

Machine Learning for the Physical Layer

Supervised Learning for Traffic Classification Lecture 3-4

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Outline

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Introduction - Why ML in the Physical Layer?

The "Model-Free" Advantage: Traditional PHY assumes Gaussian noise and linear channels. Real-world channels (high-speed rail, dense urban) are non-linear and non-stationary.

Complexity Reduction: Iterative algorithms in MIMO can be computationally expensive; ML provides a "single-pass" inference.

Adaptivity: ML can learn unique site-specific impairments that a general mathematical formula cannot capture.

The "Model-Free"

- **Traditional (Model-Based):** Engineers design a receiver based on a specific mathematical equation for the channel
 - If the real world doesn't perfectly match that equation, the receiver's performance drops.
- ▶ **AI (Model-Free):** The Neural Network does not need an equation.
 - It "observes" millions of transmitted and received signals and learns the hidden relationship between them.
 - It treats the channel as a "black box" and adapts to whatever it finds inside.

The End-to-End Communication System as an Autoencoder

- ▶ Traditional communication consists of separate blocks (Source Coding → Channel Coding → Modulation).
 - **ML Concept:** Treat the entire transmitter, channel, and receiver as a single Deep Neural Network (DNN).
 - **Goal:** Optimize the "Latent Space" (the signal) to be resilient to the specific noise of the channel.

Automatic Modulation Classification (AMC)

- ▶ **Problem:** A cognitive radio needs to identify the modulation (e.g., QAM-16 vs. QPSK) of an incoming signal without prior info.
- ▶ **ML Approach:** Using Convolutional Neural Networks (CNNs) on IQ samples
- ▶ **Features:** Raw IQ time-series data or Constellation diagrams (treated as images).

Comparison of Signal Classification Techniques

In the physical layer, "Signal Classification" usually refers to **Automatic Modulation Classification (AMC)**—the ability of a receiver to blind-identify if a signal is BPSK, QAM-16, etc.

1. Likelihood Ratio Test (LRT) - The Mathematical Gold Standard

- **Mechanism:** Uses complex statistical decision theory to calculate the probability of a signal belonging to a specific class.
- **The "Cost":** It requires perfect knowledge of the channel (noise variance, phase offset, frequency offset).
- **AI Context:** It is often used as the "Upper Bound" in research papers to see how close an AI model can get to "perfect" math.

Comparison of Signal Classification Techniques (cont.)

2. Feature-Based (Cyclostationary) - The Engineering Approach

- **Mechanism:** Extracts specific "Expert Features" like **Higher-Order Cumulants (HOCs)** or spectral correlation functions.
- **Strengths:** Does not require a large training dataset; works based on known physical properties of radio waves.
- **Weaknesses:** Fails in high-interference environments (low SNR) because the "features" get buried in the noise.

Comparison of Signal Classification Techniques (cont.)

3. CNN-Based (Deep Learning) - The Modern AI Approach

- **Mechanism:** Treats the signal's **I/Q (In-phase/Quadrature)** components as raw data or its **Constellation Diagram** as an image.
- **Strengths:**
 - **Robustness:** Can learn to "see through" non-linear distortions that break mathematical models.
 - **Inference Speed:** Once the model is trained, the "Forward Pass" (classification) is faster than calculating complex Likelihood Ratios.
- **Weaknesses:** Needs thousands of labeled signal samples (datasets like RadioML 2018.01)

Channel State Information (CSI) Estimation & Compression

- **The Problem:** Massive MIMO requires huge amounts of CSI feedback from the User Equipment (UE) to the Base Station, consuming bandwidth.
- **The ML Solution (CsiNet):** Use **Autoencoders** to compress the CSI matrix at the UE and reconstruct it at the Base Station.
- **Benefit:** Achieves $10\times$ compression with minimal loss in beamforming accuracy.

