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Cognition-based networks: applying cognitive science to wireless networking

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Outline

- Cognition-based networks
  - Evolution of cognitive communications & networks
  - New holistic concept of cognition-based networks
  - Use of machine learning tools toward this vision
- Examples of application
  - QoE-driven video streaming control
  - Context-aware handover optimization

Motivation

- Communication systems are more and more complex
  - Cognitive (white spaces) transmissions
  - Self-organizing networks
  - HetNets

- All of these are specific cases of a more general approach based on learning and context-awareness

Cognition applied to wireless

- Applying cognition is a way to deal with the complexity and challenges of future systems

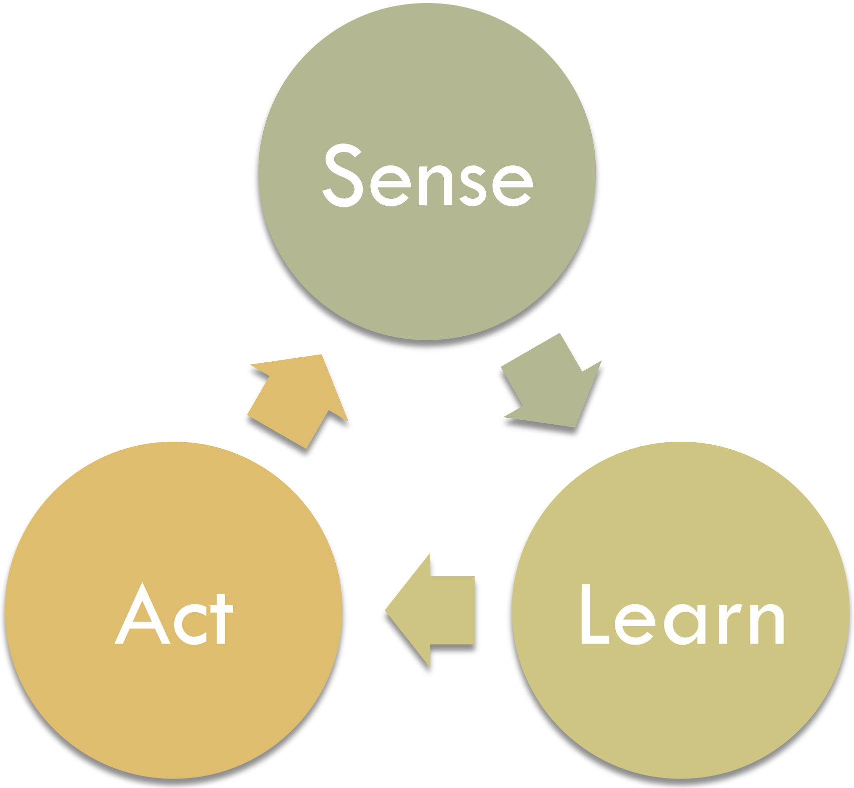
- Mitola (2000) and Haykin (2005) actually gave a very general definition of the cognitive paradigm
  - Intelligent observation, learning, decision-making

- Currently, we have only scratched the surface
  - Cognitive networking in a broad sense remains an exciting and largely unexplored research field

Evolution of the cognitive paradigm

- **Cognitive radios**
  - frequency-agile devices for opportunistic access
- **Cognitive radio networks**
  - networks of CRs
- **Cognitive networks**
  - the cognitive approach applied to networking layers and end-to-end
- **Cognition-based networks**
  - drawing from the most recent results in cognitive science

The cognition cycle (simplified)



True for humans, true for networks

- **Sense**: nowadays devices are crammed with transducers / sensing apparatuses
  - needs efficient data handling
- **Learn**: optimization algorithms can be run at each node individually
  - needs (i) efficient algos (ii) harmonization
- **Act**: network modifies the environment
  - requires convergence of multiple devices

Supervised vs unsupervised learning

- Supervised learning requires a training set and/or explicit feedback about outcomes

- Unsupervised has no prior knowledge
  - Reveals features that are not predefined, leading to the development of a data-driven worldview

Unsupervised learning

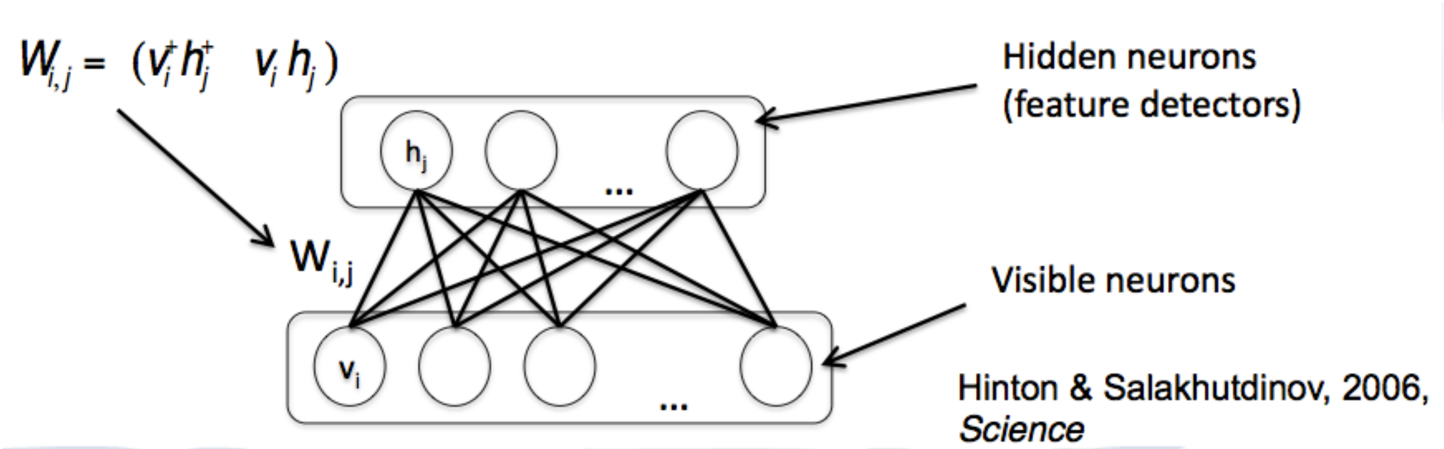
- The way we learn without prior information
- Cognitive stimuli are processed
  - We build a view of the world based on data
  - Generative model: probabilistic view of the world
  - Background for all our cognitive activities
- The worldview provided will be an extremely valuable starting point for goal-specific learning

Cognition-based Network

- Each node of the network:
  - exploits local information to achieve its goal
  - shares (part of) it with its neighbors
- Self-adaptation to the environment to achieve network wide goals
- Cognition applied to the entire network (not just at the PHY and MAC layers)
  - Both vertically and horizontally

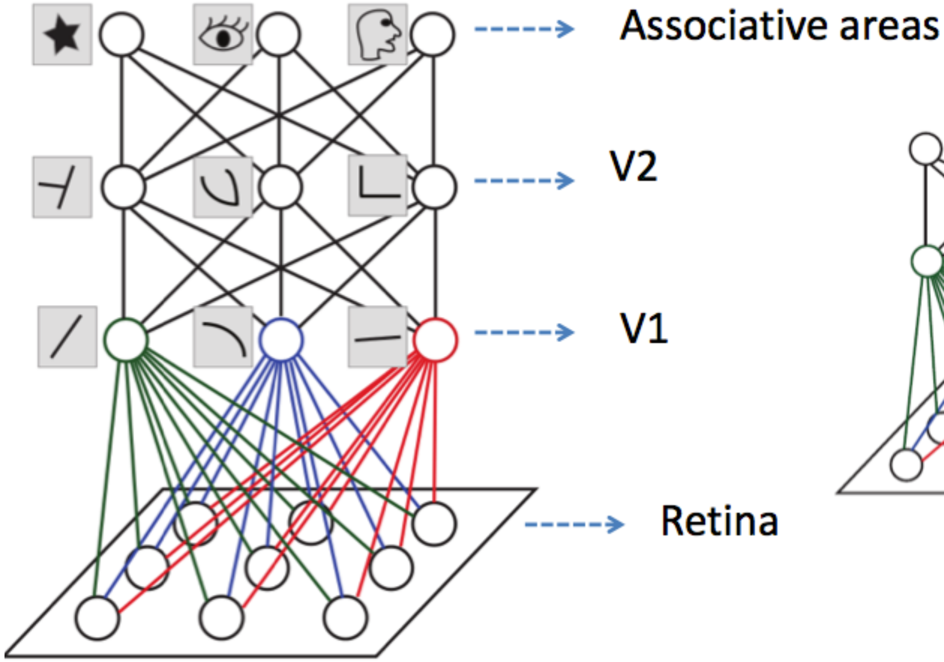
Restricted Boltzmann Machine (RBM)

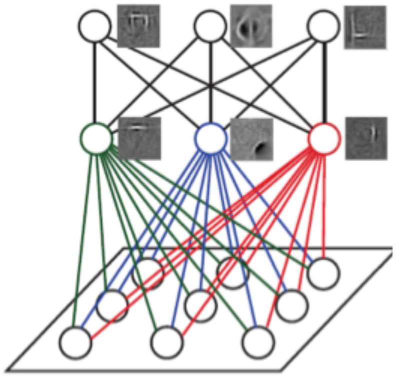
- Training objective: minimize contrastive divergence (Kullback-Liebler) between input data and (top-down) reconstruction of the data



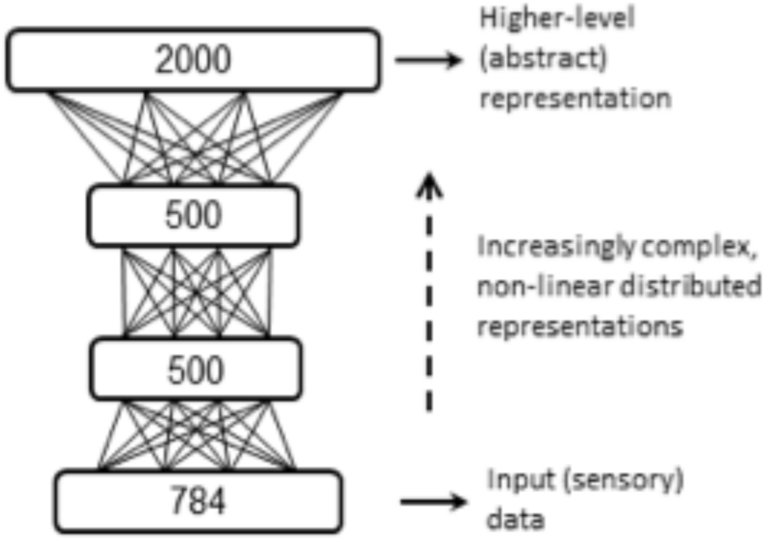
Hierarchical processing

A key feature of cortical computation





Deep learning



Large scale simulation
Deep network 9 layers (1 billion connections)
10 million (200x200) unlabeled images

(Le et al., 2012)

- Bottom-up:
  - Higher layer neurons "activate" when input presents some specific features
  - Higher layer provides an abstract representation of input features

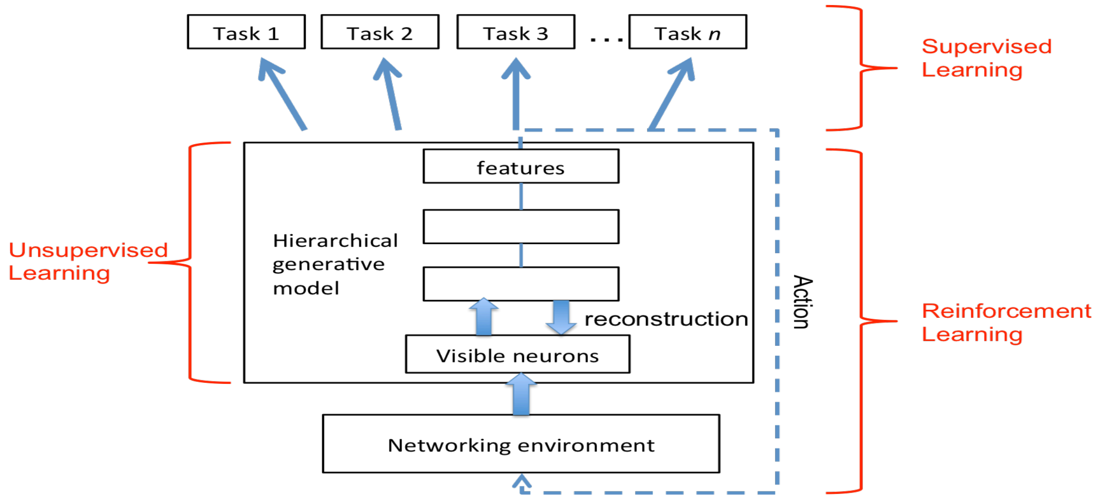
- Top-down:
  - Activating hidden layer neurons according to their weight and propagating back toward inputs we can generate signals with similar features of training signal

Properties of Unsupervised learning

- *Generative property*
  - Can be readily used to make predictions about the upcoming input information based on the recent history of the system
  - it is possible to estimate missing or noisy input terms, and detect anomalies or unexpected patterns in the input signal.
- *Feature extraction*
  - The internal representations extracted by unsupervised learning are generally more informative than those obtained with supervised training

Properties of Unsupervised learning

- *Compact data representation*
  - Internal representation provides a particular type of coding strategy
- *Synergy with reinforcement learning*



