AI FOR WIRELESS INTELLIGENT CONNECTIVITY

Insight report by Wireless Lab.

Abstract

Summary of the State or AI as it relates to wireless intelligent connectivity

Futurewei Technologies, Inc.

Insight Report

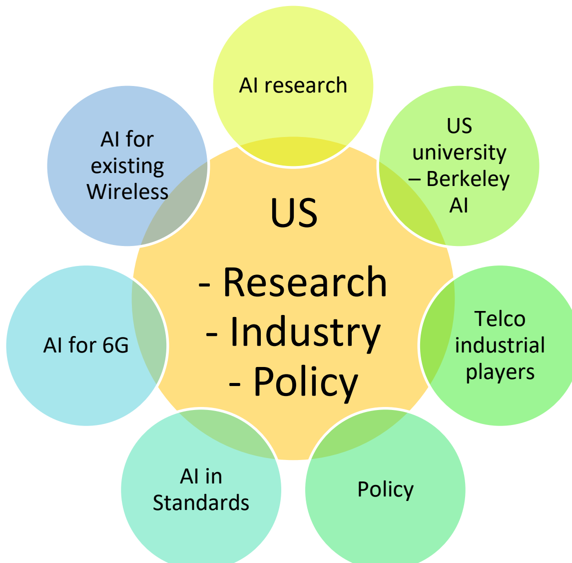
AI for Intelligent Connectivity

Futurewei Wireless Lab, 2020 April

1 Contents

2 Scope of April-2020 monthly report

This monthly insight report is centered around the theme of "AI and AI for Intelligent Connectivity". It focuses US initiated research, industry initiatives and policies (but not exclusively), as illustrated in the following chart.



3 AI - US university: Berkeley AI Research

There are two recent events from UC Berkeley that we attended. One is "Berkeley EECS Annual Research Symposium (BEARS) 2020" in Feb. Its schedule and presentation topics can be found at https://eecs.berkeley.edu/research/bears/2020/schedule. Another one is "Berkeley Artificial Intelligence Lab (***BAIR***) Spring 2020 Retreat" in March (online virtual meeting). In this section we present a few selected projects introduced in these meetings.

The research topics are very diverse and target a wide set of problems and technologies, but we will narrow the focus one of the key areas: **How to make AI systems more adaptable and flexible when operating in highly dynamic environments?** Note that, for the most part, the BAIR projects are demonstrated in the Robotics domain, however, it is expected that the main ideas can be adapted to other domains including wireless networks.

3.1 Systems Challenges for AI - A Berkeley View

To understand the context for the research projects described here, we reviewed an earlier paper "**A Berkeley View of Systems Challenges for AI**" (https://arxiv.org/pdf/1712.05855.pdf) written by several Berkeley professors. The paper presents a framework to organize the research topics based on those challenges.

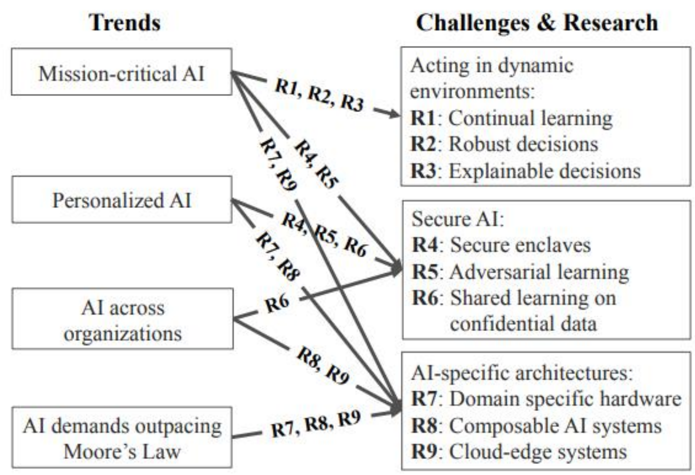
Trends Affecting AI evolution and mapping to Challenges and Research Topics

- **Mission Critical AI.** AI applications in medicine transportation, finance, home automation will be making life and death decisions.
- **Personalized AI.** Providing custom services to users may require large quantity of sensitive personal information that needs to be protected.
- **AI across organizations.** Need to go from data silos to data eco-systems to create comprehensive training datasets.
- **End of Moore's Law.** Data continues to grow exponentially but hardware improvements rate is slowing down (Stephens, Z. D. et al, 2015).

The Berkeley paper identifies the **major challenges** for the evolution of next generation AI and group them in three **categories** that are further divided into 9 topics.

- Acting in highly dynamic environments
- Secure AI
- AI-specific Architectures

The paper connects the societal and technological trends to the research topics as indicated in the figure.



3.2 Selected Project Summary

Several projects presented during the March 2020 BAIR meetings were related to the R1, R2 topics in Berkeley's model. The common theme revolved around the questions: how to make the new AI systems more adaptable and flexible? How to teach AI to improvise? How to deal with non-stationarity and temporal correlation in the real-world data, and in general **how to help AI success in very dynamic and changing environments?** The five BAIR projects reviewed represent fundamental research that address the first challenge: acting in dynamic environments. Although the results, for the most part, are demonstrated in the Robotics domain we expect that the ideas and insights can eventually be transferred to the Wireless domain. These projects are be divided in two broad topics:

Adaptable AI	P1. Teaching AI to improvise (60 % reduction in distance to goal)
	P2. Learning to adapt (1000 times less data)
	P3. Dealing with real world data achieved best performance on natural-world datasets when compared to other state-of-the-art methods
Scalable Reinforcement Learning	P4. End-to-End RL without Reward Engineering Succeeds at learning all test tasks, while other methods succeed at some tasks while failing at others
	P5. Distribution Correction for Off-Policy RL.

	Method greatly outperforms prior state-of-the-art RL algorithms.

3.3 Adaptable AI.

Robots are typically deployed with a fixed behavior (be it hard-coded or learned), allowing them to succeed in specific settings, but leading to failure in others. This research is about automatically learning when the current model may need to be updated given a change in the current situation.

1) “Improvisation through Physical Understanding: Using Novel Objects as Tools with Visual Foresight”

https://arxiv.org/abs/1904.05538 Annie Xie, Frederik Ebert, Sergey Levine, Chelsea Finn

Short Description:

The project demonstrates an approach to enable a robot to accomplish both diverse and complex tasks involving previously unseen objects with access to only raw visual inputs (Finn, C. and Levine, S., 2017). We studied the particular case of solving many different tasks that require manipulating objects as tools (Toussaint, M. et al, 2018). The approach learns from a combination of diverse human demonstration data, with many different goals, tools, and items, and autonomously collected interaction data, with diverse objects. We show how we can use this data to train a model that can predict the visual outcome of actions that cause multi-object interaction, and use these predictions to figure out how to accomplish tasks by leveraging such object-object interactions.

Left: tools used during training. Right: test tools used in our quantitative evaluation, some of which are not conventional tools.

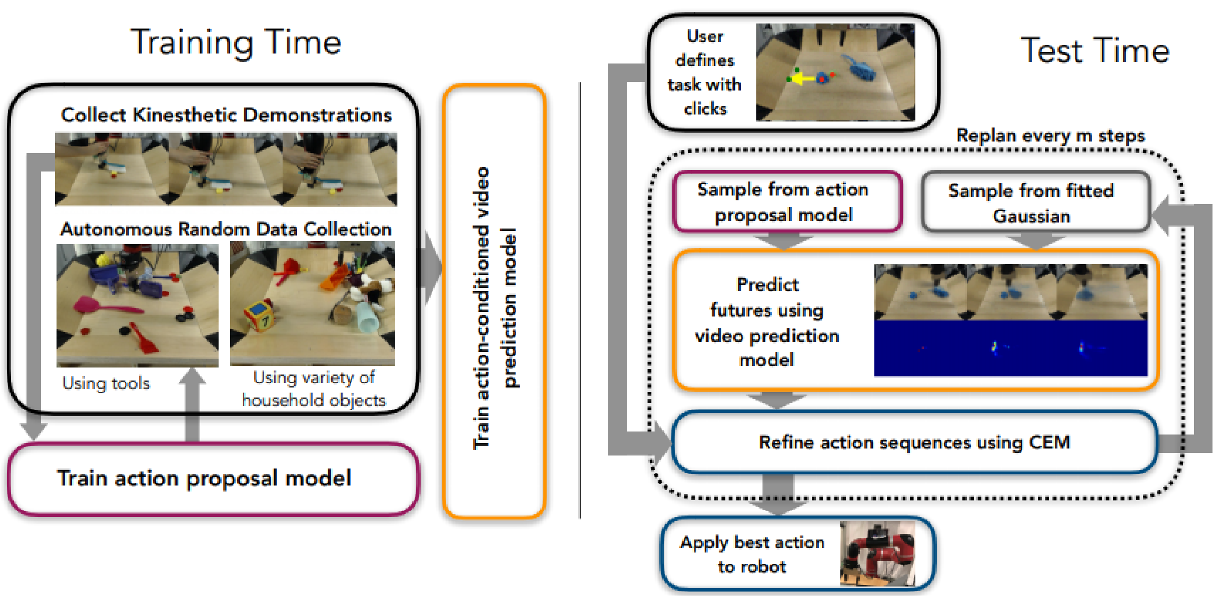
This work extends visual MPC (Finn, C. and Levine, S., 2017), also referred to as visual foresight, which is a model-based reinforcement learning approach where a deep neural network model is trained to predict future visual observations. Such methods have been used in prior work for reaching, pushing objects (Toussaint, M. et al, 2018), basic grasping and relocation, and manipulating clothes. Our aim is to extend these methods to enable improvisational tool use. Visual MPC, as well as other video prediction-based planners, generally fail (Finn, C. et al, 2016) at such temporally extended tasks. To this end, we propose to incorporate demonstrations into the algorithm to enable multi-stage tool use capabilities, while still retaining the flexibility of goal directed planning to accomplish varied user-specified goals.

Why is this important:

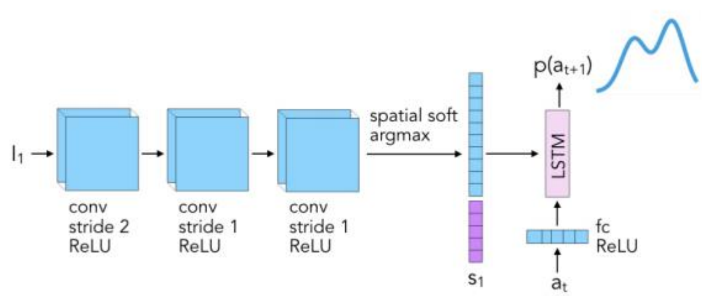
This paper studies the problem of learning generalizable behavior in the real world by using prediction. Prediction is often considered a fundamental component of intelligence. Through prediction, it is possible to learn useful concepts about the world even from a raw stream of observations, such as images from a camera. If we predict raw sensory observations directly, we do not need to assume availability of low-dimensional state information or an extrinsic reward signal. Image observations are both information-rich and high-dimensional, presenting both an opportunity and a challenge. Future observations provide a substantial amount of supervisory information for a machine learning algorithm.

Paper Summary:

The main idea is to incorporate demonstrations and autonomous data collection to learn a video prediction model and action proposal model that enable the robot to solve both a diverse range of goals that require tool use. We incorporate the action proposal model both for training data for the video prediction model and for improving the sampling-based planner at test time.



Architecture for the action proposal model using an autoregressive model to output the parameters of a Gaussian mixture model over the probability of an action at each timestep. Using recurrence and Gaussian mixtures enables the network to model diverse and multi-modal demonstration data based on the initial image.



2) LEARNING TO ADAPT IN DYNAMIC, REAL-WORLD ENVIRONMENTS THROUGH META-REINFORCEMENT LEARNING

https://arxiv.org/pdf/1803.11347.pdf Anusha Nagabandi*, Ignasi Clavera*, Simin Liu, Ronald S. Fearing, Pieter Abbeel, Sergey Levine, & Chelsea Finn

Short Description:

This project demonstrates an approach for model based meta-RL that enables fast, online adaptation of large and expressive models in dynamic environments. We show that meta-learning a model for online adaptation (Schulman, J. et al, 2015) results in a method that can adapt to unseen situations or sudden and drastic changes in the environment and is also sample efficient to train. We provide two instantiations of our approach (ReBAL and GrBAL), and we provide a comparison with other prior methods on a range of continuous control tasks. Finally, we show that (compared to model-free meta-RL approaches), our approach is practical for real-world applications, and that this capability to adapt quickly is particularly important under complex real-world dynamics

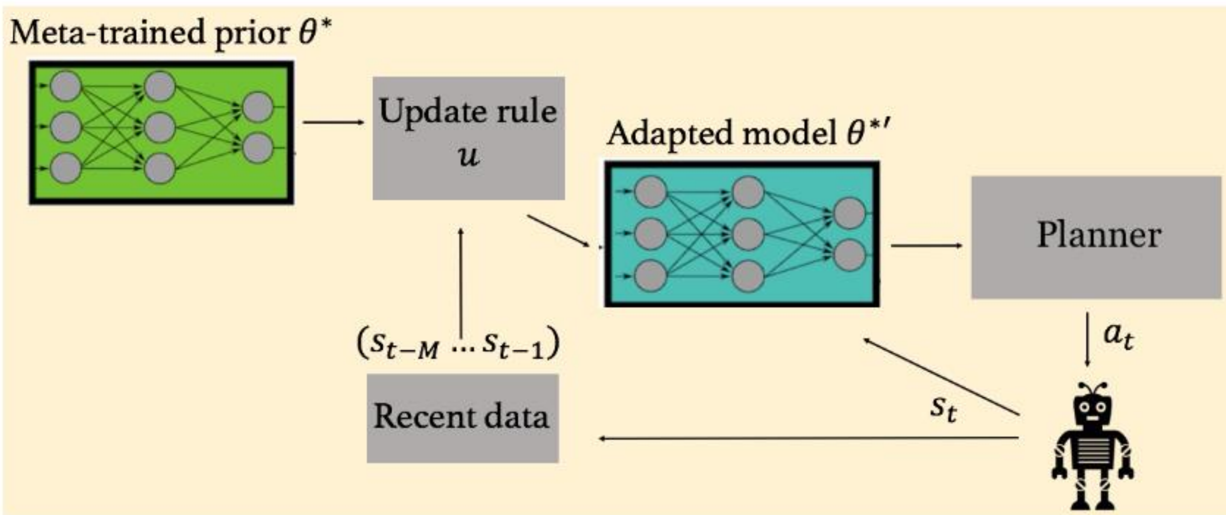
Why is this important:

Humans have the ability to seamlessly adapt to changes in their environments (Braun, D. A. et al, 2009): adults can learn to walk on crutches in just a few seconds, people can adapt almost instantaneously to picking up an object that is unexpectedly heavy, and children who can walk on flat ground can quickly adapt their gait to walk uphill without having to relearn how to walk. This adaptation is critical for functioning in the real world. Robots, on the other hand, are typically deployed with a fixed behavior (be it hard-coded or learned), allowing them succeed in specific settings, but leading to failure in others: experiencing a system malfunction, encountering a new terrain or environment changes such as wind, or needing to cope with a payload or other unexpected perturbations. The idea behind our latest research is that the mismatch between predicted and observed recent states should inform the robot to update its model into one that more accurately describes the current situation (Finn, C. et al, 2017).

Noticing our car skidding on the road, for example, informs us that our actions are having a different effect than expected, and thus allows us to plan our consequent actions accordingly (Fig. 2). For our robots to be successful in the real world, it is critical that they have this ability to use their past experience to quickly and flexibly adapt. To this effect, we developed a model-based meta-reinforcement learning algorithm capable of fast adaptation.

Idea Summary:

The method follows the general formulation shown in the figure below. Observations from recent data are used to perform adaptation of a model, and it is analogous to the overall framework of adaptive control (Sastry, S. S. and Isidori, 1989.). The real challenge here, however, is how to successfully enable model adaptation when the models are complex, nonlinear, high-capacity function approximators (i.e., neural networks). Naively implementing SGD on the model weights is not effective, as neural networks require much larger amounts of data in order to perform meaningful learning. Thus, we enable fast adaptation at test time by explicitly training with this adaptation objective during (meta-)training time Once we meta-train across data from various settings in order to get this prior model (with weights denoted as θ∗) that is good at adaptation, the robot can then adapt from this θ∗ at each time step by using this prior in conjunction with recent experience to fine-tune its model to the current setting at hand, thus allowing for fast online adaptation.



