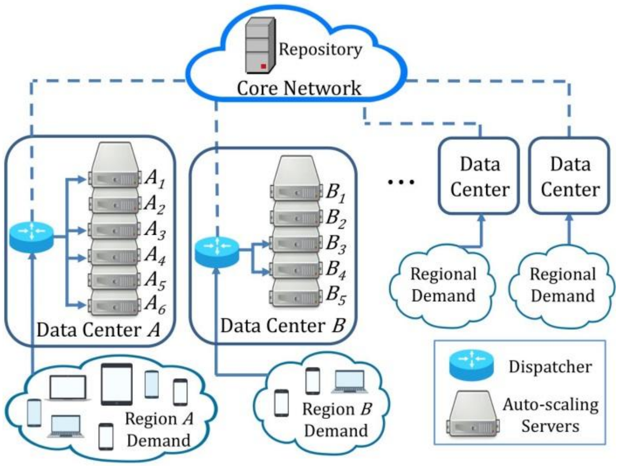

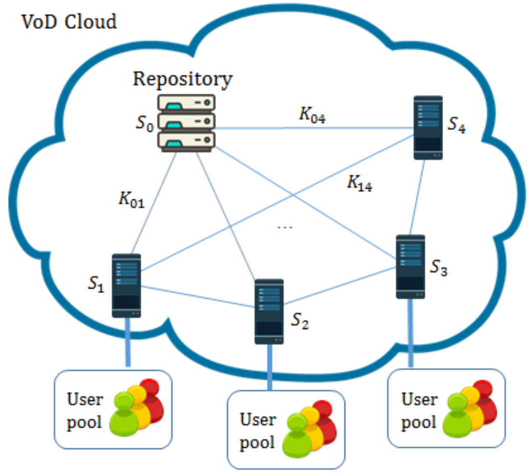

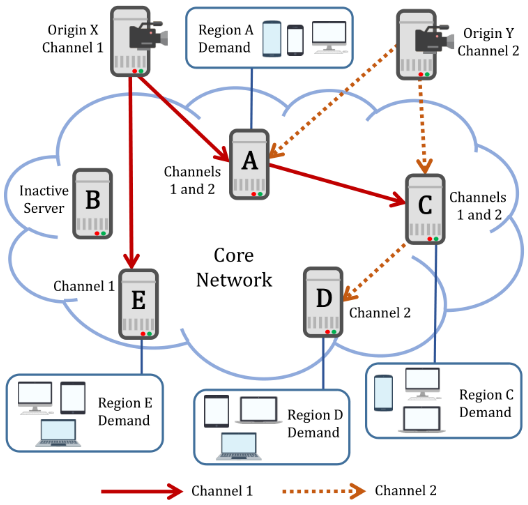

Approximation Algorithms for Auto-Scaling Video Cloud

Ph.D. Thesis Examination

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Supervised by Prof. Gary Chan

21 December 2023

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COMPUTER SCIENCE & ENGINEERING
計算機科學及工程學系

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Background: Video-on-Demand and Live Streaming

<table>
<tr><th></th><th>Video-on-Demand (VoD)</th><th>Live Streaming</th></tr>
<tr><td>Features</td><td>• Pre-recorded
• Users can access the video content anytime/anywhere.</td><td>• Created in real-time
• Geo-dispersed users access the video as it is being created.</td></tr>
<tr><td>Examples</td><td>TV shows, movies on Netflix(13.7%), Disney+(4.2%), Amazon Prime, Hulu, iQiyi, Tencent Video, etc.</td><td>Live broadcasting of sports games, news, online education (seminar/lecture), etc.</td></tr>
<tr><td rowspan="2">Resource Required</td><td>• Storage (VoD only)</td><td></td></tr>
<tr><td colspan="2">• Server Processing
• Network Link
No less than the aggregated video streaming rates</td></tr>
</table>

Background: Video Traffic's Huge Volume and Dynamic Daily Pattern

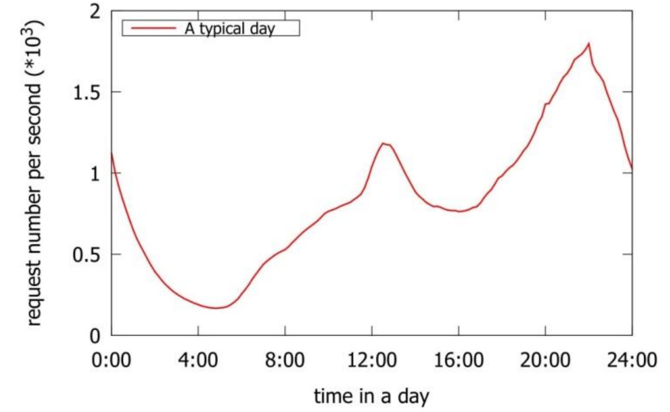
Video Traffic: Huge Volume	
Global Internet Report [Sandvine '23]	
2022 video traffic: As the percentage of total Internet traffic (excluding video calls/conferencing)	66%
2022 video traffic growth rate (compared to Year 2021)	24%

Daily Pattern: Volatile Traffic & Stable Popularity

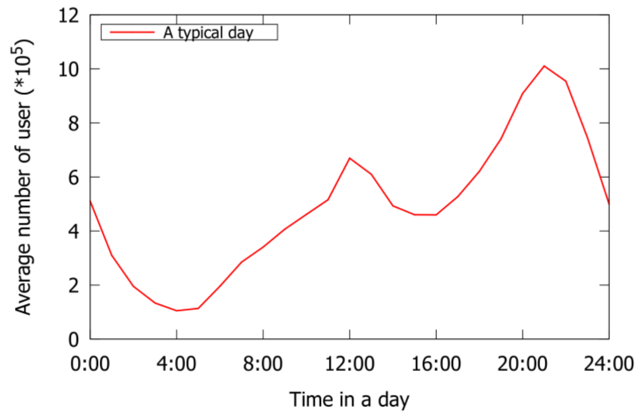
Surveys indicate:

- Traffic varies by more than an order of magnitude over merely hours
- Video popularities are stable and predictable over several days

Data source of the plots: Tencent Video



VoD: User requests over a day



Live streaming: Average user number over a day

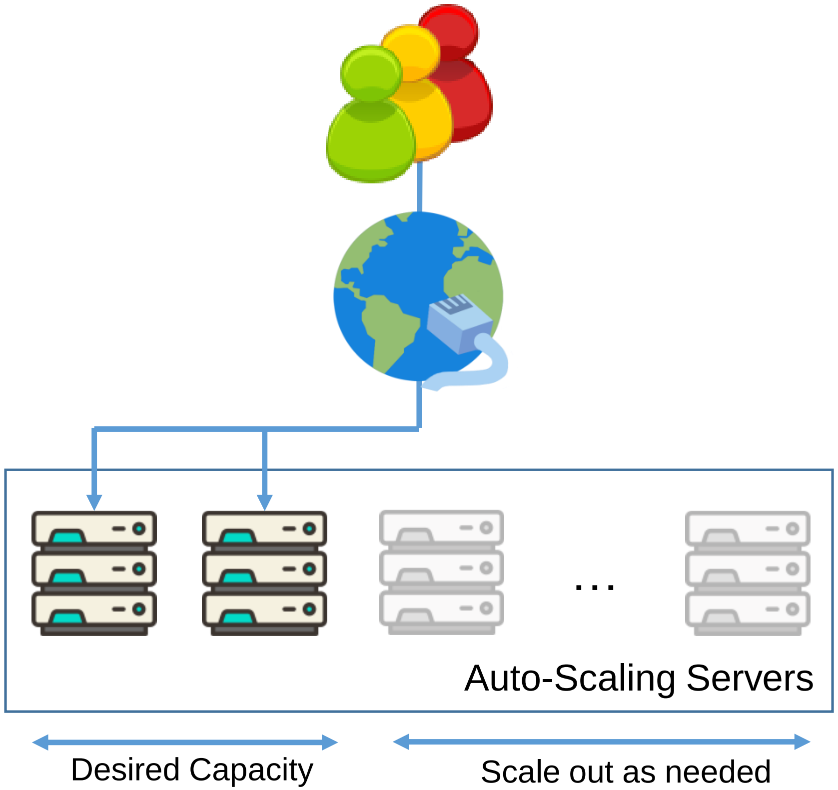
Benefit of Auto-Scaling: Allocate Geo-Dispersed Resources on the Fly

Auto-Scaling Data Center

Rescale system resources elastically:
- Deploy geo-dispersed servers *on the fly* to support local audience
- Activated or deactivate a server in a timely manner

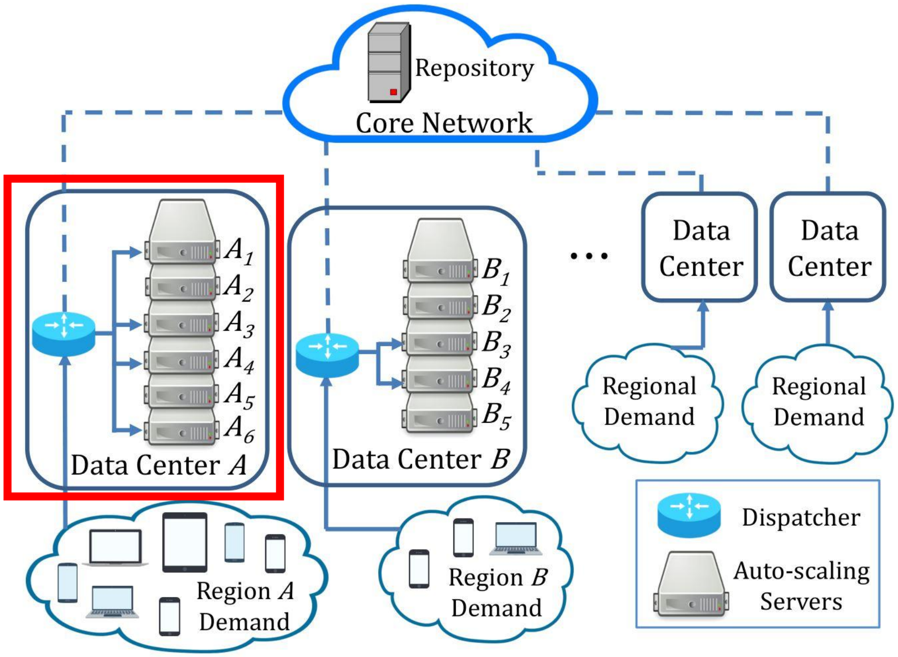
Traditional Static Provisioning (For Comparison)

- Fixed number of servers
- Not cost-effective due to daily traffic pattern
- Inevitable overprovisioning to ensure quality of service



An auto-scaling data center

Challenge I: Optimizing an Auto-Scaling VoD Data Center



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

System Settings

- Servers can be activated or deactivated in a short time
- A traffic dispatcher distributes request to an active server with the video

