

# On the Accurate Detection of Network Service Dependencies In Distributed Systems

(To appear in USENIX LISA 2012)

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Written Qualifying Examination
July 11, 2012

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# Agenda



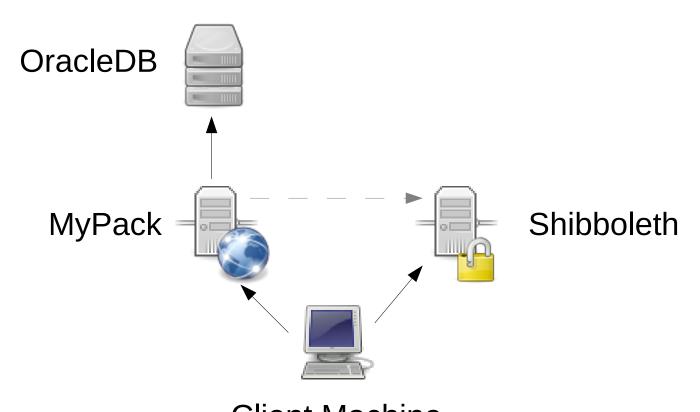
- Introduction
- Motivation
- Related Work
- Our Contributions
  - Logarithm-Based Ranking
  - Service Inference
  - Detection of Network Service Clusters
- Experimental Evaluation
- Conclusion and Future Work

#### Introduction

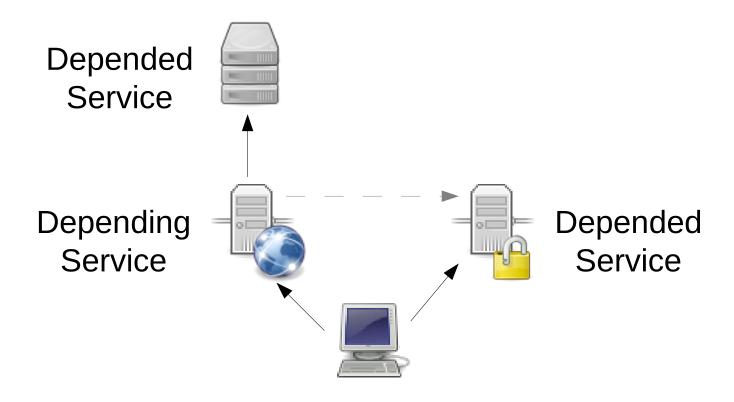


- Enterprise networks are comprised of many network services
- These network services depend on other network services for functionality and information
- This can create a complex web of interdependencies

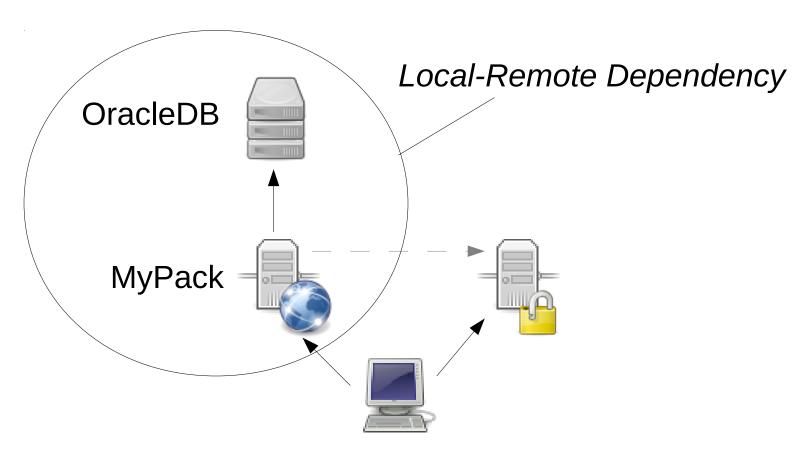




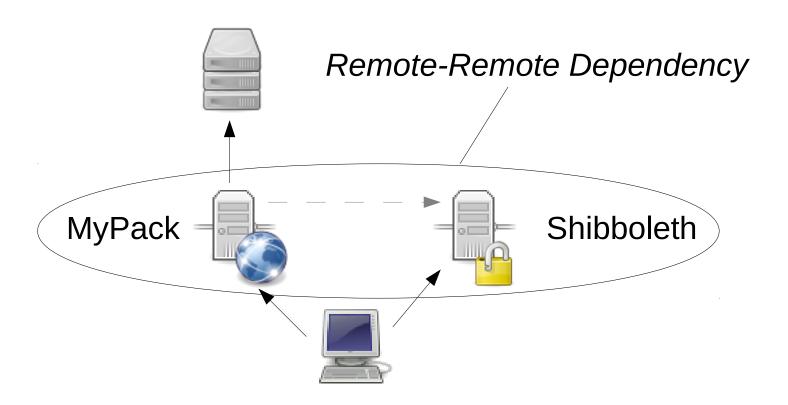












#### **Motivation**



- If a server goes down, it can potentially take down any of its depending services
- Knowing dependencies...
  - makes it easier to react to reports of system failures
  - makes it easier to identify critical components in order to harden them (through redundancy, etc)
- Automatic approaches can cope with changing configurations better than manual analysis

