TUTORIAL

Maching Learning for Spectrum Sharing in Wireless Networks

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Lisbon, Portugal

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Speakers

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Ack: Anatolij Zubow

Slides available at: www.hiit.fi/u/bayhan/pdf/crowncom2017tutorial.pdf

Outline

- **Key message**: Spectrum sharing is inevitable and mechanisms to solve coexistence challenges is still immature. Machine learning can provide efficient tools to deal with complex interactions in the coexistence settings.

- Outline:
  - Part I: Spectrum sharing essentials (10 mins)
  - Part II: Coexistence in unlicensed bands (30 mins)
  - Part III: Machine learning primer (20 mins)
  - Part IV: How ML helps for better coexistence (30 mins)
  - Part V: Summary and open research directions (5 mins)

Part I
Spectrum Sharing in Wireless Networks

- Why to share the spectrum?
- Modes of sharing
- Challenges in *harmonious* coexistence
- Current solutions for coexistence in wireless networks

Sharing

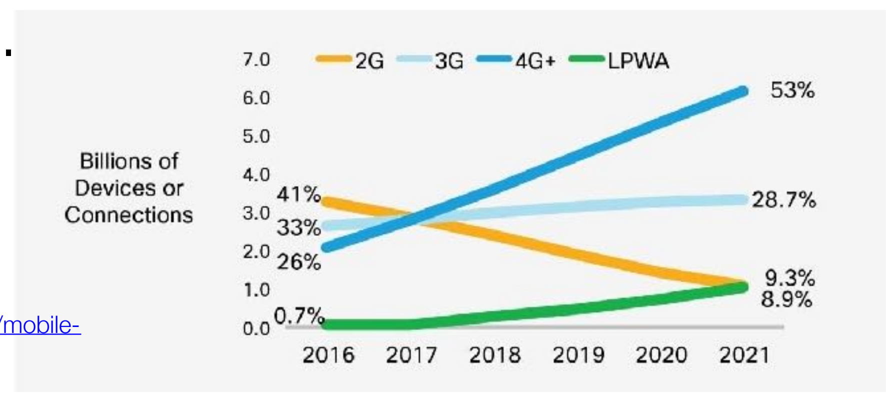
- *Spectrum sharing* covers the scenarios where at least two technologies, systems, or users utilise or are authorized to utilize the same frequency bands in a non-exclusive manner

Artist: Alan Levine

Simon Forge, Robert Horvitz and Colin Blackman, report on *Promoting the Shared Use of Europe's Radio Spectrum*, 2012.

Networks are getting denser

- High increase in wireless devices, networks, users
- Massive and continuing growth in mobile data traffic
  - Special thanks to video traffic! 60% of total mobile traffic in 2016
- More to come with IoT, M2M, 5G
- Many (cutting-edge) proposals to cope with the *exponentially* increasing wireless data demand
  - small cells, MU-MIMO, D2D, etc.



Cisco Visual Networking Index: Global Mobile Data Traffic Forecast Update, 2016–2021, 2017. https://www.cisco.com/c/en/us/solutions/collateral/service-provider/visual-networking-index-vni/mobile-white-paper-c11-520862.pdf

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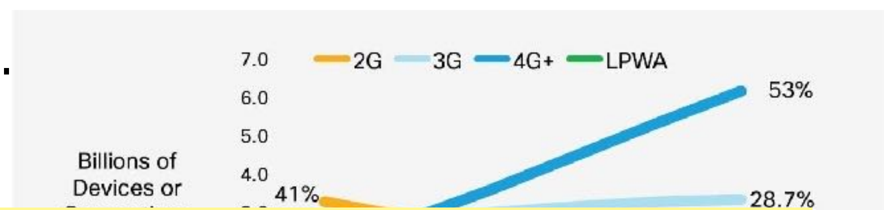

BUT: Scarcity of "*good*" spectrum for wireless communications is still the major bottleneck.

Scarcity of *good* spectrum

- Sub-6 GHz best performance
- Unlicensed bands:
  - 2.4 GHz (already very congested)
  - and 5 GHz
- New bands: *mmWave* etc.
  - for small cells and low mobility

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Scarcity of *good* spectrum

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Dynamic spectrum sharing as a remedy to cope with exponential wireless data demand and solve the **artificial** scarcity due to mis-management of the spectrum

Also sharing economy is better

- Cheaper licenses for mobile network operators if operation on the licensed bands
- Additional revenue for network operators if selling their under-utilised bands
- More-efficient spectrum utilization if shared among multiple networks (use of underused assets by others)

Please see for sharing in the licensed bands: Tehrani, Roya H., et al. "Licensed spectrum sharing schemes for mobile operators: A survey and outlook." IEEE Communications Surveys & Tutorials18.4 (2016): 2591-2623.

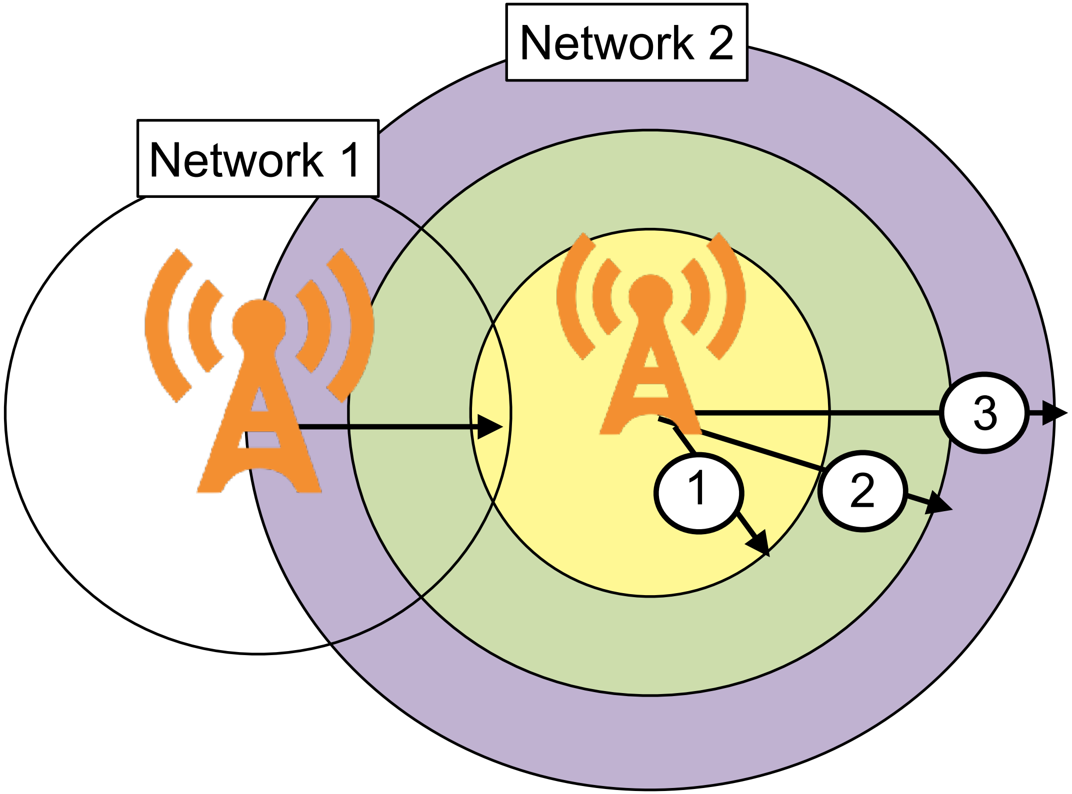
Spectrum authorities agree …

- FCC’s Notice of Inquiry July 13, 2017: *Exploring Flexible Use in Mid-Band Spectrum Between 3.7 GHz and 24 GHz*
  http://transition.fcc.gov/Daily_Releases/Daily_Business/2017/db0713/DOC-345789A1.pdf

- Ofcom’s *A Framework for Spectrum Sharing* in April 2015
  https://www.ofcom.org.uk/__data/assets/pdf_file/0032/79385/spectrum-sharing-framework.pdf

- Report for EU Commission, on *Promoting the Shared Use of Europe’s Radio Spectrum*, 2012, S. Forge et al.
  https://ec.europa.eu/digital-single-market/en/promoting-shared-use-europes-radio-spectrum

A generic coexistence scenario



1: transmission range
2: detection range
3: interference range

Coping with interference is central to the coexistence of wireless systems.

Simon Forge, Robert Horvitz and Colin Blackman, report on *Promoting the Shared Use of Europe's Radio Spectrum*, 2012.
https://ec.europa.eu/digital-single-market/en/promoting-shared-use-europes-radio-spectrum

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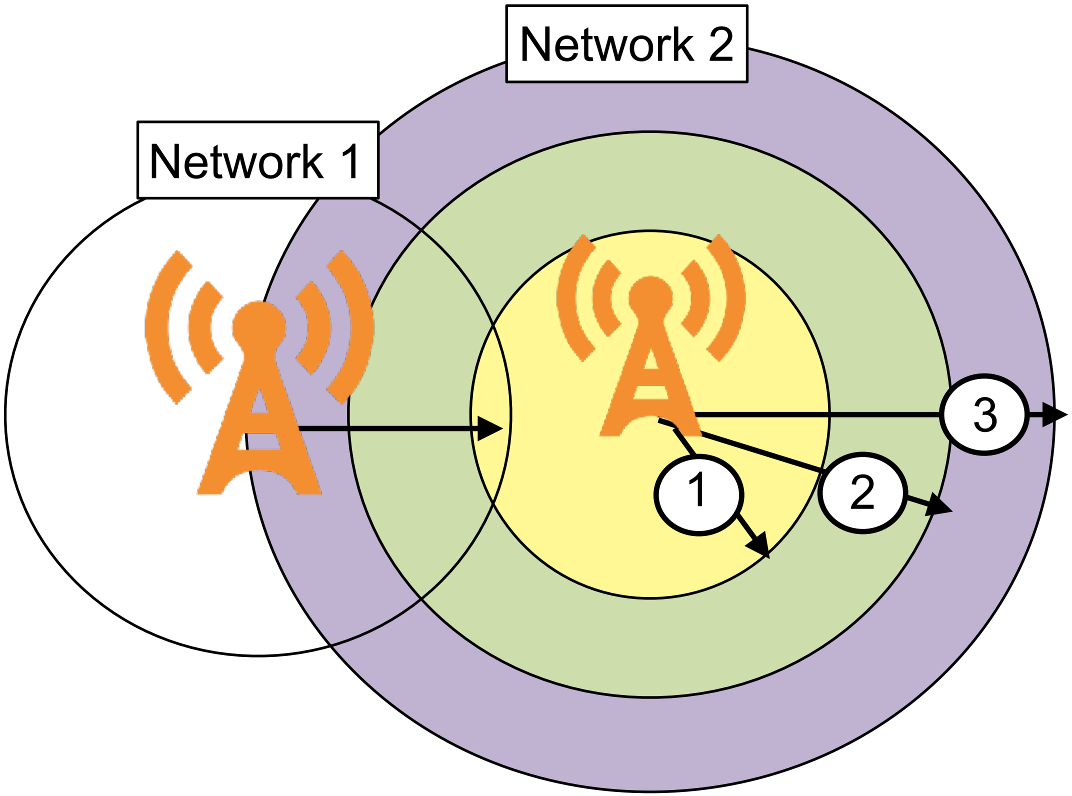


1: transmission range
2: detection range
3: interference range

Co-existence is when the operation of a radio system is capable of impairing the operation of another radio system but it does not.

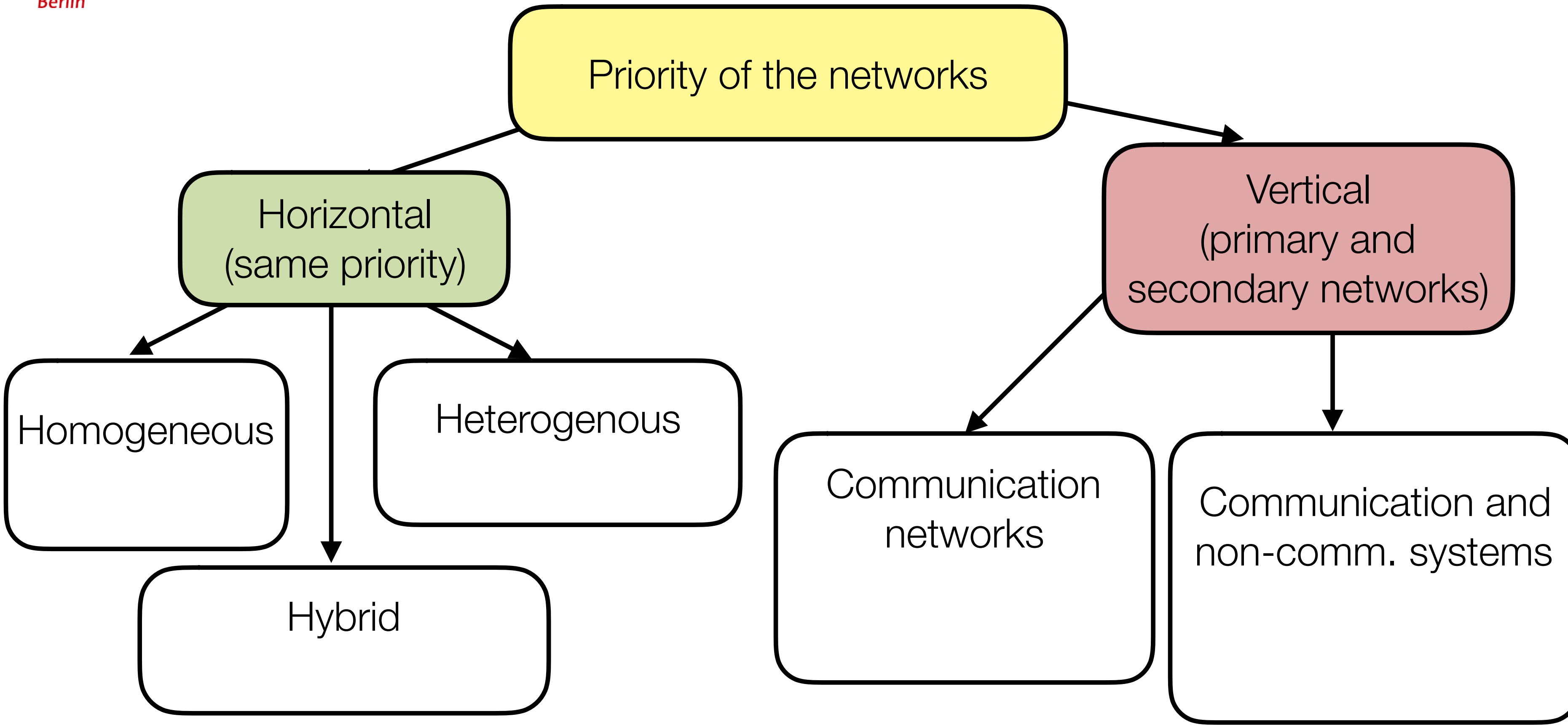
Simon Forge, Robert Horvitz and Colin Blackman, report on *Promoting the Shared Use of Europe's Radio Spectrum*, 2012.
https://ec.europa.eu/digital-single-market/en/promoting-shared-use-europes-radio-spectrum

Spectrum sharing in various domains

Frequency	Time	Space	Code
f	t	s	c

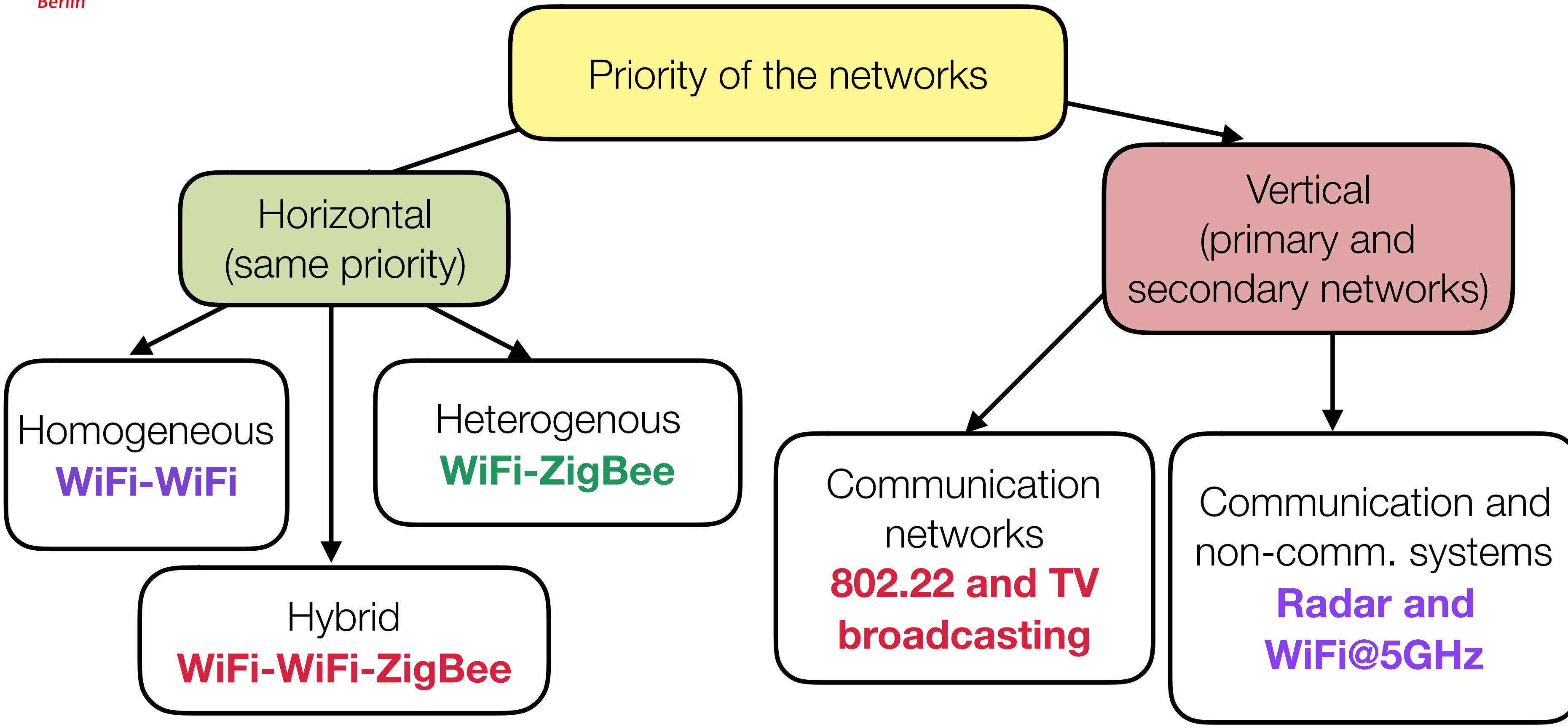
- **Frequency**: each system operates on a different spectrum
- **Time**: same spectrum used on a time-sharing basis (*DSA*, *cognitive radio* in overlay mode)
- **Space**: systems coexist in different spatial domains (e.g., protection zones, exclusion zones)
- **Code**: e.g. CDMA

Spectrum Sharing Scenarios: A Taxonomy



Han, You, et al. Spectrum sharing methods for the coexistence of multiple RF systems: A survey. *Ad Hoc Networks*, 2016

Spectrum Sharing Scenarios: A Taxonomy



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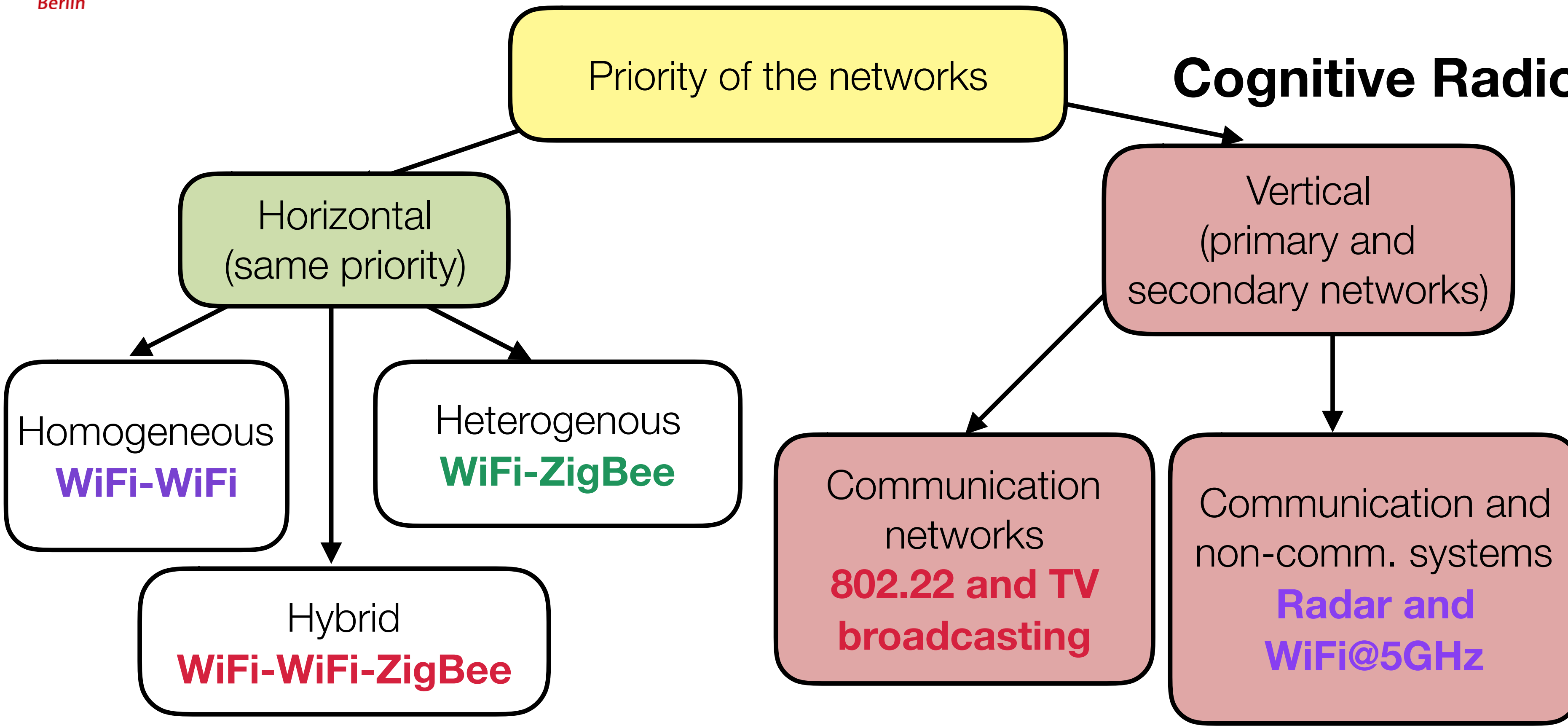

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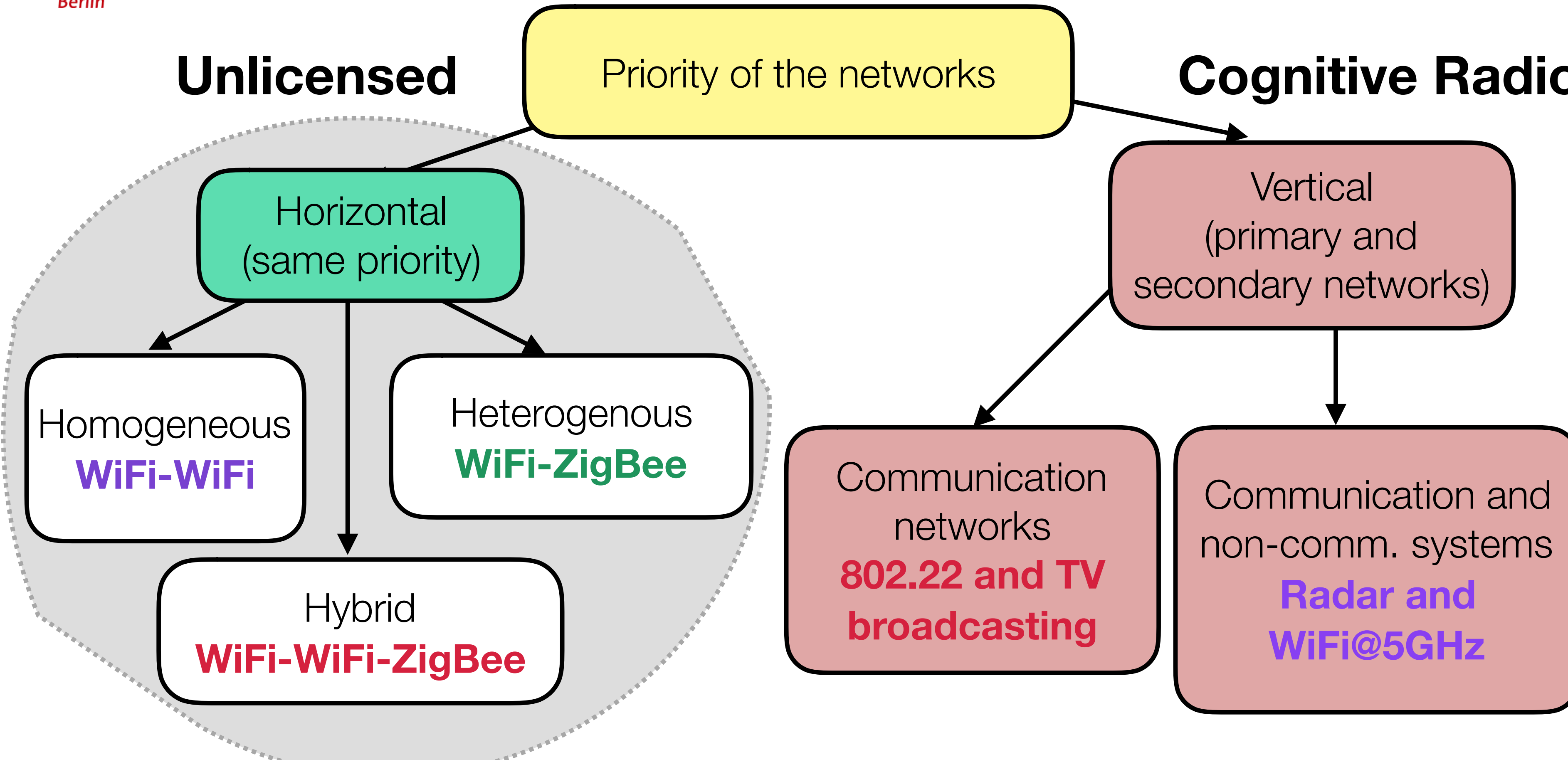
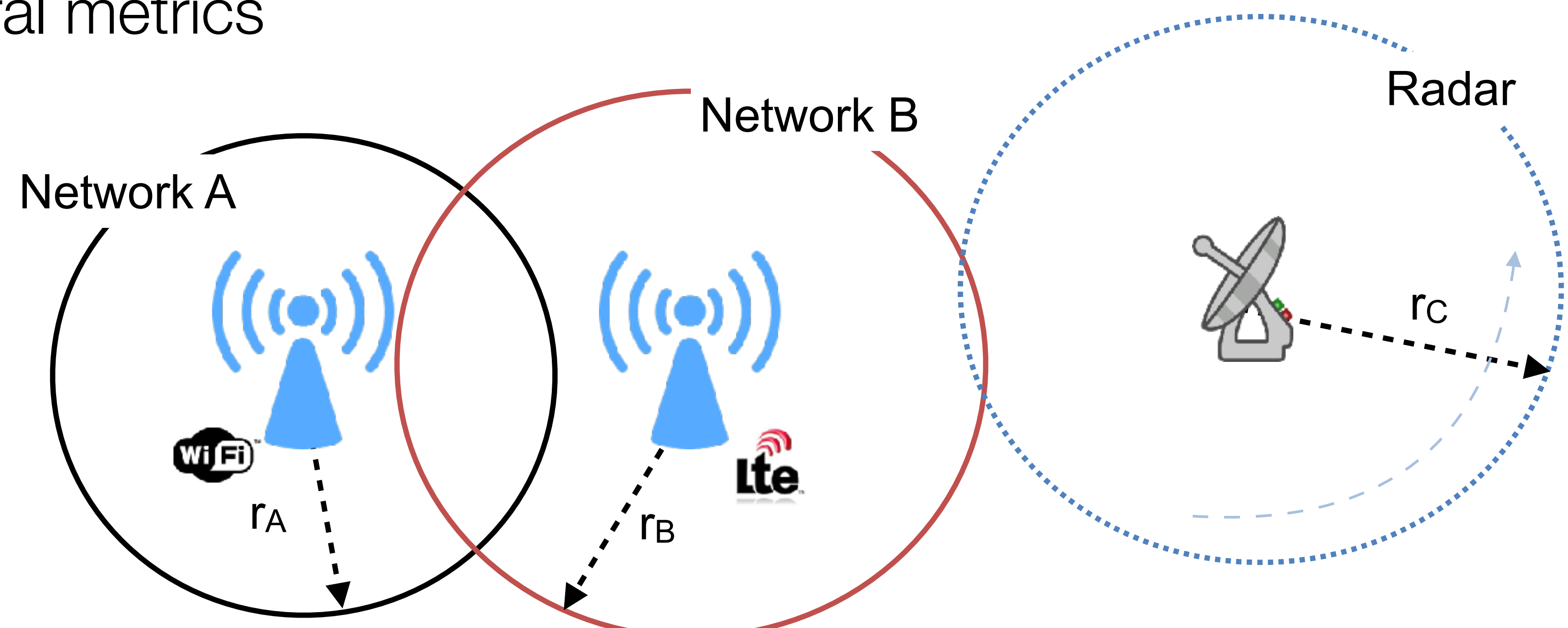


Main focus of this tutorial is on unlicensed bands

What is an **efficient** coexistence?

