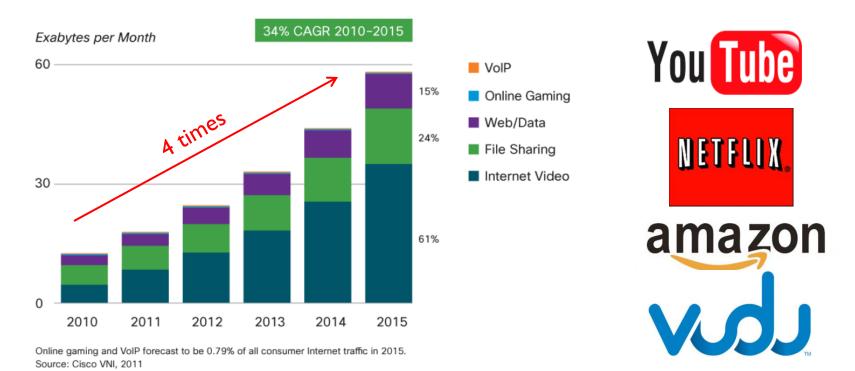
The Streaming Capacity of Sparsely-Connected P2P Systems with Distributed Control

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Joint work with Can Zhao (now at Qualcomm) and Prof. Chuan Wu (HKU)

Significant Growth of Internet Video Traffic



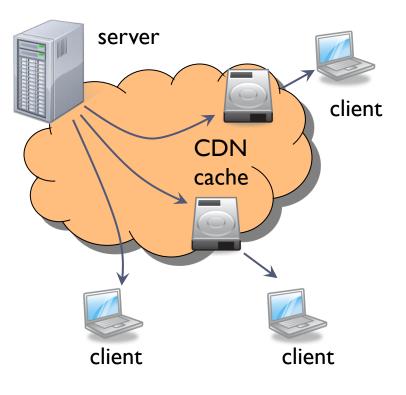
Internet video service providers: Youtube, Netflix, and many other.

- Consumer IP traffic will grow at a compound annual growth rate (CAGR) of 34%.
- By 2012, Internet video will account for over 50% of consumer Internet traffic.
- The sum of all video traffic (including TV, file sharing etc) will reach 90% of total IP traffic in 2015.

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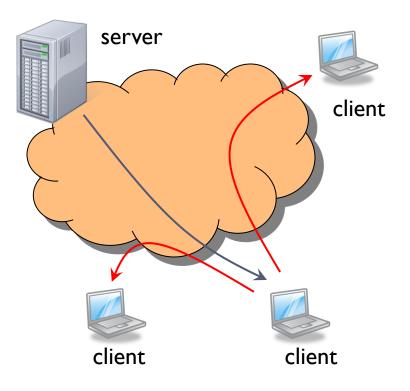
Video Streaming in the Internet: Current Status

- Video streaming directly from servers or CDNs (Content Distribution Networks) is costly
- In the US, this has been the dominant mode for video streaming
 - Credit Suisse estimated Youtube bandwidth cost in 2009 : \$360M per year
 - Google likely paid significantly less due to peering with other ISP
- Licensing of video content could cost comparably or even more.
 - Netflix's lost deal with Starz:
 \$300M for possibly a 5-year license



P2P Video Streaming: Current Status

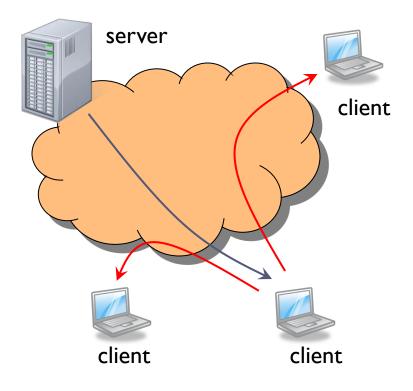
- Peer-to-peer (P2P) video streaming can potentially be much more scalable
 - Each client also contributes its upload capacity.
- In Asia, P2P streaming has become commercially successful
 - > PPLive, UUSee, PPStream, etc.
- However, content has primarily been free or pirated
- High-value content appears to also move towards the server mode



Why hasn't P2P caught on yet for high-value content?

