Mobile Networking, Analytics, and Edge Intelligence Workshop

Machine learning-empowered Spatial-Temporal Trajectory Data Analysis at Network Edge

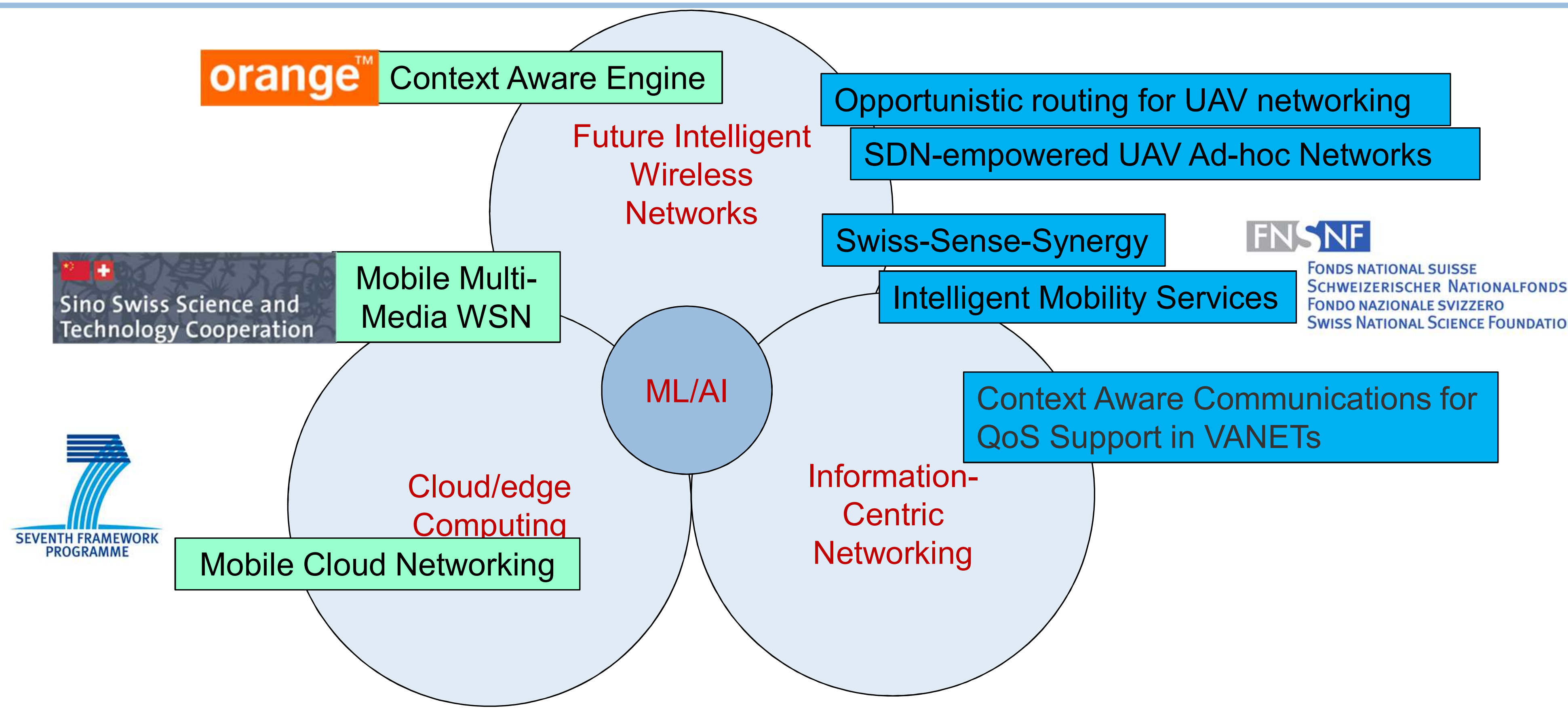
Zhongliang Zhao
Communication and Distributed Systems Group (led by Prof. Torsten Braun)
Institut für Informatik, Universität Bern, Switzerland

16.08.2019, Tsinghua University, Beijing b UNIVERSITÄT BERN

Overview

- Research Projects
- SNF: *Swiss-Sense-Synergy*
  - Machine Learning-empowered Indoor Positioning with MEC
- EU COST Action
  - VANETs Vehicle Location Prediction using Hybrid Markov Chain
- EU H2020 proposal collaboration opportunities

Research Projects



u^b UNIVERSITÄT BERN

Research Projects

No.	Project Name	Funding & Budget (CHF)	Start	End	Role
1	Intelligent Mobility Services	SNF 1/2 M	2019	2023	Participant
2	Context Awareness Engine	France Telecom 200 K	2017	2019	Co-PI
3	SDN UAVNets	SERI Mobility 4 K	2018	2019	PI
4	Fog Computing for Fog Monitoring	SERI Seed 20 K	2018	2019	Co-PI
5	Swiss Sense Synergy	SNF 1 M	2015	2018	Co-PI
6	Mobile Cloud Networking	EU FP7 12 M	2012	2016	Participant
7	Opportunistic Routing in Mobile UAV Ad-hoc Networks	SNF 200 K	2010	2014	Participant
8	Mobile Multi-Media WSNs	SNF SSSTC 100 K	2011	2012	Co-PI
9	Wireless Sensor Network Testbed	EU FP7 3 M	2009	2011	Participant
10	Resilient Communication Networks	EU COST 700 K	2016	2020	Participant

SNF Swiss-Sense-Synergy

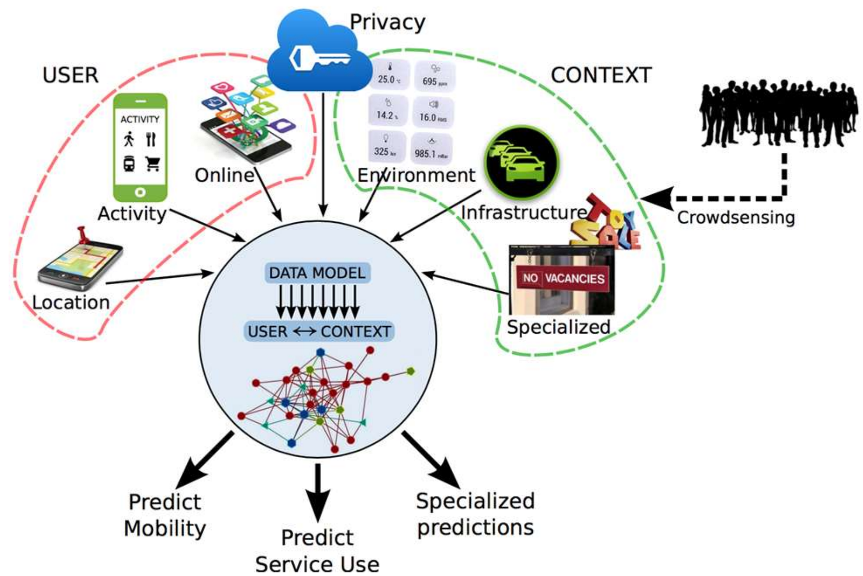
> Swiss National Science Foundation

> Project Technical Coordinator

> Consortium: 3 CH +1 SW partners

> Goal: provide a unifying framework for secure and privacy-preserving location-based service, by using synergistic information (real-time context, social profiles, etc)

