P2P:Is Big Brother Watching You?

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***Abstract*— In an effort to prosecute P2P users, RIAA and MPAA have reportedly started to create decoy users: they participate in P2P networks in order to identify illegal sharing of content. This has reportedly scared some users who are afraid of being caught. The question we attempt to answer is how prevalent is this phenomenon: how likely is it that a user will run into such a "fake user" and thus run the risk of a lawsuit? The first challenge is identifying these "fake users". We collect this information from a number of free open source software projects which are trying to identify such IP address ranges by forming the so-called blocklists. The second challenge is running a large scale experiment in order to obtain reliable and diverse statistics. Using Planetlab, we conduct active measurements, spanning a period of 90 days, from January to March 2006, spread over 3 continents. Analyzing over a 100 GB of TCP header data, we quantify the probability of a P2P user of being contacted by such entities. We observe that 100% of our nodes run into entities in these lists. In fact, 12 to 17% of all distinct IPs contacted by any node were listed on blocklists. Interestingly, a little caution can have significant effect: the top five most prevalent blocklisted IP ranges contribute to nearly 94% of all blocklisted IPs and avoiding these can reduce the probability of encountering blocklisted IPs to about 1%. In addition, we examine other factors that affect the probability of encountering blocklisted IPs, such as the geographical location of the users. Finally, we find another surprising result: less than 0.5% of all unique blocklisted IPs contacted are owned explicitly by media companies.**

I. Introduction

Content providers, such as the RIAA and MPAA, have escalated their fight against illegal P2P sharing [3], [14], [15], [16],[22], [23] with the use of fear: there have been a number of lawsuits against individuals P2P users [4], [5], [6], [7]. To make this more effective, these organizations and their collaborators have also started "trawling" in P2P networks: creating "fake users" which participate in the network and thus identify users who contribute towards illegal content sharing. However, the extent of this deployment tactic has not been quantified up to now, and this forms the focus of our work.

In response to this approach, the P2P community has spawned several projects which attempt to: (a) identify such "fake users", and (b) enable P2P users to avoid them. In more detail, there is community based effort to maintain lists of suspect IP address ranges, which are called *blocklists*. Blocklists are published by organizations which provide anti-RIAA software or by groups which focus on security [10]. Additionally, a number of free, open-source, software projects enable P2P users to avoid these blocklisted IPs automatically for most popular P2P clients such as BitTorrent, Edonkey emule, gnutella [1] [2], [9],[10] [32], [18], [28]. Note that it is not our intention here to examine how accurate and comprehensive these lists are, though this would be interesting and challenging future work. What we claim is that, the information that we use in our work is what is readily available to P2P users.

The question we attempt to answer is, how prevalent is the phenomenon of fake users. Simply put, how likely is it that a user will run into such a "fake user" without using blocklists? The answer to this question can lead us to: (a) understand the effort that content providers are putting in trawling P2P networks, and (b) justify the effort of the P2P community to isolate "fake users". Hereonwards, we refer to IP ranges of fake users listed on these blocklists as blocklisted IPs and users exchanging data with them as **being tracked**. The intention of blocklists is to identify such "tracking" entities, however all IP ranges listed on blocklists are not tracking users, but we assume the "worst" case scenario. We say that a user **hits** blocklisted IPs every time a user receives or sends a piece of data (part of a file) to that IP range. Organizations employing these blocklisted IPs are refered to as blocklisted entities, and distinct IPs signify unique individual IPs. To the best of our knowledge, such measurements have not been collected before.

We conduct an extensive measurement study employing PlanetLab [13] for a period of 90 days. We customize a gnutella client (mutella version 0.4.5) to automatically initiate meaningful queries and collect statistics from the Gnutella network. Each client initiates 100 queries for popular song found in prominent music charts [38], [31], [30]. We collect and analyze more than 100GB of TCP header data. We then examine the observed IP addresses using the most popular blocklists on the Internet [2], [10], [32].

