Automatic Identification of user goals in web search based on classification of click-through results

Thesis submitted for the Award of the Degree of

Masters of Technology in Computer Science and Engineering

by

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Certificate

This is to certify that the report entitled '**Automatic Identification of user goals in web search based on classification of click-through results**' submitted by Mr. **Amar Kumar Dani** to the Department of Computer Science & Engineering, Indian Institute of Technology, Kharagpur in partial fulfillment of the requirement for the degree of **Master of Technology** during the academic **year 2007-2008** is a record of authentic work carried by him under my supervision and guidance.

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Abstract

The Web is a huge resource for people who use search engines to search for specific pages related to their specific needs. As a result, search engines are continuously striving to improve their ranking algorithms to efficiently fulfill end users' search needs. While such algorithms are effective in handling large volumes of web documents and queries, an understanding of web queries remains quite primitive. In recent years, extensive study has been performed to characterize how users seek information on the web. Such studies focus on how users modify queries and what are the possible user goals in web search. This project is inspired by a study about identification of user goals in web search carried out by Broder which described how the goal behind a web query can be classified into three categories: Navigational searches are those which are intended to find a specific web site that the user has in mind; informational searches are intended to find information about a topic; transactional searches are intended to perform some web-mediated activity. The objective of this work is to first establish whether such a three way classification of user query is feasible and then to identify automatically if the user query has a predictable goal and if it does have a unique goal, what it really is. The results are very promising. The identification of user goals can ultimately be used to achieve efficient and effective ranking of search engine results. The approach to design a Search Engine based on user goals is also presented in the work.

Chapter 1

Introduction

Given the impact of search engines on the Web users' experience, improving the quality of search results has become the holy grail of search engine operators. As part of this endeavor, there has been a recent interest in identifying the “goal" of a user during a search, so that the identified goal can be used to improve page ranking as well as the presentation of the search results.

If we imagine seeing the world from the perspective of a search engine, our only view of user behavior would be the stream of queries users produce. Search engine designers often adopt this perspective, studying these query streams and trying to optimize the engines based on such factors as the length of a typical query. Yet this same perspective has prevented us from looking beyond the query, as to *why* the users are performing their searches in the first place.

The “why” of user search behavior is actually essential to satisfying the end user’s information need. After all, users don’t sit down at their computer and say to themselves, “I think I’ll do some searches.” Searching is merely a means to an end – a way to satisfy an underlying goal that the user is trying to achieve. By “underlying goal,” we mean how the user might answer the question “why are you performing that search?” That goal may be to gain information about some topic, to buy some gift from an online shop or to navigate to the homepage of some website.

What difference would it make if the search engine knew the user’s goal? At the very least, the engine might provide a user experience tailored toward that goal. For example, the display of relevant advertising might be welcome in a shopping context, but unwelcome in a research context. The underlying relevance-ranking algorithms that determine which results are presented to users might differ depending on the search goal. For example, if the user’s intentions are identified to be transactional, a results page representing transactional features could be ranked higher than an informational page which in case a results page representing informational goal would be ranked higher.

1.1 Classical Information Retrieval vs Web Information Retrieval

Classic IR (information retrieval) is inherently predicated on users searching for information, the so called "information need". But the need behind a web search is often not informational - it might be navigational (give me the url of the site I want to reach) or transactional (show me sites where I can perform a certain transaction, e.g. shop, download a file, or find a resource). A central tenet of classical information retrieval is that the user is driven by an information need. Schneiderman, Byrd, and Croft [1] define information need as "the perceived need for information that leads to someone using an information retrieval system in the first place." But the intent behind a web search is often not informational. In fact, informational queries constitute less than **50%** of web searches.

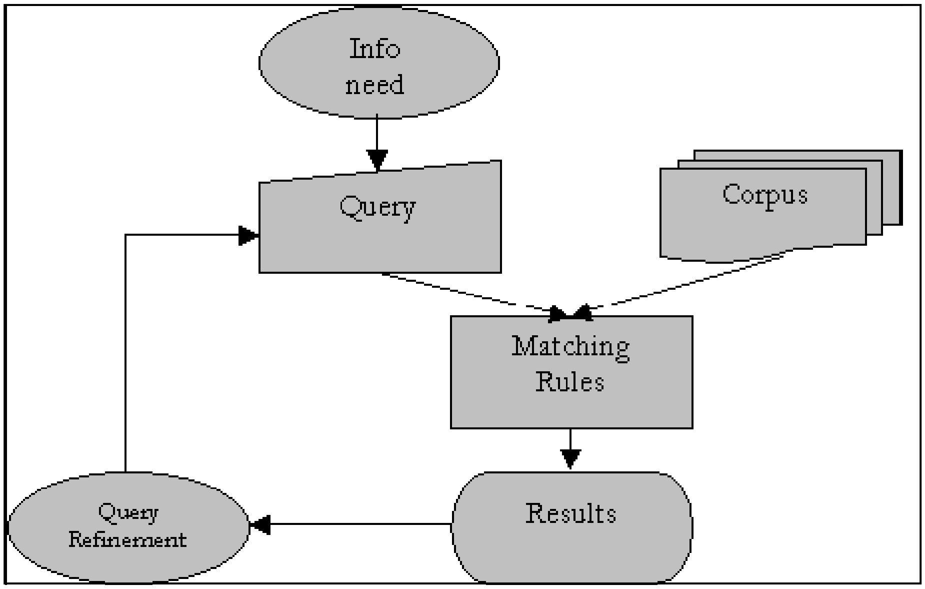


Figure 1: Classical Information Retrieval System

Figure 1 shows a classic IR system. Essentially, a user, driven by an information need, constructs a query in some query language. The query is submitted to a system that selects from a collection of documents (corpus), those documents that match the query as indicated by certain matching rules. A query refinement process might be used to create new queries and/or to refine the results or to provide the user with new reformulations of the query.

Since in the web context the human-computer interaction factors and the cognitive aspects play a significant role, it is useful to detail this model further as in Figure 2.

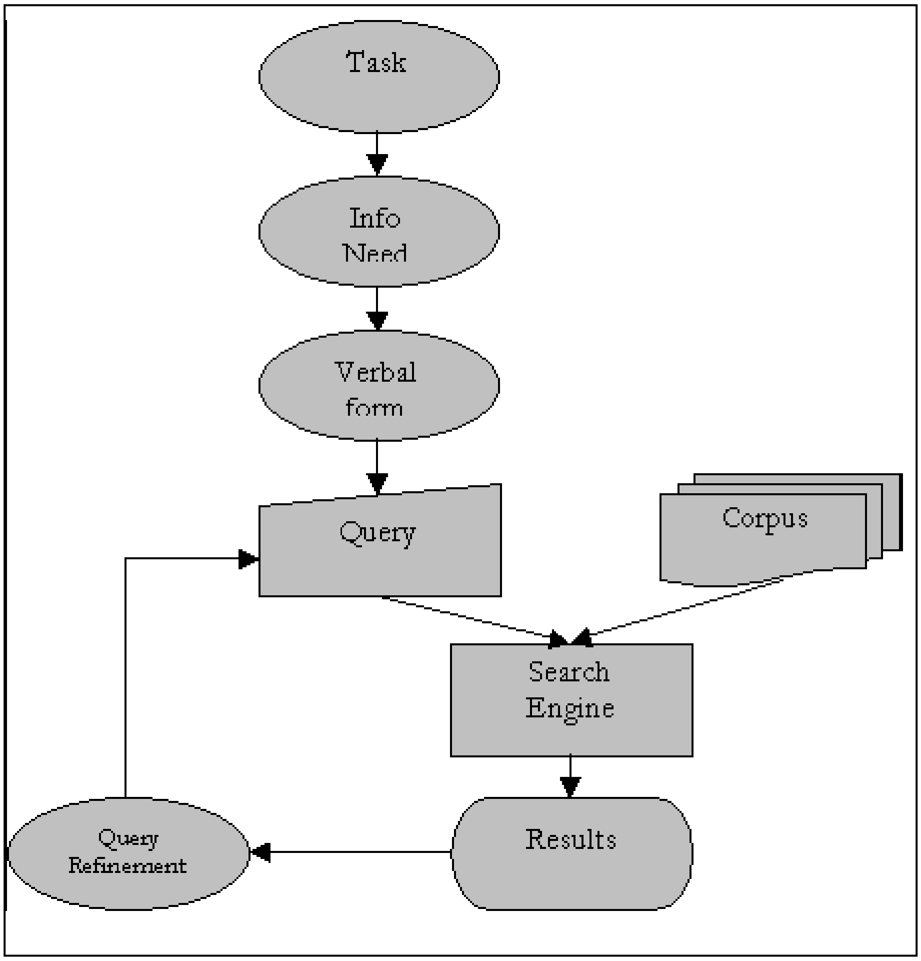


Figure 2: Web Information Retrieval System

Thus we recognize that the information need is associated with some task. This need is verbalized (usually mentally, not loud) and translated into a query posed to a search engine.

Results have confirmed that the common web search user differs significantly from the user model conceived by the traditional IR community. This is stated in the analysis carried out by Jansen and Pooch where the authors compare traditional IR with Web Searching and conclude that the "web is a unique searching environment that necessitates further and independent study". In a comparison between the two IR categories, Jansen and Pooch found out that while the mean length of a traditional IR query is between **6 and 9 terms**, the mean of a web search query is about **2 terms**. This "unique search environment" represents the recent interest in complex subject of understanding the user goals when submitting a query to a search engine. Web Search users tend to make use of short queries to represent their needs, implying that a search engine must make use of other features and algorithms that enhance the relevancy of the search results.

1.2 A taxonomy of web searches

In the web context the "need behind the query" is often not informational in nature. Broder [2] classified web queries according to their intent into 3 classes:

1. Navigational. The immediate intent is to reach a particular site.

2. Informational. The intent is to acquire some information assumed to be present on one or more web pages.

3. Transactional. The intent is to perform some web-mediated activity.

Navigational Queries

The purpose of such queries is to reach a particular site that the user has in mind, either because they visited it in the past or because they assume that such a site exists. Some examples are

- Greyhound Bus. Probable target http://www.greyhound.com

- compaq. Probable target: http://www.compaq.com.

- national car rental. Probable target http://www.nationalcar.com

- american airlines home. Probable target http://www.aa.com

- Google. Probable target http://google.com

- Yahoo. Probable target http://yahoo.com

This type of search is sometimes referred as "known item" search in classical IR. Navigational queries have usually only one "correct" result.

Informational Queries

The purpose of such queries is to find information assumed to be available on the web in a static form. No further interaction is predicted, except reading. By static form we mean that the target document is not created in response to the user query. Informational queries are closest to classic IR queries. What is different on the web is that many informational queries are extremely wide, for instance cars or San Francisco, while some are narrow, for instance normocytic anemia, Scoville heat units. Informational pages are characterized by lot of textual information which is meant to be read by the user. Examples: bird flu, kidney stones, pregnancy, etc.

Transactional Queries

The purpose of such queries is to reach a site where further interaction will happen. This interaction constitutes the transaction defining these queries. We define a transactional page as one where a user can perform some transaction where a transaction is constituted by being able to place an order for some product or to be able to download a file or get to the resource indicated by the query term. Examples:

- Resource finding: dictionary, thesaurus, myspace layouts, funny pictures
- Commercial Transaction: engagement rings, buy cars
- Download file: msn messenger, download Netscape browser

1.3 Literature Survey

Based on the taxonomy presented by Broder [2], Kang and Kim [5] proposed an automatic query goal identification scheme to distinguish between Navigational and Information queries. They divided a set of web WT10g into 2 sets, DBTopic and DBHome, and based on these sets they extracted features such as the distribution of terms in a query, the mutual information between the query terms, the usage rate of query terms as anchor texts and POS information. However, the authors concluded that there is a significant inadequacy in the proposed approach for classifying queries.

Lee et al. [6] built upon this work and substantiated the idea that the process of automatic query-goal identification is a feasible objective in Web IR. In an initial analysis following a human survey they demonstrate how more than half the queries have a predictable goal (the intention is not ambiguous) and that around 80% of those with an unpredictable goal are either software or person names. Their work also introduced two new features for automatic classification: click distribution and anchor link distribution which yielded an accuracy of 90% for query classification between navigational and informational query classes. Both features are modeled using statistical distributions from past user interaction based on the intuition that if a particular hyperlink shows authoritativeness in terms of a given query, the most probable intention is navigational.

Both Broder and Rose and Levinson [7] observe that the “need” behind considerable amount of queries is transactional. Kang proposes a scheme that serves transactional queries postulating that hyperlinks are a good indicator in classifying queries and collecting relevant pages for transactional queries. The author suggests that by observing the actions related to a hyperlink, cue expressions related to transactional queries can be extracted from tagged anchor texts and titles. These actions are determined by observing the link types of the hyperlinks extracted from relevant web documents.

A frequent occurrence of music, text, application and service link types suggest that the intention of the query is transactional. In a separate study, Li et al. [8] propose a mechanism for identifying transactional queries by building a transactional annotator from a corpus collected from the web that is capable of highly specific labeling of many distinct transaction types. The authors suggest that transactional features engineering, hand crafted regular expressions and an index of terms are suitable and robust for identifying transactional terms within a web document. The process relies on regular expressions that identify the existence of transactional patterns and a dictionary of negative patterns that evaluates the presence of any negative terms collected by the object identifier.

1.4 Motivation

Identifying the end user goal in web search can be utilized for improving the search engine results presentation in a big way. This has already been utilized in the Yahoo mindset search engine which estimates the commercial intent of the user and presents the results along with a metric estimating the commercial content of a web site. The user goals can be utilized to improve web search in the following ways:

Optimization of Relevance Ranking Algorithm

The user goal can be incorporated into the relevance ranking algorithm to reorder the ranking of search engine results. The most relevant result should be presented to the user as the first result such that the user does not have to scroll down to view the relevant result. If the end goal of the user is identified to be navigational, then only one result best matches with his goal whereas if the end goal is identified to be informational or transactional, other methods can then be employed to identify the most relevant page. These methods could include page rank algorithm used by Google or can also take the click-through results into consideration which indicates which pages have received considerable amount of clicks for a query. Further, for ambiguous queries for which the end goal cannot be determined uniquely, the top results can include top results from each class so that the goal of each user can be fulfilled.

