

Autonomous Driving SLICES

*what SLICES can bring to
Network AI research*

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Director, DataCom Lab, Paris Research Center



Artificial Intelligence (AI) & Machine Learning (ML)

AI & ML



95% of network changes
involve manual operation



70% network faults are
caused by manual error



Remove humans
from the fast loop



Keep human in
the slow loop

A new dawn



Autonomous driving



network



∞ Industry segments & requirements

High reliability



Transportation

Differentiated services



Government



Healthcare



Energy



Education

Smart O&M



Manufacturing

Real-time, high bandwidth



Mining



Finance

3 Network scenarios

Campus network

DCN

WAN

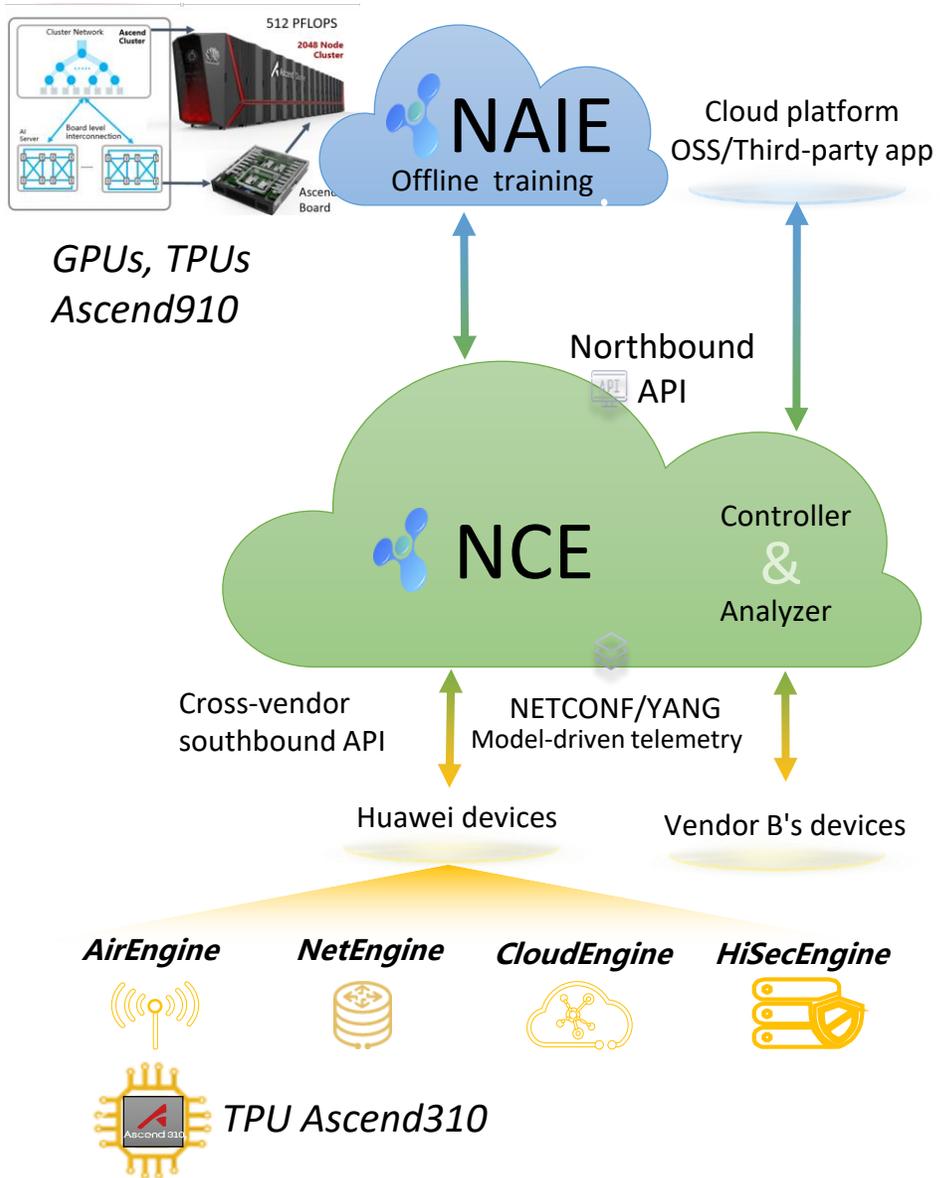
+

Security

1 Technology solution



Network AI in Huawei



iMaster^{NAIE}
 Training, data aggregation, and model generalization

iMaster^{NCE}
 Network-wide analysis, inference & closed-loop optimization

Engines
 Measurement, edge inference & real-time decision-making

General:
 Multi-vendor knowledge graph/models

Training:
 Federated Learning

Specific:
 Deep Models Quantization & Distillation

Control:
 large-scale data-driven reinforcement learning

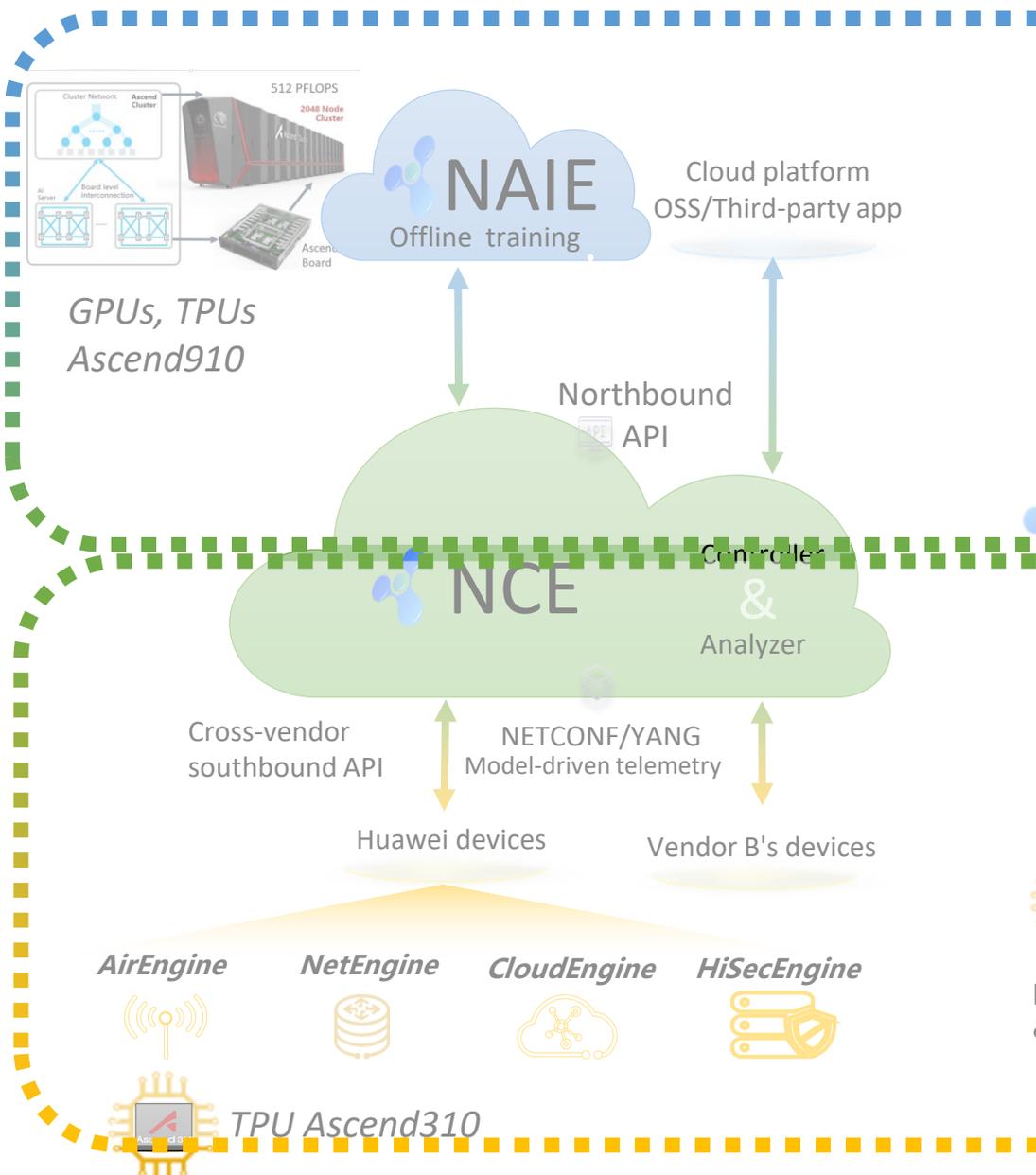
O&M:
 Unsupervised Fault detection, Semi-supervised repair

