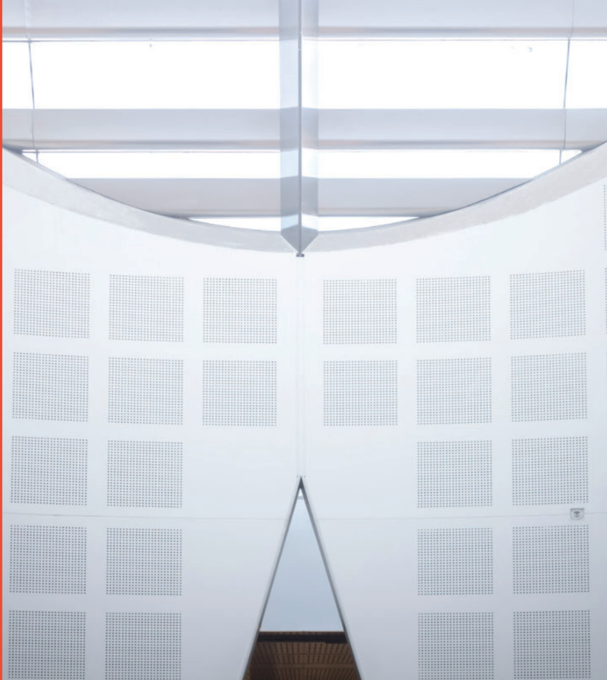
Pathway to Spectrum Intelligent Radio

Online Seminar in NJUST

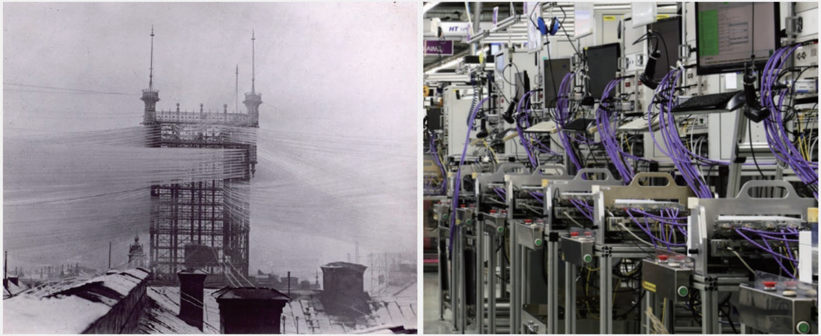
Peng Cheng

January 6, 2021

THE UNIVERSITY OF SYDNEY



Industrial 4.0



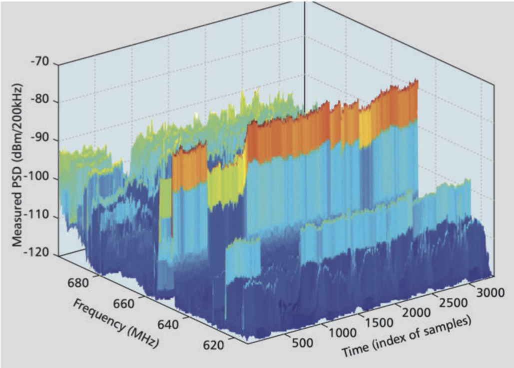
Consumers have gone wireless – factories are just starting

Smart Factory

Spectrum

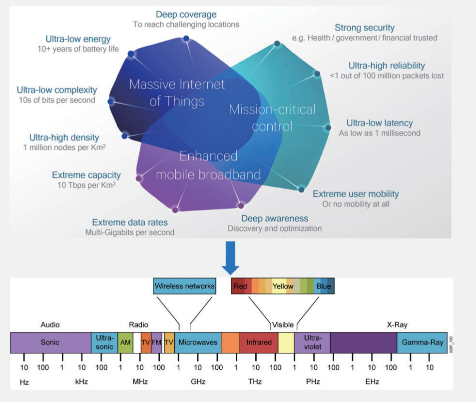
Results

Winning bidder	Spectrum sold	Winning price
TPG	10 MHz • 738 - 748 MHz paired with • 793 - 803 MHz	$1.26 billion
Vodafone Hutchinson Australia (VHA)	5 MHz • 733 MHz - 738 MHz paired with • 788 MHz – 793 MHz	$285.9 million



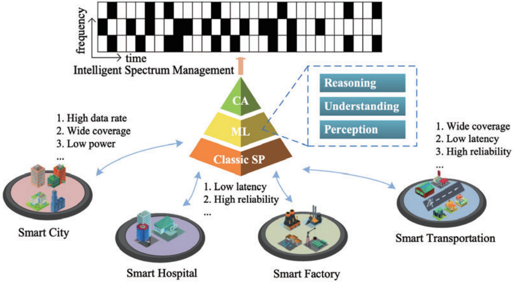
Spectrum Scarcity

How to manage this massive wireless access under the constraint of limited spectrum resources?



