USING SEMANTIC-BASED USER PROFILE MODELING FOR CONTEXT-AWARE PERSONALISED PLACE RECOMMENDATIONS

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Abstract

Place Recommendation Systems (PRS's) are used to recommend places to visit to World Wide Web users. Existing PRS's are still limited by several problems, some of which are the problem of recommending similar set of places to different users (Lack of Personalization) and no diversity in the set of recommended items (Content Overspecialization). One of the main objectives in the PRS's or Contextual suggestion systems is to fill the semantic gap among the queries and suggestions and going beyond keywords matching. To address these issues, in this study we attempt to build a personalized context-aware place recommender system using semantic-based user profile modeling to address the limitations of current user profile building techniques and to improve the retrieval performance of personalized place recommender system. This approach consists of building a place ontology based on the Open Directory Project (ODP), a hierarchical ontology scheme for organizing websites. We model a semantic user profile from the place concepts extracted from place ontology and weighted according to their semantic relatedness to user interests. The semantic user profile is then exploited to devise a personalized recommendation by re-ranking process of initial search results for improving retrieval performance. We evaluate this approach on dataset obtained using Google Paces API. Results show that our proposed approach significantly improves the retrieval performance compare to classic keyword-based place recommendation model.

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1 Introduction

1.1 Background

With technological advancements in mobile technologies like mobile data networks (GPRS and WCDMA), positioning systems (GPS), mobile phones and personal digital assistants (PDAs), there has been an increase in the use of internet-accessing devices. It is now possible to offer up-to-date information and online services to people whenever and wherever they are. With the increasing ubiquity of internet-accessing smart phones, it is now possible to offer personalized, context-sensitive recommendations. These online services are mostly useful for people in places they have never visited before. Often, tourists do not know their way, nor which restaurants, museums, shops, public services, etc. are available to them. The number of potential places to visit can be quite overwhelming, especially in touristic regions. Personalized Context-Aware Recommender systems can help a tourist to find places matching his interests and his current location.

Personalized recommender systems (PRSs) help provide personalized suggestions by analyzing users' history record and thus they expand the users' capabilities of interacting with web content [Baltrunas] [Zheng]. Traditional PRSs only focus on user-item ratings, whereas location-based recommender systems combing such ratings with real-world location information [Baltrunas] [TREC2013]. With the advancements in wireless communication and mobile location techniques, accessing users' location information in real time becomes easier and faster [Zheng] [Gruteser]. Consequently, many personalized recommendation services integrate such location information. Examples include travel recommendation [ACM], point of interests (POI, e.g., restaurants, shopping malls, etc.) recommendation [Zheng] [Bao], and commercial recommendation [Majid]. However, there are still some important open questions. For example, what could be the relationship between the users' locations and the other factors in recommendation (e.g., user's preferences, the general popularity of items)? How can the location information be effectively utilized in LBRSs?

1.2 Motivation

The size and the pace of growth of the world-wide body of available information in digital format (text and audiovisual) constitute a permanent challenge for content retrieval technologies. People have instant access to unprecedented inventories of multimedia content world-wide, readily available from their office, their living room, or the palm of their hand. In such environments, users would be helpless without the assistance of powerful searching and browsing tools to find their way through. Most popular Web search engines use the content of the Web documents and their link structures to assess the relevance of the document to the user's query. With the growth of the information available on the web as well as the ambiguity of typical user queries, it becomes difficult for such Web search engines to satisfy the user information need. The involved retrieval approaches are characterized as '*one size fits all'* that provides the same results for the same keyword queries even though these latter are submitted by different users with different intentions.

Take as an example a user who enters the query "search library" into a typical Web search engine, such as Google, Yahoo! or MSN search. Taking the query alone, we may think the user is looking for an online service for book location in e.g. some local library, bookstores, or digital libraries. But the intention of this query could also be related, for instance, to finding computer programming libraries supporting content search and retrieval functionalities. Such an ambiguous query, which by itself alone does not provide enough information to properly grasp the user's information need, is an example where personalization capabilities show their usefulness. While mainstream Web search engines return the same results to all users, a personalized system adapts the search results to the users' interests. In the example, the second interpretation (programming library) might seem more likely, and the first (book search) a bit far-fetched. Interestingly though, testing the example in Google, the results happen to be more related to the first meaning of the query: Web sites like wordcat (a book and local library locator) or the Google book search service appear at the top of the ranking.

Similarly for place recommenders, in a mobile context this contextual place suggestion system might take the form of an app that recommends interesting places and activities based on the user's location and personal preferences. Imagine a user with a young family travelling for a summer vacation to Philadelphia, Pennsylvania. A contextual suggestion system might recommend spending time at a kid's friendly museum (http://www.pleasetouchmuseum.org/), or a walk in the beautiful historic Penn Treaty Park (http://penntreatypark.org/), or to spend the day splashing in the waters at the Clementon Park Splash World (http://www.clementonpark.com). One of our main objectives in contextual IR is capturing the user interests and representing them as semantic concepts to tailor search results to achieve personalised place recommendations.

The research presented here focuses on the role of context in information retrieval (IR), and more specifically, in its smooth integration into the personalization of content retrieval. This study lies in the framework of 2013 TREC contextual suggestion challenge. The goal of this track is to develop a place suggestion IR system that given a location and user profile it can produce personalised place recommendations. As input to the task participants were given a set of example suggestions, a set of user preference profiles, and a set of geo-temporal contexts. The task was to take the profiles and contexts and to produce up to 50 ranked suggestions for each combination of profile and context. Participants gathered suggestions from the open Web.

1.3 Contributions

In this study, we propose a novel IR approach that is able to tackle the presented challenges of place recommender systems such as lack of personalization or content overspecialization and to recommend those place suggestion that capture user's interests. The proposed model aims at achieving personalization which is a significant component in recommender systems. Personalized place recommender systems aim at helping a jetsetter with the crucial travel planning decisions that he will face before travel or while on-the-move. These recommender systems necessitate the need to acquire the knowledge of interests and wants, either explicitly (by asking) or implicitly (by mining the user online activity), and suggest destinations to visit, points of interest, events or activities. The main objective of a recommender system is to ease the information search process of the traveller and additionally provide personalized search results on-the-move.

The key unique contributions in this research concern (1) construction of place ontology based on ODP ontology to extract representative concepts of user interest and information need, (2) semantic-based user profile modelling and (3) devising a concept based weighting schema to weight user profile concepts semantically in relation to the suggestions and re-ranking the suggestions in order of their scores.

One of the characteristics of semantic user profiling is conceptual representation rather than simple keywords representation to enhance the representation of user profiles. Modeling and developing domain ontologies is a fundamental framework for representing knowledge using a set of concepts and the relationships among the concepts. Web domain knowledge is developed by several different ontologies including The Open Directory Project (ODP), also known as DMOZ (from directory.mozilla.org, its original domain name), is a multilingual open content directory of World Wide Web links. In this approach we extract a sub-directory relevant to place types to develop place ontology. Previously rated attractions by the user are mapped to the place ontology where we represent positive and negative preferences under each place type which results in building user profiles. In order to identify the extent of a suggestion relevancy in relation with user profile concept(s) we weight each concept in place domain ontology according to its semantic relatedness/similarity to the original suggestion concepts. The user context (location) is used to enhance classical IR model and to calculate and assign a new score to suggestions by considering semantics.

1.4 Thesis Structure

This thesis is organized as follows: Chapter 2 presents previous contextual suggestion TREC track participations. Chapter 3 gives an overview of recommender systems types and techniques. Chapter 4 describes the background information and importance of contextualization in IR. Chapter 5 presents user personalization, an integral aspect of our study that describes that personalization process comprising of user profile modelling, user information gathering, and user profile representation. Chapter 6 describes the use of semantics and ontology and also our proposed place ontology construction using ODP. Chapter 7 describes our proposed place recommender methodology and approach. This chapter also comprises of our proposed technique for semantic user profile modeling and our algorithm for re-ranking the suggestion set. Chapter 8 describes our experimental setting including system's setting, dataset and experimental runs. Chapter 9 presents our experimental results and analysis on our proposed method and summarizes the contributions of this research. Finally, chapter 10 concludes this study and presents future work of this thesis.

2 Review of Contextual Suggestion Track TREC Participations

This chapter introduces some of the previous participations in TREC Contextual Suggestion challenge.

In TREC Contextual suggestion 2012, participants were given the option of basing their suggestions solely on the user profiles (returning suggestions appropriate to any place and time) or solely on geo-temporal context (returning suggestions appropriate to a generic user).

In [MTP12], a place recommendation approach has been proposed based on the intersection of candidate venues provided by Google Places and Foursquare. Suggestions are ranked according to a linear combination of two scores: one that captures the venue's appropriateness at the given time, by noting the number of people checked in at regular intervals, and another score that captures its appropriateness given the user's prior likes and dislikes. To match the suggestions with profiles, the description of each suggestion was first reduced to a BM25-weighted vector. Vectors were summed, with fixed multipliers of 0.75 for positive examples and -0.25 for negative examples. The resulting term weights were used to score the description for each candidate suggestion.

Fasilkom UI from Universitas Indonesia derives a user model based on Yelp's category list. A combination of user model and geo-location is used to generate the place suggestions. Search was expanded to similar categories if no results can be found in a particular category for a current location. As for scoring, they use the review rating for the places to produce the ranked results. They also try to apply diversity to results to make suggestions more interesting to the users.

HP Labs China uses a context-aware recommendation approach to produce the ranked list of suggestions. In their approach they employed Matrix Factorization for collaborative filtering to learn the latent factor of each user in profiles, and also used its category information to learn user's general preference. They use SVD++ to predict the scores of all suggestions and later use pairwise ranking model to rank a list of suggestions for a user. They use the contextual post-filtering approach to adjust the resulting set of suggestions with the help of the category feature and the information extracted from Yelp. The description for each suggestion is generated by a human designed template which includes location, category and many other features about the suggestion.

[HC12] defined a retrieval framework that combines two modules. First, a context processing module consists of using Google Places API that takes geographic coordinates and a set of place types as inputs to retrieve a list of places. Second, a preference processing consists of result personalization according to user interests. Profiles are represented by vectors relying on the Vector Space Model. For each profile, the positive user preferences were based on the positively rated examples and vice versa. The fine-grained approach consists in defining positive and negative preferences as sets of positive and negative preference examples (one vector per example). A similarity score between each place vector (from Google Places) and each preference vector based on the cosine measure was then computed.

In [MS12], recommendations were collected by using the location context as search query in Google Places and were ranked by their textual similarity to the user profiles, based on a TF- IDF measure. Initially, the cosine similarity of an initial recommendation to the positive profile determined the ranking. Further, the textual similarity was based on a point-wise Kullback Leibler divergence score which is based on the probability of observing a term in the set of examples that were rated positively, compared to the probability of observing it in the set as a whole. The sum of Kullback Leibler scores for the terms that occur in the initial recommendations determined the rank, which was later combined with a number of other rankings based on Google Search, popularity and categories in order to improve the ranking. As a final step, items that did not match the temporal context were filtered out.

[AY12] first identifies context-independent queries from the combined with new location information are sent to multiple Web search engines, such as Google, Yelp, Yellow Pages, and Bing, to crawl and build a large pool of potential contextual suggestions. A learning to rank model is then used to merge and re-rank those potential suggestions from the pool for each query, context, and user profile combination. Learning to rank model utilizes three types of profiles: a general profile based on the training suggestions given in the Toronto examples provided by TREC 2012, a city profile containing well-known attractions for each city, and a personal profile based on a user's personal interests. Moreover, the learning model makes distinctions among major personal interests, minor personal interests, and negative personal interests for all personal profiles. The detections of major, minor and negative personal interests are done by statistical analysis across users, examples, and context-independent query types.

[AM12] approaches the TREC task by devising an algorithm based on the regular expression for extracting time and address information from different websites for each place and then using this extracted information to rank suggestions along with user's context and preference.

[KKH12] uses Wikitravel as a source for travel suggestions. Wikitravel is a well-structured community-based travel guide for destinations all over the world. From pages dedicated to cities in US, suggestions are extracted for sightseeing, shopping, eating and drinking. Descriptions from positive examples in the user profiles are used as queries to rank all suggestions. The ranked suggestions are then filtered based on the location of the user ignoring temporal aspects of the context.

[PY12] collects candidate suggestions by web crawl from multiple online sources such as Yelp and Foursquare based on the geographical information from the 50 contexts. Later, ranked candidate suggestions based on their similarity to the personal profile and that to the contexts (i.e., geographic and temporal information). The ranking function is computed based on similarity between a suggestion and the places that the user likes and the dis-similarity between the suggestion and the places disliked by the user. The similarities are computed based on the either the category or description of the suggestions.

[LQ12] designed a spider framework to crawl websites from tripadvisor, in order to collect candidate pages related to attractions, restaurants etc. Pre-processing involves extracting useful information, including name, homepage, rate and comment. Next, context filtering based on season, time, and weather are applied. User modeling based on td-idf and cosine similarity function is used for re-ranking using the example suggestions.

3 An Overview of recommender systems types and techniques

Most web users have come across a recommender system in one way or another. For instance, a friend recommended a new book to read and subsequently typing the title of the book on a favourite online book store, it appears as just one of the results listed. In one area of the web page called "Customers who bought this item also bought", a list is shown of additional books that are supposedly of interest to you. A regular user of the same online bookstore, such a personalized list of recommendation would appear automatically as soon as the user enters the store. The software system that determines which book should be shown to a particular visitor is a recommendation system [IRS]. Recommender systems (RS) are a class of information filtering systems that act as a personalized decision guide for users, aiding them in decision making about matters related to personal taste. RS generally rely on in-built logical reasoning capability or algorithmic computational schemes to deliver their recommendation functionality. RS [Resnick] have found a great deal of significance in a variety of applications. These include music, online communities, web stores and travel sites and general e-commerce.

The two fundamental algorithmic techniques for computing recommendation are Content-based Filtering (CBF) and Collaborative Filtering (CF). A CBF system selects items based on the correlation between the content description and the user's preference, while a CF system chooses items by correlating the similarity in the rating of an item by several people. The hybrid approach is a third technique that tries to alleviate the limitations of the content-based and collaborative filtering approaches.

3.1 Content-based Filtering (CBF)

Content-based filtering (CBF) correlates the content description of items with the preferences selected by the user for generating recommendations. It allows automatic categorization and recommendation of information to a user based on the user's personal preferences [HerKR]. To achieve this, the content descriptions of candidate items are compared with the specified user preferences and the best-matching items are recommended.

The most well-known content-based filtering technique is derived from information retrieval and information filtering. By computing vector-space similarity between the candidate item vector and the vector containing information about the user. An example is Term Frequency Indexing [Salton] which is used in document retrieval, where vectors are used to represent the documents and user preferences. A one-dimensional vector space is used to represent each word in the database with each part of the vector containing the frequency of occurrence of the respective word in the document or the user query. The document vectors that are found to be the closest to the query vectors are considered most relevant to the user's query. This similarity is computed using the cosine similarity metric [BYat] based on the Term Frequency/Inverse Document Frequency (TF-IDF) weights obtained. In order words a document D is represented as an m dimensional vector, where each dimension corresponds to a distinct term and m is the total number of terms used in the collection of documents. The document vector is written as D = (w_1,w_2…, wm), where w_i is the weight of term ti indicating its importance. If document D does not contain term t_i then weight w_i is zero. Using the TF-IDF scheme the term weights of each ti can be determined. In this case the weight of a term depends on how often a term appears in a particular document and how frequently it occurs in the entire document collection. This is computed as:

$$w_i = tf_i . \log\left(\frac{n}{df_i}\right) \qquad \textbf{Equation 1}$$

where tf_i is the number of occurrences of term t_i in document D, n is the total number of documents in the collection and df_i is the number of documents in which term ti appears at least once. The assumptions behind TF-IDF are based on two characteristics of text documents. First, the more times a term appears in a document, the more relevant it is to the topic of the document. Second, the more times a term occurs in all documents in the collection, the more poorly it discriminates between documents. Also, user profiles can be represented just like documents by one or more profile vectors. The degree of similarity between a profile vector P, where P = (u_1,…,u_k) and the Document D can be determined by using the cosine measure:

$$\cos(D,P) = \frac{D.P}{\|D\|\|P\|} = \frac{\sum_k u_k . w_k}{\sqrt{\sum_k u_k^2 . w_k^2}} \qquad \textbf{Equation 2}$$

Examples of content-based filtering recommender systems include: Letizia [Lieber] which is a user interface that assists users browsing the web. The system tracks the browsing behaviour of a user and tries to anticipate what pages a particular user may find interesting. Syskill & Webert [PazMB] is a system that predicts web pages that a user will find interesting based on a user's rating of web pages over time.

3.2 Collaborative Filtering

The main idea of collaborative recommendation approaches is to exploit information about the past behaviour or the opinions of existing user community for predicting which items the current user of the system will most probably like or be interested in. Collaborative Filtering (CF) uses the ratings of an item by several other users to generate recommendation for a new user after sufficient similarity has been established [GNich]. Therefore CF uses valuation instead of analysis, by categorizing information based on the user's opinion instead of the information itself. With this characteristic CF offers some comparative advantages over CBF. First, it is possible to generate recommendations that are independent of the content itself. Second, it is possible to filter and recommend information based on social attributes of the user, such as taste or quality, and thirdly, it is possible to receive useful but unexpected recommendations that are relevant to the users.

3.2.1 Memory-based CF approach

This is also known as the nearest-neighbor approach [GNich]. It predicts a user's interest in an item based on the ratings for that item by other users who have similar profiles. It is an implementation of the “Word of Mouth" phenomenon. The main idea is given a ratings database and the ID of the current (active) user as an input, identify other users (peer users or nearest neighbors) that had similar preferences to those of the active user in the past. Then for every product p that the active user has not yet seen, a prediction is computed based on the ratings for p made by the peer users.

Some of the shortcomings of memory-based CF are [SarBM] [HLSe]:

i. **Sparsity**: This is a scenario where the active users have purchased or rated very limited products out of the available total. This leads to the problem of insufficient ratings for such items i.e. sparse user-item matrices, inability to locate sufficiently close neighbors and ultimately weak recommendations.
ii. **Scalability**: The nature of a user-based approach to CF is such that the number of users and items will grow over time, which is bound to increase the complexity of computation. Because of this, a typical memory-based CF system with millions of users and items will suffer from serious scalability problems as the number of user and items continue to grow.
iii. **Learning**: The memory-based CF is not based on any explicit statistical model, and as such nothing is learned about users or items that can provide a basis for generalization for future predictions.

3.2.2 Model-based CF approach

The shortcomings of memory-based CF systems, especially the lack of scalability and learning have led to the emergence of the concept of model-based CF approach [DesMK]. Model-based or item based CF has the advantage of improved computational complexity characteristics and the ability to separate the model building process from actual computation of recommendation. Particularly, in instances where there are far greater number of users than products i.e. $|U| >> |P|$. The model-based CF has been shown to have better computational performance compared to user-based CF [SarBM]. Just like the memory-based CF, recommendation computation is based on the ratings that users provide for product P, but, unlike memory-based CF, similarity values are computed for products rather than users. In this wise, two products pk and pn are considered similar, i.e., have large sim (pk, pn), if they get identical ratings from many users or user who rate one of them tend to also rate the other. This approach emulates the real-life behaviour of users, whereby a user u_i judges the value of an unknown product pk by comparing pk to known, similar items pn and considering how much u_i appreciated items pn.

However, CF systems have two drawbacks, first is the fact that recommendations are made to users based on the approximations of other humans, which means that they cannot always be accurate and objective, especially when dealing with non-commodity items, where human preference are very personal (e.g. services, tourism etc.). Another problem is the issue of sparsity, in which calculations are based on sparse and incomplete data, which means the recommendation cannot be trusted because it is based on too few data. These two reasons explain why the recommendations given by CF systems are generally correct, but sometimes very wrong. Due to this fact, CF recommendations are not usually engaged in domains where a higher risk is associated with the acceptance of a recommendation. CF and CBF are combined in many cases into an integrated hybrid filtering solution in order to override the limitations of the individual approaches. Commercial websites such as: Amazon (www.amazon.com), CDNow (www.cdnow.com), MovieFinder (www.moviefinder.com) and Launch (www.launch.com) make use of collaborative filtering approaches for recommendation.

3.3 Hybrid Approach

The hybrid approach is a combination of CBF and CF techniques in order to eliminate certain limitations of both techniques [AdGTz]. There are four main approaches for combining the two techniques into a hybrid recommender system. These are:

i. **Combining separate recommender systems:** In this approach predictions from separate implementations of content-based and collaborative techniques are combined within a single system framework [FCC]. To give a final result, the ratings obtained from the individual recommender systems are combined into a final recommendation, or the best recommendation chosen after a quality assessment of recommendations from both systems have been carried out.

ii. **Adding content-based characteristics to the collaborative approach:** In this approach some content-based characteristics are integrated into the collaborative approach. Content attributes and not the commonly rated items are used to calculate the similarity between two users. This innovation helps to overcome some of the sparsity-related problems of a purely collaborative approach, since in most cases it is not common for two users to have a significant number of commonly rated items between them [FCC]. Another benefit is that accurate recommendation can be obtained directly when the content attributes of an item match the user's profile and not until when an item gets rated by a similar user.

iii. **Adding collaborative characteristics to the content-based approach:** In this approach some collaborative characteristics are integrated into the content-based approach. One way to achieve this is to create a collaborative view of a collection of user profiles represented by term vectors [SffNC]. This will result in performance improvement when compared to a purely content-based approach.

iv. **Developing a single unifying recommendation approach:** In this approach a general framework that incorporates both content-based and collaborative characteristics is created. For example in [Basu], the use of content-based and collaborative characteristics was proposed, such as the age or gender of users or the genre of movies, in a single rule-based recommendation classifier.

3.4 Knowledge-based Recommender Systems

Knowledge-based recommenders, though sometimes regarded as fundamentally content-based systems are a class of recommender systems that exploit deep knowledge about the product domain in order to determine recommendations. They make use of knowledge about users and products to generate a recommendation and reasoning about what products meet the user's requirements. A knowledge-based recommender system avoids the problem of sparsity associated with both CBF and CF systems [FCC]. The recommendations of knowledge-based recommender systems do not depend on a base of user ratings. It does not have to gather information about a particular user because its judgements are independent of individuals' tastes. However there two major drawbacks of knowledge-based recommender systems, which are the expensive nature of knowledge engineering endeavours which makes them more costly to implement, and the static nature of their suggestions ability [BuRK].

3.5 Place Recommender System

We aim to design a content-based filtering system recommending places based on the correlation between the content of the place suggestion and the user's preference as opposed to a collaborative filtering system that recommends places based on the correlation between people with similar preferences. In this study our personalized place recommender system is described that exploits content-based filtering techniques to achieve personalization.

4 Contextualization in IR

4.1 Definition of context

In the world of computer science the idea of ‘context’ is not new: from the sixties, operating systems, language theory and artificial intelligence have by now exploited this concept. With the emergence of information retrieval systems, the term is being rediscovered and placed at the core of many IR debates. Recently, through initiatives such as the IIiX conference series[1], the HARD and contextual retrieval tracks at TREC[2], the IRIX workshops[3] and the recent mono-graph by Ingwersen and Järvelin [IngBR] we see a consolidation of activity in how contextual information can be used to design and evaluate information retrieval systems and interfaces. Indeed, as Finkelstein et al. noted in 2001 `A large number of recently proposed search enhancement tools have utilized the notion of context, making it one of the most used terms in the field, referring to a diverse range of ideas from domain-specific search engines to personalization [LFink].

