An XGBoost-based Optimization Framework for Vehicle Reidentification at Intersection Approach

Pramesh Pudasaini

Ph.D. Student

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THE UNIVERSITY OF ARIZONA
COLLEGE OF ENGINEERING
Center for Applied Transportation Sciences

Outline

- **Roots for Resilience (R4R) Scholarship**
  - Program Overview
  - FOSS Sessions
- **Vehicle Reidentification Research**
  - Study Site & Data
  - Methodology
  - Results & Discussions

Roots for Resilience (R4R) in Data Science Scholarship

Roots for Resilience in Data Science Scholarship

Background

- **Co-led by** Arizona Institute for Resilience (AIR), CyVerse, and Data Science Institute (DSI)
- **10 scholarships** awarded in Fall 2023
  - One grad student per department
- **Eligibility criteria**
  - PhD candidates or Master’s students
    - Completed qualifying exams, not defended dissertation
  - Acceptance contract from advisor
- **7,000$** scholarship

R4R Scholarship

Program Goals

- **Train** students in using **open science** and **computational** tools
  - Regular meetings with members of CyVerse and DSI

- Develop data science capabilities across AIR's participating departments and research groups.
- Accelerate research projects of participating fellows and their home department research groups.
- Build professional networks for addressing large-scale challenges and research questions of interest to AIR.
- Develop new interdisciplinary collaborations across AIR, DSI, CyVerse, and academic units for writing new proposals.
- Develop a cohort among participants (and Data Science Ambassadors) to support each other in their own research and efforts to engage their departments.

R4R Scholarship

Institutions Involved

- **Arizona Institute for Resilience (AIR)** air.arizona.edu
  - Develop and apply diverse knowledge in solving environmental problems through interdisciplinary research and experimental learning
- **CyVerse** datascience.arizona.edu
  - Computational platform for open science
  - Promotes data science training
  - Sign up with UArizona NetID for free access to
- **Data Science Institute (DSI)**
  - University-wide interdisciplinary collaboration

- 3 TB of data storage
- 20,000 compute units/year*
- Ability to run 4 concurrent jobs
- Ability to share unlimited data files or ap
- 10 permanent identifiers (DOIs) for data
- A seat at any 4 CyVerse workshops (Fo ChatGPT Prompt Engineering, etc.)
- Advanced features and APIs
- Access to webinars
- Workshop resources to use CyVerse for
- Screen share support

R4R Scholarship

Program Structure

- **Time commitment**
  - 5-10 hrs/week
  - Foundational Open Science Skills (**FOSS**) workshop
    - Weekly 2-hr sessions
  - Weekly cohort meetings (90 min)
- **Program requirements**
  - Weekly homework (journal entries on GitHub)
  - Capstone project
  - Departmental presentation at end of semester

R4R Scholarship

FOSS Sessions

foss.cyverse.org

Open Science Skills

Lessons

0. The Shell and Git
1. Open Science
2. Managing Data
3. Project Management
4. Documentation and Communication
5. Version Control
6. Reproducibility I: Repeatability
7. Reproducibility II: Containers

Week	Date	Content	Instructor(s)
Week 0	Sept 7	pre-FOSS workshop: - Unix shell basics - Git/GitHub basics - ChatGPT & LLMs	Michele Cosi & Jeff Gillan
Week 1	Sept 14	Workshop introduction: - Intro to Open Science	Tyson Swetnam, Michele Cosi, Jeff Gillan
Week 2	Sept 21	Data management: - FAIR data - Data Management Plans - Processing activity	Jeff Gillan, Michele Cosi Guest Speaker: Wade Bishop, UTK
Week 3	Sept 28	- Project management - Intro to CyVerse	Michele Cosi, Tyson Swetnam
Week 4	Oct 5	Documentation / Communication: - Internal + External Documentation - Internal + External Communication - GitHub Pages websites	Michele Cosi, Jeff Gillan
Week 5	Oct 12	Version Control - Version control as a philosophy - GitHub functionality Version control everything	Michele Cosi, Guest Speaker: Jason Williams, CSH
Week 6	Oct 19	Reproducibility I: - Software installation - Software management	Jeff Gillan, Michele Cosi
Week 7	Oct 26	Reproducibility II: - Brief intro to containers	Michele Cosi, Jeffrey Gillan
Week 8	Nov 2	Capstone Presentations	

