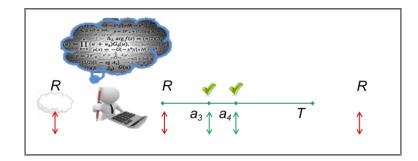
#### Worst-case Bounds and Optimized Cache on *M<sup>th</sup>* Request Cache Insertion Policies under Elastic Conditions

Niklas Carlsson, Linköping University Derek Eager, University of Saskatchewan





*Proc. IFIP Performance*, Toulouse, France, Dec. 2018.

# Motivation and problem

- Cloud services and other shared infrastructures increasingly common
  - Typically third-party operated
  - Allow service providers to easily scale services based on current resource demands
- Content delivery context: Many content providers are already using third-party operated Content Distribution Networks (CDNs) and cloud-based content delivery platforms
- This trend towards using third-party providers on an on-demand basis is expected to increase as new content providers enter the market

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- This trend towards using third-party providers on an on-demand basis is expected to increase as new content providers enter the market

Problem: Individual content provider that wants to minimize its delivery costs under the assumptions that

- the storage and bandwidth resources it requires are *elastic*,
- the content provider only pays for the resources that it consumes, and
- *costs are proportional* to the resource usage.

# **High-level picture**

- Analyze the optimized delivery costs of different *cache on M<sup>th</sup> request* cache insertion policies when using a Time-to-Live (TTL) based eviction policy
  - File object remains in the cache until a time *T* has elapsed
- Assuming elastic resources, cache eviction is not needed to make space for a new insertion
  - Rather to reduce cost by removing objects that are not expected to be requested again soon
  - A TTL-based eviction policy is a good heuristic for such purposes
  - Bonus: TTL provides approximation for fixed-size LRU caching
- Cloud service providers already provide elastic provisioning at varying granularities for computation and storage
  - Support for fine-grained elasticity likely to increase in the future

# Contributions

Within this context, we

- derive worst-case bounds for the optimal cost and competitive cost ratios of different classes of *cache on M<sup>th</sup> request* cache insertion policies,
- derive explicit average cost expressions and bounds under arbitrary inter-request distributions,
- derive explicit average cost expressions and bounds for short-tailed (deterministic, Erlang, and exponential) and heavy-tailed (Pareto) interrequest distributions, and
- present numeric and trace-based evaluations that reveal insights into the relative cost performance of the policies.

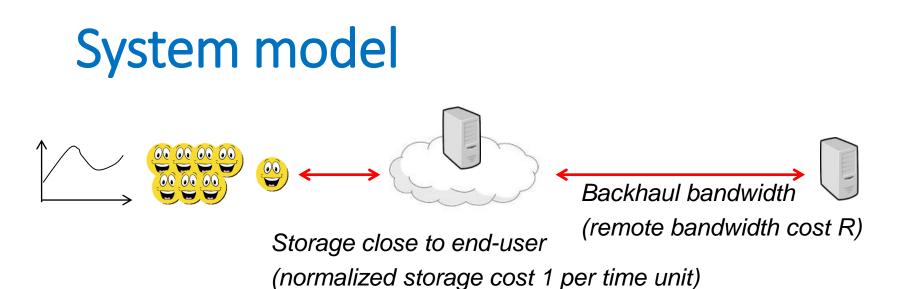
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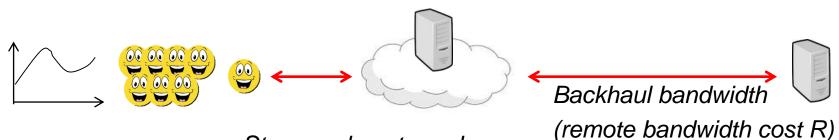
Our results show that a *window-based cache on 2<sup>nd</sup> request* policy (using a single threshold parameter optimized to minimize the best worst-case costs) provides good average performance across the different distributions and the full parameter ranges of each considered distribution

# System model



- Assumptions:
  - storage and bandwidth resources it requires are *elastic*
  - content provider only pays for the resources that it consumes
  - costs are proportional to the resource usage

# System model and problem



Storage close to end-user

(normalized storage cost 1 per time unit)

- Assumptions:
  - storage and bandwidth resources it requires are *elastic*
  - content provider *only pays for the resources that it consumes*
  - costs are proportional to the resource usage

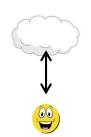
 Policy decision: At the time a request is made for a file object not currently in the cache, the system must, in an online fashion, decide whether the object should be cached or not







