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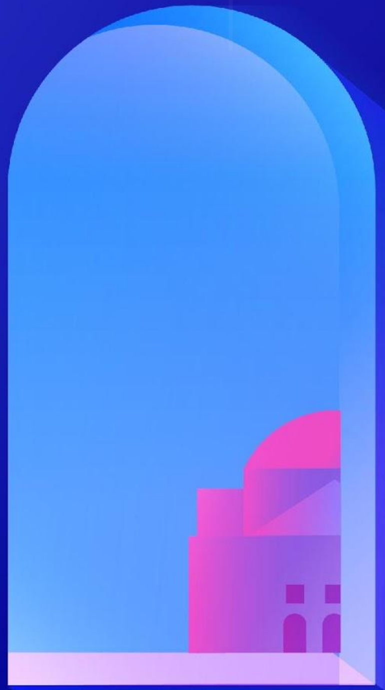
STREAM-RL: Sequential Traffic Reinforcement for Efficient Anomaly Management and Learning



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Introduction and Gaps Identified

Current traffic forecasting and anomaly detection models operate in isolation, assuming static human behavior. Real-world systems, however, involve feedback loops: predictions (e.g., congestion alerts) alter driver behavior, invalidating initial forecasts. This creates a moving target that existing methods (ARIMA, LSTM, etc.) fail to address.

Novelty:

- First unified framework combining anomaly detection, forecasting, and human feedback modeling in traffic systems.
- Closed-loop RL: Agent dynamically adapts to human responses (e.g., rerouting) by simulating feedback via hybrid real-synthetic data.
- Reward shaping based on traffic stability metrics (e.g., entropy reduction in flow variance).

Motivation for our research

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High traffic load remains a major issue, especially for big cities

Traffic can be forecasted, therefore, mitigated by changing the navigation trajectories, controling the traffic lights, etc.

This system can be fully automated by using AI models

We are building an RL-based pipeline to optimize the vehicle traffic

Existing Methods (p.1)

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1. Classical Statistical Models

- **ARIMA, Kalman Filters**
  - Effective for short-term, linear patterns
  - Limited by non-stationarity and real-world complexity

2. Machine Learning Approaches

- **k-Nearest Neighbor, Random Forest, SVM**
  - Handle non-linearity better than classical models
  - Struggle with temporal dependencies and multivariate time series
- **Gradient Boosting (LightGBM, CatBoost)**
  - Efficient on tabular + categorical data (e.g., road type)
  - Good interpretability, limited temporal learning

Existing Methods (p. 2)

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3. Deep Learning Models

- **LSTM / GRU**
  - Capture temporal dependencies
  - May fail under dynamic traffic patterns (e.g., during anomalies)

- **Hybrid Models (e.g., FD-Markov-LSTM)**
  - Combine traffic theory (FD), stochastic transitions (Markov), and memory (LSTM)
  - Achieve superior performance over standalone methods

4. Anomaly Detection

- **Autoencoders, USAD, TranAD**
  - Detect unexpected spikes/drops in traffic metrics
  - Useful for incident detection (accidents, events)

5. Control Systems & RL

- **Fixed-Time Control, Adaptive Signal Control**
  - Traditional rule-based systems

- **Reinforcement Learning (DQN, PPO)**
  - Learn optimal traffic control policies
  - Require high-fidelity simulation environments (e.g., SUMO, CARLA)

Dataset

T-Drive Trajectory Sample (Microsoft)**:**

- Location : Beijing
- Time : Feb, 2, 2008 to Feb, 8, 2008
  - A one-week trajectories of 10,357 taxis
  - 15 million points
  - Total distance of the trajectories reaches 9 million kilometers

Beijing District Points :

- ESRI Shapefile format
- Mapping buildings, roads, railways, etc. zones

Ways to Create the Traffic

How many cars are there on the road at a given time?

