Security Level:

The explorations and challenges for AI based Fault Prediction and Prevention on ICT system

Pei Ke Corporate Reliability Dept of Huawei 2012 Lab peike@huawei.com 2018.10

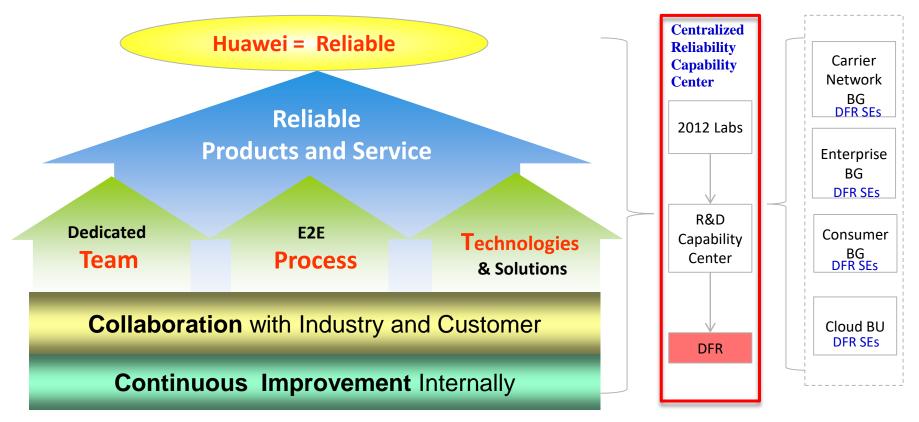
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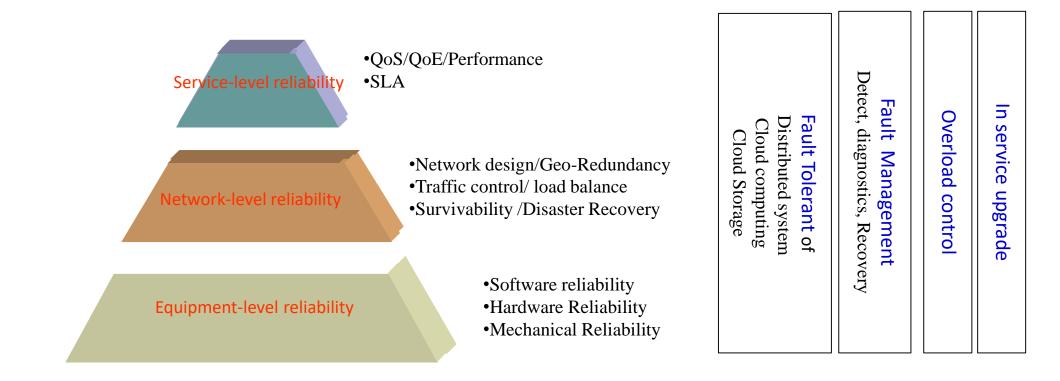
Huawei Reliability Department Introduction

- Dedicated team, Advanced technologies and solutions POC, standard, E2E process,,.....
- To break the silos between products, between reliability and product R&D engineers.





Scope of Huawei Reliability



Technology, Methodology, Architecture, Design, Tools,.....

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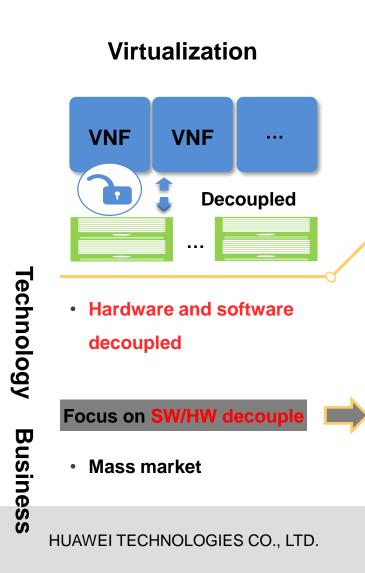


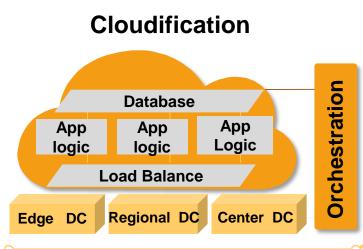
- Background
- Methodology of intelligent fault management

• The challenges and exploration



3 Levels of "All Cloud" Evolution for Telecom Industry

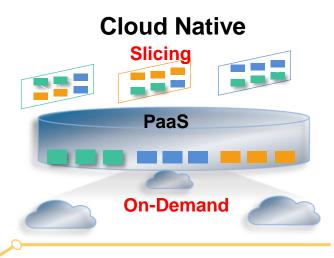




- Service Governance framework
- Stateless Design
- N-way & Cross-DC Geo Redundancy
- Graceful Scalability
- Openness with 3rd party integration

Focus on Elasticity& Resilience

- Static Slicing: MVNO, IOT, ESN...
- CloudB2B: Cloud CDN, Cloud UC, CloudVPN



- 5G oriented function decomposition
- Programmable
- DevOps & JAD: service level SW publish, A/B Test, chaos monkey
- Open platform for developers
 Micro Service