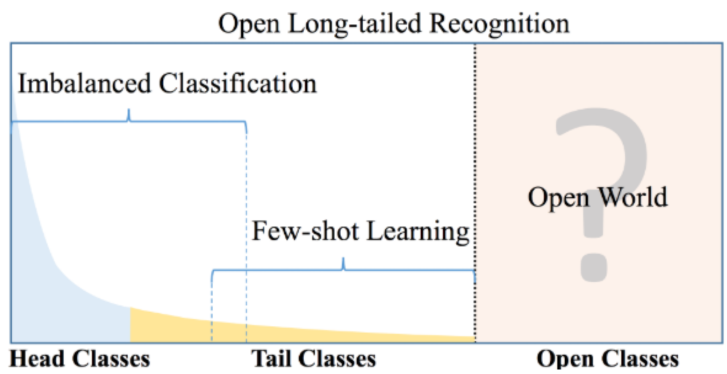
The agent uses recent experience to fine-tune the prior model into an adapted one, which the planner then uses to perform its action selection. Note that we omit details of the update rule in this post, but we experiment with two such options in our work.

3) Large-Scale Long-Tailed Recognition in an Open World

https://arxiv.org/abs/1904.05160 Ziwei Liu1,2∗ Zhongqi Miao2∗ Xiaohang Zhan1 Jiayun Wang2 Boqing Gong2† Stella X. Yu2

Short Description:

The project demonstrates an approach to learn from natural long-tail open-end distributed data that optimizes the overall accuracy over a balanced test set. We propose an integrated OLTR algorithm, dynamic meta-embedding, in order to share visual knowledge between head and tail classes and to reduce confusion between tail and open classes. We validate our method on three curated large-scale OLTR benchmarks (ImageNet-LT, Places-LT and MS1M-LT). Our publicly available code and data would enable future research that is directly transferable to real-world applications.

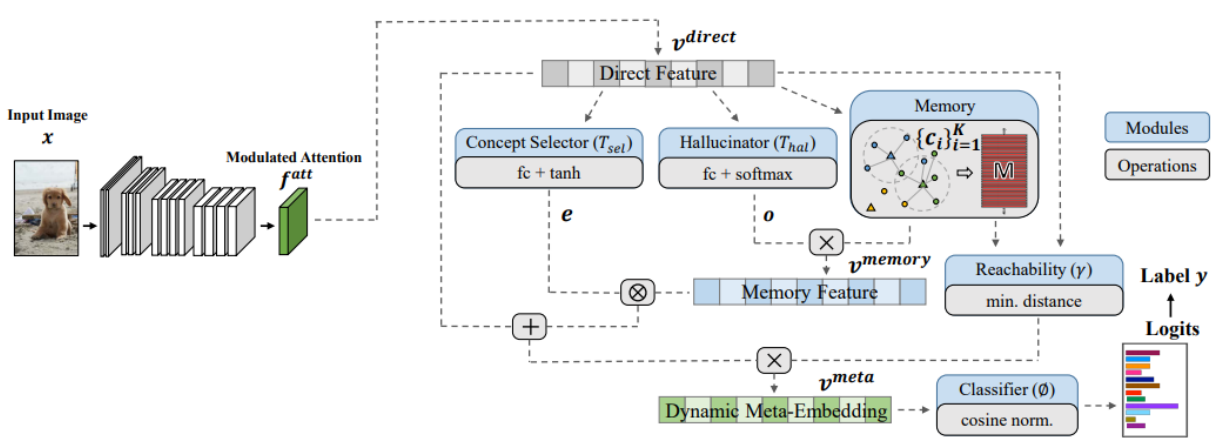


Why is this important:

Real world data often have a long-tailed and open-ended distribution. A practical recognition system must classify among majority and minority classes, generalize from a few known instances, and acknowledge novelty upon a never seen instance. We define Open Long-Tailed Recognition (OLTR) as learning from such naturally distributed data and optimizing the classification accuracy over a balanced test set which include head, tail, and open classes. OLTR must handle imbalanced classification, few-shot learning, and open-set recognition in one integrated algorithm, whereas existing classification approaches focus only on one aspect and deliver poorly over the entire class spectrum.

Idea Summary:

The method involves mapping the input image to a feature space such that visual concepts can easily relate to each other based on a learned metric that respects the closed-world classification while acknowledging the novelty of the open world. The model has two main modules: dynamic meta-embedding and modulated attention. The former relates and transfers knowledge between head and



tail classes and the latter maintains discrimination between them. The Dynamic Meta-Embedding combines a direct image feature and an associated memory feature, with the feature norm indicating the familiarity to known classes. Modulated attention is spatial attention applied on self-attention maps ("attention on attention"). It encourages different classes to use different contexts, which helps maintain the discrimination between head and tail classes.

3.4 Scalable Reinforcement Learning.

Reinforcement learning (RL) is the standard framework to teach AI how to optimally interact with a dynamic environment. This approach has proven its worth in a series of artificial domains and is beginning to show some successes in real-world scenarios. However, there are unique challenges that must be addressed to apply RL to real world problems. The papers on this section demonstrate some of challenges and promising approaches to solve them.

1) End-to-End Robotic Reinforcement Learning without Reward Engineering.

https://arxiv.org/pdf/1904.07854.pdf Avi Singh, Larry Yang, Kristian Hartikainen, Chelsea Finn, Sergey Levine

Short Description:

The project demonstrates an approach to reinforcement learning *without hand-programmed reward functions*. The method (VICE-RAQ), constructs a reward function from a modest number of user-provided examples of successful outcomes, which in practice might consist simply of pictures of the scene where the task has been successfully completed. Such examples are often substantially easier for a user to provide than either hand-programmed reward functions or full demonstrations. The initial reward is constructed out of a classifier trained on these examples and adversarially mined negatives. Beyond the initially provided success examples, the method uses a modest number of active queries, where the user is asked to label outcomes achieved by the robot as either successful or not. These additional queries are also simple to provide, and roughly correspond to the user directly reinforcing the robot's behavior. However, the user does not need to label all of the robot's experience – only about 50 queries are used in our experiments, out of tens of thousands of transitions. The method improves substantially on both naive classifier rewards and VICE in our experiments.

Why is this important:

Reinforcement learning frames policy learning through the lens of optimizing a global reward function, yet most systems have multi-dimensional costs to be minimized. In many cases, system or product owners do not have a clear picture of what they want to optimize. When an agent is trained to optimize one metric, other metrics are discovered that also need to be maintained or improved. Thus, a lot of the work on deploying RL to real systems is in formulating the reward function, which may be multi-dimensional.

Idea Summary:

Main idea is to use a set of goal images, and then train a classifier to distinguish between goal and non-goal images. The success probabilities from this classifier can then be used as reward for training an RL agent to achieve the goal. A potential problem is that when a policy is trained with this classifier, the policy can learn to exploit the classifier, reaching states that are different from those that the classifier was trained on and fool it into outputting a success label erroneously. This problem is avoided by introducing an active learning framework that queries a user for binary success labels for states that it would like to obtain ground truth labels for. This addresses two major challenges with classifier-based rewards: it removes the need for the user to provide a comprehensive set of negative examples up front, and it mitigates the classifier exploitation problem.

2) DisCor: Corrective Feedback in Reinforcement Learning via Distribution Correction

https://arxiv.org/pdf/2003.07305.pdf Aviral Kumar∗ aviralk@berkeley.edu Abhishek Gupta abhigupta@berkeley.edu Sergey Levine

Short Description:

The paper shows that bootstrapping-based Q-learning algorithms do not benefit from corrective feedback and training on the experience collected by the algorithm is not sufficient to correct errors in the Q-function. In fact, Q-learning and related methods can exhibit pathological interactions between the distribution of experience collected by the agent and the policy induced by training on that experience, leading to potential instability, sub-optimal convergence, and poor results when learning from noisy, sparse or delayed rewards. We demonstrate the existence of this problem, both theoretically and empirically. We then show that a specific correction to the data distribution can mitigate this issue. Based on these observations, we propose a new algorithm, DisCor, which computes an approximation to this optimal distribution and uses it to re-weight the transitions used for training, resulting in substantial improvements in a range of challenging RL settings, such as multi-task learning and learning from noisy reward signals.

Why is this important:

Many systems cannot be trained on directly and need to be learned from fixed logs of the system's behavior. In many cases, we are deploying an RL approach to replace a previous control system, and logs from that policy are available. In future training iterations, batches of data will be available from the most recent iteration of the control algorithm. This setup is an off-line and off-policy training regime where the policy needs to be trained from batches of data. This research shows the theoretical reason why errors in the future value functions may be introduced by training on historical data and an approach to bypass the problem.

Idea Summary:

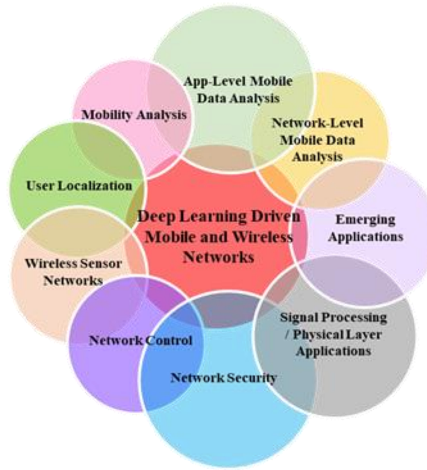
Dis**C**or (Distribution Correction), is identical to conventional ADP methods like Q-learning, with the exception that it performs a weighted Bellman backup – it assigns a weight wk(s,a) to a transition, (s,a,r,s') and performs a Bellman backup weighted by these weights, as shown below.

$$Q_k \leftarrow \arg\min_{Q} \frac{1}{N} \sum_{i=1}^{N} w_i(s,a) \cdot \left(Q(s,a) - [r(s,a) + \gamma Q_{k-1}(s',a')]\right)^2$$

This technique falls into a broader class of **abstention** based techniques that are common in supervised learning settings with noisy labels, where down-weighting datapoints (transitions here) with errorful labels (target values here) can boost generalization and correctness properties of the learned model.

4 AI for Wireless – improving existing solutions

There are many opportunities and research efforts going on focusing on how to leverage AI/ML to enhance and improve the current wireless communication products and solutions. Quite often, the underlying communication technologies remain but the goal is to seek and explore new data-driven and learning-based approaches to improve the design of the solutions and management of operations for the benefits of efficiency and user experience.



Deep Learning for Wireless Communications (modified from Fig. 7, Zhang, C. et al.)

Machine Learning and Deep Learning have started being adapted in wireless networks since 4G LTE deployment and the trend is growing faster as more complex network architectures are introduced in the field. In the following sub-sections we try to provide both a summary and an update of relevant works based on published research contributions as categorized in (Zhang, C. et al., 2019). Please note that this is not to be an exhausted list.

4.1 Network-Level Mobile Data Analysis

This area of work utilizes Deep Learning techniques to optimize wireless network configurations to improve end-user experience (QoS or QoE), such as:

- Network prediction

Applications leverage DL to perform QoS / QoE prediction (Pierucci, L. et al., 2016), cellular traffic forecasting (Wang, X. et al., 2018), cloud RAN optimization (Chen, L. et al., 2018), and channel state information (CSI) prediction (Luo, C. et al., 2018), etc.

- Traffic classification

DL (CNN, MMLP, stacked Autoencoder and LSTM) has achieved good performance in encrypted traffic classification (Wang, W., Zhu, M., Wang, J., Zeng, X., and Yang, Z., 2017), malware traffic classification (Wang, W., Zhu, M., Zeng, X., Ye, X., and Sheng, Y., 2017), etc.

- Call Data Record (CDR) mining

Using huge amount of CDR data generated in the wireless network, researches leverage ML / DL techniques in areas like metro density prediction with RNN (Liang, V. C. et al., 2016), gender and age prediction for demographics study using CNN (Felbo, B. et al., 2016), and human activity chains generation using HMM + RNN / LSTM (Lin, Z. et al., 2017), etc.

4.2 Application-Level Mobile Data Analysis

In the era of Internet of Things (IoT), devices from a wide variety of industries require (distributed) intelligence either at the cloud or at the edge. Many service providers and huge amount of application development companies are employing Deep Learning for application-level data analysis utilizing the big data generated from massive IoT devices. For example, e-healthcare system utilizes Deep Learning in many use cases, from heart rate prediction (Jindal, V., 2016), personalized health indicators monitor using smart phone sensors (Li, H. et al., 2017) to "MobiEar" application for the deaf (Liu, S. et al., 2016). Also, nature language processing (NLP) and automated speech recognition (ASR) type of applications like Siri (Siri Team, 2017) and personalized speech recognition (McGraw, I. et al., 2016) are popular in people's everyday life now.

4.3 User Mobility Analysis

Mobility analysis is used in various use cases, from network resource management to urban planning. Deep Learning becomes a promising tool for device mobility analysis thanks to its ability to capture spatial dependencies in sequential data. Many works have been published in this area. For example, LSTM was used in DeepTransport, a study for city-wide mobility prediction and transportation modeling (Song, X. et al., 2016), another research leveraged RNN for proactive mobility management via prediction (Wickramasuriya, D. S. et al., 2017), and DeepMove, using attention RNN showed promising result in human mobility forecasting (Feng, J. et al., 2018).

4.4 AI-aided User Localization for Indoor Scenario

It is well recognized that user localization is an important task in wireless networks. It also enables wide variety of location-based services in the today's market. However, high accuracy remains a challenging task for traditional method in indoor scenario. As a result, research for this top is also evolving in a fast pace. Research work as early as DeepFi in 2015 (Wang, X. et al., 2015) achieved higher localization accuracy as compared to traditional approaches when leveraging Deep Learning approach. There are many more researches followed afterwards and following are a few examples.

For indoor localization, some works proposed novel CNN architecture like CiFi (Wang, X., Wang, X., and Mao, S., 2017), and bi-model framework using Restricted Boltzmann Machine (RBM) based algorithm (Wang, X., Gao, L., and Mao, S., 2017) that achieve high accuracy using CSI or angle of arrival + average amplitudes of CSI as input.

For massive MIMO fingerprint-based positioning, CNN achieved good performance in some research work using channel fingerprint attributes as input (Vieira, J. et al., 2017; Xiao, C. et al., 2017).

For 3D indoor localization, denoising AE is a low-cost option with robust localization result as shown in (Xiao, C. et al., 2017) using Bluetooth relative received signal strength as input.

4.5 Wireless Sensor Networks

Wireless Sensor Networks (WSNs) consist of a set of homogenous or heterogenous sensors that are distributed across geographical regions. Usually WSNs collaboratively monitor physical or environment status (sensing) and transmit the collected data to a centralized server (communication) to serve various applications (analysis), e.g. sensor node localization (Bermas, M. et al., 2015), smoke monitoring, smoldering and combustion classification (Yan, X. et al., 2016), etc. Some applications require exploiting spatial and temporal correlations of data from all sensors (Wang, Y. et al., 2017). Researches showed Deep Learning can achieve high accuracy in these use cases as well as improve energy efficiency.

4.6 Network Control

Wireless network control has long been a difficult task for engineers. Traditionally it depends heavily on communication theory, domain knowledge and simulation. Deep Learning has made great breakthrough in improving traditional reinforcement learning and imitation learning (Hussein, A. et al., 2017) with powerful function approximation mechanism. Various categories of network control tasks are now relying on Deep Learning technology.

- Network optimization

With an overwhelming amount of wireless network parameters to optimize and many requiring simultaneous multi-parameter or multi-objective optimization, Deep Reinforcement Learning (DRL) has shown improved performance and shortened optimization duration comparing with domain knowledge-based approach. Examples include handover optimization (Wang, Z. et al., 2018), downlink mmWave communication performance optimization (Mismar, F. B. et al., 2017), random access optimization (Chen, Z. et al., 2018), and many more.

- Scheduling

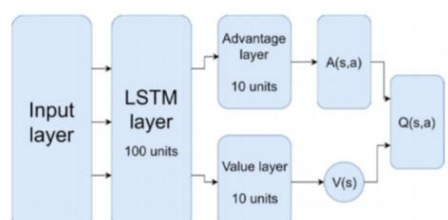
Deep Reinforcement Learning is also being used in several research works in the scheduling topic, from user scheduling and content caching for edge networks (Wei, Y. et al., 2018), traffic scheduling (Chinchali, S. et al., 2018) to deep Q learning-based dynamic voltage and frequency scaling scheduling (Zhang, Q. et al., 2017).

- Resource allocation

Wireless network resource allocation requires balance between available resources and user experience or network performance thus usually both factors are considered in constructing the objective function. In some cases, proactively predict the effect of parameters can avoid trialing on poor performing parameters. Many research works utilized multi-objective Deep Reinforcement Learning in areas like hybrid radio resource management in cognitive communications (Ferreira, P. V. et al., 2017), resource allocation in cloud radio networks (Xu, Z. et al., 2017), and resource allocation for vehicle-to-vehicle (V2V) communication (Ye, H. et al., 2018).

