

Developing an Analytics Everywhere framework for the Internet of Things in Smart City Applications

Hung Cao

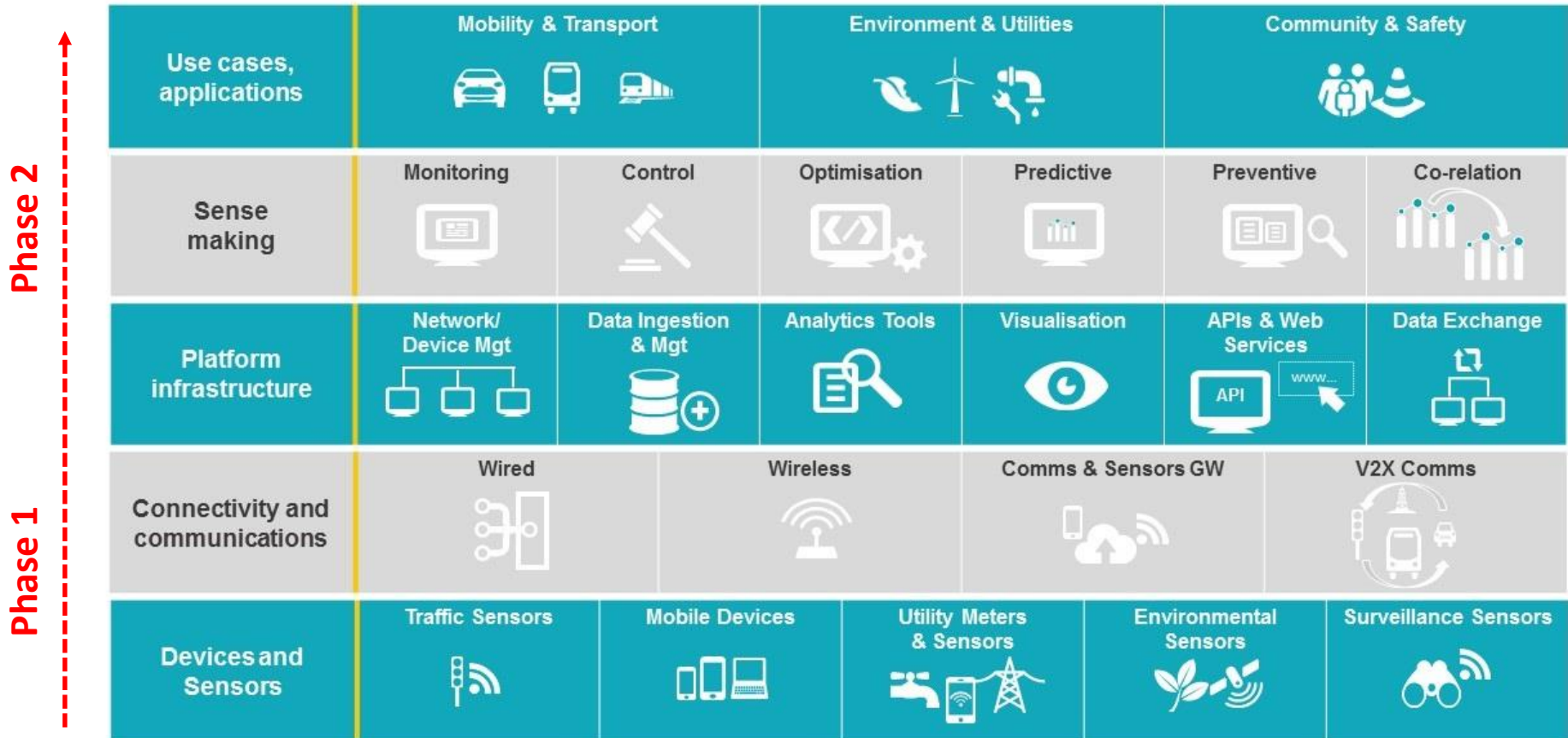
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Outline

- Background/Research Motivation
- Research Questions & Objectives
- Methodology
- Implementation
- Applications & Results
- Scientific Contributions
- Recommendations for Future Work

Current Research in IoT

Figure: <https://www.beca.com/>



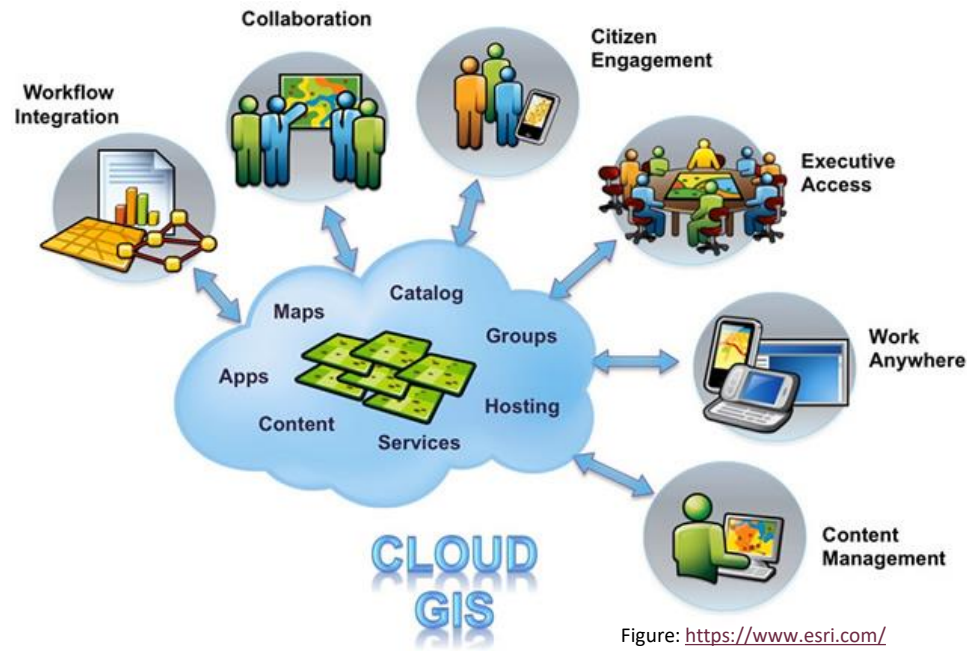
Al-Fuqaha, Guizani, Mohammadi, Aledhari, & Ayyash (2015); Li, Da Xu, & Zhao (2015); Ngu, Gutierrez, Metsis, Nepal, & Sheng (2017); Gazis (2017)

Current Research in IoT Computing

- Focus on processing & analyzing IoT data streams using one computing resource:
 - Cloud Computing
 - Fog Computing
 - Edge Computing

Current Research in IoT Geomatics

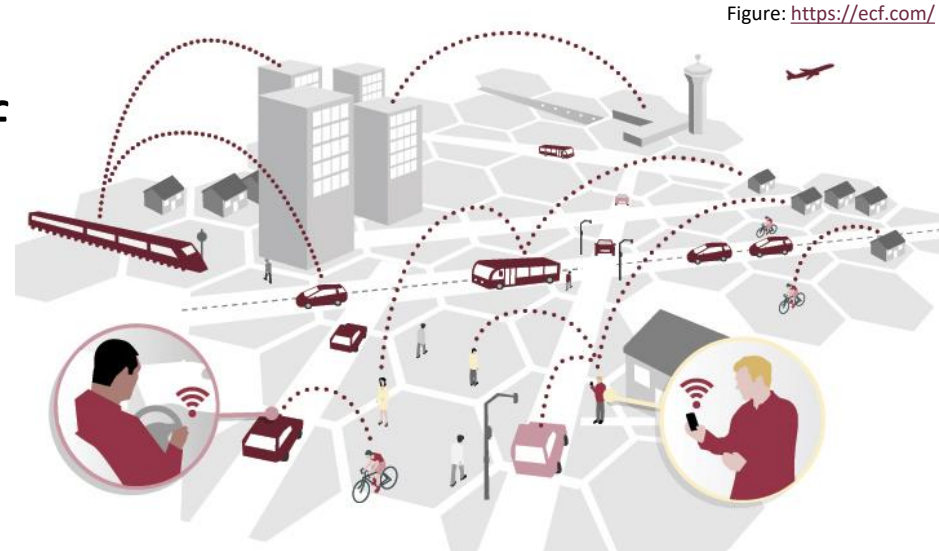
- IoT-GIS is still in its infancy.
- No GIS can handle IoT stream data
- IoT-GIS platforms are needed for contextualizing IoT data streams that can significantly improve the results of analytical workflows.



