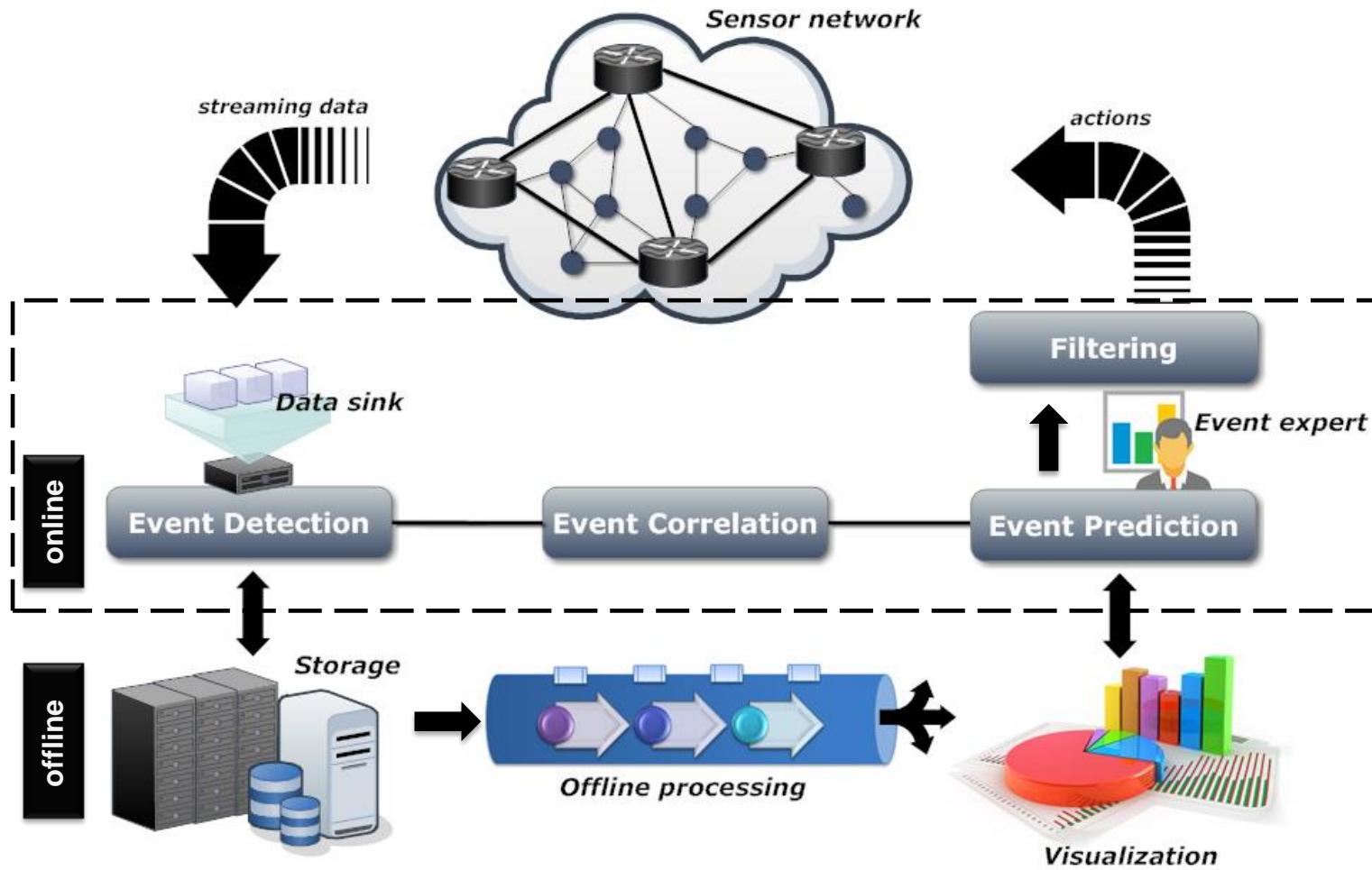


# **Event Management in Multivariate Streaming Sensor Data**

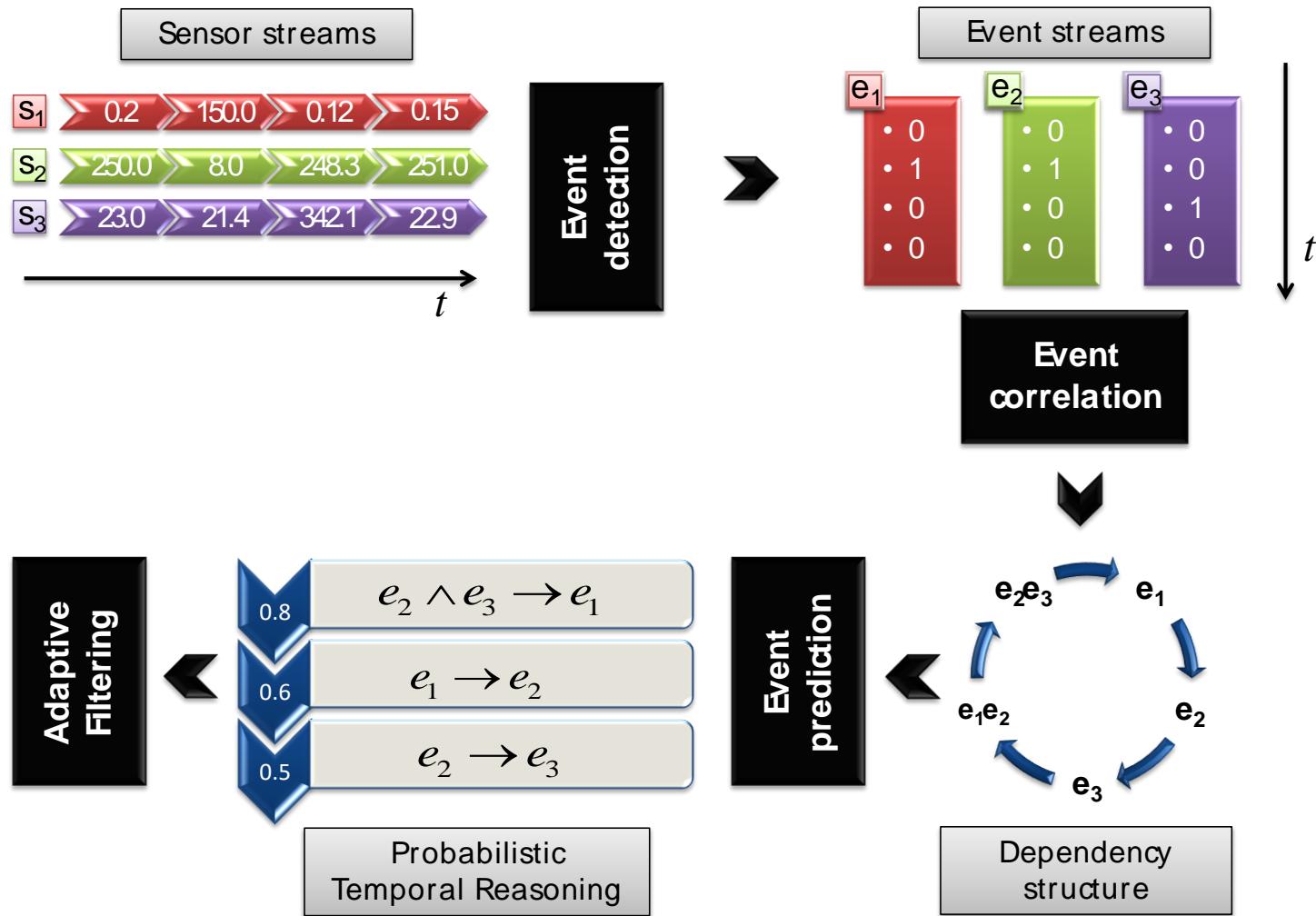
# Event management lifecycle in SN



# What is an event?

- A. Change detection
  - Continuous monitoring of sensor streams
  - Abrupt change on value distribution  
(0.12, 1.11, 1.09, 2566.04, ...)
  - Algorithms
    - Single variate regression
      - CUMSUM, Schewart Controller
    - Multi-variate regression
- B. Predefined conditions checked in real-time
- Events are stored as a ***binary table***

# Online event processing



# Change Det: Cumulative Sum (CUSUM)

---

## ALGORITHM 1. Cumulative Sum (CUSUM)

---