Real-time inference & control

Model self-awareness

Incremental & continuous learning

Network AI in Huawei



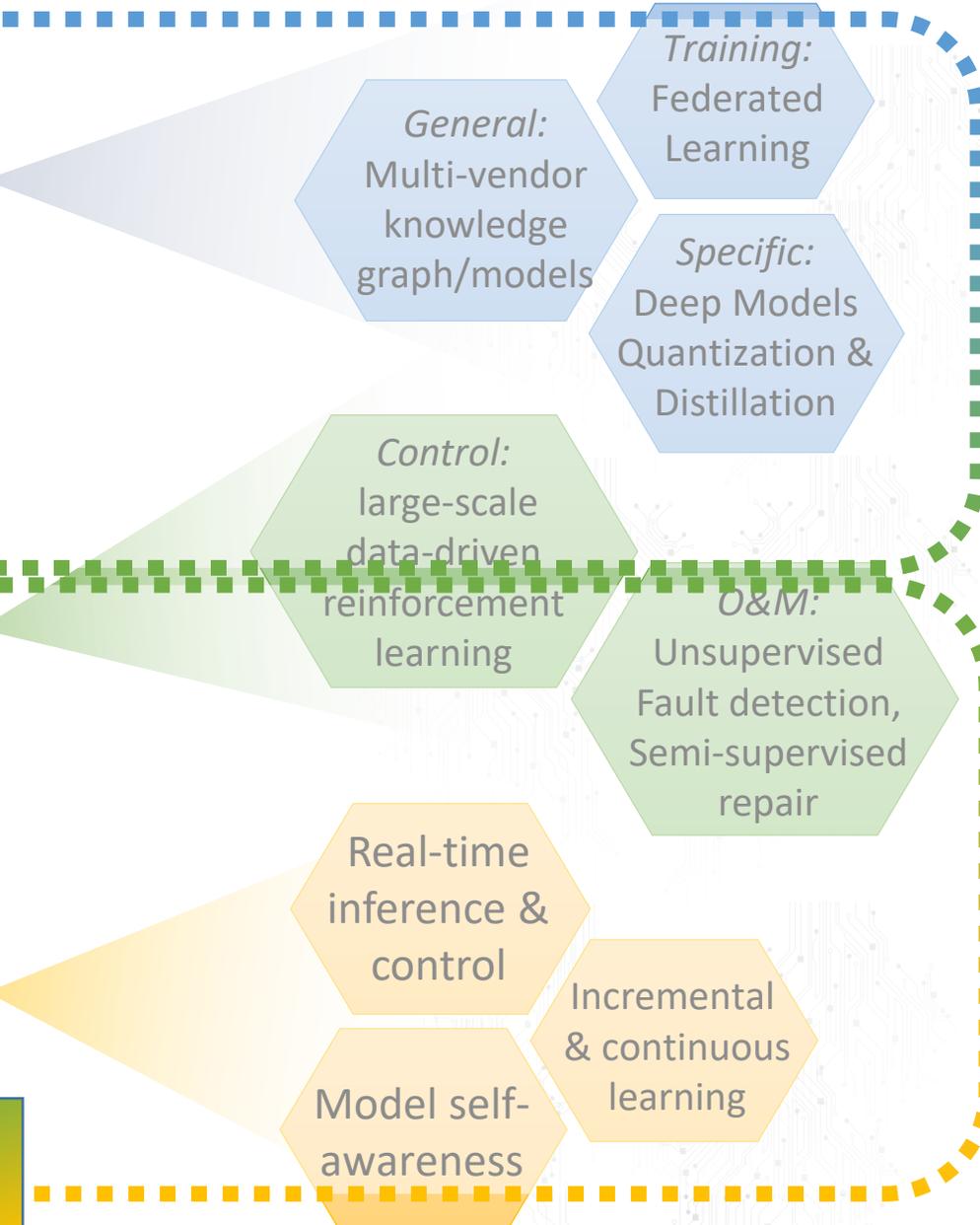
NET4AI viewpoint

iMaster_{NAIE}
 Training, data aggregation, and model generalization

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AI4NET viewpoint



Network 4 AI viewpoint

❑ Model training

- E.g., realism in federated learning from heterogeneous deployments (practical system-level AI challenge)

❑ Model-driven telemetry (MDT)

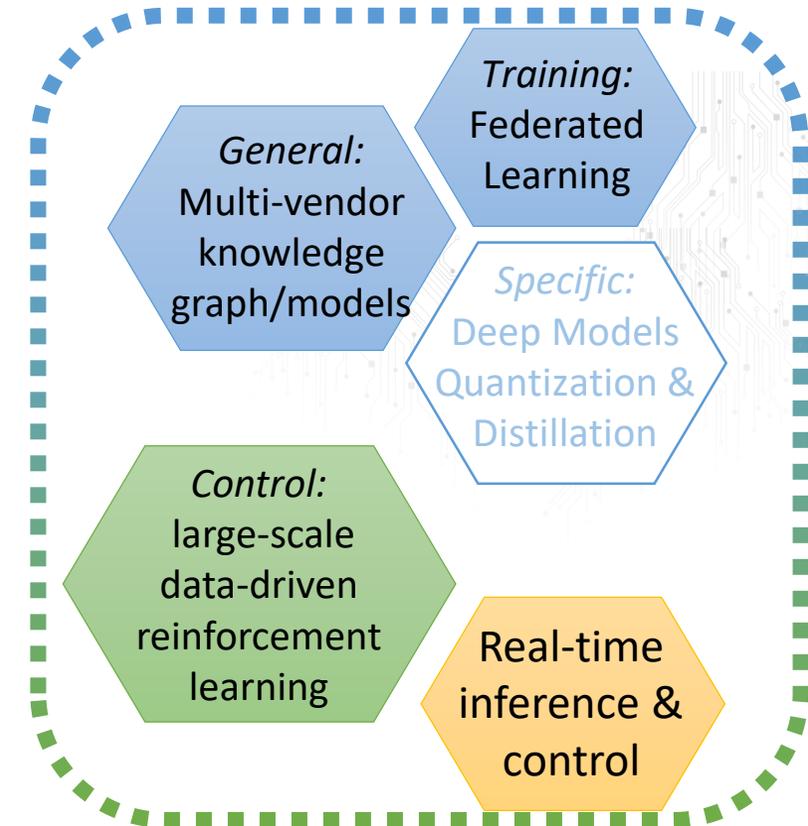
- Heterogeneity in the input data: multi-vendor (good to have “dirty data” AI problem)

❑ Real-time

- Where (Cloud vs Fog vs Edge) to allocate AI resources: architectural tradeoffs of privacy vs cost vs ...

❑ Control

- Delay+noise of MDT data streams: controllable/reproducible AI experiment in more challenging environment
- Train on simulation (e.g., DRL takes lifetimes, cannot learn from real network) refine & validate on SLICES



Large scale, heterogeneous RI

=> lower access barrier to experimental study & more realistic challenges

Large user community

=> critical mass to push reproducibility standards



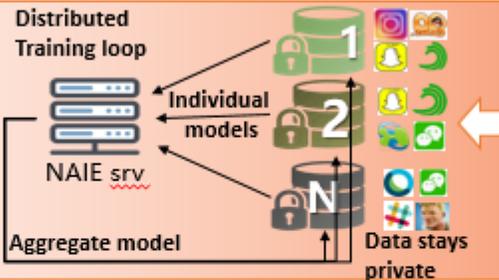
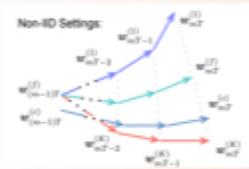
Network 4 AI viewpoint

Model training

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Federated Learning

Google FedAvg works only with i.i.d. data (in non-i.i.d. case, gradients diverge)



Signature portability issue:

- Loss of accuracy if training & testing over *different* network
- Simple solution = centralized training over *both* networks



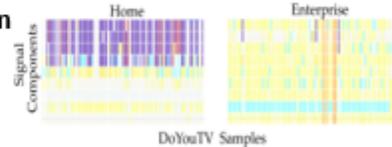
Split ANN model into **Common Backbone** + **Private Classifier**