#### **Intuition**



- Most dependencies are explicitly defined in network service configuration files
- Automated approaches look for traffic patterns that suggest dependency relationships
- If there is a dependency between services in a network, patterns will be apparent between them

#### **Previous Works**

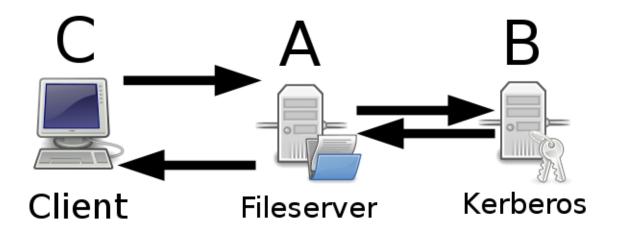


- Host-Based
  - Magpie [OSDI 2004]
  - Pinpoint [NSDI 2004]
  - Macroscope [CoNEXT 2009]
- Network Based
  - Sherlock [SIGCOMM 2007]
  - eXpose [SIGCOMM 2008]
  - Orion [OSDI 2008]
  - NSDMiner [INFOCOM 2011]

#### **NSDMiner**



- NSDMiner [INFOCOM 2011] is an effective network-based approach for finding dependencies
- Looks for nested network flows
- Unobtrusive and more accurate than prior work



#### **Limitations of Prior Work**



- Ranking of dependency candidates is unintuitive
  - Should true positives have less than 30% confidence?
  - Causes high false positives
- Hard to identify dependencies of infrequently used services
- Can't automatically take advantage of overall server configurations
  - Similar services
  - Redundant service clusters

#### **Our Contributions**

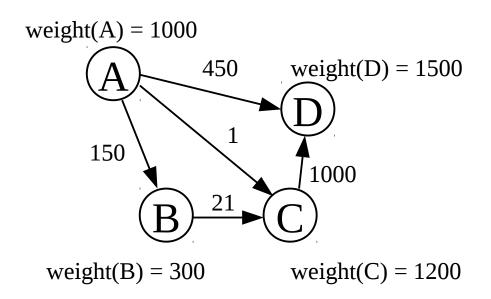


- We develop three novel approaches to improving the detection of network service dependencies
  - A logarithmic based ranking scheme that reduces false positives
  - An inference technique that discovers dependencies of infrequently used services
  - An approach to identify redundant clusters of services in a network
- We implement these as extensions to NSDMiner and evaluate them on production network traffic

### Ratio Ranking

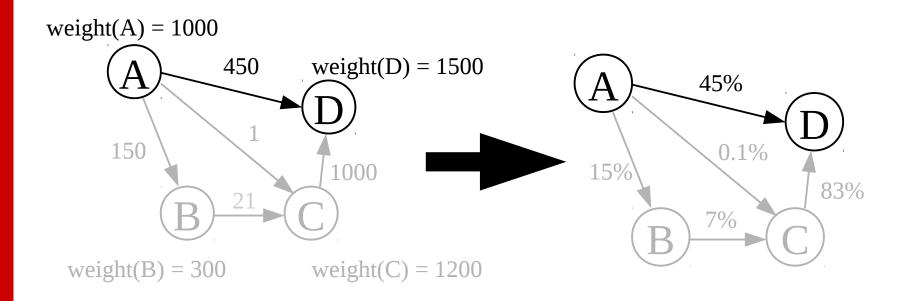


- NSDMiner originally uses a ratio-based ranking
- Confidence is weight(edge)/weight(node)
  - weight(A) = number of times A is accessed
  - weight(A → B) = number of nested flows from A to B



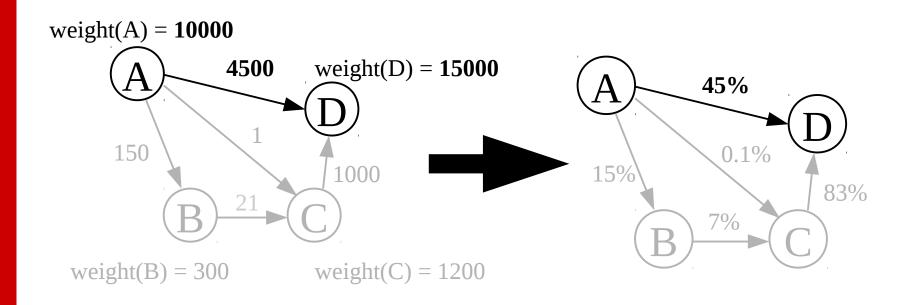


Consider  $A \rightarrow D$ : even though a nested flow to D occurs *every other time* A is accessed, it is only given a confidence of less than 45%.



