Abnormal Behavior State-of-the-art for UAVs Detection in Complex Environments

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9-10 October 2023

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  - Currently in the 2nd year of my thesis (2022-2025).

AGENDA

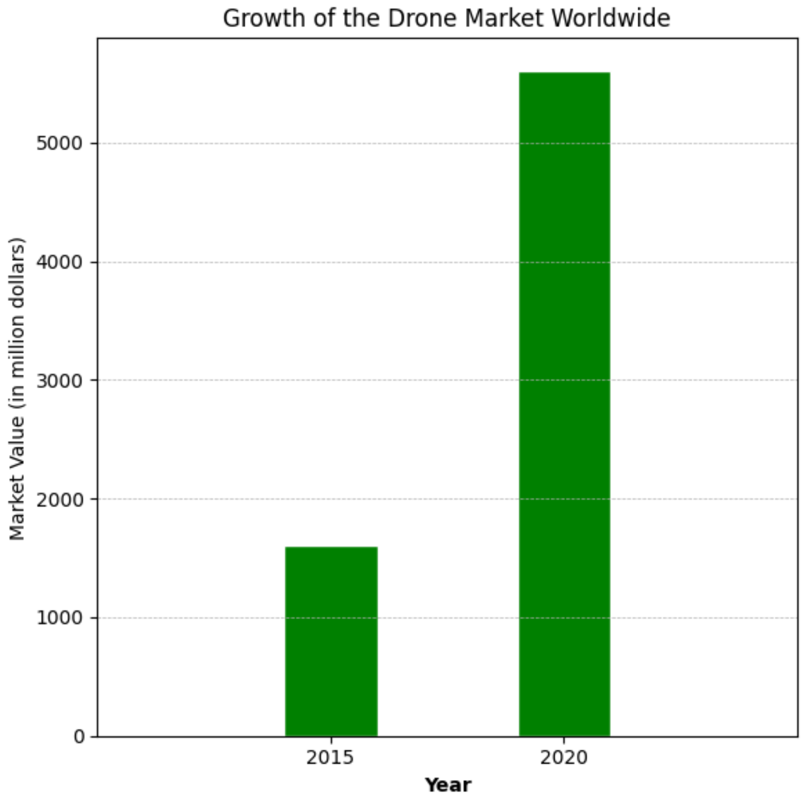
1.0 Introduction

2.0 State of the Art in Abnormal Behavior Detection

3.0 Simulations & Test

4.0 Conclusion

CONTEXT & SIGNIFICANCE



- The rise of UAVs in both civilian and military domains necessitates effective behavior detection.
- Abnormal behaviors can signify potential threats, making their detection crucial for security.
- In France, enterprises are already utilizing drones for deliveries.
  - Dedicated air currents for drone navigation have been established
  - Taxi drones have received approval to operate during the Paris Olympics Games in 2024

STATE OF THE ART IN ABNORMAL BEHAVIOR DETECTION: LEARNING METHODS

Unsupervised Learning:

- Leveraging unlabeled data
- Able of spotting inherent data patterns.
- Examples: Neighborhood Detection, Clustering

