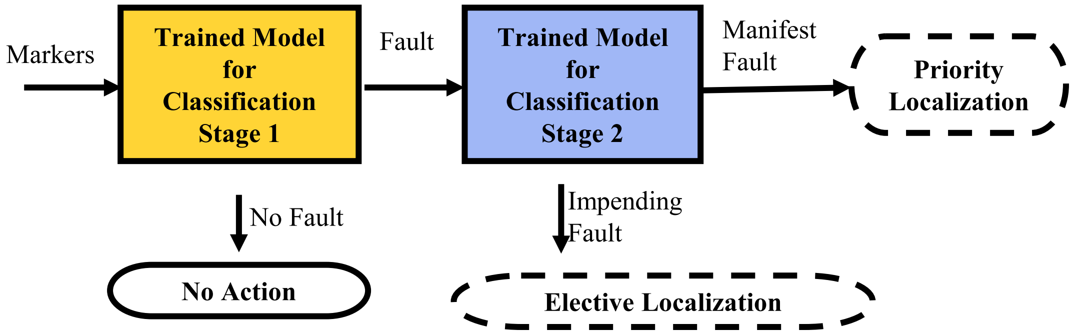
Fault and Performance Management in Multi-Cloud Based NFV using Shallow and Deep Predictive Structures



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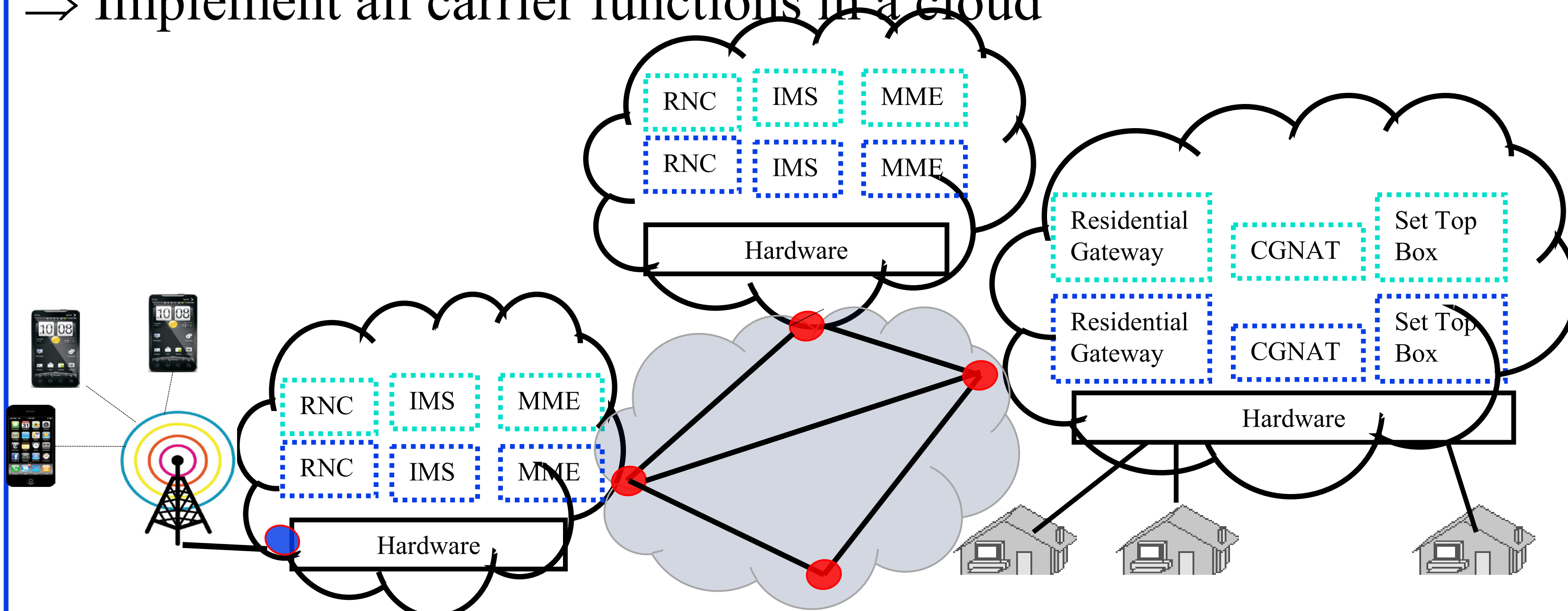
These slides and a recording of this presentation are at:
http://www.cse.wustl.edu/~jain/talks/iccn17p.htm

