INSTITUT NATIONAL DE RECHERCHE EN INFORMATIQUE ET EN AUTOMATIQUE

Project-Team rap

Réseaux, Algorithmes et Probabilités

Rocquencourt

THEME COM

Activity Report

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2. Overall Objectives

2.1. Overall Objectives

The research team RAP (Networks, Algorithms and Communication Networks) created in 2004 is issued from a long standing collaboration between engineers at France Telecom R&D in Lannion and researchers from INRIA-Rocquencourt. The initial objective was to formalize and expand this fruitful collaboration.

At France-Telecom R&D in Lannion, the members of the team are experts in the analytical modeling of communication networks as well as on some of the operational aspects of networks management concerning traffic measurements on ADSL networks for example.

At INRIA-Rocquencourt, the members of RAP have a recognized expertise in modeling methodologies applied to stochastic models of communication networks.

From the very beginning, it has been decided that the efforts of RAP project will focus on few dedicated domains of application over a period of three or four years. The general goal of the collaboration is to develop, analyze and optimize algorithms for communication networks. For the moment, the current projects are the following.

1. Mathematical Models of Traffic Measurements of ADSL traffic.
2. Design of Algorithms to Sample TCP flows.

The RAP project also aims at developing new fundamental tools to investigate *probabilistic* models of complex communication networks. We believe that mathematical models of complex communication networks require a deep understanding of general results on stochastic processes. It could be argued that, since stochastic networks are « applied », general results concerning Markov processes (for example) are not of a real use in practice and therefore that ad-hoc results are more helpful. Recent developments in the study of communication networks have shown that this point of view is flawed. Technical tools such as scaling methods, large deviations and rare events, requiring a good understanding of some fundamental results concerning stochastic processes, are now used in the analysis of these stochastic models. Two domains are currently investigated

1. Design and Analysis of Algorithms for Communication Networks. See Section 3.2.
2. Analysis of scaling methods for Markov processes : fluid limits and functional limit theorems. See Section 3.3.

3. Scientific Foundations

3.1. Measurements and Mathematical Modeling

Keywords: *Passive measurements*, *TCP traces*.

3.1.1. Traffic Modeling

Characterization of Internet traffic has become over the past few years one of the major challenging issues in telecommunications networks. As a matter of fact, understanding the composition and the dynamics of Internet traffic is essential for network operators in order to offer quality of service and to supervise their networks. Since the celebrated paper by Leland *et al* on the self-similar nature of Ethernet traffic in local area networks, a huge amount of work has been devoted to the characterization of Internet traffic. In particular, different hypotheses and assumptions have been explored to explain the reasons why and how Internet traffic should be self-similar.

A common approach to describing traffic in a backbone network consists of observing the bit rate process evaluated over fixed length intervals, say a few hundreds of milliseconds. Long range dependence as well as self-similarity are two basic properties of the bit rate process, which have been observed through measurements in many different situations. Different characterizations of the fractal nature of traffic have been proposed in the literature (see for instance Norros on the monofractal characterization of traffic). An exhaustive account to fractal characterization of Internet traffic can be found in the book by Park and Willinger. Even though long range dependence and self similarity properties are very intriguing from a theoretical point of view, their significance in network design has recently been questioned.

While self-similar models introduced so far in the literature aims at describing the global traffic on a link, it is now usual to distinguish short transfers (referred to as mice) and long transfers (referred to as elephants) [24]. This dichotomy was not totally clear up to a recent past (see for instance network measurements from the MCI backbone network). Yet, the distinction between mice and elephants become more and more evident with the emergence of peer-to-peer (p2p) applications, which give rise to a large amount of traffic on a small number of TCP connections. The above observation leads us to analyze ADSL traffic by adopting a flow based approach and more precisely the mice/elephants dichotomy. The intuitive definition of a mouse is that such a flow comprises a small number of packets so that it does not leave or leaves slightly the slow start regime. Thus, a mouse is not very sensitive to the bandwidth sharing imposed by TCP. On the contrary, elephants are sufficiently large so that one can expect that they share the bandwidth of a bottleneck according to the flow control mechanism of TCP. As a consequence, mice and elephants have a totally different behavior from a modeling point of view.

