

TELETRAFFIC MODELING OF PEER-TO-PEER TRAFFIC

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ABSTRACT

The paper contributes to the development of a framework concerning the teletraffic modeling and analysis of peer-to-peer systems that are based on a mesh-pull architecture. We look at the packet transmission processes induced by a swarm of peers disseminating multimedia objects. We provide a survey on some statistical techniques that are used to characterize the observed hierarchical popularity structure of a peer population. Using collected flow data at a single peer, we show how Generalized Pareto and exponential models can be applied to classify the behavior of the feeding peers. Our approach is illustrated by real packet data of P2P sessions generated by BitTorrent clients in a mobile WiMAX testbed in Korea. The stated techniques can be used to cope with an efficiency adaptation of P2P dissemination protocols to mobile environments.

1 INTRODUCTION

Advanced applications such as modern file sharing systems, Web services embedded in cloud computing systems with new multimedia components or IPTV, 2D and 3D live-streamed video and video-on-demand services are operating on top of next generation networks, which arise from the convergence of fixed and mobile networks, and generate new challenges for teletraffic engineering. A key issue concerns the design of a cost-effective, scalable distribution architecture of the corresponding streams of high bandwidth between the servers and the clients sharing and watching a media object of common interest.

The dissemination of multimedia content can be performed by diverse communication channels according to different paradigms including broadcast, multicast, or unicast communication patterns. Compared to traditional broadcast systems based on multicast trees several alternatives derived from new concepts such as content centric or overlay networks have been proposed. In recent years modern dissemination platforms employing modern peer-to-peer (P2P) overlay protocols derived from BitTorrent and its ramifications, e.g. GoalBit, Zattoo, PPLive, SopCast, Vodddler or Skype (see, e.g., Ali et al. (2006), Krieger and Schweßinger (2008), Peltotalo et al. (2008), Sentinelli et al. (2007), Silverston et al. (2009), Tang et al. (2009)) have gained increasing interest. They have become powerful middleware systems to disseminate media objects and streams among interested clients. Estimating the arising traffic matrices of such P2P based services and their integration into mobile environments demand a solid analysis of the generated packet streams and the required capacity on an IP underlay network (cf. Xu et al. (2011)).

Components of P2P teletraffic engineering comprise basic elements such as monitoring and analysis of overlay and underlay structures, the design of topology aware routing and QoS driven peer- as well as piece-selection algorithms and the modeling of resulting workloads. These tasks involve the statistical characterization of P2P packet flows, and the determination of an effective bandwidth regarding aggregated P2P traffic on IP network links. Regarding classical teletraffic theory of the network layer, workload modeling of datagram flows and performance analysis of the loaded basic network elements such as links, router line cards, and media players at receivers involves parametric models derived from queueing

networks or fluid-flow approaches. The sketched teletraffic engineering tasks in a multi-layer network comprising media encoding and decoding processes at sender and receiver sites, logical dissemination networks spanning an overlay among a peer population combining consumer and relay node capabilities and the packet-switched IP transport network as underlay are much more challenging. Thus, up to now, no complete solution methodology handling all described items in satisfactory, mathematically rigorous manner has been developed.

Compared to a parametric teletraffic approach, purely measurement based concepts may provide an alternative that can be integrated easily into real-time control components of P2P protocols. To respond to this rapid deployment of P2P overlay structures, we have tried to develop a comprehensive P2P traffic measurement, modeling and teletraffic analysis concept. It integrates four orthogonal dimensions to cope with the analysis of P2P structures and P2P traffic characterization: (1) traffic measurements at the packet layer combining passive and active monitoring techniques by the tool Atheris (Eittenberger and Krieger 2011a), (2) data extraction, analysis and inspection of P2P overlays based on a hierarchical multi-layer modeling concept (Markovich et al. 2010b), (3) a characterization of the overlay structure by techniques and metrics of complex networks, and, last but not least, (4) a nonparametric teletraffic modeling approach based on the statistical characterization of P2P traffic (Markovich et al. 2010a).

It is the objective of this paper to provide a survey of new building blocks of such a modeling and analysis approach. It is motivated by a statistical classification of the peer population feeding a single client by parametric change point detection techniques (cf. Chen and Gupta (2000)). The latter concept can be combined with the measurement approach to identify dynamically the most important peers providing a sufficiently large packet input rate to feed the media player without performance degradation (cf. Eittenberger et al. (2011b)). This limitation to useful peers is of particular importance if a mobile environment is considered. The recently developed system RapidStream (Eittenberger et al. 2012a, RapidStream 2012) which offers a P2P video service for Android smartphones illustrates this necessity. We illustrate the sketched classification concept by BitTorrent traces of a mobile client traveling by a bus in a WiMAX testbed in Seoul, Korea (cf. Kim et al. (2010), Eittenberger et al. (2011b)).

