



Traffic Monitoring for 3G Network Diagnostic: a Doctor's View

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This talk



Goal

share lessons learned about the role of traffic measurements data → *signals* for the diagnosis of network problems in a 3G mobile network → *system*

Outline

- Background
- Introduction to 3G cellular networks
- Traffic monitoring and Network Signals for Diagnostics
- Example: detection of congestion bottleneck

Research on 3G traffic monitoring @FTW



- Research on 3G Traffic Monitoring @FTW began in 2004
- METAWIN project
 - Measurement and Traffic Analysis in Wireless Network
 - partners: network operator, system integrator, university

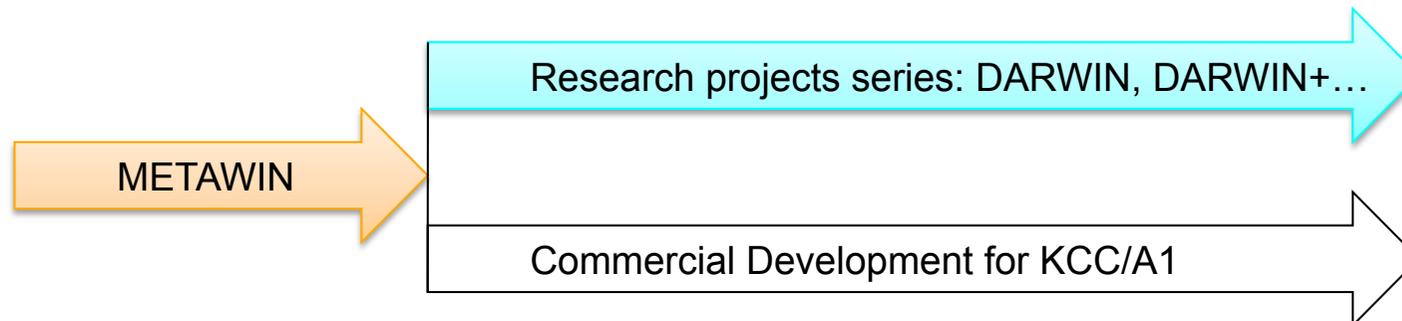


- Goals
 - Sniff packets in the 3G core Network (GPRS and UMTS)
 - Analyze traffic traces to support network planning
 - Understand “what’s going on”

Research on 3G traffic monitoring @FTW



- Results from 1st project
 - Prototype of advanced **monitoring system**
 - Developed from scratch on Linux
 - Deployed in the live network of A1 for dual use (production + research)
 - Access to real network and monitoring data for research
- Follow-up projects
 - research: analysis of traffic data
 - commercial: development/extension of monitoring system





Introduction to 3G mobile networks

Circuits and Packets



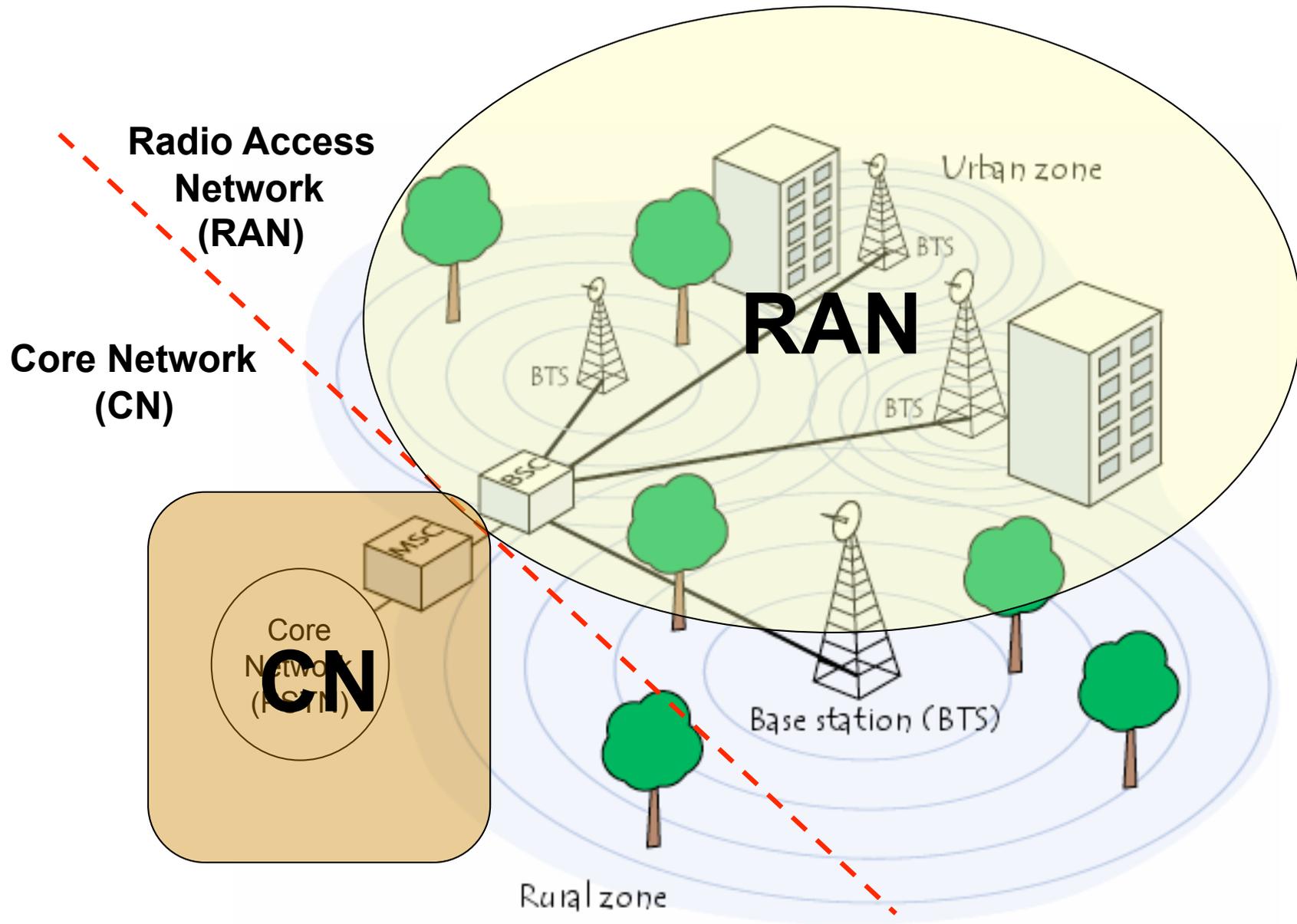
- Two main design approaches for Communication Networks
- Circuit-switched (CS)
 - nodes build a long pipe (→ “circuit”) from source to destination
 - data (e.g. voice samples) travel into the pipe



- Packet-switched (PS)
 - data travel in independent chunks → “packets”
 - packets received, processed and forwarded independently by intermediate nodes



Architecture of 2G mobile network (GSM)

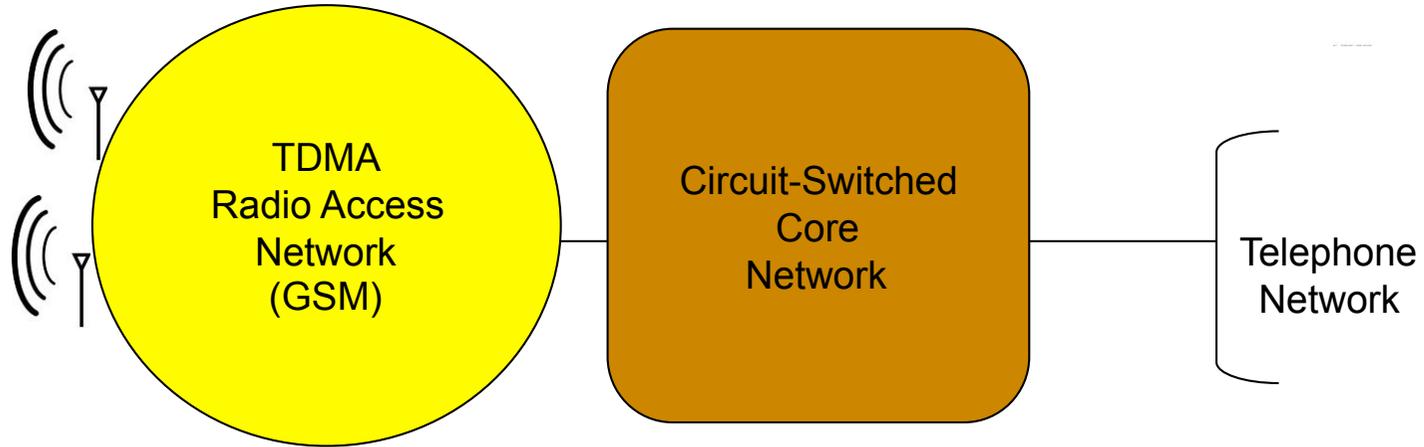


Evolution of cellular networks

2G (GSM) ...

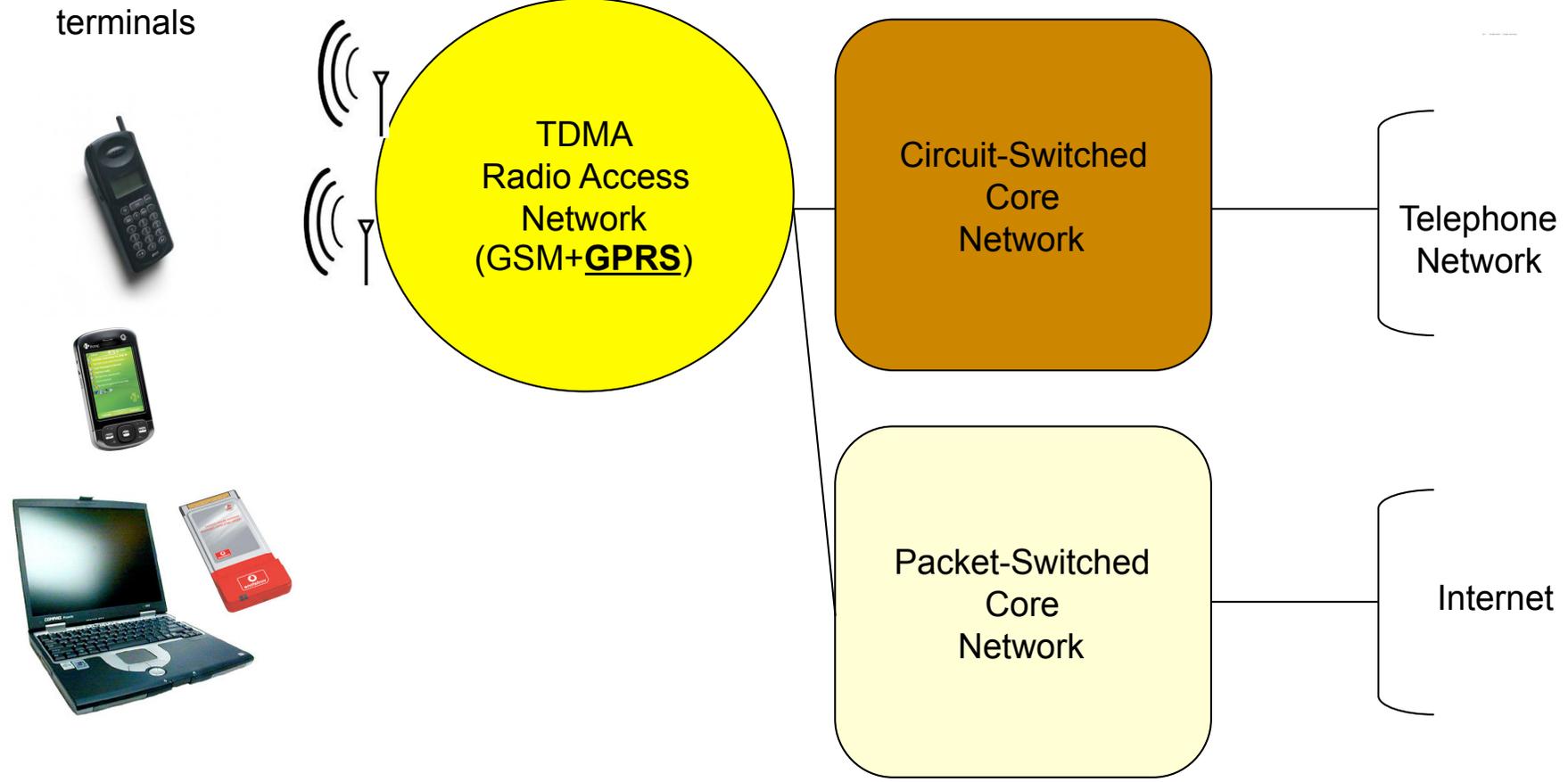


terminals



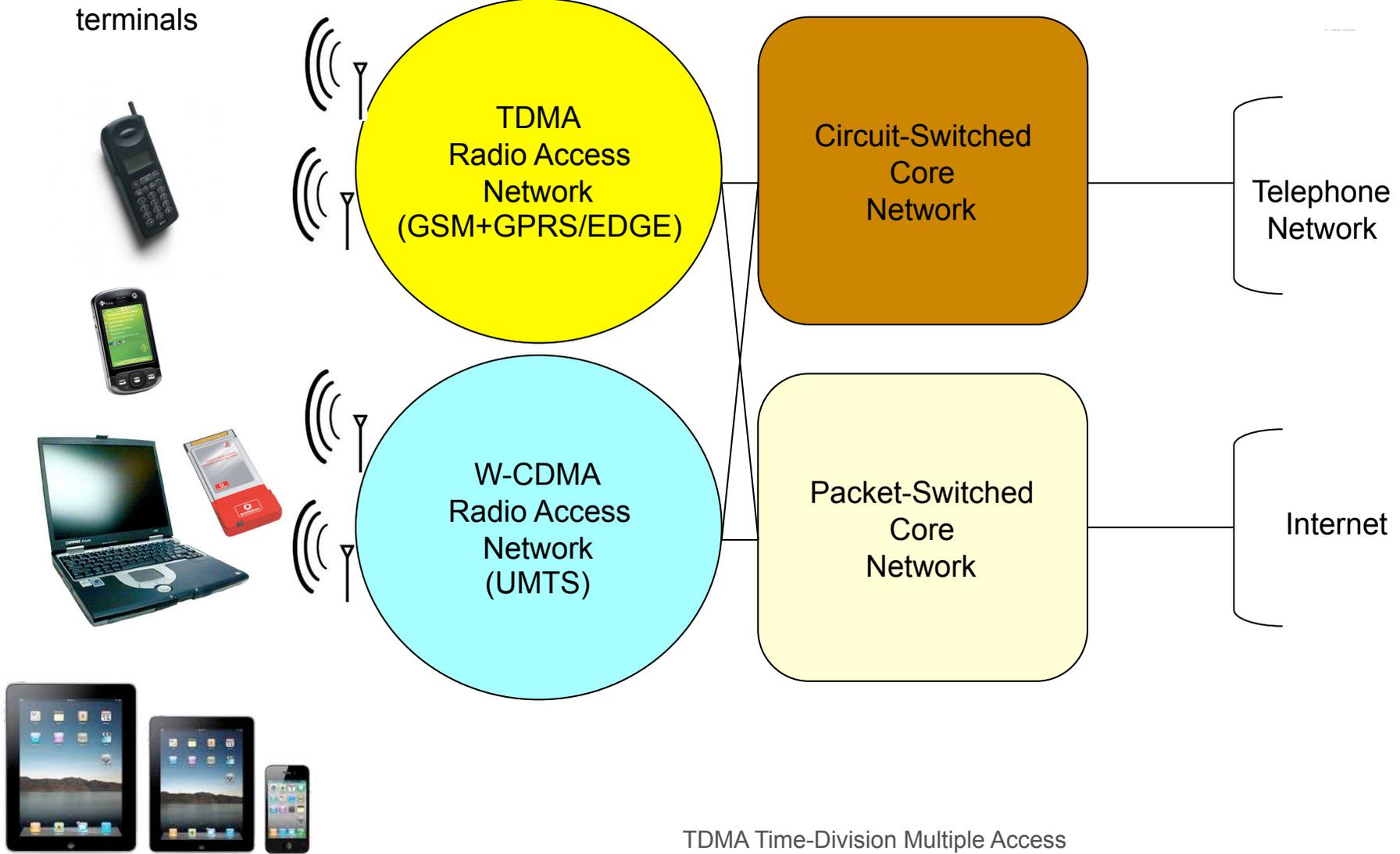
TDMA Time-Division Multiple Access

... 2.5G (GPRS) ...



