EU/H2020 GNFUV

Edge-centric Efficient Regression Analytics

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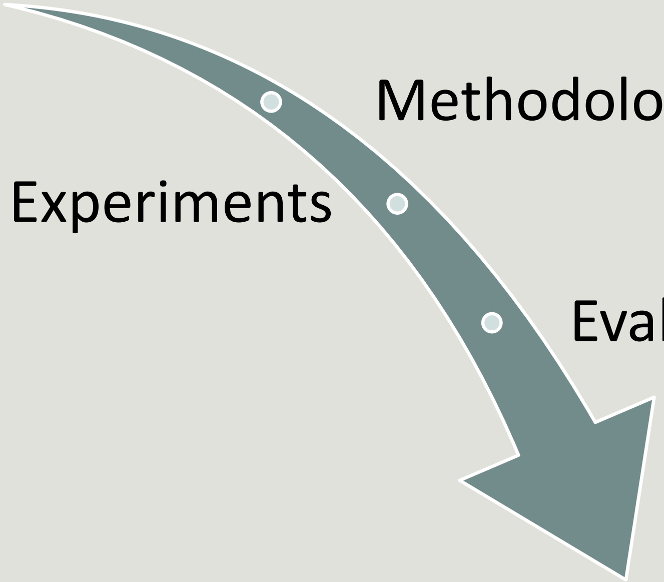
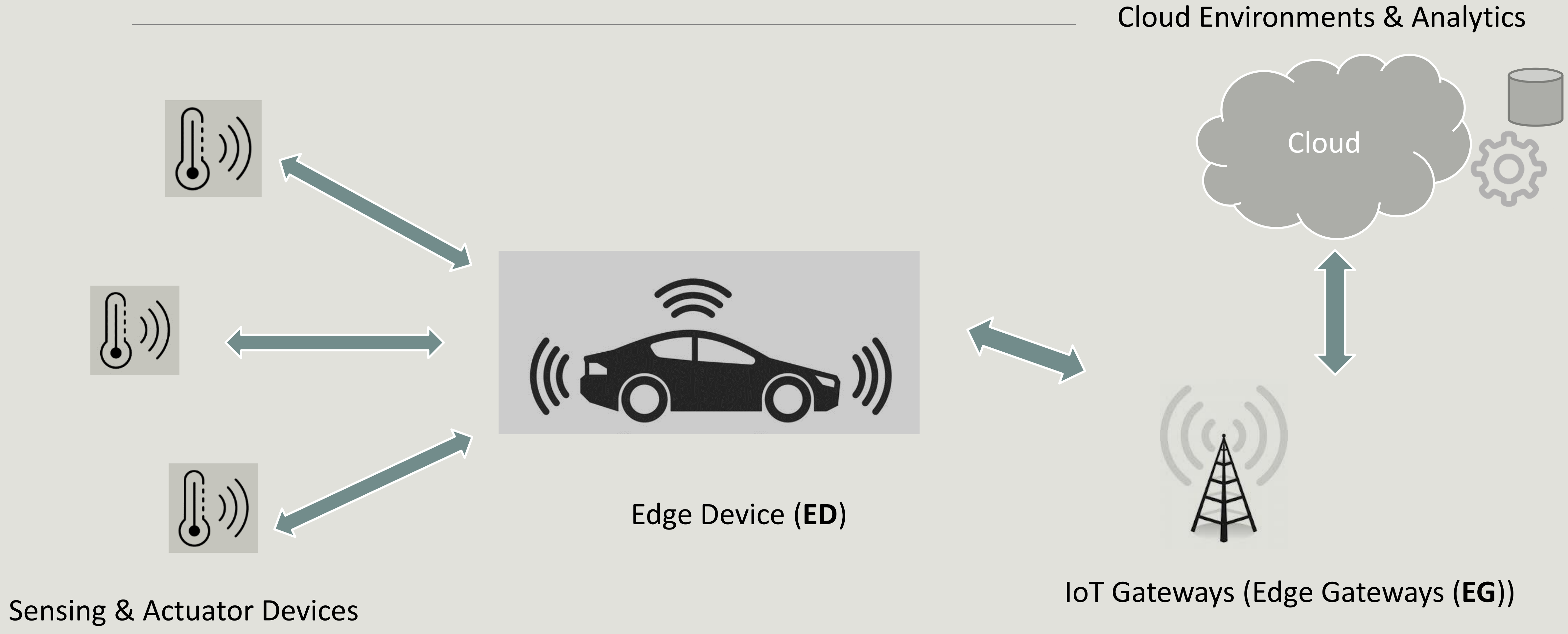
Agenda

