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Identifying topical buzz creators in discussion forums

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Identifying Topical Buzz Creators
in Discussion Forums

by

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Abstract

Online discussion forums have become important places for people to seek and share opinions. The members of these forums share different characteristics and some of them are better in reaching their peers. We call these people 'buzz creators' as they are successful in creating buzz in particular topics and making their peers talk about these topics. We develop an application to identify buzz creators.

Our approach is analyzing both the content and the structure of the forum as we focus more on utilizing the structure of the forum. A graph of users is generated by utilizing the structure of the forum. We run a set of network-based ranking algorithms, including PageRank and HITS, on this graph in order to identify the buzz creators. We try several ways to construct the graph of users and compare the performances of various link analysis algorithms on the graph. As we evaluate our work on two different forums, we prove the validity of our approach and also the added value it brings.

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Thank you Derya, for many things. Life is more beautiful with you.

Love and Peace..

August 2009, Utrecht, Netherlands

Fırat Gelbal

Contents

1. Introduction

As the World Wide Web has become widespread, now there are incredible amounts of opinion-rich resources like online review sites, personal blogs, and community discussion forums. Members of these online communities discuss about almost everything. Some individuals are better than others in starting conversations and making the community members talk about particular subjects. We call them *buzz creators*. Identifying these individuals is valuable for marketing and scientific reasons.

Buzz is a word-of-mouth marketing term which refers both to the execution of the marketing technique and the result that is created. The buzz creation is often a goal of viral marketing, public relations and advertisement. Marketeers would like to find and reach buzz creators with the expectation that the buzz creators would spread the word around in their communities and influence their peers.

Identifying buzz creators is also useful for scientific reasons because it gives insights about the community structure and the behavior of its members. This is a rather novel research topic in computer science, especially in this specific research domain: discussion forums.

1.1. Teezir

This research has been done in and for Teezir B.V., a search solutions company that uses state-of-the-art, proprietary search technology solutions to improve businesses. Detailed information about the company can be obtained at the website: http://www.teezir.com

Our research is related to one of Teezir's solutions: Opinion Mining on the web. This solution measures the perception and opinions of people by crawling and analyzing relevant sources on the web. In the analysis part, Teezir does not yet utilize the structure of the content. This also has been one of the motivations for this research, to analyze the structure in order to extract more information than found in examination of the content alone. One of the major motivations is the frequent request from Teezir's clients: "Who are the buzz creators?"

1.2. Objectives

The first goal is to develop an application integrated with Teezir's framework for identifying buzz creators in discussion forums. With this application, Teezir will be able to answer their clients' needs for finding the buzz creators.

The second goal of this research is to make a contribution to the literature with the analysis of discussion forums and our approach to the problem at hand. Being discussed in Related Work (Section 2), as far as we know, there is no existing similar research done targeting discussion forums. Our results provide insights about the users' behaviors and characteristics in such forums. We provide a definition of buzz creator and differentiate it from authority, expert and influential. In addition, our research presents the comparison of various algorithms' performances over identifying the buzz creators in discussion forums.

1.3. Buzz Creation

In June 2008, Nintendo used buzz technique during the release launch in North America of their new video game, Wii Fit which is developed for the Wii console [14]. Nintendo came to Heather Armstrong's house for a Wii Fit party [15]. Armstrong, who is a famous blogger with the pseudonym of Dooce, invited 10 of her friends and later blogged the event. An added bonus was that Nintendo gave Dooce 5 Wiis along with 5 Wii Fits, to give away to 5 of her readers. First, Dooce blogged that she loved the Wii Fit, and that Nintendo wasn't paying her to blog about the product, or to give 5 sets away to her reader [15]. She explains that:

> I get approached to do things like this all the time, but this is the first time I've done a giveaway because this is a product I use, something in my house, something I'd love to share with you. Nintendo is not paying me to do this, and just to clear up some confusion, I would never accept money to post about anything here. That's not how this website works. Everything you see in my style section is something I have bought with my own money or is a gift sent to me from one of my readers, a gift I would have gone out and bought had I known about it beforehand, something that fits right in with my aesthetic. I work very hard to make sure that you can trust that what I say here is in no way influenced by advertisers or corporations who are trying to reach a bunch of eyeballs.

In her blog post, she announced that she would pick the winners at random from among those that left a comment to that post. The contest run for 2 days and as the contest ended there were 42,232 comments for that one post.

The return on investment for this idea of Nintendo is difficult to measure but most likely higher than the total $1,800 retail cost of the giveaways. Nintendo received a product endorsement from a popular blogger, resulting in 42,232 comments. The post itself is linked to by another 40+ blogs, so there is more exposure than 42,232 commenters, it might be viewed a minimum of a few hundred thousand times. Even though, there is a chance that none of the commenters (nor any of the viewers) actually bought the product, the brand awareness of both Nintendo and their new product, Wii Fit, are certainly increased. The commenters and people hearing this news talked about it in their networks and made their friends aware of the product, which is the first goal in advertisement.

This is just one example that shows how an identified buzz creator can be useful for marketeers. Reaching the buzz creator means reaching a wider audience through the buzz creator in a more effective way and with fewer costs compared to generic mass marketing approach.

1.4. Discussion Forums

Discussion forums (also referred to as web forums and message boards), which originate from Bulletin Board Systems commencing at 1970s, are online areas where discussions are held by many users on a variety of topics. A user starts a discussion by making an initial post and other users express their opinions by replying to the original post or to other replies, forming a discussion thread or nested dialogue.

The forum consists of threads and threads are groups of posts. There may be an already built-in structure to represent parent-child relationship between posts. Or the posts may be listed one after each other with no explicit statement about the relationship among them, apart from the fact that they belong to the same thread.

Figure 1 is an example of a discussion forum thread.

Subject	Posted by	When
📑 Recommendation for travel tripod	Ring	14 days ago
✉ Re: Recommendation for travel tripod	martingrumet	14 days ago
✉ Re: Recommendation for travel tripod	martingrumet	14 days ago
✉ Sounds crazy but...	Phormula	14 days ago
✉ Re: Sounds crazy but...	boninsegni	13 days ago
✉ Re: Sounds crazy but...	Cyril Catt	13 days ago
✉ You're right, the Modo pocket	Phormula	12 days ago
✉ Re: You're right, the Modo pocket	martingrumet	12 days ago
✉ Modopocket	gordonsbuck	4 days ago
✉ Re: Modopocket	martingrumet	4 days ago
✉ Re: Modopocket	Phormula	4 days ago
✉ Re: Recommendation for travel tripod	willw	14 days ago
✉ Re: Recommendation for travel tripod	martingrumet	14 days ago
✉ Re: Recommendation for travel tripod	www451oa	12 days ago
✉ Re: Recommendation for travel tripod	Cyril Catt	14 days ago
✉ Re: Recommendation for travel tripod	martingrumet	14 days ago
✉ Re: Recommendation for travel tripod	Cyril Catt	13 days ago
✉ Re: Recommendation for travel tripod	martingrumet	13 days ago
✉ Leica table top tripod	D Lynch	13 days ago
✉ Re: Recommendation for travel tripod	John DeMott	13 days ago
✉ Thanks	Ring	12 days ago

Figure 1: Screenshot of a sample forum thread

In this image only the titles of the posts are displayed under the heading 'Subject' and the actual contents of the posts are hidden. The heading 'Posted by' shows the authors of the posts. This image illustrates the posts in a nested view. From the structure of the thread, It is easy to see who replied to whom.

In addition, discussion parts (generally called 'comments section') of blogs and online news sites are also considered as web forums. In these sites, the published blog or the news article is the starting point of discussions (instead of an initial post submitted by a user).

1.4.1. Terminology

In this paper, the terms 'author' and 'user' refer to the person who makes the post.

Additionally, the terms 'post', 'reply', 'comment' and 'document' are used to refer to the textual contribution of user, unless it is stated otherwise. A post also contains the user's details (e.g. user's nickname, email address, personal web page, signature, etc.) and the date and time it is submitted.

A post's replies are referred to as its 'children' and likewise, the post itself is referred to as the 'parent' of the replies.

1.5. Approach Overview

Generally, people talk about particular topics and consequently the buzz is context-sensitive as it is bounded to a specific topic. So, identifying the topics of content and associating the topics with users are crucial subjects for the thesis.

However, several studies have shown that people use more diverse criteria than just topicality to make judgments about information [2]. Usefulness of information is not necessarily determined by objective characteristics of information objects or sources, but by users who ultimately make judgments on the usefulness of information. So, to enrich the topicality information, the community structure should be explored as well in order to understand the implicit relationships between users.

To achieve our goal, both the content and structure of a forum will be analyzed. We use Teezir's existing technology in the content analysis part and we decided to focus on the structure analysis part by developing our approach described in this section.

Figure 2 depicts the approach to identify the buzz creators from a process-driven perspective.
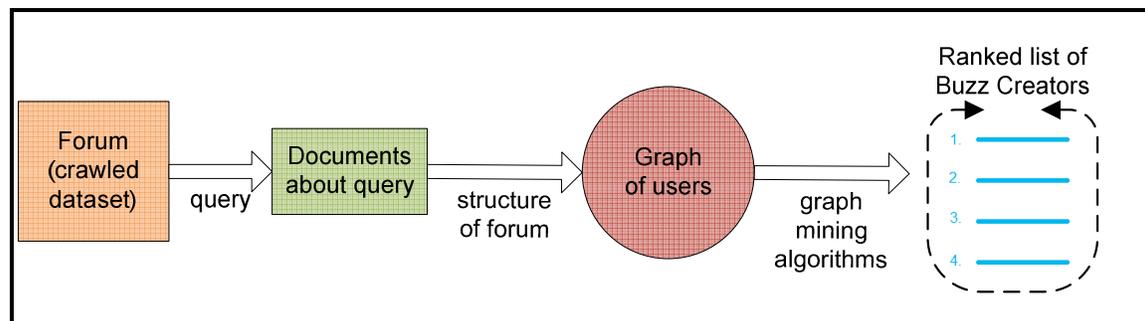
Figure 2: Step-by-step processes of the application

Choosing the forum of interest and crawling it to collect data is the first step. For our large scale empirical study, we chose a mobile phone discussion forum. This forum is interesting to Teezir as both content-wise and structure-wise it is similar to the data sources that the company uses in their solutions currently. All posts are later extracted with the post details (poster's name, the publish date, etc.) and stored individually along with the structure information (the post's parent thread). The detailed explanations of the methods used in crawling, extracting and storing data are given in Section 4.3.

The 'query' to the application determines the topic. For instance, if the goal is identifying the buzz creators for the topic 'Nokia', then the query is simply 'Nokia'. If a more specific

topic is desired, for instance the buzz creators in battery of particular product of Nokia, N97, then the query is 'n97 battery'. By querying the forum, we retrieve the documents that are related with the query, which is a subset of the original dataset.

In these query related documents, the forum structure is utilized to generate a graph of users. The given interactions among users are utilized in the construction of the graph. This graph provides us a better understanding of the relationship among users. It also opens the way to employ graph mining algorithms. The methods in creating the graph are discussed in detail at sections 4.1 and 4.2.

