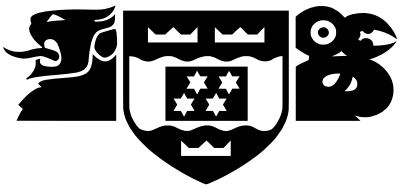
VICTORIA UNIVERSITY OF WELLINGTON
Te Whare Wānanga o te Ūpoko o te Ika a Māui



School of Engineering and Computer Science
Te Kura Mātai Pūkaha, Pūrorohiko

PO Box 600
Wellington
New Zealand

Tel: +64 4 463 5341
Fax: +64 4 463 5045
Internet: office@ecs.vuw.ac.nz

Reputation Scraper - Social Media

Iain Walker

Supervisor: Kris Bubendorfer

Submitted in partial fulfilment of the requirements for
ENGR489 - Bachelor of Engineering.

Abstract

Online reputation has become increasingly important as more social and business interactions move online. This project is concerned with investigating how basic reputation metrics may be inferred from non-traditional sources such as social media sites, in particular Twitter, Facebook and LinkedIn. A web-scraping framework is constructed that is able to retrieve data from social media sites. This tool collected a dataset of 1.7 million tweets for analysis. Using this dataset, reputation inferring metrics and policies are discussed, with the potential for wider application. These policies are evaluated and found to be too slow for use in real-time systems, although they may be useful in analytical reputation systems.

Acknowledgements

I would like to firstly thank my supervisor Dr. Kris Bubendorfer who was endlessly free with his experience and advice. Thanks also to Ferry Hendrikx for his feedback and technical advice over the course of the project, and to my family for their support during this extremely busy year.

Contents

Figures

Chapter 1

Introduction

Paragraph about social media and how social media has expanded into wide use.

Paragraph about concepts of reputation.

Give a real introduction to the problem domain. What is social media and what is reputation, etc.

Reputation is the global trust mechanism, whereas trust is one nodes impression of another in the network.

1.1 Motivation

In the digital age many social and business transactions are moving online. The size of Facebook and other Social Networking Sites (SNS) has grown exponentially with 1.05 billion monthly users on Facebook in December 2012 [16]. As such, defining who we should and should not trust becomes increasingly important, yet hard to resolve. Although SNS to some extent have inbuilt concepts of trust, using contact networks (Facebook, LinkedIn) and circles (Google+) for example, the concept of trustworthiness is more blurred. Tools to provide a snapshot, or hint of an individual's reputation and trustworthiness could be useful.

Reputation systems on trading websites have been extremely successful, despite the potential for fraudulent activity [28]. While we might expect a self-aware adult to fairly easily spot equivalent 'fraudulent' activity or deceptive behaviour on social media, many examples have shown this to be untrue. Social crowd sourcing gone wrong has also been a high-profile issue, with incidents such as the Boston Bombings [30, 14, 11].

Various strategies have been used to infer the personality or active traits of individuals online; these have been shown to be highly accurate. Applications on SNS have been used to give people an idea of their own personality. The results can then be compared against elements of the person's use of social media. This requires the express permission of the individual concerned to gain any meaningful data, when collecting information through a site's API. Which privacy concerns must be taken into account, publicly available information on an individual or company's social media account can be considered fair game. This information could be useful when judging trustworthiness. A new approach, that does not need permission to access information which is publicly-available, is needed.

1.2 Proposed Solution

A solution to the above issues is to use web-scraping strategies to anonymously retrieve reputation data. A more traditional approach would be to retrieve information directly through

an API, but few social networks provide sufficient APIs - and they all require express user permission to work. This system could be used to give a general snapshot about an individual, by using these non-traditional data sources. There are many potential applications and uses for this sort of application. Parents might wish to get a glimpse at their child's online friends, or a company might wish to automatically get some information about a potential employee for example.

The aim of this project is to demonstrate the feasibility of a tool that gathers and provides snapshot reputation data from social media sites, using web-scraping as the data gathering method. By creating such a reputation scraper, we envisage that a general impression about an individual on social media may be constructed. I create a new framework for scraping social media sites called IHPScrape, with the case study of Twitter, Facebook and LinkedIn as examples of the framework's applicability. A Twitter dataset is gathered of 1.7 million tweets, from which reputation metrics and policies are discussed. Finally I evaluate the performance and accuracy of this framework and reputation policies to analyse their potential effectiveness in a larger system.

1.3 Contributions

The primary contributions of this project are:

A web-scraper for Twitter as part of a wider scraping framework

A web-scraping framework that is suitable for extension onto more social networking sites

A set of reputation-inferring policies for use on Twitter

A dataset of 1.7 million tweets , and associated tweet meta-data.

1.4 Report Structure

The remainder of the report is structured as follows. Chapter 2 summarises background research that was undertaken in the problem domain. Chapter 3 describes the software engineering methodology used throughout the project. Chapter 4 identifies the specific requirements that the project aims to meet. Chapter 5 describes the design and implementation of the web scraping framework. Chapter 6 analyses data collected and proposes exemplar policies to determine social reputation. Chapter 7 then evaluates the scraping framework created. Chapter 8 provides conclusions and future work.

Chapter 2

Background

This section covers the background research I performed for the project, and works related to my project. I also discuss how I was able to contribute to the research domain, with points of difference to these works.

2.1 Social Media

Social Networking Sites (SNS) have achieved massive adoption and user numbers since their inception. SNS describes any web site that enables users to create public profiles and form relationships with others. The SNS market has largely stabilised, with Facebook achieving market dominance. When deciding which sites to fetch data from, research was conducted into the most popular SNS, and features that could be applied into some reputation score. In order to fetch useful information, various social media sites were investigated in the context of gathering reputation data, and seeing what could be selected.

- Facebook [1]: Publicly available information on Facebook includes data such as a user's Likes, Posts to Walls, and Friend networks.
- LinkedIn [3]: The primary business social network on which professionals can display information pertaining to their career and skills. Reputation data is fairly concrete - endorsements, skills, groups, and recommendations.
- Twitter [5]: A SNS allowing posts of up to 140 characters. Information available includes number of followers, number of profiles the person is following, number of posts, and post data itself. Post data includes retweet and favourite count, the content itself, as well as the people who retweeted the tweet itself.
- Google+ [2]: Similar to Facebook in style, and holds a large user base, but with much lower daily use than Facebook.
- Slashdot [4]: A social media and news network targeted at a 'geek' audience. Slashdot is one of few social media sites that uses a positive/negative rating system on posts. This inbuilt reputation system could be interesting to look at further, when porting data between social media platforms. It is also unique from the standpoint of identifying 'trolls' - for which the website is widely known.

This basic feature analysis was the foundation for data exploration on the social media sites scraped. As the project's primary aim was to demonstrate the fesibility of web-scraping as a means for fetching such information, research was conducted on web-scraping as a technology.

2.2 Web-Scraping

Web-scraping or *screen scraping* refers to the practice of downloading web pages directly through HTTP requests, and parsing this unstructured data into something useful. It is a well-understood data-gathering technique, and there are existing architectures and frameworks to help facilitate this. Anything online that is accessible through a browser can be scraped. Hartley gives a light introduction to the concepts and strengths of web-scraping [12]. Web-scraping is largely used as an alternative to traditional API's to websites, where these may not exist, or face a lack of support or development. Applications using web-APIs which frequently change could also benefit from switching to a web-scraping alternative. The advantage of web-scraping is that it provides direct access to the content of a website. While a site's API may not allow access to information that is quite clear from the front end, web-scraping will inherently provide this. Also, some sites do not monitor their API status as carefully as the actual front-end access. Maintaining availability to the core site is of higher business priority than developer APIs, and this is consistently reflected in respective levels of support.

The primary limitation of web-scrapers is that major user interface changes will likely result in a broken scraper. In general site's structures do not change frequently enough for this to be a major issue. The typical argument however is that a site's structure can, without any warning, change at any time. This is an unavoidable issue when considering developing a scraper, and as such the regularity of user interface changes on a website should be considered when deciding between using an API or a scraper. In general it is more sensible to inspect a site's API for applicability before constructing a web-scraper. As an example; Facebook was ruled out as a social option in this project due to its regular user interface updates.

However these interface change limitations can also be applied to modern social media APIs. Past projects fetching data from Facebook have had difficulty maintaining applications due to its too-often changed API [24]. In the course of this project, Twitter's API changed such that the possibility of fetching required data through this interface was rendered infeasible. When considering scraping data, legal and privacy considerations must also be applied.

2.2.1 Legal and Privacy Issues

Companies such as Google and Facebook are widely known to use web-scraping on SNS and other sites for the purposes of web-indexing and advertising [12]. Despite this, other entities attempting to commercialise such aggregated data have been met with threats of hostile law action. Pete Warden discusses how his data-mining experiences on Facebook nearly resulted in legal action [31]. In these cases, though, data-mining was intended to be used for commercial purposes.

As an academic project, fears of legal retaliation are much lower. However strategies were enforced in order to stay within the terms of service of social sites. By never signing into the SNS that I retrieve data from, I inherently do not agree to the user terms of service[1]. I also followed general positive web-scraping practices where possible, in order to limit possible negative effects of my scrapers upon these sites. Examples include attempting to adhere to a sites robots.txt, and the placement of reasonable pauses between requests to reduce server burden.

[1] https://twitter.com/tos

2.3 Inferring Information from Social Media

The following sections examine research conducted into what information has already been investigated on social media. In particular, private personality traits that are inferrable from publicly available data are discussed, as well as how sentiment analysis of SNS can predict unexpected variables.

2.3.1 Personality from Social Media

Studies have investigated how private details about personality traits can be inferred through behavioural analysis of individuals on social media [6, 7, 8, 20, 18, 21, 19]. Golbeck et al. demonstrate that real life personality traits may be predicted by looking at past behavioural patterns on Twitter with high accuracy [20]. Using the publicly-available figures of followers, following and posts the authors were able to classify individuals into different Big Five personality types [13]. This was verified against a 44-question personality test for 71 individuals, with accuracy of around 80%. In further papers these authors were also able to make conclusions on political preference, as well as extend their work onto Facebook and tagging behaviour [18, 21, 19]. Adali et al. [6, 7] extend this work further by predicting personality and relationship information on Facebook.

While these studies showed how private personality details can be inferred from publicly-available data, they were made using applications which had to be given express permissions to access this data. In other words, although the conclusions drawn from these papers was that massive data-mining could be undertaken on these profiles as all the data is publicly available, they never used an approach that demonstrated the true feasibility of this. Clearly as social media site API's are properly locked-down and require authorisation of the relevant users to retrieve data[2], a web-scraping approach must be used. Such an approach allows applications to only require the same permissions as any human being accessing the same page, whilst also allowing the same data to be downloaded and aggregated.

A potential weakness in these studies is that personality on SNS may not translate well into actual personality. Although this may seem like a logical conclusion (e.g. Trolls, shallow internet relationships), studies have shown it to be false. Quercia et. al. demonstrated how popular Facebook users in fact maintain meaningful relationships with their hundreds of friends, and not the superficial ones we may expect [26]. Again the Big Five personality model was used, and verified against popular Facebook users who used the MyPersonality app. Back et. al. demonstrated how Facebook profiles in fact are reflective of actual personality, and not a self-idealisation [9]. This study used manual inspection of profiles to make first impressions of individuals, which were compared against results from a Big Five personality test. Making similar predictions with computers would be an interesting and difficult challenge.

2.3.2 Sentiment and Temporal Information from Social Media

It is also possible to take sentiment and temporal-related information from social sites as a whole, and use trending information to make accurate predictions about seemingly unlinked occurances. Bollen et al. [10] demonstrated that the 'mood' of Twitter can be used as a predictor of the U.S. stock market. The authors argue that Twitter mood is an accurate predictor of the public's mood state in general, which affects human decision-making and as such financial decisions. By taking historical Twitter data and calculating mood val-

[2]https://developers.facebook.com/docs/reference/apis/

ues using a classifier, the authors showed that Twitter was an accurate predictor of the U.S. stockmarket.

In a similar temporal approach to social BigData analysis, Ginsberg et al. [17] investigate detecting influenza epidemics using Google search query data. By analysing the relative frequency of certain queries implying health information-seeking online, early predictions and detection of epidemics may be possible. These examples demonstrate that information that may be thought of as seperate can be determined from the wealth of information on social media.

2.4 Quantifying Reputation on Social Media

Although the above studies investigate the concept of personality and how we can quantify this using social media, they did not expressly address the concept of reputation. Therefore we should discuss what reputation explicitly means on social media, and how sites currently help express user reputation.

Some sites explicitly reference user reputation, a system commonly utilised on social forums. Stack Overflow [3] is a question and answer site where users are able to post code-related programming problems. It has been identified that sites such as Stack Overflow are largely dependant on the contributions of a small number of expert users, who provide a significant proportion of useful answers [25]. As such, identifying users who have the potential to become strong contributors is of significant importance to the success of the website.

Action	Reputation Change
Answer is voted up	+10
Question is voted up	+5
Answer is accepted	+15 (+2 to acceptor)
Question is voted down	-2
Answer is voted down	-2 (-1 to voter)
Experienced Stack Exchange user	onetime + 100
Accepted answer to bounty	+bounty
Offer bounty to question	-bounty

Figure 2.1: Actions and Corresponding Reputation Change on Stack Overflow [25]

Reputation in this context is entirely derivative of the actions and effectiveness of answers provided by users. Within Stack Overflow, a high user reputation score could be considered a measure of expertise.

