# Towards Autonomous IT Operations through Artificial Intelligence

**Dan Pei** 



# About myself

- Tenured Associate Professor in Computer Science @ Tsinghua University
- Homepage: <u>http://netman.aiops.org/~peidan</u>
- Email: peidan@tsinghua.edu.cn
   Wechat: peidanwechat
- Research direction: AI for IT Operations; Autonomous IT Operations
- UCLA Ph.D. Best Ph.D. Thesis Award in UCLA CS in 2005.
- Joined Tsinghua CS Department in December 2012, with Government Endorsement ("Recruitment Program of Global Talents")
- Previously a Principal Researcher at AT&T Research, a co-founder and founding CEO of a mobile health company in Beijing, before joining Tsinghua.
- ACM/IEEE Senior Member

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• During AT&T days, supervised interns from CMU, Cornell, Princeton, UCLA, GaTech, Michigan, Northwestern etc. Now @ Google, MSR, IBM, Purdue, Northeastern, HKUST

## My Research Group @ Tsinghua: NetMan

- Currently advising~15 of Ph.D. and M.S. students at Tsinghua.
- Two affiliated assistant professors and two postdocs



 Graduated 10 PhDs (3 went to MSRA, two went to Nankai University, one becomes a CEO, one goes to Alibaba)



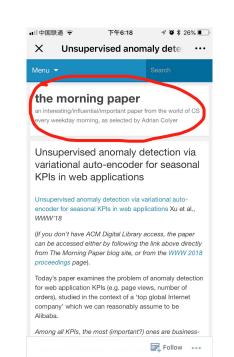


#### Industry Collaborators



#### Publications:

100+ AIOps papers and 20+ issued US Patents. Published in SIGCOMM、WWW、 SIGMETRICS、TON、 INFOCOM、IMC、CoNEXT etc. Research results are covered by technology media such as MIT technology Review, Hacker News, Mother Board, Morning paper, and many Chinese media.



MIT Technology Review

Topics+ Top Stories Maga

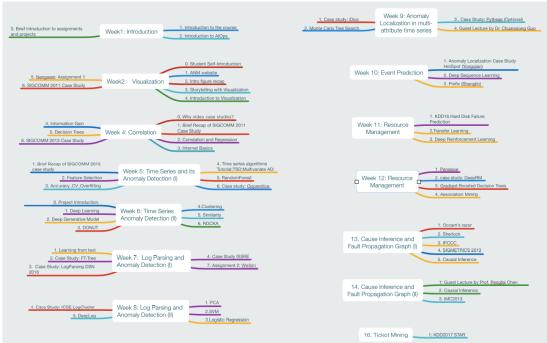
Mobile

#### Data Mining Solves the Mystery of Your Slow Wi-Fi Connection

Chinese researchers have worked out the reasons for why Wi-Fi can take so long to connect.

#### AIOps Course (in English) at Tsinghua: http://course.aiops.org





# Outline

- Al is changing the world
- AI for IT Operations
- Operations center tour

## What are AI, Machine Learning and Deep Learning?

#### Artificial Intelligence

Any technique that enables computers to mimic human behavior



#### MACHINE LEARNING

Ability to learn without explicitly being programmed



#### DEEP LEARNING

Learn underlying features in data using neural networks

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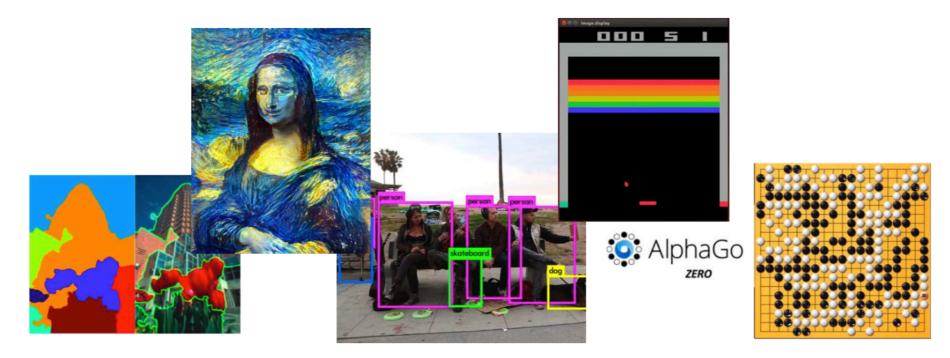
# **Deep Learning Success: Vision**

#### Image Recognition IMAGENET

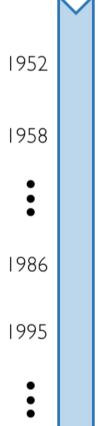
mite	container ship	motor scooter	leopard
mite	container ship	motor scooter	leopard
black widow	lifeboat	go-kart	jaguar
cockroach	amphibian	moped	cheetah
tick	fireboat	bumper car	snow leopard
starfish	drilling platform	golfcart	Egyptian cat

# **Deep Learning Success**

#### And so many more...



# Why Now?



Stochastic Gradient Descent

#### Perceptron

• Learnable Weights

Backpropagation

Multi-Layer Perceptron

Deep Convolutional NN

Digit Recognition

#### Neural Networks date back decades, so why the resurgence?

#### I. Big Data

- Larger Datasets
- Easier
   Collection &
   Storage

#### IM ... GENET



#### 2. Hardware

- Graphics Processing Units (GPUs)
- Massively
   Parallelizable



#### 3. Software

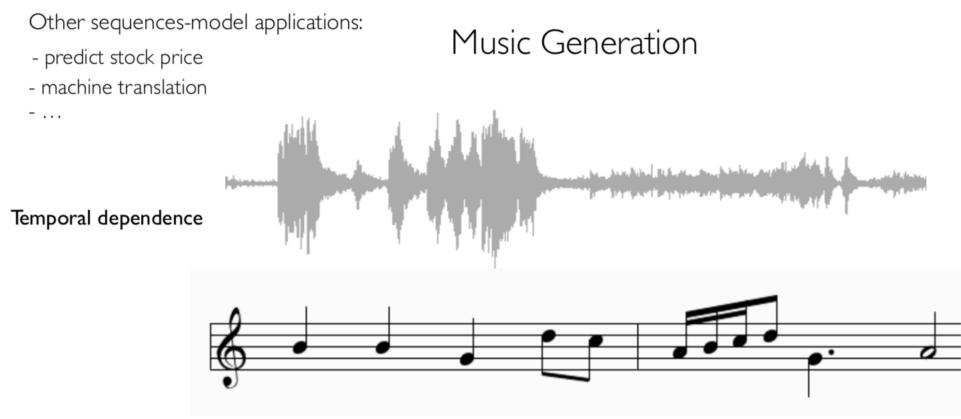
- Improved Techniques
- New Models
- Toolboxes



# Industries being changed by AI

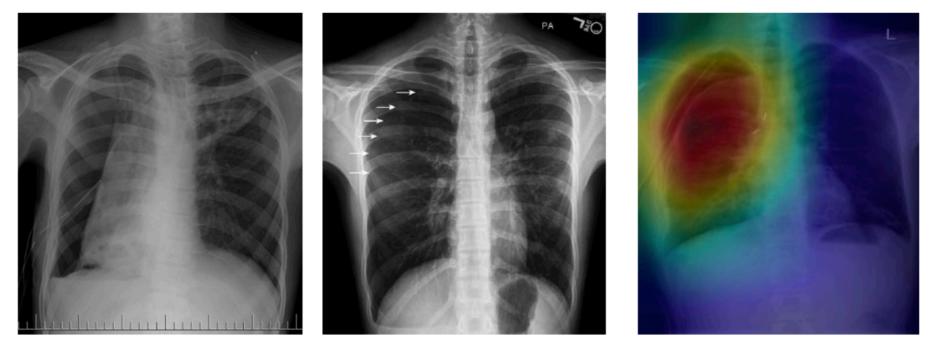
- Finance
- Education
- TMT
- Medical & Health
- Automobile
- Manufacturing

# Deep Learning Success: Audio



# **Deep Learning Success: Vision**

#### Detect pneumothorax in real X-Ray scans



#### 5 Applications Of AI In The Automotive Industry



Insurance

AI speeds up the process of filing claims when accidents do occur.



AI lends itself perfectly to powering advanced safety features for connected vehicles.

Driving Features



Car Manufacturing

Robots are driving optimisation and the rethinking of processes and production in innovative new ways.



The application of artificial intelligence cloud platforms ensure that data is available when needed.

Cloud Services 5

Driver Monitoring Al software detects driver behavior in four key areas: driver identification, recognition, monitoring and infotainment control.

https://youtu.be/nBs3K0bsxyc

## **Predictive Maintenance**





<b>(</b>	F. tas atis a		Oetails	
	Extraction		Alert: Air Filter Alert Name: Medium Voltage Filter	Current Temp: 179.3 Threshold: 175
~	Asset Sensor Details		Part SKU: 6493-MVAF107 Last Replaced: 20-July-2014 Scheduled Replacement: 20-Jul-15	Variance: 4.3 Trending: Temperature increas
fome Home	LAC-1773-551	734-DER-U14	Description Temperature increase of air passed	Solution Visit location for out-of-band pa
Extraction	Pump 435-22-EG2		through filter consistent with asset that has prematurely reached the end of its service life. Shutdown imminent. Mean Temperature	replacement, investigate the sen part and/or location to prevent f stop-production failure.
Logistics	Extraction Filter			an succession of the second
Refining				n - Predicted Alert Warning
<b>Retail</b>	Asset Health Status		Asset Sensors Detect Critical Fi	ailure Before Scheduled Maintenance. Scheduled Maintenance
Admin	89% 85% 89.1	l († 162.1 -	10 000 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0	18 19 20 21 22 23 24 25 March - Threshold
	Overall Status Tank level (%) AMPS/Rated (%			

# Machine Learning is a high-level programming language

Success in specific application scenario in specific area in specific industry: quality assurance in manufacturing industry





Tobacco Leaf

Steel Industry

8K video monitoring of the production line

Wood Floor

(Play video)

Traditional programming language: hard-coded logic Machine learning as a programming language hard-coded logic + fuzzy logic learned from data

# The capability boundary of current AI technologies

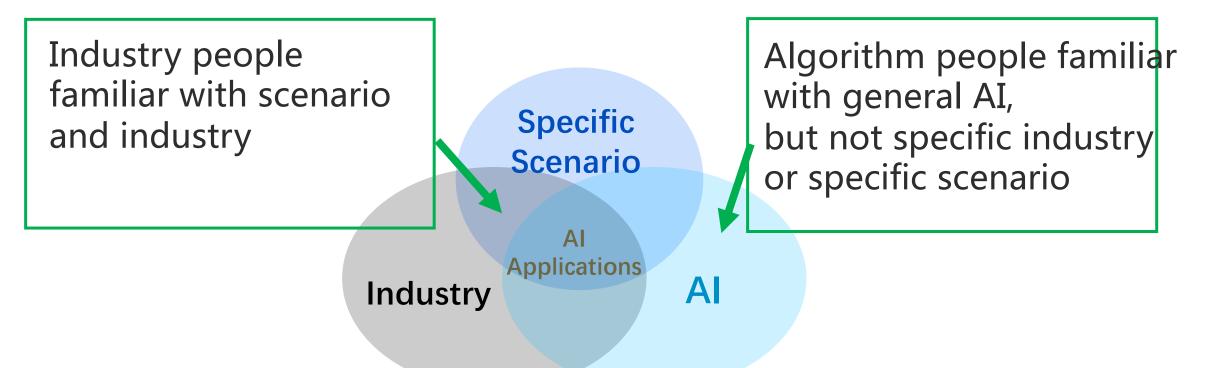


Al is good at solving problems that satisfy the following five conditions simultaneously:

- (1) With abundant data or knowledge
- (2) With deterministic Information
- (3) With complete Information
- (4) Well-defined
- (5) Single-domain or limited-domain

——CAS Fellow, Prof Bo Zhang

# Why success only in specific application scenario in specific area in specific industry?



Traditional programming language: hard-coded logic Machine learning as a programming language hard-coded logic + fuzzy logic learned from data

# Pitfalls: use ML algorithms as Blackbox to tackle a specific scenario in a specific industry

# a specific scenario in a specific industry

#### Huge Gap

### General Machine Learning Algorithms

ARIMA, Time Series Decomposition, Holt-Winters, CUSUM, SST,DiD,DBSCAN, Pearson Correlation, J-Measure, Two-sample test, Apriori, FP-Growth, K-medoids, CLARIONS, Granger Causality, Logistic Regression, Correlation analysis (event-event, event-time series, time series-time series), hierarchical clustering, Decision tree, Random forest, support vector machine, Monte Carlo Tree search, Marcovian Chain, multi-instance learning, transfer learning, CNN\_RNN\_VAF\_GAN\_NLP

