Machine Learning at the Edge

A Data-Driven Architecture with Applications to 5G Cellular Networks

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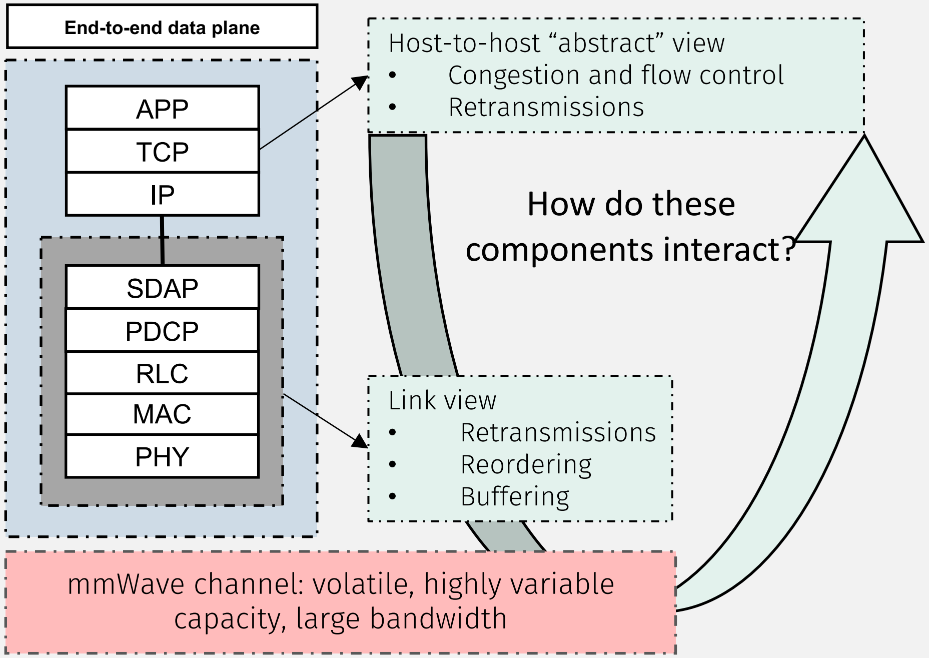
Outline

- Intro (on my research background)
- Data-driven networks: motivation
- Contribution
- The dataset
- 5G data-driven architecture
- Applications
    - Clustering in self-organizing networks
    - Prediction of the number of users in base stations
- Conclusions

5G/6G networks

- Standardization
- Architecture and protocol design
- End-to-end performance



End-to-end data plane

APP
TCP
IP
SDAP
PDCP
RLC
MAC
PHY

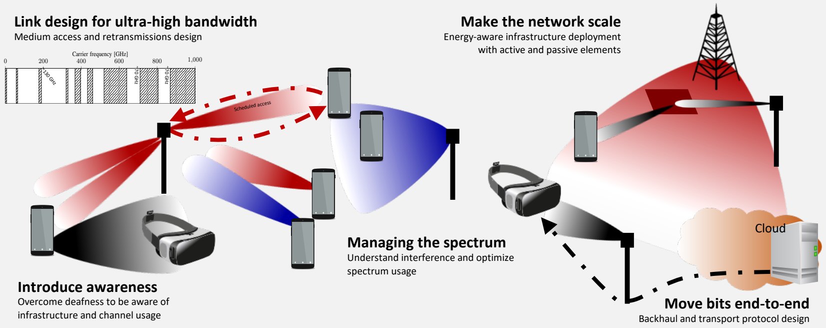
Host-to-host “abstract” view
- Congestion and flow control
- Retransmissions

How do these components interact?

Link view
- Retransmissions
- Reordering
- Buffering

mmWave channel: volatile, highly variable capacity, large bandwidth

Focus on **mmWave** and **terahertz** bands



Link design for ultra-high bandwidth
Medium access and retransmissions design

Make the network scale
Energy-aware infrastructure deployment with active and passive elements

Managing the spectrum
Understand interference and optimize spectrum usage

Introduce awareness
Overcome deafness to be aware of infrastructure and channel usage

Move bits end-to-end
Backhaul and transport protocol design

Network simulation

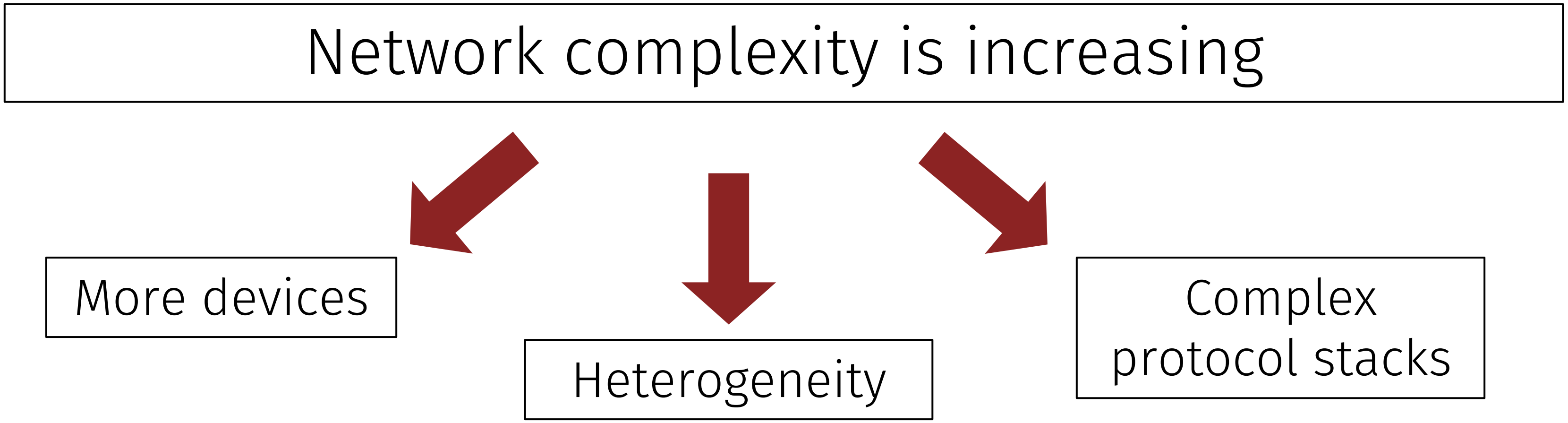
- ns-3
- New modules for mmWave and V2V communications
- Experience in software development
  - Project management
  - Gitflow
- C++

Channel modeling

- Implementation, development
- Analysis of complexity/accuracy trade offs
- 3GPP models, ray tracing

See here for the animation
http://mmwave.dei.unipd.it/research/channel-modeling/ray-tracing-results/

Data-driven networks: potentials



Network complexity is increasing

More devices

Heterogeneity

Complex protocol stacks

- Classic optimization techniques may be infeasible
- Need for autonomous orchestration and configuration
- QoE can improve with context-awareness

Use network data to drive self-optimizing ML algorithms

Data-driven networks: challenges

- Scalability of ML techniques
- **Availability of data**
- Several open questions to be addressed
  - Which pieces of information are needed from the network?
  - How is it possible to efficiently collect them?
  - How to practically deploy ML/AI algorithms?
  - Which ML techniques perform better?
  - How good is the performance of ML in real networks?

