An Approximation Algorithm to Maximize User Capacity for an Auto-scaling VoD System

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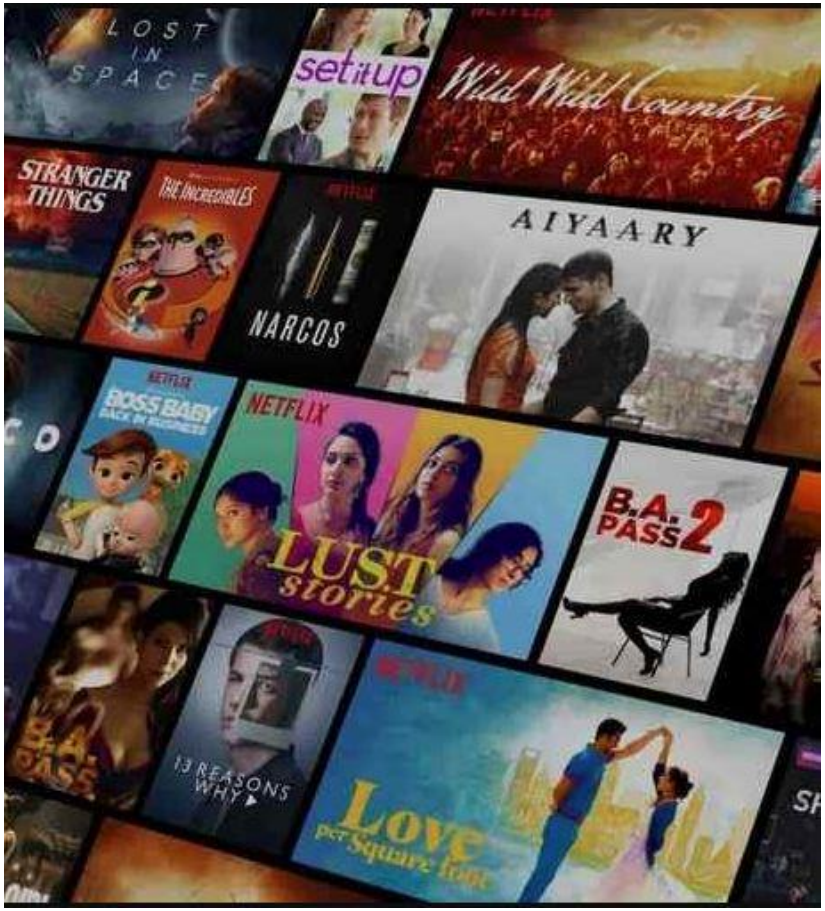
Contents

1. **Introduction and Related Work**
2. Problem Formulation and its NP-hardness
3. AVARDO: An Approximation Algorithm
4. Illustrative Trace-driven Experimental Results
5. Conclusion

User Request Pattern for Blockbuster Videos: Stable Popularity, Volatile Traffic

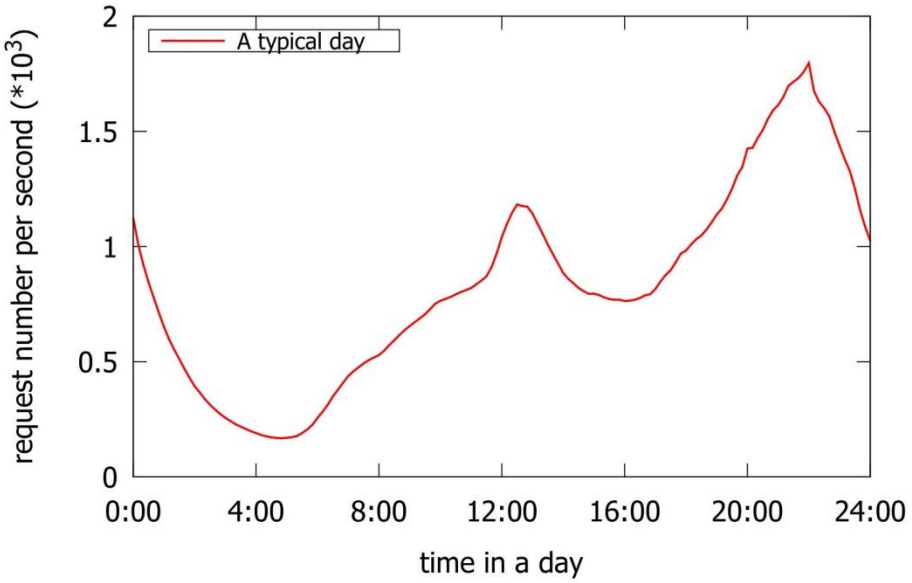


Blockbuster video service (e.g., Netflix) to a large group of audience

- **Video access popularity**: rather stable and predictable over days or weeks
- **User request traffic**: may vary by an order of magnitude in hours

- Statically allocates a fixed number of servers is not efficient.
- **Auto-scaling** can meet the demand in a **timely** and **cost-effective** manner.