Use of AI Tools

Personal Website using GitHub Pages

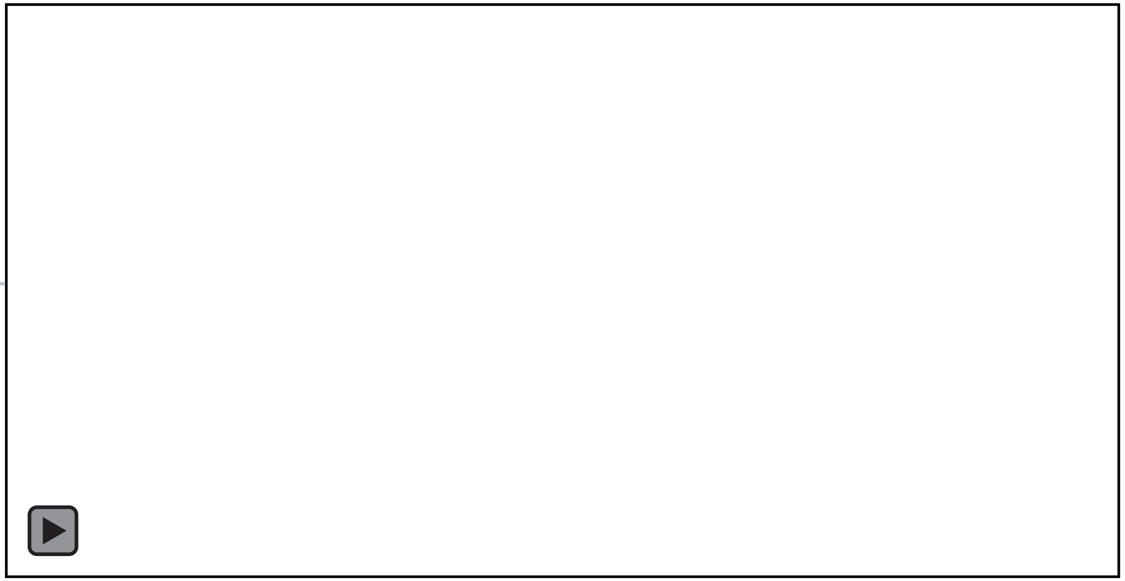
Learning Outcomes

Research on

Vehicle Reidentification

Research Motivation

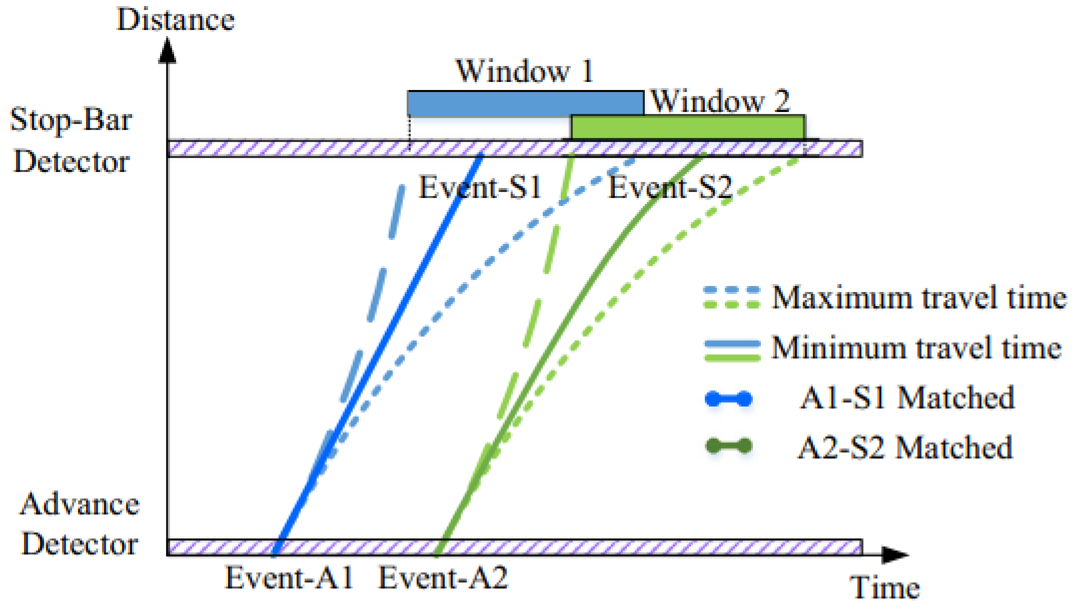
- Signalized intersections
  - Driver's behavior
  - Yellow onset
- Vehicle reidentification (ReId)
  - Advance and stop-bar detectors
  - Collect signal change & actuation data
  - Detectors: loops or video-based
  - Advantages of loop detectors
- Scope & practical implications



Existing Reidentification Methods

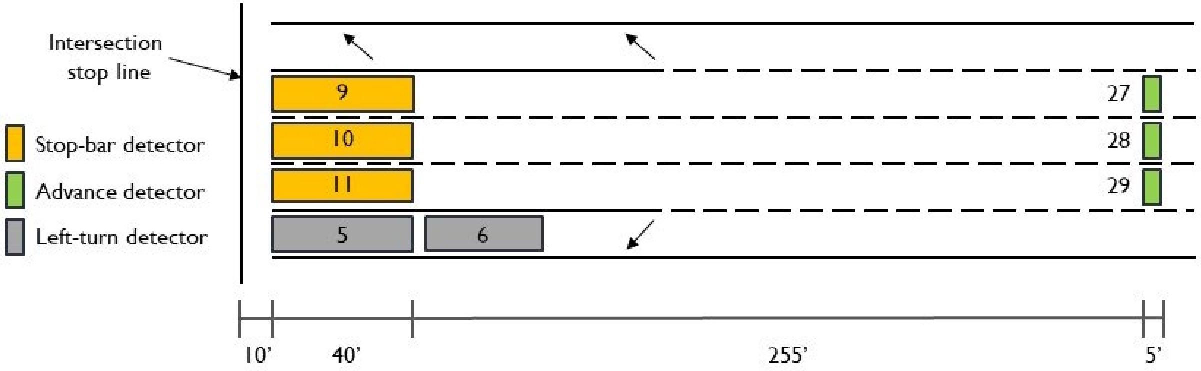
Limitations

- ReId accuracy not reported
- Velocity measured from detectors
- A priori knowledge of vehicle length
- Lane changing not considered
- Long vehicles not considered
- Not easily transferable
- Not reliably accurate



