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Gamification in a social system

Master's thesis

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UNIVERSITY OF GRONINGEN

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and Capgemini for the business unit Financial Services
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by

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Abstract

Since it was first mentioned in 2002 [46], Gamification has grown in popularity. Gamification is a term for the use of game-design elements in a non-gaming context. The consulting company Capgemini has set up a rudimentary Gamification platform called Level Up. One of the goals of Level Up is to help motivating the people volunteering to organize meetings, courses and do other extra work for the company in their own spare time. In order to reward people for their extra work, they can request badges. Badges are virtual representations of achievements, depicted using an image of a shield. When an employee organizes or goes to such activities, he or she can request such a badge. A set of other employees, known as the Badgers decide whether or not the badge is granted.

In the current state of the art, it is not clear whether people in a social structure exert influence on each other, with regards to achieving these badges and doing extra work. Information on influence can be interesting for companies in order to determine if they want to implement a Gamification platform and social media service. From a sociological point of view the information on influence is interesting to see how people react on each other, in a 'gamified' environment (an environment to which Gamification techniques are applied).

To research if influence is actually exerted, Level Up is connected to an existing company social media service. The social media service used is known as Yammer, which is a private, enterprise social network. Statistical analysis on both the social graph and the Gamification data shows if there is a correlation between the social structure and the quantity of badges or types of badges one has. It is, however, not determined whether a causality relation exists between the social structure and the quantity of badges or types of badges, or whether a third factor is responsible for the effect. In the analysis the main focus is on *authoritativeness* of people. Authoritativeness is a measure to determine how important a person in a social network is.

The conclusions drawn show that a correlation between the quantity of badges or types of badges does exist. The result makes it more visible and founded why one should implement a Gamification system and how important the social structure in the sense of social media is for the value of it.

Preface

Already since high school I have been very much interested in playing games. During this phase of my life I have spent many hours, if not the largest amount of my time on a game called *Call of Duty*. Of course Call of Duty provided me with lots of fun and game mechanics already, but there was something else which kept me playing and which kept me engaged.

I have always played this game with my friends, most of the time on the same server (a server which was actually hosted by a different university: The University of Twente). It always motivated me to become one of the best players on the server (which was shown using different kinds of statistics on a separate website). However, there was one thing that kept me playing on that server, and that was the *star*.

The star was some kind of badge, a yellow asterisk surrounded by two yellow square brackets (it looked like: [*]) which you could place behind your name *only* if you earned it. Although I never earned the badge, it kept me engaged with this specific server. It has only been since this research that I realize that this was all the reason of a powerful new motivational technique: *Gamification*.

Acknowledgments

This report has been created for the University of Groningen and Capgemini. I thank all people from Capgemini who helped me achieve this result. Especially I would like to thank Lena Bazylevzka for the coordination and motivation from the Capgemini side, as well as the Gamification and Battle of the Kings group for finding my way at Capgemini and getting to know my colleagues.

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1 Introduction

"People matter, results count."

– Capgemini, 2010

Many people enjoy playing games, in fact, research shows that more than 200 million hours are spent each day playing computer and video games in the United States alone [50, 80]. Although many games are created purely for entertainment purposes, some of the elements used in these games can be used in non-gaming contexts as well. The use of these elements in non-gaming context is also known as Gamification.

Gamification is an informal umbrella term for the use of video game elements in non-gaming systems to improve user experience (UX), motivation and user engagement [11]. Gamification tries to motivate users to put in some extra effort in return for, for example, points or other rewards. These basic gaming concepts trigger the desirable UXs, *game-* and *playfulness* of people [10].

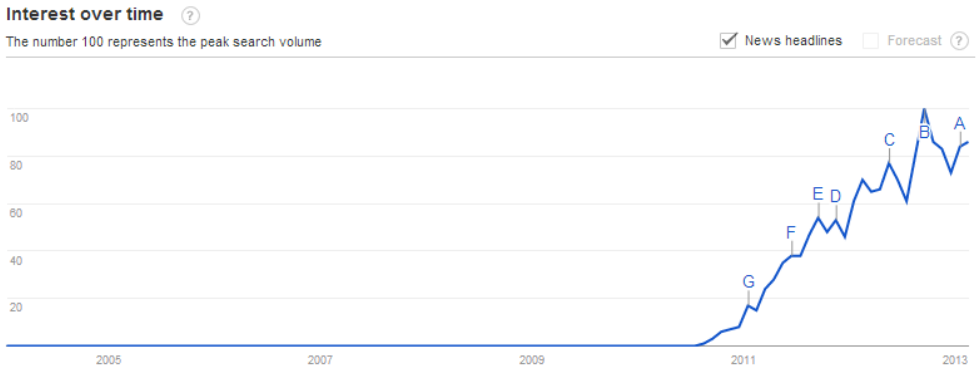

Figure 1.1: *Interest in Gamification on Google trends. Image from [26]*

Gamification has gained much interest in the last few years. One way to see the increased interest is visible in the amount of searches for the term 'Gamification' on Google Search Engine, shown in Figure 1.1. Gartner even states that "By 2015, more than 50 Percent of organizations that manage innovation processes will gamify those

processes" [20]. Analysts are predicting a fast adoption rate of Gamification, with the market growing from $100 million in 2011 to $2.8 billion in 2016 [20, 56]. Companies and universities are always trying to find new ways to motivate their people and are therefore interested in Gamification.

1.1 A Gamification platform

Gamification is a term for the use of game-design elements in a non-gaming context. Many companies are trying to fit Gamification into their organization. One of the companies designing a Gamification platform is Capgemini. Capgemini is one of the world's foremost providers of consulting, technology and outsourcing services [6].

Capgemini set up the rudimentary Gamification platform *Level Up*. Level Up gives a gaming experience for non-gaming applications. Level Up Provides a gaming experience by using basic *Game interface design patterns* [10] such as rewarding users with badges and showing a leader board to enhance competitiveness. Level Up mainly uses badges to provide a gaming experience. In Level Up a badge is an image of a shield which represents a specific achievement of a person, for example, getting a certification or helping to organize an event. Appendix A provides a list of each of these badges.

One of the goals of the Gamification platform Level Up is to help motivating the people volunteering to organize meetings, courses and do other extra work for Capgemini in their own spare time. When an employee organizes or goes to such activities, he or she can request a badge for the extra work, where other employees (in Level Up known as *The Badgers*) decide whether or not the badge is granted. A second goal of the platform is to increase engagement among the employees. Having a platform on which employees compete against each other pushes them to be more connected to Capgemini itself and maybe make the extra work more enjoyable.

Level Up is currently available for one of the six business units (or departments) of Capgemini (the business unit *Financial Services*). Level Up provides users with basic Gamification elements, i.e., a leader board and badges. However, the current platform is not maintainable. The current version of Level Up does not provide any separation between (game) logic, data storage and Graphical User Interface (GUI). Such a bad separation of concerns makes it hard to add new features and maintain existing ones. In order for software to remain usable, it needs to be maintained [25]. This project enhances the Level Up platform with new features to increase user engagement, but also focuses on re-factoring Level Up so it is be more maintainable in the future.

One of the most important features added to Level Up is a connection between the Level Up platform and existing social services, such as Yammer or LinkedIn.

Yammer is a private, enterprise social media service [84]. Yammer is a way for private communication within Capgemini. LinkedIn is a social media service focused on people in professional occupations. Due to the lack of time and difficulties with the closed, protected nature of LinkedIn, only a connection to Yammer is created.

A social media connection is important for two reasons. First of all when integrating with social media, Level Up can benefit from the popularity of the social media service [34]. Social media integration makes Level Up more visible for the employees. With more visibility the effect of Gamification is enhanced and the amount of users on the system will grow larger. A second, even more important reason, is that the social media connection is used for research purposes. Research which focuses on the social structure of Capgemini (based on the Yammer graph data) in combination with the earned badges is carried out. Research shows if there is a correlation between the social structure and the number of badges one has. Using the connection with Yammer, the social network data can be crawled from the connected social service Application Programming Interfaces (APIs) and be correlated to the available Level Up data. A crawler to gather information from Yammer and Level Up, known as Badge Crawler, is another component which is developed for doing research.

1.2 Gamification in a social structure

The research focuses on the social-structure or organizational-structure of Capgemini in combination with the earned badges. It is analyzed whether or not there is a correlation between the social structure of the people on Level Up and the number of badges they have earned. A representation of the social structure of Capgemini is captured on a social media system called Yammer [84]. Most of the employees have an account on Yammer. Yammer provides the users the option to follow each other, thus forming a social network of people and connections. With the information on how the people are connected to each other a social graph can be established. A social graph is a graph which contains the relations between people in a social structure. A graph is a set N of elements and a set of ordered pairs of elements from N [16]. The elements of N are often referred to as nodes of vertices, the set of ordered pairs of elements from N is often referred to as edges or arcs. Nodes and edges are the terms which will be used throughout this document.

In a social graph the nodes represent people and the edges represent the relation between the people (people connected to or being connected by other people). In Yammer the connections between people are either a 'following' (connected to) relation, or a 'followed-by' (connected by) relation. Now the social graph is in place, a measure is needed to determine how important or how authoritative a person is. Determining importance of people in the social graph can be done in various ways.

Because the social graph is a graph, many algorithms for determining importance in a graph can be used in the social graph. To find some algorithms for determining authoritativeness in a graph, the focus is on the algorithms used in the World Wide Web (WWW). In the WWW many algorithms are used to determine the importance of a web-page. Authoritativeness in the WWW is important because there exist many pages on the web. Without any ranking in importance, the important pages might be overshadowed by the less important pages. Therefore many algorithms (so called *reputation mechanisms*) have been developed for ranking authoritativeness.

Many of these algorithms treat the WWW as a graph. A selection of the popular algorithms to determine importance in the WWW are used to determine importance in the social graph. For determining importance of pages in the web, the pages are interpreted as nodes in the graph and the hyper-links as the edges in the graph. By viewing the WWW as a graph, many of the algorithms designed for the WWW are also applicable to other kinds of graph, such as the social graph. Authoritativeness of nodes in these algorithms is calculated by looking at the other nodes in the network and the edges connecting them. A basic way to determine the authoritativeness of a node is, for example, computed by looking at the amount of other nodes pointing or connected to it (i.e., looking at the indegree of a node).

Because indegree is a very basic way to determine authoritativeness, many other so called reputation mechanisms have emerged. For analysis, the authoritativeness of people in the social graph is computed by looking at the indegree and outdegree of a person, but also by using more elaborate reputation mechanisms. With these mechanisms the following research question will be answered:

> *"Can a correlation be shown between one's authoritativeness and the influence they exert on others regarding the amount and types of badges one has earned?"*

1.2.1 Subquestions

In order to research in a modular fashion, the research question defined in the beginning of Section 1.2 is split up into several subquestions. By answering these questions first it will be less complex to answer the main research question. The following sub-research questions are defined:

1. *Can Gamification help motivating people?*
2. *What is the state of the art in Gamification, Social Network Analysis (SNA) and reputation mechanisms in relation to the research question?*
3. *What is the current state of the Level Up platform?*

4. *Do social media websites provide a usable* API *for social network analysis?*
5. *What design decisions are made for Level Up?*
6. *Which algorithms could be used to perform the network analysis?*
7. *Which type of storage for graph data is considered usable for performing the authoritativeness algorithms on the data?*

1.2.2 Hypothesis and Assumptions

Some hypotheses are defined based on the initial research question. By analyzing the gathered data these hypotheses are tested and determined if they are correct and can be accepted. The following hypotheses are defined:

> Hypothesis 1: *"The greater ones authoritativeness is on a social network, the greater the influence they have on other people."*
>
> Hypothesis 2: *"The more active one is on a social network, the greater influence they have on other people"*

It is important to note that one's authoritativeness mentioned in these hypotheses is measured using a set of reputation mechanisms. The same goes for activeness. The influence is measured according to badges in and outside the network of a person. Some assumptions have to be made in order to be able to use these rankings in the analysis. The most important assumptions made are listed below. Note that these might not always be the case, but are used to perform more specific analysis.

> *"A person is authoritative when other authoritative people connect to this person."*
>
> *"The more active one is on a social network, the more authoritative they are."*
>
> *"The social structure corresponds to the actual social structure represented by the social media website."*
>
> *"The amount of influence exerted is measured according to the amount of corresponding badge types and by the corresponding amount of badges between two people."*
>
> *"Connections between people are solid and do not change over time"*

1.2.3 Scaling and Ranking

In order to draw a conclusion from the research, it is important to have a scale on which the results are measured and compared, that is, what is good, what is bad, what is high and what is low. For the research conducted several reputation mechanisms are used. These mechanisms determine a result representing the rank or importance of the people in the social network. For these scores goes that the higher the score, the higher the importance of a person.

When sorting these importance scores, ordinal numbers can be placed in order to rank the actual people (1st, 2nd, 3rd etc). With these ordinal numbers the reputation mechanism its score can be compared to the scores of other reputation mechanisms. For each of the mechanisms used goes that the higher the score, the higher the authoritativeness.

1.3 Scientific relevance

This thesis shows the influence of social media on the people of a Gamification platform. Although implementing a Gamification environment in a company seems very interesting and helpful, there has not been much research on combining both Gamification and the analysis of the social graph of people. The gap between the social graph and Gamification is narrowed with this research. It shows how effective the importance of the social structure on a Gamification environment is and shows if a correlation exists between influence exerted and authoritative people regarding the Gamification platform.

Furthermore, it explains how a Gamification platform could be designed and which decisions should be taken into consideration. Without proper design strategy the Gamification solution created might not be as effective as possible or might even fail. The document provides basic properties which should be taken into account while designing.

The performed analysis shows how the various reputation mechanisms used differ with respect to SNA and the Gamification data. The results show which reputation mechanisms can be used for such an evaluation and which should be avoided.

1.4 Practical relevance

For Capgemini a Gamification platform is created. It facilitates the use of Gamification concepts inside Capgemini. The goal is to get users more engaged in using the existing application and more importantly increase motivation and engagement for

the actual extra work the employees are doing. Having more motivated and engaged employees for doing extra work is useful for a company like Capgemini.

The research gives an insight in the importance of the badges for certain groups of people, for example, sharing the same job-title. These insights are important for analysis and answering the research question, but can also help the people further developing Level Up on which choices to make with regards to the available badge types.

The social aspects in the application are relevant for the research, but might also perform marketing for the application. Using social media integration the application and allowing employees to share messages on social media, the application will become more visible for all users. It might increase the social coherence between colleagues.

1.5 Document structure and overview

The thesis describes the complete path from designing the facets of the research to the results emerged from the work during the thesis. The structure of the document as well as the phases of the thesis could be described in the following six steps:

1. **Pre-research:** determining which knowledge is available and which research has already been done is examined in the first phase. Articles and other research is read in order to determine the current state of the art in relation to the research question. The state of the art is determined for the three most present components of this thesis: Gamification, SNA and reputation mechanisms.

2. **Design:** in the second phase of the project a rudimentary design of the application is established. During the design phase both a basic architecture and basic functionality of the application are determined. Both of these parts are chosen in such a way to provide support for the actual research to be done.

3. **Implement:** developing the actual application happens during the implementation phase. Implementation consists of coding the application and making sure it can interact with the essential services. The latter means that the application can actually communicate with external services which contain the data for the research.

4. **Data-acquisition:** in the data acquisition phase the data needed for the research is acquired. Data-acquisition consists of extracting information from external services (such as the social media website Yammer), but also from internal services, such as the actual Level Up platform.

5. **Analysis:** during the analysis phase the hypotheses stated for this project are tested. First several test cases are defined, after that they are executed on the data earlier acquired.

6. **Conclude:** the results of the test phase are presented and discussed in the conclusion phase. It consists of checking the acquired results, but also about providing a foundation for future research.

The thesis is composed as follows. The first chapter gives an introduction to the thesis. It gives a rough overview of the project and poses the research questions which are answered at the end. These questions are used throughout the document for doing the research. Chapter 2 describes some of the related projects and the state of the art for the several topics discussed. The topics discussed are Gamification, SNA and reputation mechanisms. The research performed in Chapter 2 will form the basis of the rest of the research. Chapter 3 provides insight on the background of the research of the thesis. The algorithms of the reputation mechanisms are provided in this chapter, and the background of Level Up is described. Chapter 4 sheds more light on the newly developed Level Up application. The three phases of development: design, architecture and implementation are described in this chapter. Chapter 5 describes the actual research conducted. The description is split into three parts: data acquisition, analysis and evaluation. The last chapter, Chapter 6 provides the final conclusion and discussion of the research. It summarizes the result of Chapter 5 and answers the research questions posed. A list of acronyms and abbreviations is provided at the end of the document.

2 Related work

"If I have seen further it is by standing on ye sholders of Giants."

– Isaac Newton, 1676

The social life of people has changed dramatically since the emerging of social media. Social media allows people to interact in ways they never imagined to be possible and, moreover, needed. The same goes for Gamification. Although Gamification is relatively new concept, it has already been successfully applied in several applications (including social media websites [64]). Because of Gamification its popularity, research has already been performed on the topic.

Researching the history and state of the art of the main subjects of this thesis will provide insights on the various subjects focused on. The research focuses on performing social network analysis on a Gamification platform. In order to do establish a theoretical framework for the research and to learn the current state of the art, three main subjects are distilled, which are:

- **Gamification**.
- **Social Network Analysis (SNA)**.
- **Reputation mechanisms**.

These subjects are the most present in both the project implementation and the research component of the project. The main goal of a theoretical framework is to determine what the current state of these subjects is and which parts are still unknown. Both the fields of Gamification and SNA have gained much interest with the emerging social media websites. However, the concepts Gamification and the combining of various kinds of complex network analysis and SNA are not new.

The chapter provides descriptions about both the history and the state of the art of each of these related subjects. The last section, Section 2.4, provides a small summary of the related work.

2.1 Gamification

"*Games are inherently fun and not serious*", according to Newman [57]. However, there have been numerous proven concepts of combining the two. Gamification is a concept which goal is to combine both fun and serious work.

Gamification is often described as: "*The use of game design elements in non-gaming contexts*" [10, 11, 78] or as: "*A process of enhancing a service with affordances for gameful experiences in order to support user's overall value creation*" [32]. The definition can be explained as using game elements, such as points, badges, awards and many more elements in a context which has nothing to do with an actual game, for example, in the context of a university or in an office [10]. Applying these game mechanics has the goal to increase engagement and motivation. Three well-known examples of effective Gamification implementations are:

Foursquare [17] Foursquare is a location-based service in which people can earn points, badges and achievements by sharing their location. Earning these status symbols is done by 'checking in' with the Foursquare application on a certain location. When a user has the most 'check ins' on a certain location, he or she will receive a special status for that location, effectively competing with the others. Foursquare is an example of Gamification in its most pure form and it is successful; Foursquare has a community of over 30 million people [17]. Moreover, the predecessor of Foursquare, known as *Dodgeball*, had issues with keeping people engaged and making it a habit for them to 'check in'. Foursquare addressed exactly these issues using Gamification.

Nike$_+$ [60] Nike$_+$ is actual hardware which measures and tracks activity of its user. The users of Nike$_+$ can see what their performance is on a certain day and share these results with others. Others can react on these results by challenging and trying to beat them on a certain aspect, for example, run a greater distance than the other.

