

Budapest University of Technology and Economics Department of Measurement and Information Systems

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On Vehicular Data Aggregation in Federated Learning – Parking Simulation and Privacy

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Introduction



Privacy Leakage

Conclusion

Vehicular Crowdsensing

Challenges of V2V crowdsensing:

- O Communication channel usage?
- Heterogeneous sensors?
- Interoperability?
- Privacy?







Privacy Leakage

Conclusion

Vehicular Federated Learning

Solved challenges of V2V crowdsensing:

- Communication channel usage √
 Heterogeneous sensors √
 Interoperability √
- Privacy √?



What about Privacy?

Introduction

Simulation

Privacy Leakage

Conclusion

Federated Learning – Ideal Case



Introduction

Simulation

Privacy Leakage

Conclusion

Federated Learning – Leakage from Gradients



A Case Study with SUMO

Privacy Leakage

Conclusion

A Parking Monitoring System – Scenario

A generated small town:

- road network: netgenerate
-) activities:
 - 10,000 inhabitants
 - 3,500 households
 - o -200, +1000 person as commuter traffic
 - 10% uniform random background traffic
 - EU rural age distribution
 - o activitygen

Parking lots:



) off-street parking facilities/garages (capacity: 1500 vehicles)



Privacy Leakage

Conclusion

A Parking Monitoring System – Simulation in SUMO

parking_activities:

- 🔘 a new Python tool (available on GitHub)
- \bigcirc enhances the output of $\verb+activitygen+$
- input: #days, trip output file of activitygen
- output: a trip file



Privacy Leakage

Conclusion

A Parking Monitoring System – Simulation in SUMO

The added parking_activities:

-) Random traffic: no modification
- Commuter traffic:
 - enters and leaves the simulated network each day
 - repeats the original movements each day
 - adds a parking stop at the destination edge



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Conclusion

A Parking Monitoring System – Simulation in SUMO

The added parking_activities:

Household traffic:

- does not leave the road network
- concatenates the separate movements of a vehicle generated by activitygen
- adds stops in parking lots between the original movements at the destination edge
- $\circ~$ in the morning ~95% of the vehicles depart within a ± 15 minutes window (following a $\mathcal{N}(0,7)$ [minutes] distribution) compared to the original activity-chains



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A Parking Monitoring System – Running the Simulation

Simulation scenarios:

- **Burn-in**: 4 simulated days
- **Stable**: 5 simulated days

During simulations:

- \bigcirc vehicles measure the parking lot occupancy with a 50 m measurement range (via TraCl)
- **ParkingAreaRerouters** handles the potential overdemand for parking lots



Privacy Leakage

A Parking Monitoring System – An Example

 $\widehat{\mathcal{O}}(p,t)$: occupancy estimate for p parking lot at t time



Privacy Leakage



A Simple Tracking Attack

- 1. Compute: $\Delta = (\widehat{\mathcal{O}}_{\rm global}(p,t) \widehat{\mathcal{O}}_{\rm local}(p,t))^2$
- 2. Location inference:
 - 2.1 Average Δ over time
 - 2.2 Select the locations of the resulted top 10 differences





A Simple Tracking Attack

- 1. Compute: $\Delta = (\widehat{\mathcal{O}}_{\text{global}}(p,t) \widehat{\mathcal{O}}_{\text{local}}(p,t))^2$
- 2. Moving time inference:
 - 2.1 Resample Δ with a w = 15 minutes window and average over parking lots $\rightarrow \widehat{\mathcal{O}}_t$ 2.2 Compute $|\frac{d}{dt}\widehat{\mathcal{O}}_t|$ 2.3 Select $\arg \max |\frac{d}{dt}\widehat{\mathcal{O}}_t|$





Results – Location





Results – Moving Time





Results – Household Moving Time

Household type vehicles separated into clusters:





Results - Household Moving Time

Household type vehicles separated into clusters:







Conclusion

- 1. SUMO parking activity simulation:
 - parking_activities tool
 - burn-in and stable phases
- 2. Vanilla vehicular federated learning leaks private information:
 - \circ Household vehicles: 80% accuracy in position, \pm 30 minutes in time!
 - \circ Commuter vehicles: 60% accuracy in position, \pm 30 minutes in time!
 - $\circ~$ Random vehicles: 50% accuracy in position, inaccurate in time $\checkmark~$