- Radio control

Deep Reinforcement Learning is known with its ability to learn to maximize the reward function in dynamic environment without requiring a priori knowledge. This unique strength makes it a good fit to carry learning problem in dynamically changing environment to extract knowledge on the fly from the networks and to automatically apply proper radio control accordingly. Research works showed good performance by leveraging DRL in use cases like radio control include dynamic spectrum access (Naparstek, O. et al., 2017, 2019), intercell interference cancelation transmit power optimization (Wijaya, M. A. et al., 2016), power control for spectrum sharing (Li, X. et al., 2018), radio transmitter setting selection in satellite communications (Ferreira, P. V. et al., 2018), and anti-jamming communication in dynamic and unknown environment (Liu, X. et al., 2018), etc.



Multi-user Deep Q-Learning for Spectrum Access
(Naparstek, O. et al., 2019)

4.7 Network Security

Modern cyber security systems can benefit from Deep Learning given its capability to: a) automatically learning signatures and patterns from experiences and generalizing to future intrusions, and b) identifying patterns that are different from previous / normal behaviors, which significantly reduces the effort of pre-defined rules. Network security includes multiple perspectives, from infrastructure level and software level to user level.

- Infrastructure Level

Many research works utilized Deep Learning in improving infrastructure level security like IoT distributed attacks detection (Diro, A. A. et al., 2017; Saied, A. et al., 2016), attack detection in smart grids (Hamedani, K. et al., 2018) and MAC spoofing detection (Jiang, P. et al., 2018).

- Software (SW) Level

Various approaches have been introduced for malware detection in Android system (Su, X. et al., 2016; Yuan, Z. et al., 2014, 2016). Other researches showed improved SW level security using Deep Learning-based approach in areas like malware traffic classification (Wang, W., Zhu, M., Zeng, X., Ye, X., and Sheng, Y., 2017), and mobile botnet detection (Oulehla, M. et al., 2016; Torres, P. et al., 2016).

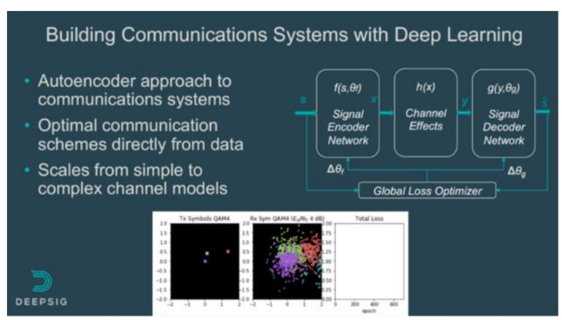
- User Privacy

User privacy protection is a general issue in Deep Learning training phase. Several approaches were proposed to preserve user privacy during training like via homomorphic encryption (Phong, L. et al., 2017), and client-server framework based on Siamese architecture where a feature extractor is used in mobile devices and classifier is located in the cloud for privacy-preserving mobile analytics (Ossia, S. A. et al., 2017), etc.

Given the nature of fast security attack pattern mutation, it is expected new mechanisms in Network Security will also evolve accordingly.

4.8 Signal Processing

Beyond system level use cases, recently Deep Learning is also gaining attention in signal processing area, e.g. modulation and coding, etc. and many research works conducted in this area have indicated ML and DL could play a key role at physical layer of wireless networks as well.



DeepSig: Generalized diagram for training a channel autoencoder

Based on research, MIMO performance is intelligently optimized based on condition when incorporating Deep Learning. For example, various DL approaches could be leveraged in signal detection in MIMO-OFDM system (Yan, X. et al., 2017), MIMO channel estimation (Neumann, D. et al., 2017), MIMO nonlinear equalization (Fujihashi, T. et al., 2018), super-resolution channel and direction-of-arrival estimation (Huang, H. et al., 2018), optimization of representations and encoding/decoding process (O'Shea, T. J. et al., 2017), and unsupervised DL (using autoencoder) for joint optimization of physical layer representation and encoding and decoding processes (O'Shea, T. J. et al., 2017), and the task list goes on.

Research also showed modulation recognition / classification accuracy can be improved with Convolutional Neural Networks (O'Shea, T. J. et al., 2016; West, N. E. et al., 2017).

4.9 Other Emerging Applications

In addition to the above-mentioned topics, Deep Learning also show great potential in new emerging applications like mobile crowdsensing via Deep Q learning (Xiao, L. et al., 2017), blockchain resource allocation (Luong, N. C. et al., 2018), data dissemination in Internet of Vehicles (IoV) (Gulati, A. et al., 2018), autonomous vehicle trajectory prediction (Cui, H. et al., 2019).

5 AI for 5G+ and 6G – enabling new technologies

Other than applying AI/ML to improve existing technologies and solutions as reported in the previous section, we have noticed very active discussions and early research efforts in combining AI/ML with much more radical and revolutionary technologies targeting 5G+ and 6G, due to the underlying technical challenges to realize those new candidate technologies. In other words, AI/ML may become a true enabler to those technologies.

5.1 AI as a driving application of 6G

In (Stoica & de Abreu, 2019) "Why even bother with thinking of sixth generation (6G)?. The answer to these rhetorical questions is that, as usual, revolution never comes from within, but is rather imposed by radical changes in exterior conditions. And that radical change, which is now beaming straight towards the wireless communication world ready to cause major disruption, is the raise of artificial intelligence (AI)". "But in order to harness the true power of such agents, **collaborative AI** is the key. And by nature of the mobile society of the 21st century, it is clear that this collaboration **can only be achieved via wireless communications**."

In (Letaief et al., 2019), it's envisioned that a new type of service is required for such AI computations. "6G will also require the support of three new service types beyond the eMBB, uRLLC, and mMTC services supported by 5G, as described below. **Computation Oriented Communications** (COC): New smart devices call for distributed and in-network computation to enable the key functionalities of AI-empowered 6G, such as federated learning and edge intelligence. Instead of targeting classical quality of service (QoS) provisioning, CoC will flexibly choose an operating point in the rate-latency-reliability space depending on the availability of various communications resources to achieve a certain computational accuracy".

5.2 6G Architecture with AI-Native approach

In (Letaief et al., 2019), “6G is going from **Network Softwarization to Network Intelligentization**. We envision that 6G will take network softwarization to a new level, namely, towards network intelligentization. As the network is becoming more complex and more heterogeneous, softwarization is not going to be sufficient for beyond 5G networks. The design of the **6G architecture shall follow an “AI native”** approach where intelligentization will allow the network to be smart, agile, and able to learn and adapt itself according to the changing network dynamics.”

In (Tariq et al., 2019), it suggests that “6G will be empowered by artificial intelligence (AI) **in almost all levels**, from network orchestration and management to coding and signal processing in the physical layer, manipulation of smart structures, and to data mining at the network and device level for service-based context-aware communications, etc.”

5.3 AI as key enabler for next frontier technologies

In (Tariq et al., 2019), for 6G Key enabling technologies, “the most certain enabling technology for 6G has to be AI. Due to the advances in AI techniques especially deep learning and the availability of massive training data, recent years have seen an overwhelming interest in using AI for the design and optimization of wireless networks, and it is a consensus that AI will be at the heart of 6G (cf. Fig. 2). In fact, recent success has motivated AI to form part of 5G although in 5G AI is only expected to operate in isolated areas in which massive training data and powerful computing facility are available. So far researchers have shown numerous successful examples of using AI on wireless communications, from physical layer designs such as channel estimation and precoding, to network resource allocation such as traffic control and cache storage management, to security and authentication, and to dynamic cell and topology formation and management, to fault prediction and detection, and etc. The list continues. It is reasonable to believe that **some form of AI will be realized as part of 5G and AI will become more of the core components in 6G.**”

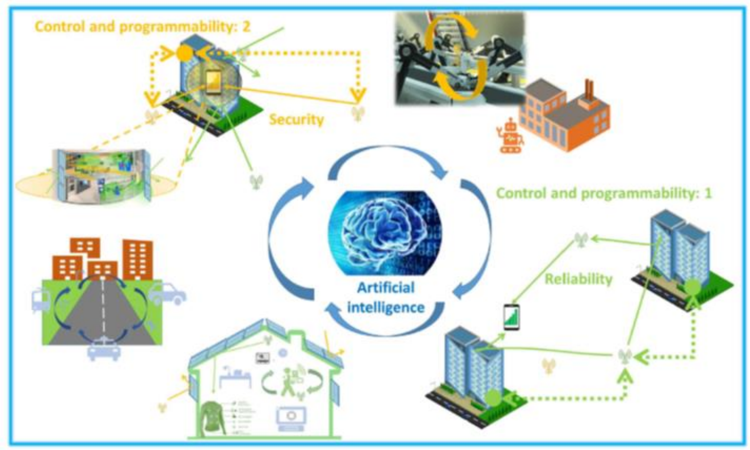
5.3.1 Intelligent PHY Layer

In (Letaief et al., 2019), “AI technologies open up the possibilities to learn the best way to communicate over combinations of hardware and channel effects. We envision an “**intelligent PHY layer**” paradigm in 6G, where the end-to-end system is capable of self learning and self optimization by combining advanced sensing and data collection, AI technologies, and domain-specific signal processing approaches.”

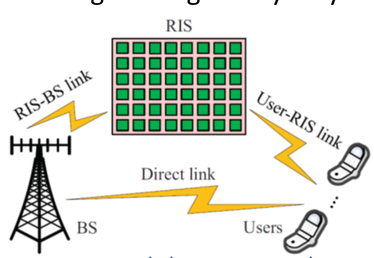
It also proposes that the network will evolve itself in a local + global fashion. “The local evolution may happen in a few neighboring cells or even in a single cell in order to flexibly apply cutting-edge developments on new waveforms, coding, and multi-access protocols in subnetworks without extensive time-consuming tests. To achieve this goal, each subnetwork should collect and analyze its local data, which may include wireless environments, user requests, mobility patterns, etc. and then exploit AI methods to upgrade itself locally and dynamically".

5.3.2 Smart Surface

As 5G communication networks are now being deployed in the world, technologies for the next generation communications (6G) are also being explored from the academic and industrial point of view. Among candidate technologies like terahertz communications, visible light communications (VLC), sensing and network-based localization, and artificial intelligence (AI) empowered networks, reconfigurable-intelligent-surface (RIS) is being regarded as a promising emerging technology as suggested in (Wu, Q. et al, 2020; Yuan, X. et al., 2020). As of now, the wireless environment is not controllable and its impact on radio waves cannot be customized. A smart radio environment with RIS is able to improve spectrum and emergency efficiency of wireless networks by reconfiguring the propagation environment of electromagnetic waves with the use of massive low-cost passive reflecting elements integrated on a planar surface, which are capable of sensing the environment and of applying customized transformations to the radio waves. As such, it has the potential to provide future wireless networks uninterrupted wireless connectivity, and with the capability of transmitting data without generating new signals by recycling existing radio waves (Di Renzo, M. et al., 2019).



Examples of artificial intelligence application areas of intelligent radio environments with RIS: higher reliability of communication connectivity, wireless security of high-profile enterprise clients. (Gacanin, H. et al., 2020)

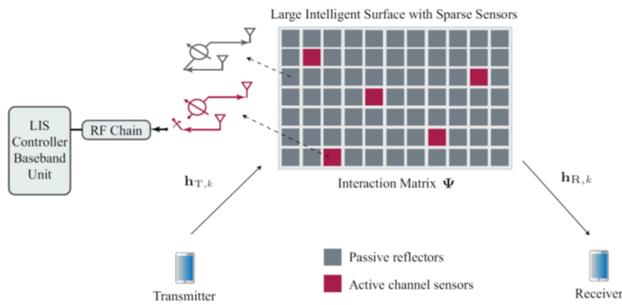


Communication links in RIS-assisted system include User-RIS and RIS-BS links (cascaded channels) (Yuan, X. et al., 2020)

With many benefits mentioned above, RIS design comes with challenges too. To be able to configure the radio environment dynamically, a fundamental problem of using massive inexpensive passive elements is that it limits the estimation of channels and phase angles at the receiver end, so the big challenge is <u>*"how can these extremely large-dimensional channels be estimated if the LIS is implemented using only reflecting elements?"*</u> (Taha, A. et al., 2019). Recently many research studies have been trying to answer this question using various novel approaches, which can be divided into following categories per (Yuan, X. et al., 2020).

Active-channel-sensor based approach

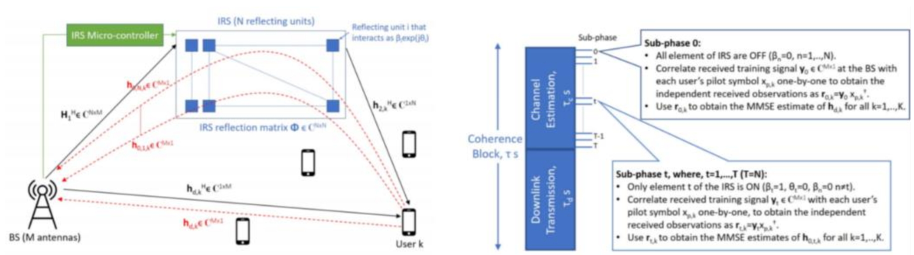
This approach is based on the insertion of a few active channel sensors into the array of passive elements for sensing channel information. As explained in (Taha, A. et al., 2019), each active channel sensor is equipped with not only an RF phase shifter like a passive reflecting element (reflection mode), but also an additional baseband processing unit for channel estimation (channel sensing mode). During channel sensing mode, the sensors receive pilot signals from the users and the base station (BS) to estimate the corresponding channel links. As the channel coefficients of a large antenna array at the RIS have strong correlation, these coefficients can be constructed based on the sampled channel information using compressive sensing methods. The channel links from the RIS to the users and to the BS can be obtained by assuming channel reciprocity.



An example of active-channel-sensor based RIS-assisted system (Taha, A. et al., 2019)

Channel-decomposition based approach

This approach decomposes the cascaded channel (user-RIS and RIS-BS links) and into a series of sub-channels that are easier to estimate. For example, one option as used in (Nadeem, Q.-U.-A. et al., 2019) is to decompose the cascaded channel into a series of rank-1 matrixes with each corresponding to a RIS element. Each sub-channel can be estimated by turning on only one RIS element (and turning off all others). Applying this to each RIS element, the CSI of the entire cascaded channel can be obtained. An alternative decomposition method is to estimate the channel by activating each user one by one, i.e., the cascaded channel is decomposed into a series of single-input multiple-output channels seen at each user (Wang, Z. et al., 2019).



(a) IRS-assisted multi-user MISO system. Red dashed lines represent the estimated uplink channel vectors.

(b) Channel estimation protocol.

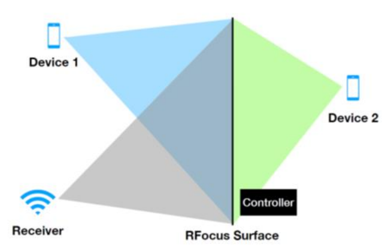
An example design of channel decomposition based RIS-assisted system (Nadeem, Q.-U.-A. et al., 2019)

Structure-learning based approach

This approach leverages the strong structural features exhibited in the cascaded channel of an RIS-aided system, such as sparsity and low-rankness. These structural features can be exploited to reduce the overheads for the channel estimation. The estimation of the cascaded channel can be done by methods like compressive sensing, sparse matrix factorization and low rank matrix recovery algorithms. Research in (He, Z.-Q. et al., 2019) used a two-stage algorithm to estimate the cascaded channel which includes a (bilinear) sparse matrix factorization stage to estimate the information of the RIS-BS channel link, and a matrix completion (via Riemannian manifold gradient-based algorithm) stage to estimate the information of the user-RIS channel link. Simulation results indicated that the proposed method achieved accurate channel estimation for Large Intelligent Meta-surface-assisted massive MIMO systems.

Folded approach (Arun, V. et al, 2020)

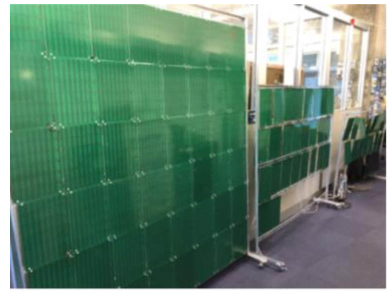
Instead of using communication theory-based methods discussed above that treat the cascaded channel as two separate components (user-RIS and RIS-BS), this approach reduces the complexity by formulating the problem as the estimation of one folded term. RFocus, introduced and built by MIT CSAIL team which moves beamforming functions from the radio end points to the environment. RFocus includes a two-dimensional surface with an array of simple elements and the surface doesn't emit any power. Each receiver periodically sends signal strength measurements to the RFocus controller. The software controller then uses this information in a majority-voting-based optimization algorithm to determine the state of each switch on the surface to focus the transmitter's signal at the intended receiver (by maximizing the signal strength at a receiver). Once configured, it can switch between different configurations in ~1 ms, allowing different pairs of endpoints to time-share the surface's beamforming abilities. The prototype implementation improves the median signal strength by 10.5X, and the median channel capacity by 2.1X.