- UNIBE: Indoor mobile device tracking



Synergistic User ↔ Context Awareness Analytics

Mobile Devices Indoor Tracking – Client-based Solution

> Indoor Positioning System
  - Estimate the indoor locations of mobile users in real-time
  - Advanced (ensemble) machine learning algorithms to enhance performance
  - Particle filter data fusion of multiple information
    - Motion estimation from smartphone embedded inertial measurement units
    - Map likelihood from indoor floor map
    - Zone transition likelihood from HMM-based zone prediction using Wi-Fi RSSI & MF signatures
    - Ranges from Wi-Fi ranging models

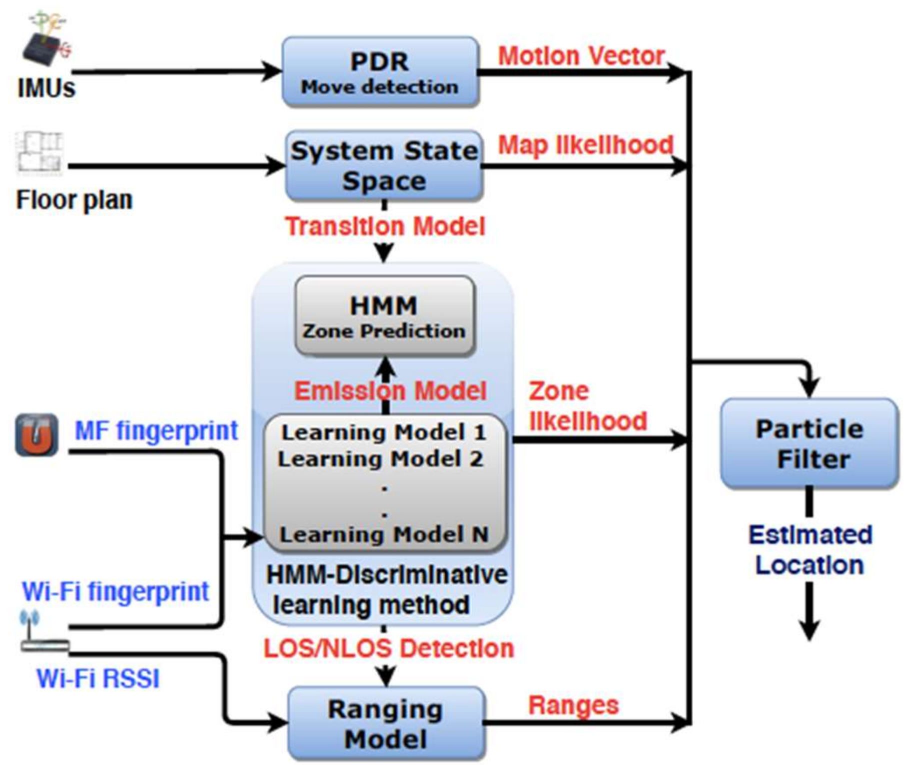


Figure 1: Indoor Localization System Architecture Overview.

UNIVERSITÄT BERN

Hidden Markov Model Discriminative Ensemble Learning (HMM-d) for Indoor Zone Detection

> Goal: indoor zone detection
> Indoor zone = HMM states
> Fingerprinting indoor landmark
  - Indoor location-specific discriminative sensor measurements
  - Wi-Fi RSSI + Magnetic field
> HMM-d model
  - Transition probability: likelihood of moving from one zone to another
  - Emission probability: likelihood of producing a particular set of observations within a zone

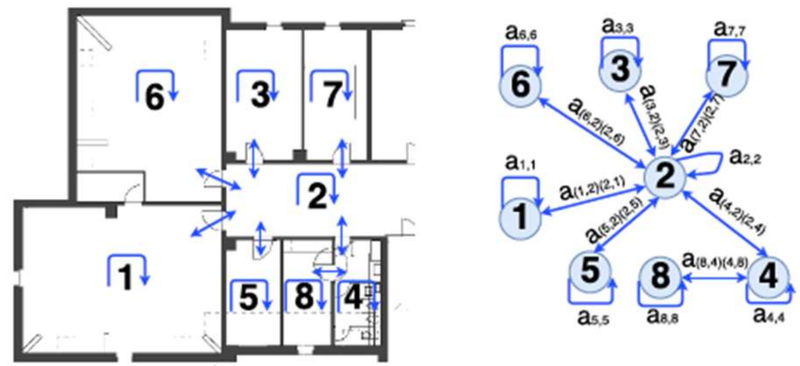


Figure 2: Zone definition and transition model for HMM-d.

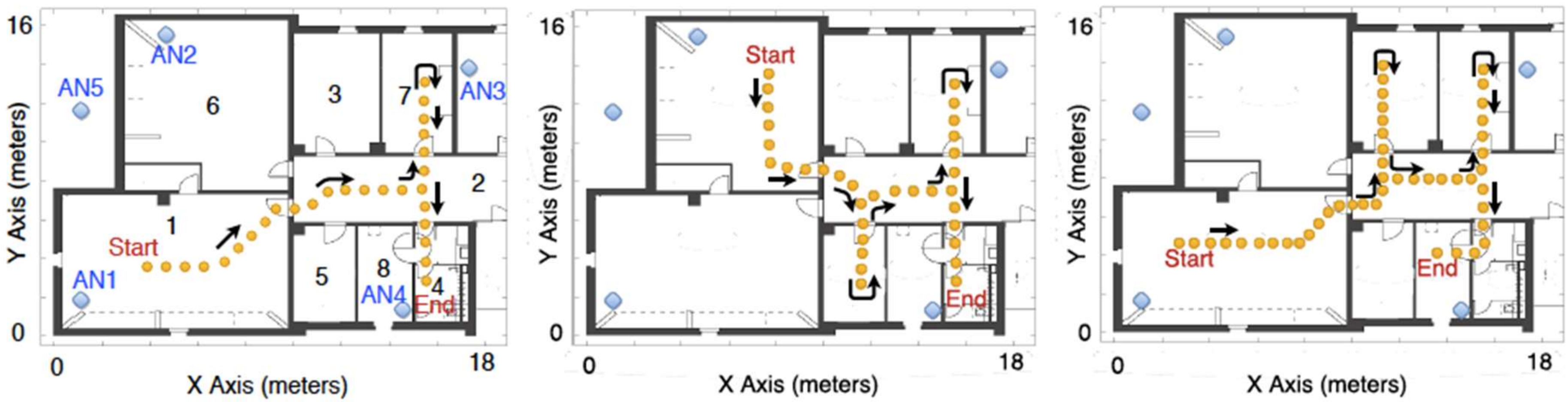
Enhanced Particle Filter (Particle Filter Ensemble Learning Method) for Indoor Tracking

