#### Microsoft

#### Thirty-Fourth AAAI Conference on Artificial Intelligence

Workshop Cloud Intelligence: AI/ML for Efficient and Manageable Cloud Services February 7th, 2020, New York, New York - USA





# Toward Intelligent Cloud Platforms and AlOps

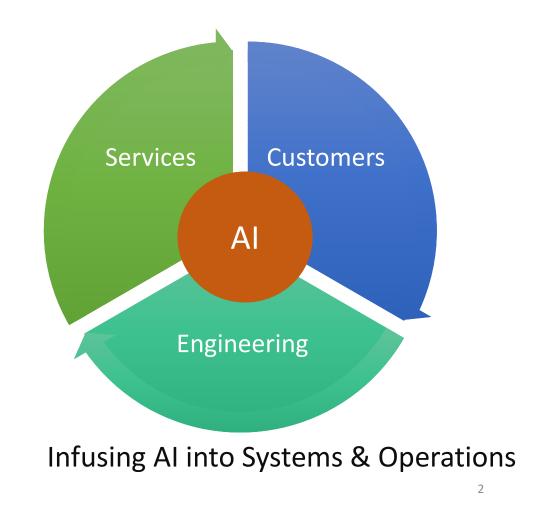
Microsoft Azure

Marcus Fontoura, Technical Fellow Murali Chintalapati, Partner SWE Manager Yingnong Dang, Principal Data Scientist Manager



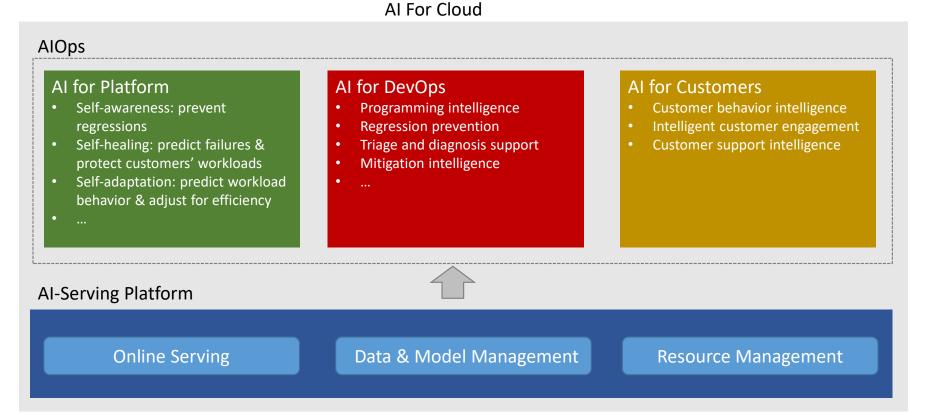
### AI for Cloud

- Ongoing digital transformation across all industries
- Scale and complexity as the biggest challenge
- AI/ML is a key technology in addressing this challenge





### Infusing Al into Systems & Operations: What Do We Need?



## Al For Cloud: Al-Serving Platform for Azure



#### Al-Serving Platform for Azure

#### **Online Serving**

- Resource Central (foundational)
- Azure ML (higher levels)

#### Data & Model Management

- Azure Data Explorer
- Azure Data Lake
- Resource Central
- Azure ML

Resource Management:

- Impact-free server defragmentation
- Safe core oversubscription
- Etc.