The RFocus system: channel between each transmitter and receiver pair is represented as:

$$h = h_Z + \sum_{i=1}^{N} b_i h_i$$

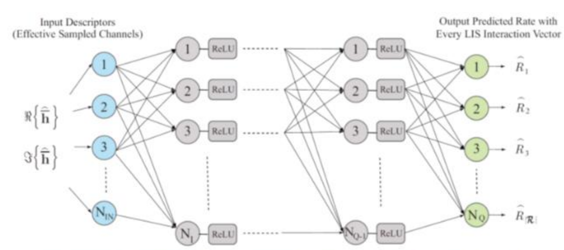
where $b_i \in \{0, 1\}$
h_z is when all elements are off
h_i is the effect of turning on the i^{th} element



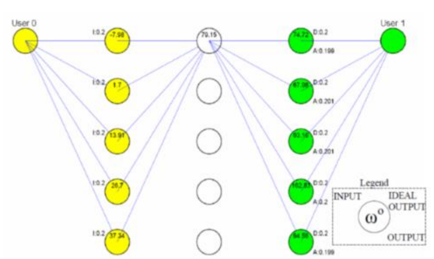
Prototype of RFocus surface

Machine Learning / Deep Learning based approach

In (Taha, A. et al., 2019), the authors also proposed a Deep Learning based channel estimation alternative. Specifically, qualities of wireless channels at all the RIS elements are learned via a deep learning network using channels seen only at the active RIS elements that are connected to the baseband. Furthermore, deep learning is used to guide the RIS to learn the optimal interaction with the incident signals.



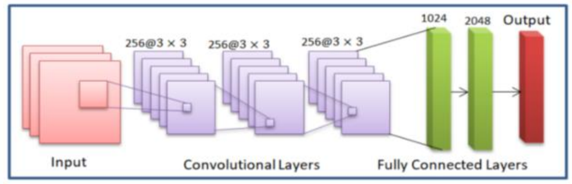
The Neural Network architecture adopted in (Taha, A. et al., 2019)



Trained neural network (3 hidden layers represent 3 RIS walls, and each layer contains 5 neurons corresponding to the 5 tiles/elements on each RIS wall) (Liaskos, C. et al., 2019)

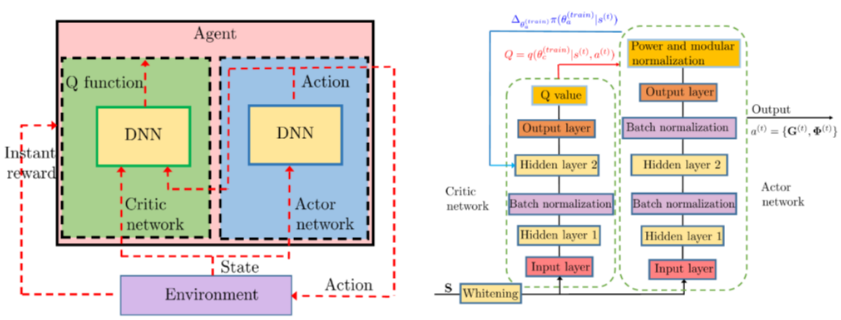
In (Liaskos, C. et al., 2019), the authors regard wireless propagation as a deep neural network and design a more interpretable NN architecture, where each RIS surface is represented as one NN layer, number of neurons are based on the number of elements on the RIS and their cross-interactions are represented as links between neurons. After training from data, the wireless network learns the propagation basics of RIS and configures them to the optimal setting.

In (Elbir, A. M. et al., 2020), the authors proposed ChannelNet, a twin convolutional neural network architecture that is fed with the received pilot signals to estimate both direct and cascaded channels. In a multi-user scenario, each user has access to the CNN to estimate its own channel. The labels for the direct channel estimation are generated with all the elements on the intelligent surface off, and the cascaded channel is estimated by transmitting pilot symbols when each of the RIS element is turned on one by one (then the least square method is used to estimate the cascaded channel).



ChannelNet Neural Network architecture (Elbir, A. M. et al., 2020)

In (Huang, C. et al., 2020), the authors introduced an actor-critic Deep Reinforcement Learning (DRL) based approach to study the joint design of transmit beamforming matrix at the base station and the phase shift matrix at the RIS together for multiuser multiple input single output (MISO) system. The design assumes direct transmissions between the base station (BS) and the users are totally blocked, and the channel matrix from the BS to the reflecting RIS and the channel vector from the RIS to all the users are perfectly known at both the BS and the RIS. The sum rate is utilized as the instant rewards to train the DRL based algorithm, and the transmit beamforming matrix and the phase shifts are jointly obtained (as the output of the DRL neural network) by gradually maximizing the sum rate through observing the reward and iteratively adjusting the parameters.



Left: Deep Reinforcement Learning approach used. Right: DNN architecture. (Huang, C. et al., 2020)

Research Challenges

As with many emerging technologies, to become a viable solution in wireless communication, RIS design faces many challenges ahead as characterized by (Yuan, X. et al., 2020).

Channel modeling and channel acquisition

The channel model of RIS-aided MIMO system has not yet been well understood. A conventional MIMO channel is usually assumed to be far-field. However, the passive antenna array of a RIS, coated on a façade of a building or on the ceiling of a room or wall can be placed very close to the BS/user terminals. It may need to consider near-field propagation properties when modeling the BS-RIS-user channels. Other propagation properties, such as line-of-sight (LOS) / non-LOS / narrowband / broadband, etc. may also be significantly different in RIS-aided MIMO systems. Therefore, these characteristics in the RIS-aided MIMO systems require more research.

System design under CSI uncertainty

Most existing designs of RIS-aided systems assume perfect CSI so that the phases of the reflecting elements of the RIS can be accurately adjusted for performance enhancement. In practice, the CSI acquisition of channel (either modeled as two cascaded channel links or as one folded channel) is difficult, thus the design and passive beamforming optimization at RIS need to be carried out under CSI uncertainty.

Theoretical limits

The fundamental performance limit of the RIS-aided system is not well understood yet. For example, it is not known that by exploiting the additional channel structures such as sparsity and low-rankness, how much gain can be achieved. As such, study and characterization of the tradeoff among the training overhead, CSI accuracy and the system performance are highly desirable.

Signal processing-based method vs. Machine Learning-based method

Traditionally, channel modeling and optimization in wireless communication are performed by utilizing advanced signal processing-based methods, such as compressive sensing, sparse matrix factorization, etc. while recently Machine Learning (ML)-based approaches have also been explored in optimizing RIS configurations to improve system performance. However, it is not clear at this time how much performance gain ML-based approach could bring for RIS-aided system, and the metrics for quantifying the gains should be investigated as well.

5.3.3 Exploring the potentials of non-RF sensing

Encouraged by recent advances in Machine Learning and computer vision, non-RF modalities, such as images from camera, Lidar point cloud, etc., have been introduced in designing the next generation wireless communication systems without sacrificing spectral efficiency. Compelling non-RF aided use cases in wireless communications systems include channel prediction, mobility management, etc. just to name a few. In addition, combing RF and non-RF modalities overcomes the issue of occlusion, which helps channel blockage prediction without pilot signaling, thus allows high-precision location prediction and tracking. Following is a brief summary of two potential use cases leveraging non-RF modality in wireless communication systems.

Opportunity 1: Multi-modal-based localization and tracking in occluded scenes (Alahi, A. et al., 2015)

Human behavior analysis in indoor spaces becomes popular in recent years, e.g. security monitoring systems thanks to technology advancements in using RGB data with depth modality (RGB-D). However, these settings are usually costly to deploy and suffer from occlusions.

For wireless-based localization, traditional approaches leverage wifi or Bluetooth and they can be categorized into two groups: a) fingerprint databases, and b) trilateration using signal propagation. While several studies showed their feasibility, the fingerprint databases-based approaches are often time-consuming and expensive, and trilateration and propagation models tend to require additional calibrations at both the antenna and the device level.

A Stanford research (Alahi, A. et al., 2015) showed promising result in more accurately localizing and tracking individuals in challenging conditions, i.e. large crowded spaces when combing visual and wireless data together.

The intuition behind leveraging data sources from both RGB cameras and wireless (wifi, Bluetooth or beacon signals) is the complementary nature of the two modalities. The RGB-based methods can accurately locate and track individuals in the absence of occlusions, but in crowded situations, their performance deteriorates significantly. On the other hand, the wireless data can associate individual's data across time domain without suffering from the occlusion problem, but it cannot precisely locate in 3D.

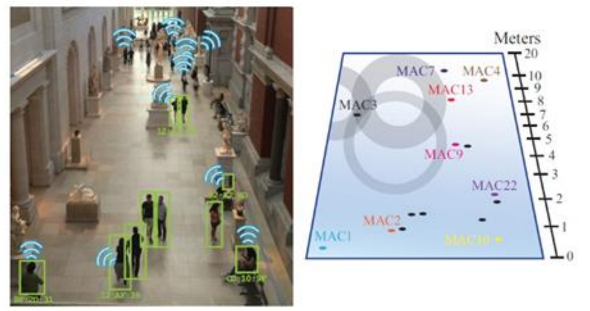


Illustration of a scene captured with RGB data (left) and W data (right)

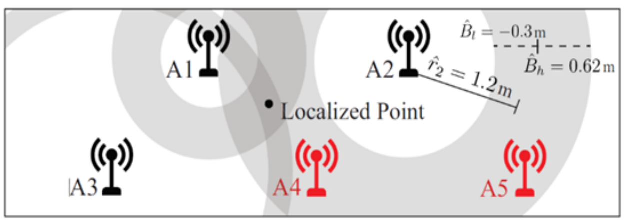


Illustration of the ring image. Antenna A4 and A5 are classified as noisy (in red). The localized point is the weighted center of mass using the intersection of non-noisy radii to antennas (in black).

First, collected wireless data (W) is represented using an embedding that captures the radius estimation, error bounds, and confidence level (via noise detection) for each antenna. To reduce error estimation, a classification framework is used to infer the quality of the W data, and only the non-noisy data points are used. The outcome of the embedded W representation is called a ring image as shown in the figure at left.

Once the ring images are produced from the W data, the foreground images from a camera and the ring images are fused together to infer the ground plane occupancy of individuals in the scene. The task is formulated as an inverse problem using a multi-modal dictionary and solved using a cascade of convex solvers: Lasso followed by Basis Pursuit De-noising on the residual error (BPDN).

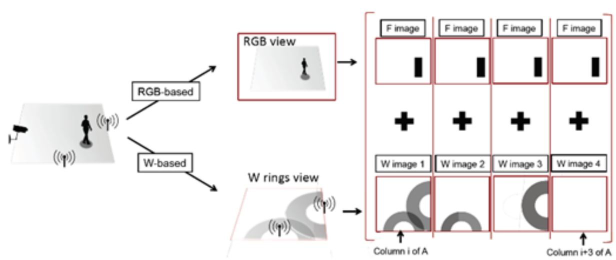
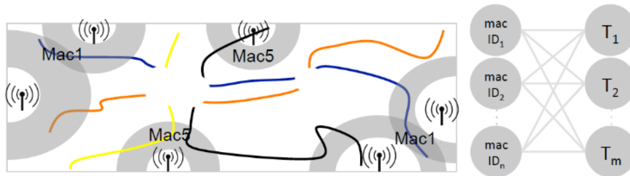


Illustration of dictionary A construction using RGB-W data. For each ground plane point, the i^{th} column is made of the foreground concatenated with the top view of ring image for various antenna responses.

To track individuals, the challenge is in the similarity measure in specific sensitive cases, e.g. when individuals interact and/or occlude each other. The proposed approach uses the combined RGB + W data to connect detections that did not encounter "sensitive" cases (referred to as *tracklets*, which represent short trajectories with high confidence). This data association problem is formulated as a bipartite graph (or bigraph) and the proposed approach uses the minimum weight bipartite matching algorithm to find the optimal assignment.



Left side is a collection of *tracklets* and the collected W data plotted as rings. Right side is the illustration of the bipartite graph.

The proposed approach was evaluated using data collected from both indoor and outdoor scenes at a density of 1 person/m$^{2.}$

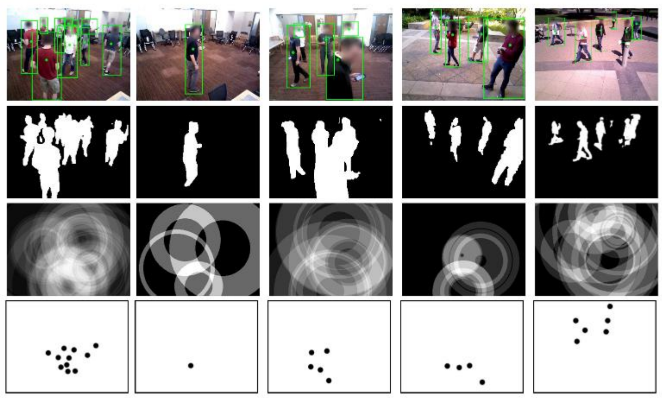
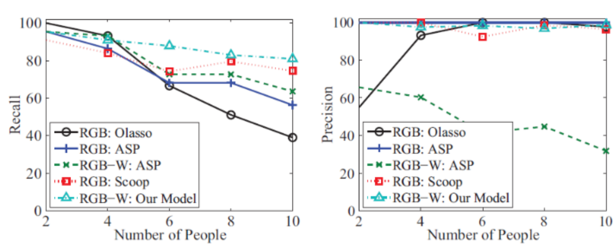


Illustration of qualitative examples of a scene observed with RGB-W data. First row: original RGB image. Second row: extracted foreground silhouettes. Third row: superimposed ring images from all individuals. Fourth row: resulting localization from RGB-W data.

The performance for localization is compared with other approaches using precision and recall as the primary metrics. A true positive is detection that is less than 1 m away from the ground truth.



		Recall	Precision
RGB Only	O-Lasso [1]	45.6%	60.1%
	Scoop [17]	43.4%	43.2%
	ASP [15]	43.4%	39.2%
W Only	Trilateration [27]	27.2%	6.1%
	Fingerprinting	27.0%	9.2%
	Our model (ring-only)	40.5%	61.7%
RGB-W	ASP [15]	43.4%	26.6%
	Our model	**69.5%**	**72.7%**

Left: Precision and recall curves for several algorithms, including the proposed RGB-W method. Right: Performance evaluation of the localization task in terms of recall and precision with respect to other methods.

The human tracking approach is evaluated based on the performance of assigning the mac IDs to the detected individuals given their rough localization in a scene that individuals were moving in highly dense manner, i.e. within 1-2 meters away from each other.

Number of People	Greedy	Our Model
2	61.7%	64.0%
4	52.0%	57.2%
6	45.6%	53.4%
8	36.1%	45.3%
10	27.3%	30.2%
12	21.0%	28.6%

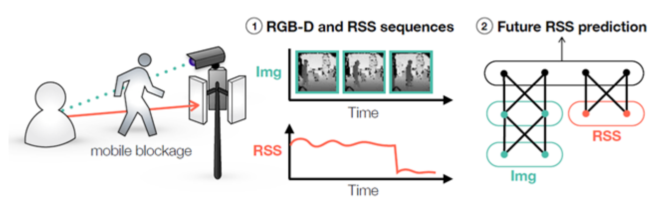
Performance of assigning the correct mac ID to an individual.

The results suggest the proposed multi-modal approach outperforms other methods in localizing individuals in occluded scenes. For human tracking, the proposed approach also performs better than the Greedy method, however, there is still room for improvement.

Opportunity 2: Image Aided mmWave Received Power Prediction

Millimeter-wave (mmWave) communication technology attracts significant attention in mobile networks. mmWave band offers a large BW in the order of several GHz, and enables Gbits/s data rates, which make it particularly attractive in supporting applications requiring high data rates and large traffic volumes and very low latency such as cloud services, virtual reality (VR), and augmented reality (AR). However, owing to its use of directive antenna, mmWave communications are more sensitive to blockage effects than signals in lower-frequency bands, which makes it very challenging to provide reliable wireless links. In particular, the receive power may undergoes a sudden decrease of 20dB or more when a LOS path is blocked by obstacles such as pedestrians and vehicles, which cause significant user experience degradation.