Examples of application

- **Content-based video management**
  - Learn video features and apply this knowledge to some useful networking task
- **Context-dependent handover in HetNets**
  - Learn environmental features and make context-based handover decisions accordingly
- **Prediction of Mobile Devices Discharging Time**
  - Learn the usage pattern and predict the battery charge duration of a smartphone
- …

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Deep Learning for Video Streaming Characterization

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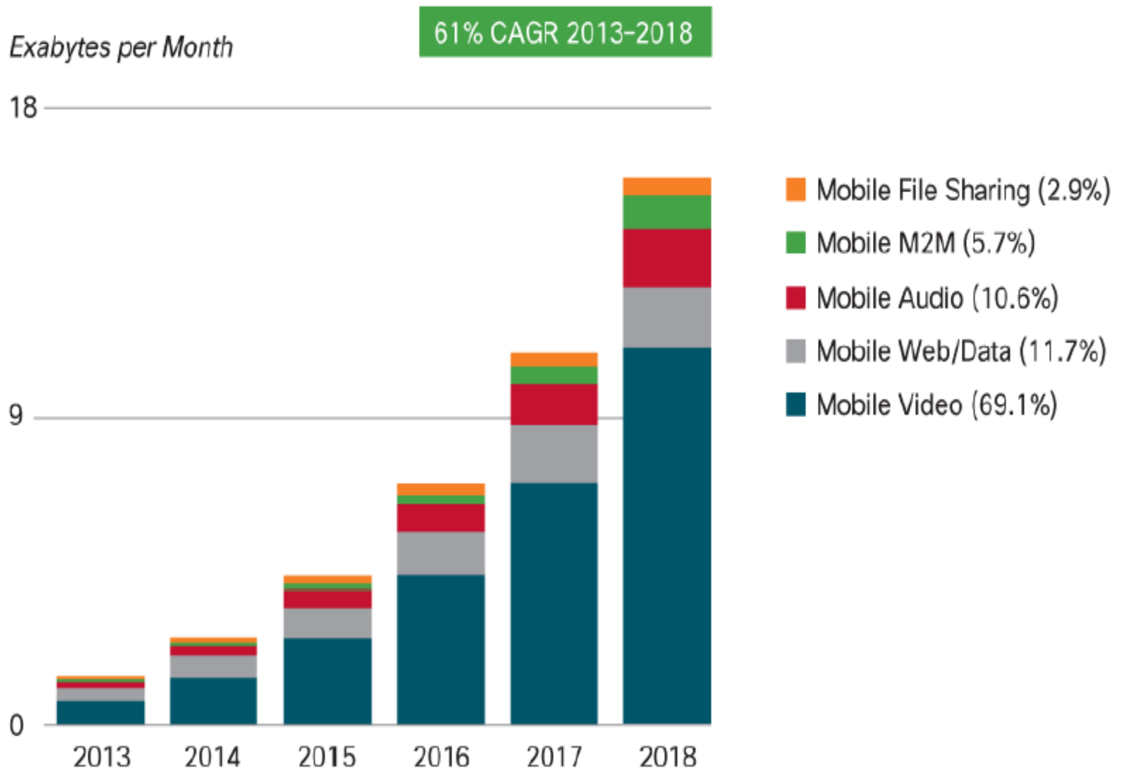
Multimedia traffic growth

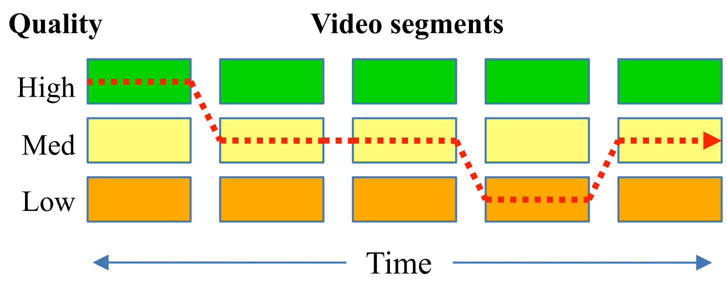


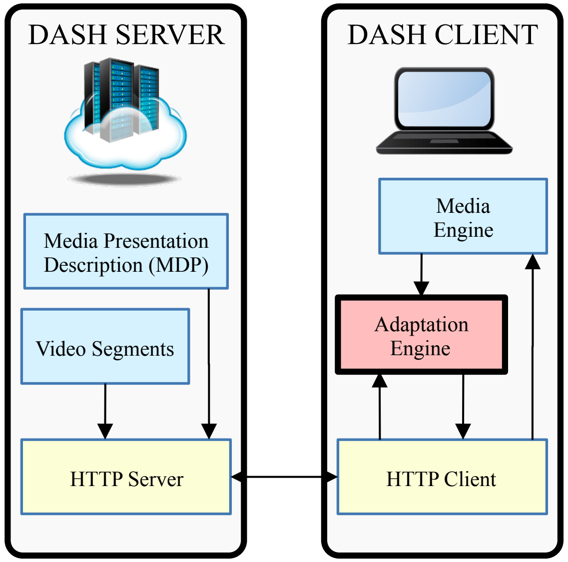
source:
Cisco report (2014)

Challenges

- Mobile video streaming is very demanding:
  - High bitrates
    - Compressed HD videos still requires 2-10 Mbit/s
  - Low delay
    - Less than 10 ms for interactive videos, less than 250 ms for real-time streaming
  - Stable links
    - Link fluctuations are counteracted by a (small) playout buffer → if the buffer empties then the play freezes!
  - Content-dependent requirements
    - Quality-rate characteristic depends on the video content

DASH - Dynamic Adaptive Streaming





- HTTP Standard Server
- Client-side Adaptation Engine
  - The client chooses the proper segments
  - Maximize Quality of Experience (QoE) e.g. avoid rebuffering...

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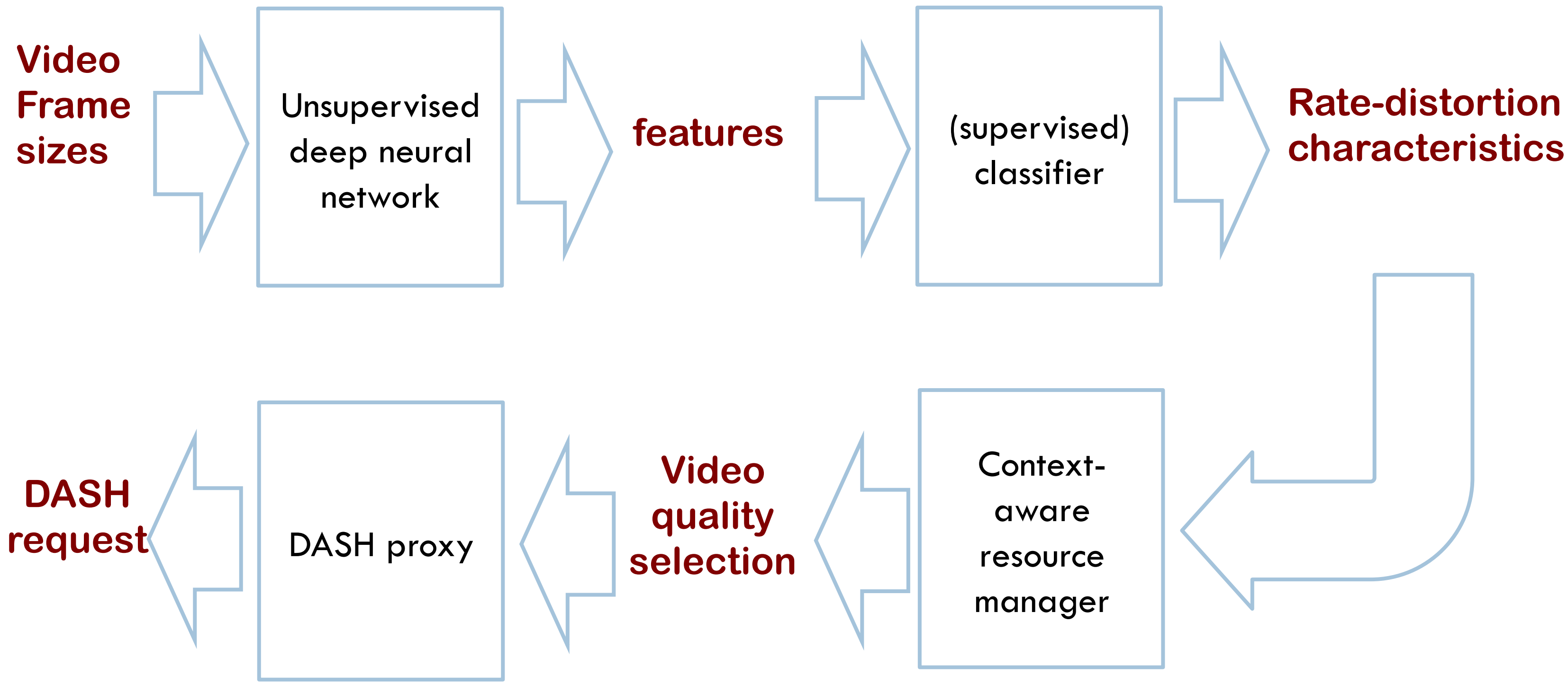
Our approach



Analysis

- 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: rv(c)
  - Rate Scaling Factor (RSF): rv(c)=log(rv(c)/rv(1))

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)

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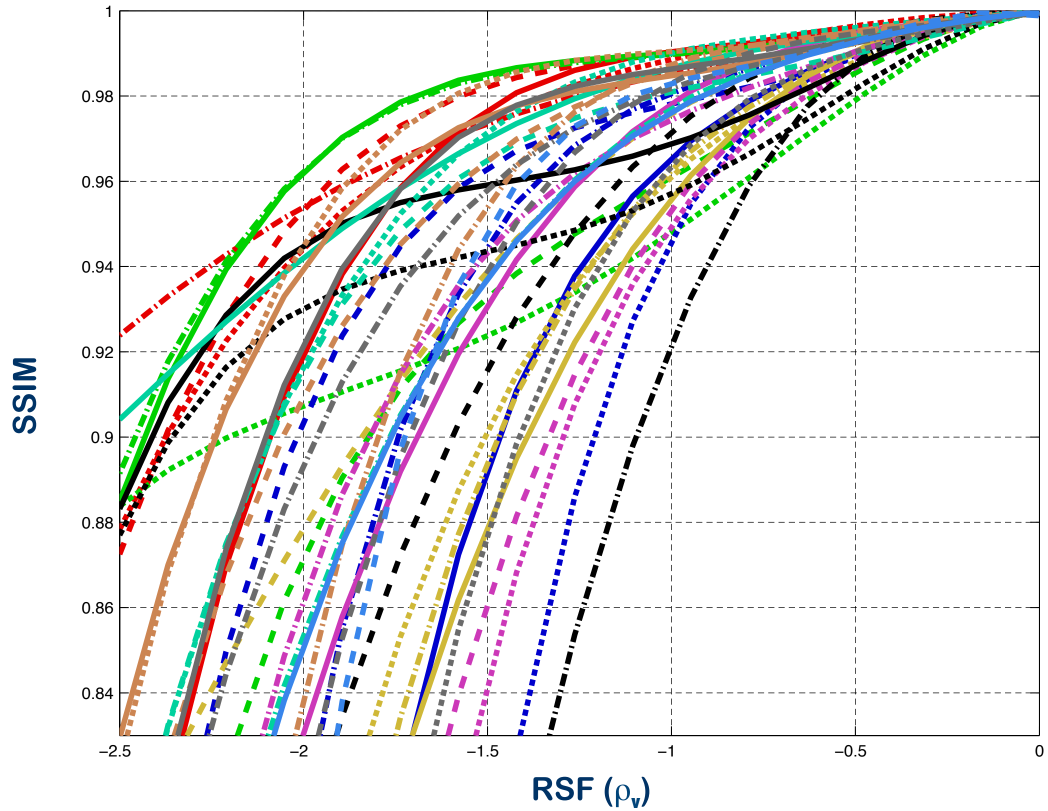
Structural Similarity (SSIM)

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

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

  - Measures image degradation in terms of perceived structural information change
  - Represents quality as seen by the human eye

SSIM versus RSF



Remarks

- 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

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

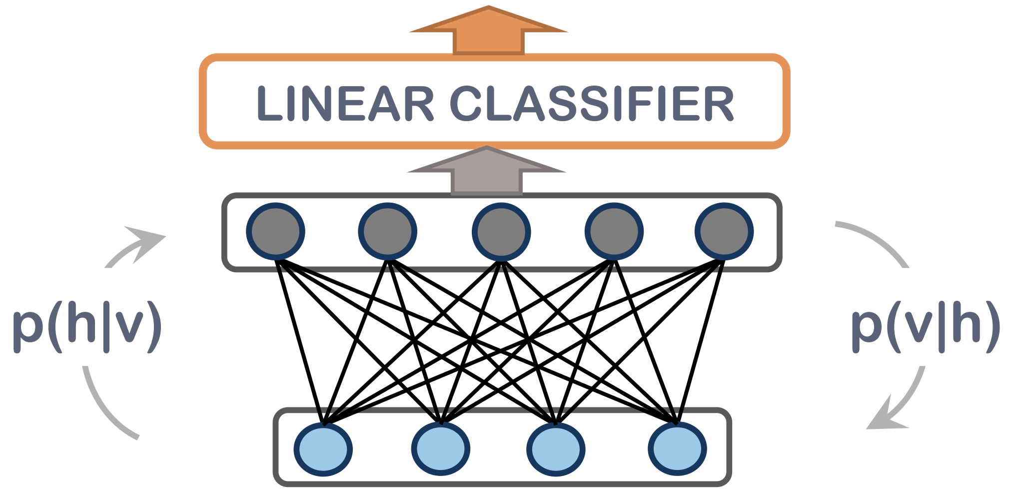
- A 4-degree polynomial provides a quite accurate approximation of the SSIM vs RSF curve

