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# *Data-driven QoE optimization techniques for multi-user wireless networks*

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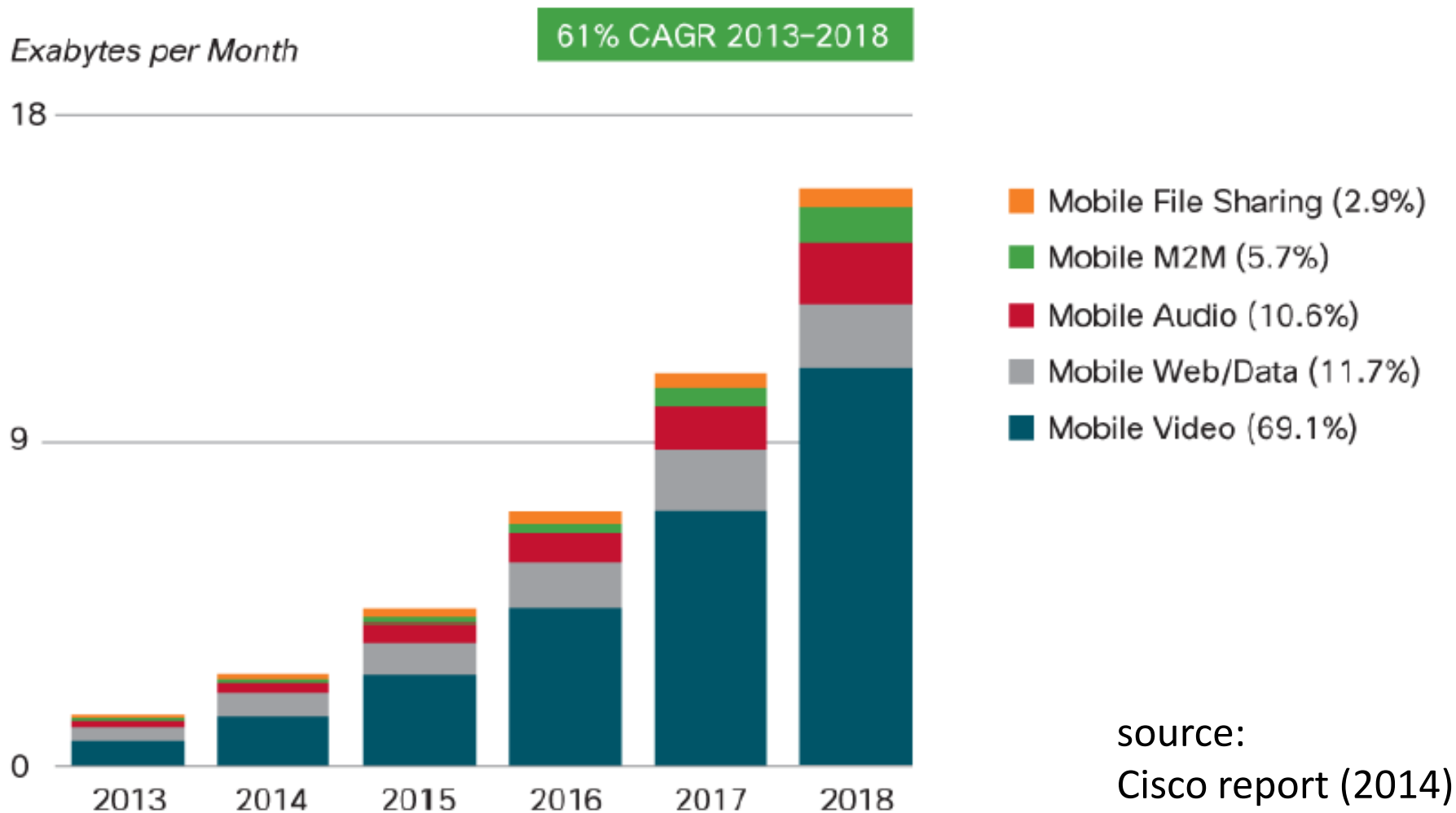
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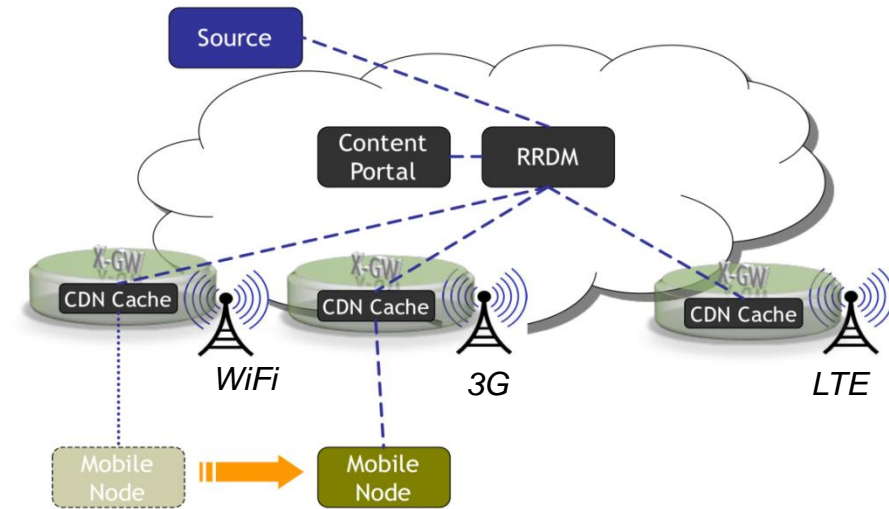
# Multimedia traffic growth



source:  
Cisco report (2014)

# Challenges for video systems

- Heavy data
- Hierarchical system
- Backhaul network capacity
- Must handle different access techniques
- Need to account for video popularity, heterogeneous user terminals
- Quality-of-Experience of video is hard to capture