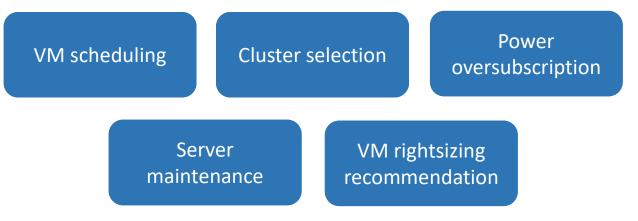


#### **Resource Central**

#### ML and prediction-serving system for improving resource management



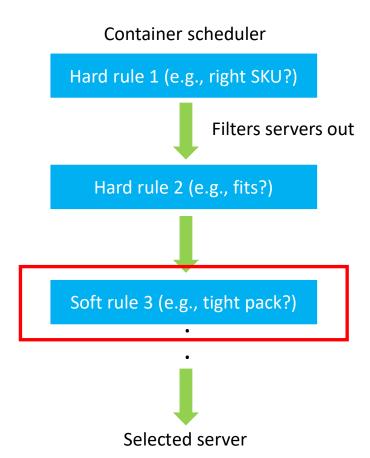
#### RC clients: Platform resource managers





### Case study: Smart CPU oversubscription

•



#### Goals:

- Be conservative! Stick with P95, 1<sup>st</sup>-party loads
- Don't oversubscribe servers running prod VMs
- Oversubscribe other servers up to a percentage over capacity and a max predicted (P95) utilization

New rule checking the sum of the P95 utilizations

Mispredictions: only issue is consistent under-prediction



### RC-informed CPU oversubscription

#### Simulation results

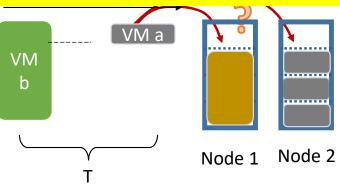
Version	Description	Behavior
Baseline	No oversubscription	Low capacity; many VM allocation failures
Naive	25% oversub without predictions	No failures; 6x resource exhaustion
<b>RC-informed</b>	25% oversub with RC predictions	No failures; rare exhaustion
RC-right	25% oversub with oracle predictions	No failures; same exhaustion



### Multi-Dimension Optimization

- Container scheduling should achieve high utilization across all resource dimensions
  - 1. Multi-dimensional resource packing
  - 2. Take into account online nature of service allocation
    - <u>Simple example</u>: Assume every VM has

# Lifetime prediction is important for container scheduling



- $\left(\frac{1}{2}\right)^2 + \left(\frac{1}{2}\right)^3 = \frac{6}{16}$
- If new VM is placed on Node 2:  $\left(\frac{1}{2}\right) + \left(\frac{1}{2}\right)^4 = \frac{9}{16}$

 $\rightarrow$  Placing new VM on Node 2 is better!



#### Resource utilization in Azure

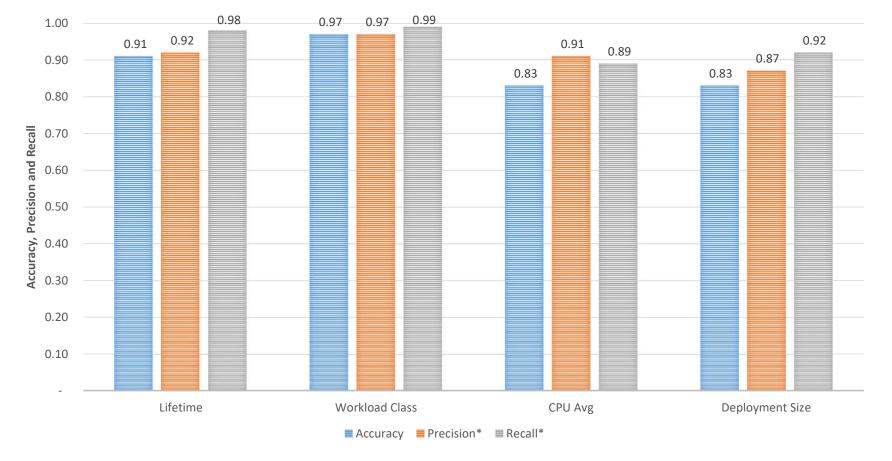
• Each 1% of utilization gain results in huge savings

Container scheduling algorithms are crucial for operating the cloud effectively!



