparenz sorgen. Deutschland sei ein sehr starkes Industrie- und Exportland. Es zeigten sich aber erste Probleme am Konsumkonvergenz. "Der Aufschwung ist kein Realwachstum".

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07. Juli 2009
Nachrichten
Seite 4

### Holzer und seine Radprofis auf Partnersuche

Der zusammen mit seiner Frau Beate die Firma HPM selbst, ein Angebot, das die in den nächsten Wochen folgen dürfte. Die Holzer-Familie ist in der Branche ein bekannter Name. Die Holzer-Familie ist in der Branche ein bekannter Name. Die Holzer-Familie ist in der Branche ein bekannter Name.

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03. Juni 2009
Nachrichten
Seite 3

### Lows klare Vorgabe: Mit Sieg in EM-Endrunde

Die deutsche Fußballnationalmannschaft hat sich für die Endrunde der Fußball-Europameisterschaft 2012 qualifiziert. Das ist ein großer Erfolg für die Mannschaft, die unter Trainer Joachim Löw steht.

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14. Juli 2009
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### Kennel nutzt Google als Marketing-Partner

Das Unternehmen Kennel hat sich mit Google als Marketing-Partner verbündet. Dies ist ein wichtiger Schritt für die Expansion des Unternehmens.

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Figure 8: Generated Layouts for Different Style Instances

and the small portion of it which is searched with the algorithms.

In addition, we conducted further experiments based on the objective function for the page score, with different types of optimization algorithms (the Grouping Genetic Algorithm by Singh et al (Singh and Baghel, 2007), Simulated Annealing and Greedy Algorithms similar to Julstrom (Julstrom, 2005)) on a corpus of news articles (with images) from DPA<sup>6</sup>. In these experiments we varied the parameters of the scoring formula as well as the settings of the style guide. The results that were obtained (cf. Figure 8) are promising and show the basic correctness of the approach and its applicability for different instances of the style.

## 6. Conclusion and Outlook

The general approach with a minimum set of aesthetic constraints was shown to be valid already, as Strecker et al showed in (Strecker and Hennig, 2009). The presented extension of the objective function to include further aesthetic measures and personal preferences results in even better structured and organized results which go far beyond the results of any existing scientific prototype or existing system. While the current evaluation is based on personal observation and the achieved scores for the different terms of the objective function, future evaluation will include user studies to ensure both the quality of the generated layout and the adherence to the personalization options.

The presented system allows for the flexible and dynamic generation of personalized newspaper without manual intervention, thus closing the gap between manual editing of newspaper layouts and personalized information consumption.

Further research could be performed in several directions. For example, additional options for each article layout could be defined, which would finally lead to an even more individual and authentic reading experience. Another option is the inclusion of additional aesthetic and content measures, e.g. the automatic grouping of articles belonging to similar topics or the combination of similar articles into a single one, of which a basic version was explored by my colleague and me in (Hennig and Strecker, 2008). An important direction is a further selection and the optimization of the algorithms used based on the properties of the search space and data set which we discovered during our research.

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<sup>6</sup>Deutsche Presseagentur

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# Personalized Learning to Rank Applied to Search Engines

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## Abstract

Learning to rank is a successful attempt of bringing machine learning and information retrieval together. With learning to rank it is possible to learn ranking functions based on user preferences. User preferences for instance depend on user background, features of results, relations to other entities and the occurrence of the searched entities in presented abstracts. The reasons why there are only some applications utilizing learning to rank for personalization can be found in the extended query response time and general additional resource needs. These resource needs come from the use of machine learning and the need to learn and use trained user models. Experiments on standard benchmark data help showing that learning to rank approaches perform well, but currently it is not possible to show how much feedback is needed for an improvement or if personalization is possible. Hence the minimal number of training data for creating a ranking function is not known. We show that keeping the training data as small as possible minimizes the resource needs and even enables the possibility of training personalized ranking functions. In this work we apply learning to rank to an existing search engine and evaluate the conditions and effects of learning personal preferences. We evaluate how much implicit feedback is needed and use this knowledge to reduce the computational requirements, enabling learning to rank based personalization.

## 1. Introduction

The success of the link analysis algorithm PageRank (Page et al., 1999) shows that preferences in information retrieval are not completely content-driven. There are ranking functions fusing several of such quality and relevance opinions. There are even some ranking algorithms trying to detect your favorite soccer team, your location and other favorites by analyzing past searches. But these ranking algorithms do not consider users individual preferences to compute a rank for a document.

There are several aspects of results which can influence preference decisions, yet user-dependent aspects are not usually being taken into consideration when presenting search results. It is very intuitive to rank results by the following preference statement: "I like to have search terms occurring in the presented title and in the presented text snippet. Also it is always good to have at last one headline in the result including the search terms." Very often the factors influencing a preference decision are unconscious and not known to the user, but can be detected by learning to rank.

### 1.1. Relevance Feedback

One way to achieve such personalization is collecting relevance feedback. Users can be asked for explicit feedback about their preferences, creating detailed user profiles. However, users may not be willing or able to explicitly provide such information and would feel bothered by such an inquiry.

One solution for avoiding this problem is to analyze the click logs of the user as proposed in (Joachims, 2002; Radlinski and Joachims, 2005). The proposed preference rules applied to implicit feedback have proven to result in representative user preferences.

### 1.2. Learning to Rank

In information retrieval learning to rank algorithms attempt to sort search results according to their individual relevance to the query. There are several learning to rank algorithms proposed each year (Herbrich et al., 2000; Freund et al., 2003; Tsai et al., 2007; Cao et al., 2007; Liu et al., 2007; Guiver and Snelson, 2008).

Learning to rank algorithms analyze user preferences creating a user model for predicting preference decisions of unseen data. With learning to rank it is possible to learn a user model for the general user, individual users or user groups. However, to authors' knowledge, there are no evaluation results for personalized learning to rank in the literature.

Based on evaluations on benchmark data, learning to rank has a very good retrieval performance. Unfortunately there are drawbacks resulting from the machine learning background of the learning to rank algorithms. The training time directly depends on the number of features and the number of training instances. Hence on given datasets performance evaluations take up to several hours. Fortunately the search scenario drawn by given datasets is not exactly the scenario of a running search engine (Zhang et al., 2009).

Nevertheless there are requirements for search engines like query response time, which have to be respected. Therefore there is a need of selecting a proper learning to rank approach, the most influential features and the most distinguished user preferences. In other words, for fast and reliable model creation it is necessary to collect and use as little, but meaningful data as possible.

### 1.3. Contribution

The best solution for seamless learning to rank at query time is to limit the time needed to rank a given set of results. In contrast to data sets, features of these results have to be retrieved first, before any learning to rank approach can make decisions based on them. To improve response

time when using reranking, ideally to real-time, we focus on efficient ways for preprocessing features.

To demonstrate our approach, we apply RankSVM (Herbrich et al., 2000), showing that the chosen learning to rank approach is not the main bottleneck in practice.

In this paper we describe algorithms and methods applied to integrate learning to rank into search engines. We especially focus on tolerable response times and personalization issues. The integration is done exemplarily on the search engine *PIA* allowing it to provide personalized search results.

Experiments with thousands of queries show that a learning to rank approach can be used in real-world search engines. In Sec. 5. it is evaluated how effectively learning to rank can be used to provide personalized result lists. Furthermore it is evaluated how much implicit feedback is necessary to successfully apply learning to rank.

## 2. Learning to Rank on Corpora

In classic information retrieval results (for instance documents as used in our work) are represented by word vectors. For learning to rank results are represented by vectors whose elements are opinions about features and relations of these results. The objective of learning to rank is to learn a ranking function which explicitly learns preferences instead of using functions like TF-IDF or BM25.

Because information retrieval performance is the main benefit of learning to rank we summarize and discuss the features of the most important learning to rank benchmark dataset to conclude features for a real world application.

Most of the current learning to rank algorithms were developed and evaluated on the *LEARNING TO RANK* datasets in LETOR (Liu et al., 2007). In different versions of LETOR different datasets were uniformly transformed to be suitable for the problem of learning to rank.

Each search result in LETOR is represented as a set of features which can be used to learn to rank these results. The information of which result should be ranked higher is derived from user given labels. Mostly these labels are 0 for not relevant and 1 for relevant results with respect to a given query. There is one dataset in LETOR with three levels of relevance, OHSUMED (Liu et al., 2007).

### 2.1. Result Features

When using LETOR datasets the data is already preprocessed and ready to be used in experiments, hence researchers do not have to prepare data sets and evaluation results are comparable to each other.

Features in the LETOR datasets are classified into low-level, high-level, hyperlink and hybrid features. Low-level features for instance are “term frequency of URL” or “document length of body”. “BM25 of title” or “LMIR of anchor” belong to the high-level features. “PageRank” and “Topical HITS authority” are part of the hyperlink features, but there also are hybrid features like “Hyperlink base score propagation: weighted in-link”.

### 2.2. Implicit Search Task

In LETOR the following search scenario is drawn (exemplary for the included dataset TD2003 of LETOR 3.0):

When a query is made, up to 1,000 results are returned. From these results feature vectors have to be extracted at query time. These feature vectors are needed for the ranking algorithms which have to be trained (offline) and used at query time to decide the optimal ranking for these results. Learning to rank is used to learn the general, non-personalized ranking function when all users have provided relevance decisions for the results of 30 queries (3/5 of number of queries in TD2003). The given relevance feedback is used to create a learning to rank model which is used to rerank each further result list.

### 2.3. Computational Performance

Extracting feature vectors for 1,000 documents, as described in Sec. 2.2., takes a lot of time. Although there is no detailed information given how much time is needed, it is clearly not feasible in real time. Additionally, building a learning to rank model or rather training the given queries takes a lot of resources, but the provided benchmark learning to rank baselines are not connected to training times. It is possible to build the model in the background or on external servers. Own experiments have shown, that the learning to rank approach RankSVM (Herbrich et al., 2000), based on the Support Vector Machine algorithm, takes the most training time and ListNet (Cao et al., 2007) is the fastest approach among those tested.

## 3. Applying Learning to Rank

Before integrating learning to rank into a search engine, the learning to rank phases have to be identified and analyzed with respect to given quality and response time restrictions. We propose to extend the learning to rank process by the phases presented in Fig. 1. These phases include recording clicks in a log, deducing the preferences, determining the online and offline features, training the learning to rank model and reranking a given result list accordingly.

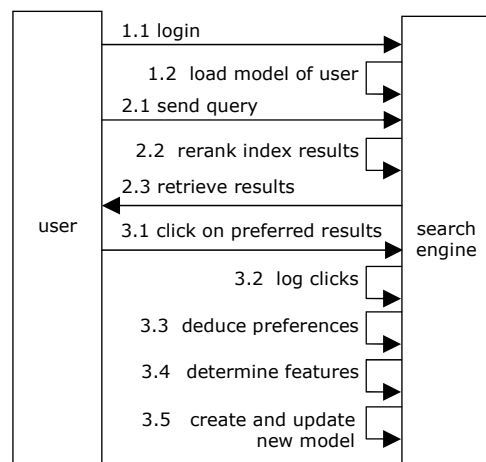


Figure 1: Interaction with a learning to rank search engine including the five phases of the learning to rank process: logging, preference retrieval, feature retrieval, training and reranking. If there is no model yet or the user does not log in, the results coming from the index are passed.

For the phases of logging, preference retrieval and reranking we follow and extend the proposed approaches of

(Joachims, 2002; Joachims and Radlinski, 2007) to apply learning to rank by respecting search engine requirements.

### 3.1. Logging

A method to compile user's preferences is the retrieval of relevance feedback. In general, it is easier to obtain implicit feedback rather than explicit feedback from a user since the user's benefit of providing feedback on search results is not clear to him. Instead of asking the user for explicit feedback, such as asking the user to rate the presented results, implicit feedback like clicks on results can be used.

The proposed logging in (Joachims, 2002) includes information about who clicked on which result for which search. This data is called clickthrough data and is retrieved by a log server for later preference retrieval. Logging can be done in parallel and does not affect the search engine's response time.

### 3.2. Preferences

Before learning preferences, the logged data has to be transformed to preference relations. Therefore the rules to generate preference relations given in (Radlinski and Joachims, 2005) were applied. With these rules and the clickthrough data, a set of preferences for each user can be deduced. These preferences will later form the training data for the learning to rank algorithm.

### 3.3. Features

There are two use cases where results have to be transformed to a feature vectors. The transformation is needed first, for training preference pairs and second for using a trained model to rerank results at query time.

Before preference pairs can be trained, the results have to be expressed as feature vectors containing relevance and quality opinions of several information retrieval strategies. Retrieving these opinions can be very time consuming. Fortunately, the transformation and the learning can often be done offline and do not have to be performed at query time. Additionally, by limiting the number of features, learning to rank algorithms usually need less training time.

The processing time of the transformation of potential results to feature vectors depends on the type of features (information retrieval strategies) used. Generally, features can be divided into two categories: Quality-based features and query-dependent features. Quality-based features can be processed offline, because they depend on general features like *number of pages* or *PageRank*. Query-dependent features are the scores coming from retrieval strategies which for instance address the *term frequency of the query terms* in different parts of a result. These features can only be processed online, at query time.

In order to compute a feature vector  $\vec{f}$  that describes a given result document, properties of results have to be used, which are expressible as real numbers. The feature vector consists of two sub-vectors:

- $\vec{g}$ , containing real values for quality-based features.
- $\vec{h}$ , containing real values for query-dependent features.

#### 3.3.1. Quality-based features

Quality-based features are features of a result that can be computed independently of the search query. They describe result properties such as word counts, age or PageRank, or in the case of documents number of authors, citations or file size. The static nature of these features makes it ideal for them to be aggregated and stored at idle server times, allowing them to be accessed much faster at real-time during a reranking procedure.