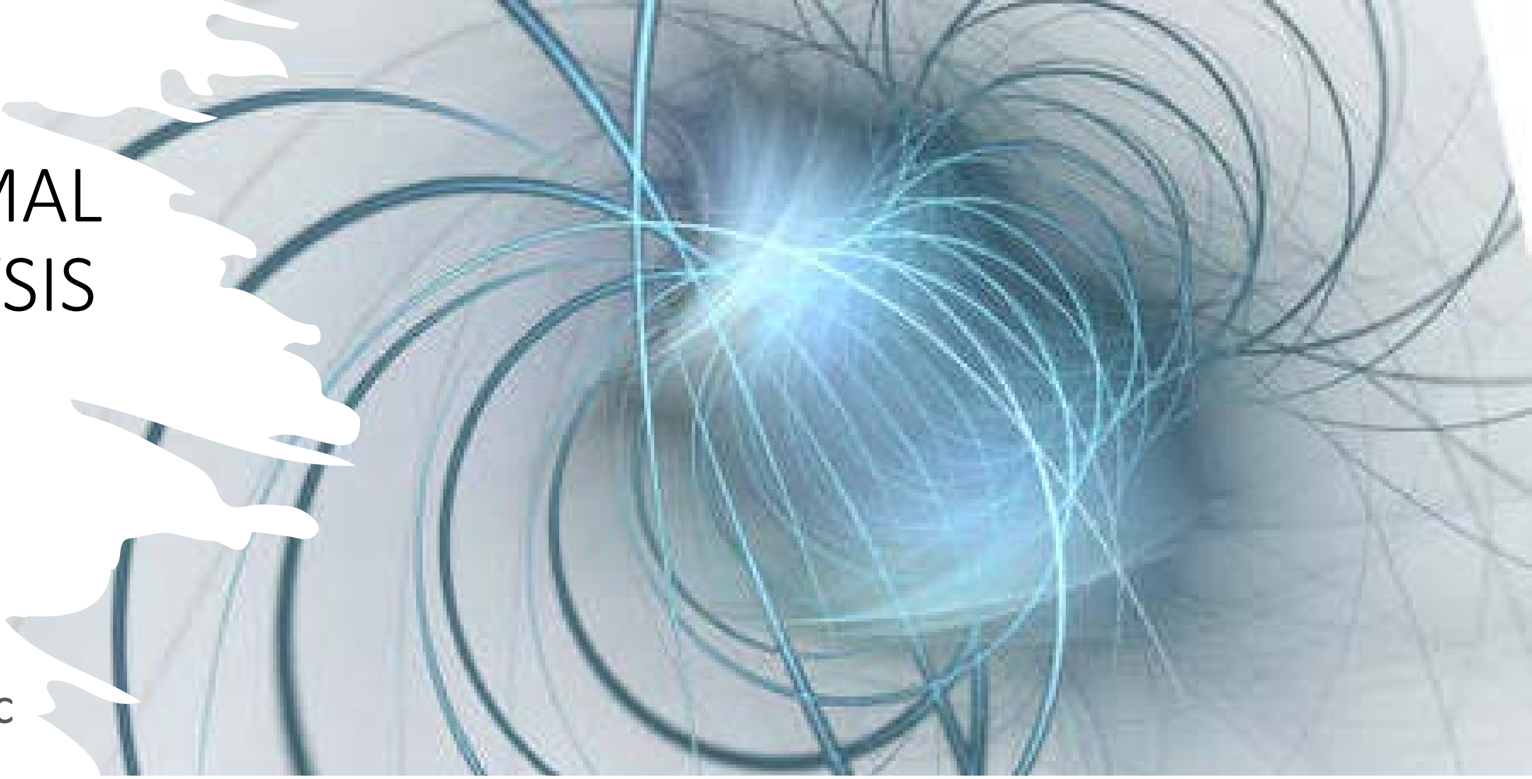
Supervised Learning:

- Training with labeled data.
- Relies heavily on the precision of labeling