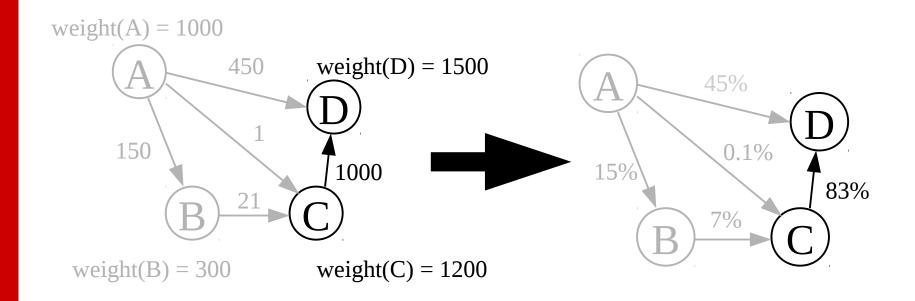


Even if the weights are increased by 10x, the confidence remains the same.



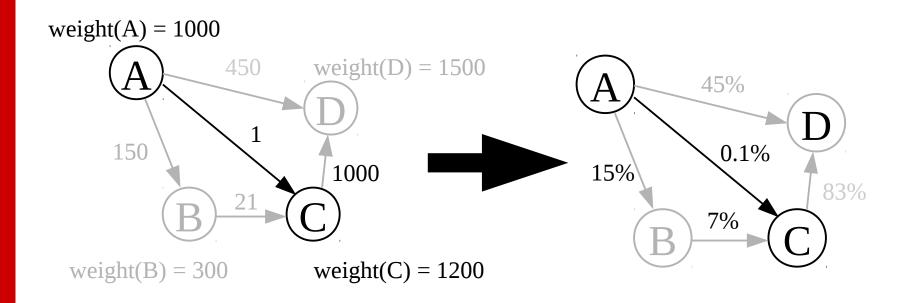


Furthermore, consider  $C \rightarrow D$ : The confidence is very high. Would an additional 100 nested flows result in any more confidence?





On the other hand, seeing 100 nested flows from A to C would be be substantially more convincing, yet the confidence would grow at roughly the same rate



# Logarithmic Ranking

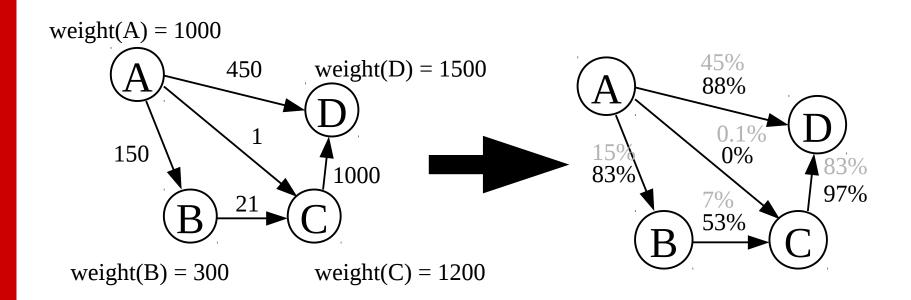


- Three issues with Ratio Ranking
  - Results in low, unintuitive confidence values
  - Having more traffic that exhibits the same behavior should give us more confidence
  - As more nested flows are observed, the rate of confidence growth should decrease
- Instead, set confidence = log<sub>weight(node)</sub> weight(edge)
  - Equivalent to log(weight(node))/log(weight(edge))
- Puts more disparity between true/false positives

# Logarithmic Ranking (cont.)



- Logarithm implicitly gives higher values to the same ratio with greater magnitude
- Logarithm also grows quickly before leveling off



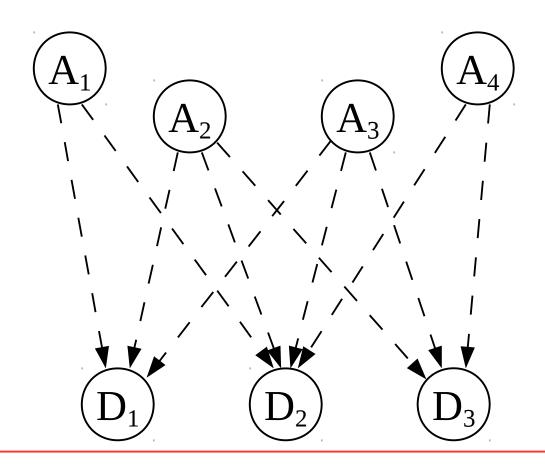
#### Service Inference



- In many networks, there are several hosts offering different instances of the same service
- Some of these services may be accessed more frequently than others
- If we can identify that two instances of services are the same type, we can infer the dependencies of a rarely used service from one that's used often
- We determine similarity using the overlap in their depended services

