Machine Learning for 6G Physical Layer Design and Interference Control

Prof . Maziar Nekovee

m.nekovee@sussex.ac.uk

6G LAB @sussex.ac.uk

Sixth Generation Mobile Communications R&I Lab at University of Sussex (We create the future today!)

Our research at 6G Lab on AI/ML

AI at the RAN:
- Intelligent initial access and handover
- Dynamic beam-management
- **Model-free PHY Design**

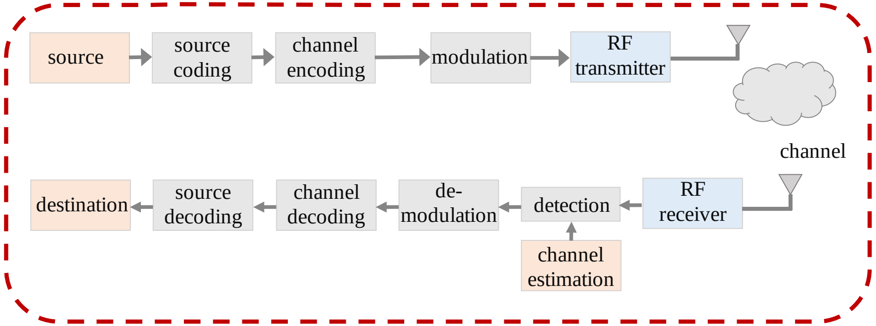
AI at the transport layer (Fronthaul, backhaul)
- Traffic pattern estimation and prediction
- **Flexible functional split...**

AI at the Core and Edge:
- **Next Generation NFV and SDN**
- Intelligent network slicing management
- service prioritization and resource sharing
- Intelligent fault localization and prediction
- Security and intrusion detection

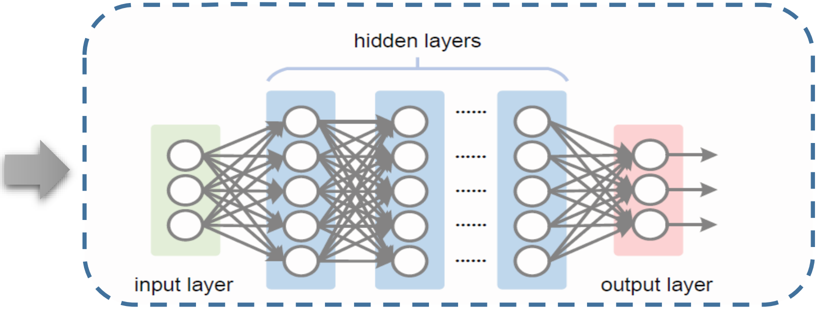
Other areas of interest
- TCP/IP suit of protocols.

Deep Learning approaches for beyond 5G/6G PHY Design

- **Conventional PHY Design (3G, 4G, 5G)**
  - 3G and 4G design was for known applications (voice, video, data) and deployment scenarios
  - 5G should work for yet unknown applications (verticals) and deployment



- **AI- Based PHY Design (beyond 5G/6G)**
  - Holistic optimization of the entire PHY processing blocks
  - Data-driven, end-to-end learning solution so reduces design cycle
  - Can adapt to changing applications and deployment environments (including channel)
  - Data-driven, end-to-end learning solution so reduces design cycle



T.O'Shea and J.Hoydis,"An introduction to deep learning for the physical layer, " IEEE Transactions on Cognitive Communications and Networking," IEEE Transactions on Cognitive Communications and Networking, vol. 3, no. 4, pp. 563-575, 2017.