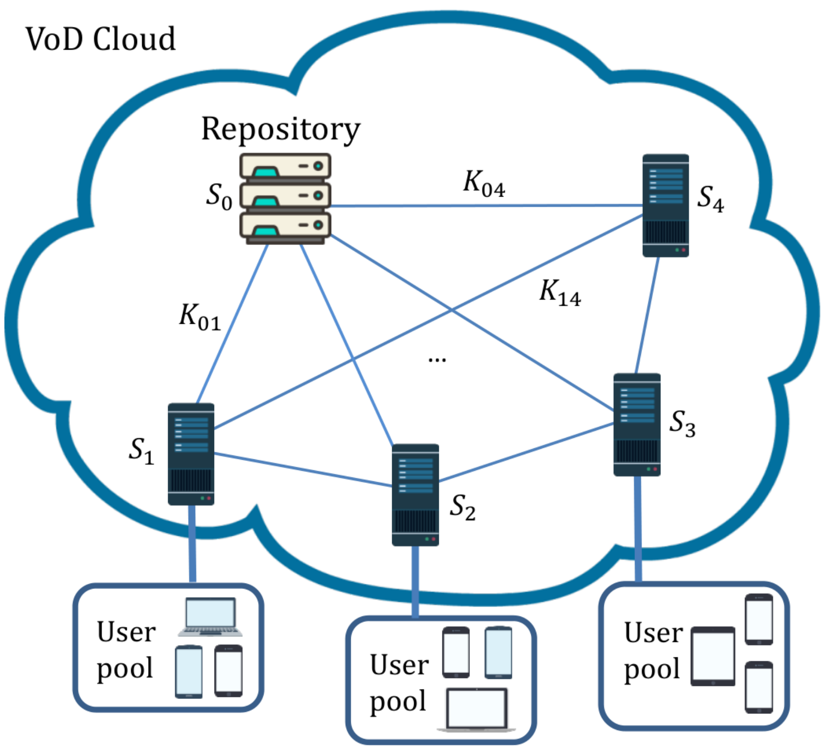
Major Tradeoff

- Cost-effectiveness:
  Minimize the number of active servers
- Quality of service:
  Allocate enough resource to serve users

Contributions

- Prove the NP-hardness
- Simple but efficient approximation algorithm
- AVARDO: *A*uto-Scaling *V*ideo *A*llocation and *R*equest *D*istribution *O*ptimization

Challenge II: Optimizing a Geo-Distributed VoD Cloud



A distributed and cooperative cloud architecture for VoD service

System Settings

- Repository: complete video replication
- Local server: partial replication to save storage
- Collaboratively serve the users to reduce cost

Major Tradeoff

Store video locally:

- Less delay, better Quality of Experience (QoE)
- Higher storage cost

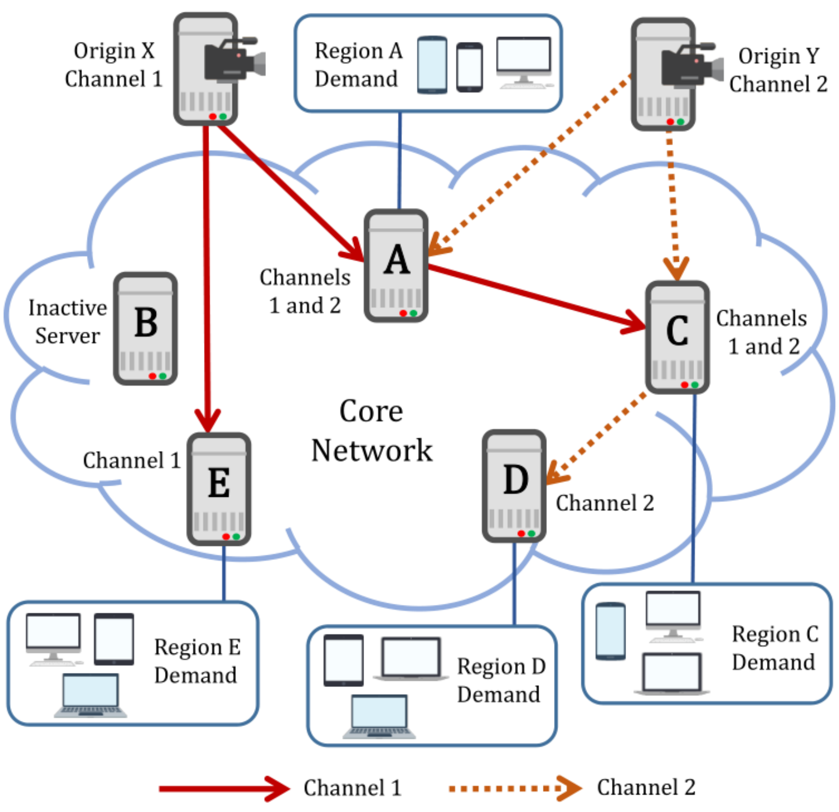
Access video from a remote server:

- More delay
- More link/processing cost; less storage cost

Contributions

- Prove the NP-hardness
- Efficient linear-programming based approximation algorithm
- **RAVO: *R*esource *A*llocation and *V*ideo Management *O*ptimization**

Challenge III: Optimizing an Auto-Scaling Live Cloud



A multi-origin multi-channel live streaming cloud.

System Settings

- Geo-dispersed auto-scaling servers
- Push each channel stream as a tree
- Cover servers demanding the channel

Major Tradeoff

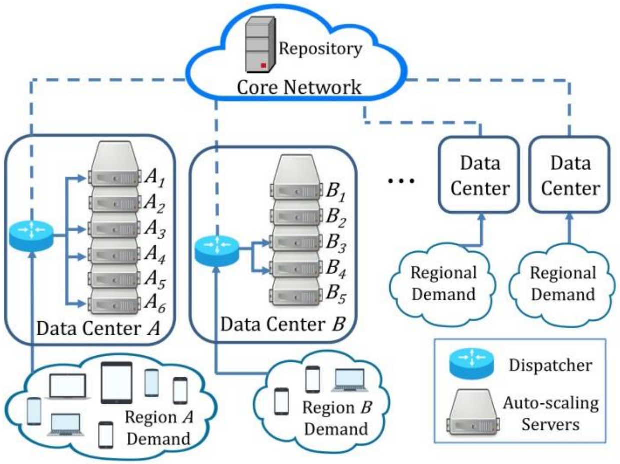
- Bi-Criteria Objective:
  - ➢ Minimize deployment cost
  - ➢ Minimize origin-to-end delays

Contributions

- Prove the NP-hardness
- Efficient linear-programming based approximation algorithm
- **COCOS: Cost-Optimized Multi-Origin Multi-Channel Overlay Streaming**

Basic Concepts: Approximation Algorithms

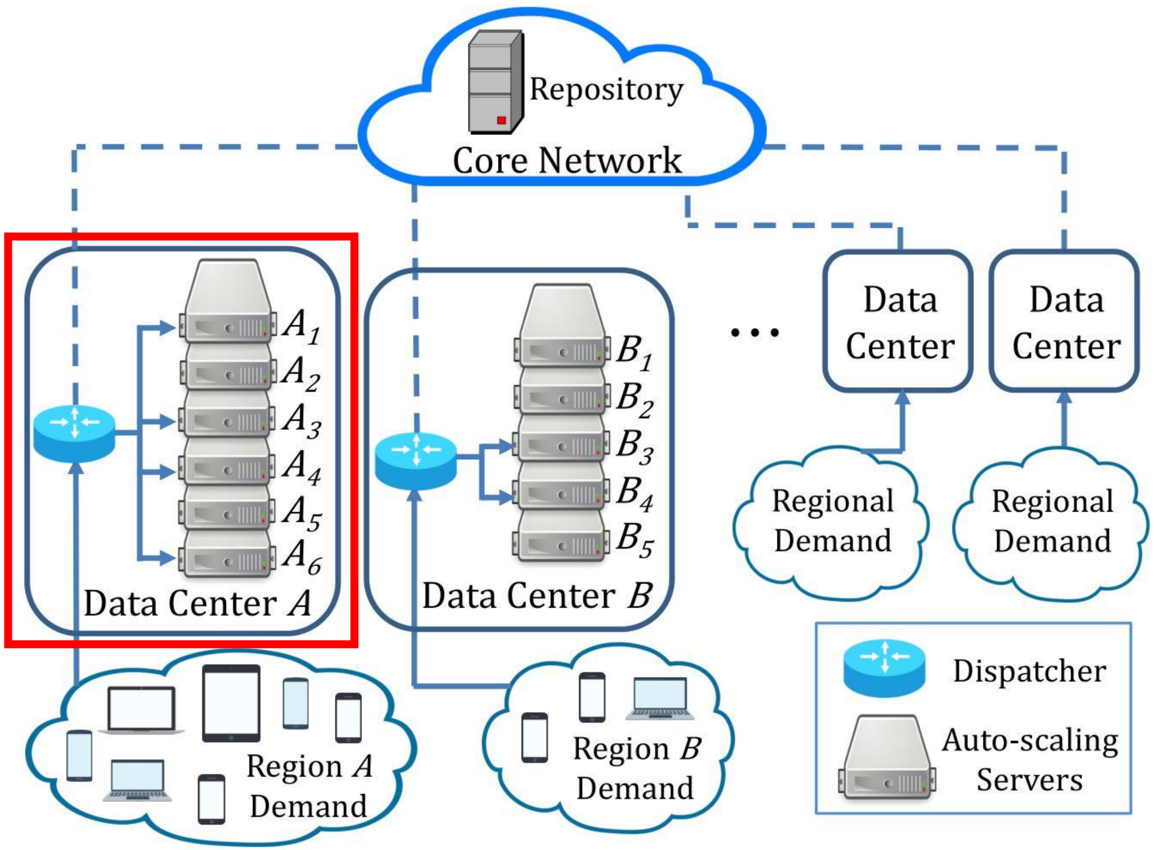
- NP-hard problem: currently no efficient solution
- Super optimum ≤ Exact optimum ≤ Experimental result ≤ Approximation solution
- Approximation ratio = $\dfrac{\text{Approximation solution}}{\text{Super optimum}}$
- Optimality gap = Approximation ratio - 1



Contents

Publication:
Z. Chang and S.-H. Chan, "An Approximation Algorithm to Maximize User Capacity for an Auto-scaling VoD System," *IEEE Transactions on Multimedia*, Vol. 23, pp. 3714-3725, October 2021.

