



The AFIT of Today is the Air Force of Tomorrow.

FaultNet

*A Deep Learning Framework for the Analysis
of Status of Heath Data at the NDC*

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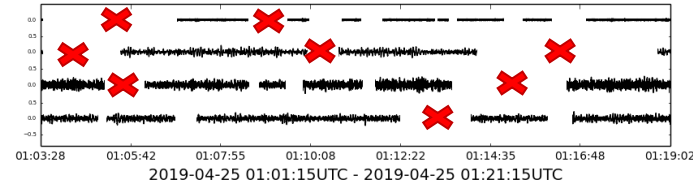
T4.2-02

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- Status of Health (SOH) Need
- SOH Foundation
- SOH Evolution
- Dataset Description
- Static Thresholds
- Project Objective
- FaultNet Framework
- Deep Learning Model
- Results
- Questions

Data gaps plague NDC's each year

- Often caused by equipment failures:



Power

Comm

Sensor

Digitizer

GPS



_Voltage

_RSSI

_Timeouts

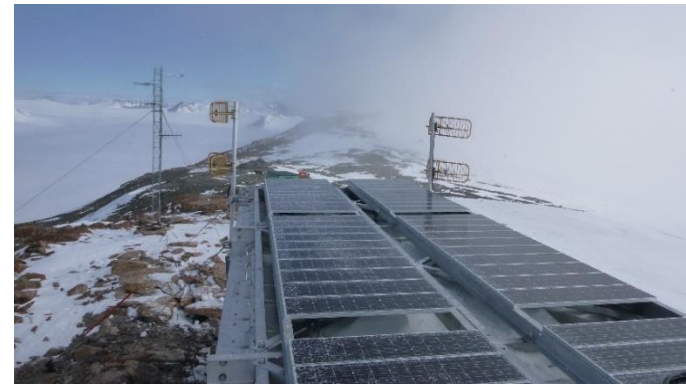
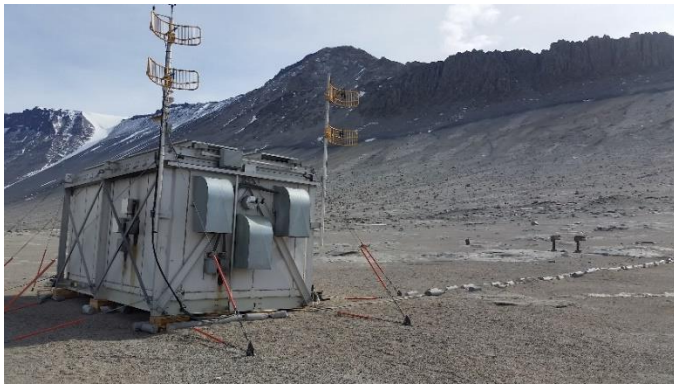
_Latency

_PPS



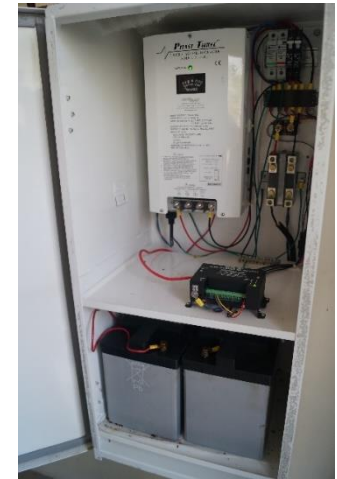
Data loss must not be first indication of a problem!

- Enterprise communication upgrade
 - Enable battery backup capability
 - Current & future system interoperability
 - Worldwide remote communication
- Engineering shift “smart” IoT devices
 - Radios, charge controllers, micro controllers, monitoring devices...