### Prediction Quality

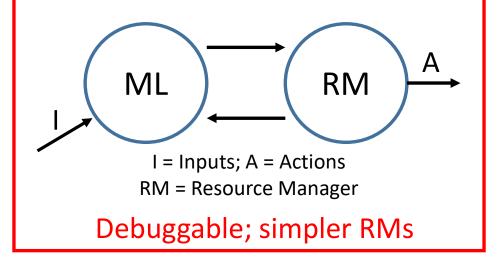
Accuracy  $\ge 83\%$ Precision<sup> $\theta$ </sup>  $\ge 87\%$ Recall<sup> $\theta$ </sup>  $\ge 89\%$ 



### Approaches to adding ML

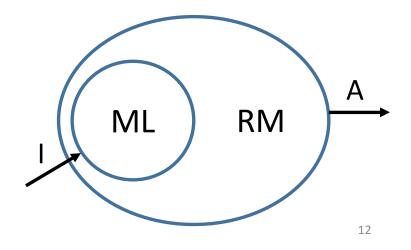
#### Passive, external to managers:

Predict load intensity, utilization Cluster workloads, resources ML as an insight provider



#### Active, built into managers:

Adjust parameters of policies Select actions to be performed ML has deep knowledge of policies



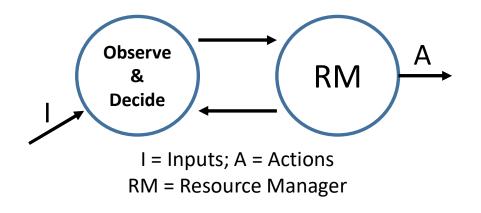


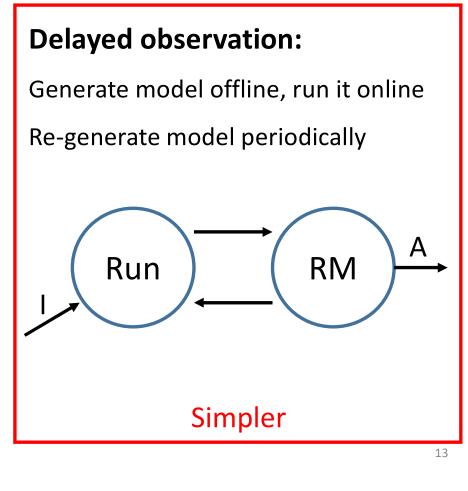


### Along a different dimension

#### Iterative observe and decide:

After each action, observe & decide Management as a control problem