- Indoor locations can be estimated from a set of noisy environment observations (posterior probability distribution)
- Weighted particles represent posterior probabilities
- Particle filter estimates the posterior probability distribution of system states from observations
  - Cartesian coordinates of the target
  - Heading directions
  - Step sizes
  - Detected zones

Algorithm 1: PF-ELM

1 Initialize particles:$x_0^i = q(X_0), i = 1, ..., N$;
2 Update the particles: $x_t^i = G \cdot x_{t-1}^i + \eta$
3 Calculate the ranging likelihood:
$$P(\hat{d}_{j,t} \mid x_t^i) = \frac{1}{\sigma_j\sqrt{2\pi}} \exp^{-\frac{[\hat{d}_{j,t} - \sqrt{(x^i - x_j)^2 + (y^i - y_j)^2}]^2}{2\sigma_j^2}};$$
4 Calculate the zone likelihood:
$$P(s_t \mid X_t^i) = \frac{P(X_t^i \mid \hat{s}_t) \cdot P(\hat{s}_t)}{P(X_t^i)};$$
5 Compute unnormalized weights:
$$\hat{w}_t^i = P(X_t^i \mid \hat{s}_t) \cdot \prod_{j=1}^{M} P(\hat{d}_{j,t} \mid X_t^i)$$
6 Normalize weights: $w_t^i = \frac{\hat{w}_t^i}{\sum_{n=1}^{N} \hat{w}_n^i}$
7 Resample the particles;
8 Compute the estimated state:$X_t = \sum_{i=1}^{N} w_t^i \cdot x_t^i$;
9 Go to step 3 for next iteration;

Experiment Settings



(a) The First Trajectory (b) The Second Trajectory (c) The Third Trajectory

Figure 3: Zones, trajectories and ANs distribution (Diamond blue points: Anchor Nodes; Yellow points: trajectories)

CS building at Uni Bern, an office area with size of 336 m²
Motorola Nexus 6 as mobile device, Wi-Fi access points

Results – Zone Prediction Accuracy

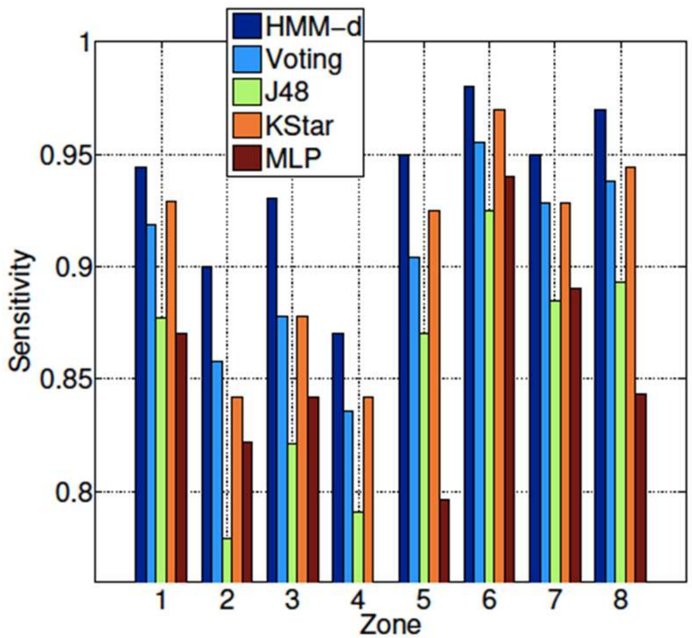


Figure 4: Zone Prediction Performance, Sensitivity score.

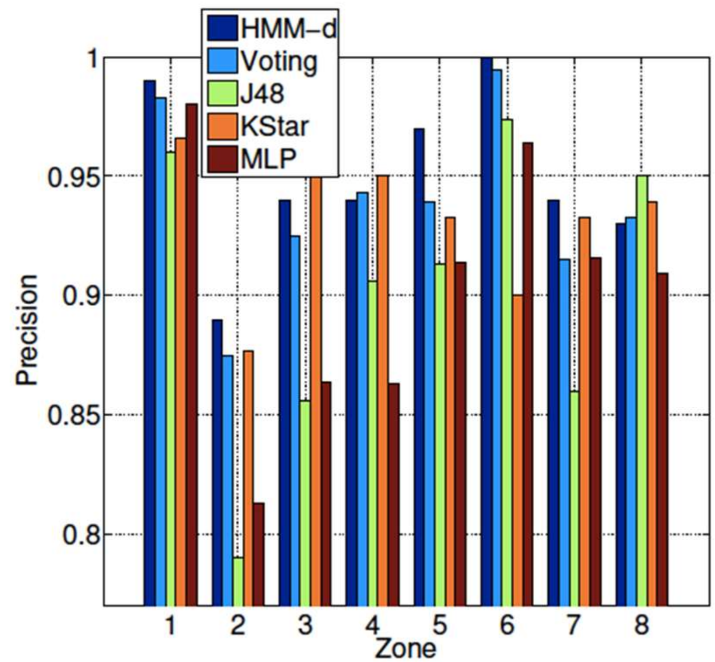


Figure 5: Zone Prediction Performance, Precision score.

Results – Tracking Accuracy

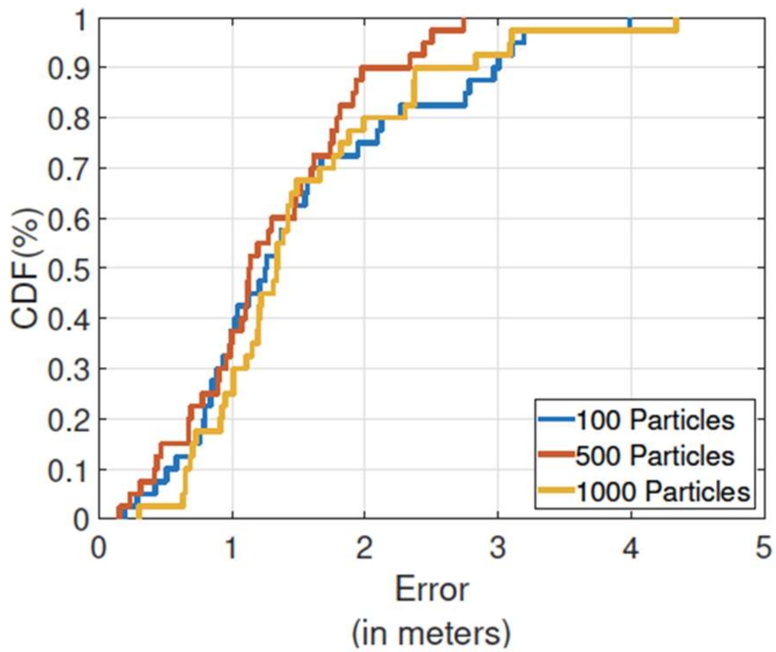


Figure 7: PF-ELM localization performance vs number of particles.

