IMPROVING NEXT-GENERATION WIRELESS NETWORK PERFORMANCE AND RELIABILITY WITH DEEP LEARNING

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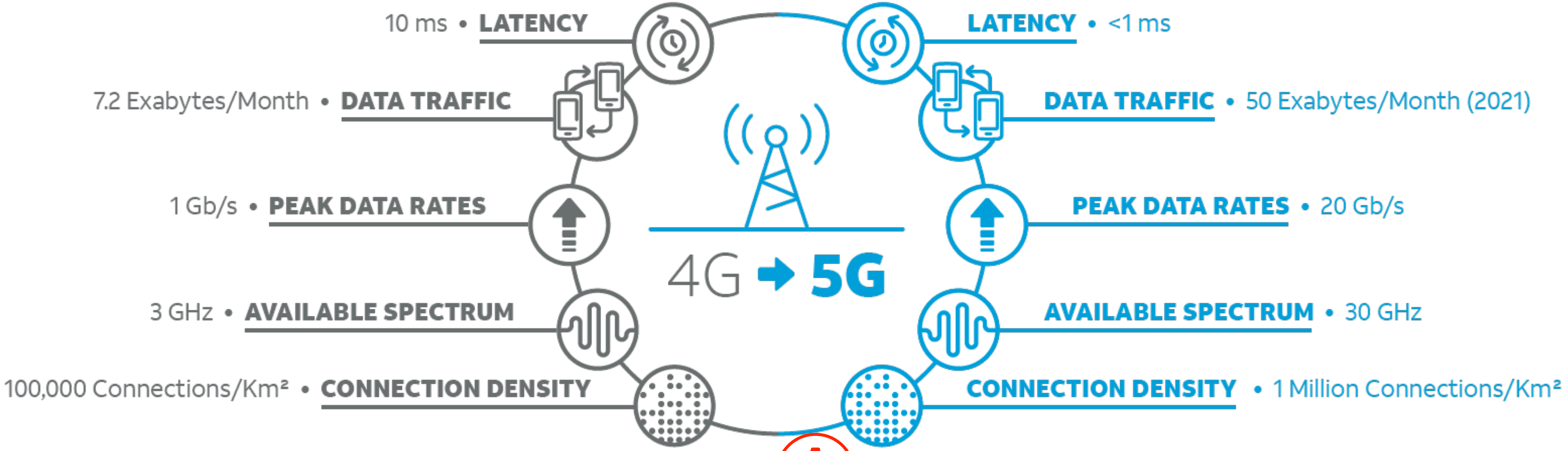
WHAT STARTS HERE CHANGES THE WORLD

ESPL

WNCG Wireless Networking & Communications Group

VISION FOR 5G COMMUNICATIONS

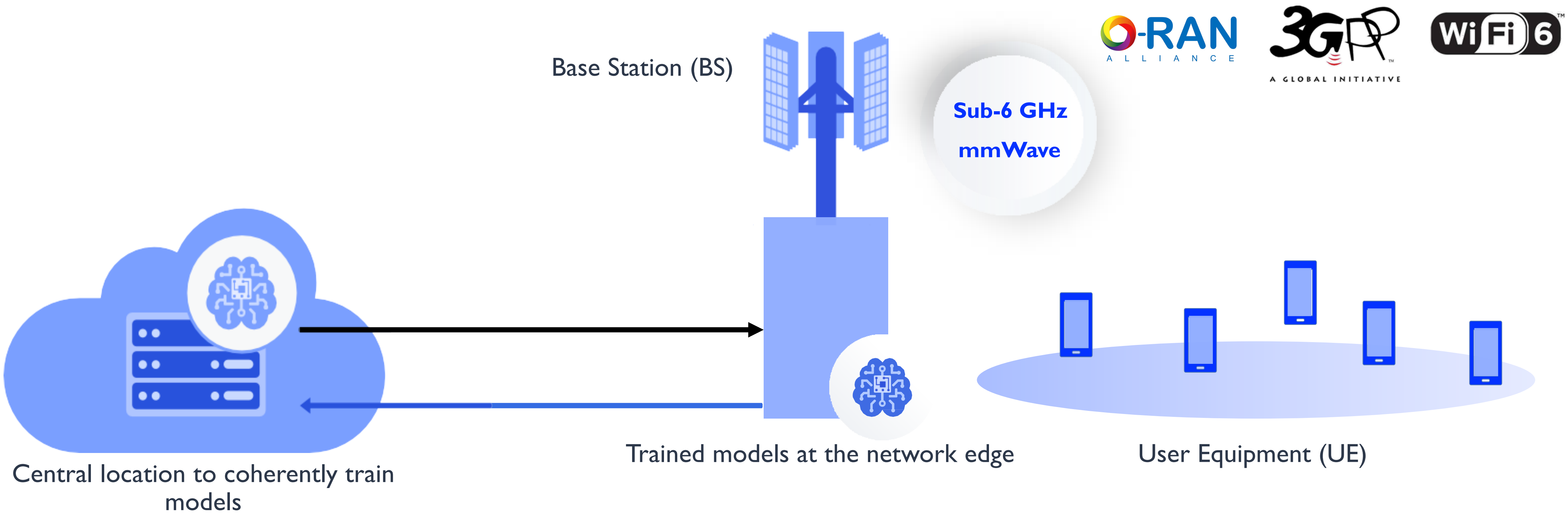


NETWORK ANALYTICS

- "Network Data Analytics Function" (3gpp)

[https://www.qorvo.com/design-hub/blog/getting-to-5g-comparing-4g-and-5g-system-requirements]

VISION FOR INTELLIGENT WIRELESS NETWORK



[https://www.qualcomm.com/media/documents/files/making-ai-ubiquitous.pdf]

Hybrid approach to unleash next-generation wireless "network intelligence"

MOTIVATION: DEEP LEARNING IN COMMUNICATIONS

- Absence of accurate mathematical formulations
  - data-driven approaches using ray-tracing datasets or field-measurements [Zappone19]
- Incremental changes in radio resource management (RRM) algorithms
  - industry standards still prefer "legacy" algorithms despite successive evolutions [3gpp15] & [3gpp18]
- Desire for fully autonomous self-organizing networks (SON)
  - operators are under constant pressure to *reduce operational expenditure* without impacting performance [Zappone19]

Long training times and high implementation complexity pose significant challenges

CONTRIBUTIONS

- How to improve next-generation wireless networks system performance?

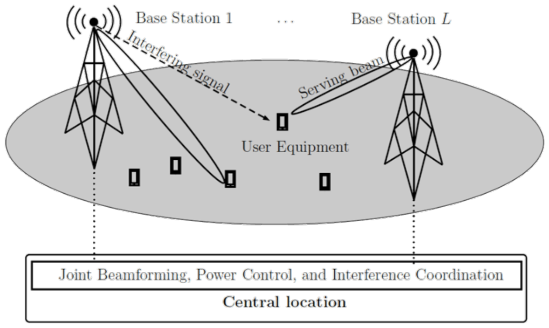
disrupt the legacy industry standards to *boost reliability and eliminate performance bottlenecks*

PHY perspective

RRM perspective

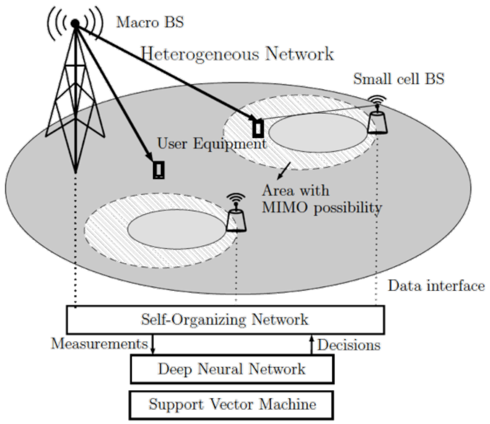
Beamforming, Power Control and Interference Coordination

Contribution 1



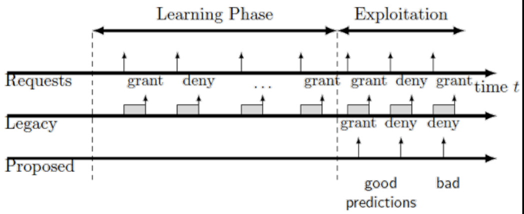
Intelligent Coordinated Multipoint

Contribution 2



Predictive Band Switching

Contribution 3



Improve user rates

Contributions are on the downlink (BS to UE)

RRM: radio resource management layer PHY: physical layer
BS: Base station UE: user equipment.

Contribution 1

JOINT BEAMFORMING, POWER CONTROL, AND INTERFERENCE COORDINATION

Discussed in the PhD Qualifying Exam and Included in the PhD Dissertation

Related publications:

[1]. F. B. Mismar, B. L. Evans and A. Alkhateeb, "Deep Reinforcement Learning for 5G Networks: Joint Beamforming, Power Control, and Interference Coordination," *IEEE Transactions on Communications,* submitted Jun. 28, 2019 and resubmitted Sep. 21, 2019 and Nov. 8, 2019.

[2]. F. B. Mismar and B. L. Evans, "Q-Learning Algorithm for VoLTE Closed-Loop Power Control in Indoor Small Cells," *Proceedings of the 52nd Annual Asilomar Conference on Signals, Systems, and Computers*, Oct. 2018.