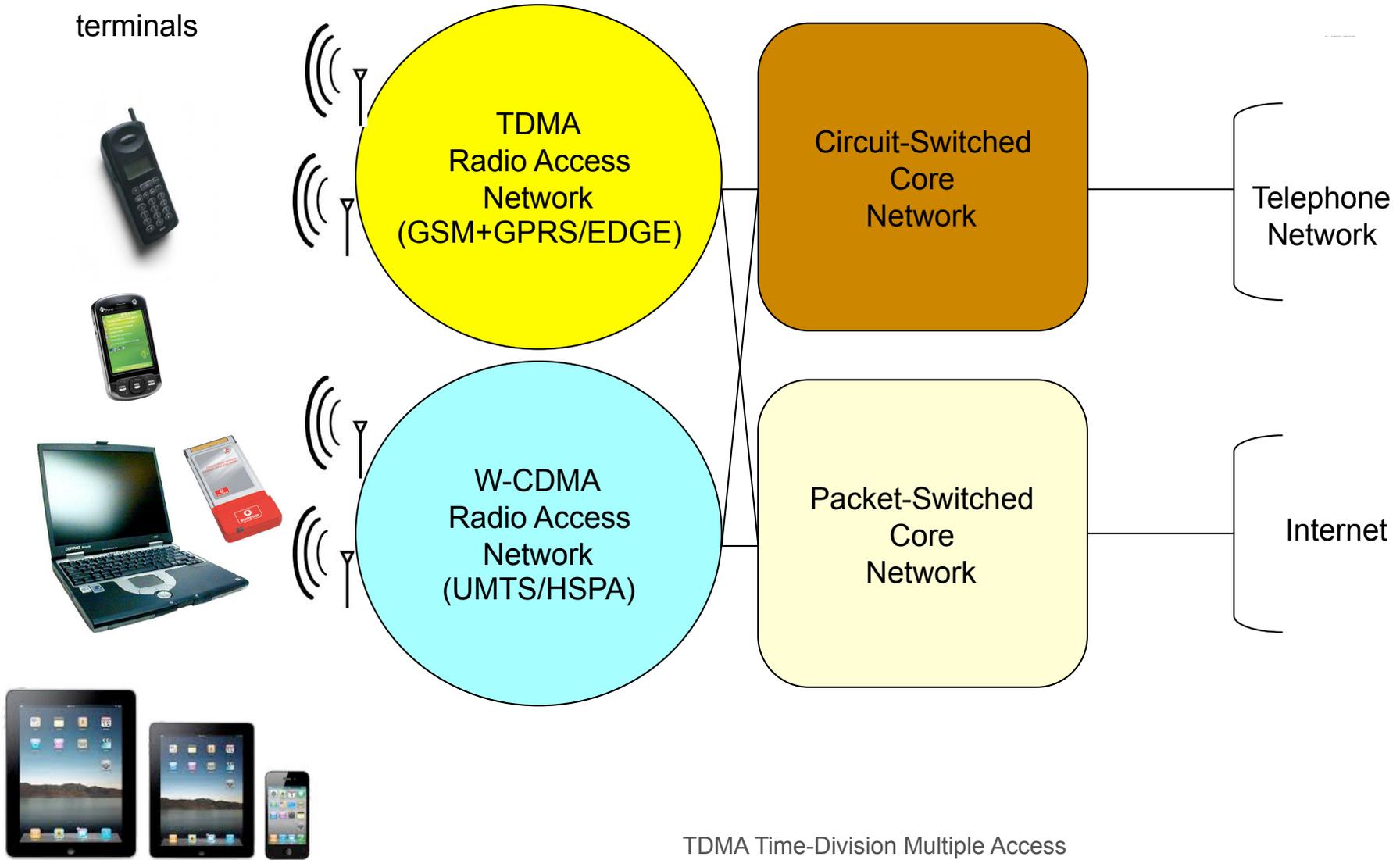
TDMA Time-Division Multiple Access
W-CDMA Wideband Code-Division Multiple Access

... 3G (UMTS) ...



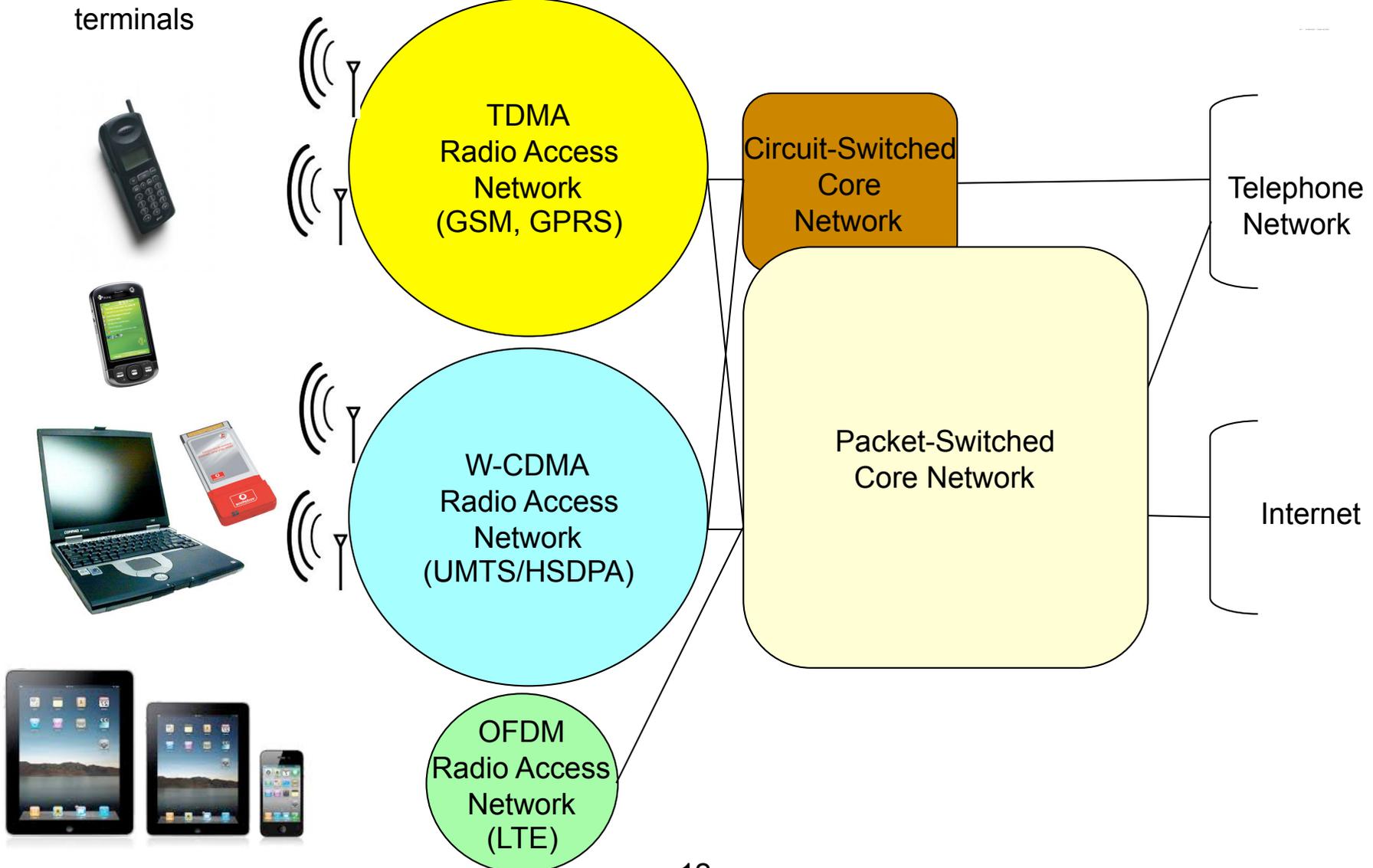
TDMA Time-Division Multiple Access
W-CDMA Wideband Code-Division Multiple Access

...3.5G (HSPA)...



TDMA Time-Division Multiple Access
W-CDMA Wideband Code-Division Multiple Access

... 4G (LTE/SAE) ...



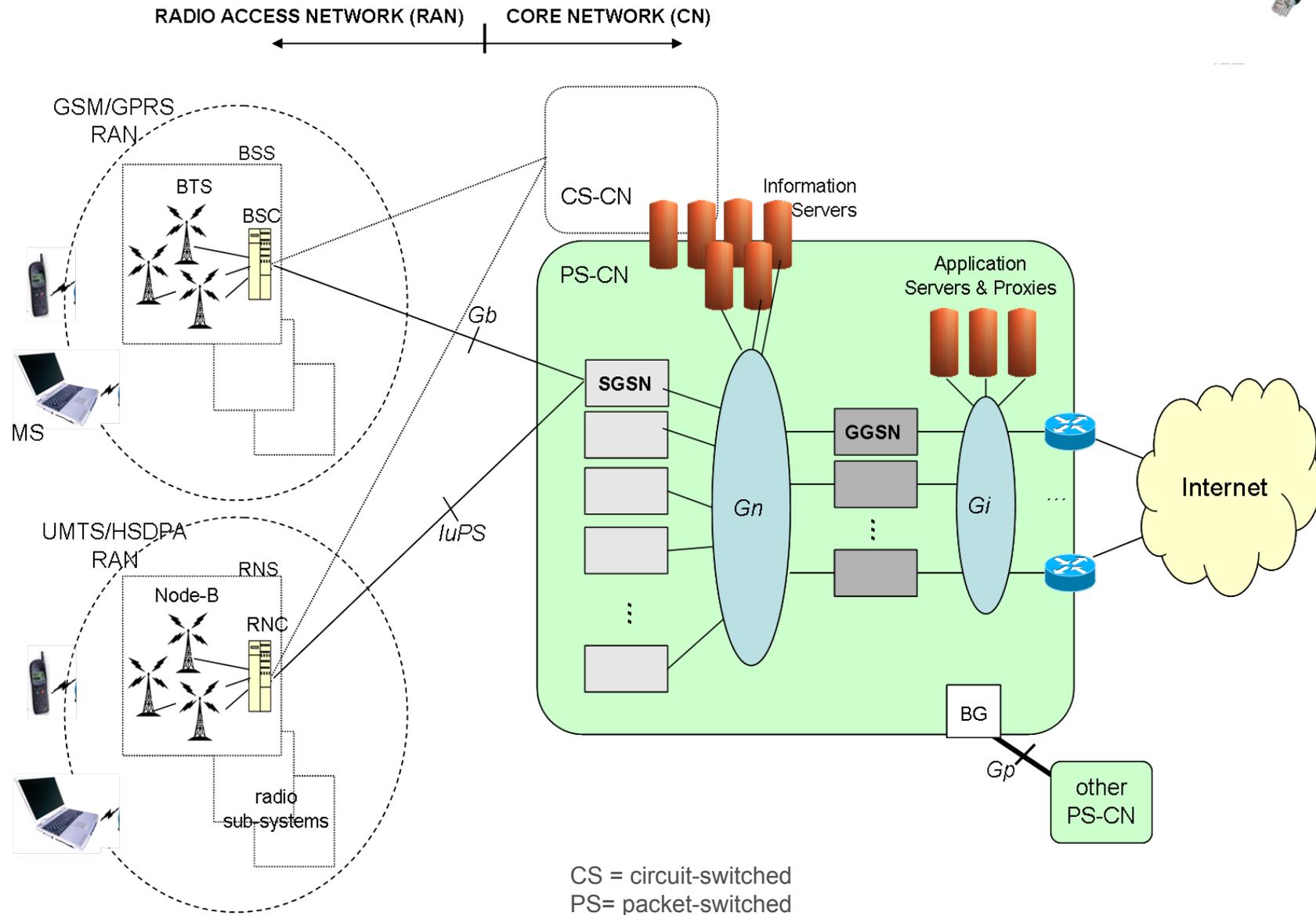
It keeps changing ...



- Cellular Network is continuously evolving system...
 - architecture evolves: GSM, GPRS, EDGE, UMTS, HSPA, LTE/SAE
 - upgrade/replacement of network equipments
 - new SW releases, new network features
 - capacity upgrades: more radio bandwidth, higher link speed
- ... embedded in a continuously evolving usage environment
 - more 3G **users**, increasing bandwidth demands, changing traffic patterns
 - more **terminals**, of new classes (laptop, smartphone, tablets... Internet of Things...) and capabilities
 - evolution of **applications**, apps, services
 - new habits: mobile tethering, wifi offloading

