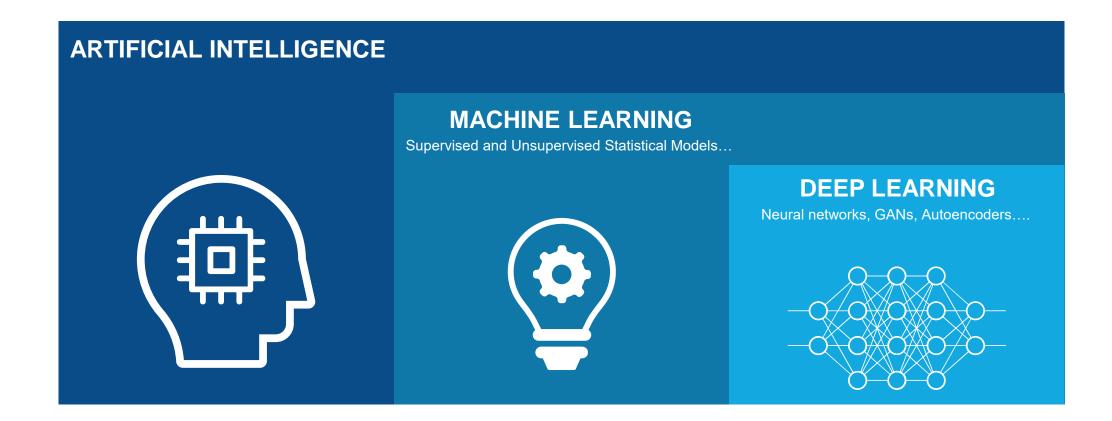
MATLAB EXPO

Building AI applications for Signals and Time-Series Data

Esha Shah, MathWorks Francis Tiong, MathWorks



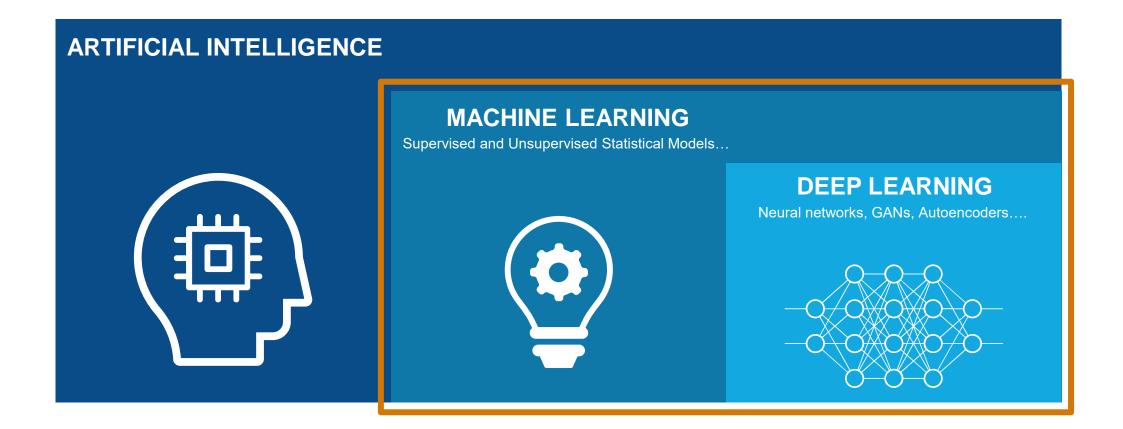
Machine Learning and Deep learning have grown rapidly over the last decade







Machine Learning and Deep learning have grown rapidly over the last decade



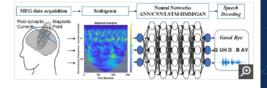




Use of AI in signal processing applications is growing rapidly

UT Austin Researchers Convert Brain Signals to Words and Phrases Using Wavelets and Deep Learning

"MATLAB is an industry-standard tool, and one that you can trust. It is easier to learn than other languages, and its toolboxes help you get started in new areas because you don't have to start from scratch."



- Dr. Jun Wang, UT Austin

Classifying the brain signals corresponding to the imagined word "goodbye" using feature extraction and deep neural networks.

Shell performs Seismic Event Detection with Deep Learning

Challenges

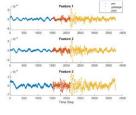
- Terabytes of passive seismic data from geophones
- Traditional methods time/labor intensive (5 months &~ \$100K)
- Event detection inconsistent/unreliable in 'low' signal to noise records

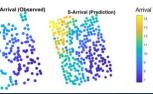
Solution

Train LSTM network to detect P-wave and S-wave arrivals via sequence-to-sequence classification

Results

- >98% accuracy for arrival prediction
- Networks generalizes to other data (sites, source mechanisms)





Battelle Neural Bypass Technology Restores Movement to a Paralyzed Man's Arm and Hand

"The algorithms we developed using MATLAB gave the participant back basic control of his arm and hand. By the end of the study, he could grip a bottle, pour out its contents, and set it down, as well as pick up a stir stick and execute a stirring motion."

- David Friedenberg, Battelle



Patient using the Battelle NeuroLife system



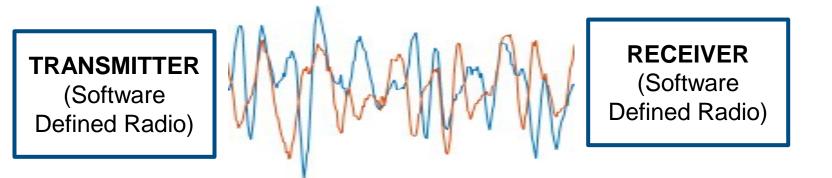
Voice Interface: The Touchscreen of the Next Century

How AI and Signal Processing Came Together to Track the DNA of Sound



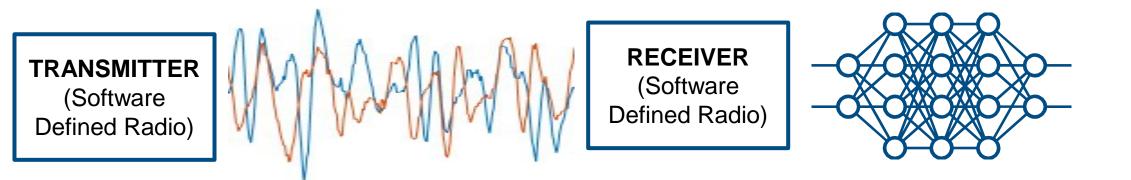


















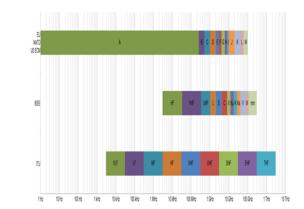




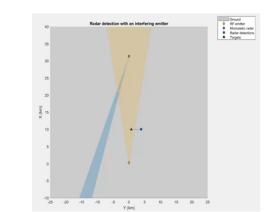




Intelligent Receivers



Spectrum Management



Radar Interference Detection









Data Preparation↓↓↓↓Data cleansing and
preparation✔Human insight↓Simulation-
generated data





