Neural Architecture Search for Telecoms

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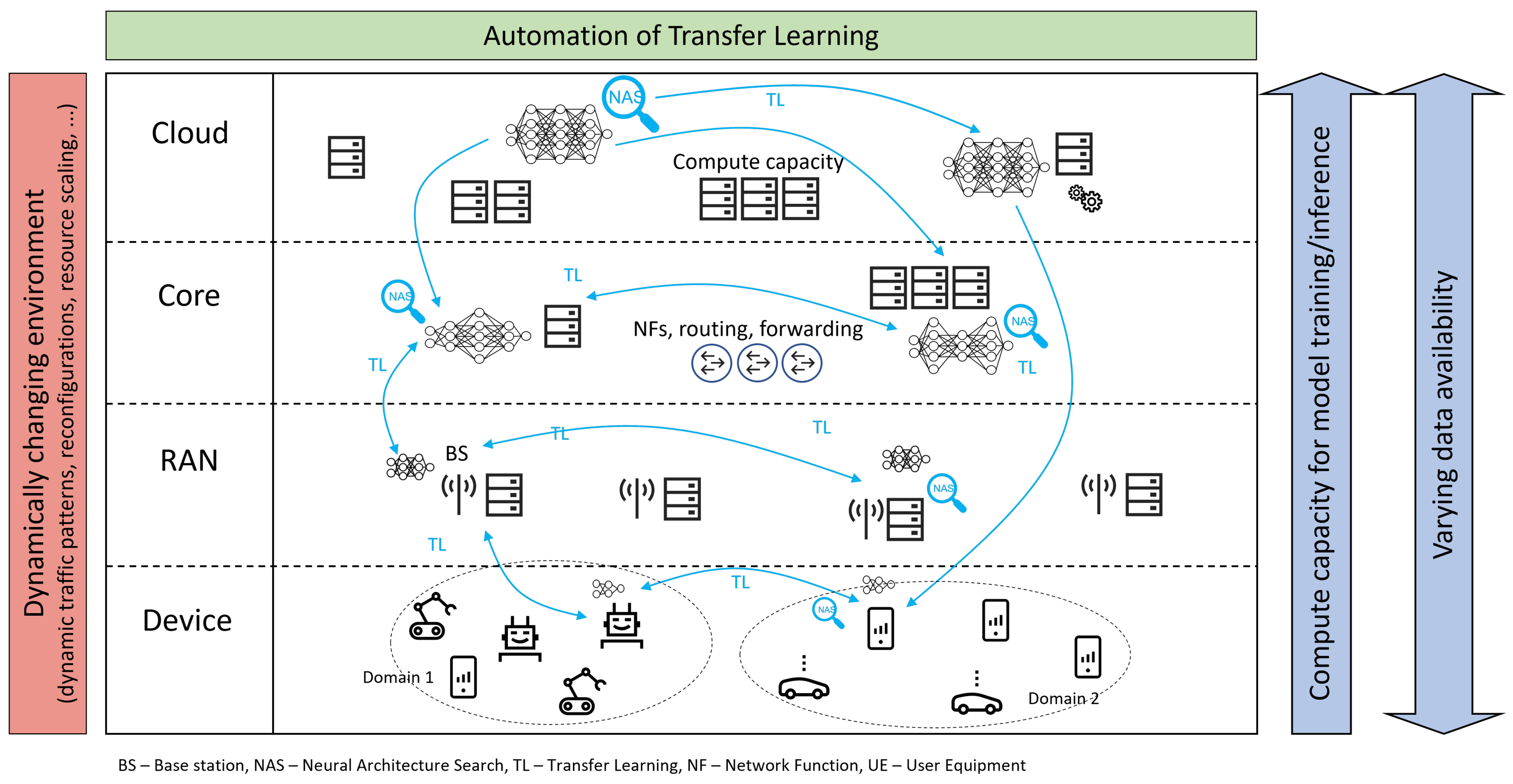
Research Goals

6G networks are expected to run various artificial intelligence-based functions and services to satisfy stringent real-time communication requirements. These applications run on different domains which are dynamically changing. Transferring knowledge from one domain to another is a solution to overcome the challenges of this dynamicity with reduced computational footprint. Fine-tuning the architecture of used models during these steps could further improve the power consumption and the performance.



