MATLAB EXPO

AI Driven Next Generation Wireless Communication Systems

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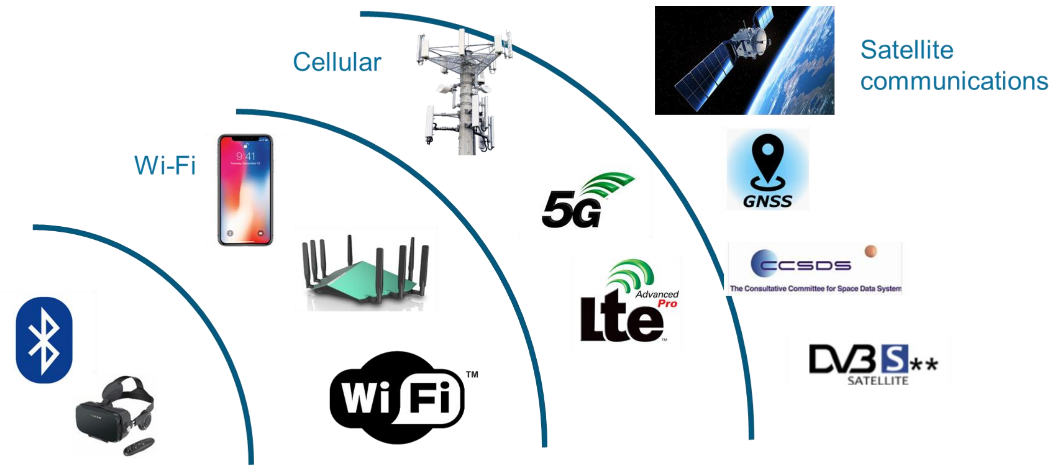
MathWorks

Agenda

1. Future of Wireless Ecosystem
2. Using AI for wireless
3. AI Workflow for Wireless
4. Reinforcement learning for 5G
5. Summary



AI-driven system design workflow

1. Data Preparation
2. AI Modeling
3. Simulation and Test
4. Deployment

Wireless Communications Everywhere
Cross-Industry Applications

5G ADVANCED

UWB

Wi Fi 7

Mobile Devices

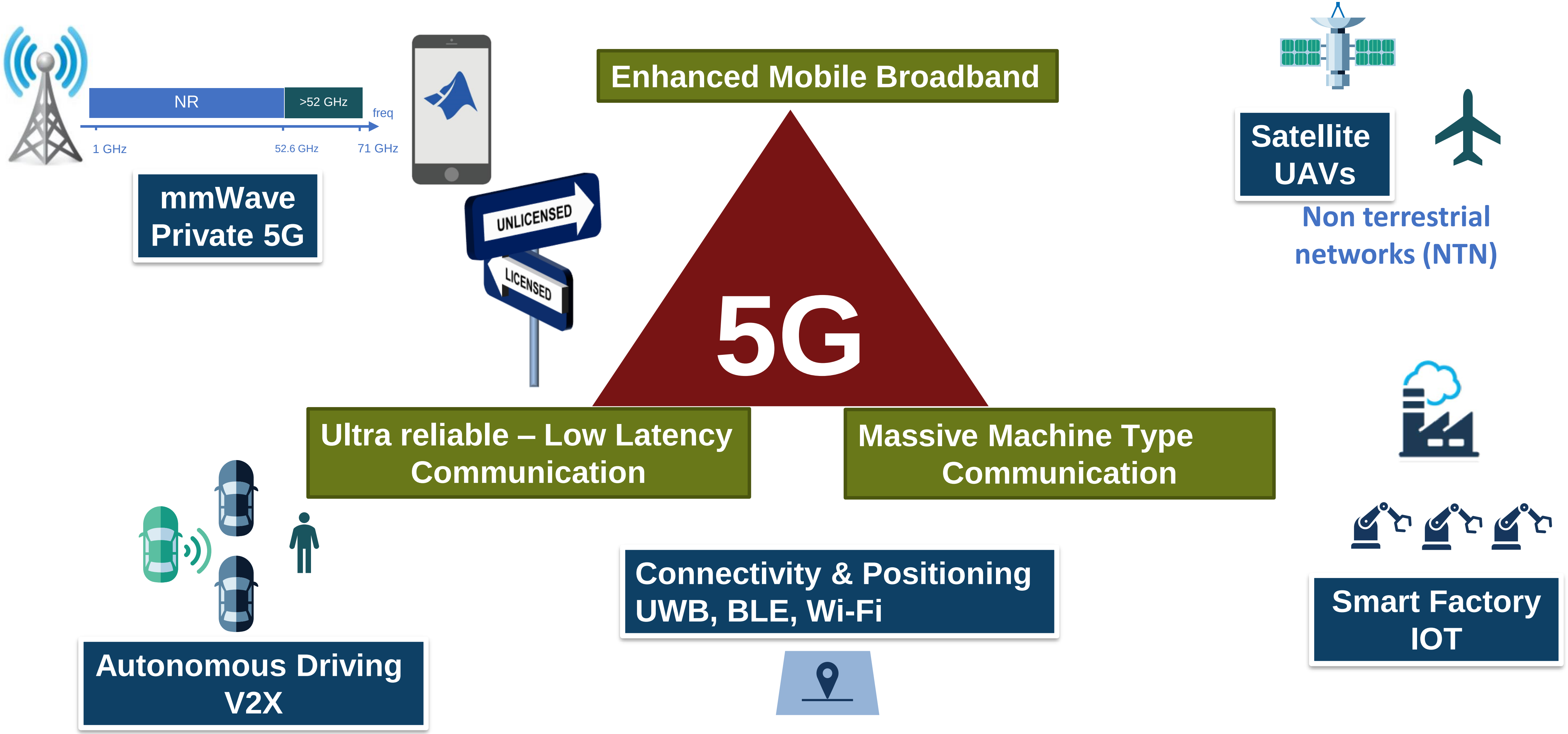
Aero Defence

Communications Infrastructure Satellite

Semiconductors and components:
Baseband, RF
Antenna

Connected Devices
- **Automotive**
- **Industrial**
- **Smart home**
- **Smart city**
- **Medical**

5G, Satellite and Connectivity (Wi-Fi, BLE, UWB)



Designing Wireless System: Baseband design

System level Simulation

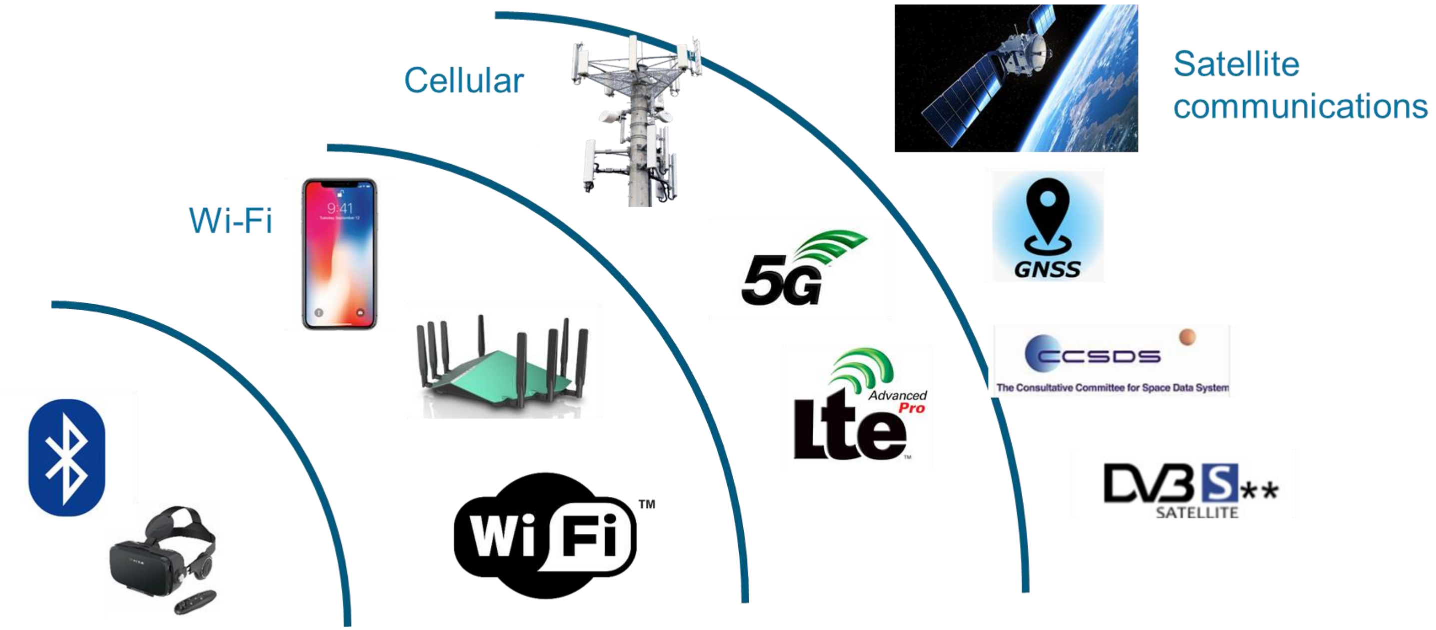
RF, antenna arrays

Digital Baseband

PHY Modeling, link simulation

Fixed-point, Resource optimizations System integrations

Implementation & test



Designing Wireless System: End-to-end Design

System level Simulation

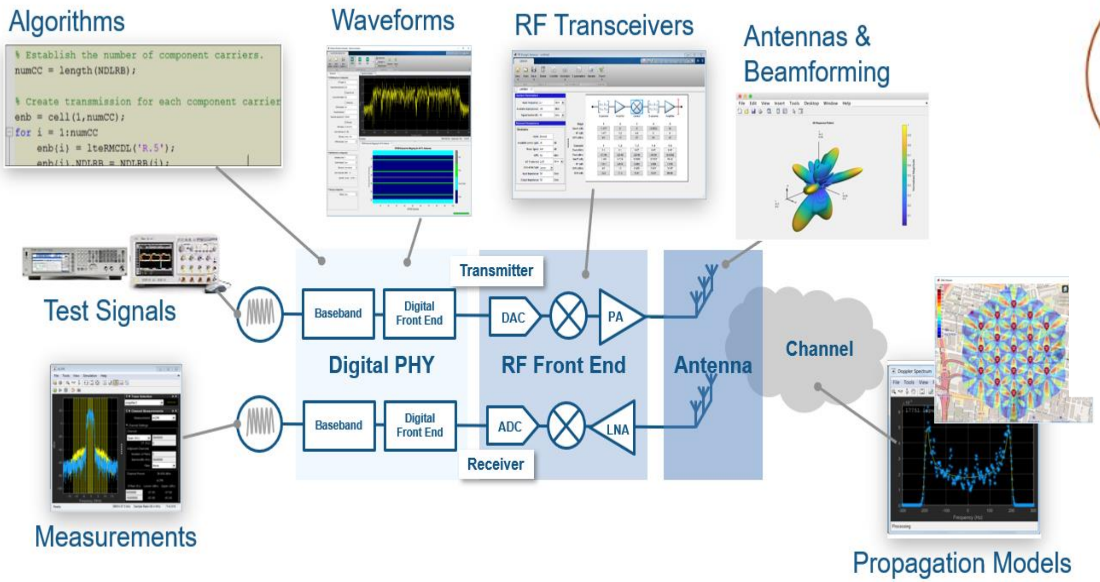
RF, antenna arrays

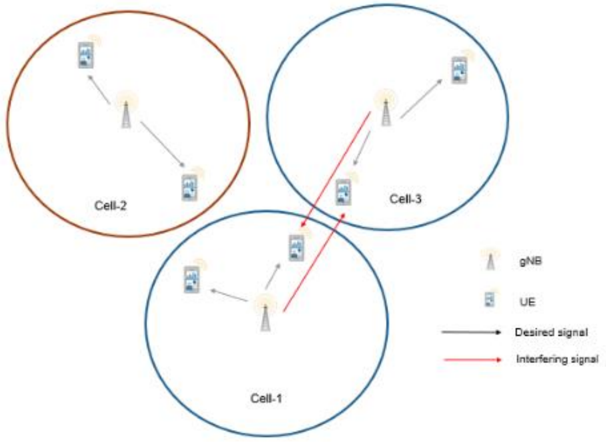
Digital Baseband

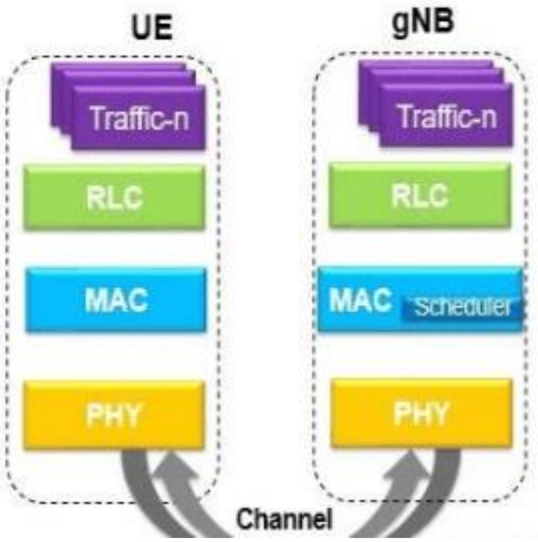
PHY Modeling, link simulation

Fixed-point, Resource optimizations System integrations

Implementation & test





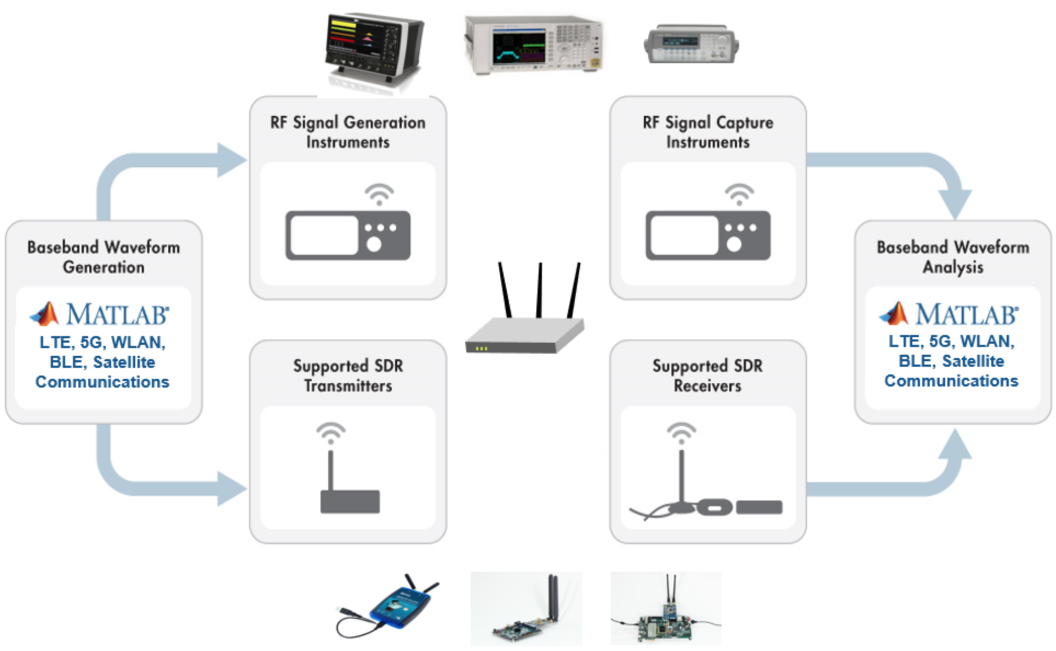


Designing Wireless System: Testing and implementation

System level Simulation

RF, antenna arrays

Digital Baseband



Implementation: C, C++, HDL

PHY Modeling, link simulation

Fixed-point, Resource optimizations System integrations

Implementation & test

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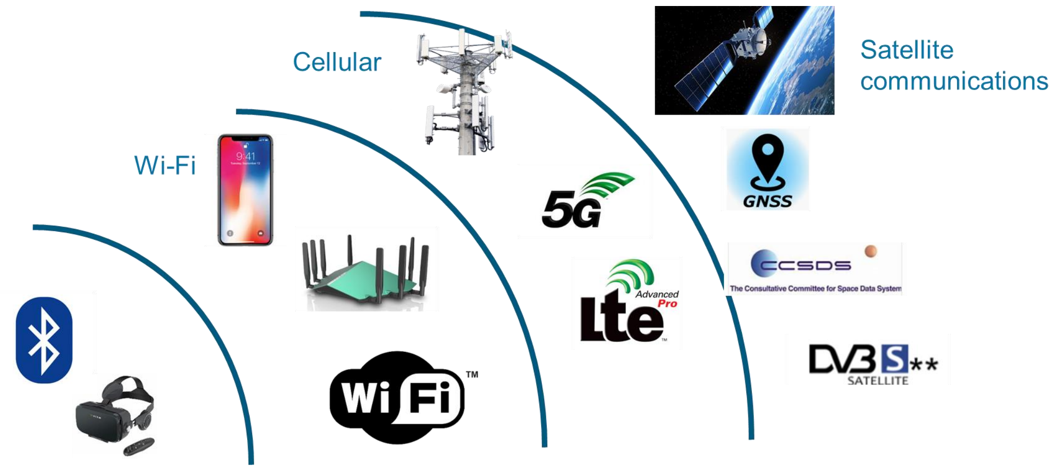


AI-driven system design workflow

Time for AI might be coming: Why now?

