

Native Network Intelligence, Fast & slow

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Agenda

Past

Present

Future



The past

(Paris, 1888)

“The farther back you look,
the further ahead you can see”

Winston Churchill



Agenda

Past

Present

Future

In the beginning...

18th century

19th century

20th century

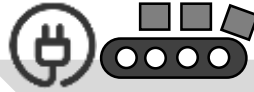
21th century



Fire



Steam



Electricity

...1001010...

Logic



Network



AI

$3.5 \cdot 10^6$
years ago

$10^3 \div 10^4$
years ago

1784
Mechanical
loom

1870
Assembly
line

1969
Programmable
Logic
Controller

1974
Internetworking

1986
Backpropagation



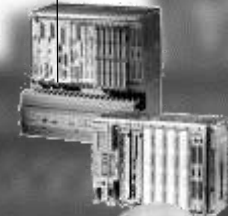
F. Flinstone



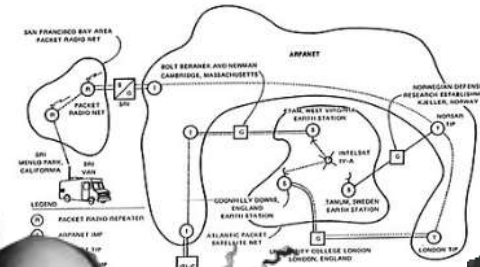
E. Cartwright



E. Whitney



D. Morley



V. Cerf & B. Kahn



Y. Benjo, G. Hinton, Y. LeCun



2004



2018



AI viewpoint

- ❑ 1955 J. McCarthy "artificial intelligence"
- ❑ 1957 F. Rosenblatt Perceptron
- ❑ 1959 A. Samuel "machine learning"

- ❑ 1986 R. Dechter "deep learning"
- ❑ 1989 G. Piatetsky-Shapiro "data mining"

- ❑ 2000 I. Aizenberg "deep neural networks"
- ❑ 2012 AlexNet... re-starts the hype on DNN

Pioneering times

1st AI winter (late 70s)

2nd AI winter (late 80s)

Independent evolution

Early cross pollination

Further independent development

**Increased adoption
AI-Assisted Networking**

Network viewpoint



- ❑ 1945 V. Bush "memex"
- ❑ 1964 P. Baran "block message"
- ❑ 1974 V. Cerf & B. Kahn Internetworking

- ❑ 1977 K. S. Narendra learning automata for telephone traffic control

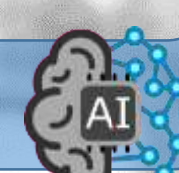
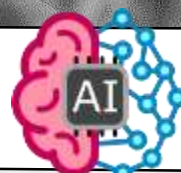
- ❑ 1989 T. Berners Lee World Wide Web
- ❑ 1990s dot com

- ❑ 2000s all-IP
- ❑ 2010s cloud-native & IoT

Pioneering times

.com bubble (late 90s)

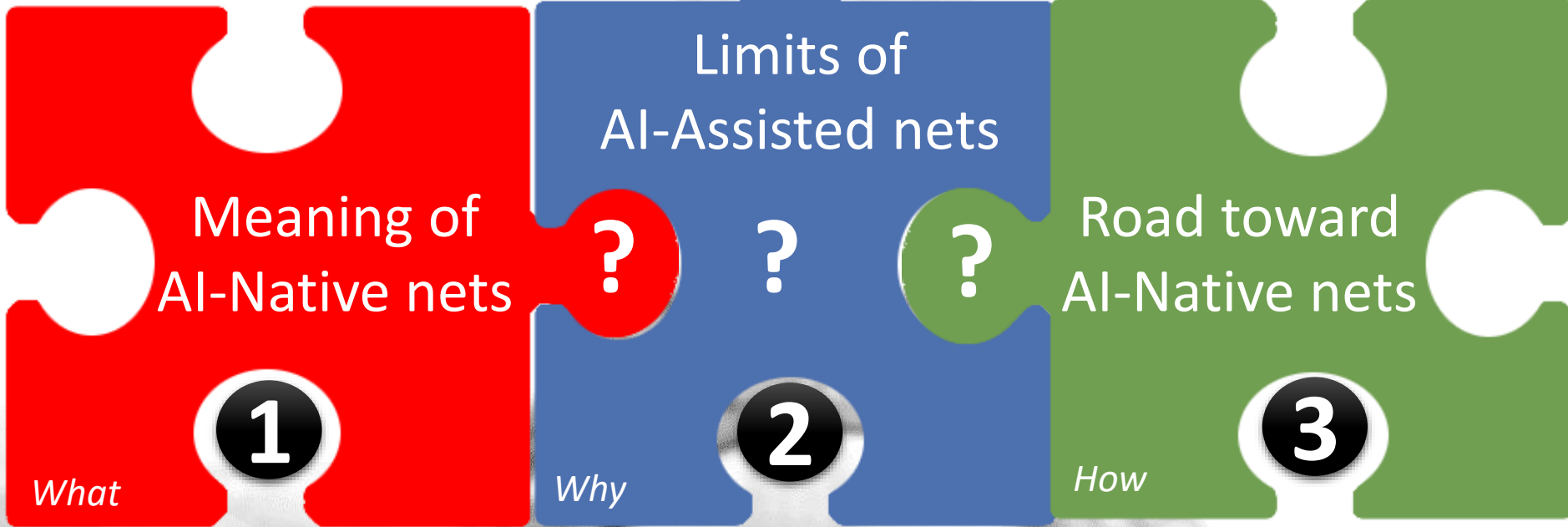
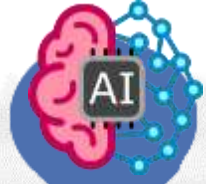
**Future confluence:
AI-Native Networking**





AI viewpoint

Network viewpoint



FAST FWD **TO THE FUTURE**

BACK **TO THE PRESENT**
AI-Native **Networking**

BACK **TO THE FUTURE**

FAST FWD TO THE FUTURE

Let's make a 1-slide trip to the future



1 What ?





AI as 1st class network citizen & starting point of the equation (AI+) instead of a later addendum (+AI)

❑ Networking paradigm where

- exploiting AI is **seamless** and **straightforward**
- AI is **pervasive** (and, if needed, **ubiquitous**)
- AI brings **cost effective** irreplaceable **added value**

(as opposite to)

- Bespoke and fragile
- Suffer chicken & egg
- Increase cost

❑ Communication system

- **tuned via** AI, systematically
- **designed by** an AI, intuitively
- **designed around** AI principles & techniques

(as opposite to)

- magic numbers
- heuristics
- model based

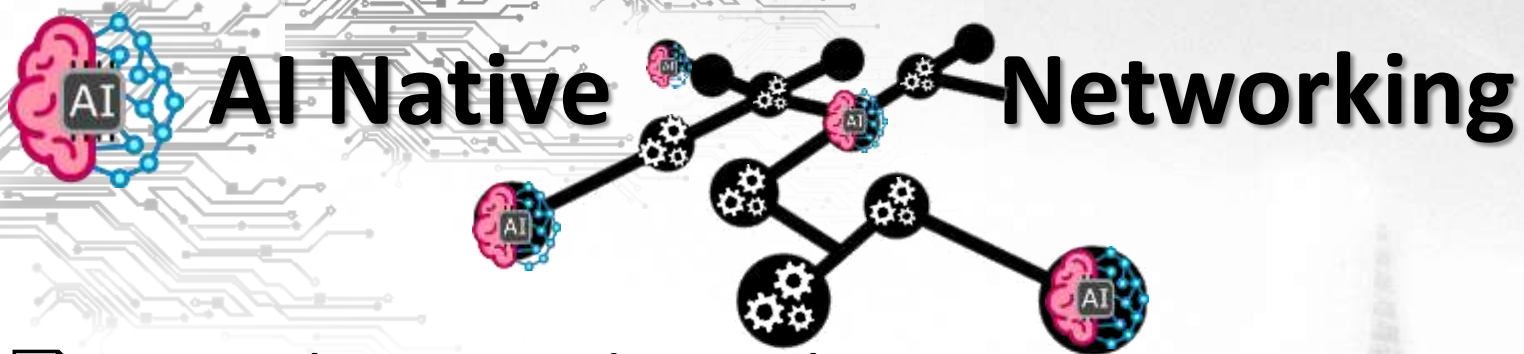
❑ Communication as a tool

- to facilitate **interconnection of AI functions/services**

(extending)

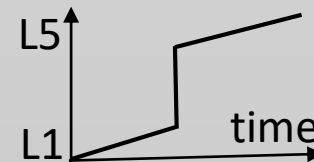
- Human or M2M

AI Native Networking



Necessary ingredients

+AI
(assisted)



AI+
(native)



❑ Networking paradigm where

- exploiting AI is **seamless** and **straightforward**
- AI is **pervasive** (and, if needed, **ubiquitous**)
- AI brings **cost effective** irreplaceable **added value**



Explainable



Automated



Fit



Green

❑ Communication system

- **tuned via** AI, **systematically**
- **designed by** an AI, **intuitively**
- **designed around** AI principles & techniques

❑ Communication as a tool

- to facilitate **interconnection of AI functions**/services

Examine AI-Assisted
networking limits



Grasp AI-Native needs

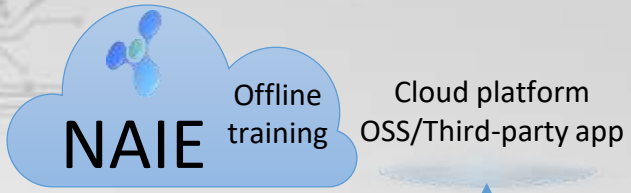




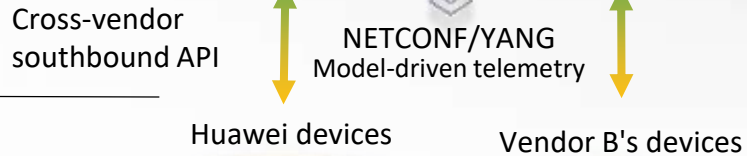
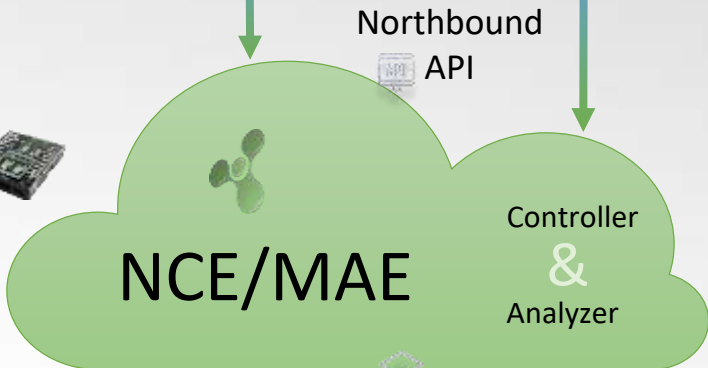
AI-Assisted networking

Evolved cloud-native 3-tiered architecture

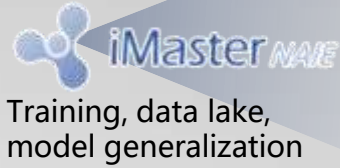
Cluster of GPUs, TPUs Ascend910



CPUs GPUs, TPUs Ascend310 Ascend910



ARM TPU Ascend310



Offline operation

Global knowledge



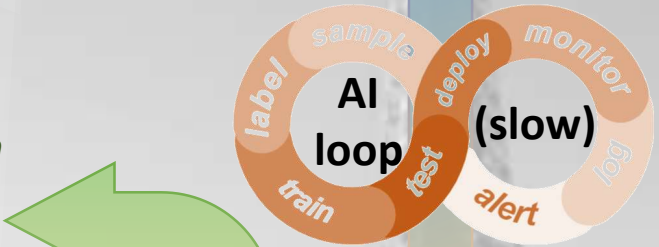
Online operation

Extended Knowledge

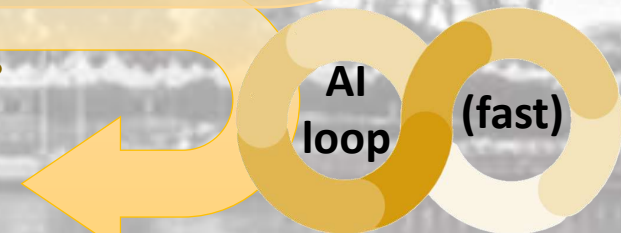


Real-time operation

Local knowledge



O&M closed-loop

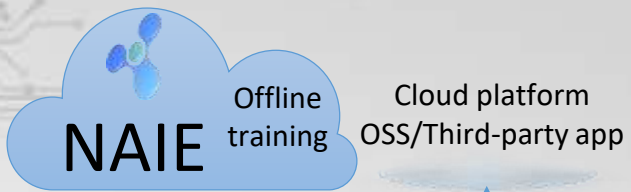




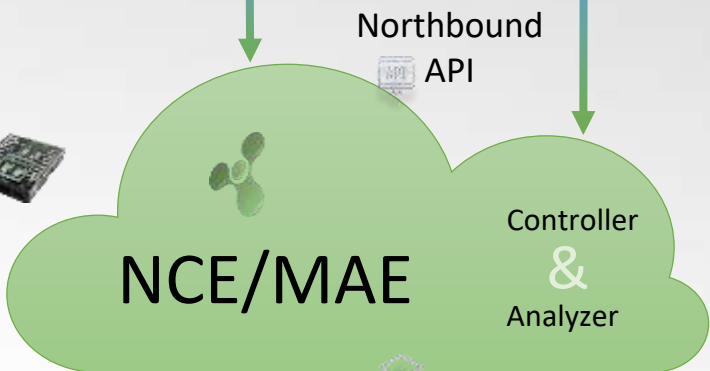
AI-Assisted networking

Evolved cloud-native 3-tiered architecture

Cluster of GPUs, TPUs Ascend910



CPUs GPUs, TPUs Ascend310 Ascend910



Huawei devices

Vendor B's devices

Air/Net/Cloud/HiSec Engines

ARM TPU Ascend310



Training, data lake, model generalization

Offline operation

Global knowledge

Specific:
Deep Models
Quantization & Distillation

General:
Multi-vendor graph/models, Transfer learn

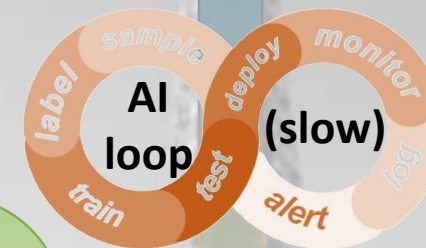
Few-shot, Incremental, Federated learning