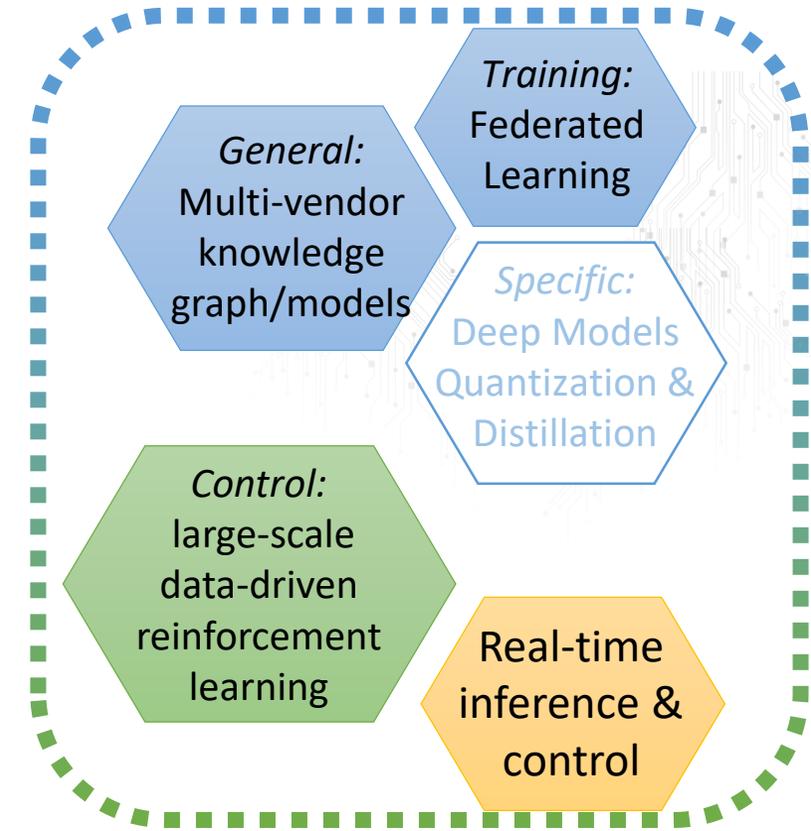
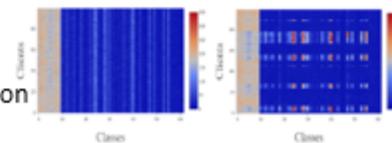
- Only the **backbone is shared & averaged** (speedup learning of common hidden layers)
- The **last layer classifier remains private** (less information share/leak, better fit to the data of each client)

Huawei traffic classification

<1% accuracy loss, 30x data reduction wrt centralized training



MNIST image dataset 1.3x faster to converge with 1.5x less communication wrt Google FedAvg



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user community critical mass to push reproducibility standards



