Cloud-based Service

Dr. Neal N. Xiong
Southwestern Oklahoma State University

Outline

- Myself
- Cloud-based Trust Computing
- Cloud-based Machine Learning for Medical Data
- Cloud-based Tele-health

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10.27.2016
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Myself

Research - Publication

- Journal papers:
  - Quality: Top 2
    IEEE JSAC (3.413-4.8), IEEE TPDS, IEEE SMC, ACM TAAS, IEEE TSC, IEEE THMS, IEEE/ACM J.
  - Quantity: Journal 100+, over 20 IEEE/ACM J.
- Conference papers:
  - Quality: Rank 1
    INFOCOM, ICDCS, Sigcomm workshop, IPDPS ICPP, ICC, LCN, Cloud Computing...
  - Quantity of Rank 1: about 20

Research - Service

- **Associate Editor,**
  IEEE Tran. on Systems, Man & Cybernetics, Systems (2.2,Top 15)
  Information Sciences (Impact Factor 3.8-4.2, Top 20)

- **Chair, Trusted Cloud Computing Task Force,**
  IEEE Computational Intelligence Society (CIS)

- **Editor-in-Chief, Journal of Parallel & Cloud Computing (PCC),**
  http://www.j-pcc.org/editorialBoard.aspx

- **IEEE Senior member, IEEE Computer Society**

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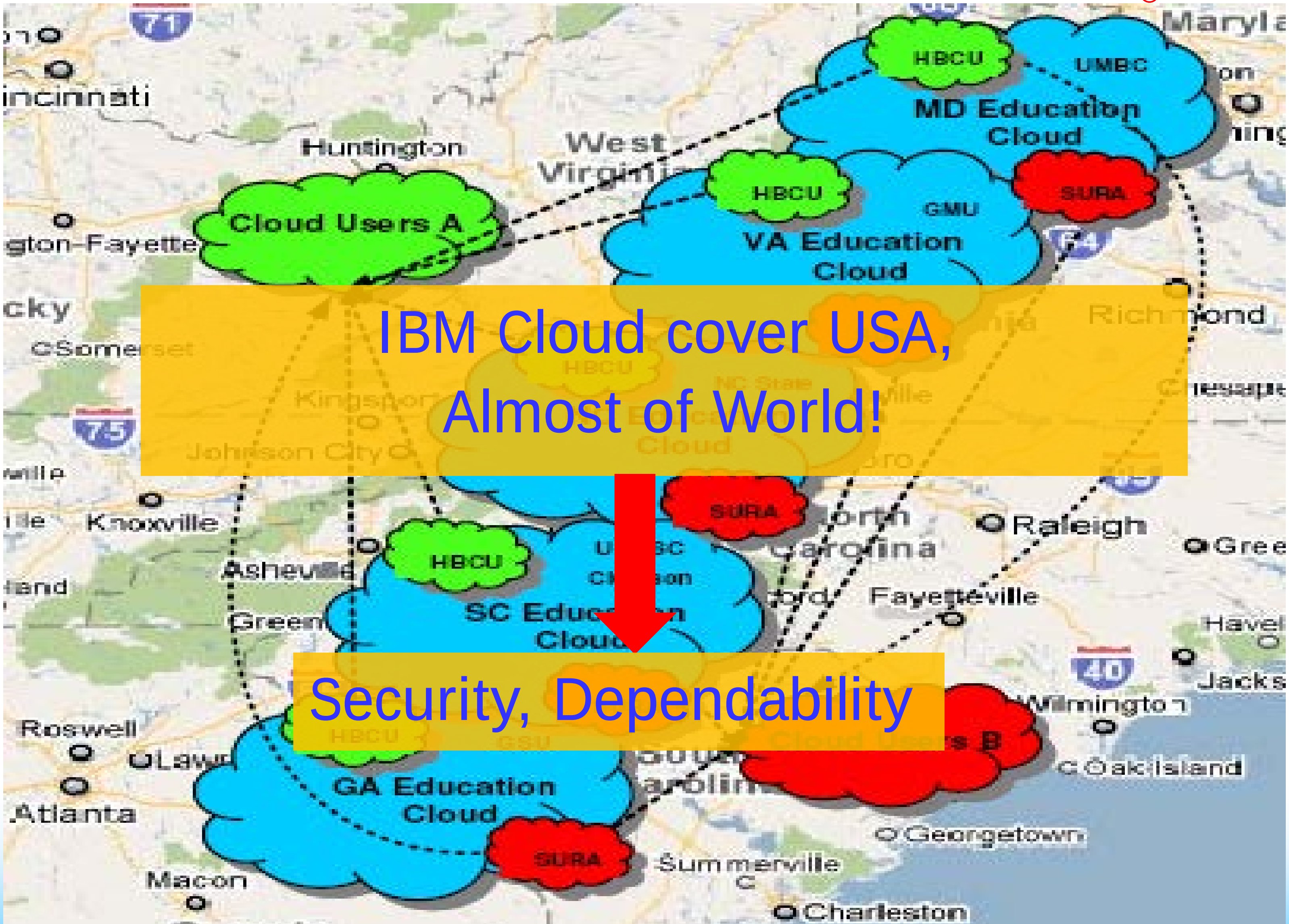
Tech. I

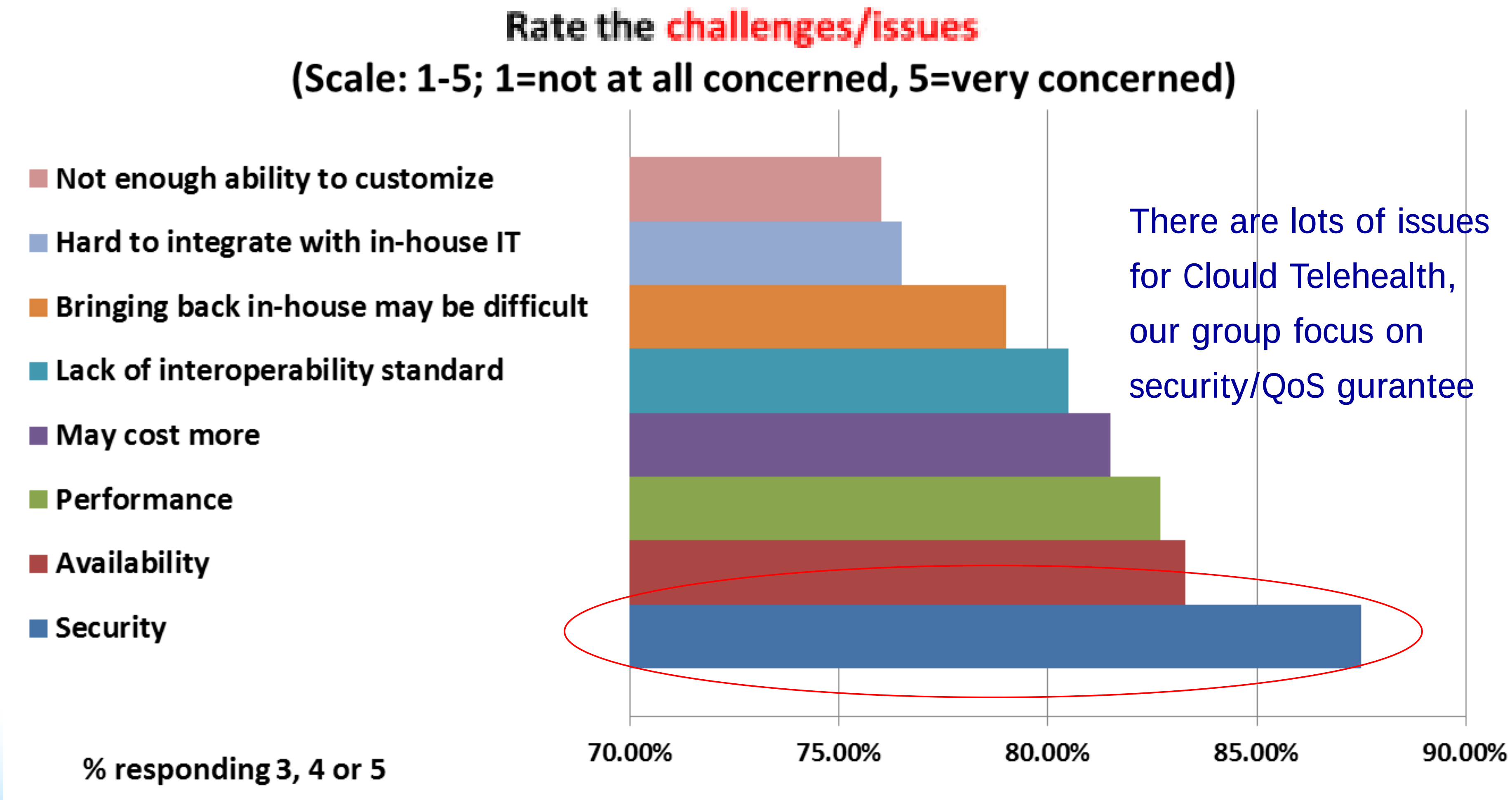
Dynamic Cloud-based network model



IBM Cloud cover USA,
Almost of World!