#### 3.3.2. Query-dependent features

Query-dependent features are features of a result that are dependent on the search query. Therefore, they have to be computed during query time. The query-dependent feature vector  $\vec{h}$  itself is divided up into two groups:

- Statistical query-dependent features  
Vector  $\vec{j}$ , which contains feature values for features that are based on statistics over search terms.
- Query reformulation query-dependent features  
Vector  $\vec{k}$ , which contains values for features that are computed through slight reformulation of the search query. The main idea is to look in adjacent directions in search space with respect to the query phrase. Using that approach makes it possible to automatically weight certain words from the search phrase lower or higher and to omit one or more words. Additionally, words that are spelled similar are detected by fuzzy search. Few documents are usually returned if one word of the search phrase is misspelled, but they should have higher values for query-dependent features that are based on similar words.

Due to the fact that the feature values depend on the search query, they have to be computed very fast, ideally in real-time, as opposed to the quality-based feature values that can be computed at fixed time points.

#### 3.3.3. The Feature vector

The feature vector  $\vec{f}$  for one result is composed of the quality-based feature vector  $\vec{g}$  and the query-dependent feature vector  $\vec{h}$ , which is subdivided into two vectors, statistical query-dependent features  $\vec{j}$  and query reformulation query-dependent features  $\vec{k}$ :

$$\vec{f} = \left\{ \vec{g}(\vec{j}\vec{k}) \right\} \quad (1)$$

### 3.4. Training

Representing search results as feature vectors  $f$ , we can deduce preference pairs. A preference consists of two results of one search. A result that have been clicked by the user and one that have not been clicked.

The training data  $T$  is defined as

$$T = \left\{ (\vec{t}_k, n_k), (\vec{t}_k^{-1}, n_k^{-1}) \right\} \quad (2)$$

where  $\vec{t}_k = \vec{f}_i - \vec{f}_j$  and the document  $d$  relation ( $d_i \succ d_j \rightarrow n_k = 1$ ). However only having  $(\vec{t}_k, n_k)$  will generate training data for one class only, namely for the class "preferred" (clicked search results). To successfully train

learning to rank algorithms, data from the class "not preferred" (search results that have not been clicked) is needed, too, since reranking also means to rank non-preferred results lower.  $(\vec{t}_k^{-1}, n_k^{-1})$  represents data from the other class, where  $\vec{t}_k^{-1} = \vec{f}_j - \vec{f}_i$  and  $(d_i \succ d_j) \rightarrow n_k = -1$ .

The training phase results in a trained model which represents a ranking function. If a single user has provided enough feedback to build a training data set, then the learning to rank algorithm can create a personalized model. For later use, this model should be persistable.

In general, creating a learning to rank model via training can be done at any time since only collected clickthrough data is needed to compute the model. For users' best search experience, result lists should become more personalized as more feedback is given. Hence, each provided feedback should start the training phase (computed in parallel). In the optimal case, the resulting model can be used for ranking the results of the next search.

### 3.5. Ranking

As soon as a user sends a query to the search engine the normal index based search is performed. The resulting list is then reranked using the latest model retrieved from the training phase (resp. deserialized model from login, see Fig. 1).

For the first  $n$  entries in the result list, feature vectors are generated. To generate the feature vectors the query-dependent features are determined and the result's quality-based features are retrieved from preprocessed data. Note that these feature vectors have to be structured in the same way as the vectors in the training phase.

The model is used to rank these feature vectors and the results have to be ranked accordingly.

When the model is used to reform a result list for a given search query, the top  $n$  (for example 30) results of the result list are ranked according to the model's ranking function. In order to do this, the feature vectors for the top  $n$  results have to be computed at query time, which increases the response time of the search engine.

## 4. Settings and Methods

In this section we describe the settings of our experiments. All evaluations are based on the search engine *PIA* which was extended to rank results by learning to rank using a SVM. The measurements were performed on a standard system with 1.3 GHz single-core Intel processor with 2 GB RAM.

### 4.1. The Search Engine *PIA*

Applying learning to rank to a search engine can be done in a completely unintrusive manner. Everything needed for reranking are result sets and connected clickthrough data. Hence it is possible to superimpose a reranking module communicating with the search engine. The only restriction is that the results can be represented as uniform features.

Because the offline retrieval of quality-dependent features can only be done when knowing the objects which are potential results, we exemplarily extended an existing search engine where the belonging content base is fixed.

Following the five phases, this section describes the implementation of learning to rank algorithms into the search engine *PIA*. *PIA* is a retrieval architecture developed by *DAI-Labor* that allows search in scientific publications. For evaluation we applied learning to rank to a *PIA* implementation where the document base is limited to ACM<sup>1</sup> documents. *PIA* includes a user management system which allows to collect not only general, but personalized user feedback.

**Training and Reranking** For applying learning to rank to *PIA* we have chosen the support vector machine approach (Herbrich et al., 2000). Using the SMOClassifier from the WEKA toolkit (Witten and Frank, 2005). The SVM was trained with the training data of each registered user individually.

In contrast to the usual approach of ranking by the distance to the class separating hyperplane, we used the model to determine the preferences of all results compared to each other. The results were then ranked by the total number of times they were preferred over any other result; in other words the reranking is based on predicted preference popularity and the most preferred result is listed on top.

We have chosen the first 30 results for reranking and left the order of the following results untouched. We did not apply any feature selection strategy.

**Preferences** For extracting preferences the two most intuitive rules were applied; namely "Click  $\succ$  Skip Above" and "Click First  $\succ$  No-Click Second" as proposed in (Radlinski and Joachims, 2005). When clicking a result, the "Click  $\succ$  Skip Above" results in preferences where the clicked result is preferred over all preceding results in the result list which were not clicked. In "Click First  $\succ$  No-Click Second" the notion is that if a user clicks on the top result and not the second ranked result, the top ranked result is preferred over the second ranked result.

**Selected Features** For the retrieval of query-dependent features, the Apache Lucene indexing architecture<sup>2</sup> is used to build small and fast temporary indexes for the top  $n$  documents. Doing this, this retrieval only has to be performed in a small RAM index instead of crawling through the main, hard-disk based index. Query-dependent features are received from these indexes by doing query reformulations like *terms as phrase* (see Appendix for a complete list). The resulting scores for each of the indexed documents are the query-dependent feature values.

Having a small index instead of a complete one influences some feature values. Nevertheless, this procedure is reasonable since we are only interested in query-dependent feature values for documents that appear in our initial search results.

For the retrieval of quality-based features we preprocessed the belonging values. Static meta-data like *number of pages* is added to the indexed documents, changing values like *PageRank* are inserted into another index which is updated when necessary.

Using an additional index is of course not helpful for fast feature retrieval. On the other hand documents in the main index do not have to be re-indexed, when quality-based

<sup>1</sup><http://portal.acm.org>

<sup>2</sup><http://lucene.apache.org/>

features change. For user-dependent future extensions like *user has seen result* such an index becomes necessary nevertheless.

Hence, to receive all necessary features for a list of results, these results are indexed to retrieve query-dependent features. Some quality-based features are taken from document fields itself and some by querying another index.

#### 4.2. User model

For testing the architecture we set up a user model to generate users which are able to click search result links automatically, from here on referred to as clickers. These clickers act independently, without *PIA* noticing that these clicks do not come from real users. Each generated user has been modeled to have different preferences which have direct impact on their clicking behavior. In this section we describe how these users are modeled and how clicked documents lead to preferences for every clicker.

Each time a user clicks on a result in a result list, preferences are expressed. Assuming that these preferences are somehow expressible with a set of given features belonging to each result, it is possible to learn these preferences and rank results accordingly.

Using these features it is possible to generate clickers that model a typical *PIA* user. With regard to *PIA* and its scientific services background, feature based preferences are the following

**clicker (1)** At least one searched phrase has to be in the title. If there are search terms which do not belong to phrases, they are treated as phrase.

**clicker (2)** At least one search term has to be in the title, even if the search term is part of a phrase.

**clicker (3)** There have to be at least three authors.

**clicker (4)** Long summaries are preferred.

**clicker (5)** At least one searched phrase has to be in the summary.

**clicker (6)** By a chance of 0.5, a result is clicked or not.

**clicker (7)** Combined clicker of (2) AND (4) AND (5).

Because these preferences are feature based, rules can be written to express these preferences. If a user  $u$  prefers a result  $r$  then the probability that  $r$  is clicked is one:

$$p_u(r) = \begin{cases} 1, & \text{if user prefers result} \\ 0, & \text{else} \end{cases} \quad (3)$$

Treating *PIA* as a black box (see Fig. 2), each generated clicker performs a login (or registration if necessary) and starts querying *PIA* for results. For each query *PIA* returns a result list and the generated clicker starts clicking on preferred results.

#### 4.3. Query Set

For the evaluation we defined a fixed list of 1000 queries. These queries were extracted from author given keywords of randomly chosen ACM documents. If a keyword included a space, it was transformed to a phrase query. Per document one or two randomly chosen keywords were transformed to an OR-query. The resulting queries look like: “*student experiments*” *teaching*. Each generated clicker used the same list of queries. We did not model query chains (Radlinski and Joachims, 2005) and each query is connected to a different information need.

#### 4.4. Preference Precision

Because it is not of interest whether a result is relevant or not, standard information retrieval performance measures can not be taken into account.

Hence, the quality of the rankings is computed by the mean average preference precision, where the preference precision is 1 if a result is preferred or 0 if a result is not preferred (see Equ. 3). The computation of this measure follows the computation of the mean average precision. Note that the preference precision depends on the user and hence it is possible to evaluate a (personalized) result list with different preference precisions to conclude if the architecture learned to rank by the individual preferences.

### 5. Evaluation

For underlining the quality of the proposed approach, we investigate the resulting degree of personalization. Furthermore we evaluate the minimal amount of necessary feedback and the additional time to achieve such personalization.

#### 5.1. Personalized Preference Learning

The first evaluation investigates whether personalized learning to rank can be applied successfully.

For this purpose clickers had to go through a set of 900 queries and click on preferred results. These clicks were recorded and used as training data for the RankSVM. After retrieving preference relations from these logs, the

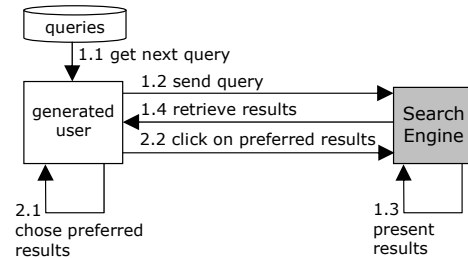


Figure 2: The generated user retrieves results from *PIA* and clicks on preferred results.

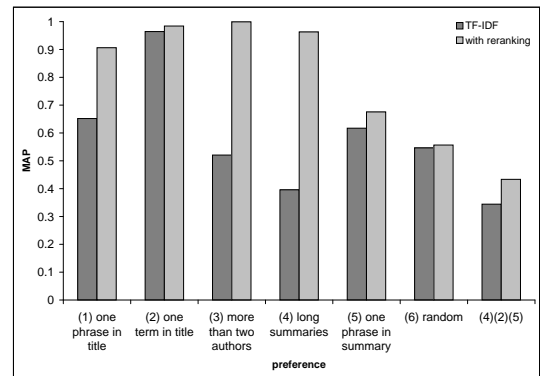


Figure 3: MAP values of results for selected preference clickers. The TF-IDF performance is based on the result lists before reranking was applied. Note that the precision does not depend on relevance but on the respective preference driven clicks.



RankSVM was trained and a personalized model was generated.

Then the clickers went through a second set of 100 queries to measure the degree of personalization of reranked results. These queries served to evaluate the difference between the original TF-IDF based ranking and reranked results.

The results of this evaluation are shown in Fig. 3. The bars in a darker shade represent the mean average precision of the results which were not reranked and are solely based on TF-IDF. Those bars in a lighter shade show the MAP of the results after the model was trained and the results were reranked.

It is quite clear to see that the MAP values with reranking exceed the MAP values solely based on TF-IDF. The results for the clickers “more than two authors” (**clicker (3)**) and “long summaries” (**clicker (4)**) look particularly promising as it is not possible for TF-IDF to map those preferences of these clickers.

As such reranking with RankSVM has increased the MAP by over 90% and 140%. The increase in MAP based on clickers “one phrase in title” (**clicker (1)**) and “one term in title” (**clicker (2)**) was 39% and 2%. The increase is not as high as those preferences can be mapped relatively well by TF-IDF. It was not possible to increase the MAP of a random clicker. For a more complex and realistic clicker who had multiple preferences the performance could be increased by 26%.

## 5.2. Amount of Feedback

The second evaluation we conducted was for investigating how much feedback is needed for personalization.

We address the question of how many queries with clicked results are needed before an effect on the reranking of the result list for a new user becomes apparent, and furthermore, after how many of such queries there is no more visible improvement of reranking. To evaluate this, we use sets of 100 randomly selected queries to be clicked by a “realistic” clicker with a complex preference model. **Clicker (7)** will click on any search result which has a non-empty description text, contains at least one phrase of the search term in this description and one word of the search term in its title. After each query, the average precision of the result clicks is calculated and stored, and the learning to rank model is retrained to include the newly obtained preferences. Queries in which no results have been clicked are discarded immediately and a different query string is substituted. After clicking on the results of 100 queries, 100 AP values are obtained, each accommodating the effects of reranking based on the preceding queries. To mitigate the variance of AP values for different search results, the AP values are averaged over 100 of such test runs. As baseline value, the result list before reranking was evaluated, displaying the search engine’s native TF-IDF based ranking. The results of the evaluation where the learning to rank model was retrained after each query can be seen in Fig. 4. This evaluation points to the question of when reranking affects the quality of results. The TF-IDF baseline which results from the evaluation of the result lists before reranking was done is more or less constant at a MAP of 0.4.