Interference Channels – *Challenges and Potential Solutions*

Challenges

Multiple functional blocks *(optimisation)*

- Equalization
- Multi-objective optimization

DL based end-to-end optimisation

Strong and very strong interference *(Multiple users)*

- Online learning
- Adaptive algorithms

AE and DRL algorithm applied

Imperfection (hardware or channel model)

- Equalization
- Adaptive/advanced modulation
- Compensation

ML based Reconstruction

Data-driven

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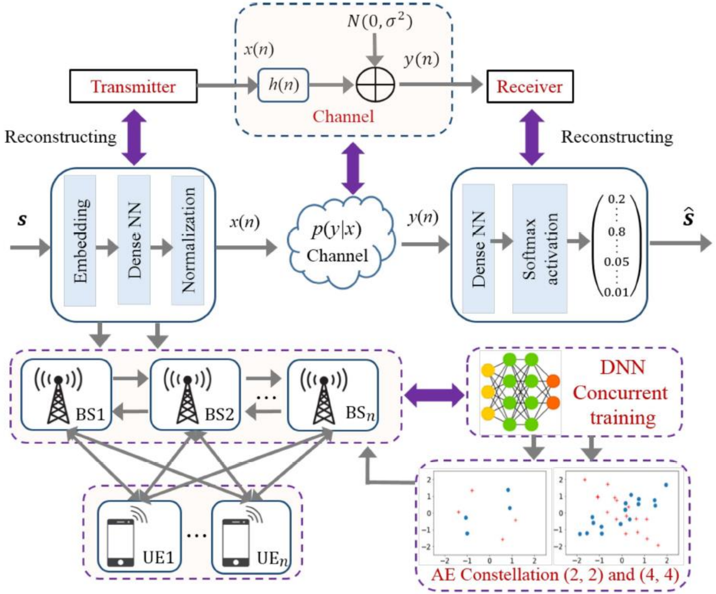
System overview



System block diagram of an adaptive deep learning (ADL) based AE for a wireless communication interference channel with *m*-user.

Ref: D Wu, M Nekovee, Y Wang, “An Adaptive Deep Learning Algorithm Based Autoencoder for Interference Channels” 2nd IFIP International Conference on Machine Learning for Networking (MLN'2019),; IEEE Access 2020

Algorithms

The structure of the AE:

Block name	Layer name	Output Dim
Block name	input:	M
	Dense+eLu	M
	Dense+Linear	$2n$
	nomalization	$2n$
Channel	Noise	$2n$
Decoder	Dense+ReLU	M
	Dense+Softmax	M

Name	$[\sigma(u)]_i$	range
ReLU	$\max(0, U_i)$	$[0, \infty)$
Tanh	$\tanh(U_i)$	(-1, 1)
Softmax	$\frac{e^{u_i}}{\sum_j e(u_j)}$	(0, 1)

The ARL algorithm estimates the interference (α).

With the predicted α, channel function is updated. Then signals are decoded.

The proposed ADL algorithm:

Algorithm 1: DRL to predict the interference

Input : • AE model and specifications: n, k, batch size, epochs number, optimizer, learning rate, etc
• the training data set l_{in}
• the variance of channel noise σ^2

Output: • the estimated interference parameter α

Initialize:
Set AE model parameters (e.g., $n \leftarrow 4$, $k \leftarrow 4$, $M \leftarrow 4$)
for i in range (training data samples) **do**
    Set $x = f(s_i) \in \mathbb{R}^{2n}$, $s_i \in \{1, 2 \ldots M\}$, encoding
    Create and Set $\hat{y}(n)$ for receiver layer
    for i in range (numble of guessing α) **do**
        DNN layer to training the data set
        Recovery pilot signal $\hat{s}_i$ according to a guessing α
        Calculate *reward* $\hat{R}_i$ according to Eqs. (5) and (6)
Set confidence interval of $\hat{R}_i$ and predict α
Update DNN layer with α according to Eqs. (7) to (10)