- Depends on the scenario (requirements of each system's operation)
- Several metrics



Coexistence metrics

- Fairness in usage of the shared resources
- Throughput
- Delay
- Spectrum utilisation (from the perspective of the regulatory bodies/ spectrum authority)

Main challenges in wireless coexistence

Challenge #1

Heterogeneity

(other challenges are also mostly due to heterogeneity)

Challenge #1: Heterogeneity

- Different rules of operation, different ethics
- PHY, MAC layer (packets may not be decoded by the other network)
- Different packet formats
- Power levels
- Different signal management functions
- Modulation schemes
- Data rates
- Channel bandwidths and separations
- Applications, communication vs. non-communication networks

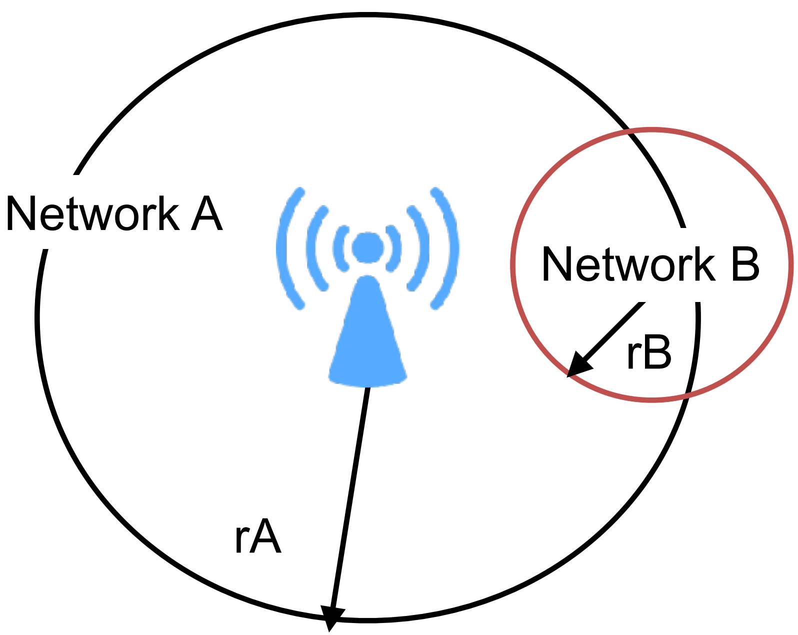
Main challenges in wireless coexistence

Challenge #2

Power asymmetry

Challenge #2: Power asymmetry

- High-power systems vs. small-cell/low-power systems



- Asymmetric interference (different tx powers, different interference regions)
- WiFi vs. ZigBee

Main challenges in wireless coexistence

Challenge #3

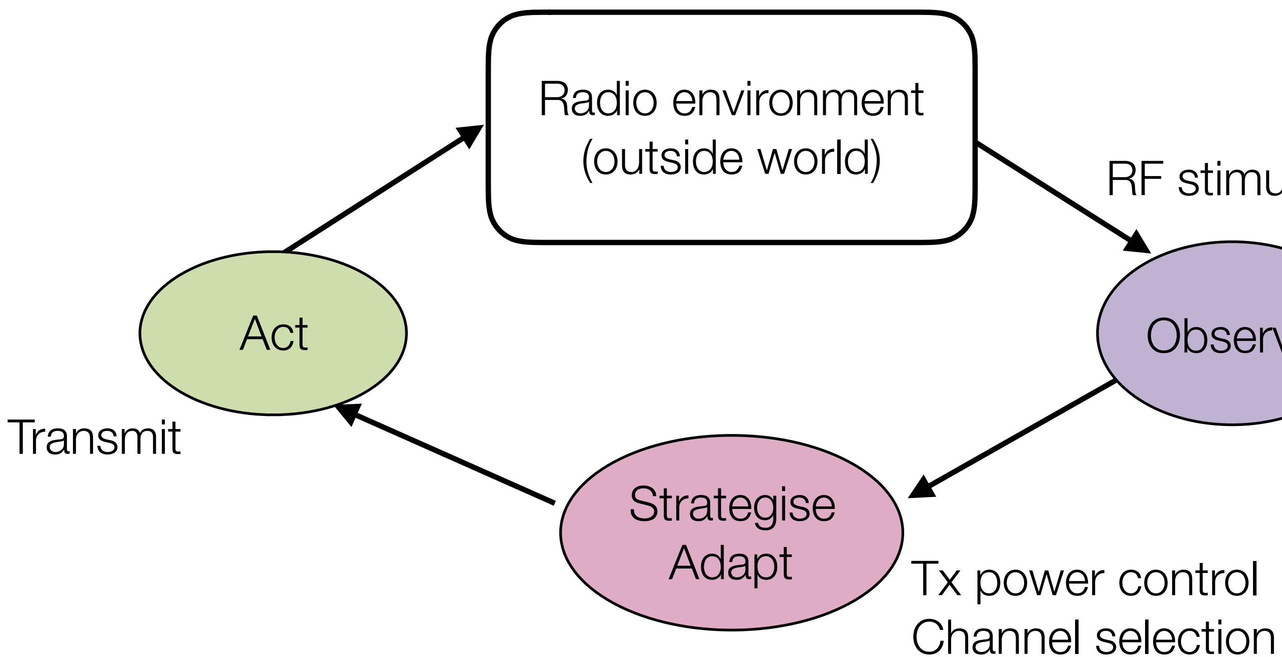
Lack of communication among co-existing networks

Challenge #3: lack of communication

- Networks controlled by different operators
- Networks using different technologies
- No well-defined means for negotiation, e.g., residential WLANs

Remember the cognition cycle

- Coexistence requires cognition



http://soma.mcmaster.ca/papers/SLIDES_NIPS_Keynote_Haykin.pdf

Some coexistence guidelines

- **IEEE 802.19** Wireless Coexistence Technical Advisory Group (TAG) within the IEEE 802 LAN/MAN Standards Committee: coexistence between unlicensed wireless networks
  - 802.19.1: Coexistence in TV bands
- **IEEE 802.15 Task Group 2**: Recommended Practice on Coexistence of IEEE 802.11 and Bluetooth
- **P802.22b amendment:** Self-coexistence protocol for 802.22 networks: Coexistence Beacon Protocol (CBP)
- **P 1932.1:** Standard for Licensed/Unlicensed Spectrum Interoperability in Wireless Mobile Networks

Summary of Part I

- Sharing is vital for meeting the demand for wireless capacity
- Coexistence is the main challenge in shared spectrum access
- Heterogeneity of networks pose substantial difficulties
- Metrics and requirements still not totally agreed upon

Further Reading for Part I

- Han, You, et al. "Spectrum sharing methods for the coexistence of multiple RF systems: A survey." *Ad Hoc Networks* 53 (2016): 53-78.
- Beltran, Fernando et al "Understanding the current operation and future roles of wireless networks: Co-existence, competition and co-operation in the unlicensed spectrum bands." *IEEE JSAC16*.
- P802.22b Coexistence Assurance Document, doc.: 22-14-0141-01-0000, Nov.2014 available at https://mentor.ieee.org/802.22/dcn/14/22-14-0141-01-0000-p802-22b-coexistence-assurance-document.docx
- Bahrak, Behnam, and Jung-Min Jerry Park. "Coexistence decision making for spectrum sharing among heterogeneous wireless systems." *IEEE TWC* 14
- K. Bian et al., Cognitive Radio Networks, Chapter 2 Taxonomy of Coexistence Mechanisms, Springer 2014
- *JSAC* Special Issue on Spectrum Sharing I, II, and III, October, November, December 2016

Part II
Coexistence in unlicensed bands

- Wi-Fi overview
- Unlicensed LTE overview
- Coexistence Issues

WiFi + femtocells carried 60% of mobile data traffic

The future is *unlicensed*

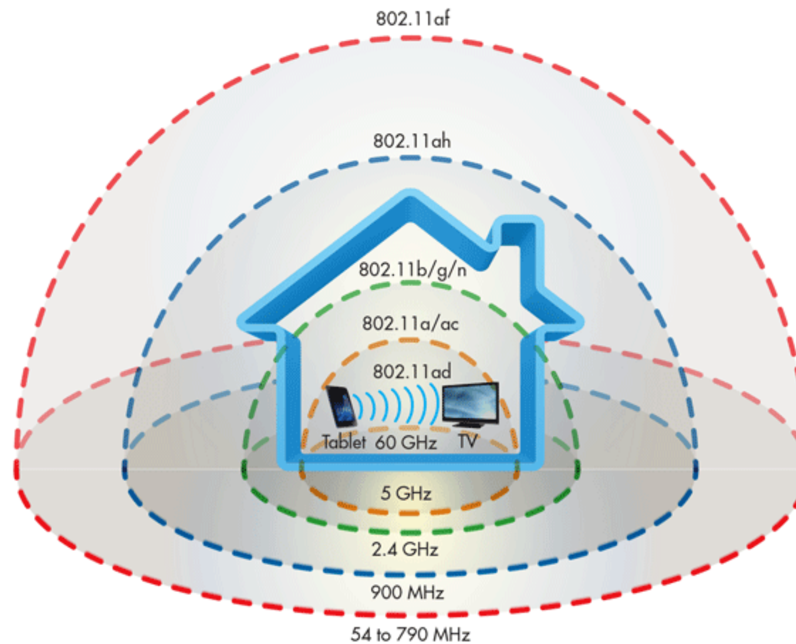
Success of WiFi attributed to operation in unlicensed bands

A brief overview of Wi Fi

IEEE 802.11 WLANs

TVWS | 900 MHz | 2.4 GHz | 5 GHz | 60 GHz

- **11a** - 20 MHz BW, **5GHz**
- **11b** - 20 MHz BW, **2.4 GHz**
- **11g** - 20 MHz BW, **2.4 GHz**
- **11n** - 20 & 40 MHz BW, **2.4 and 5GHz**
- **11ac** - 20 to 160 MHz BW, **5GHz**
- **11ad** - 2 GHz BW, **60 GHz**
- **11af** - 6/8 MHz, **TV White Space**
- **11ah-** 1/2/4/8/16-MHz, **900 MHz**



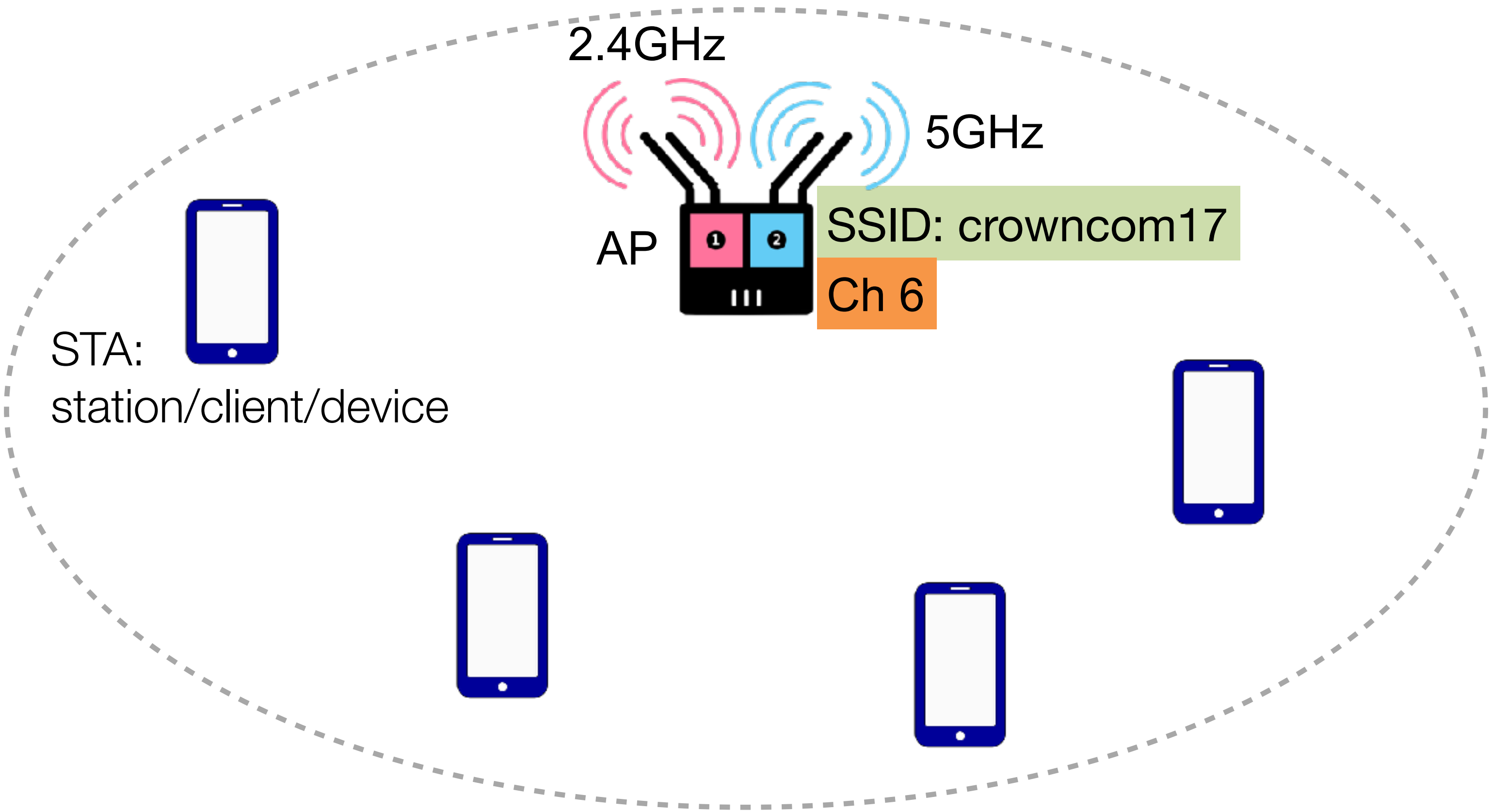
source: http://www.mwrf.com

Source: http://www.gcscte.org/presentations/2017/Wifi%20Overview.pdf

Spectrum commons: Unlicensed bands

- **2.4 GHz ISM bands: already crowded**
  - WiFi, Bluetooth, microwave ovens, Zigbee, etc.
  - WiFi: 802.11b/g/n at 2.4 GHz
  - Channels 1, 6, 11 are non-overlapping and should be used
- **5 GHz UNII bands: getting crowded**
  - WiFi, Radar, unlicensed LTE
  - WiFi: 802.11a/n/ac at 5GHz and future standards 11ax
  - Non-overlapping 20+ channels of 20 MHz

WiFi is polite: listen-before-talk (LBT)



https://commotionwireless.net/blog/2014/11/05/do-it-yourself-antennas-for-community-networks

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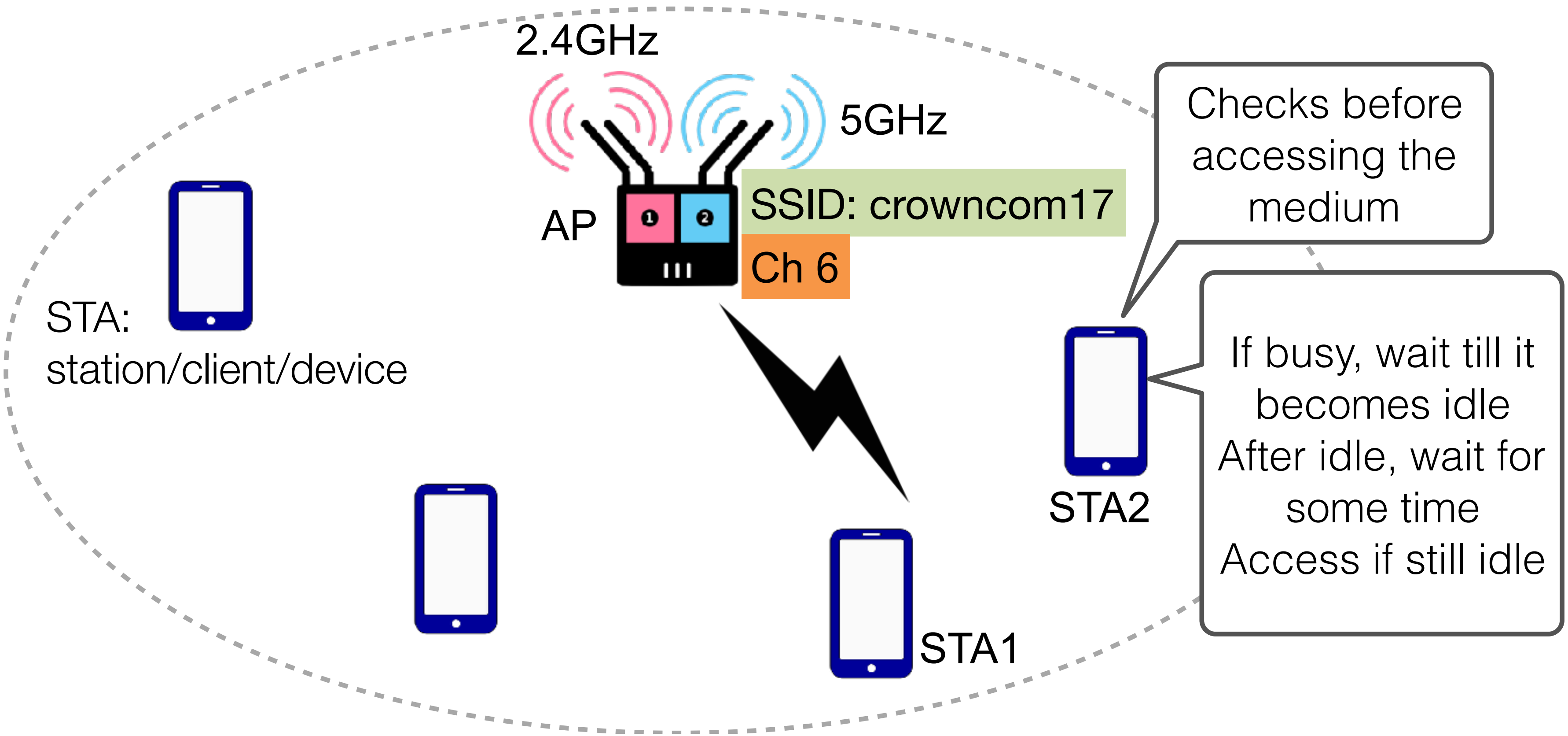
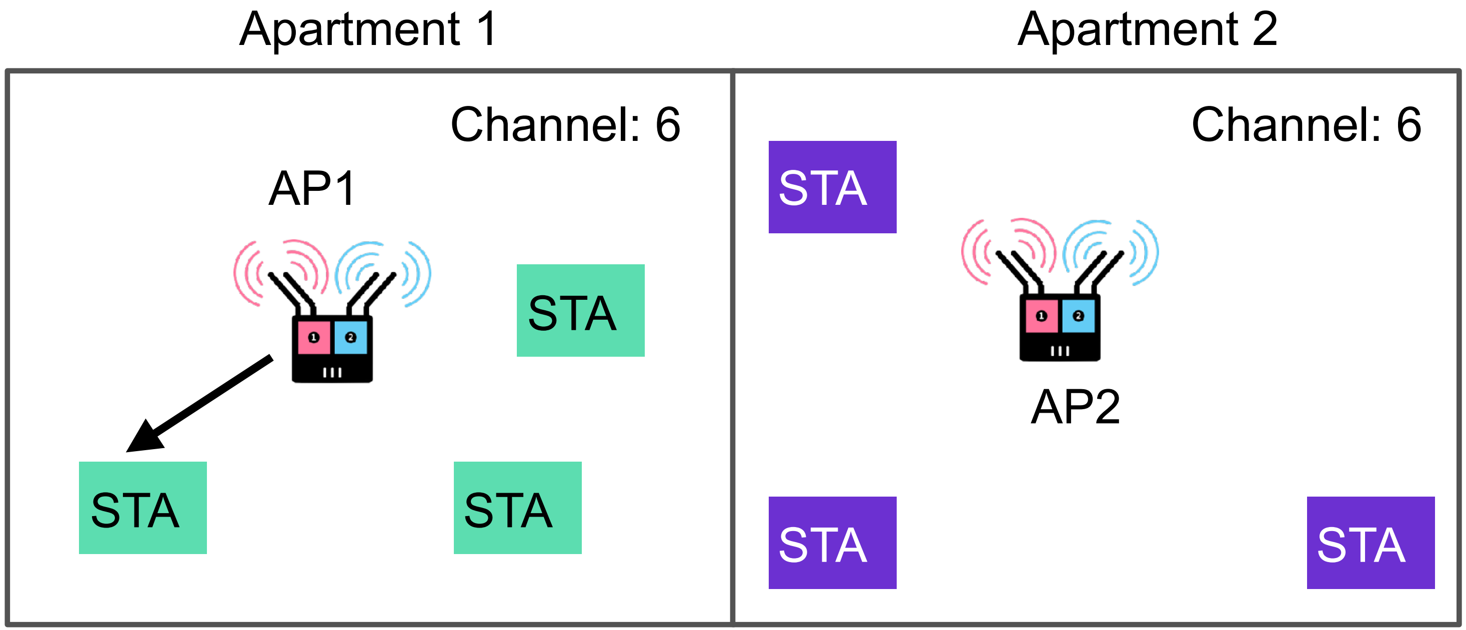


Carrier Sense Multiple Access with Collision Avoidance (CSMA/CA)

Distributed Control Function (DCF)

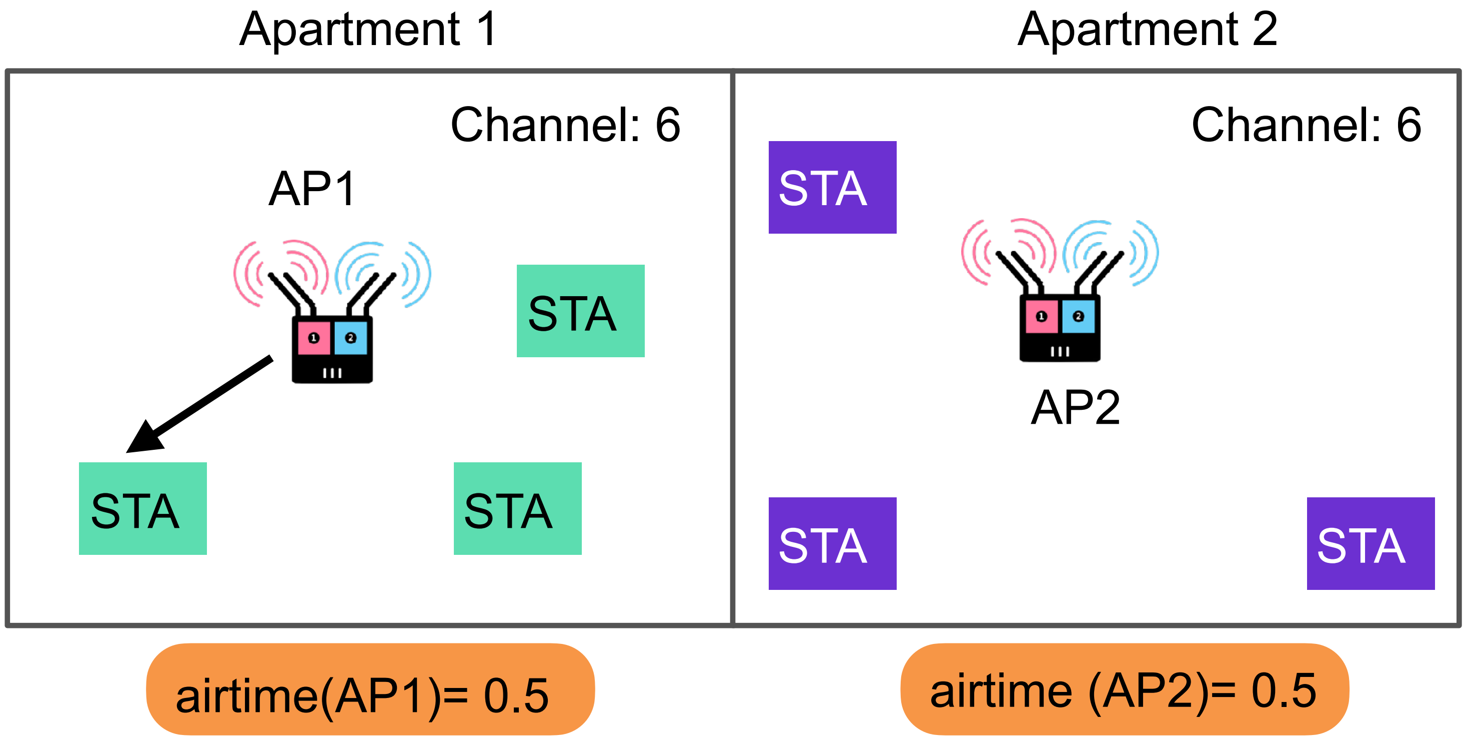
- Random access protocol
  - transmission (attempt) can happen anytime
- The same medium for all
  - uplink and downlink, control and data shares the medium
- Exponential backoff mechanism
  - Contention window size
- DIFS, SIFS amounts of waiting before continuing transmission
- Rate adaptation according to channel quality

WiFi shares the airtime with its neighbours

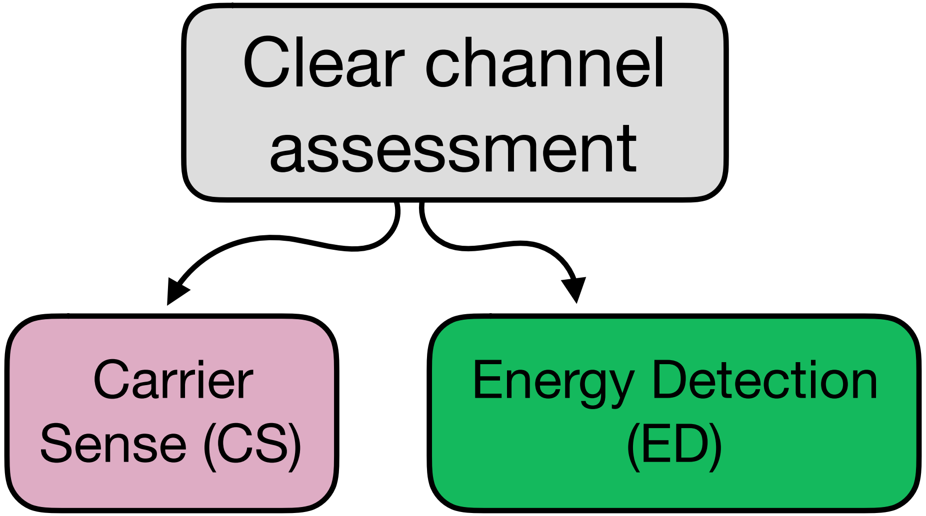


- As two APs operate on the same channel airtime is shared, e.g., only one transmitter is active at a time

WiFi shares the airtime with its neighbours

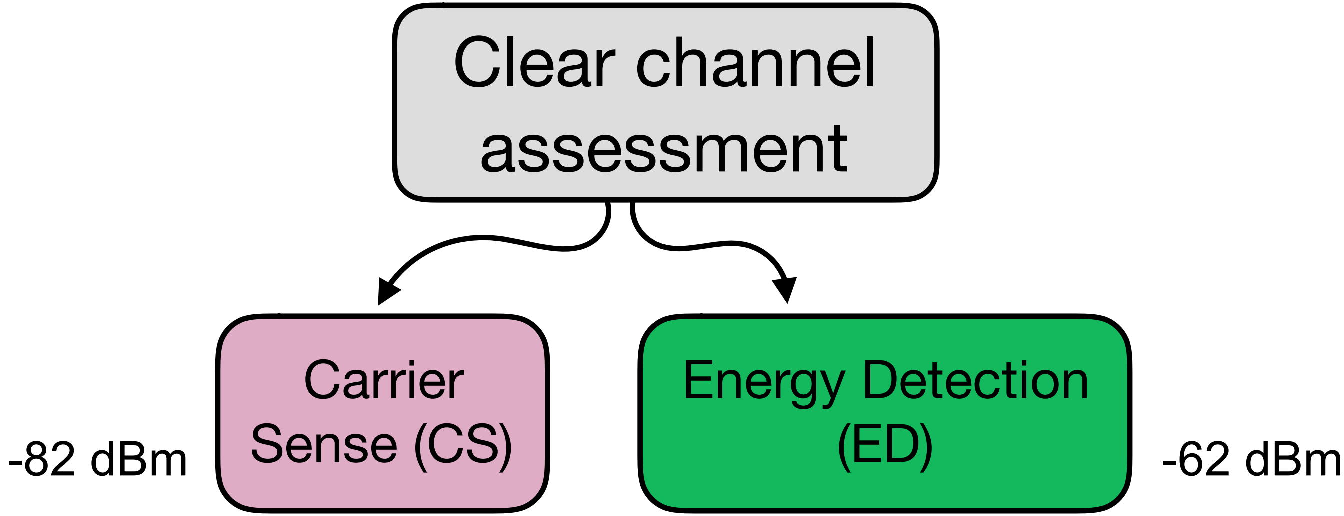


Detecting the medium state



- **Carrier sense (CS):** decode the WiFi preambles
- **Energy detection (ED):** detect that there is some (e.g., non-WiFi) signal present in the channel above some ED threshold

Detecting the medium state



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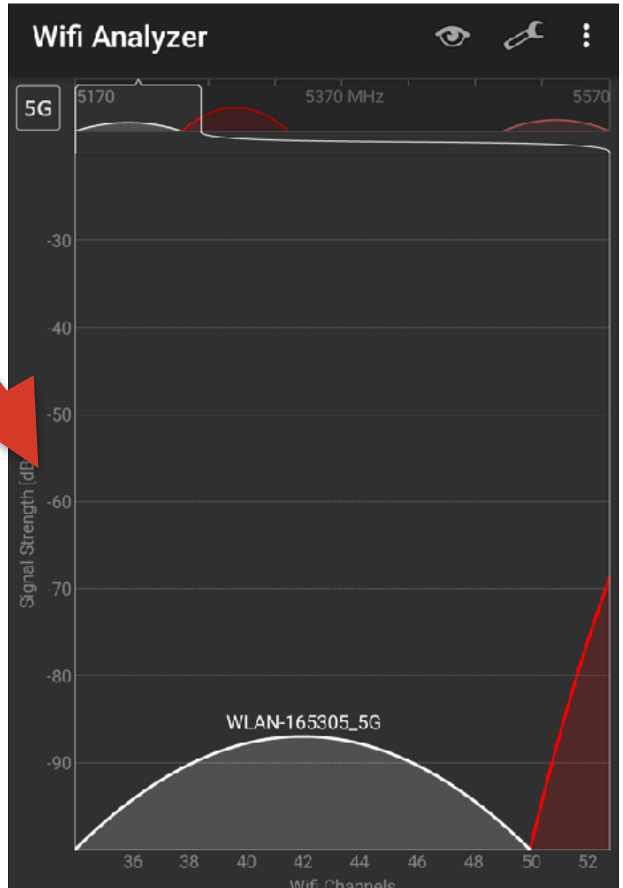
Main challenge: *chaotic* WiFi deployments

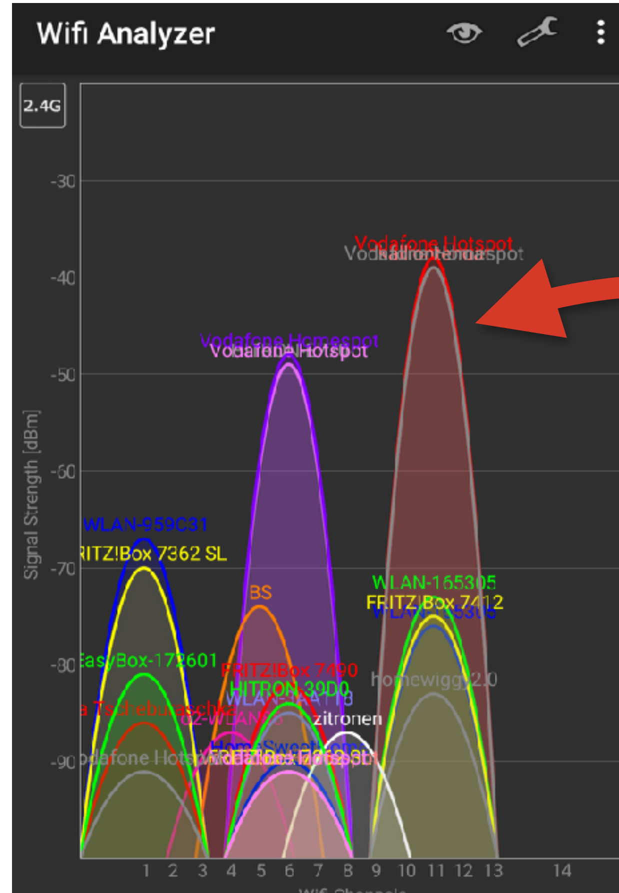
- Enterprise WLANs:
    - centrally-managed, easier coexistence
- Residential/uncoordinated WLANs: *chaotic* deployment
    - independently controlled APs (or novice user control)
    - need for coexistence mechanisms
- Co-channel interference, adjacent-channel interference, non-WiFi interference, high channel occupancy
- Main mechanism for coexistence in WLAN:
    - Channel selection, LBT parameter tuning, power control

Residential WLANs

5



expected to increase utilization



2.4 GHz

Highly congested

Berlin urban residential area

WiFi moving to 5 GHz

	Jan. 2014	Jan. 2015
802.11g	99.9%	99.9%
802.11n	95.7%	97.7%
5 GHz	48.9%	64.9%
40 MHz channels	23.4%	63.8%
802.11ac	2.5%	18.0%
Two streams	7.7%	19.3%
Three streams	2.4%	3.8%
Four streams	0.7%	1.8%

Table 4: Client capabilities advertised by all clients that connected during the same week in January for two consecutive years.