P2P Video Streaming: Issues

- Copyright issues?
- Lack of quality-of-service guarantees?
- Difficulty to maintain QoS in P2P systems:
 - Client upload capacity is time-varying
 - Peer "churns"
 - Large scale
 - Decentralized view and operation



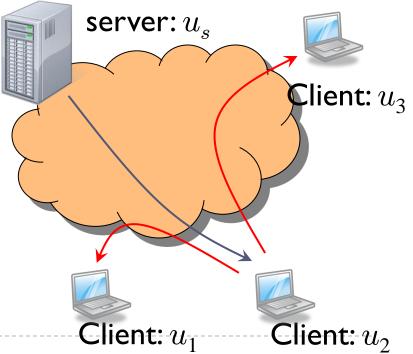
Why hasn't P2P caught on yet for high-value content?

Gap Between Practice and Theory

- Theoretical understanding of P2P streaming performance has significantly lag behind practice, which may have impeded further advance of P2P streaming.
- Our Focus: What is the best streaming rate C_f that a live-streaming P2P system can reliably support?
- Assuming upload capacity is the only constraint [Kumar et al '07]:

$$\min\{u_s, \frac{u_s + \sum_{i=1}^N u_i}{N}\}$$

Question: Can this upper bound be attained?



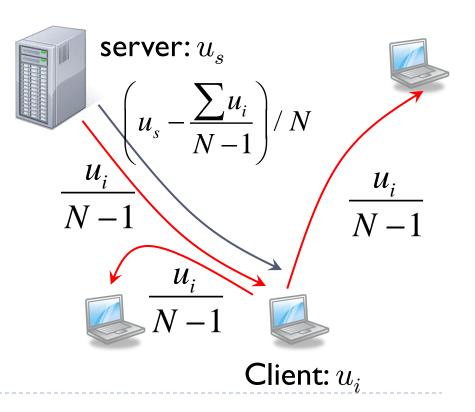
 $C_f \leq$

P2P Streaming Capacity

- Assume a complete graph: every peer can serve all other peers simultaneously [Mundinger et al '05, Chiu et al '06, Kumar et al '07]
- Each client gets

$$\begin{pmatrix} u_s - \frac{\sum u_i}{N-1} \end{pmatrix} / N + \frac{u_i}{N-1} + \frac{\sum_{j \neq i} u_j}{N-1} \\ = C_f \triangleq \frac{u_s + \sum u_i}{N}$$

How practical is this analysis?



P2P Streaming Capacity

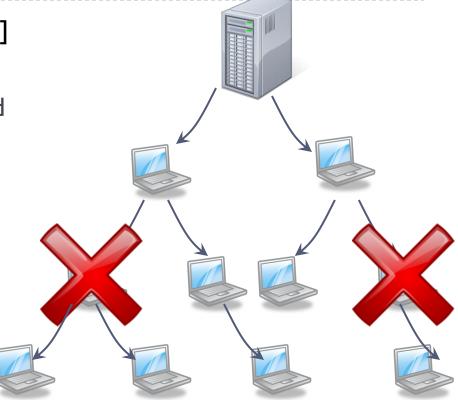
Such theoretical analysis is far from the reality in practical P2P systems!

Real P2P streaming systems are sparsely connected:

- Each peer only knows a small subset of other peers (neighbors).
- Infeasible for each peer to know all other peers!
- Real P2P systems are distributed:
 - No central entity can have the global/up-to-date knowledge to perform such a perfect rate allocation.

Sparsely-Connected P2P Systems

- A multi-tree topology [Liu et al. 2010]
 - Still a centralized construction.
 - More recent work uses distributed Markov approximation [Zhang and Chen, 2012]
- If a peer close to the root leaves or its upload capacity decreases, significant performance disruption will occur.



Open Question:

Can we achieve close-to-optimal streaming capacity with sparse connectivity and decentralized control that are robust against peer churns and variations of upload capacity ?

Our Contribution

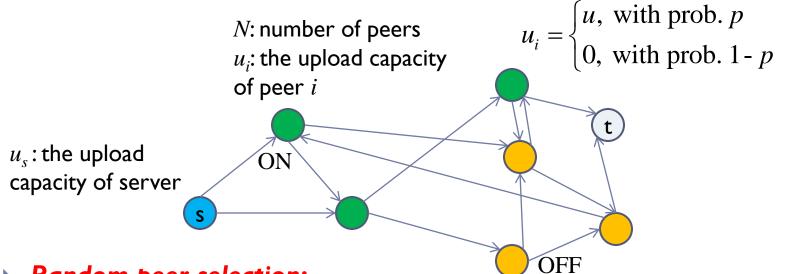
- We show that a simple distributed scheme is sufficient to achieve close-to-optimal streaming capacity with high probability for large P2P systems.
 - Each peer has a small number of downstream neighbors $M = O(\log N)$
 - Each peer can choose neighbors uniformly randomly
 - Each peer evenly divides its upload capacity among the *M* neighbors
- Our results reveal important insights into the dynamics of large P2P systems.
- We design improved control schemes based on these insights that further improve the system performance.
- Our work provides an important step towards understanding and controlling QoS in large and unreliable P2P streaming systems.

