

Towards spatial reuse in future WLANs: a sequential learning approach



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Barcelona, 7 October 2020

Spatial Reuse
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ML in Communications
ooooo

Method. & Enablers
oooo

Findings
oooo

Conclusions
o

Motivation and scope

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Problem

- Popularity of WLANs
 - unlicensed, ready-to-deploy
- Bottleneck in performance
 - density, requirements, decentralization, coexistence

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- Improve spectral efficiency
- Spatial Reuse (SR)

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Aim of this thesis

- Machine Learning (ML) approach
- Worthiness of decentralization

Spatial Reuse
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ML in Communications
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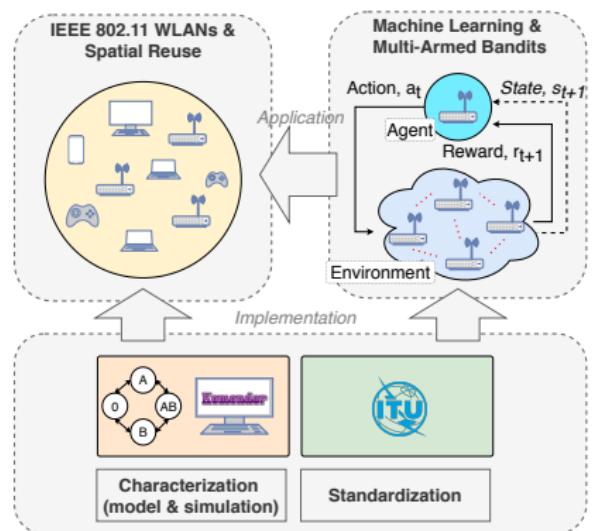
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Summary of contributions

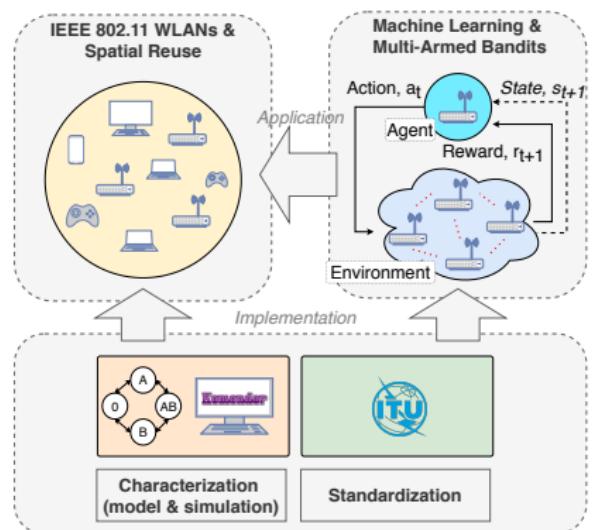
Summary of contributions



① In-depth study of IEEE 802.11ax SR technology

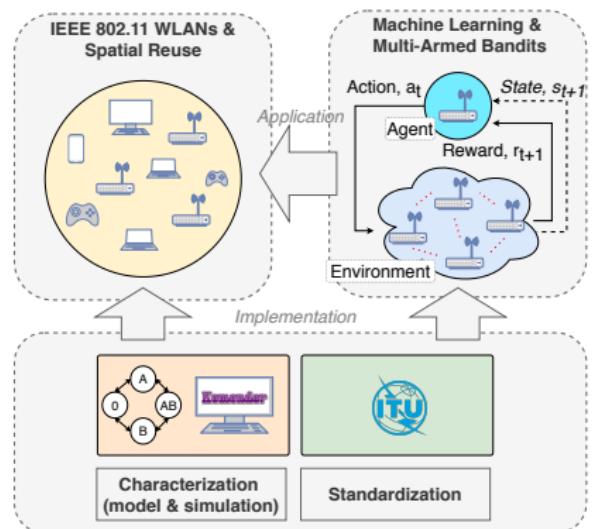
- Tutorial
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 - Suitability in decentralized WLANs
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- ③ Practical aspects for adopting ML in communications
 - Architectural considerations
 - Reliability on AI/ML

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- ① Spatial Reuse
- ② Machine Learning for Spatial Reuse
- ③ Methodology and Enablers
- ④ Main Findings
- ⑤ Conclusions

Outline

- 1 Spatial Reuse
- 2 Machine Learning for Spatial Reuse
- 3 Methodology and Enablers
- 4 Main Findings
- 5 Conclusions

Spatial Reuse in a nutshell

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Methods to address density in wireless networks

- **Time:** scheduling, medium access adaptation
- **Frequency:** Dynamic spectrum access, Dynamic channel bonding
- **Space:** Directional transmissions, Interference cancellation,
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- Improve efficiency
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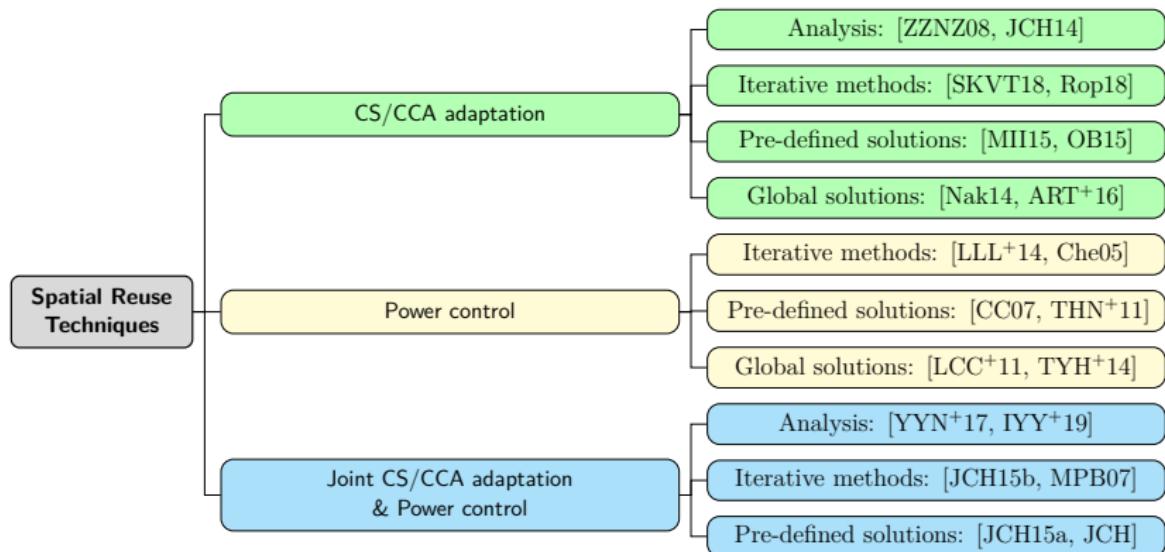
User's goals