Research Challenges

- Mobility and co-location of IoT devices in smart cities will require

- avoiding bottlenecks
- reducing data latency



- Vast amount of IoT data streams will require
 - streaming automated analytical tasks
 - manage, process, and retrieve high velocity, variety, and volumes of data.

Overall Research Goal

- Develop an “*Analytics Everywhere*” framework to explore the edge-fog-cloud continuum for performing automated analytical tasks capable of:
 - providing higher-level intelligence from continuous IoT data streams
 - generating long-term predictions from accumulated IoT data streams.

RQ1: How can **automated analytical tasks** be developed for supporting **analytical capabilities** such as **streaming descriptive/diagnostics/predictive algorithms/methods?**

- Identify the algorithms/methods that can be used for supporting automated streaming analytical tasks (analytical capability).
- Identify the potential IoT applications in smart cities while taking into account the availability of IoT data streams.

RQ2: How can **continuous** and **accumulated streams** be combined while taking into account different IoT **data life-cycles**?

- Develop data life-cycles for executing automated analytical tasks and coping with continuous IoT data streams.
- Develop data life-cycles for executing automated analytical tasks and coping with accumulated IoT data streams.
- Implement the data life-cycles for the real-world experiments.

RQ3: How can **IoT** and **GIS** be integrated into the **edge-fog-cloud continuum** without compromising **resource capabilities**?

- Identify the off-the-shelf tools that can be used to implement the proposed framework (computational resources).
- Build the architecture for this new framework based on a continuum of edge-fog-cloud nodes.

RQ4: What are the **benefits** and **limitations** of the proposed **“Analytics Everywhere”** framework in smart cities?

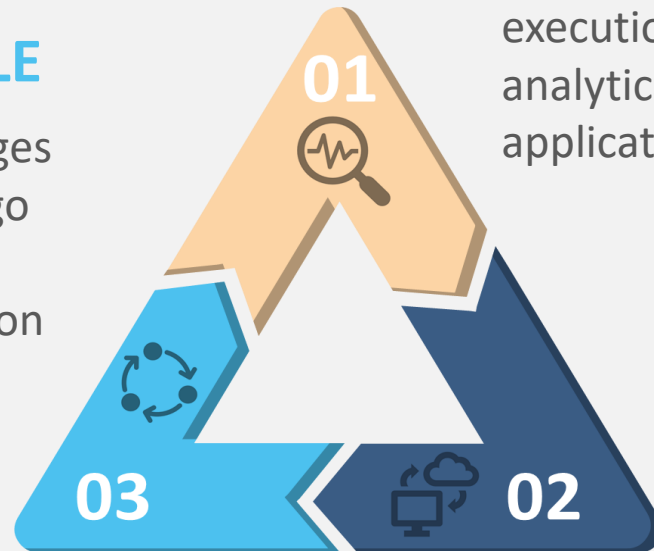
- Implement the “Analytics Everywhere” framework in real-world experiments to evaluate the proposed approach. Two experiments were selected according to data availability: smart transit and smart parking.
- Validate the proposed “Analytics Everywhere” framework.

Methodology

Analytics Everywhere Framework

DATA LIFECYCLE

Manages the changes that data streams go through during the automated execution of a network of analytical tasks



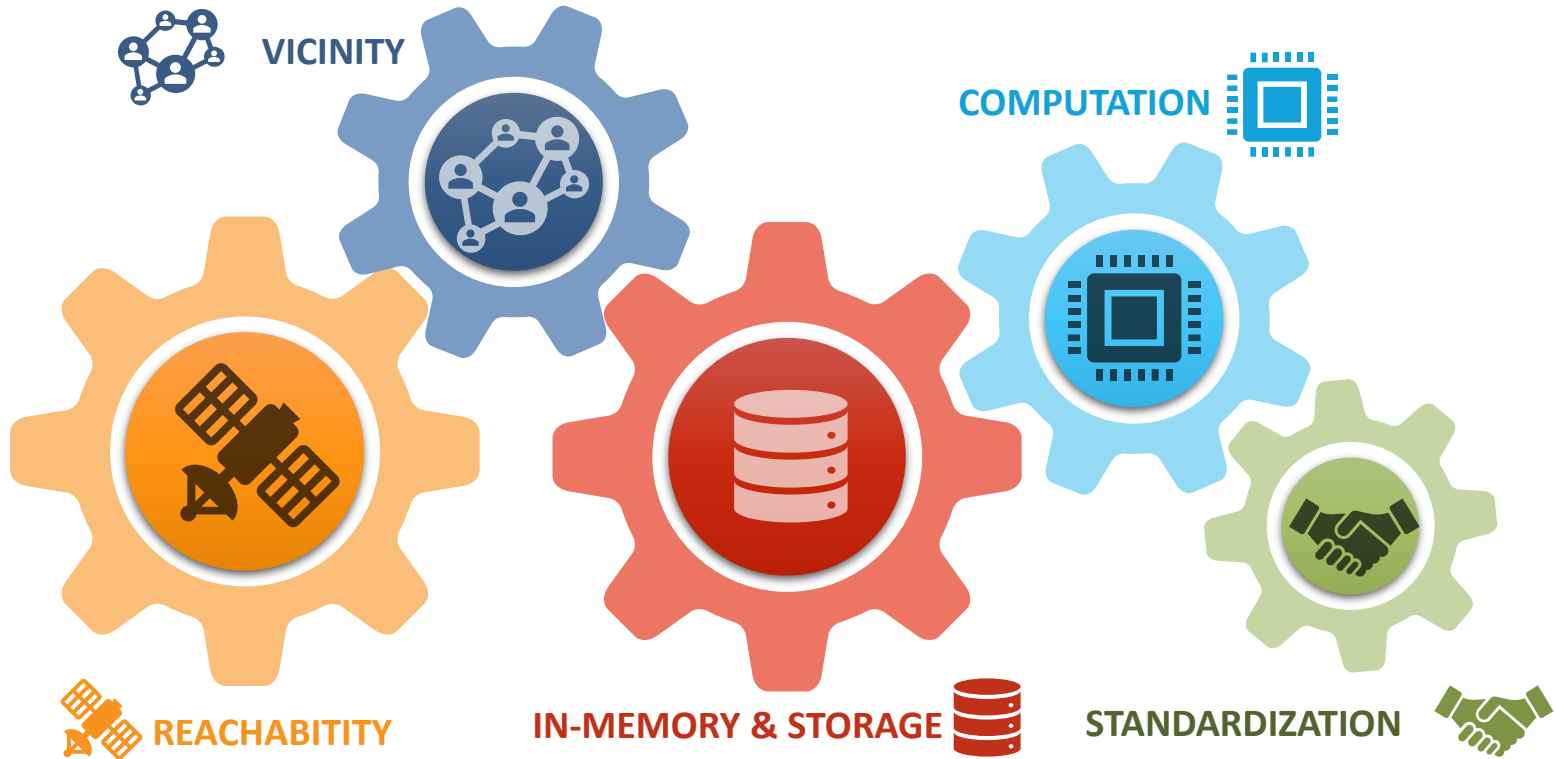
ANALYTICAL CAPABILITY

Consists of algorithms for the execution of a network of analytical tasks for IoT applications

