

## CEP, State of the Art



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# Outline

## ① Motivation

Introduction and Motivation  
Brief History

## ② Introduction to Terminology

Event  
Event Representation  
Time

## ③ Language

Language Classes

## ④ Future Work

Future Work  
Event Mining

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- ▶ understanding the system
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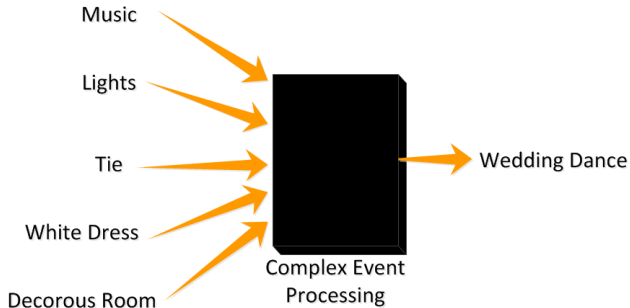
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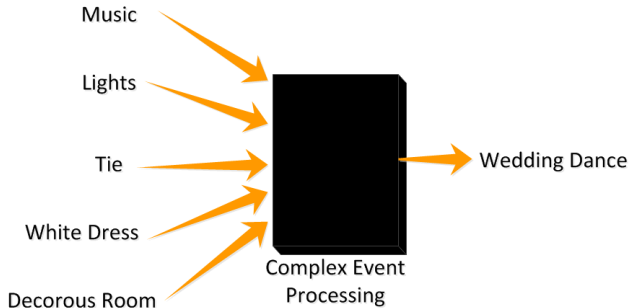
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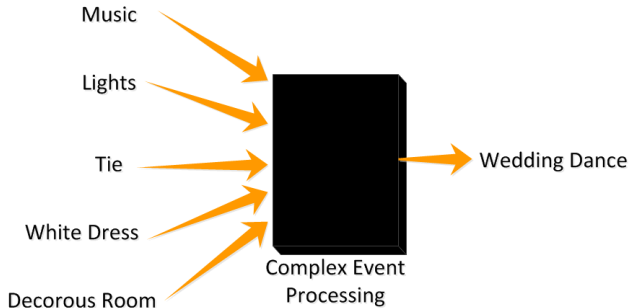


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query  $(A; B)$  against an event stream  $a_1, a_2, b_1, b_2$  ( $a_1, a_2$  of type  $A$ ,  $b_1, b_2$  of type  $B$ ). The event  $a_1$  will be used twice to generate two different complex events, one when  $b_1$  is received and one when  $b_2$  is received. When event  $b_1$  is received, two different complex event are generated at the same time, one for  $a_1$  and one for  $a_2$ .

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$$O((E_1; E_2), [t_1, t_2]) \Leftrightarrow \exists t \exists t'. t_1 \leq t < t' \leq t_2 \wedge O(E_1, [t_1, t]) \wedge O(E_2, [t', t_2])$$

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# Informal “before”

|               | Point-Point | Point-Interval | Interval-Interval |
|---------------|-------------|----------------|-------------------|
| A before B    |             |                |                   |
| A meets B     |             |                |                   |
| A overlaps B  |             |                |                   |
| A finishes B  |             |                |                   |
| A includes B  |             |                |                   |
| A starts B    |             |                |                   |
| A coincides B |             |                |                   |

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### Example

```
SELECT Istream (payment, count(id))  
FROM O [ Range 24 Hours ]  
GROUP BY O.payment
```

Number of daily payments grouped by payment type.

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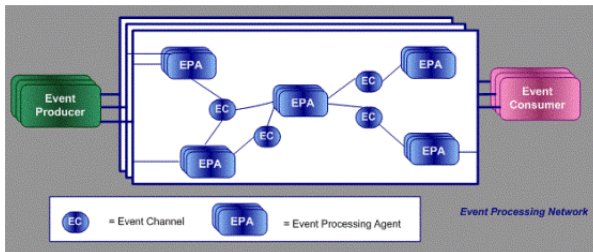


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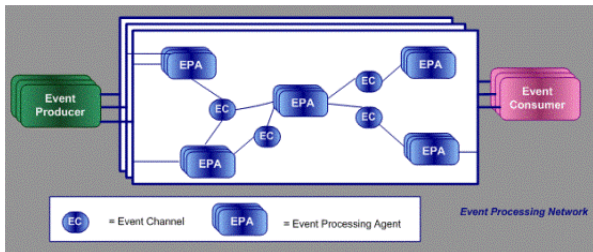
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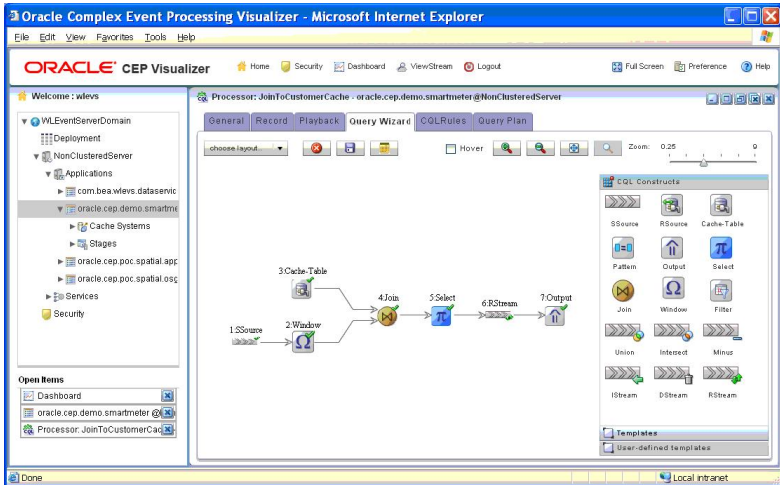


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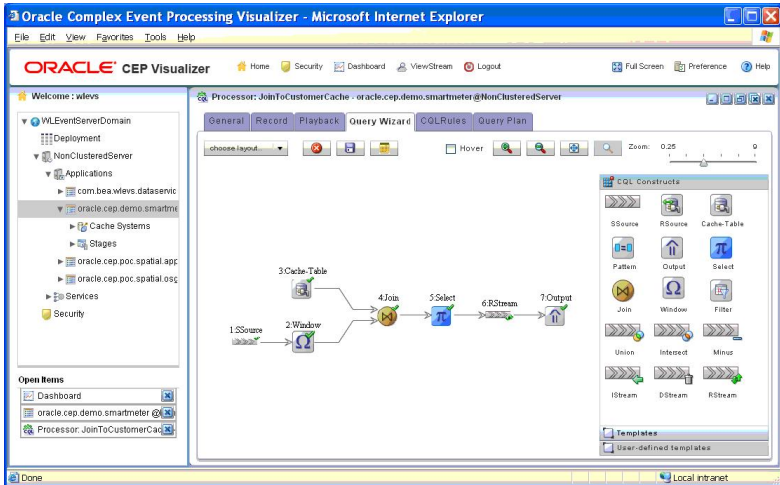
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- ▶ associative rules may help to causality detection

# Event Mining

- ▶ a priori queries  $\sim$  top-down design
- ▶ unknown patterns?  $\sim$  outlier detection
- ▶ ML-outlier = isolated (strange) data point X CEP-outlier = strange combination of events
- ▶ online clustering for identifying related events
- ▶ associative rules may help to causality detection

# Conclusion

- ▶ promising technology
- ▶ language classes

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Thank you for your attention  
*Q&A*