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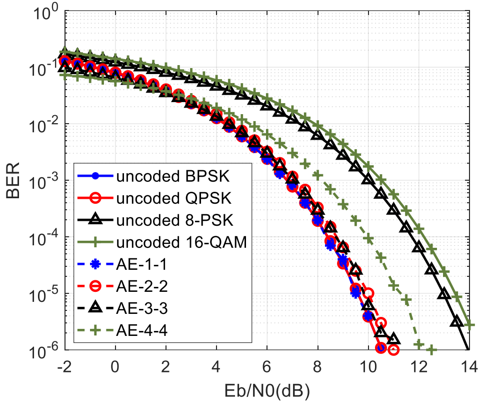
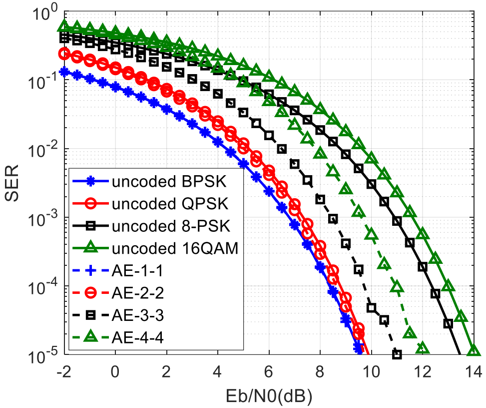
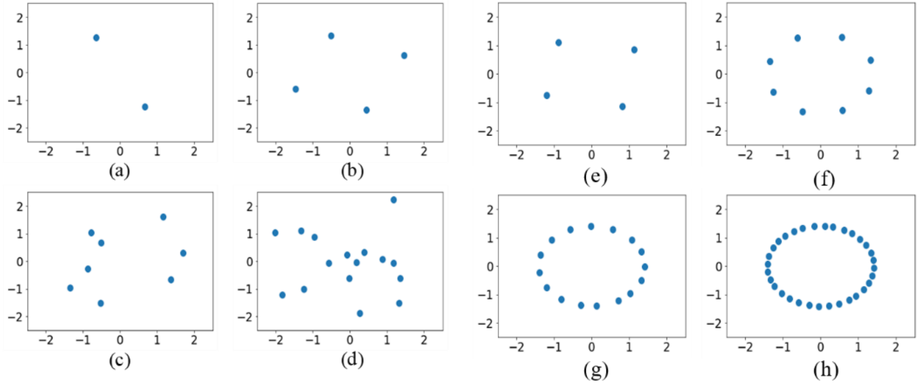
Numerical results and analysis (single user)





Bit error rate and symbol error rate vs SNR (E_b/N_0) for the AE and other modulation schemes (single user case).



Learned AE constellation produced by AE for single user case: (a) AE-1-1, (b) AE-2-2, (c) AE-3-3 and (d) AE-4-4. (e) AE-1-2, (f) AE-1-3, (g) AE-1-4, (h) AE-1-5.

Numerical results and analysis (multiple users)