Possible video applications

- Knowledge of these characteristics of the video may be useful for
  - (i) QoE-aware admission/congestion control
  - (ii) determining popular content
  - (iii) inferring user behavioral characteristics

Proposed approach

Video recognition/classification/SSIM estimation

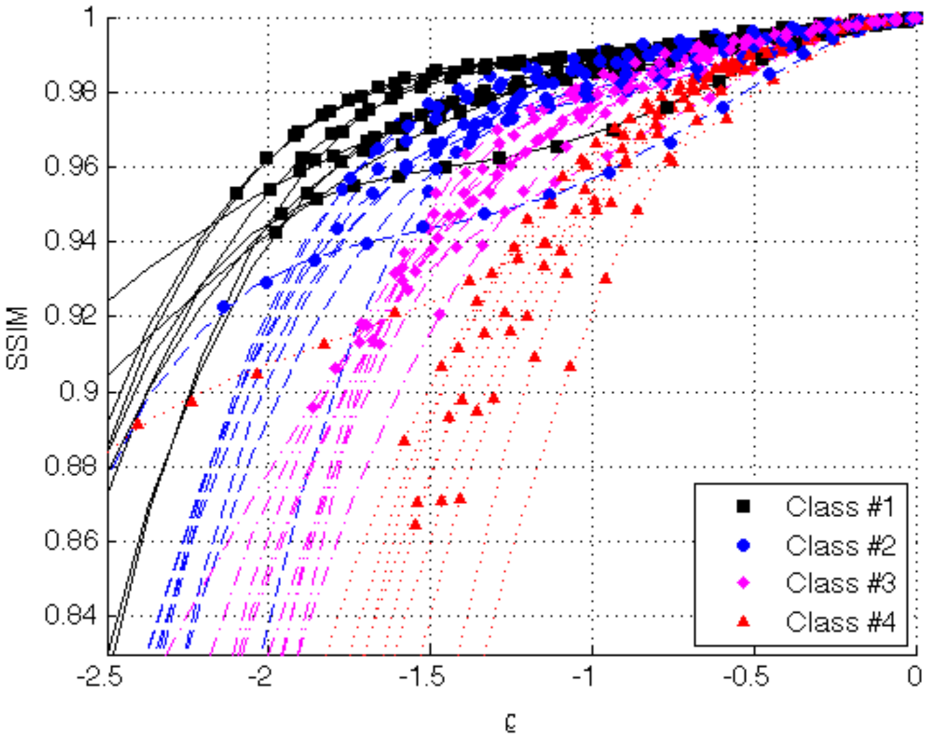


visible layer:
GoP frames' size

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

SSIM-based Video Classification



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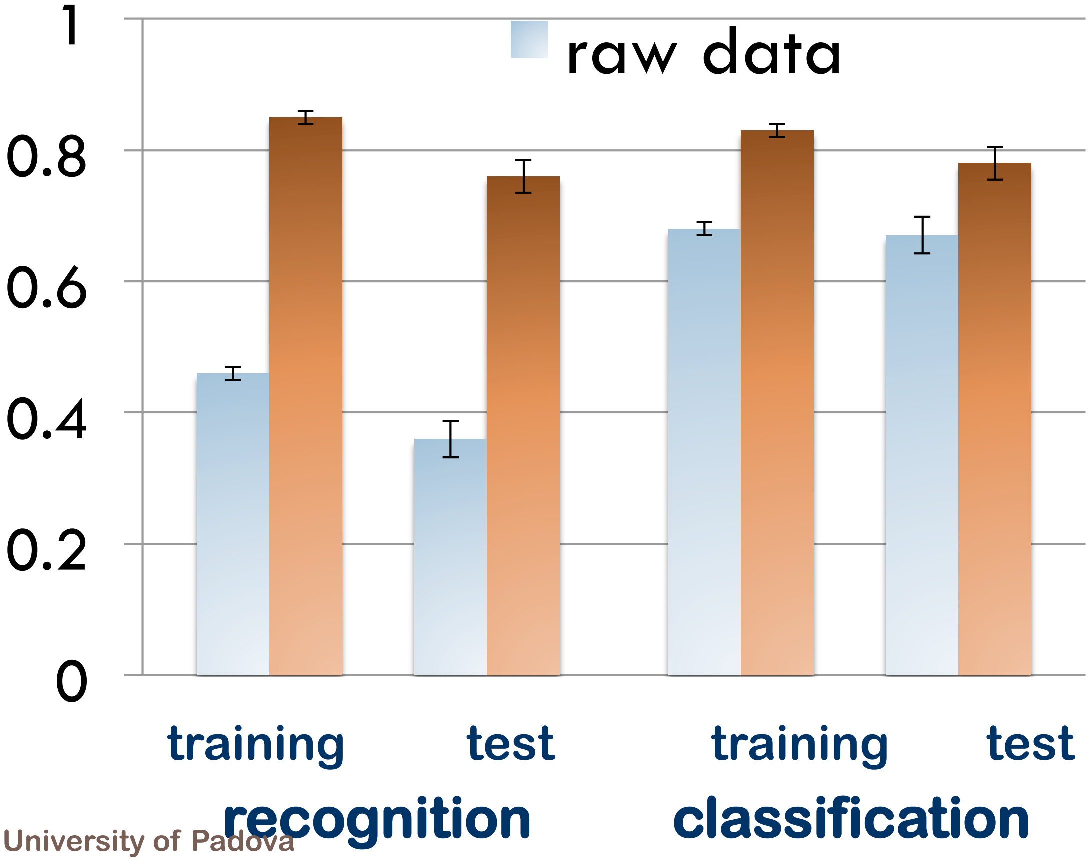
Setting the learning machine

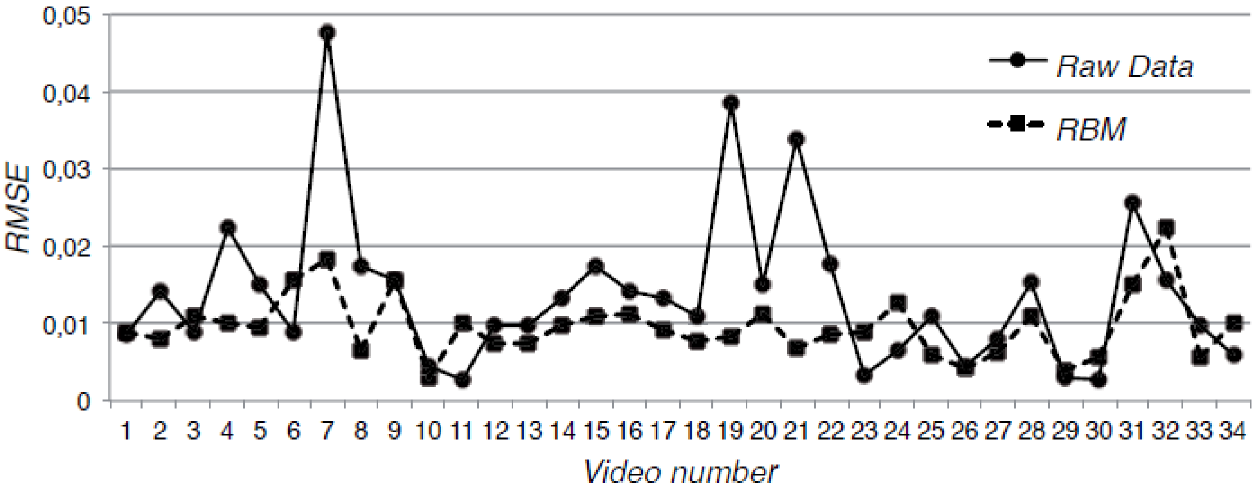
- Dataset is split: Training Set - Test Set
- Input of the RBM (visible layer): 32 units
  - for each of the 16 frames, size of the uncompressed version and of the version compressed at intermediate rate 9
- Hidden layer set (empirically) to 70 units
- The result is compared to just using the raw data as the input of the classifier

Preliminary results



Learning via RBM: accuracy

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



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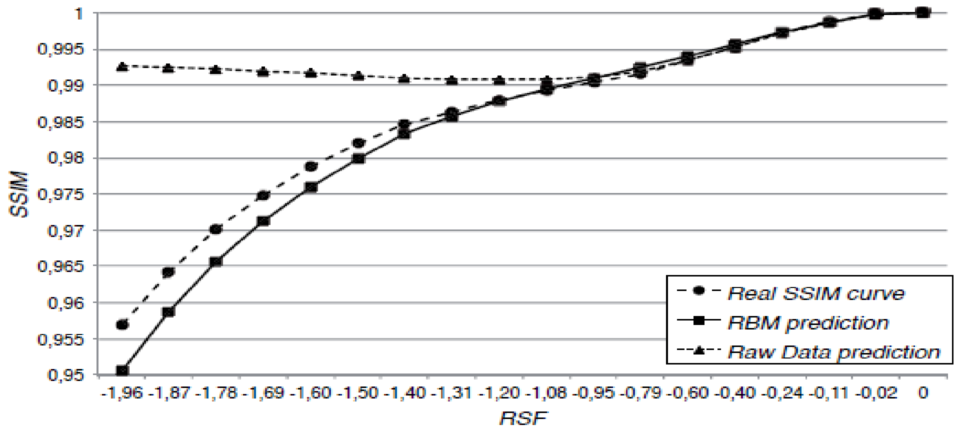
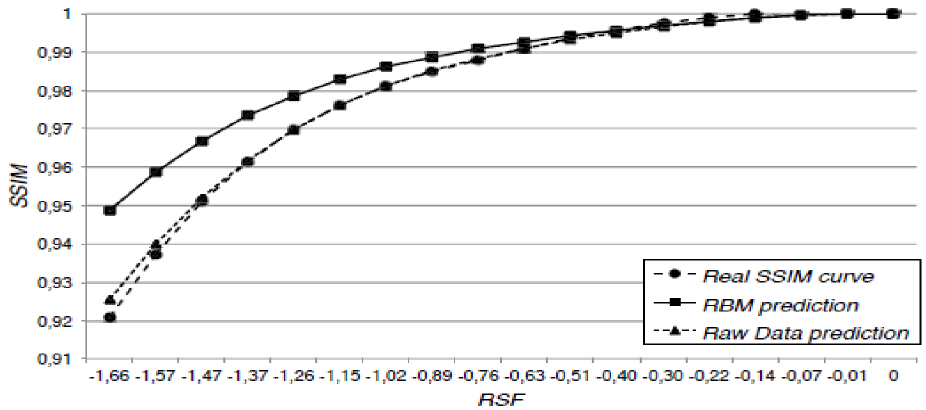
Exact vs. estimated SSIM curves for two random videos





CognitiveVideo 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*

Cognitive VAC

- At each new video flow request, VAC invokes RM to get the "best" resource allocation according to a specified policy
- RM returns the resource that can be assigned to each video
- VAC computes the SSIM of each video with the best compression level, compatible with the allotted resources
  - If estimated SSIM of all active videos is above the quality threshold the video request is accepted

Cognitive RM

- The optimization problem addressed by RM is as follows

Resource share allotted to video "v"

$$\Gamma_{\text{opt}} = \arg\max_{\Gamma} \overbrace{U(\Gamma, R, \{F_v\})}^{\text{Utility function}} \quad \text{s.t.} \quad \sum_{v} \gamma_v \leq 1$$

Rate allocation vector

Channel rate

SSIM videos' characteristics

Cognitive RM algorithms

Possible utility functions

Rate fairness (RF)

$$U(\Gamma, R, \{F_v\}) = \left[\sum_v \left|\log \frac{\gamma_v R}{r_v(1)}\right|\right]^{-1}$$

SSIM fairness (SF)

$$U(\Gamma, R, \{F_v\}) = \min_v F_v(\log(\gamma_v R / r_v(1)))$$

Resource share to be allotted:

RF:

$$\gamma_v = \frac{r_v(1)}{\sum_j r_j(1)}$$

SF:

$$\gamma_v = r_v(1) 10^{F_v^{-1}(\phi)}$$

where

$$\phi = \arg\max_\phi \left\{ \sum_v r_v(1) 10^{F_v^{-1}(\phi)} \leq R \right\}$$

Simulation setup

- Poisson video requests (0.66 req./s)
- average offered load of 11 videos
- Aggregate max rate of G = 161 Mbit/s
- F* = 0.95 SSIM value to reach MOS 4

SSIM	MOS	Quality	Impairment
≥ 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