Spectrum Intelligent Radio

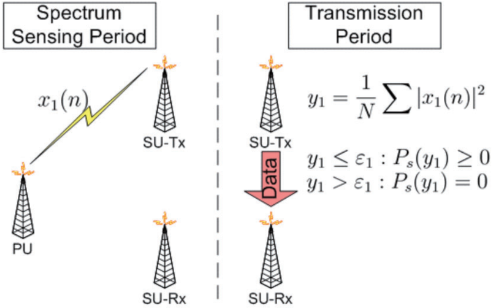
- (S1) Human-oriented classical signal processing[1]
- (S2) Machine learning (ML)
- (S3) Contextual adaptation (CA)



[1] P. Cheng, Z. Chen, M. Ding, Y. Li, and B. Vucetic, "Spectrum intelligent radio: technology, development and future trends," **IEEE Communications Magazine**, vol. 58, no. 1, pp. 12-18, Jan. 2020.

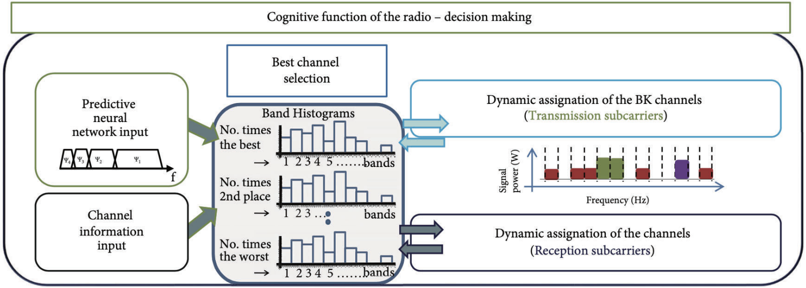
Stream 1: Human-Oriented Classical Signal Processing (1/2)

- Spectrum sensing
  - Various signal processing methods focus on a single parameter
  - Assume a homogeneous spectrum state
  - Hard to handle complex RF environments

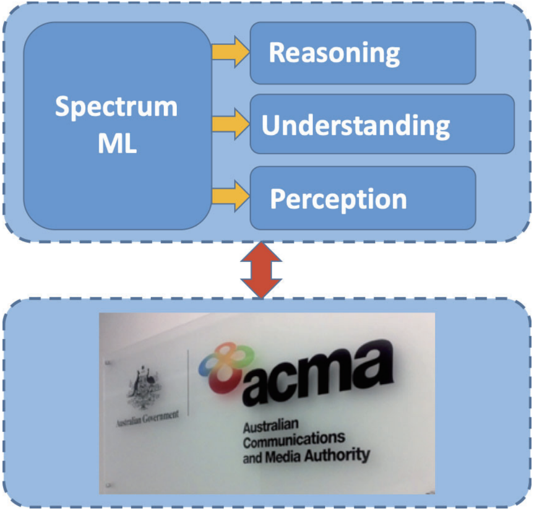


Stream 1: Human-Oriented Classical Signal Processing (2/2)

- Decision Making
  - Conventional studies use model-dependent approaches to obtain structured solutions, which require the knowledge of the parameters in the network.
  - The complexity of spectrum environment often makes it impossible to gain enough knowledge in advance.

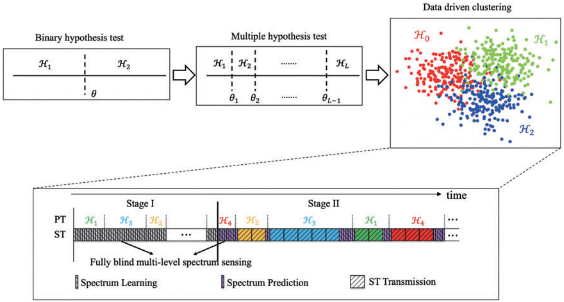


Stream 2: Machine Learning



Level 1: Perception

- Involve the autonomous multiple feature identification of signals in an unknown complicated RF environment[2]
- Observe network heterogeneity and dynamics from different perspectives.