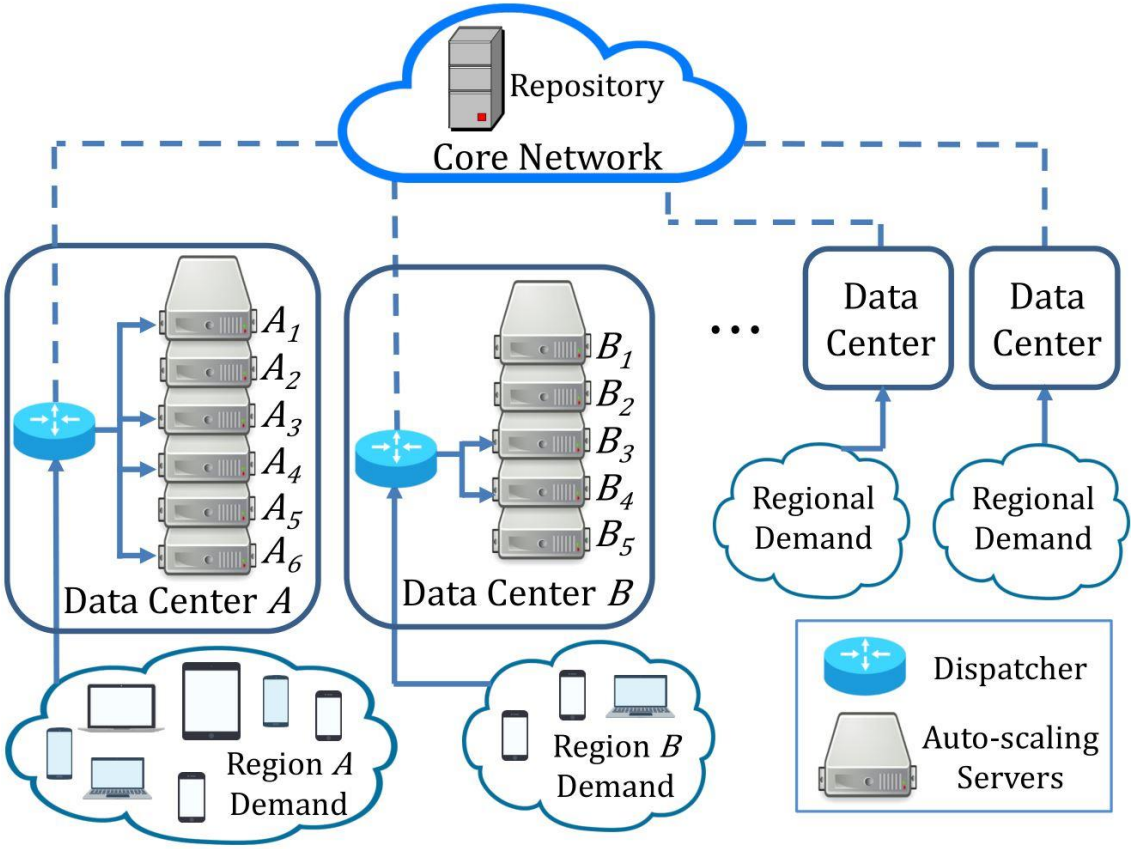
Request Rate Over a Typical Day



User request of a leading video service website in China over a day

- Blockbuster videos have rather stable and predictable over days or weeks (cf. UGC).
- Popularity remains quite stable (varies less than 10%) over a day.
- Request traffic may vary by an order of magnitude over merely hours.
- Auto-scaling is a solution to meet demand in a timely and cost-effective manner.

A Typical Auto-scaling VoD Cloud



A video cloud consisting of auto-scaling VoD data centers.

Auto-scaling Server

- Server has a certain storage and streaming capacity
- Server can be activated or deactivated in a short time
- Homogeneous servers
- Activating server according to incoming traffic