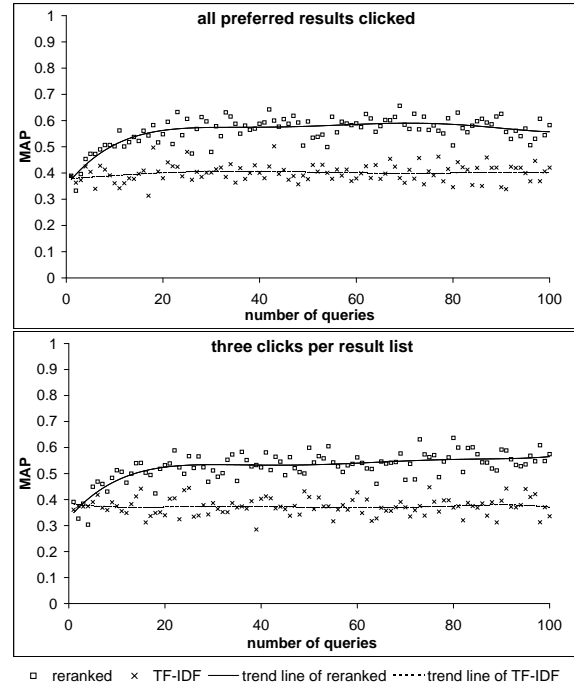


Figure 4: Comparison: MAP per query of TF-IDF and reranked results per query. The clicker clicked on all (top), or respectively on at most three (bottom), preferred results (with long summaries, at least one search term in the title, and at least one searched phrase in the summary). After each query there was a new training of the model. Data points are the mean of 100 test runs and the polynomial trend line has the order 5.

On top of Fig. 4 an evaluation can be seen, where **clicker (7)** clicked on all preferred results. On the bottom the clicker only clicked on the first three preferred results. Nevertheless the presented MAP (mean of 100 test runs) value is based on the preference of each result.

An increasing effect of reranking on the search result lists with every query can be discerned in both evaluations. After about 10 search queries that included result clicks, the MAP of reranked results increased by 0.1 compared to the TF-IDF based ranking presented by the search engine without reranking. This means that personalized reranking of results for a user has a visibly increasing effect on the search results presented to the user, as useful results had been reranked to appear higher up in the list.

For a user which intensively browses 30 result lists, the following reranked results have a MAP of about 0.55 which, compared to the MAP of about 0.4 of the native result ranking, is a 37% increase. Result lists for users which generate only a little bit of implicit feedback have a MAP of 0.5 after 30 queries, an increase of 25%. There is a slight increase in MAP for these users after query 30.

Note that these results do not point to the fact that the reranked results always perform better. There were result list where the TF-IDF ranking had a better AP. Additionally these MAP values strongly depend on **clicker (7)** which represents a user with several preferences.

After 30 queries, no further significant improvement of ranking quality can be observed, though in this test the

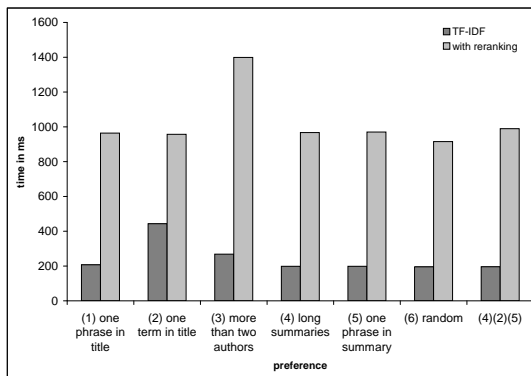


Figure 5: Time comparison between unranked and reranked results. The time for reranking includes the querying of the index, the feature vector retrieval, and the reranking of the first 30 results.

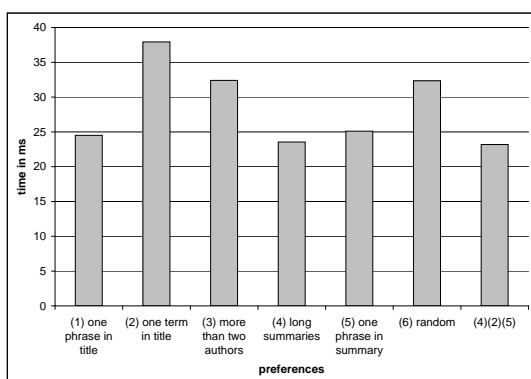


Figure 6: Mean training time for one preference.

user’s criteria that determine which results are clicked are invariable. It can be concluded that with an applied learning to rank method, distinctly personalized results for users with a non-random click-behavior can be achieved after only 10 trained queries, in which returned results were clicked by that user.

### 5.3. Additional Response Time

Learning to rank is not just based on the learning of preference data. This data has to be retrieved first. Result clicks have to be logged, transferred to preferences, and the results have to be converted to feature vectors before they can be trained. Hence there are three parts in a search engine which have to be modified or added to apply learning to rank: logging, learning, and reranking. The additional time needed is logged for evaluation.

As learning to rank involves an additional reranking step, we have measured the extra time needed to do so. In Fig. 5 it is quite clearly visible that the overhead of reranking is significant. The average time increase is at over 350%. In average the user had to wait about 1020ms until the results were presented.

In Fig. 6 the average time for training a single preference is presented. The mean training for a single preference ranges from 24.5ms to 32.2ms and averages in those clickers at around 28.4ms.

## 6. Conclusion

In this work we applied learning to rank to a real search engine. We investigated whether it is possible to use learning to rank for ranking search results by personal preferences. The evaluations have clearly shown that personalization is possible, even if the personal preferences are complex.

Applying learning to rank to search engines is possible, but unfortunately for the cost of an extended query response time. In average users of our architecture have to wait one second longer if the first 30 results are reranked by their individual preferences.

While ranking by preferences which are based on only one feature is easily be done, it is more difficult with a more complex preference scheme.

We strongly suggest preprocessing quality features of potential results offline and storing these attributes in an index. Such quality information is needed when creating a representing feature vector for each result and querying an index for this information can be done fast. This especially becomes necessary at query time where response time restrictions have to be followed.

A learning to rank search engine including the proposed preference retrieval method automatically scales by becoming better. If a search engine returns perfectly ranked results, it is not possible to extract preferences from click-through data and hence no recreation of the used model will be performed.

If there is a point of no real quality improvement when training a learning to rank model with additional preferences, there should be a general limitation to the number of used preferences in such an application. Additionally preferences might change and hence it is necessary nevertheless to dismiss old click logs.

The training of a learning to rank model should be done shortly after the user interaction which led to new preferences. The training time for creating a model for one user never exceeded one minute (on a standard system) and can be done in parallel to the interaction with the user. When the model is created, the old model can be replaced and the user benefits from learning to rank immediately.

## 7. Future Work

Possible extension to the presented approach is the implementation of explicit feedback retrieval. In addition to the extracted preference pairs from clickthrough data, users will be able to actively express their preference between two results and thus improve their personal ranking performance.

Another function to implement could be the use of query chains as presented in (Radlinski and Joachims, 2005). This would make it possible to exploit the fact that a lot of queries are interdependent, and thus improve the quality of search results for successive queries.

In our work, we use clickers with fixed probabilities of 1 to click on a preferred document and 0 to click on a random document. To produce a more realistic user model, a probabilistic click behavior that causes clickers to skip some of the preferred documents and to select some of the non-preferred documents will be included.

Since users' preferences may change over time, their result click pattern can vary. The existing clickers that combine different preference models can be extended to model this effect. Using these clickers the system can be monitored to reveal how long it takes for a trained model to adapt to changed likings.

In future work, we will introduce additional user-dependent features, like *user has read result* or *result was presented to user in an earlier search*. We are confident that such features will further improve users' search experience.

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## APPENDIX

In the following we present a list of features used.

Quality-based features:

1. Publication-related features
  - *Number of authors*
  - *Year of publication*
  - *Number of words in abstract*
  - *PageRank*
  - *Cite-impact*
  - *Number of references to other publications*
  - *Number of publications of main author*
  - *Number of publications of all authors*
2. Document file-related features
  - *Document page count*
  - *Number of words in publication*
  - *Document file size*

Query-dependent features:

1. Statistical query-dependent features:
  - *Term frequency (TF), Inverse document frequency (IDF), TF-IDF Product of TF and IDF.*
2. Query reformulation query-dependent features:<sup>3</sup>
  - *First word fuzzy:* Searches with fuzziness constraint for the first word. Three fuzziness levels with values of 0.5, 0.8 or 0.9 lead to three features.
  - *Last word fuzzy:* Searches with fuzziness constraint for the last word. Three fuzziness levels with values of 0.5, 0.8 and 0.9 lead to three features.
  - *First word only:* Searches for the first word of the query phrase.
  - *Fuzzy only first word:* Searches with fuzziness constraint for the first word from the query phrase only. Three fuzziness levels with values of 0.5, 0.8 and 0.9 lead to three features.
  - *Last word only:* Searches for the last word of the query phrase.
  - *Fuzzy only last word:* Searches with fuzziness constraint for the last word from the query phrase only. Three fuzziness levels with values of 0.5, 0.8 and 0.9 lead to three features.
  - *All words fuzzy:* Apply fuzziness constraint for all words from the query phrase. Three fuzziness levels with values of 0.5, 0.8 and 0.9 lead to three features.
  - *Words within range:* Looks whether all words from the query phrase are located within a distance of two, ten or number of words in the query. Leads to three features.
  - *Boosting first word:* Apply higher priority to the first word of the query phrase. Boosts by five or ten leading to two features.
  - *Boosting last word:* Apply higher priority to the last word of the query phrase. Boosts by five or ten leading to two features.
  - *Boosting gradient:* Increases or decreases the priority beginning with the first word to the last word. Leads to two features (increasing or decreasing priority).
  - *Fuzzy gradient:* Increases or decreases the fuzziness beginning with the first word to the last word. Leads to two features (increasing or decreasing fuzziness).
  - *Terms as phrase:* All words from the query phrase are treated as a single phrase.

The complete feature vector consists of 64 single features.

<sup>3</sup>Each query dependent feature is computed for all known document parts, like title or summary separately.

# Personalized Multi-Document Summarization using N-Gram Topic Model Fusion

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## Abstract

We consider the problem of probabilistic topic modeling for query-focused multi-document summarization. Rather than modeling topics as distributions over a vocabulary of terms, we extend the probabilistic latent semantic analysis (PLSA) approach with a bigram language model. This allows us to relax the conditional independence assumption between words made by standard topic models. We present a unified topic model which evolves from sentence-term and sentence-bigram co-occurrences in parallel. Sentences and queries are represented as probability distributions over latent topics to compute thematic and query-focused sentence features in the topic space. We find that the inclusion of bigrams improves the descriptive quality of the latent topics, and leads to a substantially reduced number of latent topics required for representing document content. Experimental results on DUC 2007 data show an improved performance compared to a standard term-based topic model. We further find that our method performs at the level of current state-of-the-art summarizers, while being built on a considerably simpler model than previous topic modeling approaches to summarization.

## 1. Introduction

Automatically producing summaries from a set of input documents is an extensively studied problem in IR and NLP (Jones, 2007). In this paper, we investigate the problem of multi-document summarization, where the task is to “synthesize from a set of related documents a well-organized, fluent answer to a complex question”<sup>1</sup>. In particular, we focus on generating an extractive summary by selecting relevant sentences from a document cluster (Goldstein et al., 2000). The condensation of information from different sources into an informative summary is an increasingly important task, since it helps to reduce information overload.

A major challenge of identifying relevant information is to model document content. A document will generally contain a variety of information centered around a main topic, and covering different aspects (subtopics) of this main theme (Barzilay and Lee, 2004). Human summaries also tend to cover different aspects of the original source text to increase the informative content of the summary. In addition, in query-focused multi-document summarization tasks, the user query often explicitly requests information about different aspects of the main theme of the document cluster (see Table 1). An ideal summary should therefore aim to include information for each of the “subquestions” of the complex user query.

Various summarization approaches have exploited observable features based on the identification of topics (or thematic foci) to construct summaries. Often, such features rely on the identification of important keywords (Yih et al., 2007; Nenkova et al., 2006), or on the creation of term-based topic signatures (Lin and Hovy, 2000; Conroy et al., 2007). However, it is well known that term matching has severe drawbacks due to the ambivalence of words and to differences in word usage across authors (Manning

and Schütze, 2001). This is especially important for automatic summarization, as summaries produced by humans may differ significantly in terms of word usage. (Lin and Hovy, 2003b).

Topic models such as Latent Semantic Indexing (LSI) (Deerwester et al., 1990), Probabilistic Latent Semantic Analysis (PLSA) (Hofmann, 1999), and Latent Dirichlet Allocation (LDA) (Blei et al., 2003) provide a means to overcome the problem of term matching, and furthermore allow for the modeling of inter- and intradocument statistical structure. These models introduce hidden variables as the origin of the observed term co-occurrences. Whereas LSI is a mapping of the original term-document vector space onto a linear subspace based on singular value decomposition, PLSA and LDA model documents as a distribution of mixture components, where each mixture component is a multinomial distribution over words. The mixture components can be interpreted as “topics”, and the corresponding word distribution characterizes the semantics of the topic.

This reduced description will generally capture some aspects of synonymy and polysemy, since words with similar meanings tend to occur in similar contexts. Furthermore, semantically similar words are clustered based on the assumption that the co-occurrence of terms signals semantic relatedness. However, words are considered independent given the topics, resulting in the standard bag-of-words assumption (Blei et al., 2003). N-Gram language models (Ponte and Croft, 1998) allow us to relax this assumption in order to capture multi-word concepts, where word order plays a critical role (Wang et al., 2007).

### 1.1. Our contribution

Our approach extends the standard topic modeling approach such that the topic model is estimated from the term co-occurrence as well as bigram co-occurrence observations in parallel. The integration of a bigram language model allows us to represent the mixture compo-

<sup>1</sup>DUC summarization track task description, <http://www.nist.gov/tac>

Table 1: A complex user query from DUC 2006.

ID	D0631D
Title	Crash of the Air France Concorde
Query	Discuss the Concorde jet, its crash in 2000, and aftermaths of this crash.

nents as multinomial distributions over terms and bigrams, leading to an improved representation of the components. Each document’s distribution over the mixture components is re-estimated based on maximizing the likelihood of the data given both the term co-occurrence and the bigram co-occurrence distributions.

Furthermore, the integration of the bigram language model allows us to relax the (conditional) independence assumption made by the standard topic model, since bigrams encode syntactic dependencies between consecutive terms. Even though one can consider a bigram simply to be a co-occurrence of two terms, and as such captured well enough by a standard topic model, our assumption is that bigram co-occurrence patterns will reinforce the observed term co-occurrence patterns. We show that this results in more descriptive latent topics, and considerably reduces the number of latent topics required for a good model.