BACKGROUND

- Problem
  - User served by a base station receives interference from neighboring base station
  - Base station serving the user causes interference to other users
- Goal
  - Maximize the signal to interference plus noise ratio (SINR) from serving base station to user
- Parameters
  - Beamforming (BF) to create a virtual sense of a user-specific channel for data
  - Power Control (PC) to control the transmit power of the serving BS towards a user
  - Interference Coordination (IC) to control the transmit power of the neighboring BSs
  - User spatial coordinates
- Approach
  - Perform binary encoding of BF, PC, and IC actions to enable joint actions
  - If SINR of all users improve, then reward actions. This resolves the *race condition*
  - Compare proposed solution with optimal solution

SYSTEM MODEL

- Multi-user downlink system
  - Multi-cell environment with single-antenna users
  - *L* total dual-band base stations
  - Uniform linear array (ULA) antennas (*M*)
  - Power control for all users
  - Codebook analog beamforming for mmWave data
  - More power control commands for sub-6 GHz voice

- Narrow-band geometric channel model

$$\mathbf{h}_{\ell,b} = \frac{\sqrt{M}}{\rho_{\ell,b}} \sum_{p=1}^{N^p_{\ell,b}} \alpha^p_{\ell,b} \mathbf{a}^*\left(\theta^p_{\ell,b}\right)$$ [Alkhateeb14]

channel path *p* gain

path loss for user served by BS *l* in area of BS *b*

angle of departure

array response vector

- suitable for both sub-6 and mmWave propagation
- smaller number of paths at mmWave (sparse)

- Beamforming vector

$$\mathbf{f}_n := \mathbf{a}(\theta_n), \qquad n = \{1, 2, \ldots, L\}$$

- Signal model for the user served by the ℓ-th BS:

Inter-cellular interference

$$y_\ell = \mathbf{h}^*_{\ell,\ell}\mathbf{f}_\ell x_\ell + \boxed{\sum_{b\neq\ell} \mathbf{h}^*_{\ell,b}\mathbf{f}_b x_b} + n_\ell$$

Gaussian noise

$$\mathbb{E}[|x_\ell|^2] = P_{\mathrm{TX},\ell}$$
$$n_\ell \sim \mathrm{Normal}(0, \sigma_n^2)$$

- Received SINR for the user served by the ℓ-th BS:

$$\gamma_\ell[t] = \frac{P_{\mathrm{TX},\ell}[t]|\mathbf{h}^*_{\ell,\ell}[t]\mathbf{f}_\ell[t]|^2}{\sigma_n^2 + \sum_{b\neq\ell} P_{\mathrm{TX},b}[t]|\mathbf{h}^*_{\ell,b}[t]\mathbf{f}_b[t]|^2}$$

MOTIVATION AND PROBLEM FORMULATION

- Improve SINR through joint power control, interference coordination, beam selection

$$\begin{aligned} \underset{\substack{P_{\mathrm{TX},j}[t],\ \forall j \\ \mathbf{f}_j[t],\ \forall j}}{\text{maximize}} \quad & \prod_{j \in \{1,2,\ldots,L\}} \gamma_j[t] \\ \text{subject to} \quad & \boxed{\begin{aligned} P_{\mathrm{TX},j}[t] &\in \mathcal{P}, & \forall j, \\ \mathbf{f}_j[t] &\in \mathcal{F}, & \forall j, \\ \gamma_j[t] &\geq \gamma_{\mathrm{target}} & \end{aligned}} \end{aligned}$$

Set of power (and interference coordination) commands

Set of beamforming vectors (where applicable)

beamforming vector of the *j*-th user

Target SINR value

received SINR of the *j*-th user

- Baseline solution for voice is obtained from fixed power allocation with adaptive coding
- Optimal solution (upper bound) for data is found through a brute force over all
  - beam patterns
  - power commands for the BSs

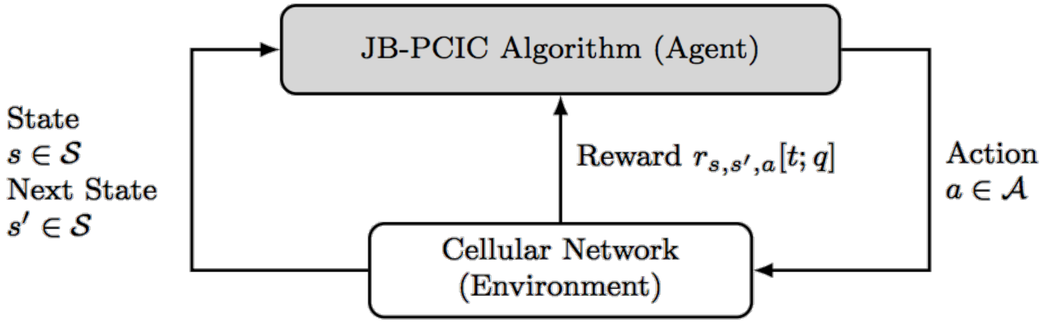
- Run-time complexity of $\mathcal{O}(M^L)$ for *M* antennas and *L* base stations.

How can we reduce the complexity?

SOLUTION

❑ Deep Reinforcement Learning

1. Create an environment from the system model
2. Create a joint reward $r_{s,s',a}[t;q]$ ← Bearer selector
3. Reward the agent for every time the SINR improves.



❑ Use deep Q-network (DQN) as an estimator for state-action value function $Q_\pi(\cdot)$

1. Greedy policy π
2. Train the DQN using minibatch samples to minimize the loss function:

DQN vectorized weights Θ

$$\underset{\boldsymbol{\theta}_t}{\text{minimize}} \qquad L_t(\boldsymbol{\theta}_t) := \mathbb{E}_{s,a}\left[(y_t - Q_\pi(s,a;\boldsymbol{\theta}_t))^2\right]$$

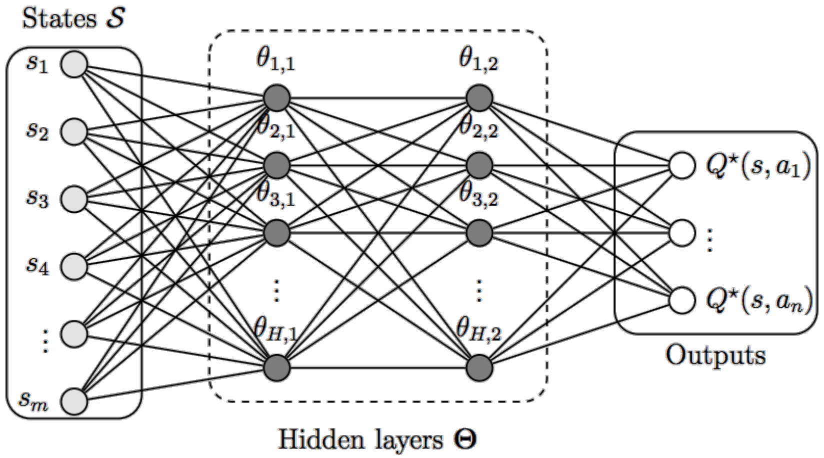
state-action value function

estimated state-action value function

$$y_t := \mathbb{E}_{s'}[r_{s,s',a} + \gamma \max_{a'} Q_\pi(s',a';\boldsymbol{\theta}_{t-1}) \mid s_t, a_t]$$

discount rate

reward



Can an ε-greedy policy do better?

SOLUTION (L = 2)

❑ Joint beamforming, power control, and interference coordination (JB-PCIC) encoding

Bearer selector

$q = 0$:

2	2
$\mathrm{IC}_\ell[t]$	$\mathrm{PC}_b[t]$

$\mathcal{P} = \{-3, -1, 1, 3\} \rightarrow \mathrm{p}(00) = -3, \mathrm{p}(01) = -1, \mathrm{p}(10) = 1, \mathrm{p}(11) = 3$

$q = 1$:

3

1	1	1	1
$\mathbf{f}_b[t]$	$\mathbf{f}_\ell[t]$	$\mathrm{IC}_\ell[t]$	$\mathrm{PC}_b[t]$

0

$\mathcal{P} = \{-1, 1\}$

enables up to 16 simultaneous actions for voice and 16 for data

Bitwise AND, masking, and shifting

$a_t \in \mathcal{A}$

string of bits in a register a

0: step down beamforming codebook
1: step up beamforming codebook

❑ Reward function

$$r_{s,s',a}[t;q] := \Big(\underbrace{\mathrm{p}(\mathbf{a}_{[0,1]}[t]) - \mathrm{p}(\mathbf{a}_{[2,3]}[t])}_{\text{voice}}\Big)(1-q) +$$

bearer selector

$$\Big(\underbrace{\gamma_b^{\mathbf{a}_{[0]}[t],\mathbf{a}_{[3]}[t]} + \gamma_\ell^{\mathbf{a}_{[1]}[t],\mathbf{a}_{[2]}[t]}}_{\text{data}}\Big)q$$

$r_{s,s',a}[t;q] := r_{\min}$ if any constraint in problem formulation becomes inactive.

$r_{s,s',a}[t;q] := r_{s,s',a}[t;q] + r_{\max}$ if the target SINR is achieved.

❑ States

$$(s_t^0, s_t^1) := \mathrm{UE}_\ell(x[t], y[t]), \qquad (s_t^2, s_t^3) := \mathrm{UE}_b(x[t], y[t]),$$