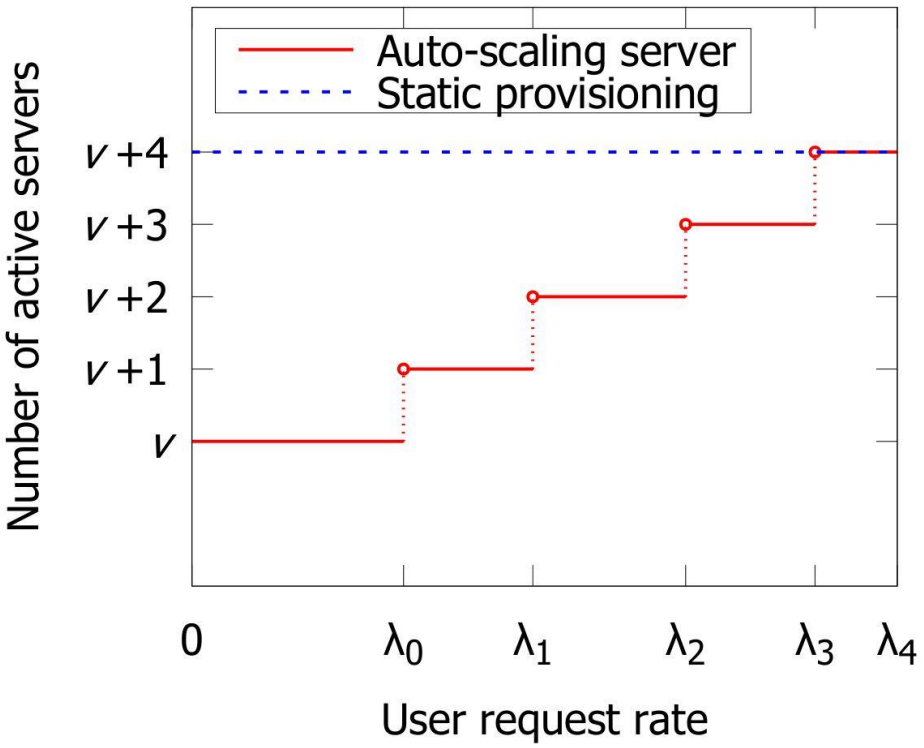
Traffic Dispatcher

- Distribute request to an active server with the video
- Otherwise to core network

Video Block

- Blocks have the same size
- Partition large video into blocks
- Video block is only for management purpose (cf. DASH segments)

Maximizing the User Request Rate Threshold



Request rate	Increase	Decrease
Auto-scaling level	Increase	Decrease
Active servers	More	Less

- The total block request rate λ (requests/second) is mapped to an **auto-scaling level** i (i=0, 1, 2, ...).
- Auto-scaling level i has a request rate threshold λ_i with a predefined set of active server V_i. V_i contains all the video blocks (at least one replica for each block).
- When $\lambda_i < \lambda \leq \lambda_{i+1}$, servers in V_{i+1} are activated.
- Let $|V_0| = \nu$, we have $|V_i| = \nu + i$.
- To minimize the deployment cost, we seek to maximize the **user capacity** supported by the active servers, which is proportional to λ_i.

Optimizing Following Inter-dependent Dimensions

Block Allocation (BA)

- A server has limited storage and cannot store all the video blocks.
- Which blocks should be allocated (or replicated) in each server?
- Servers in V_i shall store at least one replica of each video block.

Server Selection (SS)

- Which servers should be activated (i.e., in V_i) for auto-scaling level i?
- Servers in V_i shall have enough replicas for each video block.

Request Dispatching (RD)

- Some video blocks may be stored on multiple active servers.
- Which server to cater a video block request?
- The dispatcher has to balance the load of each active server.

Challenges: Timescale and Interdependence

Block Allocation (BA)

- Timescale: in day or week
- Videos are pre-allocated (preloaded) in all the servers for SS and RD
- On-the-fly BA is not necessary due to the relatively stable popularity

Server Selection (SS)

- Timescale: in hour
- SS decision should be based on a given BA

Request Dispatching (RD)

- Timescale: in second
- RD decision should be based on a given BA and SS

- We shall jointly optimize these 3 interdependent dimensions.

Contributions

Problem formulation and its NP-hardness

- Study the novel problem: maximize λ_i for each auto-scaling level
- A multi-objective mixed-integer linear programming problem
- We prove the problem is NP-hard
- Traditional static provisioning is a special case of our problem

Stack-based algorithm with proven approximation ratio

- AVARDO: Auto-scaling Video Allocation and Request Dispatching Optimization
- Efficient and closely optimal algorithm with proven approximation ratio
- Stack-based approach with minimum overhead: servers are activated (deactivated) due to the increment (decrement) of auto-scaling level

Extensive trace-driven experimental study based on real-world data

- Trace-driven experiments with real-world VoD data
- Achieve significantly lower optimality gap in active server number (by multiple times) compared with other state-of-the-art schemes

Related Work

Cloud-based VoD architecture resource provisioning

- Yet to consider some important features inside the data center due to model abstraction [1], [2], [3]
- AVARDO complements to these studies by investigating from a more detailed point of view

Content replication in traditional and cloud-based VoD data centers

- Assumes no dynamics within the data center: the server configurations and bandwidth reservation are rarely changed [4]
- Not considered the change of storage and video replication of the auto-scaling servers [5]
- AVARDO optimize for every possible auto-scaling levels

Cloud resources auto-scaling mechanism

- Predict the user demand and improves the performance in the online phase [6], [7]
- Each request or task considered in the problems is served by only one server [8]-[10]
- AVARDO considers BA and RD as some videos are too popular to be served by one server

Contents

1. Introduction and Related Work
2. **Problem Formulation and its NP-hardness**
3. AVARDO: An Approximation Algorithm
4. Illustrative Trace-driven Experimental Results
5. Conclusion

Symbol Used in Formulation

u	The streaming capacity of a server (bits/s)	p^m	Access probability of video block m
c	The storage capacity of a server (bits)	L^m	Average holding time of video block m (in seconds)
f	The file size of block (bits)	b^m	Video streaming rate of video block m (bits/s)
V	The set of all standby servers in data center	$R^m(\lambda)$	Traffic of block m (bits/s) at request rate λ
V_i	The set of active servers at auto-scaling level i	I_v^m	Binary variable indicating server v stores block m
M	The set of all blocks	$r_v^m(i)$	Probability of streaming a request of block m from server v at auto-scaling level i
M_v	The set of video blocks stored in server v		
λ	Total block request rate (requests per second)	μ	Server utilization limit to ensure quality-of-service

