Burstiness vs Frequency

Alain Jean-Marie, Yvan Calas, Tigist Alemu

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On the compromise between burstiness and frequency of events

Alain Jean-Marie Yvan Calas Tigist Alemu

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Consider a process of events with two types: good and lost. n consecutive events are called a block.

Time may be continuous

but the model will be in discrete-time and ignore actual time intervals between events.

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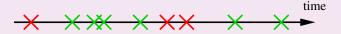
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Consider a process of events with two types: good and lost. *n* consecutive events are called a block. Time may be continuous



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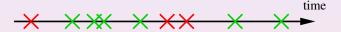
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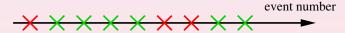
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Consider a process of events with two types: good and lost. *n* consecutive events are called a block. Time may be continuous



but the model will be in discrete-time and ignore actual time intervals between events.



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As a conclusion

Metric of interest: given h and n,

P(the block is "lost") = P(>h losses among n events)

Usual objective: find the smallest h (redundancy) such that

 $P(>h \text{ losses among } n+h \text{ events}) < \varepsilon$.

Today's objective: compare two situations

- same event loss probability
- different "burstiness" patterns

Motivation #1: Forward Error Correction

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Forward error correction at the packet level: able to repair up to h lost packets, using h packets of redundancy.

k=8 information packets

+ h=4 redundancy packets

$\blacksquare \blacksquare \times \times \times \blacksquare \blacksquare \times \blacksquare \times \blacksquare \quad LOST$

Motivation #1 (ctd)

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As a conclusion

Different queue management schemes at routers produce different loss patterns.

Assuming the loss rate is the same: is it better

- to have losses regularly spaced,
- or have losses clustered?

Additional motivation

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Reliability/real time systems:

- n tasks to be executed within a time frame each one may fail execute m = n + k of them
 - execute $m = n + \kappa$ of t
 - "k-out-of-*m*"

Bandwith reduction in a slotted network:

 frames of n slots → frames of h slots no buffer probability of overflow?

Pedestrian crossing...

Well known facts...

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Several facts are well known:

- Variability worsen things (Folk result)
 - \implies the situation with the "most regular arrivals" should be better

• The independence assumption is optimistic

If the loss events are independent, the block loss probabilities are (much) smaller than if they are correlated \implies the situation with the "most independent arrivals" should be better

Investigate the issue with a focus on the bursts of losses.

Well known facts...

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Mathematical experiment # 1: The Gilbert model

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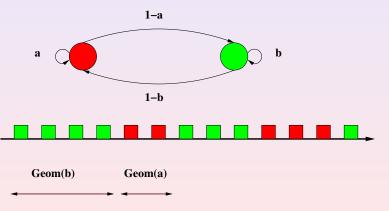
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Assumption: losses occur according to the state of a (two-state) Markov chain.



The Gilbert model (2)

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As a conclusion

Gilbert as a Markov-Additive process:

$$L_{m+1} = L_m + \mathbf{1}_{\{X_m=\bullet\}}$$
.

$$E(z^{L_n}) = \pi_0 M(z)^n \mathbf{1}$$

= $(\pi_{\bullet}, \pi_{\bullet}) \times \begin{pmatrix} az & (1-a)z \\ 1-b & b \end{pmatrix}^n \times \begin{pmatrix} 1 \\ 1 \end{pmatrix}$,

where

$$\pi_{\bullet} = \frac{1-b}{2-a-b}$$
 $\pi_{\bullet} = \frac{1-a}{2-a-b}$.

Gilbert model (3)

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Loss Run Length (LRL):

$$\mathsf{LRL} = \frac{1}{1-a}$$

Good Run Length (GRL):

$$\mathsf{GRL} = \frac{1}{1-b}$$

Stationary loss probability:

$$p = \pi_{\bullet} = \frac{LRL}{LRL + GRL}$$

Problem: with a fixed LRL (or a), the range of p is

$$\left[0, \frac{\mathsf{LRL}}{\mathsf{LRL}+1}\right)$$

Gilbert model (3)

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Skewed Gilbert Model

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Solution: make Good Runs Geometrically distributed on $\{0,1,\ldots\}$ instead of $\{1,2,\ldots\}.$

 \implies another Gilbert process with matrix:

$$\begin{pmatrix} 1-b(1-a) & b(1-a) \\ 1-b & b \end{pmatrix}$$
 ,

and

$$LRL = \frac{1}{1-a}$$
 $GRL = \frac{b}{1-b}$ $p = \frac{1-b}{1-ab}$.

Now the range of p is [0, 1] !

Skewed Gilbert Model

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$$LRL = \frac{1}{1-a} \qquad GRL = \frac{b}{1-b} \qquad p = \frac{1-b}{1-ab}$$

Now the range of p is [0,1] !

Skewed Gilbert Model

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Solution: make Good Runs Geometrically distributed on
$$\{0, 1, \ldots\}$$
 instead of $\{1, 2, \ldots\}$.