The online forum SlashDot [4] is another social site where user action affects reputation. Slashdot was created in 1997 as a 'news for nerds' message board [**?**]. As members grew rapidly, spam and poor posts became an issue, resulting in the introduction of a moderation system. A two tier moderation system now exists, where *M1* allows administration of comments on articles, and *M2* moderating the *M1* moderators. User reputation information is logged using *Karma* for logged in users as a reputation metric. Each logged in user maintains a *Karma* score from one of six discrete values: *Terrible, Bad, Neutral, Positive, Good, Excellent*. Positive moderation feedback to a user's comment will result in an increase in Karma. The opposite applies for negative moderation. Comments on SlashDot are ranked from [-1,5]. If

[3] http://wwww.stackoverflow.com
[4] http://www.slashdot.org

a user with high Karma created a comment, this will have a higher starting rank. To reduce spam, users can then filter comments based on minimum rank. For example if I wished only to see the best comments, I would set the filter value to 5.

The SlashDot reputation system is an example of effective spam filtering through the use of a reputation system in conjunction with moderation. The use of reputation in this context greatly reduces the moderation community effort to maintain the website.

2.5 Reputation Metrics Elsewhere

Reputation systems have also had considerable success on trading applications such as eBay and TradeMe. Resnick et al looked at the success of eBay's reputation system and identified the three properties that a reputation system must enforce in order to add value to such a site [27, 28].

- Entities are long-lived, so that there is an expectation for future interaction. This generates a 'shadow of the future', and provides incentive for users to behave with integrity in the short term, such that future interactions will not be impacted by a poor reputation.
- Feedback about current actions is captured and visible to others. This ensures that users are able to pay attention to their own and other's reputations, when interacting with other community members.
- Feedback from the past guides current decisions: people must pay attention to reputations for them to be valuable.

This impacts my study as it guides the creation of reputation policies; reputation data I gather should conform to these concepts. Resnick's paper also identified weaknesses within current reputation systems online. There are three weaknesses present within current reputation systems which automated policies can help address.

- Fears of retaliation - users not posting negative scores due to fear of unsolicited reciprocation.
- People not bothering to place feedback - if no incentive exists for users to place feedback, they may not see the value of doing so.
- The assurance of honest feedback - for the above two reasons, reputations may be skewed and unreflective of reality.

An automated reputation system using policies to turn reputation into access or action rights solves many of these issues instantly. There is no area in which retaliation can occur, feedback is never explicitly placed, and policies treating all users equally will assure honest feedback.

2.6 Related Systems

I will now discuss some systems which consider reputation data and apply it to access-control and service selection policies online. Firstly I examine the Generalise Recommendation Architecture and an OpenSocial access framework, in the context of access control solutions using reputation attributes as keys. Then the social-media based reputation system Klout will be discussed.

2.6.1 Generalised Recommendation Architecture

The Generalised Recommendation Architecture (GRAft) [22] is a distributed architecture that supports the collection and storage of reputation information for entities, whether these be individual users or systems. It uses the OpenID [5] infrastructure in order to maintain long-term identity for users. To ensure validity of reputation data, information within GRAft is duplicated over the nodes (using a distributed hash-table) which comprise the network.

Entities within GRAft are uniquely identified using their OpenID. The system is able to maintain a history of the entities actions, including recommendation and transactional history. In this fashion, entity 'profiles' are established, with recommendation data being pulled from multiple sources, each source acting as a 'source node'.

Although GRAft is not a system currently used in industry, the authors discuss how it could be applied in practice. The domain of a scientific wiki is one such example. This wiki consists of scientific articles, which can be read and edited by members. Using a two-tier access policy, read access to a page was is given by co-authorship. Users who had previously worked with the owner have a 1st-degree relationship; those who have worked with a person in the set of 1st-degree owners are 2nd degree owners, and so on. Once the user is granted access depending on this degree of co-authorship, editing rights are calculated by the users Hirsch-Index (H-Index) []. Another policy is then responsible for assigning editing permissions based on this value. This example demonstrates how access rights can be automatically granted for all users who fulfil requirements defined by the page owner. The group is never explicitly defined in terms of users; and as the author begins work with others, they can be automatically granted access to resources. This flexible policy comes closer to reflecting ad-hoc and informal scientific collaborative interactions, and is based on trust information that comes closer to real-life reputation.

```
$rb->logicalAnd(
 $rb['hindex']->greaterThanOrEqualTo(1),
 $rb->logicalAnd(
   $rb['degree']->greaterThanOrEqualTo(0),
   $rb['degree']->lessThanOrEqualTo(3)
  )
)
```

Figure 2.2: GRAft reputation based access policy example

2.6.2 Open Social

Zhang et al. [32] proposed an Open Social[6] based group access control framework. Open Social is a framework for deploying cloud-based social applications. It was used in this context as it provides an API useful for retrieving social connection data. It also supports OAuth [7], a protocol that allows users to grant third-part access to their protected resources.

The social trust scheme proposed in this paper consists of a multi-tenancy access control model, which can be applied to a scientific team-management scenario. Firstly the authors consider how trust in this context is a complex human-to-human relationship, developed through scientific collaboration. The authors argue that information about such relationships can be captured through data embedded on Online Social Networking (OSN) sites.

[5] http://openid.net/
[6] http://opensocial.org/
[7] http://oauth.net/

This enables friend-of-a-friend trust to be computed, enabling transitive data as also seen in GRAft(which proposed using degree of co-authorship as a trust attribute).

2.6.3 Klout

Klout [8] is a social media reputation system that generates an 'impact score' out of 100, based on how influential you are on various social media sites. In order to generate your Klout score, you sign in to Klout using OAuth to connect to your social media site of choice. Klout then interacts with these sites' APIs to fetch the relevant data. This site is useful to me as it both demonstrates how such information can be used to generate influence information, as well as how such a system can become popular. I extend this system by using the alternative approach of web-scraping. By doing so, users would be able to look at the reputation data of other users, as well as themselves.

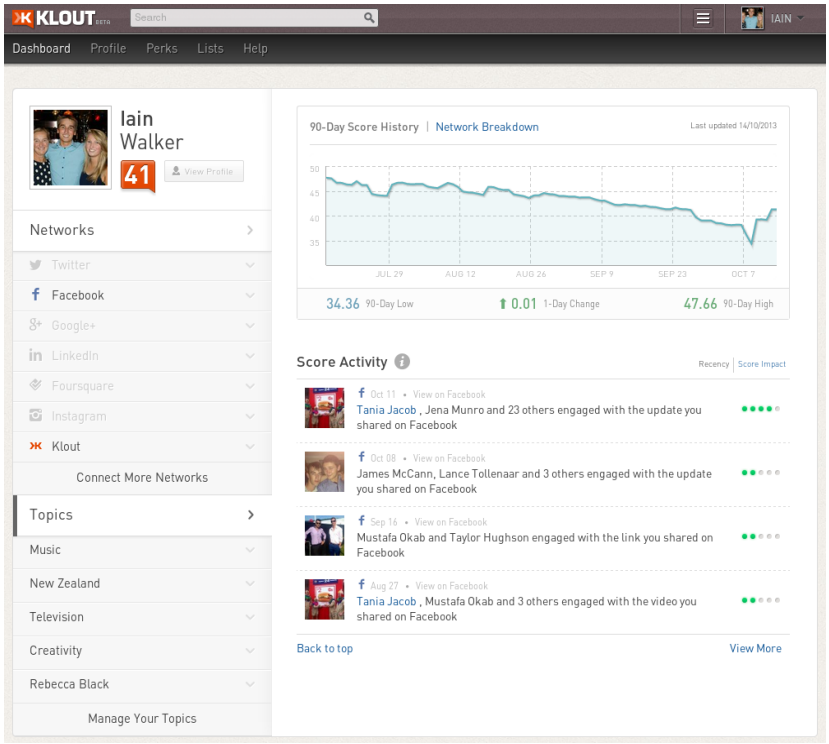


Figure 2.3: Klout impact score

2.6.4 Discussion

My proposed solution extends and borrows concepts from these related reputation systems. GRAft as a distributed reputation storage system has the potential for storage of reputation data for many different applications. By implementing reputation policies for storage within GRAft, I essentially create source nodes as a further case study example for this system. Whilst the Open Social based reputation system is useful for access control schemes, there was little discussion relating to other potential applications of its reputation schemes. As such it is of arguably less value than a more generic system such as GRAft.

Whilst Klout provides interesting reputation insight into a users profile, it is limited in that only your own profile reputation data can be viewable immediately. To view friend's

[8] http://www.klout.com

profiles, they must sign into Klout themselves. It is impossible to view the Klout scores for strangers. As such this system is only purposed for competition among friends, and little else.

Chapter 3

Methodology

3.1 Project Management Approach

The project was structured around a loose waterfall. At the start of the project, a long-term plan and major milestones were outlined. More detailed plans were added and target dates adjusted as the year progressed. Aspects of agile development practices were also used during the implementation and design stages. These included an iterative and prototyping approach to development. Prototypes were developed early in the project to investigate the feasibility of scraping various sites. From these, features were iteratively added until the final product was created.

This approach of combining aspects of waterfall and agile was reasonably effective as a project management approach. Agile methods tend to work best in a team environment, assisting with the coordination of team members. However the method of small, focused sprints contributing to the larger project were excellent in maintaining focus and direction. The waterfall element in turn outlined the more concrete and long-term deliverables of the project, which was useful with monitoring, controlling and ensuring my work did not fall behind schedule. These target goals were met in the majority of cases. I did experience delays with finishing my implementation and evaluation, as new features such as community detection were added late in the project. Reasons for this late discovery and delay were in part due to the exploratory nature of the project, as will be discussed in the design approach.

Throughout the project I had joint weekly meetings with Dr. Kris Bubendorfer, Ferry Hendrikx and Filip Dimitrievski. In these meetings, 30-45 minutes in length, we outlined progress achieved during the week, identified issues encountered and planned tasks for the coming week. In the latter half of the project, weekly reports were constructed in order to carefully monitor achievement and contribute to components of this report. A sample weekly report is attached as Appendix B. Having meetings with Filip and Ferry also present was beneficial, as there were aspects of the project for which Filip and I were able to collaborate over. Ferry, who developed the GRAft system was also able to give useful technical feedback, with his experience in the development of web-scraping tools. The design approach for development of these tools are discussed next.

3.2 Design Approach

Requirements analysis and design were completed through a combination of research and prototyping. As the project was focused on an exploration of understanding reputation data on social media, a large portion of time was given to background research.

Later in the design phase, I constructed a set of prototypes to evaluate the feasibility and

alternatives for a web-scraping solution. These covered preliminary scrapers for Twitter, Facebook, LinkedIn and Slashdot. The benefit of developing these was to both give me a better understanding of technologies involved with performing these functions, and to produce some meaningful effort early in the project, as these scrapers could be potentially useful later. There were some pitfalls in this approach however. Some effort in developing prototypes can go to waste, which occured in this project. Facebook was deemed infeasible to scrape due to its interface's constant state of flux. Also during prototyping, Twitter's API changed significantly, rendering much effort lost.

3.3 Project Complexities

The complexity of the system stems largely from the aggregation of unstructured data from a variety of sources - a difficulty often encountered in web-crawling applications. The codebase itself is not overly complex. Debugging unclear and unexpected errors from web servers also contributed to complexity of development.

Understanding the data gathered was a time-expensive challenge. The process of understanding and defining reputation data on social media was the task that occupied most of my time on the project.

The time constraint of 300 hours impacted the project at all stages. The implementation and evaluation components were particularly impacted - limitations had to be placed upon the scale of data collected from scrapers in order to compensate for time. In addition, the selected prototyping methodology was often expensive in terms of time, due to the necessity of revising code and collecting more relevant data.

Chapter 4

Requirements Analysis

To satisfy the goals of the project, the following requirements need to be addressed. These were created based upon the key issues outlined in chapter 1, and established through research conducted as part of the background.

4.1 Functional Requirements

These are the functional requirements that were proposed to be met by my system:

4.1.1 F1: Aggregation of Social Media Data

Data from multiple social media sites needs to be aggregated in a sensible manner. This requirement exists in order to construct reputation-inferring policies from multiple websites. Entire profiles should be scraped in order to provide a richer set of social data.

4.1.2 F2: Development of Reputation Policies

The most significant requirement is to generate a set of policies to assist with generating a snapshot of an individual's reputation. Policies must consider data from time periods on the order of months or years to ensure accurate predictions are made. These must consider future interactions in order to maintain user awareness and reflection upon their own reputation. Policies will need to return results within seconds to be useable in any real system.

4.1.3 F3: Extensibility and Social Media Portability of Scraping Framework

A framework should be created into which my web-scrapers conform. This framework should be suitable for application onto multiple social media platforms, and extension onto these platforms should require minimal effort.

4.1.4 F4: Resistance to Blocking Detection

In order for scrapers to continue collecting data over time periods of days or weeks, they must not be blocked by SNS servers. Scrapers that are detected by sites and are noted to be taxing on a server's resources will likely be blocked [12]. As such, my framework must firstly attempt to remain undetected as a scraping entity, and secondly recover from detection and resume scraping data if detection occurs.