1. Network Function Virtualization (NFV)
2. NFV on multiple clouds
3. Gaps in Fault, Configuration, Accounting, Performance and Security (FCAPS)
4. Fault detection using Shallow Learning
5. Fault location using Deep Learning

Network Function Virtualization

- Standard hardware is fast and cheap
  ⇒ No need for specialized hardware
- Implement all functions in software
- Virtualize all functions ⇒ Create capacity on demand

⇒ Implement all carrier functions in a cloud

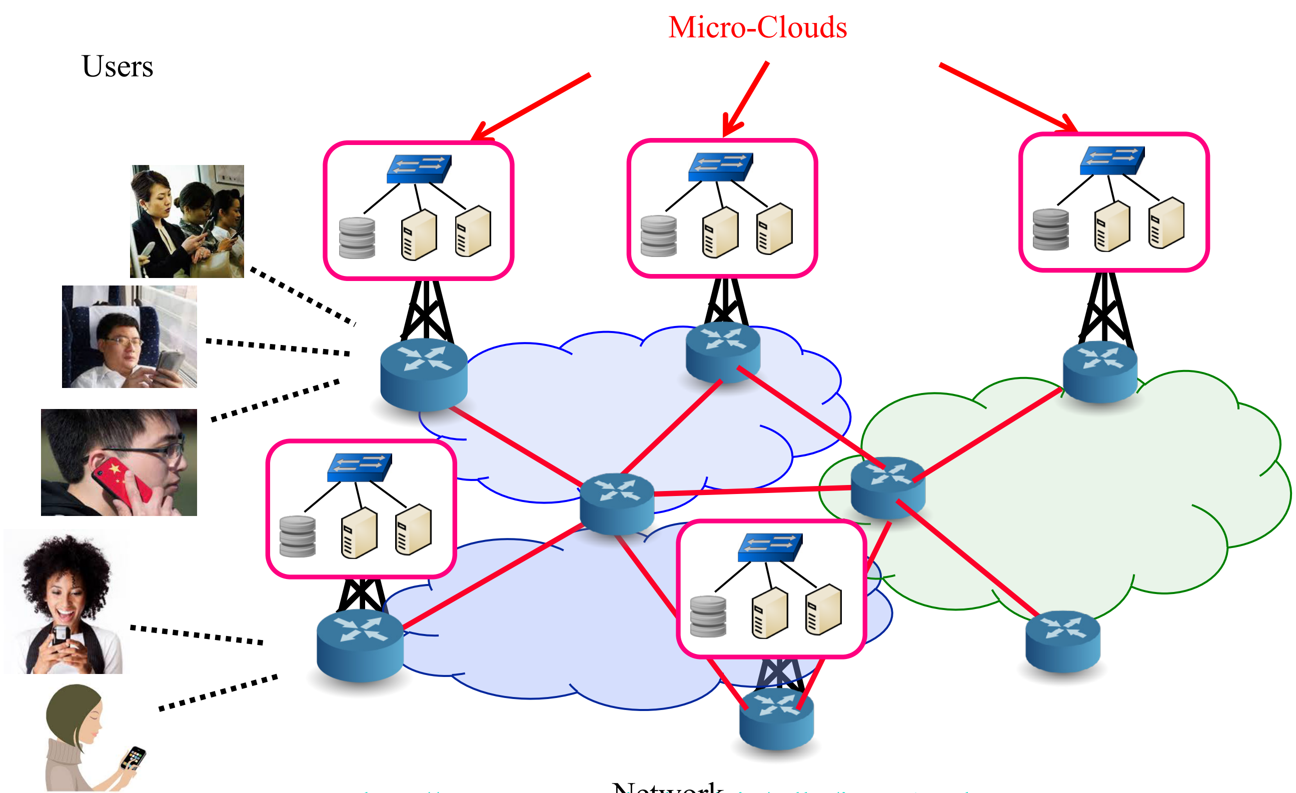


Advantages of NFV

- Reduces time to market new services
- Provides flexibility of scaling
- Lowers capital and operational costs

