University of Padova, Italy
Department of Information Engineering (DEI)

Online and Adaptive Parking Availability Mapping: An Uncertainty-Aware Active Sensing Approach for Connected Vehicles

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MaVRoC
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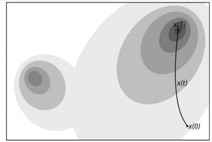
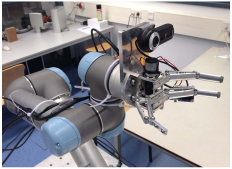
Probabilistic Active Sensing (PAS)

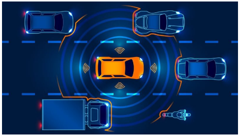
- *Active Sensing*: control of perception process
- *Probabilistic*: a belief map encodes mission knowledge



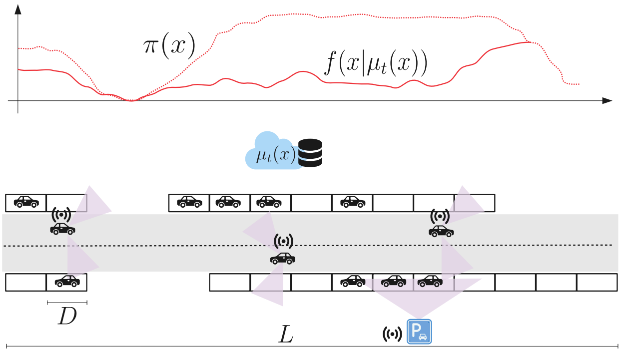
- objectives:
  - guide the platform behavior towards information gain maximization (explorative PAS) or task completion (exploitative PAS)
- why to use PAS?
  - ✓ enables autonomous perception in robotics systems
  - ✓ higher performance w.r.t passive counterparts
  - ✓ account for perception uncertainties, noisy scenarios, unmodeled dynamics
  - ✓ high adaptivity properties (through probabilistic decision making)

- Autonomous warehouse schemes
- Robotics perception
- Environmental exploration
- Target tracking
- Search & rescue
- Sensor Networks
- **ADAS systems**



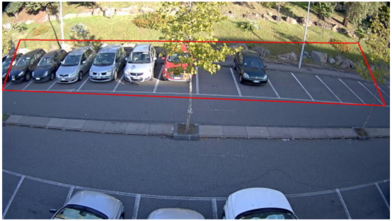


Parking Availability Map Estimation (PAME)



How to deal with ...

1. modeling:
   - environmental properties
   - traffic behavior
2. complexity:
   - big data vs runtime specifications
3. adaptivity:
   - obsolete and noisy data
4. decision making and control:
   - planning under uncertainty and on unmonitored areas

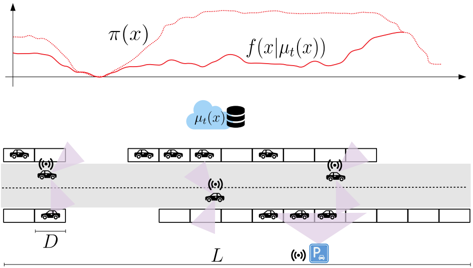


Environment

Parking Availability Map (PAM)

$$f\left(x|\mu_t(x)\right): \mathcal{X} \mapsto [0,1]$$
$$x \to \pi(x)\lambda\left(\mu_t(x)\right),$$

- $\mathcal{X} = [0, L]$: road path
- $\pi(x)$: (on-street) a-priori parking availability ⇝ environmental properties
- $\lambda(\mu_t(x))$: parking availability attenuation function ⇝ traffic conditions ⇝ $\mu_t(x)$



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Sensing platform

Vehicle equipped with

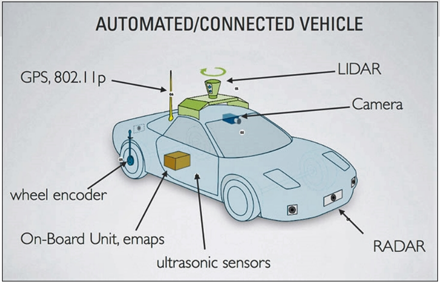
- communication capabilities (*connected vehicle*)
- sensing (e.g., LiDAR) and computational resources to detect on-street parking slots and to recognize their availability (*smart vehicle*)

State: $s_t \in \mathcal{X}$ (position over the road path)