Information seeking, the process by which humans find information is greatly a contextual activity. Using a retrieval system is only one way in which we can access information but, even with this one mechanism, number of variables can affect our information seeking activities. Major variables include our prior knowledge of a topic and resources available, our experience of searching for information, the purpose for which we want information, and a range of human factors including personality, cognitive abilities, age, gender, and learning styles. For example, if we frequently conduct the same search then a useful system response would be to show us new information on our search topic; a less useful response would be to repeatedly show us the same information. Or, if the person

1 http://iiix2010.org/
2 http://trec.nist.gov/
3 http://ir.dcs.gla.ac.uk/context/

searching is a child then retrieving and displaying complex information is not an appropriate response; a better response is presenting information that is appropriate for the child's age and reading level.

The major claim for employing contextual approaches to Information Retrieval is that, if Information Retrieval systems are capable of recognizing and utilizing differences in search contexts, then they will provide better response to user needs and preferences. To understand the challenges in contextual IR, some of the main elements of the context that have been presented in the literature.

4.2 Elements of Context

Many contextual factors may affect how we use an Information Retrieval system and how we evaluate the system's performance. A number of researchers have tried to enumerate these factors. One useful example is the context model developed by Kofod-Petersen and Aamodt in the Ambisense project [KoPA], Figure 1, which was concerned with information seeking via mobile devices.

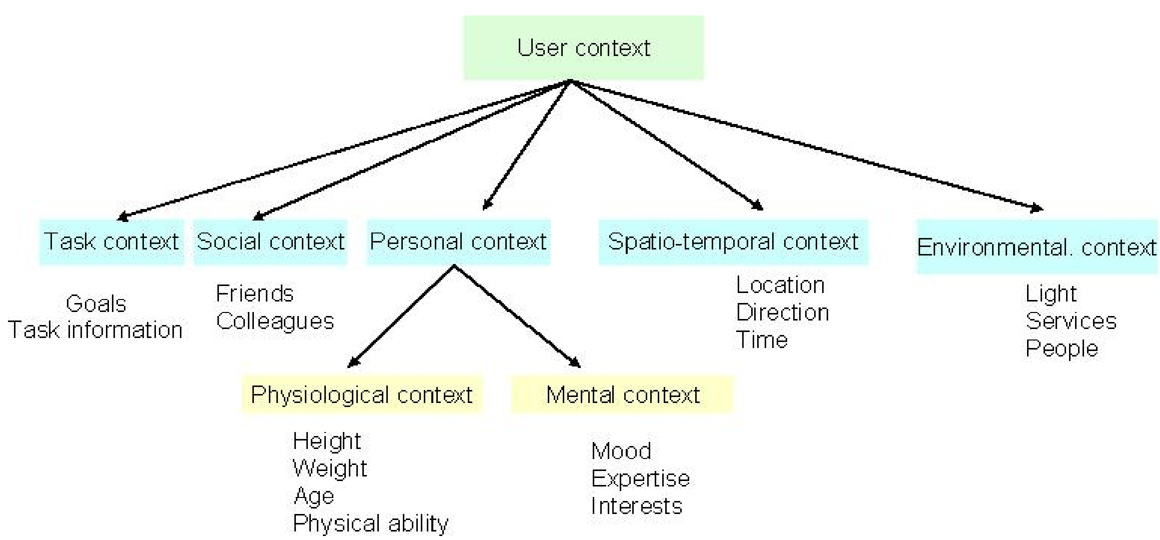

Figure 1- Ambisense model of context

i. **Task** context is a major contextual variable for IR as noted by [Vakkari]. Here a task is considered to be the information problem, e.g. finding a holiday destination, writing an essay, giving a lecture, which promotes a need for information that leads, in turn, to using a retrieval system. The nature of the task can affect which information is useful in completing a task. For example a document that might be useful in writing an historical review on search interfaces may not be useful in writing a review on state-of-the-art search interfaces, even though the two tasks have the same topic. Tasks may be strictly defined before searching begins, and only specific information will be relevant, or they may less fixed, capable of being turned into a new task depending on what information has been encountered during the search.

ii. **Social** context is a variable that has been overlooked by Information Retrieval research with most systems, at least implicitly, assuming that each person searches as an individual and for personal information needs. There are many situations in which this is true but often we do search for information that is to be used by other people, e.g. search for information for a family holiday, or where other people's preferences must be taken into account such as searching for a gift. There are also many situations, e.g. intellectual property searching [Tait] or legal searching [Oard], where professionals search on information needs described by others. Therefore the professional's knowledge of the end-user and their understanding of the search request are important. Recently retrieval system designers have responded to challenges of searching within social and organizational contexts and the systems are designed to acknowledge other searcher's activities [JSmY].

iii. **Personal** contexts have been the most commonly investigated use of context in Information Retrieval. Here the range of contextual factors that might be important is vast ranging from age, physical and cognitive ability (which may require altering the presentation of search results as well as the selection of results), learning styles, education level, or mood of searcher. The most common personal context investigated so far is the searcher's topical search interests, particularly through applications of information filtering.

iv. In some situations, e.g. information retrieval through mobile devices, a searcher's **physical** context may be important to provide situationally relevant information. For example, their direction of travel may important to suggest information on destinations that they are about to encounter [Brown]. Time may also be an important variable: a query on restaurants issued at 11.30am might indicate the searcher is looking for suggestions for lunch whereas the same query issued at 7pm would indicate suggestions for an evening meal. So far, location has been the most common physical contextual variable, partly due to the ease with which such information can be captured.

v. The **environmental** context in which information is being accessed may be important: some information may not be appropriate to show in public settings, some information is only appropriate for work, not personal, environments and so should only presented at appropriate times and what information is available to be retrieved may differ in different environments.

There is, then, a wide range of factors that may be used to improve the user's experience of Information Retrieval systems. Which ones are useful, and in which situations, provides the setting for a rich seam of research. In the next section we outline some of the practical uses for which we might adopt some of these contextual factors.

4.3 Incorporating contextual factors in Recommender Systems

In many applications, such as recommending a vacation package, personalized content on a Web site, or a movie, it may not be sufficient to consider only users and items – it is also important to incorporate the contextual information into the recommendation process in order to recommend items to users in certain circumstances. For example, using the temporal context, a travel recommender system would provide a vacation recommendation in the winter that can be very different from the one in the summer. Similarly, in the case of personalized content recommender on a Web site, it is important to determine what content needs to be delivered (recommended) to a customer and when. More specifically, on weekdays a user might prefer to read world news when she logs on in the morning and the stock market report in the evening, and on weekends to read movie reviews and do shopping. Also, [Rinner] Rinner and Raubal (2004) designed a service named Hotel Finder which by considering a user's location, spatiotemporal constraints and preferences, recommended suitable hotels.

We envision our context aware place recommender to take form as a mobile application that recommends interesting places and activities based on the users' location and personal preferences. Imagine a user with a young family travelling for a summer vacation to Philadelphia, Pennsylvania. A contextual suggestion application considers Philadelphia as a location context, would recommend interesting places where this young family can spend time together for example, a suggestion would recommend visiting a kids friendly museum (http://www.pleasetouchmuseum.org/), or a walk in the beautiful historic Penn Treaty Park (http://penntreatypark.org/), or to spend the day splashing in the waters at the Clementon Park Splash World (http://www.clementonpark.com).

5 Personalization

Personalization is a promising way in improving the web search rankings by making the user out of hiding during the search. An effective personalized search relies on two main challenging tasks, which are the user profile modeling and the search personalization. A common feature of most personalization systems is the application of user profiles to customize the systems behaviour to individual users. User models represent the information about users that is essential to support the adaptation functionality of the particular system. In this chapter we want to give a general overview about the most common techniques used for web user personalization.

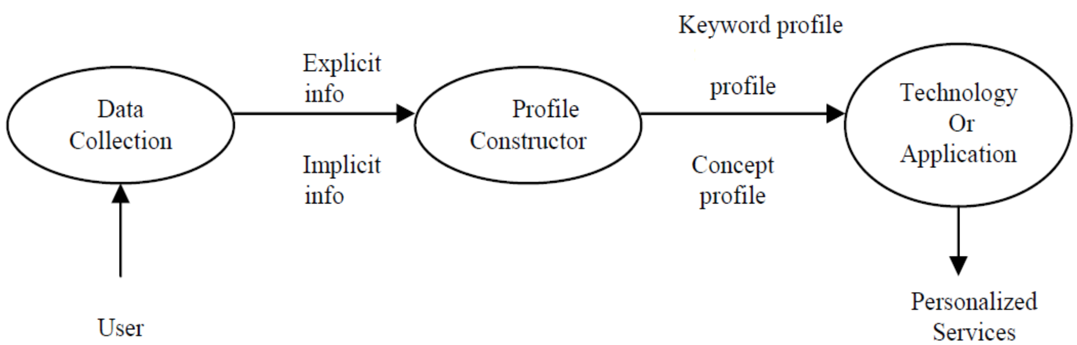

Figure 2- Overview of user-profile-based personalization

As shown in Figure 2, the user profiling process generally consists of three main phases. First, an information collection process is used to gather raw information about the user. Depending on the information collection process selected, different types of user data can be extracted. The second phase focuses on user profile construction from the user data. The final phase, in which a technology or application exploits information in the user profile in order to provide personalized services. The entire process is described in the following sections.

5.1 User profile modeling

The information about users must be collected, an internal user profile representation of the model must be established, and the collected information should be used in order to construct each user personal profile, for providing him/her with personalized facilities. We will present further the most popular techniques for collecting information about users, representing, and constructing user profiles.

5.1.1 User information collection

Usually, the first step in user profiling is concerned with obtaining individual users data. The information collected might be provided explicitly by the user or gathered implicitly by a software agent. It is possible to collect the data either on client side or on a central server machine. In this chapter we are going to give a brief introduction of the advantages and disadvantages of both explicit and implicit feedback.

5.1.1.1 Explicit Feedback

Explicit user information collection [GSCM07] basically relies on personal input by the user. A common feedback technique is the one that allows users to express their opinions by selecting a value of range. For instance MyYahoo explicitly asks the user to provide personal information that is stored to create a profile. The web site content is then automatically organized based on the user’s preferences. The main drawback of these methods is that the user has to spend a lot of time to fill out forms or to click checkboxes. In case the user is not willing to provide personal information, no profile can be build. Another problem with explicit feedback is that user’s interest may change over time, but the profile remains static and become increasingly inaccurate over time.

5.1.1.2 Implicit Feedback

The main advantage of implicit feedback [GSCM07] is that it does not require any additional intervention by the user during the process of constructing profiles. Moreover, it automatically updates as the user interacts with the system. In general, systems that collect implicit information place little or no burden on the user. Thus, they are more likely to be used in practise. Furthermore, several studies as those by R. White [WJR01] found that such systems perform as well as those using explicit feedback, and therefore are somewhat interchangeable. One drawback to implicit feedback techniques is that they typically only capture positive feedback. When a user views a page, it is assumed that this indicates some interest. However, it is not as clear when a user fails to examine some data, that this is an indicator for disinterest.

5.1.2 Web Information Gathering

Web information covers a wide range of topics and serves a broad spectrum of communities [GAntH4]. How to gather useful and meaningful information from the Web, however, becomes challenging to the Web users. By large most of the systems used toady use keyword-based techniques to search the Web, for example, Google, by finding the documents with specific terms or topics matched. Here we attempt to give a brief introduction two the gathering techniques.

5.1.2.1 Keyword-based Techniques

Keyword-based information gathering techniques are based on the feature vector of document and queries. In order to determine if a document satisfies a user information need, information gathering systems extract the features of the document and compare these features to those of the given query.

5.1.2.2 Concept-based Techniques

The concept-based information gathering techniques use the semantic concepts extracted from documents and queries. Instead of matching the keyword features representing the documents and queries, the concept-based techniques attempt to compare the semantic concepts of documents to those of given queries. Some works indicate that concept extraction needs to be improved for more specific semantic relation specification, considering the fact that the current Web is nowadays moving towards the Semantic Web [Berners].

5.2 User Profile Representation

A user profile is a structured representation of the user's habits, interests and needs. User profile representation is always domain specific and depends on the filtering method used for training the system. The profiles are inputs of the filtering method. Generally speaking, profile representation falls into three classes [Stuart]: rating-based representation, content-based representation and knowledge-based representation. Namely, rating based representation usually refers to profiling in collaborative filtering where it is difficult to differentiate items as to its content, and content-based representation usually refers to profiling in content-based filtering where items' content consist of descriptive attributes

5.2.1 Ratings-based Representations

When users receive recommendations it is common to elicit feedback on how interesting the recommendations are to the needs of the user. This type of feedback is called relevance feedback. Relevance feedback is elicited by offering the user a rating scale for each recommendation; the choice is commonly either "interesting" and "not interesting" or a 3 to 5-point scale of interest [Andrew] [Kai]. The representation of relevance feedback is thus a set of recommended items and the associated interest values provided by each user.

Relevance feedback can be acquired implicitly, allowing inference from observed user behaviour [Stuart]. The problem with implicit feedback is that the assumptions made to allow inference often introduce errors. For example, a user may read an initially interesting looking document, only to find it was actually not interesting after all when its details are known; if all documents that are read are inferred to be interesting this situation would clearly introduce an error into the relevance feedback acquired.

A balance must be made between interrupting the user to acquire high quality explicit feedback and unobtrusive methods to obtain lower quality implicit feedback. Exactly how much interruption the users will tolerate will depend upon the specific application domain.

5.2.2 Content-based Representations

Most content-based analysis is performed on textual documents such as web pages, newspaper articles or document abstracts. The reason for this is that textual documents easily break down into individual words, whereas video and audio sources require sophisticated analysis to decompose into useful sub-components. Almost all content based recommender systems work with textual content.

Term-frequency vector representation: The most common abstraction of a textual document in the machine-learning context is a term-frequency vector. To create a term frequency vector the terms within a document are counted and the frequency values stored in an n-dimensional vector [ByTak] [MJBV] [Hyoung]. The number of dimensions of the vector is the number of unique terms within a document.

Binary class profile representation: The most common profile representation for the content-based recommender systems is the binary class profile, representing user interests as a set of positive and negative examples [Soltysiak]. The positive, or "interesting", examples are represented as a collection of term-frequency vectors of documents that the user has rated as "interesting". The negative, or "not interesting", examples are likewise represented. This binary class representation is very suitable for a great many machine learning techniques.

Since relevance feedback is required to obtain the sets of positive and negative examples, a ratings-based profile is often additionally implemented to create a hybrid recommender system.

Multi-class profile representation using ontology: The alternative to the binary class representation is a multi-class representation. Rather than simply having positive and negative classes, ontology of classes can be created that map to domain concepts such as newspaper topics like "sport". A user's profile is thus represented in terms of which classes they are most interested in, abstracting away from the specific examples of interest [BLazF]. When relevance feedback is acquired, examples of interest are classified according to the classes within the ontology, and the user's interest in that class recorded.

For example, Persona [TFMuj] is exploring personalized search that exploits user profiles represented as a collection of weighted concepts based upon the Open Directory Project's concept hierarchy. The system builds a taxonomy of user interest and disinterest using a tree coloring method. As the user searches the collection of pre-classified documents in the ODP, they are asked to provide explicit feedback on the resulting pages. This feedback is then used to update their profile. Since the pages are already manually mapped into the ODP concepts, the user profile can be easily updated by keeping a count of the number of times a given concept was visited, i.e., had a page viewed by the user, and the number of positive and negative feedbacks the node received, and the set of urls associated with the node. Because the system uses pre-classified documents, the profile is able to contain any or all concepts in the ODP and the mapping of visited pages to concepts is very accurate. One difficulty with this approach is that, because the ODP hierarchy is so deep and contains so many concepts, the profile can become very large and contain many very narrow concepts.

5.2.3 Knowledge-based Profile Representation

Knowledge-based profile representations appear in the user modelling literature. Typically these approaches require questionnaires and interviews with users to acquire information about their requirements before a profile can be built [Qiubang]. Profiles consist of asserted facts about a user in a knowledge-base, from which inferences can be drawn about user stereotypes and interests. Knowledge-based profiles are often used in the related fields of agent and intelligent tutoring systems.

The literature proposes the user profile representation in three different classes as we have just overviewed. However we want to mention about another classification of profile representation. [Danny] exists in the literature classifying the profile representation problem into four topics: static content profiling, dynamic content profiling, static collaborative profiling, and dynamic collaborative profiling. Static content profiling refers to the gathering of static information regarding the user usually upon registration.

Typically, systems allow users to enter a simple profile when they first register with the system. It is static as the registration is done only once. Knowledge based representation discussed above can be considered as a static profiling. For dynamic content profiling, the system gathers information based on the dynamic changes in the behaviour of the user. This means that the system should keep track of the user's behaviour when interacting with them. Term frequency vector representation discussed within Content-Based representation is a dynamic content profiling as well. The concept of static collaborative profiling refers to explicitly clustering users with similar behaviours through user's explicit request. Every time a new user is added into the system, the system will take a period of time to collect information about the user and to construct the user's profile with information that will aid the system in serving the user's needs.

We can reduce the learning curve of the system by reusing a current user's profile by matching the new user's profile with other current user's profile. The categories or terms listed in the user's profile are matched across other users' profiles. If the term or keyword in the user's profile is found in another user's profile, the similarity measure for these two users is increased accordingly. Dynamic collaborative profiling refers to clustering users with similar behaviour into peer groups based on the user's profile and filtering information pertaining to group's interest.

6 Semantics and Ontology

6.1 What is Ontology?

The word ‘ontology’ was originally taken from the field of philosophy and is concerned with the study of the nature of being. In the context of Artificial Intelligence (AI), there exist sundry definitions of ontology [Gomez] [Noy] each one trying to introduce its own emphasis. However, one of the most common definitions of ontology in literature is that: ‘An ontology is a formal explicit specification of a shared conceptualisation of a domain’. Conceptualisation entails the use of abstract models to depict what is understood about entities in a domain of interest. Explicit means that the concepts used and the constraints on them are clearly defined while formal means that entities in the ontology are represented in full or semi-machine processable form. Also, the fact that it is shared means that the knowledge captured in the ontology is mutually agreeable to a group of people. In this thesis, we define ontology as: A formal model of a domain of interest that depicts the domain as an aggregation of its known relevant elemental concepts and the semantic relationships between them that provides a platform for knowledge sharing and reuse. This connotes that an ontology is a deliberate semantic description of what is generally known about some real world phenomena in a domain of interest using concepts and relationship abstractions in a way that is readable by both man and machine.

6.2 The Components of an Ontology

An ontology essentially consists of a vocabulary of terms in a domain of interest and their meanings. This includes definition of concepts, the properties of the concepts, and the interrelationship between concepts. Ontologies are classified into lightweight and heavyweight categories based on the nature of their composition [Gomez]. The main components of a lightweight ontology are the concepts of a domain, the interrelationship between concepts, and the properties of each concept. However heavyweight ontologies consist of concepts, concept properties and concepts interrelationships just like lightweight ontologies but have also included in their definition the axioms and restrictions on concepts, concepts properties and concepts relationships. Generally, the notion of concepts (sometimes called classes) in ontology is akin to classes in the object-oriented paradigm. The properties of a concept (sometimes called slots) are the features and attributes of that concept which can take specific value types (e.g. boolean, integer, string, float, date, etc.). The restrictions are formal logics constraints that are defined on the properties of a concept or on inter-concepts relationships.

The taxonomic relationships between classes in an ontology are mostly defined through inheritance using 'ISA' relationships which specifies a subclass A as 'a kind of' the superclass B. For example, if the class Location defines all kinds of places where people live, then all addresses will be an instance of class Location. However, City, Town, and Village are different kinds of location where people live, each of which can be represented as a subclass of the Location. Other kinds of relationship like 'part-whole' ("PartOf") or synonym ("SynOf"). Additionally, other application specific relationships that might exist can be represented in an ontology [NFQ05].

6.3 An Overview of ODP

Semantic knowledge structures, such as ontology, can provide valuable domain knowledge and user information. An ontology is specifications of concepts and relations between them. It defines "content specific agreements" on vocabulary usage, sharing, and reuse of knowledge [ZGG+ 99]. ODP[4] is an open content directory of web pages maintained by a community of volunteer editors. The web pages are classified into a hierarchical topic (directories). Figure 3 shows a part of ODP hierarchy of the Artificial Intelligence concept. We use the ODP ontology as fundamental predefined domain knowledge in our semantic user profiling component. The ODP is the most widely distributed Web directory that classifies millions of web pages into 787,774 categories[5]. Each concept is related to a set of sub-concepts through "is-a" links except the leaf nodes. Concepts of the ODP are interrelated with different relationship types. An important distinction between taxonomies and ontology such as the ODP ontology is that edges in a taxonomy are all of the same type ("is-a" links). While in the ODP ontology, edges can have additional semantic types (e.g., "symbolic", "related"), called cross links. All of the directory's data are available free to the public[6] in RDF, a common format for describing web data.

In this approach, a reference ontology is constructed based on the ODP hierarchy of topics associated with documents. The reference ontology is useful to initial derive the user modeling by using concepts generated from user's rated documents (e.g. local tourist attraction web pages) to the ontological reference.

[4] http://www.dmoz.org
[5] http://www.aef-dmoz.org/blog/l-odp-francophone-en-aout-2007
[6] http://rdf.dmoz.org

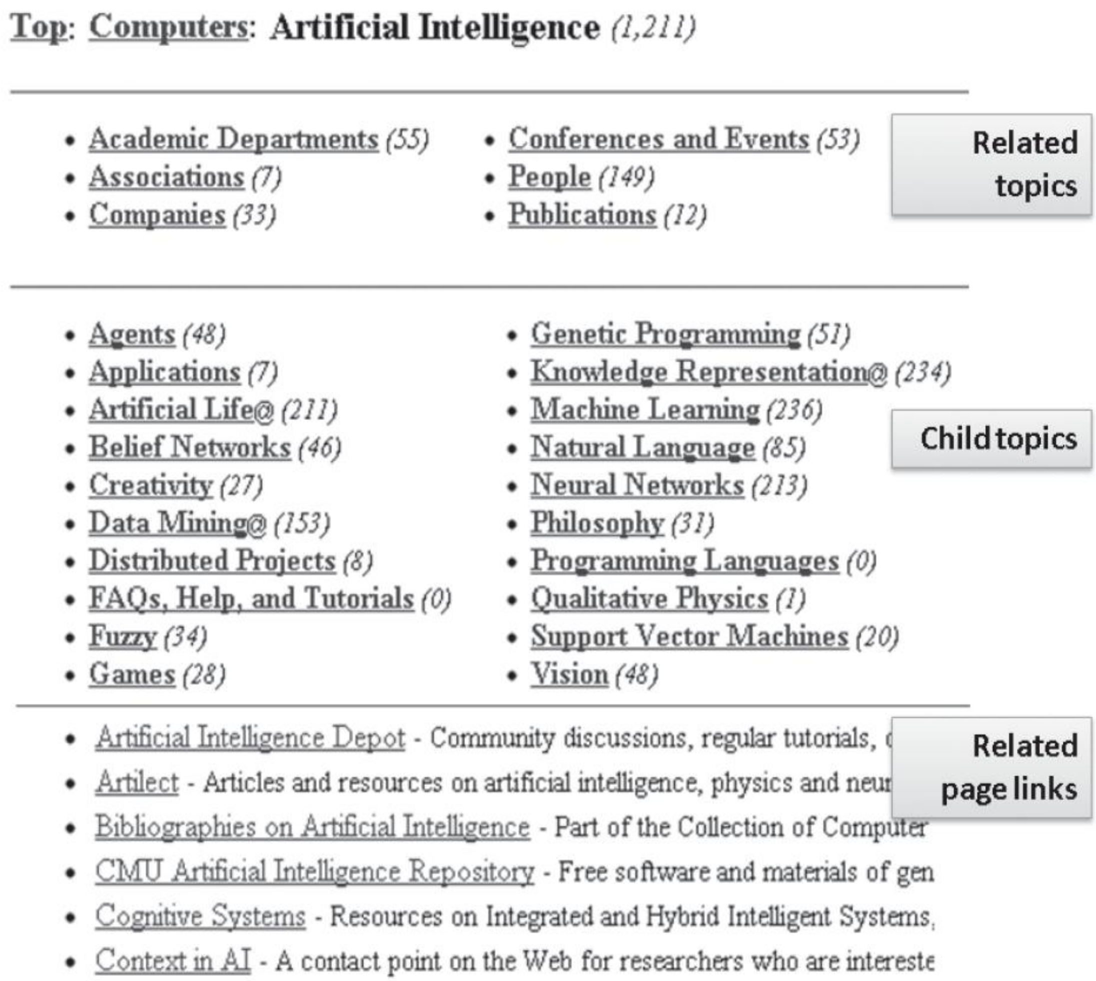

Figure 3 - ODP hierarchy of the topic Artificial Intelligence

Later, we represent the concepts by keyword vectors. For this, we used only the hierarchical relationship of the ODP and kept the transversal links between concepts in an aggregate [MDlY] form in order to use them further to activate semantically related concepts for representing the user profile. Geographic concepts classified under "Top/local" and all non-English concepts and web pages are excluded from the ODP representation. Each concept c is associated to a set of web pages classified under that concept and each of the web pages is annotated by a title and a description that explain its it by vector of terms.