- Increase transmission opportunities (TXOPs)
- Improve throughput
- Reduce delay

Effects of tuning the transmit power

Effects of tuning sensitivity

Spatial reuse techniques in wireless networks



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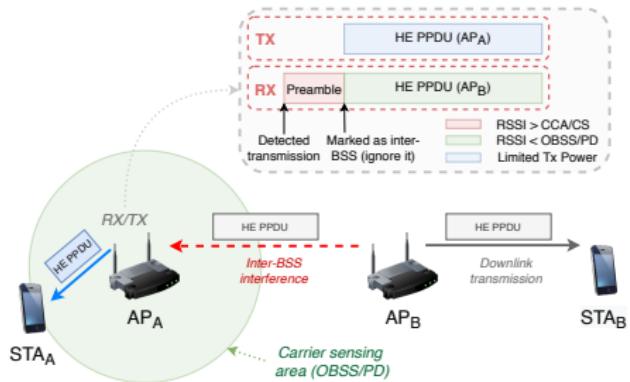
Spatial reuse in IEEE 802.11ax

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- Two mechanisms:
 - ① *OBSS/PD-based SR*
 - ② *Parametrized SR*
- Common features: fast source identification, sensitivity adjustment, tx power limitation

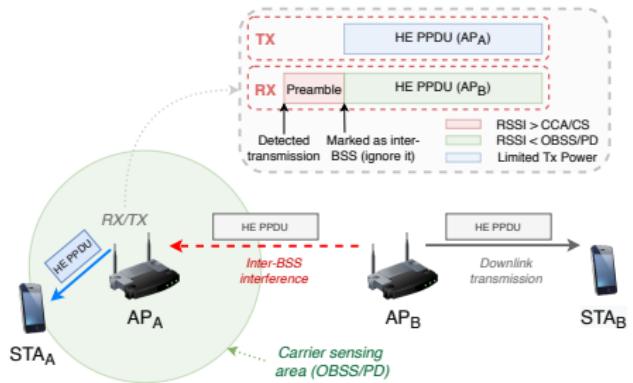
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Too conservative → Moderate gains

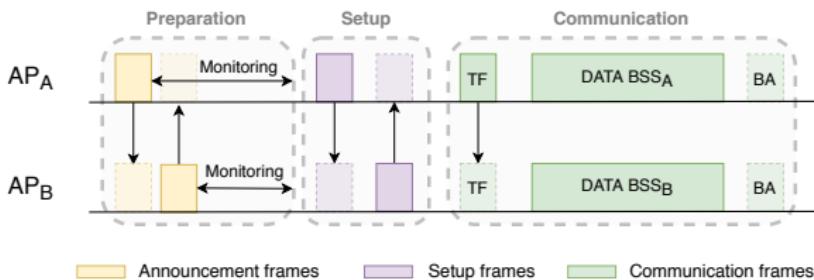
Spatial reuse in future IEEE 802.11 amendments

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- Multi-AP coordination [Jas19]
- Exchange information and coordinate **simultaneous Tx**
- Two main proposals for IEEE 802.11be:
 - ➊ **Coordinated SR (CSR)**
 - ➋ PSR with beamforming/null steering

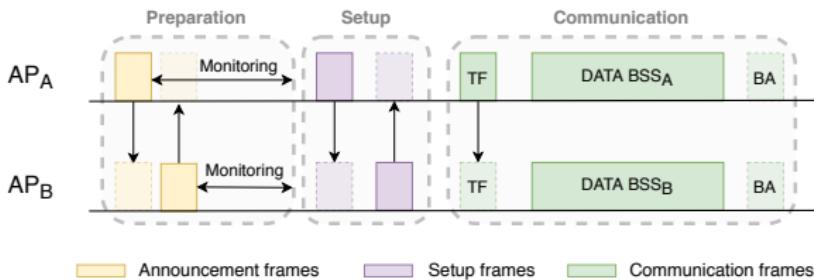
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Open discussion points: extension to UL, measurement phase, role of OFDMA, optimization goals...

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② Machine Learning for Spatial Reuse

③ Methodology and Enablers

④ Main Findings

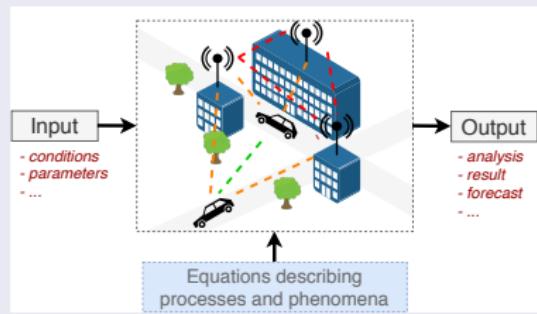
⑤ Conclusions

The emergence of AI for communications

The emergence of AI for communications

Model-based

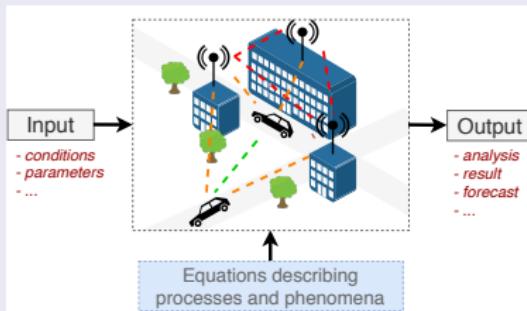
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- Generalization



