MATLAB EXPO 2019

AI Techniques in MATLAB for Signal, Time-Series, and Text Data

First name and surname

AI and Deep Learning for Signals in the News

Recommending music on Spotify with deep learning
AUGUST 05, 2014

This summer, I'm interning a

A Smart Stethoscope Puts AI in Medics' Ears

Engineers from Johns Hopkins reinvent the humble stethoscope to save lives

CNN   World » The biomedical smart jacket that diagnoses pneumonia using Bluetooth   Live TV ●   U.S. Edition +   🔍

smart jacket that
monia using Bluetooth

Deep Learning developed and evolved for image processing and computer vision applications.

It is now increasingly and successfully used on signals and time series

Video: Johns Hopkins University

Tech for a Noisy World: Researchers simulated an extremely noisy environment in the lab (the sound meter shows levels of around 70 decibels). They compared the audio heard through a top-notch commercial stethoscope, in which the breathing sounds are mixed with ambient noise, to that heard through the Johns Hopkins smart stethoscope, which uses active acoustic filtering to isolate the breathing sounds.

The Use of Deep Learning is Growing Across Industries

Aerospace, Defense and Communications

Communications devices, security
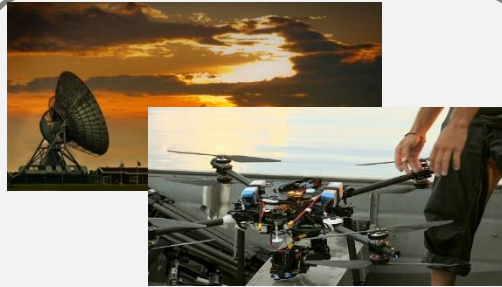
Multi-standard communications receivers, drone recognition

Consumer Electronics and Digital Health

Voice assistants

Digital health

Automotive

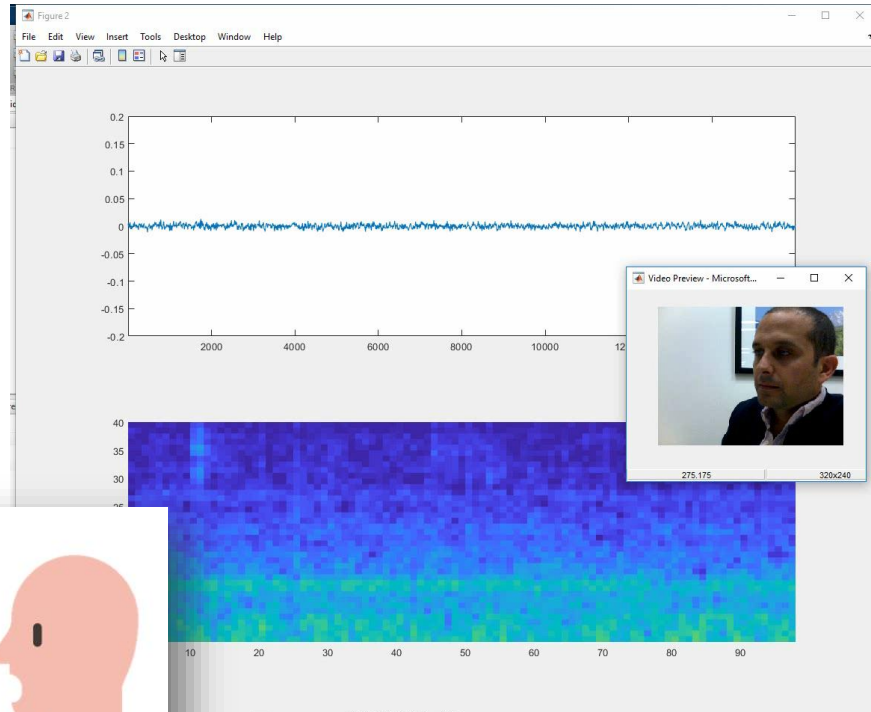**Voice control enabled Infotainment**

Sensor processing, automated driving
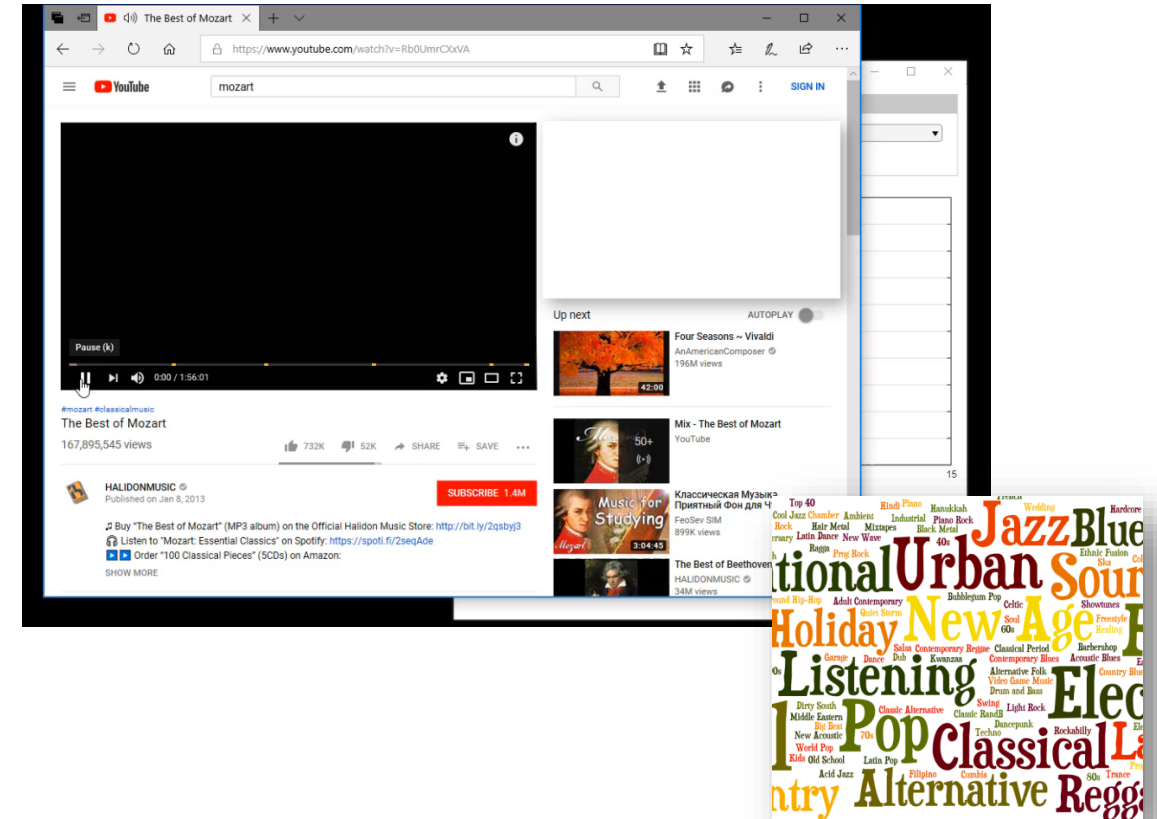
Industrial Automation

Condition monitoring

Predictive maintenance

MATLAB EXPO 2019

Application Examples Using MATLAB – Audio and Speech

Speech Command Recognition
(a.k.a. "Keyword Spotting")

https://www.mathworks.com/help/deeplearning/examples/deep-learning-speech-recognition.html
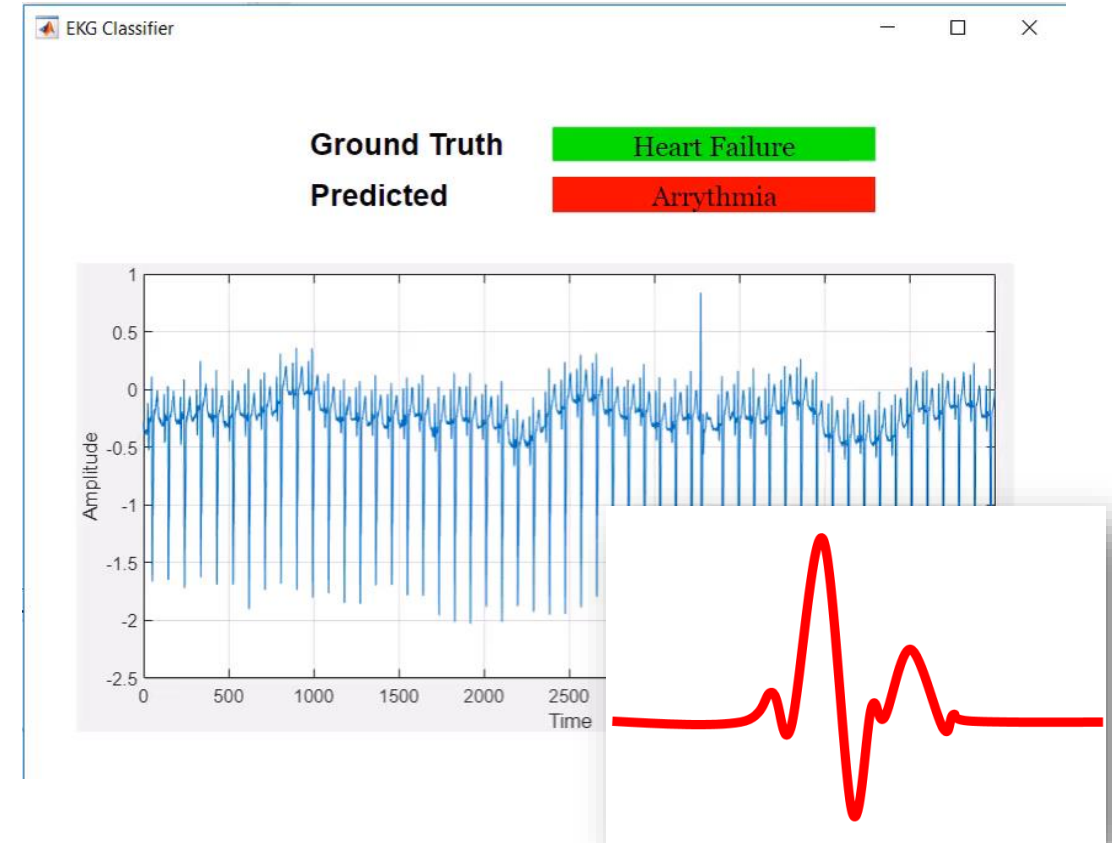

Music Genre Classification

https://www.mathworks.com/help/audio/examples/music-genre-classification-using-wavelet-time-scattering.html