**Input:** univariate time series  $x_t$ , target value  $\mu$ , above-tolerance  $k^+$ , below-tolerance  $k^-$ , above-threshold  $thres^+$ , below-threshold  $thres^-$

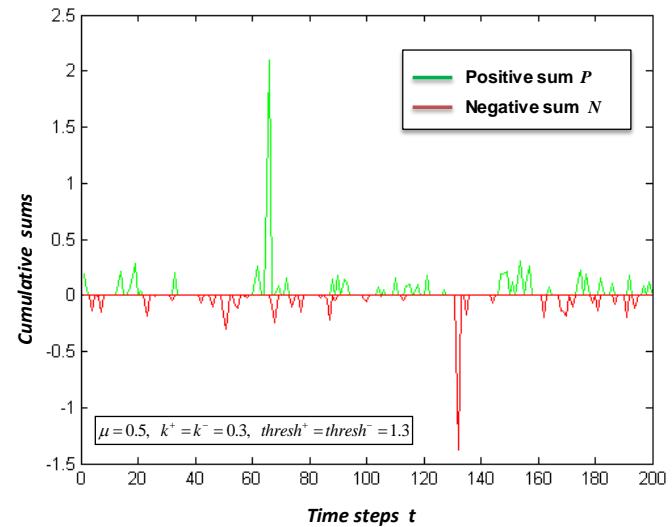
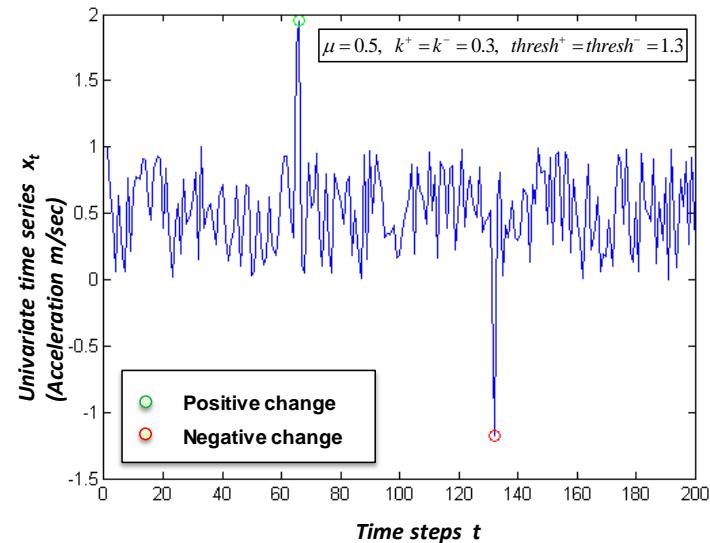
**Output:** above detection signal  $s^+$ , below detection signal  $s^-$

```

1:  $P \leftarrow 0$ ;
2:  $N \leftarrow 0$ ;
3:  $t \leftarrow 1$ ;
4: while ( true )
5:    $s^+ \leftarrow 0$ ;
6:    $s^- \leftarrow 0$ ;
7:    $P \leftarrow \max(0, x_t - (\mu + k^+) + P)$ ;
8:    $N \leftarrow \min(0, x_t - (\mu - k^-) + N)$ ;
9:   if ( $P > thres^+$ ) then
10:     $s^+ \leftarrow 1$ ;
11:     $P \leftarrow 0$ ;
12:     $N \leftarrow 0$ ;
13:   end
14:   if ( $N < -thres^-$ ) then
15:     $s^- \leftarrow 1$ ;
16:     $P \leftarrow 0$ ;
17:     $N \leftarrow 0$ ;
18:   end
19:    $t \leftarrow t + 1$ ;
20: end