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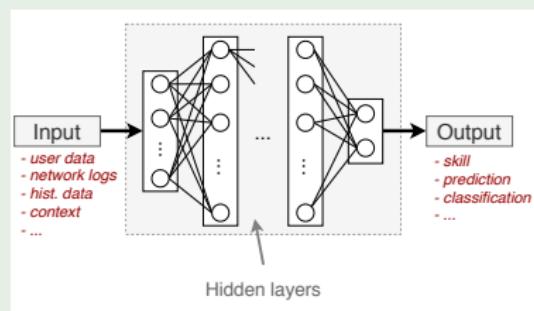
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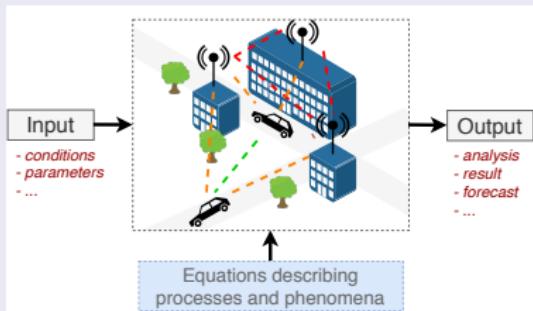
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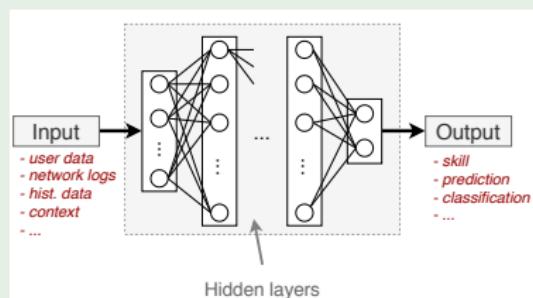
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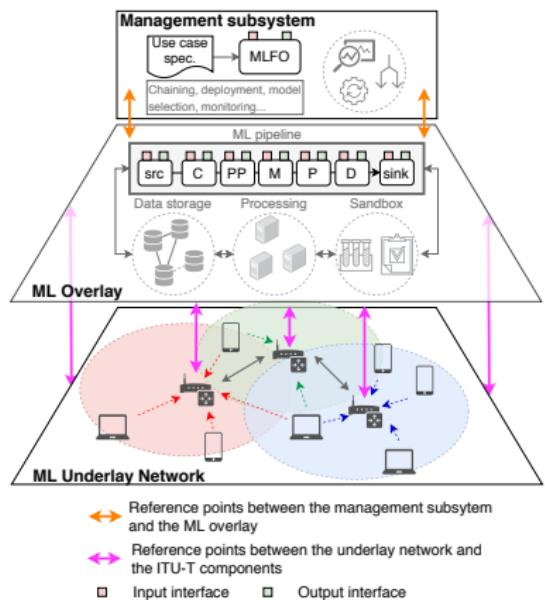
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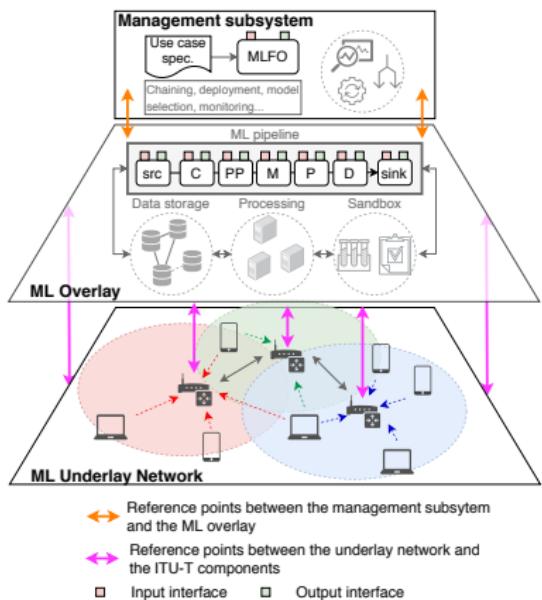
Enablers for adoption:

- Infrastructure (architecture, capacity, data)
- Reliability and trustworthiness

Machine-learning-aware communications



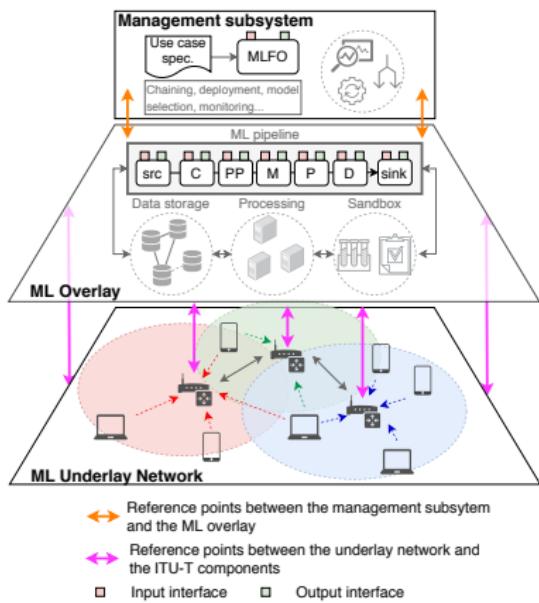
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Architectural aspects

- Framework in ITU-T Y.3172 recommendation [ITU19]
- Flexibility required for decentralized WLANs

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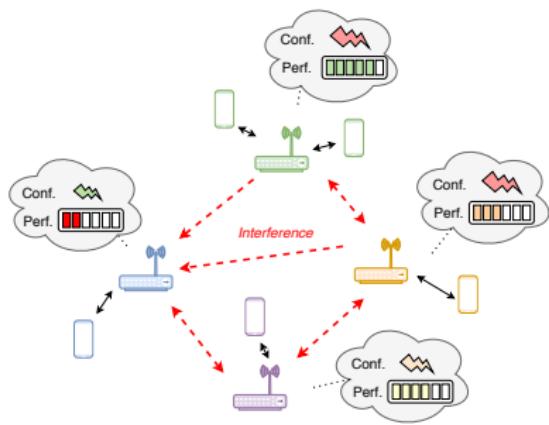
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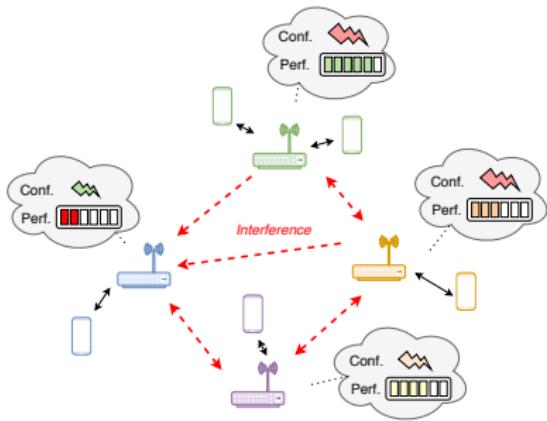
Reliability & Trustworthiness

- ML Sandbox
- **Test, train, and evaluate** ML models
- Simulators in closed-loop ML-based optimization

Multi-agent systems



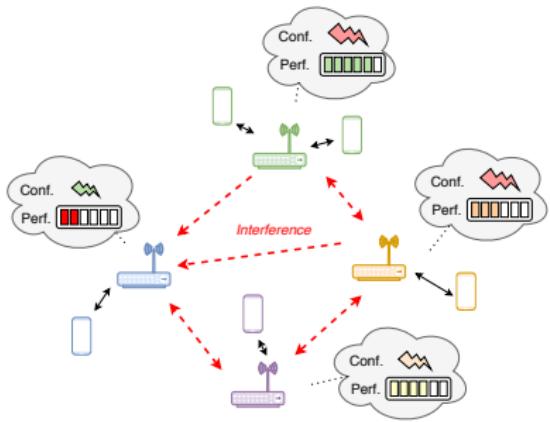
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- Distributed nature of WLANs
- Complexity of SR
- Split a big problem into sub-problems