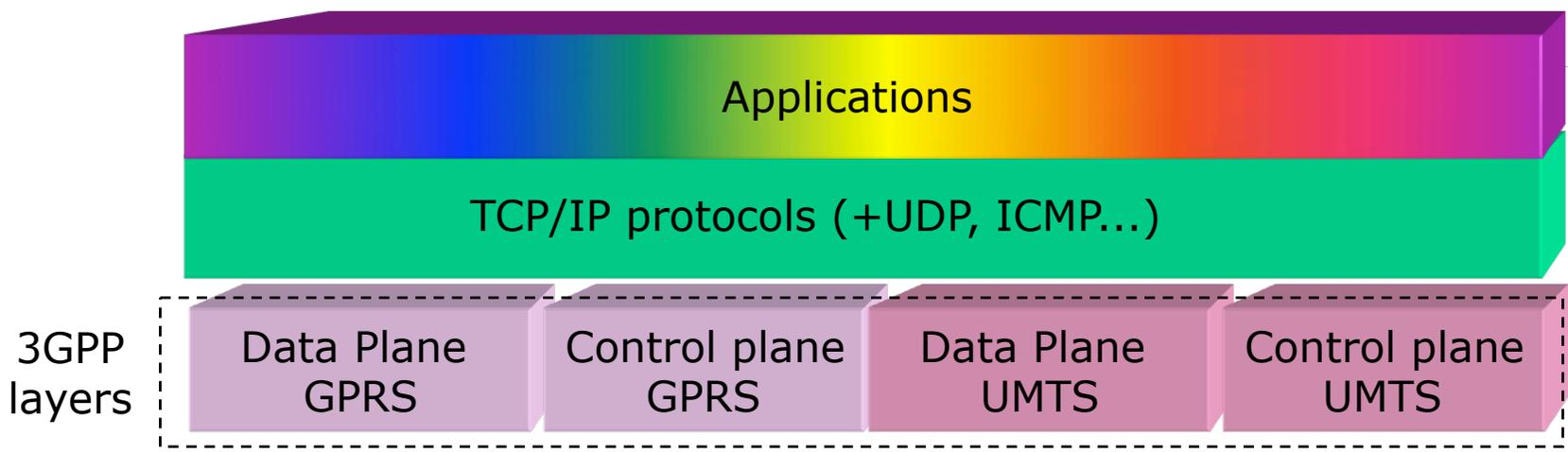


Representation of Architecture

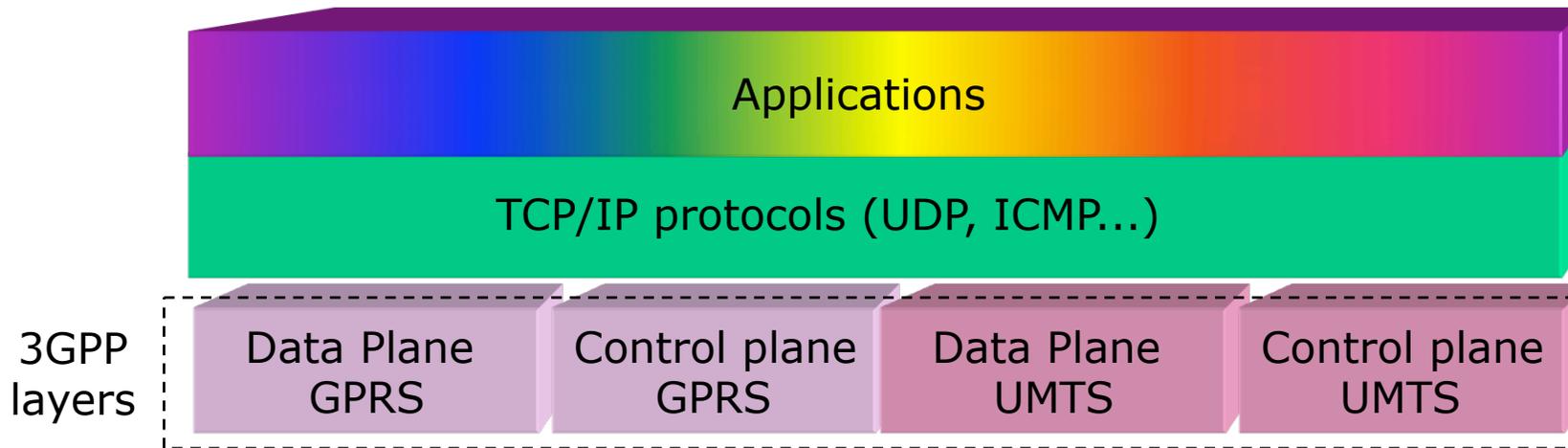


CS = circuit-switched
 PS = packet-switched

Representation of Protocol Stack



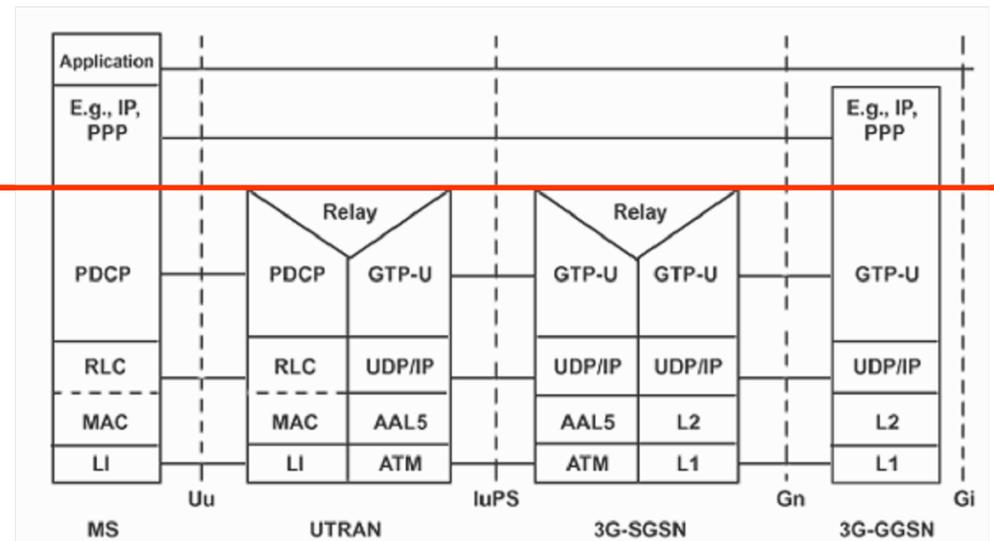
Representation of Protocol Stack



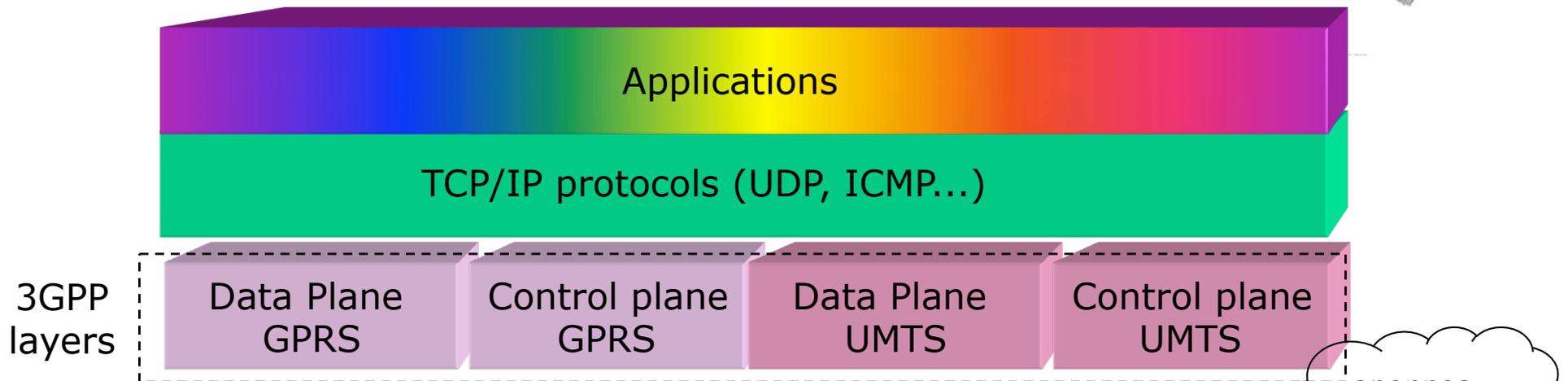
- Control Plane needs to Manage:

- Radio Resources RRM
- Mobility MM
- Connections CM

↑ User-IP
 ↓ 3GPP specific protocols



Representation of Protocol Stack

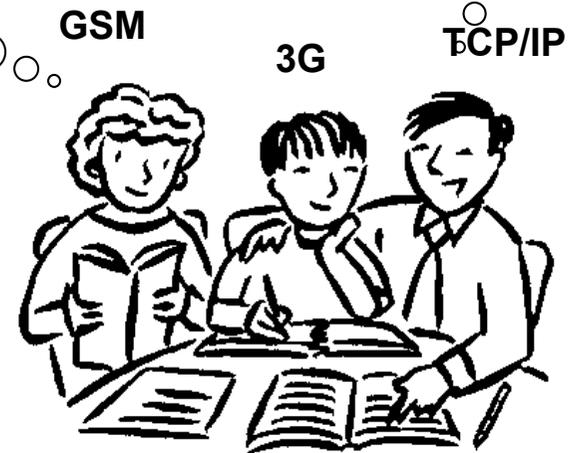


functional complexity

opennes heterogeneity

- Control Plane needs to Manage:
 - Radio Resources RRM
 - Mobility MM
 - Connections CM

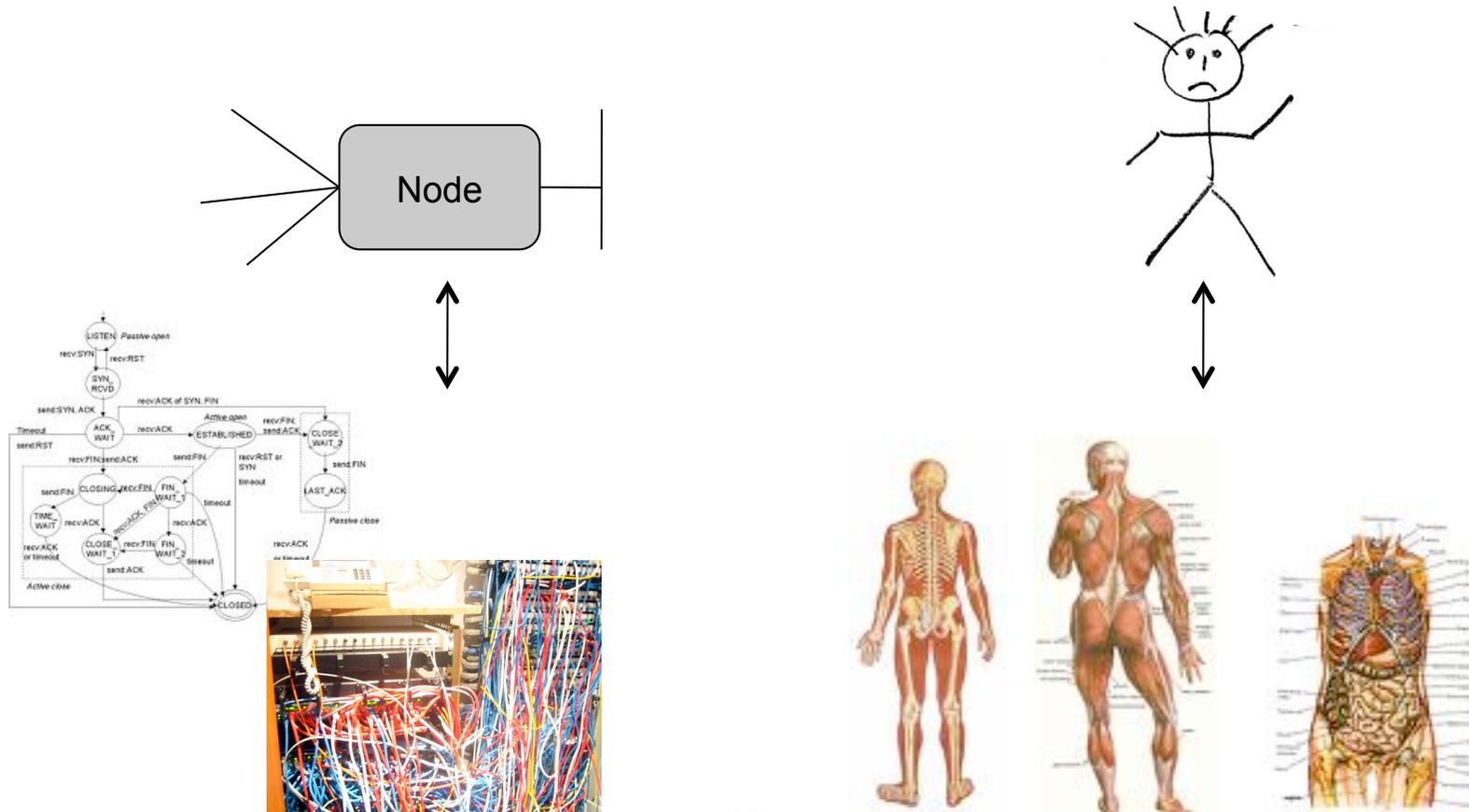
- Diversity of applications, traffic patterns, open reachability

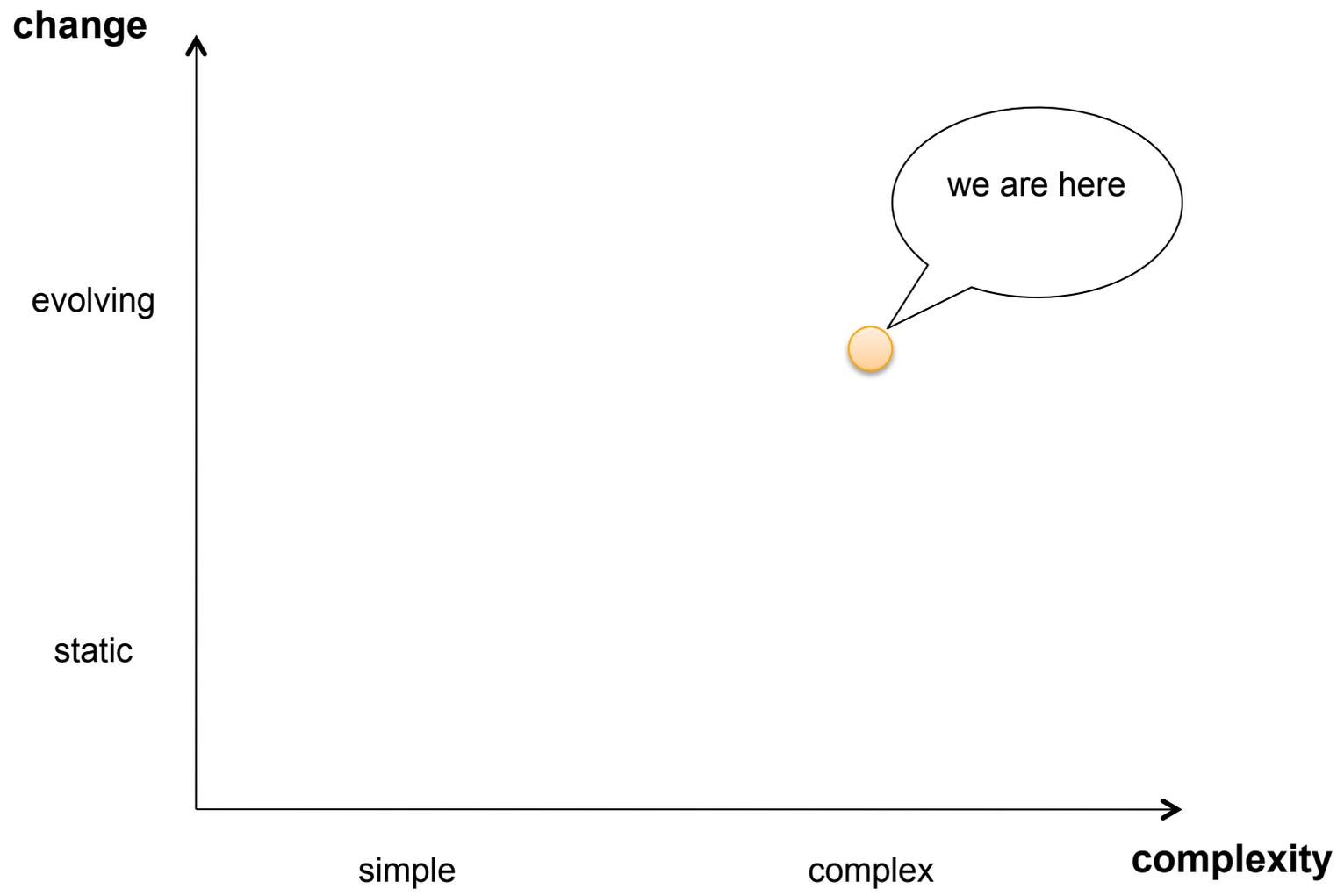


Analogy with human body



- The real **infrastructure** is much more complex than *any* of its schematic **representation**
 - Physical and logical components, dependencies, functional layers
... **like a human body!**





... keeps watching it



- 3G networks are complex and evolving systems
- → new risks, problems, anomalies arise continuously ...
- **Endogenous:** congestions, misconfiguration, failures, malfunctioning
- **Exogenous:** attacks, large-scale infections
- To operate correctly the network infrastructure, its **health** status must be monitored continuously, to reveal problems/anomalies as early as possible
- → diagnosis & troubleshooting are continuous processes (not one-shot tasks)
- *How network monitoring can help the process of diagnosis and troubleshooting ? What are the difficulties & challenges?*

Like a Doctor



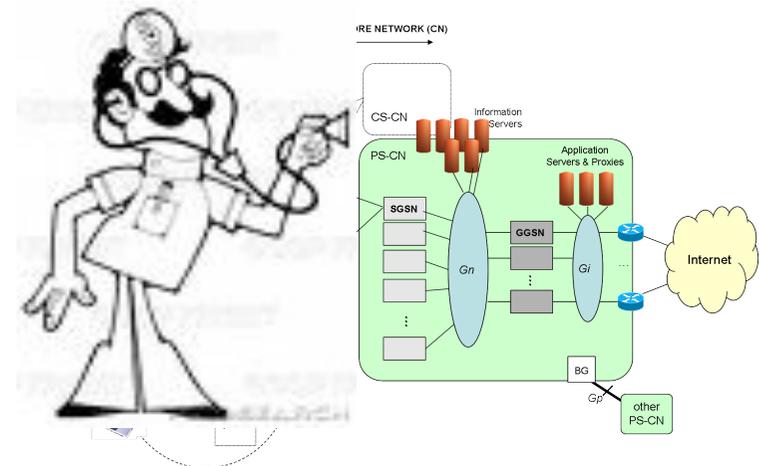
- How ?
 - Observe many “**signals**” from the infrastructure, obtained with non-invasive methods
 - Reveal “**symptoms**” of abnormal conditions and interpret possible causes → “**diagnosis**”

- Challenges

- define the “right” signals (cost vs. benefit)
- detect “abnormal conditions” (symptoms)
- interpret the root cause (diagnosis)

- Like in Medicine ...