Out of distribution detection

Semi-supervised active learning

Automated local device tuning

Fine tune model w/ local data



Network-wide analysis, closed-loop optimization

Online operation

Extended Knowledge

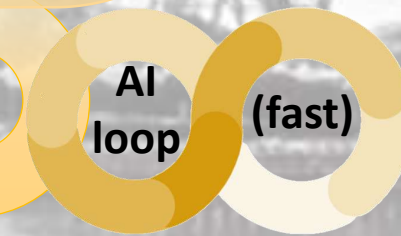
O&M closed-loop



Measurement, edge inference & real-time decision-making

Real-time operation

Local knowledge



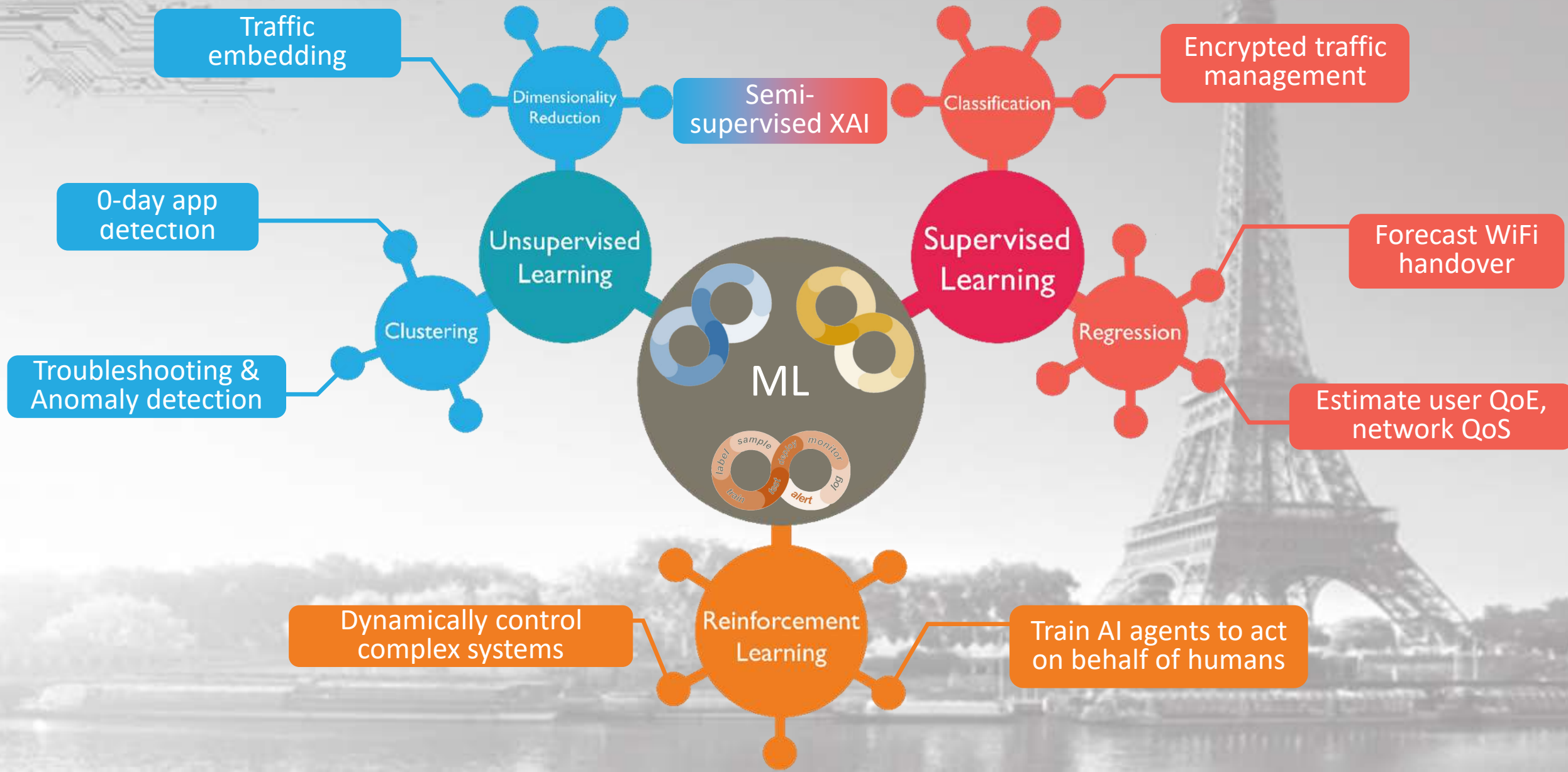


AI-Assisted networking

Sample of Lab research activities...



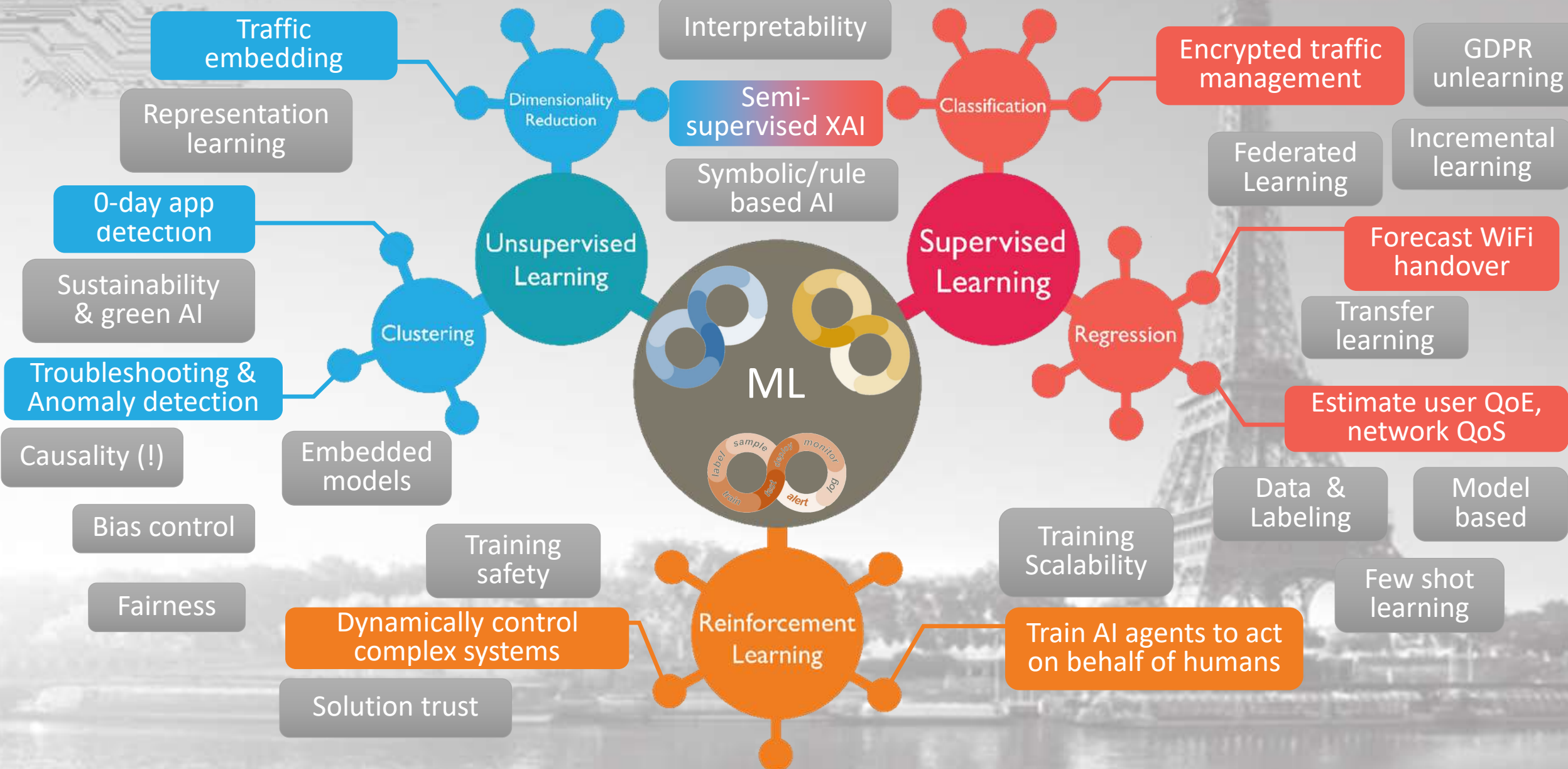
Use-cases





AI-Assisted networking




Sample of Lab research activities... and corresponding methods








AI-Assisted networking

Sample of Lab research activities + recent flagship publications, open code & dataset

 [Infocom'22]
 [IEEE Trans'21]
 [ACM SEC'21]

Traffic embedding
 [CoNEXT'21]
 [HotNets'22]

Dimensionality Reduction
 [ITC'20] Best paper

Semi-supervised XAI

Classification
 [IJCAI'20]

Encrypted traffic management

 [SIGCOMM CCR'22]

[ITC'20] Best paper

ML





Supervised Learning



Regression





Forecast WiFi handover




 [TMA'21]

Estimate user QoE, network QoS

 [WWW'19]
 [Networking'20]
 [IEEE Trans'21]

0-day app detection
 [ICML UDL'21]
 [IEEE Trans'21]

Troubleshooting & Anomaly detection
 [ICDM'20]
 [KDD'22]
 [IEEE Trans'20]
 [ITC'22]

 [Networking '21]
 [Infocom '21]
 [AAAI GLCR '22]

Dynamically control complex systems

Reinforcement Learning

 [Infocom'20]

Train AI agents to act on behalf of humans

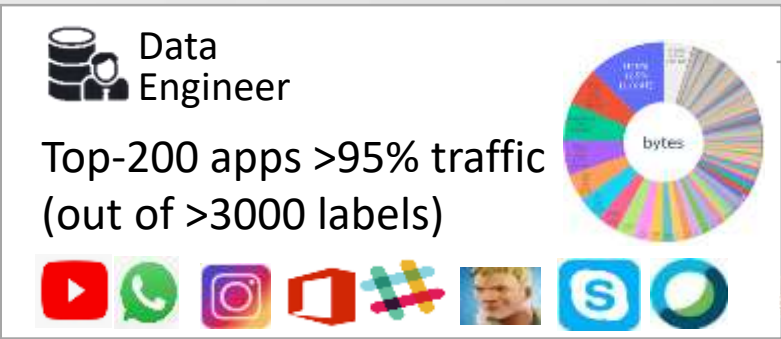
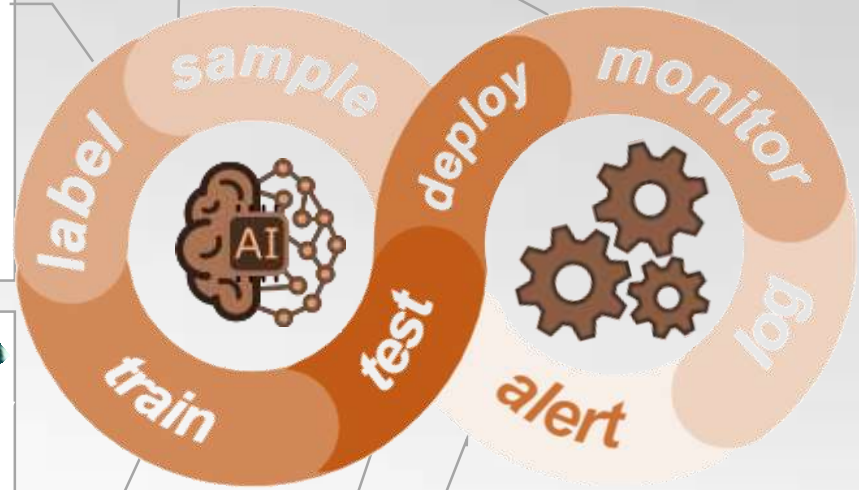
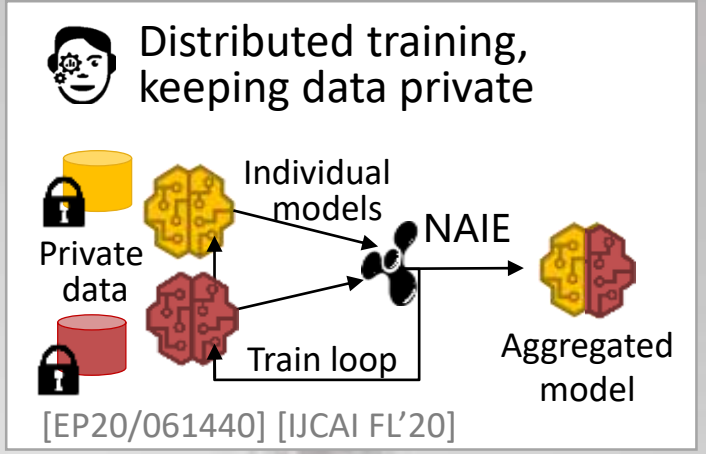
Legend:
 Open code/data
 Net  AI

...identify encrypted traffic application



Product Engineer
Enterprise + Residential
40TB, 10M flows
Commercial DPI

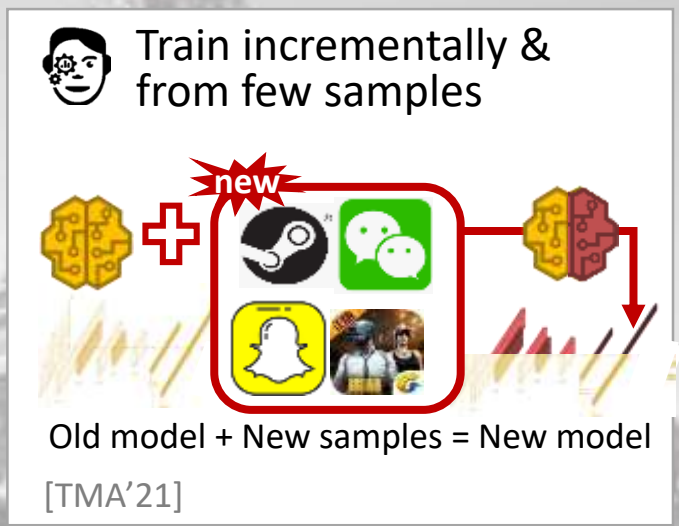
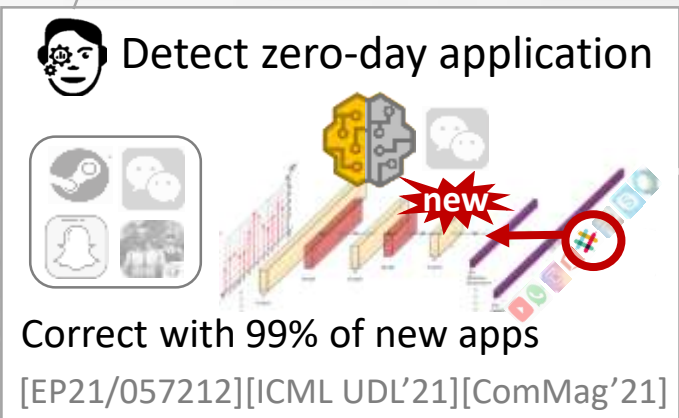
Traffic classification
Supervised learning