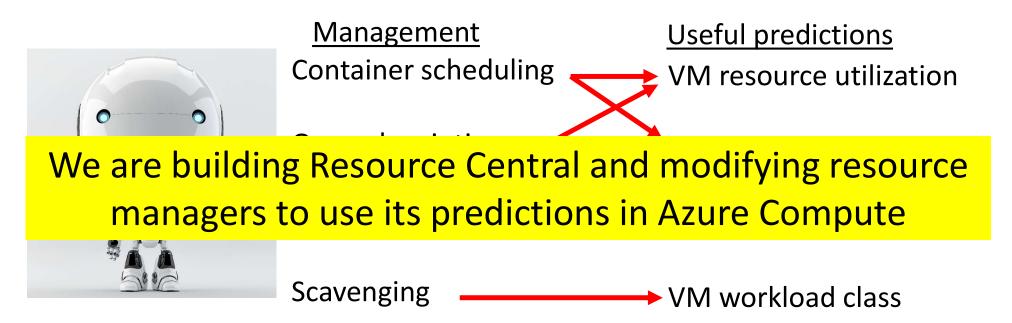






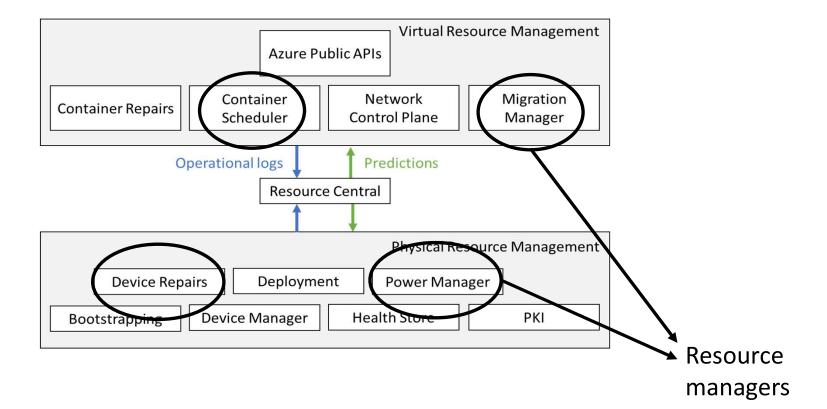
### Summary of our approach

A general, passive and delayed-observation framework for all ML tasks



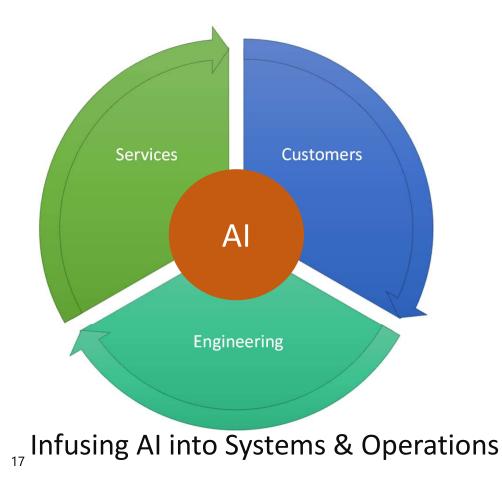


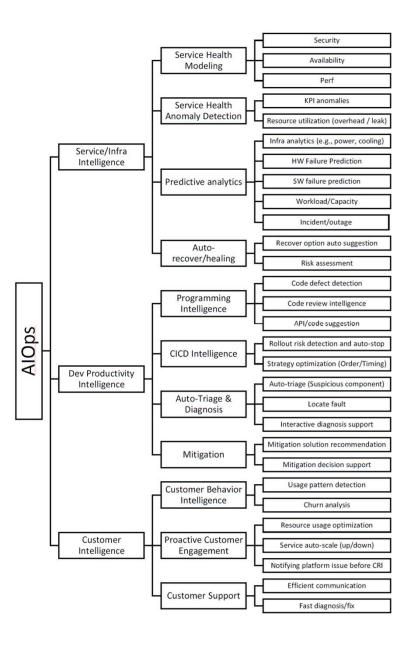
#### RC at the center of Azure Compute



## Al For Cloud: AlOps Solutions for Azure

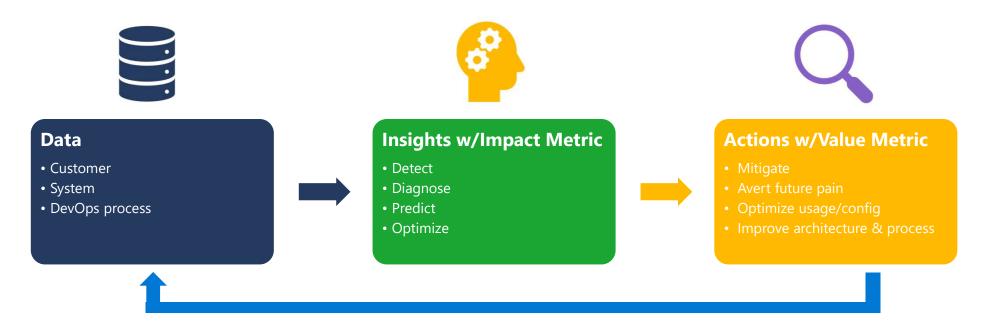
#### Problem Space







#### Methodologies: From Data to Actions



- · Measuring Customer and COGS impact of both Insights and Actions
- Improving intelligence through continuous feedback loop
- · Driving architectural improvements for scalability, availability and reliability