The rest of the paper is organized as follows. In Section 2 the features of a BitTorrent swarm are described and the traces which are collected in a mobile WiMAX testbed are discussed. In Section 3 the statistical characterization of packet flows that are feeding a monitored mobile client in the observed P2P sessions are presented. In Subsection 3.1 the involved peer population is classified both by a Generalized Pareto and an exponential model. To identify the most important peers, change point analysis techniques are further discussed in Subsection 3.3. In Subsections 3.2 and 3.4 the sketched statistical analysis techniques are applied to typical P2P traffic which is arising from BitTorrent sessions of a mobile client. Finally, some conclusions on the adaptation of peer-to-peer protocols to mobile networks are drawn.

2 ANALYSIS OF BITTORRENT TRAFFIC ARISING FROM A MOBILE NETWORK

A peer $p_i \in \mathcal{U}$ associated with a modern P2P overlay network derived from a mesh-pull architecture like BitTorrent is typically embedded in a swarm of clients \mathcal{U} that comprises more than a thousand active peers $p_i \in \mathcal{U}$ in just tens of minutes. Hence, it is vital to understand and analyze the inherent hierarchical structure of an instantiated mesh-pull topology and to explore carefully the preference relationship among the peer population based on appropriate statistical models. We have shown in our previous work (Eittenberger and Krieger 2011a, Eittenberger et al. 2011b, Markovich and Krieger 2012) that it is possible to classify the locally observed peer population of a P2P network by a Pareto model. Here we discuss an extension of this approach.

2.1 Measurement of BitTorrent Traffic in a WiMAX Network

In the following we will use BitTorrent traces that have been captured on March 16–17, 2010, in Seoul, Korea. They were first presented in Kim et al. (2010) and further analyzed in Eittenberger et al. (2011b).

The measurements have been carried out in a larger campaign on four different days in four different scenarios, three WiMAX settings and one in an Ethernet environment. The throughput of the WiMAX network ranged from 30 to 50 Mbps, and a base station covered a radius between 1 and 5 km. Three laptops equipped with WiMAX USB dongles were used for the WiMAX measurements. In the WiMAX scenario considered here the observed peer performed a bus ride through Seoul. It lasted about 30 minutes and the distance of the route was about 11 km. In this mobile scenarios the link quality highly fluctuated. Thus, sometimes the WiMAX connection was completely lost due to handoffs between base stations, and thereby the peer got a new IP address in some parts of the measurement runs.

In the following we use the flow data captured by the BitTorrent bus trace in the WiMAX testbed in Seoul on March 16, 2010, as illustrative example. In Figures 1, 2 we study visually the packet flows Φ_i , $i \in \{1, \dots, n\}$ exchanged between the home peer $p_0 \in \mathcal{U}$ and n feeding peers $p_i \in \mathcal{U}$ during this session. For this purpose we consider the number of all packets $R_i(\omega)$ of a flow Φ_i that are exchanged with the active peers $p_i, i \in \{1, \dots, n\}$ during this session and its logarithm, i.e. $\ln R_i(\omega)$, as well as the corresponding total volumes $\ln V_i^{(e)}(\omega)$ of a flow Φ_i as basic characteristics of the exchange process. Then we order these numbers as realizations of corresponding random variables $\ln R_i$ and $\ln V_i^{(e)}$, respectively, according to their observed ranks and indicate these orderings of the observed flow characteristics by the identifier i of the underlying peer p_i emitting the flow. Due to the piecewise linear shapes on a double logarithmic scale, the plots of the ordered number of all packets $\ln R_i(\omega)$ exchanged with active peers $p_i, i \in \{1, \dots, n\}$ and the corresponding volumes $\ln V_i^{(e)}(\omega)$, respectively, illustrates that we can expect a heavy-tailed behavior (see Markovich (2007)). Moreover, we see that a substantial change occurs in the flow behavior within a part of the dominant flows (on the lhs in Figures 1, 2). It is due to the separation of the feeding peer population into the groups of super peers, dominant peers and the ordinary ones (see also Eittenberger et al. (2011b)). The second trace from March 17 shows a similar behavior. Hence, we can deduce that the presented hierarchical behavior is a common feature of the BitTorrent P2P dissemination protocol.

The shown structure illustrates that only the top flows of the first two classes of super peers and dominant peers provide relevant information on the classification of the most dominant feeders within the peer population. Therefore, we will focus on the latter popularity subset of the peer population in subsequent investigations.