We apply the modified topic model in query-focused multi-document summarization, and model sentences and queries in this novel latent topic space. This allows us to compute thematic and query-focused sentence similarity features for extractive summarization.

The rest of this paper is structured as follows: We start with an overview of related work in Section 2. In Section 3. we describe our approach for integrating a language model into the PLSA algorithm. Next, in Section 4., we give details of our summarization system, the sentence-level features we use, and of our sentence ranking and selection approach. In Section 5., we describe and analyze the data sets we use to verify the assumptions of our approach, and we present experimental results. Finally, Section 6. concludes the paper.

## 2. Related work

Probabilistic topic models for the representation of document content have also been explored by Barzilay and Lee (Barzilay and Lee, 2004). They use Hidden Markov Models (HMM) to model topics and topic change in text, albeit only for generic single-document summarization. The model assumes that a topic is formed by clustering sentences based on vector space similarity, and bigram distribution patterns are learned from these topical clusters. Each sentence is assigned to exactly one topic cluster, corresponding to a HMM state. Documents are modeled as sequences of topics, representing the typical discourse structuring of texts in specific domains. In contrast, our approach models each sentence as a distribution over multiple topics, and also models queries in the latent topic space for query-focused multi-document summarization.

More related to our method is the approach of Daumé and Marcu (Daumé and Marcu, 2006), who utilize a model similar in style to LDA. However, the latent classes are chosen to capture general language background vocabulary, document- and query-specific vocabularies. Each sentence

is modeled as a distribution over these three mixture components, e.g. consisting of 60% query information, 30% background document information, and 10% general English (Daumé and Marcu, 2006). Topical information is not considered, and neither are the subtopics contained in a document.

The method proposed by Haghighi and Vanderwende takes up this approach, but constructs summaries by optimizing the KL-divergence between the summary topic distribution and the topic distribution of the source document set (Haghighi and Vanderwende, 2009). Subtopics are modeled by introducing a hierarchical LDA process. Instead of drawing words only from a generic “content” distribution they allow for either generic or topic-specific word distributions for each sentence. However, for each sentence only one distribution is selected, and all content words of that sentence are drawn from this distribution. Topic-specific distributions are ordered sequentially over sentences similar to the approach of Barzilay and Lee. The proposed approach does not allow for query-focused summarization.

In previous work, we showed that a term-sentence co-occurrence based PLSA model can be effectively used for query-focused multi-document summarization (Hennig, 2009). The proposed model outperformed existing systems on DUC 2006 data, and performed comparable to state-of-the-art summarization systems on the DUC 2007 dataset.

All of the above methods consider either unigram or bigram distributions for representing topics, but not the combination of both. In our approach, we combine unigram and bigram observations to create topic representations that consist of multinomial distributions over both unigrams and bigrams.

In the area of topic modeling, Wallach proposed an approach to relax the bag-of-words assumption in (Wallach, 2006). The LDA model she discusses incorporates, in a fashion similar to typical n-gram language models, the conditional probability of a word at position  $t$  given the word at position  $t - 1$ , such that  $p(w_t) = p(w_t|w_{t-1})$ . Each topic is represented as a set of  $W$  distributions – contrasting with the single word distribution per topic typically used – where  $W$  is the size of the vocabulary. Each of the  $W$  word distributions per topic is conditioned on the context of a previous word  $w_{t-1}$ . The number of parameters to be estimated is hence  $WT(W - 1)$ , whereas our model has  $(W - 1)T(B - 1)$  free parameters ( $B$  is the number of distinct bigrams).

## 3. Topic and Language Model Combination using PLSA

For simplicity, we utilize and adapt the PLSA algorithm to test the validity of our approach, but for all purposes this can be considered equivalent to using a more complex topic

model such as LDA.

PLSA is a latent variable model for co-occurrence data that associates an unobserved class variable  $z \in \mathcal{Z} = \{z_1, \dots, z_k\}$  with each observation  $(d, w)$ , where word  $w \in \mathcal{W} = \{w_1, \dots, w_i\}$  occurs in document  $d \in \mathcal{D} = \{d_1, \dots, d_j\}$ . Documents and words are assumed independent given the topic variable  $Z$ . The probability that a word occurs in a document can be calculated by summing over all latent variables  $Z$ :

$$P(w_i|d_j) = \sum_k P(w_i|z_k)P(z_k|d_j). \quad (1)$$

Similarly, we can associate each observation  $(d, b)$  of a bigram  $b = (ww')$ , where bigram  $b \in \mathcal{B} = \{b_1, \dots, b_l\}$  occurs in document  $d$ , with the same unobserved class variable  $z$ . We assume the same hidden topics of the term-sentence co-occurrences  $(d, w)$  as the origin of the bigram-sentence co-occurrence observations  $(d, b)$ :

$$P(b_l|d_j) = \sum_k P(b_l|z_k)P(z_k|d_j). \quad (2)$$

Notice that both decompositions share the same document-specific mixing proportions  $P(z_k|d_j)$ . This couples the conditional probabilities for terms and bigrams: each ‘‘topic’’ has some probability  $P(b_l|z_k)$  of generating bigram  $b_l$  as well as some probability  $P(w_i|z_k)$  of generating an occurrence of term  $w_i$ . The advantage of this joint modeling approach is that it integrates term and bigram information in a principled manner. This coupling allows the model to take evidence about bigram co-occurrences into account when making predictions about terms and vice versa. Following the procedure in Cohn and Hofmann (Cohn and Hofmann, 2000), we can now combine both models based on the common factor  $P(z|d)$  by maximizing the log-likelihood function

$$L = \sum_j \left[ \alpha \sum_i n(d_j, w_i) \log P(w_i|d_j) + (1 - \alpha) \sum_l n(d_j, b_l) \log P(b_l|d_j) \right] \quad (3)$$

where  $\alpha$  is a predefined weight for the influence of each two-mode model. Using the Expectation-Maximization (EM) algorithm we then perform maximum likelihood parameter estimation for the aspect model. During the expectation (E) step we first calculate the posterior probabilities:

$$P(z_k|w_i, d_j) = \frac{P(w_i|z_k)P(z_k|d_j)}{P(w_i|d_j)} \quad (4)$$

$$P(z_k|b_l, d_j) = \frac{P(b_l|z_k)P(z_k|d_j)}{P(b_l|d_j)}, \quad (5)$$

and then re-estimate parameters in the maximization (M) step as follows:

$$P(w_i|z_k) = \sum_j \frac{n(w_i, d_j)}{\sum_{i'} n(w_{i'}, d_j)} P(z_k|w_i, d_j) \quad (6)$$

$$P(b_l|z_k) = \sum_j \frac{n(b_l, d_j)}{\sum_{l'} n(b_{l'}, d_j)} P(z_k|b_l, d_j) \quad (7)$$

The class-conditional distributions are recomputed in the M-step as

$$p(z_k|d_j) \propto \alpha \sum_i \frac{n(w_i, d_j)}{\sum_{i'} n(w_{i'}, d_j)} P(z_k|w_i, d_j) + (1 - \alpha) \sum_l \frac{n(b_l, d_j)}{\sum_{l'} n(b_{l'}, d_j)} P(z_k|b_l, d_j) \quad (8)$$

Based on the iterative computation of the above E and M steps, the EM algorithm monotonically increases the likelihood of the combined model on the observed data. Using the  $\alpha$  parameter, our new model can be easily reduced to a term co-occurrence based model by setting  $\alpha = 1.0$ .

## 4. Topic-based summarization

Our approach for producing a summary consists of three steps: First, we represent sentences and queries in the latent topic space of the combined PLSA model by estimating their mixing proportions  $P(z|d)$ . We then compute several sentence-level features based on the similarity of sentence and query distributions over latent topics. Finally, we combine individual feature scores linearly into an overall sentence score to create a ranking, which we use to extract sentences for the summary. We follow a greedy approach for selecting sentences, and penalize candidate sentences based on their similarity to the partial summary. These steps are described in detail below.

### 4.1. Data Set

We conduct our analysis and evaluate our model based on the multi-document summarization data sets provided by DUC<sup>2</sup>. Specifically, we use the DUC 2007 data set for evaluation. The data set consists of 45 document clusters, with each cluster containing 25 news articles related to the same general topic. Participants are asked to generate summaries of at most 250 words for each cluster. For each cluster, a title and a narrative describing a user’s information need are provided. The narrative (query) is usually composed of a set of questions or a multi-sentence task description.

### 4.2. Sentence representation in the latent topic space

Given a corpus  $\mathcal{D}$  of topic-related documents, we perform sentence splitting on each document using the NLTK toolkit<sup>3</sup>. Each sentence is represented as a bag-of-words  $\mathbf{w} = (w_1, \dots, w_m)$ . We remove stop words for the unigram model, and apply stemming using Porter’s stemmer (Porter, 1980). We create a term-sentence matrix  $TS$  containing all sentences of the corpus, where each entry  $TS(i, j)$  is given by the frequency of term  $i$  in sentence  $j$ , and a bigram-sentence matrix  $BS$ , where each entry  $BS(l, j)$  is given by the frequency of bigram  $l$  in sentence  $j$ . We then train the combined PLSA model on the matrices  $TS$  and  $BS$ .

After the model has been trained, it provides a representation of the sentences as probability distributions  $P(z|s)$  over the latent topics  $Z$ , and we arrive at a representation of sentences as a vector in the ‘‘topic space’’:

$$\mathbf{s} = (p(z_1|s), p(z_2|s), \dots, p(z_K|s)), \quad (9)$$

<sup>2</sup><http://www.nist.gov/tac>

<sup>3</sup><http://www.nltk.org>

where  $p(z_k|s)$  is the conditional probability of topic  $k$  given the sentence  $s$ .

In order to produce a query-focused summary, we also need to represent the query in the latent topic space. This is achieved by folding the query into the trained model. The folding is performed by EM iterations, where the factors  $P(w|z)$  and  $P(b|z)$  are kept fixed, and only the mixing proportions  $P(z|q)$  are adapted in each M-step (Hofmann, 1999). We fold the title and the query of the document clusters, the document titles, and document and cluster vectors into the trained PLSA model. Query vectors are preprocessed in the same way as training sentences, except that no sentence splitting is performed. Document and document cluster term vectors are computed by aggregating sentence term vectors.

### 4.3. Computing query- and topic-focused sentence features

Since we are interested in producing a summary that covers the main topics of a document set and is also focused on satisfying a user’s information need, specified by a query, we create sentence-level features that attempt to capture these different aspects in the form of per-sentence scores. We then combine the feature scores to arrive at an overall sentence score. Each feature is defined as a similarity  $r(S, Q)$  of a sentence topic distribution  $S = P(z|s)$  compared to a “query” topic distribution  $Q = P(z|q)$ :

- $r(S, CT)$  - similarity to the cluster title
- $r(S, N)$  - similarity to the cluster narrative (query)
- $r(S, T)$  - similarity to the document title
- $r(S, D)$  - similarity to the document centroid
- $r(S, C)$  - similarity to the cluster centroid

Since measures for comparing two probability distributions are typically defined as divergences, not similarities, we invert the computed divergence. In our approach, we employ the Jensen-Shannon (JS) divergence, but a variety of other similarity measures can be utilized towards this end. The JS-divergence is a symmetrized and smoothed version of the Kullback-Leibler divergence:

$$r_{JS}(S, Q) = 1 - \left[ \frac{1}{2} D_{KL}(S||M) + \frac{1}{2} D_{KL}(Q||M) \right], \quad (10)$$

where  $M = 1/2(S + Q)$ .

As the training of a PLSA model using the EM algorithm with random initialization converges on a local maximum of the likelihood of the observed data, different initializations will result in different locally optimal models. As Brants et al. (Brants et al., 2002) have shown, the effect of different initializations can be reduced by generating several PLSA models, then computing features according to the different models, and finally averaging the feature values. We have implemented this model averaging using 5 iterations of training the PLSA model.

### 4.4. Sentence scoring

The system described so far assigns a vector of feature values to each sentence. The overall score of a sentence consisting of the features  $(r_1, \dots, r_P)$  is then defined as:

$$score(s) = \sum_p w_p r_p, \quad (11)$$

where  $w_p$  is a feature-specific weight. We optimized the features weights on the DUC 2006 data set, which is similar to our evaluation data set. We initialized all feature weights to a default value of 1, and then optimized one feature weight at a time while keeping the others fixed. The most dominant features in our experiments are the sentence-narrative similarity  $r(S, N)$  and the sentence-document similarity  $r(S, D)$ , which confirms previous research. Sentences are ranked by this score, and the highest-scoring sentences are selected for the summary.

We model redundancy similar to the maximum marginal relevance framework (MMR) (Carbonell and Goldstein, 1998). MMR is a greedy approach that iteratively selects the best-scoring sentence for the summary, and then updates sentence scores by computing a penalty based on the similarity of each sentence with the current summary:

$$score_{mmr}(s) = \lambda(score(s)) - (1 - \lambda)r(S, SUM), \quad (12)$$

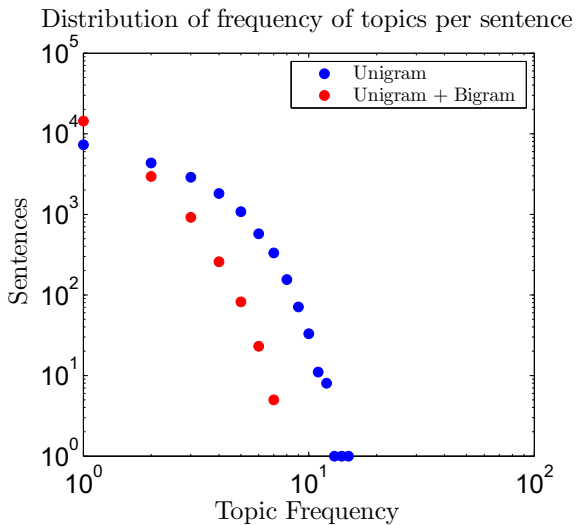
where the score of sentence  $s$  is scaled to  $[0, 1]$  and  $r(S, SUM)$  is the cosine similarity of the sentence and the summary centroid vector, which is based on the averaged distribution over topics of sentences selected for the summary. We optimized  $\lambda$  on DUC 2006 data, with the best value  $\lambda = 0.4$  used in our experimental evaluation.