Beamforming and Resource Allocation

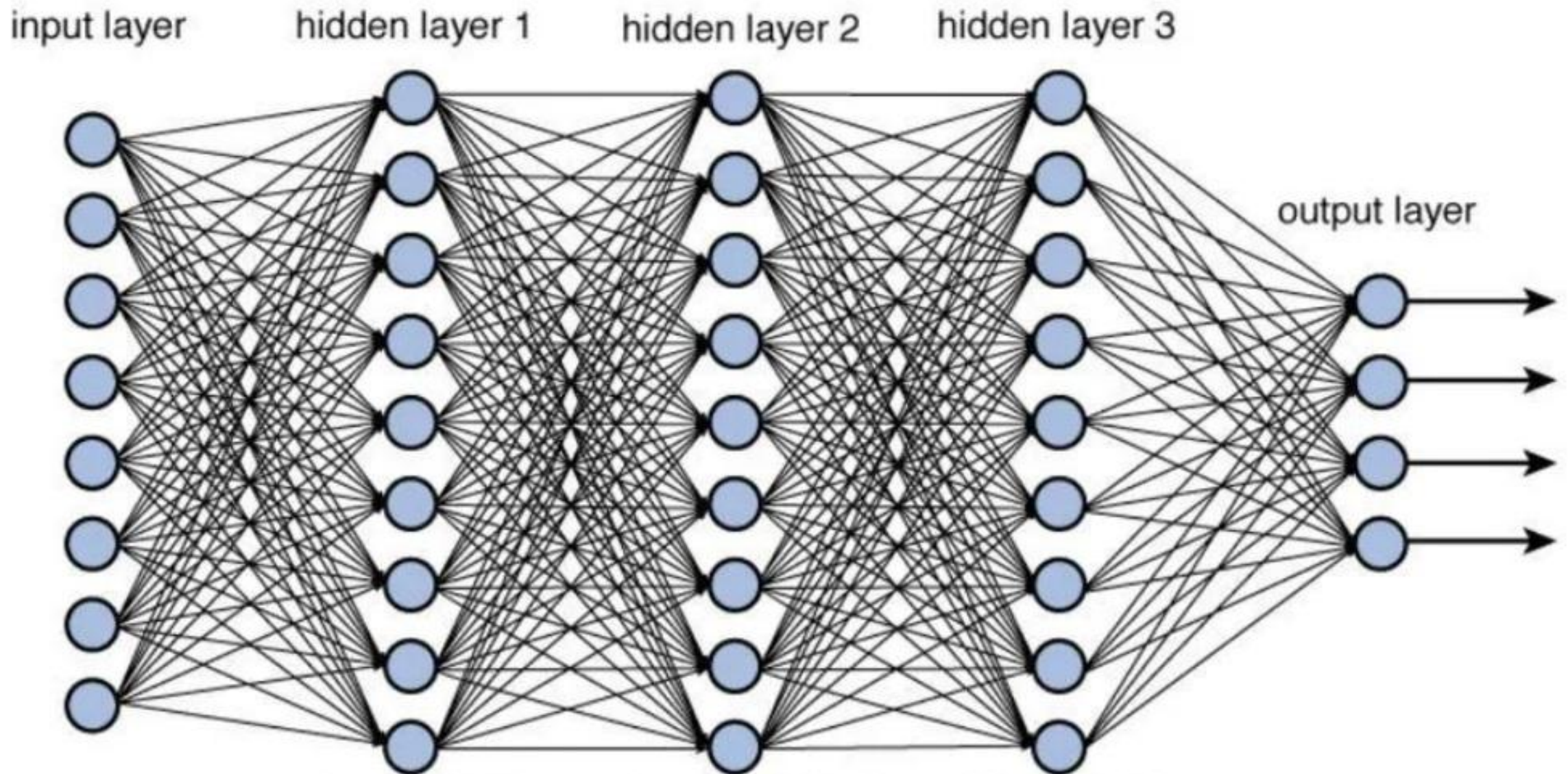
- **Traditional:** Matrix inversion and optimization (Slow).
- **ML Approach: Deep Reinforcement Learning (DRL).**
- **Mechanism:** The base station (Agent) observes the environment (User locations), takes an action (Beam direction), and receives a reward (Signal-to-Interference-plus-Noise Ratio - SINR).

Machine Learning Algorithms by PHY Task - The "Right Tool for the Job"

1. Deep Neural Networks (DNN) / MLP for Signal Detection

- **The Task:** Deciding if a received bit is a 0 or a 1 in a non-linear environment.
- **Why DNN?** Traditional detectors like the **Maximum Likelihood (ML) Detector** assume the noise is Gaussian. In real-world hardware, Power Amplifiers (PA) create non-linear distortions. A DNN can learn the "shape" of this distortion and compensate for it, acting as a non-linear equalizer.
- **Input:** Received IQ samples.
- **Output:** Hard or soft bit estimates.