Problem Formulation of AVARD: Auto-scaling Video Allocation and Request Dispatching

Objective $\max(\lambda_0, \lambda_1, \ldots \lambda_n)$ → User request rate threshold

Subject to

$$R^m(\lambda) = \lambda p^m L^m b^m, \forall m \in M$$ → Traffic of video block m (bits/s) at request rate λ

Storage

$$\sum_{m \in M(v)} I_v^m f \leq c, \forall v \in V$$ → Server cannot store video blocks beyond its storage

Streaming

$$r_v^m(i) \leq I_v^m, \forall v \in V_i, m \in M$$ → Server can serve the traffic of a block only if it has this block

$$\sum_{v \in V_i} r_v^m(i) \geq 1, \forall m \in M$$ → All the user request for each video block shall be served

QoS

$$\sum_{m \in M} r_v^m(i) R^m(\lambda_i) \leq \mu u, \forall v \in V_i$$ → The utilization of the streaming capacity of every server should not exceed a certain limit μ

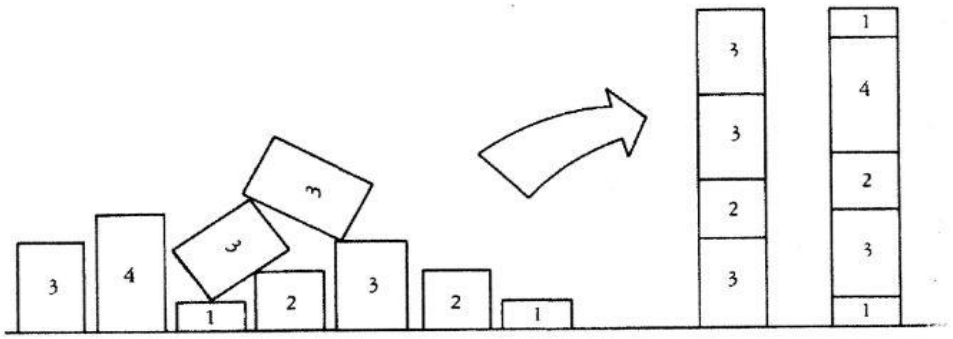
NP-Hardness of AVARD Problem

The **Partition Problem**: (NP-complete)

Whether a given multiset $S = \{s_1, s_2, \ldots, s_n\}$ of n positive integers can be divided into two subsets S_1 and S_2 such that the sums of the numbers in S_1 and S_2 are the same.

The **AVARD** problem is **NP-hard**

- The **Partition Problem** is reducible to our **AVARD** optimization problem.
- Considering that:
  - The Auto-scaling VoD system has only auto-scaling level 0.
  - We have 2 servers with storage n and streaming capacity $s/2 + n$.
  - We have 2n videos with $f = 1$.
  - Half of videos have $R^m = s_m + 1$; the other half videos have $R^m = 1$.



Contents

1. Introduction and Related Work
2. Problem Formulation and its NP-hardness
3. **AVARDO: An Approximation Algorithm**
4. Illustrative Trace-driven Experimental Results
5. Conclusion

Additional Symbol Used in Algorithm

v_i	The server to activate when auto-scaling level goes from $i-1$ to i (i.e., $V_i = V_{i-1} \cup \{v_i\}$)	G	The set of video clusters
		$G(v)$	The set of video clusters on server v
P^m	Streaming ratio of video block m	G_k	The set of video clusters that have k replicas
N^m	Number of replicas for block m stored in V_0	$P(g)$	Total streaming ratio of replicas in cluster g
N_T	Number of replicas can be stored in V_0	$C(g)$	Storage capacity used for cluster g
N_A	Number of surplus replicas in V_0 (i.e., $N_T - \|M\|$)	q_g^m	Probability of streaming a request of block m from cluster g at auto-scaling level 0
σ^m	Average replica streaming ratio of block m		
σ	Average replica streaming ratio threshold	λ_{op}	Theoretical upper limit of λ threshold

AVARDO: Approximation Algorithm for an Auto-scaling Video-on-Demand System

- **A**uto-scaling **V**ideo **A**llocation and **R**equest **D**ispatching **O**ptimization
- Jointly optimize *Video Allocation*, *Server Selection*, and *Request Dispatching*

AVARDO has a stack-based server selection scheme

- Consider the set of active servers as a stack
- Push (activate) or pop (deactivate) a server in an orderly sequence

Preprocessing: Block Replication and Clustering

- Simplify the algorithm by putting the video blocks into clusters.
- Each cluster has the same *file size* and generates same *user traffic.* Thus, it can be treated as a mega video file.

1. The *block replication* step decides how many replicas are required for a video block (i.e., N^m).
2. The *replica clustering* step decides which replicas are in a cluster (i.e., g).

Block Allocation and Request Dispatching

1. Consider cluster allocation for servers in V_0.
2. Consider server v_i incrementally.
3. Given request dispatching at auto-scaling level i.

