AI for Network Management

Network Management RG

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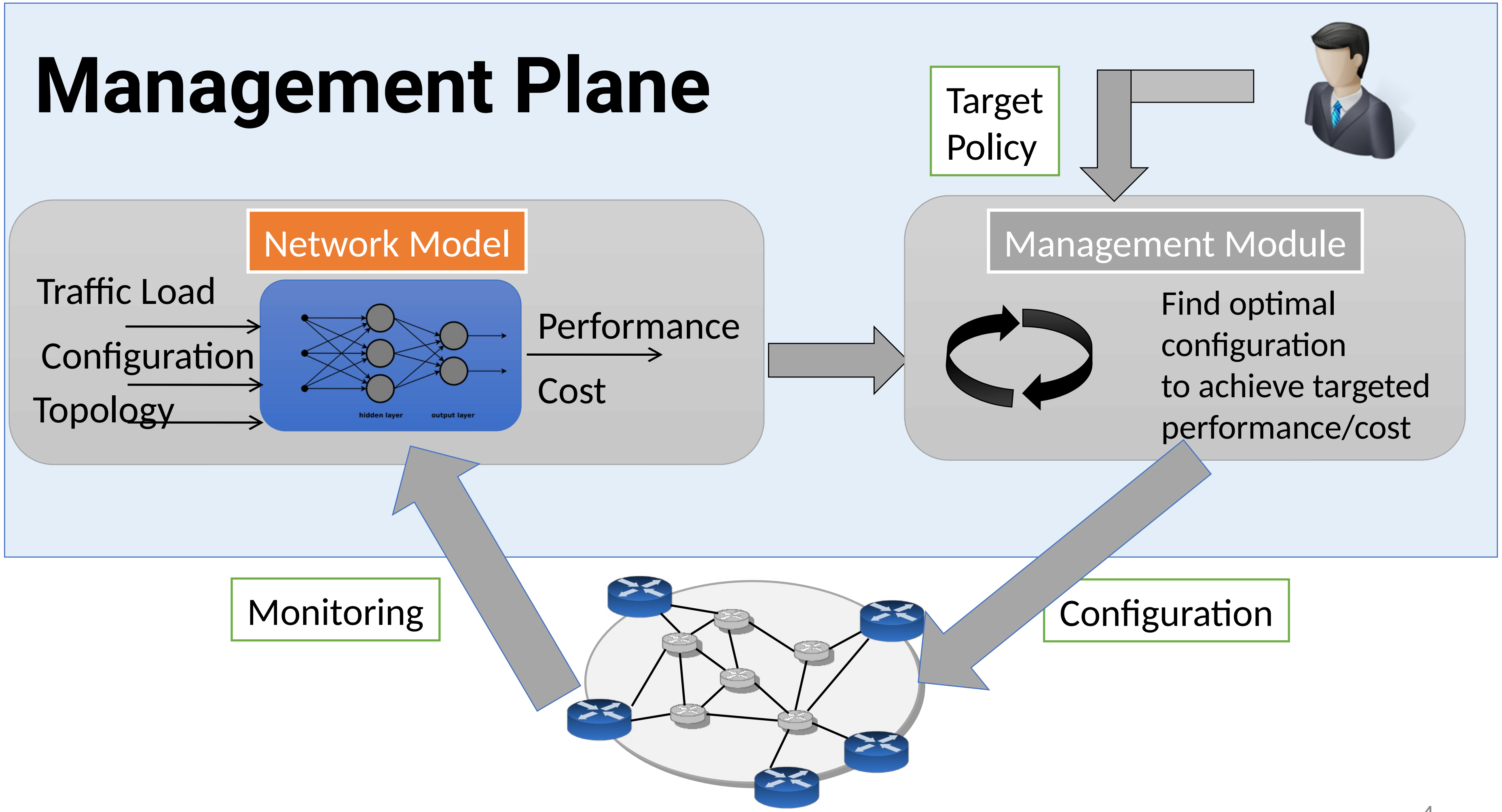
Scope of this talk

- Provide a list of potential research directions in the field of AI/ML for Network Management
- Answer this question:

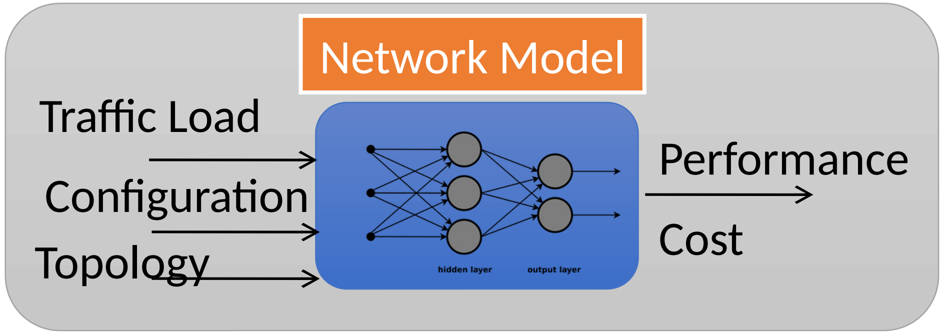
Should the NMRG work on such topics?

Context: A draft of a canonical use-case for Network Management

Context: A draft of a canonical use-case



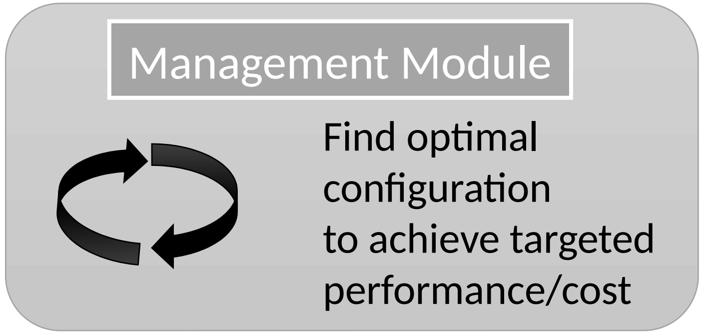
Context: A draft of a canonical use-case



Digital Twin

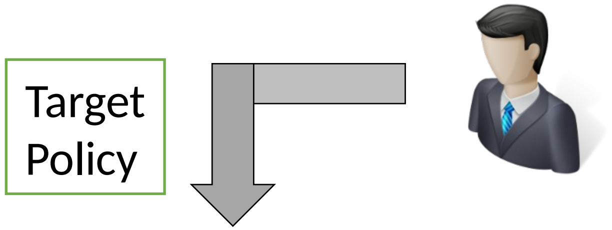
- A network model is a digital twin of the network. This is a **model already trained**
- Built with AI/ML techniques
  - Typically with Neural Networks
- Can answer questions regarding the network.
  - What happens with the utilization of the network if a link fails?
  - What will be the load of the network if a particular users doubles its capacity?
  - What will be the resulting delay if I apply a particular routing configuration?

Context: A draft of a canonical use-case



- This module operates and manages the network
- Uses the Network Module for this
- Can be implemented with AI/ML techniques or traditional deterministic algorithms
  - AI/ML (deep) Reinforcement Learning
  - Deterministic algorithms Classical optimization, management algorithms

Context: A draft of a canonical use-case

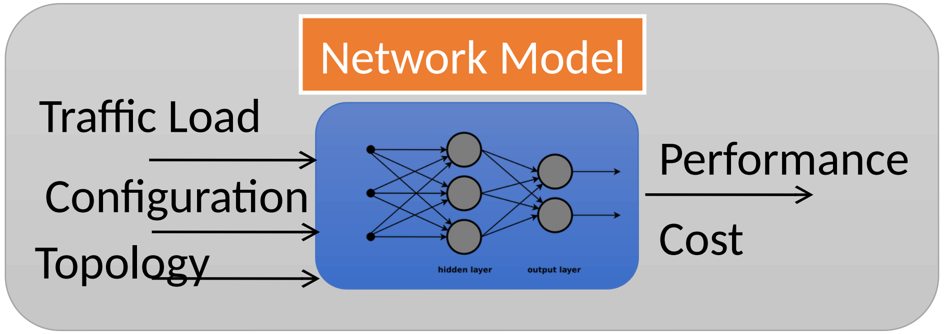


- This is a management API
- Sets the goals of the network
- Can be implemented using an Intent Language or using traditional management APIs
- Fun fact: When Deep-Reinforcement Learning is used this “Target Policy” is easily expressed as a reward function.
    - DRL is the compiler from Intent to Network Primitives

List of Topics

1. Feature Engineering and Embeddings
2. Accountability and Explainability
3. Datasets and Benchmarking
4. ML Architecture & Use-Cases
5. Distributed AI

