Applications of Machine Learning in Wireless Communications: Deployment, Challenges, and Applications

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Overview

1. Deployment
   - Distribution of Network Intelligence
   - ML based Air interface

2. AI Integration: Key areas

3. Application of AI in Wireless Networks
   - AI for Physical layer
   - AI for Resource allocation
   - AI for Mobility management
   - AI for Wireless Security and Localization

4. Examples
   - Autoencoder
   - Scheduling
Wireless Network must support flexible data pipelines for real-time decision making

Must be AI-centric: instead of transporting user data support exchange of data, models, insights algorithms

AI agent responsible for inclusion of data


5G→ 6G: Learning→ Deep Learning → Federated Learning

High degree of heterogeneity in many aspects

Need of intelligent use of communications, control, storage resources from edge to the core

Data driven network planning and operation
6G architecture (Fig 2 in [Letaief19])
### Comparison of Radio Technologies: SDR, CR, IR

<table>
<thead>
<tr>
<th></th>
<th>SDR (3/4G)</th>
<th>CR (4/5G)</th>
<th>IR (6G)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Frequency band</strong></td>
<td>Fixed</td>
<td>Adapt to Environment</td>
<td>Adapt to Env’t and Hardware</td>
</tr>
<tr>
<td><strong>Spectrum Sharing</strong></td>
<td>Fixed</td>
<td>Opportunistic</td>
<td>AI-enabled</td>
</tr>
<tr>
<td><strong>Hardware capability</strong></td>
<td>Pre-claimed</td>
<td>Pre-claimed</td>
<td>Online estimated</td>
</tr>
<tr>
<td><strong>Hardware upgrade</strong></td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>PHY Tx/Rx</strong></td>
<td>Mod/Cod/ Det/Est</td>
<td>Mod/Cod/ Det/Est</td>
<td>Deep neural net</td>
</tr>
<tr>
<td><strong>MA</strong></td>
<td>Predetermined</td>
<td>Sensing-based</td>
<td>Distributed ML</td>
</tr>
<tr>
<td><strong>Protocol L3</strong></td>
<td>Fixed</td>
<td>Fixed</td>
<td>Self-upgradable</td>
</tr>
<tr>
<td><strong>Main apps</strong></td>
<td>Voice, data</td>
<td>Multimedia, data</td>
<td>AI, In network Computation</td>
</tr>
</tbody>
</table>

**Table:** Table 1 in [Letaief19]
Distribution of Network Intelligence

Feature: The network must no longer be built to transport *user-data only* but rather designed to support *exchange of data, models, and insights*, and it is the responsibility of the AI agents to include any necessary user data. Goal: To integrate intelligent functions across the wireless infrastructure, cloud, and end-user devices with the lower-layer learning agents targeting local optimization functions while higher-level cognitive agents pursuing global objectives and system-wide awareness.

- **Autonomous** node-level AI: self-contained problems at a node/device; no data transfer
- **Localized AI** single domain network: data transfer within network; geographical localization
- **Global AI** centralized entity: global knowledge, collects data and knowledge from multiple domains
<table>
<thead>
<tr>
<th></th>
<th><strong>Autonomous AI</strong></th>
<th><strong>Localized AI</strong></th>
<th><strong>Global AI</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>node level AI</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Benefits</strong></td>
<td>Ensures privacy</td>
<td>Data shared</td>
<td>Global optima</td>
</tr>
<tr>
<td></td>
<td>Less delay</td>
<td>across domains</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No data overhead</td>
<td>Favourable for power limited devices</td>
<td></td>
</tr>
<tr>
<td><strong>Challenges</strong></td>
<td>Local optima</td>
<td>Security/privacy</td>
<td>Deployment issue</td>
</tr>
<tr>
<td></td>
<td>Device power and</td>
<td>in data sharing</td>
<td>Data transfer cost</td>
</tr>
<tr>
<td></td>
<td>memory limitation</td>
<td>Data overhead</td>
<td>Training complexity</td>
</tr>
<tr>
<td></td>
<td>Computational</td>
<td>Time delays</td>
<td></td>
</tr>
<tr>
<td>limits</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Table:** Table 1 in [Chalitta19arXiv]
Architecture and Training Challenges

- Resource shortage and negotiating of resources
- How to distribute the models and knowledge bases over the devices
- Centralized or distributed learning?
- Offline or online learning?
- How to represent and prepare data for fast consumption by algorithms
- Short-time vs Long-time scale applications

Possible training strategies: distributed ML (i.e. federated learning)
Air interface: combination of parameters of wireless link, such as power, modulation, coding, pilots, ARQ, etc to facilitate wireless data transfer between two nodes.

