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INTUITIVE MASS EVENT PREDICTOR

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ABSTRACT

Presented herein are techniques to learn mass event characteristics using time series data from existing mobile network functions/elements. The techniques presented herein also proactively identify overloaded cells at the underlying network traffic monitoring layer, during run time, based on the associated abnormal execution patterns.

DETAILED DESCRIPTION

Large scale (mass) events, such as concerts, sporting events, cultural festivals, *etc*., occur quite often and are enjoyed by many individuals worldwide. However, less enjoyable are, for example, the traffic jams created by mass events, the queues waiting to board a bus or train following a mass event, sitting in a static line of cars at the car park exit, *etc*. Typically, following mass events, mobile and WiFi networks get jammed/overloaded due to a sudden surge of users in a small area. This overloading provides a poor user experience as the users cannot use their devices effectively, which thereby results in a bad user experience for Service Providers.

The underlying problem in such situations is that there is no visibility of an upcoming traffic situation on a particular cell, which results in a broadcast storm situation where there are unexpectedly too many requests on a network. This creates a situation where the network does not have the ability to process all the requests at once and requests are then blocked.

The techniques presented herein proactively rectify mass traffic conditions and, accordingly, enable networks to take preventive actions. Typically, mobile providers deploy Self Optimizing Network (SON) technology with machine learning algorithms to understand patterns. However, with everything occurring in real-time, it is difficult to add capacity. The techniques presented herein develop a so called "Intuitive Mass Event Predictor" that can identify expected event based on pattern matching and proactively configure a network to support, for example, capacity expansion, deviation, shift, *etc*. As such, the techniques presented herein enable mobile providers to manage network capacity more intelligently.

Service Providers need intelligent solutions to proactively adapt network changes based on data traffic conditions. The techniques presented herein demonstrate methods to improve the mobile network availability and performance (congestion management/traffic steering) during high traffic events (mass events). Normally, mass events are sponsored by a venue planner or mobile provider and they are aware of a planned mass event. However, even in such situations, the venue planner or mobile provider cannot predict actual capacity requirements. In additional, there are also other adjacent operators (who are not sponsoring the event, but operating in the area) who are impacted by capacity crunch resulting from a mass event.

The techniques presented herein include new algorithms to learn mass event characteristics using time series data from existing mobile network functions/elements. The techniques presented herein also proactively identify overloaded cells at the underlying network traffic monitoring layer, during run time, based on the associated abnormal execution patterns. Key parameters are determined (e.g., based on study of data with modeling) and this information is used to dynamically configure network (with network and service orchestrations systems) to adapt to changing traffic trends and ensure high quality of experience to the end users.

The techniques presented herein are based on the profiling of the execution traffic pattern of every mass event. It is assumed that an abnormal traffic pattern for the duration between any two flow instances is given. The techniques presented herein leverage a two-layer representation of network attributes, namely: (1) combination of multiple cell attributes and corresponding configurations, and (2) all the traffic related data points which are going to help in identifying normal and abnormal patterns.

Proposed Algorithm - Co-association Matrix-Based Blend Algorithm:

Notation and Method Overview:

Let $G = (V, E, A)$ be an attributed network, and let A, $G = (V, E)$ be the Traffic attribute set and the Cell structure of the attributed network, respectively.

The goal of the mass event detection is to learn an optimum group of cells according to the feature set of attributed network, considering both the Cell structure and Traffic attributes data. In order to implement the goal, proposed herein is a novel mass event detection method, i.e., Co-association Matrix-Based Blend Algorithm (*CMBBA*).

The framework of *CMBBA* is shown in Figure 1. In the framework, the attributed network data is first divided into two categories, i.e., Cell topological structure G = (V, E) and traffic attribute set *A*. Next, nearest neighbor algorithms and clustering algorithms are applied to G = (V, E) and *A*, respectively. In addition, a set of mass event patterns is generated from each cell.