Clustering of Search Engine results

The search engine results can be presented as clusters of informational, navigational or transactional with each cluster including the top pages for each class. The search engine clusty clusters the results into various classes but the clustering is unsupervised and not into known classes. Clustering the results into these three classes and then hierarchically into smaller clusters within each higher level class can lead to better organization of search engine results and meet the requirements of all users of search engine.

Display of Advertisements

The display of advertisements is relevant only if the end user has a transactional goal. Further the relevant advertisements can be determined in case of informational goal by identifying what informational is being sought by the user. For example, if the end user is seeking information on cars, ads relevant to cars can be displayed. In case of navigational queries, the display of ads becomes irrelevant. In this way, the search engine results page can be optimized.

Display of text snippets for search engine results

The display of text snippets can be targeted based on the end users goal. If the end users goal is navigational, the display of text snippet becomes irrelevant. Further for a particular site, a different snippet must be displayed for the case if the end goal is informational and a different snippet must be displayed if the end goal is transactional. For example, for the query ‘cars’, if the goal is identified to be informational, the most relevant information on the site related to cars must be displayed. But for the query ‘buy engagement rings’, the relevant text on the site would be the cost information and the specifications of engagement rings which should be displayed as the text snippet.

1.5 Objective

All the approaches to identification of user goals in web search mentioned above have not taken all the three classes of goals into consideration. Lee et al classifies the queries into navigational and informational whereas others provide features useful for navigational and transactional query classification. But, we have seen that most researchers agree on the existence of three fold user intent in web searches as proposed by Broader: navigational, informational and transactional. To be able to utilize any information regarding user intent, any search engine must be able to detect and distinguish between the three classes of user intention. Further, the query intention identification system must be able to clearly distinguish between the ambiguous queries for which the intention is not clearly identified and the unambiguous queries where the intention is clearly identified. This work focuses on automatically identifying whether the query has a predictable goal and if so, detect the goal of the query. We first try to establish that given the search query, is it feasible to classify a web page into navigational, informational or transactional. If this is possible with a high degree of accuracy, it is feasible to say that the end user goal can be classified into navigational, informational or transactional. After establishing this, we try to estimate whether the user query has a predictable goal, and if so what the goal actually is.

1.6 Experimental Setup and Approach

Our query intention classifier takes the past user click behavior into account to classify the intention of a query entered into a search engine. The click through data of a search engine consists of the query and the url of the result clicked at by the user who issued the query. The approach is based on the intuition that user's goal for a given query may be learned from how users in the past have interacted with the returned results for this query. To classify the intent of query, the click-through pages of the query are classified as navigational, informational or transactional page. Then the dominating class is identified to determine the class of the query. Figure 3 shows the various steps involved in the query classification process.

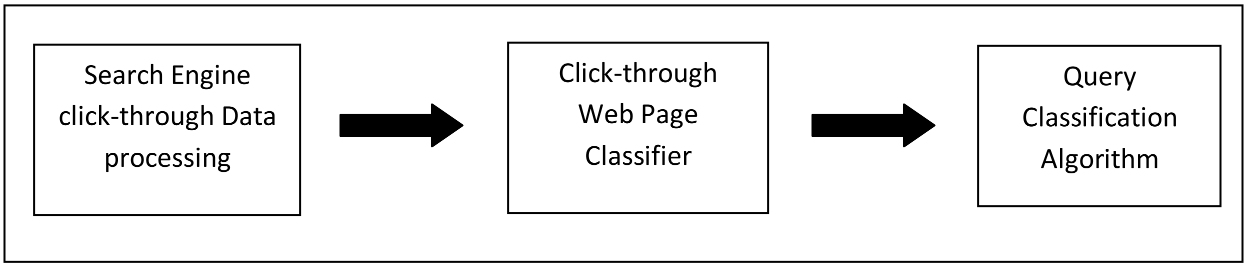

Search Engine click-through Data processing
Click-through Web Page Classifier
Query Classification Algorithm

Figure 3: Steps in Query Classification

The 1st step involves first getting the click-through data of search engine for experimental purposes and then to process it to sort the data in order of the number of clicks each query has received, extract the test set of queries, and expand the domain name of click-through via the Yahoo search API by simulating a virtual user.

The 2nd step involves building the three way web page classifier for classifying the click-through url into either navigational, transactional or informational. The corpus is first built by manually classifying a number of pages belonging to each class and then extracting several relevant features to distinguish between the classes, and finally identifying the appropriate machine learning algorithm to achieve the highest 10-fold cross validation accuracy.

The final step includes the query classification algorithm to classify the query into either ambiguous (if the query does not have a predictable goal) or classifying the query into one of the above mentioned classes. The results of automatic classification are then compared with the benchmark set of queries consisting of **65 queries** classified by a user survey involving **30** users.

Chapter 2

Search Engine Click-Through Data processing

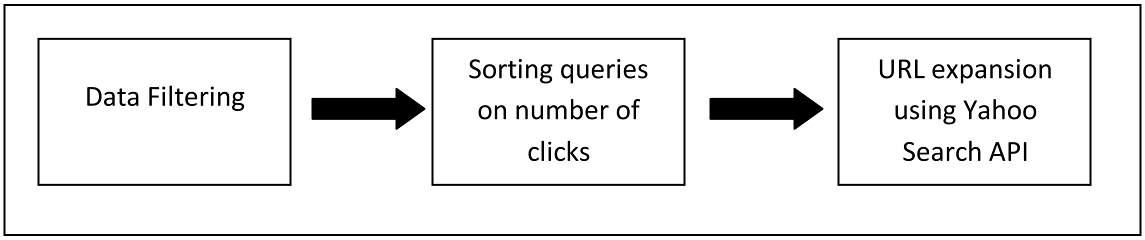
In order to build the classifier and to carry out the experiments, the click-through data of a search engine was to be obtained. AOL had released its log of search data to the public in August 2006 which has been used in our experiments. The data has to be preprocessed to extract the queries to be used in our experiments. In this chapter, the AOL data and the data processing steps are described.

2.1 AOL Search Engine click-through data

In order to manually classify the queries, we use the click-through data of AOL search engine. This data is taken from an AOL log of search data released to the public in August 2006. This includes around 36 million search queries from circa 658,000 of AOL's users taken from the period between March 01 2006 and May 31 2006. Each line of data includes an anonymous ID, the actual query, the date and time the query was submitted, the page rank and the domain portion of the URL as the click-through results. The query issued by the user is case shifted with most punctuation removed. The data represents one of two types of events. The first is a query that was not followed by the user. The other is a click-through URL returned by the search engine for that particular query.

2.2 Data processing

Figure 4 shows the various steps involved in processing the AOL search engine data before extracting the queries for classification experiments.



Data Filtering
Sorting queries on number of clicks
URL expansion using Yahoo Search API

Figure 4: Steps in Data Processing

Data Filtering

The AOL search engine data is filtered to remove extraneous information for the experiments. From the data, the required information is extracted. The data includes the id of the user issuing the query. For each query, if a query is issued by the same user at different times, it is taken to be a duplicate and counted to be one click. Such duplicates are removed for each query and then the total clicks for each query is summed up. The time stamp and the id of the user issuing the query are removed from the data as they are inconsequential in our experiment.

Data Sorting

After filtering the data, the data is stored in different files based on the different alphabets. The queries are then sorted based on the number of clicks received for each alphabet separately. So for each alphabet, we have a sorted list of queries based on the number of clicks received. From this list of sorted queries, the queries to be used for testing would be extracted. So now the data is in the following format:

```
mortgage calculator     http://realestate.yahoo.com 1   742
mortgage calculator     http://www.calculators4mortgages.com 3   742
mortgage calculator     http://www.mortgagecalc.com 3   742
mortgage calculator     http://www.fanniemae.com 4   742
mortgage calculator     http://www.interestratecalculator.com 1   742
mortgage calculator     http://www.bankrate.com 119   742
mortgage calculator     http://mortgage-calculators.org 1   742
mortgage calculator     http://mortgage-x.com 1   742
```

The first term denotes the query keyword, the second term the domain name of click-through, the third the number of clicks by different users for this url-query pair and the last term denotes the total number of clicks for this query.

URL expansion via Yahoo Search API

The AOL search engine click-through data includes only the domain name of click-through url. But for our experimentation purposes, we needed the exact url of the click-through. To facilitate this, we used the Yahoo search engine API to simulate a virtual user firing the queries into Yahoo search engine. The AOL search engine data is of the year 2006. Hence after that many of the sites have become extinct. Search is done using the Yahoo API and the keyword fired for searching includes the query along with the domain name of the click-through. The top 50 results are extracted and the first url whose domain matches with the domain of the click-through is taken to be the expanded url for the given query-click through pair.

Using the AOL data and using the Yahoo search engine for expansion is not detrimental for our experiment since it is like simulating a virtual user firing the queries. For several queries, it was manually observed that the ordering of results for the query domain pair for the AOL search engine was similar to that of the Yahoo search engine. Hence it can be assumed that the user who fired this query and visited a particular site, would have visited this particular page of the site. So the url obtained by url expansion would actually be similar to the url that the user might have actually clicked.

After expansion, the data is in the following format. Some urls that do not match with any of the results returned by the Yahoo API are denoted by DNM (did not match).

```
mortgage calculator     http://realestate.yahoo.com/calculators/payment.html  1  742
mortgage calculator     http://www.calculators4mortgages.com/  3  742
mortgage calculator     http://www.mortgagecalc.com/  3  742
mortgage calculator     http://www.fanniemae.com/homebuyers/homepath/index.jhtml  4  742
mortgage calculator     DNM  1  742
mortgage calculator     http://www.bankrate.com/brm/mortgage-calculator.asp  119  742
```

Chapter 3

Questionnaire Design and User Survey

In this chapter, we present the description of our human subject study, in which we try to (1) evaluate how many queries have clearly predictable goals and (2) build a benchmark query set against which we can evaluate our automatic identification mechanisms. Our benchmark set consists of **65 queries** selected carefully from the AOL search engine click-through data. To study whether the goals of these queries are predictable regardless of individual users, **30** graduate students were asked to indicate their most probable goal if they issued each query.

3.1 Selection of queries for manual classification

For creating the benchmark set of queries for testing the results of automatic classification, queries with sufficient number of clicks are selected from each of the alphabet sets. 300 is taken to be the threshold for defining sufficient number of clicks. It is difficult to determine what threshold to select for defining sufficient number of clicks. It can be selected by manually classifying a set of queries and then comparing with the automated classification results and comparing with the manual set till the set appears to be matching. But to get such an incremental data for a set of queries, one would need real time access to the click-through data of a search engine which was not feasible in this project. Hence, we take a decent estimate of 300 which gives good results.

After creating a set of queries having a decent number of clicks, the final set of queries for the questionnaire are selected. For the queries we have 6 classes for classification: navigational, informational, transactional and ambiguous with ambiguity of 3 forms: navigational/informational, navigational/transactional and transactional/informational. Our proposed algorithm should be able to distinguish automatically between ambiguous and non ambiguous queries and should be able to detect the type of ambiguity of the query if the query is ambiguous. So ideally, the test set of queries chosen should have representation across all the classes. But it is not possible to identify ambiguous queries across all the ambiguity classes because it is very subjective. So we try to take equal number of queries which seemed to belong to informational/navigational/transactional classes and a few queries that seemed to be ambiguous. The query set included software names and names of people which was reported to be ambiguous by an early study by Lee, Liu and Cho.

3.2 Questionnaire Design

A good design of the survey questionnaire is crucial in collecting reliable results from our user study. In the following, we describe the exact questions that we used in our survey and how our questionnaire has been refined to our final form through multiple revisions. In our initial design stage, we first evaluated whether it is appropriate to directly use the navigational-informational-transactional taxonomy in our questionnaire. For this purpose, we interacted with two participants, first educating them with the taxonomy, and then asking them to classify the 65 queries as either navigational or informational or transactional. Afterwards we interviewed each of them to gather descriptive intentions for some representative queries, and further compared such descriptive intentions with the final navigational/informational/transactional choices. From this comparison we realized that even if two participants had exactly the same descriptive intention, they might end up casting that intention into different navigational-informational-transactional choices.

This confusion was mainly due to the two potential criteria that they could use to classify the user goal. For example, a user might search a person's name in order to reach not only that person's homepage, but also some other related sites, such as news articles about the person. In this scenario, the people who used the first criterion (do you have a particular webpage in mind?) classifed the intention as navigational, because they perceived a particular Webpage (the person's homepage) and reaching that page was part of the goal. On the other hand, the people who used the second criterion (do you intend to visit multiple pages?) classified it as informational because their goal was to gather information from multiple sites including the person's homepage.

Realizing this potential ambiguity and the randomness in the user classification, we decided to ask our subjects to indicate their descriptive intentions directly. Based on their descriptive intentions, we then classify the goal of the queries ourselves. In particular, we decided to present the following three choices to our participants:

Choice 1: You already have a website in your mind (one particular website only) and your intention is to reach that website with the help of the search engine

Choice 2: Your aim is to obtain information on the “query term”

Choice 3: Your aim is to **buy** / **download** or **obtain** the resource implied by the “query term”

The users are also provided a few sample classifications so that they can get a feel of how to classify the given queries. The sample classifications have no relation with the 65 given queries and would create no bias in the end user classification. The sample classified queries given are:

1. Lycos : 1
2. Hair styles : 2
3. Funny videos : 3
4. Myspace backgrounds : 3
5. Guitar Tabs : 2
6. New York Lottery : 1

Note that under both the choices, Choice 1 is clearly navigational because the user intends to visit a single website that he has in mind. Similarly, Choice 2 is clearly informational because the user intends to explore multiple websites and no website is pre-assumed to be the single correct answer and the user is interested in getting information on the query term. Similarly, choice 3 is clearly transactional because the user is interested in undertaking some web-mediated transaction.