Security, Dependability

Cloud Challenges



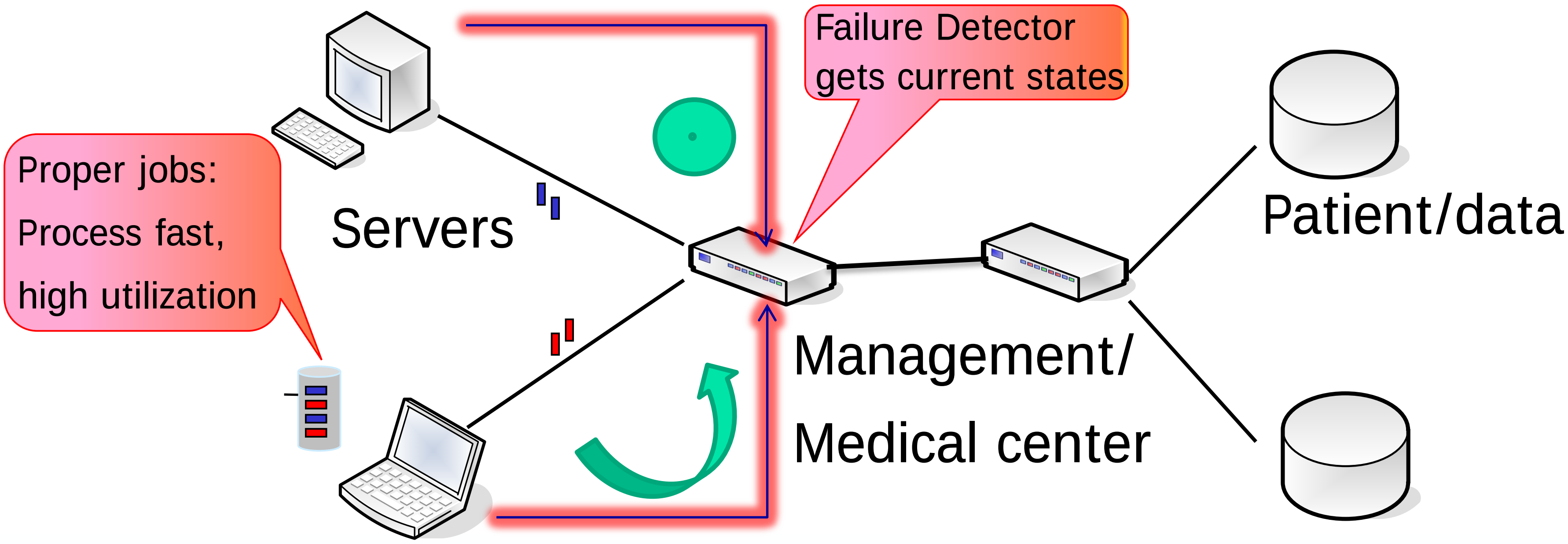
There are lots of issues for Clould Telehealth, our group focus on security/QoS gurantee

How to ensure effective service?

- How to let limited server resources serve more users (high utilization for server resources)?
- How to deliver fair services for the server load?
- How to process the uses' jobs in servers faster or in time?
- How to predict the performance of Servers?

Possible Methods

- **Method**: Use Failure Detector to get current states to dynamically adjust new assignments to the servers (Support by IBM/NSF)



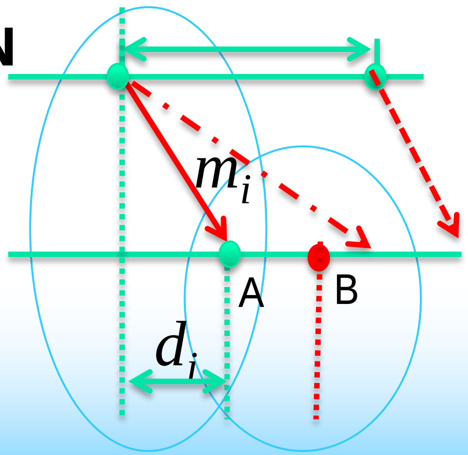
Failure Detectors (FDs): Outline

- **Problems, Model, QoS of Failure Detectors**
- **Existing Failure Detectors**
- 1. **Tuning adaptive margin FD (TAM FD): JSAC**

  Constant safety margin of Chen FD [30]
- 2. **Exponential distribution FD (ED FD): ToN**

  Normal Distribution in Phi FD [18-19]
- 3. **Self-tuning FD (S FD): IPDPS12, ToN**

  Self-tunes its parameters



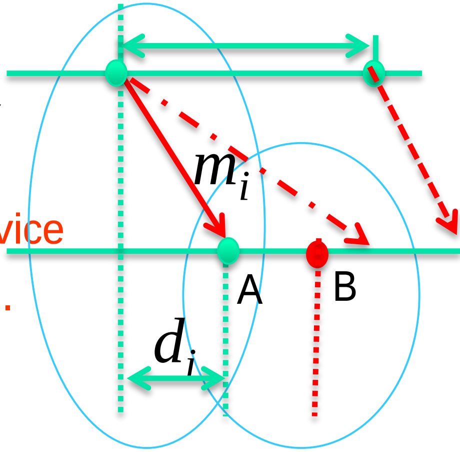
Outline of failure detectors

- **1 Tuning adaptive margin FD (TAM FD)**
- **2 Exponential distribution FD (ED FD):**
  Normal Distribution in Phi FD [18-19]
- **3 Self-tuning FD (S FD):** Self-tunes its parameters

N. Xiong, A. V. Vasilakos, Comparative analysis of quality of service and memory usage for adaptive failure detectors in healthcare systems. IEEE Journal on Selected Areas in Communications, 27(4): 495-509, 2009. Impact Factor：4.8

1. Our TAM-FD Motivation

- Basic Chen-FD scheme [1]: $\tau_{i+1} = EA_{i+1} + \alpha$
  - Probabilistic behavior;
  - Constant safety margin problem;



[1] W. Chen, S. Toueg, and M. K. Aguilera. On the quality of service of failure detectors. IEEE Trans. on Comp., 51(5):561-580, 2002.

- Tuning adaptive margin FD is presented:

How to design or predict the adaptive margin

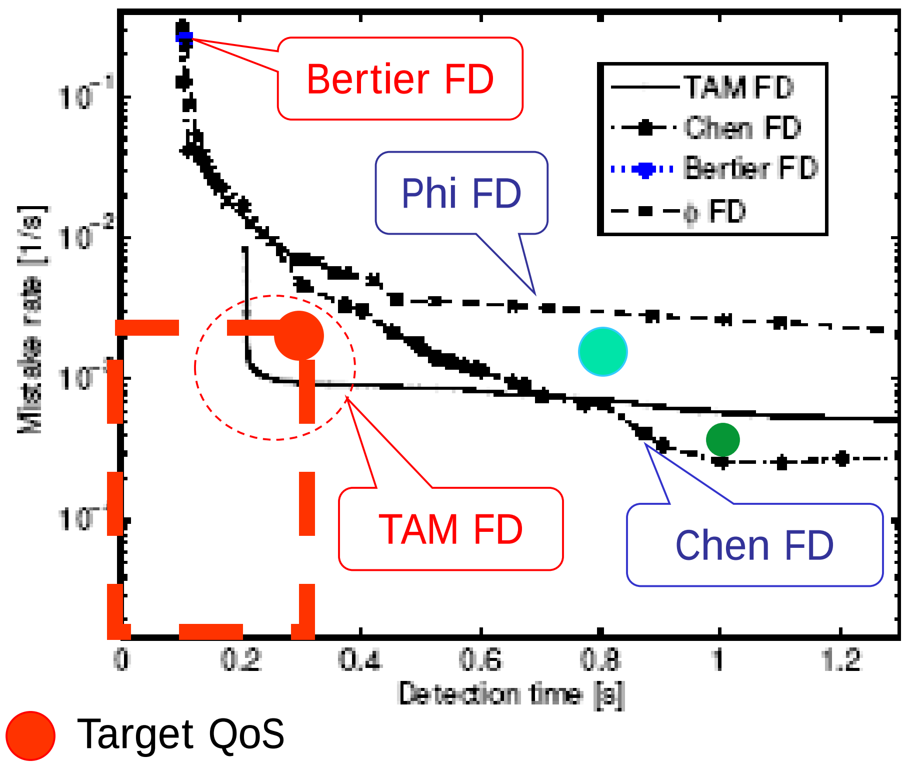
Extensive Experiments

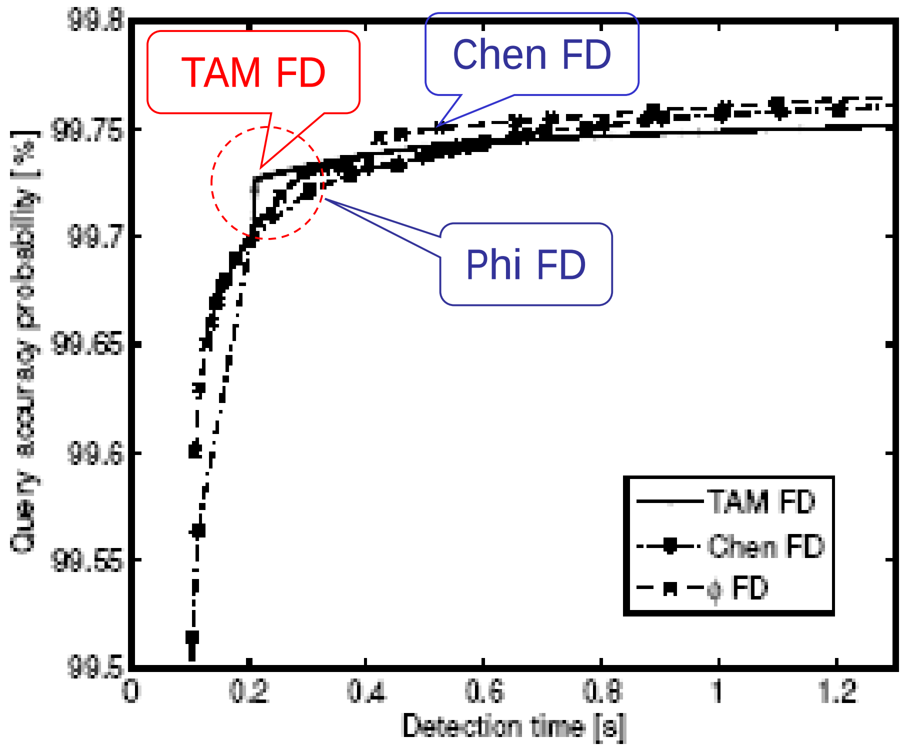
- Cluster, LAN, WIFI, WAN:

WAN case	Sender	Sender-hostname	Receiver	Receiver-hostname
WAN-1	USA	planet1.scs.stanford.edu	Japan	planetlab-03.naist.ac.jp
WAN-2	Germany	planetlab-2.fokus.fraunhofer.de	USA	planet1.scs.stanford.edu
WAN-3	Japan	planetlab-03.naist.ac.jp	Germany	planetlab-2.fokus.fraunhofer.de
WAN-4	China	planetlab2.ie.cuhk.edu.hk	USA	planet1.scs.stanford.edu
WAN-5	China	planetlab2.ie.cuhk.edu.hk	Germany	planetlab-2.fokus.fraunhofer.de
WAN-6	China	plab1.cs.ust.hk	Japan	planetlab1.sfc.wide.ad.jp

Experiment	Heartbeats		Heartbeats period				RTT
case	total (#msg)	loss rate	send (Avg.)	send (stddev)	receive (Avg.)	receive (stddev)	(Avg.)
WAN-1	6, 737, 054	0%	12.825 ms	13.069ms	12.83 ms	14.892 ms	193.909 ms
WAN-2	7, 477, 304	5%	12.176 ms	1.219ms	12.206 ms	19.547 ms	194.959 ms
WAN-3	7, 104, 446	2%	12.21 ms	1.243ms	12.235 ms	4.768 ms	189.44 ms
WAN-4	7, 028, 178	0%	12.337 ms	9.953ms	12.346 ms	22.918 ms	172.863 ms
WAN-5	7, 008, 170	4%	12.367 ms	15.599ms	12.94 ms	16.557 ms	362.423 ms
WAN-6	7, 040, 560	0%	12.33 ms	10.185ms	12.42 ms	17.56 ms	78.52 ms

1. TAM-FD Exp. WAN





MR and QAP comparison of FDs in WAN:

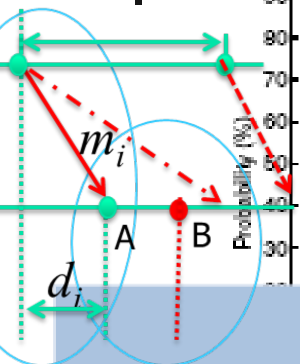
WS=1000 (logarithmic, aggressive, conservative).

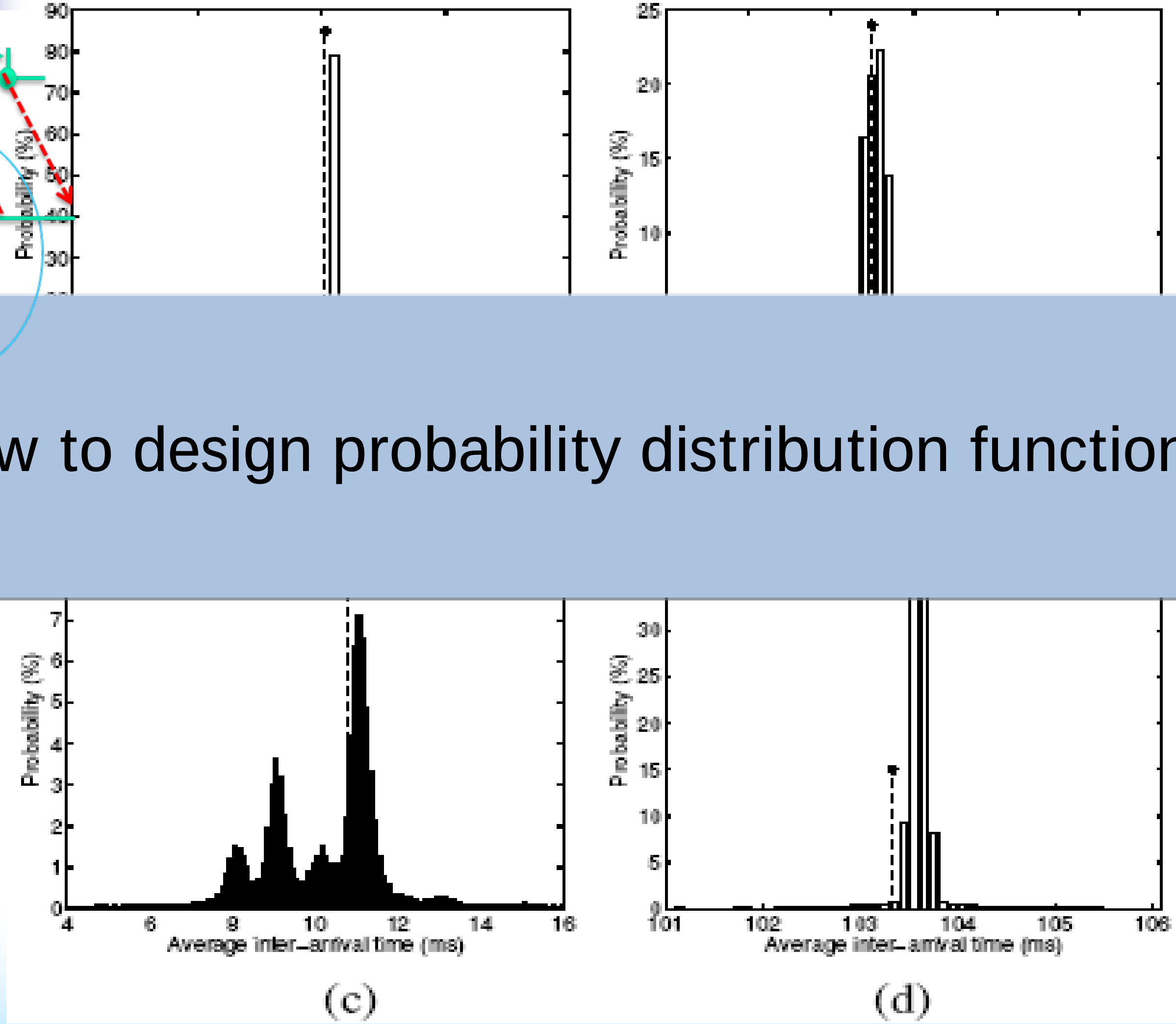
Outline of failure detectors

- 1 Tuning adaptive margin FD (TAM FD)
- **2 Exponential distribution FD (ED FD): Normal Distribution in Phi FD [18-19]**
- **3 Self-tuning FD (S FD):** Self-tunes its parameters

N. Xiong, J. Wu, Y. Richard Yang, and Y. Pan, A Class of Practical Probability Distribution Failure Detection Schemes in Efficient and Reliable Transparent Computing Systems, IEEE Transactions on Computers.

2. ED-FD Motivation 1/2





Min~Max:

50 µs~time unit

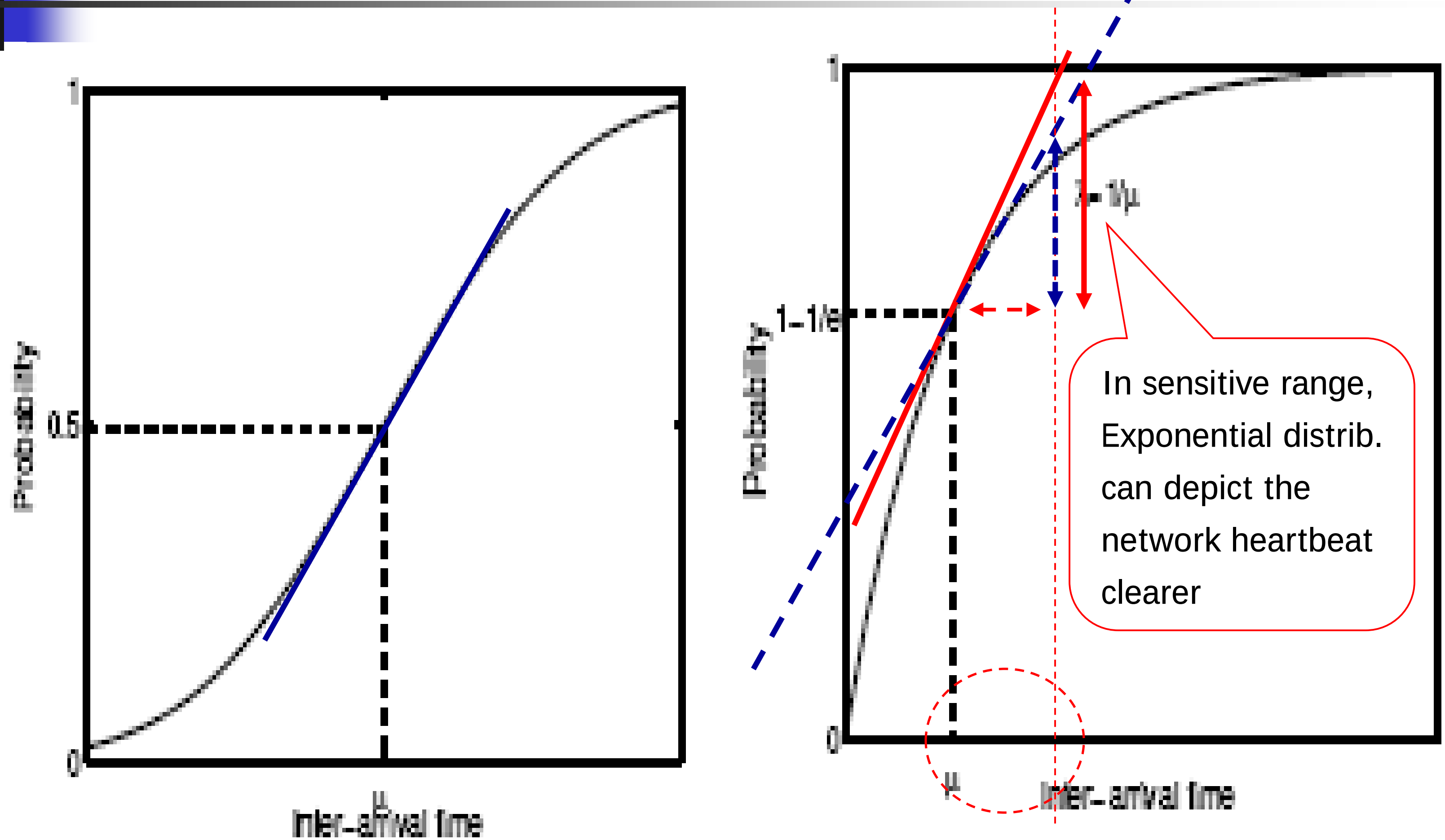
How to design probability distribution function to match it?