- coping with “soft” definitions
- some irreducible level of subjectivity





Introduction to Network Monitoring

Network Monitoring



- How the operator can monitor its network
- 1. Ask the boxes
 - Collects logs and alarms from network equipment themselves
 - Limited amount of data, coarse accuracy, sometimes unreliable

Network Monitoring



- How the operator can monitor a network
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- 2. Active measurements
 - Send end-to-end probe traffic through the network
e.g. test downloads, pings

Network Monitoring



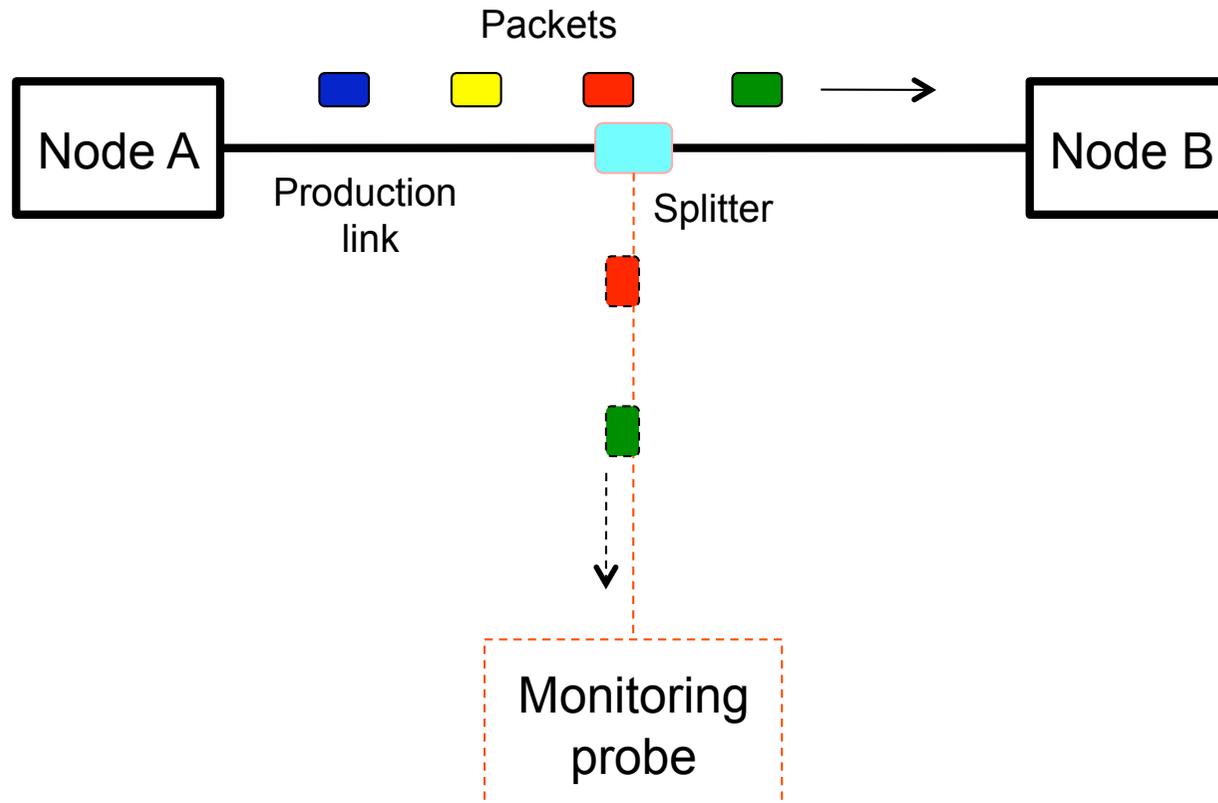
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 - 2. Active measurements
 - Send end-to-end probe traffic through the network
e.g. test downloads, pings
 - **3. Passive monitoring**
 - “sniff” packets on the wire
 - Non invasive, but requires monitoring HW installation
- Hybrid Measurements
 - send probe traffic and capture it passively inside the network

Passive monitoring

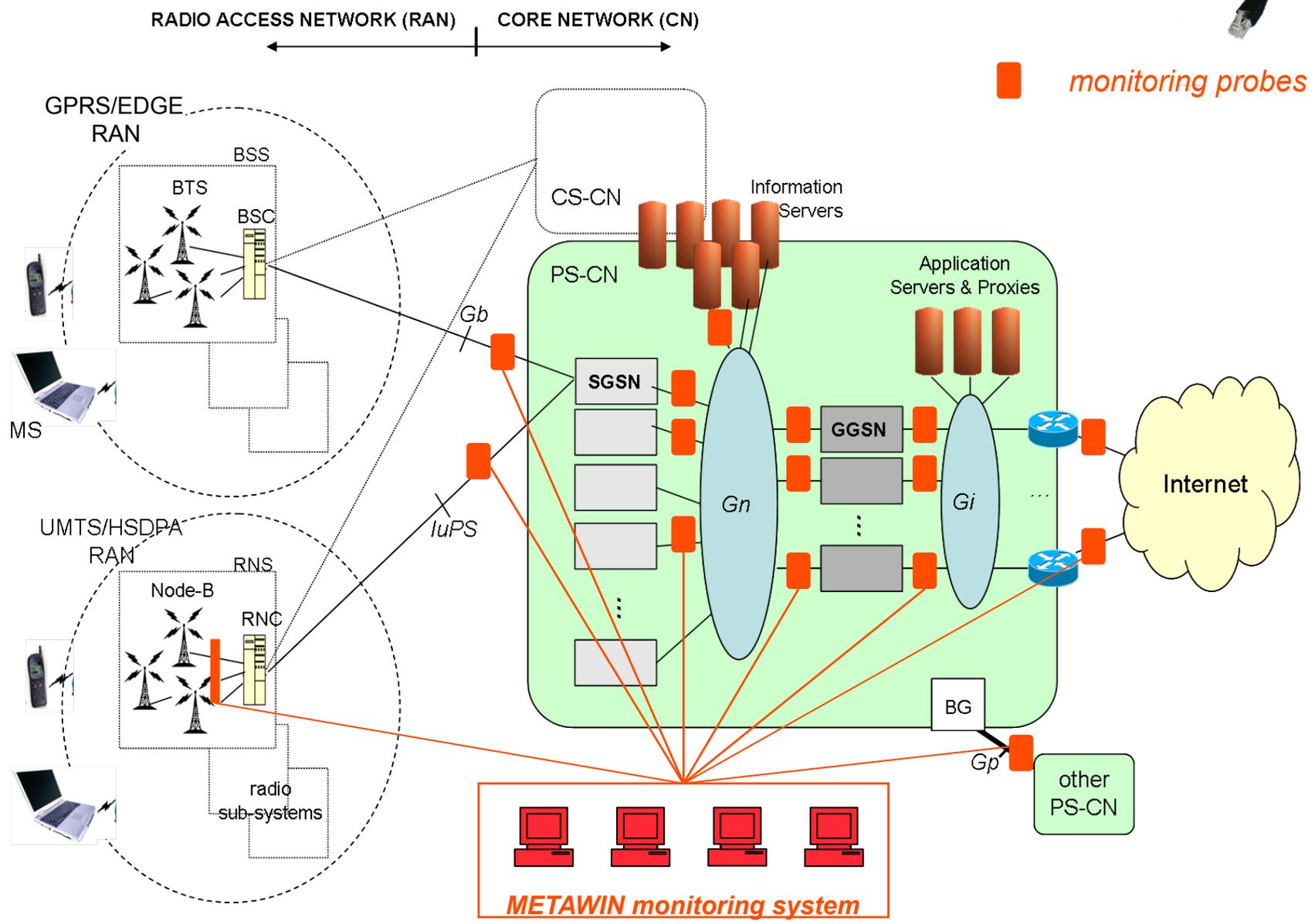


- Sniffing

- pick a copy of the packet as it traverses the wire
- Store it with additional information to each record
 - e.g. timestamps, capture interface, terminal type



Example of passive monitor deployment



Network signals



- Examples of “network signals” related to performance metrics
 - one-point measurements on data plane
 - TCP Round-Trip-Time (RTT), Retransmissions, Timeouts
 - Throughput statistics (peak, mean,...), Download times
 - higher-layer Request/Response delay (DNS, HTTP, ...)
 - two-point measurements on data plane
 - One-way delay
 - Packet loss

control-plane signals

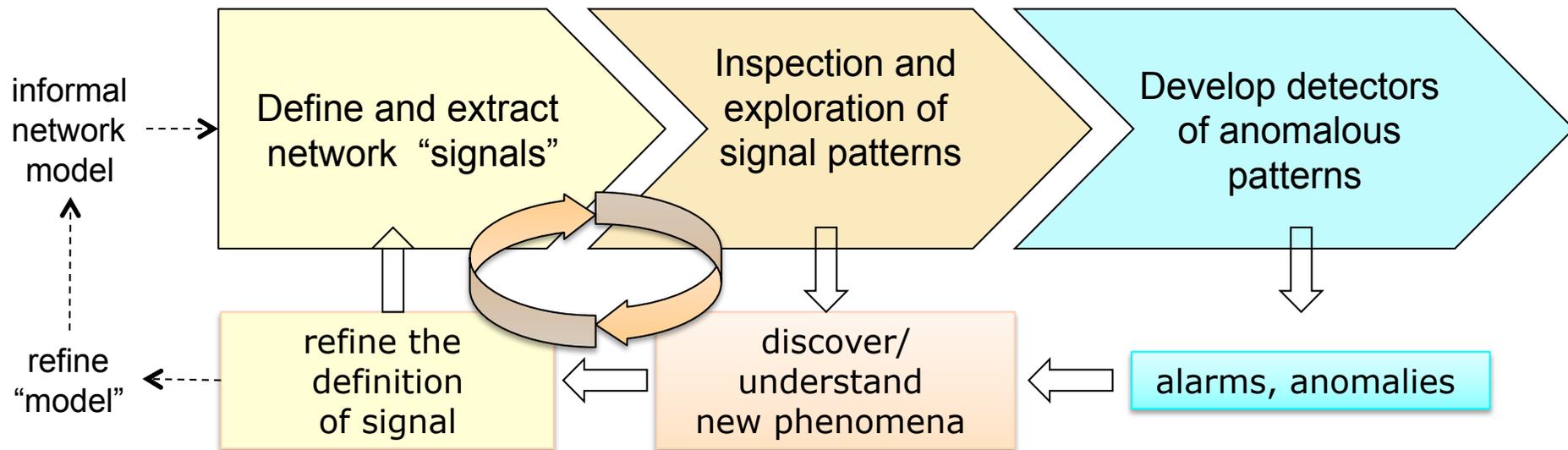
 - Frequency of error messages, latency of signaling procedures

- Signals can be partitioned across several dimensions
 - Network section
 - e.g. traffic to server Y, to peering link X, to node Z ...
 - User class, Terminal type
 - Application, Service ... etc.

Considerations



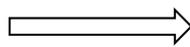
- Basic principle: network problems will impact one or several “signals”, causing abnormal patterns
 - congestion → higher loss and/or delay, lower flow throughput
 - observe the signal to infer back the problem





our mental model ...

event A



pattern on signal X

eg. "congested link"

eg. "more flows getting low throughput"

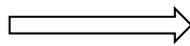
To reveal this

We measure this

the reality ...

event A

congested link



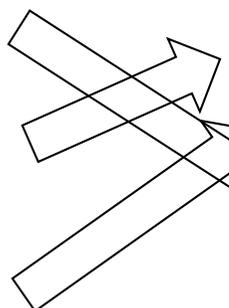
pattern on signal X

cause B

large-scale antivirus update

cause C

low-rate app getting popular



pattern on signal Y

a matter of definitions



- Q. How many sheep in this field ?
- counting is easy ...
- once you define clearly **what** to count
 - how is the "field" delimited ?
 - and what do you mean exactly by "sheep"?
 - are *lambs* counted as sheep, or only adults ?
 - do *pregnant sheeps* count for 1 or 2 ?
 - what about those *dead sheeps* over there ?
 - shouldn't we count *goats* too ?
 - ...



WHY do you want to count ? ← **WHAT to count ?**



Examples of Passive Monitoring for Network Diagnostic

Longum est iter per praecepta, breve et efficax *per exempla*

Detecting congestion bottleneck



- Congestion bottleneck

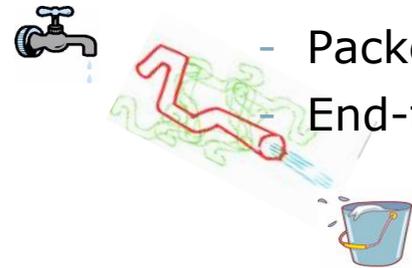
- Definition: too much traffic for too little capacity *at some point*

- Effects on packets

- Packets queued in buffers: longer transit delay

- Packet drops: retransmissions

- End-terminals react reducing the sending rate



- Impact on users

- Loooooong waiting for downloads

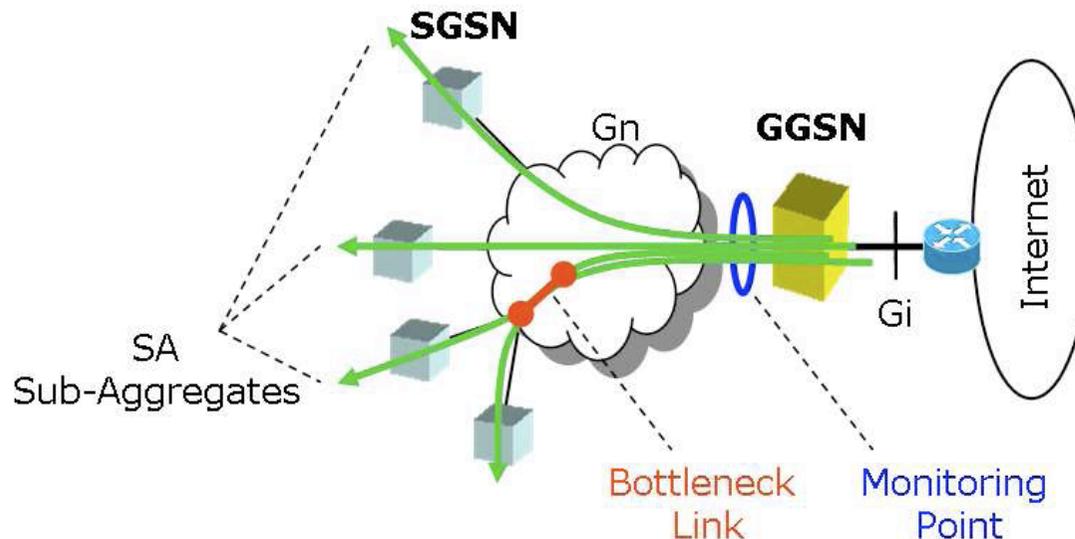
- Interactive applications don't work: voip, skype, game...