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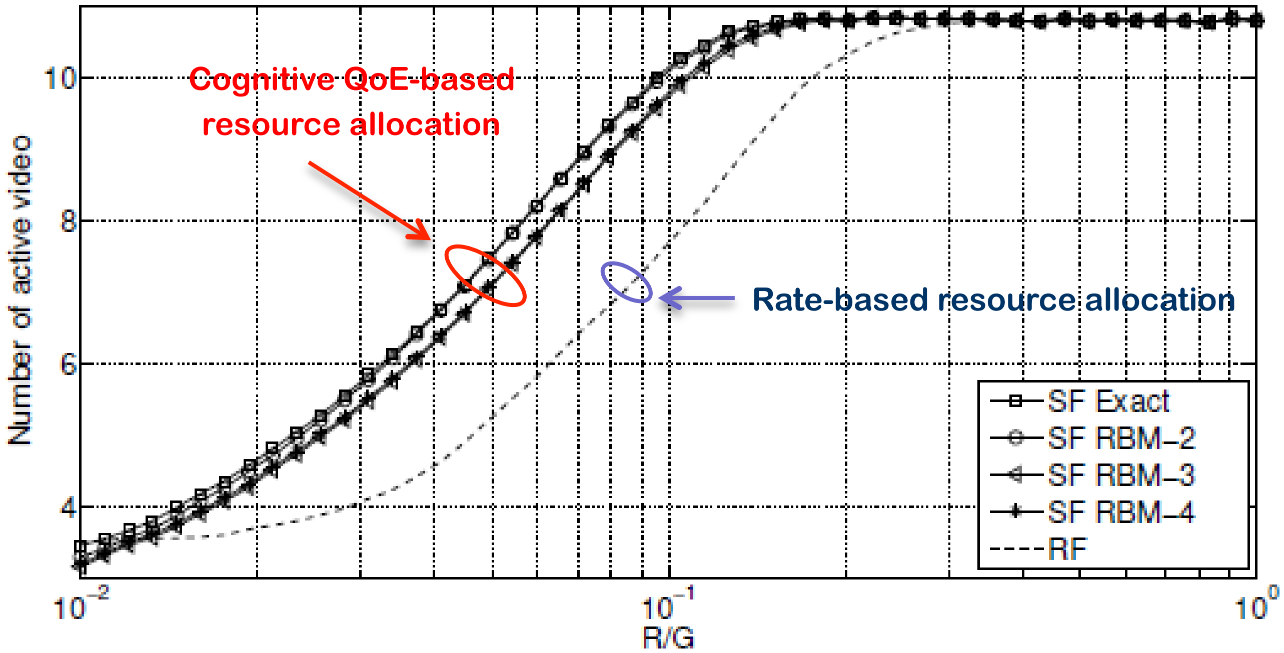
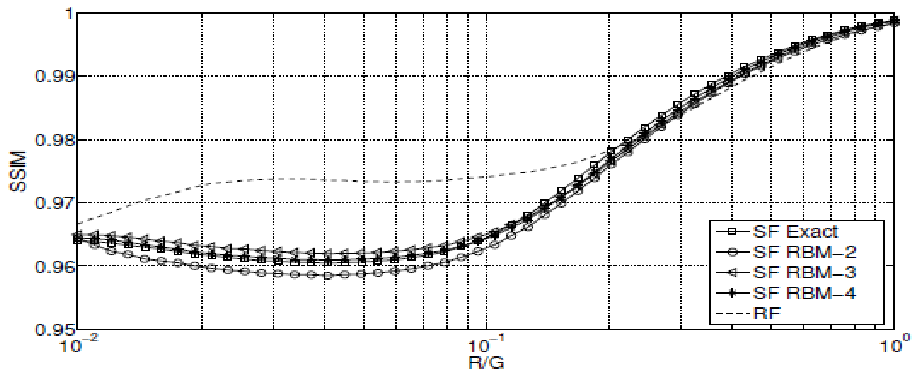
Cognitive video admission control

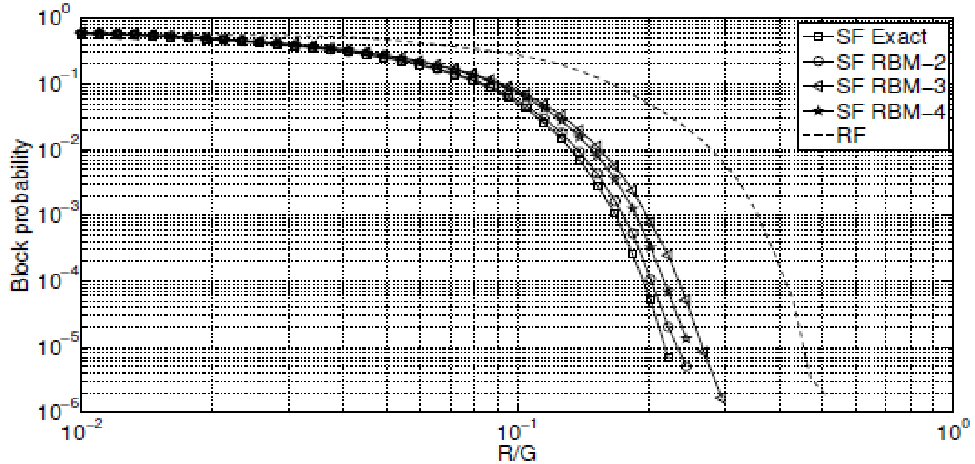


Link rate over aggregate full-quality video rate

Effect of SSIM approximation



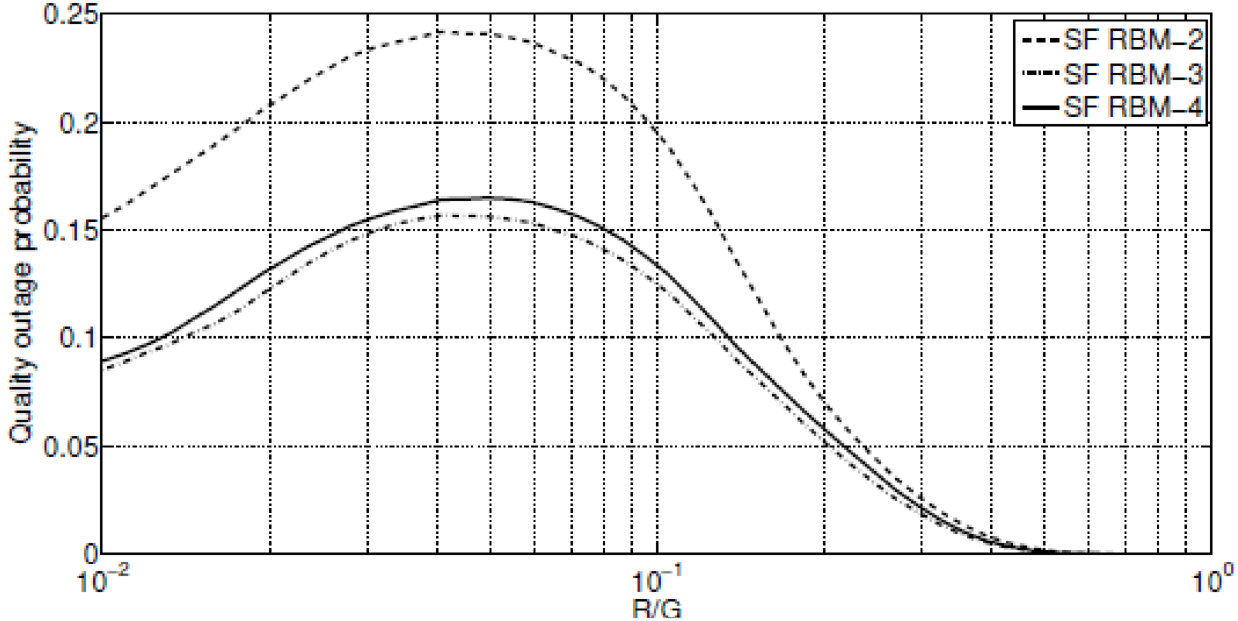
SF RBM-n: SF algorithm, with n-degree polyn. approx. of SSIM curve obtained by RBM approach



Quality outage probability

- Because of SSIM approximation errors, videos may occasionally be accepted even if quality threshold is not met
- Tradeoff on SSIM polynomial approximation: the fewer the coefficients, the coarser the approximation, but the better the RBM coefficient estimate
- Question: is it better to have a well-estimated low degree or a coarsely estimated high-degree polynomial?

Quality outage probability



- n=2 is too small, n=3 or 4 give very similar results: n=3 is the best choice in this case

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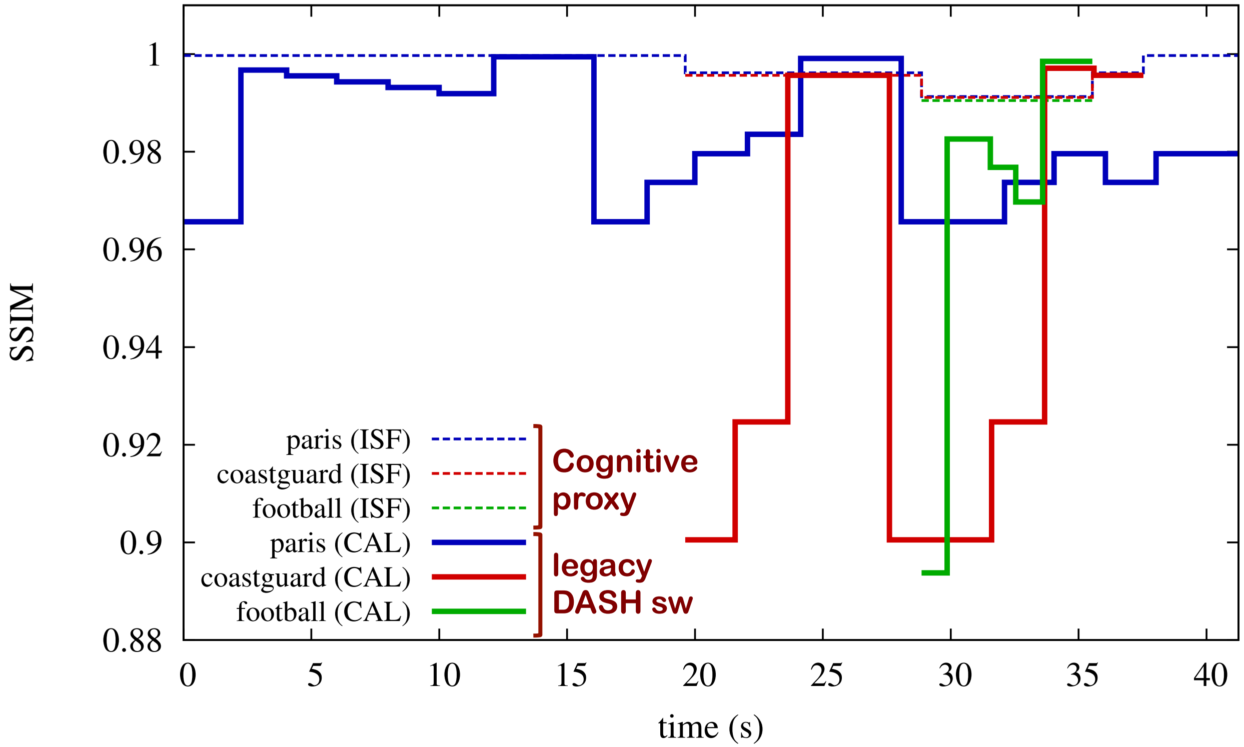
QoE-aware proxy vs legacy video clients



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Deep Reinforcement Learning for DASH Video Streaming

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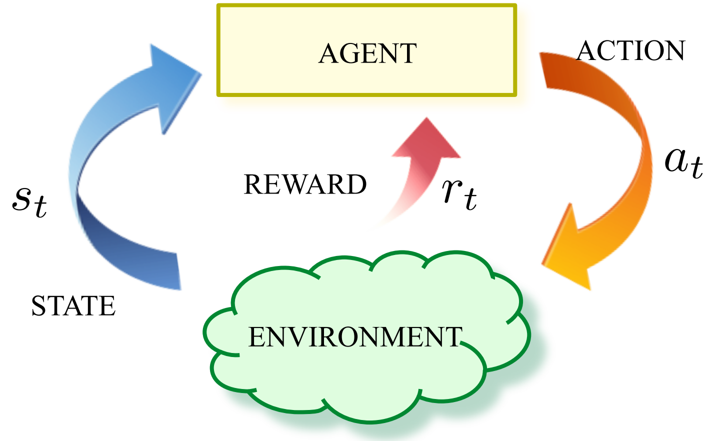
Reinforcement Learning



- At each step t the agent:
  - Receives state s_t
  - Receives reward r_t
  - Executes action a_t
- The environment:
  - Receives action a_t
  - Emits state s_t
  - Emits reward r_t

- **Policy** π is a behavior function selecting actions given states $a = \pi(s)$
- **Q-value function** $Q^\pi(s,a)$ is expected long-term reward from state s and action a under policy π

$$Q^\pi(s,a) = \mathbb{E}\left[r_{t+1} + \gamma r_{t+2} + \gamma^2 r_{t+3} + \ldots | s,a\right]$$

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Bellman equation

- Value iteration algorithm

$$Q_{i+1}(s,a) = \mathbb{E}_{s'}\left[r + \gamma \max_{a'} Q_i(s',a') \mid s,a\right]$$

$$i \rightarrow \infty$$

- Optimal value function

$$Q^*(s,a) = \mathbb{E}_{s'}\left[r + \gamma \max_{a'} Q^*(s',a') \mid s,a\right]$$

Can be approximated by a **deep** neural network?