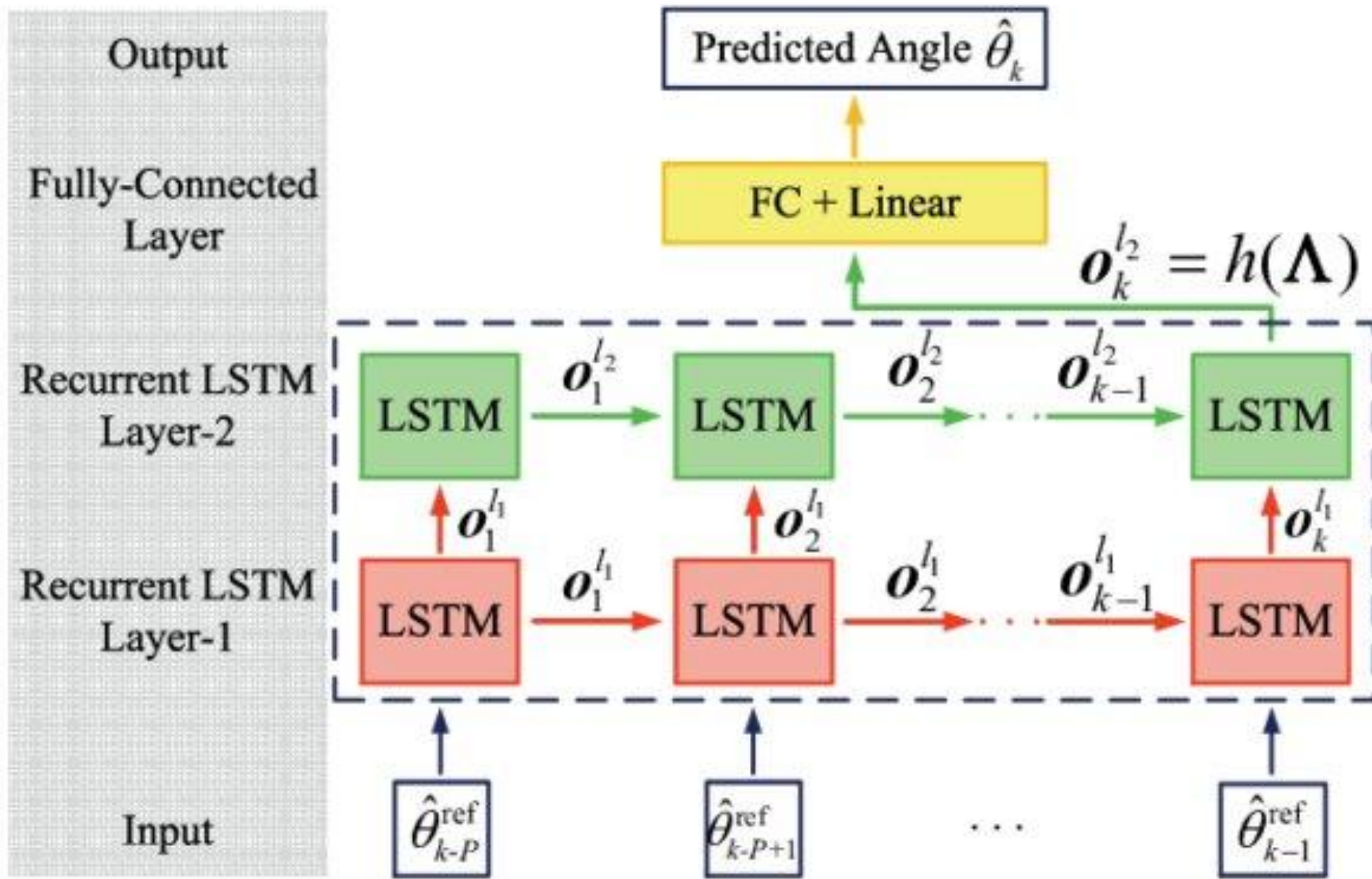
Deep Neural Network



Machine Learning Algorithms by PHY Task (cont.)