P_i~ i

Statistics: (a) Cluster; (b) WiFi; (c) Wired LAN; (d) WAN (N_{unit}/N_{all})

f1+f2+f3+f4=graph; 4 single f for each part; nor F + tag F

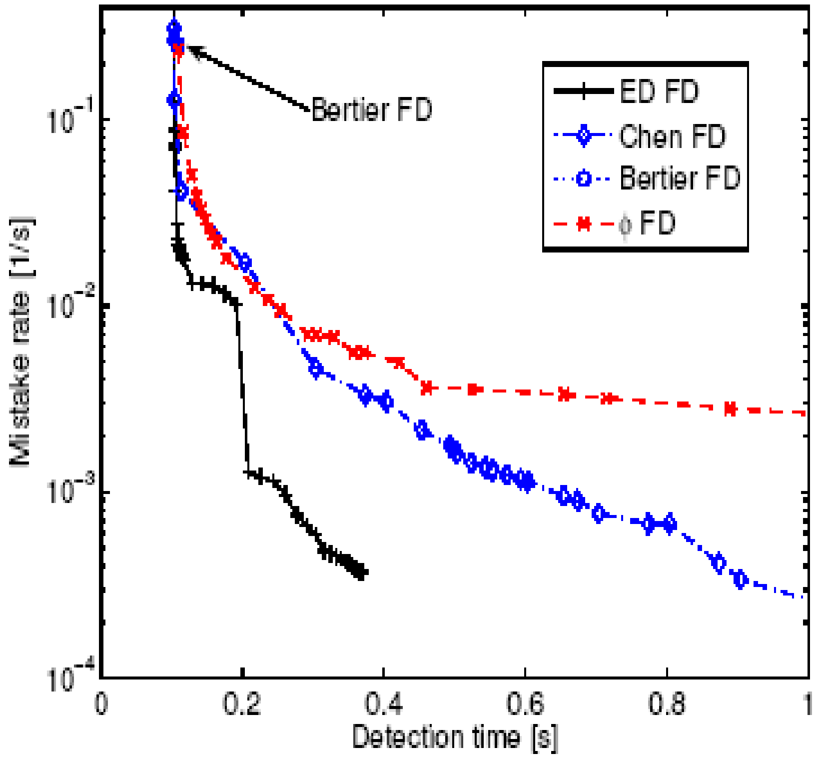
2. ED-FD Motivation 2/2

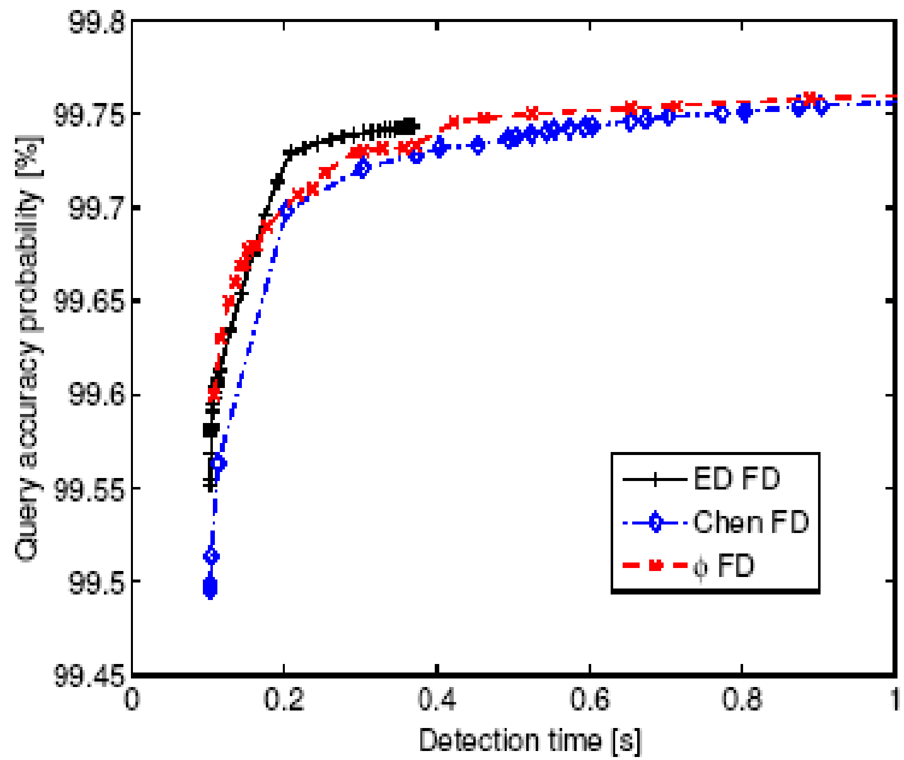


Probability distribution vs. inter-arrival time: Phi FD [18]; ED FD (Normal distribution~ Exponential distribution, slope)

2. ED-FD Exp. WAN2

- Experiment 2:





MR and QAP comparison of FDs in WAN.

Outline of failure detectors

- 1 Tuning adaptive margin FD (TAM FD)
- 2 Exponential distribution FD (ED FD):

  Normal Distribution in Phi FD [18-19]
- **3 Self-tuning FD (S FD): Self-tunes its parameters**

N. Xiong, A. V. Vasilakos, J. Wu, Y. Richard Yang, A. Rindos, Y. Zhou, W. Song, Y. Pan, A Self-tuning Failure Detection Scheme for Cloud Computing Service. IEEE IPDPS 2012: 668-679.

3. Self-tuning FD

- Users give target QoS, How to provide corresponding QoS?

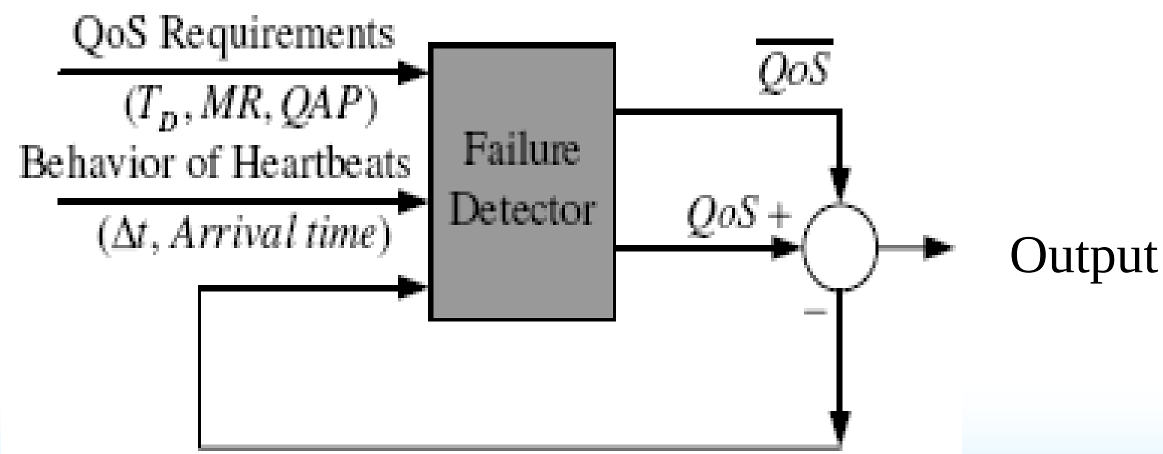
Chen FD [30]

- Giving a list of QoS services for users -- different parameters
- For certain QoS service -- match the QoS requirement
- Choose the corresponding parameters -- by hand.

Problem: it is not applicable for actual engineering applications.

3. Self-tuning FD

- Output QoS of FD does not satisfy target, the feedback information is returned to FD； -- parameters
- Eventually, FD can satisfy the target, if there is a certain field for FD, where FD can satisfy target
- Otherwise, FD gives a response:



How to design Self-tuning schemes to match it?