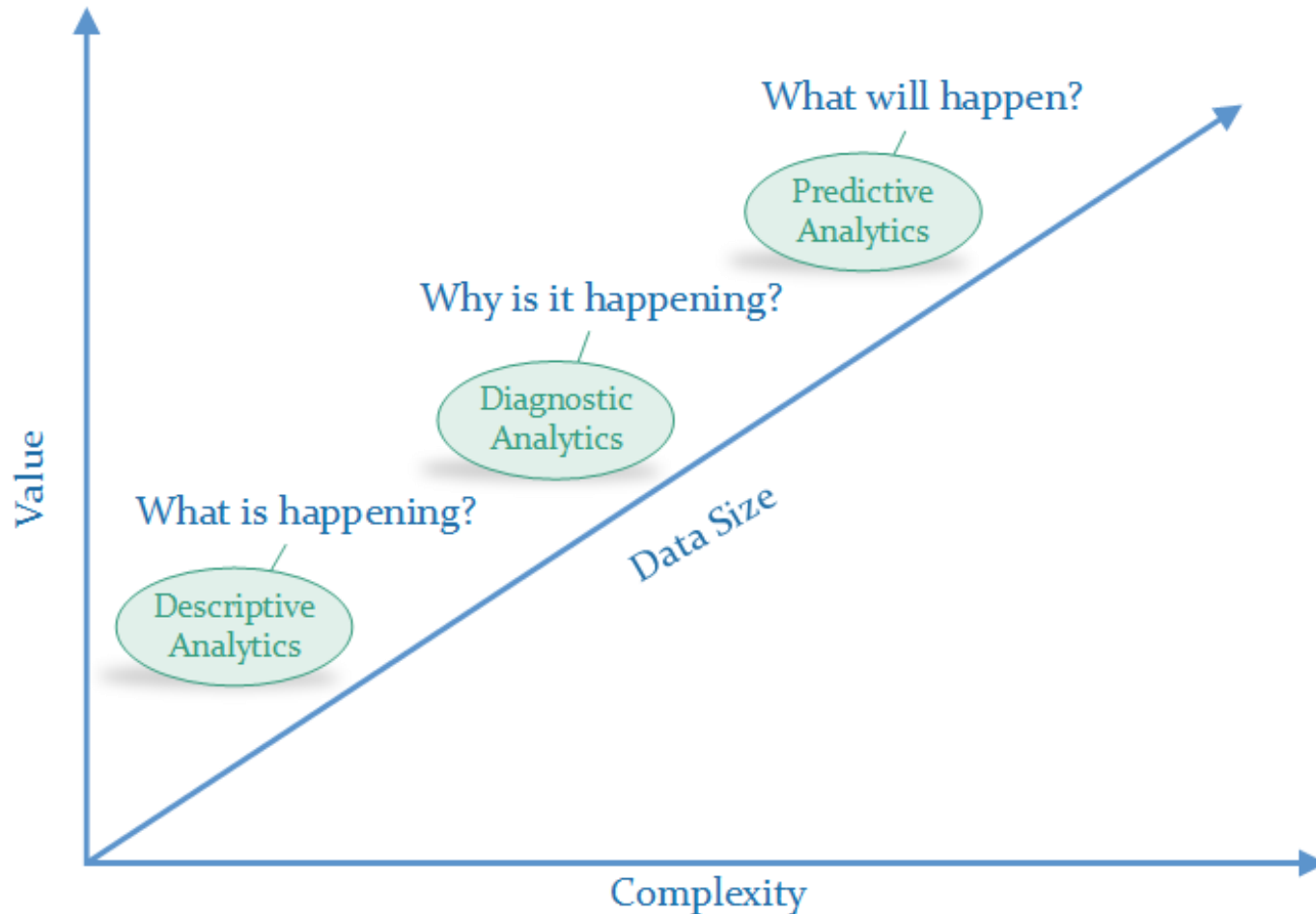
RESOURCE CAPABILITY

Consists of distributed compute nodes (i.e. cloud, fog, and edge nodes) that provide I/O, storage, computation and processing power for the execution of a network of analytical tasks

Resource Capability



Analytical Capability



Data lifecycle

Raw Data

$$T_i = (S_i, x_i, y_i, t_i)$$



Raw

Aggregated Data

$$\begin{cases} \forall T_i \in (T_1, T_2, \dots, T_n) : T_i = (S_i, x_i, y_i, t_i) \\ \mathbb{D} = (T_1, \dots, T_n) \xrightarrow[\text{on attribute } S]{\Phi} \hat{\mathbb{D}} = (Q_1, \dots, Q_m) \\ \forall Q_j \in (Q_1, \dots, Q_m) : Q_j = (Agg_value_1, Agg_value_2, \dots) \end{cases}$$



Aggregated



Transformed

Transformed Data

$$\begin{cases} \forall T_i \in (T_1, T_2, \dots, T_n) : T_i = (S_i, x_i, y_i, t_i) \\ \mathbb{D} = (T_1, \dots, T_n) \xrightarrow{\Upsilon} \bar{\mathbb{D}} = (K_1, \dots, K_n) \\ \forall K_i \in (K_1, \dots, K_n) : K_i = (Trans_value_1, Trans_value_2, \dots) \end{cases}$$

Extracted Data



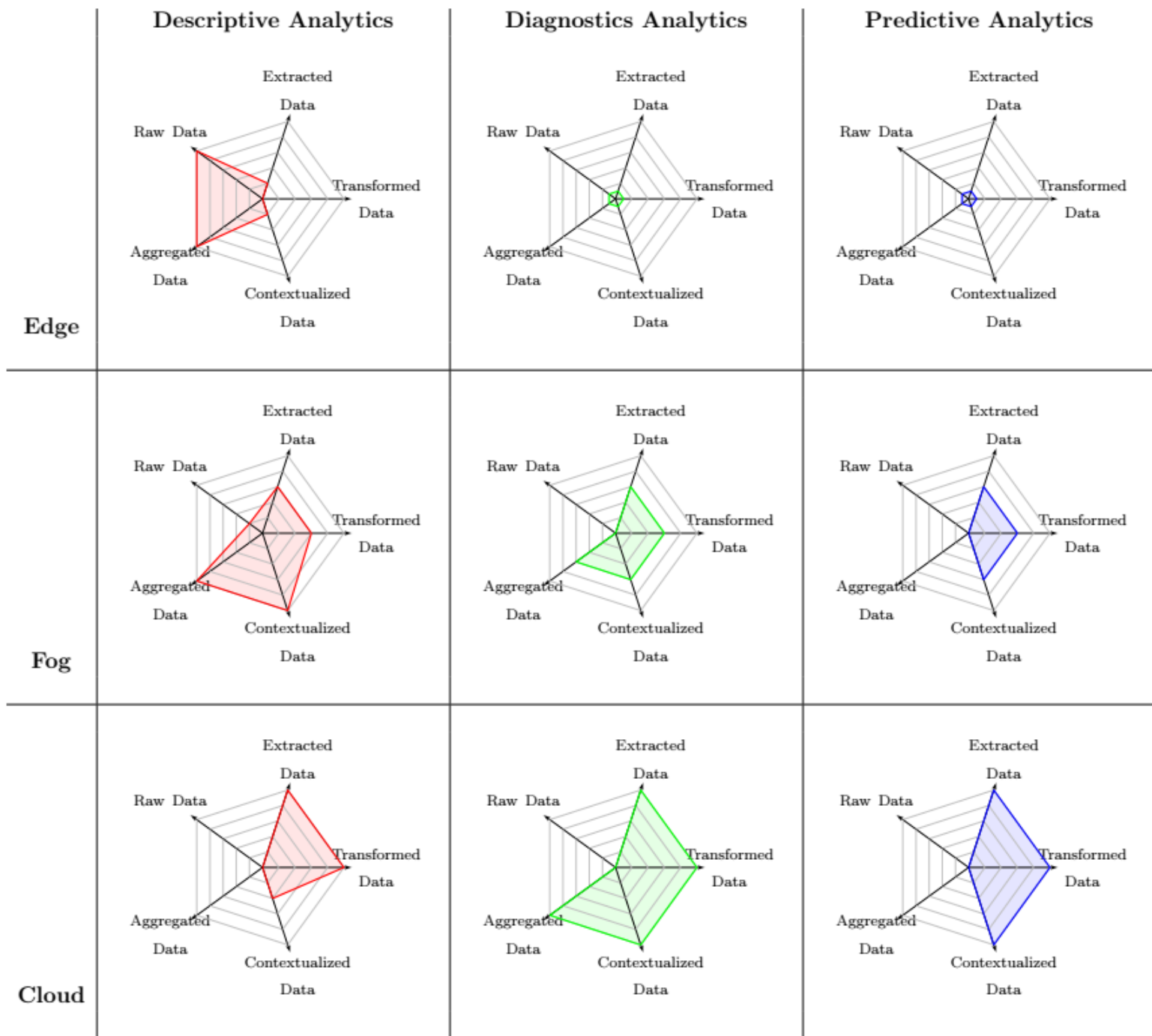
Extracted

Contextualized Data

$$\begin{cases} \forall T_i \in (T_1, T_2, \dots, T_n) : T_i = (S_i, x_i, y_i, t_i) \\ \mathbb{D} = (T_1, \dots, T_n) \xrightarrow{\Psi} \bar{\mathbb{D}} = (P_1, \dots, P_n) \\ \forall P_i \in (P_1, \dots, P_n) : P_i = (S_i, x_i, y_i, t_i, Context_1, Context_2, \dots) \end{cases}$$