In our approach, we think that describing statistical properties of the Internet traffic at the packet level is not appropriate, mainly because of the strong dependence properties noticed above. It seems to us that, at this time scale, only signal processing techniques (wavelets, fractal analysis, ...) can lead to a better understanding of Internet traffic. It is widely believed that at the level of users, independence properties (like for telephone networks) can be assumed, just because users behave quite independently. Unfortunately, there is not, for the moment, a stochastic model of a typical user activity. Some models have been proposed, but their number of parameters is too large and most of them cannot be easily inferred from real measurements. We have chose to look at the traffic of elephants and mice which is an intermediate time scale. Some independence properties seem to hold at that level and therefore the possibility of Markovian analysis. Note that despite they are sometimes criticized, Markovian techniques are, basically, the *only* tools that can give a sufficiently precise description of the evolution of various stochastic models (average behavior, distribution of the time to overflow buffers, ...).

3.1.2. Sampling the Internet Traffic

Traffic measurement is an issue of prime interest for network operators and networking researchers in order to know the nature and the characteristics of traffic supported by IP networks. The exhaustive capture of traffic traces on high speed backbone links, with rates larger than 1 Gigabit/s, however, leads to the storage and the analysis of huge amounts of data, typically several TeraBytes per day. A method of overcoming this problem is to reduce the volume of data by sampling traffic. Several sampling techniques have been proposed in the literature (see for instance [20], [23] and references therein). In this paper, we consider the deterministic $1/N$ sampling, which consists of capturing one packet every other N packets. This sampling method has notably been implemented in CISCO routers under the name of NetFlow which is widely deployed nowadays in commercial IP networks.

The major issue with $1/N$ sampling is that the correlation structure of flows is severely degraded and then any digital signal processing technique turns out very delicate to apply in order to recover the characteristics of original flows [23]. An alternative approach consists of performing a statistical analysis of flow as in [20], [21]. The accuracy of such an analysis, however, greatly depends on the number of samples for each type of flows, and may lead to quite inaccurate results. In fact, this approach proves efficient only in the derivation of mean values of some characteristics of interest, for instance the mean number of packets or bytes in a flow.

3.1.3. Algorithms of Sampling

Deriving the general characteristics of the TCP traffic circulating at some edge router has potential applications at the level of an ISP. It can be to charge customers proportionally to their use of the network for example. It can be also to detect what is now called « heavy users ».

Another important application is to detect the propagation of worms, attacks by denial of service (DoS). And, once the attack is detected, to counter it with an appropriate algorithmic approach. Due to the natural variation of the Internet traffic, such a detection (through sampling !) is not obvious. Robust algorithms have to be designed to achieve such an ambitious goal. An ultimate (and ambitious !) goal would be of having an automatic procedure to counter this kind of attacks.

3.1.4. Goals

- Propose a fairly *simple and accurate* estimation of the traffic circulating in an ADSL network. A limited number of parameters should characterize the traffic at the first order. Note that ADSL traffic is significantly different from the usual academic traffic analyzed up to now (more than 80% of the ADSL traffic is from Peer to Peer networks).
- *Infer* through sampling the parameters of the model proposed to describe the ADSL traffic.
- *Design and analyze algorithms* to detect in sampled traffic attacks by worms or DoS and more generally unusual events.

3.2. Design and Analysis of Algorithms

Keywords: *Data Structures*, *Stochastic Algorithms*.

The stochastic models of a class of generic algorithms with an underlying tree structure, the splitting algorithms, have a wide range of applications. To classify the massive data sets generated by traffic measurements, these algorithms turn out to be fundamental. Hashing mechanisms such as Bloom filters are currently investigated at the light of these new applications. These algorithms have also been used for now more than 30 years in various areas, among which

— Data structures. Fundamental algorithms on data structures are used to sort and search. They are sometimes referred to as divide and conquer algorithms.
— Access Protocols. These algorithms are used to give a distributed access to a common communication channel.
— Distributed systems. Recently, algorithms to select a subset of a group of identical communicating components like ad hoc networks, sensor networks and more generally mobile networks are using a related approach.