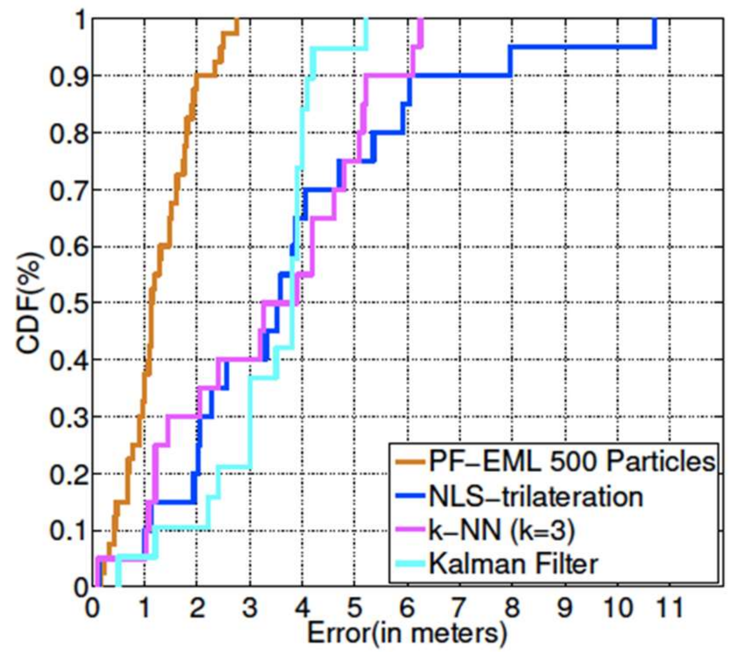
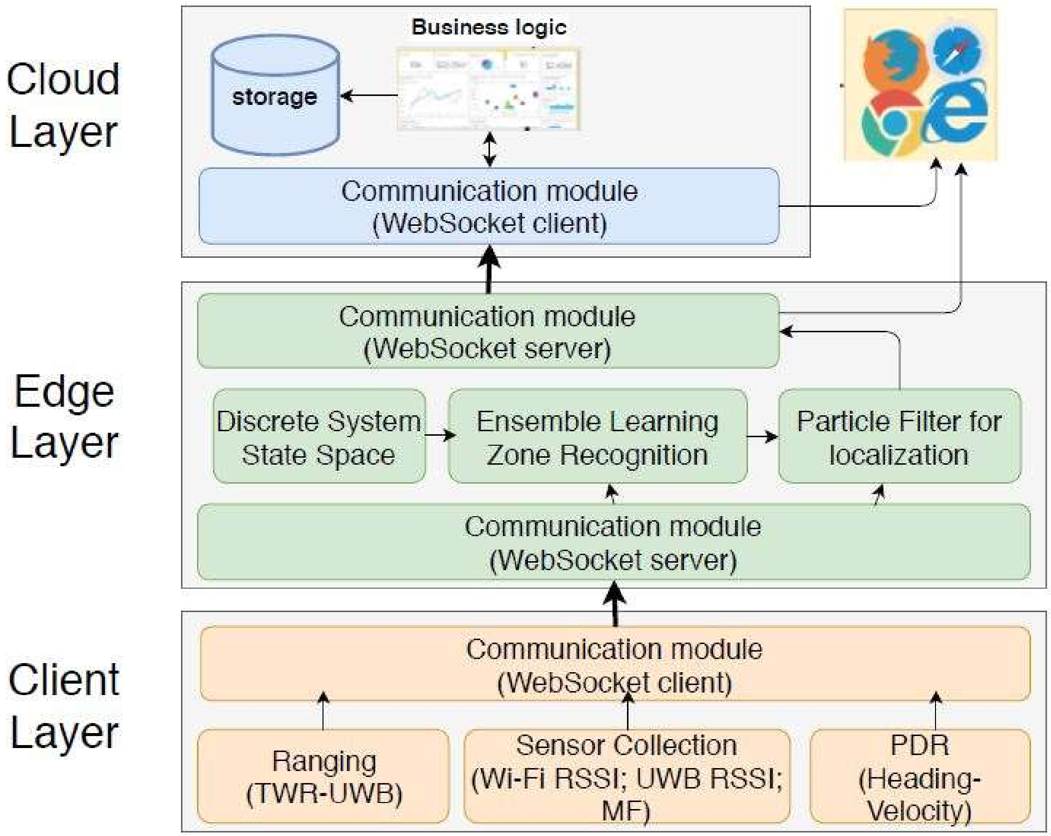


Figure 9: Localization error CDF of PF-ELM (500 particles), NLS, k-NN (k=3) and KF.

Mobile Devices Indoor Tracking – Edge-based Solutions



- An Reinforcement Learning module to provide system robustness against system failures
- A distributed machine learning architecture:
  - Lightweight ML (indoor zone detection) running on the devices
  - Heavy ML algorithms (RLPF) offloaded to nearby edge servers

Reinforcement Learning-based Particle Filter at Network Edge

- Poor particle distribution may lead to long convergence time and localization failure (kidnapping robot problem)
- Resampling method to eliminate particles with low importance weights
- Q-learning enables the learning agent (localization algorithm) to learn the optimal behaviour/action (5 particle distributions strategies) at each state
- System state detection (starting/localizing/failure)

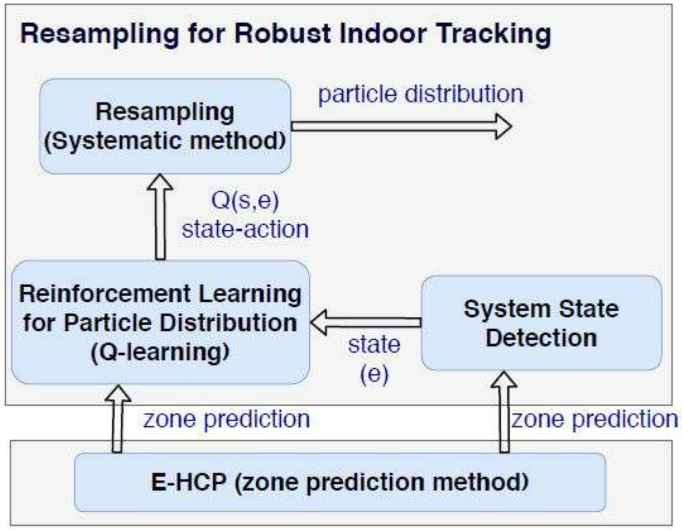


Figure 2: Reinforcement Learning Method for Robust Indoor Tracking Resampling.