Overview

System Model

- Single-Channel: Uniform Rate Allocation
- Single-Channel: Adaptive Rate Allocation
- Multi-Channel Live Streaming
- Conclusion and Discussion

System Model: Single-Channel P2P Live Streaming with Random Peer Selection



- Random peer-selection:
 - \blacktriangleright Each peer randomly selects M downstream neighbors
 - \blacktriangleright Server randomly selects M ON peers as downstream neighbors
 - Easy to implement and robust to peer churns.
- C_{ii} : the capacity that peer *i* contributes to peer *j*.
- C_{ij} =0 if peer i is OFF or peer j is not a downstream neighbor of peer i $\sum_{j: i \to j} C_{ij} \le u_i \text{ and } \sum_{j: s \to j} C_{sj} \le u_s$

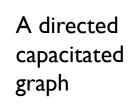
System Model

S

T

- Streaming rate to destination peer t:
 - The minimum cut between s and $t: C_{\min}(s \to t)$

 $i \in T, j \in V \setminus T$



 $V \setminus T$

• The streaming rate of the entire system:

ON

• The minimum cut across all destination peers t:

$$C_{\min-\min}(s \to V) = \min_{t \in V} C_{\min}(s \to t)$$

Can be achieved in a distributed manner by network coding [Ahlswede et al 2000] or a latest-useful-chunk transmission policy [Massoulie and Twigg 2008]

Problem Statement

 C_f: The optimal streaming capacity assuming complete connectivity and centralized control

$$E[C_f] = \min\left\{u_s, \frac{u_s + upN}{N}\right\}$$

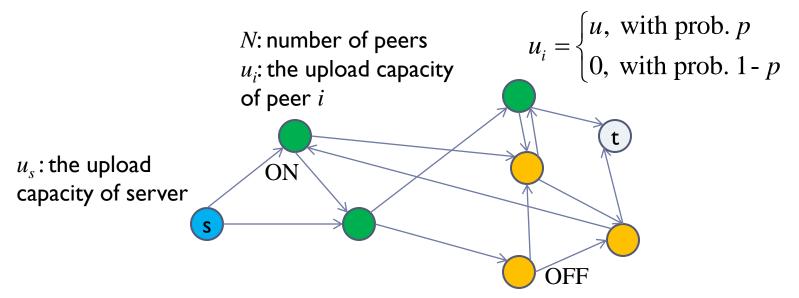
- Research Problems:
 - How much performance penalty (compare to the optimal C_f) is incurred due to random peer-selection?
 - Are there simple and robust rate-allocation schemes that can achieve close-to-optimal capacity with minimal overhead?

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Single-Channel: Uniform Rate-Allocation



- Uniform rate-allocation:
 - Each peer evenly divides its upload capacity to its M downstream neighbors
 - Same for server
- C_{ij} : the link capacity from peer *i* to peer *j*.

$$C_{ij} = \begin{cases} u / M, \text{ if peer } i \text{ is ON and } i \rightarrow j \\ 0, \text{ otherwise} \end{cases}$$

Main Result

For any $\varepsilon \in (0,1)$ and d > 1, there exists $\alpha > 0$ such that if $M = \alpha \log N$, then

$$P(C_{\min-\min}(s \to V) \le (1 - \varepsilon)E[C_f]) \le O\left(\frac{1}{N^{2d-1}}\right)$$

Even with simple random peer-selection and uniform rate-allocation, the system can achieve close-to-optimal streaming capacity with very high probability!

Implications

Sparse connectivity is sufficient!

• $M = \alpha \log N$

Simple and decentralized control

 Random peer selection and uniform rateallocation

Larger is better!

• The larger the network size, the easier to achieve close-to-optimal capacity

Robustness

- Even if a peer leaves, only its upstream peer needs to re-select a downstream neighbor.
- When a peer switches from ON to OFF, its neighbors do not need to change anything (unless it is connected to the server directly).
- No need to reconstruct the global topology!