Background:
A Typical Auto-scaling VoD Cloud



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

Auto-scaling Server

Auto-scaling

- Server can be activated or deactivated in a short time

Homogeneous

- Server has same storage and streaming capacity

Traffic Dispatcher

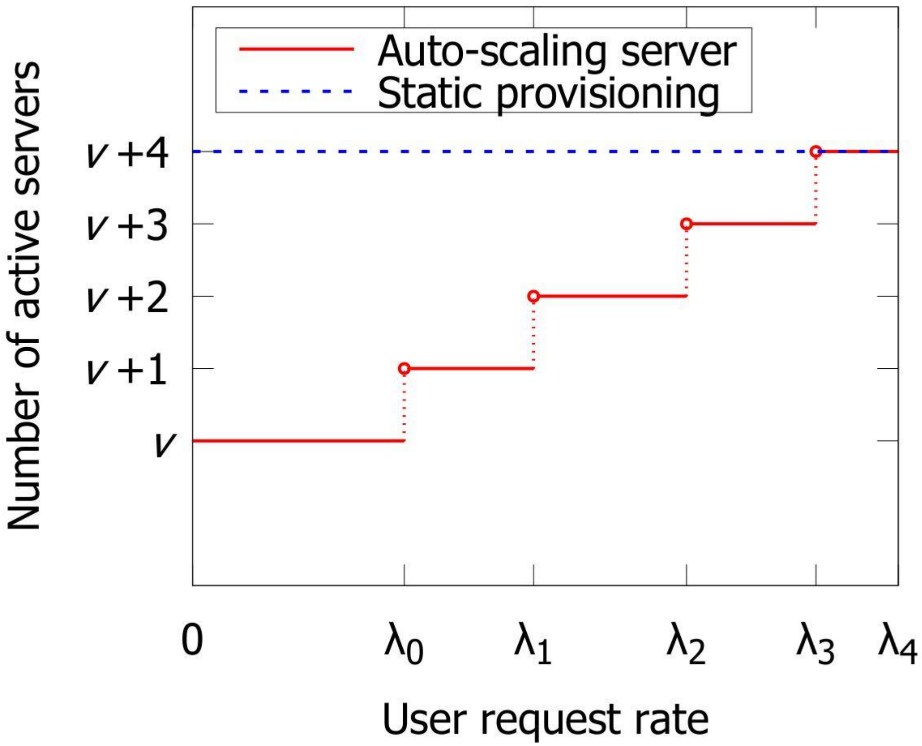
- Distribute request to an active server with the video
- Otherwise to core network

Video Block

Only for management purpose (cf. DASH segments)

- Blocks have the same size
- Partition large video into blocks

Objective:
Maximizing the User Request Rate Threshold λ_i



- **Auto-scaling level** i (i=0, 1, 2, ...) based on user request rate
- At level 0, we activate ν servers with full replicas.
- At level i, we activate $\nu + i$ servers to support at most λ_i user request rate.
- We want to maximize λ_i for every level i.

Optimization Parameters

	Block Allocation (BA)	Server Selection (SS)	Request Dispatching (RD)
Question	Which blocks should be allocated in each server?	Which servers should be activated for current traffic?	Which server for a request?
Constraints	• Number of blocks a server can store	In active servers: • At least one replica for each block • Popular blocks in enough servers	• Avoid overload of any active servers
Timescale	In day or week	In hour	In second
Dependency	Pre-allocated Videos for SS and RD	Based on BA	Based on BA and SS

- Major challenge: optimize **one** BA to fit **multiple** SS and RD

Related Work

	Related Work	AVARDO
Cloud-based VoD resource provisioning	• Data center as a black box • Yet to consider features inside the data center [Yang et al. Infosys '14]	• Investigating from a more detailed point of view
Content replication in traditional and cloud-based VoD	• Static provisioning [Yang et al. IEEE TMM' 18] • Assume no change of storage [Bourtsoulatze et al. IEEE TMM '18]	• Optimize for every auto-scaling levels
Cloud resources auto-scaling mechanism	• Predict the user demand and improve the online phase [Zhao et al. Multimedia Tools Appl '19] • A video is served by only one server [Du et al. IEEE TMM' 16]	• Considers both BA and RD

Problem Formulation: Major Symbol Used in AVARDO

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 **(SS)**	I_v^m	Binary variable indicating server v stores block m **(BA)**
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 **(RD)**
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

Modeling an NP-Hard Problem: Auto-scaling Video Allocation and Request Dispatching

Objective $\max(\lambda_0, \lambda_1, \ldots \lambda_n)$ → Maximize 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

$$\sum_{m \in M(v)} I_v^m f \leq c, \forall v \in V$$

→ Storage limit of each server (BA)

Streaming

$r_v^m(i) \leq I_v^m, \forall v \in V_i, m \in M$ → Server only serve the video it has (SS)

$$\sum_{v \in V_i} r_v^m(i) \geq 1, \forall m \in M$$

→ User request shall be served (RD)

QoS

$$\sum_{m \in M} r_v^m(i) R^m(\lambda_i) \leq \mu u, \forall v \in V_i$$

→ Utilization limit of each server (RD)

Multi-Objective Mixed Integer Programming

The NP-complete Partition Problem is reducible to our problem. It is **NP-hard**!

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

Simplification: Block Replication and Clustering

- Replicate some very popular videos
- Group video blocks into clusters (mega videos).
- Each cluster has the same *file size* and similar *user traffic.*

Solution: From Cluster to Video Blocks

The system satisfies the following constraints:

1. At auto-scaling level 0, the active servers has all clusters.
2. When activate a new server, we can evenly offload traffic from the existing active servers.

This can be formulated as a linear system, and has closed-form solution.

AVARDO has a stack-based server selection scheme

- Push (activate) or pop (deactivate) a server when auto-scaling level goes up or down
- Minimize the server selection overhead
- Optimality gap under practical setting: less than 1%

Experimental Setup

Parameter	Baseline
Number of blocks $\|M\|$	ca. 3×10^6
Video block size	100MB
Maximum 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

- Real-world data trace is from a leading video website (Tencent Video) in China over 2 weeks with 1.5 million videos in total.
- Synthetic date with Zipf's distribution

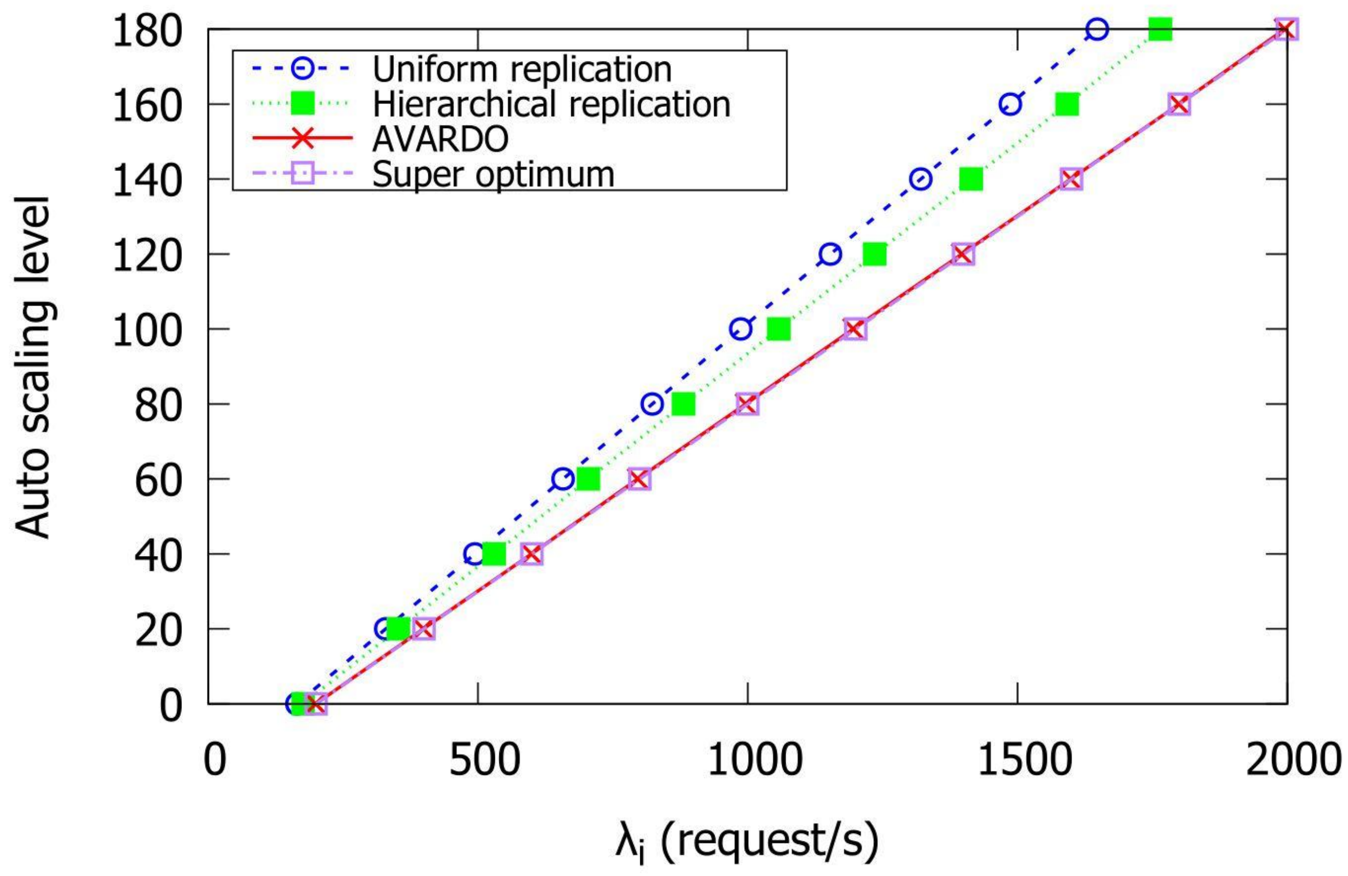
Performance Metrics

- Request rate threshold λ_n
- Optimality gap (versus super optimum)
- Number of active servers
- Fairness of active server utilization

