A4E: WHEN AI MEETS WIRELESS

The Emerging Role of AI/ML in Next-Generation Networks Panel

IEEE INFOCOM 2022 Workshop—A4E: AI/ML for Edge/Fog Networks
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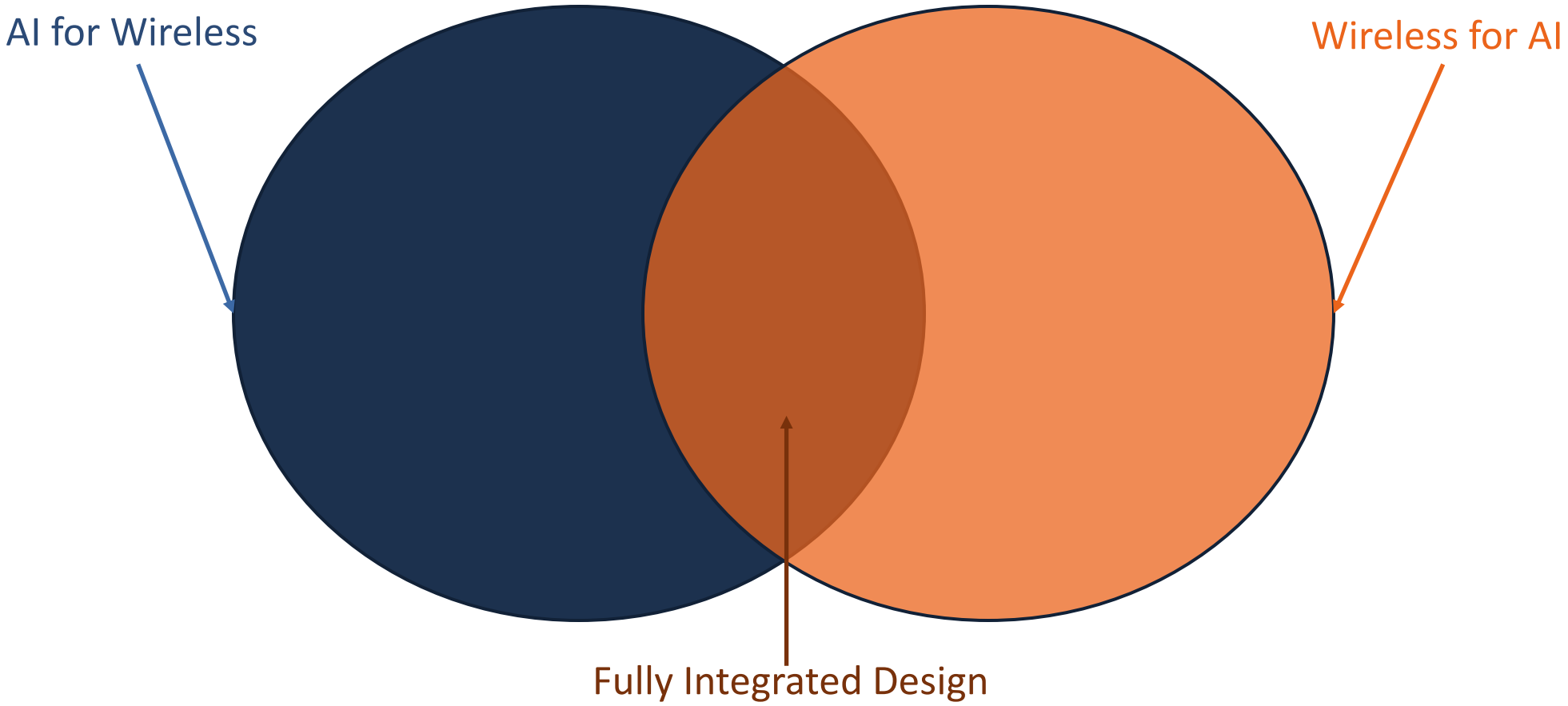
AI + Wireless: Evolution over Time