[2] R. Zhang, P. Cheng*, Z. Chen, Y. Li, and B. Vucetic, "A learning-based two-stage spectrum sharing strategy with multiple primary transmit power levels," **IEEE Transactions on Signal Processing**, vol. 67, no. 18, pp. 4899-4914, Sep. 2019.

Performance of the PT Power Level Identification

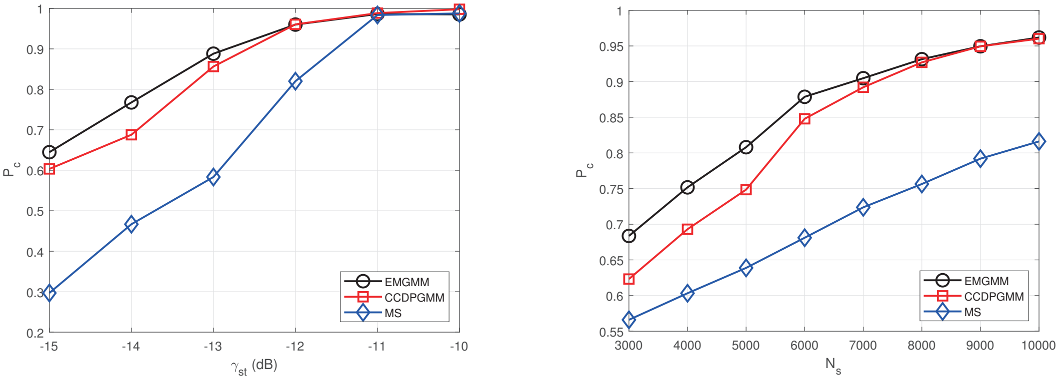


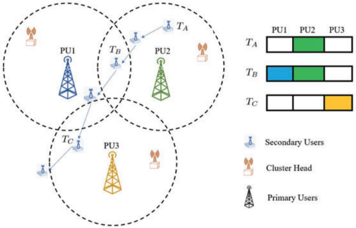
Figure: The probability of correct PT power level prediction in the first stage (P_c).

Vision

- Future networks demand automated extraction of far more features with no or minimal prior information.
- The physical layer information (spectrum occupancy, transmit power level, modulation, constellation, and channel coding) and upper layer features (application types, network topology, and communication protocols) should be mined under a unified framework.
- Automate the extraction of a multitude of features. This represents a new trend for RF landscape perception.

Level 2: RF Environment Understanding

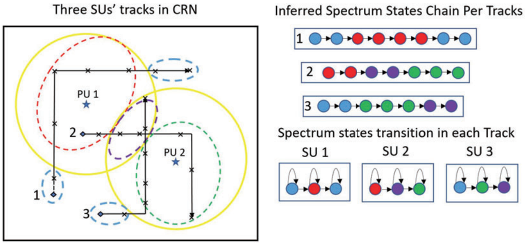
- To learn the structure of the RF environment in a large-scale complex network, and establish the ongoing RF activity map[3]
- Deploy many static SUs at different locations to carry out spectrum sensing simultaneously

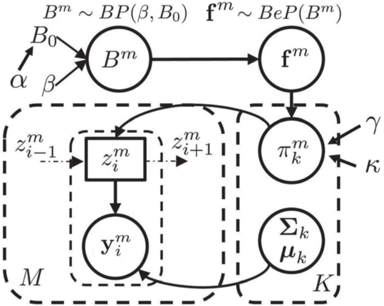


[3] Y. Xu, P. Cheng*, Z. Chen, Y. Li, and B. Vucetic, "Mobile collaborative spectrum sensing for heterogeneous networks: A Bayesian machine learning approach," **IEEE Transactions on Signal Processing**, vol. 66, no. 21, pp. 5634–5647, Nov. 2018.