2.2 Factor Analysis of the Exchanged Flow Data

We denote the number of packets that a monitored home peer $p_0 \in \mathcal{U}$ has received from a feeding peer $p_i \in \mathcal{U}_{p_0} := \mathcal{U} \setminus \{p_0\}$ in the overlay network during a monitored P2P session by R_i . Let $V_i^{(i)}$, $V_i^{(o)}$ and $V_i^{(e)}$ denote the volume of the inbound traffic received from peer p_i , the outbound traffic sent from p_0 to peer p_i and the overall traffic exchanged with peer p_i , respectively. Their underlying generic random variables

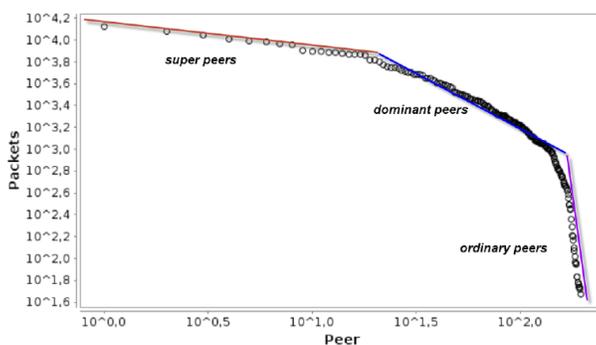


Figure 1: Logarithm of the number of packets $\ln R_i(\omega)$ exchanged with a peer p_i in the BitTorrent bus trace.

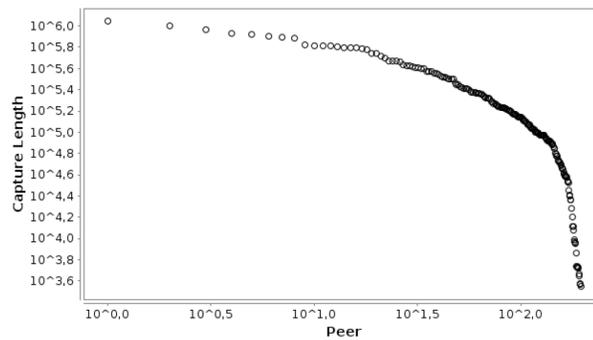


Figure 2: Logarithm of the volume of packets $\ln V_i^{(e)}(\omega)$ exchanged with a peer p_i in the BitTorrent bus trace.

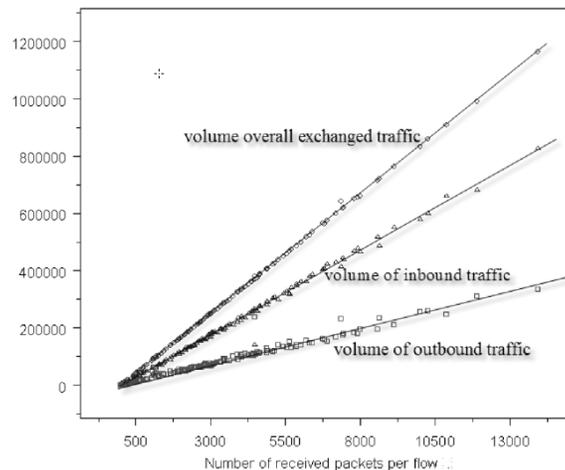


Figure 3: Linear dependence of the attribute variables in a BitTorrent bus trace.

are denoted by $R, V^{(i)}, V^{(o)}, V^{(e)}$, respectively, and shall be governed by a common distribution each. To investigate the issue whether there is a most informative entity in the flow statistics, we have studied the potential correlation among the attribute variables of the packet flows feeding a home peer during a P2P session (cf. Markovich and Krieger (2012)). If the random variables $Y \in \{V_i^{(i)}, V_i^{(o)}, V_i^{(e)}\}$ derived from the packet sizes of an exchanged flow and the simple counting statistics R_i are linearly correlated, then there should exist a corresponding linear function $y = f_k(x)$ such that the regression $V^{(k)} = f_k(R) = a_k R + b_k, k \in \{i, o, e\}$, holds. In this case a visual representation of the relationships $(R, V^{(k)}), k \in \{i, o, e\}$ should arrange the data of the peer flows along straight lines. Methods arising from factor analysis such as principal component analysis (PCA) have been applied to study this issue in a rigorous manner (cf. Markovich and Krieger (2012)).

Applying this regression concept to all flows of packets exchanged with the home peer p_0 and a feeder p_i of the BitTorrent bus trace from March 17, for instance, we realize in Figure 3 that there exists a perfect linear matching among all these variables as expected. A factor analytic study of this data set by principal component analysis shows that 99.49% of the variance of the data is explained by a major principal component depending on all four attributes $R, V^{(k)}, k \in \{i, o, e\}$ while each attribute of the flow data contributes between 24.7 to 25.1% to this dimension. The other components simply reflect the influence of the volume variables $V^{(k)}, k \in \{i, o, e\}$.

We conclude that the simplest attribute R_i =number of packets exchanged with (or incoming to) a certain

peer $p_i \in \mathcal{U}_{p_0}$ is sufficient to perform a sound classification analysis. Therefore, our subsequent change point detection approach is based only on this random variable.

3 CLASSIFICATION OF A PEER POPULATION BY CHANGE POINT ANALYSIS

In the following Section we want to show that traffic flows which are realized in a modern P2P overlay network by a population $\mathcal{U}_n = \{p_0, p_1, \dots, p_n\} \subset \mathcal{U}$ of active clients generate a characteristic load pattern at a single measurement point of an involved, monitored client p_0 during a typical P2P session and how it can be described by a generalized Pareto model and its exponential simplification. The classification of the observed population of feeding peers $\mathcal{U}_{p_0} := \mathcal{U}_n \setminus \{p_0\}$ can be based on this information and determine an understanding of the underlying flow graph of the P2P network.