Preprocessing Stage: Block Replication

$$P^m = \frac{p^m L^m b^m}{\sum_{m \in M} p^m L^m b^m}, \forall m \in M$$

Streaming Ratio P^m is proportional to the traffic of video block m

The Block replication is a popularity-based scheme (in terms of P^m)

1. The least popular block has at least one replica in V_0 (i.e., $N^m \geq 1$).
2. For the most popular block m, each server has at most one replica (i.e., $N^m \leq \nu$).
3. For the other blocks, N^m is proportional to P^m .

$$N^m = \begin{cases} \nu, & \text{if } P^m > \nu\sigma, \\ \lceil P^m/\sigma \rceil, & \text{if } \sigma < P^m \leq \nu\sigma, \\ 1, & \text{if } P^m \leq \sigma. \end{cases}$$

→ fully replicated blocks

→ partially replicated blocks

Average replica streaming ratio threshold σ

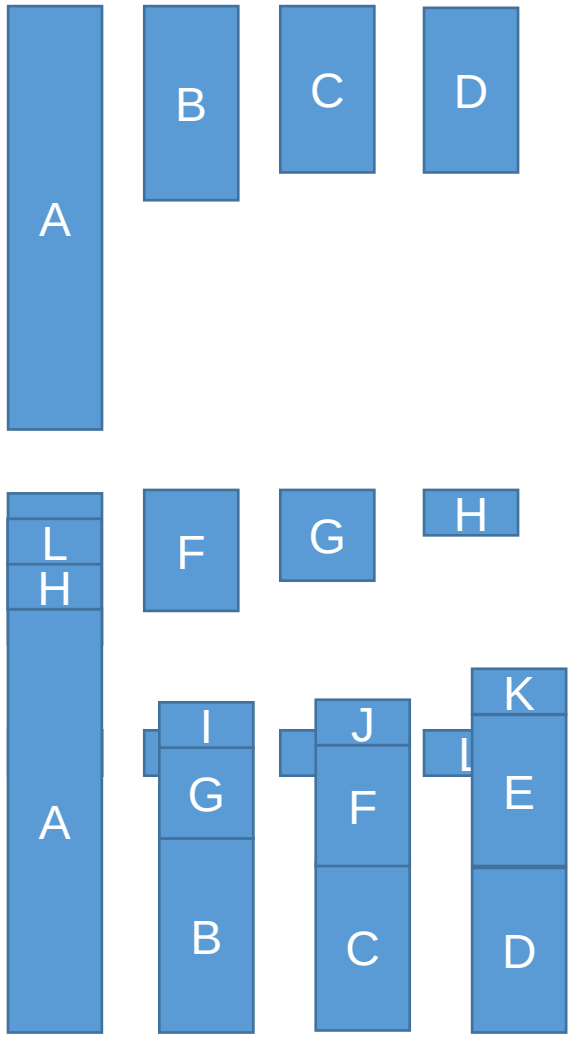
- A smaller σ will increase the number of video replicas.
- We find the smallest possible σ through binary search.

Preprocessing Stage: Replica Clustering

Algorithm 1: AVARDO replica clustering

Initialization: $P(g) = 0$, $C(g) = 0$, $\forall g \in G$;
Put all partially replicated replicas into priority queue $\mathbb{Q}$;
while $\mathbb{Q} \neq \emptyset$ **do**
    Pop top v^2 replicas with max σ^m from $\mathbb{Q}$;
    Put these v^2 replicas into priority queue $\mathbb{Q}_m$;
    while $\mathbb{Q}_m \neq \emptyset$ **do**
        Pop the replica m with max σ^m from $\mathbb{Q}_m$;
        Pop the cluster g with min $P(g)$ from $\mathbb{Q}_g$;
        Store a replica m in g: $g \leftarrow m$;
        Update parameters: $P(g)$ += σ^m, $C(g)$ += f;
    end
end

Objective: Each cluster has the same *file size* and generates similar *user traffic.*



Block Allocation and Request Dispatching

For auto scaling level $i > 0$, we write $i = kv + j$ such that $k \geq 0$ and $1 \leq j \leq v$.

Block Allocation

1. All the servers shall store fully replicated blocks.
2. For $v \in V^0$, we distribute the v^2 clusters into v servers such that each server $v \in V^0$ stores v unique clusters.
3. For server v_i such that $i \leq v$, it shall pick one unique cluster from every server $v \in V^0$ where the cluster has not been picked by the other server v_l such that $l \leq v$.
4. For server v_i such that $i = kv + j$ with $k \geq 1$, we let $G(i) = G(j)$ (i.e., server v_i and v_j have the same block replication).