4.1.5 F5: Develop a Metric of Reliability Based Upon Quantity of Data

A metric of reliability based upon the quantity of data collected about an entity needs to be created. This is due to the time taken to fetch an entire profile being potentially highly time-consuming, possibly ruling out the feasibility of scraping an entire user profile for use in a policy. Thus smaller quantities of information could be considered instead, with a reliability metric value attached. As a result of the greater time spent analysing Twitter data than expected, this requirement had to be removed from the scope of the project.

4.1.6 F6: Storage of Reputation Information in GRAft

Reputation policy construction will effectively enable my framework to act as a provider node for storage of data within the GRAft system. This requirement specifies that the final product should interface with the GRAft reputation system to ensure confidential and secure long-term storage of data. However this task necessitates the construction of a business model for such a system to be viable. A community effort would be required to maintain the code, and as such this was removed from the scope of my project.

4.2 Non-Functional Requirements

The following are the non-functional requirements that my scraping framework aims to meet:

4.2.1 NF1: Resistance to User-Interface Change

The scraping framework should have built-in resilance to user interface layout and design change. Small changes should not result in a scraper no longer functioning as expected. This does not mean that wholesale site restructures should not affect the scraper, as this is an infeasible challenge. Instead, I expect that the framework should be mindful of what dependancies are most likely to change, and cater for this accordingly.

4.2.2 NF2: Scraper Performance Fast Enough for Use as part of Real-Time System

This requirement refers to the speedof my web-scrapers. The web-scraping tools developed must perform with sufficient speed to generate snapshots of an individual's reputation for use in constructed policies. In order to create policies that are useful for future works, these scrapers must be able to gather and make conclusions about an individual in a matter of seconds.

4.2.3 NF3: Accuracy of Data Collected

In order to generate meaningful data analysis, discussion and policies, data collected by my scrapers must be accurate. Data gathered must be accurate and represent what is actually displayed on a profile. Any innacuracies in collected data should be clearly highlighted and explained. As web-scraping through HTTP requests can sometimes produce unexpected return values some innacuracies will be expected, but these should be known-bugs.

Chapter 5

Scraper Design and Implementation - IHPScrape

In this section I discuss the design and implementation of the web scraping components of the project. I highlight important decisions made during the course of the project, as well as steps taken to implement the system based on requirements detailed in chapter four.

5.1 Architecture

Two potential architectures were considered when designing the web-scraper components.

- A database storage approach
- A text/XML storage approach

The text/XML design was used in the final solution. The time investment of setting up a database, as well as performance gains in using file storage over database storage were the primary contributors to this decision. The database approach was deemed to be over-engineered.

5.1.1 Database Storage Architecture

A possible approach to meeting the requirements of the project was to store fetched data in a relational database. In this design, the scrapers would gather data over an extended period of time, writing retrieved information into a database. Analysis components would then fetch data from the database as necessary, saving results in separate tables within the same schema.

This approach provides long-term extensibility benefits, as per requirement F3. All of the advantages that come with database storage would have been present in this solution - specifically selection of individual profile elements and updates to these elements would have been more straightforward. However this design was deemed to be over-engineered for the purposes of the project. Given that data retrieved is in HTML, JSON or XML format there is a large impedance mismatch between retrieved data and relational database tuple format. This is compounded when retrieving data from the store for analysis - many third party analysis tools require input data in a variety of text forms. The analysis components were also largely contingent on the fetching of a whole profile, rather than specific elements, lessening the need for querying against specific elements in my data storage structure.

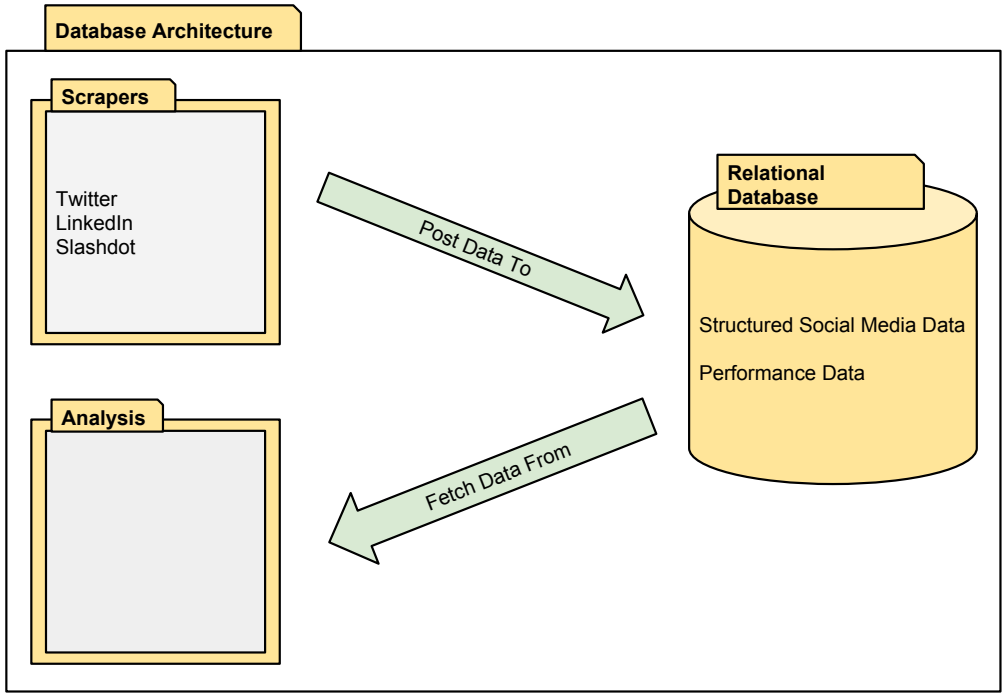


Figure 5.1: Proposed Architecture for Database Storage Solution

5.1.2 XML Storage Architecture

The alternative and ultimately selected architecture involves the scraper and analysis components interacting with a shared XML storage system. Again in this structure, scrapers run over time whilst saving data to a common XML-based file system. Analysis components could then annotate and enrich the original dataset. Note that analysis components in this architecture essentially act as source nodes for the GRAft system, through generating some reputation metrics associated with a profile.

This design largely simplifies the scripting and scraper construction. Little setup was required during prototyping to construct schemas against which to save data. An informal XML approach also allowed for straightforward manipulation of data structures, and additions to what was being stored. Performance of storing to files is also known to be much faster and less server-taxing than the use of a database.

The primary disadvantage to the XML approach is difficulties associated with selecting individual slices of data in XML. Technologies such as xQuery exist for querying against XML, but were deemed unnecessary for the project. This is due to entire profiles being used for input into analysis components, rather than selected components only.

5.2 Technology

The web-scraper components were written entirely in Ruby. The development of screen scrapers is largely independent upon language choice; however Ruby was selected due to its large number of libraries suitable for scraping, and straightforward scripting nature. Ruby also has a significant Open Source following in comparison to many more conventional

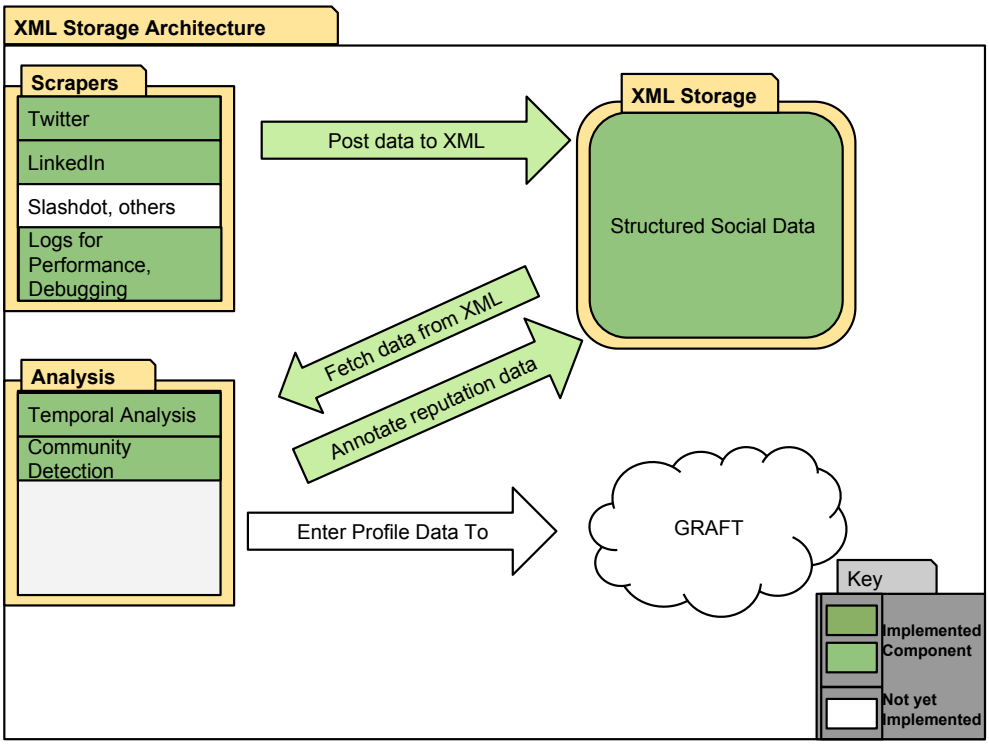


Figure 5.2: Architecture for XML Storage Solution.

languages like Java. This was considered necessary early in the project, when looking at a model for future maintenance of the scrapers, especially for the discarded requirement of aggregating data for GRAft.

Alternatives to Ruby were considered; Java, which does not have the same open source following as Ruby, as well as a larger degree of lower-level network coding for web-scraping software; and PHP, which was rejected due to time constraints limiting personal capabilities to learn the language to a competent level during the project. PHP would have given the advantage of being more consistent with past works, however [**?**], as well as being the same language as my policies are described in. This is just a 'nice-to-have' feature however, and would not have added any real value to the project design.

5.3 Framework Design

Various framework designs were considered when designing the IHPScrape framework. I will discuss four options that were considered:

- Extend the scrAPI framework
- Implement a browser-automation application
- Use site APIs
- Develop my own framework from scratch, using various Ruby Gems.

5.3.1 Extend scrAPI

scrAPI is a Rubyforge project, allowing for fast implementation of web scrapers. The core benefit of scrAPI is allowing data to be fetched from HTML pages using CSS selectors. In addition it hides processes such as the actual fetching of pages. It is a much higher-level framework than what was eventually implemented.

Extending scrAPI was ultimately discarded, due to its heavy reliance on CSS files remaining constant. Any change to style sheet files would likely have broken the scrapers. Arguably these style sheets are less likely to change than layout manipulations (for example consider xpath on HTML as an alternative); however on sites such as Twitter and Facebook large design teams frequently make changes to these files. Given that requirement NF1 was to make scrapers resistant to user-interface change, this resulted in scrAPI being deemed unfit for purpose.

5.3.2 Extend A Browser-Automation Model

Browser automation options were considered as an alternative architecture. Frameworks such as Watir [1] allow users to simulate user interaction with web pages, by driving an actual browser instance.

A browser automated-scraper would likely have had little problem with site detection or blocking, due to the use of a real browser - providing genuine user agents, downloading CSS selectors and such. This would have been effective at fulfilling requirement F4. Despite this, performance would have been significantly poorer using this option, violating requirement NF2. As browser automation scripts are entirely dependant on site layout and interface naming conventions, this would have violated the requirement of resisting user interface change NF1.

5.3.3 Use the API

Although the project title from the outset was 'Reputation Scraper', we investigated the use of site's APIs before settling on the scraping option. A basic application interacting with the Twitter API was constructed early in the project. Twitter's API version 1.0 was actually highly suitable for the needs of the project. However the changes in REST API v 1.1 rendered this infeasible. The earlier API allowed fetching of up to 800 statuses from any public profile, along with more public data[2]. Version 1.1 however implemented more requirements for authentication, and limited functions such as downloading tweets to the individual's account only[3]. Facebook's developer API is even more restricted. On Facebook, permissions must be obtained from the appropriate users before fetching data from their profile. LinkedIn's policy is similar.

5.3.4 Implement a new Framework

The fourth approach considered was to develop a new framework, built upon a number of Ruby libraries. This approach allowed for more flexibility when constructing scrapers, and consider new approaches to the user interface dependancies of web-scrapers.

The most obvious disadvantage to this approach is the argument that by implementing my own scraping framework I was 'reinventing the wheel'. However by building the framework around existing libraries to perform the networking technicalities of web-scraping, I

[1] http://watir.com/

[2] https://dev.twitter.com/docs/api/1

[3] https://dev.twitter.com/docs/api/1.1

greatly lessen the developer burden. Also this approach allowed me to build a scraper framework tailored for social media, which was not present in frameworks I researched.

The libraries upon which my scrapers were built included:

- Nokogiri [4]: a widely used HTML and XML parsing framework, allowing for straightforward interpretation of raw HTML documents. Nokogiri has many extensions, and can be effectively used to parse HTTP body responses into sensible HTML structure, which can then be parsed using xPath expressions to retrieve data of interest.
- Mechanize [5]: an extension of the Nokogiri framework, that simulates browser actions on web-pages.
- Rest-Client [6]: Ruby's most popular HTTP client. Rest-Client allows the use of all HTTP verbs, and can be adjusted for user-agent, proxy, and custom field input.