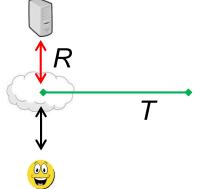


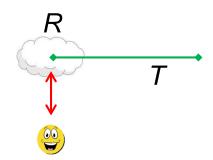


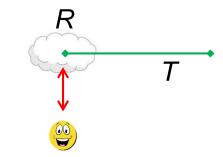


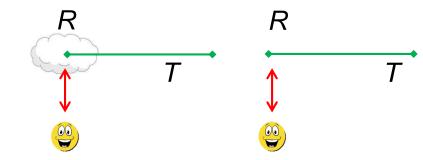


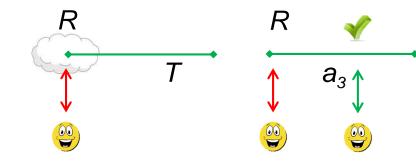


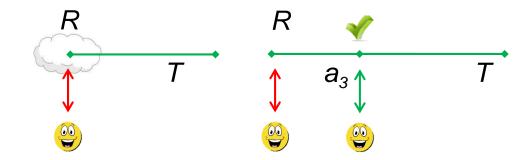


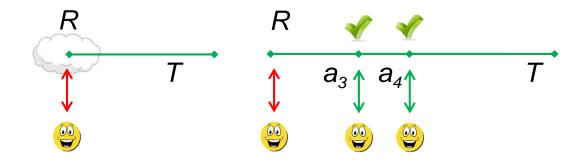


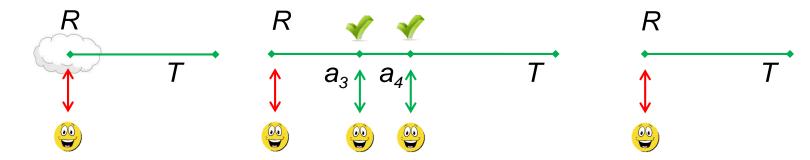


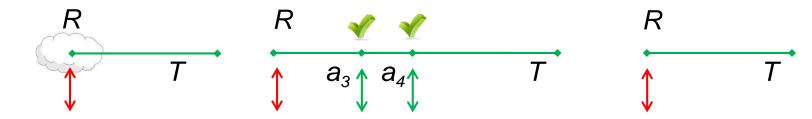


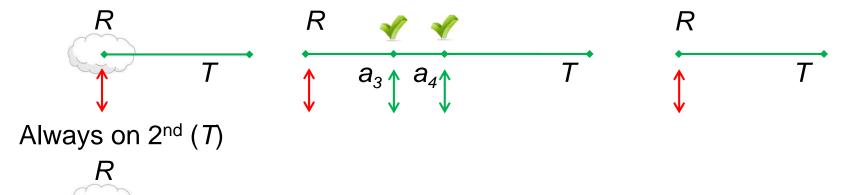


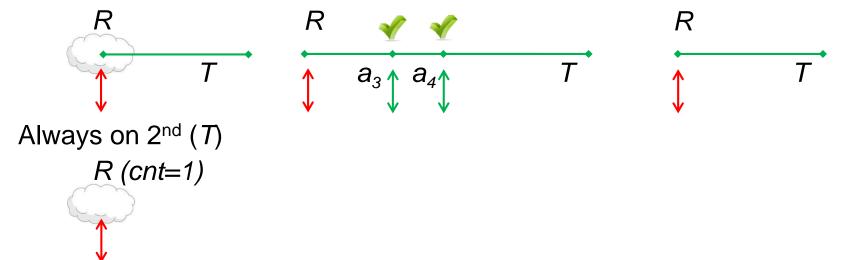


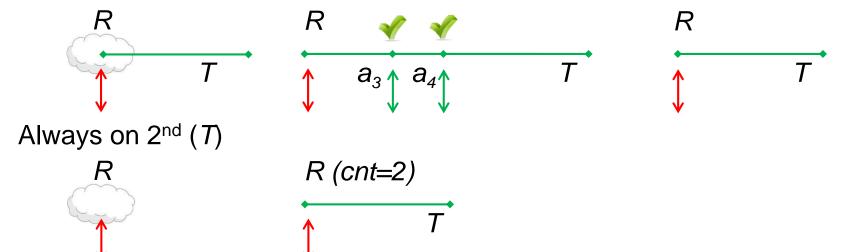


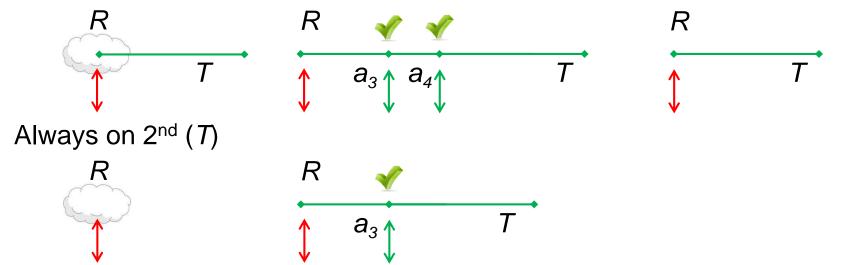


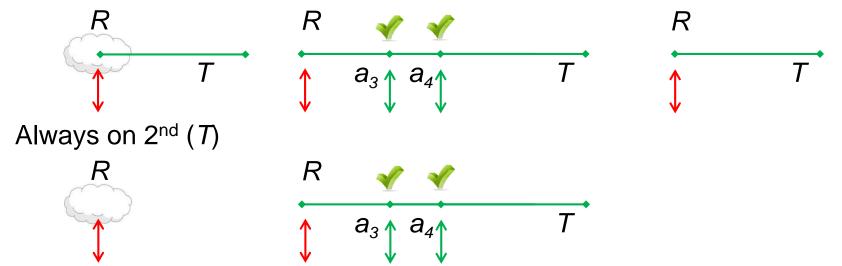




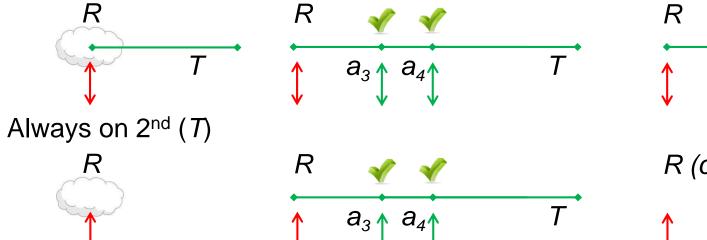


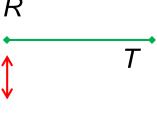






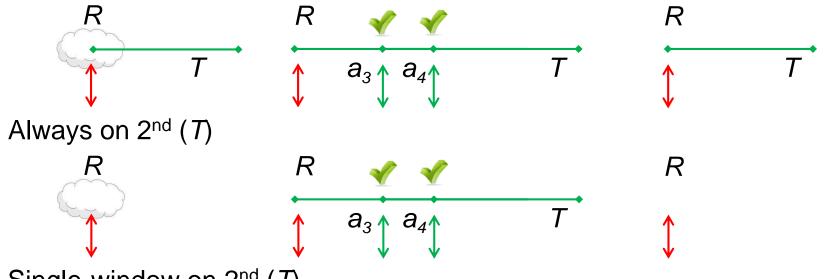
Always on 1<sup>st</sup> (*T*)





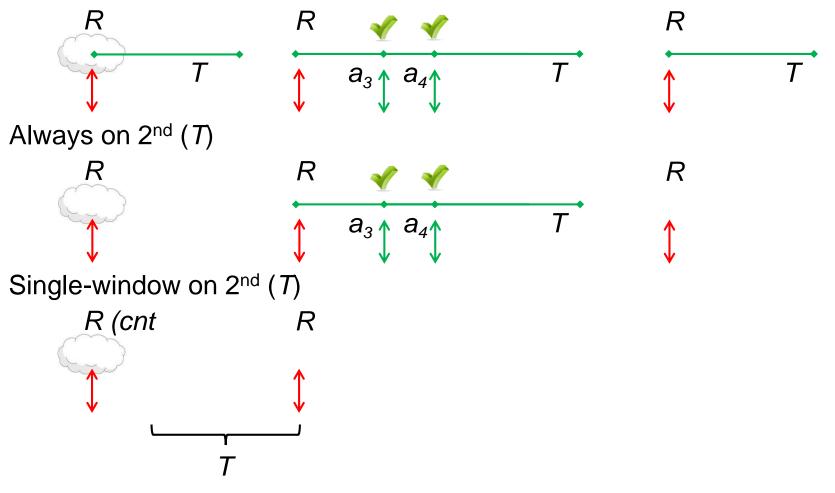
R (cnt=1)

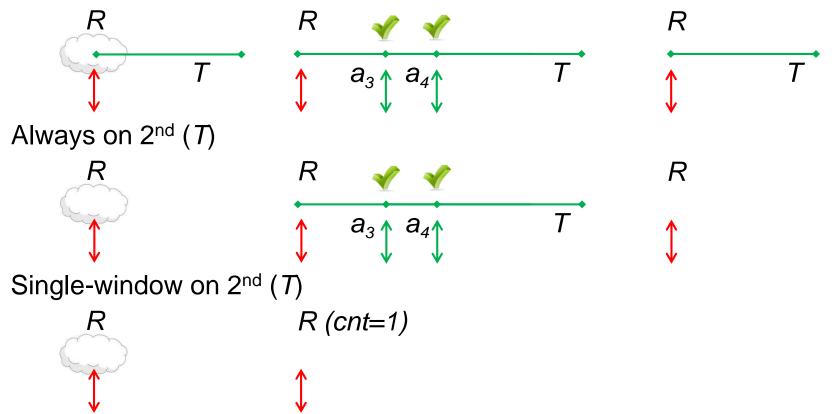
Always on 1<sup>st</sup> (*T*)

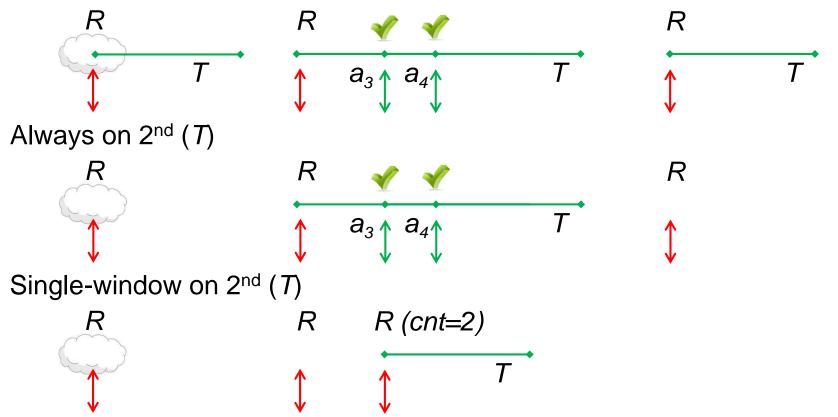


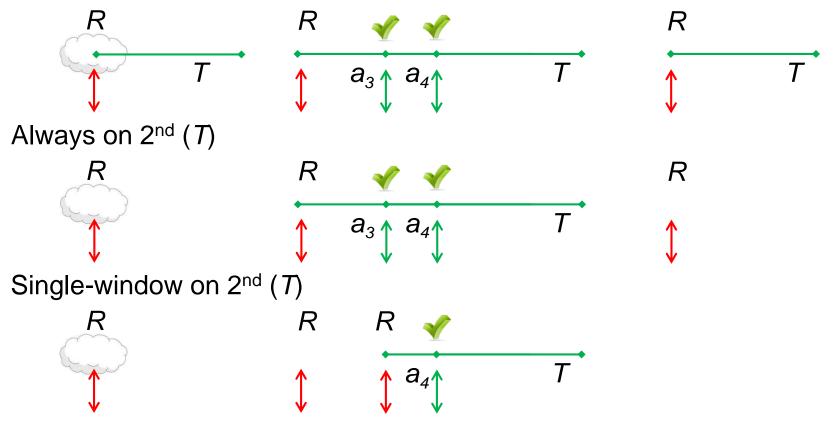
Single-window on 2<sup>nd</sup> (T)

