FORENSIC ENTROPY ANALYSIS OF MICROSOFT WINDOWS STORAGE VOLUMES

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Abstract: The use of file or volume encryption as a counter-forensic technique depends on the ability to plausibly deny the presence of such encrypted data. Establishing the likely presence of encrypted data is highly desirable for forensic investigations. We claim that the current or previous existence of encrypted volumes can be derived from studying file and volume entropy characteristics using knowledge of the development of volume entropy over time. To validate our hypothesis, we have examined several versions of the Microsoft Windows operating system platform over a simulated installation life-cycle and established file and volume entropy metrics. Similarly we verified the hypothesis that the ageing through regular use of an installation is identifiable through entropy fingerprint analysis. The results obtained and tests devised allow the rapid identification of several volume-level operations and also detect anomalous slack space entropy indicative of the use of encryption techniques.

Key words: File System Entropy, Installation Aging, Encrypted File Systems

1. INTRODUCTION

The use of volume encryption by itself is insufficient to keep data confidential or as a counter-forensic technique when access to key material can be obtained or enforced. This may occur e.g. pursuant to Part III of the *UK Regulation of Investigatory Powers Act 2000*, requiring that a suspect supply decrypted information and/or cryptographic keys to authorised government representatives [1]. A skilled adversary will hence aim to use a combination of cryptography and steganography*to achieve plausible deniability, whilst forensic investigators must identify the presence of encrypted volumes for further analysis as an in-depth manual inspection may not always be feasible.

Entropy is a measure of the amount of information present in a signal or file.**A low entropy measurement implies a well-ordered, well-structured signal whilst a high entropy measurement indicates a signal with little apparent order or structure. Encrypted information, however, must not show discernible order or structure lest this make the encryption vulnerable to various forms of statistical attack i.e. encrypted data must have high entropy. Measurements of entropy and randomness taken against a computer system should reveal some information about the current state of that system and the data stored on it even when file signature evidence has been removed or replaced.

The very presence of high entropy data on a system may therefore prevent a suspect from plausibly denying the presence of encrypted information. However, file compression may result in similar high entropy encoding, requiring a more careful analysis. We have hence sought to characterise the relative entropy found for encrypted and unencrypted (including compressed) data, but also the effects of utilising different operating system versions as well as usage patterns. The research reported in this paper aimed to determine experimentally the extent to which measures of entropy and randomness can differentiate between encrypted and unencrypted data, different computer operating system versions and configurations and typical and atypical computer usage. A large number of Microsoft Windows workstation installations are run through a simulated ageing process consisting of —

- applying patches and updates,
- installing and configuring applications, and
- creating and deleting large numbers of data files of known types.

Forensic images of each workstation were captured at key points during the ageing process and entropy and statistical randomness measurements were taken from each image for each storage volume and every installed image file. In order to verify the results obtained through simulation, a number of images captured from production workstations are analysed and compared.

As Microsoft Windows is by far the dominant platform in terms of desktop systems deployed, we focus here on this platform; analogue experiments for the Linux environment have, however, been conducted with broadly comparable results, only some of these are reported here in the interest of completeness. However, the

*see e.g. the United Nations Office on Drugs and Crime report "The use of the Internet for terrorist purposes", Sep. 2012 discussing steganographic mechanisms used for covert communication by terrorist entities with a case study involving the Revolutionary Armed Forces of Colombia (FARC).

**We rely on the standard Shannon entropy in the following.

Based on "Forensic entropy analysis of Microsoft Windows storage volumes", by P. J.Weston and S. D. Wolthusen which appeared in the Proceedings of Information Security South African (ISSA) 2013, Johannesburg, 14 to 16 August 2013.

existence of several alternative file systems and more frequent significant release changes reduces the time series available for equivalent analysis. The remainder of this paper is structured as follows: In section 2. we briefly outline related work, followed by a description of the experimental setup in section 3. used for the subsequent analyses in sections 4. and 5. for file and volume analysis, respectively. We discuss key findings in section 6. before describing our conclusions and future work in section 7.

2. RELATED WORK

Research into signature and content analysis forms the basis of many file identification techniques, while work on multimedia data in particular is seen as vital to digital forensics. As this is a crucial pre-requisite for effective carving in the presence of fragmented or deleted data, file system behaviour allowing the effective grouping and identification of fragments has been studied by a number of researchers; Holleboom and Garcia investigated and performed experiments on information retention in slack-space for micro-fragments of previous files occupying the same clusters [2] with extensions by Blacher for the case of NTFS [3]; this also provides a further bound on the entropy of such clusters that is to be expected over the life-cycle of a frequently-reused storage medium.

A recent overview of the state of the art of multimedia forensic investigations is given by Poisel and Tjoa [4] while Ahmed *et al*. give examples of advanced methods used to improve file identification [5]. Shannon's analysis of ASCII and entropy scoring building on his namesake's work is of particular interest [6], as is recent work by Wu *et al*. showing how entropy and randomness testing can be used on encrypted images [7]; the tool `TCHunt` by 16 Systems identifies TrueCrypt images specifically by combining a search for volume (including sparse volumes) characteristics of TrueCrypt with a simple entropy analysis. Statistical analysis of file system clusters can yield insights on file types even for isolated clusters as discussed by Veenman [8]; for more specific file analyses, Lyda and Hamrock describe an entropy-driven approach for detecting encrypted malware, albeit relying only on block frequency (binning) to obtain a relatively coarse metric [9]. For the case of packed malware — which is beyond the scope of the present paper — this may not be sufficient if counter-forensic techniques are employed as recently described by Ugarte-Pedrero *et al*. [10]. This is also closely related to the need to predict the composition of file fragments; algorithms for which have e.g. been studied by Calhoun and Coles [11] with related approaches for classification described by Roussev and Garfinkel [12].

3. EXPERIMENTAL SETUP

The focus of the present work is, without loss of generality, on the Microsoft Windows operating system platform. Initially, eight production disk images were captured from pre-existing Microsoft Windows workstation installations using forensic capture tools. A total of 7 variants of Microsoft Windows 7, Vista, and XP were installed in default VMware Fusion 3.1 virtual machines (VM) using the VMware "*Easy Install*" wizard [13] at this time. At a later date, 2 variants of Microsoft Windows 7 and 8 were installed in default VMware Fusion 5.0 virtual machines and a Windows 8 production disk image was captured. The Boot volume of each installation was analysed. In all cases, the file system used was NTFS, and the cluster size set to eight 512 byte sectors. Except as noted, all storage sectors were zeroed prior to installation of the operating system instances. All images captured during this project were captured from Windows installations after the operating system had been shut down. Microsoft Windows workstation installations are categorised in this paper as either "Home" or "Business" depending upon the usage pattern and the installed applications and data. A common application suite — consisting of Microsoft Security Essentials, Adobe Acrobat and Flash Player, and VMware Tools — was installed on all virtual machine images. In addition, Oracle Java and Microsoft Office were installed on business VM images. Open Office, Mozilla Firefox and Thunderbird, Google Picasa, Apple iTunes and the Steam client application were installed on home virtual machine images to reflect different usage patterns. All applications were the latest versions at time of installation (June 2012 or September 2013). Document, music, picture, video and archive files were added to each virtual machine image; business virtual machine images contained relatively more document files, whilst home virtual machine images contained relatively more media files of different types. The relative proportions of each file type is the same in all cases but a different set of files were used for the later workstation images.

A total of 69 VM images were created through a simulated production life-cycle consisting of patching Windows, copying and deleting data files on the Boot volume, and exercising the installed applications. In ascending order of age, the simulated life-cycle stages are referred to in this paper as "*Initial*", "*Patched*", "*Base*", and "*Copyx*" (where *x* is the number of iterations). Captured images are referred to as "*Actual*" with a number identifying the image and a letter suffix indicating life-cycle stage where known ("a" is older than "b", etc.). Newer images are identified by the "new" suffix. So as to obtain images reflecting realistic longer-term use, the authors relied on images obtained from volunteers for validation. However, whilst all images and scripts utilised in obtaining the results described here can be made freely available on request, this does not apply to these validation images for privacy reasons. Encrypted data was obtained by creating TrueCrypt containers of various sizes using AES, Serpent and Twofish encryption algorithms and RIPEMD-160, SHA-512 and Whirlpool hash algorithms; AES with RIPEMD-160 was the default configuration. The same (weak) password was used in all cases, although all algorithms are sufficiently robust to eliminate influence on the entropy of encrypted data.

Data sectors were extracted from the volume images using tools provided in *The Sleuth Kit* [14]. Entropy and randomness calculations were performed on extracted data

	7-Zip File	7-Zip Cluster	TrueCrypt File	TrueCrypt Cluster
Count	237	1539	99	1024
Mean	7.999	7.955	8.000	7.955
Median	7.999	7.955	8.000	7.955
Min.	7.996	7.940	8.000	7.942
Max.	8.000	7.967	8.000	7.967

Table 1: 7-Zip and TrueCrypt Entropy (Bits/Byte)

at the byte level using the ent utility [15]. Where byte-level entropy calculations are impractical or inappropriate, data compression has been used as an analogue; all compression ratios reported in this paper result from GZIP compression at the "-4" compression level, utilising the Lempel-Ziv algorithm at its core [16], albeit utilising the DEFLATE format [17]. We note that not all applications were available for each version of the platform, resulting in some results not being available for all points of a time series; these data sets are reported as far as compatibility was retained. The results do not address possible changes of behaviour of users over time such as migrating from one application or platform to another as such behavioural changes and hypotheses underpinning behaviour were beyond the scope of the research.