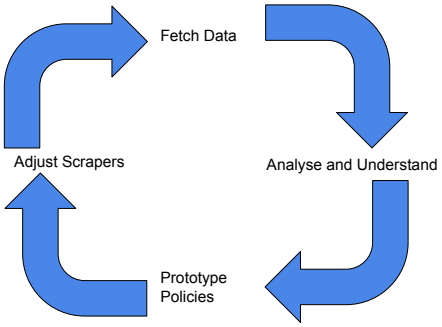


Figure 5.3: Scraper Development Feedback Loop

5.4 Framework Implementation

Developing the project solution consisted generally of a cyclic, iterative prototyping approach as detailed in figure 5.3. This generally consisted of four phases; Implementing and adjusting scrapers, fetching data, analysing the data, and prototyping policy concepts as a result of this analysis. The first scraper developed was for Facebook.

5.5 Facebook Crawler

A Facebook scraper was prototyped early in the project, and allowed for experimentation with many of the technologies that were used later. Firstly, strategies for authenticating against Facebook had to be developed. While public profiles do exist, these are primarily for company pages or politicians, which is not what the project aimed to solely investigate. Authentication was implemented using a dummy Facebook account, through the Mechanize Ruby framework. Mechanize allows for form data on pages to be populated and submitted through either HTTP or HTTPS. Once authentication was achieved, an authentication token was passed as an attribute of further requests. New authentication tokens are obtained after an adjustable time period, or on a new scraper run.

[4] http://nokogiri.org/
[5] http://rubygems.org/gems/mechanize
[6] https://github.com/rest-client/rest-client

Having obtained the necessary authentication tokens, profile pages could be fetched. The planned approach was to crawl through friend networks via friend lists, and scrape profiles in this manner. Downloaded profiles would then be parsed using Nokogiri, and relevant data extracted via xpath expressions. Posts, likes, friends are examples of information identified as useful to collect. However as mentioned in chapter 3, this scraper was eventually discarded as infeasible. Scraping large amounts of content reliably through Facebook was infeasible within the project's scope due to its highly dynamic content, and frequently changing interface. Maintaining and updating a scraper to fetch accurate data from Facebook during the project would have been too time-consuming and as a result was removed from the project scope. However the technologies experimented with whilst developing this prototype were useful later when developing the more robust Twitter scraper.

5.6 Twitter Crawler

The Twitter Crawler users a Google Twitter search function to search for profiles to fetch at the top level. An input text file of random names delimited by lines is accepted by the scraper. These names are looped through in order, with the scraper fetching the profiles of these top ten results returned through Google. Bias is introduced through this approach, since only the top ten search results are analysed.

Due to this bias, alternative approaches were considered. A potentially better scientific approach to randomising the selection of profiles to scrape would have been to crawl through an already-generated set of random profile names. However searches did not reveal any such databases to exist, excluding 'celebrity-exclusive' ones which would have been significantly worse than my current approach. I also considered crawling via embedded links on Twitter, starting from any profile and following re-tweet links through to new profiles. However this introduces new complexities - how will the algorithm detect infinite loops (potentially huge loops), or detect repeated profiles? As the project was ultimately about reputation and not scraping algorithms, the simple name-searching approach was selected.

Once the ten profile names are selected (for the current input name in the text file), the application will perform the scraping of each of these profiles in order. The definition of a Twitter profile changed throughout the project, as more information was chosen to be analysed. The final schema of stored data for the standard Twitter scraper is contained in appendix 1.1. Essentially all tweets are captured where possible, along with associated re-tweets, favourites, and the profile names of users who re-tweeted this item. Profile meta data is also stored, such as number of followers, number following, and total number of tweets.

Technical difficulties exist with fetching such profiles and meta data, which we will now discuss. Firstly, a Twitter page does not immediately display all tweets for a user for obvious latency reasons. To view more than the initial tweets, users must scroll through an 'infinite scrolling' window which requests more data through AJAX calls. To simulate this interaction, I used Google Chrome's 'network capture' feature to inspect requests to the page during the scrolling function. The URL is of the following form:

```
/timeline/with_replies?include_available_features=1&include_entities=1&max_id=12345
```

The JSON returned is then parsed to retrieve relevant information. As a Twitter profile may contain re-tweets from other profiles, checks have to also be taken at this stage to ensure the content is originally generated by the user of interest. This is as simple as checking the user name who posted the content originally. In order to increase the performance of extra tweet fetching, various tweet window sizes were experimented with. This was ultimately ineffective at maximising speeds, reasons for which are covered now.

5.6.1 Parallel Tweet Fetching

Although tweet content can be fetched from the base profile page, useful data such as re-tweet and favourite count is initially hidden. To view tweet detail, a further request must be sent, to mimic the user interaction of clicking on the tweet. Fortunately this process can be parallelized for each tweet within a tweet window. In the final twitter scraper a thread pool of 15 threads is created, one for each potential tweet in the window. Each thread then fetches and parses each tweet individually. To ensure parallel performance is not lost, any tweet-fetching process that fails here will simply be thrown away. Parallelization of tweet fetching resulted in huge performance gains, which will be discussed further in chapter 7. Parallel fetching was not considered earlier in the project as I expected the resulting simultaneous requests to end in more frequent detection by sites.

5.6.2 Detection Avoidance and Recovery

Operating on the University network likely resulted in less chance for blocking detection by Twitter, due to the large IP range allocated to Victoria University. Regardless, steps were taken to limit detection rates. Multiple strategies for avoiding detection were considered, and several employed simultaneously. The Request-Handler package handles the implementation of these strategies.

The first and most straightforward strategy is to include random pause times between requests. The goal of this approach is to reduce potential server burden, and lessen the possibility of an aggressive scraper being permanently blocked due to its flooding the site. However this approach imposes a very low ceiling for performance and tweet fetch rates. Resources such as [] recommend a ten to fifteen second delay between requests, but such a wait was infeasible for the needs of the project. As such, pauses between requests were only implemented in certain special cases; failed requests and at the end of a profile.

The second strategy employed is to send requests that spoof a browser user-agent, in order to appear as a legitimate browser instance at the server end. Before scraping a new tweet window, a new user-agent string is randomly selected from a list.

A third strategy that was considered but not implemented was the downloading of CSS and other markup, in order to behave as browser-like as possible. This was discarded because of questions of its feasibility, as well as uncertainty as to the level of potential benefits from constructing such a solution.

I rarely encountered rate limiting at University, and was never blocked outright on the University machines. Early in the project, when prototyping a Facebook scraper I was briefly banned from Facebook at home. 503 errors (indicating resource unavailability) reveal detection on Twitter. 500 errors (indicating server error) were encountered throughout the project also, but these were due to coding errors.

5.6.3 Dealing with Authentication

The original scraper did not require authentication, since the majority of Twitter profiles are viewable to individuals who do not have a Twitter account, or are not signed in. However to fetch the names and profiles of users re-tweeting posted content, an authentication feature had to be added. Fortunately the authentication strategy employed by the Facebook prototype was able to be re-used for this component. The same strategy as constructed for Facebook of logging into a dummy account at the beginning of a scraping run was used.

5.6.4 Parsing Poorly Formed Markup

A concern earlier in the project was the scraping of content containing poorly formed HTML or JSON markup. Thankfully the sensitivity of HTML parsers to poor markup is largely library-dependant. This was not well-documented in the gems I found, so experimentation with various options had to suffice. Nokogiri was sufficient for HTML parsing, and the default ruby JSON parsing library was most effective at parsing incomplete JSON data.

5.7 LinkedIn Scraper

The LinkedIn Scraper was developed towards the close of the project, and as a result data analysis of what was collected using this tool was not carried out. However developing this tool, which is able to scrape multiple LinkedIn profiles in parallel, was able to prove the extensibility of the IHPScrape framework in the context of a new social media site. The LinkedIn scraper was developed in one week's construction time. This was much less time than was spent developing and debgguing the original Twitter scraper and framework, and is evidence of the portability of the framework. However consideration must be given to the simplicity of the LinkedIn website as compared to Twitter. Also, the first iteration of my Twitter scraper only took approximately two and a half weeks (this build did not include the infinite scroll scraping feature).

5.8 Code instrumentation

The code was instrumented using a Ruby logger system written for the application. Given complexities and difficulties debugging errors on web-scraping applications, logging had to be performed to a very fine level of granularity. Any action changing system state such as fetching a page triggers the logging mechanism. The logger would then take note of the timestamp and write to the appropriate file the nature of the action. For example, if the scraper sent an HTTP request to retrieve a given URL, it would record the timestamp and URL requested.

The logger would write to the appropriate log file based on the nature of the supplied action. Because these scrapers were running over long periods of time, using traditional IDE debugging tools was not effective at detecting errors. As a result, I used multiple debugging files with different purposes in an attempt to catch these errors. The debug.log captured all interaction information at a basic level. Error.log captures error information that is non-fatal to scraping an individual's profile, e.g. on Twitter. Commonly these errors were due to application logic flaws, such as performing operations on null entities. As a result the error.log assisted greatly in identifying these edge cases. Finally the failure.log was used to record fatal exceptions that would prevent me from scraping a profile. Occurrences such as 404, 500 or 503 responses from servers are examples that would result in a record being written to the failure log. The failure log would write system state at the time of failure to a high level of detail, sometimes even writing the entire HTML document before the failure to disk. This again assisted with debugging, when reviewing how a particular run had gone.

To limit the performance overhead of writing to these logging files, a buffered approach was taken in order to achieve the least impact.

Chapter 6

Data Discussion and Policy Construction

In this section I discuss the construction of my reputation policies for use on Twitter. In particular the development of analysis tools for achieving greater understanding of the Twitter dataset created will be discussed, and discussion of hypotheses generated from this data and how we experimented with these. Only Twitter data is discussed due to the richness of the dataset mined. As such multiple analysis approaches were taken.

Data was collected during scraper implementation, as per the feedback loop in figure 5.3. Profiles scraped earlier contain less detail than data collected later. For example, names of retweeters was not a feature collected on earlier profiles. In total, 1767 separate profiles were scraped, totalling 1,745,161 tweets.

6.1 Retweet Analysis

I now present the results of retweet analysis on Twitter. Retweets were considered as a basis for more policies as more semantic information can be retrieved from retweets than favourites. When retweeting content users are able to comment and add extra value to the post, whereas this is not possible for favourites.

The first question we asked was in the use of retweet and favourite functionality on Twitter. When 'retweeting' content on Twitter, the post will appear on the users own wall, as a tweet. A 'favourite' instead is added to a user's list of favourite tweets, which may be viewed separately by other members of Twitter. To demonstrate policy examples later, and to simplify data collection, we put forward that tweets similar in popularity will have equivalent amounts of retweets and favourites.

H1. As a measure of impact, the number of retweets and favourites for an item on Twitter are equivalent.

A simple approach to demonstrate that the use of retweets and favourites is equivalent in terms of impact or response is to check the correlation between these figures on a set of tweets. We find that retweets and favourites have a strong positive correlation, with a Pearson's coefficient r of 0.875 (3.s.f), n = 1,048,576.

6.1.1 An Impact Factor

We created an 'impact factor' measurement based upon a Twitter user's retweet count, and tweet activity. This formula is upon the Hirsch-index [23] measurement for an academic's

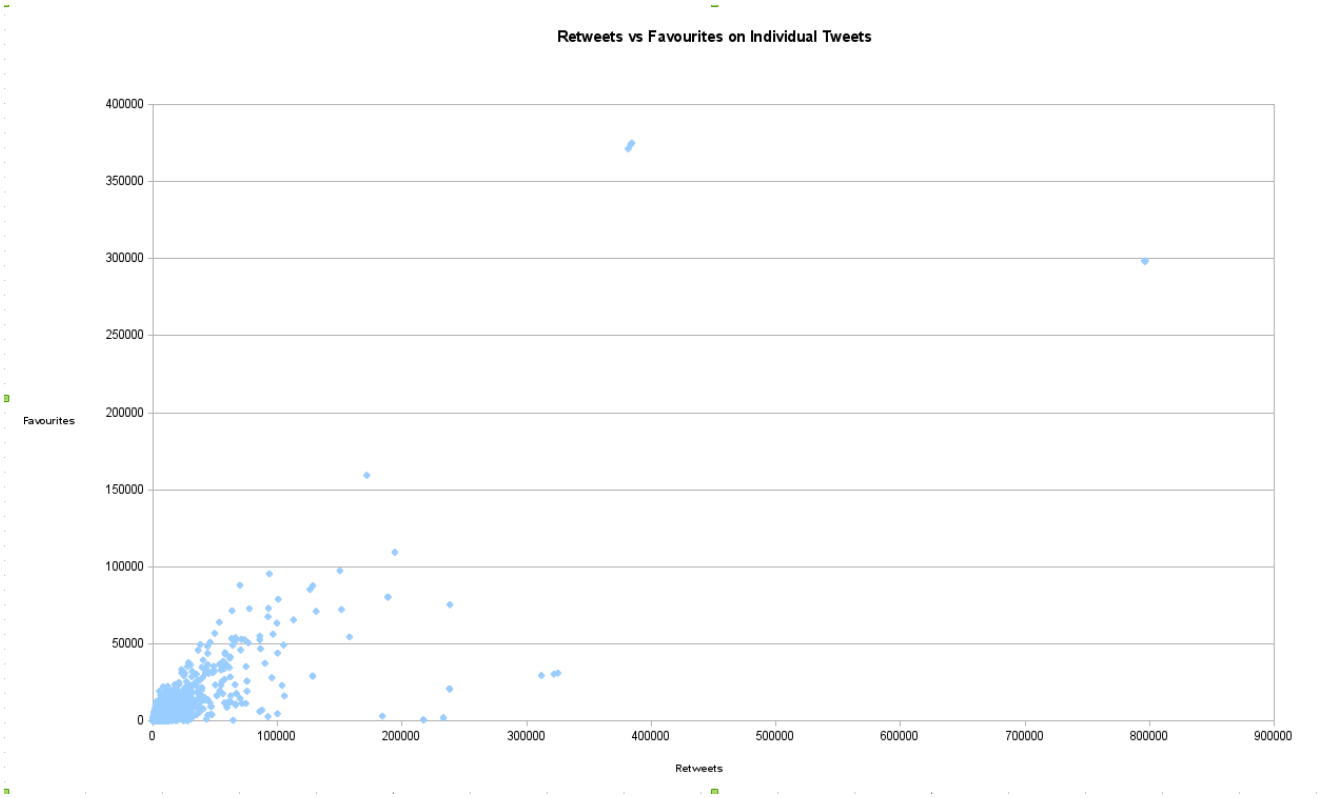


Figure 6.1: Correlation of Retweet and Favourite Count

contribution to literature. It attempts to measure both the impact (number of retweets) and productivity (number of tweets) of a Twitter user.