# Outline

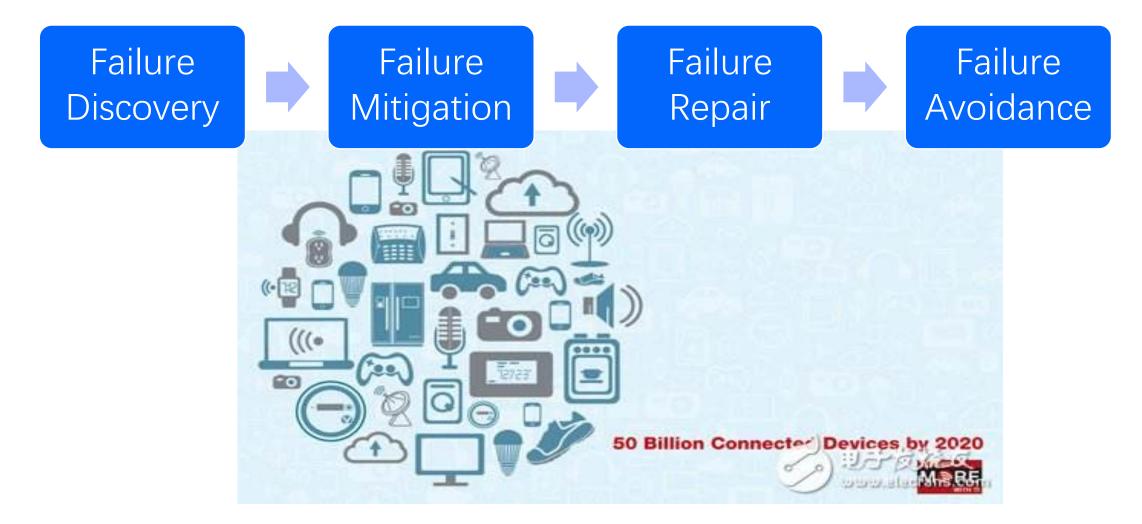
- Al is changing the world
- AlOps: Al for IT Operations and Autonomous IT Operations
  - What is AlOps
  - Value of AIOps: brief case studies
  - Industry Leader's Opinion
  - Is AlOps necessary?
  - Is AIOps feasible?
  - An in-depth case study
- Operations center tour

*IT Operations* is one of the technology foundations of the increasingly digitalized world.



IT operations are responsible for ensuring the digitalized businesses and societies run reliably, efficiently and safely, despite the inevitable failures of the imperfect underlying hardware and software.

But IT Operations are currently labor-intensive, heavily relied on human experience, very stressful, and ineffective.





### AIOps: Autonomous IT Operations through Machine Learning



- Imagine that you are running an Internet-based service with hundreds of thousands of servers and many software modules, a large, complex, cross-layer, and rapidly evolving distributed system.
- You want to achieve 99.999% service reliability, but the terabytes of machine-generated monitoring data and hundreds of operators (IT operation engineers) alone won't get you there, because of the high complexity and sheer scale of the software/hardware system and the vast amount of machine-generated data.
- Machine learning is the direction to enable Autonomous IT Operations autonomous.

# **Towards Autonomous IT Operations**



Manual-Driven



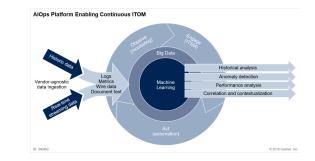


Automated but with Manual Decision

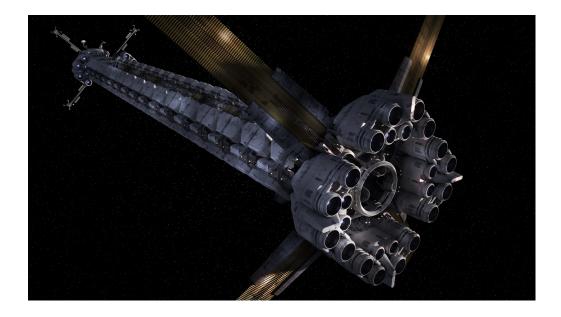
Autonomous







# **Ultimate Goal: Autonomous IT Operations**



Spaceship Covenant: 2000 passengers and 15 crew members all in hibernation. Flying towards Planet Origae-6. Only one awaken android crew.



Spaceship Avalon: 5000 passengers and 258 crew members. Flying towards Planet Homestead II, 120-year trip.

# Autonomous IT Operations: Automatically deal with all four causes of changes to IT systems

- Software & hardware failures--> Automatic Healing
- Software changes --> Autonomous software deployment
- Change of user request amount & Pattern --> Elastic Resource Allocation
- Malicious Attacks-->Autonomous Defense



"Most people overestimate what they can do in one year and underestimate what they can do in ten years."

-- Bill Gates

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#### Reduced Business Loss: Rapid Assessment of Software Changes

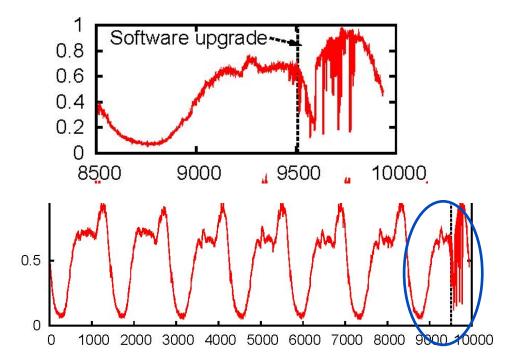
- A buggy deployment causes significant revenue Loss
- Manual trouble shooting takes 1.5 hours

Customer Inspecting Troubleshooting

• AlOps solution takes less than 10 minutes

30

Joint Work with Baidu Published in ACM CoNext 2015

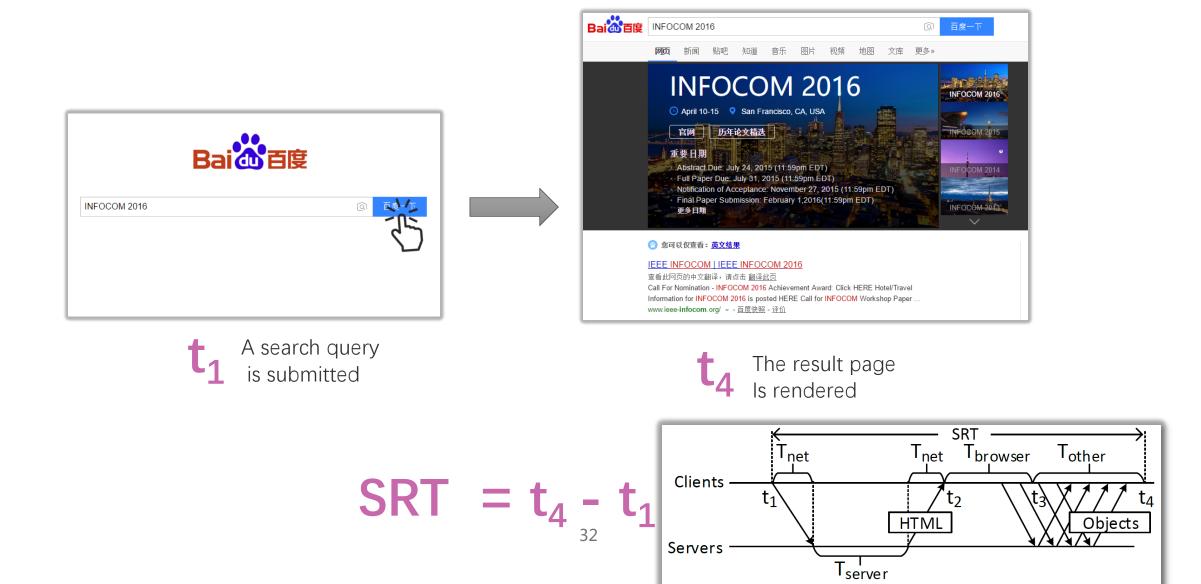


### **Web Search Engines**





### Search Response Time (SRT)



### **Search Response Time Matters**





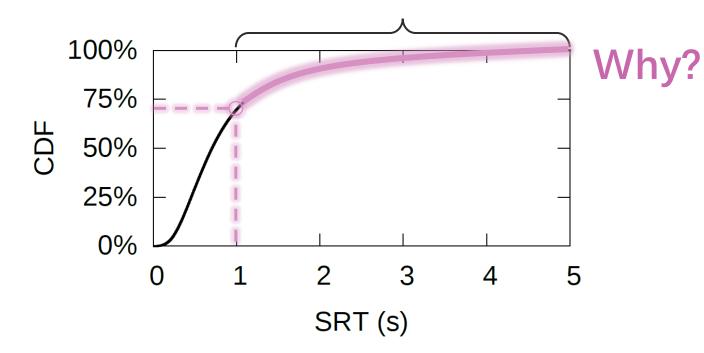
+100ms~400ms queries - 0.2%~0.6% [Jake Brutlag, Google]



Given two content-wise identical search result pages, users are more likely to perform clicks on the fast page [SIGIR 2014]

### Search Response Time in the Wild

User's flow of thought is interrupted if pages take **longer than 1s** to load



### **Monitoring SRT: Search Logs**

#### Measurable attributes that can potentially impact SRT

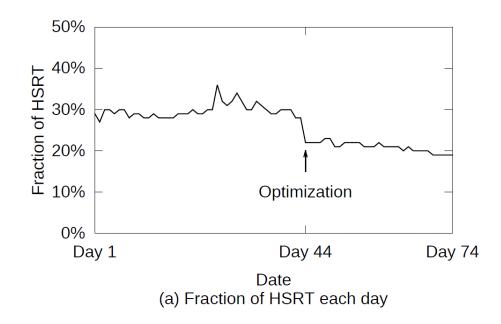
SRT	User's ISP	Browser engine	# of Images	Ads	Server Load	
800ms (Low SRT)	China Unicom	WebKit	10	Yes	1000 queries/s	
1200ms (High SRT)	China Telecom	Trident 5.0	5	No	500 queries/s	

### **Improved Revenue: Reduced Page Response Time**



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Google -100ms~400ms -> Revenu 0.2%~0.6% [Jake Brutlag, Google] After deploying the solutions suggested by AlOps :

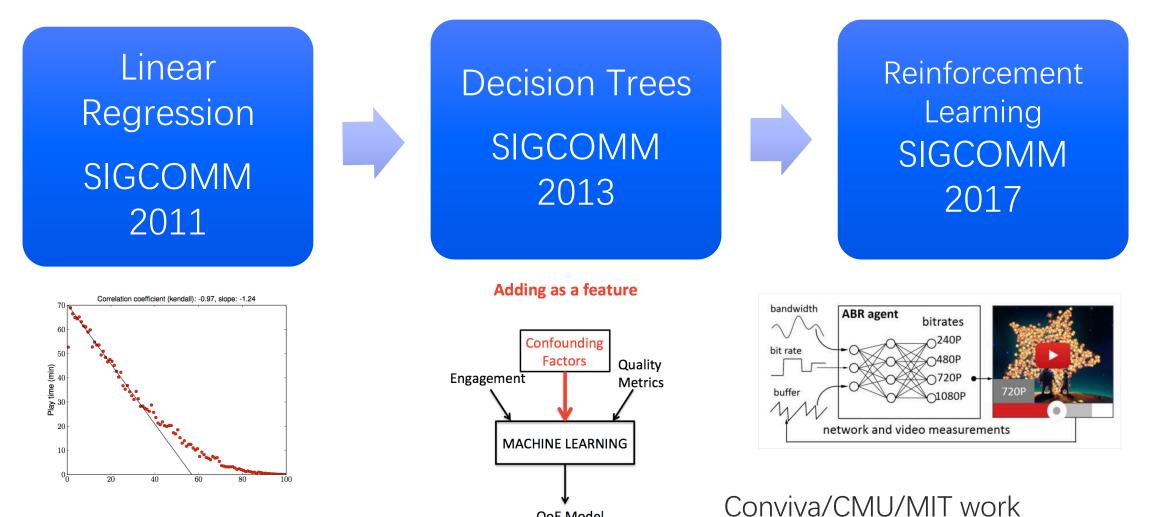


Slow responses (>1s) are reduced from 30% to 20%

80th-percentile response time is reduced by 253 ms

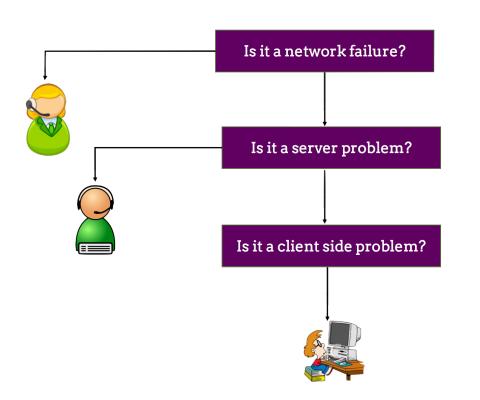
Saves 30 man-months (estimated) of manual analysis