Ford Fusion [86, 27] The Ford fusion is just one of the many examples of hybrid cars using Gamification to reduce the use of energy. In the Ford fusion reducing energy is done by providing feedback on how ecologically the driver drives. The Ford Fusion, for instance, shows the user a digital tree, which grows or withers according to their ecological performance.

The idea behind Gamification itself is not new [29]. Gamification finds its roots in psychology. For example, Skinner [72] described these reward and punishment techniques already in his *Reinforcement Theory* [43], as well as smaller motivational

components, such as adding or removing privileges. The psychologist Maslov describes what people need and how much they need [48, 71]. The interesting part is that people can be much more interested in intangible goods, such as respect and status, in contrary to tangible goods such as money, when able to maintain their basic needs. These forms of motivation are the same principles which form part of the basics of Gamification in general.

Motivation can be split into *Extrinsic Motivation* and *Intrinsic Motivation*. Extrinsic motivation is, according to Pink [65], provided by rewarding with goods outside of an individual (such as money or actual things). Pink states that those extrinsic motivators are important, but will have less effect when a certain threshold is reached. After the threshold is reached the intrinsic motivators become more important. Intrinsic motivation is motivation which comes from the inside of an individual (people actually want to do a something, for example, not based on the amount of money they get). Pink describes intrinsic motivators as autonomy (be able to do what you want to do), mastery (learn from it), purpose (know that you are doing it for something) and relatedness (feel a connection to what you are doing). These intrinsic motivators are much stronger than the extrinsic motivators [65].

On the other hand, Mauss [49] describes how people build strong relationships when giving and receiving gifts. Gamification is partly based on the fact of receiving rewards, in the sense of *engagement*. In the case of Gamification, engagement describes how captivated people get by their work due to the fact of the Gamification platform. The 'giving of gifts' in the Gamification case is rewarding the user with a badge etc. Rewarding people is an important aspect also found in Gamification, where people get engaged by social comparison [14], for example, seeing the results of their colleagues or friends on a leader board.

The reason why Gamification works so well in the current generation of people is, according to Prensky [67], due to the fact that most people grew up with technology all around them. The people in the current generation grew up with playing games and are therefore still engaged by them. Important to note is that not all Gamification techniques fit all 'players' evenly well. According to Bartle [3], it depends on which *player type* one has, in order to define which Gamification techniquees triggers a person the best. Bartle has defined four player types: *Killers*, *Achievers*, *Socialisers* and *Explorers*, which are shown in Figure 2.1. The player types can be defined as follows:

- **Killers:** the killers are players into winning the game, they want to be on the first place, no matter what. Killers want to compare themselves to others and be better than others.

- **Achievers:** the achiever player type are more into earning as much as possible,

for example earning all badges which are possible. Achievers focus on getting the best result for themselves, not to show of to others.

- **Socializers:** these players play games for the interaction with others.
- **Explorers:** these players want to know everything about the game, they want to know all options the game provides.

Although Bartle's player types have been designed for Massively multiplayer online role-playing games (MMORPGs) and not specifically for Gamification [45], these types remain a set which is easy to understand and fit Gamification well. Establishing the types of users is important for developing a well fitting Gamification application and is therefore further discussed in Appendix B. Bartle's player types show much resemblance with Social value orientations (SVO). SVO is the magnitude of the concern people have for others [55]. When looking at, for example, the *ring measure* by Liebrand [41] a few similarities can be noted. In the ring measure people are classified according to how they would 'treat' themselves and how they would treat others. Some of the classifications can be directly mapped to Bartle's player types, such as Sadism or Competitive could be coupled to Killers, Socializers to Cooperation and Individualists to Explorers and Achievers. The ability of making the mapping between Liebrand and Bartle shows why Bartle's player types do provide a meaningful base for Gamification.

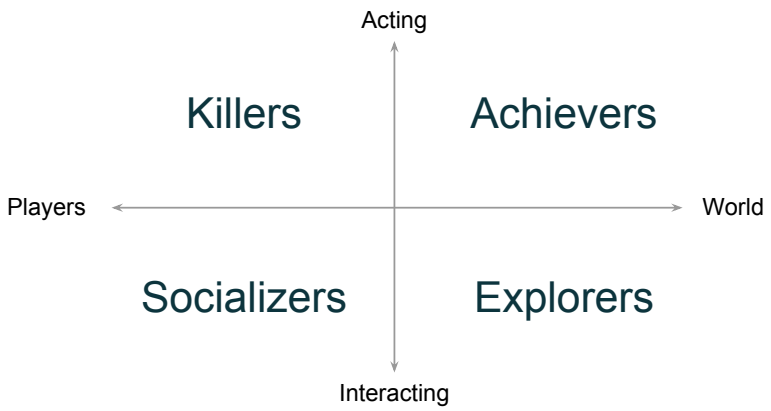

Figure 2.1: *Different kinds of players. Image from [3]*

Gamification is all about boosting motivation and engagement and improves both engagement and motivation by giving small rewards and making a normal task more game-like. However, the types of rewards given are important for the success of the gamified system. One of the main systems and hierarchies for rewards is Status,

Access, Power and Stuff (SAPS) [86, 73], which can be seen as the Gamification actualization of Maslow's hierarchy of needs [71]. According to the SAPS system the biggest reward is giving status: show to others what a person has done (for example, badges on a leader board), secondly access: giving people more privileges (for example, allowing a student to keep a cell phone in the classroom), third power: allowing people more power over other players in the game (for example, moderator on a forum) and last stuff, where players actually get a tangible gift.

One of the uses of Gamification is for making a simple, sometimes even boring, task more interesting. An example of boring tasks made more interesting are the so called Games With a Purpose (GWAPs) [80]. GWAPs are assignments, often repetitive and non challenging tasks, which are not originally challenging, but are made more interesting by introducing a gaming element. The actual purpose of such a game is significant for the company. It is often a task which is easy for people to do, but to hard for computers to be automated. As Von Ahn and Dabbish [80] describe, creating a GWAP is a technique widely used by companies to let people do the work (without them actually knowing and caring about it). For example, GWAPs such as the StyleCam [76] and the ESPgame / Google Image Labeler [79] aim to use game-like interaction to increase enjoyment and engagement with the software, while actually people are labeling data for the company.

A noteworthy project, which actually formed part of the base of this thesis, is the project by Martiarena [47], in which Martiarena developed an application for the use of Gamification in an application to reduce the energy consumption of a household [47]. Martiarena his approach incorporates the use of a tablet PC, which provides insight to the user on its energy consumption. The application creates engagement and creates awareness of the energy usage of the person. Besides providing insight, the application also focuses on motivational factors to reduce the energy consumption, such as self-comparison, comparison with others, goals and rewards. Although the actual word 'Gamification' was not used in Martiarena his paper, it is exactly what is done. The use of leader boards and comparison of results / motivation by others [10], is one of the basics behind the Gamification concept.

Gamification should not be confused with *serious gaming*. Whereas 'serious game' describes the design of full-fledged games for non-entertainment purposes, 'gamified' applications merely incorporate elements of games [10]. Gamification is merely a small part of serious gaming. The definition of serious gaming posed by Ritterfeld et al. [69] is as follows: "*Any form of interactive computer-based game software for one or multiple players to be used on any platform and that has been developed with the intention to be more than entertainment*". The definition of Gamification fits in the definition of serious gaming, but the definition of serious gaming is much broader.

As shown in Figure 2.2, both of these concepts contain game elements, however,

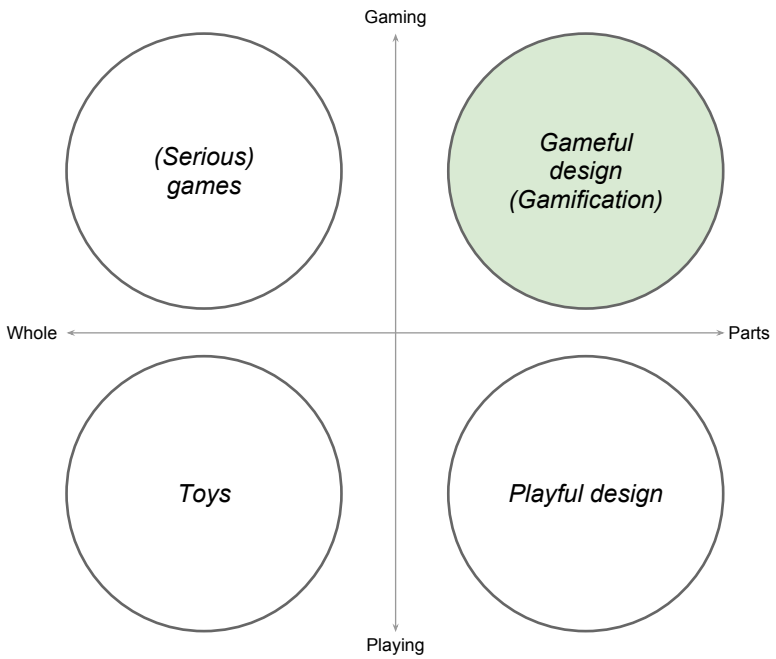

Figure 2.2: *Gamification uses parts of games, however, it does not provide a full gaming experience such as in Serious gaming. Image from [10]*

Gamification uses only parts of the game, where a serious game provides a full-fledged game. The main goal of serious gaming is to actually play a 'real' game, where the goal of the game is to actually learn something, such as for instance a simulator. Serious gaming consists of an actual 'serious game', where Gamification focuses more on a non-gaming context and combines that with gaming elements for the purpose of motivation. Gamification should never be a goal, merely a means for achieving a goal.

2.2 Social network analysis

Social networks have been at the core of human society since the era of hunters and gatherers [33]. SNA is the study of social relationships between individuals in a society [70]. The purpose of SNA is comparable to graph analysis, in which the nodes are actual people in their social structure. There exist various properties of the social network can be analyzed in order to create metrics. In general these metrics can be subdivided into three main groups; *connections*, *distributions* and

segmentation [33]. Section 2.2.1 describes the background of SNA. The section gives the history of SNA and shows some of the aspects on which a social network can be analyzed. Section 2.2.2 is dedicated to describe the current use of social networks on social media platforms.

2.2.1 Social Network Theory

Social networks have already been studied by a number of sociologists [53]. Some important research performed in the history of SNA are described here. The research carried out is subdivided into three main groups: connections analysis, distribution analysis and segmentation analysis. Although most SNA researches combine all three of the metrics, the explanation given is based upon one of the metric types.

Connection analysis: performing SNA based on the connections of a node, for example, the number of connections one has, or the similarity of connections in the social network, is deemed Connection analysis. The *Milgram Experiment* dating from 1967 [52] is a research looking at the connections of people. Milgram studied the average number of hops between two random people and estimated it to be about 5.5 (also known as the *Six degrees of separation* [28, 83]). Milgram his research clearly shows the connections and distributions.

Distribution analysis: distribution analysis focuses on the distribution of the nodes in the network. Distribution analysis shows, for example, which nodes are important for keeping short path lengths or for keeping the network connected. When doing (social) network analysis based on the distribution of the network, one can look at many different properties. Four of these properties are, for example [8, p. 23]:

- **Degree:** the number of nodes a certain node is directly connected to (that is, the number of edges in a node its ego centered network connected to the node).
- **Betweenness-centrality:** the likeliness of a node being the most direct route between two other nodes. When a node connects many nodes, that is, is a bridge between others and thus has a high betweenness, the node is important for having short path lengths between nodes (or in the case of SNA, people).
- **Closeness-centrality:** the minimal number of nodes one has to pass before reaching everyone in the network, that is, the shortest path between one node and all others.
- **Eigenvector-centrality:** the influence of a node in a graph, measured according to its relative position, that is, according to the influence of the nodes with which the node is connected. For example, PageRank [62] determines influence using eigenvector-centrality.

Segmentation analysis: segmentation analysis is comparable to distribution analysis, although segmentation analysis focuses on finding clusters or communities in a network, that is, finding segments in the network. A research performed by Strongatz and Watts [83] on the small worlds phenomenon shows some important segmentation characteristics for social networks. The research shows that social networks are neither completely regular networks nor completely random networks, but show properties of both; they can be highly clustered, like regular networks, yet have small characteristic path lengths, like random graphs [83]. Social networks are created in the same way, as people tend to cluster and form communities. Only few nodes (in the case of SNA people) will bridge these groups [23]. Newman and Girvan have proposed different methods and algorithms to find these clusters / communities in a network [58, 59].

According to Garton et al. [22] one can do SNA by looking at the social network from two different perspectives: the *whole networks* perspective and the *ego centered networks* perspective. When looking at the whole networks perspective, one sees all nodes in the network and treats them as a whole. The ego centered networks perspective in contrary handles the network as seen from one node in the network [8, 82]. The actual definition of an ego centered network according to Wasserman and Faust [82] is: "full information (edges and node properties) about a user and all its one-hop neighbors". So in the ego centered network of a node only its neighbors or first level-connections are shown. An example of both a whole networks and an ego centered network is shown in Figure 2.3, the first image shows a whole network perspective and the second image an ego centered network perspective (seen from the green dot).

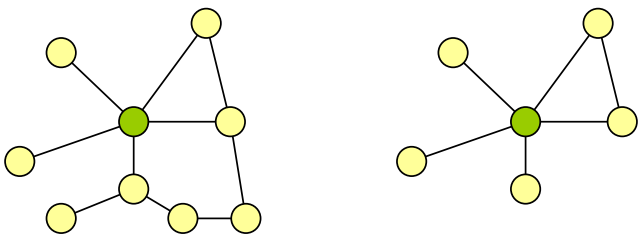

Figure 2.3: *Different network perspectives; a whole network perspective on the left and a ego centered perspective on the right.*

2.2.2 Social Media

According to Ahlqvist et al. [1] social media is the means of interactions among people in which they create, share and exchange information and ideas in virtual communities and networks. Nowadays it is almost impossible for many people to imagine a life without social media. Social media is therefore used daily by many people, for example, the social media website *Facebook*, which reported to have one billion monthly active users as of October 2012 [12], or *LinkedIn*, which said to have 187 million users in over 200 countries in September 2012 [42]. Besides sharing information and maintaining relationships these website contain a lot of data regarding the social structure or social network of a user. These networks can be seen as an ordinary graph, in which the nodes are the people using the platform and the edges the relationships connecting them. Such a graph is known as a social graph.

SNA can be performed on the data from one's personal network graph (or social graph), to extract information. An example of one use for personal network data is the *RefWorks project* [35], which can be used for locating people with the interests or expertise another user is looking for [35]. Also research and applications exist for performing SNA on Facebook [7]. In the research performed by Noordhuis et al. [61] the social media website *Twitter* [77] is crawled to gather information about its users. The information gathered is augmented using a reputation mechanism to propose the most important (or authoritative) people on the network. Reputation mechanisms are elaborated in Section 2.3.

2.3 Reputation mechanisms

According to Pujari [68] a reputation system is a system that collects, distributes and aggregates feedback about behavior. Reputation mechanisms are mechanisms used in these systems. In this section the focus is on reputation systems which are used to calculate importance (or authoritativeness) in networks (or graphs). Authoritativeness is important for the analysis of this thesis as authoritative people (based on experience and relative position in a hierarchy) have remained relevant in differentiating mere compliance (obedience) [9].

The attention is divided among two different types of reputation mechanisms in the sense of ranking. First a description is provided of several *static* ranking algorithms. These static algorithms gather data first and then perform some analysis on the data. The second type described are the *dynamic* ranking algorithms. Dynamic algorithms use dynamic data, such as the flow in a network to measure ones importance.

2.3.1 Static ranking

Static ranking algorithms perform their calculations on a static set of information. Many algorithms exist for calculating the reputation of nodes in a graph, ranging from simple and intuitive algorithms to more elaborate ones. A basic example of a static ranking algorithm is using degree. Degree of a node is the amount of edges connected to and connected from the said node. A distinction is made between indegree and outdegree (relatively incoming and outgoing edges of a node). In Figure 2.4 a graph is shown, together with its degree. In Figure 2.4 the indegree of a node is used as the measure of authority, which is shown in the table next to Figure 2.4. A ranking algorithm based on only indegree would consider *node 2* to be the most important.

Node	Indegree	Outdegree	Rank
1	0	2	4
2	3	2	1
3	2	1	2
4	1	1	3
5	0	1	4
6	1	0	3

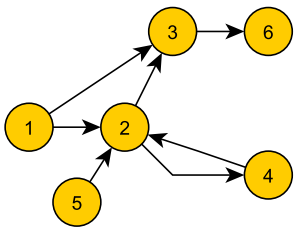

Figure 2.4: *Image showing a graph with six nodes and seven edges together with a table showing the indegree, outdegree and a rank based on indegree.*

The degree ranking method only uses a node its first degree connections in order to determine its authority. There exist somewhat more complex and elaborate algorithms which also take the importance of the connections of a connection into account [18]. Such algorithms are implemented for various purposes, for example, the algorithm by Pinski and Narin [66], which analyses the importance of Journals by looking at the journals citing the journal;

"*A journal is influential if it is cited by other influential journals.*" [66]

An important reputation mechanism in the WWW is the PageRank algorithm by Page et al. [62] . PageRank is an algorithm which has uses in the WWW for performing its task as a reputation mechanism [62, 39]. The main purpose of PageRank, when it was developed, is for the development of the *Google Search Engine*, to determine the authoritativeness of pages on the web. The authoritativeness score of a page is calculated by looking at all other pages linking to that page. However, for determining the PageRank of one page, also the PageRank assigned to the pages hyper-linking to that page is taken into account [62]. Figure 2.5 shows a simple directed graph together with the ranks calculated using the PageRank algorithm.

Node	PageRank	Rank
1	0.057	5
2	0.280	1
3	0.201	3
4	0.176	4
5	0.057	5
6	0.228	2

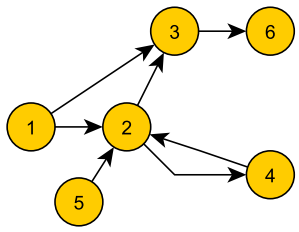

Figure 2.5: *Image showing a graph with six nodes and seven edges together with a table showing the PageRank and the rank based on the PageRank. For calculating the PageRank $\alpha = 0.85$ is used.*

Besides using PageRank for the WWW, Hog and Adamic [30] propose using the PageRank algorithm for determining the authoritativeness of people in a social network. Using the PageRank algorithm for calculating authoritativeness has been successfully carried out on the social network site Twitter in the research performed by Noordhuis et al. [61]. Twitter is a 'micro-blog' website on which people can connect to others and post messages, up to 140 characters in size [77]. In the research of Noordhuis et al. network information is gathered from Twitter and for each of the gathered nodes the PageRank is calculated. Using PageRank Noordhuis et al. can determine the authoritativeness of people according to the people they are connected to, which provides an accurate representation of the authoritativeness in the real world [61].