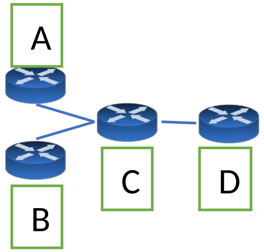
1.- Feature Engineering and Embeddings



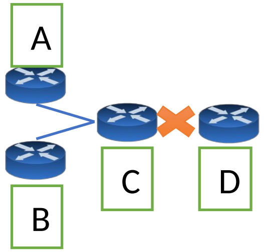
- Neural Networks require representing input and output parameters in meaningful ways
  - This is called feature engineering
- This is the first thing you need when applying Neural Nets to any field
- How do you represent an IP address?
  - It´s not a number since it has a structure

1.- Feature Engineering and Embeddings

- How do you represent the topology or routing?
  - It is actually a graph
- Existing graph embeddings are not useful



	A	B	C	D
A	1	0	1	0
B	0	1	1	0
C	1	1	1	1
D	0	0	1	1



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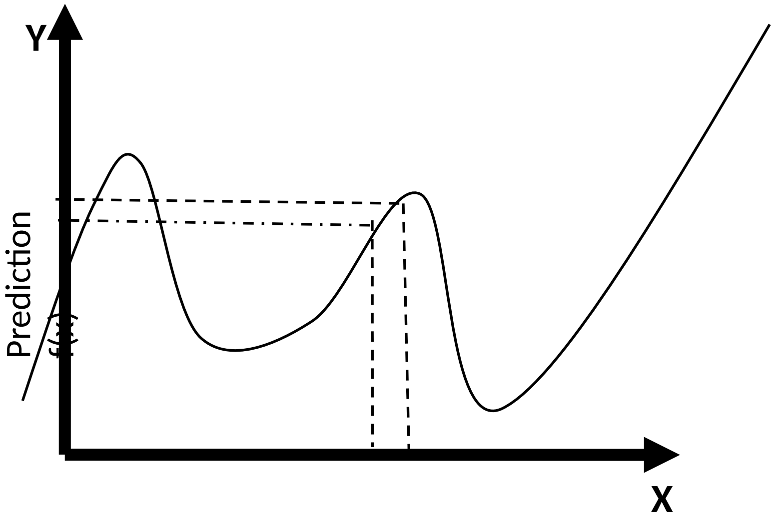