Data Preparation

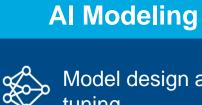


Data cleansing and preparation



Human insight





Model design and tuning



Hardware accelerated training Hardware







Data Preparation



Data cleansing and preparation



Human insight

Simulation-generated data





Model design and tuning



대 Hardware 라고 accelerated training Hardware



Deployment



Embedded devices



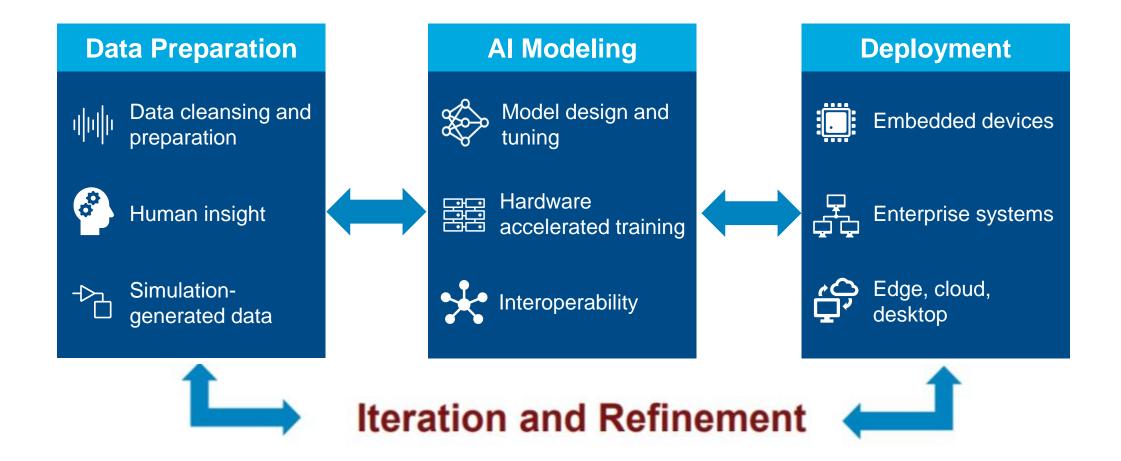
Enterprise systems



Edge, cloud, desktop

MATLAB EXPO









Preparing and labelling data

Data Preparation

IIIIIData cleansing and
preparation





Simulation-generated data

Preparing and labelling data

Data Preparation



Data cleansing and preparation



Human insight



Simulation-generated data

Q. How to label collected data?

Preparing and labelling data

Data Preparation



Data cleansing and preparation



Human insight

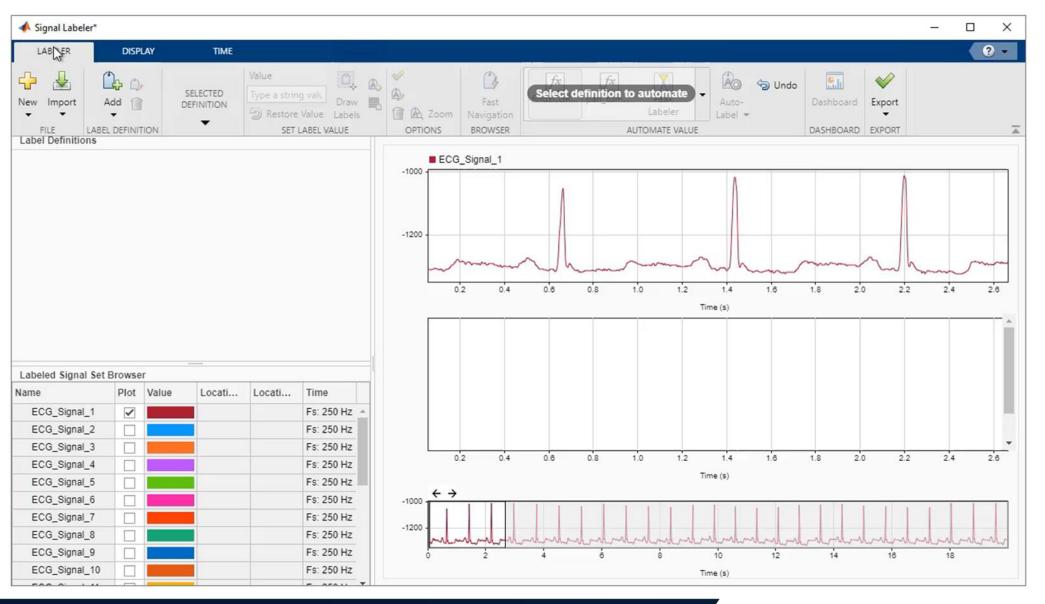


Simulation-generated data

Q. How to label collected data?

Q. What if it is not possible to collect data?

Labeling Signals with Signal Labeler App

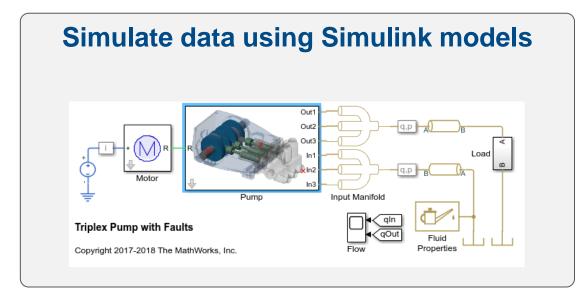






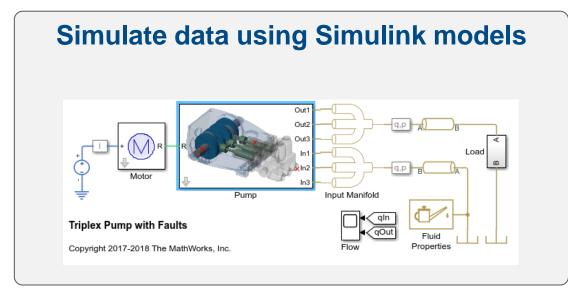




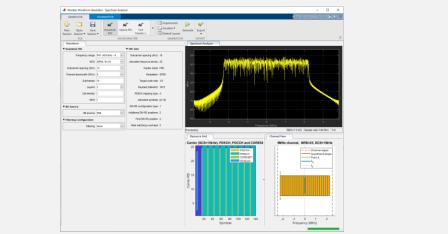






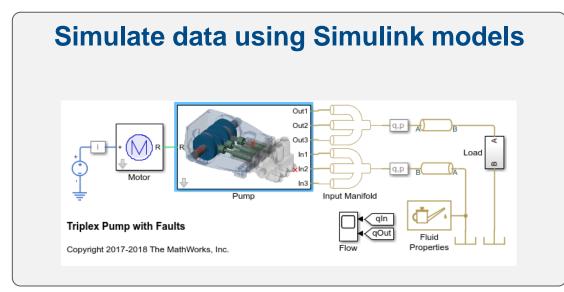


Generate wireless waveforms

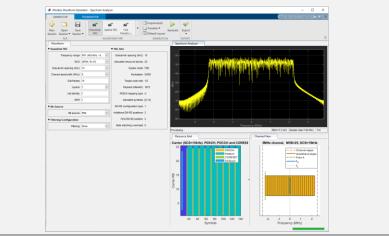








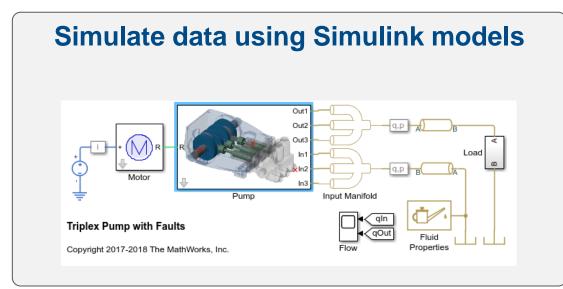
Generate wireless waveforms



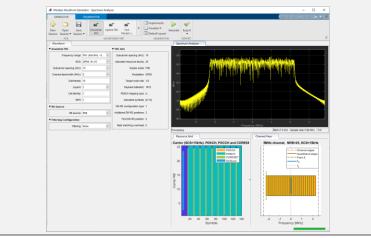
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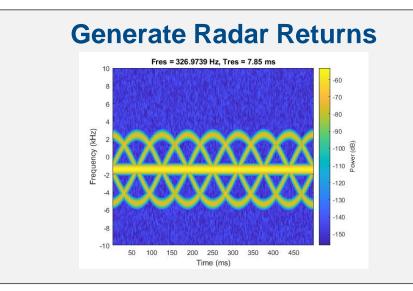




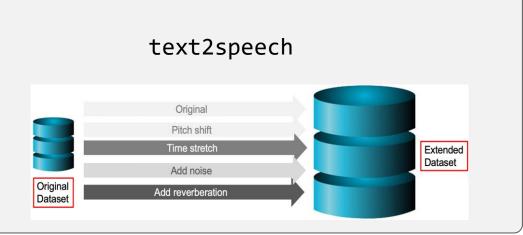


Generate wireless waveforms





Generate and Augment Audio Data



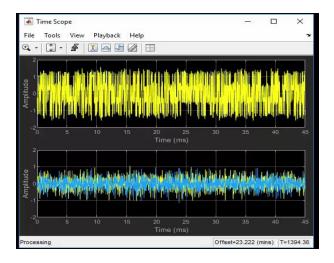


MATLAB EXPO





•Modulate digital baseband signals using built-in functions •BPSK, QPSK, 8PSK, FM, DSB-AM, SSB-AM, GFSK, PAM4



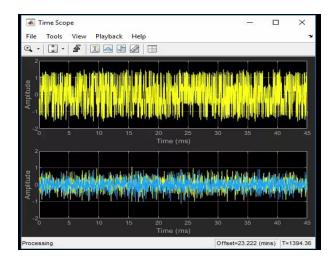




•Modulate digital baseband signals using built-in functions •BPSK, QPSK, 8PSK, FM, DSB-AM, SSB-AM, GFSK, PAM4

Easily account for various impairments
 RF / Hardware impairments (Frequency/ Phase Offsets etc.)

• Channel Impairments (Multipath Fading Channels)



Rician Multipath

multipathChannel = comm.RicianChannel(...
'SampleRate', fs, ...
'PathDelays', [0 1.8 3.4]/fs, ...
'AveragePathGains', [0 -2 -10], ...
'KFactor', 4, ...
'MaximumDopplerShift', 4)

multipathChannel =
 comm.RicianChannel with properties:

SampleRate: 200000 PathDelays: [0 9.0000e-06 1.7000e-05] AveragePathGains: [0 -2 -10] NormalizePathGains: true KFactor: 4 DirectPathDopplerShift: 0 DirectPathInitialPhase: 0 MaximumDopplerShift: 4 DopplerSpectrum: [1x1 struct]

Show all properties



MATLAB EXPO

Modulate digital baseband signals using built-in functions
BPSK, QPSK, 8PSK, FM, DSB-AM, SSB-AM, GFSK, PAM4

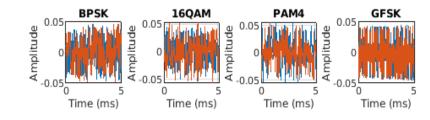
•Easily account for various impairments •RF / Hardware impairments (Frequency/ Phase Offsets etc.)

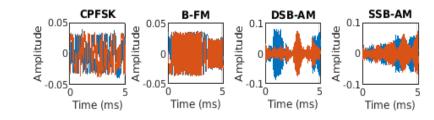
• Channel Impairments (Multipath Fading Channels)

Generate Datasets for Deep Learning

MATLAB **Expo**

- 5000 frames generated for each modulation type
- 80% data Training; 10% data Validation; 10% data Test