There also exist algorithms specifically designed for SNA. For example, the model proposed by Katz [36], in which he sees a social network as a directed graph, where people are shown as nodes and people can choose to endorse others (which is not necessarily the other way around). According to Franceschet [18] Katz his model is later generalized by Hubbel [31]. In Hubbel his model people can also exert a negative influence and therefore have a negative score / ranking. The vision of Katz and Hubbel their algorithms can be described as follows:

> "*A person is prestigious if he is endorsed by prestigious people.*" [36]

Although PageRank is a proven successful algorithm for both the WWW [18] and SNA [61], there are more interesting algorithms which use comparable properties like PageRank. The Hyperlink-Induced Topic Search (HITS) algorithm by Kleinberg [37] is another algorithm which uses hyper-links between web-pages to determine the a measure of importance of pages. HITS uses hubs and authorities as its base and provides the user with two scores for each node; *authoritativeness* and *hubness*. Hubs and authorities are defined as follows:

> "*Good authorities are pages that are pointed to by good hubs and good hubs are pages that point to good authorities.*" [18]

For example, when looking at the WWW one could say that a web-page is authoritative when it contains relevant information according to one's search query. However, there also exist pages which do not contain actual relevant information, but do contain links pointing to relevant web pages. Such pages can be very useful when the search query is not specific, but very wide and abstract. Such a page can than be a portal (or hub in the case of HITS) towards other pages [18, 44]. Figure 2.6 shows the HITS algorithm applied to the graph next to it.

Node	Authority	Hubness	Rank
1	0.0	0.125	4
2	0.364	0.25	1
3	0.273	0.25	2
4	0.182	0.25	3
5	0.0	0.125	4
6	0.182	0.0	3

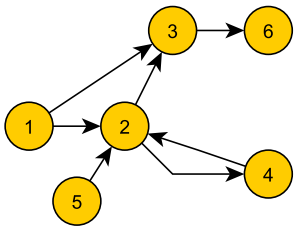

Figure 2.6: *Image showing a graph with six nodes and seven edges together with a table showing the authority, hubness and a rank based on authority.*

Besides other algorithms, there also exist variations on the PageRank algorithm. For example a combination between PageRank and HITS has been made; the Stochastic Approach for Link-Structure Analysis (SALSA) [40]. Which uses the stochastic approach of PageRank combined with the hubs and authorities approach of HITS

In the research by Farahat et al. [13] a comparison is made between the three different algorithms PageRank, HITS and SALSA. In their paper they conclude that both HITS and SALSA can yield inaccurate and unstable results, depending on the initial node and the structure of the graph. These are unwanted results when performing any kind of analysis.

2.3.2 Dynamic ranking

Instead of performing measurements on a static amount of data, one could also look at dynamic aspects which could make a person important. Flow between nodes can be a useful measure for determining importance [75]. For example, when looking at the road networks: when looking at the congestion of cars towards the beach on a sunny day, one can see this is an intuitive way for determining the importance of this place. Dividing the amount of traffic towards such a location by the amount of roads

going to it gives an actual measure of the importance of the location in comparison to other locations [75].

An algorithm which uses traffic as a measure to determine the importance of web pages is TrafficRank [75]. In comparison to the static ranking algorithms described in Section 2.3.1, the TrafficRank algorithm takes the actual flow between to two pages / nodes into account. Although measuring traffic is extremely difficult to do on the WWW, regarding the amounts of data, the company *Alexa* has developed a tool-bar which actually measures and sends traffic data to a processing application [2].

TrafficRank can have more uses than just web-page ranking. When gathering data from social media / social networking sites, one could look at the amount of messages one posts on their profile page (or *wall* as Facebook calls it [12]). The messages posted can be seen by others in the network. The person posting the message might therefore be able to exert influence on others reading these messages.

2.4 Summary

The Sections 2.1, 2.2 and 2.3 provide an overview of the important subjects: Gamification, SNA and reputation mechanisms. It seems that no research has been done for the combination of the three (Gamification, SNA and Reputation Mechanisms). Although some papers, for example Noordhuis et al. [61], show the combination of a Social Network and a reputation mechanisms, it is not performed in combination with the combination of Gamification, SNA and reputation mechanisms. The lack of the combination between the three subjects is one of the reasons the thesis will focus on the combination of these subjects. The research performed by Farahat et al [13]. show unwanted results for the SALSA algorithm, making it a better option to go for (a derivative of) PageRank.

3 Background

"Only those who attempt the absurd will achieve the impossible. I think it's in my basement, let me go upstairs and check"

– Maurits Cornelis Escher

In order to develop a new product it is often not effective to just start creating something without any background information. It is important to determine how to create the product to fit the needs of the users and to determine which algorithms are used during the research. Two main applications are developed: Badge Crawler and Level Up. Badge Crawler is the application which performs the ranking algorithms on the data and yields results which can be used during research. Level Up is Capgemini its Gamification platform. The background of both projects is discussed in this chapter.

3.1 Ranking

In order to perform research some data needs to be processed and some data needs to be gathered from external services, such as Yammer. The application created for data crawling and analyzing purposes is Badge Crawler. Badge Crawler its function is to gather graph information from the Yammer Representational State Transfer (REST) service for each of the people found in the Gamification data. Badge Crawler can also execute various algorithms defined in Section 2.3 on the data from Yammer. Although the architecture of this application is not very elaborate, the application does contain some other interesting components. This section gives a description about two parts of the application; the data crawling, which is described in Section 3.1.1, and the algorithms used, described in Section 3.1.2. The application is implemented using the Scala programming language.

3.1.1 Data crawling

The Badge Crawler application has two main functionalities: gathering data and processing data into manageable information. For the research, two types of data need to be gathered: personal data and social graph data. Section 3.1.1 describes what the personal data entails and how the personal data is gathered. In Section 3.1.1 the focus is on the data from the social graph.

Personal data

The application has the ability to gather data from several sources of media. First of all it gathers all email addresses of all users in the Level Up application by reading in a simple text file. This file is delimited using newlines, which are used to parse these email addresses. The second resource Badge Crawler can gather information from is Yammer. It uses the various email addresses gathered in the previous step to collect the Yammer user information of each person. The information which can be gathered is personal and relative to each person, such as its ID, name and department information.

Social graph

The social graph data is based on the Yammer connections of a person. In this graph the nodes are the actual people of the company. The edges linking them together are the connections between the people on Yammer. The graph has directed edges, meaning that it is possible that, for example, node #1 is connected to node #2, although node #2 is not connected to node #1. In Yammer the edges from node #1 to node #2 is called a 'following' relation for node #1 and a 'followed by' relation for node #2. This is summarized in Figure 3.1.

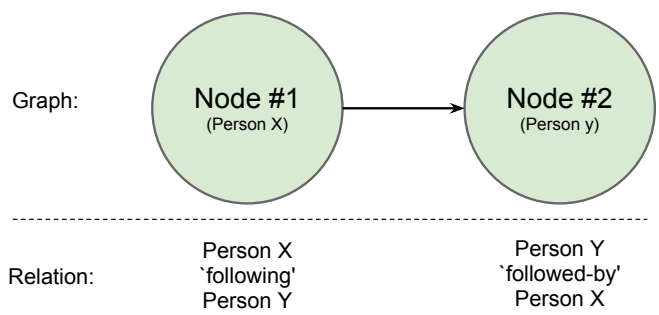

Figure 3.1: *Yammer's way of describing edges.*

Badge Crawler can access the social graph data via the Yammer REST API (see Appendix C for the used parts of the actual API). The information can be retrieved using the ID described in Section 3.1.1. The graph information provided by this API shows the connections using these IDs, therefore in order to build the graph, these IDs are needed.

Saving the graph data is done using the GraphML format. GraphML is a file format which uses Extensible Markup Language (XML) to store graph information. The GraphML file format is used as it is supported by a variety of graph visualizing applications.

3.1.2 Ranking algorithms

Gathering the data is one step of the process. Data gathered should also be processed before it can be used in actual research. For this the Badge Crawler application supports multiple algorithms. These algorithms are described in this section. The actual Scala implementations are shown in Appendix E.

Degree

The degree of a node is the number of edges that connect to it. Degree could be split into two types: indegree and outdegree. Badge Crawler allows calculation of both. It calculates indegree and outdegree by looping through all nodes twice, once to select a node and a second time to check if the connection between the two nodes exists. The implementation of calculating the outdegree of a set of nodes is shown in Listing E.1.

PageRank

The function used in order to calculate the PageRank is based upon the original PageRank function [39]. Equation (3.1) describes what the implemented PageRank algorithm does. Equation 3.1 is implemented so it calculates the PageRank $\forall P \in G$. It is calculated for a certain number of iterations, until the result converges. In this case P_i is the node to calculate the PageRank on, $in(P_i)$ the incoming edges of P_i and $out(P_i)$ the edges going out of an edge.

$$pagerank_{k+1}(G) = \forall P_i \in G : \left[\sum_{P_j \in in(P_i)} \frac{r_k(P_j)}{\mid out(P_j) \mid} \right] \tag{3.1}$$

Before this equation can be carried out, each node needs to get a default rank. For PageRank the rank is set on $1/n$ for each of the nodes in G, where n is the

number of nodes in the network, as shown in Equation (3.2).

$$\forall P_i \in G : r_0(P_i) = 1/n \tag{3.2}$$

All values are stored in an *Adjacency Matrix* H, a means to represent which nodes of the graph are adjacent or connected to each other. If there is a connection between two nodes, the matrix denotes a number larger then zero and denotes a zero otherwise. In order for PageRank to work with sinks as well, the default values in the adjacency matrix need to be made *stochastic*, which means that all values need to add up to one. Otherwise the sinks would attract all of PageRank. Equation (3.3) shows the stochastic adjustment. In Equation (3.3) the parameter a is a vector containing a representation of all sink nodes (it denotes a 1 for sinks and a 0 otherwise) e^T is the unit vector.

$$H_s = H + a(1/n \cdot e^T) \tag{3.3}$$

The last adjustment to make to the data before the PageRank can be calculated, is the primitivity adjustment. The primitivity adjustment in the WWW is needed to facilitate for random jumps to random pages, that is, a user directly browsing to a website (for example by specifying a URL). For a graph the primitivity adjustment is needed for the PageRank to converge. Here, primitivity means that there only exist non-zero elements in the matrix (that is, each node is always a little connected to others) The equation for the primitivity adjustment is shown in Equation (3.4). In Equation (3.4) H_s is the stochastic adjacency matrix, n the number of nodes, e the unit vector and α a parameter from 0 to 1 representing the probability of a random jump.

$$H_{s,p} = \alpha H_s + (1 - \alpha) \cdot 1/n \; e \; e^T \tag{3.4}$$

All equations stated earlier have been implemented in Scala. The following listings show the actual implementation of these equations. Equation (3.1) is shown in Listing E.2, Equation (3.3) in Listing E.3, a normalization step in Listing E.5 and Equation (3.4) in Listing E.4.

HITS

Another algorithm implemented is HITS [37]. The HITS algorithm provides ranking in a comparable way as the PageRank algorithm. However, the HITS algorithm provides two values: authority and hubness. A more detailed description about these scores is provided in Section 2.3. The actual implementation is based upon the equations

provided in [18]. These are shown in Equation (3.6) (authority update role) and in Equation (3.5) (the hubness update rule).

$$hits_{hubness}(P_i) = \sum_{P_j \in out(P_i)} authority(P_j) \tag{3.5}$$

$$hits_{authority}(P_i) = \sum_{P_j \in in(P_i)} hubness(P_j) \tag{3.6}$$

Both $authority(P)$ and $hubness(P)$ are $\forall P \in G = 1$ in the beginning. In order to update the scores of the complete graph G, Equation (3.6) and Equation (3.5) are both calculated $\forall P \in G$. Just like the PageRank algorithm, HITS is should be executed for a certain amount of iterations. After each rounds the results can be normalized. Normalization is carried out according to Equation (3.7). The actual implementation of the HITS algorithm is shown in Listing E.6.

$$hits_{normalized} = \forall p \in G : \frac{rank(p)}{\sqrt{\sum_{p \in G} rank(p)^2}} \tag{3.7}$$

TrafficRank

TrafficRank [75] is the last of the algorithms which is implemented in the Badge Crawler application. In contrary to the earlier described algorithms TrafficRank is a dynamic ranking algorithm. The ranking in this case is calculated according to the amount of traffic that flows from one node to the other. A more elaborate description of TrafficRank is provided in Section 2.3.

The TrafficRank algorithm used is the network flow approach, based on the ideal PageRank model [75]. The original algorithm of network flow approach TrafficRank is shown in Equation (3.8). In Equation (3.8) G is the graph to calculate TrafficRank on, G_E are the edges of G, y_{ij} the number of people following ij per unit time and H_j is the amount of 'hits' j has per unit of time.

$$H_j(G) = \sum_{i|(i,j) \in G_E} y_{ij} \tag{3.8}$$

The original algorithm, however, has one downside for SNA. Because TrafficRank has been developed for the web, it ranks nodes according to their incoming traffic. In order to determine authoritativeness according to sent messages, it is more useful to rank according to outgoing traffic. Equation (3.8) has been adapted slightly to perform in this way. The adapted version of TrafficRank is shown in Equation (3.9). In Equation (3.9), for this research, y_{ij} the number of messages flowing from $i \rightarrow j$

per unit time and H_i is the amount of messages over the complete network flowing from i to its network per unit of time.

$$H_i(G) = \sum_{j|(i,j)\in G_E} y_{ij} \tag{3.9}$$

In order to compare the results to the other ranking methods, the data from Equation (3.9) needs to be normalized. Equation (3.10) shows the normalization step. In this equation Y is the total amount of traffic on the network and d_i the outdegree of i.

$$r_{trafficrank}(P_i) = \frac{H_i}{Yd_i} \forall (i,j) \in G_E \tag{3.10}$$

However, in Equation (3.10) case the model calculates the importance of the separate edges, i.e., H_i is divided by Yd_i (the total amount of traffic multiplied by the outdegree), which means each out edge gets a portion of the TrafficRank. For this research it is more interesting to determine a node its authoritativeness according to the amount of traffic flowing to each of the nodes it is connected to. Therefore Equation (3.10) has been altered. The result is shown in Equation (3.11). In Equation (3.11) the TrafficRank of a node increases with the amount of outgoing edges. Equation (3.11) is the algorithm used.

$$p_{i,j} = \frac{H_i d_i}{Y} \forall (i,j) \in G_E \tag{3.11}$$

3.2 Level Up

The Level Up platform provides users with the ability to request badges and view a leader board showing the other employees with their assigned badges. Both the leader board and badges are examples of basic Gamification elements [78].

In order to provide an understanding of what the application does and what its goal is, the main procedures, functionality and some of the user stories of Level Up are described in this section. Section 3.2.1 describes the process of applying for a badge. Section 3.2.2 describes the purpose and procedures of the leader board. Section 3.2.3 gives a more elaborate idea about the annual event known as “The Battle of the Kings”. A more elaborate list of functional requirements can be found in Appendix G.

3.2.1 Requesting a badge

One of the most important goals of Level Up is to facilitate badge-management. Badge-management is the request, approve and displaying cycle of the badges. The first step, requesting a badge, allows users to apply for a badge they think they have earned. The badges which are currently available in the system are listed in Appendix A.

An important aspect of Level Up is badges are only granted to a person when actually requested by that person. A user needs to initiate the badge request, it is not granted automatically. People should therefore 'feel' that the badge is something they actually want and that it does not come for granted.

The second step in the cycle is the approving of the badge. When a badge is requested, it is not evident that the badge request will actually be approved. A selection of people also known as the Badgers are in control of whether or not they think someone has deserved the badge.

The actual process of requesting a badge is a straightforward task. The user browses to the Level Up application and fills in a form in which he or she says which badge is applied for and provides a description why the request should be approved. After the request has been made the Badgers receive the request and determine whether or not the request should be approved.

3.2.2 Viewing the leader board

Besides requesting badges, people have the ability to view achieved badges. It is possible for each user to see a leader board containing all other players together with the badges they have received. In the current state of the application the leader board is sorted alphabetically on name, not on the amount of badges.

Besides showing the badges all people have earned, Level Up shows two other game mechanisms: Star badges and King badges. The first of the two special badges is the Star badge. The Star badge is automatically achieved whenever a person has earned three or more of the same badges. That means, the software automatically grants the Star badge when a user possesses three or more badges of the same category.

The other special badge, the King badge, is awarded to each person who has earned three or more badges of different categories. Like the Star badge it is automatically granted when a person has three or more different badges. The King badge is shown on the leader board whenever it has been achieved. Besides being a status symbol, the King badge also has a different purpose. Whenever a player has achieved a King badge, the player is allowed to compete in the Battle of the Kings. Section 3.2.3 elaborates on the Battle of the Kings event.

3.2.3 Battle of the Kings

Besides the purely digital Level Up application, there is the annual event known as the Battle of the Kings. The Battle of the Kings is an important event in the game Level Up. With the Battle of the Kings a connection between the (fictional) digital badges and a real-life appreciation is created.

In Level Up players earn badges. However, when three or more badges in different categories are earned in one year, the player receives the King badge. At the Battle of the Kings event the people with a King badge fight for the title of 'Conqueror'. Earning the title Conqueror provides you with a new badge, the Conqueror badge, but also with actual prizes.

As an example, the previous Battle of the Kings event consisted of three rounds. Each round is dedicated to a certain quality important in Capgemini. In the first round the players are asked to create a so called 'elevator pitch' of themselves. In the pitch each person tries to tell the others why they should be the conqueror of the current year and tries to persuade the listeners to vote for them. At the end of the round the people in the crowd are asked to vote for the person which they think is the best. In the second round the players try to communicate a set of words to two other people from the crowd. For the so called 'communication' round each player has a timespan of two minutes. In order to keep the crowd engaged, each word which was not guessed by the king can be guessed by the people in the crowd. In the last round the top three players of the first two rounds will try and convince the jury with selling a business case. The person which defended his proposal the best wins the Battle of the Kings.

4 Level Up realization

"To the man who only has a hammer, everything he encounters begins to look like a nail."

– Abraham Maslow, 1966

Level Up is the main platform enabling Gamification at Capgemini. It supports basic badge management and a leader board on which the players can compare themselves to other players (or coworkers). This chapter provides a more elaborate description about the new version of Level Up. It describes how the actual system is designed and explains the architecture of Level Up. Besides the architecture decisions and design decisions made, this chapter also elaborates on the use and purpose of social media in Level Up.

4.1 Design and Architecture

One of the goals of this project is to re-factor the current application and provide integration with several social media websites. In order to perform a useful refactoring step, the current state of the application needs to be determined. This section provides a small summary about the current state of the application.

The current application is written in a set of programming languages. First of all the front end, which has been written in HyperText Markup Language (HTML), Cascading Style Sheet (CSS) and JavaScript. Most of the JavaScript code is enhanced using a framework called jQuery. By only using these techniques the developers are forced to create a separation between the front- and back-end code, which would be less the case when using, for example, Java Servlet Pages (JSP). Also using jQuery makes the front-end more efficient, as jQuery helps the user with using techniques like Ajax, with which merely JavaScript Object Notation (JSON) data is exchanged, instead of exchanging complete websites.

The new version of Level Up is built from the ground up. During the build of an application such as Level Up many decisions are made. The important high-level architectural decisions and design decisions are listed in the Sections 4.1.1 and

Section 4.1.2.