- Introduction
- Methodology
- Experiments
- Evaluation
- Results



Context


Cloud Environments & Analytics
Cloud
Edge Device (**ED**)
IoT Gateways (Edge Gateways (**EG**))
Sensing & Actuator Devices

Constraints at the Edge

1. Limited Bandwidth
2. Energy
3. Limited Computational Power
4. Storage Capacity

Idea:
Observe Model Performance &
Update the network Edge

- **Exploit the limited** computational power of Edge Devices
- **Push Intelligence** to the Edge:
  - inferential tasks, on-line statistical learning, classification, localized detection,…**are pushed at the Edge**

Hypotheses & Actions

Given the **constraints** of an IoT network, let us **hypothesise** the following actions:

- **Action 1: Reduce** the communication overhead
  - **Hypothesis 1**: **No raw data** transfer is needed for inferential & regression analytics, i.e., **Learn More With Less**!
- **Action 2: Perform** real-time predictive & regression analytics for instant action & autonomous decision making
  - **Hypothesis 2:** use the limited computational power to **infer** and take decisions for regression models updates in an **On-Line Manner**!
- **Action 3: Provide** high quality predictive analytics tasks, e.g., prediction accuracy, model fitting
  - **Hypothesis 3:** decide **which** is the best diverse model to select based on given data statistics, i.e., **Be Intelligent On What You See**!

Challenges & Problem Definition

- Reduce **unnecessary** communication between/among devices and/or the Cloud
- **Problem 1:** Conditionally Model Forwarding Problem at the **Edge Device**