### 4.5. Topic distribution over sentences

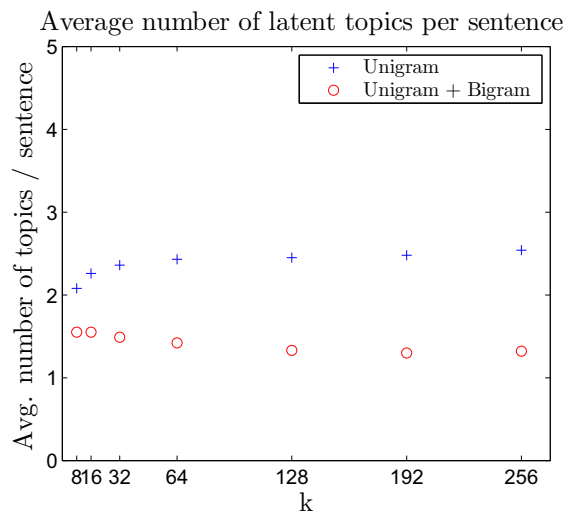
It is well known that documents cover multiple subtopics related to the main theme of the document (Barzilay and Lee, 2004). Standard topic models such as LDA therefore represent a document as a distribution over a set of latent topics. In our approach, we extend this notion and treat each sentence as a document, thus assuming that a sentence covers one or more topics of the document set. For example, a sentence of a news article related to a meeting of government leaders may provide information on the people who have met as well as on the location of the meeting. Our intuition is that the number of topics that a sentence covers should be rather low, but greater than one.

Figure 1(a) shows the distribution of the number of topics per sentence for a PLSA model based on terms only and for the PLSA model combining unigrams and bigrams. We only consider topics with a probability greater than some small value  $\epsilon$  ( $\epsilon > 0.01$ ). We see that the distributions follow a power law: There are very many sentences which are assigned a single dominant topic, and very few sentences which are assigned many topics. We note that the combined model assigns less topics to a sentence than the term-based model.

From Figure 1(b) we see that the average number of topics assigned to a sentence is relatively robust to varying the value of  $k$  (the free parameter specifying the number of latent topics for the PLSA algorithm). Even for  $k \leq 16$ ,



(a) DUC 2007: Topic distribution



(b) DUC 2007: Average number of topics

Figure 1: (a) Distribution of number of topics per sentence ( $p(z|d) > 0.01$ ) for a  $k = 128$  factor decomposition of the DUC 2007 document sets, using terms only or the combined model; and (b) Average number of topics per sentence ( $p(z|d) > 0.01$ ) for different values of  $k$ , using terms only or the combined model

where  $k$  is actually smaller than the number of input documents, on average more than one topic is assigned to a sentence. This confirms our intuition that sentences may cover multiple subtopics. Again we see that the combined model on average assigns less topics to a sentence, which suggests that the descriptive quality of the topics better fits the available data.

## 5. Experiments

For the evaluation of our system, we use the data set from the multi-document summarization task in DUC 2007. For all our evaluations, we use ROUGE metrics<sup>4</sup>. ROUGE metrics are recall-oriented and based on n-gram overlap. ROUGE-1 has been shown to correlate well with human judgements (Lin and Hovy, 2003a). In addition, we also report the performance on ROUGE-2 (bigram overlap) and ROUGE-SU4 (skip bigram) metrics.

### 5.1. Results

We present the results of our system in Table 2. We compare our results to the best peer (*peer 15*) and to a *Lead* sentence baseline system. The *Lead* system uses the first  $n$  sentences from the most recent news article in the document cluster to create a summary. In the table, system *PLSA* uses a standard term co-occurrence based model, and system *PLSA-F* combines term and bigram co-occurrences, based on the best value for parameter  $\alpha = 0.6$ . The *PLSA-F* system outperforms the standard *PLSA* model on ROUGE-1, ROUGE-2 and ROUGE-SU4 scores, although the improvements are not significant. More interestingly, the *PLSA-F* achieves its best score using only  $k = 32$  latent classes, compared to  $k = 256$  for the *PLSA* system. This suggests

Table 2: DUC-07: ROUGE recall scores for best number of latent topics  $k$ . The *PLSA* system uses term co-occurrences only, the *PLSA-F* combines term and bigram co-occurrence information, with  $\alpha = 0.6$ . The *PLSA-F* variant outperforms the best participating system (*peer 15*) on ROUGE-1.

System	k	Rouge-1	Rouge-2	Rouge-SU4
peer 15	-	0.44508	0.12448	0.17711
PLSA-F	32	<b>0.45400</b>	0.11951	0.17573
PLSA	256	0.44885	0.11774	0.17552
Lead	-	0.31250	0.06039	0.10507

that the information supplied by the bigram co-occurrence observations indeed reinforces the term co-occurrence observations, such that the model can better represent the different latent topics contained in the document cluster.

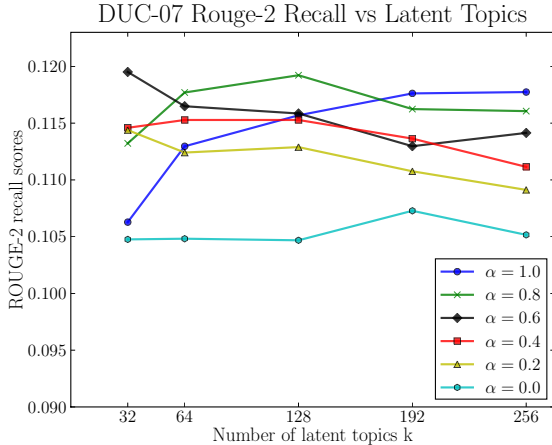
Our combined approach outperforms *peer 15* on ROUGE-1 recall, and is not significantly worse on ROUGE-SU4 recall. For ROUGE-2, our system’s performance is only slightly lower than the 95%-confidence interval of the top system’s performance (0.11961–0.12925). The results of our system are also comparable to the topic modeling approach of Haghghi and Vanderwende (Haghghi and Vanderwende, 2009), who report a ROUGE-2 score of 0.118 for a model based on bigram distributions, but are significantly better than the 0.097 they report for an unigram-based model.

### 5.2. System variations

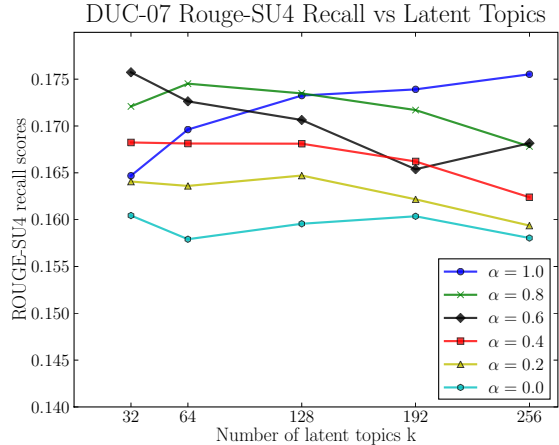
To verify the experimental observation that the combined model allows for a better representation of the latent topics, we conducted a series of experiments varying the number of latent classes and the weight of the parameter  $\alpha$ . The results of these experiments are shown in Figure 2. We have

<sup>4</sup>ROUGE version 1.5.5, with arguments -n 4 -w 1.2 -m -2 4 -u -c 95 -r 1000 -f A -p 0.5 -t 0





(a) DUC 2007 Rouge-2



(b) DUC 2007 Rouge-SU4

Figure 2: Summarization performance on DUC 2007 data in terms of ROUGE-2 (a) and ROUGE-SU4 (b) recall for different values of latent topics  $k$  and parameter  $\alpha$ .

omitted results for  $k < 32$ , where none of the models can cope with the complexity of the data. We also do not show results for  $k > 256$ , since the performance of all models either stabilizes with respect to their performance at  $k = 256$ , or the models start to overfit, resulting in lower ROUGE scores. We observe that the models combining term and bigram co-occurrence information outperform the models based only on term co-occurrence ( $\alpha = 1.0$ ) respectively bigram co-occurrence ( $\alpha = 0.0$ ) for small numbers of latent classes  $k$ . As  $k$  increases, the performance of the combined models decreases, or exhibits only small variations (e.g.  $\alpha = 0.6$  for  $k = 256$ ). This suggests that the quality of the learned latent topics is starting to decrease, as the algorithm creates topics with idiosyncratic word combinations (Steyvers and Griffiths, 2006). The performance of the term-based model, however, increases until  $k = 256$ , reaching a maximum ROUGE-2 recall of 0.11776, before also overfitting (not shown here).

Our observations therefore indicate that the information obtained from the combined model allows for a more descriptive representation of the latent topics contained in the document collection. The most interesting observation shown in Figure 2 is that adding bigram-sentence co-occurrence observations to a standard PLSA model can substantially improve ROUGE-2 scores and significantly reduce the number of latent classes required for a good model. The effect is less pronounced for ROUGE-SU4 scores, but still recognizable. All combined models outperform the term and bigram baseline models on ROUGE-2 for  $k = 32$  latent classes.

We further note that the term-based model ( $\alpha = 1.0$ ) consistently outperforms the bigram-based model ( $\alpha = 0.0$ ), indicating that bigram co-occurrence information alone captures less of the topical relations that exist in the document collection.

We also find that the effect of varying the parameter  $\alpha$  follows an expectable pattern: For  $\alpha = 0.8$ , the term-based model dominates the latent topic model, and the ROUGE-2 score curve follows that of the model with  $\alpha = 1.0$  (for

$k \leq 128$ ). The experimentally optimal value of  $\alpha = 0.6$  weights term and bigram co-occurrences almost equally, with ROUGE-2 scores similar for  $\alpha = 0.4$ . For lower values of  $\alpha$ , the summarization performance of the model decreases substantially, ROUGE-SU4 scores are constantly lower than for the other models.

## 6. Conclusion

We introduced a novel approach to query-focused multi-document summarization that combines term and bigram co-occurrence observations into a single probabilistic latent topic model. The integration of a bigram language model into a standard topic model results in a system that outperforms models which are based on term respectively bigram co-occurrence observations only. Furthermore, it requires fewer latent classes for optimal summarization performance.

We observe that the distribution of topic frequencies across sentences follows a power law. On average, sentences are assigned more than two latent topics for a standard topic model, but only between one and two topics for our combined model. This suggests that the combined model results in a better representation of the underlying subtopics of a document set. We also find that the average number of topics assigned to a sentence is relatively robust with respect to variations in the number of latent classes.

Our results are among the best reported on the DUC-2007 multi-document summarization tasks for ROUGE-1, ROUGE-2 and ROUGE-SU4 scores. We have achieved these excellent results with a system that utilizes a considerably simpler model than previous topic modeling approaches to multi-document summarization.

In future work, we plan to implement our approach using LDA instead of PLSA to address shortcomings of PLSA such as overfitting and the lack of generative modeling at the document level.

## 7. References

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# Population and Enrichment of Event Ontology using Twitter

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## Abstract

In this paper we present an approach towards creating and enriching an event ontology from social media data gathered from Twitter. Such an ontology is useful in providing accurate, up-to-date information in response to user queries from around the globe. The dynamic nature of Twitter and the broad coverage of user tweets allow us to consolidate information about a wide range of events from conferences to concerts, festivals, and so on. To enrich the ontology we have established a methodology for learning new types of events, so that, in parallel with population of the ontology, completely automatic enrichment is performed as well, fully.

## 1. Introduction

Ontology can be described as an explicit, formal specification of a domain of interest that should be expressed in a machine-readable way (Gruber, 1994). It should be restricted to a given domain of interest and therefore model concepts and relations that are relevant to a particular task or application domain. During the last few years, there has been a growing interest in ontologies due to their ability to explicitly describe data in a common and structured way.

Currently, information about events are available either through local websites (that publish information only on local events) or through the event publisher websites<sup>1</sup>. Common feature of both kinds is that the information published there are either manually inserted or purchased from a third party supplier. As a result of the latter, data about events are often incomplete, when it comes to lower profile events. End users are therefore often faced with the pointless search of the event information about those events that are not that well known.

The goal of this paper is to populate an ontology with the most recent events extracted from social media. Because of this, we needed to choose a social media format which contains information about currently occurring events. We chose *Twitter* as an online social network based on a micro blogging platform used by millions of people around the world.

Data obtained from Twitter are then parsed and mined for various features which are later placed in the event ontology. In the process, data obtained are also analyzed for the purpose of ontology enrichment. Enhanced ontology allows having finer grained and more sophisticated queries about events.

## 2. Related work

There are several research work where the main objective is to identify events from news documents (e.g., newswire, radio broadcast) (Allan et al, 1998; Kumaran & Allan, 2004; Yang et al, 1998). Our task of event extraction is similar to those event detection tasks. But these traditional event detection tasks aim to discover and cluster events

found in textual news articles which are in the form of standard text in nature. Therefore, most state-of-the-art event detection approaches leverage between NLP tools such as named-entity extraction and POS tagging (Makkonen et al, 2004; Zhang et al, 2007). However, these approaches have been developed mainly for standard written text. Event detection has not been developed for unstructured text organized in the form of social media like Twitter where the tweets (basic text message unit of Twitter) are noisy, abbreviated, and condensed in nature.

Twitter has evolved from such a simple text message-based communication system to a powerful platform for distributing and consuming all types of information. The dataset of available tweets is extremely large and dynamic with a great diversity of topics and large number of users from all around the globe (Buzzgain, 2010). Twitter's content gives a wide range of events from conferences to concerts, festivals, and so on. Java et al (2007) found many users report latest news or comment about current events on Twitter. Twitter is no longer just a system to provide simple status updates of personal information; Twitter plays a significant role in time sensitive information seeking and decision making in less urgent and everyday activities (Brooks & Churchill, 2010; Sutton et al, 2008).