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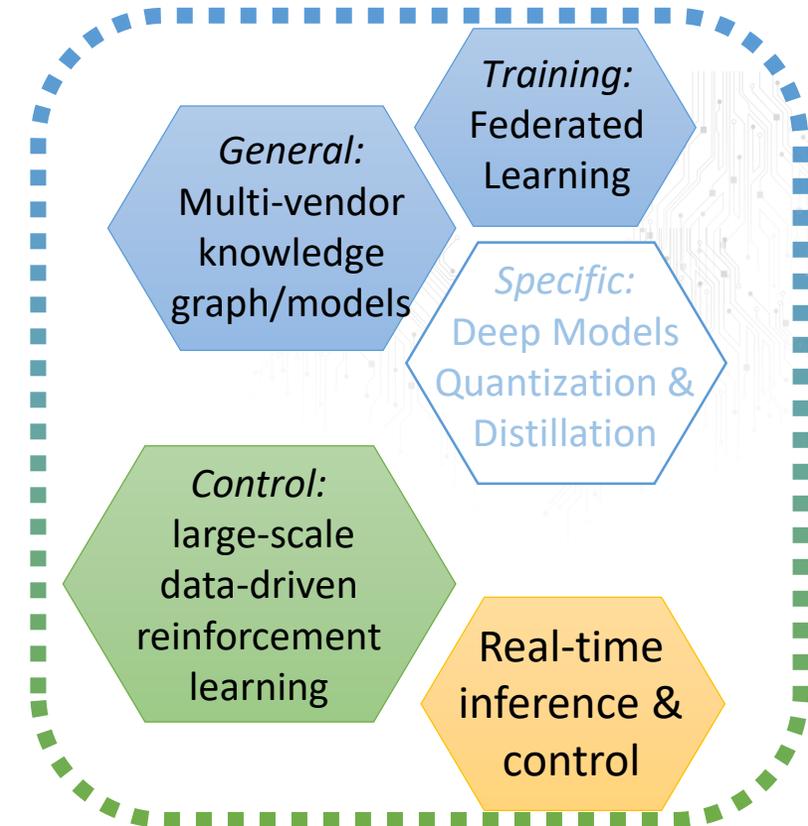
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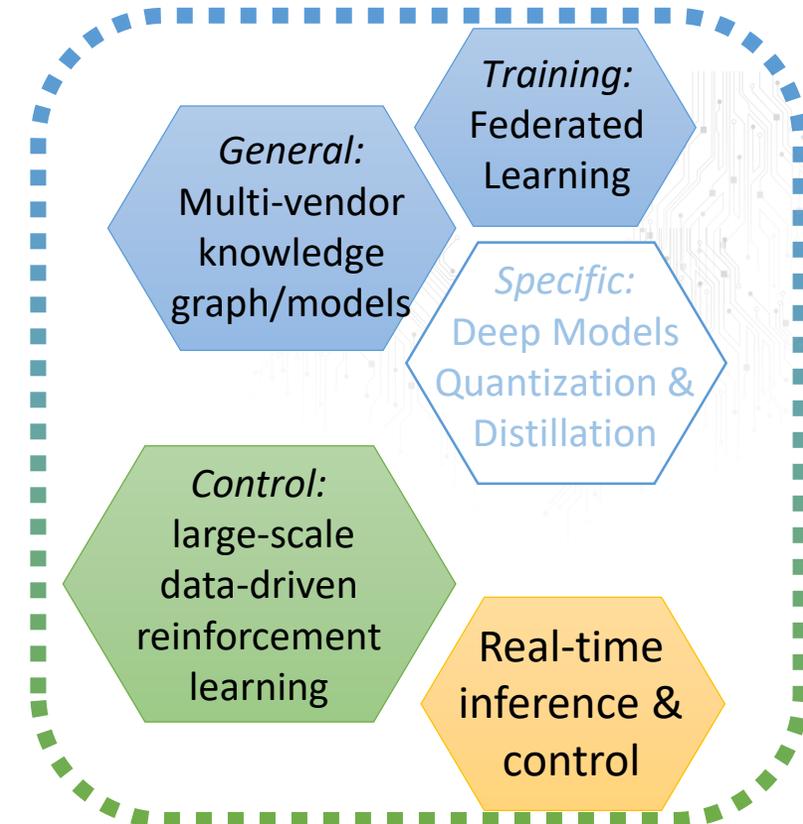
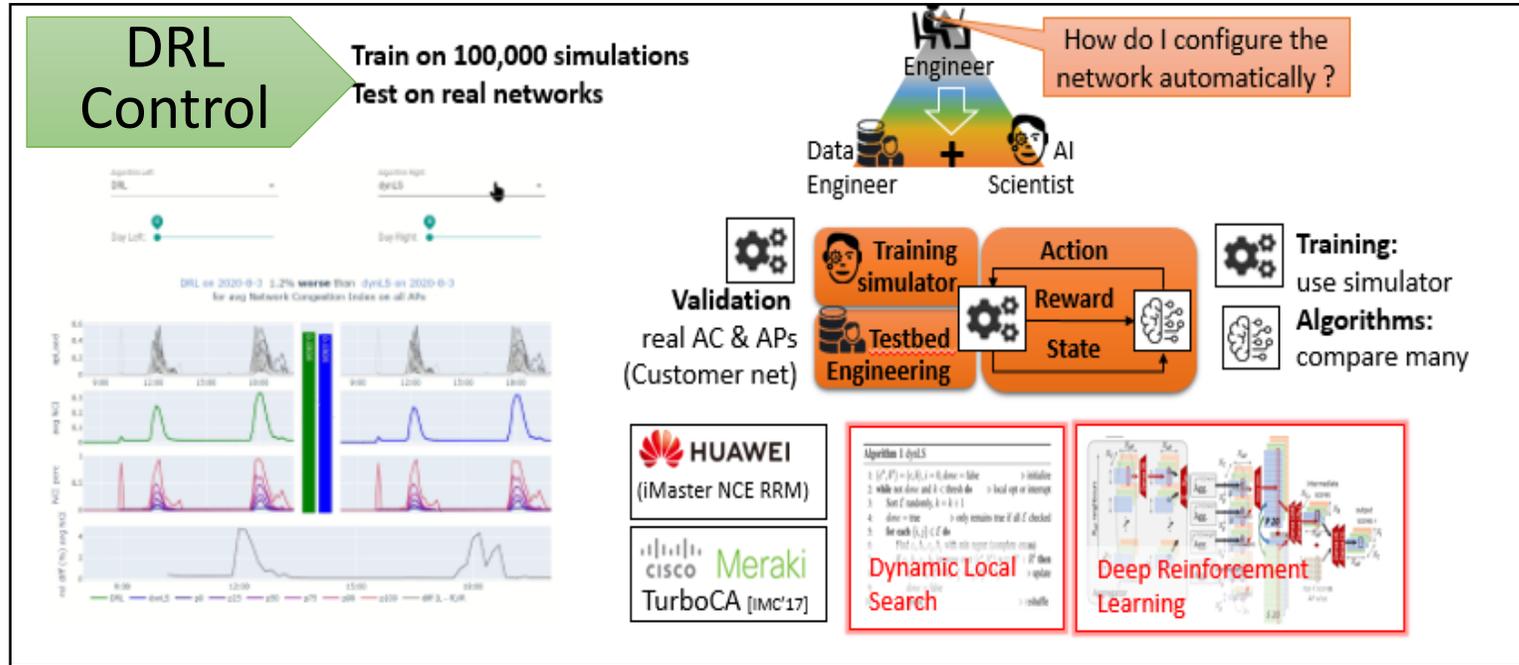
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Note: I was happy to find the "heterogeneity" keyword in Jon's keynote 😊

AI 4 Network viewpoint