3. Self-tuning FD

- Basic scheme:

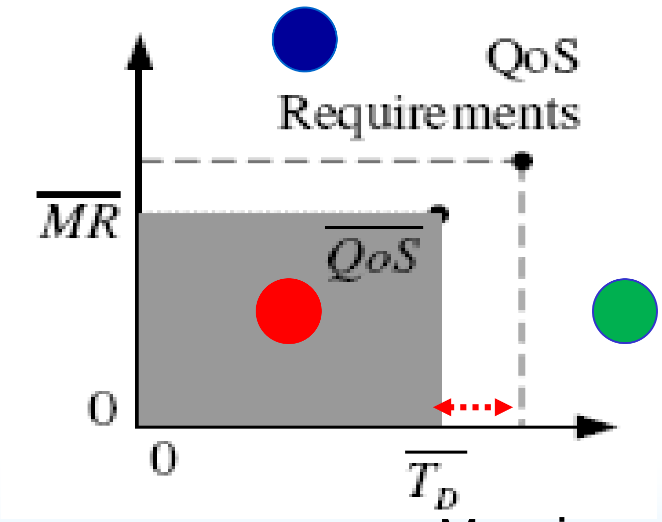
$$\tau_{(k+1)} = SM + EA_{(k+1)},$$

$$SM_{(k+1)} = SM_k + Sat_k\{QoS, \overline{QoS}\} \cdot \alpha,$$

=0;

>0;

<0;



Margin

Variables:

EA_{k+1}: theoretical arrival;

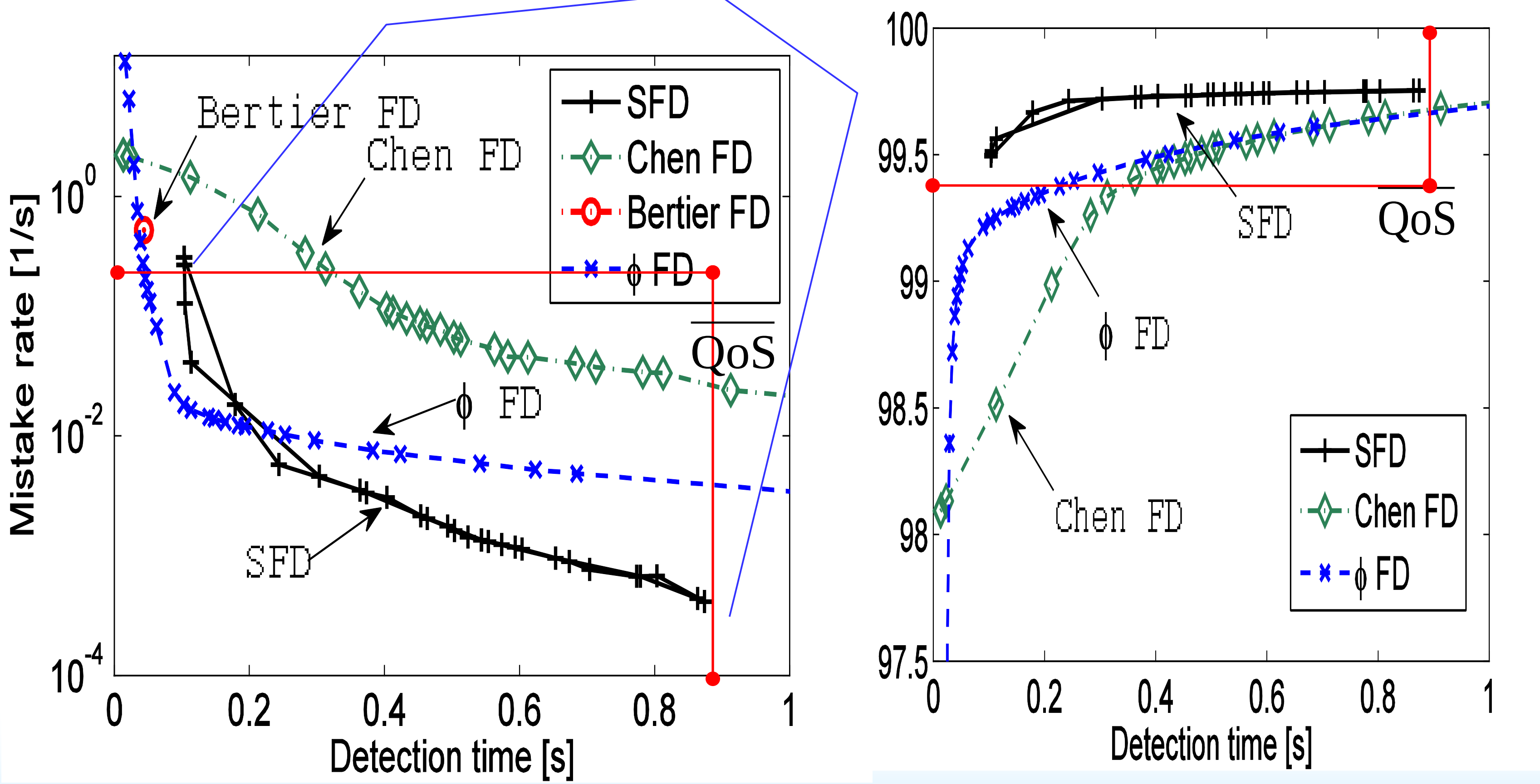
SM: safety margin;

τ_{k+1}: timeout delay;

α : a constant;

3. Self-tuning FD

SFD adjusts next freshness point to get shorter MR, led to larger DT.



MR and QAP comparison of FDs (logarithmic).

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Overview

1 **Introduction**

X. Wang, Y. Ren, Y. Yang, W. Zhang and Neal N. Xiong, A Weighted Discriminative Dictionary Learning Method for Depression Disorder Classification using fMRI Data, DBCloud 2016, Atlanta, GA, USA, Oct 20-23, 2016.

Methods

Experiments and Results

3 **Summary**

Introduction----Background

1.Depression will be the second cause of global disease burden by the year 2020.

2.The diagnosis of depression disorder is mainly dependent on clinical signs and symptoms.

There are evidences for altered fMRI activation patterns in patients with depression disorder.

Developing automatic depression disorder classification methods of fMRI data is of great importance.

Introduction----Problem

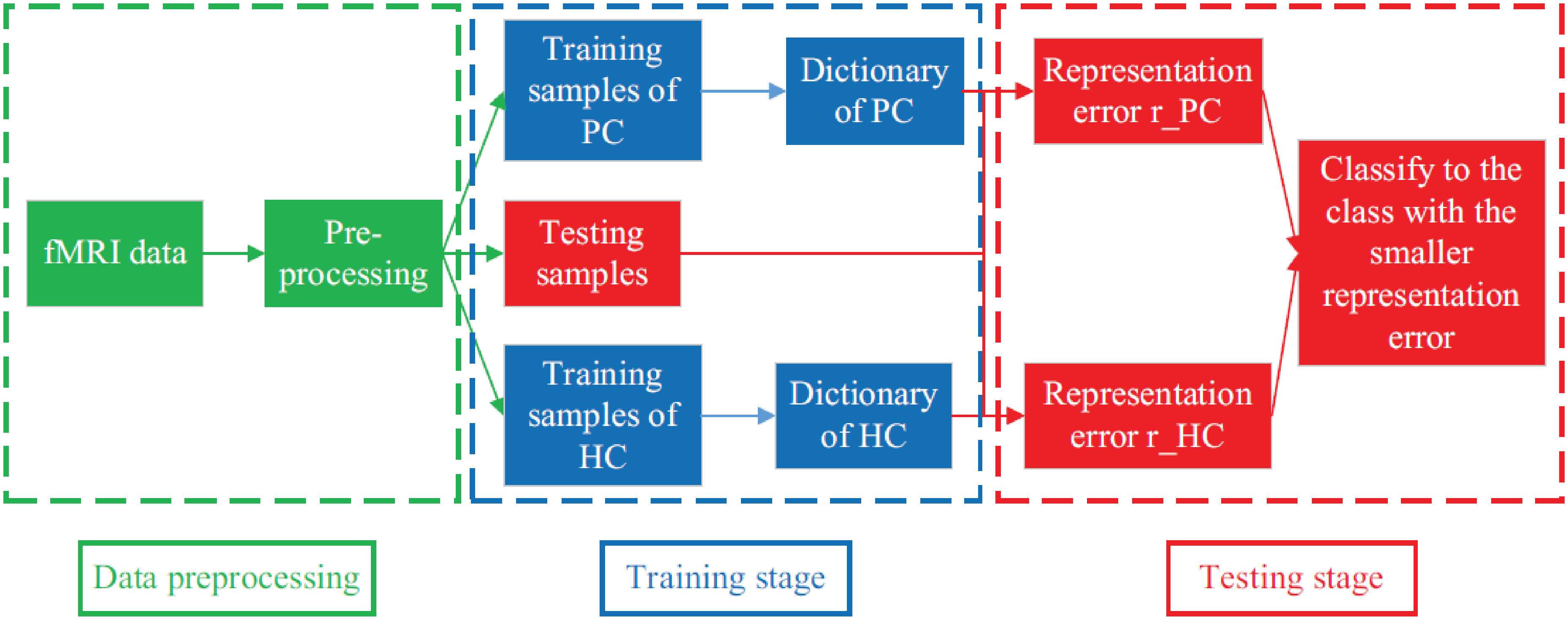
- How to represent fMRI data?
- How to classification fMRI data of patient class and healthy class?

Sparse representation based classification model can represent fMRI data and classification at the same time, such as SRC, DFDL, FDDL.

Drawback

These methods ignore the valuable relationship between the samples and dictionary atoms.

Methods----flow chart



Methods----weighted discriminative dictionary learning(WDDL)

The aim of training stage is to learn dictionary for healthy class and dictionary ' for patient class.