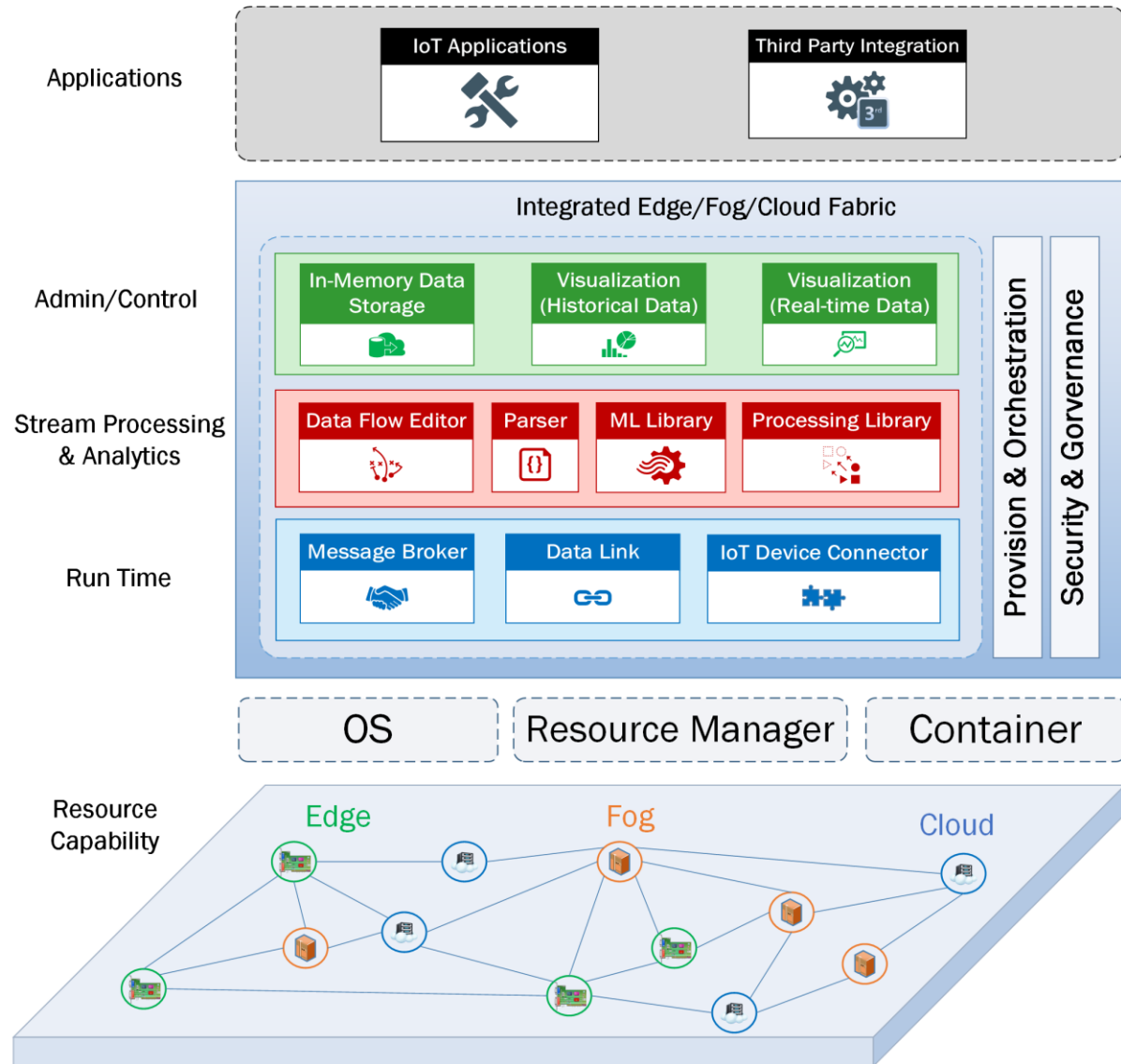


Contextualized



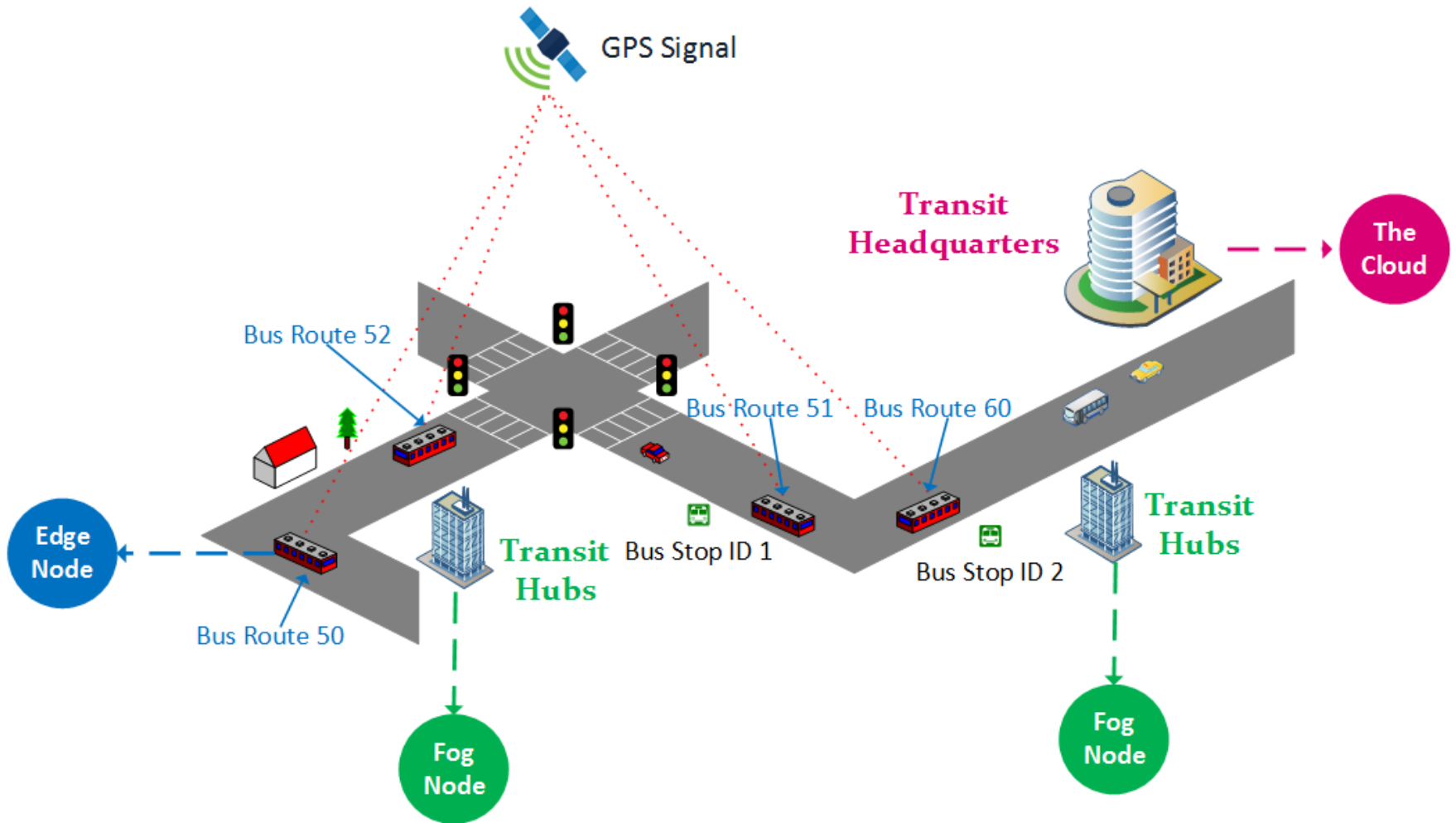
Implementation

Architecture

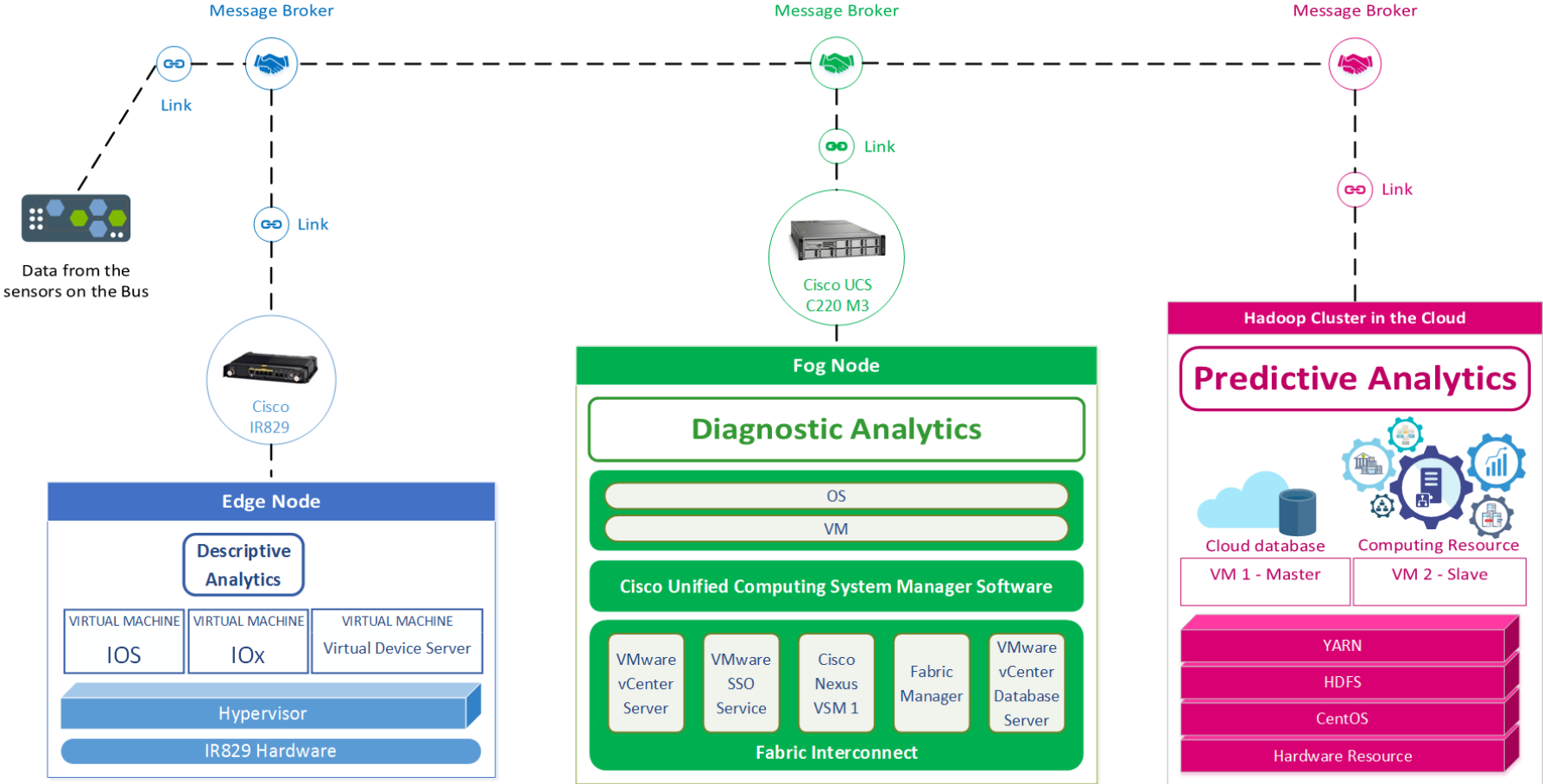


IoT Use Cases	Analytical Capability	Techniques	Applications	Target Group of Users
Smart Transit	Descriptive	Statistics	Schedule adherence	Transit Operators
	Diagnostic	Affinity Propagation Clustering	Abnormalities detection	Bus Drivers
	Predictive	Random Forest	Trip behaviors prediction	Passengers
Smart Parking	Descriptive	Statistics	Parking usage	Parking Commission
	Diagnostic	Agglomerate Hierarchical Clustering	Events/Incidents diagnostic	Policy makers
	Predictive	Adaptive Random Forest	Empty spot prediction	Drivers