❑ Model-driven O&M

- Unsupervised algorithms still need ground truth for benchmark
- Large SLICES crowd: can the community crowdsource anomaly detection database beyond KDD99 (s/ImageNet/AnomalyNet/)?

❑ Heterogeneity (again)

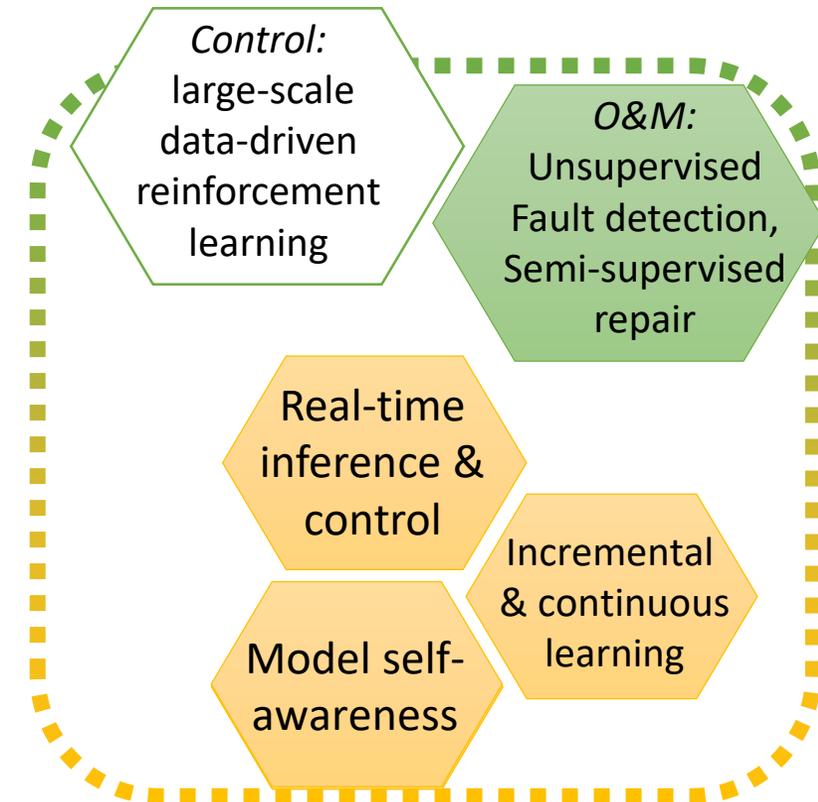
- Model ages and data drifts: study ageing of models imperative for deployment in a full AI lifecycle