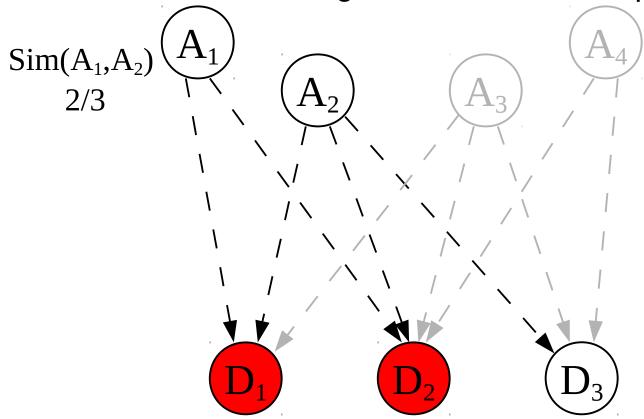


We begin with a communication graph. In this case, weights are not relevant.



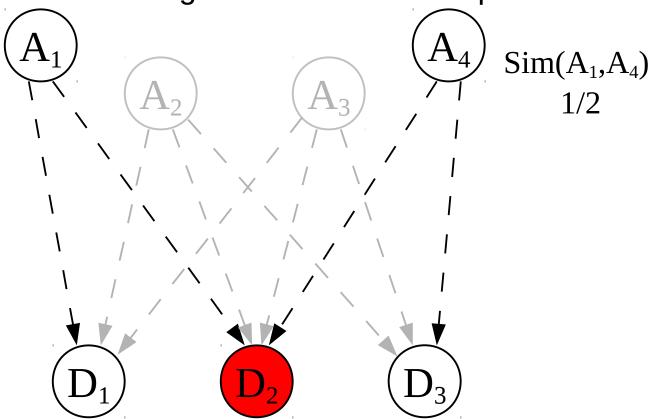


The similarity of two services is defined as the number of common depended services over number of dependencies of the service with the greater number of dependencies.



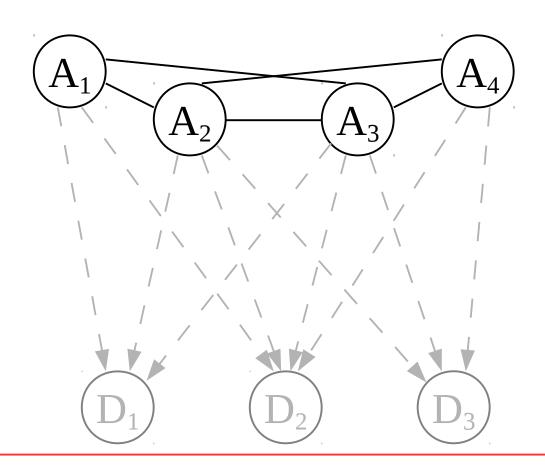


The similarity of two services is defined as the number of common depended services over number of dependencies of the service with the greater number of dependencies.



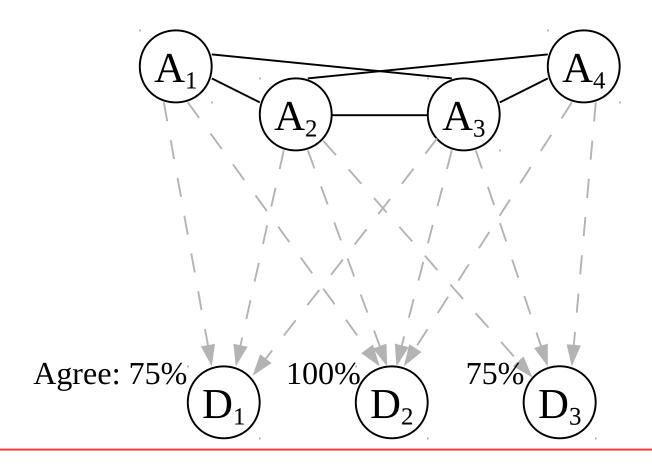


We draw edges between all similar services. Each connected subgraph is considered a similar "group".



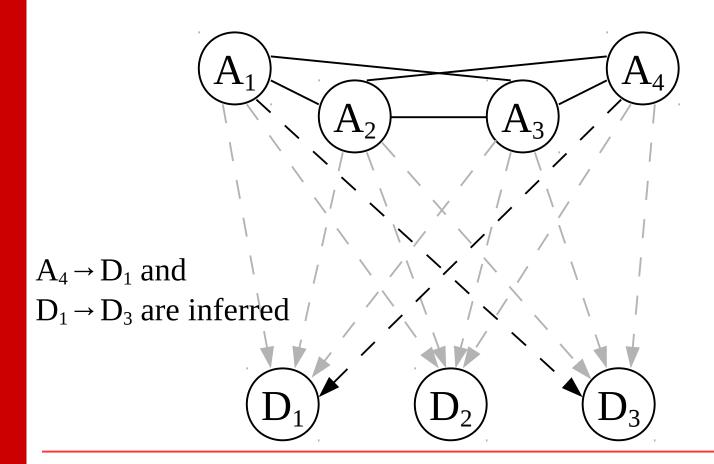


The agreement of a service is equal to the fraction of members of the group that depend on it.