Large P2P streaming systems are in fact extremely

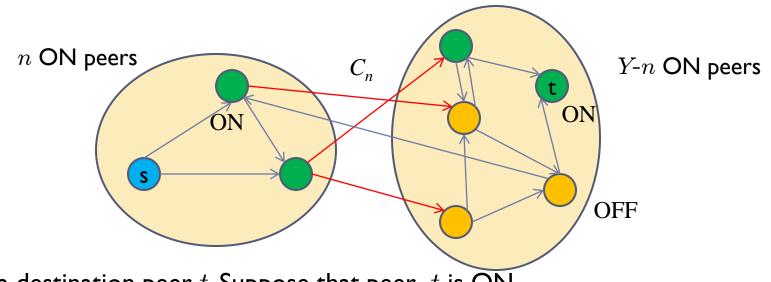
scalable

and

robust!

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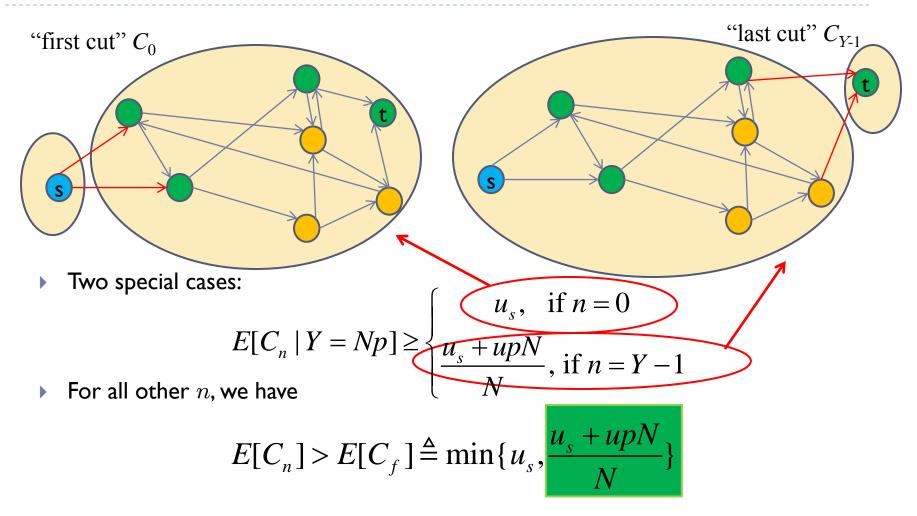
Intuition Behind the Main Result



- Fix a destination peer t. Suppose that peer t is ON.
- Let Y be the total number of ON peers: $Y \approx Np$
- C_n : the random capacity of a cut that has n ON peers on the server side

$$\mathbf{E}[C_n \mid Y] \ge \frac{u_s(Y-n)}{Y} + \frac{un(Y-n)}{N} = \begin{cases} u_s, & \text{if } n = 0\\ \frac{u_s + upN}{N}, & \text{if } n = Y-1 \end{cases}$$

Intuition Behind the Main Result



Since the number of edges in a cut, nM(Y-n)/N, is large when M and N increase, the capacity of any cut C_n should be no less than $(1-\varepsilon) C_f$ with high probability

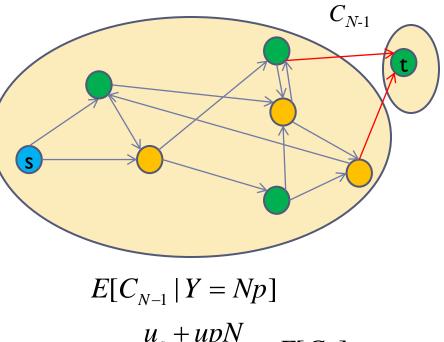
Insights for P2P Protocol Design

The most critical cut is the last cut C_{N-1}

The probability that C_{N-1} fails (less than (1-E) of optimal streaming rate C_f) is much larger than the probability that any other cut fails

Two main reasons:

- The expected capacity E[C_{N-1}] is the smallest
- The expected number of edges is the smallest: nM(N-n)/N=M when n=N-1



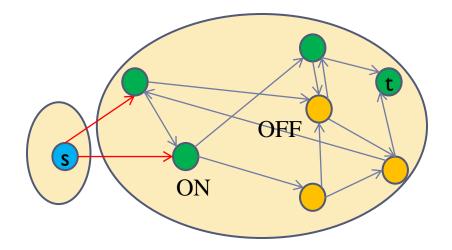
$$=\frac{u_s + upN}{N} = E[C_f]$$

Improved P2P control scheme should focus on improving the capacity of the last cut

Insights for P2P Protocol Design

ON/OFF status of each peer's upload capacity:

- A common wisdom is that peers close to the server should choose ON peers as downstream neighbors
- Our analysis indicates that only the server needs to be careful choosing ON peers.