Source: Biswas, Sanjit, et al. "Large-scale measurements of wireless network behavior." *ACM SIGCOMM15*

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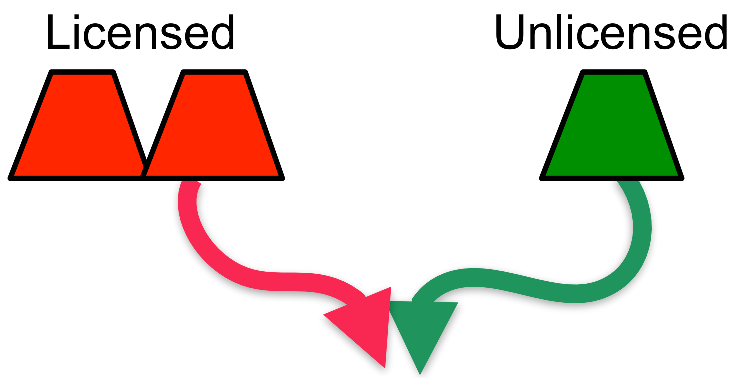
A brief overview of unlicensed **LTE**

LTE in unlicensed bands

- Cellular operators benefit from WiFi a lot, but
  - WiFi has low spectral efficiency under high number of users due to losses in **contention based access**
  - MAC efficiency<1

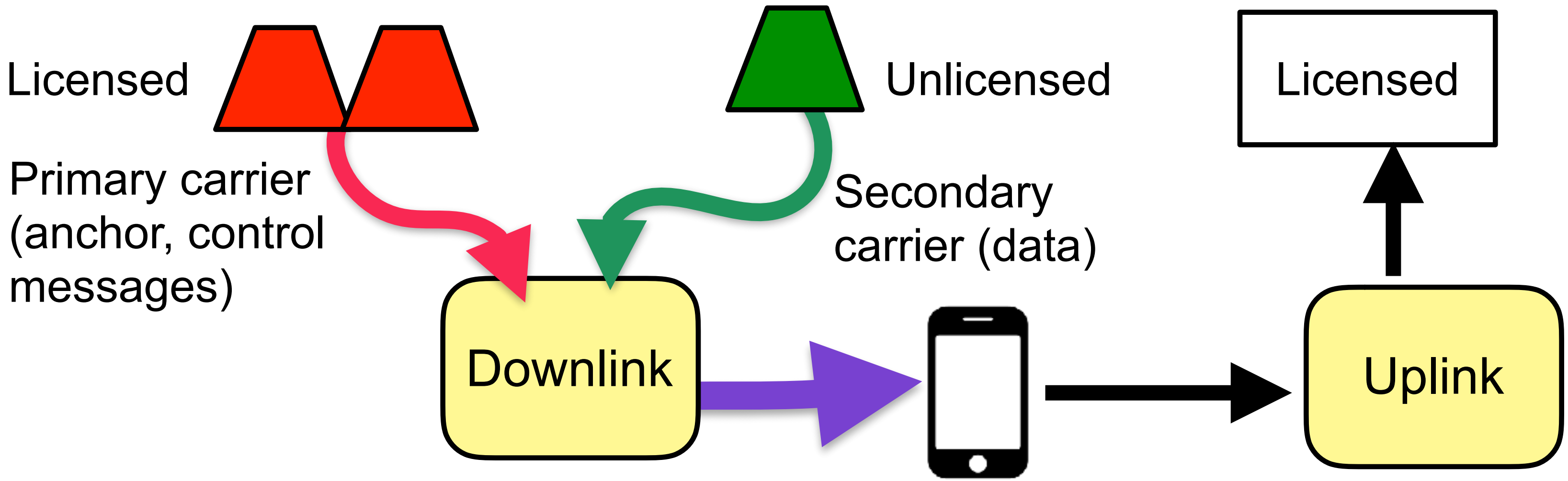


Solution: LTE in the unlicensed bands (Qualcomm, 2013)

Why LTE in unlicensed bands?

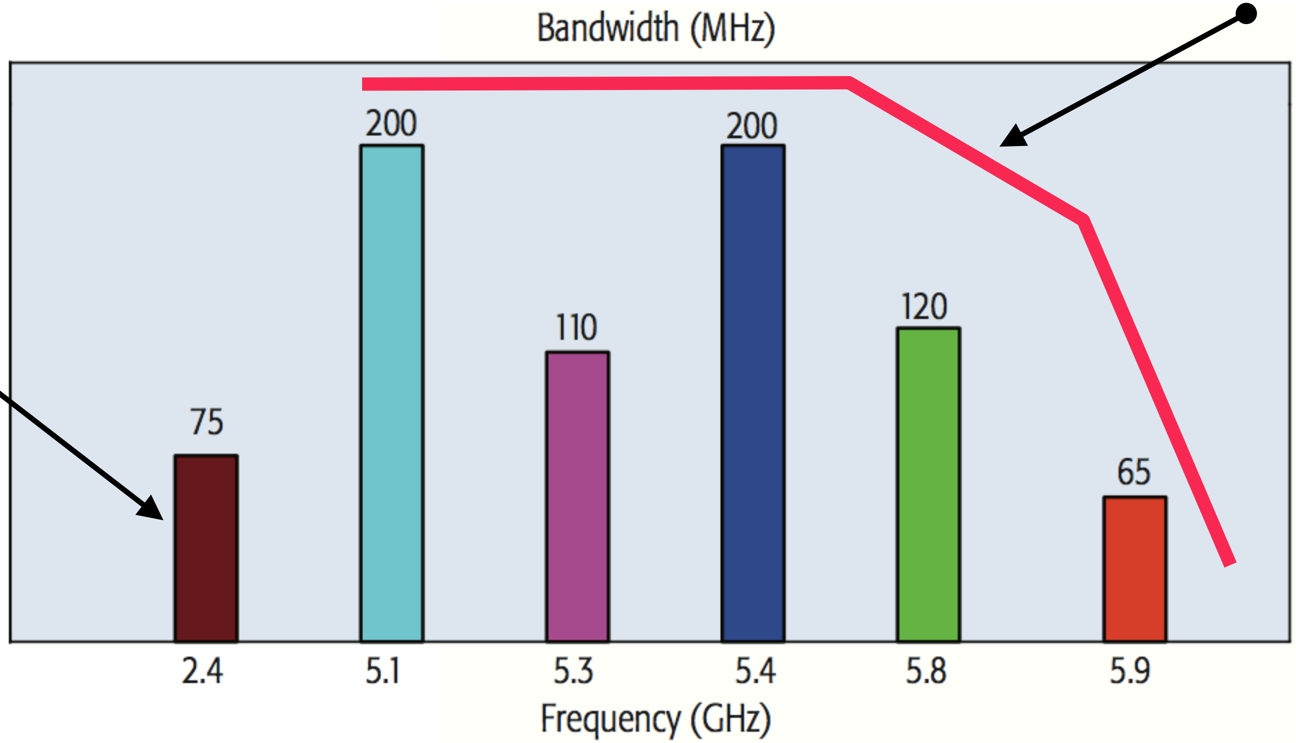
- Unified control at the same core:
  - authentication, management, and security procedures
- higher spectral efficiency in the unlicensed bands
  - Centrally-scheduled access
- Better error control at LTE
  - HARQ vs. ARQ
- other interesting convergence solutions not discussed here: MuLTEfire, LWA

Boosting capacity with unlicensed carriers



- Augment the licensed capacity with unlicensed capacity *when the data boost is needed (opportunistic use)*
- carrier aggregation: two or more carriers combined in a virtual bw.
- supplementary downlink (SDL), downlink: 80-90 % of total traffic

Available spectrum in unlicensed bands

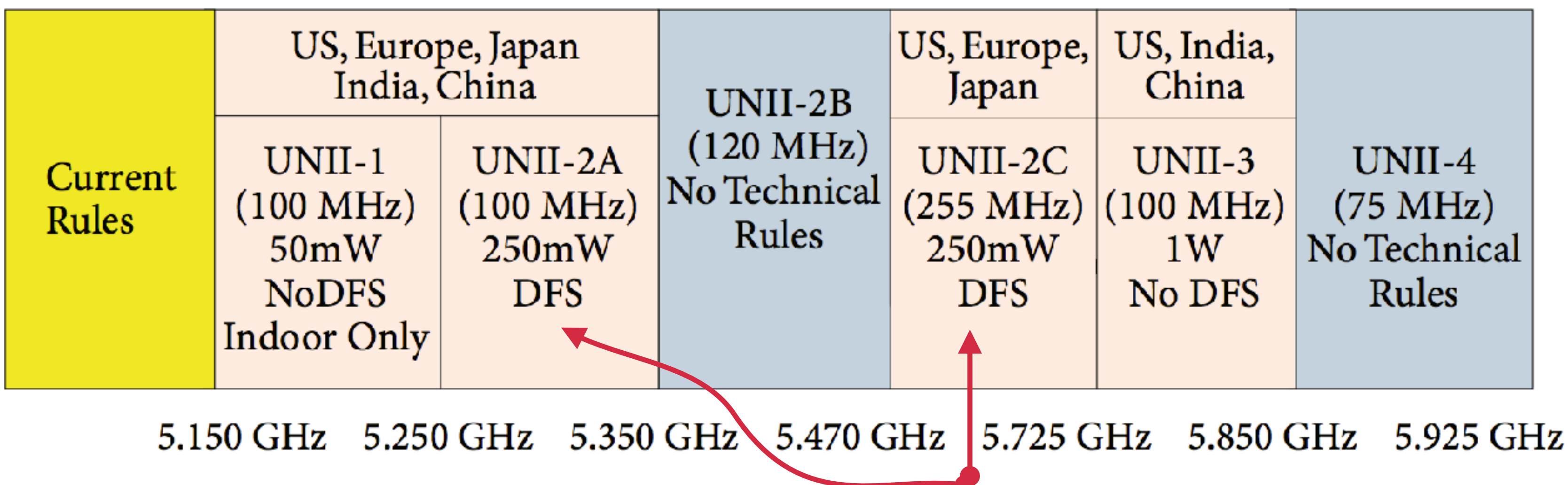


Already highly occupied

5 GHz better candidate

Source: Cui, Haixia, et al. "LTE in the Unlicensed Band: Overview, Challenges, and Opportunities." *IEEE Wireless Communications* (2017).

Regional regulations for 5GHz bands

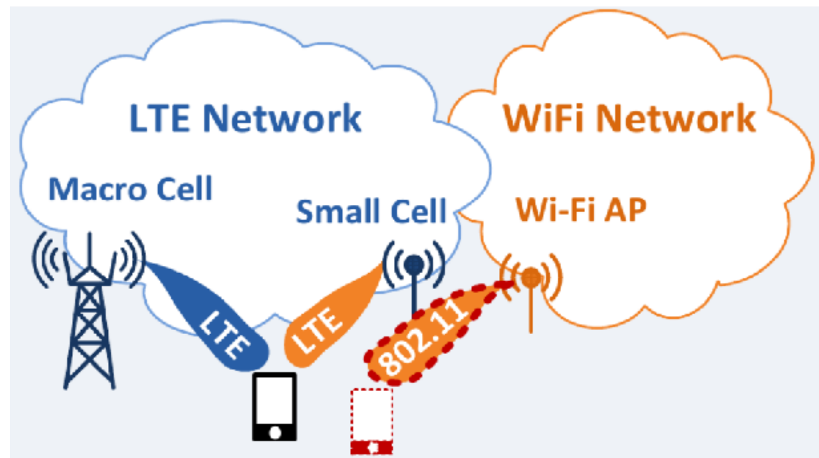


DFS: dynamic frequency selection for **radar** avoidance

Wang, Xuyu et al. "A survey of LTE Wi-Fi coexistence in unlicensed bands." *GetMobile: Mobile Computing and Communications* 2017

LTE unlicensed for small cell deployment

- Current trend: small cells for better frequency reuse
- But additionally,
  - Unlicensed spectrum: power restrictions
  - 5 GHz: lower coverage compared to 2.4 GHz
- Hence, LTE unlicensed is for small cells



Source: Korea Communication Review, Jan. 2015

Unlicensed LTE and WiFi coexistence

Channel access

LTE: centralized, strict time slots
WiFi: contention-based random access

Scheduling

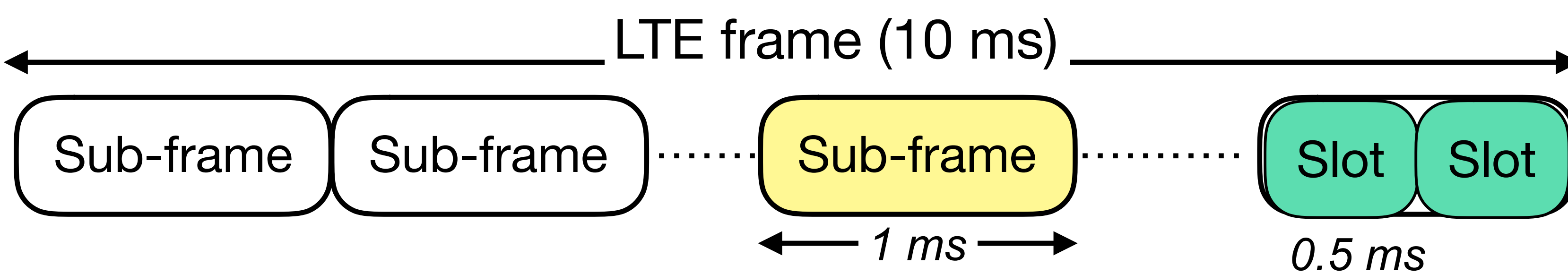
LTE: multiple users (time and freq)
WiFi: one user

Channel usage

LTE: always on, frames
WiFi: demand based, on-off

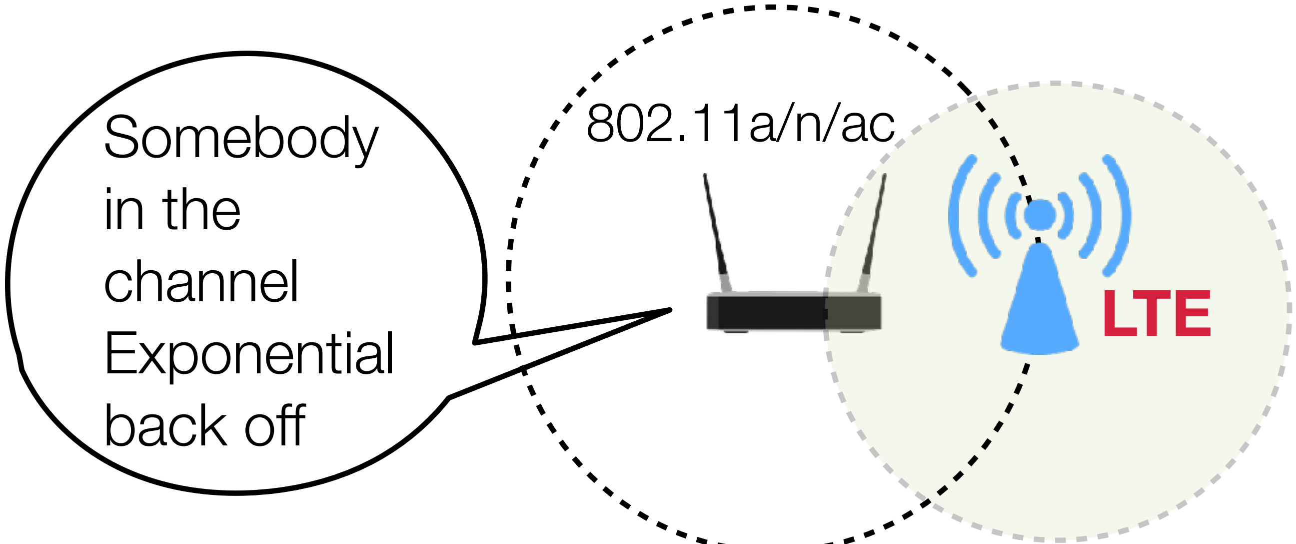
Interference

LTE: Cross/co-tier interference
WiFi: Hidden/exposed terminal, collision



Unlicensed LTE and WiFi coexistence

- Main problem: different PHY and MAC rules

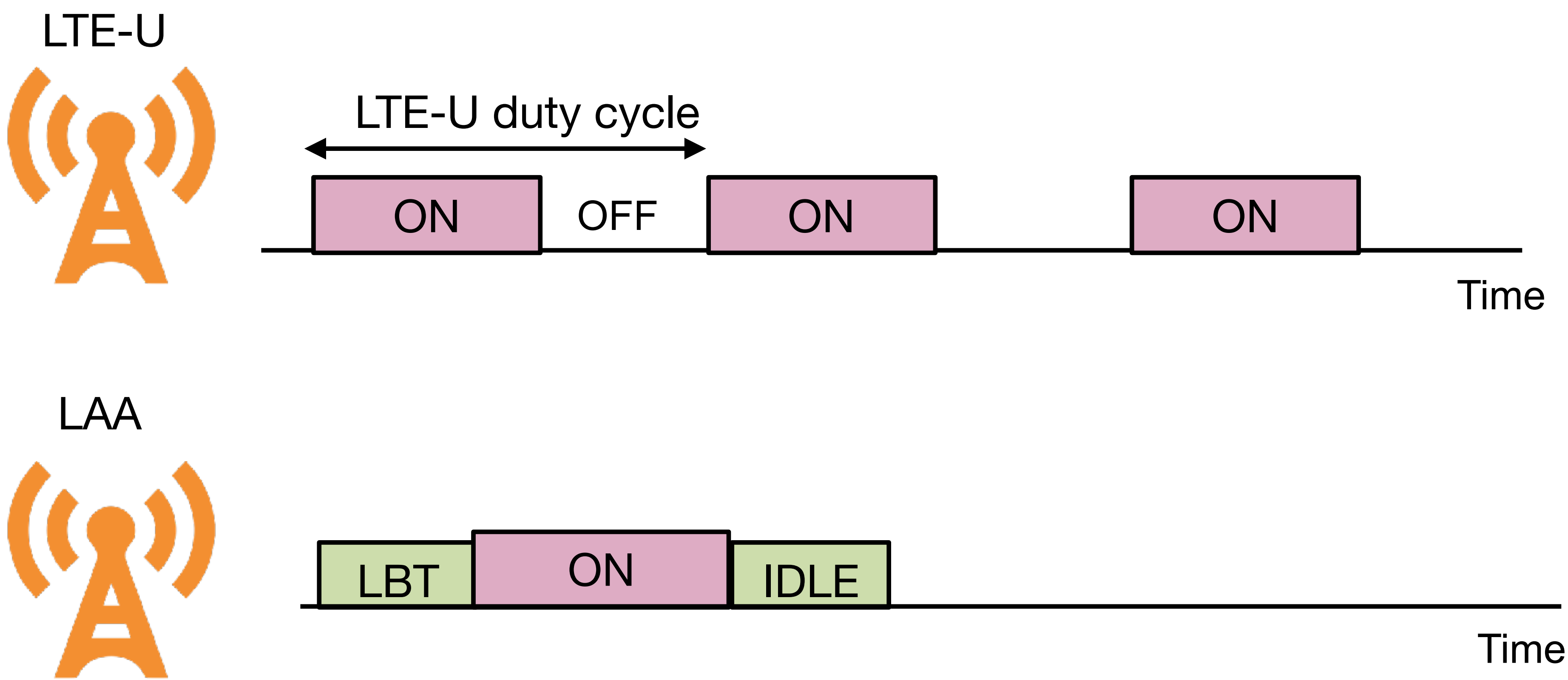


- Expected result: WiFi suffers from LTE, if LTE does not adapt coexistence mechanisms!

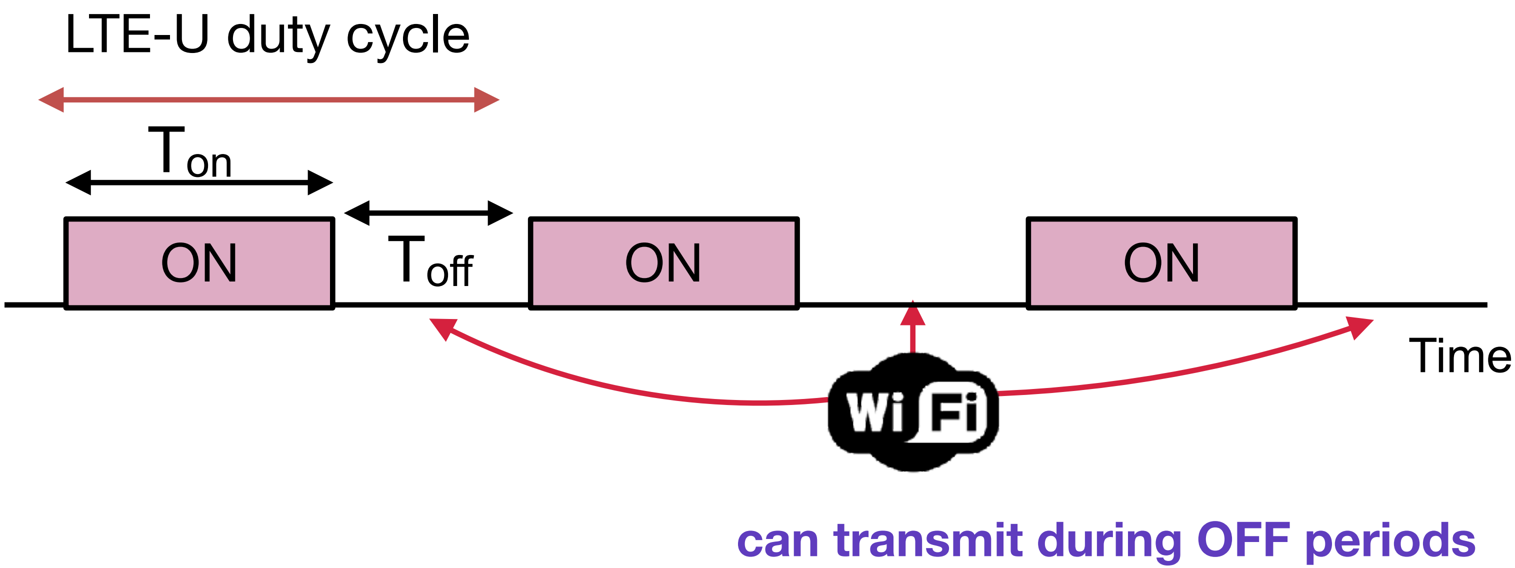
Two variants: LAA and LTE-U

- LBT required or not
  - **License Assisted Access LAA**: LBT mandatory
  - **LTE Unlicensed (LTE-U)**: no LBT
- LAA: by 3GPP, LTE-U: by LTE-U forum
- LAA: Europe, Japan, LTE-U: US, Korea, China
- LAA: Release 13 (requires changes to LTE air interface)
- LTE-U: Release 10/11/12
- LAA: a global standard, LTE-U: faster time to market

LAA vs. LTE-U

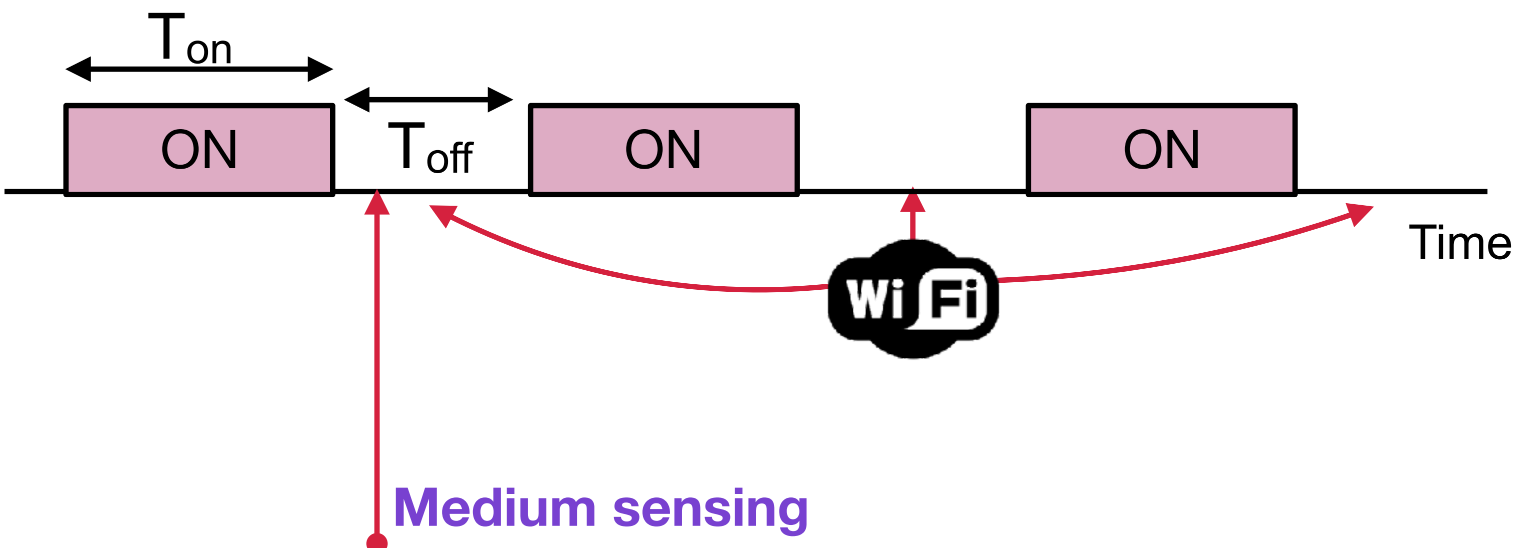


LTE-U duty-cycle



- MAC time sharing
- Duty cycle: $T_{on}/(T_{on}+T_{off})$

LTE-U duty-cycle



- CSAT (carrier sense adaptive transmission): adaptive duty cycle
- Adaptation according to WiFi medium utilisation and number of WiFi nodes observed by user devices or small base stations

How to set the ON-OFF durations?

- **Medium sharing**: if X is LTE's duty-cycle, airtime for WiFi is (1-X)
- But some caveats:
- **Length of ON-duration**: WiFi has to wait till the end of ON period which may affect latency-sensitive applications, e.g., high QoS frames.

How to set the ON-OFF durations?

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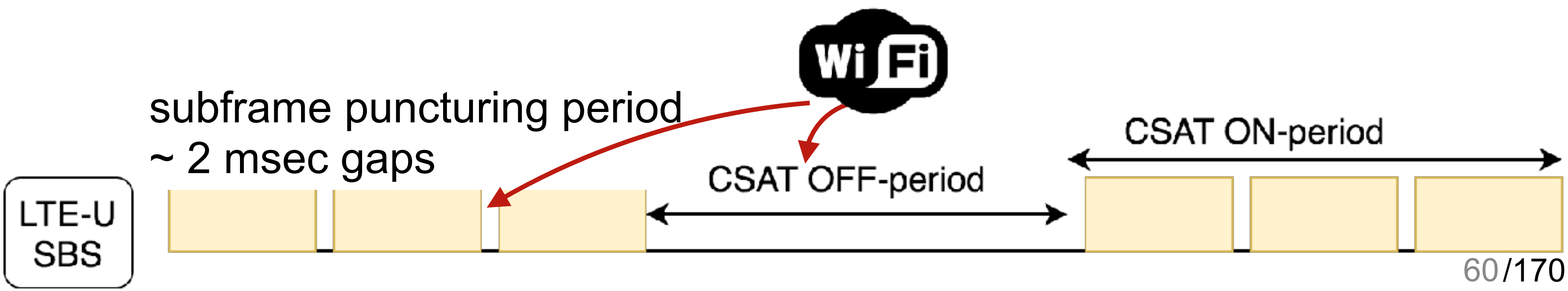
  - subframe puncturing
  - max ON duration 20 ms



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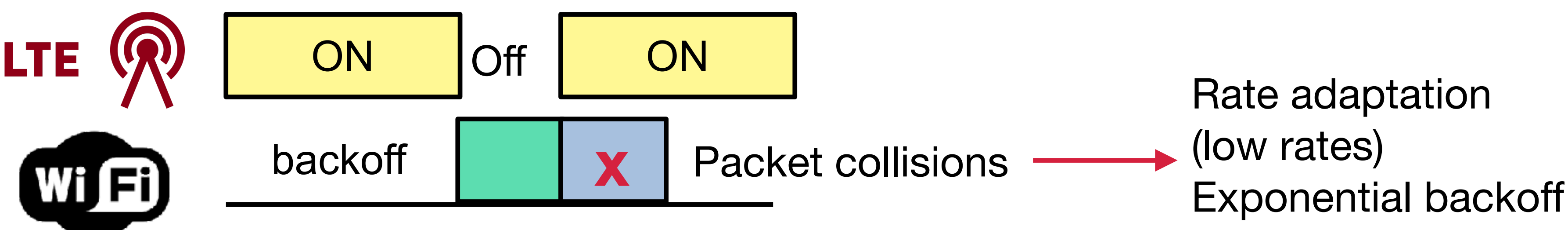
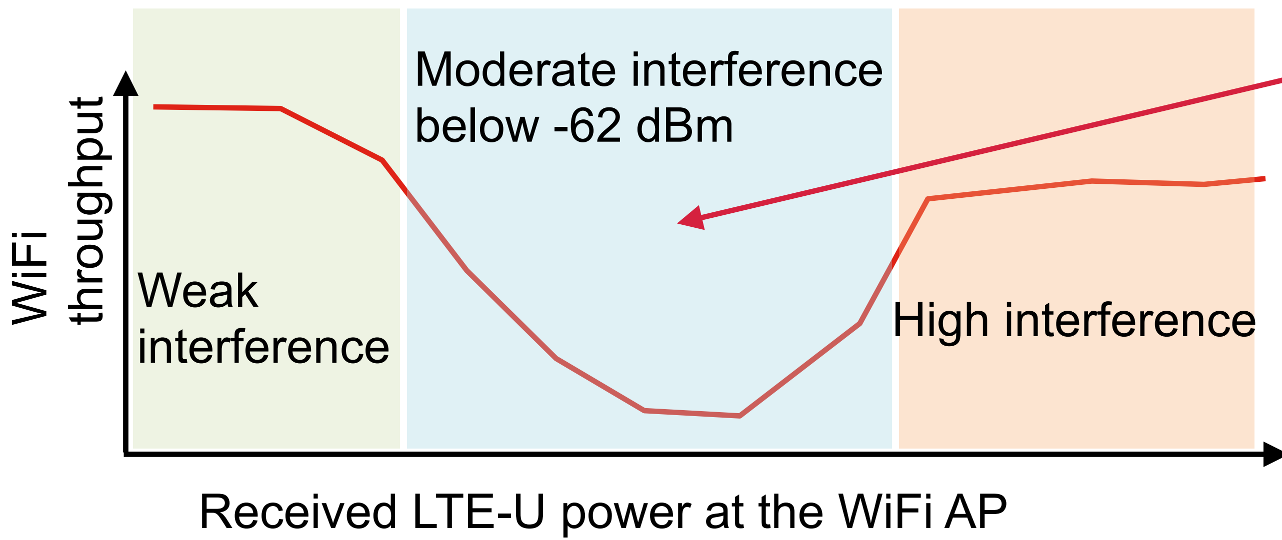
- But some caveats:
- **Length of ON-duration**: WiFi has to wait till the end of ON period which may affect latency-sensitive applications, e.g., high QoS frames.
- **Length of OFF-duration**: typically 40/80 ms



Moderate LTE interference more detrimental to WiFi than high interference

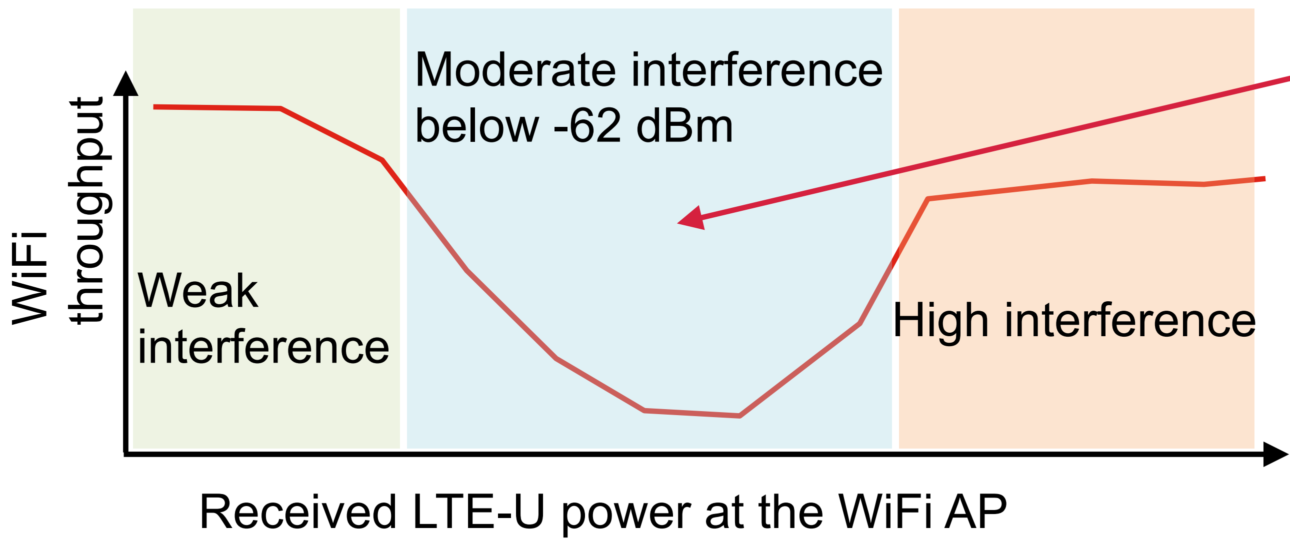
Severe impact on WiFi

Hidden LTE node



N. Jindal et al, "LTE-U and Wi-Fi: A coexistence study by Google," Wi-Fi LTE-U Coexistence Test Workshop, 2015. https://goo.gl/x6r0Ac

Moderate LTE interference more detrimental to WiFi than high interference



Severe impact on WiFi

Hidden LTE node

Less impact on LTE: LTE PHY more resilient to interference

N. Jindal et al, “LTE-U and Wi-Fi: A coexistence study by Google,” Wi-Fi LTE-U Coexistence Test Workshop, 2015. https://goo.gl/x6r0Ac

LAA medium access

release 14
UL (TDD)

release 13
DL

- LBT:
  - default -72 dBm ED threshold: adaptation based on bandwidth and transmission power
  - Congestion window size adaptation based on HARQ NACK
- DTX (Discontinuous transmission):
  - transmission time limited to 10 ms (4 ms in Japan, as opposed to 20 ms in LTE-U)
- A new frame type
- Type 3 frame: DL transmission can start at the next *slot* not next subframe

Kwon, Hwan-Joon, et al. "Licensed-Assisted Access to Unlicensed Spectrum in LTE Release 13." *IEEE Communications Magazine* 55.2 (2017): 201-207.