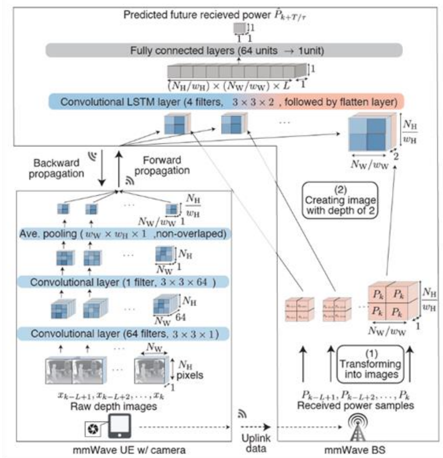
The key to achieve high reliability in communication using mmWave is to enable the network to conduct proper actions prior to the link quality degradation (i.e. a predictive control system has to be in place to predict the future receive power at least hundreds of milliseconds prior to the blockage). Several previous studies tried to use timeseries-based models to predict future link quality, such as signal to noise ratio (SNR) and packet reception rate (PRR). However, human or other obstacle blockages are typically aperiodic, which means signs of blockage are nonexistent till the received power begins to degrade, thus it's very difficult to achieve good accuracy in predicting a long-term timeseries for future received power using the wireless signals alone.



Vision aided future received signal strength prediction (Park, J. et al., 2020)

Recent research conducted by Kyoto University and University of Oulu (Koda, Y. et al., 2020; Mikuma, T. et al., 2019; Park, J. et al., 2020) demonstrated the feasibility of accurate prediction for future mmWave received power leveraging camera images and Deep Learning. The intuition is that depth camera images may capture the geometry and dynamics of the communication environment, which represents wireless signal propagation.

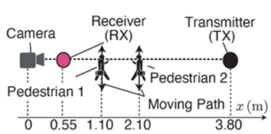
Key challenges in acquiring depth images in communication environment are two-fold, namely, a) communication latency, and b) data privacy as the images obtained may not be in the same location of the RF received power observed. In (Koda, Y. et al., 2020), the authors proposed a multi-modal split learning (MultSL) framework, which combines RF and image modalities by exchanging only neural network (NN) activations and gradients.



Neural Network Architecture (NN) for mmWave Received Power Prediction: Multi-modal Split Learning (MultSL) based on both RF Signals and Depth Images (Koda, Y. et al., 2020)

In addition to prediction accuracy, over-the-air latency for transmitting forward propagation (FP) signals, and data privacy are involved to determine the overall performance and practicality of the technology. To address the two issues, the authors evaluated various degrees of compressing the final convolutional layer's output before sending the payload data over-the-air to the base station. The proposed approach uses non-overlapping pooling to compress the final layer's output. This approach not only achieved higher communication efficiency, thus improved latency but also preserved more data privacy since compressed images make it harder to understand what the images reflect as depicted in the following figure.

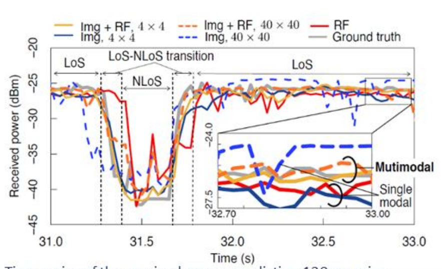
Raw depth images and output images of trained convolutional layers in MultSL with different pooling dimensions. (Koda, Y. et al., 2020)



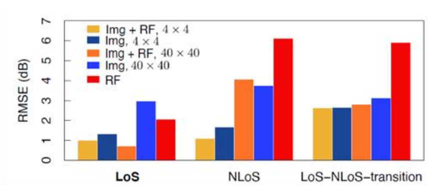
Experimental Environment Setup for measuring the communication channel and depth image data. (Koda, Y. et al., 2020)

To validate the proposed approach and evaluate effect of different pooling dimensions, a simple experimental environment was used as pictured left.

The proposed approach (Img + RF) was compared with two baselines that utilized solely on either image sequences (denoted as Img) or received power sequences (denoted as RF) using RMSE in validation dataset. Following 2 figures summarized the prediction performance comparisons.



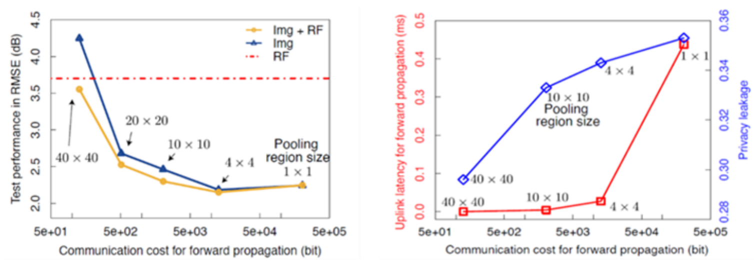
Time series of the received power prediction 120 ms prior to the observation (Koda, Y. et al., 2020)



RMSE in different channel conditions (Koda, Y. et al., 2020)

It should be noted that it's more important to predict the received power accurately prior to the blockage (i.e. LoS to NLoS transition). The results indicate using RF signal alone doesn't perform well enough compared with the prediction result using Img+RF. There is also a significant departure from the ground truth when using RF alone.

For the communication cost and data privacy, the following two diagrams compare different pooling dimensions and their impact to the test prediction performance in terms of communication cost and privacy protection.

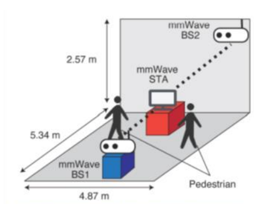


Left: Test RMSE in different pooling dimensions vs. communication cost for transmitting FP signals.
Right: Uplink latency for transmitting FP signals and privacy leakage in different pooling dimensions.
(Koda, Y. et al., 2020)

The results suggest that prediction accuracy is convex shaped over the pooling dimension (roughly). Best performance (i.e. lowest test RMSE) is achieved when 4 x 4 pooling dimension is used (~93% compressed of the output). At this pooling dimension, the privacy leakage is also much lower than transmitting uncompressed output data directly over-the-air. An interesting point to note in the result is that the prediction performance is noticeably worse when no compression is applied to the last convolutional layer output. This is likely due to the very large output dimension causing the LSTM layer biased towards the image sequences while ignoring the received power sequences.

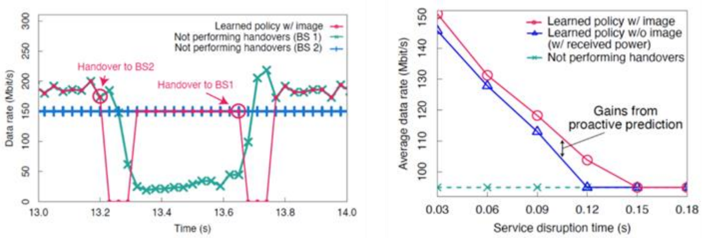
The ability to more accurate predict received power in mmWave networks can help the wireless network to make better handover or cell selection decisions to ensure user experience is protected when a blockage occurs. Typically, handover decision is purely based on RF attributes, however, as discussed above the variation in the received powers before the blockage is not necessarily informative in predicting future behavior in mmWave links. By extending the network state space to include time-consecutive images, which capture spatiotemporal dynamics of moving obstacles, the system is expected to make in-time handover decision, thus, to protect the user experience.

Some researches (Koda, Y. et al., 2019; Nishio, T. et al., 2019) studied the user experience improvement by proactively predict the received power in mmWave networks. One of the studies done by University of Kyoto (Koda, Y. et al., 2019) used two base stations in the setup as depicted in the diagram at right for the handover study.



Experiment setting for Handover scenario
(Koda, Y. et al., 2019)

In the study conducted by (Koda, Y. et al., 2019), a Deep Reinforcement Learning (DRL) framework was used to predict future data rate degradations in mmWAve links caused by moving obstacles using the extended state space (Img+RF) to facilitate the maximization of the expected cumulative sum of the future data rates, which is used as the reward function in the reinforcement learning framework.



Left: Portion of the time series of the data rate vs. handover timing learned by the algorithm using extended state space information. Right: Performance comparison between Img+RF based framework vs. RF-only based framework under various service disruption times. (Koda, Y. et al., 2019)

Results showed that proactive prediction of future long-term performance using extended state space that includes time-consecutive camera images and typical RF attributes in handover decisions improves accumulated data rates in the network. Charts at left show some of the comparisons.

Research in this area indicated that leveraging consecutive camera images to proactively predict performance in handover scenario has potential to improve user experience and system performance in mmWave networks.

5.3.4 3D Network with NTN

It has been envisioned that 3D networking is a key feature of 6G (Chowdhury et al., n.d.; Kodheli et al., 2020; Saad et al., 2019). “The 6G system will integrate the ground and airborne networks to support communications for users in the vertical extension. The 3D BSs will be provided through low orbit satellites and UAVs. The addition of new dimensions in terms of altitude and related degrees of freedom makes 3D connectivity considerably different from the conventional 2D networks.”

In (Kodheli et al., 2020), “**Satellite Communications in the New Space Era: A Survey and Future Challenges**” (to appear in “IEEE Communication Survey and Tutorials”), it points out that “in the context of satellite systems, the application of ML has been already being explored in several scenarios including opportunistic weather monitoring, earth observation applications, satellite operations and sensor fusion for navigation. Furthermore, with the growing trend of investigating the applicability of ML in wireless communications, investigating its applications in the satellite communications has recently received increasing attention from the academia as well asSatCom industries/agencies. The ML/AI techniques can find potential applications in addressing various issues in satellite communications including interference mitigation to enable the coexistence of satellite systems with terrestrial systems, optimization of radio resources (spectrum, power), optimization of SatCom network operation, and management of large satellite constellations.

In the above context, some promising use-cases to investigate the applications of ML techniques include: (i) adaptive allocation of carrier/power for the hybrid satellite-terrestrial scenarios, (ii) adaptive beamforming to enhance the performance of multibeam satellites with non-uniform demand, (iii) scheduling and precoding to mitigate interference in multibeam satellites, (iv) beamhopping and resource scheduling in multi-beam satellite systems with heterogeneous traffic demand per beam, and (v) detection of spectrum events in spectrum monitoring applications.

Actually a few years ago, it’s reported that “**NASA Explores Artificial Intelligence for Space Communications**” (Garner, 2017). “NASA spacecraft typically rely on human-controlled radio systems to communicate with Earth. As collection of space data increases, NASA looks to cognitive radio, the infusion of artificial intelligence into space communications networks, to meet demand and increase efficiency.” “Modern space communications systems use complex software to support science and exploration missions,” said Janette C. Briones, principal investigator in the cognitive communication project at NASA’s Glenn Research Center in Cleveland, Ohio. “By applying artificial intelligence and machine learning, satellites control these systems seamlessly, making real-time decisions without awaiting instruction.”

5.3.5 Mobile Edge Computing and Edge AI

In (Saad et al., 2019), it suggests that the imminent 6G use cases for AI (particularly for reinforcement learning) revolve around creating Self-Sustainable Networks that can autonomously sustain high KPIs and manage resources, functions, and network control. AI will also enable 6G to automatically provide Multi-Purpose Services to its users and to send and create 3D radio environment maps. These short-term AI-enabled 6G functions will be complemented by a so-called “collective network intelligence” in which network intelligence is pushed at the edge, running AI and learning algorithms on edge devices to provide distributed autonomy. This new edge AI leap will create a 6G system that can integrate the services, realize 3CLS (Communication, Computation, Control, Location and Sending service), and potentially replace classical frame structures.

6 AI for Wireless – US Industry players

6.1 Qualcomm on 5G + AI

Qualcomm published an article titled “***5G+AI: The ingredients fueling tomorrow’s tech innovations***” (Qualcomm, 2020)

“5G and AI are two of the most disruptive technologies the world has seen in decades. While each is individually revolutionizing industries and enabling new experiences, the **combination of 5G and AI** is going to be truly transformative. In fact, this intersection is fundamental to our vision of the intelligent wireless edge, in which on-device processing, the edge cloud, and 5G go hand-in-hand to create a ubiquitous connectivity fabric of smart devices and services.”

6.1.1 AI is making 5G better — in the network and on the device

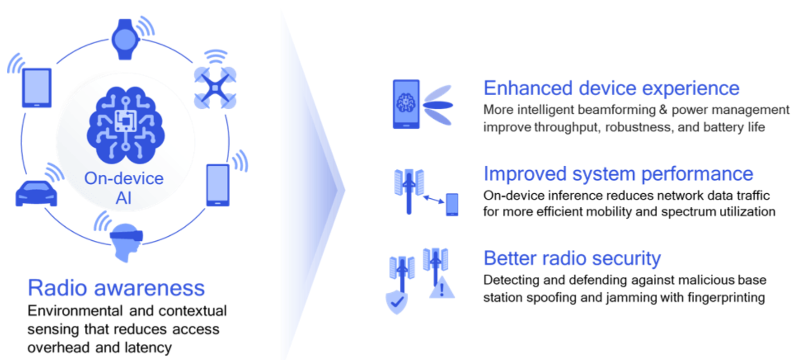
Applying AI to both the 5G network and the device will lead to more efficient wireless communications, longer battery life, and enhanced user experiences. AI is a powerful tool, and the key to harnessing AI to improve wireless is to focus on important wireless challenges that are both difficult to solve with traditional methods and are also a good fit for machine learning. Deep wireless domain knowledge is required to know where to use AI’s capabilities. That domain knowledge fits right in Qualcomm Technologies’ strengths thanks to our longstanding research in both wireless and AI.

Much of the talk in the wireless industry has been around how AI will make the 5G network better. And it is very clear that AI will have a strong impact on several key areas of 5G network management -- such as enhanced service quality, simplified deployment, higher network efficiency, and improved network security. For example, AI could be used to detect anomalies in network traffic, such as flooding or impersonation, by detecting unusual spectrum usage.

5G+AI: The ingredients fueling tomorrow's tech innovations" (Qualcomm, 2020)

Figure: AI enables intelligent 5G network management

<u>Discussed less often is how on-device AI is going to improve the 5G end-to-end system</u>. Radio awareness is at the heart of how AI will improve 5G since machine learning, rather than a hand-crafted algorithm, is the perfect tool to make sense out of the complex RF signals around the device. Increased radio awareness enables a variety of improvements, such as enhanced device experience, improved system performance, and better radio security.



5G+AI: The ingredients fueling tomorrow's tech innovations" (Qualcomm, 2020)

Figure: On-device AI improves the 5G end-to-end system

6.1.2 5G is making AI-powered experiences better

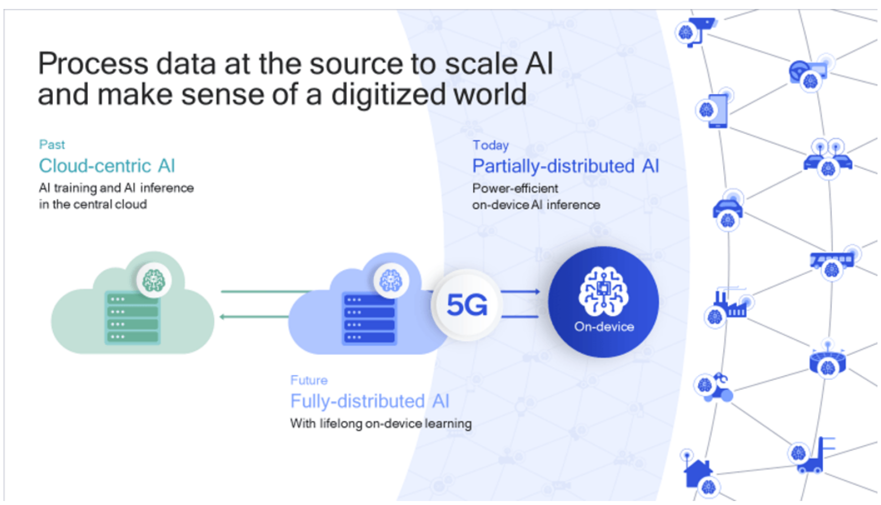
The low latency and high capacity of 5G will also allow AI processing to be distributed among the device, edge cloud, and central cloud – enabling flexible system solutions for a variety of new and enhanced experiences. This wireless edge architecture is adaptable and allows appropriate tradeoffs to be made per use case. For example, performance and economic tradeoffs may help determine how to distribute workloads to reach the required latency or compute requirements for a particular application.

We see 5G making AI-enhanced experiences better in scenarios such as personalized retail through boundless XR, intuitive virtual assistants through vastly improved voice UI, and the reconfigurable factory of the future through adaptive optimization.