4. FILE ANALYSIS

Entropy and randomness was measured at the byte-level for a statistically significant number of test files of various types: the mean and median number of files of each type analysed were 716 and 255 respectively with the minimum number of files of any one type being 11. Media and modern document file formats were found to exhibit high mean entropy in the range 7.270 to 7.981 bits/byte; most executables and older document formats exhibited lower mean entropy in the range 3.822 to 5.989 bits/byte. This reflects the use of improved compression algorithms in the newer file formats.

For file archives, entropy results reflect the relative performance of the compression algorithms used: LZNT1 shows the lowest mean entropy (947 files analysed, mean 7.558 bits/byte) and (G)ZIP and 7-Zip the highest mean entropy (96 files, mean 7.981 and 237 files, mean 7.999 bits/byte respectively). Encrypted TrueCrypt files consistently exhibit the highest possible byte-level entropy. TrueCrypt and 7-Zip clusters analysed in isolation, however, exhibit very similar (lower) entropy to each other (see Table 1).

χ-square, byte mean value, Monte Carlo π, and serial correlation values were calculated for all tested files. The χ-square test indicated that, with few exceptions, only 7-Zip and TrueCrypt files exhibit uniform randomness at the byte level. At the file level it was also noted that TrueCrypt containers consistently return χ-square results slightly closer to uniform randomness than the tested archive files; this does not apply when TrueCrypt containers are viewed at the cluster level (see Table 2).

	7-Zip File	7-Zip Cluster	TrueCrypt File	TrueCrypt Cluster
Mean	256.353	253.776	254.078	254.652
Median	258.247	253.375	254.073	253.750
Min.	190.077	182.750	204.452	185.500
Max.	324.218	340.375	322.160	326.500

Table 2: 7-Zip/TrueCrypt Chi-Square Statistics

4.1 Media File Analysis

Specific analyses were conducted for a number of file types including text, formatted text (XML, PDF), document (different Microsoft Office formats as well as Open Document format files), and media (image, video, and audio) data. Of particular interest in the context of the present paper are compressed file formats, which are characteristic of media data, but also more recent modern file formats noted above. Here, we have analysed basic descriptive statistics for file samples

	MP3	M4A
Count	6465	1088
Mean Entropy	7.967	7.981
Standard Deviation	0.041	0.011
Sample Variance	0.002	0.000
Kurtosis	334.617	80.982
Skewness	-15.283	-7.736
Minimum	6.710	7.822
Maximum	7.995	7.994
Confidence Level(95%)	0.001	0.001

Table 3: Entropy - Descriptive Statistics (Music files)

Table 3 shows that the compressed MP3 and M4A music file formats exhibit very high mean levels of entropy (similar to the entropy levels exhibited by compressed image file formats). Music file formats similarly also exhibit very little variance or deviation from their mean entropy value. For the music file types tested, χ-square randomness indicators have values well above values expected for random data (see Table 4). We can see easily that the tested music file formats do not exhibit randomness at the byte level; this is to be expected given the internal structure of the formats used, but yields a usable and efficient distinguishing feature. It is clearly necessary to perform this type of analysis as can be seen from the compression levels found in common file types; figure 1 provides a summary of the mean entropy for file types; this distribution is notably different once entropy is studied at the block or cluster level.

4.2 System File Analysis

Entropy and randomness values were calculated for Windows system and meta-data files at various points in the (simulated) Windows life-cycle. Entropy-frequency plots of the complete set of files forming each Microsoft operating system were found to be quite different to a

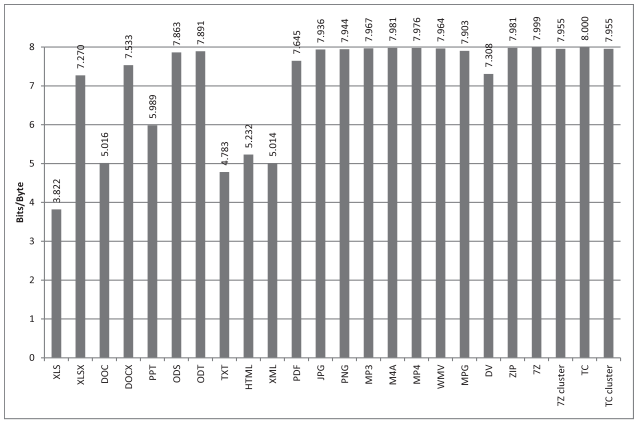

Figure 1: Overall File Mean Entropy (by Type). At least 1000 files per format were analysed.

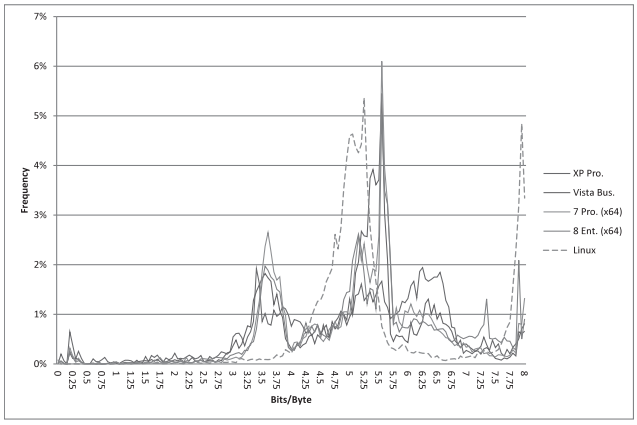

Figure 2: Operating System File Entropy (Initial Installation)

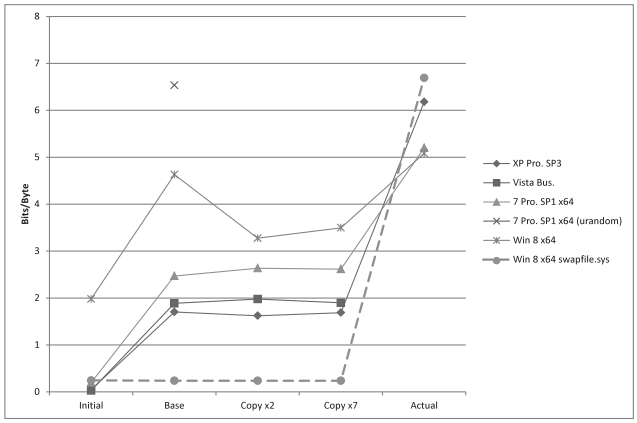

Figure 3: PAGEFILE.SYS File Entropy

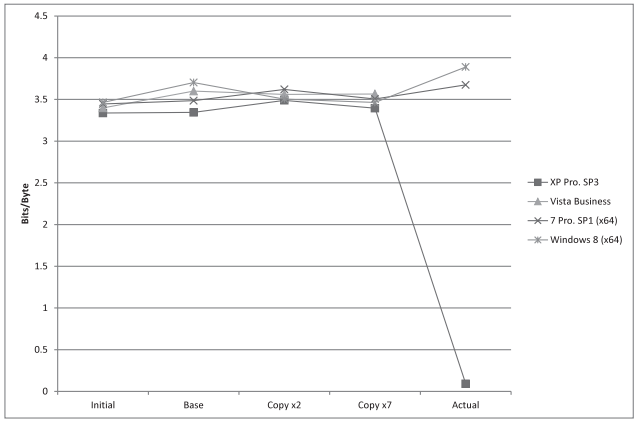

Figure 4: $LOGFILE File Entropy

similar plot of a recent Linux distribution. Figure 2 shows how different versions of Windows were observed to have relatively distinct entropy-frequency plots at initial installation. These distinctions tended to dissipate as data files were added to each installation although it was always possible to differentiate between Windows and Linux instances.

Windows uses the file `PAGEFILE.SYS` for virtual memory management. This paging file is not, by default, cleared when Windows is shut down [18] and hence entropy results can be expected to reflect data that has been swapped from main memory during Windows operation. Windows 8 "*Modern*" Apps use an additional `SWAPFILE.SYS` file to store their whole (private) working when suspended [19].

Figure 3 shows how the entropy of the Windows paging files generally increases over time. The test results indicate that the entropy of the paging file reflects the memory resources available on the host system. The Windows 8 (x64) test images, for instance, show significantly higher paging file entropy because they were generated on a virtual machine with half of the minimum memory requirement for this operating system. The greatest entropy of any paging file observed during testing was a "*Base*" Windows 7 image installed on a disk that had first been initialised by a UNIX urandom device. Paging files with unusually high entropy values may therefore be able to give some information about the history of a Windows system.

Windows 8 "*Modern*" Apps were not consciously exercised on the Windows 8 test images and consequently the Windows 8 `SWAPFILE.SYS` file exhibits extremely low entropy values on the test images. "*Modern*" Apps were, however, used on the production Windows 8 image and in this case swap file entropy is much higher. Entropy figures for the Windows 8 `SWAPFILE.SYS` file may therefore give some indication about the types of applications used on a Windows 8 sytem.