Any service in the group that does not depend on an agreed depended service has that dependency inferred.



# Service Inference (cont)



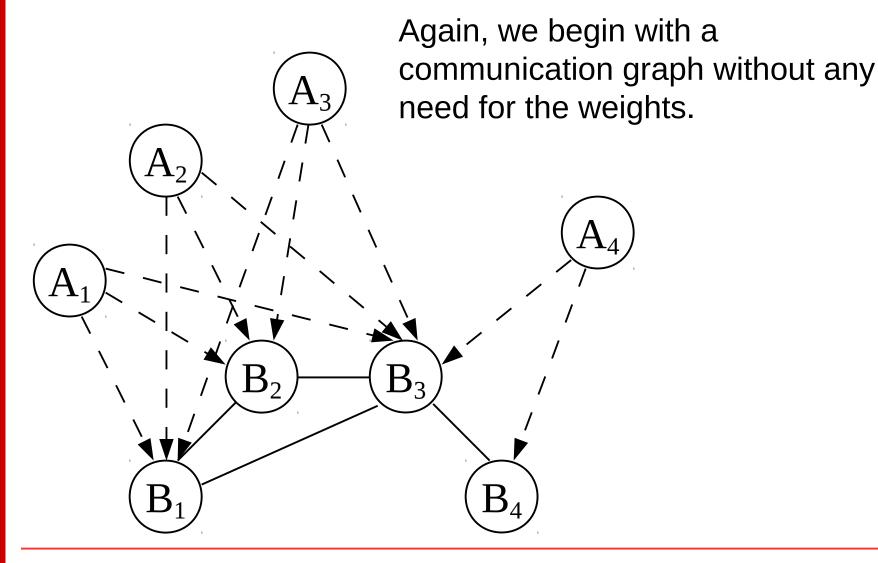
- This approach is configured with two thresholds:
- The similarity threshold
  - Defines how large groups of similar services become
- The agreement threshold
  - Defines how many dependencies are inferred from these groups
- In networks with lots of redundancy, high thresholds can still yield usable results

# Cluster Discovery

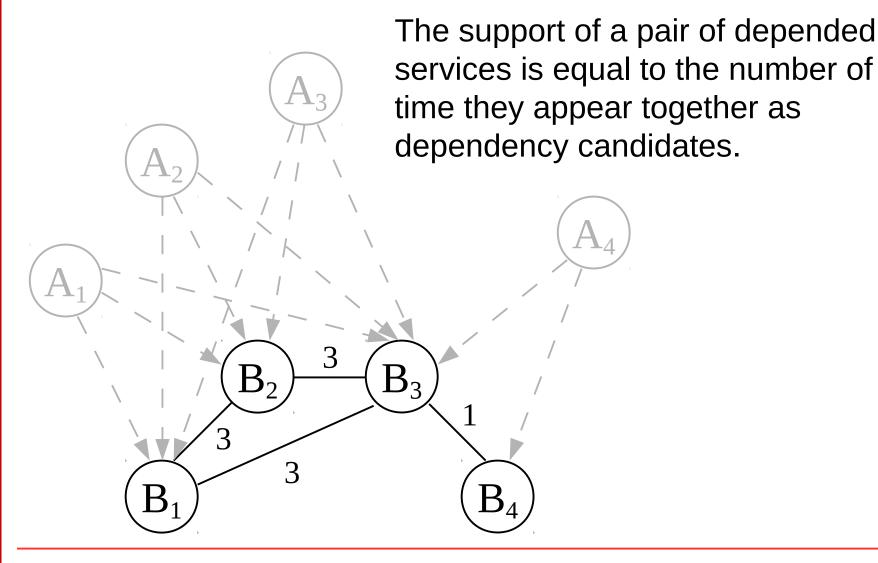


- Network services often rely on redundant service clusters
  - Nodes in load-balancing service cluster can be used interchangeably by depending services
  - Nodes in back-up clusters will replace primary nodes in the event that they fail
- In both cases, the services in a cluster will appear in a list of depended services together
- We use this observation to drive our approach to discovering service clusters