# Our approach

- We propose a way to facilitate video handling
- Proposed approach:
  - Represent video characteristics in terms of rate
  - Capture the relationship between rate and QoE
  - Use this to determine resources needed
  - Make admission decisions based on QoE
- We consider a set of video clips and apply machine learning techniques





- We consider a test set of 38 video clips, all encoded in an H.264-AVC format
- All the videos are encoded with a 16-frame structure (1 I-frame, 15 P-frames) and compressed with 18 different quantization strategies

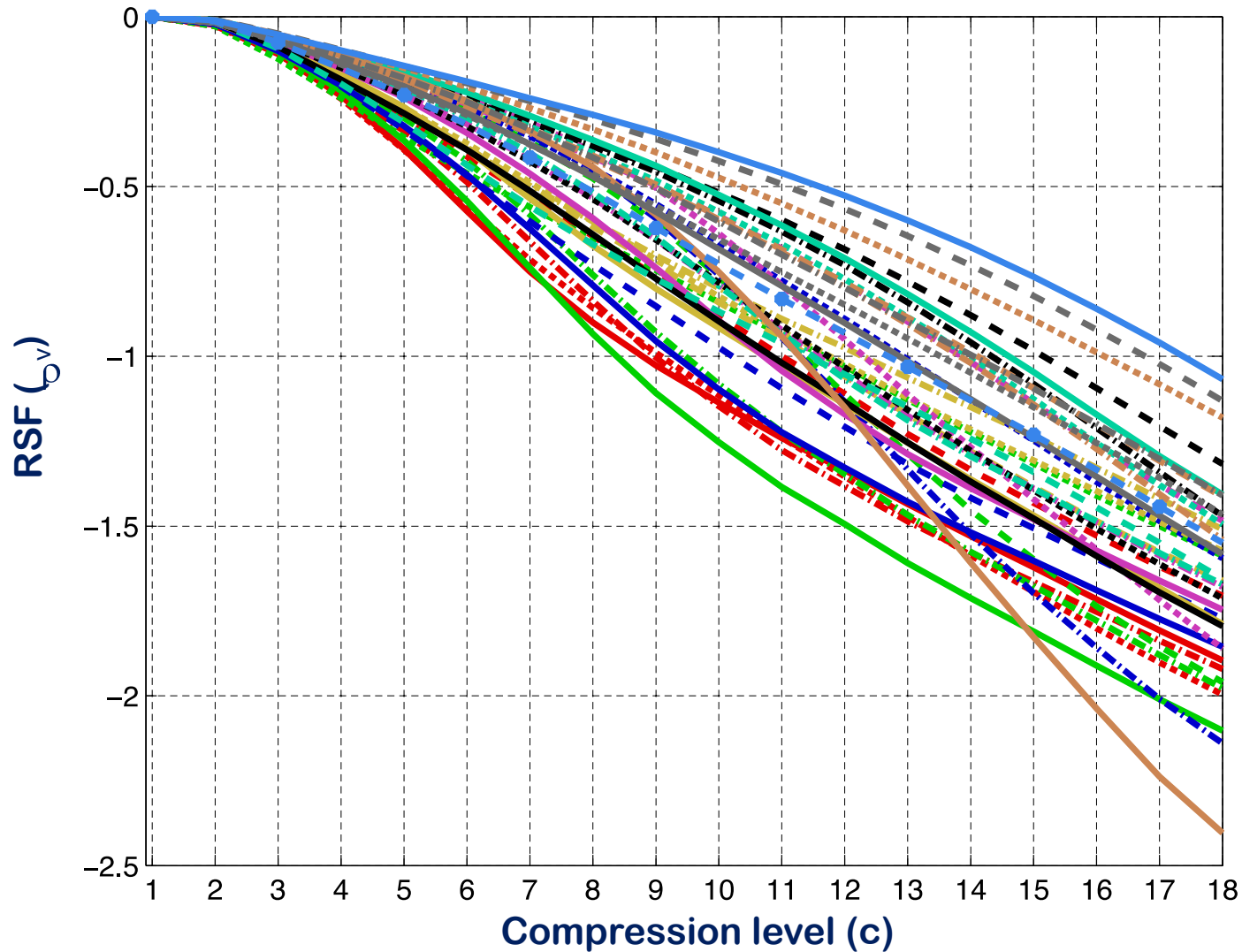
Transmit rate [bit/s] of video  $v$  at compression level  $c$ :  $r_v(c)$

Rate Scaling Factor (RSF):  $\rho_v(c) = \log(r_v(c)/r_v(1))$





# Rate Scaling Factor vs compression





# QoE characterization

- Depending on the content, the perceived quality of a given compression level changes
- There are several metrics to measure quality of a video signal
- Here, video quality is expressed in terms of Structural Similarity (SSIM)

SSIM	MOS	Quality	Impairment
$\geq 0.99$	5	Excellent	Imperceptible
[0.95, 0.99)	4	Good	Perceptible but not annoying
[0.88, 0.95)	3	Fair	Slightly annoying
[0.5, 0.88)	2	Poor	Annoying
$< 0.5$	1	Bad	Very annoying





# Structural Similarity (SSIM)

- SSIM measures the closeness of square sets of pixels, and is computed as

$$SSIM(X, Y) = \frac{(2\mu_X\mu_Y + c_1)(2\sigma_{XY} + c_2)}{(\mu_X^2 + \mu_Y^2 + c_1)(\sigma_X^2 + \sigma_Y^2 + c_2)} \quad (1)$$