### Example: Dealing with Mem Leaks in Cloud



#### Data

Memory usage per Process for many instances

**Training data**: past several weeks, numerous time-series, large number of pivots

Volume: TBs of process data



#### Insights

Process Foo has memory leak

Mem consumption increase to '2n' MB on average (previous baseline: 'n' MB) in past **x** days

**Geo scope**: **y** machines in **z** clusters

**Customer impact**: creating new VMs in these nodes has 50% probability to fail



Mitigation: restart process Foo

#### **Repair**:

- Collect memory dump
- Identify root cause
- Bug fix
- Testing in Stage
- Rollout to production
- Validation in production



#### Case Studies

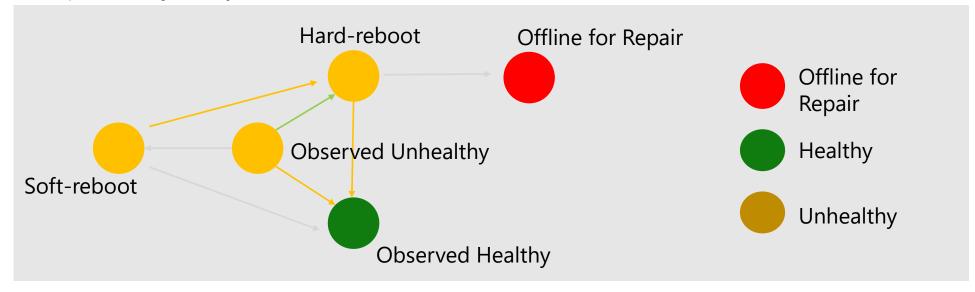
- 1. Self-adapting platform through smart thresholds
- 2. Resilient platform through failure prediction
- 3. Preventing platform regressions through Safe deployment



### A Typical Problem: When to Timeout?

- Hard-coded thresholds in the platform leading to suboptimal decisions
- Thresholds can't be optimized in isolation

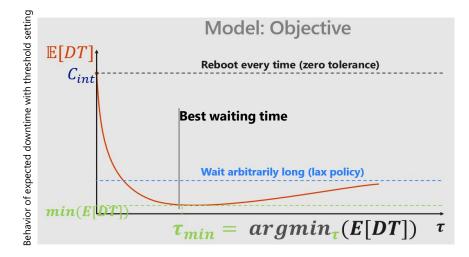
#### Example: node journey between online and offline





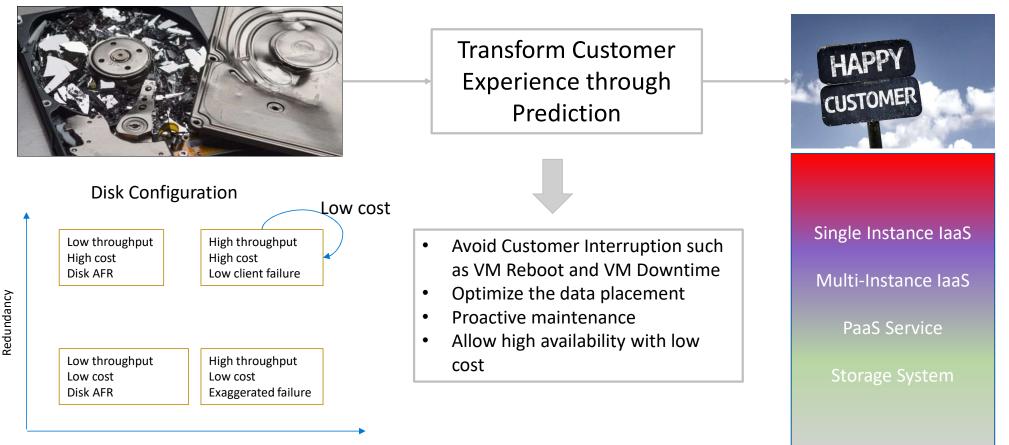
### Self-Adapting Platform: Optimizing Timeout Thresholds

- Objective: minimize customer downtime caused by unhealthy host
- Unhealthy host: reboot or wait for auto-recovery?
  - Waiting too long will lead to long downtime duration.
  - Waiting too little will lead to more VM reboots.