>10x simpler & faster than state of the art

- 150us on single ARM core (A72)
- ARM Cache + Ascend310 support

[SEC'21][SIGCOMM'20 Demo][INFOCOM'22]



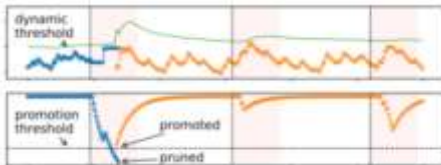
Unsupervised Outlier detection

Generic algorithms
Test several datasets,
including network data

RHF (Batch)
[ICDM'20]

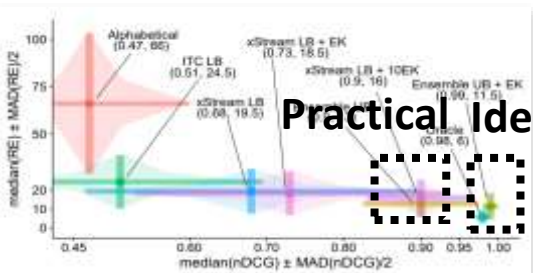
ODS (Streaming)
[IEEE Trans'21]

$$RHT_i(p) = \log \left[\frac{1}{P_{Q_j}} \right], \quad p \in S(Q_j)$$

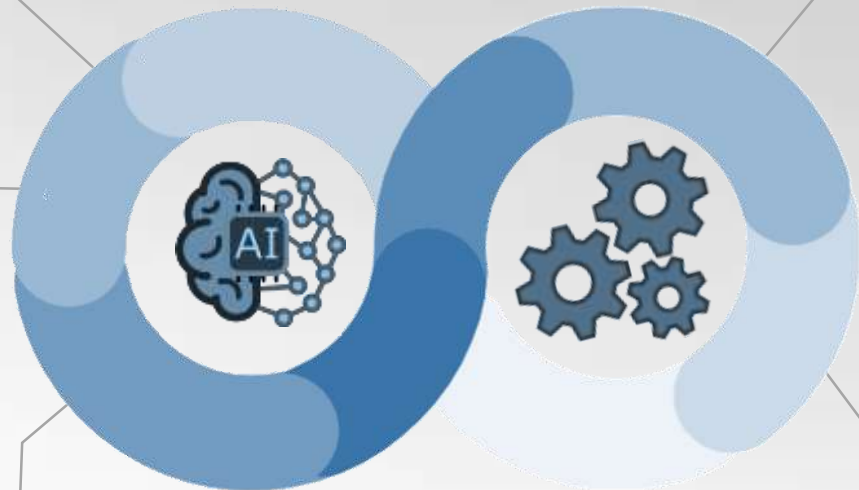


Semi-supervised XAI

Complementary expert knowledge
Best paper at [ITC32]

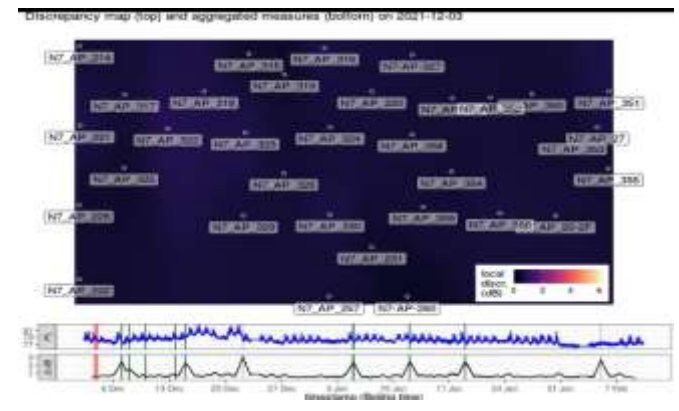


Practical Ideal



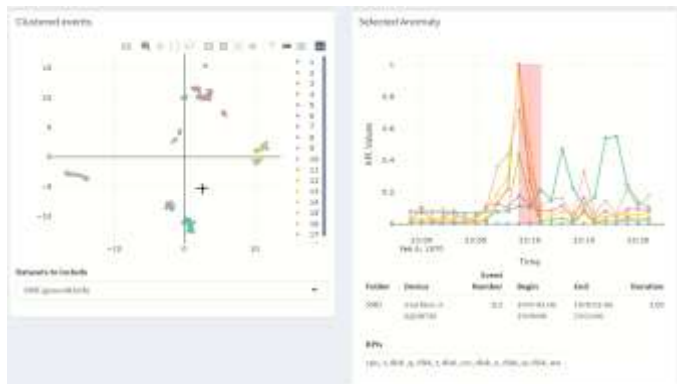
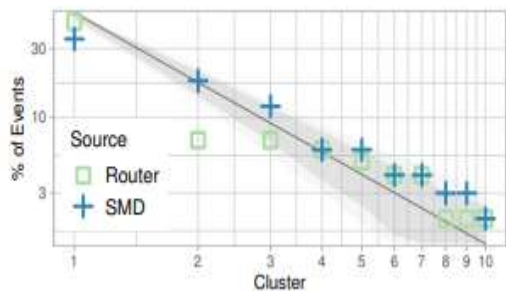
Changepoint detection

Focus on detection of impactful events



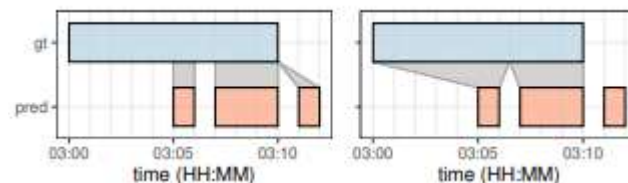
Clustering

Business-specific anomaly DB



Unbiased evaluation [KDD'22]



Theoretically principled metrics, provably robust against adversarial prediction



Train on simulator

Validate on controlled settings

Test on real network

Actions = Channel , Power 

Reward = $f(\text{coverage, interference})$

State = AP KPIs or 802.11k STA data



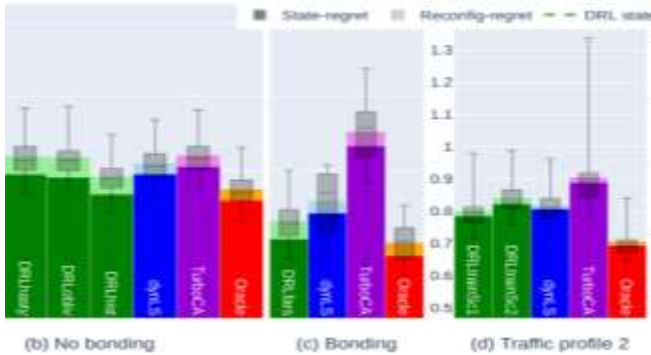
Autonomous network configuration



Reinforcement Learning 

Simulation

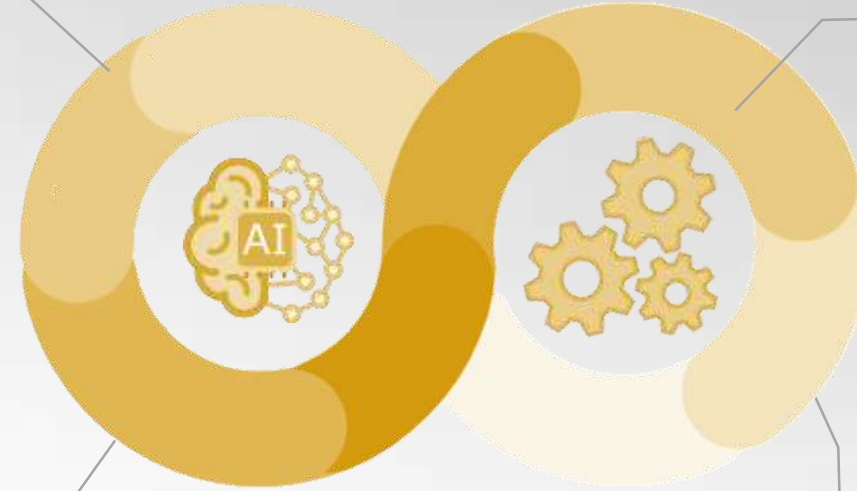
Compare **Deep RL** vs **Optimal oracle** / **TurboCA**



[Networking'21]



Principled >100,000 states explored at training, unbiased academic-style comparison



Controlled
Generalization ability validated on different settings w.r.t. training

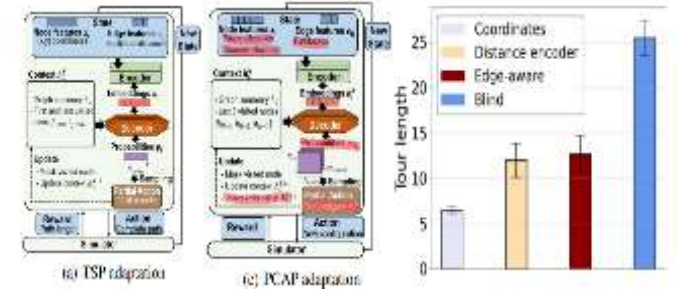
clear-cut-threshold

16	60.1%	58.0%	58.6%	55.6%	54.7%	47.5%
8	22.1%	21.9%	21.5%	23.0%	25.7%	29.2%
4	7.9%	8.0%	8.6%	10.1%	15.0%	23.3%
2	4.4%	3.9%	4.2%	6.1%	11.3%	18.9%
1	1.8%	2.2%	2.4%	4.5%	9.2%	18.2%
0	0.0%	0.6%	1.8%	3.3%	8.0%	16.3%
1	0.4%	0.4%	1.0%	2.5%	7.1%	14.8%
2	0.6%	0.7%	0.8%	2.0%	6.3%	14.2%
4	1.2%	1.4%	1.2%	1.7%	4.5%	11.4%
8	2.0%	2.0%	2.2%	2.2%	3.3%	8.9%
16	4.7%	4.6%	4.6%	4.4%	4.0%	6.0%
	0	1	2	4	8	16

Noise std. [dB]

[ArXiv'22]

Innovate, and loop again



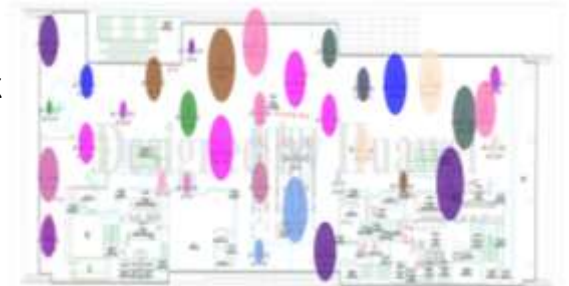
[AAAI GLRC'22]



Transformer-based
(the T in GPT-3 stands for transformer)



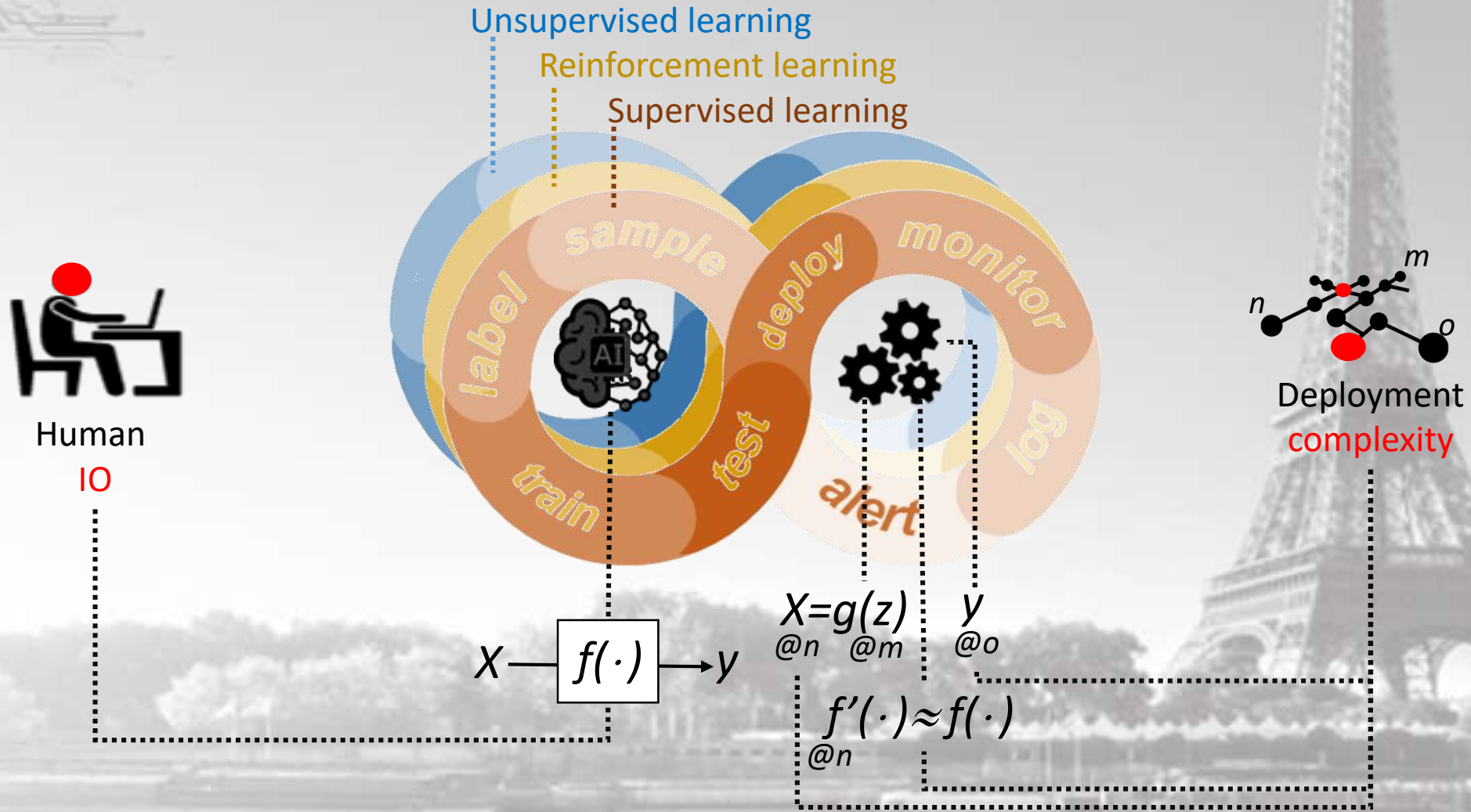
Real network
Real deployment, Months of operation with >10,000 users