Feature Extraction

Data Preparation









Simulation-generated data

Feature Extraction

Data Preparation



Data cleansing and preparation



Human insight



Simulation-generated data

Q. Can I use raw data?

Feature Extraction

Data Preparation



Data cleansing and preparation



Human insight



Simulation-generated data

Q. Can I use raw data?

Q. How do I extract the right features for my data?

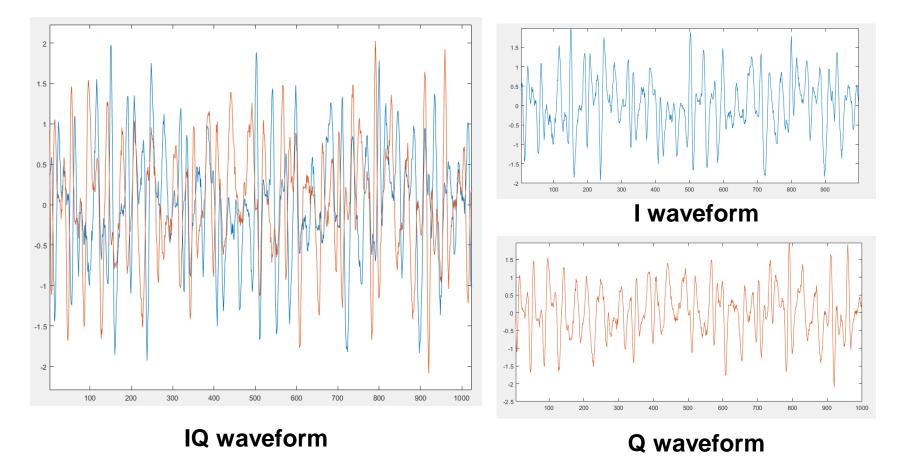
Use of raw data for AI models





Use of raw data for AI models

MATLAB EXPO

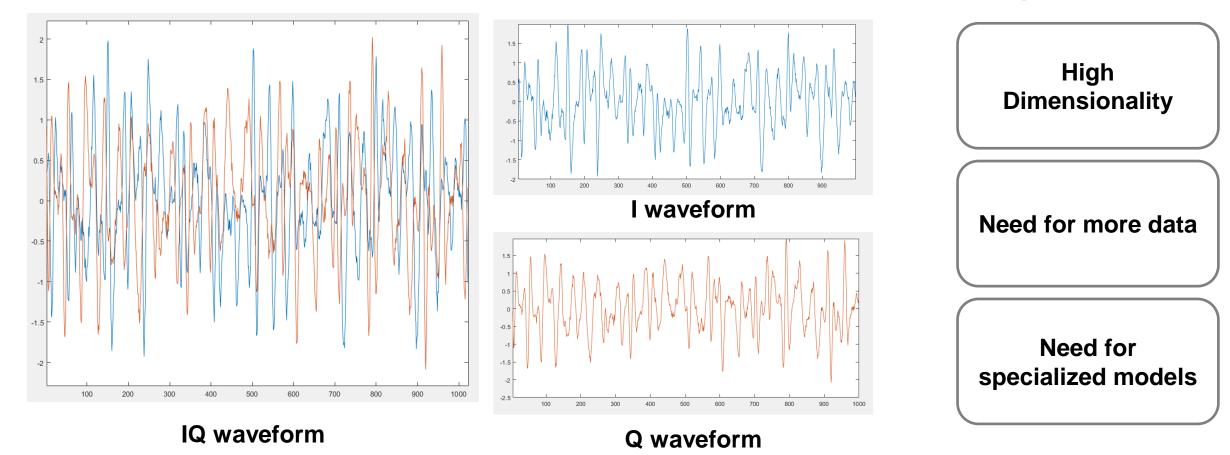






Use of raw data for AI models

MATLAB EXPO



Challenges with Raw Data



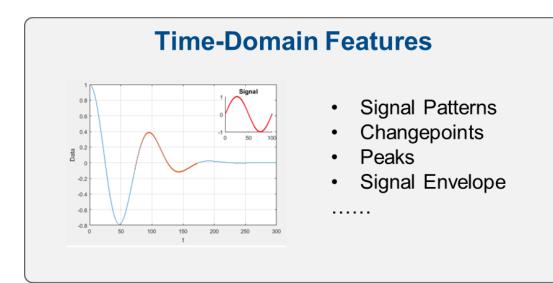


Feature extraction with signal processing techniques





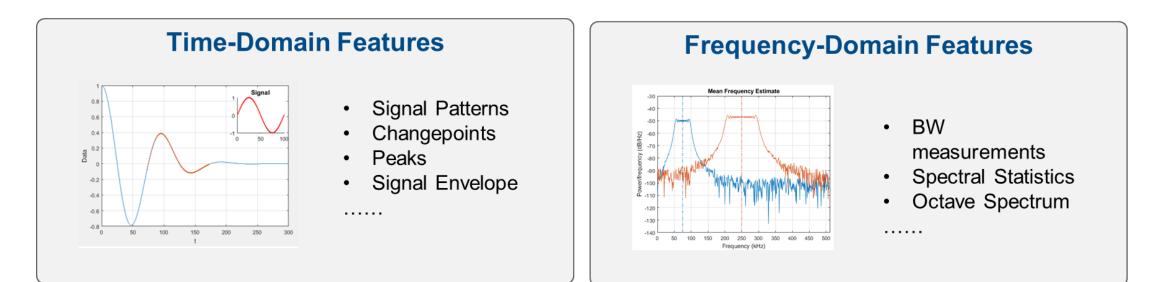
Feature extraction with signal processing techniques







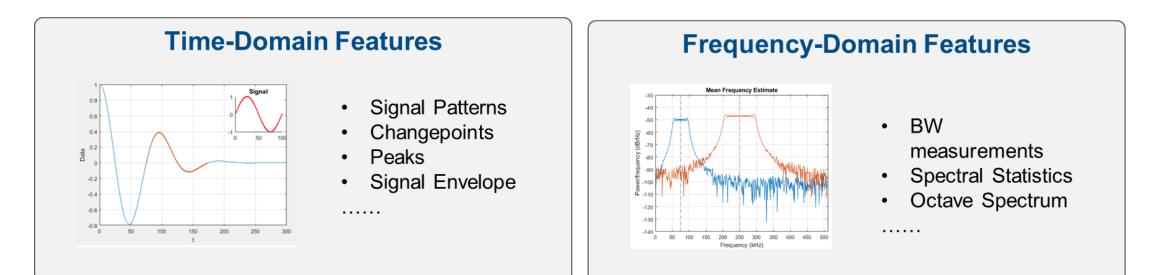
Feature extraction with signal processing techniques

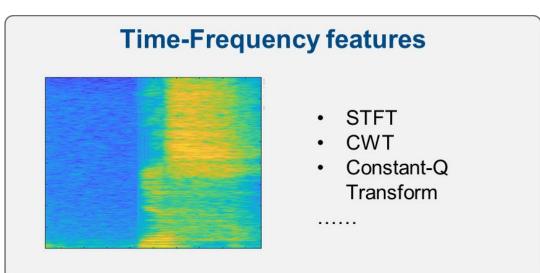






Feature extraction with signal processing techniques

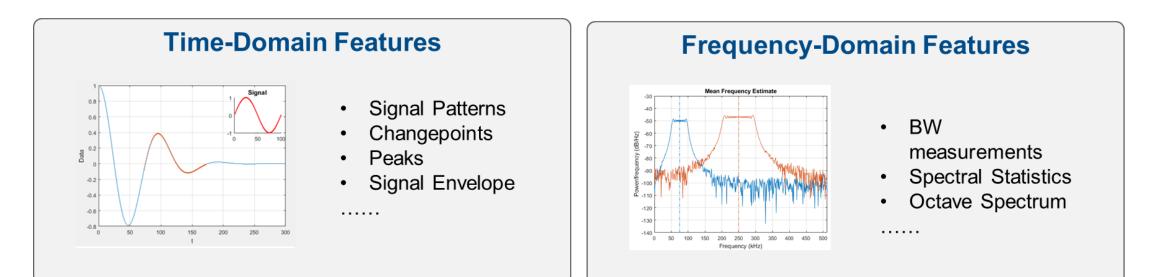




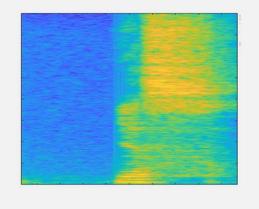
MATLAB **EXPO**



Feature extraction with signal processing techniques



Time-Frequency features

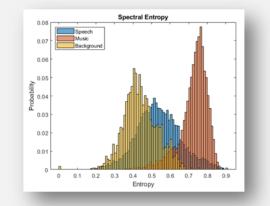


- STFT
- CWT

.....

Constant-Q Transform

Domain-Specific Features



- Speech and audio
- Navigation and Sensor Fusion
- Radar
- Communication

.....



Building the AI models

AI Modeling





Hardw
accele





Building the AI models

Al Modeling



Model design and tuning



Hardware accelerated training



Q. How do I select the right model for my application:

Building the AI models

Al Modeling



Model design and tuning



Hardware
 accelerated training



Q. How do I select the right model for my application:
If I do not have enough data?
If I do not have domain expertise?
If I need an easily interpretable model?

Start by using published literature and MATLAB examples





Start by using published literature and MATLAB examples

Deep Neural Network Architectures for Modulation Classification Xiaoyu Liu, Diyu Yang, and Aly El Gamal Automatic Modulation Recognition Using Wavelet School of Electrical and Computer Engineering Purdue University Email: {liu1962, yang1467, elgamala}@purdue.edu Transform and Neural Networks in Wireless Systems Abstract-In this work, we investigate the value of employ- convolutional neural networks (CNN) to the task of radio K. Hassan, I. Dayoub, W. Hamouda 🗠 & M. Berbineau ing deep learning for the task of wireless signal modulation modulation recognition [1] recognition. Recently in [1], a framework has been by generating a dataset using GNU radio that 2010, Article number: 532898 (2010) Cite this article fections in a real wireless channel, and uses Time-Frequency Analysis based Blind Modulation Classification for Multiple-Antenna modulation types. Further, a convolutional neural ne architecture was developed and shown to deliver **1**etrics Systems that exceeds that of expert-based approaches. He ∞ the framework of [1] and find deep neural network that deliver higher accuracy than the state of the s the architecture of [1] and found it to achieve an Weiheng Jiang^a, Xiaogang Wu^a, Bolin Chen^a, Wenjiang Feng^a, Yi Jin^b roximately 75% of correctly recognizing the mo We first tune the CNN architecture of [1] and [^aSchool of Microelectronics and Communication Engineering, Chongqing University, Chongqing 400044, China. with four convolutional layers and two dense layer ^bXi'an Branch of China Academy of Space Technology, Xi'an 710100, China an accuracy of approximately 83.8% at high SN develop architectures based on the recently introd V int characteristics used in signal waveform Residual Networks (ResNet [2]) and Densely Connec (DenseNet [3]) to achieve high SNR accuracies of a or automatic digital modulation recognition is 83.5% and 86.6%, respectively. Finally, we introdu lutional Long Short-term Deep Neural Network (C ed using higher-order statistical moments (HOM) achieve an accuracy of approximately 88.5% at his Abstract a features set. A multilayer feed-forward neural Blind modulation classification is an important step to implement cognitive radio networks. The multiple-input multiple-output I. INTRODUCTION (MIMO) technique is widely used in military and civil communication systems. Due to the lack of prior information about channel tion learning algorithm is proposed as a classifier. 3 Signal modulation is an essential process in w parameters and the overlapping of signals in the MIMO systems, the traditional likelihood-based and feature-based approaches rent M-ary shift keying modulation schemes and munication systems. Modulation recognition ta cannot be applied in these scenarios directly. Hence, in this paper, to resolve the problem of blind modulation classification in erally used for both signal detection and demod MIMO systems, the time-frequency analysis method based on the windowed short-time Fourier transform is used to analyse the nal information. Pre-processing and features signal transmission can be smoothly processed or time-frequency characteristics of time-domain modulated signals. Then the extracted time-frequency characteristics are converted signal receiver demodulates the signal correctly, H analysis is used to reduce the network complexity , into RGB spectrogram images, and the convolutional neural network based on transfer learning is applied to classify the modulation the fast development of wireless communication types according to the RGB spectrogram images. Finally, a decision fusion module is used to fuse the classification results of all The proposed algorithm is evaluated through and more high-end requirements, the number of methods and parameters used in wireless commu the receive antennas. Through simulations, we analyse the classification performance at different signal-to-noise ratios (SNRs). pability. The proposed classifier is shown to be tems is increasing rapidly. The problem of how the results indicate that, for the single-input single-output (SISO) network, our proposed scheme can achieve 92.37% and 99.12% modulation methods accurately is hence becomin - average classification accuracy at SNRs of -4 dB and 10 dB, respectively. For the MIMO network, our scheme achieves 80.42% me with high accuracy over wide signal-to-noise lenging and 87.92% average classification accuracy at -4 dB and 10 dB, respectively. This outperforms the existing classification methods Traditional modulation recognition methods us Gaussian noise (AWGN) and different fading based on baseband signals. prior knowledge of signal and channel parameter be inaccurate under mild circumstances and need Keywords: Time-Frequency Analysis, Blind Modulation Classification, Multiple-Antenna Systems, RGB Spectrogram Image ered through a separate control channel. Hence, autonomous modulation recognition arises in wire where modulation schemes are expected to chang → 1. Introduction fast modulation classification and blind modulation classificaas the environment changes. This leads to cons modulation recognition methods using deep neur tion (BMC). By contrast, the FB approaches cannot obtain the The increase in communication demands and the shortage Deep Neural Networks (DNN) have played a sig optimal result, but they have lower computational complexity of spectrum resources has caused the cognitive radio (CR) and and do not require prior information. The FB methods usually multiple-input multiple-output (MIMO) techniques to be immultiple-input multiple-output (MIMO) techniques to be implemented in wireless communication systems. As one of the include two steps: feature extraction and classifier design. The higher-order statistics, instantaneous statistics, and other feaessential steps of CR, modulation classification (MC) is widely tures are calculated in the feature extraction. Then the nonular applied in both civil and military applications, such as specclassification methods, such as decision tree [7], support vector trum surveillance, electronic surveillance, electronic warfare, machine [8] [9], and artificial neural network (ANN) [10] [11] and network control and management [1]. It improves radio are adopted as the classifiers. > spectrum utilisation and enables intelligent decision-making for With the rapid rise of artificial intelligence and the emergcontext-aware autonomous wireless spectrum monitoring sysing requirements of intelligent wireless communication, deep tems [2]. However, most of the existing MC methods are folearning-based approaches are now becoming widely studied cussed on single-input single-output (SISO) scenarios, which and used in different aspects of wireless communication, such cannot be directly applied when multiple transmit antennas are as the transceiver design at the physical layer [12] and BMC equipped at the transceivers [3]. Therefore, it is crucial to reproblems [13] [14] [15] [16] [17] [18]. As for BMC in SISO search the performance of the MC method for MIMO commuscenarios, the raw in-phase and quadrature phase (IQ) data or nication systems the time-domain amplitude and phase data can be directly used Traditional MC approaches for the SISO systems discussed as the input of the deep learning neural network. More specifin the literature can be classified into two main categories: likelihood cally, the authors in [13] presented convolutional long short-