Our results can be summarized as follows:

1) **Pessimistic result:** A user without any knowledge of blocklists, will almost certainly be tracked by blocklisted IPs. We found that **all** our clients exchanged data with blocklisted IPs. In fact, of all distinct IPs contacted by any client, 12-17% were found to be listed on blocklists.
2) **Optimistic results:** We find that *a little information goes a long way*: Avoiding just the top 5 blocklisted IPs reduces the chance of being tracked to about 1%. This is a consequence of a skewed preference distribution: we find that the top 5 blocklist ranges encountered

during our experiments contribute to nearly 94% of all blocklist hits.

3) **Most blocklisted IPs belong to government or corporate organizations**: We quantify the percentage of hits to blocklisted entries of each type, i.e. government and corporate, educational, spyware proliferators and Internet advertisement firms. We find that the number of hits which belong to government and corporate lists, is approximately 71% of total number of hits, nearly 2.5 times more than educational, spyware and adware lists put together. Interestingly, some blocklists mention unallocated IP ranges called BOGONS, which we discuss later.
4) **Very few blocklisted IPs belong to directly to content providers**: We find that, 0.5% of all blocklisted IPs hits could actually be traced back to media companies, such as Time Warner Inc. However, it is an open question whether other blocklisted IPs are indirectly related to content providers.
5) **Geographical bias:** We find that there is geographical bias associated with how users hit entities listed on blocklists. The way in which users located on the two opposite coasts, east and west, of mainland US, Europe and Asia, hit blocklisted entities is quite different.
6) **Equal opportunity trawling:** We find that Ultra-peers (UPs) [1] and leaf nodes have equal probability of associating with a blocklisted IP, with less than 5% variation in the average number of distinct blocklisted IPs. This comes in contrast to the popular belief that UPs are tracked more aggressively by blocklisted entities [11], [12], than leaf users.

The rest of the paper is organized as follows. Section II presents relevant literature, followed by Section III which discusses the experimental setup and blocklisted entries. Section IV investigates geographical bias and section V addresses the Ultra/Super peer versus leaf node debate.

II. Relevant Literature

P2P networks are now an everyday reality inside the Internet. A plethora of networks, ranging from FastTrack, Gnutella [15], BitTorrent, Emule/Donkey and a host of others along with extremely long lists of clients, written in all posible languages for nearly all operating systems, being free to download generate significant amounts of traffic criss-crossing the Internet [14], [16]. P2P networks have recently been touted as the future for content distribution technologies [17], and for similar exciting and promising applications. However, the fact remains that, these overlay networks, still do act as significant enablers in the movement of copyrighted material over the web. Organizations such as the RIAA and MPAA have been extremely vociferous in their support for anti-P2P policies, since it is these organizations that lose out on revenue due to the exchange of copyrighted songs and movies [6], [8].

Recently, a slew of reports in the electronic and print media, have led to members of P2P communities pondering over the ramifications of such illegal resource sharing [19]. It is to pacify such a threat, of a possible lawsuit that users have resorted to downloading and deploying anti RIAA/MPAA software, which blocks computers owned by these organizations from accessing users on the P2P networks [9], [2], thereby effectively dissociating them from quorums of P2P users and preventing them from gaining critical information, leading to generation of detailed user behavior log files which may be used for legal action. The number of such free software, easily available, from popular websites, is large. Many variants exist for different clients, networks and Operating Systems.

Previous work on modelling and analysis of P2P systems [25], [26], [27], have focused on developing a viewpoint based on performance metrics of such overlay systems. Our work differs greatly from these important earlier research efforts. We conduct research to specifically ascertain if the RIAA is active on P2P networks or not. We try to quantify the probability of a P2P user of being tracked by entities listed on the most popular blocklists. Also, we attempt to identify if there is any geographical bias associated with observing how P2P users run up against blocklisted entites. To the best of our knowledge, we believe that our research is the first which specifically targets an in-depth study of whether such a threat is a reality for a generic P2P user. Moreover, our work is significant for understanding *who do we talk to* while connected on these P2P networks, sharing copyrighted resources. Additionally, we intend to verify reports suggesting that some so-called organizations enlisted by the RIAA *target UPs in preference to leaf nodes* [11], [12], in order to break the backbone of the entire overlay structure.

