Viterbi Algorithm for Intrusion Type Identification in Anomaly Detection System

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Context

Intrusion Type

- Buffer overflow
  - xlock vulnerability
  - lpset vulnerability
  - kcms_sparc vulnerability
- S/W security vulnerability
- Setup vulnerability
- Denial of service

Markov Chain

A markov Chain is defined by :

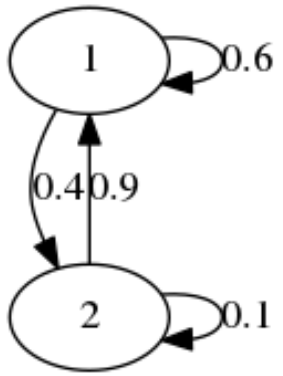
- S, A finite set of N states
- π, A vector of initial probabilities over S :

$$\pi_i = P(S_1 = i), 1 \leq i \leq N$$

- A, A matrix of probabilities of transitions over SxS :

$$a_{ij} = P(S_t = j | S_{t-1} = i), 1 \leq i \leq N$$

- Markov assumption :
$P(S_t|S_{t-1}, S_{t-2}, \ldots, S_1) = P(S_t|S_{t-1})$



$$A = \begin{pmatrix} 0.6 & 0.4 \\ 0.9 & 0.1 \end{pmatrix}$$

Figure: Simple example of Markov Chain

HMM - Hidden Markov Model

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- Hidden Markov Model can be viewed as a Bayesian Network
- We define a HMM including :

  V, A finite set of M observations

  B, A a matrix of probabilities of observations over state :

$$b_i(k) = P(0_t = V_k | S_t = i)$$

HMM - Forward Algorithm

input : λ The model, O Observed sequence
output : $P(0|\lambda)$
Step 1, Initialization : $\forall i, \alpha_1(i) = \pi_i b_i(0_1)$
Step 2, Induction :
for $t \leftarrow 2 : T$ **do**

$$\forall in \alpha_t(i) = \left[\sum_{j=1}^{N} \alpha_{t-1}(i) a_{ij}\right] b_j(O_t)$$

end
Step 3, Termination : $P(0|\lambda) = \sum_{i=1}^{N} \alpha_t(i)$

[1]

[1] L. R. Rabiner (1989). "A tutorial on hidden Markov models and selected applications in speech recognition". In: *Proceedings of the IEEE* 77.2, pp. 257–286

HMM - Viterbi Algorithm

input : O Observed sequence
output : $\arg\max_{\lambda \in \Lambda} P(0|\lambda)$
Step 1, Initialization :
for $i \leftarrow 1 : N$ **do**
  $\delta_1(i) = \pi_i b_i(0_1)$
  $\psi_1(i) = 0$
end
Step 2, Recursion :
for $t \leftarrow 2 : T$ **do**
  for $j \leftarrow 1 : N$ **do**
    $\delta_t(j) = \max_i[\delta_{t-1}(i)a_{ij}]b_j(0_t)$
    $\psi_t(j) = \arg\max_i[\delta_{t-1}(i)a_{ij}]b_j(0_t)$
  end
end
Step 3, Termination :
$P^* = \max_{s \in S}[\delta_T(s)]$
$S_T^* = \arg\max_{s \in S}[\delta_T(s)]$
Step 4, Backtracking :
for $t \leftarrow T - 1 : 1$ **do**
  $S_t^* = \psi_{t+1}(s_{t+1}^*)$
end
return S^*

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[2] A. Viterbi (1967). "Error bounds for convolutional codes and an asymptotically optimum decoding algorithm". In: *IEEE Transactions on Information Theory* 13.2, pp. 260–269

Normal Behaviour Modeling

Normal Behaviour is modelised by a left-to-right HMM λ.

The forward allgorithm is used to decide whether normal or not with a threshold.

Intrusion Detection

Initialization

Show Example

Intrusion Detection

Induction

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Intrusion Detection

Termination

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Intrusion Detection

Decision

if $log(P(0|\lambda)) > \ thresold$ **then**
  return *Normal Behaviour*
else
  return *Intrusion*
end

Show Example

Intrusion Detection

Results

Table: The performance of HMM-based IDS. Best results are in bold

Length	Thresold	Detection Rate	F-P Error
10	-9.43	100%	2.626
15	-9.43	100%	3.614
10	-14.42	100%	1.366
15	-14.42	100%	2.718
10	-16.94	100%	0.789
15	-16.94	100%	2.618
10	-18.35	100%	0.553
15	-18.35	100%	2.535
10	-19.63	100%	0.476
15	-19.63	100%	2.508
10	**-20.83**	**100%**	**0.372**
15	-20.83	100%	2.473

Intrusion Type Identification

Process in two steps :

- Viterbi algorithm used to find the optimal state sequence
- Euclidiant distance to identify the intrusion type with the optimal state sequence

Intrusion Type Identification

Initialization

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Intrusion Type Identification

Recursion

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Intrusion Type Identification

Termination

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Intrusion Type Identification

Backtracking

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Intrusion Type Identification

Decision

Show Example

Intrusion Type Identification

Results

Table: The performance of Viterbi-based Intrusion Type Identification

Attack	Trial	Correct	Incorrect	Rate
Buffer Overflow	20	18	2	90%
Denial of Service	25	9	16	36%
Buffer Overflow	45	27	18	60%

Limitations & Remarks

Try other distance metrics for Intrusion Type Identification : Ja-Min Koo and Sung-Bae Cho (2005). "Effective Intrusion Type Identification with Edit Distance for HMM-Based Anomaly Detection System". In: *Pattern Recognition and Machine Intelligence*. Ed. by Sankar K. Pal, Sanghamitra Bandyopadhyay, and Sambhunath Biswas. Springer Berlin Heidelberg

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No baseline to compare results with other methods

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Baseline