PA observation model: estimated parking availability at current position

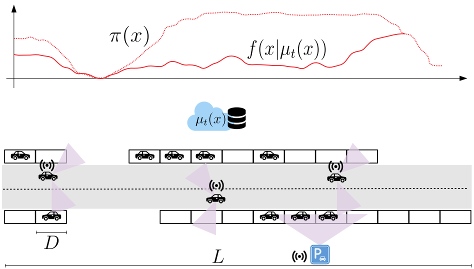
$$y_t(s_t) \approx f(s_t|\mu_t(s_t)) + \epsilon_t$$

$$\epsilon_t \sim \mathcal{N}\left(\epsilon \,\middle|\, 0, \sigma^2\right)$$



External information sources

1. cloud database (DB)
   - stores up-to-date and noiseless information on the traffic density level over $\mathcal{X}$ $\rightarrow$ the platform has access to $\mu_t(x)$, $\forall x \in \mathcal{X}$, $\forall t > 0$
2. other connected vehicles (V2V) and smart parking stations (V2I)
   - $\mathcal{V}_t = \{v_{t,i}\}_{i=1}^{N_t}$: set of connected external sources at time t
   - $v_{t,i}$, placed in x_i, sends $y_t(x_i)$,
     $y_t(\cdot)$ follows the same observation model of the platform for any i



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$\downarrow$

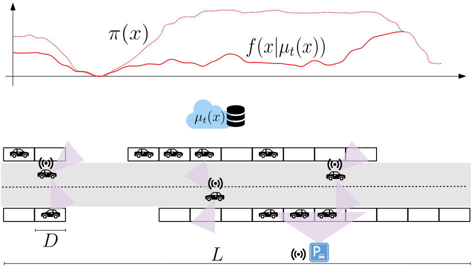
Incremental data accumulation

$$\mathbf{X}_t = \mathbf{X}_{t-T} \cup s_t \cup \{x_i\}_{i=1}^{N_t}$$
$$\mathbf{y}_t = \mathbf{y}_{t-T} \cup y_t(s_t) \cup \{y_t(x_i)\}_{i=1}^{N_t},$$

At time t, the dataset is $\mathcal{D}_t = (\mathbf{X}_t, \mathbf{y}_t)$, with cardinality $|\mathcal{D}_t| = t + \sum_{\tau=1}^{t} N_\tau$

Problem formulation (PAME)

Exploit local and remote data in $\mathcal{D}_t$
to *reconstruct the latent PAM function* $f(x|\mu_t(x))$,
over the road path $\mathcal{X}$ and under dynamic traffic conditions.



METHODOLOGY

Overview

1. design of a GPR scheme that incrementally and adaptively learns $f(x|\mu_t(x))$
2. GPR coupled with an uncertainty-aware data acquisition policy
3. $\mu_t(x)$ exploited to adapt to traffic changes

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Contributions

1. V2V/I communication guarantees online learning and *continuous map update*
2. knowledge of $\mu_t(x)$ allows *adaptivity* w.r.t. the time-varying fluctuations of the traffic density level
3. first attempt to design a parking mapping algorithm by *leveraging PAS within the framework of connected vehicles*

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Results

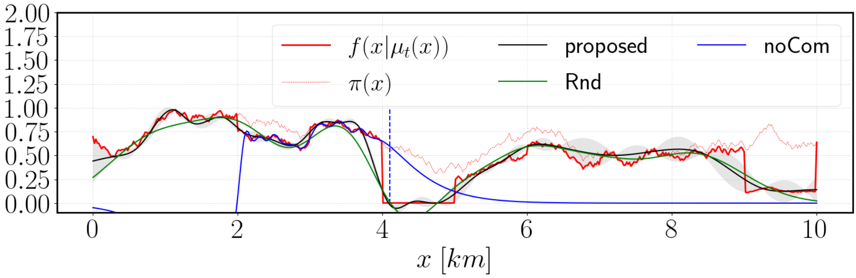
- high adaptivity capabilities
- small computational and storage demands (w.r.t. standard multi-source learning procedures and usual GPR schemes)

GPR-based PAME

- model the PAM as a GP with zero mean function and Matern covariance function

$$\hat{f}(x|\mu_t(x)) \sim \mathcal{GP}\left(0, k(x, x')\right)$$

- *iterative procedure*: a new GPR is performed as the dataset D_t is updated with incoming data