```

---



# Change Det: Shewhart controller

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## ALGORITHM 2. Shewhart Control Chart

---

**Input:** univariate time series  $x_t$ , tightness  $k$

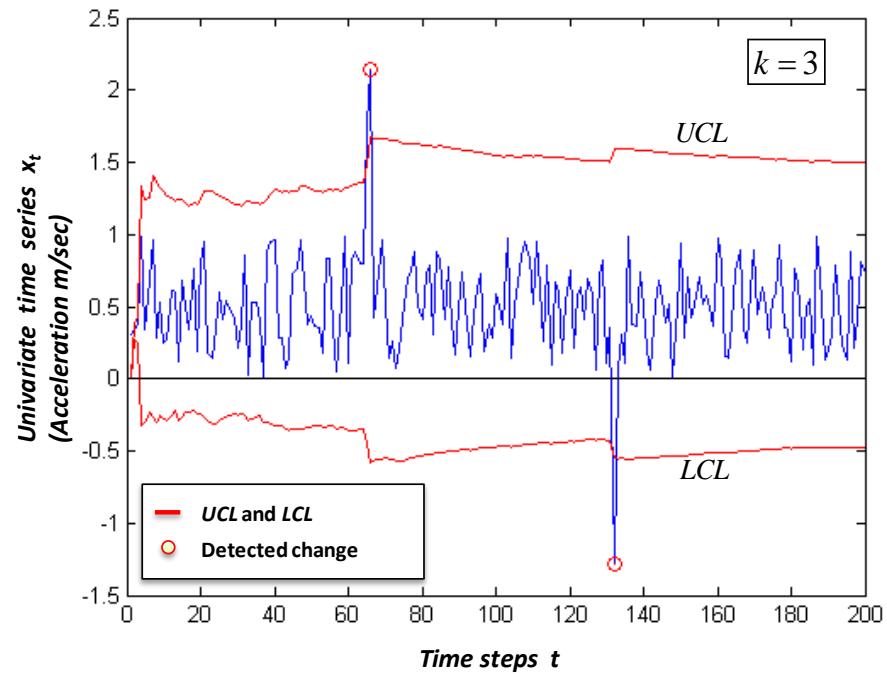
**Output:** detection signal  $s$

```

1:    $\bar{x}_0 \leftarrow 0$  ;
2:    $\sigma_0 \leftarrow 0$  ;
3:    $t \leftarrow 1$  ;
4:   while ( true )
5:      $\bar{x}_t \leftarrow \bar{x}_{t-1} + \frac{x_t - \bar{x}_{t-1}}{t}$  ;
6:      $\sigma_t \leftarrow \sqrt{\frac{1}{t}((t-1)\cdot\sigma_{t-1}^2 + (x_t - \bar{x}_t)(x_t - \bar{x}_{t-1}))}$  ;
7:      $UCL_t \leftarrow \bar{x}_t + k \cdot \sigma_t$  ;
8:      $LCL_t \leftarrow \bar{x}_t - k \cdot \sigma_t$  ;
9:     if (( $x_t > UCL$ ) or ( $x_t < LCL$ )) then
10:        $s \leftarrow 1$  ;
11:     else
12:        $s \leftarrow 0$  ;
13:     end
14:      $t \leftarrow t + 1$  ;
15:   end

```

---



# Change Det: Multivariate Autoregressive Model (MAR)

**ALGORITHM 3.** MAR-based change detection

**Input:** multivariate time series  $\mathbf{x}_t = (x_{1,t}, \dots, x_{n,t})$ , number of training samples  $k$ ,

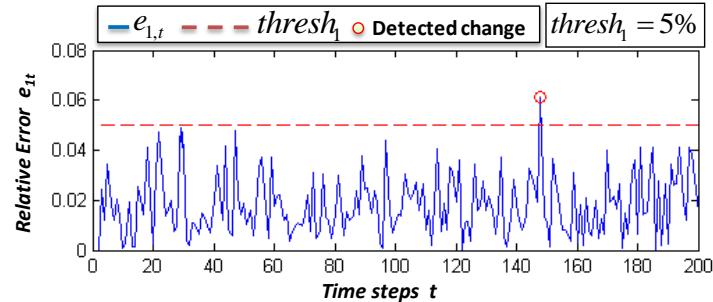
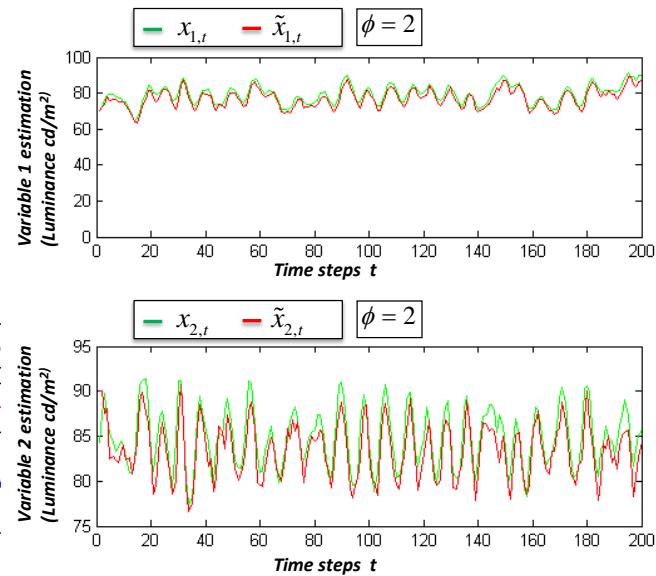
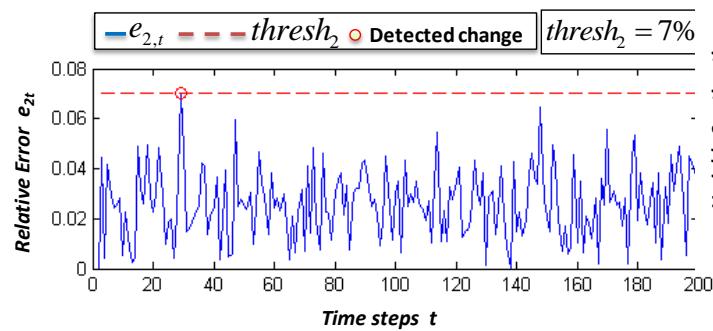
thresholds  $(\text{thresh}_1, \dots, \text{thresh}_n)$