- Particularly effective in well-defined scenarios.
- Examples: SVM, Neural Networks

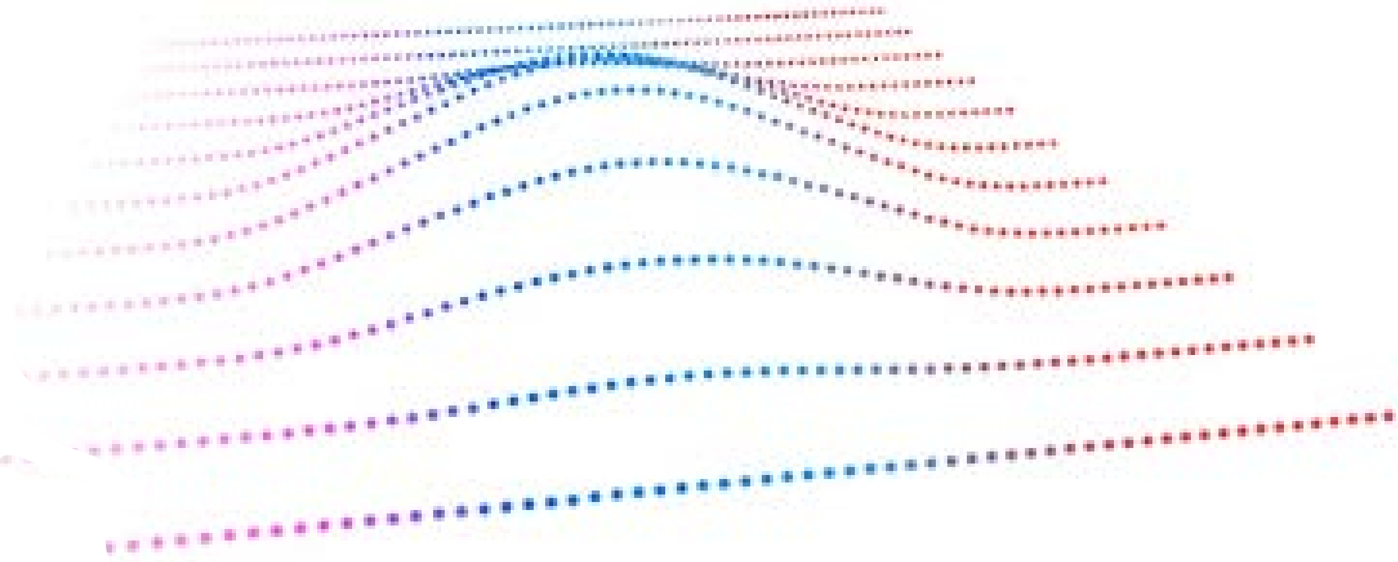
Deep Learning:

- Intricate pattern detection.
- Deciphers intricate patterns, yet susceptible to overfitting.
- Offers potential for high precision but demands judicious application.
- Examples: Deep Neural Networks, Generative Models

STATE OF THE ART IN ABNORMAL BEHAVIOR DETECTION: ANALYSIS & PATTERNS

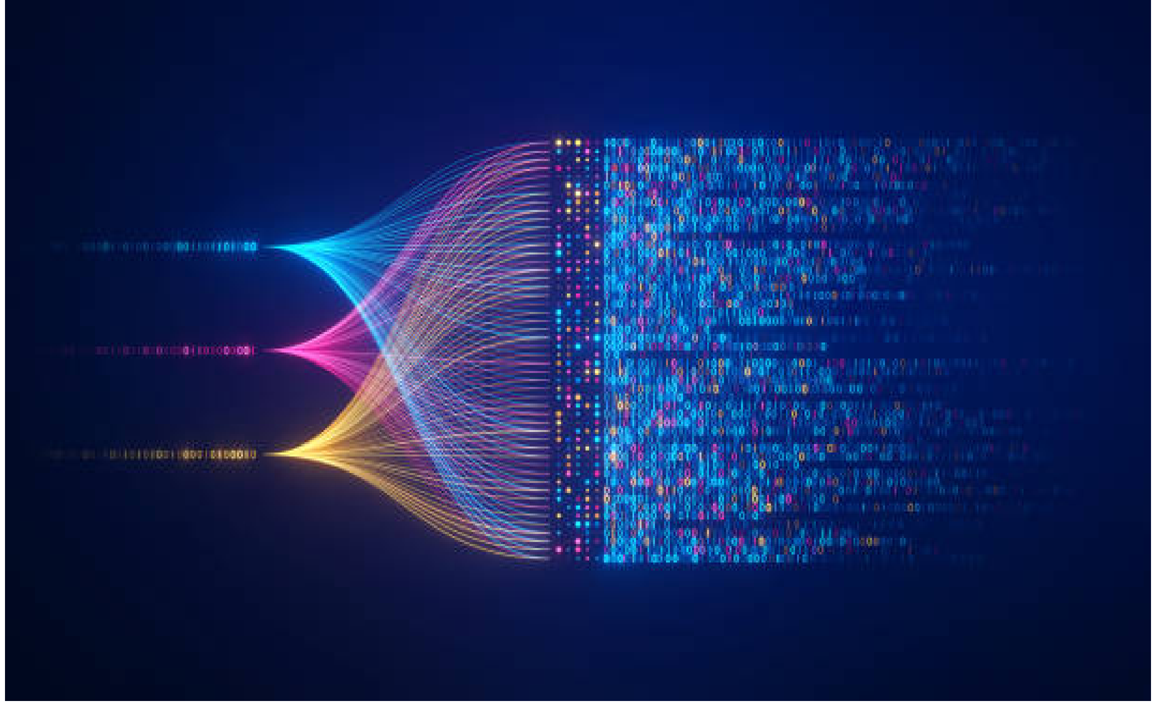


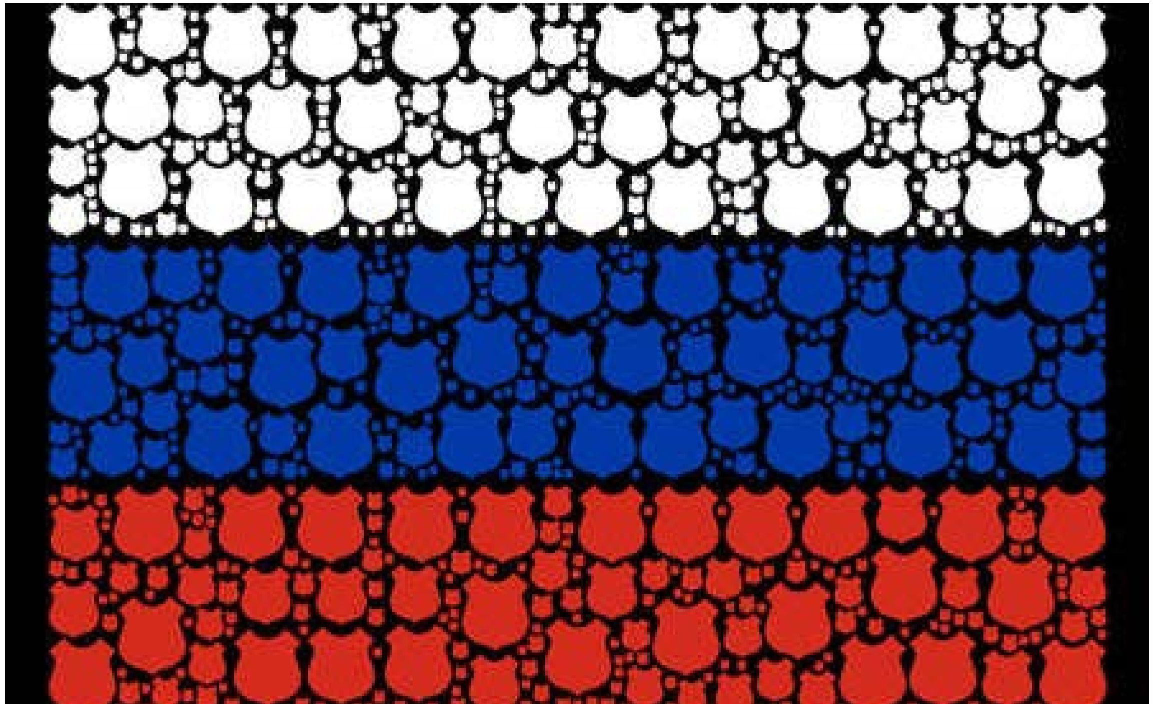
- Information Theory:
  - Employs mathematical measures, like entropy.
  - Independent of data distribution assumptions, but reliant on the specific measure used.
- Frequent Patterns:
  - Spotting recurring patterns.
  - Marks deviations from the norm as anomalies.
- Specialized Analysis:
  - Tailored for unique data types.
  - Examples: Time Series Analysis, Graph-based Models