The NTFS journal attribute (`$LOGFILE`) is a fixed size circular log of 4 Kilobyte record pages where each journal page records the changes to be made to the file system [14, pp. 391-392]. Figure 4 shows that the NTFS journal entropy remains stable at around 3.5 bits per byte in most cases; this is to be expected given that the journal file is relatively small and journal pages are regularly reused. Note, however, that the Windows XP "*Actual*" journal contains few journal records and has an unusually low entropy. No explanation for this observation is available

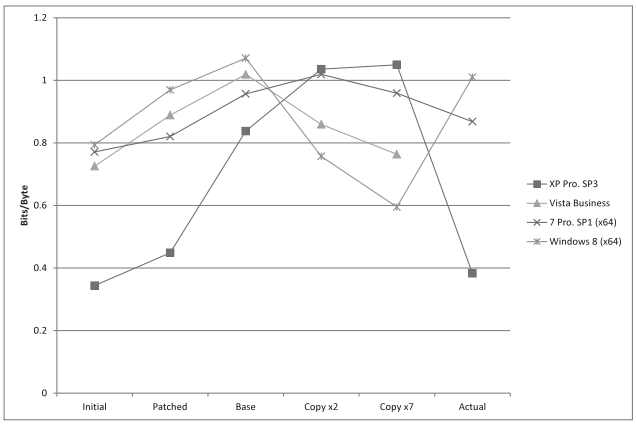

Figure 5: $BITMAP File Entropy

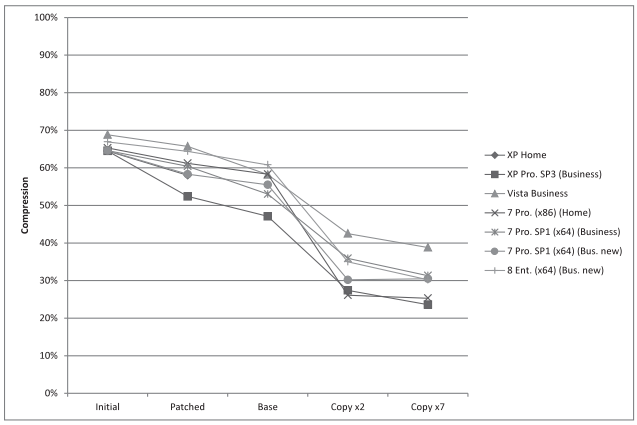

Figure 6: Boot Volume Allocated Space (GZIP)

but such a significant deviation from the norm suggests that the journal file may be an area worthy of further investigation.

The entropy of the NTFS cluster allocation map attribute (`$BITMAP`) should remain low because Windows implements file allocation strategies that aim to minimise file fragmentation and performs regular de-fragmentation in the background. Test results confirm that the `$BITMAP` attribute has low entropy in all cases (see Figure 5).

5. VOLUME ANALYSIS

Storage clusters within the Windows Boot volume are flagged as either allocated or unallocated by the NTFS MFT `$BITMAP` attribute. Allocated clusters are known to contain current, live data whilst unallocated clusters may contain old, disused data. Sequence numbers within the NTFS MFT are incremented as MFT file and directory entries are (re)allocated and give an indication of the likelihood that unallocated and slack space will still contain the initial zeroed values. For the images described in this paper, maximum sequence numbers in the ranges 32 to 13015 and 11775 to 63655 were observed for the VM and production images, respectively.

Volume analysis was performed across the entire Boot volume. The MFT zone — a proportion of an NTFS volume reserved for MFT entries — is not considered in this analysis. When considering Windows XP volumes that have had more than 87.5% of their space allocated, it should be borne in mind that such volumes will have relatively fewer zeroed clusters than other XP volumes due to files having been allocated in the large MFT zone [20]. Figure 6 illustrates how the overall compressibility of allocated space on the Windows Boot volume decreases over time on all tested operating systems (i.e. entropy increases). The compressibility curve for all tested Windows versions begins to flatten in the 25–35% range as high entropy data files are added to the volume over time.

Overall compressibility of unallocated space on the Windows Boot volume decreases over time on all tested

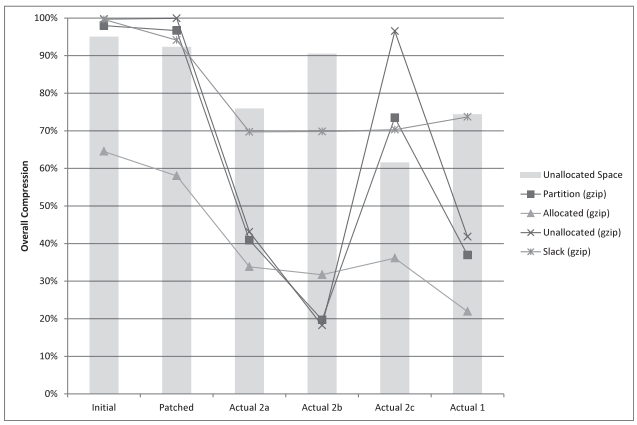

Figure 7: Boot Volume Compressibility (XP Home)

operating systems (i.e. entropy increases), as may be expected. Compressibility of unallocated space remains very high until used sectors containing high entropy data begin to be deallocated. The VM images show a smooth, gradual increase in the entropy of unallocated space as the Windows Boot volume ages. No such progression was seen on production images, however (see figure 7). The results for the "*Actual 2*" production Windows XP image demonstrate that it is possible for the entropy of unallocated space on a file system to be both lower or higher than allocated space entropy depending upon the usage history of the underlying media.

For the "*Actual 2*" image shown in figure 7, the allocated clusters from original media "*Actual 2a*" were copied onto media "*Actual 2b*" that had previously been used almost exlusively for media file storage. The file system was then subsequently copied onto new, zeroed media "*Actual 2c*". While both allocated and slack space compression ratios remained relatively constant during these relocations, compression ratios for unallocated space varied dramatically depending upon the original content of the new media.

The Microsoft NTFS file system stores data in fixed size allocation units called clusters. Files themselves, however,

	Chi-Square
MP3	9984.491
M4A	53119.803

Table 4: Minimum Chi-Square (Music files)

are seldom exact multiples of the cluster size and hence a certain proportion of the last cluster allocated to a file is not used and data could potentially be hidden there [21]. The unused space in a cluster is known as file slack. It is well-known that Microsoft Windows will fill unused space in the last sector into which data is written with zeros ("RAM slack"), but that it will not write data into any completely unused sectors in the cluster [14, 22].

Each file will therefore have one potentially lower entropy sector containing RAM slack plus potentially several further sectors which retain the data from whatever previously occupied them. In the case of a clean (zeroed) disk, therefore, slack space should overall have very low entropy because most of the sectors allocated to file slack are zeroed. Over time, however, as files are deleted and sectors are reallocated then the overall entropy of slack space should increase (although it should always remain comparatively low due to the zeroed RAM slack).

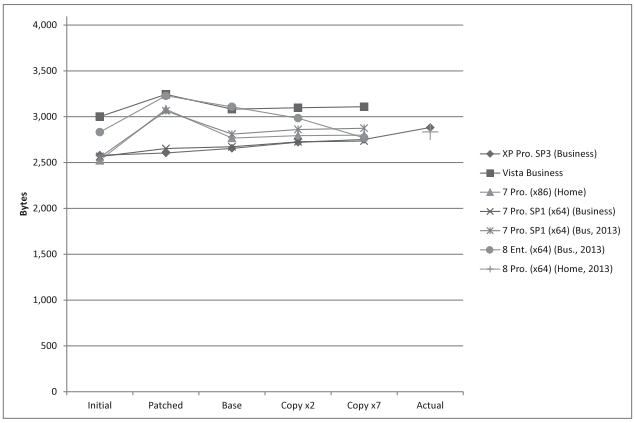

Figure 8: Mean Slack Space per File

Figure 8 shows that the mean slack space per file remains relatively constant over the life cycle of the Microsoft Windows operating system and applications, and that there is no significant difference in the mean value between versions of Windows investigated here. For all tested images the mean slack space per file on the Boot volume is well above the 2048 byte value that we would expect for purely random usage of 4096 byte clusters. This is potentially caused by Windows installations containing many files that are much smaller than half a cluster in size but may be an area worthy of further investigation.

Figure 9 shows that in the early part of the Windows life-cycle, slack space entropy — on initially zeroed storage media — is very low and then begins to gradually increase as the Windows installation ages and clusters are reallocated. The lowest slack space compression

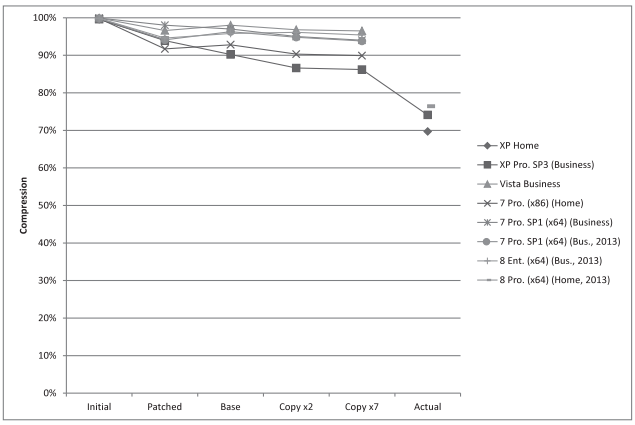

Figure 9: Slack Space Compressibility

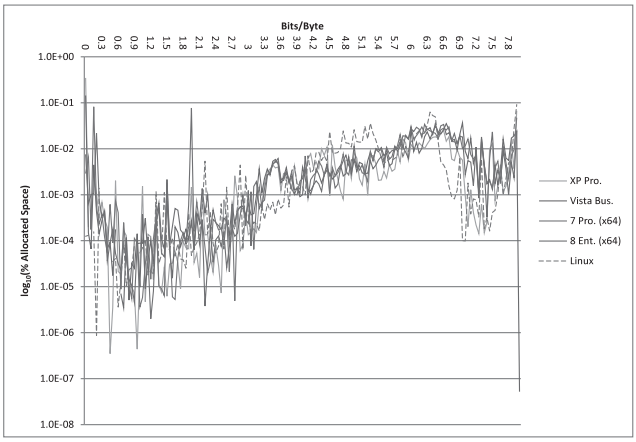

Figure 10: Allocation Unit Entropy (New Installation)

ratios were observed on the production Windows images and varied between 65% and 81%. In an attempt to identify an upper bound for slack space entropy, a boot volume was initialised to pseudo-random values (using a Unix "`urandom`" device) before Windows was installed; a slack space compression ratio of 57% was observed in this (approximate worst) case. We note that at the time of writing no actual volumes that had been in use for sufficiently long existed for Microsoft Windows 7, hence figure 9 only shows these data points for the case of Microsoft Windows XP volumes.