Network weights

$$Q(s,a,\boldsymbol{\theta}) \approx Q^\pi(s,a)$$

- Objective function (minimized by Gradient Descent algorithms)

$$L(\boldsymbol{\theta}) = \mathbb{E}\left[\left(r + \gamma \max_{a'} Q(s',a',\boldsymbol{\theta}) - Q(s,a,\boldsymbol{\theta})\right)^2\right]$$

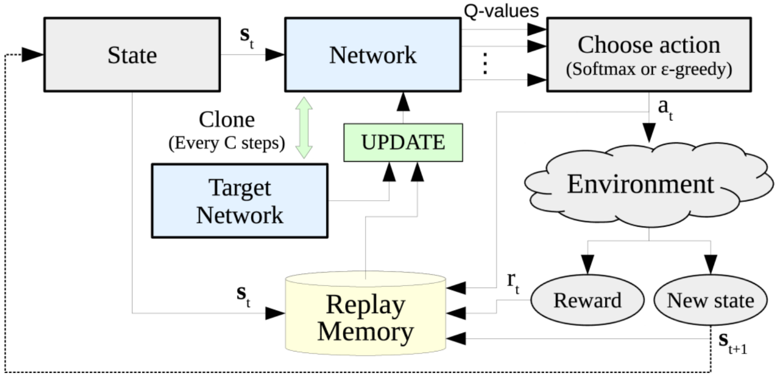
Deep Q-Learning

- Find optimal policy from experience:
  - Initially try with random policies
  - Reinforce actions that yield better rewards
  - Progressively move form exploration to exploitation

- Deep Q-learning
  - approximate action-value function Q(s,q) through a neural network

System architecture

- Experience Replay
  - Learn from past experience
  - Greater data efficiency
  - Less correlated training data
- Target Network
  - More stable training
  - Break correlation between target function and Q-network



$$L(\boldsymbol{\theta}) = \mathbb{E}_{(s,a,r,s')\sim U(R)} \left[\left(r + \gamma \max_{a'} Q(s', a', \boldsymbol{\theta}^T) - Q(s, a, \boldsymbol{\theta}) \right)^2 \right]$$

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DASH-DQN

- State

$$s_t = [q_{t-1}, \boldsymbol{C}_t, D_t, B_t]$$

  - Buffer size
  - Video segment complexity
  - Channel capacity vector
  - Previous quality

- Quality of Experience (QoE)

Freezing time

$$r(q_t, q_{t-1}, f_t) = q_t - \beta \| q_t - q_{t-1} \| - \lambda f_t$$

- Structural SIMilarity (SSIM) index
- 8 Segment Qualities (Possible Actions)

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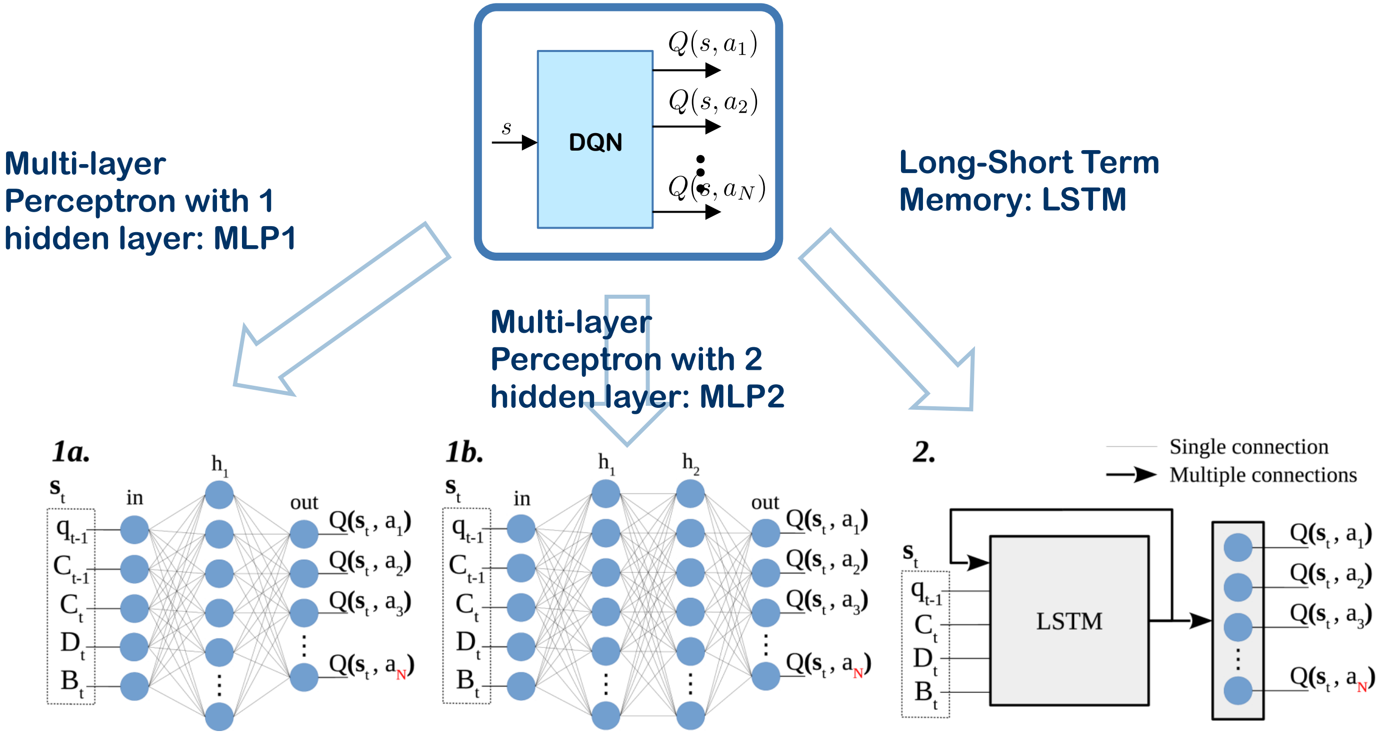
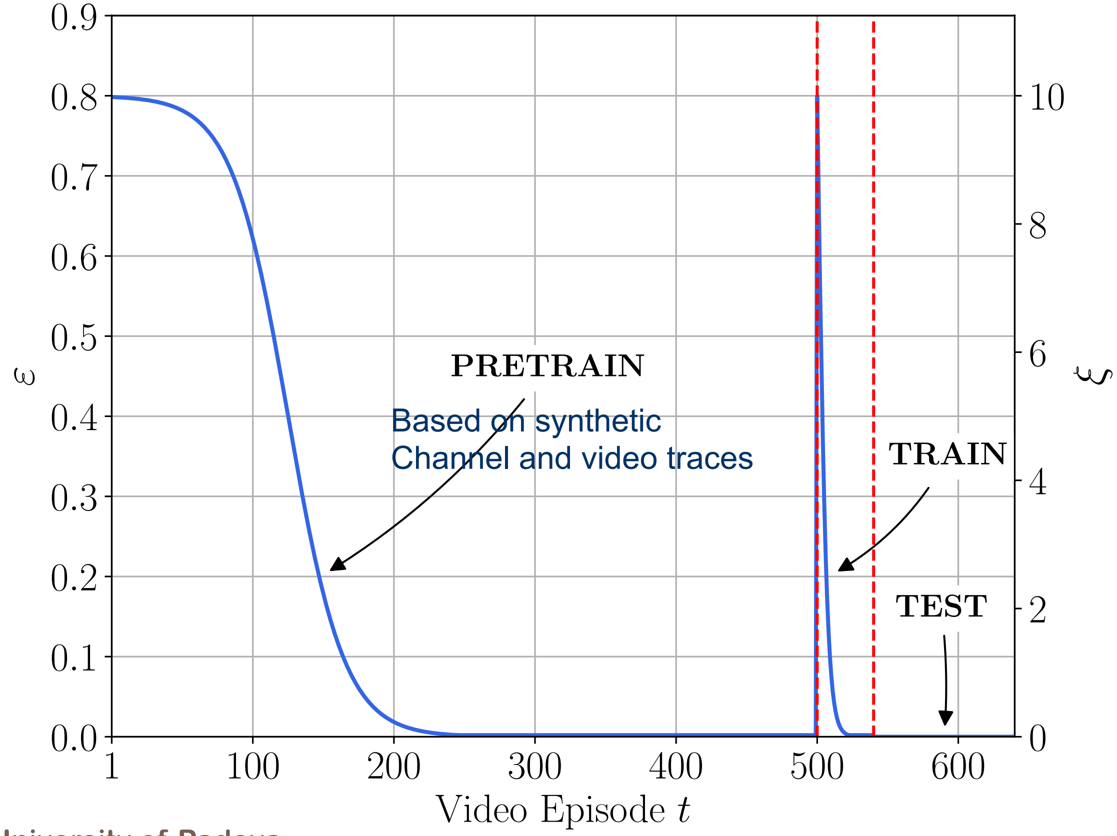
Deep Q-Network (DQN)



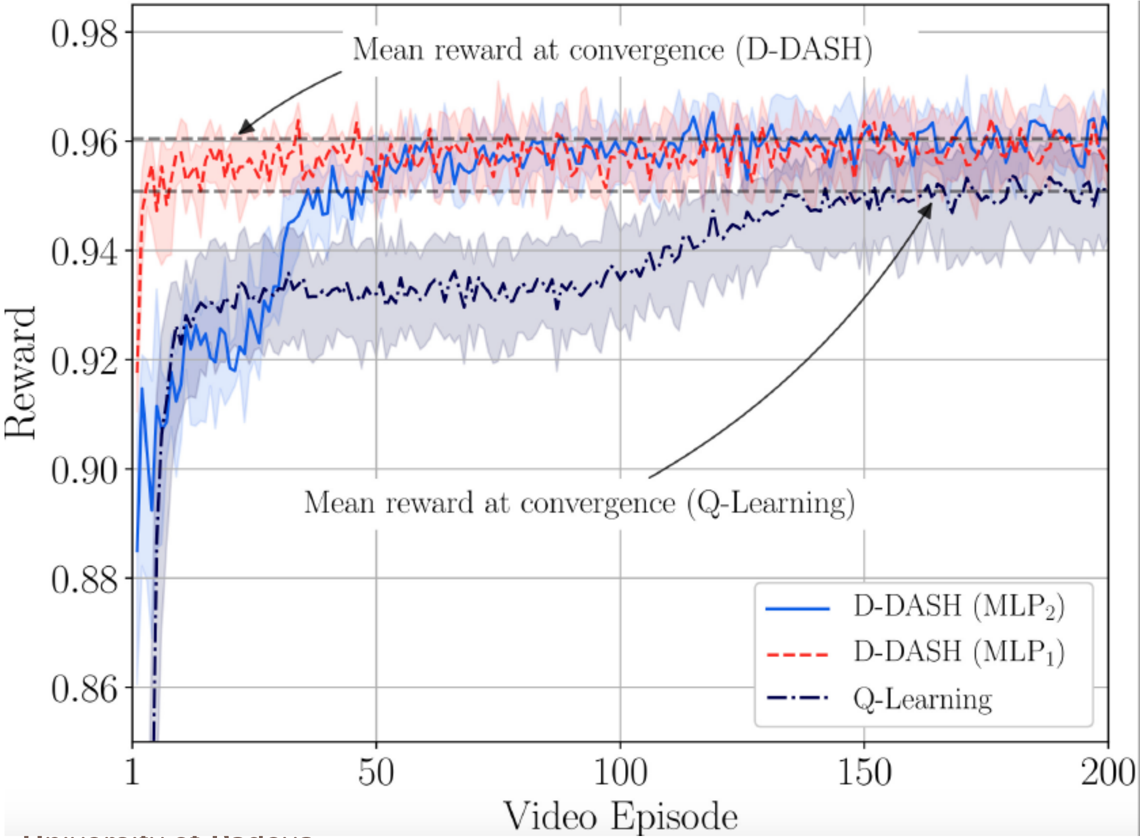
Simulation

- Video model: 5 complexities, exponential scene duration
- Capacity model
  - Markov - 500 pre-training videos
  - Real - 40 training videos + 100 test videos
  - NS3 - 40 training videos + 100 test videos
- Comparison
  - Rate-based
  - FESTIVE
  - Q-Learning

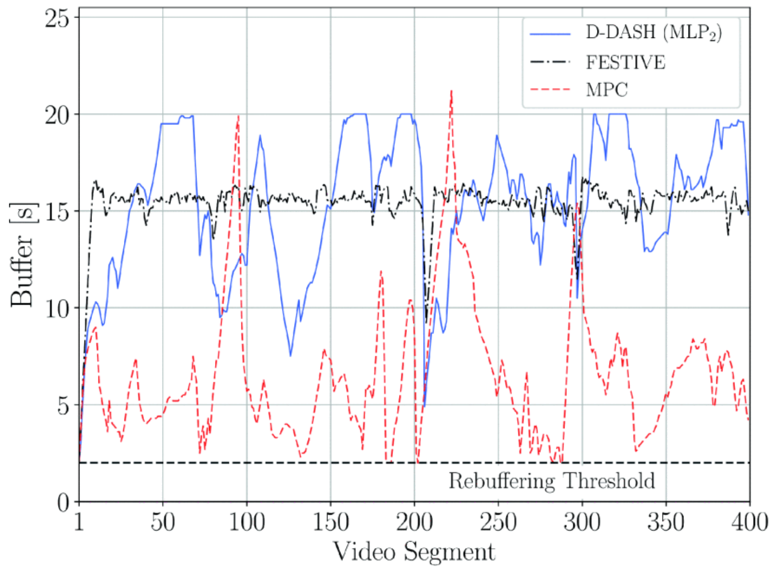
Exploration/training/test



Convergence time



Buffer



- D-Dash fully exploits the buffer to survive connection fluctuations while keeping constant video quality
- Legacy DASH clients try to keep buffer level constant, adapting video quality (worse QoE)