❑ Incremental training

- Incremental training: system-level problems bring algorithmic challenges

❑ Real-time inference

- Inference: real-time low cost accurate inference



Large scale, heterogeneous RI

=> critical piece to stress test generalization & transfer

Large user community

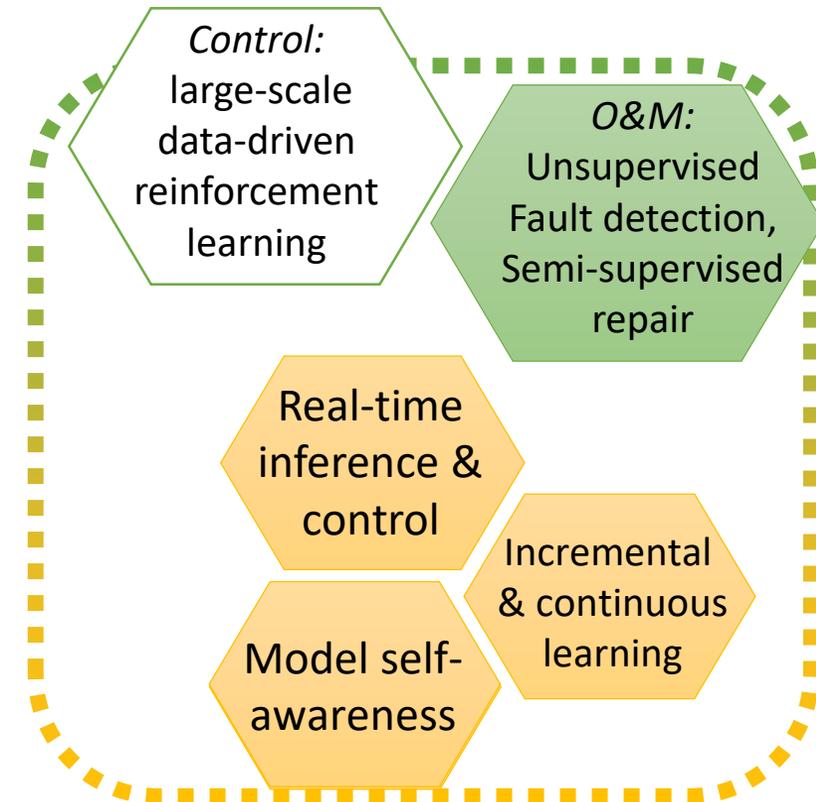
=> critical mass for crowd-sourcing labeling expertise



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Unsupervised MDT O&M

Anomaly detection & root-cause analysis

Challenges

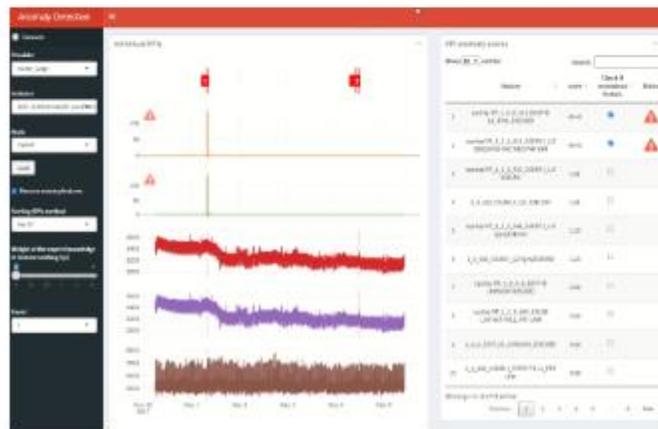
- ❑ Anomalies are rare -> unsupervised learning
- ❑ Need to correlate faults -> multi-variate methods
- ❑ Need to correlate KPI and logs -> multi-mode methods
- ❑ Cannot store all data -> stream-based learning
- ❑ Interact with operator -> explainability (XAI)

❑ Algorithm benchmarking

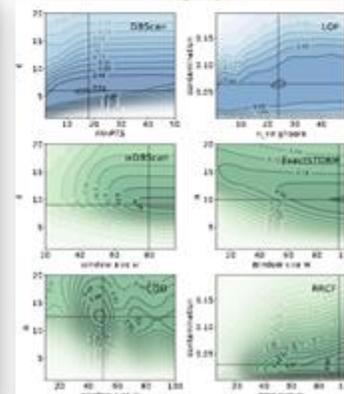
- ❑ Still requires labels !