III. Who is watching?

In this section we discuss the experimental setup we employ followed by a synopsis of our findings regarding which blocklisted entities are most prevalent on P2P networks.

Experimental set-up:We initiate our experiments in a manner so as to be able to emulate the typical user and yet be able to measure large scale distributed network wide inter-node interaction characteristics of such P2P networks. We measure statistics based on trace logs compiled from connections initiated using PlanetLab. The duration of measurements spanned more than 90 days, beginning January 2006. We initiate connections using nodes spread not only across the continental US, but also Europe, and Asia in order to determine any geographical nuances associated with, which entities on blocklists seems to be more active than others, in specific locations. We were able to customize mutella 0.4.5 clients [29], a vanilla console based gnutella client, and intitiate connections to the Gnutella network. Moreover, clients were made to switch intechangeably from

[1]Ultra-peers are high bandwidth nodes that act as local centers, facilitate low bandwidth *leaf* nodes, and enable the scalability of gnutella-like networks.

UP to leaf modes in order to verify if network wide inter-node behavior of UPs is significantly different from leaf nodes.

Search strings used for probing the P2P network were compiled as a list of popular songs, from Billboards hot 100 hits [30], top European 50 hits [31] and Asian hits [38]. Each node injected about 100 queries during every run. In the process, we analyzed more than 100GB of TCP header traces, using custom scripts and filters to extract relevant information which helps us develop a deeper insight into who do we interact with, while sharing resources on P2P networks.

Before we present results obtained from our measurements we must discuss what BOGON IPs [36] mean as they hold special siginificance to the collected information. BOGON is the name used to describe IP blocks not allocated by IANA and RIRs to ISPs and organizations plus all other IP blocks that are reserved for private or special use by RFCs. As these IP blocks are not allocated or specially reserved, such IP blocks should not be routable and used on the internet, however some of these IP blocks do appear on the net primarily used by those individuals andorganizations that are often specifically trying to avoid being identified and are often involved in such activities as DoS attacks, email abuse, hacking and other security problems.

The majority of the most active blocklisted entities encountered are hosted by organizations which want to remain anonymous. Table III lists the top fifteen entities we encounter on the P2P network while exchanging resources, throughout the complete duration of our active trace collection. Surprisingly, we find these entities operate from BOGON IP ranges. This observation is made on the basis of the various popular blocklist resources, and suggests that *these sources deliberately wish to conceal their identities while serving files on P2P networks*, by using up IP ranges which cannot be tracked down using an IP-WHOIS lookup to locate the operator employing these anonymous blocks. Only three out of the top fifteen entries in table III do not use unallocated BOGON IP blocks and are listed on PG lists [2], the rest of the BOGON entities, are listed on both Trustyfiles [32] and Bluetack [10] lists. Most of the BOGON IP ranges point to either ARIN or RIPE IP ranges. We must however mention that these BOGON IP ranges were found to point back to these generic network address distribution entities at the time of our experiments. It is quite possible that these ranges may have now been allocated to firms or individuals and may no longer remain truly anonymous.

Content providers such as the RIAA do not participate in large scale eavesdropping into P2P networks using their own IPs. We observe that a whopping 99.5% of blocklisted IPs contacted either belong to BOGON, commercial entities, educational institutions and others. Among all blocklisted IPs contacted, about 0.5% could actually be traced back to record companies, such as Time Warner Inc. This is a clear indication of the miniscule presence of record companies themselves, trawling P2P networks in a proactive manner.