The "aging" of installation also is a potentially relevant element of information in that it not only affects the entropy of different elements of the volume such as overwritten but subsequently deleted or otherwise orphaned storage, but also serving as an indicator of an attempt to remove potential evidence by wiping a file system and subsequently replacing files; this may e.g. be the case if a system that had previously been infected with malware is replaced with a known good instance prior to the analysis taking place. Figure 10 shows the initial entropy per allocation units (normalised as bits per byte) plotted against the fraction of the volume occupied by allocation units (files) of this entropy.

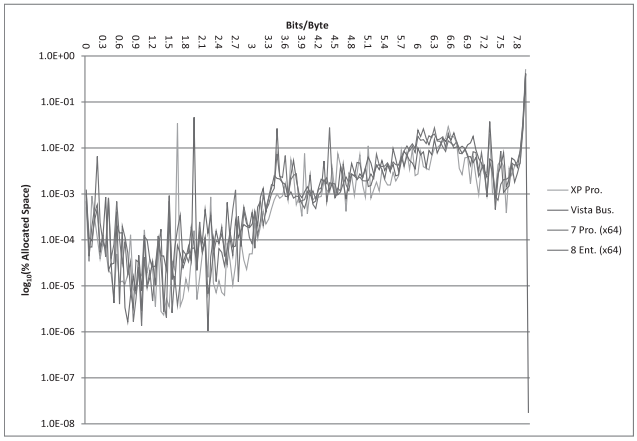

Figure 11: Allocation Unit Entropy (7 Generations of Use, Approx. 2 Years)

Figure 11 then shows the changes in entropy per allocation unit after seven aging iterations approximating 2 years of regular desktop use. Even without a detailed statistical analysis, the "aging" effect is clearly visible. However, whilst one would naïvely expect the entropy distribution to shift rightward, this is not necessarily the case.

We note that figure 10 also contains a plot for the initial distribution for a Linux installation; resource limitations did not allow analogous experiments to be conducted for Linux, so only results for different Windows variants are reported here.

6. ANALYSIS

A combination of entropy and randomness testing appears to be capable of detecting encrypted files from file content alone. Encrypted and highly compressed data prove to be effectively indistinguishable when only small amounts of each are analysed; a size boundary for reliable differentiation is not established in this paper.

Frequency analysis of the entropy of files on a Boot volume can give an indication about which type of operating system is installed. The system files located on a Windows Boot volume have relatively low entropy. High overall entropy in both allocated and unallocated space therefore indicates the presence of significant quantities of (high entropy) user data on the volume.

Allocated space compression ratios of around 30% appear to be typical for production Windows Boot volumes that have been used for some time; ratios significantly below this can be considered anomalous. Unallocated space on a Windows Boot volume does not appear to have a "typical" entropy value. An unallocated space entropy value significantly lower than the typical allocated space entropy value may merit further investigation.

Unallocated space with very low entropy indicates a recently created volume or one that has been deliberated wiped. When data is copied between volumes, it is likely that slack space will be transferred but unlikely that unallocated space will be transferred; this may lead to a mismatch between slack space entropy and unallocated space entropy from which we might infer a transfer or volume sanitisation.

Slack space compression of 65-75% is typical for a Windows installation that has been used for some time. Slack space compression ratios below 60% are unlikely to occur in normal Windows operation and would merit further investigation.

7. CONCLUSIONS

The results presented in this paper demonstrate that entropy and randomness measurements may be able to differentiate between encrypted and unencrypted data files with a reasonable degree of confidence, permitting automation. These same measurements may also help identify atypical Windows usage such as volume copies, volume wipes and unusually high entropy slack space. A strong result obtained in the analysis is the correlation of the compression ratio for slack space with the age of an installation, as any anomaly is likely to warrant further investigation. For the case of files we have found that — provided sufficiently large files are available for analysis — a combination of entropy and randomness tests will suffice to identify characteristics of encrypted data without having to rely on meta-data.

An adversary aware of these findings may attempt to cast doubt upon these measurements by highlighting that similar results can be obtained when analysing highly compressed files. When small amounts of data are involved then this can be an effective defence because entropy and randomness tests struggle to reliably differentiate encrypted and highly compressed data. For larger amounts of data, however, an adversary may be forced to use alternative defences such as filling unallocated storage with high entropy data and monitoring slack space entropy. Such countermeasures may themselves be identified as atypical usage which trigger further investigation.

Future work will seek to study the applicability of the results reported here to other types of (local) file systems and newer editions of the operating systems studied. We are particularly interested in analysing the characteristics of newer, log-based file systems as this has thus far not been studied to the best of our knowledge.

A further natural extension of the work described here is also the development of counter-forensic mechanisms that either avoid yielding tell-tale signatures identified, or to provide extensive decoys to increase the work-load and extent of manual investigation required as well as creating a plausible deniability scenario. Attention has been paid in the present work to facilitate automation of measurements as far as possible; it appears to be highly desirable to repeat measurements particularly at the file analysis level regularly as changes in file formats and e.g. encoders in

case of multimedia files may change over time, skewing results.

The data and mechanisms used in generating the results described here are freely available from the authors subject to licensing conditions for the software used in the image files themselves except where privacy restrictions do not permit the release of personally identifiable information.

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MOVING REPUTATION TO THE CLOUD

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Abstract: Reputation is used to regulate relationships of trust in online communities. When deploying a reputation system, the requirements and constrains of the specific community needs to be accommodated in order to assist the community to reach their goals. This paper identifies a need for a framework for a configurable reputation system with the ability to accommodate the requirements of a variety of online communities. Such a reputation system can be defined as a service on the Cloud, to be composed with the application environment of the online community. Consequently, this paper introduces the concept of RaaS (Reputation-as-a-Service) and discusses a potential framework to support the creation of a RaaS. In order to define the framework, research is conducted into features of SaaS (Software-as-a-Service) architecture components, user requirements for trust and reputation, and features of current centralized online reputation frameworks that can be configured in order to support a reputation service on the Cloud.

Key words: Reputation-as-a-Service, trust, reputation, Software-as-a-Service, reputation framework, cloud service.

1. INTRODUCTION

Online shopping has grown significantly in the past years and it is predicted that such sales will increase annually by 10% for the next 4 years [1, 2]. People are influenced by product reviews to make purchasing decisions and therefore tend to buy from online stores with a good reputation [1]. As online shopping is characterized by insecurity, anonymity, lack of control and potential opportunism, online communities should take the necessary steps to ensure that participants are trustworthy.

For online trading communities such as eBay, a centralized online reputation system is used to compute and publish reputation scores for service providers, services, products or entities such as buyers and seller within a community. The reputation score reflects the collection of opinions or ratings that entities have about the objects. Ratings are provided to a reputation algorithm to compute reputation scores [3]. In order to be effective, reputation managers need to accommodate the specific needs of the communities where they are deployed.

Consider the example of Organization ABC, an online store for a start-up company that sells products to consumers over the mobile web. As trust and reputation is a major component to enable m-commerce, the online store of Organization ABC needs to deploy a reputation system to control trust relationships between consumers, suppliers and their portal. As there is no off-the-shelf reputation system to integrate into their application environment, and it is expensive to custom develop, the m-commerce web site may initially be implemented without it. Ideally, Organization ABC needs a reputation system that is simple to use, with easy to understand ratings between 0 and 5 to ensure the growth of the community. In another type of online community, where crime incidents are posted and recorded with mobile phones, a reputation system is needed to ensure that no malicious or false incidents are reported. The requirements for this reputation system may be very different to those of the online store of Organization ABC. This highlights that a configurable or customizable reputation system is needed that can support multiple online communities in a cost-effective and efficient manner.

Recently, a business model for software applications namely SaaS (Software-as-a-Service) has emerged which lowers the cost of development, customization, deployment and operation of applications [4]. As SaaS applications generally support the concept of software application configuration and customization, this research proposes to present a configurable reputation system as a SaaS solution. Here, a multi-tenant architecture is followed where organizations pay only for the features that they access, and are able to configure or customize the reputation system to suit their community's needs.

The contribution of this paper is to identify requirements and challenges in order to define a RaaS (Reputation-as-a-Service) framework. As trust and reputation systems can be very complex, the focus of this research is the definition of a RaaS framework that provides similar but configurable functionality currently supported by central online reputation systems.

In the next section, trust and reputation is defined for this research. Five general components of reputations systems are given which is referred to throughout the paper. The requirements for a RaaS component is identified by considering SaaS configuration aspects, user requirements for trust and reputation and finally requirements from

Based on "Towards reputation-as-a-service", by C. Hillebrand and M. Coetzee which appeared in the Proceedings of Information Security South African (ISSA) 2013, Johannesburg, 14 to 16 August 2013.

reputation frameworks. A RaaS framework is presented and the paper is concluded.

2. TRUST AND REPUTATION

Trust and reputation is present in a variety of online communities. Trust is the individual's perspective on a particular service or product and reputation is a group's perspective on a particular service or product [5]. As trust and reputation are concepts that are often used interchangeably, they are now defined for the purposes of this research.

2.1 Trust

Trust is challenging to define as it manifests itself in many different ways in varying contexts. Almost every aspect of daily life is supported by some form of trust. For example, in Figure 1, consumer X, the trustor, orders products from organization ABC, the trustee. For this research, the following definition of trust is adopted. The trust of consumer X in organization ABC is defined as the level of subjective probability that organization ABC will deliver high quality products on time [6].