The objective function related to the healthy class of our WDDL method is formulated as follows. (The model of patient class can be solved in a similar way)

$$
\begin{aligned}
\mathrm{J} = \arg \min_{\mathbf{D},\mathbf{S},\tilde{\mathbf{S}}} & \Big(\frac{1}{K}\sum_{i=1}^{K} \mathbf{w}_i \|\mathbf{y}_i - \mathbf{D}\mathbf{s}_i\|_2^2 \\
& - \frac{\rho}{\tilde{K}} \sum_{j=1}^{\tilde{K}} \tilde{\mathbf{w}}_j \|\tilde{\mathbf{y}}_j - \mathbf{D}\tilde{\mathbf{s}}_j\|_2^2\Big) \\
& s.t. \|\mathbf{d}_k\|_2^2 = 1, \|\mathbf{S}\|_0 < \epsilon_1, \|\tilde{\mathbf{S}}\|_0 < \epsilon_2, k = 1, ..., r,
\end{aligned}
$$

$$\mathbf{w}_i = \frac{1}{Z} exp(-\|\mathbf{y}_i - \overline{\mathbf{d}}\|_2^2)$$

Experiments and Results----Experiments

Data

29 patients with depression (14 females, 15 males)

29 age-, sex- and education-matched healthy controls (15 females,14 males)

Evaluation

we employ leave-one-out cross-validation to classifiers. each of the subjects is treated as testing sample in turn, and the rest of subjects are treated as training samples.

Experimental Results

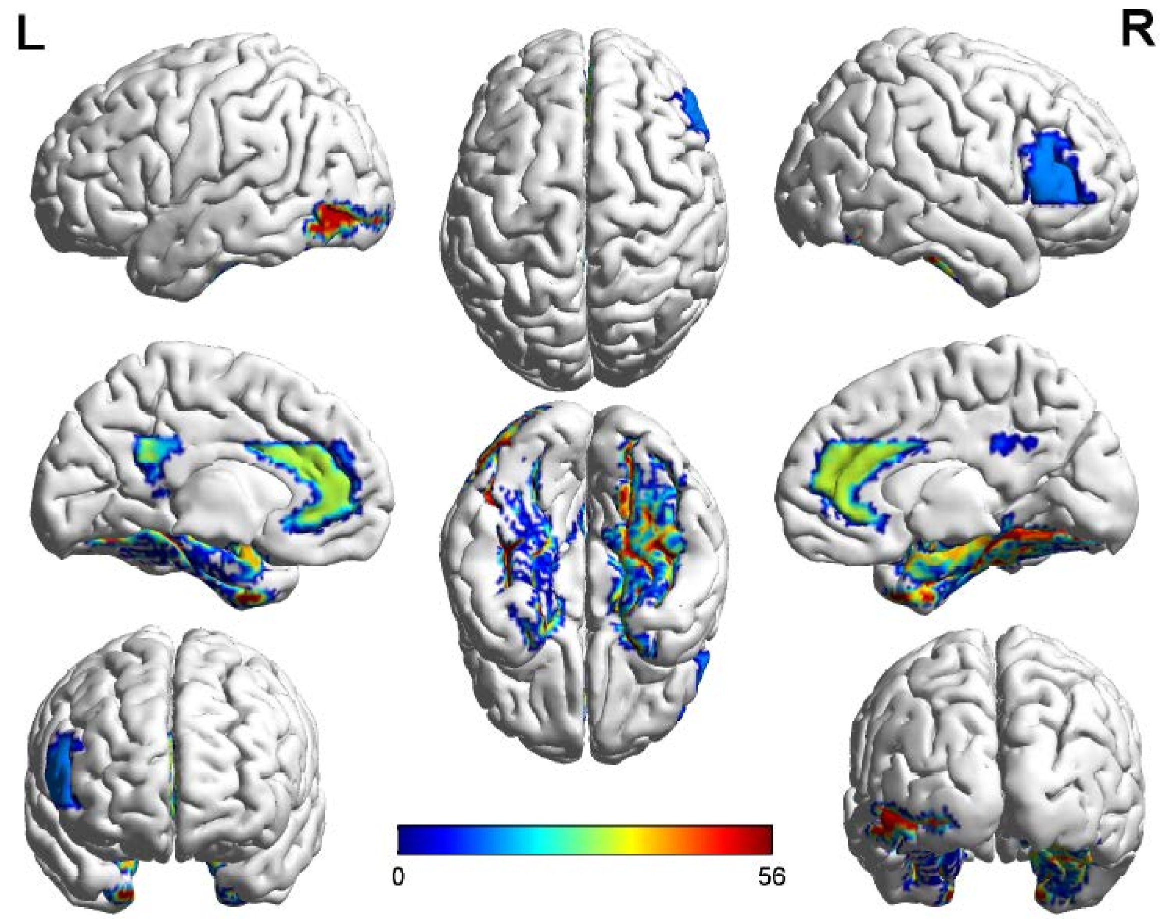


Fig. 2. The ten most discriminative brain regions in patients with depression compared with healthy controls. The color bar indicates the index of brain regions shown in this figure.

Experimental Results

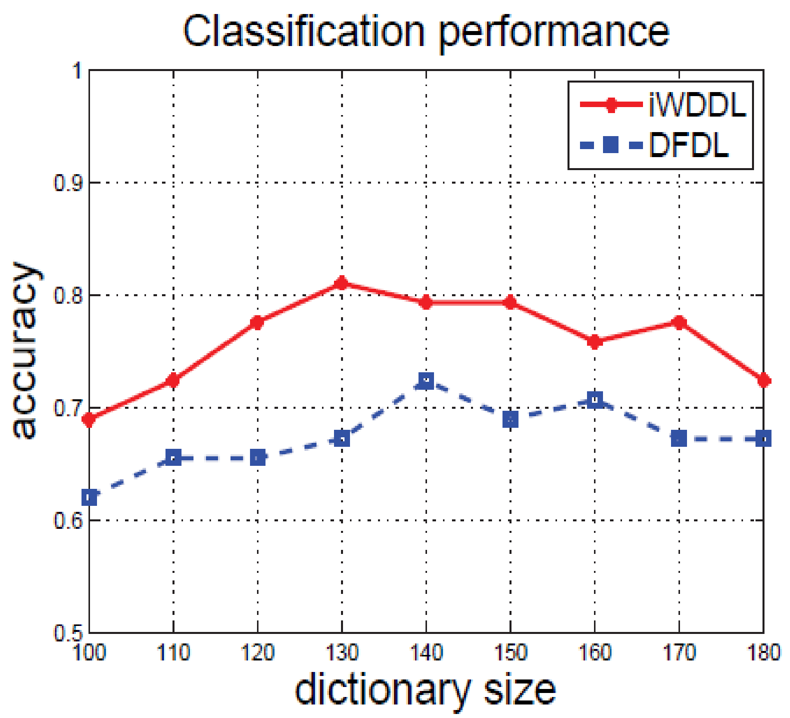


Fig. 3. Classification performance of iWDDL and DFDL with different dictionary size on Depression database.

Experimental Results

Table 4. Classification performance of iWDDL and the compared methods on ADHD database.

Algorithm	Accuracy(%)	Sensitivity(%)	Specificity(%)
SVM	72.73	33.33	87.50
NB	63.64	0.00	87.50
SDC	54.55	33.33	62.50
SRC	72.73	**66.67**	75.00
DFDL	63.64	33.33	75.00
WDDL	81.82	**66.67**	87.50
iWDDL	**90.91**	**66.67**	**100.00**

Summary

- In this paper, we proposed a depression disorder classification method named WDDL, in which classification is based on representation error.
- Weighting scheme was introduced into the representation model to improve classification performance.
- Experimental results demonstrated the effectiveness and improved classification performance of WDDL.

Tech. III

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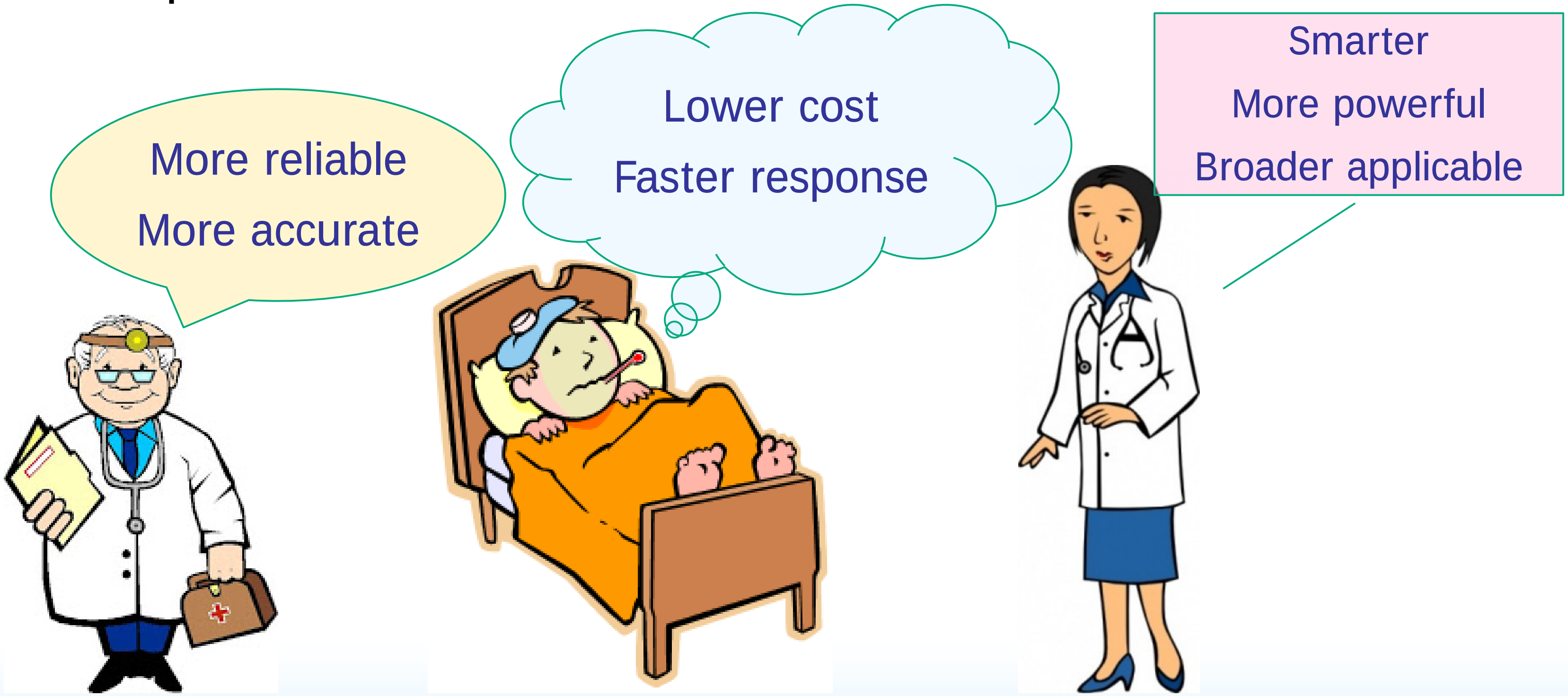
Telehealth