Window Searching Method

Study Site & Data



Indian School Rd & 19th Ave in Phoenix, AZ

High-resolution events data

TimeStamp	EventID	Parameter
2022-12-06 07:45:46.700	1	2
2022-12-06 07:46:35.000	8	2
2022-12-06 07:46:38.600	10	2
2022-12-06 07:47:35.400	1	2
2022-12-06 07:48:35.000	8	2
2022-12-06 07:48:38.600	10	2
2022-12-06 07:49:51.700	1	2
2022-12-06 07:50:35.000	8	2
2022-12-06 07:50:38.600	10	2

Signal phase changes

TimeStamp	EventID	Parameter
2022-12-06 07:46:12.300	82	11
2022-12-06 07:46:12.300	81	9
2022-12-06 07:46:12.400	81	10
2022-12-06 07:46:12.800	82	29
2022-12-06 07:46:13.100	82	10
2022-12-06 07:46:13.100	81	29
2022-12-06 07:46:13.200	82	9
2022-12-06 07:46:13.300	81	11
2022-12-06 07:46:14.100	81	10

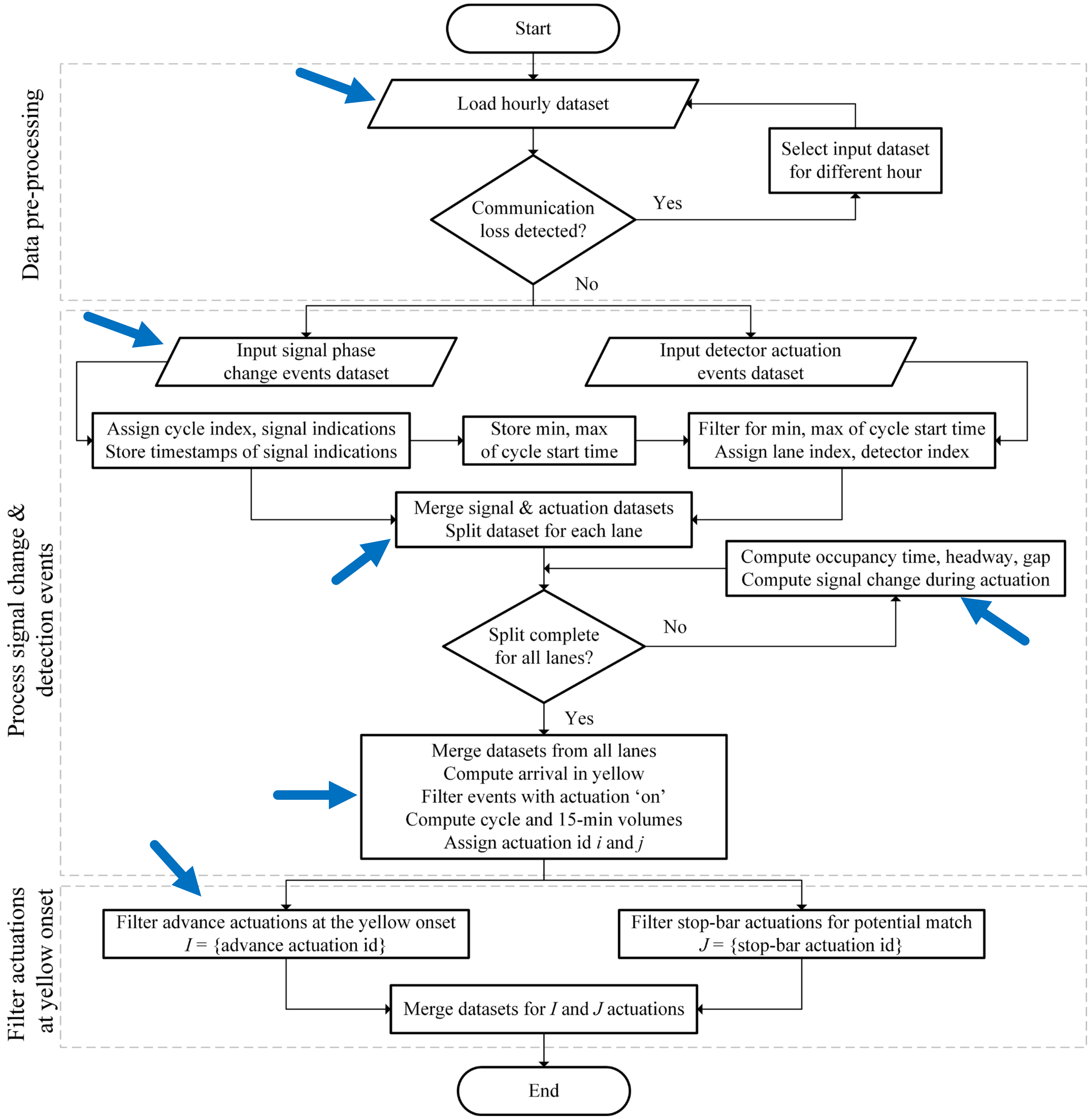
Detector actuations

Dataset 1: with video recordings
- Period: 7.5 hours
- Date: 12/6/2022, 12/14/2022, 3/27/2023

Dataset 2: without video recordings
- Period: 14 days
- Date: January 1-7 & 15-21 in 2023