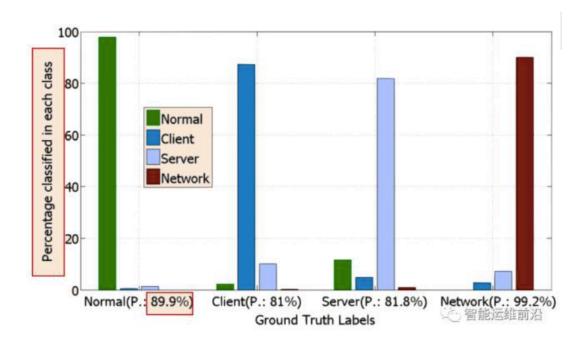
Joint Work with Baidu Published in IEEE INFOCOM 2016 AlOps Leads to Better User Experience -> Longer Engagement -> More Revenue



QoE Model

## AIOps Quickly Decides the Responsibility Boundary: Reduced loss

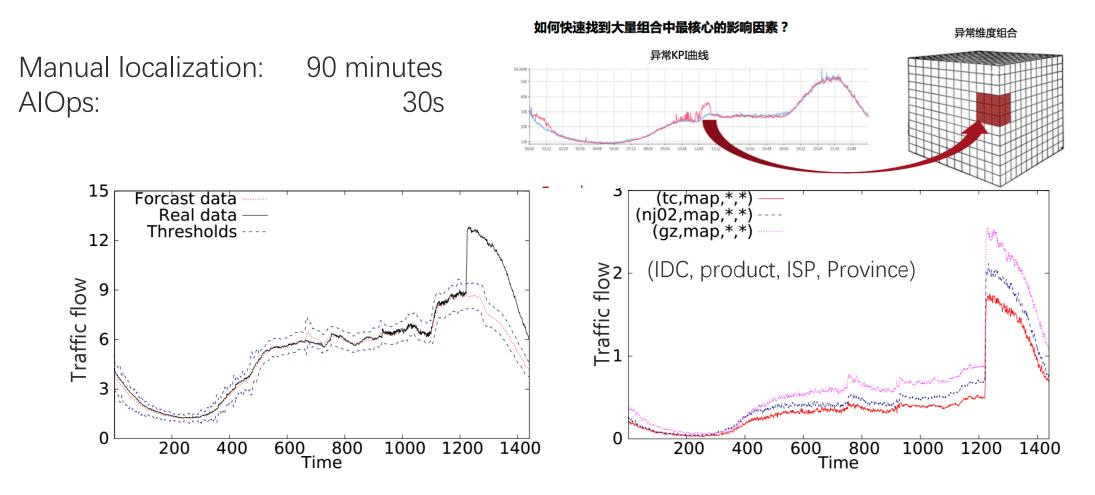




Microsoft Azure Work. Published in SIGCOMM 2016

# Localizing the Anomalous Regions: Reduced Loss

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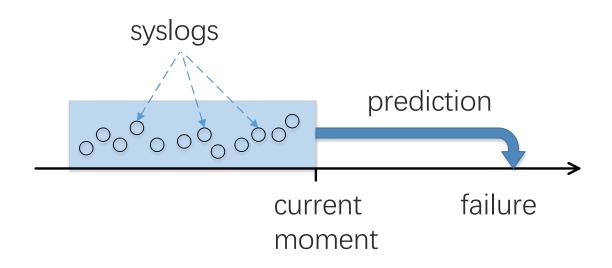


Collaboration with Baidu. Tencent implemented a variant to improve its video streaming service

### DC Switch Failure Prediction->Preventive Replacement->Avoided Loss

Problem: Baidu-customized switches intermittently drop/delay packets, causing QoE drop at the application layer.

Reboot stops the problem for some while. Question: Can we predict the this problem 2 hours before it happens again? Then just switch the traffic away from this switch and reboot it.



- Precision: 82.15%
- Recall: 74.74%
- **FPR**: 3.75×10<sup>-5</sup>

#### Table 2: One Example of Benign Request.

Original RequestPOST http://localhost:8080/tienda1/publico/autenticar.jsp modo=entrar&login=caria&pwd=egipciaca&remember=off&B1=E ntrarToken Sequencetienda1 publico autenticar jsp modo entrar login _OTHER_ pwd _OTHER_ remember off b1 entrarRecovered Token Sequencetienda1 publico autenticar jsp modo entrar login _OTHER_ pwd _OTHER_ remember on b1 entrarBLEU0.8091Malicious Score0.1909				_
Token Sequence       _OTHER_ remember off b1 entrar         Recovered Token Sequence       tienda1 publico autenticar jsp modo entrar login _OTHER_ pwd _OTHER_ remember on b1 entrar	0	modo=entrar&login=caria&pwd=egipciaca&remember=off&B1=E		
Token _OTHER_ remember on b1 entrar Sequence				
BLEU         0.8091         Malicious Score         0.1909	Token			
	BLEU	0.8091	Malicious Score	0.1909

#### Table 3: One Example of Malicious Request.

		-	-			
	POST http://m.thepaper.cn/admin_UploadDataHandler.					
	WebKitFormBoundaryRvkd1dbq3x1OJhUH\x0D\x0AContent-					
	Disposition: form-data; name=\x22uploadify\x22;					
	filename=\x2220170215180046.jpg\x22\x0D\x0A					
	Content-Type: image/j	peg\x0D\x0A\x0D\x0A				
Original	<%eval request(\x22T\x22) %>\x0D\x0A					
Request	WebKitFormBoundaryRvkd1dbq3x1OJhUH\x0D\x0AContent-					
Kequest	Disposition: form-data	;				
	name=\x22saveFile\x22\x0D\x0A\x0D\x0At.asp\x0D\x0A					
	WebKitFormBoundaryRvkd1dbq3x1OJhUH\x0D\x0AContent-					
	Disposition: form-data;					
	name=\x22Upload\x22\x0D\x0A\x0D\x0ASubmit Query\x0D\x0A-					
	WebKitFormBoundaryRvkd1dbq3x1OJhUH					
	_OTHER_ ashx _OTHER_ content disposition form data name					
T I	uploadify filename _pnum_0_ jpg content type image jpeg eval					
Token	request onechr _OTHER_ content disposition form data name					
Sequence	OTHER_ onechr asp _OTHER_ content disposition form data					
	name upload submit query _OTHER_					
	OTHEROTHERdo php _OTHER eval					
	get_magic_quotes_gpc stripslashes _post chr _pnum_0_ chr					
Recovered	_pnum_1 _ post chr _pnum_2 _ chr _pnum_3+_ z0 _pnum_3+_					
Token	ini_set display_errors _pnum_3+_ set_time_limit _pnum_3+_ set_magic_quotes_runtime _pnum_3+_ echo onechr dirname					
Sequence						
	_server script_filename if onechr onechr dimame _server					
	path_translated					
BLEU	• —	Maliaiana Caana	1.0			
DLEU	0	Malicious Score	1.0			

# Detecting previously unseen attacks: 99% accuracy --> more secure

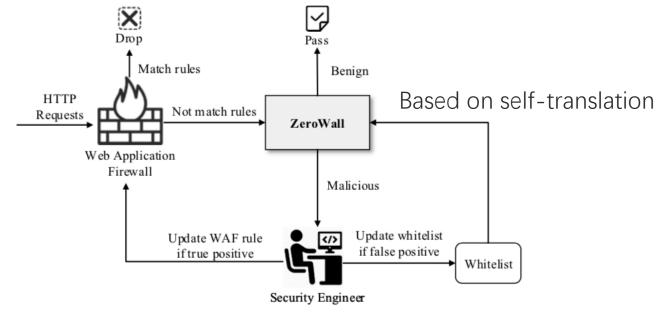
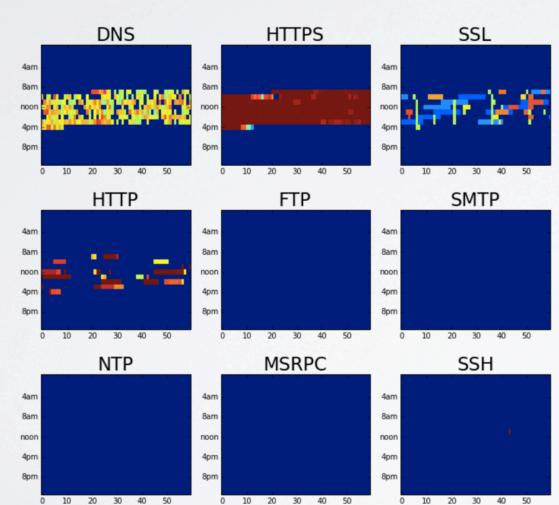


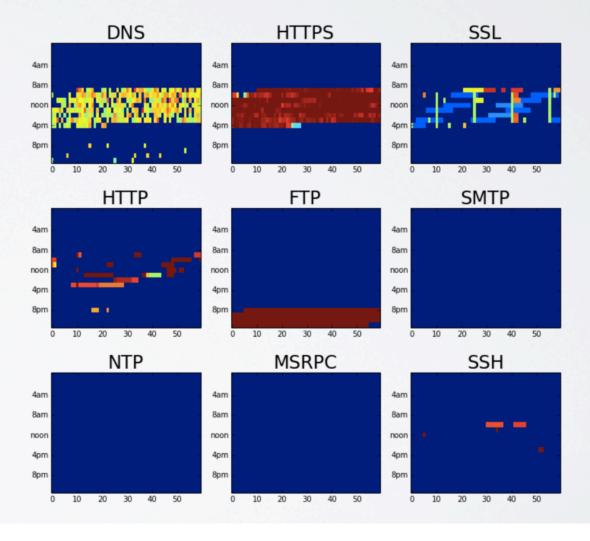
Figure 1: The workflow of ZeroWall.

## **BEHAVIOR ANOMALY USER | EXFILTRATION**



#### User – Before Compromise

#### **User – Post Compromise**



## **BEHAVIOR ANOMALY IOT DEVICE | DATA DOWNLOAD**

SSL

SMTP

50

40

4am

8am

noon

4pm

8pm

4am

8am

noon

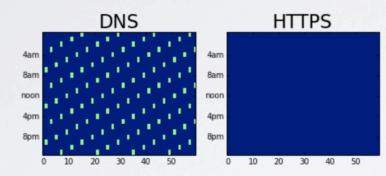
4pm

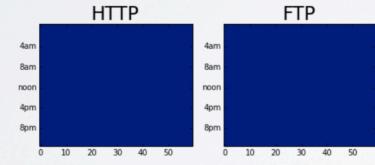
8pm

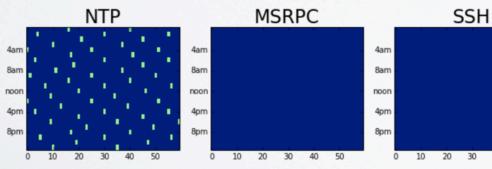
0 10 20 30 40 50

0 10 20

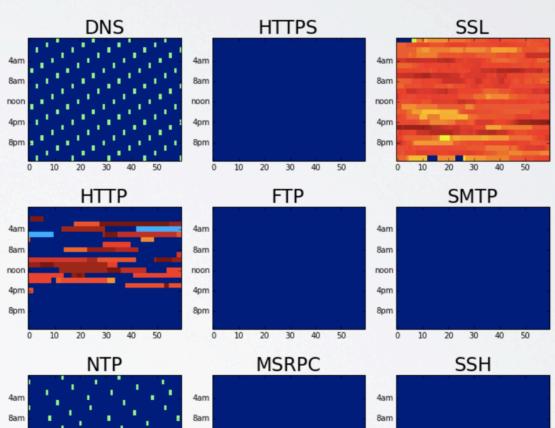
#### **Dropcam – Before Compromise**







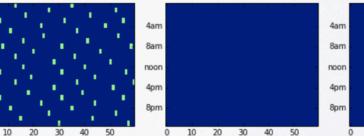
#### **Dropcam – Post Compromise**



10

20 30

40 50



noon

4pm

8pm

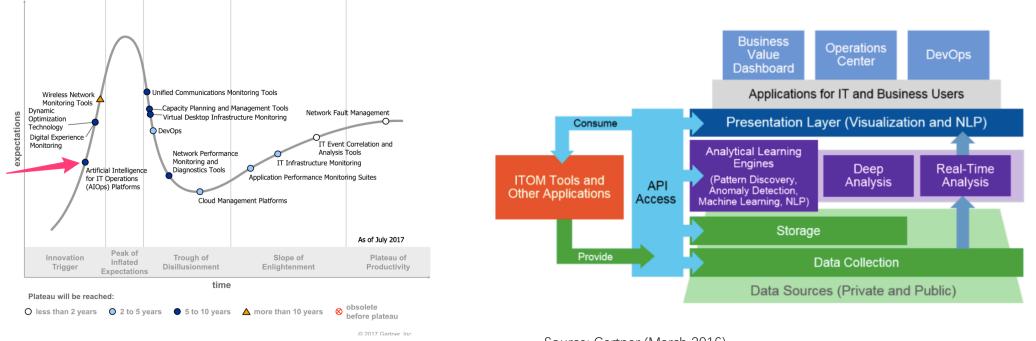
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# **AIOps is rising**

- According to Gartner Report :
- AlOps global deployment ratio: 10% (2017)  $\rightarrow$  50% (2020)



Source: Gartner (July 2017)

Source: Gartner (March 2016)

"In addition to control plane and data plane, Internet needs an AI-based knowledge plane" - Dave Clark, the Architect of the Internet, in his SIGCOMM 2003 paper.