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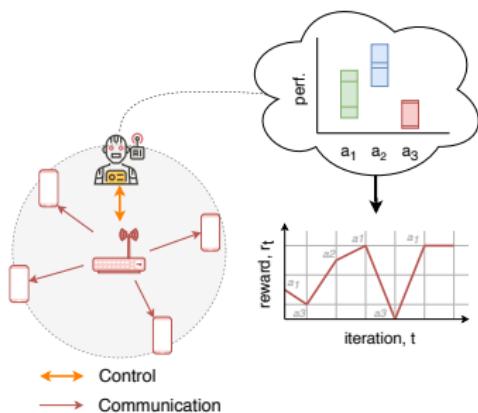
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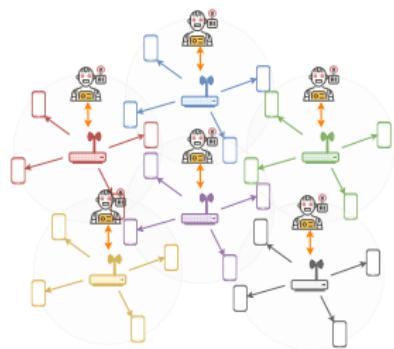
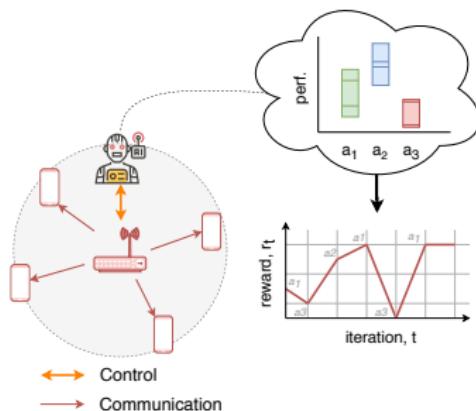
Considerations

- Conflicting requirements
- Non-stationarity / Equilibrium
- Suboptimal performance
- Nexus with Game Theory

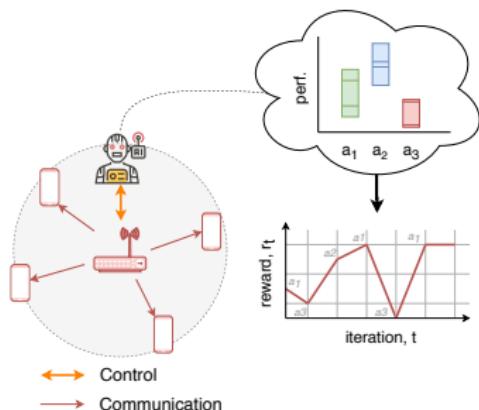
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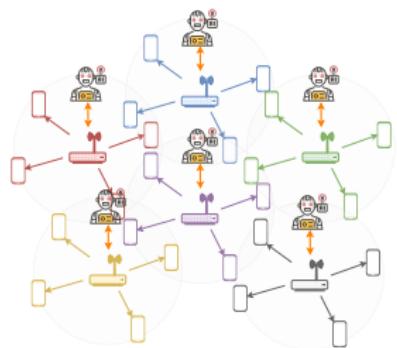
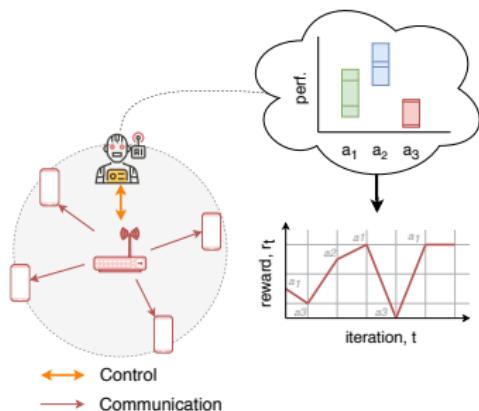


Suitability

- Bandit feedback
- Statistical characteristics
- Non-stationarity
- Fast improvements



Multi-Armed Bandits for SR



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Contribution

- Analysis: performance, convergence, adaptability
- Local vs shared information
- Algorithms: ϵ -greedy, UCB, EXP3, Thompson sampling

MAB-based applications for communications

Problem	Modeling	Goals	Baseline algorithms	References
Spectrum access & Channel selection	Stochastic, non-stochastic, restless, contextual, Markovian bandits	Decentralized optimal allocation, optimize number of secondary transmissions, ϵ -correct ranking	UCB, ϵ -greedy, calibrated forecasting	[AMTS11, MS15]
Power control	Non-stochastic bandits	Optimize SINR	Follow the perturbed leader, exponential weighted average	[MS14]
User association	Sleeping, Bernoulli, non-stochastic bandits	Energy saving, improve the throughput	UCB, ϵ -greedy	[MH17, CB20]
Inter-cell coordination	Adversarial, stochastic, non-stochastic, contextual bandits	Optimize inter-cell frequency resources, energy saving, map SON configurations and operator objectives	EXP3, UCB, ϵ -greedy	[CKC15, DJD17]
Dynamic rate selection	Structured, Markovian bandits	Maximize the number of packets successfully transmitted, learn changes in the channel	UCB	[CP14, ZQKJ20]
LTE/Wi-Fi coexistence	Convex bandits	Fair channel sharing	Online gradient descent	[CN18]

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Typically, the results in the literature lack of applicability in realistic scenarios

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Model and analysis of SR

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Importance of models

- Represent phenomena in wireless communications
- Useful to understand particular technologies

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Related work for modeling SR

- **Baseline:** Bianchi [Bia00], SINR-based models [GRC03], Stochastic geometry [ZWL⁺16]
- **Drawbacks:** assumptions, focus on the PHY or MAC only

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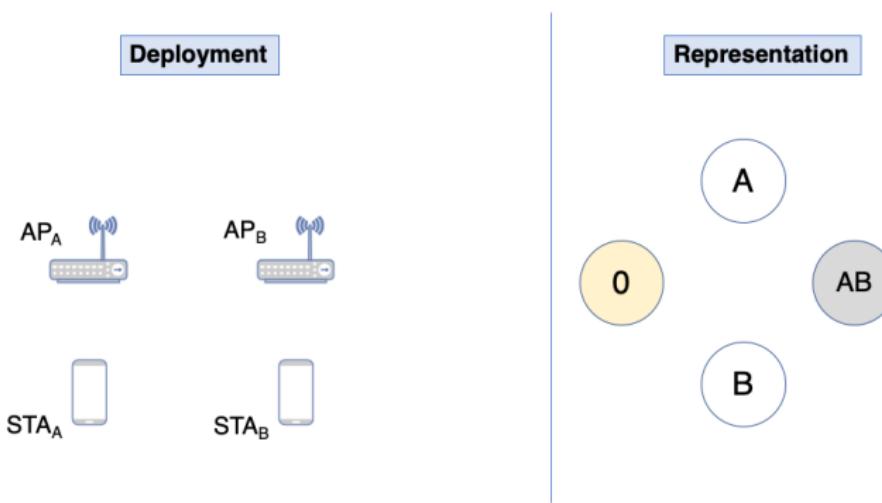
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Continuous Time Markov Networks (CTMNs)