3.3 Manual Classification Results

After collecting the survey results from 30 users, the queries are classified into the 6 classes based on the belongingness value of the query in each of the classes navigational/transactional/informational. For each query q, values i(q), n(q) and t(q) are defined which denote the percentage of candidates who have indicated the goal of the query to be informational or navigational or transactional respectively. If the difference between the maximum belongingness value and the 2nd maximum belongingness value is greater than .2, then the query is said to have a predictable goal else the query is said to have belongingness in both the classes. The following tables give the belongingness values of the manually classified queries.

Navigational Queries

Query	N(q)	I(q)	T(q)
Hotmail	1.00	0.00	0.00
Google	1.00	0.00	0.00
Espn	1.00	0.00	0.00
Imdb	0.90	0.10	0.00
Honda	0.67	0.23	0.10
Yahoo	1.00	0.00	0.00
Ask	0.80	0.20	0.00
Amazon	0.83	0.00	0.17
Thesaurus	0.67	0.10	0.23
Suzuki	0.67	0.13	0.20
Microsoft	0.80	0.20	0.00
Encyclopedia	0.70	0.07	0.23
Dell	0.77	0.00	0.23
Pogo games	0.70	0.00	0.30
Ebay	0.90	0.00	0.10

Table 1: Manual classification results for Navigational Queries

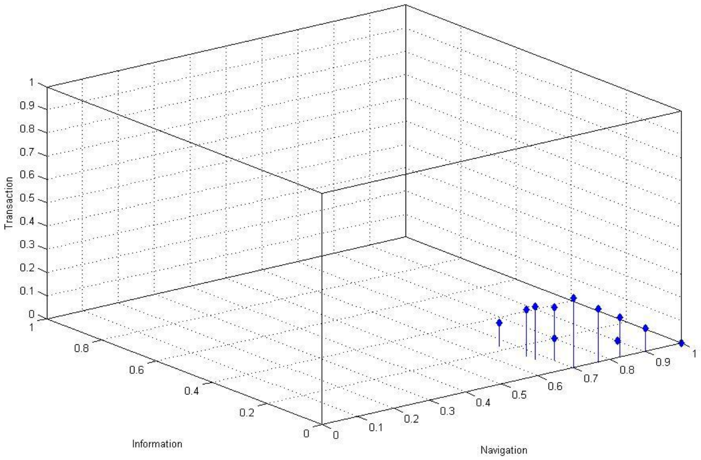


Figure 5: Distribution of navigational queries

Transactional Queries

Query	N(q)	I(q)	T(q)
Mortgage Calculator	0.00	0.20	0.80
Myspace Layouts	0.00	0.23	0.77
Tattoos	0.00	0.33	0.67
Cigarettes	0.00	0.23	0.77
Funny Pictures	0.00	0.20	0.80
Free music downloads	0.00	0.23	0.77
Msn messenger	0.00	0.20	0.80
Free ringtones	0.00	0.03	0.97
Download	0.27	0.00	0.73
Ipod	0.03	0.20	0.77
Screensavers	0.00	0.03	0.97
Netscape	0.23	0.07	0.70

Deal or no deal	0.24	0.13	0.63
Shoes	0.00	0.20	0.80
Airsoft guns	0.00	0.27	0.73
Aol media player	0.13	0.03	0.84
Itunes	0.17	0.07	0.76
Internet explorer	0.20	0.03	0.77
Sudoku	0.07	0.13	0.80

Table 2: Manual classification results for Transactional Queries

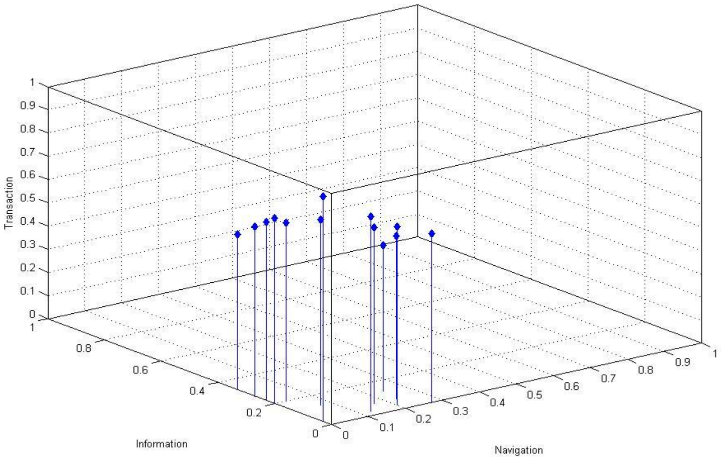


Figure 6: Distribution of transactional queries

Informational Queries

Query	N(q)	I(q)	T(q)
Kidney stones	0.00	1.00	0.00
Bird flu	0.10	0.90	0.00
Employment	0.00	1.00	0.00
Motorcycles	0.00	0.73	0.27
Html	0.00	1.00	0.00

Pregnancy	0.00	1.00	0.00
Snakes	0.00	1.00	0.00
Optical illusions	0.00	0.90	0.10
Exe	0.00	0.73	0.27
Guns	0.00	0.63	0.37
Florida lottery	0.23	0.63	0.14
Airline tickets	0.00	0.63	0.37
Anna benson	0.13	0.6	0.27
Jessica simpson	0.07	0.63	0.30
Paris Hilton	0.10	0.63	0.27
Baby names	0.00	0.70	0.30
Jessica alba	0.03	0.70	0.27
Kelly blue book	0.00	0.63	0.37
Recipes	0.00	0.70	0.30

Table 3: Manual classification results for Informational Queries

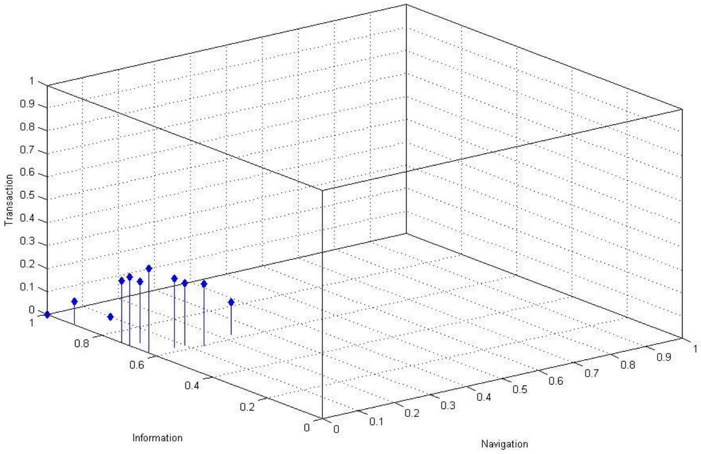


Figure 7: Distribution of informational queries

Informational-Transactional Queries

Query	N(q)	I(q)	T(q)
Furniture	0.00	0.43	0.57
Online games	0.03	0.40	0.57
Costa rica	0.13	0.40	0.47
Britney spears	0.07	0.50	0.43
Shakira	0.13	0.47	0.40
Kelly Clarkson	0.10	0.43	0.47
Reverse lookup	0.00	0.60	0.40
David blaine	0.07	0.50	0.43
Movies	0.13	0.40	0.47
Cars	0.00	0.57	0.43

Table 4: Manual classification results for Informational-Transactional Queries

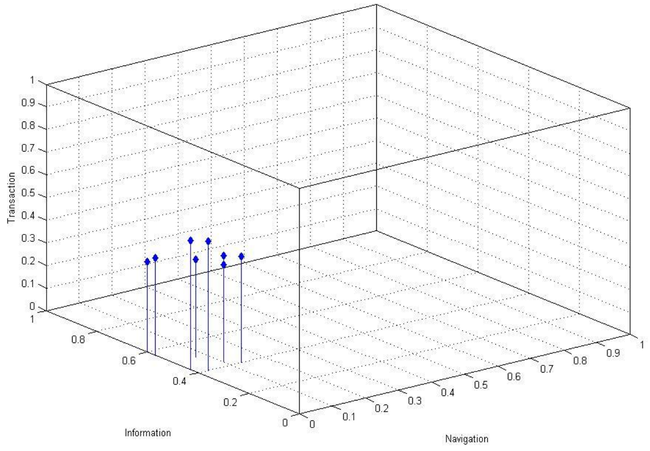


Figure 8: Distribution of informational-transactional queries

Informational-Navigational Queries

Query	N(q)	I(q)	T(q)
Harry Potter	0.43	0.37	0.20

Table 5: Manual classification results for Informational-Navigational Queries

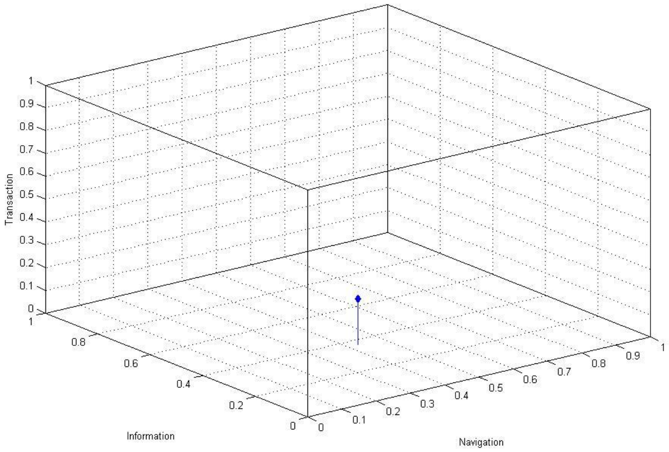


Figure 9: Distribution of informational-navigational queries

Transactional-Navigational Queries

Query	N(q)	I(q)	T(q)
Bible	0.40	0.10	0.50

Table 6: Manual classification results for Transactional-Navigational Queries

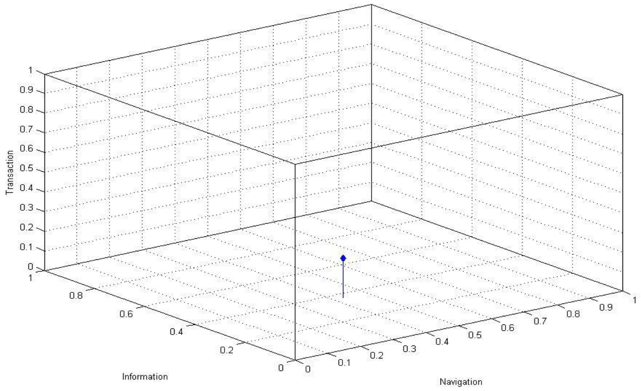


Figure 10: Distribution of navigational-transactional queries

Chapter 4

Web Page Classification

We build a web page classifier which classifies the web page into three classes: navigational, informational and transactional. Features are defined for classifying a web page as navigational or informational or transactional. The web page classifier is the central concept in our query classification algorithm. The features defining a page to be transaction/informational/navigational would ultimately identify a query to be navigational or transactional or informational. Navigational pages are the home pages of web sites and if a person has a navigational intent, he would visit the home page of the web site. So, it is relatively easy to identify whether the visited page is navigational or not. The key to the classification is identifying the features defining transactional and informational pages. The features can be altered based on the final aim of the search engine.

There are two approaches to define transactional/informational pages. One is to define the possible transactions possible like resource finding / download / commercial transactions and then identify the features for each of the type of pages. We observed that if the goal of a user is transactional, he might also visit several navigational pages of sites offering those services. For example for the query dictionary, there were several navigational pages, i.e. home pages of sites which the end user visited. Classifying these pages into transactional would be very difficult and would lead to reduction of accuracy. Hence, to handle such cases the final query classification algorithm was modified.

Another approach which we have also adopted is to define informational pages and transactional pages by the style of presentation. Informational pages have lots of textual material to be read and the amount of text per paragraph also dominates. Further, on a transactional page, the amount of different HTML elements like tables, images, download buttons, etc dominate. We have combined the two approaches to include both transaction identifying features via the bag of words features and identified the HTML elements via HTML features.

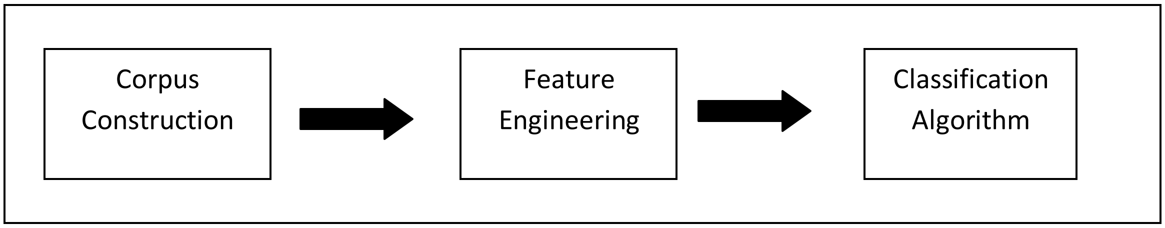


Figure 11: Steps in Web Page Classification

4.1 Class description

The classifier classifies the pages into three classes navigational / informational / transactional each of which are defined by several features identified and extracted from the HTML page, url and query keyword of the query-url pair.

Navigational Class

Navigational pages are the home pages of web sites and if a person has a navigational intent, he would visit the home page of the web site. So, it is relatively easy to identify whether the visited page is navigational or not. It is possible that a person having a transactional goal visits several home pages of different sites. In such a case, it might not be feasible to denote the home page of the site to be navigational. But, classifying the home page of a site as a transactional page when it bears similarity with a navigational page would lead to reduction of accuracy of our classifier. Hence, to overcome such a scenario, the query classification algorithm is altered rather than reduction in accuracy of the classifier. A person having an informational goal is very unlikely to visit the home page of a particular site which is also observed from the AOL search engine click-through data.