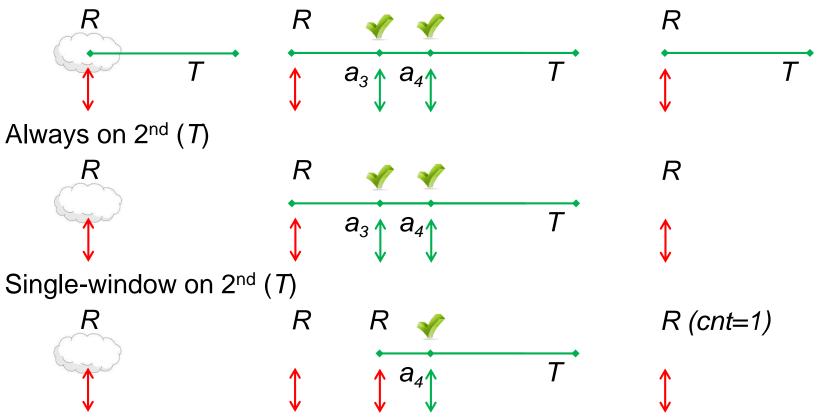
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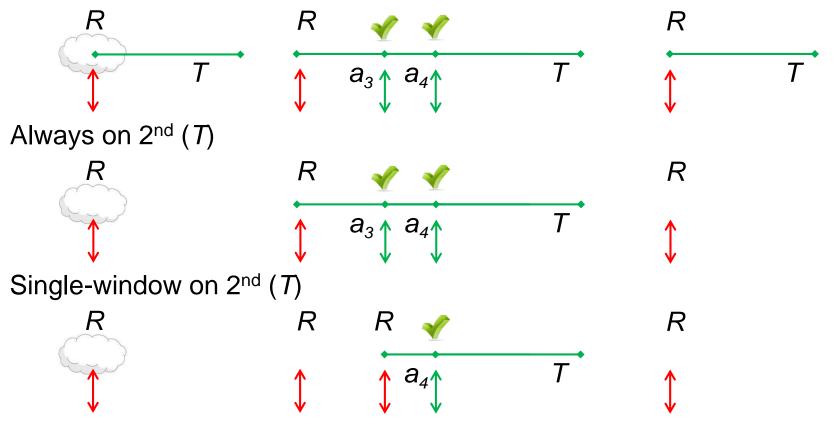






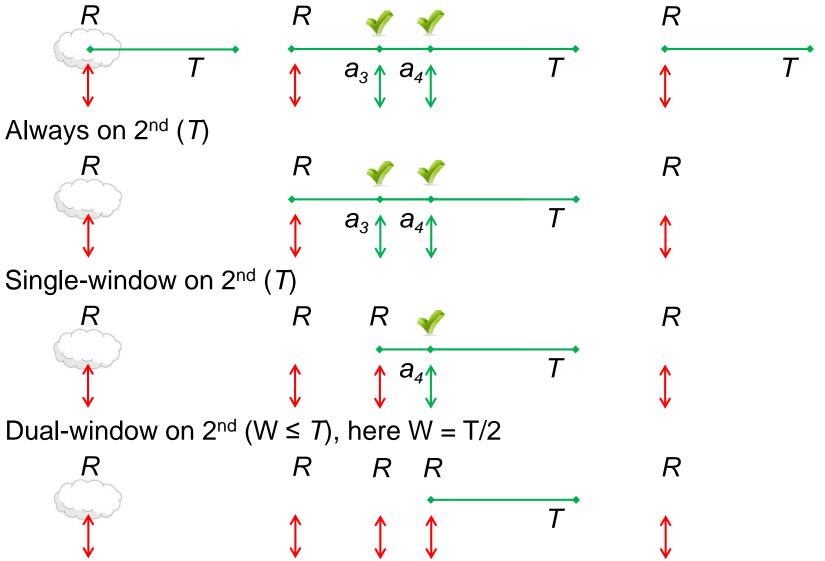






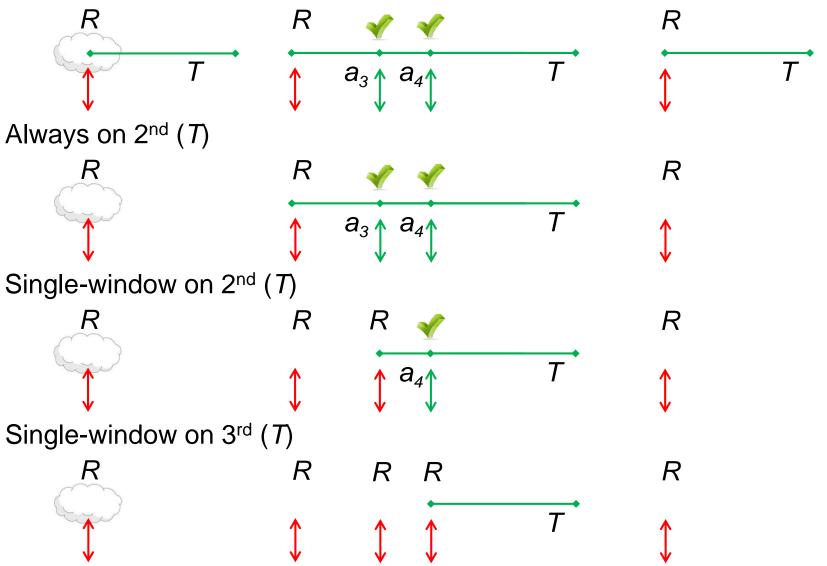
## **Insertion policies**

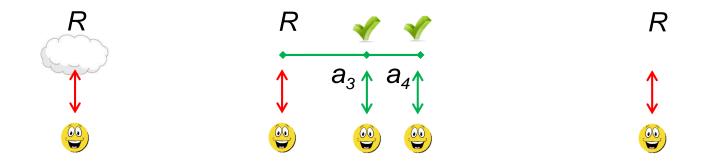
Always on 1<sup>st</sup> (*T*)

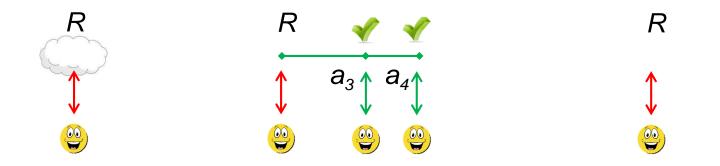


## **Insertion policies**

Always on 1<sup>st</sup> (*T*)





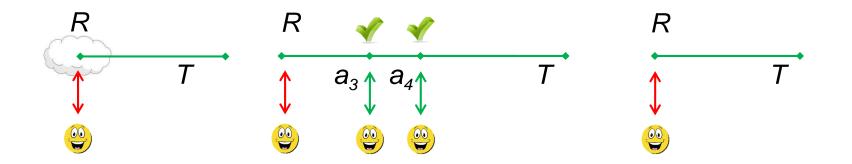


**"Oracle" policy:** Keep in cache until (at least) the next inter-request arrival i whenever  $a_i < R$ ; otherwise, do not cache.