3.1 A Generalized Pareto Model of Peer-to-Peer Exchange Patterns

We determine a mathematically sound procedure that efficiently generates a reasonable partitioning of the set of all active peers feeding the observed home peer. From a statistical point of view, we consider a sample $\mathcal{X}^{(n)} = \{X_1, X_2, \dots, X_n\}$ of iid random variables (rvs) $X_i, i \in \{1, \dots, n\}$, with a common distribution function (df) $F(x)$ of the generic rv X . We interpret X_i as number of transferred packets to or from peer $p_i, i \in \{1, \dots, n\}$, during a monitored session. Our previous studies of the BitTorrent data sets (cf. Eittenberger et al. (2011b), see also Subsection 2.1) and other data sets of peer-to-peer live streaming traffic (cf. Markovich et al. (2010b), Markovich and Krieger (2012)) have shown that the related df obeys asymptotically a heavy-tailed law of Pareto-type, i.e.,

$$1 - F(x) = \mathbb{P}\{X > x\} \sim l(x)x^{-1/\gamma},$$

for large $x \in \mathbb{R}^+$ where $l(x)$ is a slowly varying function (cf. Markovich (2007), Def. 10, p. 4). The positive tail index $\alpha = 1/\gamma > 0$ characterizes the slow decay of the tail of the distribution at infinity as basic model parameter (cf. Markovich (2007), §1.2, p. 6f).

If we consider the conditional rv $Z = X - u \mid X > u$ of the absolute excess $X - u$ of the heavy-tailed rv X over a high threshold $u > 0$ subject to the condition of the exceedence $X > u$, we can conclude by the peaks-over-threshold method (POT) of extreme-value theory (Markovich 2007, p. 14) that for increasing thresholds $u \rightarrow \infty$ the asymptotic distribution of rv Z is determined by a Generalized Pareto df (GPD(γ, σ))

$$\Psi(z) = \mathbb{P}\{Z \leq z\} = 1 - (1 + \gamma z / \sigma)^{-1/\gamma}, \quad z \geq 0. \tag{1}$$

Here the scaling parameter $\sigma > 0$ is depending on the threshold u , i.e., $\sigma(u)$, and the EVI $\gamma > 0$ can be determined by the sample (cf. Markovich (2007), Sec. 1.2.3, p. 13, Castillo et al. (1997)). An appropriate threshold u can be determined by quantile estimation techniques which have been developed in extreme-value theory, in particular for POT methods, regarding heavy-tailed distributions (see Markovich (2007)). The details are out of scope of this paper.

Then we know that the transformation $Y = \frac{1}{\gamma} \ln(1 + \frac{\gamma}{\sigma} z)$ yields an exponentially distributed rv with unit scale parameter $\lambda = 1$, i.e., $\mathbb{P}\{Y \leq y\} = 1 - \exp(-y), y \geq 0$, (cf. Johnson and Kotz (1970), Chap. 19.5.5, p. 240).

If Z obeys a GPD(γ, σ) law, then we see that

$$\mathbb{P}\{Z - w \leq z \mid Z > w\} = \frac{\mathbb{P}\{w < Z \leq z + w\}}{\mathbb{P}\{Z > w\}} = 1 - (1 + \gamma z / (\sigma + \gamma w))^{-1/\gamma} \tag{2}$$

holds and, hence, for all $w > u > 0$ the conditional rv $Z(w) := Z - w \mid Z > w$ satisfies also a GPD law with the modified scale parameter $\sigma(w) = \sigma + \gamma w > 0$ depending in a linear manner on the EVI γ . It means that we can consistently study GPD-like tail models of our original sample for all higher thresholds $w \geq u$ after identifying an appropriate initial threshold value $u > 0$ such that the GPD hypothesis approximately

holds (Castillo et al. 1997)).

Compared to a simple ordering of flows illustrated in Subsection 2.1, the proposed statistical approach of fitting a parametric model to the observed data set has theoretical and practical advantages. It allows us to reduce the collected data sets to small, simple parameter sets. These enable a simplified comparison of the peer-to-peer behavior and furthermore the statistically justified computation of the aggregated flow rate offered to a home peer by the subset of dominant peers using the sized-weighted df (cf. Markovich et al. (2010b), Markovich and Krieger (2012)). The latter is derived from the well-known excess wealth transform (see Li et al. (2004) for more details) and relevant in P2P protocol design.