Detecting congestion bottleneck



- Causes for congestion bottleneck
 - Traffic grew faster than provisioning cycle
 - gap between nominal vs. actual capacity (e.g. due to misconfigurations, malfunctioning, ...)
- Problem: not *every* link/node can be monitored
- Goal: detect congestion on link/node X from the analysis of traffic at a different point M
 - without a priori information about *actual* link capacity
 - without topology information



Look at TCP



- Idea: look at TCP
 - TCP is closed-loop → protocol dynamics have end-to-end interactions → local problem on link X should be visible at any other path section
 - >90% of traffic is TCP

- Possible approaches: analysis of ...
 - Distribution of Traffic Rate
 - Frequency of Retransmission Timeouts (RTOs)
 - Round-Trip Times (RTT)
 - Per-flow Throughput

Detecting congestion bottleneck



- Detecting congestion from aggregate rate analysis
 - a real case study

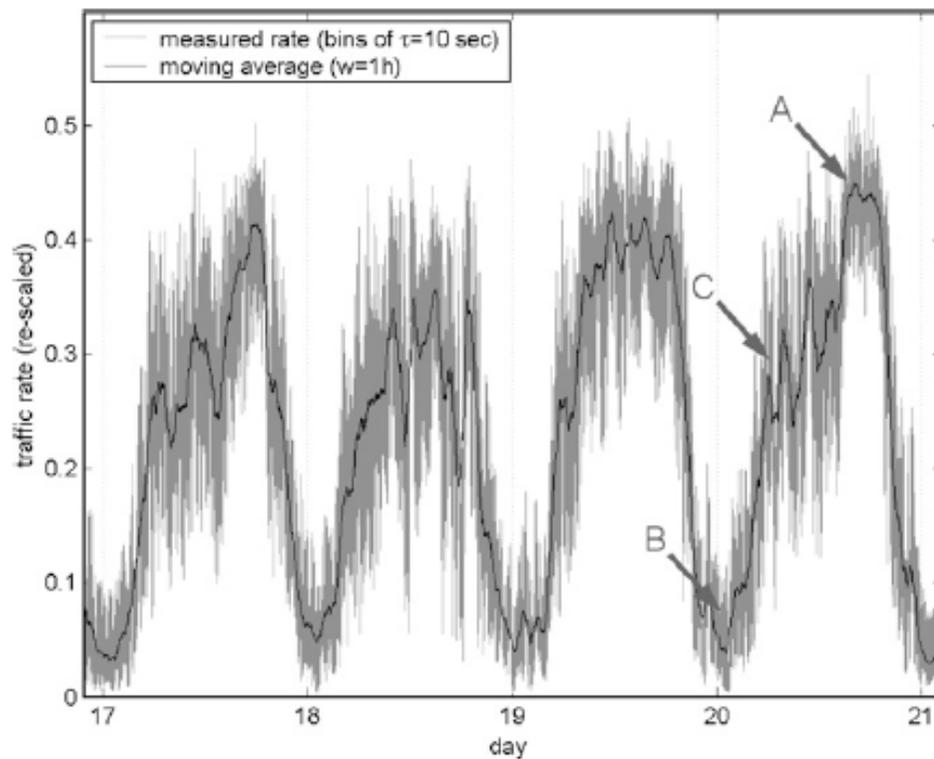


Fig. 3. SA total rate for days 17–20 (10 s bins).

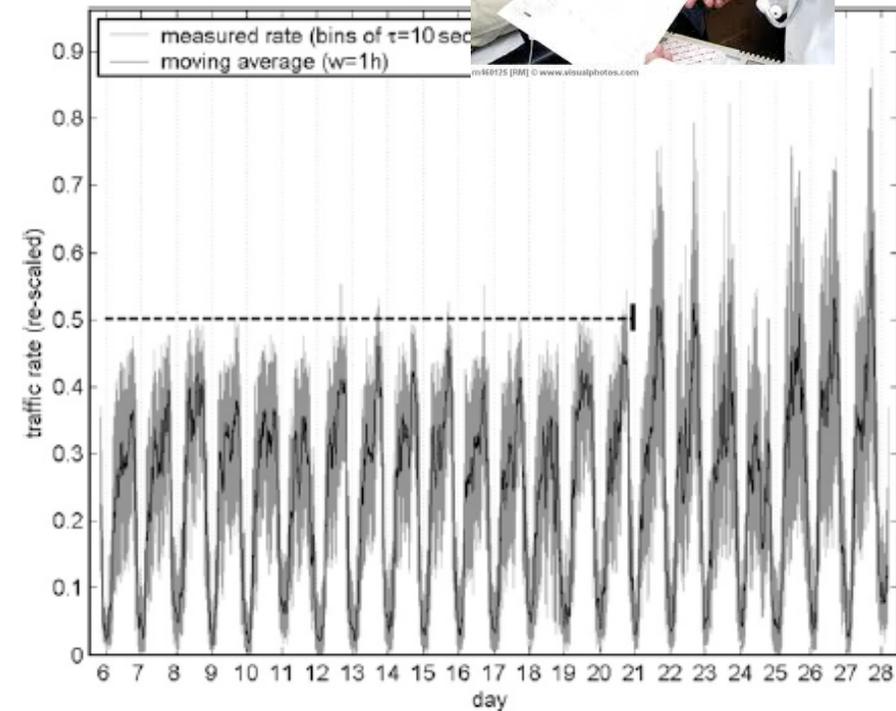


Fig. 2. SA total rate for the monitored period (10 s bins, rescaled values).

Aggregate Rate Analysis - Background



■ Background

- The simplest traffic model for infinite capacity: superposition of *independent* On/Off flows
 - Poisson arrivals of rate λ , holding time of mean ϑ
 - fixed rate $r=1$ (M/G/ ∞ queue)
- Aggregate rate (marginal) is Poisson distributed
 - Variance = Mean
 - Skewness = Mean^{-1/2}

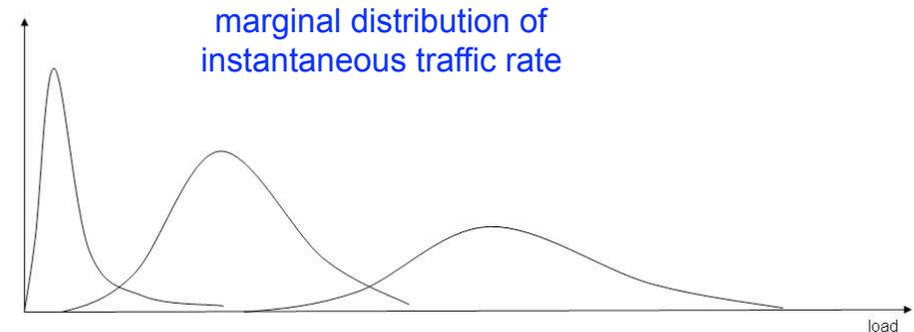
$$p_R(k) = \frac{e^{-A} A^k}{k!}$$

$$VAR(R) = E(R) = A$$

$$SKEW(R) = 1/\sqrt{A}$$

■ Bottleneck-free conditions

- Variance of marginal rate increases with mean load
- Variance is higher at peak-hour
- Skewness is lower at peak-hour

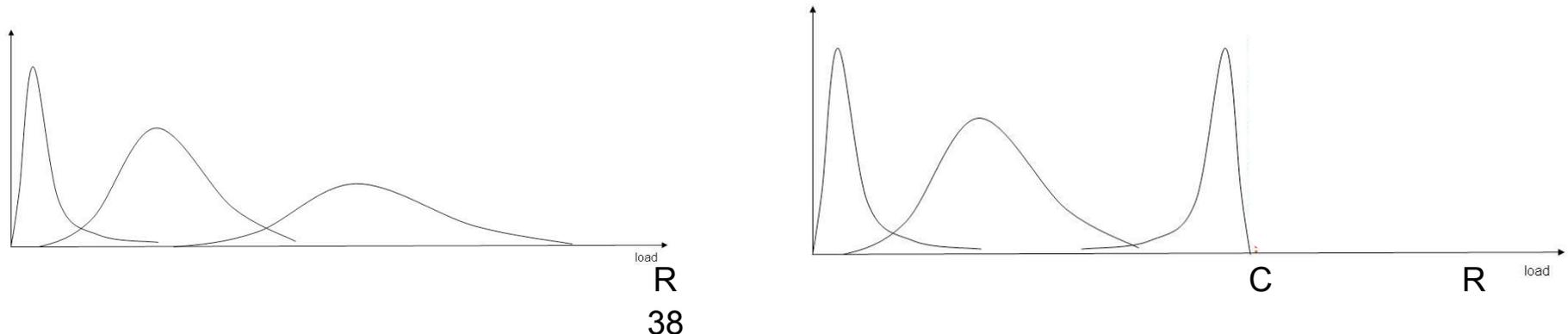


Aggregate Rate Analysis – the idea



- Conjecture on bottleneck-constrained traffic
 - Instantaneous rate R can not exceed path capacity C
 - Bottleneck induces *correlation* between flow rates as $R \rightarrow C$
 - via congestion control loop
 - reflecting barrier at $R=C$
 - Variance reduction and left-skewness as $R \rightarrow C$

Idea: use trajectories of VAR-MEAN and SKEW-MEAN to infer the presence of a bottleneck (and value of C)
without a priori information on C !

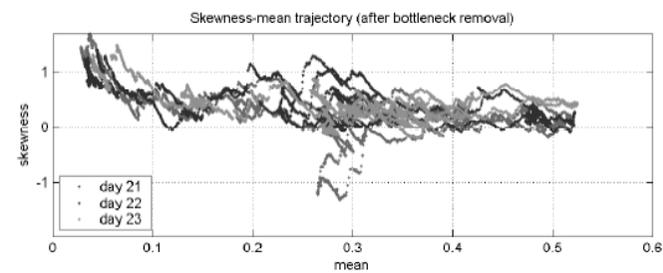
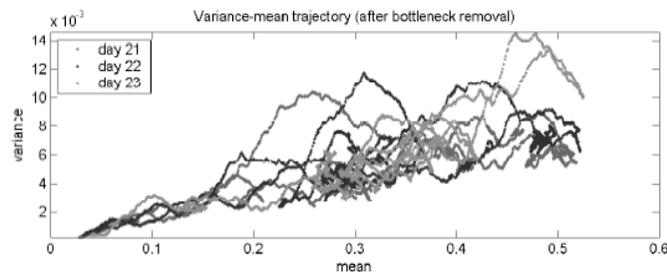
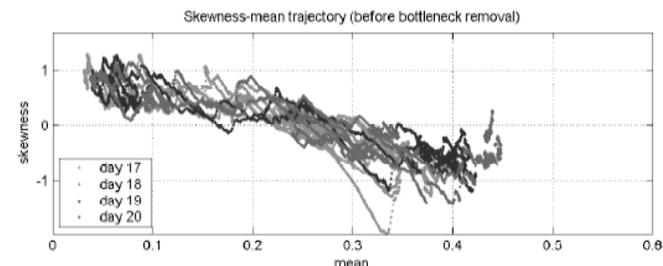
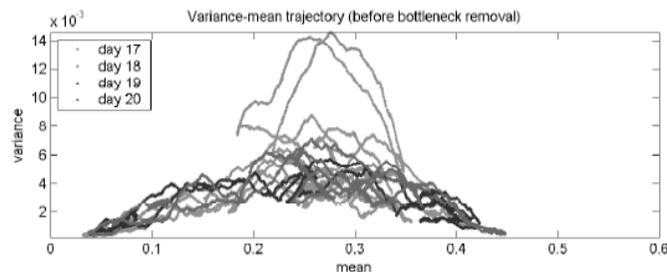


Time-scales



- Importance of time-scales

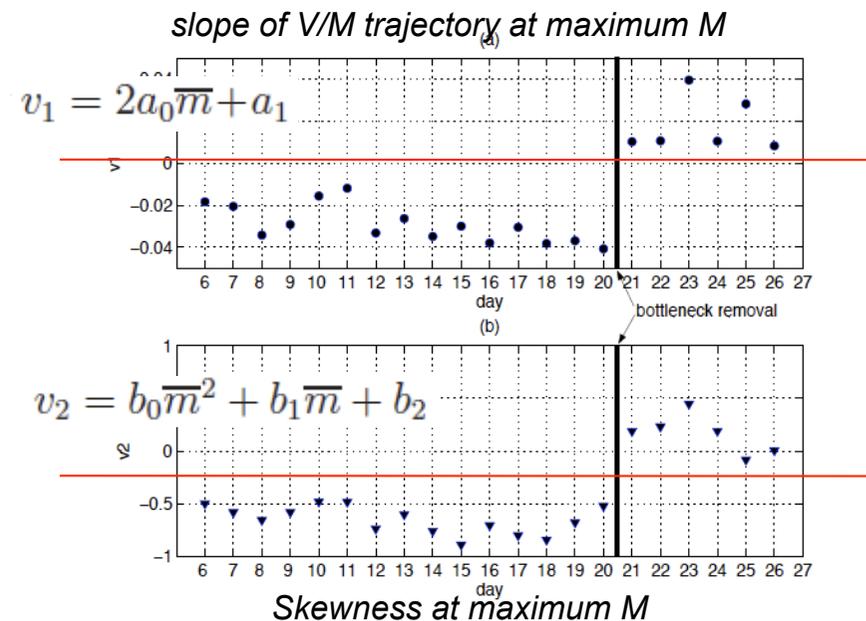
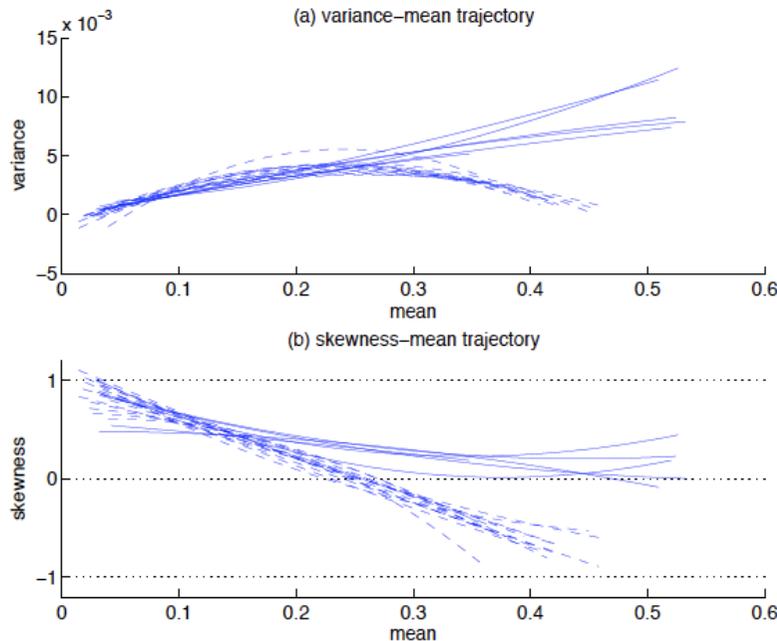
- aggregate rate $R(t)$ is measured in time-bins of length \mathbf{T}
- moments (MEAN, VAR, SKEW) are estimated in window of length \mathbf{W}
- time-scales constraints
 - $T \geq$ a few RTTs (to close the CC loop)
 - $W \gg T$ (to have enough samples)
but small enough to ensure stationarity (time-of-day fluctuations)
 - our setting: $T=10$ sec, $W=1$ hour.