LEMMA 4.1. Given an arbitrary request sequence  $\mathcal{A}$ , the minimum total delivery cost of the optimal offline policy is:

$$C_{opt}^{offline} = R + \sum_{i=2}^{N} \min[a_i, R].$$
(1)

### Example: Always on 1<sup>st</sup>



$$C_{M=1,T}^{always} = R + T + \sum_{i=2}^{N} x_i,$$

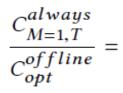
$$x_i = \begin{cases} T + R, & \text{if } a_i > T \\ a_i, & \text{otherwise.} \end{cases}$$
(2)
(3)

### Worst-case ratio: Always on 1<sup>st</sup>

THEOREM 4.2. The best (optimal) competitive ratio using always on  $1^{st}$  is achieved with T = R and is equal to 2. More specifically,

$$\max_{\mathcal{A}} \frac{C_{M=1,T=R}^{always}}{C_{opt}^{offline}} \le \max_{\mathcal{A}} \frac{C_{M=1,T}^{always}}{C_{opt}^{offline}}$$
(4)  
for all T, and  $\frac{C_{M=1,T=R}^{always}}{C_{opt}^{offline}} \le 2$  for all possible sequences  $\mathcal{A} = \{a_i\}.$ 

### Worst-case ratio: Always on 1<sup>st</sup>

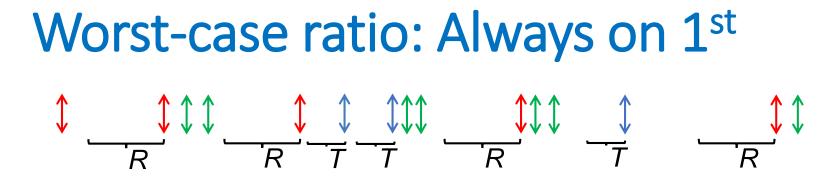


?? Given arbitrary worstcase request sequence

$$C_{M=1,T}^{always} = R + T + \sum_{i=2}^{N} x_i,$$

$$x_i = \begin{cases} T + R, & \text{if } a_i > T \\ a_i, & \text{otherwise.} \end{cases}$$
(2)
(3)

$$C_{opt}^{offline} = R + \sum_{i=2}^{N} \min[a_i, R].$$
(1)



Case: 
$$T \le R$$

$$S = \{i | a_i \leq T\},\$$
  

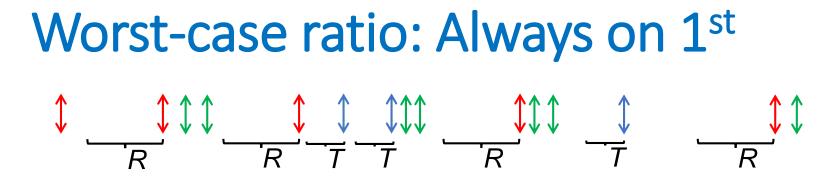
$$S' = \{i | T < a_i \leq R\},\$$
  

$$S'' = \{i | R < a_i\}.\$$

$$\frac{C_{M=1,T}^{always}}{C_{opt}^{offline}} = ??$$

$$C_{M=1,T}^{always} = R + T + \sum_{i=2}^{N} x_i, \qquad (2)$$
$$x_i = \begin{cases} T + R, & \text{if } a_i > T\\ a_i, & \text{otherwise.} \end{cases} \qquad (3)$$

$$C_{opt}^{offline} = R + \sum_{i=2}^{N} \min[a_i, R].$$
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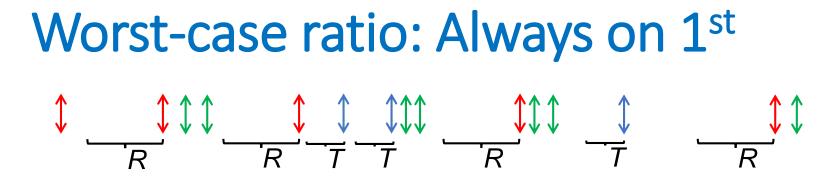


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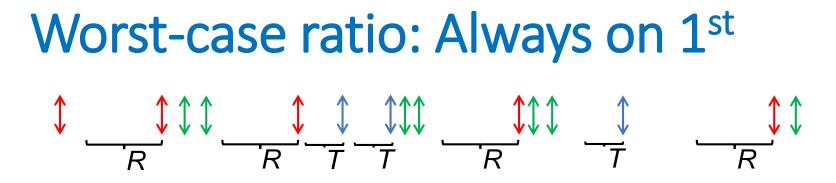
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$$S'' = \{i | R < a_i\}.\$$

$$\frac{C_{M=1,T}^{always}}{C_{opt}^{offline}} = \frac{R + \sum_{i \in S} a_i + (|S'| + |S''|)(T+R) + T}{R + \sum_{i \in S} a_i + \sum_{i \in S'} a_i + |S''|R} \\
\leq \frac{(R+T)(1+|S''|) + (R+T)|S'|}{R(1+|S''|) + \sum_{i \in S'} a_i} \\
\leq \frac{(R... [some steps]_{R...}T)|S'|}{R(1+|S''|) + |S'|T} \leq \frac{R+T}{T}.$$



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\leq \frac{(R... [some steps]_{R...,T})|S'|}{R(1+|S''|) + |S'|T} \leq \frac{R+T}{T}.$$

Bound monotonically decreasing in range  $0 \le T \le R$ .

Bound tight when  $T \rightarrow R$  (and equal to 2); achieved with  $T+\varepsilon$  spacing

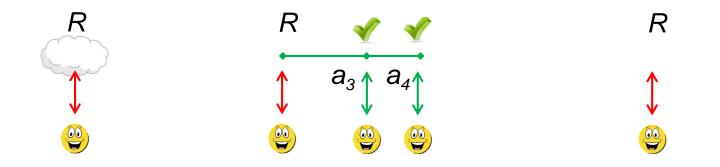
Similar approach for case when  $R \leq T$ 

Policy	Parameters	Optimal choice	Tight bound
Always 1 <sup>st</sup>	Т	T = R	2
Always M <sup>th</sup>			
Single-window <i>M</i> <sup>th</sup>			
Dual-window 2 <sup>nd</sup>			

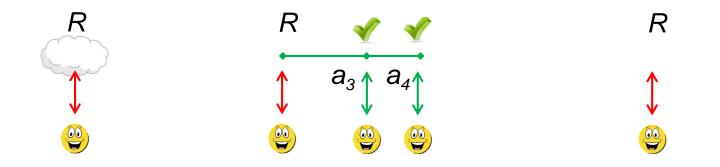
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Dual-window 2 <sup>nd</sup>	W, T	W = T = R	3

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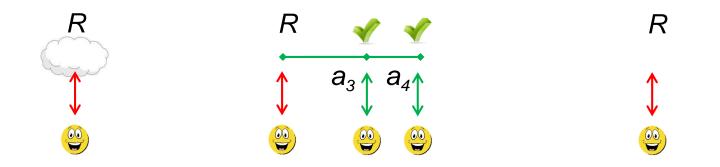
 Although M+1 worst-case bounds may seem discouraging, we will see that window-based policies are good on average (across different distributions and distribution parameters) Steady-state analysis



$$C_{opt}^{offline} = \frac{1}{E[a_i]} \left[ \int_0^R tf(t) dt + R \int_R^\infty f(t) dt \right]$$



$$C_{opt}^{offline} = \frac{1}{E[a_i]} \left[ \int_0^R tf(t) dt + R \int_R^\infty f(t) dt \right]$$
  
Rate of new Cost  $a_i$  Cost  $R$   
requests (per request) (per request)



$$C_{opt}^{offline} = \frac{1}{E[a_i]} \left[ \int_0^R tf(t) dt + R \int_R^\infty f(t) dt \right]$$
$$= \frac{1}{E[a_i]} \left[ [some \ steps](..., dt + R(1 - F(R))] \right]$$
$$= \frac{1}{E[a_i]} \left[ R - \int_0^R F(t) dt \right].$$
(12)

Table 1: Summary of costs for different distributions and insertion policies. To make room, for Erlang, we simplified expressions using  $F(t) = 1 - \sum_{n=0}^{k-1} \frac{1}{n!} e^{-\lambda t} (\lambda t)^n$  and  $\Phi(T) = \frac{e^{-\lambda T}}{\lambda} \sum_{m=1}^k \sum_{n=0}^{m-1} \frac{(\lambda T)^n}{n!}$ .

