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EFFECTIVE EVENT DERIVATION OF UNCERTAIN EVENTS IN RULE-BASED SYSTEMS

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EFFECTIVE EVENT DERIVATION OF UNCERTAIN EVENTS IN RULE-BASED SYSTEMS

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Abstract- There is a growing need for systems that react automatically to events. While some events are generated externally and deliver data across distributed systems, others need to be derived by the system itself based on available information. Unpredictability of future events which influence the outcome of the present decisions but have not yet occurred and no one can predict what they will be like. In this process, it finds out the uncertain events using the rules. Here it uses the Event Instance Data for find out the efficient process. This performs the two mechanisms are select ability is for calculation of the exact probability space and sampling techniques. For this process it uses the efficient algorithms that are calculate selectable EID and Rule stamp algorithm. In this paper, we also emphasized the important role that event select ability plays in uncertain event derivation. We demonstrated not only that it plays a significant semantic role, but also, that the proper usage of select ability can significantly improve performance, and result in a framework that is much more suited to applications with a high event throughput. This system provides the better results and provides the efficient process.

Index Terms- *rule-based reasoning, Event Uncertainty Management*

1. INTRODUCTION

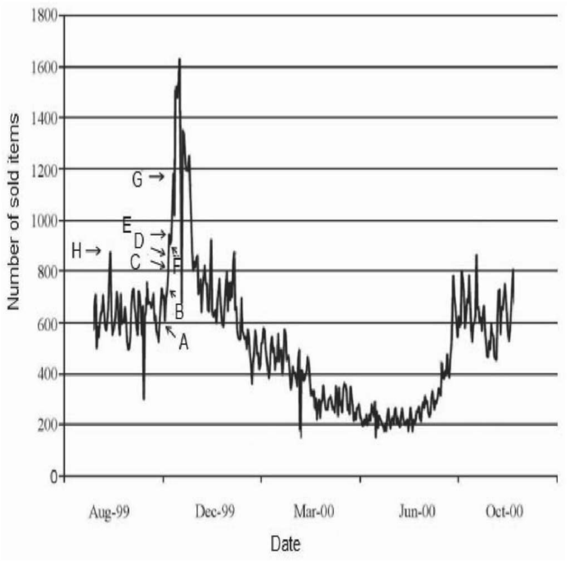
Knowledge and data engineering is the computer-assisted process of digging through and analyzing enormous sets of data and then extracting the meaning of the data. Data mining tools predict behaviors and future trends, allowing businesses to make proactive, knowledge-driven decisions. Data mining tools can answer business questions that traditionally were too time consuming to resolve. They scour databases for hidden patterns, finding predictive information that experts may miss because it lies outside their expectations. Data mining derives its name from the similarities between searching for valuable information in a large database and mining a mountain for a vein of valuable ore. Both processes require either sifting through an immense amount of material, or intelligently probing it to find where the value resides.

In recent years, there has been a growing need for active systems that react automatically to events. The earliest active systems were in the database realm, impacting both industry and academia. New applications in areas such as Business Activity Monitoring, Business Process Management, sensor networks, security applications, engineering applications, and scientific applications all require sophisticated mechanisms to manage events and materialize new events from existing ones.

An event is a mechanism for delivering data to an active system. Some events are generated externally and deliver data across distributed systems, while other events and their related data are materialized by the active system itself, based on other events and a mechanism for predefined event pattern specifications. Event materialization has a clear trade-off between materializing events with certainty, using full and complete information, and the need to provide a quick notification of newly revealed events. Timely event materialization is therefore hampered by the gap between the actual occurrences of events, to which the system must respond, and the ability of active systems to accurately generate events. This gap results in uncertainty and may be attributed to unreliable data sources, an unreliable network, or the inability to determine with certainty whether a phenomenon has actually occurred.

One way of managing the gap between actual events and event notifications is to explicitly handle uncertainty. This could be done by modeling events uncertainty as a probability associated with each event, whether such events are generated externally or derived. However, a major challenge in such explicit management of events' uncertainty is that rule-based systems need to process multiple rules with multiple event sources. While taking into account various types of correctly calculating event probabilities of uncertainty is not trivial. Clearly, correct quantification of the probability of derived events serves as an important tool for decision making. Event generation under uncertainty should therefore be accompanied with an appropriate mechanism for probability computation.

Another major challenge, related to the need to enable timely response to events, is efficient event derivation, sometimes under a heavy load of incoming events from various sources. Event derivation should also scale for a large number of rules and complex rules that involve several sources of evidence. Clearly, a brute force solution in which the arrival of a new event is evaluated against all possible rules does not scale, as it may involve an exponential number of evaluations. To illustrate this point, consider a natural way of interpreting uncertain events by assigning an explicit probability to each possible subset of events. Clearly, such explicit representation is practically infeasible. Therefore, our main goal is to provide an efficient and accurate mechanism for reasoning with uncertain events. In this process, it presents a generic framework for representing events and rules with uncertainty.