$$s_t^4 := P_{\mathrm{TX},\ell}[t], \qquad s_t^5 := P_{\mathrm{TX},b}[t],$$

$$s_t^6 := \mathbf{f}_\ell[t], \qquad s_t^7 := \mathbf{f}_b[t],$$

A total of 8 states

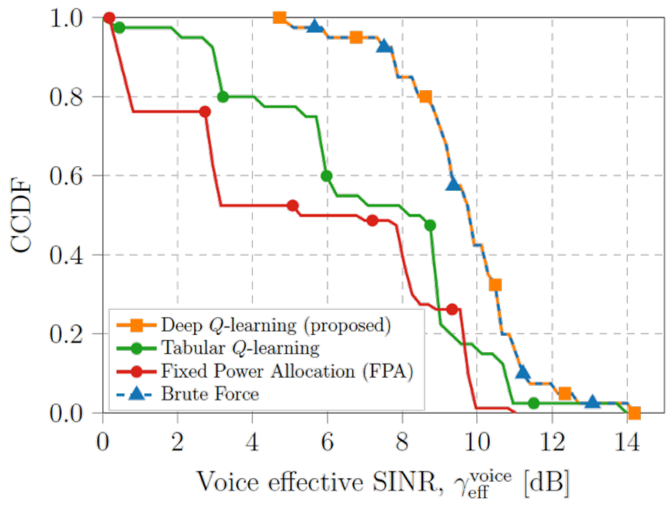
SIMULATION

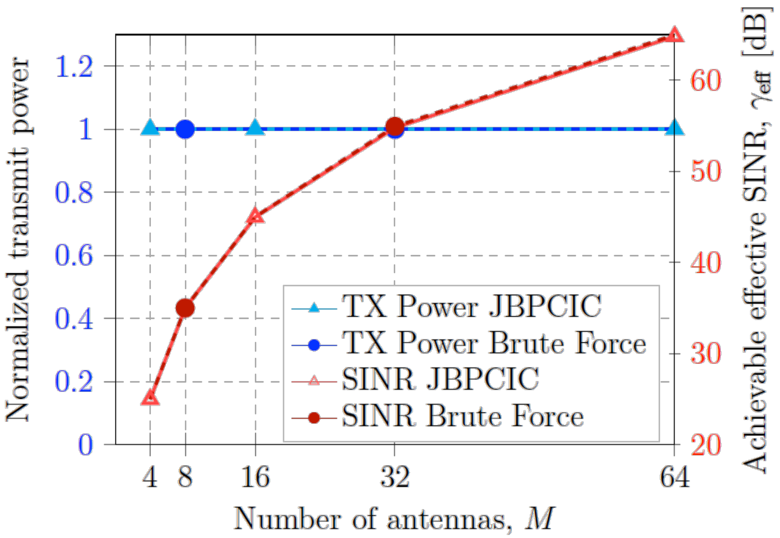
Communication System Parameters

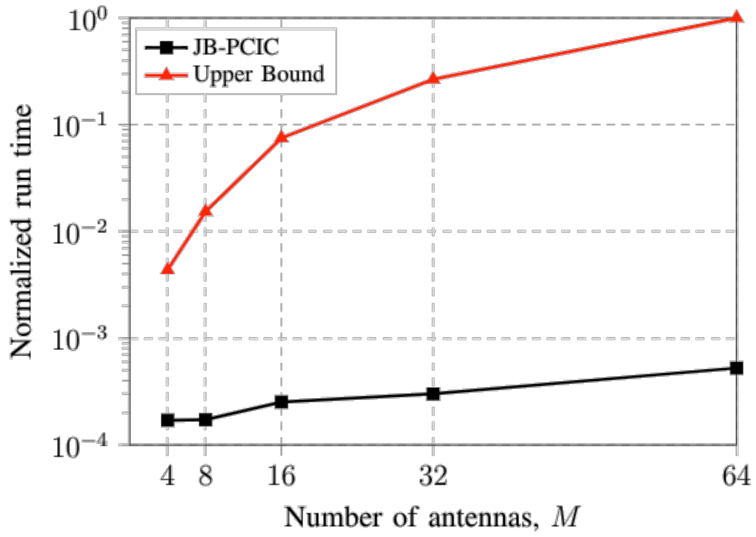
Parameter	Value	Parameter	Value
Base station (BS) maximum transmit power P_{BS}^{max}	46 dBm	Downlink frequency band	(2100 MHz, 28 GHz)
Cellular geometry	circular	Cell radius r	(350, 150) m
Propagation model (voice, bf)	(COST231, [63])	User equipment (UE) antenna gain	0 dBi
Antenna gain ($G_{TX}^{voice}, G_{TX}^{bf}$)	(11, 3) dBi	Inter-site distance R	(525, 225) m
Max. number of UEs per BS N	10	Number of multipaths N_p	(15, 4)
Probability of LOS $p_{LOS}^{voice}, p_{LOS}^{bf}$	(0.9, 0.8)	UE average movement speed v	(5, 2) km/h
Number of transmit antennas M^{voice}, M^{bf}	$(1, \{4, 8, 16, 32, 64\})$	Radio frame duration T^{voice}, T^{bf}	(20, 10) ms

Deep Reinforcement Learning Hyperparameters

Parameter	Value	Parameter	Value
Discount factor γ	0.995	Exploration rate decay d	0.9995
Initial exploration rate ϵ	1.000	Minimum exploration rate ($\epsilon_{min}^{voice}, \epsilon_{min}^{bf}$)	(0.15,0.10)
Number of states $\lvert\mathcal{S}\rvert$	8	Number of actions $\lvert\mathcal{A}\rvert$	16
Deep Q-Network width H	24	Deep Q-Network depth	2







JB-PCIC algorithm achieves upper bound on performance but without exhaustive search in action space

SUMMARY

Optimize users' received SINR

I. Voice bearers
   - Perform power control for the serving cell
   - Coordinate transmit power for the other cells
   - Voice uses adaptive coding

II. Data bearers
   - Perform power control for the serving cell
   - Coordinate transmit power for the other cells

Optimal

- Exponential in number of base stations
- Uses brute force

Proposed

- Uses deep reinforcement learning
- Encoding to facilitate joint actions
- Avoids exhaustive search in the action space

Contribution 2

IMPROVED DOWNLINK COORDINATED MULTIPOINT PERFORMANCE

Related publications:

[1]. F. B. Mismar and B. L. Evans, "Deep Learning in Downlink Coordinated Multipoint in New Radio Heterogeneous Network," *IEEE Wireless Communications Letters*, vol. 8, no. 4, pp. 1040-1043, Aug. 2019.

[2]. F. B. Mismar and B. L. Evans, "Machine Learning in Downlink Coordinated Multi-point in Heterogeneous Networks," *Technical Report*, Feb. 2019. [Online]. arXiv:1608.08306.

BACKGROUND

- Problem
  - Industry implementations trigger coordinated multipoint (CoMP) based on user SINR
  - This yields low user throughput
- Goal
  - Develop triggering function to improve the user throughput
- Parameters
  - Block Error Rate (BLER) target for codeword reception error
  - Channel State Information (CSI) to help derive transmission rank
- Approach
  - Train a classifier to learn the relationship between the reported measurements and the BLER
  - If a user is predicted to have a BLER lower than the target, configure rank-2 transmission
  - Compare with SINR-based trigger

SYSTEM MODEL

- Multi-user downlink system
  - Multi-cell environment with multiple-antenna users
  - Small cells scattered in the service area
  - Macro cells and small cells can form a distributed MIMO channel with n_t transmit antennas
  - Zero-Forcing (ZF) receiver at the user end

- Signal model for the i-th user (narrowband):

$$\mathbf{r}_i = \sqrt{\frac{E_{s,i}}{n_t}}\mathbf{H}_i\mathbf{s}_i + \mathbf{v}_i$$

[Tse05]

Gaussian noise

distributed MIMO channel (both large- and small-scale gain)

energy per symbol

- The received SNR for the i-th user at the j-th antenna

$$\gamma_j^{(i)} = \frac{P_{\mathrm{BS}}^{(i)}}{n_t\sigma_{\tilde{v}}^2}/[\mathbf{H}_i^*\mathbf{H}_i]_{j,j}^{-1}, \qquad j = 1,\ldots,n_s := \min(n_r, n_t)$$

ZF receiver enhanced noise power

number of receive antennas

- The received power for the i-th user at the j-th antenna:

$$P_{\mathrm{UE},j}^{(i)} := \sigma_{\tilde{v}}^2\gamma_j^{(i)} = \frac{P_{\mathrm{BS}}^{(i)}}{n_t}/[\mathbf{H}_i^*\mathbf{H}_i]_{j,j}^{-1}, \qquad j = 1,\ldots,n_s$$

- The received reference symbol power (RSRP) for the i-th user:

number of resource blocks

$$P_{\mathrm{RS}}^{(i)} = P_{\mathrm{UE},j=1}^{(i)}/(N_{\mathrm{SC}}N_{\mathrm{PRB}})$$

number of subcarriers in a resource block

UE received power measured at the first antenna

- The codeword block error rate (BLER) for the i-th user:

$$\beta_i := 1 - \prod_{j=1}^{n_s}(1-\beta_{j,i})$$

BLER for the codeword transmitted to the j-th antenna

MOTIVATION AND PROBLEM FORMULATION

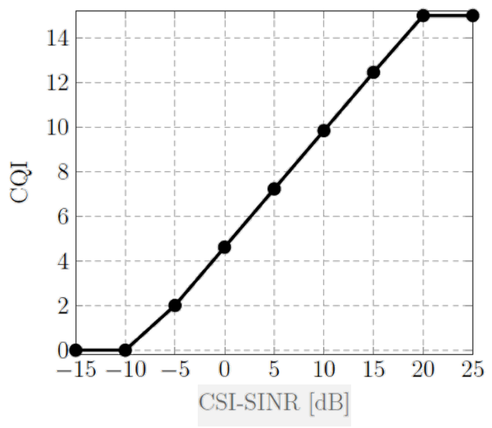
- ❑ Industry approach is to use the users' reported CSI to determine proper transmission rank
- ❑ BLER increases as the transmission rank increases
  - Throughput decreases as BLER increases
  - Throughput increases as transmission rank increases, assuming decorrelated transmission streams

$$R^{\text{eff}} = \sum_i R_i^{\text{eff}} := (1-\beta_i) n_s B \log_2(1+\gamma_i)$$

effective rate of the *i*-th UE

bandwidth

Users report a "quantized" SNR value known as the channel quality indicator (CQI)



- ❑ How to optimize this group of conflicting variables?
- ❑ Answer: main idea:
  - When the BLER is low, try to increase the transmission rank, if the second spatially decorrelated stream (i.e., rank-2) is possible.
  - Otherwise, default to a rank-1 transmission.

Can a dynamic data-driven approach help?

CSI: Channel State Information BLER: Block Error Rate

SOLUTION

- ❑ Simplify the problem to rank-2 MIMO channel and build a binary classifier
- ❑ For the binary classifier:
  - Labels are a function of the BLER meeting the standard threshold
  - Use standard-compliant CSI as learning features that help define the transmission rank
- ❑ Invalidate the learned model after the channel coherence time passes.