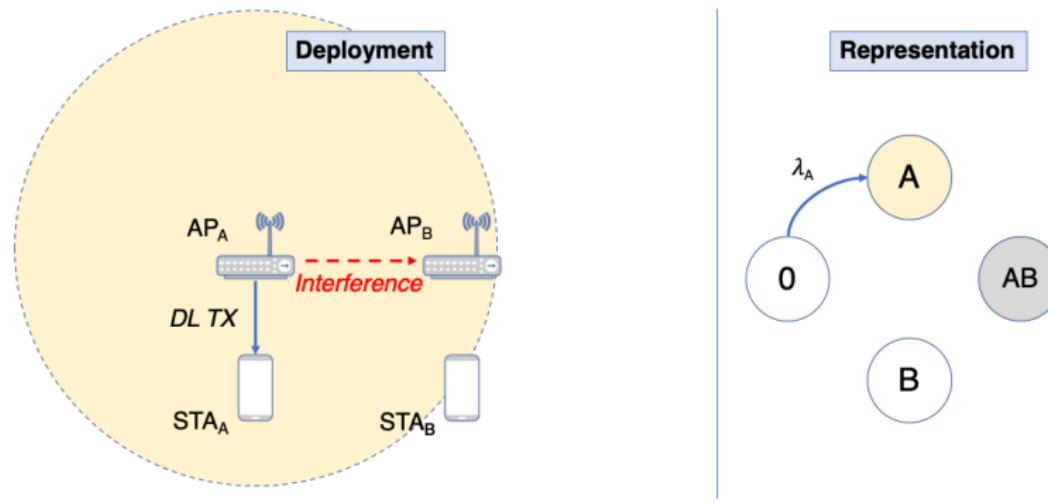
- Additive interference [BMWB19]
- Implementation of OBSS/PD-based SR
- Validate SR and understand it in toy scenarios

Continuous Time Markov Networks (I)