Navigational pages also have a very high number of clicks because if the goal of a query is navigational, many people would visit the same site but if the goal is informational or transactional, users would visit different informational/transactional pages because of which the clicks would get distributed. Hence other home pages which do not have a high ratio of clicks relative to the total number of clicks for the query tend to be more transactional in nature. These home pages are classified as navigational pages but the end query classification algorithm is modified to take this into consideration.

Informational Class

The informational class includes pages which contain lots of textual material to be read up. The informative pages are generally not the home pages of sites and have a high url depth. Further, it can be observed that the query keyword occurs more frequently in the latter part of the url not including the domain name. This is also true for the transactional urls but for navigational pages, the query term frequently is the domain name of the web site or it occurs frequently in the domain name of the url. The fact that textual material dominates on informational pages according to our definition, lexical features become essential in distinguishing these pages from the transactional pages which have more of HTML elements dominating relative to the textual material. Lexical features include the count of number of paragraphs, total number of characters occurring in the text, average text length in the paragraphs, etc.

Transactional Class

We define a transactional page as a web page that a user visits to either carry out a commercial transaction or to download something or to find some online resource. Like the informative pages, the transactional pages are generally not the home pages of sites and have a high url depth. Further, it can be observed that the query keyword occurs more frequently in the latter part of the url not including the domain name.

To distinguish the pages defining commercial transaction, we can observe that these pages have very little textual material and common commercial terminology is used like ‘product specification’, ‘hot product’, ‘buy’, ‘sell’, etc. Further these pages have lots of specifications of the product which are also present on the download pages where the software specifications are specified. Hence the bag of words features becomes useful in identifying these pages. For the pages consisting of online resources like dictionary, thesaurus, myspace layouts etc. there are no standard features identifiable other than the fact that more of HTML elements like images, tables, divs dominate on such pages than the textual elements. This is also true for other transactional pages including commercial transaction pages and download pages. Hence, the basic features used for distinguishing transactional pages from informational pages include the lexical features defining the amount of textual material on the HTML page and the HTML features defining the amount of HTML elements relative to the textual material.

4.2 Corpus construction

The corpus consists of the pages of each of the classes used to train the classifier. A good corpus is essential for a good classifier and must encompass all types of pages defining a particular class. The pages for different classes to be used for training are chosen from the AOL search engine click-through expanded urls so that the pages would be representative of the pages that would have to be classified to predict the type of the query.

A total of **322 instances** were manually classified for training the three-fold classifier with **127 navigational** pages, **92 informational** pages and **103 transactional** pages. It was relatively easy to identify navigational pages as the home pages of web sites. The confusion was with classifying a page into transactional or informational page. Initially the corpus was built taking the first approach into consideration where we tried to define the possible transactions possible like resource finding / download / commercial transactions and then identify the features for each of the type of pages. Other pages were classified as informational pages. We saw that it was difficult to identify resource finding pages. Hence we resorted to the second approach whereby the pages which had sufficient textual material as information would be classified as informational pages whereas pages with more transactional features as defined above would be classified as transactional pages.

4.3 Feature Engineering

A total of **152 features** are extracted from the HTML pages by writing a parser of the HTML page and extracting features including HTML, url based features and bag of words features. Then, feature selection algorithm was run to extract the important features. The supervised attribute selection algorithm resulted in **12 best features** whose importance for each class and description is given in the next chapter.

Figure 6 shows the various steps involved in feature extraction from the web page and the url, query keyword and number of clicks given as input to the Html parser and feature extractor written in Python. The various features extracted include the url features, html features and lexical features which are described below. In many cases the Html page is corrupt and has to be cleaned. This is done using the Html tidy software which cleans the html markup wherever possible. After this various features are extracted and written in an arff file which is taken as input file into the weka software which is used to run several classification algorithms.

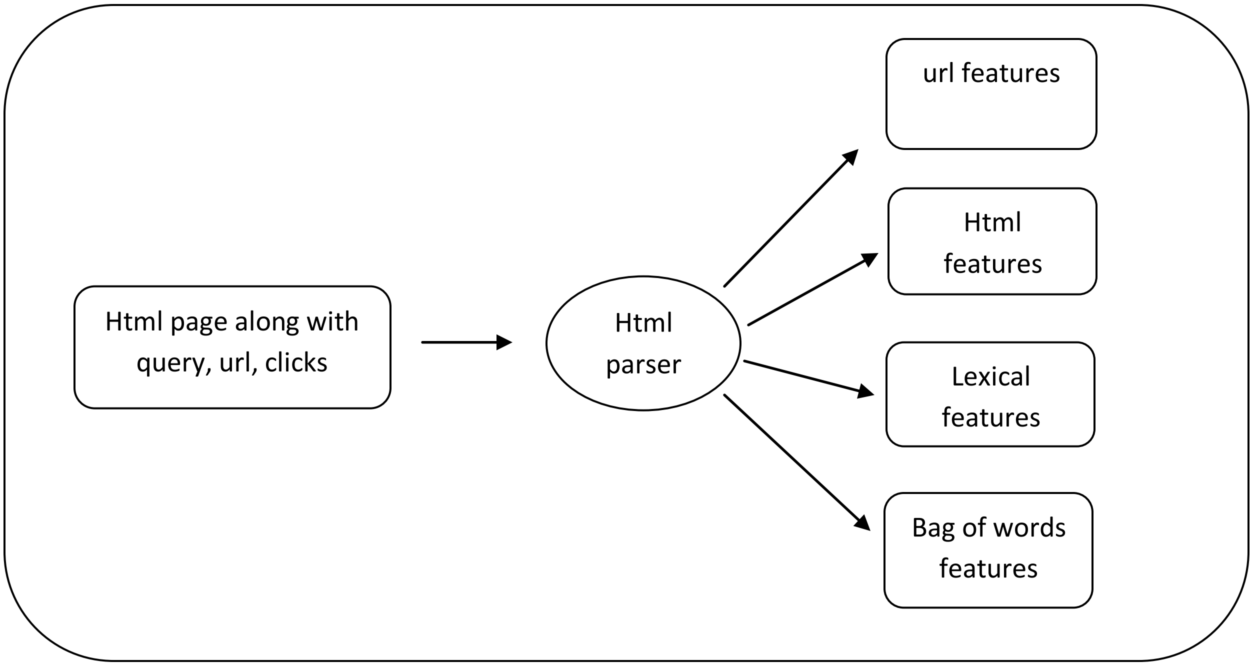


Figure 12: Steps in feature extraction from web page

Url Features

The navigational pages are generally the homepages of web sites and hence have a less depth than other pages of either transactional or navigational pages. The url features used are:

1. url depth
2. length_url
3. Occurrence of query keyword in the domain name
4. Occurrence of query keyword in the latter part of the url
5. Ratio of clicks received for this url to total number of clicks received for the query

HTML Features

The HTML page corresponding to the url is downloaded and saved. The HTML page is parsed and the Title text, anchor text, headings, paragraphs, special texts are stored in different data structures. Several features are used including the frequency and ratio of commonly occurring tags like img, anchor, input boxes, inner hyperlinks(hyperlinks pointing to the same domain), outer hyperlinks(hyperlinks pointing to other domains), table, div, list, form and other commonly occurring html tags.

Lexical Features

The lexical features are based on the fact that for different classes, the lexical features might have distinctive values. The lexical features are specially helpful in distinguishing between the transactional and informational pages. The lexical features used are:

1. chars_per_word
2. sentences_per_p
3. words_per_p
4. sentencess_per_p
5. length_text
6. no_of_words
7. no_of_sentences

Bag of Words Features

This feature is based on the fact that some words are common for specific classes. Occurrence of these words is characteristic for the particular class. These words are selected by manually going through the various pages for the classes. Further the words are weighted differently by its occurrence in meta text, title text, headings, special text, anchor text, alternate text and input text. The bag of words features can be used to identify navigational pages and transactional pages but not informational pages since one cannot identify commonly occurring keywords for all domains of information.

The keywords used in the bag of words feature set include: 'basket', 'buy', 'cart', 'catalogue', 'checkout', 'cost', 'delivery', 'offer', 'order', 'pay', 'price', 'purchase', 'rebate', 'save', 'sell', 'trolley', 'story', 'store', 'shop', 'shipping', 'homepage', 'corporate', 'welcome', 'our', 'my', 'company', 'business', 'products', 'services', 'cost', 'purchase', 'shopping', 'cart', 'now', 'delivery', 'item', 'sale', 'quantity', 'specification', 'dollar', 'customer', 'availability', 'download', 'home page’, ‘products & services', 'online store', 'hot product', 'add to cart', 'shopping cart', 'order now', 'buy now', 'item number', 'product features', 'product details', 'product description', 'product review', 'list price', 'sale price', 'sold out', and 'download now'.

From the above set we see that most of the keywords are to identify the transactional pages whereas a few are to identify navigational pages which include 'homepage', 'corporate', 'welcome', 'our', 'my', 'company', 'business', 'products', and 'services'.

Feature selection Algorithm

After extracting the features and storing the features in an arff file format, the file is opened using the weka tool. The weka tool allows applying several feature selection algorithms which selects the best few features out of the given set of features. This helps to eliminate the features which are not required and selecting the best set of features at the same time. **CFS** (Correlation-based Feature Selection) algorithm is applied to select a subset of correlated features for our classifier. The CFS algorithm is based on the hypothesis that a good feature subset is one that contains features highly correlated with (predictive of) the class, yet uncorrelated with (not predictive of) each other.

Applying the CFS feature selection algorithm, we get the following 12 best features:

1. ratio_outer_hyperlinks
2. url_depth
3. length_url
4. no_query_first
5. no_query_others
6. ratio_hits
7. length_text
8. no_title
9. no_cost
10. no_rebate
11. no_homepage
12. no_hot_product

4.4 Classification Algorithm and Classification Results

Several classification algorithms including NaiveBayes, J48, Random Forest, SMO and RandomCommittee Meta classifier were experimented with after running the feature selection algorithm. We report the 10 fold cross validation accuracy which is a standard metric used to evaluate the learned classifier. In a 10 fold cross validation evaluation scheme, the training data is divided into 10 sets. The classification model is learned from the first 9 sets and is tested on the 10th set. The process is repeated for all the 10 sets learning on 9 sets and testing on the 10th set. We report the confusion matrix across the three classes and 10 fold cross validation accuracy achieved using all the classification algorithms. We achieve the highest accuracy using the RandomCommitte meta classifier which is finally used to classify the web pages corresponding to the queries used in our experiment.

Naïve Bayes Algorithm

A naive Bayes classifier is a simple probabilistic classifier based on applying Bayes theorem with strong (naive) independence assumptions among the features. Abstractly, the probability model for a classifier is a conditional model given by equation

$$p(C|F_1,\dots,F_n) \text{.......................} (1)$$

over a dependent class variable C with a small number of outcomes or classes, conditional on several feature variables F1 through Fn. Using Bayes theorem, we can write

$$p(C|F_1,\dots,F_n) = \frac{p(C)\ p(F_1,\dots,F_n|C)}{p(F_1,\dots,F_n)}. \text{.......................} (2)$$

The numerator is equivalent to the joint probability model

$$p(C,F_1,\dots,F_n) \text{.......................} (3)$$

Now the "naive" conditional independence assumptions come into play: assume that each feature Fi is conditionally independent of every other feature Fj for j not equal to i. This means that

$$p(F_i|C,F_j) = p(F_i|C) \text{.......................} (4)$$

This means that under the above independence assumptions, the conditional distribution over the class variable C can be expressed like this:

$$p(C|F_1,\dots,F_n) = \frac{1}{Z} p(C) \prod_{i=1}^{n} p(F_i|C) \text{.......................} (5)$$

where Z is a scaling factor dependent only on F1,…,Fn i.e., a constant if the values of the feature variables are known.

Applying the Naïve Bayes algorithm for our data set using the Weka took, we achieve **87.8%** 10 fold cross validation accuracy.

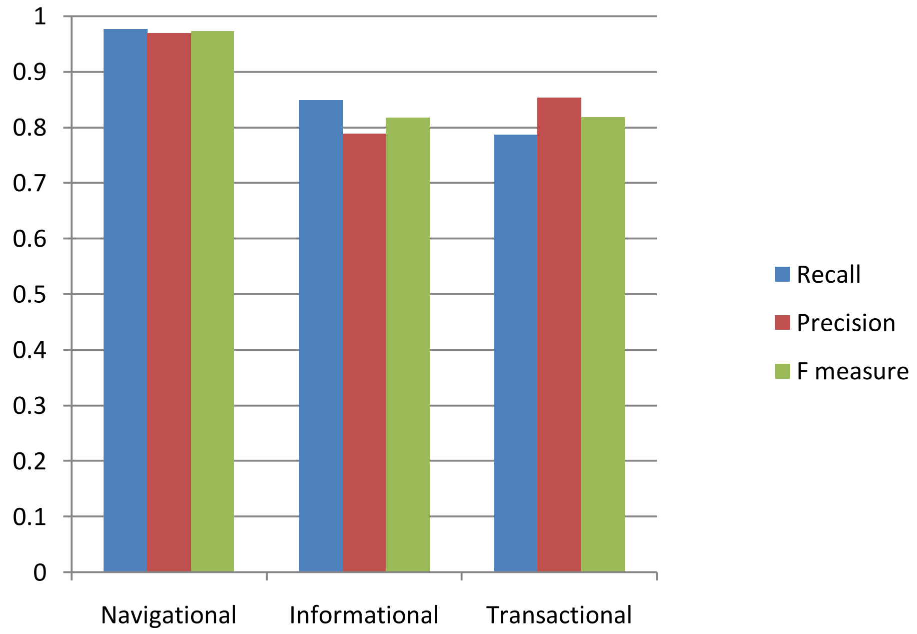


Figure 13: Classification accuracy across classes using Naïve Bayes Algorithm

Navigational	Informational	Transactional	← Classified as
124	1	2	Navigational
2	**78**	12	Informational
2	20	**81**	Transactional

Table 7: Confusion Matrix for classifier using Naïve Bayes Algorithm

J48 Algorithm

Applying the J48 algorithm, which is a standard decision tree algorithm for classification, for our data set using the Weka tool, we achieve **87.8%** 10 fold cross validation accuracy.