Start by using published literature and MATLAB examples

Deep Neural Network Architectures for Modulation Normal Signa Classification Xiaoyu Liu, Diyu Yang, and Aly El Gamal Automatic Modulation Recognition Using Wavelet School of Electrical and Computer Engineering Purdue Universit Email: {liu1962, yang1467, elgamala}@purdue.edu Transform and Neural Networks in Wireless Systems AFib Sign. Abstract-In this work, we investigate the value of employ- convolutional neural networks (CNN) to the task of radio K. Hassan, I. Dayoub, W. Hamouda 🗠 & M. Berbineau ing deep learning for the task of wireless signal modulation modulation [1]. recognition. Recently in [1], a framework has been by generating a dataset using GNU radio that 2010, Article number: 532898 (2010) Cite this article fections in a real wireless channel, and uses Time-Frequency Analysis based Blind Modulation Classification for Multiple-Antenna 15 modulation types. Further, a convolutional neural ne 4 architecture was developed and shown to deliver **1**etrics Systems that exceeds that of expert-based approaches. He the framework of [1] and find deep neural network ∞ **Classify ECG Signals** Waveform Segmentation Iterative Approach for that deliver higher accuracy than the state of the a Using Long Short-Term Creating Labeled Signal the architecture of [1] and found it to achieve an Using Deep Learning Weiheng Jiang^a, Xiaogang Wu^a, Bolin Chen^a, Wenjiang Feng^a, Yi Jin^b oximately 75% of correctly recognizing the mo Sets with Reduced Huma... Memory Networks We first tune the CNN architecture of [1] and [^aSchool of Microelectronics and Communication Engineering, Chongqing University, Chongqing 400044, China. with four convolutional layers and two dense layers ^bXi'an Branch of China Academy of Space Technology, Xi'an 710100, China an accuracy of approximately 83.8% at high SN Use deep learning to decrease the develop architectures based on the recently introd Classify heartbeat electrocardiogram Segment human electrocardiogram V nt characteristics used in signal waveform Residual Networks (ResNet [2]) and Densely Conne (DenseNet [3]) to achieve high SNR accuracies of a data using deep learning and signal signals using time-frequency human effort required to label or automatic digital modulation recognition is 83.5% and 86.6%, respectively. 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This outperforms the existing classification methods 100 H H 17084 Traditional modulation recognition methods us Gaussian noise (AWGN) and different fading based on baseband signals. prior knowledge of signal and channel parameter be inaccurate under mild circumstances and need Keywords: Time-Frequency Analysis, Blind Modulation Classification, Multiple-Antenna Systems, RGB Spectrogram Image ered through a separate control channel. Hence, autonomous modulation recognition arises in wire 1 1.5 2 2.5 3 3.5 4 4.5 Seconds where modulation schemes are expected to chang → 1. Introduction fast modulation classification and blind modulation classificaas the environment changes. This leads to cons modulation recognition methods using deep neur tion (BMC). 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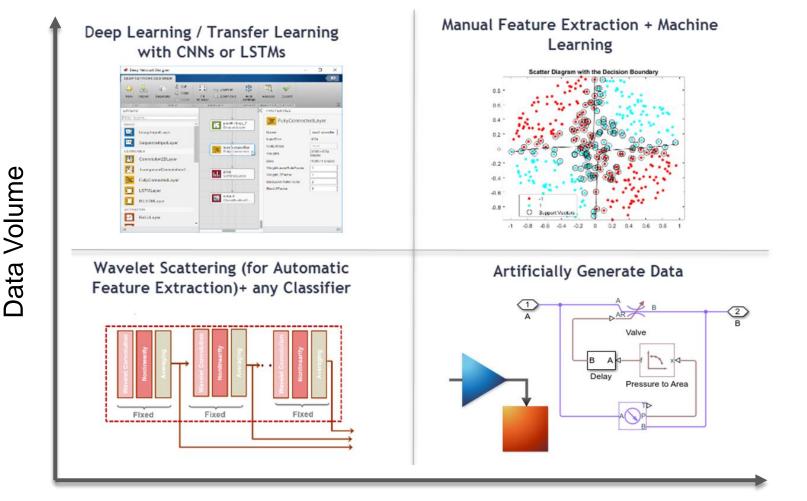
Understanding tradeoffs for model selection







Understanding tradeoffs for model selection

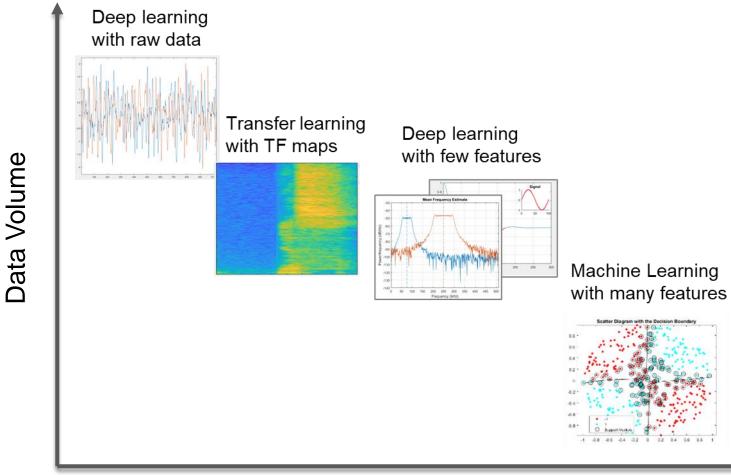


Time Required





Understanding tradeoffs for model selection



Signal Processing / Domain Knowledge









imageInputLayer([2 spf 1], 'N 'Input Layer') convolution2dLayer(filterSize 'Name', 'CNN1') batchNormalizationLayer('Name reluLayer('Name', 'ReLU1') maxPooling2dLayer(poolSize, Max Ponlilin

fitcauto/fitrauto

Writing code





2

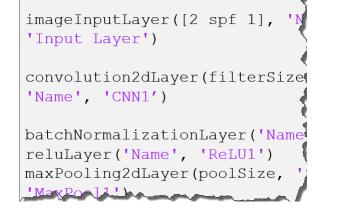
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fitcauto/fitrauto

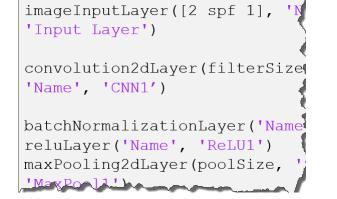
A Deep Network Designe 🖌 Cut 💽 🕄 🔍 Zoom In - 🚔 -III (pool2-3x3_s2 maxPoolino2d imageInputLayer v v Inception_3a-... convolution2d.... mage3dInputLay inception_3a-r... inception_3a... convolution2dL... inception_3a-... convolution2dL inception_3a-... convolution2d inception_3a+... transposedConv2dLave inception_3a-... depthConcaten ... 📉 📲 osedConv3dLave 1.1 💮 Tree Last charge: Filte Tree Accuracy: 94.0% 44 features 1.2 🚖 Tree Last change: Mediur Accuracy: 94.0% 44 features Accuracy: 94.0% 4H features 3 🗇 Tree Accuracy: 98.0% 4/4 features st change: Linear Dis Accuracy: 97.3% 4/4 features 1.6 💠 Naive Baver Accuracy: 94,7% 4/4 features Accuracy: 96.0% 414 features f 🏫 Naive Bayes st charge: Kernel N Accuracy: 96.7% 1.8 ☆ SVN odel 1.4: Traine 4.5 6 6.5 SepalLength 7.5 5.5

Writing code

Interactively Design Models with Apps







fitcauto/fitrauto

A Deep Network Designer		
Deep Network Designer		
👍 🗋 🐇 Cut 🔝 @ Zoom		
🕼 Paste to View	Arrange 👻	
NETWORK BUILD NAVIGATE	LAROUT ANALYSIS DRPORT Designer Data Training O	
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Writing code