Uncertainty-aware active sampling

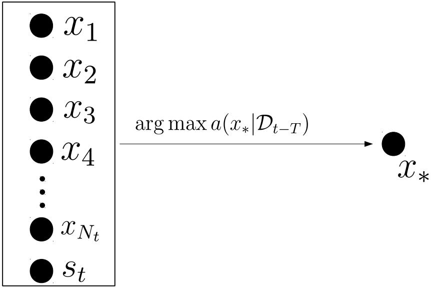
- GPR becomes quickly intractable, due to data accumulation

↓

- consider only *one sample per iteration*, according to the following selection strategy

$$x_t = \underset{x_* \in s_t \cup \{x_i\}_{i=1}^{N_t}}{\arg\max} \; a(x_* | \mathcal{D}_{t-T}),$$

- use an *uncertainty-aware policy* $a(x_*|\mathcal{D}_{t-T}) = \sigma_{*,\mathcal{D}_{t-T}}$ (predictive std. dev. at x_*) → choose the most informative sample



Adaptation to time-varying traffic density

- $\mu_t(\cdot)$ changes over time

$\downarrow$

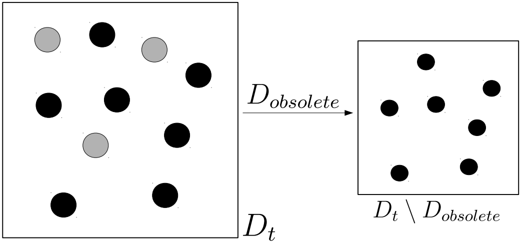
- some data in $\mathcal{D}_t$ become obsolete

$$\mathcal{D}_{obsolete} = \{(x_j, y_j) \in \mathcal{D}_t : \mu_{t-T}(x_j) \neq \mu_t(x_j)\} \subseteq \mathcal{D}_t$$

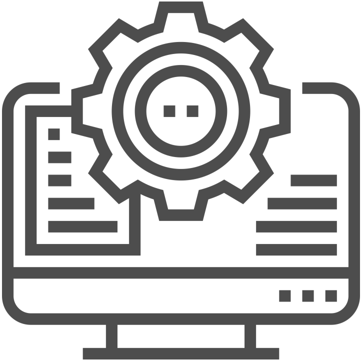
- the platform can access the DB, compute $\mathcal{D}_{obsolete}$ and remove it from $\mathcal{D}_t$

$\downarrow$

- successive GPR iterations are not contaminated by spurious information



NUMERICAL RESULTS



- Python-based synthetic environment (https://github.com/luca-varotto/Pparking)
- Monte Carlo (MC) experiment with $N_{tests} = 10$ tests (capture the performance variability)
- $L = 10$ km, $N_t \sim \mathcal{U}(0, 10)$
- $\mu_t(x)$ time-varying according to a spatio-temporal random variable (uniform in space, Bernoullian in time)

Performance indices:

1. *Learning curve* (estimation quality): $RMSE_t/RMSE_0$, where
   - $RMSE_t = \sqrt{\frac{1}{L}\int_0^L \left[\hat{f}(x|\mu_t(x)) - f(x|\mu_t(x))\right]^2 dx}$
   - $RMSE_0$ is computed before any measurement is collected (i.e., during model initialization) and it is equal for all baselines

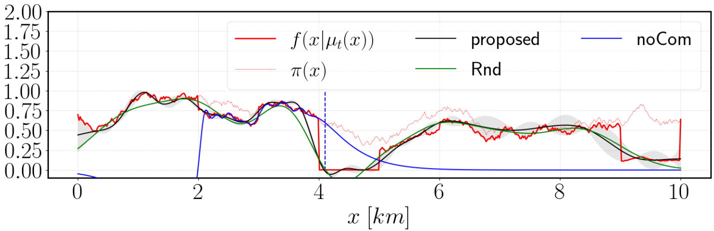
2. *Processing time ratio* (computational demand of a GPR iteration: model training and prediction):

$$\tau_t = \frac{T_{C,t}^{(proposed)}}{T_{C,t}^{(noSel)}}$$

Baselines:

- *NoCom*: non-connected vehicle $\rightarrow$ local measurements only
- *NoSel*: connected vehicle, but no active sampling applied
- *Rnd*: connected vehicle; active sampling with random acquisition function