4.1.1 Design

According to the theoretical background described in Section 2.1, correct design is important for the usefulness of a Gamification platform. Gartner even states: "in 2014, 80% of all gamified applications will fail, because of bad design" [21]. This section elaborates on the various game mechanics used in Level Up. Figure 4.1 shows most of these game mechanics used in the actual implementation of Level Up. Note that the people in Figure 4.1 are made anonymous. The several game mechanics shown in Figure 4.1 and used in Level Up are elaborated in the paragraphs of this section.

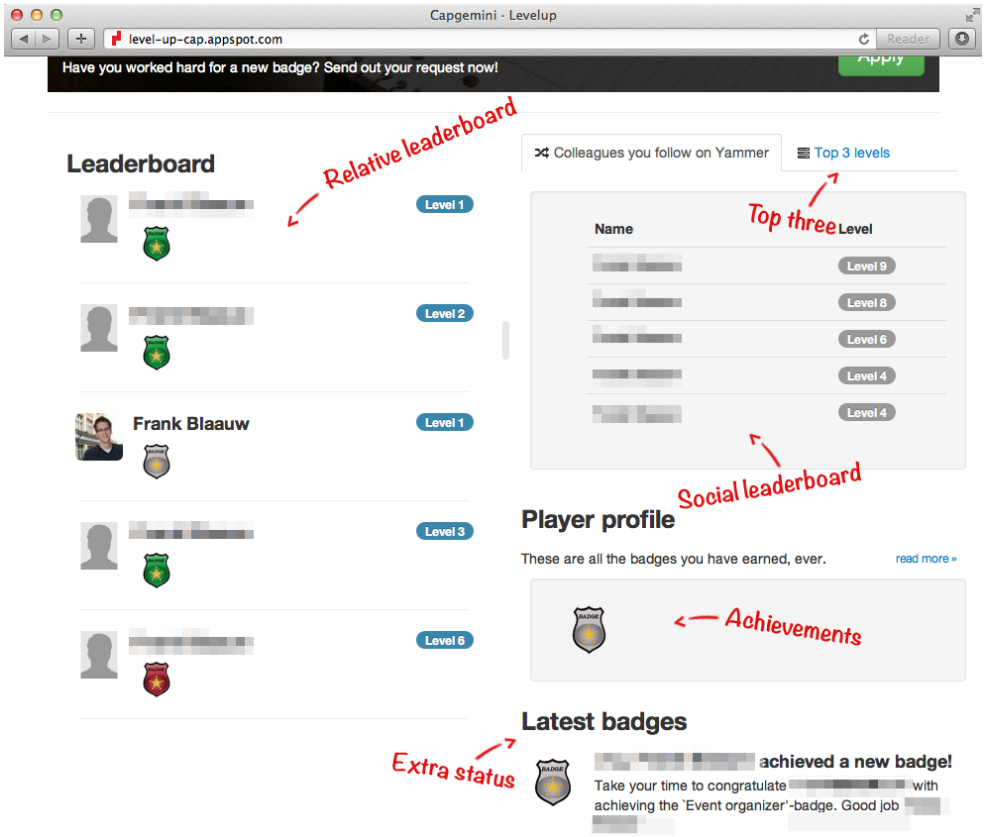

Figure 4.1: *Several game mechanics on the Level Up dashboard.*

Leader boards

One of the most important mechanics in Level Up are the leader boards [86]. Leader boards are used to make simple comparisons between people. Level Up implements four types of leader boards each with their own purpose:

- **no-disincentive leader board:** a no-disincentive leader board shows the current user always in the middle of the board, with some players above and some players below. It does not matter if a player is on place #5 or #50. Using such a leader board takes care that people which are on a lower score are not de-motivated by the amount of people having a higher score.
- **infinite leader board:** an infinite leader board is the traditional leader board which lists the people together with their score. The list of people is sorted on the amount of badges one has earned.
- **social leader board:** the social leader board shows only the scores of the people in your social network, gathered via a social media service. With the social leader board one can compare himself or herself directly to his or her connections. A social leader board is important for both socializer and killer type players.
- **top three leader board:** a top three leader board just shows the top three of all people. The top three leader board is an important for killer type players, so they can directly see if they are in the top three or not.

Badges

The most important game mechanic used in Level Up are the badges. Badges can be used for multiple purposes, such as awarding players and signaling status [86]. In Level Up people are instantly shown which badges they have earned, which tries to create a feeling of proudness and increase engagement. The 'Player profile' location Figure 4.1 shows an achievement box containing the badges a person has earned.

Avatars

Another mechanic used when designing Level Up are avatars. The avatar in Level Up is the actual profile image which a player uses on Yammer. The reason for an avatar is to allow for customization [86] (people can use their own avatar) and to make the system more personal and familiar (players see pictures of people which they already know from the social media website). Also, the avatar provides more status for the people which have earned a badge.

4.1.2 Architecture

Multiple design patterns are used to create a maintainable and modular system. The most present and most important architectural pattern used is the *Layer Pattern* (Buschman et al. [5]). Figure 4.2 shows the different layers defined in Level Up. How these layers are filled, and what their actual function is is described in the remainder of the section.

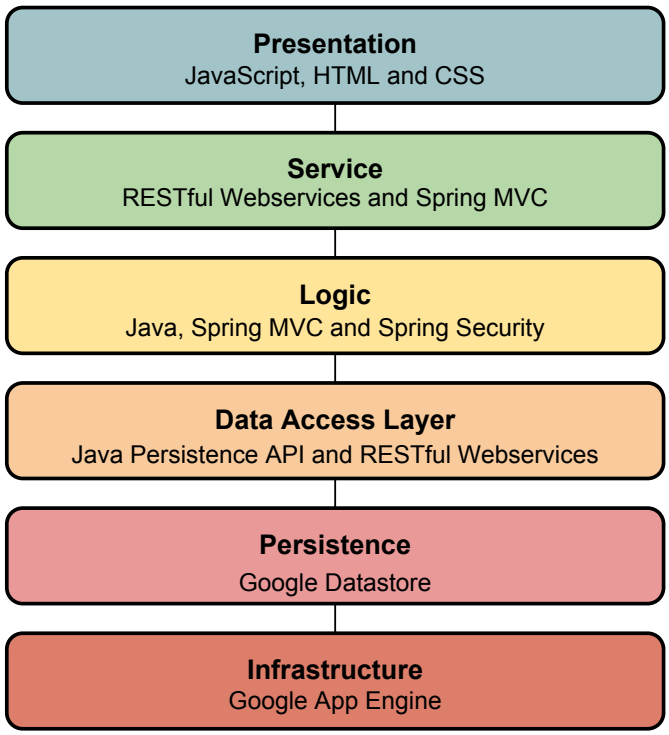

Figure 4.2: *Architecture of the new Level Up application.*

Presentation layer

The presentation layer is the layer which is directly shown to the client (that is, the front end). Level Up should provide its services mainly in a web-browser. That is why mainly web and hypertext techniques have been used for designing the presentation layer. The views are written in HTML using CSS for separating the content from the design. For designing the application a framework called *Twitter Bootstrap*[1] is used,

[1] Twitter Bootstrap website: http://twitter.github.io/bootstrap

which provides many layout features and makes the application responsive.

The front-end does not contain any business logic. The data shown on the pages is retrieved using JavaScript and the JavaScript library *jQuery*[2], which supplies many functions to provide communications with the Service Layer. Data is transfered to and from the Service layer using JSON.

Service layer

The actual communication to the service layer is done using a REST web service. Level Up implements a Restful interface. Implementing a Restful interface means external applications can access the Level Up application via REST calls.

An example of such an external component is the presentation layer. The presentation layer is only connected to the Level Up back-end using REST. The front end issues a REST call, such as a GET request, POST request, PUT request or DELETE request and gets appropriate data back to process on the front-end view. The data exchanged between the front-end and back-end is pure JSON. This means that the actual front-end runs completely client side. Only the necessary information is sent to the front-end. The Service is implemented using Spring Model View Controller (MVC) controllers.

Logic layer

The responsibility of the logic layer is to decouple the business logic from the actual application. The logic layer takes care of all altering of business objects / models before they are actually persisted in the data store. That is, for example, assembling business objects from Data Transfer Objects (DTOs) received via the REST service.

The logic layer is the layer which mainly takes care of security, although security is present in the service layer as well. The logic layer defines which services are accessible and handles the actual authentication of a person.

Data access layer

The data access layer consists of multiple Data Access Objects (DAOs) which provide access to the persistence layer. The data access layer can be subdivided into two types of DAOs: ones which communicate with the underlaying persistence layer and ones which use REST to communicate with external services.

In the case of the first, the communication with the underlaying persistence layer, the DAO uses Java Persistence API (JPA) to connect to the persistence layer. JPA itself is an abstraction layer between the DAO and the actual persistence layer underneath.

[2]jQuery website: http://jquery.com

It provides Object-relational Mapping (ORM) so the application can persist actual objects into the datastore.

The second case consists of objects which communicate to external services, such as, social media websites. The connection could be implemented in many ways, for example, using a Restful web service. In the case of Level Up the objects are used to gather information about users and their network from social media websites.

Persistence layer

The persistence layer used for Level Up is implemented using the *Google AppEngine DataStore*. The AppEngine datastore provides the developer with a NoSQL database to persist the data business objects in. A NoSQL database is a database management system which provides a mechanism for storage and retrieval of data that use looser consistency models than traditional relational databases. Using a looser consistency model allows for horizontal scaling and can provide higher availability. The objects from AppEngine are used to pass information between the various layers in the application.

Infrastructure layer

The complete application is deployed on Google AppEngine. AppEngine is a cloud service provided by Google for developers to host their own applications on. The main advantage of using the AppEngine service is that the complete infrastructure is managed by a third party company. Because Google takes care of the hosting, there is no need for actual acquisition of hardware and the management of both the hardware and software.

4.2 Social integration

Nowadays many applications provide some kind of social integration. According to Zichermann [86] it is more engaging to challenge people you know, than people you do not know. Level Up therefore has an interface to connect to external social media websites. Besides going with the social flow, the connection to social media has four main purposes:

1. **Propagation:** first of all the social media connection is used to propagate the application to other employees. The visibility of the application is increased when users share their earnings (for exampl, an 'I have earned this badge' message) on a social media website. Higher visibility might attract new users for the application.

2. **Engagement:** a second reason for using the social media integration is the increased engagement with the application. Level Up tries to increase engagement by, for example, allowing users to compare their score and share messages with their direct colleagues, that is, the people in their network provided by the social media service. This social type of engagement is specifically important for triggering Bartle's *socializers* [3].

3. **Authentication:** users of the application are authenticated using the social media service Yammer. By using a social media service for authentication the created application can use Capgemini its Single Sign On (SSO) service without needing to directly access the SSO service. This is a good alternative because it is not (easily) possible neither allowed for an external application to use the SSO service.

4. **Data gathering:** one of the most important reasons for creating the social media integration is for research purposes. When users allow the application to access their data, the social media information can be used for performing research. For example, a user providing information about the social network is very important for doing SNA.

5 Analyzing the game

"Education is not the piling on of learning, information, data, facts, skills, or abilities - that's training or instruction - but is rather making visible what is hidden as a seed."

– Thomas Moore

Authoritativeness on a Gamification platform is one of the pillars of the research question posed in Section 1.2. Analysis is done in order to determine if the people on engaged on the Gamification platform are influenced by social media. The analysis focuses on the combination of the social media data and the Gamification data. The steps performed for the analysis are described in the sections of this chapter. It describes the acquiring of the actual data, establishing a plan on how to analyze the data and analyzing the data.

5.1 Data acquisition

In order to perform research, having a sufficient amount of data is very helpful, if not necessary. Acquiring data for the research conducted can be split up into two different types of data: *Gamification data* and *Social data*. For collecting both the Gamification data and Social data an extra application is created, called Badge Crawler. The following three sections give a description on the various kinds of data gathered by Badge Crawler and on the quantity of data collected and period over which the data was collected.

5.1.1 Gamification data

Gamification data is the actual data in which is noted who has earned which badge. The Gamification data is collected and maintained using a private service. This private service is directly accessible. Collecting the Gamification data can be done by exporting all records to a Comma Separated File (CSV) file, which can be read by the analysis application.

The data consists of various components, each of which are shown in Table 5.1, with a small description. All of the data available can be used for the research and is therefore extracted.

Table 5.1: *List of all Gamification data components available in Level Up.*

Name	Type	Description
Type	Enumeration	The name of the badge describes for which one can earn it.
Description	String	A short description about the actual badge.
Date altered	Date	The date the last action was performed on a badge request. Date altered is for example when the badge was requested, when it has been approved or when it has been rejected. Note that it can only be one of each.
Quantity	Number	The number of badges a person has.
Quantity per type	Number	The number of badges a person has of a certain type.
Opposite types	Enumeration	Some badges are opposing to each other, for example, a trainer and trainee badge.
E-mail	String	The email of the person who has earned the badge.

5.1.2 Social data

Social data is gathered using the available REST services of Yammer, which is the used social media service. Yammer has a REST service which provides access to a lot of information of anyone who is a member of the Capgemini Yammer network. A more extensive description of the Yammer REST service is shown in Appendix C.

The first thing the application does for gathering the social data is adding each person p in the Gamification data g to the graph G (shown in Equation (5.1)). For each of these persons the ID of the user on Yammer is also retrieved. The ID can be found by matching the email address in Level Up to the email address on Yammer. By using the Level Up data it is certain that the data only contains people which are using the Level Up application.

$$\forall p \in g \mid G \cup p \tag{5.1}$$

After selecting the people from Level Up, check if there exists an edge in the

Yammer graph G_y for each of person p in G. Also check if the person the edge points to is an element of G. If the the person the edge points to is an elementof G, add the edge to the edges of G (G_E), as shown in Equation (5.2).

$$\forall p \in G \mid (\exists p_{i,j} \in G_y) \cap (p_{i,j}.p \in G) \rightarrow G_E \cup p_{i,j} \tag{5.2}$$

Now all graph data from both systems is combined in G. The combined data is enough to perform the various kinds of static analysis defined in Section 2.3. Gathering the data for the dynamic analysis is more complex. In the case of dynamic analyisis, for each p in G the Yammer REST service is checked for outgoing and incoming messages. Incoming and outgoing messages are determined according to the edges determined in the first step, where the actual message can be retrieved from the Yammer service. The social data which is available on Yammer and which can be used for this research is shown in Table 5.2.

Table 5.2: *List of all social data components available in the current system.*

Name	Type	Description
Name	String	The name of the person on the social network.
Email	String	The email address of the person on the social network.
ID	Long	The id of the person on the social network.
Followed by	List of ID's	A list with all people on the social network which are followed by the selected person.
Following	List of ID's	A list with all people which are following the selected person.
Title	String	The title of the person of the company, when filled in on the social network.
Date Registered	Date	The date when the selected person has signed up on the social network site.
Messages	String, Group ID, Date	All messages a person has sent on the social network, with the group it was placed in and the date it was placed.

5.1.3 Data quantity

The amount of data acquired is limited to the amount of people engaged in Level Up. Level Up has been available from March 2012. Since then the application is available for all people of Capgemini Financial Services, although not all people are

playing Level Up. The Gamification data is collected from 1/3/2012 until 7/5/2013 (d/m/y). On 7/5/2013 the number of people involved in Level Up is 80.

The gathered social media data is limited to the amount of Gamification data. Only for the people participating in Level Up the social media data is collected. Therefore the data gathered from Yammer is based on the 80 people of Level Up. When looking at these data in the sense of social graph information, Yammer consists of 80 nodes having a total amount of 316 edges. The data gathered from Yammer is captured on 7/5/2013 and represents the state of the social graph at that moment. The Yammer message information is gathered in one day as well, but contains message data of all time.

5.2 Analysis

Several tests are created in order to draw a conclusion and test the hypotheses stated in Section 1.2.2. All tests are performed on the data acquired in Section 5.1. The following two sections describe, according to the hypotheses, what is tested and how these tests are performed. The actual results of the tests are provided in Section 5.3. The actual conclusions drawn from the analysis are given in Chapter 6.

5.2.1 First hypothesis

The first hypothesis defined in Section 1.2.2 is: *"The greater ones authoritativeness is on a social network, the greater the influence they have on other people."*. Two properties of the first hypothesis have been extracted as being important for the first hypothesis: *authoritativeness* and *influence*.

The authoritativeness or authority of a person in a social network is determined using reputation mechanisms. These mechanisms provide a measure of importance of a person determined on its network. In order to determine the authoritativeness score for each of the people in Level Up and the social graph, three mechanisms are used: degree (indegree and outdegree), PageRank and HITS. Each of these mechanisms are explained in Section 2.3.1. For both the HITS and PageRank algorithm 100 iterations are used. With 100 iterations both algorithms seem to converge well. For the PageRank algorithm an α value of 0.85 is used. An $\alpha = 0.85$ is selected because it is the default option and seems to yield the best results [4, 62].

Influence is the actual result which is captured in this research. In order to capture influence, the authoritativeness (the social media data) described earlier is connected to the actual badge data (Gamification data). In order to test these criteria, multiple tests are created:

T01 - Rank and amount of badges: comparing the rank of people and the amount of badges sheds a light on if both are related to each other. Rank and amount of badges are compared by analyzing whether there is a correlation between rank and amount of badges, for example, do persons with high ranking have more badges in comparison to persons with a low rank? In order to compare amount of badges and rank, Analysis of variance (ANOVA) and *Pearson's* correlation are used [54].

ANOVA is a statistical method which determines if a difference exists between the population means of a set of groups created from the data. ANOVA splits the variance of the complete dataset into the variance *between* the groups and the variance *within* the groups. When the variance between the groups is significantly higher compared to the variance within the groups, the group separation captures a difference in the dataset. The ratio of the variance between the groups and the variance within the groups is used to determine whether the difference is significant. This ratio is known as the F-value. Significance of the F-value can be determined using the $F_{critical}$ value. The $F_{critical}$ value can be calculated using an α value and the number of elements in the population. The α in this case is the amount of certainty the F-value should provide. When the F-value is higher than the $F_{critical}$ value, the difference is significant with a chance of $1 - \alpha$, according to ANOVA. The chance of the data being not significant (that is, that the result is randomly achieved) is known as the P-value. When the P-value is lower than α the result is significant for that α value. Significance means that the chance of the differences between the groups for the measurements are random with a chance $< \alpha$.

In order to use ANOVA the data is split into three categories: people having one badge, people having two badges and people having three or more badges. For each group the data of each of the reputation mechanisms (PageRank, indegree, outdegree and HITS) is used. That is, group contains the scores of the reputation mechanisms for the people with one badge, group two contains the scores of the reputation mechanisms for the people with two badges and group three contains the scores of the reputation mechanisms for the people with three or more badges. After grouping the data ANOVA is used to see if the difference between these groups is actually larger than the difference within the groups. ANOVA calculates the probability of the difference being random.

The second analysis performed is calculating the correlation. The correlation between the ranks of the various reputation mechanisms of all people and the amount of badges connected to that rank is calculated. The correlation is compared to Pearson's critical values of r (r is the correlation) to determine

whether or not the correlation is significant. In order to determine the critical values of r, an α value should be determined, to denote the certainty of the significance of the correlation. Pearson's critical value is a value which describes which amount of correlation is significant for which Degrees of freedom (DF) and which α.