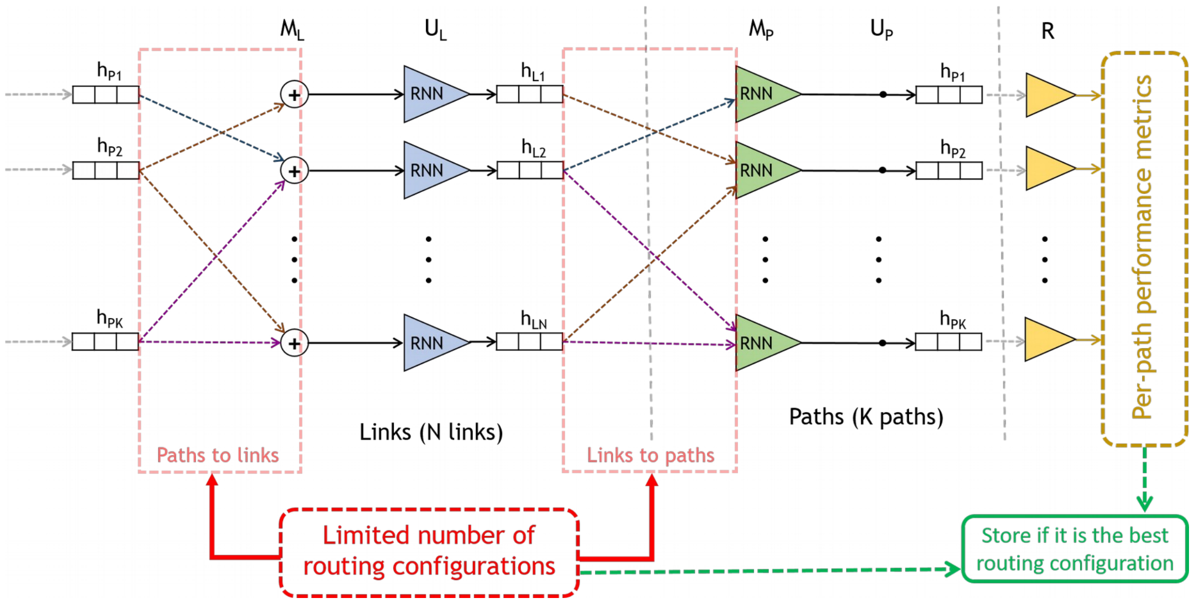
1.- Feature Engineering and Embeddings

- Each application has developed their own NN architectures
  - Fully Connected = Units → Non-linear regression
  - CNN = Grid elements → Images
  - RNN = Sequences → Text processing, Time-Series
  - GNN = Nodes + Edges → Networks

Component	Entities	Relations	Rel. inductive bias	Invariance
Fully connected	Units	All-to-all	Weak	-
Convolutional	Grid elements	Local	Locality	Spatial translation
Recurrent	Timesteps	Sequential	Sequentiality	Time translation
Graph network	Nodes	Edges	Arbitrary	Node, edge permutations

Battaglia, Peter W., et al. "Relational inductive biases, deep learning, and graph networks." *arXiv preprint arXiv:1806.01261*(2018).

1.- Feature Engineering and Embeddings



RouteNet from [1]

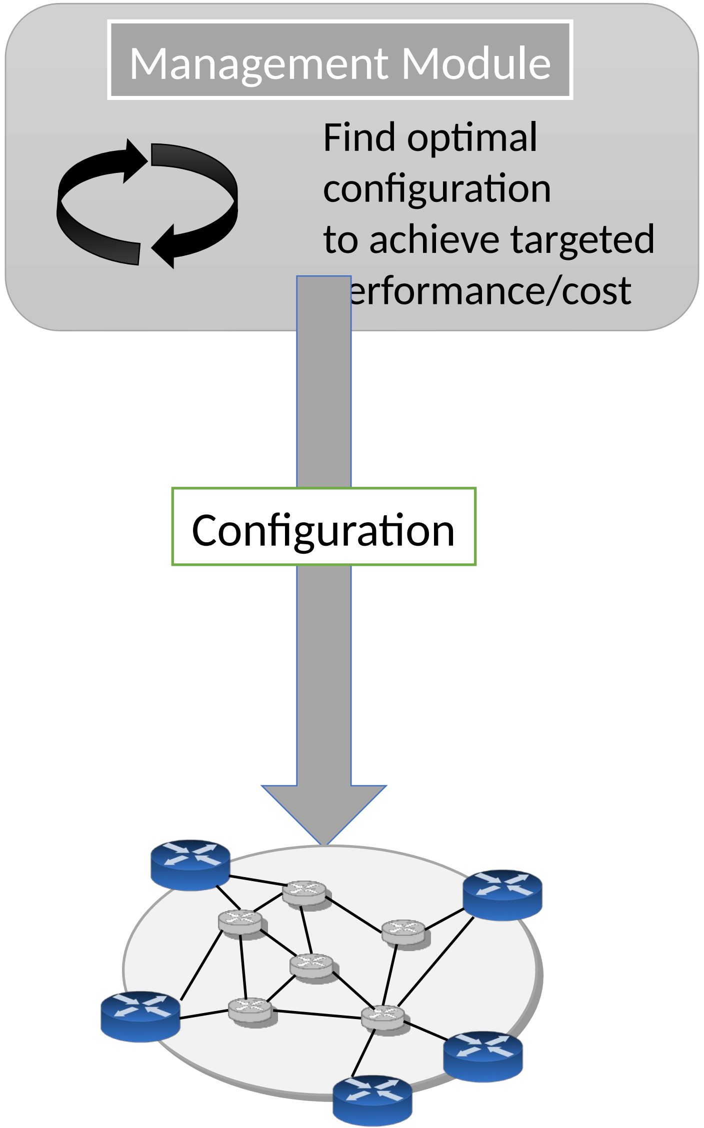
- Graph Neural Networks are an architecture to learn graphs
- They may represent a **fundamental tool** for Network Machine Learning
  - As Convolutional Neural Networks are a fundamental tool for Computer Vision
- RouteNet is able to learn and **generalize** networks
  - Trained with one topology
  - Perform accurate predictions over an unseen topology

[1] Unveiling the potential of Graph Neural Networks for network modeling and optimization in SDN
https://arxiv.org/pdf/1901.08113.pdf