2. Recurrent Neural Networks (RNN/LSTM) for Channel Estimation

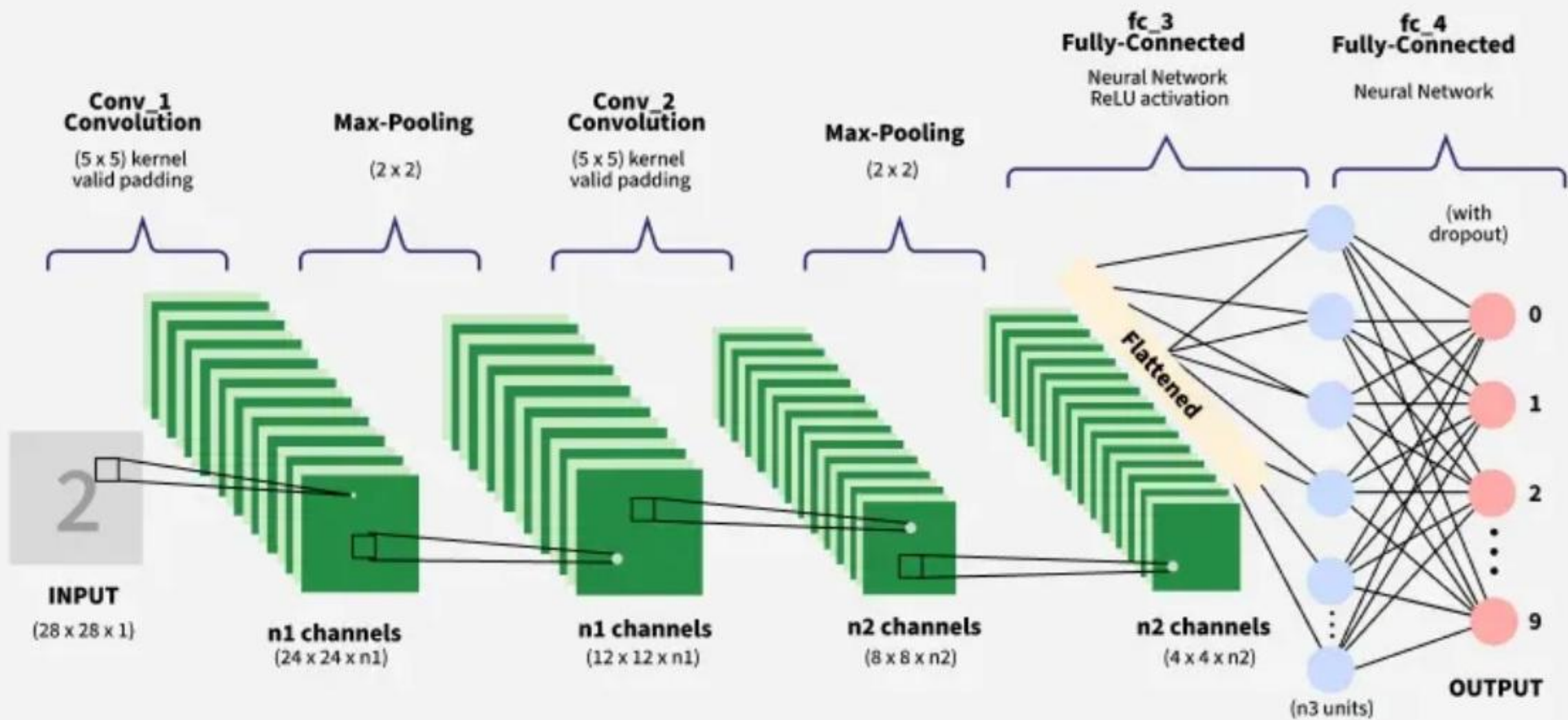
- **The Task:** Predicting the "Channel State" (how the signal will fade) in the next millisecond.
- **Why RNN?** Wireless channels have **temporal correlation** (the channel at time t is related to $t-1$). LSTMs (Long Short-Term Memory) are designed to remember sequences.
- **Input:** A history of previous Channel State Information (CSI) measurements.
- **Output:** A prediction of the future channel, allowing the base station to adjust its beam before the user moves.



Machine Learning Algorithms by PHY Task (cont.)

3. Convolutional Neural Networks (CNN) for Spectrum Sensing

- **The Task:** Identifying "Whitespaces" (empty frequencies) in Cognitive Radio.
- **Why CNN?** Spectrum data can be represented as a **Spectrogram** (Time vs. Frequency vs. Energy).
- A CNN treats this spectrogram as an image, identifying the "textures" of different signals (LTE, Wi-Fi, 5G) even when they overlap.
- **Input:** Spectrogram or Power Spectral Density (PSD) plots.