Proposed Learning Model

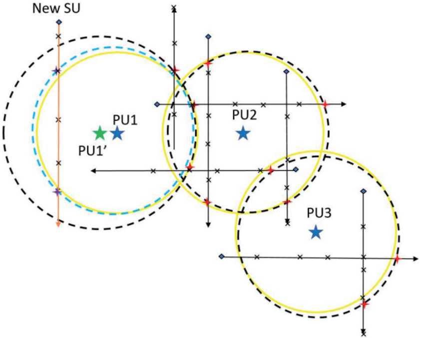
- Exploit the mobility nature inherent to most wireless devices to explore the spectrum footprint across a network
- BP-SHMM





Prediction of Spectrum Availability

- Prediction of PUs' locations and transmission ranges based on classification results
- Refinement based on previous predictions



Input:

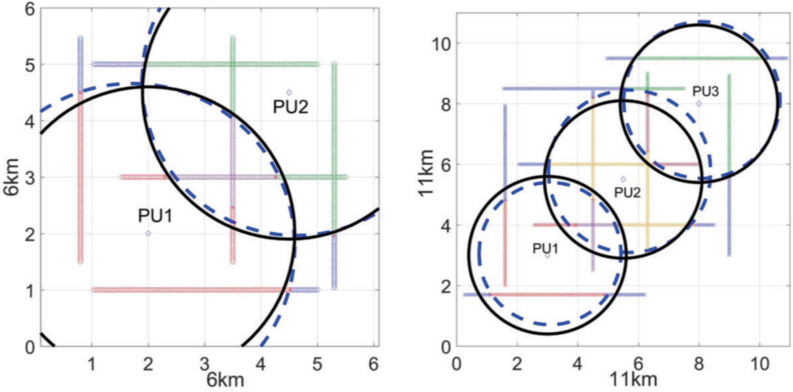
Initialize $\mathbf{a}_0 = (x_c^0, y_c^0, R^0)$; Initial L-M parameter λ; Hyperparameter ϵ, ξ, υ;

Output:

The final result, $\mathbf{a} = (x_c, y_c, R)$;

1: Compute $\mathcal{F}^0 = \mathcal{F}(x_c^0, y_c^0, R^0)$ based on initial guess $\mathbf{a}_0$;
2: Assuming that (x_c^k, y_c^k, R^k) are known, compute $\partial d_i/\partial x_c, \partial d_i/\partial y_c, \partial d_i/\partial R$ for all i;
3: Compute the matrix $\mathbf{N} = \mathbf{J}^T\mathbf{J}$, $\mathbf{N}_\lambda = \mathbf{N} + \lambda\mathbf{I}$ and the vector $\mathbf{J}^T\mathbf{d}$;
4: Compute new $\Delta\mathbf{a} = -(\mathbf{N}_\lambda)^{-}\mathbf{J}^T\mathbf{d}$;
5: If $\|\Delta\mathbf{a}\|/R_k < \epsilon$ (small tolerance), then terminate the procedure;
6: Use $\Delta\mathbf{a} = \{\Delta x_c, \Delta y_c, \Delta R\}$ to update the parameters $x_c^{k+1} = x_c^k + \Delta x_c$, $y_c^{k+1} = y_c^k + \Delta y_c$, $R^{k+1} = R^k + \Delta R$;
7: Compute $\mathcal{F}^{k+1} = \mathcal{F}(x_c^{k+1}, y_c^{k+1}, R^{k+1})$.
8: If $\mathcal{F}^{k+1} \geq \mathcal{F}$ or $R^{k+1} \leq 0$, update $\lambda \mapsto \xi\lambda$ and return to Step 4; otherwise increment k, update $\lambda \mapsto \upsilon\lambda$, and return to Step 2.

PUs' location and Transmission Range Prediction



(a) $N' = 2$ (b) $N' = 3$

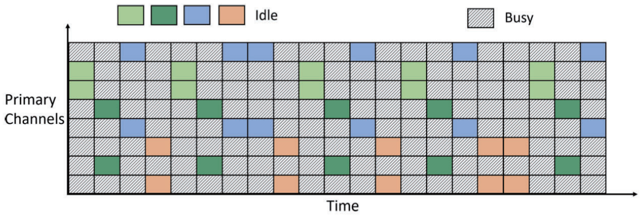
Figure: Prediction results for $N' = 2$ and $N' = 3$, respectively.

Vision

- Focus on the spectrum heterogeneity
- How to handle the envisioned scenario with fast-changing dynamics and interference is still an open problem.