5 GHz not congested yet, but it is highly likely that it will soon

Coexistence mechanisms to be implemented

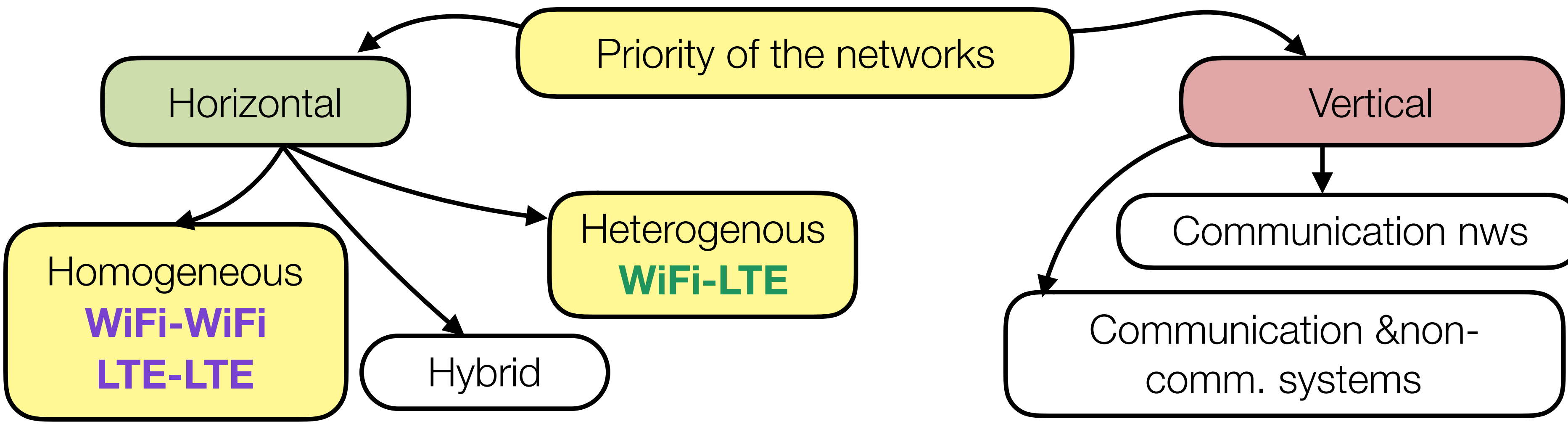
Coexistence goal of LTE unlicensed
A better neighbour than WiFi

- with WiFi: no worse impact in terms of both throughput and latency than another WiFi network
- with LTE: ***fair*** resource sharing

Peaceful Coexistence in Unlicensed Spectrum

Coexistence scenarios in the unlicensed bands

- Homogeneous scenario: WiFi-WiFi
  - Intra-technology coexistence, self-coexistence
- Heterogenous scenario: LTE-U and WiFi coexistence
  - Inter-technology/cross-technology coexistence



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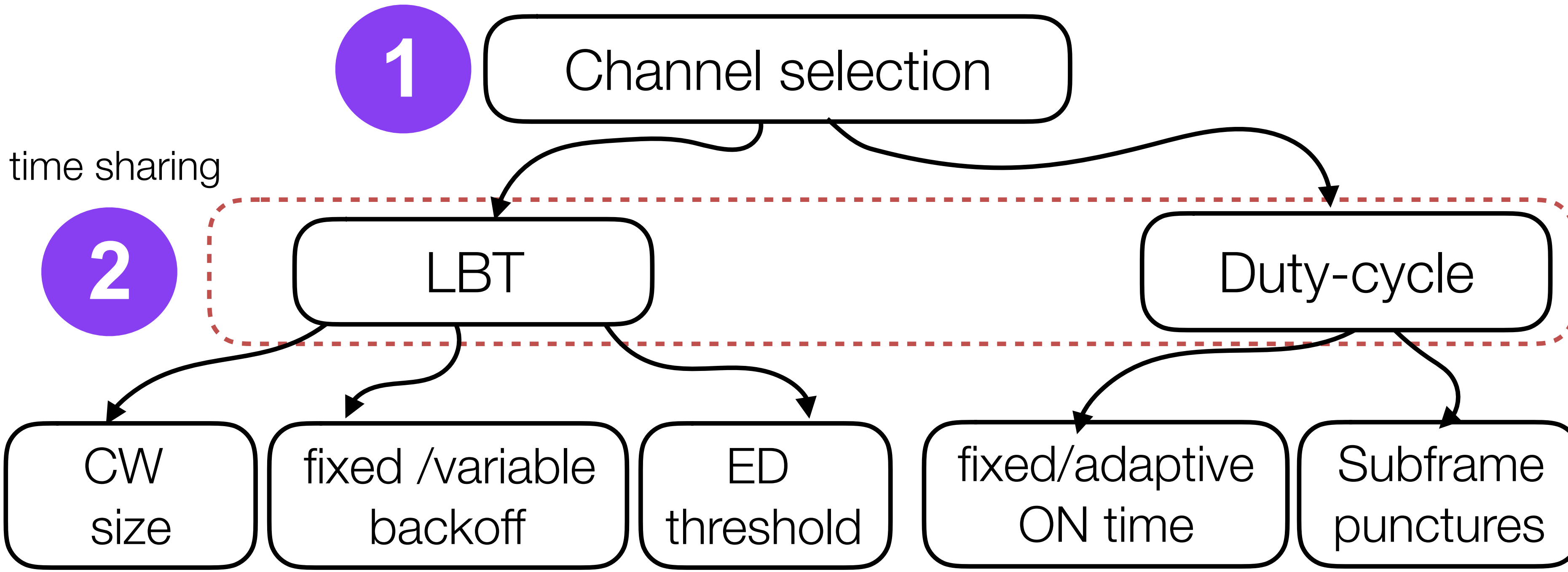
Current literature on WiFi self-coexistence

- Have a control channel among APs for coordination
  - ResFi [Zehl16], SAW [Herzen13]
- Have a controller. e.g., APs of the same network provider, OpenFlow SDN
  - COAP [Patro15]
- Beacon analysis based channel selection
  - Min-#of-STAs [Achanta06]
- **For a more complete set of proposals, see:**
  Surachai Chieochan et al, Channel Assignment Schemes for Infrastructure-Based 802.11 WLANs: A Survey, IEEE Tut.&Surveys, 2010

Coexistence solutions



- Tuning these parameters efficiently not straightforward and depends on the scenario
- Duty-cycle: LTE defines the degree of fairness/sharing

Selected Literature

- Make LTE and WiFi communicate via a control channel
  - LtFi [Gawlowicz17]
- Make LTE Base Station transmit WiFi channel reservation messages
  - ULTRON [Chai16]
- Cooperation through a cloud-based controller
  - [Maglogiannis17],[Al-Dulaimi15]
- Embed LTE-U within Wi-Fi Bands
  - Hyper AP[Chen17]
- Make WiFi estimate LTE airtime and duty cycle
  - WiPLUS [Olbrich17]

Summary

- coexistence in the unlicensed bands is vital for everybody
- difference in WiFi and LTE: random access vs. time scheduled access
- industry: LTE unlicensed is coexistence-friendly
- research and experiments: it is not, e.g., [ChaiMobicom16, Jindral2015]
- need for smarter and adaptive co-existence schemes
- coexistence test scenarios defined by Wi-Fi Alliance in 2016

Thanks!

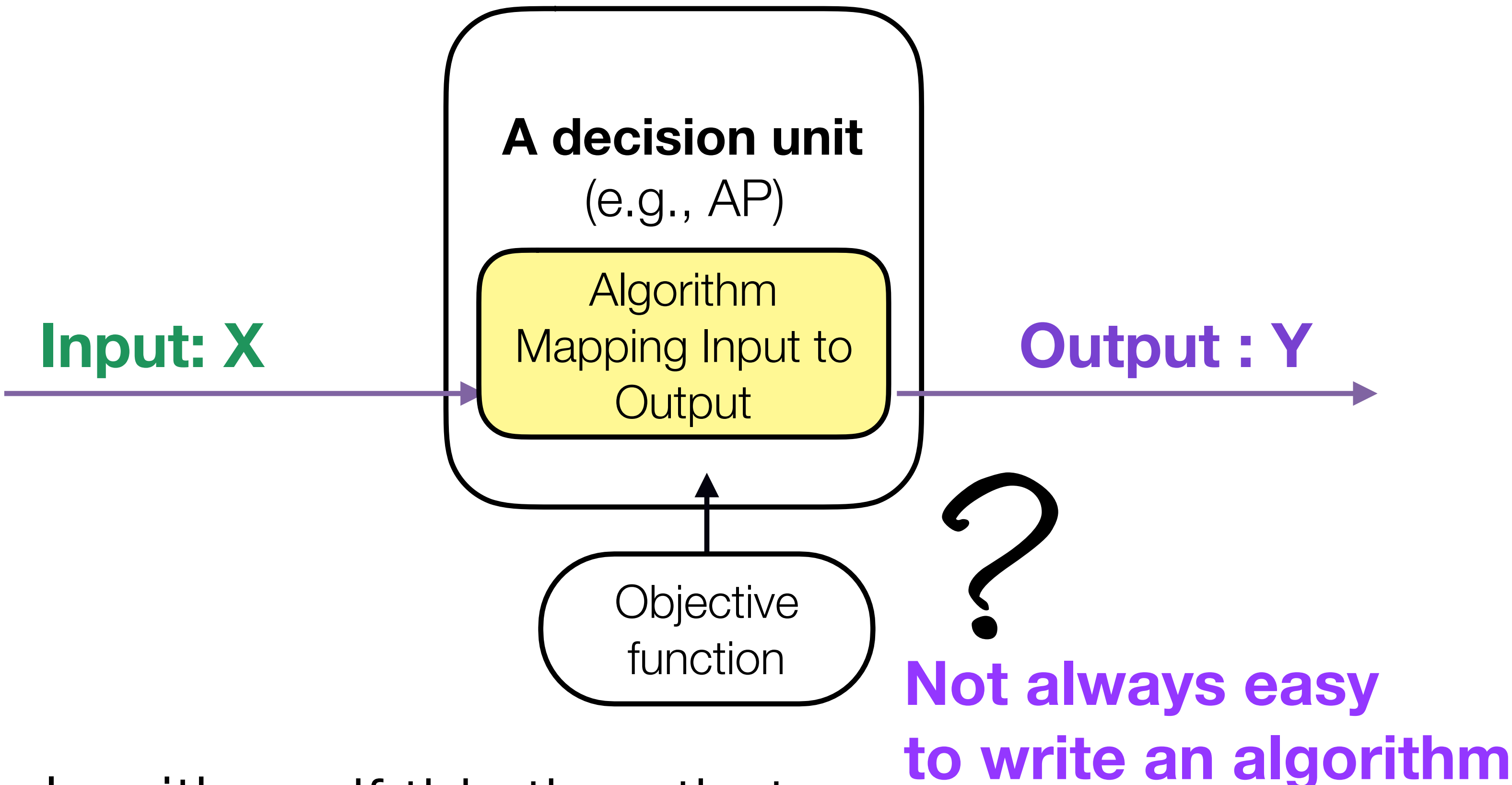
References

- Florian Kaltenberger, Carrier Aggregation and License Assisted Access Evolution from LTE-Advanced to 5G, Summer school on Spectrum Sharing and Aggregation for 5G, 2016.
- Chen et al. "Coexistence of LTE-LAA and Wi-Fi on 5 GHz with corresponding deployment scenarios: A survey."IEEE Comm.SurveysTutorials, *2017.*
- 3GPP TS 36.101 / TS 36.521-1 for UE testing
- 3GPP TS 36.104 / TS 36.141 for eNB testing
- 3GPP, "Study on licensed-assisted access to unlicensed spectrum," TR 36.889 TSG RAN, Rel. 13 v13.0.0, Jun. 2015
- Wang, Xuyu, Shiwen Mao, and Michelle X. Gong. "A survey of LTE Wi-Fi coexistence in unlicensed bands." *GetMobile: Mobile Computing and Communication, 2017*
- Beltran, Fernando, Sayan Kumar Ray, and Jairo A. Gutiérrez. "Understanding the current operation and future roles of wireless networks: Co-existence, competition and co-operation in the unlicensed spectrum bands." *IEEE JSAC 2016.*
- Voicu, Andra M., Ljiljana Simić, and Marina Petrova. "Inter-technology coexistence in a spectrum commons: A case study of Wi-Fi and LTE in the 5-GHz unlicensed band." IEEE JSAC 2016

Part III
A very brief overview of Machine Learning

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

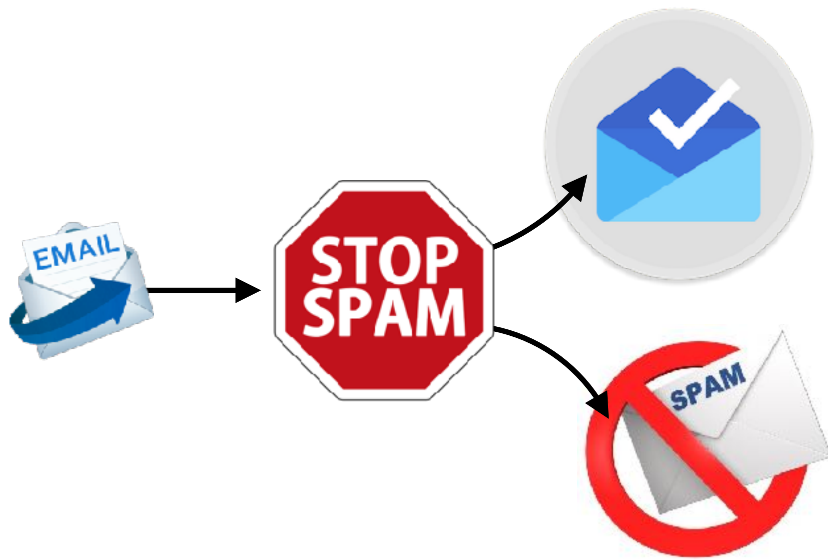
An abstraction of a system in operation



- the algorithm: if this then that

Why machine learning?

- For some tasks, we cannot easily write the algorithm: if this then that
  - there is no simple algorithm, e.g., autonomous cars
  - it is very challenging to define rules (e.g., dynamic environments)



Learn from data or past experience

- When we cannot write algorithm directly, we use learning from *data* or *past experience* (meta-programming)

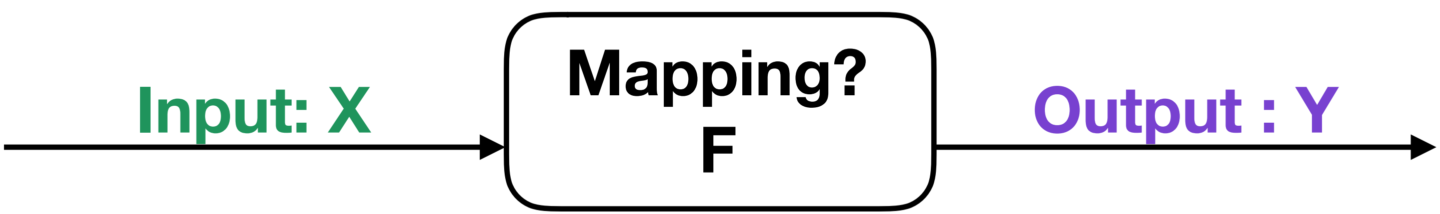
- Machine learning: generalisation from examples, e.g., detect certain **patterns** or **regularities**
  - Because mapping from input to output is not random!

Wireless communication: complex interactions

How to learn the mapping?

Based on the available data:

1. both the inputs and outputs are available: **(x,y)**
2. only the inputs are available **(x)**
3. no direct access to the **«correct»** output, but some measure of the quality of (x,y) mapping



How to learn the mapping?

Learning Algorithms

categorized by the amount of knowledge or feedback provided to the learner

S
U
RL

Supervised Learning

both the inputs and outputs are available **(x,y)**

predict output y for a new x

Unsupervised Learning

only the inputs are available **(x)**

uncovering hidden patterns from unlabelled data

Reinforcement Learning

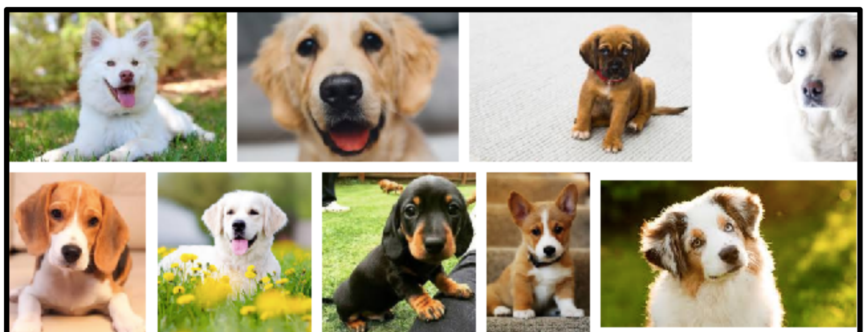
no direct access to the **«correct»** output

an agent learns to select an action to maximize its payoff, e,g., AlphaGo

Supervised Learning

Examples fed to the system

label: **cat**



label: **dog**

a binary classification problem

?

cat

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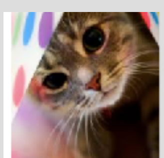
Terminology

training data set (D_{train})

	Input	Target
example 1		$\rightarrow$ cat
		$\rightarrow$ dog
example K		$\rightarrow$ cat

Input: N-dimensions (features, attributes)

K examples

$X_1 = (x_{1,1}, x_{1,2}, x_{1,3}, \ldots, x_{1,N}) \longrightarrow Y_0$

$X_2 = (x_{2,1}, x_{2,2}, x_{2,3}, \ldots, x_{2,N}) \longrightarrow Y_1$

$X_i = (x_{i,1}, x_{i,2}, x_{i,3}, \ldots, x_{i,N}) \longrightarrow Y_i$

$X_K = (x_{K,1}, x_2, x_3, \ldots, x_{K,N}) \longrightarrow Y_K$

Y: category or a class {cat, dog}

Classification and Regression

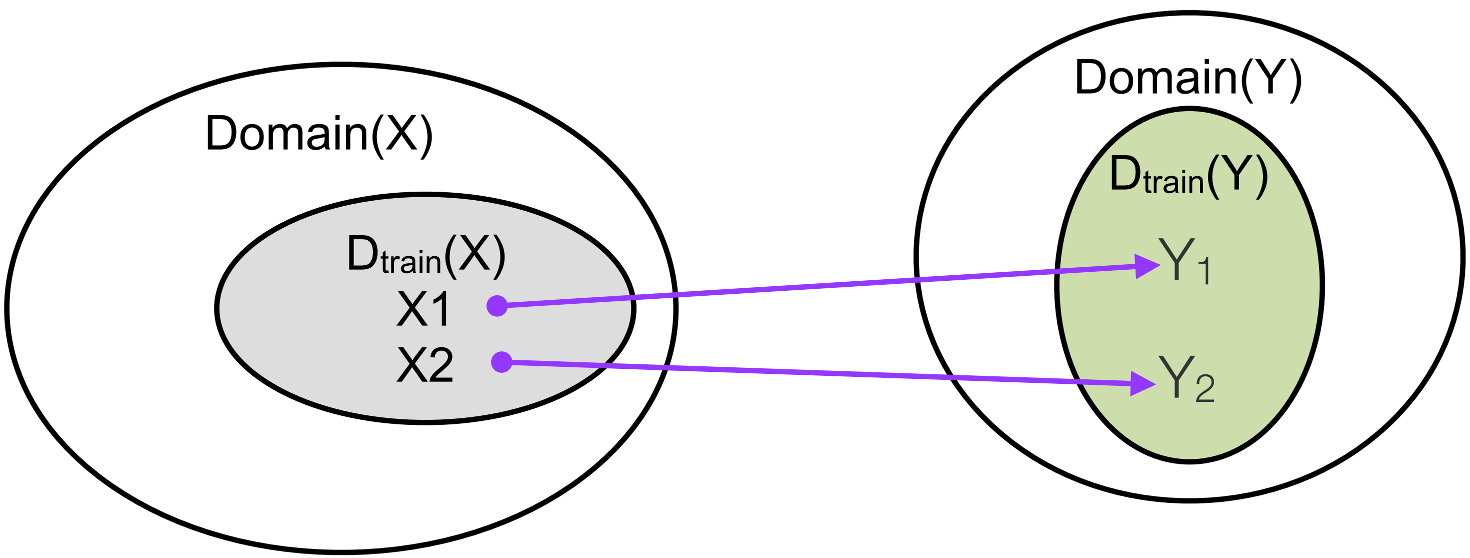
- **Supervised Learning:** given x, predict y
  - **Classification**: y is discrete
  - **Regression**: y is continuous

Predictive models

- **Unsupervised Learning:** Descriptive models

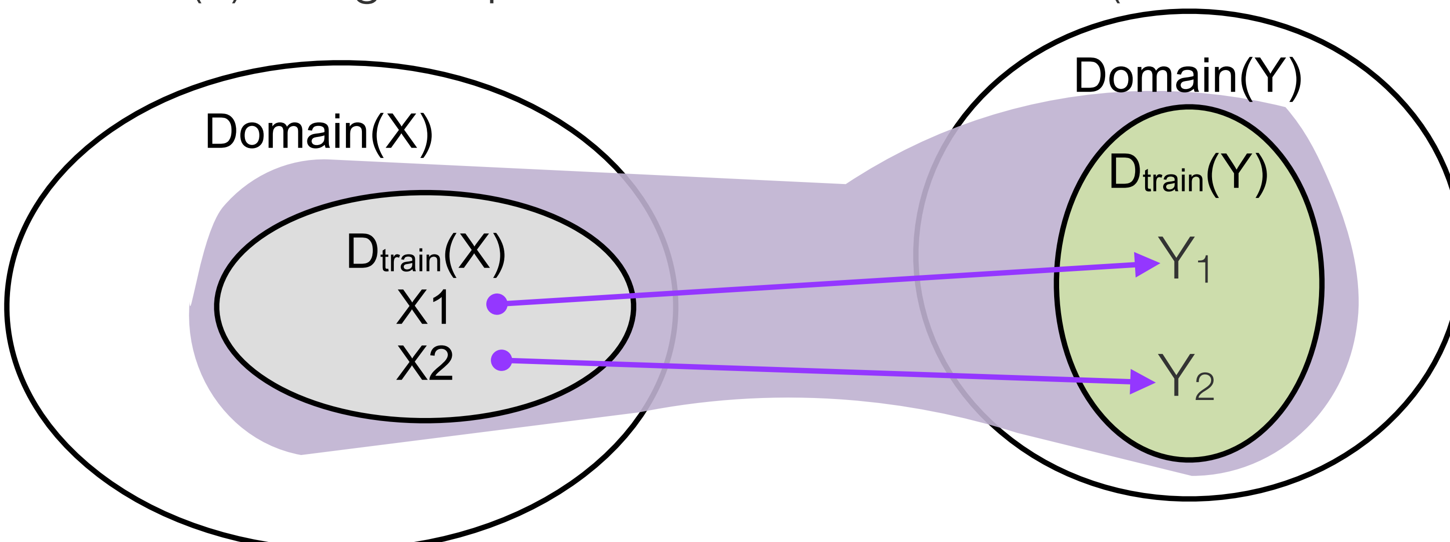
What to learn?

- Learn a predictive function **$f : X \rightarrow Y$** , which maps the input variables into the output domain



What to learn?

- Learn a predictive function **$f : X \rightarrow Y$** , which maps the input variables into the output domain
- **Approach**: f predicts well **on the training set D_{train}**
  - f(X) is a good predictor for the value of Y (f is called the **hypothesis**)



What to learn?

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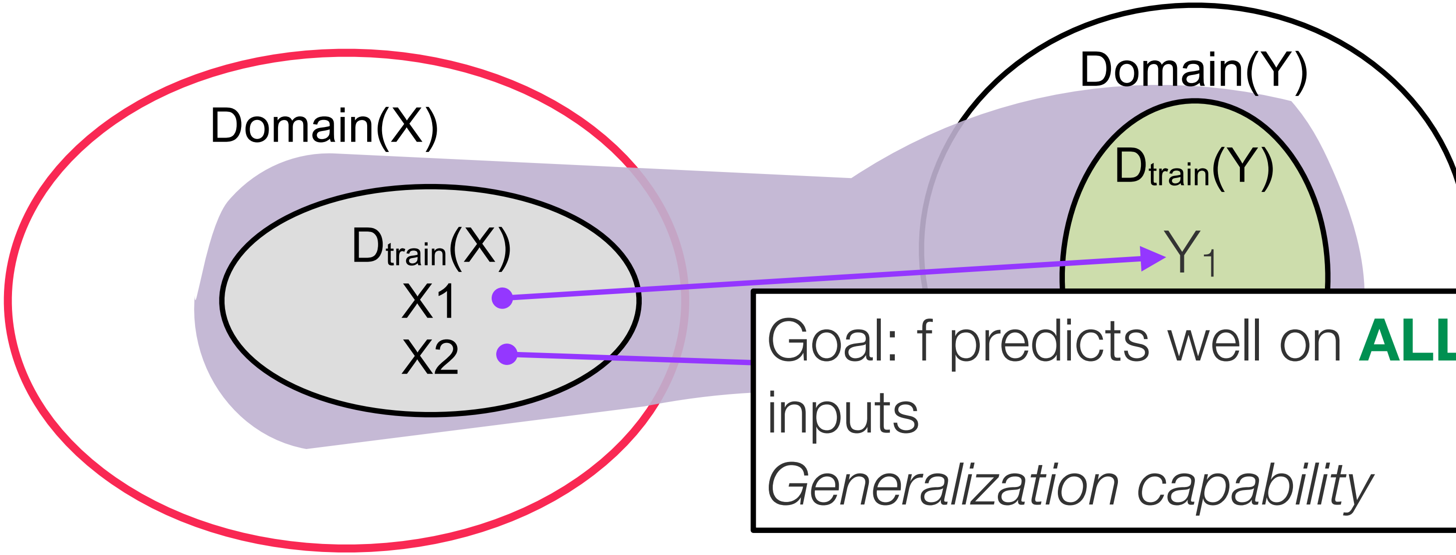


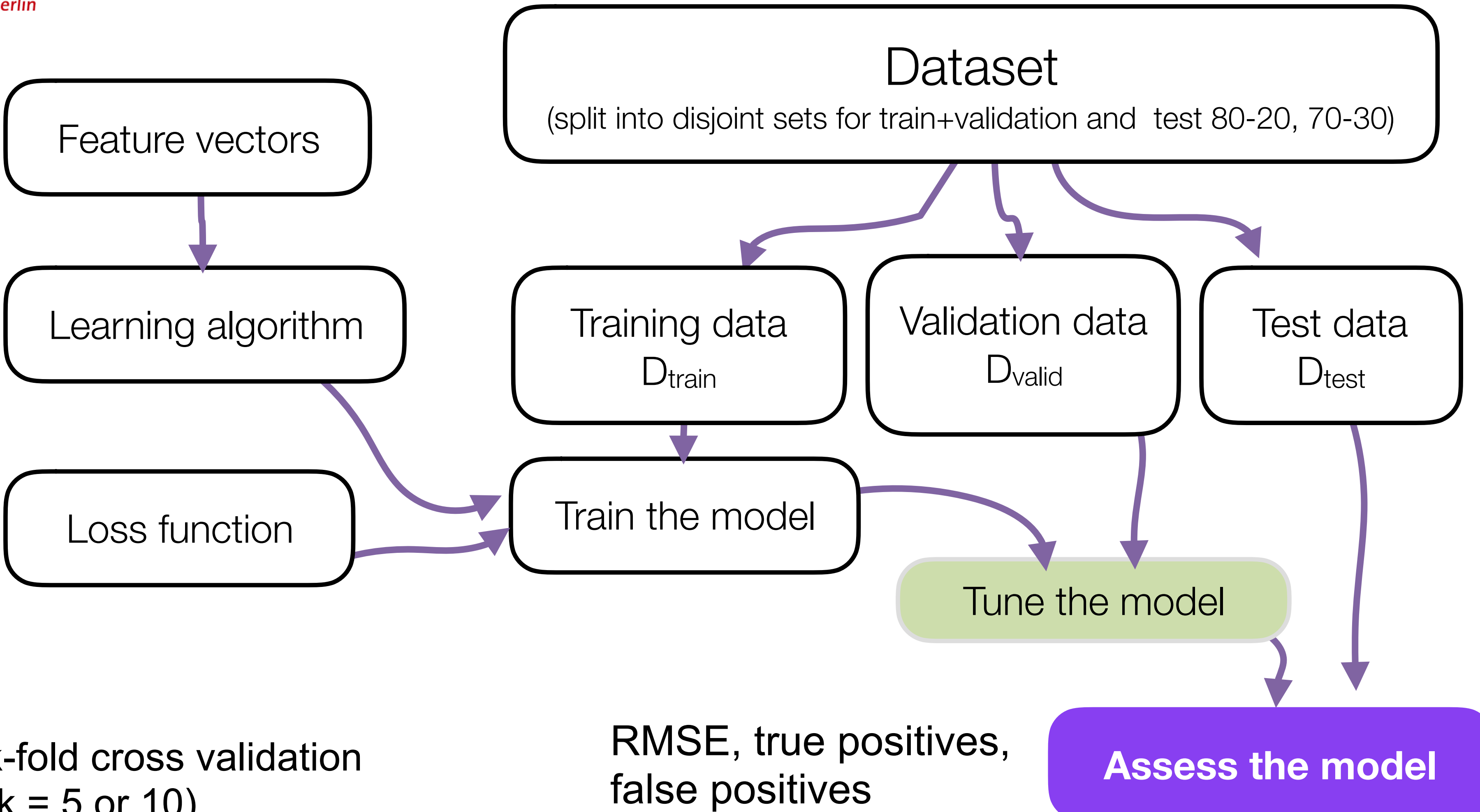
Goal: f predicts well on **ALL** possible inputs
Generalization capability