As presented in Related Work (Section 2), forming a graph and applying social network analysis methods (graph mining algorithms) on the graph are proven to be useful for identifying users with particular characteristics. Our claim is the identification of the buzz creators might be achieved by performing these algorithms. sections 2.4 and 4.4. explain the algorithms.

The output of the application is a ranked list of buzz creators on a particular topic.

1.6. Empirical Studies

We have performed our approach on two different forums. The first one is a smaller scale study in terms of data volume and the time period that data spans. At the beginning of the project, we had a rather vague problem definition and consequently the approach was not clear. This small scale experiment helped us to clarify the problem definition, refine our approach and aided us in our decision process. In the second study, the larger scale experiment, we had the chance to test our approach and the algorithms on a volume-wise more realistic data set.

Another major difference between our two dataset is their structure. In the first one, there is a detailed structure as each post has a parent post and this is explicitly stated in the structure. However, this kind of structure is not present in the second dataset and the only hierarchical information available is the chronological ordering of posts in a thread. This brings a significant challenge to construct the graph of users, as the interactions between them are not obvious. This issue is further discussed in Section 4.

It is important to state that evaluation has been the major challenge of our work. There is no explicit gold standard defined or objective measurement method to evaluate the algorithms and validate the results. So we tried two different evaluation methods in our two different experiments. As we had relatively manageable amount of data in the first experiment, we have manually annotated the dataset for 2 chosen topics to compare the algorithms. This evaluation method is further explained in Section 5.4. Since the second

experiment encompasses larger amount of data, it is not feasible to manually annotate it. Instead, we chose a double-blind evaluation method to cover 20 different topics. The details of this evaluation are presented in Section 6.3.

The differences between two experiments are summarized in Table 1:

	Data Volume (# of posts)	Data Period	Graph Construction	Evaluated Topics	Evaluation
Small Scale	95,314	20 days	Forum Structure	2	Manual annotation of all posts
Large Scale	645,950	1 year	Chronological Order	20	Double-blind: Annotation of top 10 users' posts

Table 1: Comparison of two experiments

1.7. Contributions

• Definition of buzz and buzz creator in the context of discussion forums are made.

• We propose an approach to combine topicality information with the link analysis algorithms in order to identify buzz creators.

• An application is developed, which identifies topical buzz creators in discussion forums and it is integrated with Teezir's framework.

• Two detailed experimental studies are conducted using real-life forum data sets. We evaluate the performance of our approach and also compare various algorithms. The empirical studies show that our approach produces satisfactory performance.

1.8. Structure of the dissertation

Section 2 reviews the related work and explains our variations from the existing research. Section 3 focuses on our design decisions by telling the story of our process and the rationalization behind our solution. Section 4 explains our approach more in detail. In Section 5, we present the empirical study on small scale with the background knowledge, evaluation method, results and our findings. Structure of Section 6 is the same with Section 5, but this time the contents are from our larger scale experiment involving another dataset. Finally, Section 7 concludes this dissertation with discussions and suggestions for future work.

2. Related Work

There have been several studies about identification of particular individuals in various contexts of the web, such as identification of authorities, experts, influentials. To the best of our knowledge, there has not been any preceding study conducted in identifying buzz creators in discussion forums. We make use of these previous studies and apply existing solutions in our context with necessary modifications.

In our research, we basically integrate two different techniques: content analysis and link structure analysis. Both analysis techniques have been tried separately before and found useful in similar research domains. However, each one has its advantages and disadvantages and many researchers believe that these techniques would produce finer results when applied together.

We believe there are significant differences between previous studies and ours. The variations of our approach from the previous ones are presented in corresponding parts of this section.

2.1. Expert Finding with Link Analysis

Most current expert finding systems use modern information retrieval techniques to discover expertise from electronic resources. A person's expertise is usually described as a term vector and is used later for matching expertise queries using standard information retrieval techniques. The result usually is a list of related people with no intrinsic ranking order or ranks derived from term frequencies. It may reflect whether a person knows about a topic, but it is difficult to distinguish that person's relative expertise levels. Thus, relying on word and document frequencies has proven to be limited in identifying experts [3].

To improve this limitation, Campbell et al. [4] and Dom et al. [5] used graph-based ranking algorithms in addition to content analysis to rank users' expertise levels. They constructed graphs using a similar approach to ours described in Section 2.3. They applied several graph-based algorithms on these graphs, including PageRank and HITS (explained under section 3.4), to rank correspondents according to their degree of expertise on subjects of interest. They found that using a graph-based algorithm effectively extracts more information than is found in content alone. However, the weakness of these studies is that the size of their networks is very small and does not reflect the characteristics of realistic social networks. Zhang et al [3] conducted a similar study to rank users in a larger forum. Their experiment reveals that a simple link-based metric could be a powerful tool for measuring the expertise level of users in question-answering communities.

These graph-based algorithms provide a global ranking of users in a community, so they are valuable when the interactions between users are around one specific topic only. Zhang et al [3] do not take the content of the posts into account but leave it as a future work since they also believe this is necessary to differentiate specific knowledge and develop more advanced expertise finders.

We are conducting a similar study in line with these previous works and our main focus is link analysis, utilizing the forum's network structure on users. Our major difference is we are not interested in finding experts but buzz creators. Another key variance is we don't have predefined topics. In previous studies, the datasets are around one topic whereas our data set contains various topics. One of our challenges is to distinguish different topics and identify buzz creators who talk about these topics. We overcome this challenge by using topicality tools.

2.2. Expert Finding in Question-Answer Forums

Recent research about identifying experts and influentials focuses on question-answer forums [3, 6]. In this type of forums, a user asks a question and other members answer the question. The researchers claim that the answerers are more knowledgeable on the subject than the asker. Therefore, when creating the social network graph, the direction of the edge is chosen to be from asker to all repliers.

Zhang et al [3] proved that the simple counting of the number of questions a user asks and answers is a good measurement method to find the experts in their domain.

General discussion forums are different from question-answer forums as well. We cannot make the assumption that the replier is more knowledgeable and affects the answerer. Because, in our case, it is quite common that the askers start a conversation by posing an opinion and getting replies back. For our research, the direction of edges is chosen from replier to asker. The reason for the choice is that this direction shows the replier read the parent's comment and cares to write a reply. So we believe getting replies is a sign of buzz creation.

2.3. Influence in Product Review Sites

Another domain for similar research is product review sites. In this research [13], influence is defined as following. For example, in a product review site, two users are monitored: Derya and Mehmet. Derya reviews the mobile phone she just bought and Mehmet writes a

comment on this review. One week later, Mehmet posts a review for the same mobile phone. Derya influenced Mehmet to buy the same phone. (Of course, the researchers make the assumption that writing a review means buying the product). Hence, Richardson and Domingos [13] use reviews and comments data as their ground truth to identify influentials in the product review sites. The explicit ratings given by users on reviews and on other users are also used as ground truth [13]. In this kind of sites, users rate the reviews according their usefulness and users may rate also reviewers, in a sense, to explicitly state their trust.

Our data type is general discussion forums and we don't have any explicit declaration of influence or any other data source to use as indication of influence (unlike the case of product reviews). Furthermore, the product review sites are not Teezir's current focus and at the moment their major data source is discussion forums. In our data corpus, the only records are the conversations themselves. The only way to derive influence from the conversations is to analyze them with various computer science techniques. However, as described in Section 3.3, advance content analysis techniques are omitted from our research scope as we focus on link analysis.

2.4. Graph Mining Algorithms

There are several algorithms designed to automatically deduce a user's influence level. Following are the descriptions of the ones that we use and compare in our research. PageRank and HITS were the pioneering approaches that introduced Link Analysis Ranking, in which hyperlink structures are used to determine the relative authority of a Web page. However the very same methods that have proven successful for social networks to retrieve reputation of individuals. In the above explained research domains (Question-Answer Forums and Product Review Sites), the researchers applied PageRank, HITS and InDegree Centrality to prove their claims.

2.4.1. InDegree Centrality

A simple statistical technique that can be used to measure the authority of participants is the InDegree. With the InDegree measure, the authority of a node (user) is measured by the number of nodes that link to this node. Adding weighting of the links would fine-tune this measure. Thus, the InDegree of a node is the sum of the weights of edges that point to this node.

We use this measure as it is.

2.4.2. HITS

In [1], Kleinberg claims that the InDegree measure is not sophisticated enough to capture the authoritativeness of a node in the context of a Web hyperlink environment. In this paper, he presents HITS algorithm. HITS is based on the notions of hub and authority to model the two aspects of importance of a webpage. The HITS algorithm determines two values for each node: its hub score and its authority score.

In our context, a good hub is one who replies to many buzz creators, while a good authority (a buzz creator) is a user who get replies from many good hubs. In principle, good hubs tend to link to good authorities and vice versa. In our study, authority value of HITS is used to rank users.

2.4.3. PageRank

The basic idea of PageRank [12] is as follows: the link from a webpage to another can be regarded as an endorsement of the linking page, the more links pointed to a page, the more likely it is important, and this importance information can be propagated across the vertices in the graph. The algorithm takes into account not only the number of pages linking to it, but also the number of pages pointing to those pages and so on. So, a link from a popular page is given higher weighting than one from an unpopular page.

HITS and PageRank work with unweighted graphs and most of the researchers believe weighted edges would bring value as the weight of an edge gives more information about the relation between two nodes. So, we also modify these two algorithms to work with weighted edges.

2.4.4. NodeRanking

Pujol [7] claims that experts who are well-known and highly regarded by most of the members in a community are easily identified as highly connected nodes in the social network. He extracts the reputation of a node based on its location in the social friendship network by utilizing a slightly modified PageRank algorithm.

In PageRank, there is a probability of jumping from one node to another in order to break the cycles on the graph [12]. For all nodes, this jumping probability is fixed (recommended value is 0.15) in the original PageRank. NodeRanking dynamically changes this probability

for each node, according to the number of out-going links. Figure 3 is the formula of jumping probability calculation for a node n.

$$\Pr_{jump}(n) = \frac{1}{\#outEdges(n)+1}$$

Figure 3: NodeRanking – jumping probability calculation

In his study, Pujol compares NodeRanking with PageRank on a social network of academicians, constructed by using the citations in their research papers. The rankings obtained from an independent scientific publication ranking agency is used as ground truth. In this social network, Pujol proved that NodeRanking is better than PageRank in social networks on extracting reputation. This is due to the fact that social networks show different graph topologies than web [3, 7]. By dynamically changing the jumping probability, the algorithm adapts itself to different network structures, regardless the topology.

Unlike HITS and PageRank, NodeRanking is designed to run on graphs by only using the local information. In our implementation of NodeRanking, we make use of global knowledge of the graph, so it's more similar to PageRank in our case.

3. Problem Definition Decisions

At the start of the project, we had a rather vague problem statement. Teezir wanted to identify certain individuals but the characteristics for these entities were not clear. So, we went through several arguments in order to clarify the target. This section summarizes our discussions and rationalizes our design decisions.