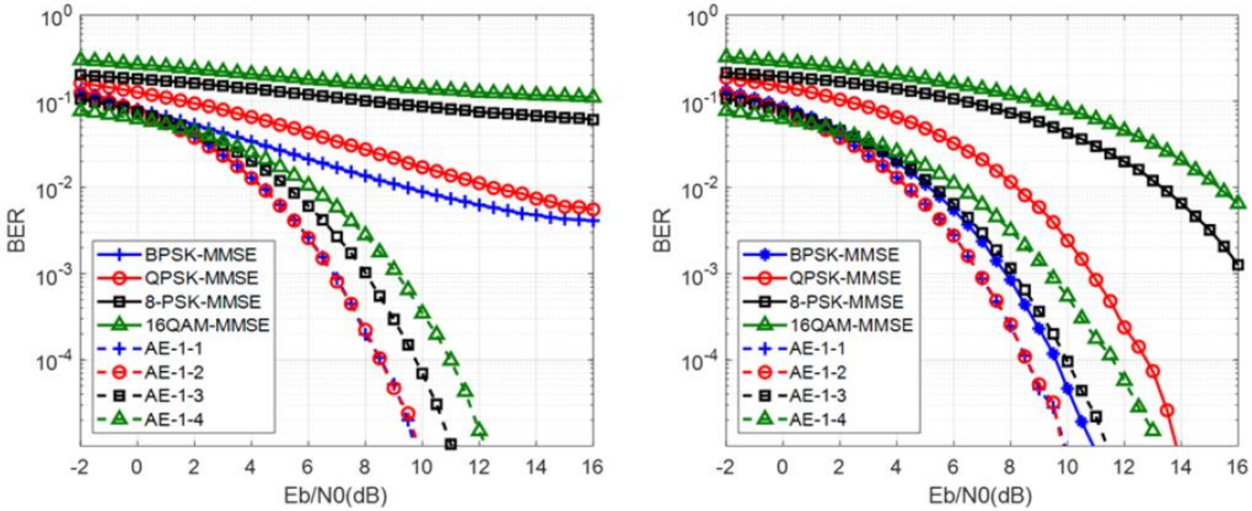
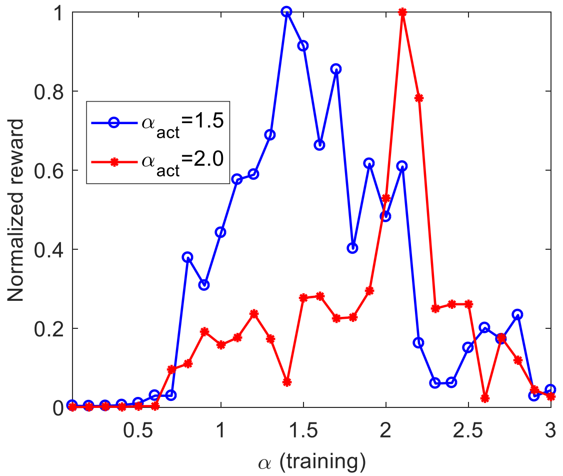
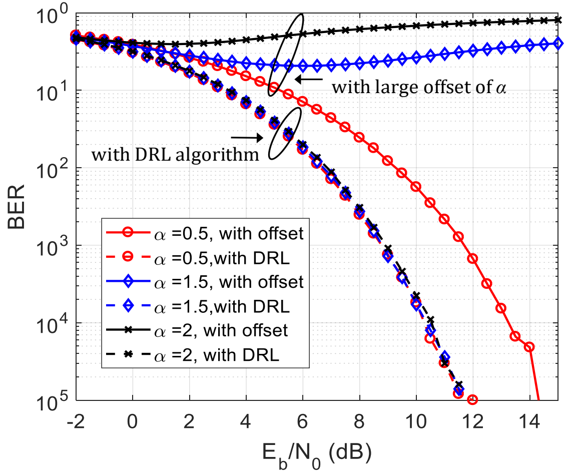


FIGURE7: Bit error rate vs SNR (E_b/N_0) of AE and several modulation schemes with MMSE equalizer for two-user symmetric and asymmetric interference channel.

Numerical results and analysis (multi-user)





Normalized reward versus predicted α: strong interference α = 1.5 and very strong interference α = 2.0

BER versus SNR: comparison for strong and very strong interference channel, with and without the proposed DRL algorithm

Without adaptive learning the DL-based PHY is less robust than conventional PHY

- A predicted α (interference) can be obtained through a learning
- ADL based AE is capable of robust performance over the entire range of interference levels, even for the worst case in a very strong interference channel

Ref: D Wu, M Nekovee, Y Wang, “Deep Learning based Autoencoder for m-user Wireless Interference Channel Physical Layer design”, IEEE Acess 2020

Concurrent DL for distributed multi-user interference scenario

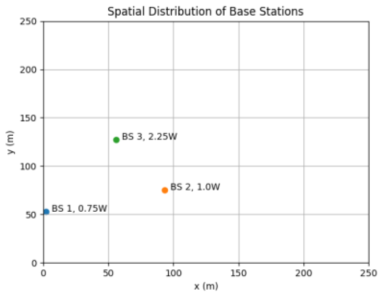


Fig. 2. Distribution of base stations in the 3 user simulation.