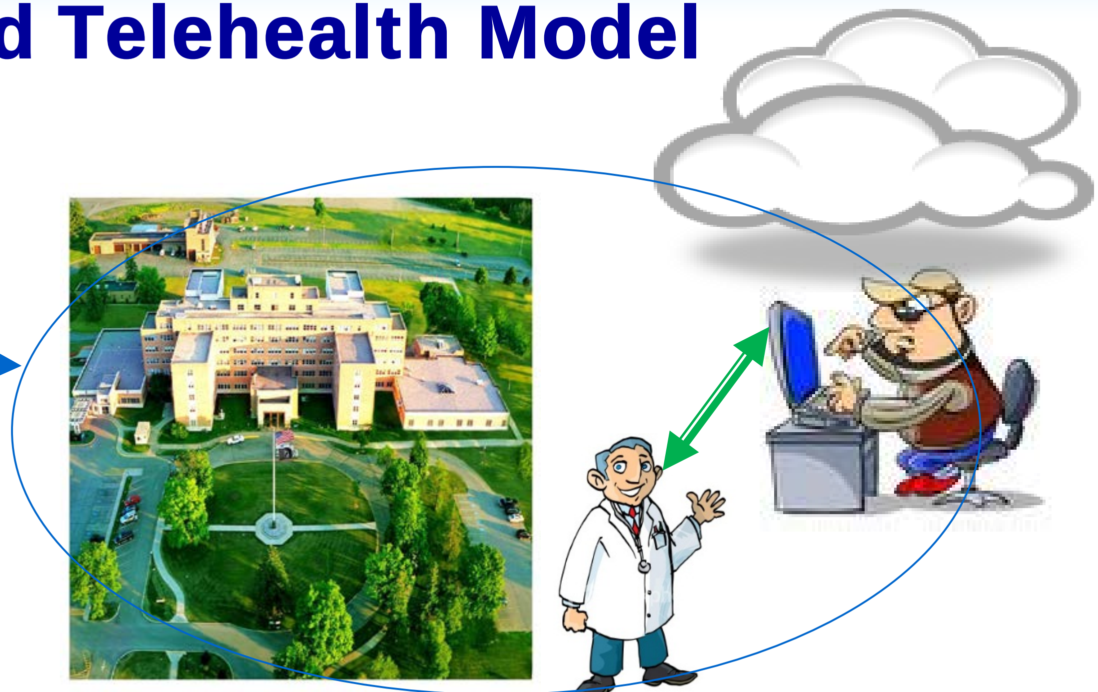
- Increasing Demands
- Doctors/patients have more new demands for Telehealth.



Solution

- Solution: use Cloud Telehealth.
- This is where Cloud Telehealth comes in.

Cloud Telehealth Model



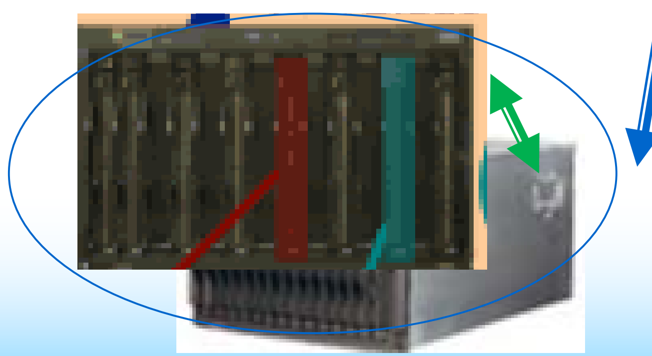
Patient

Doc

Manager/Gateway

Data center

Servers

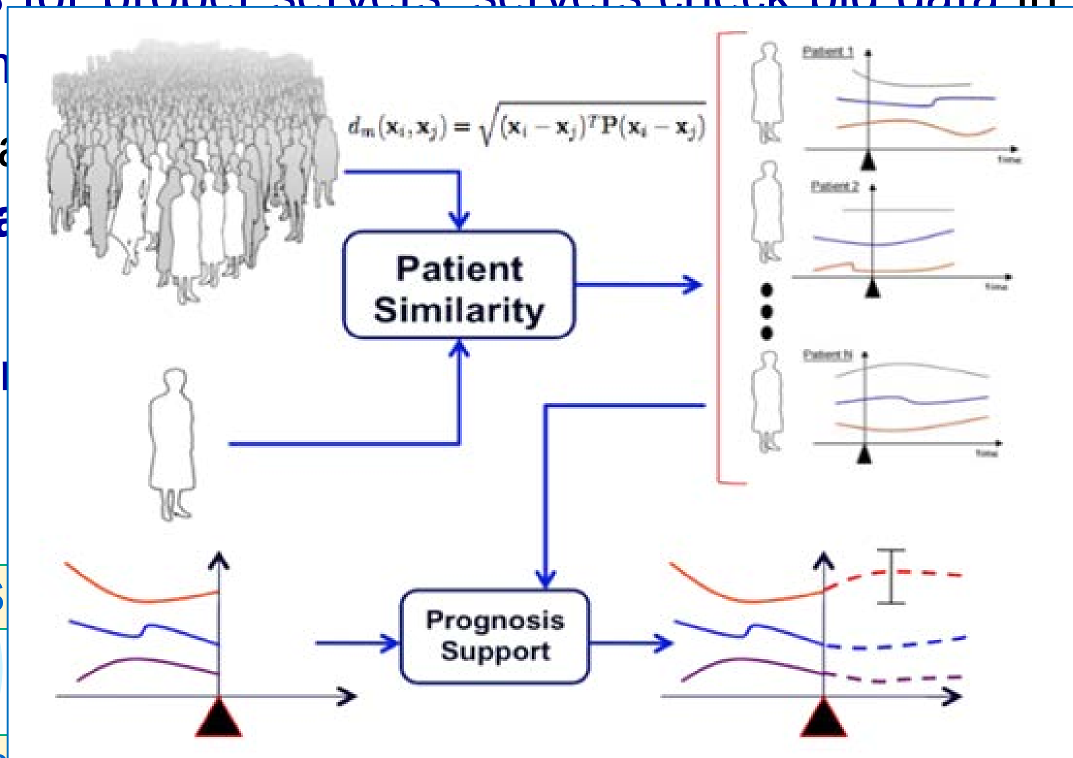


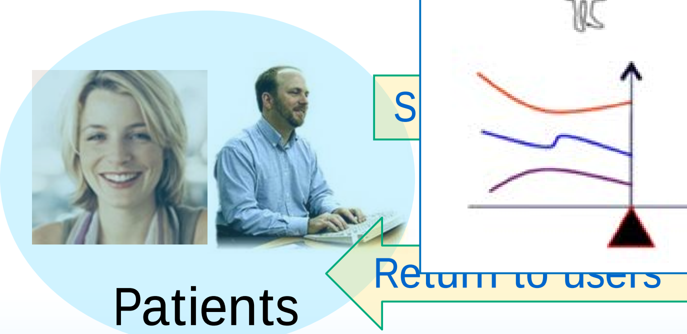
Cloud Telehealth

- 3 key points of Cloud Telehealth
  - **Speed:** is a race against time and death, people expect highly on the speed.
  - **Accuracy:** take a long time if we want to get high accuracy results with complex algorithms. simple and rough methods, fast response -- unreliable results
  - **Reliability:** sometimes, keep the interactions between patients and doctors continuously even if the host server is busy, especially telesurgecy.

Cloud Telehealth: Case 1

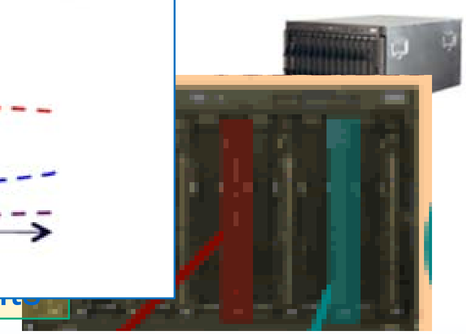
- Manager looks for proper servers, servers check big data in distributed centers to com me.
- Tasks of compa Servers. **Guarantee ea**
- **How to do?** **HB (**lead to la es) **or FD…**