1.- Feature Engineering and Embeddings

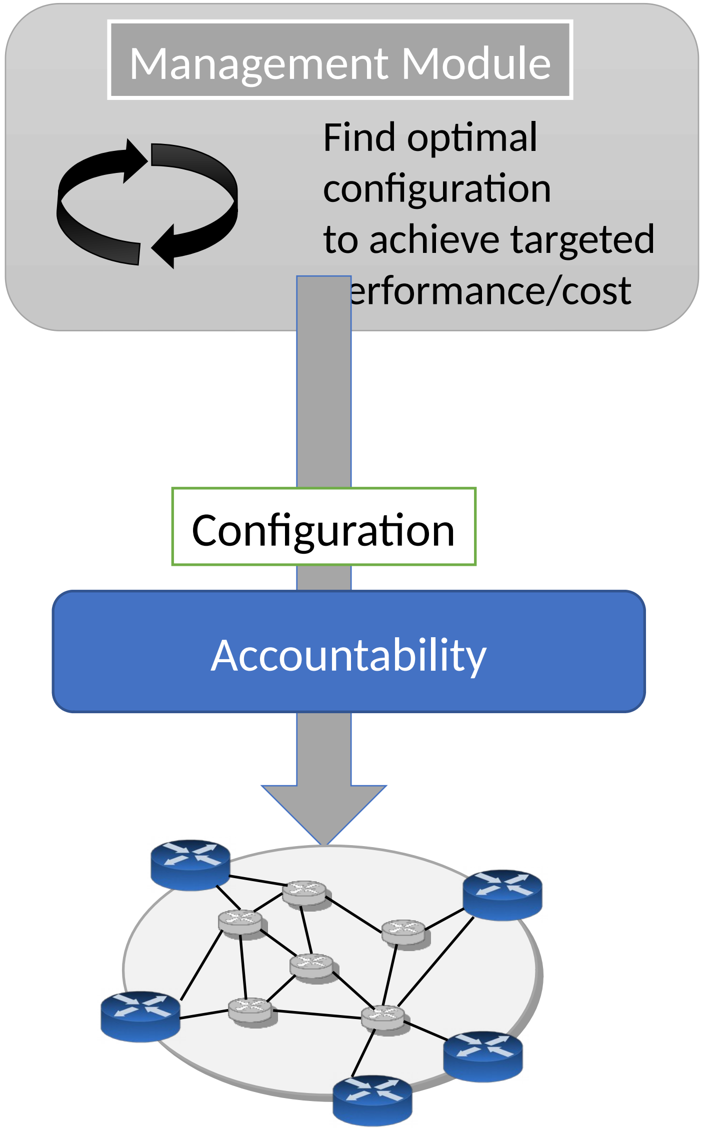
Should the NMRG work on providing guidelines or mechanisms to represent common network parameters?

2. Accountability and Explainability



- AI algorithms are mostly a black-box
- AI algorithms operate in a **probabilistic** way
- Existing network algorithms are **deterministic**
  - Disruptive and profound change
- How can we troubleshoot and provide performance and reliability guarantees?

2. Accountability and Explainability



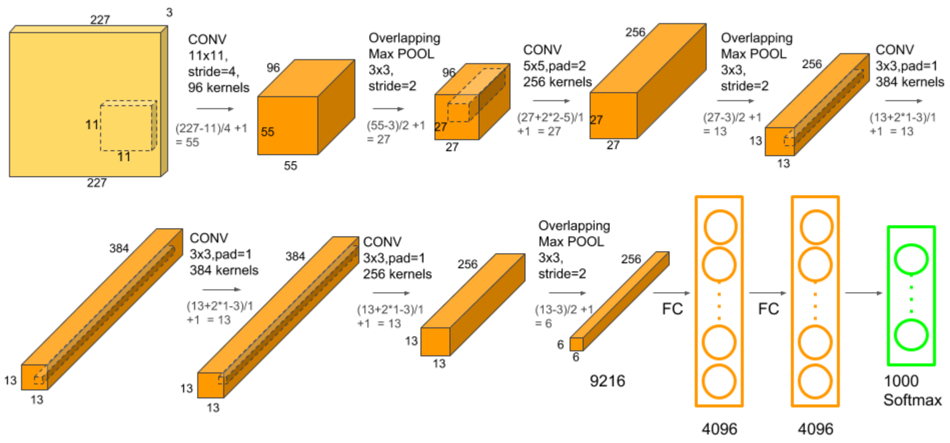
- Explainability ▭ Techniques to “look inside the neural networks”, designers are able to explain why the NN reached a decision.
- Accountability ▭ Complement the AI algorithm with mechanism monitoring and help guaranteeing certain operational bounds or limit the AI to remain in safe bounds, i.e. “human-compliant” configurations

2. Accountability and Explainability

Should the NMRG work on providing guidelines, mechanisms and architectures to support accountability?