3.1. Definitions

With the purpose of presenting a basis for the concepts that we are looking at, we begin with a set of commonly used terms and their dictionary definitions:

Term	Definition
Influential	able to have a powerful effect on people and what they do, or on events
Authority	an accepted source of information or advice, either an expert on the subject or a persuasive force.
Expert	someone widely recognized as a reliable source of technique or skill
Reputation	recognition by other people of some characteristic or ability
Credibility	a quality of being believable, trustworthy.
Trust	a reliance on the integrity, ability, credibility of a person or source of information
Popularity	the quality of garnering the favor of the general public or a particular group of people

Table 2: Definitions of terms

As seen from the definitions, those terms are quite similar and yet not the same. For each of these concepts, there are several studies in the literature. Though researchers use different terms, sometimes the intentions of these distinct researches are the same. Most frequently we see that authority, expert and influential are used interchangeably for the same meaning. Of course, quite often use of different vocabulary is necessary as the objectives of

the researches are unlike. Still, the researches in these different concepts aid each other with use of similar techniques or mere inspiration.

We have started our research with the goal of identifying 'influentials'. This goal led to several important questions: What is influence in our context? How is it measured? Shall we use the same techniques that are employed in the studies of authority, expertise, popularity, trust? Or is it a combination of all of them? The remainder of this section describes the discussions about these questions along with how and why the research subject changed from 'influentials' to 'buzz creators'.

3.2. Influentials vs. Experts

Influentials do not necessarily have to be authorities or experts. Being an expert is not equal to being an influential. Influential is the one who reaches other members of the community and who affects them. So even if a person is not an authority in a particular topic, he can be an influential. Thus, our research is different from expert finding systems as the aim is not to find experts and the reach of users is more valuable than the quality of what they write.

3.3. Limiting Content Analysis

One can argue that analysis of content can disclose more information about the interactions of users and enrich the link structure analysis. This is true and we have considered this in our research. Deep analysis of the content may show the trail of information and the ways how the information disseminates in the network. One example is observing repetitive occurrences of quotes from particular users, or user names. In some way, this also shows the reputation of a user. Another example would be detecting the changes of user ideas after a conversation and also the actual sentiments of users towards each other. From this, trust among users can be deducted. However, these kinds of extensive content analysis require additional techniques (e.g. natural language processing, semantics, opinion mining) and additional time to research. In the existing researches, to measure the quality of the content, simple content analysis methods are proposed and tried: e.g. length of posts, number of common words in different posts of the same thread, count of hyperlinks in the post, etc. We believe these kinds of shallow analysis would not bring much value to our research. So, the content analysis part is bounded to distinguish just topics of posts and the rest is left out of scope.

The majority of the forum sites that are interesting for Teezir do not have explicit statement of trust or reputation scores among users. Along with the exclusion of deep content analysis from our research, the calculation of implicit trust or reputation values is also disregarded.

We chose to focus our work on analyzing the link structure of a forum and we use Teezir's topicality tools in order to determine the topics of the documents.

3.4. From Influentials to Buzz Creators

During our research, we found out that 'finding influentials' is not the main goal but 'identifying buzz creators' is. Analyzing our research domain and carrying out further discussions have caused this change.

Teezir is interested in finding people who create buzz, the users that excite the community, the members who start conversations and get their peers talk about particular topics. The buzz creators that we are looking for do not necessarily have to be influentials. The important matter is finding the users who get reactions when they talk about a particular topic.

4. Approach Details and Methodology

In this chapter, we provide details of our approach in construction of graph and handling of data. Section 4.1 and 4.2. describe how the graph of users is constructed in two different ways. The graph is composed in order to apply the link analysis algorithms. Understanding the construction of graph is important as the algorithms' performances and, consecutively, the results depend on it. Section 4.3 explains the use of Teezir's framework in data management: gathering, extraction and storage of data. In the last part of this section, 4.4, the compared algorithms are listed.

4.1. Graph Construction Using the Forum's Structure

Using the thread structure of a forum, we can create a social network graph. Each user corresponds to a node in the graph and a reply from User B to User A is a directed edge. The weight of this edge is the total number of replies from User B to posts of User A. It's important to note that only the thread structure is used in the creation of graph and other possible relations, like mentioning a user within the reply text, are not considered. Further semantic analysis is required to get over this drawback. The identification of such links is beyond the scope of this thesis.

Figure 4 and Figure 5 demonstrate a basic example to illustrate the generation of this graph. In Figure 3, the structural relationships between the posts of two threads are displayed.

In Thread 1, User A starts a thread by making the first post. This post gets the attention of User B and User C, so they reply. User C's reply triggers the replies from User D and User E. User D and User E exchanges replies on following User D's first reply. User B also replies but does not get a reply back. For the Thread 2, this time User D makes the initial post and get replies from User A and User E. User A's post causes User C to reply. Finally, User E posts two replies to User C's comment.
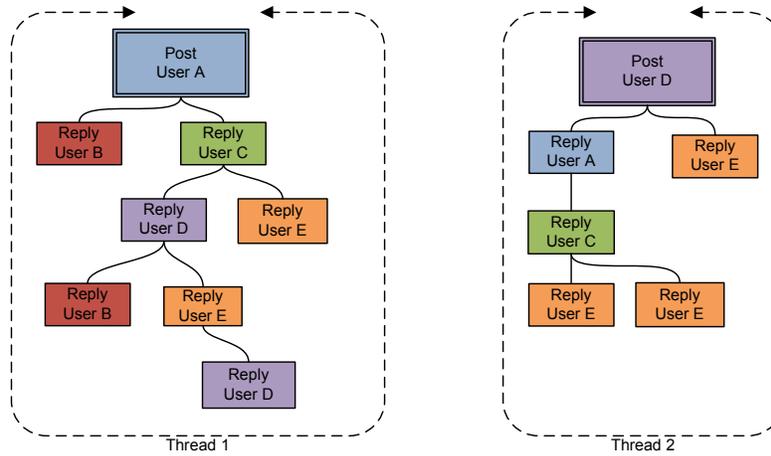
Figure 4: Graph construction example - 1.

Figure 5 is the social network graph that is constructed by utilizing the structural information of the threads given in Figure 3. Each number is the weight of the corresponding edge.
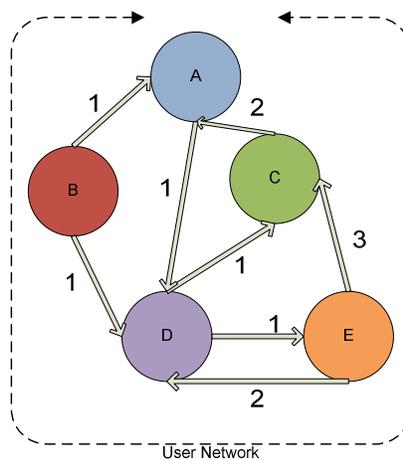
Figure 5: Graph construction example - 2.

This network graph is not simply a social network as it is not intentionally built by the users for the purpose of forming ties. Instead, it reflects the users' shared interests. The reason that a user replies to a topic is usually because of an interest in the content of the topic. Furthermore, the direction of the edge is an important indication. We believe that a user replying to another indicates that the replier is influenced, although their sentiments about the topic may differ. Assuming that the posts are on the same topic, the user who is getting replies is the one creating buzz on this particular topic. So the direction is chosen from the replier to parent post's author. Only this direction is used in the construction of the graph.

4.2. Graph Construction Using Chronological Ordering

The above described way of graph construction is applied in our smaller scale experiment (Section 5). For the larger scale experiment (Section 6), the graph of users is constructed in a different way, which is explained in this section.

The majority of the discussion forums that Teezir analyzes does not have the above described parent-child structure of posts. In these forums, the only available structure is the chronological linear ordering of posts in a thread. So each new post to a thread is added below of the previous post in the respective thread.

This type of structure brings an additional challenge to construct the graph of users. Because now there are various possibilities to create links between users: A new post might be a reply to the previous one or in fact it's a reply to the first post of the thread which is 3 posts ago. Of course there is the possibility that the new post is not a reply to any preceding posts but just a completely new post in the thread.

In such forums, the order of the posts is utilized in order to construct the graphs. The underlying idea is the same with the previous method but since there is no explicit reply structure this time, we are projecting reply links among posts. The direction of the links is the same with the previous approach: from the replier to the author of the parent post.

We use two different methods to construct the graph: *'Window of N'* and *'window of duration'.* The first way, window of N, is using the order of the posts regardless of the posting times. Essentially, every post is regarded as a reply to 'N' number of previous posts in the same thread. The second way, window of duration, is to utilize the posting times. Every post is considered a reply to all previous posts that is published in the previous 'duration' of some hours.

To illustrate with an example, in Figure 6, we continue with an example of 3 different threads with varying number of posts which are linearly ordered according to their published times. The numbers next to the posts represent the time that the posts are published.
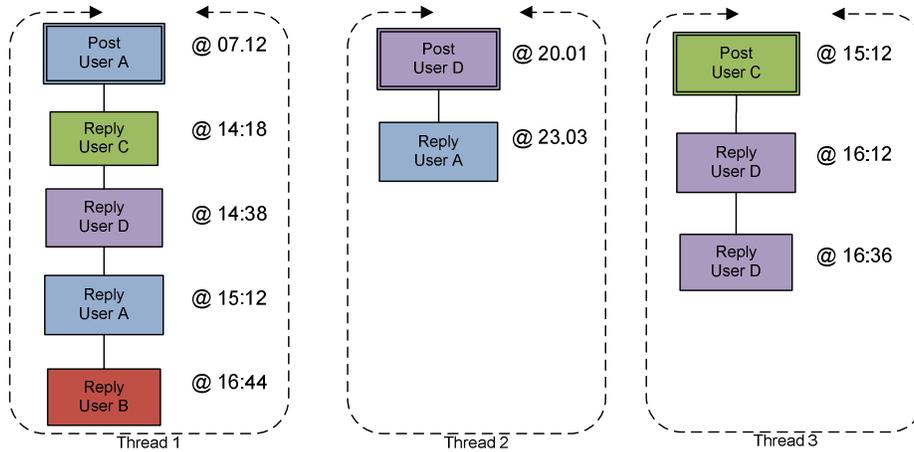
Figure 6: Threads chronologically ordered

In Figure 7, we generate 3 different graphs by using different parameters for 'N' and 'duration' with the threads in Figure 6. For the first graph N is 1 and duration is 0. This means, every post is a reply to the previous one. In the second graph, duration is still 0 but N is 2: i.e. Every post is a viewed as a reply to the previous post and to the previous of the previous. So, for instance, in first graph, there is one link created from User B to User A while in the second graph the additional link from User B to User D is created as well.