Data reduction



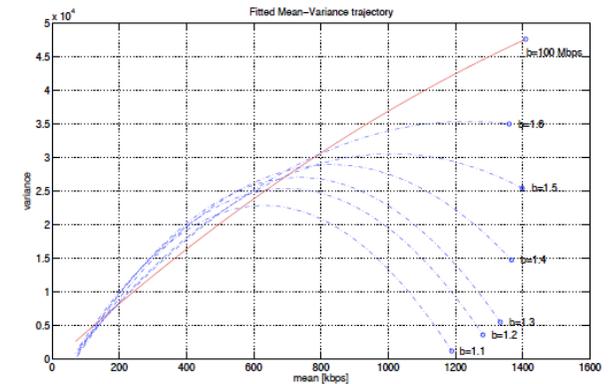
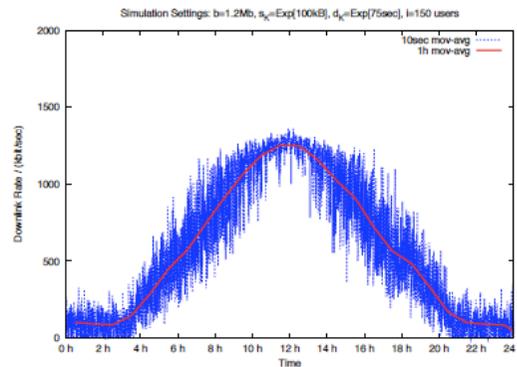
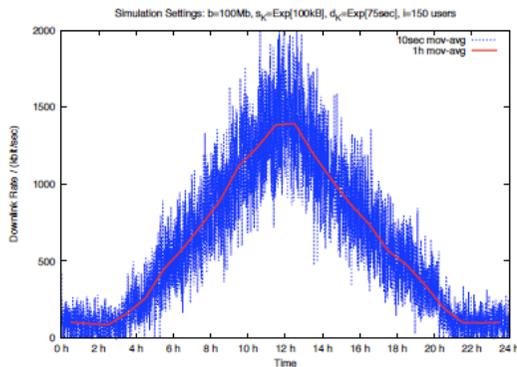
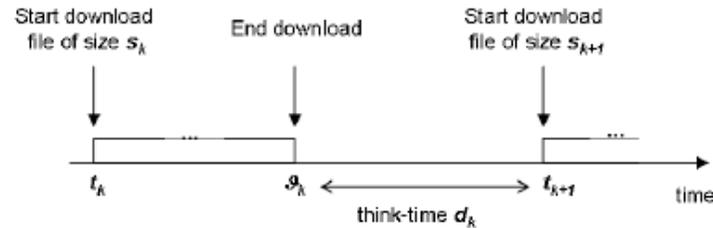
- Data reduction
 - Our goal is only to discriminate increase/decrease trends
 - apply quadratic regression on V/M, S/M data
 - benefits: reduces noise, impact of outliers → robustness
 - *don't use more data than you actually need!*
 - fitted polynomial parameters give synthetic indicators that can be thresholded to trigger alarm



Validation by simulation



- Simulation set-up (ns-2)
 - simple closed-loop user model
 - allows testing different congestion levels, bottleneck types (buffering vs. discarding excess packets) than real bottleneck



Retransmission TimeOuts



- Bottleneck → Congestion at peak hour → more packet loss
→ more retransmissions due to timeout expirations
- Idea: infer congestion from Frequency of Retransmission Timeouts (RTO)s in some timebin T

$$F_{\text{RTO}}(T) = \frac{\text{\# of RTO events in T}}{\text{\# of DATA packets in T}}$$

- Expectation: bottleneck causes large increase of F_{RTO} in peak-hour compared to off-peak periods
- Tool to infer TCP RTOs from DATA-ACK (mis)matching
 - classifies different types of RTOs (spurious, ...)
 - measure frequency of RTOs in timebins of 1 min

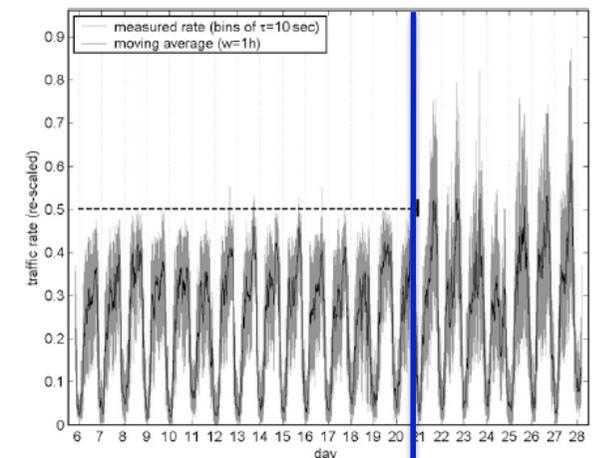


Fig. 2. SA total rate for the monitored period (10 s bins, rescaled values).

Raw RTO measurements



- On the right way, but “noise” would cause false alarms ...

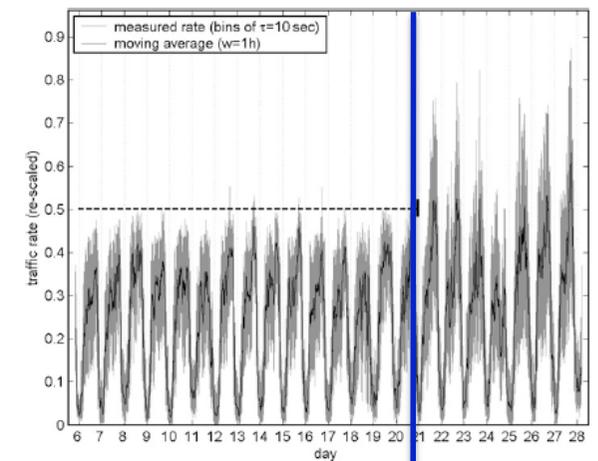
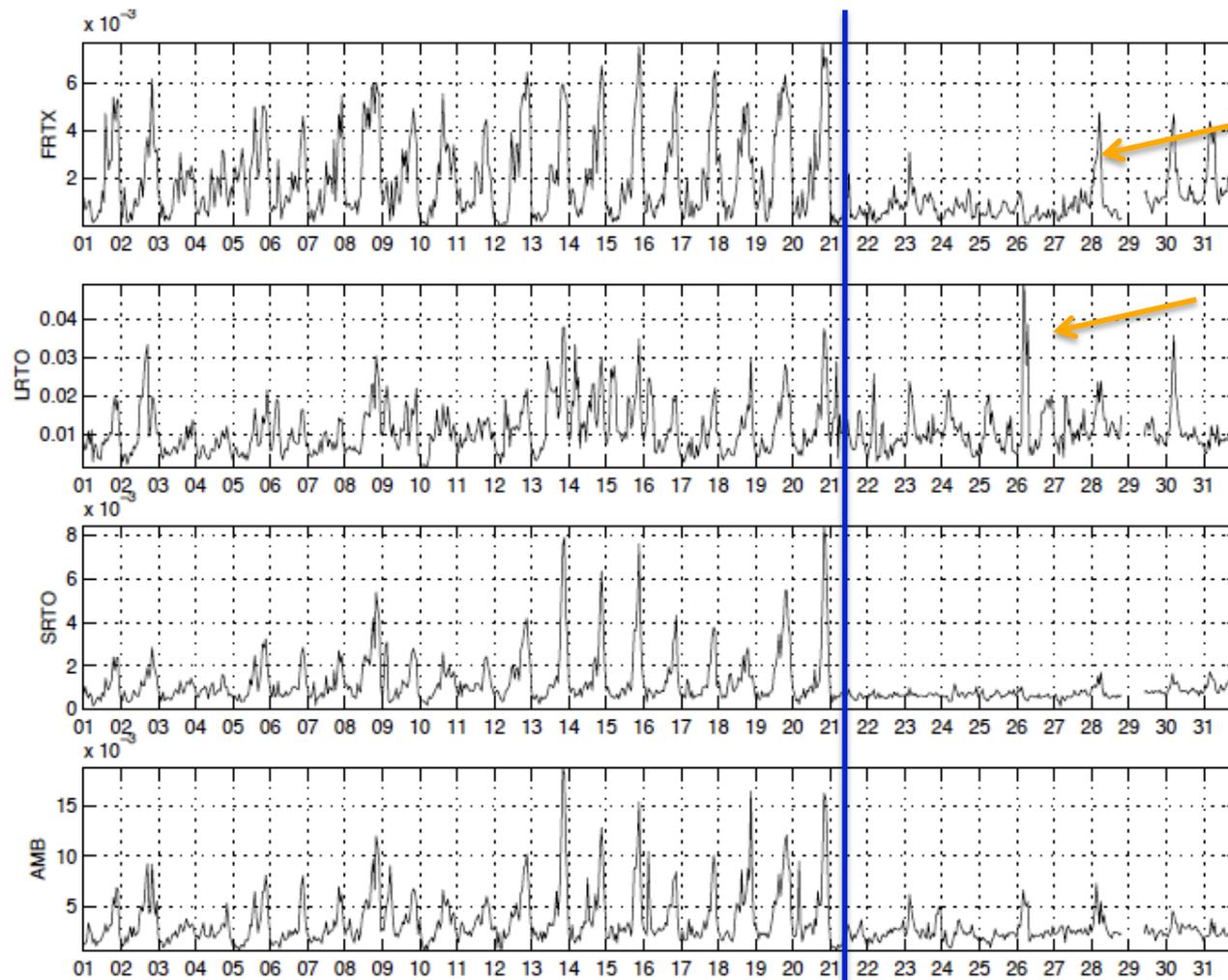
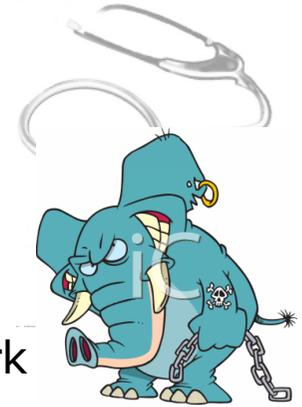
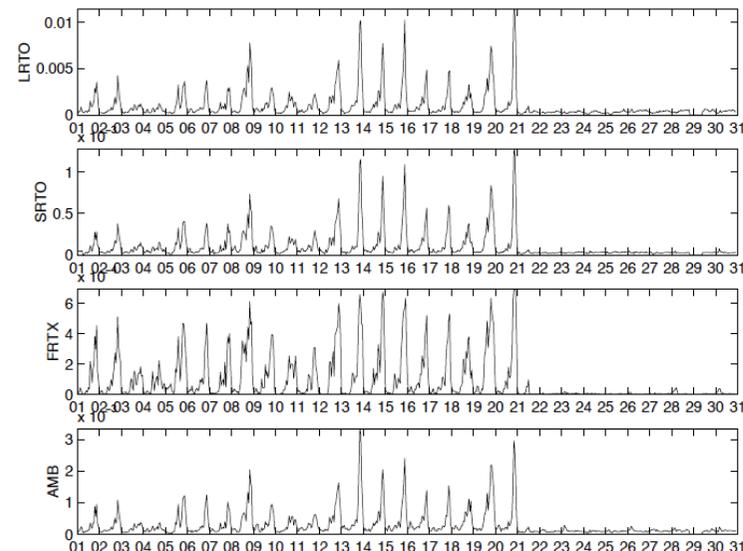
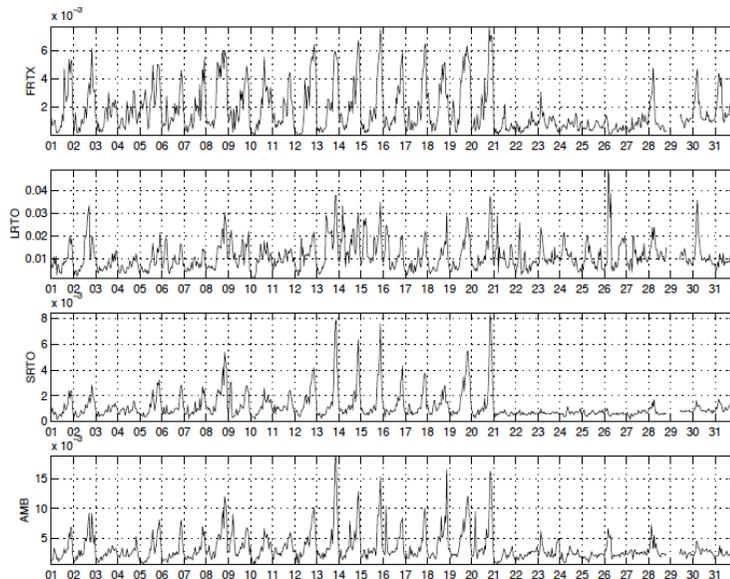


Fig. 2. SA total rate for the monitored period (10 s bins, re-scaled values).

Filtered RTO measurements



- Noise due to heavy-hitters “bad elephants” (BE)
 - few clients, with high traffic volume (elephant) and poor network conditions (“bad”) due to local causes
 - biasing the ratio $\frac{\text{\# of RTO events}}{\text{\# of DATA packets}}$ in some timebins
- Workaround
 - identify BE by some heuristic (e.g. the top-10 with most RTOs) and filter them away



Stepping into a more general problem...



- The problem of “bad elephants” is more general, and is encountered often in the field of networking
 - traffic distributions are heavy-tailed
 - → there are always some “elephants” around
 - poor performance sometimes due to local conditions
 - e.g. congestion of dedicated resources, terminal errors ...
 - → some elephants will be “ bad”
 - many common KPI are just global percentages!

$$KPI = \frac{\# \text{ of failed attempts}}{\# \text{ of attempts}}$$

- *Can we provide a theoretically-founded solution (in place of heuristics) ?*

A. Coluccia, F. Ricciato, P. Romirer, On Robust Estimation of Network-wide Packet Loss in 3G Cellular Networks, Proc. of 5th IEEE Broadband Wireless Access Workshop (BWA'09).

System Modeling



USER



REQUEST

packet, SYN, attach_request, ...

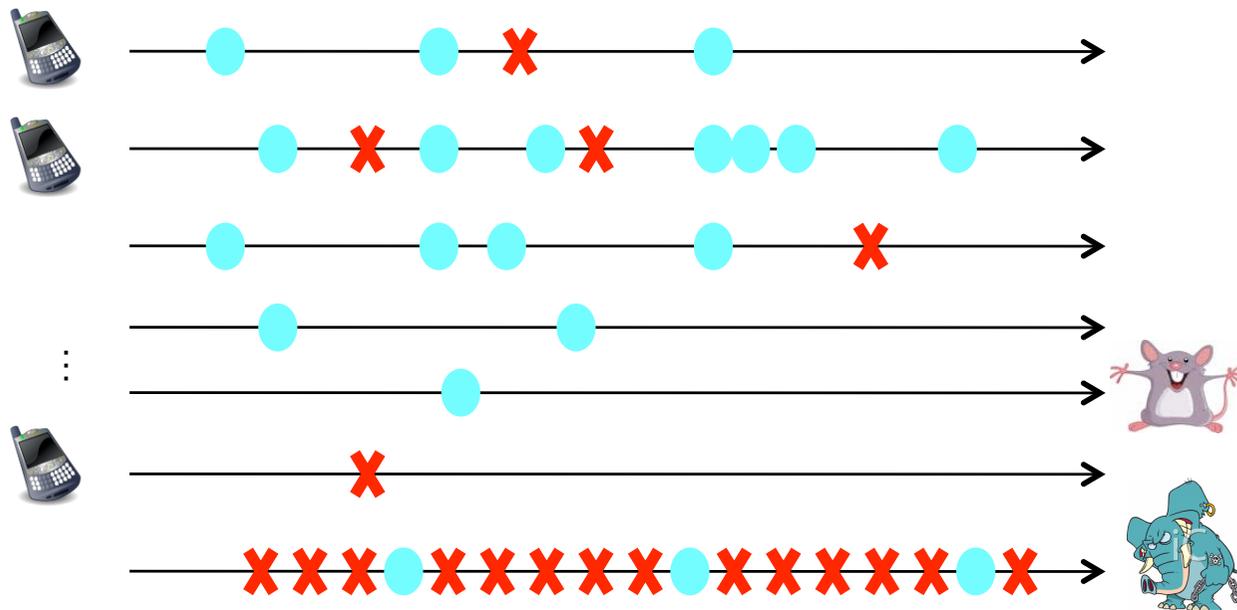


SUCCESS



FAILURE

lost, late, failed, unanswered ...