This class of algorithms is fundamental, their range of applications is very large and, moreover, they have a nice underlying mathematical structure. Trees are the main mathematical objects to describe them. The associated stochastic processes can be seen as a discrete version of fragmentation processes which have been recently thoroughly investigated by Bertoin, Pitman and others. They are also related to random recursive decompositions of intervals introduced by Mauldin and Williams and their developments in fractal geometry by Falconer, Lapidus, etc...

A very large subset of the literature has been devoted to the static case analysis, mainly because of its applications in theoretical computer science. In the dynamic case, i.e. when the shape of the tree changes according to some random events, little work has been done for this class of algorithms. Their analysis has been, for the moment, mainly achieved by using analytical methods with functional transforms, complex analysis techniques and inversions theorems. Curiously, despite of the intuitive underlying stochastic structures, probabilistic studies of these algorithms are quite scarce.

3.2.1. Goals

— *Static case*. Generalize and simplify the results currently proved by using analytic tools. Prove limit theorems for *distributions* instead of averages as it is currently the case.
— *Dynamic case*. Study renormalization techniques to analyze tree algorithms under heavy traffic. The understanding of the fundamental features of these algorithms with a traffic of requests is a major issue in this domain. Because of the quite complex technical framework, the partial results obtained up to now with analytical tools hide, in some way, the general phenomena.

3.3. Scaling of Markov Processes

Keywords: *Fluid Limits*, *Functional Limit Theorems*, *Statistical Physics*.

As the complexity of communication networks increases (and, consequently, the algorithms regulating them), the classical mathematical methods used to estimate the stationary behavior, the transient behavior show more and more their limitations. For a one/two-dimensional Markov process describing the evolution of some network, it is sometimes possible to write down the equilibrium equations and to solve them. When the number of nodes is more than 3, this kind of approach is not, in general, possible. The key idea to overcome these difficulties is to consider limiting procedures for the system.

— By considering the asymptotic behavior of the probability of some events like it is done for large deviations at a logarithmic scale or for heavy tailed distributions, or looking at Poisson approximations to describe a sequence of events associated to them.
— by taking some parameter η of the model and look at the behavior of the system when it approaches some critical value η_c. In some cases, even if the model is complicated, its behavior simplifies as $\eta \to \eta_c$: some of the nodes grow according to some classical limit theorem and the rest of the nodes reach some equilibrium which can be described.
— by changing the time scale and the space scale with a common normalizing factor N and let N goes to infinity. This leads to functional limit theorems, see below.

The list of possible renormalization procedures is, of course, not exhaustive. But for the last ten years, this methodology has become more and more developed. Its advantages lies in its flexibility to various situations and also to the interesting theoretical problems it has raised since then.

3.3.1. An Example of Scaling Methods : TCP

In our past work, the Congestion Avoidance Algorithm of the TCP protocol has been analyzed by using such a technique. The equilibrium of the *one*-dimensional Markov chain associated to this algorithm is not known for the moment. A large number of papers have been written on this famous AIMD Algorithm. But either it was, in some way, idealized or approximations were used without justifications. In a series of papers, Dumas *et al.* [2], Guillemin *et al.* [3], a conveniently rescaled (time and space) Markov process has been analyzed in the limit when the loss rate of packets of some long connection was converging to 0. It provided a *rigorous* analysis to the scaling properties of this important algorithm of TCP.

3.3.2. Fluid Limits

A fluid limit scaling is a particular important way of scaling a Markov process. It is related to the first order behavior of the process, roughly speaking, it amounts to a functional law of large numbers for the system considered.

It is in general quite difficult to have a satisfactory description of an ergodic Markov process describing a stochastic network. When the dimension of the state space d is greater than 1, the geometry complicates a lot any investigation : Analytical tools such as Wiener-Hopf techniques for dimension 1 cannot be easily generalized to higher dimensions. It is possible nevertheless to get some insight on the behavior of these processes through some limit theorems. The limiting procedure investigated consists in speeding up time and scaling appropriately the process itself with some parameter. The behavior of such rescaled stochastic processes is analyzed when the scaling parameter goes to infinity. In the limit, one gets a sort of caricature of the initial stochastic process which is defined as a *fluid limit*.