- Services expected from the system exceeds the capability of traditional approaches
- Exponential increase in system complexity
- AI shows promising results in other domains

AI can contribute in multiple ways:

- System architecture flexibility
- Improved performance
- Better results

TSG RAN priorities

Release 18

RAN1 led - Radio Layer 1 (Physical layer)

- MIMO Evolution for Downlink and Uplink
- Study on Artificial Intelligence (AI)/Machine Learning (ML) for NR Air Interface
- Study on Evolution of NR Duplex Operation
- NR sidelink evolution
- Study on expanded and improved NR positioning
- Study on further NR RedCap UE complexity/cost reduction
- Study on network energy savings
- Further NR coverage enhancements
- Study on NR Network-Controlled Repeaters
- Enh. of NR Dynamic spectrum sharing (DSS)
- Study on low-power Wake-up Signal and
- Receiver for NR
- Multi-carrier enhancements for NR

RAN2 led - Radio layer 2 & layer 3 Radio Resource Control

- NR Mobility Enh.
- Study on XR Enh. for NR
- NR sidelink relay enh.
- NR NTN (Non-Terrestrial Networks) enh.
- IoT NTN enh.
- NR Support for UAV
- Dual Tx/Rx MUSIM
- In-Device Co-existence (IDC) enh. for NR and MR-DC
- Mobile Terminated-Small Data Transmission (MT-SDT) for NR
- Enh. of NR Multicast and Broadcast Services

RAN3 led - UTRAN/E-UTRAN/NG-RAN architecture & related network interfaces

- Mobile IAB
- Artificial Intelligence (AI)/Machine Learning (ML) for NG-RAN
- Further enh. of data collection for SON (Self-Organising Networks)/MDT (Minimization of Drive Tests) in NR and EN-DC

RAN4 led - Radio Performance and Protocol Aspects*

- Further RF requirements enh.for NR frequency range 1 (FR1)
- NR RF requirements enh. for frequency range 2 (FR2), Phase 3
- Req. for NR frequency range 2 (FR2) multi-Rx chain DL reception
- RRM enh. for NR and MR-DC
- Enh.on NR and MR-DC Measurement Gaps and Measurements without Gaps
- NR demodulation performance evolution
- Study on simplification of band combination specification
- Study on enh. for 700/800/900MHz band combinations
- NR BS RF requirement evolution
- Study on NR frequency range 2 (FR2) Over-the-Air (OTA) testing enh.
- Support of intra-band non-collocated EN-DC/NR-CA deployment
- Enh. NR support for high speed train scenario in frequency range 2 (FR2)
- BS/UE EMC enh.
- Air-to-ground network for NR
- NR support for dedicated spectrum less than 5MHz for FR1

*There are other approved items related to Rel-17 continuation; more spectrum-related items are expected to be approved later.

TSG CT priorities

Rel-18 Workplan for TSG CT

CT will work on stage 3 completion and ASN.1 code and OpenAPI freeze of Rel-17 until June 2022 (TSG#96).

Work Item discussion on Rel-18 stage 2 / stage 3 (under CT) from June 2022.

CT waits for a stable output of the stage 2 work in SA and RAN before initiating the work on Rel-18 (expected TSG#99 March 2023). Completion of stage 3 is targeted for TSG#103 March 2024.

A look at the research in AI for Wireless Networks

Network-Level Mobile Data Analysis Network prediction/ Traffic classification	**App-Level Mobile Data Analysis**	**User Mobility Analysis**
User Positioning and Localization	**SON- Self Optimizing Network**	**Networks Control** Network optimization/ Routing/ Scheduling/ Resource allocation/ Radio control
Network Security	**Signal Processing** Beamforming/ Modulation/ Coding/ Spectrum Sensing/ Channel estimation	**Emerging Mobile Network Application**

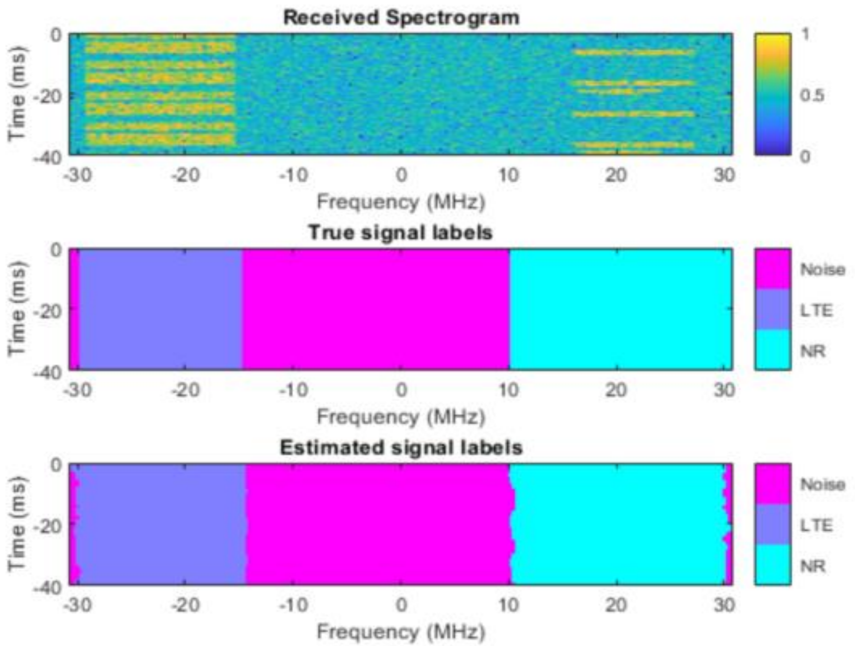
Identify Spectral Content in a Wideband Spectrogram

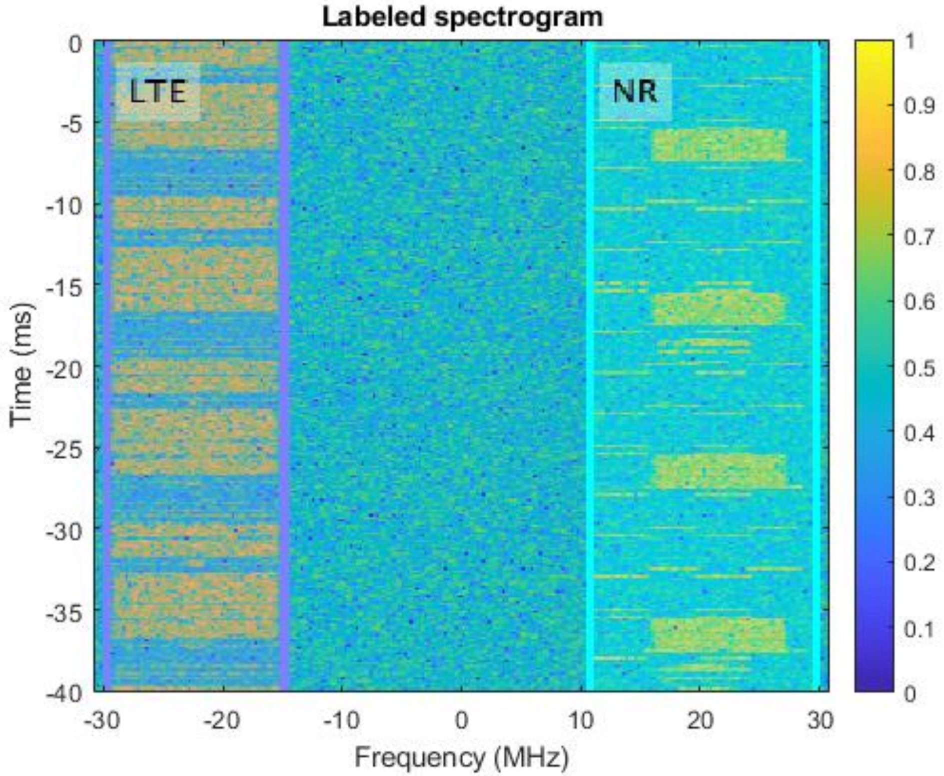
Spectrum sensing & signal classification:

- Characterizing spectrum occupancy is key to spectrum monitoring

- Neural network can be trained to identify 5G NR and LTE signals in a wideband spectrogram in a specific time for a frequency

- This can be done by applying transfer learning to a semantic segmentation network

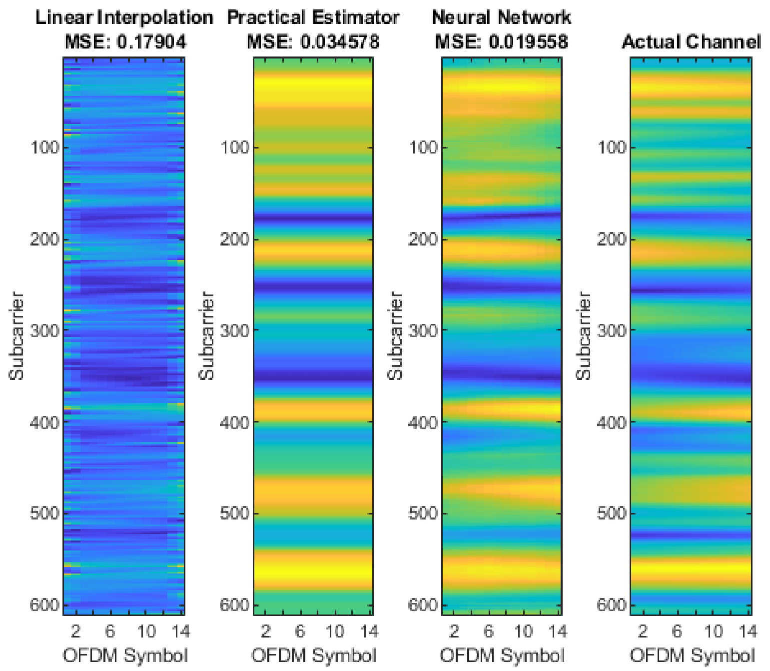


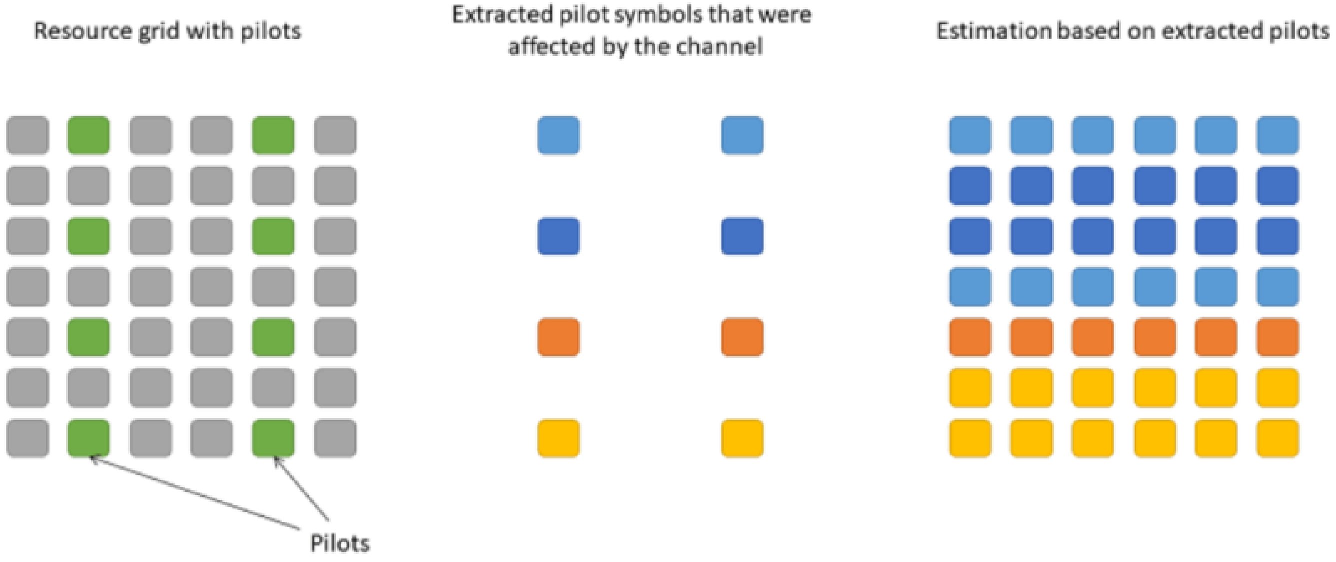


Estimate the 5G Channel

Deep Learning Data Synthesis for 5G Channel Estimation:

- Estimating the accurate channel is a key to 5G System design and performance
- CNN can be trained to various channel conditions and environments with the 5G signal
- This can be an alternate to the traditional channel estimation algorithms