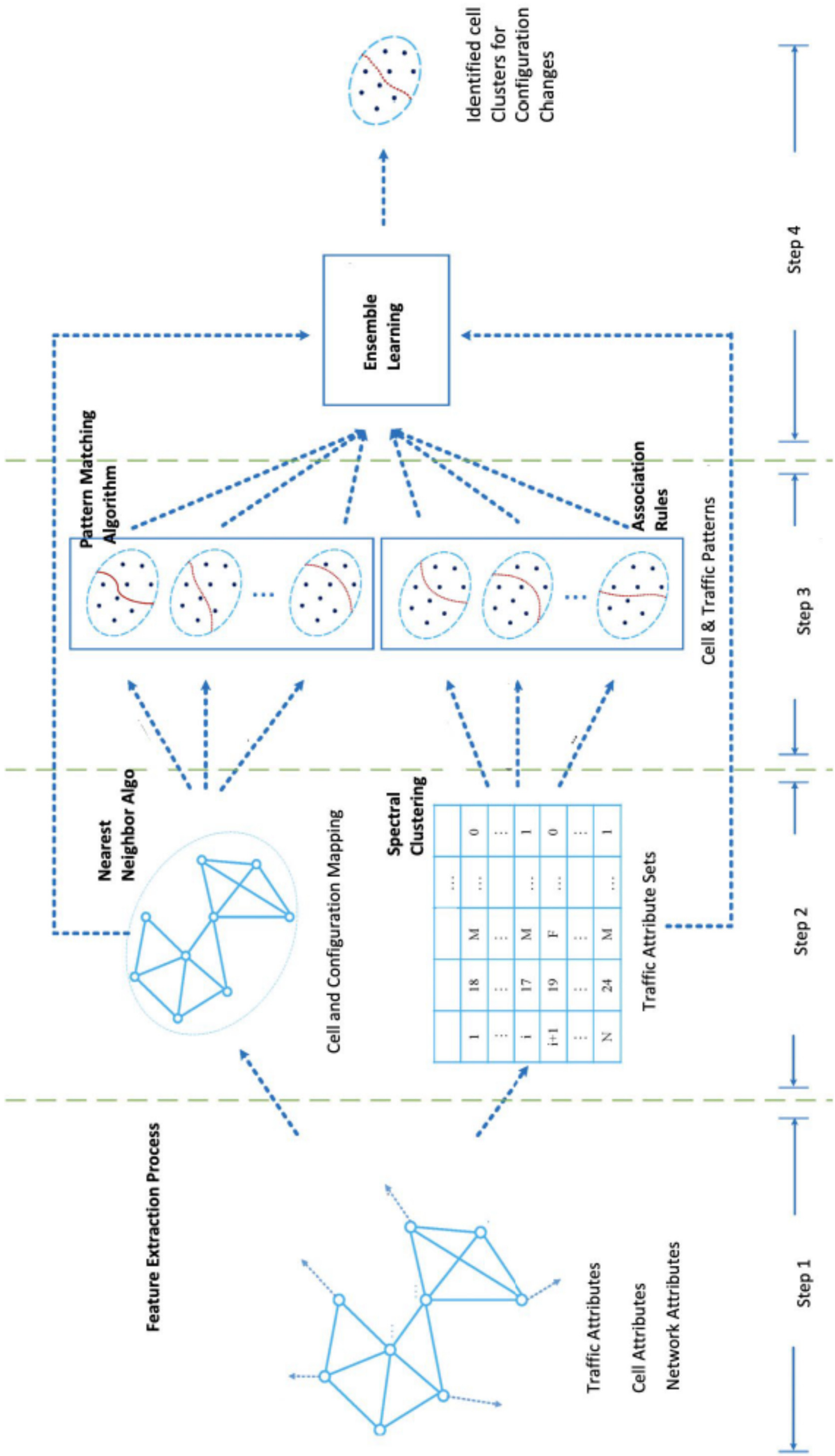

Figure 1: FRAMEWORK OF CO-ASSOCIATED MATRIX BASED BLEND ALGORITHM

Algorithm Steps:

Step 1:

The first step of the algorithm includes detection of various fields related to the Cell and Traffic from Network attributes. The first step also includes the performance of a feature selection process to identify relevant features to be considered for cell identification and correlated traffic attributes from the network.