STATE OF THE ART IN ABNORMAL BEHAVIOR DETECTION: ADAPTIVE & COMBINED TECHNIQUES

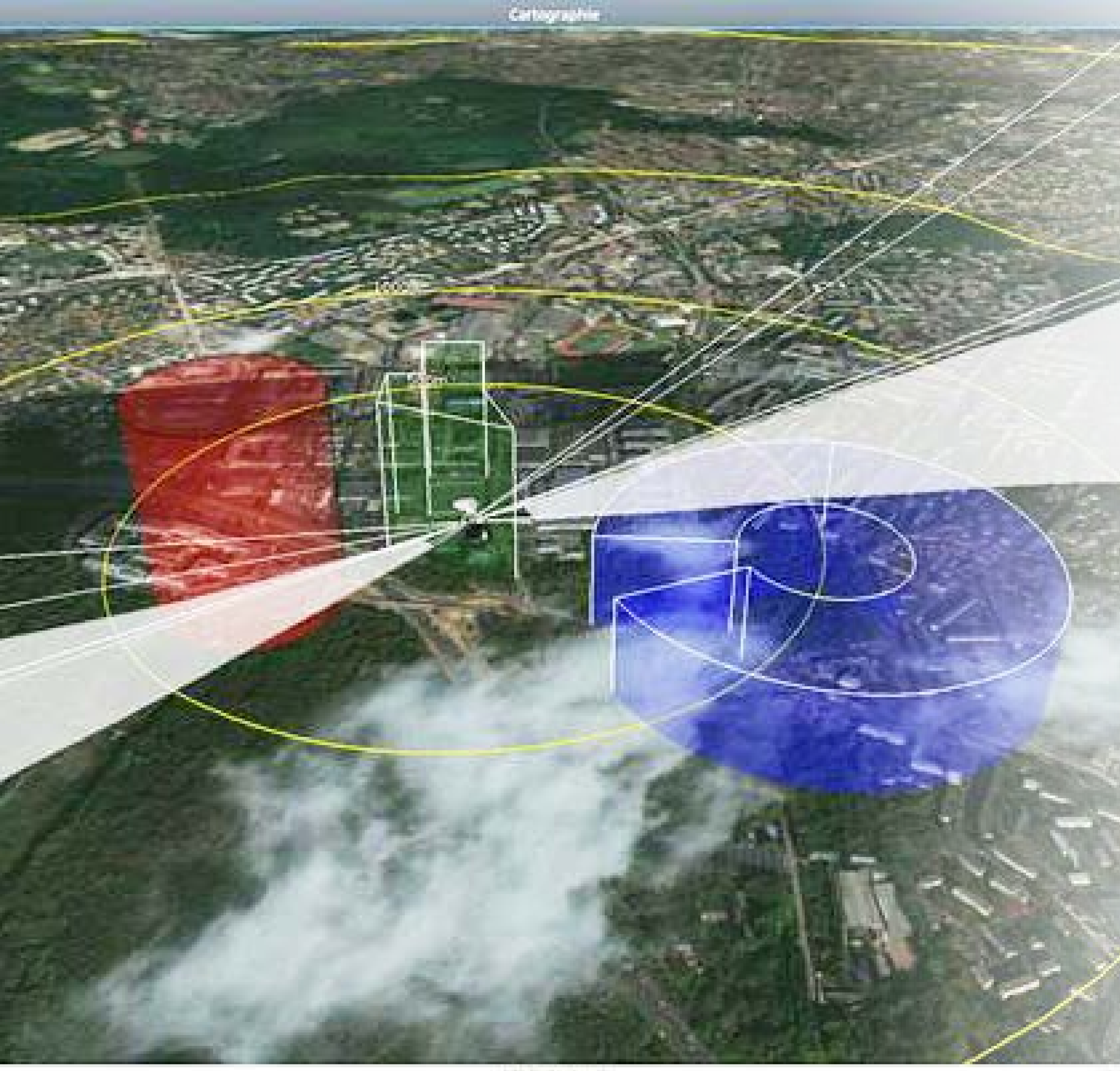
- Reinforcement Learning:
  - Systems that adaptively learn optimal actions.
  - Seeks to minimize anomaly risks through iterative feedback.
- Ensemble & Subspace Techniques:
  - Aggregates multiple methods for robustness.
  - Focuses on data subspaces for precision.
  - Examples: Feature Bagging, Random Forest





ABNORMAL BEHAVIOR DETECTION IN UAVS

- Detecting deviations from expected behaviors helps identify potential threats or malfunctions.
- Data Sources:
  - Onboard sensors, Real-time video, radar, acoustic detection, and RF signals monitoring.
- Integrative Approaches:
  - Hybrid Systems: Combines sensor-based detection, computer vision, and RF signal analysis for enhanced reliability and accuracy



CHALLENGES IN UAV ABNORMAL BEHAVIOR DETECTION

- Data Fusion:
  - Defined by the Joint Directors of Laboratories (JDL) as refining estimates and evaluation through multi-source data.
- Exploring JDL Data Fusion Levels:
  - Level 0 - Data Processing: Source preprocessing.
  - Level 1 - Object Refinement: Entity assessment.
  - **Level 2 - Situation Refinement: Interpretation.**
  - Level 3 - Impact Refinement: Projections & estimations.
  - Level 4 - Resource Management: System adaptation.
- Complex Environments and Heterogeneous Data:
  - Challenges: Managing uncertainty, sensor variability, modeling nonlinear relationships.
  - Need for standardized performance metrics measures for consistent evaluation.