**Output:** detection signal  $s$

```

1: Estimate the model  $\langle c, \phi, \Pi_1, \Pi_2, \dots, \Pi_\phi \rangle$  that fits the training data  $\{\mathbf{x}_t\}$ ,  $\forall t \in [1, k]$ 
2:  $t \leftarrow k + 1$ ;
3: while (true)
4:    $\tilde{\mathbf{x}}_t \leftarrow c + \Pi_1 \mathbf{x}_{t-1} + \dots + \Pi_\phi \mathbf{x}_{t-\phi}$ ;
5:   for  $i \leftarrow 1$  to  $n$ 
6:      $e_{i,t} \leftarrow \frac{\|\mathbf{x}_{i,t} - \tilde{\mathbf{x}}_{i,t}\|}{\|\mathbf{x}_{i,t}\|}$ ;
7:     if ( $e_{i,t} > \text{thresh}_i$ ) then
8:        $s \leftarrow 1$ ;
9:     else
10:       $s \leftarrow 0$ ;
11:    end
12:  end
13: end

```



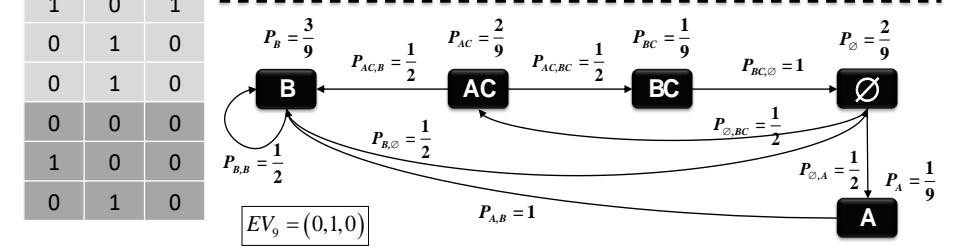
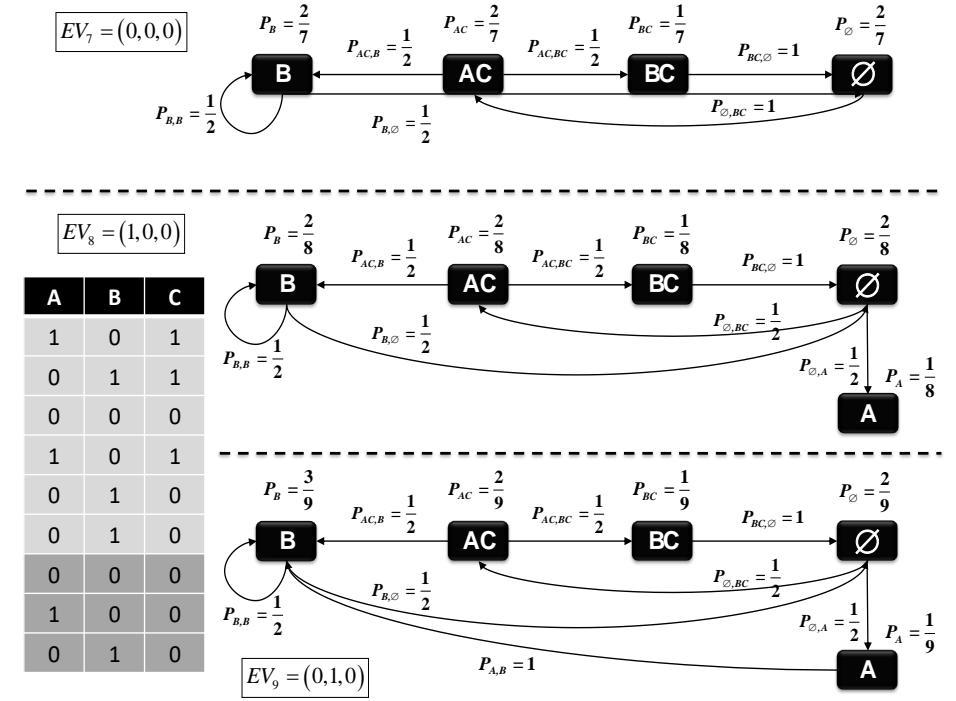
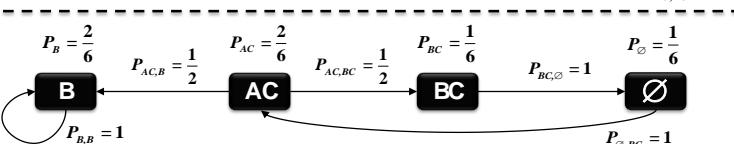
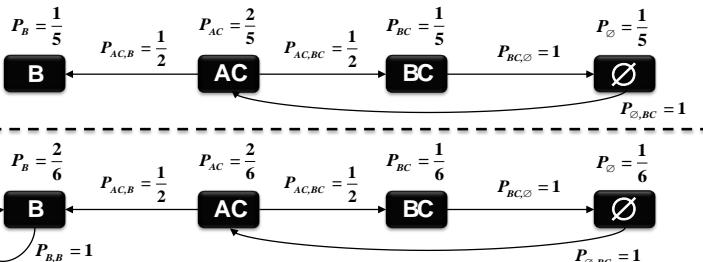
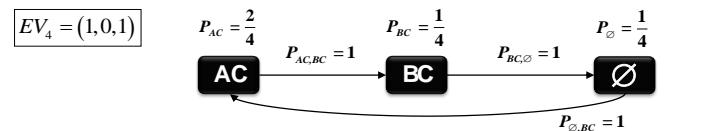
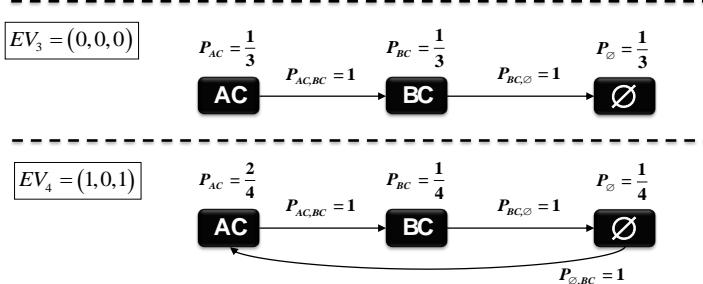
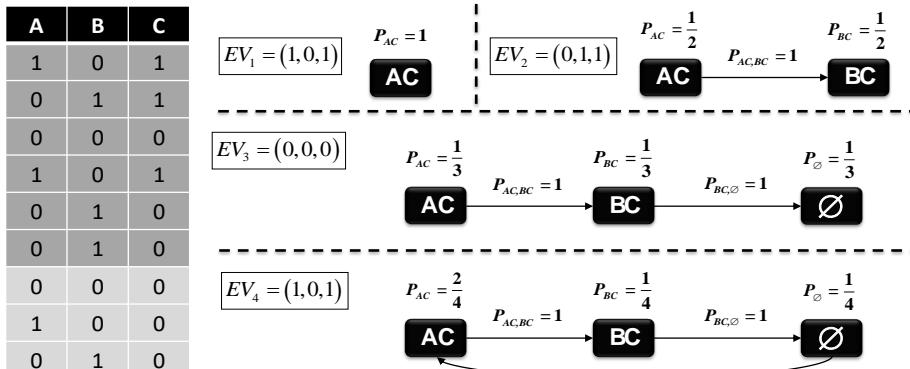
# Event Correlation Engine (ECE)

