CS259D: Data Mining for CyberSecurity

Administrativia

- HW due tonight
- Time for guest lecture on Friday
- Projects

Web security

- Web servers accessible by outside world
- Web apps developed with security as an afterthought
- Example: Target breach

Popularity of web-related attacks

Year	Total	Web-related	Percentage
1999	809	109	13.5%
2000	800	186	23.3%
2001	588	120	20.4%
2002	376	100	26.6%
Total	2573	515	20.0%

Web-related attack detection

- Misuse-based
  - Example: Snort
    - 1037 out of 2464 signatures
  - Hard to keep up-to-date
    - Time-intensive, error-prone, requires significant security expertise
  - Challenge with apps developed in-house
- Anomaly-based
  - Applicable to custom-developed web apps
  - Support detection of new attacks

Anomaly detection method

- Input: web server log files
  - Common Log Format (CLF)
- Analysis: build profiles for apps & active docs
  - Lower error rates than generic profiles
  - Use multiple models
    - Reduce vulnerability to mimicry attacks
- Output: anomaly score for each web request

Data: Model

- An ordered set $U = \{u_1, u_2, \ldots, u_m\}$ of URIs
  - Extract from successful GET requests
    - $200 \leq$ return-code < 300
- Components of u_i
  - Path to desired resource: $path_i$
  - Optional path information: $pinfo_i$
  - Optional query string: q
    - Following a ? Character
    - Passing parameters to referenced resource
    - Attributes and values: $q = (a_1, v_1), (a_2, v_2), \ldots, (a_n, v_n)$
    - $S_q = \{a_1, a_2, \ldots, a_n\}$
- URIs without query strings not included in U
- U_r: subset of U with resource path r
  - Partition U
  - Anomaly detection run independently on each U_r

Data: Example record

- Entry: 169.229.60.105 – johndoe [6/Nov/2014:23:59:59 -0800] "GET /scripts/access.pl?user=johndoe&cred=admin" 200 2122
- Path: /scripts/access.pl
- q: user=johndoe&cred=admin
- a_1 = user, v_1 = johndoe
- a_2 = cred, v_2 = admin
- S_q = {user, cred}

Anomaly score

- Each model
  - returns probability p of normalcy
  - Has an associated weight w
    - default value = 1
- Anomaly score =

$$\sum_m w_m \times (1 - p_m)$$

Attribute length

- Fixed size tokens
  - Session identifiers
- Short input strings
  - Fields in an HTML form
- Example:
  - Buffer overflow: shell code & padding
    - Several hundred bytes
  - XSS

Attribute length

- Learning: Estimate mean μ and variance σ^2 of lengths in training data
- Chebyshev ineqaulity:

$$p(|x-\mu|>t)<\frac{\sigma^2}{t^2}$$

- Detection:
  - strings with length larger than mean
    - If length < mean, p = 1
    - Padding not effective

$$p=p(|x-\mu|>|l-\mu|)<\frac{\sigma^2}{|l-\mu|^2}$$

Attribute character distribution

- Observations about attributes:
  - Regular structure
  - Mostly human readable
  - Almost always contain only printable characters
- Character distribution: sorted relative frequencies
  - Example: passwd => 0.33, 0.17, 0.17, 0.17, 0.17, 0,…, 0
  - Fall smoothly for human-readable tokens
  - Fall quickly for malicious input
- Example:
  - Buffer overflow: needs to send binary data & padding
  - Directory traversal exploit: many dots in attribute value

Attribute character distribution

- Learning:
  - character distribution of each observed attribute is stored
  - Average of all character distributions computed
- Detection:
  - Variant of the Pearson χ^2-test
  - Bins: {[0], [1, 3], [4, 6], [7, 11], [12, 15], [16, 255]}
  - For each query attribute:
    - Compute character distribution
    - Observed values $\mathbf{O_i}$: Aggregate over bins
    - Expected values $\mathbf{E_i}$: Learned character distribution attribute length
    - Compute: $\chi^2 = \sum_{i=0}^{5} \frac{(O_i - E_i)^2}{E_i}$
    - Read corresponding probability