#### A Knowledge Plane for the Internet

David D. Clark\*, Craig Partridge\*, J. Christopher Ramming<sup>†</sup> and John T.

\*M.I.T Lab for Computer Science 200 Technology Square Cambridge, MA 02139 {ddc,jtw}@lcs.mit.edu ◆BBN Technologies 10 Moulton St Cambridge, MA 02138 craig@bbn.com

333 Rav Menlo Par chrisramm

**†SR**J

#### ABSTRACT

We propose a new objective for network research: to build a fundamentally different sort of network that can assemble itself given high level instructions, reassemble itself as requirements change, automatically discover when something goes wrong, and automatically fix a detected problem or explain why it cannot do so.

We further argue that to achieve this goal, it is not sufficient to improve incrementally on the techniques and algorithms we know today. Instead, we propose a new construct, the Knowledge Plane, a pervasive system within the network that builds and maintains highlevel models of what the network is supposed to do, in order to provide services and advice to other elements of the network. The knowledge plane is novel in its reliance on the tools of AI and cognitive systems. We argue that cognitive techniques, rather than traditional algorithmic approaches, are best suited to meeting the uncertainties and complexity of our objective. transparent network with rich end-sy deeply embedded assumption of administrative structure are critical stre users when something fails, and high much manual configuration, diagnosis a

Both user and operator frustrations arise design principle of the Internet—the with intelligence at the edges [1,2]. without knowing what that data is, or combination of events is keeping dat edge may recognize that there is a prob that something is wrong, because the c be happening. The edge understands expected behavior is; the core only dea network operator interacts with the core as per-router configuration of routes ar for the operator to express, or the netw

## Leaders' opinions about AlOps

#### Huawei CEO Ren Zhengfei:

"Al is the most important tools for managing the networks.

#### 一、巨大的存量网络是人工智能最好的舞台

为什么要聚焦GTS、把人工智能的能力在服务领域先做好呢?对于越来越庞大、越来越复杂的网络,人工智能是我们建设和管理网络的最重要的工具,人工智能也要聚焦在服务主航道上,这样发展人工智能就是发展主航道业务,我们要放到这个高度来看。如果人工智能支持GTS把服务做好,五年以后我们自已的问题解决了,我们的人工智能又是世界一流。

首先,是解决我们在全球巨大的网络存量的网络维 护、故障诊断与处理的能力的提升。我们在全球网络 存量有一万亿美元,而且每年上千亿的增加。容量越 来越大,流量越来越快,技术越来越复杂,维护人员 的水平要求越来越高,经验要求越来越丰富,越来越 没有这样多的人才,人工智能,大有前途。

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#### Jeff Dean Head of AI, Google

"We can improve everywhere in a system that have tunable parameters or heuristics"

Anywhere We've Punted to a User-Tunable Performance Option!

Many programs have huge numbers of tunable command-line flags, usually not changed from their defaults

```
--eventmanager_threads=16
--bigtable_scheduler_batch_size=8
--mapreduce_merge_memory=134217728
--lexicon_cache_size=1048576
--storage_server_rpc_freelist_size=128
...
```

Anywhere We're Using Heuristics To Make a Decision!

**Compilers**: instruction scheduling, register allocation, loop nest parallelization strategies, ...

**Networking**: TCP window size decisions, backoff for retransmits, data compression, ...

**Operating systems**: process scheduling, buffer cache insertion/replacement, file system prefetching, ...

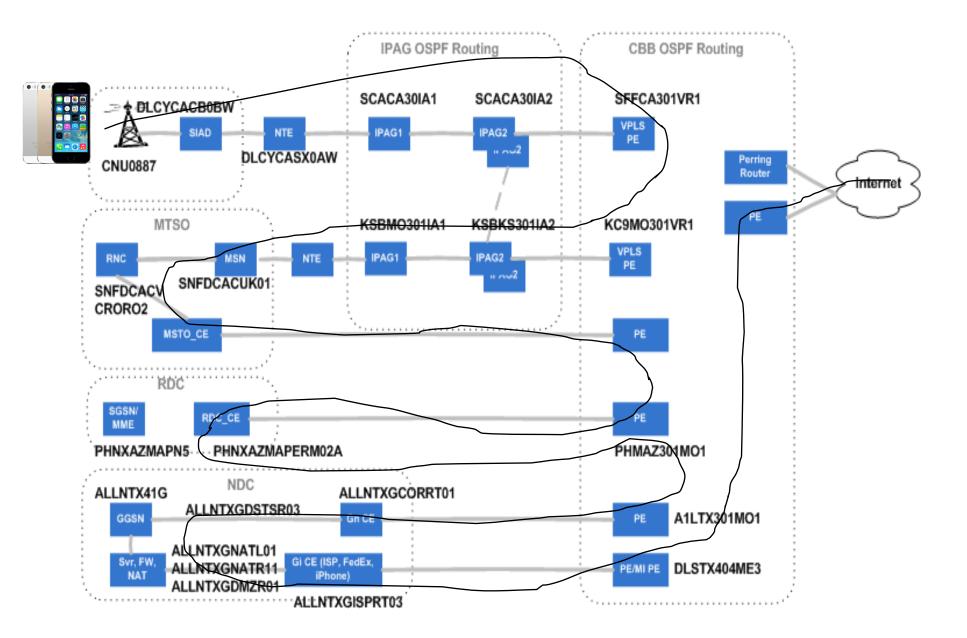
Job scheduling systems: which tasks/VMs to co-locate on same machine, which tasks to pre-empt, ...

ASIC design: physical circuit layout, test case selection, ...

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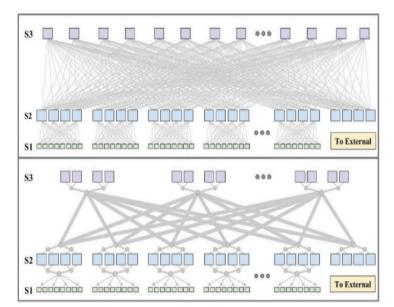
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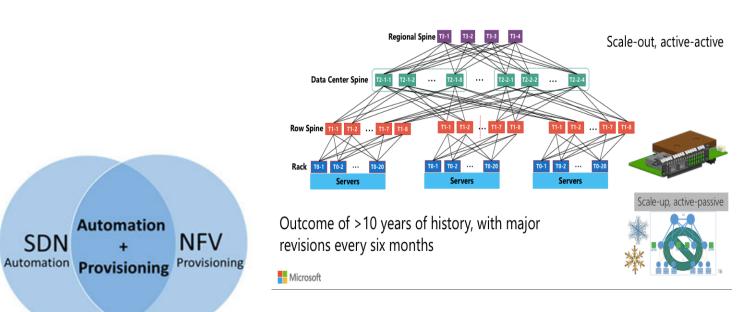
## Complex Access Networks

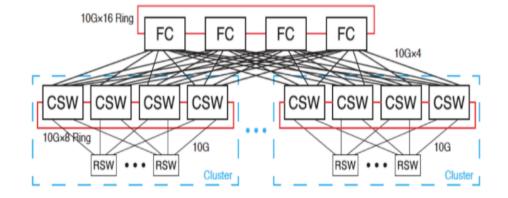




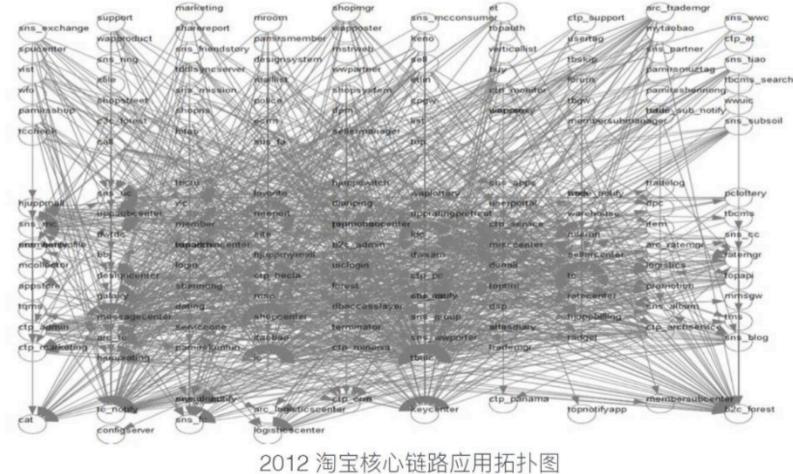
SDN



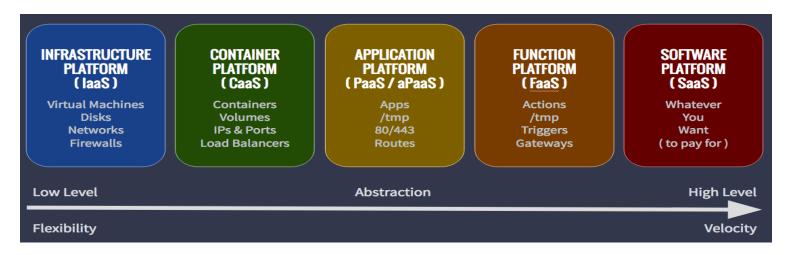


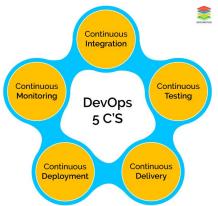


#### Taobao's application dependency in 2012



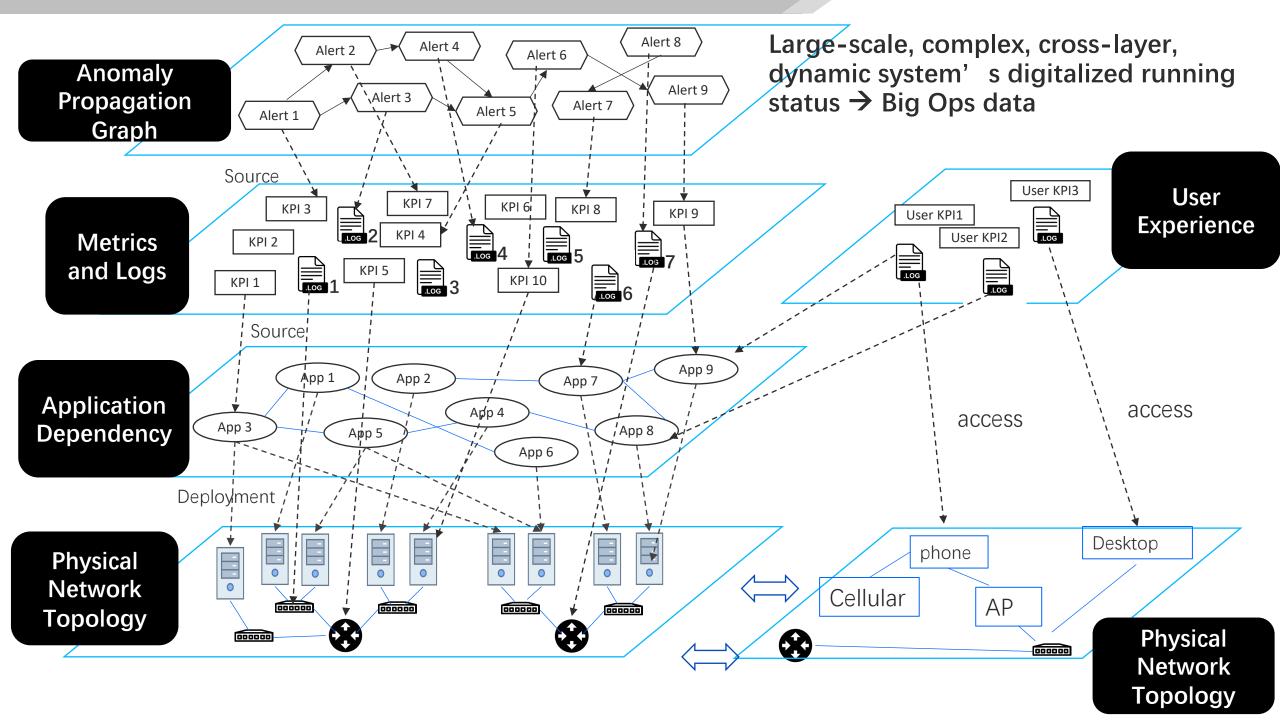
# **Evolving Techniques Enable Frequent Software Changes**