## 3. Methodology

### 3.1 Tweet retrieval

The main purpose of this module is to retrieve all tweets containing information about events (hereby referred to as *event tweets*), and for that purpose we used the Twitter API. We found that a search of Twitter by keywords proved to be the most efficient retrieval method. For a keyword-based search, a basic set of 28 event types was compiled. For the purpose of improving retrieval process, we have extended base set with the synonyms from WordNet using NLTK<sup>2</sup>. When retrieved, tweets were filtered on a simple criterion – the existence of a time and/or a date in the tweet, based on reasoning that an event cannot be an event if this component is not present.

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<sup>1</sup><http://eventful.com/>, <http://eventguide.com/>

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<sup>2</sup><http://www.nltk.org/>

### 3.2 Extraction of event features

The base ontology consisted of five properties, the features of event: *Name*, *Date and/or Time*, *Location*, *Type*, and *URL*. For date and time we used the existing ontology Time<sup>3</sup> (Hobbs & Pan, 2004), adopted by W3C. The NLP methods of feature extraction from event tweets are described below:

For *Date and Time* extraction, regular expressions were used. This date/time information was then stored in Time ontology (Hobbs & Pan, 2004) mentioned earlier. A link (*URL*) is a very common feature found in twitter events, and we included this information to allow users to access a detailed description of event. For *Location and Name*, a set of various linguistic cues such as pre-modifiers, parts of speech, and word capitalization was used to identify candidates for locations or names; these candidates were then compared against the Alexandria Digital Library Gazetteer (1999) to find and validate proper locations which were then placed in our own version of the Gazetteer for future reference to improve the overall efficiency of the system. We used the expanded set of keywords to identify candidates for different event types (*Type*). These type words were then matched to the types already present in ontology, and if found, they were then instantiated as those types for the specific event being examined. The set of types can be iteratively expanded and it can serve as basis for ontology enrichment process.

These events were then checked against and mapped into our ontology, according to their type. We present an example of a good event tweet below:

5th Annual Winter Wildlands Alliance (*Name*) Film Festival (*Type*) in Seattle (*Location*) – 1/22/20108 (*Date*)  
<http://bit.ly/4syypF> (*URL*).

In the final step, results were taken directly from our established format of tagged events and were mapped into the OWL file by converting them from XML to RDF format.

## 4. Results

The average number of retrieved tweets was 200 per hour. From every request made towards the Twitter API, at least two (out of fifteen returned) candidate event tweets were retrieved after filtering. The dataset for our experiment was created using Twitter API for a whole day. Out of a total of 470 filtered tweets, 413 were found to be event tweets, so our ontology contained 413 instances. Out of 413 found event tweets, 386 were correctly classified event tweets. Rest 27 was wrongly classified non-event tweets. These results yield overall precision of 95.76% and recall of 93.46%, which gives F-measure of 94.59. Note that evaluation presented here is done on already filtered tweets based on date existence criteria as already previously described.

Despite the success of our processing techniques, certain number of event tweets were either wrongly classified or

missed out. This is due to the fact that there some irregularities in the data that made extraction of event features more difficult, namely misspellings (due to the chat-like structure of tweets) and structural irregularity (missing parameters of events like name or type of event). These irregularities could be smoothed and reduced to a minimum by improving NLP techniques for event feature extraction, which is one of our objectives for the future development of the system.

## 5. Conclusion and future work

Initial results suggest that this is a promising method for building an event ontology, as one can easily acquire a lot of information about events from Twitter. The choice of Twitter as the source for building and populating the event ontology is a sensible one, because of the large volume and dynamic nature of data available.

We believe that in employing ontology, our system helps introduce the necessary structure needed for efficient exploitation of these easily accessible data which are currently being underutilized. Storing these data in ontology has the following advantages over storage in a traditional database:

- Data availability: instead of keeping the data stored in a database and retrieving them via methods specific to that database, in an ontology, these data are available in the common language platform and so it is much simpler to retrieve them.
- Inference power: by employing the inference mechanisms of ontology languages, lists of specific types of events can easily be obtained for users (Walton, 2007).

As far as the domain of future work is concerned various following improvements of the system could be explored:

- Ontology enrichment: by considering the words in context around the event type and their frequency of appearance new subtypes/sub-concepts could be introduced. For instance, if the phrase “press conference” appeared frequently in event tweets, we would consider it to be a new sub-concept of the concept “conference”. Along with ontology enrichment process the inference power of ontology would increase as well
- Recommendation system: by using the data that Twitter has on its users (geo-targeting, possibly age and gender information), specific events could be recommended to them. Also if the user is following large number of twitter feeds, there is a possibility that he might miss an event, as stated in (Bernstein et al, 2010). Specifically, a priority could be given to the tweets that come from the Twitters that user is following, as oppose to tweets that come from other feeds.

In sum, we believe that the methodology described in this paper possesses great potential for extracting useful information from the source, which is free, global, and up-to-date. Mapping these data into an ontology makes their use of them easier and more efficient, due to the underlying expressive power of ontology languages.

<sup>3</sup><http://www.w3.org/TR/owl-time/>

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# Semantic TV Engine: An IPTV Enabler for Personalized Recommendations

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## Abstract

With today's availability of an increasing amount of media content delivered by IPTV systems, the need for personalized content preparation arises. In order to organize media content tailored to the users' needs, we are faced with challenges regarding data representation, integration and user profiling issues. Our approach is to use semantic technologies to build a unified data integration layer based on well-known ontologies and to apply a recommender system on top of the data plane that provides personalized recommendations considering the user's context. In this paper we introduce a high level overview of an enabler component for IPTV infrastructures, which combines semantic data management and recommendation functionalities. As a proof of concept we have developed an IPTV application that interacts with the new enabler.

## 1. Introduction

Today's IPTV systems allow the delivery of all kinds of multimedia content. The ever-increasing amount of available multimedia resources requires filter and recommendation mechanisms to assist the user in content selection. Widely researched and used approaches are content-based, collaborative or hybrid filter and recommendation methods. Content-based methods determine the similarity between program metadata and user preferences, whereas collaborative methods are based on correlations between users and their consumption behaviour. Hybrid approaches combine both methods to minimize the drawbacks of each of both methods.

The use of recommenders for personalized TV environments is common practice and the utilization of semantic techniques for the underlying data representation, on which the recommenders are working, is fairly adopted. AVATAR is an automatic content recommender based on Semantic Web technologies to enable hybrid recommendations. This content recommender approach utilizes a hierarchical TV content classification based on a self-defined ontology to infer new knowledge, in order to match user profiles with TV content. Here, similarity of content is derived from nearness in the defined classification hierarchy and the discovery of relations between contents (Fernandez et al., 2006). However, in the user profile only the related content items are stored. To further enhance recommendations more context from the user can be incorporated. SenSee, a framework for personalized access to TV content, improves recommendations by the evaluation of user context attributes such as location, time and audience (Aroyo et al., 2007). For SenSee heterogeneous meta-data sources (TV-Anytime, XML-TV, IMDB movie meta-data) are transformed into TV-Anytime representation to enable uniform data access for their recommender. iFancy, an application based on SenSee, uses in contrast to AVATAR well-known ontologies for time, geography and linguistic concepts, in which TV Anytime data is mapped (Akkermans et al., 2006).

As seen above TV content describing meta-data is provided by different sources in different formats, so we are facing the challenge to represent all data needed by a recom-

mender in a uniform format. An issue that is not considered by most TV recommendation research issues is the integration of a recommender and the related data management functions in existing, standardized IPTV infrastructures. So we identified this as a second challenge.

In this paper we present the *Semantic TV Engine*, an enabler for personalized recommendations which uses semantic technologies to build a data integration layer that combines content metadata with user related information like interests, attention and interaction data. The use of a unified representation and well known ontologies allows us to easily extend the data plane with almost any information source. On top of the semantic data layer we set up a recommender system that is used to calculate the most appropriate content tailored to the user's needs. We show how the *Semantic TV Engine* could be integrated in the standardized IPTV infrastructure developed by the ITU-T.

For testing and demonstration purposes, a user application has been developed, which allows the user to watch TV streams, to view a TV program guide, to commit ratings, or to select and define TV program preferences such as genres and favorites. Using these data as input, the application makes use of the Semantic TV Engine to estimate a personalized *MyTV channel*, which consists in a sequence of recommended program items.

The remainder of the paper is organized as follows: In Section 2 we introduce our approach to build a semantic data organization enabler, whereas in Section 3 we describe its individual components in more detail. In Section 4 we discuss the representation of data and metadata and an overview of the ontologies we use. Section 5 outlines the integration of *Semantic TV Engine* as an enabler in a standardized IPTV architecture and its use by a demonstrator application. Section 6 concludes the paper with a brief outlook.

## 2. Semantic TV Engine Architecture

The Semantic TV Engine Architecture consists of four main components; the Data Retrieval and Transcription component, the Semantic Store, the Universal Recommender, and the Semantic Services Exposure (Figure 1).

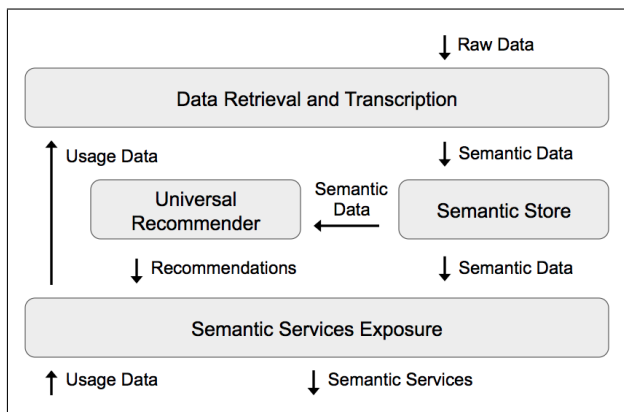


Figure 1: Semantic engine architecture

The *Data Retrieval and Transcription* component deals with the retrieval and transformation of unstructured or semi-structured data into a semantic format. All transformed data is stored in the *Semantic Store*, which is a storage entity for the management of semantic data graphs. The third component is the *Universal Recommender*, which uses the data stored in the semantic store to calculate recommendations delivered by the *Semantic Services Exposure* component. The *Semantic Services Exposure* component is providing the enabler interface to multiple client applications allowing the retrieval of metadata, such as EPG, the request for recommendations, and MyTV channel composition. The *Semantic Services Exposure* also provides interfaces to applications for collecting user and usage data through the *Data Retrieval and Transcription* component, which in turn is stored in the semantic store linked to content metadata. Next we present a more detailed overview of each component within the Semantic TV Engine.

### 2.1. Data Retrieval and Transcription

In the general case, datasets can be modeled as a set of entities connected by relationships, whereas complex datasets contain multiple relationship types. This is especially true when several datasets are combined. As a result such datasets form a semantic network, connecting several entity types through typed relationships. To model a semantic network, the semantic TV engine takes unstructured and semi-structured data and transforms it to a linked data graph represented in RDF (Resource Description Framework). Therefore content metadata (e.g. TV Anytime, proprietary channel lists, etc.) is gathered via Web Service requests against a content provider middleware, whereas usage data is gathered through REST interfaces provided by the semantic TV Engine itself. The retrieved usage data and metadata are parsed and mapped to entity and relationship types defined by well known ontologies. To implement the mapping we have analyzed the data and selected appropriate ontologies beforehand. By its modular design, the *Data Retrieval and Transcription* component is easily extendable by new retrieval adapters, mapping modules and ontologies. With the completion of the semantic modeling process, the component stores the data in the semantic store.

### 2.2. Semantic Store

*Semantic Store* is the component responsible for storing all the information retrieved from external metadata sources and user interactions. By linking both sets of information via ontologies together, a hybrid recommender combining collaborative and content-based approaches is empowered. The *Semantic Store* uses the open-source semantic web framework Jena for organizing the data. Jena can be used as an abstraction layer on top of a triple or quad store. A semantic triple consists of three parts: subject, predicate, and object, where the subject is an identifiable node in the semantic graph, the predicate is a named directed edge and the object is the node which relation to the subject is described through the predicate. This triple structure reflects the structure of the widely adopted RDF (Resource Description Framework).

The semantic store incorporates two beneficial characteristics regarding data integration:

- Subjects or even subgraphs identified by URIs are automatically updated during a storage transaction
- Relationships that connect entities are automatically added to the semantic model, which allows easy extension of the dataset by new information resources

In extension named graphs, represented as quads where the fourth element denotes the affiliation to a specific graph, are used to cope with the transient nature of metadata in live TV. The named graphs are annotated with a timestamp and named as aging graphs to enable efficient memory management. The access to the *Semantic Store* is done via SPARQL (SPARQL Protocol and RDF Query Language). However, the actual data representation is described in Section 3.

### 2.3. Universal Recommender

*Universal Recommender* (UR) is the component in the described architecture responsible for the generation of personalized recommendations (Kunegis et al., 2009). Functionally, a recommender takes an entity as input (e.g. user or content-id) and outputs a list of ranked entities (e.g. program items).

Designed for the use of semantic datasets that generalizes domain-specific recommenders such as content-based, collaborative, social, bibliographic, lexicographic, hybrid and other recommenders, the UR applies to any dataset that allows a semantic representation. In addition, the UR is capable of working with any number of entity and relationship types and can learn all its parameters without human interaction through advanced machine learning techniques.

We apply the UR to the metadata about the ongoing program as well as the usage data collected from users.

### 2.4. Semantic Services Exposure

The *Semantic Services Exposure* component exposes services through a multi-purpose interface to a client application, which can be a user-client or a server-side IPTV function. The services provided by the *Semantic Services Exposure* component can be grouped according to three different use-cases: Plain metadata retrieval, recommendation

requests, and submitting user feedback (including different user actions, such as rating, marking as favorite, and consumption) to the *Semantic TV Engine*.

These interfaces follow the REST (Representational State Transfer) model, whereas the exchanged data is represented as a JSON formatted payload. REST allows the lightweight access needed by user-clients as well as high performance throughput due to the implicit caching possibilities since it is based on HTTP. Furthermore, it suits the set/get nature of the data communication of the presented application.

An example for a request could be `/programs/now`, which may return all the information about the current programs.

### 3. Data Representation

To enable hybrid recommendations, which combines content-based and collaborative techniques, the integration of heterogeneous data is an important task. The approach for data integration presented in this paper is the exploitation of semantic methods as seen in the Semantic Web.