- Data-driven approach (no pre-defined model)
- Facilitates decision-making process
  - Post-analysis of events (***offline mode***)
    - Root Cause – RC determination, Cause analysis
    - Explanation (the sequence of events that led to an event triggering)
  - Prediction (***online mode***)
    - Predict system behavior in the near future (events that will be possibly triggered – coming with a probability value)

# Event Correlation: Stepwise approach

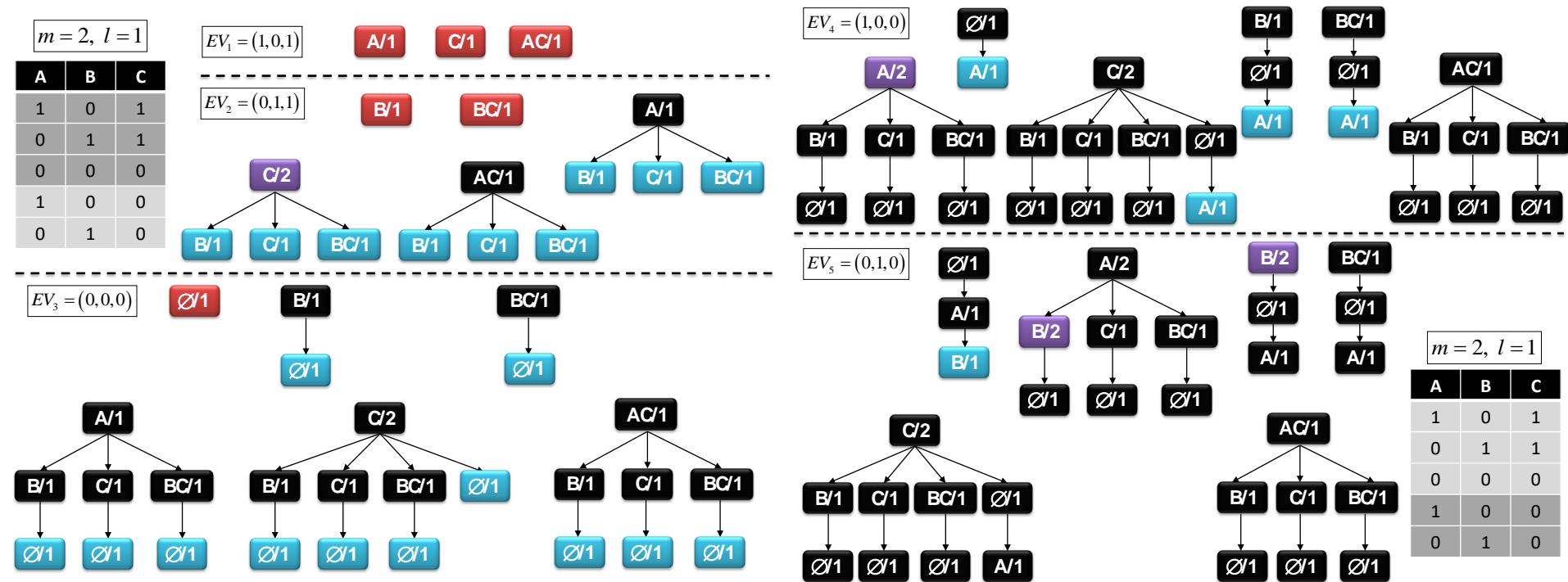
$$(\forall t \in N)(\forall I_l, I_m \subseteq I) P_{I_l I_m}^{\overline{I}} = P(I_m | I_l, \overline{1:t}) =$$