Traffic Dispatching

We first consider the $i = 0$ case:

$$q_g^m = \begin{cases} 1/N^m, & \text{if } m \in g, \\ 0, & \text{otherwise.} \end{cases}$$

$$r_v^m(0) = \sum_{g \in G(v)} q_g^m, \forall m \in M, v \in V_0.$$

We then consider the $i > 0$ case:

- For the servers $v \in v_1, \ldots, v_i$, we have

$$r_v^m(i) = \frac{v}{v+i} \sum_{g \in G(v)} q_g^m, \forall m \in M.$$

- For the servers in $v \in V^0$, denoting $G_x = G(v) \cap G_{k+2}$ and $G_y = G(v) \cap G_{k+1}$, for all $m \in M$ we have

$$r_v^m(i) = \frac{j}{v+i} \sum_{g \in Gx} q_g^m + \frac{v+j}{v+i} \sum_{g \in Gx} q_g^m.$$

Optimality and Time Complexity

Time Complexity: $O(|M|\log|M| + |M||V|^2)$

- Searching for σ can be done in $O(|M|)$.
- The major component of clustering is to get the replicas from the priority queue. The time complexity is thus $O(|M|\log|M|)$.
- Computing each $r_v^m(i)$ requires constant time. Total time is $O(|M||V|^2)$.

Theoretical Optimality Gap of AVARDO: $\nu^2\sigma$

- Lemma 1: σ is less than $1/N_{\mathrm{A}}$.
- Lemma 2: For every video cluster $g \in G$, its streaming ratio $P(g)$ is no more that $1/\nu^2 + \sigma$.
- The optimality gap, given by $\lambda_{\mathrm{op}}/\lambda - 1$, is no more than $\nu^2\sigma$.
- ν is proportional to video number, and σ is proportional to block size f.

Upper bound of optimality gap in real-world setting: less than 1%

- A nowadays video server can store more than 10^5 videos ($\sigma < 10^{-5}$).
- For auto-scaling level 0, 30 servers are more than enough ($\nu \leq 30$).
- We can further reduce σ by partitioning the video files into smaller blocks.

Contents

1. Introduction and Related Work
2. Problem Formulation and its NP-hardness
3. AVARDO: An Approximation Algorithm
4. **Illustrative Trace-driven Experimental Results**
5. Conclusion

Simulation Environment

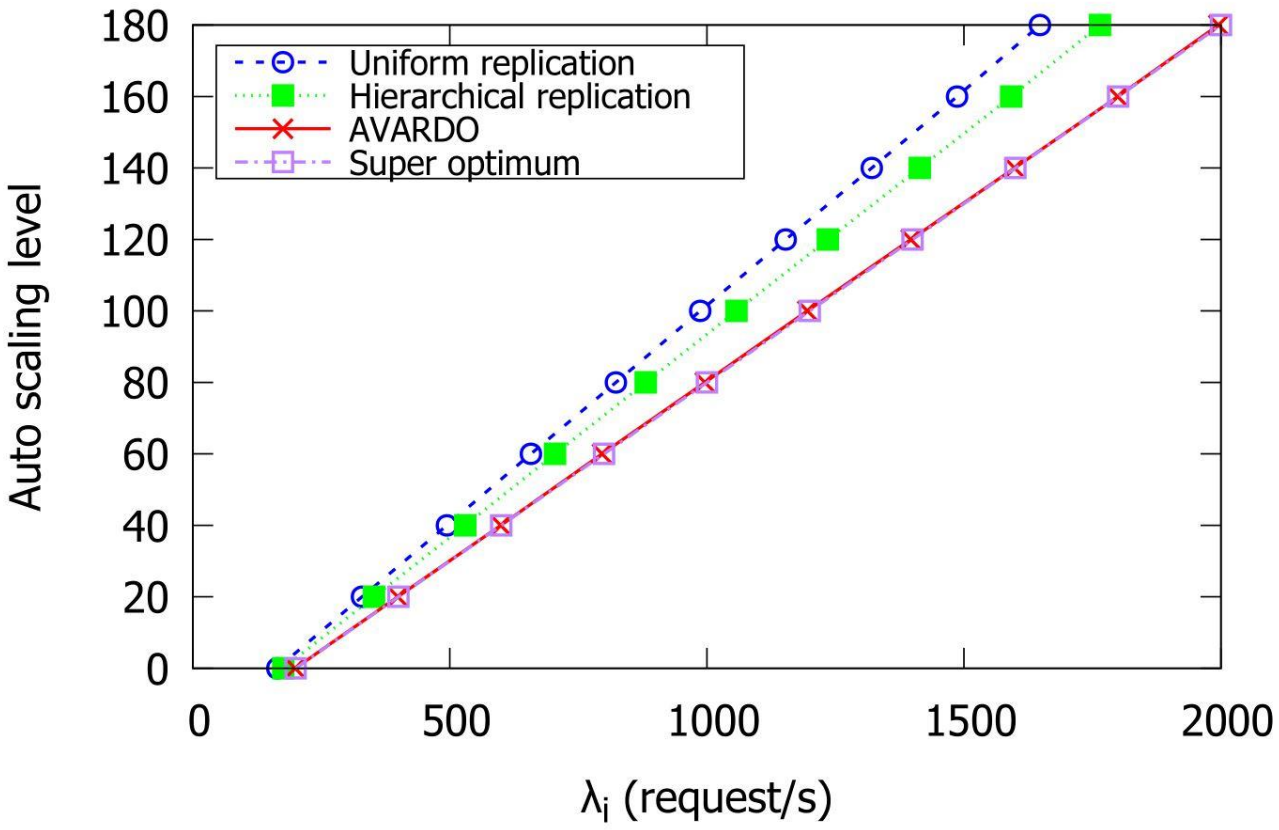
Parameter	Baseline value
• Number of blocks $\|M\|$	around 3×10^6
• block request rate λ (requests/s)	2,000
• Number of blocks in a server c/f	6×10^5
• Server streaming capacity u (Gbps)	25
• Server utilization limit μ	0.9

- The real-world data trace is from a leading video service website in China over 2 weeks.
- We partition the videos into the blocks of the same size of 100MB.
- When a video has multiple resolutions and bit rates, we treat them as multiple video files.