A fluid limit keeps the main characteristics of the initial stochastic process while some stochastic fluctuations of second order vanish with this procedure. In « good cases », a fluid limit is a deterministic function, solution of some ordinary differential equation. As it can be expected, the general situation is somewhat more complicated. These ideas of rescaling stochastic processes have emerged recently in the analysis of stochastic networks, to study their ergodicity properties in particular. See Rybko and Stolyar [25] for example. In statistical physics, these methods are quite classical, see Comets [19].

Multi-Class Networks. The state space of the Markov processes encountered up to now were embedded into some finite dimensional vector space. For $J \in \mathbb{N}$, $J \geq 2$ and $j = 1$,...J, λ_j and μ_j are positive real numbers. It is assumed that J Poissonnian arrivals flows arrive at a single server queue with rate λ_j for $j = 1$,..., J and customers from the jth flow require an exponentially distributed service with parameter μ_j. All the arrival flows are assumed to be independent. The service discipline is FIFO.

A natural way to describe this process is to take the state space of the finite strings with values in the set $\{1, ..., J\}$, i.e. $\mathcal{S} = \cup_{n\geq 0}\{1, ..., J\}^n$, with the convention that $\{1, ..., J\}^0$ is the set of the null string. If $n \geq 1$ and $x = (x_1, ..., x_n) \in \mathcal{S}$ is the state of the queue at some moment, the customer at the kth position of the queue comes from the flow with index x_k, for $k = 1$, ..., n. The length of a string $x \in \mathcal{S}$ is defined by $\|x\|$. Note that $\|\cdot\|$ is not, strictly speaking, a norm. For $n \geq 1$, there are J^n vectors of length n ; the state space has therefore an exponential growth with respect to that function. Hence, if the string valued Markov process $(X(t))$ describing the queue is transient then certainly the length $\|X(t)\|$ converges to infinity as t gets large. Because of the large number of strings with a fixed length, the process $(X(t))$ itself has, a priori, infinitely many ways to go to infinity. Bramson [18] has shown that complicated phenomena could indeed occur. It turns out that the « classical » fluid limits methods of the finite dimensional case cannot be used in such a setting. This is probably one of the most challenging question in the domain to be able to propose new methods to tackle the problems due to the infinite dimension of the state space. Dantzer and Robert [1] derives results in this direction. See also the corresponding chapter of Robert [5].

3.3.3. Goals

The general goals are, in some way, contained in the previous sections. They will consist in developing scaling techniques in the various cases encountered in sampling problems or tree algorithms where the traffic will be supposed to be close to saturation. The following fundamental questions will be analyzed :

- Study the impact of randomness in fluid limit processes. This has been already partially investigated in Dantzer and Robert [1].
- Develop techniques to investigate metastability phenomena observed in some models of networks in the scaling limit due to mean field approach. See Kelly [22].

4. New Results

4.1. Analysis of Splitting Algorithms

Participants: Hanène Mohamed, Philippe Robert.

Algorithms with an underlying tree structure are quite common in computer science and communication networks. Splitting algorithms are examples of such algorithms.

A splitting algorithm is a procedure that divides recursively into subgroups an initial group of n items until each of the subgroups obtained has a cardinality strictly less than some fixed number D. A common problem is, given an initial number n of requests, to estimate the time it takes to complete the algorithm. In the language of trees, it amounts to give an asymptotic expression of the number R_n of nodes of the corresponding tree.

4.1.1. Dynamic tree algorithm

This is a dynamic version of a class of algorithms analyzed by Mohamed and Robert [4]. The splitting procedure is the same, but a phenomenon of immigration has to be considered : on every leaf of the associated tree, every time unit, new messages arrive following a Poisson process of parameter λ. Contrary to the static case, the boundary conditions turn out to complicate a lot the resolution of the problem. A new probabilistic tool has to be used ; an auto-regressive process whose invariant density plays an important role to determine the asymptotic behavior of the cost of the algorithm.

It is not trivial to prove the stability of this dynamic algorithm, i.e. that the process terminates almost surely or equivalently the associated tree is finite. This question was investigated in Mohamed and Robert [4]. Under general assumptions on the distribution of the inputs A and on the branching mechanism, it is proved that the tree algorithm is stable for a sufficiently small arrival rate. As far as we know, this is the first stability result for these algorithms with non-Poissonnian arrivals.