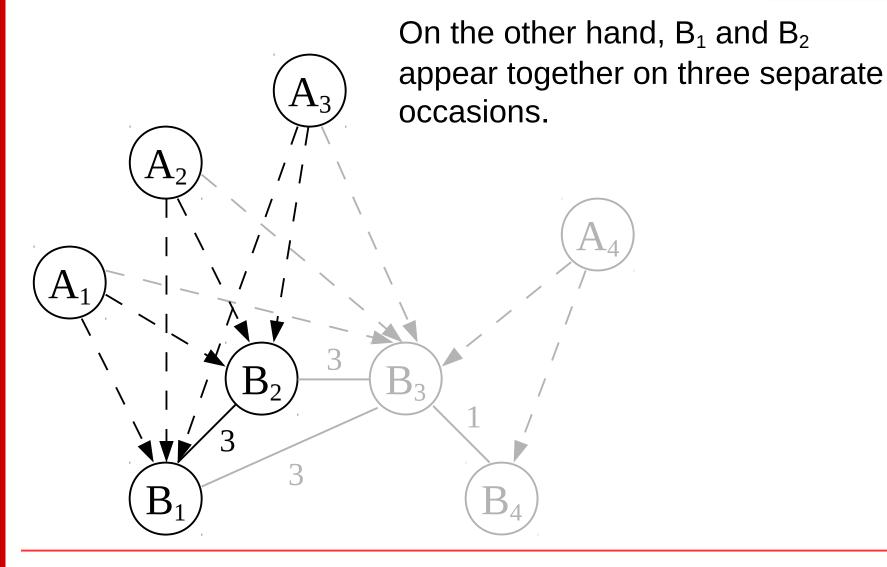




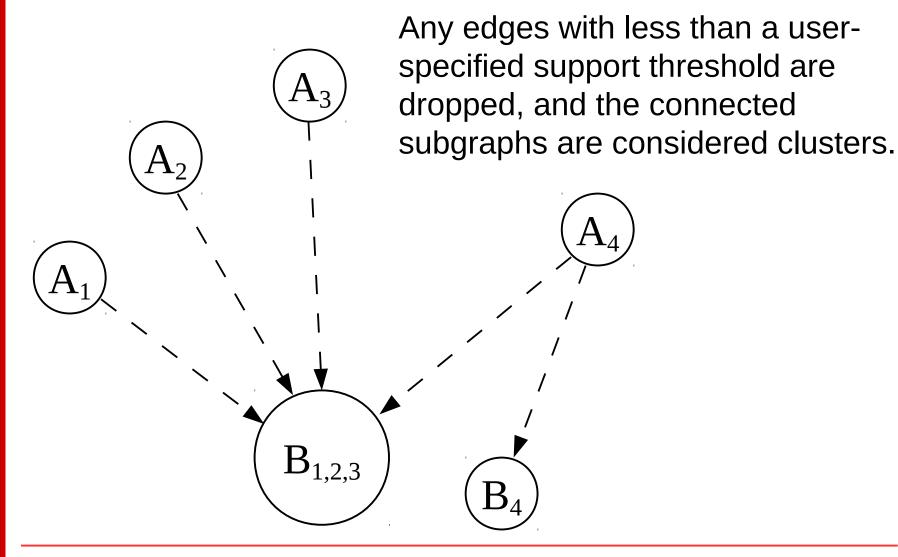


B<sub>3</sub> and B<sub>4</sub> only appear together for one service, A<sub>4</sub>.  $B_3$ 





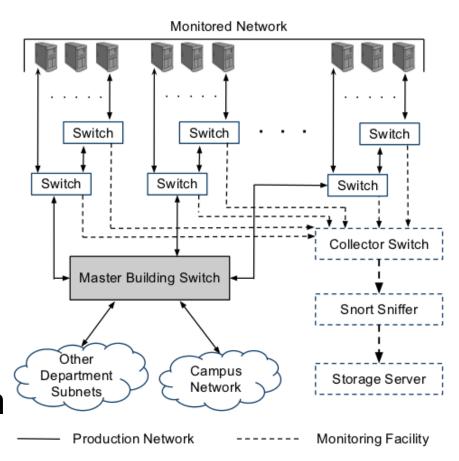




#### **Evaluation**



- We evaluate on the same dataset as NSDMiner's 2011 iteration
- Collected from the traffic on the second floor of EB2's CSC wing
- Ground truth built with help from CSC IT



# Logarithmic Ranking



 Logarithmic ranking was an improvement, especially for infrequently used services