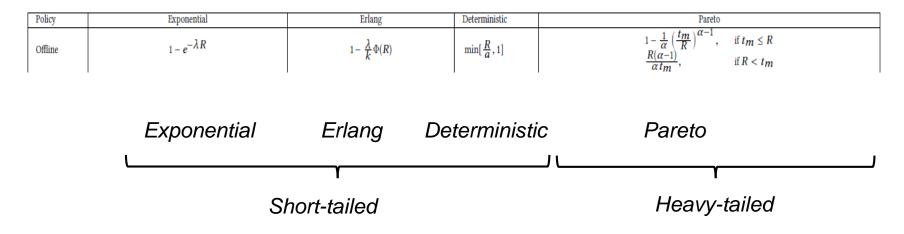
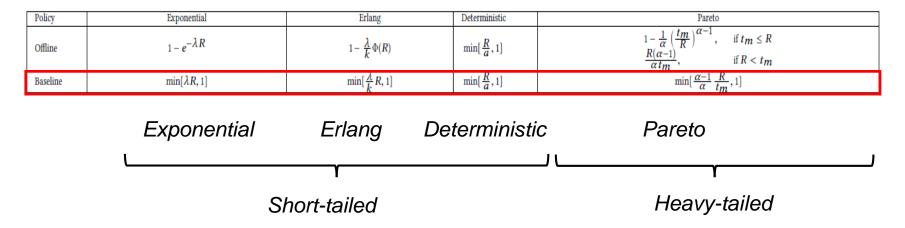
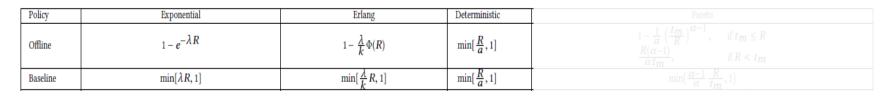


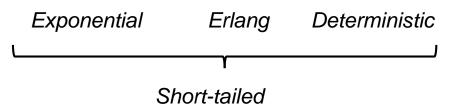
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"Static baseline" policy: Either "always remote" or "always local".

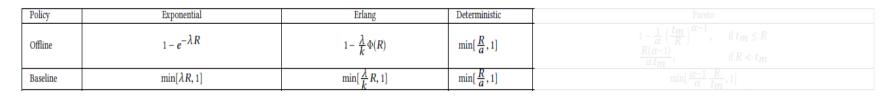
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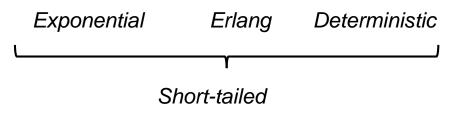




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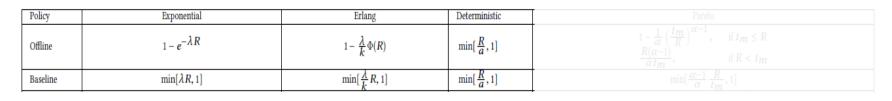


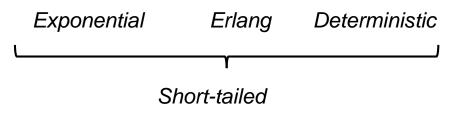


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THEOREM 6.1. Static baseline achieves the minimum cost of any online policy when the inter-request distribution has an increasing or constant hazard rate.

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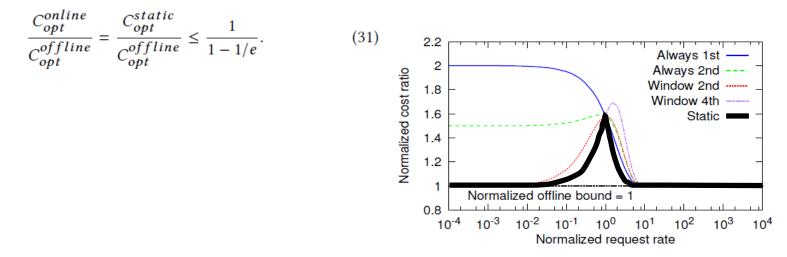
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... is online optimal for these cases!!

### Gap between online and offline optimal

THEOREM 6.3. Under Poisson requests we have



THEOREM 6.1. Static baseline achieves the minimum cost of any online policy when the inter-request distribution has an increasing or constant hazard rate.

#### Gap between online and offline optimal

THEOREM 6.3. Under Poisson requests we have

$$\frac{C_{opt}^{online}}{C_{opt}^{offline}} = \frac{C_{opt}^{static}}{C_{opt}^{offline}} \le \frac{1}{1 - 1/e}.$$
(31)

THEOREM 6.4. Under Erlang inter-request times, we have

$$\frac{C_{opt}^{online}}{C_{opt}^{offline}} = \frac{C_{opt}^{static}}{C_{opt}^{offline}} \le \frac{1}{1 - e^{-k}\frac{k^k}{k!}}.$$
(32)

THEOREM 6.5. Under deterministic inter-request times, we have

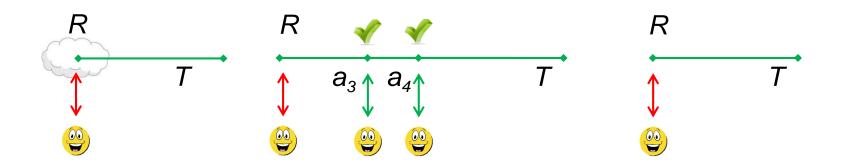
$$\frac{C_{opt}^{online}}{C_{opt}^{offline}} = \frac{C_{opt}^{static}}{C_{opt}^{offline}} = 1.$$
 (36)

THEOREM 6.1. Static baseline *achieves the minimum cost of any* online policy *when the inter-request distribution has an increasing or constant hazard rate.* 

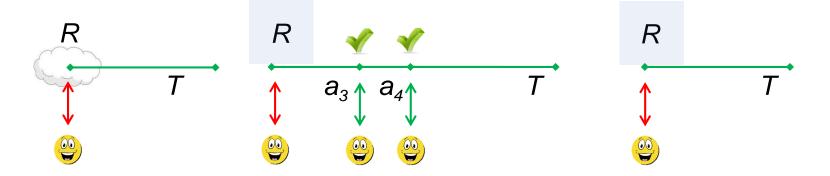
#### However, not true for heavy-tailed ...

... in fact, for Pareto the optimal static baseline can be far from optimal

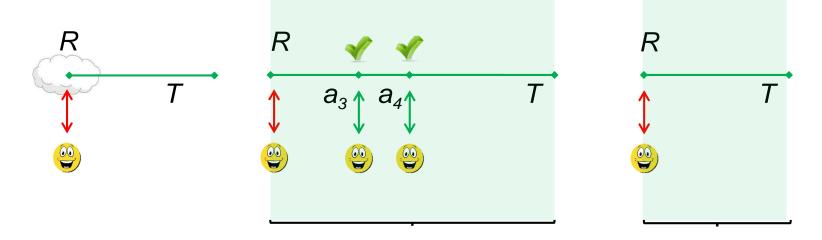
THEOREM 6.6. With Pareto inter-request times, the worst-case cost ratio for the optimal static baseline is unbounded. In particular,  $\frac{C_{opt}^{static}}{C_{opt}^{offline}} \to \infty$ (37) when  $\alpha = \frac{1}{1 - \frac{t_m}{R}}$  and  $\frac{t_m}{R} \to 0+$ .