Figure 6.2 displays the distribution of impact factor values, over the set of twitter profiles collected. We can see that the impact score follows a roughly exponentially decreasing curve, with the vast majority of users getting a low impact score. This is reflective of past research, studying the behaviours of Twitter users [29]. That is, user patterns can be broken up into users who follow others and do not post much content themselves, and users who are more active and are followed by others. The extremely high impact scores are likely celebrities - the profile with the highest impact score of 216 was the Jonas Brothers (a pop band) profile, which happened to feature in the dataset.

The impact factor calculation differs from other social media impact algorithms in that there is no upper limit on score. Other methods are arbitrarily capped at values like 10 or 100, which restricts the comparative value of such tools for the high echelons of impacting-users. The algorithm also automatically takes into account the length of time a user has been active on Twitter when performing the calculation.

Extensions to the impact factor algorithm could include use of data such as number of followers, as well as frequency or consistency of posting. For example, users which have a large following but whom only have very low retweet counts may imply that content posted is somewhat stale. Also, an individual who had a strong impact in the past but who has not posted recently should logically receive a lower current impact; the current algorithm will not differentiate from an active user and an inactive one. This temporal structuring and analysis for a reputation policy is worth exploring further.

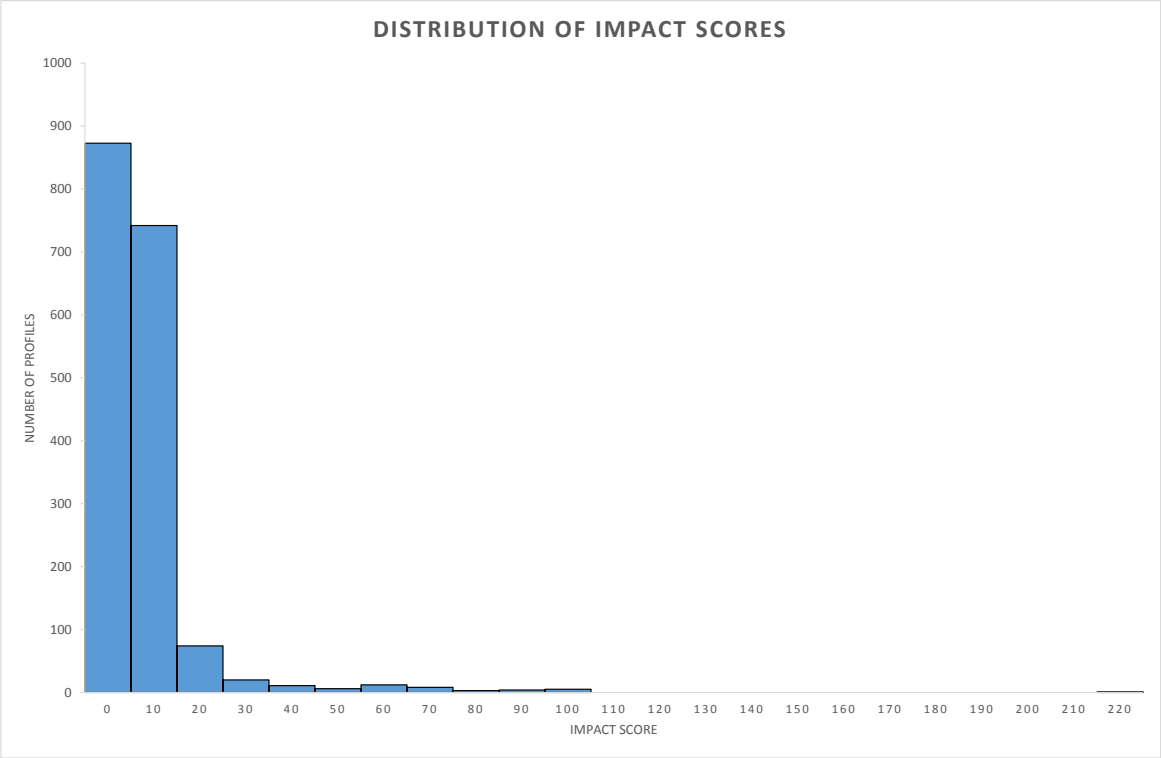


Figure 6.2: Distribution of Impact Score Among Users

6.1.2 Temporal Clustering and Impact Factor

In order to differentiate from one-hit-wonders and 'constant emitters' in my reputation policies, some view of activity over time was discussed. We refer to this as temporal clustering. One approach is to cluster impact score calculation into separate months. This reveals how consistently influential a person is, and gives the potential for detecting inactive users. Various bucket sizes were experimented with - days were much to varying to interpret a clear underlying trend, whilst years were too coarse to solve the issue of inactive users receiving a high impact score. Thus months are used as a bucketing measure.

This technique can be used to link real-world events to a person's influence. As an example I take Barack Obama. In October and November of 2012, the US presidential elections were at their peak. The corresponding impact score of 47 for Obama in October is reflective of this.

To demonstrate this on another individual, take Chris Hadfield (Twitter name Cmdr_Hadfield), made famous through his cover of David Bowie's 'Space Oddity'. The below chart shows how Hadfield's popularity spiked around the time of this video's explosion in popularity - June this year.

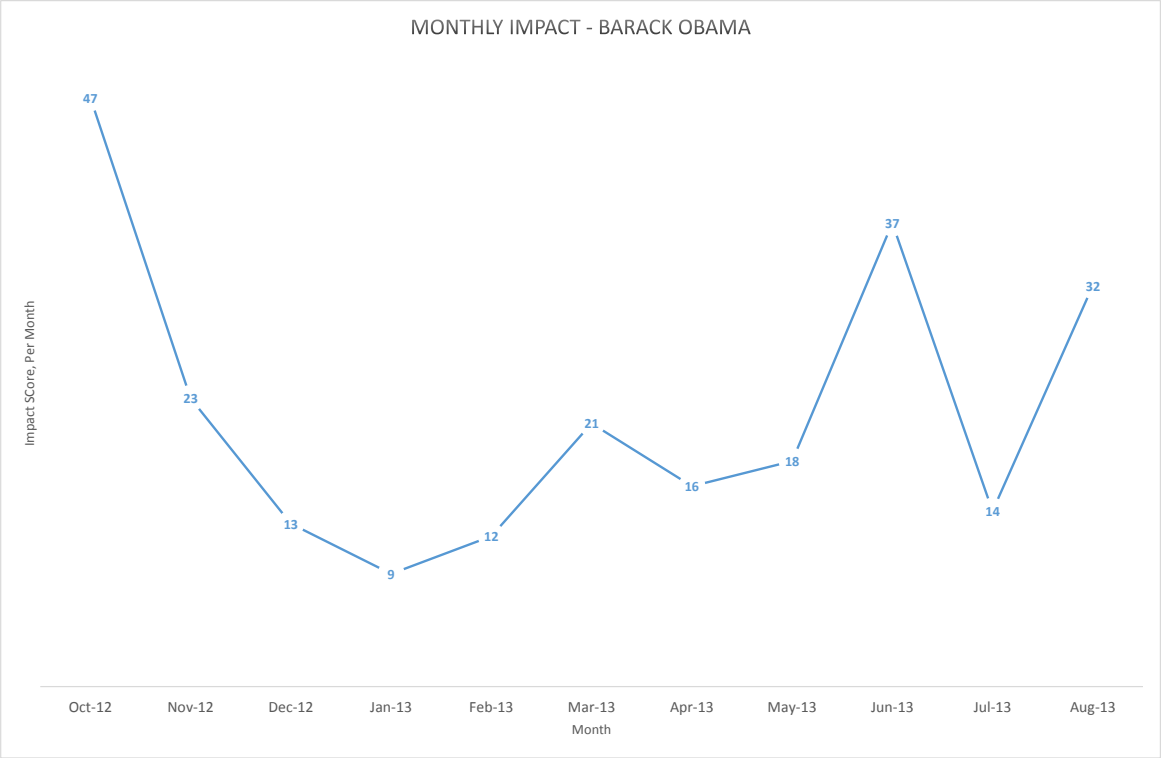


Figure 6.3: An Example of Monthly-Impact Score Bucketing - Barack Obama

6.2 Community Detection

The second primary data exploration factor explored community detection on Twitter. I propose the following.

H2. Embedded social networks exist within Twitter, and can be detected using IHPScrape. Detection of these communities will be possible through two means; follower and following links, and connection through retweets.

Data collected for detecting communities consists of two sets to verify this claim; the retweet links, and follower links. These sets are largely disconnected, and as such discussion of these two techniques must also be separated.

6.2.1 MapEquation Tool

MapEquation is a leading community-detection software tool, which uses graph-traversing techniques to detect the presence of sub-communities in a network [15]. In short, the algorithm aims to cluster neighbouring nodes into modules, then supermodules, and so on. Such an algorithm allows for a good clustering of a network in a very short time, and makes community detection feasible among millions of nodes.

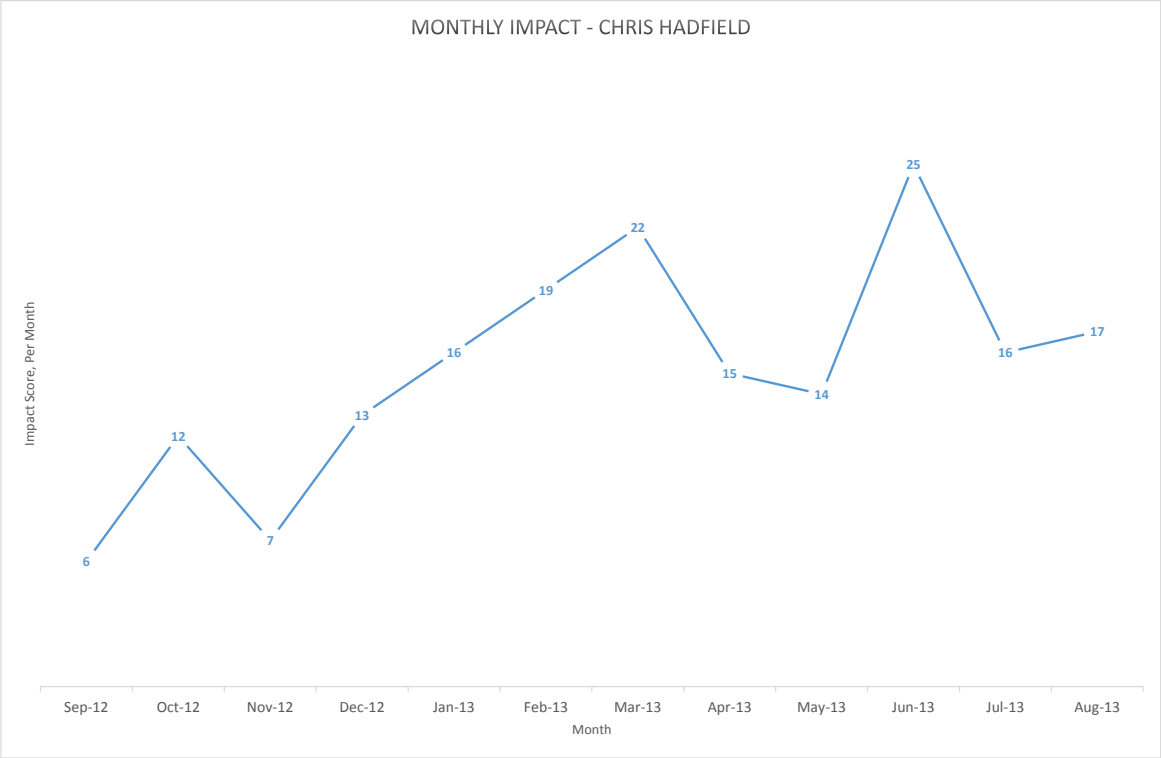


Figure 6.4: The Monthly Impact of Chris Hadfield - Famous Astronaut

The InfoMap software package distributed by mapequation is compatible with a Flash-based MapGenerator application, also hosted at the MapEquation site [1]. This allows communities output through the InfoMap package to be visualised in a sensible manner. The following results were generated by gathering data, running community detection algorithms upon these sets, and visualising the results. Unfortunately the Flash tool is limited in terms of the numbers of nodes which may be loaded. My data consisted of millions of nodes and edges, and often the browser-based applet would cease functioning after data on the order of tens-of-thousands of nodes was loaded. The designers of the application are currently working on a newer version, to allow for larger quantities of data to be loaded through the MapGenerator tool, which would allow for more interesting community analysis in the future.

