# Deepview: Virtual Disk Failure Diagnosis and Pattern Detection for Azure

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# Compute-Storage Separation

- Virtual hard disks (VHDs) and VMs on different physical clusters
- Easy VM migration when VMs are unavailable
  - Can create VM on different host/cluster
  - Simply attach VHD
- Load balancing through many-to-many relationship
  - Many VMs can use the same VHD
  - One VM can use multiple VHDs
- VHD driver in hypervisor level send RPCs to storage service

# VHD Failure

- In Azure, shutdown guest OS if unresponsive for 2 minutes
  - Mainly to protect data integrity
  - Notify the customers of VHD access failure
  - Maintain customers' SLAs

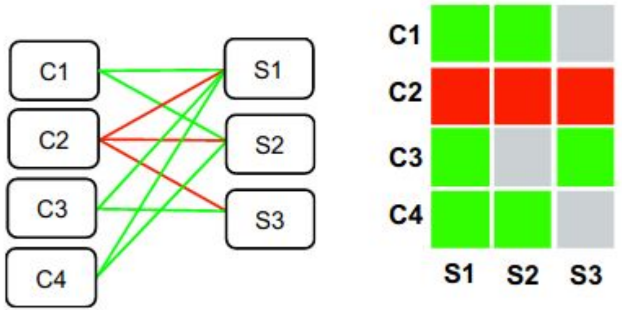
| VHD Failure | SW Failure | HW Failure | Unknown |
|---|---|---|---|
| 52% | 41% | 6% | 1% |

Table 1: Breakdown of the causes of VM downtime. VHD failures cause the majority of VM downtime.

# Previous Approach

- SREs examined different parts of the system
    - Compute team, storage team, and network team
- 10s of minutes or sometimes hours to localize the failure
- One network failure led to 363 incidents
    - Incident was moved from one team to another
- In short, not accurate and not efficient

# Bipartite Model




(a) Bipartite model (b) Matrix view

Figure 3: The bipartite model and the corresponding matrix view of a downtime event.

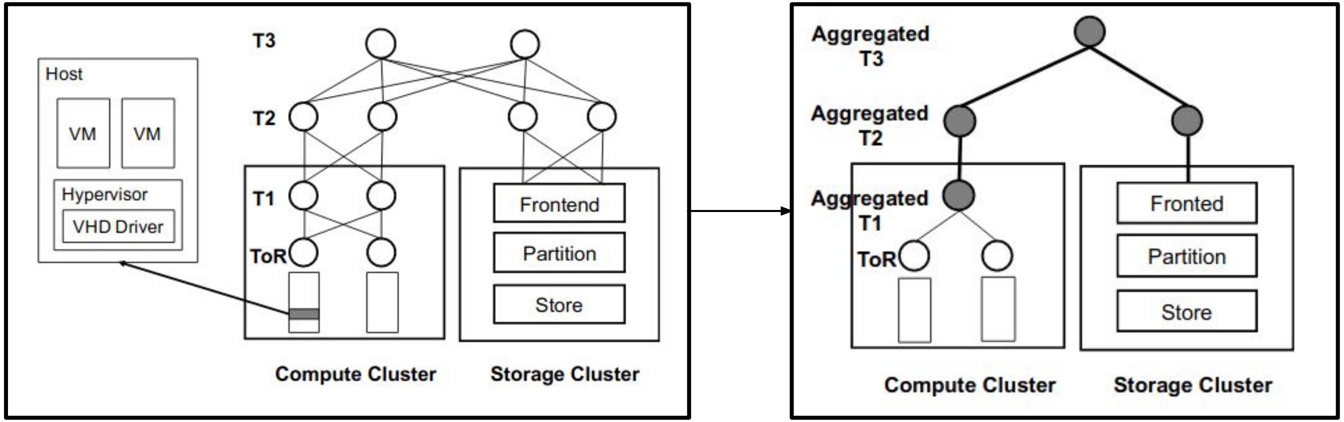
# Goals of the Paper

- Stronger granularity
  - Simple bipartite model does not work for multi-tier networks
- Detection of Gray failures
- Fast detection
  - Aim for 15 minutes (availability objective)

# Model - Network

- Represent Clos topology as tree
    - Start from Top-of-Rack switches
    - Group every Tier 1 switch that connects to ToR
    - Group every Tier 2 switch that connects to T1 switch
    - And so on....
    - Finally, determine midpoint by collecting shortest paths
- Discussion: Valid approach?