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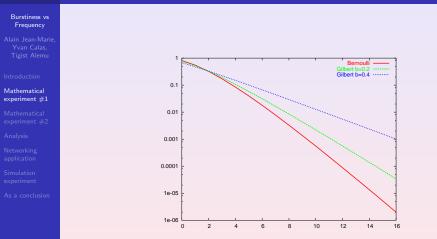
$$egin{pmatrix} 1-b(1-a) & b(1-a) \ 1-b & b \end{pmatrix}$$
 ,

and

$$LRL = \frac{1}{1-a} \qquad GRL = \frac{b}{1-b} \qquad p = \frac{1-b}{1-ab}$$

Now the range of p is [0, 1] !

Comparison Bernoulli/Gilbert



Loss probability of a block of size n = h + 16, depending on h.

Comparison experiments (1)

Burstiness vs Frequency

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$\begin{array}{l} {\sf Mathematical} \\ {\sf experiment} \ \#1 \end{array}$

Mathematical experiment #2

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As a conclusion

Experiment: consider two cases 1 and 2.

- Fix tho Loss Run lengths: LRL₁ < LRL₂ ($a_1 < a_2$),
- fix a block length k and a "redundancy" quantity h
- vary the Loss Probability p
- plot the difference:

 $\Delta_h(p) = P($ block saved in case 1)- P(block saved in case 2)

Comparison experiments (2)

Burstiness vs Frequency

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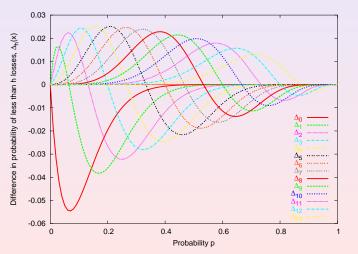
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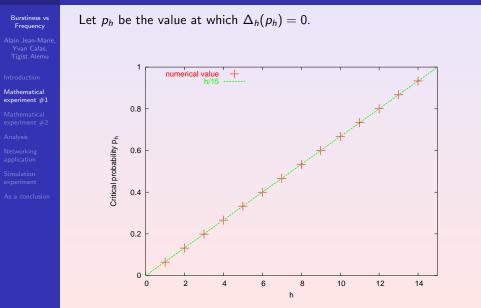
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As a conclusion

h grows from 0 (left, red) to 13 (right, yellow).



Comparison experiments (3)



Work in progress

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$\begin{array}{l} \mathsf{Mathematical} \\ \mathsf{experiment} \ \#1 \end{array}$

Mathematical experiment #2

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As a conclusion

Empirical finding: when *n* is large,

$$x_h \sim \frac{h}{n-1}$$

How to prove it? If the loss rate is p = h/n,

$$P(\leq h \text{ losses}) = [z^h] \frac{1}{1-z} \begin{pmatrix} (1-c)z & cz \\ 1-b & b \end{pmatrix}^n$$

with

$$c = (1-b)rac{n-h}{n}$$
.

Work in progress...

A Compound Poisson Model (1)

Burstiness vs Frequency

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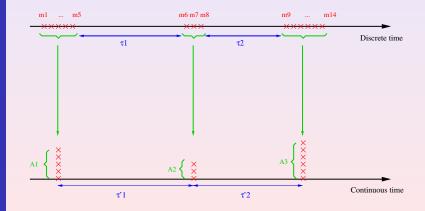
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Simplification: move to continuous time



A Compound Poisson Model (1)

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Process of loss:

• groups of losses occur according to a Poisson process with rate λ ,

• groups have random sizes with identical distribution and mean a. Global loss rate: $p = \lambda \times a$

Distribution of the number of losses:

$$\sum_{k} z^{k} P(k \text{ losses in } [0, t)) = e^{\lambda(A(z)-1)}$$

Comparison experiments (1)

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Comparison of two cases:

- Small bursts case: losses of 1 with proba 0.9,
 - 2 with proba 0.1
- Larger bursts case: losses of 1 with proba 0.6,
 - 2 with proba 0.4
- Same average packet loss number $x = p \times T$

 $\Delta_h(x) = P($ block saved with small bursts)- P(block saved with larger bursts)

Comparison experiments (2)

Burstiness vs Frequency

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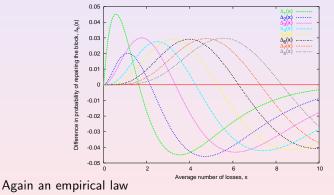
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As a conclusion

Difference $\Delta_h(x)$ as the average number of losses x grows



 $x_h \sim h + C$.