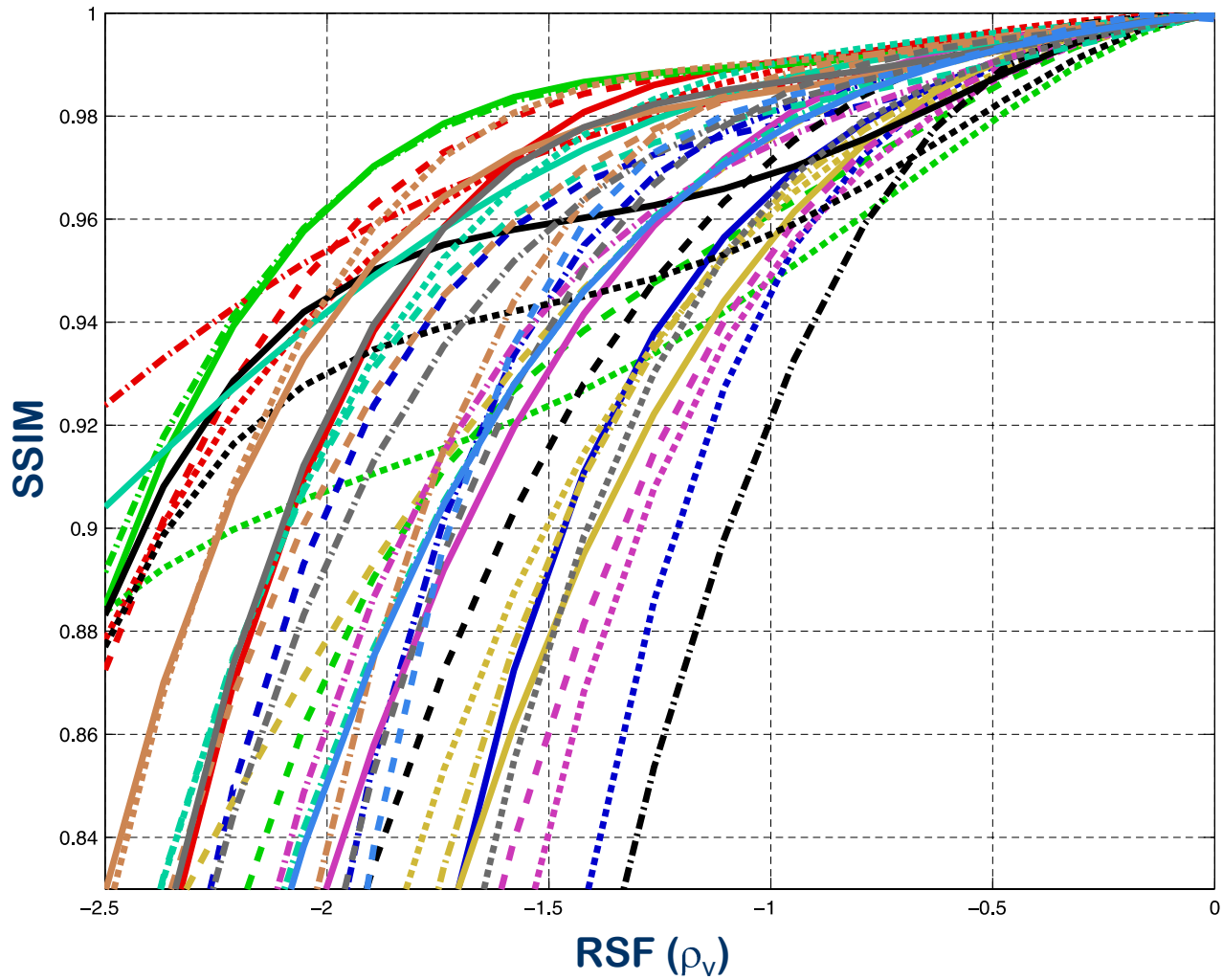
with  $\mu$  and  $\sigma^2$  denoting the mean and variance of the luminance value in the corresponding window, and  $c_1$  and  $c_2$  being variables to stabilize the division with weak denominator

Measures image degradation in terms of perceived structural information change

Represents quality as seen by the human eye



# SSIM versus RSF





- All the videos exhibit similar trends
  - monotonic descent
  - a steep “fall” after a threshold
- However, there are quantitative differences
  - different perceived end quality
  - different resource requirements
- These characteristics are roughly consistent within the same (homogeneous) video