Supervised Learning Methodology

1. Decide what the **input-output** pairs are.
2. Decide how to **encode** inputs and outputs (X and Y).
3. Choose a class of **hypotheses**/representations F:
   - F known as **function family** of f.
4. Choose **an error/loss function L** to define the **best hypothesis** f* in F
   - *Error, loss, cost* function to assess how wrong a hypothesis f predicts
5. Choose a way for finding the **best function f* in F** efficiently through the space of hypotheses
6. Find the best function f* in F, using L on D_{train}
7. Tune your model
8. Test your model

slide credit:Doina Precup

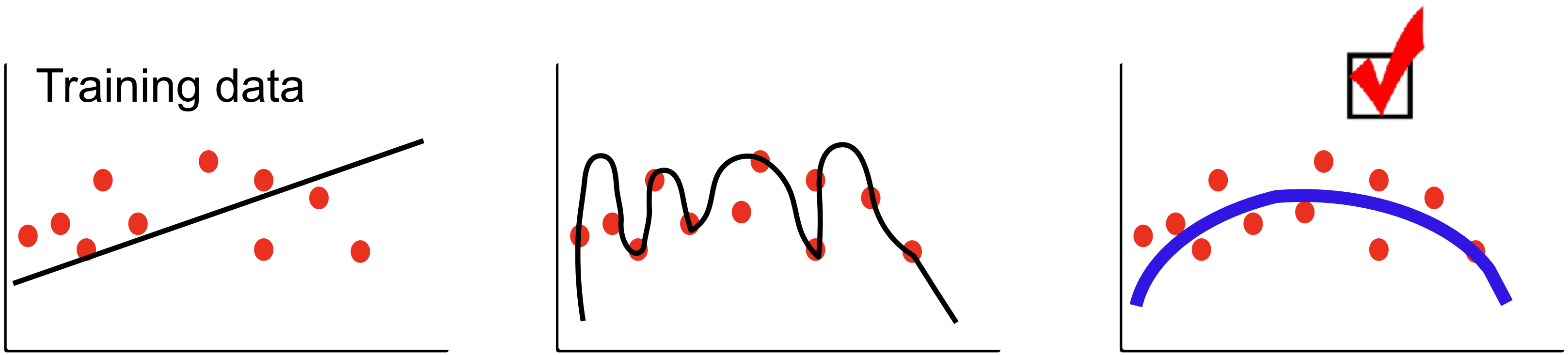
Dataset split into three **disjoint** sets



k-fold cross validation
(k = 5 or 10)

RMSE, true positives,
false positives

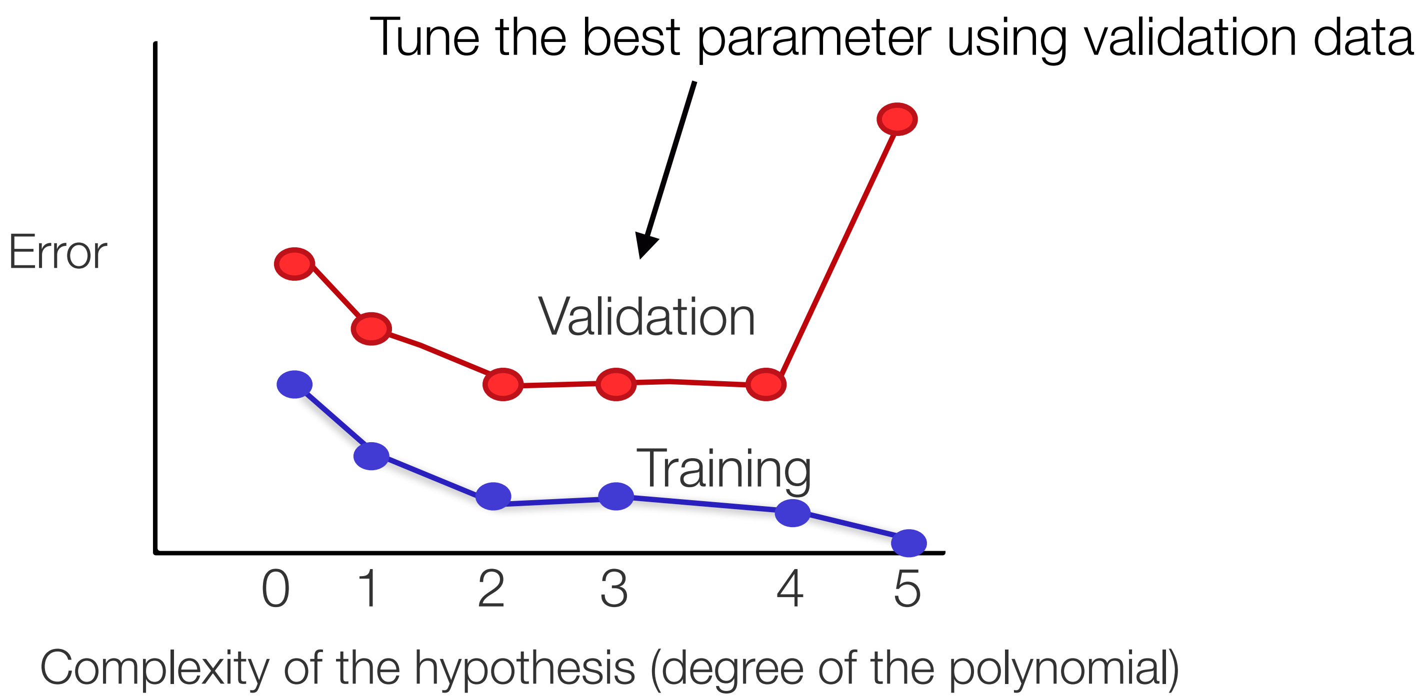
Bias-variance problem: overfitting, underfitting



- **Underfit**: model is too simple **(high bias)**
  - even the prediction error on D_{train} is high
  - Increase the complexity of the hypothesis
- **Overfit**: a model failing to generalize well **(high variance)**
  - learning even the noise or the random errors! Not desirable
  - add more training data
  - decrease complexity

Checking for bias-variance error: validation data

Remember that D_{train} and D_{valid} and D_{test} **disjoint** sets



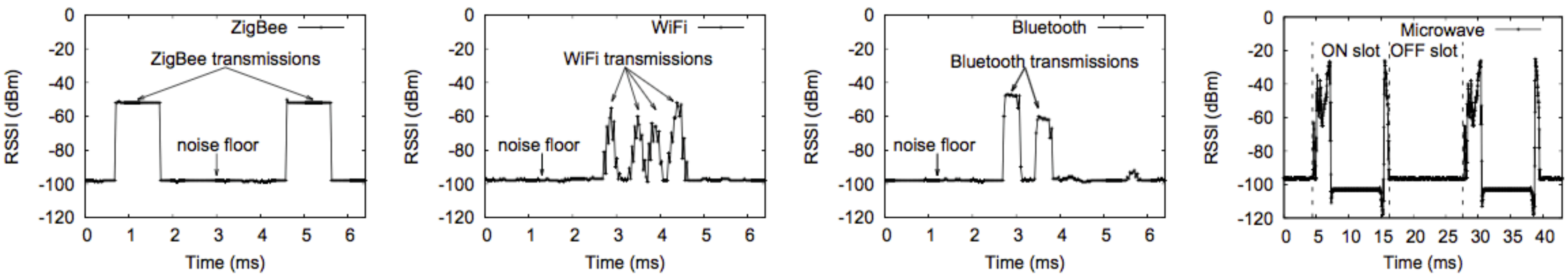
Checking for bias-variance error: validation data

- Similarly, learning curves to see the number of training examples needed (better to have smarter data than smarter models)

Classification

S → Regression
S → Classification
U
RL

- Is this observed signal a WiFi signal, a Bluetooth, a ZigBee or Microwave Oven?



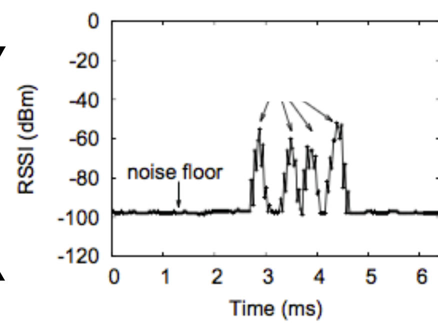
(a) ZigBee (b) WiFi (c) Bluetooth (d) Microwave oven

Source: Zheng, Xiaolong, et al. "ZiSense: towards interference resilient duty cycling in wireless sensor networks." ACM Sensys, 2014.

S → Regression, Classification
U
RL

Classification

- Is this observed signal a WiFi signal, a Bluetooth, a ZigBee or Microwave Oven?

f(

) = WiFi

Source: Zheng, Xiaolong, et al. "ZiSense: towards interference resilient duty cycling in wireless sensor networks." ACM Sensys, 2014.

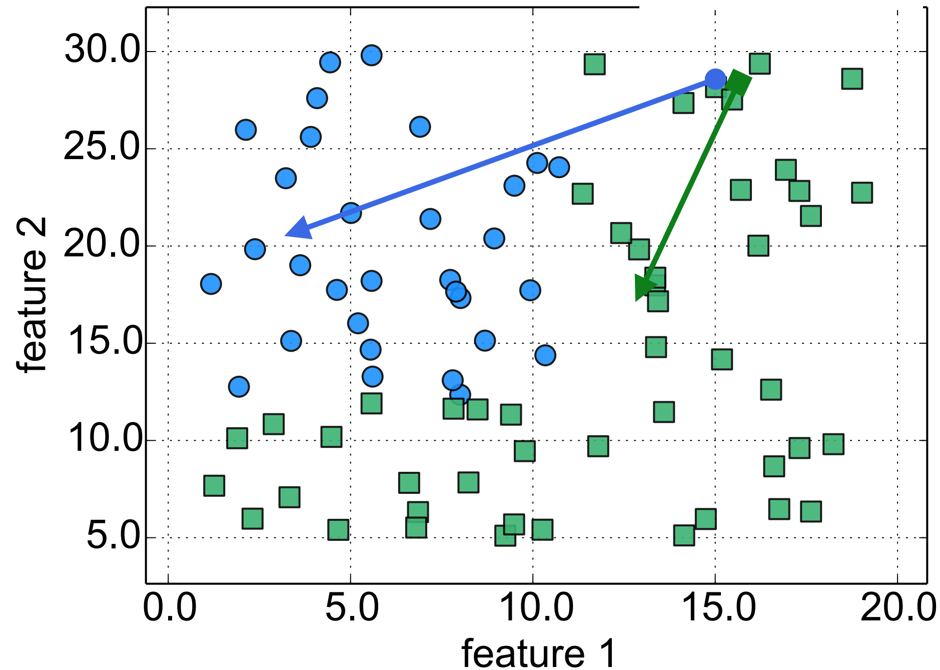
Classification algorithms

- K-Nearest Neighbour (KNN) Classifier
- Support Vector Machine (SVM)
- Logistic regression (probabilistic classifier)

K-nearest neighbours (KNN)

- Memorize the example set
- Majority voting among the K nearest neighbours

Two classes



K-nearest neighbours (KNN)

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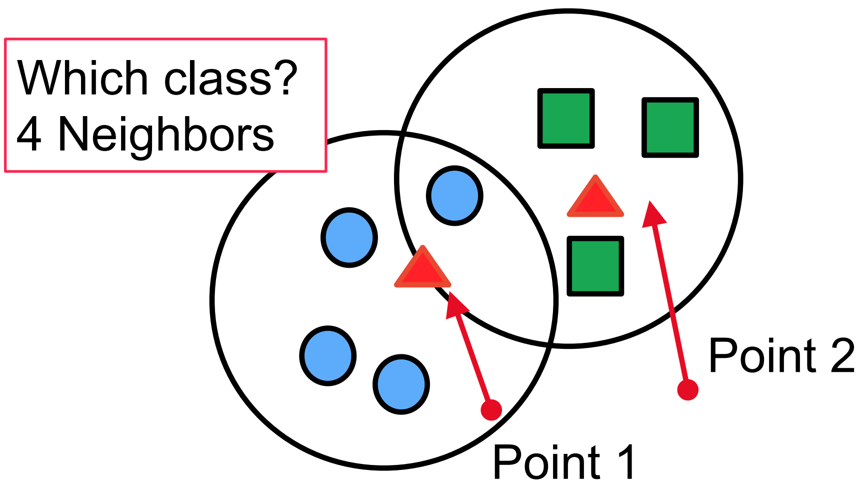

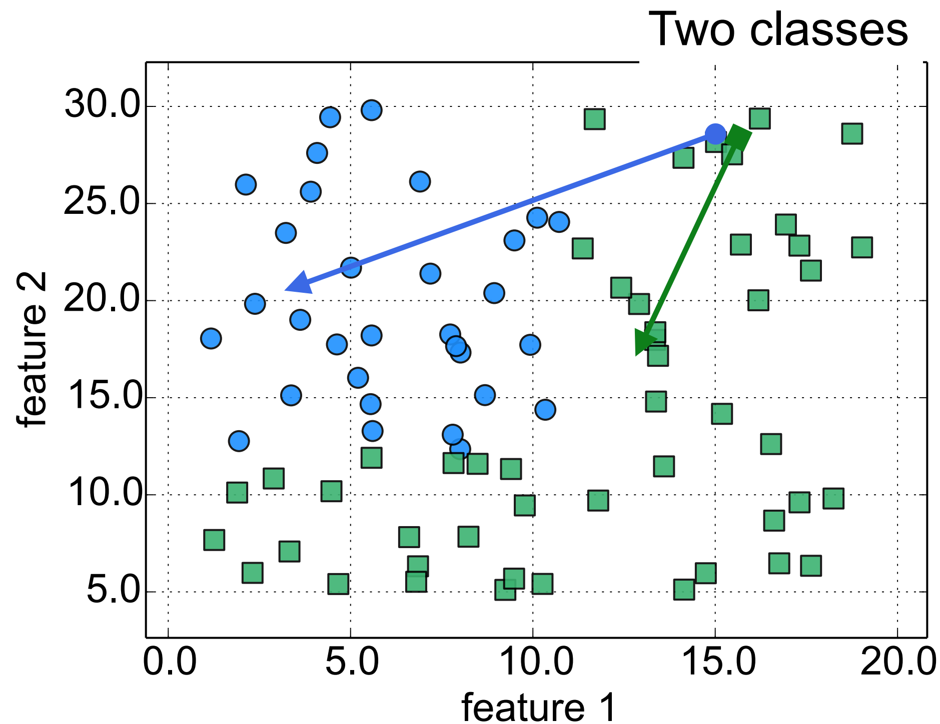

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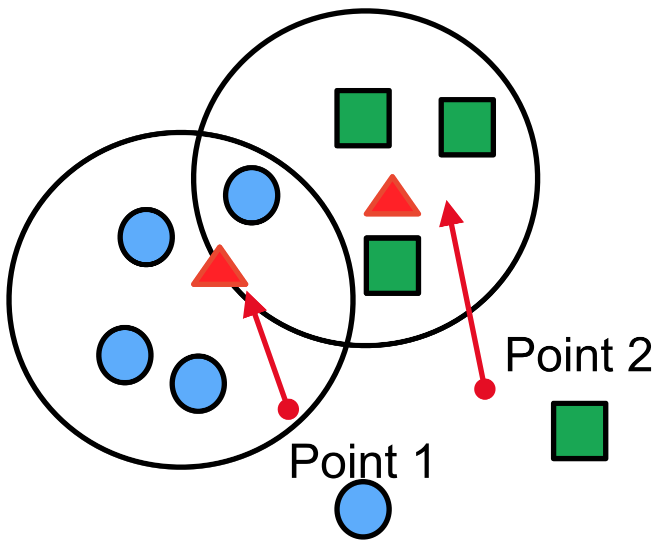
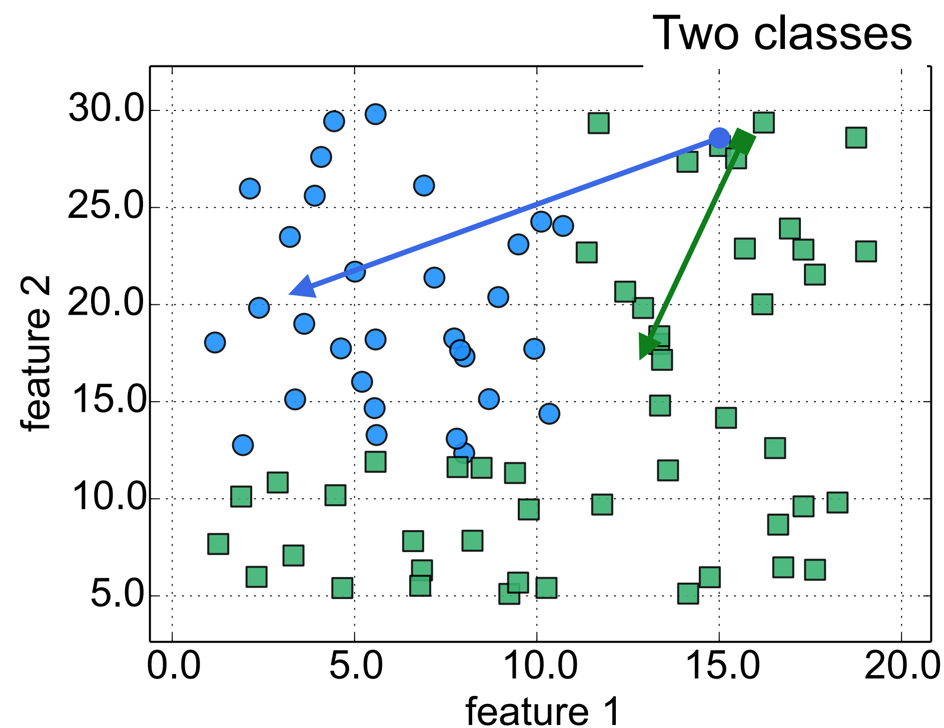
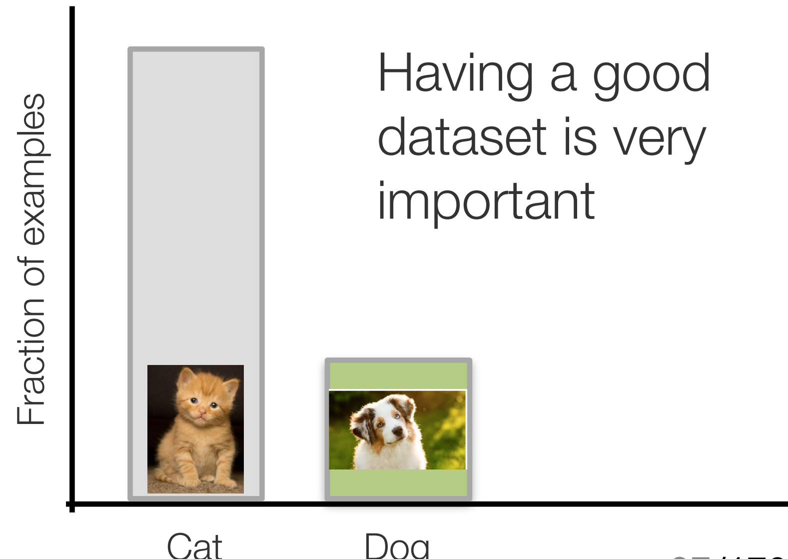




KNN

- Deal with ties (odd number of neighbors)
- Distance measure, e.g., euclidean
- Weighted distance
- How to choose K?
- Imbalanced data problem
- Accuracy of classification:
  - Precision: TP/(all predicted pos.)
  - Specificity: TN/(TN+FP)
  - Recall: TP/(all real positives)
  - ROC curve



Having a good dataset is very important

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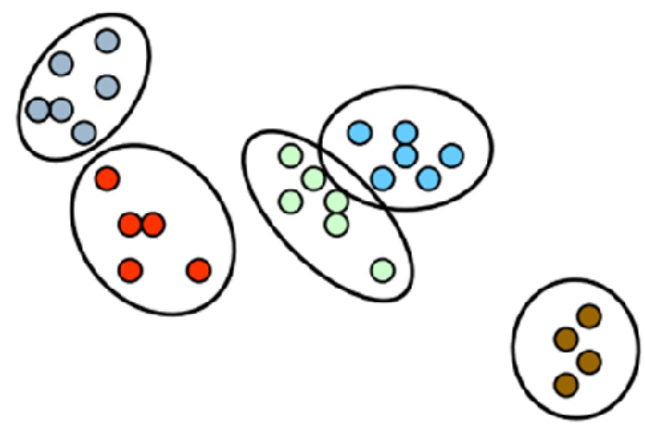
Unsupervised Learning

S
U
RL

- No labeled data
- Can we group our data according to their feature?
- The main goal is to *classify* or *cluster* the input, find outliers
- Extracting useful information out of (big) data
- Dimension reduction (or summarization): identify the important components of the data while preserving much of the information

K-means clustering

- Measure of similarity
- Number of clusters, K
- Goal: maximum similarity within a cluster, low similarity among clusters



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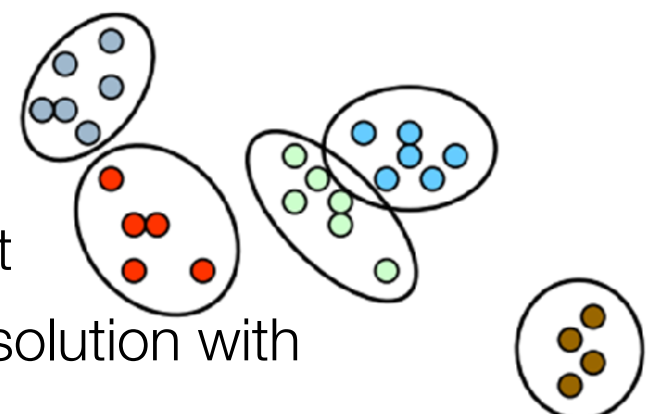
K-means clustering

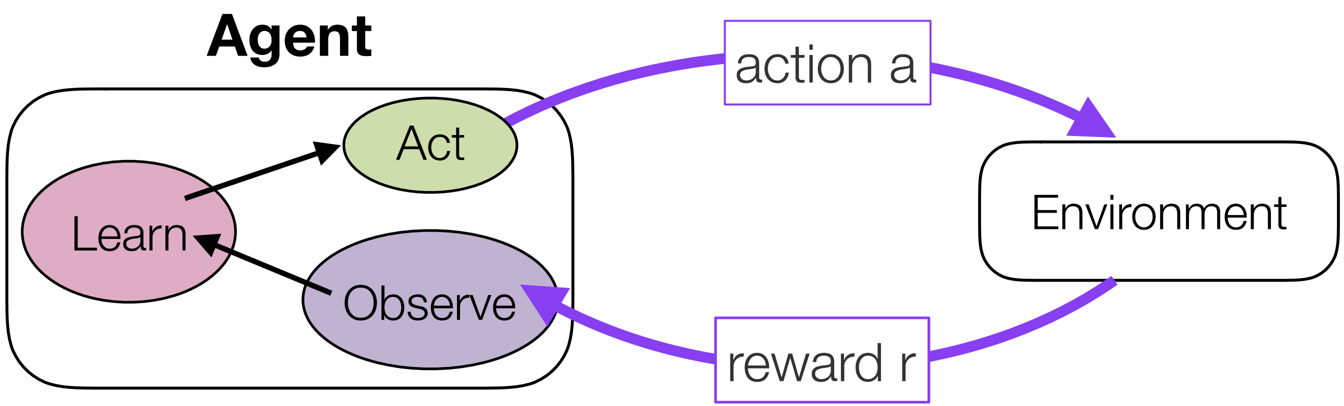
- Step 1: Pick K random points as cluster centers (centroid)
- Step 2: Iterate till no points' assignments change

  1. Assign data points to the closest centroid
  2. Change the cluster centroid to the average of its cluster members

- K-means is a heuristic
- sensitive to outliers
- selection of initial cluster centers is important
- Run K-means multiple times and select the solution with the smallest cost function



Reinforcement Learning (RL)



- No explicit supervision
- Learn through self-experience (*refine* the behavior based on *reward or punishment*)

Modeling approach: Markov Decision Processes (MDP)

- **Four elements (S, A, R, P)**
- S: finite set of states (remember scalability)
- A: actions (discrete)
- R: reward signal (a real number) for each (*state*, *action*) pair from the environment
  - (should reflect the purpose of the task)
  - undesired actions can be discouraged with a negative reward value
- P: state transition model $P(s|s, a)$ with $s' \in S$ $P(s'|s, a) = 1$.
- Goal: Find the **policy** that maximize the expected reward

Reward (r)

Discount factor in [0,1), used to scale future rewards in the total value of a policy

Immediate reward

$$V^{\pi}(s_t) = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} \cdots = \sum_{i=0}^{\infty} \gamma^i r_{t+i}$$

Value of a state:
cumulated discounted value
starting in s_t following arbitrary policy π

Q-learning: the most popular RL method

- **Q-value**: expected discounted reward for executing action *a* at state *s* and following policy π
- Select action a at state s with probability ~ Q(a,s)
- Initiate Q-values
- store values in Q-table

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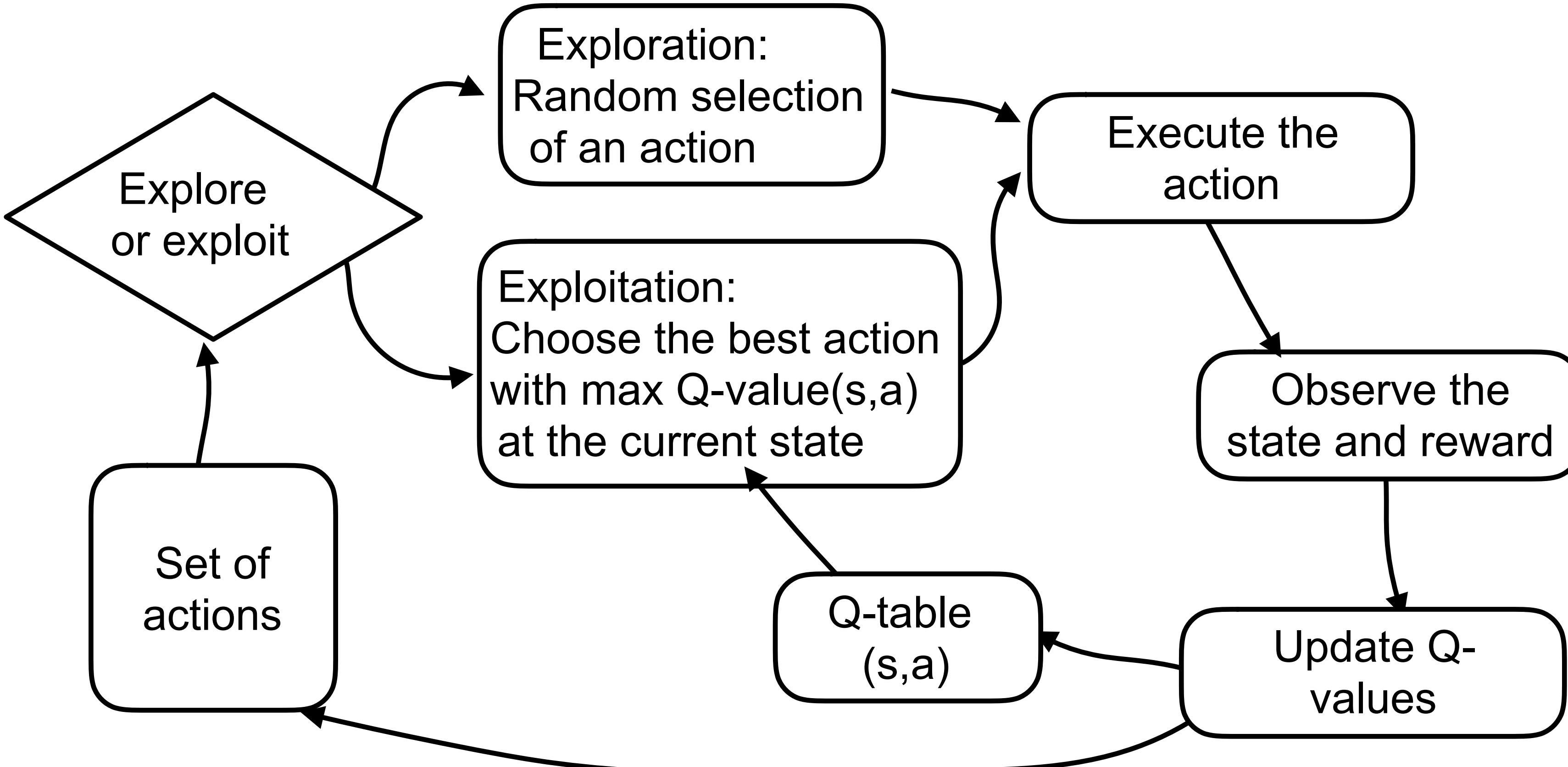
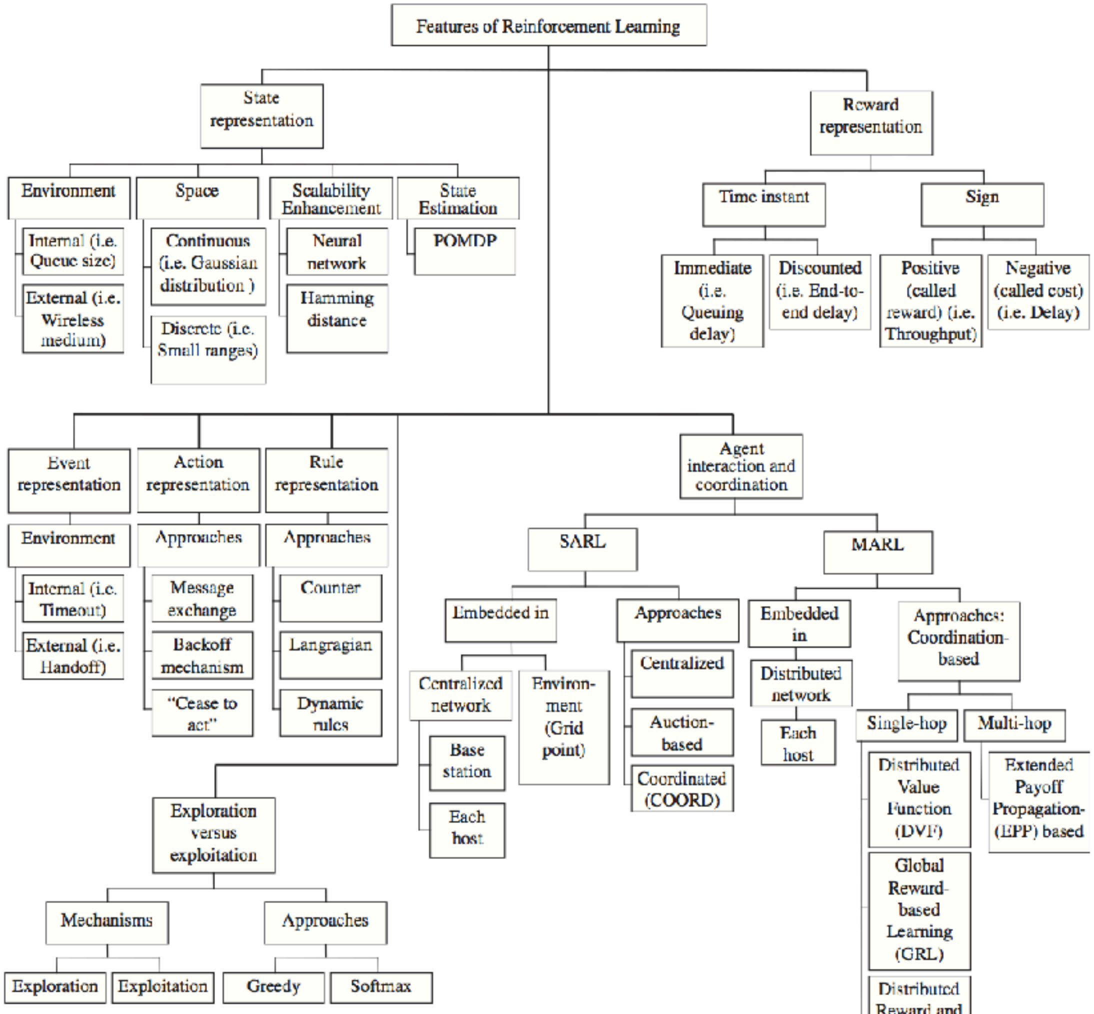
Practice makes perfect

- Exploit the past actions that have resulted in high reward
- Explore new/untried actions to discover reward-producing actions
- Tradeoff
- Examples: ε-greedy, softmax
- ε greedy policy:
    - probability ε, act randomly
    - probability 1-ε, act according to current policy
    - less exploration after some number of interactions: lower ε over time

Flowchart of RL



source: Yau, Kok-Lim Alvin et al. "RL for context awareness and intelligence in wireless networks: Review, new features and open issues." *JNCA*12.