System Modeling

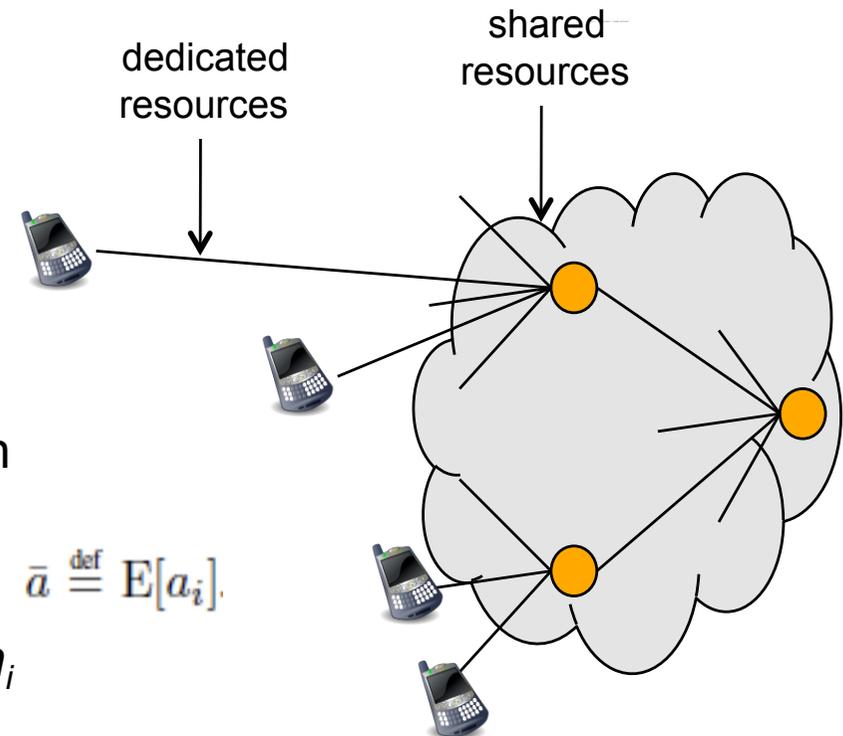


■ Notation

- in a generic timebin t user i ($i=1\dots I$)
- generates n_i “requests” (e.g. packets)
- out of which m_i “fail” (e.g. lost)

■ Assumptions

- failures are independent and occur with (unknown) probability a_i
- a_i 's are iid random variables with mean $\bar{a} \stackrel{\text{def}}{=} E[a_i]$.
- independency between traffic volume n_i and failure prob. a_i



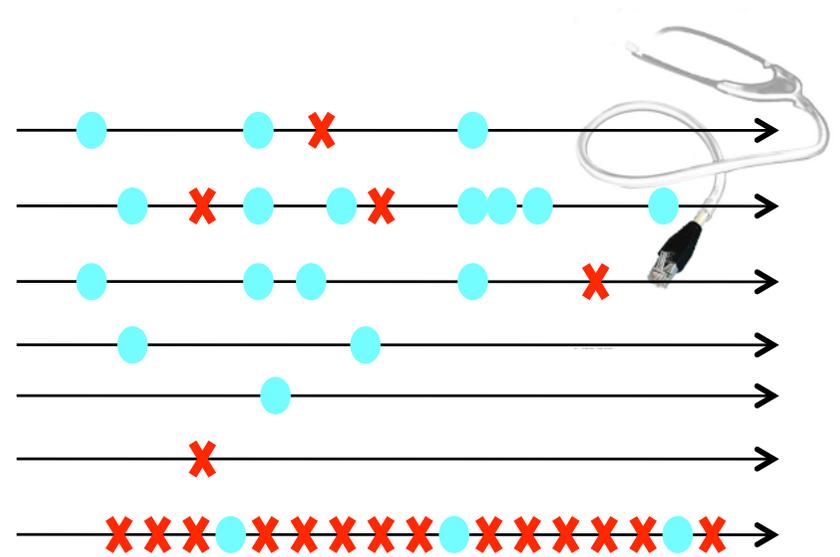
- Goal: estimate $\bar{a} \stackrel{\text{def}}{=} E[a_i]$. given a set of measurements $\{n_i, m_i\}$

Estimators

- Goal: estimate $\bar{a} \stackrel{\text{def}}{=} E[a_i]$, given $\{n_i, m_i\}$
- The Ideal Estimator
 - is unbiased
 - has minimum variance
 - is simple: fast to compute, easy to implement, easy to understand by practitioners!
 - is general: not bound to a specific (class of) traffic distribution (n_i 's)



Basic Estimators



- Empirical Global Ratio
 - Global Percentage

$$EGR = \frac{\# \text{ of total failures}}{\# \text{ of total requests}} = \frac{\sum_i m_i}{\sum_i n_i}$$

- Empirical Mean Ratio

- Arithmetic mean of individual ratios $r_i = \frac{m_i}{n_i}$

$$EMR = \frac{1}{I} \sum_i r_i = \frac{1}{I} \sum_i \frac{m_i}{n_i}$$

- NB: EMR is more costly to implement than EGR, requires per-user counters → need to extract event-to-user associations

NB: $r_i = m_i/n_i$ is the minimum variance unbiased estimator (MVUE) for a_i

EWR - definition



- Both EGR and EMR can be “corrected” by filtering away very big (for EGR) or very small (for EMR) samples
 - discarding lots of data, especially for long-tailed n_i 's
- Can we do something more clever than *discarding* data ?
 - *weighting* data !

- **Empirical Weighted Ratio (EWR)**

$$EWR = \sum_i w_i \frac{m_i}{n_i} = \sum_i w_i r_i = \underline{w}^T \underline{r}$$

with $w_i > 0$, $\sum_i w_i = 1$

- EGR, EMR are special cases of EWR
 - w_i constant $\rightarrow w_i = 1/I \rightarrow EWR = EMR$
 - w_i proportional to $n_i \rightarrow w_i = n_i/N \rightarrow EWR = EGR$

EWR - optimization



- Problem: Find the *optimal* weights w_i 's that minimize the variance of the estimator $\text{VAR}(S(\mathbf{w}))$

$$S(\mathbf{w}) = \mathbf{w}^T \mathbf{r} \quad \text{with} \quad |\mathbf{w}| = 1, \mathbf{w} \geq \mathbf{0}$$

- Resolution
 - compute variance of estimator as function of weights $\text{VAR}(S(\mathbf{w})) = f(\mathbf{w})$
 - constrained minimization, solve by Lagrangian multipliers

- Exact optimal solution

$$\hat{\mathbf{w}} = \arg \min_{\substack{\mathbf{w} > 0 \\ \sum_i w_i = 1}} \text{VAR}[S(\mathbf{w})]$$

$$\hat{w}_i = \frac{\hat{n}_i}{\sum_{j=1}^I \hat{n}_j} \quad \text{with} \quad \hat{n}_i \stackrel{\text{def}}{=} \frac{1}{\sigma_a^2 + \frac{(\bar{a} - \sigma_a^2 - \bar{a}^2)}{n_i}}$$

EWR – weight setting

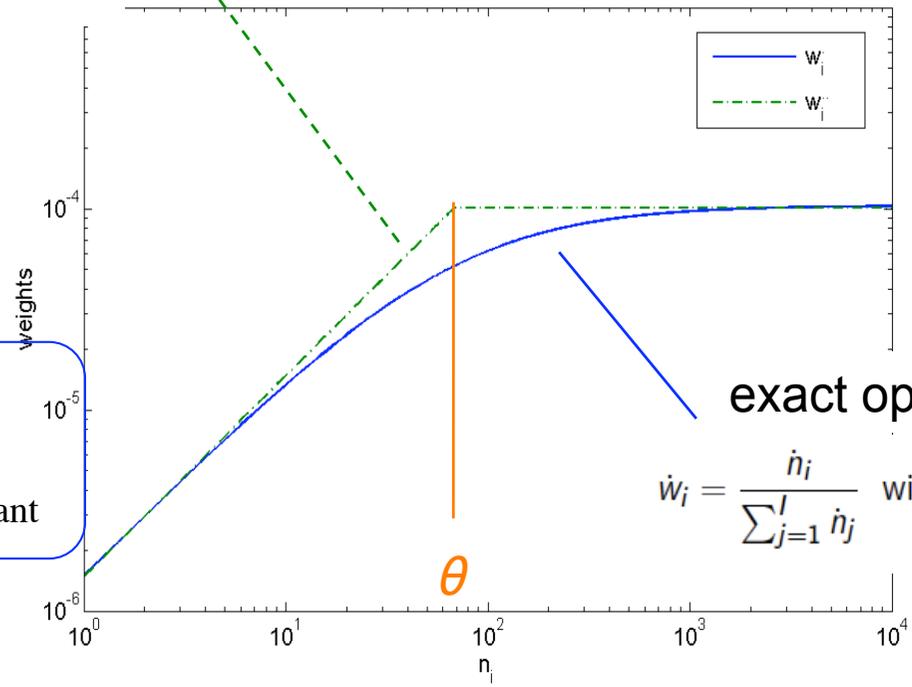
piece-wise linear approximation (EPWR)



$$\ddot{w}_i = \frac{\ddot{n}_i}{\sum_{j=1}^I \ddot{n}_j} \quad \ddot{n}_i \stackrel{\text{def}}{=} \min(n_i, \theta)$$

where $\dot{\theta} \stackrel{\text{def}}{=} \frac{\bar{a} - \sigma_a^2 - \bar{a}^2}{\sigma_a^2}$

$n_i < \theta \rightarrow w_i = n_i \cdot c$
 $n_i \geq \theta \rightarrow w_i = \theta \cdot c$
 with c a normalization constant



exact optimal solution

$$\dot{w}_i = \frac{\dot{n}_i}{\sum_{j=1}^I \dot{n}_j} \quad \text{with} \quad \dot{n}_i \stackrel{\text{def}}{=} \frac{1}{\sigma_a^2 + \frac{(\bar{a} - \sigma_a^2 - \bar{a}^2)}{n_i}}$$

- setting the knee-point θ
 - optimal value depends on first two moments of $p(a)$: \rightarrow unknown ☹
 - final estimator performance are weakly sensitive to exact location of knee-point, as far as “extreme” settings (very low, very high) are avoided
 - simplest solution: set to fixed value, e.g. $\theta=20$.

Bayesian Estimators

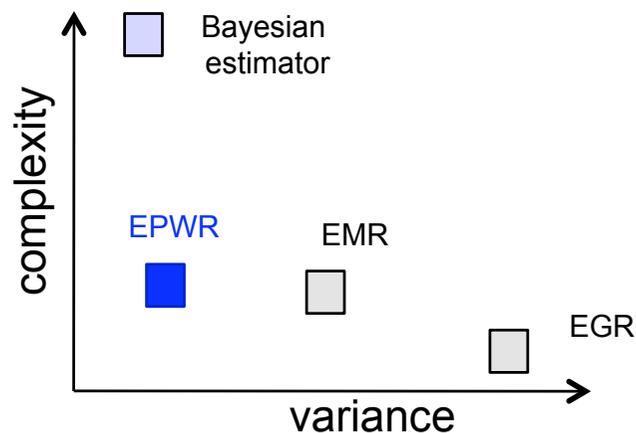


- Empirical Piece-wise Linearly Weighted Ratio (EPWR)
 - single parameter θ (set heuristically to $\theta=20$)
 - very simple conceptually and computationally
 - requires individual per-user counters, as EMR

$$S(\mathbf{w}) \stackrel{\text{def}}{=} \sum_{i=1}^I w_i r_i = \mathbf{w}^T \mathbf{r}$$

$$\ddot{w}_i = \frac{\ddot{n}_i}{\sum_{j=1}^I \ddot{n}_j} \quad \ddot{n}_i \stackrel{\text{def}}{=} \min(n_i, \theta)$$

- Alternative approach: Bayesian estimators
 - Bayesian hierarchical model: $p(\mathbf{a}) \rightarrow \{a_i\} \rightarrow \{m_i\}$
 - Approach: empirical parametric Bayes + conjugate prior (*)
 - elegant maths, closed formula, but in practice same performance as EPWR



(*) Fabio Ricciato, Angelo Coluccia, and Peter Romirer, Bayesian Estimation of Network-wide Mean Failure Probability in 3G Cellular Networks, Proc. of PERFORM 2010 Workshop, Vienna, 14-16 October 2010, LNCS vol. 6821.

Results DATA:INV

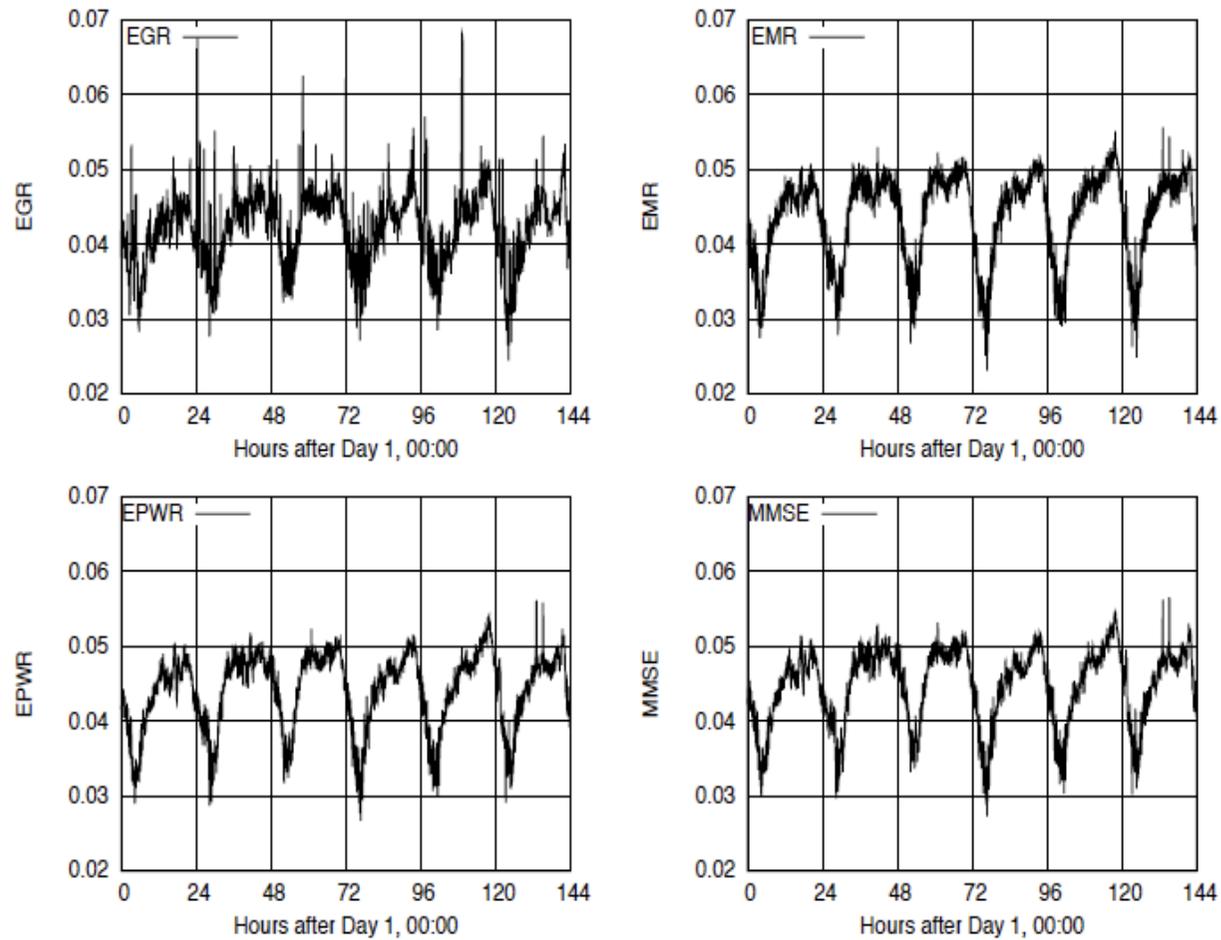


Fig. 2. Estimated mean failure probability for DATA:INV dataset (missing or ambiguous SYNACK/ACK associations).