Interactively Design Models with Apps

Use Transfer Learning for Deep Learning





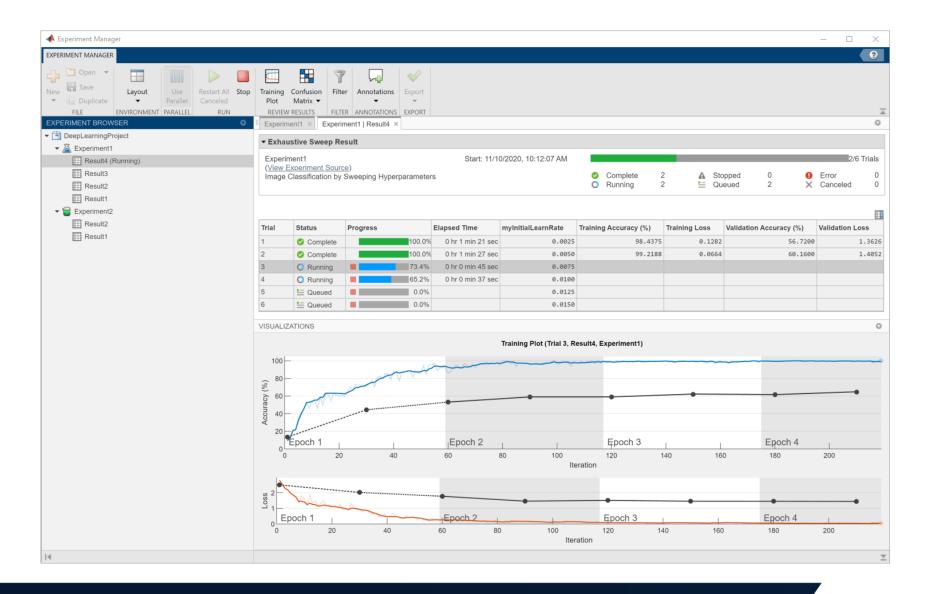




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MATLAB EXPO





Find optimal training options





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Find optimal training options

Compare the results of using different data sets





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MATLAB EXPO

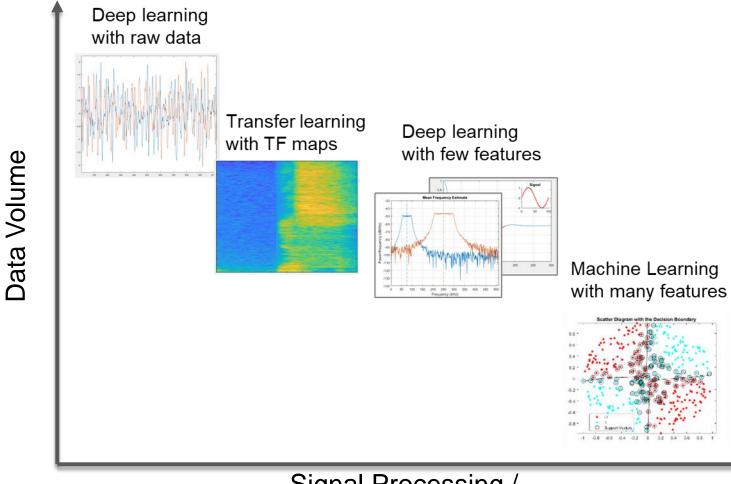
Find optimal training options

Compare the results of using different data sets

Compare the results of using different models



Selecting the Right Model : Understanding Tradeoffs

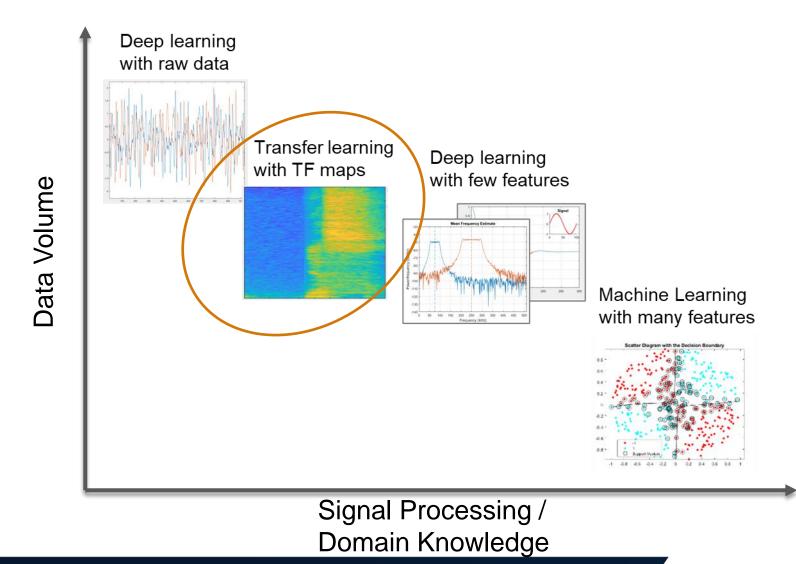


Signal Processing / Domain Knowledge





Selecting the Right Model : Understanding Tradeoffs





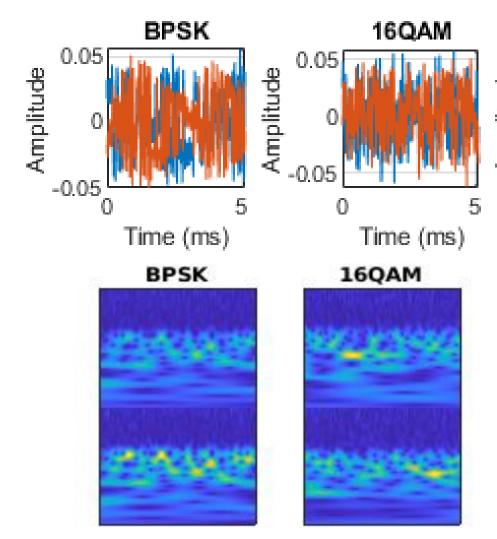






•One line of code for generating wavelet timefrequency visualization in MATLAB. Works for any signal

>> cwt(inputSignal)



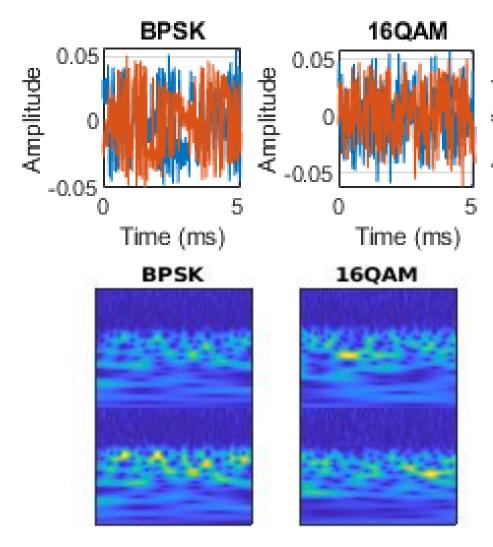




•One line of code for generating wavelet timefrequency visualization in MATLAB. Works for any signal

>> cwt(inputSignal)

 Localizes sharp transients and slowly varying oscillations simultaneously



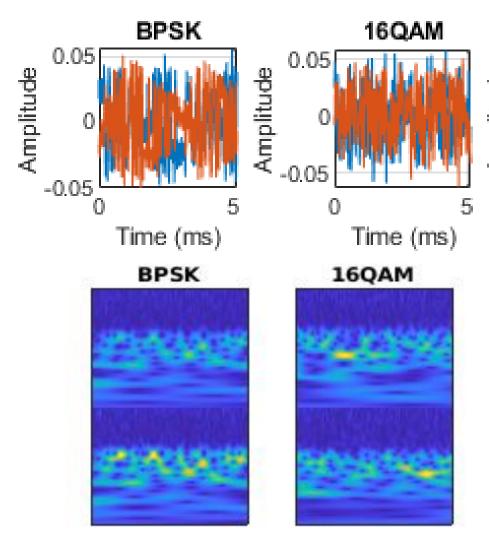




•One line of code for generating wavelet timefrequency visualization in MATLAB. Works for any signal

>> cwt(inputSignal)

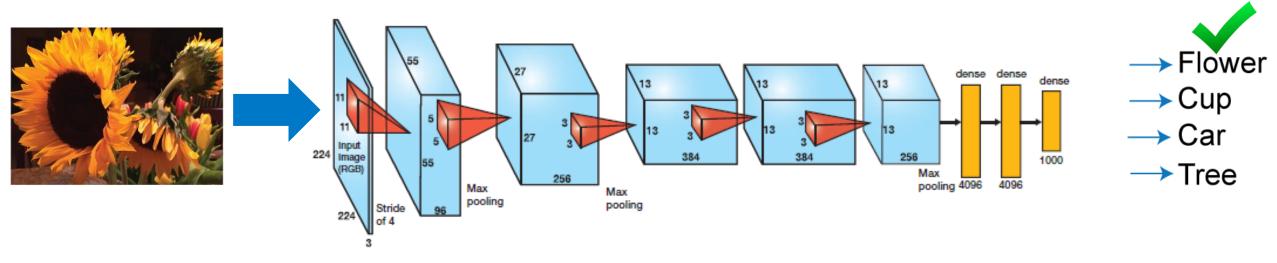
- Localizes sharp transients and slowly varying oscillations simultaneously
- Works with complex data





MATLAB EXPO

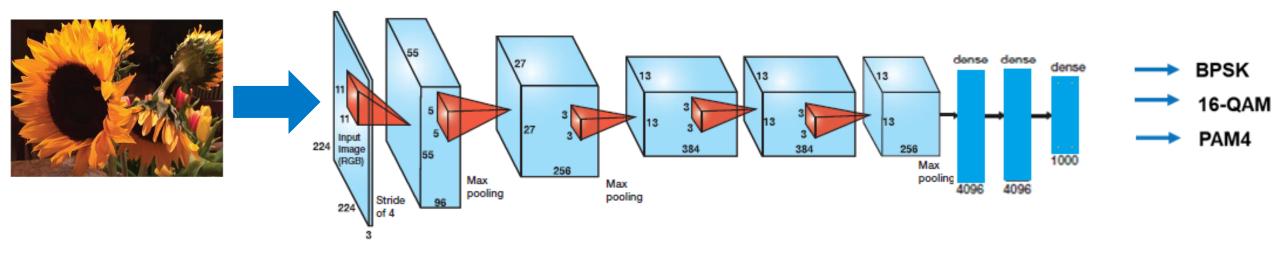
Using time-frequency maps as inputs to a pretrained CNN







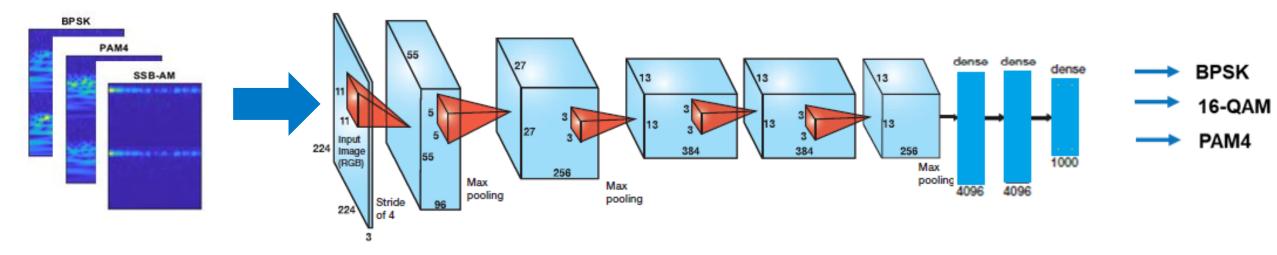
Using time-frequency maps as inputs to a pretrained CNN