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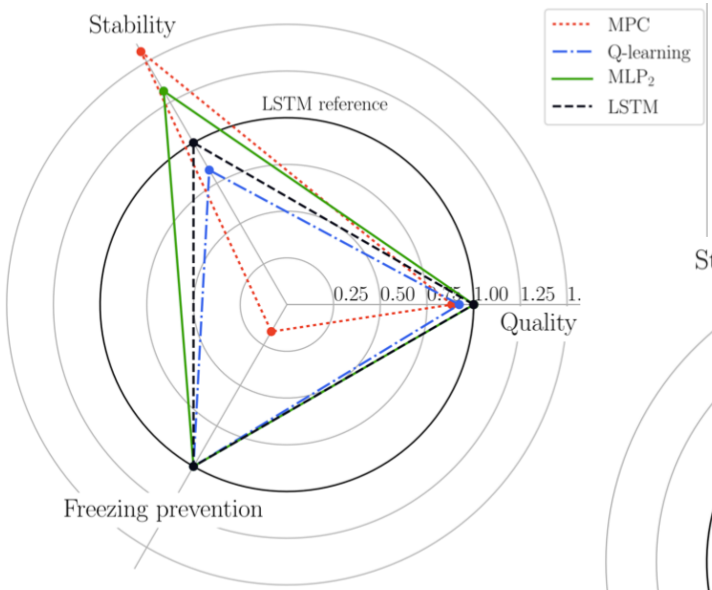
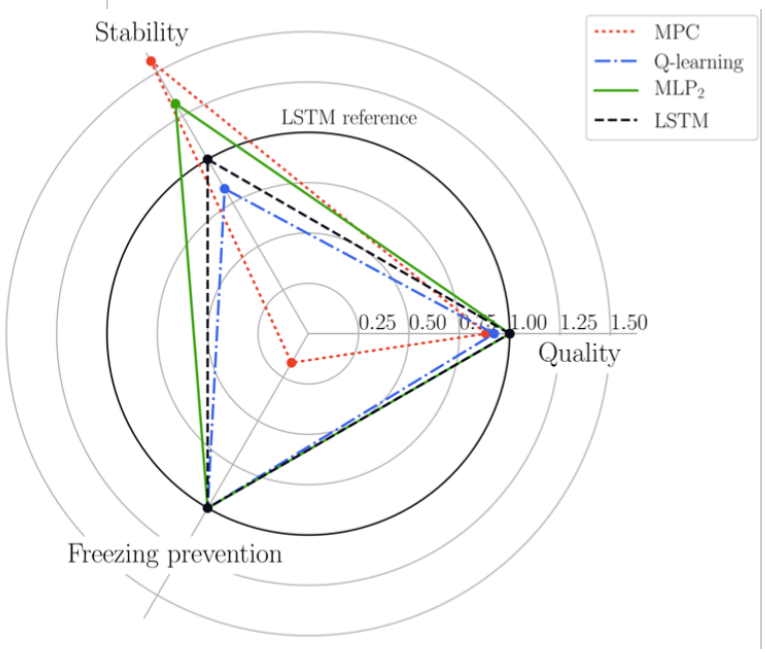
Comparison



Synthetic traces

Real traces



Conclusions

- Optimizing resource allocation for video transmission is challenging
  - many numerical parameters involved
  - subjective QoE issues
  - high signaling exchange
- Learning-based approaches are useful to
  - obtain a compact representation
  - extrapolate the most significant data
  - Provide a framework with no need for prior models

Publications

- 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

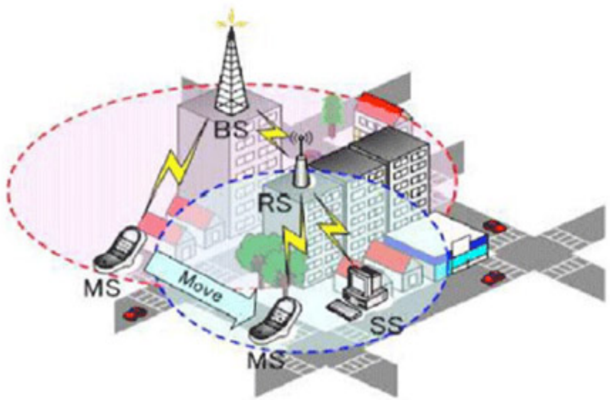
- Alberto Testolin, Marco Zanforlin, Michele De Filippo De Grazia, Daniele Munaretto, Andrea Zanella, Marco Zorzi, Michele Zorzi, "A Machine Learning Approach to QoE-based Video Admission Control and Resource Allocation in Wireless Systems" in the Proceedings of IEEE IFIP Annual Mediterranean Ad Hoc 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.

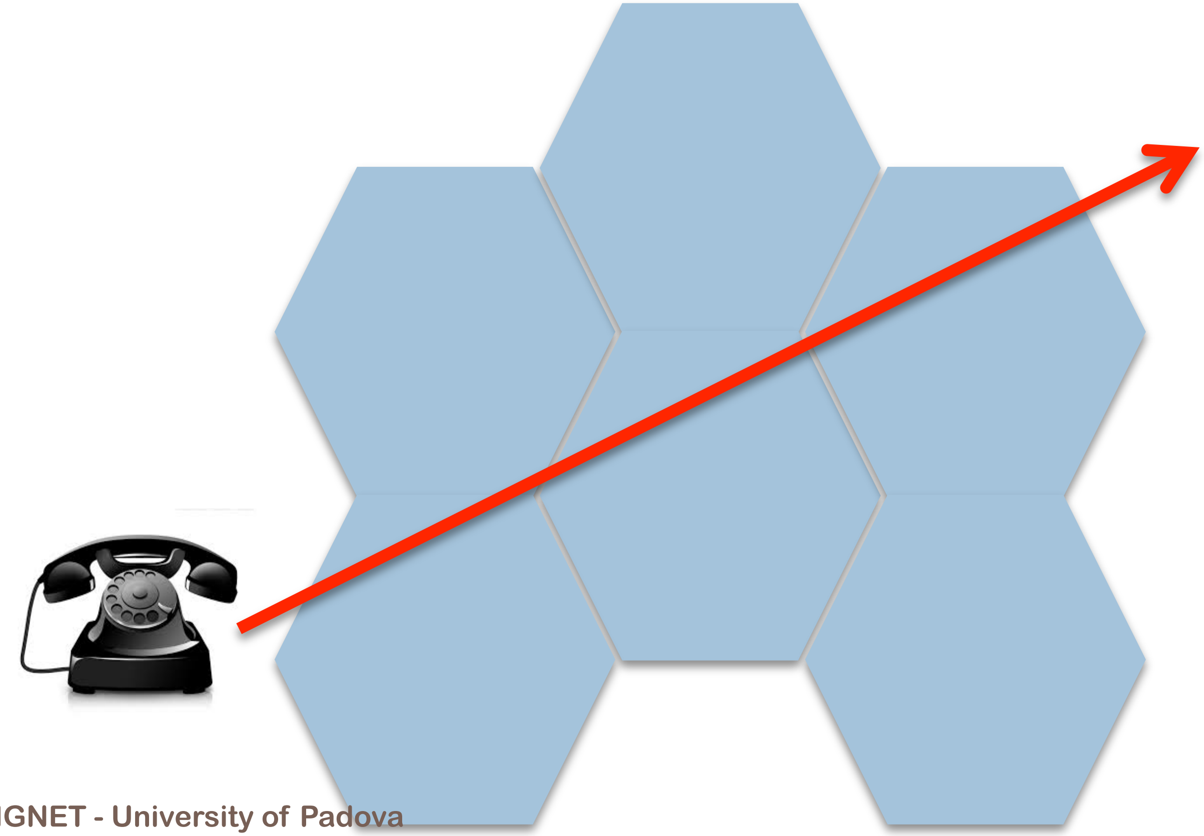
- Marco Zanforlin, Daniele Munaretto, Andrea Zanella, Michele Zorzi, "SSIM-based video admission control and resource allocation algorithms" in the Proceedings of WiOpt workshop WiVid'14, May 12-16, 2014, Hammamet, Tunisia.

Handover process

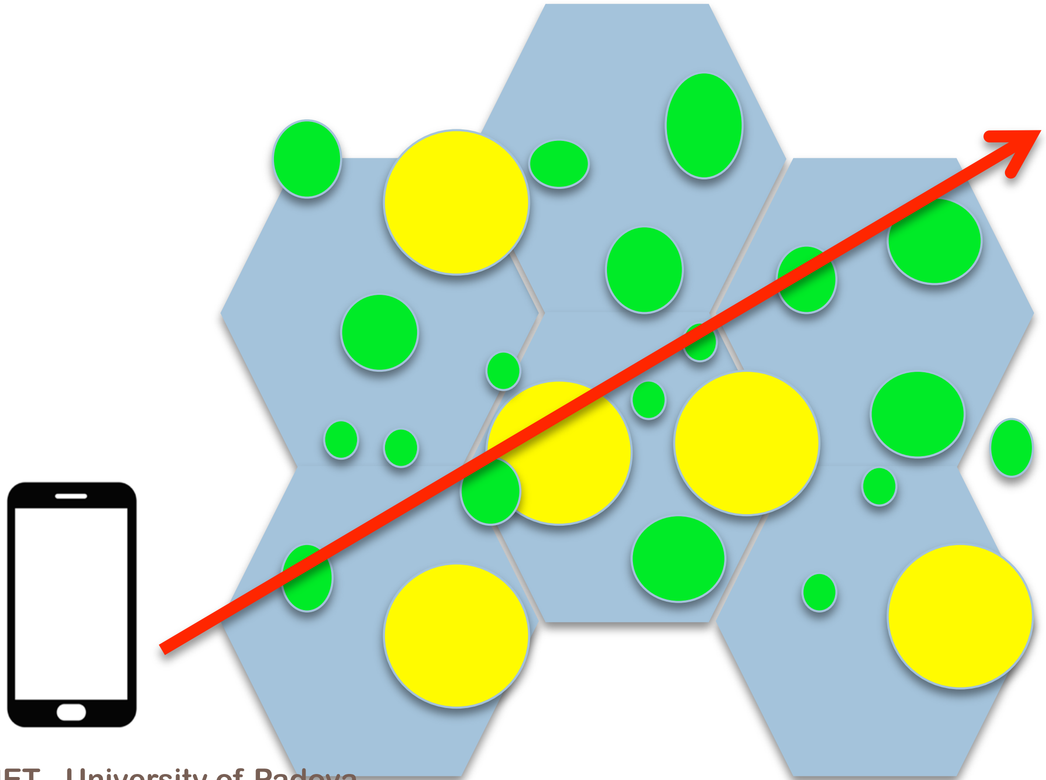
- In cellular telephone systems, the term **handover** refers to the process of keeping a mobile active user connected to the BS that offers the strongest radio signal



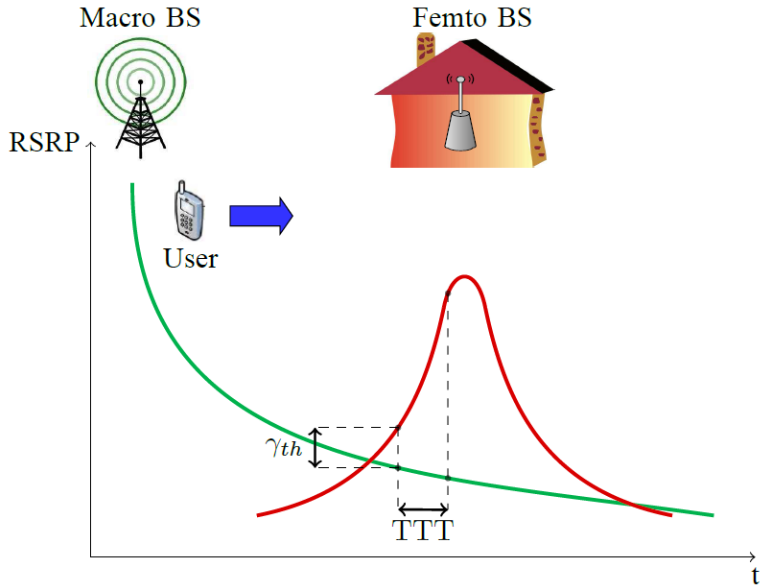
Traditional Cellular network



Heterogeneous Networks



Standard 3GPP Handover Procedure



Long **TTT** → Handover Failure

Short **TTT** → Ping-Pong

Objective

- Develop context-aware cognitive handover strategies to maximize the performance of each single mobile user and of the system as a whole in a HetNets scenario

Steps

① Develop a theoretical model that describes the evolution of the UE state along its trajectory by means of a non homogeneous Markov Chain