Structural inference

- Simple manifestations of an exploit
  - Unusually long parameters
  - Parameters containing repetitions of non-printable characters
- Evasion
  - Replace non-printable characters by groups of printable characters
- Parameter structure: regular grammar describing all of its legitimate values
- Detect exploits requiring different parameter structure
  - Examples: Buffer overflow, directory traversal, XSS

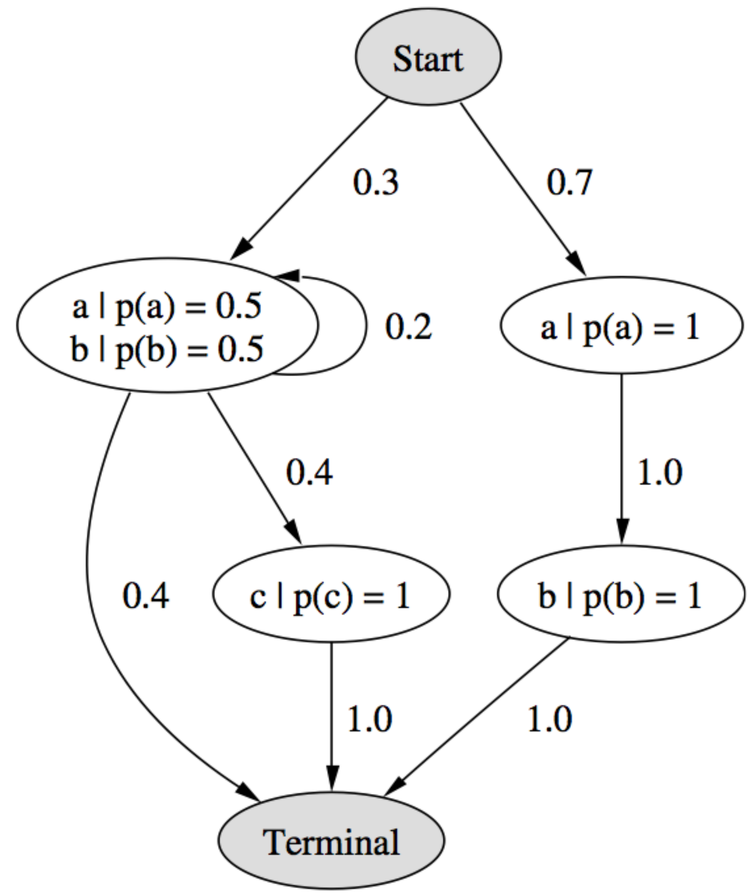
Structural inference

- Learning: Markov model/Non-deterministic finite automaton (NFA)
  - $P_S(o)$: probability of emitting symbol o at state S
  - $P(t)$: probability of transition t
  - Output: paths from Start state to Terminal state
- For a word $w = (o_1, o_2, \ldots, o_k)$

$$p(w) = p(o_1, o_2, \ldots, o_k) = \sum_{p:paths} \prod_{S_i \in p} p_{S_i}(o_i) \times p(t_i)$$

Structural inference

- w = ab
- P(w) = 0.3*0.5*0.2*0.5*0.4 + 0.7*1.0*1.0*1.0*1.0 = 0.706



Structural inference

- Goal: Find a model with highest likelihood given training examples
- Bayesian model induction:

  P(model | training data) = p(training data| model)* p(model)/p(training data)
- P(training data) a scaling factor; ignored
- P(training data| model) computed as last slide
- P(model): preference towards smaller models
  - Total number of states: N
  - Total number of transitions at each state S: T(S)
  - Total number of emissions at each state S: E(S)

$$P(Model) \propto \frac{1}{\prod_{S} (N+1)^{T(S)} \times (N+1)^{E(S)}}$$

Structural inference: Learning

- Start with a model exactly reflecting input data
- Gradually merge states
- Until posterior probability does not increase
- Cost: **$O((n*L)^3)$** with n training input strings, and L maximum length of each string
  - Up to n*L states
  - (n*L)(n*L-1)/2 comparisons for each merging
  - Up to n*L-1 merges
- Optimizations
  - Viterbi path approximations
  - Path prefix compression
  - Cost: **$O(n*L^2)$**

Structural inference: Detection

- First option: Compute probability of query attribute
  - Issue: probabilities of all input words sum up to 1; all words have small probabilities
- Output:
  - p = 1 if word is a valid output of Markov model
  - p = 0 otherwise

Token finder

- Goal: determine whether values of an attribute are drawn from an enumerated set of tokens
- Example: flags, indices
- Learning:
  - Growth in # of different argument instances compared to total # of argument instances
  - Compute correlation between these numbers:
  - $F(x) = x$
  - $G(x) = G(x-1) + 1$ if x-th value is new
  - $G(x) = G(x-1) - 1$ if x-th value was seen before
  - $Corr = Covar(F, G)/Sqrt(Var(F) * Var(G))$
  - If $Corr < 0$, then enumeration
  - If enumeration, then store all values for use in detection phase

Token finder: Detection

- If enumeration: value expected to be among stored values
  - Output p = 1 or p = 0 correspondingly
- If random: p = 1

Attribute presence/absence

- Observation: URIs typically produced not directly by user, but by scripts, forms, client-side programs
  - Result: regularity in number, name, order of parameters
  - Hand-crafted attacks typically break this regularity
    - Incomplete or malformed requests to probe/exploit web app
      - Missing argument
      - Mutually exclusive arguments appearing together

Attribute presence/absence

- Learning: Record set S_q for each query q during training in a hash table
- Detection: Lookup the attribute set in hash table
  - Return p = 1 or p = 0 correspondingly

Attribute order

- Legitimate invocations often contain same attributes in same orders
  - Sequential program logic preserves order even when some attributes left out
- Learning:
  - Attribute a_s precedes a_t if as and at appear together in parameter list of at least one query and a_s comes before a_t when they appear together

Attribute order

- Directed graph
- # vertices = # attributes
- For each training query, add edges between nodes of ordered attribute pairs
- Find all strongly connected components (SCC) of the graph
- Remove edges between nodes in same SCC
- For each node, find all reachable nodes
- Add corresponding pairs to set of precedence orders

Attribute order

- Find all order violations
  - Return $p = 0$ or $p = 1$ correspondingly

Access frequency

- Frequency patterns of different server-side web applications
- Two types of frequencies:
  - Frequency of application being accessed from a certain client (IP address)
  - Total frequency of all accesses
- Attacks
  - Probing
  - Guess parameter values
  - Evasion: slow down

Access frequency

- Learning:
  - divide training time to intervals of fixed time (e.g., 10 sec)
  - Count accesses in each interval
  - Find total and client-specific distributions
- Detection:
  - Chebyshev probability for total, and for client
  - Return average of the two probabilities

Inter-request time delay

- Regular delay between each successive request
  - Surveillance
  - Scripted probes
- Learning: Find distribution of normal delays
  - Similar to character distribution model
- Detection: Pearson χ^2-test

Invocation order

- Order of invocation of web-based applications for each client
  - Infer session structure regularity
  - Similar to structural inference model
- Learning: group queries based on source IP
  - Session: Queries within an interval of time
  - Build NFA for sessions
- Detection: $p = 1$ or $p = 0$ depending on session being an output of NFA

Evaluation

Data set	Number of alerts	Number of queries	False positive rate	Alarms per day
Google	206	490,704	0.000419	4944
UCSB	3	4617	0.000650	0.01
TU Vienna	137	713,500	0.000192	1.71

Reference

- “A multi-model approach to the detection of web-based attacks”, 2005