6.4 Ontological Reference Building

The hierarchy of concepts are extracted from ODP base. The process of the reference ontology generation is depicted as Fig. 4. There are two following main steps to construct the feature vector for the concept. First step, using the vector space model tf/idf to construct the generalization of the documents. Second step, for each leaf concept, the feature vector is calculated as the feature vector of set of documents associated with the concept [TRNaZ]. For each none-leaf concept, the feature vector is calculated by taking into consideration contributions from the documents directly associated with the concept and its direct sub-concepts.

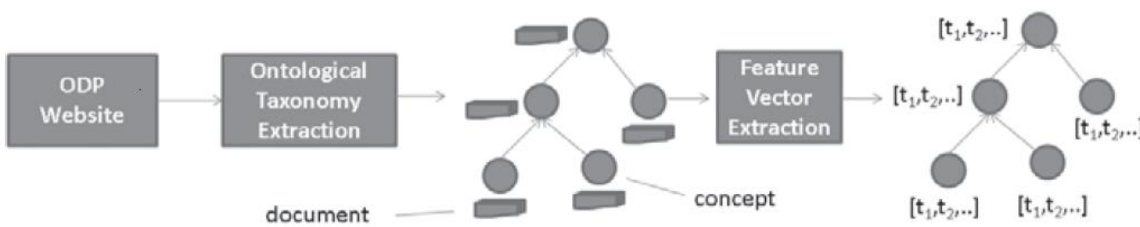

Figure 4 - Reference Ontology generation

6.5 Semantic Modeling

User modeling is an important component in personalized search to decrease the search ambiguity and present search results that are more likely to be interesting to a particular user. User's preferences and interest are represented in an ontological model which formed a user profile for an individual user. This approach has been successfully applied and tested by researchers to reduce the cold start problem in recommendation system and personalize search results.

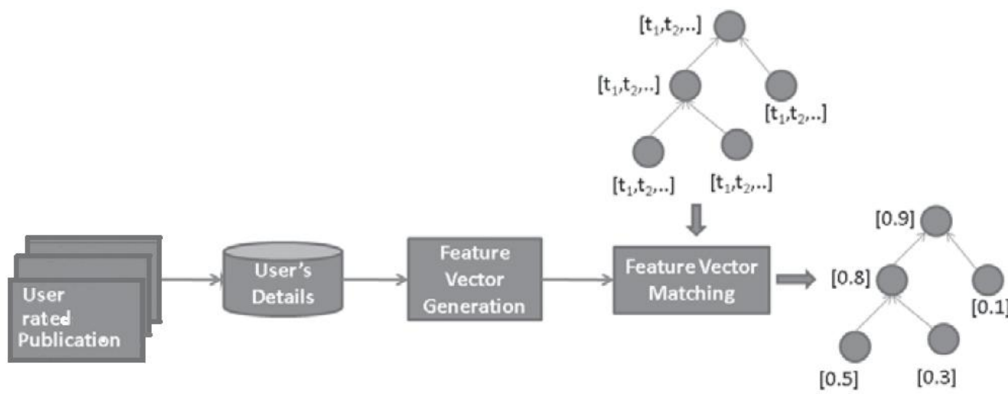

Figure 5 – User profiling using ontological model

User profiles may include general information about users such as name, age, educational background, etc., and specific information such as the interests and preferences. The information may be collected explicitly, through direct user intervention, or implicitly, observing the user's behaviors. The collected details of users can be modeled with ontological model to semantically represent their preferences as show in figure 5. A new ontology can be developed or an existing hierarchical taxonomy can be reused as a reference ontology, to represent user preferences. Here, an initial ontological profile is generated by aligning feature vectors deriving from user's information to the reference ontology. The user's information can be derived from user rated publications [DUdd9].

7 Our Place recommender methodology and approach

Our place recommender framework has been designed to provide best suggestion results according to the user's context and interest. The proposed framework utilizes geo-tools and services, place ontology and re-ranking methodology to achieve personalised results. We identified two major stages for the process flow of this framework. One is the context processing where given a context or location we request places for the location from a geo-service like google radar API. Once we get the list of places we extract the place reference ID and using it we further request for the place URL and description. Later we merge the url, description to build a pool of upto 50 contextual suggestion list of places for each context.

The second major stage is the sematic personalization. This is the part where the emphasis on the user profiling in order to re-rank the existing pool of suggestion list to bring the most suitable user personalized suggestions on top. This stage involves in user preference processing where we identify the positive and negative preference based on the examples rated by the user. Later we build a feature vector by mapping user positive and negative preferences onto concepts of the place ontology. Later we use the re-ranking approach to achieve the personalised suggestion list. Figure 6 shows our place recommender framework. Sections 7.1, 7.2 and 7.3 discuss in detail the methodology and approach to designing our recommender system.

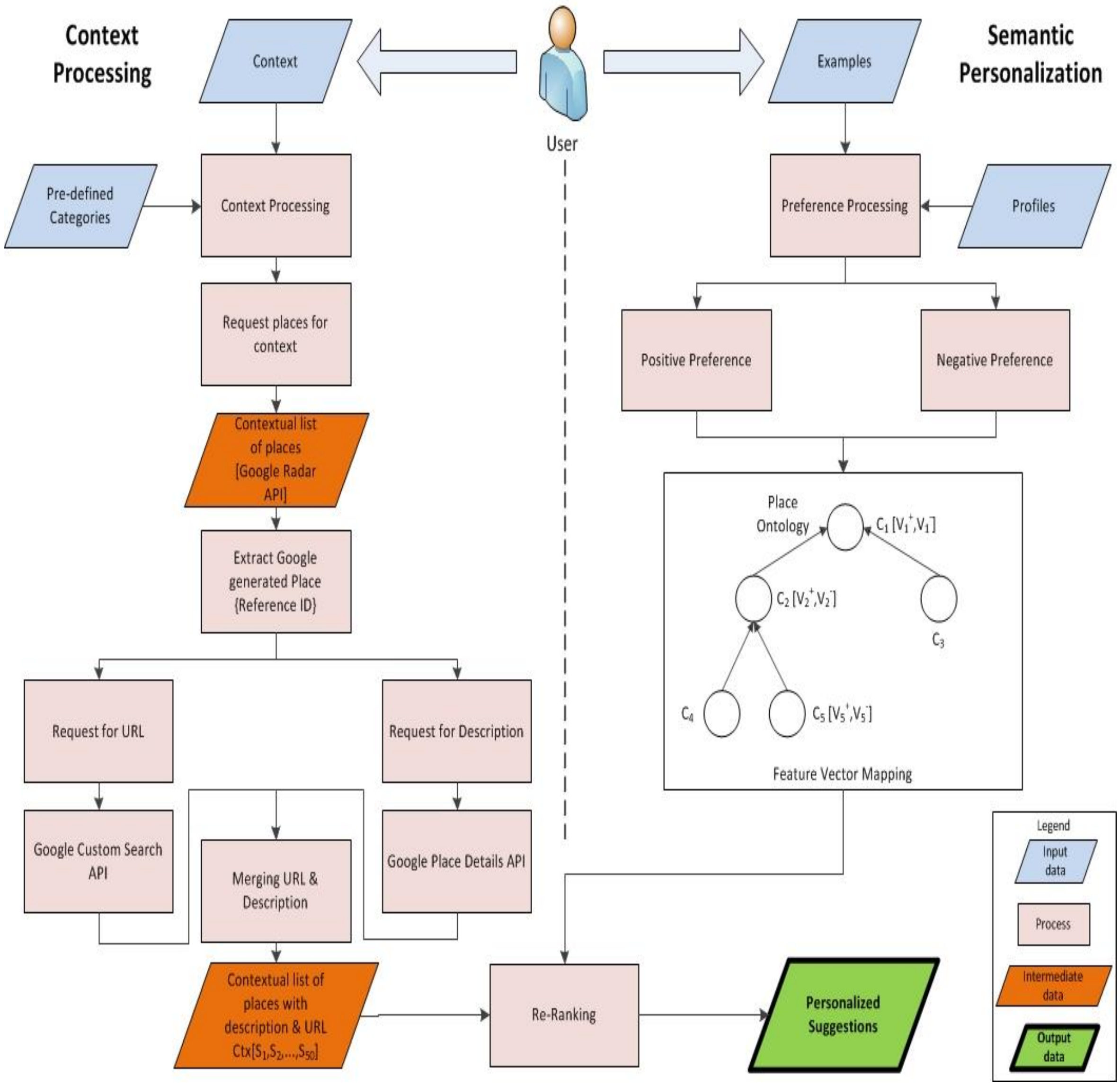

Figure 6 – Personalized Place Recommender Framework

7.1 Constructing a place ontology

When initially learning user interests, systems usually perform poorly until they collect enough relevant information. Since initial user behaviour information is matched with existing concepts and relations between them, using ontologies as the basis of the profile helps to avoid or ease this problem. To achieve personalization we build a place ontology based on the ODP ontology. We only extract concepts in ontology that are related to place types and that could represent the user interests in places. We consider both generic and specific concepts of the ODP ontology. Generic concepts represent general user interests among different place types. For example, a user is more interested in museums than restaurants or parks. A specific concept represents specific user interest under a generic place type. For instance, a user is more interested to visit a cultural museum than a science museum.

The place ontology takes into account several main concepts such as Museums, Travel, Food, Shopping etc. Specific concepts under each generic concept are also considered in order to capture specific user interests and also to differentiate between different user's tastes. Concepts such as science museum, history museum, arts and entertainment museum and cultural museum are different kinds of museums that allow capturing specific user interests.

There are different levels in this place ontology; the depth can vary between two to seven levels. The depth of the ontology construction signifies that a user's interest is captured at a granular level.

For instance, a user looking for a place to snack specifically a sandwich, such an interest can be mapped to one or more ontology sub-tree Business/Hospitality/Restaurant Chains/Sandwich and Deli and Recreation/Food. Figure 7 presents a portion of the place ontology that we constructed based on the ODP ontology.

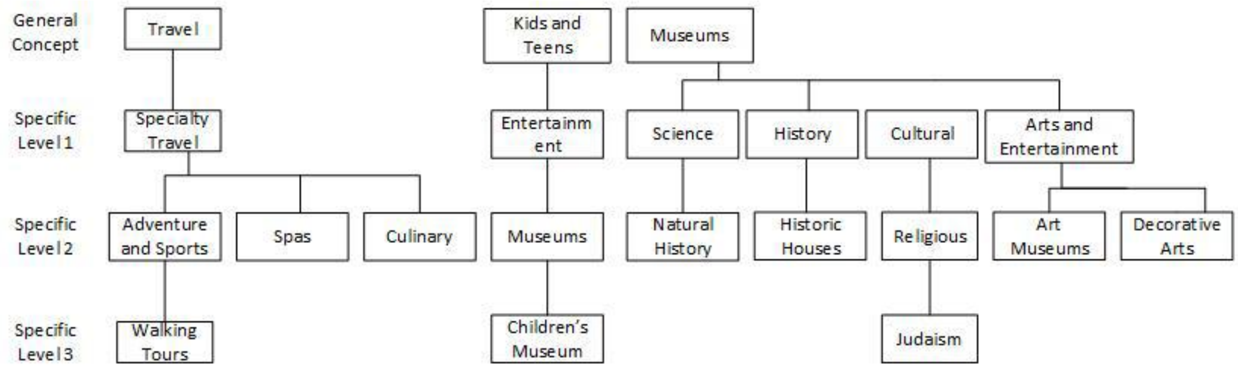

Figure 7 - A portion of our place ontology

From ODP, we extracted a sub-directory relevant to place types. For example, as most recommendations we retrieved from Google Places are related to places to visit, we extracted the concepts associated with travel categories of the ODP.

7.2 Semantic user profile modeling

We propose a new user profiling that refers to the construction of a profile via semantic means using the ODP place ontology. Each user profile is represented as an instance of the place ontology that gathers positive and negative user interests. More precisely, each concept (place type) of the ontology is represented with positive and negative term vectors.

For each user, we build the user profile by mapping the previously rated places on the Place ontology. This mapping results in classifying the rated web pages into one or more concepts of the place ontology. We map the user-rated example suggestions on the Place ontology. Each will be mapped to one or more ontology concepts. Each concept of the ontology is represented by a pair of contexts: a negative and a positive context. The positive context is represented by a vector of terms issued from the positively rated examples mapped to it. The negative context is also represented by a vector of terms issued from the negatively rated examples mapped to it. For instance, the user that has highly rated the web page http://clementonpark.com/ is classified under: Recreation/Theme Parks/Water Parks. The web page has given poor rating such as http://studio34yoga.com/ is mapped to Society/Religion and Spirituality/Yoga/Teachers and Centers on the Place Ontology.

Consider concept Ci of the place ontology, and a set S of previously rated pages classified under concept Ci, we partition S into positive set S^+ and negative set S^- where S^+ contains the web pages rated above 3 and S^- contains the set of web pages rated below 3 by the user. Each page in S^+ and S^- is represented with a term vector. Based on S+ and S- we derive positive context Vector C_i^+ and a negative context vector C_i^-. C_i^+ and C_i^- are derived as being the centroid vector in the sets S^+ and S^- respectively. The following matrix represents how to derive the positive and negative contexts for each concept. Each row represents one page, and each column represents a term.

Positive Concept Matrix: M^+ Negative Concept Matrix: M^-

$$\begin{array}{c} \\ p_1^+ \\ p_2^+ \\ \vdots \\ p_n^+ \end{array} \begin{pmatrix} t_1 & t_2 & . & t_n \\ w_{11} & w_{12} & . & w_{1n} \\ w_{21} & w_{22} & : & w_{2n} \\ \vdots & \vdots & & \vdots \\ w_{n1} & w_{n2} & . & w_{nn} \end{pmatrix} \qquad \begin{array}{c} \\ p_1^- \\ p_2^- \\ \vdots \\ p_n^- \end{array} \begin{pmatrix} t_1 & t_2 & . & t_n \\ w_{11} & w_{12} & . & w_{1n} \\ w_{21} & w_{22} & : & w_{2n} \\ \vdots & \vdots & & \vdots \\ w_{n1} & w_{n2} & . & w_{nn} \end{pmatrix}$$

The positive concept vector is calculated as the centroid vector of positively rated pages in M^+ and the negative concept vector is calculated as the centroid vector of negatively rated pages in M^- .The weight of term t in C_i^+ is calculated as the average weight of the term in the positive pages. The weight of term t in C_i^- is calculated as the average weight of the term in the negative pages. Hence the weight W t_k^+ of term t_k in the centroid C_i^+ is calculated as follows:

$$Wt_k^+ = \sum_{i=1}^{n} w_{ik} \qquad \textbf{Equation 3}$$

The same formula applies for constructing the negative centroid vector C_i^-.

The user profile is then represented as an instance of the place ontology where each concept is associated with a positive vector and a negative vector. For instance, an example of a user profile with a Museum category (Reference/Museums/History) is represented by positive and negative weighted vectors as follows:

Negative concept vector: community=1, evolution=1, history=2, nation=3, time=1.

Positive concept vector: eastern=2, history=3, interest=1, penitentiary=1, philadelphia=4, state=2, visit=1.

7.3 Personalized Re-ranking Methodology

A typical IR re-ranking can be defined as a post-processing method that considers the initial ranking of documents and exploits additional information to improve the performance of IR systems. Our approach for a personalized recommendation is based on re-ranking the suggestions returned by Google places API using the user profile, thus by taking into account positive and negative user interests. Our main motivation for considering positive and negative user interests is to privilege the positive suggestions in the top ranks of the result list presented to the user. The re-ranking approach helps in differentiating between positive and negative suggestions that belong to the same place type. Our approach is represented in algorithm 1.

Algorithm 1: Re-ranking the suggestion set for personalized recommendation

INPUT: Context Ctx, Suggestions S = $\{S_1, S_2, \ldots S_{50}\}$,
Profiles P = $\{C_1(C_1^+, C_1^-), C_2(C_2^+, C_2^-) \ldots, C_N(C_N^+, C_N^-)\}$
OUTPUT: Result Suggestions R = $\{R_1, R_2 \ldots R_{50}\}$,
for each $S_i \in S$ do
  for each $C_i \in P$ do
    //do the following steps
    $Score^+(S_i) = cos(C_i^+, S_i)$
    $Score^-(S_i) = cos(C_i^-, S_i)$
    $Score\ (S_i) = \sum Score^+(S_i) - \sum Score^-(S_i)$
  end for
end for
// sort suggestion set according to score SORT S
// re-ranked result set R = S

Context Ctx, suggestion set S and profile P are inputs to our reranking approach. Ctx is a city location represented by its geographical coordinates (latitude, longitude). S a set of top 50 suggestions returned by a basic place recommender system for corresponding Ctx. P is the user profile represented in terms of place concepts C_1, C_2 , ..., C_n of the place ontology. Each concept C_i is represented by two vectors C_i^+ and C_i^-. For each suggestion in S we calculate a positive score and a negative matching score with each concept Ci in P. There are a large number of similarity measures proposed in the literature, the best similarity measure doesn't exist (yet!). So, using the benchmark cosine similarity function positive scores are calculated using the cosine similarity between the positive concept vector and the suggestion vector. Similarly, we build a negative score. The final score of a suggestion is calculated by subtracting the positive and negative score. This is repeated for the remaining 49 suggestions. We re-rank the suggestions in the descending order of their scores. This process is repeated for every context and profile pair.

8 Experimental Settings

Section 8.1 of this chapter explains our information retrieval settings. Section 8.2, 8.3, 8.4 and 8.5 describes dataset, profiles, contexts and suggestion collection. In section 8.6 and 8.7 we also explain Contextual Suggestion TREC's retrieval task, relevance judgments. Section 8.8 explains TREC baseline run. Section 8.9 describes the TREC evaluation measures. Section 8.10 describes and explains our experimental runs.

8.1 Information Retrieval System Settings

In our search experiments, we use Terrier [TQPlaV] for indexing and retrieval. This choice relies on the fact that Terrier is a highly flexible, efficient, and effective open source search engine and readily deployable on large-scale collections of documents such as TREC collections or also used for small-scale document collection such as TREC examples dataset. It also implements state-of-the-art indexing and retrieval functionalities (http://terrier.org/). To index our example dataset we use simple indexing offered by Terrier.

8.2 Dataset

The data that is used to develop and test our approach is provided within the context of the TREC (Text Retrieval Conference) contextual suggestion track challenge. The Text Retrieval Conference is an ongoing series of workshops and its purpose is to support research in different areas of information retrieval techniques and retrieval environments and to provide the essential infrastructure for large-scale text retrieval including large test collections, evaluation software and uniform scoring procedures. This conference helps to accelerate the transmission of new methodologies from research labs to commercial search engines. Most of the technologies implemented in current's commercial search engines are first developed in TREC (www.trec.nist.gov/overview.html).

Previous TREC participants assessed a variety of information retrieval areas such as multimedia retrieval, question answering and cross-language retrieval. In 2013, TREC has released eight different tracks including contextual suggestion track, crowdsourcing track, federated web search track, knowledge base acceleration track, microblog track, session track, web track and temporal summarization track.

The goal of the Contextual Suggestion track is to support research on systems that are able to anticipate user needs and respond with information appropriate to the current context without the user having to issue an explicit query. The so-called "Entertain Me" app is one example of such a system in which the system suggests interesting places and activities based on the user's current location and preferences for past activities. The Entertain Me app is the focus of the track. TREC contextual suggestion records are composed of user profiles, contexts and relevance judgments. In this section we first describe the inputs and suggestion collection and then we clarify the retrieval task.

8.3 Profiles

Profiles indicate a user's preferences to a list of 50 example suggestions within Philadelphia, PA. These profiles are built by conducted a survey advertised to both University of Waterloo students and Mechanical Turk users. A screen shot of the survey is shown in Figure 9.

Profiles are split into two files: examples2013.csv and profiles2013.csv. The file examples2013.csv contains a list of 50 suggestions which each consist of an id, a title, a description, and a url. Figure 8 shows a few suggestions from the file examples2013.csv.

```
<id>53</id>
<title> Edgar Allan Poe National Historic Site </title>
<desc> A bit of a hike from the other attractions in Independence
National Historic Park is the house where Edgar Allen Poe, author of
"The Raven" and "The Tell-Tale Heart" lived and wrote.
Poe fans will find many activities to enjoy, including a video
presentation of Poe's life, ranger-led tours, and perhaps an
encounter with "Poe" himself.</desc>
<url> http://nps.gov/edal </url>

<id>54</id>
<title> Round Guys Brewing Co</title>
<desc> Round Guys Brewing Co.  - No Monkey Business...Just Well
Rounded Beers!  </desc>
<url>http://roundguysbrewery.com</url>

<id>55</id>
<title>Academy of Natural Sciences</title>
<desc>Founded in 1812, the Academy of Natural Sciences of Drexel
University is a world-class natural history museum dedicated
to advancing research, education, and public engagement in
biodiversity and environmental science.</desc>
<url>http://www.ansp.org/</url>

<id>56</id>
<title>Reading Terminal Market</title>
<desc>America's oldest farmer's market is a bustling indoor public
market hall, with produce markets, bakeries, arts and crafts,
a beer garden, and virtually every type of cuisine present.  Be
sure to make some time to stroll around and sample as much as
you can.  Despite the market's stated hours, individual vendors
operate their own schedules; some restaurants will be open for
dinner, and some, particular the Pennsylvania Dutch shops,
are closed on Sundays.</desc>
<url>http://readingterminalmarket.org</url>
```

Figure 8 – Suggestions from example2013.csv

For this track contained 562 user profiles. The second file contains a list of ratings for each suggestion in examples2013.csv given by each user, below are a few example lines from profiles2013.csv:

id	attraction_id	rating description	rating website
35	51	0	4
35	52	1	4
35	53	3	3

Table 1 - An excerpt from profiles2013.csv

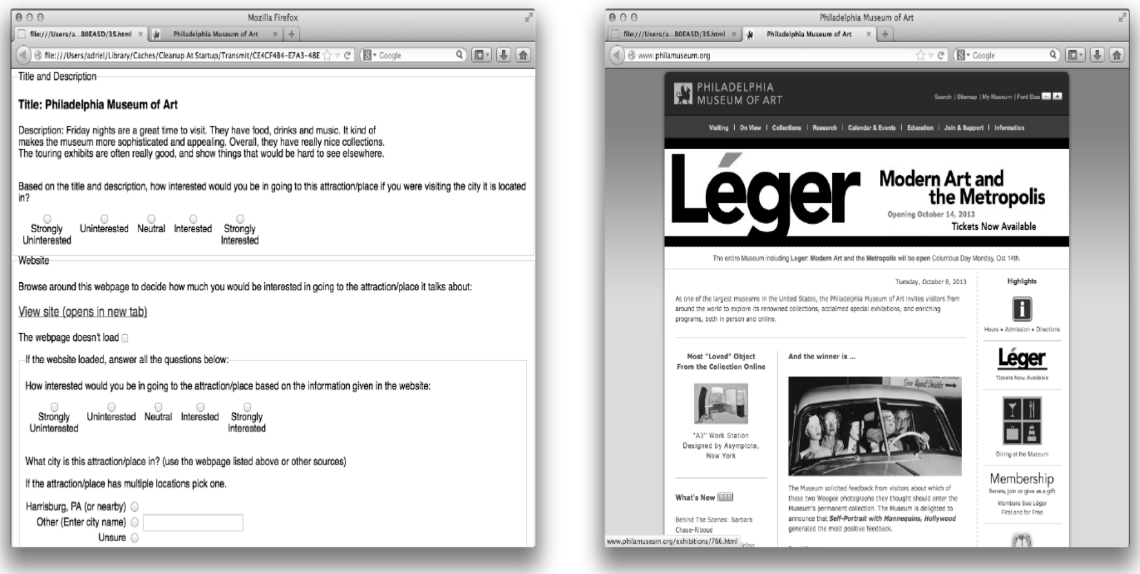

Figure 9 - Screenshots of survey seen by users

8.4 Contexts

Contexts describe which city a user is currently located in. There were 50 cities chosen randomly from the list of primary cities in metropolitan areas in the United States (which are not part of a larger metropolitan area) excluding Philadelphia, PA (the seed city). The list of metropolitan areas was taken from Wikipedia[7].