Using time-frequency maps as inputs to a pretrained CNN







Transfer Learning with Deep Network Designer App

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Train and Test Deep Network

Training Progress (05-Mar-2021 12:18:33) \times Training Progress (05-Mar-2021 12:18:33) Training iteration 2 of 12260. ۲ 100 **Training Time** 90 05-Mar-2021 12:18:33 Start time: Elapsed time: 19 sec 80 **Training Cycle** 70 Epoch: 1 of 20 Accuracy (%) 60 Iterations per epoch: 613 50 12260 Maximum iterations: 40 Validation 50 iterations 30 Frequency: 20 Other Information Single GPU Hardware resource: 10 Epoch 1 Learning rate schedule: Constant 0 Learning rate: 0.0001 10 20 30 40 50 60 70 80 90 100 0 Iteration i Learn more Accuracy Training (smoothed) 3 ross 2 ----- Training - - - Validation Loss Training (smoothed) Epoch 1 0 ----- Training 30 40 50 70 90 10 20 60 80 100 0 Iteration - - - Validation



MATLAB EXPO

22

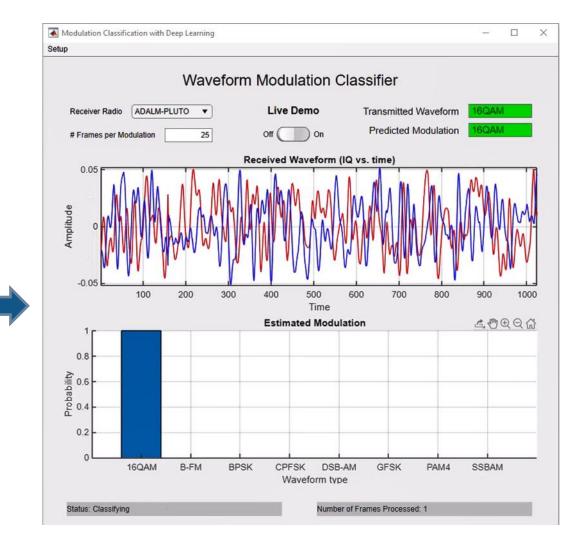
Test Deep Network

Confusion Matrix (overall accuracy: 0.9769) 16QAM 996 99.6% 0.4% 4 B-FM 1000 100.0% BPSK 993 99.3% 0.7% 7 CPFSK 997 3 99.7% 0.3% DSB-AM 919 81 91.9% 8.1% True Class GESK 999 1 99.9% 0.1% PAM4 28 972 97.2% 2.8% 6.1% SSB-AM 939 93.9% 61 100.0% 97.0% 100.0% 93.8% 100.0% 98.8% 92.1% 100.0% 3.0% 1.2% 7.9% 6.2% **BPSK** 16QAM **B-FM CPFSK** DSB-AM GFSK PAM4 SSB-AM Predicted Class

MATLAB EXPO



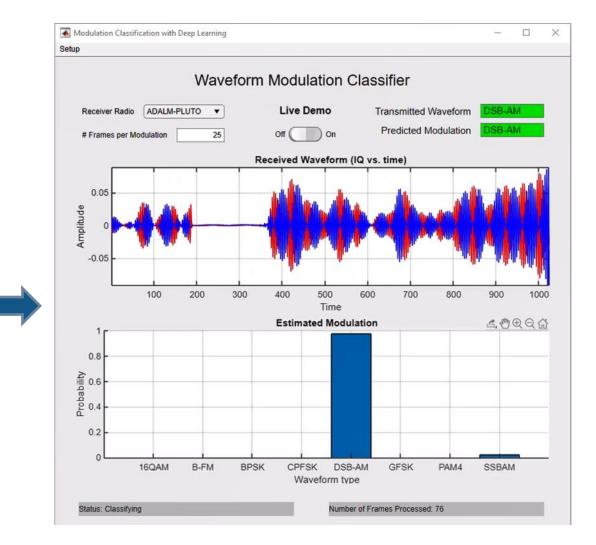








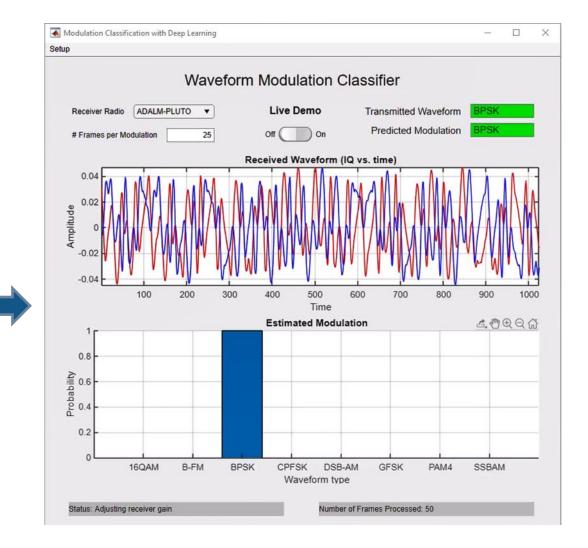








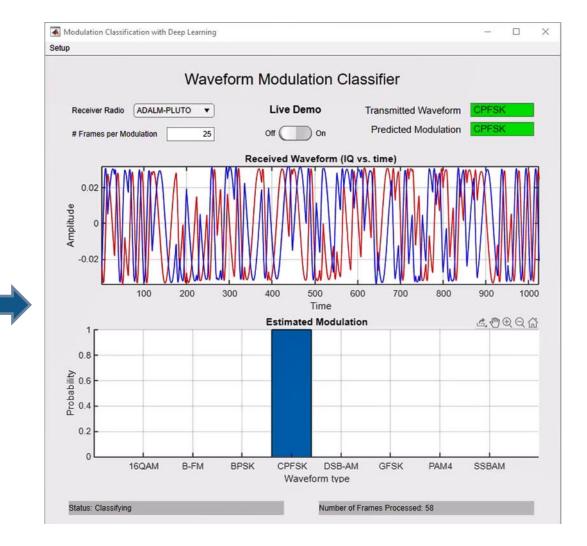
















Al-assisted system design

Data Preparation



Data cleansing and preparation



Human insight



Simulationgenerated data



Model design and tuning

AI Modeling



Hardware accelerated training



Deployment



Embedded devices



Enterprise systems

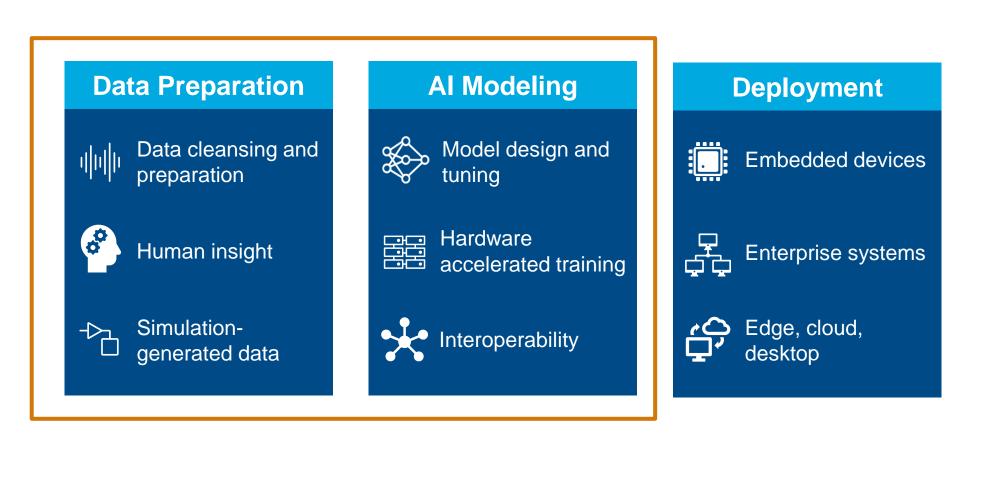


Edge, cloud, desktop





Al-assisted system design

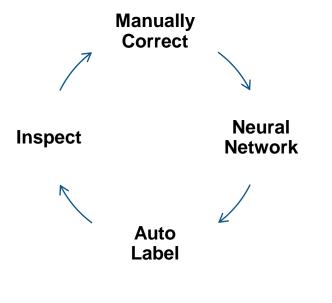








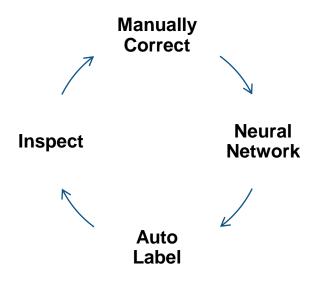




Labeling assistance



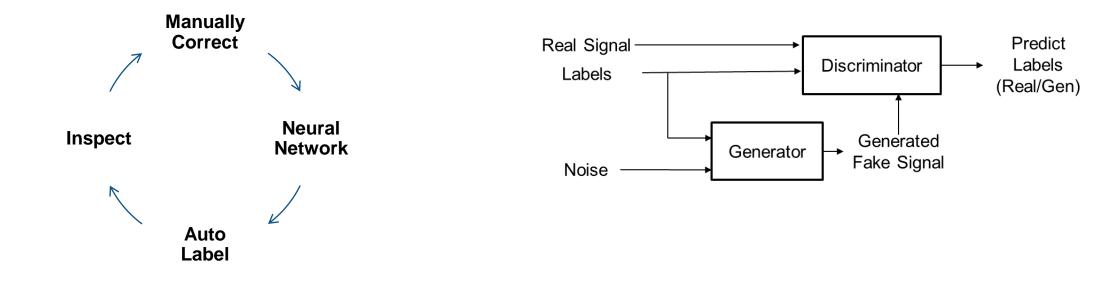




Labeling assistance classifySound (YAMNet),GoogLeNet, fitcecoc(ResNet18)



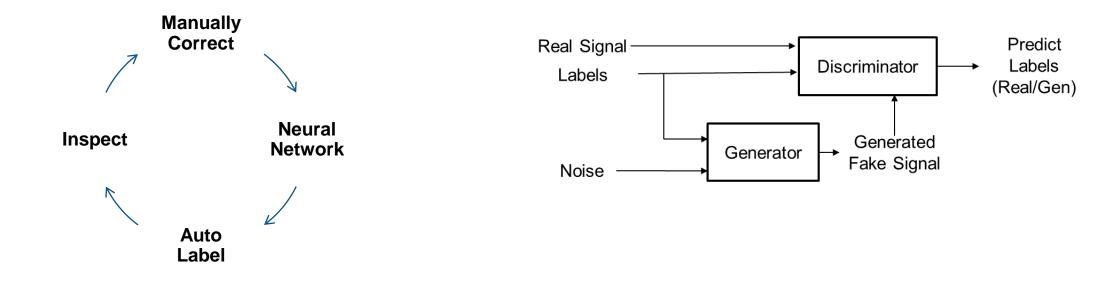




Labeling assistance classifySound (YAMNet),GoogLeNet, fitcecoc(ResNet18) Synthetic Data Generation