Intelligence: will be the definitive feature of the NextG



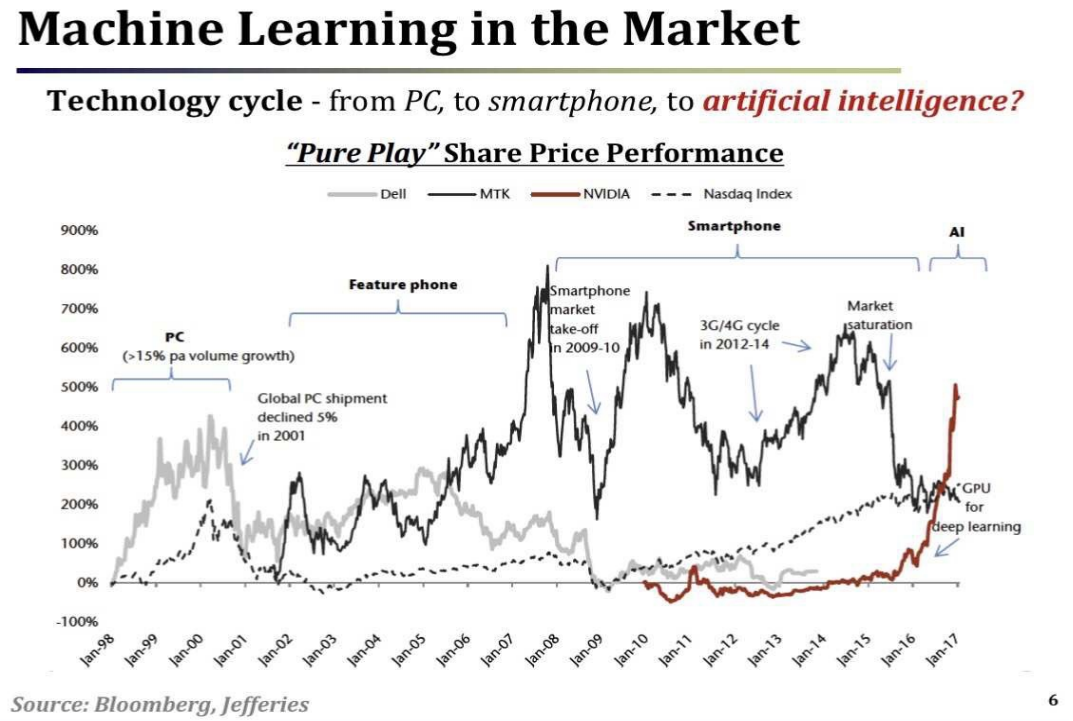
AI for Wireless

Wireless communications and networks:

- Well studied with good understanding, lot of models and theory
- But systems get more and more complicated, heterogenous, large-scale, and dynamic

AI/ML:

- Huge success in other fields: natural langrage processing, computer vision, gaming, … ➔ can be replicated in NextG
- Epic events (good advertisement):
  - IBM Deep Blue vs. World Chess Champion Garry Kasparov (1997)
  - IBM's DeepQA project: quiz show Jeopardy! won the first-place prize (2011)
  - Google DeepMind's AlphaGo/AlphaGo Zero: beat Ke Jie, the world No.1 ranked *Go* player (2017)
  - Facebook/CMU's Pluribus: beat 15 of the world's top poker players (2019)
  - Dr. Fill, Champion of the 43rd Annual American Crossword Puzzle Tournament (2021)
  - DeepMind: solved a 50-year-old challenge in biology, and helped crack two mathematical puzzles that stumped humans for decades (2021)
  - …
- Technology is ready:
  - Availability of: Data, Computing power, and open-source Platforms
  - Wireless designs: historically based on probabilistic models (e.g., traffic, channel, interference, …), and are fault tolerant