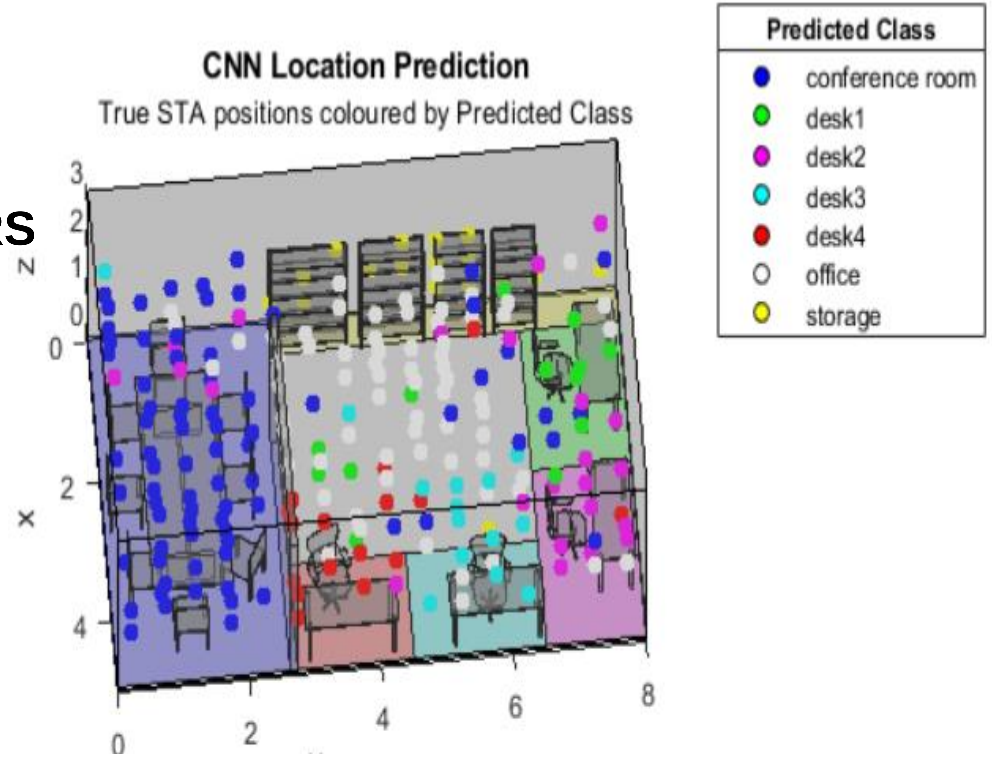


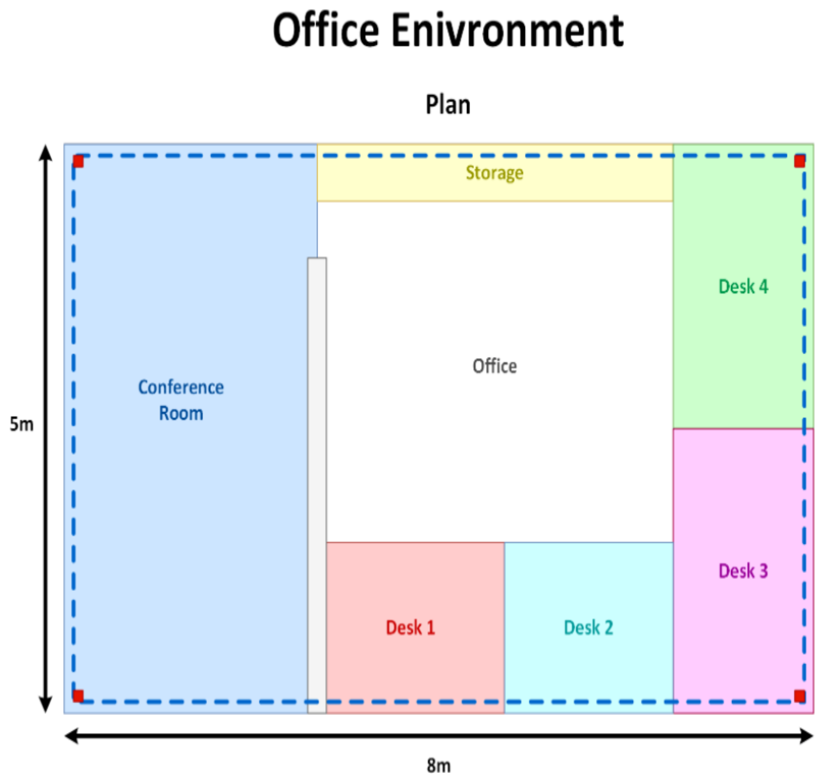


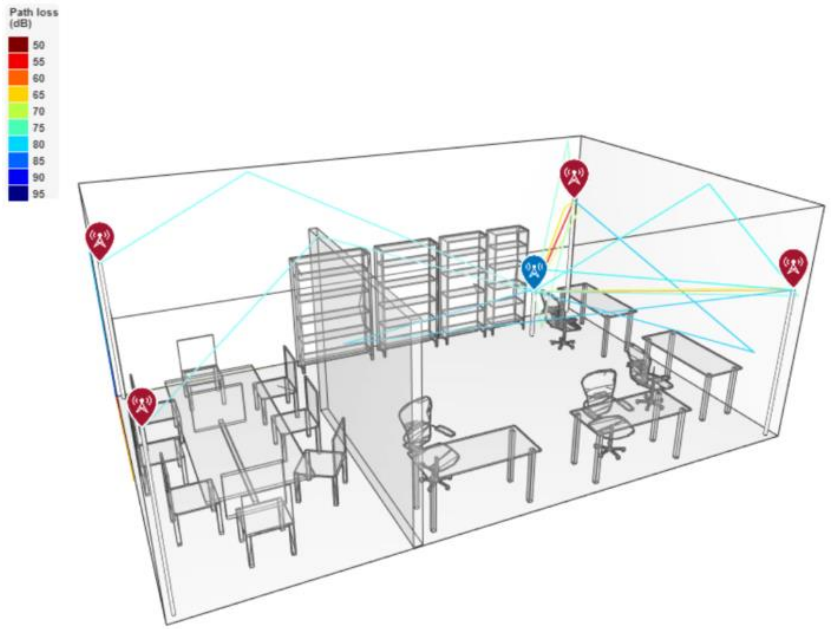
Identify the location of a user

Three-dimensional positioning with WLAN 802.11 az/ 5G NR PRS

- Next generation positioning (NGP) provides physical layer features for ranging and positioning
- This rely on LOS conditions and spatial info for computing position
- CNN can be an alternate for NLOS multipath environment with better accuracy





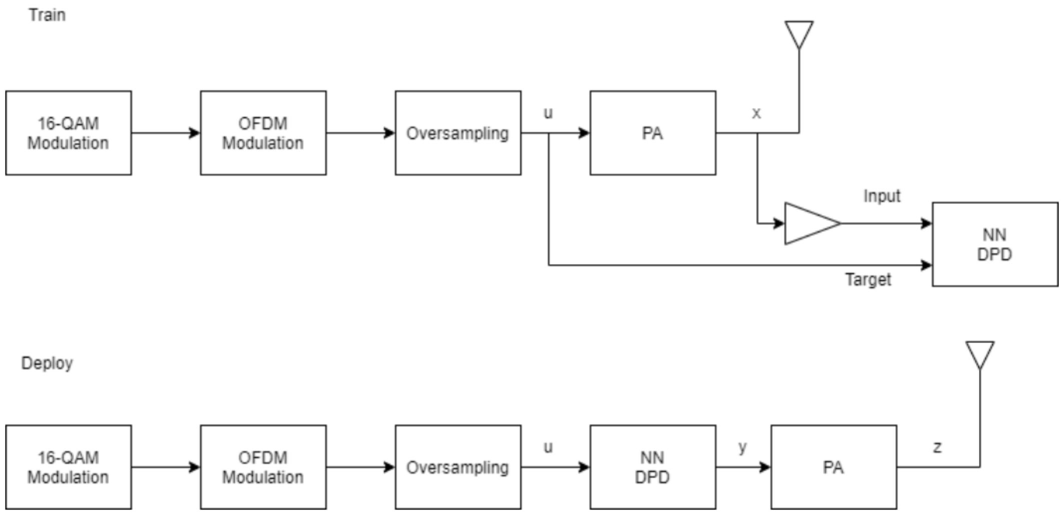


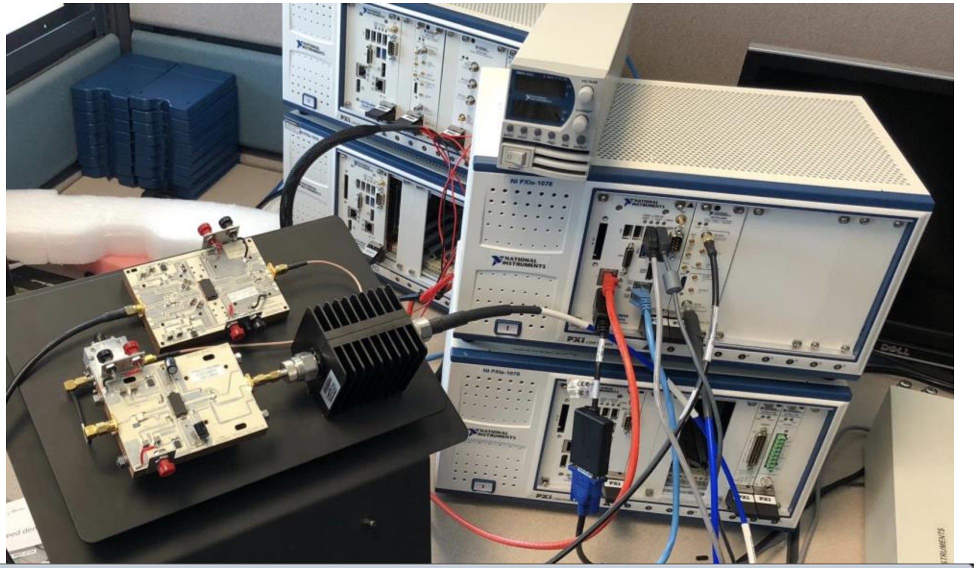
Power Amplifier -Digital Pre-Distortion modeling

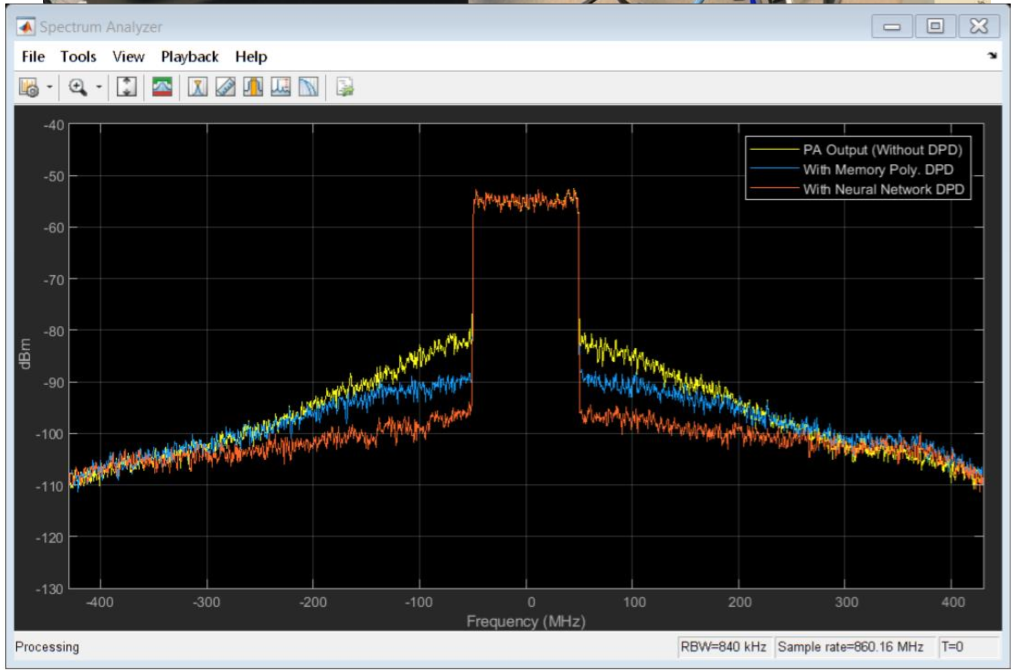
Nonlinear behavior of PA results in signal distortion. DPD helps in neutralize the effect

Neural Network based PA-DPD design

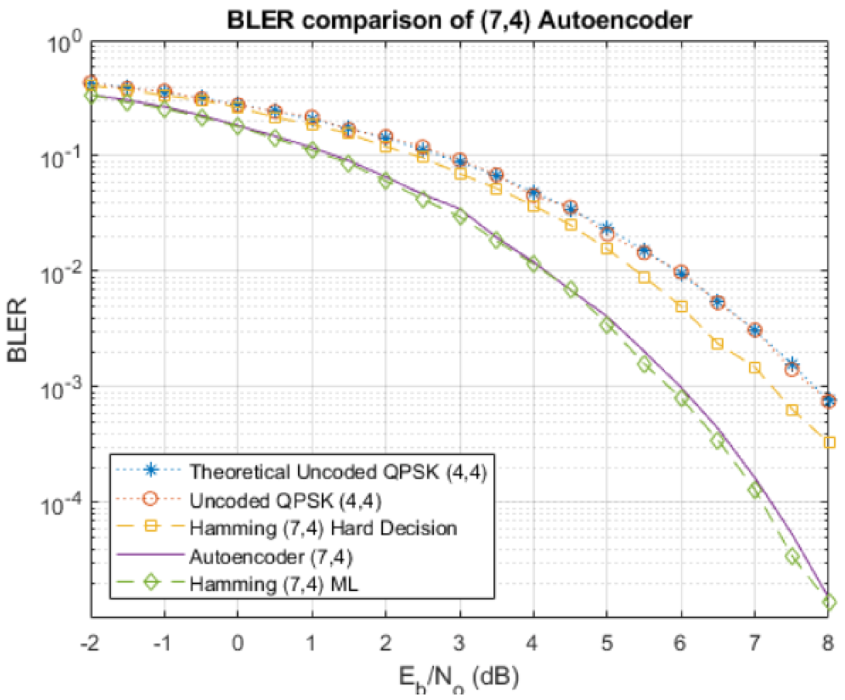
- Collect data from a real PA using test instrument hardware or characterize the PA and use the model for simulation
- Train a neural network using real PA data or simulation data
- Test the network with real data using the hardware