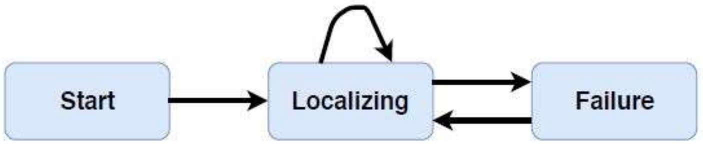
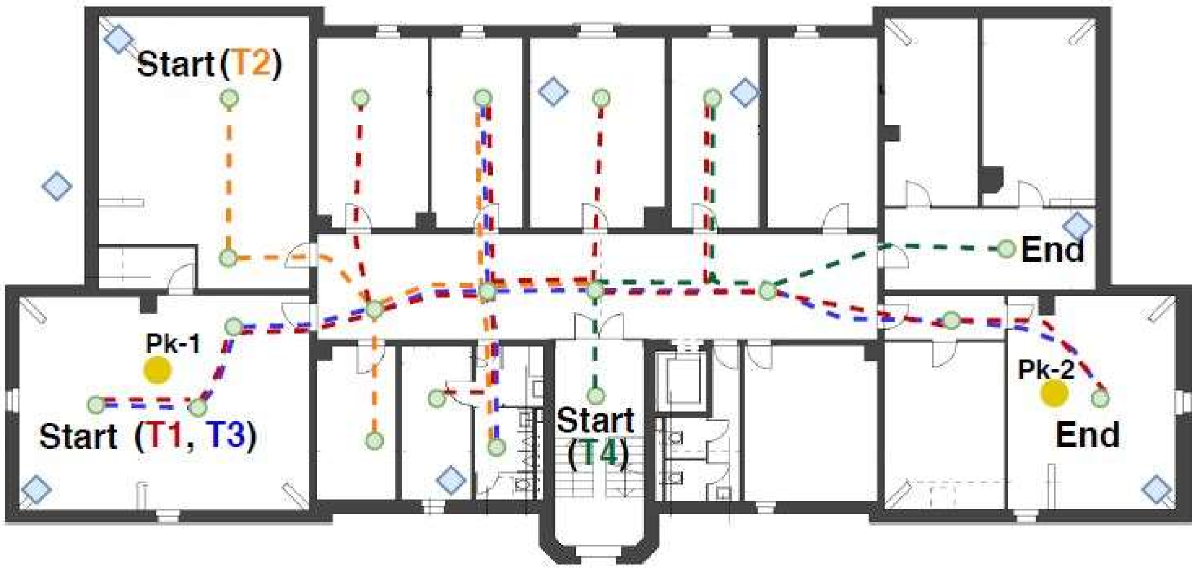


Figure 3: PFRL transition model learner agent.

Experiment Settings



CS building at Uni Bern, an office area with size of 672 m²
Yellow points are the kidnapped robot check points

u^b UNIVERSITÄT BERN

MEC-based IPS Results – Accuracy & Failure Recovery Time

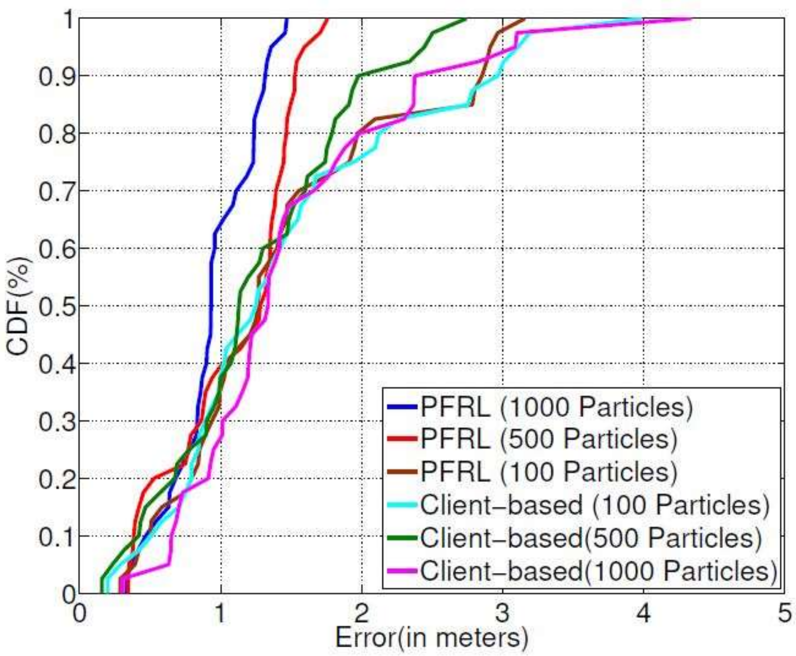


Figure 11: Impacts of particle numbers on performance of PFRL and client-based PFRL in scenario 1.

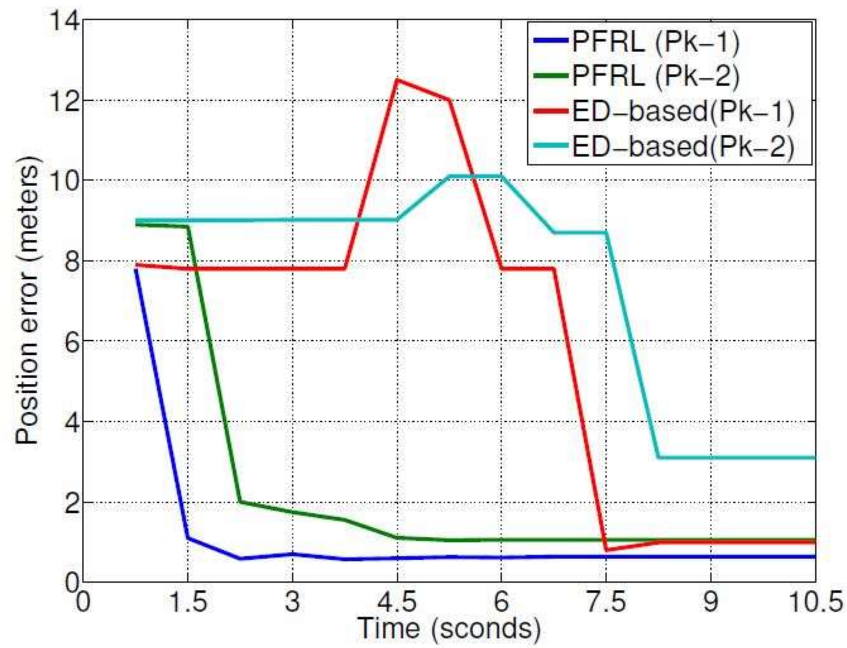


Figure 15: Scenario 1: Global Localization Failure recovery. Particles convergence time after localization failure