Patients

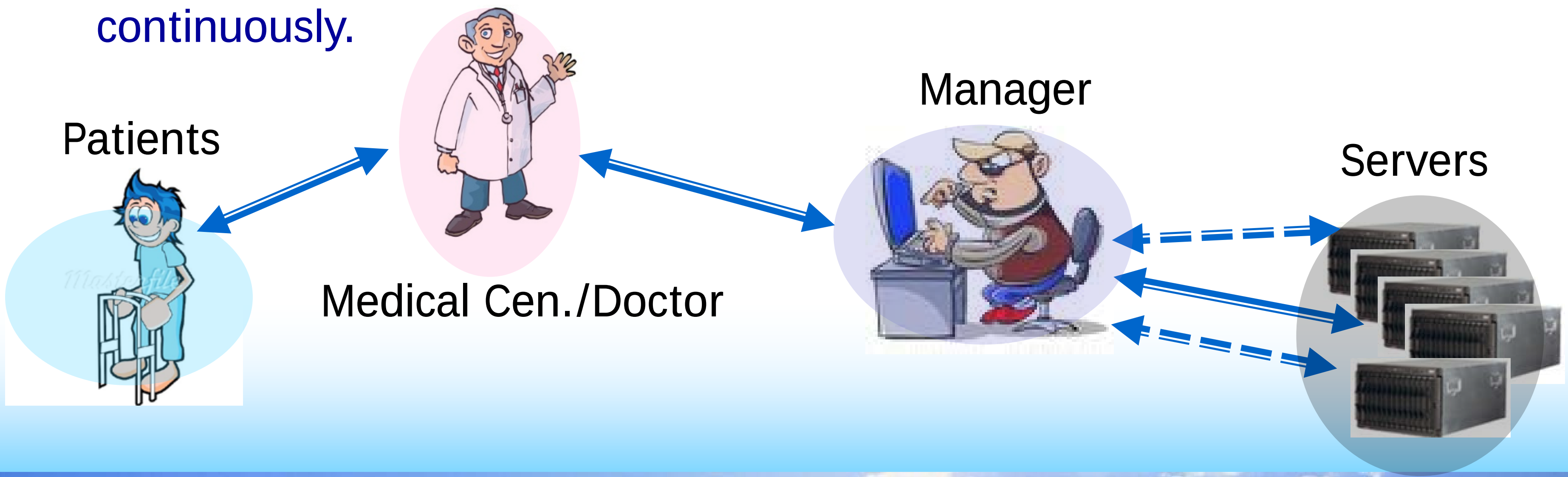
Medical Cen. & Manager



Servers

Cloud Telehealth: Case 2

- For the telesurgery, Server supports the service for Doctor, and this session should be stable.
- If Server is not stable, this session/patient is at risk. Manager should choose/monitor these servers, and predict the service performance.
- If this service is not good enough, manager can find a backup server.
- **Guarantee** Servers support Doctor with Info (images) by Manager continuously.



Questions?

धन्यवाद
Hindi

多謝
Traditional Chinese

ขอบคุณ
Thai

Спасибо
Russian

Gracias
Spanish

Thank You
English

شكراً
Arabic

Merci
French

Obrigado
Brazilian Portuguese

Grazie
Italian

多谢
Simplified Chinese

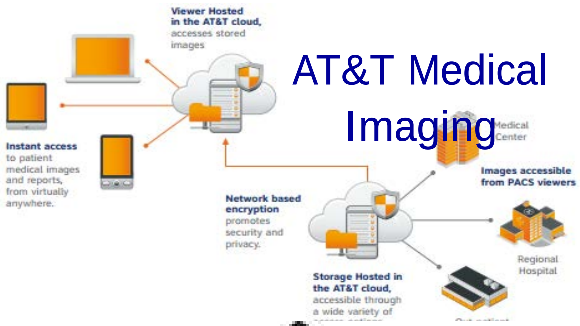
Danke
German

நன்றி
Tamil

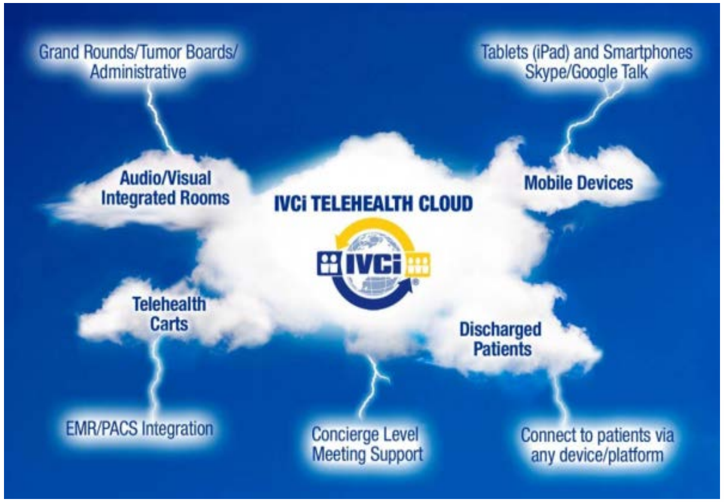
ありがとうございました
Japanese

감사합니다
Korean

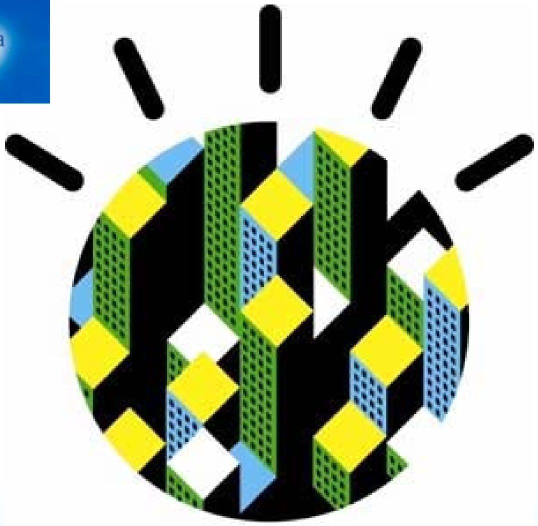
Cloud Telehealth Applications



AT&T Medical Imaging



CTN CALIFORNIA TELEHEALTH NETWORK



IBM Smarter Healthcare

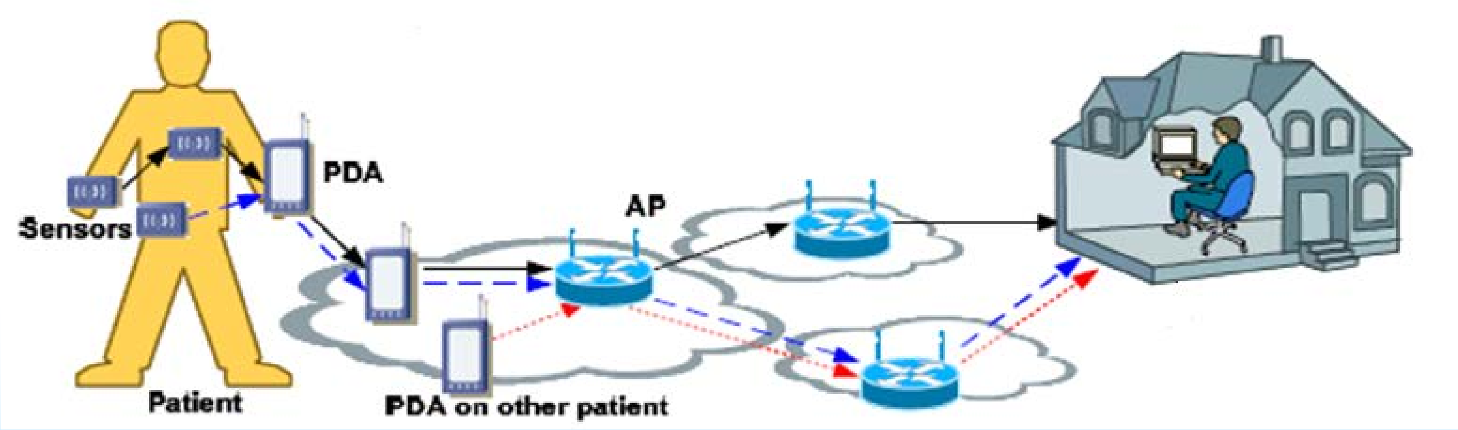
IBM Healthcare Solutions for Cities

Cloud Telehealth vs Traditional Telehealth

- Advantages
  - Has the medical center + massive amounts of medical data in widely located servers:
    Get more reliable results by comparing and analyzing huge database,
    Has immense computing power and nearly limitless storage.
  - Doctors can make more accurate diagnosis effectively, and get more assistance.
  - For doctors and hospitals, can broaden scope of their services and reduce cost. the vulnerable group may benefit from Telehealth.
    Also can enhance their medical capabilities.

Telehealth

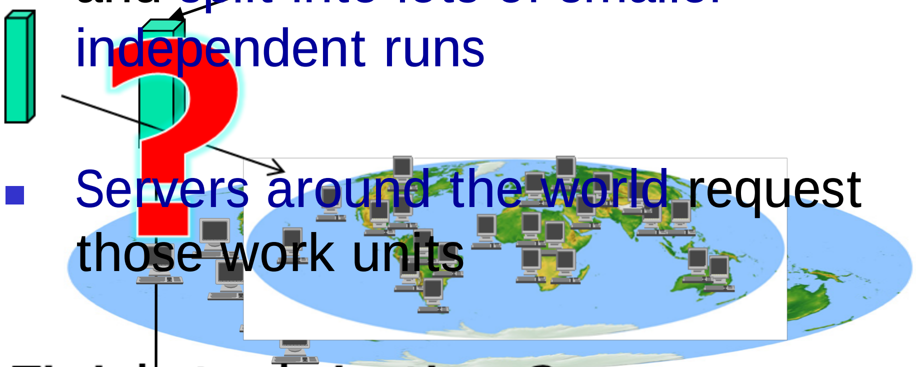
- What is Traditional Telehealth?
  - Telehealth is delivery of health-related services via telecommunications technologies, it is a service based on advanced technologies solution for both doctors and patients.
  - For patients, get necessary assistance in emergency
  - For doctors, Telehealth can help them to make a diagnosis



Challenge: Case 1

- Historical big data is distributed and split into lots of smaller independent runs
- Servers around the world request those work units
- Each server compares related historical big data with this patient info, and get its result.
- Merge all results into statistic result for Doctor.

Millions of nodes, which one?



Finish task in time?

No congestion?

Reasonable delay?

Reliability, fast response