❑ Algorithm selection & tuning

- ❑ Requires skills and time
- ❑ Lot of algorithms exist
- ❑ Each algorithm has many hyper-parameters



| Algorithm | Stream/Batch |
|---|--------------|
| <i>Proximity-based using distance</i> | |
| KNN [20], [21] | Batch |
| DB-outlier [22] | Batch |
| STORM [23] | Stream |
| <i>Proximity-based using density</i> | |
| DBSCAN [25] | Batch |
| LOF [43] | Batch |
| LOCI [28] | Batch |
| HC3 [14] | Batch |
| ABOD [33] | Batch |
| <i>Proximity-based using clustering</i> | |
| CBLOF [34] | Batch |
| MCOF [35] | Stream |
| CADEFS [36] | Stream |
| <i>Ensemble-based using tree</i> | |
| IF [38] | Batch |
| RHF [39] | Batch |
| RRCP [40] | Stream |
| HST [41] | Stream |
| <i>Ensemble-based using subspaces</i> | |
| Feature bagging [42] | Batch |
| RS-Hash [19] | Stream/Batch |
| Loda [17] | Stream/Batch |
| sStream [18] | Stream |



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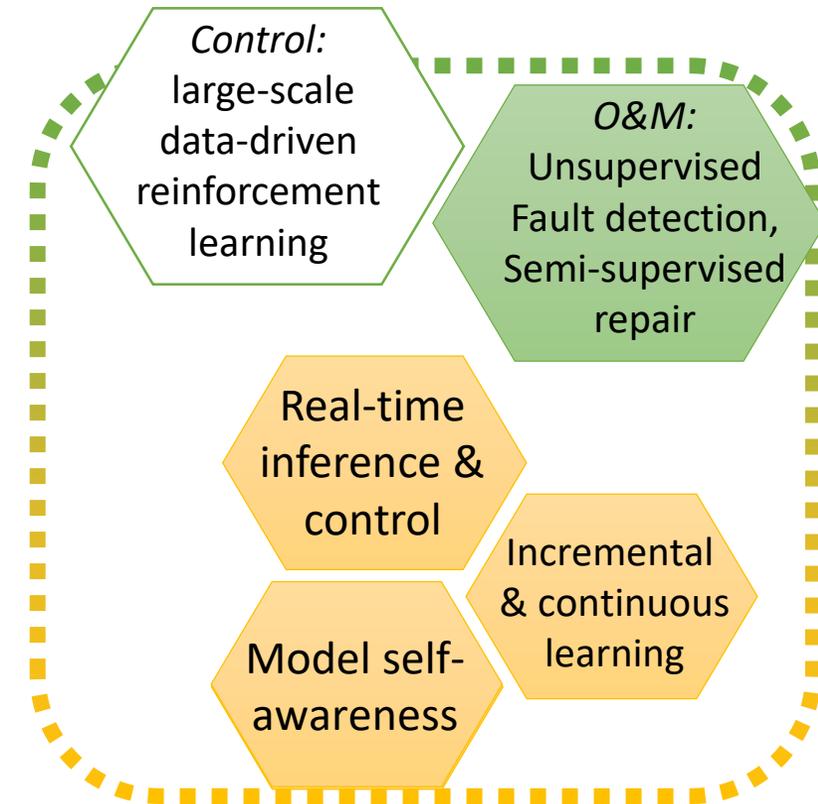
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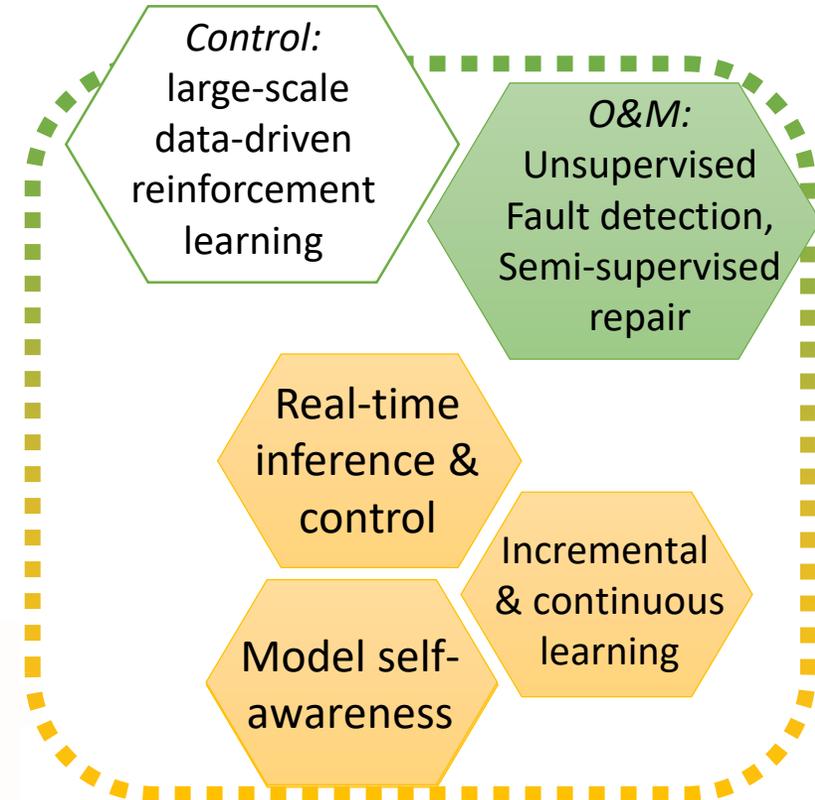
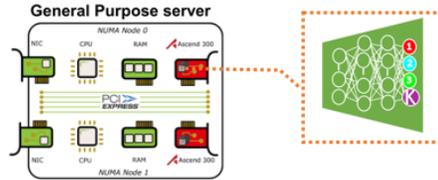
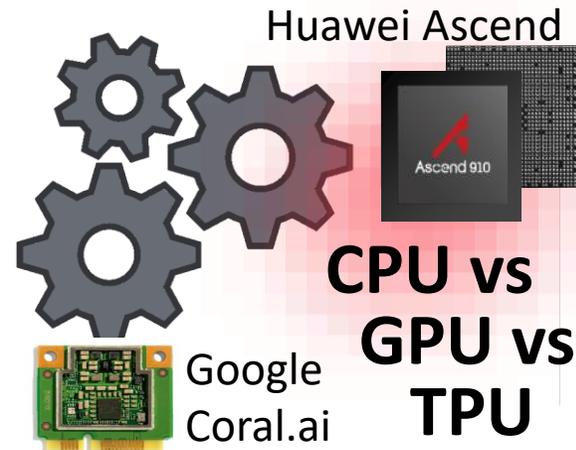
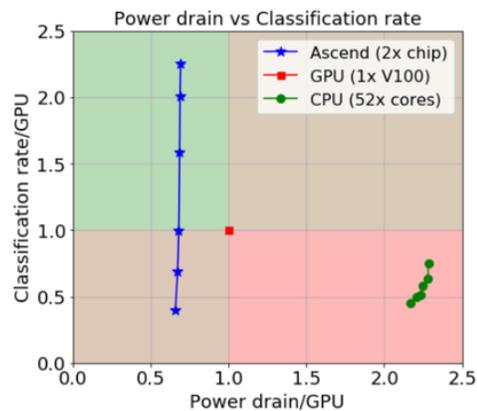
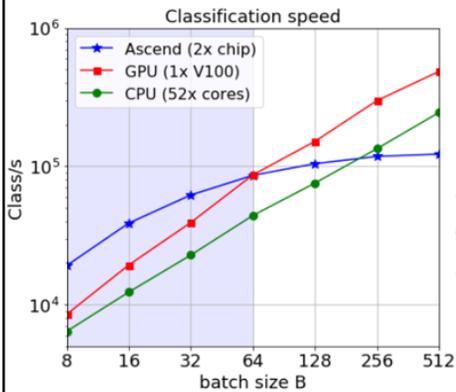
Real-time Inference

