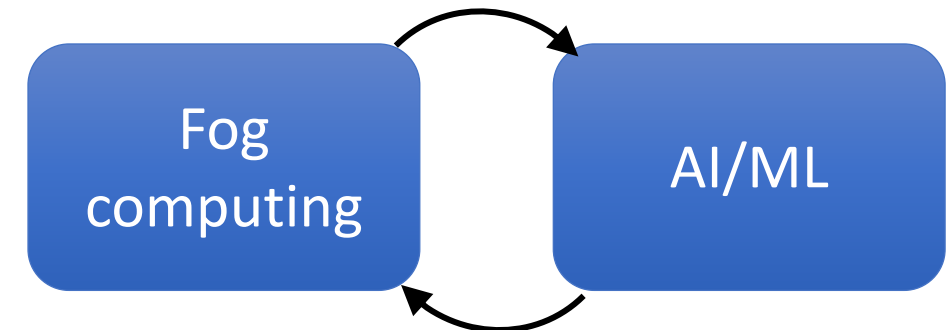


ECE 60022: Wireless Communication Networks

Christopher G. Brinton
Spring 2022

Who am I?

- Prof. Christopher G. Brinton (Chris)
- Assistant Professor in ECE
 - Director of the [ION Lab](#): Intelligence and Optimization for Networks
- Research interests
 - Wireless networks and optimization
 - Machine learning
 - Edge and fog computing
 - Education innovation



What is this course about?

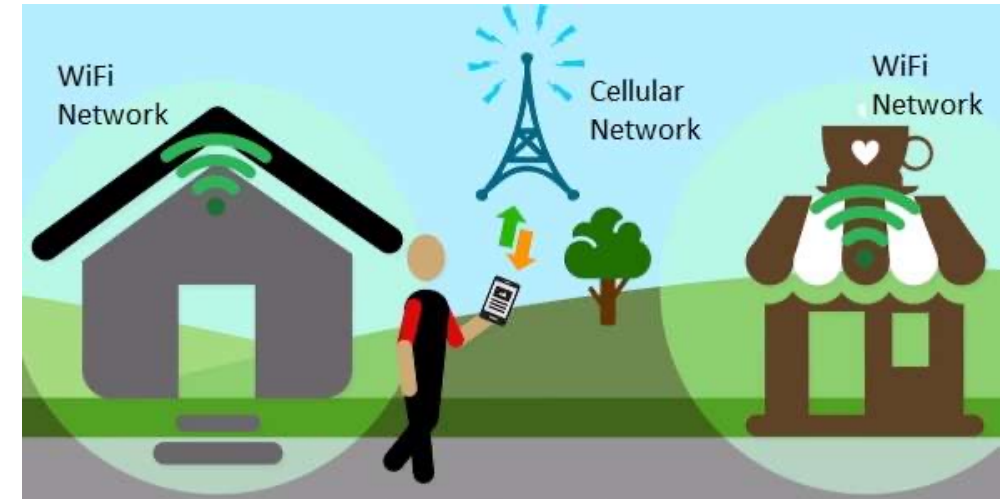
- Fundamental problems in **wireless networks**, such as ...
 - Channel modeling
 - Resource allocation
 - Cross-layer optimization
 - Mobility management
- Wireless **standards**
 - 2G/3G/4G/5G/6G/...
 - IEEE 802.11x
 - But emphasis really on **fundamentals** prevailing across various generations



IEEE Standard	802.11a	802.11b	802.11g	802.11n	802.11ac	802.11ax
Year Released	1999	1999	2003	2009	2014	2019
Frequency	5Ghz	2.4GHz	2.4GHz	2.4Ghz & 5GHz	2.4Ghz & 5GHz	2.4Ghz & 5GHz
Maximum Data Rate	54Mbps	11Mbps	54Mbps	600Mbps	1.3Gbps	10-12Gbps

What is this course about?