Application Examples Using MATLAB – Industrial and physiological sensors
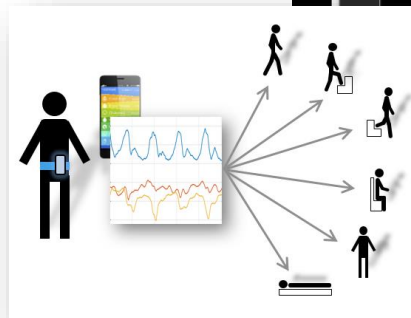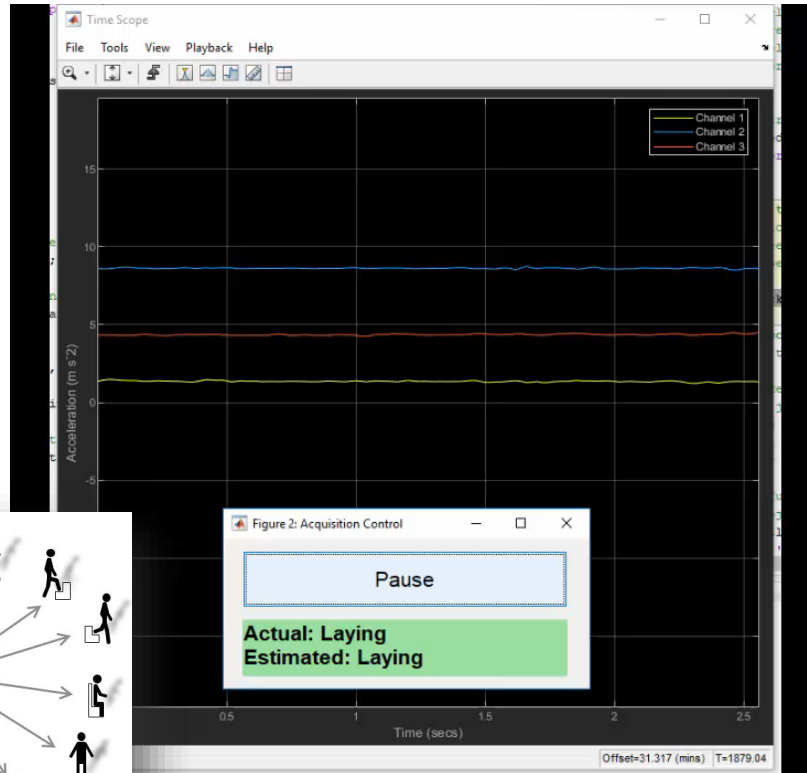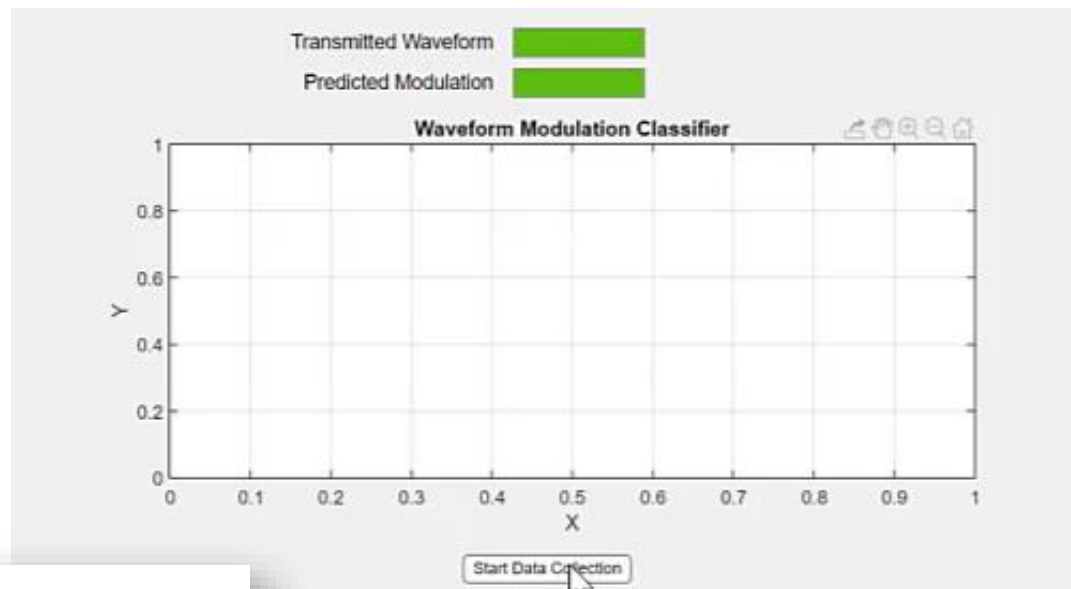

Human Activity Recognition

https://www.mathworks.com/help/deeplearning/examples/sequence-to-sequence-classification-using-deep-learning.html

ECG Signal Classification

https://www.mathworks.com/help/signal/examples/classify-ecg-signals-using-long-short-term-memory-networks.html

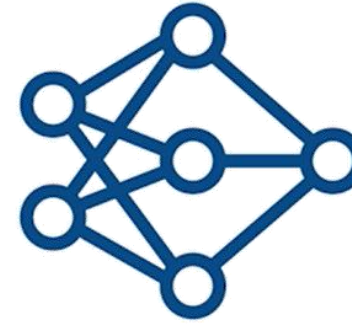# Application Examples Using MATLAB – Radar and Communications

Modulation Classification

http://www.mathworks.com/help/comm/examples/modulation-classification-with-deep-learning.html
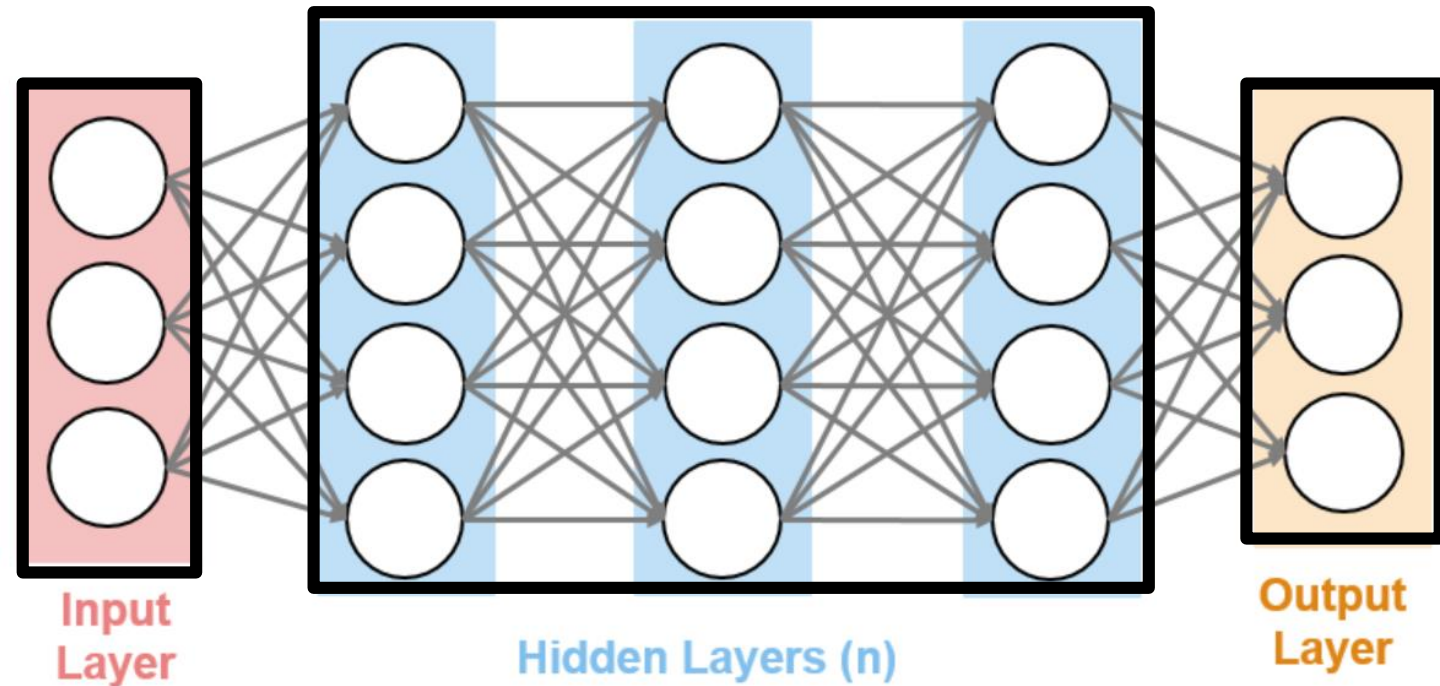
Agenda

- Deep Learning – Basic ideas

- Deep Learning Model Development for Signals, Time Series, and Text

- Conclusions

What is Deep Learning?
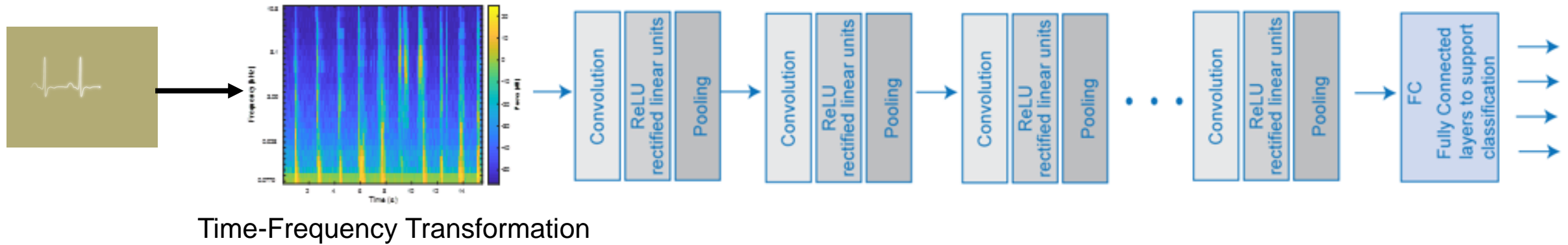
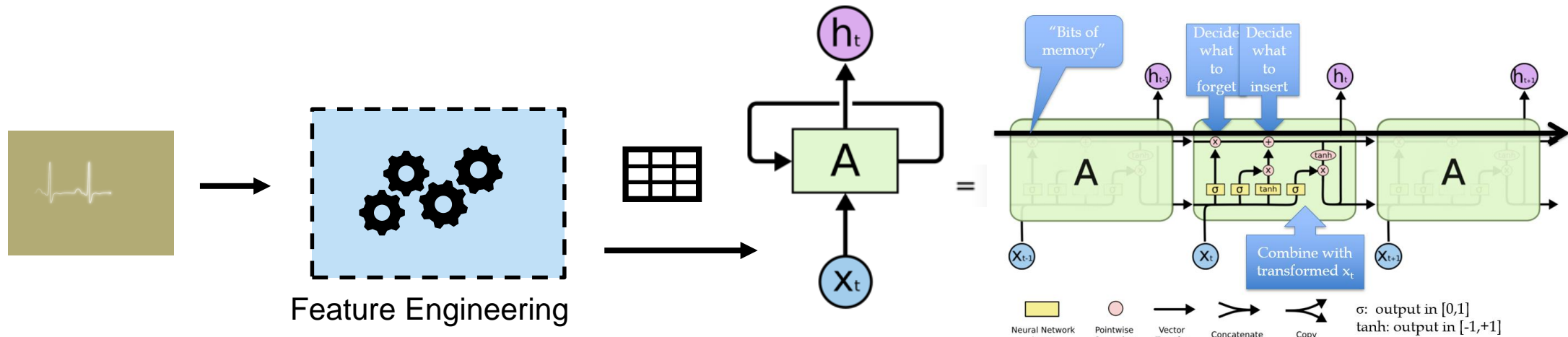Deep learning is a type of machine learning in which a model learns from examples.

Input Layer

Hidden Layers (n)

Output Layer

Common Network Architectures - Signal Processing

Convolutional Neural Networks (**CNN**)

Time-Frequency Transformation

Long Short Term Memory (**LSTM**) Networks

Feature Engineering

Common Network Architectures – Text Analytics

Convolutional Neural Networks (**CNN**)

Feature Engineering

Long Short Term Memory (**LSTM**) Networks

Feature Engineering

σ: output in [0,1]
tanh: output in [-1,+1]

Neural Network Layer | Pointwise Operation | Vector Transfer | Concatenate | Copy

Deep Learning Workflow

Deep Learning Workflow Challenges – Signals and Time Series

Data Labeling

Limited Data Availabiliy

Deep learning models only as good as training data

CREATE AND ACCESS DATASETS	PREPROCESS AND TRANSFORM DATA	DEVELOP PREDICTIVE MODELS	ACCELERATE AND DEPLOY
Data sources	Pre-Processing	Import Reference Models/ Design from scratch	Desktop Apps
Simulation and augmentation	Transformation	Hardware-Accelerated Training	Enterprise Scale Systems
Data Labeling	Feature extraction	Analyze and tune hyperparameters	Embedded Devices and Hardware