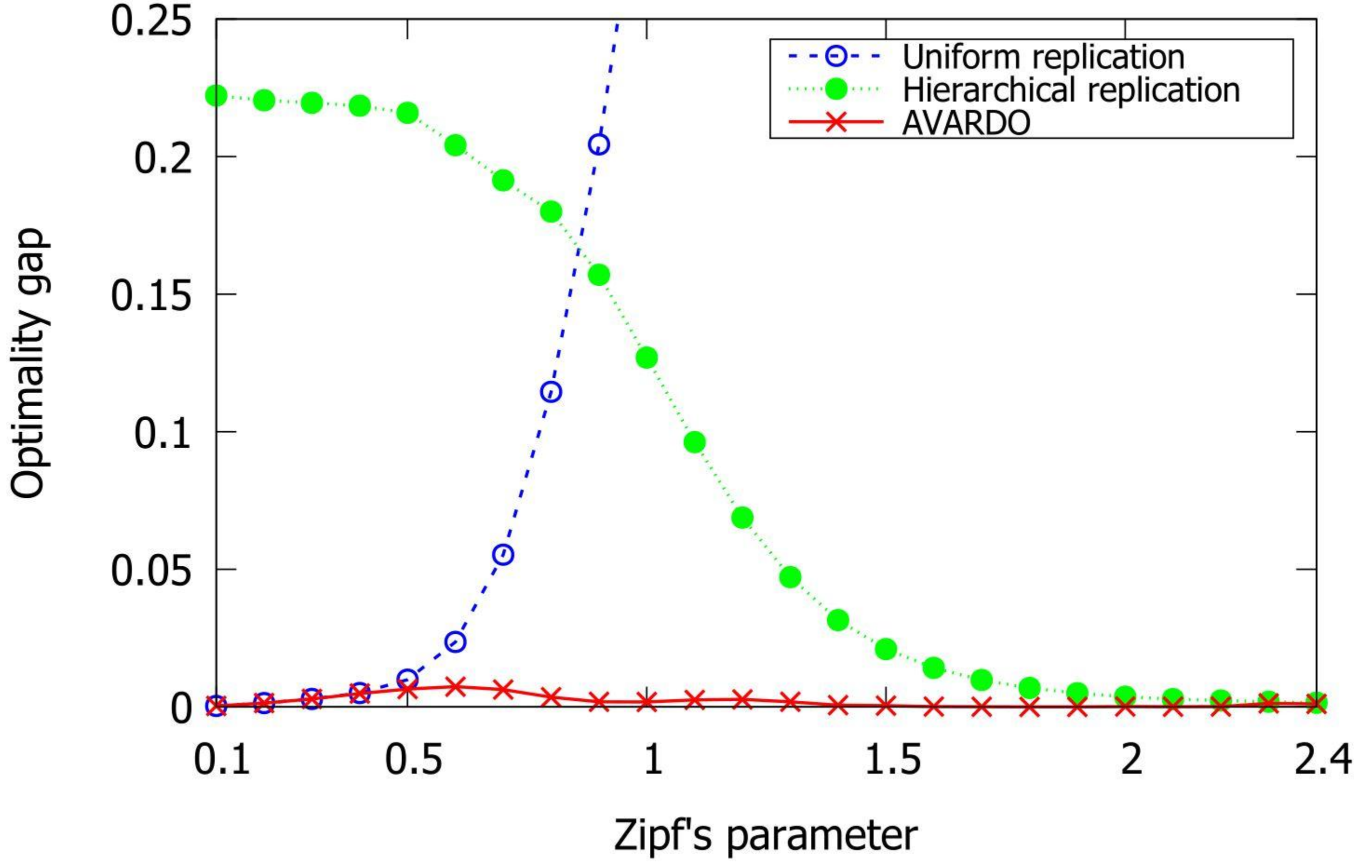
Comparison Schemes

- Uniform replication
- Hierarchical popularity replication
- Super optimum

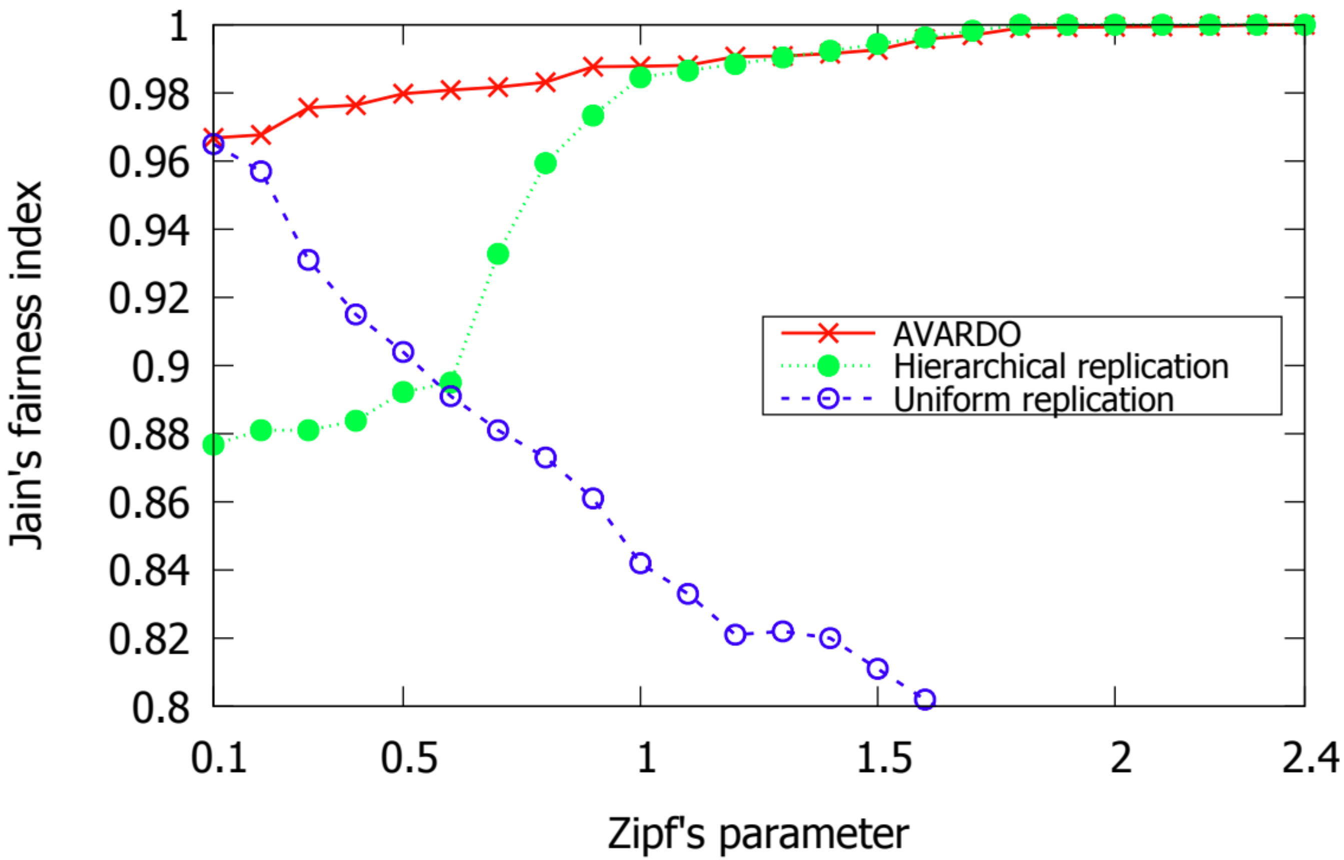
Near Optimal Performance

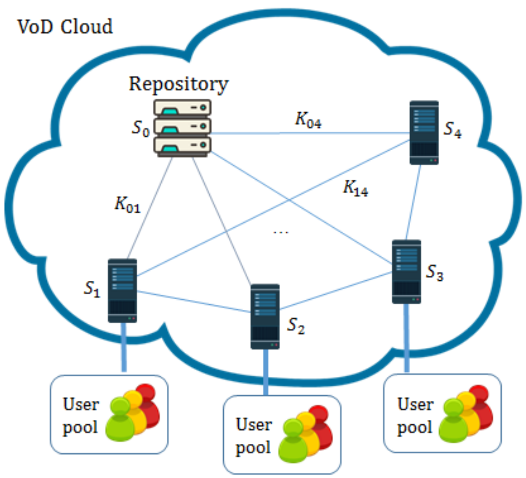


Outperform State-of-the-art Schemes



Better Load Balancing

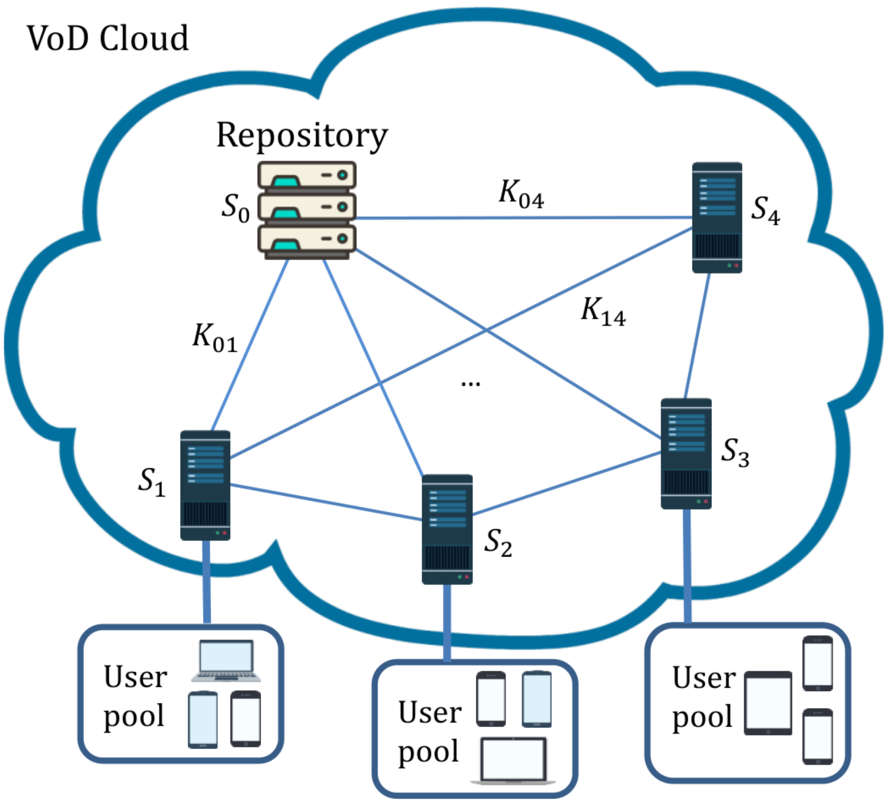




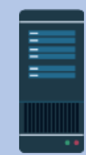
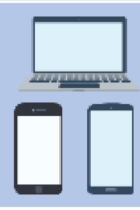
Contents

Publication:
Z. Chang and S.-H. Chan, "Video Management and Resource Allocation for a Large-scale VoD Cloud," *ACM Transactions on Multimedia Computing, Communication and Applications (TOMM) Special Issue on Multimedia Big Data: Networking*, Vol. 12, No. 5s, pp. 72:1-72:21, Sept 2016.