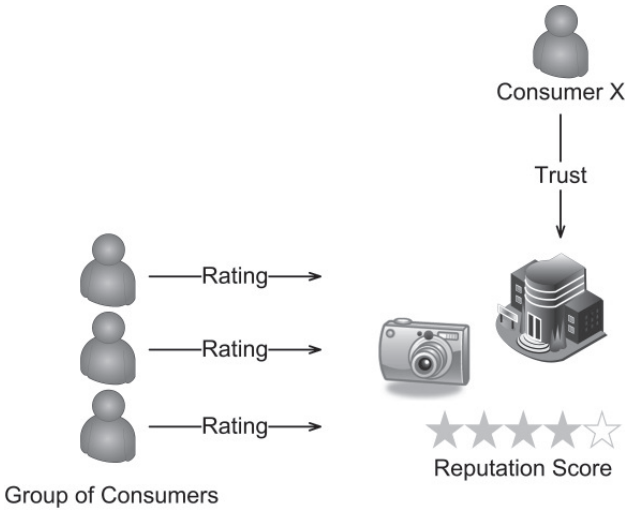

Figure 1: Trust and Reputation

The trust of consumer X in Organization ABC is affected by trust properties such as transitivity, subjectivity and the asymmetric nature of trust [7]. If Organization ABC has the reputation of delivering high quality products, consumers automatically assume that any product of Organization ABC is also of high quality due to the property of transitivity, suggesting that trust is transferable. But, as both consumer X and Z can have different levels of trust towards the same organization ABC, trust is subjective. The asymmetric property of trust is defined by the fact that consumer X needs to trust that organization ABC will deliver the necessary services, but organization ABC needs to trust consumer X to pay on time.

Closely related to trust, is reputation. In the next section the concept of reputation is addressed in order to identify elements that it consists of.

2.2 Reputation

Reputation can be considered as a collective measure of trustworthiness [8]. In order to better regulate relationships in online communities, opinions about interacting parties' past behavior is collected and aggregated in order to define a summary evaluation, or reputation. The predictive power of reputation supposes that past behavior of a participant is indicative of their future behavior.

In Figure 1, reputation is illustrated by a group of consumers' opinion on a specific product. The group of consumers in Figure 1 gives a product a good rating over time, ensuring that the product has a good reputation score [9]. In this paper the term "rater" is used to represent a participant or consumer who assigns ratings for others. Reputation is calculated by incorporating past experiences, direct experiences and recommendations using various algorithms and models for this purpose [10]. One party can thus trust another based on their "good" or "bad" reputation.

A reputation system is an application that facilitates the process of calculating and evaluating reputation for a specific community. The five main components found in reputation systems and models are [11]:

1. *Gathering behavioral information* where direct experiences, and experiences of acquaintances of consumers, recommendations from others, transaction history, pre-trusted entities and raters reliability are collected.

2. *Scoring and ranking* of entities are done next resulting in a reputation score, computed using averages, fuzzy logic, or Bayesian networks.

3. *Entity selection* is done next using the reputation score and other utility functions as specified.

4. *Transaction* is carried out with the selected entity.

5. *Reward and punishment* is finally given by assessing the transaction and giving a rating.

Most current reputation systems are built using these common components, but for a specific context and application domain, using proprietary vocabularies [12]. Each defines its own method to query, store, aggregate, infer, interpret and represent reputation information.

In order to be able to define a cloud-based reputation service that can be usable by different communities, the next section investigates the requirements that such a reputation service framework or RaaS framework should comply to.

3. REQUIREMENTS FOR A RAAS FRAMEWORK

In order to determine requirements to define a RaaS framework, this research now reports on the two main drivers for a RaaS framework namely general SaaS application requirements and current state-of-the-art reputation system requirements to create a comprehensive list of requirements for the RaaS framework.

3.1 Requirements for SaaS applications

SaaS applications are deployed on cloud infrastructures and exposed to applications or users to be consumed over the Internet. SaaS is pay-per use, meaning organizations only have to pay for the features they want to use in an application, making it a cost effective solution [13, 14]. The main motivation for organizations adapting SaaS applications is to reduce IT support costs, ensure business agility and outsource hardware and software maintenance. SaaS architecture, design attributes and application requirements are now investigated to identify requirements that a cloud reputation service needs to meet.

SaaS application architecture: A SaaS application such as a reputation service or RaaS is integrated with existing enterprise systems, as shown in Figure 2. The architecture is based on service-oriented architecture design principles.

To create a cohesive application that incorporates a RaaS, the orchestration of the flow of data from the service to the end user is crucial. For example, it is important to send data such as a valid rating for a specific product to the right retail system at the right time. Furthermore, SaaS-to-enterprise integration poses challenges such as semantic mediation, data quality, interface mediation and other logical operations when moving data between domains so that the data is useable when it reaches the target system. Depending on the business requirements and integration capabilities of the chosen SaaS product, the integration approach is generally not trivial. Even though SaaS applications are exposed via comprehensive APIs to ease the integration process, it may still be the case that a custom SaaS integration layer is needed.

To support application integration, SaaS application architecture generally consist out of 3 main layers namely the consumption, service and data layer [13]. Starting at the bottom of Figure 2 the service and data layers are found in the *SaaS component*. Here are reusable software components and their data are exposed as services preferably using REST APIs (Representational state transfer) [15]. Messages are formatted in in JSON (JavaScript Object Notation) [16] format style or in XML (Extensible Markup Language) [17] format.

The service layer is defined by multiple sub-layers such as the service wrapping, schedule and service technology application layers. Support is provided to administrators of tenants to customize services. To persist SaaS specific data, the data layer stores rating, reputation and other relevant information.

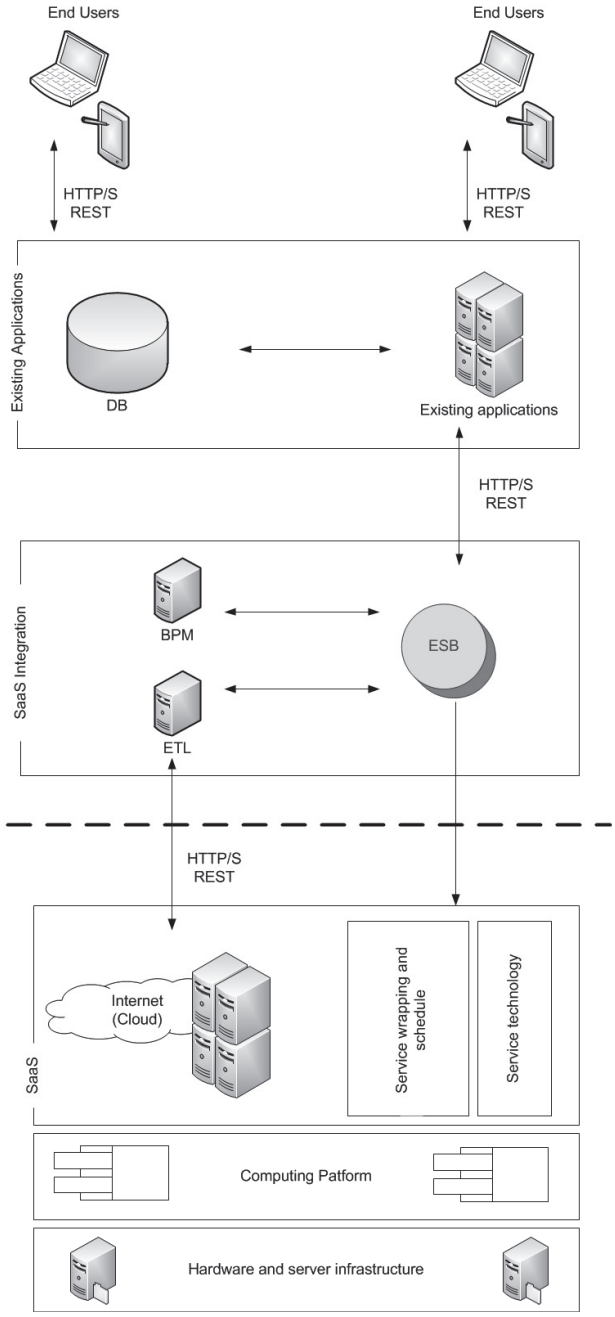

Figure 2: SaaS Architecture Layers

Towards the middle of the architecture, enterprise integration is supported by the *SaaS integration component* using integration products such as an ESB (Enterprise Service Bus) that provides orchestration capabilities. In this way, enterprise activities performed by existing enterprise applications are combined with activities of SaaS applications.

Finally, the consumption layer presents end users with an integrated view of information generated by these orchestrated applications.

To be successfully integrated into other enterprise applications, an important requirement for SaaS applications is to

ensure that integration with other applications is seamless. To ensure that many types of enterprises can integrate SaaS applications, design attributes, discussed next should be addressed.

SaaS design attributes: In order to design a RaaS component, several design attributes should be taken into consideration to ensure conformance to a typical SaaS application [18]:

- Multi-tenancy to ensure that a single instance of a RaaS can be used by multiple tenants and their clients with different needs and functionalities.
- Single version provides the capability that only one version of the RaaS is exposed to clients.
- Logical data separation accommodates the storage of different tenants' data such as configuration and rating data is in their own data domain.
- Application integration, as mentioned in the previous section, should be supported so that applications of tenants can integrate functions of the RaaS into their applications with ease.

To ensure the flexibility of SaaS applications, an application is configured in such a way to support design attributes and integration processes. Next, SaaS application requirements for RaaS are discussed to support configuration.

SaaS application requirements for RaaS: The focus of a RaaS model is to deliver software functions to many clients over the Web with a single instance of a software application running on a multi-tenancy platform [19]. However, every tenant that needs to use a RaaS supported with this model can be unique, requiring changes to the reputation system.

Tenants may have a different industry focus, their customers may behave differently, they may support diverse product offerings and have different regulations, organizational culture and operational strategy. These features require RaaS components to be tailored, by leveraging two major approaches namely configuration and customization [19].