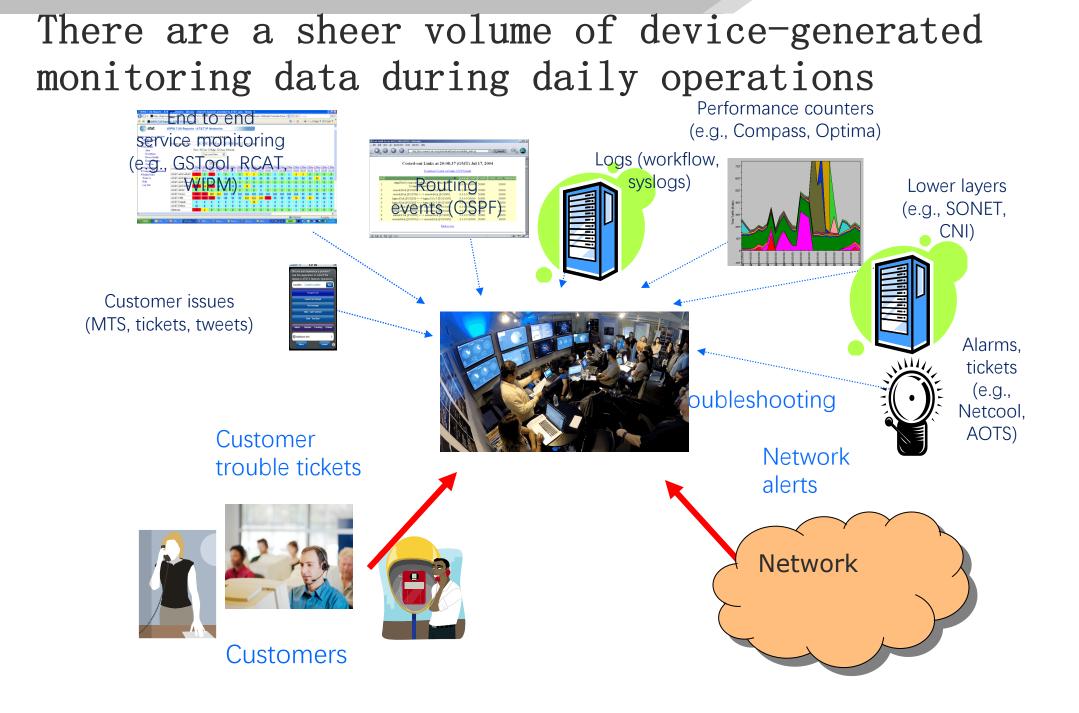




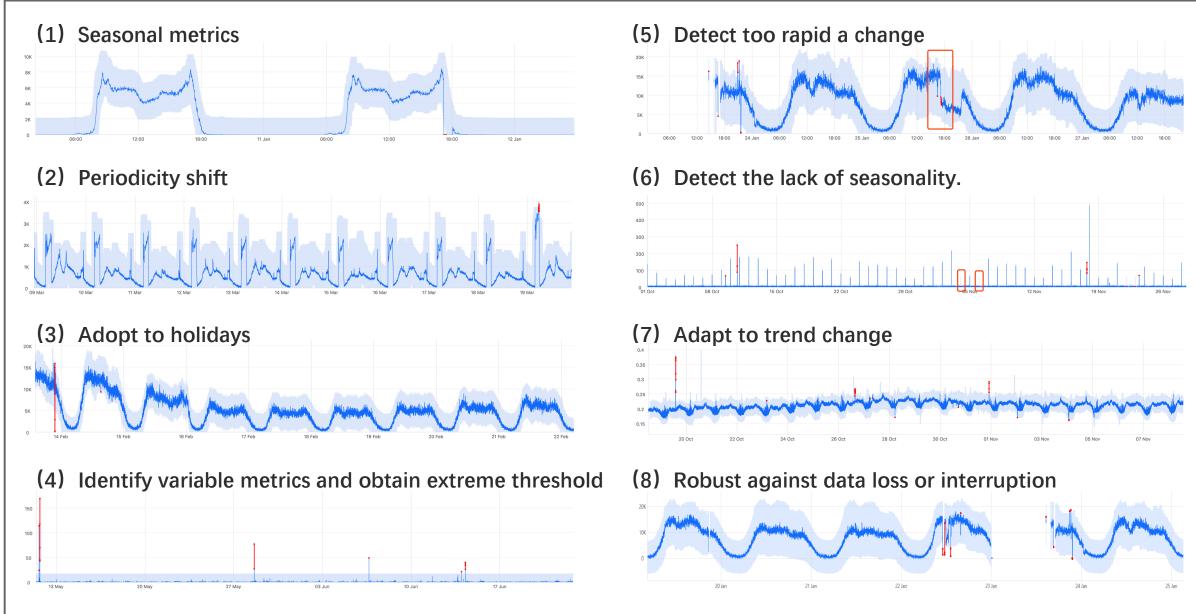
DevOps Enabler Tools v2 (Caution!!!! : Consider only after DevOps mindset is established)







## **Diverse Metrics and Their Diverse Anomalies**



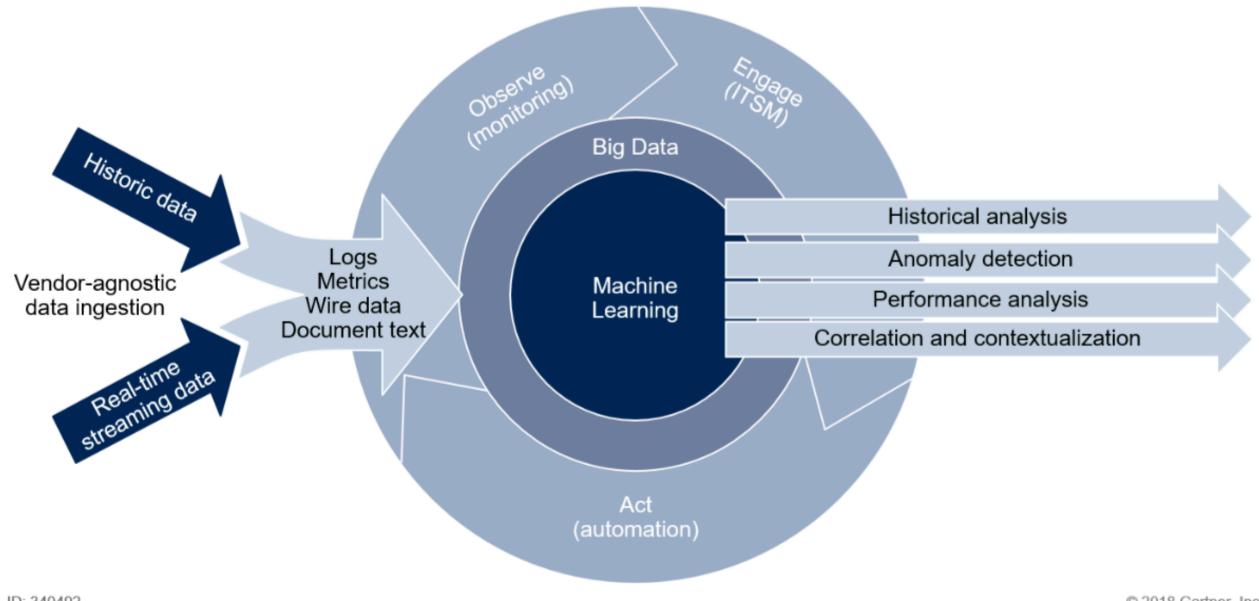
# There are more than one thousand types of logs in top 20 banks in China

2018-10-10 20:53:51,194 [JAgentSocketServer.cpp:121] WARN agent 9995 - Listening Port : 205104 Network Device 2018-10-10 20:53:51,194 [RequestHandlerService.cpp:189] WARN agent 9995 - RequestHandlerService::handle\_input(ACE\_HANDLE=38) 2018-10-10 20:53:51,195 [ResponseCOUNT.cpp:159] INFO agent 9995 - IO: Command (1) INITIALISE\_PROCESS V Logs 2018-10-10 20:53:51,195 [ResponseCOUNT.cpp:302] INFO agent 9995 - ResponseCOUNT: rc=04 App logs 交换机日志 2018-10-10 20:53:51,199 [ResponseCOUNT.cpp:159] INFO agent 9995 - IO: Command (2) INITIALISE\_ROOT 4 路由器日志 2018-10-10 20:53:51,199 [ResponseCOUNT.cpp:302] INFO agent 9995 - ResponseCOUNT: rc=04 防火墙日志 2018-10-10 20:53:51, 204 [ResponseCOUNT.cpp:159] INFO agent 9995 - IO: Command (3) INITIALISE\_THREAD V F5日志 OS logs INFO [WebContainer : 15] - queryForList:IDA TEMPLATE.LISTDATA MOST CLICK↓ • • • • • INFO [WebContainer : 8] - queryForList:IDA\_NOTICE.LISTDATA\_BY\_USER DB logs com. teradata.ida.auth.dto.SysUserVO@2c3d3e1d↓ Environment • [8/10/18 8:29:31:581 CST] 00000032 SystemOut 0 INFO [WebContainer : 1] - gueryForList:IDA TEMPLATE AUTH. findTemplateByRoleId4 Oracle日志 Windows日志Logg力日志 DEBUG [WebContainer : 7] - 2018-08-10 08:29:32 DEBUG [CsParamSetAction|showAtomsBygid|Start||start=0|limit=25|page=1|fromIndex=0|toInd DB2日志 INFO [WebContainer : 7] - queryForList:SEG BIZ ATOM DEF.findAtomByRoleAndShowArea Informix日志 Middlge-ware Logs SQLServer日志 MySQL日志 • MO日志 EXPLANATION: 4 Tuxedo日志 Channel program 'CS\_EDI\_S' ended abnormally. ↓ Weblogic日志 ACTION: ↓ Tomcat日志 Look at previous error messages for channel program 'CS\_EDI\_S' in the error Apache日志 files to determine the cause of the failure. . . . . ----- amgrmrsa.c : 487 -----08/07/2018 10:14:54 AM - Process(29670.329016) User(mqm) Program(amgrmppa) AMQ9513: Maximum number of channels reached. 4

# We have no choice but relying on AI to take advantage of the Big Data from Ops

- Volume
- Velocity
- Variety
- Value

#### **AlOps Platform Enabling Continuous ITOM**



# Outline

- Al is changing the world
- AlOps: Al for IT Operations and Autonomous IT Operations
  - What is AlOps
  - Value of AIOps: brief case studies
  - Industry Leader's Opinion
  - Is AlOps necessary?
  - Is AIOps feasible?
  - Levels of AIOps
  - An in-depth case study
- Operations center tour