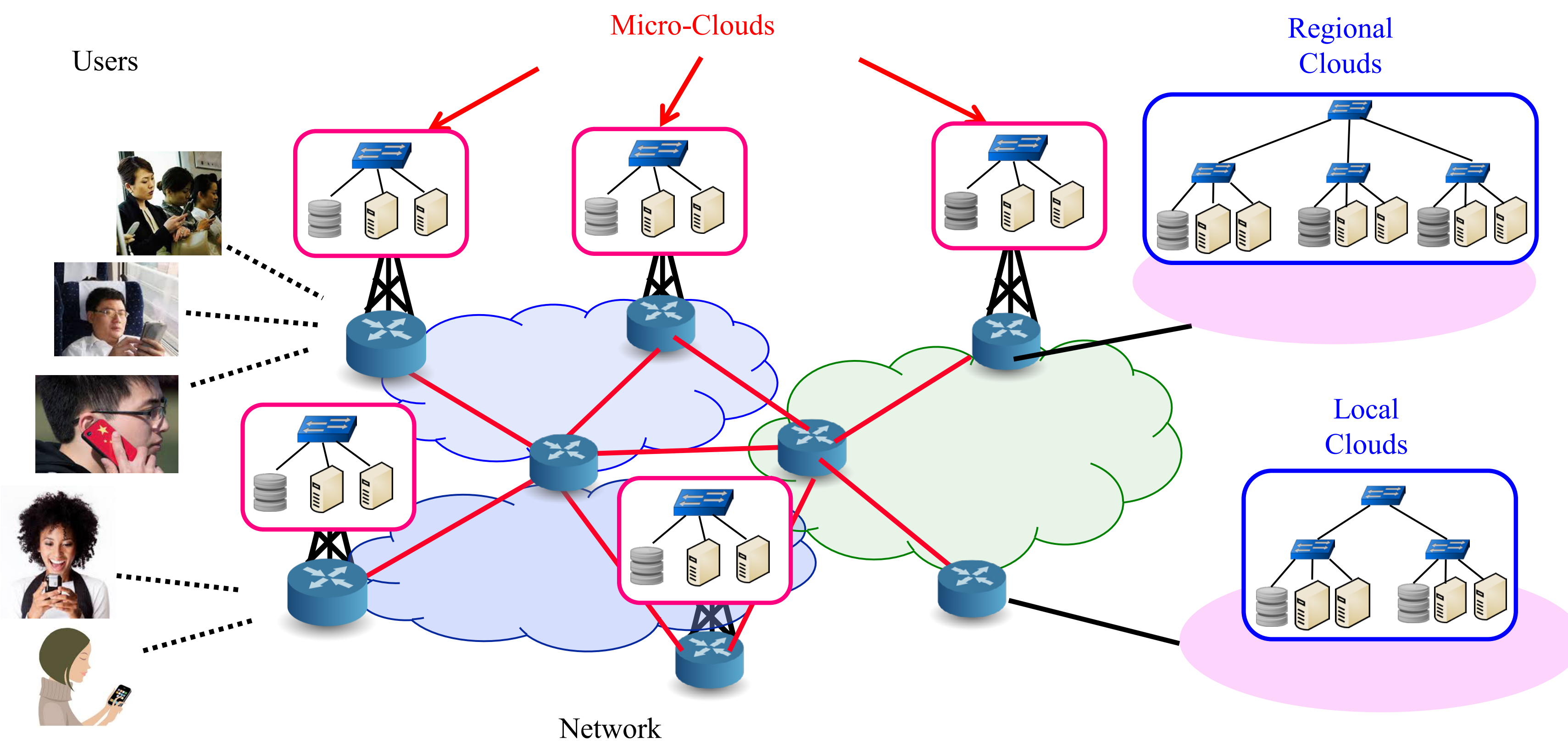
Trend: Computation in the Edge

- To service mobile users/IoT, the computation needs to come to edge ⇒ Mobile Edge Computing