Configuration does not involve source code change of the RaaS application and support differences through setting pre-defined parameters, or leveraging tools to change application functions within pre-defined scope, such as adding data fields, changing field names, modifying drop-down lists, adding buttons, and changing business rules. On the other hand, customization involves RaaS application source code changes to create functionality, leading to a more costly approach for both SaaS vendors and clients.

There are seven fundamental configuration and customization requirements that can be tailored, to make the RaaS component as flexible as possible [19] namely:

- Support for different organization structures require the ability to add, delete and changes roles.
- Support for different types of data can be made possible by adding custom fields and types, and deleting data not needed.
- Support for different processes requires tasks to be switched, added and reordered and their roles to be changed.
- Business rules can be modified by changing or setting rules and the rule triggers.
- Reputation computations can be made more generic by adding or changing actions or triggering actions at different points.
- The user interface can be changed with respect to the look and feel, the data presented and the addition of data.
- Reporting can be changed with respect to style, dataset used and query rules.

In summary, the RaaS should be developed to have standardized software features to serve as many clients as possible using a configuration approach. The RaaS developer needs a strategy to enable self-defined configuration by their tenants without changing the SaaS application source code for any individual tenant [19].

The RaaS environment needs to be thoroughly analyzed to determine the common configuration requirements. In conjunction, a sophisticated web based tool is needed to allow clients to configure the RaaS service themselves.

The next step is to investigate the second main driver to determine RaaS requirements, namely those stemming from trust and reputation systems.

3.2 Trust and reputation system requirements for RaaS

Centralized online reputation systems, which is the focus of this research, collects users' opinions on products, transactions and events as reputation information, to aggregate and publish it. Many trust and reputation models have been proposed, each targeting different contexts, with their own unique features. While most research focuses on addressing the ever-increasing complexity, not much attention has been paid to the process of integrating reputation systems into applications. The next section has the aim of identifying a set of basic requirements to be addressed the RaaS by firstly investigating real-world user requirements, and then general trust and reputation system components.

User requirements for trust and reputation systems: Previous research [10] collected formal user requirements for trust and reputation systems from system developers. It was found that users required a clear, layered and pluggable architecture for representing the calculation process of the trust score. Categorized user requirements were found to be closely coupled with the previously discussed five components found in reputation systems [20].

User needs for each of the first three components were identified as follows:

- Information Gathering
  - The success of each interaction needs to be rated and quality parameters continuously monitored.
  - Simple and intuitive rating scales should be used.
  - The quality parameters of a service should be controlled and certified by a trusted party; ratings of such a party can be used as a starting point for trust computation.
  - Raters reliability must be controlled as they could provide dishonest ratings.
  - Initial rating should not influence or bias subsequent votes.
  - Similarity between recommenders' preferences should be considered.
  - Trust values decay and become invalid over time.
- Scoring and Ranking
  - There is a need for a single trust rating which is calculated by taking into account different service aspects and their weights.
  - The calculation should be an aggregation of all weighted aspects, similar to an "average".
- Entity Selection
  - When entities or services are selected, they should be sorted according to their trust rank and made comparable to each other.

By considering such a user-centered design approach, the proposed RaaS component can be created to fulfill the needs of users as far as possible. General reputation framework requirements are discussed next.

Reputation system framework requirements for RaaS: The focus of this section is to identify major characteristics of reputations systems to identify requirements for the RaaS component. In order to achieve this, an adapted framework is defined from the work of others [21–23]. There are eight elements which are discussed following the phases of reputation management components from information gathering, to scoring and ranking and entity selection. The elements, shown in Figure 3 include:

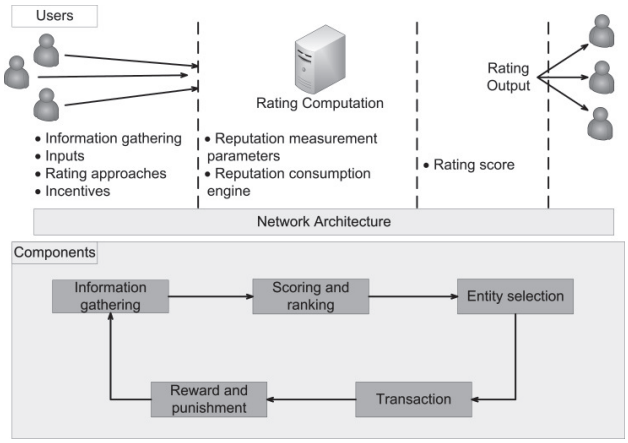

Figure 3: Reputation Manager Framework

1. Network architecture
2. Information gathering
3. Inputs
4. Rating approaches
5. Incentives
6. Reputation measurement parameters
7. Reputation computation engines
8. Rating score

Figure 3 shows how the eight elements at the top of the diagram fit in with the first three components at the bottom. Network architecture supports the framework across all components, whereas information gathering, inputs and rating approaches and incentives are found under the *Information Gathering* component. Reputation measurement parameters and reputation computation engines fall under the *Scoring and Ranking* component and rating score under the *Entity Selection* component.

Each of these elements are now described, starting with the network architecture.

a) Network architecture: The network architecture of a reputation system can either be a centralized, decentralized or hybrid architecture [8]. The network architecture determines how information is gathered and stored. For this research, the RaaS component needs to follow the cloud architecture, thereby limiting the scope of architecture choice. In a centralized architecture, all data is stored in a central repository with all reputations scores publicly available to participants. For distributed or hybrid reputation systems, there is no central point where ratings are submitted or feedback can be obtained. Instead, each participant is given the responsibility to collect ratings from others. For a RaaS component this is not a viable option as the cost and complexity level would be too high. A centralized architecture is simple and cost-efficient, and

conforms to the RaaS and user requirements identified previously. This choice directly influences the discussion of the next elements, as they need to comply with this requirement.

Next the elements related to the *Information Gathering* component are discussed. For this research, a transaction between two participants is the basis of a rating. Generally, a participant cannot rate another one without having had a transaction with him. After a transaction, participants usually have no direct incentive for providing rating about the other party. The information gathering phase should be carefully designed to address this issue.

b) Information gathering: The information gathering phase collects rating inputs over a period of time. There are a numbers of important aspects to consider such as [24]:

- the collection channel,
- the information sources,
- the number of raters, rating granularity and reputation of raters,
- collection costs.

Collection channels can be direct or indirect. Direct channels collect information from raters just after the transaction, by sending emails asking them to do a rating or by using a 3rd party for rating collection. Indirect channels collect information from other reputations systems, increasing complexity of information gathering.

Most online reputation systems consider reputation ratings from a global perspective. For example, eBay's feedback forum provides feedback profiles of sellers and buyers publicly to the all users. The shortcoming of such a global view is that these values lack personalization [5]. Information can be gathered from past experiences, direct experiences and recommendations [20]. The gathered information plays a major role to calculate a reputation score for a particular user or product. This information might come from several sources such as direct experiences with the targeting entity, neighbours of participants, acquaintances, the group the participant belongs to or organizations. In this regard it is important to consider the set of raters, their expertise and credibility [24].

A sufficient number of raters who rate transactions can help a reputation system to avoid personal bias whereas a restriction on the number of raters may influence level of detail between raters and objects being rated. A reputation system can be defined to have no restrictions on the number of raters leaving ratings, which means anyone can rate; or only registered participants can provide a rating; or only some registered raters can provide a rating after a transaction has finished such as eBay allows. It should not be allowed to rate a transaction or object more than once, for example, in eBay if buyers and sellers transact, the reputation system will only allow one rating per transaction to avoid the manipulation of the reputation score.

Directly related to the number of raters who rated objects is granularity [25], which indicates if the model is context-dependent or not. As raters may have a good reputation for their expertise in one domain, and a low reputation for another, granularity identifies how information sources associates to the reputation object. When a system allows any raters to do a rating, the granularity is usually very loose. If a reputation system requires information sources to have a good credibility to leave reviews this increases the cost for a rater to provide a rating which in turn reduces the number of invalid ratings.

The reputation of the rater should be considered by having other participants to give feedback on those ratings. Some reputation systems have a ranking mechanism for their users, called the Karma mechanism that records every action of a user and gives points to it [23].

Finally, the input collection costs should be considered. This is the cost that indicates how much time it takes to collect a single unit of reputation information, where collection channels can have an important effect on this cost [24].

Next, the type of information source is described.

c) Inputs: Different information formats can be chosen based on the way in which they will be used in a reputation system. Some reputation systems support arithmetic operations and other evidence where numeric quantification is more appropriate. It can also be possible to provide a mapping from qualitative to numeric labels. For example, ratings such as a score between 0 and 10 can easily be aggregated to an overall score, to give a comparable value between reputation objects. On the other hand, text reviews contain detailed information which can be very useful.

Generally, a rating can be expressed as either a quantitative or Boolean format [21]. A quantitative metric is a measurable input such as a value between 0 and 10 whereas a Boolean format is either 0 or a 1 to represent ”like” or ”dislike”. As it is important that the reputation score is useful to the community where it will be used, the RaaS can be configured for this purpose.

In order to ensure the completeness of ratings collected, rating approaches are discussed next.

d) Rating approaches: A larger variety of rating information can give a better view of a reputation object as it provides a more complete picture. For example, travel reputation systems can allow participants to rate hotels for their value, rooms, location, cleanliness and service separately [24].

In single-criterion rating systems or binary rating systems, participants reveal their general opinion with regards to a

reputation object, resulting in reputation information that is not too reliable and accurate.

In systems where multiple-criteria can be used, better quality reputation scores can be defined. A set of criteria needs to be defined and a rating is provided for each. This can allow a participant to choose a partner based on specific criteria that matches his own. On the down side, many rating criteria may reduce the evaluators' motivation on leaving ratings. This can be overcome by making some criteria optional to rate.