Level 3: Reasoning for Instantaneous Spectrum Access

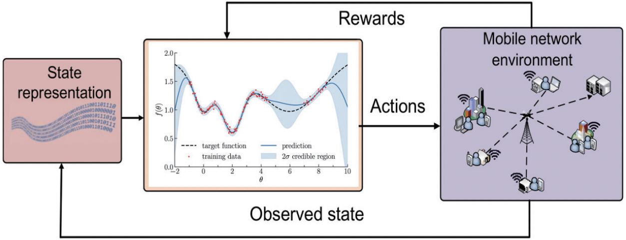
- Open question[4]
  - POMDP (Conventional model-based)
  - Unknown network dynamics + Channel correlations



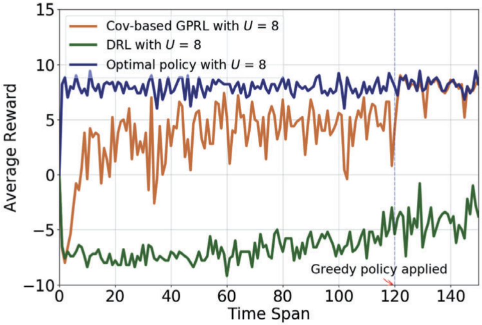
[4]Z. Yan, P. Cheng*, Z. Chen, Y. Li, and B. Vucetic, "Gaussian process reinforcement learning for fast opportunistic spectrum access," **IEEE Transactions on Signal Processing**, vol. 68, pp. 2613-2628, Apr. 2020.

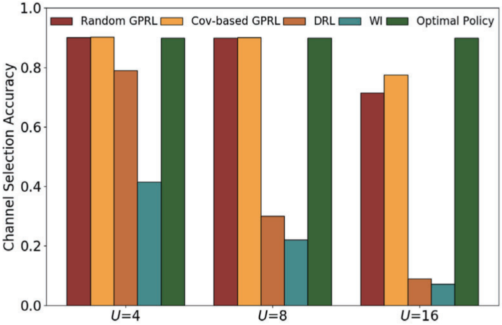
Gaussian Process Reinforcement Learning (GPRL)

- Enable the SU to directly interact with the unknown RF environment
- Incorporate GP with Bayesian inference into RL
- Enable a much more efficient Q-function approximation compared to DRL, eliminating the need for a large number of training samples



Experimental Results

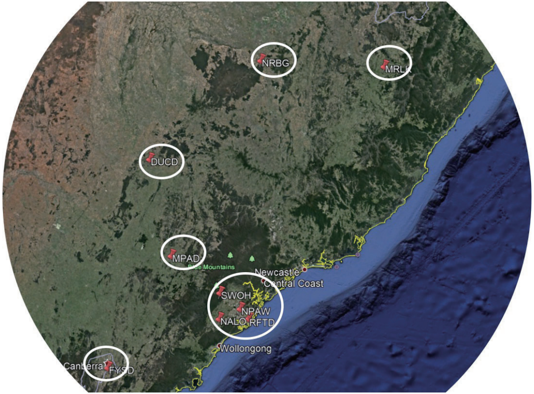




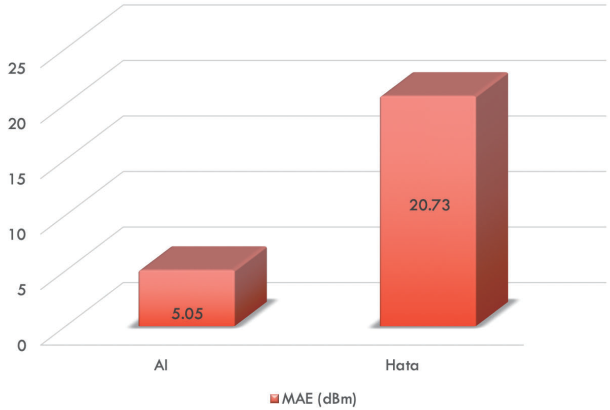
Vision

- GPRL only suit a single-user scenario.
- The multi-user setting is much more challenging.
- Due to interactions among users, it is highly desirable to develop a model-free distributed multi-user method without coordination or message exchange among users.

Wireless Signal Strength Prediction

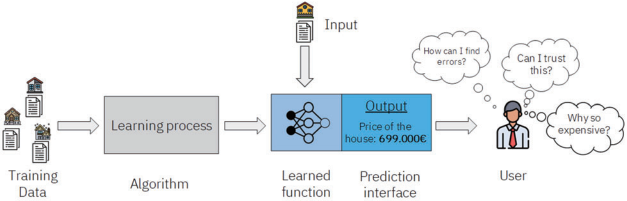


Prediction Results



Stream 3: Contextual Adaptation

- Envisioned to feature contextual adaptation, and meet the need for future massive connectivity with its full intelligence
- Future networks demand automated extraction of far more features with no or minimal prior information.
- Explainable ML[5][6]