Analysis of limits

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As a conclusion

Analysis of extreme cases: consider the probability of success of a block

$$P(N_T \leq h) = \sum_{n=0}^h \frac{x^n}{(\mathbb{E}A)^n n!} e^{-xT/\mathbb{E}A} P(A_1 + \ldots + A_n \leq h) .$$

/ Assume that

$$\frac{\mathbb{P}(A^{(1)} > h)}{\mathbb{E}A^{(1)}} < \frac{\mathbb{P}(A^{(2)} > h)}{\mathbb{E}A^{(2)}}$$

Then $\Delta_h(x) > 0$ when $x \to 0$. ii/ Assume that $m^{(1)} < m^{(2)}$. Then $\Delta_h(x) < 0$ when $x \to \infty$.

Asymptotic Analysis (1)

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Consider the quantity:

$$d_h(y) = P(\leq h \text{ losses in } h + y \text{ time units}).$$

Then we find:

$$d_h(y) = \frac{1}{2} + \frac{1}{\sqrt{2\pi h}} \sqrt{\frac{\mu_1}{\mu_2}} \left(\frac{1}{2} + \frac{\mu_3}{2\mu_2} - y\right) + o(h^{-1/2}),$$

where $\mu_1 = EA$, $\mu_2 = E(A^2)$, $\mu_3 = E(A^3)$.

Asymptotic Analysis (1)

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Consider the quantity:

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where $\mu_1 = EA$, $\mu_2 = E(A^2)$, $\mu_3 = E(A^3)$.

Asymptotic analysis (2)

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As a conclusion

Accordingly: for all real y, we have:

$$\Delta_h(h+y) = \frac{1}{\sqrt{2\pi h}} (C_0 - C_1 y) + o(h^{-1/2}) ,$$

where:

$$\begin{split} \mathcal{C}_{0} &= \sqrt{\frac{\mu_{1}^{(1)}}{\mu_{2}^{(1)}}} \left(\frac{1}{2} \,+\, \frac{\mu_{3}^{(1)}}{6\mu_{2}^{(1)}}\right) \ -\, \sqrt{\frac{\mu_{1}^{(2)}}{\mu_{2}^{(2)}}} \left(\frac{1}{2} \,+\, \frac{\mu_{3}^{(2)}}{6\mu_{2}^{(2)}}\right) \\ \mathcal{C}_{1} &= \sqrt{\frac{\mu_{1}^{(1)}}{\mu_{2}^{(1)}}} \,-\, \sqrt{\frac{\mu_{1}^{(2)}}{\mu_{2}^{(2)}}} \,. \end{split}$$

Asymptotic analysis (3)

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Finally, we have indeed:

$$\Delta_h(h+y_h) = 0 \implies y_h \sim \frac{C_1}{C_0},$$

and therefore

$$x_h \sim \frac{C_1}{C_0} + h$$

FEC and the Queue Management

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As a conclusion

Packet queues inside network routers are handled by a Queue Management scheme.

Two common ones:

 Tail Drop
 Drops packets if and only if the buffer is full

 ⇒
 tends to produce bursts of losses

 RED
 Drops packets at random preventively

 ⇒
 tends to produce isolated losses

Two loss paterns: which one works better with FEC?

Application of the model

Burstiness vs Frequency

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As a conclusion

Admitting that the smaller bursts (RED) work better when

 $x \leq h + C$

for some constant *C*. Equivalently, RED better if:

> small block $k \leq \frac{1}{k}$ arge redund. ratio $\frac{h}{k} \geq \frac{1}{k}$ small loss rate $p \leq \frac{1}{k}$

$$f \leq \frac{1-p}{p}h + \frac{C}{p}$$

$$\geq \frac{p}{1-p} - \frac{C}{1-p}\frac{1}{k}$$

$$f \leq \frac{h+C}{h+k}.$$

Application of the model

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As a conclusion

Admitting that the smaller bursts (RED) work better when

$$p(k+h) \leq h + C$$

for some constant *C*. Equivalently, RED better if:

small block $k \leq \frac{1-p}{p}h + \frac{C}{p}$ large redund. ratio $\frac{h}{k} \geq \frac{p}{1-p} - \frac{C}{1-p}\frac{1}{k}$ small loss rate $p \leq \frac{h+C}{h+k}$.

Experimental setup

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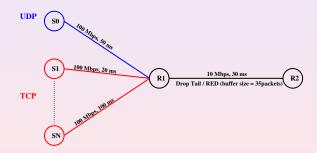
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Simulations with the ns-2 program.

- Source of packets with the UDP protocol, 5-10% of the BW
- Background traffic of TCP flows, saturating the BW.



Statistics collected about Packet Loss Rate Before Correction and after correction.

Results of Simulations

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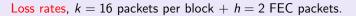
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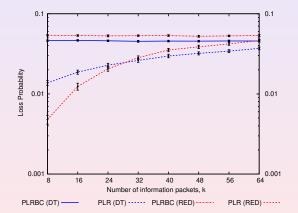
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RED does not always win...

An Explanation

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As a conclusion

There is a compromise between loss "burstiness" and loss rate. Assume blocks protected with h = 1 packet.

An Explanation

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Low loss rate/small blocks

An Explanation

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High loss rate/large blocks