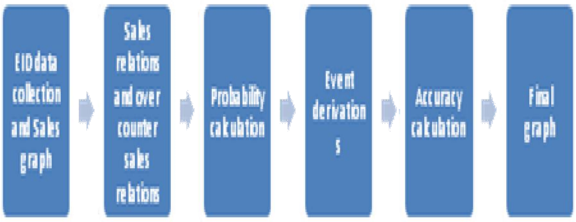
It presents a mechanism to construct the probability space that captures the semantics and defines the probabilities of possible worlds using an abstraction based on a Bayesian network. In order to improve derivation efficiency we employ two mechanisms: The first mechanism, which we term select ability, limits the scope of impact of events to only those rules to which they are relevant, and enables a more efficient calculation of the exact probability space. The second mechanism it employs is one of approximating the probability space by employing a sampling technique over a set of rules.

Over counter sales relations

EID	Date	Daily Sales (Rounded)
113001	Nov 30	600
120101	Dec 1	700
120201	Dec 2	800
120301	Dec 3	900
120401	Dec 4	950
120501	Dec 5	930

EID data collection and sales graph:
EID data collection is the process of collect the real data from the user. EID is the Event Instance Data. This data contains the fields of EID, Syndrome, Date and Number of items. This data are used to find out the probabilistic. After the data collection, the system provides the graphs for the collected data. This graph is said to the Over-the-counter cough medication sales (sales graph). This graph is load between the data and the number of sales items. This graph shows the realistic of the data that the user store in the EID collections.

Sales relations and over counter sales relations:
After the data collection and graph generations process moves to the sales relations. These sales relation is process of display the items in the table. These items are EID, date, Daily Sales. It shows all the details of the EID, date and Daily sales. EID instance data items and date is which date the product should be sold and daily sales is counting of the product sales. After that system moves to the over counter sales relations. This process is used to identify the over counter of the sales products.

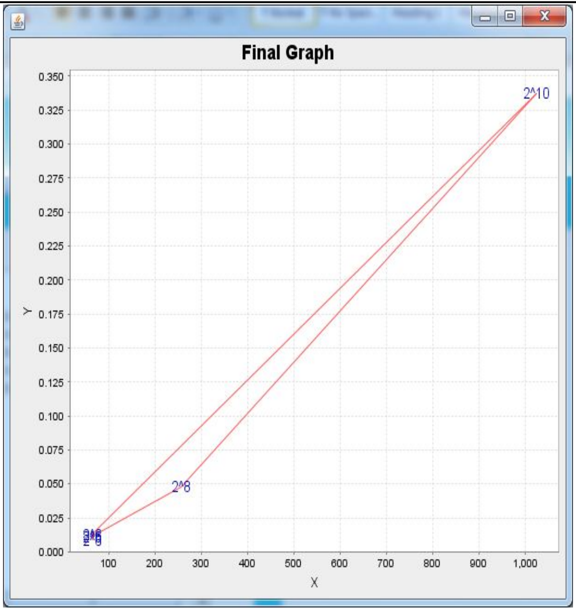


PROBABILITY CALCULATION:

Next this process moves to the probability calculations. This probability is based on the two types of probability rules. A rule defines how many new events (or EIDs) should be derived and helps calculate their attributes and probabilities. After the probability calculation process performs the select ability process. But this select ability is the internal process.

Event derivations:
After the select ability process is complete, the process goes to the event derivation process. This derivation is based on the conditional probability. Finally it generates the table for the event derivations. In this step, the Bayesian network is constructed from explicit events and rule definitions that describe the desired probability space.

Accuracy Calculations:
In this accuracy calculation process, it uses the algorithm of sampling algorithm. This sampling algorithm is implemented by the rule stamp process. After the satisfaction is probability rules and possible worlds, then system find out the accuracy calculation. Accuracy table contains the Rank, average, Minimum and maximum of the intervals. After that it generates the graphs of the Event rate as a function of possible worlds and Event rate as a function of precision.



CONCLUSIONS:

In this work, we presented an efficient mechanism for event derivation under uncertainty. We experimented with the sampling algorithm, showing it to be comparable to the performance of a deterministic event composition system. It is scalable under an increasing number of possible worlds (and uncertain rules), while a Bayesian network algorithm for the same purpose does not scale well. Finally, the sampling algorithm provides an accurate estimation of probabilities. Our contribution can be summarized as follows: The introduction of a novel generic and formal mechanism and framework for managing and deriving events under uncertainty conditions.

The approach we have taken is really one of several possible approaches. Another possibility is the direct creation of statistical models (e.g., regression) or a model created using machine learning techniques from a large historical set of data. However, our approach allows a clearly and explicitly defined relationship between events that serve as input and the derived events. Also, any specification language within the framework allows clear and intuitive definitions of concepts such as event selection.

Moreover, modeling the connection between the evidence to the output as a set of rules is more accessible to a wide variety of users then models such as Bayesian networks. Specifically, the growing community of people using deterministic composite event systems is expected to find our framework to be a natural extension. Finally, our approach is general, suitable for enabling uncertain inference for any event-driven system. We decouple the modeling language from the inference algorithm by specifying the language in very generic term.

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