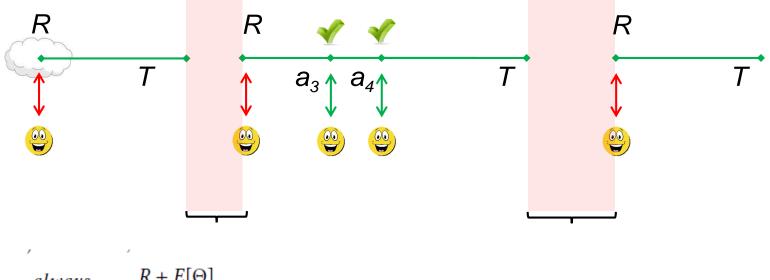
$$C_{M=1,T}^{always} = \frac{R + E[\Theta]}{E[\Delta_1] + E[\Theta]},$$
(42)



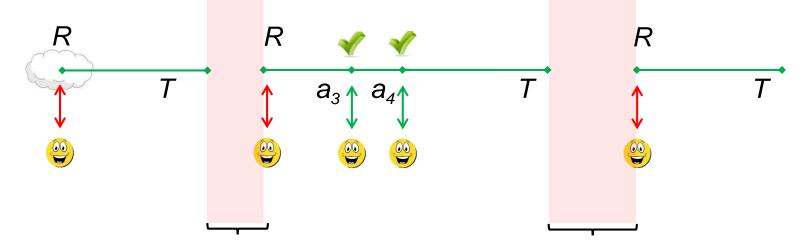
$$C_{M=1,T}^{always} = \frac{R + E[\Theta]}{E[\Delta_1] + E[\Theta]},$$
(42)



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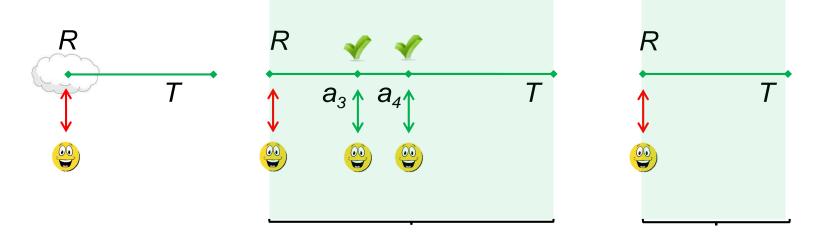


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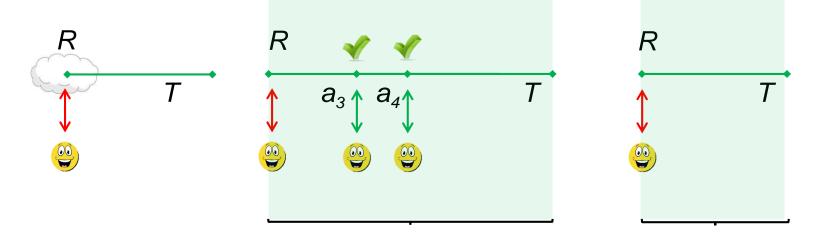
$$E[\Delta_1] = E[a_i|a_i > T] - T = \frac{1}{1 - F(T)} \left( E[a_i] + \int_0^T F(t) dt - T \right),$$
(43)



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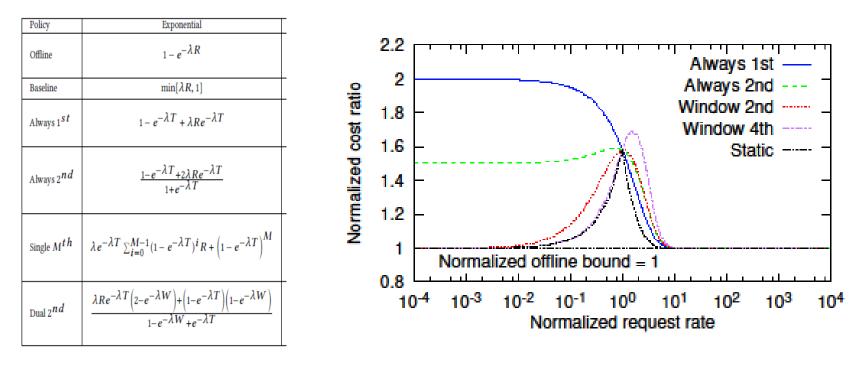
$$E[\Theta] = (1 - F(T))T + F(T)(E[a_i|a_i < T] + E[\Theta]), \quad (44)$$
  
No extension Extension case

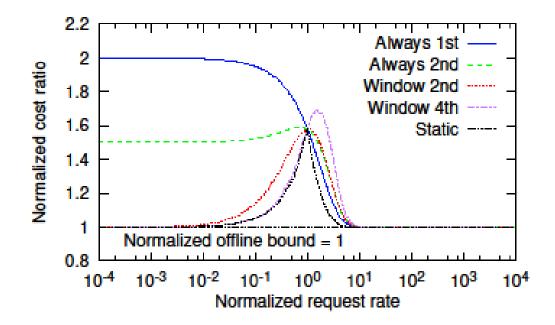
### **Results for example distributions**

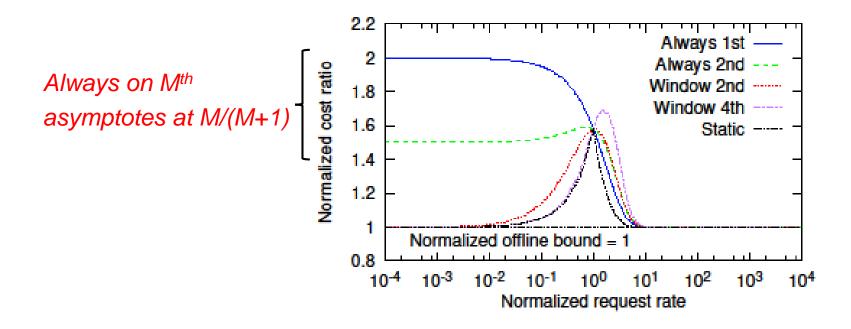
### Example distributions: Summary of costs

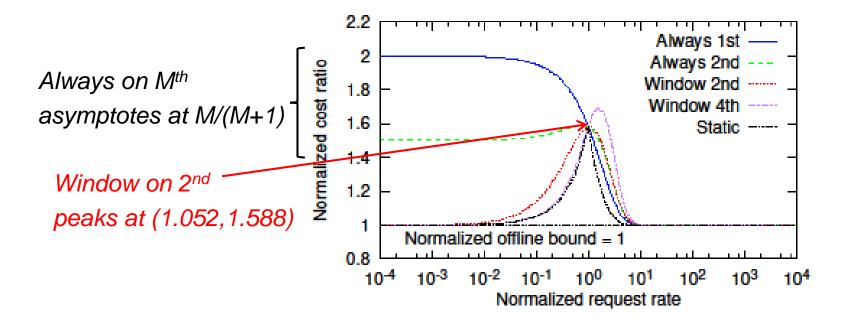
Table 1: Summary of costs for different distributions and insertion policies. To make room, for Erlang, we simplified expressions using  $F(t) = 1 - \sum_{n=0}^{k-1} \frac{1}{n!} e^{-\lambda t} (\lambda t)^n$  and  $\Phi(T) = \frac{e^{-\lambda T}}{\lambda} \sum_{m=1}^k \sum_{n=0}^{m-1} \frac{(\lambda T)^n}{n!}$ .