Enable early detection of problems

- Exploratory – manual analysis on individual data sets
 - Input power outage
 - RF transmission degradation
 - Remote engineering studies
- Conditional-based – manual analysis on stacked data sets
 - Battery refreshment
 - Maintenance frequency (VSWR)
- Automated operation – automated analysis on stacked data sets
 - Alarm on threshold exceptions



Transforming data into information requires expert knowledge

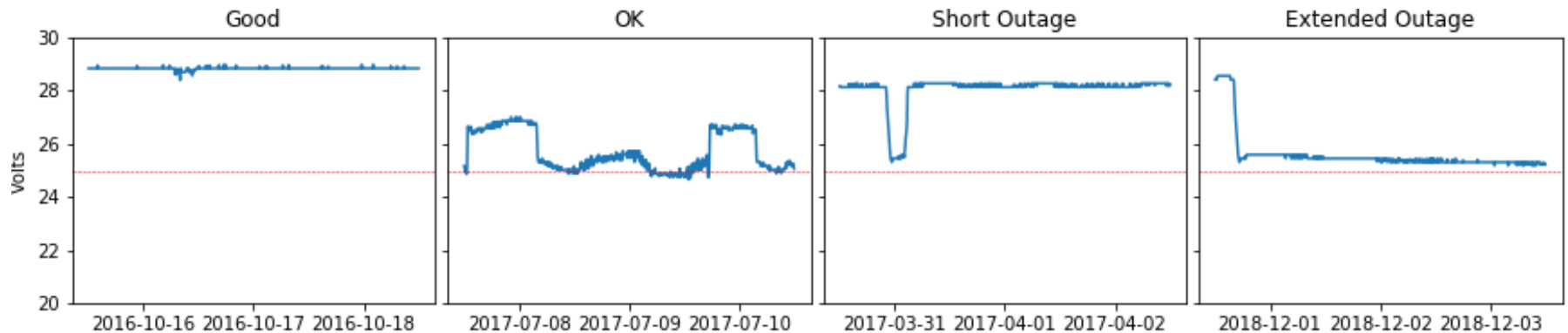
- Dataset
 - 2+ years of SOH data
 - 13 SOH streams
 - 148 sensor sites
- Diverse Sources
 - Radios
 - Chargers
 - Digitizers
 - NDC Databases
- Using Nagios XI
 - 5 min resolution
 - 5700 service checks
 - 1900 host checks

| Name | Type | Description |
|------------------------------|-------|--|
| Latency_to_IDC | FLOAT | Delay in seconds between data timestamp and arrival at the IDC |
| Data_Received | FLOAT | Seconds of data received at the IDC during the previous 5 minutes |
| CIM3_Timeouts | INT | Number of times the CIM3 had to re-request data from the digitizer |
| Latency_to_Station_Processor | FLOAT | Delay in seconds between data timestamp and arrival at the station processor |
| GPS_Antenna_Detected | BOOL | GPS antenna is connected to digitizer |
| GPS_PPS_Signal | BOOL | GPS is receiving valid pps |
| GPS_Set_Time | BOOL | GPS time is reset |
| Intrusion_Alarm_I0 | FLOAT | Intrusion alarm zero is activated |
| CIM3_Receive_Rejects | INT | Number of times the station processor has to re-request data from the CIM3 |
| Intrusion_Alarm_I1 | BOOL | Intrusion alarm one is activated |
| Radio_RSSI | FLOAT | Radio receive signal strength indicator |
| Radio_Board_Temperature | FLOAT | Radio board temperature in degrees Celsius |
| Radio_Voltage | FLOAT | Radio voltage in volts |

Here, we focus on the Battery Voltage at the Radio

AFTAC currently uses Static Threshold Alarms:

- Can not effectively account for location differences:
 - Good is what we want
 - OK is what we get, no actionable alerts
 - Short Outage goes undetected
 - Extended outage takes too long to alert



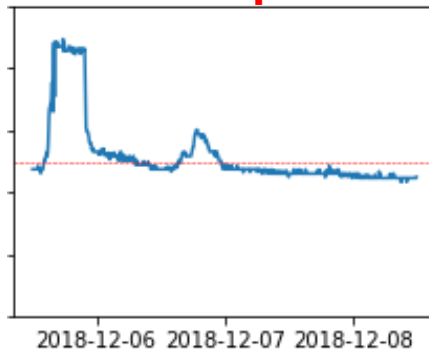
Static Thresholds don't work

FaultNet Objectives:

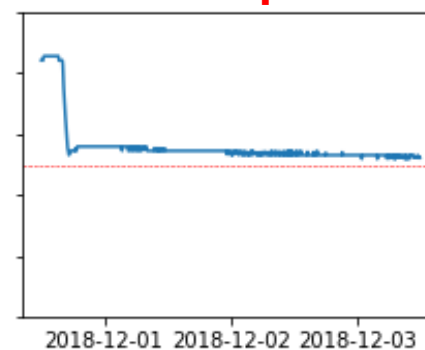
1. Build a Deep Learning (DL) framework for the analysis of SOH data at NDC
2. Build binary classifier for **alarm conditions** vs normal operation

Alarm Conditions for Battery Voltage:

**Photovoltaic
Power Outage
Example**

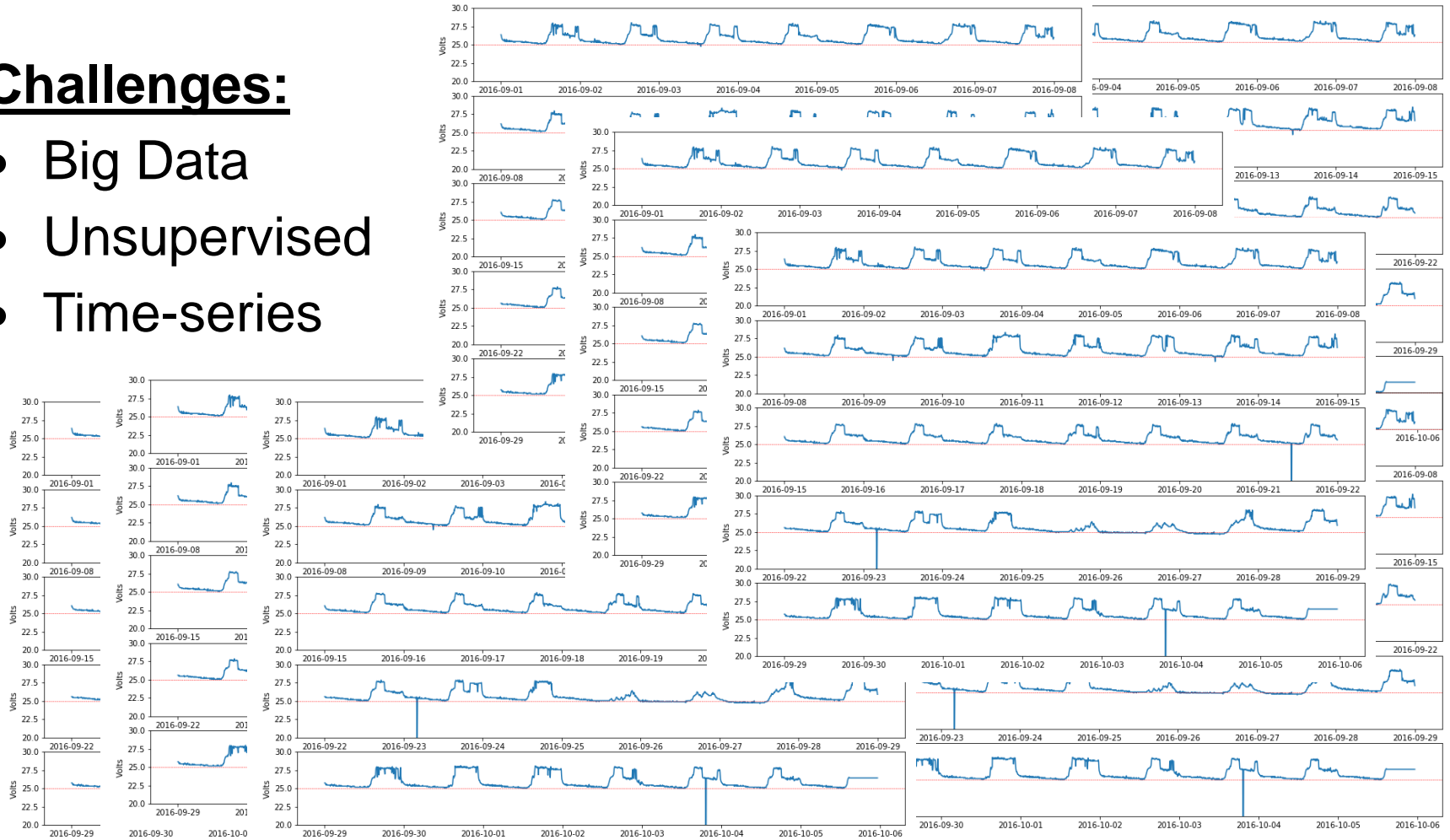


**Commercial
Power Outage
Example**



Challenges:

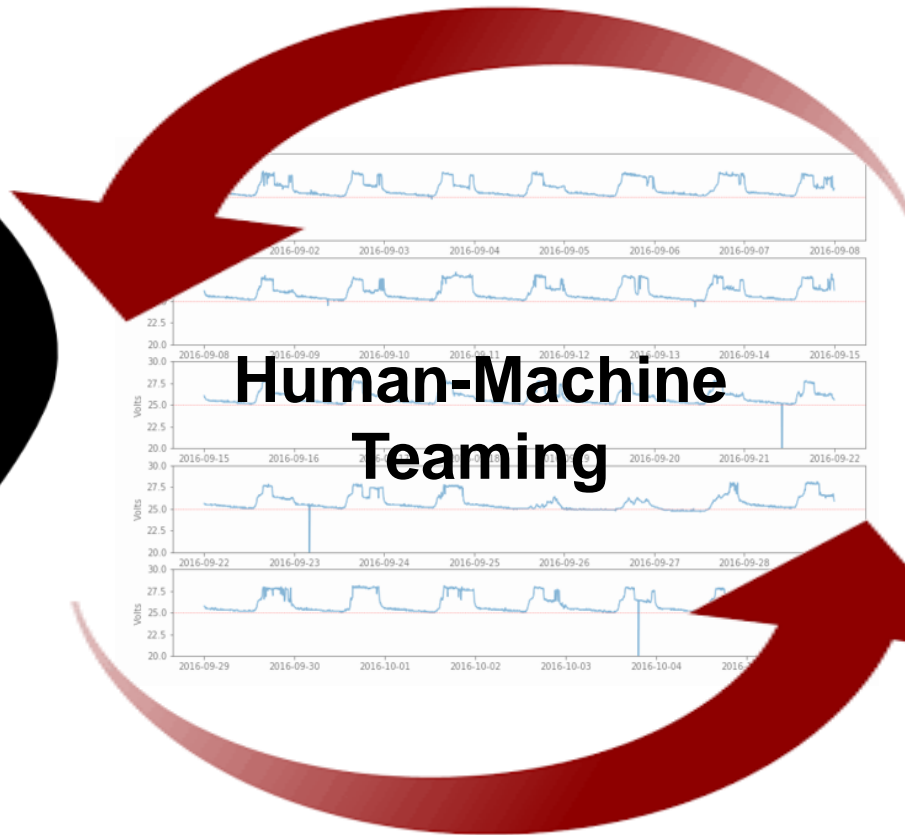
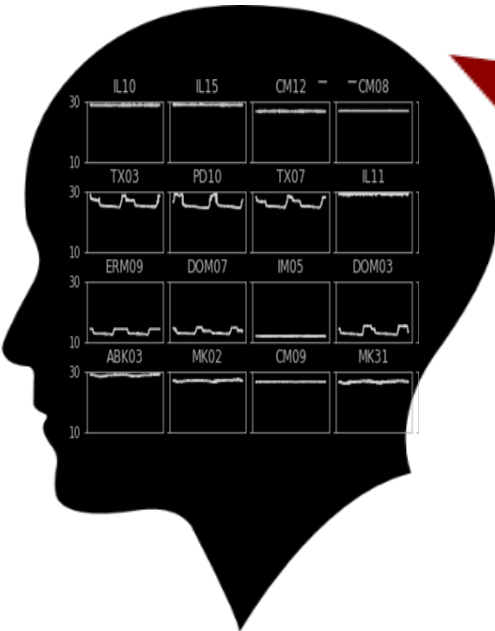
- Big Data
- Unsupervised
- Time-series