**Goals**: provide efficient data transmission, low energy consumption, acceptable delay, proper control signalling.

**ML/AI suitability** ML is well adapted to optimize efficiency of transmission (modulation, coding, transmit power) since lots of data being transmitted and received.

**ML/AI challenges** Situation awareness, control channel training (no data transmitted, received)

**ML/AI initial deployment** Mixed with 4G assisted and 5G NR technologies, focus on efficiency of data transfer
ML air Interface supported by control plane through other network 4G/5G (Fig 1 in [Chalitta19arXiv])
Human designed RAT can be used to train ML autoencoder with indicating what bits are to be expected at the receiver and feedback losses.
1. Big Data Analytics
2. Closed Loop Optimization
3. Intelligent Wireless Comm
6G for AI applications

1. Trends and challenges

2. Comm for distributed learning: training Federated Training

3. Comm for distributed learning: inference Wireless MapReduce
Federated Learning

Local model update

Global model update

\[ \sum_{i=1}^{n} \frac{m_i}{m} \Delta z_i \]
AI Integration: Key areas

- Data Acquisition
- Data Security and Integrity
- Confidential computing
- Efficient AI implementation
- Reinforcement learning in cell networks
- Efficient training process
- AI alignment
- Active learning
- Explainable AI
- Real time intelligence
Background and Motivation

- Use: context information prediction, network changes adaptation, proactive radio resource management
- AI based solutions will be introduced along short/long term tracks
- **Short term** targets separate blocks (, modulation scheduler, mobility management, *etc.*)
- **Long term** cross-layer optimization based on QoE metrics, end-to-end performance, violation of OSI stack, full ML Air interface
- Importance of efficient UE measurements reporting procedures
AI for Physical layer

- ML based modulations (precoder + OFDM)
- Pilotless demodulation schemes
- Intelligent Surfaces (IS) control
- Fast changes detection
AI for resource allocation

- Generally NP-hard
- ML may provide useful heuristic instead of exact solutions
- Beam alignment
- Scheduling
- Beamforming
AI for Mobility management

- Use 6 GHz and above range in NR cause huge measurement overhead
- Leverage predictive power of ML for tracking and prediction
- Use lower frequency coverage measurements to predict high frequency coverage
- Multimode positioning and localization/location estimation
- Scene dependent representation of information
Example of coverage prediction

Multiple frequency coverage map and coverage prediction using lower frequencies (Fig 4 in [Chalitta19arXiv])
Leverage ML classification potential for the following tasks

- False base station identification
- Rogue drone detection
- Rogue messaging
- Attack detection
Any features can be used by unintended receiver to detect or even decode the message. Ideal **Jamming-Resilient (JR) signalling/Low Probability Detection (LPD)** must satisfy the following principles:

- Gaussianity (noise like) with minimum correlation
- Below noise floor (low power spectral density)
- Physical layer security
- Non-repetition
- Uncoordinated synchronization
Classical DSSS Receiver

(Fig 1 in [Shakeel18milcom])
ML DSSS Receiver

(Fig 1 in [Shakeel18milcom])
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training algorithm</td>
<td>One-step secant backpropagation</td>
</tr>
<tr>
<td>Number of hidden layers</td>
<td>1</td>
</tr>
<tr>
<td>Number of inputs- Input layer</td>
<td>256</td>
</tr>
<tr>
<td>Number of neurons - Hidden layers</td>
<td>256</td>
</tr>
<tr>
<td>Number of neurons - Output layers</td>
<td>256</td>
</tr>
<tr>
<td>Activation function - Hidden layer</td>
<td>Linear</td>
</tr>
<tr>
<td>Activation function - Output layer</td>
<td>Softmax</td>
</tr>
<tr>
<td>Loss function</td>
<td>Cross-entropy</td>
</tr>
<tr>
<td>Channel</td>
<td>AWGN</td>
</tr>
<tr>
<td>Trained SNR</td>
<td>$\infty$</td>
</tr>
<tr>
<td>Number of trained weights</td>
<td>131584</td>
</tr>
</tbody>
</table>