NAS is a key enabler for improved TL and model management [2]

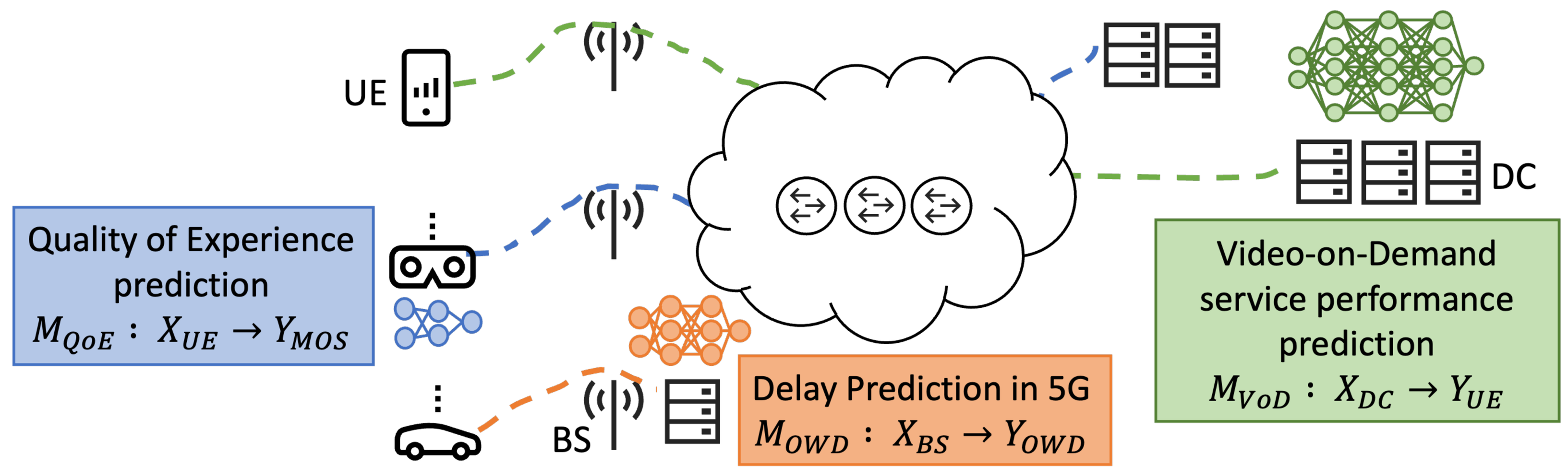
Challenges

• Telecom data is typically in tabular format while majority of existing NAS methods are designed for image data.
• Edge environments put constraints on resources and scale, such as: computational power, energy consumption and memory.
• Dynamics in the environment stemming from network reconfigurations and scaling of resources introduces challenges in finding more effective architectures during transfer learning.

References

- Orucu, Adam, et al. "On Multi-Objective Neural Architecture Search for Modeling Network Performance." *2024 15th International Conference on Network of the Future (NoF)*. IEEE, 2024.
- Orucu, Adam, et al. "Towards Neural Architecture Search for Transfer Learning in 6G Networks." *arXiv preprint arXiv:2406.02333* (2024).