Domain-specific data processing desirable

Limited reference research

Deployment and Scaling to various platforms
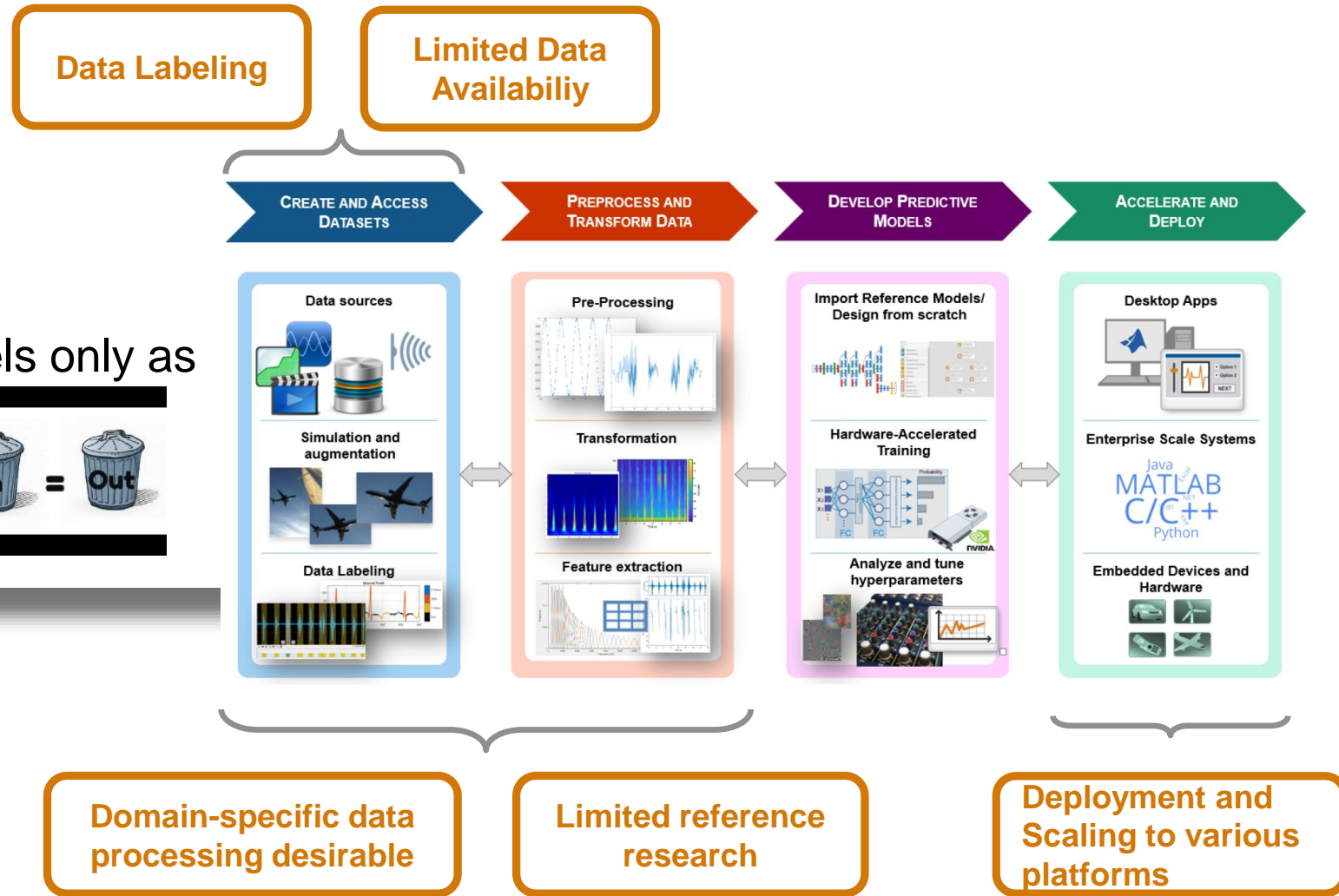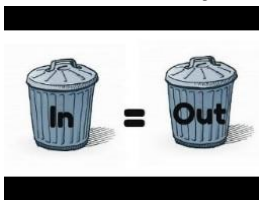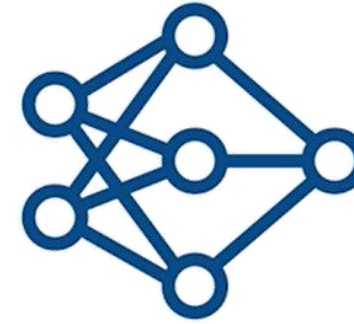
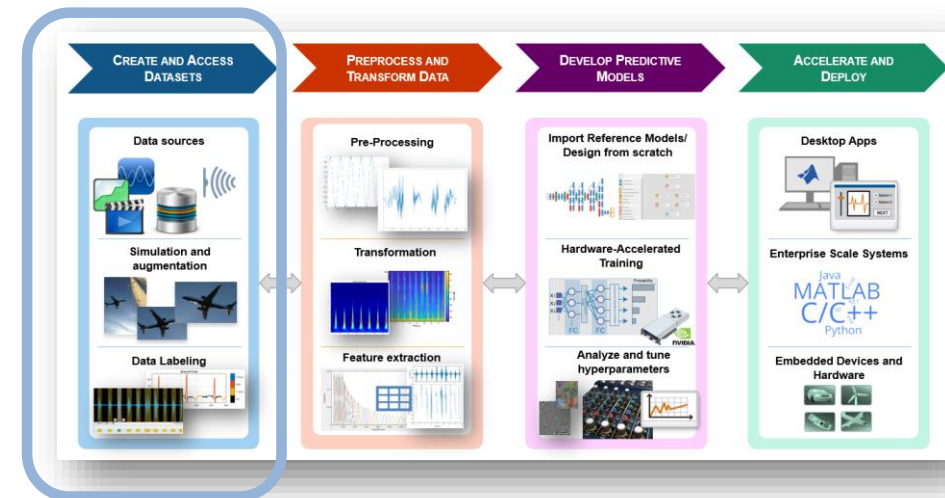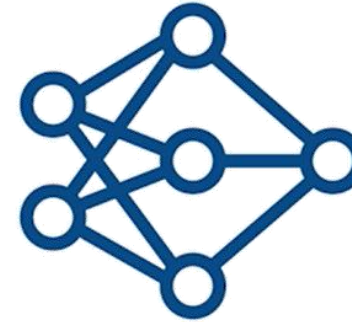# Agenda

- Deep Learning – Basic ideas

- **Deep Learning Model Development for Signals, Time Series, and Text**

  – Data

  – Processing and transformation

  – Model design and optimization

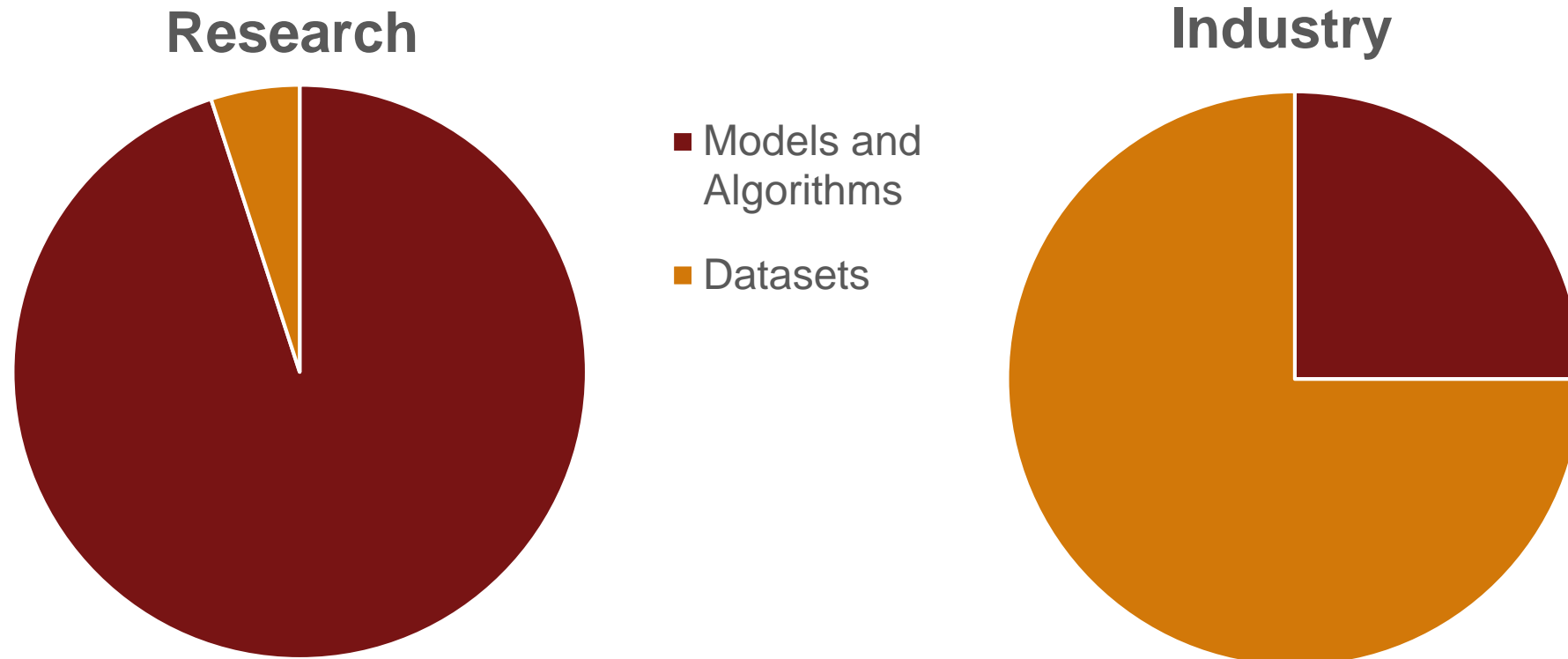 – Acceleration, prototyping, and deployment
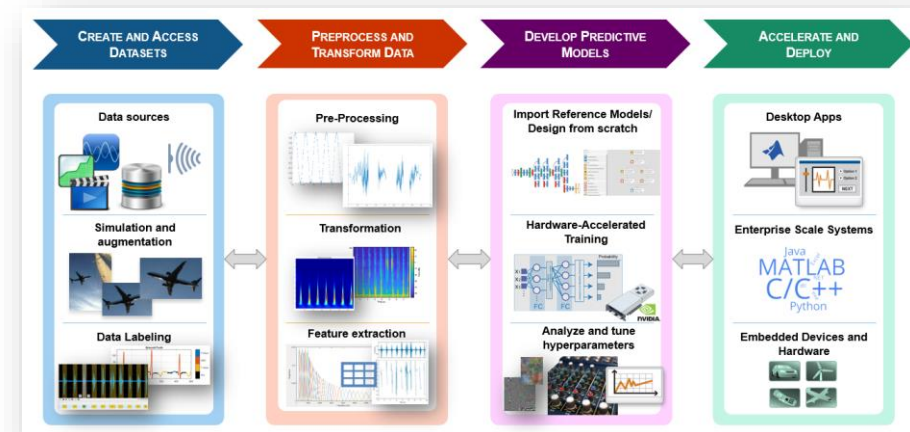
- Conclusions

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Current Investments – Models vs. Data

Research

Industry

- ■ Models and Algorithms
- ■ Datasets

From "Troubleshooting deep neural networks" (Josh Tobin et al., Jan 2019)

What does a large dataset look

How to navigate, index, read (a

audioDatastore

imageDatastore

fileDatastore

Custom Datastores

How to...

- Build a list of all data and labels?

- Review basic statistics about available data?

- Select data subsets without nested `for` loops, `dir`, `ls`, `what`, ... aplenty?

- Jointly read data and labels?