T02 - Rank and badge type: besides rank and amount of badges, there might also be a connection between one's rank and the type of badges. T02 tests whether or not there exists a correlation between one's rank and the types of badges achieved, that is, does someone with a certain authoritativeness tend to go for specific badges? For example, will someone with a low rank apply for a more passive badge (following a course) instead of a more active badge (present a course)? In order to test this, all available badges are listed and mapped to the set of rank-scores of all people who have achieved such a badge. Calculating the rank-scores is done using Equation (5.3).

$$typerank(b) = \frac{1}{\mid b.p \mid} \sum_{P \in b.p} rank(P) \tag{5.3}$$

In Equation (5.3) the parameter b is the badge for which the average rank should be calculated, $b.p$ the set of all people having the same badge and $rank(p)$ the rank of a given person (the rank could be established by either of the algorithms discussed in Section 3.1.2). Note that in Equation (5.3), when a person has earned a badge twice, its rank is also counted twice. After the rank and badge type calculation the average rank for each badge is determined.

T03 - Job-title and amount of badges: for job-title and amount of badges is tested if there exists a correlation between one's job-title and the amount of badges one has, for example, are senior consultants more (or less) active on achieving badges compared to young professionals? To test if a correlation exists, all titles are enumerated and combined with the amount of badges for each of these titles, to see which title on average has the most badges.

It is important to sanitize the data before processing it. People are free to decide upon their job-title on Yammer and are therefore not forced to choose from an enumerated set of choices. Having freedom to choose a job-title results in many different names for the same title (for example, Senior consultant and senior consultant). Besides inconsistent names for job-titles, some of the people did not provide job-title information. The information for those people is gathered from other resources, the mapping between the provided job-titles and generalized job-titles is provided in Appendix D.

T04 - Job-title and badge type: besides checking the correlation between the amount of badges and one's title, job-titles are also combined to the the types of badges. The analysis shows whether there is a correlation between the types of badges one earns and the job-title one has, that is, do people having a specific job-title go for a specific set of badges? Testing if specific titles go for a specific (set of) badges is done by listing all available badges together with a set of titles of persons who have achieved the badge.

T05 - Department and badge type: The fifth test checks if the correlation exists between departments and the badge types achieved in that department, that is, are people of a specific department going for the same badges? The test is comparable to T04, but in this case performed on the department instead of the job-title.

T06 - Network and badge type: the network an badge type test elaborates on test T02 and is more elaborate compared to the previous tests. The network and badge type test does not focus on rank directly, but on the actual ego centered network of the people. The network and badge type test examines if there is a correlation between the ego centered network of a person and the types of badges they have earned. It could be summarized as: do my direct colleagues earn the same badges, and does this depend on my authoritativeness? Testing is done by putting the amount of corresponding badges into a matrix, and applying the δ function in Equation (5.4) to that value. The actual implementation of Equation (5.4) and the other parts of the approach is defined in Listing E.7, which can be found in Appendix E.

$$\delta(P_{i,j}) = \begin{cases} 1 & \text{if } P_{i,j} \in G_E \\ 0 & \text{otherwise} \end{cases} \tag{5.4}$$

After applying the δ function the amount of corresponding badges (b_c) is divided by the total amount of badge one has (b_t) and multiplied by 100, giving a percentage of corresponding badges between to persons, i.e., $\frac{b_c}{b_t} \times 100$.

In order to be able to draw a conclusion from these measurements the results need to be compared. to compare results, the calculation has been performed on the opposing data, that is, the amount of badges being the same with others which are not in the direct network. It is exactly the same as described for the first test, however in this case the δ^{-1} function in Equation (5.5) is used.

$$\delta^{-1}(P_{i,j}) = \begin{cases} 0 & \text{if } P_{i,j} \in G_E \\ 1 & \text{otherwise} \end{cases} \tag{5.5}$$

For each person the average number of corresponding badges among all corresponding people is calculated. For the first case, in which only badges of the actual network are taken into account, the average number is calculated by dividing the sum of the percentage of the corresponding badges by the outdegree of a person. Equation (5.6) shows how to calculate the average percentage of corresponding badges.

$$average_{network}(P_i) = \frac{1}{\mid out(P_i) \mid} \sum_{P_j \in G} \delta(P_{i,j}) \cdot \frac{b_c}{b_t} \times 100 \tag{5.6}$$

The same function as Equation (5.6) is used for determining all people outside of the network of a person, only in that case the δ function is swapped for the δ^{-1} function, and the $\mid out(P_i) \mid$ is replaced with the total amount of players minus the outdegree of P_i. Equation (5.6) is carried out $\forall P \in G$. At the end the correlation between both lists and their ranking is calculated in order to give a result.

An example of applying Equation (5.6) can be shown using the schematic graph in Figure 5.1.

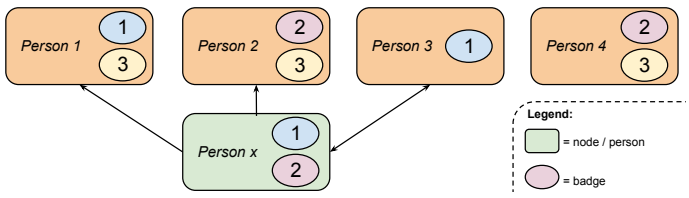

Figure 5.1: *Schematic of people and their badges.*

Figure 5.1 shows people with their badges and their connections to other people in the population. When calculating the percentage of corresponding badges between *Person x* and *Person 1*, from the perspective of Person x, is 50% (Person x has two badges of which one corresponds to Person 1, thus $\frac{1}{2} = 50\%$). When looking at the total graph, Person x has $50\%_{Person1} + 50\%_{Person2} + 50\%_{Person3} = 150\%$, which is on average $\frac{150\%}{3} = 50\%$ corresponding in the ego centered network from the perspective of Person X.

5.2.2 Second hypothesis

Besides using static analysis on the data, it is also possible to perform dynamic analysis on the social network. For the second hypothesis defined in Section 1.2.2, recall: *"The more active one is on a social network, the greater influence they have*

on other people", the dynamic analysis algorithms can be used. The hypothesis can be distilled into two important parts: *activity on the social network* and *influence*. Activity in this sense is measured in the amount of messages one posts on the Yammer website. This activity is mapped to authoritativeness in the sense that more activity makes a person more authoritative. The second part of the hypothesis is influence. Influence in this sense is the same as in Section 5.2.1, that is, the amount of badges and types of badges correlated in this research.

In order to determine the authoritativeness, the TrafficRank [75] algorithm is used. The TrafficRank algorithm uses the number of messages over a certain period of time to assign a rank of authoritativeness to a person. The actual implementation and a explanation of the algorithm is provided in Section 3.1.2. The interesting thing about TrafficRank is that it can be calculated dynamically, that is, for certain periods in time. With TrafficRank, for example, the actual dates of the badge requests and dates of messages could be compared to see if there is a relation between them. In order to test the second hypothesis the following test has been created:

T07 - Activity and badge type: for the activity and badge type analysis the focus is on the activity of a person and the badge types requested. Both the badge requests and activity are measured over time. When comparing the dates of badge requests and social media activity, does this show a correlation? For the activity and badge type test it is important to look at individual cases with their direct network. The reason for looking at individual cases is that the messages will often only be shown to one's direct colleagues, or the complete group the message is placed in.

In order to perform the test, the dates of both the messages and badge requests are needed. Then the correlation between the badge requests in a period and both the three people with the highest TrafficRank and total TrafficRank is calculated. When the correlation between the top three TrafficRank and the amount of approved badges is higher than the total TrafficRank and the amount of approved badges, a relation might exist.

5.3 Evaluation

After conducting the actual research the results can be evaluated. Where Chapter 5 describes the research of this project, this evaluation section provides the actual results gathered. All results are coded according to their test code described in Section 5.2.

5.3.1 T01 - Rank and amount of badges

The goal of test T01 is to determine if there is a correlation between rank and the amount of badges. Determining the relationship between rank and amount of badges is done using ANOVA and *Pearson* his correlation. In order to see if a relation exists, the several ranking methods from Section 3.1.2 are used.

First of all the distribution of the badge data is determined. A graphical representation of the distribution of these data is depicted in Figure 5.2. From Figure 5.2 it can be determined that the data is not normal distributed, but seems to show properties of a negative exponential distribution.

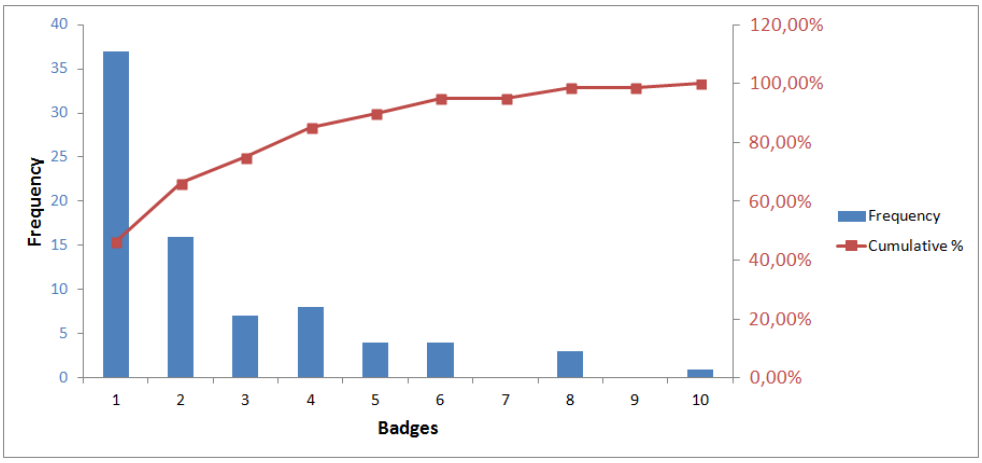

Figure 5.2: *The distribution of the amount of badges in Level Up*

The ANOVA calculated for the the ranking algorithms described in Section 5.2.1 (outdegree, indegree, PageRank and HITS) is extensively described in Appendix F. Table 5.3 gives a short summary of the ANOVA. For calculating the ANOVA an $\alpha = 0.05$ is used, yielding an $F_{critical}$ value of 3.1381.

Interestingly the three scores which are significant (indegree, PageRank and HITS - authority) are the three scores which intuitively resemble authoritativeness the best. In contrary, HITS - hubness and outdegree simply mean one *connects to* different people. Both do not say whether one is *connected by / from* other people.

Unfortunately, further analysis shows that the ANOVA results cannot be used. It seems that some of the assumptions of ANOVA are not met. First of all in order to use ANOVA, the data should have a normal distribution. This is not the case (both not in the groups or on the total data, see Figure 5.2). Second of all, when looking at the ANOVA summary in Appendix F.1, it seems that the standard deviations of the groups differ with a factor larger than two, which also indicates ANOVA cannot

Table 5.3: ANOVA *results the given algorithms in the first column and the amount of badges of a person. In the last column is provided whether the result is significant on the* $\alpha = 0.05$ *level and a* DF *of two.*

Algorithm	F-value	P-value	Significant
Outdegree	2.89	6.27E-02	No
Indegree	5.64	5.52E-03	Yes
PageRank	3.39	3.98E-02	Yes
HITS - hubness	2.37	1.02E-01	No
HITS - authority	4.57	1.39E-02	Yes

be used. Instead of a parametric test, a non-parametric test should be used in this case. Non-parametric tests provide more robustness for not normally distributed data. An instance of a non-parametric test is the Kruskal-Wallis test. Kruskal-Wallis is comparable to ANOVA, however, Kruskal-Wallis does not require a specific distribution of the data. The results for the Kruskal-Wallis test (on the same data on which the ANOVA is performed) are shown in Table 5.4. The Chi-squared value in Table 5.4 describes the amount of difference between the distributions of the said groups. This is the actual outcome of the Kruskal-Wallis test. The DF are the number of groups used minus one. The results are significant if the P-value larger is than 0.05 (or if the Chi-squared value larger is than 5.99, which is the critical value of Chi-squared with $\alpha = 0.05$ and DF $= 2$).

Table 5.4: *Kruskal-Wallis results the given algorithms in the first column and the amount of badges of a person. In the last column is provided whether the result is significant on the* $\alpha = 0.05$ *level and a* DF *of two.*

Algorithm	Chi-squared	P-value	Significant
Outdegree	4.358	0.113	No
Indegree	7.151	0.028	Yes
PageRank	3.720	0.156	No
HITS - hubness	2.766	0.251	No
HITS - authority	5.899	0.052	No

According to Kruskal-Wallis with an $\alpha = 0.05$, there only exists a significant difference in groups when looking at indegree (although HITS - authority is nearly significant). A non-significant difference means that the difference between the distributions of the groups do not vary enough from each other, in order to be significant with a chance greater than $1 - \alpha$. Therefore it is not possible to say for the results, except indegree, they are not random with a chance > 0.95.

The correlation between the ranking algorithms described in Section 5.2.1 (outdegree, indegree, PageRank and HITS) and the amount of badges per person is shown in Table 5.5. Besides the correlation between a ranking algorithm and amount of badges, also the means and standard deviations are provided. Both the means and standard deviations are calculated from the actual data generated by the algorithm (or reputation mechanism) shown in the first column. The last column shows whether the correlation is significant. Significance is determined using the critical values for *Pearson's r*, for a two tailed test with a level of 0.01. The critical value threshold for the correlation for a level of 0.01 and a DF of 78 is approximately 0.284.

Table 5.5: *Correlation between the given algorithms in the first column and the amount of badges of a person. Also the mean and standard deviation for the data of the algorithms is provided. The last column shows if the result is significant for a level of* 0.01 *and a* DF *of* 78

Algorithm	**Correlation**	**Mean**	**Stdev**	**Significant**
Outdegree	0.469	4.188	5.975	Yes
Indegree	0.514	4.188	5.596	Yes
PageRank	0.416	1.250E-02	1.41E-02	Yes
HITS - hubness	0.442	0.073	0.085	Yes
HITS - authority	0.465	0.075	0.083	Yes
Badges	1.000	2.350	2.176	Yes

Table 5.5 shows the correlations are quite low, however, they are significant. An important aspect of the data to take into account is that it contains some outliers, which heavily influence these correlations.

It can be noted that the correlation based on indegree is higher in comparison with the others, but only slightly. It could mean that a person does exert influence, but only on the connections directly connected to the person. That idea would make sense as in general posted messages will only show up on the Yammer 'dashboard' of the direct colleagues. The result for indegree is also reflected in the results of Kruskal-Wallis. The probability of having non random variances between distributions of the indegree groups and amount of badges is $> 97.20\%$. A percentage of $> 97.20\%$ with a determined $\alpha = 0.05$ is large enough to say that there exists a non random difference between the groups. However, the relationship described is merely a correlation, not causality. Therefore the results could be further investigated in order to determine if a causality relation exists.

5.3.2 T02 - Rank and badge type

The second test, test T02, determines if there is a correlation between the types of badges and the rank of the people earning those badges. To determine if a correlation exists first of all the badges are listed. Then for each of these badges the average rank for each badge is calculated. A graphical representation of T02 is shown in Figure 5.3. Note that Figure 5.3 shows the percentage of PageRank and not of the other algorithms. The reason for only showing one figure is because the results provided by the various algorithms did not vary a lot (the average correlation between the results of the algorithms is > 0.83); each would result in the same conclusion.

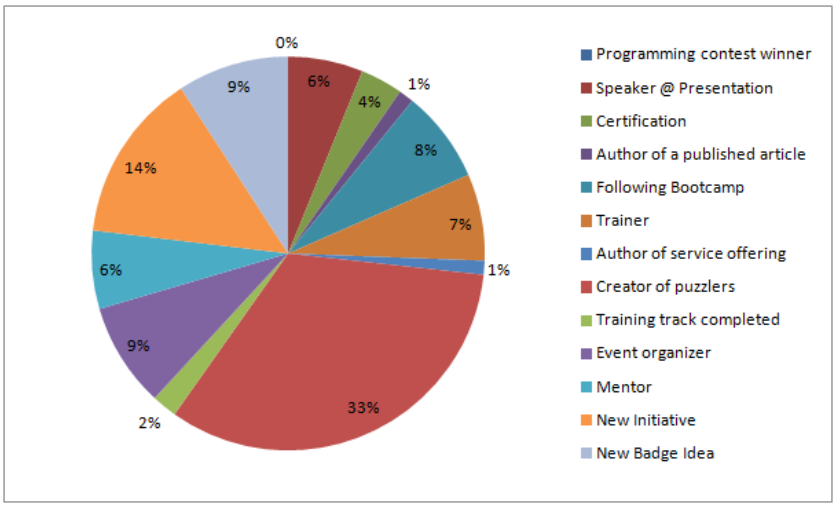

Figure 5.3: *The average PageRank for each of the badge types.*

From Figure 5.3 it seems that there actually is a relation between rank and badge type. The badges 'Creator of puzzlers' and 'New Initiative' seem to have a very high rank compared to the other types of badges. Although it could be the case that the relation exists, the data for these two badges is questionable. In the data the 'Creator of puzzlers' badge was achieved by only one person. The person who achieved this badge has a very high PageRank, thus increasing the rank of the badge type.

5.3.3 T03 - Job-title and amount of badges

T03 analyzes the correlation between job-title (that is, the job-title of a person) and the amount badges earned. In order to perform this research, several steps are performed. First of all the collected data is sanitized. In the sanitizing step the provided job-titles are categorized and divided into thirteen cases. Categorizing is

needed because all people have the ability to provide their own description for their title. So, for example, a person could use the job-title Senior IT Consultant, which in fact could be the same as Senior Consultant. These different titles are treated the same in this chapter. Appendix D shows the mapping between the actual provided titles and the set of generalized titles.

After the sanitizing and generalization step the actual data can be determined. For determining the actual data the amount of badges for each of the job-titles is calculated. In order to take care that the amount of people with a certain job-title does not influence the result, the amount of badges per job-title is divided by the number of people having that job-title. The percentages of badges per job-title is shown in Figure 5.4.

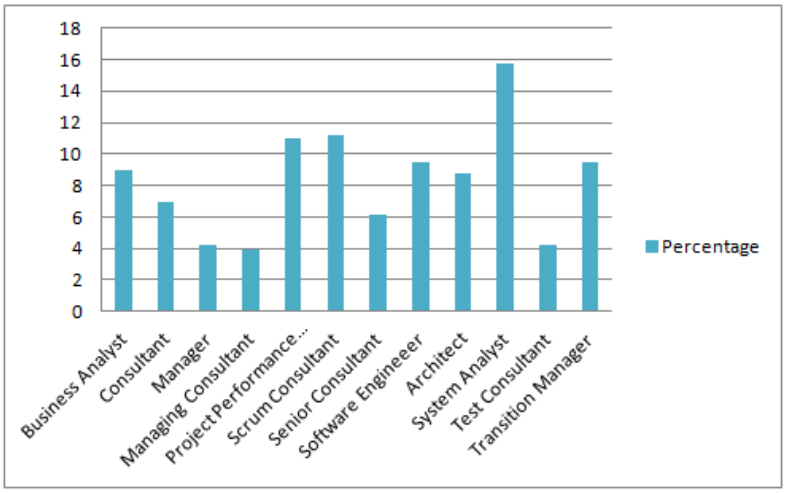

Figure 5.4: *Graph showing the percentage of badges per job-title*

Figure 5.4 shows that the largest quantity of badges are earned by the 'System Analysts' job-title. The second and third place go to 'Project Performance Improvement consultants' and the 'Scrum Consultants'. Besides analyzing the specific data, also the more high level categories are analyzed. The high level categories selected are the group 'Junior consultants' and the group 'Senior consultants'. It seems that the relative amount of badges is nearly the same for both groups. Figure 5.5 shows the percentages badges per junior and senior level.