According to popular perception in the P2P community, and discussions on blocklist hosting sites, such as Phoenix Labs [37], the entry FUZION COLO [33], [34] in Table III, is viewed with distrust, and is understood to propagate self installing malware, and in general as an anti P2P entity. Xeex [35], is more of a mystery. It hosts an inconspicious site which provides absolutely no information as to what the company is really involved in. Going by the discussion groups hosted on the PG website, xeex does turn up frequently in blocklist hits for a large number of users. Other individuals or organizations deliberately employing BOGON IPs to participate in the exchange of resources on P2P networks are certainly attempting to cloak themselves, possibly from the RIAA. Another vein of reasoning would suggest that they could be the ones who keep tabs on what users download.

$Rank$	$Top15HitRanges$	$Type$
1	72.48.128.0-72.235.255.255	Bogon
2	87.0.0.0-87.31.255.255	Bogon
3	88.0.0.0-88.191.255.255	Bogon
4	72.35.224.0-72.35.239.255	FuzionColo
5	71.138.0.0-71.207.255.255	Bogon
6	70.229.0.0-70.239.255.255	Bogon
7	70.159.0.0-70.167.255.255	Bogon
8	70.118.192.0-70.127.255.255	Bogon
9	216.152.240.0-216.152.255.255	xeex
10	216.151.128.0-216.151.159.255	xeex
11	70.130.0.0-70.143.255.255	Bogon
12	87.88.0.0-87.127.255.255	Bogon
13	71.66.0.0-71.79.255.255	Bogon
14	87.160.0.0-87.255.255.255	Bogon
15	70.82.0.0-70.83.255.255	Bogon

Table I: Listing of top 15 blocklist entities encountered on P2P network.

Table II and Table III display the top five entities that registered hits on the educational and research institutions list and the government and commercial organizations lists. We observe that FuzionColo and XeeX appear prominently in this categorization along with two other commercial organizations which host servers on ed2k and gnutella networks. We find that hits to entities listed on commercial and government blocklists are much more frequent than hits on any other different kind of blocklists such as Internet ad companies, educational institutions and others. Even though the number of IPs which belong explicitly to content providers such as the RIAA may be small, the fact that IPs listed on commercial and government blocklists are providing content to P2P users is of concern. The scenario wherein commercial organizations are hired by content providers to collect user profile data in these networks cannot be ruled out, furthermore, the possibility that these commercial organizations such as the ones listed in Table III are not aware of P2P traffic emanating from their servers and are too lax about security does not seem very plausible since some of these bocklisted entities kept tracking our clients nearly every time files were exchanged. It is clear that these commercial IP ranges which serve files to P2P users have a very large cache of popular in-demand media and have extremely low downtime, which seems improbable if in fact the machine were turned into a bot. In fact, the number of hits to commercial and government blocklisted entities is nearly

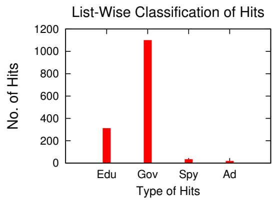


Fig. 1. Classification of blocklist hits according to their type. We observe that hits on the commercial and government blocklist is significantly larger than hits on the other blocklists.

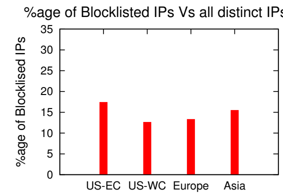
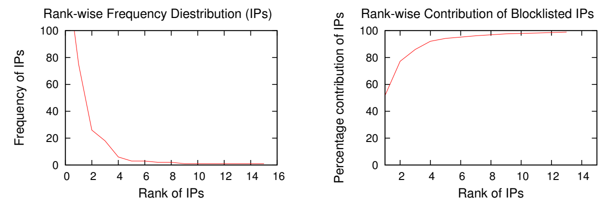


Fig. 2. Percentage of distinct blocklist IPs contacted, per user, out of the total number of distinct IPs logged.