# Model - Network



# Derivation of Probabilities

$$\mathbb{P}(\text{path i is fine}) = \prod_{j \in \text{path}(i)} \mathbb{P}(\text{component j is fine})$$

# Derivation of Probabilities

$$\frac{n_i - e_i}{n_i} \approx \prod_{j \in \text{path}(i)} p_j$$

$n_i$ is the number of VMs
$e_i$ is the number of VMs with VHD failures for a given period
$p_j$ is the probability that the path is fine

Next step: Model approximation with noise and create system of equations

# Derivation of Probabilities

$$y_i = \sum_{j=1}^{N} \beta_j x_{ij} + \varepsilon_i, \qquad \varepsilon_i \overset{i.i.d.}{\sim} N(0, \sigma^2)$$

$$\begin{aligned}
y_1 &= \beta_{c1} + \beta_{net} + \beta_{s1} + \varepsilon_1 \\
y_2 &= \beta_{c1} + \beta_{net} + \beta_{s2} + \varepsilon_2 \\
y_3 &= \beta_{c2} + \beta_{net} + \beta_{s1} + \varepsilon_3 \\
y_4 &= \beta_{c2} + \beta_{net} + \beta_{s2} + \varepsilon_4.
\end{aligned}$$

# Interpretation of Equations

- A significantly negative $B_j$ usually suggests to blame that component
- Necessity to modify data
  - Failures are normally independent from each other
  - Array of *B* should theoretically be mostly 0's
  - Apply Lasso estimate with a parameter ƛ (black-box)
    - Tradeoff: goodness-of-fit versus sparsity

$$\hat{\beta} = \underset{\beta \in \mathbb{R}^N, \beta \leq \mathbf{0}}{\arg\min} \ ||\mathbf{y} - \mathbf{X}\beta||_2^2 + \lambda \, ||\beta||_1 \, .$$

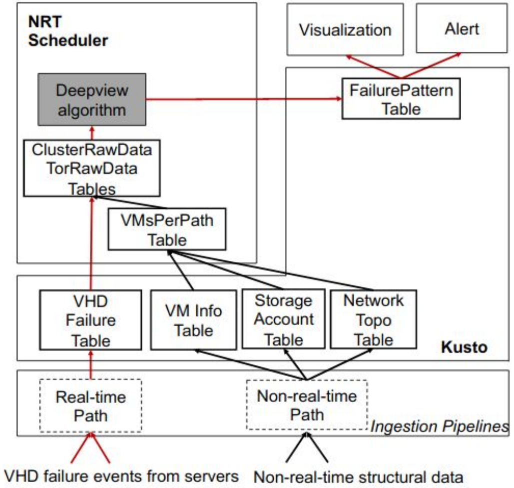
# Hypothesis Testing

1. Define a z-score from the mean and standard deviation of a value
2. Compute the p-value
   - In this paper, assume Gaussian distribution
   - Is this a safe assumption?
3. Make decision based on the p-value
   - If the p-value is less than 1%, blame the component

# Deepview System

- Non-real-time information
  - Network topology, account information, compute-storage
  - Periodic snapshots every few hours
    - Sufficient?
- Real-time information
  - VHD failures send signals
  - Implement a streaming system

# Deepview System




| Table Name | Schema |
|---|---|
| VHDFailure | (ts, vm_id, vhd, str_account) |
| VMInfo | (ts, vm_id, comp_cluster, tor) |
| StorageAccount | (ts, str_account, str_cluster) |
| NetworkTopo | (ts, cluster, tor_list, t1_list, t2_list, t3_list) |
| VMsPerPath | (tstart, tend, num_vms) |
| ClusterRawData | (tstart, tend, comp_cluster, str_cluster, num_vms, num_failed_vms) |
| TorRawData | (tstart, tend, comp_cluser, tor, str_cluster, num_vms, num_failed_vms) |
| FailurePattern | (tstart, tend, region, type, loc, pval, visual_url) |