Demo@[Infocom'21]

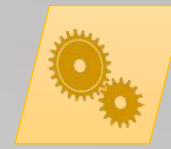


Limits of AI-Assisted networking





Limits of AI-Assisted networking

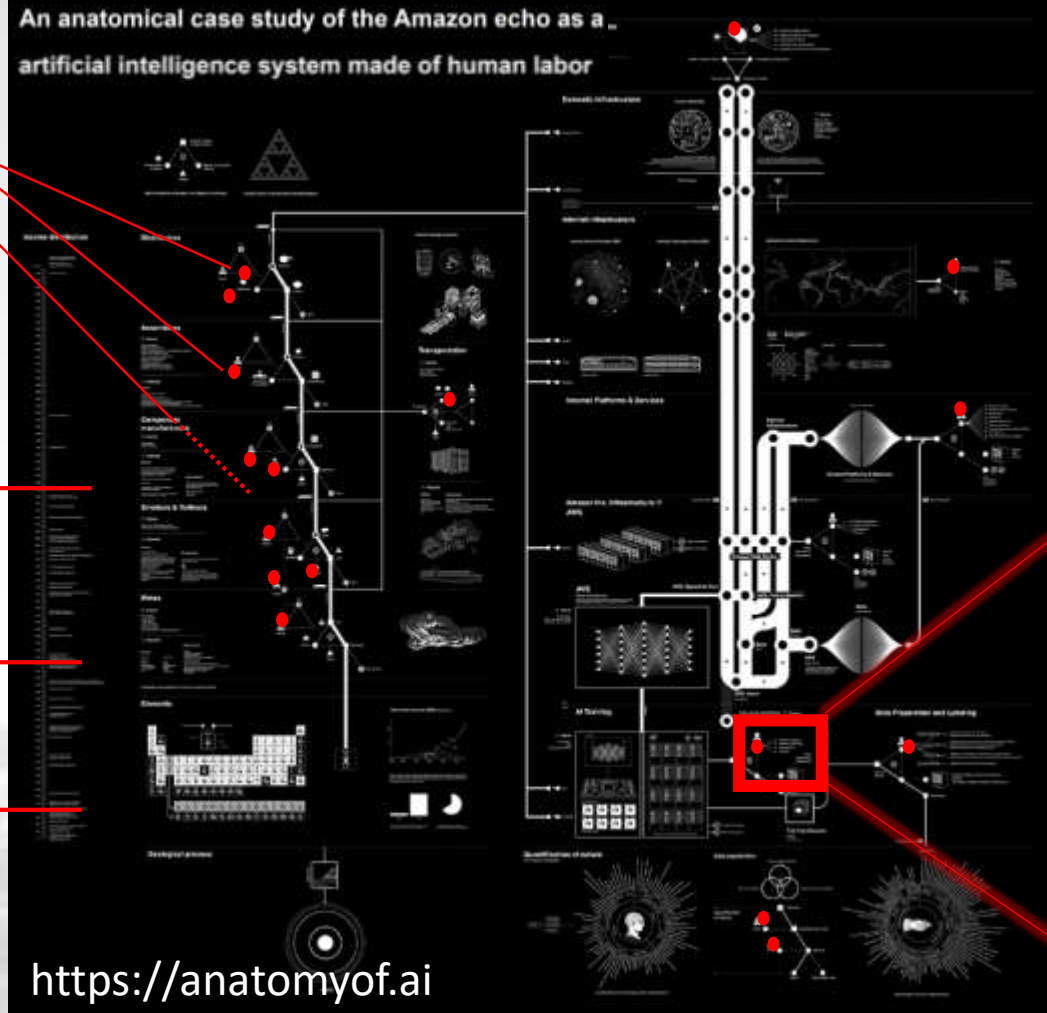


Human IO
Input



Anatomy of an AI system

An anatomical case study of the Amazon echo as a ... artificial intelligence system made of human labor



Humans

Salary
USD/mo

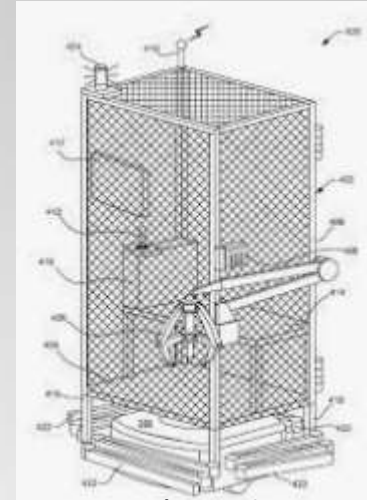
10k

5k

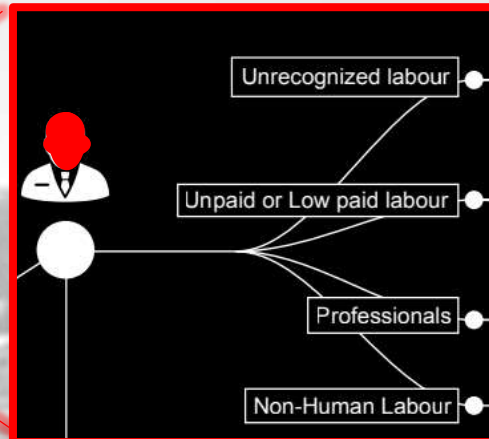
1k

US
poverty
line

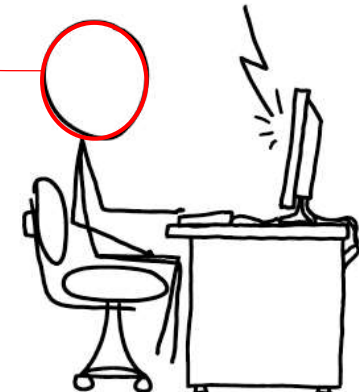
<https://anatomyof.ai>



Amazon's worker cage
[US Patent 9,280,157]



TO PROVE YOU'RE A HUMAN,
CLICK ON ALL THE PHOTOS
THAT SHOW PLACES YOU
WOULD RUN FOR SHELTER
DURING A ROBOT UPRISING.



<https://xkcd.com/2228/>



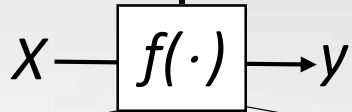
Limits of AI-Assisted networking



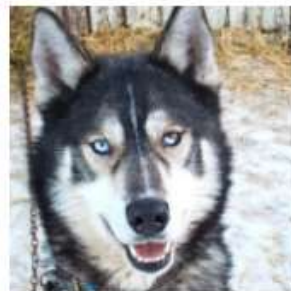
Human IO
Output



ML System → Output



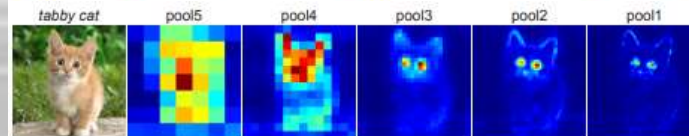
“Clever hans” models, good (or bad) for the wrong reason



(a) Husky classified as wolf



(b) Explanation



tabby cat

pool5

pool4

pool3

pool2

pool1

THIS IS YOUR MACHINE LEARNING SYSTEM?

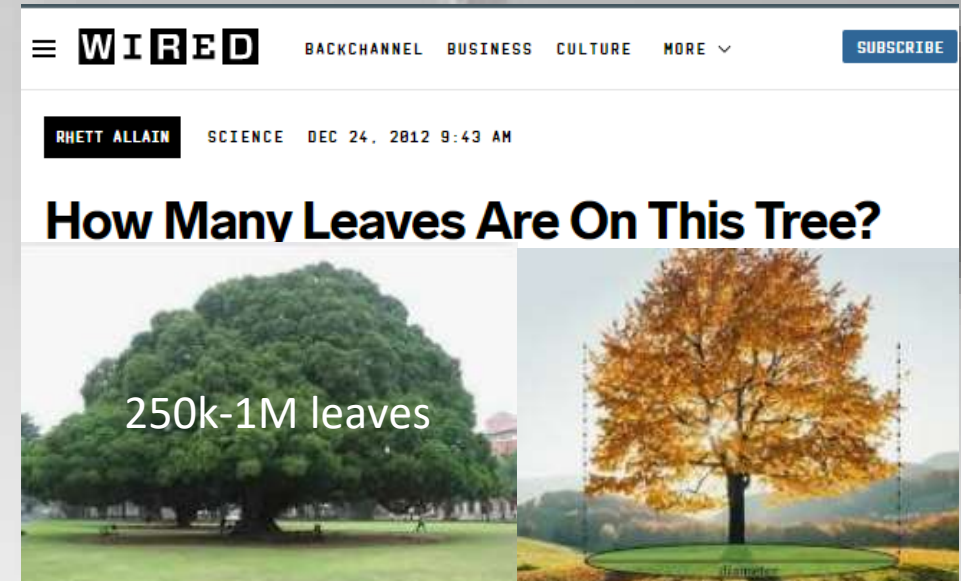
YUP! YOU POUR THE DATA INTO THIS BIG PILE OF LINEAR ALGEBRA, THEN COLLECT THE ANSWERS ON THE OTHER SIDE.

WHAT IF THE ANSWERS ARE WRONG?

JUST STIR THE PILE UNTIL THEY START LOOKING RIGHT.



<https://xkcd.com/1838/>



250k-1M leaves

(I've seen RF models >>1M)

“Tree are interpretable”

Activation & feature maps, gradient back-propagation: interpretable only for images !



Limits of AI-Assisted networking



Deployment complexity

Google on AI Technical debt [NeurIPS 2015]

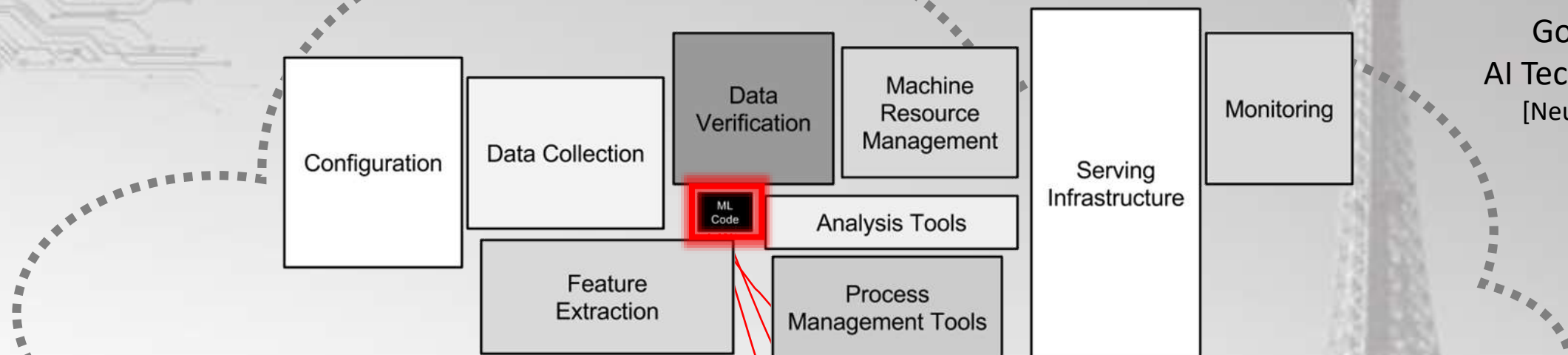
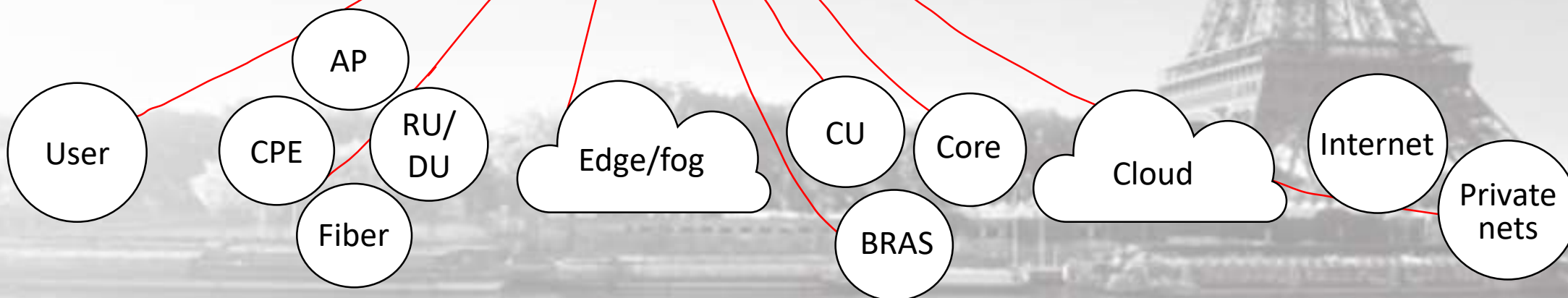


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.