EU COST VANET Vehicle Mobility Prediction

- City of Porto VANETs testbeds
- Infrastructures
  - Testbed deployed in the City of Porto, Portugal
  - On Board Units (OBUs): 460+ cabs with GPS and 3/4G & 600+ bus/garbage trucks
  - Road Side Units (RSUs): 200+
  - IEEE 802.11p/WAVE protocols for OBU-RSU communications
- Services
  - Free Internet access onboard
  - DTN for non-urgent city-scale sensor data collection

Over-The-Top Content Pre-fetching using Vehicle Mobility Prediction

> Predict OBU's future connected RSUs
  - Prefetch the OTT content before connected to next RSU

> Approach
  - 3-tier caching architecture
  - First order Markov chain
  - Second order Markov chain
    - Current & last connected RSUs
  - Hybrid solution based on trace quality
  - Linear/exponential interpolation
    - Bus

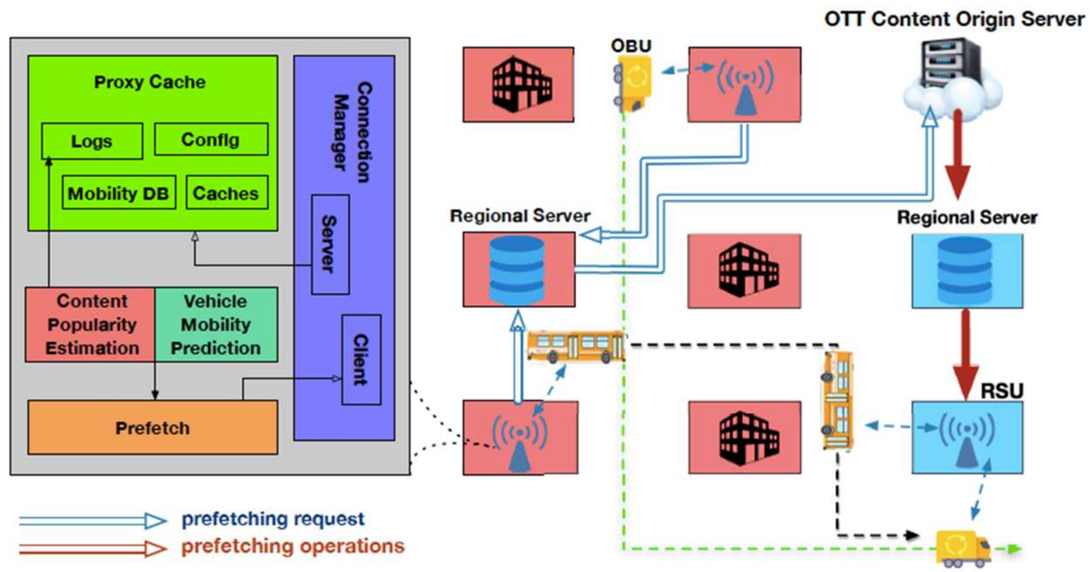


Figure 1: System Architecture.

UNIVERSITÄT BERN

Models & Algorithms

Table I: Vehicle mobility prediction algorithm parameters

Parameter Name	Parameter Definition
S_i	State i in the Markov chain
$Pr\{S_{i+1}(t)\}$	Probability of at State $(i+1)$ at t
RSU_i, OBU_i	RSU ID j, OBU ID j
D, T_i	Weekday and time of being at State i
λ, t	Future time interval and current time
$C = \{RSU_1, .., i\}, \|C\| = I$	Set of RSUs, I is the total numbers
$U = \{OBU_1, .., j\}, \|U\| = J$	Set of OBUs, J is the total numbers
$N_{RSU_i}(t)$, $N_{RSU_i}(t+\delta)$	Number of OBUs connected with RSU i at time t and $t+\delta$ (*e.g.*, m and M)
$N_{in,RSU_i}(t+\delta)$	Number of OBUs that may be connected with RSU i at time $t+\delta$ (*e.g.*, n1)
$N_{out,RSU_i}(t+\delta)$	Number of OBUs that may be disconnected from RSU i at time $t+\delta$ (*e.g.*, n2)
$F_{RSU_i(t)}$, $F_{RSU_{i'}(t)}$	Subset of OBUs that are connected and not connected with RSU_i at time t
P_{j_1} , $OBU_{j_1} \in F_{RSU_{i'}(t)}$	$P\{OBU_{j_1}\ is\ in\ F_{RSU_{i'}(t)}\ at\ time\ t\} \times P\{OBU_{j_1}\ connects\ to\ RSU_i\ at\ time\ t{+}\delta\}$
P_{j_2} , $OBU_{j_2} \in F_{RSU_i(t)}$	$P\{OBU_{j_2}\ is\ in\ F_{RSU_i(t)}\ at\ time\ t\} \times P\{OBU_{j_2}\ leaves\ RSU_i\ at\ time\ t{+}\delta\}$

$$Pr\{S_{i+1}(t+2\lambda)\} = \begin{cases} Pr\{S_{i+1}|S(t+\lambda)=S_i, D, T(t+\lambda)=T_i\} & S_{i-1}=0 \\ Pr(S_{i+1}|S(t)=S_{i-1}, S(t+\lambda)=S_i, \\ T(t)=T_{i-1}, T(t+\lambda)=T_i, D) & S_{i-1}\neq 0 \end{cases} \quad (2)$$

$$Pr\{S_{i+1}|S(t+\lambda)=S_i, D, T(t+\lambda)=T_i\} = Pr\{S_{i+1}|S(t+\lambda)=S_i\} + Pr\{T(t+\lambda)=T_i, D\} \quad (3)$$

$$\begin{aligned} &Pr(S_{i+1}|S(t)=S_{i-1}, S(t+\lambda)=S_i, T(t)=T_{i-1}, T(t+\lambda)=T_i, D) \\ &= Pr\{S_{i+1}|S(t)=S_{i-1}, S(t+\lambda)=S_i\} \\ &+ Pr\{T(t)=T_{i-1}, T(t+\lambda)=T_i, D\} \end{aligned} \quad (4)$$

u^b
UNIVERSITÄT BERN

Evaluation Setup

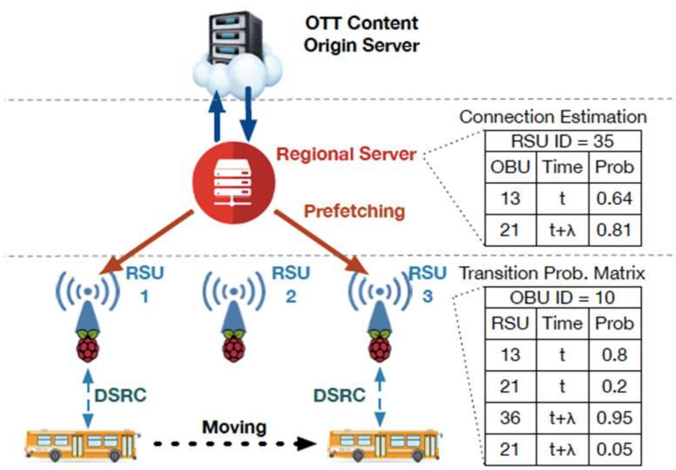


Figure 7: Prototype Implementation Topology at *Aveiro testbed*

- 3 Raspberry Pi as 3 RSUs & 1 client as OBU
- RSU (Raspberry Pi) with 500MB cache size
- 1700 content object requests
- Evaluation metrics: CPU load/memory consumption/offloaded traffic/cache-hit ratio/average consumer latency