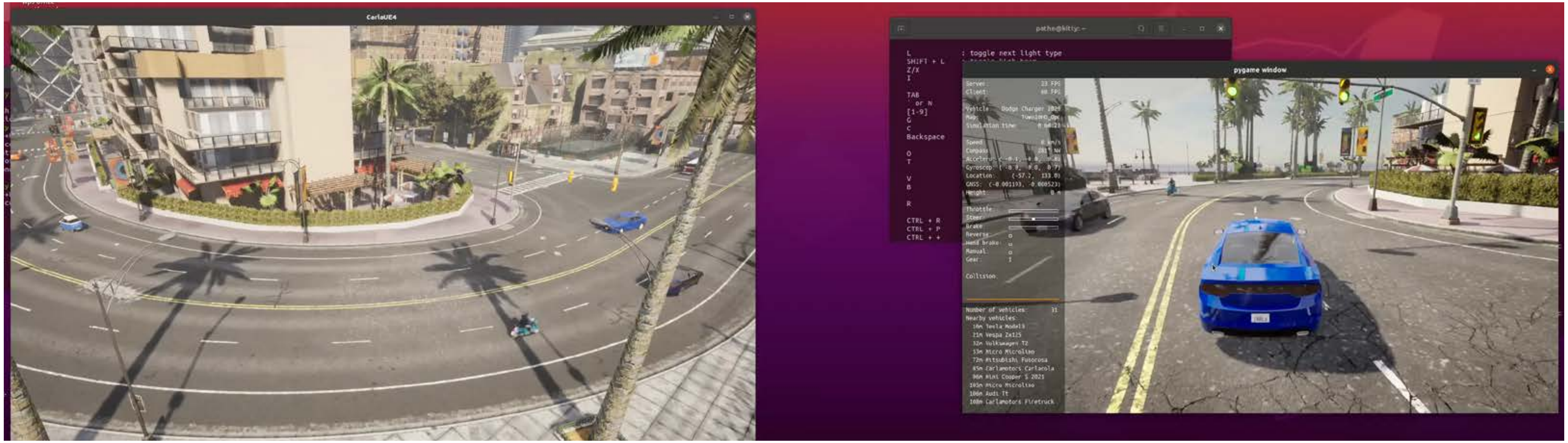
ASSOCIATIONS IN ABNORMAL BEHAVIOR DETECTION & DATA FUSION

Article (Author)	Data Fusion Technique	Abnormal Behavior Detection
"An Anomaly Detection Based on Data Fusion Algorithm in Wireless Sensor Networks" (Guo et al., 2015)	PAA + Hybridization	K-Means and AIS
"HMM Based Falling Person Detection Using Both Audio and Video”, (B. U. Töreyin et al., 2005)	‘AND’ operation-based fusion	Hidden Markov Models (HMM)
"Data fusion algorithms for network anomaly detection: classification and evaluation" (Chatzigiannakis et al., 2007)	Dempster-Shafer’s Theory	PCA
"A Multi-Sensor Approach for Activity Recognition in Older Patients" (Crispim-Junior et al., 2012)	Decision-Level Fusion	Recognition of IADLs

Table 1: Associations of methods in references articles.

TESTS & SIMULATIONS

- Simulation Environment:
  - CARLA replicates real-world roadways.
  - Radar data: Noise-free; Lidar data: Contains realistic noise.
  - Simulated anomalies: Speed variations, erratic lane changes, traffic rule violations, collisions, etc.
- Simulation Overview:
  - Abnormal behavior algorithms tested: Logistic Regression, Isolation Forest, One-Class SVM, Random Forest Classifier, Gradient Boosting Classifier.
  - Data Source: CARLA simulator (radar, lidar).



RESULTS

- Methodology:
  - Tools: Python, scikit-learn library.
  - Data cleaning: Noise and irrelevant features removed.
  - Tuning: Grid search with cross-validation.
- Results:
  - Key Takeaway: Fused radar and lidar data consistently superior.

Data Source	Algorithm	Accuracy	Precision	Recall	F1-score
Radar	Logistic Regression	0.90	0.94	0.76	0.81
Lidar		0.90	0.86	0.51	0.49
Fused		0.90	0.94	0.78	0.83
Radar	Isolation Forest	0.83	0.78	0.64	0.67
Lidar		0.43	0.52	0.55	0.37
Fused		0.85	0.82	0.67	0.71
Radar	One-Class SVM	0.78	0.70	0.76	0.72
Lidar		0.23	0.51	0.52	0.23
Fused		0.88	0.81	0.84	0.82
Radar	Random Forest	0.93	0.90	0.91	0.90
Lidar		0.73	0.55	0.60	0.54
Fused		1.00	1.00	1.00	1.00
Radar	Gradient Boosting	0.96	0.93	0.94	0.93
Lidar		0.75	0.57	0.65	0.57
Fused		0.99	0.99	0.97	0.98

CONCLUSION

- **Key Findings:**
  - Fused data enhances the performance of abnormal behavior detection.
- **Limitations & Considerations:**
  - Data sourced from CARLA: How transferable are results to real-world unpredictability?
- **Implications:**
  - Beyond academia: Potential for preemptive threat identification and enhanced security.
  - Crucial for defense and security sectors.
- **Looking Ahead:**
  - Incorporating additional characteristics into the data fusion process, such as environment, weather, map details, and contextual information.
  - Transition from simulated to real-world data collection.
  - Aim: Robust detection mechanism for real-world challenges.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