RL relevant terms

Yau, Kok-Lim Alvin et al. "RL for context awareness and intelligence in wireless networks: Review, new features and open issues." *JNCA*12.

Summary: important points

- Representation is very important: What are the right features?
  - Curse of dimensionality
  - Domain knowledge
- Data comes in all shapes and sizes
  - Normalization such that each feature has a mean of zero and unit variance
- Train, validate, test
- Overfitting, underfitting analysis

Thanks!

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Please see below for more details

- Pascal Vincent, Introduction to Machine Learning, Deep Learning Summer School, 2015. http://videolectures.net/deeplearning2015_vincent_machine_learning/
- Doina Precup, Introduction to Machine Learning, Deep Learning Summer School, 2016. http://videolectures.net/deeplearning2016_precup_machine_learning/?q=Doina%20Precup
- Kulin, Merima, et al. "Data-driven design of intelligent wireless networks: An overview and tutorial." Sensors 16.
- Yau, Kok-Lim Alvin et al. "Reinforcement learning for context awareness and intelligence in wireless networks: Review, new features and open issues." *JNCA*12.
- Jiang, Chunxiao, et al. "Machine learning paradigms for next-generation wireless networks." IEEE Wireless Communications 24.2 (2017): 98-105.
- Bkassiny, Mario, Yang Li, and Sudharman K. Jayaweera. "A survey on machine-learning techniques in cognitive radios." IEEE Communications Surveys & Tutorials 15.3 (2013): 1136-1159.
- Ding, Guoru, et al. "Kernel-based learning for statistical signal processing in cognitive radio networks: Theoretical foundations, example applications, and future directions." *IEEE Signal Processing Magazine* 30.4 (2013): 126-136.

Part IV
Machine Learning for Coexistence in Wireless Networks

Case Studies

1. Is the channel idle or busy? — **Classification**
2. Which carrier should LAA BS select? — **RL**
3. How to select the carrier and ON-time for LAA? — **RL**
4. Can WiFi exploit ML for LTE-U duty cycle estimation? — **Clustering**
5. Traffic analysis in a WiFi residential network? — **Regression**

Attention!

Please see the original papers for more details

ACK: figures are adapted or copied from the relevant papers

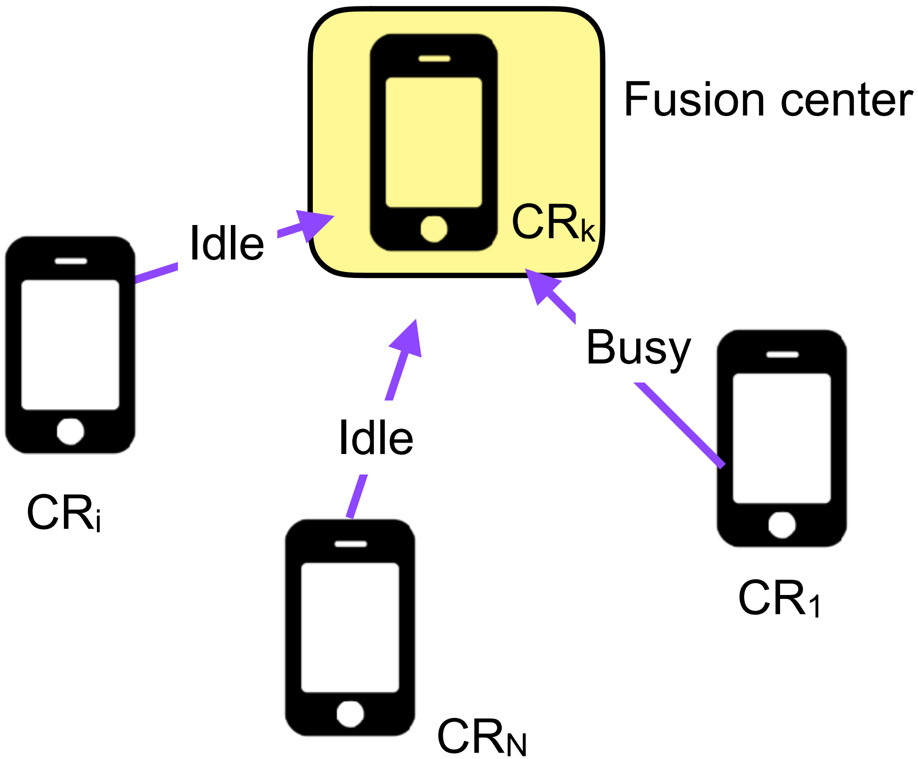
Case study #1

Is the channel idle or busy?

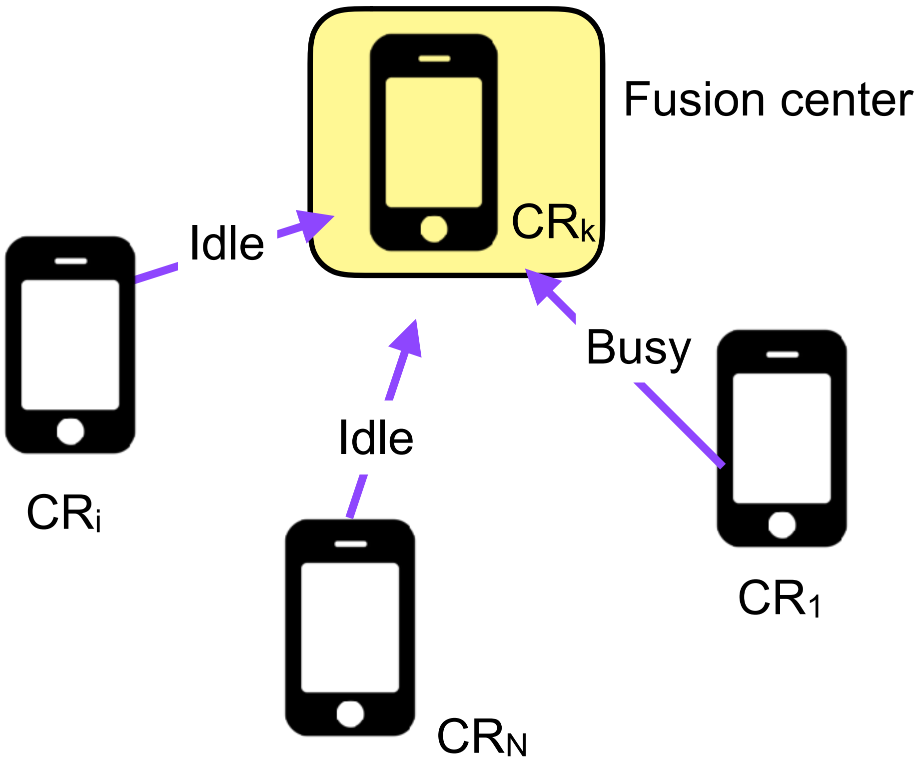
Classification

Thilina, K.M., Choi, K.W., Saquib, N. and Hossain, E., Machine learning techniques for cooperative spectrum sensing in CRNs. IEEE JSAC 2013

Is the channel idle or busy?



Is the channel idle or busy?



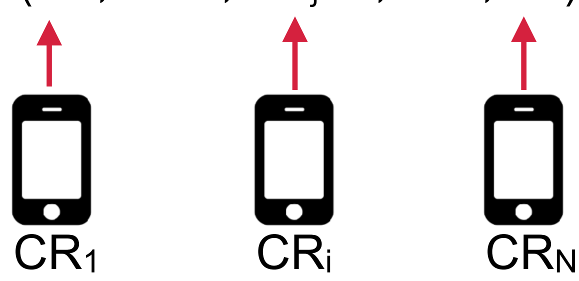
- **Cooperative spectrum sensing (CSS)**: N radios deciding on the state of the channel
- **Traditional approach**: decision fusion with AND, OR, k-out-of-N rules
- **Performance metrics:**
  - PU detection probability (true+) ↑
  - False alarm probability (false+) ↓

Conflicting!

ML approach for CSS in CRNs

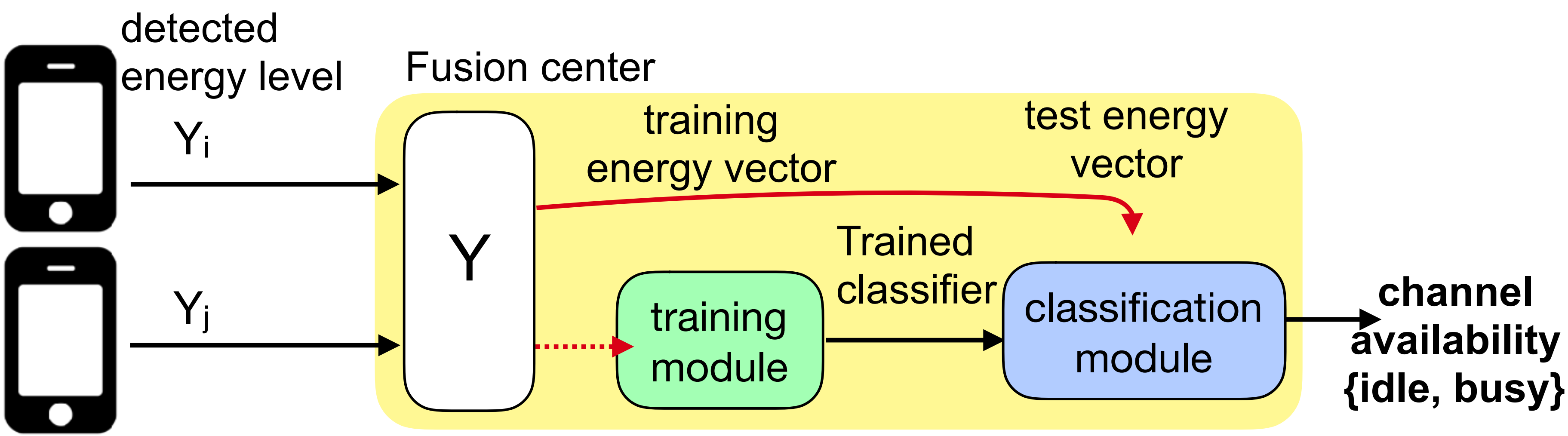
- **Binary classification problem:**
  - class 1: idle, class 2: busy
- **Different classifiers**
  - unsupervised: K-means, Gaussian MM - *more practical*
  - supervised: KNN, SVM - *needs real state of the channel*
- **Features**:
  - Energy level detected by each CR, N-dimensional vector

$$\mathbf{Y} = (Y_1, \; \ldots \;, \; Y_j \;, \; \ldots \;, Y_N)^T$$



CSS as binary classification problem

- M static primary users, N static cognitive radios
- Energy vector at the fusion centre: $\mathbf{Y} = (Y_1, \ldots, Y_N)^T$



- KM Thilina et al. "ML techniques for cooperative SS in CRNs." IEEE JSAC (2013)

Unsupervised learning for CSS

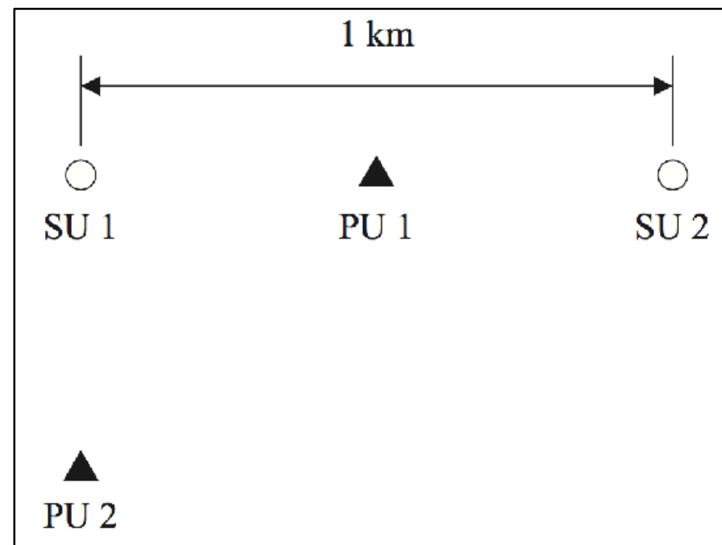
- M primary users
- State of all PUs: $\mathbf{S} = (S_1, \ldots, S_M)^T$
- Probability of state s = v(s) = Pr[S=s]

Y: multivariate Gaussian

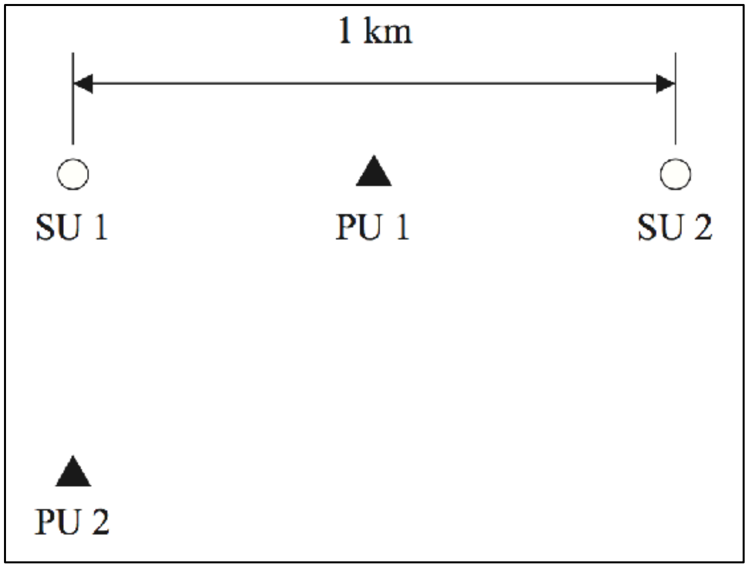
$$\boldsymbol{\mu}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}} = (\mu_{Y_1|\mathbf{S}=\mathbf{s}}, \ldots, \mu_{Y_N|\mathbf{S}=\mathbf{s}})^T,$$

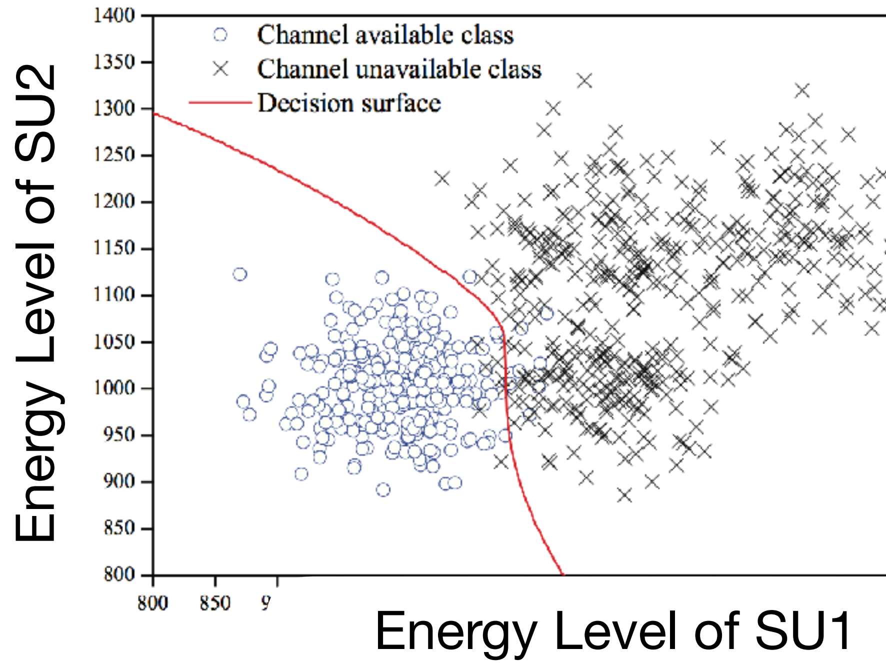
$$\boldsymbol{\Sigma}_{\mathbf{Y}|\mathbf{S}=\mathbf{s}} = \mathrm{diag}(\sigma^2_{Y_1|\mathbf{S}=\mathbf{s}}, \ldots, \sigma^2_{Y_N|\mathbf{S}=\mathbf{s}})$$

- 2^M cluster: {all PUs off, at least one is on, ….}
- Only cluster 1: channel is idle
- Other clusters: channel is busy



Unsupervised learning for CSS

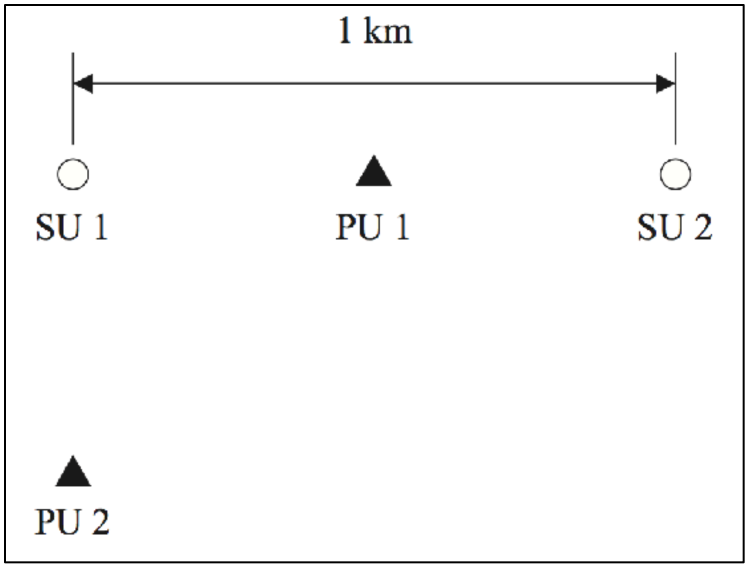


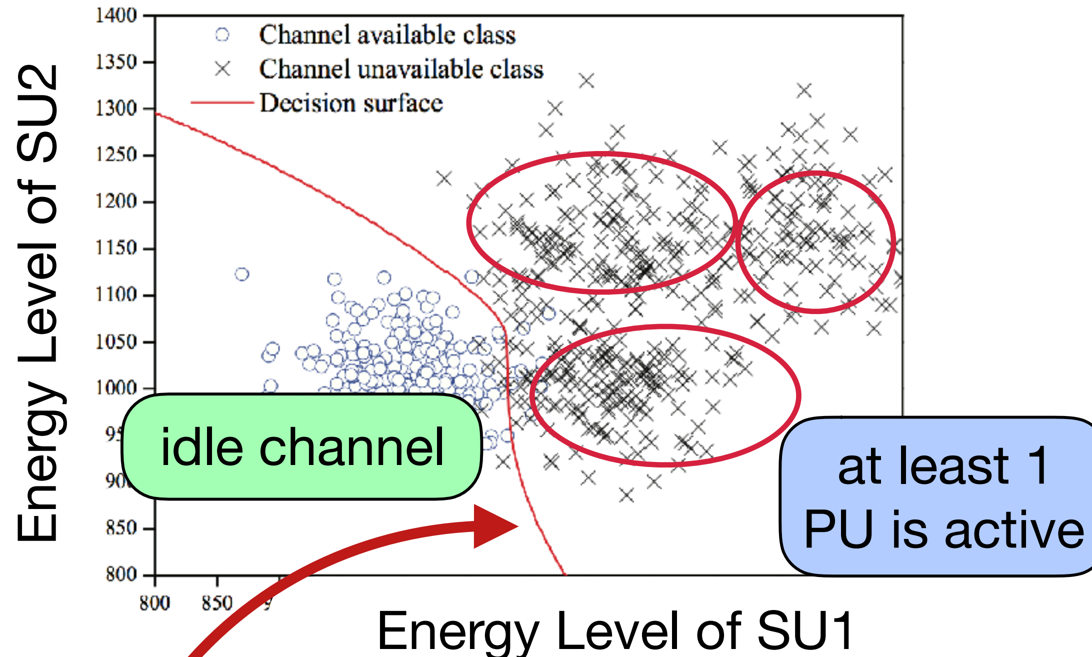


- Only 1 cluster: channel idle
- Others: channel busy

Training vectors are generated from a Gaussian mixture distribution for all PU state combinations (0,0), (0,1), (1,0), (1,1)

Unsupervised learning for CSS





- Only 1 cluster: channel idle
- Others: channel busy

(a) Scatter plot of energy vectors in Scenario I when the transmit power of each PU is 200 mW.

decision boundary

K-means based classification

- **Training phase**:
  - Training examples: y = {y(1), …, y(L)}
  - Apply K-means to training examples
  - First cluster centroid α_1^* fixed to the mean of (Y|no primary signal)
  - Other centroids: mean of training energy vectors in that cluster
- **On-line classification phase**: given y* as test energy vector, channel is ***busy*** if:

First cluster

$$\frac{||y^* - \alpha_1^*||}{\min_{k=1,\cdots,K} ||y^* - \alpha_k^*||} \geqslant \beta$$

Tune probability of detection vs. false alarm

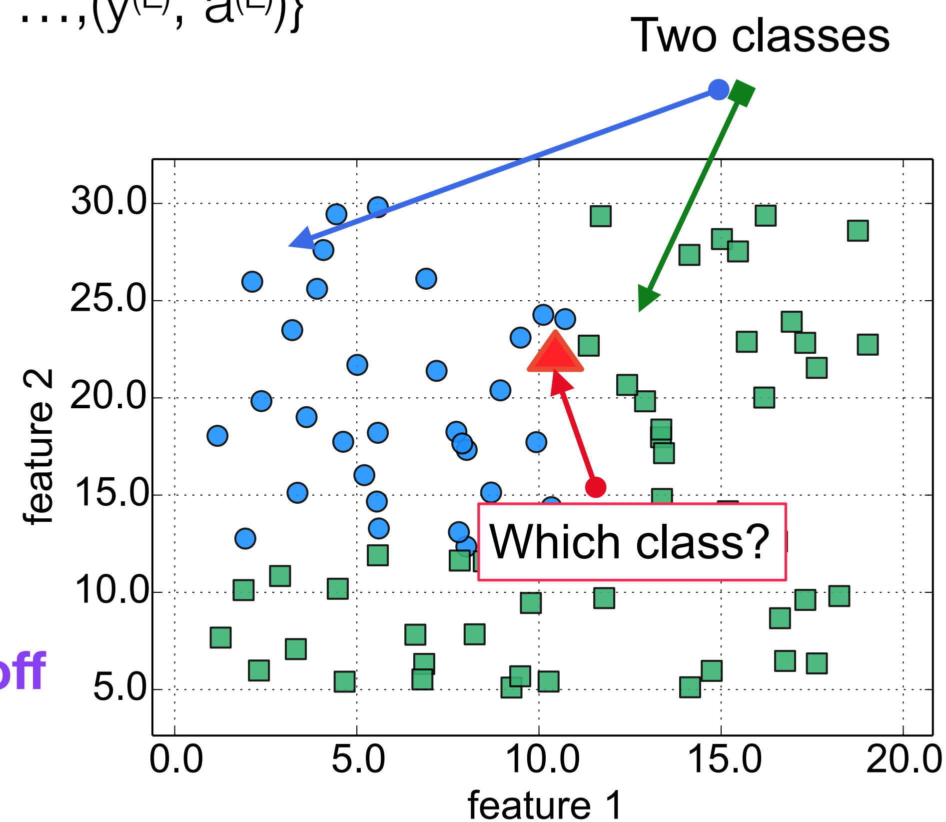
centroid of cluster k found in training phase

KNN-based classification

- Real labels **a** provided for each training example
- Training examples: $y = \{(y^{(1)}, a^{(1)}), \ldots, (y^{(L)}, a^{(L)})\}$
- majority voting of neighbors
- define a distance function
- choose K nearest neighbors
- **busy** if following holds

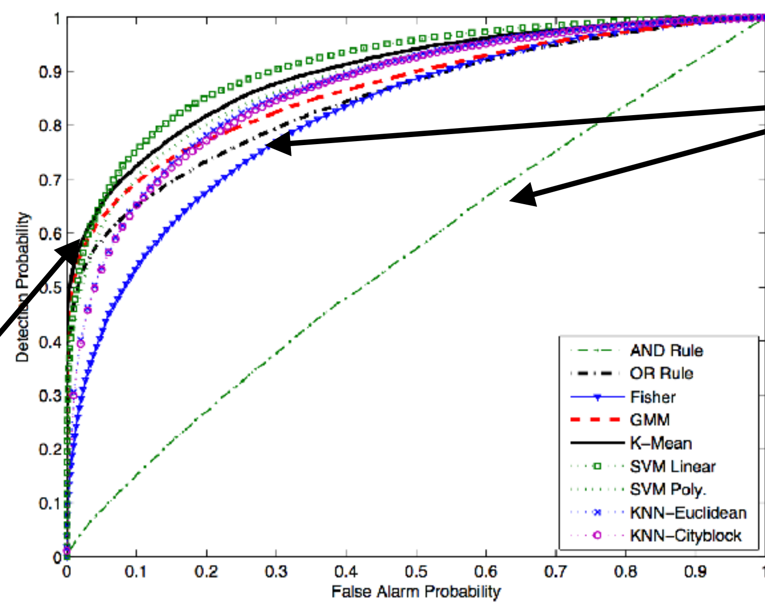
$$\frac{NN_{busy}}{NN_{idle}} \geqslant \beta$$

Tune the tradeoff detection vs. false alarm



Comparison of classifiers

- training time, classification delay, ROC curve



Traditional approach
AND
OR

+ K-means close to best classifier (supervised, SVM)
+ classification delay, detection capability, and training time

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Case study #2

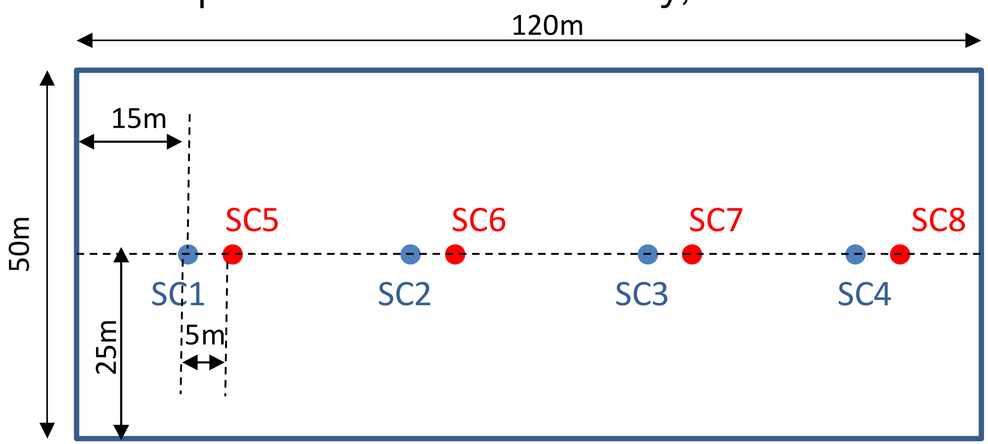
Which carrier should LAA BS select?