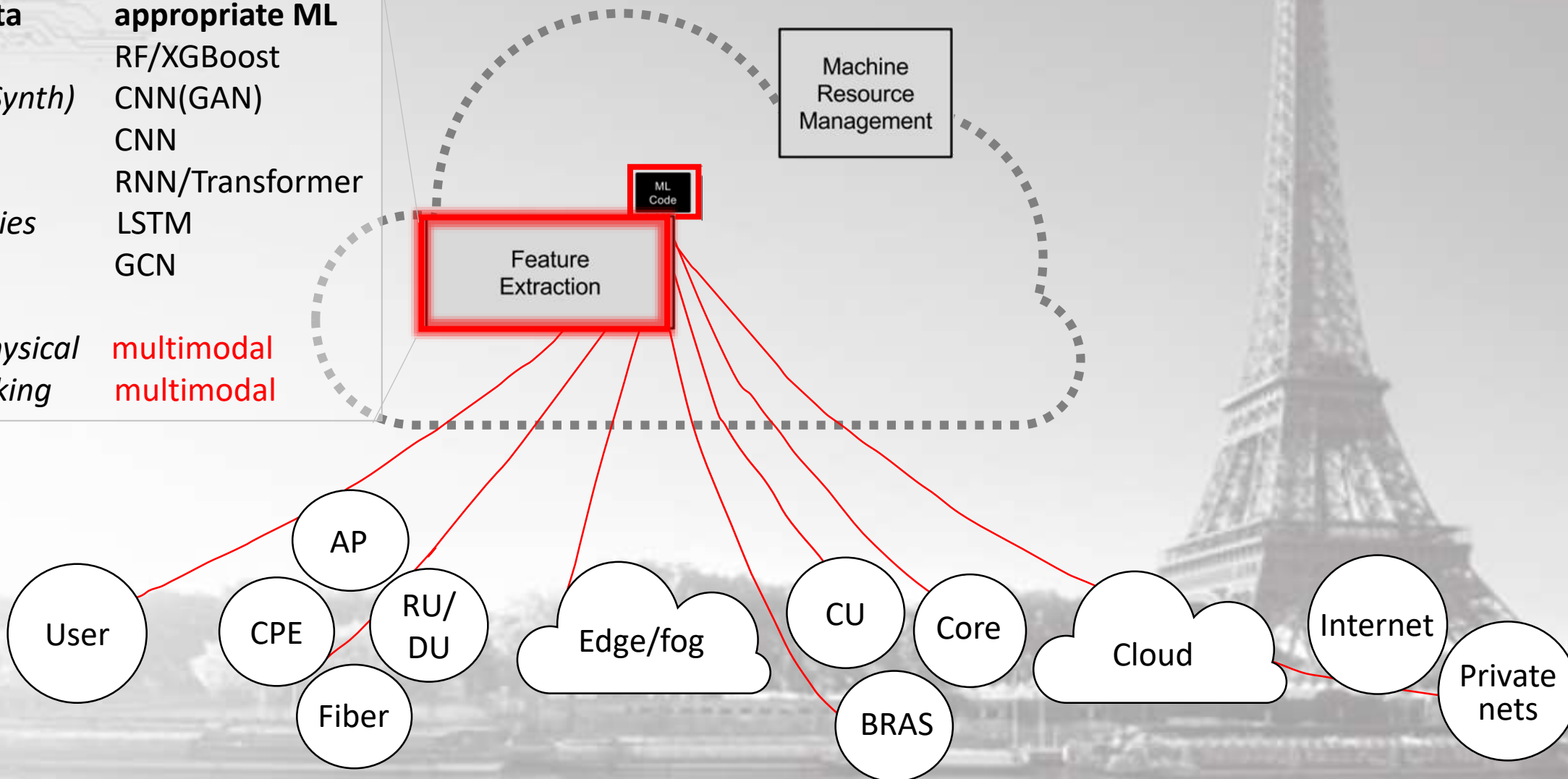


Limits of AI-Assisted networking



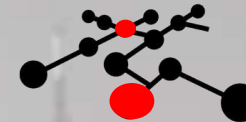
Heterogeneity
complexity

Raw data	appropriate ML
Tabular	RF/XGBoost
Image(Synth)	CNN(GAN)
Audio	CNN
Text	RNN/Transformer
Timeseries	LSTM
Graphs	GCN
Cyberphysical Networking	multimodal multimodal



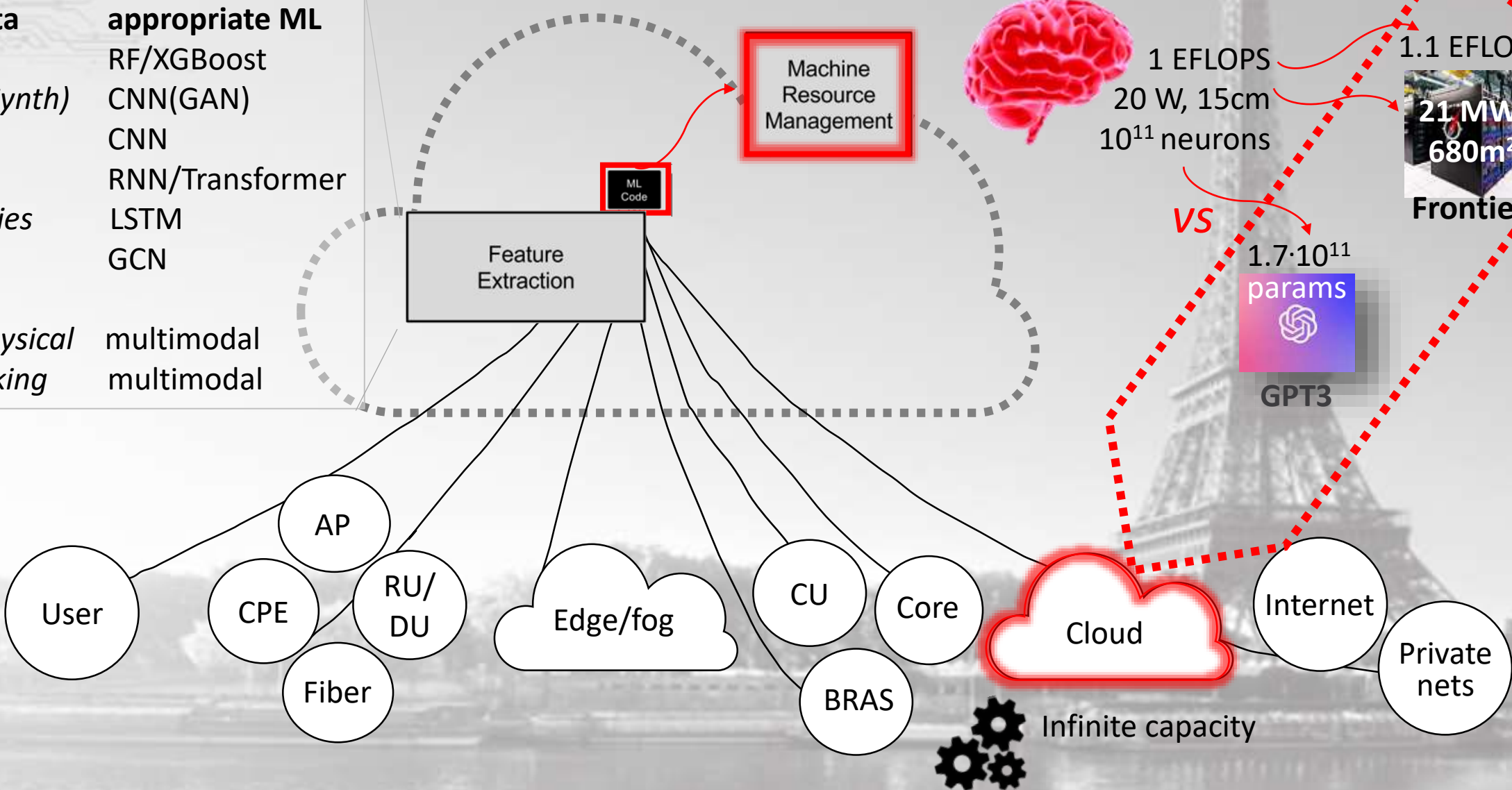


Limits of AI-Assisted networking



Model complexity

Raw data	appropriate ML
Tabular	RF/XGBoost
Image(Synth)	CNN(GAN)
Audio	CNN
Text	RNN/Transformer
Timeseries	LSTM
Graphs	GCN
Cyberphysical Networking	multimodal multimodal



VS

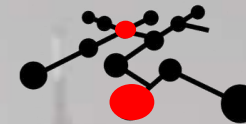
1 EFLOPS
20 W, 15cm
10¹¹ neurons

1.1 EFLOPS
21 MW
680m²
Frontier

1.7·10¹¹
params
GPT3

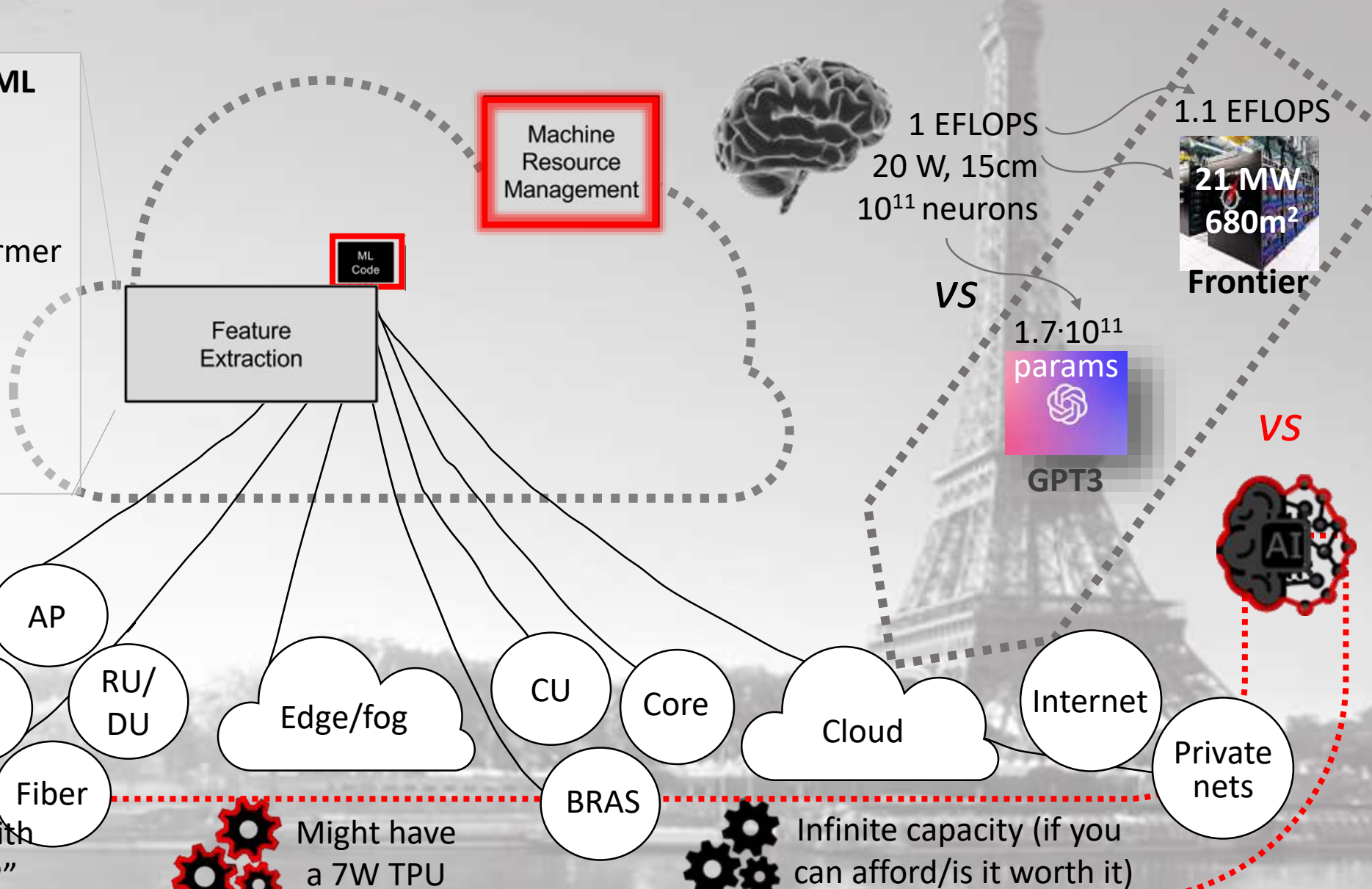


Limits of AI-Assisted networking



Model complexity

Raw data	appropriate ML
Tabular	RF/XGBoost
Image	GAN
Audio	CNN
Text	RNN/Transformer
Timeseries	LSTM/GAN
Graphs	GCN
Cyberphysical Networking	multimodal multimodal



“What can you do with 1% of an ARM core ?”

Might have a 7W TPU

Infinite capacity (if you can afford/is it worth it)

BACK TO THE FUTURE



How **3**





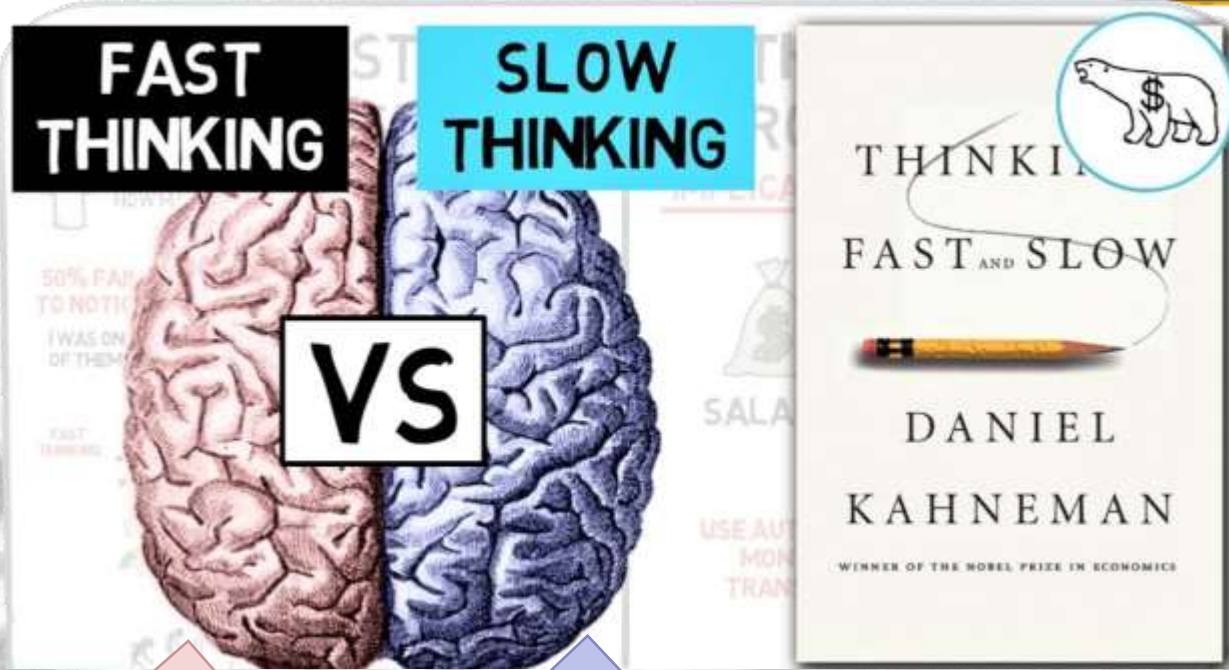
Principles of AI-Native networking

AI algorithms & compute

Highly inappropriate analogy
Do not interpret as first-degree



Explains irrational bias in human decision related to economics



FAST THINKING

Correct on simple repetitive tasks. Low cost but prone to bias and errors.