The third graph, in Figure 7, illustrates the parameters of N is 0 and duration is 2 hours. So we project links between the authors of the posts that are published in consecutive 2 hours. For example, we see that there is a link from User B to User A but no link exists from User B to User D as User D's post is published more than 2 hours before User B's.
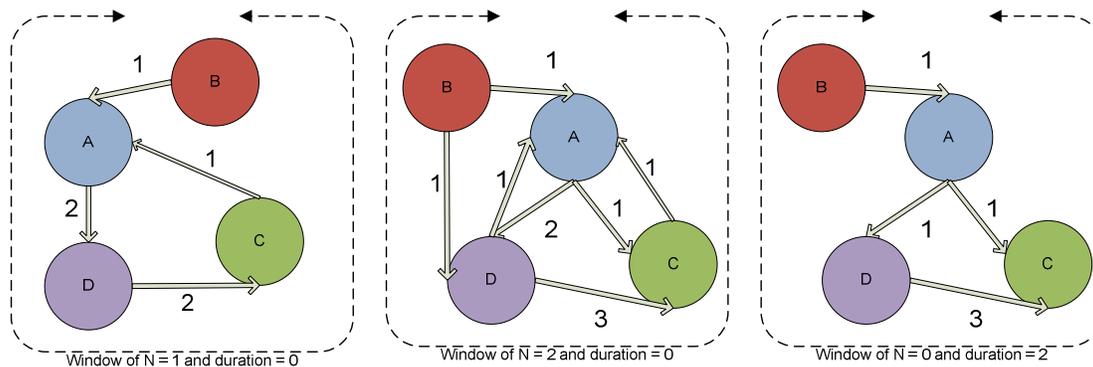
Figure 7: Different User Graph via different parameters

In our larger experiment, we make these parameters N and duration to be variable and evaluate how the algorithms perform with the changing values of N and duration. We also

consider the combination of these two methods and create links twice where applicable. So if the parameters are chosen as N = 1 and duration = 4, one link is created from a post to the previous post and also additional links created from a post to the pre-posts in a window of 4 hours. Following this example, if the previous post is published in 4 hours, the weight of the link is 2: 1 from N and 1 from duration.

4.3. Data Handling and Use of Teezir's Framework

Teezir's search platform provides the functionality for the overall process of disclosing data, namely content gathering, analyzing/extracting documents, building indices, and searching for information. All these different aspects of the framework have been employed in our research.

One of the stages in content gathering is crawling. Crawling is an automated process of collecting data typically in hyperlinked documents. A crawler systematically follows the hyperlinks between documents and stores the local copies in the database. Teezir's crawler is configured and used to gather the necessary data for our research.

Then in the analysis part, using the explicitly stated structure, the forum is decomposed into posts and each post is saved in the following format:

Field	Description
ID	The post's id
PARENT	Id of the post's parent post if there exists one (this is '0' for initial posts)
AUTHOR	Author of the post
DATE	Submission date of the post
TITLE	Title of the post - This is empty if the forum doesn't provide title for posts
TEXT	Actual content of the post
URL	Web address of the thread that the post belongs to

Table 3: Each post is decomposed into above fields

This defined dataset is not only stored in a relational database but is also indexed. Each post is indexed with the corresponding user by removing stopwords and applying stemming. Since indexing is not the focus of this research, it will not be discussed here in detail. It is good to note that already existing modern algorithms and Teezir's implementations of them are used.

While retrieving the documents, the PL2F model is used to retrieve the relevant documents, which is proved to be effective [8]. PL2F is a state-of-the-art document retrieval function. PL2F is effective to rank matching documents according to their relevance to a given search query. However, we are not interested in the ranking order as we use it in simple sense, to retrieve all the documents containing the query term. In our approach the relevance ranking provided by the information retrieval model is completely ignored, though utilizing this ranking of the documents can bring value.

Some discussion forums, like the one in our first experiment, allow anonymous posts, so the author's identity is not known. In this case, we consider every anonymous post is from a unique user and these anonymous authors are added in the graph of users with their one post. Even though they are employed in the link analysis part, anonymous users are omitted from the result list of buzz creators.

The content analysis is limited with the existing topicality tools of Teezir, as the reasons behind this decision are stated in Section 3.3. The process of identifying buzz creators in a forum starts with providing a topic and the topic is represented in terms of keywords. The documents that contain the keywords are retrieved from the index.

4.4. Link Analysis Algorithms

The algorithms described in Section 2.4 are run on the constructed graph. Their performances are compared in the evaluations of two experiments. So one of the goals of the evaluations is to find the most suitable algorithm in identifying the buzz creators.

Additionally, in order to prove the value that the graph construction and link analysis algorithms bring, the stated four algorithms are compared with a very simple metric: Total number of post counts on topic. So the users with the highest amount of posts form the fifth result set.

5. Empirical Study on Smaller Scale

In this section, we introduce our first experiment. First, we start with an introduction to the web forum we use and present data statistics that we collected. Onwards Section 5.3, the evaluation method, metrics and results are given. Then, further analytical study of the dataset is made. The discussions on the evaluation, results and analysis is located in the final part of this section.

5.1. Slashdot

Slashdot is a technology-related news website (http://slashdot.org) that houses an online community of computer enthusiasts. The website presents short news and allows the community to post comments on these stories. Since the users may reply to other comments, Slashdot can be regarded as a discussion forum site. The website allows comment posts from anonymous users in addition to its registered and logged in users.

The site labels itself as "News for Nerds" and the featured news almost always relate to computers and computer culture in some way. To name a few, topics include computer companies, operating systems, programming languages, book, video game and movie reviews. The website and community are known for their pro-open source bias. Further analysis of the philosophy and demographics of the website and community is made by Poor in [9].

The site publishes short news posts daily and the threads on these posts may trail for over a week. One single post can easily attract more than 300 comments which are mainly replies to previous comments rather than direct responses to the original story. Statistical analysis of the discussion threads in Slashdot have been performed by Gomez et al. in [10].

5.2. Data Statistics

Slashdot's discussion forum style comments section is analyzed in this research. We collected thread data (along with the original news stories data) from Slashdot, using Teezir's crawler technology. The crawled data consists of all the published news stories from any category and we did not discriminate a particular topic. Anonymous posts are also gathered and are part of the analysis though anonymous posters are excluded from the output.

In our dataset, there are 350 threads that span 20 days. In total there are 95,314 comments and 74,448 of them are from logged-in users. There are 14,658 unique logged-in users who made posts in our dataset.

5.3. Evaluation Method

In the dataset, there is no explicit ranking data defined to evaluate the algorithms and validate our claims. So we needed to use human intuition to generate a gold standard for comparison. As it was not possible for us to rate the whole collection, we have chosen 2 topics to manually annotate and use as comparison samples.

All of the compared algorithms produce continuous values that can differentiate between the users and so the buzz creators can be ranked. However, it's very difficult for humans to sort all the users by operating on intuition. It is also hard to compare two users when they have posted in different threads and have not replied to each other.

Decision of whether a user is buzz creator or not is made by using human intuition. If a user talks about the given topic and get reactions on topic, this user is considered a buzz creator. Appendix II holds an example on how the human evaluator judges whether a user is buzz creator or not (the example is from the larger scale experiment data set).

Based on our observations of the forum, we decided to label the users as '*top buzz creator*', '*buzz creator*' or '*not a buzz creator*', instead of constructing a complete ranked list.

We queried the whole dataset for each topic and gathered the documents containing the topic. Then we have further retrieved the children of these relevant documents. By reading the parent post and its replies, we have decided whether a user creates buzz in that given topic and then we labelled the user as 'buzz creator' or 'not a buzz creator'. Then we differentiated a 'buzz creator' as 'top buzz creator', if the user created buzz about this particular topic in several threads or several times in the same thread. In the final part of the evaluation, two comparisons are made: one is to check how the algorithms perform in identifying all buzz creators (including top buzz creators) and the other one is to test the algorithms for finding only the top buzz creators.

We have performed this described evaluation process for two chosen topics: 'Dell' and 'Japan'. We chose these topics since they are neither too broad nor too specific. We chose noticeably unrelated topics to prove that buzz creators are, indeed, bounded with topics.

5.4. Evaluation Metrics

We apply the metrics used for the expert finding task in the TREC Enterprise Track [11]. As we have the manually ranked list of the buzz creators, we simply compare this list with the results of the algorithms.

Many of the most frequently used retrieval evaluation measures are derived in some way from recall and precision. Precision is the proportion of retrieved users who are indeed buzz creators, and recall is the proportion of buzz creators that are retrieved. In this evaluation, we use precision at N users retrieved (Precision@N or P@N) and mean average precision (MAP).

Precision at 10 users retrieved counts the number of relevant users (buzz creators) in the top 10 users in the ranked list returned for a topic. This measure is easy to interpret as it simply tells the percentage of correctly identified buzz creators in the first 10 retrieved. However, this measure does not tell how well the algorithm scores overall, so MAP is also used.

MAP is the average precision score after each relevant user is retrieved, using zero as the precision for relevant users that are not retrieved [16]. MAP contains both recall and precision oriented aspects and it is sensitive to entire ranking. For two result sets of size 5 and 3 relevant results, the one with the relevant results ranked higher have a higher MAP score. Though, it is difficult to interpret MAP, it still allows to compare the algorithms with each other.

5.5. Evaluation Results in topic 'Dell'

When we query our data corpus, 337 comments are retrieved. There are 49 anonymous posts and the rest is from 242 logged-in users.

Manually, there are 19 identified buzz creators of which 3 are ranked as top buzz creators.

Figure 8 shows the correlations between the human ratings and various algorithms in identifying all buzz creators without differentiating top ones.
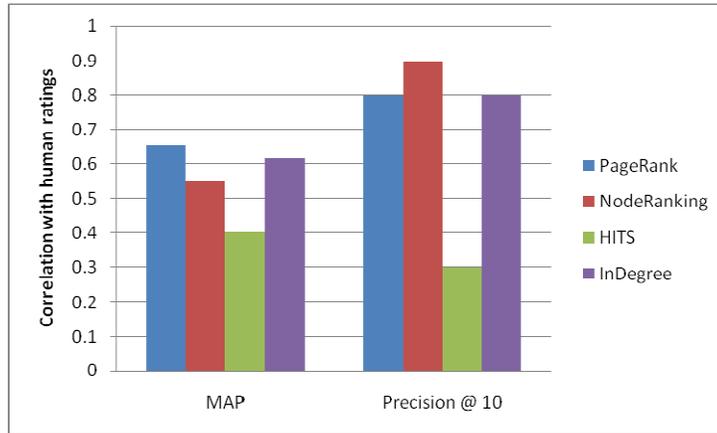
Figure 8: The performance of graph mining algorithms on 'Dell' topic

While HITS fails to impress, other algorithms score fairly well in the evaluation and there is no major difference among them. The following chart, Figure 9, displays the performance of algorithms in retrieving top buzz creators.
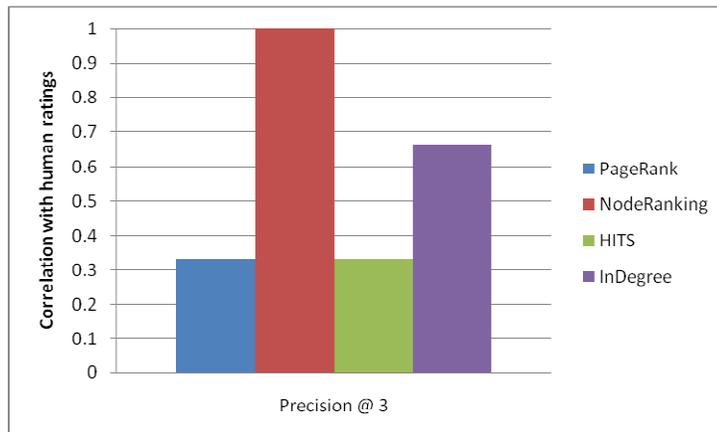
Figure 9: The performance of graph mining algorithms retrieving top 'Dell' buzz creators

As clearly can be seen, NodeRanking is the best scorer and correctly identifies all of the top buzz creators. Surprisingly, InDegree performs comparatively well and better than more complex algorithms (i.e. PageRank and HITS). Precision@3 score of InDegree says that InDegree correctly identified 2 top buzz creators and missed 1 while PageRank and HITS found only 1.