3.2 Application to BitTorrent Data of the WiMAX Bus Trace

Regarding the bus trace collected in the WiMAX testbed on March 17, 2010, an analysis of the dominant flows by a peaks-over-threshold (POT) methodology with a relatively high threshold u should reveal this behavior (see also Markovich and Krieger (2012)). We have chosen $u = 4000$ exchanged packets as separator of the flows. The design of a peer-to-peer protocol implies that the flow data R_i exchanged by different peers $p_i \in \mathcal{U}$ with a home peer have no relevant internal correlations. Thus, a fit of the available packet flow data $R_i, i = 1, \dots, n = 2184$ of the WiMAX trace by the maximum likelihood method does not cause statistical difficulties. In our example it yields the parameter estimates $\hat{\sigma} = 2344, \hat{\gamma} = 0.02107$ of a Generalized Pareto distribution regarding the generic rv $Z = R - u \mid R > u$ of exchanged packets

The visual comparison of the counted flow data and the GPD model by a probability plot, a QQ plot, a histogram and density plot as well as a sketch of the return levels with associated confidence intervals in Figure 4 illustrates that the data of all dominant flows are relatively well covered by the GPD distribution.

3.3 Analyzing Peer-to-Peer Exchange Patterns by Change Point Detection Techniques

The question arises how we can determine the segmentation of the population of most productive peers feeding an observed home peer based on a self-adaptive, mathematically rigorous technique that uses only the information of the captured simple packet counts of the flow statistics.

Regarding the flows to a home peer p_0 , we see in Figure 1 that the partitioning of the peers into the different groups of super peers and dominant peers as well as ordinary peers should be determined based on the available statistical characterization of the count variable R of the packet flows. In the preceding Subsection we have shown that a Generalized Pareto distribution (GPD) $\Psi(z)$ in (1), which describes the random variable $Z := R - u \mid R > u$ and is determined by the conditional exceedences of the exchanged packet numbers R above a predefined threshold $u > 0$, constitutes the most adequate tool to handle this issue.

Further, the characteristic, significant changes in the linear structure of the exchanged volumes R on a double logarithmic scale in Figure 1 indicate that we can determine the different clusters of the peers, in particular, the boundary between the groups of super peers and dominant peers on one hand and not productive ordinary ones on the other hand by a change point detection. In particular, the latter should reveal the inflexion point between the linear segments of the ordered set of flow data exchanged with a home peer.

Classical change point analysis regarding the tail behavior of a GPD model can support us to solve this issues (cf. Chen and Gupta (2000), Chap. 6, Dierckx and Teugels (2010)). We know by our investigations that the packet count R of the realized packet flows can be described, at least asymptotically for large x , by a heavy-tailed random variable of Pareto type, i.e., its distribution has the form

$$F(x) = \int_{x_0}^x f_R(s) ds = \mathbb{P}\{R \leq x\} = 1 - Cx^{-\beta} = 1 - \left(\frac{x}{x_0}\right)^{-\beta} \quad (3)$$