# SSIM polynomial approximation

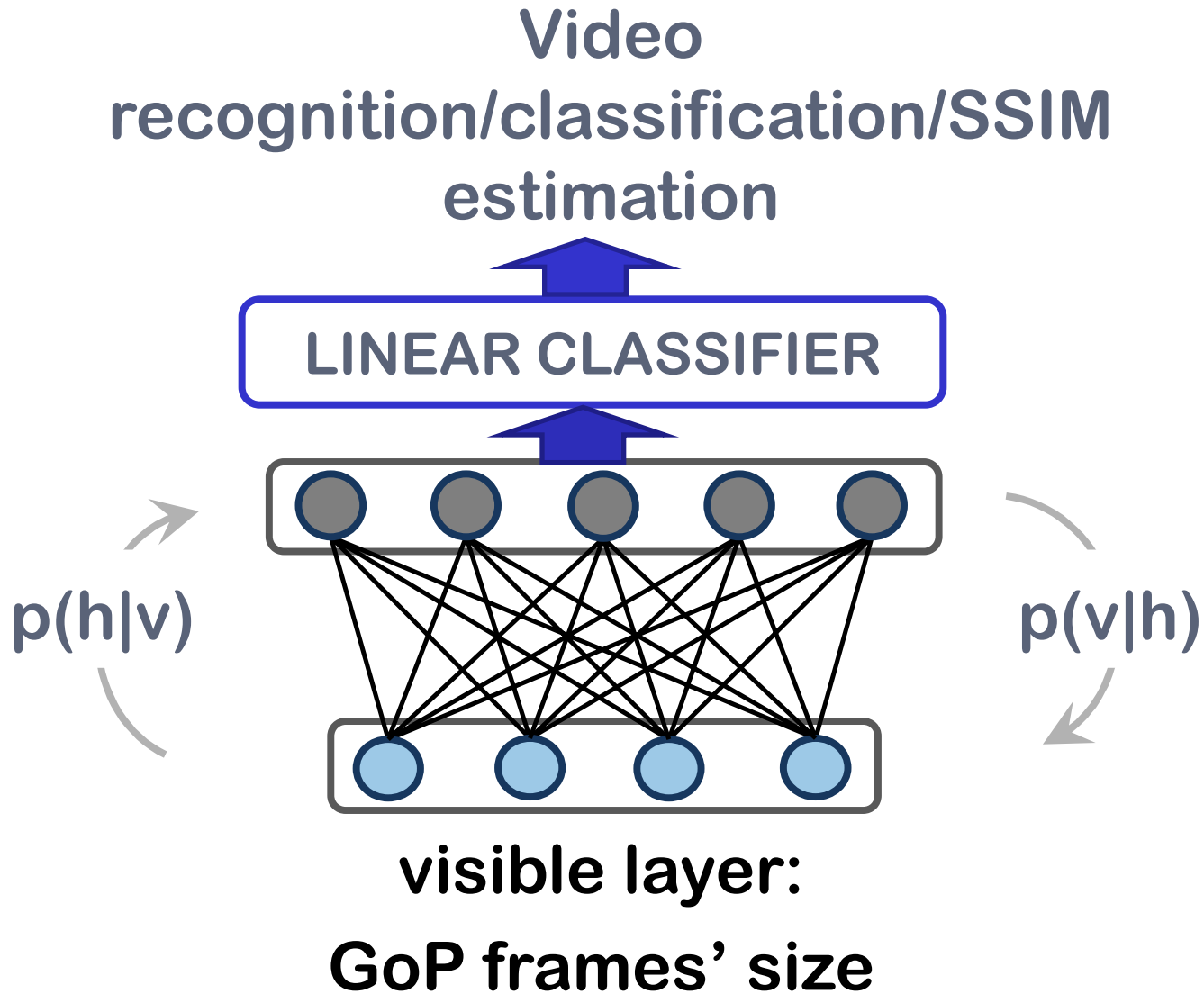
- We introduce a polynomial approximation to express SSIM behavior

This provides a compact representation for use in VAC and RM

$$F_v^{(n)}(\rho) \simeq 1 + a_{v,1}\rho + a_{v,2}\rho^2 + a_{v,3}\rho^3 + \dots + a_{v,n}\rho^n$$

- A 4-degree polynomial provides a quite accurate approximation of the SSIM vs RSF curve

# Proposed approach





# Proposed approach

- Input to the RBM: **frame size only**

This is done for a whole GoP (isolated)

The RBM “learns” by creating certain patterns in the hidden layer

This enables a sparser representation of the input in the hidden layer

- After that, we apply a linear classifier for recognition / classification / SSIM estimation

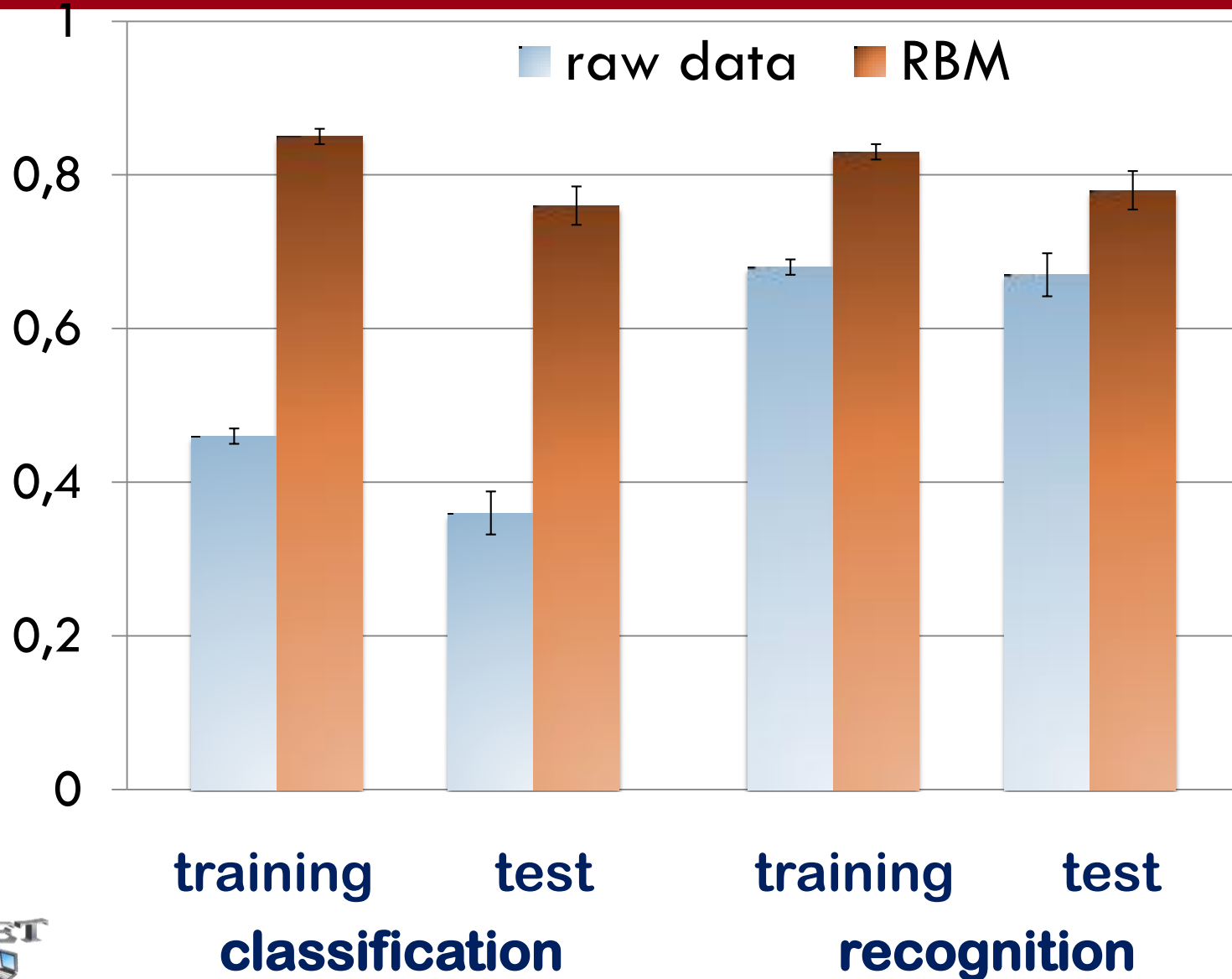
Note: we must train a different linear classifier for each case, while the RBM is trained just once for all