Another problem is to describe the asymptotic behavior of the average size of the tree, denoted by $\mathbb{E}(R_n)$, with n items at the roots as n goes to infinity, when the arrivals follow a Poisson processes of intensity λ. First, following a similar approach as the static case, the explicit expression of the mean size is established in term of $D+1$ unknown constants $(c(0),\ c(1), ...,\ c(D-1),\ c(\infty))$. Then, it is proved that the asymptotic behavior of the dynamic tree algorithm is similar to the static one using similar techniques, specially the renewal theorem.

To determine the $D+1$ constants $(c(0),\ c(1), ...,\ c(D-1),\ c(\infty))$, a new probabilistic tool has to be used ; an auto-regressive process whose invariant density, added to the D boundary conditions

$$R_i = 1 \quad \text{for } 0 \leq i \leq D-1,$$

establish a linear system which gives furthermore the stability condition.

4.1.2. Leader election algorithm

A related algorithm, a leader election algorithm, has been analyzed. It has been previously investigated by Janson and Szpankowski with analytic methods. This algorithm is used in the context of a distributed system of n stations sharing a common channel of communication that can transmit only one message by unit of time. We assume that every station which sends a message to the network can listen at the same time to the channel and so discern one of three possible informations on the state of this one ; a collision when there is at least two attempts of transmission, a silence when none of the stations tried to send its message or a success when exactly one station tried transmission. The question is then how these stations can, by using the same protocol, identify one of them as a leader to coordinate the whole system ?

Such algorithm based on a process of random elimination has various applications in distributed systems such as cell telephones and networks of wireless communications. The problem of leader election in computer science is an important issue to establish communications and synchronization of different components of the system.

Formally, the algorithm of leader election divides an initial group of n items into two subgroups, eliminates one of them, and continues with the other subgroup the same process until the group has exactly one element. If at some point the current group is empty, the previous group is used.

Our study, based on probabilistic techniques, allows to simplify the analysis of such algorithm and especially gives an explicit expression for its asymptotic behavior. Besides, an explicit representation of the associated oscillation phenomenon has also been obtained. These results are obtained via a careful analysis of the following probabilistic functional equation

$$h(x) = h(px) + h(qx)\, e^{-px} + f(x) = \mathbb{E}\left(\frac{h(Ax)}{A}\, e^{-Bx}\right) + f(x),$$

where f is some given function, the couple of random variables (A, B) has the distribution

$$\mathbb{P}(A = p, B = 0) = p,\ \mathbb{P}(A = q, B = p) = q,$$

and is introduced to make direct iteration possible to acquire an explicit expression of the average cost of the algorithm $\mathbb{E}(H_n)$.

It is proved that the centered average cost of the algorithm $H_n - \lfloor -\log_p(n) \rfloor$ is asymptotically identical to a periodical function F of $-\log_p(n)$

$$\mathbb{E}(H_n) - \lfloor -\log_p(n) \rfloor = F(-\log_p(n)) + O(\frac{1}{n^\delta}),$$

where F is expressly defined and $\delta \in]0, 1[$.

4.2. Stability Properties of Loss Networks

Participants: Nelson Antunes, Christine Fricker, Philippe Robert, Danielle Tibi.

A new class of stochastic networks has been introduced and analyzed. Their dynamics combine the key characteristics of the two main classes of queueing networks : loss networks and Jackson type networks.

1. Each node of the network has finite capacity so that a request entering a saturated node is rejected as in a loss network.
2. Requests visit a subset of nodes along some (possibly) random route as in Jackson or Kelly's networks.

This class of networks is motivated by the mathematical representation of cellular wireless networks. Such a network is a group of base stations covering some geographical area. The area where *mobile users* communicate with *a base station* is referred to as *a cell*. A base station is responsible for the bandwidth management concerning mobiles in its cell. New calls are initiated in cells and calls are handed over (transferred) to the corresponding neighboring cell when mobiles move through the network. A new or a handoff call is accepted if there is available bandwidth in the cell, otherwise, it is rejected.