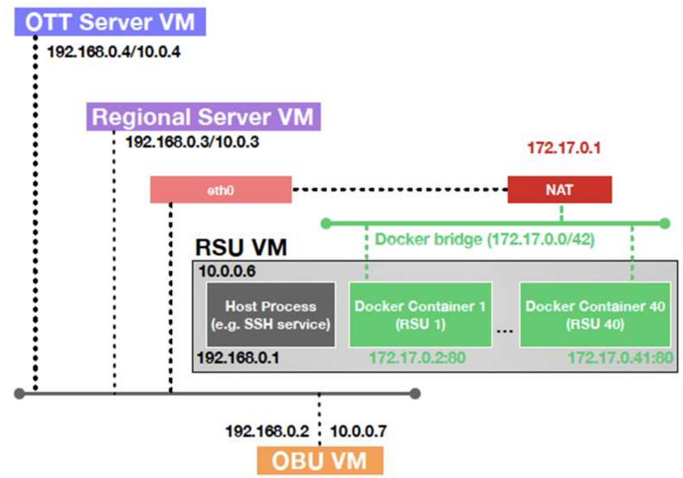


Figure 8: OpenStack Experiment Topology at *Bern testbed*

- 1 RSU VM with 40 Docker container as 40 RSUs & 1 OBU VM
- 9400 content object requests
- Evaluation metrics: prediction accuracy/cache-hit ratio/average consumer latency

Results – Prediction Algorithm Accuracy

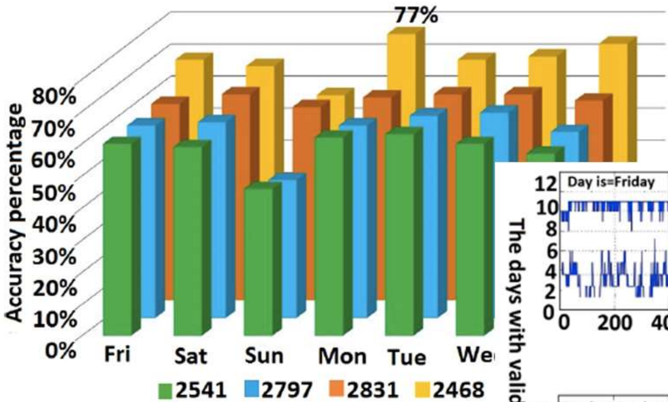


Figure 10: Prediction accuracy of *hybrid predictor*

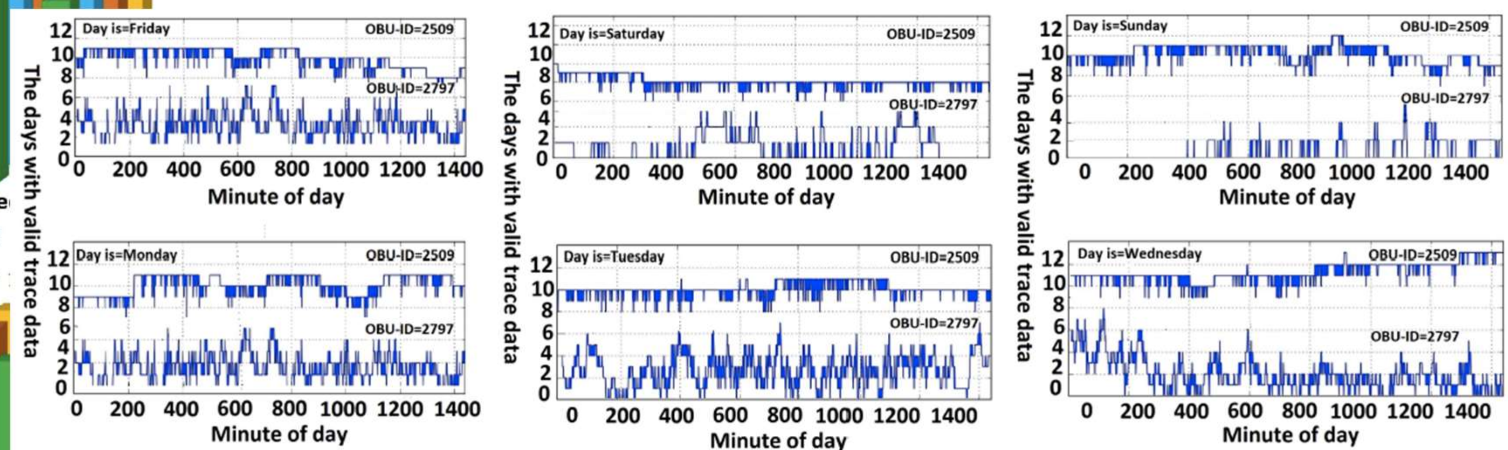


Figure 12: Trace qualities of OBU_ID 2509/2797 on weekdays.

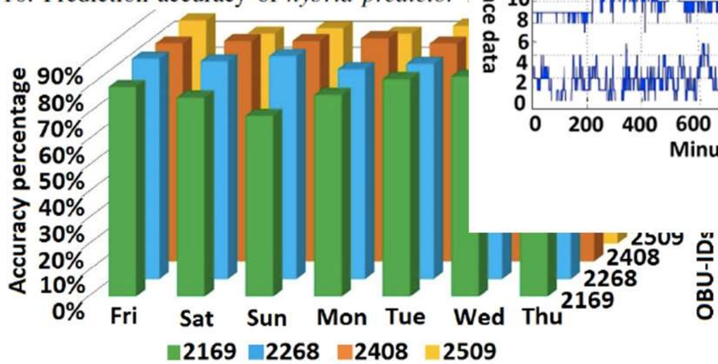


Figure 9: Prediction accuracy of *hybrid predictor* for OBUs with good quality

Results – Bern OpenStack Testbed
Prefetching Mechanisms (Cache Hit Ratio & RSU CPU)