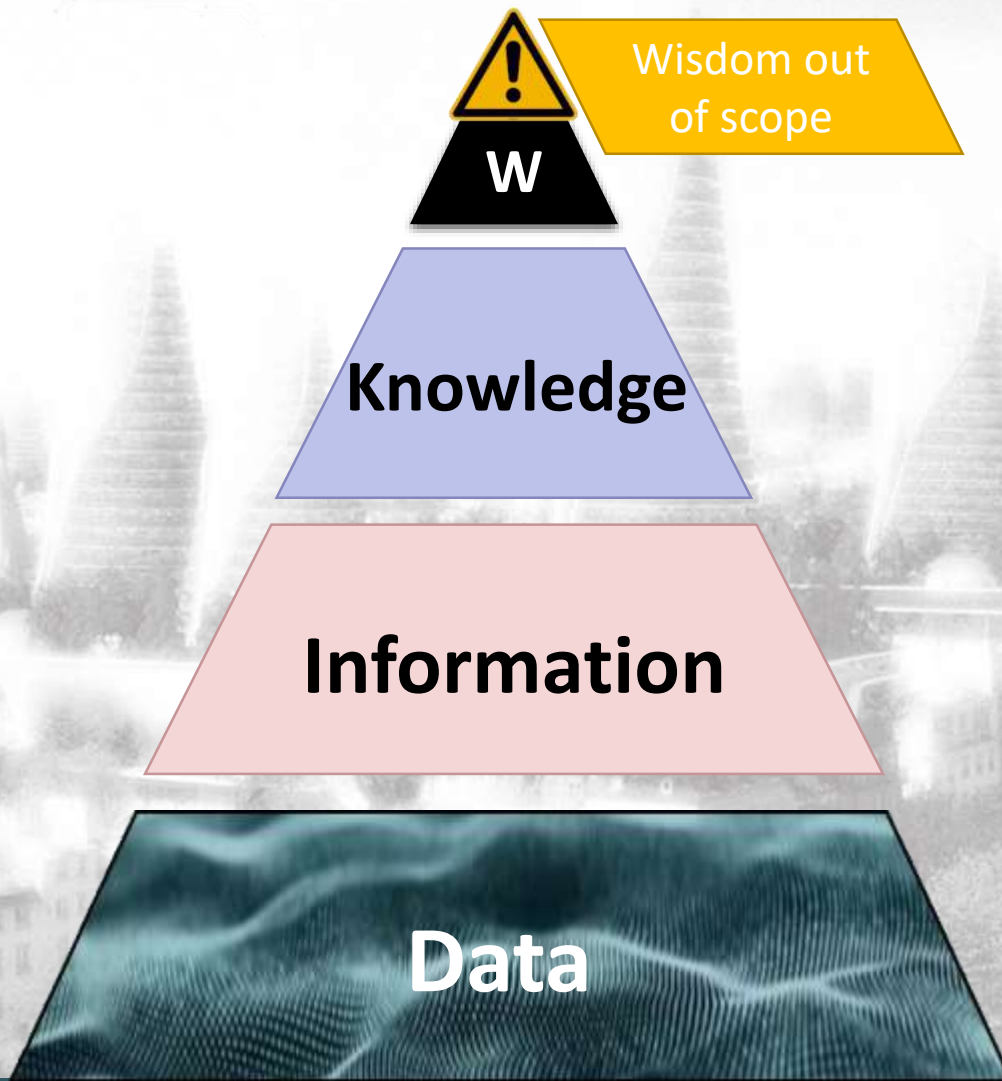
Advanced capabilities required for difficult tasks, or missing information. Significant cognitive effort.

SLOW THINKING



Principles of AI-Native networking

DIKW pyramid





Principles of AI-Native networking

DIKW pyramid

Out of distribution detection

Inference,
Regression
Classification

Lossy compression,
Representation
Learning

Wisdom out
of scope

W

Knowledge

" 1% of an
ARM core"

Widespread
(to ubiquitous)

FAST
THINKING

Information

Data

User

CPE

AP

Fiber

RU/
DU

Edge/fog

CU

BRAS

Core

Cloud

Internet

Private
nets



Principles of AI-Native networking

DIKW pyramid

Out of distribution detection

Inference,
Regression
Classification

Lossy compression,
Representation
Learning

Wisdom out
of scope

W

Knowledge

More capacity (when
affordable & worth)

Fine tuning, transfer learning

In/decremental learning
Few/0 shot learning

Knowledge distillation,
causal explanation

" 1% of an
ARM core"

Widespread
(to ubiquitous)

FAST
THINKING

Information

SLOW
THINKING



May need
Cloud compute

Some devices
may benefit

Greater
Deployment
complexity

Pre-existing
knowledge

Model-based

Academia

Industry best
practices

Data

User

CPE

AP

Fiber

RU/
DU

Edge/fog

CU

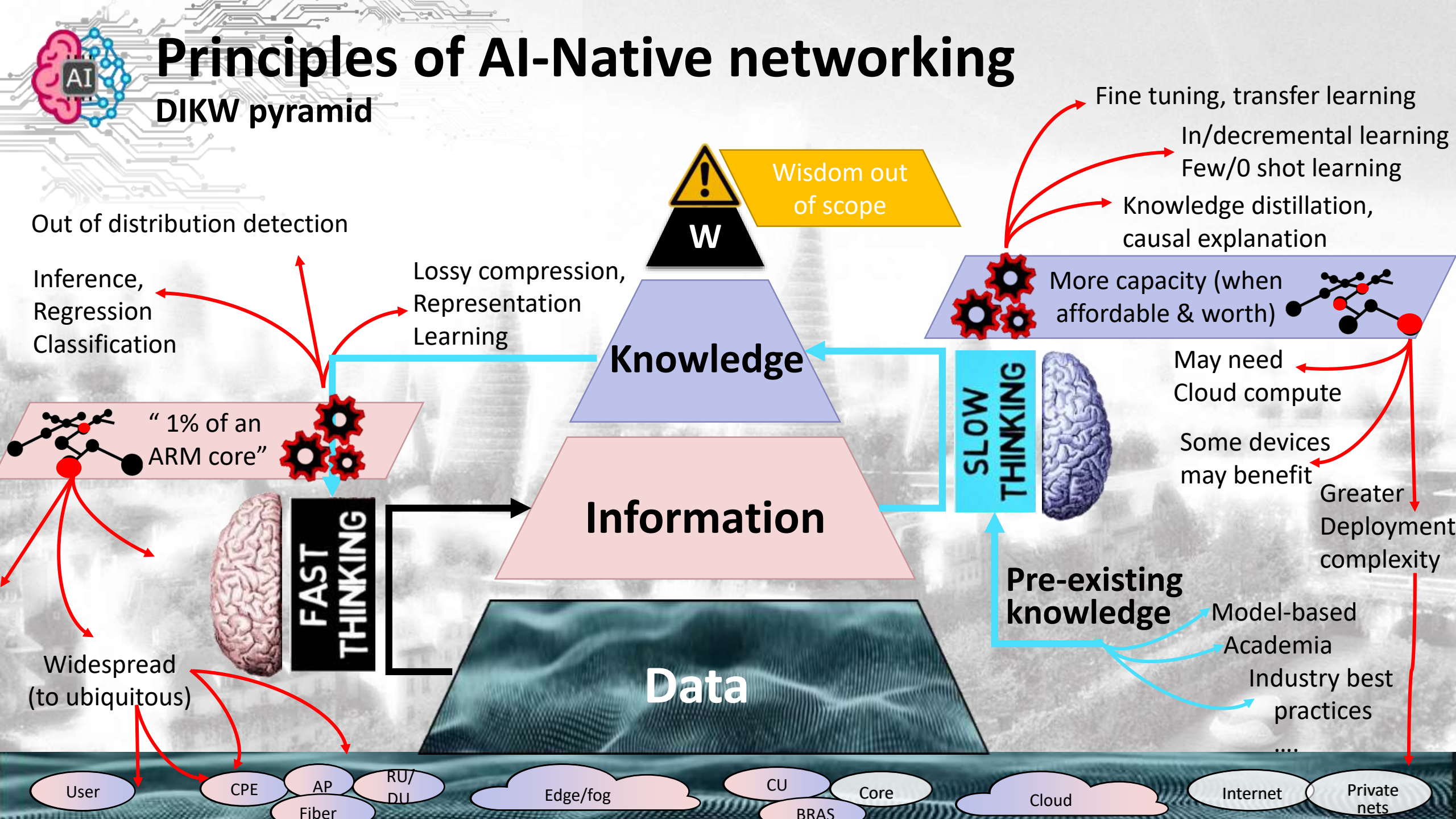
BRAS

Core

Cloud

Internet

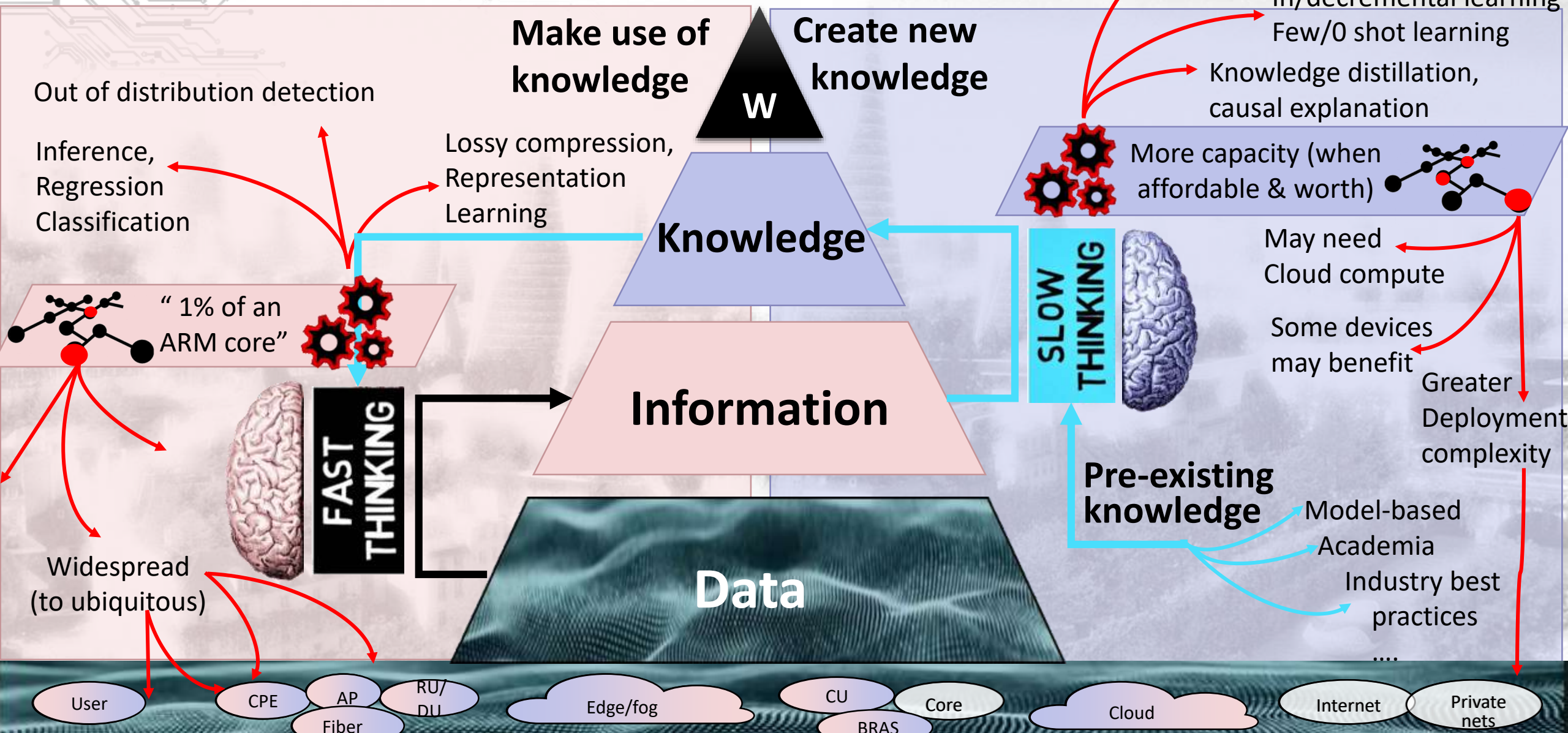
Private
nets





Principles of AI-Native networking

DIKW pyramid





Ingredients of AI-Native networking

 Explainable

 Automated

 Fit

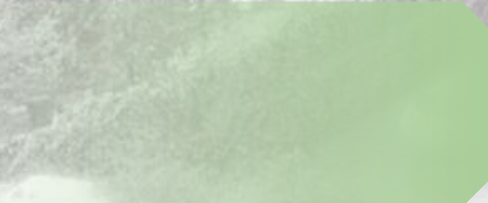
 Green



Human
IO



Deployment
complexity



**SLOW
THINKING**



**FAST
THINKING**



Ingredients of AI-Native networking


 **Explainable** Complex law landscape (AI Act)

 **Automated** Algorithmic complexity

 **Fit** Infrastructural complexity

 **Green** Model complexity

 Human IO

 Deployment complexity

Need interpretable & faithful models

Automate knowledge & models maintenance

Efficiently orchestrate & execute AI functions

Need lightweight & energy efficient AI

SLOW THINKING



FAST THINKING

AI Native

Artificial Intelligence Act

New EU legislation ~GDPR extended to AI processing, primordial for *biometric* data (eg. Facial recognition) to avoid *bias* (eg. Racial discrimination) or privacy leaks



Complex law landscape (AI Act)

Explainable

Automated

Fit

Green

Network AI issues/risks

- **Bias:** ensure effective transferability of AI models
- **Accountability:** business-policy explanation of AI decision
- **Compliance:** legal aspects of accountability
- **Interpretability:** AI decisions inherently less interpretable than human-made heuristics
- **Verifiability:** what can be proven, can be more easily trusted

Need to explain models outputs (XAI)