Challenges: data, generalization, explainable

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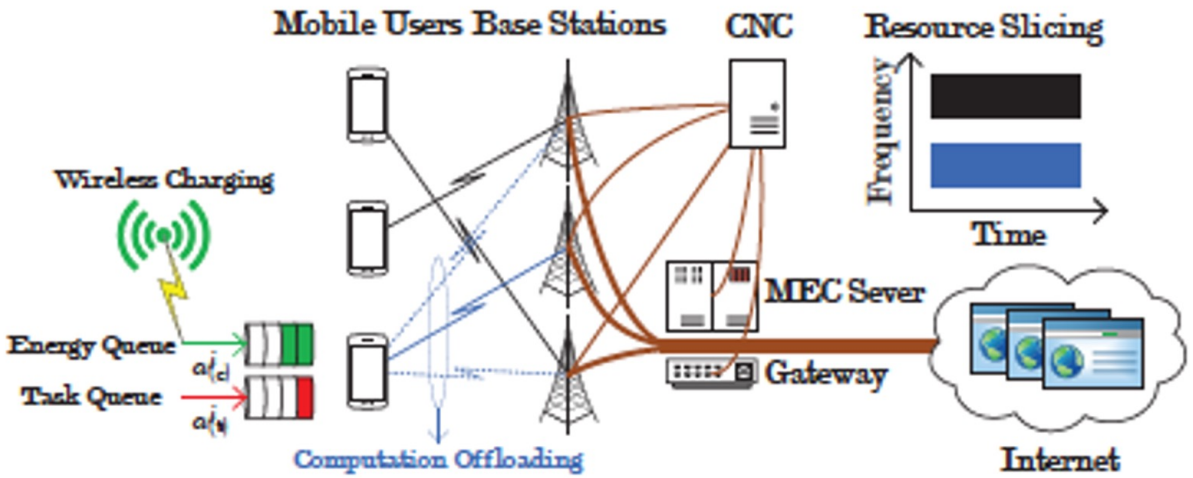
Case Study: Edge Computing/Offloading

- Considers:
  - Local execution, and offloading (to which BS)
  - CPU frequency tuning
  - Energy harvesting
  - Mobility/handover
- Control knobs (c^j, e^j):
  - c^j: offloading or local execution
  - e^j: energy allocation
- A Markov Decision Process: to maximize the long-term utility by offloading decisions made with the current system state: task queue state, energy queue state, channel quality
  - A double deep Q-network (DQN) algorithm to learn the optimal offloading policy
  - Exploiting the additive structure of the utility function, decompose the Q-function and use a "virtual" agent to learn each of the decomposed element

Traditional analytical methods is not capable of handling such formulated problems



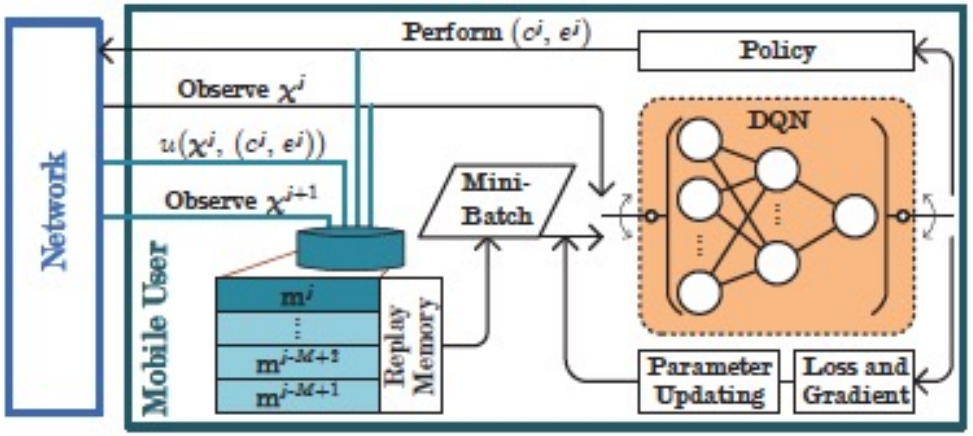


Fig. 2. Double deep Q-network (DQN) based reinforcement learning (DARLING) for stochastic computation offloading in a mobile-edge computing system.