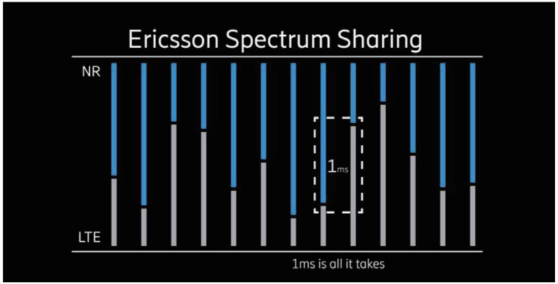


[5] Y. Lu, P. Cheng*, Z. Chen, Y. Li, W. H. Mow and B. Vucetic, “Deep Autoencoder Learning for Relay-Assisted Cooperative Communication Systems,” **IEEE Transactions on Communications**, vol. 68, no. 9, pp. 5471-5488, Sept. 2020

[6] Y. Lu, P. Cheng*, Z. Chen, Y. Li, W. H. Mow and B. Vuceti, “Deep Multi-Task Learning for Cooperative NOMA: System Design and Principles, **IEEE Journal on Selected Areas in Communications**, vol. 39, no. 1, pp. 61-78, Jan. 2021.

Standardization

- Ericsson Spectrum Sharing[7,8]

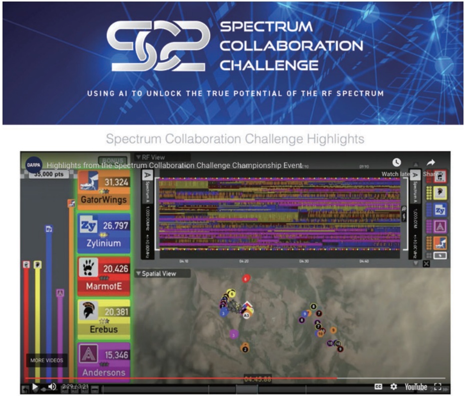


[7] https://www.rcrwireless.com/20200312/network-infrastructure/outlook-for-dynamic-spectrum-sharing

[8] https://www.vodafone.com/perspectives/blog/dynamic-spectrum-sharing

Development Roadmap

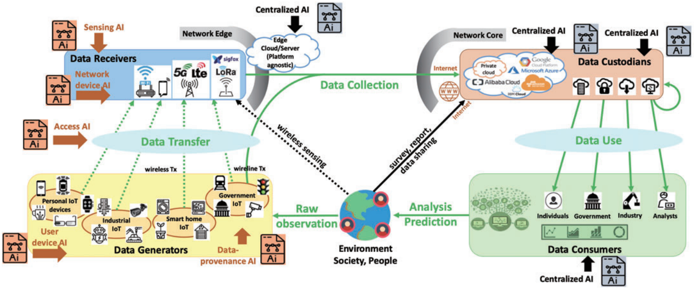
- DAPRA ML-based spectrum management[9]



[9] https://archive.darpa.mil/sc2/

Wireless AI

- A Data Life Cycle Perspective[10][11]

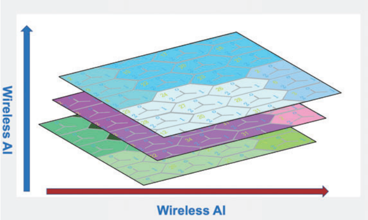


[10] D. Nguyen, P. Cheng*, M. Ding, et.al, "Enabling AI in Future Wireless Networks: A Data Life Cycle Perspective," to appear in **IEEE Communications Surveys & Tutorials**, Sept. 2020.

[11] P. Cheng, C. Ma, M. Ding, Y. Hu, Y. Li, and B. Vucetic, "Localized small cell caching: A machine learning approach based on rating data," **IEEE Transactions on Communications**, vol. 67, no. 2, pp. 1663–1676, Feb. 2019.

Wireless AI

- System Perspective[12][13]



[12] Y. Xu, P. Cheng*, Z. Chen, Y. Li, and B. Vucetic, "Task Offloading for Large-Scale Asynchronous Mobile Edge Computing: An Index Policy Approach," to appear in **IEEE Transactions on Signal Processing**, Dec. 2020.

[13] Z. Yan, P. Cheng*, Z. Chen, Y. Li, and B. Vucetic, "Two-Dimensional task offloading for mobile computing networks: An imitation learning framework," submitted to **IEEE/ACM Transactions on Networking**, Dec. 2020.

Wireless AI

- Application Perspective