Focus on Business Agility

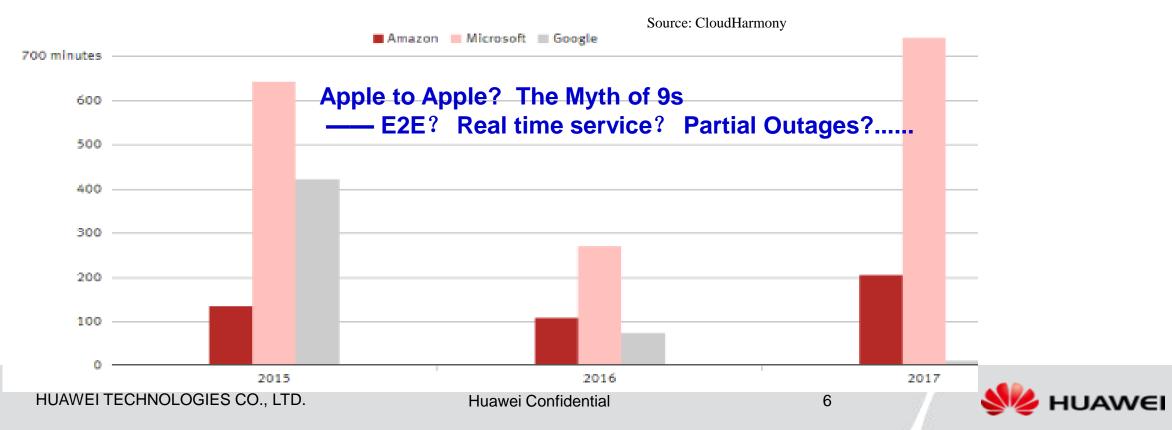
- Dynamic Slicing: AR/VR, V2X, Industry 4.0
- Market place for millions of apps



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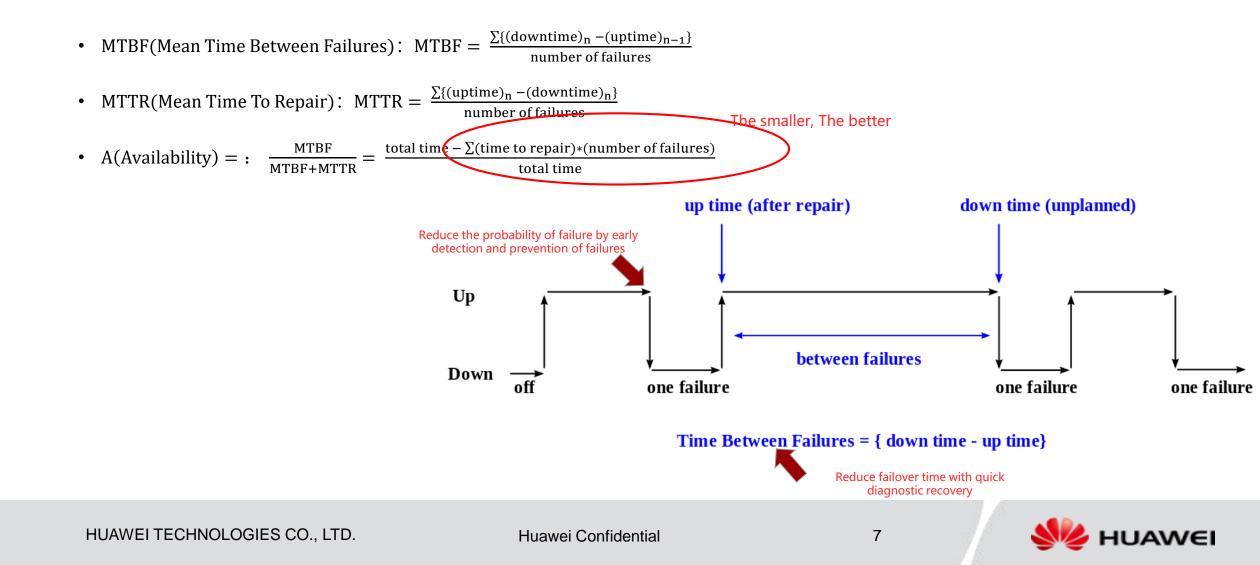
The Reality of Public Cloud Reliability

- Google Compute Engine, 2017-01-30, 4hrs
- > AWS's S3 outage, 2017-02-28, 4hrs
- **Facebook**, 2017-02-24, 3hrs
 - Microsoft Azure Storage loses power for eight hours due to "software error", 9hrs, 2017-03-16
- Microsoft Office 365, 17hrs, 2017-03-21,
- Apple's iCloud backup outage, 2 days, 2017-06-28