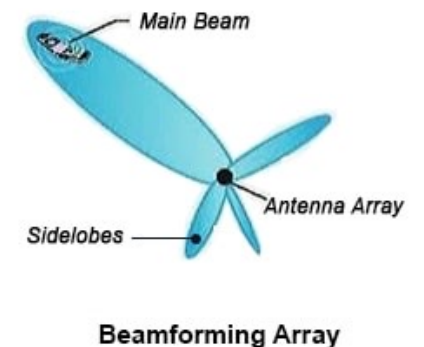
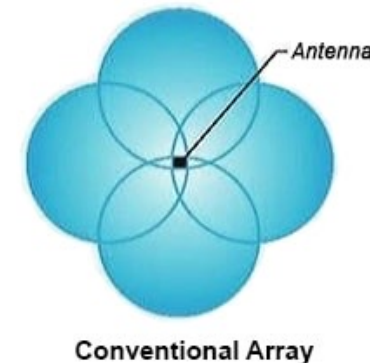
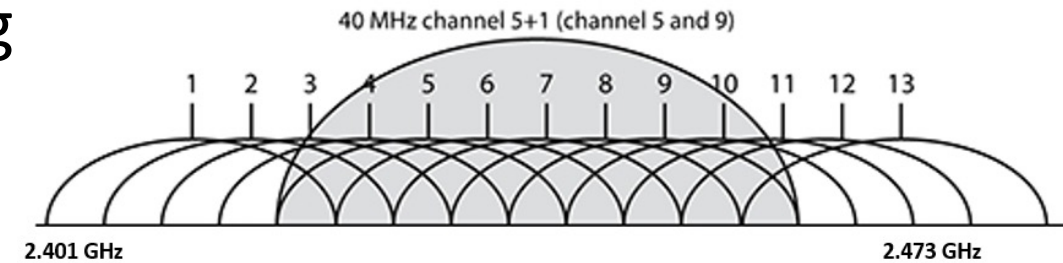
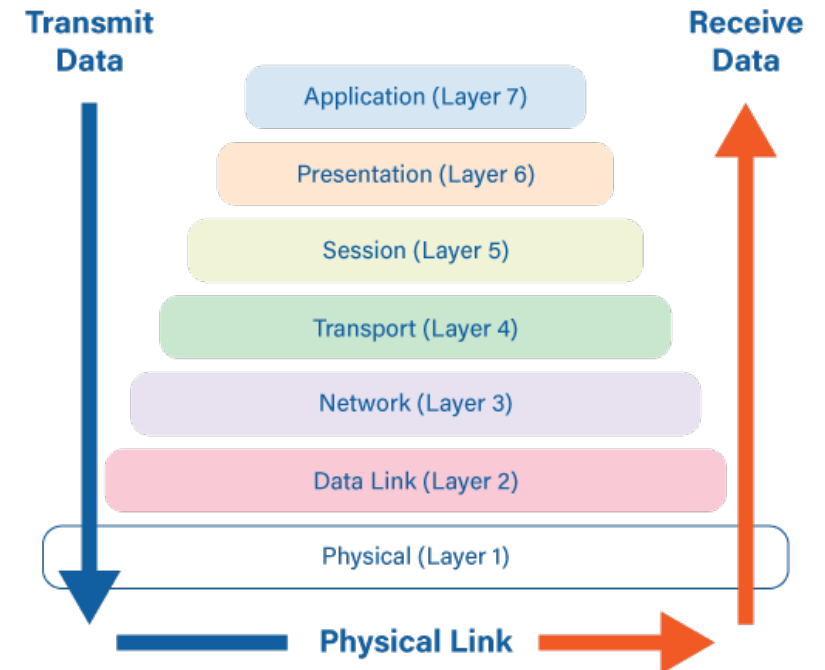
- A key theme will be the two rough “classes” of wireless networks
 - (Legacy) cellular: Regulated, controlled, structured
 - LAN / ad hoc: Less structured, loosely designed, more dynamic
 - Fixed assigned vs. random access
- Key research questions driven by contemporary deployments, e.g.,
 - Fog computing and IoT
 - Machine learning / AI features



How is this course organized?