Data-driven networks: our contributions

- Mobile-edge controller-based architecture:
    1. Deployable in **5G NR and O-RAN** networks
    2. Capable of handling **data** collection and providing *real-time* analytics and decisions
    3. Makes better use of data analytics than 4G-based architectures

- Demonstration of data-driven gains and opportunities in real networks:
    a. Data-driven dynamic clustering of base stations
    b. Prediction accuracy of the number of UEs per base station

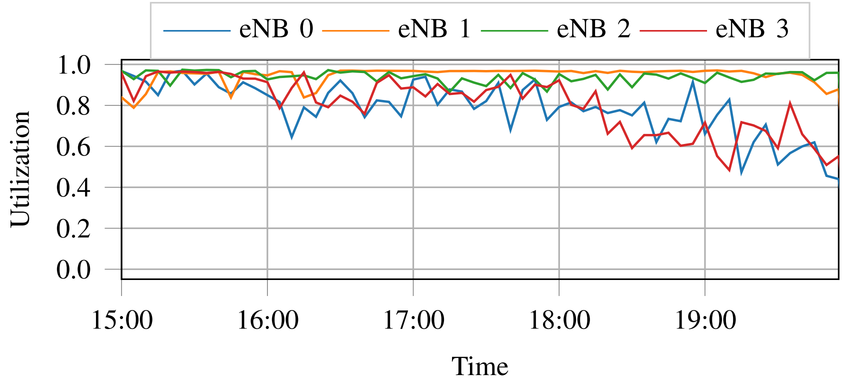
Dataset with hundreds of base stations from major US operator

M. Polese, R. Jana, V. Kounev, K. Zhang, S. Deb, M. Zorzi, "*Exploiting spatial correlation for improved user prediction in 5G cellular networks*" in Proc. of the Information Theory and Applications Workshop (ITA), San Diego, CA, 2019.

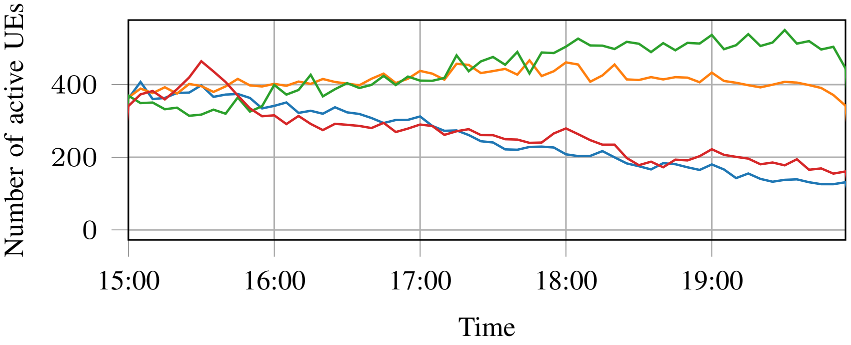
M. Polese, R. Jana, V. Kounev, K. Zhang, S. Deb, M. Zorzi, *"Machine Learning at the Edge: a Data-Driven Architecture with Applications to 5G Cellular Networks"*, submitted to IEEE Transactions on Mobile Computing

The dataset

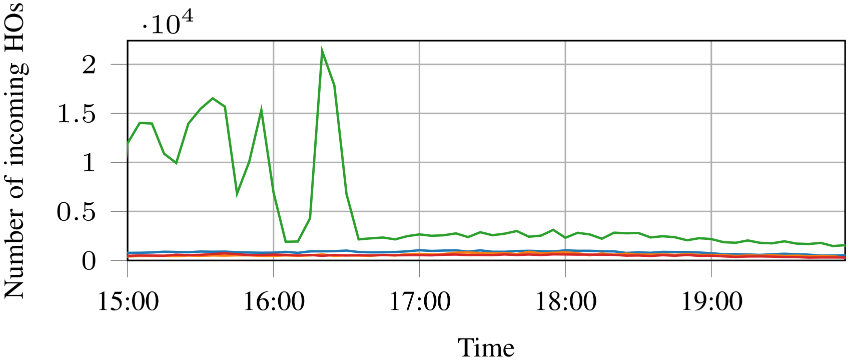
- 472 eNBs in San Francisco
  - February 2017
  - Every day, 3 P.M. to 8 P.M.
- 178 eNBs in Palo Alto
  - June-July 2018
  - Whole day
- 4G LTE deployment
- Data collected:
  - Resource utilization
  - Number of incoming and outgoing handovers
  - Number of active UEs



(a) Utilization (averaged over a 15-minute interval).

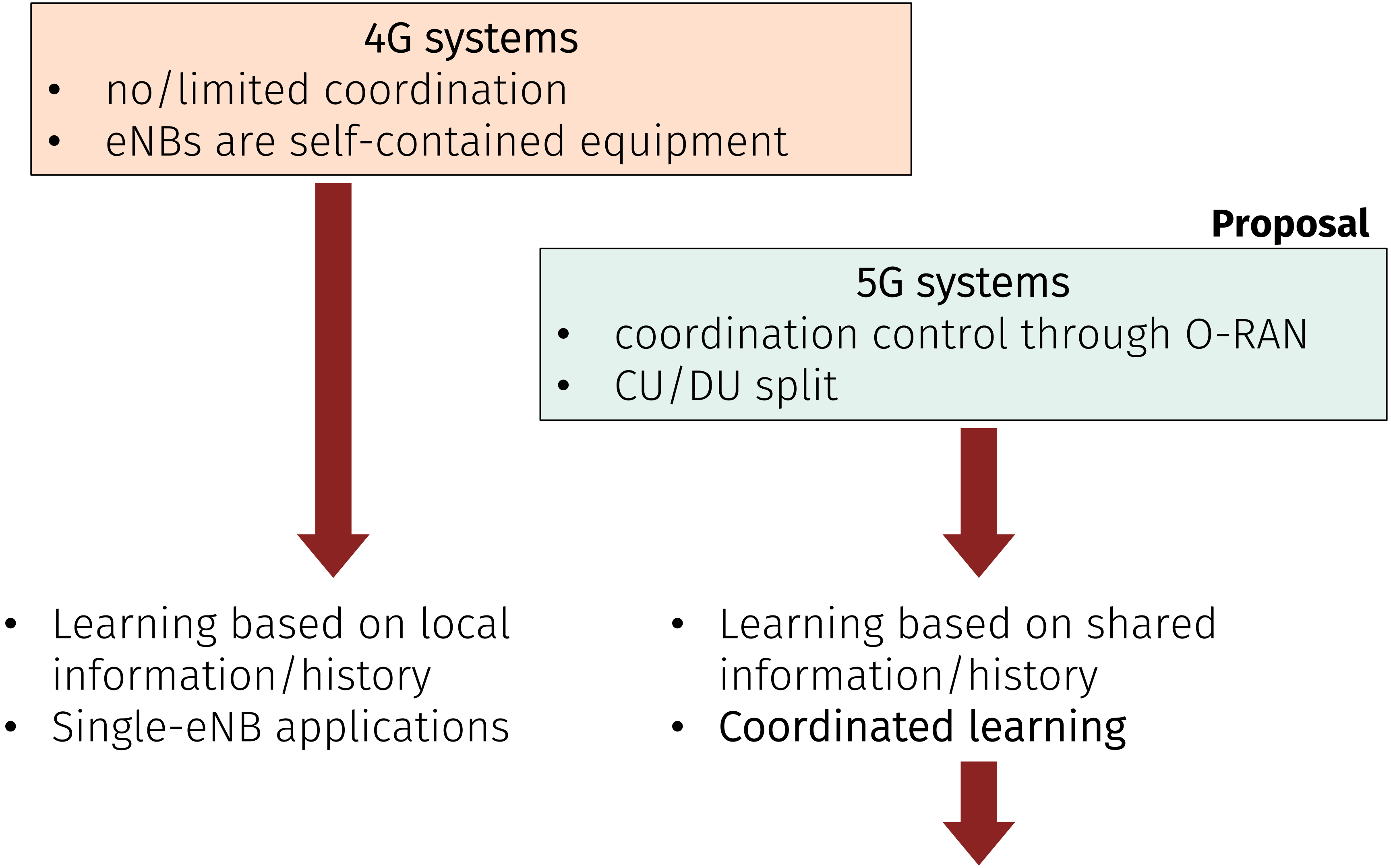


(b) Number of active UEs (summed over a 15-minute interval).



