A robust approach of detecting anomalous hosts

Network Anomaly Diagnosis Workshop 2006

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Motivation

- Anomalous host
  - A host whose behavior is *not* normal
    - worm-infected hosts, bots
      - vertical, horizontal scanning
    - attackers or victims of DDoS
    - misconfigured servers
    - etc…
- We need to find anomalous hosts
  - to protect users/customers
  - to learn their characteristics
    - to create a new ACL/signature
    - to learn the dynamics/mechamisms
    - to make workload models

Motivation cont.

- Problems:
  - anomalous activities could be **buried** under the normal activities
  - Super spreader $\neq$ worm-infected hosts
    - public stratum-1 NTP server, TLD DNS server
  - We need a robust approach of identifying anomalous hosts.

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Idea

- Characterizing communication pattern of each host
  - no payload information
    - can be extracted from NetFlow record
  - anomalous hosts exhibits intrinsic communication pattern

- Naïve Bayes Classifier (NBC) for analyzing communication pattern
  - Simple approach
    - calculation cost is low while the accuracy is good
  - Robust identification
    - E.g., classifying spam messages

Communication pattern of each host

- We analyze source IPs in this work

- Definition of the communication pattern
  - For each source IP:
    - A1: # of dst IPs / # of flows (0～1)
    - A2: # of dst ports / # of flows (0～1)
    - A3: # of acked dst IPs / # of dst IPs (0～1)
    - A4: # of flows / # of packets (0～1)

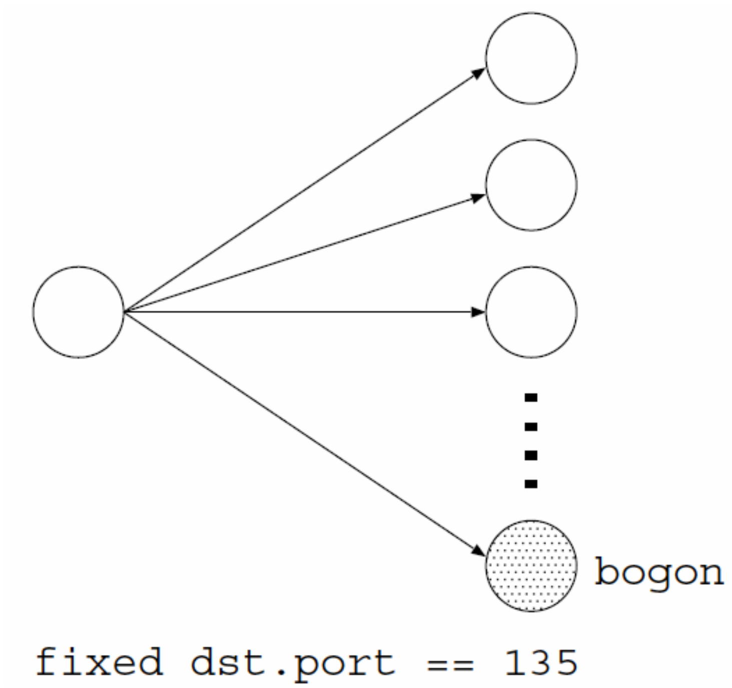
- Other metrics were also considered
  - bogon ratio, src ports statistics etc.
  - We chose the best 4 attributes in term of mutual information

Communication pattern of each host

- Merit
  - It can express concentration and dispersion easily
    - entropy-like statistics
  - more rich and flexible than entropy-based statistics
    - E.g., mean #pkts / flow, bogon ratio etc.
- Demerit
  - It needs to extract "cardinality" from massive flow data
    - Some counting techniques such as probabilistic counting or Bloom filter will be required.

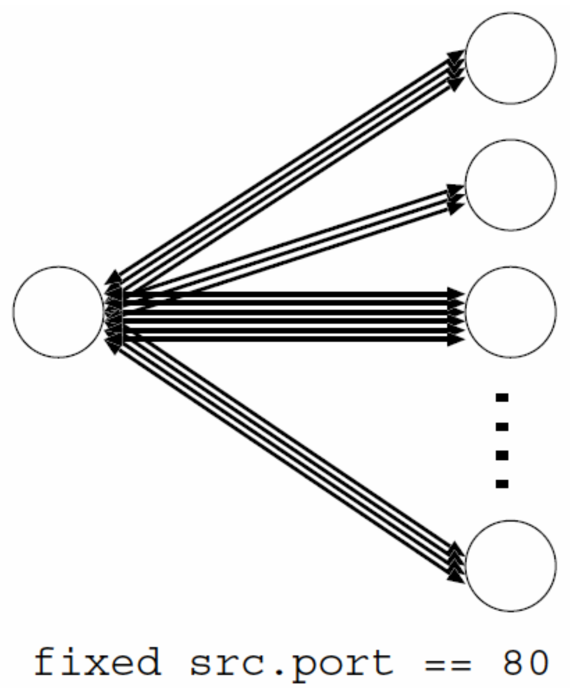
Typical examples (mental model)