	Shared Mode						Exclusive Mode					
	Ratio (0.5%)			Log (45%)			Ratio (0.5%)			Log (44%)		
Service	TP	FP	FN	TP	FP	FN	TP	FP	FN	TP	FP	FN
webservice	8	9	1	9	12	0	8	4	1	8	7	0
email	3	1	0	3	3	0	3	0	0	3	2	0
ssh(realm-4)	10	1	0	10	1	0	10	1	0	10	1	0
ssh(realm-5)	41	14	10	43	12	8	40	10	11	43	9	8
svn	4	1	0	4	0	0	4	1	0	4	0	0
proxy DHCP	2	1	0	2	0	0	2	1	0	2	0	0
DHCP	1	6	0	1	1	0	1	6	0	1	1	0
endpoint mapper	6	43	0	6	4	0	3	6	3	3	1	3
WDS (RPC)	4	10	0	3	1	1	4	1	0	2	0	2
DFS replication (RPC)	8	4	0	6	3	2	7	0	1	5	1	3
SMB	9	7	1	9	9	1	9	3	1	9	5	1
TFTP	-	1	-	-	1	-	-	0	-	-	0	-
database	-	1	-	-	2	-	-	1	-	-	2	-
Invalid Services	-	34	-	-	29	-	-	30	-	-	17	-
Total	96	133	12	96	78	12	91	64	17	90	46	18

### Logarithmic Ranking

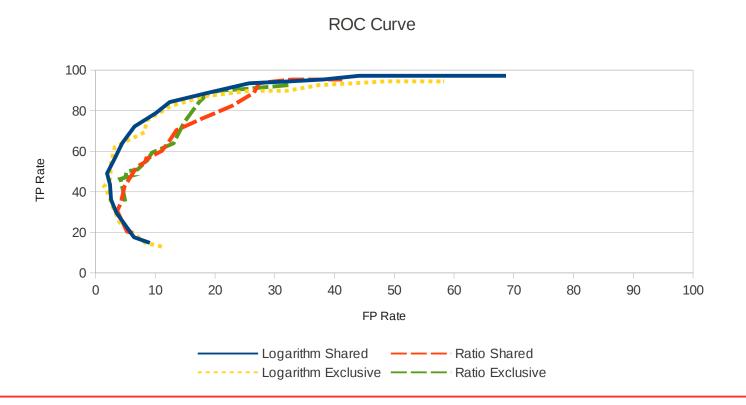


 The greatest improvements in False Positives came from services that were infrequently used.

	Shared Mode						Exclusive Mode					
	Ratio (0.5%)			Log (45%)			Ratio (0.5%)			Log (44%)		
Service	TP	FP	FN	TP	FP	FN	TP	FP	FN	TP	FP	FN
webservice	8	9	1	9	12	0	8	4	1	8	7	0
email	3	1	0	3	3	0	3	0	0	3	2	0
ssh(realm-4)	10	1	0	10	1	0	10	1	0	10	1	0
ssh(realm-5)	41	14	10	43	12	8	40	10	11	43	9	8
svn	4	1	0	4	0	0	4	1	0	4	0	0
proxy DHCP	2	1	0	2	0	0	2	1	0	2	0	0
DHCP	1	6	0	1	1	0	1	6	0	1	1	0
endpoint mapper	6	43	0	6	4	0	3	6	3	3	1	3
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SMB	9	7	1	9	9	1	9	3	1	9	5	1
TFTP	-	1	-	-	1	-	-	0	-	-	0	-
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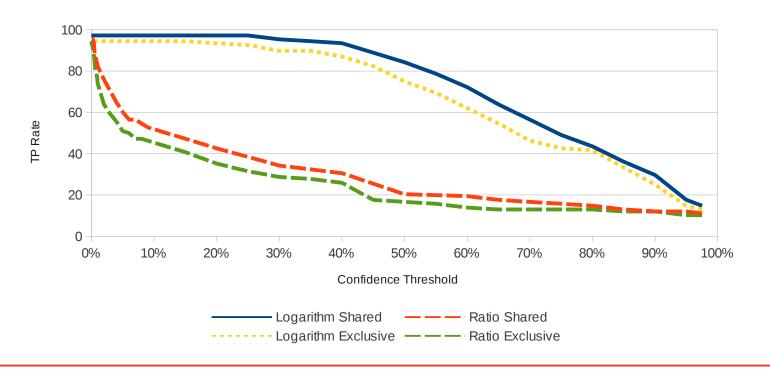
 The Receiver-Operator Characteristic curve shows the overall improvement of log ranking





 Note that the number of true positives drops gradually as the confidence threshold increases