- Automatically distribute computations?
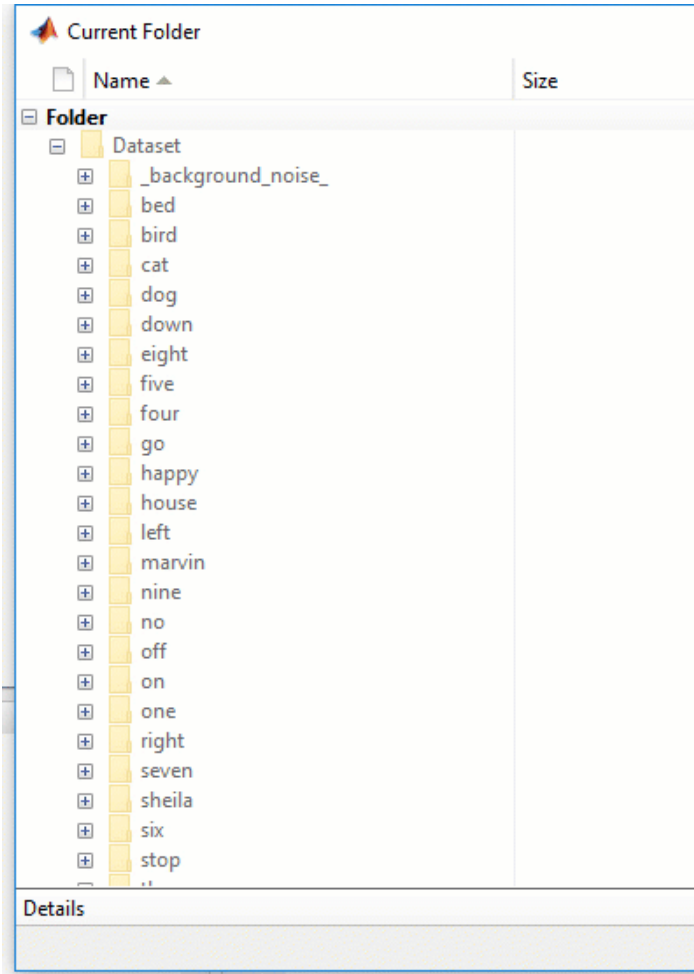
Label quality impacts model performance as much as the quality and quantity of the actual recordings
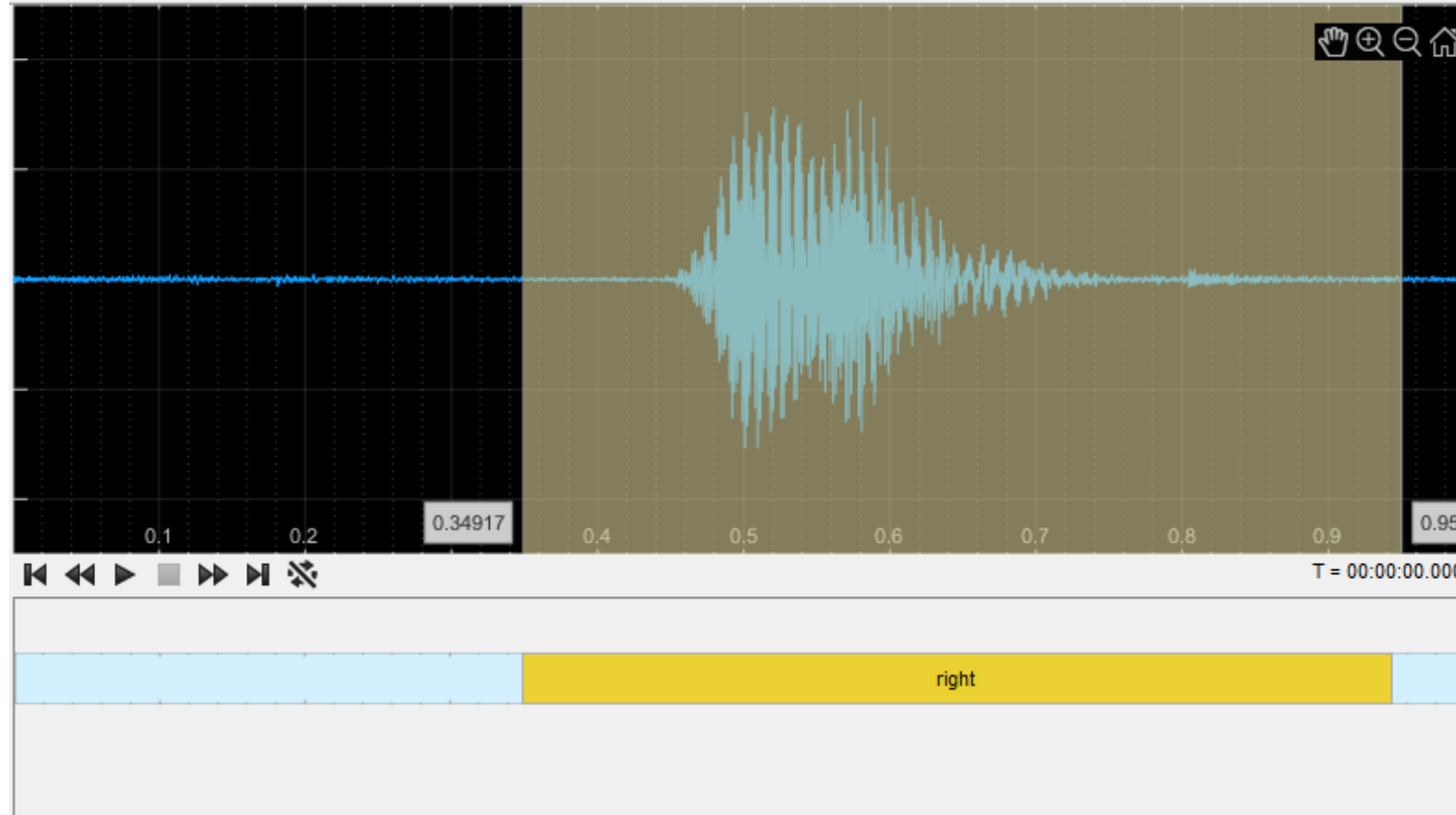
Use appropriate tools to help you label signals

- Programmatically…

- … or via Apps

What if available data isn't enough?

Original
Dataset

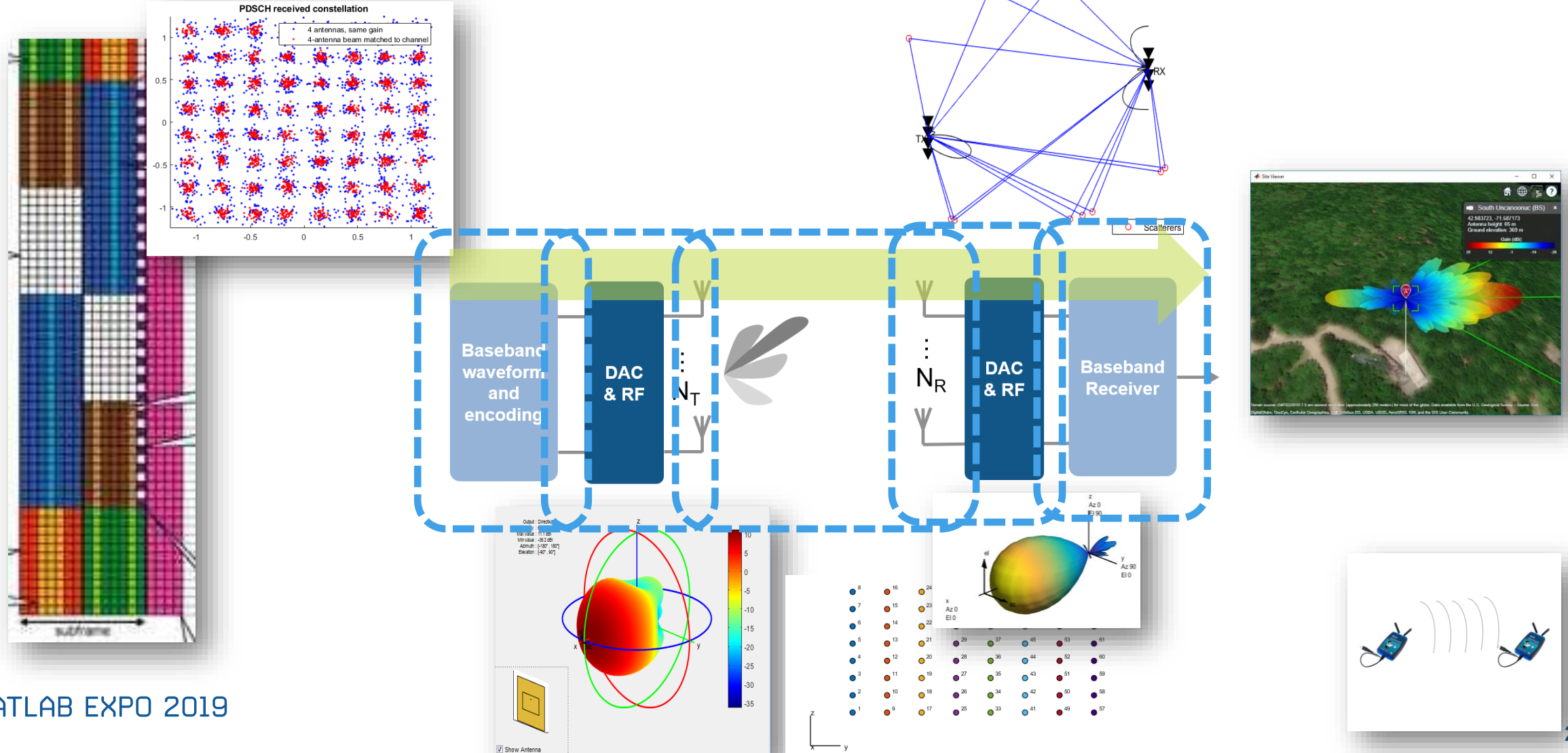Pitch shift

Time stretch

Add noise

Add reverberation

Augmented
Dataset

N times as
much data
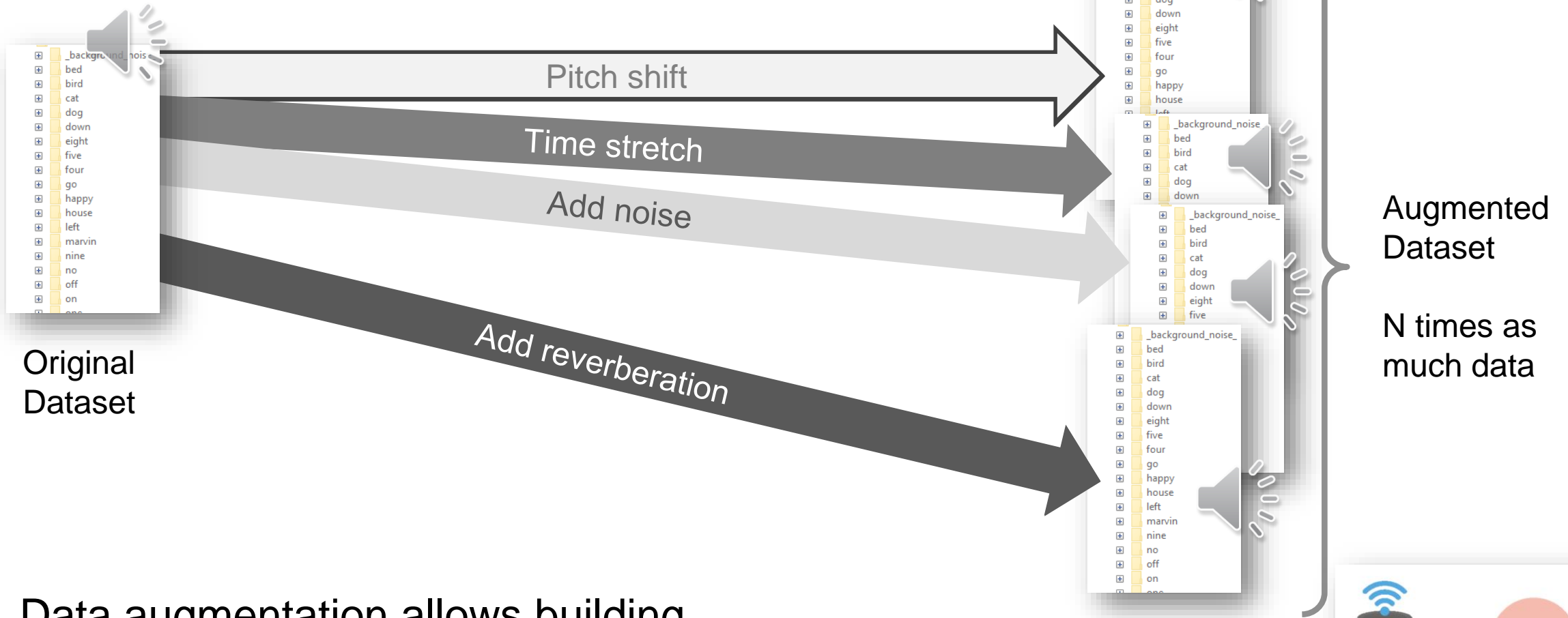
Data augmentation allows building
more complex and more robust models
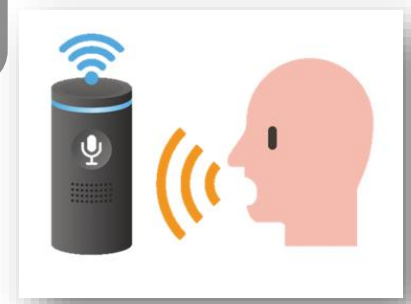
Simulation is key if recording and labelling real-world data is impractical or unreasonable – Communications Signals
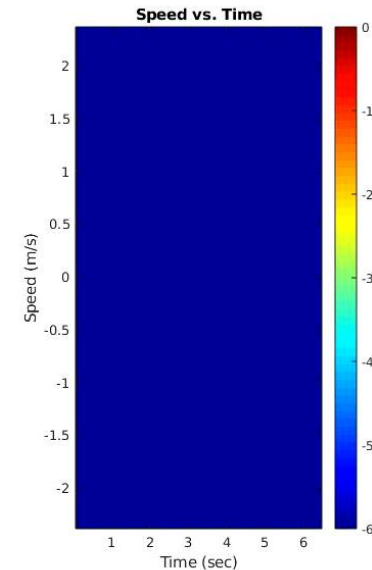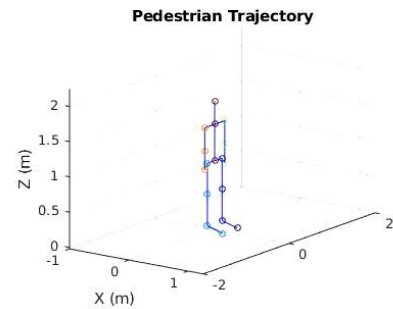