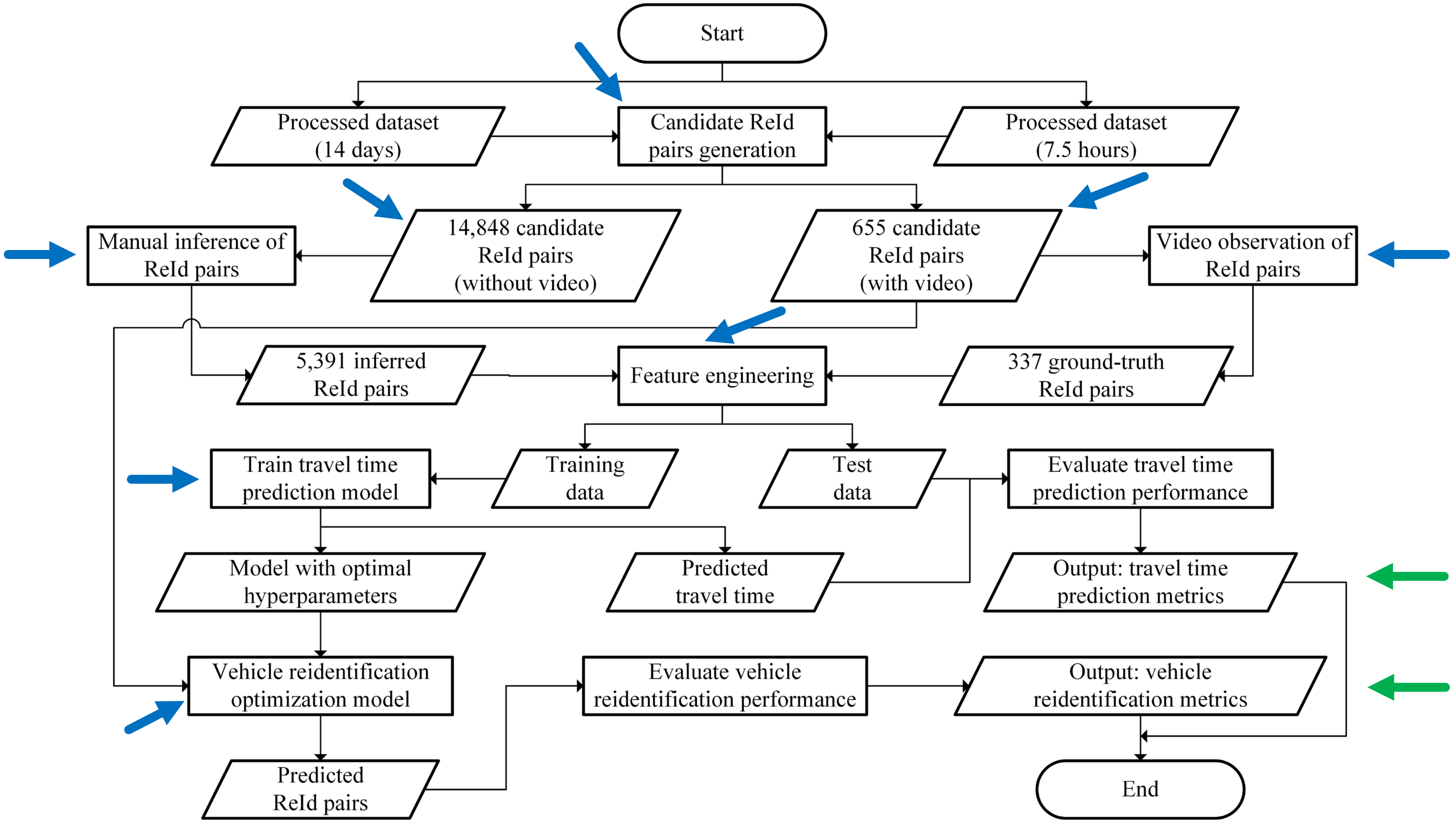
Data Processing

1. Pre-processing
2. Processing signal change & actuation events
3. Filtering actuations at yellow onset



Methodology

Proposed Reidentification Framework



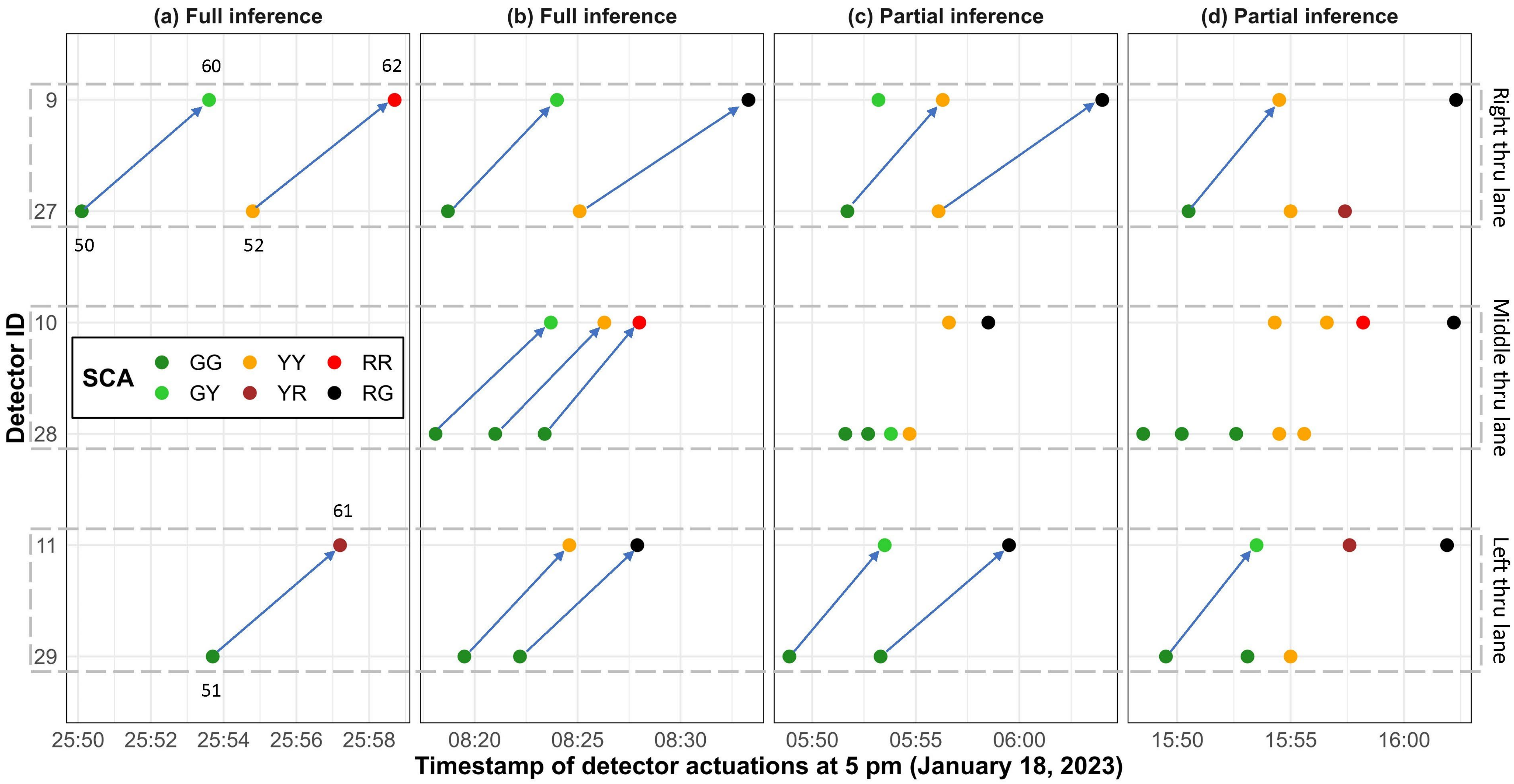
Methodology

Manual Inference of ReId Pairs

Right lane

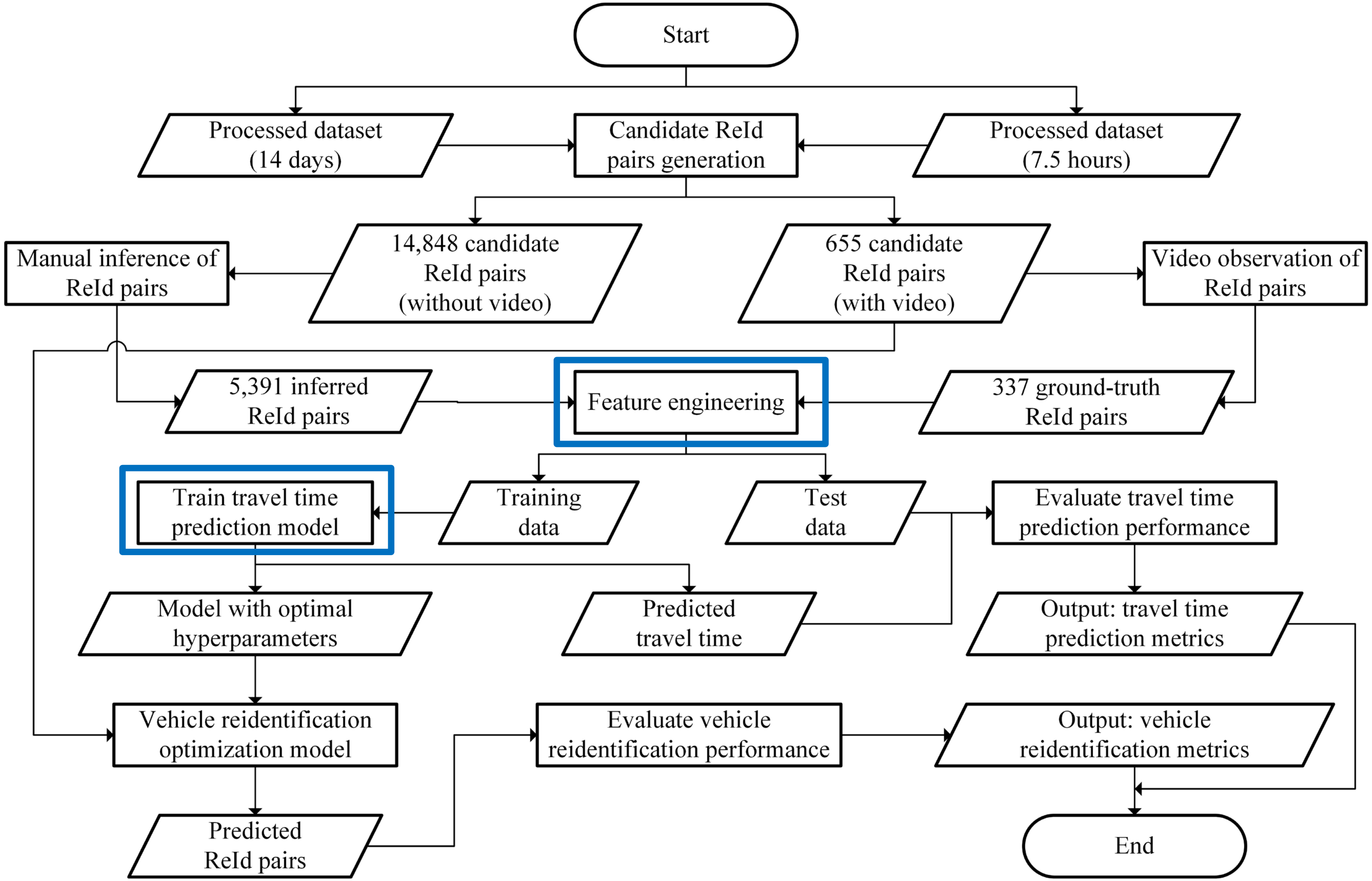
Middle lane

Left lane



Methodology

Travel Time Prediction



Methodology

Features for Travel Time Prediction

Category	Feature names	Feature description	Feature type
Detector actuation	volume_15	Arrival volume at advance location during 15-min interval	Count
	volume_cycle	Arrival volume at advance location during a cycle	Count
	car_follow	Car-following behavior at advance detector (1 = yes, 0 = no)	Binary