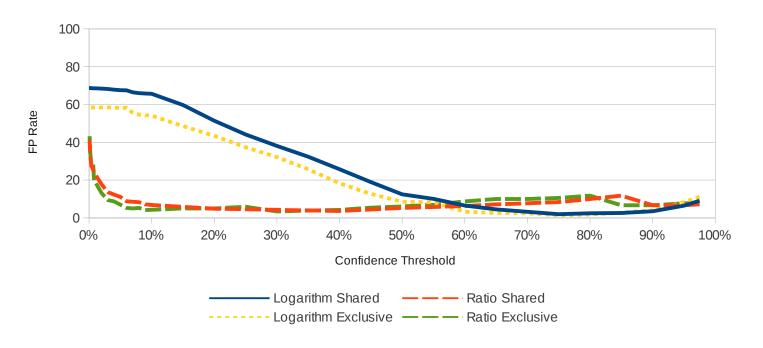
TP Rate vs Threshold





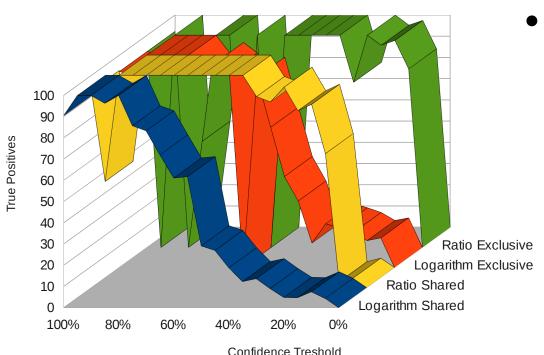
... as does the False Positive rate







 In logarithmic ranking, the confidence value accurately predicts whether a dependency is true

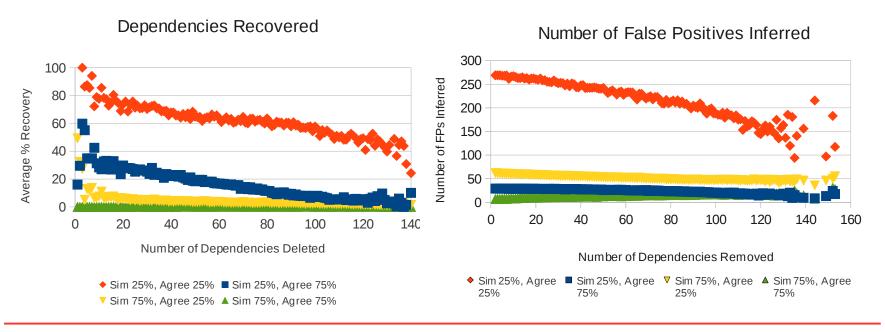


This graph
 shows the
 candidates
 divided into
 bins based on
 their
 confidence.

#### Service Inference



- We removed flows related to some dependencies from the ground truth and tried to re-infer them
- Note that while False positives were inferred, they still had low confidence values (<30%)</li>

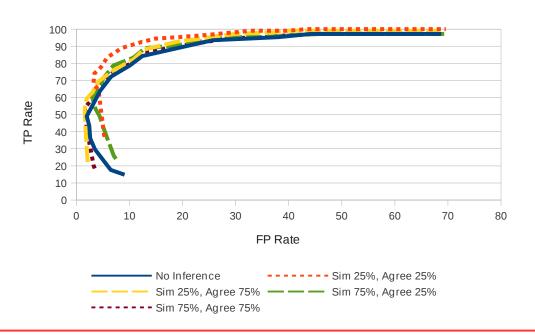


### Service Inference (cont)



- This shows the ROC curve for various service inference parameters compared to log ranking
- Note that we can achieve 100% coverage!

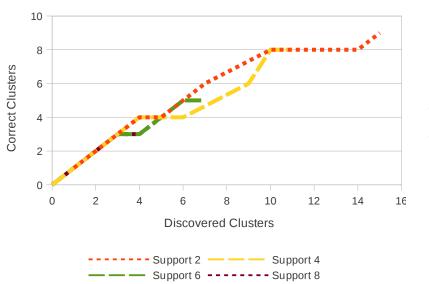


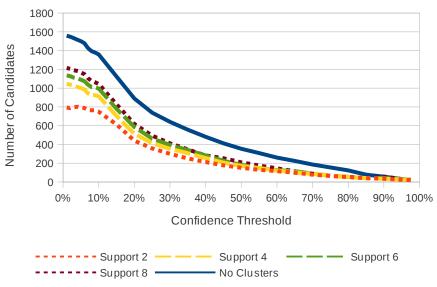


#### Cluster Discovery



- We accurately detect our network's ten clusters
- By aggregating them, we can reduce the size of the output substantially





#### In Conclusion...



- We introduce three novel approaches for the detection of network service dependencies
- We implement and test our approaches on production network traffic
  - Our approach improves false positives and negatives on top of NSDMiner's original improvements

#### **Future Work**



- Identification of remote-remote dependencies
- Ability to monitor dependencies in real time
- Collection of a newer, larger dataset (first and third floor)

### Acknowledgments



- The CSC IT Staff for their support in maintaining our collection infrastructure and discovery of our ground truth
- Arun Natarajan, for helping troubleshoot NSDMiner (even after his graduation)
- This work is supported by the U.S. Army Research Office (ARO) under MURI grant W911NF-09-1-0525

# Thank you for your attention!