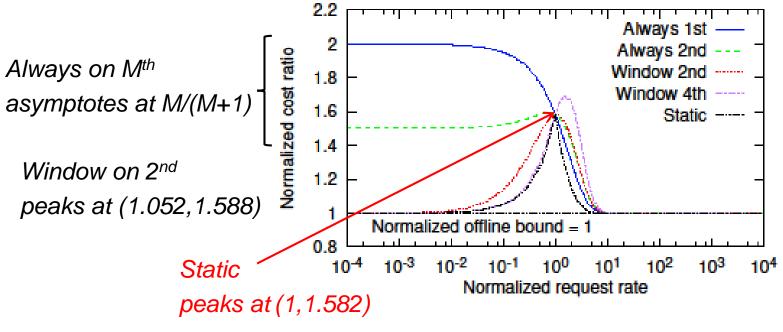
Policy	Exponential	Erlang	Deterministic	Pareto
Offline	$1 - e^{-\lambda R}$	$1 - \frac{\lambda}{k} \Phi(R)$	$\min[\frac{R}{a}, 1]$	$\frac{1 - \frac{1}{\alpha} \left(\frac{t_m}{R}\right)^{\alpha - 1}}{\frac{R(\alpha - 1)}{\alpha t_m}},  \text{if } t_m \le R$
Baseline	$\min[\lambda R, 1]$	$\min[\frac{\lambda}{k}R, 1]$	$\min[\frac{R}{a}, 1]$	$\min[\frac{\alpha-1}{\alpha}\frac{R}{t_m}, 1]$
Always 1 <sup>s t</sup>	$1 - e^{-\lambda T} + \lambda R e^{-\lambda T}$	$(1-F(T))\frac{\lambda}{k}R+(1-\frac{\lambda}{k}\Phi(T))$	1, if $a \le T$ $\frac{R+T}{a}$ , if $T < a$	$\frac{\frac{\alpha-1}{\alpha}\left(\frac{tm}{T}\right)^{\alpha}}{\frac{(R+T)(\alpha-1)}{\alpha tm}} + \left(1 - \frac{1}{\alpha}\left(\frac{tm}{T}\right)^{\alpha-1}\right),  \text{if } tm \leq T$
Always 2nd	$\frac{1 - e^{-\lambda T} + 2\lambda R e^{-\lambda T}}{1 + e^{-\lambda T}}$	$\frac{(1-F(T))\frac{\lambda}{k}2R+(1-\frac{\lambda}{k}\Phi(T))}{2-F(T)}$	1, if $a \le T$ $\frac{2R+T}{2a}$ , if $T < a$	$\frac{\frac{\alpha-1}{\alpha}\left(\frac{tm}{T}\right)^{\alpha}\frac{2R}{tm} + \left(1 - \frac{1}{\alpha}\left(\frac{tm}{T}\right)^{\alpha-1}\right)}{1 + \left(\frac{tm}{T}\right)^{\alpha}},  \text{if } tm \leq T$ $\frac{2R+T}{2}\frac{\alpha-1}{\alpha tm},  \text{if } T < tm$ $\frac{\alpha-1}{\alpha}\left(\frac{tm}{T}\right)^{\alpha}\sum_{i=0}^{M-1}(1 - \left(\frac{tm}{T}\right)^{\alpha})^{i}\frac{R}{T}$
Single M <sup>th</sup>	$\lambda e^{-\lambda T} \sum_{i=0}^{M-1} (1 - e^{-\lambda T})^i R + \left(1 - e^{-\lambda T}\right)^M$	$ \begin{array}{l} (1-F(T))\frac{\lambda}{k}\sum_{i=0}^{M-1}F(T)^{i}R\\ +\left(1-\frac{\lambda}{k}\Phi(T)\right)F(T)^{M-1} \end{array} $	1, if $a \le T$ $\frac{R}{a}$ , if $T < a$	$ + \left(1 - \frac{1}{\alpha} \left(\frac{t_m}{T}\right)^{\alpha - 1}\right) \left(1 - \left(\frac{t_m}{T}\right)^{\alpha}\right)^{M - 1},  \text{if } t_m \le T \\ \frac{R(\alpha - 1)}{\alpha t_m},  \text{if } T < t_m $
<sub>Dual 2</sub> nd	$\frac{\lambda R e^{-\lambda T} \left(2 - e^{-\lambda W}\right) + \left(1 - e^{-\lambda T}\right) \left(1 - e^{-\lambda W}\right)}{1 - e^{-\lambda W} + e^{-\lambda T}}$	$\frac{(1\!-\!F(T))\Big(2\!+\frac{1\!-\!F(W)}{F(W)}\Big)R\!+\!\Big(\frac{k}{\lambda}\!-\!\Phi(T)\Big)}{\frac{k}{\lambda}(1\!+\!\frac{1\!-\!F(T)}{F(W)})}$	1, if $a < W \le T$ $\frac{R}{a}$ , if $W < a$	$ \begin{array}{ll} \displaystyle \frac{(\alpha-1)\Big(\frac{t_m}{T}\Big)^{\alpha}(2-\Big(\frac{t_m}{W}\Big)^{\alpha}\Big)R+(1-\Big(\frac{t_m}{W}\Big)^{\alpha}\big)(t_m\alpha-T\Big(\frac{t_m}{T}\Big)^{\alpha}\Big)}{\alpha t_m(1-\Big(\frac{t_m}{W}\Big)^{\alpha}+\Big(\frac{t_m}{T}\Big)^{\alpha}\big)}, & \text{if } t_m \leq W \\ \displaystyle \frac{R(\alpha-1)}{\alpha t_m}, & \text{if } W < t_m \end{array} $

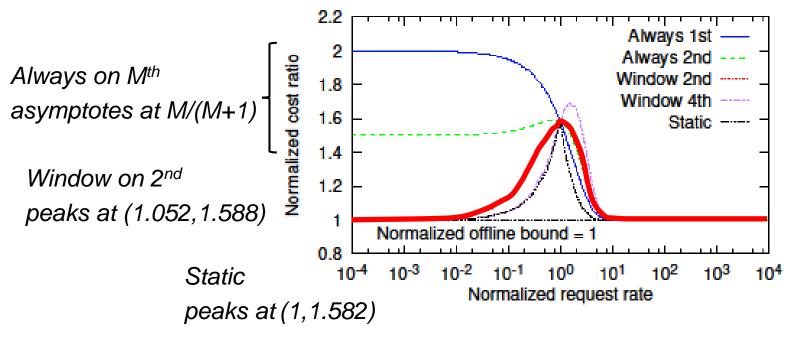




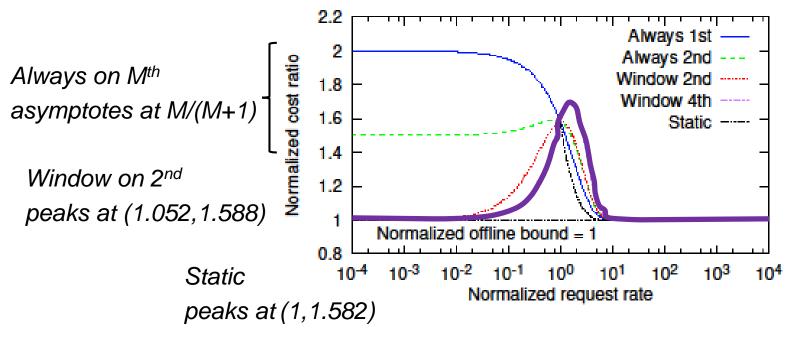




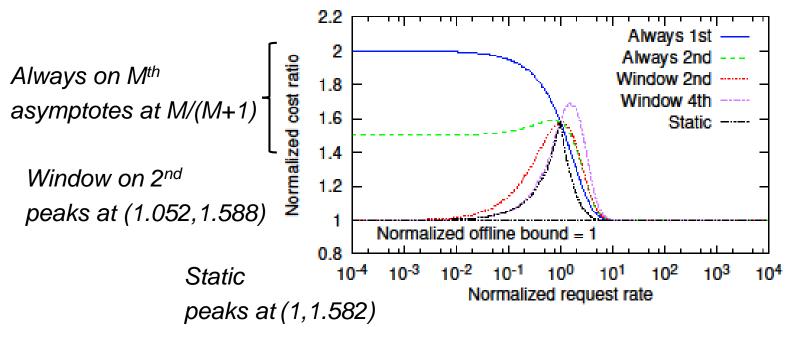




- Results with W = T = R
- Window on 2<sup>nd</sup> performs good throughout
- Window on 4<sup>th</sup> performs somewhat better for lower request rates, but at an increased peak cost (at somewhat higher rates)