Contexts are distributed to participants in the file contexts2013.csv (as with the profile files, a JSON file with the contexts is also distributed).

[7] http://en.wikipedia.org/wiki/List_of_metropolitan_areas_of_the_United_States

id	city	state	lat	long
1	New York City	NY	40.71427	-74.006
2	Chicago	IL	41.85003	-87.6501
3	Los Angeles	CA	34.05223	-118.244

Table 2- An excerpt from contexts2013.csv

In table 2, the first row in the table means that context number 1 represents New York City (city), NY (state) with latitude of 40.71427 and a longitude of -74.006. For contexts the latitude and longitude are provided as a convenience and are synonymous with the city and are not meant to represent the exact position of the user. Contexts represent locations at the granularity of a city-level.

8.5 Suggestion Collection

The objective of the Contextual Suggestion Track 2013 was to recommend interesting places and activities from either the open web or ClueWeb12. In our case, we used the open web. First, we generate appropriate queries and submit them using a java application that calls Google Radar API to build our baseline suggestion set. These queries have as parameters the geographical location (latitude and longitude) of context and a set of place types that will probably have interest for the users. The set of place types used here are:

Place Types: *Amusement Park, Aquarium, Art Gallery, Bar, Book Store, Bowling Alley, Cafe, Movie Theater, Museum, Park, Restaurant, Shopping Mall, Zoo, Grocery Store / Supermarket, Casino, Night Club, Beauty Salon, Travel Agency, Jewelry Store, Library, Church.*

Google Radar API to returns a list of 200 suggestions for each context. We take only top 50 suggestions for our experiment. We enrich these suggestions by getting detailed description for each suggestion or from Google Custom Search API, and for more information, we use Google Place Detail search API to get website (url), type, location, etc.

For the purpose of this study we build xml documents for all profile-context pairs. Each suggestion document contains suggestions raked according to Google Radar API for a given context. These suggestions will later be re-ranked according to their profiles by exploiting the semantic-user based profiles proposed in earlier sections. A sample of the suggestion document is shown in figure 10.

```xml
<?xml version="1.0" encoding="UTF-8" standalone="no"?>
<PlaceSearchResponse>
 <GroupID>YORK</GroupID>
 <RunID>york13cr1</RunID>
    <ProfileID>537</ProfileID>
    <ContextID>41</ContextID>
    <Rank>1</Rank>
        <Title>Lake Pointe Grill</Title>
        <Description>Springfield's Only Authentic Wood Burning Pizza Oven.
                     Great food at affordable pricing.
                     Something for the whole family.
                     Lake Pointe Grill. 1386 Toronto Rd, Springfield, IL 62712-7387. 217-679-3900.
        </Description>
        <Url>http://www.lakepointegrill.com/</Url>
 <Group ID>YORK</Group ID>
 <Run ID>york13cr1</Run ID>
    <Profile ID>537</Profile ID>
    <Context ID>41</Context ID>
    <Rank>2</Rank>
        <Title>Brickhouse Grill &amp; Pub</Title>
        <Description>Brick House Grill is located in what is known today as Spencer's Corner.
                     An upscale gastropub, located in downtown Huntington, Indiana.
                     Offer's the area's best sandwiches, steaks and seafood.
        </Description>
        <Url>http://www.brickhousegrill.net/</Url>
<Group ID>YORK</Group ID>
 <Run ID>york13cr1</Run ID>
    <Profile ID>537</Profile ID>
    <Context ID>41</Context ID>
    <Rank>3</Rank>
        <Title>Dublin Pub</Title>
        <Description>The Pub at Vinegar Hill is a great place to eat or just hang out with family and friends.
                     Come on down and dine with us today for lunch or dinner.
                     You will love our fresh baked pizzas.
        </Description>
        <Url>107 West Cook Street, Springfield</Url>
```


Figure 10 - Sample Suggestion Document

8.6 Retrieval Task

The retrieval task of the TREC contextual suggestion track is an ad hoc suggestion recommender task that can be used to identify cohorts for comparative effective research. According to the given profiles and contexts the designed system should be able to produce a list of up to 50 ranked suggestions for each profile-context pair that satisfies the geographic correctness and profile relevance.

8.7 Relevance Judgments

Judging was split up into two tasks. Suggestions were judged with respect to their profile relevance by users and with respect to the contextual relevance by assessors at NIST as well as users.

8.7.1 Profile Relevance

In order to judge the relevance of suggestions with respect to profiles a second survey was conducted, which was similar to the first one. Some users were invited back to give ratings for the attraction descriptions and websites of the top 5 ranked suggestions for each run for their profile and one or two randomly chosen contexts.

The judgements given were one of:

-2 Could not load
0 Strongly uninterested
1 Uninterested
2 Neutral
3 Interested
4 Strongly interested

Some users were not invited back to give judgements on suggestions. While completing both surveys users were asked whether suggestions were geographically appropriate and the amount of time user took to make judgements was also recorded. In the initial survey used to generate profiles 5 suggestions not in Philadelphia, PA were included with the 50 suggestions in Philadelphia, PA. A score was generated for each user after the first survey that was based on how long users took to make judgements and how many geographical judgements users got correct. If users took too little time in making judgements or got too many geographical judgements incorrect they were not invited back. In total 223 context-profile pairs were judged by users.

Judgements of the relevance of suggestion with respect to profiles are distributed in desc-doc.qrels.

```
run profile context document description_judgement document_judgement description_diff document_diff
york13cr1 205 52 http://www.cheyennedepotmuseum.org/ 3 4 48 1
york13cr1 205 52 http://www.terrybisonranch.com/ 3 4 10 32
york13cr1 205 52 http://www.walmart.com/ 2 1 -1 21
york13cr1 205 52 http://wyomuseum.state.wy.us/ 3 4 8 3
york13cr1 216 68 http://floridastateparks.org/ 2 2 1 5
```

Listing 1 - An excerpt from desc-doc.qrels

Here the first line means that the user was interested (3) in the attraction based on the description provided by run york13cr1 for profile 205, context 52, and the website http://www.cheyennedepotmuseum.org/ and also the user was strongly interested (4) in the attraction based on the content of the website. The last two numbers mean that the user took 48 sec. to rate the description and 1 sec. to rate the website. A "-1" means that no timing data is available. This timing data is not used as part of the scoring calculations for runs.

8.7.2 Geographical Relevance

In order to judge the geographical relevance of suggestions users were asked, during the survey, whether the attraction was in the city it was submitted for or not. Additionally assessors at NIST were also asked to make the same judgement for attractions. The list of context-profile pairs judged by users and those judged by NIST were not the same list however there was an overlap of approximately nine thousand judgements. Of the documents judged for context by both NIST assessors and users there was an agreement on judgements of 77% if judgements of “marginally appropriate" and “appropriate" are considered the same.

-2 Could not load
0 Not geographically appropriate
1 Marginally geographically appropriate
2 Geographically appropriate

Judgements of geographical appropriateness are distributed in geo-nist.qrels and geo-user.qrels for NIST assessments and user assessments respectively.

```
context document geographical_judgement

 51 http://www.rogersandhollands.com 2
 51 http://www.route66-drivein.com 2
 51 http://www.saputos.com 2
 51 http://www.schnucks.com 2
 51 http://www.sebastianshideout.com 2
```

Listing 2 - An excerpt from geo-nist.qrels

Here the first line means that for context 51 the website http://www.rogersandhollands is geographically appropriate (2).

8.8 TREC Baseline Run

Baseline A takes the top 50 attractions returned by the Google Places API when provided with the city in the context. For the description, a Google Places provided description, review, or a blurb from the meta-description tag on the website is used.

8.9 Measures

Three measures are used to rank runs. Our main measure, Precision at Rank 5 (P@5), is supplemented by Mean Reciprocal Rank (MRR) and a modified version of Time-Biased Gain (TBG).

8.9.1 P@5

An attraction is considered relevant for P@5 if it has a geographical relevance of 1 or 2 and if the user reported that both the description and document were found to be interesting (3) or strongly interesting (4).A P@5 score for a particular topic (a profile-context pair) is determined by how many of the top 5 ranked attractions are relevant, divided by 5.

8.9.2 MRR

For MRR, an attraction is considered relevant using the same criteria used for P@5. A MRR score is calculated as 1 k, where k is the rank of the first relevant attraction found. If there are no relevant attractions in the first 5 attractions in the ranked list a score of 0 is given.

8.9.3 TBG

In an effort to develop a metric better suited to evaluating this task the organizers of this track developed a metric based on TBG metric introduced by Smucker and Clarke [Mark]. The modified version of TBG is calculated by the equation described by Dean-Hall, et al.[Adriel]:

$$\sum_{k=1}^{5} D(T(k))A(k)(1-\Theta)^{\sum_{j=1}^{k-1} Z(j)} \qquad \textbf{Equation 4}$$

- D is a decay function.
- T(k) is how long it took the user to reach rank k, calculated using the following two rules:
    - The user reads every description which takes time *Tdesc* .
    - If the description judgement is 2 or above then the user reads the document which takes time *Tdoc*.
- A(k) is 1 if the user gives a judgement of 2 or above to the description and 3 or above to the document, otherwise it is 0.
- Z(k) is 1 if the user gives a judgement of 1 or below to either the description or the document, otherwise it is 0.

For this metric, the user always gives a rating of 0 to the document if the document has a geographical rating of 0. The four parameters for this metric are taken from Dean-Hall et al. [Adriel] :ɵ = 0:5, T_{desc} = 7:45s, and T_{doc} = 8:49s, and the half-life for the decay function H = 224.

8.10 Experimental Runs

This section explains and describes a set of runs conducted on the TREC 2103 Contextual Suggestion Track. Runs are of two kinds, base line run and personalised place recommendation run. Descriptions of our runs are presented as follows:

- **york13cr1:** this is our baseline run. For each context, profile pair we query Google places and get the list of top 50 suggestions ranked by google given a set of predefined place types.
- **york13cr2:** this is our personalized place recommendation run. This run is performed using the designed personalised place recommender system. It utilizes semantic user profile modeling technique that involves in re-ranking the baseline for each context, profile pair according to algorithm 1.

9 Experimental Results

In this chapter we report the results obtained from the runs described in section 8.8. Our evaluation objective is to assess the effectiveness of our proposed model and examine the extent of its usefulness in improving the performance of Personalized Contextual IR systems. Performance of personalized place recommender baseline run and our approach run at TREC 2013 are reported in section 9.1. and results of our baseline run at P@5, MRR, TBG are reported in section 9.1.1 and results of our approach run at P@5, MRR, TBG are reported in section 9.1.2. Finally, performance analysis of our personalized run are reported in section 9.3.

9.1 Performance of york13cr1 and york13cr2 runs

This section reports the results obtained from all the TREC contextual suggestion track participants. Table 3 lists the scores for all open web runs for all TREC 2013 participants in three metrics. And the table is sorted by their P@5 score (main metric).

Run	P@5 Rank	P@5 Score	TBG Rank	TBG Score	MRR Rank	MRR Score
UDInfoCS1	1	0.5094	1 (-)	2.4474	1 (-)	0.6320
UDInfoCS2	2	0.4969	2 (-)	2.4310	2 (-)	0.6300
simpleScore	3	0.4332	4 (Down 1)	1.8374	4 (Down 1)	0.5871
complexScore	4	0.4152	5 (Down 1)	1.8226	6 (Down 2)	0.5777
DuTH_B	5	0.4090	3 (Up 2)	1.8508	3 (Up 2)	0.5955
1	6	0.3857	8 (Down 2)	1.5329	7 (Down 1)	0.5588
2	7	0.3731	7 (-)	1.5843	5 (Up 2)	0.5785
udel_run_D	8	0.3659	9 (Down 1)	1.5243	8 (-)	0.5544
isirun	9	0.3650	6 (Up 3)	1.6278	9 (-)	0.5165
udel_run_SD	10	0.3354	16 (Down 6)	1.2882	10 (-)	0.5061
york13cr2	11	0.3309	12 (Down 1)	1.3483	15 (Down 4)	0.4637
DuTH_A	12	0.3283	14 (Down 2)	1.3109	12 (-)	0.4836
york13cr1	13	0.3274	15 (Down 2)	1.2970	14 (Down 1)	0.4743
UAmsTF30WU	14	0.3121	17 (Down 3)	1.1905	13 (Up 1)	0.4803
IRIT.OpenWeb	15	0.3112	10 (Up 5)	1.4638	11 (Up 4)	0.4915
CIRG_IRDISCOA	16	0.3013	18 (Down 2)	1.1681	16 (-)	0.4567
CIRG_IRDISCOB	17	0.2906	20 (Down 3)	1.1183	19 (Down 2)	0.4212
uncsils_param	18	0.2780	13 (Up 5)	1.3115	18 (-)	0.4271
uogTrCFP	19	0.2753	11 (Up 8)	1.3568	17 (Up 2)	0.4327
ming_1	20	0.2601	22 (Down 2)	1.0495	22 (Down 2)	0.3816
uncsils_base	21	0.2565	19 (Up 2)	1.1374	20 (Up 1)	0.4136
ming_2	22	0.2493	23 (Down 1)	0.9673	23 (Down 1)	0.3473
uogTrCFX	23	0.2332	21 (Up 2)	1.0894	21 (Up 2)	0.4022
run01	24	0.1650	24 (-)	0.7359	24 (-)	0.2994
baselineA	25	0.1372	25 (-)	0.5234	25 (-)	0.2316
csui02	26	0.0565	26 (-)	0.1785	26 (-)	0.1200
csui01	27	0.0565	27 (-)	0.1765	27 (-)	0.1016

Table 3 - P@5, TBG, and MRR ranking for all open web runs

9.1.1 Our baseline run at P@5, MRR, TGB

This section reports the performance of our baseline at three measures stated in Figure 10. Figure 11, 12, 13 presents the histogram of the run that shows the difference from median for each profile, context pair that has been evaluated.

Mean over all evaluated profiles and contexts	
P(5):	0.3274
MRR:	0.4743
TBG:	1.2970

Figure 11 – york13cr1- Mean over all evaluated profiles and contexts

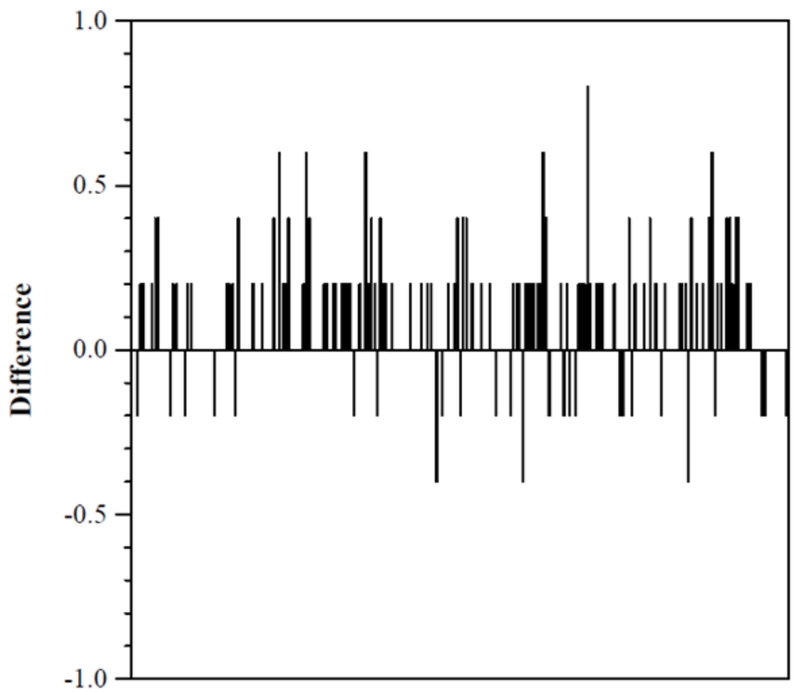

Figure 12 – york13cr1- Difference from median P(5) per [profile, context] pair

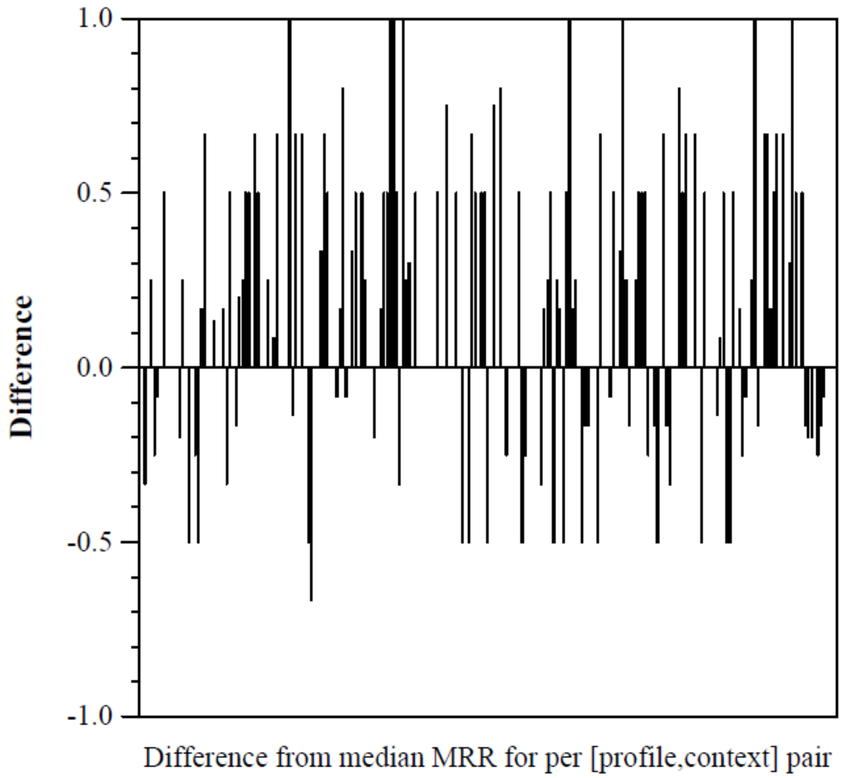

Figure 13 – york13cr1- Difference from median MRR for per [profile, context] pair

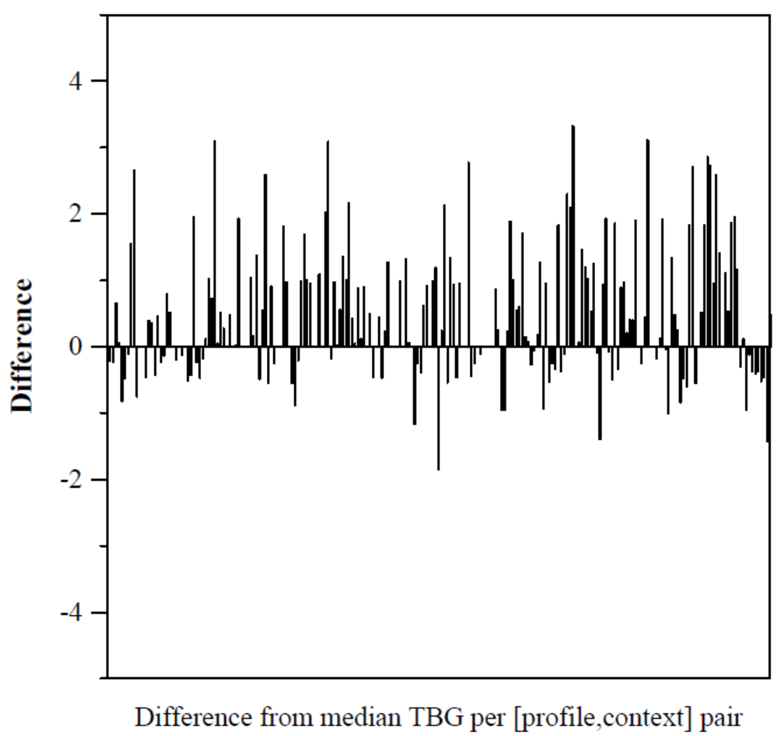

Figure 14 – york13cr1- Difference from median TBG per [profile, context] pair

9.1.2 Our approach run at P@5, MRR, TGB

This section reports the performance of our baseline at three measures stated in Figure 14. Figure 15, 16, 17 presents the histogram of the run that shows the difference from median for each profile, context pair that has been evaluated

Mean over all evaluated profiles and contexts	
P(5):	0.3309
MRR:	0.4637
TBG:	1.3483