	occ_time	Occupancy time over advance detector	Continuous
	headway_foll	Headway between target and leading vehicle at advance detector	Continuous
	headway_lead	Headway between target and following vehicle at advance detector	Continuous
	gap_foll	Gap between target and leading vehicle at advance detector	Continuous
Signal phase change & detector actuation	AIY	Arrival time in yellow at advance detector	Continuous
	is_SCA_GY	Signal change during actuation = GY? (1 = yes, 0 = no)	Binary
	is_SCA_YY	Signal change during actuation = YY? (1 = yes, 0 = no)	Binary
	is_SCA_YR	Signal change during actuation = YR? (1 = yes, 0 = no)	Binary
Lane position	is_lane_R	Lane position = right? (1 = yes, 0 = no)	Binary
	is_lane_M	Lane position = middle? (1 = yes, 0 = no)	Binary

Methodology

ML Models for Travel Time Prediction

- **4 models**
  - Decision Tree Regression
  - Support Vector Regression
  - Random Forest
  - XGBoost
- **Model output**
  - Predicted travel time from advance to stop-bar
- **Training procedure**
  - Train/validation/test splits

T1: model trained on training data & evaluated on validation set

T2: model trained on training data & evaluated on test set

T3: model trained on combined training and validation data & evaluated on test set

Methodology

Optimization Model for Reidentification

Parameters

$$L_{ij} = \begin{cases} 1, & \text{if candidate ReId pair } (i,j) \text{ belongs to the same lane} \\ 0, & \text{otherwise} \end{cases}$$

Decision variables

$$y_{ij} = \begin{cases} 1, & \text{if candidate ReId pair } (i,j) \text{ is selected} \\ 0, & \text{otherwise} \end{cases}$$