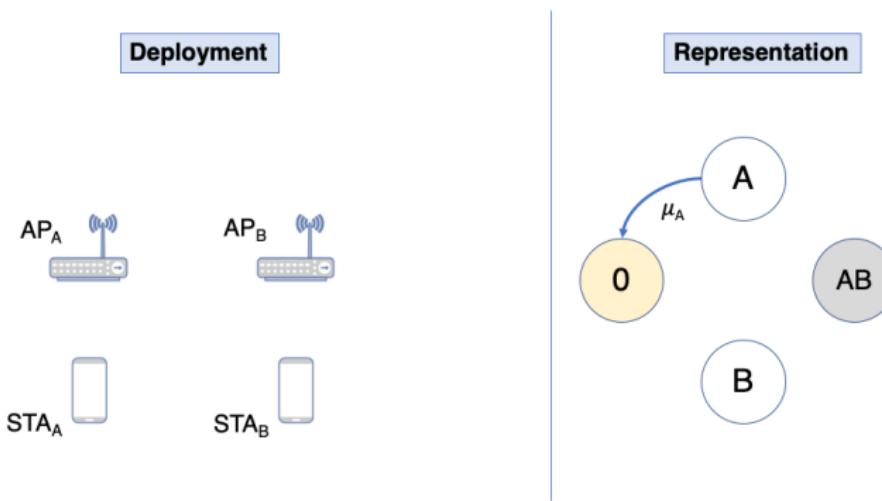
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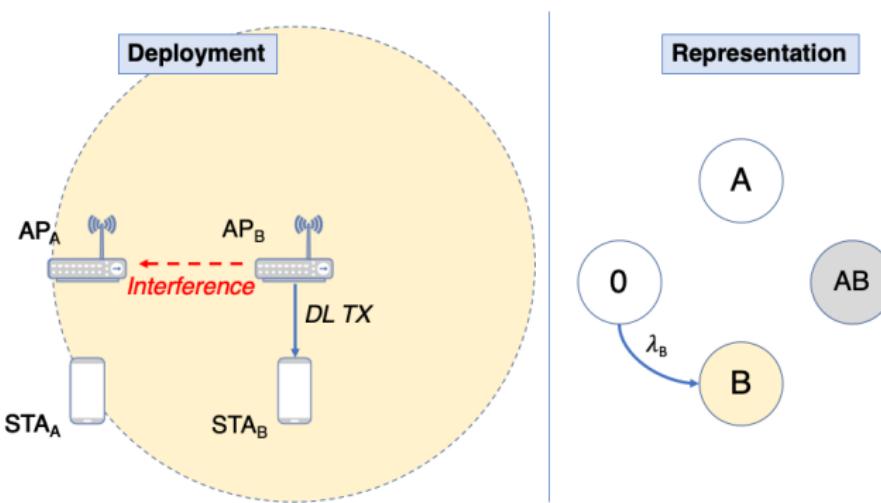
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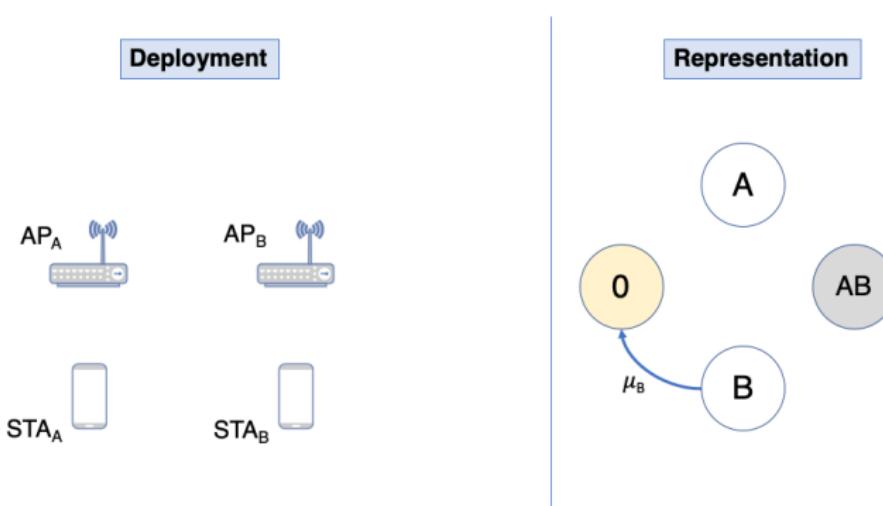
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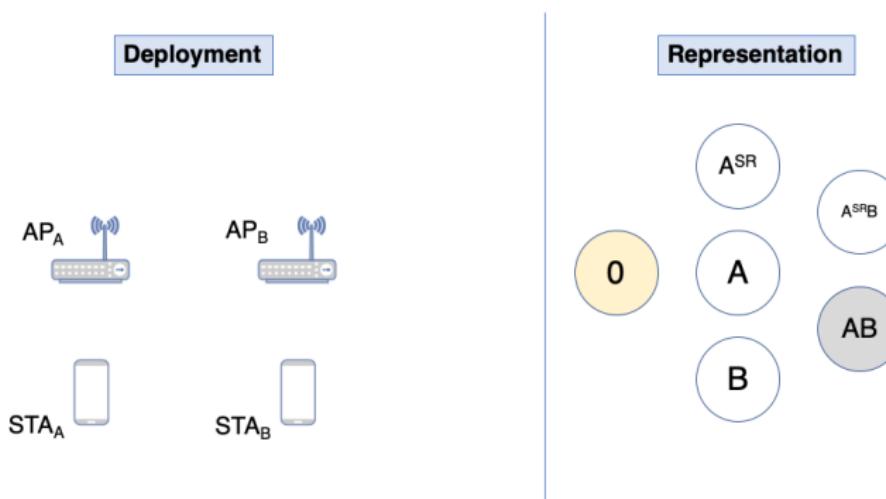
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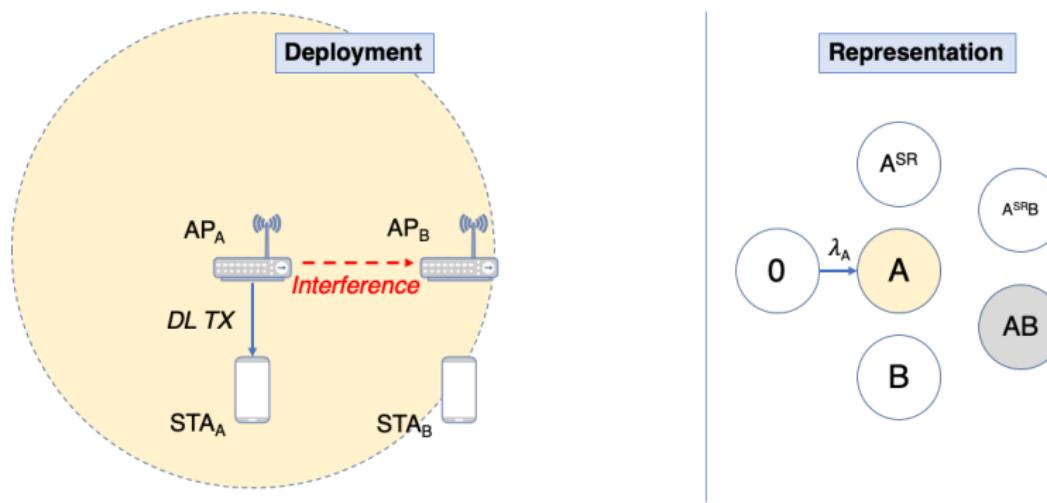
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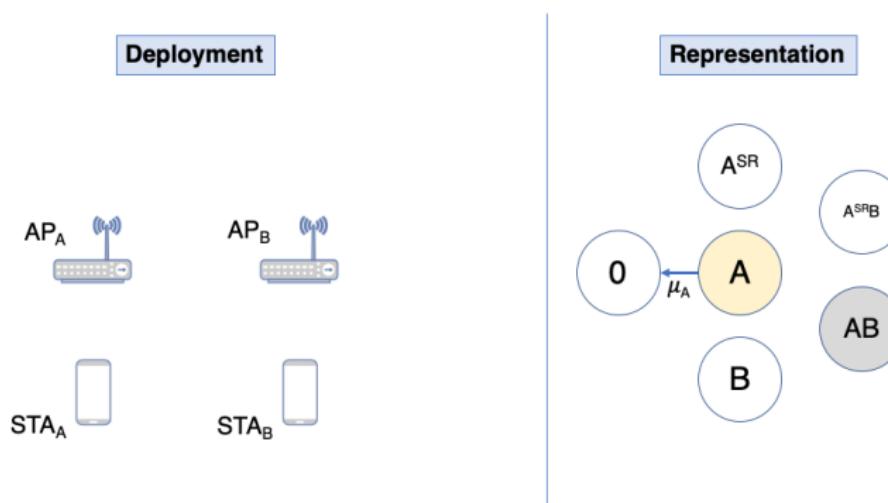
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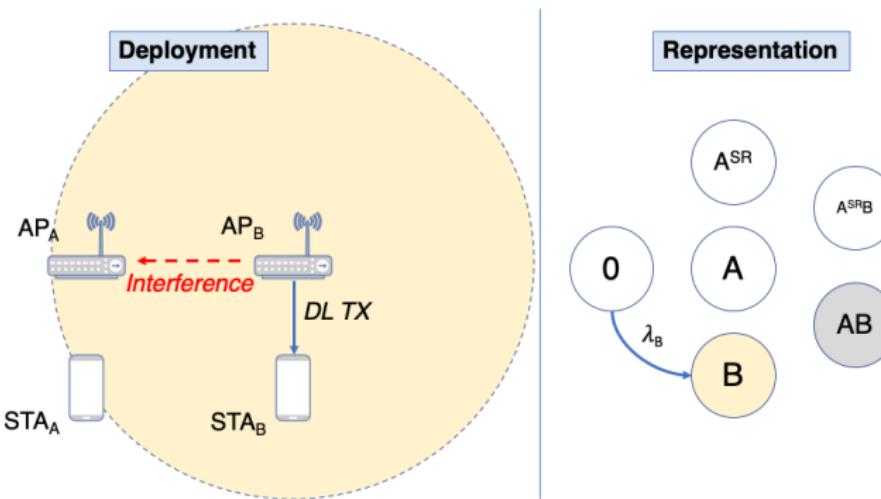
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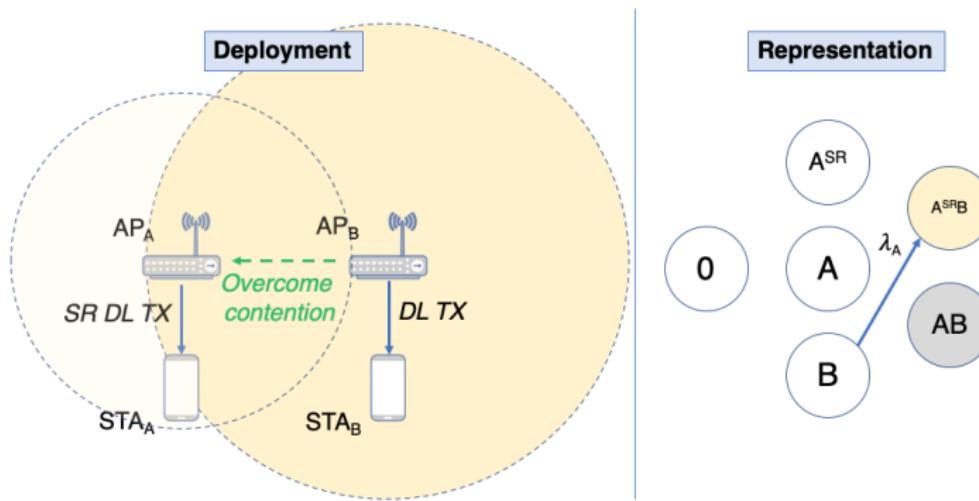
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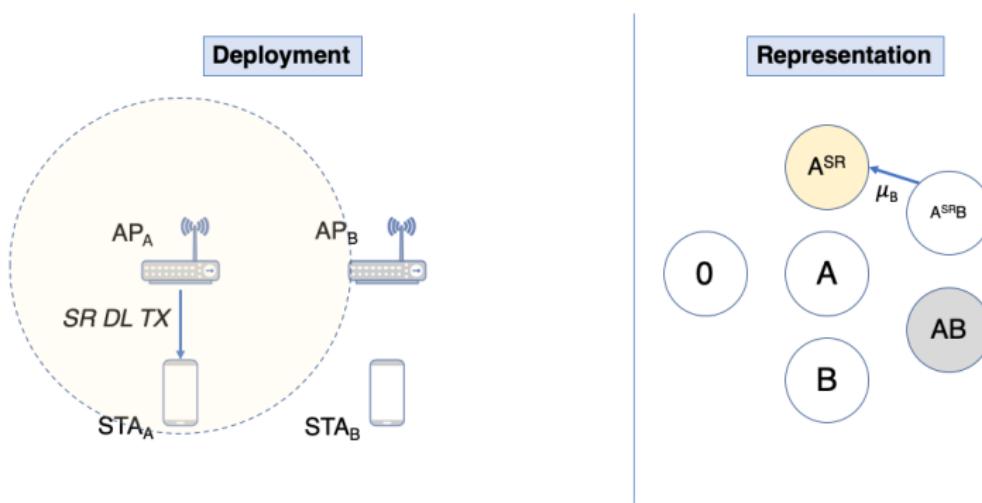
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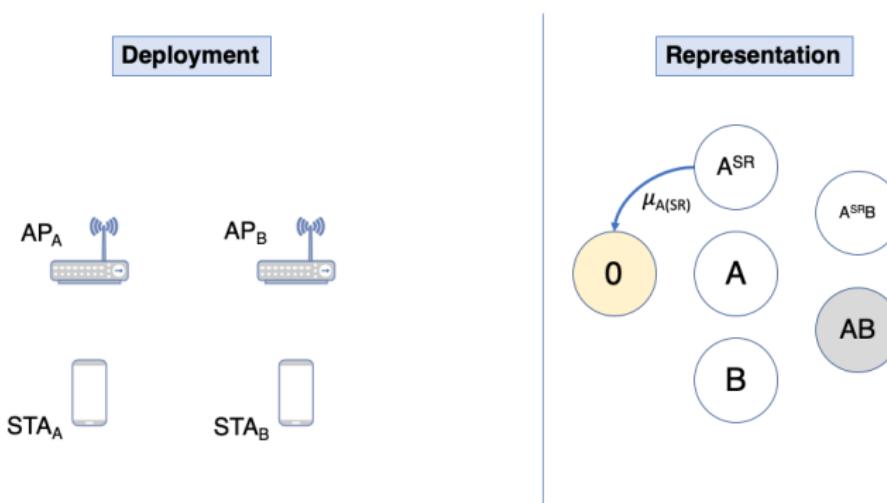
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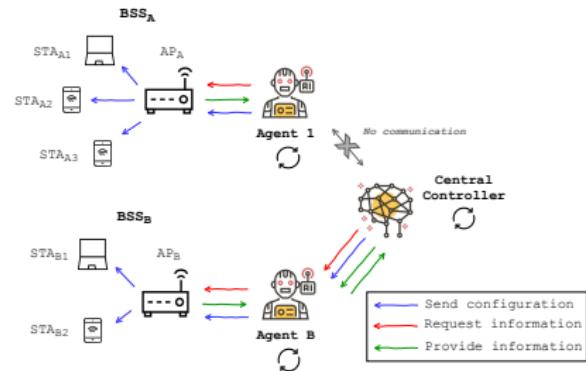
Characterization of intelligent IEEE 802.11 WLANs