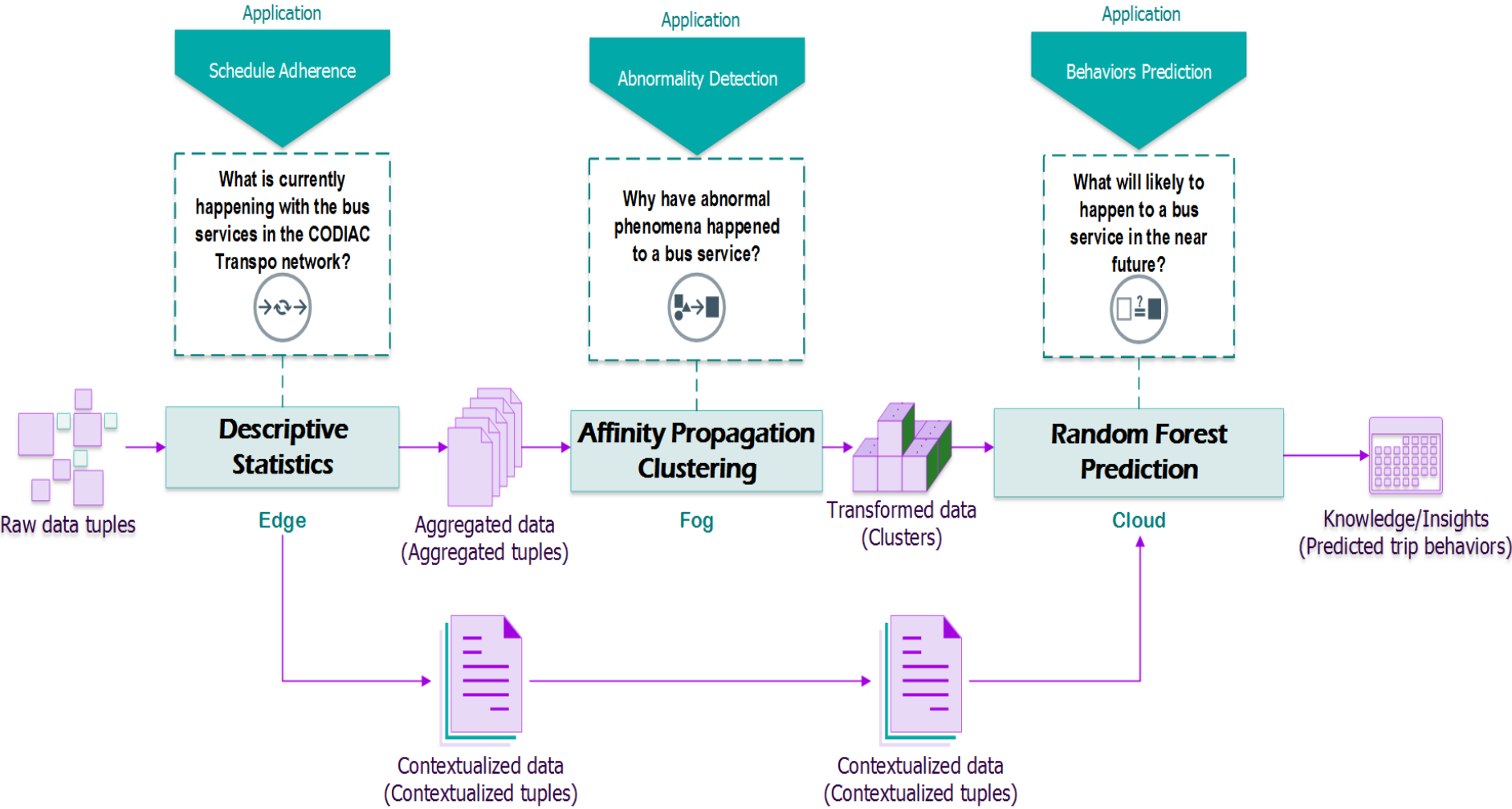
Smart Transit



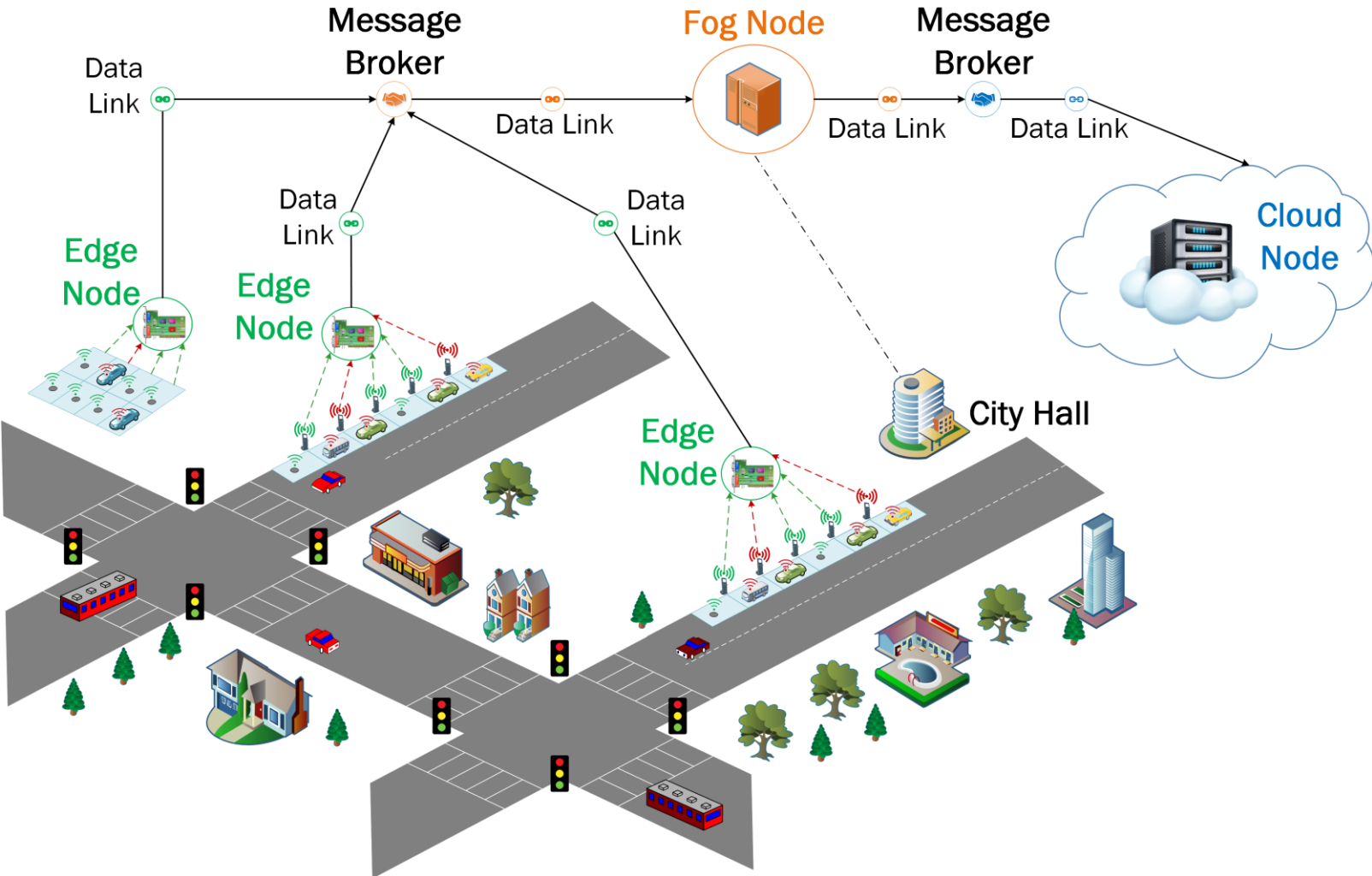
Smart Transit



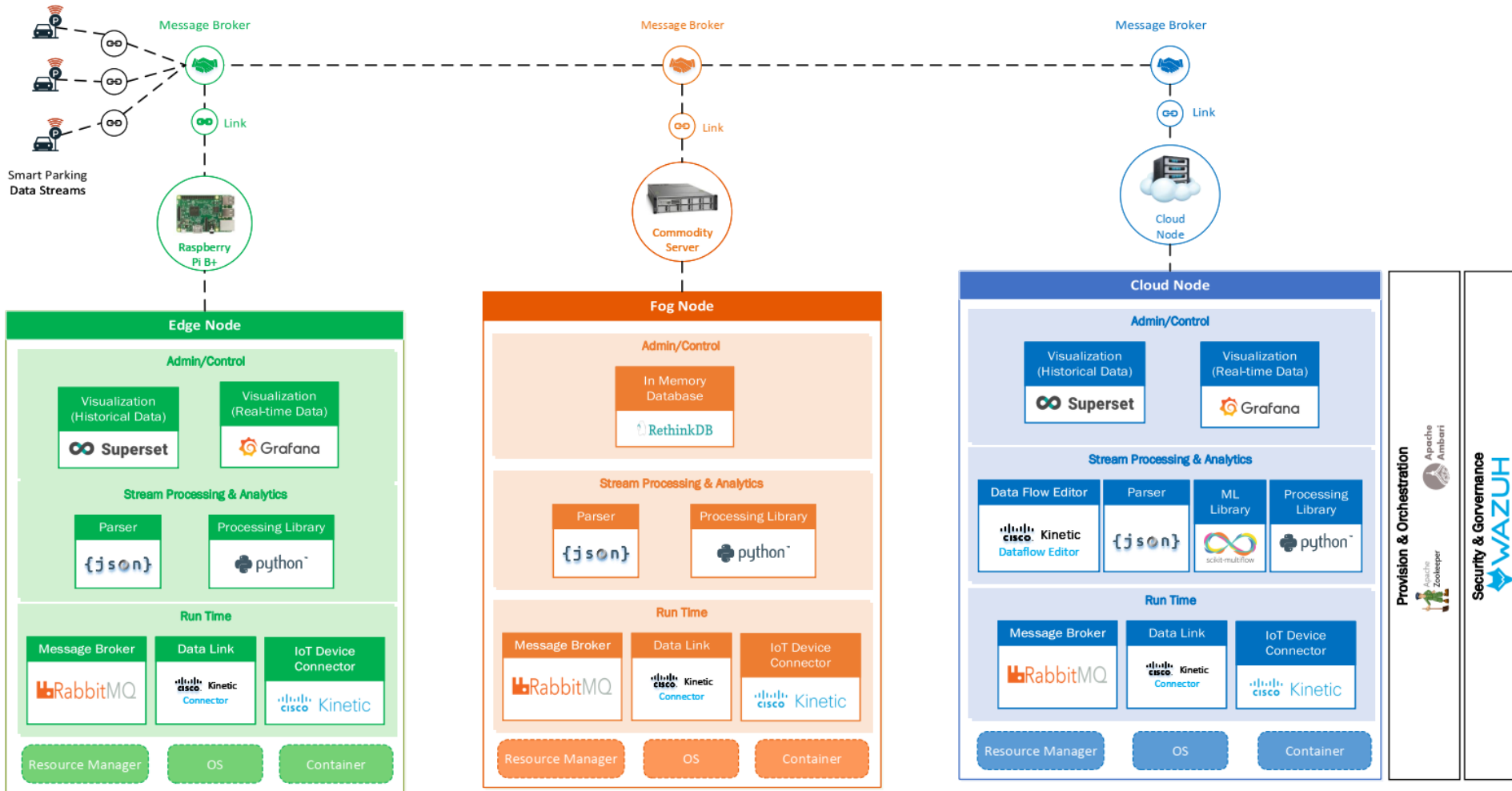
Smart Transit