Low-overhead P2P control scheme could focus on peer-selection and recovery at the server only.

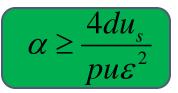
Insights for P2P Protocol Design

Number of neighbors that each peer needs: $M = \alpha \log N$

In order that

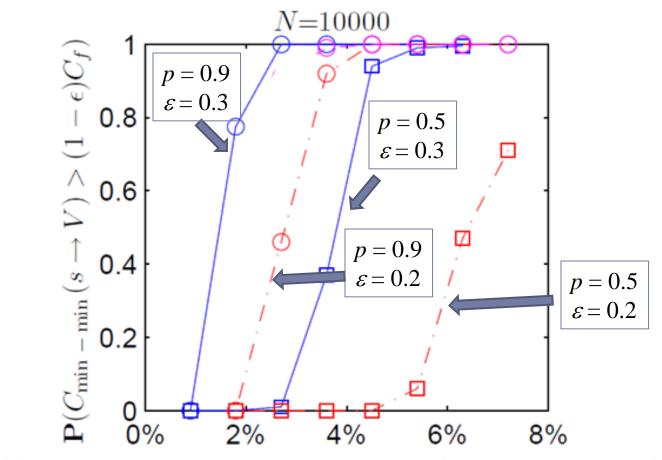
$$P(C_{\min-\min}(s \to V) \le (1 - \varepsilon)E[C_f]) \le O\left(\frac{1}{N^{2d-1}}\right)$$

the constant α must be



- Require a larger number of neighbors when
 - faster convergence rate (larger d)
 - fewer high bandwidth users (smaller p)
 - higher streaming rate requirement (smaller ε)
- > This factor may be further reduced by improving the capacity of the last cut

Simulation Result – Single Channel



Number of downstream neighbors M as a fraction of N

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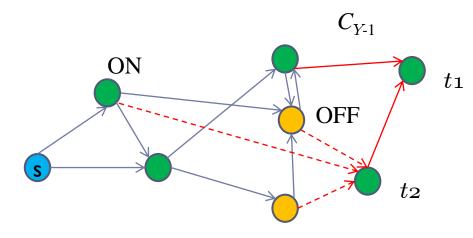
Adaptive Rate Allocation: Motivation

• Number of neighbors each peer needs $M = \alpha \log N$

$$\alpha \geq \frac{4du_s}{pu\varepsilon^2}$$

- As $\epsilon \to 0, \alpha$ increases inversely proportional to ϵ^2
- > The number of neighbors of each peer can still be quite large
- Recall that the most critical cut is the last cut C_{N-1}
 - The capacity that each peer receives directly from its immediate upstream neighbors
- Will improving the capacity of the last cut reduce α ?

From Uniform to Adaptive Rate Allocation



Uniform rate-allocation:

- Each edge from an ON peer contributes u/M capacity
 - However, the number of such edges to a peer is random
- Adaptive rate-allocation: Balance the capacity of the last cut by carefully assigning C_{ij} (the upload rate from peer *i* to peer *j*)

$$\sum_{j:i \to j} C_{ij} \le u_i, \text{ for all } i, \text{ and}$$

$$\sum_{i: i \to j} C_{ij} \ge (1 - \varepsilon) C_f, \text{ for all } j$$

Caveat: no capacity guarantee on all other cuts!