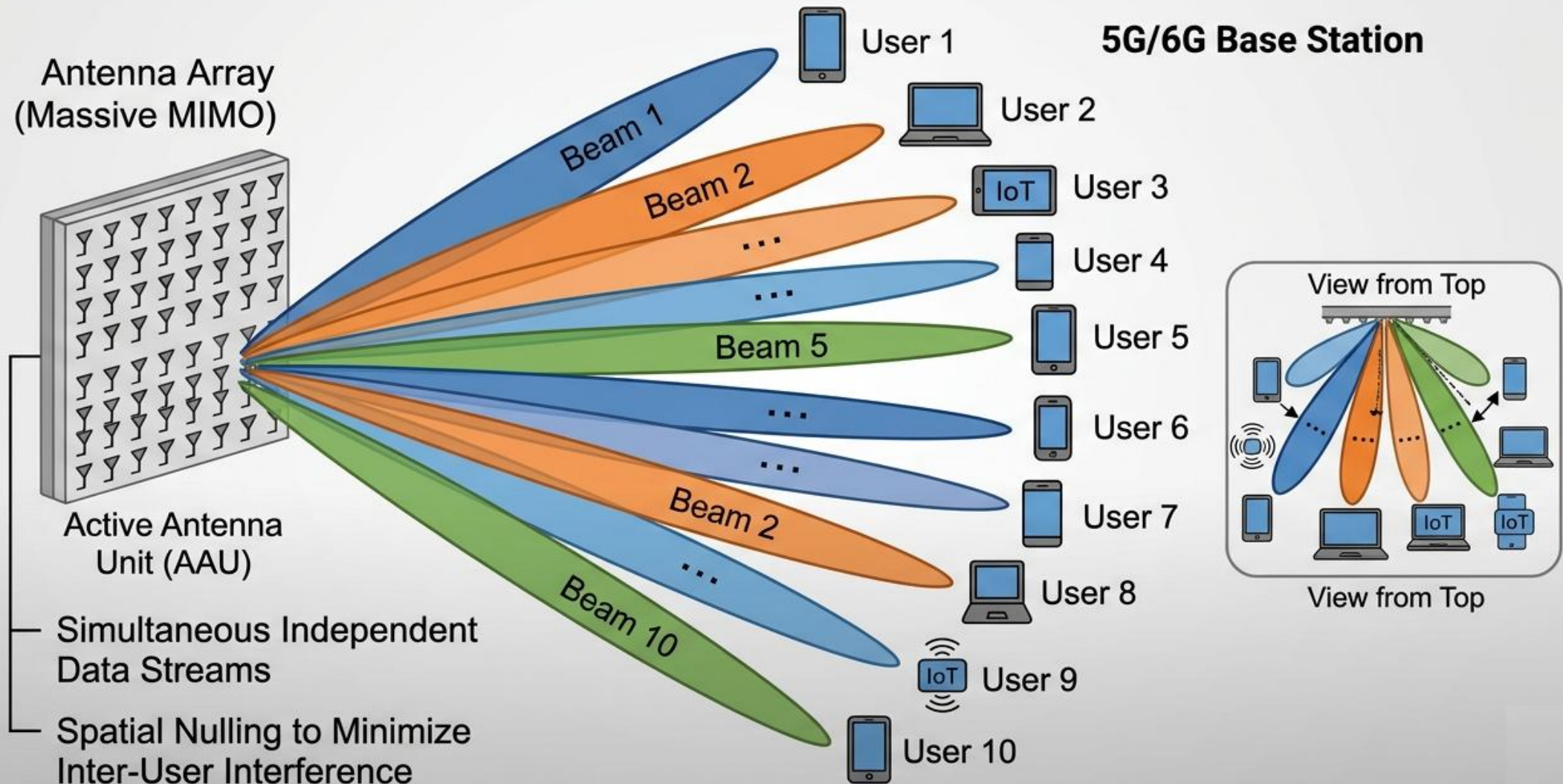


Machine Learning Algorithms by PHY Task (cont.)

4. Reinforcement Learning (RL) for Resource Allocation

- **The Task:** Choosing the best frequency, power level, and beam direction for 100 users simultaneously.
- **Why RL?** This is a dynamic "Game." If the Base Station (Agent) changes the power for User A, it affects the interference for User B. RL learns through **Trial and Error** to find a "Policy" that maximizes the total network throughput (Reward).
- **Algorithm:** Deep Q-Networks (DQN) or Proximal Policy Optimization (PPO).