Figure 15 - york13cr2- Mean over all evaluated profiles and contexts

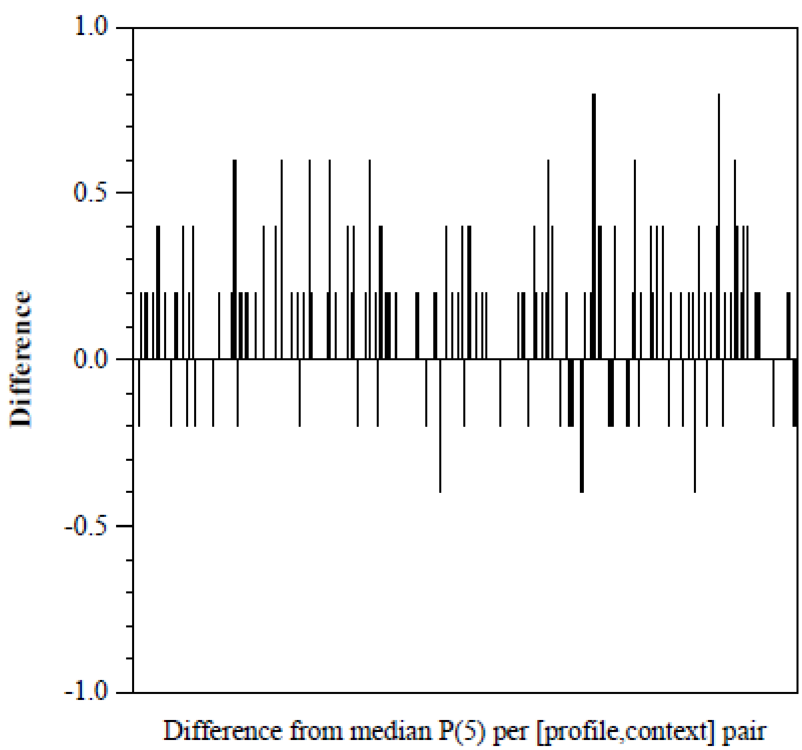

Figure 16 - york13cr2- Difference from median P(5) per [profile, context] pair

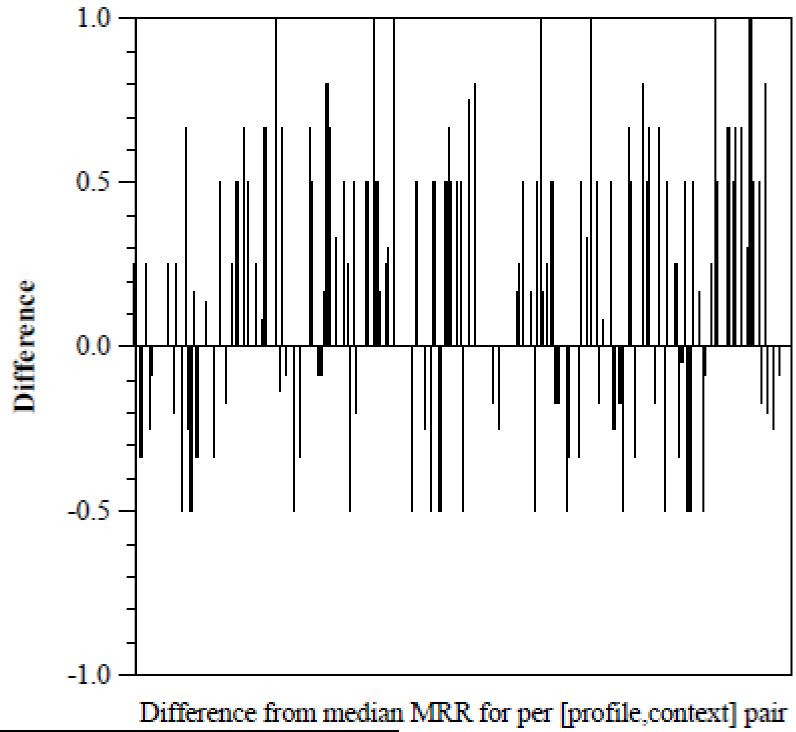

Figure 17 - york13cr2- Difference from median MRR for per [profile, context] pair

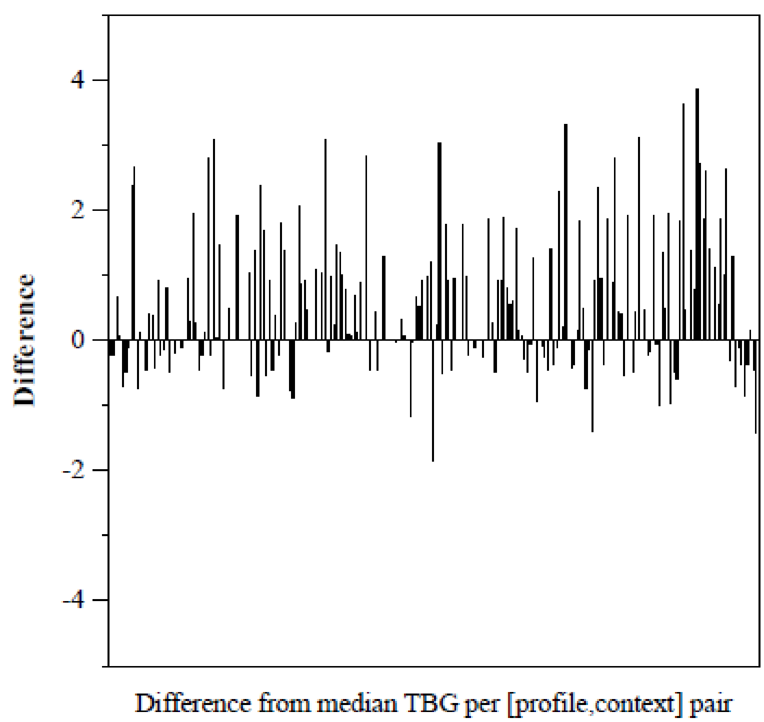

Figure 18 - york13cr2- Difference from median TBG per [profile, context] pair

9.2 Performance Analysis of Our Personalized Run

In this section we discuss and analyze the influence of semantic user profiling and contextual modelling approach in personalizing retrieval framework and the impact on retrieval performance.

Results						
Measures	P@5		MRR		TBG	
	Baseline	Ours	Baseline	Ours	Baseline	Ours
Average	0.3273	0.3309	0.4742	0.4636	1.2969	1.3483
%Improvement	1.10%*		-2.24%**		3.96%*	

Table 4 - Baseline and personalized recommendation results in terms of p@5, MRR, TBG. * And ** refers to significance test according to Wilcoxon statistical test

The results show that our approach for personalized recommendation outperforms significantly the baseline results returned by Google places API at P@5 and TBG measures as shown in table 4. The improvement has been shown statistically significant according to the Wilcoxon test at P@5 and TBG. However, our personalized approach has decreased the recommendation performance at MRR measure. This means that our approach has shifted more relevant suggestions to the top 5 results presented to the user. In terms of TBG, the gain obtained using our personalized approach has exceeded the gain obtained in the baseline. We believe that the profile accuracy and level of granularity has a great impact on the personalization effect. Also, there is variability in the performance of the personalized recommendation for different profile/context pairs. We plan to analyse the result performance of the personalized search with respect to the quality of the user profiles and the diversity of the suggestion list.

10 Conclusions and Future Work

In this chapter we summarize our contributions on exploiting semantic information for improving personalized place recommender systems. First we summarize our contribution on using semantic place ontology construction for improving personalized suggestion retrieval and then we summarize our contribution on using semantic user profiling for improving personalized suggestion retrieval. Moreover, this chapter discusses conclusions and future work of our study.

10.1 Semantic place ontology construction for improving personalized suggestion retrieval

The Web has developed to the biggest source of information and entertainment in the world. By its size, its adaptability and flexibility, it challenged our current paradigms on personalized information retrieval. Assisting a jetsetter with the crucial travel planning decisions that he will face before travel or while on-the-move necessitate the need to acquire the knowledge of interests and wants, either explicitly (by asking) or implicitly (by mining the user online activity), and suggest destinations to visit, points of interest, events or activities. The main objective of a place recommender system is to ease the information search process of the traveller and additionally provide personalized search results on-the-move.

This new place suggestion system, which relates place suggestions with the user, heavily relies on the quality of the underlying user profile. As mentioned earlier, the traditional methods (keyword-based profile representations) and their extensions (e.g. semantic networks) do not suffice to capture all subtleties caused by the properties of natural languages (e.g.: polysemy, synonymy). Presented approach use background knowledge in form of taxonomies and/or ontologies to bridge this gap and go a step further by including the semantic relations that are identified between the concepts of the ontology into the profile and thus, extending it from a set of keywords to a profile ontology.

In this study, we propose a novel approach to building a place ontology that acts as profile ontology for achieving personalized suggestion retrieval. We have chosen to construct our own ontology based on ODP as we believe a well-defined ontology schema will provide interesting support for structuring knowledge in user profiles.

10.2 Semantic user profiling for improving personalized suggestion retrieval

In this study, we propose a novel IR approach that is able to tackle the presented challenges of place recommender systems such as lack of personalization or content overspecialization and to recommend those place suggestion that capture user's interests. The proposed model aims at achieving personalization which is a significant component in recommender systems. Personalized place recommender systems aim at helping a jetsetter with the crucial travel planning decisions that he will face before travel or while on-the-move. These recommender systems necessitate the need to acquire the knowledge of interests and wants, either explicitly (by asking) or implicitly (by mining the user online activity), and suggest destinations to visit, points of interest, events or activities. The main objective of a recommender system is to ease the information search process of the traveller and additionally provide personalized search results on-the-move.

The key unique contributions in this research concern (1) construction of place ontology based on ODP ontology to extract representative concepts of user interest and information need, (2) semantic-based user profile modelling and (3) devising a concept based weighting schema to weight user profile concepts semantically in relation to the suggestions and re-ranking the suggestions in order of their scores.

One of the characteristics of semantic user profiling is conceptual representation rather than simple keywords representation to enhance the representation of user profiles. Modeling and developing domain ontologies is a fundamental framework for representing knowledge using a set of concepts and the relationships among the concepts. Web domain knowledge is developed by several different ontologies including The Open Directory Project (ODP), also known as DMOZ (from directory.mozilla.org, its original domain name), is a multilingual open content directory of World Wide Web links. In this approach we extract a sub-directory relevant to place types to develop place ontology. Previously rated attractions by the user are mapped to the place ontology where we represent positive and negative preferences under each place type which results in building user profiles. In order to identify the extent of a suggestion relevancy in relation with user profile concept(s) we weight each concept in place domain ontology according to its semantic relatedness/similarity to the original suggestion concepts. The user context (location) is used to enhance classical IR model and to calculate and assign a new score to suggestions by considering semantics.

10.3 Future Work

The TREC Contextual Suggestion Track presented a place recommendation task where the challenges are to model the user interests and exploit them for recommendation. In this paper, we present our participation in the Contextual Suggestion Track of TREC 2012. We submit two runs: one run based on Google places API and another one based on re-ranking Google places API results using a semantic user profile. The experimental results show that when we utilize semantic user profile modeling techniques, the performance improves in terms of P@5. This indicates that we need to focus in the same direction and elaborate ways to make full use of user profiles. Future work will focus on exploring strategies incorporating place type along with user profile modeling for identifying the most relevant recommended places to the user. And also focus on finding a way to integrate public reviews/ratings of tourist attractions into the framework to be able to suggest interesting place recommendations to user.

Furthermore to future work, we plan to use some external resources to help achieve diversity in the suggestion list. In other words we plan to use travel sites such as YELP, FourSquare, etc. along with Google Place to attain a list of unique and appealing place recommendation that would aid in satisfying user-specified interestingness. We will also examine the impact of place description enrichment in place suggestion in TREC Contextual Suggestion Track 2014.

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Appendix A: Sample Personalized run [Context, Profile]

resultid	title	description	url
Ctx23R1	Berkshire Community College	Degree and Certificate programs at BCC in Pittsfield, MA, a community college with campus and online classes. Student courses of study at this education centerÂ ...https://wa.berkshirecc.edu/WebAdvisor/WebAdvisor?TYPE=W&PID=UT-WNTW&CONSTITUENCY=WBDF. For new Students, your initial password is the last 6Â ...Current Temp: 67 Â°F Weather Station Â· About BCC Â· President's Welcome Â· BCC Foundation Â· Foundation Events Â· Board of Trustees Â· BOT Agenda Â· BOT Bylaws Â ...BCC Admission services include admissions counselors, financial aid assistance , application instructions, international student services, help paying for school,Â ...If your Moodle password has expired, you must login to MyBCC to get to your Moodle courses. Log In to MyBCC https://portal.berkshirecc.edu/ The first time youÂ ...	http://www.berkshirecc.edu/
Ctx23R2	The Sterling and Francine Clark Art Institute	The Sterling and Francine Clark Art Institute, 225 South Street in Williamstown, Massachusetts. Admission is free November 1 - May 31, and $15.00 June 1Â ...Museum Program. The Clark collection is best known for an extraordinary collection of French Impressionist paintings, which take their place within a wider Â ...Current Exhibitions. A variety of special exhibitions is offered throughout the year, bringing together works from collections around the world and presenting themÂ ...Employment. The Sterling and Francine Clark Art Institute offers a broad range of career opportunities â€“ professional and support, seasonal and year-round,Â ...http://francine.clarkart.edu:2082/search. The library will be closed from June 1 through September 3, 2013 to accommodate installation of a new fire protectionÂ ...	http://www.clarkart.edu/
Ctx23R3	Troy Public Library	Summer Reading Club begins June 24th for young people age 3 through young adult. Stop by either branch of the Troy Public Library on or after this date to pick Â ...Jun 11, 2013 ... There is a silent auction being held at the Troy Library. All Library District #1 patrons are encouraged to participate. Stop by the Troy LibraryÂ ...Our Troy Room Collection contains hundreds of books, pamphlets, and other local history and genealogy documents. Works by local authors, Troy CityÂ ...We are happy to accept donations of books or other materials that are in good condition. If we do not add the items to our collection, they will be given to ourÂ ...Main	http://www.thetroylibrary.org/

		Library 100 Second Street Troy, NY 12180 518.274.7071 phone 518.271. 9154 fax. Hours: Monday â€“ Thursday: 9 am â€“ 8 pm. Friday and Saturday: 9 amÂ ...	
Ctx23R4	Hancock Shaker Village	Poultry House Gallery Two new exhibits are open this summer, included with general admission. Customize your visit Register.Calendar Â· Contact Â· Directions Â· HSV HOME Â· Sign-Up for E-News Â· facebook. twitter. youtube. â€“ Main Menu â€“, WELCOME, WEDDING PACKAGES, EVENTÂ ...Season 2013: April 13 â€“ October 27. More Information Â». Site design by Studio Two. Â© 2013 Hancock Shaker Village - All Rights Reserved. Privacy Policy.Hancock Shaker Village, the Shakers' \City of Peace	\" beckons you to discover the way of life of America's most ... Web Site: www.hancockshakervillage.org.39th Annual Shaker Seminar July 24-28
Ctx23R5	Norman Rockwell Museum	George B. Bridgman drawings in NRM collections. Posted on June 11, ... Marge Champion, the original Snow White, in her own words: http://t.co/HztV1gxfVKFeaturing a vast selection of Norman Rockwell prints, books, and other merchandise. The Norman Rockwell Museum is dedicated to the enjoyment and study ofÂ ...NRM Twitter. Marge Champion, the original Snow White, in her own words: http://t .co/HztV1gxfVK - Wednesday Jun 12 - 9:20pm. Just in time for Father's Day,Â ...The National Railway Museum in York and Shildon is home to the UK's national rail collection. Includes museum visitor info, events, exhibitions and collections.Google Maps & Directions are correct! http://maps.google.com/. * Please help us .... We're all looking forward to presenting his artwork starting this July @ NRM!	http://www.nrm.org/
Ctx23R6	Bard College at Simon's Rock	Bard College at Simon's Rock: The Early College is the only four-year college of the liberal arts and sciences specifically designed to provide bright, highlyÂ ...Bard College at Simon's Rock: The Early College is the only four-year college of the liberal arts and sciences specifically designed to provide bright, highlyÂ ...Bard College at Simon's Rock: The Early College is the only four-year college of the liberal arts and sciences specifically designed to provide bright, highlyÂ ...Simon's Rock is an \early college\Is early college right for you? Bard College at Simon's Rock is an unusual (extraordinary	actually) place to be. Most people go to college after they finish highÂ ..."
Ctx23R7	New York State Museum	Science, education, art exhibits, and programs for all ages. The museum's collections include scientific and historical material of national and internationalÂ ...Empire State Oil and Gas Information System, New York State Geological Survey, NYSGS, NYS Museum.Longhouse model. A Mohawk Iroquois Village: An Exhibit at the New York State Museum. Three dioramas in this exhibit depict life in a Mohawk Iroquois villageÂ ...Call our Summer Quest Registration Line: (518) 474-5843 Monday - Friday, 9 a.m. to 3 p.m. Visit us online at	http://www.nysm.nysed.gov/

		www.nysm.nysed.gov/summerquest or write to us atÂ ...Current Exhibitions The Museum offers approximately 12 new exhibitions each year on a wide range of subjects. Exhibitions are often developed with our ownÂ ...	
Ctx23R8	Canyon Ranch in Lenox	Canyon Ranch - Destination resort in Lenox, Massachusetts is an award-winning health resort offering luxury spa treatments & wellness programs.The full Momtrends review of Canyon Ranch Lenox. http://www.momtrends.com/ 2013/06/canyon-ranch-lenox-review/. 1 Â· June 18 at 9:27amÂ ...Explore This Week at Canyon Ranch, your guide to classes and presentations at Canyon Ranch. This Week at Canyon Ranch June 16 - June 22, 2013Based on that success, the Zuckermans opened Canyon Ranch in Lenox in ..... http://www.canyonranch.com/lenox/plan-your-stay/featured-events/legendary-Â ...Canyon Ranch in Lenox is a unique spa vacation experience. Our caring, expert staff is at your service to answer your questions, explain our programs andÂ ...	http://www.canyonranch.com/lenox/
Ctx23R9	Southern Vermont College	Employment Opportunities. Founded in 1926, Southern Vermont College offers a liberal arts education with 17 academic degree programs for approximatelyÂ ...Graduates SVC tell you what success means. More ... See our SVC Training Calendar ... http://t.co/AOc63TXLiU; OFFICER, DISPATCH/ SURVEILLANCE AguaÂ ...Directions to Campus. From pennsylvania/new jersey/New York City/albany. Take Route 78 east to Route 287 in New Jersey. Take 287 north into New York.Offering 17 career-launching majors nursing, criminal justice business, and communications.Southern Vermont College is accredited by the New England Association of Schools and Colleges. SVC is a member of the Association of Vermont IndependentÂ ...	http://www.svc.edu/about/
Ctx23R10	Ten Broeck Mansion	The official home page of the Ten Broeck Mansion and Albany County Historical Association. Contains history, events ... WMHT Auction: http://auction.wmht.orgÂ ...The Ten Broeck Mansion joined with the Cornell Cooperative Extension of Albany County invite you to visit our gardens ... email: wendy@ tenbroeckmansion.orgÂ ...The official home page of the Ten Broeck Mansion and Albany County Historical Association. Contains history, events, information about the Ten BroeckÂ ...Albany County Historical Assn. and Ten Broeck Mansion - http://www. tenbroeckmansion.org/ A mansion in a very old part of Albany that is home of AlbanyÂ ...Albany County Historical Association presents Living History Day Sunday, May 5, 12-4 pm Ten Broeck Mansion, 9 Ten Broeck Place, Albany, NY Fre.	http://www.tenbroeckmansion.org/

Ctx23R11	Berkshire Museum	Community-based museum emphasizing art, natural sciences and history. Permanent displays and exhibits, plus special exhibits throughout the year. Plus LittleÂ ...Outdoor education can be an inspirational, fun way to interact with the natural world.Based on the eleven lesson plans in the Living Landscapes: Teaching inÂ ...May 9, 2012 ... 28; lbeck@berkshiremuseum.org. Images available: http://www.flickr.com/photos/ berkshiremuseum/sets/72157629649695388/Â .. .Jan 21, 2012 ... On earth since the dinosaur, birdsâ€"the fascinating creatures that flock, roost, migrate, sing, fly, and have adapted to some of the most extremeÂ ...The Berkshire Museum [Pittsfield]; Chesterwood [Stockbridge]	http://www.berkshiremuseum.org/
Ctx23R12	Mabee Farm Historic Site	Jun 2, 2013 ... Mabee Farm Historic Site's Homepage. ... Welcome to the Mabee Farm Historic Site, the oldest standing home in the Mohawk Valley. This 300+Â ...The Mabee House at the Mabee Farm Historic Site is the oldest house still .... from \http://en.wikipedia.org/w/index.php?title=Mabee_House&oldid=498020784 \".Sep 7	2011 ... Mabee Farm Historic Site 1080 Main Street Rotterdam Junction
Ctx23R13	Crailo	We're excited to announce The NY State Parks App for iPhone. This FREE app will give visitors who are on-the-go info on all of our properties. Download nowÂ ...NY.gov Portal State Agency Listing Search all of NY.gov. Andrew M. Cuomo Governor Rose Harvey Commissioner. NYSOPRHP. State Parks; |; Historic Sites Â ...New York's State Historic Preservation Office (SHPO) helps communities identify, evaluate, preserve, ... NY.gov Portal Â· State Agency Listing Search all of NY.gov.Jun 17, 2013 ... NY.gov Portal State Agency Listing Search all of NY.gov. Andrew M. ... Visit http:// regionalcouncils.ny.gov for the CFA Workshop Calendar.For information about camping in the Adirondack and Catskill Parks visit http:// www.dec.ny.gov/outdoor/camping.html Leaving New York State ParksÂ ...	http://www.nysparks.state.ny.us/
Ctx23R14	Albany Institute of History & Art	Founded in 1791, the Albany Institute of History & Art is one of the oldest museums in the United States. It also is the major repository for the region's heritage,Â ...Jun 11, 2013 ... Curious visitors can see the cap online, right down to its needlepoint claws, in a recently launched database at http://www.albanyinstitute.org.Family programs, museum events & exhibits, school programs, museum education.Skip navigation Â· Exhibitions Â· Current Exhibitions Â· The Making of the Hudson River School Â· Sixty Years and Still Collecting Â· Robert Hewson Pruyn: An AlbanianÂ ...Albany Institute for History and Art. Wednesday | June 19, 2013 ... Avenue Albany , NY 12210. TEL: 518.463.4478. E-MAIL: information@albanyinstitute.org.	http://www.albanyinstitute.org/

Ctx23R15	Olana State Historic Site	VISIT: Directions. Olana State Historic Site 5720 Route 9G Hudson, NY 12534. Getting to Olana State Historic Site is easy. To travel by train, take Amtrak toÂ ...http://www.olana.org/visit_directions.php. Can't believe you've never been, the place is amazing! Olana: the Persian style home of Hudson River artist FredericÂ ...Borrow an \Olana on the Move\" backpack from the Wagon House. Find your ... Bring Olana home â€“ the Museum Store has treasures galore. Stop and smell the Â ...http://govisland.com/html/history/history.shtml	\"The Trust for Governors ... Governors Island Alliance; ^ http://govisland.com/html/visit/directions.shtml .... New Windsor Cantonment Â· Olana Â· Old Croton Aqueduct Â· Old Erie Canal ..... Retrieved from \"http://en.wikipedia.org/w/index.php?title=Governors_Island&oldid =558832862\".VISIT: Directions. Olana State Historic Site 5720 Route 9G Hudson
Ctx23R16	Arrowhead Museum	Home of Herman Melville from 1850-1862, it is owned and operated by the Berkshire County Historical Society.Moby-Dick; or, The Whale is a novel by Herman Melville, first published in 1851. It is considered ...... Librivox at http://librivox.org/moby-dick-by-herman-melville/Â ...Genealogy || Historical Societies || Historic Sites || Museums || Research Collections. Genealogy: The Berkshire Athenaeum Local History Room 1 WendellÂ ...Oct 18, 2012 ... When designing a cover for a classic in the book publishing world, there is usually room for some artistic experimentation and subtlety. This isÂ ...Moby Dick; Or, The Whale by Herman Melville. No cover available ... Plain Text UTF-8, http://www.gutenberg.org/ebooks/2701.txt.utf-8, 1.2 MB. More Filesâ€¦	http://www.mobydick.org/
Ctx23R17	Berkshire Scenic Railway Museum	Our scenic train rides are fun for the whole family, located in the historic Berkshire Hills of Western Massachusetts.Schedules and fare information for the Berkshire Scenic Railway Museum train ride and museum experience.BSRM 67 is a 50-ton, diesel-electric industrial switcher built by General Electric in Erie, PA.The Berkshire Scenic Railway Museum is an all-volunteer, non-profit organization founded in 1984. Its mission is to preserve the history of railroading, Â ...www.berkshirescenicrailroad.org. Have you ... http://registercitizen.com/articles/ 2013/06/06/news/ ... Berkshire Scenic Railroad Museum hopes for more visitors.	http://berkshirescenicrailroad.org/
Ctx23R18	Martin Van Buren National Historic Site	See http://tps.cr.nps.gov/nhl/detail.cfm?resourceId=585&resourceType= Building. ... http://www.oldnorth.com; see also http://www.oldnorth.com/info.htm. The Church has ...... Pittenger, 421 U.S. 349, 366 (1975); accord Wolman v. Walter, 433Â ...The Autobiography of Margaret Sanger. Courier Dover Publications. p. 366. ISBN 0-486-43492-3. ^ Baker p 161 ... Historic Landmark Program\. Tps.cr.nps.gov.May 13	2013 ... National Park Service. http://tps.cr.nps.gov/nhl/detail.cfm?ResourceId= 1196&ResourceType=Building. Retrieved 2008-06-30.It is 1
Ctx23R19	John Boyd	Along the Helderberg Escarpment, park is home	http://nysparks.com/parks/128/