3. Datasets and Benchmarks

http://www.image-net.org/



ALEXNET

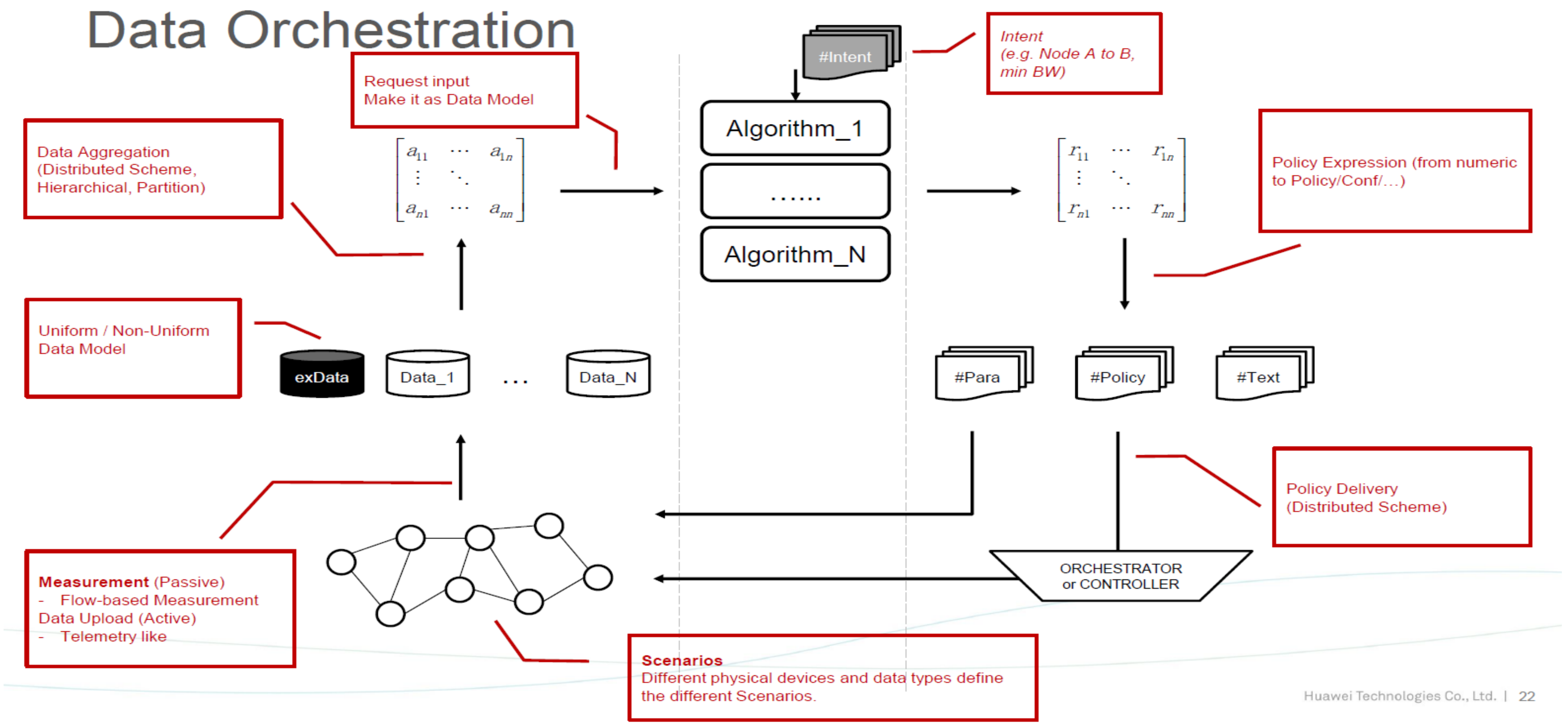
- ML needs data
- In well-established ML fields (Computer Vision) they have:
  - Open Datasets (e.g., Imagenet)
  - Well-established benchmarks (e.g., AlexNet)
- This helps
  - Education
  - Research
  - Benchmarking (e.g, Imagenet challenge)