Trend: Multi-Cloud

- Larger and infrequent jobs serviced by local and regional clouds



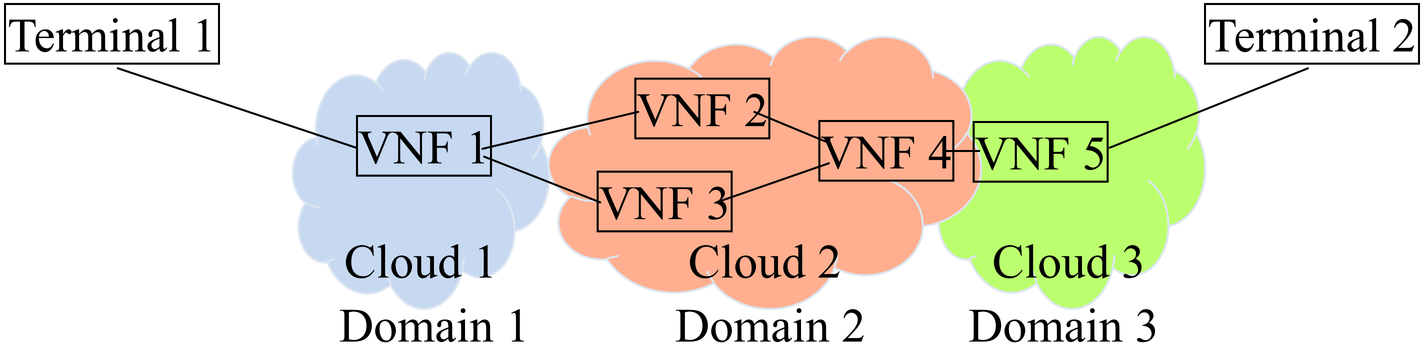
Advantages of NFV on Multi-Cloud

- Wider footprint for distributed services.
- Lower risk of total failure.

Issues in Multi-Cloud NFV Deployments

- Cloud downtime higher than five nines requirement of NFV (99.999% $\Rightarrow$ 3 min 15sec downtime in 1yr).
- Higher complexity of virtual environments
- FCAPS framework is weak compared to traditional carrier networks.
- Not yet carrier grade
- In this paper we deal primarily with the FCP part of FCAPS.
- From now on: Fault = Faults and Performance Issues

Network Services (NS)



- **Network Service**: An ordered set of virtual network functions (VNFs), e.g., IMS, Mobility Management Entity (MME), …
- VNFs are chained into **service function chains (SFC)** or VNF graphs
- Multiple levels of management
  - VNFs by NFV-MANO (Management and Orchestration)
  - Virtual Machines (VMs) by Multi-cloud Management and Control Platform (MMCP)
  - Network services by BSS/OSS (Business and Operation Support Systems) of the carrier.

FCP Problem Description

1. Study of ***markers*** and ***metrics***
2. **Detection**: of manifest and impending faults and that could cause performance degradation or failure.
3. **Localization**: of manifest and impending faults and performance issues.
4. **Severity**: In case of impending faults severity level should be predicted.

Markers and Metrics

- **Markers:** Alarms, notifications, warning or error messages, measurements and counter values.

Mobile Network	**Fixed Network**	**Broadband**
Radio Link Time Out	No Dial Tone	Intermittent Connection
Time Slot Shortage	Line Cart Port Faulty	Repeated Training

- **Metrics:** Performance Measures

CDR (call drop rate)	CSSR (call set up success rate)	SDCCH congestion	TCH Congestion	Packet loss
$\leq 2\%$	$\geq 95\%$	$\leq 1\%$	$\leq 2\%$	$\leq 1\%$
SDCCH: Standalone Dedicated Control Channel; TCH: Traffic Channel				

Description of Training Datasets

The Telstra Dataset (2016) [1]

- The Telstra datasets (2016) are derived from the fault log files containing real customer faults
- Table 1: Training dataset containing location and severity of faults (0 indicating no fault, 1 indicating a few faults and 2 indicating many faults.). These are identified by the "id" key.
- Table 2: Test dataset for prediction of fault severity
- Table 3: Event type gives the type of fault
- Table 4: Resource involved in the fault
- Table 5: Severity type gives warning given by the system
- Table 6: Feature dataset contains various markers