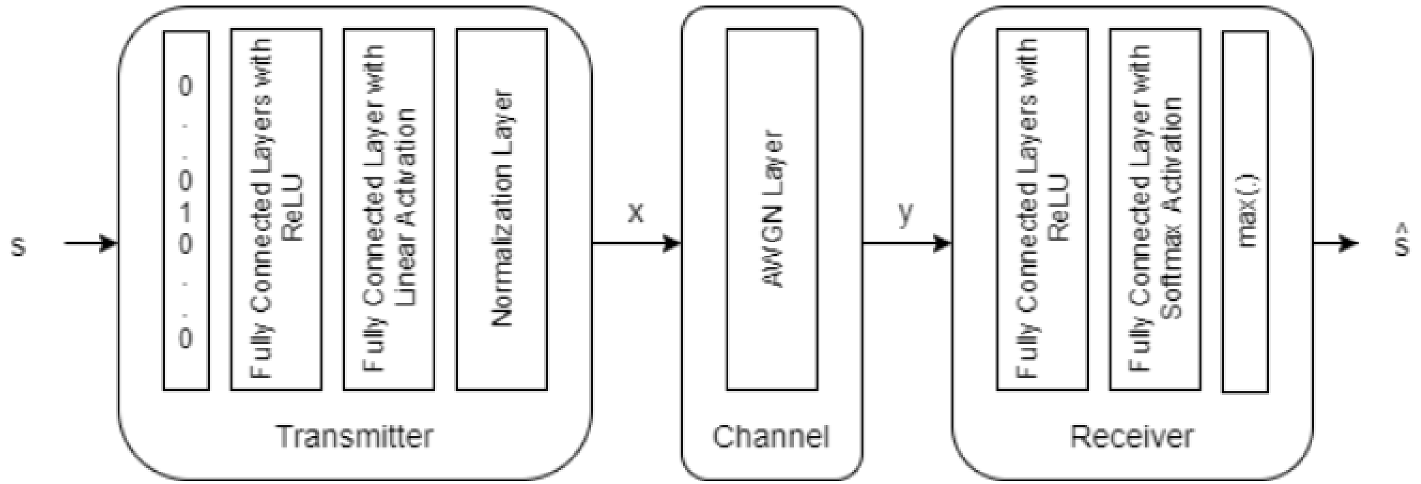


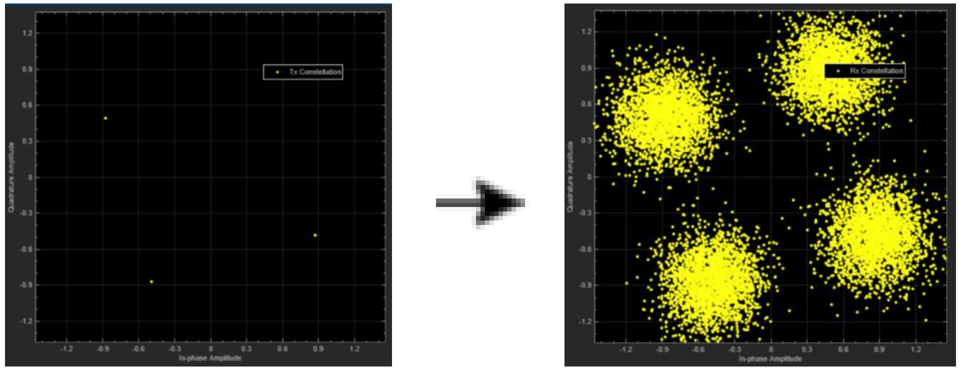
Improve Reliability with Autoencoders



Autoencoder for reliable transmission of information bits over a wireless channel:

- Encoding and decoding is one of the operation in Wireless Communication
- An AI-based autoencoder can jointly optimizes the transmitter and the receiver as a whole
- Autoencoder adds redundancy and tries to minimize the number of errors in the received information for a given channel while learning to apply both channel coding and modulation in an unsupervised way





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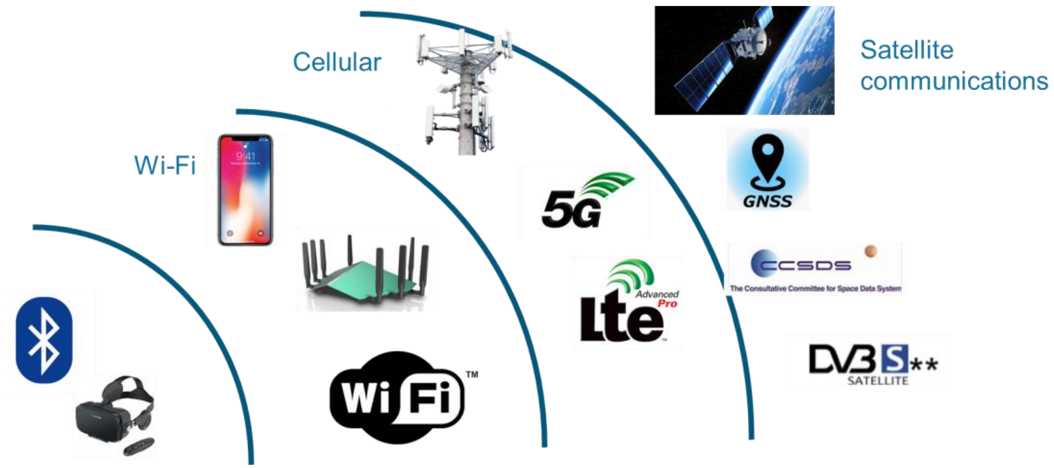


AI-driven system design workflow

AI-Driven Wireless System Design

Data Preparation

- Data cleansing and preparation
- Human insight
- Simulation-generated data

AI Modeling

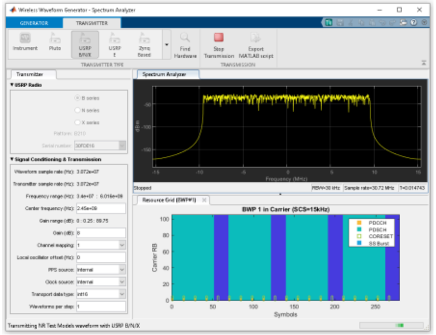
- Model design and tuning
- Hardware accelerated training
- Interoperability

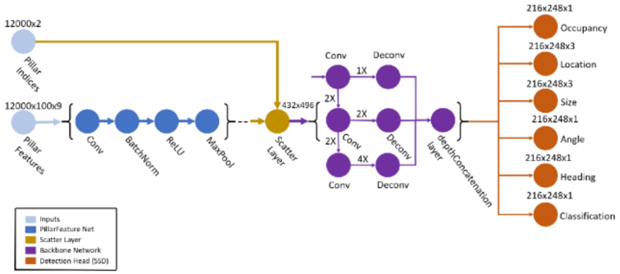
Simulation & Test

- Integration with complex systems
- System simulation
- System verification and validation

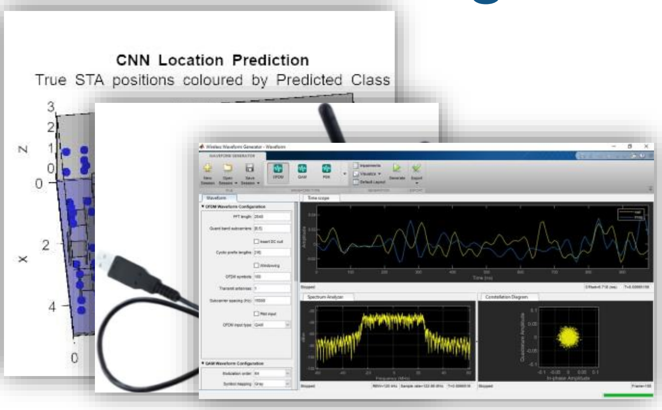
Deployment

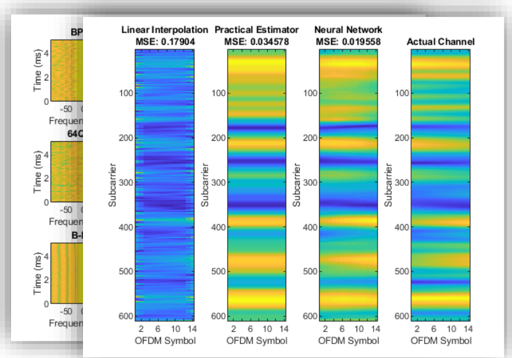
- Embedded devices
- Enterprise systems
- Edge, cloud, desktop

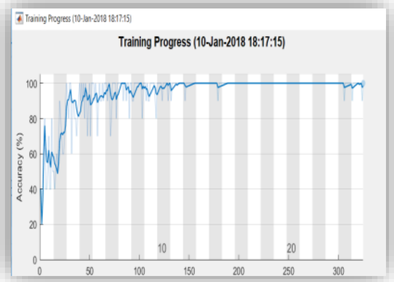


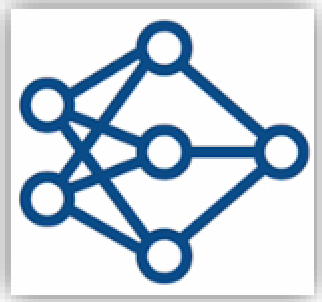


AI-Modeling workflow



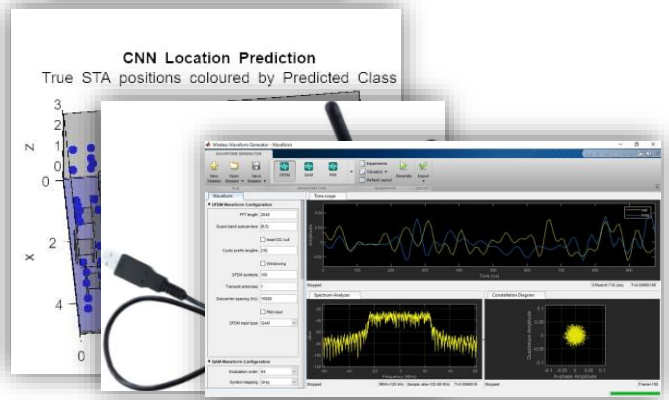


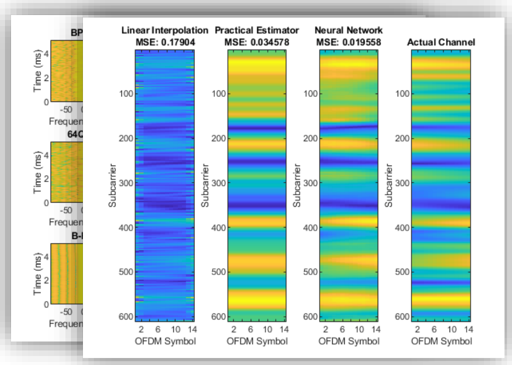


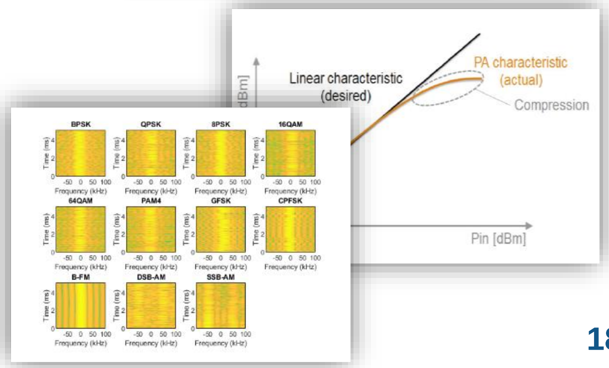


Pre-labeled synthesized or live data → Transform → Train AI Model → Trained Model

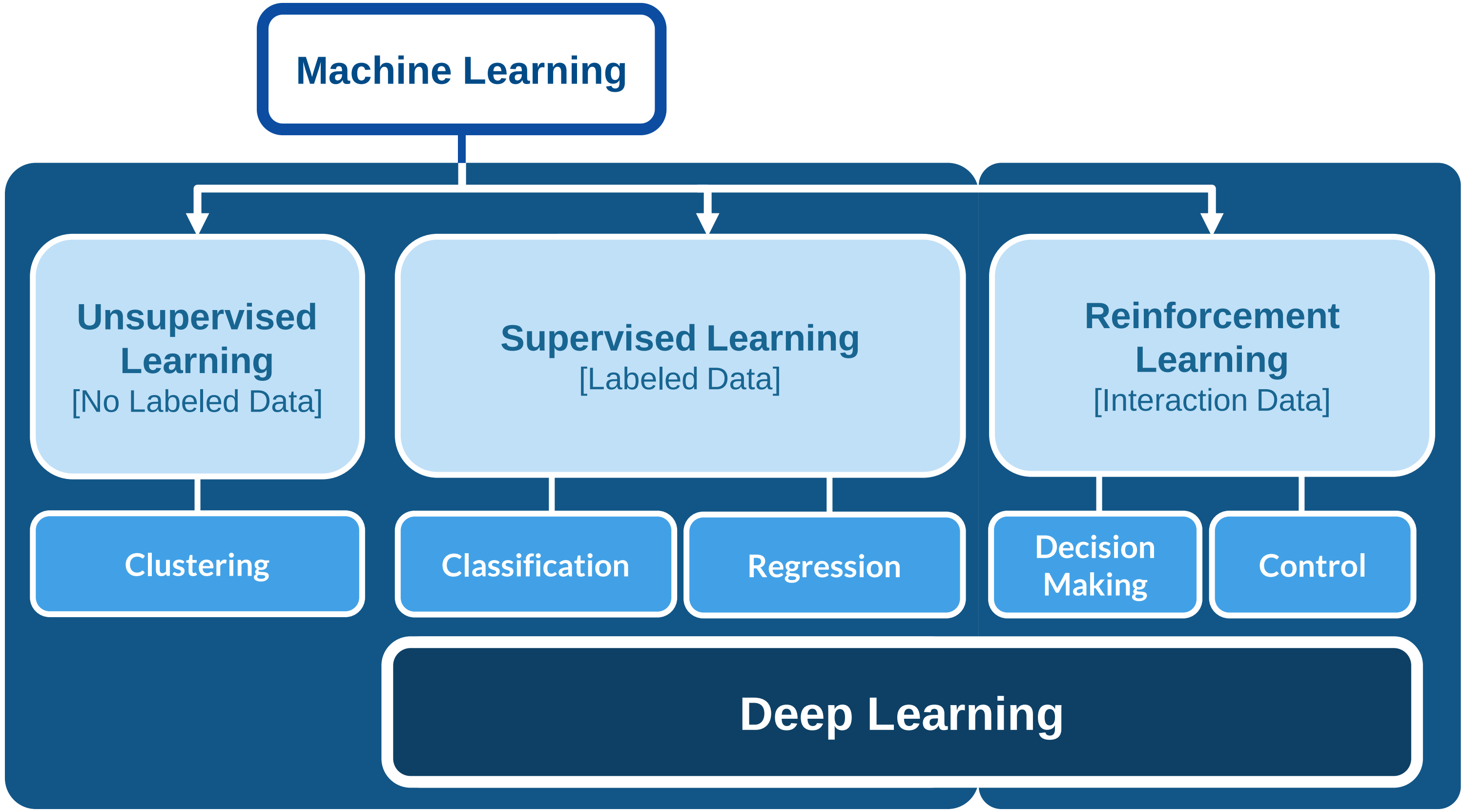
New Data → Transform → Pre-Trained Model → Classification/ Regression





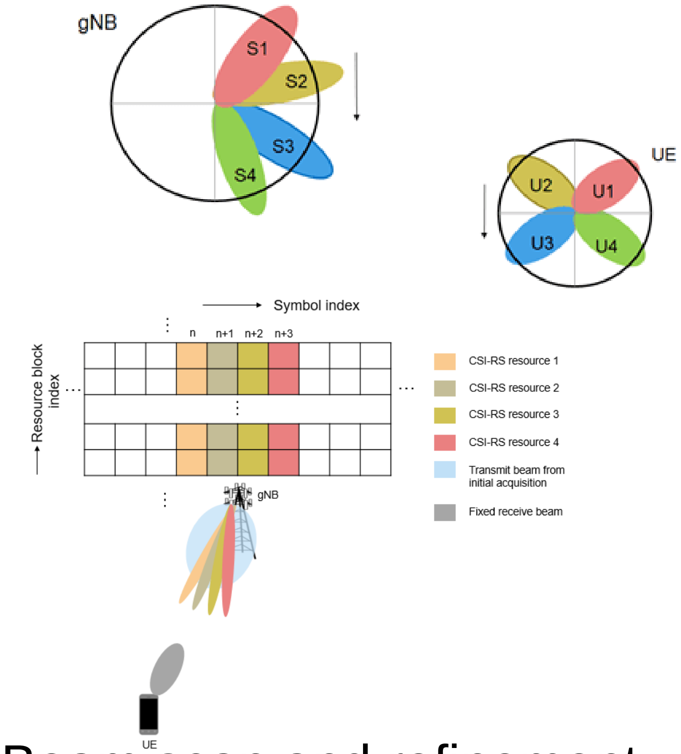


Machine Learning and Deep Learning Taxonomy



Reinforcement learning:

- Learning through trial & error [*interaction*]
- It's about learning a **behavior** or accomplishing a **task**



Beam scan and refinement

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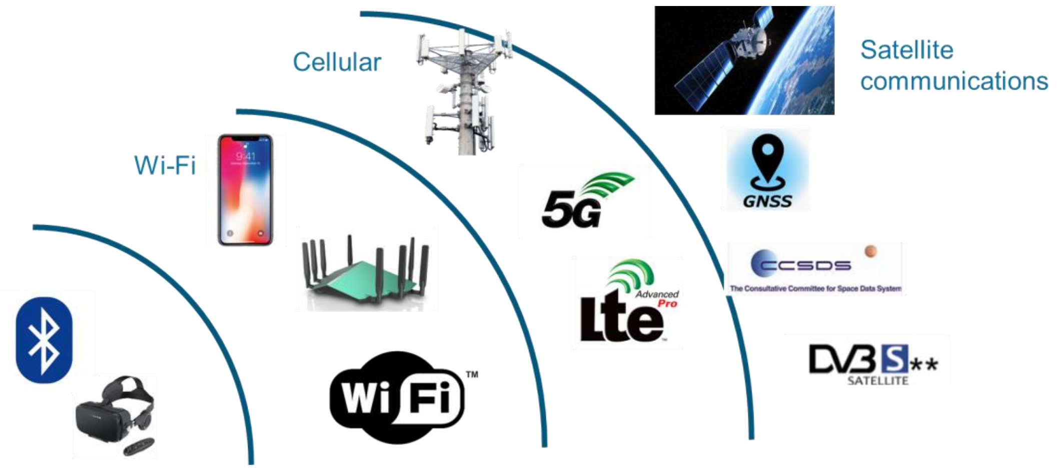
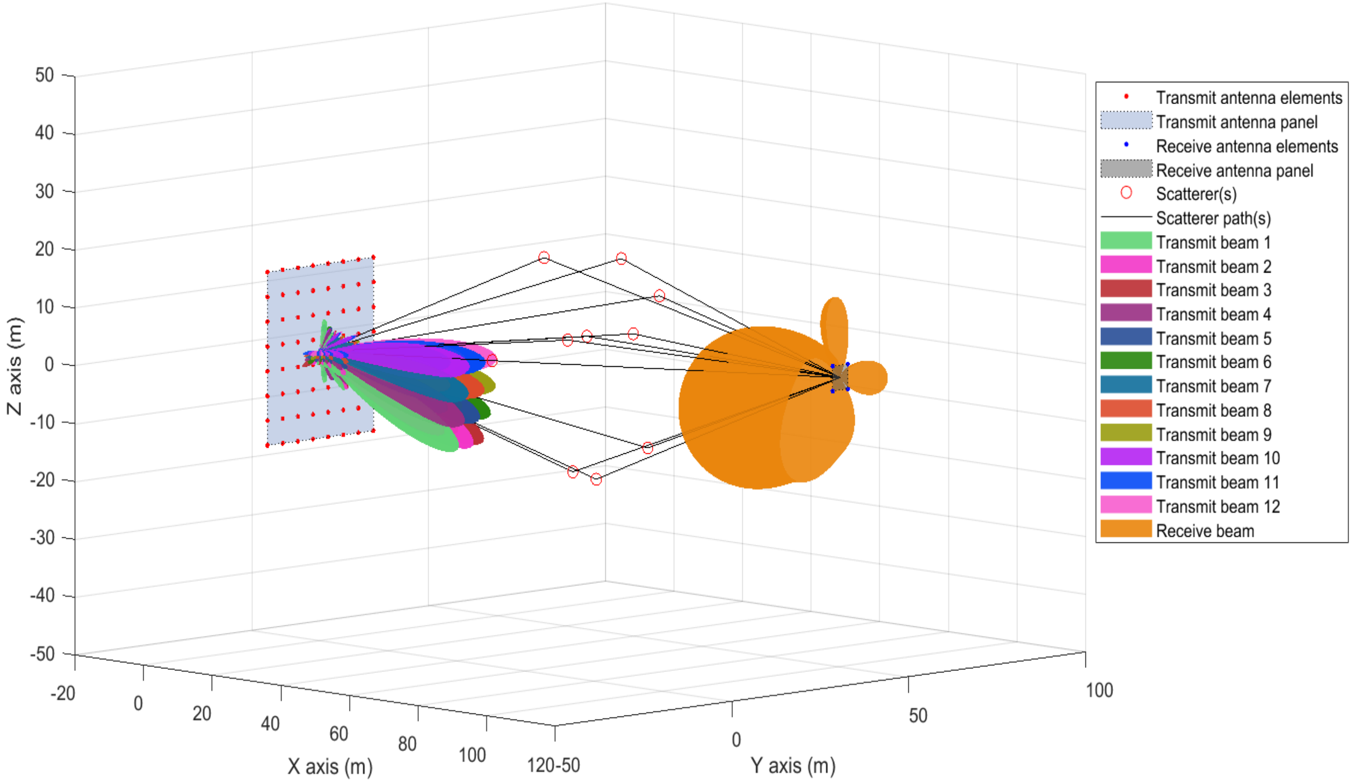


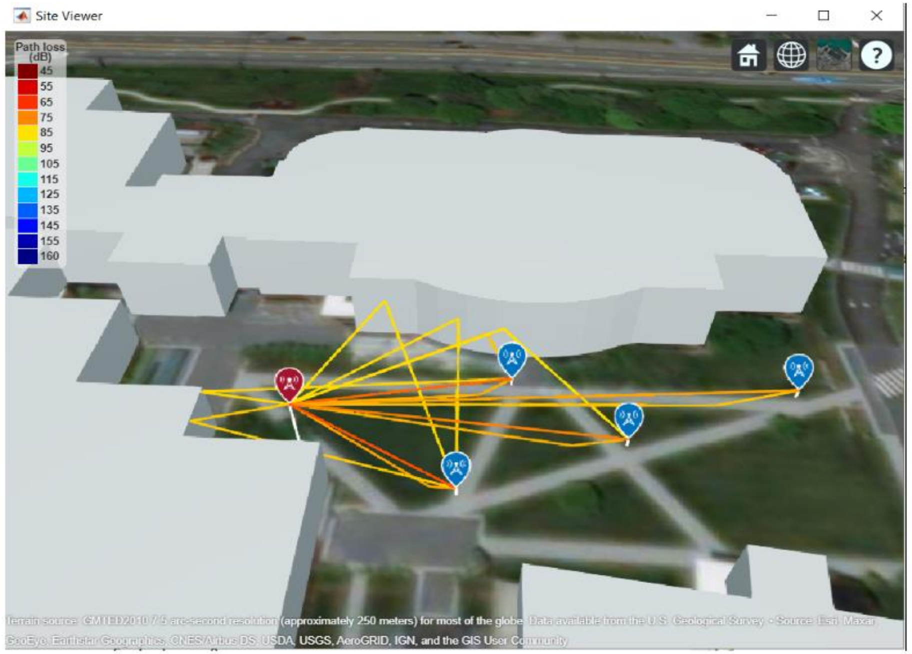
AI-driven system design workflow

1 Data Preparation → 2 AI Modeling → 3 Simulation and Test → 4 Deployment

Beam management for mmWave Communication

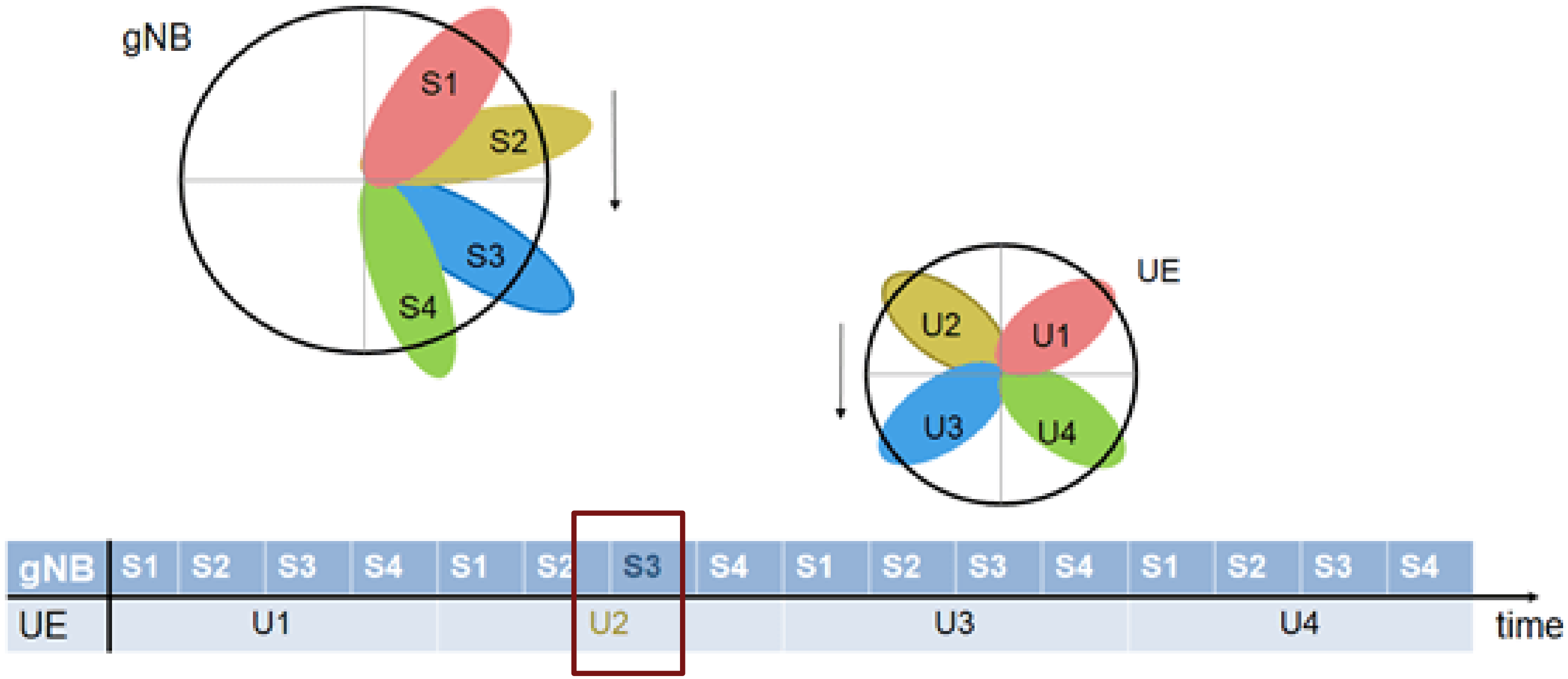
- Beam sweeping
- Beam measurement
- Beam determination
- Beam reporting
- Beam tracking
- Beam recovery

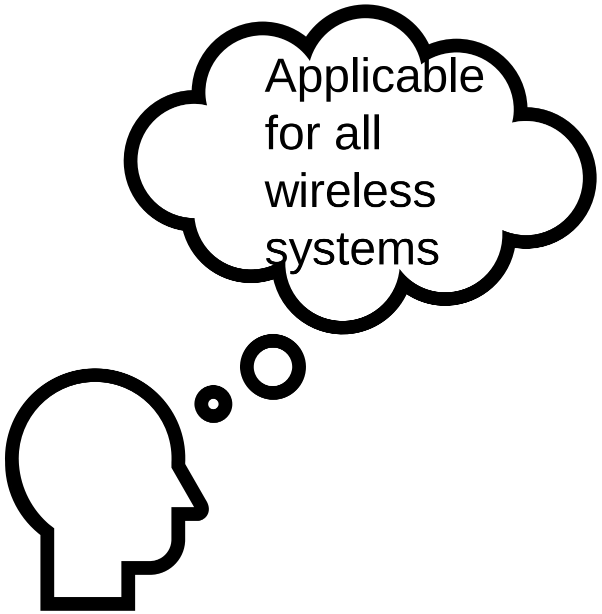




White Paper: [5G NR Beam Management]

5G NR SSB Beam Sweeping procedure

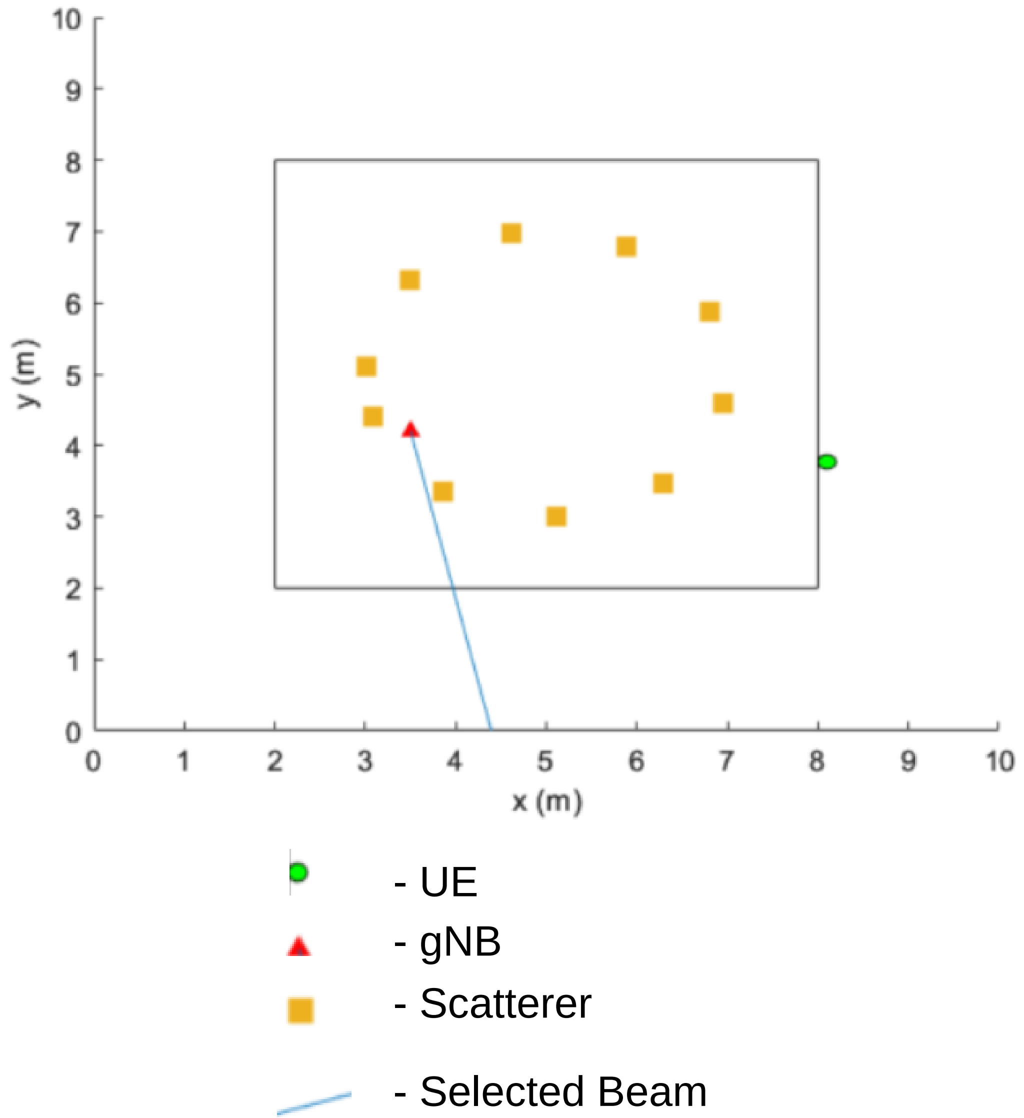




This Tx/Rx beam pair results in the highest reference signal received power (RSRP)