Baseband waveform and encoding

DAC & RF

N_T

N_R

DAC & RF

Baseband Receiver

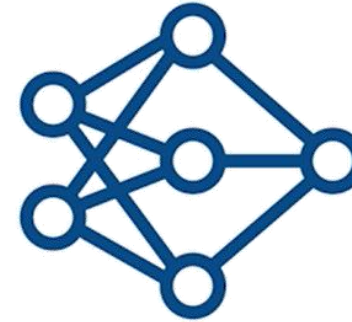# Simulation is key if recording and labelling real-world data is impractical or unreasonable – Radar Signals
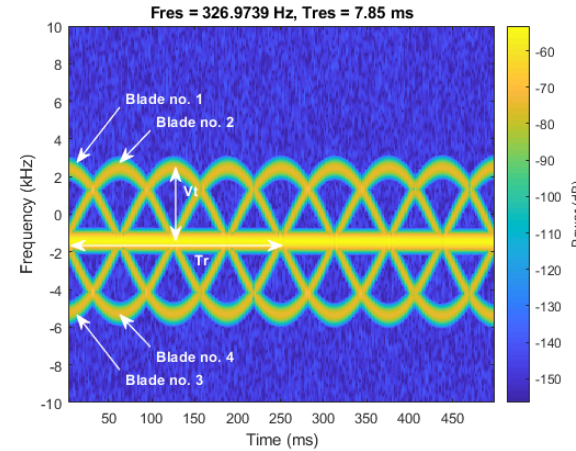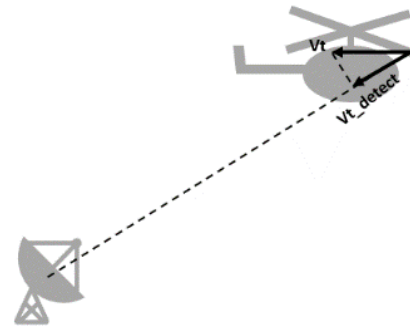
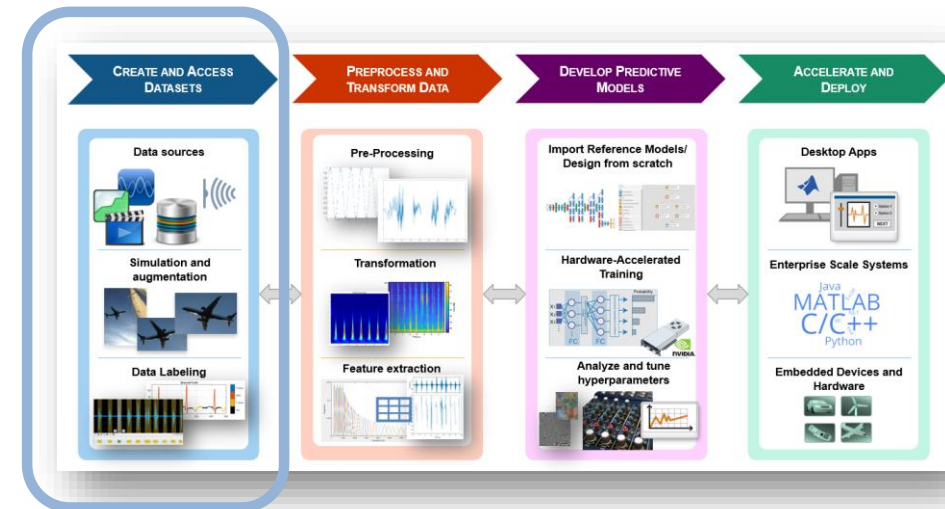

Radar Target Simulation
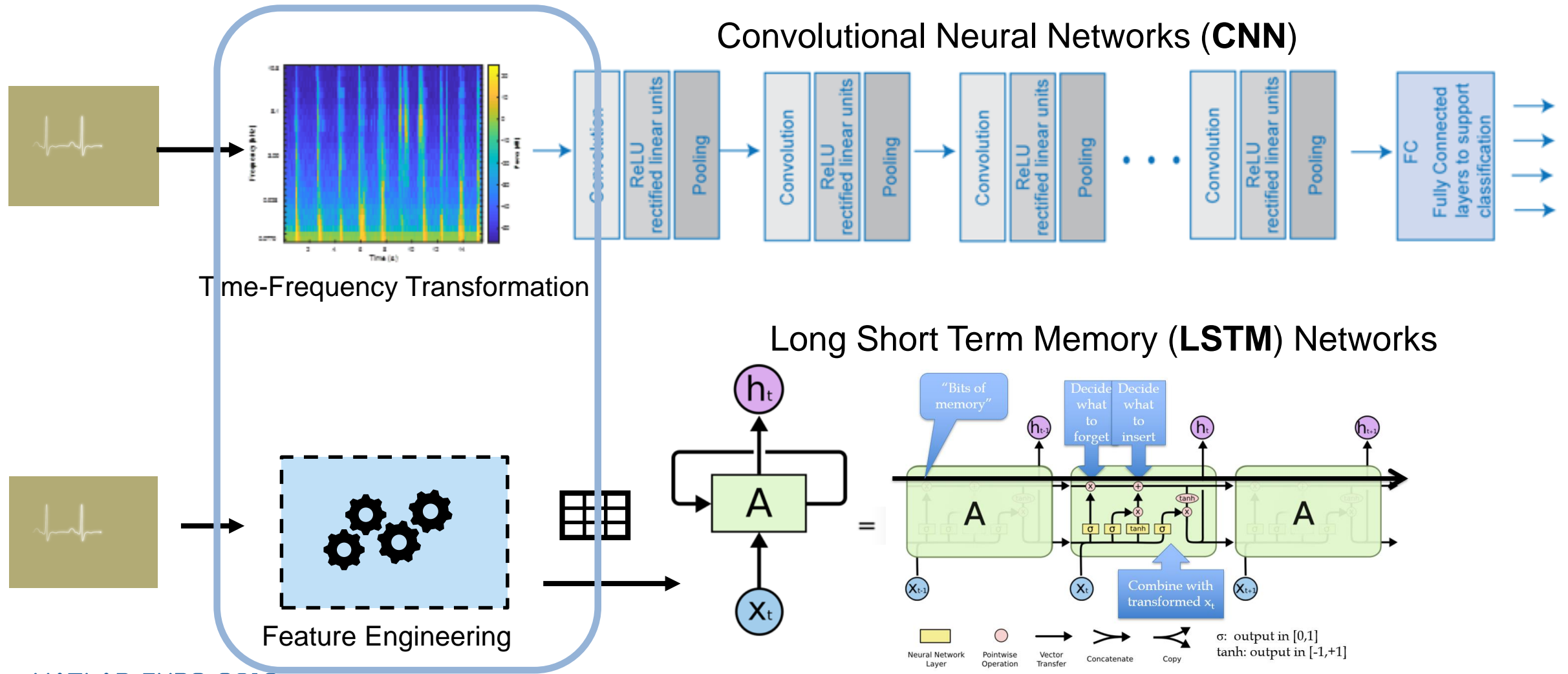
Micro-Doppler Analysis

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  - **Processing and transformation**

  - Model design and optimization
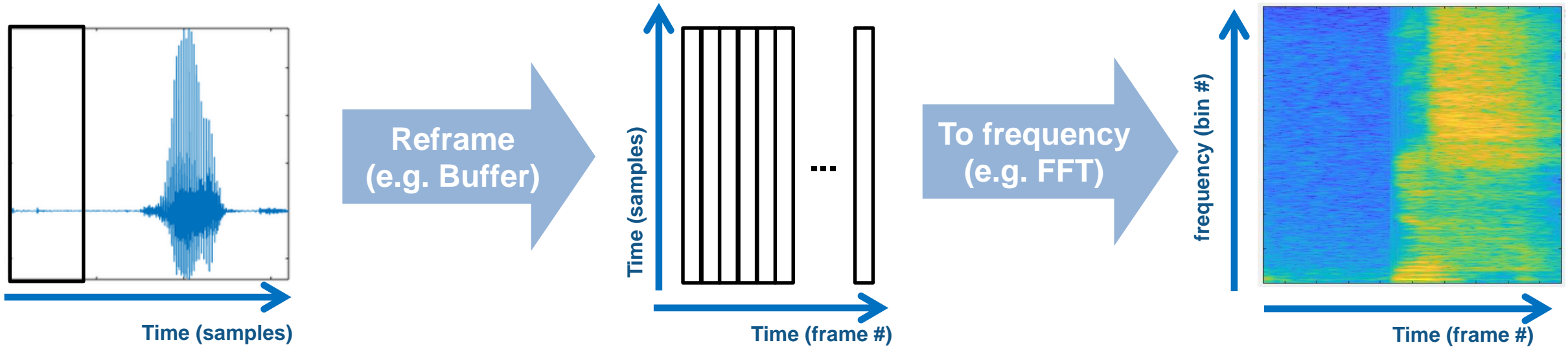
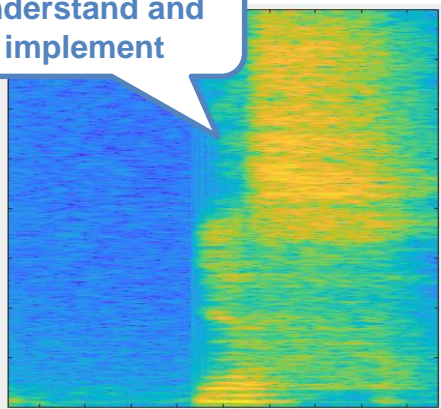 - Acceleration, prototyping, and deployment

- Conclusions

Common types of network architectures used in signal processing and text analytics applications

Convolutional Neural Networks (**CNN**)
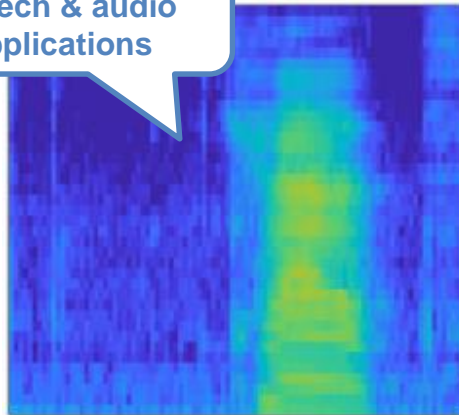
Time-Frequency Transformation

Feature Engineering

Long Short Term Memory (**LSTM**) Networks

Time-Frequency Transformations

Time (samples)

Reframe (e.g. Buffer)

Time (samples)

Time (frame #)

To frequency (e.g. FFT)

frequency (bin #)

Time (frame #)

Easiest to understand and implement

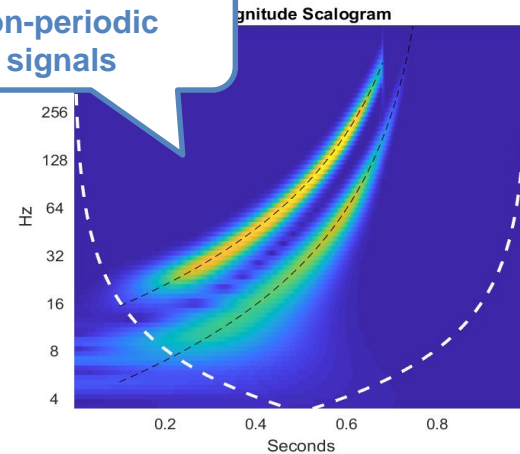Basic spectrogram
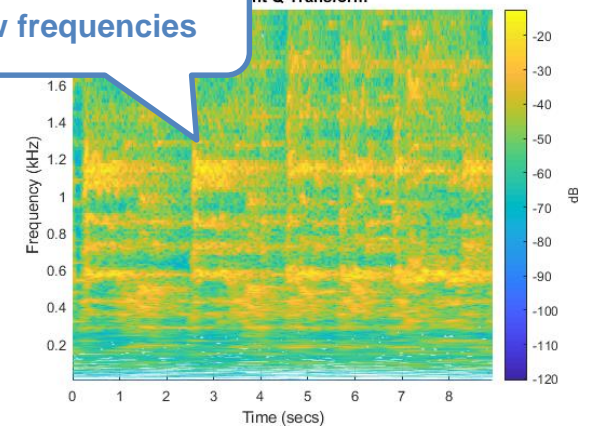
More compact for speech & audio applications