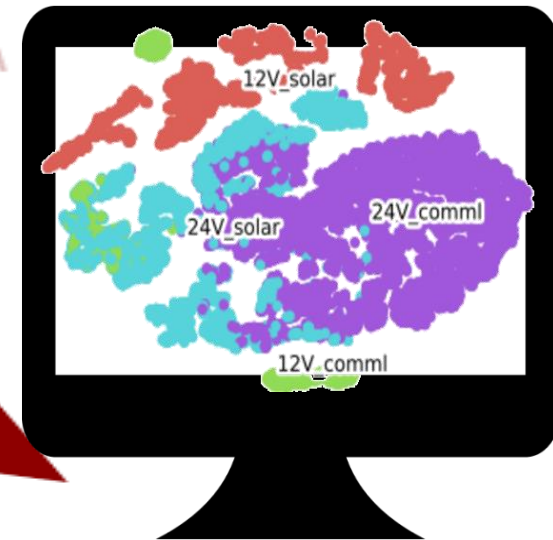
Unsupervised ML for time-series is an active area of research with many challenges

AI-centric toolkit for rapid exploration, clustering and classification

Raw Time-series



Feature-Rich Encodings

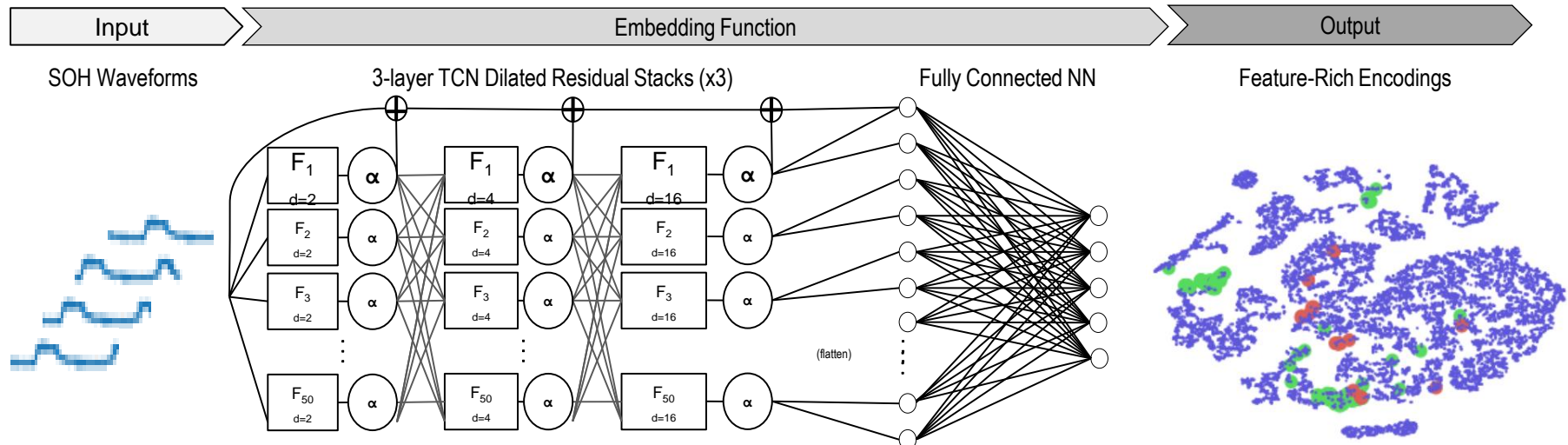


Siamese-Shift Encoder:

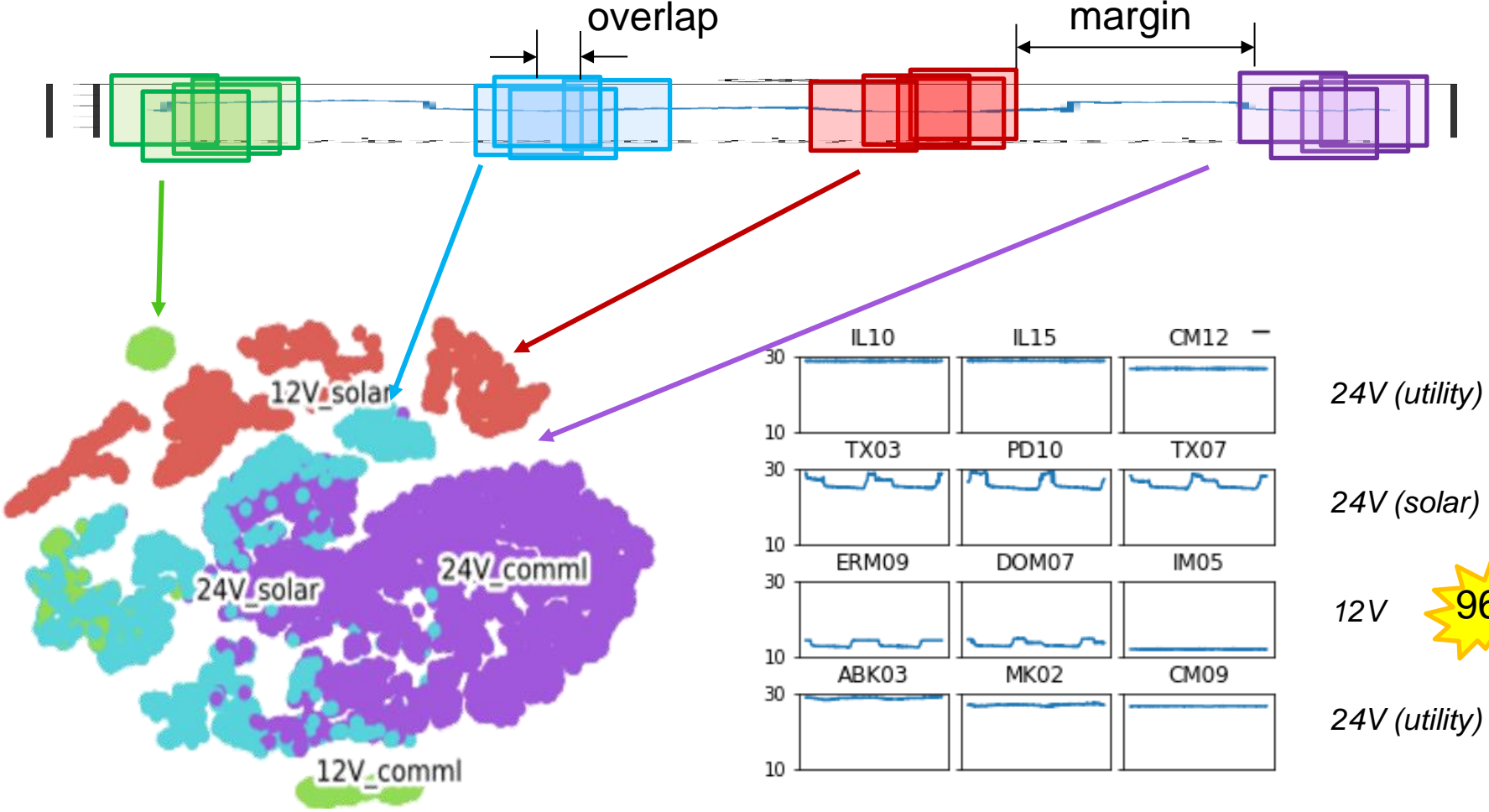
- Input: raw unlabeled time-series
- Output: feature-rich, low-dim, self-organized, Euclidean encoding space
- Encodings are optimized to be meaningful to the application