5.3.4 T04 - Job-title and badge types

In the fourth test, T04, the goal is to see the correlation between job-titles and the types of badges. Tests show if certain job-titles have a preference for certain badge

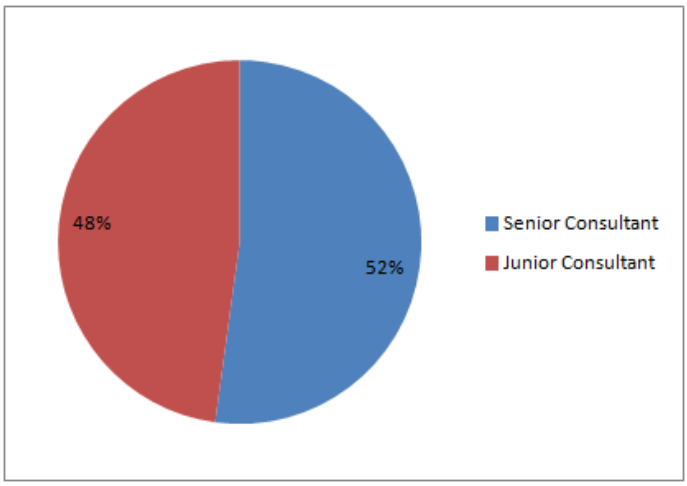

Figure 5.5: *Pie chart showing the percentage of badges per junior and senior level.*

types. In order to test if a preference exists, the same sanitizing and generalizing step as described in Section 5.3.3 and Appendix D are performed. A graph showing the actual data, the fraction of badge types per job-titles, is shown in Figure 5.6. A graph with the job-titles per badge is shown in Figure 5.7.

Both Figure 5.6 and Figure 5.7 show some interesting facts. First of all the 'Certification' badge. The 'Certification' badge is provided when one receives a certification. Both Figure 5.6 and Figure 5.7 show that almost all job-titles show a large amount of 'Certification' badges. The reason for the distribution of the 'Certification' badge could be due to the fact that for most of the job-titles people are required to earn certifications. The same goes for following so called boot-camps ('Following Bootcamp' badge. These boot-camps are crash courses of a few days to gain experience on a certain subject.

On the other hand, the group 'Scrum Consultants' might be, for example, interested into expressing their ideas. The 'Scrum Consultants' group is one of the two groups involved in publishing articles ('Author of a published article' badge) and also the second most active with regards to speaking at a presentation ('Speaker @ presentation' badge).

It seems there is no clear difference between the job-titles of 'Consultants' and 'Senior Consultants', the graph in Figure 5.6 looks approximately the same for both job-titles (which was also the case in Figure 5.5). Besides that it could be the case that 'Consultants' and 'Senior Consultants' behave in the same way, the relation could have multiple reasons: first of all people might not change their title on Yammer

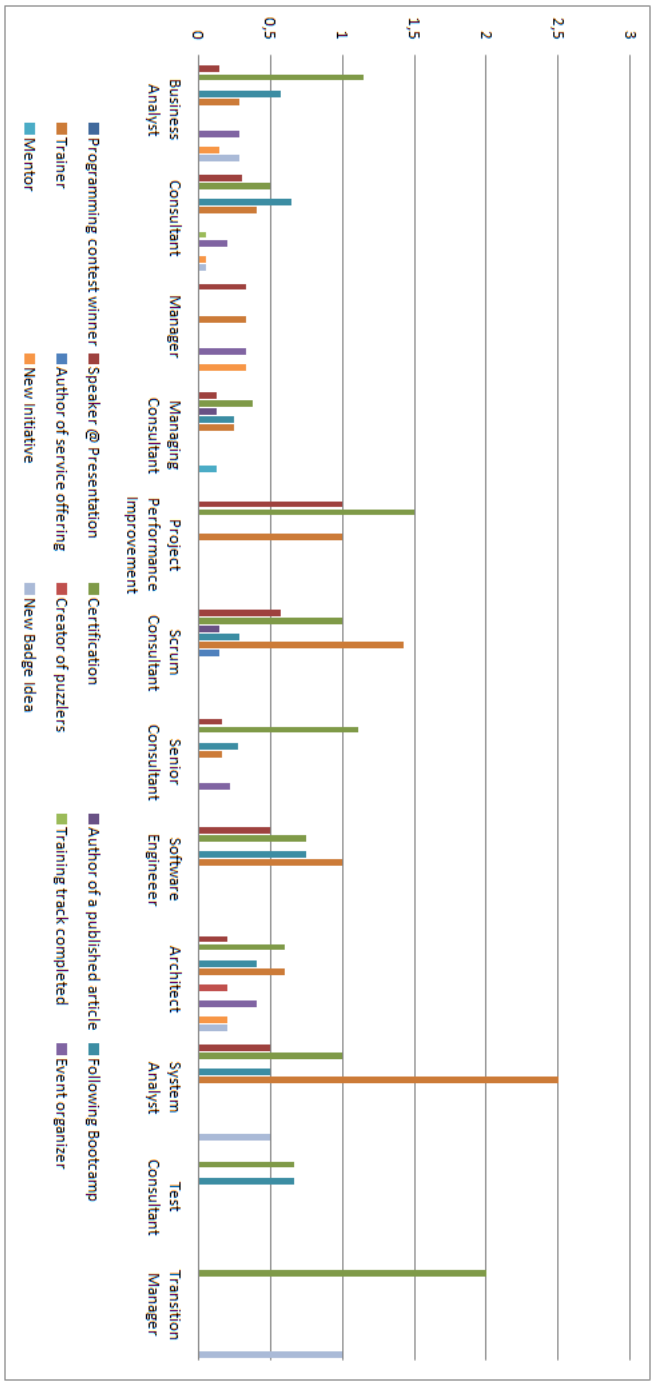

Figure 5.6: *Graph showing the fraction of job-titles per badge type.*

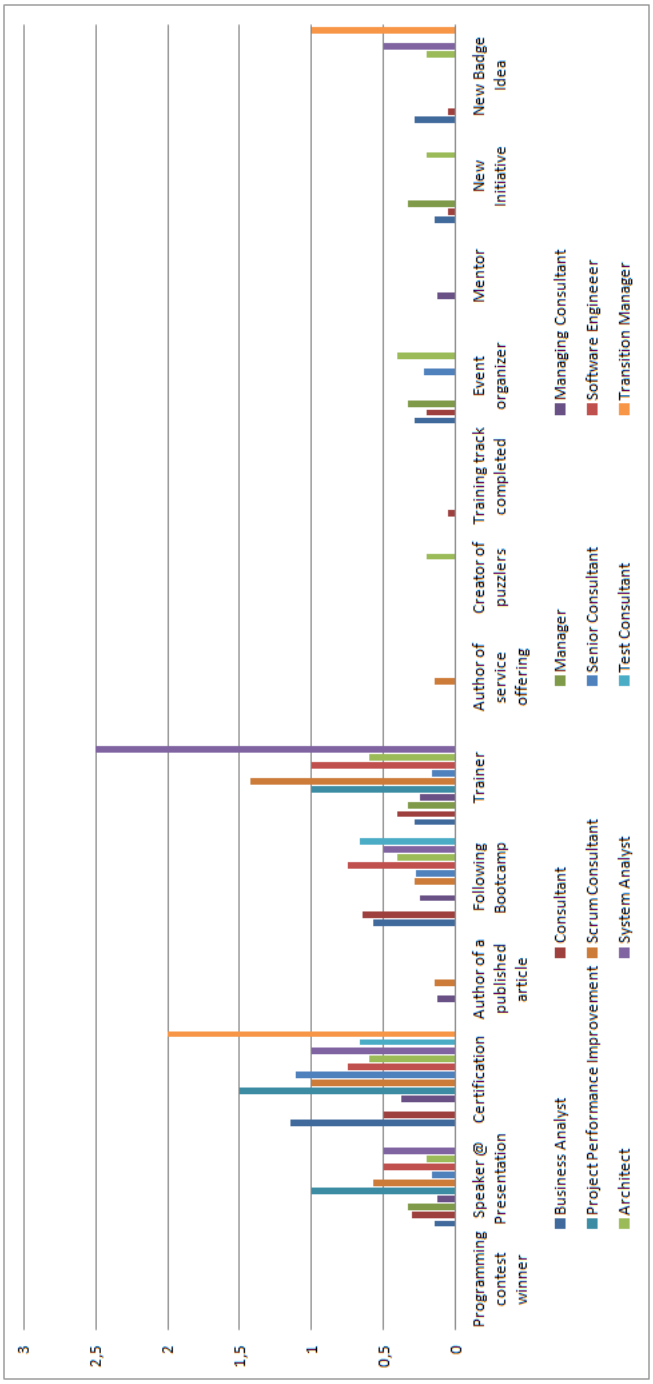

Figure 5.7: *Graph showing the fraction of badge types per job-title.*

when promoted to 'Senior Consultant'. Second of all both titles are generic and might therefore be spread among to many other job-titles. Actually most of the other job-titles described are also a subset of 'Senior Consultant', only those people have given a more in depth description of their function.

5.3.5 T05 - Department and badge type

In the fifth test the correlation between department and badge type is researched. The employees are categorized according to their department, just as in T04 with their title. However, during the research it seems that categorizing the people and generalizing the data is not possible with the current data. A large percentage of people in the population, 26% did not supply any information about the department. Besides not providing the information, many provided a very generic description (approximately 65% of the people who provided the data). The amount of usable data would in this case be to less to provide substantial conclusions.

5.3.6 T06 - Network and badge type

The sixth analysis is directly related to the research question posed at the beginning of the research. It tests if the relation exists between a person his or her ego centered network and the types of badges earned. For a relation between network and badge type to exist, the average amount of corresponding badges in one's ego centered network should be higher than the average amount of corresponding badges not in one's ego centered network. The results of the various tests are listed in Table 5.6. In Table 5.6 the average provided is the total percentage of the corresponding badges of a person divided by the amount of people.

Table 5.6: *The amounts of corresponding badges in and outside of one's ego centered network.*

Type	**In ego centered network**	**Not in ego centered network**
Average	24%	25%
Correlation with rank	0.06	-0.22

The results of the test show that the difference between the corresponding badges in a network and the corresponding badges outside of the network is very small. Therefore, no direct relation can be shown. Also the correlations calculated between the rankings and the corresponding badges are not significant, not even on a level of

0.10. The correlations are too low to show that a correlation between rank and the in-network corresponding badges actually exists.

5.3.7 T07 - Activity and badge type

For test T07 the correlation between badge types and network activity is calculated. Network activity is calculated using TrafficRank. Calculation of the correlation is done for the three most authoritative according to TrafficRank and for the total amount of TrafficRank. In order to calculate the TrafficRank of the three most authoritative persons is measured. The TrafficRank of these three people over time is shown in Figure 5.8. The barchart in Figure 5.8 shows the total amount of TrafficRank that period. Figure 5.8 represents the TrafficRank over time, with datapoints measured each month, that is, each datapoint is the TrafficRank calculated over the total amount of messages sent by that person in the given month.

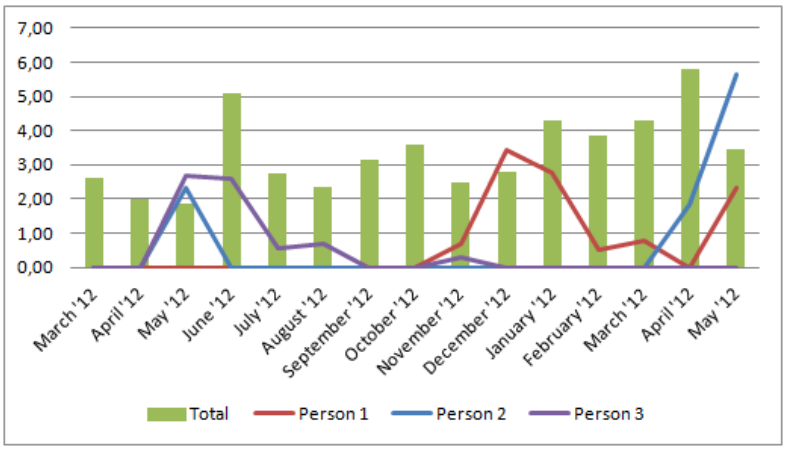

Figure 5.8: *Three most authoritative people according to the TrafficRank implementation.*

Unfortunately, the temporal data known for the badges people have earned or have requested is not accurate. The previous version of Level Up with which these badge requests and approvals have been registered, has overwritten the date-field every time the badge request was altered. The overwritten date-field causes that for the not approved badges the date equals the date on which the badge has been requested, but for badges which have been approved, the request date has been overwritten with the date on which the badge has been approved. However, according to the Badgers, the approval date was (most of the time) actually really close to the date on which badges are requested. With this notice, the data are not accurate enough to draw actual conclusions and calculate correlation, but nonetheless interesting to look at.

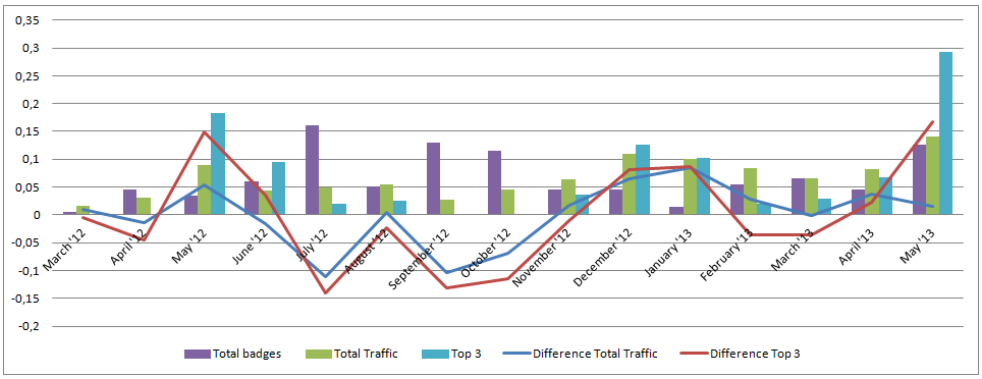

Figure 5.9: *Graph showing the differences between TrafficRank and amount of approved and rejected badges*

Figure 5.9 shows several statistics on both TrafficRank and badge approvals. The horizontal axis shows the month for which the data is captured, the vertical axis the amount of that period of time. First of all the bar-chart part of the graph shows the total amount of badges rejected and approved, denoted by *Total badges*, the sum of the TrafficRank denoted by *Total Traffic* and the sum of the top three its TrafficRank denoted by *Top 3*. On the bar-chart two line-charts are plotted. One shows the difference between the total amount of badges (approved and rejected) and the total TrafficRank, and the other shows the amount of badges (approved and rejected) and the top three people according to TrafficRank. All data is normalized.

From Figure 5.9 it seems that the difference between the total TrafficRank and total amount of approved and requested badges is very similar to the difference between the top three TrafficRank and the total amount of approved and requested badges. Sometimes even, the amount of difference between badge requests and top three traffic is much larger, in comparison with total traffic. When the ranking would actually influence the amount of badges rejected and approved, the difference between the top three in TrafficRank and the total amount of approved badges would be closer to zero. However, the difference between the top three and amount of badge requests is not closer to zero, therefore it seems that the amount of badges requested and approved is not influenced by the amount of traffic of the three most active people on the network.

5.4 Summary

The previous sections provide the results of the analysis performed during the research. Seven different kinds of analysis are performed and show some interesting results. It seems that significant differences exist between the distributions of the groups of people having one, two or three and more badges in comparison with indegree (according to the Kruskal-Wallis test). The difference does not imply causality, only the difference between the distributions of the groups. It seems that there exists a significant correlation between the ranking algorithms and the amount of badges one has.

Secondly, it seems that people with different ranks tend to be interested in specific badges. The analysis also looks at a person his or her influence on the direct network. Influence on the direct network is measured according to the amount of corresponding badges in a person his or her direct network. It does, however, not seem that this is the case, not for authoritative people nor for non authoritative people.

Besides specific people groups of people are analyzed. For analyzing groups, the people are generalized into groups of their job-title. It seems that specific groups of people are interested in specific badges, but there also exist badges which are interesting for all people (for example the 'Certification' badge). The relations described are, however, not proven causal relations, meaning that there could be other variables influencing the result.

It is hard to tell if the implementation of Gamification was successful. No actual data is available for proving the success. Determining if the implementation was successful could be analyzed by comparing with a control group. The results of the 'gamified' group can then be compared to a regular, not gamified, group. Differences between these groups could show whether the Gamification is successful.

6 Discussion and Conclusion

"Insanity: doing the same thing over and over again and expecting different results."

– Albert Einstein

The presented work gives a description on how to perform SNA on a social network, in combination with a Gamification platform. The results presented give an idea about the impact of the social influence of people on the ability to virtually achieve goals in a Gamification environment. With the analysis provided and the results gathered, the (sub-) research questions from Section 1.2 can be answered. These questions are answered in Section 6.1. In order to provide a scientific base for others to built upon, a critical look on the actual work is inevitable. Section 6.2 discusses the results achieved. Section 6.3 describes which aspects could be further researched, but were outside of the scope of this research.

6.1 Conclusion

According to much research in Gamification and behavioral psychology, Gamification does motivate people to put in just a little extra effort. Although the actual research performed does not directly show whether or not this is true, the literature reviewed in Section 2.1 does clearly conclude this. Gamification, however, is not a silver bullet solution. When designing a Gamification approach, one should really take into account for whom it is built and with what purpose, otherwise it has a high risk of failing.

With the results presented in Section 5.3 the research question described in Section 1.2 can be answered. The research question created is: *"Can a correlation be shown between one's authoritativeness and the influence they exert on others regarding the amount and types of badges one has earned?"*. Taking into account all results of Section 5.3, there does seem to be a correlation between amount of badges and the authoritativeness of people. Each of the ranking algorithms (indegree, outdegree, PageRank, HITS - hubness and HITS - authority) show a correlation to be significant

with a chance > 0.99. Besides the correlation, the difference between the distributions of authoritativeness, determined using indegree, is significant with a chance > 0.95 according to Kruskal-Wallis, when the data is grouped into three groups: people having one badge, people having two badges and people having three or more badges.

It seems there exists an, although small, relation between the type of badges and the actual rank of a person. Some badges show a considerable larger ranking than other badge types. The relation between rank and badge type could mean that people are connected and are influenced by each other. However, it could also be the case that other variables influence this result. In order to achieve this result, the assumption was made that connections do not change over time. However, in the actual situation it could be the case that the social graph changes. It could be, for example, that people work together on a project and earn a badge for this, but become connections on Yammer afterwards. This shows that the results presented are merely correlations and do not imply causality.