Step 2:

In the second step of the algorithm, given an attributed network ***G= (V , E,A)***, a nearest neighbor algorithm is applied on the identified Group of Cells data **G(V , E)** and Spectral Clustering Algorithm is leveraged on traffic attributes *A* to identify various events and connected attributes. An outcome of this step is a combination of various Cell Events and Traffic Patterns. This information can be represented in terms of network flows as an instance ***I = (E, N, T)***.

Event ID: Number,
Network Flow: [Numbers],
Time delays: [Numbers]

The Event ID is an identifier of the identified Event, while the Network Flow is a set of attributes contributed while generating a traffic pattern. The Time delays is an ordered list of time delays between the occurrence of attributes listed under Network Flow. In the following Example 1, a mass event has an Event ID of 1 caused by network attributes 5, 7, 4 and 8 to occur in order, and the time delays between the occurrence of attributes will be commonly 1.

Example 1:

Event ID:1,
Network Flow: [5, 7, 4, 8],
Time delays: [1, 1, 1]

Step 3:

In the third step of the algorithm, all the instances of pattern ***I = (E, N, T)***, get validated by the Pattern Matching Algorithm and then stored in Netlist for real-time learning. FIG. 2, below, illustrates the pattern matching process.

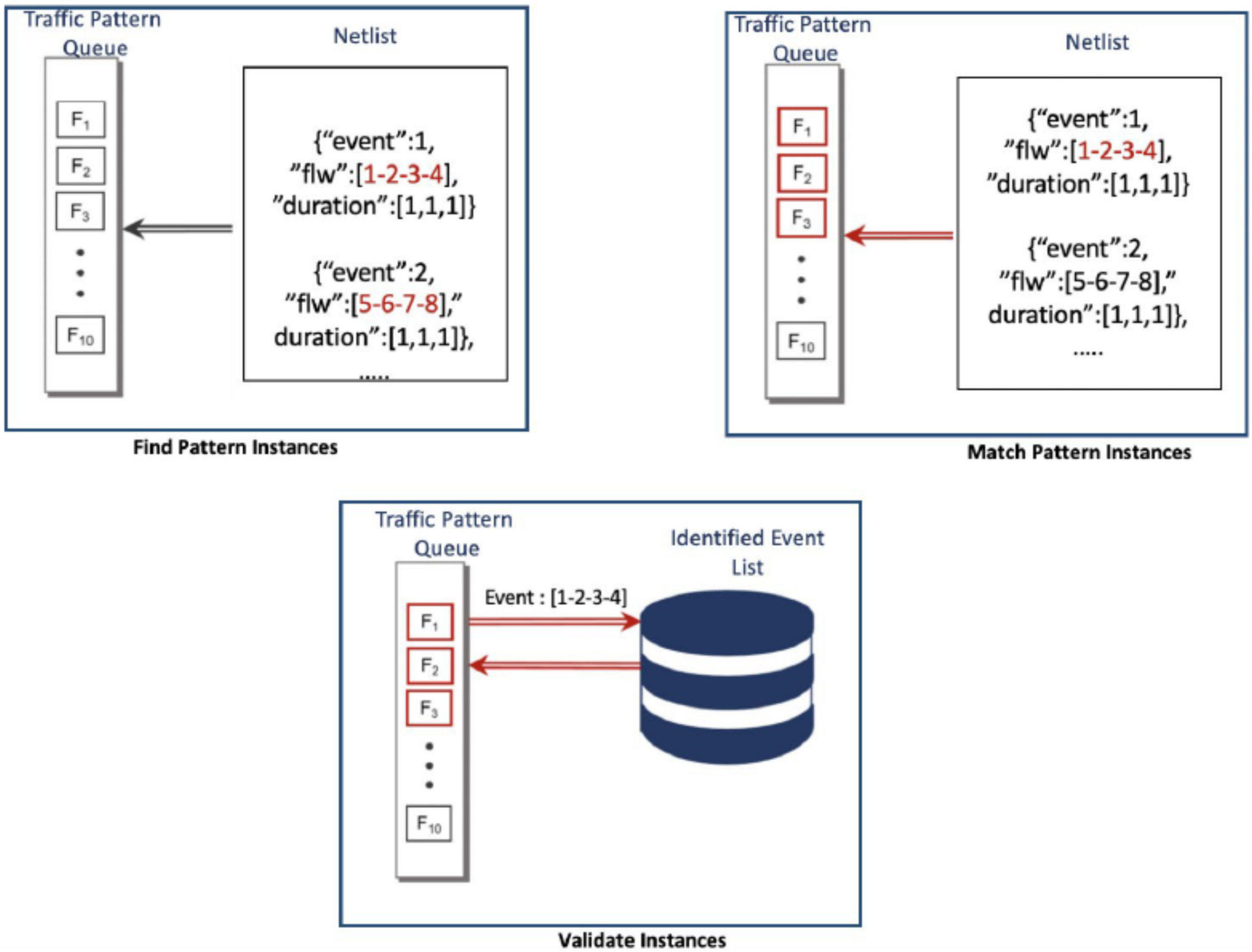

Figure 2: PATTERN MATCHING PROCESS

Based on the instance ***I* = (*E, N, T*)** on associated cells, it is possible to develop a time-based sliding window of traffic instances and to generate Co-associative Rules of different traffic patterns for mass events, with help of rule mining algorithms (arluleminer/nbruleminer). FIG. 3, below, illustrates an example time-based sliding window of rules. These rules represent a combination of various contributed Instances, Time window and Associated Cells *R*=(I, W, G, C)

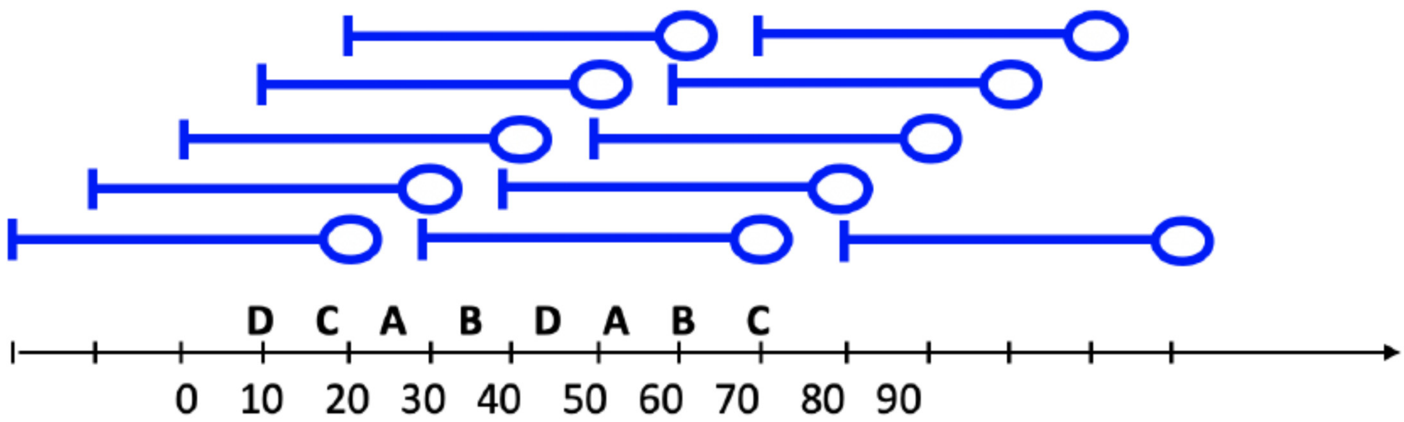

Figure 3: SAMPLE VIEW OF SLIDING WINDOW OF RULES

Step 4:

In step 4 of the algorithm, the rules go through an Ensemble Learning Methodology to ensure the validity of rules and the Cells are grouped based on the rules similarity for any mass event. As an outcome we get dynamically identify prospective cell clusters. Now we can apply right configuration profile to individual cluster.

As noted above, presented herein is a novel methodology to proactively identify overloaded cells at the underlying network traffic monitoring layer, during runtime, based on associated abnormal execution patterns.