Background:
A Geo-Distributed Auto-Scaling VoD Cloud



A distributed and cooperative cloud architecture for VoD service

	**Repository**: Complete video replication
	**Local cloud server**: Auto-scaling data centers to serve their user pool
	**User pool:** Heterogeneous video popularities

Geographic Heterogeneity
of Video Popularities

- Local servers have partial video replication to save storage
- Reduce network load through co-operation among local servers

Tradeoff: Deployment Cost vs. Quality-of-Service (QoS)

Store Video Locally

+
- Less delay
- Less link & processing capacity
- Better collaboration

-
- More storage capacity

Access Video Remotely

+
- Less storage capacity

-
- More delay
- More link & processing capacity
- Less collaboration

Objectives:
- Satisfy the quality-of-service constraints
- Minimize total deployment cost

Optimization Parameters

Video Management (VM)

Storage (content replication)

- What video to store at each server?
- Planned on a longer time scale (days)

Retrieval (server selection)

- Which servers to stream the missing video from?
- Decided when a request comes

Resource Allocation (RA)

Server Resource

- Total **storage** and **processing capacity** at a server

Link Resource

- **Link capacity** reserved between pairs of servers

Related Work

Fundamental difference:
RAVO is an **approximation** algorithm

	Related Work	RAVO
Traditional resource allocation	• Based on heuristic approach • The optimality gap is not clear [Adhikari et al. Infocom' 12]	• Discretized from LP solution • Proven approximation ratio
Content Storage and Retrieval for VoD	• Need resource allocation result first • Static resource provisioning [Applegate et al. Co-NEXT'10]	• One-step algorithm for both resource allocation and content management • Auto-scaling feature
Current resource allocation for cloud service	• Assume full replication • Only consider link capacity allocation [Lin et al. Infocom' 11]	• Flexible replication to reduce the storage cost • Servers help each other to fully utilize the resource

Problem Formulation: Major Symbols Used in RAVO

S	The set of servers (central and proxy servers)	Γ_{mn}	Average transmission rate from server m to n (bits/s)
V	The set of videos	U_m	Total upload rate of server m (bits/s)
$L^{(v)}$	Length of video v (seconds)	$\boldsymbol{K_{mn}}$	Link capacity from server m to n (bits/s) **(RA)**
$P_m^{(v)}$	Access probability of video v at server m	$\boldsymbol{\Lambda_m}$	Processing capacity of server m for streaming (bits/s) **(RA)**
$\boldsymbol{I_m^{(v)}}$	Boolean variable indicating whether server m stores video v **(VM)**	C_{mn}^{N}	Link cost due to directed traffic from server m to n
$\boldsymbol{H_m}$	Storage capacity of server m (bits) **(RA)**	C_m^{S}	Cost of server m
$\boldsymbol{R_{mn}^{(v)}}$	Probability of streaming video v from server m to n **(VM)**	D_{mn}^{N}	Delay due to directed traffic from server m to n
μ_m	Request rate at server m (requests/second)	D_m^{S}	Delay due to upload streaming of server m

Modeling an NP-Hard Problem: Joint Optimization on Video Management and Resource Allocation

Server cost Link cost

minimize $\sum_{m \in S} \mathbb{C}_m^{\mathrm{S}}(H_m, \Lambda_m, U_m) + \sum_{m,n \in S} \mathbb{C}_{mn}^{\mathrm{N}}(\Gamma_{mn}, K_{mn})$ → System deployment cost

Storage **Processing Capacity** **Access** bandwidth (consumed)

Subject to

Storage $I_m^{(v)} \in \{0,1\}, \forall m \in S, v \in V$ → Store a video as a whole

Retrieval $0 \le R_{mn}^{(v)} \le I_m^{(v)}, \forall m, n \in S, v \in V$ → Only retrieve video from a server with it

$\sum_{v \in V} I_m^{(v)} L^{(v)} \gamma^{(v)} \le H_m, \quad \forall m \in S$ → Server storage constraint

$\sum_{m \in S} R_{mn}^{(v)} = 1, \quad \forall n \in S, v \in V$ → User request must be served

$\Gamma_{mn} = \sum_{v \in V} p_n^{(v)} \varepsilon_n^{(v)} \mu_n R_{mn}^{(v)} L^{(v)} \gamma^{(v)}, \forall m, n \in S$ → Remote traffic

QoS $\mathbb{D}_{mn}^{\mathrm{N}}(\Gamma_{mn}, K_{mn}) + \mathbb{D}_m^{\mathrm{S}}(U_m, \Lambda_m) \le \bar{D}, \forall m, n \in S$ → Delay

The NP-complete Dominating Set Problem is reducible to our problem. It is **NP-Hard**!

RAVO: Relaxing the Joint Formulation as a Linear Program and Quantization of the Solution

Step 1: Linear Program

Formulation Relaxation

- Continuous storage decision $\hat{I}_m^{(v)}$ $(0 \leq \hat{I}_m^{(v)} \leq 1)$
- Piecewise linear function
- To approximate delay and cost
- *Efficient algorithm* for solving linear programming

Solve LP for Super-optimum

- Video storage: $\hat{I}_m^{(v)}$
- Video retrieval: $\hat{R}_{mn}^{(v)}$

Step 2: Quantization

Video Management

- *Randomized round* $\hat{I}_m^{(v)}$ to get $I_m^{(v)}$
- Request from the *repository* if no other local server can help
- Otherwise we obtain $R_{mn}^{(v)}$ proportional to $\hat{R}_{mn}^{(v)}$ for server having the video

Resource Allocation

- Calculate the parameters according to the formulation
- Approximation Ratio (1+1/e)

Reducing the Algorithmic Time Complexity: Spectral Clustering for Video Group

- Time complexity: $O(|S|^6|V|^3)$, but $|V|$ could be large
- **Cluster** the videos with similar popularities into a mega video
- Use **spectral clustering method** to solve multi-dimensional *K-means*
- After solving the linear program,
    1. Evenly place the video from the same group and
    2. Let $\hat{R}_{mn}^{(v)} = \hat{R}_{mn}^{(g_i)}, \forall\, v \epsilon g_i$
    3. Then go for parameter quantization
- Reduce the complexity by $O(|V|^2)$

Experimental Setup

Video popularity

Real data

- From a leading IPTV provider (China Telecom) over 2 weeks

Synthetic data

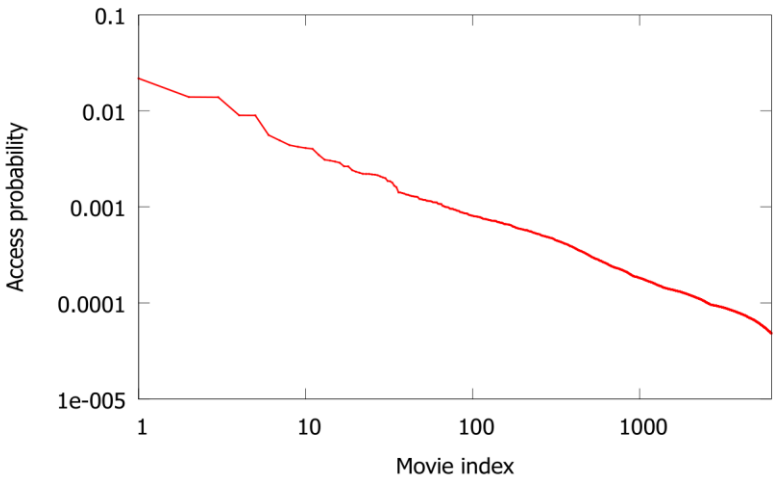
- *Zipf's* distribution: $f(i) \propto 1/i^z$
- Geographic heterogeneity

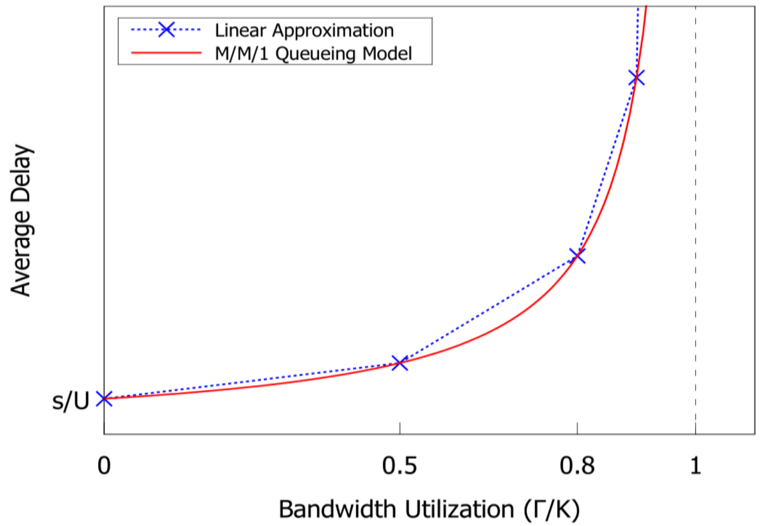
Cost functions

- *Proportional* to resource
- Server cost: $C_m^S = \sigma_m H_m + c_m \Lambda_m$
- Link cost: $C_{mn}^N = c_{mn} K_{mn}$

Delay Function

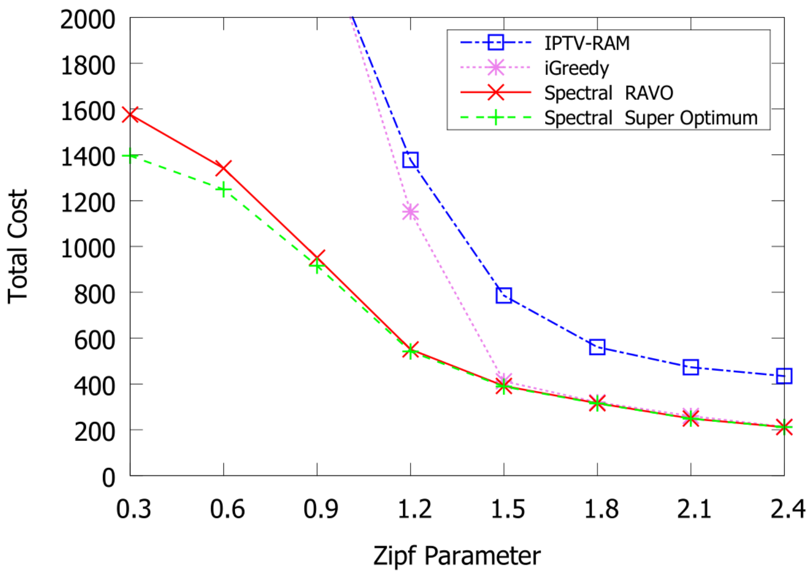
- *M/M/1* queueing model
- *Piece-wise linear* approximation