Ref: Kaggle datasets, https://www.kaggle.com/datasets

Telstra Dataset Samples

Table 1 Training Dataset (7381 examples)

id	location	fault_ severity
14121	location 118	1
9320	location 91	0
14394	location 152	1
8218	location 931	1
14804	location 120	0
1080	location 664	0
9731	location 640	0
15505	location 122	0
3443	location 263	1
13300	location 613	1

Table 2 Test dataset (11171 examples)

id	location
11066	location 481
18000	location 962
16964	location 491
4795	location 532
3392	location 600
3795	location 794
2881	location 375
1903	location 638
5245	location 690
6726	location 893

Table 3 Event type dataset (31170 records)

id	event_type
6597	event_type 11
8011	event_type 15
2597	event_type 15
5022	event_type 15
5022	event_type 11
6852	event_type 11
6852	event_type 15
5611	event_type 15
14838	event_type 15
14838	event_type 11

Table 4 Resource type dataset (21076 records)

id	resource_type
6597	resource_type 8
8011	resource_type 8
2597	resource_type 8
5022	resource_type 8
6852	resource_type 8
5611	resource_type 8
14838	resource_type 8
2588	resource_type 8
4848	resource_type 8
6914	resource_type 8

Table 5 Severity type (18552 records)

id	severity_type
6597	severity_type 2
8011	severity_type 2
2597	severity_type 2
5022	severity_type 1
6852	severity_type 1
5611	severity_type 2
14838	severity_type 1
2588	severity_type 1
4848	severity_type 1
6914	severity_type 1

Table 6 Feature dataset (58671 records)

id	log_feature	volume
6597	feature 68	6
8011	feature 68	7
2597	feature 68	1
5022	feature 172	2
5022	feature 56	1
5022	feature 193	4
5022	feature 71	3
6852	feature 201	2
6852	feature 56	1
6852	feature 80	2