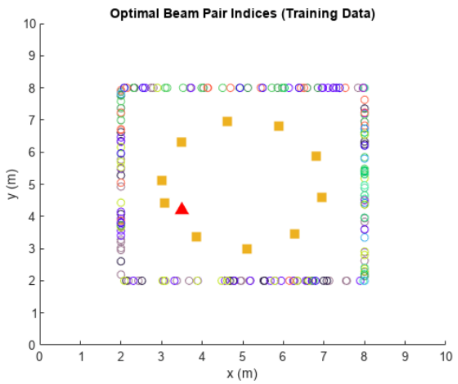
5G NR SSB Beam Sweeping Simulation

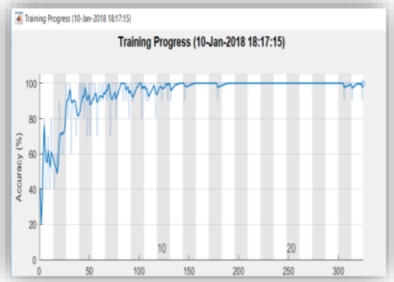
- Design fixed Transmitter and scatters, mobile receiver
  - TX Array: 8x8, RX Array: 2x2 - URA
- Add AWGN/ channel effect
- At each location, perform [NR SSB Beam Sweeping](), and calculate RSRP for each beam
  - Repeat SSB beam sweeping for 4 times to average out the effect of noise
- True optimal beam pair is the one with *highest average RSRP*

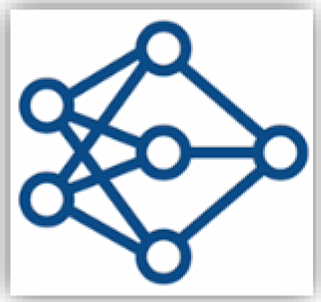


Challenge:
When the number of beams goes up, beam sweeping is time-consuming and costly – hence overhead is exponential

Mapping with the workflow we discussed

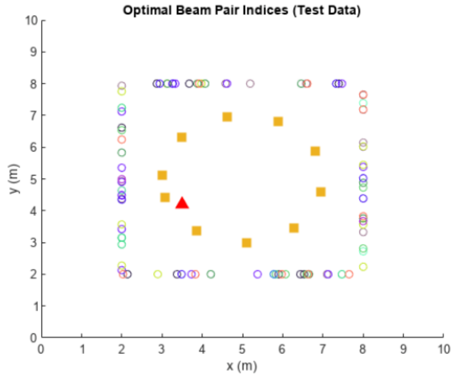






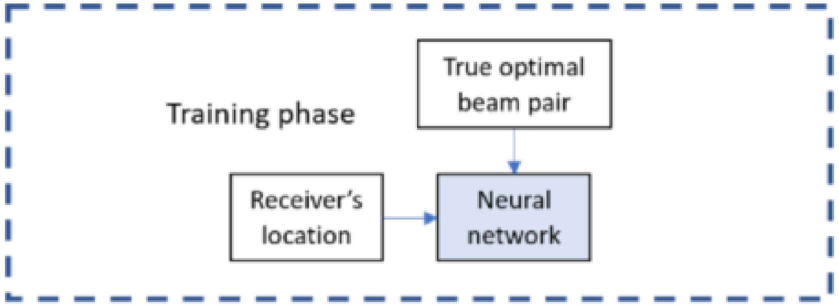
Pre-labeled synthesized → Train AI Model → Trained Model

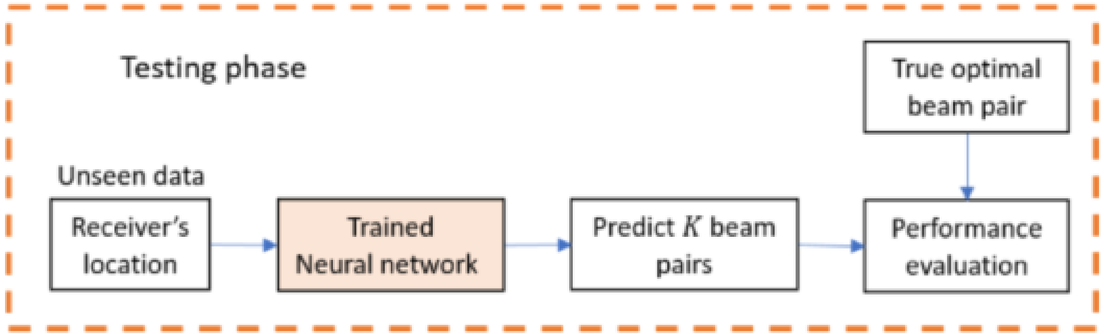
New Data → Pre-Trained Model → Classification

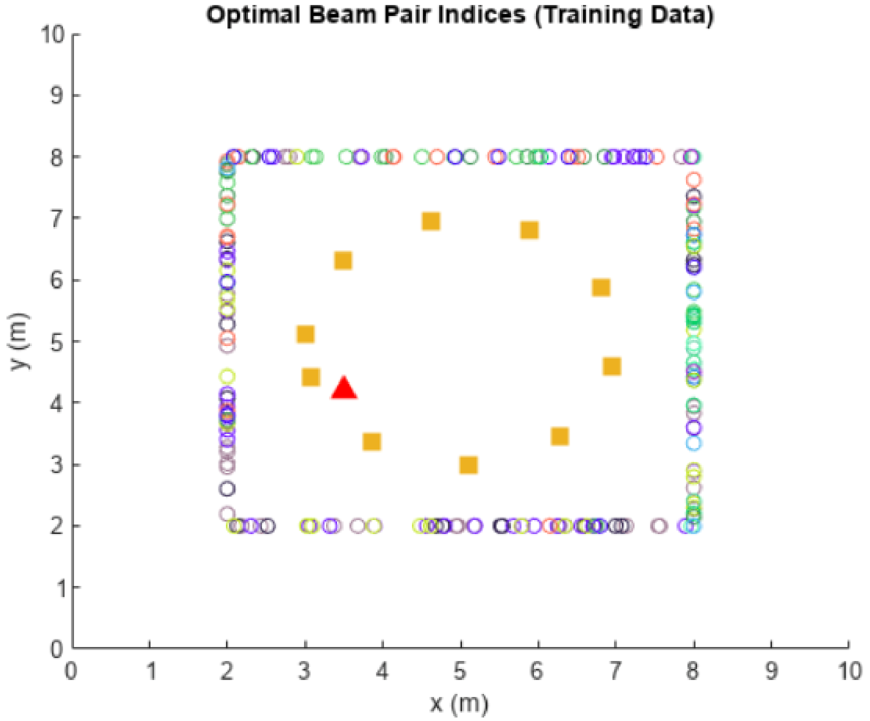


Optimal Beam Pair

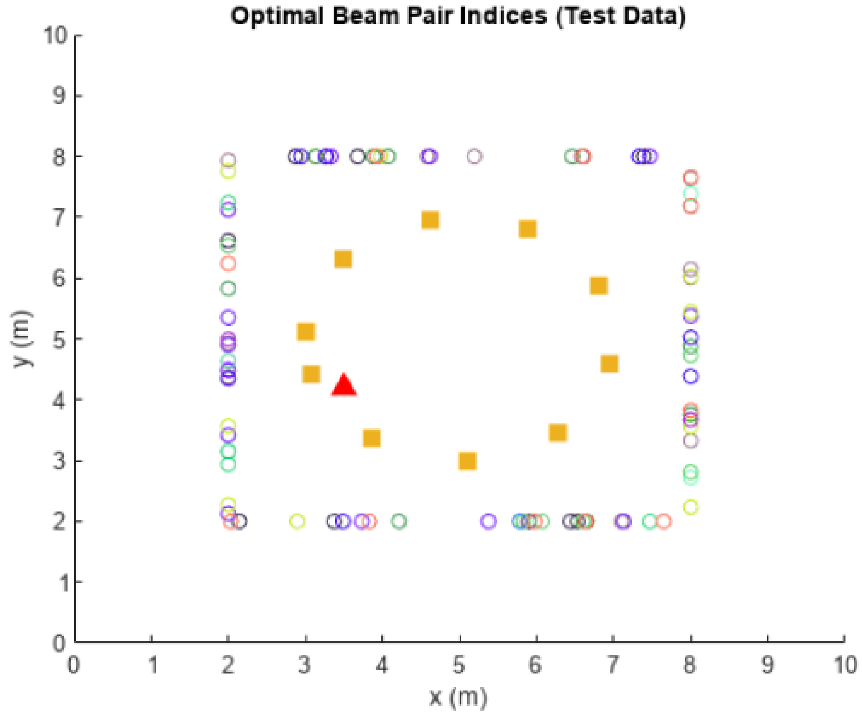
Applying the Classical Deep Learning workflow







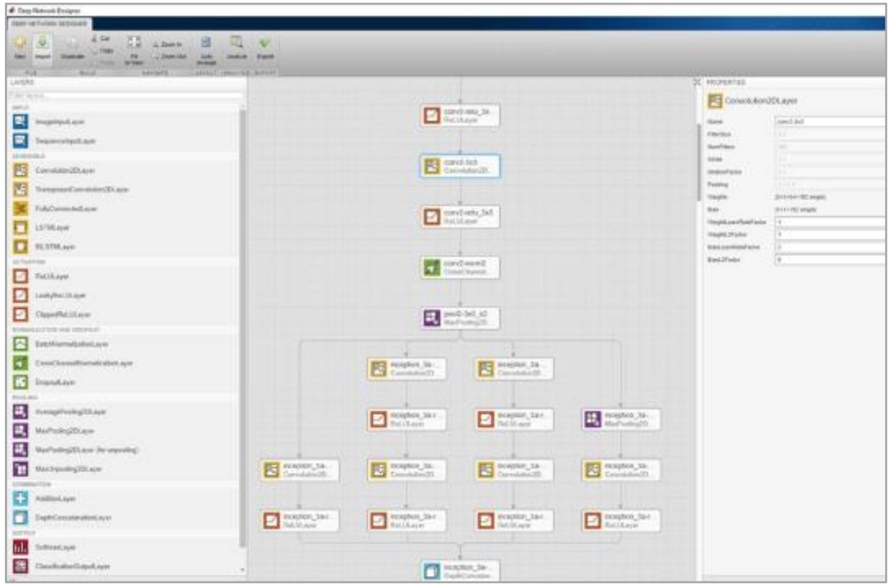
Train



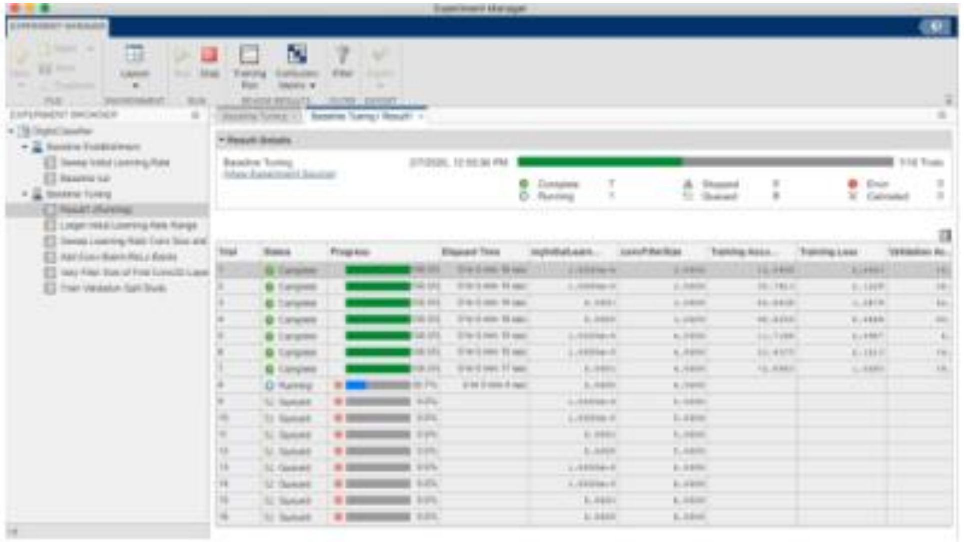
Test

Why MATLAB for AI + Wireless?

Increase productivity using Apps for design and analysis



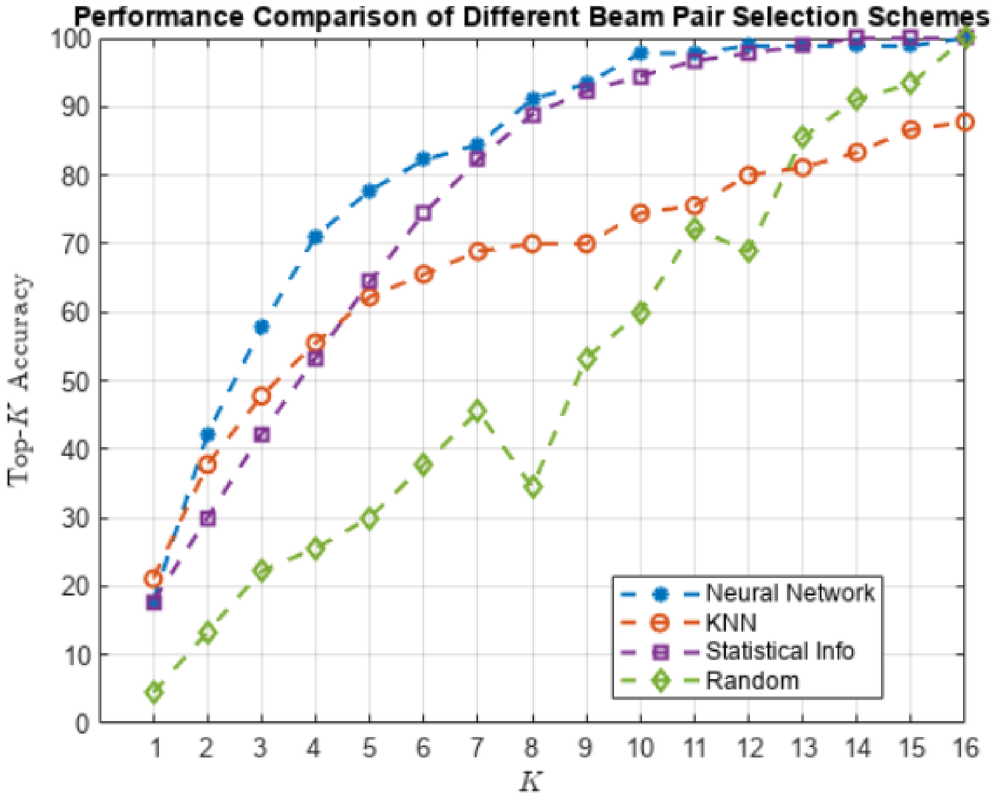
Deep Network Designer app to build, visualize, and edit deep learning networks



Experiment Manager app to manage multiple deep learning experiments, analyze and compare results and code

Applying the Classical Deep Learning workflow

?