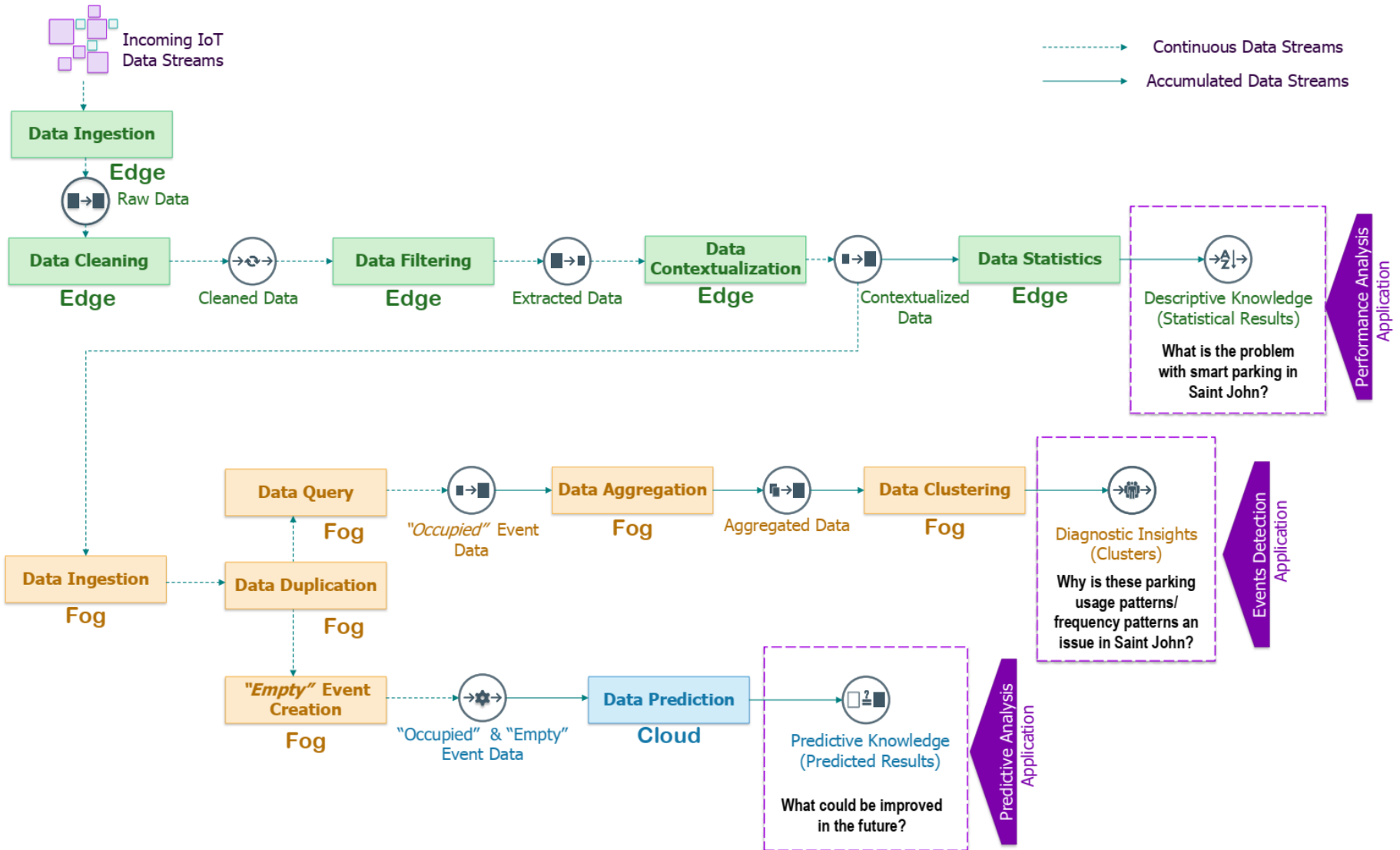
Smart Parking



Smart Parking



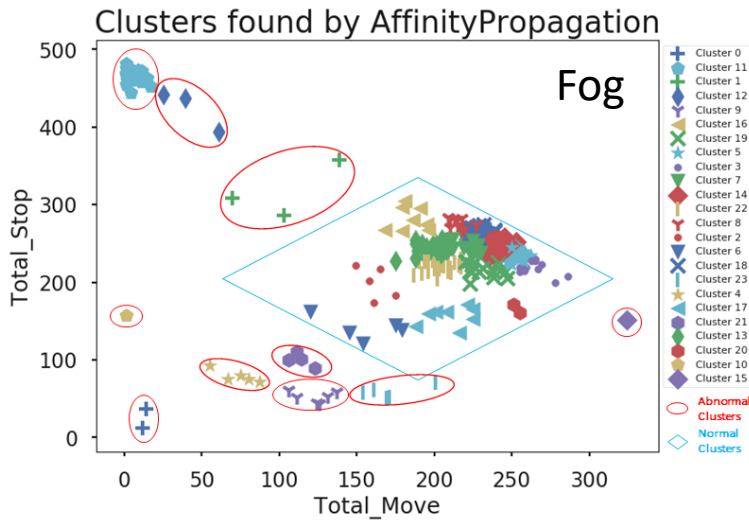
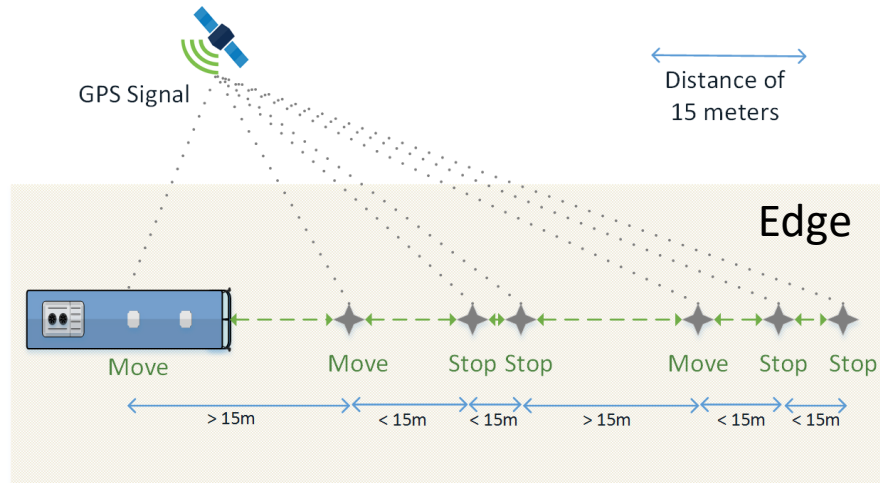
Smart Parking