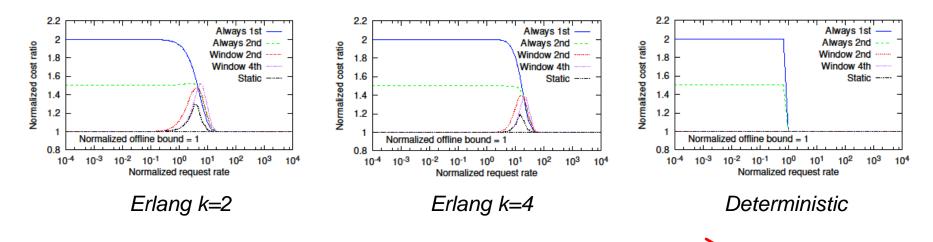


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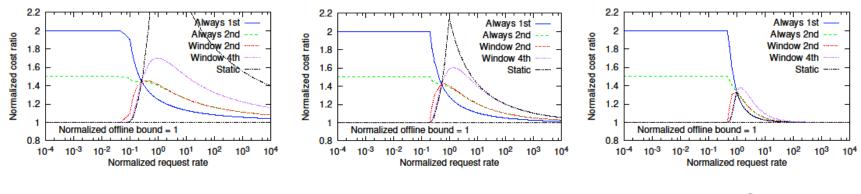
# Example distributions: Low variability distributions



Increasingly deterministic inter-request times

 Peak cost ratio for single-window on 2<sup>nd</sup> reduces as k increases and inter-request times become increasingly deterministic (rightmost fig)

### **Example distribution: Pareto**





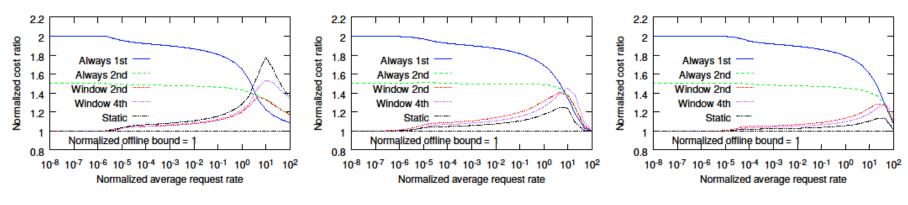


α = 2

- As per Theorem 6.6, static baseline performs very poorly when  $\alpha \rightarrow 1$  (and  $t_m$  is small). E.g., large peak cost ratio in left-most fig
  - For larger  $\alpha$  (e.g.,  $\alpha$  = 2), this peak reduces substantially.
- Otherwise, the results are similar as for the other inter-request distributions, suggesting that single-window on 2<sup>nd</sup> with T = R is a good choice

# **Multi-file evaluation**

# **Example distributions**



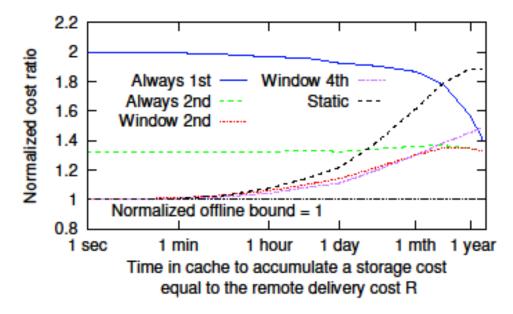
*Pareto,* α =1.25

Exponential

Erlang, k=4

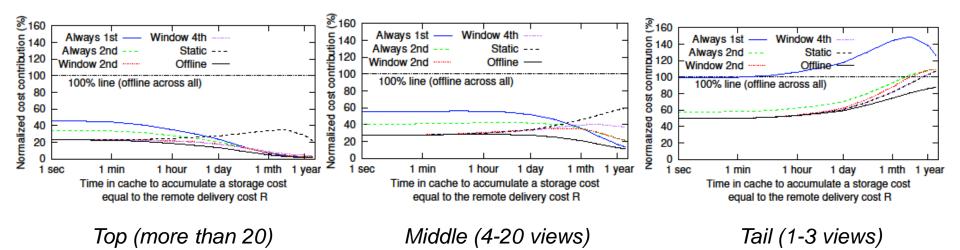
- Setup: 1,000,000 objects with Zipf popularity
  - Here,  $\gamma = 1$  (but results with  $\gamma = 0.75$  and  $\gamma = 1.25$  similar)
  - W = T = R
- Significant benefits to being selective
  - Window on 2<sup>nd</sup> significantly outperforms always on M<sup>th</sup>
- *Window on 2<sup>nd</sup>* good throughout
  - Close to static optimal when Exponential and Erlang
  - Outperform static when Pareto
  - Has a peak cost-ratio of 1.4

### **Trace-based simulations**



- Setup: 20-month long university trace with YouTube viewings
  - 5.5 M video request to 2.4 M unique videos
  - Long tail of less popular videos
  - W = T = R
- "Static" (highly optimistically) assumes "oracle" knowledge of which choice is better (*always local* or *always remote*) for each individual video ...
- Yet, window on 2<sup>nd</sup> outperform static
  - Highlights value of policy when request rates are unknown and variable

# **Break-down of cost contributions**



• Tail contribute to most of the costs ...

... highlighting importance of selective insertions.

Conclusions

# Conclusions

Worst-case bounds for the optimal cost and competitive cost ratios

• E.g., Best worst-case bounds of M+1 are achieved by selecting W = T = R

Average cost expressions and bounds

- Arbitrary inter-request distributions
- Example inter-request distributions (both short-tailed and heavy-tailed)
- *Static* is *online optimal* for constant and decreasing hazard rates, but can be arbitrarily bad when heavy tailed or request rates are not known

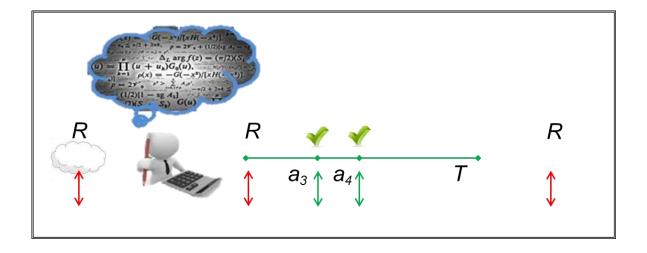
Numeric and trace-based evaluations reveal insights into the relative cost performance of the policies

Substantial cost benefits of using window-based with intermediate M (e.g., 2-4) and the optimal worst-case parameter setting (i.e., W = T = R)

*Window-based cache on 2nd request* policy using a single threshold optimized to minimize worst-case costs provides good average performance

• Attractive choice for a wide range of practical conditions where request rates of individual file objects typically are not known and can change quickly ...

# Thanks for listening!



#### Worst-case Bounds and Optimized Cache on *M<sup>th</sup>* Request Cache Insertion Policies under Elastic Conditions

Niklas Carlsson and Derek Eager



Niklas Carlsson (niklas.carlsson@liu.se)