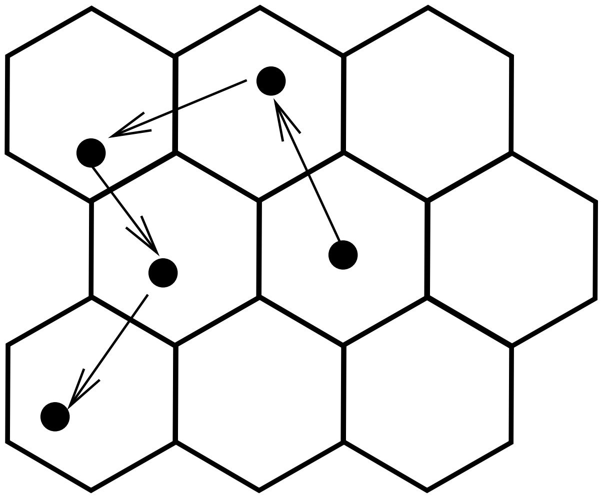

Figure 1.

The time evolution of these networks has been analyzed by considering two limiting regimes

— Heavy traffic limits.
The arrival rates and capacities at nodes are proportional to some factor N which gets large.

— Thermodynamic limits.
The number of nodes of the network goes to infinity.

The time evolution of the network can be (roughly) described as follows. A stochastic process $(\overline{X}_N(t))$ associated with the state of the network for the parameter N is introduced : $\overline{X}_N(t)$ is the vector describing the number of requests of different classes at the nodes of the network. As N goes to infinity, it is proved that $(\overline{X}_N(t))$ converges to some function $(x(t))$, satisfying the deterministic equation

$$\frac{d}{dt}x(t) = F\left(x(t)\right), \qquad t \geq 0. \tag{1}$$

The equilibrium points of the limiting process are contained in the set of solutions x of the equation $F(x) = 0$.

It was shown in Antunes *et al.* [9] that for the heavy traffic limit, there is a unique equilibrium point. The proof uses a dual method approach to study the fixed point equations together with some convenient inequalities.

For the thermodynamic limit, it is shown in Antunes *et al.* [15] that, for the completely connected network, there are situations where *several equilibrium points* coexist. This result has practical important implications for communication networks : It implies that, in some cases, the network will stay a long time in a set of states where a class of calls will be rejected and after this long time, it will switch to a set of states where this class of calls has a higher acceptance rate and, again after a long time, it switches back to the first set of states and so on. At the mathematical level, this is the situation where the function F has at least two stable points and a saddle point. The proof uses an interesting correspondence between two energy functions defined in different state spaces. In Antunes *et al.* [11], we considered a network with a planar topology and showed through an extensive set of simulations that a metastability phenomenon still occurred.

It must be stressed that, though it is quite common that the state of networks oscillates between several classes of states, it is *very uncommon* that its sojourn time in each of them is very long. In this situation average performance measures, such as outage probability, new and handoff call blocking, forced termination or total average bit rate are not meaningful. Indeed, each of these characteristics is generally estimated as a time average over a reasonable time window but, due to very long sojourn times, this estimation will probably take place while the network stays around some particular set of states. Much later, the same estimation will, very likely, lead to a different value provided that the set of states has changed. Because of this phenomenon of long time scale, the quality of service experienced by a user depends on the set of states where the network is when the call is established, and not on a general average on all the possible states. This phenomenon is clearly very undesirable since, in this situation, the operator in charge of such a network is not able to guarantee some level of quality of service, except perhaps through rough lower bounds.

4.3. Mathematical Models of Traffic Measurements

Participants: Nelson Antunes, Youssef Azzana, Yousra Chabchoub, Christine Fricker, Fabrice Guillemin, Philippe Robert.

4.3.1. Sampling ADSL traffic

The exhaustive capture of traces on high speed backbone link leads to the storage and the analysis of huge amount of data. In order to limit the consumption of memory in routers, passive traffic measurements employ sampling at the packet level. Sampling techniques (NetFlow) are implemented on CISCO routers. Flow statistics are gathered by routers from the sampled sub stream of packets. Sampling entails of course a loss of information. The main question in this domain is how one can use sampled traffic to get an accurate estimation of the characteristics of the original traffic, or to detect attacks at some router.