- *Temporal data division* (aggregate the traffic every 15 mins / 1 hour / …)
- *Spatial data division*
  - Beijing Districts
  - 1 km / 5 km / … resolution grid cells (preferred)

Percentage change between the current time period and the previous time period?

- Check how many more cars there are now compared to the previous time period (l2 / l3 / … previous time period)
- Use the cumulative sum approach (if the traffic was increasing for several periods, it means that it is very high)

How fast the cars are going within the trajectories (10 mins / 15 mins / …)

- Take into account the location features (traffic lights / type of the road, etc.)
- Create a function that maps the aggregated speed to the numerical traffic estimation

Methodology

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Proposed PipeLine (p.1)

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I. Data Preprocessing & Anomaly Detection

Dataset: T-Drive Trajectory (Microsoft)

Forecasting

Use SOTA DL-model (e.g., **FD-Markov-LSTM,** integrates statistical and DL approaches to capture both congested and uncongested traffic states, achieving significant improvements over benchmarks) to predict the traffic.

Use Gradient Boosting (e.g., LightGBM, CatBoost), as it can effectively use categorical features (like type of the road)

Anomaly Detection

Use SOTA DL-models (e.g., USAD, TranAD) to flag sudden drops in speed/flow (accidents) or surges (events).

Use Gradient Boosting (e.g., LightGBM, CatBoost), as it can effectively use categorical features (like type of the road)

II. Hybrid Simulation Environment

SUMO simulator : allows modelling of intermodal traffic systems including road vehicles, public transport and pedestrians

CARLA simulator : an open-source autonomous driving simulator.

Feedback Modeling: Simulate driver responses to RL actions (e.g., 30% reroute on Waze alerts, stochastic delays in reaction time).

Proposed PipeLine (p.2)