(c) Number of incoming handovers (summed over a 15-minute interval).

Data-driven 5G architecture



4G systems

- no/limited coordination
- eNBs are self-contained equipment

- Learning based on local information/history
- Single-eNB applications

Proposal

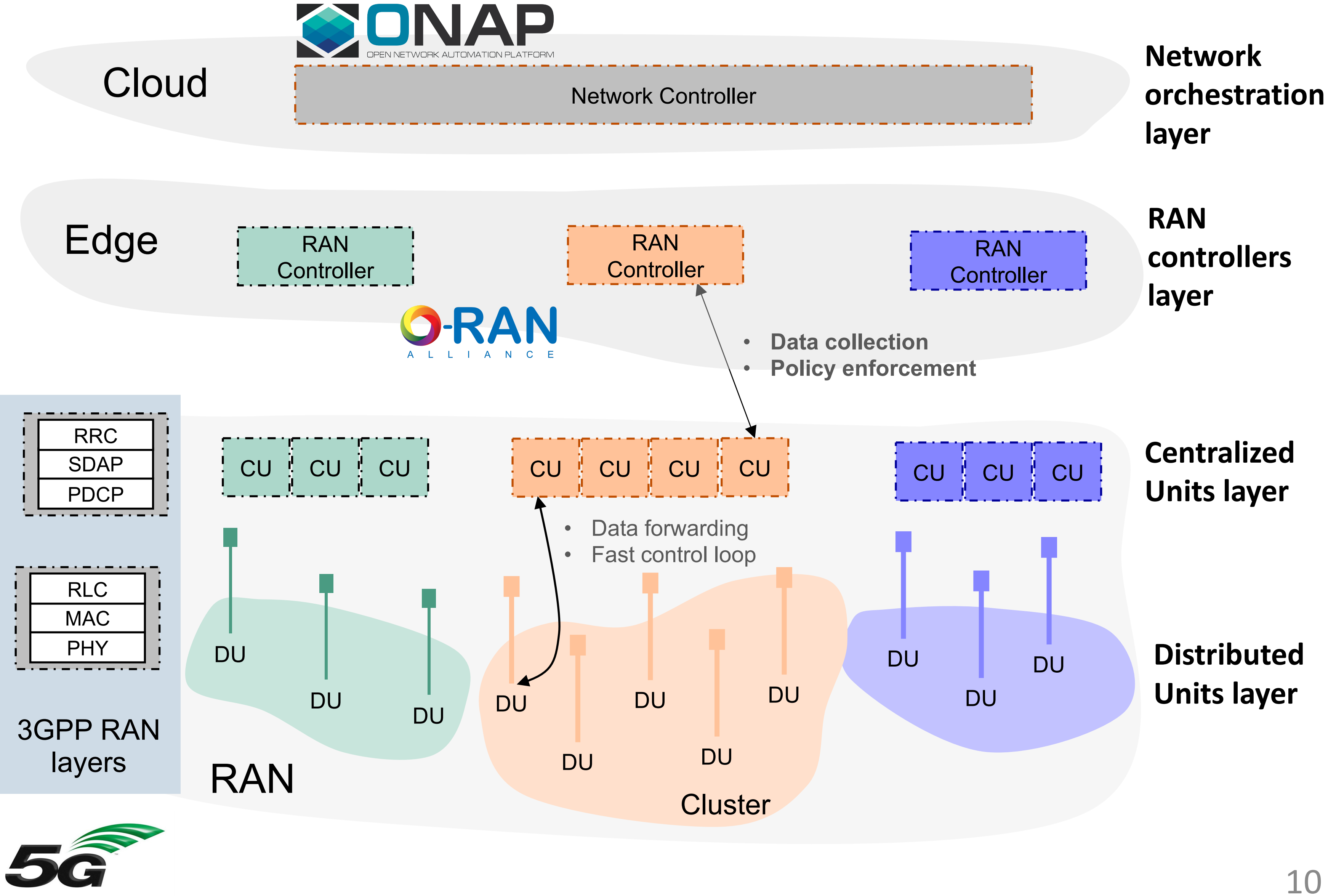
5G systems

- coordination control through O-RAN
- CU/DU split

- Learning based on shared information/history
- Coordinated learning

Exploit the spatial correlation naturally introduced by user mobility

Multi-layer architecture



Multi-layer architecture: key components

- 3GPP NR **CUs/DUs** for data plane & **local** control decisions

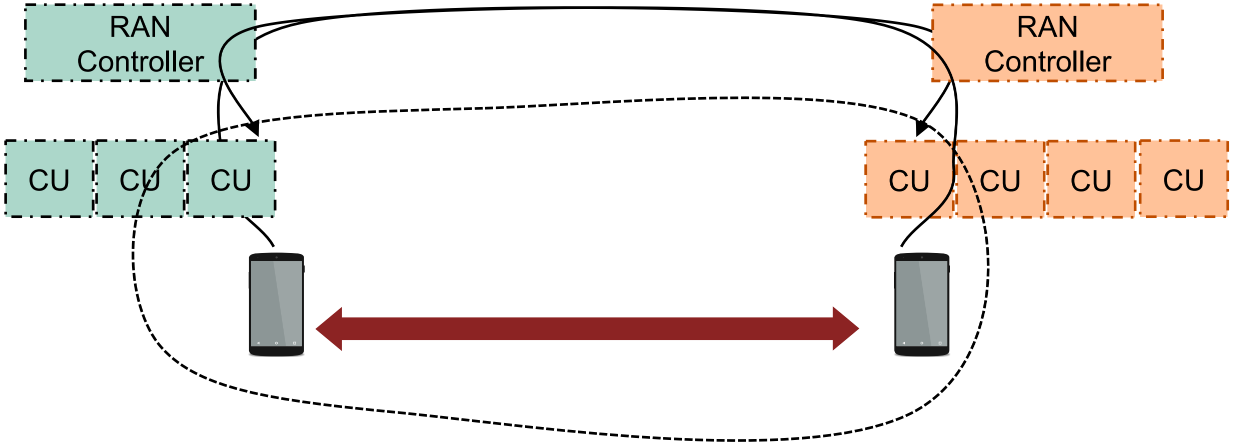
- RAN controllers (O-RAN Alliance)
  - Orchestrate CUs/DUs
  - Manage user status, mobility events, deploy scheduling policies
  - **Clustered** view on the network
  - Collect data from CUs/DUs to control the network –> use it also to **train and deploy ML algorithms**
  - Deployed at the edge