- ❑ Coordinated Multipoint (CoMP) trigger function:

$$D[t] = \arg\max_{y} f_{\mathbf{y}}(y[t])$$

found from either standards-compliant or proposed CoMP "votes"

CoMP trigger (MIMO), based on the majority of votes

a frequency function: percentage of y=0 and y=1 samples (i.e., an empirical probability): $f_{\mathbf{y}}(y_i) := \#(\mathbf{y} = y_i)/M, \mathbf{y} \in \{0,1\}^M$

Standards-Compliant

$$y_i[t] = \mathbb{1}[\gamma^{(i)}[t] \geq \gamma_{\text{CoMP}}]$$

uses SINR as a measure of decorrelation

Proposed

$$\hat{y}_i[t] := \text{surrogate}(\mathbf{x}_i[t])$$

CSI reported by the *i*-th user

a machine learning function

SOLUTION

- Construct the surrogate function from:
  - fully connected deep neural network (DNN)
  - support vector machine (SVM)
- Define the classification label based on the BLER being within target $y_i[t] := \mathbb{1}[\beta_i \leq \beta_{\text{target}}]$
- Train classifiers to minimize loss objective

$$\underset{\boldsymbol{\Theta}}{\text{minimize:}}\ L(\mathbf{y}, \hat{\mathbf{y}}; \boldsymbol{\Theta}) := -\sum_k y_k \log \hat{y}_k + (1 - y_k)\log(1 - \hat{y}_k)$$ binary cross-entropy for DNN

The i-th support vector

$$\underset{\mathbf{w}}{\text{minimize:}} \left[\frac{1}{M}\sum_{i=1}^{M} \max(0, 1 - y_i(\mathbf{w}^\top \mathbf{x_i} - b))\right] + \alpha\|\mathbf{w}\|^2$$ hinge loss and regularization for SVM

hyperplane weights

	Parameter	Type	Description
$\mathbf{x}_0$	Bias term	Float	Equal to unity
$\mathbf{x}_1$	CSI-RSRP	Float	Narrowband received power
$\mathbf{x}_2$	CQI	Integer	Wideband received SNR on the first antenna (linear)
$\mathbf{x}_3$	Rank	Integer	Number of received streams j

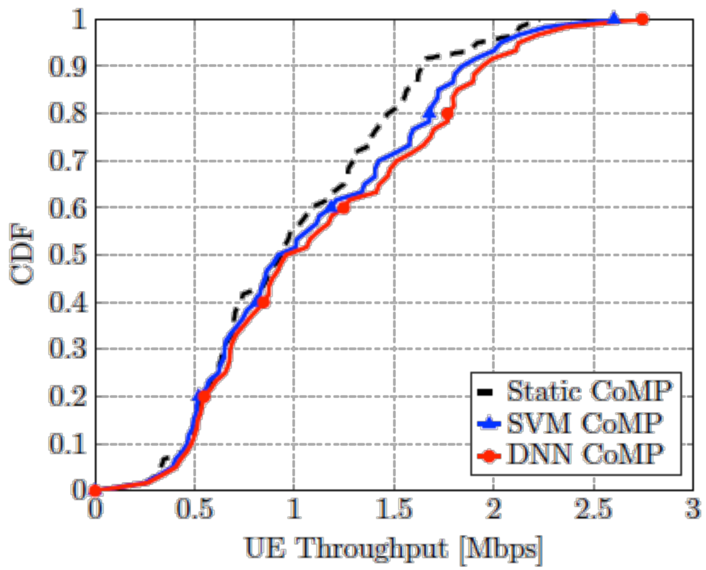
SIMULATION

DNN Hyperparameter	Search range	SVM Hyperparameter	Search range
DNN depth d	{1,3,5}	Kernel	{`gaussian`, `polynomial`*}
DNN width w	{1,3,10}	Box constraint C_{Box}	{0.01,1,10}
Optimizer	Stochastic Gradient Descent	Kernel scale γ	`auto` [73]

* Degrees $p \in \{1, 2, 3, 4\}$.

Algorithm	Asymptotic run-time	Number of features
Static	$\mathcal{O}(1)$	$\mathcal{O}(1)$
SVM CoMP	$\mathcal{O}(M^3)$	$\mathcal{O}(p)$
DNN CoMP	$\mathcal{O}(Mw^d)$	$\mathcal{O}(w^d)$

Parameter	Value
Bandwidth B	10 MHz
Downlink center frequency f_c	2100 MHz
Downlink user scheduler	Proportional Fair
Macro BS maximum power	46 dBm
Small cell BS maximum power	37 dBm
Maximum number of streams n_s	2
Number of PRBs N_{PRB}	50



	Average				
Algorithm	User Throughput [Mbps]	BLER β_i	Streams n_s	CQI	CSI-RSRP [dBm]
Static‡	1.02	-	-	-	-
SVM CoMP	1.10	7.15%	1.59	3	−58.17
DNN CoMP	**1.16**	3.76%	1.55	3	−58.17

‡ Quantities not reported in the published version.

CoMP: Coordinated Multipoint, DNN: Deep Neural Network, PRB: Physical Resource Block, SVM: Support Vector Machine.

Because CoMP decision is an "imbalanced" classification, DNN does better

SUMMARY

Optimize users' achievable rate

- Achievable rate depends on a group of features, some of which have opposing effects on the rate.
- The use of a data-driven approach to find an improved achievable rate is possible.
- Higher transmission rank does not always lead to better achievable rates.

Static

- Triggers rank-2 based on reported SINR (absolute cutoff).

Dynamic

- Triggers rank-2 based on a surrogate function based on deep learning.
- The surrogate function is relearned every time the channel coherence time passes.

SVM

DNN

More features and more complicated models lead to better performance

Contribution 3

DEEP LEARNING PREDICTIVE BAND SWITCHING IN WIRELESS NETWORKS

Discussed in the PhD Qualifying Exam and Included in the PhD Dissertation

Related publications:

[1] F. B. Mismar, A. AlAmmouri, A. Alkhateeb, J. G. Andrews, and B. L. Evans, "Deep Learning Predictive Band Switching in Wireless Networks," *IEEE Transactions on Wireless Communications*, submitted Oct. 2, 2019.

[2] F. B. Mismar and B. L. Evans, "Partially Blind Handovers for mmWave New Radio Aided by Sub-6 GHz LTE Signaling," *Proceedings of IEEE International Conference on Communications Workshops*, May 2018.

BACKGROUND

- Problem
  - Users want to switch to a different frequency band if they expect to get higher throughput
  - Switching between frequency bands requires a "measurement gap" which reduces user throughput
- Goal
  - Improve user throughput by exploiting the spatial correlation to eliminate the measurement gap
- Parameters
  - Band switch *request* threshold which defines the rate below which UE requests a band switch
  - Band switch *grant* threshold which defines the rate above which the UE request is granted
  - Percentage of users in sub-6 GHz or mmWave vs total users
  - User spatial coordinates
- Approach
  - Employ a data-driven approach using a ray-tracing dataset
  - Use deep learning to rank the downlink channel quality based on the users' coordinates
  - Grant a band switch if predicted to improve the user throughput (no need for the gap)

SYSTEM MODEL

- Multi-user downlink system
  - Single-cell with multiple transmit antennas
  - Sub-6 GHz and mmWave bands (28 GHz)
  - Analog beamforming using DFT-based codebook

- Signal model for the i-th user at the j-th frequency band:

$$r_{(i,j)} = P_{\mathrm{TX}}^{(j)} \mathbf{h}_{(i,j)}^{*} \mathbf{f}_{(i,j)} s_{(i,j)} + n_{(i,j)}$$

[Tse05]

Gaussian noise

beamforming precoder

channel vector

transmit power and large scale channel gain

- The received SINR for the i-th user at the j-th frequency band

$$\gamma^{(i,j)}[t] = \frac{P_{\mathrm{TX}}^{(j)}[t]}{\sigma_n^2} |\mathbf{h}_{(i,j)}^{*}[t] \mathbf{f}_{(i,j)}^{\star}[t]|^2$$

noise power

SINR-optimal beamforming precoder

- The received *instantaneous* rate for the i-th user at the j-th frequency band:

$$R^{(i,j)}[t] = B^{(j)} \log_2(1 + \gamma^{(i,j)}[t])$$

bandwidth

received SINR

- The received *effective* achievable rate for the i-th user at the j-th frequency band:

$$R_E^{(i,j,k)}[t] = \left(1 - \frac{T_B^{(j)} + T_H^{(k)}}{T_C^{(j)}}\right) R^{(i,j)}[t]$$

beam training time

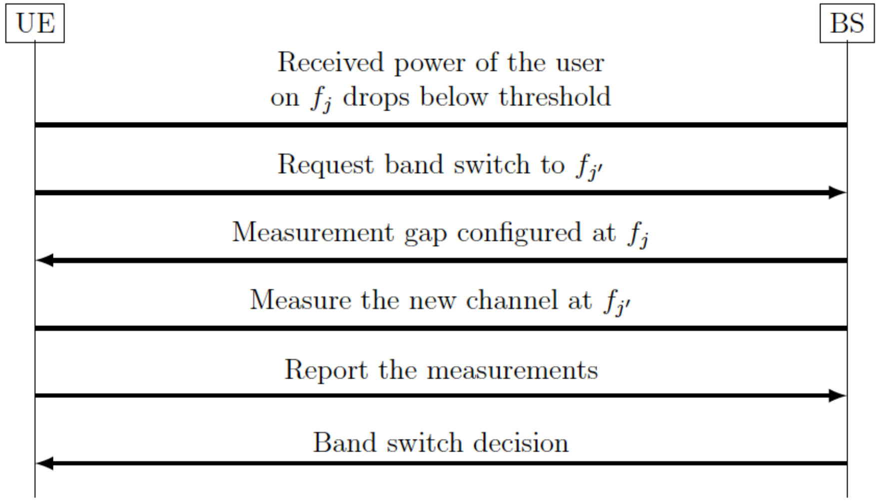
band switching overhead

channel coherence time

Here, k is the band switching algorithm.