6.2.2 Followers and Following

The first community detection approach considers those clustered around profiles, through links in following (profiles an individual is following) and followers (users who are following the current profile). I found that disconnected communities are clustered around popular figures. The below example, taken from Steven Adams profile, is a visualisation of

[1] http://www.mapequation.org/code.html

the community formed through a subset of his followers.

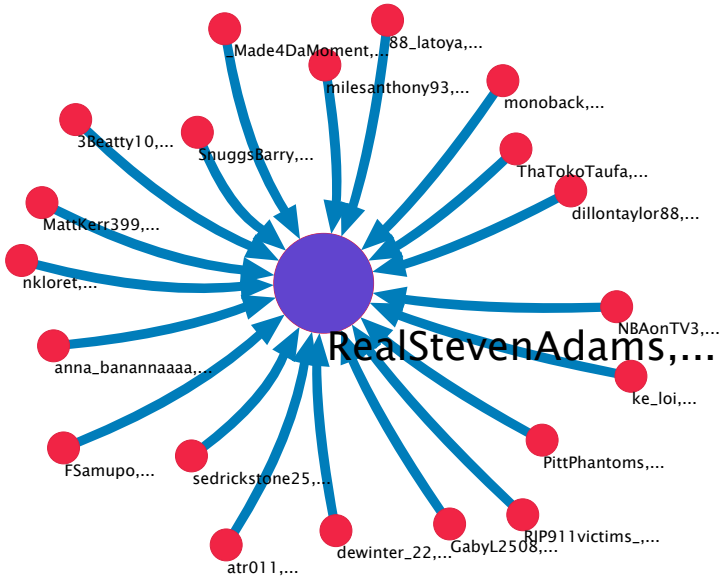


Figure 6.5: Followers of Steven Adams

Unfortunately due to the limitations of the tool used, larger sets of data were not able to be loaded in this context. I feel that with more results, larger and connected communities would be evident through the follower and following connection on Twitter.

6.2.3 Retweet Communities

The second approach taken considers the communities formed on Twitter through retweeting of content. I consider two profiles to be connected if one retweets the other. This is ordered by the retweeter being connected to the original poster, respectively. Heavier weight is added to the connection if a user retweets posts from the user multiple times. As this retweet connection is richer, visualisations of communities formed are of more interesting structure.

Unfortunately the MapGenerator tool did not allow for any entire set of profile and retweet data that was collected to be visualised in one piece. This is due to the extremely large quantity of nodes that are generated through the fetching of a single profile, and the entire collection of retweet links associated with this profile. This largely reduced the use of current retweet communities, and the visualisation options for generating meaningful understanding of data collected, as arbitrary divisions in data necessary to be loaded into the tool introduce bias. Figures 6.6 and 6.7 are the retweet communities generated from the first quarter of one Twitter profile scraped.

6.2.4 Community Discussion

The scrapers allowed for detection of communities for the two groups of followers and following, as well as detection of communities among retweeting circles. While the tools available certainly allowed for the detection of these communities, there is no way with the

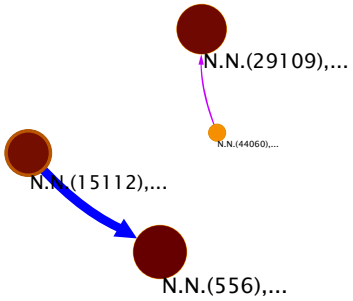


Figure 6.6: Retweets detected community modules

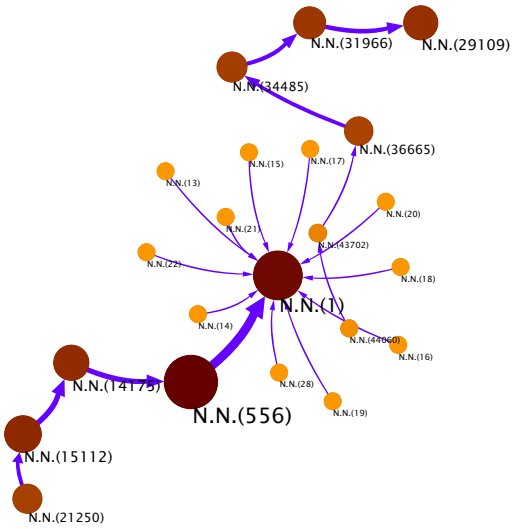


Figure 6.7: Retweets source nodes

analysis tools currently provided to associate any real meaning with these groups. Future projects could assign meaning with the data I have made available - for example with sentiment or keyword classifying of tweet conversation topics for a profile. This would allow for meaningful classification of communities on Twitter, rather than simply grouping around profile names such as the grouping shown around Steven Adams profile. As this is not an A.I. project, it was perfectly reasonable to leave this implementation detail to the future work. Due to the large potential for extension of this community detection function, the policies ahead make assumptions on the classification of these groups being possible.

6.2.5 Sentiment Analysis

One avenue for enriching the community data would be to use sentiment-detection methods. Filip Dimitrievski's project was primarily focused on classifying social media posts based upon sentiment, and constructing policies based on this information. He was able to use data collected from my scrapers to classify tweets according to sentiment, with varying success with different classifiers such as Sentiment140[2]. Although the classifier was not trained specifically to Twitter data and in the long run the approach was abandoned, this demonstrated the feasibility of such an approach. Further exploration of this is left to future work, given that the project was not Artificial-Intelligence focused.

6.3 Policy Examples and Discussion

Reputation-inferring policies can be constructed from the data collected. I discuss 2 exemplar policies in particular which could be built as part of any system requiring reputation data related to a user's profile. I apply these policies in relation to a theoretical case study, that requires access policies based upon user reputation from an external source.

[2]http://www.sentiment140.com/

6.3.1 Case Study - Discussion Forum

In order to introduce exemplar reputation policies, I use the concept of an interactive forum. This concept is inspired by Hendrikx at al's application of GRAft to a social forum, using a pure reputation access control system [22]. In this example, forum access control may be modified by restricting or granting additional rights to users based upon calculated reputation. Reputation is turned into access control rights by these policies.

As in the GRAft paper, I provide policy fragments, using Ruler [3] to demonstrate how such a policy engine may operate. The following policy fragment restricts access based upon the impact factor of the given user, combined with the community that the individual is a part of. For example, on a computer science forum the administrator may only desire users with a significant social media impact to do with the engineering discipline to be able to post. Here I propose that the calculated impact factor of the user is greater than or equal to 1, and the computed community discipline is related to the current forum, in order to post.

Policy 1: Impact Factor and Community Participation

```
$rb->logicalAnd(
 $rb['impact_factor'] -> greaterThanOrEqualTo(1),
 $rb['community_value'] -> in_array(['computer_science','engineering'])
)
```

Whereas for read-only rights, the person may only need to be part of the relevant discipline.

```
$rb['community_value'] -> in_array(['computer_science','engineering'])
```

On the same forum, administrator rights may be granted to consistently active users. Some evidence of consistent activity on social media might be required for effective administration of the site. In this exemplar policy, administration rights are granted to the user if their average monthly computed impact is greater than or equal to 3, and they are part of the computer science or engineering community.

Policy 2: Impact Factor, Community Participation and Temporal Consistency

```
 $rb->logicalAnd(
  $rb['temporal_impact_average'] -> greaterThanOrEqualTo(3),
  $rb['community_value'] -> in_array(['computer_science','engineering'])
)
```

[3] https://github.com/bobthecow/Ruler

Chapter 7

Evaluation

Following the completed scraper implementation and data analysis, an evaluation of the project was carried out on both the scrapers and policies. The evaluation was designed primarily to verify whether or not the scraper and policies created were succesful in fulfilling the requirements of the project. The following aspects of the IHPScrape framework were evaluated: accuracy, performance, resistance to user interface change, and resistance to detection.

7.1 Scraper Accuracy

Requirement NF3 stated that data gathered needs to be accurate in order to generate meaningful results, and that any potential innacuracies in data collected should be well understood. Quantitatively evaluating the accuracy of figures gathered by IHPScrape was difficult without a dataset to compare results against. Given that one of the primary reasons for implementing a scraper was due to this lack of a valid dataset, such an evaluation was not possible within the time constraints of the project. As such I performed a qualitative evaluation of aspects of scraper accuracy.

To measure relative scraper accuracy, manual inspection of 15 random Twitter profiles that were fetched in the final build was conducted. Figure 7.1 displays the data checked for accuracy on the user's Twitter profile pages, and scraped xml file. Details checked for correctness were as follows:

- The number of users following the test subject (Number of Followers Correct)
- The number of users the subject follows (Number of Following Correct)
- The number of posts by the users (Number of Tweets Correct)
- Whether retweet counts recorded were accurate (Retweet Counts Accurate)
- Whether the set of profile names recorded as retweeting a post was correct and complete (Retweeter Names Correct)
- Whether the entire set of tweets posted by the subject were collected (Tweet List Complete)

The results of this sample test were encouraging. Static and unchanging values such as Number of followers, number following, and number of tweets were always correct. Dynamic lists such as the retweet names were sometimes incomplete. This was a design decision that I had to make earlier in the project, and it is known behaviour that for large

Profile Name	Number of Followers Correct	Number Following Correct	Number of Tweets Correct	Retweet counts accuracte	Retweeter Names Correct	Tweet List Complete
_Eduardofficial	Yes	Yes	Yes	Yes	Incomplete	Yes
MichaelaCNN	Yes	Yes	Yes	Yes	Incomplete	Yes
Natalyacoyle	Yes	Yes	Yes	Yes	Incomplete	Yes
OpheliaDagger	Yes	Yes	Yes	Yes	Incomplete	Yes
NitaLowey	Yes	Yes	Yes	Yes	Yes	Yes
mims	Yes	Yes	Yes	Yes	Incomplete	No
sherlynroy	Yes	Yes	Yes	Yes	Yes	Yes
Natpolitic	Yes	Yes	Yes	Yes	Yes	Yes
portereduardo	Yes	Yes	Yes	Yes	Yes	Yes
NatbyNature	Yes	Yes	Yes	Yes	Incomplete	No
NewzMuse	Yes	Yes	Yes	Yes	Yes	Yes
NitaLakeLodge	Yes	Yes	Yes	Yes	Yes	Yes
MirellaVieiraa	Yes	Yes	Yes	Yes	Yes	No
JanuarySeraph	Yes	Yes	Yes	Yes	Incomplete	No
MissKacieMarie	Yes	Yes	Yes	Yes	Incomplete	No

Figure 7.1: Accuracy Metric Results

converstation chains, or large lists of retweeters, not all of the names will be present. Since extended lists of retweet names require further HTTP requests, fetching the entire list would have resulted in performance penalties. The number of incomplete profiles from my sample here is consistent with incomplete profiles fetched overall in the final build. The common denominator for an incomplete profile is due to too large quantities of tweets being posted by the user, on the order of 10,000 or more. This is a known problem with the IHPScrape solution, as after a number of tweets the Twitter server will respond saying no more Tweets exist, where this is untrue. Fetching the entire profile of a user with 10,000 + tweets however is largely infeasible for use with reputation policies though, which is justified in the performance evaluation section.

Having evaluated accuracy of results it was also noted that the order of tweets saved was occasionally different to the order posted by the subject, within the tweet window size of seven. This was due to the parallization of tweet fetching. Given that none of the policies designed require accurate ordering of tweets, this is not an issue within the scope of my project.

The experiment to verify scraper accuracy positively suggests that data collected is of good quality. I consider requirement NF3 to have been met, as data was accurate where required, and innacuracies in data are well understood. I acknowledge that the small sample size covered was not ideal, but was feasible within the timeframe for evaluation. If possible a better evaluation would compare collected data against the same figures from an existing dataset. However, since no such dataset existed for the project, this factor being a driving force for scraper implementation, my ability to conduct a thorough quantitative assesment of the scraper's accuracy was limited.

7.2 Performance Evaluation

I evaluate the performance of IHPScrape with respect to the average time taken to fetch and parse a tweet. The major limiting factor for scraping twitter was that each tweet had to be fetched with a separate HTTP request. Figure 7.2 displays the average time taken to fetch and parse each tweet, with respect to the 4 builds completed. Performance data was calculated using the inbuilt logging mechanism, and dividing the time taken to fetch an entire profile by the number of tweets fetched. To reduce bias caused by varying speeds on the University network across the day, IHPScrape was run over extended periods of time for each test. Performance gains in each build were resultant from the following features:

- Build 1 - Base performance. Outliers in performance (e.g. 8 seconds to parse a tweet) were due to unreliable and slow parsing libraries. The parsing problems were also reflected in failure rates for the first build.