Labeling assistance classifySound (YAMNet),GoogLeNet, fitcecoc(ResNet18)

MATLAB EXPO

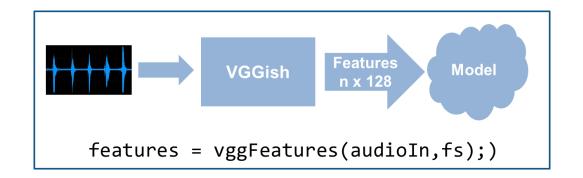
Synthetic Data Generation Generative Adversarial Networks (GANs)







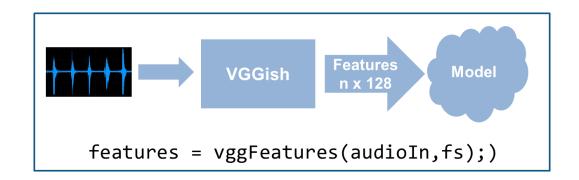


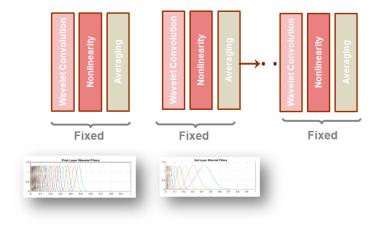


Feature Extraction





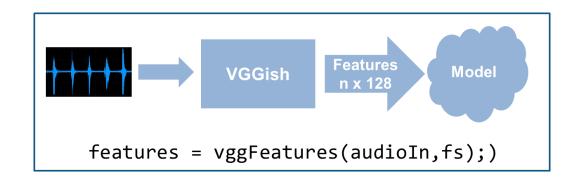


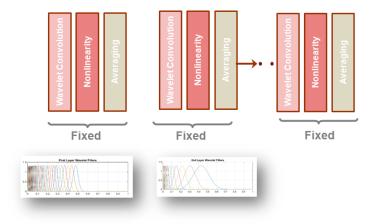


Feature Extraction







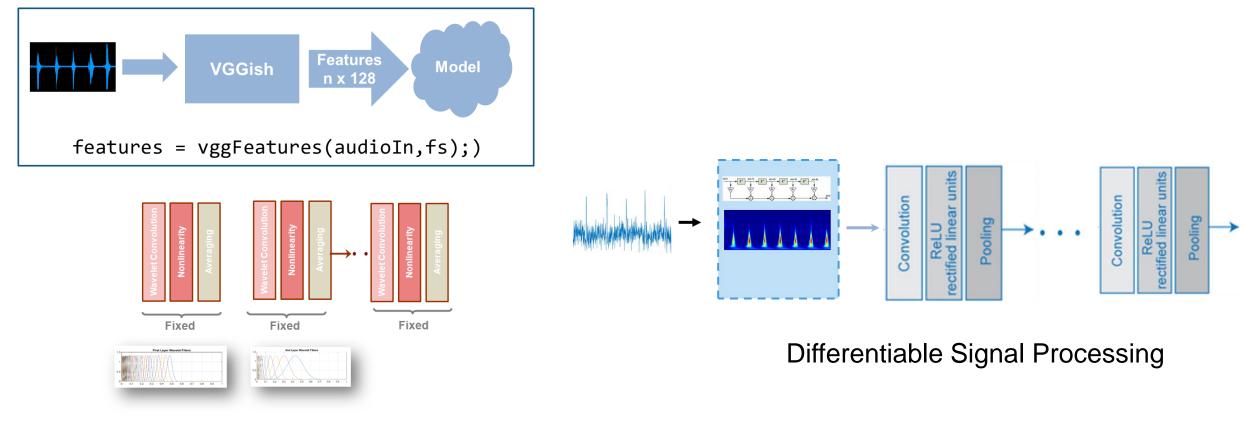


Feature Extraction

vggFeatures, waveletScattering



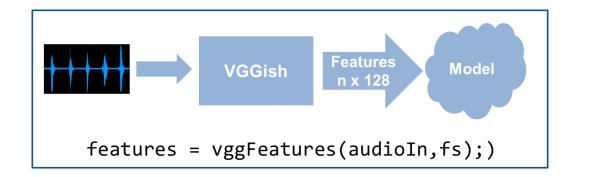


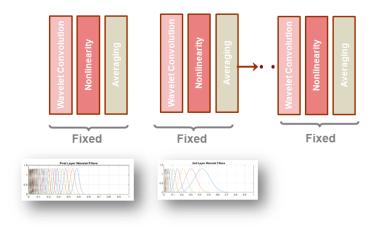


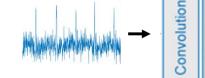
Feature Extraction

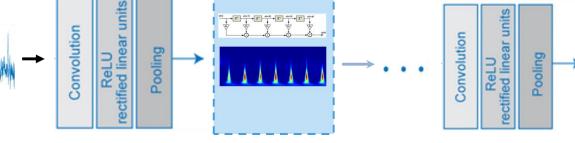
vggFeatures, waveletScattering









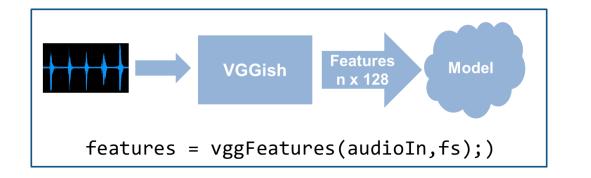


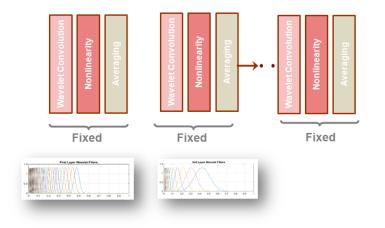
Differentiable Signal Processing

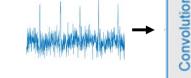
Feature Extraction

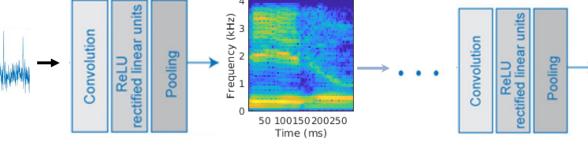
vggFeatures, waveletScattering











Differentiable Signal Processing

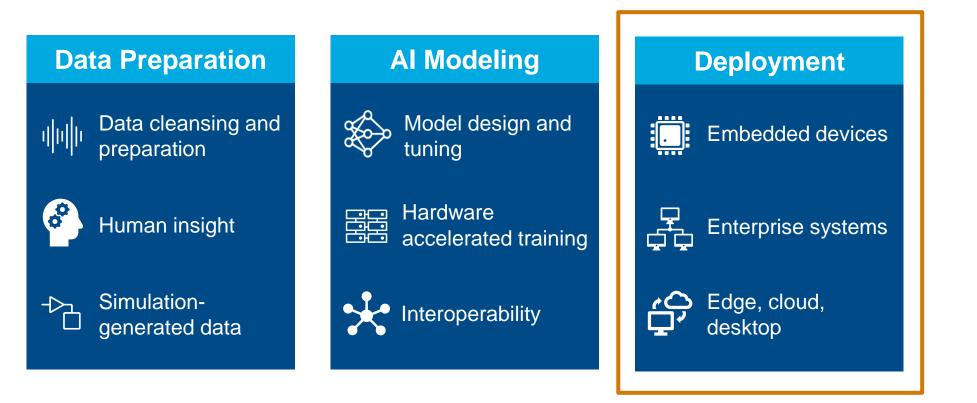
dlstft (Differentiable STFT)