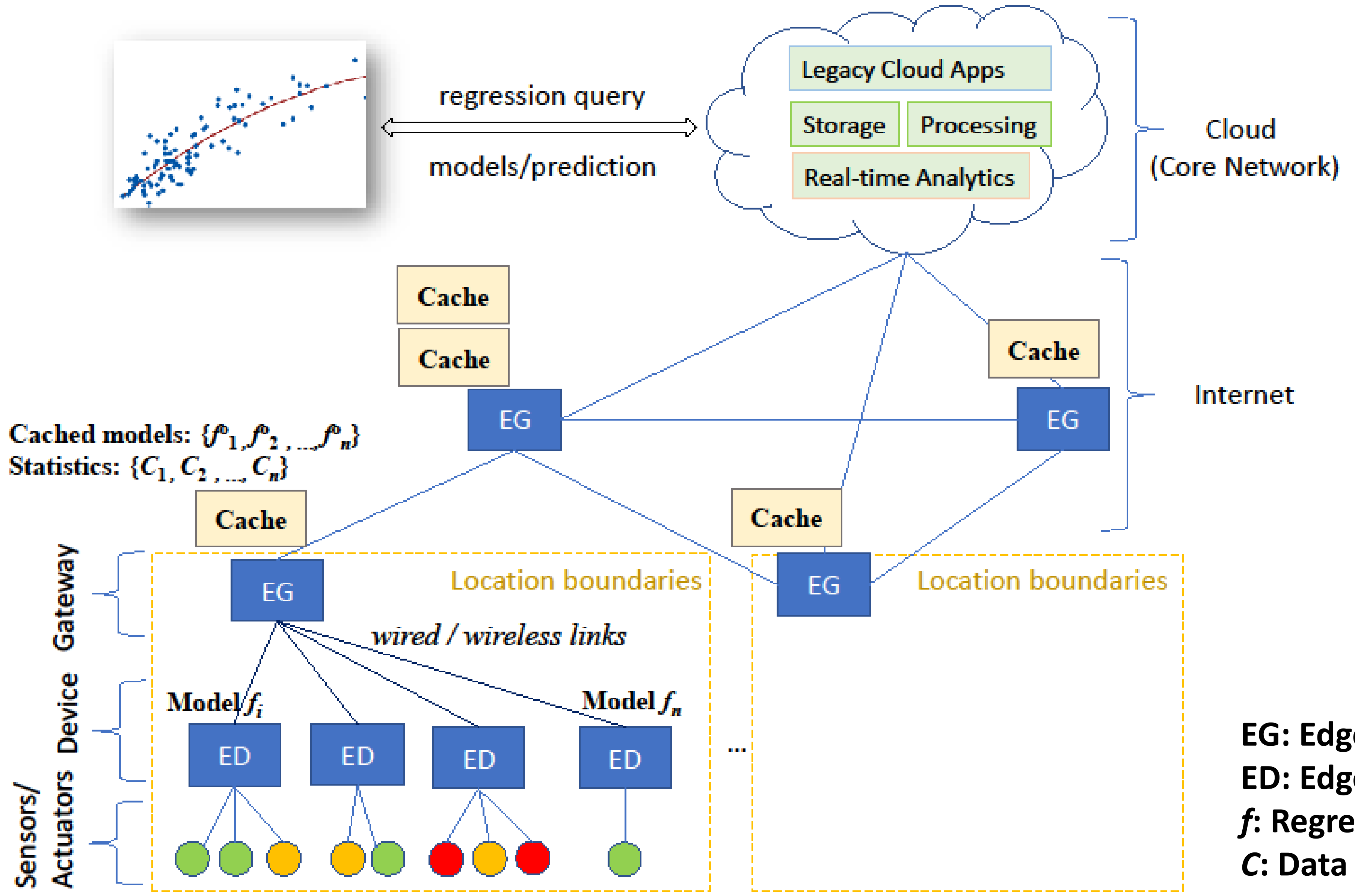
- Decide **which** model to select given all cached diverse models to maximize the predictive analytics accuracy
- **Problem 2:** Diverse Model Selection Problem at the **Edge Gateway**

- Decide **which** statistics to communicate **to support** the selection at the Gateway
- **Problem 3:** Time-optimized Data Selection Problem at the **Edge Gateway**

- Decide **when** to deliver/send updated models and **what** to send in light of maximizing the predictive analytics accuracy
- **Problem 4:** Time-optimized Model Delivery Scheduling at the **Edge Device**