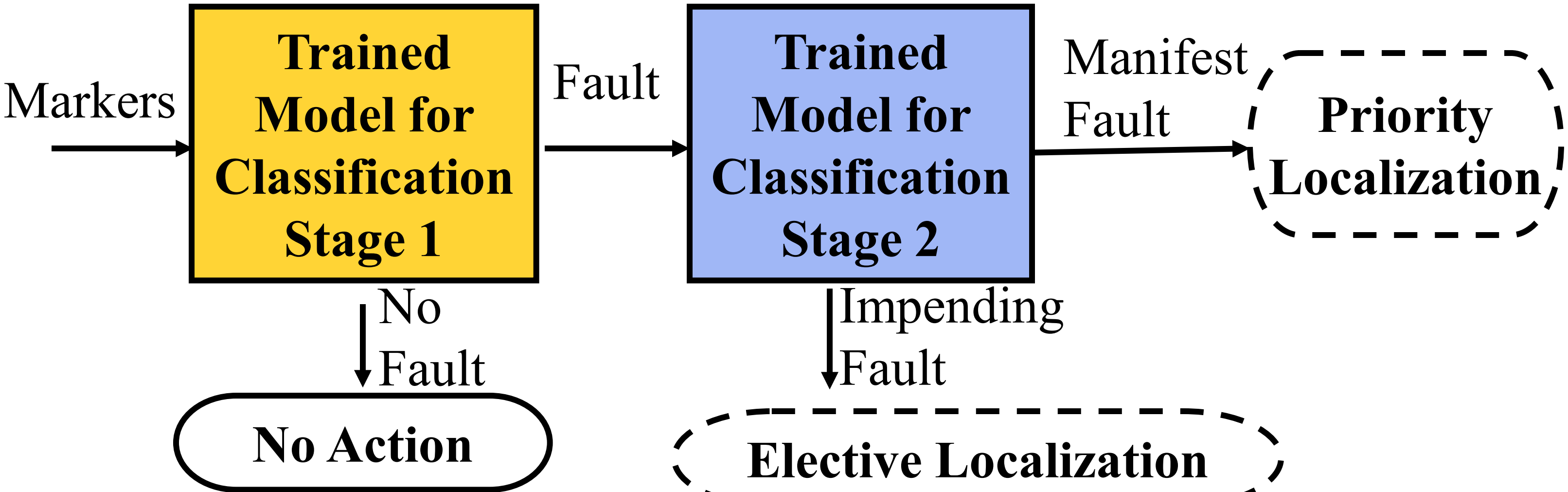
KDE dataset

- This is a synthetic dataset generated through multivariate kernel density estimation (KDE) technique [2]
- Some of the features and classes are shown in the table

	Features		Classes
1	BTS hardware	1	Call drop
2	Radio link phase	2	Call setup
3	Antenna tilt	3	No Roaming
4	C/I ratio	4	Weak Signal
5	TCH congestion	5	No registration
6	BCC fault	6	No outgoing
7	Time slot short	7	Data not working
8	Rx Noise		

Fault Detection

- Goal: Correlate markers to infer *manifest* or to predict *impending* performance and fault conditions.
- Two stage machine learning model:



- Minor faults and warnings are the main contributors to the impending faults and need to be analyzed.

Detection of Faults and Performance Problems

- 'Fault', "No Fault' binary classification tested with Support Vector Machine (SVM), Alternating Decision Trees (ADT) and Random Forests (RF)
- Each of the models was trained with 240 examples and 10% cross-validation.
- SVM had highest accuracy and precision, high true positive (TP) rate for class 1 (fault cases)

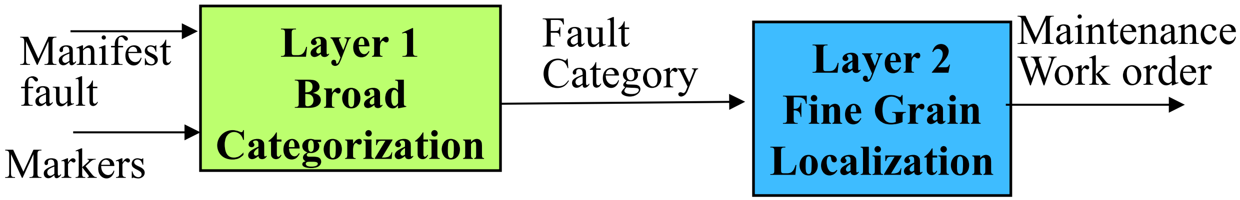
	SVM	ADT	Random Forests
Correctly classified instances	95.42%	95.00%	86.67%
Precision (Average)	95.7%	95.2%	86.9%
Mean absolute error	0.0458	0.0859	0.2509
True positive for class 1	97.6%	96.4%	69.9%
False positive for class 0	2.4%	3.6%	30.1%

Detection (cont.)

- The second model was trained to classify fault as *manifest* or *impending*.
- Prediction rate was 100% with SVM in test set for predicting impending faults from warning cases.
- Comparison with other works:
  - In [3] the authors used SVM to classify wind turbine faults using operational data and achieved 99.6% accuracy.
  - In [4] wind turbine faults were detected with accuracy 98.26% for linear SVM and 97.35 for Gaussian.
  - In [5] authors achieved 99.9% accuracy of classification of faults in rotating machinery with SVM.

Localization of Faults

- Two layered machine learning model for localizing manifest faults:



- Deep learning (Stacked Autoencoder) for impending faults:

- Reasons:
  - Automatic selection of features from high dimensional data
  - Filtering information through the layers for better accuracy
  - Gives improved results in other areas