- Network controller (ONAP)
  - **Centralized** cloud facility
  - RAN controllers orchestration and app-layer services

Data-driven operations: RAN clustering

- How can the network automatically match the CU and controllers?
- Goal: minimize the interaction among different controllers
  - Avoid inter-controller sync-up
  - Avoid the exchange of inter-controller messages

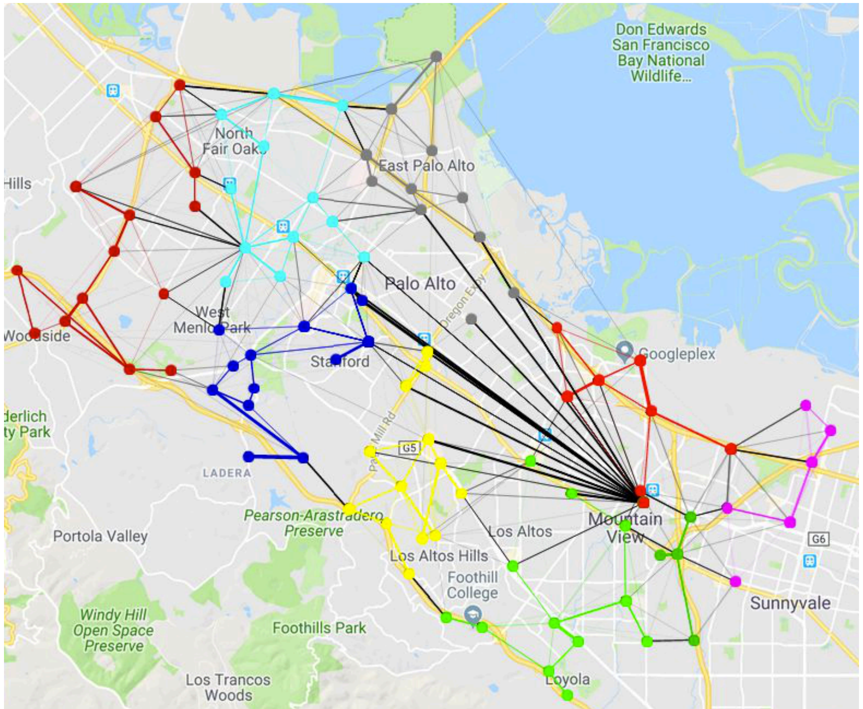
Minimize the control plane latency



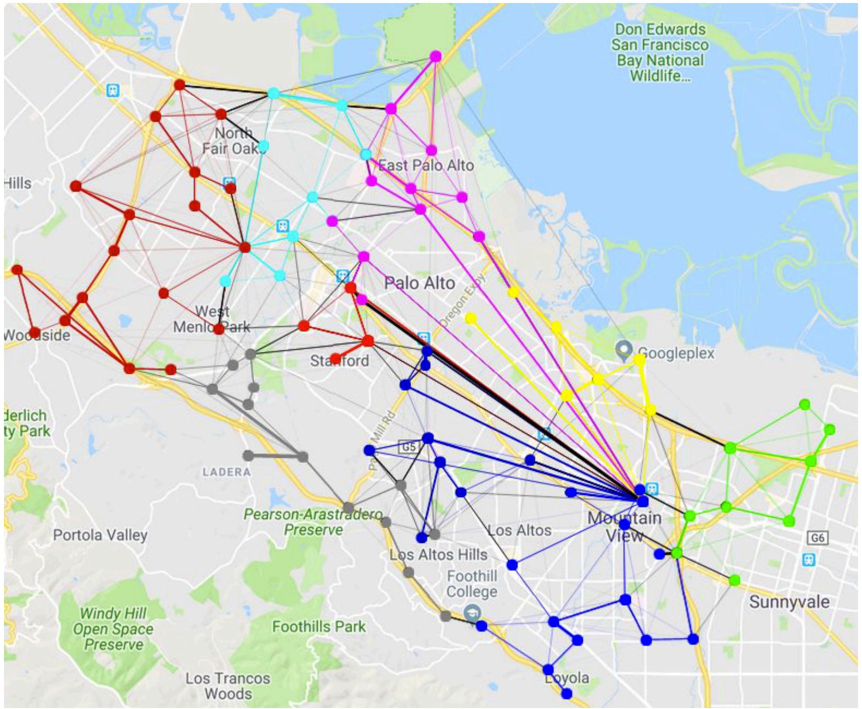
Data-driven operations: RAN clustering

Goal: minimize inter-controller interactions
(impact on control plane latency)

Clustering based on
base station positions
(fixed, no dynamic data)