We move to our next evaluation and leave the discussions for the section 5.9.

5.6. Evaluation Results in topic 'Japan'

There are 553 comments in our collection that contains the query 'Japan'. These posts are made by 310 unique logged-in users and there are 264 anonymous comments.

Manually, there are 48 identified buzz creators and 9 of them are ranked as top buzz creator.

Figure 10 shows the correlations between the human ratings and various algorithms in identifying all buzz creators without differentiating top ones for the topic 'Japan'.


Figure 10: Comparison of results in topic 'Japan' for relevant comments

The results here are very similar to the previous ones; all algorithms, except HITS, score fairly well.

Figure 11 is the comparison of algorithms in identifying the top buzz creators.
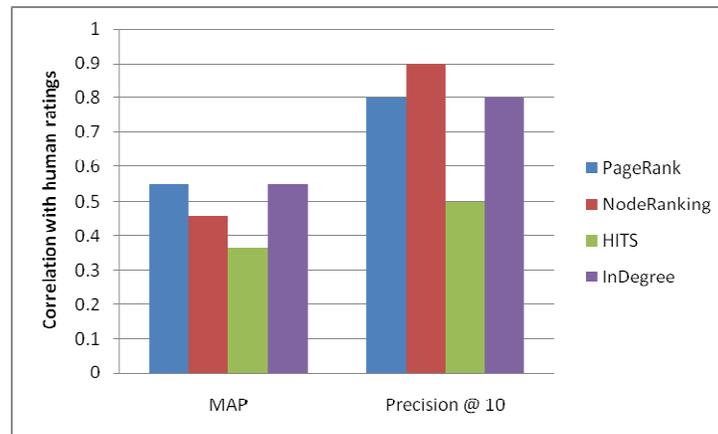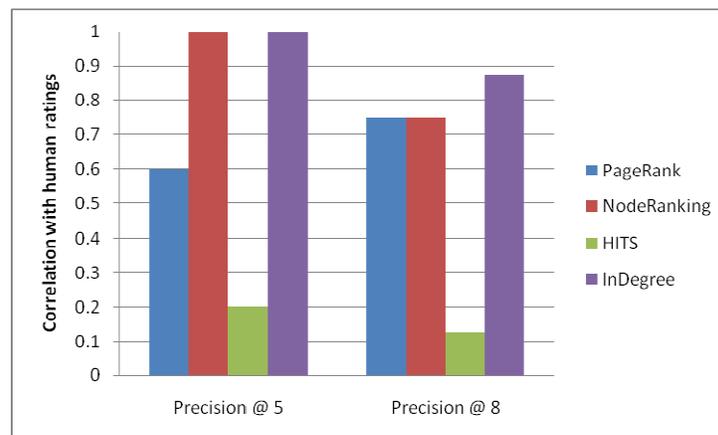

Figure 11: The performance of algorithms in retrieving top buzz creators for topic 'Japan'

This time, InDegree is the best in Precision@8 by finding 1 more top buzz creator than PageRank and NodeRanking.

5.7. Further Analysis of Slashdot

As the evaluation results give us the insight that InDegree is a useful measure, we went back to our dataset to check if there is any correlation between the total number of posts from a user and the amount of replies he gets per post. So we are testing now whether the amount of replies a user gets per posts increases as the user makes more posts.
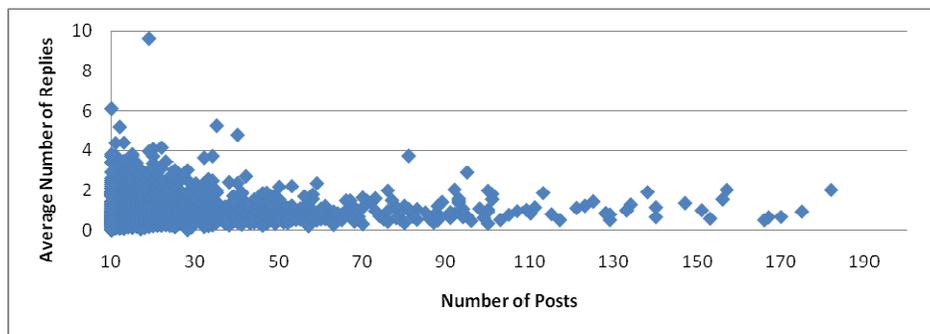
Figure 12: Number of Posts vs. Number of Replies per post

In Figure 12 we make this comparison. For each user, we calculated the number of comments that he posted and the average number of replies he got. The horizontal axis labels are the number of posts and the vertical axis shows the average number of replies of each user. Only the users with 10 and more posts are included in the graph as we are interested in users who post regularly.

The Pearson's correlation coefficient of the plotted graph is -0.00739. So certainly there is no clear pattern proving that a user will start getting higher amount of replies as he increases his post count.

The chart shows that there are certain users who are better in getting large amounts of replies. Yet, without topicality knowledge, finding these individuals doesn't bring any value. It is important to understand what these users are talking about and in which topics they are successful at getting replies.

When we do a similar comparison in the topic 'Japan' and look at the statistics of the manually identified top buzz creators versus all users, the chart at Figure 13 is acquired.
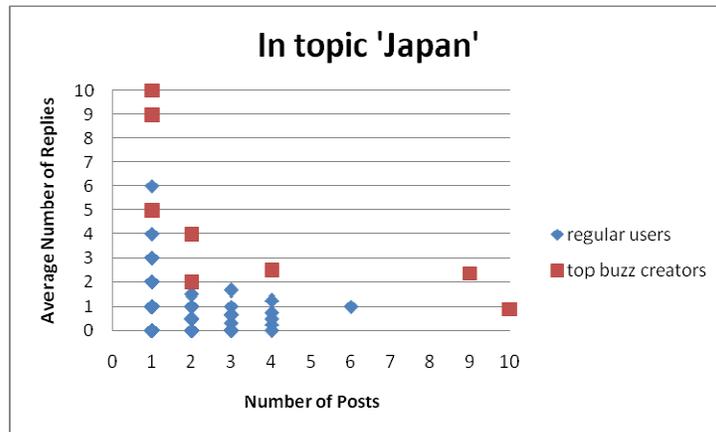
Figure 13: Number of Posts vs. Number of Replies per post in the topic 'Japan'

The Pearson's correlation coefficient is 0.1 which means there is little or no correspondence between increasing post count and getting higher amount of replies, also on topic as it is the same result in general case.

However, this figure clearly shows that the top buzz creators are the users with high amount of replies per post. This explains the success of simple InDegree method.

5.8. Evaluations vs. Moderation Scores

We check how the manual annotation evaluates over the moderation scores of Slashdot.

Slashdot has a community based moderation system whereby every comment posted has a starting score which can be incremented or decremented by moderators. The score ranges from -1 to +5 and users can set a personal threshold where no comments with a lesser score are displayed. This moderation mechanism is explained in detail in the article by Poor [9].
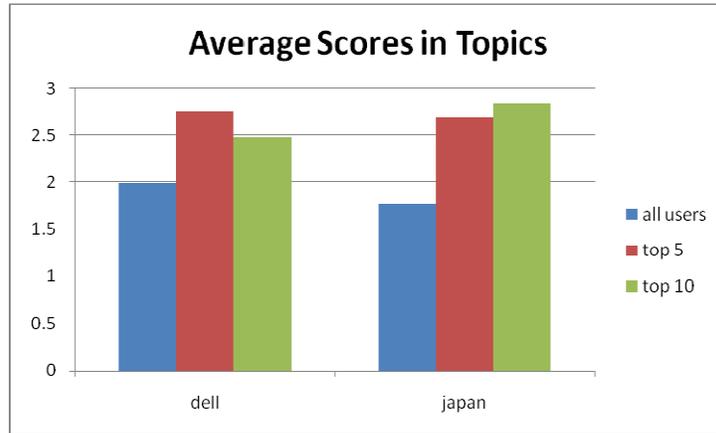
Figure 14: Comparison of gold standard with moderation scores

For the retrieved comments about the topics, the average scores are calculated. In Figure 14, we compare the average score of all comments with the average scores of the comments from 'Top 5' and from 'Top 10' identified buzz creators. The comments of 'Top 5' and 'Top 10' identified buzz creators have higher average scores than the average of all comments about the topic.

This has two implications: The comments from the buzz creators are found valuable by also the moderators and scored highly. This first conclusion shows that the buzz creators are the users who write quality posts. The other conclusion from this figure is rather different. Since the moderation gave higher scores to these comments, they gained the opportunity to reach a wider audience. To put in other words, the high scores might be the reason that those comments got more attention and have a larger amount of replies. This second implication can be interpreted as a bias in the dataset. The authors of these posts became buzz creators with the aid of the moderation scores.

5.9. Discussions

It is interesting to see that a simple solution, InDegree, performs fairly well as compared to more complex algorithms. In a sense, this is not very surprising. Our definition of 'buzz creator' is in accordance with what we measure by InDegree. To put in a simpler way, we can define the buzz creators as the people who get lots of replies. Since the network is constructed by using the posts that are relevant to the query, we ensure that replies are in the same topic with the parent post.

Although, the evaluation method might seem like simply counting the number of on topic replies to a post; in fact it is more than that. We argue that our approach and the evaluation do not form a circular reasoning. The human assessor is instructed to look for users who

start conversations about the topic. The assessor used human linguistic skills and intuition on the decision to identify the buzz creators.

Another interesting result is that NodeRanking performs slightly better than PageRank. This result was expected since the PageRank algorithm is designed and fixed to rank Web pages and NodeRanking is tuned to perform over any kind of network structure.

Then, we checked if there are any correlations between the buzz creators lists of 'Dell' and 'Japan'. There are none, albeit 3 buzz creators in 'Dell' (1 is top buzz creator) and 3 buzz creators in 'Japan' (1 is top buzz creator) have posts in both of the collections. The results from this further analysis of the dataset can be considered as empirical proves that buzz creation is topical.

The failure of HITS gives hints about the characteristics of the forum. In the evaluation, we have seen that the buzz creators are the users who have strong opinions about a topic. These users start controversial conversations which attract the other buzz creators on the same topic who have different opinions. The topic is the most important aspect for a buzz creator, so the buzz creator joins the conversation about the topic, regardless of the originator user's identity. The buzz creators have high authority and hub scores since they tend to have conversations among each other. As the buzz creators reply to non buzz creators, the buzz creators propagate high authority scores to these non buzz creators.

6. Empirical Study on Larger Scale

This chapter details the larger scale experiment which is conducted in another forum site. We start with introducing the new dataset that is significantly greater (both in volume and in time period it spans). This greater size of the dataset brought the necessity of applying different evaluation method, which is described in Section 6.3. The evaluation results and insights that we derived are presented in the last part of this chapter.