- Build 2 - A slightly larger tweet window was used, when fetching further tweets. This did not result in large performance gains due to each tweet in the window still needing to be fetched individually, after the tweet window is loaded.

- Build 3 - All tweets fetched before parsing.

- Build 4 - Fetching of tweets performed in parallel. This resulted in the scraper increasing in performance by a factor of six (Average time reduced from 1.4s to 0.2s).

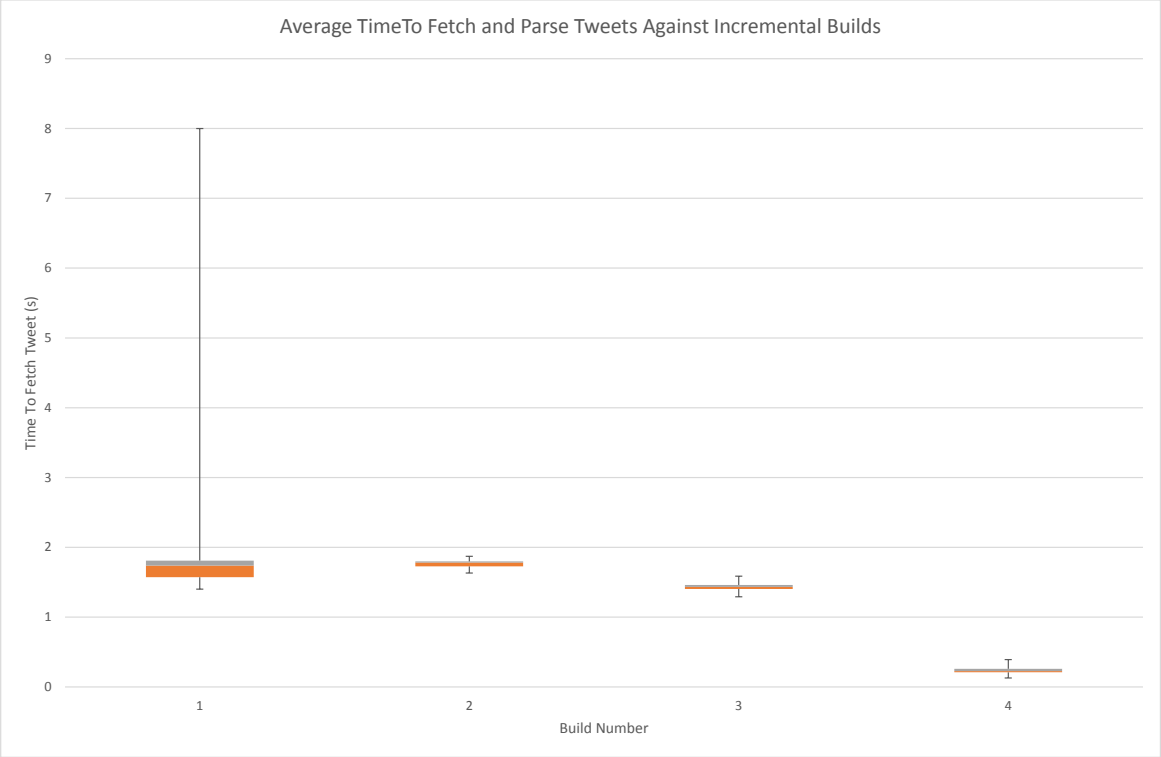


Figure 7.2: Scraper performance improvements across incremental builds.

7.2.1 Resulting Policy Performance

Based upon the final build results, I am able to evaluate performance of the examplar policies proposed in chapter 6. As policies must fetch the entire profile to generate the impact factor calculation, time to fetch profiles is the primary metric against which I evaluate policy performance. The analysis components calculating impact factor perform on the order of one to two seconds, depending on profile size. Thus I measure policy performance entirely against profile fetch times, as these are by far the most time-consuming factor to reputation metric calculation. The average time to fetch profiles is shown in figure **x**, using the parallel performing build. Despite the time taken to fetch a single tweet having been dramatically reduced in this version, an entire profile still takes hundreds of seconds on average.

Therefore I conclude requirement NF2 to not have been met, as policies resulting from are too slow for use in a real-time system. In the Twitter case study this is due to the necessity for a seperate HTTP request to fetch every single tweet. Although parrelisation of tweet fetching greatly improved performance, this requirement was largely infeasible. for websites with more static content such as LinkedIn, I propose that this would be possible however.

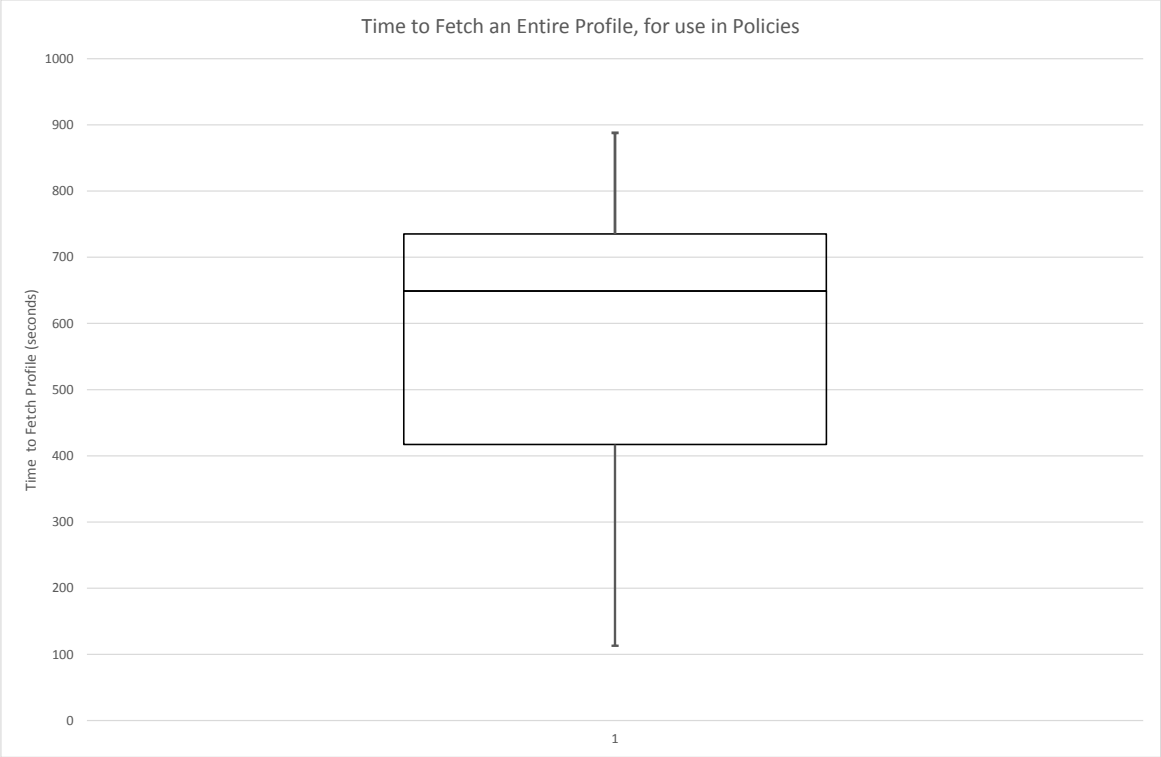


Figure 7.3: Average Times to Fetch an Entire Twitter Profile, for use in Policies

7.3 Resistance to Interface Change

Evaluation of scraper resistance to interface change was conducted qualitatively. I summarise the critical points which, if changed, would result in the scraper failing. Discussion of the likelihood of these components changing is conducted in order to asess their reliability.

IHPScrape is reliant on two components remaining constant; URLs to fetch resources and xPath expressions to fetch specific values. URLs are less likely to change, as this implies some level of large backend change or migration. xPath expressions are much more brittle, especialy when hard-coded based upon document structure (for example document/v1/li/test/ is more brittle than //**[li]). To evaluate the resistance of my Twitter scraper against user interface or backend change, I constructed a summary of all hard-coded URL and xPath expressions used to fetch data.

Taken in the context of the entire scraper, the number of absolute interface dependancies is low. Over the course of the project, the Twitter user interface did not change, nor the URL structure. As such it is difficult to test whether any change would genuinely result in the scraper breaking, and how difficult this change would be to fix. From the analysis performed, I conclude that requirement NF1 was met; small changes should not result in the scraper breaking, unless they affect the specific points of failure outlined in figure 7.3. Wholesale interface redesigns will of course result in scrapers breaking, but such resistance was deemed infeasible.

Feature	Nature of Dependancy
Google Twitter Search - searching for Twitter profiles by name. URL is modified to input name parameter.	URL
Twitter base profile. URL is modified to search for Twitter page with given user name.	URL
Fetch extra tweets. Backend HTTP request to load more tweets for the current profile.	URL
Fetch tweet detail. HTTP request to load tweet detail for the current tweet, using ID as a parameter.	URL
Fetch retweeter list. HTTP request to fetch the retweeters for the current tweet, using ID as a parameter.	URL
Google Twitter Search - retrieve names. The names are located at specific points on the result page.	xPath
Fetch core profile statistics. Name, number of tweets, number of followers, number following.	xPath
Fetch detailed tweet information. Retweets, favourites, favourites, content, date_time.	xPath
Fetch retweeter names.	xPath

Figure 7.4: Scraper Interface Dependancies

7.4 Resistance to Detection

Evaluation of scraping detection was performed throughout the data collection phase, by logging events where a scraper was blocked. The primary event indicating Twitter had blocked or limited my scraper was primarily the 503 error code. This has been experienced by other Twitter scrapers, confirming that this code indicates rate limiting and not a coding failure. The secondary event recorded to indicate blocking was 500 error codes - this was in fact a mistake, as 500 errors were in response to coding errors in IHPScrape.

Figure 7.4 shows the percentage of failed profiles against incremental builds for the Twitter scraper. The definition of failure here is a profile that was not fetched in its entirety. As such the rates of failure look worse than is the case. In the first build, the parsing code was not sufficiently reliable, and in many cases parse errors were encountered midway through scraping a profile. These were for special case events such as photo posts that I had not considered. The second build vastly improved the parsing quality, and gave way to detection issues, which were in turn subsequently reduced. The final build had an extremly small percentage of genuinely failed profiles, and only approximately 1 in 10 profiles not entirely fetched. As mentioned earlier, many incomplete profiles are of such size that further fetching is somewhat redundant.

I conclude that the requirement F4 was half met. The final Twitter build demonstrates that mechanisms in place to avoid detection were effective, as only extremly large profiles result in detection and incompleteness. However recovery from failure was not implemented for Twitter, as it was impossible to distinguish for example the end of a profile and the Twitter server responding with false information.

Figure 7.5: Incomplete profiles fetched, with reasons for Failure.

Chapter 8

Conclusions and Future Work

This section summarises work completed over the project, and reflects on successes with relation to the issues identified at the beginning of the project.

8.1 Web-Scraper Implementation

A social media web-scraping framework was developed. This framework was developed firstly for Twitter, and was extended onto LinkedIn. I was able to demonstrate how web-scraping technologies are suitable for retrieval of basic reputation metrics. Performance of the scraper was greatly increased through incremental builds, with the final build performing a factor of 6 times better than the previous one.

Unfortunately performance to fetch and parse an entire Twitter profile was shown to be too slow to prove viable in a real-time analytical system. The lower than anticipated performance was due to the dynamic nature of today's social sites, necessitating in potentially hundreds or thousands of separate requests to retrieve an entire profile. Data retrieved was shown to be accurate, withholding some elements which can remain incomplete should their size exceed the threshold selected. Detection avoidance of the framework was also evaluated to have been successful, again up until the point of 7,000 + tweets being fetched.

8.2 Data Analysis and Resulting Policies

Data analysis was performed against the Twitter dataset collected of 1.7 million tweets. Retweets were firstly discussed, due to their greater semantic depth than the equivalent 'favourite' mechanism. Using retweet counts as a measure of impact, an 'Impact Factor' calculation is proposed, based upon the Hirsch-Index calculation. This calculation measures productivity and response values on Twitter. Combining this figure with average monthly impact gives a view of average activity, and allows for inactive users to be detected. Different bucketing sizes may be used; in this project, a month was the bucket size of choice.

Community detection was also experimented with, and the links of retweets and follower/following relationships explored to reveal existence of sub-communities within Twitter. Unfortunately visualisation of entire retweet communities was not achieved due to limitations with the selected visualisation tool. As the MapGenerator tool is currently undergoing improvement, there is potential for improvement in this feature.

Exemplar policies were provided, with respect to the case study of a social forum. Combination of community detection, impact factor, and temporal reputation information was demonstrated to be useful in regards to access policy constructs.

8.3 Future Work

8.3.1 Community Detection Extension

In its current state, the community detection component of my project only detects community patterns and is not able to associate meaning with these various communities. In order to support a richer set of reputation-defining policies, some form of sentiment or classification of profiles within these communities would be required. In order for more meaningful visualisation of such results, the MapGenerator tool will need to have advanced to a capable level for handling larger amounts of data. As such this was left to future work.

Further, small-world network analysis could be compared to communities detected within Twitter, and my dataset.