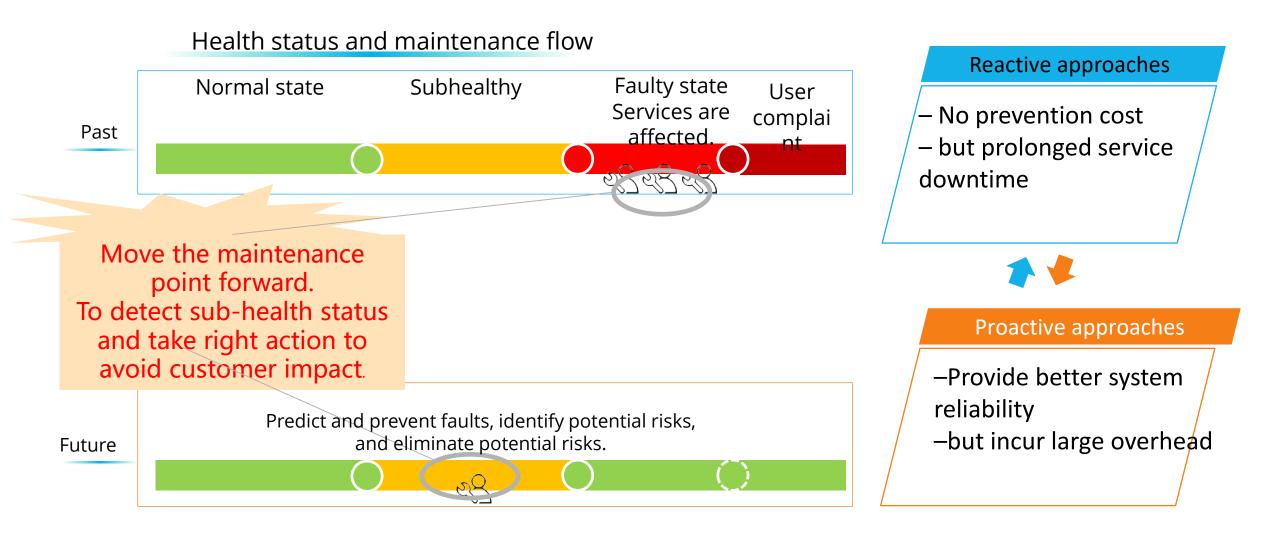


Actually there are much more outages happened, far more the ones list here.

How to improve it?



Idea: From Fire-Extinguishing to Fire-Prevention

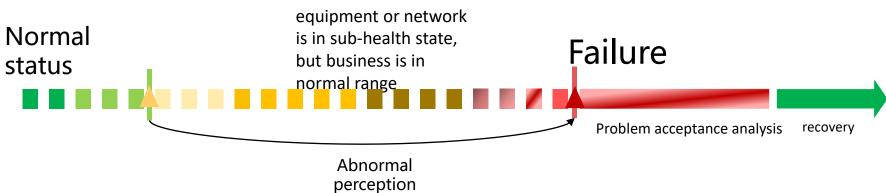


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Our Vision

Sub health:

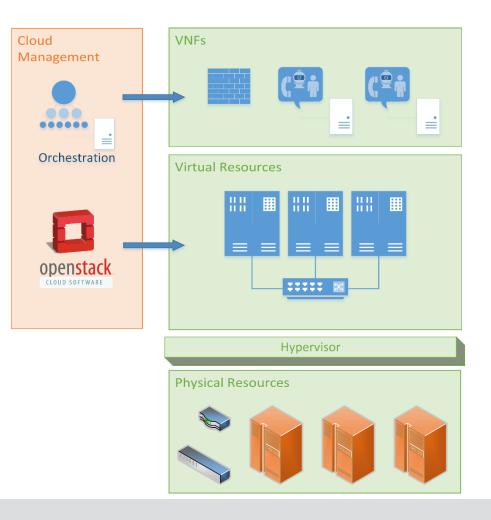


- Level 1: Data pipeline is ready or not
- Level 2: AI knows abnormal or not?
- Level 3: AI knows "what happened? "
- Level 4: AI can knows " what will happen? "
- Level 5: AI can suggest" what action need to be taken? ",

which are carried out manually.

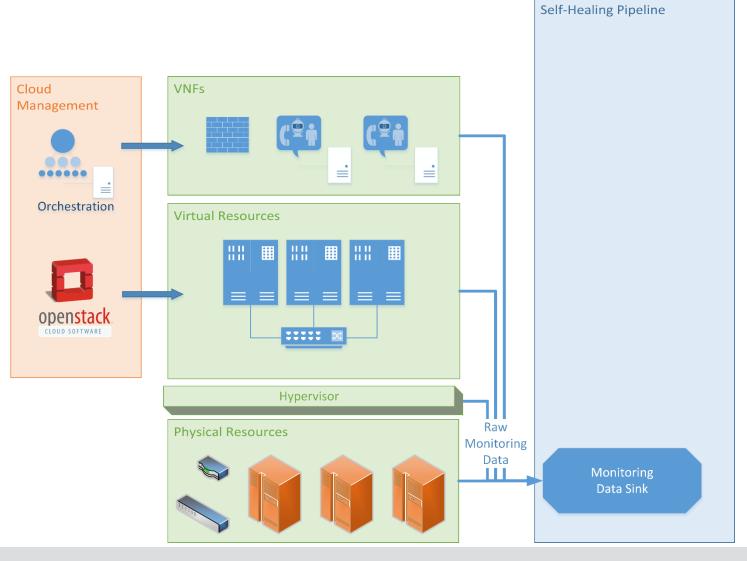
Level 6: full automation enables self-healing.





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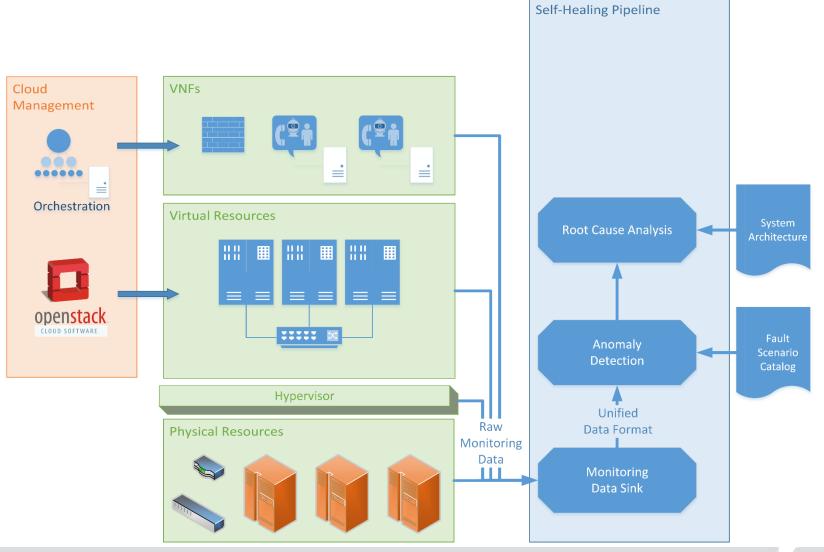