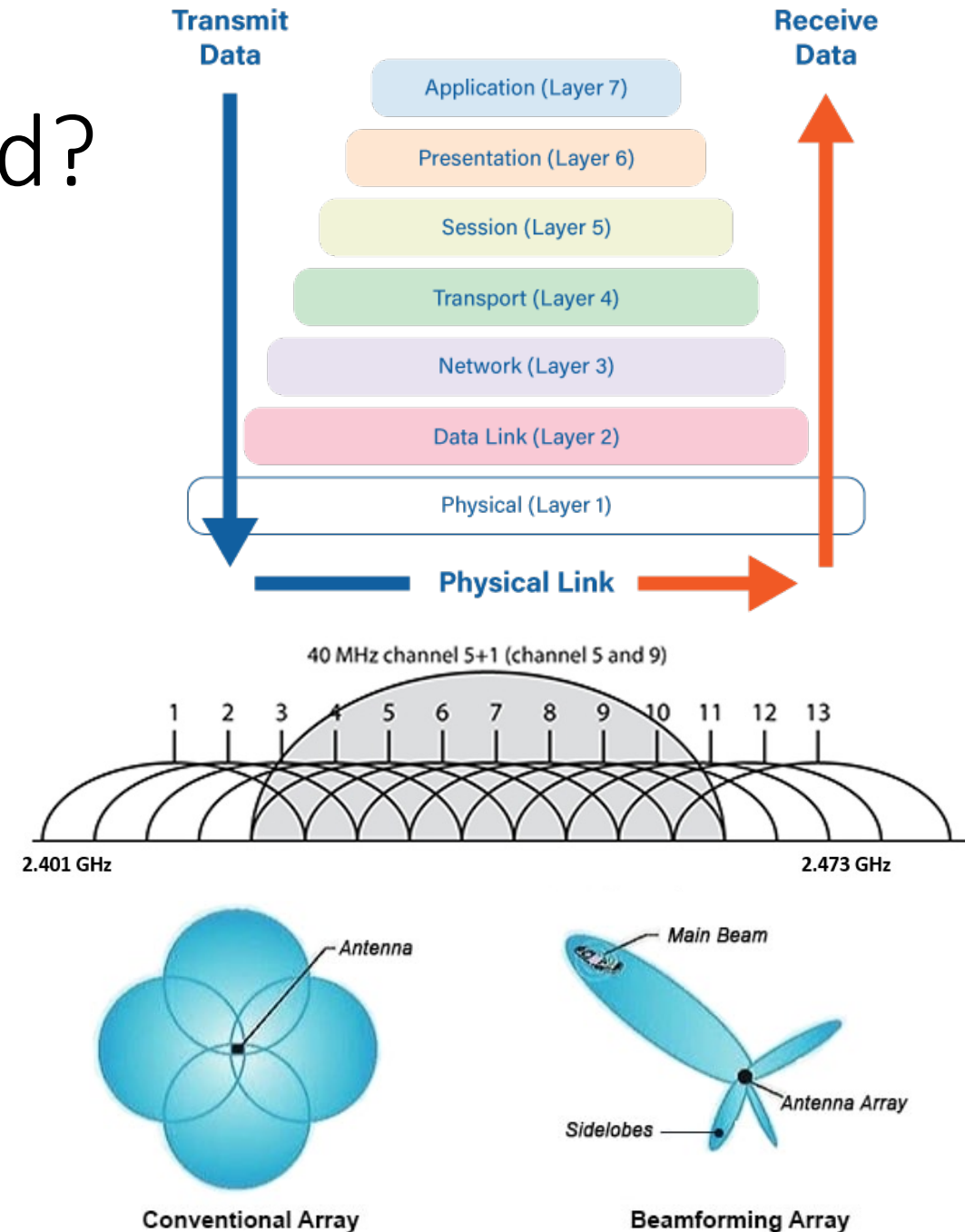
- Divided into 10 modules

1. Overview of Wireless
2. Wireless Channel: Propagation & fading
3. Capacity and Channel Allocation
4. Optimal Resource Allocation
5. Cross Layer Design and Control



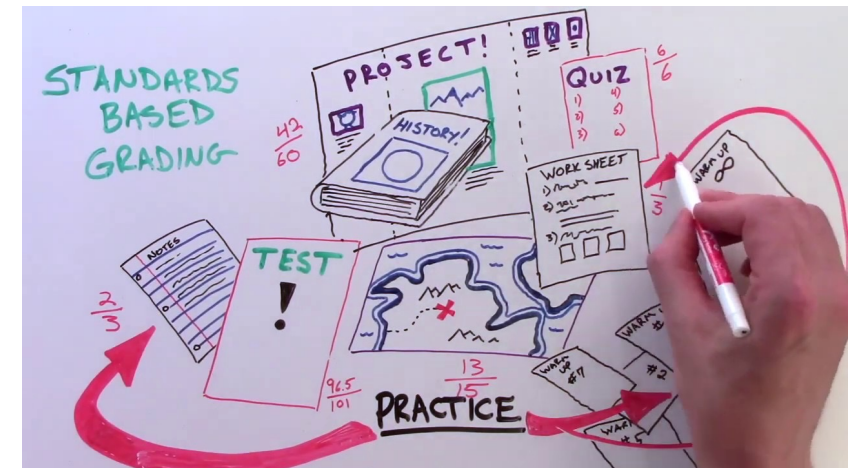
How is this course organized?

6. Stochastic Geometry and Scaling
 7. Cellular System Architectures
 8. Wireless LANs and Random Access
 9. Massive IoT and Beamforming
 10. Wireless Machine Learning
- Any suggestions you have!



How will you be graded?

- **Homeworks** (25%)
 - Five graded (equally weighted), one optional
 - Math-type problems
 - Must be turned in as a hard copy
- **Exams** (35%)
 - Two, non-cumulative, equally weighted
 - Mid-February and Mid-April
 - Likely both in-class
- **Projects** (40%)
 - Mini-project, assigned topic (10%)
 - Term project, student-selected (30%)



What is the term project?