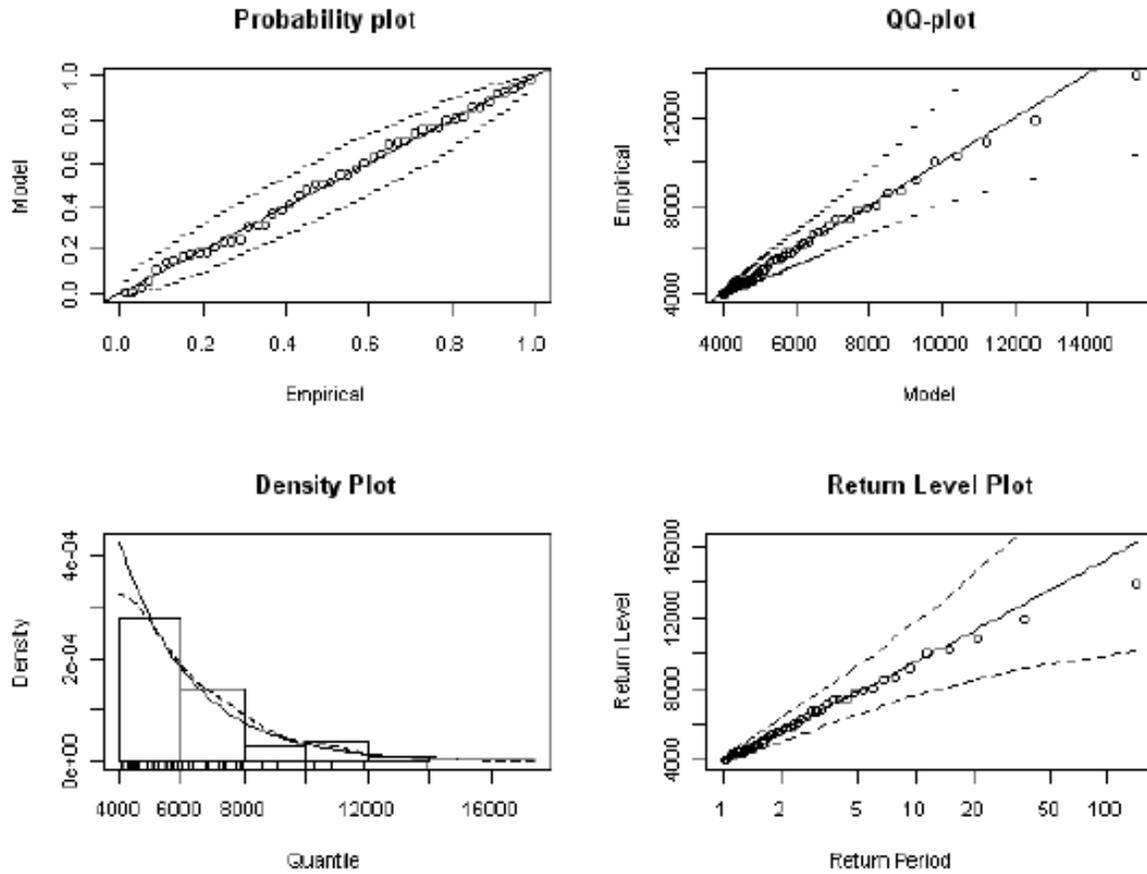


Figure 4: Fitted GPD tail model for threshold $u = 4000$.

with $x \geq x_0$ and the tail index $\beta = 1/\gamma > 0$ and extreme-value index (EVI) $\gamma > 0$. Then we conclude from extreme-value theory that the conditional exceedence over a threshold $u > 0$ $Z := R - u | R > u$ can be modeled by a GPD law (1). Due to Dierckx and Teugels (2010), Dierckx (2011) we know that the properly scaled variable of the conditional relative excess $Y := R/u$ given $R > u$ follows asymptotically an exponential distribution with the extreme-value index as mean, i.e.,

$$\mathbb{P}\{Y > z | R > u\} = \mathbb{P}\{R/u > z | R > u\} \rightarrow z^{-1/\gamma(u)}, \quad u \rightarrow \infty. \quad (4)$$

Thus, we see that for sufficiently high threshold u we can approximate $Z_1 := R/u | R > u$ by an exponentially distributed random variable Y after a logarithmic transformation $Y := \ln Z_1$, i.e.,

$$\mathbb{P}\{Y \leq y\} = 1 - \exp\left(-\frac{y}{\gamma(u)}\right),$$

with mean $\gamma(u)$ and variance $\gamma(u)^2$.

Moreover, we know that the absolute conditional excess $Z_2 := R - u | R > u$ follows a GPD law (2)

$$\Psi(z) = \mathbb{P}\{Z_2 \leq z\} = 1 - (1 + \gamma(u)z/\sigma(u))^{(-1/\gamma(u))}, \quad (5)$$

as the threshold $u \rightarrow \infty$ evolves. Thus, the logarithmically transformed, linearly scaled variable

$$Y = \ln Z_3 := \ln \left[\frac{\gamma(u)}{\sigma(u)} (R - u) + 1 \right] | R > u$$

satisfies asymptotically an exponential law

$$\mathbb{P}\{Y \leq y\} = 1 - \exp\left(-\frac{y}{\gamma(u)}\right).$$

In conclusion, we realize that by an appropriate transformation of the ordered data of exceedences above a high threshold u we can study the change point of the tail behavior in terms of the mean of an exponential variable Y by parametric statistical change point analysis. Following Chen and Gupta (2000), Chapter 6, we consider the ordered transformed sample of exceedances over u

$$Y_i = \ln R_i / u \quad \left(\text{or } Y_i = \ln \left[\frac{\widehat{\gamma(u)}}{\sigma(u)} (R - u) + 1 \right] \right)$$

with individual distribution functions

$$F_i(y) = 1 - \exp(-\lambda^{(i)}y), \lambda^{(i)} = \frac{1}{\gamma^{(i)}}$$

and test the null hypothesis

$$H_0 : Y_1, Y_2, \dots, Y_{n+1} \sim F(y) = 1 - \exp(-\lambda y), \lambda = \frac{1}{\gamma} \quad (6)$$

of identical parameters, i.e., a constant extreme-value index

$$\gamma^{(1)} = \gamma^{(2)} = \dots = \gamma^{(n+1)} = \gamma,$$

against the alternative of a single change point at the unknown flow index k , such that

$$H_0 : Y_1, Y_2, \dots, Y_k \sim F(y) = 1 - \exp(-\lambda_1 y), \lambda_1 = \frac{1}{\gamma_1} \quad (7)$$

$$Y_{k+1}, Y_{k+2}, \dots, Y_{n+1} \sim F(y) = 1 - \exp(-\lambda_2 y), \lambda_2 = \frac{1}{\gamma_2} \quad (8)$$

i.e.,

$$\gamma_1 = \gamma^{(1)} = \gamma^{(2)} = \dots = \gamma^{(k)} \neq \gamma^{(k+1)} = \dots = \gamma^{(n+1)} = \gamma_2$$

