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Implementation of Three Possible Partitioning Methods and a Parallel Activity-Search Detection (PASS-Detect) Algorithm That Coordinates Computations across Nodes in the Cluster

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Abstract:

Given a set A of activities expressed via temporal stochastic automata, and a set O of observations (detections of low level events), we study the problem of identifying instances of activities from A in O. While past work has developed algorithms to solve this problem, in this paper, we develop methods to significantly scale these algorithms. Our PASS architecture consists of three parts: (i) leveraging past work to represent all activities in A via a single "merged" graph, (ii) partitioning the graph into a set of C sub graphs, where (C + 1) is the number of compute nodes in a cluster, and (iii) developing a parallel activity detection algorithm that uses a different compute node in the cluster to intensively process each sub graph. We propose three possible partitioning methods and a parallel activity-search detection (PASS Detect) algorithm that coordinates computations across nodes in the cluster. We report on experiments showing that our algorithms enable us to handle both large numbers of observations per second as well as large merged graphs. In particular, on a cluster with 9 compute nodes, PASS can reliably handle between 400K and 569K observations per second and merged graphs with as many as 50K vertices.

Keywords:

Activity detection, temporal stochastic automata, parallel computation.

Applications:

1. Fraud in call data records
2. Online market place looks for fraudulent transaction in web transactions logs
3. Future situations of brokerage house

Existing System:

We address the problem of scalably identifying instances of known activities (i.e., where activity models are known to the application developers such as in the cases listed above) in a high throughput stream of observations. We assume that activities are expressed as temporal stochastic (TS) automata, following the framework of and its predecessor. In particular, took a set of known activity models expressed as temporal stochastic automata and merged them into a single graph and then proposed an algorithm to track activities in observation streams consisting of up to 28.5K observations per second on merged graphs consisting of under 1000 vertices. In this paper, we build upon the work in and scale it up in two directions. First, we are able to look for far more activities than could—our merged automata go to up to 50K vertices. Second, we are able to increase the throughput of observations to between 400K-569K observations per second.

Disadvantages:

1.It does not detect all fraud transactions efficiently.
2.Its provide the reliable solution.

PROPOSED SYSTEM:

In order to achieve this, in our PASS system we adopt a three-pronged approach illustrated in. We assume that we start with an initially given set A of activities expressed as temporal stochastic automata.
Step1: In the very first step, shown in Fig. 1 with a 1 in a circle, we merge all of the activities in A into a single temporal multi-activity graph (TMAG). A TMAG captures all states and transitions present in any of the activities in A. TMAGs were first proposed in [2] which showed that merging graphs allowed multiple automata to be processed efficiently.

Step2: PASS implements activity detection on a compute cluster consisting of (C + 1) compute nodes or processors. What we try to do in the second step, shown in Fig. 1 with a 2 in a circle, is to partition the TMAG into C sub graphs. The idea is that one processor is used as a submit node and the remaining C processors are each assigned one of the sub graphs generated by partitioning. Splitting the TMAG allows us to scale the number of activities we can process as well as improves our processing time by using a compute cluster. Each component of the TMAG resulting from the split can be processed on an individual compute node in the cluster. We present three ways to partition a TMAG. The Minimal Overlap Partitioning (MOP) algorithm splits the TMAG by assigning to each vertex a "temporal extent". Intuitively, the temporal extent captures the period of time when the vertex can be active after the start of any activity in which that vertex is present.

The intuition underlying minimal overlap partitioning is that if two vertices in a TMAG have similar temporal extents, then we should assign them to the same compute node. The Temporal Incidence Partitioning (TIP) method associates an "incidence" measure with any time interval. This incidence measure intuitively measures the number of vertices that can be active within a time interval. Some vertices, for instance, may occur at different time slices in different activities and as such, may have very wide time intervals. However, even with a very large temporal extent, the vertex may only be active infrequently within that temporal extent. TIP tries to split TMAGs by minimizing the standard deviation of these incidence measures. The Occurrence Probability Partitioning (OPP) algorithm transforms the TMAG into a weighted graph where the weights are learned by looking at actual observation (automaton state) streams to understand the true probability that one observation is seen after another observation.

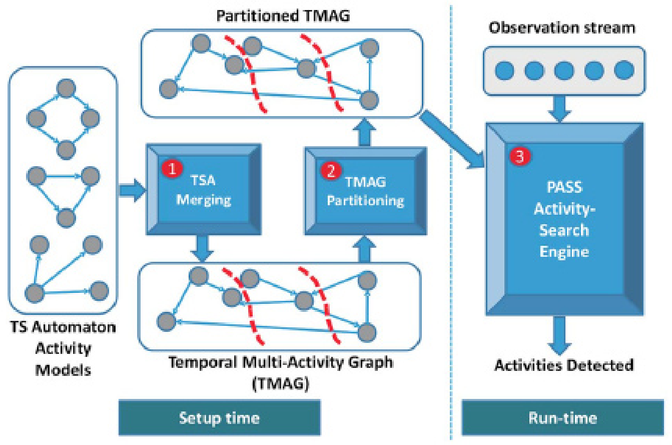
The idea is that if two observations occur consecutively very often within the real stream of observations being monitored, then these two observations often need to be processed very shortly after one another and hence, the corresponding two TMAG vertices should stay on the same compute node. OPP therefore weights edges in the TMAG using these co-occurrence probabilities and then partitions the TMAG using edge cuts after pruning away edges with very low weights.