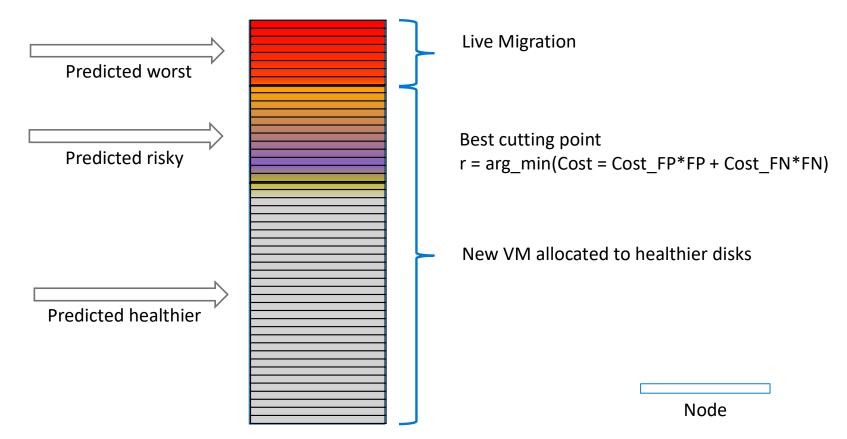
#### Prediction Helps Improve Customer Experience



Disk Striping



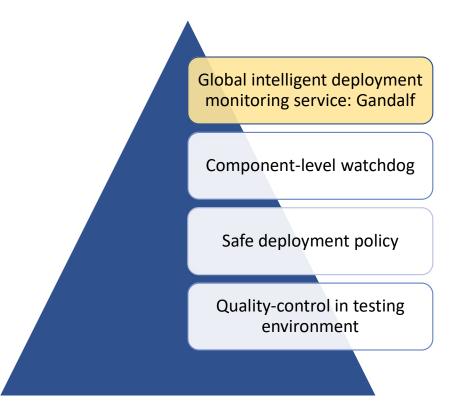
#### Approach: Ranking Instead of Classification



Improving Service Availability of Cloud Systems by Predicting Disk Error, USENIX ATC 2018

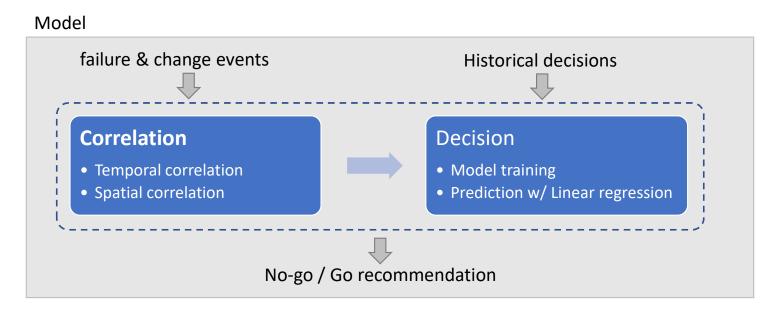


### Azure's Four-layer Mechanism to Ensure Safe Deployment





### Gandalf: Intelligent Global Watchdog



#### System

- Lamda architecture for supporting both batch and stream-processing based decisions
- REST API to notify rollout orchestrator and Web frontend for supporting evidence

Gandalf: An Intelligent, End-To-End Analytics Service for Safe Deployment in Large-Scale Cloud, NSDI'20



### AlOps in Azure: Summary

- AIOps is critical for digital transformation and an emerging innovation area
- AlOps is a cross-discipline research area involving software engineering, software analytics, systems, big data, machine learning and visualization
- AlOps is comprehensive: from making the system smart and resilient to enhancing developer efficiency and improving customer experience
- AIOps is what makes modern clouds scale to the next generation of Computing
- AlOps calls for close collaboration between the industry and academia