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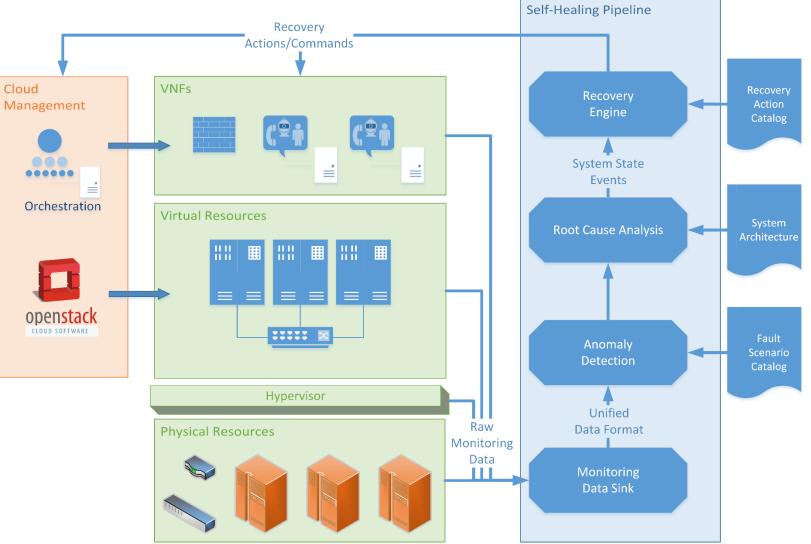




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Three elements of AI project success



Data:

Algorithms without data are useless. Data is the core of the algorithm, so getting a lot of data will become the top priority.

Algorithm:

Google acquired DeepMind to gain competitive advantage. FB has acquired Wit.ai to enhance speech recognition and voice interface services

Computing power:

 Google TPU
 2016.5

 NVIDIA Tesla
 P100 GPU 2016.4

 Microsoft FPGA
 2016.9

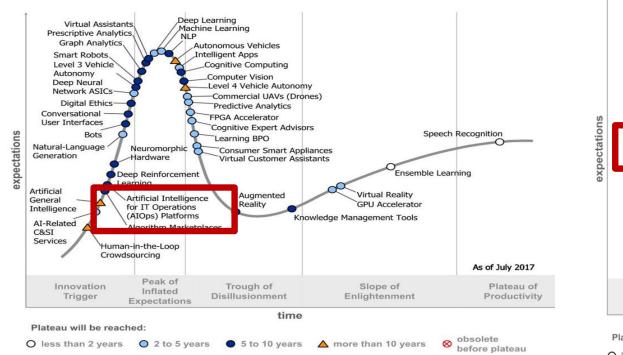
 HW Ascent910/310
 2018.10

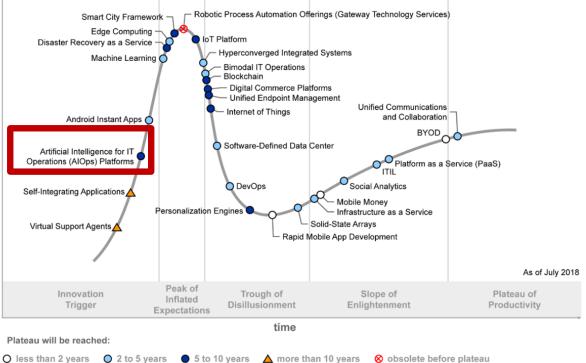
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Gartner Hype Cycle state

Gartner think it's in "Innovation trigger" stage from 2017 to now, no change, It need takes five to ten years to mature. So pessimistic ?