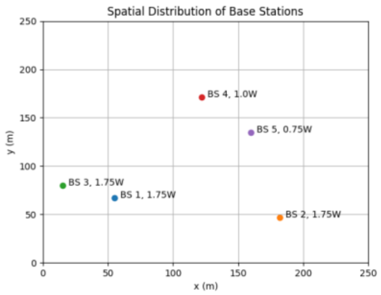
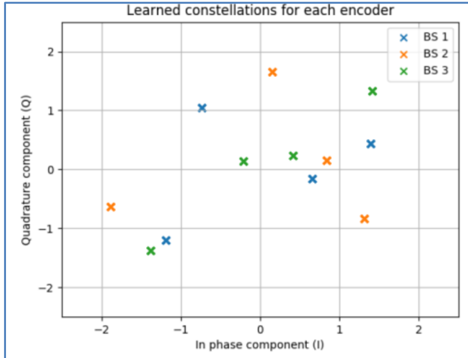


Fig. 3. Distribution of base stations in the 5 user simulation.



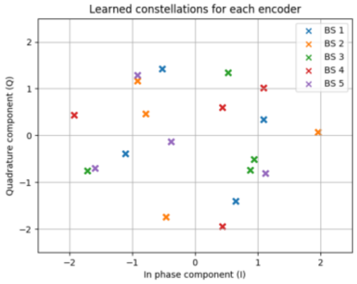


Fig. 7. Learned constellations for all of the autoencoders in the 5 BS system.

- 3 and 5 interfering BS randomly distributed in 200x200m

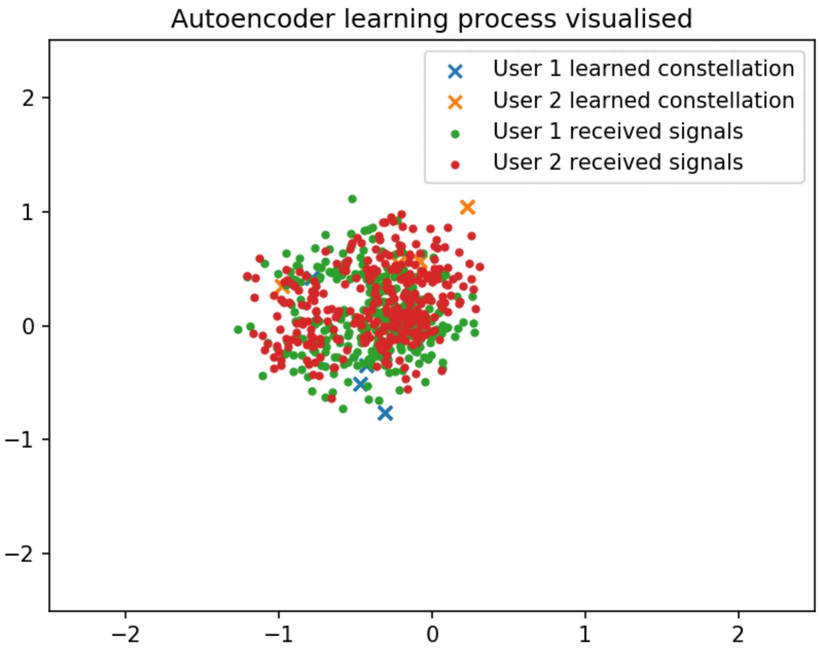
$$PL = 32.4 + 21 \log d + 20 \log(f_c) + \sigma_{SF}$$

Ref: L. Pellatt, D Wu, M Nekovee, “Deep Learning based Autoencoder for Concurrent Learning of the Interference channel”, IEEE Comm. Letters (Su

Adverbial DL for distributed two-user interference scenario

Zero sum two-player game

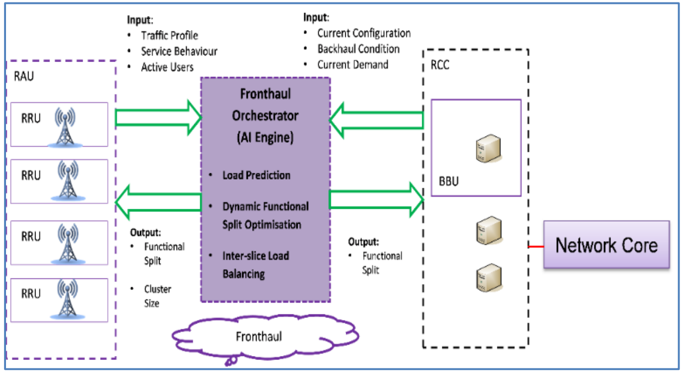
Converges to Nash equilibrium



- A Concurrent Deep Learning based auto encoder for the scenario of a two-user interference channel: the visualization demo of the constellation evolving as learning progress/