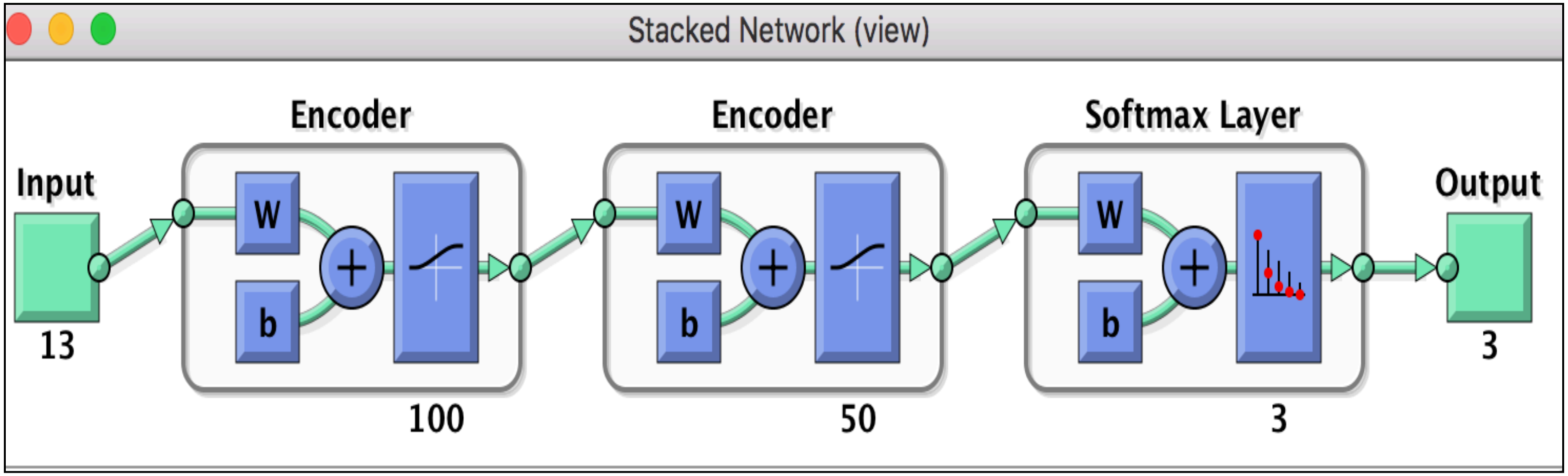
Localization of Faults and Performance Problems

- Telstra dataset was adapted for evaluation

1	Id	5	Resource type 1 to 10
2	Location	6	Severity type 1 to 5
3	Features 1 to 386	7	Event type
4	Volumes for features	8	Fault severity level

- Fault severity level classes: No fault (0), a few faults (1) and many faults (2) and are based on actual faults reported by users
- Severity Type: Intensity of the warning – predicts impending faults

Stacked Autoencoder



- 100 Hidden layers in the first encoder
- 50 Hidden layers in the 2nd encoder
- Softmax layer provides supervised back-propagation improvement of the weights learned during unsupervised training.

Confusion Matrix

W/O Sparsity Regularization

Output Class \ Target Class	1	2	3	
1	12 44.4%	0 0%	0 0%	100% 0%
2	1 3.7%	7 25.9%	0 0%	87.5% 12.5%
3	0 0%	0 0%	7 25.9%	100% 0%
	92.3% 7.7%	100% 0%	100% 0%	96.3% 3.7%