- Explicit quantification of *confidence* in the model output
- *Step-by-step, multi-level* explanation
- *Faithfulness, i.e.,* explanation of actual model decision (vs surrogate)
- Explicit warnings about input *data quality*

Cost of explainability

- May tradeoff with accuracy loss, or with increased complexity
- As for security, you need to budget the risk of *not having* faithful explainability

AI Native

Artificial Intelligence Act

New EU legislation ~GDPR extended to AI processing, primordial for *biometric* data (eg. Facial recognition) to avoid *bias* (eg. Racial discrimination) or privacy leaks

Explainable

Complex law landscape (AI Act)

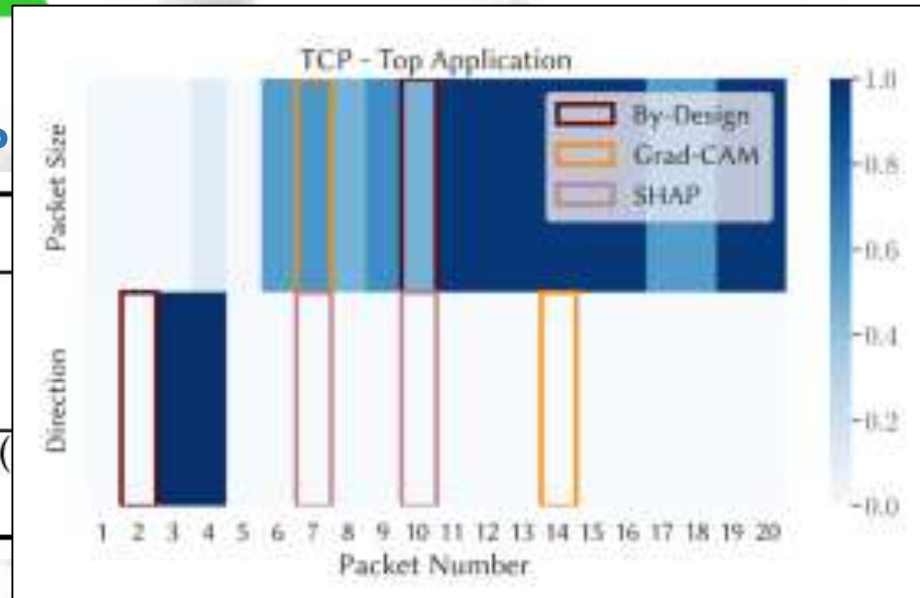


Automated

Cost of explainability?

Metric

- Accuracy (%)
- Inference GPU (μ s/sample)
- Inference CPU (μ s/sample)
- Number of Trainable Params (FLOPs - Multiply-Adds (M))



State of the art faithful XAI model

ProtoPNet

- 81.6
- 5.5
- 169.7
- 201
- 2 Prototypes/class

Fit

(Of course we have something better but it's not public :)

	Grad-CAM	SHAP	XAI Correctness	ProtoPNet
Top 2 Accuracy (%)	8.7	6.1	100%	100%
Top 10 Accuracy (%)	39.9	27.8	100%	100%

Green

AI Native

Top-5 bottlenecks holding back AI adoption ?

<https://www.oreilly.com/radar>



Explainable

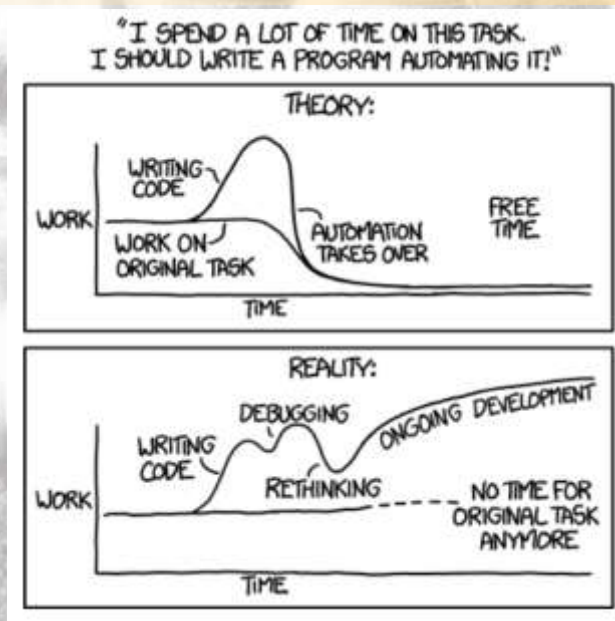
Automated



Taming algorithmic complexity

Fit

Green



<https://xkcd.com/1319/>

- ❑ **Compensate lack of skills**
 - Network Architecture Search (autoML/NAS) though inherently non-
 - Class incremental learning (CIL)
 - Automated hyperparameter selection for anomaly detection (autoAD/metaOD)
- ❑ **Compensate lack of data and label**
 - Few-shot learning (FSL)
 - Self-supervised learning (SSL)

AI Native

Explainable

Automated

Fit

Green

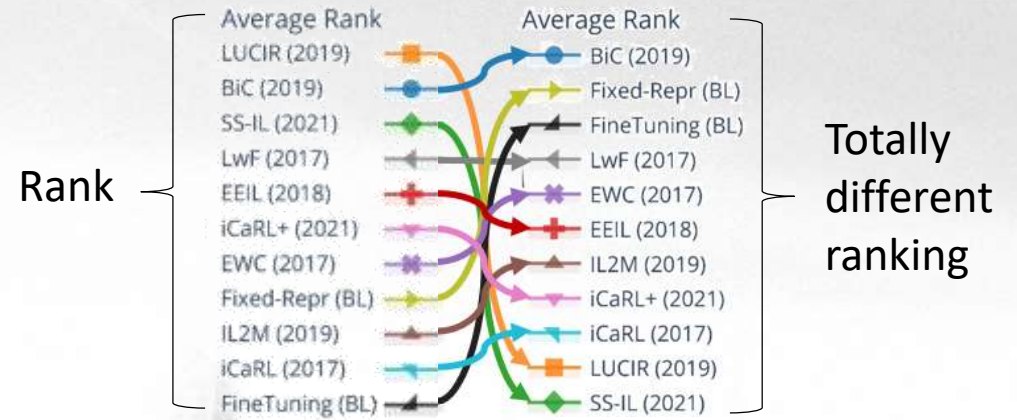
Supervised learning

Class Incremental Learning (CIL)

- Rank the state of the art
- Same dataset, difference in adding many classes once vs few classes several times

Image-style scenario

Network-like problem



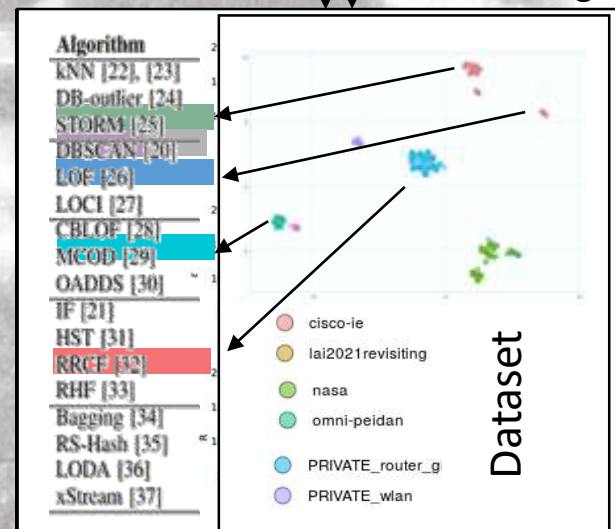
Taming algorithmic complexity

Unsupervised Learning

- ✓ No training
- ✓ Generalize better
- ✗ Lots of algorithms
- ✗ Hyperparametrization time-consuming even for AI experts

Unsupervised Meta-learning

Multi-variate KPI time-series Computational budget



Auto Anomaly Detection (AutoAD)

Expert-level algorithm selection / ensembling



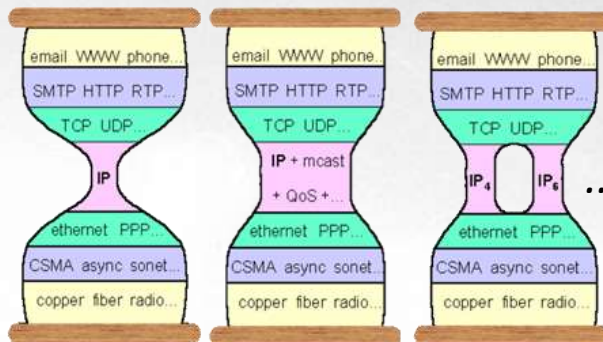
Hyper-parameter auto-tuning



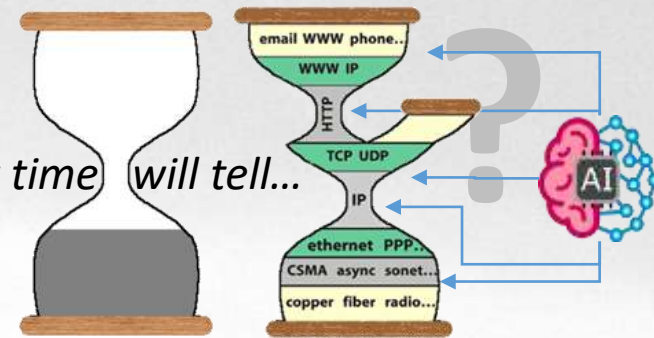
AI Native

AI latest kids on the Networking block

IP Network originally designed for connectivity (neither for QoS, mobility, nor security... nor AI!)



Watching the Waist of the Protocol Hourglass
Steve Deering @IETF51 (2001)



Evolution of the IP Model
Dave Thaler @IETF73 (2009)

..only time will tell..

Explainable

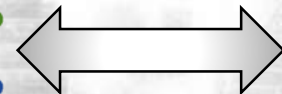
Automated

Fit

Green



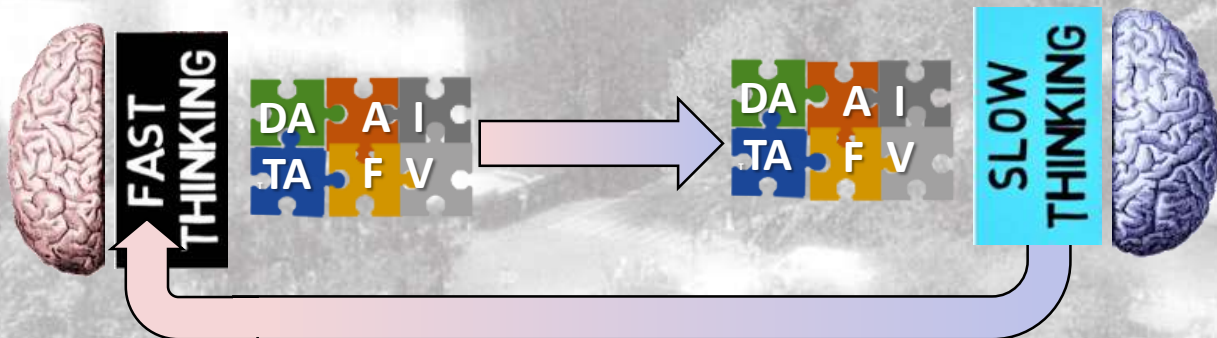
Network data representation (& governance)



Networked AI functions (& architecture)



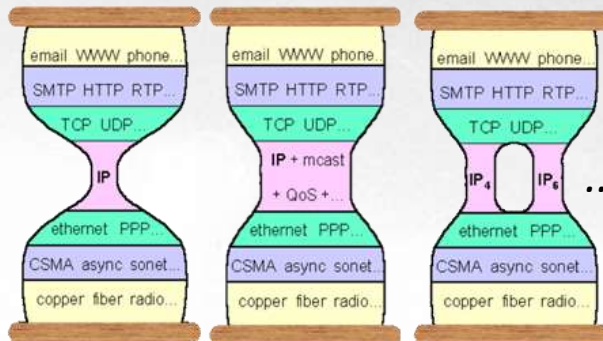
Taming infrastructural complexity



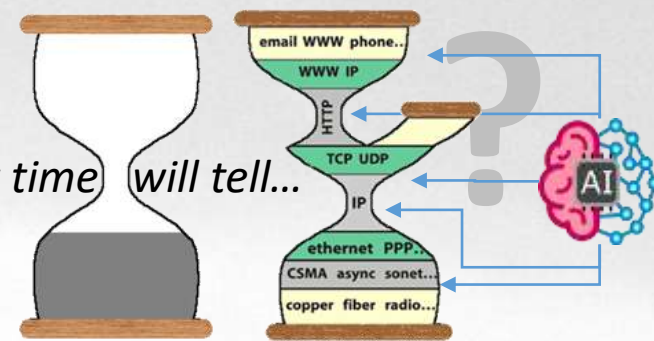
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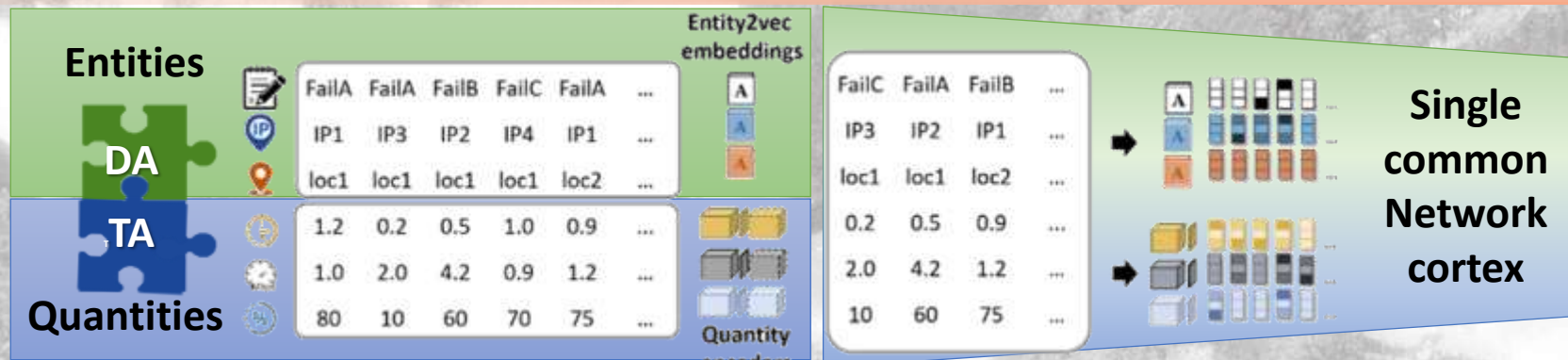
Network data representation & governance



- Universal network data representation (multimodal)
- Fit for AI processing (common network cortex, many AI tasks)
- Fit for AI Act & GDPR (eg. ACL, data boundaries, ...)