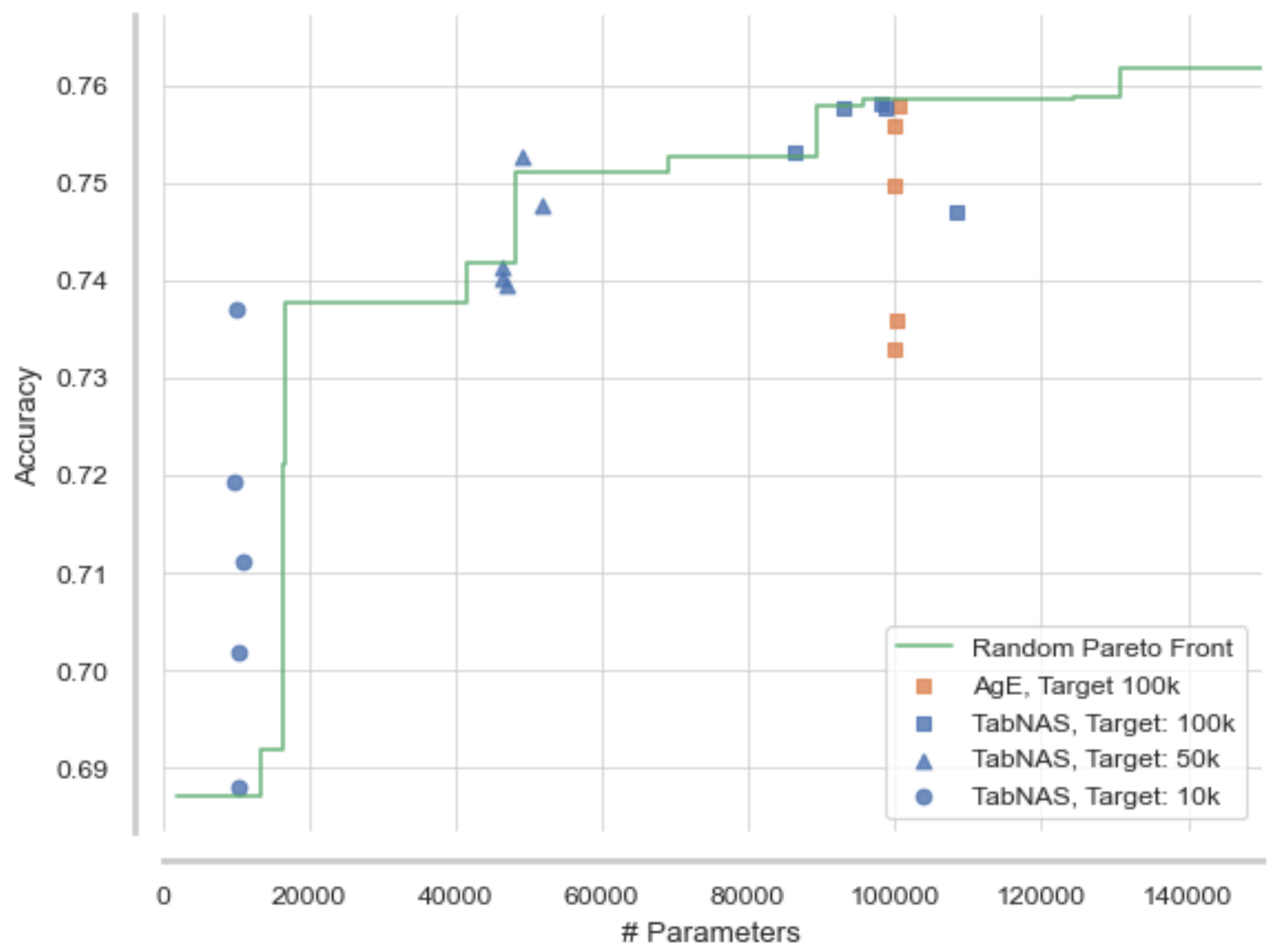
Multi-objective NAS for telco



UE – User Equipment, BS – Base station, DC – Data Centre,
VoD – Video on Demand, QoE – Quality of Experience, OWD – One Way Delay
M – ML model, X – Input, Y – Target

Different prediction tasks in telecoms have different goals and constraints [1]

We propose a modification to existing NAS methods designed for tabular data to adapt them for multi-objective search and evaluate their performance in different network management and performance modelling scenarios, including scenarios where limited data is available during NAS.



Our modified methods compared to random search as baseline [1]

We demonstrate the effectiveness of NAS techniques in learning from telecom datasets and identifying optimal neural network architectures for telecom application.

Data	Method	Termination	# Layers	Performance	# Parameters
VoD	AgE	200 iterations	2-10	0.7143 ± 0.0248	588,202
	TabNAS	Until converge	3	**0.7436 ± 0.0064**	172,112
	TabNAS	Until converge	5	0.7381 ± 0.0302	153,580
	TabNAS	Until converge	10	0.7338 ± 0.0197	315,193
	RandomNAS	200 iterations	2-10	0.7233 ± 0.0201	418,954
	RandomNAS	20 iterations	2-10	0.7249 ± 0.0341	277,206
QoE	AgE	200 iterations	2-10	0.7515 ± 0.0409	276,683
	TabNAS	Until converge	3	0.7565 ± 0.0406	12,461
	TabNAS	Until converge	5	**0.7745 ± 0.0054**	74,859
	TabNAS	Until converge	10	0.6758 ± 0.2221	108,943
	RandomNAS	200 iterations	2-10	0.7043 ± 0.1574	125,596
	RandomNAS	20 iterations	2-10	0.7324 ± 0.1195	16,861
5G	AgE	200 iterations	2-10	**0.9472 ± 0.0022**	189,470
	TabNAS	Until converge	3	0.9445 ± 0.0069	38,841
	TabNAS	Until converge	5	0.9471 ± 0.0018	330,004
	TabNAS	Until converge	10	0.9348 ± 0.0184	385,419
	RandomNAS	200 iterations	2-10	0.9442 ± 0.0108	125,418
	RandomNAS	20 iterations	2-10	0.9471 ± 0.0023	137,411

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