The test statistic on changes of the mean can be derived from a maximum likelihood ratio procedure test (MLRPT)

$$LRT(\widehat{\lambda}, \widehat{\lambda}_1, \widehat{\lambda}_2) = L_0(\widehat{\lambda}) / L_1(\widehat{\lambda}_1, \widehat{\lambda}_2) \quad (9)$$

that uses the ML-estimates of mean of the samples, or the corresponding inverse mean, respectively:

$$\widehat{\lambda} = \frac{n+1}{\sum_{i=1}^{n+1} Y_i} \quad (10)$$

$$\widehat{\lambda}_1 = \frac{k}{\sum_{i=1}^k Y_i} \quad (11)$$

$$\widehat{\lambda}_2 = \frac{n-k+1}{\sum_{i=k+1}^{n+1} Y_i} \quad (12)$$

MLRPT uses a modified test statistic of the maximum likelihood ratio

$$LRT(\lambda, \lambda_1, \lambda_2) = L_0(\lambda)/L_1(\lambda_1, \lambda_2) \tag{13}$$

$$L_0(\lambda) = \lambda^{n+1} \exp(-\lambda \sum_{i=1}^{n+1} Y_i) \tag{14}$$

$$L_1(\lambda_1, \lambda_2) = \lambda_1^k \exp(-\lambda_1 \sum_{i=1}^k Y_i) \cdot \lambda_2^{n-k+1} \exp(-\lambda_2 \sum_{i=k+1}^{n+1} Y_i) \tag{15}$$

namely,

$$D = \max_{1 \leq k \leq n} D(k) = \max_{1 \leq k \leq n} [-2 \log LRT(\hat{\lambda}, \hat{\lambda}_1, \hat{\lambda}_2)] \tag{16}$$

$$= \max_{1 \leq k \leq n} \left(-2 \log \left[\frac{\hat{\lambda}^{n+1}}{\hat{\lambda}_1^k \hat{\lambda}_2^{n-k+1}} \right] \right) \tag{17}$$

The insertion of the MLE estimates (10, 11, 12) yields the following complex statistics (cf. Chen and Gupta (2000), Chap. 6):

$$\begin{aligned} D &= \max_{1 \leq k \leq n} \left(-2 \log \left[\left(\frac{n+1}{\sum_{i=1}^{n+1} Y_i} \right)^{n+1} \cdot \left(\frac{\sum_{i=1}^k Y_i}{k} \right)^k \cdot \left(\frac{\sum_{i=k+1}^{n+1} Y_i}{n-k+1} \right)^{n-k+1} \right. \right. \\ &\quad \left. \left. \cdot \exp(-(n+1-k-(n-k+1))) \right] \right) \\ &= \max_{1 \leq k \leq n} \left(-2 \log \left[\left(\frac{k}{n+1} \right)^{-k} \cdot \left(\frac{\sum_{i=1}^k Y_i}{\sum_{i=1}^{n+1} Y_i} \right)^k \right. \right. \\ &\quad \left. \left. \cdot \left(1 - \frac{k}{n+1} \right)^{-(n-k+1)} \cdot \left(1 - \frac{\sum_{i=1}^k Y_i}{\sum_{i=1}^{n+1} Y_i} \right)^{n-k+1} \right] \right) \end{aligned}$$

A test statistics much larger than zero indicates that a structural change has occurred at a certain change point k^* which satisfies $D(k^*) = \max_{1 \leq k \leq n} [-2 \log LRT(\hat{\lambda}, \hat{\lambda}_1, \hat{\lambda}_2)]$. The computation can be performed by numerical optimization techniques (cf. Chen and Gupta (2000)).

The asymptotic convergence of a scaled version of $D(k)$ to a Gumbel distribution can be proved and exploited to derive quantiles of the ratio test procedure.

Variants of the test statistic like

$$D = \sqrt{\left(\max_{1 \leq k < n+1} D(k) \right)}$$

may be considered as well and the weak convergence to a Brownian bridge process be proved (see Dierckx and Teugels (2010)).

In case that a more complex scaling $Y_i = \ln \left[\frac{\hat{\gamma}(u)}{\hat{\sigma}(u)} (R-u) + 1 \right]$ is used we have to treat the scale term $\sigma(u)$ as unknown nuisance parameter and to adapt the test procedure accordingly (see Dierckx and Teugels (2010)). A simultaneous test on multiple change points in the mean-variance structure of the exponentially distributed sequence $\{Y_1, Y_2, \dots, Y_{n+1}\}$ can be derived in a similar manner (see Chen and Gupta (2000), Chap. 6.3).

3.4 Application of the Change Point Analysis to BitTorrent Data

We can apply the described parametric change point detection procedure to the BitTorrent flow data of a peer population \mathcal{U}_{p_0} to determine the different local classes of peers feeding an observed home peer p_0 .