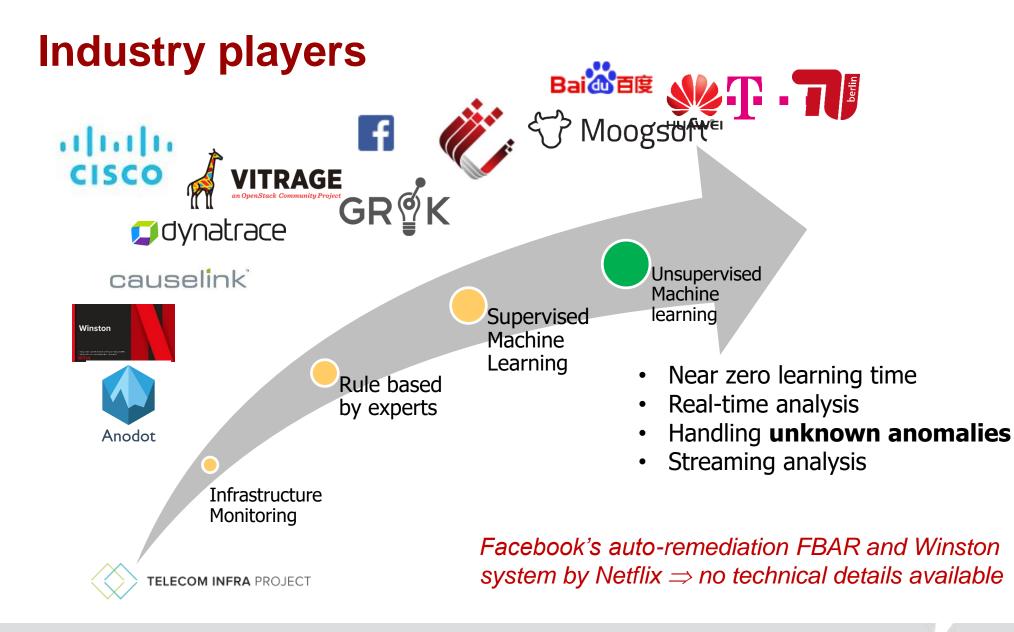


Source: Gartner Hype Cycle for artificial intelligence 2017

Source: Gartner, Hype Cycle for ICT in India, 2018

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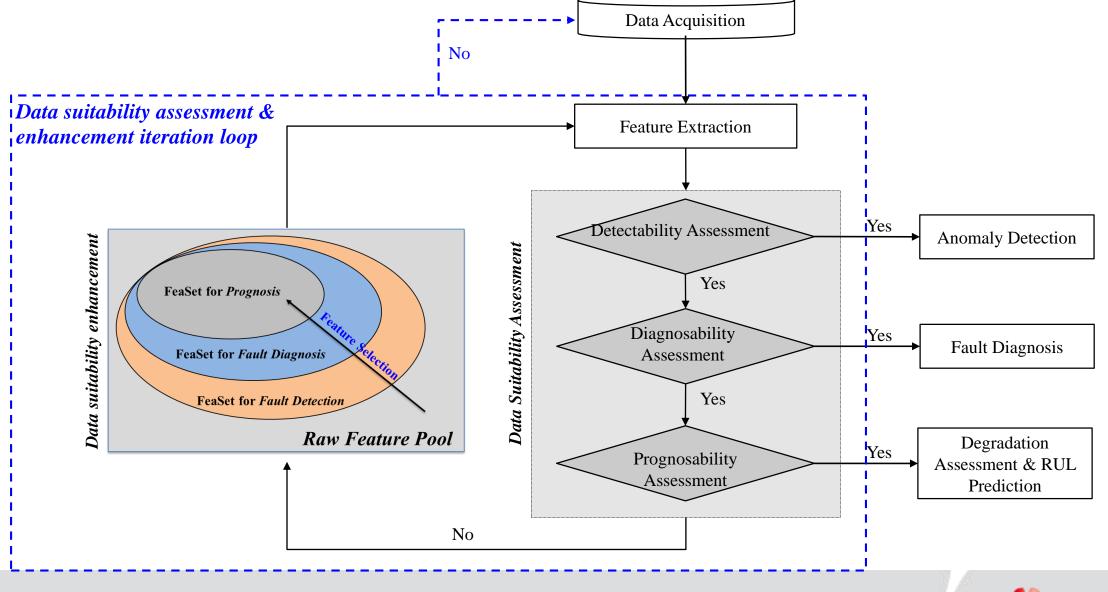




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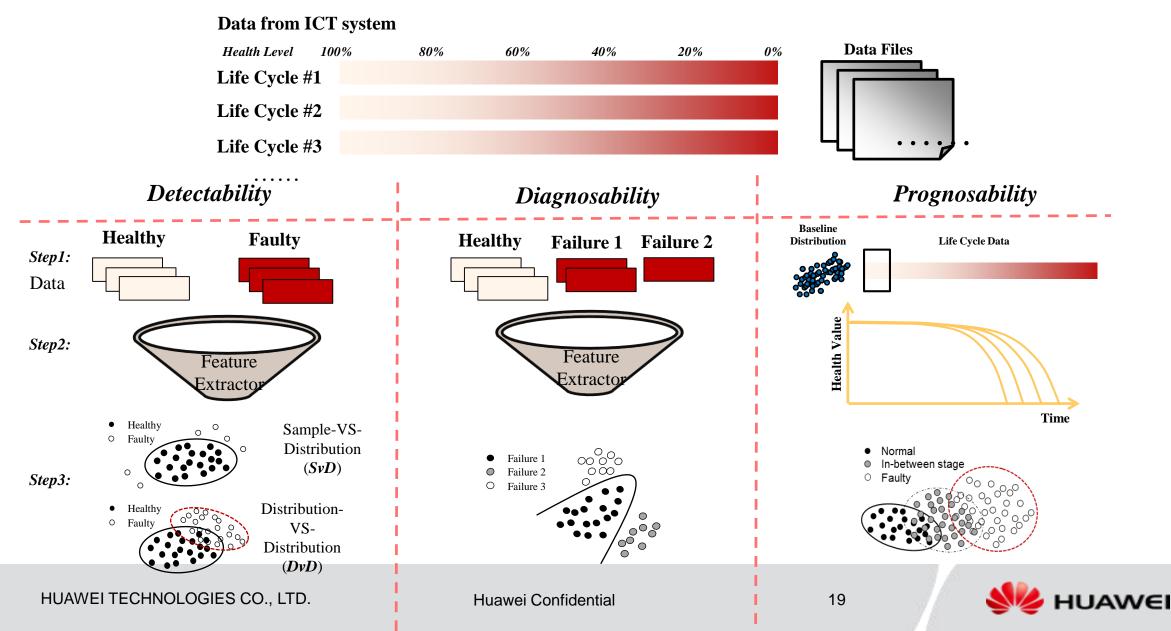
Methodology -- An Overview of FPP data pipe