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The Komondor simulator

- IEEE 802.11ax-oriented discrete-event simulator^a
- Fast performance & ML
- Joint contribution

^ans-3 11ax available since late 2019

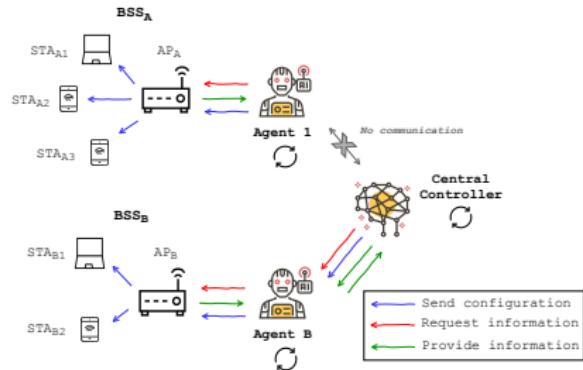


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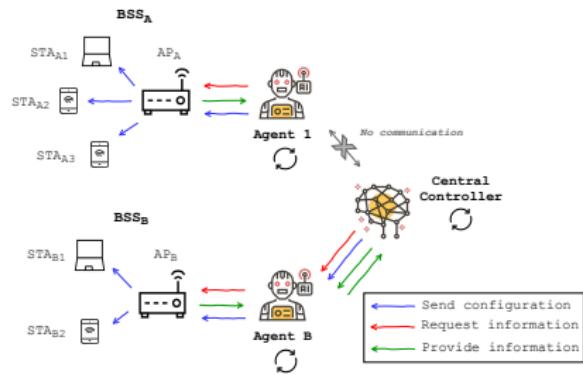
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Komondor is an open-source project: <https://github.com/wn-upf/Komondor>

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Non-intrusive behavior of OBSS/PD-based SR

Finding #1: SR is a fair mechanism that allows increasing the number of simultaneous transmissions in dense OBSSs, thus enhancing the throughput in high-interference scenarios