6.1. Howard Forums

HowardForums.com is a mobile phones discussion board that has an active mobile enthusiasts community (http://www.howardforums.com/). The site consists of several subforums all with mobile phone related topics, including manufacturers, carriers (service providers), industry and technological advances. Although the emphasis is on the North American (USA and Canadian) market, the moderators and contributors are from around the globe. The founders describe that HowardForums.com is founded in 2001 to address the lack of cell phone focused websites and now the forums aim to reach all types of mobile phone users: a teenage girl who is considering her first phone purchase on her allowance budget as well as the tech-savvy business guy posing opinions about his third phone this year. The site requires registration to make posts and there are 1,015,614 registered users to this date (21 July 2009).

6.2. Data Statistics

The first stage of the experiment has been the data gathering and extracting, as described in section 4.3. The crawler is configured to collect data from manufacturer discussion forums which include subforums about well known brands such as: Nokia, Sony Ericsson, Motorola, LG, Samsung, RIM and Apple. Without discriminating any particular topic, all publicly available data, which is generated in the last year, is collected.

There are 34,582 threads and 645,950 comments in total, which are posted by 63,806 users.

6.3. Evaluation Method

There was no explicit knowledge given in the dataset to be used as ground truth for the identification of buzz creators, like it was the case in Slashdot. So again we needed a way to test the algorithms' performances. Similar to Slashdot evaluation, it is not possible to manually annotate the whole collection and there is a necessity to choose topics. However, even when filtered with topics, the collections of posts are very large in volume to be read one by one. Additionally, this time we wanted to compare the algorithms' performances on more than 2 topics. Because of these reasons, 'double-blind' method is chosen, which is widely used in medical experiments.

In double-blind trials, the human rater is unaware which results belong to which algorithms so there is no conscious or unconscious observer bias towards any algorithm. Like the previous experiment, the whole dataset is queried for each topic and the documents containing the topic are gathered. On this subset of topic, the algorithms are run and top ten rankings of the algorithms are acquired. Then the human rater reads a significant number of posts written by each user listed in the rankings as well as other posts in the thread. All users in any of the result ranking is labelled as 'buzz creator' or not.

For each evaluated topic, the top 10 results of all compared algorithms are gathered in a pool. All these users in the pool are checked whether they are buzz creator or not. Then for each algorithm's results, the precision of correctly identified buzz creator is calculated. So basically, we are evaluating the performance of the algorithms in terms of 'Precision@10'.

This method lets us compare the precisions of algorithms but does not scientifically measure the recall. In other words, there is the risk of missing some buzz creators, if all the algorithms perform badly and none of them returns all possible buzz creators. However, throughout the manual annotation part, a sense of recall is obtained which we note as sufficient.

The human assessor is also asked to rank the algorithms using his intuition, so this ranking is used instead of MAP. The assessor sorts the algorithms from 1 to 5 according to the ranking of buzz creators in the results for each topic. If the assessor finds two best algorithms, they are both ranked as #1 and the third algorithm is ranked as #3, thus no algorithm gets the ranking of #2.

Appendix II holds an example on how the human evaluator judges whether a user is buzz creator or not.

6.4. Evaluation Setup

The described evaluation method is tried out in 20 different topics. Table 4 shows the topic queries along with the number of manually identified buzz creators, the number of distinct users, threads and posts.

Query	Total Buzz Creators	Users	Threads	Posts
8800	16	647	622	1277
android	9	586	631	1352
bold battery	12	454	501	908
c905	11	335	316	826
dare	11	2376	1955	7921
dare screen	9	734	684	1395
e71	10	1241	1532	4814
g1	14	656	581	1253
iphone audio	14	444	478	737
iphone battery	19	1615	1784	3534
iphone bluetooth	14	949	946	1672
lg bluetooth	11	779	773	1137
n85	12	506	666	2805
n96	10	443	515	1524
n97	16	660	791	4875
nokia battery	8	882	1020	1566
omnia	13	880	776	2389
storm	8	2132	1882	7060
thunder	10	353	303	1026
u600	11	336	193	835

Table 4: Comparison of gold standard with moderation scores

The topics are chosen to be neither too specific nor too broad. The criterion in the selection of topics are to cover different users and have sufficient amount of data to do evaluation. Two-keyword topics are queried to run evaluations on more specific data sets.

As seen from the table, there is no correlation between the number of manually identified buzz creators and other statistics, number of users, threads, posts (for all of them the Pearson Correlation coefficients are between 0.05 and -0.05).

As described in Section 4.2, *'window of N'* and *'window of duration'* methods are applied while constructing the graphs that the link analysis algorithms run on. These two methods are employed individually and also together in order to find the most suitable and accurate solution. We make N to be variable between 1 and 10, the duration to be either 2 or 4 hours. Thus, there are 32 different combinations of graph generation that are evaluated.

The compared algorithms are the same with the previous experiment: PageRank, NodeRanking, HITS and InDegree. Additionally, the top 10 users with the highest number of posts on topic are compared with the link analysis algorithms' results. This extra compared algorithm, which we call *PostCount*, validates the value of graph construction and using link analysis algorithms.

6.5. Evaluation Results

In Appendix I, there are the two tables with the average scores of all parameter combinations in constructing the graph and their standard deviations over all evaluated topics.

The first observation of the results is that in the construction of graph, the 'window of duration', considering publish dates of the posts, does not bring additional value. 'Window of N' method, creating links according to the order of the posts, is better by itself.

Figure 15 illustrates the comparison of algorithms with the changing value of N. The values are the average of the Precision@10 percentages over all topics.
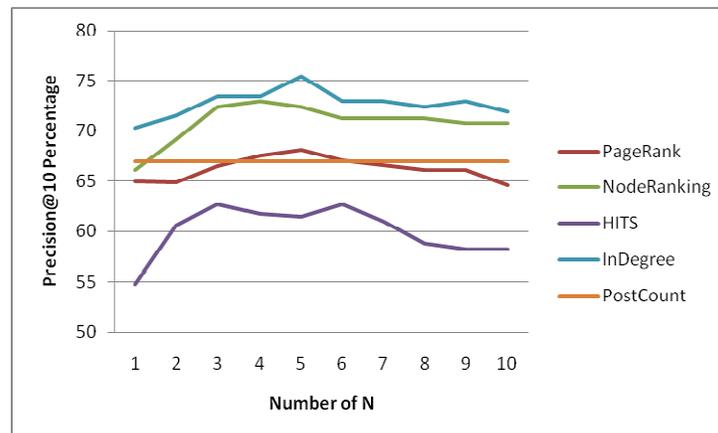
Figure 15: Comparison of algorithms with the variable N

Judging from the average of all scores, the optimum value of N is seen as 5, given that the overall highest Precision@10 is achieved when N is 5. In addition, during manual evaluation, the human assessor confirms that 5 is the optimal value. So, we take the graph which is constructed with a window of 5 as our basis to compare the algorithms' performances.

Figure 16 shows the Precision@10 comparisons of the algorithms' performances on the graph that is generated with window of N, N equals to 5.
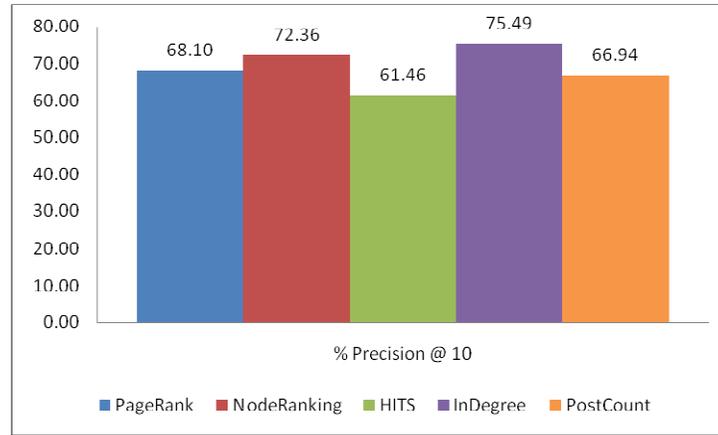
Figure 16: Comparison of algorithms' performances

From the figure, one can see that all of the algorithms give a relatively high correlation with human-assigned ratings. The order of the algorithms' scores are also in line with the preceding experiment, InDegree and NodeRanking score higher than the other algorithms. Surprisingly, the very simple count of posts (PostCount) performs fairly well and even better than HITS.

Table 5 shows the ranking of the algorithms that are compared by the human assessor. The values are the rankings averaged over all topics.

InDegree	NodeRanking	PageRank	PostCount	HITS
1.5	1.85	2.35	3.1	3.9

Table 5: Comparison of algorithms' performances

The results in Figure 15, Figure 16 and Table 5 are corresponding and they all present the same ranking of the algorithms. InDegree is clearly the best solution and NodeRanking is the second with a comparable performance.

To check how the amount of posts per topic affect the algorithms' performances, the results are divided in two groups: topics that have more than 1500 posts and topics that have less than 1500. There are exactly 10 topics in each group.

The evaluation for the topics with greater amount of posts is presented in Figure 17.
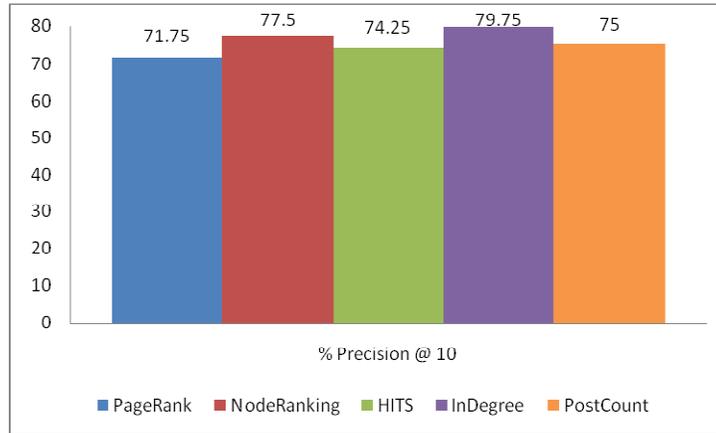
Figure 17: Algorithms' performance on topics which have greater than 1500 posts

Although the order is slightly changed, InDegree and NodeRanking are still the best performing algorithms. However, it is clearly notable that there is no major difference among algorithms. It is safe to conclude that the performances of algorithms increase with greater data volume. When we further check the results for these topics with high amount of posts, we see that top 5 results of all algorithms are exactly the same in almost all of the evaluated topics: The users with the highest number of posts on topic are the top buzz creators. However, in the bottom 5 results, InDegree is better in identifying the buzz creators who have less total amount of posts.