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Methodology – Data Exploration of FPP data pipe

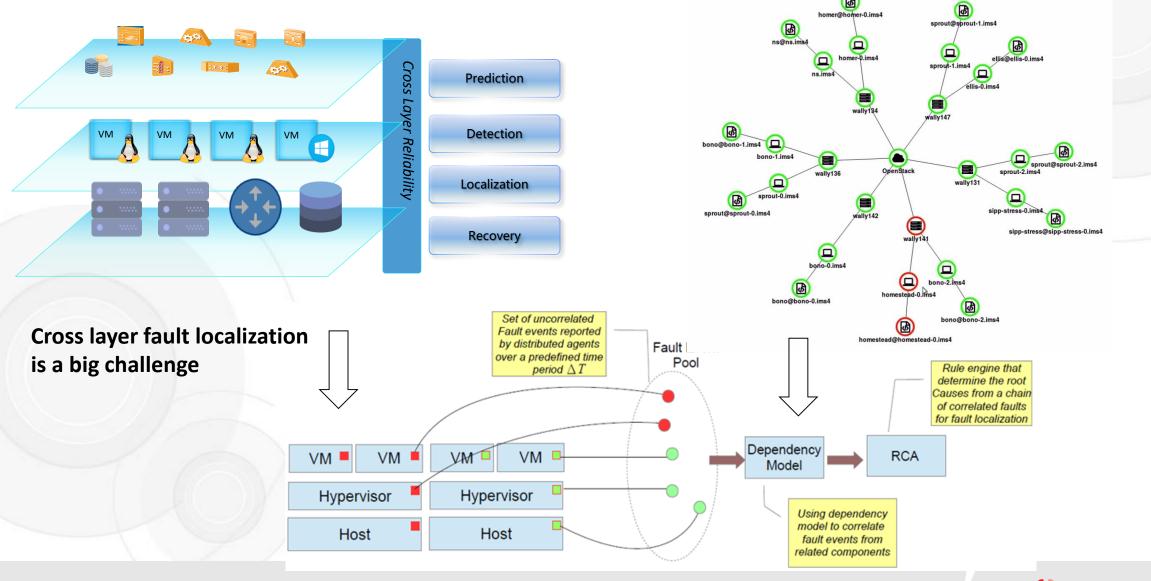


Algorithm Selection: The algorithm is widely used

Scenarios	Health PrognosisAnomaly DetectionFault DiagnosisData pre-processModel TrainingPredictionTake Action	Horizontal NE Vertical layer Inter-NE
Mathma tic	Clustering Regression Clarification TS analysis Correlation	
Base		ision Tree、 /LSTM, RL、 PID
Platform	Beam Spark TensorFlow Huawei Huawei Info Insight Mind	



Case Study. NFV Cross Layer fault localization





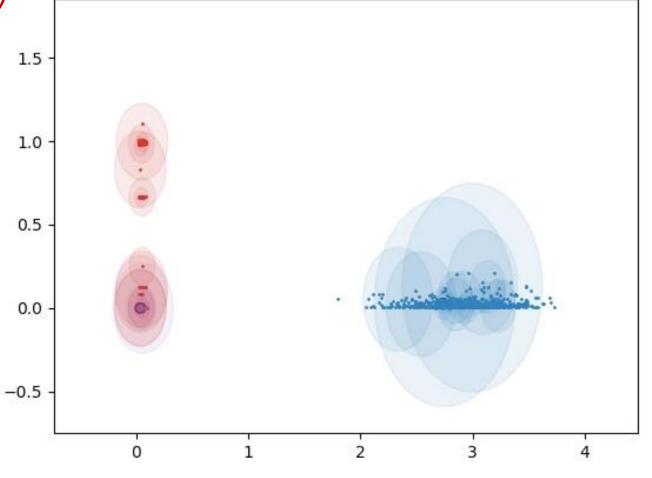
Case Study. NFV Cross Layer fault localization

Learn <u>normal</u> system state and identify deviations as anomalies

Root cause of the fault is judged according to the deviation degree of each operation environment factor

distA

distB





Accuracy: 0.96



Agenda

- Background
- Methodology of intelligent fault management

• The challenges and exploration



The real challenge is data

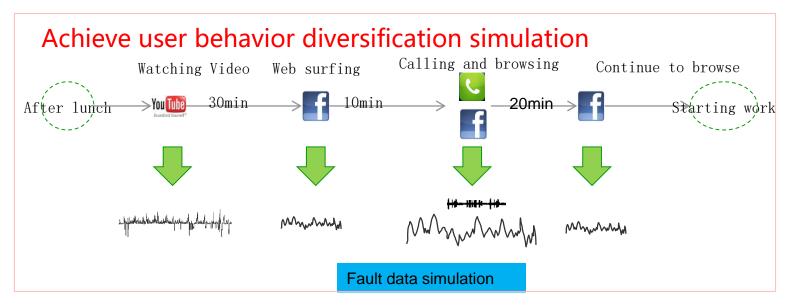
Garbage in, Garbage out: The quality and integrity of data is crucial for building an efficient model of AI