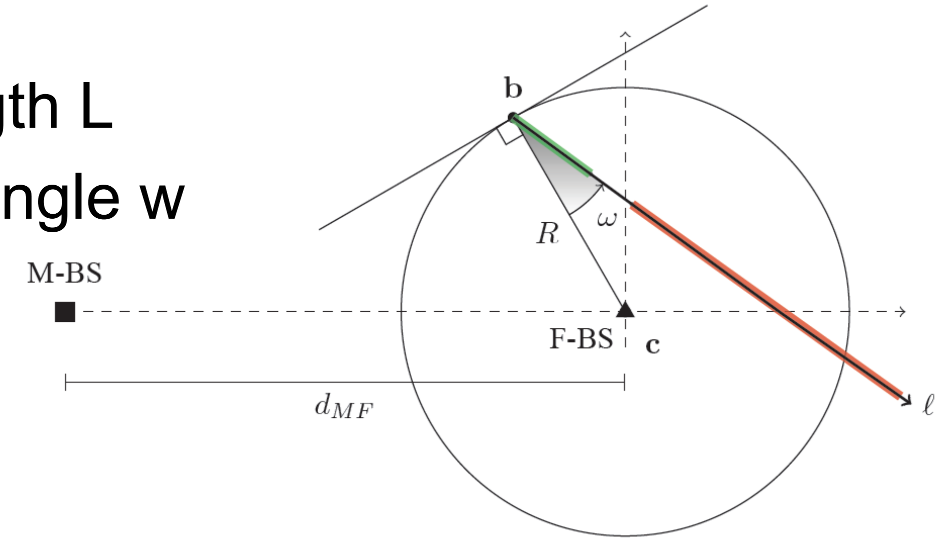
② Express the average UE performance as a function of the context parameters

③ Derive a context-aware HO policy (CAHP) that selects the best HO strategy for a UE approaching a femtocell

④ Develop cognitive mechanisms to infer context parameters [still in progress]

System Model

- 1 Master (M-BS) and 1 Femto Base Stations (F-BS), placed at distance dMF
- Femtocell coverage area as a circle of radius R
- UE constant speed
- Straight path of length L
- Uniform incidence angle w



Propagation & handover models

- RSRP from the h-BS: $\Gamma_h(\mathbf{a},t) = \Gamma_h^{tx}\, g_h(\mathbf{a})\, \alpha_h(t) \qquad h \in \{M, F\}$
- where

  Γ_h^{tx} : h-BS transmit power

  $g_h(\mathbf{a})$: Pathloss gain

  $\alpha_h(t)$: Fast-fading channel gain

- Handover model

  T : Time-To-Trigger

  T_H : Time for Handover signaling and BS switching

  γ_{th} : SINR threshold to trigger handover

Average UE capacity

Sampling at time Tc > channel coherence time → independent fading samples → average Shannon capacity experienced by UE along the trajectory is

$$\bar{\mathcal{C}}_L = \frac{1}{\pi}\int_{-\pi/2}^{\pi/2} \frac{1}{N_L}\sum_{k=1}^{N_L} \sum_{S\in\{M,F,H\}} \bar{C}_S(\mathbf{a}_k(\omega))\mathrm{P}_S[\mathbf{a}_k(\omega)]\,\mathrm{d}\omega$$

where

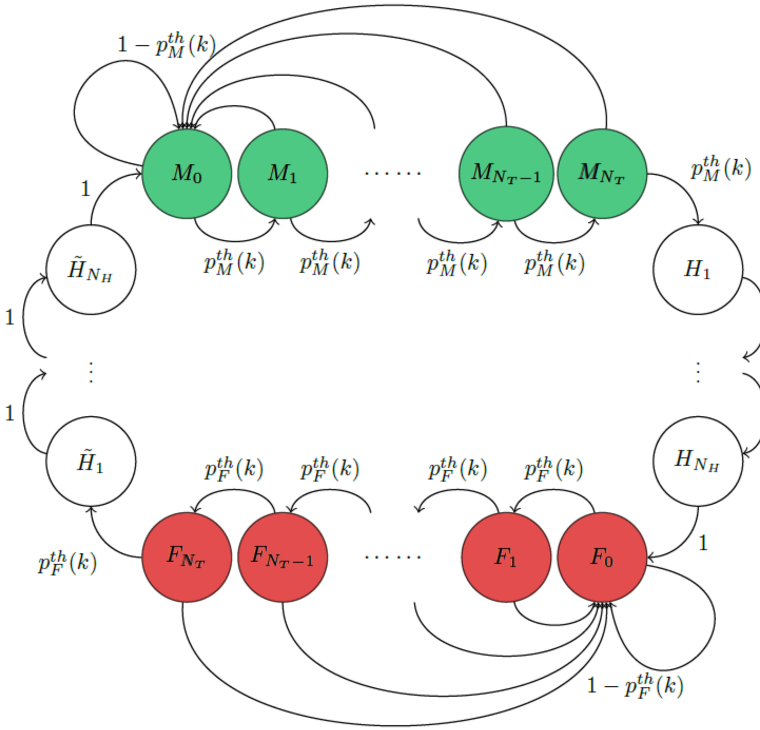
$$\bar{C}_S(\mathbf{a}_k(\omega)) = \mathbb{E}\left[\log_2\left(1+\gamma_S(\mathbf{a}_k, kT_c)\right)\right] = \log_2\left(\bar{\gamma}_S(\mathbf{a}_k)\right)\frac{\bar{\gamma}_S(\mathbf{a}_k)}{\bar{\gamma}_S(\mathbf{a}_k)-1}$$

$$\bar{C}_H(\mathbf{a}_k(\omega)) = 0 \qquad\qquad S\in\{M,F\}$$

Average SINR:

$$\bar{\gamma}_M(\mathbf{a}_k) = \frac{\Gamma_M^{tx}\, g_M(\mathbf{a}_k)}{\Gamma_F^{tx}\, g_F(\mathbf{a}_k)} \qquad \bar{\gamma}_F(\mathbf{a}_k) = \frac{1}{\bar{\gamma}_M(\mathbf{a}_k)}$$

UE's state: non homogeneous Markov Chain



M_j : connected to the M-BS

F_j : connected to the F-BS

H_j : switching from M-BS to F-BS

$\tilde{H}_j$: switching from F-BS to M-BS

Solving the MC

Transition probabilities

$$p_M^{th}(k) = \mathrm{P}\left[\gamma_M(\mathbf{a}_k, kT_c) < \gamma_{th}\right] = \frac{\gamma_{th}}{\gamma_{th} + \bar{\gamma}_M(\mathbf{a}_k)}$$

$$p_F^{th}(k) = \mathrm{P}\left[\gamma_F(\mathbf{a}_k, kT_c) < \gamma_{th}\right] = \frac{\gamma_{th}}{\gamma_{th} + \bar{\gamma}_F(\mathbf{a}_k)}$$

Transition matrix

$$\mathbf{P}(k) = \begin{bmatrix} \mathbf{M}(k) & \mathbf{V}_M^H(k) & \varnothing & \varnothing \\ \varnothing & \mathbf{H}(k) & \mathbf{V}_H^F(k) & \varnothing \\ \varnothing & \varnothing & \mathbf{F}(k) & \mathbf{V}_F^{\tilde{H}}(k) \\ \mathbf{V}_{\tilde{H}}^M(k) & \varnothing & \varnothing & \tilde{\mathbf{H}}(k) \end{bmatrix}$$

State probability vector

$$\mathbf{p}(k) = \mathbf{p}(0)\prod_{i=0}^{k-1}\mathbf{P}(i) \qquad \mathbf{p}(0) = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix}$$

UE state probabilities

$$\mathrm{P}_S[\mathbf{a}_k(\omega)] = \sum_{i\in\{S_j\}} p_i(k) \qquad \textbf{with} \qquad S \in \{M, F, H \cup \tilde{H}\}$$

Accounting for cell load

- HO policy maximizes UE's estimated average capacity neglecting cells traffic load

- Assuming pilot signals include indication about cell traffic load, we define the load-**scaled average capacity** of UE in state S as

$$\bar{C}_S^{load}(\mathbf{a}_k) = \lambda_S \bar{C}_S(\mathbf{a}_k) = \lambda_S \log_2(\bar{\gamma}_S(\mathbf{a}_k)) \frac{\bar{\gamma}_S(\mathbf{a}_k)}{\bar{\gamma}_S(\mathbf{a}_k) - 1}$$

Fraction of available resources of *S*-BS

Load-aware HO policy

- Keep standard SINR-based HO mechanism
- Set Cell Individual Offset λ_S such that relative performance gain is constant:

$$\frac{\bar{C}_M(\mathbf{a}_k^*)}{\bar{C}_F(\mathbf{a}_k^*)} = \frac{\bar{C}_M^{load}(\mathbf{a}_k^*)}{\bar{C}_F^{load}(\mathbf{a}_k^*)}$$

$$\gamma_{th}^{M,load} = \gamma_{th}^{M}\frac{\lambda_F}{\lambda_M} \qquad \gamma_{th}^{F,load} = \gamma_{th}^{F}\frac{\lambda_M}{\lambda_F}$$

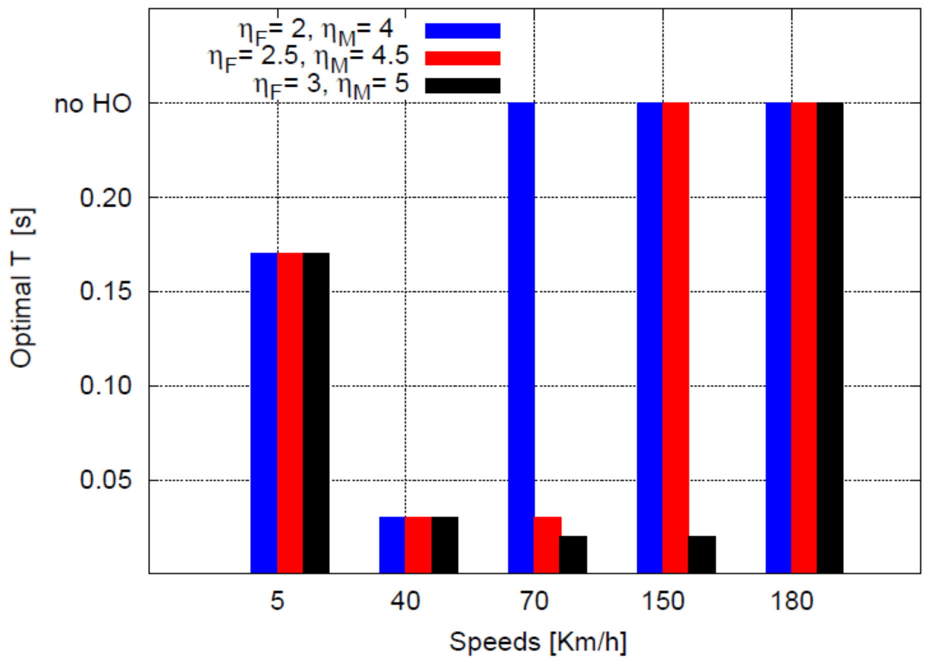
Simulation parameters

Parameter	Value
M-BS/F-BS Transmit Power	46 dBm/24 dBm
Distance between BSs	500 m
Macro/Femto Pathloss exponent	4.5/2.5
Fading	Rayleigh distribution
Handover execution time	200 ms
SINR threshold	0 dB

Algorithms

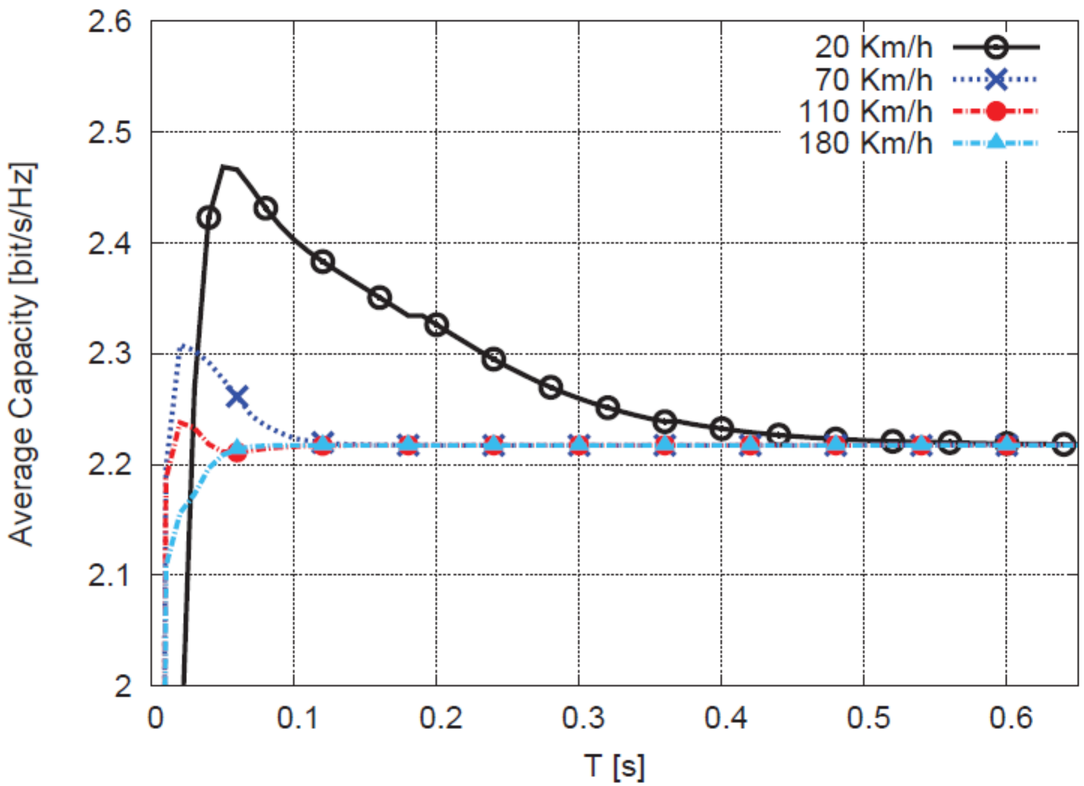
- **CAHP**: Context-Aware Handover Policy:
  - For a certain scenario, and according to the UE speed, it either selects the value of the Time-To-Trigger that gives the maximum average capacity or avoids the HO procedure
- **FIX**: Fixed Time-To-Trigger Policy:
  - A static value T of TTT is used
    - 100 ms, 256 ms, 512 ms

