WELCOME





What learning can do for 5G?

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...........

What is 5G? Nobody knows! (yet)



So...

What could be 5G?





of subscribers (= human or machine)



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5G VISION

5G = unified ecosystem ...



Serving both traditional as well as potential new applications like drones, real time video surveillance, mobile augmented and virtual reality, IoT...

Ultra-broadband

Offering higher bitrates and supporting extreme traffic densities for the evolution of comms and entertainment

Ultra-narrowband

Efficient sensing and control added to LTE broadband; massive densities of low traffic devices and bearers

Consistent user experience

Ultra low latency

immersive virtual

specialized services and

Mission critical

reality

Better bits rather than simply more cheap bits to offer a more wireline like experience

Plus ..

Multi-carrier LTE remains in place to carry bulk of wide area broadband traffic WLAN continue to play a key role to carry local broadband traffic



5G BY ... 5GPPP





- End-to-End latency of < 1ms
- Ubiquitous 5G access including in low density areas



DIRECTIONS FOR IMPROVEMENT



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LTE-A EVOLUTION WILL TAKE US SOME OF THE WAY WITH KEY 5G FOUNDATION TECHNOLOGIES





- More and more (and more)* data traffic
- More spectrum to handle
- More complex radio techniques (Massive MIMO, CoMP, ICIC, low latency, ...)
- More density of network (smaller cells) and IoT
- More resources to manage in a better way

Then...

(A PART OF) THE ANSWER IS NETLEARN



ANR NETLEARN

Projet ANR "Orchestration d'algorithmes d'apprentissage distribués pour la gestion

Project Presentation

NETLEARN is a collaborative research project financed by the french national agency for research (ANR) and which aims at developing new tools based on recent advances in learning theory for the management of various resources in mobile networks. It started the 21 Oct. 2013 and will end the 20 Apr. 2017. Partners of the projects are: INRIA (LIG), UVSQ (PRISM), University Paris Dauphine (LAMSADE), Institut Mines-Telecom (Telecom ParisTech), Alcatel-Lucent Bell Labs and Orange Labs. It is organized in four work packages.

The main objective of the project is to propose a novel approach of distributed, scalable, dynamic and energy efficient algorithms for managing resources in a mobile network. This new approach relies on the design of an orchestration mechanism of a portfolio of algorithms. The ultimate goal of the proposed mechanism is to enhance the user experience, while at the same time to better utilize the operator resources.



AT A GLANCE

Objectives



Challenges:

- Which algo is the best for which case?
- Detect case and apply corresponding algorithm
- Smooth shift from one algorithm to another

- ...

AT A GLANCE

Partners:

- Alcatel-Lucent Bell Labs
- Dauphine/LAMSADE
- **INRIA** Grenoble •
- **Orange Labs**
- Telecom ParisTech (
- UVSQ/PRISM •

Duration:

42 months (ends in April 2017)



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RESULTS SO FAR PRESENTED TODAY

- 1. Distributed load balancing using Cell Range Expansion (CRE)
 - Partial information is sufficient for practical implementation
- 2. Massive MIMO optimization
 - tracks the system's optimum transmit policy as the environment evolves over time
- 3. Self-learning and prediction method to optimize resources allocation in CDN
 - Phase identification in content utilisation to select the best algorithm per phase
- 4. Category in learning

- Use one learning vector per distinct case leads to better result than one vector



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LEARNING IN HETNETS

Objective: Distributed load balancing using Cell Range Expansion (CRE) association and Almost Blank Subframes (ABS) Methodology: Use log-linear learning algorithms in near-potential game framework with complete or partial information in order to minimize an alpha fairness objective function.



CONVERGENCE RESULTS

- LLLA for complete information: BS knows the cost of every feasible action
- BLLLA for partial information: BS knows only the cost of his current action
- (B)LLA are guaranteed to converge to the best Nash Equilibrium even in presence of shadowing



Communication is needed only in the BS close neighborhood
Partial information is sufficient for practical implementation



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NEXT STEPS

- 1. Orchestration:
- Several LLLA with different parameters



ONLINE OPTIMIZATION IN (MASSIVE) MIMO SYSTEMS

Objective: Optimize the achieved throughput (or energy efficiency) in dynamically varying MIMO (or MIMO-OFDM) systems

Methodology: Employ advanced exponential learning and online mirror descent methodologies to design an adaptive learning scheme that tracks the system's optimum transmit policy as the environment evolves over time

- MIMO/OFDM multiple access channel
- Dynamic channels (fading, mobility)
- Reactive system (users modulate transmit characteristics constantly)

Transmit controls: signal covariance matrix Objective: sum rate (bits/sec/Hz) or energy efficiency (bits per transmit Watt)





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LEARNING RESULTS

NETLEARN contribution: Matrix Exponential Learning (MXL)



Requires same information as distributed water-filling
Variant implementation: just one bit of feedback per iteration



CONTENT CACHING IN CDN



- Objective:
 - maximizing hits number while satisfying constraints
 - Cache size
 - Network load
- Solution:
 - Put most popular contents close to the users
- Challenge:
 - Predict popularity of content



VARIOUS ALGORITHMS WITH VARIOUS PERFORMANCES

Experts learning strategies:

- 1 Basic: difference between the two last known demands
- 2. Single Exponential Smoothing SES: weighted average of the previous observed values in an observation window and the last prediction

the

Double Exponential Smoothing DES Brown: takes into account and predicts some 3. form of trend in the environment values evolution





Basic expert is reactive and accurate when there is a phase change, defined by a change in the slope of the solicitation curve.

Selecting at each time the more efficient expert for the dynamic situation



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CATEGORY IN LEARNING

Case: Distributed cell resource allocation

- Mobiles send ressource demand
- Cell allocates resource depending on demand and own capacity
- Category depends of cell load
 - Mobile uses learning vector corresponding to the category





CURRENT RESULTS

3 categories of load





Best learning when using same number of vectors than number of category

Next steps:

- Analysis of behavior depending on demand strategy
- Categorization strategy

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PERSPECTIVE

- Whatever the technologies used in 5G, complex resources management will be needed
 - Large amount of resources to manage in different ways
 - Huge amount of users
- Not one unique algorithm
 - Depends on case, time, etc.
- Need for orchestration of learning algorithms
 - How and when to select which algorithms ?



NETLEARN CONTRIBUTIONS

- Demonstrating value of orchestration
 - Analysis, simulation, tesbted and demo
 - Two use cases for demo: wireless network (CRE), CDN
- Proposing architecture and solution for orchestration of learning algorithms
 - OpenFlow framework considered
 - Will benefit to future 5G architecture



NETLEARN PARTNERS INVITE YOU TO



http://tinyurl.com/WorkshopNetlearn

Issy-les-Moulineaux



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