Worm-infected host



$A^* = \{1,0,0,1\}$

Large-scale web server



$A^{**} = \{0,1,1,0\}$

Measured data

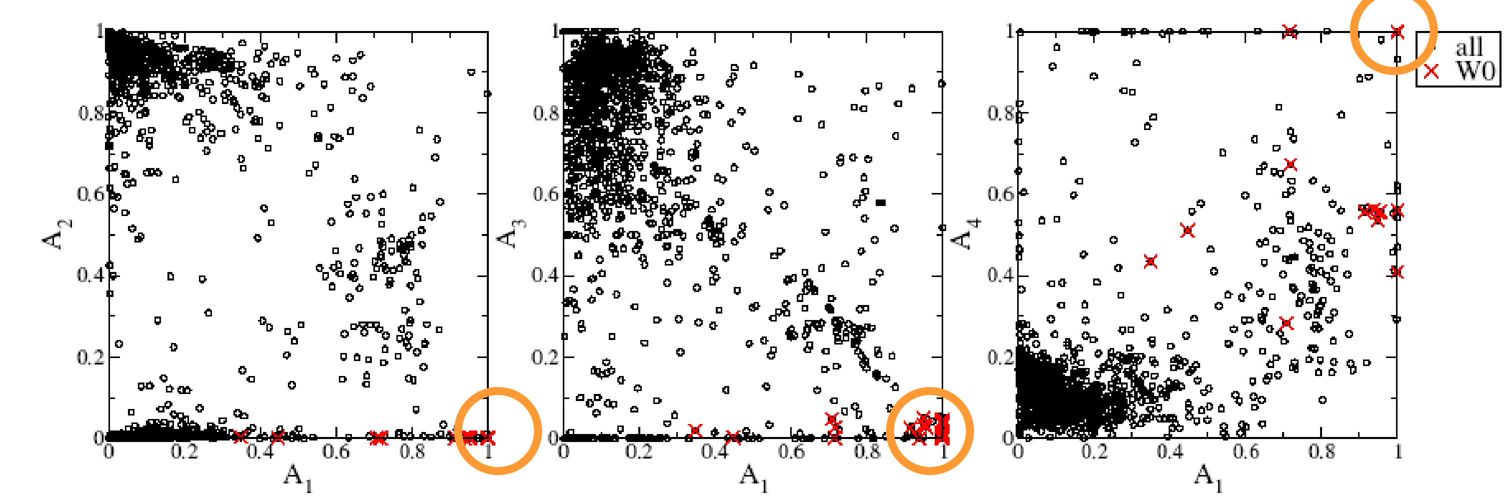
- 1Gbps Internet backbone link
- 5 minutes of measurement
- Number of source host = 116,889 (H)
- Number of host that generates more than 300 flows = 1,340 (H')
  - Mean flow generation rate >= 1 fps

Communication pattern

W0:
A set of heuristically extracted worm-infected hosts

protocol	destination port	example of worms
TCP	135	Blaster
TCP	139	Welchia
TCP	1433	Slammer
UDP	1434	Slammer

1340 hosts were examined; # of W0 hosts was 26



NBC (1)

- Machine learning method based on Bayesian inference
- Supervised classification technique
- Used in many network applications
  - Spam filtering, passive OS fingerprinting, intrusion detection etc.
- Calculation cost is low
  - linear to data size
- Robust classification

NBC (2)

- **learning: likelihood probability**
  - the probability that the attribute vector of a host is A, given that the class of the host is Ci,

$$P\left(\mathbf{A}|C_i\right) = P\left(A_1, A_2, \ldots|C_i\right)$$

- **classification : a priori probability**
  - the probability that the class of a host is Ci, given that the attribute of the host is A (measured attribute)
  - Bayse theorem + assumption of independence

→Ci is obtained by the maximum a priori probability (MAP)

$$P\left(C_i|\mathbf{A}\right) = \frac{P\left(C_i\right)}{P\left(\mathbf{A}\right)} \prod_j P\left(A_j = a_{jk}|C_i\right)$$