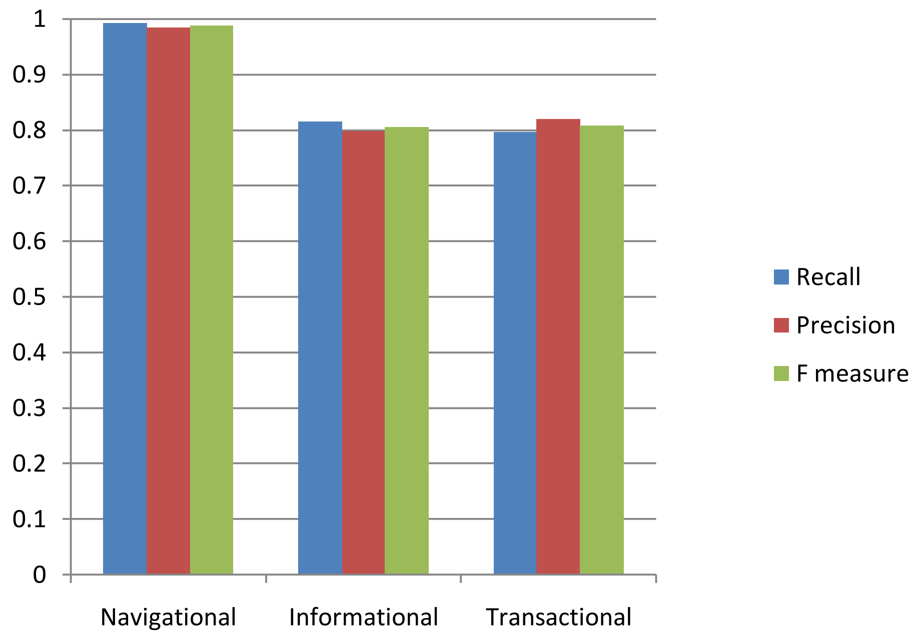


Figure14: Classification accuracy across classes using J48 Algorithm

Navigational	Informational	Transactional	← Classified as
126	0	1	Navigational
0	**75**	17	Informational
2	19	**82**	Transactional

Table 8: Confusion Matrix for classifier using J48 Algorithm

Random Forest Algorithm

In machine learning, a random forest is a classifier that consists of many decision trees and outputs the class that is the mode of the classes output by individual trees. Each tree is constructed using the following algorithm:

1. Let the number of training cases be N, and the number of variables in the classifier be M.
2. We are told the number m of input variables to be used to determine the decision at a node of the tree; m should be much less than M.
3. Choose a training set for this tree by choosing N times with replacement from all N available training cases (i.e. take a bootstrap sample). Use the rest of the cases to estimate the error of the tree, by predicting their classes.
4. For each node of the tree, randomly choose m variables on which to base the decision at that node. Calculate the best split based on these m variables in the training set.
5. Each tree is fully grown and not pruned (as may be done in constructing a normal tree classifier).

Applying the Random Forest algorithm for our data set using the Weka took, we achieve **90.0621%** 10 fold cross validation accuracy.

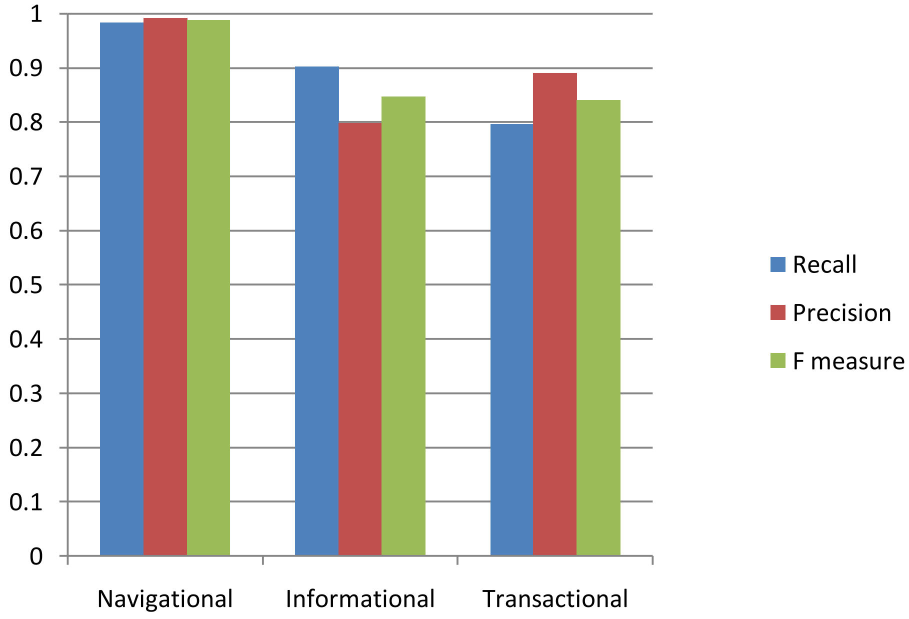


Figure 15: Classification accuracy across classes using Random Forest Algorithm

Navigational	Informational	Transactional	← Classified as
125	1	1	Navigational
0	**83**	9	Informational
1	20	**82**	Transactional

Table 9: Confusion Matrix for classifier using Random Forest Algorithm

SMO Algorithm

Sequential Minimal Optimization (or SMO) is a fast method to train Support Vector Machines (SVMs). Support vector machines (SVMs) belong to a family of generalized linear classifiers. Viewing the input data as two sets of vectors in an n-dimensional space, an SVM will construct a separating hyperplane in that space, one which maximizes the "margin" between the two data sets. We are given some training data, a set of points of the form

$$\{(\mathbf{x}_1, c_1), (\mathbf{x}_2, c_2), \ldots, (\mathbf{x}_n, c_n)\}$$

where the ci is either 1 or −1, indicating the class to which the point xi belongs. Any hyperplane can be written as the set of points x satisfying

$$\mathbf{w} \cdot \mathbf{x} - b = 0.$$

The vector w is a normal vector: it is perpendicular to the hyperplane. The parameter b determines the offset of the hyperplane from the origin along the normal vector w. We want to choose the w and b to maximize the margin, or distance between the parallel hyperplanes that are as far apart as possible while still separating the data. These hyperplanes can be described by the equations

$$\mathbf{w} \cdot \mathbf{x} - b = -1.$$

$$\mathbf{w}\cdot\mathbf{x}-b=1$$

As we also have to prevent data points falling into the margin, we add the following constraint: for each i either

$$\mathbf{w}\cdot\mathbf{x}_i-b\geq 1$$

for the first class and

$$\mathbf{w}\cdot\mathbf{x}_i-b\leq -1$$

for the second class. This can be stated as the following optimization problem:

chose w,b to minimize $|\mathbf{w}|$ subject to

$$c_i(\mathbf{w}\cdot\mathbf{x_i}-b)\geq 1,\quad \text{for all } 1\leq i\leq n \text{........................} \ (6)$$

Hence, the SVM classifier reduces the classification problem to an optimization problem. Applying the Random Forest algorithm for our data set using the Weka took, we achieve **84.7826%** 10 fold cross validation accuracy.

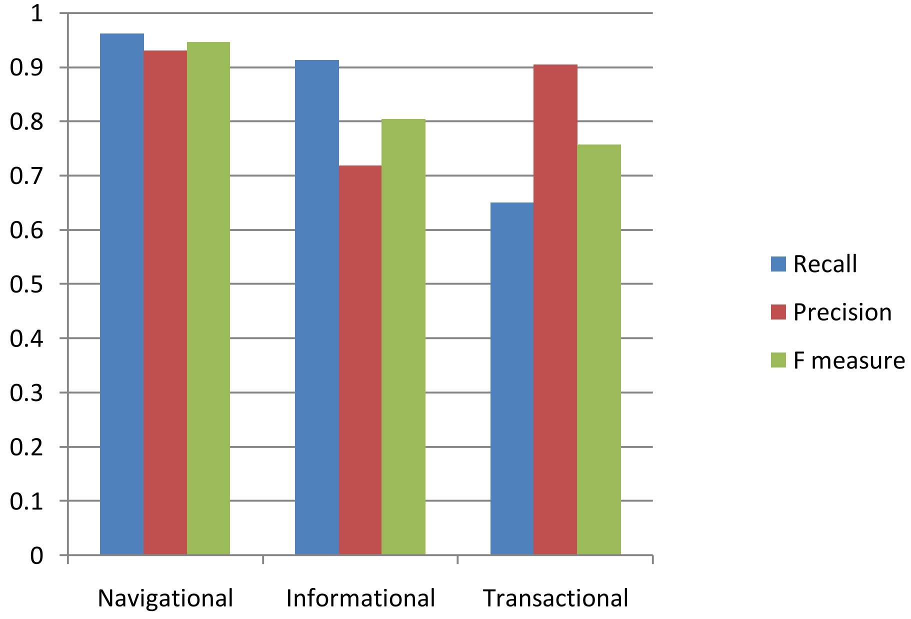


Figure 16: Classification accuracy across classes using Random Forest Algorithm

Navigational	Informational	Transactional	← Classified as
122	5	0	Navigational
1	**84**	7	Informational
8	28	**67**	Transactional

Table 10: Confusion Matrix for classifier using SMO Algorithm

RandomCommitte Algorithm

The RandomCommittee is an ensemble classifier which uses Random Tree classifier as individual classifiers. Applying the RandomCommittee algorithm for our data set using the Weka took, we achieve **91.3043%** 10 fold cross validation accuracy.

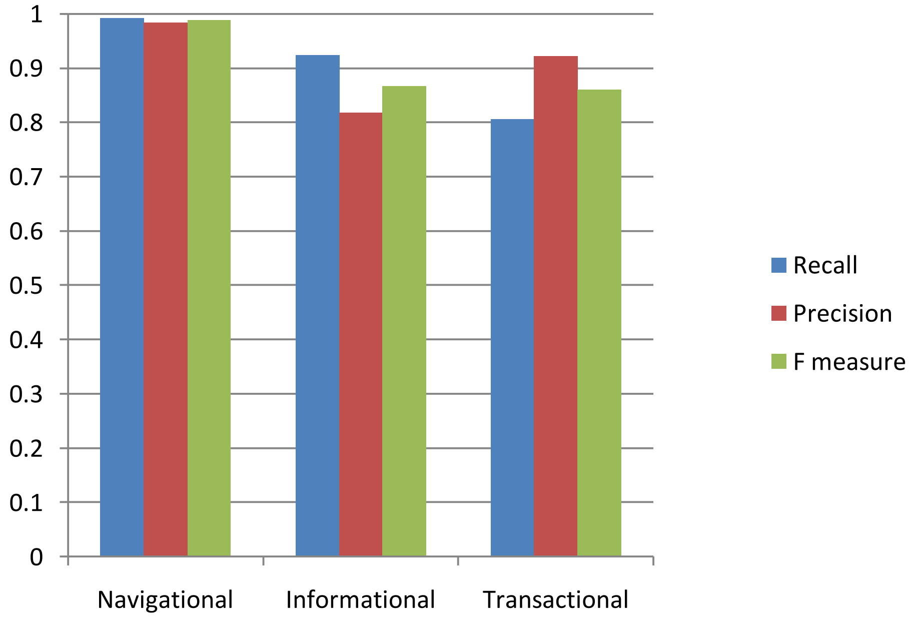


Figure 17: Classification accuracy across classes using Random Forest Algorithm

Navigational	Informational	Transactional	← Classified as
126	0	1	Navigational
1	**85**	6	Informational
1	19	**83**	Transactional

Table 11: Confusion Matrix for classifier using RandomCommittee Algorithm

Comparison of different classification algorithms

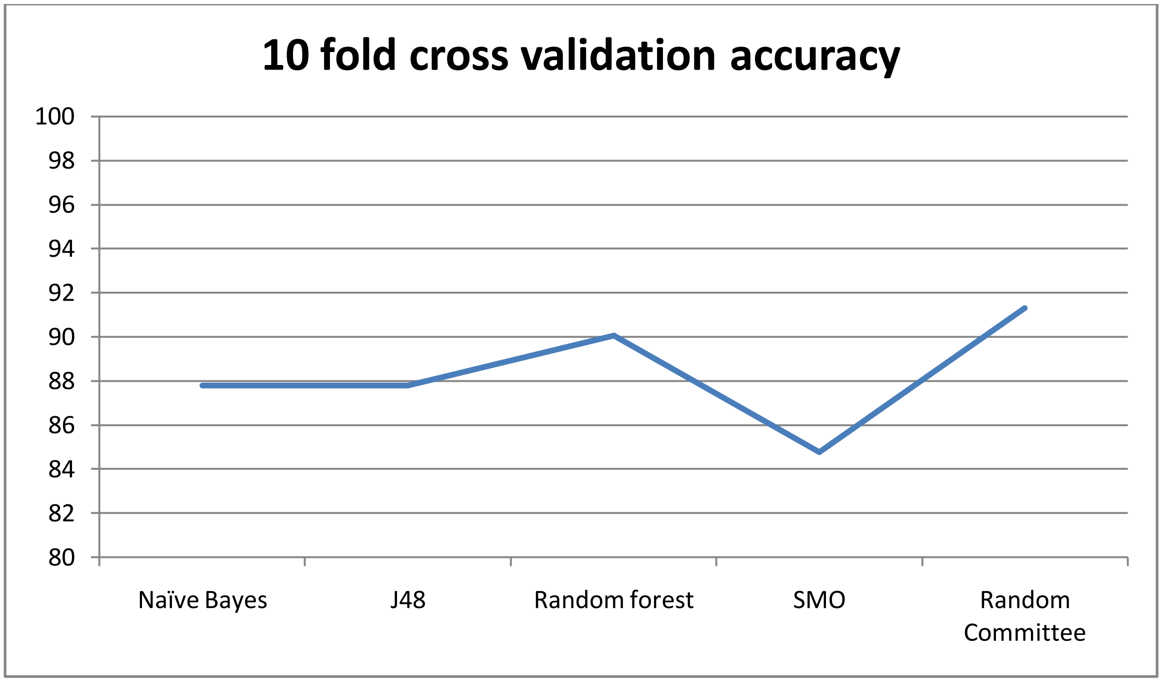


Figure 18: 10 fold cross validation accuracy for different classification algorithms

Hence, we see that we get the best classification results using the RandomCommittee classification algorithm and 12 best features identified by the CFS algorithm.