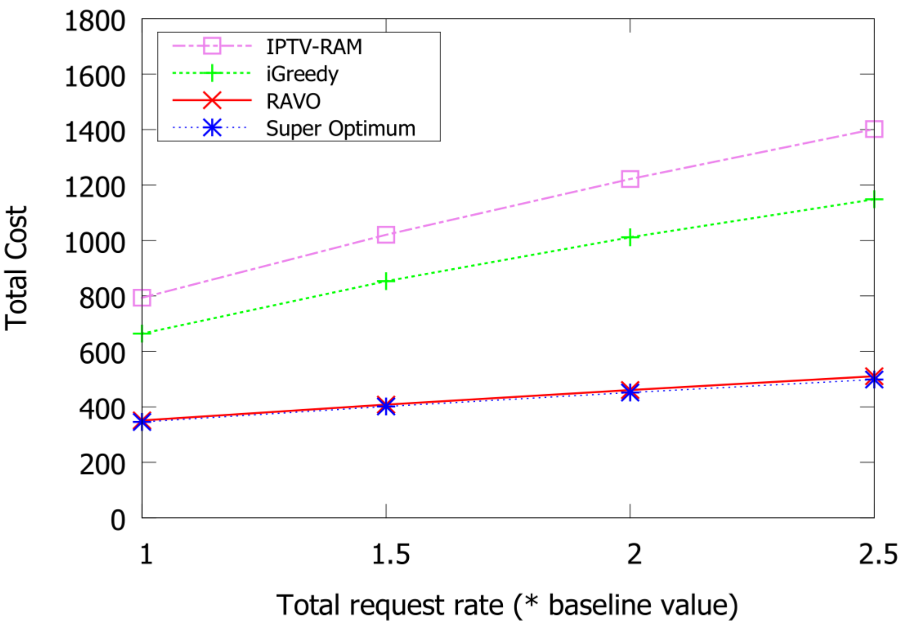


Near-Optimal Performance

Synthetic Data



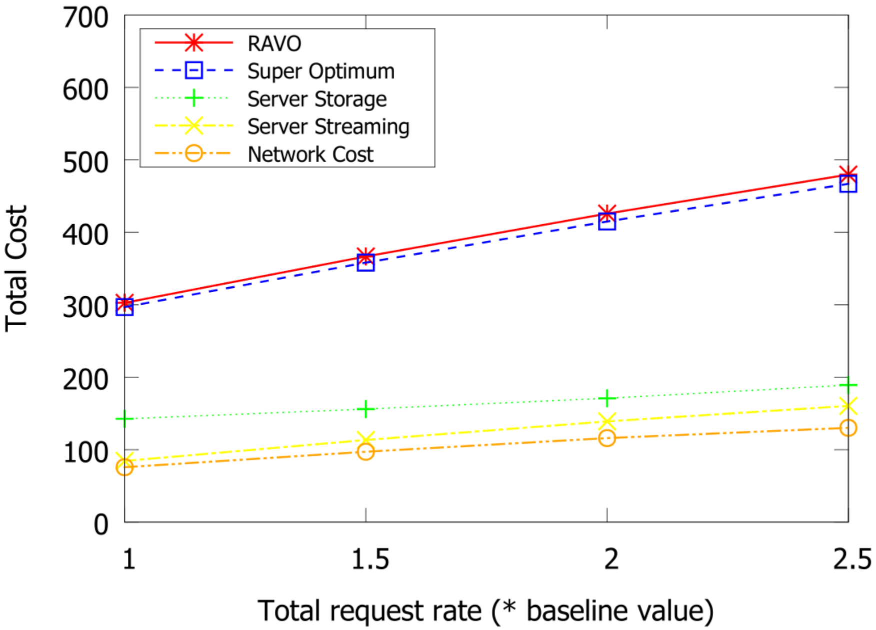
Real Data



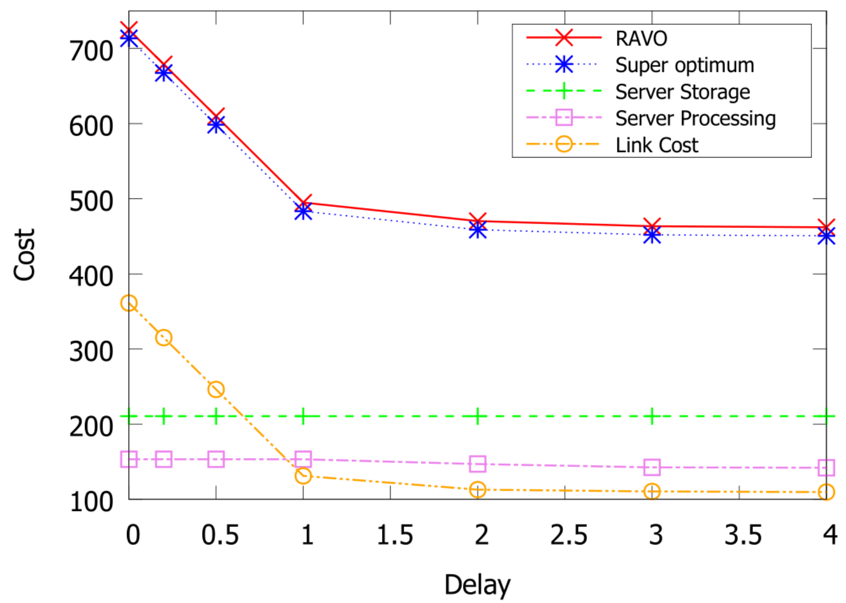
- RAVO outperforms the comparison schemes with large margin
- Close to the super optimum

Effective Use of Resources

Deployment cost given different request rate

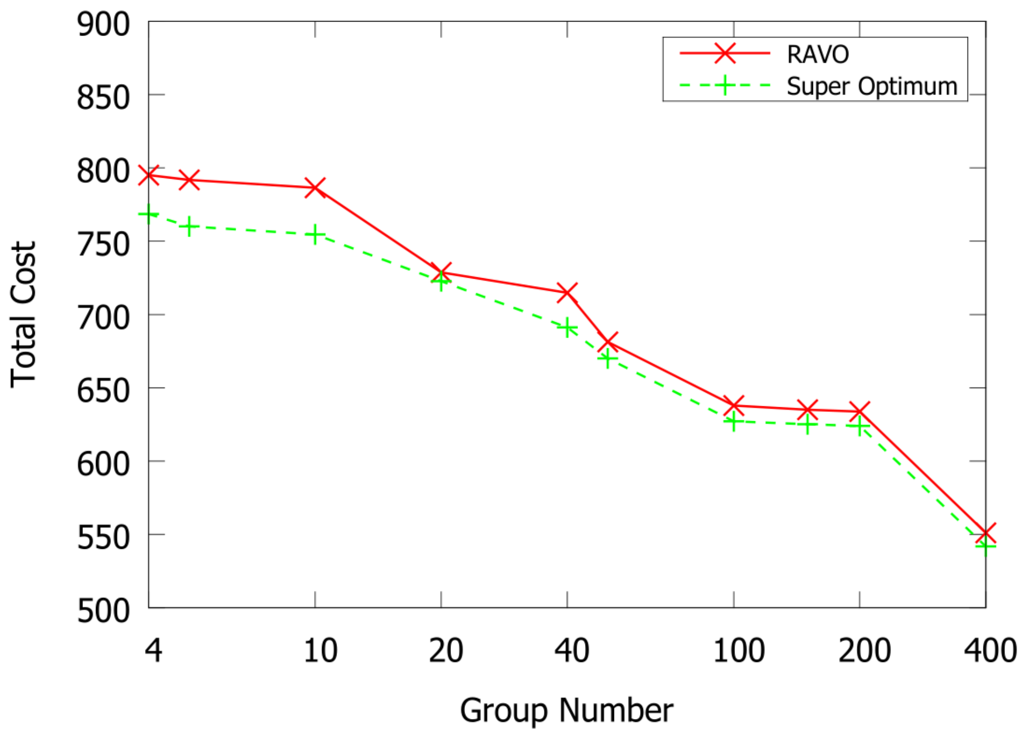


Cost versus Delay Requirement

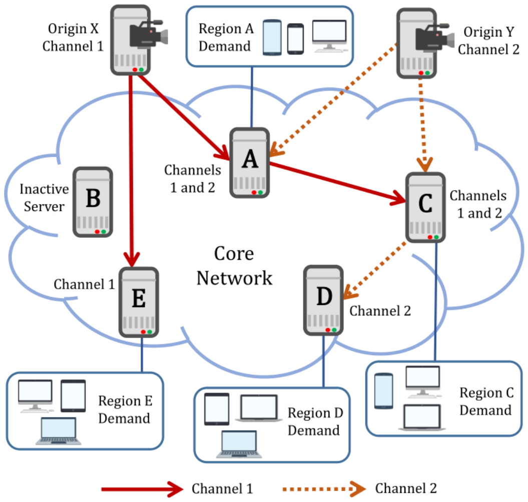


- The change of cost is distributed into all the components

Effective Clustering Method



- The cost decreases with more groups (and more computation time)

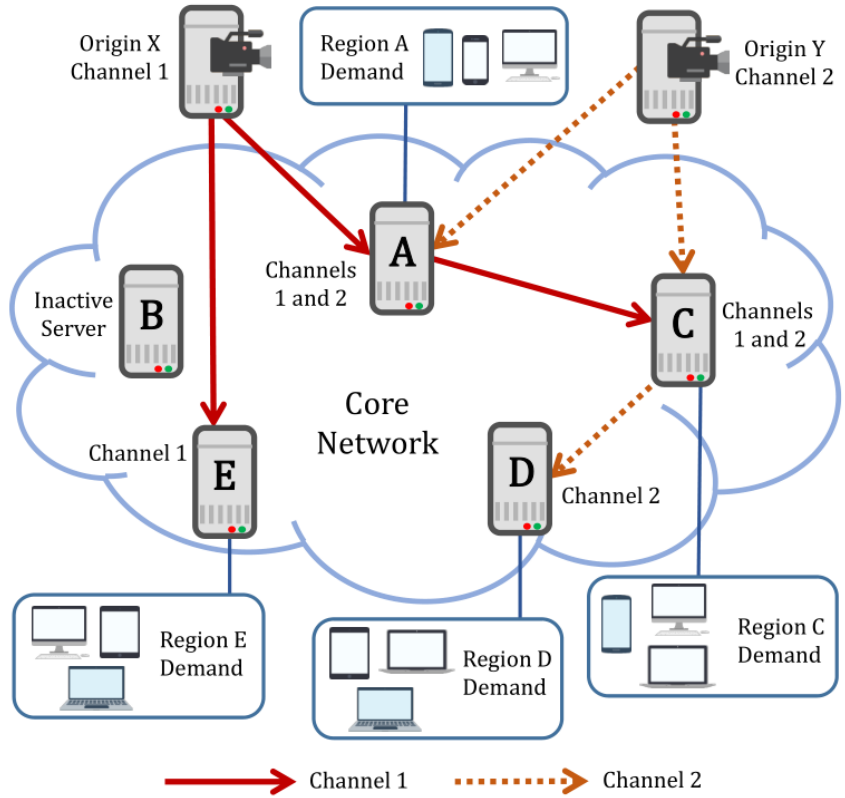


Contents

Publication:
Z. Chang and S.-H. Chan, "Bi-Criteria Approximation for a Multi-Origin Multi-Channel Auto-Scaling Live Streaming Cloud," *IEEE Transactions on Multimedia*, Vol. 25, pp. 2839-2850, July 2023.

Background: Multi-source Multi-channel Live Streaming Cloud

Major Components in a Live Streaming Cloud	
Origin Server	Source of live video channels.
End Server	Stream the live content to its associated local users. (e.g., a CDN node, server farm, data center, etc.)
Channel	Multiple streaming rates



- **An end server** *requests* channels based on local demand and *serves* its local users.
- **End servers** (with user demands) help each other in streaming contents.
- **Channels** are *pushed* from the sources to the servers.