(a) (b)

Fig. 3. (a)Frequency of popularity of blocklisted IPs, following a skewed distribution.(b)Percentage contribution by Blocklisted IPs. The 5 most popular blocklisted IPs contribute to nearly 94.2% of all blocklist hits.

2.5 times greater than hits to any other kind of blocklisted IP we were tracked by.

Rank	*Top5EucationalHitRanges*
1	152.2.0.0-152.2.255.255-Univ. of N. Carolina
2	64.247.64.0-64.247.127.255-Ohio University
3	129.93.0.0-129.93.255.255-Univ. of Nebraska
4	128.61.0.0-128.62.255.255-Georgia Tech
5	219.242.0.0-219.243.255.255-CERNET

Table II: Listing of top 5 educational entities encountered on P2P networks

Rank	*Top5CommercialHitRanges*
1	72.35.224.0-72.35.239.255-FuzionColo
2	216.152.240.0-216.152.255.255-XeeX
3	216.151.128.0-216.151.159.255-XeeX
4	38.113.0.0-38.113.255.255-Perf.SystemsInted2k
5	66.172.60.0-66.172.60.255-Netsentryed2kserver

Table III: Listing of top 5 commercial entities encountered on P2P networks

IV. Probability

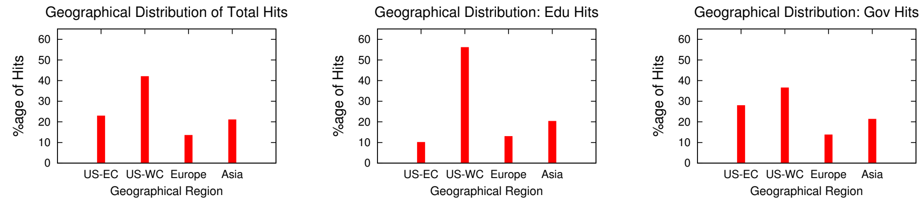
In this section it is our intention to estimate the probability of a typical user of being tracked by entities listed on these blocklists while surfing P2P networks. This gives an idea of how aggressive these lists are and what percentage of entities we talk to while surfing P2P networks are not considered trustworthy. We observe throughout the complete duration of our measurements, **100% of all our nodes were tracked by entities on blocklists and on average, 12-17% of all distinct IPs contacted by any of our clients were listed on blocklists**. As illustrated in Fig. 2, the percentage of IPs listed on blocklists which a node is tracked by is quite significant, about 12-17% of all distinct IPs contacted, per node. In fact this trend was reflected throughout the complete duration of measurements, which suggests that the presence of blocklisted entities on P2P networks is not an ephemeral phenomenon.

Popularity of blocklisted IPs tracking P2P users follows an extremely skewed distribution. We observe thisbehavior clearly as displayed in Fig. 3a. A small number of entities register a large number of hits while most blocklisted entities are infrequently visible on P2P networks. This fact is of great consequence to users who wish to avoid contact with block-listed entities and thus reduce their chances of running into anti-P2P entities. *Simply filtering out the five most popular entities on these networks leads to a drastic reduction in the number of hits to them, to the tune of 94%*. This interesting statistic is displayed in Fig. 3b. In fact **avoiding just these top 5 popular IPs can reduce the chances of a user being tracked significantly, down to nearly 1%**. Users can use this fact to tweak their IP filters to to increase their chances of safely surfing P2P networks and bypassing the most prevalent blocklisted entities. This is critical considering that, a naive user, without any information of blocklists will almost certainly be tracked by blocklisted entities. Also, the fact that 100% of all nodes regardless of geographical location were tracked by blocklisted IPs, indirectly points to the completeness of the blocklists we compiled from the most popular sources.