Optimal TTT values



Optimal T values obtained for different speeds and scenarios according to CAHP approach

Analytical average capacity



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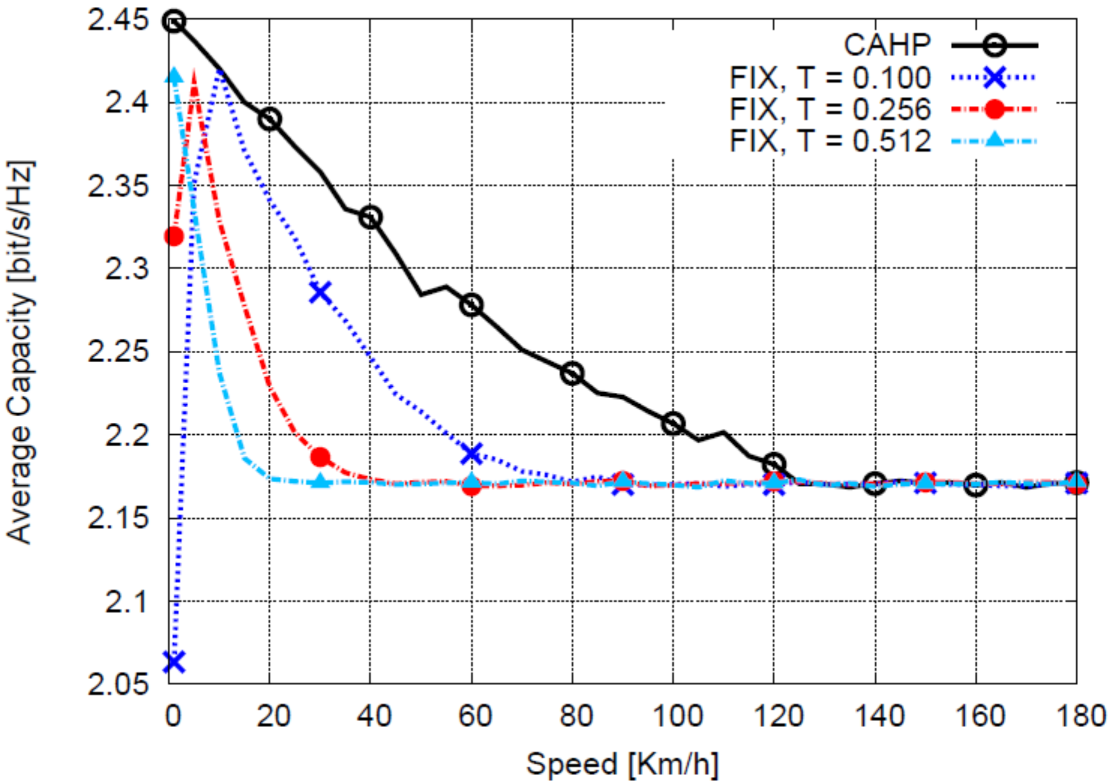
Average capacity with different HO policies



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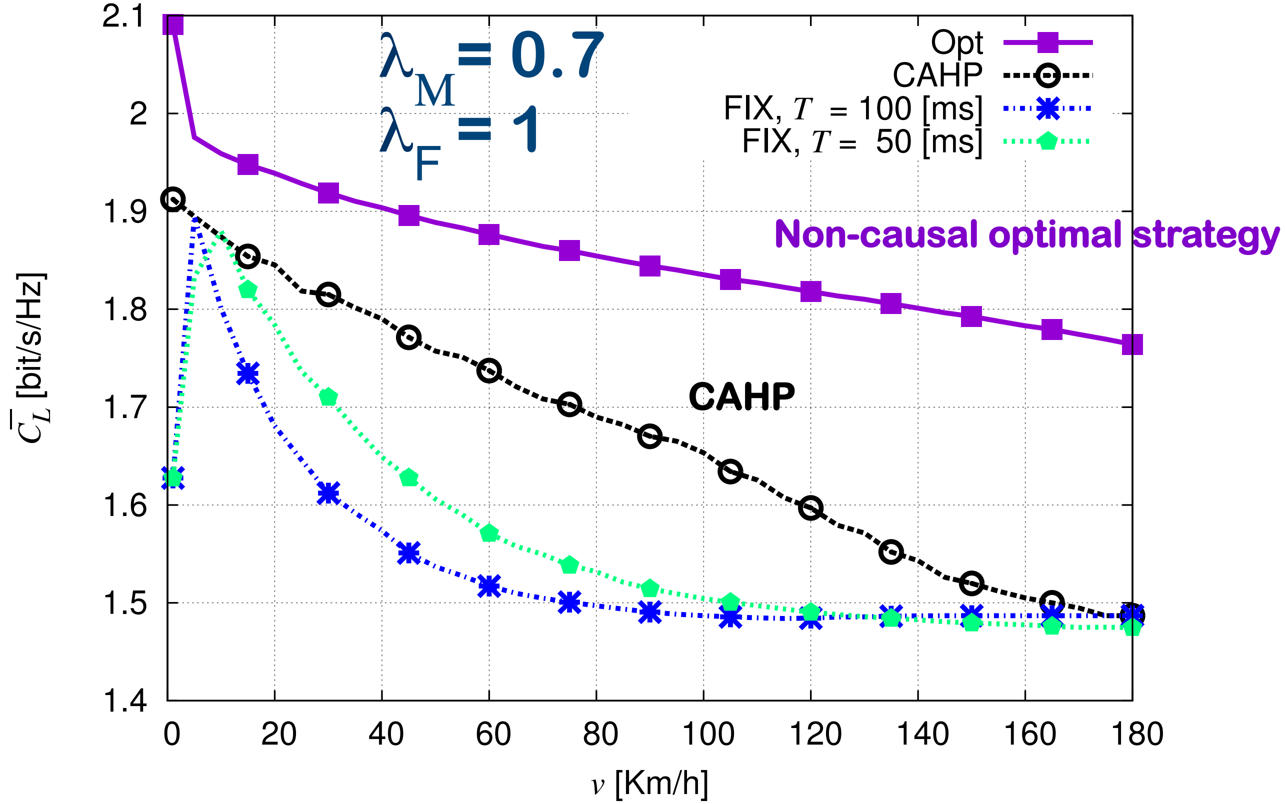
Average capacity



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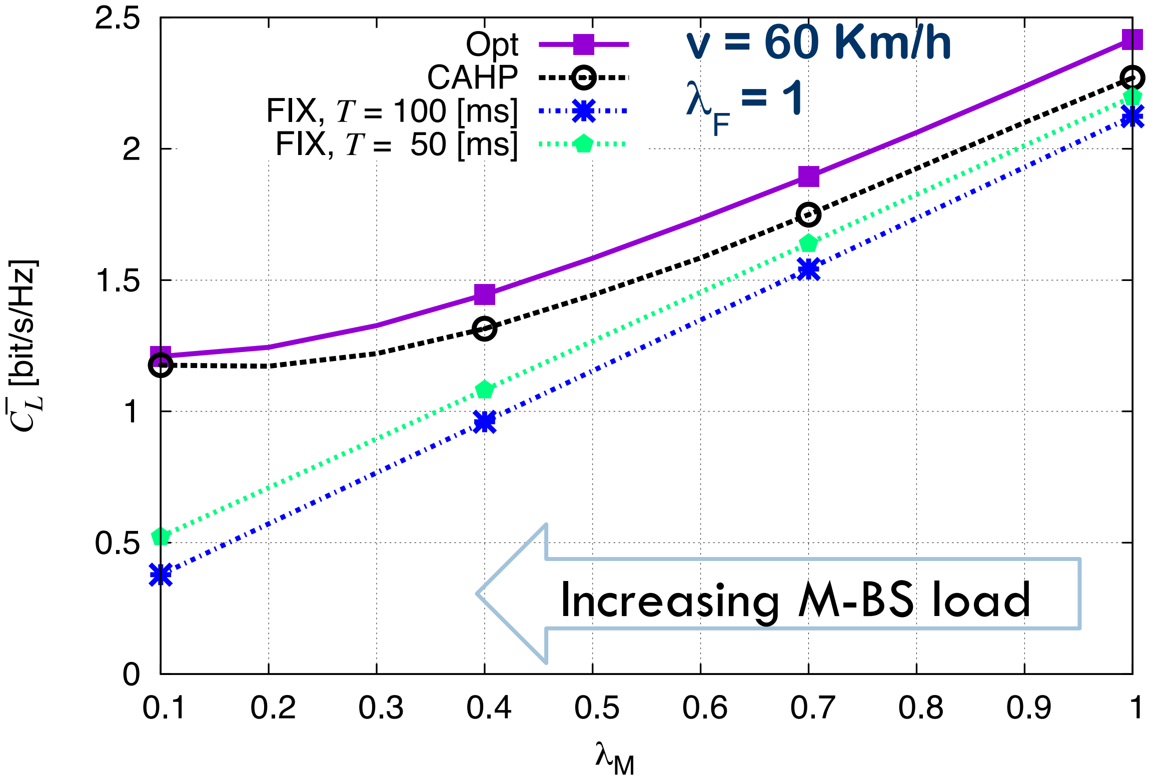
Average capacity

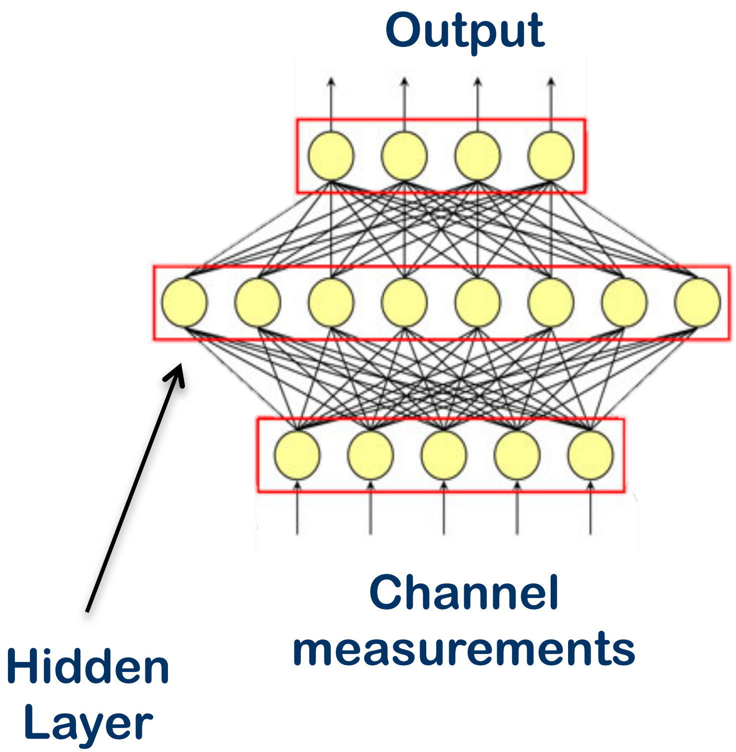


Conclusions

- In heterogeneous cellular scenarios, a context-aware Handover policy is beneficial for UEs with respect to conventional Handover management techniques
- Our optimal context-dependent Handover criterion is based on a solid mathematical analysis and validated by means of simulations
- Future work:
  - SINR threshold parameter optimization
  - More complex scenarios (multiple BSs and UEs)
  - Machine-learning context estimator

Future work: Neural Networks

- Parameter estimation:
  - UE speed v
  - Pathloss exponents
  - Transmit power
  - Distance M-BS - F-BS
- Prediction:
  - Handover? Yes/No



Publications

- Francesco Guidolin, Irene Pappalardo, Andrea Zanella, Michele Zorzi , "Context-Aware Handover in HetNets" in the Proceedings of the European Conference on Networks and Communications 2014, June 23/26, 2014, Bologna, Italy. **[Best paper Award]**

- Francesco Guidolin, Irene Pappalardo, Andrea Zanella, Michele Zorzi, "A Markov-based Framework for Handover Optimization in HetNet" in the Proceedings of IEEE IFIP Annual Mediterranean Ad Hoc Networking Workshop, Med-Hoc-Net 2014, June 2-4, 2014, Piran, Slovenia

Conclusions

- We have discussed the concept of cognition-based networking:
  - Holistic approach (network-wide, end-to-end, cross-layer)
  - Using the most advanced understanding drawn from cognitive science
  - Machine learning a key ingredient
- Most of the current approaches are too limited and do not address the essence of cognition
- Initial examples show the potential gains
- Although we have been hearing about cognitive radio and networks for years, now it's time to do it

Thanks to our sponsors

- Several agencies have funded our work in this area, including
  - The European Commission (ARAGON project)
  - The US Army Research Office (ARO)
  - The CaRiPaRo Foundation in Padova

A new venue for cognet research

- COMSOC has just started a new journal
- IEEE Transactions on Cognitive Communications and Networks
  - Started as a JSAC series by Y.C. Liang
  - Now greatly expanded in scope
- I am Associate Editor, and my colleagues Prof. Michele Zorzi is the EiC of TCCN
- Senior advisors: Simon Haykin and Joe Mitola
- We have started accepting submissions Jan 21, 2015
- Inaugural issue Sep. 2015

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