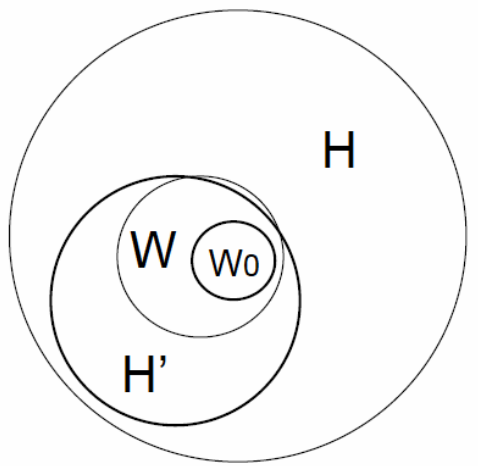
Identification procedure

- D_1: training data
- D_2: test data
- C_1: class of worm-infected hosts
- C_2: class of other hosts

- Learning: Calculate the likelihood probability $P(A|Ci)$ for D_1
- Classification: calculate the a priori probability $P(Ci|A)$ for D_2

How to train the classifier in reality?

- Problem : we don't have complete labeled data
  - ideal labeling : W → C1, H'\W → C2
- Solution :
  - heuristic labeling : W0 → C1, H'\W0 → C2



H: total hosts
H': target hosts
W: worm-infected hosts
W_0: heuristically extracted worm-infected hosts

If the #H' >> #W_0, this assumption holds

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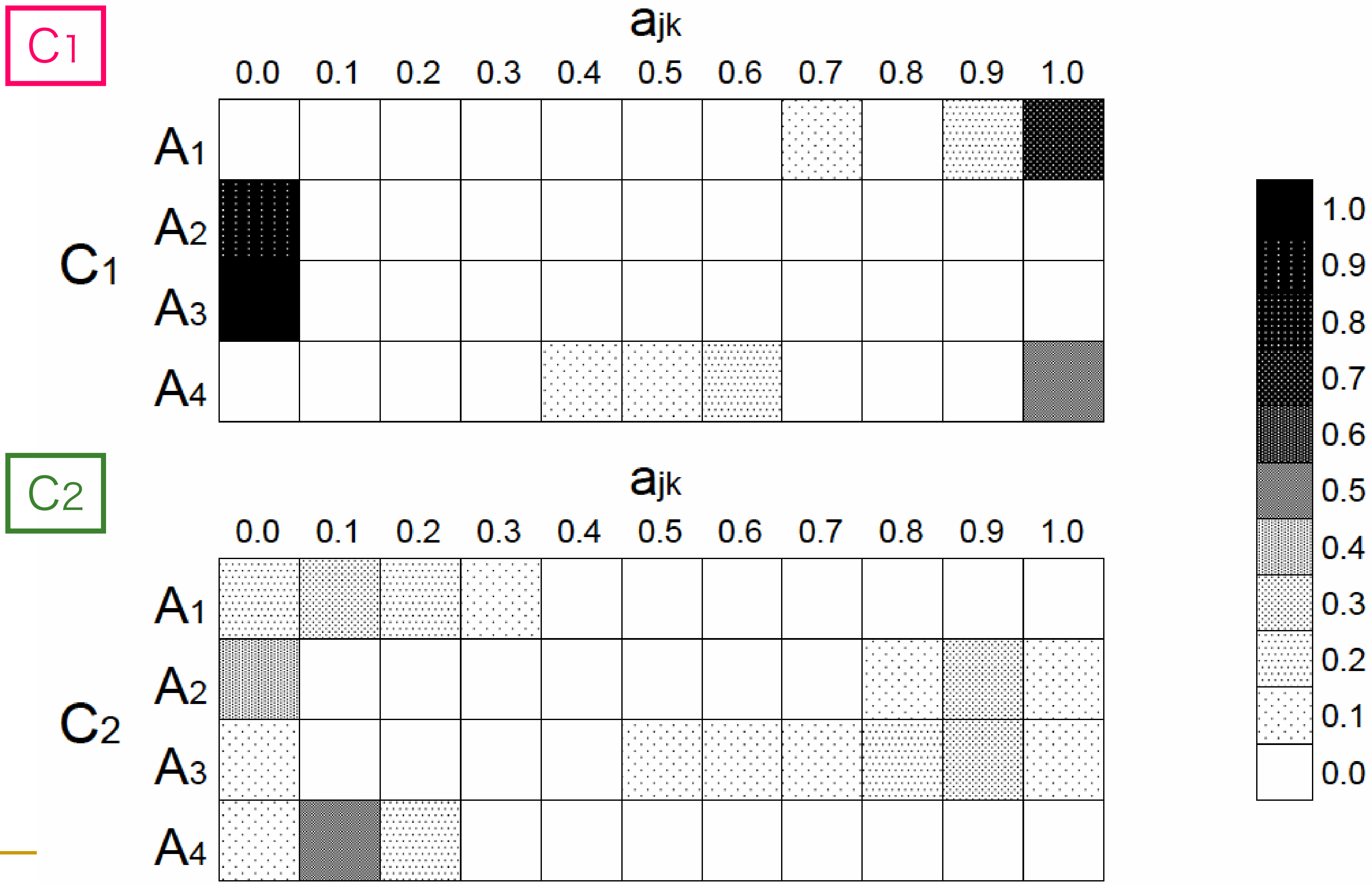
Statistics of measured data