Results DATA:RTT

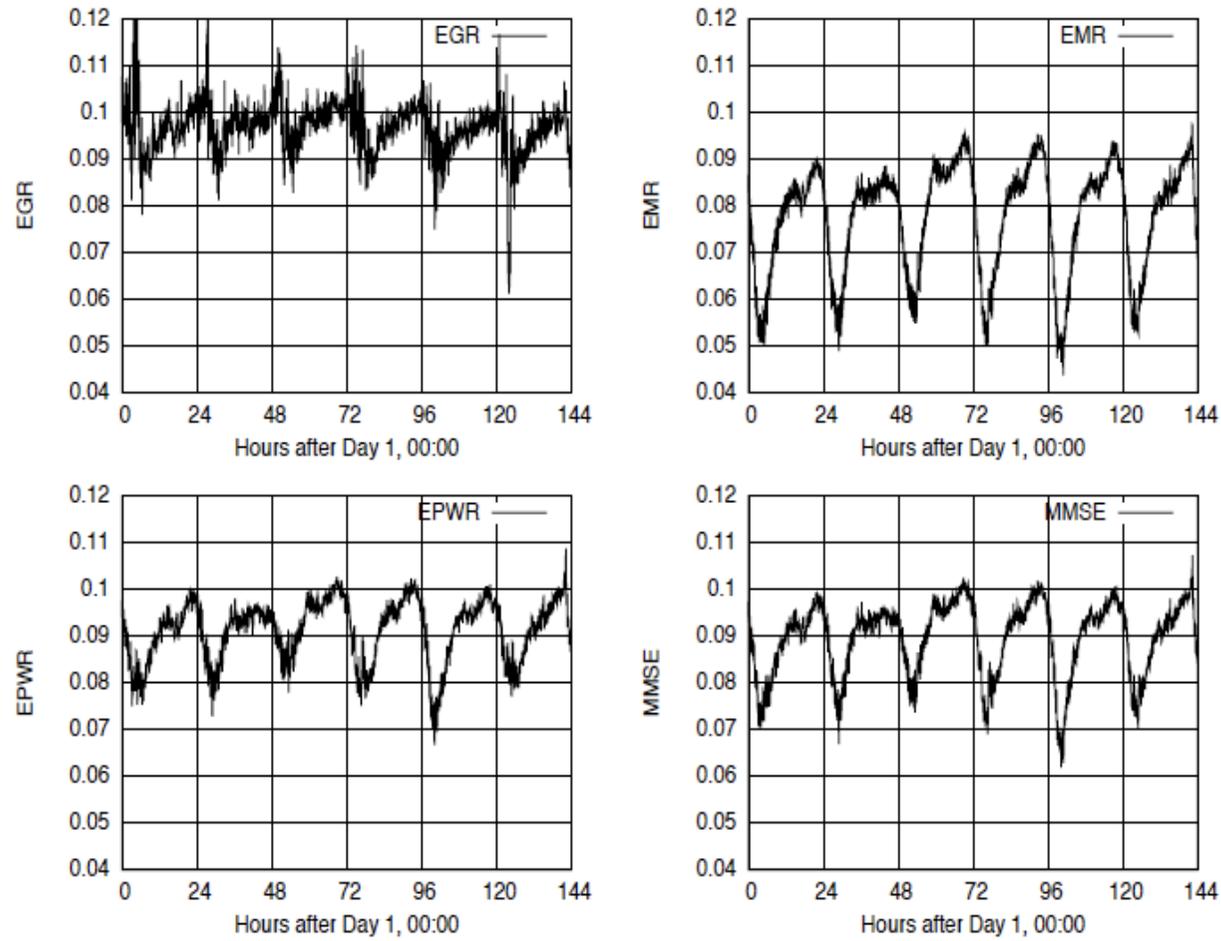
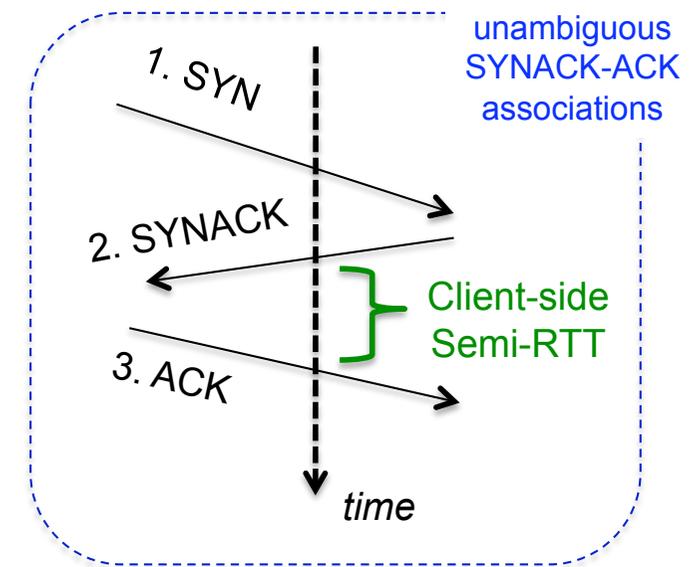
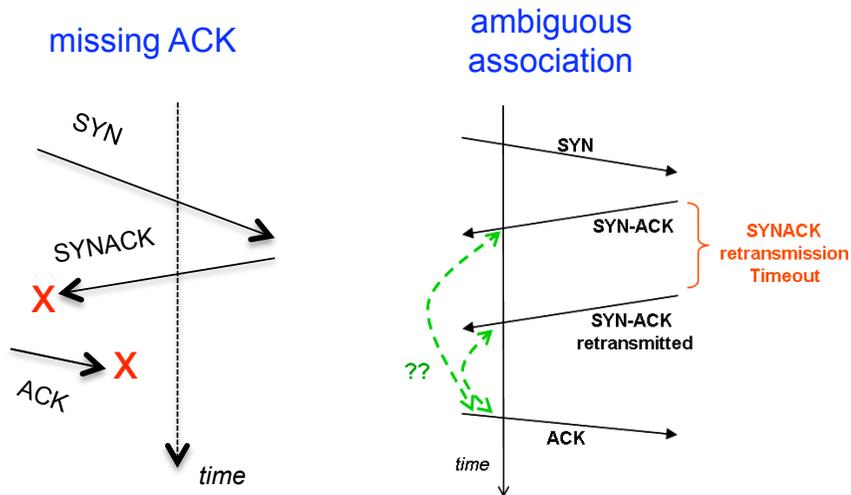
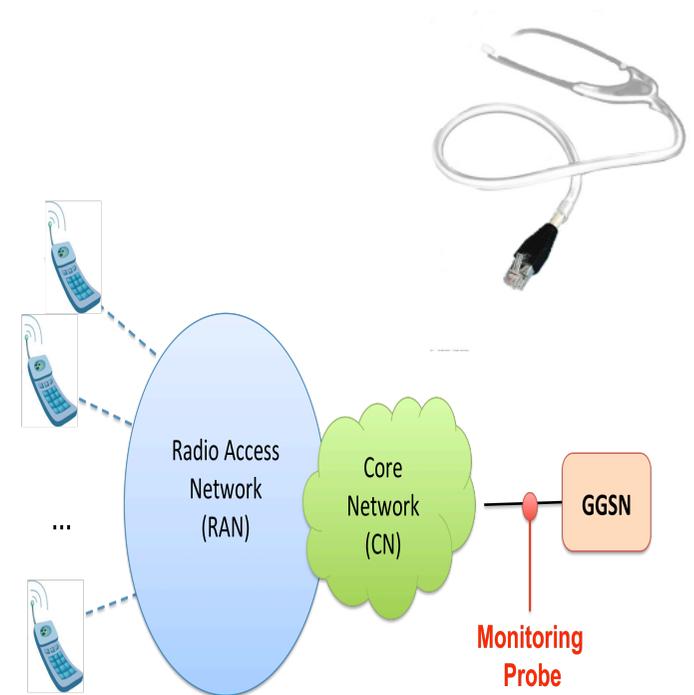


Fig. 3. Estimated mean failure probability for DATA:RTT dataset (unambiguous SYNACK/ACK pairs with semi-RTT exceeding 500 ms).

Results from a real dataset

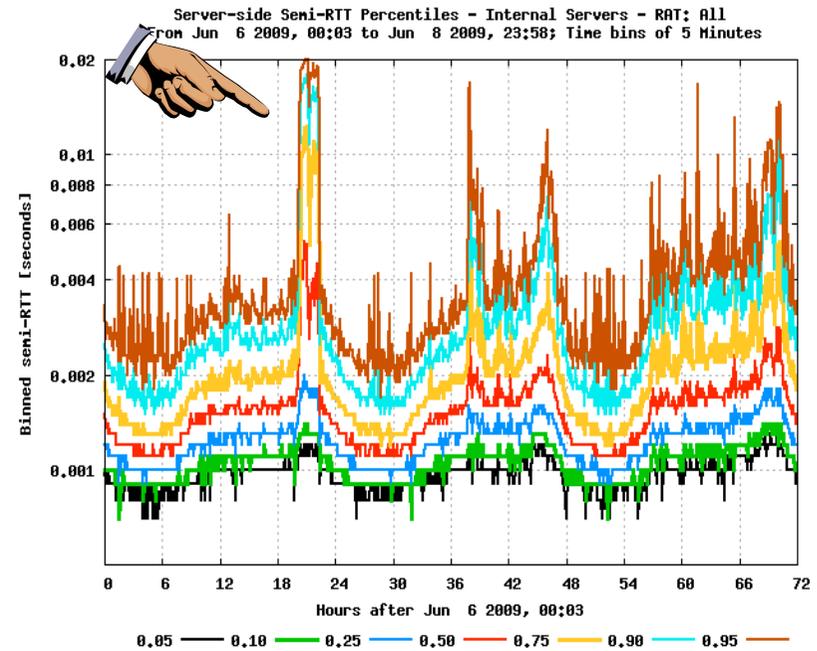
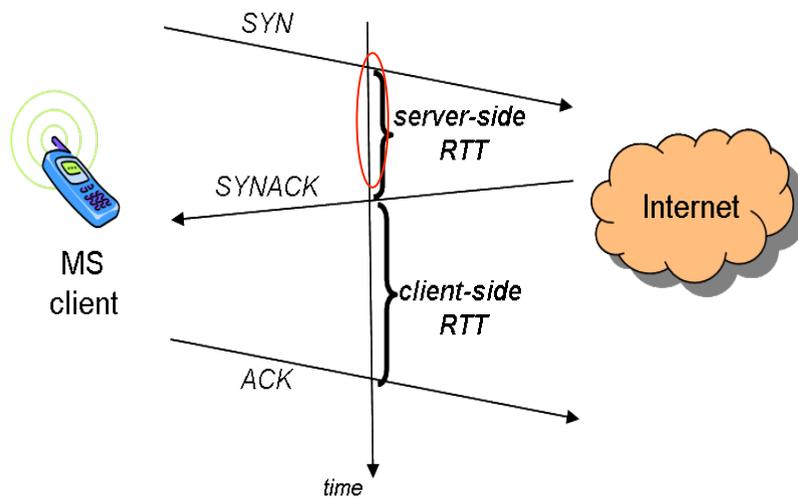
- Datasets from on a real UMTS/HSPA network
- DATA:INV
 - REQUEST := every SYNACK in DL
 - SUCCESS := unambiguous ACK in UL
- DATA:RTT
 - REQUEST := unambiguous SYNACK/ACK pair
 - SUCCESS := RTT < 500 ms



Detecting congestion bottleneck



- Detecting *upstream* congestion from server-side RTT
 - SYN-SYNACK associations



Next step

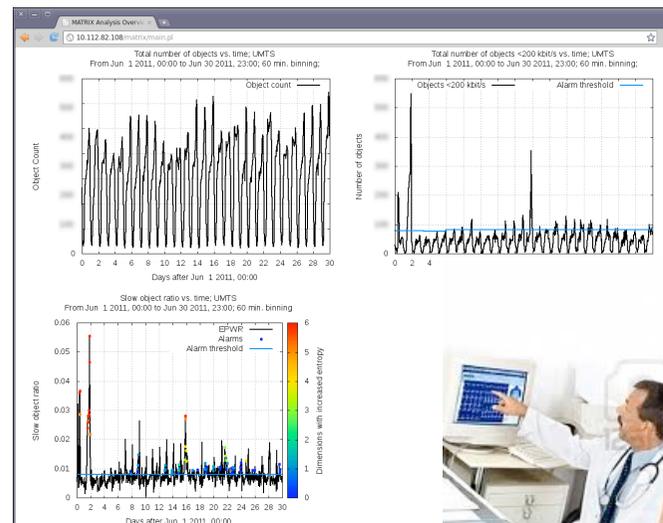


- The proposed approaches (rate/RTO/RTT) helped to detect instances of serious congestion in the real network
- Next goal: detecting *pre*-congestion events
 - 3G network capacity is becoming the bottleneck
- Approach: analyse per-flow throughput
 - extract relevant “signal” from per-flow throughput measurements
 - ongoing work

Working with online data



- Doctors need to practice on real patients ...
- It's important to analyse recent data → online analysis
 - external information needed for drill-down is still available
 - *you can still talk to the patient*
 - timely identification of real anomalies has immediate impact
 - makes research more interesting, but also more costly
 - *need cooperation with the patient*



Wrap-up on Lessons Learned



- Research on 3G Traffic Monitoring ...
- is interesting
 - as any research on real systems
- is useful
 - 3G network systems are too complex/large to be error-free
- is costly
 - data collection eats lot of engineer works
 - analysis and explorations of real data is often lengthy
 - every analysis task requires own methodology
 - need domain-specific knowledge about 3G networks, protocols
- lot of space for problem-driven & curiosity-driven research

Wrap-up on Lessons Learned



- Automatic anomaly-detection like a medical tool
 - **Yes, it empowers the doctor**
 - **No, it cannot replace the doctor**
-
- About network problems
 - Recurring problems: can be detected and diagnosed automatically (but also prevented...)
 - Novel problems: symptoms can be detected automatically, but need doctor for interpretation and drill-down
 - *healthy network = no recurring problems, only new ones*



Follow-up



- Publications:
- <http://userver.ftw.at/~ricciato/publications.html>

- email:
- ricciato@ftw.at