MOTIVATION AND PROBLEM FORMULATION

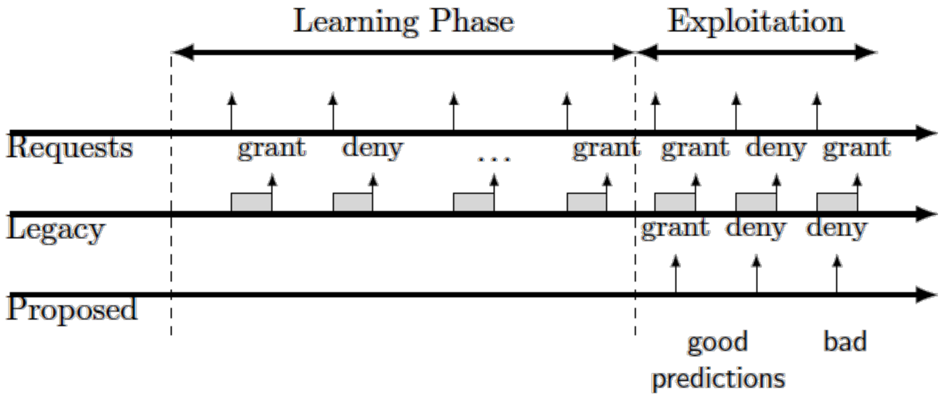
- Next-generation wireless networks will use more frequency bands.



- The band selection problem becomes more complicated:
  - How does user choose a band to improve their rate?

- Problem: [3gpp18]
  - Measurement gap reduces users' effective achievable rates — Legacy
  - Blindly switching user eliminates need for gap but risks rates — Blind

- Solution:
  - Main idea: rank bands based on their quality
  - Grant switch to band with the highest rank if requested.



Data-driven approach to eliminate the "measurement gap"

SOLUTION

- Optimal solution (upper bound)

$$R_E^{\star(i)}[t] = \max_{j \in \{\text{sub-6}, \text{mmWave}\}} \left(1 - \frac{T_B^{(j)}}{T_C^{(j)}}\right) R^{(i,j)}[t]$$

Use DeepMIMO ray-tracing dataset and engineer more features [Alkhateeb19]

- Proposed solution
  - Exploit the spatial correlation between frequency bands based on the location of the user
  - Define the band switch request and the band switch grant decision as follows:

band switching threshold

$$x_{\text{br}}^{(i)}[t] = \mathbb{1}[(R^{(i,j)}[t] < r_{\text{threshold}})], \qquad y^{(i)}[t] = \mathbb{1}[(\hat{R}^{(i,j')}[t] > R^{(i,j)}[t])], \qquad \forall i$$

estimated instantaneous rate based on other users

  - Train a machine learning algorithm using the following features

	Parameter	Type	Description
$\mathbf{x}_0$	Bias term	Integer	Equal to unity
$\mathbf{x}_1$	Effective rate at sub-6	Float	Based on (2) with *j* = sub-6
$\mathbf{x}_2$	Effective rate at mmWave	Float	Based on (2) with *j* = mmWave
$\mathbf{x}_3$	Source technology	Boolean	(1 = for sub-6 and 0 for mmWave)
$(\mathbf{x}_4, \mathbf{x}_5, \mathbf{x}_6)$	Coordinates	Float	The latitude, longitude, and height of the user (from the BS)
$\mathbf{x}_7$	Band switch requested	Boolean	Did UE request band switch? $x_{\text{br}}^{(i)}$
$\mathbf{y}$	Band switch decision	Boolean	Was this requested switch granted? $y^{(i)}$

SIMULATION

❑ Scenarios

Scenario	Users at Start
A	100% sub-6 GHz
B	100% mmWave
C	70% sub-6 GHz and 30% mmWave

❑ Parameters (DNN: deep neural networks, XGBoost: Extreme Gradient Boosting)

DNN		XGBoost	
Parameter	Value	Parameter	Value
Exploitation split $r_{\text{exploitation}}$	0.8	Exploitation split $r_{\text{exploitation}}$	0.8
K-fold cross-validation K	2	K-fold cross-validation K	2
Optimizer	[101]	ℓ_1 regularization term α	{0,1}
Learning rate η	0.05	ℓ_2 regularization term λ	{0,1}
Activation function $\sigma(\cdot)$	sigmoid	Complexity control term γ	{0, 0.02, 0.04}
Depth of neural network d	{1,3,5}	Sample weights	{0.5, 0.7}
Width of the hidden layer w	{3,5,10}	Child weights	{0, 10}

Parameter	Value
Subcarrier bandwidth (sub-6, mmWave)	(180, 1800) kHz
Center frequency	(3.5, 28) GHz
UE noise figure	7 dB
DeepMIMO Scenario O1 Base Station	3
DeepMIMO Scenario O1 number of antennas (M_x, M_y, M_z)	(1, 64, 4)
DeepMIMO Scenario O1 OFDM limit	64
Band switch threshold for sub-6 GHz $r_{\text{threshold}}^{\text{sub-6}}$	1.72 Mbps
Band switch threshold for mmWave $r_{\text{threshold}}^{\text{mmWave}}$	7.00 Mbps
Measurement gap fraction of coherence time ρ	0.6

❑ DNN requires a run-time of $\mathcal{O}(nw^d)$, while XGBoost requires a run-time of $\mathcal{O}(n \log n)$.

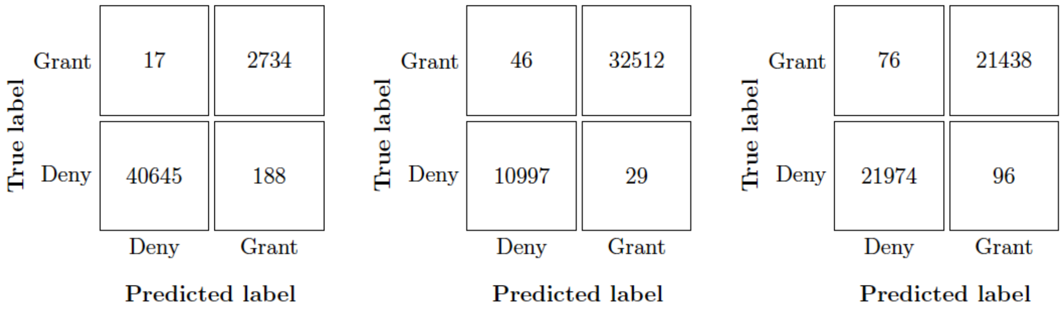
Number of rows in the feature matrix

DNN depth

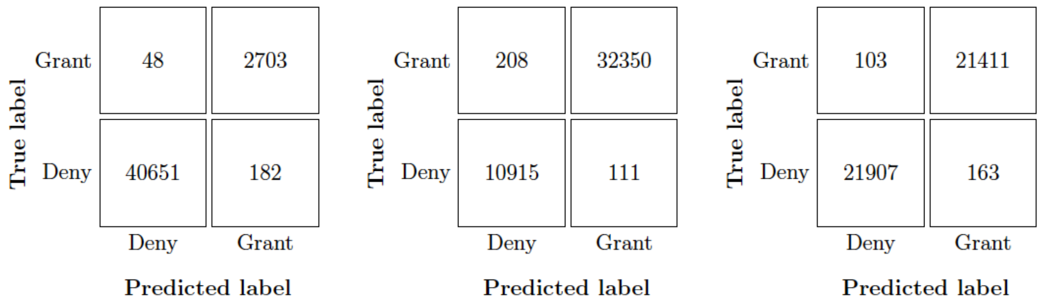
DNN width

❑ DNN outperforms XGBoost in receiver operator characteristic area and classification accuracy.

❑ Confusion Matrix



DNN Confusion Matrix (Scenarios A, B, and C)



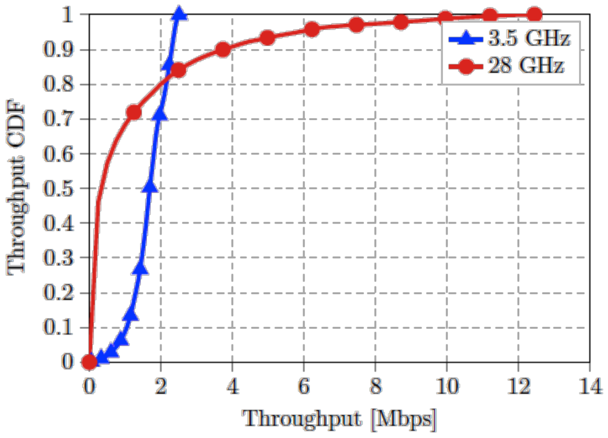
XGBoost Confusion Matrix (Scenarios A, B, and C)

SIMULATION

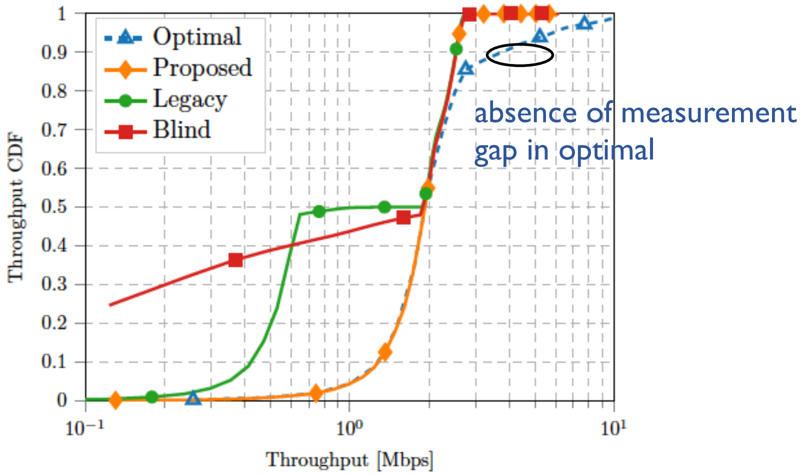
- Impact of the band switching threshold on the performance

	$r_{\text{threshold}}$	Normalized mean effective throughput R_E [Mbps]			
		Legacy	Blind	Proposed	Optimal
Scenario A	1.72	0.55	0.54	0.75	1.00
	2.00	0.45	0.46	0.77	1.00
	2.60	0.34	0.60	1.00	1.00
Scenario B	2.00	0.43	0.88	1.00	1.00
	9.00	0.39	0.84	1.00	1.00
	12.50	0.33	0.76	1.00	1.00

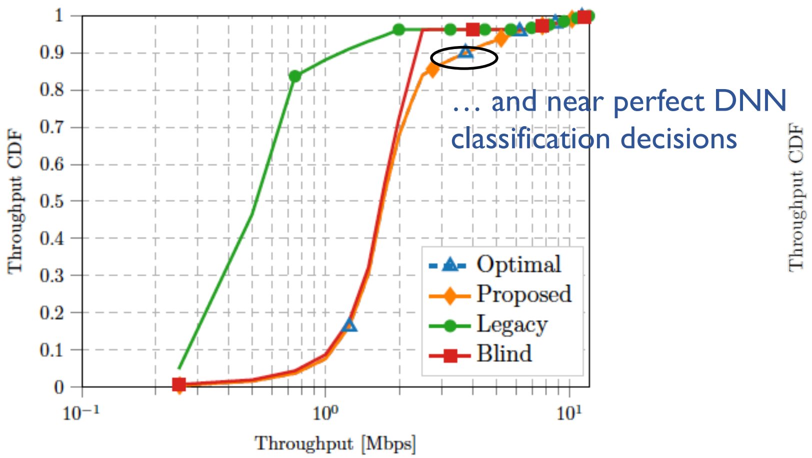
Higher band switching thresholds cause the legacy approach performance to do worse.