Train a neural network to learn the relationship

Receiver's location	Optimal beam index
(1, 2, 0)	1
(-2, 5, 0)	5
(3, -7, 0)	11
…	…

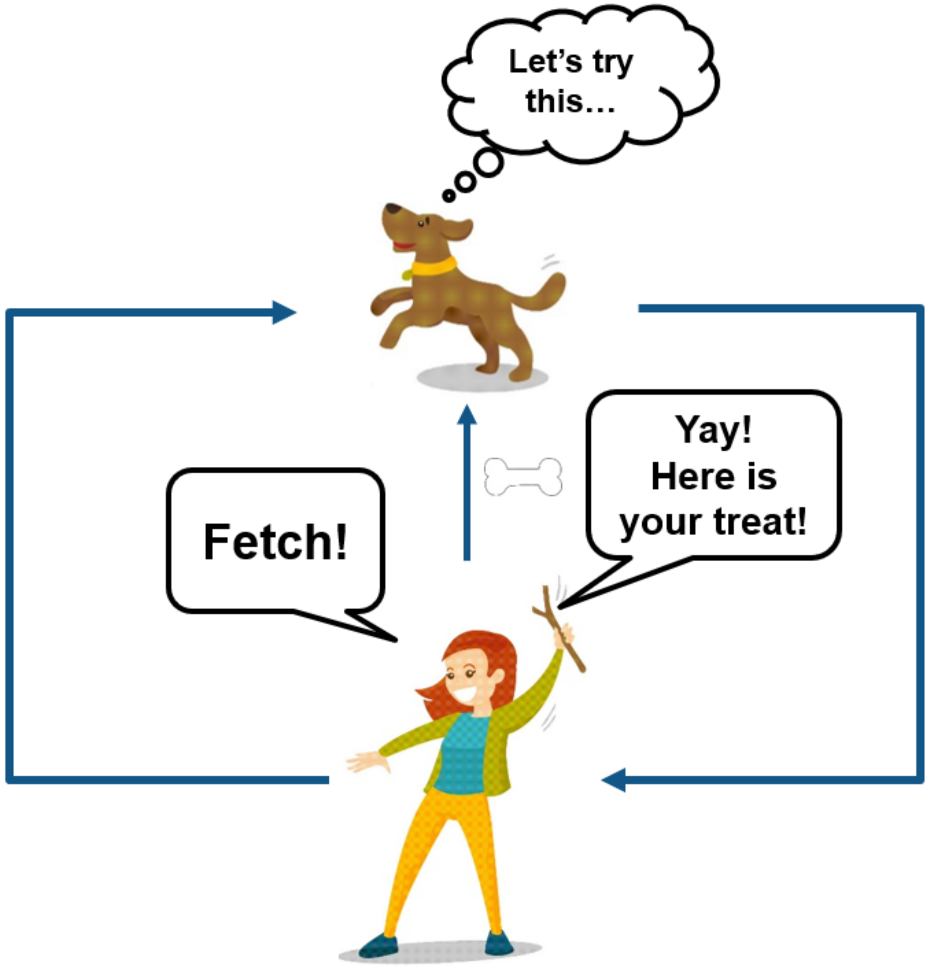
Testing

Receiver's location	Recommend a set of 3 good beams	True optimal beam index
(-1, -2, 0)	[1, 2, 9]	9 ✓
(-9, -8, 0)	[3, 4, 8]	1 ✗
(2, -1, 0)	[11, 12, 3]	12 ✓
…	…	

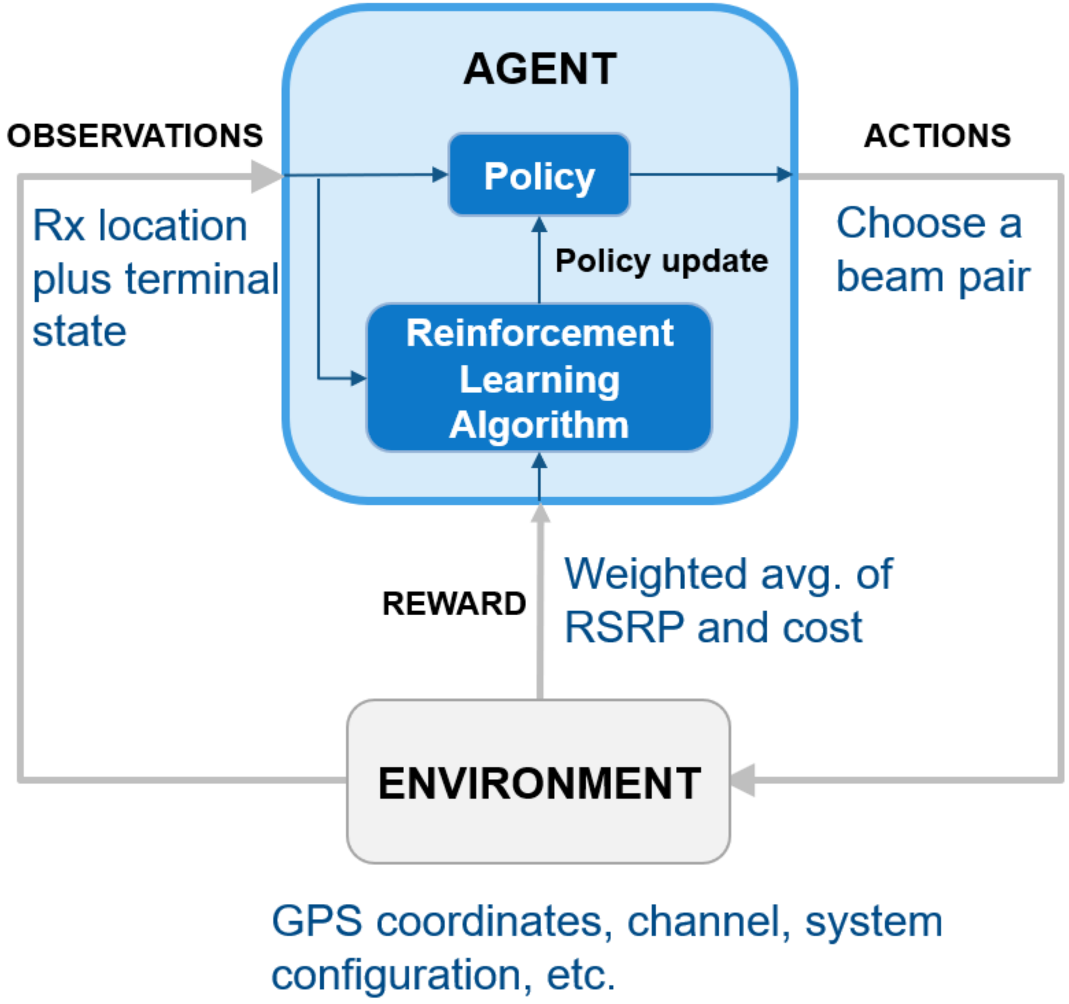
Top-K accuracy

Optimal Beam Selection with Reinforcement Learning

Analogies with pet training



Reinforcement learning works through **trial and error.**



Reinforcement Learning in few Steps

- Create Environment specifies the reward function

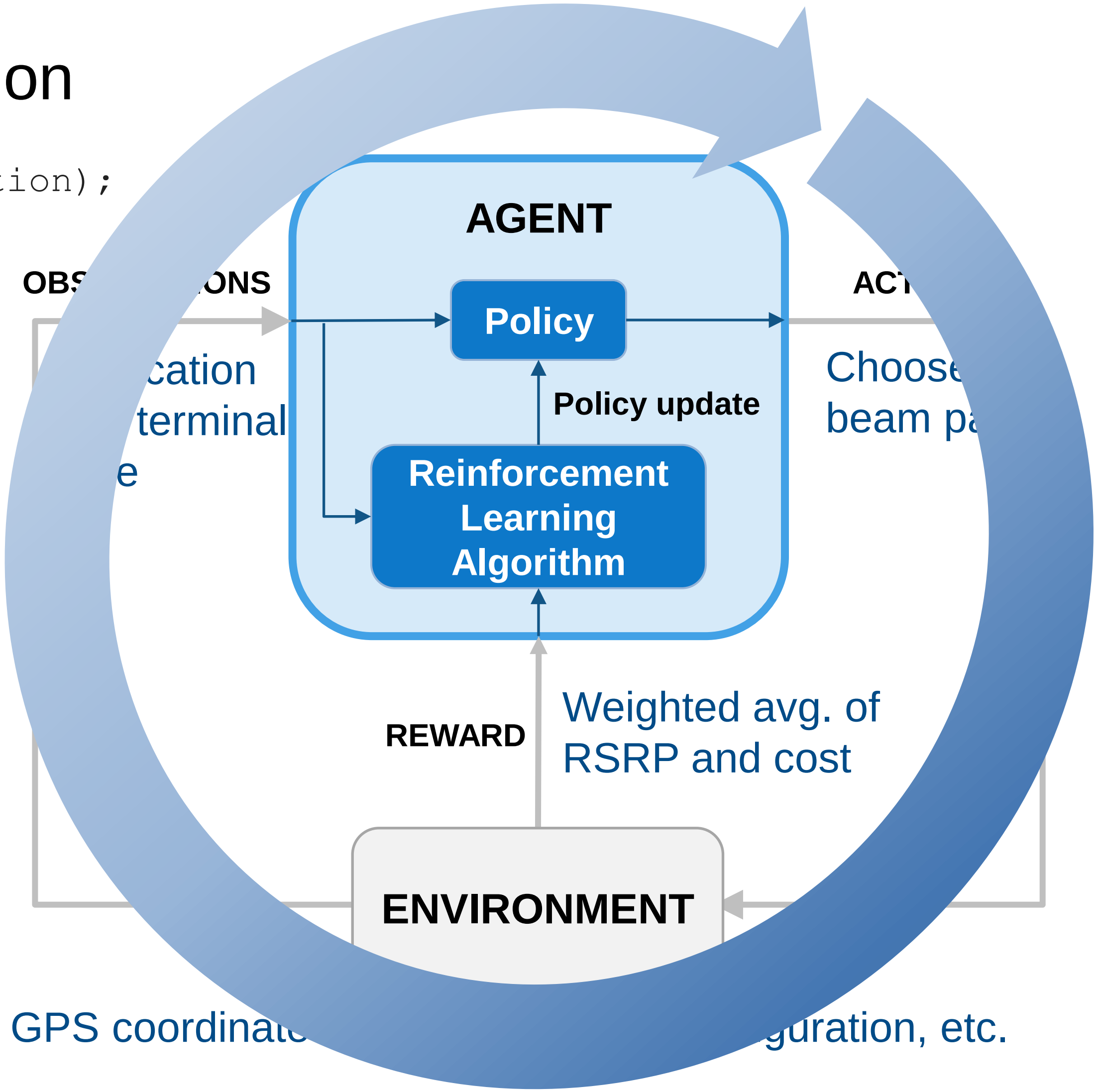
```
envTrain =
BeamSelectEnv(locationMat,avgRsrpMatTrain,rotAngleMat,position);
```

- Create RL Agent

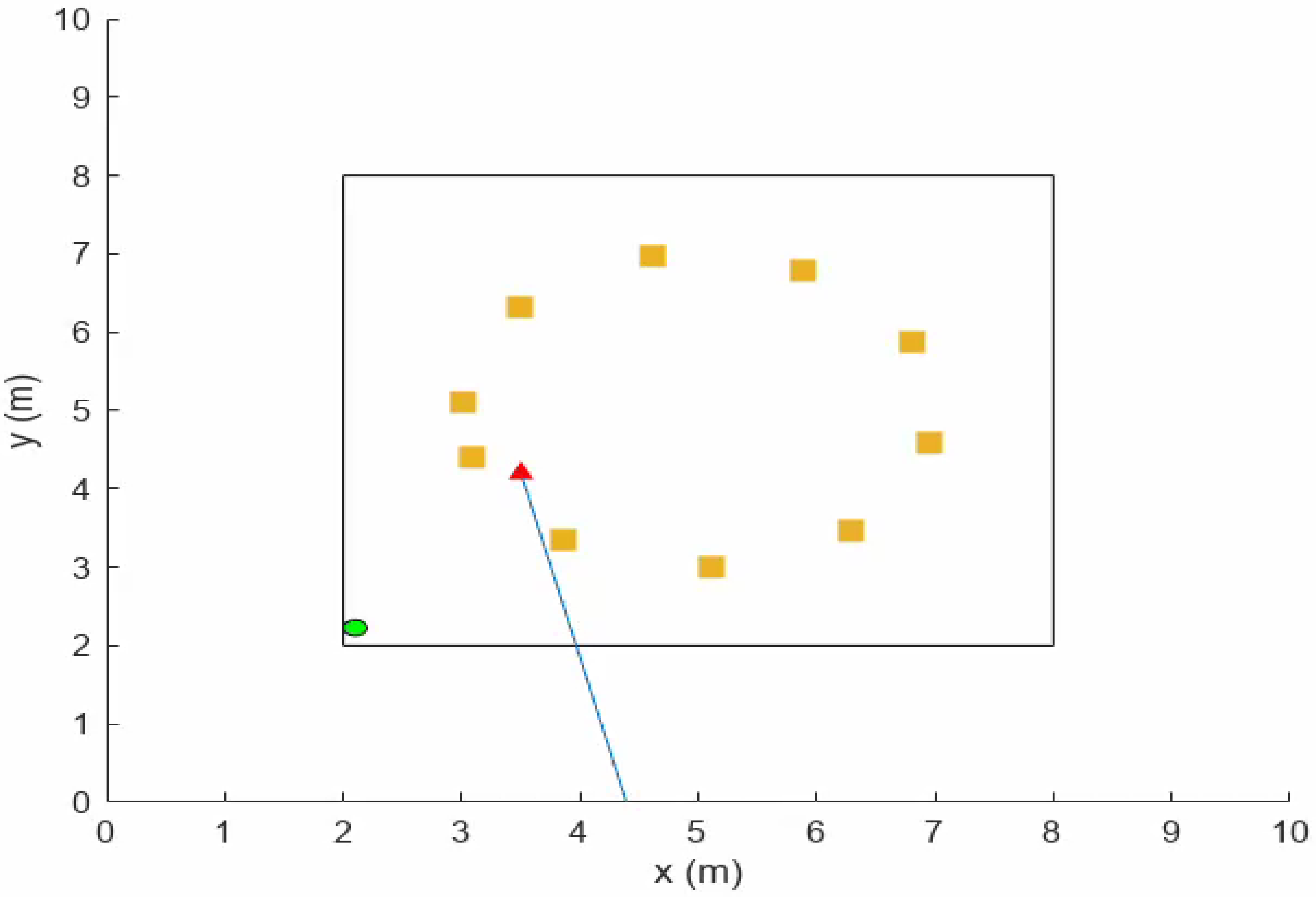
```
obsInfo = getObservationInfo(envTrain);
actInfo = getActionInfo(envTrain);
agent = rlDQNAgent(obsInfo,actInfo);
```