Uniform versus Adaptive Rate Allocation: Pros and Cons

- Uniform rate allocation
 - The last cut is the most difficult
 - Other cuts have larger capacity
- Adaptive rate allocation
 - Balance the capacity for the last cut
 - No capacity guarantee for other cuts

Hybrid scheme

- Reserve a fraction of the upload capacity of each peer for uniform rate allocation
- Perform adaptive rate allocation with the remaining upload capacity

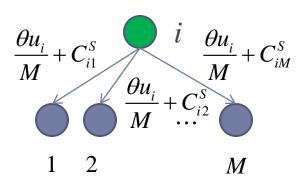
Hybrid Scheme - Details

- Still perform random peer-selection
- Each link capacity C_{ij} consists of two parts $C_{ii} = C_{ii}^U + C_{ii}^S$
- Reserve a fraction θ of the upload capacity for uniform allocation

$$C_{ij}^U = \theta u_i / M$$

- Take care of all other cuts with high probability
- The capacity C_{ij}^{S} for adaptive rate allocation is given by the the solution of

$$\sum_{\substack{j:i \to j \\ i:i \to j}} C_{ij}^{S} \leq (1 - \theta)u_{i}, \text{ for all } i$$
$$\sum_{i:i \to j} C_{ij}^{U} + C_{ij}^{S} \geq (1 - \varepsilon)C_{f}, \text{ for all } j$$

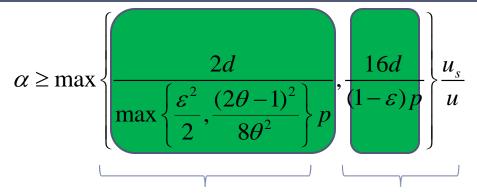


- The solution exists with high probability take care of the last cut.
- There exist fully-distributed algorithms to compute the solution.

Hybrid Scheme - Main Result

For $0.5 < \theta < 1$, the hybrid scheme could achieve a close-tooptimal streaming rate with high probability

$$P(C_{\min-\min}(s \to V) \le (1 - \varepsilon)E[C_f]) \le O\left(\frac{1}{N^{2d-1}}\right)$$

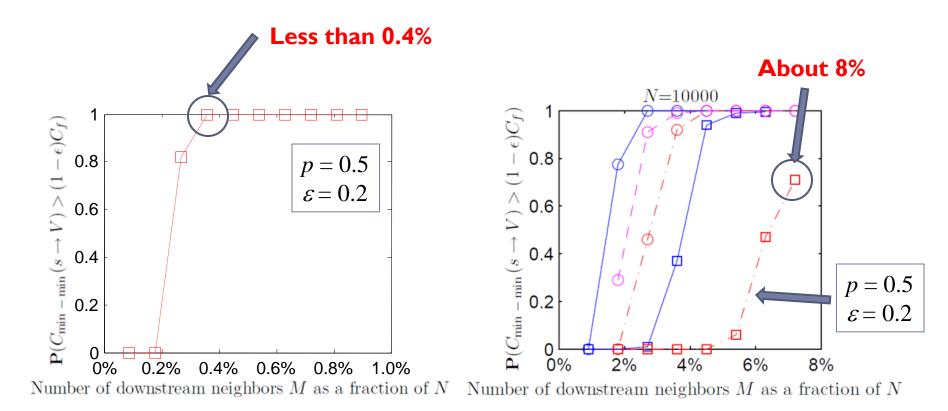


For other cuts For the last cuts

- The dependency on small \mathcal{E} is virtually eliminated!
- Assume $\theta = 0.9$, $\varepsilon = 0.1$
 - Uniform rate allocation: $\alpha > 400 du_s/pu$
 - Hybrid Scheme: $\alpha > 17.8 du_s/pu$

if

Hybrid Scheme – Simulation Result



Hybrid (N=10000)

Uniform (N=10000)

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Multi-Channel P2P networks

- Existing P2P systems typically serve a large number of channels/videos at the same time
- Traditionally, each channel is treated separately
 - > Peers viewing a channel only serve other peers in the same channel
- View-Upload Decoupling (VUD [Wu et. al. 2009])
 - Peers can view one channel but serve/upload videos for peers in a different channel
 - Streaming capacity for multi-channel P2P system is improved
 - Still assume complete connectivity and centralized operation

Our work

- We propose a simple distributed scheme that has a similar flavor of VUD
- Close-to-optimal streaming capacity region can still be achieved for multi-channel systems