3. Datasets and Benchmarks

- The networking community needs data-sets and benchmarks
    - Some early attempts (KDN Dataset and Benchmark [1])
- Reference datasets
    - Many network dimensions
    - **Start by agreeing on one specific use-case?**
- Cross-RG/WG activity (e.g, MAPRG, IPPM, OPS) to define measurements to create the data-sets
- Benchmarking methodology for ML algorithms applied to networking problems.

[1] https://github.com/knowledgedefinednetworking/

3. Datasets and Benchmarks



3. Datasets and Benchmarks

Should the NMRG work on providing guidelines and help producing reference datasets and benchmarks?

Potentially narrowing things down to one relevant use-case in a first phase

4.- ML Architecture & Use-Cases

- Which is an abstract “**network-friendly**” ML reference architecture?
- Which are the right subsystems and the interfaces among them?
- There is previous work on identifying use-cases
  - Are there common functionalities?
  - Can they be used for validation of a reference architecture?
- ML metalanguage, do we need one for networking?
- ML Architecture to manage datasets generated by AI module vs. ML-augmented architecture for Traffic Engineering or Traffic Analysis
- AI(ML/DL/RL) algorithms have different structural approach architectural impact, uniform use/operation of (diverse) AI systems, integration generalisation
- Towards AI based/assisted Network Management

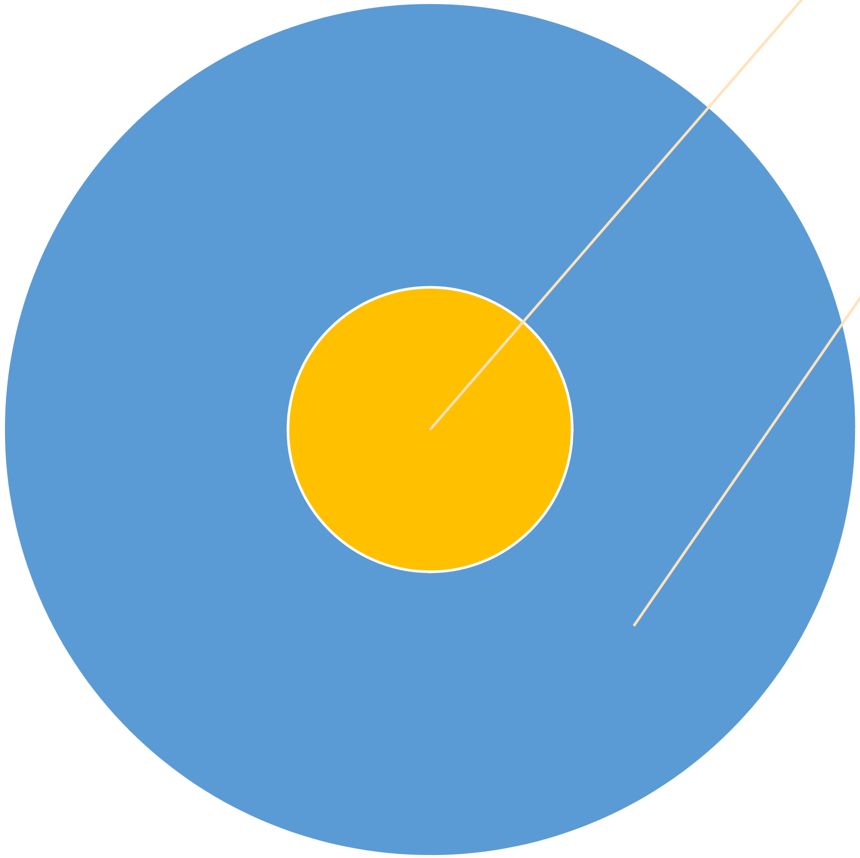
4.- ML Architecture & Use-Cases

Should the NMRG work on use-cases and/or defining a reference architecture?

5.- Distributed AI

- Network is a **critical** and geographically **distributed** systems □ **distributed** and **accountable** AI
- Aggregation of knowledge, accumulation of decisions
- Cooperative vs independent vs selfish AI agents (adversarial ML)
- Fixed vs dynamic agent
- Multiple objectives as once
- Monitoring and orchestration of the agents (new models? New protocols? New interfaces? How to measure the individual contribution of each agent?)
- …. Again requirements? Architecture?