Next the role of incentives in information gathering is discussed.

e) Incentives: Raters of a reputation system may have different motivations for providing ratings. Incentives are important as their absence drives only some of the users to voice their opinions and report feedback where those with a moderate outlook are unlikely to provide ratings [25]. This results in an unrepresentative sample of ratings and opinions. For example, reputation systems have incentives for raters such as sellers to behave honestly in order to be chosen by buyers as this can increase their profit through the increased amount of transactions. These incentives are necessary because fabricated ratings can promote specific sellers or to discredit others - e.g. authors can write fake reviews on Amazon in order to boost the sale of their own books. In order for RaaS to be implemented successfully, the motivations for providing a rating should be identified.

There are various types of motivations [23] such as altruistic motivation which is in favour of doing good to users being rated and can be classified as tit-for-tat, friendship and exploiting opinionated incentives. Commercial motivation, is used to generate revenue and is categorized as direct revenue incentives and branding incentives. Egocentric motivation is used for self-gratification and is categorized as fulfilment incentives and recognition incentives.

By explicitly rewarding participants for reporting feedback, rewards made by the reputation systems must cover the cost of reporting feedback to encourage more participants to report, giving a more representative set of ratings. In addition, rewards must be designed so that selfish participants are convinced to rate truthfully to advance themselves [25].

The next section now considers the next reputation component namely the *Scoring and Ranking* of ratings. Here, the reputation computation engine and rating approaches are discussed.

f) Reputation computation engines: One of the most critical features of a reputation system is the reputation computation aggregation algorithm. Such an algorithm integrates ratings into one score, and at the same time needs to ensure that bad raters are identified and removed to obtain accurate ratings. There are many complex aggregating algorithms that have been proposed such as fuzzy models and Bayesian systems.

Currently, most online reputation systems as eBay and Amazon choose to use simple algorithms [8], such as summation, average or percentage. Simple summation adds all of the ratings, regardless if it is positive, neutral or negative and the calculation is easily understood and adopted by users [8, 21]. Unfortunately, this feedback metric is flawed, for example, if a user has 10 positive feedback points out of 10 transactions and another has 20 positive and 10 negative feedback points out of 30 transactions, they would have the same reputation score [5].

Average rating is based on the same principle as simple summation, however average rating is perceived as more accurate. Ratings can also be calculated by means of weighted average ratings. This infers that each user has a credibility score that determines their weight ratio [5]. Many interesting aggregating algorithms have been proposed that can be classified into five categories [26]:

- By averaging ratings, simplicity in algorithm design is ensured and low cost in system execution.
- Weightings are introduced by weighting the ratings of acquaintances but those of strangers are averaged.
- Only ratings from witnesses are used, who have interacted with the entity being rated. In such a weighted majority algorithm only the ratings from witnesses are aggregated, and the weight of witnesses is decreased if it differs from self-own recognition.
- The weight of ratings is based on the similarity of the experience between the rater and the other participant to improve accuracy.
- Ratings can be aggregated and weights of raters can be updated through deriving the expectation of the Beta distribution.

In simulation [26] it was found that most complex algorithms will have better results. However, in several circumstances the simple algorithm can outperform the complicated algorithms. In particular, the first average algorithm is found to be more resistant to different type of bad raters [26].

To configure the reputation aggregation algorithm for a RaaS, one of these aggregation algorithms can be chosen as they may be able to accommodate a variety of communities and would be understood and adopted by users [5].

g) Reputation measurement parameters: There are crucial parameters which may increase the accuracy of the expected reputation score namely transitivity rate and time [21].

Transitivity rate represents the fact that recommendations from third-hand ratings with a transitivity degree of three may have the least influence on the trustworthiness measurement. Therefore, in a recommendation chain,

recommendations from known participants who already have had interaction with the requested party should have more weight as first-hand recommendations, than those who are known but have not had any previous interactions with the requested party or those who are unknown.

Time influences the effect of ratings on the computation as the most recent rating will have a higher weight ratio than ratings that are older. Thus ratings decay over time. The advantage is that users benefit from having a rating value that reflects how the most recent services performed. These parameters attempt to ensure that ratings are more accurate as weight ratios are an effective way to counteract "bad" raters.

Finally, the *Entity Selection* component is considered where the resultant reputations is now used.

h) Rating score: The reputation system finally reports its results to users in two different formats namely aggregated reputation scores and individual ratings and opinions [24]. Reputation scores are the result of the scoring and ranking component, whereas the individual ratings are collected through the information gathering component.

When reputation scores are presented, the time line it represents should be provided to assist users with decision-making. Reputation information is disseminated to end users via different access methods such as web sites, emails or RSS (Rich Site Summary) feeds. Certain information may be made publicly available, whereas others may require a subscription fee.

Next, the requirements for a RaaS framework are presented.

3.3 Requirements for a RaaS framework

Table 1 and Table 2 briefly provides the most relevant requirements for a RaaS framework. The requirements are given according to the two main drivers and the first three components of reputation systems. It has been indicated on the table where a high cost is associated with a set of requirements. In the last case, the list of requirements identifies a set of configurable features that should be present.

SOFTWARE-AS-AS-SERVICE REQUIREMENTS			
SAAS application architecture	• SOA layered architecture • Well-designed interfaces • Standards-based messaging • Support for integration and data semantics		
SAAS design attributes	• Multi-tenancy • Single version • Logical data separation		
	Information gathering	**Scoring and ranking**	**Entity selection**
SAAS application requirements using configuration	• Add, delete and changes roles • Custom fields and types, and deleting data not needed • User interface look and feel, data presented.	• Tasks switched, added and reordered and task roles to be changed • Business rules modified by changing or setting rules and the rule triggers. • Reputation calculation - adding or changing actions or triggering actions at different points. **(HIGH COST)**	• Reports changed with respect to style, dataset used and query rules.

Table 1: SaaS Requirements for RaaS

SaaS requirements: From the list of requirements in Table 1, the design of the RaaS component is driven by considering integration features, SaaS design considerations and configuration features. SaaS application architecture and design attributes are requirements that should all be applied when designing and implementing the RaaS and are not configurable in nature.

Configurable features: SaaS application feature requirements shown in the last section in Table 1 provide an indication of the possible configurable options that should be present to administrators of tenants. Important configuration options are those allowing the configuration of input data such as roles, data types such as rating and reputation scores, rules that apply the strictness by which types of raters are allowed to rate or incentives, actions by which algorithms are applied, and reporting of ratings and reputation scores. This list only provides an indication of the types of configurable features that should be present. These features can be fleshed out in more detail after Table 2 is reviewed.

Trust and reputation system requirements: Table 2 summarises the requirements elicited from users, and those from investigating trust and reputation system components. Between these two sets, some overlap can be noted. Both sets highlight that the manner in which ratings are done - preferably after each and every transaction - is important to apply. Furthermore, that the results produced by the reputation algorithm can be understood with ease, that the reputation of the rater needs to be verified, the decay of trust and the sorting of reputation scores needs to be implemented.

Configurable features: Trust and reputation system

TRUST AND REPUTATION SYSTEM REQUIREMENTS			
	Information gathering	**Scoring and ranking**	**Entity selection**
User trust and reputation requirements	• Each interaction needs to be rated • Simple and intuitive rating scales • Initial ratings should be treated differently • The quality parameters of a service should be controlled and certified by a trusted party • Raters reliability must be controlled • Similarity between recommenders is important. • Trust values decay and become invalid over time.	• A single trust rating calculated by taking into account different service aspects and their weights. • Computation should be an aggregated of all weighted aspects, similar to an "average". **(HIGH COST)**	• Services should be sorted according to their trust rank • Providers should be made comparable to each other.
Reputation system framework requirements	• Direct or indirect collection channels • Restrictions on who can rate • Context-dependant ratings • Collection costs • Simple rating format • Single/multiple criteria • Incentives **(HIGH COST)**	• Complexity of aggregation algorithm • Weighting of recommendations • Decay of trust **(HIGH COST)**	• Reputation score / individual ratings • Time reported

Table 2: Trust and Reputation Requirements for RaaS

requirements provide more detail as to the configurable options that should be present to administrators of tenants. Configurable features are now presented according to the three reputation system components.

For the *Information Gathering* component, important configurable features are the type of collection channel, the type of rating information such as from direct experience, the context of the rating such as cost and/or quality of a product, the reputation of the rater and its maintenance, the format of the score and the incentives provided to raters. A high cost factor is the use of collection channels used to source ratings and feedback.

The most complex set of configurable features are those of the *Scoring and Ranking* component, where reputation computations are performed. There are many possible configurable features such as the order of tasks executed, choice of algorithms, and rules and weightings of criteria. The *Scoring and Ranking* component is not trivial to apply and is very complex in nature.

The result of the reputation computation is used in the *Entity Selection* component, where aspects such as the reputation scores and individual ratings can be provided to end users.

Next a RaaS framework is proposed in light of the identified requirements.

4. RAAS FRAMEWORK

A RaaS framework is defined using the requirements defined in this paper. First the architecture is given by considering only RaaS functional components and not business components such as billing and metering. RaaS framework configuration is described followed by the RaaS-to-enterprise integration process.

4.1 RaaS architecture

The RaaS component is integrated with the applications of tenants. As organizations may make use of more than one service eg PayPal, the RaaS is can be more accurately described as a SaaS Mashup service.

Figure 4 gives the architecture of the RaaS component integration, based on how SaaS integration is implemented. At the bottom of Figure 4, the RaaS component is defined over a basic cloud infrastructure found in data centres where hardware and software are used to define virtual machines that are provided to tenants to run their applications on.

The RaaS component exposes REST APIs to tenants to support various features such as input collection channels, users, roles, incentives, weightings, rating measures, calculations, rater reputations, rating criteria, entity selection and reputation reports. For each tenant, the context of interaction needs to be maintained, uniquely supported by their set of configurable features. A configuration tool allows administrators of tenants to configure features.