Multi-channel - System Model

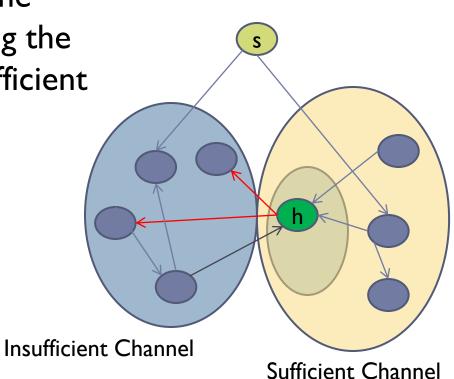
- Consider a multi-channel P2P system with J different channels
- \mathcal{N}_j : the set of peers that are viewing channel j
 - $N_j = |\mathcal{N}_j|$: The number of peers in channel j
- $u_{s,j}$: the capacity that server allocates to channel j
- R_i : the targeted streaming rate of channel j
- For each single channel, the optimal achievable streaming rate is

$$C_{f,j} = \min\left\{u_{s,j}, \frac{u_{s,j} + \sum_{i \in \mathcal{N}_j} u_i}{N_j}\right\}$$

- For a given **R**,
 - ▶ some channels may have a $C_{f,j} > R_j$, \blacksquare sufficient channels
 - some channels may have a $C_{f,j} < R_j$ insufficient channels

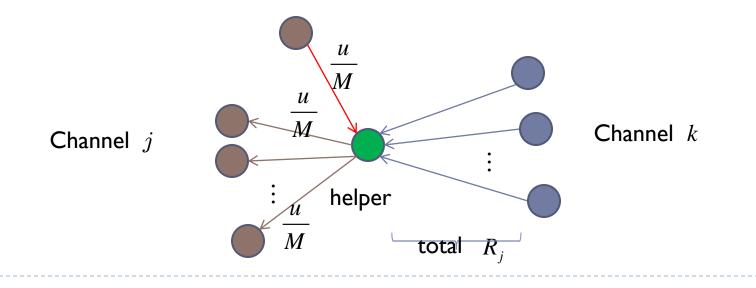
Multi-channel – View-Upload Decoupling

 VUD: Some peers from the sufficient channels become helpers to help improving the performance of the insufficient channels



Multi-channel - Helper

- A helper that is viewing channel k and helping channel j
 - Receives full streaming rate R_k of the content of channel k
 - Must be ON
 - Receives a rate u/M of the content of channel j
 - All of its downstream neighbors are peers viewing channel *j*



Multi-channel: Capacity Region

- R_i : the targeted streaming rate of channel j
- We can define the capacity region Λ as the set of streaming rate vectors $\mathbf{R} = [R_1, R_2, \dots, R_J]^T$ such that any $\mathbf{R} \in \Lambda$ is supportable by some control algorithm.
- The largest possible capacity region

$$\Lambda = \left\{ \mathbf{R} \middle| \underbrace{\sum_{j=1}^{J} N_{j} R_{j}}_{\text{Total capacity demand}} \leq u_{s} + \underbrace{\sum_{i \in V} u_{i}}_{\text{Total capacity demand}}, \underbrace{\sum_{j=1}^{J} R_{j}}_{\text{Total capacity upload capacity}} \right\}$$

Given R ∈ (I-ε) Λ, can this rate vector R be achieved by a simple and distributed control scheme?

Multi-channel - Algorithm

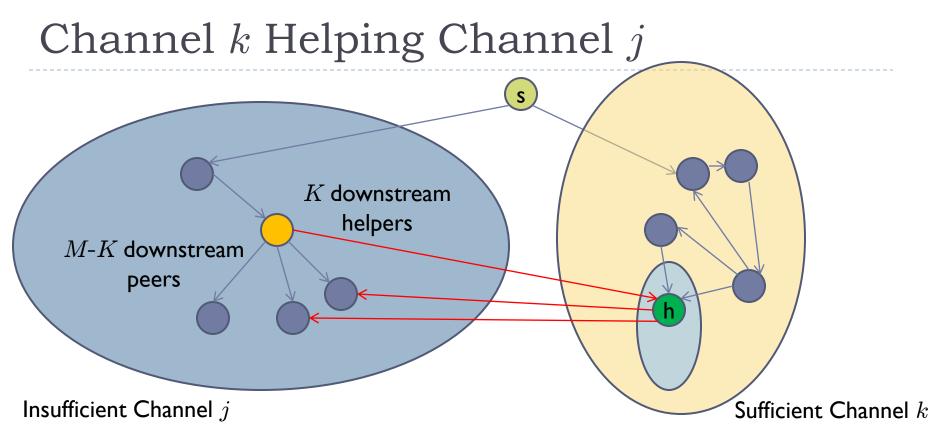
- Let H_j be the number of helpers that channel j needs
- We would like to choose H_i so that

$$C_{f,j} = \min\left\{u_{s,j}, \frac{u_{s,j} + \sum_{i \in \mathcal{N}_j} u_i + \sum_{i \in \mathcal{H}_j} u_i}{N_j}\right\} = \frac{R_j}{1 - \varepsilon}$$