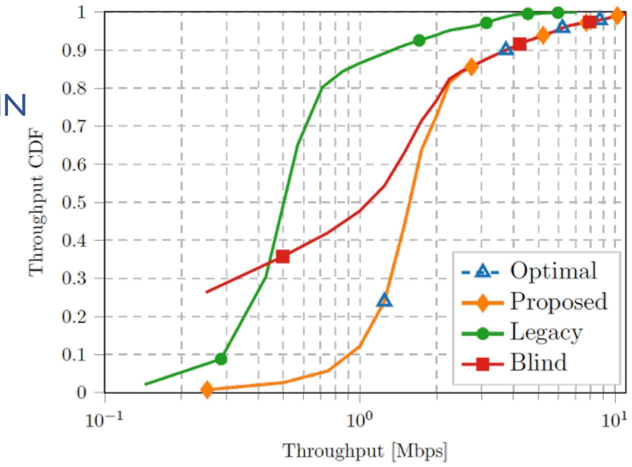
Higher band switching thresholds enable my proposed algorithm to do even better



Scenario A: 100% users sub-6 GHz



Scenario B: 100% users mmWave



Scenario C: 30%-70% users

Legacy approach performs better than blind in low throughput regime.

SUMMARY

Optimize users' achievable rate

- Band switching grows in importance with successive evolutions of wireless technology
- The use of a data-driven approach to rank channels by their estimated quality is possible.
- Using measurement gaps for the band switching procedure is a "performance overkill."

Industry

- Use a gap to measure the candidate frequency band.
- Blindly switch to a different band.

Legacy

Blind

Proposed

- Does not require a measurement gap.
- Exploits the spatial and spectral correlation of frequency bands at a given location.
  - Predicts the quality and ranks the bands.

XGBoost

DNN

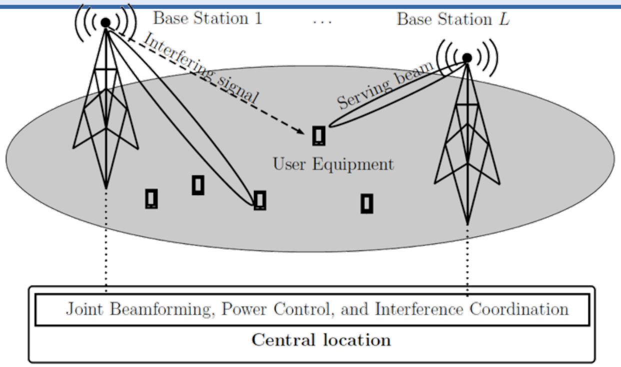
I disrupt the need to use a measurement gap in band switching

DISSERTATION SUMMARY AND CONCLUSION

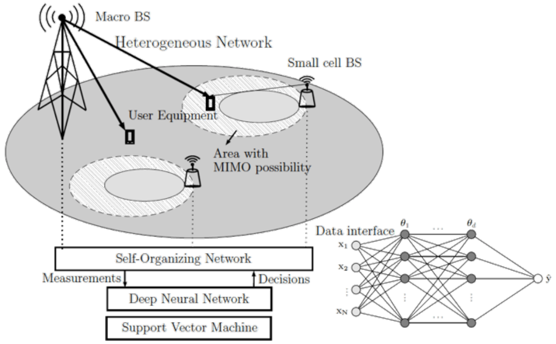
- ❑ Next-generation wireless networks will require intelligent predictive and prescriptive abilities
  - boost reliability and eliminate performance bottlenecks
  - disrupt reactive legacy standards

PHY Layer Perspective

Beamforming, Power Control and Interference Coordination

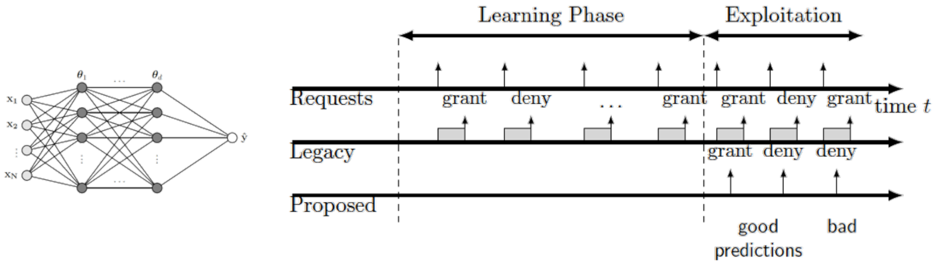


Intelligent Coordinated Multipoint



RRM Layer Perspective

Predictive Band Switching



FUTURE WORK IN DEEP LEARNING FOR COMMUNICATIONS

- Optimal hybrid beamforming
  - I used simple DFT-based analog beamforming, but digital beamforming generates more patterns
    - at mmWave, a disjoint solution exists, but may not be optimal.
    - Exploit powers of two in the number of antennas
- Improved Cell-Free Massive MIMO
  - Use coordinated BS capabilities with massive MIMO to improve joint-beamforming capabilities
- Generalized multi-band predictive handoff
  - Introduce mobility over *multiple base stations* and build a multi-class classifier

PUBLICATIONS

Journal articles

- **Faris B. Mismar**, Ahmad AlAmmouri, Ahmed Alkhateeb, Jeffrey G. Andrews, and Brian L. Evans, “Predictive Band Switching in Wireless Networks,” *IEEE Transactions on Wireless Communications* (submitted).
- **Faris B. Mismar**, Brian L. Evans, and Ahmed Alkhateeb, “Deep Reinforcement Learning for 5G Networks: Joint Beamforming, Power Control, and Interference Coordination,” *IEEE Transactions on Communications* (submitted).
- **Faris B. Mismar**, Jinseok Choi, and Brian L. Evans, “A Framework for Automated Cellular Network Tuning with Reinforcement Learning,” *IEEE Transactions on Communications*, vol. 67, no. 10, pp. 7152-7167, Oct. 2019.
- **Faris B. Mismar** and Brian L. Evans, “Deep Learning in Downlink Coordinated Multipoint in New Radio Heterogeneous Networks,” *IEEE Wireless Communications Letters*, vol. 8, no. 4, pp. 1040-1043, Aug. 2019.

Conference papers

- **Faris B. Mismar** and Brian L. Evans, “Deep Q-Learning for Self-Organizing Networks Fault Management and Radio Performance Improvement,” *Proceedings of the 52nd Annual Asilomar Conference on Signals, Systems, and Computers*, Oct. 2018.
- **Faris B. Mismar** and Brian L. Evans, “Q-Learning Algorithm for VoLTE Closed-Loop Power Control in Indoor Small Cells,” *Proceedings of the 52nd Annual Asilomar Conference on Signals, Systems, and Computers*, Oct. 2018.
- **Faris B. Mismar** and Brian L. Evans, “Partially Blind Handovers for mmWave New Radio Aided by Sub-6 GHz LTE Signaling,” *Proceedings of IEEE International Conference on Communications Workshops*, May 2018.

SOFTWARE RELEASES

Available at https://github.com/farismismar

- **Faris B. Mismar** and Brian L. Evans, "Band Switching with Deep Learning," Python 3 code to accompany a paper entitled "Predictive Band Switching in Wireless Networks," Version 1.0 (Sep. 28, 2019). [Online].
  Available: https://github.com/farismismar/Bandswitch-DeepMIMO
  Builds on top of the 3.5 GHz and 28 GHz ray tracing dataset from ASU.

- **Faris B. Mismar** and Brian L. Evans, "Deep Reinforcement Learning for 5G Networks: Joint Beamforming, Power Control, and Interference Coordination," Python 3 code to accompany a paper entitled "Deep Reinforcement Learning for 5G Networks: Joint Beamforming, Power Control, and Interference Coordination," Version 2.0 (Nov. 6, 2019). [Online].
  Available: https://github.com/farismismar/Deep-Reinforcement-Learning-for-5G-Networks

- **Faris B. Mismar** and Brian L. Evans, "Deep Q-Learning for SON Performance Improvement," Python 3 and MATLAB codes to accompany a paper entitled "A Framework for Automated Cellular Network Tuning with Reinforcement Learning," *IEEE Transactions on Communications*, 2019. Version 2.0 (Jun. 27, 2019). [Online].
  Available: https://github.com/farismismar/Deep-Q-Learning-SON-Perf-Improvement
  Builds on top of Vienna University of Technology (TU Wien) Vienna LTE-A Downlink System Level Simulator v1.9.

- **Faris B. Mismar** and Brian L. Evans, "Deep Learning in Downlink Coordinated Multipoint in New Radio Heterogeneous Networks," Python 3 and MATLAB codes to accompany a paper entitled "Deep Learning in Downlink Coordinated Multipoint in New Radio Heterogeneous Networks," *IEEE Wireless Communications Letters*, 2019. Version 2.0 (Jul. 30, 2019). [Online].
  Available: https://github.com/farismismar/DL-CoMP-Machine-Learning
  Builds on top of Vienna University of Technology (TU Wien) Vienna LTE-A Downlink System Level Simulator v1.9.