Taming infrastructural complexity

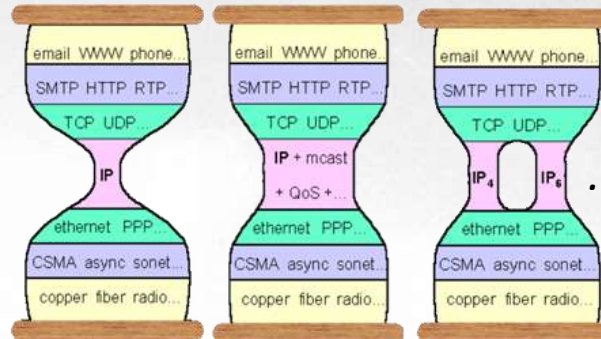


Many heads, many tasks

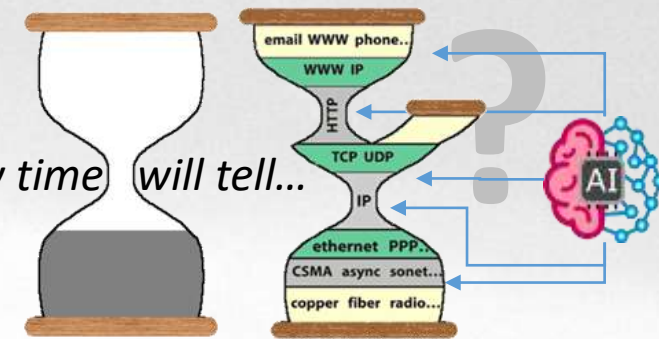
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Green

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Taming infrastructural complexity



Network AI functions & architecture



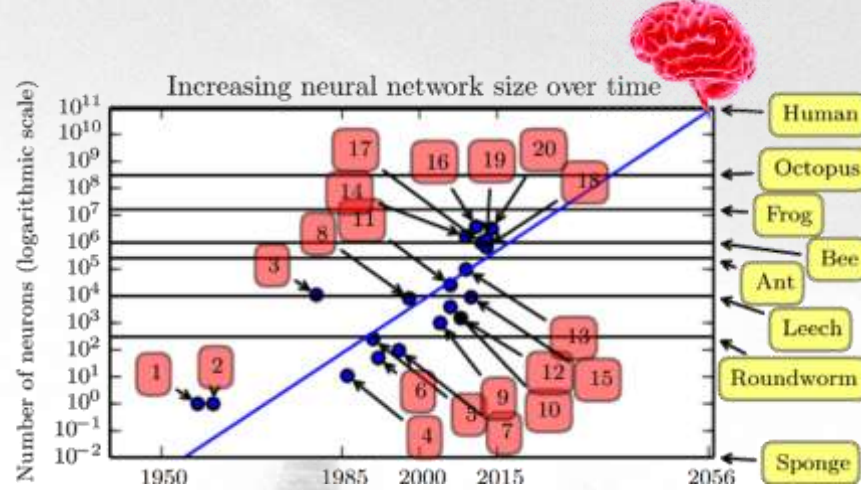
- Cloud-native architecture not enough, Edge/fog/serverless neither. P4/SDN at the other extreme. Reminiscence of Tennenhouse's Active networking (1996) ?
- Which network functions are best fit to be replaced/auto-tuned by AI ? How to systematically compose, execute AIFV ?



AI Native

AI models growth exceeds Moore law

Deep learning, MIT Press
<https://deeplearningbook.org>



Model size in 2020 exceeds 2015 forecast by 10,000x!

Human brain scale reached in 2020 (30+ years earlier than expected)



Need energy efficient AI models

- Raise awareness of computational complexity
- Set explicit “accuracy/joule” targets for certification (~“km/liter” for cars, or A-D energy labels)
- Applies to many AI aspects (training, inference, etc.)

Small is beautiful (but not too small)

- Huge models race is for NLP/CVPR (like the quantum qubit race)
- AI researchers produce huge models, system researchers use tiny ones

Explainable

Automated

Fit

Green

Taming (unnecessary) model complexity

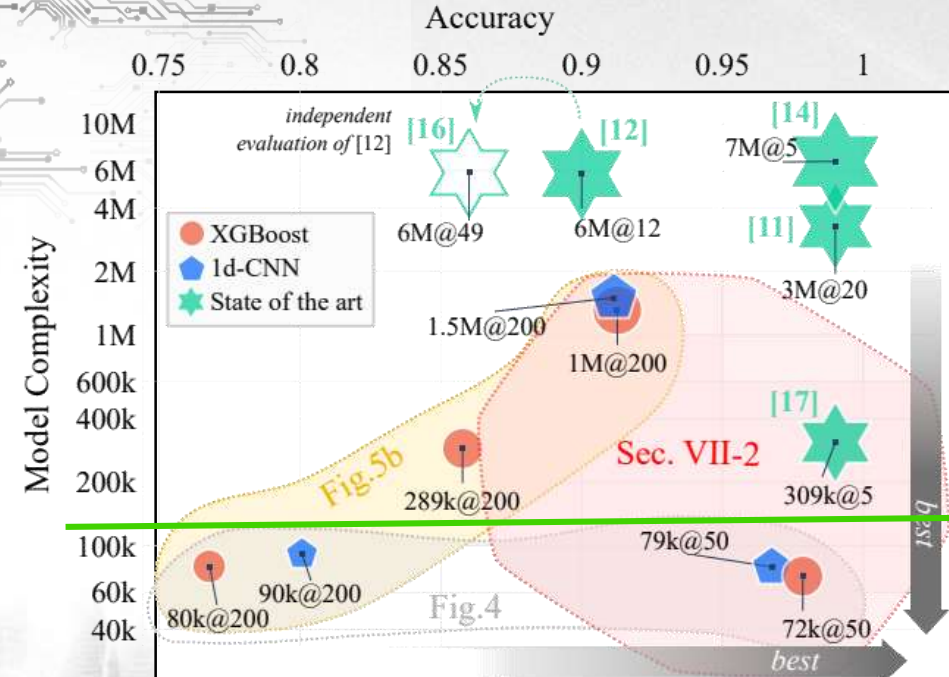
AI Native

Explainable

Automated

Fit

Green



AI researchers: Unnecessarily big !

	Method	$W [\times 1k]$	K	$W/K [\times 1k]$	Acc. [%]
State of the art	[14]	6,640	5	1,328	99
	[17]	309	5	61	99
	[12]	5,800	12	483	90
	[11]	3,270	20	163	99
	[16]	5,800	49	119	86
1d-CNN		79	50	1.44	96
		90	200	0.450	81
		1,479	200	7.5	91
XGBoost		72	50	1.44	96
		80	200	0.4	76
		289	200	1.44	85
		1,307	200	5	91

$O(10^6)$

~100k-large overall [TNSM'21b] [SEC'21]
 ~5k weights/class AI-viewpoint + system

$O(10)$
 ASIC: 3 layers, 100 neurons (overall!)
 SmartNIC: 50 neurons (overall!)

Small is beautiful (but not too small) System researchers: too small !

- Huge models race is for NLP/CVPR (like the quantum qubit race)
- AI researchers produce huge models, system researchers use tiny ones

Taming (unnecessary) model complexity



Native network intelligence,

FAST THINKING



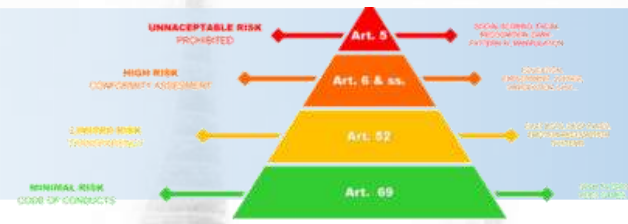
&



SLOW THINKING

Explainable

Complex law landscape (AI Act)



Need interpretable & faithful models

Automated

Algorithmic complexity



Tooling to automate ML model maintenance

Fit

Infrastructural complexity



Efficiently orchestrate & execute AI functions

Green

Model complexity



Need lightweight & energy efficient AI



Recent stuff

Internet: <https://nonsns.github.io/>

Intranet: <https://frc-datacom.rnd-gitlab-eu-c.huawei.com/ai4net/>

2022 20 ↑

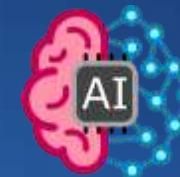
- [CoNEXT-NNI-22a] Boffa, Matteo and Vassio, Luca and Drago, Idilio and Mellia, Marco and Milan, Giulia and Houidi, Zied Ben and Rossi, Dario, [📄](#) "On Using Pretext Tasks to Learn Representations from Network Logs" ACM CoNext workshop on Native Network Intelligence (NNI) dec. 2022, [Conference](#) [Abstract](#) [Bibtex](#)
- [CoNEXT-NNI-22b] Rossi, Dario and Liang, Zhang, [📄](#) "Native Network Intelligence, Fast and Slow" ACM CoNext workshop on Native Network Intelligence (NNI) dec. 2022, [Conference](#) [Abstract](#) [Bibtex](#)
- [CoNEXT-GNN-22] Fernandes, Danilo Marinho and Krolikowski, Jonatan and Houidi, Zied Ben and Chen, Fuxing and Rossi, Dario, [📄](#) "Cross-network transferable neural models for WLAN interference estimation" ACM CoNext workshop on Graph Neural Networks (GNN) dec. 2022, [Conference](#) [Abstract](#) [Bibtex](#)
- [AICCSA-22] Nestic, Stefan and Putina, Andrian and Bahri, Maroua and Huet, Alexis and Navarro, Jose Manuel and Rossi, Dario and Sozio, Mauro, [📄](#) "StreamRHF: Tree-based unsupervised anomaly detection for data streams" 19th ACS/IEEE International Conference on Computer Systems and Applications (AICCSA 2022) dec. 2022, [Conference](#) [Abstract](#) [Bibtex](#)
- [HotNets-22] Houidi, Zied Ben and Azorin, Raphael and Gallo, Massimo and Finamore, Alessandro and Rossi, Dario, [📄](#) "Towards a systematic multi-modal representation learning for network data" ACM HotNets nov. 2022, [Conference](#) [Abstract](#) [Bibtex](#)
- [TNSM-22] Rossi, Dario and Zhang, Liang, [📄](#) "Landing AI on Networks: An equipment vendor viewpoint on Autonomous Driving Networks" In IEEE Transactions on Network and Service Management (TNSM), Vol. 19, sep. 2022, DOI 10.1109/TNSM.2022.3169988 [Journal](#) [Abstract](#) [Bibtex](#)
- [ITC34] Navarro, Jose Manuel and Huet, Alexis and Rossi, Dario, [📄](#) "Rare Yet Popular: Evidence and Implications from Anomaly Detection Datasets" ITC34 sep. 2022, [Conference](#) [Abstract](#) [Bibtex](#)
- [SIGMETRICS-PER-22] Roberts, James and Rossi, Dario, [📄](#) "Size-Based Scheduling vs Fairness for Datacenter Flows: A Queuing Perspective" In ACM SIGMETRICS Perform. Eval. Rev., Vol. 50, No. 2, sep. 2022, [Journal](#) [Abstract](#) [Bibtex](#)
- [PATENT-PCT/EP2022/075646] YANG, Lixuan and FINAMORE, Alessandro and CHEN, Fuxing and ROSSI, Dario, [📄](#) "A device and method for network traffic classification", sep. 2022, [Patent](#)
- [KDD-22] Huet, Alexis and Navarro, Jose Manuel and Rossi, Dario, [📄](#) "Local Evaluation of Time Series Anomaly Detection Algorithms" ACM SIGKDD Conference on Knowledge Discovery and Data mining (KDD) aug. 2022, [Conference](#) [Abstract](#) [Bibtex](#)
- [SIGCOMM-CCR-22] Wang, Chao and Finamore, Alessandro and Yang, Lixuan and Fauvel, Kevin and Rossi, Dario, [📄](#) "AppClassNet: A commercial-grade dataset for application identification research" In ACM SIGCOMM Computer Communication Review, Vol. 52, jul. 2022, DOI <https://doi.org/10.1145/3561954.3561958> [Journal](#) [Abstract](#) [Bibtex](#)
- [ComCom-22] Houidi, Zied Ben and Rossi, Dario, [📄](#) "Neural language models for network configuration: Opportunities and reality check" In Elsevier Computer Communication, Vol. (to appear), jul. 2022, [Journal](#) [Abstract](#) [Bibtex](#)
- [ArXiv-22-DRL] Iacoboalea, Ovidiu and Krolikowski, Jonatan and Houidi, Zied Ben and Rossi, Dario, [📄](#) "From Design to Deployment of Zero-touch Deep Reinforcement Learning WLANs" Jul. 2022, [arXiv](#) [Tech.Rep.](#) [Abstract](#) [Bibtex](#)
- [ICML-22] Franzese, Giulio and Rossi, Simone and Yang, Lixuan and Finamore, Alessandro and Rossi, Dario and Filippone, Maurizio and Michiardi, Pietro, [📄](#) "How much diffusion time is enough?" ICML 2022 workshop on Continuous time methods for machine learning Jun. 2022, [Conference](#) [Abstract](#) [Bibtex](#)
- [INFOCOM-22] Finamore, Alessandro and Roberts, James and Gallo, Massimo and Rossi, Dario, [📄](#) "Accelerating Deep Learning Classification with Error-controlled Approximate-key Coching" IEEE INFOCOM may. 2022, [Conference](#) [Abstract](#) [Bibtex](#)
- [PATENT-PCT/EP2022/059292] FINAMORE, Alessandro and YANG, Lixuan and ROSSI, Dario, [📄](#) "Method to address extreme class imbalance in AI based classifiers", apr. 2022, [Patent](#)
- [PATENT-PCT/EP2022/057757] NAVARRO, Jose Manuel and HUET, Alexis and ROSSI, Dario, [📄](#) "Aggregation of Anomalies in a Network", mar. 2022, [Patent](#)

AI Assisted

["Landing AI on Networks: An equipment vendor viewpoint on Autonomous Driving Networks" | n IEEE TNSM, Vol. 19, sep. 2022, DOI 10.1109/TNSM.2022.3169988](#)

AI Native

["Native Network Intelligence, Fast and Slow" ACM CoNext workshop on Native Network Intelligence \(NNI\) dec. 2022](#)



Thanks!
// || ??

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Director, DataCom Lab, Paris Research Center