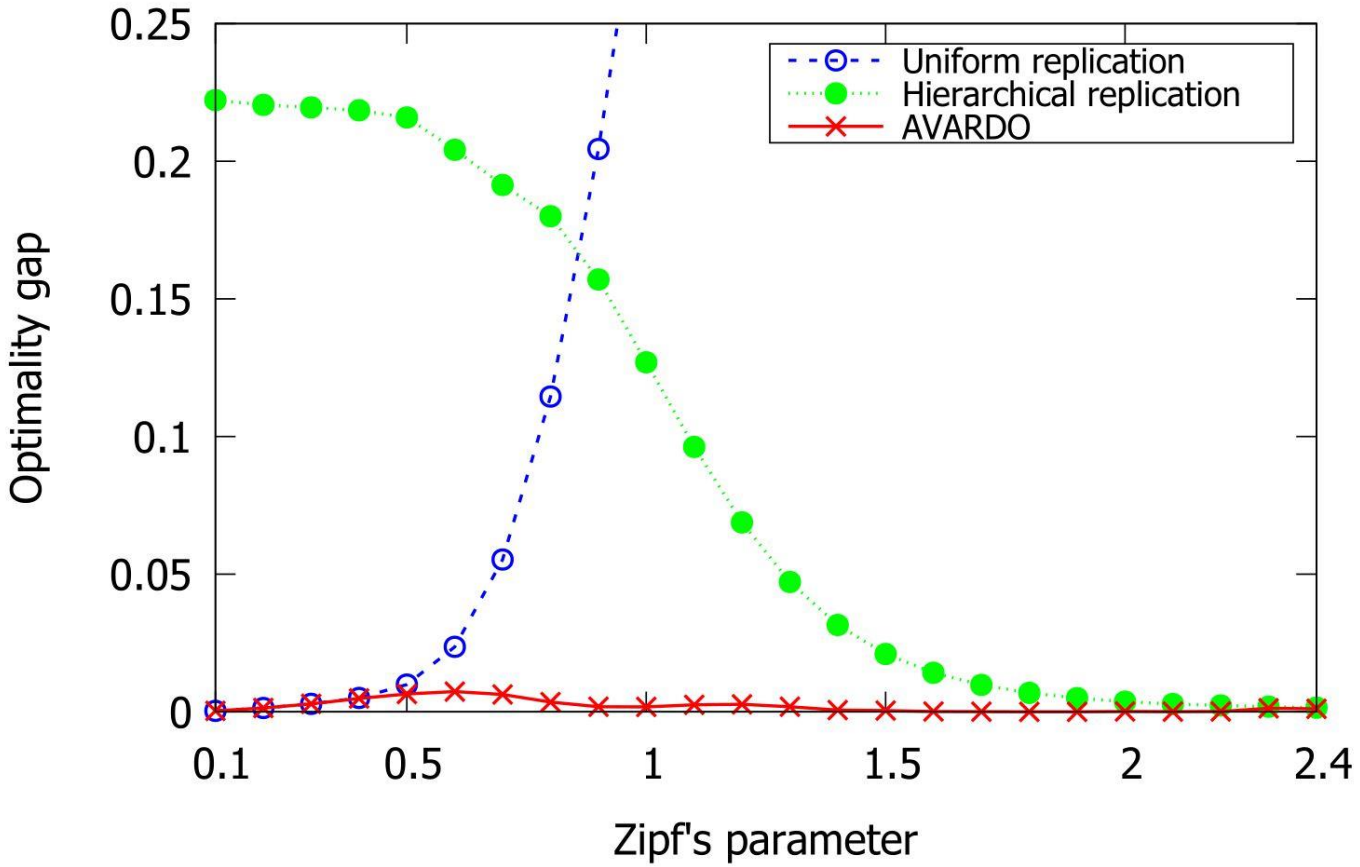
Performance Metrics

Performance Metrics	
• Request rate threshold λ_n	Optimization objective of AVARDO
• Optimality gap of λ_n	Difference between scheme performance and the theoretical performance bound
• Number of active servers	Operation cost over a given time period
• Fairness of active server utilization	Jain's Fairness Index, which is between 0 and 1 (a higher index indicates a fairer load sharing)
Comparison Schemes	
• Uniform replication	Every video has the same number of replicas. The videos are randomly stored in the servers.
• Hierarchical popularity replication	2 types of server: repository and cache. Repository servers collaboratively store all. Caches only store popular videos.
• Super optimum	Serves as the theoretical performance bound. We assume that a video can be partitioned infinitesimally (i.e., $f \to 0$).