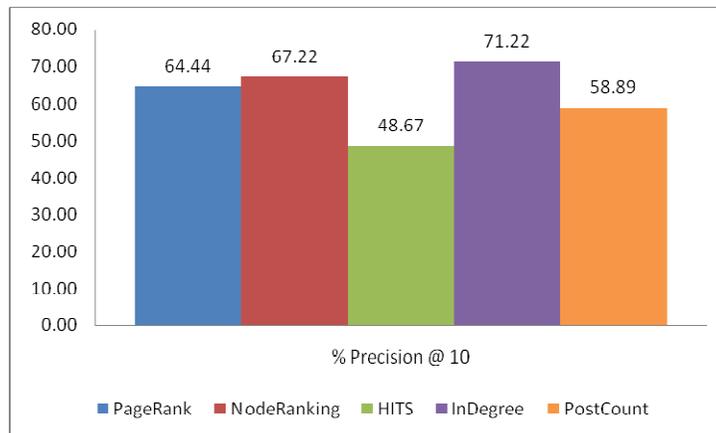Figure 18 shows the evaluation for the topics which have less than 1500 posts.

Figure 18: Algorithms' performance on topics which have less than 1500 posts

InDegree is clearly the best performing algorithm in identifying the buzz creators on topics with relatively smaller number of posts. The performance decrease in PostCount shows that in these data collections, it is harder to identify the buzz creators as the high number of posts is not a distinguishing feature.

6.6. Discussions

The evaluation results are in correspondence with the smaller scale experiment's results: According to both precision metrics and intuitive ranking of algorithms, InDegree and NodeRanking are the best and InDegree is slightly better. A statistical significance test is made over the results of InDegree and PostCount, which shows InDegree is significantly better than PostCount.

In the manual evaluation, we have seen that the buzz creators are often the influentials on the given topic. The users of the forum talk about these buzz creators and their opinions about the topic. We have seen several examples of users getting affected by buzz creators. Some users wait to hear the buzz creators' opinions before making a decision. We have also seen that the buzz creators are the frequently the experts on the given topic. They inform the community by answering questions about the topic and making reviews of phones. However we have also seen buzz creators who are neither experts or influentials. This kind of buzz creators are users with strong opinions about the given topic who starts controversial conversations and attract other users.

To prove our claim about the importance of topicality, we make a further analysis. There are in total 169 unique buzz creators and 70 of them have posted at least 10 posts in more than 1 topic. 33 out of 70 are found to be buzz creator in all the topics they have written as 47 are not.

Another proof of topicality's importance is that the related topics share buzz creators. The query terms, which are all manufactured by Nokia, 'N85', 'N96', 'N97' and 'Nokia battery' have 2 buzz creators in common as N85 and N96 have 6. Similarly, the query terms 'Thunder' and 'Storm' share 4 buzz creators, noting that Thunder is the pre-release codename of Storm. The topics from different manufacturers share less or no common buzz creators although there are buzz creators who posted more than 10 posts in cross topics.

7. Conclusions

The goal of this thesis was to identify buzz creators in discussion forums. The idea for a solution is to use existing methods that are used in identifying experts and influentials in social media websites. We implemented an application to prove our claims and successfully identify buzz creators. We evaluated this application over two experimental studies. Performing two experiments offered us the chance to test the application in two different types of forums with diverse structures, data sizes and topics.

7.1. Approach

Firstly, the terms, buzz and buzz creator, are defined in the context of discussion forums. The different characteristics of a buzz creator from an expert or an influential are explained. To the best of our knowledge, there is no existing study that is conducted to identify individuals in our domain: discussion forums. The differences in both the target group and domain bring the necessity of proposing our approach: Combining the topical knowledge of the data with the performance of link analysis algorithms. We used Teezir's existing topicality tools and we focused on developing link analysis part along with finding ideas to combine these two parts.

7.1.1. Topicality

We claim and later observe that buzz and accordingly buzz creators are topic sensitive. There is a need to distinguish the topics of the conversations in discussion forums. As Teezir already has the technology, we find it convenient to index all the posts and derive keywords that define the topic of the posts. So in the first step of the application, we filter the whole data corpus by querying the topic keywords. Pulling the posts that contain the query terms, not only we acquire a more manageable data subset, but also we clear out the off topic posts. Because we observe that topic drift in discussion forums is highly common and most of the time not all posts in the same thread share a common topic. Using keyword(s) to determine the topic is proved to be sufficient. Additionally, we verified our claim that the buzz creators are bounded with topics by showing different analysis of the datasets.

7.1.2. Link Analysis Algorithms

In order to utilize the link analysis algorithms, a graph of users is constructed. We followed the existing solutions with link analysis algorithms on social networks and made the design decisions to create directed and weighted graphs of users with edges being the post interactions among users. We developed two ways to construct the graph, depending on the forum structure. In our first experiment, the forum has a detailed parent-child post structure and therefore the straightforward solution is to create a link from the author of child post to the author of parent post. The reason behind is the author of the parent post being the buzz creator on this topic since he is getting a reaction. The second experiment's forum is less structured and instead of parent-child posts relationship, all the posts in the same thread are linearly ordered. So we come up with alternative ways to create links between users. We used the posting order and the posting times in creating links. While using the post times does not bring additional value, the most successful parameter is found to be 'window of 5': i.e. creating link from every new post to all the 5 previous posts.

We evaluated the performances of 4 link analysis algorithms and a simple metric: users with the highest amount of posts in a given topic. Both of the studies produced the same results and InDegree centrality is the best in identifying topical buzz creators, best and surprisingly it scores better than more complex algorithms, like PageRank and HITS. The reason behind InDegree's success lies in the definition of buzz creator: The person who gets reactions and makes other users talk. Simply, a high number of on topic replies is an indication of buzz creation.

NodeRanking has scored as the second best algorithm in both of the evaluations, beating PageRank. NodeRanking is a variant of PageRank with the small modification to perform independent of graph structure. This shows that network structure affects the algorithms' rankings and as PageRank is designed for world wide web networks, NodeRanking is better in social network graphs.

Although PostCount, the total number of a user's on topic posts, scores higher than HITS; InDegree and NodeRanking are significantly better. This validates our claim that the graph construction and link analysis over the graph bring value.

It is valuable to mention that all these algorithm rankings are in accordance with the literature. Zhang et al [3] has also demonstrated that InDegree performs over PageRank and HITS on identifying experts in question-answer forums. Pujol [7], who founded NodeRanking, states in his paper that his algorithm scores higher than PageRank on extracting reputation in a social network of academicians. The reason is NodeRanking's adaptive nature to various network structures.

7.2. Insights

In this work, we found:

- Structural information can be used for the identification of buzz creators. Using social network-based algorithms brings value over the information found in content alone. So the combination of topicality and link analysis algorithms is proven to be useful.

- Knowing the topicality of the content is highly crucial for the algorithms to work accurately.

- The network's structural characteristics and the size of data affect the performance of the algorithms. When there is abundance of data, the selection of an algorithm does not really matter.

- The algorithms scored nearly as good as human rater. The simple measure, InDegree, is the best performer at all times and the difference over other algorithms is significant when the dataset size is relatively smaller.

7.3. Suggestions for Future Work

Our research has made the first step in combining content information with the structural information. Further steps in improving the analysis of content and structural studies will aid in developing more advanced online community based identifiers.

Since we have limited our content analysis, it might be interesting to test the possibilities in this part. One idea is to track how information disseminates through the network. With advanced content analysis, one can find out who is being quoted or rephrased. So by following the trail of sentences or keywords, the original source of the buzz and the paths that the buzz goes through can be detected. Using Natural Language Processing techniques, there is the possibility to identify opinion changers, influentials. For example, these techniques can tell us, following the discussions with the buzz creator about a phone, whether the repliers bought the same phone or not. Another idea for content analysis is identifying subtopics in a given topic by using related keywords. This better grab of topicality will most likely increase the performance of link analysis algorithms.

Another possibility is to test our approach's performance over identifying other individuals: authorities, experts, influentials.

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Appendix I: Larger Scale Experiment Evaluation Results

The average Precision@10 percentages of the compared algorithms over 20 topics. For each topic there are 32 different graph constructed using two variables: Window of N and window of duration. Window of duration is given in hours.

Window of N	Window of Duration	PageRank	NodeRanking	HITS	InDegree	PostCount
1	0	64.93	66.13	54.78	70.31	66.94
2	0	64.86	69.17	60.58	71.54	66.94
3	0	66.49	72.36	62.71	73.49	66.94
4	0	67.54	72.93	61.71	73.49	66.94
5	0	68.10	72.36	61.46	75.49	66.94
6	0	67.10	71.24	62.71	72.99	66.94
7	0	66.60	71.24	61.00	72.93	66.94
8	0	66.10	71.24	58.75	72.43	66.94
9	0	66.10	70.74	58.25	72.93	66.94
10	0	64.54	70.74	58.25	71.93	66.94
0	2	47.69	56.94	49.14	57.38	66.94
1	2	63.06	68.92	52.76	69.11	66.94
2	2	62.49	67.86	58.38	69.43	66.94
3	2	62.99	68.86	58.76	70.93	66.94
4	2	64.61	70.86	57.82	72.56	66.94
5	2	65.49	70.86	58.25	72.49	66.94
6	2	65.61	69.86	58.25	73.11	66.94
7	2	66.11	71.36	59.75	72.61	66.94
8	2	65.17	70.36	60.19	72.61	66.94
9	2	64.54	70.36	59.69	73.11	66.94
10	2	64.54	70.36	58.69	72.61	66.94
0	4	50.26	57.32	52.21	62.63	66.94
1	4	64.56	67.18	54.21	68.06	66.94
2	4	62.99	69.36	56.76	69.06	66.94
3	4	62.99	67.74	57.32	72.61	66.94
4	4	65.54	69.86	61.32	72.61	66.94
5	4	65.99	70.36	61.32	73.49	66.94
6	4	65.49	70.36	60.32	74.61	66.94
7	4	64.49	70.86	59.82	71.61	66.94
8	4	65.04	70.36	59.26	72.61	66.94
9	4	64.54	69.86	59.26	73.11	66.94
10	4	64.54	69.86	58.76	71.61	66.94

The averages of the standard deviations of the scores given in the above table.

Window of N	Window of Duration	PageRank	NodeRanking	HITS	InDegree	PostCount
1	0	19.71	18.23	24.70	17.28	19.97
2	0	20.84	18.09	20.44	14.61	19.97
3	0	23.06	17.67	21.53	15.82	19.97
4	0	23.60	17.25	19.59	15.14	19.97
5	0	23.43	15.45	21.75	15.22	19.97
6	0	22.63	16.17	20.78	15.43	19.97
7	0	22.68	16.50	20.38	15.94	19.97
8	0	22.48	16.50	23.23	15.86	19.97
9	0	22.48	16.37	23.98	15.60	19.97
10	0	23.01	16.37	23.98	14.73	19.97
0	2	23.15	20.45	23.53	18.72	19.97
1	2	19.47	18.10	23.10	14.43	19.97
2	2	22.50	17.25	20.82	15.38	19.97
3	2	22.56	18.24	20.97	15.86	19.97
4	2	22.42	15.78	20.73	16.28	19.97
5	2	22.41	15.78	20.29	16.35	19.97
6	2	22.88	16.13	19.49	16.18	19.97
7	2	23.32	16.87	17.74	15.78	19.97
8	2	23.75	16.61	17.70	15.78	19.97
9	2	23.29	16.92	17.85	16.18	19.97
10	2	23.29	16.92	17.80	15.45	19.97
0	4	20.38	19.16	25.79	17.48	19.97
1	4	19.30	19.35	22.92	18.05	19.97
2	4	20.61	17.53	21.97	17.24	19.97
3	4	23.02	19.19	21.54	14.75	19.97
4	4	22.83	17.08	19.64	16.44	19.97
5	4	23.32	17.23	19.09	14.79	19.97
6	4	23.11	17.23	19.68	15.97	19.97
7	4	23.33	17.06	18.72	16.89	19.97
8	4	22.84	16.29	19.57	17.67	19.97
9	4	22.60	16.13	19.57	17.44	19.97
10	4	22.60	16.13	19.67	16.57	19.97

Appendix II: Example of Buzz Creator Identification

In this section, a thread from HowardForums.com is partially displayed to portray buzz and buzz creation example in our context. To save space and in order to present more clearly, the thread is summarized to include only the posts' author and textual content. The original thread can be seen at http://www.howardforums.com/showthread.php?t=1481224.