4.5 Feature Analysis

The CFS algorithm selects 12 best features out of the set of features provided to the classifier. Amongst the 12 features, the ones important for identification and distinguishing the navigational pages include url_depth, length_url, no_query_first, no_query_others, no_homepage (bag of words feature including the term 'homepage'). The other features are more important to distinguish between the transactional and informational pages. Hence, we can divide the set of features into two sets, the first including the 5 features which are important for distinguishing the navigational pages and the other set including the other features which are ratio_outer_hyperlinks, ratio_hits, length_text, no_title, no_cost, no_rebate and no_hot_product. We term the first set of features 'navigational' features and the second set of features 'informational-transactional' features and present the confusion matrix resulting from training the classifier only from one set of features.

Navigational	Informational	Transactional	← Classified as
123	2	2	Navigational
1	**72**	19	Informational
1	31	**71**	Transactional

Table 12: Confusion Matrix for classifier built using 'navigational' features

Navigational	Informational	Transactional	← Classified as
97	17	13	Navigational
19	**59**	14	Informational
16	16	**71**	Transactional

Table 13: Confusion Matrix for classifier built using 'informational-transactional' features

From the above confusion matrix, we can see that using only the navigational features for classification result in the navigational pages correctly classified with the confusion being high among the informational/transactional pages.

Classifying using only the 'informational-transactional' features result in high degree of confusion among the navigational/informational and navigational/transactional pages. The confusion among the informational/transactional pages has reduced on the other hand.

4.6 Conclusion

We have achieved **91.3043%** accuracy in classifying a web page into navigational/ informational/ transactional given the search query. Hence, we can successfully conclude that it is feasible to classify user goal in web search into navigational or transactional or informational. Building such a three fold classifier with such high accuracy would not have been possible if the search query was not given.

Our approach to classify a page into navigational / informational / transactional has been to first identify the navigational pages as the home pages of sites and then identify informational / transactional pages by using lexical and Html based features. It is possible that a user having a transactional goal visits the home page of web sites like a user having a resource finding goal of finding a dictionary visits the url http://dictionary.com. We have classified the home pages of sites as navigational in spite of the fact that at times the goal might be transactional. This would increase the accuracy of our web page classification since it seems to be infeasible to detect whether the end user was trying to find some resource on the home page of the site. Further, this would not affect our overall goal of classifying the query since this would require a minor modification to the query classification algorithm. Hence we decide to classify the home page of sites into navigational and not transactional.

We next present the query classification algorithm which uses the classification results predicted by the web page classifier built. The accuracy of the web page classifier is the key to the accuracy of the query classification algorithm.

Chapter 5

Automatic Classifier for Queries

Once the classifier is ready, we can continue with the automatic classification of our queries. We test our query classification algorithm on the benchmark set of queries that have been manually classified by 30 users. The web pages corresponding to the click-through urls of the queries are downloaded and classified by the RandomCommittee Meta classifier built. The approach to classify the queries is simple. For each query, we check how many users (clicks) have visited navigational pages, how many have viewed transactional pages and how many have viewed informational pages. While counting the navigational pages, it has to be kept into consideration that there exists only one correct navigational page for a query. Hence, the navigational page with maximum clicks is taken to be navigational clicks whereas the clicks for other navigational pages are added to the transactional clicks. If a clear majority exists for a particular class type, the query is said to be having that user goal else the query is termed to have no predictable goal.

5.1 Algorithm for Automatic Query Classification

Following are the steps of the algorithm used to classify a query into navigational, informational, transactional or ambiguous query:

1. For each query, classify each click-through result into three classes: navigational, informational or transactional
2. Count the number of informational and transactional clicks for the query
3. For the navigational results, compare the domain name of the website to compare the similarity. If they are similar, add their counts into one
4. For the navigational results, the navigational result with the maximum clicks is taken to be the navigational representative. Other navigational clicks are added to transactional clicks for the query
5. The belongingness value for each class is calculated by dividing the number of clicks for each class with the total number of clicks for the query
6. The class with maximum belongingness value and the one with 2^{nd} maximum belongingness value are chosen and the difference d between them calculated. If d is greater than a threshold value t, the query is classified to belong to the class with maximum belongingness value else it is termed ambiguous with belonging to both the maximum and 2^{nd} maximum classes. Various values of threshold are experimented with and the value chosen for t is finally .2

Following table shows the click-through and classification of corresponding click-through pages for the query ‘Microsoft’.

Query	Click-through url	Clicks	Class of Web Page
Microsoft	http://www.microsoft-watch.com/	1	N
Microsoft	http://windowsupdate.microsoft.com/	256	N
Microsoft	http://office.microsoft.com/	38	N
Microsoft	http://microsoft.com/	600	N
Microsoft	http://toolbar.msn.com/desktop/results.aspx	1	I
Microsoft	http://www.joewein.de/sw/joewein.htm	2	I
Microsoft	http://adcenter.looksmart.com/security/login	2	I
Microsoft	http://terraserver.microsoft.com/image.aspx?PgSrh:NavLon=86.405&PgSrh:NavLat=32.73694	2	T
Microsoft	http://connect.microsoft.com/onenote	2	I
Microsoft	http://www.lindqvist.com/en/el-gordo-de-la-primitiva-lottery-international-promotions-programmes	1	T
Microsoft	http://www.symantec.com/security_response/writeup.jsp?docid=2000-122015-2522-99	1	I
Microsoft	http://moneycentral.msn.com/investor/home.asp	1	I
Microsoft	http://messenger.msn.com/Resource/Emoticons.aspx	1	T
Microsoft	http://support.microsoft.com/	104	N
Microsoft	http://research.microsoft.com/aboutmsr/labs/cambridge	1	I

Table 14: Click-through and classification information for query ‘Microsoft’

As we can see, the navigational pages http://microsoft.com/, http://www.microsoft-watch.com/, http://windowsupdate.microsoft.com/, http://office.microsoft.com/ and http://support.microsoft.com/ have the same domain name and hence their clicks are added up into one navigational page’s clicks. By summing up we find that total navigational clicks are 999, transactional pages are 4 and informational pages are 10. The belongingness values in navigational/transactional/informational are respectively 0.986(999/1013), 0.004(4/1013) and 0.010(10/1013). Hence the query is classified as navigational with the difference between the max class (navigational) and 2nd max class (informational) is >.20

5.2 Results

Now we present the automatic classification results in the order they were presented in the manual classification results section. The queries not classified correctly are analyzed and the reason behind the wrong classification presented. The comparison between the manual classification and the automatic classification results are presented in the appendix.

Navigational Queries

Out of the 15 navigational queries, all were detected to be navigational by our query classification algorithm. The respective belongingness values for the queries for various classes are presented in the following table:

Query	N(q)	I(q)	T(q)	Predicted Type
Hotmail	0.924	0.039	0.037	Navigational
Google	0.971	0.005	0.025	Navigational
Espn	0.801	0.02	0.179	Navigational
Imdb	0.932	0.006	0.062	Navigational
Honda	0.782	0.11	0.207	Navigational
Yahoo	0.975	0.025	0.005	Navigational
Ask	0.924	0.009	0.068	Navigational
Amazon	0.926	0.005	0.069	Navigational
Thesaurus	0.792	0.068	0.140	Navigational
Suzuki	0.726	0.016	0.258	Navigational
Microsoft	0.986	0.010	0.004	Navigational
Encyclopedia	0.698	0.256	0.046	Navigational
Dell	0.611	0.080	0.310	Navigational

Pogo games	0.634	0.072	0.294	Navigational
Ebay	0.984	0.001	0.015	Navigational

Table 15: Automatic classification results for Navigational Queries

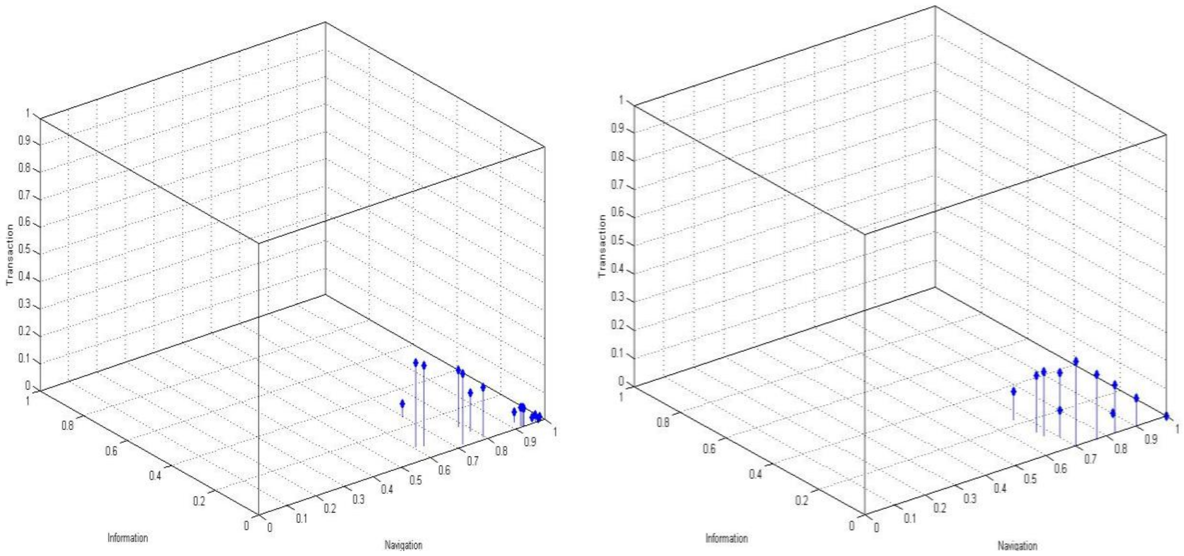


Figure 19: Automatic classification vs. manual classification of navigational queries

Transactional Queries

Out of the **19 transactional queries**, **18** were correctly identified as transactional by our classification algorithm. The respective belongingness values for the queries for various classes are presented in the following table:

Query	N(q)	I(q)	T(q)	Predicted Type
Mortgage Calculator	0.005	0.011	0.984	Transactional
Myspace Layouts	0.252	0.009	0.739	Transactional
Tattoos	0.203	0.273	0.524	Transactional
Cigarettes	0.111	0.333	0.556	Transactional
Funny Pictures	0.317	0.019	0.665	Transactional
Free music downloads	0.157	0.319	0.524	Transactional

Msn messenger	0.034	0.000	0.996	Transactional
Free ringtones	0.252	0.214	0.535	Transactional
Download	0.238	0.629	0.132	**Informational**
Ipod	0.095	0.047	0.858	Transactional
Screensavers	0.057	0.343	0.600	Transactional
Netscape	0.234	0.012	0.753	Transactional
Deal or no deal	0.001	0.041	0.958	Transactional
Shoes	0.064	0.242	0.694	Transactional
Airsoft guns	0.143	0.218	0.639	Transactional
Aol media player	0.000	0.048	0.952	Transactional
Itunes	0.007	0.050	0.943	Transactional
Internet explorer	0.000	0.021	0.979	Transactional
Sudoku	0.300	0.152	0.548	Transactional

Table 16: Automatic classification results for Transactional Queries

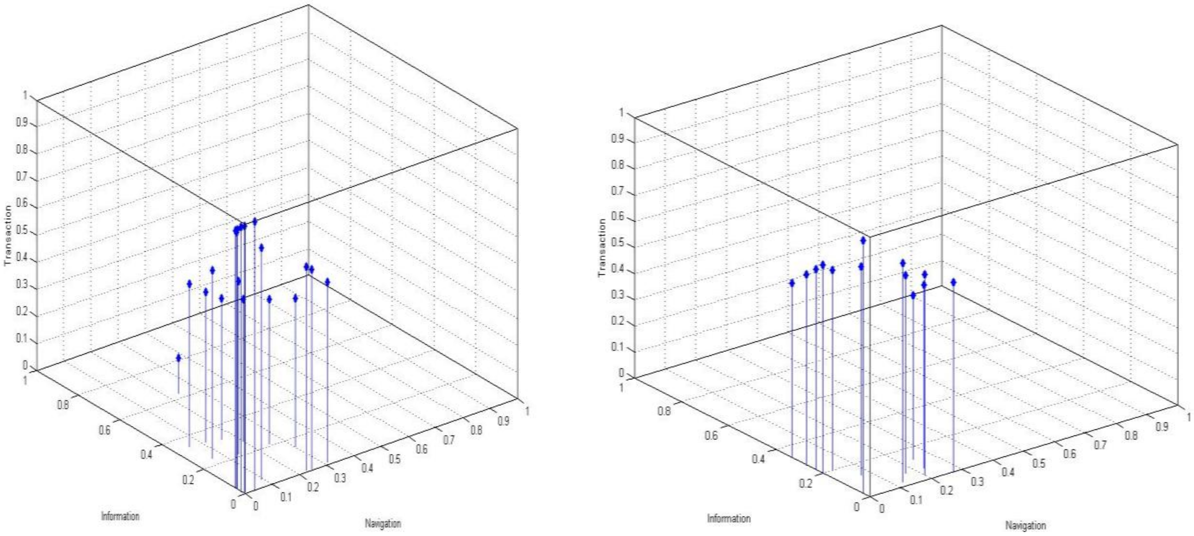


Figure 20: Automatic classification vs. manual classification of transactional queries