#### Al for Cloud: Related Research Areas

#### • Software Analytics

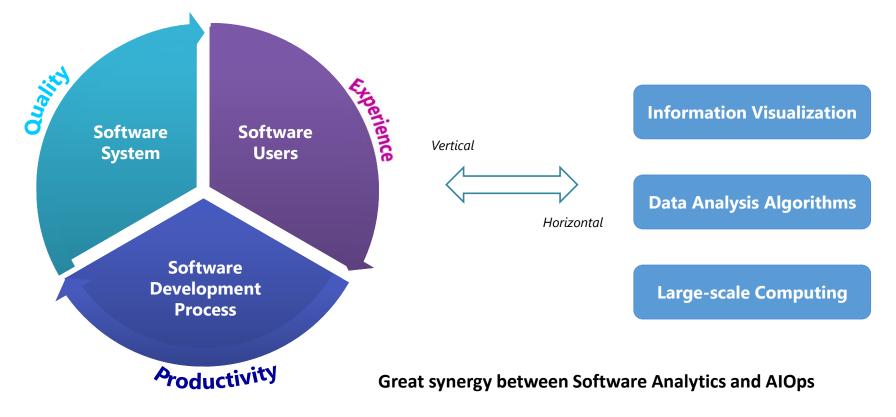
- "Software analytics aims to obtain insightful and actionable information from software artifacts that help practitioners accomplish tasks related to software development, systems, and users." – Dongmei Zhang, Microsoft Research
- Machine learning for systems
  - "Traditional low-level systems code (operating systems, compilers, storage systems) does not make extensive use of machine learning today " – Jeff Dean, Google Brain
  - MLCS 2018: First workshop on Machine Learning for Computing Systems

And more...





### Software Analytics Research: 10+ Years from Microsoft Research Asia



### Making Industrial and Academic Impact

#### Contributing to broad Microsoft products





### Contributing to multiple research communities: Software Engineering, Systems, Data Mining, and ML

- An Intelligent, End-To-End Analytics Service for Safe Deployment in Large-Scale Cloud, NSDI'20
- Robust Log-based Anomaly Detection on Unstable Log Data, FSE'19
- Towards More Efficient Meta-heuristic Algorithms for Combinatorial Test Generation, FSE'19
- Local Search with Efficient Automatic Configuration for Minimum Vertex Cover, IJCAI'19
- Cross-dataset Time Series Anomaly Detection for Cloud Systems, USENIX ATC'19
- AIOps: Real-World Challenges and Research Innovations, Tech briefing, ICSE'19
- An Empirical Investigation of Incident Triage for Online Service Systems, SEIP, ICSE'19
- Outage Prediction and Diagnosis for Cloud Service Systems, short, WWW'19
- Identifying Impactful Service System Problems via Log Analysis, FSE'18
- Predicting Node Failure in Cloud Service Systems, FSE'18
- BigIN4: Instant, Interactive Insight Identification for Multi-Dimensional Big Data, SigKDD'18
- Improving Service Availability of Cloud Systems by Predicting Disk Error, USENIX ATC'18
- iDice: Problem Identification for Emerging Issues, ICSE 2016
- Log Clustering based Problem Identification for Online Service Systems, SEIP, ICSE 2016
- An Empirical Study on Quality Issues of Production Big Data Platform, SEIP, ICSE 2015
- YADING: Fast Clustering of Large-Scale Time Series Data, VLDB 2015
- Log2: A Cost-Aware Logging Mechanism for Performance Diagnosis, USENIX ATC 2015
- Correlating Events with Time Series for Incident Diagnosis, SigKDD'14
- Identifying Recurrent and Unknown Performance Issues, ICDM, 2014
- Mining Historical Issue Repositories to Heal Large-Scale Online Service Systems, ICDSN, 2014
- Where Do Developers Log? An Empirical Study on Logging Practices in Industry, ICSE 2014
- Contextual Analysis of Program Logs for Understanding System Behaviors, MSR 2013
- Software Analytics for Incident Management of Online Services: An Experience Report, ASE 2013
- Healing Online Service Systems via Mining Historical Issue Repositories, ASE 2012
- Performance Issue Diagnosis for Online Service Systems, SRDS 2012
- Mining Invariants from Console Logs for System Problem Detection, USENIX ATC 2010
- Mining Program Workflow from Interleaved Traces, SigKDD 2010
- Execution Anomaly Detection in Distributed Systems through Unstructured Log Analysis, ICDM, 2009
- Mining Dependency in Distributed Systems through unstructured log analysis, SIGOPS O<sup>3</sup>Creview 2009