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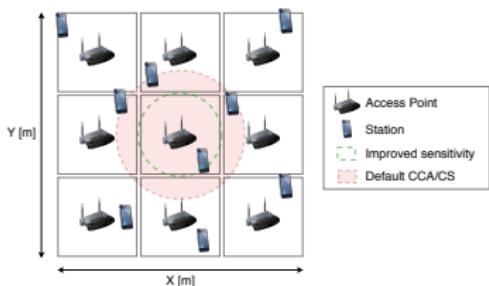
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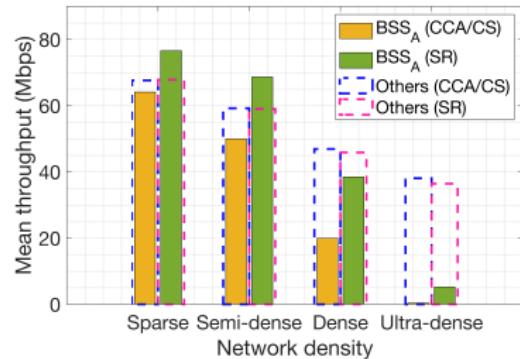
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- Compare performance of BSS_A and rest of the BSSs

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Finding #2: SR allows to significantly improve the delay in dense deployments

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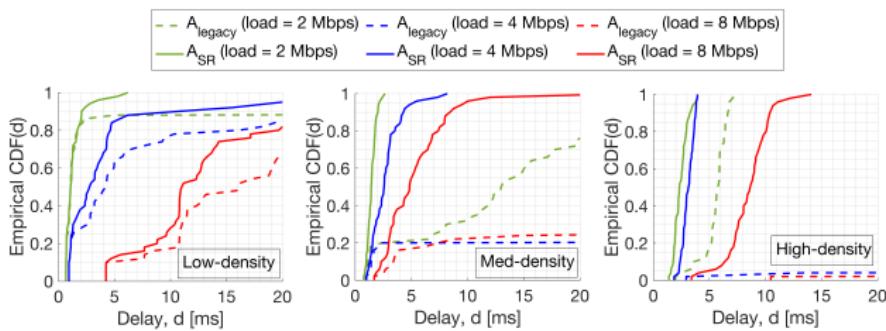
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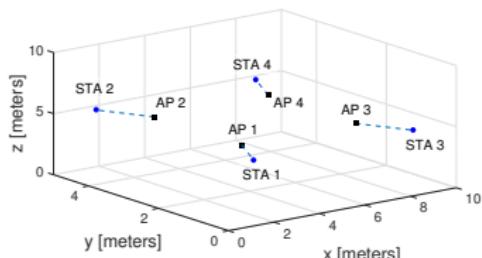


Considerations for adopting SL-based SR

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Considerations for adopting SL-based SR

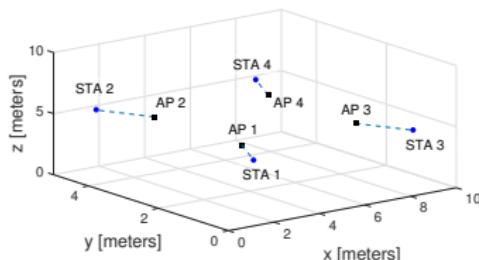
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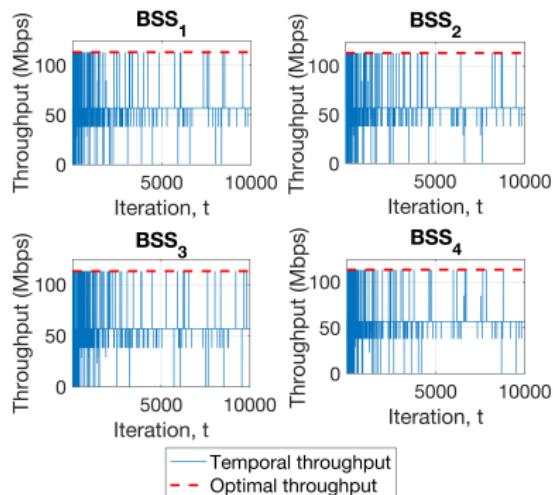
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- Stateless Q-learning applied concurrently
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Potential of sequential learning to address SR

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Potential of sequential learning to address SR

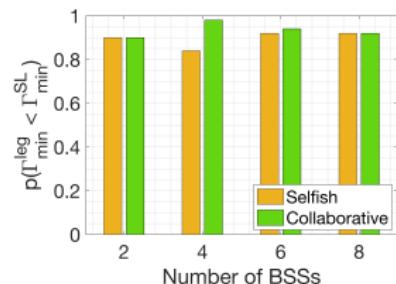
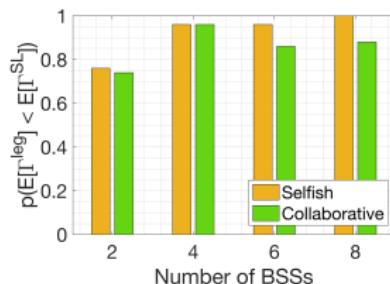
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- Random scenario
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Outline

1 Spatial Reuse

2 Machine Learning for Spatial Reuse

3 Methodology and Enablers

4 Main Findings

5 Conclusions

Final remarks

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- Increasing popularity of SR
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Future of SR

- Evolution of SR towards coordinated settings
- AI/ML can enable end-to-end optimization along with other technologies (e.g., OFDMA)

Funding Sources and Project Acknowledgments

- The Spanish Ministry of Economy and Competitiveness, *Grant number: Maria de Maeztu Units of Excellence program, MDM-2015-0502*
- Generalitat de Catalunya, “Ajuts per donar suport a les activitats dels grups de recerca”, *Grant number: 2017-SGR-11888*
- The Spanish Ministry of Science and Innovation, “Proyectos de I+D de Generación de Conocimiento 2018”, *Grant number: PGC2018-099959-B-I00 (MCIU/AEI/FEDER, UE), WINDMAL (Machine Learning for Wireless Networking in Highly Dynamic Scenarios)*
- Cisco University Research Program fund, a corporate advised fund of Silicon Valley Community Foundation, *Grant number: Project CG No. 890107, Towards Deterministic Channel Access in High-Density WLANs*
- Santander Universidades, “Becas Iberoamérica. Santander Investigación”, 2018/19. *Project: Performance Inference in Dense WLANs to Achieve Environment-Aware Learning.*
- StandICT.eu, European Commission under the Horizon 2020 Programme, *Short Term (ST) Grant Agreement no. 780439*

Questions



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Outline

6 Back-up content

List of publications

- ① Wilhelmi, F., Bellalta, B., Cano, C., & Jonsson, A. (2017, October). *Implications of decentralized Q-learning resource allocation in wireless networks*. PIMRC.
- ② Wilhelmi, F., Cano, C., Neu, G., Bellalta, B., Jonsson, A., & Barrachina-Muñoz, S. (2019). *Collaborative spatial reuse in wireless networks via selfish multi-armed bandits*. Ad Hoc Networks.
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