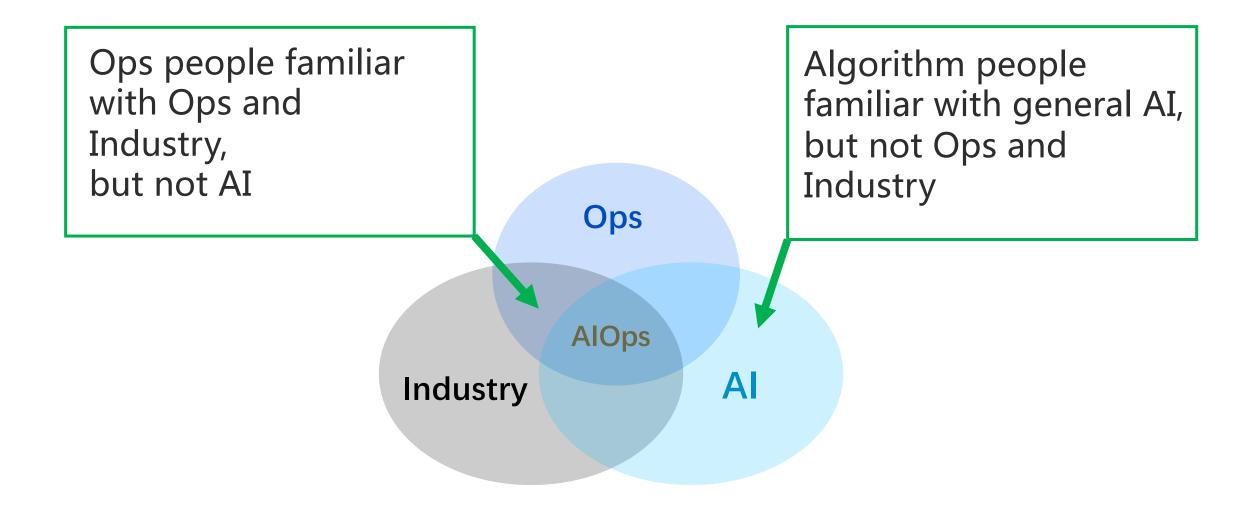
## AlOps has the necessities required for successful ML applications

- Machine learning tools (algorithms and systems)
- Applications that show the value
- Large amount of data

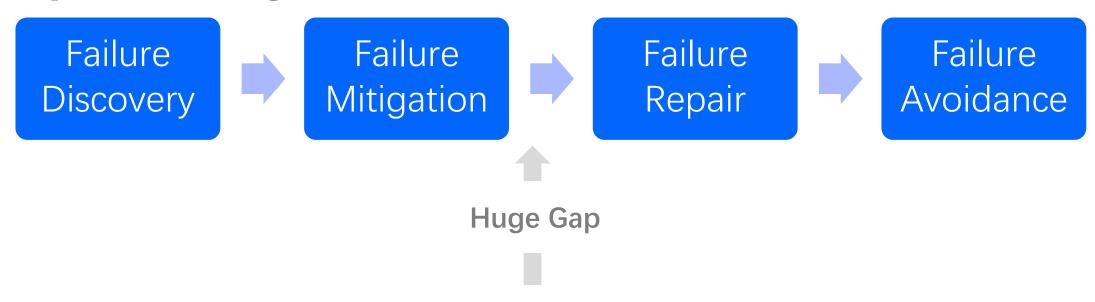
60

• Labels and the experts who can label

### AIOps is still challenging because its interdisciplinary nature

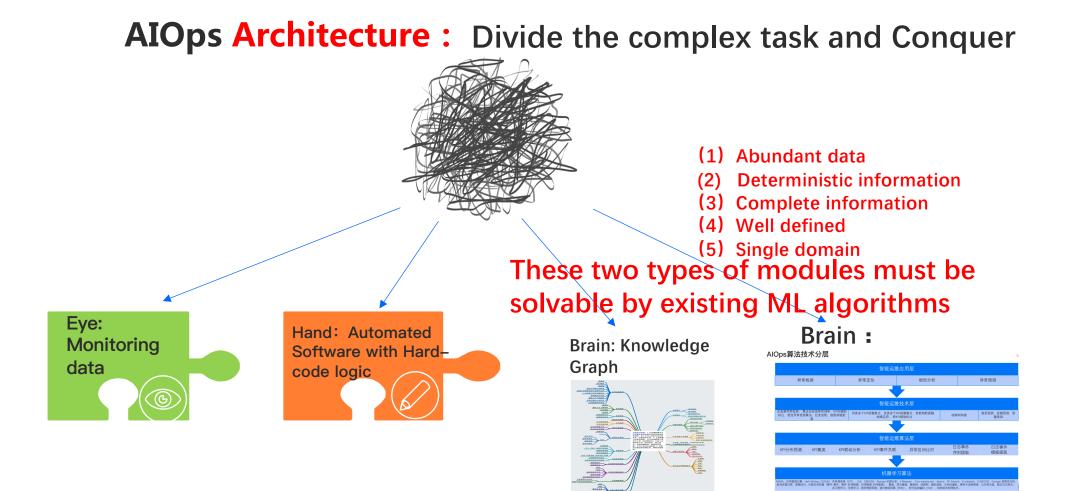


## Pitfalls: use ML algorithms as Blackbox to tackle Ops challenges

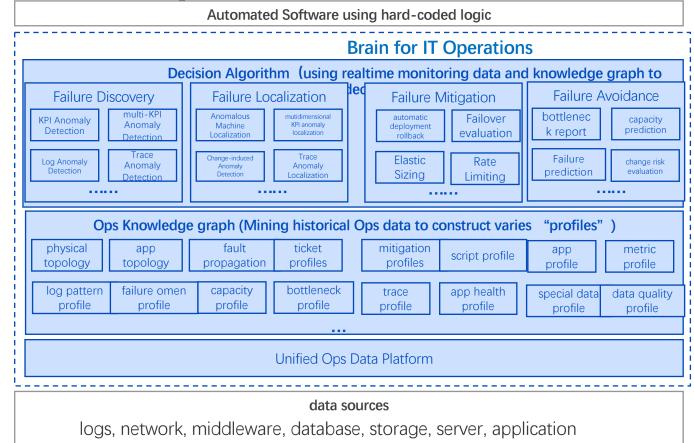


## General Machine Learning Algorithms

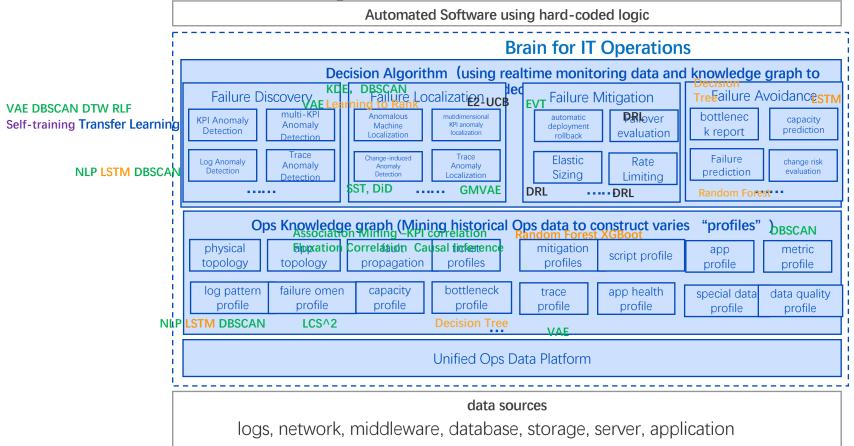
ARIMA, Time Series Decomposition, Holt-Winters, CUSUM, SST,DiD,DBSCAN, Pearson Correlation, J-Measure, Two-sample test, Apriori, FP-Growth, K-medoids, CLARIONS, Granger Causality, Logistic Regression, Correlation analysis (event-event, event-time series, time series-time series), hierarchical clustering, Decision tree, Random forest, support vector machine, Monte Carlo Tree search, Marcovian Chain, multi-instance learning, transfer learning, CNN\_RNN\_VAF\_GAN\_NLP

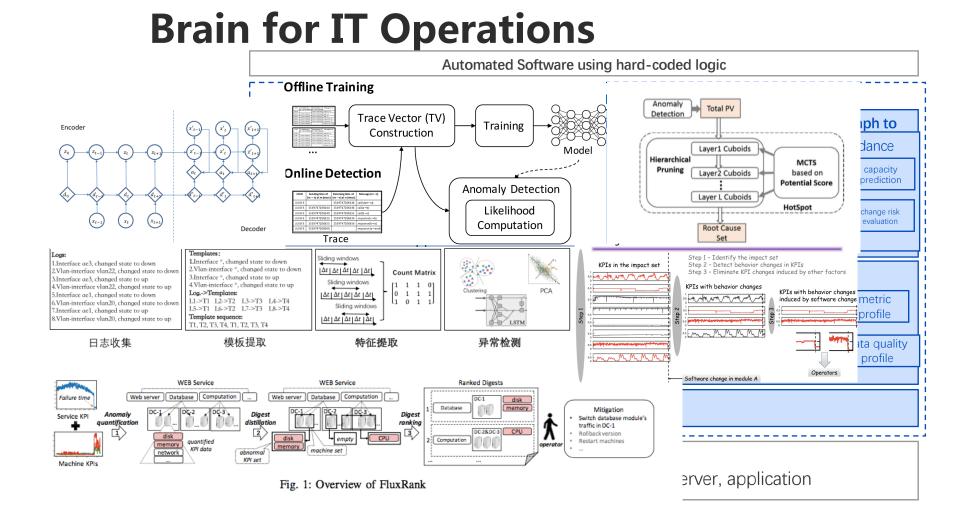


### **Brain for IT Operations**



### **Brain for IT Operations**





Unsupervised Reinforcement Learning Supervised but with labels Semi-supervised Learning Transfer Learning

# Outline

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## **Levels of Autonomous IT Operations**

- Cores Per Op (CPO): The average number of x86bCPU cores managed by an Op (40hours/week)
- Assumption: Organization tries their best to achieve certain reliability.
- Try to decoupled with the following factors:
  - Business sectors, scale, architecture, technology, part-time
- Count operators of server, storage, network, middleware, database, application
- Count the hours of operators for triggering scripts, monitoring the big screen, browsing the monitoring data, deal with alerts, troubleshooting, planning, idle time while on duty.
- Do not count the hours of operators for developing IT operations tools.

Level=[Log (CPO/100)]	Cores Per Op (CPO)	Typical Enterprises
Level 0	O(100)	Finance
Level 1	O(1K)	Medium Internet companies running on public clouds
Level 2	O(10K)	Large Internet companies
Level 3	O(100K)	
Level 4	O(1M)	
Level 5	O(10M)	

# Example1 : Internet Company A

- All x86 servers: 500K with 12 cores each, 500K with 24 cores each。 In total there are 13M cores.
- Labor: (200\*0.5+200\*0.8)\*60/40=390 Op
  - 200 operators for server, storage, database, and network
    - 60 hours/week; 50% of working time is for manual operations, and 50% of working time is for tool development.
  - 200 operators for applications and middleware
    - 60 hours/week; 80% of working time is for manual operations
- CPO=13M cores/390 Op=33K cores/Op
- Level =[ Log (CPO/100) ]=2

## **Example2 : Internet Company B**

- All x86 servers: 500K with 12 cores each, 500K with 24 cores each。 In total there are 13M cores.
- Labor: (200\*0.5+200\*0.8)=130 Op
  - 100 operators for server, storage, database, and network
    - 40 hours/week; 50% of working time is for manual operations, and 50% of working time is for tool development.
  - 100 operators for applications and middleware
    - 40 hours/week; 80% of working time is for manual operations
- CPO=13M cores/130 Op=100K cores/Op
- Level = [ Log (CPO/100) ]=3

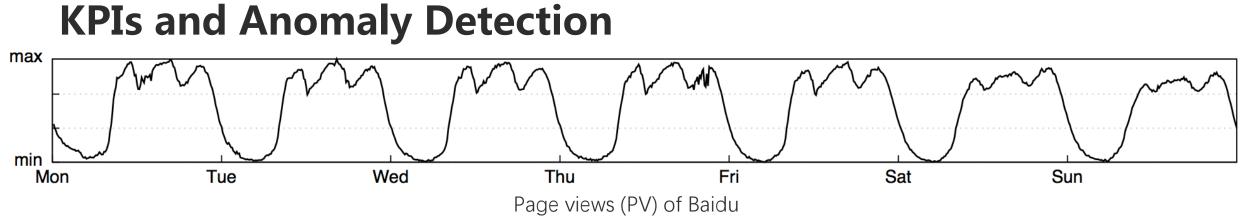
## Example 3 : Bank C

- 10K x86 servers with 12 cores each. 500 small computers, each equivalent to 100 cores. 5 Mainframe computers, each equivalent to 2K cores. 180K cores in total
- Labor (100\*0.5+100\*0.8+200)\*60/40=495 Op
  - 100 operators for server, storage, database, and network
    - 60 hours/week; 50% of working time is for manual operations, and 50% of working time is for tool development.
  - 100 operators for applications and middleware
    - 60 hours/week; 80% of working time is for manual operations
  - 200 Outsourced Operators
    - 60 hours/week; full time on manual operations
- CPO=180K Cores/495 Op=363/Op
- Level =[ Log (CPO/100) ]=0
- plan to have 100K x86 servers, and the number of cores increases to 1.26M
  - Keep the CPO, and increase the #Ops to to 1.26M/263=3360, or
  - Keep the #Op=495, but increase the CPO=1.26M/495=3545 cores/Op; <sup>71</sup>
     Level=1