8.3.2 Social Media Expansion

In order to further validate the scraping framework constructed, more social media sites should be explored. This would enable richer still policies and data analysis to be performed. Not all sites would be suitable for scraping, and indeed in some cases the API may be of more use. Sites with more static content are more suitable for web scraping.

8.3.3 Further Evaluation

Further verification of IHPScrape with respect to resistance to change is required. No Twitter user interface changes were experienced during the course of the project. For the scraper to be applied as part of a legitimate reputation system, verification of its resistance to interface change must be conducted. Comparison against API changes would be more valuable still.

8.3.4 Reliability Metric

Requirement F5 stated that a metric of reliability should be developed based upon quantity of data collected. The performance of policies demonstrated that fetching a full profile for use is not feasible within a real-time system. As such using only a subset of profile data could be more practical, with the attachment of some form of metric pointing to the reliability of data collected.

8.3.5 GRAft integration

As analysis components and policies developed effectively act as a source node in the GRAft model, actual implementation of this could be useful. Community effort would be required to maintain such a solution.

Bibliography

[1] Facebook. `https://www.facebook.com/`. Accessed: 17-10-2013.

[2] Google+. `https://plus.google.com/`. Accessed: 17-10-2013.

[3] Linkedin. `http://www.linkedin.com/`. Accessed: 17-10-2013.

[4] Slashdot. `http://slashdot.org/`. Accessed: 17-10-2013.

[5] Twitter. `https://twitter.com/`. Accessed: 17-10-2013.

[6] ADALI, S., AND GOLBECK, J. Predicting personality with social behavior. In *Advances in Social Networks Analysis and Mining (ASONAM), 2012 IEEE/ACM International Conference on* (2012), IEEE, pp. 302–309.

[7] ADALI, S., SISENDA, F., AND MAGDON-ISMAIL, M. Actions speak as loud as words: Predicting relationships from social behavior data. In *Proceedings of the 21st international conference on World Wide Web* (2012), ACM, pp. 689–698.

[8] BACHRACH, Y., KOSINSKI, M., GRAEPEL, T., KOHLI, P., AND STILLWELL, D. Personality and patterns of facebook usage. In *Proceedings of the 3rd Annual ACM Web Science Conference* (2012), ACM, pp. 24–32.

[9] BACK, M. D., STOPFER, J. M., VAZIRE, S., GADDIS, S., SCHMUKLE, S. C., EGLOFF, B., AND GOSLING, S. D. Facebook profiles reflect actual personality, not self-idealization. *Psychological Science 21*, 3 (2010), 372–374.

[10] BOLLEN, J., MAO, H., AND ZENG, X. Twitter mood predicts the stock market. *Journal of Computational Science 2*, 1 (2011), 1–8.

[11] BRABHAM, D. C. Crowdsourcing as a model for problem solving an introduction and cases. *Convergence: the international journal of research into new media technologies 14*, 1 (2008), 75–90.

[12] BRODY, H. I don't need no stinking api: Web-scraping for fun and profit. `http://blog.hartleybrody.com/web-scraping/`, 2013.

[13] DE RAAD, B. *The Big Five Personality Factors: The psycholexical approach to personality.* Hogrefe & Huber Publishers, 2000.

[14] DOAN, A., RAMAKRISHNAN, R., AND HALEVY, A. Y. Crowdsourcing systems on the world-wide web. *Communications of the ACM 54*, 4 (2011), 86–96.

[15] EDLER, D., AND ROSVALL, M. The mapequation software package. available online at `http://www.mapequation.org`, 2013.

[16] FACEBOOK. Facebook quaterly earnings slides, q4 2012. http://www.scribd.com/doc/123034877/Facebook-Q4-2012-Investor-Slide-Deck, 2012.

[17] GINSBERG, J., MOHEBBI, M. H., PATEL, R. S., BRAMMER, L., SMOLINSKI, M. S., AND BRILLIANT, L. Detecting influenza epidemics using search engine query data. *Nature 457*, 7232 (2008), 1012–1014.

[18] GOLBECK, J., AND HANSEN, D. Computing political preference among twitter followers. In *Proceedings of the 2011 annual conference on Human factors in computing systems* (2011), ACM, pp. 1105–1108.

[19] GOLBECK, J., KOEPFLER, J., AND EMMERLING, B. An experimental study of social tagging behavior and image content. *Journal of the American Society for Information Science and Technology 62*, 9 (2011), 1750–1760.

[20] GOLBECK, J., ROBLES, C., EDMONDSON, M., AND TURNER, K. Predicting personality from twitter. In *Privacy, security, risk and trust (passat), 2011 ieee third international conference on and 2011 ieee third international conference on social computing (socialcom)* (2011), IEEE, pp. 149–156.

[21] GOLBECK, J., ROBLES, C., AND TURNER, K. Predicting personality with social media. In *Proceedings of the 2011 annual conference extended abstracts on Human factors in computing systems* (2011), ACM, pp. 253–262.

[22] HENDRIX, F., AND BURBENDORFER, K. Malleable access rights to establish and enable scientific collaboration. Accepted to eScience 2013 Conference.

[23] HIRSCH, J. E. An index to quantify an individual's scientific research output. *Proceedings of the National academy of Sciences of the United States of America 102*, 46 (2005), 16569.

[24] KOSINSKI, M., STILLWELL, D., AND GRAEPEL, T. Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences* (2013).

[25] MOVSHOVITZ-ATTIAS, D., MOVSHOVITZ-ATTIAS, Y., STEENKISTE, P., AND FALOUTSOS, C. Analysis of the reputation system and user contributions on a question answering website: Stackoverflow.

[26] QUERCIA, D., LAMBIOTTE, R., STILLWELL, D., KOSINSKI, M., AND CROWCROFT, J. The personality of popular facebook users. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work* (2012), ACM, pp. 955–964.

[27] RESNICK, P., KUWABARA, K., ZECKHAUSER, R., AND FRIEDMAN, E. Reputation systems. *Communications of the ACM 43*, 12 (2000), 45–48.

[28] RESNICK, P., AND ZECKHAUSER, R. Trust among strangers in internet transactions: Empirical analysis of ebay's reputation system. *Advances in applied microeconomics 11* (2002), 127–157.

[29] STATISTICS, B. An exhaustive study of twitter users across the world. http://www.beevolve.com/twitter-statistics/, 2012.

[30] WADWHA, T. Lessons from crowdsourcing the boston bombing investigation. http://www.forbes.com/sites/tarunwadhwa/2013/04/22/lessons-from-crowdsourcing-the-boston-marathon-bombings-investigation/, 2013.

[31] WARDEN, P. How i got sued by facebook. http://petewarden.typepad.com/searchbrowser/2010/04/how-i-got-sued-by-facebook.html, 2010.

[32] ZHANG, H., WU, W., AND LI, Z. Open social based group access control framework for e-science data infrastructure. In *E-Science (e-Science), 2012 IEEE 8th International Conference on* (2012), IEEE, pp. 1–8.

Appendix A

Data Schemata

A.1 Twitter Data Schema

```
 <?xml version="1.0" encoding="ISO-8859-1" ?>
<xsd:schema xmlns:xsd="http://www.w3.org/2001/XMLSchema">
<xsd:element name="profile">
<xsd:complexType>
<xsd:sequence>

<xsd:element name="key_values">
<xsd:complexType>
<xsd:sequence>
<xsd:element name="number_followers" type="xsd:string"/>
<xsd:element name="number_tweets" type="xsd:string"/>
<xsd:element name="number_following" type="xsd:strng"/>
</xsd:sequence>
</xsd:complexType>
</xsd:element>

<xsd:element name="tweets">
<xsd:complexType>
<xsd:sequence>
<xsd:element name="tweet" minOccurs="0" maxOccurs="unbounded">
<xsd:complexType>
<xsd:sequence>
<xsd:element name="tweet_content" type="xsd:string"/>
<xsd:element name="retweet_count" type="xsd:positiveInteger"/>
<xsd:element name="favourite_count" type="xsd:positiveInteger"/>
<xsd:element name="retweet_names">
<xsd:complexType>
<xsd:sequence>
<xsd:element name="name" minOccurs="0" maxOccurs="unbounded" type="xsd:string"/>
</xsd:sequence>
</xsd:complexType>
</xsd:element>
</xsd:sequence>
</xsd:complexType>
<xsd:attribute name="tweet_id" type="xsd:string" use="mandatory"/>
```

```
</xsd:element>
</xsd:sequence>
</xsd:complexType>
</xsd:element>

</xsd:sequence>
</xsd:complexType>
</xsd:element>


</xsd:schema>
```

A.2 LinkedIn Data Schema

```
 <?xml version="1.0" encoding="ISO-8859-1" ?>
<xsd:schema xmlns:xsd="http://www.w3.org/2001/XMLSchema">
<xsd:element name="profiles">
<xsd:complexType>
<xsd:sequence>
<xsd:element name="profile" minOccurs="0" maxOccurs="unbounded">
<xsd:complexType>
<xsd:sequence>
<xsd:element name="num_connections" type="xsd:string"/>
<xsd:element name="num_recommendations" type="xsd:string"/>
<xsd:element name="current_position" type="xsd:string"/>
<xsd:element name="skills">
<xsd:complexType>
<xsd:sequence>
<xsd:element name="skill" minOccurs="0" maxOccurs="unbounded" type="xsd:string"/>
</xsd:sequence>
</xsd:complexType>
<xsd:attribute name="num_skills" type="xsd:positiveInteger" use="mandatory"/>
</xsd:element>
<xsd:element name="groups">
<xsd:complexType>
<xsd:sequence>
<xsd:element name="group" minOccurs="0" maxOccurs="unbounded" type="xsd:string"/>
</xsd:sequence>
</xsd:complexType>
<xsd:attribute name="num_groups" type="xsd:positiveInteger" use="mandatory"/>
</xsd:element>
</xsd:sequence>
</xsd:complexType>
</xsd:element>
</xsd:sequence>
</xsd:complexType>
</xsd:element>
</xsd:schema>
```

Appendix B

Weekly Report Example. 2nd of September

B.1 Progress

Multi-threading is now working, items were built to cooperate with the sentiment140 API.

B.1.1 Multi-Threading

I learned how to do multi-threading in ruby, and implemented it. A thread pool of 15 is created. Each thread then sends an HTTP request to fetch the detailed tweet data, allowing retweets, favourites, date/time data to be accessed by the scraper. If a request fails, it is simply discarded in order to not reduce the benefit of parellisation. Multi-threading has increased performance dramatically. In my evaluation, I may make the point that fetching an entire profile as a policy might be too time-consuming to be useful. A good policy input might be to specify the number of tweets required for reputation analysis.

B.1.2 Sentiment

I can input my tweets, and retrieve a response positive/neutral/negative. Initial results included, I save these as csv format to import into excel more easily.

B.1.3 Blockers

Found the issue causing the correlation between month/overall impact to be incorrect. The graph indeed showed that there was a problem with the data collected. This was in fact from the scraper. Scraper was in fact including tweets NOT posted by the page owner (retweets) and counting these as retweets towards the individual's impact factor. Have fixed this, but did not have enough time to gather sufficient and accurate data for the meeting.

This is not such a massive problem overall - but it will have largely skewed impact results for less popular pages in the past.

B.1.4 Targets

Targets for this week; gather lots more data (accurate) and do the correlation analysis on this. With this more accurate data, look at how sentiments - positive and negative, correlate

with the impact formula calculation. Case studies; contraversial individuals and the like.

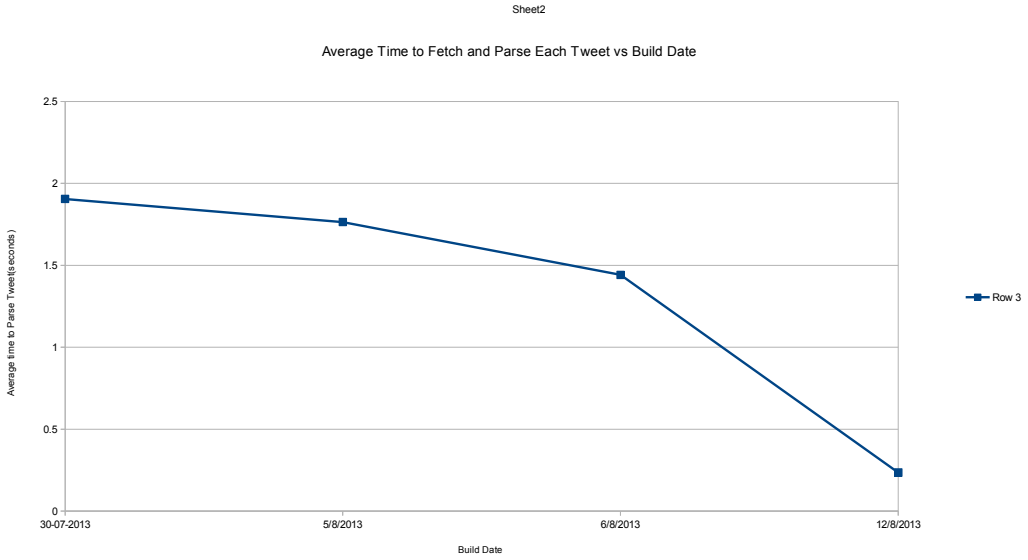


Figure B.1: The Average Time to Fetch and Parse a Tweet, Ordered by Builds