Perceptually-spaced (e.g. Mel, Bark) Spectrogram
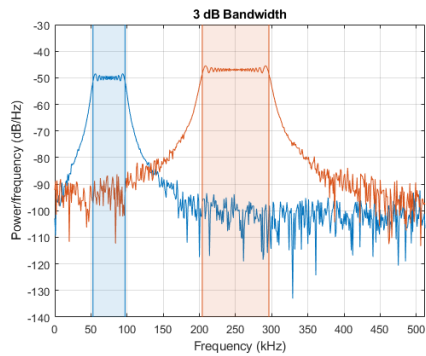
Best resolution, for non-periodic signals

Magnitude Scalogram

Wavelet scalogram

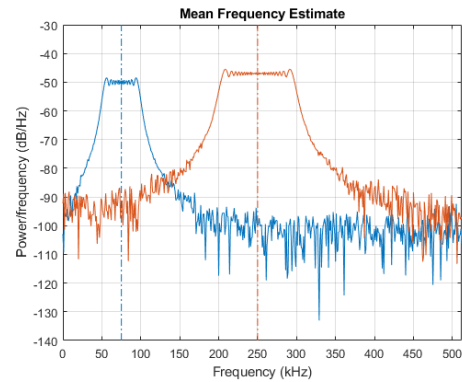Better resolution at low frequencies

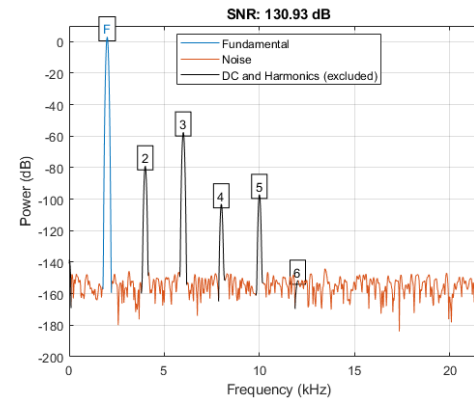Constant Q-Transform

Constant Q transform

Extracting Features from Signals: Application-Agnostic Examples
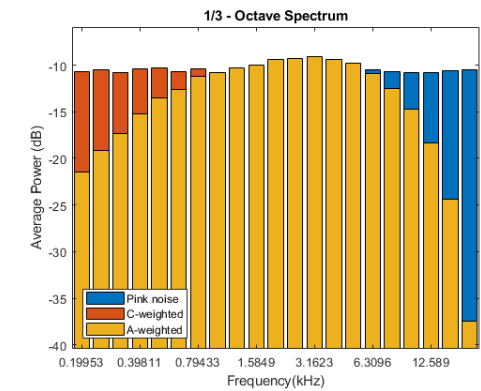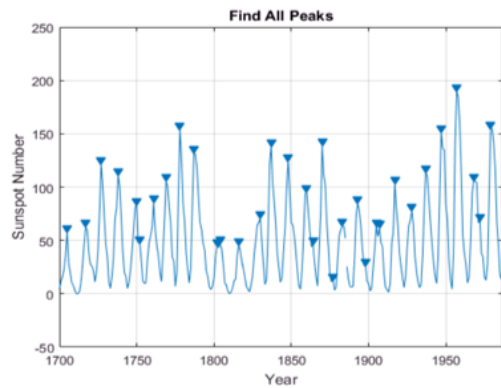

BW measurements

Spectral statistics

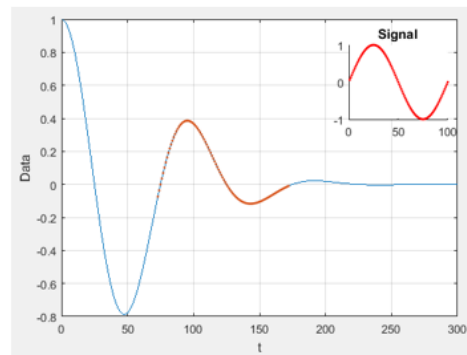Harmonic analysis

Octave spectrum
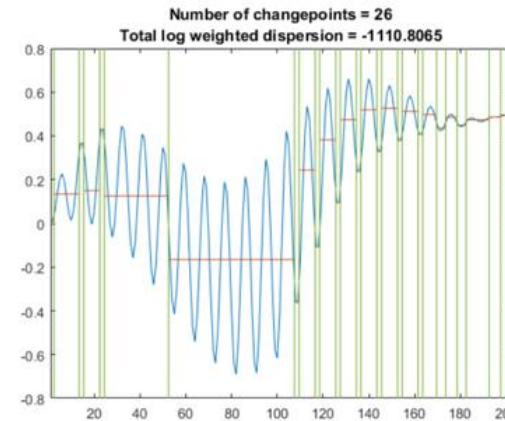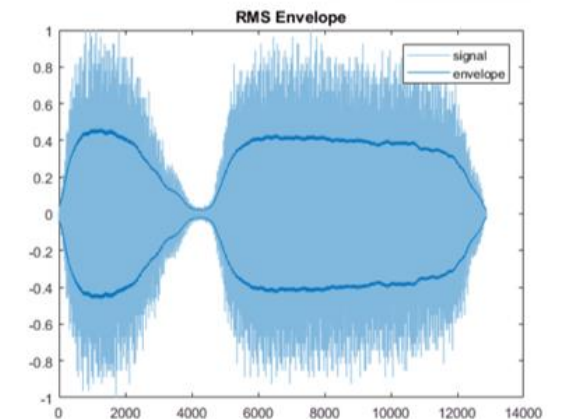
Frequency domain

Time domain

Find peaks

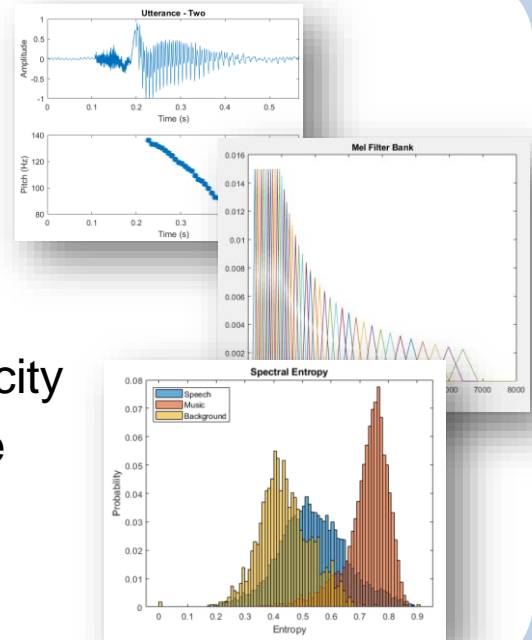Find signal patterns

Detect change points

Find signal envelope

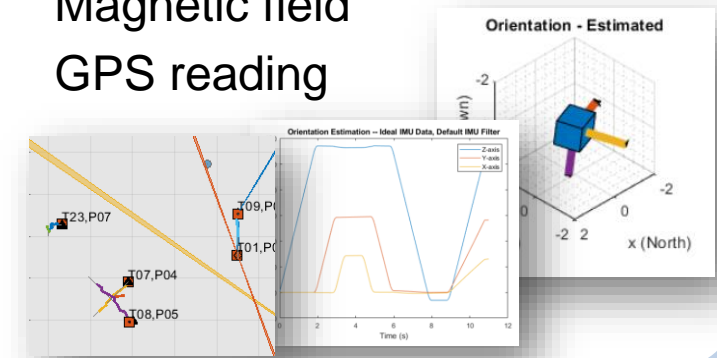# Domain-Specific Features and Transformations – Examples

Speech and Audio

- MFCC
- GTCC
- MDCT
- Pitch, harmonicity
- Spectral shape descriptors
- ...

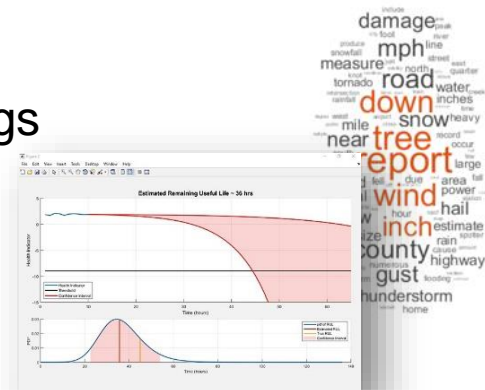## Navigation and Sensor Fusion

- Orientation
- Height
- Position

  } from {

- Acceleration, angular velocity
- Magnetic field
- GPS reading
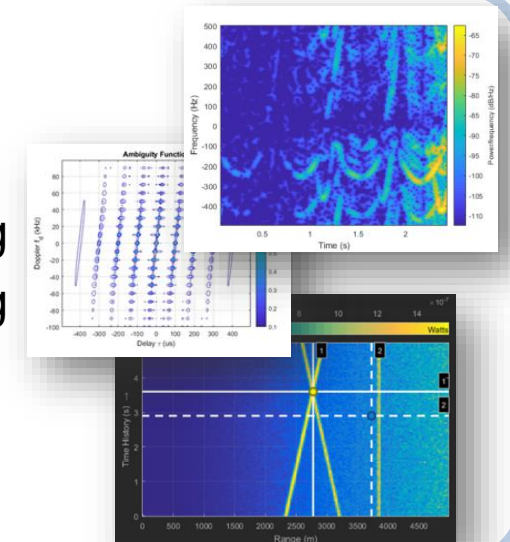
- Multi-object tracking
- …

Text Analytics

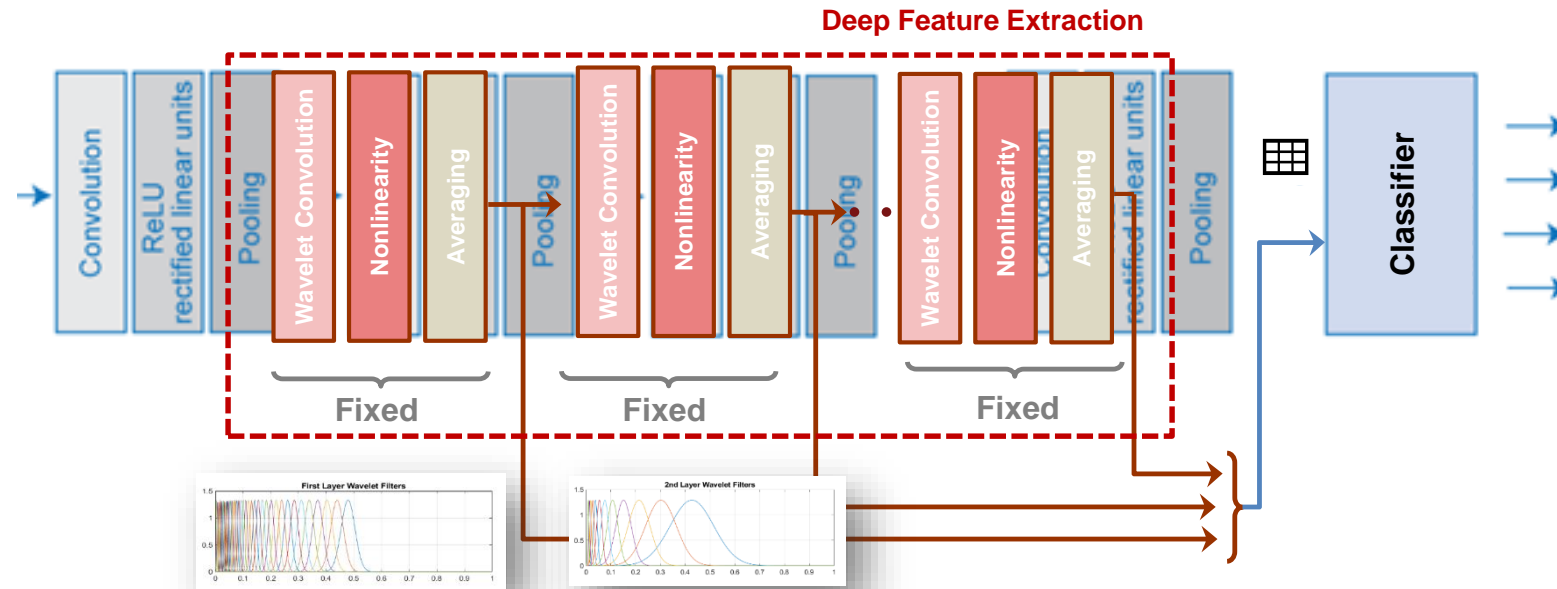- Train Word Embeddings
- Word2Vec
- Topic Modeling
- ...