	$\mathbf{D_1}$	$\mathbf{D_2}$
Total # of packets	53,811,483	52,207,374
$n(\mathbf{H})$	116,889	115,690
$n(\mathbf{H}')$	1,340	1,358
$n(\mathbf{W_0}) = n(\mathbf{C_1})$	26	25
$n(\mathbf{C_2})$	1,314	1,333

Likelihood probability P(A|C)



Confusion matrix

		estimated class	
	$\rightarrow$	$\widehat{C_1}$	$\widehat{C_2}$
labeled class	C_1	24	1
	C_2	22	1,311

- Classified 46(=24+22) hosts as C_1
  - Newly found 22 <u>suspicious</u> hosts (== W*)
- Misidentified 1 host as C_2 (false negative)
  - The host seems to communicate with a honeypot

Analysis of communication of W*

combination	# of src hosts	# of dst hosts	# of packets	name of worms etc.
(TCP,445)	9	19,821	37,830	Sasser
(TCP,6129)	2	8,916	10,199	DameWare scan
(UDP,1026)	2	8,838	10,661	MS Messenger spam
(UDP,1027)	2	8,810	10,659	MS Messenger spam
(TCP,3306)	2	4,963	8,855	MySQL UDF Worm (Bot)
(ICMP,—)	1	1,939	1,939	Welchia
(UDP,137)	4	1,730	1,735	Qaz, OpaSoft
(TCP,15118)	1	1,192	2,520	Dipnet/Oddbob
(TCP,135)	1	298	529	Blaster, Lovsan
(TCP,9898)	1	180	180	Dabber, Doomran

Extracted hosts that sends the packets with some of these combinations to more than 300 destination addresses (1 address / sec)
→20 of 22 hosts matched the condition
the rest 2 hosts are also likely to be worm-infected

Results for other data

- Training data = D1
- Test data = D3
  - measured at different network, 100Mbps international backbone link, WIDE MAWI dataset

Estimated class

Labeled class

$\rightarrow$	$\widehat{C_1}$	$\widehat{C_2}$
C_1	33	0
C_2	15	74

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Results for other data cont.

- Number of newly found suspicious hosts = 15
- Found *unknown* combination
  - TCP 445, ICMP, UDP 1028, TCP 80, UDP 137 etc.
    - udp.1028 : Kilo, SubSARI or messenger spam (?)

- 14 of 15 hosts sent the packets with some of these combination to more than 900 dst hosts (1 address / seconds)

- It is very likely that those newly found hosts are worm-infected.

summary

- Method of identifying anomalous hosts was presented
- idea
  - communication pattern of each host
  - leveraged the NBC
- Validation through the measured data (for worm-infected hosts)
  - newly found (unknown) worm-infected hosts
  - correctly classify the hosts whose attribute vectors deviated from the typical pattern.
    → thus, it is robust
  - there exists estimation error
    - Needs for better data set

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Future/ongoing work

- Labeling
  - in this work, we trained the classifier with heuristic labeling
  - use the labeled + unlabeled data set for NBC
    - Class of unlabeled item can be estimated with the EM algorithm + NBC [NIGAM 99]

- Improvement of the training data
  - Coping with the honeypot etc.

- Counting distinct elements efficiently
  - data streaming approach
    - K. Ishibashi et al., "Finding top N hosts in cardinality", IEEE NetDB 2006
    - T. Mori et al., "NetDelta", submitted

Acknowledgement

This work was supported by Ministry of Internal Affairs and Communications, Japan.