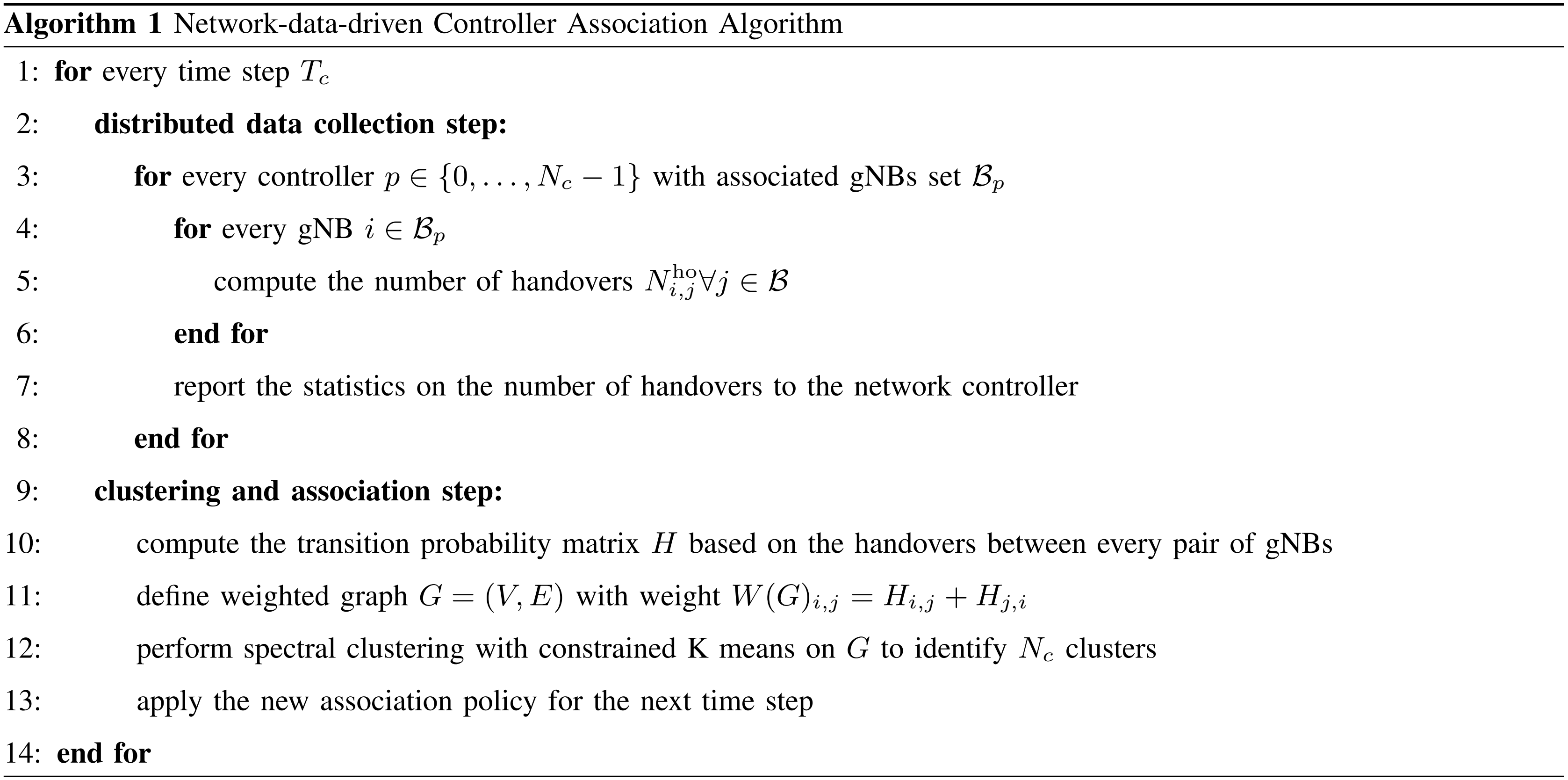


Clustering based on
handover transitions
(dynamic, based on network data)



Data-driven operations: RAN clustering

Goal: minimize inter-controller interactions
(impact on control plane latency)

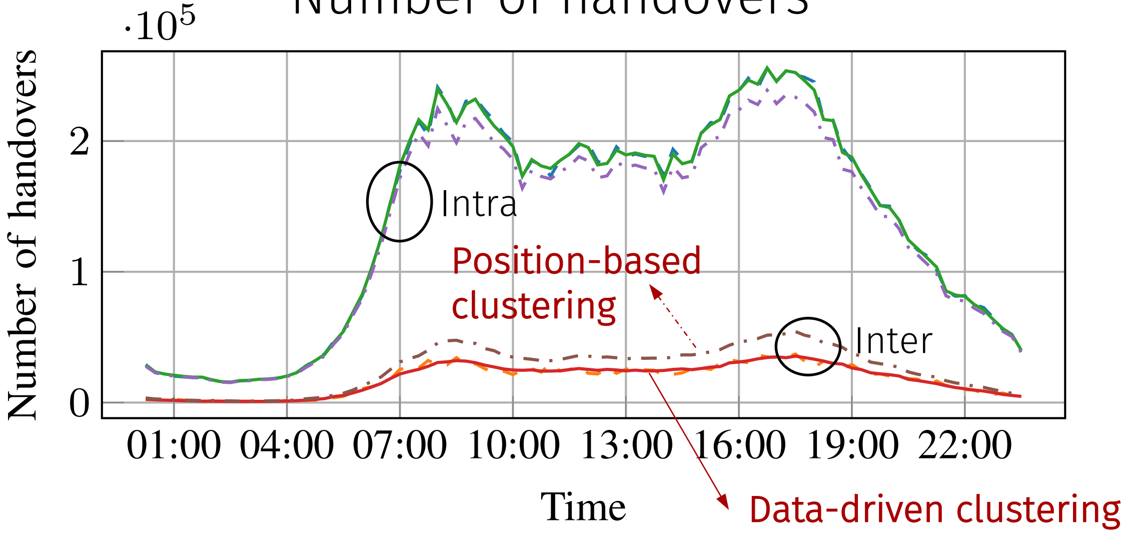


Algorithm 1 Network-data-driven Controller Association Algorithm

```
for every time step $T_c$
    distributed data collection step:
        for every controller $p \in \{0, \ldots, N_c - 1\}$ with associated gNBs set $\mathcal{B}_p$
            for every gNB $i \in \mathcal{B}_p$
                compute the number of handovers $N^{\mathrm{ho}}_{i,j} \forall j \in \mathcal{B}$
            end for
            report the statistics on the number of handovers to the network controller
        end for
    clustering and association step:
        compute the transition probability matrix $H$ based on the handovers between every pair of gNBs
        define weighted graph $G = (V, E)$ with weight $W(G)_{i,j} = H_{i,j} + H_{j,i}$
        perform spectral clustering with constrained K means on $G$ to identify $N_c$ clusters
        apply the new association policy for the next time step
end for
```

Data-driven operations: RAN clustering

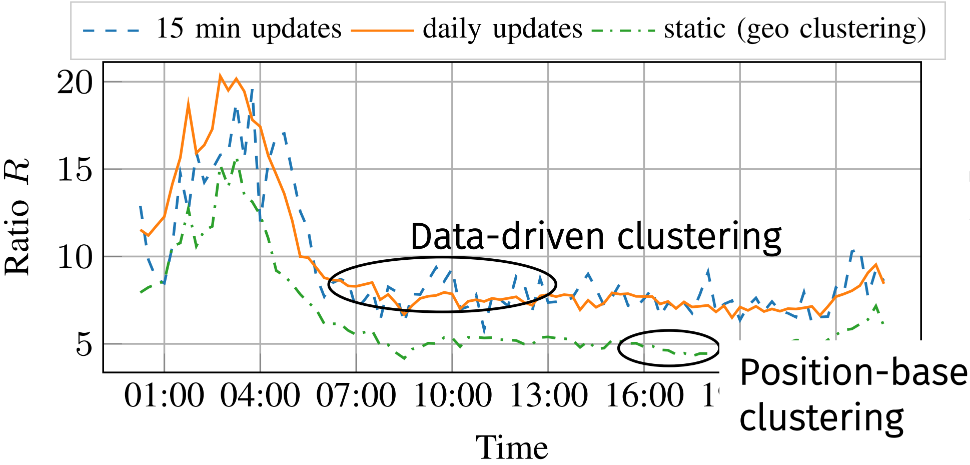
Number of handovers



Position-based clustering

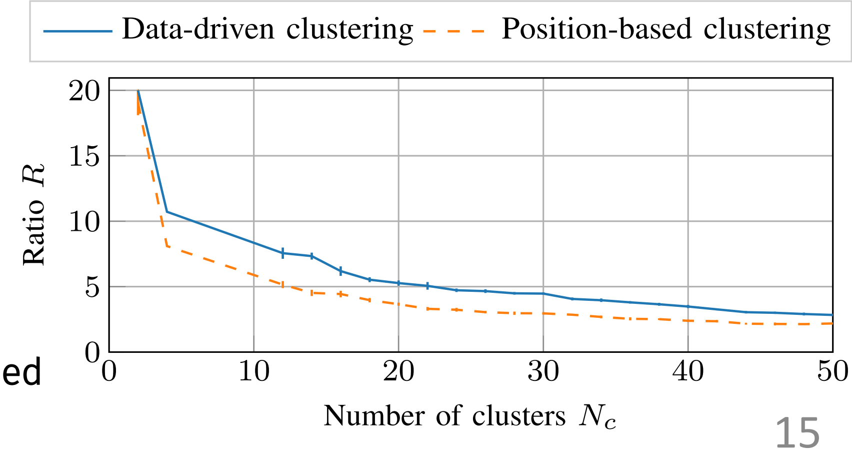
Data-driven clustering

Ratio intra/inter-cluster HOs



Data-driven clustering

Position-based clustering



Data-driven operations: prediction

Predict the number of active UEs

- Local-based method: train a different model in each BS to predict the number of UEs in each single BS
  - This is what is possible in 4G LTE networks
- Cluster-based method: train a model per cluster, predict a vector with the number of UEs in each BS of the cluster
  - Enabled by our architecture
  - Exploit spatial correlation to improve the prediction