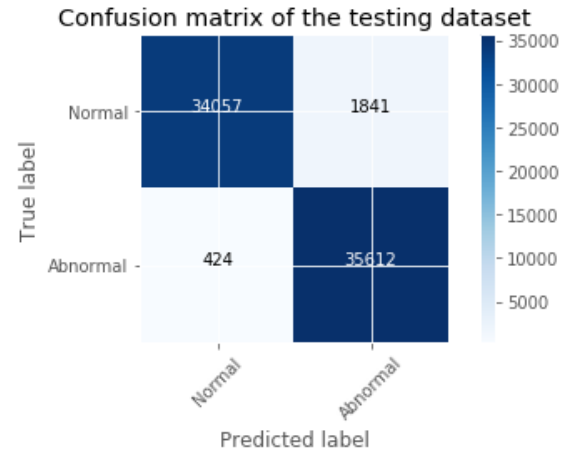
Results

Smart Transit

Analytics at the Edge-Fog-Cloud continuum

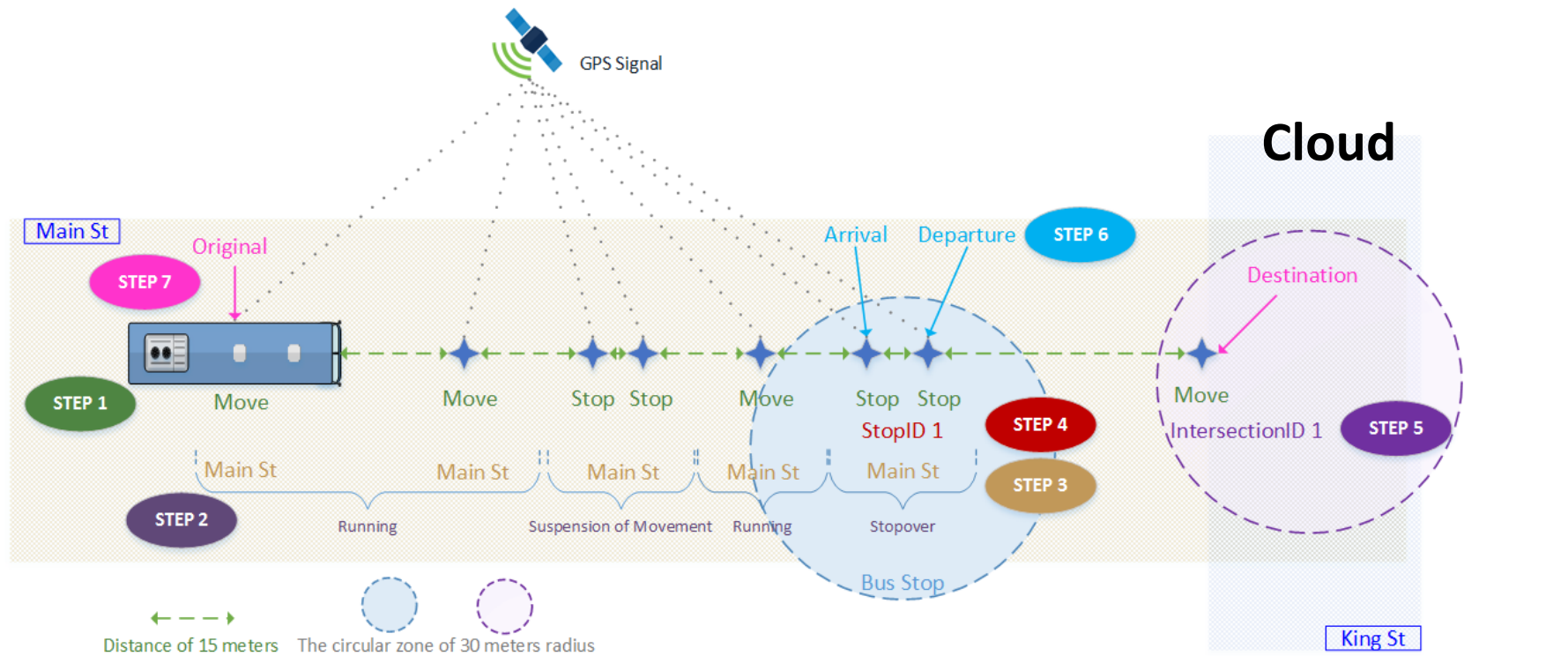


Cloud

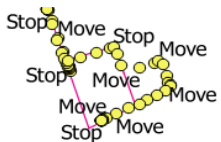


Smart Transit

Integrating GIS into our Edge-Fog-Cloud continuum



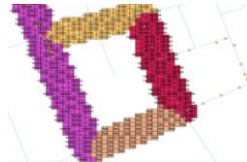
Step 1



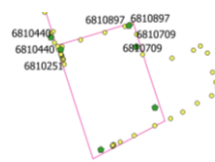
Step 2



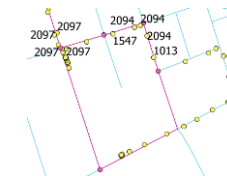
Step 3



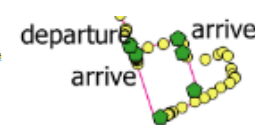
Step 4



Step 5



Step 6



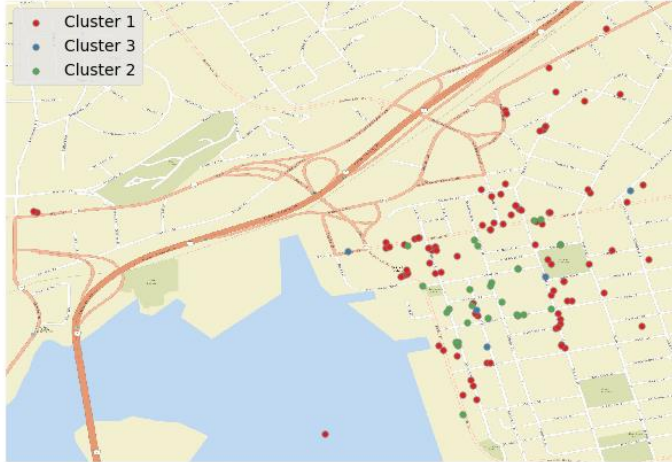
Step 7



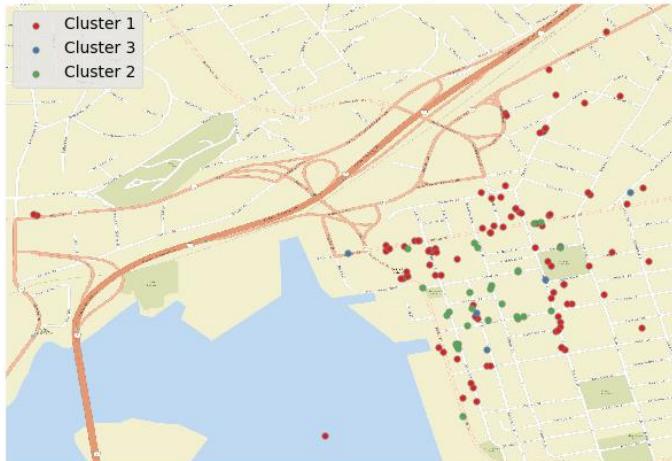
Smart Parking

Why are the discovered usage patterns an issue in Saint John?

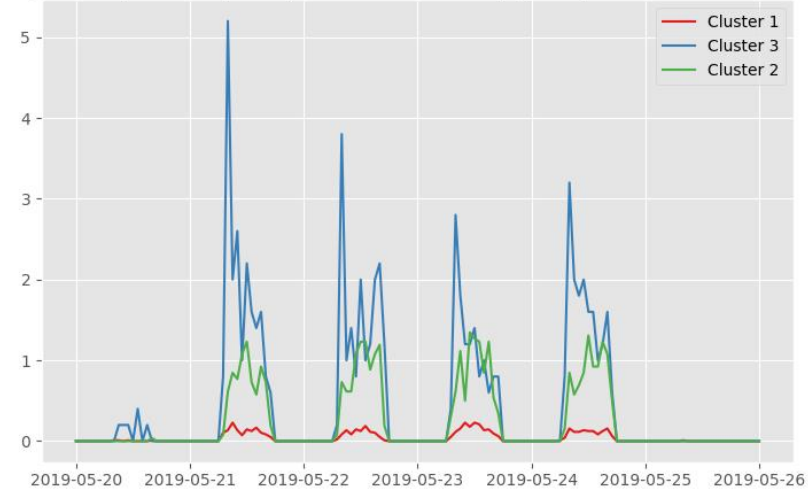
Agglomerative Clustering using PCA (Week 2 - May 20-26)



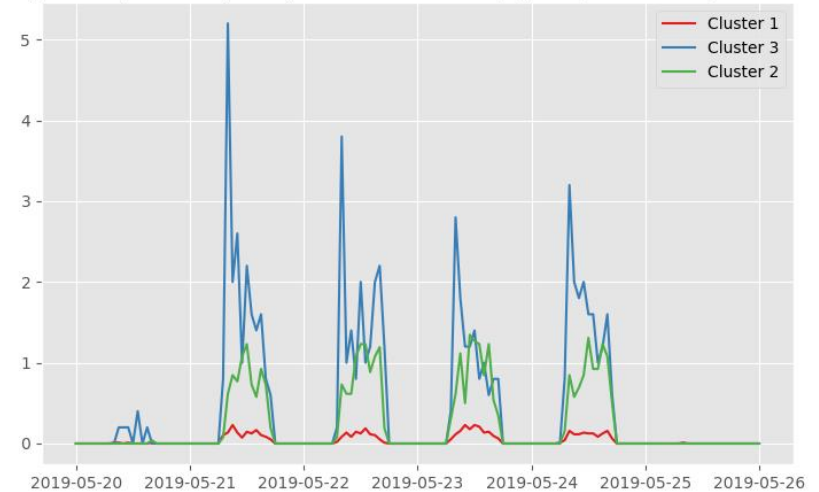
Agglomerative Clustering using PCA (Week 2 - May 20-26)



Average Occupied Frequency for each cluster (n_components=5, distance>19)



Average Occupied Frequency for each cluster (n_components=5, distance>16)



Scientific Contributions



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Analytics Everywhere: Generating Insights From the Internet of Things

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Article

An Edge-Fog-Cloud Architecture of Streaming Analytics for Internet of Things Applications

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The design of an IoT-GIS platform for performing automated analytical tasks

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1. Proposed an “*Analytics Everywhere*” framework which demonstrates that a single computational resource is not sufficient to support IoT applications.
2. Proposed a new architecture based on an integrated fabric of edge-fog-cloud nodes for executing a network of analytical tasks.
3. Automated analytical tasks have been implemented into a IoT-GIS platform which is capable of handling accumulated streams.
4. Implemented the proposed framework using two use cases in smart transit and smart parking.

Recommendations for Future Work

- The Analytics Everywhere framework
 - Streaming analytical tasks and computational resources could be **dynamically** mapped together in the next development step.
 - Extending GIS functionalities to the edge and fog computing environment
- The proposed architecture could be extended by considering:
 - Security
 - Latency
 - Fault tolerance
 - Privacy requirements of IoT applications
 - Concept-drift

Recommendations for Future Work

- The next research question is:
 - *How can a streaming analytical task in the network of tasks reuse and exploit the gained knowledge from the other tasks to resolve its own problems?*
- A potential approach that could answer this research question is the transfer learning methods.

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