- time-invariant traffic density
- *why a multi-source approach?*



- *noCom* has not access to remote data

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- it can not replace obsolete data with more up-to-date samples

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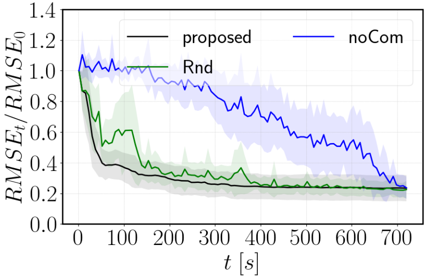
- poor adaptivity capabilities
- good estimation only locally

→ multi-source data collection is necessary
  → *Rnd*
  → *proposed*

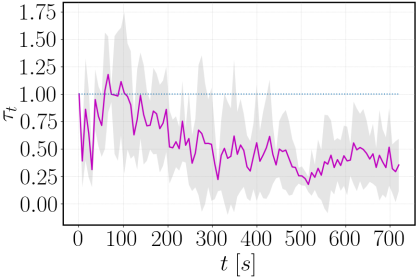
time-invariant traffic density → analyze the asymptotic estimation properties



- RMSE smaller than *Rnd* for the 66% of the times
- RMSE smaller than *noCom* for the 96% of the times

- PAS: drives the data collection process towards the highest information gain → fastest and highest quality mapping performance
- *noCom*:
  - slowest convergence
  - no spatial predictive capabilities → need to wait until the end to have accurate reconstruction

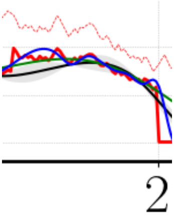
- *why employing data selection?*
- consider the time required to train and evaluate the GP, at every iteration until $s_t = L$

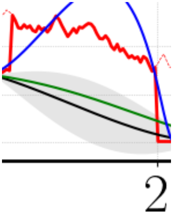


- 83% less processing demand w.r.t. *noSel*
- the computational gap increases with t, as $|\mathcal{D}_t| = t + \sum_{\tau=1}^{t} N_\tau$ suggests

data selection is necessary when GPR meets big data

- time-invariant traffic density → time-varying traffic density
- *why uncertainty-aware policy?*

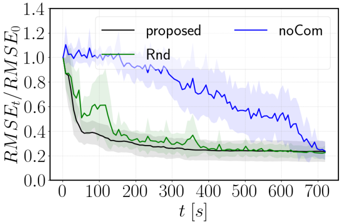




- The uncertainty of the GP model increases where obsolete datapoints are removed (i.e., where traffic changes)

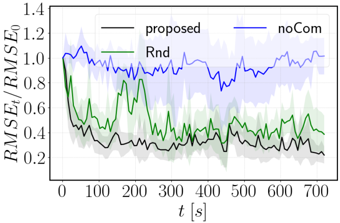
- time-invariant traffic density $\rightarrow$ time-varying traffic density
- *why uncertainty-aware policy?*

time-invariant case



$\rightarrow$

time-varying case



- The uncertainty of the GP model increases where obsolete datapoints are removed (i.e., where traffic changes)
- the uncertainty-aware policy prioritises high-variance query points
- fast recovery under dynamic environments

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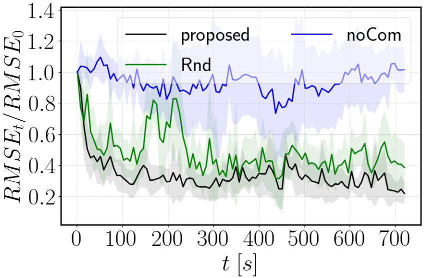

- RMSE smaller than *Rnd* the for 80% of the times (14% more than the time-invariant case)

- The uncertainty of the GP model increases where obsolete datapoints are removed (i.e., where traffic changes)
- the uncertainty-aware policy prioritises high-variance query points
- fast recovery under dynamic environments

CONCLUSIONS & FOLLOW-UPS

- Summary:
  - ✓ online and adaptive learning of on-street parking availability in the framework of connected vehicles.
  - ✓ incremental learning via GPR in a multi-source data collection scenario
  - ✓ computational and storage intractability issues prevented through probabilistic active sensing

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- Future works:
  - extension to multi-platform cooperative scenarios
  - extension to online routing problems

Thank you for your time!

Any question?

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