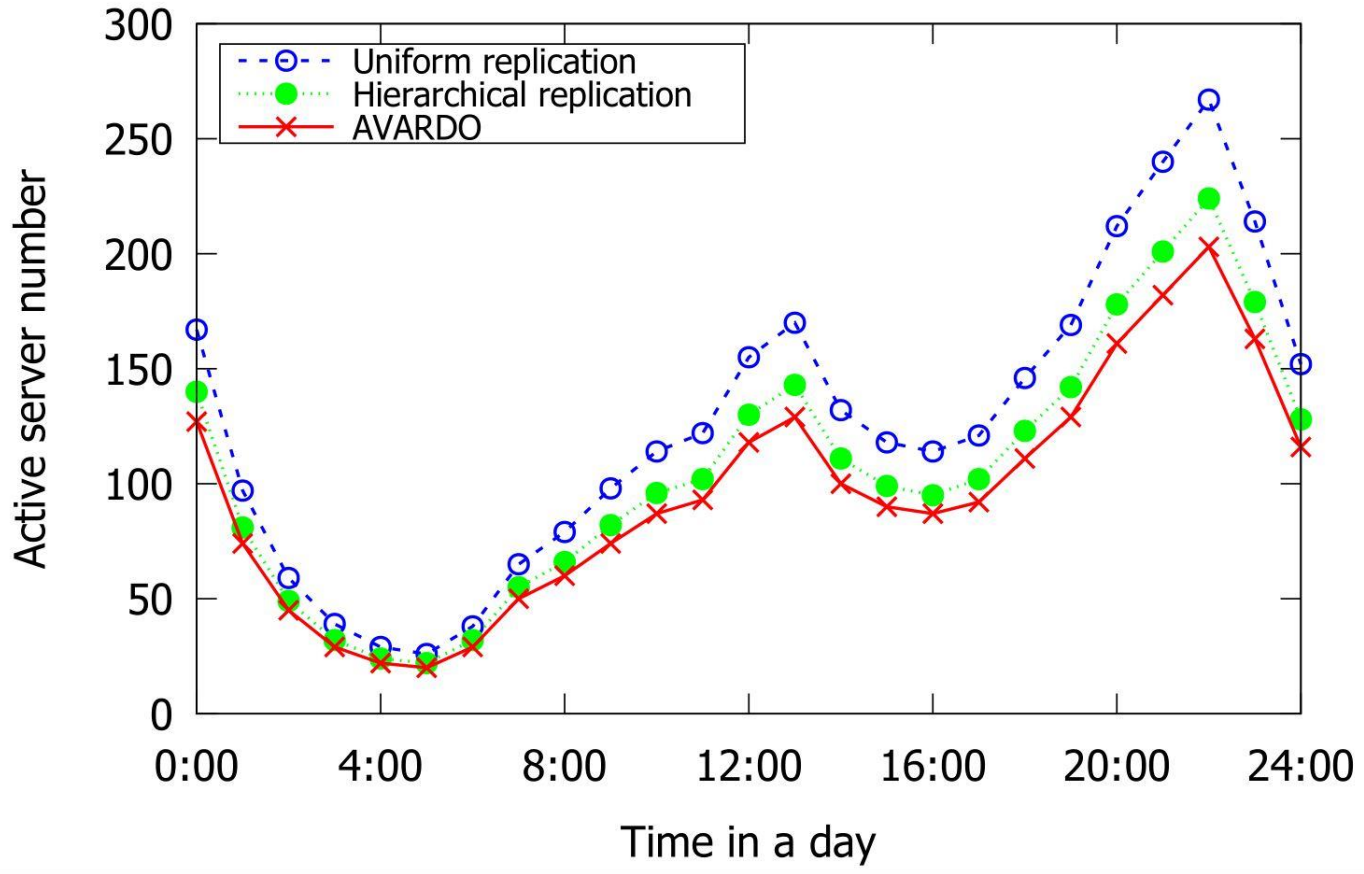
Asymptotic Optimality



Outperform State-of-the-art Schemes



Closely Optimal Over a Typical Day



Contents

1. Introduction and Related Work
2. Problem Formulation and its NP-hardness
3. AVARDO: An Approximation Algorithm
4. Illustrative Trace-driven Experimental Results
5. **Conclusion**

Conclusion

Problem Formulation and NP-hard analysis	• Formulation the problems as multi-objective mixed-integer linear programming • Prove that AVARD problem is NP-hard
Stack-based approximation algorithm with provable performance	• AVARDO: Auto-scaling Video Allocation and Request Dispatching Optimization • A novel and closely-optimal approximation algorithm with proven optimality gap • Stack-based approach to minimize overhead
Extensive trace-driven experimental results	• Real-world VoD data traces • Outperform the state-of-the-art schemes • Significantly lower optimality gap (often 1/20)

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Thank You!

Any Questions?