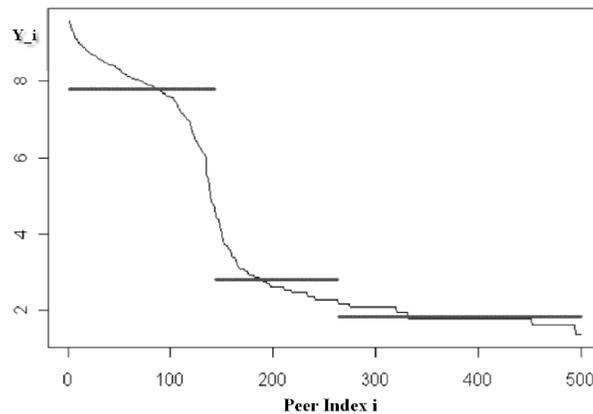


Figure 5: Classification of the BitTorrent peer population of the WiMAX bus trace from March 17 using a change point analysis based on the incoming packets flows to an observed mobile peer.

To illustrate our concept, we will use the ordered inbound traffic arising from the bus trace of March 17 above a threshold of $u = 4000$ packets. It approximately results in 500 most productive flows. Applying the procedure 'cpt.meanvar' of the R-package 'changepoint' (R Changepoint 2012) which implements the Chen-Gupta approach, we have derived the following classification of the flows into the groups of super peers, dominant peers and ordinary peers. The latter are separated by the flow numbers 143 and 263, i.e., the super and dominant peer group is constituted by the largest 142 flows, and the less productive ordinary peers by the consecutive 120 flows, see Figure 5.

This outcome is similar to the result arising from a manual inspection technique described in Eittenberger et al. (2011b) which generated 158 peers in the dominant group.

The sketched change point procedure illustrates that it is possible to determine the classification of peers by an automatic procedure based on collected flow data. In this way, one can learn automatically the popularity set of super and dominant peers that provide a peer with the required upload capacity to stream or download a requested multimedia file quickly.

4 CONCLUSIONS

Currently, teletraffic engineering has to respond to the challenges arising from the rapid deployment of advanced multimedia applications of the Web like the sharing of multimedia content by client swarms, HTTP live streaming, IPTV, live-streaming and video-on-demand of 2D and 3D movies. These services may be provided by new peer-to-peer overlay networks like those induced by BitTorrent and BitTorrent live or SopCast on top of packet-switched IP networks. Developing a teletraffic engineering approach to address these issues, we have presented a comprehensive analysis concept (Markovich et al. 2010b, Eittenberger et al. 2011b, Markovich and Krieger 2012) integrating modeling, measurement, and statistical analysis of peer-to-peer traffic flows at the packet and session levels.

In this paper we have provided a survey on statistical analysis methods which are focussing on the insight gained by a single monitoring point in a P2P overlay network. We have pointed out the possibility to characterize peer populations of popular P2P overlay networks derived from a mesh-pull architecture by appropriate statistical techniques. Using collected flow data at a single peer, we have shown how Generalized Pareto and exponential models can be applied to classify the behavior of the feeding population of a peer and how to partition it into groups. We have introduced this innovative classification schemes of the peer population of BitTorrent-like P2P networks into different categories to support the dynamic adaptation of the peer selection strategies to the real needs of mobile clients (cf. Eittenberger et al. (2011b), Eittenberger et al. (2012b)).

Our approach has been illustrated by real flow data of P2P sessions generated by mobile BitTorrent clients in a WiMAX testbed. Considering the popularity classification of these BitTorrent flows a generalized Pareto model can be applied successfully. In particular, we have investigated the data distribution of the most productive region and found strong indications that this part of the peer population contributes nearly the complete data volume. A statistical technique using a change point detection technique can be applied successfully to characterize this most productive part of the peer population.

We have further realized that a BitTorrent-like protocol, especially BitTorrent's choking algorithm, is not well adapted to the fluctuating conditions in a mobile environment (cf. Eittenberger et al. (2011b)). Therefore, we recommend the following adaptations of BitTorrent-like systems to wireless networks. The sketched dynamic classification techniques can be applied to cope with an efficiency awareness of a P2P dissemination protocol in mobile environments. In general, it is recommended not to overload the base stations in wireless scenarios by too many open connections. Regarding the transport protocol it is proposed to use UDP instead of TCP since a connection-oriented protocol like TCP suffers from the fluctuating link conditions and by the handoffs during movements. Lehrieder et al. (2010) have investigated the positive effect of caches in a BitTorrent-like network. Supplying a dedicated infrastructure with local caches could foster the dissemination performance of BitTorrent-like systems in wireless networks.

The limitation of our study is due to the single point of measurement provided by our new public source monitoring tool Atheris (Eittenberger and Krieger 2011a, Atheris 2012). In the near future we want to extend our teletraffic results by a measurement and analysis of peer-to-peer flows in UMTS and LTE networks (cf. Eittenberger et al. (2012b)).

We are convinced that the presented statistical techniques can be applied successfully to similar classification and analysis tasks arising in simulation models of distributed systems if the latter include heavy-tailed distributions or similar popularity models governed by generalized Pareto distributions.

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