Radar

- Micro-Doppler analysis
- Range-Doppler processing
- Synthetic aperture imaging
- Spectral analysis
- Waveform ambiguity
- ...

Automated Feature Extraction: Wavelet Scattering
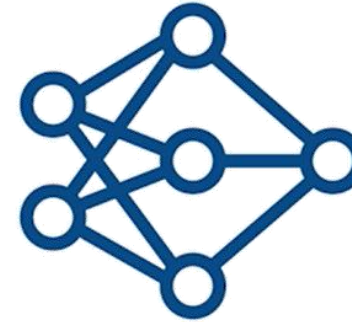

Deep Feature Extraction

- Can relieve requirements on amount of data and model complexity
  - Featured in leader-boards a number of research competitions

- Framework for extracting features [1]

[1] Joan Bruna, and Stephane Mallat, P. 2013. Invariant Scattering Convolution Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 35, No. 8, pp. 1872-1886.

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  – **Model design and optimization**

  – Acceleration, prototyping, and deployment

- Conclusions
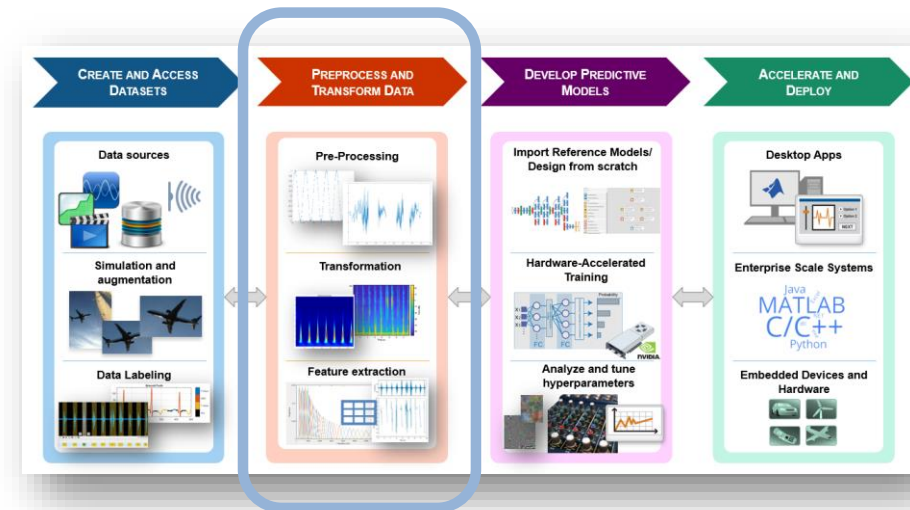
Developing Deep Learning Models

Design Network
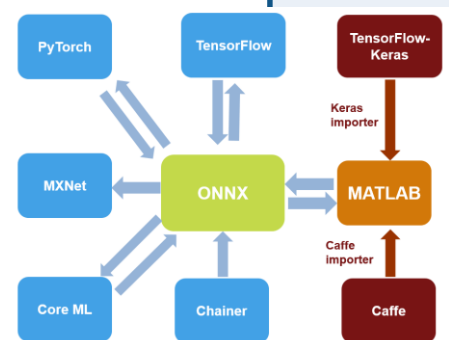
Train

Accelerate Training

MATLAB as a container on NGC

NVIDIA. GPU CLOUD

Design

Optimize

Model Exchange

Pre-trained Networks

AlexNet
PRETRAINED MODEL

VGG-16
PRETRAINED MODEL

ResNet-50
PRETRAINED MODEL

ONNX Converter
MODEL CONVERTER

Caffe
IMPORTER

GoogLeNet
PRETRAINED MODEL

TensorFlow-Keras
IMPORTER

Inception-v3
MODELS
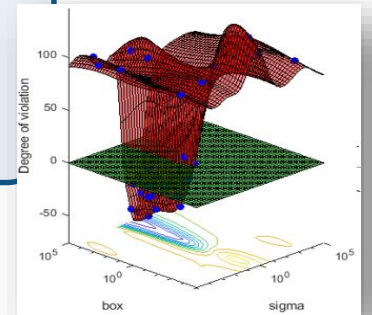
Bayesian Hyperparameter Optimization

MATLAB EXPO 2019

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Exchange Models With Deep Learning Frameworks
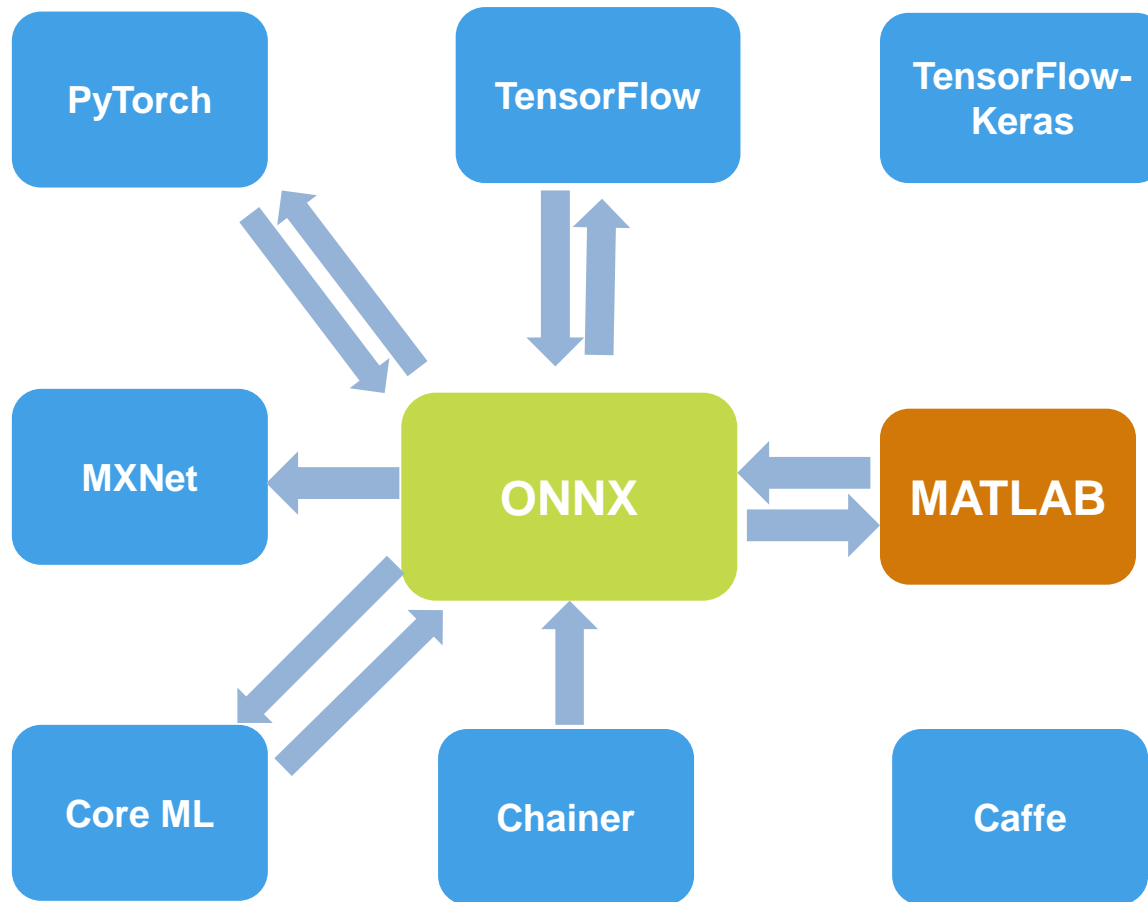
ONNX = Open Neural Network Exchange Format

Exchange Models With Deep Learning Frameworks
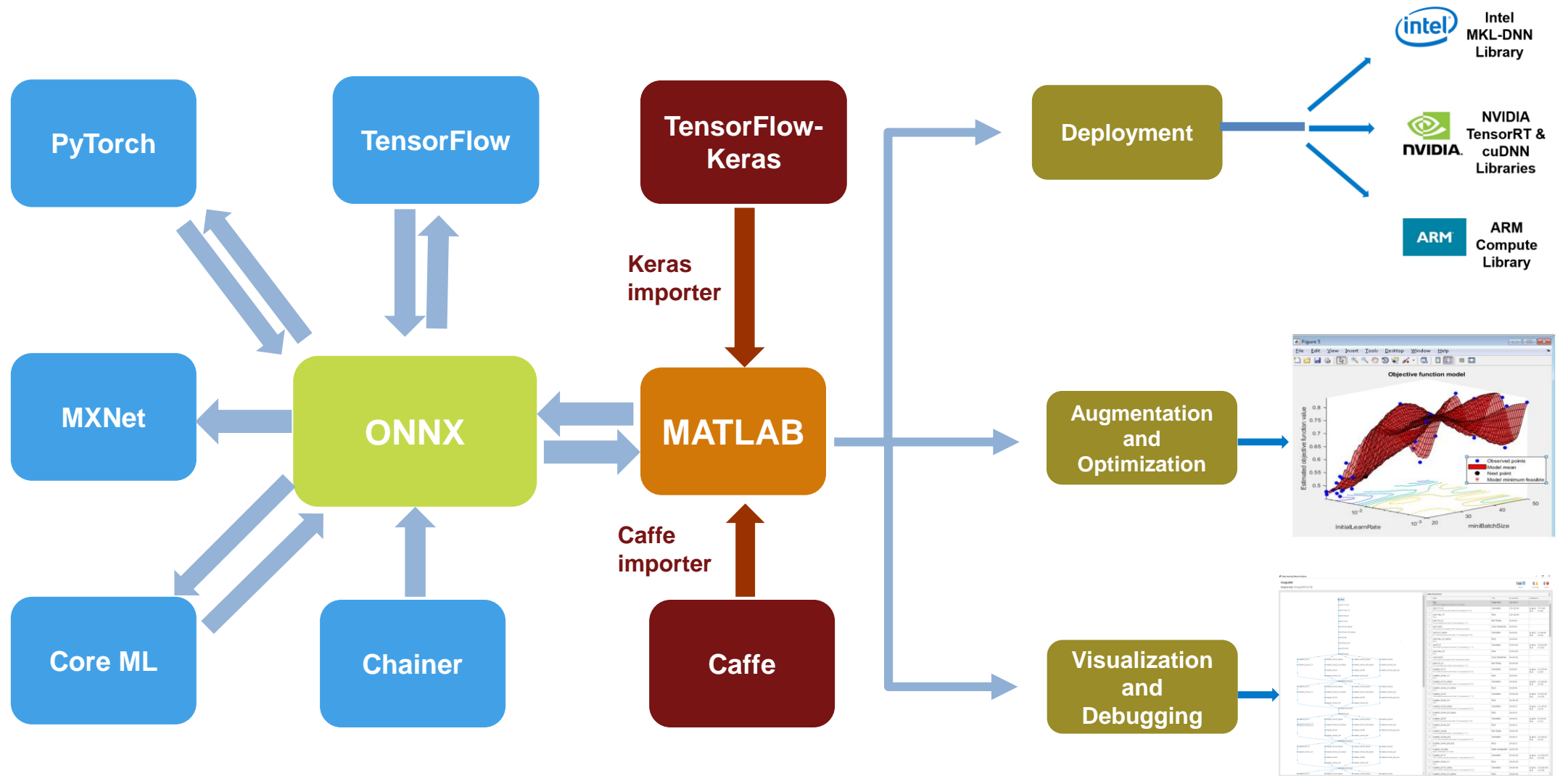
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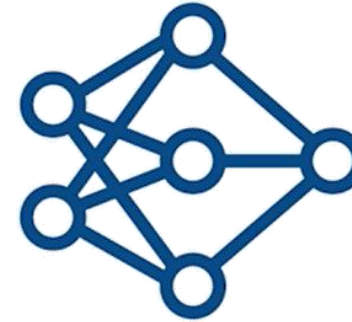
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Deployment and Scaling for A.I.