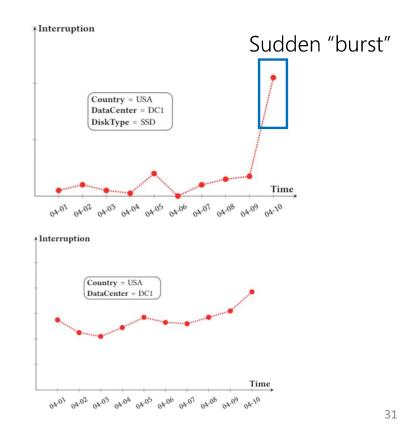
Microsoft

### iDice – Identifying Emerging Issues From High Dimensional Data

Daily aggregation of	of Service	e Interruptions
----------------------	------------	-----------------

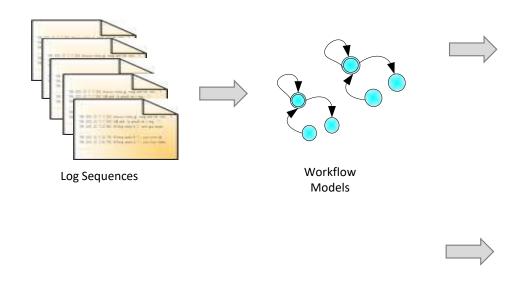
,	2011			
Time	Country	Datacenter	Disk Type	Interruption
2019-04-01	USA	DM1	SSD	1
2019-04-01	Australia	MEL21	SSD	1
2019-04-01	USA	DC1	HDD	4
2019-04-01	India	BL1	SSD	10
2019-04-01	UK	SN6	Hybrid	3
2019-04-01	USA	DM1	HDD	0

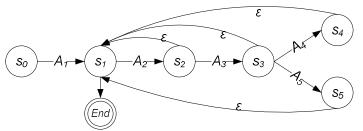
iDice: Problem Identification for Emerging Issues, ICSE 2016



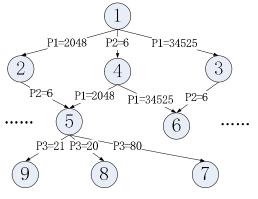


### Interpreting System Behavior Semantics through Recovering Program Workflow from Logs





 $A_{12}$ : Find State Order Items;  $A_{22}$ : Verify State Order Items;  $A_{32}$ : Is Using ATP;  $A_{42}$ : Deallocate Existing Inventory Cmd;  $A_{52}$ : Deallocate Expected Inventory Cmd.



Learn Contextual Factors

\*Mining Program Workflow from Interleaved Traces, SigKDD 2010

\*Contextual Analysis of Program Logs for Understanding System Behaviors, MSR 2013

32



#### Conclusion

- Al for Cloud: an important vertical that Al can generate great value
- Our vision is infusing AI into platform and DEVOps process
- Azure experience and learnings on AI for Cloud
- Contributions to multiple research communities



# You are welcome to visit Microsoft booth during main conference Feb 8-11!



#### Microsoft booth is #211 the 2<sup>nd</sup> floor - Rhinelander



## Thank You!