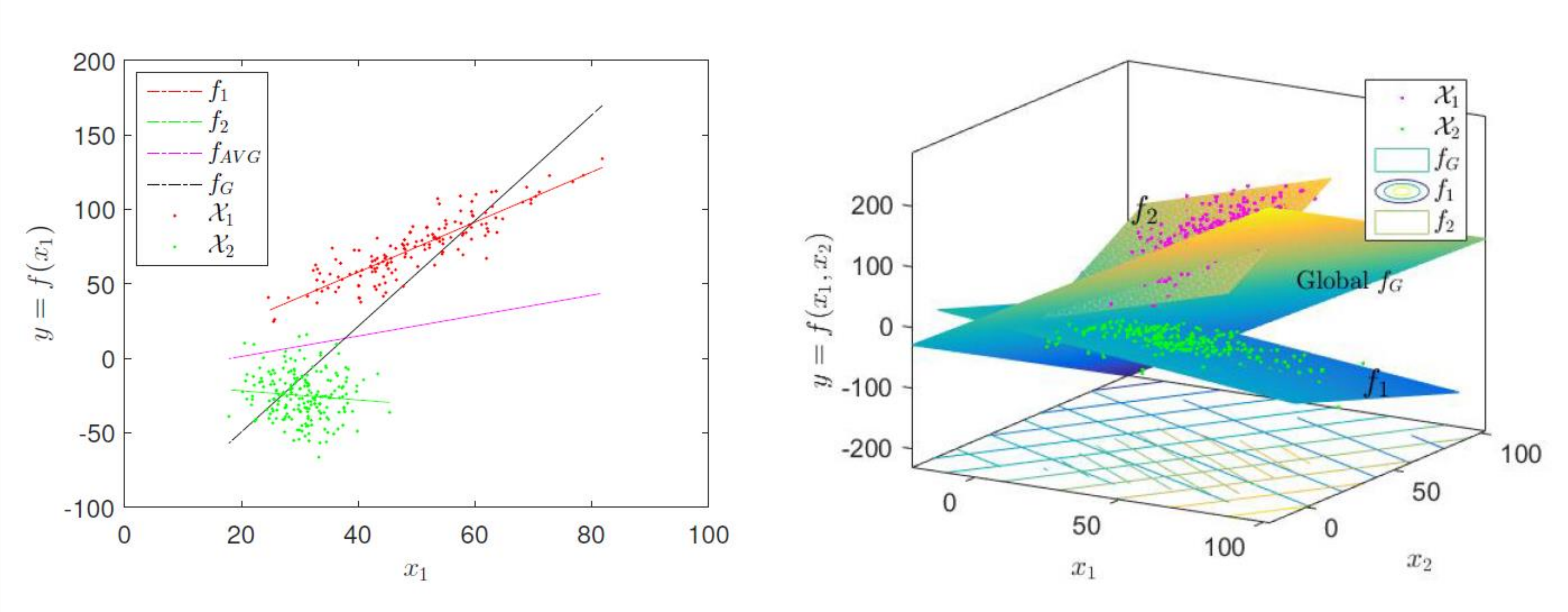
Contribution

- ✓Introduce an **communication efficient** scheme that transmits **only** regression model parameters & sufficient statistics in the Edge Network for cached model updates in Edge Gateways.
- ✓Novel diverse model selection algorithms at Edge Gateways exploiting model statistics delivered by Edge Devices.
- ✓**Domain:** Regression Analytics at the Edge with model selection at the Edge Gateway



EG: Edge Gateway
ED: Edge Device
***f*: Regression Model**
***C*: Data Statistics**