# Possible video applications

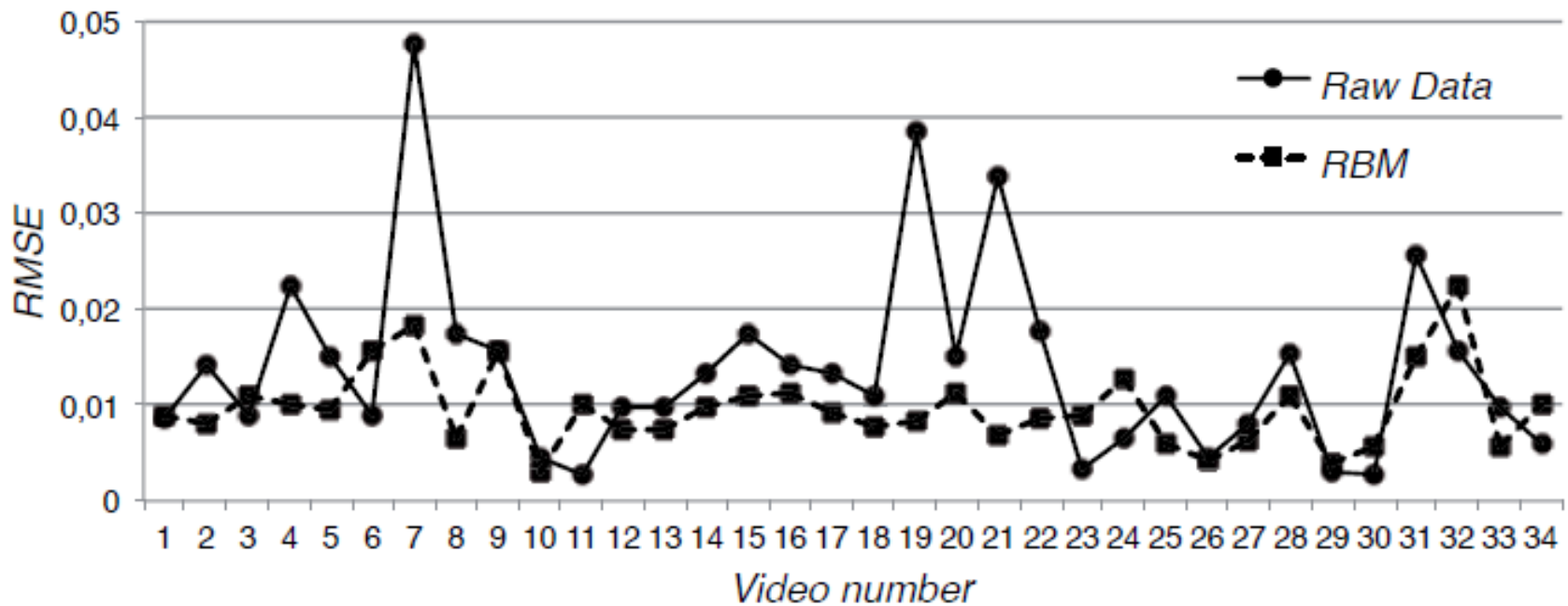
- Knowledge of these characteristics of the video may be useful for
  - (i) QoE-aware admission/congestion control
  - (ii) estimating resources required by popular videos for better planning of replica servers
  - (iii) inferring user preferences
- Two different tasks can be envisioned:
  - video recognition (exactly identify it)
  - video classification (just categorize it)

# Preliminary results



# Learning via RBM: accuracy

- Root Mean Square Error (RMSE) between exact SSIM and polynomial approximation with estimated coefficients