Ref: L. Platt, D Wu, M Nekovee, “Deep Learning based Autoencoder for Concurrent Learning of the Interference channel”, IEEE ISCW 2021 (published)

AI for 5G/beyond-5G Fronhaul slicing

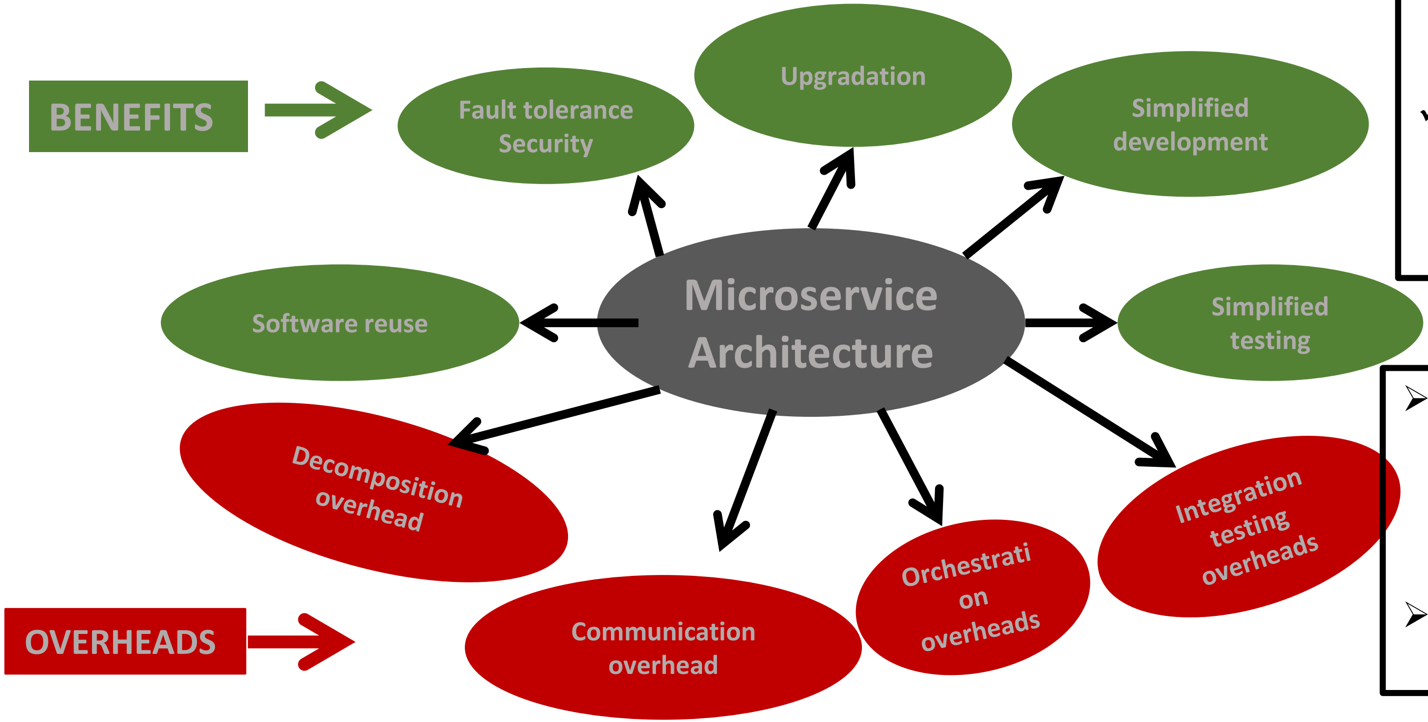


- Next generation fronthaul interface (NGFI) targets redefining flexibility and network function split between Raddio Remote Aggregation Units (RRU)s and Radio Cloud Centre (RCC).