Objective function

$$\min Z = \sum_i \sum_j y_{ij} E_{ij}$$

Constraints

$$t_{min} \leq t_{ij} \leq t_{max} \qquad \forall (i,j)$$

$$E_{ij} = \left| t_{ij} - t_i^{pred} \right| \qquad \forall (i,j)$$

$$\sum_j y_{ij} \leq 1 \qquad \forall i$$

$$\sum_i y_{ij} \leq 1 \qquad \forall j$$

$$y_{ij} \in \{1,0\} \qquad \forall (i,j)$$

$$L_{ij} \in \{1,0\} \qquad \forall (i,j)$$

$$y_{ij} = L_{ij} \qquad \forall (i,j)$$

Methodology

Performance Evaluation

Travel Time Prediction

Ground-truth: t_{ij}

Predicted: t_{ij}^{pred}

Reidentification

Ground-truth: y_{ij}^{ground}

Predicted: y_{ij}^{pred}

337 ReId pairs as test samples

Performance Evaluation

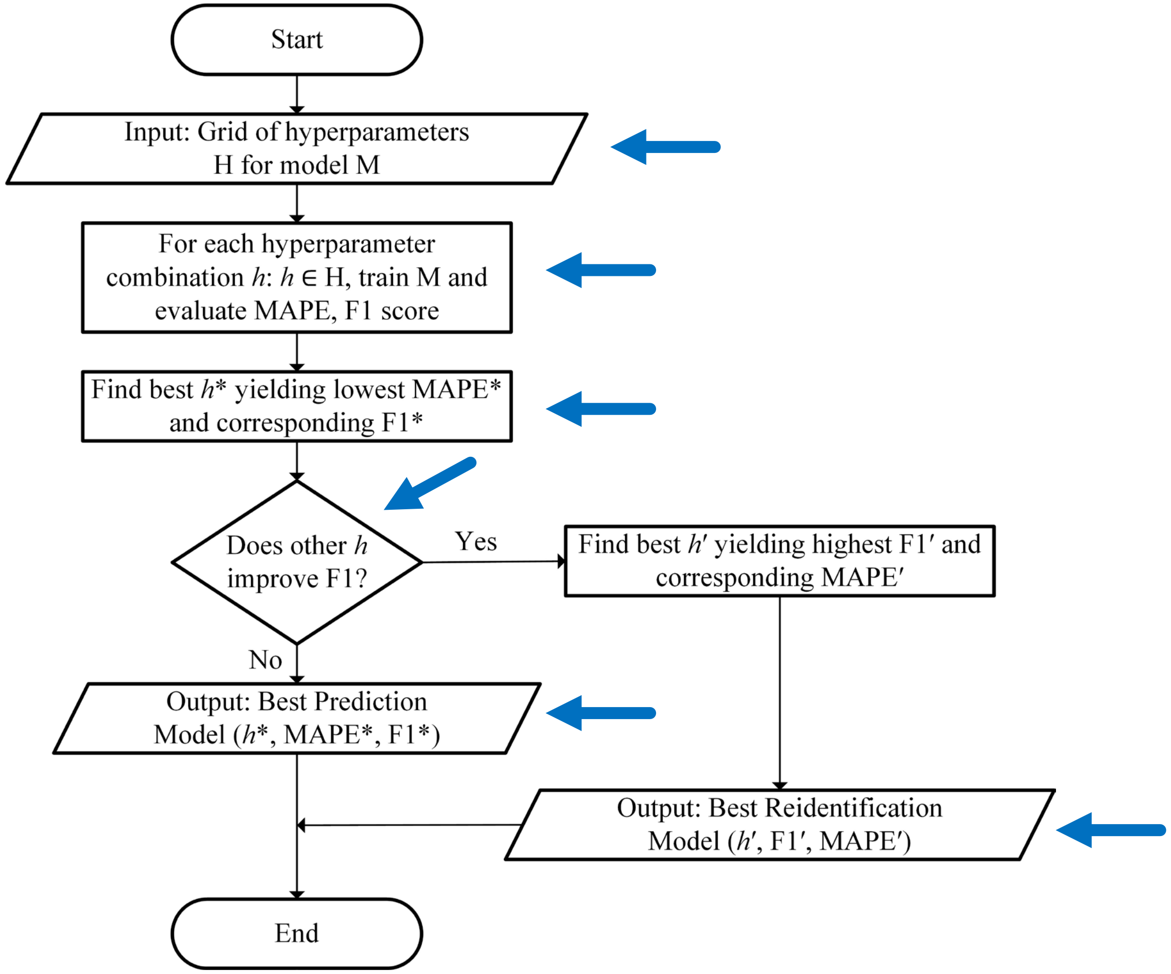
$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{t_{ij} - t_{i}^{pred}}{t_{ij}}\right| \cdot 100\,\%$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(t_{ij} - t_{i}^{pred}\right)^2}{n}}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall}$$



Hyperparameter Tuning

Results

Model Performance Metrics

Metrics	Best Travel Time Prediction				Best Vehicle Reidentification			
	DTR	SVR	Random Forest	XGBoost	DTR	SVR	Random Forest	XGBoost
MAPE$^{(T1)}$	12.18%	13.23%	12.05%	12.05%	12.34%	13.42%	12.01%	12.20%
MAPE$^{(T2)}$	11.84%	13.99%	12.19%	11.49%	11.91%	14.15%	12.18%	11.82%
MAPE$^{(T3)}$	11.68%	13.97%	12.04%	**11.31%**	11.71%	14.27%	12.24%	**11.70%**
RMSE$^{(T1)}$	0.9196	0.9574	0.8663	0.8618	0.9386	0.9535	0.8622	0.8718
RMSE$^{(T2)}$	0.9679	1.0287	0.9160	0.8858	0.9723	1.0194	0.9219	0.8873
RMSE$^{(T3)}$	0.9513	1.0366	0.9118	**0.8722**	0.9505	1.0281	0.9163	**0.8717**
TP	303	303	302	308	304	304	306	310
FP	19	18	22	17	18	16	19	15
FN	34	34	35	29	33	33	31	27
Precision	94.10%	94.39%	93.21%	**94.77%**	94.41%	95.00%	94.15%	**95.38%**
Recall	89.91%	89.91%	89.61%	**91.39%**	90.21%	90.21%	90.80%	**91.99%**
F1 score	0.9196	0.9210	0.9138	**0.9305**	0.9226	0.9254	0.9245	**0.9366**

Note: $^{(T1)}$ indicates model trained on training data and evaluated on the validation set; $^{(T2)}$ indicates model trained on training data and evaluated on the test set; $^{(T3)}$ indicates model trained on combined training and validation data and evaluated on the test set; DTR = Decision Tree Regression; SVR = Support Vector Regression; TP = true positive; FP = false positive; FN = false negative

Results

Metrics: Best Prediction Model

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Results

Training Procedure & Model Performance

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Results

Model Hyperparameters

The **best travel time prediction** models, compared to the vehicle reidentification models, tended to **marginally overfit** the predicted travel time.