One major concept for the Semantic Web is the use of reusable ontologies. Ontologies are a formal representation of entities and the relations between them. Ontologies can be used to classify and order entities hierarchically, but are in most cases restricted to specific domain. They can be used to identify similar concepts in different and independent datasets, which is an important task in data integration. For our context we identified several well known ontologies, which we use to model our data semantically; BBC Programme Ontology (Raimond et al., 2009), FOAF (Brickley and Miller, 2010), Event Ontology (Raimond and Abdallah, 2007a), Timeline (Raimond and Abdallah, 2007b), RDF Review Vocabulary (Ayers and Heath, 2007), Tag Ontology (Ayers et al., 2005) and an ontology of our own, which we call *Program Ontology Extensions*.

Data following the BBC Programme Ontology is central in our data representation since all TV broadcasts and programs are modeled accordingly. Channel and program descriptions gathered from TVA (TV Anytime) program information table is modeled with the ontologies' core entities *Broadcast*, *Service* and *ProgramItem*, whereas the schedule information table is mapped to Entities derived from the Timeline and Event Ontology interlinked with BBC programs. For the modeling of users we use the well known FOAF ontology and link usage data with *foaf:Person* entities representing users. The usage data is modeled following the Review Vocabulary and the Tag Ontology that allow the semantic representation of e.g. ratings and tags. For other parts of the user profile, such as the viewing history and user preferences, we introduce the Program Ontology Extensions. The extension also interlinks information available in TV Anytime with the Program Ontology that is not a priori defined by it (e.g. parental guidance information).

### 4. Semantic TV Engine Integration in an IPTV Environment

In our IPTV system development we are following an IP Multimedia Subsystem (IMS) based approach, which is announced by several standardization bodies like the ETSI

TISPAN, ITU-T and Open IPTV Forum. Here the IPTV service control functions and applications are built on top of an IMS based service control core that makes use of the Session Initiation Protocol (SIP) to provide user profile based service control (TISPAN, 2009) (ITU-T, 2008) (OpenIPTV, 2009). Since we see the Semantic TV Engine as an additional IPTV service enabler, we integrate it in IPTV service providers' IPTV applications layer, on top of the IMS service control core and IPTV service support and control functions. This achieves the smooth interaction with other IMS and IPTV service enablers and applications like IPTV service control and applications, IPTV user profiles, presence server and XDMS based group management.

#### 4.1. Example Integration with the ITU-T IPTV architecture

The following describes the integration especially with the architecture of an IPTV system recommendation of the ITU-T. We foresee the Semantic TV Engine located in the Application Functions layer, between the Content Preparation Functions and the content and meta data sources. The Content Preparation Functions transform all available content (VOD data, EPG, metadata, TV streams) to the required format requested by the IPTV applications and content delivery functions. By accessing the content and meta data sources through the Semantic Services Exposure component, the Content Preparation Functions are able to provide enhanced data to the IPTV applications.

In this integration the Data Retrieval and Transcription component of the Semantic TV Engine collects metadata produced by content providers and service providers to describe multimedia content, as well as metadata produced by metadata clients to describe user preferences or context. The metadata is stored in the Semantic Store and is accessed by or contributed from metadata clients through the Semantic Services Exposure component.

In our current development metadata clients are HTML/Javascript based applications running in a Web-browser on the IPTV client, accessing the REST interface of the Semantic Services Exposure component.

#### 4.2. Integration with the user application

Our WebTV user application depicted in Figure 2 is a hybrid application consisting of a web application based on ECMA and HTML/CSS for the EPG and recommendation views and a Java based application utilizing SIP and H.264 streaming for live TV stream delivery. The web based approach allows the platform-independent integration of our application as long as a web browser is available.

Beside its other functionalities the user application provides an EPG program, the recommendation base MyTV program and a preferences configuration view. From the EPG program view the user can trigger streaming of the current broadcasts, mark program items as personal favorite, rate program items and recommend program items to other users. In the preferences configuration view the user defines a set of genres he likes.

All these user input actions are tracked by the application and sent via AJAX requests to the REST interface of the Semantic Services Exposure component. However, other ap-



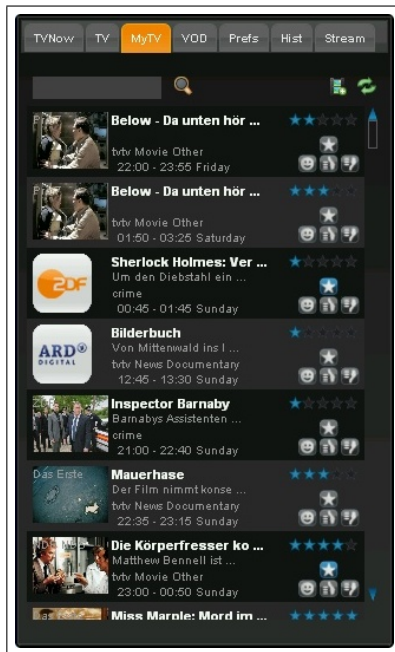


Figure 2: WebTV application: MyTV recommendations view

proaches are possible; for instance a special SIP application server placed in the SIP signaling path can provide tracked user actions to the Semantic Services Exposure component. EPG data and the MyTV program is asked by the user application from the Semantic Services Exposure component, too.

## 5. Conclusion and Outlook

For the future we plan to enrich our metadata with data provided via linked open data (LOD). Large amounts of information is publicly available in the so-called LOD-cloud, which is assumed to be very valuable to integrate with our application and the IPTV context. We envision integrating linkedMDB data, a semantic integration of the famous iMDB service providing detailed information about movies, TV series etc. Another valuable integration would be the interlinkage with DBpedia, which is a semantic dataset derived from Wikipedia articles (Kobilarov et al., 2009). In the future we may extend our semantic TV engine by modules that are able to compute owl:sameAs relationships, which expresses equivalence between entities in two different datasets.

Additional work has to be done to exploit semi-structured application data that is already in use throughout standardized IPTV systems operated by e.g. telecommunication providers. We expect a huge potential in the semantic exploitation of communications related information (e.g. presence data, social web applications). Exploiting these information bears large potential to improve personalized recommendations. Furthermore, this kind of data might form an interesting new dataset, which can be contributed to the LOD-cloud as a basis for new intelligent information services. A similar goal is described in (van Aart et al., 2009).

An interesting research topic in this direction will be the modeling and representation of real-time information and events in semantic formats. Regarding real-time information, a next step will be the integration of social web services to our application, since this is nearly a mandatory feature of multimedia applications today.

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# Summarization and Visualization of Digital Conversations

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## Abstract

Digital conversations are all around us: recorded meetings, television debates, instant messaging, blogs, and discussion forums. With this work, we present some solutions for the condensation and distillation of content from digital conversation based on advanced language technology. At the core of this technology we have argumentative analysis, which allow us to produce high-quality text summaries and intuitive graphical visualizations of conversational content enabling easier and faster access to digital conversations.

## 1. Introduction

Conversations have been central to the Internet since its birth. One of the first Internet applications, IRC (Internet Relay Chat), was of conversational nature. Later, conversational systems have proliferated in various forms. With the advent of Web 2.0, the Internet has become more collaborative and in many situations, new modes of information sharing were based on conversation (e.g. blogs, social media, remote conferencing, wiki).

Communication through conversation is very effective because it releases users from the commitment to engage in the full process of content publishing, which was the original model of the Web. Conversations are situated within a context and users can avoid using a narrative style in their communications. This effectiveness also leads to the fact that individual contributions to the conversation are often impossible to be isolated from their context thus leading to some difficulties in retrieving relevant information from this type of data. For instance, in online reputation management<sup>1</sup>, tracking the users' attitude towards a product or a brand in public forums may become very challenging. Simply considering the polarity of individual contributions could lead to misinterpretations of data in cases such as those when a user negatively comments on another user's comment. In such a case, the attitude cannot be simply understood as negative to the main topic but it needs to be understood in its own context, namely as a reply to a (possibly negative) comment to the main topic.

The above is only one of the possible problems that a standard approach to the analysis of Internet conversation might generate. Other problems are the absence of certain keywords that might be used to retrieve passages of conversations that are not uttered by the participants. For instance, if one wants to retrieve passages where someone disagreed with someone else in a forum, the term “disagree” is not likely to be found in the conversation. In these cases, it is essential to enrich the conversational content with metadata so that a retrieval system can find relevant information not just from the content terms.

<sup>1</sup> [en.wikipedia.org/wiki/Online\\_reputation\\_management](http://en.wikipedia.org/wiki/Online_reputation_management).

We provide a solution to the above problems by presenting a new approach to the indexing and retrieval of conversational data. This approach is based on the reasonable assumption that, when engaged in conversations, users follow a flexible but well-defined discourse structure. This structure is very often an *argumentative structure* where participants contribute with specific dialogue acts with a precise argumentative force. This model might not be applicable to every conversation, especially those which do not have a clear purpose. However, we believe that a great deal of digital conversations are purposeful and that users almost always pursue the goal of either seeking agreement or consensus from other participants on their opinions, or trying to convey their arguments in favor or against other participant's opinions.

The article is organized as follows. In section 2 we explore the domain of digital conversations with a special focus on Internet conversations. We advocate the need of new tools to provide more appropriate ways for accessing this type of content. In section 3 we present an approach for the analysis of conversations from the argumentative perspective making the case for a new way of indexing conversational data under specific conditions. In section 4 we present a diagrammatical visualization which provides users with an intuitive global view of digital conversations by highlighting their argumentative structure. Finally, we showcase a summarization tool for digital conversations which produces high-quality memos based on both automatically extracted thematic and argumentative structure. We conclude the article with an assessment of the current state of our research and propose a roadmap for future work.

## 2. Digital conversations

*Digital Conversational Systems* (DCSs) are systems that support the creation of digital records of conversations<sup>2</sup>. DCSs can be based on stand-alone or interconnected computer systems (e.g. networked through Internet). We

<sup>2</sup> The term Digital Conversation is also used in marketing to denote new ways of advertising based on dialogue between producers and consumers. See [en.wikipedia.org/wiki/Digital\\_conversation](http://en.wikipedia.org/wiki/Digital_conversation).

review different types of DCSs by outlining what are the essential retrieval requirements for each type. We distinguish two main categories of DCSs: synchronous and asynchronous. Synchronous DCSs are those in which the exchange between participants occurs in real-time and no history of the conversation (before one joins in) is maintained by the system whatsoever. When the user joins an already started conversation there is no means of retrieving what has been said before joining, and when the user leaves the conversation what follows is no longer accessible to the user. In this category we find Instant Messaging and VoIP systems and meeting recording systems. Asynchronous systems, in contrast, allow users to keep track of the whole conversations even when they are not directly participating to them. In this category we find the most advanced Internet collaborative technologies such as discussion forums, blogs, micro-blogs, wikis, and social media.

Conversations from synchronous systems can be recorded and made accessible after the conversation is over similarly to asynchronous systems. However, we need to bear in mind that because of its nature, these conversations might be shorter and more focused than asynchronous ones. Consider for instance the case of a recording of a chat conversation from the moment one user enters the chat to the moment the user leaves it. It is likely that there was an already started conversation going on at the joining time. The user will have to listen to the ongoing conversation for a while in order to figure out the current topic. When the user starts to actively participate in the conversation we can assume that the context is clear enough for the user and we can interpret the utterances only relying on that (limited) context. When looking for an argumentative discourse structure, we can no longer assume that we will find the root of the argument (i.e. the initial topic) in the recorded conversation.

Asynchronous ICSs have a more consistent structure because roots of arguments can be easily identified. However, they might have a mixed narrative and argumentative structure thus making sometimes the analysis more difficult. For example, consider a blog or a social media where there is an initial post or video and a sequence of comments attached to it. Clearly, the initial post provides a wealth of context for the interpretation of the related comments. Comments can relate both to the main topic (established in the post or in the video) and to other comments.

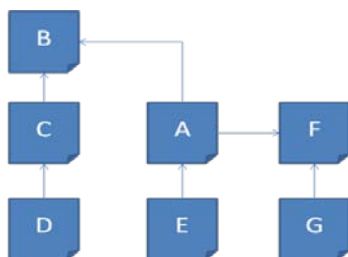


Figure 1: Conversational Structure of Blogs

The case of blogs is also challenging because the conversations are distributed over different sites. Rolling out a blog conversation can be very difficult because comments to the initial post can be contained as individual posts in other blogs. The distribution of

conversational content implies that any retrieval technique needs to perform a crawl of the sites where the contributions are stored. This also entails that there may be multiple entry points in the conversations and that one post can contribute to several conversations.

In Figure 1, the post A participates in two conversations (B<A<E and A>F<G), while the post B has started two independent conversations (B<C<D and B<A<E)<sup>3</sup>. Notice that the same author might have posted multiple posts (e.g. A and D), but also that authors are by default unaware of the replies to their post unless they explicitly search for them. In order to avoid this loss of information, blogging platforms have enabled an acknowledge system that informs the author of a post when the post is referenced in another blog post. This mechanism is referred to as *linkback*<sup>4</sup>.

Being actually fully fledged websites, blogs offer a wealth of media and can contain any amount of metadata. As a matter of fact, blogs are hosted in content management systems and the way the media are integrated can be sometimes rigid. From the indexing and retrieval perspective, blogs still retain their document connotation. Blog search engines (such as Technorati<sup>5</sup>) index blogs on their textual content. Additionally, relevance ranking is modified and restricted to inter-blogs links. In such a way it would be impossible to retrieve all blog posts that commented (i.e. linked) a specific post. Moreover, inter-blogs comments are not treated separately and in the best case they are simply excluded from the index. While blogs represent a huge portion of Internet conversations they are not treated in an appropriate way and the conversational structure is typically not made explicit for search.

### 3. Argumentative indexing of conversations

Conversations are a pervasive phenomenon in our digital society. We need to consider appropriate techniques to analyze conversational content from different perspectives beyond classical thematic indexing approaches. We advocate that recognizing the argumentative structure of digital conversations can help in improving the effectiveness of standard retrieval techniques in simple cases and even overcome their limitations in complex cases. To better understand the impact of argumentative analysis we will provide in this section a real example of how argumentative indexing can solve outstanding problems in indexing and retrieval of conversational content. In our approach, we adopt a representation of conversational structure based on argumentation theory (Pallotta 2006). The argumentative structure defines the different patterns of argumentation used by participants in the dialog, as well as their organization and synchronization in the discussion.