	Thacher State Park	to one of the richest fossil- bearing formations in the world and provides scenic ... Please see the flyer for details.Thatcher Park for the beautiful Indian Ladder Trail with lookouts from the Helderberg Escarpment: http://nysparks.com/parks/128/details.aspx - Saratoga NationalÂ ...I-86 west bound to Rt.280 south (Quaker Area ASP Rte 3) will detour to ... of 130 campsites, 144 cabins, 128 of them winterized and three group camps ... http:// www.dec.ny.gov/animals/7253.html and http://www.dec.ny.gov/animals/28722. htmlÂ ...http://nysparks.state.ny.us/parks/165/details.aspx. Lansing Manor: A museum and park located about 5 minutes North of our lodge, is a historically preservedÂ ...Nine-acre waterfront park located between the Manhattan and Brooklyn Bridges. Profile, photograph, travel information.	details.aspx
Ctx23R20	Saratoga National Historical Park	Park Tools. View Park Map Â· FAQs Â· Contact Us Â· Site Index Â· EspaÃ±ol. There are park alerts in effect. hide Alerts Â». Horse Trail Closure. Due to extensive recentÂ ...Jun 16, 2013 ... Park Tools. View Park Map Â· FAQs Â· Contact Us Â· Site Index Â· EspaÃ±ol. There are park alerts in effect. hide Alerts Â»Â ...Park Tools. View Park Map Â· FAQs Â· Contact Us Â· Site Index Â· EspaÃ±ol. There are park alerts in effect. hide Alerts Â». Horse Trail Closure. Due to extensive recentÂ ...Park Tools. View Park Map Â· FAQs Â· Contact Us Â· Site Index Â· EspaÃ±ol. There are park alerts in effect. hide Alerts Â». Horse Trail Closure. Due to extensive recentÂ ...ico. hackerhandbooks.com Â· Contact the editors .... 4, http://www.ilt.columbia.edu/ publications/dewey.html. Dewey ..... Last modified April 9, 2010. http://www.nps. gov/choh/index.htm. ... Sara Lehman, e-mail message to author, August 13, 2009.	http://www.nps.gov/sara/contacts.htm
Ctx23R21	Bennington Museum	New England history and art featuring Grandma Moses paintings, genealogy library, nature trail and picnic area.The Bennington Museum's research library has an excellent collection of historical material on Vermont and genealogical and biographical data on Vermont andÂ ...The Bennington Museum offers a variety of programs for adults including lectures , workshops, concerts, films and more, vacation workshops for children, as wellÂ ...Employment Opportunities. Be a part of the Bennington Museum team. Current Employment Opportunities. Visitors' Services Associate. The premier art, cultural Â ...Exhibitions Calendar. Bennington Vt Museum. Permanent and changing exhibitions maintain the excitement that comes with visiting the Bennington Museum.	http://www.benningtonmuseum.org/
Ctx23R22	C H Evans Brewing	Albany brewpub. Descriptions of beers, brewing process, history, awards, menus, catering	http://www.evansale.com/

	Co	information, and newsletter.Our people are friendly, reliable, efficient and entrepreneurial. Our compensation plans include salary and bonuses and are based on achievement. U.S andÂ ...Inherent in each pint of Evans' Ale is two-hundred and twenty-five years of fine brewing craftsmanship. From the eighteenth century to the twenty-first, ourÂ ...The Pump Station is open seven days a week, and is conveniently located near many Albany attractions. Reservations are accepted, and we urge you to verifyÂ ...Beer Flavor Primer #1: Diacetyl. by George de Piro. Author's note: This is the first in a series of articles about different flavors that occur in beer. Each piece willÂ ...	
Ctx23R23	Rensselaer County Historical Society	Museum and archives located in the Hart-Cluett Mansion in downtown Troy; research information and background on architectural styles.Then join RCHS. http://www.rchsonline.org/member-benefits/ And THANKS for supporting us. Member Benefits | Rensselaer County Historical Society.Hudson-Mohawk Industrial Gateway- http://hudsonmohawkgateway.org/ ... http:// people.hofstra.edu/John_I_Bryant/Melville A largely ... www.rchsonline.orgAbout the organization and the County History Museum in the old post office in downtown Springfield.Adams A Backward Glance, Timothy R. Henson, Ordering Information: http://www .rchsonline.com/products.htm. Authenticated History of the Bell Witch, M. V.Â ...	http://www.rchsonline.org/
Ctx23R24	Lenox Town Library	18 19 items sent from Lenox have been scanned into the Internet Archive... http:// archive.org/search.php?query=collection%3Alenoxlibrary&sort=-publicdateÂ ...Calendar: View our Calendar online and see all of the special events and activities for the year! You will see Youth programs, OLLI Class schedules and otherÂ ...We want to give you the information you want to know about our library. Hours- so that you know when to come see us! Directions â€“ so that you know how to get Â ...Administrative Offices (413) 637-2630. Sharon Hawkes â€“ Executive Director (shawkes@lenoxlib.org); Rebecka McDougall â€“ Development Director; Jenny RaeÂ ...Meeting Spaces: ptableside. Meeting space in the Legacy Bank Community Room or the Welles Gallery is available on a limited basis. Typical rates are: $75 perÂ ...	http://lenoxlib.org/
Ctx23R25	Peebles Island	Offers spectacular river and rapids views for walkers and joggers. Picnickers & fishermen come to relax & winter activities are available as well.July 20 - 21 - Thunder in the Valley Intertribal Pow Wow Big Indian Park,8293 Rt. 28,Big ..... Point, New York www.nysparks.com/historic-sites/34/details.aspx.Nine-acre waterfront park located between the Manhattan and Brooklyn	http://www.nysparks.com/parks/111/details.aspx

		Bridges. Profile, photograph, travel information.111 Main Street. http://www.yelp.com/biz/gourmet-whaler-cold-spring-harbor. (631) 659-2977 .... http://nysparks.com/parks/23/details.aspx. (631) 423-1770.On November 28, 1776, the same year that 56 Americans signed the Declaration of Independence, well over 200 colonial New Yorkers placed their signaturesÂ ...	
Ctx23R26	October Mountain State Forest	Largest state forest in Massachusetts offers camping and hiking. Includes trail map, park directions and reservations.Mass.Gov logo, * ... find events happening in State and Urban Parks ... contact DCR ... of Vermont, and is the first mountain barrier encountered rising west of the Connecticut River Valley. ... Camping season is from mid-May to mid-October.find events happening in State and Urban Parks Â· find a park by name ... out about Universal Access Â· contact DCR Â· Self-Guided Family Hikes in Western MA ... A $5 fee per vehicle is charged from May through mid-October. Parking is free forÂ ...dcr ... Parking is free for ParksPass holders, vehicles with Handicapped, disabled ... Camping is available from mid-May through mid-October in the designated ... From East and West/MassPike (I-90): Take I-90 Exit 4, follow signs to I-91 north.Gov logo, * ... find events happening in State and Urban Parks ... contact DCR ... DCR offers a limited All Terrain Vehicle (ATV) and Off Highway Motorcycle (OHM) trail system at Pittsfield State ... Camping season is from mid-May to mid-October. ... From East or West/MassPike (I-90): Take Exit 2 in Lee and follow U.S. Rte.	http://www.mass.gov/dcr/parks/western/octm.htm
Ctx23R27	Rensselaer Technology Park	About the Park Tenant Companies Online Tour Contacts and Directions. Rensselaer logo. Copyright Â© Rensselaer Technology Park.Wednesday Toddler Explore and More Time 1:00 - 5:00 PM. Thursday - Sunday 10:00 AM - 5:00 PM. Thursday Mornings 9:00 AM - 10:00 AM Members OnlyÂ ...Who we are: MESO, Inc. (http://www.meso.com) has been a leader in atmospheric ... Region at the Rensselaer Technology Park (http://www. rpitechpark.com/). ... Perl, Python, PHP, bash or c-shell scripting, HTML; Experience with PostgreSQL,Â ...China http://www.hspark.com/news_info.php?cid=1&id=339 .... USA http://www. rpitechpark.com .... Norway http://www.fpaktos.no/fparktos/index.htmlÂ ...tourismguide Rensselaer County and the surrounding region offer a tremendous quality of life to residents. Click the links below to learn more. You may alsoÂ ...	http://www.rpitechpark.com/index.php
Ctx23R28	Bennington Battle Monument	The Vermont State Historic Sites Program encourages the discovery and appreciation of the state's rich heritage through the stewardship and interpretation ofÂ ...2:00 â€“ 4:00 p.m..	http://www.historicsites.vermont.gov/

		See history where it happened. To begin your experience visit: www.HistoricSites.Vermont.gov. FREE Admission to Vermont History Museum,Â ...Attorney General's Office (Vermont Attorney General William H. Sorrell) GOV External Link; Auditor's Office ... Historic Sites, Vermont State GOV External LinkÂ ...Vermont.gov Â· Home Â· Travel Planner Â· Vermont By Season Â· Fall ... Vermont Historic Sites. Vermont Historic Sites ... http://historicsites.vermont.govÂ ...The Official Website of the State of Vermont - Your gateway to information about living ... visiting, and doing business in Vermont, and to Vermont state government.	
Ctx23R29	Rev. Adonijah Bidwell House Museum	Georgian saltbox originally built circa 1750 as a parsonage. Collections include early 19th century furniture, quilts, needlework, silver, baskets, rugs, artwork and Â ...The Bidwell House Museum re-creates the history of family life in the Berkshires in the frontier ... http://www.thetrustees.org/places-to-visit/berkshires/missionBidwell House Museum Articles and Posts: Explore Williamstown and Great Barrington â€“ 2 Berkshire Gems. Explore Williamstown and Great BarringtonBirmingham. AL www.artsBMA.Org. Free to the public. Southern Museum of Flight. Birmingham. AL ..... http://www.californiapioneers.org/ AAM Members admitted free. Museum of Vision ...... www.bidwellhousemuseum.org/. AAM MembersÂ ...Willow Creek Rd. at Housatonic St., Lenox. http://www.berkshirescenicrailroad.org. TOP. Bidwell House Museum Colonial life comes alive in 1750 Reverend'sÂ ...	http://www.bidwellhousemuseum.org/
Ctx23R30	Fulton-Montgomery Community College	2805 State Highway 67, Johnstown, NY 12095 â€¢ (518) 736-FMCC (3622). Copyright Â© 2013, Fulton-Montgomery Community College. All rights reserved.Students. Find Courses Register ANGEL Computer Use Policy MyAid MyAppointment Student Email Return to FM HomeÂ ...FMCC's diverse student body brings together students from Fulton, Montgomery, and adjacent counties as well as Metropolitan New York City and twentyÂ ...Find it all here. Last Updated: Jun 10, 2013 URL: http://libguides.fmcc.edu/home Print Guide RSS Updates ShareThis Â· Welcome; About Us; Classes & EventsÂ ...â€œI was able to graduate with an Associates Degree while playing soccer and working two jobs. The affordability and flexibility of FM allowed me to achieve my Â ...	http://www.fmcc.edu/
Ctx23R31	Bennington Free Library	Serves the communities of Bennington, North Bennington, Shaftsbury and Woodford, Vermont. Site features library news and events, recent acquisitions, links ofÂ ...Check our online calendar: http://benningtonfreelibrary.org/calen dar.htm for	Bennington Banner newspaperÂ ..."

		current programs and events. Connect With Your Children @ Your Library.Library Mission Statement: The Bennington Free Library provides materials and services that will meet the educational, informational, cultural, and recreationalÂ ...Bennington Free Library is a public library in Bennington, Bennington ... \http://en. wikipedia.org/w/index.php?title=Bennington_Free_Library&oldid=511570945\".Reference staff are happy to assist visitors with their research. In the Library includes descriptions of the Reference Collection	
Ctx23R32	Macy's	Macy's 4th of the July Fireworks, live in NYC and on NBC July 4Â ...Macy's Westfield Santa Anita. Wedding Registry. Directions | Catalogs. 400 S. Baldwin Avenue. Arcadia, CA 91006. 626/445-5711. Today's Hours : 10:00AMÂ ...Macy's 4th of the July Fireworks, live in NYC and on NBC July 4Â ...Store Locations & Hours. Your entry is not formatted correctly. Please try again. store locations & hours. Search by ZIP Code or City and State: Error Zip. OR.Take $20 Off, shop a couple's registry and then save big! learnÂ ...	http://www1.macys.com/store/locator/index.ognc?action=locatorSearch&City=ENTER+CITY&State=NOSELECTION&ZipCode=01237
Ctx23R33	Beartown State Forest	Beartown State Forest. 69 Blue Hill Rd. P.O. Box 97. Monterey, MA 01245 (413) 528-0904. Located at intersection of Brett Road and Blue Hill Road. BeartownÂ ...Gov logo, * ... find events happening in State and Urban Parks ... contact DCR ... of Vermont, and is the first mountain barrier encountered rising west of the Connecticut River Valley. ... Be bear aware: Don't forget you are in Black Bear country.Hunting is open (in season) for all types of game including turkey, bear and deer. ... Parking is free for ParksPass holders, vehicles with Handicapped, disabled veteran ... Tolland State Forest is located in the southern Berkshires in western Massachusetts. ... The DCR is not responsible for the content of external internet sites.Gov logo, * ... dcr ... Parking is free for ParksPass holders, vehicles with Handicapped, disabled ... Be bear aware: Don't forget you are in Black Bear country. ... From East and West/MassPike (I-90): Take I-90 Exit 4, follow signs to I- 91 north.Gov logo, * ... find events happening in State and Urban Parks ... contact DCR ... DCR offers a limited All Terrain Vehicle (ATV) and Off Highway Motorcycle (OHM) trail system at Pittsfield ... Be Bear Aware: Don't forget you are in Black Bear country. ... From East or West/MassPike (I-90): Take Exit 2 in Lee and follow U.S. Rte.	http://www.mass.gov/dcr/parks/western/bear.htm
Ctx23R34	Williams College Museum of Art	Emphasizes modern and contemporary art, American art from the late 18th century to present, and the art of world cultures. Contains details of exhibits andÂ ...Associate Director of Academic and Public Engagement. Williams College. Williams College Museum of Art.	http://wcma.williams.edu/

		Lawrence Hall. 413-597-2183. Sonnet.Firsthand observation of works of art has helped train generations of Williams students who have gone on to become museum directors, curators, gallerists, andÂ ...Mar 22, 2013 ... Phillip's work, A Humument, a collage created over the text of WH Mallock's 1892 novel A Human Document, is currently on view in WCMA'sÂ ...February 2, 2013 - August 18, 2013. Teaching with Art: The Persian Image. Teaching with Art: The Persian Image supports Art History 564, â€œSeeing is (perhapsÂ ...	
Ctx23R35	Scotia Branch Library	Hours, events, activities, and online catalog for member of the Upper Hudson Library System.SEARCH â€"; SCPL Catalog Â· Catalog Help and Tutorials; Other Libraries' Catalogs. Cabrillo Â· San Jose Â· UCSC Â· UCSC Map/Atlas Catalog Â· UCSC Map RoomÂ ...About Your Library Card. \u003e\u003e\u003eCheck My Account. With your card, you will be able to borrow from our extensive collection of books, magazines, audiobooks,Â ...Do you recall the first time you walked into a library? When you got your first library card? Do you have fond memories of a particular librarian who made aÂ ...Download eBooks and digital audiobooks to your eReader, Nook, Kindle, mobile device, tablet, or computer for FREE using your SCPL library card. AudiobooksÂ ...	http://www.scpl.org/
Ctx23R36	Old Stone Fort	Information about the Old Stone Fort museum complex at Schoharie, NY 12157, and Schoharie County Historical Society.http://www.mvls.info/lhg/besthouse/home.html (518) 817-4239 ... http://www. landisarboretum.org (518) 875-6935 ... theOldStoneFort.org. 1743 Palatine HouseÂ ...List of names chiseled into the wall at the Old Stone Fort, Schoharie N.Y..... Landis Arboretum www.landisarboretum.org; Museums at the Old Stone Fort www.TheOldStoneFort.org; Plattekill Bike Park www.plattekill.comÂ ...We have many traditional buildings and exhibits and are starting to develop virtual exhibits. Complete v-exhibits may be offered as part ofÂ ...	http://www.theoldstonefort.org/
Ctx23R37	Prospect Park	Prospect Park 65 Prospect Park Road, Troy NY 12180. Prospect Park is a city owned park centrally located within the City of Troy. One of three major parks inÂ ...Prospect Park in Troy, New York, is an 80-acre (32 ha) city park that was designed in 1903 by Garnet Baltimore, the first African-American graduate of the Â ...Troy City Hall: 433 River Street, Troy NY 12180 Hours: 8:30 am - 4:30 pm ... Prospect Park is a unique gem in the middle of the City. It provides spectacularÂ ...3 Reviews of Prospect Park \I'm lucky enough to live mere blocks from this beautiful park. Open green space	tennis courts

Ctx23R38	Apple Barn Country Bake Shop	APPLES,pancake mix,VT products,Vermont products,apples,honey,maple syrup, jams and jellies,pick your own blue berries,maple candy,Apple Barn,appleÂ ...Located in the Smoky Mountains of Tennessee. Offers many varieties of apples, apple candy, fruit wines, ciders and other apple products.Frequent User - Van Smith - Jun 23, 2013 - Report this comment. I love this new version. Mapquest needed too much input. All I wanted too know is how to getÂ ...May 17, 2011 ... The Apple Barn has a long and varied history in this valley and started out in 1911 as the first dairy barn in the area to have a concrete floor.http://farmflavor.com/us-ag/tennessee/tennessee-food/tennessee-wine-industry- ... Located on the banks of the Little Pigeon River in the Apple Barn Village, theÂ ...	http://www.theapplebarn.com/
Ctx23R39	Furnace Brook Winery	head, Furnace Brook Winery in the Berkshires of western Massachusetts, MA, free wine tasting year, head, Free wine tasting at Hilltop Orchards' Furnace Brook Â ...21604 Long Hill Dr Leander, TX 78641 http://www.arguscidery.com/ ... Furnace Brook Winery 508 Canaan Rd Richmond, MA 01254-5116 (413) 698-3301Â ...head, Furnace Brook Winery in the Berkshires of western Massachusetts, MA, free wine tasting year, head, Free wine tasting at Hilltop Orchards' Furnace Brook Â ...Hilltop Orchards -- an historic apple orchard in the Berkshires and home to award -winning Furnace Brook Winery â€" invites you to visit and explore our 200 acreÂ ...head, Furnace Brook Winery in the Berkshires of western Massachusetts, MA, free wine tasting year, head, Free wine tasting at Hilltop Orchards' Furnace Brook Â ...	http://www.furnacebrookwinery.com/
Ctx23R40	Orchard Creek Golf Club	Public golf course and Cider House Restaurant. Offering grass driving range, practice putting green, 18 holes, pro shop, tournaments and lessons.Offers assisted living and care facilities to the senior community. Includes details for specialized services, lists amenities, and includes floor plans, slide shows,Â ...Orchard Creek Golf Club is the home of Ciderhouse Restaurant, a restaurant offering a large variety of food, wine and spirits to tantalize almost anyone's tastes .Check out our online E-specials. Gift cards available on line. New for 2013 - The Orchard Creek loyalty program. Orchard Creek Employment Form. Please fillÂ ...Orchard Creek Cottages are nestled in a quiet corner of Spearfish, South Dakota, near Mt. Rushmore, the Sturgis Motorcyle Rally, the Badlands, Devil's Tower,Â ...	http://www.orchardcreek.com/
Ctx23R41	Mount Greylock State Reservation	North Adams, Adams, Lanesborough, Cheshire, Williamstown and New Ashford ... Camping. At 3,491 feet, Mount Greylock is the highest point in Massachusetts.Rustic stone and wood Lodge perched atop Mount Greylock in western	beautiful. ... Every year

		Massachusetts. Built by the ... Greylock Adams, Massachusetts ... In 1898, the State legislature established Mt. Greylock as the Commonwealth's first State Reservation.Summit Hikes (pdf) Suggested hikes from the summit of Mount Greylock. Greylock Glen (pdf): Detail map of trails and trailheads in Greylock Glen, Adams. ... (.pdf): Detail map of trails and trailheads for Taconic Trail State Park in Williamstown.9 Reviews of Mount Greylock State Reservation \Oh	
Ctx23R42	Bombers Burrito Bar	A Mexican-American Bar and Grill serving huge burritos, cold beers and much more.176 Reviews of Bombers Burrito Bar \When I went to UAlbany a few years ago	this ... http://www.bombersburritobar.com ... 176 reviews for Bombers Burrito Bar.Founded in 1997 by Matt Baumgartner on $15
Ctx23R43	Congress Park	Visit Congress Park in Saratoga Springs NY to get your fill of history, health and horses! Plus, learn more about Congress Park weddings, parking and directions Â ...Canfield Casino and Congress Park is a 17-acre (6.9 ha) site in Saratoga Springs, New York, United States. It was the site of the former Congress Spring BottlingÂ ...SARATOGA SPRINGS NY â€" Are the kids ready to go for a spin? The Carousel in Congress Park is an historic wooden carousel that has all the charm ofÂ ...Congress Park, Saratoga Springs: See 89 reviews, articles, and 6 photos of Congress Park, ranked No.3 on TripAdvisor among 19 attractions in SaratogaÂ ...Aug 6, 2009 ... 5 Reviews of Congress Park \Congress Park is located along Broadway in the charming little town of Saratoga Springs	NY. Saratoga SpringsÂ ..."
Ctx23R44	Golden Harvest Farms Inc	Welcome to Golden Harvest Farms Our retail farm market is. OPEN DAILY YEAR ROUND from 8 am to 5 pm. Golden Harvest Farms Inc. 3074 US Route 9,14 Reviews of Golden Harvest Farms \The high water mark of cider donuts. I keep searching for Golden ... (518) 758-7683. http://www.goldenharvestfarms.comÂ ...BAKERY. Famous Cider Donuts made everyday. 5 Machines! Fruit Pies Baked Daily. Also	call for orders. Apple & Cherry Turnovers
Ctx23R45	Price Chopper	Price Chopper offers the freshest foods at affordable prices with personalized customer service. Visit us in New England, New York, and Pennsylvania.T. T. T. Select a flag on the map or scroll down for store details. Price Chopper #1. 1640 Eastern Parkway , Schenectady, NY, 12309. Sun - Sat: 24 h;. (518) 372-Â ...Price Chopper has a variety of positions available for talented team members. View our job openings and apply easily online.Price Chopper offers the freshest foods at affordable prices with personalized customer service. Visit us in New England, New York, and Pennsylvania.Enter your user name and password to access your MyAdvantEdge Account to view your Fuel	http://www.pricechopper.com/