Experimental setup

- 2 Servers Intel Xeon Platinum 8164 CPUs @2.00GHz (L1/L2/L3 caches: 32 data+32 instruction/1MB/36MB)
- 1.5TB RAM (64GBx24 DDR4 @ 2666MT)
- 100 Gbps NICs (Mellanox MCX515A-CCAT ConnectX-5)
- Huawei Atlas 300I:3010 Inference Card (4x Ascend 310)

Input traffic

- 3 datasets (2 internal and 1 publicly available)
- Adversarial analysis at 100 Gbps (speedup traces): 30-50kclass/sec depending on scenario



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Real-time inference

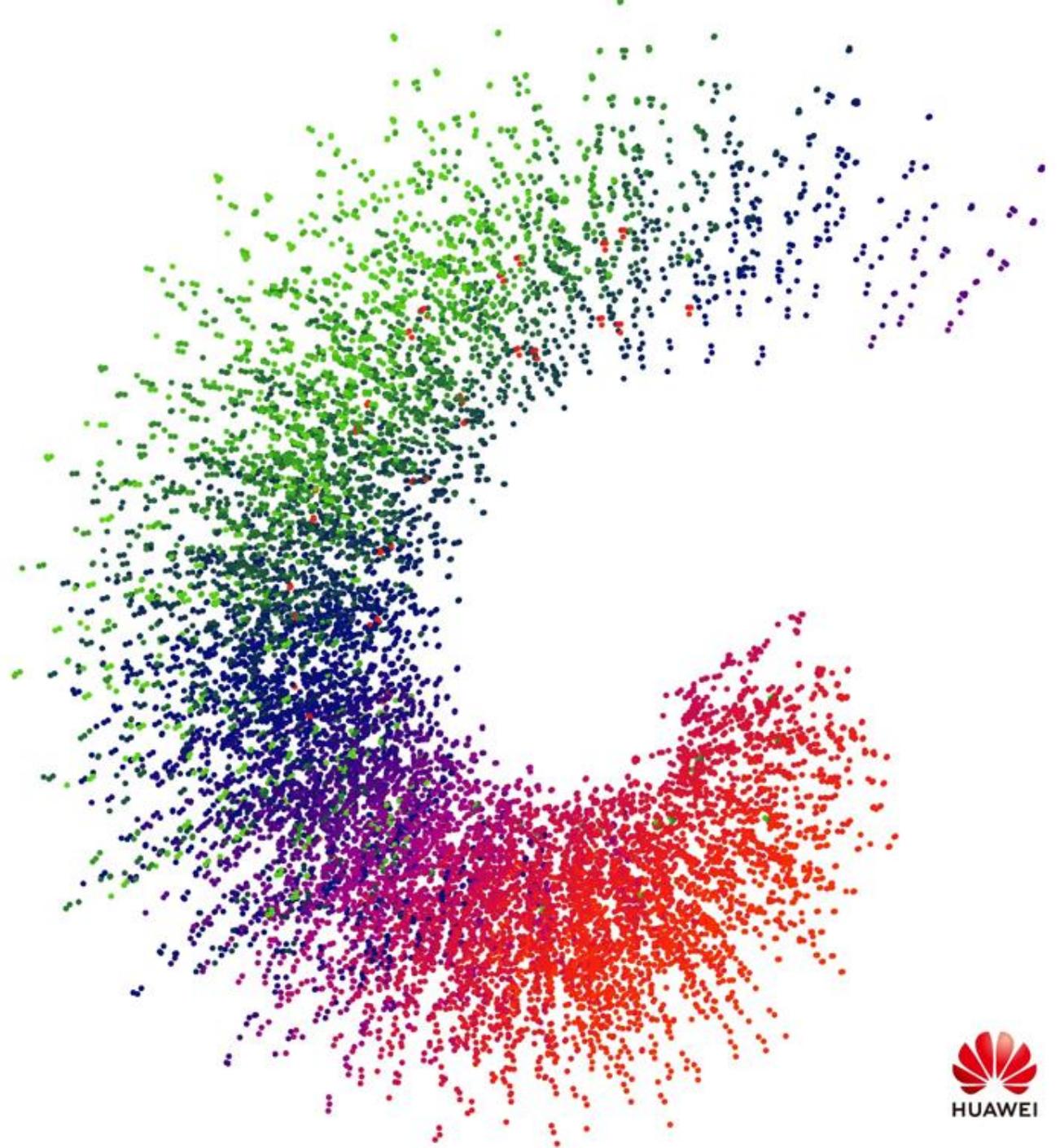
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Thanks



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public research resources

<https://nonsns.github.io>