6.2 Discussion

The results of the research do encourage some discussion. The research was performed with some limitations on the actual data used. These limitations are enumerated and discussed here:

1. **Amount of data:** the first limitation in this research is the actual amount of data available. For the analysis a dataset consisting of 80 people was used, from an application which had been available for approximately one year. During this year approximately 240 badges are requested, of which 189 have been approved. Both the people and badge data is little compared to the size of Capgemini, or even to the size of Capgemini Financial Services, at which this project is carried out. Performing this research again with a larger data set might yield a different result.

   Using a larger quantity of data might also allow for using ANOVA. It might be the case that the complete population is indeed normally distributed and has a difference in standard deviation of a factor less than two. It would be interesting to see what the results of ANOVA will be in that case.

2. **Representativeness of data:** during the beta phase of Level Up (which is the complete phase until the new version described in this document has been released), the application has been available for the people of only one department of Capgemini. The amount of people actually allowed to compete

in Level Up was approximately 900. With 81 people actually engaged in this game, this is less then 10%. This might not be a representative subset of the complete population, and therefore the results may vary for the complete population.

There are multiple reasons for the low percentage of players. First of all marketing, Level Up was communicated to the coworkers via email, presentations and word of mouth marketing. However, even with marketing, only a small amount of people actually know Level Up. A second reason is the interest in Gamification. Some people are very skeptical about Gamification. Gamification is sometimes deemed unnecessary, for people who do not see the added value of the badges. They are not challenged by the idea of earning badges. When people are not challenged, Gamification will most probably not have any effect.

3. **Reward type:** the reward type of Level Up are badges. In the research the amount of badges has been used. In this case the various types of badges are compared with each other, although each badge requires very specific and often very different skills. Badges allow for comparing between the types of badges, which is done in this research. Comparing types of badges gives an insight in which groups of people (according to job-title) want which badges. Comparing the number of badges might not give the best results in comparison to, for example, a more generic point system.

4. **Assumptions:** several assumptions made during this thesis might not reflect reality. It might be that for some reason people do not want to be active on a social network (instead of just not being active on the social network), thus not complying to the assumption made. Another assumption made is that the connections among the people in the social network remains the same during the research. In the case that people are active on a social network, the connections between them do change (people will add or remove connections, people might even leave the company). However, without this assumption it would be very difficult to do the research, as all historical data of both Level Up and Yammer are needed.

5. **Reputation mechanism:** using various reputation mechanisms show interesting results. It is interesting to see that the indegree reputation mechanism shows significant Kruskal-Wallis results, while the other reputation mechanisms do not. Reasoning about why this is the case is an interesting topic when further researching the topic.

Besides the reputation mechanisms results with Kruskal-Wallis, it is also interesting to see the resemblance between certain types of reputation mechanisms. For the data used the difference between, for example, the PageRank algorithm and indegree measure was actually not very big. This might raise the question if it is really necessary to perform such a heavy to calculate reputation mechanism instead of a simple indegree measure.

6. **Yammer:** a large quantity of the data used is gathered from Yammer. Yammer is the private social network of Capgemini. Although Yammer has been implemented at Capgemini for a certain amount of time, it is still not used by all employees. However, all people conducted in this research were actual members of Yammer. It might be the case that the set of people on Level Up are the early adopters and most active of the department. Using only early adaptors or active people means that the subset of people on Level Up is a very specific one and therefore not a correct representation of the complete population of the department nor of Capgemini.

   Another aspect of social media to take into account is the flow in which new connections are made. For this example the assumption is made that people are connected to each other at first and afterwards earn their badges. This might just be the other way around. People can work together during, for example, the organization of an event and afterwards make the connection with the people with which they organized the event with. Making connection afterwards does not say anything about actual influence.

6.3 Future research

Due to time and data constraints some parts of the research could be elaborated or changed in future research projects. Advice on criteria to take into account when further researching this subject can therefore be helpful for other researchers. In this section the provided advice is split into two subjects: research and Gamification design. In the Section 6.3.1 the ideas on how to improve and further research the project is elaborated. Section 6.3.2 focuses on the actual implementation of Gamification in Level Up.

6.3.1 Research proposals

In the research conducted during this research, the focus is mainly on the badges people have earned. Badges are a very good way to represent status and achievement. However, it is hard to actually compare two completely different badges with each

other. For future research it is more interesting to look at a more general reward system, such as a point system. Points in that case are general awards which can be scaled to the importance of the achievement.

Analysis can be performed on the data flowing from and to people. In this research merely the amount of messages over time are measured, but in the future one could look at the actual content of the messages, for example, scan messages for the term Level Up and only count those messages. Scanning the actual content of messages is outside of the scope of this project.

The research performed only used information gathered from Yammer. Although Yammer is the only official social network inside of Capgemini, it is also interesting to perform this research on data gathered from other social media websites, such as LinkedIn. These data might provide other insights in the actual network of people and their importance. It would be interesting to compare these results.

It might be interesting to compare the amount of badges and types of badges with the end of the year bonuses or conclusions of appraisal interviews. Comparing these factors can show how well the Gamification achievements correspond to the traditional means of rewarding people and assessing people.

Finally, several (cor)relations are found between Gamification data and authoritativeness measured using the selected reputation mechanisms. Now it is interesting to research if an actual causal relationship exists. That is, when a person is more authoritative, will the person try to gather more badge? Another explanation could be, for example, a person is active and is therefore more authoritative on a social network. Therefore the person tries to get more badges. In this example case a causality would exist between an active person and his or her badges, but not between authoritativeness and his or her badges.

6.3.2 Gamification design

One extraordinary thing to mention about Level Up is the combination of badges and leader boards. According to Zichermann and Cunningham [86] badges are used to resemble status. Badges are not actually meant as a means to compare two people. The reason for this is that badges are very specific and it is hard to compare two different kinds of badges with each other. For a leader board it would be better to use points (or any generic type of reward system) instead of badges.

The second advice for Level Up is finding out if people return to Level Up and if not, how they can be motivated to do so. The application should provide some means to keep players coming back, also for a longer period of time. In order to implement a means to accomplish this, it is useful to know what actual purpose is felt by the player. When the actual purpose is known that might be used to create features

which are appealing for the players. To create these features the Level Up platform should be used for a while so enough data and opinions about the application can be gathered. Looking at the future of the game is important, maybe Level Up is just be a hype and then disappear after some time. This is one thing only time will tell.

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Appendix A

Badges

Table A.1 shows the available badges in the Level Up application, downloaded and created on 14/1/2013. The date on which the badges are retrieved is important as the amount of badges increases over time (people can submit new badge ideas). Also, Table A.1 merely shows the normal badges. When a 'player' earns three of the same kind of badges, this person will receive a so called 'star-badge'. These badges are not shown in this appendix.

Table A.1: *The available badges in the Level Up application (14th of January, 2013)*

Badge	Title	Description
	King Badge	On winning three different badges in a calendar year, you're automatically updated to Level 'King'.
	Programming contest winner	On winning a programming contest organized at Capgemini.
	Speaker @ Presentation	On being the speaker at 2 presentations. These presentations could be at one of the community meetings, expert group meetings, or any internal or external event.
	Certification	On receiving any internal or external certificate. (Examples: OCJP, Scrum PSM I or II, SE Level 1, etc.).

Continued on next page

Table A.1 – continued from previous page

Badge	Title	Description
	Author of a published article	On an article which is published on an internal or an external forum. Examples of internal forums: SE newsletter, Technical Blogs, etc. Articles in practice newsletters are not considered.
	Following Bootcamp	On participating in one of the bootcamps organized at Capgemini. You must have had atleast 75% attendance at the bootcamp and a working application at the end of it.
	Trainer	On being the trainer at one of the bootcamps or workshops organized at Capgemini. A bootcamp is program consisting of 3 or 4 evenings where a set of trainers train a group of people in a certain competency. A workshop is a hands-on training focusing on a particular technology.
	Author of service offering	On writing a service offering, making it known to the Business Units, and getting them to sell it to our customers.
	Creator of puzzlers	On creating 7 puzzles. Mostly, Yammer is the forum for creating these puzzles. But another medium is acceptable if other colleagues know about them.
	Training track completed	On completing one of the training tracks created by the communities of practice (Software Development, Software Design, Agile, BPM Lions).
	Event organizer	For organizing an internal or external event. Examples of events: Business Technology event, Requirements event, Java Night, etc.

Continued on next page

Table A.1 – continued from previous page

Badge	Title	Description
	Mentor	For mentoring another colleague. Substantial mentoring effort (in terms of hours and results) needs to be shown for earning this badge. Mentoring could be on any ground - technical skills, soft skills, etc.
	New initiative	When the player is considered to be a major contributor to an initiative that is seen as a success with added value in the eyes of its stakeholders within Capgemini and that is not related to his/her daily work.
	New badge idea	On a new idea for a badge.

Appendix B

Player types

Each person has different needs and each person is motivated by different things. This is important to take into account when implementing a Gamification approach. The Gamification approach will have a higher impact when the desires of the players are addressed. In Figure B.1 a table is shown which graphs these human desires against the game mechanics available. Which desires people have is again subject to what player type one is (for these player types, see Bartle [3]).

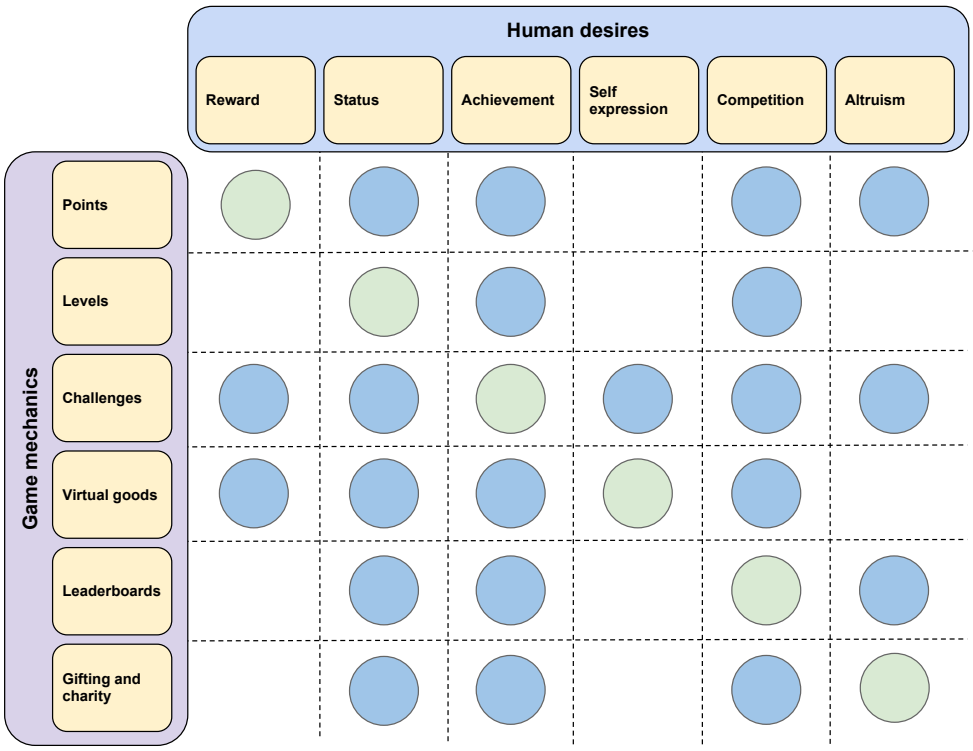

Figure B.1: *Different human desires with the best fitting game mechanics. Image from [86]*

Appendix C

Yammer rest specification

One of the main sources of information used is the social network information from Yammer. With these data the several reputation mechanisms could be used to determine importance and authoritativeness. This chapter gives a more elaborate specification of the Yammer's REST service used during the development of the Badge Crawler and Level Up application. The information gathered from this service is in XML format. The calls described to the webservice are all GET requests. Note that all information in this chapter comes from the Yammer Developers website / guide [85]. The rest services used for this research are listed in Table C.1.

Table C.1: *The Yammer* REST *specification*

Resource	URL	Description
User info	https://www.yammer.com/api/v1/users/<id>	Shows the information about a certain user. The ID of the user should be provided, instead of <id>.
User info	https://www.yammer.com/api/v1/users/by_email?email=<email>	Shows the information about a certain user. However, this REST service allows for gathering information on email address. The email address of the user should be provided, instead of <email>.
Messages	https://www.yammer.com/api/v1/messages/from_user/<id>	The user's feed, based on the selection they have made between "Following" and "Top" conversations. The ID of the user should be provided, instead of <id>.
Followed by	https://www.yammer.com/api/v1/users/followed_by/<id>	Shows a list of all people followed by a user. The ID of the user should be provided, instead of <id>.

Continued on next page

Table C.1 – continued from previous page

Resource	URL	Description
Following	https://www.yammer.com/api/v1/users/following/<id>	Shows a list of all people which are following the given user. The ID of the user should be provided, instead of <id>.

Appendix D

Job titles

In order for research to be performed on the actual job titles of the people in the system, the titles need to be generalized. This means that they need to be subdivided into a set of titles, so the people can be catagorized. Table D.1 shows the mapping from the actual titles to the generalized titles. The titles have been divided according to the first title provided in the Actual title and using other resources, such as LinkedIn.

Table D.1: *The actual and generalized job titles (20th of April, 2013)*

Actual Title	**Generalized title**
Solution Architect, Selling Consultant, Gamification thinker	Architect
Solution Architect	Architect
Scrum Master	Scrum Consultant
Software Developer	Software Engineer
Senior Java Consultant	Senior Consultant
Software Architect	Architect
System Analyst	System Analyst
Consultant	Consultant
Application Developer	Software Engineeer
BPM consultant	Business Analist
Requirements Specifier	Consultant
Software Engineeer	Software Engineeer
Senior Consultant	Senior Consultant
Business analyst	Business Analyst
Senior Manager Project Performance Improvement	Project Performance Improvement
Scrum Leader	Scrum Consultant

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Table D.1 – continued from previous page

Title	Generalized title
Managing consultant	Managing Consultant
Business Analist	Business Analyst
Scrummaster, Agile change agent, coach	Scrum Consultant
Agile coach	Scrum Consultant
System Analyst (Req. Mgt)	System Analyst
Scrum Coach	Scrum Consultant
Expert Group Manager Testing Belgium FS NBS	Manager
Manager	Manager
Specialist in Project Performance Improvement	Project Performance Improvement
Scrum master / coach	Scrum Consultant
Test analyst	Test Consultant
Test Consultant	Test Consultant
Transition Manager	Transition Manager
Engagement Manager	Managing Consultant
Senior Software Engineer	Software Engineer
Senior BPM Consultant / Pega Senior System Architect	Senior Consultant
Thoughtleader mobile & user experiences	Senior Consultant
Senior Consultant / Engagement "Manager" / Expert group Leader BAT	Senior Consultant
Business Analyst/ Requirement Manager	Business Analyst
Young Professional	Consultant
Expert Group Manager	Manager
Trainee	Consultant
ICT consultant	Consultant
Business Technology Consultant	Consultant
Business Analyst - Senior Consultant	Business Analyst

Appendix E

Code samples

During this thesis a lot of application code is written. In this appendix the most interesting parts of thw Badge Crawler-application are listed, catagorized according to their function or algorithm.

E.1 Degree code

Listing E.1: *In and out degree implementation*

```
/**
  * This method calculates the in or outdegree of the given set of nodes,
  * depending on the parameter degree supplied. If
      <code>degree.equals("indegree)"</code>
  * the indegree is calculated. If <code>degree.equals("outdegree)"</code>
      the
  * outdegree is calculated.
  *
  * @param nodes The nodes for which to calculate the degree
  * @param matrix The adjacency matrix which contains the connections
      between the nodes
  * @param degree a string representing either in or out degree.
  * @return a map representing each node with its degree
  */
private def getDegree(nodes: Map[String, Double], matrix: NamedMatrix,
    indegree: Boolean): Map[String, Double] = {
  nodes.foreach({ currentNode =>
    var degree =
      if (indegree) matrix.incommingEdges(currentNode._1).size
      else matrix.outgoingEdges(currentNode._1).size;
     nodes += (currentNode._1 -> degree)
   })
  nodes
}
```

E.2 PageRank code

Listing E.2: *PageRank implementation*

```
/**
  * Calculates the actual pageRank of a given graph. This works using matrix
      multiplication
  *
  * @param nodes the list of nodes for which to calculate the pagerank.
  * @param matrix the adjacency matrix containing the edges of the graph.
  * @return a Map containing the pagerank values of each of the nodes given.
  */
def calculatePageRank(nodes: Map[String, Double], matrix: NamedMatrix):
    Map[String, Double] = {
  var rankedNodes: Map[String, Double] = Map()
  var rank: Double = 0D;

  //Loop through all nodes
  nodes.foreach({ pi =>
    rank = 0D;
    // Look at all incommingEdges of the node
    matrix.incommingEdges(pi._1).foreach({ pj =>
      rank += nodes(pj) * matrix.get(pj, pi._1)
    })
    rankedNodes += (pi._1 -> rank)
  })
  rankedNodes
}
```

Listing E.3: *Stochastic adjustment*

```
/**
  * This method turns the given matrix into a stochastic matrix.
  *
  * @param matrix the adjacency matrix of the graph, containing the edges
  */
def normalizeStochastic(matrix: NamedMatrix) {
  var i: Int = 0
  var rowSum: Double = 0D
  // For each node in the graph
  matrix.getNodes.foreach { node =>
    // Sum all values on the nodes row
```

```
    rowSum = matrix.getRow(node).sum
    // For each node on that row
    matrix.getRow(node).foreach { c =>
      // Normalize the data
      if (rowSum > 0D) matrix.getRow(node)(i) = c / rowSum else
          matrix.getRow(node)(i) = (1D / numberOfNodes)
      i += 1
    }
    i = 0
  }
}
```

Listing E.4: *Primitivity adjustment*

```
/**
  * Primitivity adjustment; Sometimes the surfers do not follow any link on a
  * page, even if available, but jump randomly to a new page.
  *
  * @param matrix the adjacency matrix of the graph, containing the edges
  */
def randomSurfer(matrix: NamedMatrix) {
  var i: Int = 0
  var rowSum: Double = 0D
  // For each node in the graph
  matrix.getNodes.foreach { node =>
    // Sum all values on the nodes row
    rowSum = matrix.getRow(node).sum
    // For each node on that row
    matrix.getRow(node).foreach { c =>
      // Normalize the data
      matrix.getRow(node)(i) = alpha * matrix.getRow(node)(i) + (1 - alpha) *
          1 / numberOfNodes
      i += 1
    }
    i = 0
  }
}
```

Listing E.5: *Normalization adjustment*

```
/**
```

```
  * Normalization adjustment. Takes care all values will add up to one in
      the end.
  *
  * @param matrix the adjacency matrix of the graph, containing the edges
  */
def normalize(matrix: NamedMatrix) {
  var i: Int = 0
  var rowSum: Double = 0D
  // For each node in the graph
  matrix.getNodes.foreach { node =>
    // Sum all values on the nodes row
    rowSum = matrix.getRow(node).sum
    // For each node on that row
    matrix.getRow(node).foreach { c =>
      // Normalize the data
      if (rowSum > 0D) matrix.getRow(node)(i) = c / rowSum
      i += 1
    }
  i = 0
  }
}
```