The traffic considered is ADSL traffic from France Telecom. The analysis of traces is achieved by modeling the traffic at a backbone link by a $M/G/\infty$ queue where the customers are flows and the service time their duration and with an additional random variable associated to each flow which is the rate of transmission. This rate is random and not constant over time. Sampling the queue every time step Δ consists in choosing at each sampling time one customer with probability proportional to its instantaneous rate. A first mathematical analysis of this sampled queue shows that, at first order, the variability of this instantaneous rate is negligible when one considers for example the probability that a flow is sampled k times ($k \geq 0$) in a given time interval. It has been also shown that the flows can seen as permanent on a fixed time interval by adjusting the transmission rate so that the volume transferred is the same. As a consequence a model for the deterministic sampling of traffic at a rate p is achieved by taking a proportion of p packets among all the packets, each of them from flow i with probability the proportion of packets of flow i.

Deterministic sampling at rate p has been compared to random sampling (take each packet independently with probability p). Let N be the number of packets of a flow in the original traffic and n (respectively $\tilde{n}$) be the number of packets of a flow after deterministic (respectively random) sampling. It is proved that, as the total number of packets in the sampling interval becomes large, n and $\tilde{n}$ converge in distribution to some probability measure Q defined by $Q(k) = E(p^k N^k e^{-pN}/k!)$. Moreover, by the Chen-Stein method applied to independent indetically distributed Bernoulli variables, the distance between the two variables can be explicitly bounded. As in practice N has a Pareto tail distribution, this formula is used to give a method to infer the Pareto parameters and the number of long flows.

The results have been validated successfully by experiments on different traffic traces (ADSL, ...). Another well known sampling result is, for some heavy-tailed distributions (Pareto and Weibull with parameter $\beta \in]0, 1/2[$), that the number of packets of a flow after random sampling at rate p has a heavy-tailed distribution of the same kind, more precisely the probability that $\tilde{n}$ exceeds l is equivalent as l tends to infinity to the probability that N exceeds l/p. In our study, the relative error is estimated via probabilistic arguments.

4.3.2. On-line Algorithm for Traffic Measurements : Detection of attacks

These algorithms are used to detect Denial of Service attacks. Such attacks consist in neutralizing a node by sending to its address a huge number of short flows from different sources. The destination cannot match this demand, waiting for acknowledgments to the SYN packets it receives. In such a situation, the traffic exhibits a huge number of SYN packets to a given destination. These packets can be considered as *flows*, i.e. a sequence of packets with common characteristics : a SYN tag and the same destination address.

The idea is to detect these few very long flows using a Counting Filter Algorithm (or Parallel Bloom Filters Algorithm) developed by *Youssef Azzana* in his PhD Thesis for a different purpose. The parameters of the algorithm must be adapted to this case. The strength of such a method is that the response time of the algorithm is quite short. It can take into account intensive attacks (a huge amount of SYN in a short time) and progressive attacks (a moderated number of SYN but steadily growing on a long duration time). Moreover the destination of the attack can be returned by the algorithm.

Simulations have been done on two traces given by France Telecom for the research project Oscar : a OTIP sampled trace of 65 hours with DoS attacks and a ADSL trace of 3 hours. The adaptive mechanism to refresh filters of Parallel Bloom Filters Algorithm must be more drastic than in *Youssef Azzana* 's work. It has been shown that, for the traces considered, the threshold must be maintained at 20%. The main difficulty of the algorithm is to determine the number of parameters which can be chosen independently of the traffic (and to have few of them). On the contrary some parameters must be adapted to the traffic.

5. Contracts and Grants with Industry

5.1. Contracts

Participation to the CRE with France Telecom « Mathematics of Internet Measurements ». Two years contract starting from 2005.

Participation to the RNRT project « OSCAR » on the attack detection in the Internet. Two years contract starting from April 2006.

Participation to the ACI Masse de données « FLUX » on the probabilistic counting methods of large data sets occurring in traffic measurements, biological sequences, dictionaries. Participants : INRIA (Algo project), INRIA (Rap project) and University of Montpellier. Three years contract starting from 2004.

Participation to the ANR Projet Blanc « SADA » on the Discrete Random Structures, three year contract starting from 2005. Participants : University of Bordeaux, University of Caen, Computer science department of Ecole Polytechnique, INRIA Algo and Rap projects, University of Versailles.