Step 3: once the set A of activities we wish to detect are merged together into a TMAG and the resulting TMAG is partitioned across C different compute nodes, we are ready to process an observation stream and identify instances of the activities in A in the observation stream. To achieve this requires the core run-time component of the PASS system, shown in Step 3 (circle with a 3 embedded in it) in Fig. 1. The Activity-Search Engine automatically processes the observation stream using a decentralized algorithm that allows multiple nodes to concurrently process different portions of the observation stream with seamless handoffs occurring as needed from one compute node to another.

Advantages:

1.Detect the frauds in different number of applications
2.Reliable detection of all number frauds
3.Quick detection is also possible here using the parallel activity search system.

Architecture:



Modules Description:

1.Design communication model.
2.Temporal stochastic autometa.
3.Partitioning TMAG (temporal multiple activity graph)
4.Parallel activity detection.
5.Performance evolution.

Design communication model:

We implemented PASS in Java. As the implementation required balancing fast network communication and simplicity of use. When we were assessing the performance of the system by varying the number of compute nodes. First randomly creates a user specified number of vertices and then randomly generates outgoing edges based on a Gaussian distribution.

Temporal activity graphs assume a temporal progression from a start node to an end node, that is, all paths through the graph have a temporal ordering.

Temporal stochastic autometa:

Hidden Markov Models and Dynamic Bayesian Networks have been used extensively for representing activities. A slight variant of these methods, stochastic automata, was used to represent activities in and subsequently, a slight extension called Temporal Stochastic Automata was introduced showing that multiple stochastic automata can be merged together to recognize activities. This section does not contain new material instead it recapitulates definitions first provided in. A time span distribution specifies such transition probabilities, which may vary over time. In the following definition, a time interval is a closed interval of the set T of time points, which in turn can be assumed to be non-negative integers.

Partitioning TMAG (temporal multiple activity graph)

Two phenomena occur:

1) There may be thousands of known normal activities and as a consequence, TMAGs can be quite large, consisting of tens of thousands of vertices and hundreds of thousands of edges;

2) The number of observations made per second is very high, consisting of hundreds of thousands of observations per second. In this paper we propose techniques that exploit a cluster of (C+1) compute nodes by partitioning the set of vertices of a given TMAG G into C components so that each component can be separately processed by a different compute node. The additional compute node is used as a submit node.

After building a partition P = {P1, . . . , PC} of G, node N(Pi) will thus handle all tuples f such that f .obs € Pi. We assume that each compute node includes an implementation of a sequential activity detection algorithm such as. Our framework is capable of working with any sequential activity detection algorithm within a node as long as the “inter-node” communications and handoffs are handled properly. In Section 4 we will discuss how this occurs in our system, where we employ our PASS Detect algorithm.

Parallel activity detection:

When we have (C + 1) cluster compute nodes available in a cluster for activity detection, PASS uses one of those compute nodes as a submit node and the other C compute nodes each store the component Pi of a partition P = {P1, . . . , PC} of the TMAG G associated with a given set A of activities. Each compute node N(Pi) stores the restriction of G to the vertices in the component Pi, denoted G(Pi). Moreover, each compute node stores information about the set of frontier vertices w.r.t. Pi. A frontier vertex w.r.t. Pi is a vertex vj Pj with i _= j such that there exists a vertex vi Pi such that either (vi, vj) or (vj, vi) is an edge in the TMAG. When vj is a frontier node w.r.t. Pi, N(Pi) also stores the location of N(Pj). This way, during activity detection, if vj is observed, then a smooth handoff can be made to compute node N(Pj).

Performance Evolution:

The performance of our partitioning schemes in terms of time to compute the partitions when varying TMAG sizes and number of compute nodes. OPP performs best in the majority of cases, with a performance gain that increases with larger TMAGs. On the other hand, it appears to suffer more than MOP and TIP4 from the density of large TMAGs. All partitioning schemes scaled well with the size of the input TMAGs, and their performance is almost independent of the number of partition size.

CONCLUSION:

In this paper we investigate on set of activities presented via temporal stochastic automata, partitions of activities based on level based events, and also review the PASS architecture with various implementation parts with that coordinates computations across nodes in the cluster and also shown that this algorithms enables to handle both large numbers of observations per second as well as large merged graphs.

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