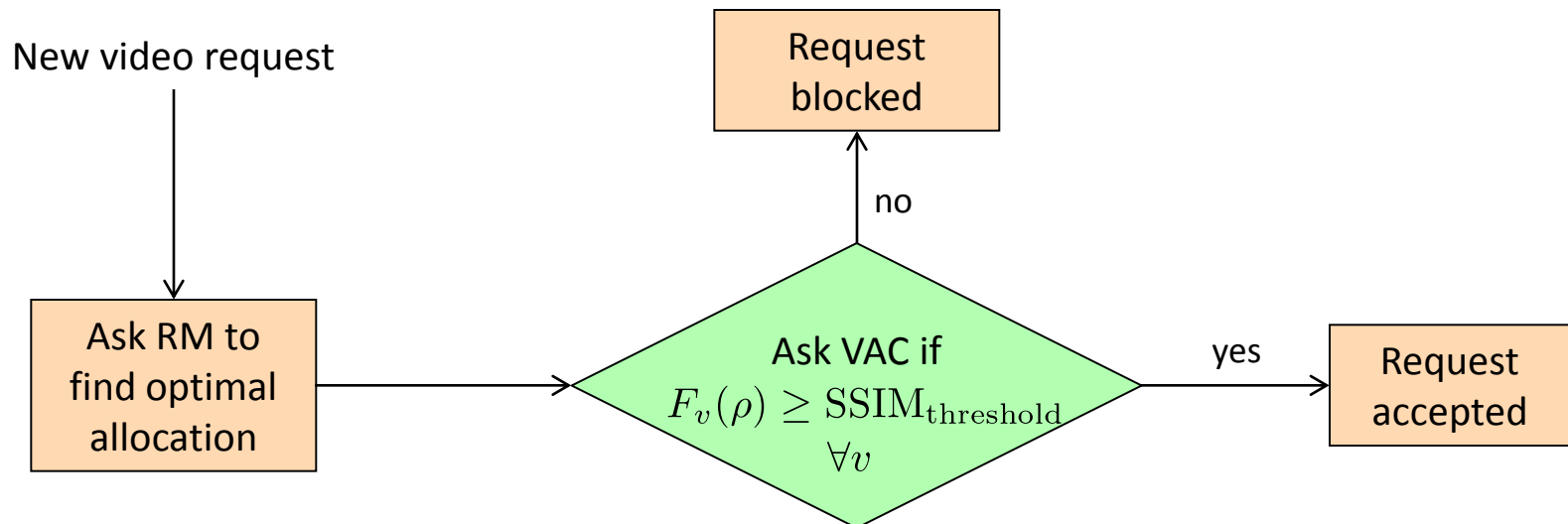


# Cognitive Video Admission Control & Resource Management

- Videos multiplexed into a shared link of capacity  $R$
- **Resource Manager (RM)**: detects changes and triggers optimization to adapt video rates to maximize QoE utility function
- **Video Admission Controller (VAC)**: determines whether a new video request can be accepted without decreasing QoE of any video below a threshold  $F^*$



- A proxy intercepts video requests and operates as
  - **Video Admission Controller (VAC):** determine whether a new video request can be accepted
  - **Resource Manager (RM):** adapt video rates to maximize QoE





- Users are divided in **bronze**, **silver** and **gold** classes in increasing order of minimum guaranteed QoE
- Videos are multiplexed onto a shared link of capacity  $R$



# The resource allocation problem

- Channel allocation vector

$$\Gamma = \{\gamma_v\}$$

- The optimization problem addressed by RM is:

$$\Gamma_{\text{opt}} = \underset{\Gamma}{\operatorname{argmax}} U(\Gamma, R, \{F_v\}) \quad \text{s.t.} \quad \sum_v \gamma_v \leq 1$$

**Utility function**
**Resource share allotted to video "v"**

**Rate allocation vector**
**Channel rate**
**SSIM videos' characteristics**



# Rate Fairness (RF)

$$\gamma_{\text{opt},v} = \frac{r_v(1)}{\sum_j r_j(1)}$$



Each video flow gets a channel share directly proportional to its full quality bitrate



# SSIM Fairness (SF) – the idea

$$U(\Gamma, R, \{F_v\}) = \min_v (F_v(\tilde{\rho}_v) - F_{q(v)}^*)$$

where  $q(v) \in \{1, 2, 3\}$  is the class of the user watching the  $v$ th video flow and  $F_{q(v)}^*$  is the SSIM threshold relative to class  $q(v)$



Each video flow has the same increase  $\alpha$  wrt the minimum quality level imposed to its class

If  $\alpha=0.01$ , the SSIM of videos belonging to the three classes will be:

Class	SSIM
Gold ( $F^*=0.98$ )	0.99
Silver ( $F^*=0.95$ )	0.96
Bronze ( $F^*=0.9$ )	0.91