<sup>3</sup> We use the notation “>” to indicate the “replies-to” relation: A>B means A replies to B.

<sup>4</sup> Three linkback protocols are commonly in use in different blogging platforms: pingback, trackback and reback.

<sup>5</sup> [www.technorati.com](http://www.technorati.com).

A dialog is decomposed into several argumentative episodes such as issues, proposals, elaborations and positions, each episode being possibly related to specific aggregations of elementary dialog acts. We adopted an argumentative coding scheme, the Meeting Description Schema (Pallotta et al. 2004) where the argumentative structure of a meeting is composed of a set of topic discussion episodes (a discussion about a specific topic). In each topic discussion, there exists a set of issue episodes. An issue is generally a local problem in a larger topic to be discussed and solved. Participants propose alternatives, solutions, opinions, ideas, etc. in order to achieve a satisfactory decision. Meanwhile, participants either express their positions and standpoints through acts of accepting or rejecting proposals, or by asking questions related to the current proposals. Hence, for each issue, there is a corresponding set of proposal episodes (solutions, alternatives, ideas, etc.) that are linked to a certain number of related position episodes (for example a rejection to a proposed alternative in a discussed issue) or questions and answers.

We illustrate the power of this approach by contrasting the limitation of classical term-based indexing for retrieving relevant content of a conversation. Consider the following conversation excerpt from the ICSI meetings corpus (Janin et al. 2003):

1702.95 David: *so – so my question is should we go ahead and get na- - nine identical head mounted crown mikes?*

1708.89 John: *not before having one come here and have some people try it out.*

1714.09 John: *because there's no point in doing that if it's not going to be any better.*

1712.69 David: *okay.*

1716.85 John: *so why don't we get one of these with the crown with a different headset?*

For a query such as: "Why was the proposal on microphones rejected?", a classical indexing schema would retrieve the first turn from David by matching the relevant query term "microphone". There is no presence of other query terms such as "reject" or "proposal". Moreover, it is not possible to map the Why-question onto some query term (e.g. reason, motivation, justification, explanation). This makes it impossible to adequately answer the query without any additional metadata that highlight the argumentative role of the participants' contributions in the conversation.

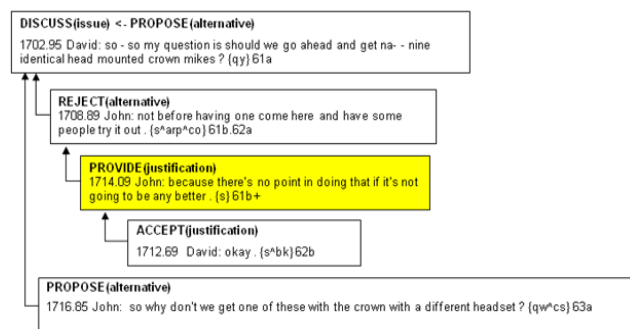


Figure 2: Argumentative Structure of a conversation.

In Figure 2, we show the argumentative structure of the conversation excerpt that allows us to correctly answer the query by selecting the third turn. In fact, the

Why-question is mapped to a query term which is found as an argumentative index, "justification", for that turn. Of course, finding justification is not enough, and the retrieval algorithm needs to check whether that justification has been provided as a rejection of a "proposal" (or "alternative") made to an issue on the topic of microphones. This can be done by navigating back through the argumentative chain up to the "issue" episode whose content thematically matches the "microphone" query term.

#### 4. Argument extraction

We have developed a system that computes the argumentative structure of conversations. This system makes it possible to perform argumentative indexing as well as visualizing arguments with the method discussed in section 5 and for generating summaries as described in section 6.

The core of our solution for argument extraction is based on adapting and extending GETARUNS (Delmonte. 2007; 2009), a natural language understanding system developed at the University of Venice. Automatic argumentative annotation is carried out by a special module of GETARUNS activated at the very end of the analysis of each conversation, taking as input its complete semantic representation.

To produce argumentative annotation, the system uses the following 21 discourse relations:

*statement, narration, adverse, result, cause, motivation, explanation, question, hypothesis, elaboration, permission, inception, circumstance, obligation, evaluation, agreement, contrast, evidence, hypoth, setting, prohibition.*

These are then mapped onto five general argumentative labels:

**ACCEPT,  
REJECT/DISAGREE,  
PROPOSE/SUGGEST,  
EXPLAIN/JUSTIFY,  
REQUEST.**

In addition we use the label DISFLUENCY for all those turns that contain fragments which are non-sentences and are not semantically interpretable. Details of the algorithm are available in (Delmonte et al. 2009), which has been evaluated on conversations from the ICSI meeting corpus (Janin et al. 2003) annotated with argumentative structure during the user study carried out by (Pallotta et al. 2007).

On a total of 2304 turns, 2251 have received an argumentative automatic classification, with a Recall of 97.53%. We computed Precision as the ratio between Correct Argumentative Labels/Found Argumentative Labels, which corresponds to 81.26%. The F-score is 88.65%.

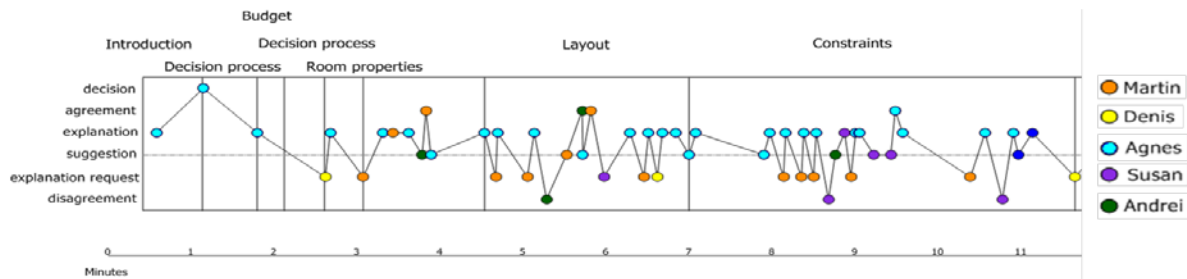


Figure 3: Conversational Graph

## 5. Visualization of arguments

Argumentative indexing of conversations is relatively novel in the field of information retrieval and visualization, and there are not yet standard metadata schemas for structuring and indexing conversations, or for visualizing their structure (Pallotta et al., 2004; Verbree, 2006). Previous work on visualizing argumentation has mainly been driven by the need for tools to improve argumentation in real-time meetings (Bachler et al., 2003; Fujita et al., 1998; Michaelides et al., 2006; Rienks et al., 2005). Some research has also addressed the use of such visualizations for browsing past conversations, and end user evaluations have been positive (Rienks and Verbree, 2006).

In this paper, we propose a visualization of arguments as *conversation graphs*, to help users search in digital conversations using argumentative and thematic indexing of conversations. Conversation graphs are diagrams that summarize what topics were discussed, how long they were discussed, which participants were involved in the discussion, and what type of arguments they contributed with (see Figure 3).

An important criterion in the design of the graphs is that the visualization of the argumentative structure has to be intuitive so that users do not need to spend effort on learning the argumentative categories before being able to use them for searching in digital conversations. For this purpose, the graph representation introduces the notion of "positive" and "negative" contributions in discussions. Positive contributions, such as agreements and decisions, are visualized as peaks and negative contributions, such as disagreements, as valleys along the time axis. Suggestions are neutral in polarity and are positioned in the middle.

The goal is that users will use conversation graphs to make more efficient queries about digital conversations by combining topical, argumentative and participant criteria rather than perform pure content-based search. For example if a user wants to find out what objections a participant had about some proposal, the argumentation graph shows that the selected participant disagreed several times during the discussion about that topic. Displaying this information should make it intuitive to search for the relevant meeting episodes by specifying argumentative search criteria rather than simple content-based criteria.

The second aspect of how conversation graphs can be useful in conversational information retrieval is that they can help users to browse the results of their search. When a user opens a conversation transcript and browses through the highlighted sections that correspond to their

search criteria, they can compare these highlighted sections with the argumentation points in the graph. By referring to the graph the user can extract information about how many sections of the conversation correspond to their search criteria (in our example, as many as there are disagreements by a participant in the graph). The users may then derive that some, but not necessarily all, of the search results in the transcript are relevant for answering their original question.

First results of user studies have shown that conversation graphs are indeed promising tools both for querying and browsing indexed digital conversations (Ailomaa and Rajman, 2009; Ailomaa, 2009).

## 6. Abstract Summarization of Conversations

A complementary way to provide users with simplified access to conversational content is by means of summaries. Analyzing and summarizing conversations (or dialogues) is very challenging (Maybury 2007). Many existing summarization techniques are tailored for the narrative genre and can hardly be adapted to the dialogue genre. Moreover, most of the techniques are based on extractive summarization (Zechner 2002; Murray et al. 2005; Garg et al. 2009) that proves to be inadequate for summarizing conversations. In fact, this method has severe limitations due to the intrinsic characteristics of the source data: conversations are not as coherent as ordinary narrative text (such as news or scientific articles) and obtaining a coherent text from conversations is practically impossible using the extractive approach. Moreover, any system that performs extractive summarization must be evaluated against human-annotated test datasets. As pointed out in (Buist et al., 2005), inter-annotator agreement is very low for this type of task, which makes test data nearly useless for evaluation. Intuitively, selecting salient content from conversations is a really difficult task and subjective selection of excerpts leads to fairly different results. In any case, the proposed solutions for extractive summarization of meetings have already reached their qualitative upper bounds as shown by (Riedhammer et al. 2008).

We advocate for abstractive summarization of conversational content. Abstractive summarization of narrative texts is typically based on sentence compression and/or paraphrase (Mani & Maybury 1999). This approach is clearly not appropriate for conversations because turns are already highly compressed. Instead, our abstractive summarization system generates descriptions of the conversation dynamics based on both thematic content and argumentative structure we are able to automatically extract as described in the previous sections.

Our approach differs from that of (Kleinbauer et al. 2007) who provide short abstractive indicative summaries of conversations exclusively based on thematic content.

The output of our system consists instead of several sections, namely describing the conversational settings, participants' number and names, statistics about the interactivity of participants (e.g. the degree of competitiveness), the topics discussed, and the arguments.

Arguments are grouped into episodes bound together by thematic cohesion. All this information is extracted by the system described in section 4. For instance, in more formal meetings we expect to map these episodes to agenda items.

The following is an example of a memo which can be generated with our system from the analysis of ICSI meetings (only turns and speaker with no additional annotations):

MEETING MEMO

GENERAL INFORMATION ON PARTICIPANTS

- The participants to the meeting are 7.
- Participants less actively involved are Ami and Don who only intervened respectively for 38 and 68 turns.

LEVEL OF INTERACTIVITY IN THE DISCUSSION

- The speaker that has held the majority of turns is Adam with a total of 722 turns, followed by Fey with a total of 561.
- The speaker that has undergone the majority of overlaps is Adam followed by Jane.
- The speaker that has done the majority of overlaps is Jane followed by Fey.
- Jane is the participant that has been most competitive.

DISCUSSION TOPICS

The discussion was centered on the following topics:  
**schemas, action, things and domain.**

The main topics have been introduced by the most important speaker of the meeting.

The participant who introduced the main topics in the meeting is: **Adam.**

The most frequent entities in the whole dialogue partly coincide with the best topics, and are the following:  
**action, schema, things, 'source-path-goal', person, spg, roles, bakery, intention, specific, case, categories, information, idea.**

ARGUMENTATIVE CONTENT

The following participants:  
**Andreas, Dave, Don, Jane, Morgan**  
expressed their dissent 52 times. However Dave, Andreas and Morgan expressed dissent in a consistently smaller percentage.

The following participants:  
**Adam, Andreas, Dave, Don, Jane, Morgan**  
asked questions 55 times.

The remaining 1210 turns expressed positive content by proposing, explaining or raising issues. However Adam, Dave and Andreas suggested and raised new issues in a consistently smaller percentage.

The following participants:  
**Adam, Andreas, Dave, Don, Jane, Morgan**  
expressed acceptance 213 times.

EPISODE ISSUE No. 7

In this episode we have the following argumentative exchanges between the following speakers: **Don, Morgan.**

Morgan provides the following explanation:  
[oh, that-s\_, good, .]

then he , overlapped by Don, continues:  
[because, we, have, a\_lot, of, breath, noises, .]

Don accepts the previous explanation:  
[yep, .]

then he provides the following explanation:  
[test, .]

Morgan continues:  
[in\_fact, if, you, listen, to, just, the, channels, of, people, not, talking, it-s\_, like, ..., .]

then he , overlapped by Don, disagrees with the previous explanation  
[it-s\_, very, disgust, ..., .]

Don, overlapped by Morgan, asks the following question:  
[did, you, see, hannibal, recently, or, something, ?]

Morgan provides the following positive answer:  
[sorry, .]

then he provides the following explanation:  
[exactly, .]  
[it-s\_, very, disconcerting, .]  
[okay, .]  
...

## 7. Conclusions

In this article we have presented the core language technology for analyzing digital conversations and producing from their analysis intuitive visualizations and high-quality summaries.

We addressed the issue of capturing the conversational dynamics through the adoption of argumentation theory as the underlying model for making pragmatic analysis of conversations.

We made the case for the importance of such a type of analysis showing how the shortcomings of classical information retrieval techniques can be overcome adopting our approach.

We provided an evaluation of the performance of the current analysis system with respect to the important task of automatically recognizing argumentative force of conversational contributions.

Finally, we presented two applications of our analysis system for the visualization and summarization of conversational data in order to demonstrate the effectiveness of our approach in presenting condensed and distilled conversational data.

### 7.1 Future Work

We are currently working on a new application that will analyze and summarize (micro)-blog conversations (e.g. Twitter, Google Wave) for online reputation management.

We also expect to start an evaluation campaign for assessing the quality of the abstractive summaries and to investigate how conversational graphs scale in terms of length of conversation and number of participants.

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