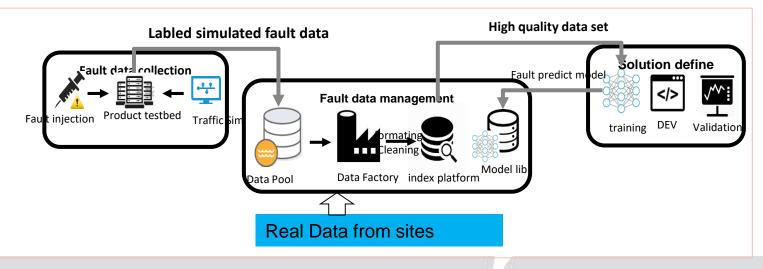
Hard to acquisition	small data samples , unlabeled and unbalanced.	Data format is not uniform
	•labeled fault data is	
•fewer commercial sites	difficult	 Data format is not uniform,
Data is sensitive and	•There are many problems	each product data format
hard to access to	type, but few sample data	up to 200+
analysis	for each.	• Data loss
A small amount of fault	 The fault problem of 	Lack of standardization
data can not be	existing network is	Instrumentation
deposited for long time	complex, which requires a	incomplete
acposited for long time	lot of resources to locate.	



Less sample data - both simulated data and real data

- Simulated data combined with real network verification
 - Simulation of real network
 traffic tool
 - Fault Injection tool
 - NFV testbed and mirror env
- Successful case:
 - Slow disk detection
 - Wireless CPRI fault generation
 - Optical module failure
 - Memory leak failure
- The simulation of complex scenes remains to be improved







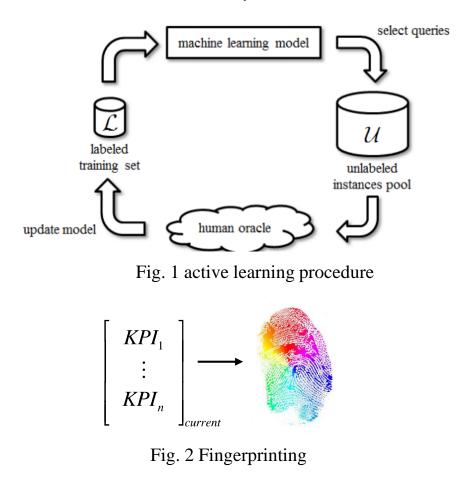
Few labeled data- semi supervised learning

0.3 ELLOL 0.2

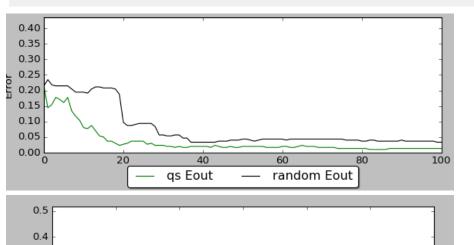
0.1

0.0

 Idea: When label are difficult to automatically acquire, it is usually label them manually by a human oracle. Intuitively, randomly selecting instances to label experts is not the best strategy. Active Learning means ask Experts to lable the selected "best value "sample."



In our experiments, we learned to automatically pick out the "most valuable" fault fingerprints and label them with domain experts. To achieve the same classifier accuracy, the number of samples required for active learning only needs one fifth or less of the traditional supervised learning.



150

Result in our case::

- 1. The more labeled samples, the lower the error rate.
- no matter how many sample labels are selected, active learning is always better than traditional supervised learning
- The more samples are selected, the lower the cost performance.
- The initial marker sample is 10, and the sample size of active learning is about 20.

Green is active learning , Black is for traditional supervise ML, total samples: 900, intimal labeled 10

200

random Eout

250



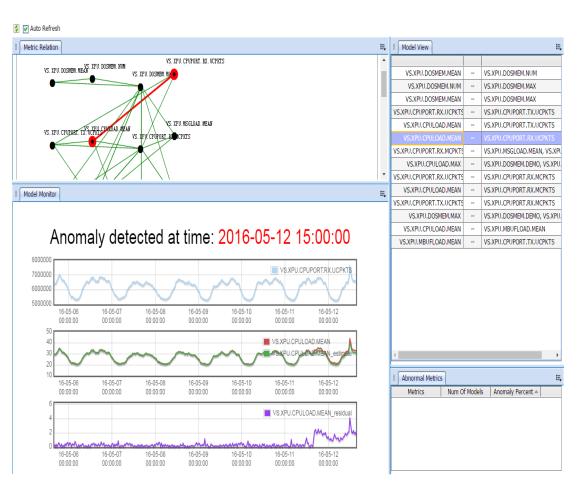
100

as Eout

50

Algorithm: Al+ expert experience are equally important

- Feature extraction is an important part of traditional ML and also DL, and algorithm performance depends on human experience.
 - There is a saying in the industry of ML: if the feature is not done well, tuning the parameter will never stop.
- Fault data labeling needs expert feedback confirmation
 - Labeling heavily depends expert knowledge
 - EAI: It can significantly reduce the risk of "intelligent mis-operation" in complex tasks.
- Expert knowledge is a very important asset in the weak AI stage, which needs better management and solidification.
 - Rule based case can cover 80%, only 20% for AI based
 - Case intelligent search and knowledge map