[1] X. Chen, H. Zhang, C. Wu, S. Mao, Y. Ji, and M. Bennis, "Optimized computation offloading performance in virtual edge computing systems via deep reinforcement learning," *IEEE Internet of Things Journal*, vol.6, no.3, pp.4005-4018, June 2019.

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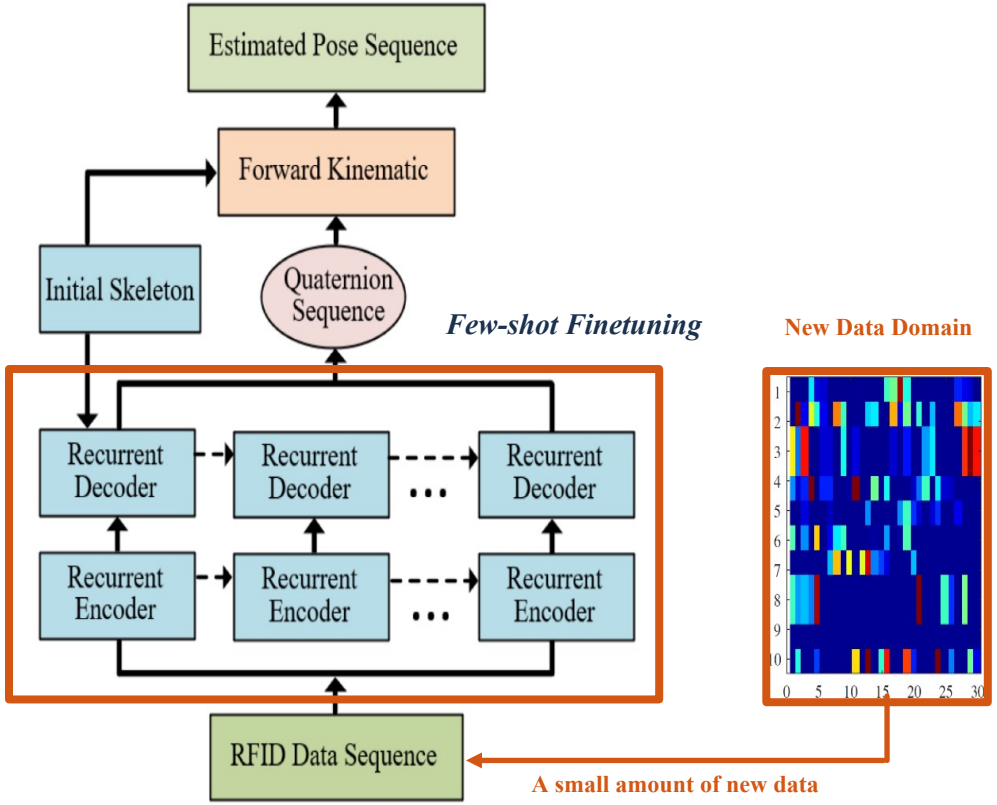
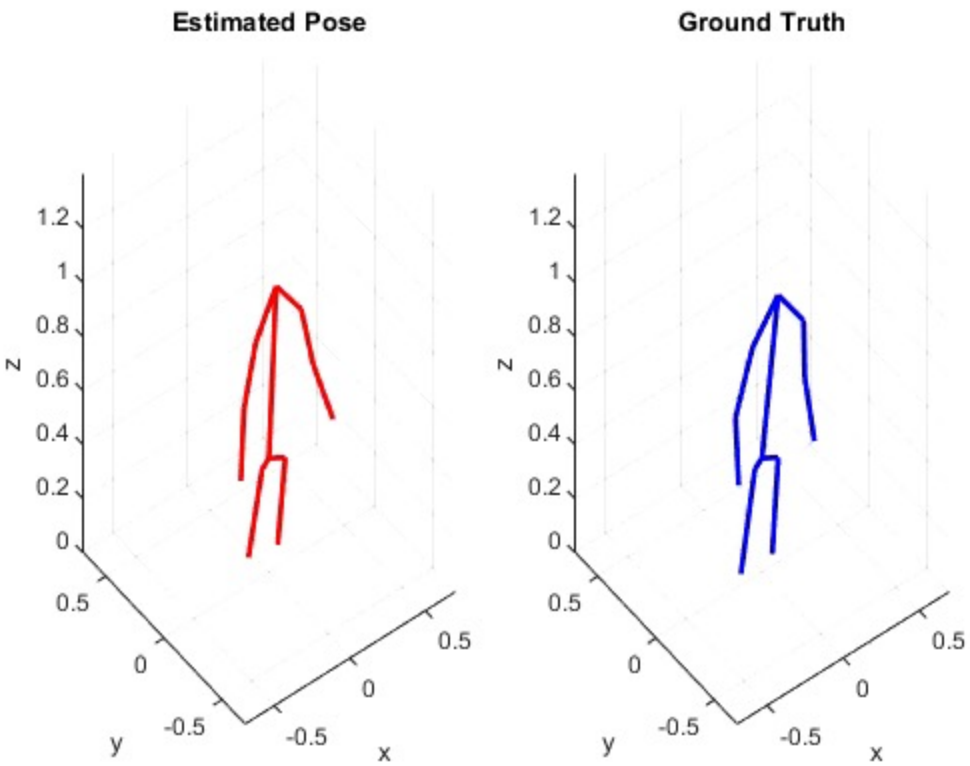
Case Study: RF Sensing/3D Human Pose Tracking