Data preprocessing

- The number of active users is averaged every 5 minutes
- Scaling and log(1+x) applied to the dataset

Local-based prediction

- Target: number of active users in each eNB, with a look-ahead step $L \in \{1, 2 \ldots, 9\}$ 5-minutes steps
- Features:
  - Boolean flag – weekend or weekday
  - Hour of the day
  - Past W samples of the number of active users

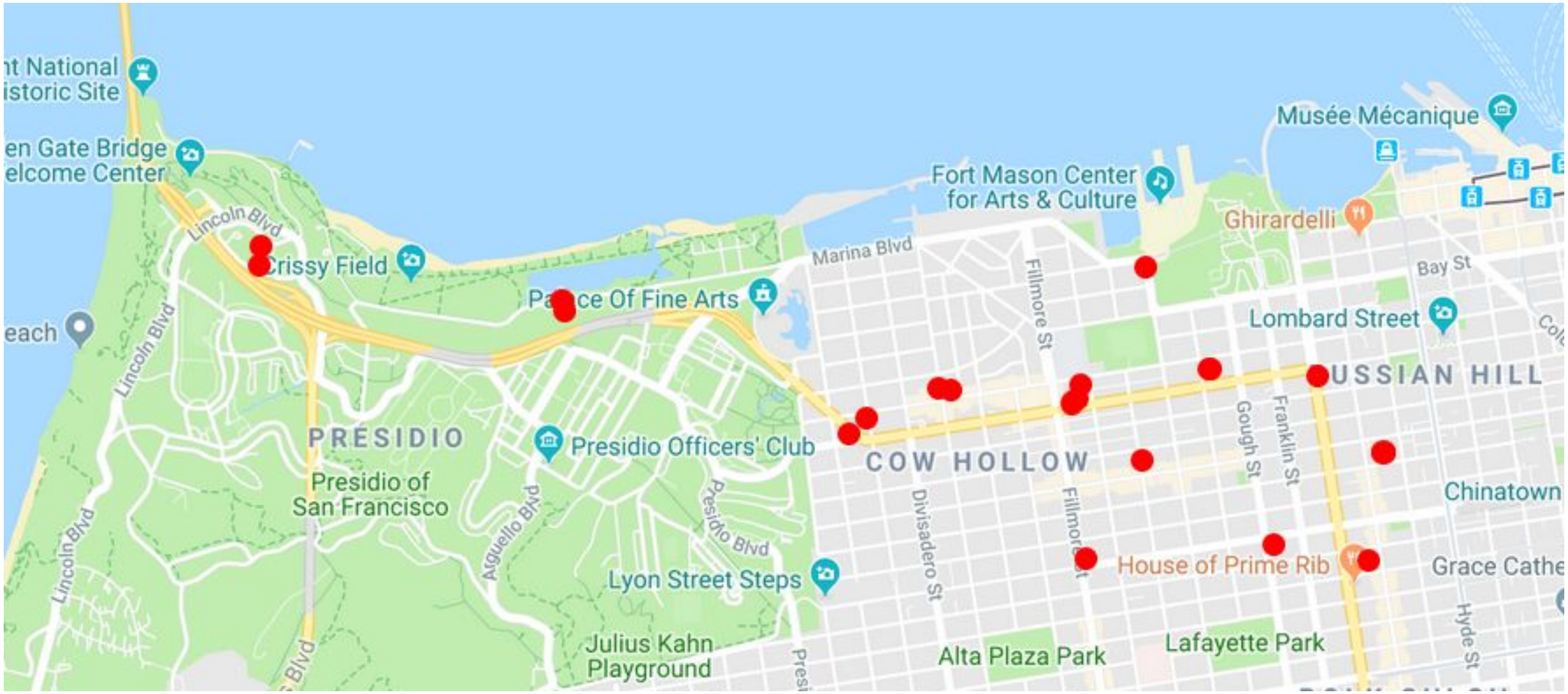
Data preprocessing

- The number of active users is averaged every 5 minutes
- Scaling and log(1+x) applied to the dataset

Cluster-based prediction

- Target: vector with the number of active users in each eNB of the cluster, with a look-ahead step $L \in \{1, 2 \dots, 9\}$ 5-minutes steps
- Features:
  - Boolean flag – weekend or weekday
  - Hour of the day
  - Vector with past W samples of the number of active users in each eNB of the cluster

Data preprocessing



- Sample cluster in San Francisco
- 22 base stations

Algorithms

- Bayesian Ridge Regressor (BRR)
  - Local-based only
- Random Forest Regressor (RFR)
  - Local- and cluster-based
- Gaussian Process Regressor (GPR)
  - Local- and cluster-based
  - Combined kernel with
    - Dot product kernel (non stationary behavior)
    - Rational quadratic kernel (mixture of stationary behaviors)
    - White kernel (noisy input)

Hyperparameters

Bayesian Ridge Regressor [18], [19]	
α	$\{10^{-6}, 10^{-3}, 1, 10, 100\}$
λ	$\{10^{-6}, 10^{-3}, 1, 10, 100\}$
Random Forest Regressor [20], [21]	
Number of trees N_{rf}	$\{1000, 5000, 10000\}$
Gaussian Process Regressor [22]	
α	$\{10^{-6}, 10^{-4}, 10^{-2}, 0.1\}$
σ_k	$\{0.001, 0.01\}$

Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011.