Let's imagine how shopping and retail might look like in the future. With boundless XR, rendering and AI processing workloads can be split between the device and edge cloud over a low-latency 5G link.

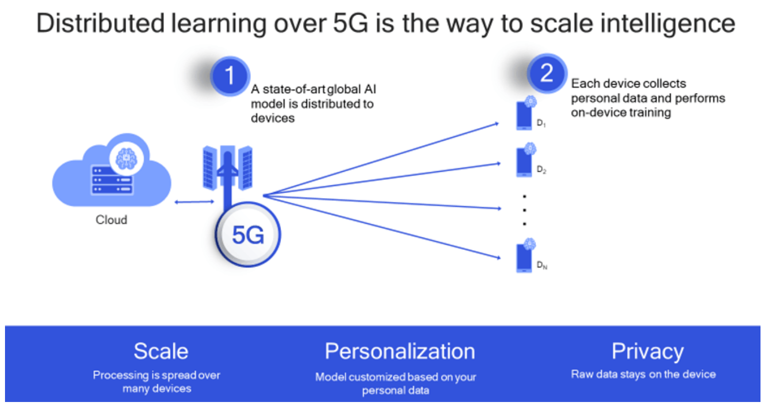
6.1.3 A new computing paradigm: distributed learning over wireless

In order to scale and make sense of the digitized world, we need to move beyond the idea of cloud-centric AI. Today, we see partially distributed AI thanks to the proliferation of power-efficient on-device AI inference, which allows devices to refine the data before it is passed on to the cloud for aggregated analysis. The next step for on-device AI is to go beyond inference itself and do training on the device as well. In the future, we see fully distributed AI with lifelong on-device learning that allows for the next level of personalization with privacy. How do we get there?

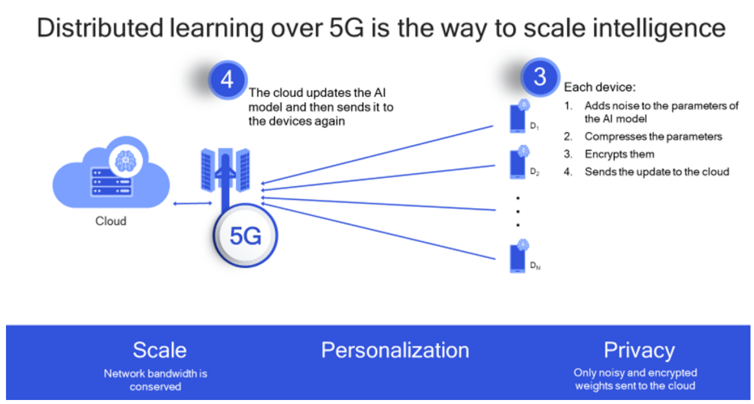


5G+AI: The ingredients fueling tomorrow's tech innovations" (Qualcomm, 2020)

Distributed learning over 5G is the way to scale training beyond the cloud. Let's walk through how this could work at a high level. The first step is that a central or edge cloud sends a state-of-art global AI model to the devices. Next, each device collects personal data and performs on-device training (see Figure 6). Large scale training is very computationally intensive, which is why it has been done in the cloud until now. By doing small training runs on smaller datasets, the workload becomes more manageable. Plus, on-device AI capabilities have been increasing exponentially, along with improvements in algorithms and software.



5G+AI: The ingredients fueling tomorrow's tech innovations" (Qualcomm, 2020)



5G+AI: The ingredients fueling tomorrow's tech innovations" (Qualcomm, 2020)

6.2 ATT – Network AI, Open Source

6.2.1 ATT Updates on Network AI

In (ATT, 2019), ATT provides an update on the recent progress of its Network AI vision with open source approach.

"We've seen first-hand how collaboration is driving the next technology revolution. When you combine open source efforts with technologies like software-defined networking (SDN), 5G, edge computing and artificial intelligence (AI), you get the full picture – Network AI. It is the foundation on which we're building and integrating software, tools, applications and platforms.

So, what's new?

In the past 2 years, we've contributed more than 10 million lines of code to the open source community. Think of these lines of code as pieces to a much larger, complicated puzzle. Together with dozens of other companies, we've helped progress the development of Network-AI by contributing to open source key technologies like artificial intelligence (AI), edge computing, SDN and 5G. Here's the latest:

- **Acumos AI**, an industry-first AI platform and marketplace, announced its second public code release, named Boreas. This version of Acumos AI provides an enhanced user experience, model training capabilities and support for licensing and commercialization of models. Future releases will continue to build upon each other as we work to make AI accessible to everyone.
- A few short weeks ago, Akraino Edge Stack, a software platform for edge computing systems and applications, issued its first release, R1. Akraino is comprised of 11+ blueprints supporting a variety of edge use cases. One of these being the Radio Edge Cloud (REC), the first example of the Telco Appliance Blueprint family which provides a reusable set of modules that will be used to create sibling blueprints for other near real-time appliances. Its main use case is supporting the near real-time RAN Intelligent Controller (RIC), a new network element that enables external applications to control aspects of the 5G radio network. Partnering with Nokia, we contributed the seed code for RIC in April to the Linux Foundation as part of an O-RAN-led project. As a founding member of the O-RAN Alliance, we remain committed to creating an open and intelligent next generation RAN.
- And finally, ONAP is poised to announce its next iteration, Dublin, in the coming weeks. ONAP Dublin promises new and enhanced blueprints, standards alignment and the addition of several new LF Networking members.

We're not just testing ideas in a lab or discussing possibilities. We're laying out a vision and using open source to expedite the development of Network-AI to make it a reality."

6.2.2 AT&T turns up AI for drones, load balancing, 5G build out

In another article (FiereceTelecom, 2019), it's reported that AT&T is testing drones in New Jersey to inspect cell sites, and researching the use AI to define network policies.

While AT&T has successfully embraced virtualization of its network using software-defined network (SDN) and network function virtualization (NFV)—it's on track to reach its goal of 75% virtualization of the core network by next year—Gilbert said that's not enough in a world of 5G and IoT and increasing consumption of bandwidth.

"The network can't be just software," said Gilbert, vice president, advanced technology systems, AT&T Labs. "The network needs to be autonomous and pretty much zero touch. It needs intelligence to know when it repairs itself, when it secures itself. The network needs to be contextual, personalized."

AI is the key ingredient for implementing numerous projects and platforms for AT&T. Gilbert said AT&T is putting more intelligence into its mobile edge compute (MEC) at the customer edge and into its radio access network (RAN.) It's using AI to manage its third-party cloud arrangements, such as Microsoft, and in its internal cloud and hybrid clouds.

"We're rethinking the RAN completely," he said. "We're pushing some of that intelligence to the RAN, where it's needed, all the way to the data centers, national, local, regional data centers."

AT&T is using AI and machine learning (ML) to build its 5G infrastructure to map its cell towers, fiber lines, and other transmitters that exist today, and to pinpoint the best location for 5G build outs in the future.

Gilbert said that AT&T has more than 75,000 macro cells in its network and plans to build hundreds of thousands of small cells as well adding picocells, all of which will be guided by AI, AT&T's internal network data and third-party data.

"We have fiber now that passes over 12 million, 13 million businesses," Gilbert said. "And, you can imagine that figuring out where to put the fiber, where to put the cell, a small cell, or picocell as well, that's not an easy exercise. So, we use data and machine learning to take into account our current infrastructure, our competitor's infrastructure.

"We take into account the local policies for the township that allow us to build. We identify utility poles in the country all automatically using machine learning. We identify the type of pole, the material, and the height of the pole all automatically using the data with satellite images."

If AI detects a cell site isn't functioning properly, it will signal another tower to pick up the slack. If one area is experiencing a high volume of usage, AI will trigger lower-use cell sites to ensure that speed isn't compromised.

A "perfect marriage" of AI, ML and SDN will help enable the speeds and low latency of 5G, according to Gilbert.

"I'm really excited about this because really it's the data behind this infrastructure, behind this transformation, is what's really going to open up a lot of opportunities," Gilbert said.

Gilbert said AT&T is testing the use of flying drones in New Jersey. The drones fly around cell sites and AT&T's premises testing and validating the RF signals, and testing whether the cell itself is functional.

"Is there rust? Are the wires connected? Is there dirt, which is one of the primary reasons why some of these cells malfunction, etc.," Gilbert said "We're doing that with purely drones where the intelligence is sitting at the edge. The drones simply have video capabilities to take video in real time. We're able to diagnose whether humans really are required to go and climb the radio cell site."

AT&T is also researching using AI to define policies that are currently set by systems and employees. AI and the data analytics tell AT&T if any of the policies have conflicts prior to defining them.

AT&T is using AI to load balance traffic, such as video, on its network and use machine learning to detect congestion on small cells on 5G networks before it happens. By putting intelligence closer to the edge, AT&T is starting to load balance traffic across these small cells and move traffic around when needed.

AI, data and open source, mainly ONAP, are used to for operation automation in AT&T's networks.

"Clearly, our biggest cost is in planning, design, installing the network, and also maintaining the network and securing the network," Gilbert said. "So, we have built these templates of intelligent agents. These are nothing more than closed-loop systems. Closed loop systems that capture data that can be configured for different problems. We push those in our network to collect data."

AI will also help enable SLAs from networking slicing offerings to AT&T's customers. AI is being pushed into customer premises, such as IoT sensors in a factory. AI can remove malfunctioning IoT sensor in milliseconds, according to Gilbert.

While AI is playing a key role in the core network and the RAN, Gilbert said "There's a lot of intelligence that needs to happen closer and closer to the edge."

6.3 Cisco embeds more AI, machine learning across the network

In (ZDNet, 2019), ZDNet published an article summarized the latest announcement and progress of Cisco about its AI/ML for Networks, and its Intent based Network initiative.

"Cisco on Monday debuted a series of software enhancements designed to put AI and machine learning deeper into the network. Key features include new network automation and analytics tools that are meant to help enterprise IT teams glean more insights and visibility from network data.

On the visibility side, new machine learning features collect relevant data from local networks and correlates it against aggregate deidentified data, creating individualized network baselines that constantly adapt as more devices, users and apps are added. Meanwhile, Cisco's ML is also correlating network data against baselines to uncover potential network issues and alert IT before problems occur.

Cisco is also touting new machine-reasoning algorithms for improved troubleshooting, giving IT admins and network engineers the ability to detect and correct issues and vulnerabilities more quickly.

Cisco also made updates to its intent-based networking technology, which the company has been integrating across its enterprise access portfolio to help customers manage more users and devices. Cisco is furthering this effort through multi-domain integrations designed to provide end-to-end security, segmentation and application experience.

7 AI in wireless standards (3GPP)

With 5G networks being actively deployed around the world, the 5G network is expected to meet the challenges of joint optimizations of larger amount of performance metrics that are used as indicators for both system performance as well as proxy to end-user experiences. Operators see traditional human-machine interaction as slow, error-prone, expensive, and cumbersome to handle these challenges. Machine Learning (ML) or Artificial Intelligence (AI) algorithms are viewed as powerful tools to help operators reduce the network complexity and improve end-user experience, by analyzing collected data and autonomously looking for patterns that can yield further insights. Recently efforts across 3GPP RAN groups have been studying potential AI frameworks that could be used commonly in the current or future networks to support not only use cases concerning RAN operations like energy saving, traffic steering, mobility, optimization and load balancing, but also use cases for different forms of devices, e.g. VR/AR devices, robots, etc.

At RAN level, initial discussion started from RAN #86 meeting on data collection for NR, aka AI enabled 5G RAN. CMCC initiated a RAN SID proposal ("R17 SI enhancement of data collection for NR") to study additional data collection requirements to support AI applications and the impact on the signaling links. This proposal has gained support from large number of 3GPP members, from equipment vendors to operators alike. As there are still concerns across 3GPP members, the discussions are organized into 2 phases:

Phase 1: Collecting company views on related questions

Phase 2: Toward the actual drafting of the SID based on company inputs

Currently Phase 1 discussions are on-going and the schedule is likely to be impacted due to recent pandemic. This topic is scheduled to be discussed during the plenary meeting in July 2010 if not later.

At System Architecture (SA) level, a new Artificial Intelligence (AI) / Machine Learning (ML) Model Distribution and Transfer (AMMT) Study Item (SI) has been approved for Rel. 18. The objectives of the SI include:

- Studying the use cases and potential service and performance requirements for identifying traffic characteristics of AI/ML model distribution, transfer and training for various applications, e.g. video/speech processing, automotive, other verticals, including:
  - Traffic characteristics and performance requirements for AI/ML operation splitting between AI/ML endpoints
  - Traffic characteristics and performance requirements for AI/ML model/data distribution and sharing over 5G system
  - Traffic characteristics and performance requirements for Distributed/Federated Learning over 5G system
- Gap analysis on performance requirements for AI/ML model distribution and transfer, e.g.
  - Data rate, latency, reliability, coverage and capacity, etc. for AI/ML model downloading/uploading.

Note: Studying AI/ML models themselves are not in the scope of the SI.

As the output of the SI, a new TR 22.874 will be generated, which will cover proposed use cases like splitting AI / ML operations between endpoints, model / data distribution and sharing, and distributed and federated learning across mobile devices.

8 AI general – highlights of recent progresses

AI is perhaps the most active area now in terms of research and publications. In this section we selected two topics to report. The first one is about self-supervised learning which has seen a growing interest and, to some extent, technology breakthrough, in the past couple of years. This is well worth noting, after the big success of supervised learning. The second topic is about optical computing especially targeting AI inference.

8.1 Self-supervised Learning from unlabeled data

Deep neural networks (DNN) have been successfully applied to solve a wide variety of complex supervised learning problems, from image classification by ResNet (He, K. et al., 2016) to Google's neural machine translation (Wu Y. et al., 2016). In addition to DNN capacity and architecture, performance of DNN-based supervised learning largely depends on the amount of human labeled training data for each specific task, e.g., 1.3 million labeled images in ImageNet for computer vision (Deng L. et al., 2009). However, collecting human labeled data is expensive, time consuming and not scalable. In contrast, substantially more unlabeled or uncurated data is either free available or cheap to collect (from internet or in the real world), e.g., 45 millions of webpages in OpenAI's WebText (Radford A. et al., 2019), public image from internet, sensor data from self-driving car (Chiaroni F. et al., 2019). How to extract useful information from those large-scale unlabeled data poses great challenge for unsupervised learning.

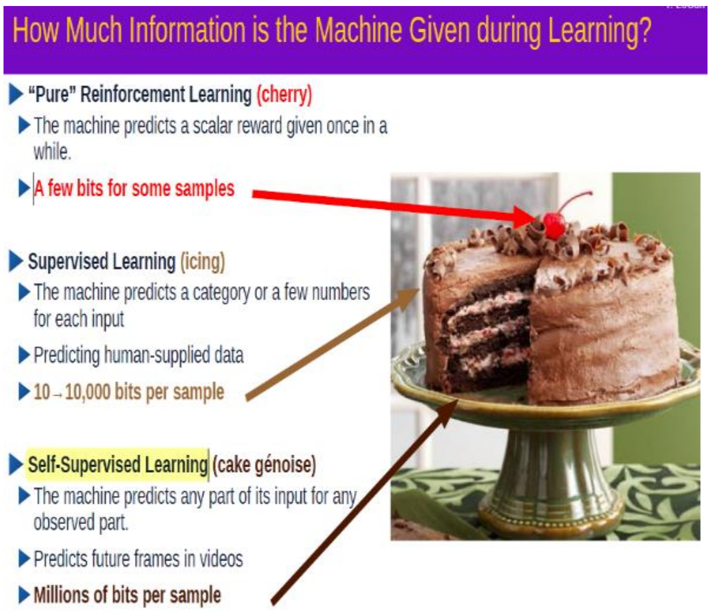
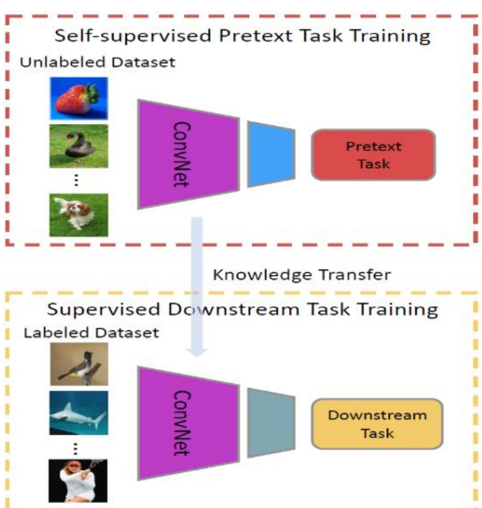


Figure 1 "Cake Analogy" by Yann LeCun from Facebook, AAAI 2020

Recently, a new paradigm of unsupervised learning, named self-supervised learning, has been proposed to automatically generate virtually unlimited labels from the unlabeled data itself and train in a supervised manner, by predicting one part of the unlabeled data from other parts (LeCun Y. 2020). This AI breakthrough has achieved state of the art results in wide range of unsupervised learning problems, from natural language processing (Devlin J. et al., 2018, Radford A. et al., 2019), image (Gidaris S. et al., 2018, He K. et al., 2020), video (Wei D. et al., 2018) to reinforcement learning (van den Oord A. et al., 2018).