RL

Sallent, O., Pérez-Romero, J., Ferrús, R. and Agustí, R., 2015, June. Learning-based coexistence for LTE operation in unlicensed bands *2015 IEEE International Conference on Communication Workshop*

Channel selection via learning for LAA inter-operator coexistence

- Setting [Sallent-ICC15]:
  - Indoor scenario
  - M small cells from 2 operators
  - K channels
  - Bandwidth B MHz
  - LBT
- Assumptions: downlink-only, full buffers

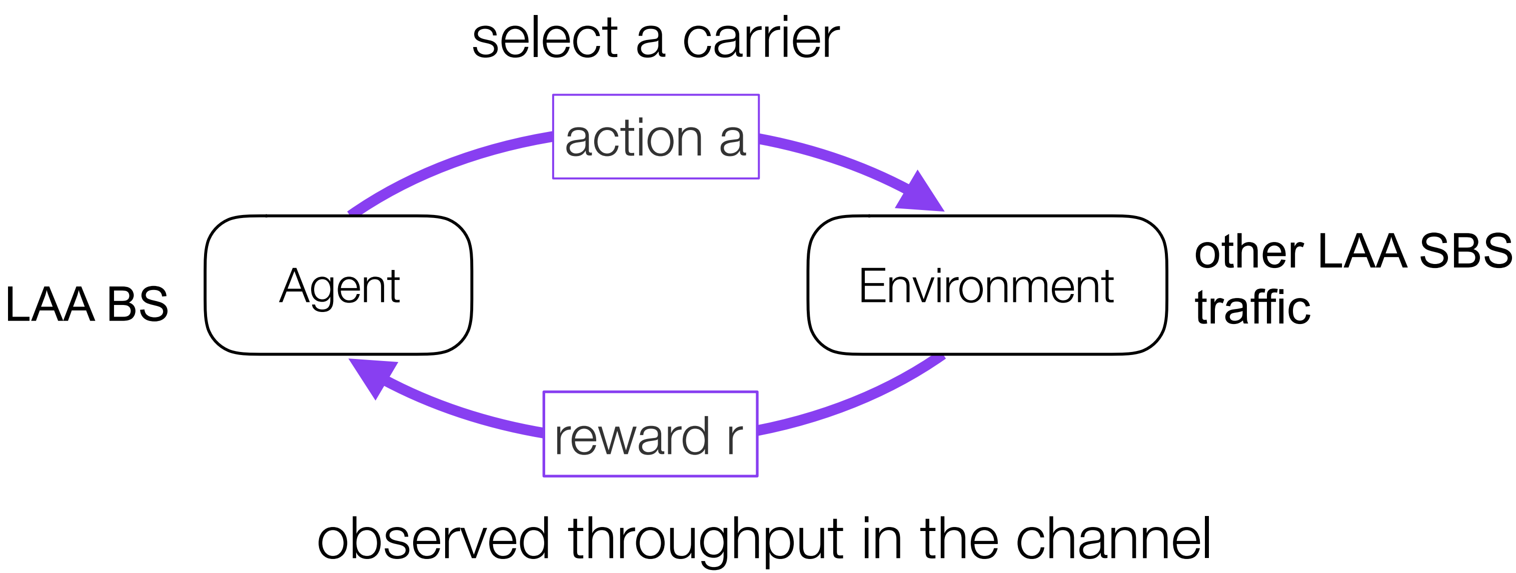


Challenge:
Select a channel at each small cell to achieve high throughput in a cell

Learning approach:
Q-learning

Why learning:
quasi-static environment (deployment)

Agent-environment framework



Channel selection via learning for LAA inter-operator coexistence

- Reward: observed throughput in the channel
- Q-value (k, i) for small cell i if it selects channel k
- Initiate Q-values to some random value

$$Q(i,k) \leftarrow (1-\alpha)Q(i,k) + \alpha r(i,k)$$

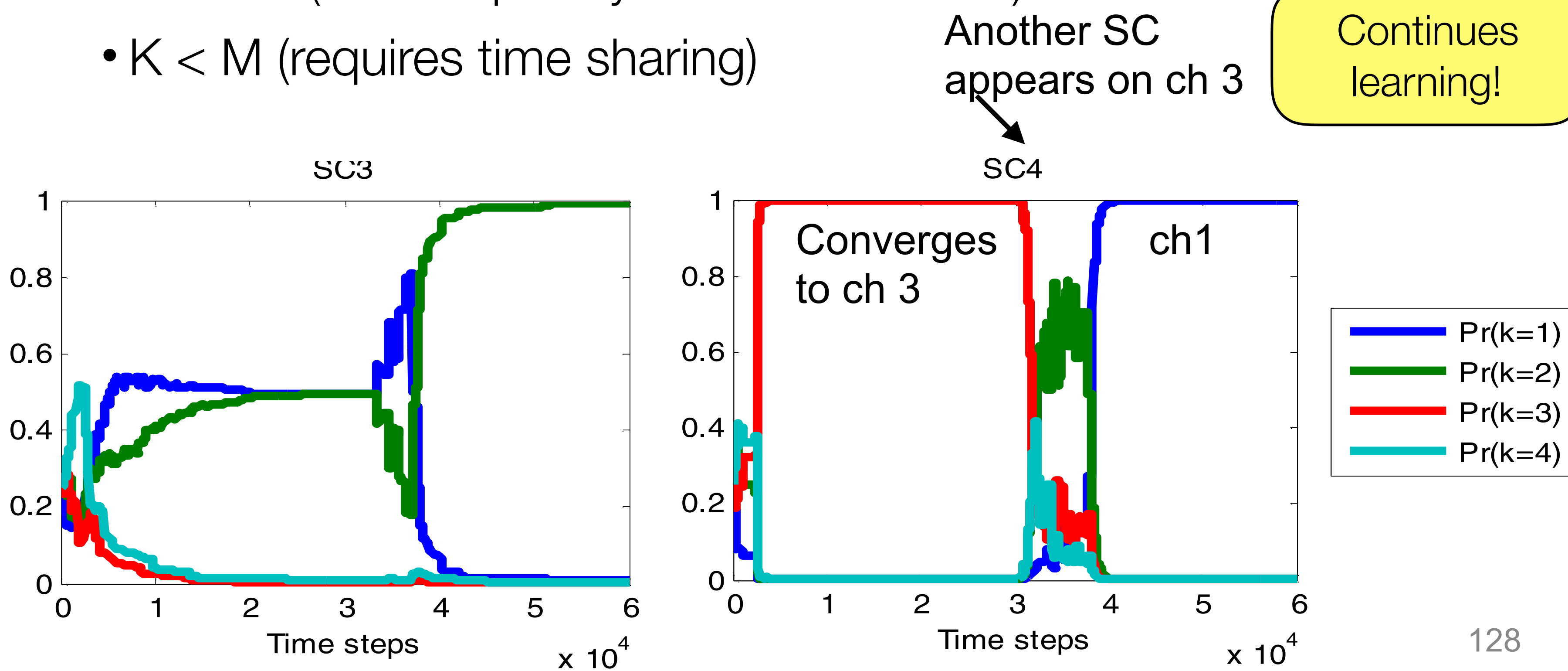
Learning rate

reward of the transmission at ch k: throughput normalised by maximum exp. throughput

- Select a channel k with probability $P_k \sim F(Q(i,k))$
- F: exploitation vs. exploration (softmax)
- Decrease exploration by time (logarithmic cooling function)

Channel selection via learning for LAA inter-operator coexistence

- Convergence analysis
  - K >= M (one frequency for each LAA BS)
  - K < M (requires time sharing)



Performance of Q-learning based carrier selection

- Throughput analysis
  - comparison with optimal and random

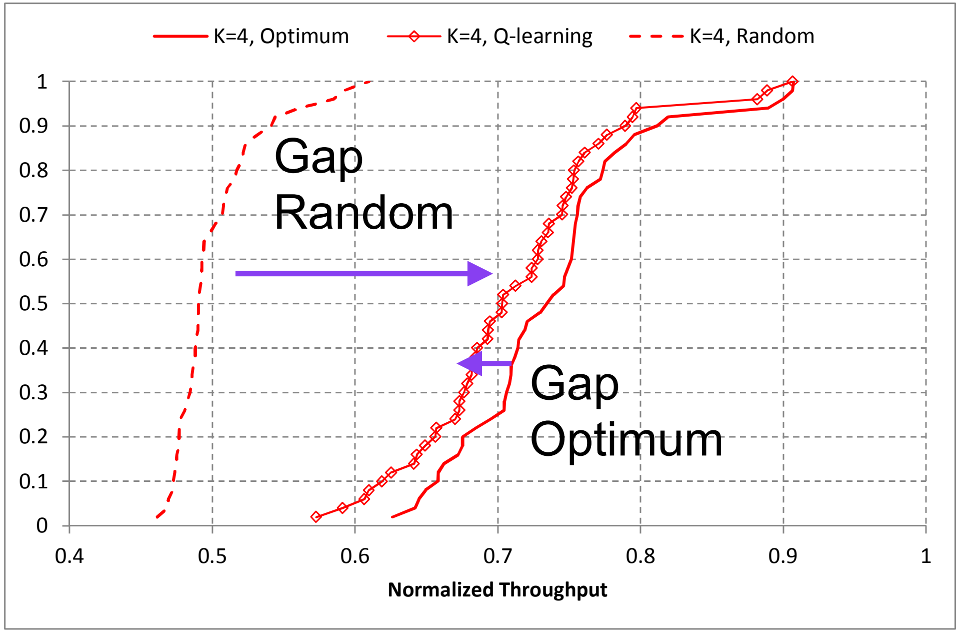


Fig. 8. CDF of the achieved normalized throughput for K=4 when the two operators apply Q-learning.

Channel selection via learning for LTE-WiFi Coexistence: frequency domain coexistence

- Q-learning for inter-operator coexistence
- Extension to WiFi coexistence is straightforward
- Many parameters to tune
- What happens till convergence?
    - harmful interference, coexistence is an issue

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Case study #3

Carrier Selection and On-time Adaptation in LAA

RL

Galanopoulos, Apostolos et al. "Efficient coexistence of LTE with WiFi in the licensed and unlicensed spectrum aggregation." IEEE Transactions on Cognitive Communications and Networking, 2016.

WiFi channel occupancy estimation using Q-learning in LAA

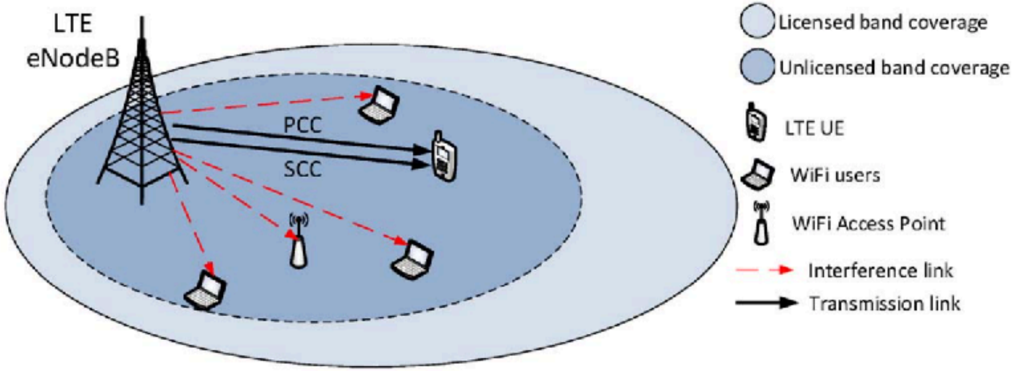


Fig. 1. Licensed Assisted Access (LAA) Deployment Model.

Setting:

Single LAA cell, multiple WiFi nodes/channels

Goal: both high WiFi and LTE performance

Challenge:
which unlicensed carrier to aggregate?
How long to transmit on this carrier?

Learning approach:
Q-learning

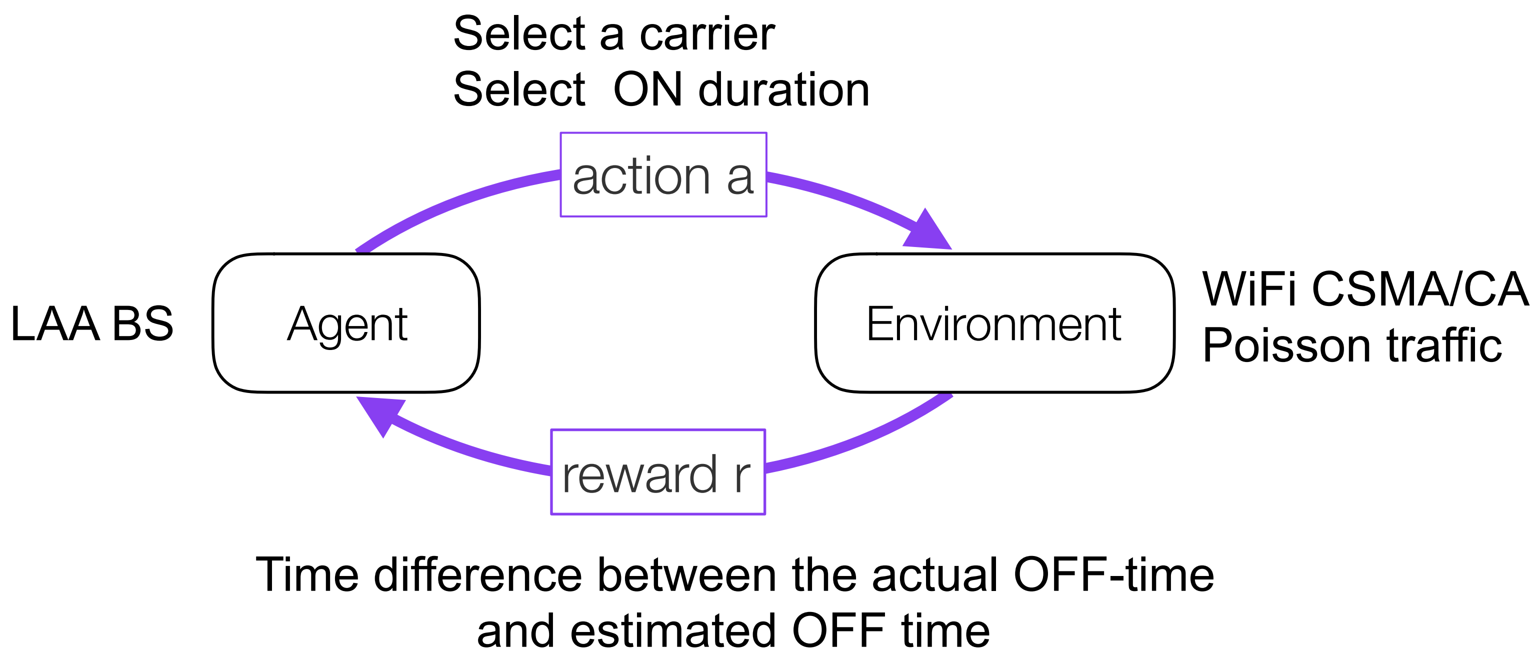
What to learn?

unlicensed band activity

LAA on-time based on WiFi channel occupancy

- **Channel-occupancy based channel and ON-time selection (COT)**
  - tune LAA ON-time according to channel occupancy
  - Occupancy measurement of each channel via ED on subframes when LTE is not transmitting
  - Channel occupancy = # of busy samples/ # of all samples
  - ON-time = (1-occupancy)* 10 ms
  - Switch channel in the next frame if it has a smaller occupancy than the current one
- **Q-learning based channel and ON-time selection**
  - learn from experience
  - Idle time measurement of each channel via ED

Agent-environment framework



- Carrier selection: every frame
- Information collection: every subframe when LAA is not transmitting check WiFi traffic activity

Q-learning framework

- **States**: The channel selected for carrier aggregation {1,.., N}
- **Actions**: Transmission time in the selected carrier i {1,…, 9}ms
- **Action time**: At the beginning of each frame
- **Reward**: difference between real off time of the carrier - off-time from the previous sensing period (Toff updated after each sensing)

$$r(s, a) = T_s^{off'} - T_s^{off}$$

Negative reward (punishment) for degrading WiFi performance!

Q-value initial value and update rule

Select a channel with low occupancy (high off duration)

Select transmission time matching the channel off time

$$Q_0(s,a) = T_s^{off} - |a - T_s^{off}|, \ \forall s \in \mathcal{N}, \forall a \in \mathcal{A}$$

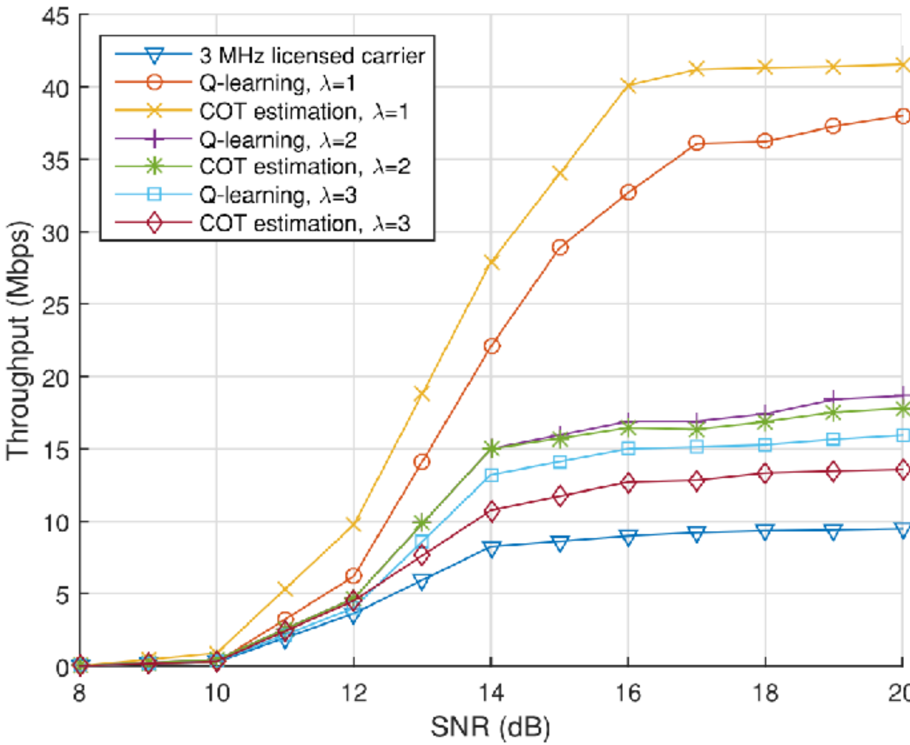
$$Q_{t+1}(s_t, a_t) \leftarrow (1-\alpha)Q_t(s_t, a_t) + \alpha r(s_t, a_t)$$

Only immediate reward, discount factor = 0

- **Optimal action** (a: LAA transmission duration) depends on the selected channel's availability time

$$\boxed{s_{t+1} = \arg\max_{s \in \mathcal{N}} Q_t(s,a)}$$

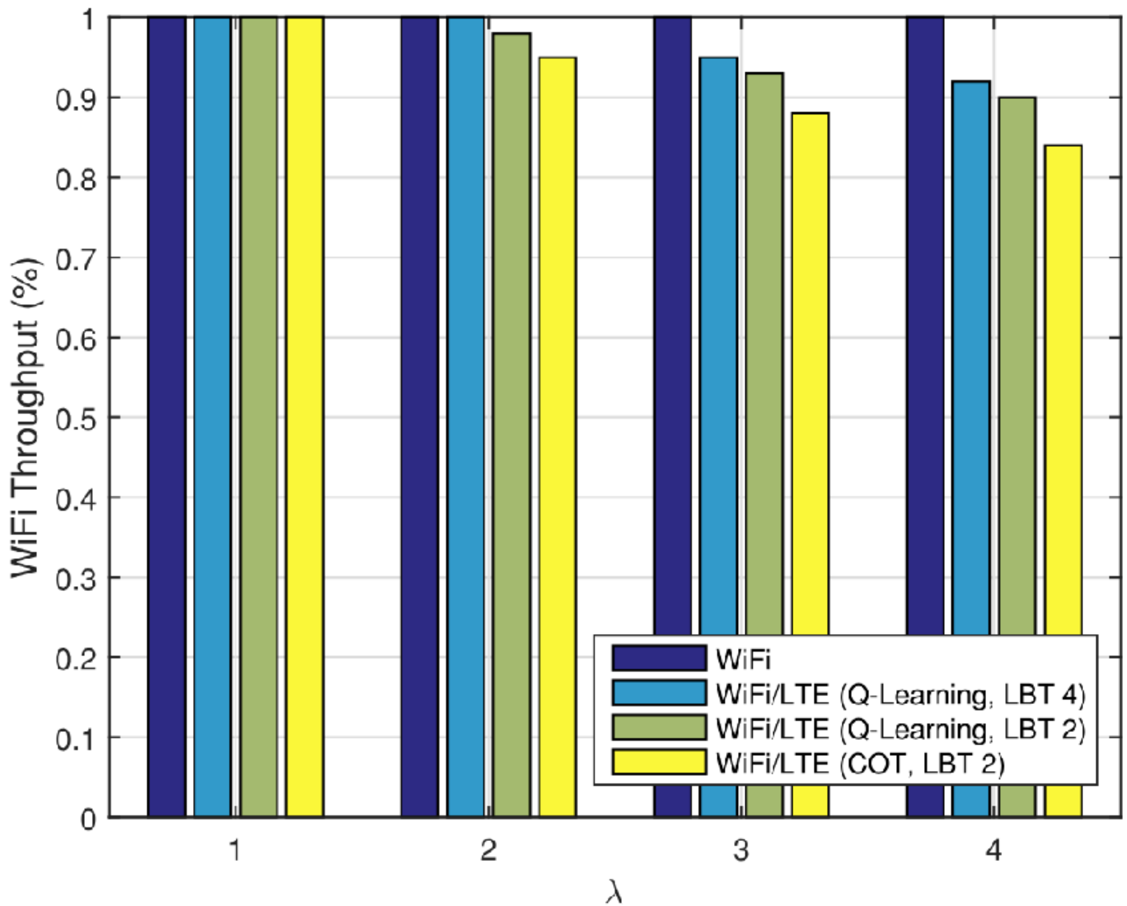
Q-learning overperforms COT under high WiFi load



Low WiFi traffic
COT is better

Moderate to high WiFi traffic
Q-learning is better
COT predictions may not represent real channel occupancy under high WiFi load

WiFi performance analysis



WiFi performance Q-learning over performs COT-based access

Case study #4

Can WiFi exploit ML for protecting itself from LTE interference?

yes, WiPLUS!

Olbrich, M., Zubow, A., Zehl, S. and Wolisz, A. "WiPLUS: Towards LTE-U Interference Detection, Assessment and Mitigation in 802.11 Networks", in European Wireless 2017 (EW2017), *Best Paper Award*, May, 2017.

WiPLUS: detecting LTE duty cycle

- Estimate LTE-U ON and OFF phases
- Quantify available airtime for WiFi on each link

- Online algorithm running on WiFi AP,
- MAC-layer passive and low-complexity monitoring
- commodity 802.11 hardware
- covering the whole LTE-U interference range

Atheros AR95xx 802.11n chip

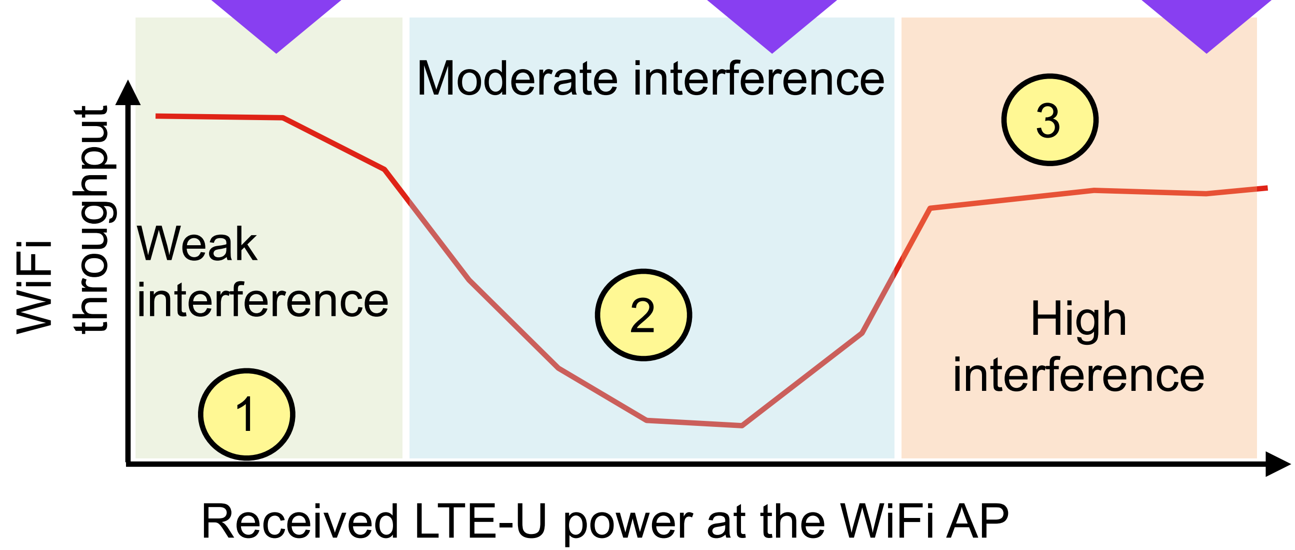
Key idea of WiPLUS

- Analyse MAC Finite State Machine (FSM) transitions of the Network Interface Card (NIC)
    - States: RX, TX, IDLE, OTHER_BUSY (=ED)
- Analyse the Automatic Repeat reQuest (ARQ) frame retransmissions
    - ACK_FAIL
- If LTE is detected, calculate airtime and LTE-ON duration for a link

MAC FSM: No ED
Packet reception
No ACK Fails

MAC FSM: No ED
ARQ: ACK Fails

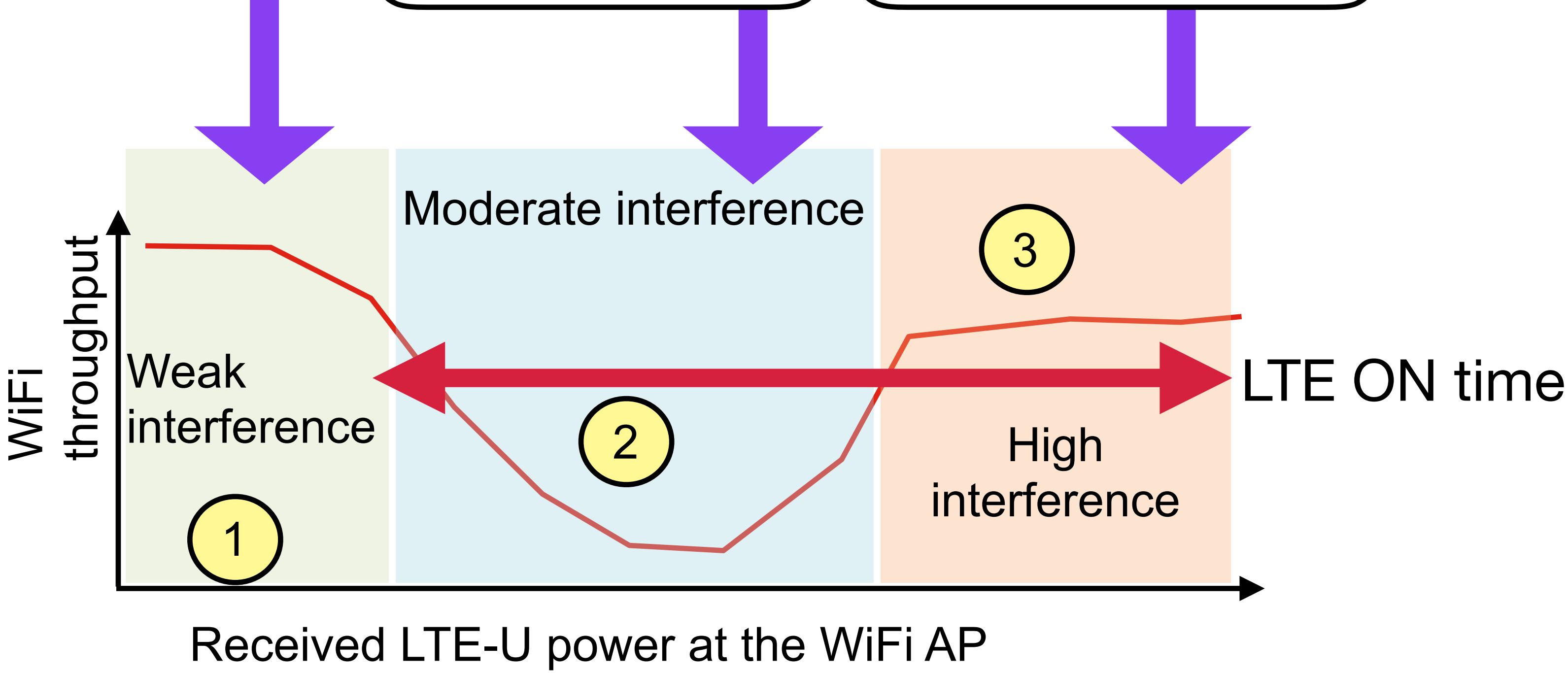
MAC FSM: ED
No packet reception



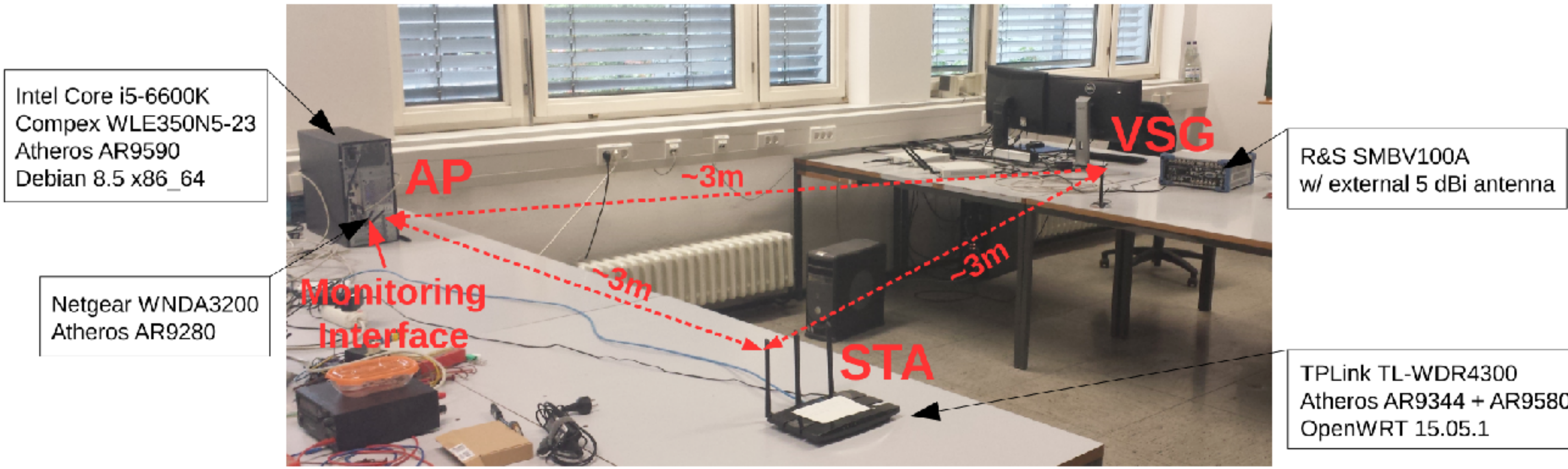
MAC FSM: No ED
Packet reception
No ACK Fails

MAC FSM: No ED
ARQ: ACK Fails

MAC FSM: ED
No packet reception



Approach: data collection from the testbed



ML approach: data analysis

Data:

- data collection via periodic samples from the NIC
- Fraction of time in each MAC-state, ARQ number of packet retransmissions during the respected sampling

Raw data

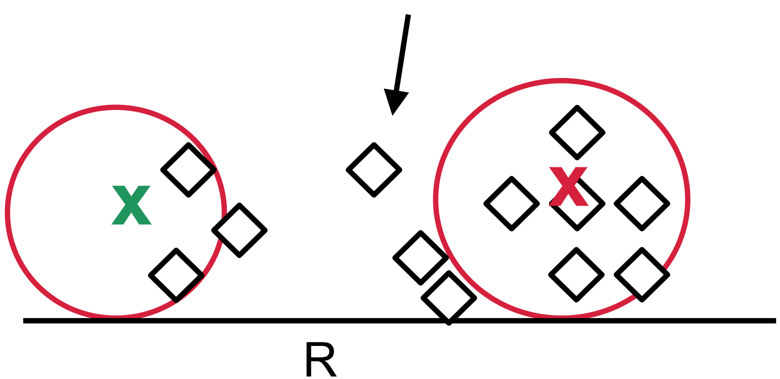
$$S_t^{\mathrm{TX}}, S_t^{\mathrm{RX}}, S_t^{\mathrm{OTHER}}, S_t^{\mathrm{ACK\_FAIL}}, \forall t \in 0 \ldots W$$

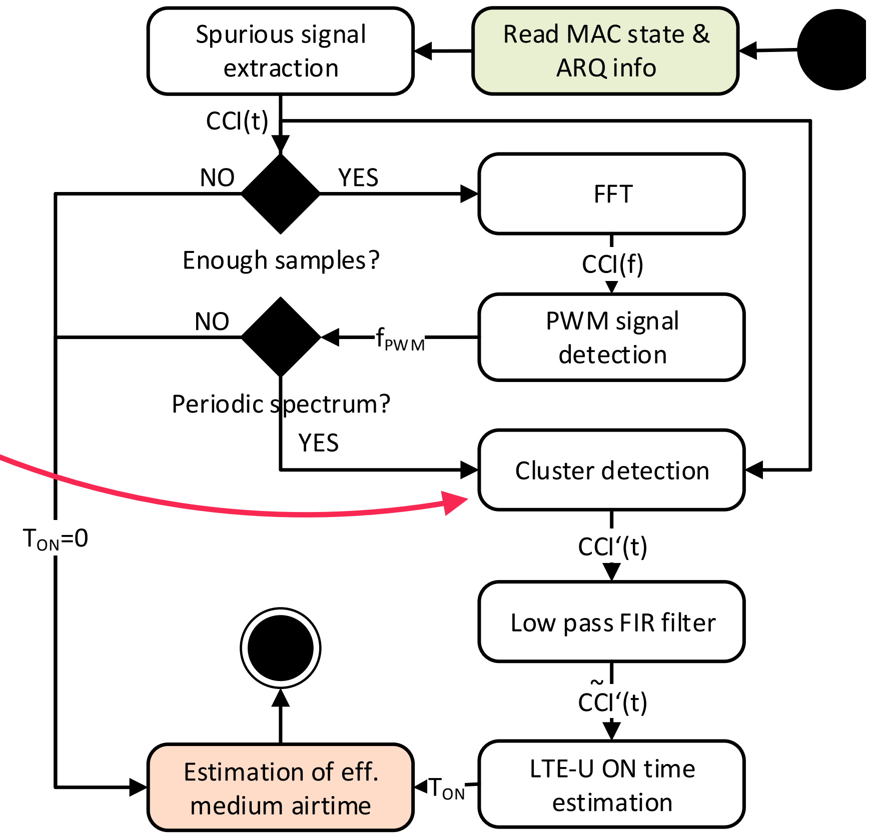
total MAC time spent in
transmission in the
sampling period