Relationship between model complexity and data

Data Requirements

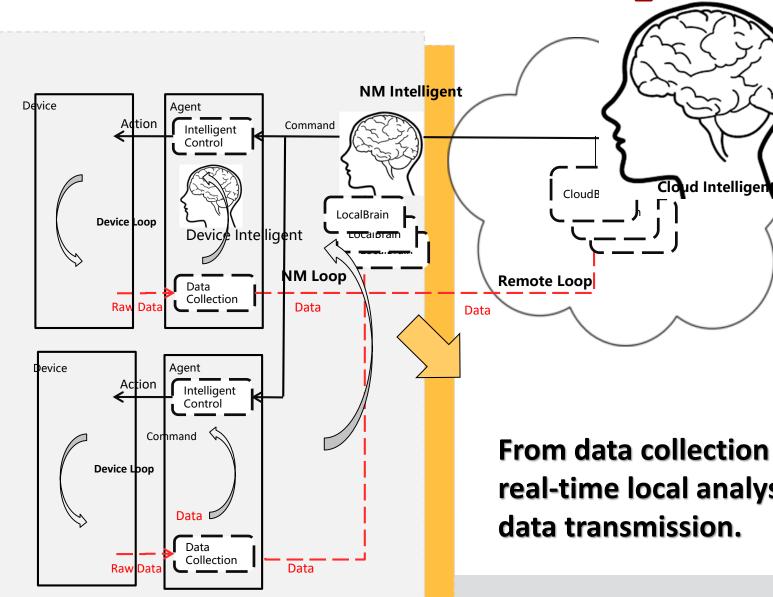
- Complex models are used to solve complex problems, and simple models solve simple problems
- For limited data, simple models may be better than complex models for complex problems
- Once data is enough, complex models can generate accurate results.

	Software fault prediction (Simulated Data doesn't work)	
Hardware fault prediction (Simulated Data work)		
ML Anomaly Detection	Software Anomaly Detection LSTM、AE/VAE	
Hardware, Devices, resources Deterioration prediction		

Model complexity



Architecture – Hierarchical intelligence



Hierarchical Intelligence /distributed ML:

- Intelligent Agent.
- Network Management Level Intelligence
- Cloud Intelligence

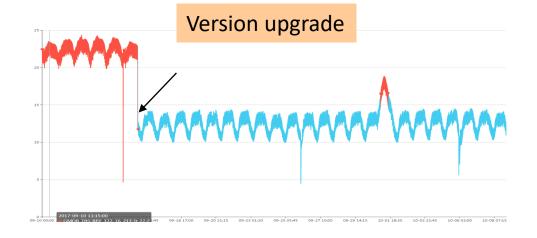
From data collection to abnormal perception, real-time local analysis of closed loop, reduce data transmission.



Challenge 1- algorithm model

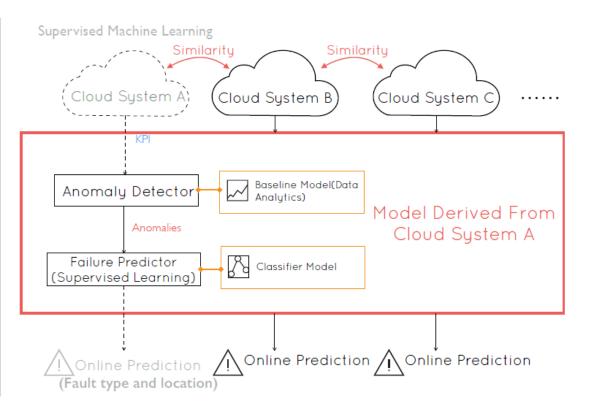
- Challenges of updating system state change models: for example, upgrades, operational promotions, resulting in changes in KPI sample distribution, and increased failure types (model evolvable)
- Requiring model reuse in a similar environment where sufficient data is difficult to obtain: model reuse, transfer learning needed

Google infrastructure upgrades will evolve into continuous upgrades of the network, incremental upgrades. New features and configurations are pushed into the product every week, so upgrades will be made every day, even multiple times a day. Note: 2016 Sigcom articles and 2017blog from Googe

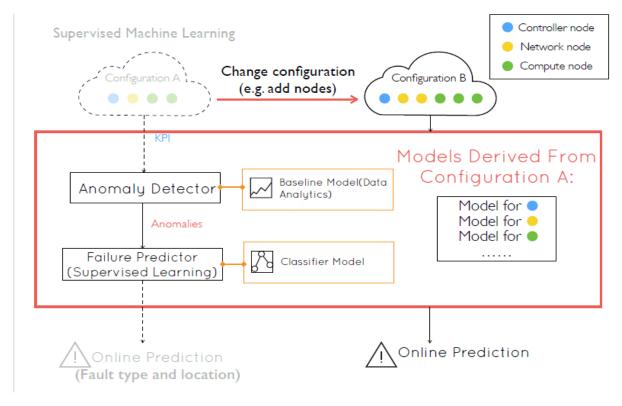




Inter and Intra system Prediction Models transfer challenges



Inter DC model transfer



Intra DC model transfer

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Challenge 2- development mode need be changed

Challenges to the existing development process: online data closed-loop algorithm model tuning, update. (flexible) - to collect data from the existing network to form iterative feedback.

Requirements for development environment: we need to combine the existing network data to optimize the model.



Summary

- Al can assist to improve system availability in some cases but not all.
- AI based fault predict and prevention presents many challenges, we long way to go.
- Domain expertise is very important in define the solution
- Data suitability analysis before model development is a must
- Define models should based on what data you have. Simple models may have good results.





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