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- [Zappone19] A. Zappone, M. Di Renzo and M. Debbah, "Wireless Networks Design in the Era of Deep Learning: Model-Based, AI-Based, or Both?," *IEEE Transactions on Communications*, vol. 67, no. 10, pp. 7331-7376, Oct. 2019.

ACRONYMS AND ABBREVIATIONS

3GPP 3rd Generation Partnership Project

BLER Block Error Rate

BS Base Station

CDF Cumulative Distribution Function

CoMP Coordinated Multipoint

CQI Channel Quality Indicator

CSI Channel State Information

DFT Discrete Fourier Transform

DNN Deep Neural Network

DQN Deep Q-Network

DRL Deep Reinforcement Learning

FDD Frequency Division Duplex

FPA Fixed Power Allocation

JBPCIC Joint Beamforming Power Control and Interference Coordination

LOS Line of Sight

LTE(-A) Long Term Evolution (-Advanced)

MAC Medium Access Control

MIMO Multiple Input Multiple Output

ML Machine Learning

NLOS Non-Line of Sight

NR New Radio

O-RAN Open Radio Access Network

OFDM Orthogonal Frequency Division Multiplexing

PHY Physical Layer

PRB Physical Resource Block

QoE Quality of Experience

RAN Radio Access Network

RL Reinforcement Learning

ROC Receiver Operating Characteristic

RRM Radio Resource Management

RSRP Reference Symbol Received Power

SGD Stochastic Gradient Descent

SINR Signal to Interference plus Noise Ratio

SNR Signal to Noise Ratio

SON Self-Organizing Networks

SVM Support Vector Machine

TTI Transmit Time Interval

UE User Equipment

ULA Uniform Linear Array

UPA Uniform Planar Array

VoLTE Voice over Long Term Evolution

ZF Zero-Forcing

DISSERTATION CONTRIBUTIONS

	1. Joint BF, PC, IC	2. Improved CoMP	3. Band Switching
Dissertation Chapter	2	3	4
Reference	[Mismar&Evans20a]	[Mismar&Evans19a]	[Mismar&Evans20b]
Frequency band	mmWave and sub-6 GHz	sub-6 GHz	mmWave and sub-6 GHz
Stack layer	PHY	PHY	RRM
Algorithm	DRL	DNN and SVM	DNN and XGBoost
Direction	Downlink		
Users	Multi-User		

BF: Beamforming, CoMP: Coordinated Multipoint, DNN: Deep Neural Network, DRL: Deep Reinforcement Learning,
IC: Interference Coordination, PC: Power Control, PHY: Physical Layer, SON: Self-Organizing Network, XGBoost: Extreme Gradient Boosting.

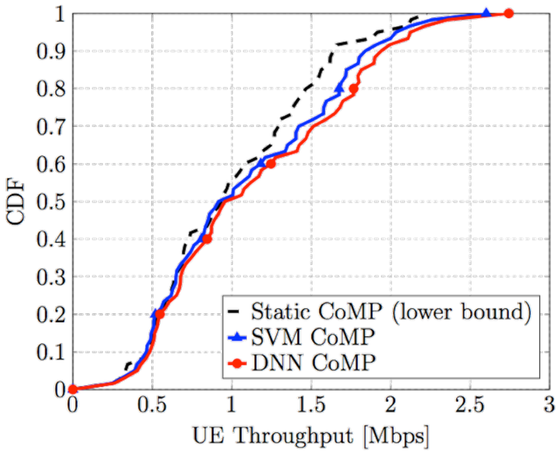
SIMULATION

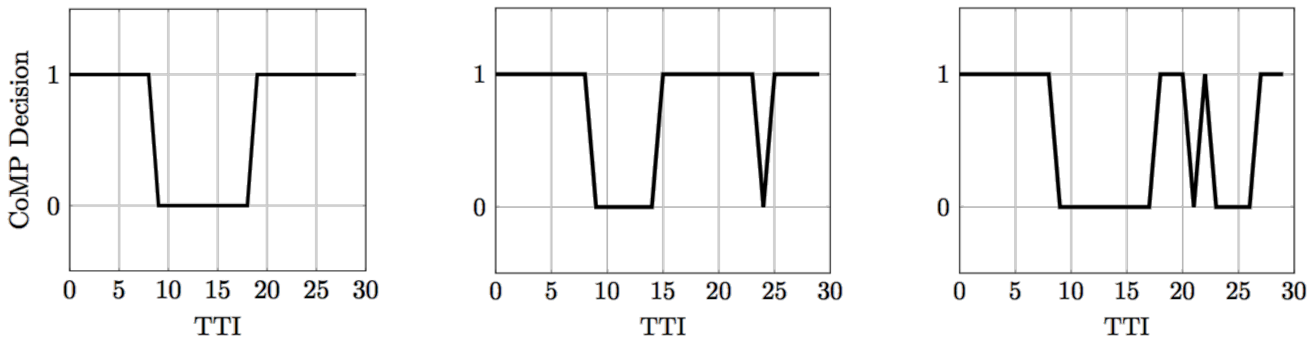
Algorithm	Average				
	User Throughput [Mbps]	BLER β_i	Streams n_s	CQI	CSI-RSRP [dBm]
Static‡	1.02	-	-	-	-
SVM CoMP	1.10	7.15%	1.59	3	−58.17
DNN CoMP	**1.16**	3.76%	1.55	3	−58.17

‡ Quantities not reported in the published version.

Parameter	Value
Bandwidth B	10 MHz
Downlink center frequency f_c	2100 MHz
Downlink user scheduler	Proportional Fair
Macro BS maximum power	46 dBm
Small cell BS maximum power	37 dBm
Maximum number of streams n_s	2
Number of PRBs N_{PRB}	50

Algorithm	Asymptotic run-time	Number of features
Static	$\mathcal{O}(1)$	$\mathcal{O}(1)$
SVM CoMP	$\mathcal{O}(M^3)$	$\mathcal{O}(p)$
DNN CoMP	$\mathcal{O}(Mw^d)$	$\mathcal{O}(w^d)$





(a) Static (b) SVM (c) DNN

CoMP decisions are "imbalanced" and DNN does better

CoMP: Coordinated Multipoint, DNN: Deep Neural Network, PRB: Physical Resource Block, SVM: Support Vector Machine.

SOLUTION

❑ Why DNN?

- Support Vector Machines

m-th support vector

$$\underset{\boldsymbol{\lambda}}{\text{maximize:}} \quad \sum_i \lambda_i - \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\lambda_m\lambda_n y_m y_n K(\mathbf{x}_m, \mathbf{x}_n)$$ [Cortes95]

Kernel

$$\text{subject to:} \quad \sum_{m=1}^{M}\lambda_m y_m = 0,$$

$$0 \leq \lambda_m \leq C_{\text{Box}}, \qquad m = 1, \ldots, M$$

"Box" constraint to control overfitting

Lagrangian multipliers

SVM Hyperparameter	Search range
Kernel	{gaussian, polynomial*}
Box constraint C_{Box}	{0.01,1,10}
Kernel scale γ	auto [71]

* Degrees $p \in \{1, 2, 3, 4\}$.

- Can be faster than DNN, but suffers from bias towards majority class.

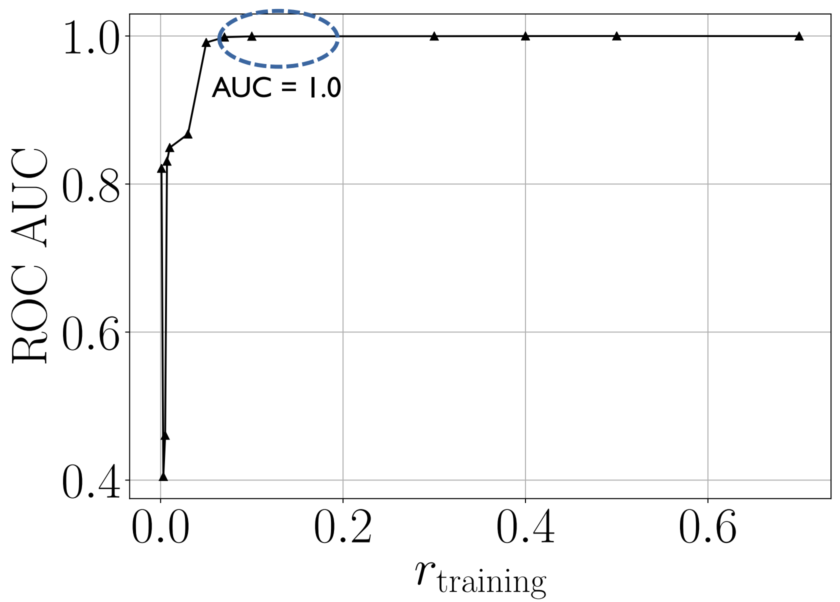
$$\#(\mathbf{y} = 0) = 1,522 \quad \#(\mathbf{y} = 1) = 7,658$$

$$M = 9,180$$

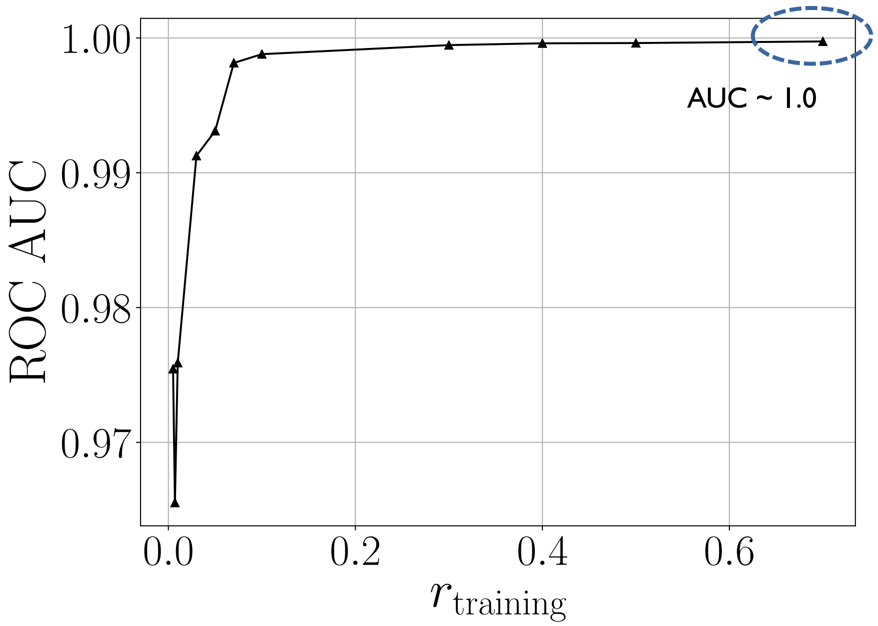
SVM will trigger more rank-2s than DNN, but at the wrong time!