		AdvantEdge savings, get a replacement card, update accountÂ ...	
Ctx23R46	Albany Marriott	The Albany Marriott is a perfect place for travelers looking for something extra from hotels in Albany, NY. With excellent amenities & a free airport shuttle, ourÂ ...Albany Marriott, Albany: See 186 traveler reviews, 29 candid photos, and great deals for Albany Marriott, ranked #24 of 49 hotels in Albany and rated 3.5 of 5 atÂ ...For driving directions to Albany Marriott in Albany use the online tool.Here's the promotion code and special pricing: http://www.marriott.com/hotels/ hotel-deals/albny-albany-marriott/. My One & Only June 6 - 16, 2013. For ticketsÂ ...With endless career paths and opportunities at Marriott, you are sure to find the area of work perfect for you. Start developing your career and carve your pathÂ ...	http://www.albanymarriott.com/
Ctx23R47	Barnes & Noble	Items 1 - 10 of 35 ... View upcoming sales and events or get directions and hours of operation. ... http:/ /store-locator.barnesandnoble.com/store/2275|||ColonieÂ ...Retail stores that carry MAKE. ... MAKE magazine is available at the Maker Shed store, in the magazine section of Barnes & Noble, Micro Center, and Fry'sÂ ...4th of July Mall Hours - 10am - 6pm. Department store andÂ ...visited the store on my vacation!! very impressed and highly recommended 2 all comic book collectors, loved the figures and movie items ... http://www. midtowncomics.com/store/search.asp?q=becky+cloonan ... 20 hours ago near New York, NY ...... Jacob Salas, Ruben Salas, Robert Rodriguez and 2,275 others like this.4th of July Mall Hours - 10am - 6pm. Department store andÂ ...	http://store-locator.barnesandnoble.com/store/2275
Ctx23R48	Mohawk Honda	Mohawk Honda is a Honda dealer located in Scotia, near Albany, Latham, and Saratoga Springs, NY. We have new Hondas, Honda service, and more. Stop by Â ...Mohawk Honda has used Hondas for the Scotia, Albany, Saratoga Springs, and Latham, NY area. Our Honda dealership provides the best service in the region.Mohawk Honda - Supporting the home team! http://www.highschoolsports.net/ NextFiveDays/Burnt-Hills-Ballston-Lake-CSD-Burnt-Hills-NY/Football/Varsity/ Boys/Â ...Mohawk Honda is happy and excited to be able to offer this military honda discount program for the men and women of the armed forces and their families.About our dealership. See why our customers rank us the highest Honda Albany dealer.	http://www.mohawkhonda.com/
Ctx23R49	Hotel Vienna	Looking for Windham, New York hotels? The Hotel Vienna provides comfortable lodging to guests. Complimentary breakfast, an indoor heated pool & more.... with a 32\ LCD with DVD	phone

Ctx23R50	74 State Hotel, Downtown Albany NY	For Albany hotels, it doesn't get much better than 74 State. Luxurious hotels, professional meeting facilities and unparalleled service make this Albany, NY hotelÂ ...As a boutique hotel in Albany, 74 State has wonderful rooms and superior service. And with out great rates and special packages, whether you are on businessÂ ...Looking for an Albany jazz bar? Or perhaps a watering hole with a piano bar atmosphere? Head to the Bistro/Bar at 74 on State Street in downtown Albany.Meetings & Private Dining - Meetings and Conferences We've assembled a team of highly skilled hospitality professionals who make sure that your event goesÂ ...*74 State (7.03mi from campus) 74 State Street Albany, NY, 12207 (518) 434- 7410 http://www.74state.com *Hotel Albany (7.05 mi from campus) 30 Lodge Street	http://www.74state.com/

Appendix B: TREC examples file

id	description	url
51	Elfreths Alley Museum is a reputable museum. A lovely little piece of history. Definitely a must while visiting Philadelphia... To walk down the oldest residential street in the country is just something I think everyone should do at least once if in the area! I really enjoyed it.	http://www.elfrethsalley.org
52	My girlfriend and I took a trip to Philly with intent of visiting Eastern State and we were not disappointed at all. The tour we took was interesting and we wish there was even more locations we could venture off into than we were allowed to. I was even shocked that the gift shop was so reasonable in prices. Love the hoodie I bought there. We cannot wait to go back again.	http://www.easternstate.org/
53	A bit of a hike from the other attractions in Independence National Historic Park is the house where Edgar Allen Poe, author of "The Raven" and "The Tell-Tale Heart," lived and wrote. Poe fans will find many activities to enjoy, including a video presentation of Poe's life, ranger-led tours, and perhaps an encounter with "Poe" himself.	http://nps.gov/edal
54	Round Guys Brewing Co. - No Monkey Business...Just Well Rounded Beers!	http://roundguysbrewery.com
55	Founded in 1812, the Academy of Natural Sciences of Drexel University is a world-class natural history museum dedicated to advancing research, education, and public engagement in biodiversity and environmental science.	http://www.ansp.org/
56	America's oldest farmer's market is a bustling indoor public market hall, with produce markets, bakeries, arts and crafts, a beer garden, and virtually every type of cuisine present. Be sure to make some time to stroll around and sample as much as you can. Despite the market's stated hours, individual vendors operate their own schedules; some restaurants will be open for dinner, and some, particular the Pennsylvania Dutch shops, are closed on Sundays.	http://readingterminalmarket.org
57	Wait Chinatown as a whole? Well in that case, it's worth gong early and exploring before you eat. So much to see, so much to eat. I would recommend anywhere. It's all great, and you may just find some hidden gems :)	http://www.phillychinatown.com/
58	Welcome to Darling's Diner, Home of The Original Philadelphia Cheesecake. We serve a full menu of freshly prepared items (including breakfast) 24 hours a day, 7 days a week. We also have a full bar, including carry out beer from 7am-2am Mon-Sat, 9am-2am Sun. There is indoor & outdoor seating on our Patio, and we also offer room service delivery to Piazza Residents.	http://www.darlingsdiner.com
59	Hands-on museum where adults and children can learn and explore together.	http://www.pleasetouchmuseum.org/

60	Harry's Smoke Shop is a great place for shopping. Love everything about it :)	http://www.harryssmokeshop.com
61	Granite Run Mall is a fun place to shop, eat and check out an event! The Mall is situated in the heart of the major tourist areas of central Philadelphia, Valley Forge and the Brandywine Valley.	http://www.shopgraniterunmall.com
62	A Pump It Up party combines imagination and inflatables to create the most exciting party your child has ever had. It's always stress-free and easy to do.	http://www.pumpitupparty.com/nj/marlton/home-p1q100011.htm
63	Buy fresh, high quality loose leaf teas online from Teavana. From Rooibos to Oolong and everything in between, Teavana has great tea gifts and products for enjoying afternoon tea.	http://www.teavana.com
64	Scavenger hunt-style tour, all from your own cell phone. Explore the best of Philly completing fun challenges texted to your phone. For tourists locals.	http://www.strayboots.com/locations/philadelphia/
65	Red Mango is committed to providing the healthiest and best tasting all-natural nonfat frozen yogurt and fresh fruit smoothies. No wonder Zagat ranked us #1, twice.	http://www.redmangousa.com
66	A True Irish Pub serving Irish Classics as well as lip-smacking BBQ favorites.	http://fergies.com/
67	Clementon Park / Splash World - Whether it is Rides, Slides or Attractions youÂ´re looking for, we have them all.	http://www.clementonpark.com
68	Dedicated to Preserving a Waterfront Treasure	http://penntreatypark.org/
69	This museum offers dynamic and always intriguing exhibits. The history and evolution of the American Jewish community from colonial times onwards is chronicled.	http://www.nmajh.org/
70	The Wilma Theater, located at 265 S Broad St, near Washington Square West and Avenue of the Arts South, is a good place for performing arts. Enjoy the performing arts? Wonderful performances by every actor.	http://www.wilmatheater.org
71	Maggiano's Little Italy, located at 1201 Filbert St, near Market East, is an Italian restaurant. Food is outstanding, beverages are well served, service is warm and the atmosphere is relaxed.	http://www.maggianos.com
72	Carpenters' Hall is an incredible landmark. This place is historically significant, and the staff is very informative. This is where the 1st Continental Congress met as far back as 1724!	http://www.ushistory.org/carpentershall
73	Distrito is a neat place for jazz & blues. I am a huge Garces fan, and Distrito is definitely my favorite. I get the Mahi Mahi tacos every time, and they never fail! Save room for churros for dessert, too.	http://www.distritorestaurant.com
74	Taking a self-guided tour of the first and largest US Mint in America is an interesting but often overlooked activity. The tour allows visitors to see how new money is made, and exhibits describe the history and coinage of the Mint.	http://www.usmint.gov/mint_tours/index.cfm?flash=no&action=philadelphia

	A gift shop sells commemorative and new coins. Please note that visitors will be asked to show government-issued ID before entering.	
75	Rescue Rittenhouse Spa is Philadelphia's premier day spa destination. Enjoy a highly personalized, integrative and comprehensive approach to skin care.	http://www.rescuerittenhousespa.com
76	Philadelphia PA chocolate store, Featuring Chocolate Covered Pretzels, Anatomically Correct Chocolate Hearts, Dutch Licorice, Chocolate Covered Apples, peanut clusters, white chocolate and dark chocolate.	http://www.chocolatebymueller.com/index.htm
77	Bowling PA, Fun Center PA, Conference Center PA: Facenda Whitaker fun center in PA also provides conference center, banquet hall bowling in PA. Looking for bowling alleys for bowling in PA (fun center PA), conference center or banquet hall in PA? Call with your banquet hall, fun center conference center needs now!	http://www.facendawhitaker.com
78	Club 27 is a popular night club for younger people in Philadelphia. If you are 17 or older go to Club 27 on Saturday and Thursday nights. It is very easy to get to and is very close to many restauraunts in the Old City area. It is also about a block away from the Frankford-Market street line. With different specials and many different concerts and celebrity guests, it is one of the hot spots for kids 17 and older.	http://www.club27philly.net
79	Located under the shadow of I-95, Tony Luke's is popular with locals, and more difficult to get to for tourists without cars. Unlike Pat's, Geno's or Jim's, Tony Luke's offers a much wider variety of cheesesteak types, as well as burgers. Outdoor seating only.	http://tonylukes.com
80	We provide a platform for licensed, local, freelance tour guides to lead tours at no upfront costs, so that you may enjoy an interesting sightseeing tour for whatever price you like, even free. You get to determine what a tour was worth, if anything, after the tour, thus ensuring that your tour guide must strive to give his or her best on every tour. We believe that traveling can be affordable â€“ even free!	http://www.freetoursbyfoot.com
81	Famous on the outside for the steps seen in the film "Rocky" and famous on the inside for one of the world's largest collections of art, the Philadelphia Museum of Art is home to many rotating collections as well as a standard selection of pieces always on display. The permanent collection is especially strong in Asian and medieval art, impressionist paintings, and furniture.	http://philamuseum.org
82	Philadelphia Chamber Music Society is a solid place for performing arts. These series are truly one of Philadelphia's cultural hidden gems. Having seen some great shows through them, I'm now a subscriber via their Young Friends Unlimited which is a bargain and I've seen some incredible shows.	http://www.pcmsconcerts.org
83	Estia is an entertaining mediterranean restaurant. If you like high-end Greek/Mediterranean fare, Estia is a great	http://www.estiarestaurant.com

	place to have a nice dinner. The mezes are excellent, and the fish was phenomenal. This is a great place to take your colleagues and friends if you're in Philly visiting on a conference.	
84	Tria Wine Room is a neat bar. The ambiance and service were superb. The only two types of alcohol I will drink are beer and wine, so it was appropriate to come to a wine bar.I ordered: 1) ALLAGASH WHITE- Ahhh, it was so refreshing! Belgium wheat beer!We also ordered a platter of soft cheese to share at the table. Absolutely delicious! If I am in the area, I would love to go back :)	http://www.triacafe.com
85	The Little Apple is a well-regarded place for shopping. This is the cutest shop on Main Street! Best place to get that unique, last minute birthday gift!	http://www.thelittleapplestore.com
86	Spa Terme Di Aroma, a holistic day spa located in Philadelphia, PA, specializing in massage, facial and body treatments.	http://www.termediaroma.com
87	Features information, history and adventure in the region. Find photos, ticket information and contact details.	http://www.independencevisitorcenter.com
88	Studio 34: Yoga | Healing | Arts is a 5,000-square-foot healing and creative arts space in vibrant, diverse West Philadelphia. Opened in March 2008, it offers yoga, Pilates, healing, creative arts events, and community programs. Just 15 minutes from City Hall on SEPTA's Route 34 Green Line trolley.	http://studio34yoga.com/
89	If you are a shopper then you have picked the right place to shop! In the Far Northeast is the Franklin Mills Mall which is a huge outlet mall. Located on Knights Road, Franklin Mills Mall is home to over 200 stores, X-games skate park, restaurants, and movie theatre	http://www.simon.com/mall/?id=1245
90	This museum, "where history inspires the future," is located just around the corner from the Liberty Bell and Independence Hall, features a hands-on and comprehensive history of America's "birthplace" and founding city. Unique to the museum is a "walkable" map of the region on the floor of the museum. In minutes, you can walk between suburban Montgomery County and the heart of Philadelphia in Center City!	http://philadelphiahistory.org
91	The Philadelphia Zoo, Americaâ€™s first zoo, is a 42-acre Victorian garden that is home to more than 1,300 animals, many of them rare and endangered.	http://www.philadelphiazoo.org
92	This 2 hour experience is a great way to start off a great night in Olde City. City Food Tours Philadelphia - what a great way to spend an afternoon getting to know the ins and outs of local Philly food businesses. City Food tours is a great way to experience some of Philly. The guide was great and funny and everyone at city food tours was extremely helpful	http://www.cityfoodtours.com/philadelphia/philly-food-tours-general-info.html
93	The Irish Memorial national monument at Front and Chestnut Streets in Olde Philadelphia.	http://www.irishmemorial.org/index.html

94	Walnut Street Theatre is a stylish place for performing arts. Friendly staff, delightful, historical theatre and an AWESOME show!Hubs took me to see the Buddy Holly Story here this weekend and it was definitely awesome. The production value was top notch, the seats were wonderful (great view no matter where you sit!) and I loved all the wonderful photographs on the wall in the waiting areas.Definitely would visit again on future trips to Philly!	http://www.walnutstreettheatre.org
95	Rangoon Burmese Restaurant is a qualified dim sum restaurant. Thousand Layer Bread + Potato Curry = Spicy and Yummy!I had the cold Burmese noodles and hubs ordered the Pineapple fish - great meals both! The prices are reasonable, the staff was very friendly and attentive and the decor was tasteful without going overboard.I'd also recommend the coconut juice :)	http://www.phillychinatown.com/rangoon.htm
96	If you're in Center City during the summer months, be sure to take advantage of Center City Sips , a downtown-wide Happy Hour every Wednesday from 5PM-7PM where many bars and restaurants all participate in drink specials: $2 beers, $3 wines and $4 cocktails, and usually some selection of food specials. As it's right after the hump of the office work week, you'll see a lot of young professionals in business casual, and some places will get really crowded, but the prices are definitely right.	http://centercityphila.org/life/Sips.php
97	Flying Fish Brewing is the largest of the approximately 20 craft breweries in New Jersey. The key word to describe all Flying Fish beers is balance. The beers, with Belgian and English influences, are full-flavored, yet highly drinkable.	http://flyingfish.com/
98	Leziz Turkish Cuisine, located at 611 E Passyunk Ave, near Queen Village and South Street District, is a restaurant, serving Turkish, Middle Eastern, Vegetarian, etc. Food is outstanding, beverages are well served, service is warm and the atmosphere is relaxed. Private parking lot.	http://www.lezizturkishcuisine.com
99	Encompasses the collections of the Rosenbach brothers, including decorative arts and rare books and manuscripts. Located in Philadelphia, Pennsylvania.	http://www.rosenbach.org
100	Philadelphia Flyers, located at The Wachovia Center, is a good place for professional sports teams. Come to support your team. You will like it.	http://www.philadelphiaflyers.com

Appendix C: TREC context file

id	city	state	lat	long
51	Springfield	IL	39.80172	-89.6437
52	Cheyenne	WY	41.13998	-104.82
53	Fargo	ND	46.87719	-96.7898
54	Kennewick	WA	46.21125	-119.137
55	La Crosse	WI	43.80136	-91.2396
56	Valdosta	GA	30.8327	-83.2785
57	Houma	LA	29.59577	-90.7195
58	Greenville	NC	35.61266	-77.3664
59	Hickory	NC	35.73319	-81.3412
60	Cincinnati	OH	39.162	-84.4569
61	St. Louis	MO	38.62727	-90.1979
62	Asheville	NC	35.60095	-82.554
63	Beckley	WV	37.77817	-81.1882
64	Myrtle Beach	SC	33.68906	-78.8867
65	Orlando	FL	28.53834	-81.3792
66	Washington, D. C.	DC	38.89511	-77.0364
67	Anniston	AL	33.65983	-85.8316
68	Crestview	FL	30.76213	-86.5705
69	Youngstown	OH	41.09978	-80.6495
70	Macon	GA	32.84069	-83.6324
71	Monroe	LA	32.81513	-92.2057
72	Tampa	FL	27.94752	-82.4584
73	Albany	NY	42.65258	-73.7562
74	Sumter	SC	33.92044	-80.3415
75	Wenatchee	WA	47.42346	-120.31
76	Lakeland	FL	28.03947	-81.9498
77	Appleton	WI	44.26193	-88.4154
78	Lewiston	ID	46.41655	-117.018
79	Lima	OH	40.74255	-84.1052
80	Rochester	NY	43.15478	-77.6156
81	Gulfport	MS	30.36742	-89.0928
82	Johnson City	TN	36.31344	-82.3535
83	Lynchburg	VA	37.41375	-79.1423
84	Atlanta	GA	33.749	-84.388
85	Williamsport	PA	41.24119	-77.0011
86	Corpus Christi	TX	27.80058	-97.3964
87	Dothan	AL	31.22323	-85.3905
88	Parkersburg	WV	39.26674	-81.5615
89	Wichita	KS	37.69224	-97.3375
90	Greenville	SC	34.85262	-82.394
91	Yakima	WA	46.60207	-120.506
92	Cedar Rapids	IA	42.00833	-91.6441
93	Kahului	HI	20.89472	-156.47
94	Harrisburg	PA	40.05567	-75.0252
95	Bismarck	ND	46.80833	-100.784
96	Saint George	UT	37.10415	-113.584
97	Montgomery	AL	32.36681	-86.3
98	Palm Bay	FL	28.03446	-80.5887
99	Rockford	IL	42.27113	-89.094
100	Manhattan	KS	39.18361	-96.5717

Appendix D: TREC profile file

id	attraction_id	description	website
35	51	0	4
35	52	1	4
35	53	3	3
35	54	0	1
35	55	2	3
35	56	3	2
35	57	0	2
35	58	1	2
35	59	1	0
35	60	0	2
35	61	2	2
35	62	0	1
35	63	2	3
35	64	3	4
35	65	3	4
35	66	1	1
35	67	0	2
35	68	0	2
35	69	1	1
35	70	1	1
35	71	2	2
35	72	0	2
35	73	1	3
35	74	3	3
35	75	1	2
35	76	3	1
35	77	0	1
35	78	1	1
35	79	2	3
35	80	1	0
35	81	3	2
35	82	3	3
35	83	3	1
35	84	0	2
35	85	1	1
35	86	1	0
35	87	1	2
35	88	1	1
35	89	2	2
35	90	3	4
35	91	3	4
35	92	2	2
35	93	0	0
35	94	3	4
35	95	3	0
35	96	2	0
35	97	1	1
35	98	1	2
35	99	1	2
35	100	0	1
…	…	…	…
…	…	…	…
669	51	1	0
669	52	2	3
669	53	3	0
669	54	3	2
669	55	0	1
669	56	1	0
669	57	2	0
669	58	3	3
669	59	4	4
669	60	1	0
669	61	1	2
669	62	3	3
669	63	2	3
669	64	2	3
669	65	3	3
669	66	4	3
669	67	2	2
669	68	0	0
669	69	0	0
669	70	0	2
669	71	3	3
669	72	0	0
669	73	1	3
669	74	0	0
669	75	2	3
669	76	3	0
669	77	0	0
669	78	4	4
669	79	3	2
669	80	3	0
669	81	2	0
669	82	3	1
669	83	0	0
669	84	1	2
669	85	2	3
669	86	3	3
669	87	1	0
669	88	2	3
669	89	1	3
669	90	2	3
669	91	4	4
669	92	2	0
669	93	2	3
669	94	2	3
669	95	3	0
669	96	1	0
669	97	3	4
669	98	0	2
669	99	0	2
669	100	1	0