[2] C. Yang, L. Wang, X. Wang, and S. Mao, "Environment adaptive RFID based 3D human pose tracking with a meta-learning approach," *IEEE Journal of Radio Frequency Identification*, to appear. DOI: 10.1109/JRFID.2022.3140256.

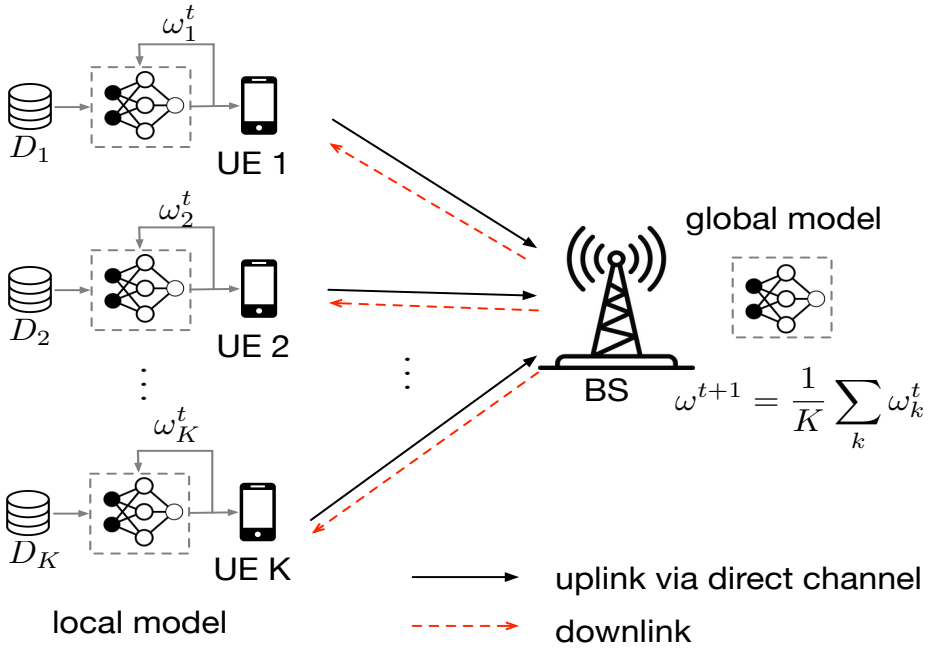
Wireless for AI

Motivation:

- ML usually involves a large amount of data, large-sized models, high computing requirements, and stringent delay requirements
  - For example: autonomous driving
    - One autonomous car will use 4,000 GB of data/day [2]
    - 70 miles/hour ➔ 31.3 m/s: decision should be made in ms or 10s of ms
- Limited computing power and storage at mobile devices
- Privacy concerns: not willing to share data

Solutions:

- Distributed machine learning over wireless networks
  - Federated Learning
  - Vertical or horizontally partition a large ML model
- Fundamentally new wireless communication protocols to support future machine learning applications



Federated learning scenario with K devices and a central server

Benefits:

- Improvement in energy efficiency
- Improvement in bandwidth utilization
- Improvement in latency
- Training ML model in a privacy-preserving manner

Challenges

- Communication efficiency
- System heterogeneity
- Statistical heterogeneity, non-*i.i.d.* data
- Privacy preservation, comprised devices, polluted data

[3] https://www.networkworld.com/article/3147892/one-autonomous-car-will-use-4000-gb-of-dataday.html.

Case Study: IRS-assisted Federated Learning

Problem: Intelligent reflecting surface (IRS) assisted federated learning for higher energy efficiency

- Federated learning is a distributed learning algorithm for better protecting user data privacy, with many applications
- IRS: regarded as a candidate technology for 6G, can create a smart radio environment
- Wireless for Machine Learning: how to use IRS to make more efficient federate learning

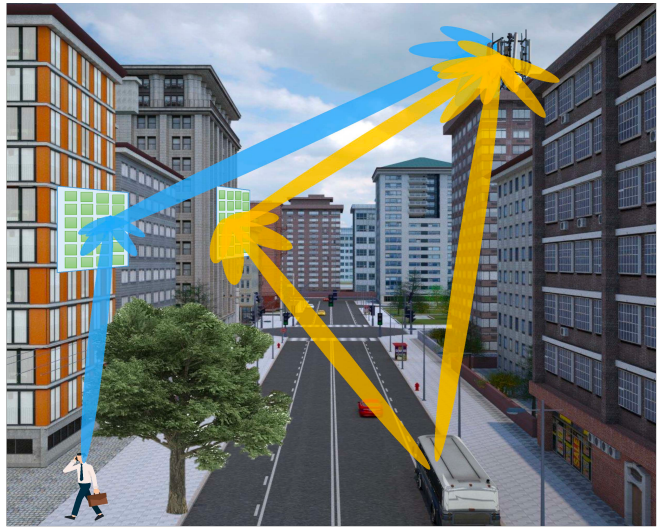
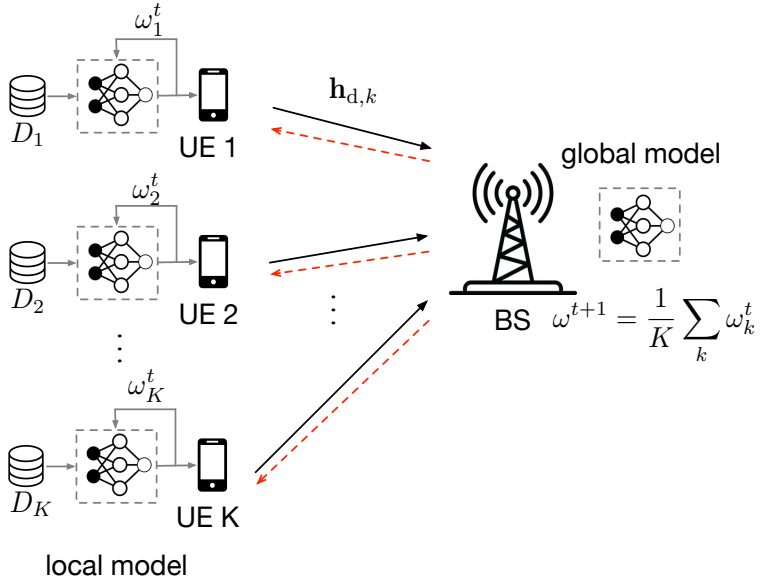
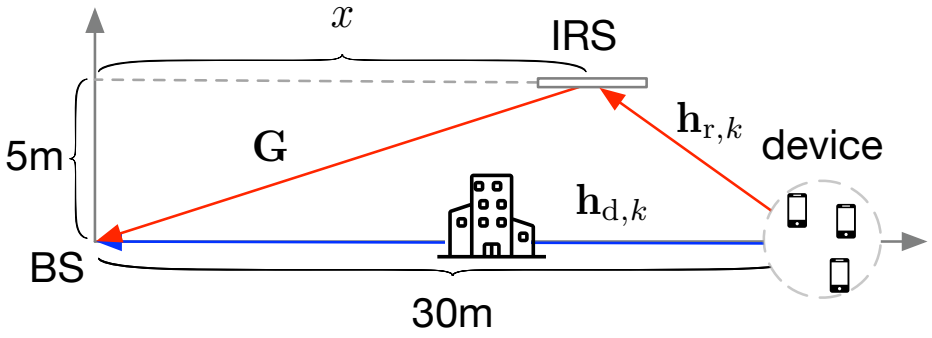