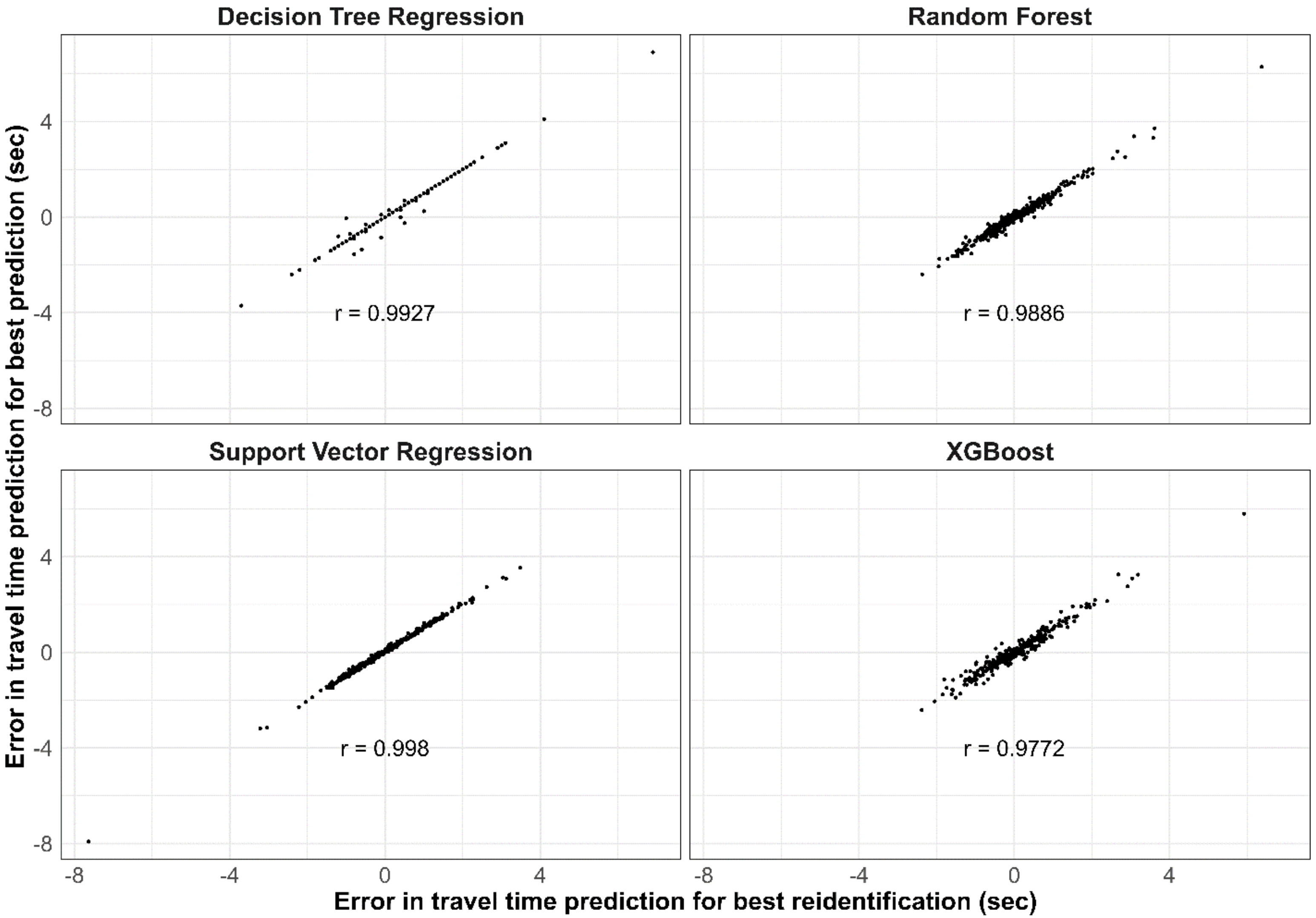
Model	Total combinations	Hyperparameters	Values
Decision tree regression	270	max_depth min_samples_split min_samples_leaf max_features criterion	[None, **5**, 10, 20, 30] [**2**, 5, 10] [**1**, 2, 4] [**None**, 'sqrt', 'log2'] ['friedman_mse', '**absolute_error**']
Support vector regression	108	kernel C epsilon degree	['**linear**', 'rbf', 'poly'] [0.1, **1**, 10] [0.01, 0.1, 0.2, **0.5**] [**2**, 3, 4]
Random forest	360	n_estimators max_depth min_samples_split min_samples_leaf max_features	[50, 100, **200**, 500] [None, 5, **10**, 15, 20] [2, **5**, 10] [1, **2**, 4] ['**sqrt**', 'log2']
XGBoost	6480	n_estimators learning_rate max_depth min_child_weight gamma reg_alpha reg_lambda	[50, 100, **200**, 300] [0.01, 0.1, **0.2**] [**3**, 4, 5, 7, 10] [1, 3, **5**, 7] [0, **0.1**, 0.2] [0, 0.1, **0.5**] [0, **0.1**, 0.5]

Note: optimal hyperparameter combination for the best travel time prediction results are underlined, while that for the best vehicle reidentification results are in bold

Results

Correlation of Error in Travel Time Prediction

XGBoost model's hyperparameter combination for best reidentification predicted travel time values with **less overfitting** (with some noise or randomness).



Results

Comparison with Analytical Methods

Reidentification Methods	TP	FP	FN	Precision	Recall	F1 score
Ding's analytical method*	241	29	96	0.8926	0.7151	0.7941
Lu's analytical method*	260	29	77	0.8997	0.7715	0.8307
Proposed framework**	310	15	27	0.9538	0.9199	0.9366

Note: * vehicle lengths of 18 ft in Ding's method and 20 ft in Lu's method were estimated through a sensitivity analysis to yield best reidentification metrics; ** based on the hyperparameter combination for best reidentification; TP = true positive, FP = false positive, FN = false negative

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Conclusions

- **Contributions**
  - Superior reidentification accuracy compared to existing models
    - **95.38% precision, 91.99% recall**
  - Easily transferrable for ReId at other intersections and detectors
  - Advances using ML models and high-resolution data for vehicle ReId
  - Travel time predicted using info from advance detector only
    - Real-time applications & adaptive signal control strategies
- **Future work**
  - Dilemma zone boundary analysis

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Pramesh Pudasaini

pramesh@arizona.edu

pudasaini.com

Research GitHub repo:

https://github.com/prameshpudasaini/vehicle_reidentification

THE UNIVERSITY OF ARIZONA
COLLEGE OF ENGINEERING
Center for Applied Transportation Sciences