# Outline

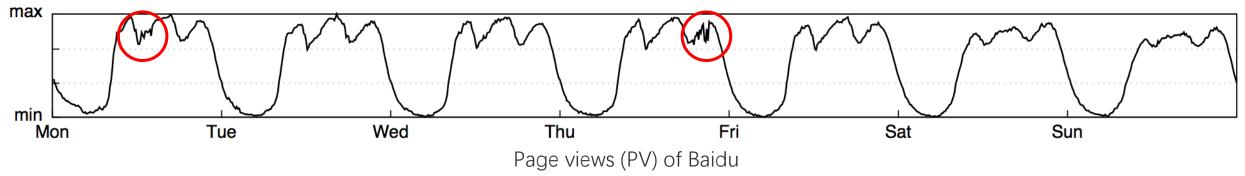
- Al is changing the world
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2010/19g8\_iu (liudp10@mails.tsinghua.edu.cn)



**KPIs (Key Performance Indicators):** A set of performance measures that evaluate the service quality

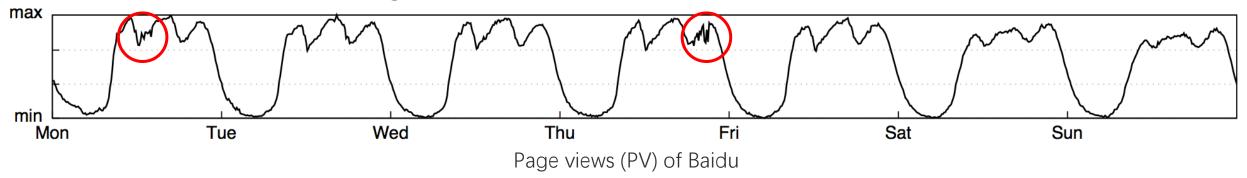




**KPIs (Key Performance Indicators):** A set of performance measures that evaluate the service quality

KPI anomalous (unexpected) behaviors → Potential failures, bugs, attacks...





**KPIs (Key Performance Indicators):** A set of performance measures that evaluate the service quality

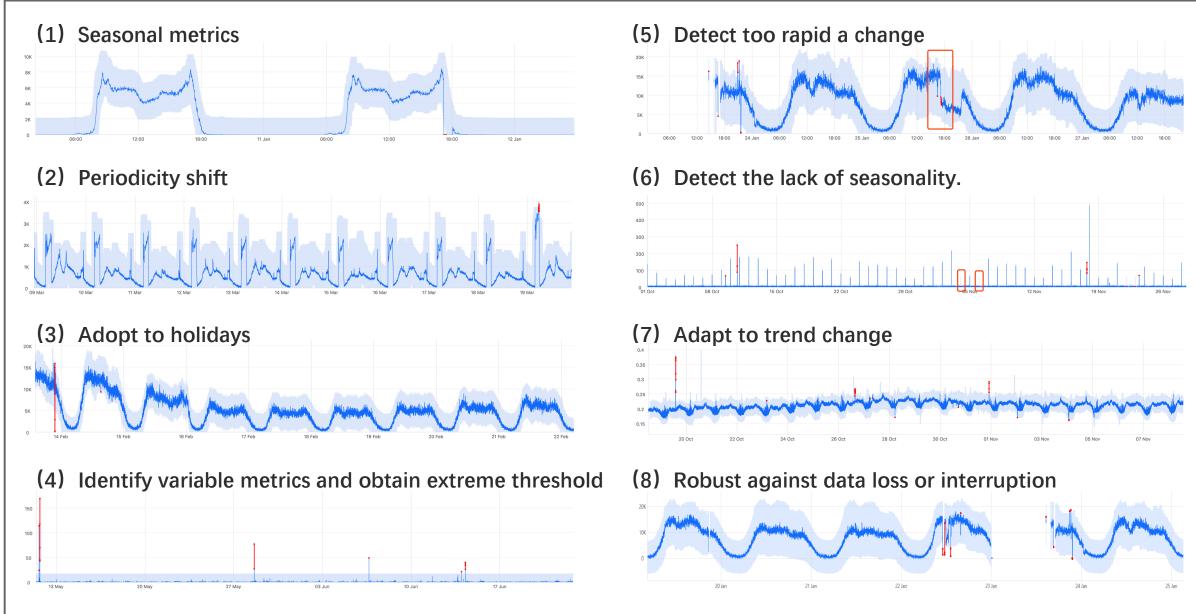
**KPI anomalous (unexpected) behaviors** → Potential failures, bugs, attacks...

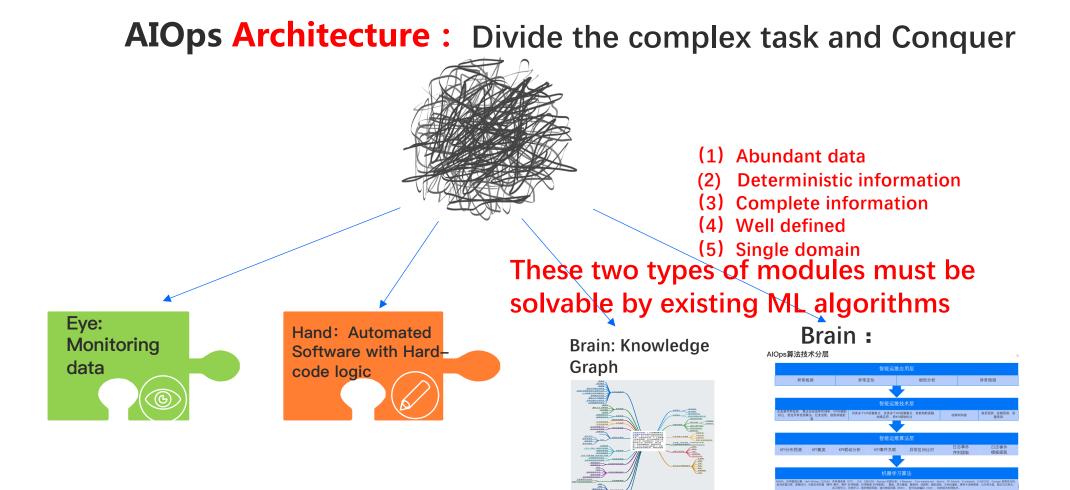
Anomaly detection matters: Find anomalous behaviors of the KPI curve

 $\rightarrow$  Diagnose and fix it

 $\rightarrow$  Avoid further influences and revenue losses

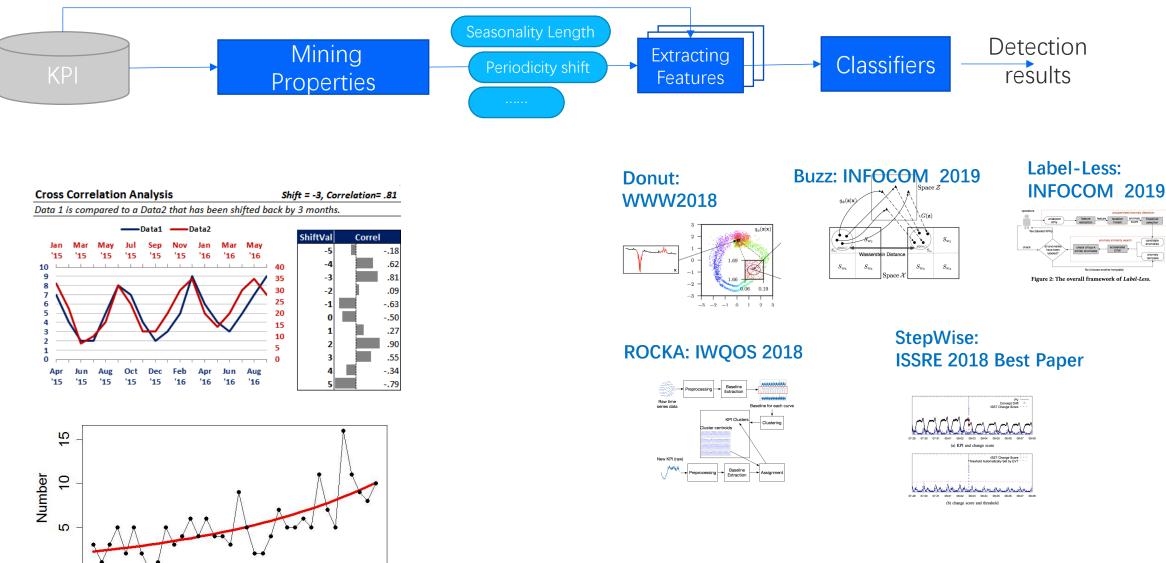
### **Diverse Metrics and Their Diverse Anomalies**





### Architecture

0



### **Donut: supervised->unsupervised: smooth KPIs**

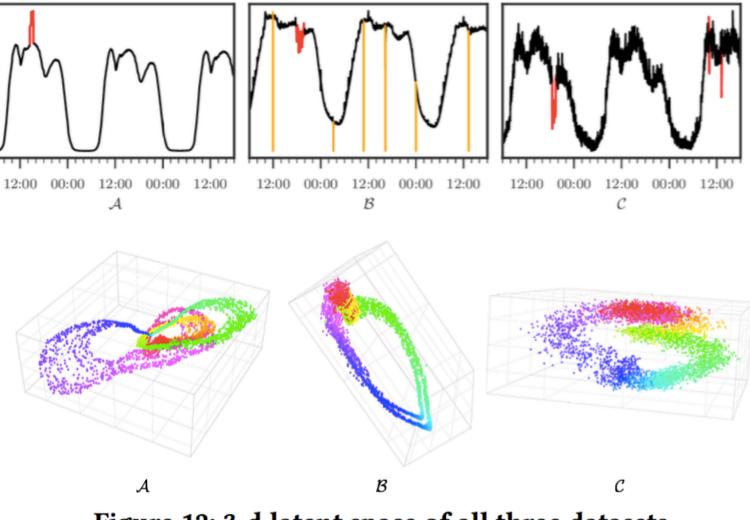


Figure 12: 3-d latent space of all three datasets.

# Latent Variable Models

Frey Faces:

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### MNIST:

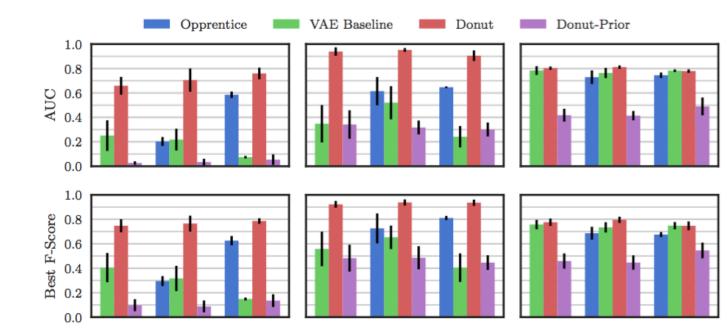
00000000000000 6 60 0 77

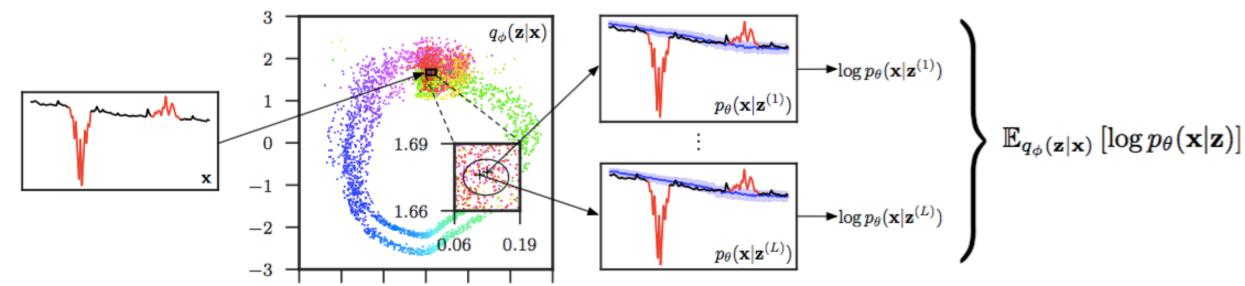
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#### Unsupervised KPI Anomaly Detection Through Variational Auto-Encoder

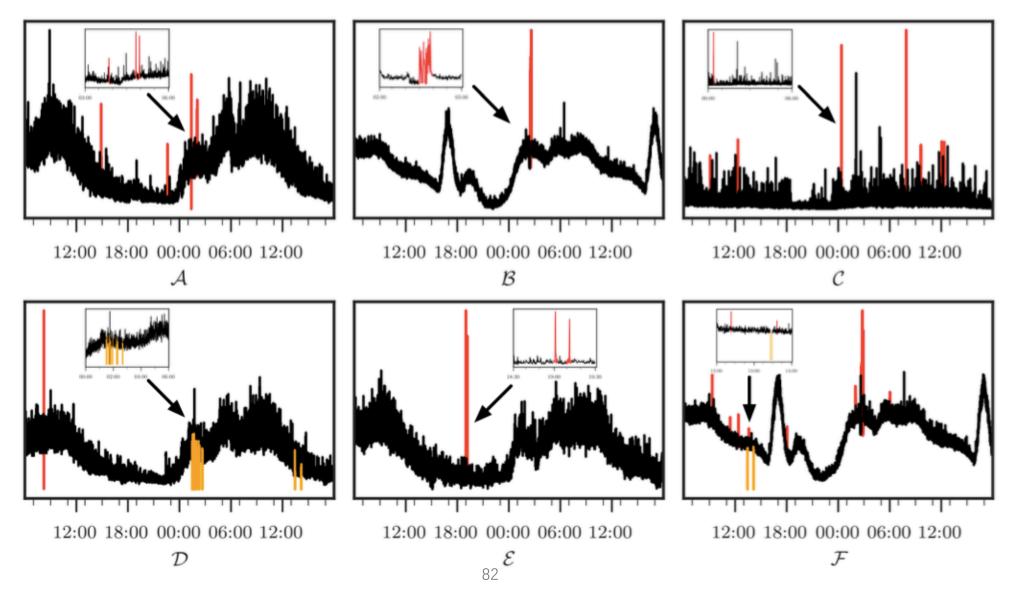
#### WWW2018

Accuracy of  $0.8 \sim 0.9$ , even better than supervised approach.