Figure Source: https://m.c114.com.cn/w118-1168348.html



Main results:

- Joint beamforming and resource allocation problem, aiming to optimize the energy efficiency under federated learning's training time constraint
- Developed an alternative optimization approach, which decompose the original problem into multiple semidefinite programming (SDP) problems
- Leveraged the majorization-minimization (MM) algorithm and developed a low-complexity algorithm with greatly reduced complexity with similar optimality performance
- Considerable energy savings found in our simulation study



IRS deployment

[4] Ticao Zhang and Shiwen Mao, "Energy-efficient federated learning with intelligent reflecting surface," *IEEE Transactions on Green Communications and Networking*, to appear. DOI: 10.1109/TGCN.2021.3126795.

Fully Integrated Intelligent Systems

Three levels of problems of communications (Shannon and Weaver)

- Technical – How a channel causes a problem
- Semantic – Is the meaning of message sent and received very different
- Influential – How effectively does the message cause reaction by the receiver

Semantic communication: the shared and local knowledge, extracted from the set of transmission contents, helps compress transmission information and correct the transmission errors according to semantic correlation

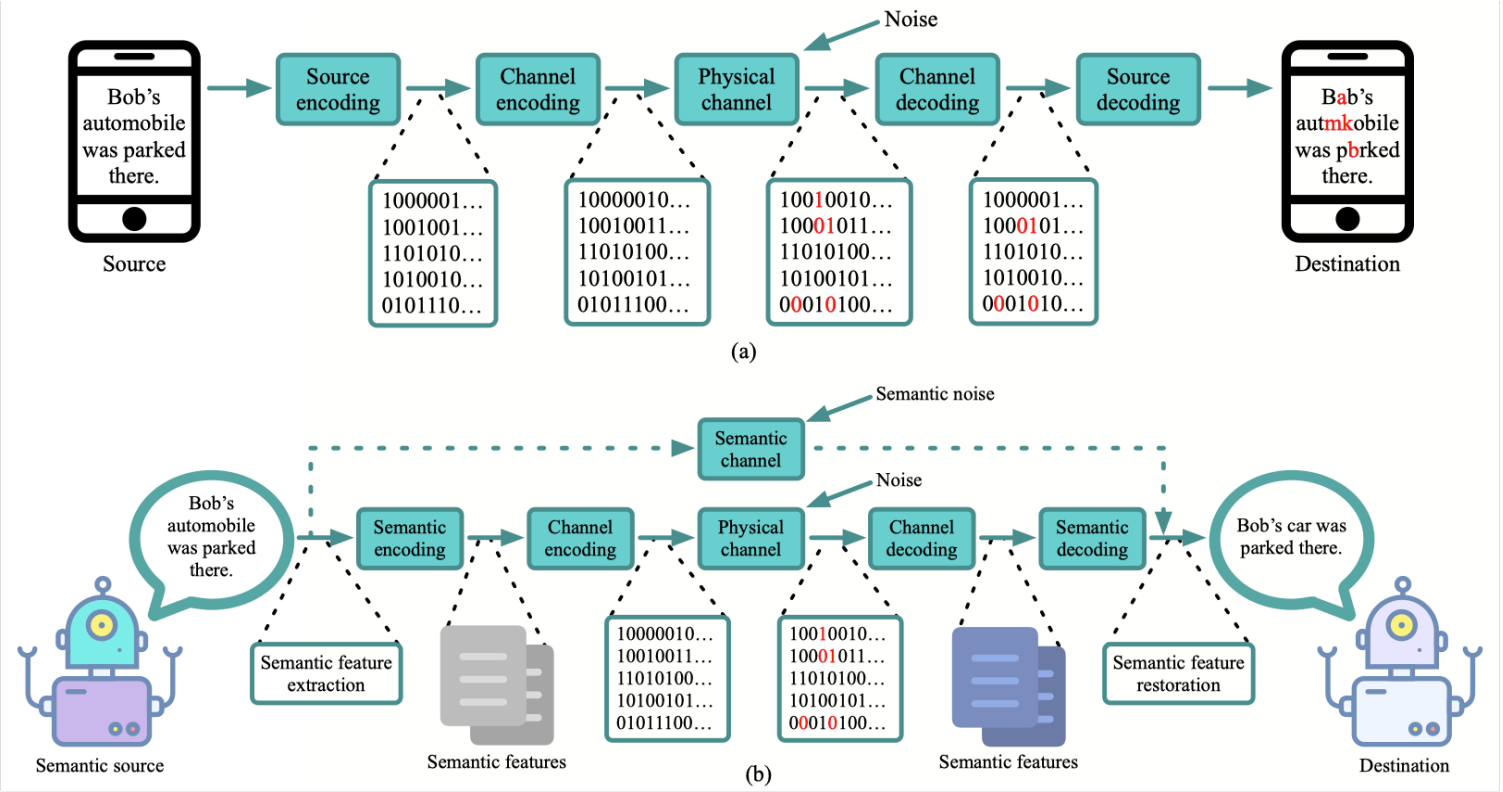


Fig. A comparison between (a) tradition communication and (b) semantic communication (This figure is from [1])