Is CoMP triggered in a balanced fashion in a cell?

SIMULATION



Scenario A – DNN



Scenario A – XGBoost

DNN achieved ROC AUC = 1.0 with far less training samples than XGBoost

SUPPORT VECTOR MACHINES

- Primal

$$\underset{\mathbf{w}}{\text{minimize}:} \left[\frac{1}{M}\sum_{i=1}^{M} \max(0, 1 - y_i(\overbrace{\mathbf{w}^\top\mathbf{x_i} - b}^{= \hat{y}_i})\right] + \alpha\|\mathbf{w}\|^2$$

hinge loss

- Dual

$$\underset{\boldsymbol{\lambda}}{\text{maximize}:} \quad \sum_i \lambda_i - \frac{1}{2}\sum_{m=1}^{M}\sum_{n=1}^{M}\lambda_m\lambda_n y_m y_n K(\mathbf{x}_m, \mathbf{x}_n)$$

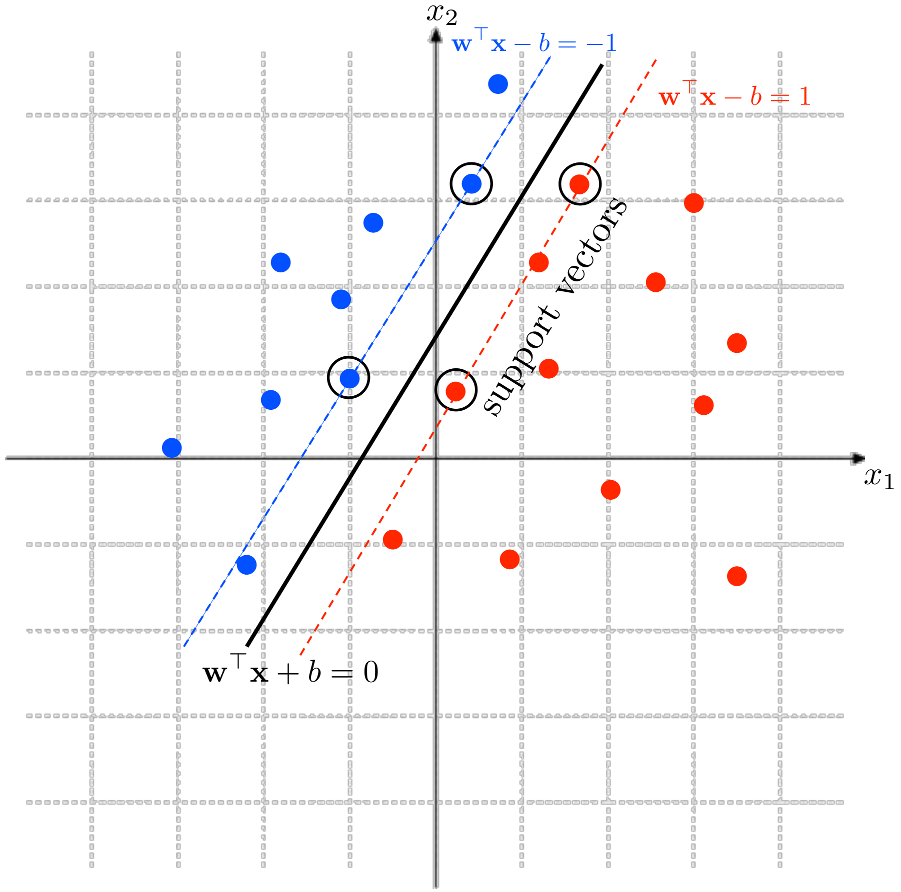
kernel

$$\text{subject to:} \quad \sum_{m=1}^{M}\lambda_m y_m = 0,$$

$$0 \le \lambda_m \le C_{\text{Box}}, \qquad m = 1, \ldots, M$$

[Cortes95]

Computationally more efficient, exploits strong duality, and enables the kernel "trick"



XGBOOST

- A tree-ensemble learning technique, which minimizes this objective function

regularization terms

$$\text{minimize:} \qquad \text{Obj}(\hat{\mathbf{y}}) := L(\mathbf{y}, \hat{\mathbf{y}}) + \alpha\|\mathbf{w}\|_1 + \frac{1}{2}\lambda\|\mathbf{w}\|_2^2 + \gamma T$$

convex loss function (e.g., logistic loss)

weight vector

number of leaves

minimum loss reduction required to make a further partition (i.e., complexity control)

- Fast and accurate hence used in many data mining contests

- Uses the sub-gradient (or derivative if differentiable) for the first (gradient) and second order (Hessian) of the objective function

$$g(t) := \partial_{\hat{\mathbf{y}}} \text{Obj}(\hat{\mathbf{y}}; t) \qquad\qquad h(t) := \partial^2_{\hat{\mathbf{y}}} \text{Obj}(\hat{\mathbf{y}}; t)$$

- Logistic loss function:

$$L(y, y_i) := y_i \log \frac{1}{1 + e^{-\hat{y}_i}} + (1 - y_i) \log \frac{e^{-\hat{y}_i}}{1 + e^{-\hat{y}_i}}$$

- Using the gradient and Hessian, compute the "gain" for both the right and left subtrees. Choose the direction with the maximum gain.

[Chen16]

DEEP NEURAL NETWORKS

- Perceptron

$$y := \sigma(\mathbf{x}^\top \boldsymbol{\theta} + b) \quad \mathbf{x}, \boldsymbol{\theta} \in \mathbb{R}^M$$

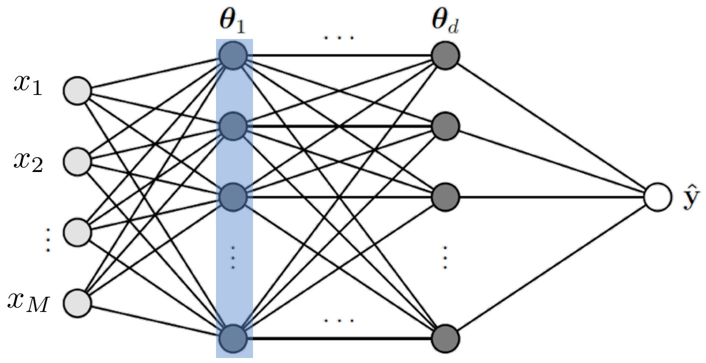
input feature vector

Non-linear activation function

bias term

perceptron weights

- Deeper and wider neural networks
  - Feed-forward (no loops, adjusts weights $\boldsymbol{\theta}$)
  - Backpropagation (method of calculating the gradient with respect to the neural network weights)



$\boldsymbol{\Theta} := [\boldsymbol{\theta}_\ell]_{\ell=1}^{d+1}$

- Optimizers
  - Stochastic Gradient Descent $\boldsymbol{\theta} := \boldsymbol{\theta} - \eta \nabla L(\mathbf{y}, \hat{\mathbf{y}}; \boldsymbol{\theta})$

    learning rate

    loss function
  - Adaptive moments "Adam" Uses the gradient and its second moment (i.e., gradient squared). Adapts the learning rate.

- Slower execution time compared to SVM and XGBoost

[Goodfellow]

DEEP Q-LEARNING

- Reinforcement learning
  - Learns through interaction with an environment
  - Seeks to maximize the expected future reward of an agent
- Policy: defines a mapping from states to the actions taken
  - Stochastic $\pi_{\mathbf{\Theta}}(a \,|\, s) : \mathcal{S} \times \mathcal{A} \to [0, 1]$
- Experience

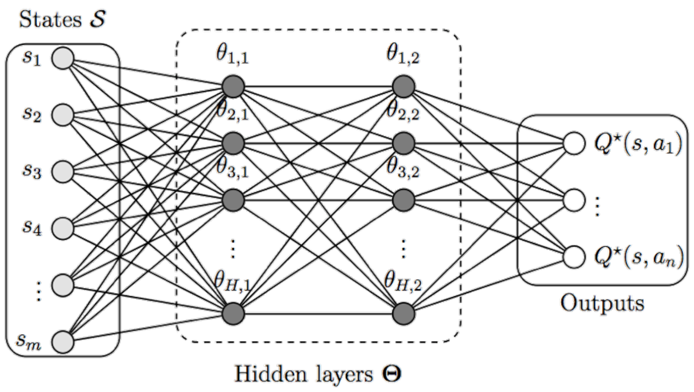
$$e_t := (\underset{\text{current state}}{s_t}, \underset{\text{current action}}{a_t}, \overset{\text{current reward}}{r_t}, \overset{\text{next state}}{s_{t+1}})$$

Stored in a replay buffer

- Replay
  - Samples from prior experience (i.e., the replay buffer) to remove potential correlation and improve stability of DQN
- Bellman

$$Q^\star_\pi(s_t, a_t) := \mathbb{E}_{s'}\left[r_{s,s',a} + \overset{\text{discount rate}}{\gamma} \underbrace{\max_{a'} Q^\star_\pi(s', a')}_{\text{future discounted reward}} \,\Big|\, s_t, a_t \right],$$

[Sutton]



Deep Q-Network (DQN)

$$\lim_{t \to +\infty} Q_\pi(s, a; \mathbf{\Theta}_t) = Q^\star_\pi(s, a)$$

Universal approximation theorem

- Exploration vs exploitation
  - Select a random action w.p. ϵ
  - Find action that maximizes $Q^\star_\pi(s, a)$ w.p. $(1 - \epsilon)$

ϵ-greedy has linear "regret"

[Silver]