ρ=0.05, β=1, Accuracy=96.3%

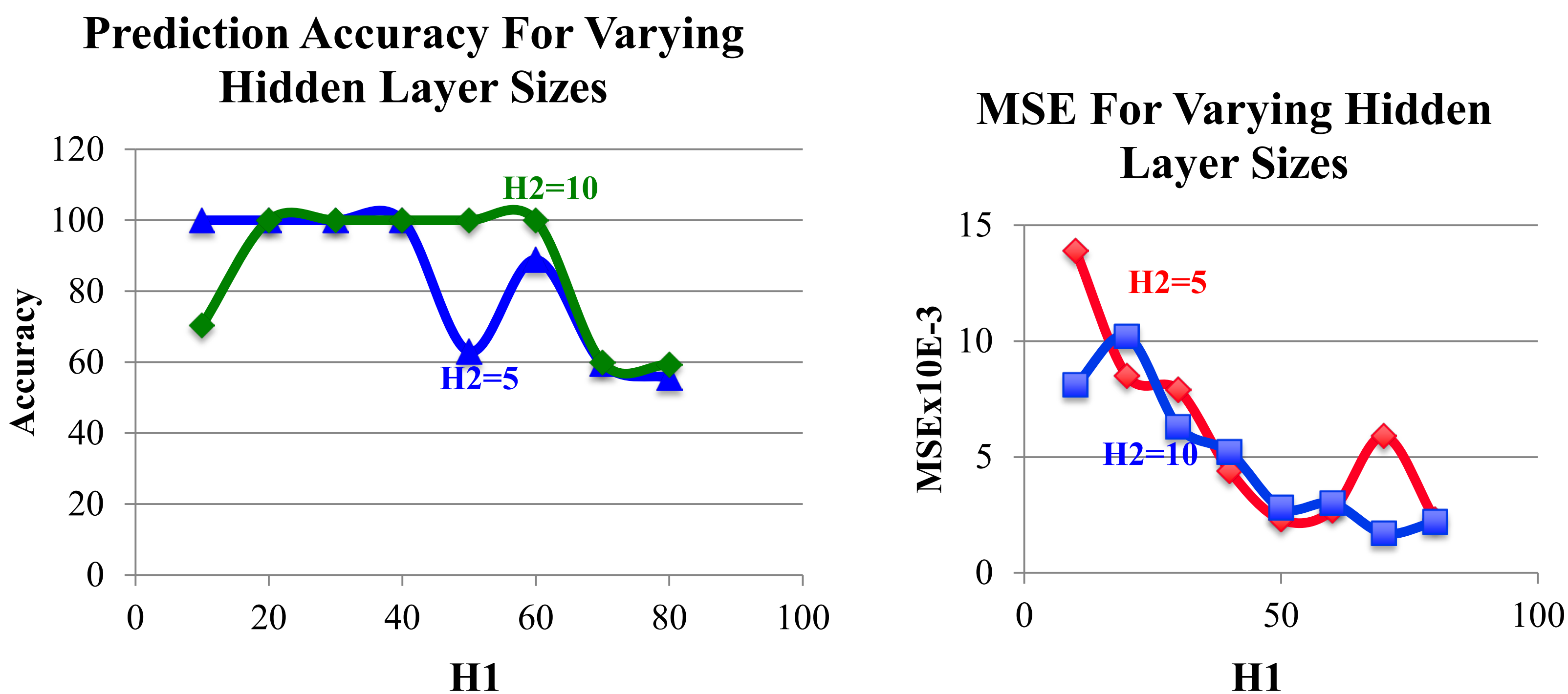
W Sparsity Regularization

Output Class \ Target Class	1	2	3	
1	13 48.1%	0 0%	0 0%	100% 0%
2	0 0%	7 25.9%	0 0%	100% 0%
3	0 0%	0 0%	7 25.9%	100% 0%
	100% 0%	100% 0%	100% 0%	100% 0%

ρ=0.1, β=4, Accuracy=100%

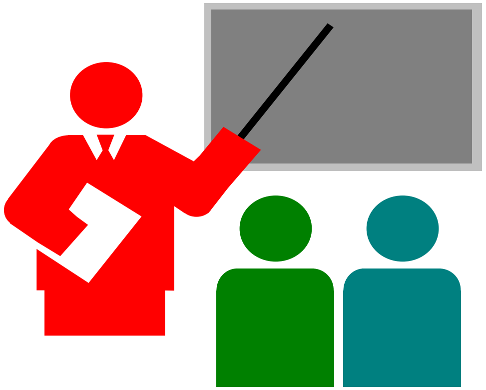
- Confusion matrix shows how many are correctly and incorrectly classified.
- A well tuned model give 100% accuracy. This is good compared to deep learning model for HVAC where accuracy is reported as ≥ 95% [6].

Effect of Relative Sizes of Hidden Layers



- H1=Size of hidden layer 1, H2=Size of hidden layer 2
- Accuracy and MSE are good for certain ranges of H1 and H2

Summary



- Handling fault and performance anomalies is crucial for the success of NFV deployments over clouds.
- A combination of shallow and deep learning structures works well for detection and localization of manifest and impending fault and performance issues.
- Evaluation has been done using real and synthetic datasets and results are comparable to or better than fault detection and localization in other areas.

References

1. Kaggle datasets, https://www.kaggle.com/datasets
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