[1] X. Luo, H.-H. Chen, and Q. Guo. "Semantic communications: Overview, open issues, and future research directions," *IEEE Wireless Communications*, vol.29, no.1, pp.210—219, Feb. 2022.
[2] W. Weaver, "Recent contributions to the mathematical theory of communication," *The Mathematical Theory of Communication*, vol.10, no.4, pp.261—281, 1953.

Fully Integrated Intelligent Systems

Benefits:

- Consumes less radio resources
- Reduced latency
- Relatively insensitive to channel noise, improved transmission reliability
- Potentially avoid the co-channel interference
- Integrated with DNN well, enable intelligent end-to-end communication

Challenges

- Insufficient theory
- Performance metrics, design trade-offs
- Inconsistent knowledge base (KB) between the source and destination
- Semantic resource allocation
- Practical implementation

Applications:


Self-driving


IoT smart home

Virtual reality

Industrial IoT


Photo


Text


Video


Speech

[3] Z. Qin, X. Tao, J. Lu, and G.Y. Li, “Semantic communications: Principles and challenges,” *arXiv preprint arXiv:2201.01389*, Dec. 2021.
[4] E.C. Strinati and S. Barbarossa, “6G networks: Beyond Shannon towards semantic and goal-oriented communications,” *Elsevier Computer Networks*, vol. 190, pp. 107930, May 2021.

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For more information: http://www.eng.auburn.edu/~szm0001/

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