Feature Extraction

vggFeatures, waveletScattering



Al-driven system design

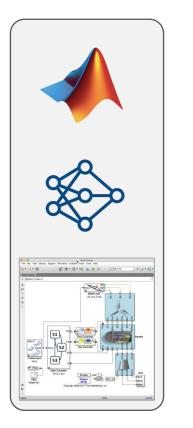








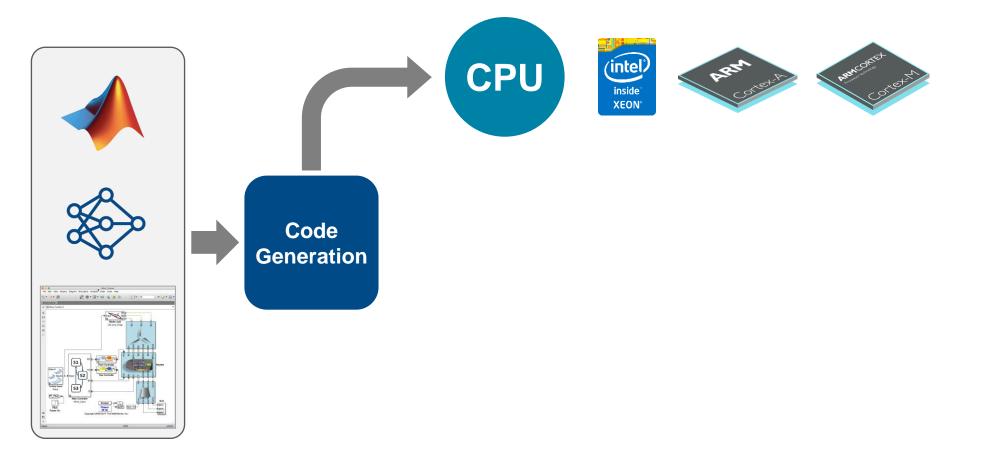




Preprocessing, Feature Extraction, Al Model

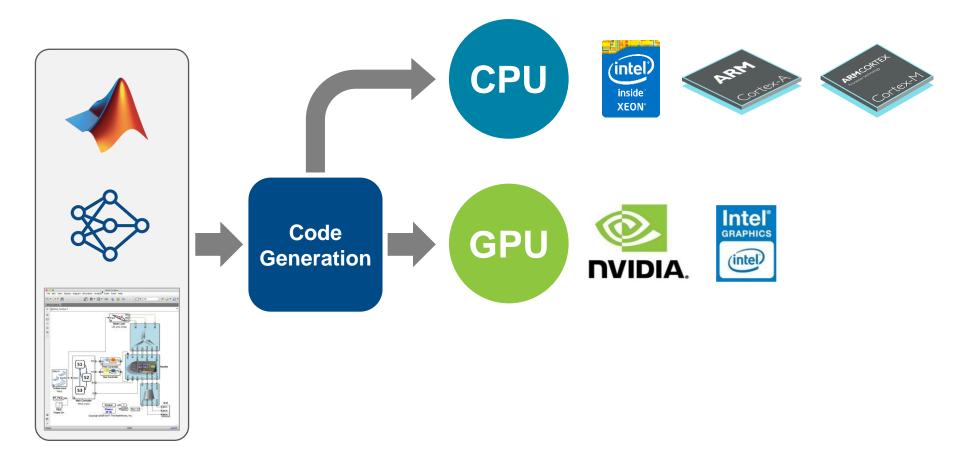






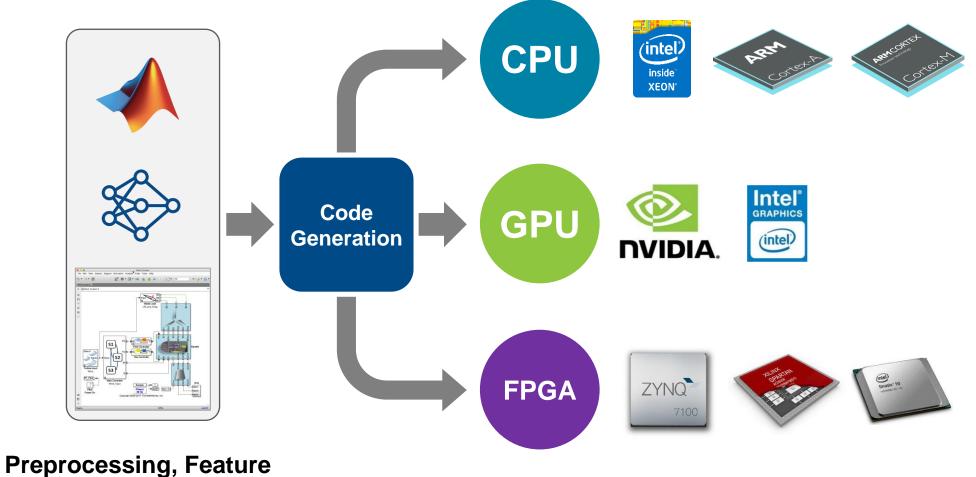
Preprocessing, Feature Extraction, AI Model





Preprocessing, Feature Extraction, AI Model

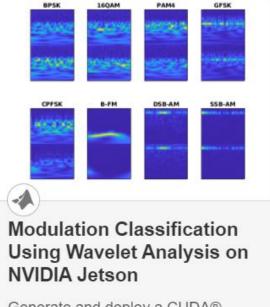




Extraction, Al Model



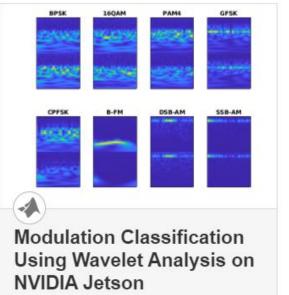




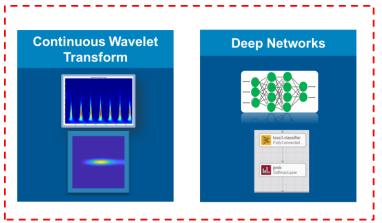
Generate and deploy a CUDA® executable that performs modulation classification using features extracted by the continuous wavelet





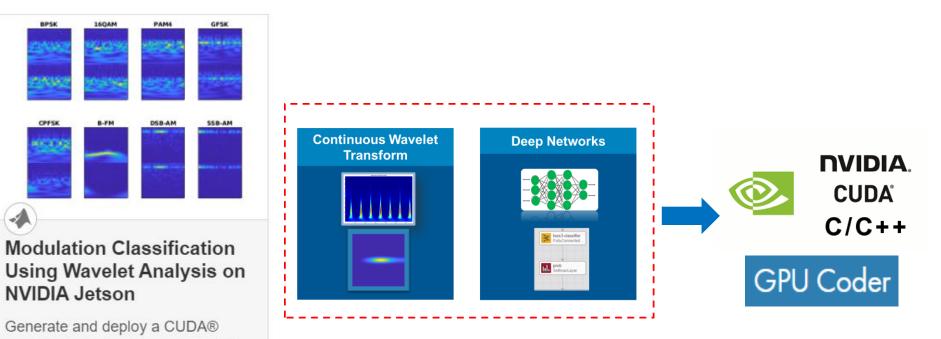


Generate and deploy a CUDA® executable that performs modulation classification using features extracted by the continuous wavelet





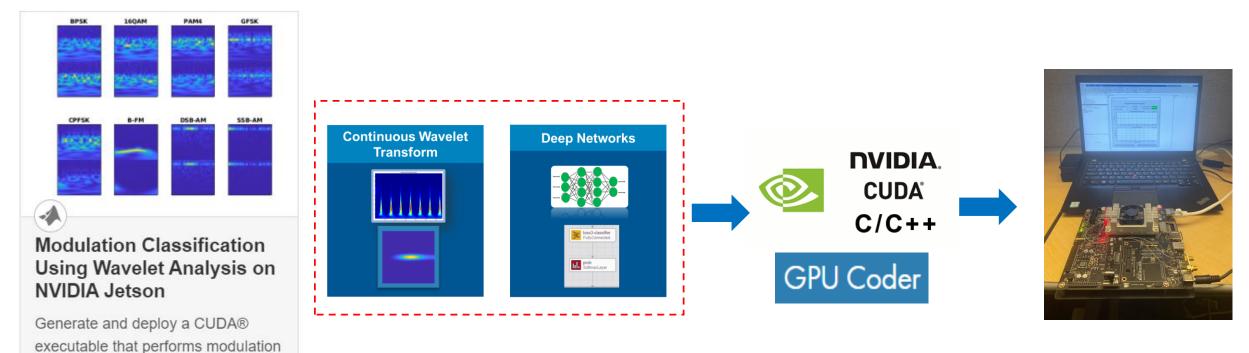




executable that performs modulation classification using features extracted by the continuous wavelet





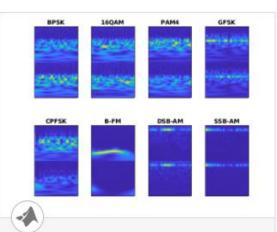




classification using features

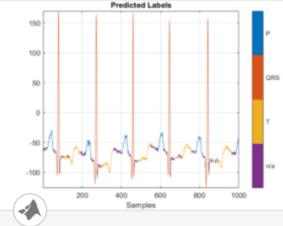
extracted by the continuous wavelet





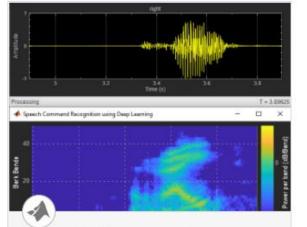
Modulation Classification Using Wavelet Analysis on NVIDIA Jetson

Generate and deploy a CUDA® executable that performs modulation classification using features extracted by the continuous wavelet



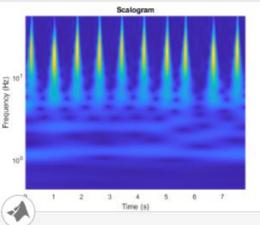
Deploy Signal Segmentation Deep Network on Raspberry Pi

Generate a MEX function and a standalone executable to perform waveform segmentation on a Raspberry Pi™.



Speech Command Recognition Code Generation with Intel MK...

Deploy feature extraction and a convolutional neural network (CNN) for speech command recognition on Intel® processors. To generate the



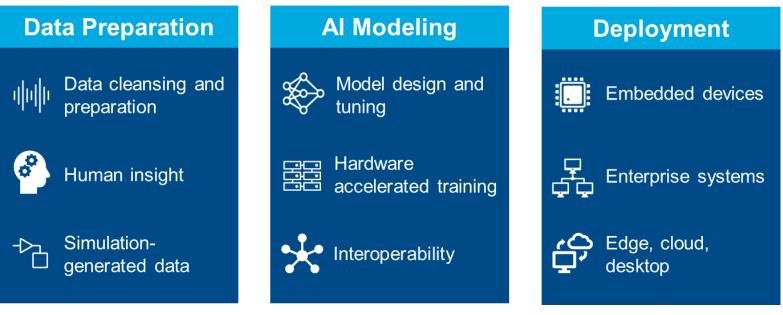
Classify ECG Signals Using DAG Network Deployed To FPGA

Classify human electrocardiogram (ECG) signals by deploying a trained directed acyclic graph (DAG) network.





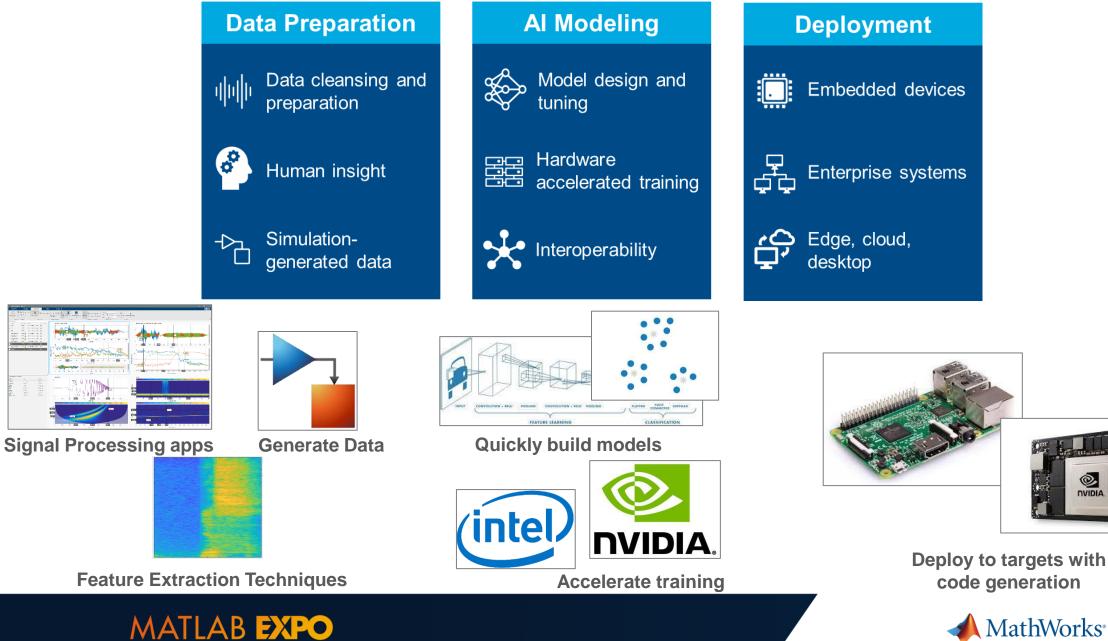
MATLAB supports the entire Al-driven system design







MATLAB supports the entire Al-driven system design





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