Bi-criteria Objectives: Deployment Cost and Source-to-end Delay

Minimize Origin-to-End Delay

Server-to-Server (S2S) Delay:
- Time to travel through a link

Origin-to-End (O2E) Delay:
- Delay from the origin server to an end server demanding the channel
- Sum of the S2S delays of links forming the path

Minimize Deployment Cost

Deployment cost consists of **Server Cost** and **Link Cost**

Server Cost: Due to the servers allocating its uploading capacity to the other servers

Link Cost: Due to the pairwise link capacity allocated between servers

Optimizing the Bi-criteria Problem

Equivalently to

- **Minimizing** *deployment cost*
- Subject to *source-to-end delay* constraint

Overlay construction (OC):

- How to build the delivery tree of each channel?
- *To what servers* and *what channel* should a server forward?

Resource Allocation (RA)

Regularly re-optimize the overlay when parameter changes

Related Work

Fundamental difference:
COCOS is an **approximation** algorithm

	Related Work	COCOS
Traditional P2P live streaming	• Different objective: reduce server load [Tran et al. ICISA' 17, Ha et al. MTA'16, Roverso et al. MMSys'15]	• Optimize cost and delay
Crowdsourced live streaming	• Deliver contents from an end server to local audience [Hu et al. IEEE JSAC'17, H. K. Yarnagula et al. IEEE TMM '19, I. Irondi et al. IEEE TMM '19]	• Orthogonal to our problem
Live streaming works focus on other objectives	• Focus on QoS objectives [R.-X. Zhang et al. MM'20, R.-X. Zhang et al. NOSSDAV'19, F. Haouari et al. ICC'19] • Maximizing bandwidth or minimizing source load [Chen et al. P2P Netw. Appl.'17, S. Budhkar et al. P2Pr Netw. Appl'19]	• Different objective

Problem Formulation: Major Symbols Used in COCOS

S	The set of sources	$\boldsymbol{b_{ij}}$	Link capacity of edge $\langle i,j\rangle$ (bits/s) **(RA)**
R	The set of auto-scaling servers	$T(m)$	The delivery tree of channel m
V	The set of all sources and servers ($V = S \cup R$)	$\boldsymbol{x_{ij}(m)}$	Binary variable indicating whether link$\langle i,j\rangle$ is in $T(m)$ **(OC)**
$\langle i,j\rangle$	The directed edge from node i to j	L_{ij}	Server-to-Server (S2S) delay of link $\langle i,j\rangle$
E	The set of all edges	$D_i(m)$	Origin-to-End (O2E) delay of channel m at server i (in second)
M	The set of all channels	$\mathbb{D}_i(m)$	O2E delay upper bound of channel m at server i (in second)
$R(m)$	The set of servers that demand channel m	Θ_i	Server cost of server i (per second)
M_i	The set of channels that server i demands	θ_i	Unit price of uploading streaming at server i (per bit)
$\tau(m)$	Streaming rate of channel m (bits/s)	Φ_{ij}	Link cost due to traffic through link $\langle i,j\rangle$ (per second)
$s(m)$	The live source of channel m	ϕ_{ij}	Unit price of data transmission through link $\langle i,j\rangle$ (per bit)
$\boldsymbol{u_i}$	Uploading capacity of node i (bits/s) **(RA)**	C	Total deployment cost (per second)

Modeling an NP-Hard Problem: Minimum Cost Streaming with Delay Constraints

Minimize the total cost:

$$C = \sum_{\langle i,j\rangle \in E} \Phi_{ij} + \sum_{i \in V} \Theta_i$$

Cost function
• Server Cost $\Theta_i = \theta_i u_i, \forall i \in V.$
• Network Cost $\Phi_{ij} = \phi_{ij} b_{ij}, \langle i,j\rangle \in E.$

NP-complete Restricted Shortest Path Problem (RSP) is reducible to our problem. It is **NP-Hard**!

Delay Constraints
• Source-to-end Delay of Node j: $D_j\ (m) = D_i\ (m) + P_{ij} + Q_i$
• Source-to-end Delay Constraint: $D_j\ (m) \le \mathbb{D}_i\ (m), \forall i \in R(m), m \in M.$

Fulfill Demand of Channels

$$x_{ij}(\psi) = \begin{cases} 1, & \text{if } \langle i,j\rangle \in T(\psi); \\ 0, & \text{otherwise.} \end{cases}$$

$$\sum_{\langle i,j\rangle \in E} x_{ij}(\psi) \ge 1,$$

$$\forall j \in R(m), \psi \in \Psi(m), m \in M_i.$$

Overlay Construction and Resource Allocation

Relaxed to a LP problem

We transform the original problem through the following relaxation:

- LP solution can have arbitrary number of substream paths
- Each substream can have arbitrary bitrate
- Constraints on source-to-end delay: Use average substream delay

Topology construction

Given a node i and a channel m

- Remove top $1/\alpha$ traffic with the longest delay.
- Remove top $1/\beta$ traffic with the greatest marginal cost.

$$1/\alpha + 1/\beta \leq 1$$

- Construct the delivery tree with remaining k substreams

Cost approximation ratio: $\alpha + \delta$

Delay approximation ratio: β

Experimental Setup

Performance Metrics

Deployment cost

- Server cost
- Link cost

Delay

Comparison Schemes

Nearest Neighbor

- Consider local popularity
- No cooperative replication

Prim

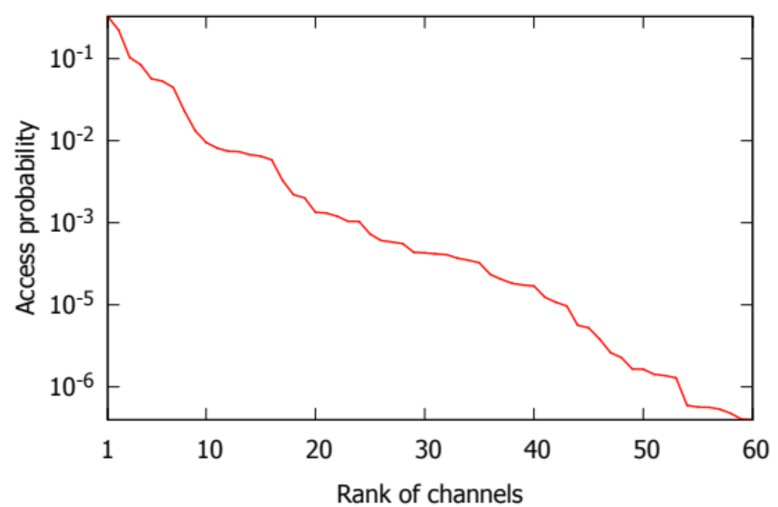
- Minimum cost tree
- Modified to meet delay constraints

Super-optimal

- LP solution (performance bound)

Table 5.4. Baseline parameters used in experiments of COCOS.

Parameter	Value
Server number (origin and end) $\lvert V\rvert$	100
Number of channels $\lvert M\rvert$	60
Delay upper bound $\mathbb{D}$	800 ms
Streaming rate mean μ_τ	1.2 Mbps
Streaming rate standard deviation σ_τ	0.2 Mbps
Server price mean μ_θ	0.1 per Mbit
Server price standard deviation σ_θ	0.05 per Mbit
Link price mean μ_ϕ	0.1 per Mbit
Link price standard deviation σ_ϕ	0.05 per Mbit
Zipf's parameter z	0.5
Tradeoff parameter ε	5
Number of substreams k	10



Good Tradeoff between Cost and Delay

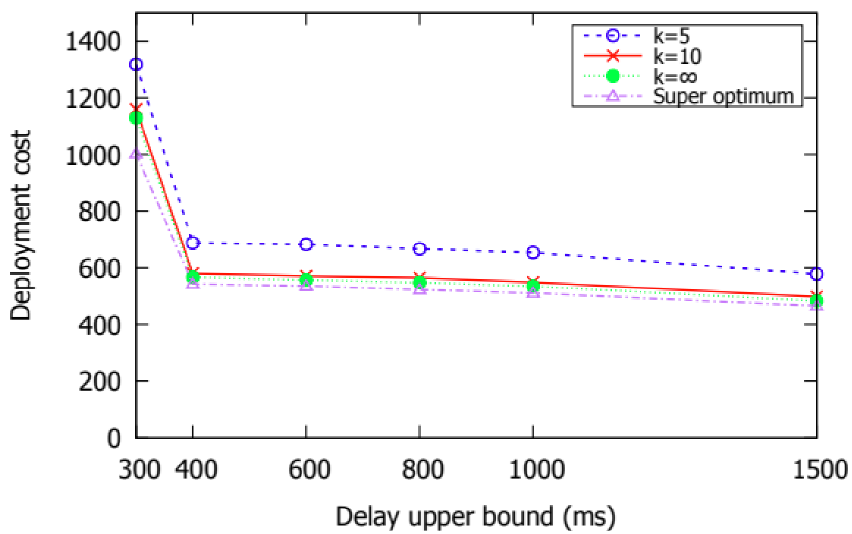


Figure 5.6. Deployment cost versus delay upper bound given different number of substreams.

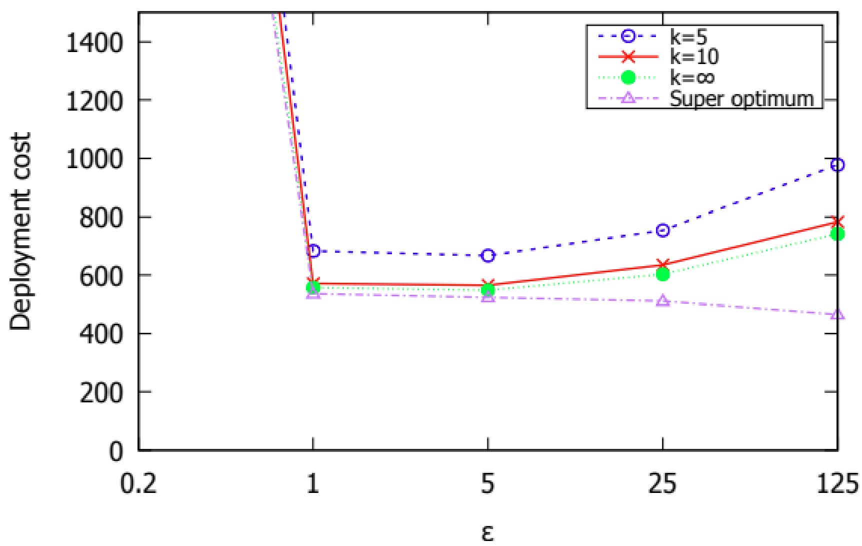
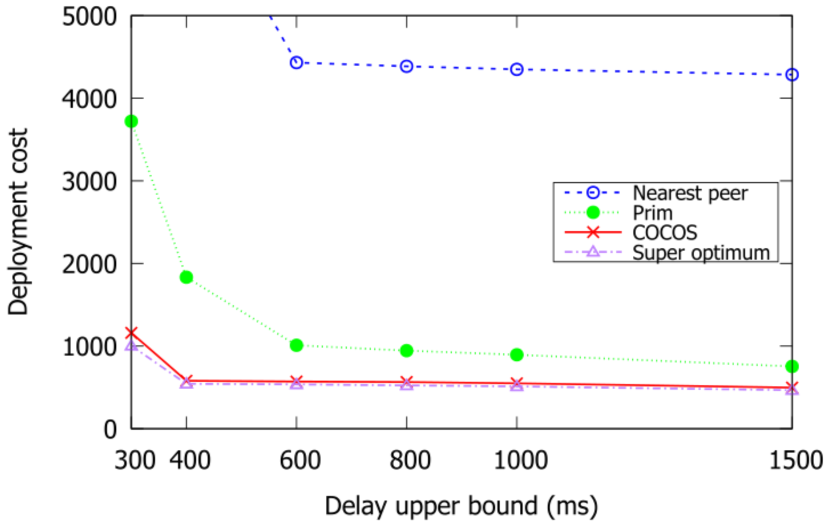