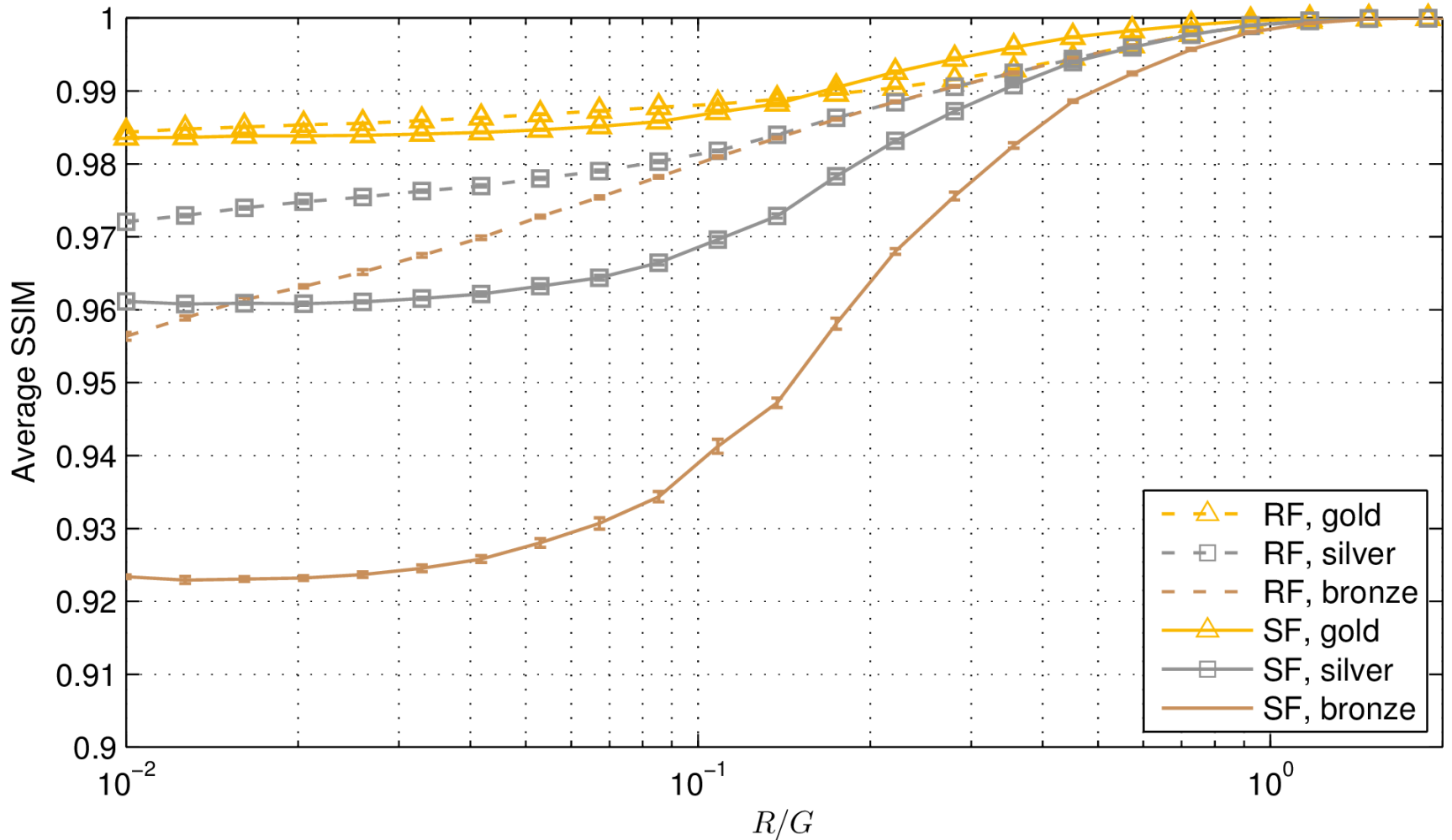




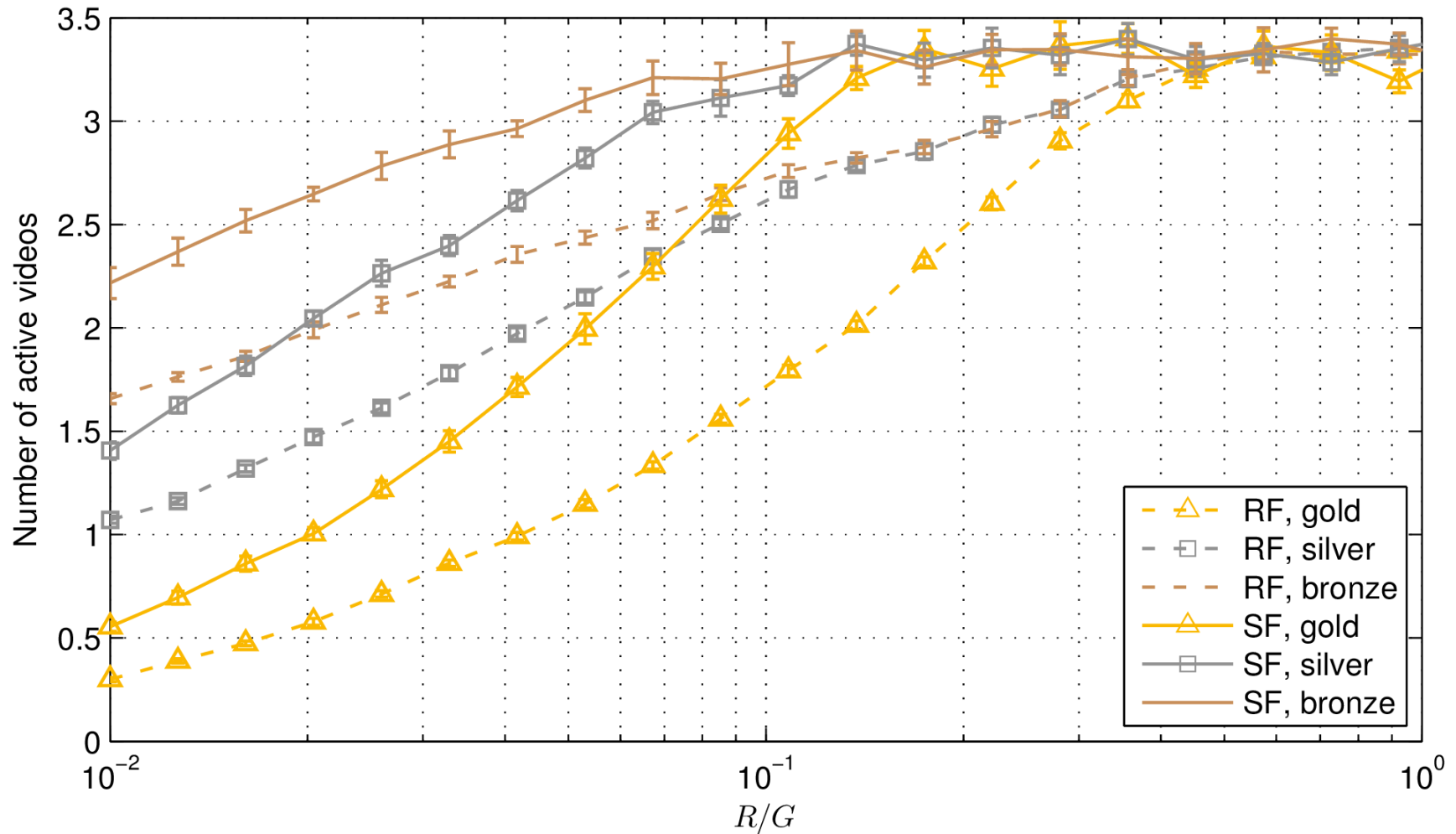
- Poisson video requests (0.1 req./s)
- Exponential video duration, mean 100 s
- Average offered load of  $0.1 \cdot 100 = 10$  videos
- QoE for each class:

Class	Minimum SSIM	Approximate target MOS
<b>Gold</b>	<b>0.98</b>	<b>5</b>
Silver	0.95	4
<b>Bronze</b>	<b>0.9</b>	<b>3</b>

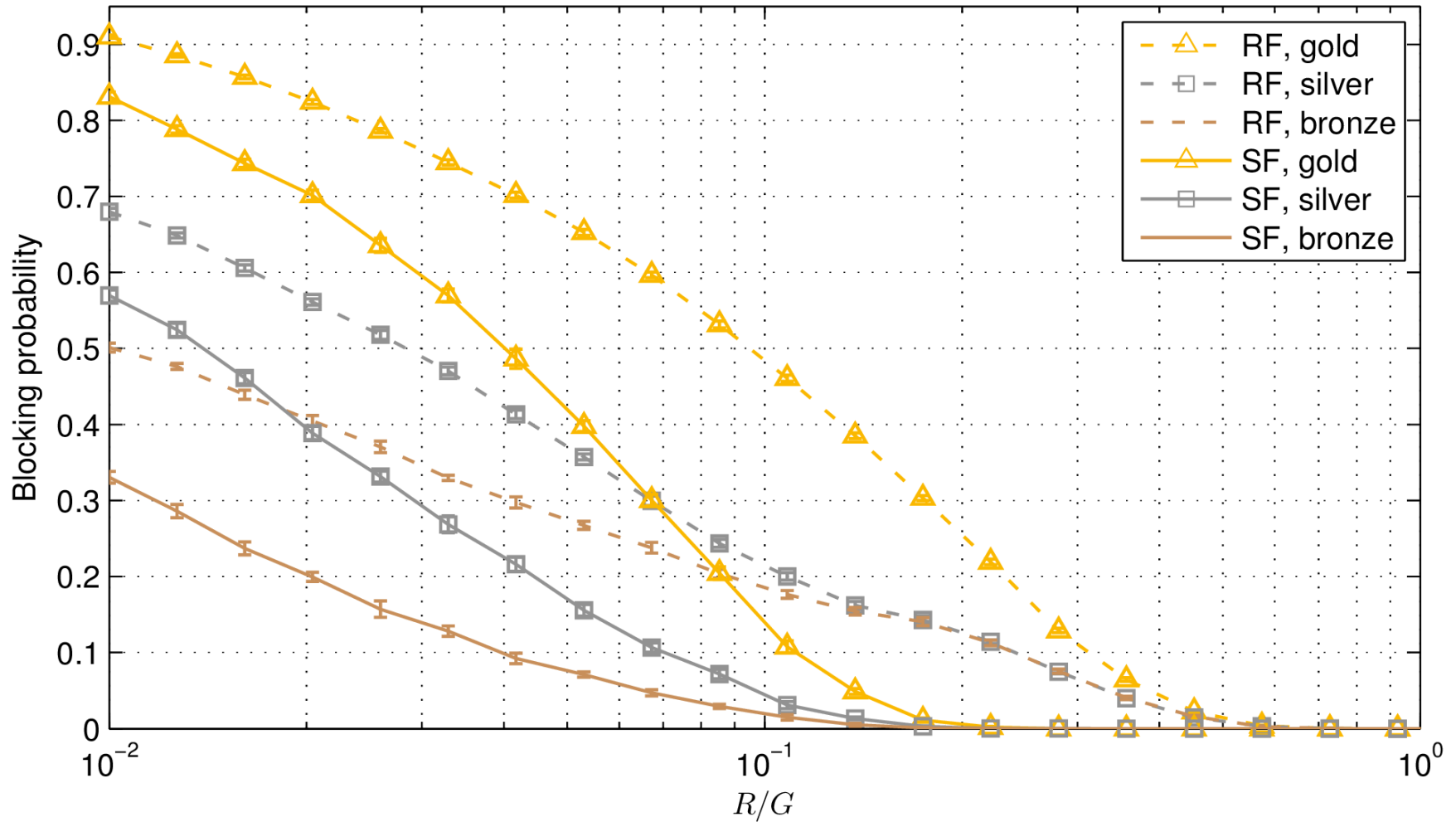
# Average SSIM



# Number of active videos



# Blocking probability





- Optimizing resource allocation for video transmission is challenging
  - many numerical parameters involved
  - subjective QoE issues
  - high signaling exchange
- We designed a framework for resource allocation that does not need prior models
- Simulations show that QoE-aware strategies outperform QoE-agnostic video admission techniques in terms of QoE delivered and admitted videos





- Daniele Munaretto, Andrea Zanella, Daniel Zucchetto, Michele Zorzi, "Data-driven QoE optimization techniques for multi-user wireless networks" in the Proceedings of the 2015 International Conference on Computing, Networking and Communications, February 16-19, 2015, Anaheim, California, USA
- Alberto Testolin, Marco Zanforlin, Michele De Filippo De Grazia, Daniele Munaretto, Andrea Zanella, Marco Zorzi, Michele Zorzi, "A Machine Learning Approach to QoE-based Video Admission Control and Resource Allocation in Wireless Systems" in the Proceedings of IEEE IFIP Annual Mediterranean Ad Hoc Networking Workshop, Med-Hoc-Net 2014, June 2-4, 2014, Piran, Slovenia.
- Leonardo Badia, Daniele Munaretto, Alberto Testolin, Andrea Zanella, Marco Zorzi, Michele Zorzi, "Cognition-based networks: applying cognitive science to multimedia wireless networking" in the Proceedings of Video Everywhere (VidEv) Workshop of IEEE WoWMoM'14, 16 June, 2014, Sydney, Australia.
- Marco Zanforlin, Daniele Munaretto, Andrea Zanella, Michele Zorzi, "SSIM-based video admission control and resource allocation algorithms" in the Proceedings of WiOpt workshop WiVid'14, May 12-16, 2014, Hammamet, Tunisia.