V. Geographical Distribution

In this section we focus attention towards whether geographical bias if any is observed with respect to blocklisted IPs tracking our clients from various geographical locations. To achieve this we needed to develop a mechanism allowing us multiple points of entry, geographically speaking, into a P2P network. We employed over 50 different nodes on PlanetLab, encompassing the continental US, Europe and Asia to measure this metric. We monitor individually, PlanetLab nodes located in the continental US as nodes situated on the east coast (US-EC) and on the west coast (US-WC), to observe if there is any variation in behavior within mainland US and surprisingly we find that measurements gathered from PlanetLab nodes located on US-EC and US-WC do not concur in unison regarding various metrics discussed in the following sections.

Geographical location influences observed tracking activity:To provide an idea of how blocklisted IPs track P2P users over a complete geographical spectrum we present Fig. 4a. We observe that the percentage of blocklisted IP



(a) (b) (c)

Fig. 4. UP Vs Leaf: (a)Distribution of Blocklisted IPs contacted in different geographical zones.(b)Distribution of Blocklisted IP hits, to Educational lists, in different geographical zones.(c)Distribution of Blocklisted IP hits, to Government and Commercial lists, in different geographical zones.

hits is highest in US-WC followed by US-EC, Asia and Europe. *The percentage of hits to blocklisted IPs, per node, as a percentage of total hits to IPs contacted by each node, located on the US-WC seems to be nearly twice that of nodes located on US-EC*. Quite obviously, this suggests that users accessing the P2P network from these two vantage points, within the mainland US, encounter different levels of tracking activity. We believe this observed inequality springs from the following reason, that difference in user behavior and possible difference in levels of monitoring activities by entities on the blocklists could directly be responsible for such a skewed trend. Fig. 4b depicts the distribution of blocklisted IP hits from the "educational" range, comprising of academic and research institutions. Again we observe a similar trend, nodes located on US-WC notch up a higher percentage of blocklist hits compared to nodes located on US-EC, Asia and Europe. In fact, the difference in measurements between US-WC and US-EC is more than five times than that of readings gathered from US-EC. Fig. 4c depicts the distribution of blocklisted IP hits in the government and commercial domain. Once again, we observe that figures collected for nodes situated on US-WC are higher than nodes on US-EC, Asia and Europe. Given that the period of observation, the UTC time when data was logged, the number of queries input into the P2P network, the order in which queries were injected were identical, we surmise that, throughout the duration of our experiments, *the consistent skewed distribution between US-WC and US-EC can be due to difference in user behavior and the local prevalence and difference in tracking activity levels of blocklisted entities in these different geographical settings*.

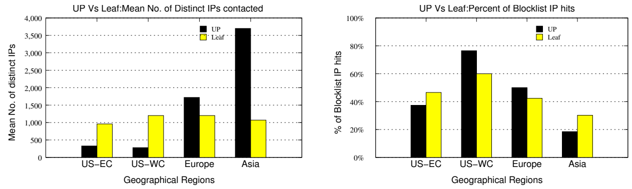
Users on US-WC experience aggressive tracking activity:Analyzing information depicted in Fig. 2, 4a-c, we observe that users located on US-WC run into a smaller number of distinct blocklisted IPs but at the same time register a larger number of hits to these ranges, a clear indication of heightened tracking activity vis-a-vis other geographical locations.

Nodes located in Europe consistently registered a lower number of blocklisted IP hits when compared to nodes located in Asia. We attempt to maintain a balance while conducting experiments and deploy our code on nearly the same number of nodes in different geographical settings, log data during synchronized time periods. The only difference while gathering measurements in these settings was that we used different lists of queries which were injected into the P2P network for nodes located in separate continents. For nodes located in Europe we constructed query lists based on European 50 hits [31] and for nodes in Asia we constructed query lists based on Asian hits [38]. The magnitude of difference observed between nodes in Europe and Asia was found to be more or less consistent across the different types of blocklisted IPs. They were however significantly different from measurements gathered across the mainland US. We believe that this difference could again be due to dissimilarity in user behavior and tracking activity across geographical boundaries.