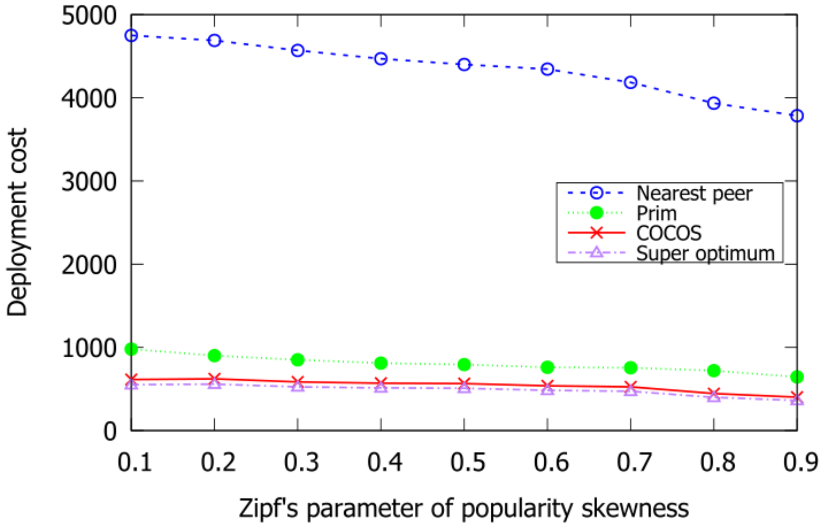
Figure 5.5. Deployment cost versus approximation ratio tradeoff parameter.

$$\alpha = 1 + \varepsilon$$

$$\beta = 1 + 1/\varepsilon$$

Near-Optimal Performance





Real-world data trace:

- From a leading video service website in China (Tencent) over 2 weeks

Near-optimal performance:

- Outperform state-of-the-art schemes

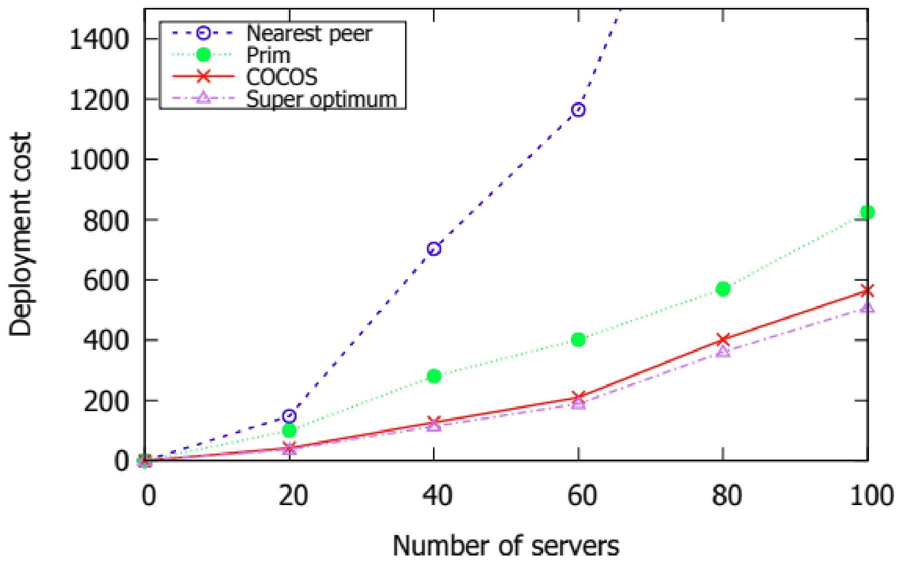
Synthetic data:

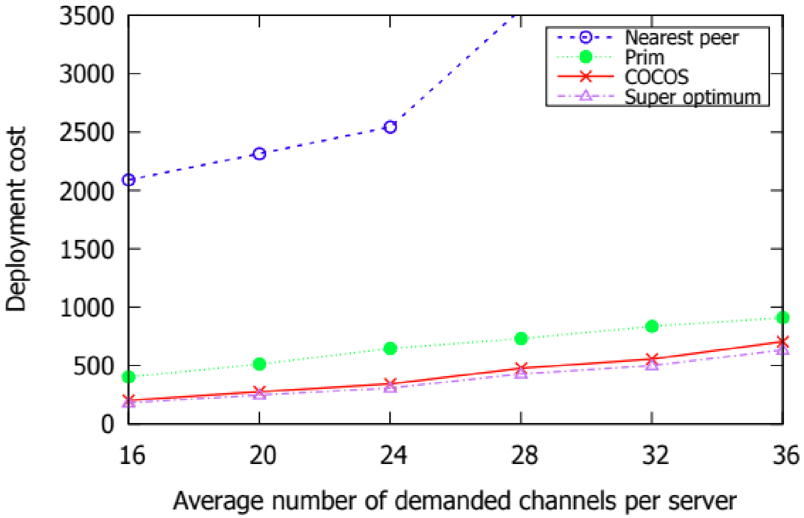
- Verify the performance given difference video popularity

Stable performance:

- Given different video popularity

Scalable Scheme





Contents

Conclusion

Motivations	• Video traffic: Huge volume and dynamic daily pattern • Auto-scaling: Rescale the resource elastically
Objective	• Minimize the deployment cost • Ensure the user experience
Contribution	**VoD data center** • AVARDO: Stack-based approximation algorithm **Geo-distributed VoD cloud** • RAVO: LP-based approximation with video clustering **Multi-origin multi-channel live cloud** • COCOS: Bi-criteria approximation algorithm
Future Work	• Integrate fog devices into our cloud system

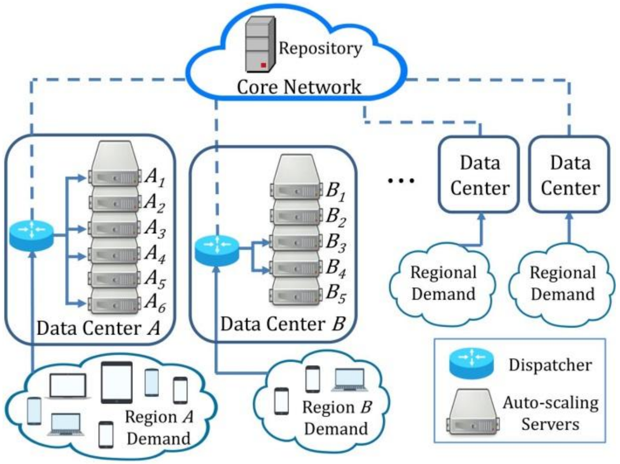
List of Publications

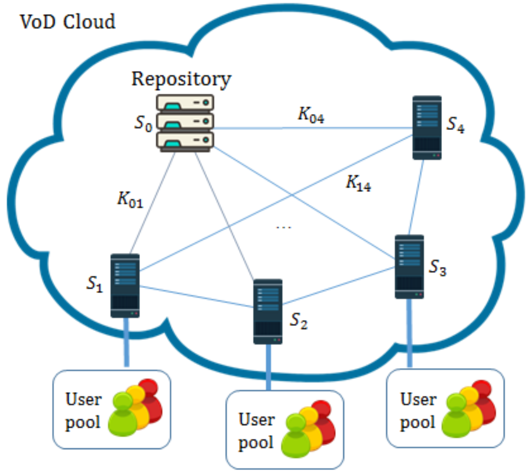
Journal publications

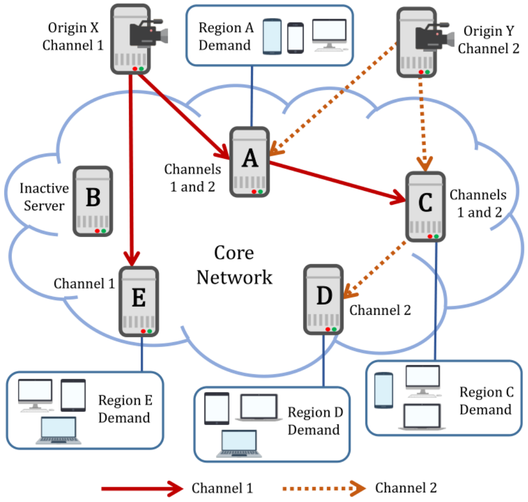
1. **Z. Chang** and S.-H. Chan, "Bi-Criteria Approximation for a Multi-Origin Multi-Channel Auto-Scaling Live Streaming Cloud," *IEEE Transactions on Multimedia*, Vol. 25, pp. 2839-2850, July 2023.
2. **Z. Chang** and S.-H. Chan, "An Approximation Algorithm to Maximize User Capacity for an Auto-scaling VoD System," *IEEE Transactions on Multimedia*, Vol. 23, pp. 3714-3725, October 2021.
3. **Z. Chang** and S.-H. Chan, "Video Management and Resource Allocation for a Large-scale VoD Cloud," *ACM Transactions on Multimedia Computing, Communication and Applications (TOMM) Special Issue on Multimedia Big Data: Networking*, Vol. 12, No. 5s, pp. 72:1-72:21, Sept 2016.
4. **Z. Chang** and S.-H. Chan, "Bucket-Filling: An Asymptotically Optimal VoD Network with Source Coding," *IEEE Transactions on Multimedia*, Vol. 17, No. 5, pp. 723-735, May 2015.

Conference publications

1. J. Dai, **Z. Chang** and S.-H. Chan, "Delay Optimization for Multi-source Multi-channel Overlay Live Streaming," in *Proceedings of IEEE ICC 2015 - Communications Software, Services and Multimedia Applications Symposium (ICC'15)*, (London, United Kingdom), pp. 8587-92, 8-12 June 2015.







Thank You!

Any Questions?