6. Other Grants and Activities

6.1. European initiatives

RAP is participating to the E-next network of excellence of EC. This network involves many research teams throughout Europe. In France, participants include LIP6, INRIA-Sophia, LAAS, ...This network is a continuation of the efforts of RAP team in the domain of traffic measurement.

6.2. Visiting scientists

RAP team has received the following people :
Sindo Nunez-Queija (CWI, Amsterdam), Nelson Antunes (University of Algarve), Matthieu Jonckheere (CWI, Amsterdam), Kavita Ramanan (Carnegie Mellon University), Ravi Mazumdar (University of Waterllo, Canada), Isi Mitrani (University of Newcastle, UK) and Ahmed Kharroubi (University of Casablanca).

7. Dissemination

7.1. Leadership within scientific community

Philippe Robert is the Chairman of the Project Committee of INRIA-Rocquencourt.

Philippe Flajolet and *Philippe Robert* organized the ALEA conference in Luminy at CIRM (Marseille).

Philippe Robert is associate Professor at the École Polytechnique in the department of applied mathematics. He is in charge of lectures on mathematical modeling of networks.

A working group on Large Networks with regulars conferences has been set up at INRIA-Rocquencourt.

7.2. Teaching

Christine Fricker gives Master2 lectures « Stochastic Processes » at the University of Versailles St-Quentin. She gave Master2 lectures « Stochastic Networks » at the University of Tunis from February 5 to 9.

Philippe Robert gives Master2 lectures « Stochastic Networks » in the laboratory of the Probability of the University of Paris VI. He is also giving lectures in the « Majeure de Mathématiques Appliquées et d'Informatique » on Networks and Algorithms at the École Polytechnique. He gave lectures on algorithms at the University of Tunis from January 23 to 27.

7.3. Conference and workshop committees, invited conferences

Yousra Chabchoub and *Christine Fricker* were at the RNRT project Oscar meeting (October 5 to 6) at INRIA Sophia-Antipolis, *Yousra Chabchoub* and *Philippe Robert* attended to RNRT project Oscar meeting in Rennes (June 21 to 22.

Yousra Chabchoub visited France Telecom R&Din Lannion (July 3 to 7).

Christine Fricker gave a talk at the Madrid Conference on Queueing Theory from July 3 to 7 in Madrid, Spain. She visited France Telecom R&Din Lannion (April 18 to 21).

Hanène Mohamed gave a talk on leader election algorithm at the conference « Algorithms, Trees, Combinatorics and Probabilities » in Nancy, September 18 to 21.

Philippe Robert has been invited in Lunteren (Holland) to give lectures on algorithms and scaling methods (January 17 to 19). He gave talks at Eurandom (Eindhoven) January 16 to 17 and CWI (Amsterdam) January 20 on large networks. He gave a talk on tree algorithms at the University of Tunis on January 26. He visited Columbia University (New-York City) April 24 to 25 and Carnegie Mellon University (Pittsburgh) where he gave a colloquium conference on tree algorithms and a conference on large networks. He gave a lecture on May 5 at the Lycée of Longjumeau on communication networks, later this talk has been registered at INRIA-Rocquencourt. It is available on the INRIA web site. He also gave a shortened version of this talk at the « Comité de centre ». He attended the ACM-Sigmetrics conference in Saint Malo June 27 to 29 where he gave a talk on queueing systems with impatience. He gave a seminar at the « Laboratoire de Probabilités » (Paris VI) on tree algorithms on November 28 and finally defended his « Habilitation à diriger des recherches » on December 1st at the University of Paris VI.

8. Bibliography

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[6] Y. AZZANA. *Mesures de la topologie et du trafic Internet*, Ph. D. Thesis, Université de Paris 6, July 2006.

[7] P. ROBERT. *Réseaux Stochastiques et Algorithmes*, Habilitation à diriger des recherches, Ph. D. Thesis, Université Pierre et Marie Curie, December 2006.

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[8] N. ANTUNES, C. FRICKER, F. GUILLEMIN, P. ROBERT. *Perturbation Analysis of a Variable $M/M/1$ Queue : A probabilistic Approach*, in "Advances in Applied Probability", vol. 38, n^{o} 1, 2006, p. 263–283, http://www-rocq.inria.fr/~robert/src/papers/2004-9.pdf.

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