$$\frac{N(I_l^{t-1}, I_m^t | \overline{1:t})}{N(I_l | \overline{1:t-1})} = \frac{\sum_{k=2}^t \prod_{e_i \in I_l, e_j \in I_l} \prod_{e_p \in I_m, e_q \in I_m} e_i^{k-1} \cdot \bar{e}_j^{k-1} \cdot e_p^k \cdot \bar{e}_q^k}{\sum_{k=1}^{t-1} \prod_{e_i \in I_l, e_j \in I_l} e_i^k \cdot \bar{e}_j^k}$$



# Event Correlation: Variable-order approach

- Similar to the previous approach, but now multiple Markov models are considered
- Markov-chains of order  $1, \dots, m$  are combined to predict event sequences of length up to  $m$



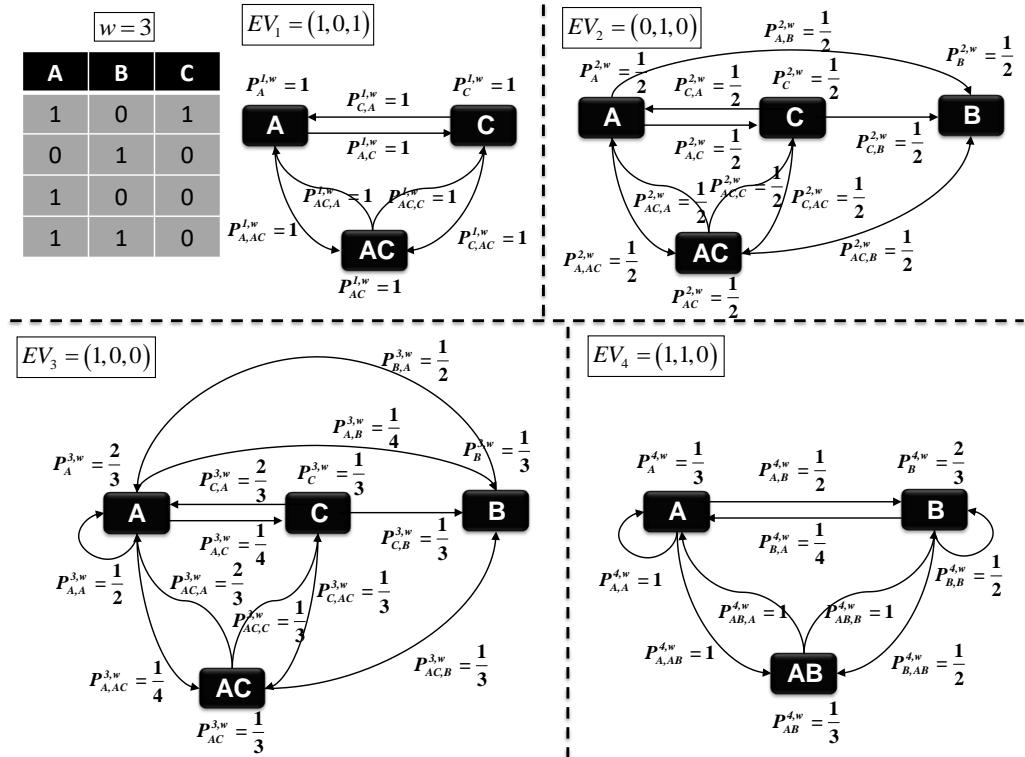
# Event Correlation: Sliding-window approach

$$\alpha_v^t = \begin{cases} 1 & \text{if } \prod_{e_i \in I_V} e_i^t = 1 \\ 0 & \text{otherwise} \end{cases}$$

$$\beta_{uv}^{t_1, t_2} = \begin{cases} 1 & \text{if } \prod_{e_i \in I_u, e_j \in I_V} e_i^{t_1} \cdot e_j^{t_2} = 1 \\ 0 & \text{otherwise} \end{cases}$$

$$(\forall u, v \in V) \quad N_{uv}^{t,w} = \sum_{i=t-w+1}^t \sum_{j=i}^t \beta_{uv}^{i,j}$$

$$(\forall u, v \in V) \quad P_{uv}^t = \frac{N_{uv}^{t,w}}{\sum_{j=t-w+1}^t \alpha_u^j \cdot (t-j+1)}$$



# Dependency Graph

- Probabilistic Directed Graph (cycles are possible)
- $V$  (nodes): attributes (in our case *sensors*)
- $E$  (edges): event transition
- $P_{ij}$ : conditional probabilities of event pairs  $V_i - V_j$
- Parameters
  - $w$ : look-ahead window
  - $p_c$ : cutoff probability
  - $a$ : aging factor
- Formal transformation into “if...then” rules (SWRL)
- Possible execution inside a probabilistic rule engine