RaaS API calls and results are composed with those of the existing applications of the tenant using integration tools. End users of a tenant such as Organization ABC do not directly communicate with the RaaS, but interacts with the RaaS component via web interfaces. Reputation data is sent into the system programmatically, using a REST API.

From the list of configurable features given previously, it is

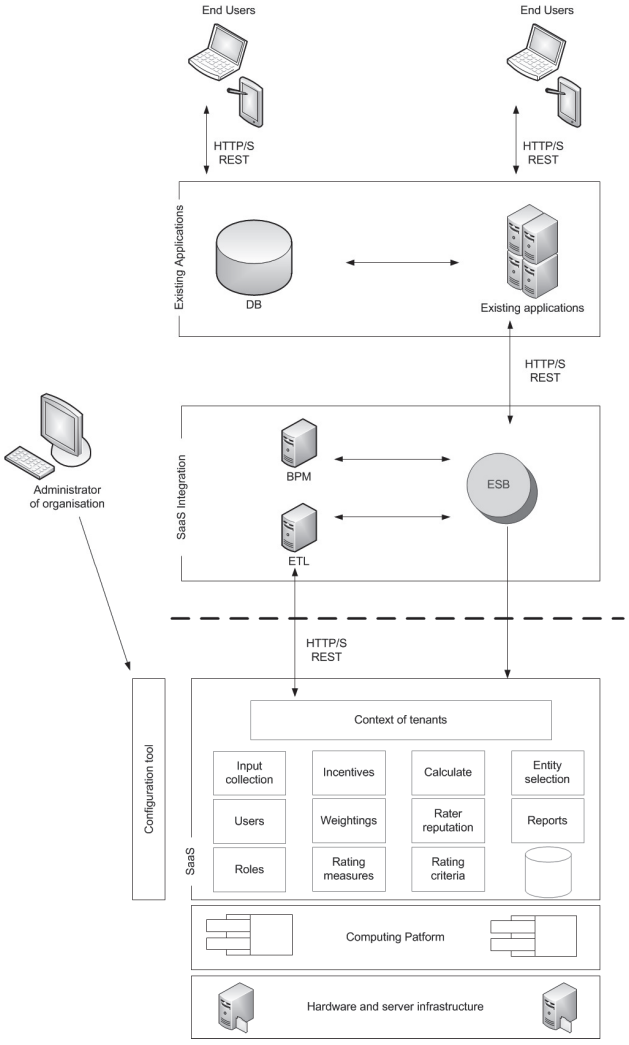

Figure 4: RaaS Architecture

clear that RaaS configuration is not straightforward. This aspect is described next in more detail.

4.2 RaaS configuration

The RaaS architecture supports a configuration tool to allow administrators of tenants to uniquely define features to suit their community needs. The RaaS configuration tool should be designed to be easy and intuitive for the administrators, but at the same time be able to satisfy the needs of tenant requirements. Without this feature, it would be impossible to use the single instance of the software for different tenant applications.

The RaaS component supports many functions such as input collection channels, incentives, users and roles, ratings and reputation calculations. The configuration of these functions is no trivial matter, and much intelligence is required to ensure that options are set that would ensure a reputation score that is a true reflection of the behaviour of quality of the entity being rated. Careful consideration should be given to aspects such as the type of data that is exposed, the type of rating format is required by specific algorithms, whether weights can be set or not, which groups of raters may be granted the ability to rate, which objects can be rated and the number of criteria to be used.

Considering the above mentioned complexities in configuring reputation computation this research now proposes a two level reputation configuration approach, one for novice users, and one for knowledgeable users who understand the implications of their choices.

For novice users, there may be a few options available, based on the risk the organization may experience, to select from such as:

- Low - reputation computation with basic summation of values.
- Medium - reputation computation that encourages strangers by initially bootstrapping their trust to a level to ensure participation.
- Strict - reputation computation that is strict with “bad” behavior as the risk is high.

An advanced configuration panel may be made available to knowledgeable users to select a variety of options.

In both cases, the RaaS should make available a simulation feature that will illustrate to the administrator what the effect of the choice will be, in order to avoid any misunderstandings.

Next, a RaaS application integration example is described.

4.3 RaaS application integration example

The utilization of the RaaS is now discussed according to a set of sample requirements. This discussion now returns to the case of Organization ABC. This organization is an online store for a start-up company that sells products to consumers over the mobile web. It requires a reputation system that is simple and easy to understand, easy to integrate into their applications, favour good behaviour, encourage users to rate, decay older ratings and allow any product to be rated that is sold to customers.

The administrator of Organization ABC configures the RaaS via a configuration menu page after he/she is authenticated by the system. The configuration menu provides the administrator with the capability to view past settings of the RaaS, configure new settings and view reports on the activity of the users within the RaaS.

When an administrator configures a new RaaS, he/she choose the “Low” configuration option based on the organizational requirements that sets initial values for a number features. A few features are further configured as follows:

- Input data such as those relating to the types of entities to be rated, user profiles and rating values (out

of 5) are set. Initial values are provided by the "Low" configuration features that can be adjusted.

- Input collection channel is set to prompt the user directly after a transaction to save on collection costs.
- Incentives are set to be of altruistic nature to encourage users to rate. Rewards are given every time a rater rates a transaction. The rater is given a public reputation score to encourage others to rate.
- Reputation calculation is set to a simple average rating calculation so that users can easily understand and interpret it.
- Rating criteria is set to single, indicating that a product purchased is rated by the buyer.
- Trust decay is set so that previous ratings decay by 50% when older than 6 months and by 100% when older than 18 months.

After configuration features are set, the RaaS is programmatically integrated with the orchestrated calls and responses of the existing applications of Organization ABC.

Figure 5 illustrates a typical web interface displaying rating data. Buyer X views the product search page of Organization ABC on the web browser or app via the mobile device. He has searches for a product and sees its ratings displayed as star ratings out of 5. The page is programmatically created, by sending a REST request such as "https://www.example.com/sendReputation/11", where 11 is the product code that is sent to the RaaS, and displaying the result.

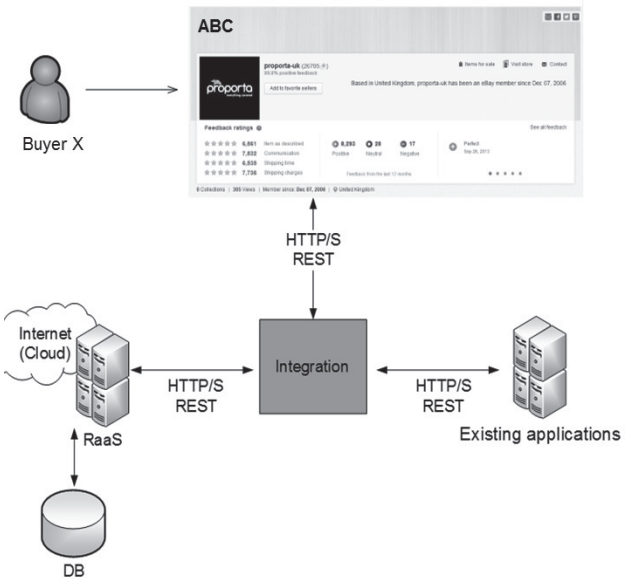

Figure 5: RaaS Communication

In the background, for all transactions processed, ratings are sent to the RaaS to enable the calculation of a reputation score of meaning. Reputation scores are stored with their product profiles. Rater reputation is maintained in the same manner to support the altruistic incentives configuration.

The RaaS thus gives organization a competitive edge as they do not experience a delay in time to market for their new online store, and at the same time they have a sophisticated reputation system to support their online store.

4.4 RaaS framework challenges

There are many challenges that stem from the creation of a RaaS framework:

- Organizations may be challenged by the fact that their data is housed externally. Even though SaaS providers have better security than many of their clients, the transfer of control over corporate data is a difficult decision.
- Configuring reputation computation and behavior is complex. As workflows allow automation of processes involving human and machine-based activities it may be important to apply it in this context.
- Each tenant has specific needs with respect to their data requirements. To address this, a template for storing data can be provided that meets most requirements, with options to add fields to tables.
- As tenants of the RaaS component have a large variety of users, and the responsibility for creating individual accounts for end users, and granting access to resources lies with the tenant, a well-developed access control component should be provided.
- The management of raters and other identities is complex. In most cases, user accounts are managed and stored independently by each tenant and authentication occurs within the organizational boundary. This means that the identity of the user, with any relevant credentials is sent to the RaaS to allow identification and access control. Different types of identities and credentials need to be managed.
- A key factor for SaaS is availability. For mission-critical applications, network availability is a dangerous point of failure.

5. CONCLUSION

The main aim of this paper was to identify requirements for a RaaS framework. Here, this has been done only at a theoretical level. Although a comprehensive set of requirements have been identified, more research and analysis is still needed. To the best of our knowledge, this is the first attempt at identifying requirements for such a framework.

The example scenario indicates that it is plausible to create a configurable reputation system to accommodate a variety of online communities. This research focussed on elements that exist in reputation systems and how these elements can be configured. Further, RaaS framework requirements were identified by considering SaaS application requirements, user requirements and reputation framework requirements. RaaS exposes services by utilizing the proposed architecture.

Future work will address the definition of more detailed configuration features and how they affect reputation scores in different scenarios. A RaaS prototype is to be defined for which simulations are to be performed to experiment with the different configurable components to identify which elements are more appropriate to configure.

6. ACKNOWLEDGEMENT

The support of SAP P&I BIT Mobile Empowerment and the National Research Foundation (NRF) under Grant number 81412 and 81201 towards this research is hereby acknowledged. Opinions expressed and conclusions arrived at are those of the authors and not necessarily to be attributed to the companies mentioned in this acknowledgement.

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