E.3 HITS code

Listing E.6: HITS *algorithm implementation*

```
/**
  * This method calculates the hubness and authority of a set of nodes.
  * Hubness is set on HUBNESS and authority on AUTHORITY.
  *
  * @param nodes The nodes for which to calculate the hits authority and
      hubness
  * @param matrix The adjacency matrix which contains the connections
      between the nodes
  * @param hitsType either HUBNESS or AUTHORITY can be calculated
  * @param normalized should the result be normalized or not
  * @return a map representing each node with its authority and hubness.
  */
private def calculateHubOrAuthority(nodes: Map[String, Array[Double]],
    matrix: NamedMatrix, hitsType: Int, normalize: Boolean): Map[String,
    Array[Double]] = {
```

```
  var rankedNodes: Map[String, Array[Double]] = Map();

  // Instantiate the normalization variable
  var norm: Double = 0D

  // Set the other type (if calculating authority, the other type is hubness)
  var otherType = if (hitsType == AUTHORITY) HUBNESS
                  else AUTHORITY

  // First calculate the authority for each node
  nodes.foreach({ pi =>

    //Copy the values to a new array (pass by value, not reference)
    var values: Array[Double] = new Array[Double](2)
    values(AUTHORITY) = pi._2(AUTHORITY)
    values(HUBNESS) = pi._2(HUBNESS)

    rankedNodes += pi._1 -> values
    rankedNodes(pi._1)(hitsType) = 0D;

    var edges = if (hitsType == AUTHORITY) matrix.incommingEdges(pi._1)
              else matrix.outgoingEdges(pi._1)

    edges.foreach(pj => if (nodes.contains(pj)) rankedNodes(pi._1)(hitsType)
        += nodes(pj)(otherType))

    norm += scala.math.pow(rankedNodes(pi._1)(hitsType), 2)
  })
  norm = scala.math.sqrt(norm)
  // If needed, normalize the authorities
  if (normalize) rankedNodes.foreach({ pi => pi._2(hitsType) =
      pi._2(hitsType) / norm })

  return rankedNodes
}
```

E.4 Corresponding Badges code

Listing E.7: *Same badges matcher*

```
Sub Calculate()
  Dim r As Integer, c As Integer, z As Integer
  Dim people As Integer, badges As Integer
  'Set the correct amount of people and badge types
  badges = 13
  people = 81 'Worksheets("Sheet3").Range("A1").CurrentRegion.Rows.Count - 1
  Dim result As Integer
  'Check if this action was actually intended
  result = MsgBox("This will take approx. 3 min, continue?", 1, "Warning!")
  If result = 1 Then
    'Clear all data
    Sheet12.Range("B2:CC81") = 0
    'For each person
    For r = 2 To people
      'Check their badges
      For c = 2 To badges
        'If they have more than one of a certain type
        If Sheet4.Cells(r, c).Value > 0 Then
          'Check with all other people if they also have one
          For z = 2 To people
            'But skip yourself
            If z <> r Then
              'Add the lowest amount of correlated badges
              If Sheet4.Cells(z, c) < Sheet4.Cells(r, c) Then
                Sheet12.Cells(r, z) = Sheet12.Cells(r, z) + Sheet4.Cells(z, c)
              Else
                Sheet12.Cells(r, z) = Sheet12.Cells(r, z) + Sheet4.Cells(r, c)
              End If
            End If
          Next z
        End If
      Next c
    Next r
  End If
End Sub
```

Appendix F

Anova results

ANOVA is used to analyze the variance of the data collected from Level Up and the social media service. With ANOVA is determined whether the variance between the groups (Sum of squares between (SSB)) is different from the variance within the groups (Sum of squares within (SSW)). When the SSB is larger than the SSW, this could mean that the difference is not random. Summing the SSB and SSW yields the total amount of variation in the dataset (Sum of squares total (SST)). The Sum of squares (SS), Mean of squares (MS) and DF are used to calculate the F-value and P-value. Before calculating ANOVA, first a α value should be determined. With this α and the various DFs the $F_{critical}$ value can be determined. In order for the variance to be significant, the F-value should be larger than the $F_{critical}$ value. If that is the case, the probability of the result being random is $< \alpha$ (the chance of having an actual difference between the groups is $> 1 - \alpha$. The precise probability of the result being random is denoted as a P-value.

F.1 Anova summary of T01

For each of the algorithms for which the ANOVA was carried out, a small summary is provided. In the summary the count of participants per group, the sum of the data groups, the average of the groups and the standard deviation is provided.

Table F.1: ANOVA *summary of the indegree scores.*

Group	Count	Sum	Average	Standard deviation
One badge	25	63	2.52	2.74
Two badges	16	43	2.69	2.27
Three or more badges	27	193	7.15	8.08

Table F.2: ANOVA *summary of the outdegree scores.*

Group	Count	Sum	Average	Standard deviation
One badge	25	70	2.80	3.35
Two badges	16	58	3.63	2.94
Three or more badges	27	182	6.74	8.93

Table F.3: ANOVA *summary of the PageRank scores.*

Group	Count	Sum	Average	Standard deviation
One badge	25	0.24	9.52E-03	7.38E-03
Two badges	16	0.14	8.83E-03	5.52E-03
Three or more badges	27	0.50	1.84E-02	2.10E-02

Table F.4: ANOVA *summary of the* HITS-*authority scores.*

Group	Count	Sum	Average	Standard deviation
One badge	25	1.37	5.47E-02	5.34E-02
Two badges	16	0.91	5.71E-02	4.22E-02
Three or more badges	27	3.11	1.15E-01	1.10E-01

Table F.5: ANOVA *summary of the* HITS-*hubness scores.*

Group	Count	Sum	Average	Standard deviation
One badge	25	1.41	5.63E-02	6.54E-02
Two badges	16	1.13	7.07E-02	5.88E-02
Three or more badges	27	2.90	1.07E-01	1.13E-01

F.2 Anova results of T01

The ANOVA results of each of the algorithms are provided in this chapter. Table F.6 provides the ANOVA results of the indegree, Table F.7 the ANOVA results of the outdegree, Table F.8 the ANOVA results of the PageRank scores, Table F.9 the ANOVA results of the HITS authority scores and Table F.10 the ANOVA results of the HITS hubness scores. The $F_{critical}$ value for the values described in the following tables is 3.1381, when taking $\alpha = 0.05$.

Table F.6: ANOVA *results of the indegree scores.*

Source	SS	DF	MS	F-value	P-value
SSB	339.19	2	169.60	5.64	0.006
SSW	1955.08	65	30.08		
SST	2294.28	67			

Table F.7: ANOVA *results of the outdegree scores.*

Source	SS	DF	MS	F-value	P-value
SSB	2.20E+02	2	1.10E+02	2.89	6.27E-02
SSW	2.47E+03	65	3.80E+01		
SST	2.69E+03	67			

Table F.8: ANOVA *results of the PageRank scores.*

Source	SS	DF	MS	F-value	P-value
SSB	1.38E-03	2	6.88E-04	3.39	3.98E-02
SSW	1.32E-02	65	2.03E-04		
SST	1.46E-02	67			

Table F.9: ANOVA *results of the* HITS *- authority scores.*

Source	SS	DF	MS	F-value	P-value
SSB	5.78E-02	2	2.89E-02	4.57E+00	1.39E-02
SSW	4.11E-01	65	6.32E-03		
SST	4.69E-01	67			

Table F.10: ANOVA *results of the* HITS *- hubness scores.*

Source	SS	DF	MS	F-value	P-value
SSB	3.55E-02	2	1.78E-02	2.37	1.02E-01
SSW	4.88E-01	65	7.50E-03		
SST	5.23E-01	67			

Appendix G

Functional requirements

A high level, basic list of requirements formed the base of the product developed in this research. These requirements are listed in this chapter in Table G.1. These are also the criteria on which the application has been tested by the test-team. These requirements are not prioritized as each of them needs to be in the eventual product.

Table G.1: *Functional requirements determined for Level Up*

Code	Name	Description	Rationale
FR001	Login	A user should be able to log into Level Up using his Yammer credentials. No other way of login is provided.	Yammer is behind SSO and therefore provides a simple way of implementing SSO type of security for Level Up.
FR002	Restricted user access	Only logged in users should be able to access Level Up and its features.	The application contains sensitive user information, which should not be publicly available.
FR003	Access to images	It should be possible for external applications to access the badge -images	When a person shares a badge approval on Yammer, the image of the badge is retrieved from this service.
Code	**Name**	**Description**	**Rationale**

Table G.1 – continued from previous page

Code	Name	Description	Rationale
FR004	Roles and Functions	Level Up should be able to distinguish between two types of people; players and badges	Some of the functions should not be available for all people in the game.
FR004-1	Player roles	A player in Level Up should be able to: Request badge (FR005), View leader board (FR006), View Player Dashboard (FR007), View Badges (FR008), View latest badge approvals	These are the basic functions needed for the Gamification system to work.
FR004-2	Badger roles	A badger is a player who should be able to access the following additional functions: Access to Management functions (FR009)	A set of people should be able to manage Level Up.
FR005	Request badge	A player should be able to request a badge . On submission of the request an email is sent to the player on behalf of the badgers mailing list.	Requesting badges is the base of Level Up.
FR005-1	Badge request details	The following data should be captured in this request: Player name, Badge name, Request date, Request motivation	These data are needed to confirm a person has actually earned the badge.
FR006	View leader board	A player should be able to view the leader board. It displays the badges earned by all players playing Level Up.	A leader board is an important game mechanic in Gamification and is implemented for engagement and motivation.
Code	**Name**	**Description**	**Rationale**

Table G.1 – continued from previous page

Code	Name	Description	Rationale
FR007	View Player Dashboard	A player should be able to see his dashboard. This consists of the following: A relative leader board containing the two players above (if possible), and two players below the person (if possible). For each person entry its name, badges earned this year and level (the sum of all badges received by the user) should be shown. If a person on the leader board is a king, this should be shown using a King icon and the word "King" in front of the person's name. Player profile, which shows all badges the person has earned from this year, but also from previous years, The latest badge approval, Friends on Yammer and their level (the sum of all badges received by the user)	A dashboard can help engage the player in the game, as the game is made more personal.
FR008	View badges	A player can view the categories in which badges can be earned in Level Up. The list should be populated from the database, whenever a badger adds a new badge , it should be added here.	In order for people to apply for badges, they should be aware which badges exist.
FR009	Management Functions	A badger should have the following functions: A badger can assign other badgers to investigate badge requests, A badger can view its assigned badges, A badger can approve or reject badge requests (For this the badger can provide a message), A badger can add or remove roles of existing users in the system, A badger can add new badges to the system.	The system should be manageable and adaptable to the future needs.
Code	**Name**	**Description**	**Rationale**

Table G.1 – continued from previous page

Code	Name	Description	Rationale
FR010	Email	An email should be sent when: A player submits a badge request (FR005), A badger is assigned to work on a badge request (FR009)	Level Up won't be daily routine neither for the badgers nor for the players. In order to keep people informed on this information, sending emails helps.
FR011	King badge	A King badge is awarded when a player earns 3 different badges in a calendar year. It has the following features: It is an automatic assignment based on the above algorithm. A player does not request for this badge. It has one image. It's displayed on the leaderboard (FR006) and the player dashboard (FR007). The calendar year is determined by the badgers, preferably through management functions), It expires when the calendar year ends.	The King badge is needed in order to select the kings for the Battle of the Kings at the end of the year.
FR012	Star badge	A Star badge is awarded when a player earns 3 badges in the same badge category. It has the following features: It is an automatic assignment based on the above algorithm. A player does not request for this badge. It has one image per badge category. It's displayed on the leaderboard (FR006) and the player dashboard (FR007). It never expires	This is a game mechanic for keeping people engaged in the application.

Acronyms

ANOVA Analysis of variance. xi, xii, 43, 48, 49, 62, 91–94

API Application Programming Interface. 3, 5, 25, 35, 99

CSS Cascading Style Sheet. 31, 34

CSV Comma Separated File. 39

DAO Data Access Object. 35

DF Degrees of freedom. xi, 44, 49, 50, 91, 93, 94

DTO Data Transfer Object. 35

GUI Graphical User Interface. 2

GWAP Game With a Purpose. 13

HITS Hyperlink-Induced Topic Search. xi, xii, 19, 20, 26, 27, 42, 43, 48–50, 61, 88, 92–94

HTML HyperText Markup Language. 31, 34

HTTP HyperText Transfer Protocol. 103

JPA Java Persistence API. 35

JSON JavaScript Object Notation. 31, 35

JSP Java Servlet Pages. 31

MMORPG Massively multiplayer online role-playing game. 12

MS Mean of squares. 91, 93, 94

MVC Model View Controller. 35

ORM Object-relational Mapping. 36

REST Representational State Transfer. xi, 23, 25, 35, 40, 41, 81

SALSA Stochastic Approach for Link-Structure Analysis. 20, 21

SAPS Status, Access, Power and Stuff. 12, 13

SNA Social Network Analysis. 4, 6–9, 14–17, 19, 21, 27, 37, 61

SS Sum of squares. 91, 93, 94

SSB Sum of squares between. 91, 93, 94

SSO Single Sign On. 37, 95

SST Sum of squares total. 91, 93, 94

SSW Sum of squares within. 91, 93, 94

SVO Social value orientations. 12

UX user experience. 1

WWW World Wide Web. 4, 18–21, 26, 104

XML Extensible Markup Language. 25, 81, 102

Glossary

Ajax this abbreviation stands for: Asynchronous JavaScript and XML. It is one way of creating interactive websites, using JavaScript and XML (or Json) to perform the communication. 31

AppEngine a service provided by Google for third party developers to host their software on. 36

badge a basic gamification strategy to reward people with. A badge in the case of Level Up is an image of a shield. A badge is used to show accomplishment and to reward people with. iii, ix–xi, 2, 3, 5, 7, 10–13, 28–31, 33, 39, 40, 42–53, 56–59, 61–65, 75, 91, 92, 95–98, 102, 104

Badge Crawler the application created to gather and process data for the research of this thesis. 3, 23–25, 39, 81, 85

Badger a select group of people which are allowed to approve and request badges on the Level Up platform. iii, 2, 29, 57

betweenness the quality or state of being between two others in an ordered mathematical set (Merriam Webster). 15

Capgemini a large consulting company at which this research was carried out. ii–iv, 1–3, 6, 7, 23, 30, 31, 37, 40, 41, 62, 64, 65, 75–77, 102

Chi-squared a measure to see the amount of difference between the distributions of the a set of groups. 49

degree the number of edges pointing to a and going out of a certain node. This is the sum of the indegree and outdegree. 18, 25, 42

edge a connection between two nodes in a graph. ix, 3, 4, 15–20, 24, 25, 27, 28, 40–42, 102–104

ego centered network the nodes and edges in a graph which form the first level connections of a selected node. xi, 15, 16, 45, 46, 56

F-value the F-value describes the statistically expected level of heterozygosity in a population. It is defined as the total variance or mean square between groups divided by the total variance or mean square within groups (Wikipedia, F-Statistic and Oxford Reference). 43, 49, 91, 93, 94, 102

$F_{critical}$ value the $F_{critical}$ value is the threshold for which the F-value becomes significant. When the F-value is greater than the $F_{critical}$ value, the data for which the F-value was calculated is significant, meaning the data is not random with a chance $> 1 - \alpha$. The α should be determined in order to calculate the $F_{critical}$ value. 43, 48, 91, 93

Gamification a technique which uses game design elements in non-gaming contexts to drive motivational and engagement factors. iii, ix, xi, 1–4, 6–14, 21, 23, 28, 31, 32, 39, 40, 42, 59, 61, 63–65, 79, 96, 102, 103

graph a data structure which consists of a finite (and possibly mutable) set of ordered pairs, called edges or arcs, of certain entities called nodes or vertices (Wikipedia, Graph (data structure)). ix, 3–5, 14–20, 23–27, 40, 41, 46, 102, 103

GraphML GraphML is an XML-based file format for storing and representing graphs (Wikipedia, GraphML). 25

indegree the number of edges pointing to a certain node. ix, xi, 4, 18, 25, 42, 43, 48–50, 59, 61–64, 91, 93, 101

King badge a special badge in the game Level Up. This badge is received when a player earns three badges of three different categories. 29, 30, 98

Kruskal-Wallis a non-parametric statistical analysis tool which determines the difference in the distribution in a set of groups. xi, 49, 50, 59, 62–64

Level Up the Gamification platform created by Capgemini in order to motivate and engage its employees. iii, ix, xi, 2–5, 7, 8, 23, 24, 28–37, 40–42, 48, 57, 62–66, 75, 81, 91, 95–98, 101, 102, 104

Nike$_+$ an activity tracking device which measures and records the distance and pace of a walk or run, and which applies Gamification techniques on fitness activities (Wikipedia, Nike+ipod and Nike+ FuelBand). 10

node representation of the interconnected elements in a graph. Also known as vertex (Wikipedia, Graph). ix, 3, 4, 14–21, 24–28, 42, 101–104

NoSQL database management system which provides a mechanism for storage and retrieval of data that use looser consistency models than traditional relational databases in order to achieve horizontal scaling and higher availability (Wikipedia, NoSQL). 36

outdegree the number of edges going out of a certain node. ix, xi, 4, 18, 25, 28, 42, 43, 46, 48–50, 61, 92, 93, 101

P-value the probability of obtaining a test statistic at least as extreme as the one that was actually observed, assuming that the null hypothesis is true (Wikipedia, P-value). 43, 49, 91, 93, 94

PageRank a link analysis algorithm that assigns a numerical weighting to each element of a graph with the purpose of "measuring" its relative importance within the set (Wikipedia, PageRank). ix, xi, xii, 15, 18–21, 25–27, 42, 43, 48–51, 61, 64, 86, 92, 93

reputation mechanism a mechanism which computes and publishes reputation scores for a set of objects within a community or domain, based on a collection of opinions that other entities hold about the objects (Wikipedia, Reputation system). 4–8, 17, 18, 21, 42, 43, 50, 63–65

reputation system a system that collects, distributes and aggregates feedback about participants behavior. 17

Restful a style of software architecture for creating webservices using HyperText Transfer Protocol (HTTP) functions. 35, 36

Scala a programming language which allows functional programming in Java. 23, 25, 26

sink a node which only has incoming edges. All traffic flows trough a sink, never from a sink. 26

social graph a graph which shows how people are connected to each other. In a social graph people are represented by nodes and their connections by edges. iii, 3, 4, 6, 17, 24, 25, 42, 62

social media websites and applications that enable users to create and share content or to participate in social networking (Oxford dictionary). iii, 3, 5–7, 9, 15, 17, 21, 31, 33, 36, 37, 39, 40, 42, 47, 64, 65, 91, 104

Star badge a special badge in the game Level Up. This badge is received when a player earns three badges of the same category. 29, 98

TrafficRank an algorithm used to determine the importance of pages on the WWW according to the amount of traffic flow from and to a page. x, 21, 27, 28, 47, 57, 58

Yammer a private, enterprise social media service. Yammer is used for private communication within organizations or between organizational members and predesignated groups (Wikipedia, Yammer). iii, 2, 3, 7, 23–25, 33, 37, 40–42, 44, 47, 50, 53, 62–65, 81, 95