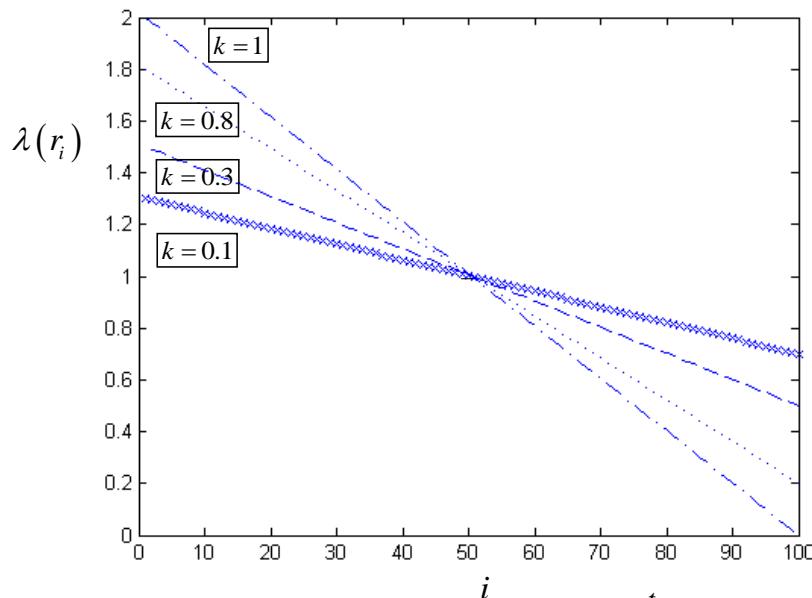
# Event prediction

- Event prediction by probabilistic temporal reasoning
  - *probabilistic temporal rules* [Shakarian et al. 2011]  
 $A \rightarrow B : [t, p]$
  - $A, B$  are (ground) formulae consisting of (ground) atoms and typical logic programming operators for conjunction, disjunction and negation while the (ground) formula  $B$  is annotated with a probability value  $p$  and a time unit  $t$ .

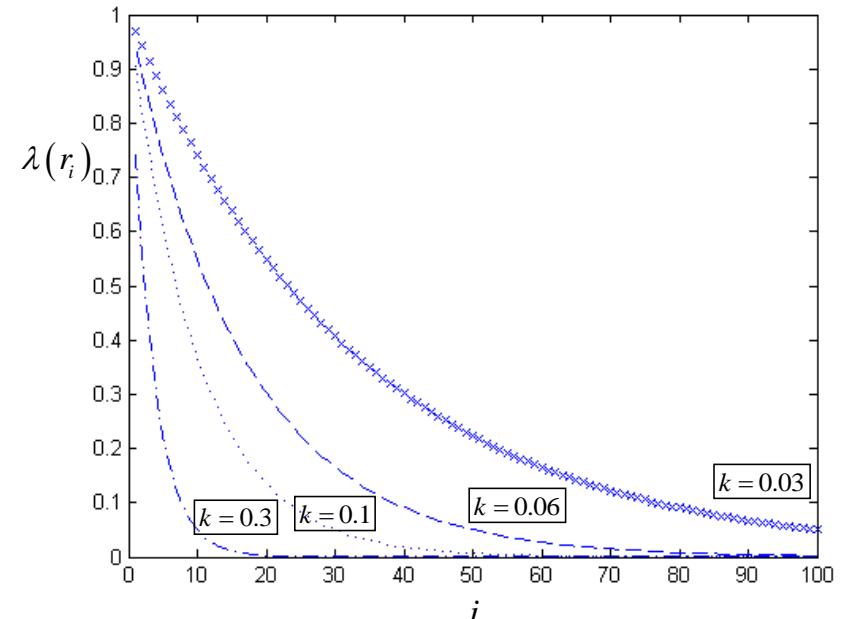
# Adaptive filtering of rules

- Use of *aging* or *decay function*  $\lambda(r_t) = f(t)$
- $f(t)$  : Linear or exponential degradation