Informational Queries

Out of the **19 Informational queries**, **11** were correctly identified as informational by our classification algorithm. The respective belongingness values for the queries for various classes are presented in the following table:

Query	N(q)	I(q)	T(q)	Predicted Type
Kidney stones	0.059	0.715	0.226	Informational
Bird flu	0.509	0.366	0.125	**Navi / Informational**
Employment	0.024	0.847	0.129	Informational
Motorcycles	0.057	0.665	0.278	Informational
Html	0.045	0.829	0.126	Informational
Pregnancy	0.183	0.510	0.183	Informational
Snakes	0.141	0.772	0.087	Informational
Optical illusions	0.135	0.723	0.142	Informational
Exe	0.009	0.846	0.145	Informational
Guns	0.177	0.622	0.201	Informational
Florida lottery	0.186	0.707	0.106	Informational
Airline tickets	0.018	0.618	0.365	Informational
Anna benson	0.002	0.130	0.868	**transactional**
Jessica simpson	0.014	0.324	0.662	**transactional**
Paris Hilton	0.004	0.373	0.622	**transactional**
Baby names	0.319	0.011	0.670	**transactional**
Jessica alba	0.279	0.420	0.301	**Info/transactional**

Kelly blue book	0.000	0.174	0.826	**transactional**
Recipes	0.097	0.154	0.749	**transactional**

Table 17: Automatic classification results for Informational Queries

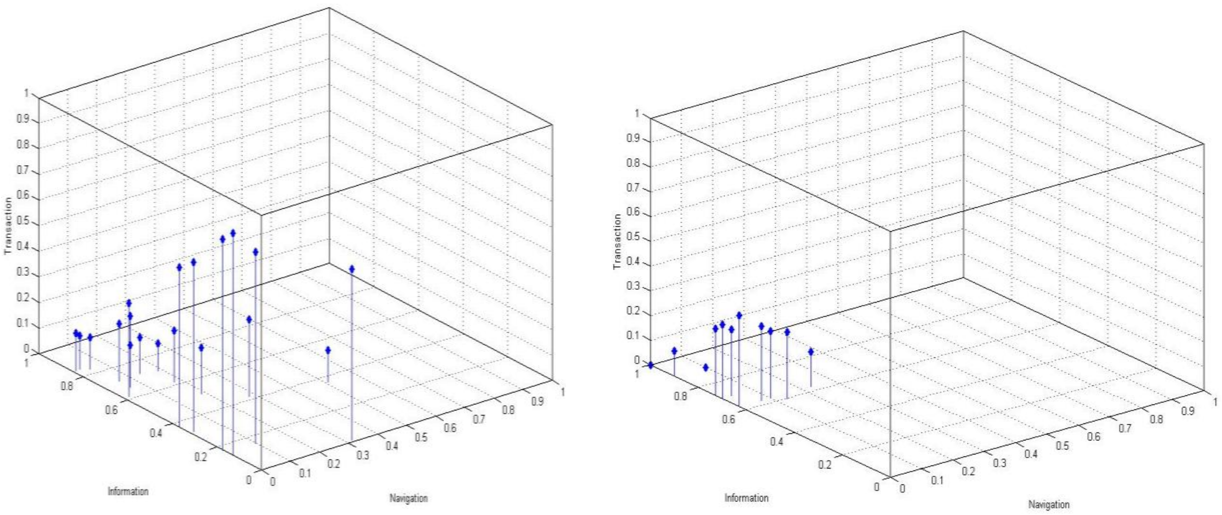


Figure 21: Automatic classification vs. manual classification of informational queries

Informational-Transactional Queries

Out of the **10 informational-transactional queries, only 2** were detected to be so by our classification algorithm. The respective belongingness values for the queries for various classes are presented in the following table:

Query	N(q)	I(q)	T(q)	Predicted type
Furniture	0.112	0.391	0.498	Info / transactional
Online games	0.112	0.369	0.519	Info / transactional
Costa rica	0.338	0.053	0.609	Transactional
Britney spears	0.003	0.213	0.784	Transactional
Shakira	0.627	0.323	0.049	Navigational
Kelly Clarkson	0.139	0.198	0.663	Transactional

Reverse lookup	0.003	0.962	0.035	Informational
David blaine	0.522	0.064	0.413	Navi / Transactional
Movies	0.435	0.201	0.364	Navi / Transactional
Cars	0.307	0.279	0.414	Navi / Transactional

Table 18: Automatic classification results for Informational-Transactional Queries

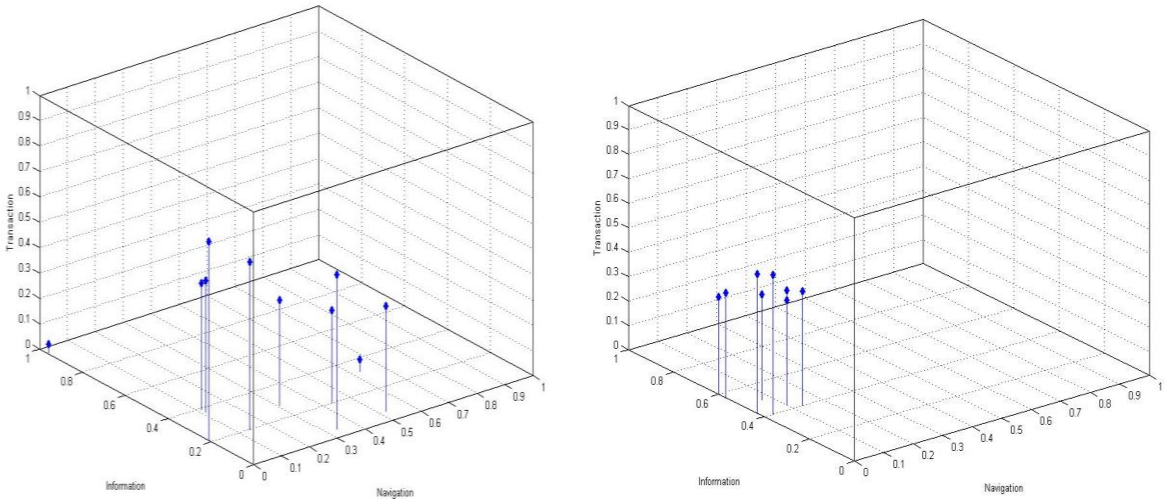


Figure 22: Automatic classification vs. manual classification of Informational-Transactional queries

Informational-Navigational Queries

Out of the **only navigational-informational query,** it was detected to be so by our classification algorithm. The respective belongingness values for the queries for various classes are presented in the following table:

Query	N(q)	I(q)	T(q)
Harry Potter	0.347	0.406	0.247

Table 19: Automatic classification results for Informational-Navigational Queries

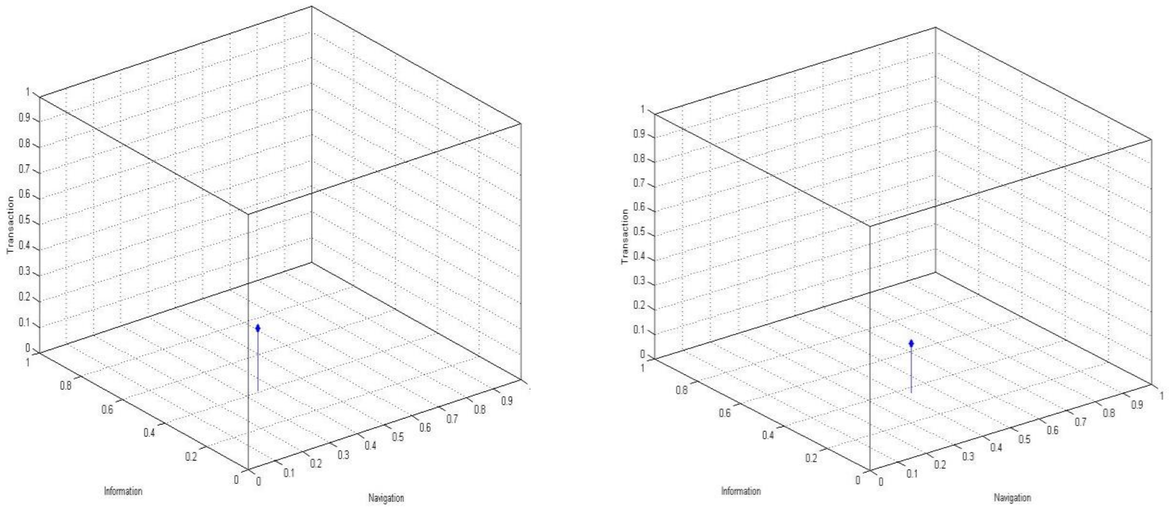


Figure 23: Automatic classification vs. manual classification of Informational-Navigational queries

Transactional-Navigational Queries

Out of the **only navigational-transactional query,** it was detected to be so by our classification algorithm. The respective belongingness values for the queries for various classes are presented in the following table:

Query	N(q)	I(q)	T(q)
Bible	0.424	0.126	0.450

Table 20: Automatic classification results for Transactional-Navigational Queries

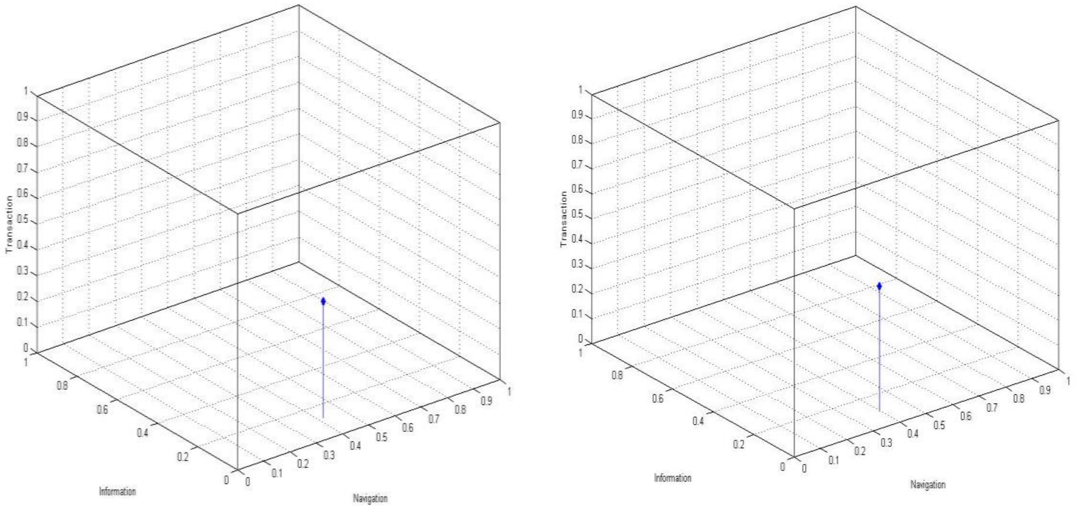


Figure 24: Automatic classification vs. manual classification of Transactional-Navigational queries

5.3 Analysis of Classified Queries

Navigational Queries

The 15 queries that were classified as navigational by the user survey were correctly identified by our automatic classifier. This accuracy is due to the fact that the web page classifier is very accurate in classifying a navigational page. Hence we can say that if we have sufficient number of click-through information and the query is navigational, one can predict the goal of the user to a high degree of accuracy.

Transactional Queries

Out of the 19 transactional queries, 18 were correctly identified as transactional by our classification algorithm. The one query that has been misclassified is '**Download**' and it has been classified as informational. The total number of clicks for this query is 281. After expanding the click-through via the yahoo API, a lot of domains do not match due to which the effective number of clicks is about 155. So one reason for misclassification could be the low number of effective click information for the query. Another reason could be the fact that the download pages consist of very few Html elements compared to the textual material like the pages http://free.aol.com/tryaolfree/cdt.adp?532446 and http://get.live.com/messenger/overview because of which they are classified as informational pages. These pages could have been classified as transactional using the bag of words features which was excluded by the feature selection algorithm. Hence, this misclassification can be overcome by training the classifier appropriately.

Informational Queries

Out of the 19 Informational queries, 11 were correctly identified as informational by our classification algorithm. The misclassified queries include 'bird flu', 'Anna Benson', 'Jessica Simpson', 'Paris Hilton', 'Jessica Alba', 'Kelly Blue Book', 'recipes' and 'baby names'.

'Bird Flu' is a true example of a query where the goal is clearly informational but one informational source dominates which gets a large number of clicks. In this case the total number of clicks is 447 (before DNM) and a navigational page http://www.cdc.gov/flu gets 224 clicks. The other pages are more or less correctly classified as informational and hence the query gets termed as navigational/informational.

'**Anna Benson'**, '**Jessica Simpson**', '**Paris Hilton**', '**Jessica Alba**' are the name of famous celebrities. Each of the celebrities has their own sites but generally the users are not aware of these sites and the end goal of the user is to either get some information about these celebrities or to download their pictures or some video of the celebrity. If the sites of these celebrities get a high number of clicks it is only because these pages are ranked higher on the search engine results page. Most of these queries have been classified as transactional by our automatic classifier excluding 'Jessica Alba' which is classified as informational/transactional. This is due to the fact that our classifier finds that most of the pages corresponding to these celebrities have lots of other Html elements compared to the textual material like the pages http://www.doubleagent.com/play/jessica-simpson-these-boots-are-made-for-walking or the page http://www.absolutely.net/Jessica_Simpson/ which has downloadable images. Hence for the name of celebrities, it is very subjective based upon the web page classifier or the person designing the search engine whether to classify these pages into transactional or informational.