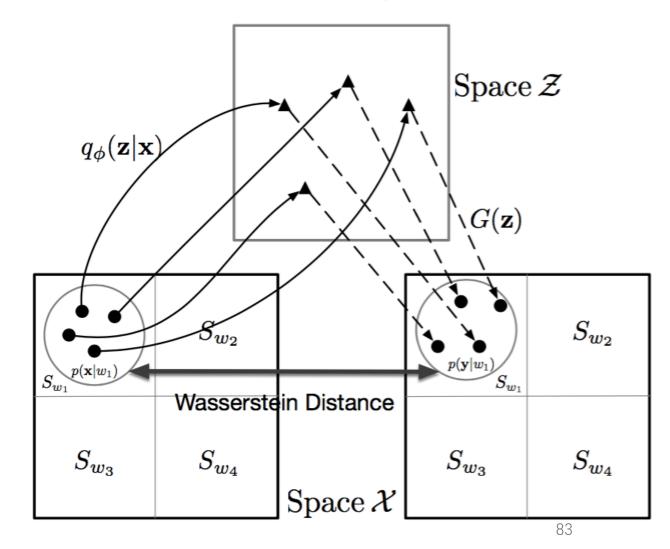




# **Buzz: Apply Adversarial Training for non-Gaussian noise**



### Unsupervised Anomaly Detection for Intricate KPIs via Adversarial Training of VAE



#### **INFOCOM 2019**

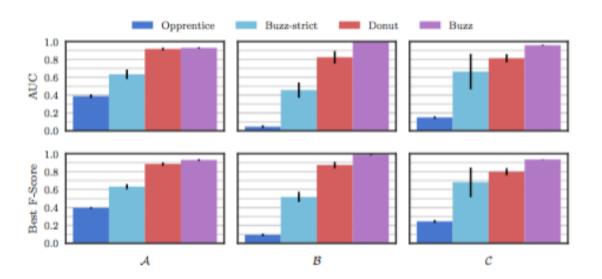
We use two major ideas in Buzz:

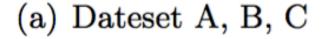
- Wasserstein distance: the distance between the two probability distributions
- Partitioning from measure theory.
   a powerful and commonly used analysis method for distribution in measure theory.

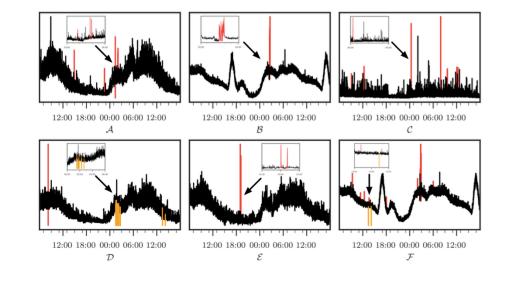
# Best F-Score outperforms Donut by up to

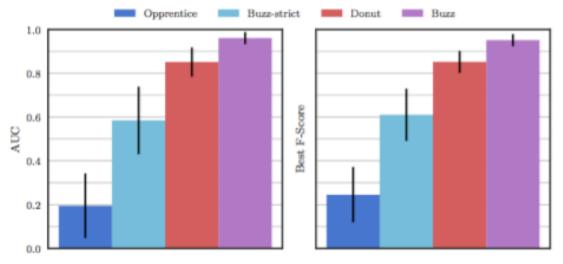
**Experiment Results** 

0.15







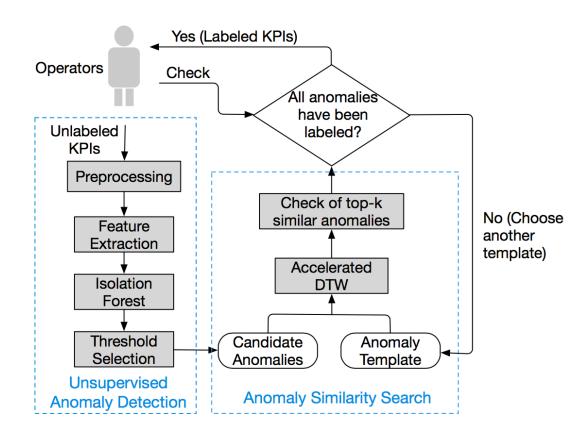


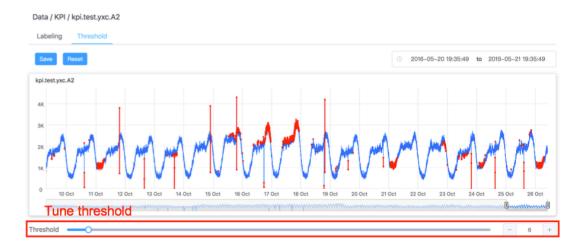
#### (b) Average of 11 KPIs

### Label-Less: A Semi-automatic Labeling Tool for KPI Anomalies

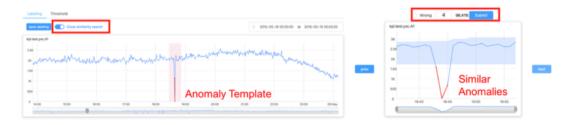
85

- Best F-score : 0.95
- Real-time response time : less than 0.5 second
- Reduce operators' labeling overhead by more than 95%





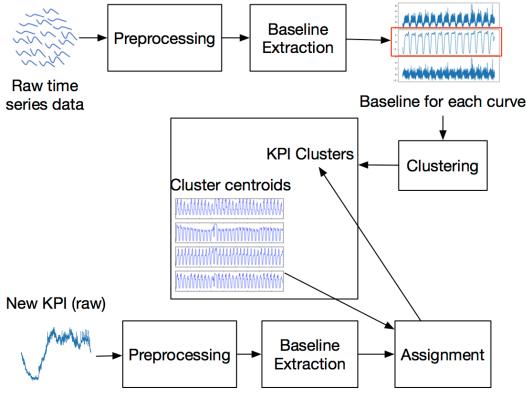
(a) Interface of candidate potential anomalies (labeled in red) given by unsupervised anomaly detection.



(b) Interface of anomaly similarity search. On the left is the anomaly template labeled in pink band; on the right is the similar anomalies given by *Label-Less* sorted by similarity.

**IWQOS 2018** 

# **Clustering + Transfer Learning to reduce training overhead**



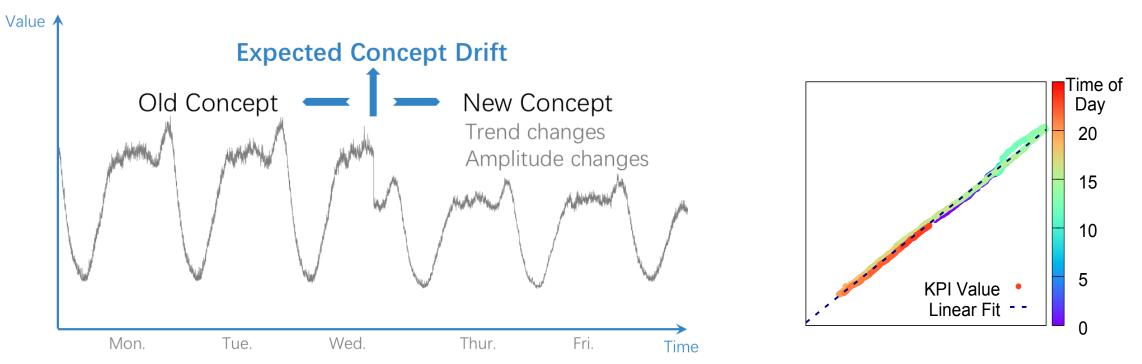
	Original DONUT [WWW2018]	ROCKA+DONUT+KPI-specific threshold
Avg. F-score	0.89	0.88
Total training time (s)	51621	5145

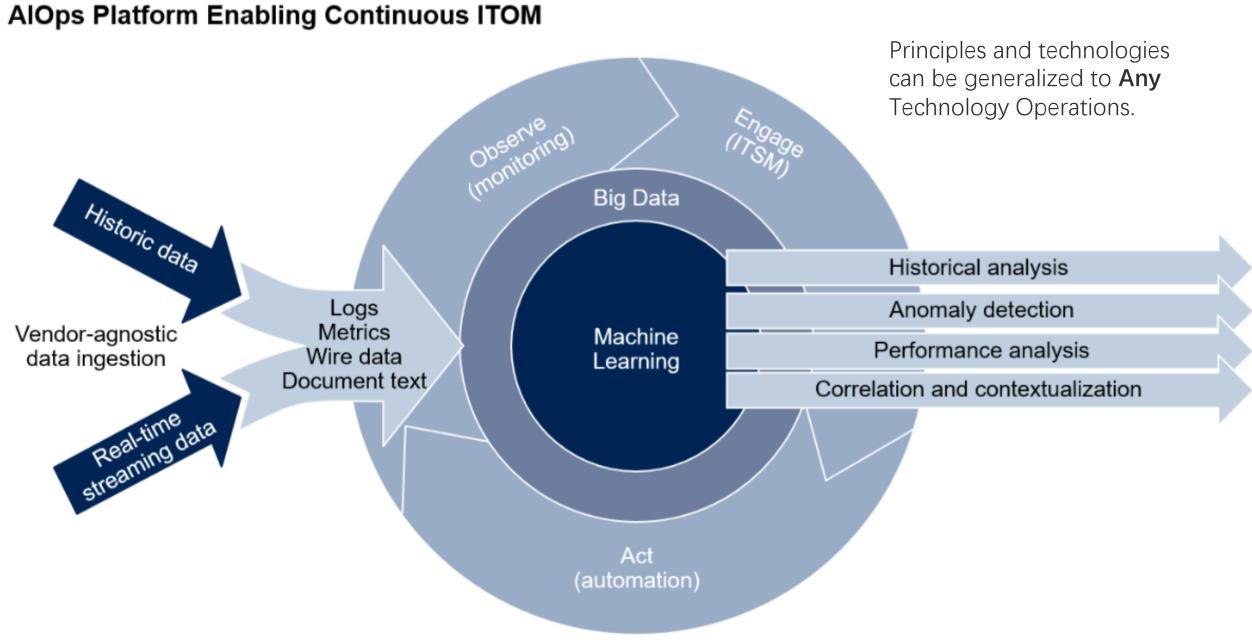
# **Adapt to Concept Drift**

ISSRE (Class B) 2018 Best Paper

concept drift adaption improve anomaly detection Fscore by 203% (**0.225 to 0.681**)

# Observation: Old and New Concept Can Be Linearly Fitted





# Summary

- Al is changing the world, but so far only in specific scenario of specific area in specific industry
- Al applications need be "coded" using domain (industry, area, scenario) knowledge-based "architecture"
- AlOps is a foundational technology in the increasingly digitalized world
  - What is AlOps
  - Business Value of AlOps: more revenue, less loss, more secure
  - Industry Leader's Opinion: AIOps is very promising
  - AlOps is necessary
  - AlOps is feasible
  - Defining Levels helps AlOps get accepted
  - AlOps can be very deep technologically

AlOps is needed for all technology operations, not just IT operations.