- Orchesstrator Engine dynamically split the traffic on UL and DL per RAU across multiple fronthaul slice based on predicted levels of load, ensuring for each slice end-user requirements are met.
- The Orchestrator Engine balances the bandwidth reservation versus latency provision across different frothaul slices in an on-demand fashion by learning the load patterns and dynamic fumctional split per RAU-RCC

Ref: M. Nekovee, Wu, Wang, Shariat, "Artificial Intelligence and Data Analytics in 5G/beyond-5G Wireless Networks", in AI for Emerging Verticals, IET Publishing 2020

Microservice Architecture: Benefits vs Overheads

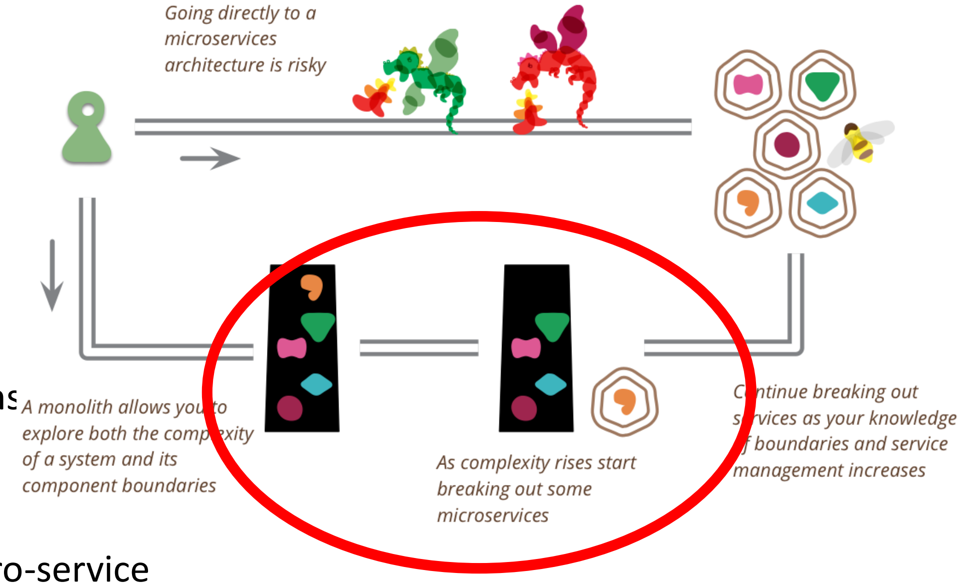


- ✓ For cloud services benefits outweigh overheads.
- ✓ Cloud companies are rapidly adopting micro services (Ali Baba, Amazon, Netflix)

- ➢ For telco's network service (core functions) microservice adoption requires careful design to see benefits
- ➢ The problem is complex interdependencies

Automating Micro-service aggregation/de-aggregation with ML

- How to decompose a network function?
  - Machine learning can help in deciding decomposition by predicting
    - A resource intensive micro-function
    - A faulty subcomponent
    - Anomaly detections
    - Optimal placements of micro-functions
    - QoS of micro functions
- Troubleshoot a micro-service network
  - Machine learning can help find which micro-service is actually causing problem



Nekovee et al, Towards AI-enabled Microservice Architecture for Network Function Virtualization, Proc. IEEE ComNet 2020

Conclusion

- **Adaptive DL auto-encoder** is a promising approach for design of next generation Physical Layer
- Outperform conventional PHY in scenarios where a-priori modelling of the environment (channel, interference) is not tractable or takes significant time
  - High interference 6G small cell networks^
  - 6G vertical application environments (manufacturing, health etc)
- For *non-cooperative interference scenarios* the problem has a zero-sum game theoretic formulation, convergence to Nash-equilibrium through concurrent DL
- Our ultimate aim is to significantly reduce the time to standardisation release of beyond-5G/6G PHY design by using learning-based adaptive design
- Other promising applications are AI/ML for next generation core and edge design with microservices and fronthaul

THANK YOU!

m.nekovee@sussex.ac.uk

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