'kelly blue book' is a site where used cars are transacted in US. Of around 2930 total clicks http://www.kbb.com/kbb/UsedCars/default.aspx got 2092 clicks and this has been correctly classified as transactional page. Perhaps the people who classified this as informational were not known about the site and wanted to know about 'kelly blue book'. This is an error due to introduction of a query in the questionnaire which the manual classifiers were not informed about.

'Recipes' was classified as informational by the manual classifiers although 30 percent of the users indicated it to be transactional. Again as with the celebrity queries, the pages corresponding to recipes consist of very few text to be read and lots of downloadable or viewable pictures of recipes because of which our automatic classifier classifies them to be transactional. http://allrecipes.com/Recipes/World-Cuisine/Canada/Main.aspx, http://www.kraftfoods.com/kf/CookingSchool/CookingTechniques/ are example of such pages. '**baby names**' is a query which is classified as transactional because of several navigational pages including http://www.yeahbaby.com/, http://baby-names.adoption.com/ , etc. where the user navigates to carry out further search to get 'baby names'. Clicks for these pages had been counted as transactional clicks and rightly so because users visit these pages to carry out further interaction to reach to their information. Both 'recipes' and 'baby names' are examples of queries where the user wants to get the query term and where he would end up on a page where he would further interact to get to the specific information. Hence, these pages which do not consist of much information to be read are classified as transactional. The users find it more intuitive to classify such queries as informational since the final goal is to get some information which would be the baby name or the recipe. But the immediate goal is to reach to a site where further searching/browsing is done to get to the final recipe.

Informational-Transactional Queries

Out of the 10 informational-transactional queries in the questionnaire, 2 were correctly detected to be so by our classification algorithm. Out of the 8 queries classified wrongly include 4 queries on celebrities including '**Britney Spears**', '**Shakira**', '**Kelly Clarkson**', '**David Blaine**' and one is the name of a place '**Costa Rica**'. Again for such queries it is very difficult to predict which class they might belong to. It would depend on how the results of the search engine have been presented and the resultant page consisting of several or more pictures than text in which case the query would be classified as transactional which is the case with this classifier.

The remaining wrongly classified queries include 'movies', 'cars' and 'reverse lookup'. The query '**movies**' is classified as navigational/transactional. The navigational page http://movies.go.com/ has 400 clicks of the total 991 clicks which give the query a navigational outlook. The query '**cars**' is also classified as navigational/transactional. The navigational page http://www.cars.com/go/index.jsp gives it a navigational outlook and it has 141 out of 566 clicks and there are about 60 DNM pages.

The queries '**reverse lookup**' is wrongly classified probably due to the page http://www.reversephonedirectory.com/lookup2.htm having 216 clicks out of a total of 459 clicks being wrongly classified as informational rather than transactional. There are also around 100 DNM pages. This is a daring example of a query which is wrongly classified due to wrong classification of a particular page having lots of clicks.

5.4 Conclusion

From the results, we can conclude that most queries issued to a search engine have a predictable goal which can be identified automatically. Of the 53 queries with a unique goal, 44 were correctly classified and of the 12 ambiguous queries, 5 queries were wrongly classified as having a predictable goal whereas others were correctly detected as not having a predictable goal though not all gave the same class of unpredictability. Most queries that were misclassified were the names of people or places in which case, the users indicated an informational goal whereas the classifier detected a more transactional goal. Such a distinction between informational / transactional pages is very subjective and should be done taking the final goal of optimizing search engine results presentation into consideration.

Hence, we can conclude that our algorithm is good at automatically detecting queries with a predictable goal although it could not successfully detect the type of ambiguity. This might be due to the unavailability of enough click information (for detecting ambiguity in goals, one might need more click information) but it also depends on the classifier and the search engine results presentation. We cannot conclude much regarding such queries since our questionnaire consisted on only 12 such queries and more study should be carried out in this direction.

5.5 Comparison with Related Work

Lee et al. demonstrated in an initial analysis following a human survey that more than half the queries have a predictable goal (the intention is not ambiguous) and that around 80% of those with an unpredictable goal are either software or person names. Their work focuses on distinguishing between navigational and informational query classes after removing the unambiguous queries from the classification data. Our work also substantiates the fact that more than half the queries have a predictable goal (53/65) and extends the work of Lee et al. significantly since we do not remove the ambiguous queries from the classification data before the classification process. We intentionally included person names (Anna Benson, Jessica Alba, etc.) and software names (msn messenger, aol media player, netscape, internet explorer) in our test query set to see if they have a predictable goal. We find that most users classified the software names as transactional whereas amongst the person names, 5 out of 9 were classified as not having a predictable goal. The differences are mainly because they had a 2 way classifier whereas we have built a 3 way classifier including the transactional class of queries. We also find that there are queries other than person names or software names (‘furniture’, ‘cars’, ‘movies’, ‘online games’) which can also be ambiguous.

Their approach to automatically determine the query goal was to classify the query directly into informational/navigational using the click distribution of queries, average number of clicks per query and anchor link distribution of queries. Further, they carried out their experimentation on the click-through data collected from their CSE department whereas we conduct our experiments on real AOL search engine data.

Chapter 6

Generations of Search Engine

In view of the taxonomy discussed so far we identify three stages in the evolution of web search engines:

First generation: use mostly on-page data (text and formatting) and are very close to classic IR. They support mostly informational queries. This was state-of-the art around 1995-1997 and was exemplified by AltaVista, Excite, WebCrawler, etc.

Second generation: use off-page, web-specific data such as link analysis, anchor-text, and Click-through data. This generation supports both informational and navigational queries and started in 1998-1999. Google was the first engine to use link analysis as a primary ranking factor and DirectHit concentrated on click-through data. By now, all major engines use all these types of data. Link analysis and anchor text seems crucial for navigational queries.

Third generation: emerging now, attempts to blend data from multiple sources in order to try to answer ‘‘the need behind the query’’. For instance on a query like San Francisco the engine might present direct links to a hotel reservation page for San Francisco, a map server, a weather server, etc. Thus third generation engines go beyond the limitation of a fixed corpus, via semantic analysis, context determination, natural language processing techniques, etc. The aim is to support informational, navigational, and transactional queries. This is a rapidly changing landscape.

6.1 First Generation Search Engines

The first generation search engines mostly used on-page data (text and formatting) and were very close to classic IR. They supported mostly informational queries. This was state-of-the art around 1995-1997 and was exemplified by AltaVista, Excite, WebCrawler, etc.

In the beginning, search results were very basic and largely depended on what was on the Web page. Important factors included keyword density, title, and where in the document keywords appeared. First generation added relevancy for META tags, keywords in the domain name, and a few bonus points for having keywords in the URL. Basic spam filters emerged that got rid of keyword stuffing and same color text. The portals also made their appearance, and engines started looking like giant billboards and overstuffed yellow pages.

First generation search engines technique was then replaced with the novel page ranking algorithms and techniques introduced by the Google which analyzed the web graph for ranking of returned results.

6.2 Second Generation Search Engines

Second generation search engines added much in the way of off page criteria and link analysis. A few of the major components they employ are tracking clicks, page reputation, link popularity, temporal tracking, and link quality. Then they started adding in term vectors, stats analysis, cache data, and context where two-word keyword pairs were extracted from a page to better categorize it. The essence of this generation was Google's PageRank system and DirectHit's method of tracking clicks and the length of visits.

To compute the rank of search engines, the second generation search engines maintain a term vector database, and then weigh page keyword density to calculate the page vector, which is compared and stored relative to the term vector. They then compute a Web page reputation by graphing interconnectivity and link relevancy, making sure the reputation of the page and the content on the page actually match. The closest matches get the highest search engine positioning.

Hence, the second generation search engines basically add off-page criteria to help determine relevancy.

6.3 Third Generation Search Engines

Third generation search engines go well beyond the aging Google model, using intelligent clustering of results, natural language processing, taking more human input and detecting user intentions automatically to improve search results. **Clusty** is one such search engine, which tries to cluster results into categories. This is especially helpful when a search query tends to include results from more than one topic area, which happens a lot. When you get search results back, you can quickly pick the appropriate cluster and throw away a lot of irrelevant information. For example, if you put in the word 'record,' which can have different meanings in different contexts, Clusty returns 199 clusters, with the top ten results sets on the first page. It is pretty likely one of those sets is the correct one.

Another interesting one is **Lexxe**, which uses natural language processing to improve query results. The 3rd generation search engine Lexxe applies Natural Language Processing (a.k.a.

Computational Linguistics) technologies in search, because search is seen as a language understanding process in the first place. An important principle carried out in the design of search algorithms is language first, computing second. Such an approach is called "Linguistic Computing" for search, which is paradigmatically different and a level higher in terms of the degrees of system difficulty and complexity. Phrase Recognition and Short Question Answering are two main ones NLP techniques employed by Lexxe search engine.

6.4 Search Engine Based on User goals

Search engines are continuously trying to improve the relevancy of their search results. This can be further improved by automatically determining the end user search goal and presenting the results accordingly. Yahoo Mindset search is one such search engine that tries to estimate the commercial intent of the end user and ranks the results accordingly. The user can indicate through an indicator bar whether their intent is commercial or more information oriented. This is the first instance where end user goals are taken into consideration while presenting the search engine results.

One approach to design a search engine based on user goals would be to cluster the results into three categories including navigational/informational/transactional. As we have already seen, this is a feasible clustering of the results given the search query. After clustering the results into the three classes, the results in each of the informational and transactional clusters can be hierarchically clustered by identifying the information topics for the informational cluster and identifying the possible transactions in the transactional cluster.

Another approach for a design of search engine keeping end user goal into consideration would be to rank the results in such a way that it includes results of each class navigational/informational/transactional in the top few results such that whatever be the user goal, they are fulfilled in the top few results of the search engine. The number of pages of each class in the top few results would be determined based on the belongingness value for the particular class. So for example, if for a query the belongingness value for transactional class in .9, a good fraction of the top 20 results should be transactional. It should be borne in mind that for a transactional query, different users might engage in different transactions for the same query. For example, for the query ‘online games’, some user might want to buy an online game while other might just want to download some online game.

Chapter 7

Conclusion and Future Work

On the web "the need behind the query" might be Informational/Navigational/Transactional Search engines need to deal with all three types although each type is best satisfied by very different results. An understanding of this taxonomy is essential to the development of successful web search. Our results confirm the feasibility of automatically identifying the intent of a web search query in the context of Broder’s taxonomy. We have presented a novel approach to automatically identifying the intention of web search user which is based on the intuition that the user goal for a query can be identified from the interaction of past users with the search engine results. From the results, we can conclude that this technique can be successfully adopted to automatically identify user search intentions in web search.

Future work for our system would encompass testing of the system over queries which are ambiguous and improving the performance of our query classifier over these queries. Our test set included only 12 such queries and hence, we cannot conclude decisively whether our system is robust enough to detect ambiguity of queries. Further, it would be interesting to work out a fuzzy representation of our classifier whereby the classification of a query, url pair would not be concretely a class but would be a fuzzy representation. More work is also required to fine tune the classifier to take into account transaction pages which were misclassified. Also, pages corresponding to celebrities are classified as transactional. It might be worked out to classify these pages as informational by defining informational pages differently. Further work can be done to hierarchically classify the transactional pages into the types of transactions including commercial transactions, download pages or resource finding pages. Our classifier approach is scalable and easily extendible to such a classification system.

Appendix A

Questionnaire for User Survey

Several queries are given below. You have to mark the queries with choices 1 or 2 or 3 depending on what **intention** you would have if you give the **query** to a **search engine**.

The description of choices 1, 2, 3 is as follows:

Choice 1: You already have a website in your mind (one particular website only) and your intention is to reach that website with the help of the search engine

Choice 2: Your aim is to obtain **information** on the “query term”

Choice 3: Your aim is to **buy** / **download** or **obtain** the resource implied by the “query term”

For example the choices for the following queries are:

1. Lycos : 1
2. Hair styles : 2
3. Funny videos : 3
4. Myspace backgrounds : 3
5. Guitar Tabs : 2
6. New York Lottery : 1

Queries (Indicate choice beside the query)

1. Hotmail :
2. Mortgage calculator :
3. Baby Names :
4. Google :
5. Espn :
6. Kidney Stones :
7. Jessica Alba :
8. Furniture :
9. Imdb :
10. Kelly Blue Book :
11. Honda :
12. Costa rica :
13. Bird Flu :
14. Myspace layouts :
15. Tattoos :
16. Exe :

17. Britney Spears :
18. Yahoo :
19. Employment :
20. Ask :
21. Cigarettes :
22. Motorcycles :
23. Html :
24. Funny pictures :
25. Pregnancy :
26. Download :
27. Amazon :
28. Msn messenger :
29. Free ringtones :
30. Online games :
31. Shakira :
32. Bible :
33. Ipod :
34. Screensavers :
35. Netscape :
36. Thesaurus :
37. Anna benson :
38. Microsoft :
39. Suzuki :
40. Engagement Rings :
41. Deal or no deal :
42. Shoes :
43. Jessica Simpson :
44. Airsoft Guns :
45. Paris Hilton :
46. Aol Media Player :
47. David Blaine :
48. Florida Lottery :
49. Encyclopedia :
50. Itunes :
51. Internet Explorer :
52. Dell :
53. Harry Potter :
54. Pogo Games :
55. Sudoku :
56. Reverse lookup :
57. Airline Tickets :
58. Snakes :
59. Cars :

60. Ebay :
61. Guns :
62. Optical Illusions :
63. Movies :
64. Kelly Clarkson :
65. Recipes :

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