**Table**: Table 1 in [Shakeel18milcom]
ML DSSS Receiver BER
Conclusions

- De-facto off-line training
- Channel is not realistic to allow off-line training but could be used to create a code book
- No noise considered in training
- Deep network will be required for longer messages
System consists of $K$ UE with packet arrival intensity $\lambda$

Each moment of time $B$ resource blocks are available

$N$ time transmission intervals are considered for planning

Multi-objective optimization problem with three performance measures

1. Jain’s fairness index (JFI)
2. System Throughput (THP)
3. Packet drop rate
Schedulings, cont’d

- Three objectives interrelated and cannot be optimized independently
- Pareto optimization results into a trade-off curve (Pareto Front)
- Full solution is computationally prohibitive, especially real time
- Genetic algorithms, Heuristics
Scheduling: Deep Reinforcement Learning approach

- Model: Markov decision process (MDP): \( S, A, R, r \)
- State \( S \): contains all UE observations: rates, buffer state, etc
- Action \( A \): indicates which UE is selected for transmission
- Reward \( r = \alpha THP + \beta JFI - \delta PDR \)
- Actor-Critic (A2C) algorithm is used optimization (policy based Deep Reinforced Learning): directly parameterises policy \( \pi_{\theta}(a|s) \)
- Updates gradient descent of expected return

\[
g = \nabla_{\theta} \mathcal{E} \left[ \sum_{t=0}^{\infty} \gamma^t r_t \right]
\]
Algorithm 1 A2C algorithm

Initialize all environments
Initialize actor network $\pi_\theta$ and critic network $V_\phi$
Initialize experience buffer $E$

for iteration = 1, $M$ do
  SAMPLE_BATCH($n$, $\pi_\theta$)
  Update discounted reward $r_i$ for $i$th experience
  Policy objective $J_\theta = \sum_i (r_i - V_\phi(s_i)) \log \pi_\theta(a_i|s_i)$
  Entropy term $H_\theta = -\sum_i \pi_\theta(a_i|s_i) \log \pi_\theta(a_i|s_i)$
  MSE of value $L_\phi = \sum_i (r_i - V_\phi(s_i))^2$
  SGD with $G = - (\nabla_\theta J_\theta + \lambda_c \nabla_\theta H_\theta) + \lambda_v \nabla_\phi L_\phi$
end for

function SAMPLE_BATCH($n$, $\pi_\theta$)
  Clear $E$
  for $t = 1, n$ do
    Observe $s_t$
    Choose action $a_t \sim \pi_\theta(s_t)$
    Take action $a_t$, observe $s_{t+1}$ and $r_t$
    Store $(s_t, a_t, r_t, s_{t+1})$ into $E$
  end for
end function
Civilian use of drones (unmanned aerial vehicles)

- Precision Agriculture
- Inspection and Monitoring
- Delivery
- Photography
- Mobile base stations, sidelobe BS enhancers and relays

**Problem:** Rogue drones can pose as legitimate UE drones, especially drone with attached registered UE like a cell phone. may cause additional interference.
Problem statement

- Detect a UE which is unauthorized drone
- Use of service area handover triggering event A3 and radio measurement
- \( f(x) \rightarrow p: f(\circ) \) is ML model, \( x \) UE reported measurement, \( p \) probability of being a drone
Constructing the ML model

- Supervised learning
- Data is generated through 3GPP model simulations (training and test sets)
- Legitimate drones are labelled as such
- Mixture of drone and land mobile UE is used
- Feature metric: RSSI, RSSI-gap, RSSI-STD
- Logistic regression

\[
p = \frac{1}{1 + \exp(-\alpha - \beta_1 x_1 - \cdots - \beta_n x_n)}
\]
Results

Fig. 4. \{RSSI, RSRP-STD\} samples for three UEs of different types
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The End