Models Diversity



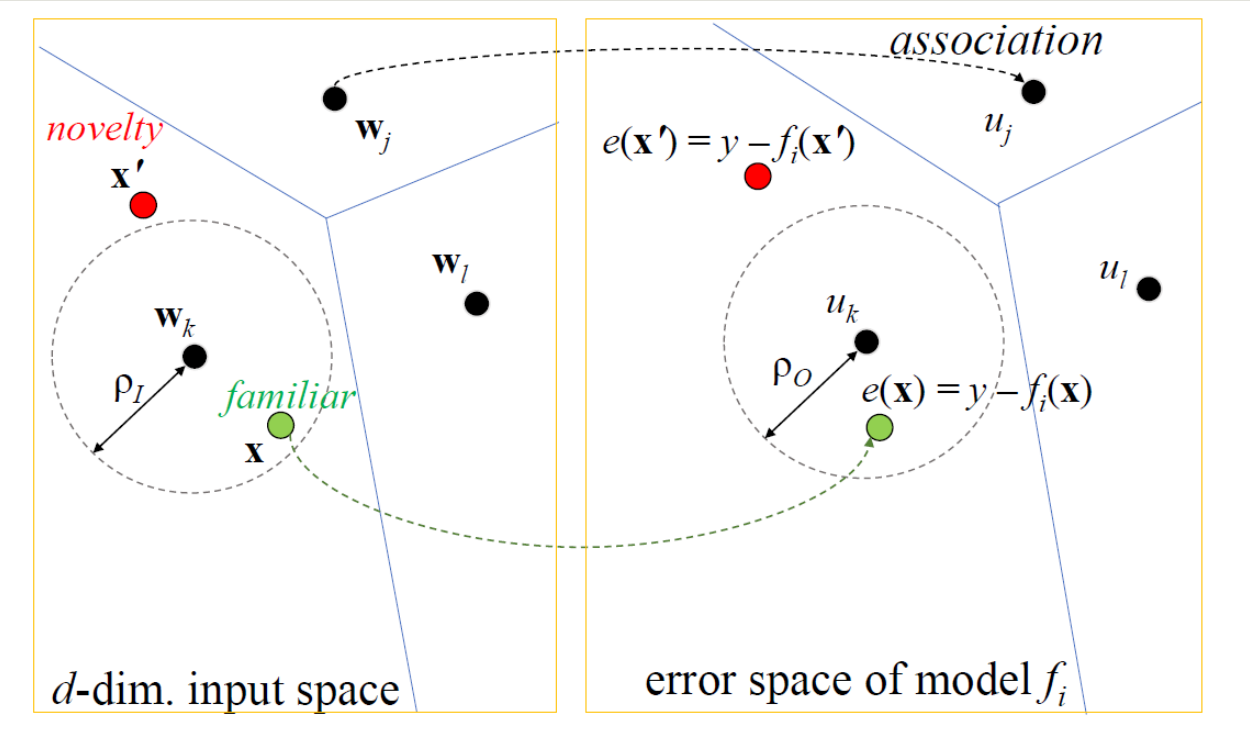
Edge Device Tasks

- Check **familiarity** of a new measurement
- Sliding Window of recent measurements

$(\boldsymbol{x}, y)_t$	$(\boldsymbol{x}, y)_{t-1}$	$(\boldsymbol{x}, y)_{t-2}$	…	$(\boldsymbol{x}, y)_{t-N}$

- Generate Statistics for **Input-Error Space** quantization
- Performing On-line Regression on this window to generate a model → $f_i(x)$
- Keeping locally at the Edge Device a copy of the recent model sent to Edge Gateway $\rightarrow f^{O}{}_{i}(x)$
- Update Edge Gatewat **only** with updated model parameters w.r.t. statistics of **input-error space**.

Edge Device Familiarity & Input-Error Space Quantization



Edge Device Model Update Mechanism

After identifying Familiarity :

1. Append new measurements in Sliding Window
2. Retrain/adapt model $f_i(x)$
3. Calculate model prediction error with the **new model** at the Edge Device
4. Calculate model prediction error with the **most recent model** sent to the Edge Gateway
5. Compare the **difference of the prediction errors**
   - If absolute difference is above a threshold → Send the **new model parameters** to Edge Gateway

Edge Gateway Tasks

- Collecting all diverse Models (Model Caching)
- Collecting all Statistics (from Input-Error Space Quantization)
- Receiving regression queries from Cloud/analysts and producing output
- Select the most appropriate **subset** of the cached models

Edge Gateway Model Selection Algorithms

1. Simple Model Aggregation (SMA)

   - Averaging over all predictions $\hat{y} = \frac{1}{n}\sum_{i=1}^{n} {f^0}_i(x)$

2. Input-space Aware top-K Model (IAM)

   - Selects the model $f(x)$ whose the input prototype is the closest to query q compared to all input prototypes

3. Input/Error-space Aware top-K Model (IEAM)

   - Select the model $f(x)$ whose the input prototype is the closest to query q compared to all input prototypes and best associated performance reflected by the error prototype

Methodologies

1. **Baseline**: Sending continuously data from Edge to Cloud and generate one global model

2. **Hybrid Optimal Vector Forwarding** (HOVF): Optimal Stopping Theory for data delivery [2]

3. **DPB**: Predict data using linear forecasting models [1]