- Train Agent

```
trainOpts = rlTrainingOptions("MaxEpisodes", 1000, ...
"MaxStepsPerEpisode", 200);
trainingStats = train(agent,envTrain,trainOpts);
```



Testing Reinforcement Learning in Test Environment



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Pros & Cons of Reinforcement Learning

Pros

- **No data** required before training
- **New possibilities** with AI for hard-to-solve problems
- Complex **end-to-end** solutions can be developed
- **Uncertain**, **nonlinear** environments can be used

Cons

- Trained policies are **hard to verify** (no performance guarantees)
- Many trials/data points required (**sample inefficient**)
  - Training with real hardware can be expensive and dangerous
- Large number of **design parameters**
  - Reward signal
  - Network architectures
  - Training Hyperparameters

Simulations are key in Reinforcement Learning

Simulations and Virtual Models are Key in Reinforcement Learning

Cons of Reinforcement Learning

- Trained policies are **hard to verify** (no performance guarantees)
- Many trials/data points required (**sample inefficient**)
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  - Reward signal
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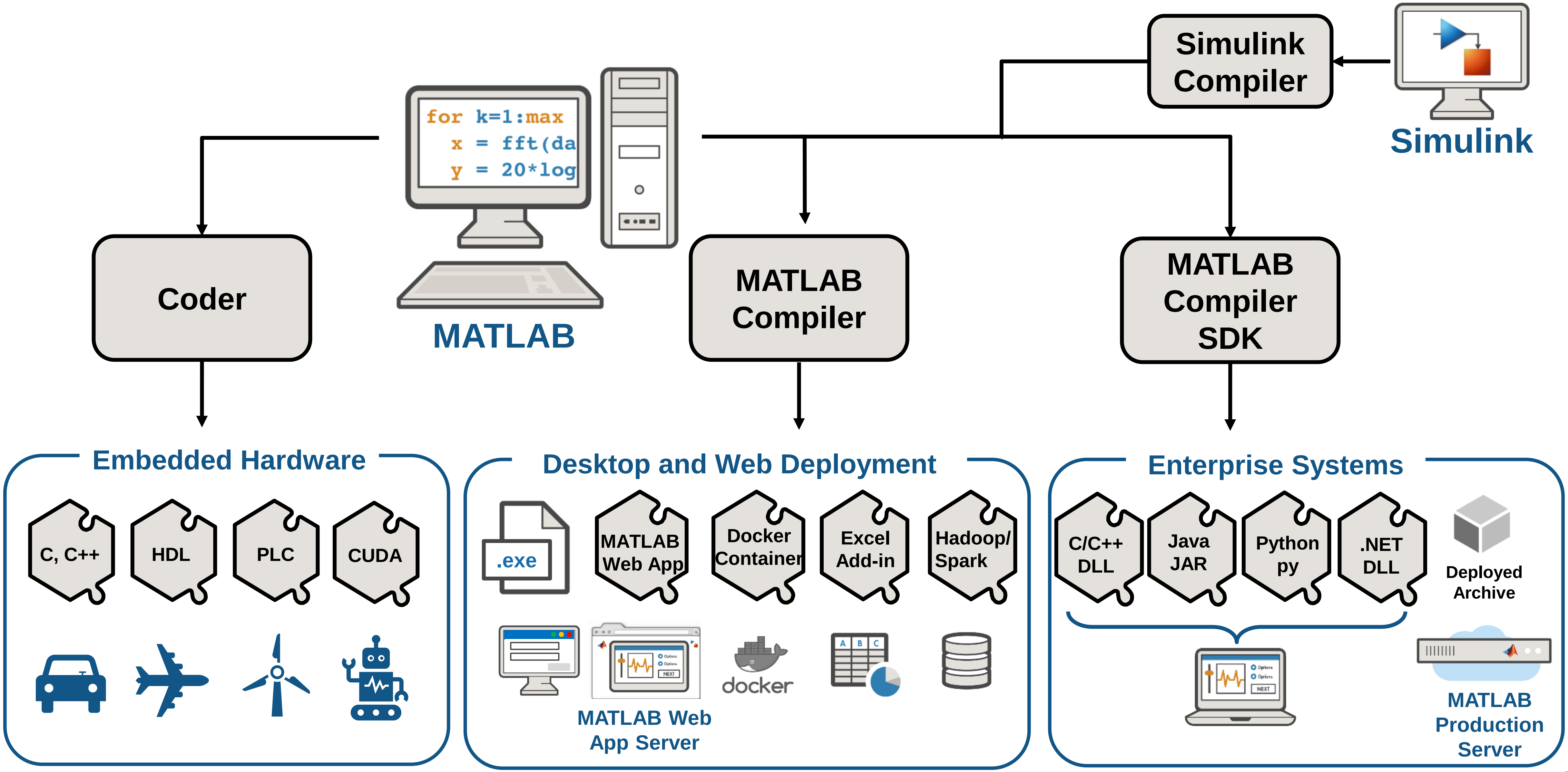
MATLAB® & SIMULINK®

- **Reuse** existing code and models for environments
- Use simulations for **policy verification**
  - Simulate extreme scenarios
- Run simulation trials **in parallel** to accelerate training
- Consult Reinforcement Learning Toolbox **examples**
  - Iterative tuning with simulations

Ways to Deploy,..



Agenda

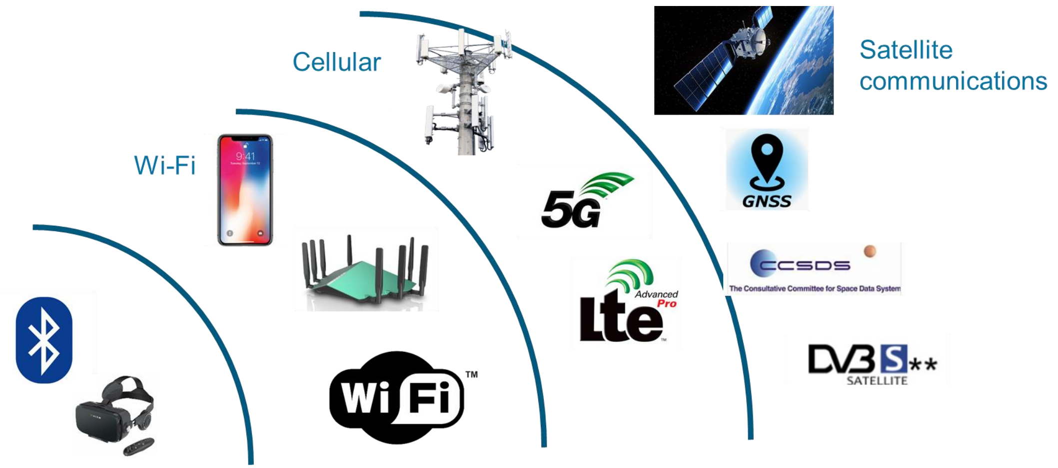
1 Future of Wireless Ecosystem

2 Using AI for wireless

3 AI Workflow for Wireless

4 Reinforcement learning for 5G

5 **Summary**



AI-driven system design workflow

1. Data Preparation
2. AI Modeling
3. Simulation and Test
4. Deployment

Summary:

You can solve advance Wireless problem with AI using MATLAB

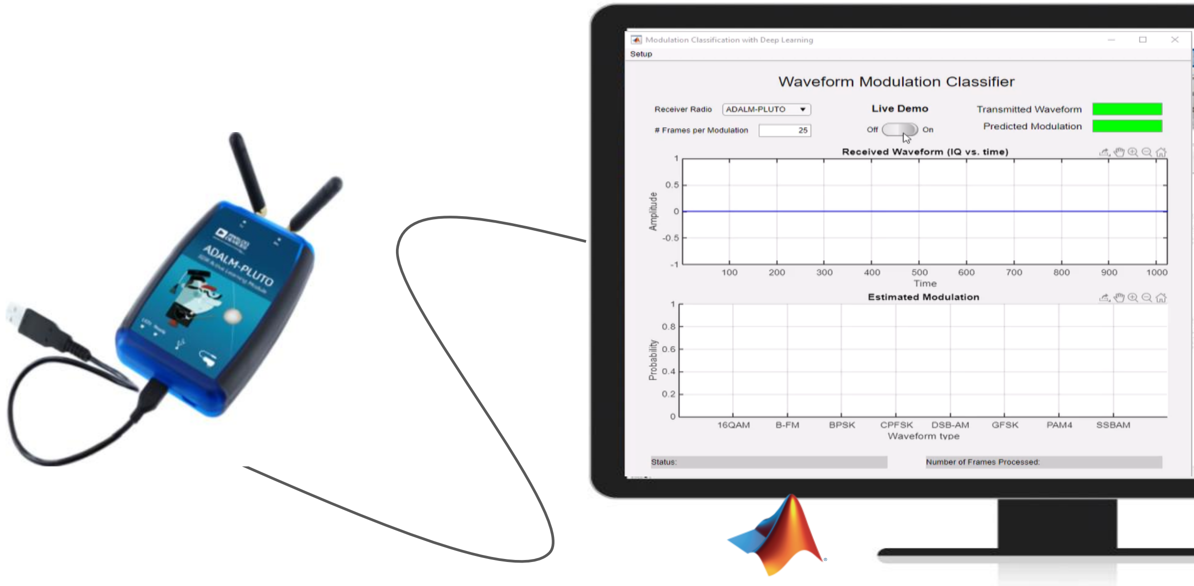
Wireless Communications:

- **Synthetize data** (5G, LTE, WLAN, Satellite, Radar, Lidar, GPS, etc)
- Benefit from standard compliant **channel models**
- Build **link-level simulation** (PHY layers + RF front end+ Antenna) and **Network level Simulation**
- From MATLAB to the real world… and back: **Connect to test equipment and SDR**

+

AI:

- Build and train your AI network in MATLAB by low-code/no-code workflow
- Accelerate the training with no code change
- Collect over-the-air data using SDR and test/retrain your network with real-world data
- Deploy AI network to hardware/ embedded system

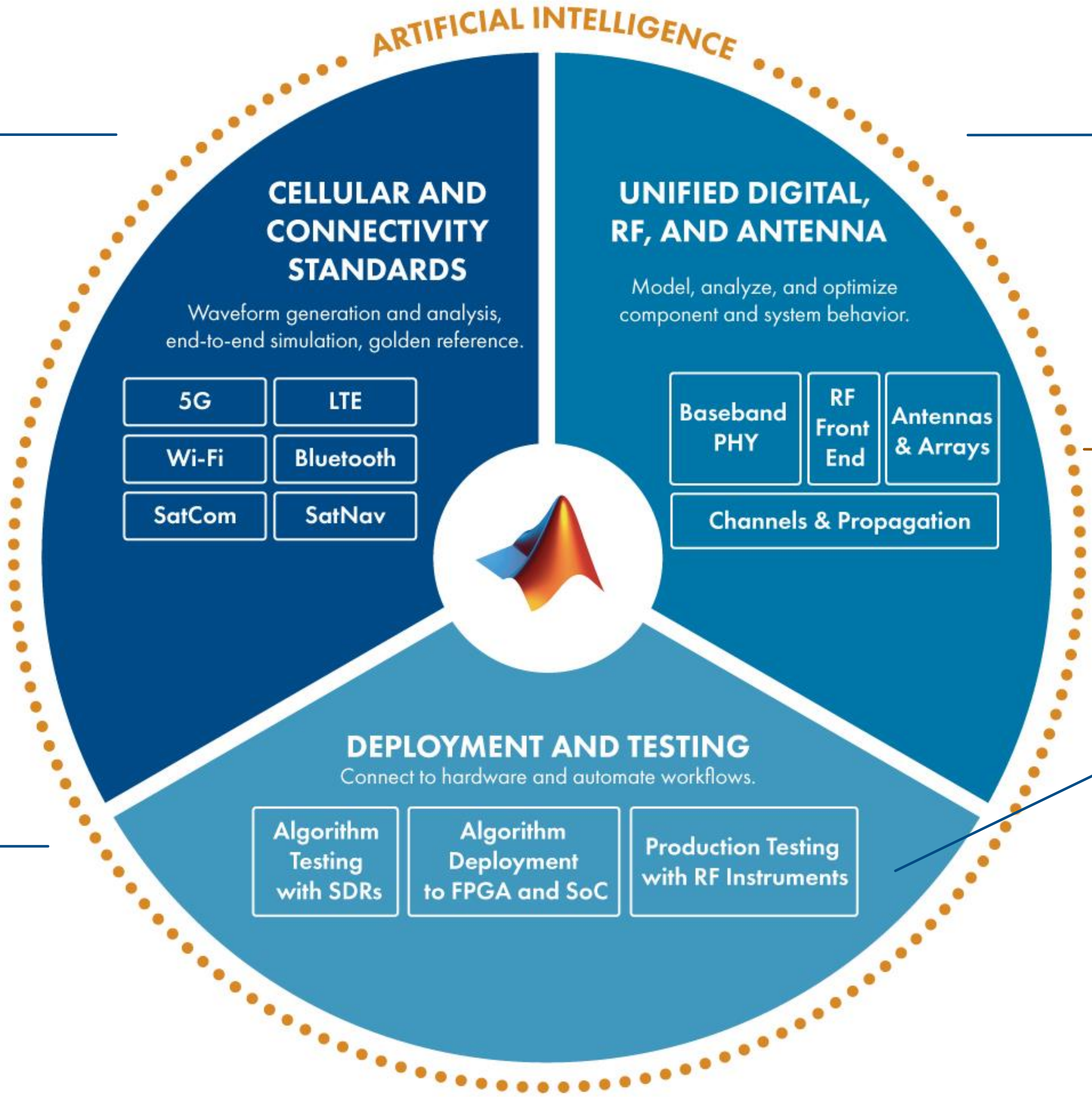


Wireless Communications Development with AI

with MATLAB and Simulink

Related Products

5G Toolbox
LTE Toolbox
WLAN Toolbox
Bluetooth Toolbox
Satellite Communications Toolbox
UWB Addon



Related Products

Communications Toolbox
RF Toolbox
RF Blockset
Antenna Toolbox
Phased Array System Toolbox

AI Products

- Statistics and Machine Learning Toolbox
- Deep Learning Toolbox
- Reinforcement Learning Toolbox

Related Products

Instrument Control Toolbox
Wireless Testbench Toolbox
Software-Defined Radio Add-ons
MATLAB Compiler
HDL Coder
Wireless HDL Toolbox
SoC Blockset

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NanoSemi Improves System Efficiency for 5G

Challenge

Accelerate the design and verification of RF power amplifier linearization algorithms used in 5G and Wi-Fi 6 devices

Solution

Use MATLAB to characterize amplifier performance, develop predistortion and **machine learning algorithms**, and automate standard-compliant test procedures

Results

- Development time reduced by 50%
- Iterative verification process accelerated
- Early customer validation enabled

[Link to user story]

NanoSemi linearization IP development and verification using MATLAB.

"At a small company like ours, it's critical for engineers to work with as little overhead as possible. With MATLAB, our team can deliver leading-edge IP faster, enabling our customers to increase bandwidth, push modulation rates higher, and reduce power consumption."

- Nick Karter, NanoSemi

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Thank you

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