AI element – Features Management framework

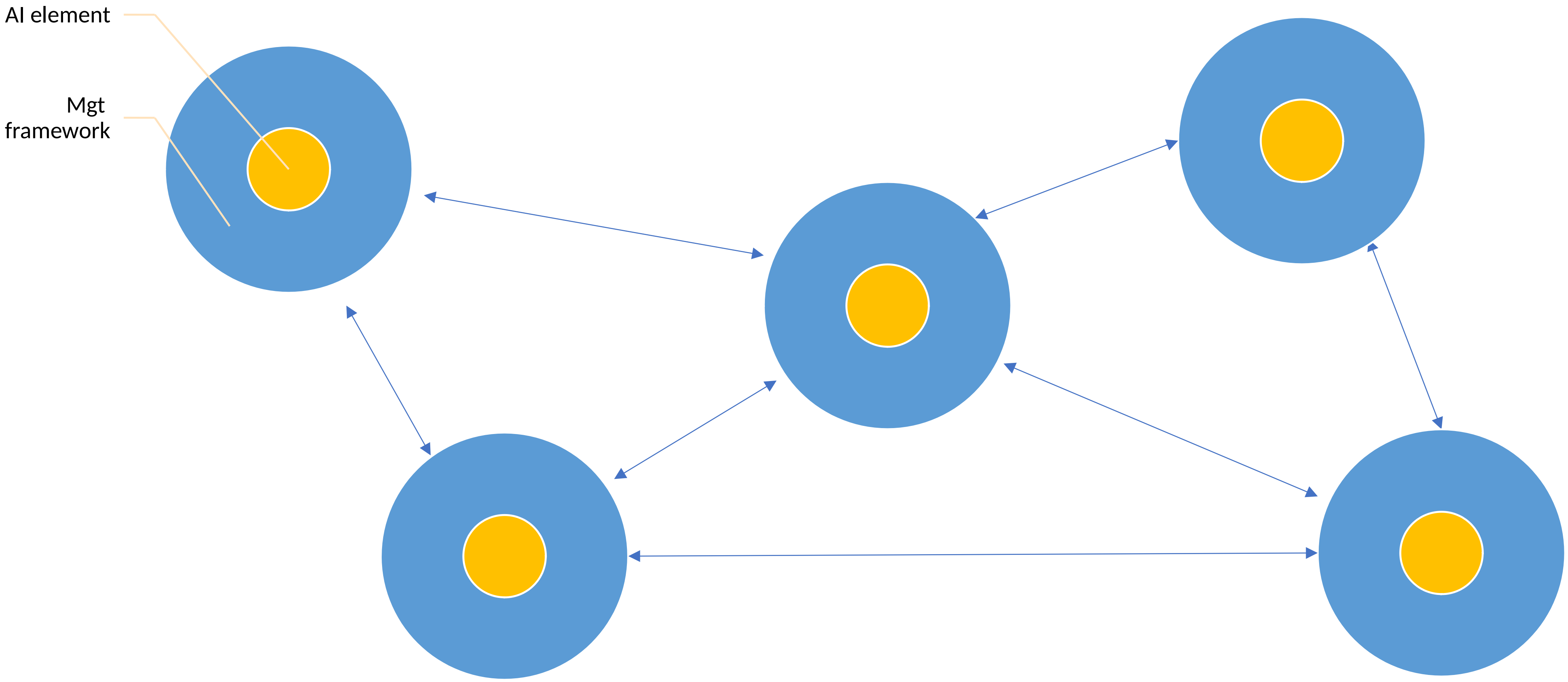


AI element

Features management framework

- Performance
- Testing
- Accountability
- Explainability
- Benchmarking
- Robustness

Manage the interplay between AI elements



5.- Distributed AI

Should the NMRG work on defining distributed AI for networks?

Open mic discussion

Should the NMRG work on:

1. providing guidelines or mechanisms to represent common network parameters?
2. providing guidelines and help producing reference datasets and benchmarks?
3. providing guidelines, mechanisms, architectures to support accountability?
4. use-cases and/or defining a reference network AI/ML architecture?
5. coordination of distributed learning agents, federated learning?