Multi-User MIMO (MU-MIMO): Spatial Multiplexing with Beamforming



Case Study 1 - The "DeepReceiver" (5G Intelligent Receiver)

- In traditional 5G systems, the receiver is a chain of independent, manually designed blocks: **Channel Estimation** → **Equalization** → **Demodulation** → **Decoding**. Each block is optimized separately.
- **The "DeepReceiver" Concept:** Replace the entire traditional processing chain with a single **End-to-End Convolutional Neural Network (CNN)**.

The Analogy: The Foggy Window

- Imagine someone is holding up a sign behind a **dirty, foggy** window.
- **The Signal:** The message on the sign.
- **The Channel:** The dirty, foggy glass.
- **Channel Estimation:** The process of looking at the edges of the window to figure out how thick the fog is and where the dirt is. Once you "estimate" the dirt pattern, you can "subtract" it from your vision to read the sign clearly.

The "DeepReceiver" (5G Intelligent Receiver)

1. The Problem: High-Speed Mobility

- **Environment:** A passenger on a High-Speed Train (300 km/h).
- **The Physical Challenge:** Rapidly changing channels and **Doppler Shifts** (frequency stretching) make it nearly impossible for traditional "Pilots" (reference signals) to track the channel accurately.
- **Traditional Failure:** The MMSE (Minimum Mean Square Error) equalizer becomes "stale" before it can even finish its calculation.

The Problem: Rapidly Changing Channels

- In a static environment (sitting in a room), the "Channel" (the obstacles between you and the tower) is constant.
- We send a Pilot (a known reference signal) every few milliseconds to "measure" the air, and that measurement stays valid for a long time.
- **The Challenge:** When you move at 120 km/h, the environment changes so fast that by the time the Receiver has used the Pilot to "measure" the channel, the channel has already changed.
- The "measurement" is now obsolete.
- This is called **Channel Aging**. It's like trying to draw a map of a city while the buildings are physically sliding around.

The AI Architecture

The DeepReceiver uses a **1D-CNN** or a **ResNet (Residual Network)** architecture to map the raw received I/Q samples directly to the transmitted bits.

- **Input Layer:** $2 \times N$ matrix (In-phase and Quadrature components).
- **Hidden Layers:** Convolutional layers that act as adaptive filters, automatically "learning" the Doppler shift and Multipath interference.
- **Output Layer:** Soft-max or Sigmoid layer providing the probability of each bit (0 or 1).

Performance Comparison: DeepReceiver vs. Traditional MMSE

A. Bit Error Rate (BER) and Noise Resilience

In traditional systems, it is assumed the noise is "Gaussian" (clean/white noise). In reality, 5G signals face impulsive noise and hardware imperfections.

- **The "*3dB* Gain" Phenomenon:** Under high-mobility scenarios (e.g., 300 km/h), the DeepReceiver often achieves a *3dB* improvement over traditional MMSE.
 - *What this means for the user:* You can achieve the same connection quality with half the transmission power, significantly extending the battery life of IoT devices and smartphones.
- **Pilot-Aided vs. Pilot-Less:** Traditional receivers fail if "Pilot" signals (reference signals used to "guide" the receiver) are sparse. The DeepReceiver can "blindly" decode data by learning the underlying structure of the waveform, making it 10-15% more spectrally efficient.

Performance Comparison: (cont.)

B. Computational Complexity (The Math Shift) This is the most important technical takeaway.

- **Why it matters:** Matrix inversion ($O(N^3)$) is the "bottleneck" of 5G. By replacing it with a Neural Network's "Forward Pass" (which is just a series of additions and multiplications), we bypass the most computationally expensive part of radio design.

Performance Comparison: (cont.)

C. Latency and Hardware Acceleration

- ▶ **Inference Time:** Modern DeepReceivers (like *DeepRx*) are designed to achieve inference latencies of less than 1ms on specialized hardware (NPUs or NVIDIA A100/H100 GPUs).
- ▶ **Joint Optimization:** Because the AI performs Channel Estimation, Equalization, and Demapping simultaneously in one pass, it eliminates the "waiting time" between separate processing blocks in the traditional chain.
- ▶ **Non-Gaussian Resilience:** In environments with heavy "Co-Channel Interference" (other radios talking on the same frequency), the DeepReceiver's BER stays flat, while traditional receivers' BER spikes (fails) because their mathematical assumptions are no longer true.