Deep Neural Network Architecture:

- WaveNet model from audio processing
- Residual and Skip connections from computer vision
- Siamese Architecture from Facial Recognition (Batch-Hard Loss)



Batch-hard Encoding



Machine-Encoded Clusters

Expert Assigned Labels

Shift-encoded Clusters

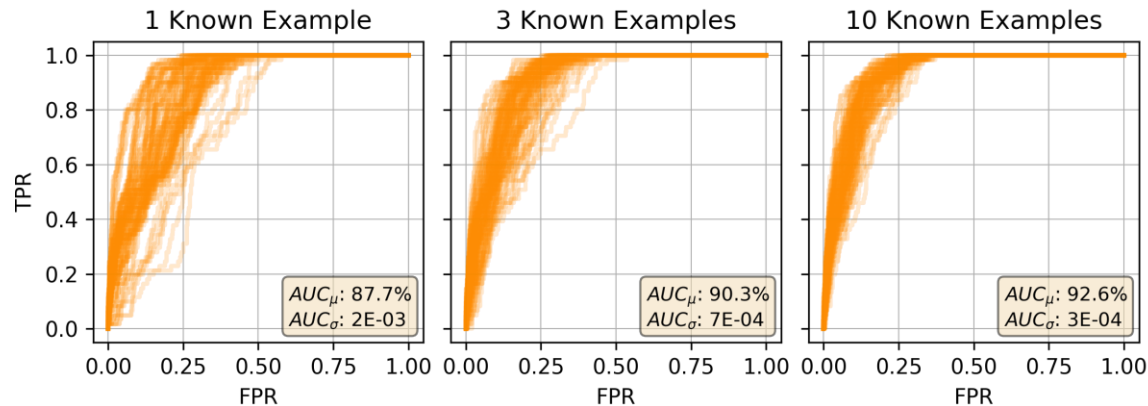


Visually Assigned Labels

- 12V PV (good)
- 24V AC (good)
- 24V PV (good)
- 24V PV (cloudy)
- 24V PV (cloudy)
- 24V PV (cloudy)
- 24V PV (outage)
- 24V AC (poor)
- 24V AC (outage)

Excellent intra-cluster homogeneity and inter-cluster distinction

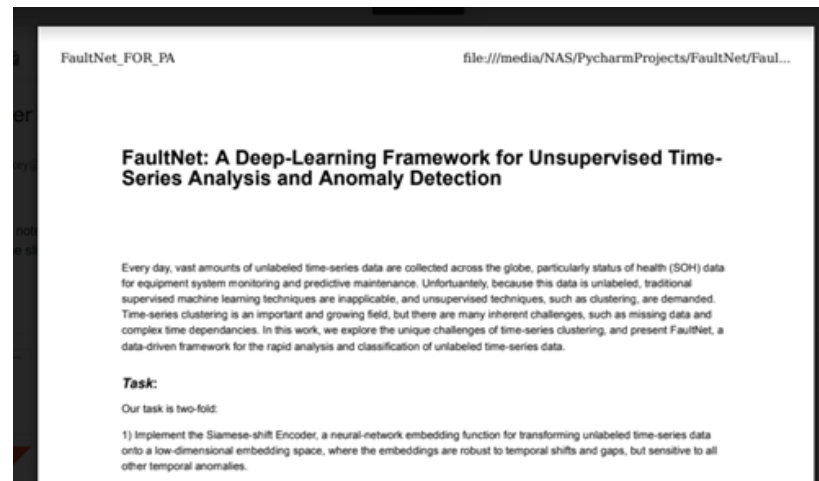
- With 10 templates and
- 0.05 Type-I error rate
- Acc: 93%
- Recall: 64%
- Precision: 43%



Effective Fault Detection with as few as 10 fault templates.

- **Full Code Made Available on Github:**
 - Jupyter Notebook w/ detailed exploration
 - Easily adaptable to *your* unlabeled data!

<https://github.com/joshuadickey/FaultNet>



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