VI. Role Dependent Tracking

This section delves into whether, according to popular perception in P2P communities [11], [12], the probability of being tracked by blocklisted entities varies with the role played by a P2P node. The question we answer is: *are UPs are tracked with higher probability by entities on blocklists versus regular leaf nodes*. We find that **there is no role based bias in blocklisted entities tracking P2P nodes**. To ascertain the veracity of this possibility we repeatedly configured nodes to shift from UP to leaf mode and back. We observe in Fig. 5a that leaves in the network, located in the US, seem to interact with a larger number of distinct IPs than do UPs. However, this is not the case in either Europe or Asia, where UPs connect to larger number of distinct IPs than leaves. This observation could be due to the false perception, hyped primarily in the US that UPs are being watched with more vigour by entities on the blocklists vis-a-vis leaf users. Since significant legal action against users of P2P networks has been directed towards users in the US, it is obvious that peers would refrain from voluntarily switching their P2P client's mode of operation to become a UP. Therefore, we see a much lesser intensity of UP interaction within P2P networks in the US. While in Asia, where the threat of legal action has yet to create a dent, users will hardly shy away from switching clients to UP mode. Hence, we observe a much larger UP based interaction in Asia. We believe that the same vein of thought holds true for the scenario for Europe based nodes.

In Fig. 5b we observe the comparison between the percentage of blocklisted IP hits as recorded by UPs and leaf



(a) (b)

Fig. 5. UP Vs Leaf:The black bar signifies UP while the yellow bar signifies leaf users (a)Comparison of average number of distict IPs contacted by UPs and leaves.(b)Comparison of percentage of blocklisted IPs as encountered by UPs and leaf users.

nodes. This metric clearly depicts if there is any correlation whatsoever between UPs being tracked preferentially over leaf nodes irrespective of geographical location. We find that UPs in US-WC encounter higher numbers of blocklisted IP ranges versus leaf nodes. This trend is consistent with Europe based nodes. However for US-EC and Asia based nodes we observe that UPs encounter lesser numbers of blocklist IPs compared to leaf nodes. In fact we observe less than 5% variation in the average number of blocklisted IP hits by UPs versus leaf nodes on these P2P networks and thereby do not find any supporting evidence for claims of UPs being preferentially tracked by entities on these lists vis-a-vis leaf nodes. From our experiments we understand that a UP has nearly the same probability of running into blocklisted entities as leaf users and do not find any significant variation in the number of blocklisted entities contacted by either. It must be noted though that measurements collated as a result of our experiments do suggest a definite disparity in P2P user behavior between US-WC and US-EC as has been discussed in previous sections. Data depicted in 5b, only strengthens this hypothesis, even though the magnitude of difference is small.

VII. Conclusion

To the best of our knowledge, this work is the first to quantify the probability that a user will be tracked and thus run the risk of a lawsuit. Using Planetlab, we conduct large-scale active measurements, spanning a period of 90 days, from January to March 2006, spread over 3 continents, yielding over a 100 GB of TCP packet header data. **A naive user is practically guaranteed to be tracked:** we observe that 100% of our peers run into blocklisted users. In fact, 12% to 17% of all distinct IPs contacted by a peer are blocklisted ranges. Interestingly, a little caution can have significant effect: the top five most prevalent blocklisted IPs contribute to nearly 94% of all blocklisted IPs we ran into. Using this information users can reduce their chances of being tracked to just about 1%. At the same time, we examine various different dimensions of the users such as the geographical location and the role of the node in the network. We find that the geographical location, unlike the role, seems to affect the probability of encountering blocklisted users. Finally we answer, who owns blocklisted IP addresses. Interestingly, we find that 0.5% of all blocklisted IP hits belong explicitly to media companies. The majority of blocklisted users seem to belong to commercial and government organizations and a sizeable portion of the most popular belong to BOGON ranges.

Our work is the first step in monitoring the new phase of "wars" between the content providers and the P2P community. It will be very interesting to continue to monitor the evolution of this conflict. For example, one could analyze the accuracy and completeness of the blocklists, and the speed with which a new blocklisted entity is flagged.

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