- You will select **your own project topic**
 - Must be related to wireless, communications, **OR** networks
 - Must be **research-oriented**
 - Perfectly fine (and encouraged!) for it to be inspired by your existing research
- Roughly three project types
 - **Survey** of state-of-the-art research (recommended for non-thesis students)
 - **Simulation** of a new idea (recommended for masters thesis students)
 - **Analysis and simulation** of a new idea (recommended for PhD students)
- Projects are **individual**, but collaboration is perfectly fine

Abstract—The conventional federated learning (FedL) architecture distributes machine learning (ML) across worker devices by having them train local models that are periodically aggregated by a server. FedL ignores two important characteristics of contemporary wireless networks, however: (i) the network may contain heterogeneous communication/computation resources, while (ii) there may be significant overlaps in devices' local data distributions. In this work, we develop a novel optimization methodology that jointly accounts for these factors via intelligent device sampling complemented by device-to-device (D2D) offloading. Our optimization aims to select the best combination of sampled nodes and data offloading configuration to maximize FedL training accuracy subject to realistic constraints on the network topology and device capabilities. Theoretical analysis of the D2D offloading subproblem leads to new FedL convergence bounds and an efficient sequential convex optimizer. Using this result, we develop a sampling methodology based on graph convolutional networks (GCNs) which learns the relationship between network attributes, sampled nodes, and resulting offloading that maximizes FedL accuracy. Through evaluation on real-world datasets and network measurements from our IoT testbed, we find that our methodology while sampling less than 5% of all devices outperforms conventional FedL substantially both in terms of trained model accuracy and required resource utilization.

I. INTRODUCTION

The proliferation of smartphones, unmanned aerial vehicles (UAVs), and other devices comprising the Internet of Things (IoT) is causing an exponential rise in data generation and large demands for machine learning (ML) at the edge [1]. For example, sensor and camera modules on self-driving cars produce up to 1.4 terabytes of data per hour [2] with the objective of training ML models for intelligent navigation. The traditional paradigm in ML of centralized training at a server is often not feasible in such environments since (i) transferring these large volumes of data from the devices to the cloud imposes long transfer delays and (ii) users are sometimes

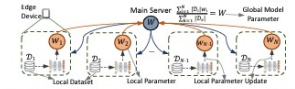


FIGURE 1: Architecture of conventional federated learning (FedL). however, as its implementations scale to networks consisting of millions of heterogeneous wireless devices [6], [7].

At the same time, device-to-device (D2D) communications that are becoming part of 5G and IoT can enable local offloading of data processing from resource hungry to resource rich devices [8]. Additionally, we can expect that for particular applications, the datasets collected across devices will contain varying degrees of similarity, e.g., images gathered by UAVs conducting surveillance over the same area [9], [10]. Processing similar data distributions at multiple devices adds overhead to FedL and an opportunity for efficiency improvement.

Motivated by this, we develop a novel methodology for *smart device sampling with data offloading* in FedL. Specifically, we formulate a joint sampling and data offloading optimization problem where devices expected to maximize contribution to model training are sampled for training participation, while devices that are not selected may transfer data to those that are. This data offloading is performed according to estimated data dissimilarities between nodes, which are updated as transfers are observed. We show that our methodology yields superior model performance to conventional FedL while significantly reducing network resource utilization. In our model motivated by paradigms such as *fog learning* [7], [11], [12], data offloading only occurs among trusted devices; devices that have privacy concerns are exempt from data offloading.

arXiv:2101.00787v1 [cs.NI] 4 Jan 2021

What is the term project?

- Project deliverables
 - 1 page [proposal](#) (due in early March)
 - 10-minute [presentation](#) (in last week of classes): Think of a short conference presentation
 - 6-page [report](#) (due on April 30): Must have ingredients of a [short conference paper](#), written in [IEEE two-column format](#) (<https://www.ieee.org/conferences/publishing/templates.html>)

- Tips on how to succeed
 - Start early
 - Talk to me early, especially if you need ideas for a topic
 - Update me on your progress often
 - Make the project something you are excited about



What do you need to be successful?

- A **loose set of prerequisites**
 - Basic understanding of probability, linear algebra, calculus, and digital communications as would be obtained at the undergraduate level
 - ECE 547: Introduction to Computer Communication Networks is more than sufficient
- A **desire to learn** advanced topics in wireless communication networks and the state-of-the-art techniques and questions
- A **desire to challenge yourself** intellectually through the term project

Are there any textbooks?

- Difficult to find a single, representative textbook
 - Lots of them exist on the physical-layer
- Suggest obtaining a copy of the following book:
 - Mischa Schwartz, *Mobile Wireless Communications*, Cambridge University Press, 2005
 - Copy available in engineering library if necessary
- It could also be helpful to have these books:
 - S. Sesia, I. Toufik, and M. Baker, *LTE-the UMTS Long Term Evolution: From Theory to Practice*, John Wiley & Sons, 2011
 - E. Dahlman, S. Parkvall, J. Skold. *5G NR: The Next Generation Wireless Access Technology*. Elsevier, 2018

Who are you?

- Name
- MS/PhD
- Year
- Advisor/Department
- Research interests
- What are the topics that interest you?