III. RL Agent Design

A. State Space: Time series features (flow, speed) + anomaly flags + simulated driver adherence rates.

B. Action Space: Adjust traffic light cycles, send reroute suggestions, activate dynamic lane reversals.

C. Reward Function:

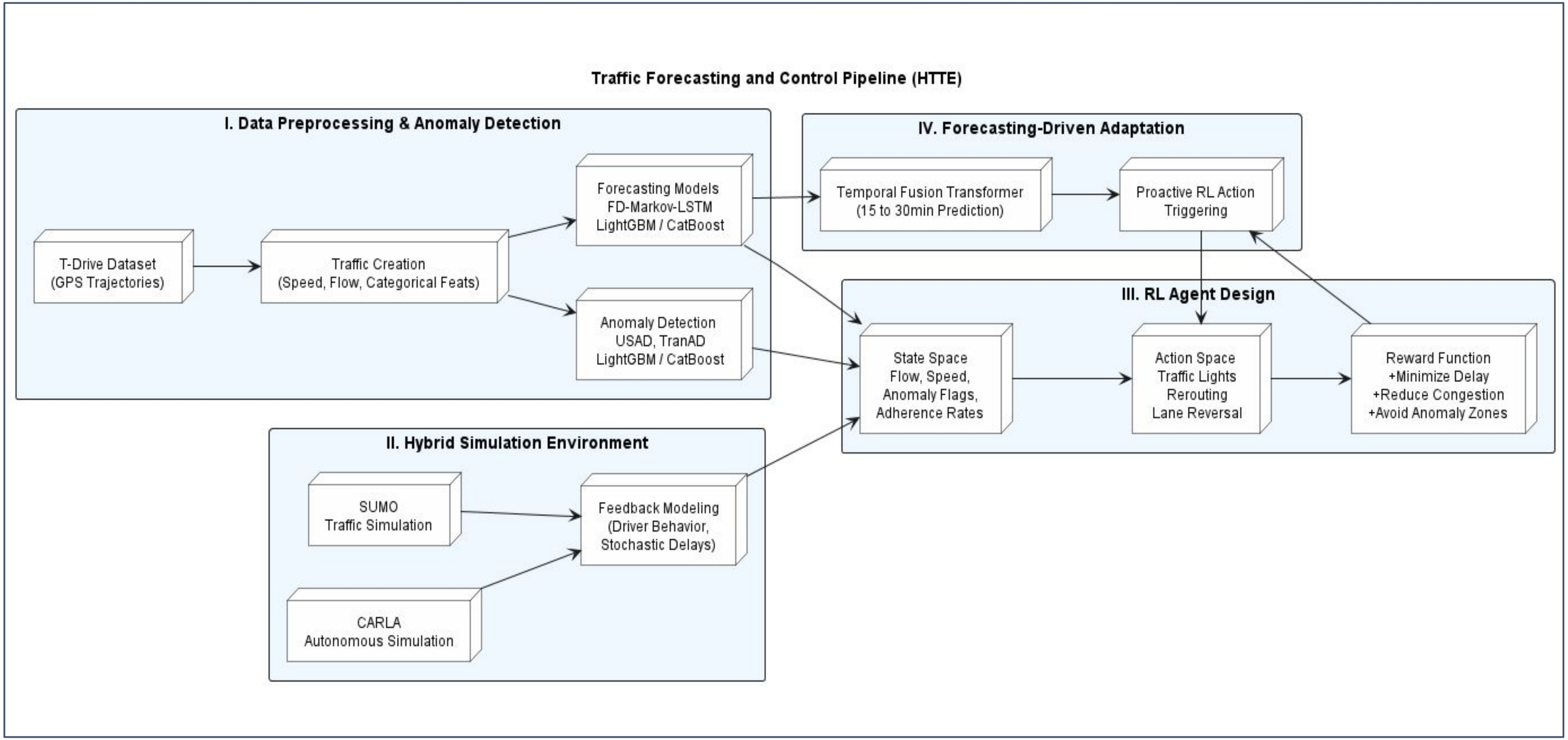
$$R = \underbrace{\alpha \cdot TravelTimeReduction}_{ForecastingGoal} + \underbrace{\beta \cdot AnomalySeverityReduction}_{DetectionGoal} - \underbrace{\gamma \cdot FlowEntropy}_{StabilityPenalty}$$

IV. Forecasting-Driven Adaptation

A. Train a chosen model (e.g., Temporal Fusion Transformer (TFT) to predict traffic states 15–30 mins ahead.

B. Use forecasts to preemptively trigger RL actions (e.g., preempt congestion by rerouting before anomalies escalate).

Pipeline Diagram



Data Simulation & Validation

SUMO (Simulation of Urban MObility):

- ➔ Microscopic, multi-modal traffic simulator
- ➔ Models traffic lights, vehicle interactions, pedestrian dynamics
- ➔ Ideal for simulating urban-scale traffic flow and rerouting strategies
- ➔ Generate synthetic but realistic traffic under varying congestion, events
- ➔ Test RL agent policies: traffic light optimization, lane reversals, rerouting

CARLA (Car Learning to Act):

- ➔ High-fidelity autonomous driving simulator
- ➔ Supports camera/LiDAR sensors, dynamic weather, and driver behavior
- ➔ Ideal for validating vehicle-level decision-making and perception
- ➔ Simulate stochastic behavior:
  1. ~30% driver compliance with navigation reroutes
  2. Delays in reaction time to traffic events
- ➔ Validate real-world plausibility of control strategies

Challenges

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2008 Dataset:

Outdated Traffic Patterns : Traffic volumes and congestion points have evolved since 2008
Evolving Transportation Modes : The rise of ride-sharing, cycling, and micro-mobility options has changed traffic dynamics
Infrastructure Changes : New roads, altered intersections, and modified traffic controls since 2008

Many ways to create roads:

Multiple methods to generate the roads, and need to select the most appropriate one

Data simulation for RL model training:

Many traffic scenarios possible, making the RL model training more difficult because it cannot capture irregular maneuver and complex scenarios

Difficulty to train RL model:

RL model for traffic prediction can be computionnaly intensive and hard due to its complexity

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Thank You!