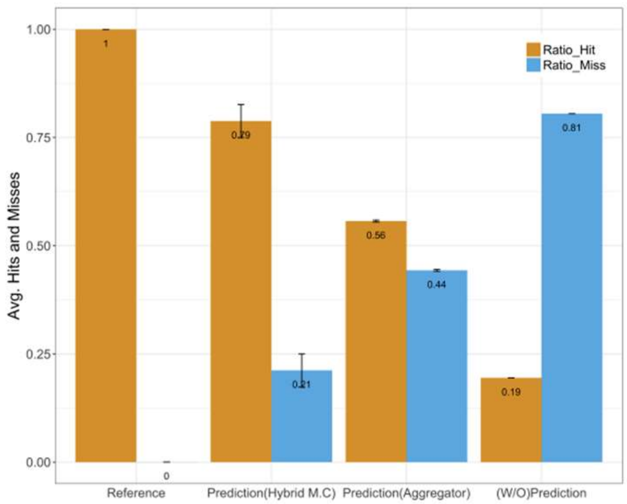


Figure 18: RSU Cache Hit-Miss Ratio of Bern Testbed

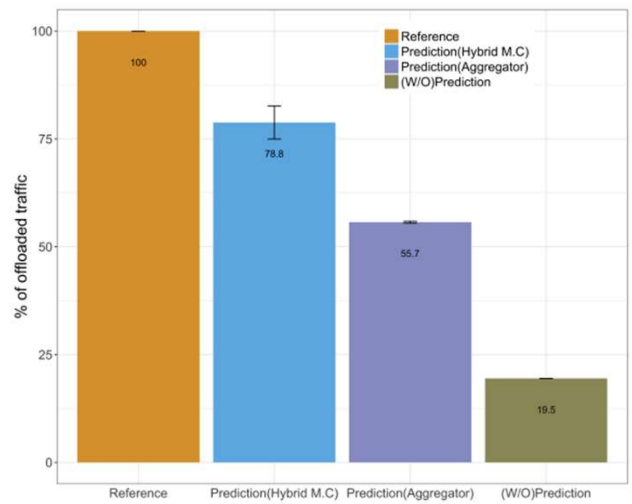


Figure 19: RSU Total Offloaded Traffic of Bern Testbed

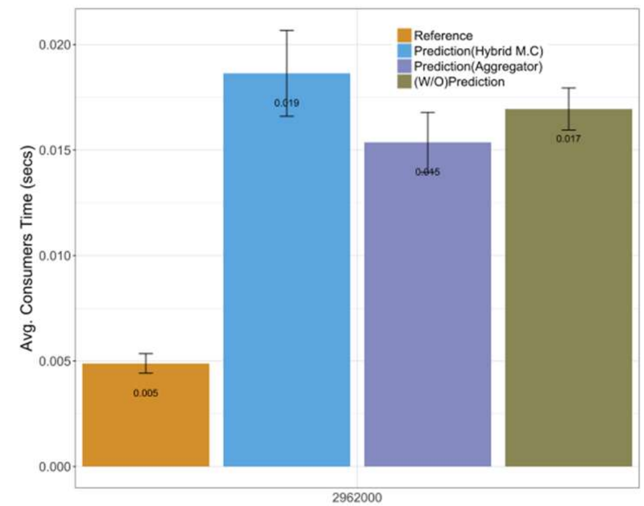


Figure 21: Average Consumer Times of Experiments on the Bern Testbed

UNIVERSITÄT BERN

Relevant Publications

> Jose Carrera, Zhongliang Zhao*, Torsten Braun, Zan Li. A Particle Filter-based Reinforcement Learning Approach for Reliable Wireless Indoor Positioning (In Press). IEEE Journal on Selected Areas in Communications (IEEE JSAC).

> Zhongliang Zhao, Lucas Guardalben, Mostafa Karimzadeh, Jose Silva, Torsten Braun, Susana Sargento. Mobility Prediction-Assisted Over-the-Top Edge Prefetching for Hierarchical VANETs (In Press). IEEE Journal on Selected Areas in Communications (IEEE JSAC).

> Zhongliang Zhao, Eryk Schiller, Eirini Kalogeiton, Torsten Braun, Burkhard Stiller, Mevlut Turker Garip, Joshua Joy, Mario Gerla, Nabeel Akhtar, Ibrahim Matta. Autonomic Communications in Software-driven Networks. IEEE Journal on Selected Areas in Communications (IEEE JSAC).

> Jose Carrera, Zhongliang Zhao*, Torsten Braun, Augusto Neto (September 2017). A Robust Real-time Indoor Tracking System in Smartphones. Elsevier Journal of Computer Communications (Elsevier COMCOM).

> Zhongliang Zhao, Mostafa Karimzadeh, Florian Gerber, Torsten. Braun. Mobile Crowd Location Prediction with Hybrid Features using Ensemble Learning (In Press). Elsevier Journal of Future Generation Computer Systems (Elsevier FGCS).

> Zhongliang Zhao, Pedro Cumino, Arnaldo Souza, Denis Rosario, Torsten Braun, Eduardo Cerqueira, and Mario Gerla. Software-Defined Unmanned Aerial Vehicles Networking for Video Dissemination Services (In Press). Elsevier Journal of Ad hoc Networks (Elsevier AdHocNets).

> Augusto Neto, Zhongliang Zhao*, Joel Rodrigues, Hugo Camboim, Torsten Braun. Fog-based Crime-Assistance in Smart IoT Safety Transportation Systems (February 2018). IEEE ACCESS.

> Zan Li, Torsten Braun, Xiaohui Zhao, Zhongliang Zhao, Fengye Hu, Hui Liang. A Narrow-Band Indoor Positioning System by Fusing Time and Received Signal Strength via Ensemble Learning (January 2018). IEEE ACCESS.

> Denis Rosario, Zhongliang Zhao*, Aldri Santos, Torsten Braun, Eduardo Cerqueira. A Beaconless Opportunistic Routing Based on a Cross-Layer Approach for Efficient Video Dissemination in Mobile Multimedia IoT Applications (June 2014). Elsevier Journal of Computer Communications (Elsevier COMCOM).

> André Gomes, Bruno Sousa, David Palma, Vitor Fonseca, Zhongliang Zhao, Edmundo Monteiro, Torsten Braun, Paulo Simoes, Luis Cordeiro (2016). Edge caching with mobility prediction in virtualized LTE mobile networks. Elsevier Journal of Future Generation Computer Systems (Elsevier FGCS).

UNIVERSITÄT BERN

EU H2020 Project Proposal – 5G for Connected and Automated Mobility (CAM)

- Deadline: November 13, 2019
- Expectations:
  - Validation of 5G technologies and architectures in a CAM context
  - 5G for connected and automated mobility (CAM) applications
  - Multi-technologies integrations (IEEE 802.11p, C-V2X, 5G-V2X)
  - AI for advanced 5G-CAM use cases in automotive and railway
  - Dataset management of connectivity and sensors
  - European cloud infrastructure supporting Europe-wide CAM service roaming
  - Understanding CAM market players and public authorities
- Project budget
  - EUR 7 – 10 M

Thank You for Your Attention !

UNIVERSITÄT BERN

> zhao@inf.unibe.ch
> http://cds.unibe.ch