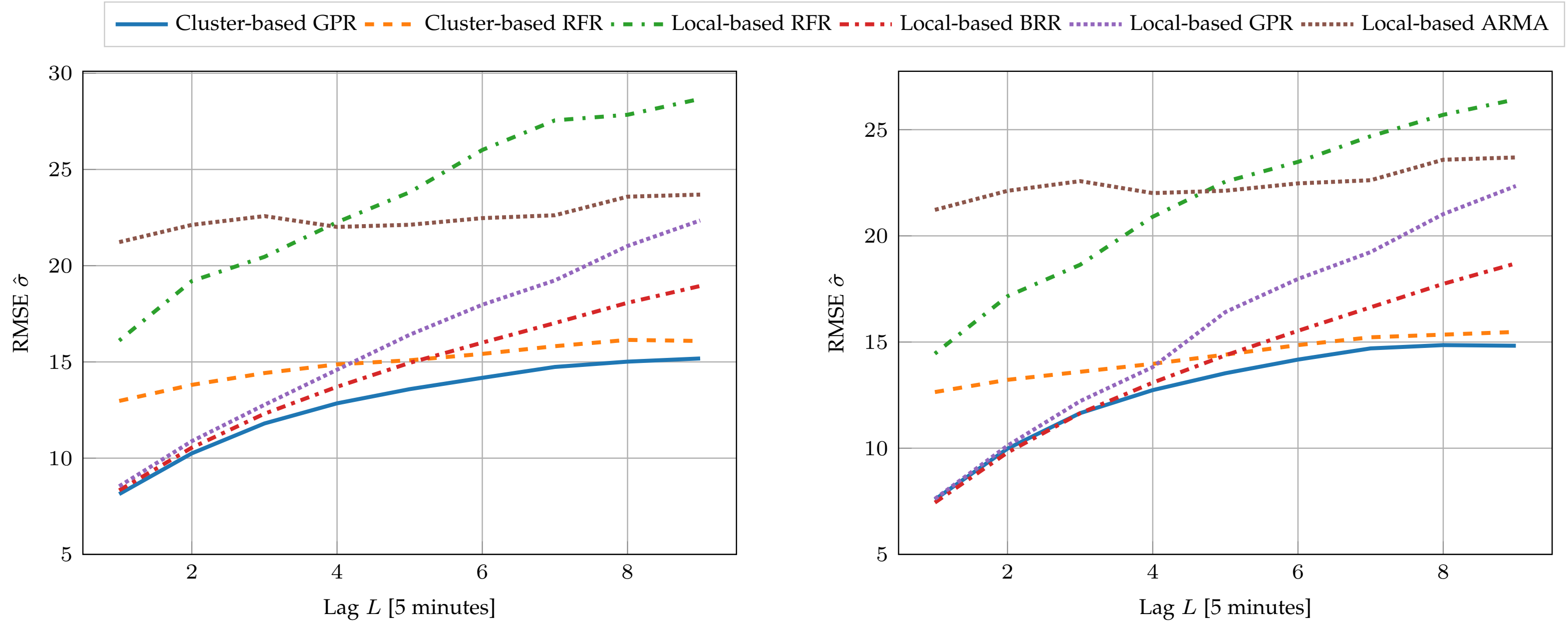
Training and testing

- 3-fold cross validation to select hyperparameters (with time-consistent split)
- RMSE considered for the prediction error:

$$\sigma_i = \sqrt{\frac{1}{N_{te}} \sum_{t=1}^{N_{te}} (y_i(t) - \hat{y}_i(t))^2}$$

- The RMSE is averaged over the base stations of each cluster
- Training dataset from 01/31 to 02/20
- Testing dataset from 02/21 to 02/26

Performance evaluation



Fixed $W = 1$ for each 5-minute step

Best W for each L

Look-ahead step L	1	2	3	4	5	6	7	8	9
BRR	6	6	4	4	3	3	3	2	2
cluster-GPR	3	2	2	2	2	1	6	5	4

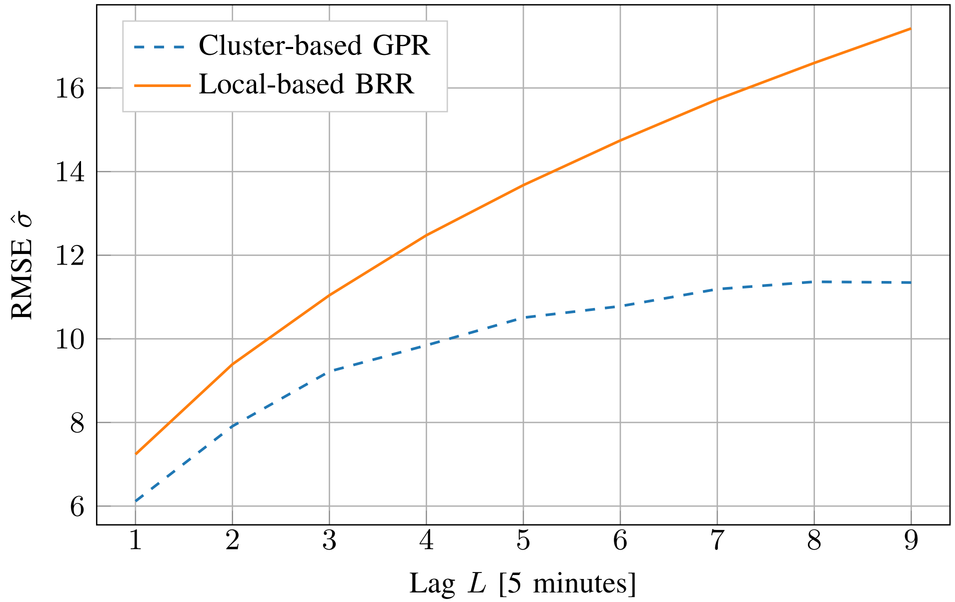
Performance evaluation

- Spatial correlation (cluster- vs local-based) is more impactful than temporal correlation

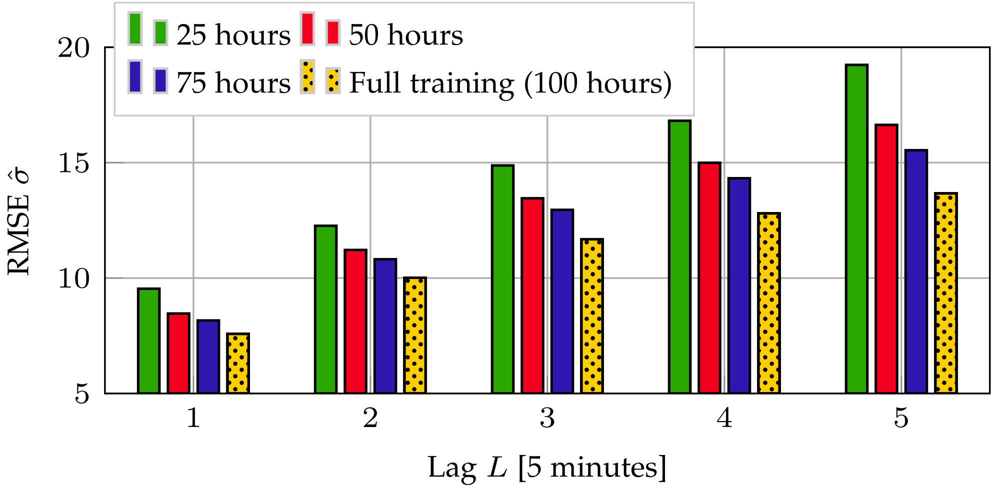
53% RMSE reduction

5% RMSE reduction when increasing W

- Exploit geographic constraints on mobility flows
- When considering all the 472 eNBs (in 22 clusters):



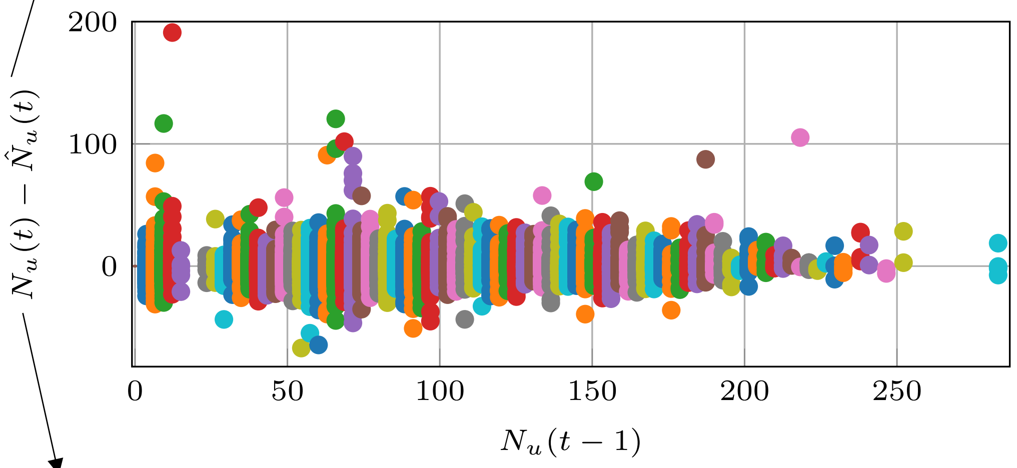
Performance Evaluation



Varying the training set size:

- performance improves with more data
- performance difference is more marked for more distant forecasts

Predicted number of users



Real number of users

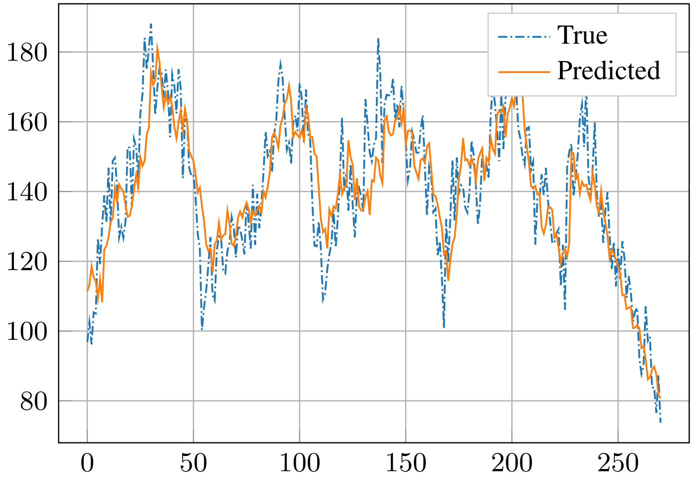
Residual analysis:

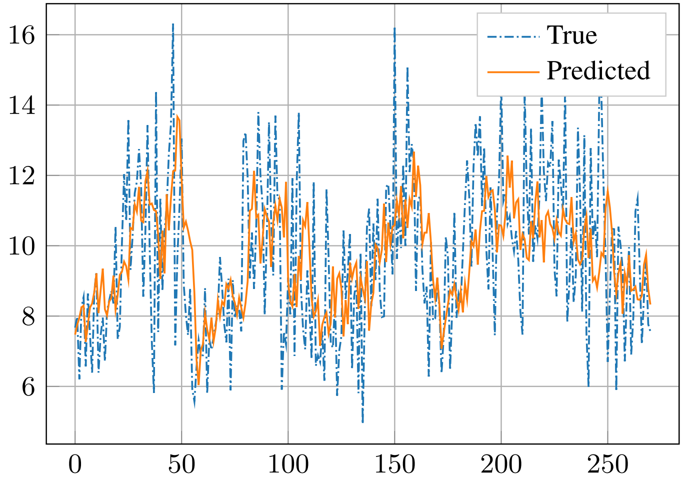
- x-axis quantized in 100 bins
- largest errors for transitions from small to large number of users (left part of the plot)

Example of predicted timeseries

- Cluster-based GPR
- High number of users

- Low number of users



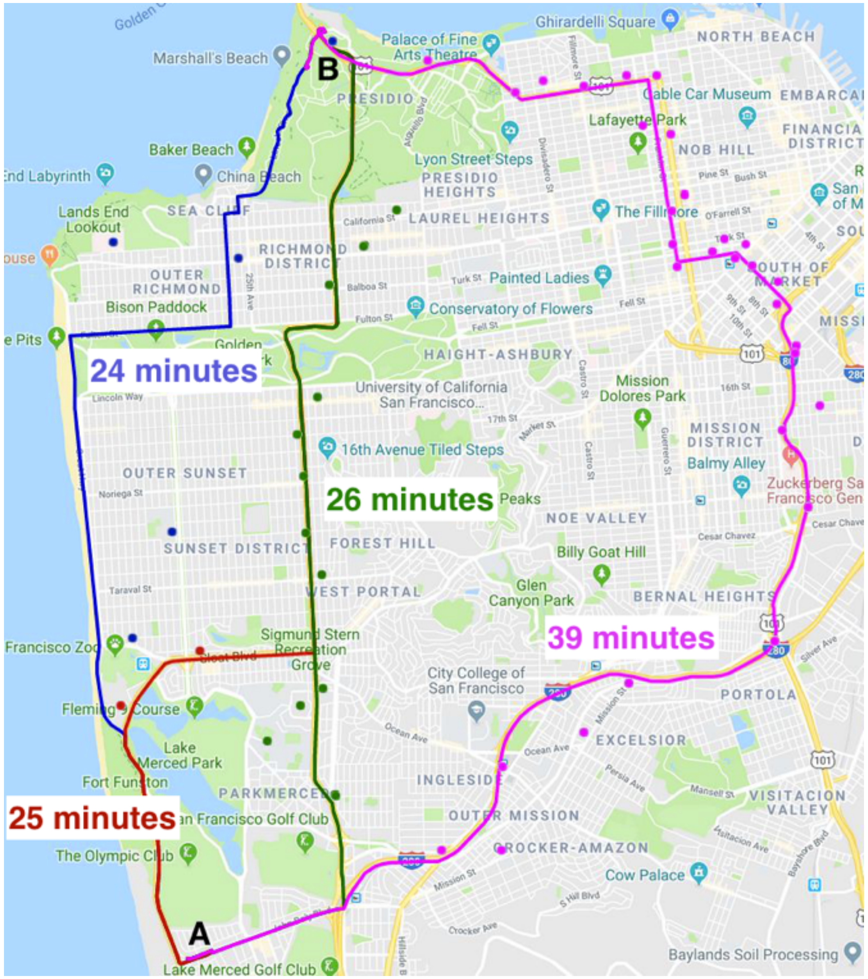


Good tracking of daily patterns
Very noisy traces

Use cases for the prediction

- Medium-timescale horizon (5 – 45 minutes)
- Network management and operations:
    - Predictive load-balancing
    - Bearer pre-configuration for anticipatory mobility
    - Radio resource scaling
- New services to the end-users
    - Vehicular route optimization with network KPIs
      (*provide transit directions tailored on the network performance)*

Vehicular route optimization with network KPIs



Predicted throughput
(as a function of number of active users)

Route	R1	R2	R3	R4
	Feb. 23rd, 19:00			
$\hat{S}$ [Mbit/s]	1.93	2.51	2.36	2.74
$D_{o,\max}$ [s]	133.47	157.8	172.5	171.2
	Feb. 24th, 19:00			
$\hat{S}$ [Mbit/s]	1.72	2.00	2.28	2.89
$D_{o,\max}$ [s]	152.4	157	148.8	169.1
	Feb. 24th, 19:20			
$\hat{S}$ [Mbit/s]	2.05	2.49	1.98	2.86
$D_{o,\max}$ [s]	152.1	123.7	172.5	116.7

Predicted outage duration
(as a function of number of active users)

Conclusions

- Proposed a data-driven architecture for 5G networks
- Evaluation of learning approaches on a large-scale dataset from a network operator
    - RAN clustering
    - Prediction
- Exploiting spatial correlation is beneficial for medium-term prediction
- Reduction of the prediction error up to 53%
- Enabler of new use cases – both for RAN control and innovative user services

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