Appendix E: Java Program for Context Processing

```
public class GoogleAPI {
public static final String GOOGLE_API_KEY = "AIzaSyCa2conBaMNt8s83qgT4MFVq1hr49dX4nA";
private static final HttpClient client = new DefaultHttpClient();
 public static void RetreiveTwoGoogleAPIResults(int firstNContexts) throws SAXException, IOException,
TransformerException, ParserConfigurationException
   {        GetGooglePlacesResult(firstNContexts);
            for (int i=1; i<=firstNContexts; i++)
            {
                        System.out.print(i+"...");
                        System.out.println("Inside the for loop of RetreiveTwoGoogleAPIResults");
                        AddDecriptrionToSearchResultXML(i);
                        System.out.println("finish");
                        System.out.println("stage 1");
            }    }
private static void GetGooglePlacesResult(int firstNContexts) throws ParserConfigurationException,SAXException,
IOException
            {  //call run example
                        List<Context> contexts = GetContextsFromXML();
                        String result = "";
                        //System.out.println("number of places: "+contexts.size());
                        try
                        {
                        String bufferText = "";
                        for (int i=0; i<firstNContexts; i++)
                        {
                        //FileWriter fstream = new FileWriter(Setting.GooglePlacesOutput+(i+1)+".xml");
                        String file= Setting.GooglePlacesOutput+(i+1)+".xml";
                         Context con = (Context) contexts.get(i);
                        System.out.println("context:"+(i+1));
                        String txt=performSearch(con.GetPlaceType(), con.getlongitude(), con.getLatitude());
                        System.out.println(txt);
                              BufferedWriter out = new BufferedWriter(new OutputStreamWriter (new
FileOutputStream(file),"UTF8"));
                         out.write(txt);
                         out.close(); } }
                        catch (Exception e){//Catch exception if any
              System.err.println("Error: " + e.getMessage());      }
private static void AddDecriptrionToSearchResultXML (int xmlNumber) throws SAXException, IOException,
TransformerException, ParserConfigurationException            {
              System.out.println("In Add Description To Search Method")
               DocumentBuilderFactory factory =DocumentBuilderFactory.newInstance();
                  DocumentBuilder builder = factory.newDocumentBuilder();
                  File f = new File(Setting.GooglePlacesOutput+xmlNumber+".xml");
                  Document XML1 = builder.parse(f);
                  NodeList placesList = XML1rootElement.getElementsByTagName("result");
                              for (int i = 0; i < placesList.getLength(); i++) {
                              Node result = placesList.item(i);
                               String town = Utility.GetXMLNodeValueByNodeTag(result, "vicinity");
                               town = town.substring(town.lastIndexOf(',')+1);
                               String searchTest = Utility.GetXMLNodeValueByNodeTag(result, "name") +" " + town;
                               //Node for description
                               Node description = XML1.createElement("description");
                               description.setTextContent(resultSnippet1[0]);
                               result.appendChild(description);
                               //Node for website
                               Node website = XML1.createElement("website");
                               website.setTextContent(resultSnippet1[1]);
                               result.appendChild(website);
                  }
                  Transformer transformer = TransformerFactory.newInstance().newTransformer();
                  transformer.setOutputProperty(OutputKeys.INDENT, "yes");
                  //initialize StreamResult with File object to save to file
                  StreamResult streamresult = new StreamResult(new StringWriter());
                  DOMSource source = new DOMSource(XML1);
                  transformer.transform(source, streamresult);
                                    BufferedWriter out = new BufferedWriter(new OutputStreamWriter
```

```
                                                  (new
FileOutputStream(Setting.GoogleSnippetOutput+xmlNumber+".xml"),"UTF8"));
                 String xmlString = streamresult.getWriter().toString();
                          out.write(xmlString)
                          out.close(); }
      public static List<Context> GetContextsFromXML() {
                         //get the factory
                         DocumentBuilderFactory dbf = DocumentBuilderFactory.newInstance();
                         List<Context> contexts = new ArrayList<Context>();
                         try{          //Using factory get an instance of document builder
                                       DocumentBuilder db = dbf.newDocumentBuilder();
                                       //parse using builder to get DOM representation of the XML file
                                       Document dom = db.parse("Context2013.xml");
                                       Element docEle = dom.getDocumentElement();
                                       //get a nodelist of <context>element
                                       NodeList nl = docEle.getElementsByTagName("context");
                                       if(nl != null && nl.getLength() > 0) {
                      for(int i = 0 ; i < nl.getLength();i++) {
                                           //get the city and state element
                                           Element el = (Element)nl.item(i);
                                           String city = getTextValue(el,"city");
                                           String state = getTextValue(el,"state");
                                           double latitude = Double.parseDouble(getTextValue(el,"lat"));
                                           double longitude = Double.parseDouble(getTextValue(el,"long"));
                                           //add it to list
                                           contexts.add(context);}}
                                       }catch(ParserConfigurationException pce) {
                                       pce.printStackTrace();
                         }catch(SAXException se) {
                                       se.printStackTrace();
                         }catch(IOException ioe) {
                                       ioe.printStackTrace();
                         }
                         return contexts;}
      private static String getTextValue(Element ele, String tagName) {
                         String textVal = null;
                         NodeList nl = ele.getElementsByTagName(tagName);
                         if(nl != null && nl.getLength() > 0) {
                                       Element el = (Element)nl.item(0);
                                       textVal = el.getFirstChild().getNodeValue();
                         }
                         return textVal;}
   public static String performSearch(final String types, final double lon, final double lat)
              //throws ParseException, IOException, URISyntaxException
  {
final URIBuilder builder = new
URIBuilder().setScheme("https").setHost("maps.googleapis.com").setPath("/maps/api/place/radarsearch/xml");;
      builder.addParameter("location", lat + "," + lon);
      builder.addParameter("radius", "50000");
      builder.addParameter("types", types);
      builder.addParameter("sensor", "true");
      builder.addParameter("key", GoogleAPI.GOOGLE_API_KEY);
  try{        final HttpUriRequest request = new HttpGet(builder.build());
              final HttpResponse execute = GoogleAPI.client.execute(request);
               String response = EntityUtils.toString(execute.getEntity());
              return (response);
      }catch(Exception ex){
              return ("error in performSearch:" + ex.toString());
      }}
   //PERFORM SEARCH RETURNS DESCRIPTION
   private static String GetSnippet(String searchText)
   {   String text="";
      searchText = searchText.replaceAll(" ", "+");
      String key="AIzaSyCa2conBaMNt8s83qgT4MFVq1hr49dX4nA";
      String cx= "006325740541168945513:igrohg0rva4";
      URL url;
      try {
         url = new URL(
               "https://www.googleapis.com/customsearch/v1?key="+key+
               "&F="+ cx +
```

```
                "&q="+ searchText + "&alt=json");
        HttpURLConnection conn = (HttpURLConnection) url.openConnection();
        conn.setRequestMethod("GET");
        conn.setRequestProperty("Accept", "application/json");
        BufferedReader br = new BufferedReader(new InputStreamReader(
                (conn.getInputStream())));
        System.out.println(br);
        String output;
        int iteration =0;
       while ((output = br.readLine()) != null && iteration<5) {
            if(output.contains("\"snippet\": \"")){
                String snippet = output.substring(output.indexOf("\"snippet\": \"")+("\"snippet\": \"").length(), output.indexOf("\","));
                //System.out.println(snippet);
                text=text.concat(snippet);//Will print the google search links
                iteration++;
            }  }
        conn.disconnect();
        } catch (MalformedURLException e1) {
            // TODO Auto-generated catch block
            e1.printStackTrace();
            return "";
        } catch (IOException e) {
            // TODO Auto-generated catch block
           e.printStackTrace();
           return "";
        }return text;}
 //PERFORM SEARCH RETURNS DESCRIPTION AND WEBSITE
private static String[] GetSnippet1(String searchText)
                {               String[] text = {"",""};
                                String[] er = {"",""};
                                searchText = searchText.replaceAll(" ", "+");
                                String key="AIzaSyCa2conBaMNt8s83qgT4MFVq1hr49dX4nA";
                                String cx= "006325740541168945513:igrohg0rva4";
                                URL url;
                                                try {
                                                                url = new URL(
                                                                                                "https://www.googleapis.com/customsearch/v1?key="+key+
                                                                                                "&cx="+ cx +
                                                                                                "&q="+ searchText + "&alt=json");
                                                                HttpURLConnection conn = (HttpURLConnection) url.openConnection();
conn.setRequestMethod("GET");
conn.setRequestProperty("Accept", "application/json");
BufferedReader br = new BufferedReader(new InputStreamReader( (conn.getInputStream())));
System.out.println(br);
String output;
int iteration =0;
int iteration1 =0;
while ((output = br.readLine()) != null && iteration<5 && iteration1<5) { if(output.contains("\"snippet\": \"")){
String snippet = output.substring(output.indexOf("\"snippet\": \"")+("\"snippet\": \"").length(), output.indexOf("\","));
//System.out.println(snippet);
text[0]=text[0].concat(snippet);//Will print the google search links
iteration++;
}
if(output.contains("\"formattedUrl\": \"")){
String formattedUrl = output.substring(output.indexOf("\"formattedUrl\": \"")+("\"formattedUrl\": \"").length(),
output.indexOf("\","));
//System.out.println(formattedUrl);
text[1]=text[1].concat(formattedUrl);//Will print the google search links
iteration1++;}                                                  }
conn.disconnect();
} catch (MalformedURLException e1) {
// TODO Auto-generated catch block
                e1.printStackTrace();
                return er;
                } catch (IOException e) {
                // TODO Auto-generated catch block
                e.printStackTrace();
                return er;
                }
                return text;
```

```
            }
//THREE GOOGLE API CALLS
public static void RetreiveThreeGoogleAPIResults(int firstNContexts) throws SAXException, IOException,
TransformerException, ParserConfigurationException
{//GetGooglePlacesResult1(firstNContexts);
            for (int i=26; i<=firstNContexts; i++)
            {
                        System.out.print(i+"...");
                        System.out.println("Inside the for loop of RetreiveThreeGoogleAPIResults");
                        String[] refid = GetRefID(i);
                        AddDecriptrionToSearchResultXML1(i,refid);
                        System.out.println("finish");
                        System.out.println("stage 1");
            } }
private static void GetGooglePlacesResult1(int firstNContexts) throws ParserConfigurationException,SAXException,
IOException {                       //call run example
                        List<Context> contexts = GetContextsFromXML();
                        String result = "";
                        //System.out.println("number of places: "+contexts.size());
                        try
                        {
                                    String bufferText = "";
                        for (int i=0; i<firstNContexts; i++)
                        {
                                                //FileWriter fstream = new FileWriter(Setting.GooglePlacesOutput+(i+1)+".xml");
                                    String file= Setting.GooglePlacesOutput+(i+1)+".xml";
                              Context con = (Context) contexts.get(i);
                                    System.out.println("context:"+(i+1));
                                    String txt=performSearch(con.GetPlaceType(), con.getlongitude(), con.getLatitude());
                                    System.out.println(txt);
                              BufferedWriter out = new BufferedWriter(new OutputStreamWriter
                                                      (new FileOutputStream(file),"UTF8"));
                            out.write(txt);
                                     out.close();}}
catch (Exception e){//Catch exception if any
              System.err.println("Error: " + e.getMessage());}}
//To get Reference ID from Radar Search
private static String[] GetRefID(int xmlNumber) throws SAXException, IOException, TransformerException,
ParserConfigurationException
{ System.out.println("In GetRefID To Search Method");
DocumentBuilderFactory factory =DocumentBuilderFactory.newInstance();
DocumentBuilder builder = factory.newDocumentBuilder();
 File f = new File(Setting.GooglePlacesOutput+xmlNumber+".xml");
 NodeList placesList = XML1rootElement.getElementsByTagName("result");
     ArrayList list = new ArrayList();
     for( int i = 0; i < 220; i++ )
     list.add("");
      String[] searchref = new String[ list.size() ];
            for( int j = 0; j < searchref.length; j++ )
           searchref[ j ] = list.get( j ).toString();
for (int i = 0; i < placesList.getLength(); i++) {
            Node result = placesList.item(i);
                   String reference = Utility.GetXMLNodeValueByNodeTag(result, "reference");
                   searchref[i] = reference.substring(reference.lastIndexOf(',')+1);  }
     Transformer transformer = TransformerFactory.newInstance().newTransformer();
     transformer.setOutputProperty(OutputKeys.INDENT, "yes");
     //initialize StreamResult with File object to save to file
     StreamResult streamresult = new StreamResult(new StringWriter());
     DOMSource source = new DOMSource(XML1);
     transformer.transform(source, streamresult);
           BufferedWriter out = new BufferedWriter(new OutputStreamWriter
                                 (new FileOutputStream(Setting.GoogleSnippetOutput+xmlNumber+".xml"),"UTF8"));
    String xmlString = streamresult.getWriter().toString();
            out.write(xmlString);
            out.close();
            return searchref; }
private static void AddDecriptrionToSearchResultXML1(int xmlNumber, String[] placerefid) throws SAXException,
IOException, TransformerException, ParserConfigurationException{
           String terms[] = {"","","",""};
           System.out.println("In Add Description To Search Method");
```

```
                  DocumentBuilderFactory factory =
                         DocumentBuilderFactory.newInstance();
                     DocumentBuilder builder = factory.newDocumentBuilder();
                     Element XML1rootElement = XML1.getDocumentElement();
NodeList placesList = XML1rootElement.getElementsByTagName("result");
              String[] urldesc ={"","","",""};
for (int i = 0; i < placesList.getLength(); i++) {
                             Node result = placesList.item(i);
                                      //Node for title
                                      Node title = XML1.createElement("title");
                                      title.setTextContent(terms[0]);
                                      System.out.println(terms[0]);
                                      result.appendChild(title);
                                      //Node for Type
                                      Node type = XML1.createElement("type");
                                      type.setTextContent(terms[3]);
                                    System.out.println(terms[3]);
                                      result.appendChild(type);
                                  ///Node for context and rank number
                                      int j=i+1;
                                      Node resultid= XML1.createElement("resultid");
                                      String ctxr = "Ctx"+xmlNumber+"R"+j;
                                      resultid.setTextContent(ctxr);
                                      System.out.println(ctxr);
                                      result.appendChild(resultid);}
                    Transformer transformer = TransformerFactory.newInstance().newTransformer();
                     transformer.setOutputProperty(OutputKeys.INDENT, "yes");
                    //initialize StreamResult with File object to save to file
                     StreamResult streamresult = new StreamResult(new StringWriter());
                     DOMSource source = new DOMSource(XML1);
                     transformer.transform(source, streamresult);
BufferedWriter out = new BufferedWriter(new OutputStreamWriter
(new FileOutputStream(Setting.GoogleSnippetOutput+xmlNumber+"TYPE"+".xml"),"UTF8"));
                    String xmlString = streamresult.getWriter().toString();
                   out.write(xmlString);
                    out.close();
}
//to get url when website call to place details api
private static String[] GetUrl(String searchRefID)
{
              String[] plusgoogle={"","","",""};
              String[] er = {"",""};
              String key="AIzaSyCa2conBaMNt8s83qgT4MFVq1hr49dX4nA";
              URL url;
                            try {
                            url = newURL("https://maps.googleapis.com/maps/api/place/details/json?reference="+searchRefID+
                                                        "&sensor=true"+
                                                        "&key="+ key);
                                          System.out.println(url);
                                          HttpURLConnection conn = (HttpURLConnection) url.openConnection();
                                          conn.setRequestMethod("GET");
                                          conn.setRequestProperty("Accept", "application/json");
                                          BufferedReader br = new BufferedReader(new InputStreamReader(
                                                        (conn.getInputStream())));
                                          String output;
                                          int iteration =0;
while ((output = br.readLine()) != null && iteration<300)
                            {             if(output.contains("\"url\"")){
                                                        System.out.println("Inside url if loop");
                                                        String website = output.substring(output.indexOf("\"url\": \"")+("\"url\":
\"").length()+8, output.lastIndexOf("\"")); //indexOf("/\"")+1);
plusgoogle[0]=plusgoogle[0].concat(website);                      }
else if(output.contains("\"name\"")){
//System.out.println("Inside name if loop");String name = output.substring(output.indexOf("\"name\": \"")+("\"name\":
\"").length()+8, output.lastIndexOf("\""));//output.indexOf("\",");
}
else if(output.contains("\"vicinity\"")){
String vicinity = output.substring(output.indexOf("\"vicinity\": \"")+("\"vicinity\": \"").length()+8, output.lastIndexOf("\""));
//indexOf("/\"")+1);
plusgoogle[2]=plusgoogle[2].concat(vicinity);
```

```
}
iteration++;
}conn.disconnect();
//title + vicinity//String SearchTxt = text[0]+" "+text[2];
                                        String SearchTxt = "";
                                        SearchTxt = plusgoogle[1]+"+"+plusgoogle[2];
                                        String Desc = GetDetails(SearchTxt);
                                        plusgoogle[3] = plusgoogle[3]+Desc;
                           }
                            catch (MalformedURLException e1) {
                                        // TODO Auto-generated catch block
                                        e1.printStackTrace();
                                        return er;
                           } catch (IOException e) {
                                        // TODO Auto-generated catch block
                                        e.printStackTrace();
                                        return er;
                           }
                           return plusgoogle;
}
private static String GetDetails(String searchText)
{
   String text="";
   searchText = searchText.replaceAll("," , " ");
   searchText = searchText.replaceAll("\\s+", " ");
   searchText = searchText.replaceAll(" " , "+");
   System.out.println(searchText);
   String key="AIzaSyAf3lVkccTXwIMapOUEyWbI_XSipvyDmX0";
   String cx= "005143112037301272660:geksgcbpwnu";
   URL url;
   try { url = new URL(
                                                     "https://www.googleapis.com/customsearch/v1?key="+key+
                                                     "&cx="+ cx +
                                                     "&q="+ searchText + "&alt=json");
            System.out.println(url);
   HttpURLConnection conn = (HttpURLConnection) url.openConnection();
   conn.setRequestMethod("GET");
   conn.setRequestProperty("Accept", "application/json");
   BufferedReader br = new BufferedReader(new InputStreamReader(
         (conn.getInputStream())));
   int iteration =0;
  while ((output = br.readLine()) != null && iteration<5) {
      if(output.contains("\"snippet\": \"")){
         String snippet = output.substring(output.indexOf("\"snippet\": \"")+("\"snippet\": \"").length(), output.indexOf("\","));
         text=text.concat(snippet);
         iteration++;}   }
   conn.disconnect();
   System.out.println(text);
   } catch (MalformedURLException e1) {
      // TODO Auto-generated catch block
      e1.printStackTrace();
      return "";
   } catch (IOException e) {
      // TODO Auto-generated catch block
     e.printStackTrace();
     return "";
   }
   return text;
}
//Get context from contexts.xml
public static List<Context> GetContextsFromXML1() {
            //get the factory
            DocumentBuilderFactory dbf = DocumentBuilderFactory.newInstance();
            List<Context> contexts = new ArrayList<Context>();
try {
//Using factory get an instance of document builder
                           DocumentBuilder db = dbf.newDocumentBuilder();
                           Document dom = db.parse("Context2013.xml");
                           Element docEle = dom.getDocumentElement();
                           NodeList nl = docEle.getElementsByTagName("context");
```

```
                if(nl != null && nl.getLength() > 0) {
                        for(int i = 0 ; i < nl.getLength();i++) { String city = getTextValue(el,"city");
                                String state = getTextValue(el,"state");
                                double latitude = Double.parseDouble(getTextValue(el,"lat"));
                                double longitude = Double.parseDouble(getTextValue(el,"long"));
                                int number = Integer.parseInt(el.getAttribute("number"));
//Create a new context with the value read from the xml nodes
                                Context context = new Context(number, city, state, latitude, longitude);
//add it to list
contexts.add(context);  }}

        }catch(ParserConfigurationException pce) {
                pce.printStackTrace();
        }catch(SAXException se) {
                se.printStackTrace();
        }catch(IOException ioe) {
                ioe.printStackTrace();
        }
        return contexts;
} }
```

Appendix E: Java Program for Place Ontology Mapping

```
public class OntologyMapping {
		static void ReadWritetxt(int t) throws ParserConfigurationException,SAXException, IOException
		{
		String txtln ="";
		String[] parts = {"","","","","",""};
		String file = "C:\\Users\\Sushma\\Desktop\\Profiling\\PWORK\\PosSugg\\"+t+"Sugg.txt";
int i = 0;
 try{
BufferedReader br=new BufferedReader(new
FileReader("C:\\Users\\Sushma\\Desktop\\Profiling\\PWORK\\profiles2013.csv"));
txtln=br.readLine();
int k=t;
	while ((txtln=br.readLine())!=null){
if (k==t){
		System.out.println("khfdskjgkjdfh");
		FileWriter writer = new FileWriter(file, true);
		 writer.write("hello"+k+System.lineSeparator());
		 writer.flush();
		 writer.close();
}k++;
parts = txtln.split(",");
if (Integer.parseInt(parts[0])==t && (Integer.parseInt(parts[2])==3 || Integer.parseInt(parts[2])==4)){
System.out.println(parts[1]);
try {
	FileWriter writer = new FileWriter(file, true);
	 writer.write(parts[1]+System.lineSeparator());
	 writer.flush();
	 writer.close();
		} catch (IOException e)
		{
		    e.printStackTrace();
		}
string+=line+"\n";
i++;
	}
	br.close();
    }
    catch (Exception e){
	System.out.println(e.toString());
    }}}
```

Appendix F: Java Program for Calculating Semantic Relatedness and Suggestion Re-Ranking

```
public class re-ranking{
static Double GetTerms(String Rank,String Category,String goo,String prof) throws
ParserConfigurationException,SAXException, IOException
        {

                String Cparts[] = new String[4];
                String Pparts[] = new String[4];
                String Ctext = new String();
                String Ptext = new String();
                String Cfile = "C:/Users/Sushma/Desktop/Google/"+goo;
                String Pfile = "C:/Users/Sushma/Desktop/Profiling/STAGE3/"+prof;
                Double total= 0.0;
                int g,h,k,i,k1,len,l;
                String CWords[][] = new String[300][2];
                String PWords[][] = new String[300][2];
                String Part = "";
                Double score;
                Integer sum= new Integer(0);
                Integer csum= new Integer(0);
                Integer psum= new Integer(0);
                String r;
                String Cparts[] = new String[4];
                String rank[][]=new String[51][2];
                String Ctext = new String();
                String Cfile = "C:/Users/Sushma/Desktop/Profiling/scores/"+t;
                String file="C:/Users/Sushma/Desktop/Profiling/rank/"+t;
                String temp;
                int cnt=1;
                Double sum=0.0,sum2=0.0;
try{
                        BufferedReader br=new BufferedReader(new FileReader(Cfile));
                        System.out.println("Rank:"+Rank);
                        for (g=0,k=0; g <=2000 && (Ctext=br.readLine())!=null;g++ )
                        {Cparts = Ctext.split("=");
                        if (Cparts[1].equals(Rank)){
                                        CWords[k][0]=Cparts[2];
                                        CWords[k][1]=Cparts[3];
                                        System.out.println(CWords[k][0]+"  "+CWords[k][1]);
                                        l=Integer.parseInt(CWords[k][1]);
                                        csum=csum+(l*l);
                                        k++;
                                }}
                        BufferedReader pr=new BufferedReader(new FileReader(Pfile));
                        System.out.println("Cat:"+Category);
                        for(i=0,k1=0;i<=10000 && (Ptext = pr.readLine())!=null;i++ )
                        {
        Pparts = Ptext.split("=");
        Part = Pparts[0]+"="+Pparts[1];
                                if (Part.equals(Category)){

                                        PWords[k1][0]=Pparts[2];
                                        PWords[k1][1]=Pparts[3];
                                        System.out.println(PWords[k1][0]+"  "+PWords[k1][1]);
                                        l=Integer.parseInt(PWords[k1][1]);
                                        psum=psum+(l*l);
                                        k1++;
                                }
                        }

//Calculation of cosine function
len=Math.max(k,k1);
for(i=0;i<len && CWords[i][0]!=null;i++)
        {
                for(int j=0;j<len  && PWords[j][0]!=null;j++)
                        {
```

```
                              if(CWords[i][0].equals(PWords[j][0]) )
                                    {
                                     System.out.println(CWords[i][0]+" "+PWords[j][0]);
                                Integer x=Integer.parseInt(CWords[i][1])*Integer.parseInt(PWords[j][1]);
                                sum=sum+x;
                                System.out.println(sum);
                                CWords[i][1]=x.toString();
                                    }
                              }
                        }
                        System.out.println(sum);
                        score=sum/(Math.sqrt(psum)+Math.sqrt(csum));
                        System.out.println();
                        System.out.println("score!!!!!!!!!!!!!!!!!!!!!!!:"+score);
                        total = score;
}
                        catch(IOException e){
                              System.out.println("In Catch ContextTable");
                              e.printStackTrace();
}
                  return total;
            }
}
                  try{
                        BufferedReader br=new BufferedReader(new FileReader(Cfile));
                        for(int mn=0; mn<=5000 && (Ctext = br.readLine())!=null; mn++)
                        {
                              Cparts = Ctext.split("=");
                              r = "R"+Integer.toString(cnt);
                              if(r.equals(Cparts[0])){
                                if(Cparts[2].equals("POS"))
                                          sum=sum+Double.parseDouble(Cparts[3]);

                                else
                                          sum=sum-Double.parseDouble(Cparts[3]);

                              rank[cnt][0]=r;
                              rank[cnt][1]=Double.toString(sum);
}
                              else{
                                    cnt++;
                                    sum=Double.parseDouble(Cparts[3]);
                              }}
for(int i=1;i<50;i++){
for(int j=1;j<50;j++){
int x=Double.compare(Double.parseDouble(rank[i][1]), Double.parseDouble(rank[j][1]));
                                    if(x==1){
                                     temp=rank[i][0];
                                     rank[i][0]=rank[j][0];
                                      rank[j][0]=temp;
                                    }}}
                        FileWriter writer = new FileWriter(file);
                        for(int i=1;i<=50;i++){
                         System.out.println(rank[i][0]);
                         String write =rank[i][0];
                        writer.write(write+System.lineSeparator());
                        }
                        writer.flush();
                        writer.close(); }
                  catch(IOException e)
                  {
                        System.out.println("In Catch ContextTable");
                        e.printStackTrace();
                  }
            }
}
```