The thread is initiated with the Nokia N85 review of JP. In his post, JP explains his experiences with N85 and makes a thorough review by detailing different aspects of the phone (build quality, reception, battery, display, performance, etc.). He also compares N85 with, his old phone, N95 and ends his post by motivating the readers to change from N95 to N85.

We see that all the users who join the conversation appreciates JP's post as some users express that they are buying an N85 after reading this review. More importantly, JP's post makes the users to talk about N85 and N95. JP is definitely a buzz creator in the topics of N85 and N95.

The user with the pseudonym, josesxi, disagrees with JP's review and some users react to him by agreeing or disagreeing, in any way talking about N95. So josesxi is a buzz creator in N95.

Another interesting observation is that after RogerPodacter joins the conversation with his post about E71 (another Nokia phone), discussions about E71 begin. RogerPodacter is a buzz creator in the topic of E71, though he is not in N85 nor N95.

Title: JP Review ~ Nokia N85 : The Formidable Underdog (+ N85 vs N95 comparison)

JP
INTRO:
Ladies & Gents, It has been over a year since I wrote my last review (on the N95-3). Partly because I've been busy, partly because the phones that have come and go haven't been inspiring. For well over a year, I have spent 95% of my time with an N95. I replaced the N95 I got in July 2007 with the N95 8GB in April 2008 and have been enjoying that until now, putting them on pause briefly only to try the iPhone, E71 and Samsung Innov8 i8510. Using this awesome phone over the holidays made me want to do a review. However, it's a bit all over the place, so I hope you can bear with me. I'm just not into doing reviews anymore :-(… [Review of Nokia N85, text is omitted to save space]

roncito
Yes, it has encouraged me to get an N85 asap .... nice review thanks

THETRUTH#34
Great review once again jp, although i have not had any issues with video playback, as a matter of fact i loaded some seinfeld episodes in my n95-4 and then on my n85 and n95-4 didnt play it and the n85 did, but the n96 is the king in that area. As for the camera i actually think the n85 in your first pic with canadian post looks better when blown up to the full size

the tree on the n95 looks like a blur where is on the n85 a little more detail, plus colors look a little nicer on the n85 but it seems in low light the n85 cant handle the brightness of lights like the n95 does. I overall recommend the phone also.

YNOTT

Thanks again I have been on the fence about an upgrade to my n 95 and this phone is very close but I would still prefer a larger display

JP

Quote:

> Originally Posted by **THETRUTH#34**
> *Great review once again jp, although i have not had any issues with video playback, as a matter of fact i loaded some seinfeld episodes in my n95-4 and then on my n85 and n95-4 didnt play it and the n85 did, but the n96 is the king in that area.*

Interesting. I only tried playing a divx movie (Wanted) using the DivX Mobile Player and it stuttered...something it didn't do with my N95.

I'll try MP4 files and Core Player.

Donnation

Very nice review JP! I had an N85-3 for a while and while it was a cool phone I still prefer the form factor of the N96 that I have now. I did however not like the keypad that you mention above. I found it too stiff to type on, but that is all based on opinion.

I did notice (and posted on it a while back) that the camera was also a let down from the N95 which doesn't really make much sense. The other thing I noticed about the camera was trouble focusing on certain objects. It had trouble locking on and I would have to re-press the button. But like you said it could be corrected with an update.

Thanks again for the review.

rapidstar

Good review. I had N85 for few weeks & had to let it go coz of the stiff soft keys & OLED screen which doesn't display the colors properly. In my view it is not an upgrade from N95-3/4.

twofaze

nice review...
I'm up on my contract w/ T-mobile, contemplating a move to AT&T.....
(especially if I get a job at one of their wireless stores)
I was contemplating the N85-3 or the N95-3....

you've helped push me a lil' more towards the N85-3....

ipodlover77

great review, good thing you did a review before you lost all your touch
favorite line, "not from dumb bimbos who are only interested in pearls, touches and iphones."
LOL. Good sum up.

Rcadden

honestly, you've convinced me to give the N85 NAM another go. I'd written it off after my experience with the N85 Euro.

Blaxx

Great review as usual JP. When are you gonna pick up another E71 and give that the thorough review process? I'll let you borrow one of mine for a month LOL

josesxi

IMHO there is no reason to upgrade to this phone unless you're absolutely bored with your N95. .....I am, but I still won't do it. That OLED screen is sooo overrated! (The display of my N95-3 is brighter, crispier and shows more natural colors).

1-worse camera
2-worse speakers
3-buggy software
4-lousy D-Pad
5-questionable build quality
6-and did I mention the overrated screen?

I am sorry I can not do it, not now.

RogerPodacter

Man i'm so undecided on this phone. I'm stuck with this e71 and the only phone that interests me was the n85. But i just dont know.

THETRUTH#34

why are u undecided, what is it you would like to know.

THETRUTH#34

Quote:

> Originally Posted by **josesxi**
> *IMHO there is no reason to upgrade to this phone unless you're absolutely bored with your N95. .....I am, but I still won't do it. That OLED screen is sooo overrated! (The display of my N95-3 is brighter, crispier and shows more natural colors).*

I agree if u arent bored wit the n95 no reason to upgrade, that being said i do disagree with screen its much nicer than the n95-3 not sure if it lives up to all the hype but its an amazing screen considering its the same resolution,
my software is pretty stable
better slide for sure
the device is more solid than the n95-3 or 95-4
1-better battery life
2-better music quality
3-better music playback times
4-3.5mm jack on top now
5-usb charging

But like you said if you dont have to upgrade there isnt a need to, i sold my n95-4 and made 100.00 buying the n85-3 so it was a no brainer for me.

THETRUTH#34

Hey Jp i can confidently say better battery life, i do charge my phone daily also, but this is the first nseries phone i leave on 3g when im out delivering my route, i usually talk for a good 2hrs to various people, and both the n95-4 or n95-3 would be down to about 3 bars by the time i finish my route, my n85 is still full.

Blaxx

Quote:

> Originally Posted by **RogerPodacter**
> *Man i'm so undecided on this phone. I'm stuck with this e71 and the only phone that interests me was the n85. But i just dont know.*

Stuck? You say that like it's a bad thing to have an E71. I love this phone, so much so that I have 2. (Still trying to unload the white one)

---

illmatic416

Quote:

> Originally Posted by **josesxi**
> *IMHO there is no reason to upgrade to this phone unless you're absolutely bored with your N95. .....I am, but I still won't do it. That OLED screen is sooo overrated! (The display of my N95-3 is brighter, crispier and shows more natural colors).*

+1...I got rid of my N85-1 after a month...was already bored of it after two two weeks

---

Rcadden

I don't know what you're talking about with the screen. After using the Euro N85 for a few weeks, everything just looks washed out.

RogerPodacter

Quote:

> Originally Posted by **THETRUTH#34**
> *why are u undecided, what is it you would like to know.*

well most important feature of a cell phone to me is the loudspeaker, and the n85 isnt quite as good as the my n95-4. i also dont like the stiff softkeys i've read about. and finally i need a camera and the n85 seems to be poorer than the n95-4. maybe firmware can fix this, but do we know that for sure? maybe the n85 has different hardware and different lens than the n95. maybe its just lesser quality overall.

RogerPodacter

Quote:

> Originally Posted by **Blaxx**
> *Stuck? You say that like it's a bad thing to have an E71. I love this phone, so much so that I have 2. (Still trying to unload the white one)*

i'm totally bored with the e71. it cant play any videos well, the music quality is not good. and the camera is so bad it might as well not even have one. i just want to go back to an Nseries with a decent camera, and n85 was the only one that interested me. but some of the negative things are turning me off to it, like the poor Dpad/softkeys and poor camera compared to n95.

THETRUTH#34

Quote:

> Originally Posted by **RogerPodacter**
> *i'm totally bored with the e71. it cant play any videos well, the music quality is not good. and the camera is so bad it might as well not even have one. i just want to go back to an Nseries with a decent camera, and n85 was the only one*

> *that interested me. but some of the negative things are turning me off to it, like the poor Dpad/softkeys and poor*
> *camera compared to n95.*

have you seen pics taken by the n85, jp did say that he thought his n85 euro took better pics than his n95.

---

gordonshowers

Quote:

> Originally Posted by **RogerPodacter**
> *but some of the negative things are turning me off to it, like the poor Dpad/softkeys...*

At first I thought they were poor, but after a week they felt great. They even made my wife's N95 8GB d-pad feel too "loose".
Believe me, you should not be put off the N85 because of the d-pad/softkeys.

---

illmatic416

Quote:

> Originally Posted by **RogerPodacter**
> *i'm totally bored with the e71. it cant play any videos well, the music quality is not good. and the camera is so bad it*
> *might as well not even have one. i just want to go back to an Nseries with a decent camera, and n85 was the only one*
> *that interested me. but some of the negative things are turning me off to it, like the poor Dpad/softkeys and poor*
> *camera compared to n95.*

Personally, I also prefer the E71. Roger, it sounds like the 5800 XM NAM might be what you should be waiting for. I'm not a fan of touchscreens, but the 5800 has impressed so far in video and music use.

Dro

Nice review. Now I just have to find a way to get it in Toronto. JP, where did you get yours?

---

rapidstar

Quote:

> Originally Posted by **josesxi**
> *IMHO there is no reason to upgrade to this phone unless you're absolutely bored with your N95. .....I am, but I still won't*
> *do it. That OLED screen is sooo overrated! (The display of my N95-3 is brighter, crispier and shows more natural colors).*

Agree 100%.

Blaxx

Quote:

> Originally Posted by **RogerPodacter**
> *i'm totally bored with the e71. it cant play any videos well, the music quality is not good. and the camera is so bad it*
> *might as well not even have one. i just want to go back to an Nseries with a decent camera, and n85 was the only one*
> *that interested me. but some of the negative things are turning me off to it, like the poor Dpad/softkeys and poor*
> *camera compared to n95.*

I love the E71 so much that I parted with my N95 for it. I don't find the D-Pad or the softkeys poor at all. I'm able to use all the one-touch keys with my leather gloves on so. I knew the camera would be a downgrade but I don't care much for the camera on cellphones, it's a gimmick that became a standard.