One solution:

$$H_{j} = \left[\frac{N_{j}R_{j}}{(1-\varepsilon)u} - \frac{u_{s,j}}{u} - pN_{j}\right]$$

H_j > 0 for an insufficient channel (needing helpers)
 H_j < 0 for a sufficient channel (providing helpers)



- Each helper behaves like an OFF peer in channel k
- Each ON peer in channel j reserves K (downstream) slots for helpers
- Each helper finds a normal ON peer randomly from channel j as its upstream neighbor
- Each helper picks M downstream peers randomly from channel j
- Uniform rate allocation. Helpers do not connect to helpers

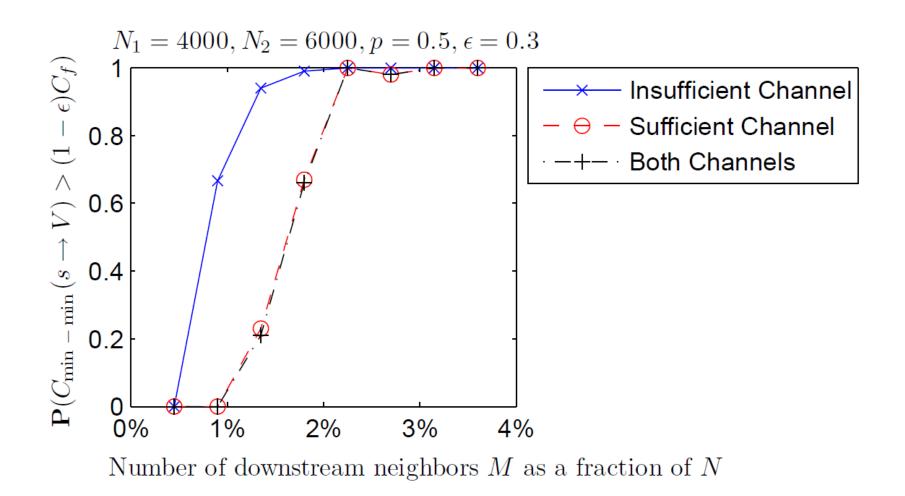
Multi-channel – Main Result

For any $\varepsilon > 0$, d > 1 and $\mathbf{R} \in (1-\varepsilon)\Lambda$, there exists α such that if $M = \alpha \log N$, then for all channel j

$$P(C_{\min-\min}(s \to \mathcal{N}_j) \le R_j) \le O\left(\frac{1}{N^{2d-1}}\right)$$

- \mathcal{N}_j : The set of peers that are viewing channel j
- Λ is the largest possible capacity region.
- Our proposed scheme can achieve close-to-optimal capacity with sparse connectivity and decentralized control.
 - Each peer still needs only O(log N) neighbors
 - Helpers are chosen randomly

Simulation Result – Multi-Channel



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Summary

- Close-to-optimal streaming capacity can be achieved with high probability using
 - O(log N) downstream neighbors for each peer
 - Random peer-selection
 - Uniform rate-allocation
- Our results reveal important insights into the dynamics of large P2P streaming systems
- Based on these insights, we design a hybrid scheme that further improves the system performance.
- With "helpers", a similarly simple scheme could also achieve a close-to-optimal streaming capacity region for multi-channel P2P systems

On-Going and Future Work

P2P Video-on-Demand (VoD) Systems

- Timing of each neighbor is important
- Users may jump forward/backward
- Cache placement policy is also critical
- We show that simple and distributed control with sparseconnectivity will still suffice

On-Going and Future Work

The packet scheduling problem

- May use generation-based random linear network coding.
- > There is a tradeoff between rate, delay, and overhead
- BATS code?
- Incorporating scalable video
 - Video encoding rate may be adjusted based on the optimal streaming rate
 - Layered video

Multiple ISPs

- Cross-ISP traffic may encounter new bottlenecks
- Will random peer-selection and simple rate-allocation strategies still be sufficient?

Wireless versus wireline

Thank You!

Can Zhao, Xiaojun Lin and Chuan Wu ``The Streaming Capacity of Sparsely-Connected P2P Systems with Distributed Control," in *IEEE INFOCOM*, Shanghai, China, April 2011

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