# Deepview System

- Computation DAG
- NRT Scheduler
- Sparse Matrix/Region Filtering
  - Used to reduce runtime
- Coordinate Descent
  - One of the fastest ways to solve Lasso regression
- Cross-validation for $\lambda$

# Evaluation: ToR Reboot

- All VMs communicate with a single ToR
  - Failure means lack of communication with VHD
- Deepview predicts and verifies prediction
- Chose the correct ToR out of 288 components
  - p-value much less than 0.01

# Evaluation: Storage Gray Failure

- At hour 0, three components with failure probability > 0
  - Storage cluster S0 - 0.34
  - Compute cluster C0 - 0.002
  - Compute cluster C1 - 0.047
- Only S0 corresponded to p-value less than 1%
- Similar case for network failures

# Other Algorithms

- Boolean-Tomo and SCORE
  - Greedy algorithms
  - Goal: Identify bad paths based on threshold
  - Iterative discovery or computation
- Approximate Bayesian Network
  - Exponential runtime
  - Lack of meaningful results

# Precision and Recall

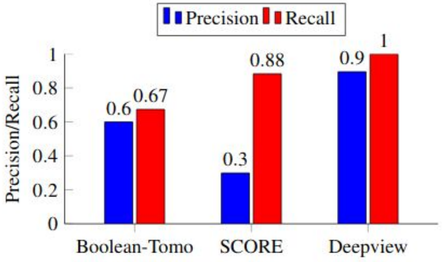



Figure 10: Precision/Recall comparison.

| | Compute | Storage | Net | ToR |
|---|---|---|---|---|
| Precision | 0.85 | 0.875 | 1.0 | 1.0 |
| Recall | 1.0 | 1.0 | 1.0 | 1.0 |

Table 3: Precision/Recall by failure type for Deepview.

# How well does it perform?

- Lasso regression
  - Impossible to find universally optimal Lambda
- Hypothesis testing
  - Even with low failure probability, hypothesis testing works
  - Example: Storage cluster gray failure case
- Runtime of Deepview
  - Worst-case: 18.3 seconds
- TTD: under 10 minutes

# ToR - Single-point-of-Failure

- Questions about ToR as bottleneck for availability
- Deepview detects ToR failure
  - More data!
- First, <0.1% of switches experience ToR reboots
- Second, 90% of reboots are soft

$$1 - \frac{0.9 \times 20 + 0.1 \times 120}{1000 \times 30 \times 24 \times 60} = 99.99993\%$$

# Network Path

- Distribution of network path
  - 51.4% go up to T2
  - 41.0% go up to T3
  - Rest go beyond
- Leverage Deepview data
- 11.4% increase in VHD failure rate with T3 or above
- Maybe beneficial to keep VHD and VM close

# Machine Learning

- Can a ML approach work in this situation?
- Possible weakness: Need richer signals
- Paper mentions NetPoirot
  - Features: TCP statistics
  - Labels: failure locations
  - Complementary
- BUT can a ML approach replace or outperform Deepview?

# Pros and Cons

Pros:

- Application of simple statistical ideas in a real-world system problem
- Presentation of valuable lessons learned through the data acquired in Deepview

Cons:

- Some parts of the model have to be inferred through reading different parts (could have been more clear)
- Lack of discussion on more examples of cases

# References

## Figures, equations, and content used from:

Qiao Zhang, Guo Yu, Chuanxiong Guo, Yingnong Dang, Nick Swanson, Xinsheng Yang, Randolph Yao, Murali Chintalapati, Arvind Krishnamurthy, and Thomas Anderson. 2018. Deepview: virtual disk failure diagnosis and pattern detection for azure. In *Proceedings of the 15th USENIX Conference on Networked Systems Design and Implementation* (*NSDI'18*). USENIX Association, USA, 519–532.