More useful

representation R_t which represents (possible) LTE ON-time

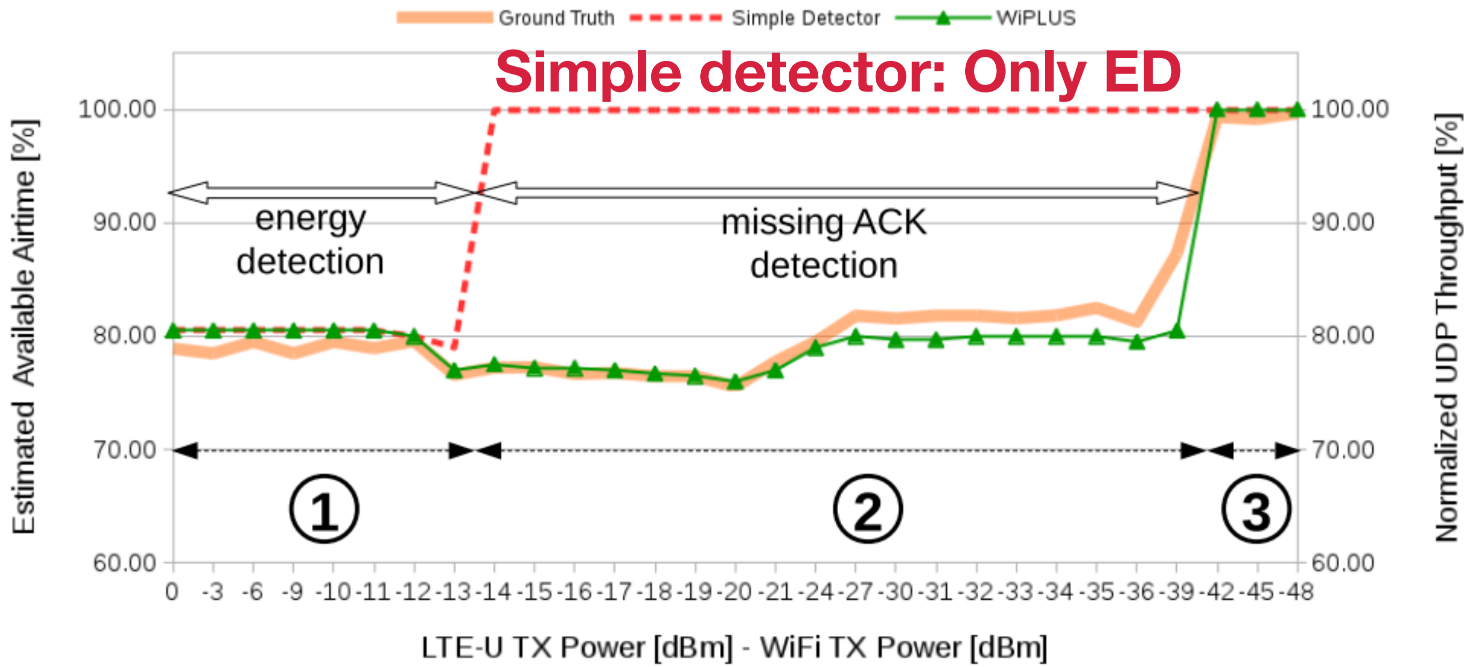
K-means clustering to detect the clusters of transmission duration and clean the outliers





WiPLUS detector pipeline

WiPLUS protoype

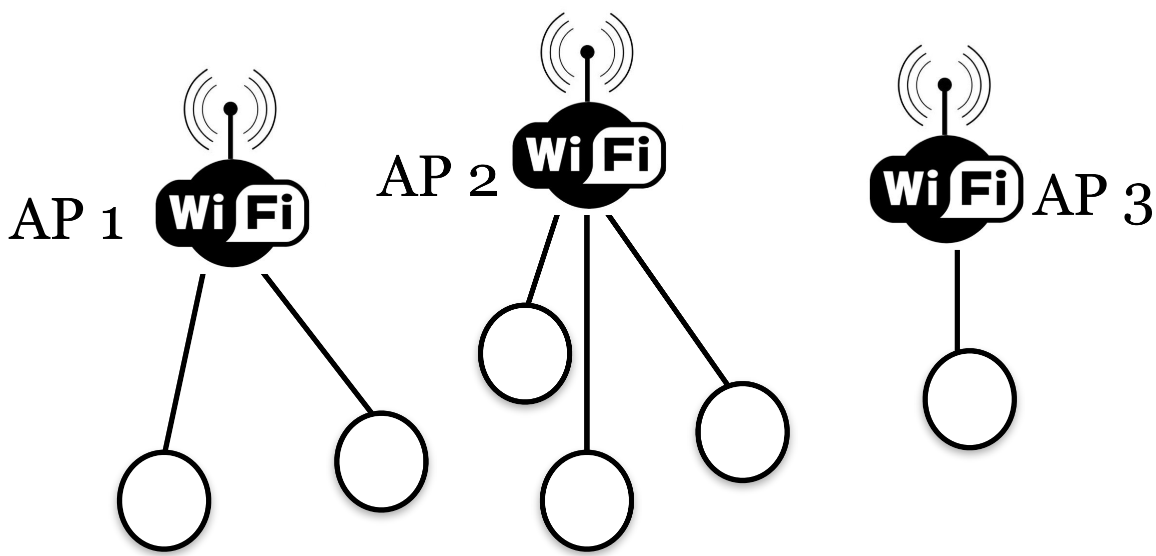


- WiPLUS can estimate airtime quite accurately! (RMS < 3% for DL)
- Possible use of this capability: select channel based on observed LTE activity
- Python's Scikit-learn

Case study #5

WiFi performance estimation

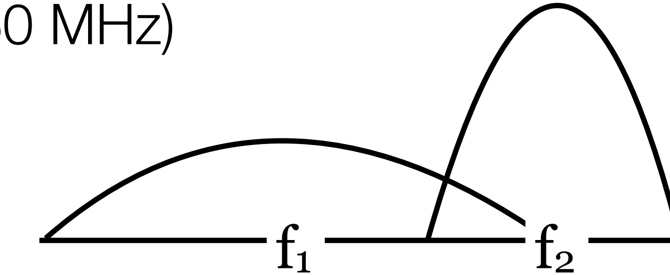
Regression

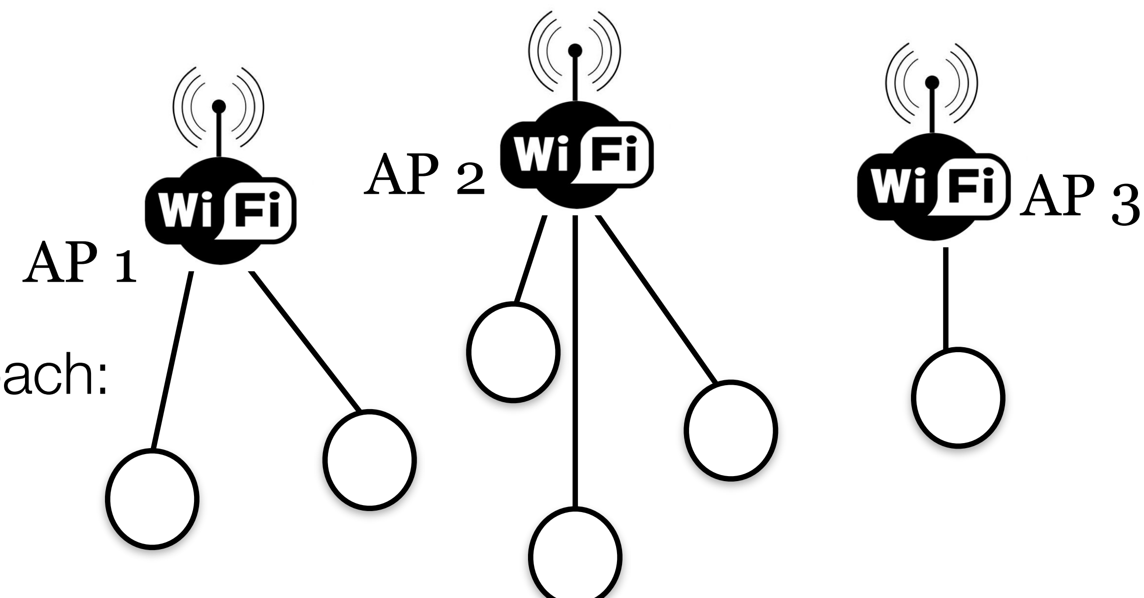


Herzen, Julien, Henrik Lundgren, and Nidhi Hegde. "Learning Wi-Fi performance." IEEE SECON 2015

Selecting the best link in a multi-AP WiFi setting

- 802.11ac variable bandwidths (20, 40, 80, 160 MHz)
- Overlapping channel interference
- How to estimate the link capacity for a given configuration (bandwidth, center f)?

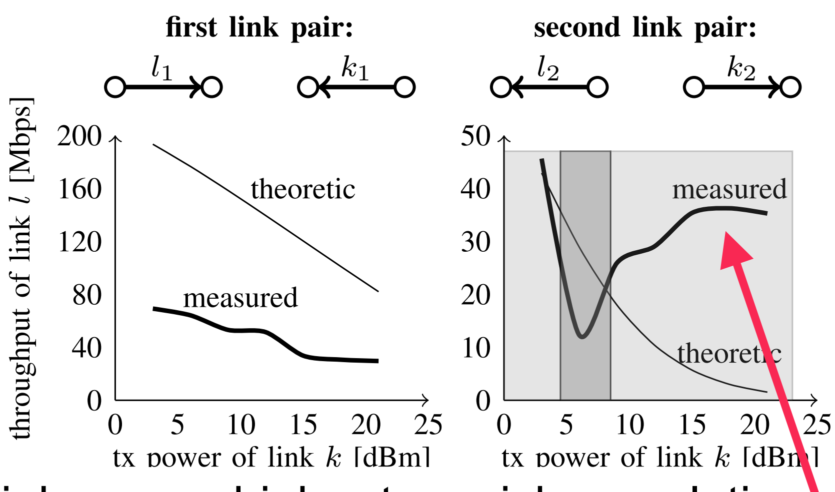




Traditional approach:
SINR based

Coexistence in Uncoordinated WiFi Networks

- Modelling performance *realistically* due to complex PHY-MAC interactions is difficult
  - channel width, partial-overlaps with other links, transmission power, PHY rate
- Proposed approach: *learn* Wi-Fi Performance via measurements
- Estimate link capacity and decide on the best setting



High power, high rate, quick completion
more airtime for link l2

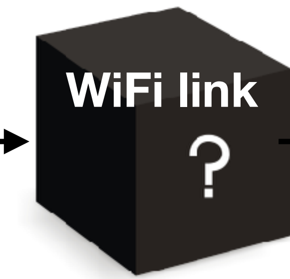
The trend similar to LTE-U
moderate interference level

Takeaway: theoretic analysis may fall short of capturing the reality

Coexistence in Uncoordinated WiFi Networks

State parameters

- transmission power
- traffic load
- channel quality
- transmission bandwidth
- transmission channel



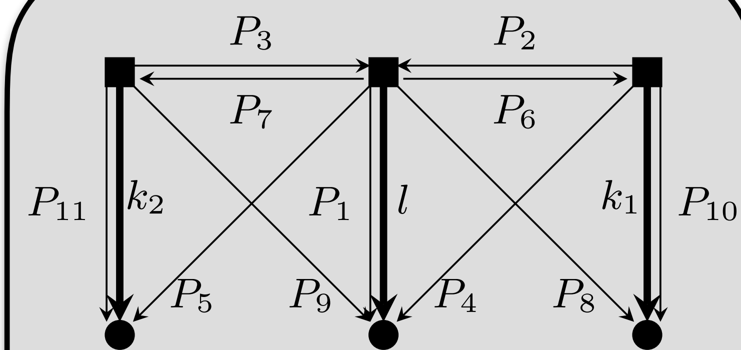
Link performance
e.g., throughput

Methodology

- **Step 1**: Real-world measurements from a testbed (public data: http://www.hrzn.ch/data/lw-data.zip)
- **Step 2**: Supervised learning: different link configurations -> measured throughput
- **Step 3**: Prediction of a link throughput based on the learned black-box model
- **Step 4**: An AP selects the configuration using Gibbs sampling and estimated capacities

Supervised learning framework

- **Features (X)**: (commodity hw. can capture)
  - All received powers: 5K + 1
  - channel width of *l*, and its NL: K+1
  - spectral separation of channel of *l* and its NL: K
  - average traffic loads of NL: K
  - PHY rates of NL: K
- **Labels (Y)**: measured throughput on link l
- **Goal:** Answer the question "*given a setting, what is the expected throughput of l?*"



link of interest *l*
neighbouring links (NL): k_1, k_2

Supervised learning framework

- **Features (X)**: (commodity hw. can capture)
  - All received powers: 5K + 1
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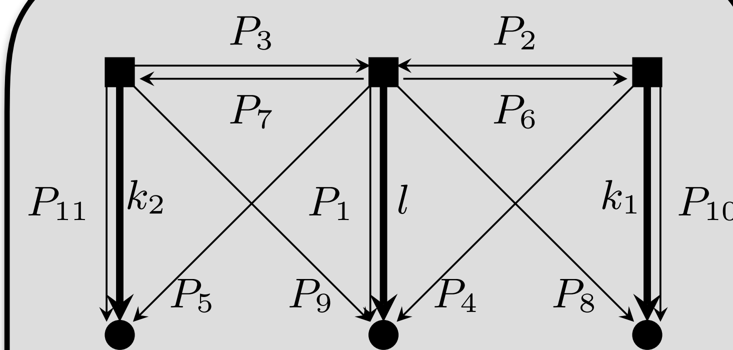


link of interest *l*
neighbouring links (NL): k_1, k_2

This is a regression problem

Used tools for this regression problem

- Regression tree, Gradient Boosted Regression Trees (GBRT), Support Vector Regression (SVR)
- Comparison baseline: SINR-based model
- accuracy of predictions: coefficient of determination R^2, RMSE
- Python scikit-learn package
- 50-fold cross-validation

Improved prediction accuracy compared to SNIR model

In terms of R^2-score, learned SVR and GBRT models improve the prediction accuracy by 54% and 71%, respectively, compared to SINR models

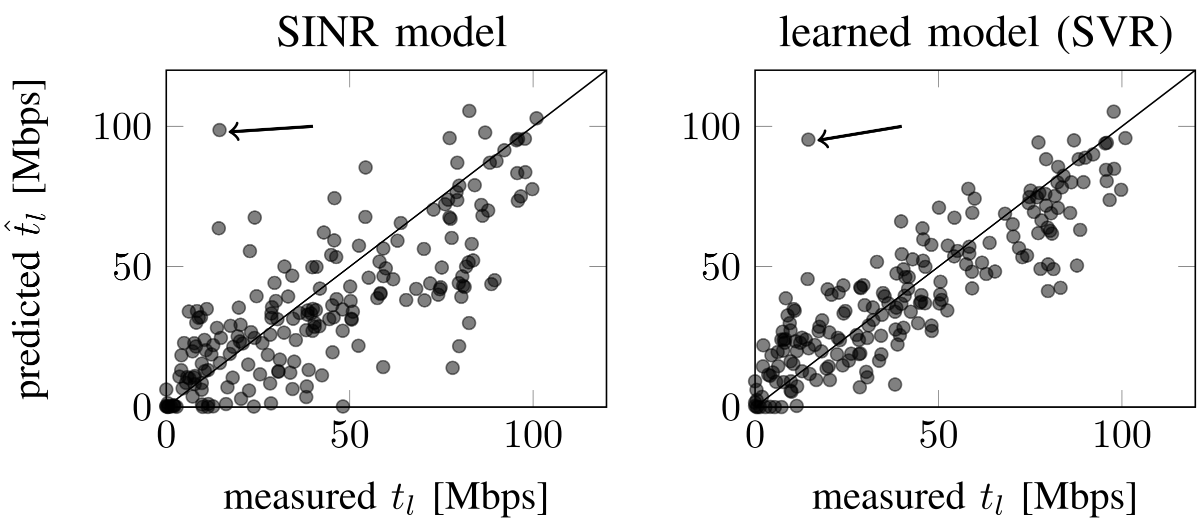
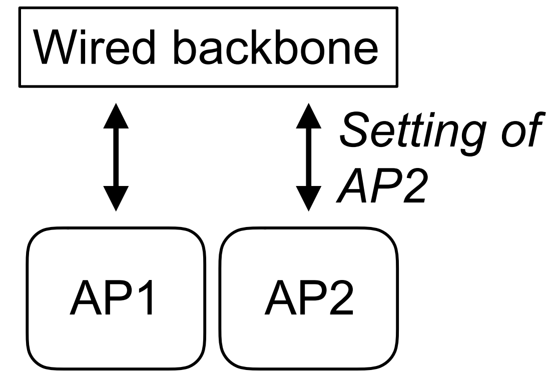


Figure 6: Predicted versus measured throughput, for SINR and a learned model, on a test set of 200 points.

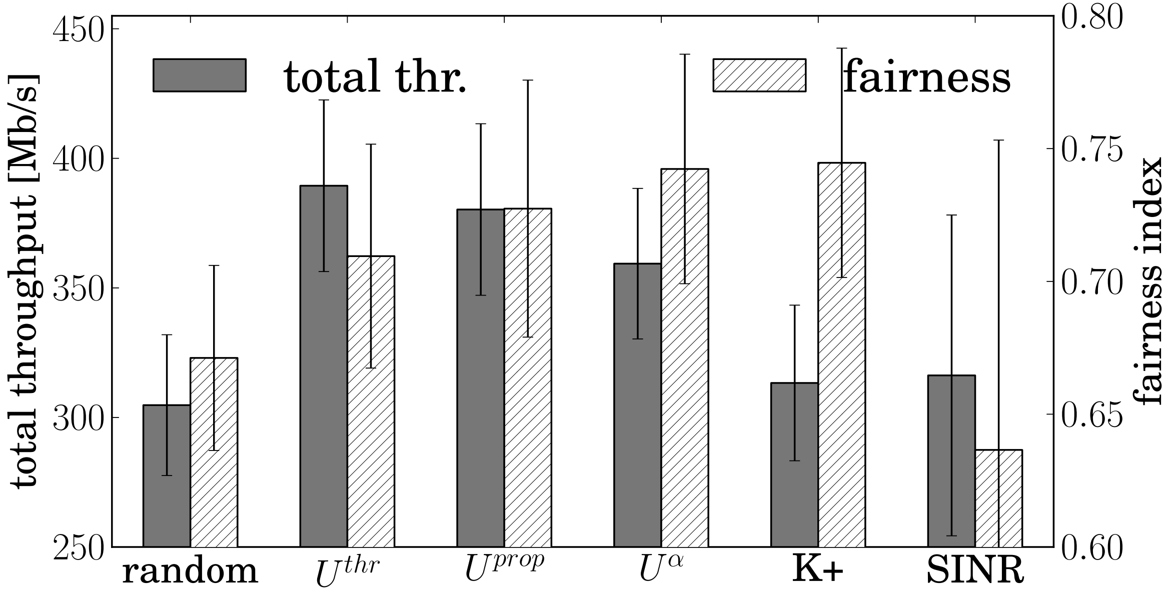
How to use this information for coexistence?

- Select channel center frequency, bandwidth, and transmission power
- Distributed algorithm
- An AP randomly wakes up and collects information from its neighbours, e.g., via wired backbone
- The AP predicts the achievable throughput on each of its attached links, for each possible configuration of spectrum and transmit power
- AP samples a new configuration using the Gibbs distribution with more weight to configurations with large achievable utilities



Learning helps increasing fairness

- Prediction-based configuration selection over performs SINR-based selection
- Fairness: key pillar of peaceful coexistence

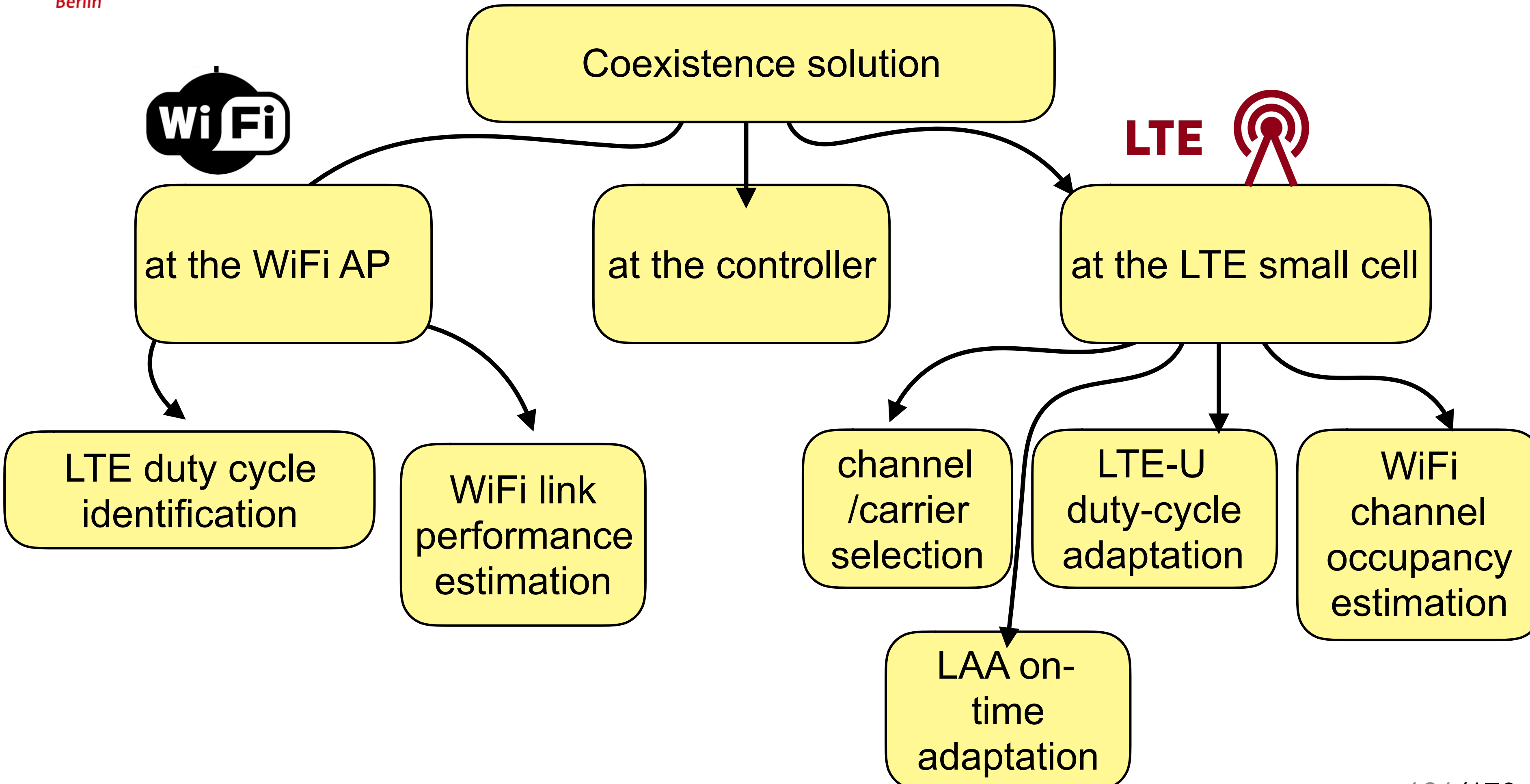


Selected Literature

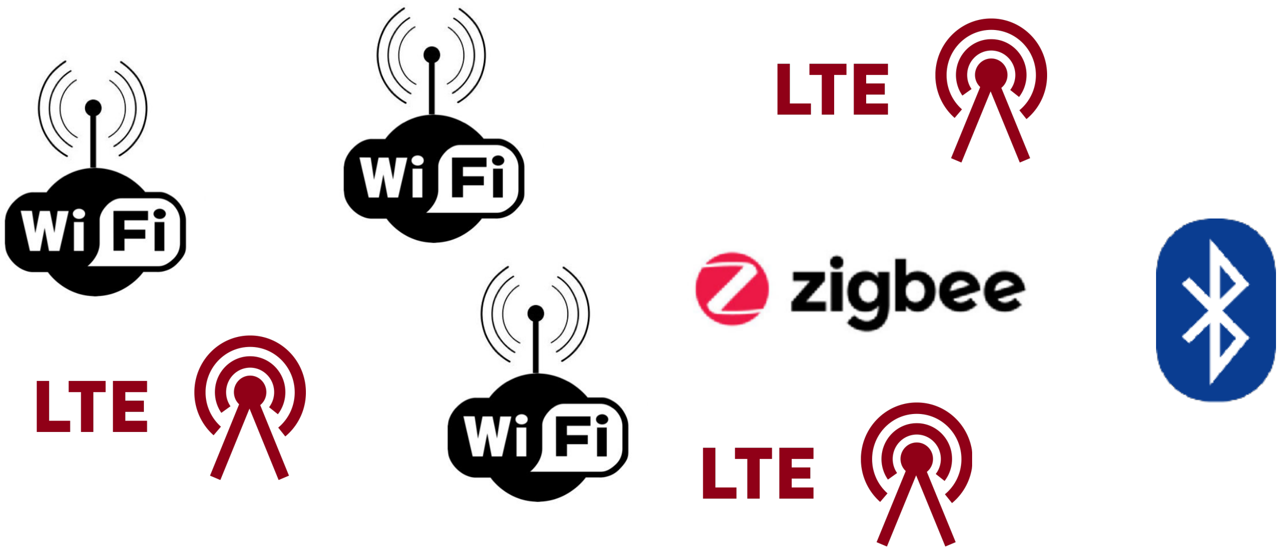
- Sallent, Oriol, et al. "Learning-based coexistence for LTE operation in unlicensed bands." IEEE ICCW15
- Galanopoulos, Apostolos et al. "Efficient coexistence of LTE with WiFi in the licensed and unlicensed spectrum aggregation." *IEEE TCCN*16
- Challita, Ursula, et al. "Proactive resource management in LTE-U systems: A deep learning perspective." *arXiv17*
- Cai, Feng'en, et al. "Spectrum sharing for LTE and WiFi coexistence using decision tree and game theory." IEEE WCNC16
- Rupasinghe, Nadisanka et al. "Reinforcement learning for licensed-assisted access of LTE in the unlicensed spectrum." IEEE WCNC15
- Jiang, Chunxiao, et al. "Machine learning paradigms for xG wireless networks." *IEEE Wcomm, 2017*
- Azmat, Freeha et al. "Analysis of spectrum occupancy using machine learning algorithms." *IEEE TVT,* 2016
- L. Gavrilovska et al. "Learning and reasoning in CRNs," IEEE Commun. Surveys Tuts. 2013
- Daniels, Robert C. Machine learning for link adaptation in wireless networks. Diss. 2011.
- M.Bkassiny, et. al. "A survey on ML techniques in CRs." *IEEE Comm Surveys 2013.*

Part IV
Summary and open research directions

A taxonomy of the literature



Real coexistence scenario consisting of many networks



- Hybrid scenarios are more realistic
- More complex requiring more intelligence/adaptation

Desirable properties of coexistence solutions

- standards compliance
- soft solutions rather than hardware based
- distributed vs centralized/controller based

Challenges of applying ML approaches

- Feasibility in practical settings
  - Complexity
  - Real-time convergence time
  - What happens till convergence?
  - Is it really possible to learn?
    - Mobile or other dynamic environments
- Where to implement ML?
  - AP, nodes, network-core, cloud

Challenges for wireless researchers

Machine learning requires lots of data to learn useful things

- bad news: researchers mostly are limited in access to such real data
- good news: publicly-available data (some better than none)
- https://crawdad.cs.dartmouth.edu/

- Limited applicability to computation-limited devices,
  - bad news: ML requires high resources which are mostly not available in e.g., embedded devices, IoT devices
  - good news: ML is very active and searching for smart algorithms with lower complexity
  - Fog/Cloud can be exploited for such devices

- Weka, R, Python

DARPA challenge

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The Radio Frequency Spectrum + Machine Learning = A New Wave in Radio Technology

The radio frequency spectrum is becoming increasingly crowded and a new DARPA program will examine how leading-edge machine learning can help understand all the signals in the crowd

OUTREACH@DARPA.MIL
8/11/2017

https://www.darpa.mil/news-events/2017-08-11a

Machine learning in 5G

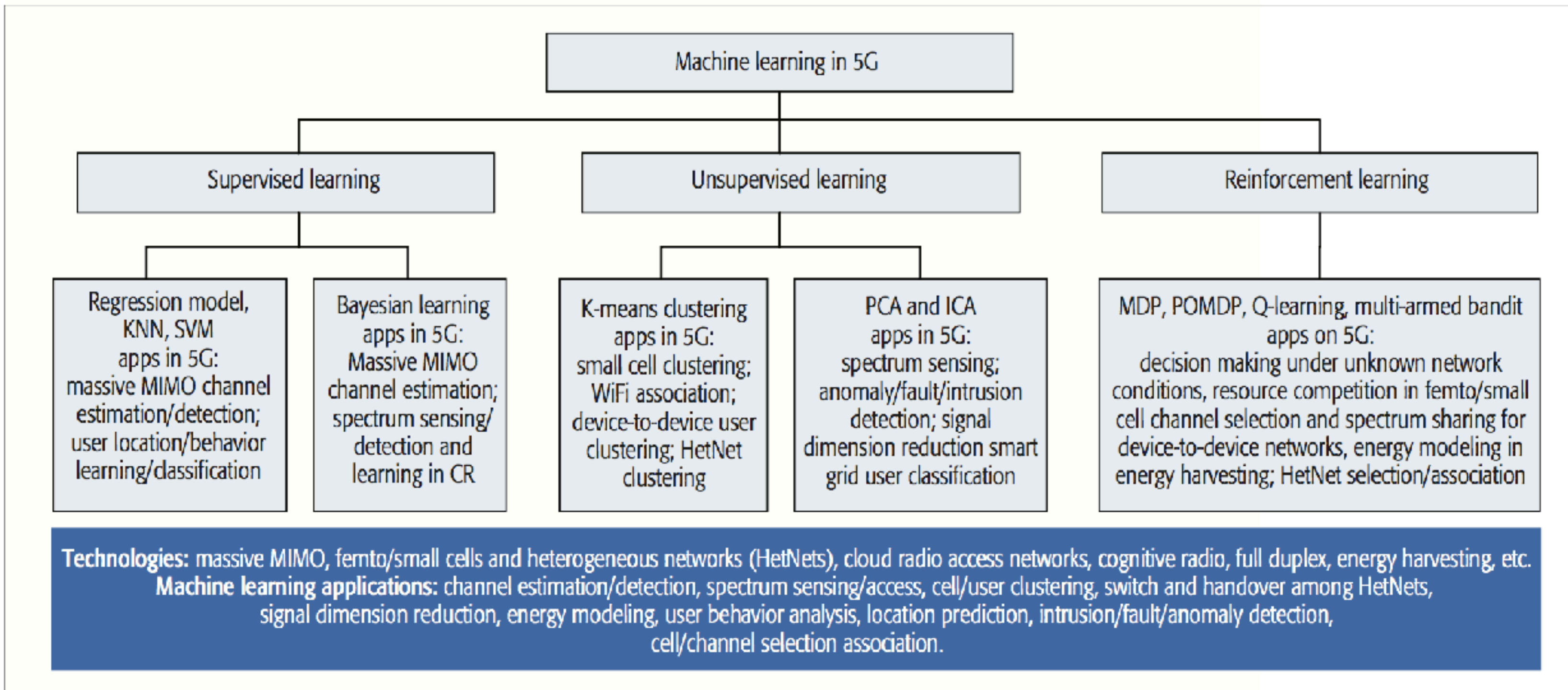

FIGURE 2. Radio learning architecture.

Jiang, Chunxiao, et al. "Machine learning paradigms for next-generation wireless networks." *IEEE Wireless Communications* 24.2 (2017): 98-105.

Summary

- The future is unlicensed
- Coexistence of such unlicensed networks is a big challenge
- ML can provide the capability to embrace uncertainty

Thanks!