As in "cake analogy" made by Facebook AI Chief Yann LeCun (Figure 1, LeCun Y. 2020): if intelligence is a cake, self-supervised learning is the bulk of the cake, supervised learning is the icing, and reinforcement learning is the cherry.



General pipeline of self-supervised learning involves two stages (Figure 2, Jin L. et al., 2019):

- Self-supervised pretext task training: Based on attributes of the unlabeled data, automatically generates pseudo labels and inputs for supervised learning on pretext (auxiliary) tasks relevant to downstream task.
- Transfer learning to downstream tasks: After self-supervised training on pretext tasks, learned features (e.g., low-level feature like edge, texture, or high level semantic feature) is transferred to relevant downstream tasks (especially when only small amount of data is available) for finetuning to improve performance and avoid over-fitting.

Figure 3 Pipeline of self-supervised learning, from CUNY (Jin L. et al., 2019).

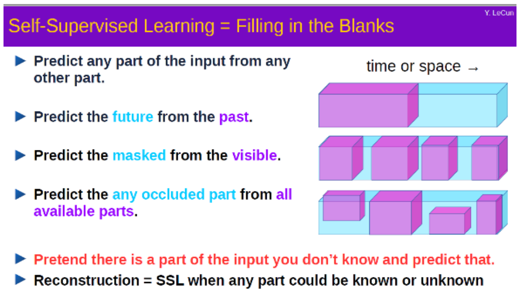


Figure 2 LeCun's slide at AAAI 2020

Typically, the performance of self-supervised learning is measured by the downstream task, rather than pretext task.

As illustrated in Figure 3 (LeCun Y. 2020), a general way to get supervision from the unlabeled data itself in pretext task training is to predict subset of the information (as pseudo labels) from the rest (as inputs) of the unlabeled data, for example, predicting the future from the past (Devlin J. et al., 2018, Wei D. et al., 2018), predicting one part of the image from other parts (Zhang, R. et al., 2016), predicting the masked words in a sentence from neighboring words (Devlin J. et al., 2018).

8.1.1 Context-based self-supervised learning

The first category of self-supervised learning uses the context information (e.g., nearby words in the sentence, relationship among components in the image) from the unlabeled data as supervisory signal to design pretext tasks.

Masked language model in BERT (Google AI)

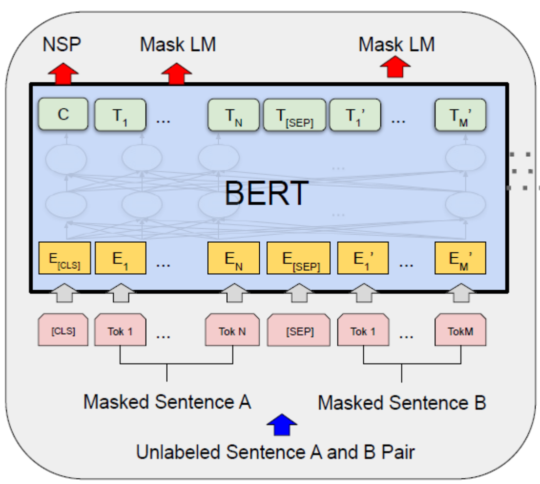


Figure 4 Mask LM and next sentence prediction in BERT, from Google (Devlin J. et al., 2018)

In the past few years, Transformer (Vaswani A. et al., 2017) based models and self-supervised learning have seen tremendous success in national language processing (NLP), such as BERT (Devlin J. et al., 2018), GPT-2 (Radford A. et al., 2019), XLNet (Yang Z. et al., 2019), MT-DNN (Liu X. et al., 2019). In BERT, masked language model (LM) is designed as pretext task to learn deep bidirectional representation by jointly conditioning on both left and right context (Figure 4, Devlin J. et al., 2018). Masked LM randomly masks some of the tokens in the text and pretext task is to predict the masked word (as pseudo label) from its left and right context (as pseudo input). This allows BERT to pretrain bidirectional transformer. Next sentence prediction (NSP) pretext task is also designed in BERT to jointly train text-pairs representation by predicting next sentence (as pseudo label) from previous sentence, in order to understand the semantic relationship between two sentences. Even though Bert is conceptually simple, it is empirically very powerful and obtains state-of-the art performance on 11 NLP tasks.

T5 (Google AI Research)

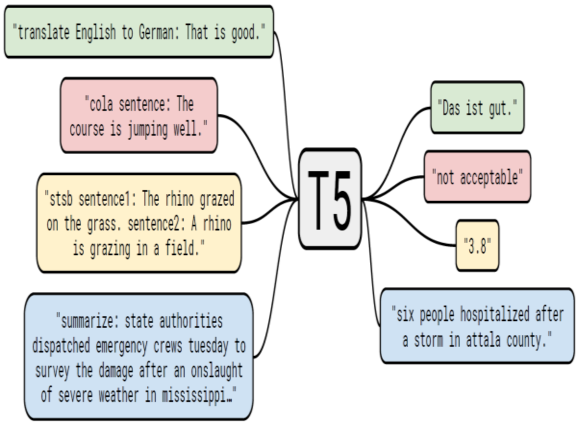


Figure 5 Diagram of text-to-text framework (Raffel C. et al., 2020)

At the end of 2019, after a systematic study of various self-supervised learning methods, Google proposes a unified framework, called T5 (Text-To-Text Transfer Transformer), in order to converts any language problem (e.g., document summarization, question answer, sentiment analysis) to text-to-text format, by casting every language task as pretext task (Raffel C. et al., 2020). This allows same model to be used across diverse set of NLP tasks. After training on a new large dataset of clean English text scraped from web, called C4 (Colossal Clean Crawled Corpus, 745GB), T5 achieves better performance on many benchmarks (e.g., summarization, text classification).

Image Colorization (UC Berkeley)

As illustrated in Figure 6 (Zhang, R. et al., 2016), colorization of a grayscale input image is designed as a pretext task for self-supervised feature learning, by training a CNN to map from a grayscale input (*lightness* channel of the image as pseudo input) to color outputs (*ab* color channels of the image), acting as a cross-channel encoder. Each image is represented in CIE Lab colorspace, with *lightness* channel for lightness from black to white, *a* channel for green to red, and *b* channel from blue to yellow (https://en.wikipedia.org/wiki/CIELAB_color_space).

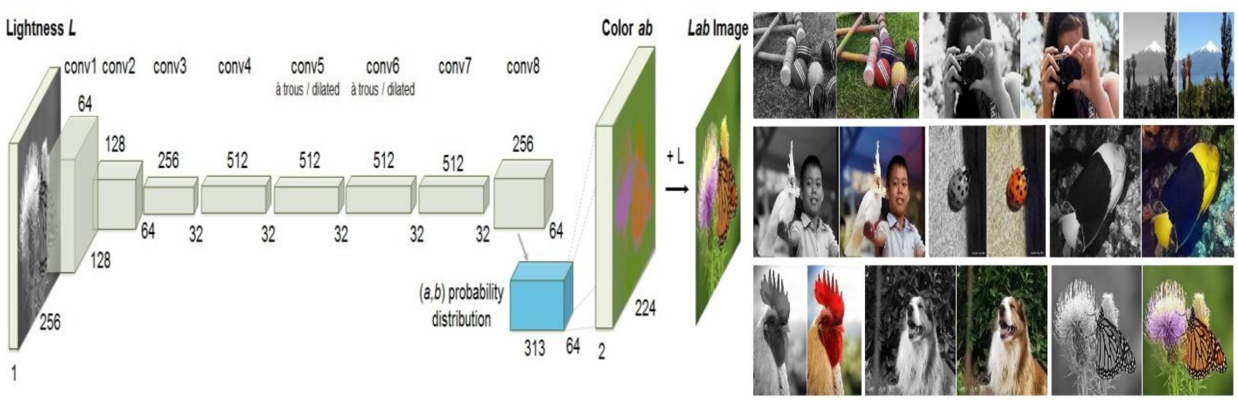


Figure 6 Image colorization: neural network architecture and sample results, from UC Berkeley (Zhang, R. et al., 2016)

Image Rotation (University Paris-Est)

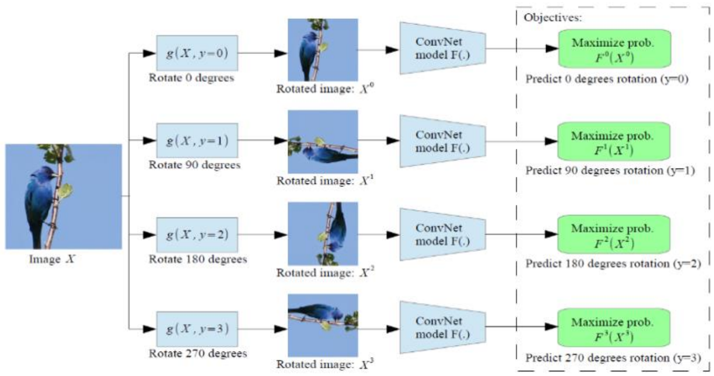


Figure 7 Rotation as pretext task, from University Paris-Est (Gidaris S. et al, 2018)

Image rotation is another simple way to design a pretext task (Figure 7), by randomly rotating an image and training a CNN to predict the rotation [0^o, 90^o , 180^o , 270^o] applied to the image (as pseudo label) from the rotated image (Gidaris S. et al., 2018). By providing powerful supervisory signal from image itself, model successfully learns high level sematic object parts in the image, e.g., eyes, nose, heads, and their relative positions, rather than low level features.

8.1.2 Temporal-based self-supervised learning

The second category of self-supervised learning uses the temporal information from the unlabeled data (e.g., language, video, speech) as supervisory signal to design pretext tasks. For example, sequence of frames in a video contains not only low-level temporal information but also high-level semantic information: neighboring frames are closer in time and more semantically correlated than frames far away from each other.

GPT-2 (OpenAI)

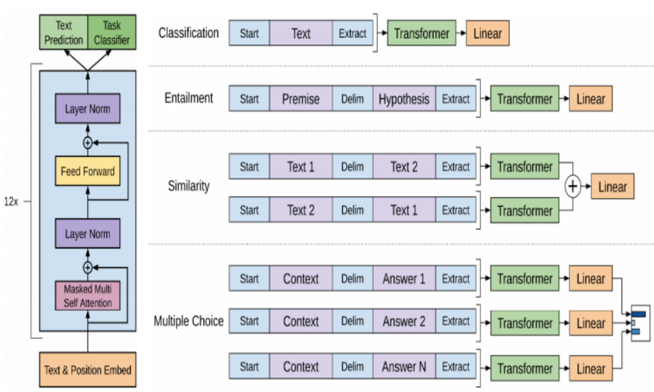


Figure 8 Transformer Architecture and Training Objective (Radford et al., 2018)

As a direct successor to GPT (Figure 8, Radford et al, 2018), GPT-2 is a large Transformer with 1.5 billion parameters (Radford A. et al., 2019), ~10x larger than GPT. A simple pretext task used in GPT-2 is to predict next word using previous words in the text. After training on WebText (containing 45 millions of webpages) without any explicit supervision, GPT-2 outperforms other language models on 7 out of 8 testing datasets, by learning by itself to perform wide range of downstream tasks from their naturally occurring demonstration.

Video Tracking (Carnegie Mellon University)

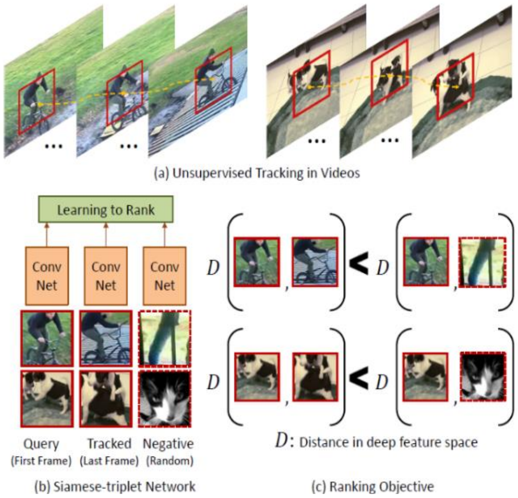


Figure 9 Visual tracking of moving object, from Carnegie Mellon (Wang X. et al, 2015)

Inspired by a simple idea, two patches (of same object) connected by a moving track across frames of a video should have similar visual representation in deep feature space, Wang and Gupta (Wang X. et al., 2015) use a Siamese-triplet network with ranking loss function to train a CNN representation from 100k unlabeled videos. In the pretext task, first and last frame of the same moving object in the video are used as positive sample pair, and a third random frame (typically from different object) is used as negative sample. By using a ranking loss function to enforce that the distance between positive pair (first and second) to be closer than that between first and third in the feature space, the model learns visual representation that achieves 52% mAP without bounding box regression.

Arrow of time (Harvard University)

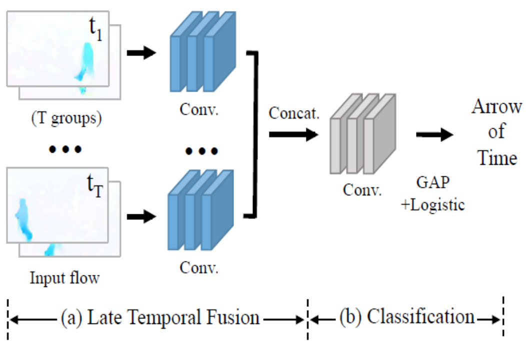


Figure 10 Temporal class-activation map network for arrow of time, from Harvard (Wei D. et al, 2018)

Arrow of time (playing forward or backward, Wei D. et al., 2018) in a video indicates important cue for high level semantics for event reasoning (e.g., riding a horse) or low level understanding of physics (e.g., gravity). To learn and visualize the arrow of time from unlabeled video, groups of temporal chunk (each contains a number of frames of optical flow) are fused as input to predict the arrow of time. By using arrow of time as supervisory signal in unlabeled video, this pretext task improves the performance of downstream tasks, such as action recognition and video forensics (e.g., determining if reversed time special effect is presented in movie clips).

Autonomous Vehicles Perception (Universit´e Paris-Saclay)

Figure 11 Self-driving car with sensors (Chiaroni F. et al., 2019)

Traditional machine learning methods used in self-driving car generally rely on either hand-crafted features that is difficult to be applied on high-dimensional perception data, or large labeled training data that is difficult and costly to obtain (Chiaroni F. et al., 2019). Self-supervised learning allows autonomous vehicles to self-predict from the incoming perception data and dynamically adapt to the environment, by automatically labeling the sensor data using the intrinsic spatiotemporal information, e.g., camera frame, stereo-vision, depth sensor, temporal sequence (Chiaroni F. et al., 2019).

8.1.3 Contrastive-based self-supervised learning

The third category of self-supervised learning uses the contrastive loss (Hadsell R. et al., 2006, Gutmann M. et al., 2010, van den Oord A. et al., 2018), by minimizing the distance between a query/anchor sample and a positive sample as well as maximizing the distance between this query sample and negative samples, in order to provide supervisory signal for pretext task training.

Contrastive Predictive Coding (DeepMind)

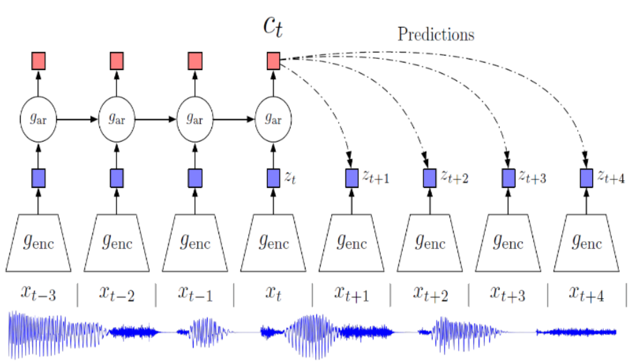


Figure 12 Contrastive predictive coding for audio, from DeepMind (van den Oord A. et al. 2018)

Based on noise contrastive estimation (Gutmann M. et al., 2010), contrastive predictive coding (van den Oord A. et al., 2018) predicts the future in latent feature space by using autoregressive models and probabilistic contrastive loss, in order to capture context latent features that span many time steps and is maximally useful to predict future samples. The learned representations achieve good performance on tasks in speech, images, text and reinforcement learning.

