

# Neurosymbolic Complex Event Recognition Optimized across IoT Platforms

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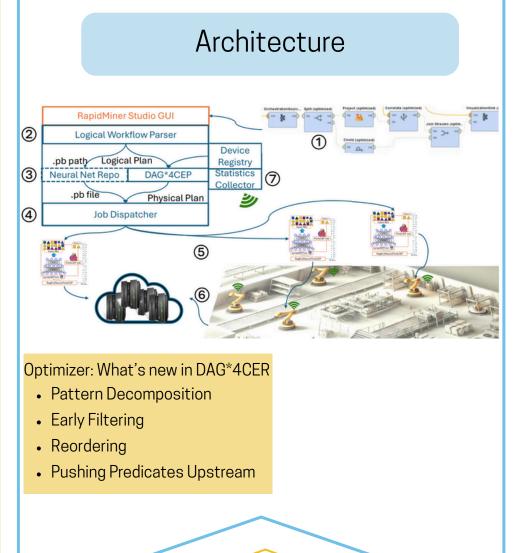


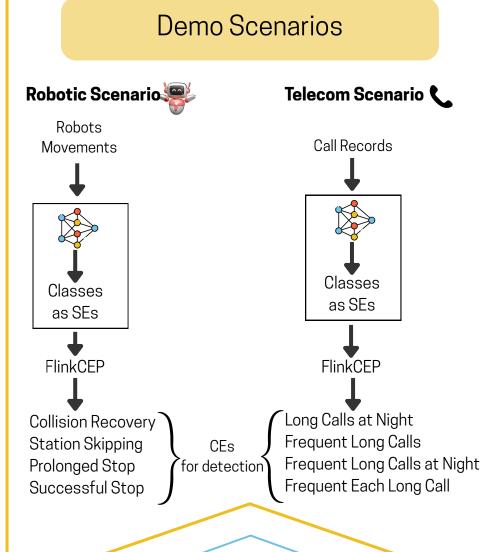
### Problem & Gap

- Neural Net (aka sub-symbolic representation): From raw streams to Simple Events (SE) → symbols with learned instead of crisp definitions
- Symbolic Representations: Rules/Patterns expressing Complex Business Events (CEs) of interest
- **Neurosymbolic CER:** Neural Inference for SEs+ Patterns for CEs

**Challenge**: Neurosymbolic engine that scales (a) with the volume and velocity of rapid streams (b) across IoT platform

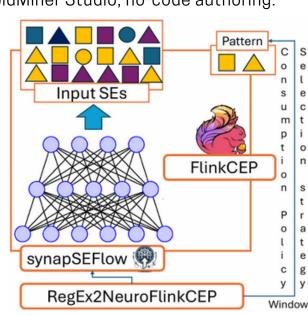
From extended RegEx → auto-generated FlinkCEP jobs per device, with embedded neural inference and an optimizer that places operators across cloud/edge.





#### Contribution

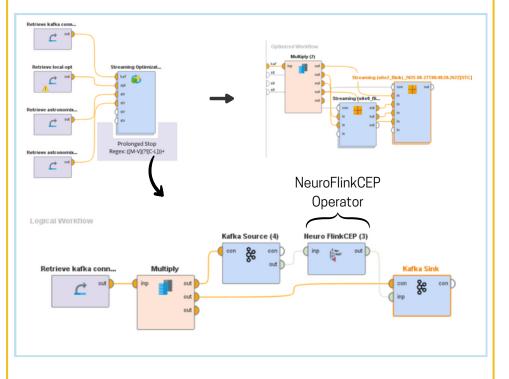
- First neurosymbolic CER framework on a state-of-theart Big Data platform (Flink) with IoT-aware optimization
- synapSEflow: embed TensorFlow (.pb) models inside Flink jobs
- RegEx2NeuroFlinkCEP: compile extended RegEx patterns into FlinkCEP code (with window, selection, consumption policies).
- DAG\*4CER Optimizer: extends DAG\* with CER-specific rewrites for optimal edge/cloud placement
- Integration in RapidMiner Studio, no-code authoring.



## **User Experience**

- 1. **Design** Logical workflows with NeuroFlinkCEP operators
- 2. **Optimize** physical workflow
- 3. Human in the Loop, Modify workflows before submitting
- 4. Deploy across the Cloud to Edge Continuum
- 5. Visual Analytics Dashboards

Care for manual physical plan creation?



### **DataSets**

#### **Robotic Stream**



**Record format:** robotID, time, px/py/pz, vx/vy, idle, linear, rotational, Deadlock\_Bool, RobotBodyContact

**Neural net**: predicts goal\_status → mapped to simple events A-V (e.g., moving/stopped @ station). These feed CEP patterns **Simple events:** A-V = collision (A), stopped-unknown (B), moving to 0-9 (C-L), stopped at 0-9 (M-V)

#### Telecom Stream



**Record format:** date/time, caller/callee, direction, charge, duration

**Neural net**: multi-label for A/B/C (premium, night, expensive) can co-occur. CEP then derives E via aggregates.

**Simple events:** A=Call made to a premium location, B=Call made during night hours, C=Long call, E=Sum of call durations exceeds 60 minutes

# **Intrested for more**