$$\lambda(r_i) = -\frac{2k}{n-1}(i-1) + k + 1$$



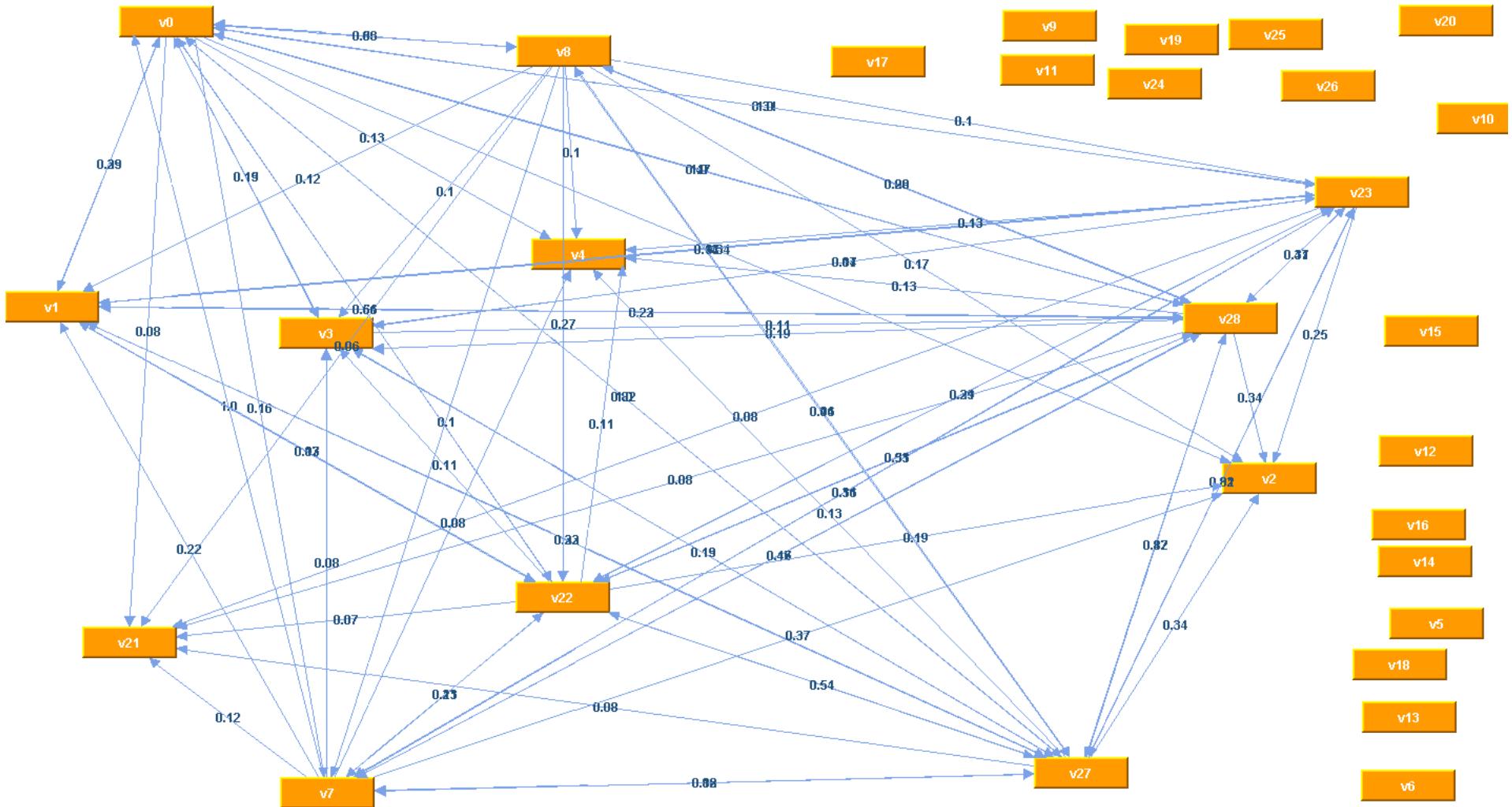
$$\lambda(r_i) = \exp(-ki)$$



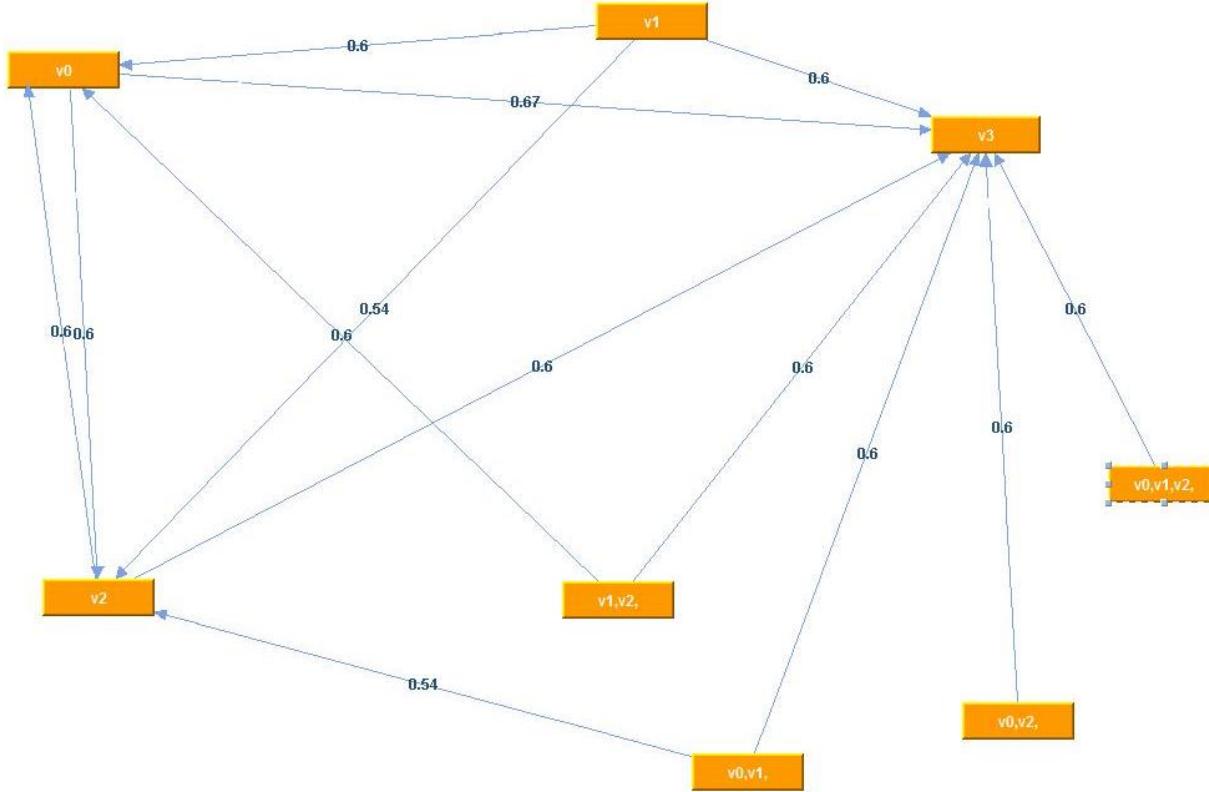
$$p_{r,\Delta t} = \frac{\sum_{i=t-\Delta t+1}^t \lambda(r_i) \cdot p_{r,i}}{\sum_{i=t-\Delta t+1}^t \lambda(r_i)}$$

**Rules probability**

# Complete Graph



# Extract Useful Correlations



- Implementation technologies
  - *Java, Oracle DB, JGraphT lib for visualization*