4. **Model Selection Mechanism (SMA, IAM, IEAM)**

[1] U. Raza, A. Camerra, A. L. Murphy, T. Palpanas, G. P. Picco, 'Practical Data Prediction for Real-World Wireless Sensor Networks', IEEE TKDE, 27(8):2231–2244, Aug. 1 2015
[2] N. Harth, C. Anagnostopoulos, 'Quality-aware Aggregation & Predictive Analytics at the Edge'. IEEE Big Data 2017, Boston

Experimental Evaluation

Real contextual data:

- Intel Berkley Research Lab Dataset → 2 Edge Gateways, 25 Edge Devices each (sensors) measuring 3-dim. environmental data (humidity, temperature, light)

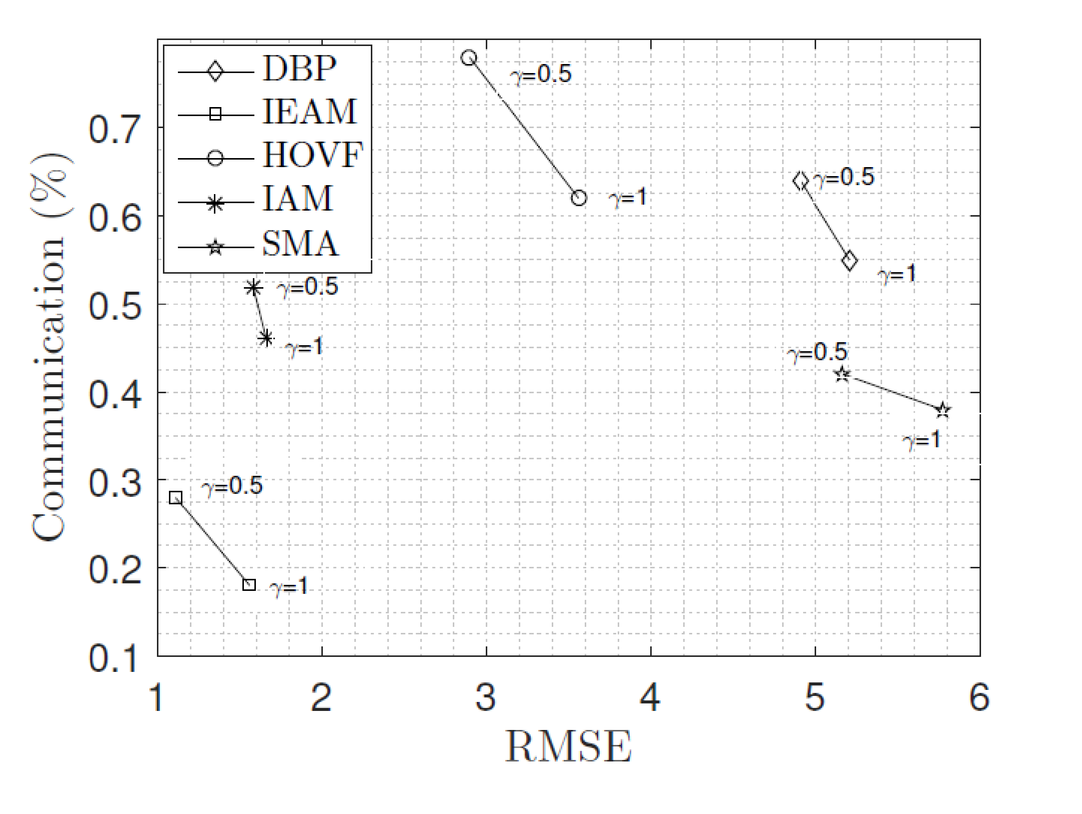
Queries:

- Last 120 measurements of each Edge Device → 3000 total

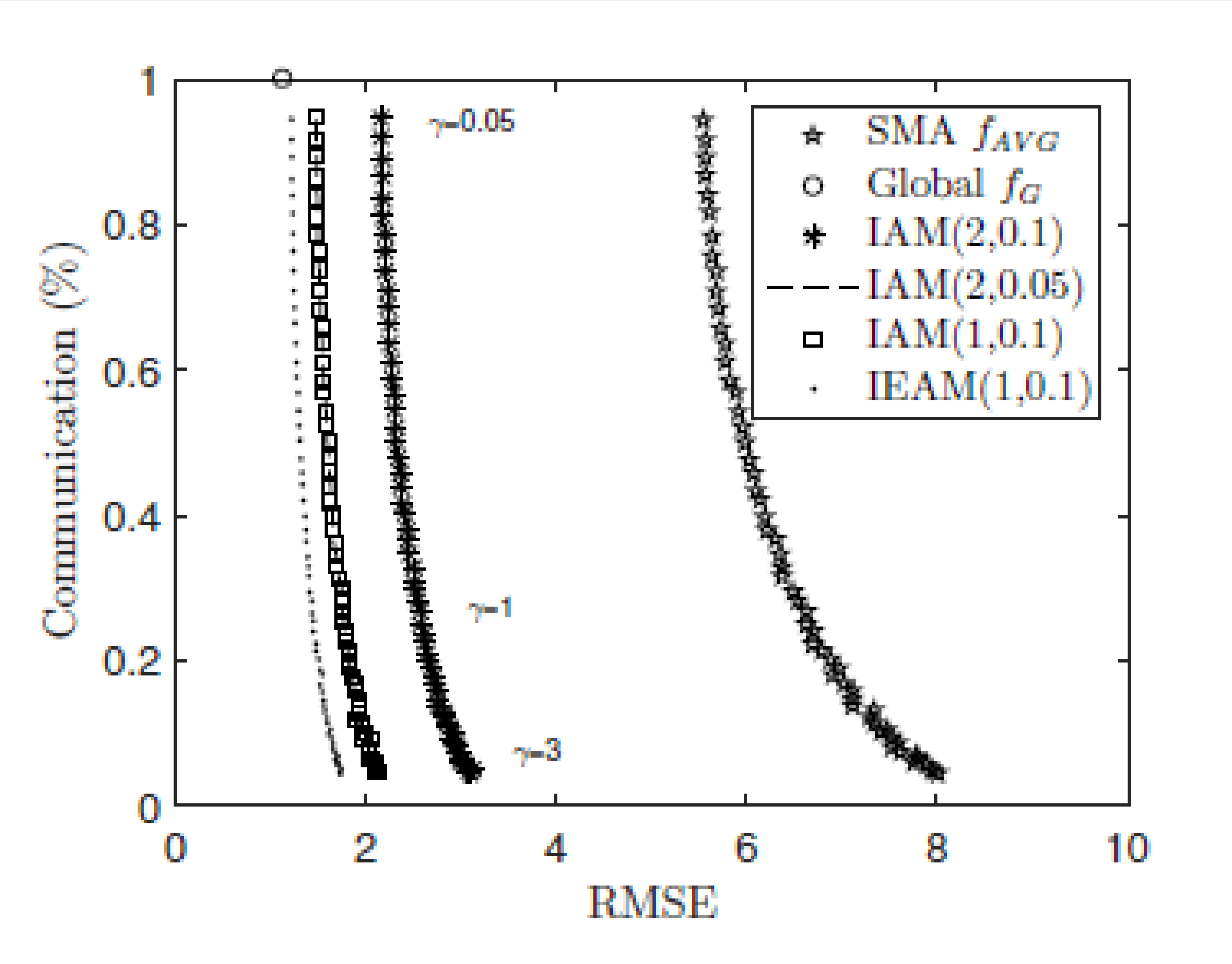
Evaluation Metrics:

1. **Communication:** number of messages sent from EDs to EG
   - Percentage of remaining communication w.r.t the baseline solution
2. **Analytics quality at the Edge Gateway**
   - Regression performance discrepancy w.r.t. ground truth
     - Root Mean Squared Error (RMSE)
     - Mean Absolute Error (MAE)

Efficiency: Communication vs. Analytics Error



Efficiency: Communication vs. Analytics Error



γ: fraction of the error difference median

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THANK YOU!

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