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FOG COMPUTING FOR IOT

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Abstract :

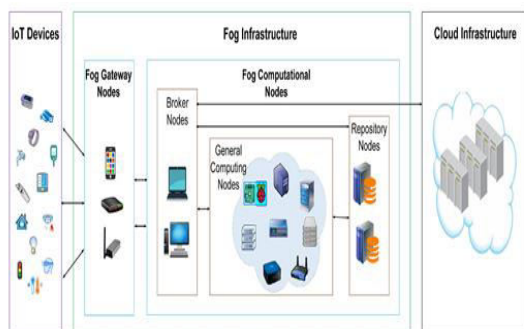
The era of Internet of Things (IoT) devices has introduced a challenge: how to handle real-time streaming data from sensors and actuators effectively. This data needs rapid processing, analysis, and actionable insights for immediate decision-making and on-field actions. However, relying on distant cloud servers for this real-time processing isn't practical due to network latency issues. The time it takes to transmit data back and forth between the field and a remote cloud server is incompatible with the stringent demands of mission-critical applications.

In response to this, a novel technology architecture called 'Fog Computing' has emerged. Unlike traditional cloud setups, Fog Computing places a Fog server in close proximity to IoT devices like sensors and actuators. This server instantly processes incoming data without experiencing significant latency delays. The Analytics Software on the Fog server rapidly derives conclusions, makes decisions, and triggers actions in real time, ensuring the immediate needs of critical applications are met.

1. Introduction

1.1 The Fog Computing Ecosystem

Fog computing, also known as fogging or fog networking, extends computing applications, data, and services from centralized clouds to the network edge. The FogBus framework [6] acts as a bridge, integrating various hardware components via software elements. This system enables structured communication and platform-independent execution of applications. Key hardware components include IoT devices, Fog Gateway Nodes (FGN), Fog Computational Nodes (FCN), and Cloud data centers, forming the foundation of the FogBus architecture.



1.2 Applications of Fog Computing

Numerous mission-critical scenarios demand swift, real-time solutions. Vital sectors like

healthcare, transportation, and industrial IoT exemplify domains where IoT devices play a pivotal role. These applications can't afford the delays caused by processing data on distant clouds. Traditional machine learning techniques and algorithms are designed for static data, making them ill-suited for processing real-time data streams. This necessitates the development of innovative machine learning algorithms tailored to stream data for Fog Analytics Applications. This paper offers an overview of such pioneering algorithms that have been cultivated in the realm of research to handle real-time, streaming data. It also delves into novel machine learning approaches, such as classification and clustering, specifically designed for processing real-time data streams.

2. Considerations in Machine Learning Algorithms for Data Streams

2.1 Real-Time Analytics

Real-time analytics represents a critical facet of the big data landscape, enabling users to obtain immediate insights as new data arrives promptly.

2.2 Data Streams

Data streams provide algorithmic frameworks that support real-time analytics. A data stream consists of sequences of data items, each with a timestamp, establishing a sequential chronological order. Challenges encountered in processing data streams include the large and rapid nature of these streams, the need for real-time information extraction, and the necessity to balance accuracy with time and memory constraints. Moreover, data evolution demands adaptable models to accommodate shifting patterns.

2.3 Time and Memory

Key considerations in machine learning algorithms for data streams encompass accuracy, time efficiency, and memory utilization.

3. Application Scenarios

Data streams find relevance across diverse application scenarios, including:

Sensor Data and IoT: Deploying sensors in various domains, such as city environments, telecommunication, and industrial settings, requires real-time processing for monitoring and analysis.

Social Media: The constant influx of social media posts necessitates real-time analytics for tasks like sentiment analysis and community discovery.

Computer Security: Protecting systems from threats and intrusions demands instantaneous data analysis to identify anomalies.

Consumer Sales and Marketing: Detecting fraud in real-time transactions and analyzing sales trends require swift data processing.

Healthcare: Monitoring patient vital signs, lab results, and medical reports in real time aids diagnosis and patient care.

Epidemics and Disasters: Integrating internet-originated data streams with official statistics can aid in detecting epidemics and natural disasters.

4. Machine Learning Algorithms for Data Streams

Machine learning algorithms tailored for data streams must fulfill several essential requirements:

Process instances individually, inspecting each only once.

Operate within defined time constraints.

Utilize minimal memory.

Provide timely predictions or patterns.

Adapt to evolving data patterns.

4.1 Classification

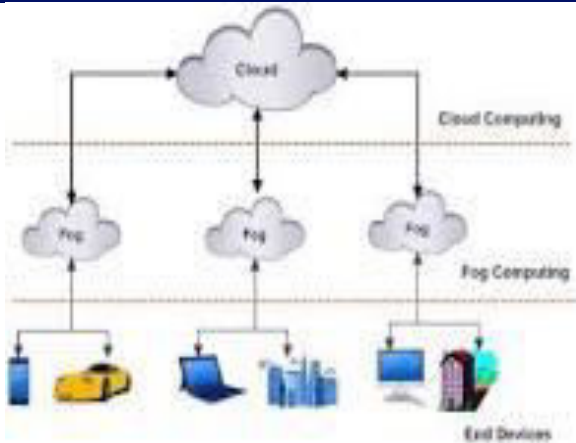
In the context of data streams, classification faces distinct challenges due to the interleaved nature of training, evaluation, and prediction phases. The evolving nature of data and potential lack of labeled instances introduce complexities. The Hoeffding Tree algorithm offers a solution, as it builds a decision tree by waiting for enough instances to make confident split decisions, adapting to evolving data distributions.

4.2 Clustering

Clustering involves grouping similar unlabelled data instances. Traditional K-means clustering is unsuitable for streaming scenarios. Methods like BIRCH and CLUSTREAM provide solutions by creating micro clusters from incoming data, allowing efficient periodic application of offline clustering techniques.

4.3 Mass Online Analysis (MOA)

MOA serves as an open-source framework equipped with a range of machine learning algorithms for data stream analysis. Its tools and algorithms cater to classification, regression, clustering, pattern mining, change detection, outlier detection, and recommender systems.



Conclusion

This paper has illuminated the requisites of machine learning algorithms for data streams within the Fog Computing Ecosystem. It has provided a succinct overview of classification and clustering techniques tailored for real-time applications in this ecosystem.

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