Momentum Contrast (Facebook AI Research)

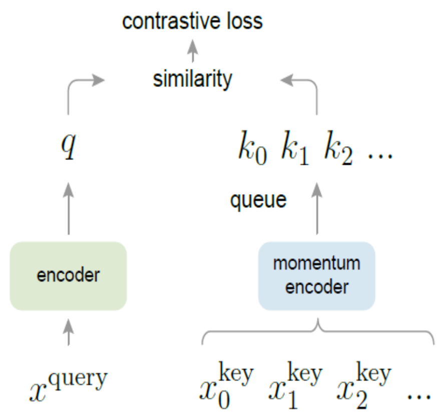


Figure 13 Illustration of momentum contrast, by Keiming He from Facebook AI Research (He K. et al, 2020)

By viewing contrastive learning (Hadsell R. et al., 2006) as dictionary look-up, Kaiming He from Facebook (He K. et al., 2020, Chen X. et al., 2020) proposes momentum contrast (MoCo) to train an encoder for visual representation using contrastive loss. MoCo achieves this by building a dynamic dictionary for look up: an encoded query input is expected to be similar to its matching key (as pseudo label) and dissimilar to negative samples. Momentum update is used to slowly and progressively update the query encoder to enable a large and consistent dictionary.

When the visual representations learned by MoCo are transferred to downstream tasks, better performance is achieved in 7 detection/segmentation tasks than its supervised pre-training counterpart. This suggests that the "*gap between unsupervised and supervised representation learning has been largely closed in many vision tasks*." (He K. et al., 2020).

SimCLR (Google Brain)

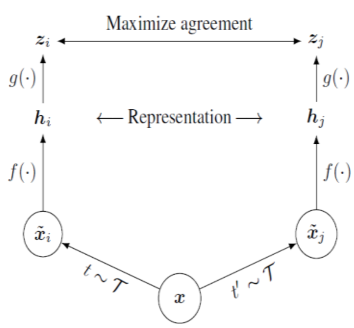


Figure 14 Simple framework for contrastive learning, from Hinton's group (Chen T. et al, 2020)

In February 2020, Hinton's group proposed a surprisingly simple yet powerful framework, named SimCLR, for contrastive learning of visual representation, without requiring specially designed architectures or memory bank (Chen T. et al., 2020). In its pretext task, N positive pairs (anchor and positive sample) are obtained by randomly applying different data augmentation (e.g., crop, color distortion) to the same input for two correlated views, and negative samples are from other 2(N-1) augmented views (given a positive pair). Contrastive loss is used to learn representation in latent space by maximizing agreement between differently augmented views (positive pair) of same input. SimCLR outperforms other self-supervised and semi-supervised learning methods on ImageNet.

8.2 Optical computing and quantum computing

Lightelligence's funding ($26 million Series A round, $10.7 million Seed round)

In April, 2020, a MIT-born photonic AI chip startup, Lightelligence (https://www.lightelligence.ai/), completed a $26 million Series A round financing, which is led by Matrix Partners China and China International Capital Corporation (source: avcj.com), after a Seed round of $10.7 million from Baidu in 2018 (source: americaninno.com).

"*In the past two years, photon computing has received considerable attention around the world. It is no longer a scientific research project, but a productive technology. Many startups and large companies have entered the market*," said Yichen Shen, founder of the Lightelligence (source: pandaily.com).

First photonic AI chip prototype from Lightelligence

As shown in Figure 15, in April, 2019, Lightelligence announced its first photonic AI chip prototype, which successfully run the convolutional neural network to process MNIST dataset. Lightelligence's photonic AI chip prototype performed more than 95% of computation and is ~100x faster than conventional electronic chip [(source: technology-info.net).](#)

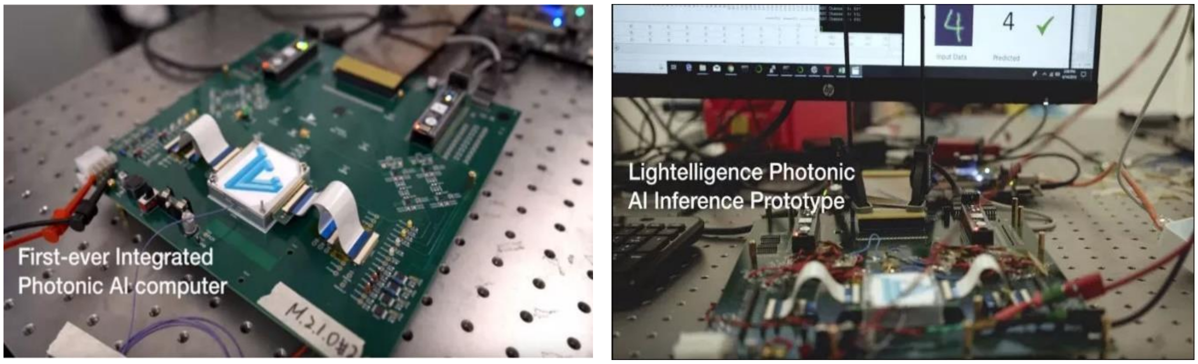


Figure 15 Photonic AI chip prototype from Lightelligence [*(image from technology-info.net)*](#)

Lightelligence's core technology for optical neural network (Nature Photonics, 2017)

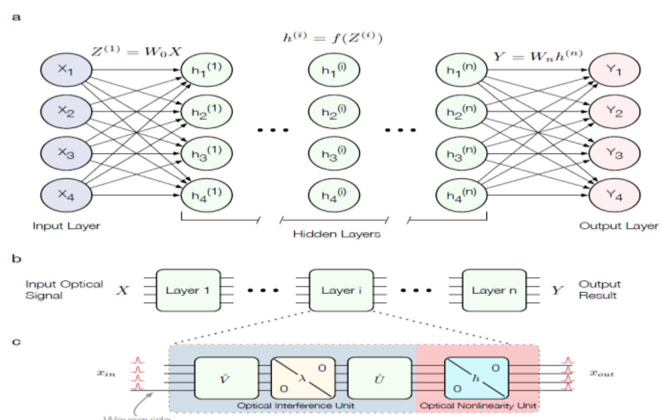


Figure 16 Optical neural network, from Lightelligence (Shen Y., et al., 2017)

Given the inefficiency of totay's electronic computing hardware for neural networks, Shen et al. proposed a new architecure for optical neural network in Nature Photonics (Shen Y. et al., 2017), which promises much faster computational speed (2 orders of magnitude) and much higher power efficiency (3 orders of magnitude) over conventional electronic CPUs and GPUs. As shown in Figure 16, input signals are encoded in the amplitude of optical pulses passing through waveguide. Optical interference unit (OIU) is used to implement optical matrix multiplication and optical nonlinearity unit (ONU) is used for nonlinear activation.

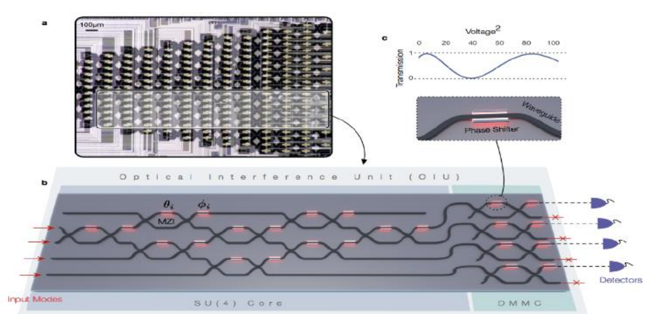


Figure 17 Optical inference unit (Shen Y. et al., 2017)

As illustrated in Figure 17 for optical inference unit, an array of 56 Mach-Zehnder interferometers (MZIs) and 213 phase shifting elements are used to realize the programmable nanophotnic processor for coherent optical neural network (Shen Y. et al., 2017). Two waveguide couplers sandwiching an thermo-optic phase shifter are used to control the splitting ratio of output modes, and the relative phase of the output modes is controled by a second modulator.

Optical quantum computing for Ising model by Lightelligence (Nature Communications, 2020)

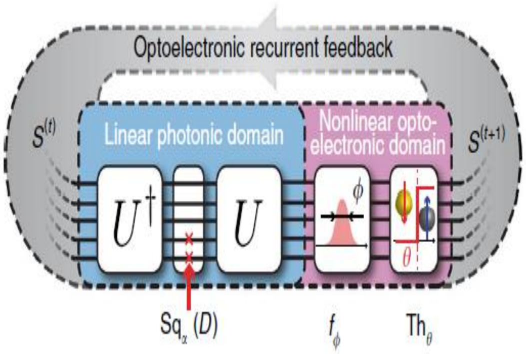


Figure 18 Photonic Recurrent Ising Sampler (Roques-Carmes C. et al, 2020)

Ising model (https://en.wikipedia.org/wiki/Ising_model) is well-known NP-complete problem and has been used to formulate strongly-interacting systems in quantum chromodynamics (Halasz M. et al., 1998). In a paper published in Nature Communication in January, 2020, photonic recurrent Ising sampler (PRIS) was implemented by photonic parallel network (e.g., optical chip from Lightelligence) in order to allow fast and efficient sampling from distributions of arbitrary Ising problems (Roques-Carmes C. et al., 2020).

As illustrated in Figure 18, current spin state is encoded as a photonic signal and is transformed in linear photonic and nonlinear optoelectronic domains (Roques-Carmes C. et al., 2020). Then transformation result is recurrently fed back to this passive system as input. By converging in probability to associated Gibbs distribution, sample solutions to the ground state of Ising models can be found by PRIS efficiently. The intrinsic dynamic noise in photonic network also makes it more efficient to find the solution.

9 US ICT Policies

9.1 ATIS "Call to Action – Promoting U.S. Leadership on The Path to 6G"

ATIS is an industrial consortium for North American ICT industries including network operators, equipment vendors and OTT players. (for more information about ATIS see https://www.atis.org/).

In April 2020, ATIS issued a "***Call to Action – Promoting U.S. Leadership on The Path to 6G***" letter sent to regulatory, policy, and legislative leaders within the U.S. government. It advocates the following goals:

- Achieve a more cohesive strategy for U.S. leadership in the early stage of 6G thought and research – across industry, government and academia.
- Recognize the benefits of strong global leadership, including R&D, standardization, manufacturing and commercialization.
- Align on a set of core principles that will help to direct government actions and incentivize U.S. investment; and
- Propose a set of technology development focus areas that embody U.S. leadership and innovation.

Here are the abstracts from the letter.

The Need for Vision

History has shown that the path to the next generation of advanced networks most often begins a decade in advance, as research creates the aspirational view of *what is possible* and development translates into market reality. What is the vision for a sixth generation of networks, devices and applications? The answer goes well beyond just more bandwidth, less latency, additional spectrum and greater reliability. 6G will apply new cognitive, predictive and contextual capabilities to deliver a *yet-to-be-imagined* level of user experience.

Core 6G Technologies

While innovation should not be limited to meet a common goal, there is a national benefit in defining a set of core technologies that will drive U.S. ingenuity and rapid development in the ICT sector. These core developments include:

- **AI-Enabled Advanced Networks and Services** – AI is already recognized as a breakthrough area of development that will significantly impact how people and things interact with one another and with their environment. Although the embedding of AI into consumer devices today provides an early view of the opportunities, those only hint at AI's full potential to improve society. Early development in these areas will make the next decade the timeframe that fulfills the full promise of AI-enabled applications, with the U.S. being the innovation lab for the future.
- **Advanced Antennas and Radio Systems** – The future of wireless communications (both licensed and unlicensed) depends on rapid development and market availability of ultra-high-frequency devices that operate above 95GHz and in THz spectrum. These devices will be deployed in a highly dense manner to offer ubiquitous connectivity and optimized performance.
- **Multi-Access Network Services** – Integration of various types of terrestrial networks (wireless and fixed) with the growing potential for non-terrestrial solutions, such as unmanned aerial systems and satellites, will deliver ubiquitous reach over any terrain, geography or physical environment.
- **Healthcare** - By many estimates, healthcare spending is expected to exceed 20 percent of U.S. GDP in the next few years. The current COVID-19 pandemic has demonstrated the need for government and industry to work together in the immediate term on innovative approaches to expanding telehealth capabilities and diagnosing patients outside of healthcare facilities. The country is taking remarkable steps to meet this challenge. As we look to the future, there will be many new opportunities for industry to partner with the healthcare industry on smart health, remote diagnostics and telesurgery, using new capabilities such as multi-sensory applications, the tactile internet and ultra-high-resolution 3D imagery.
- **Agriculture** - It is estimated that the farming industry will need to produce 70 percent more food by 2050. *Agriculture 4.0: The Future of Farming Technology* (from the World Government Summit) notes the difficulty in applying water, fertilizers and pesticides uniformly across entire fields. In the future, technologies such as wireless sensors/IoT, robotics, autonomous farming vehicles, drones, satellite imagery, big data and AI will enable a new era of precision agriculture.

Recommended Governmental Action to Spur 6G Leadership

From an industry perspective, the U.S. can best counter these technology barriers by adopting a national plan for technological excellence that relies on a set of committed principles and actions:

1) **First, the federal government should make available additional R&D funding focused on a core set of technological breakthrough areas where the U.S. can lead.** … ATIS urges the government to acknowledge the important role that standards play in R&D and in the development and deployment of innovative technologies by confirming that the R&D funding would also include

funding for enhanced governmental participation in those standards development organizations that are producing 6G standards.

2) **Second, the government should expand R&D tax credits to encourage massive investment in a set of core technologies that will promote U.S. leadership.** An expanded tier of R&D tax credits, including credits for industry participation in standards-setting, that can be directly attributed to a national framework of technology leadership areas would further incent industry to align around a set of common goals, promoting U.S. leadership in both development and adoption.
3) **Third, the U.S. government should work with industry to develop a consumer- and business-centric solution to wireless spectrum challenges by creating a national spectrum policy.** Recent experience has demonstrated that fast-tracking the availability of new wireless spectrum in both licensed and unlicensed bands can promote more rapid adoption by the market and accelerate innovation across industry. This spectrum policy should synchronize market needs with spectrum availability of low-, mid- and high-frequency spectrum to promote and encourage advanced applications to market — and realize the full benefits of U.S. leadership.
4) **Fourth, the U.S. should explore innovative ways to promote widespread commercial adoption of U.S.-developed and -produced hardware/software through financial incentives to public and private sectors.** Cities and other local municipalities can act as technology labs and innovation zones that promote U.S. technology leadership. These zones should also include rural markets, as U.S. leadership should also generate opportunities in the areas of smart agriculture, smart energy, remote learning and public safety. In addition, integration with vertical industries and enterprise markets as first adopters could be incentivized through tax credits and grant opportunities.

9.2 AT&T, Verizon part of new 31-member Open RAN Policy Coalition

As reported by FierceWireless on May5 (https://www.fiercewireless.com/regulatory/at-t-verizon-among-new-31-member-open-ran-policy-coalition), a new coalition, backed by a wide range of players in the mobile ecosystem, including U.S. operators AT&T and Verizon, has formed to advocate for government policy that helps drive open RAN adoption.

Executive director for the 31-member Open RAN Policy Coalition, launched today, is former Acting Administrator of the NTIA Diane Rinaldo.

“As evidenced by the current global pandemic, vendor choice and flexibility in next-generation network deployments are necessary from a security and performance standpoint," said Rinaldo in a statement. "By promoting policies that standardize and develop open interfaces, we can ensure interoperability and security across different players and potentially lower the barrier to entry for new innovators."

Dish Network, which has stated plans to build its forthcoming 5G wireless network based on open RAN architecture, is part of the group. So are international operators that have been early proponents of open RAN efforts, including Telefónica, Vodafone, NTT and Rakuten. Rakuten launched its new fully virtualized 4G network early this year, embracing open interfaces.

Cloud players including Amazon AWS, Google, and Microsoft are in the mix, along with companies Dell, Intel, IBM, VMWare, Samsung, and Qualcomm.

Joining them are familiar open RAN players like Airspan, Altiostar, Mavenir, NEC, Parallel Wireless, and Cisco, along with CommScope, Fujitsu, Juniper Networks, NewEdge Signal Solutions, Oracle, US Ignite, World Wide Technology, and XCOM-Labs.

T-Mobile is not listed as a member, nor are its biggest vendors Ericsson and Nokia.

Rinaldo in a post outlined some steps the group thinks policymakers can take to facilitate the open RAN ecosystem, including: support global development of open and interoperable wireless technologies; signal government support for open and interoperable solutions; use government procurement to support vendor diversity; and fund research and development.

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