Embedded Devices

MATLAB

Enterprise Systems

Deploying Deep Learning Models for Inference

With GPU Coder, MATLAB is fast

Single Image Inference (Titan V, Linux)

R2019a

GPU Coder is faster than TensorFlow, MXNet and Pytorch

- ■ TensorFlow
- ■ MXNet
- ■ GPU Coder
- ■ PyTorch

Intel® Xeon® CPU 3.6 GHz - NVIDIA libraries: CUDA10 - cuDNN 7 - Frameworks: TensorFlow 1.13.0, MXNet 1.4.0 PyTorch 1.0.0

Enterprise Deployment
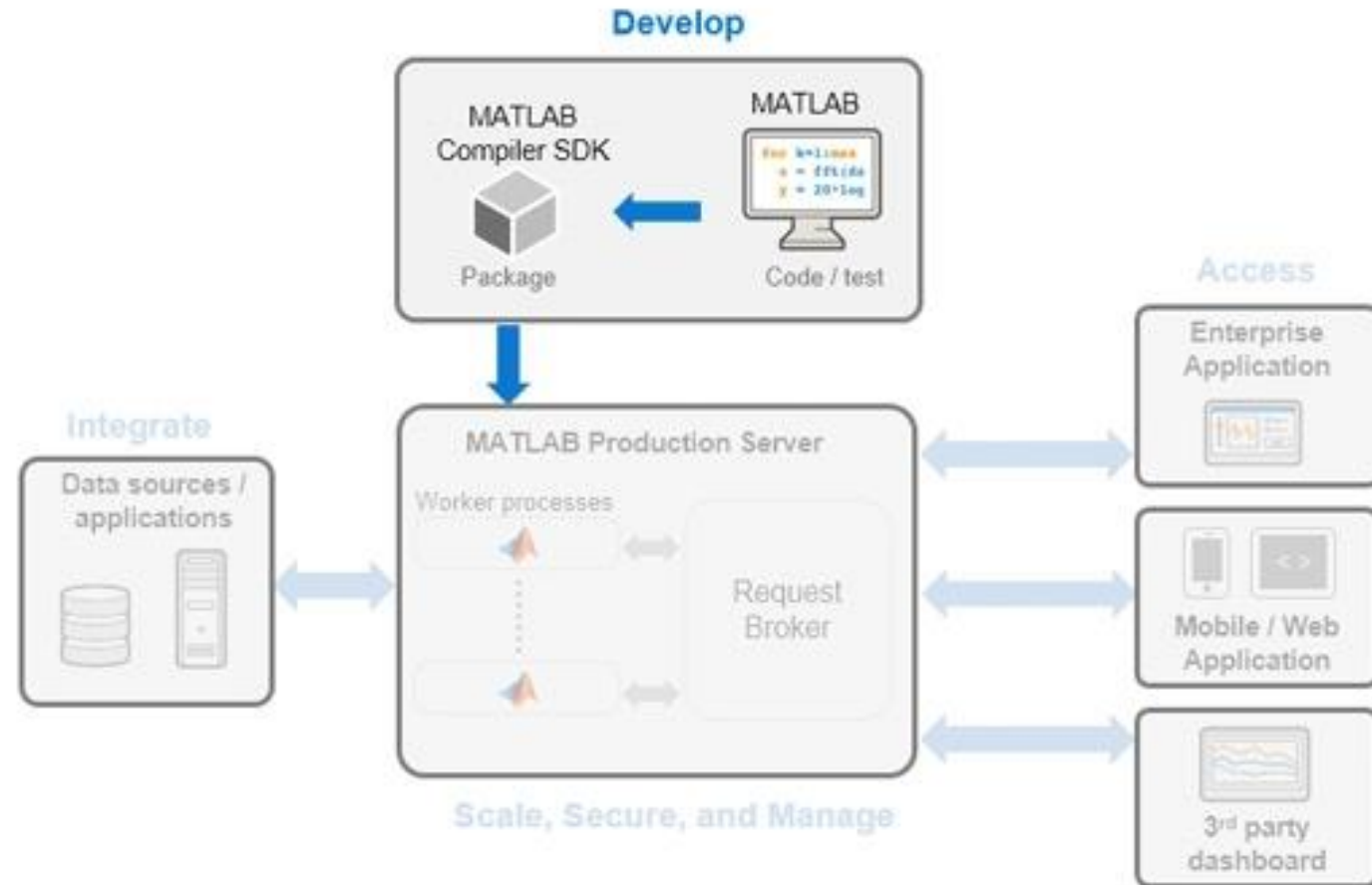
Deployment to the cloud with MATLAB Compiler and MATLAB Production Server
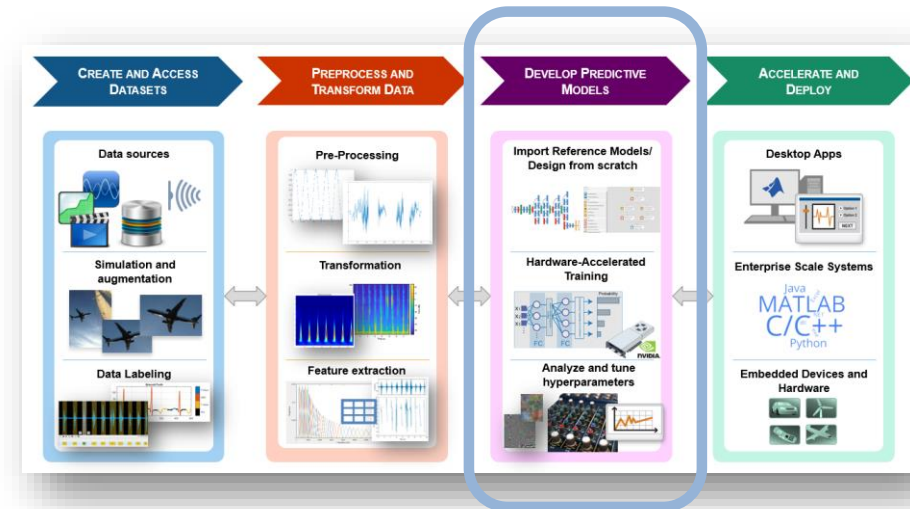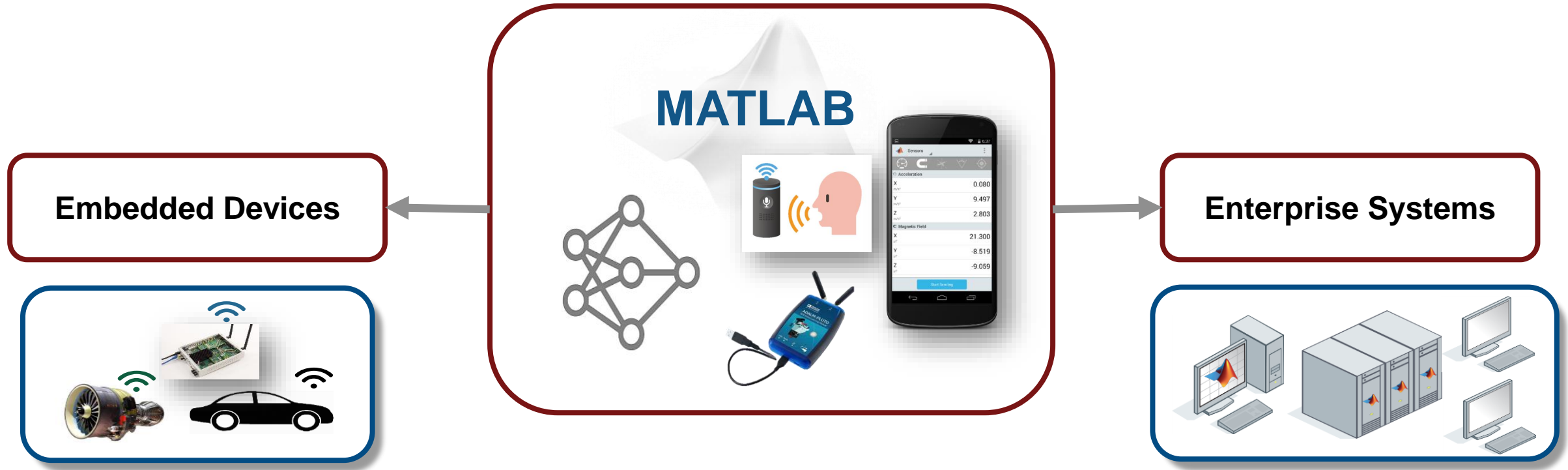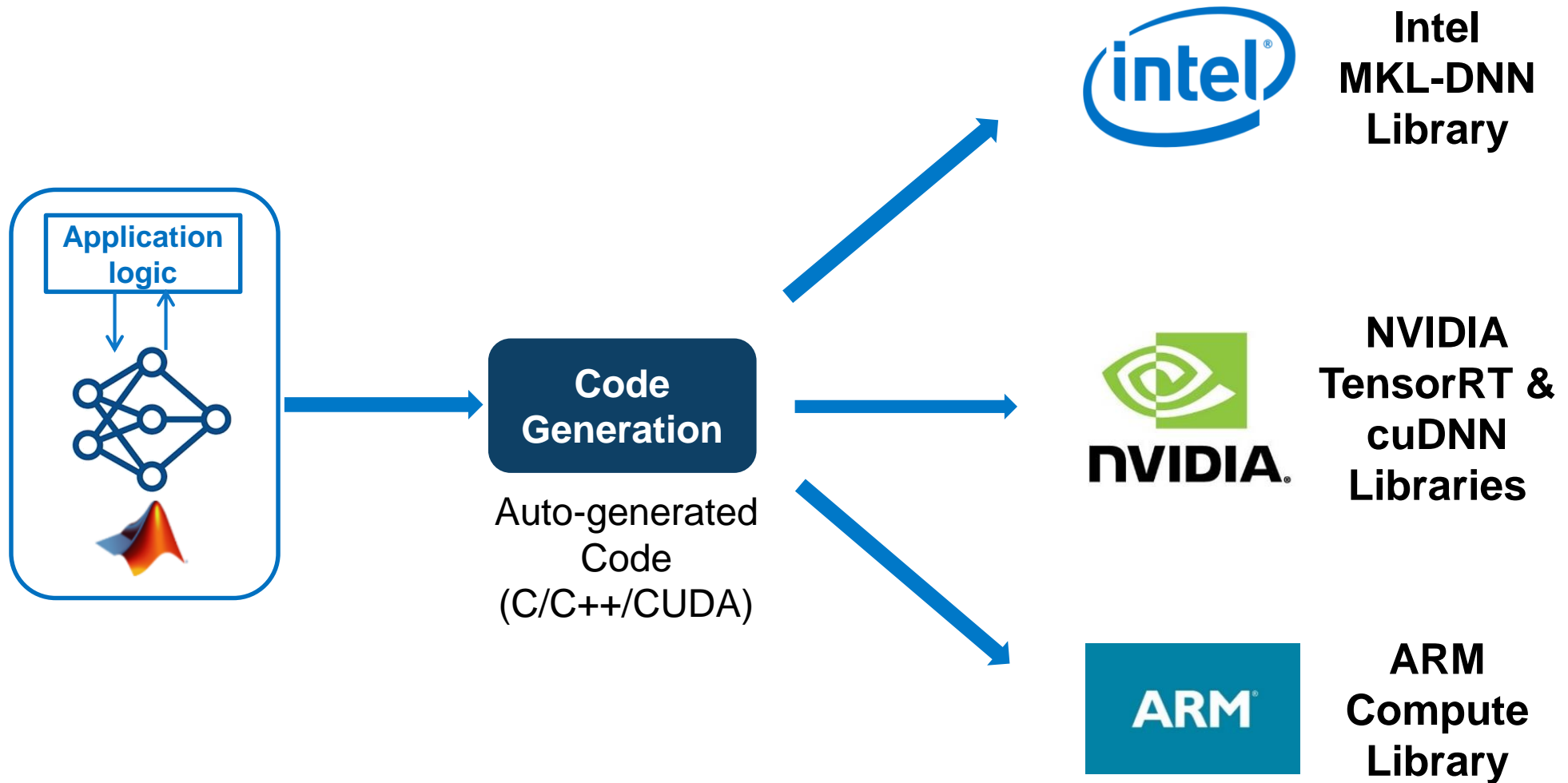
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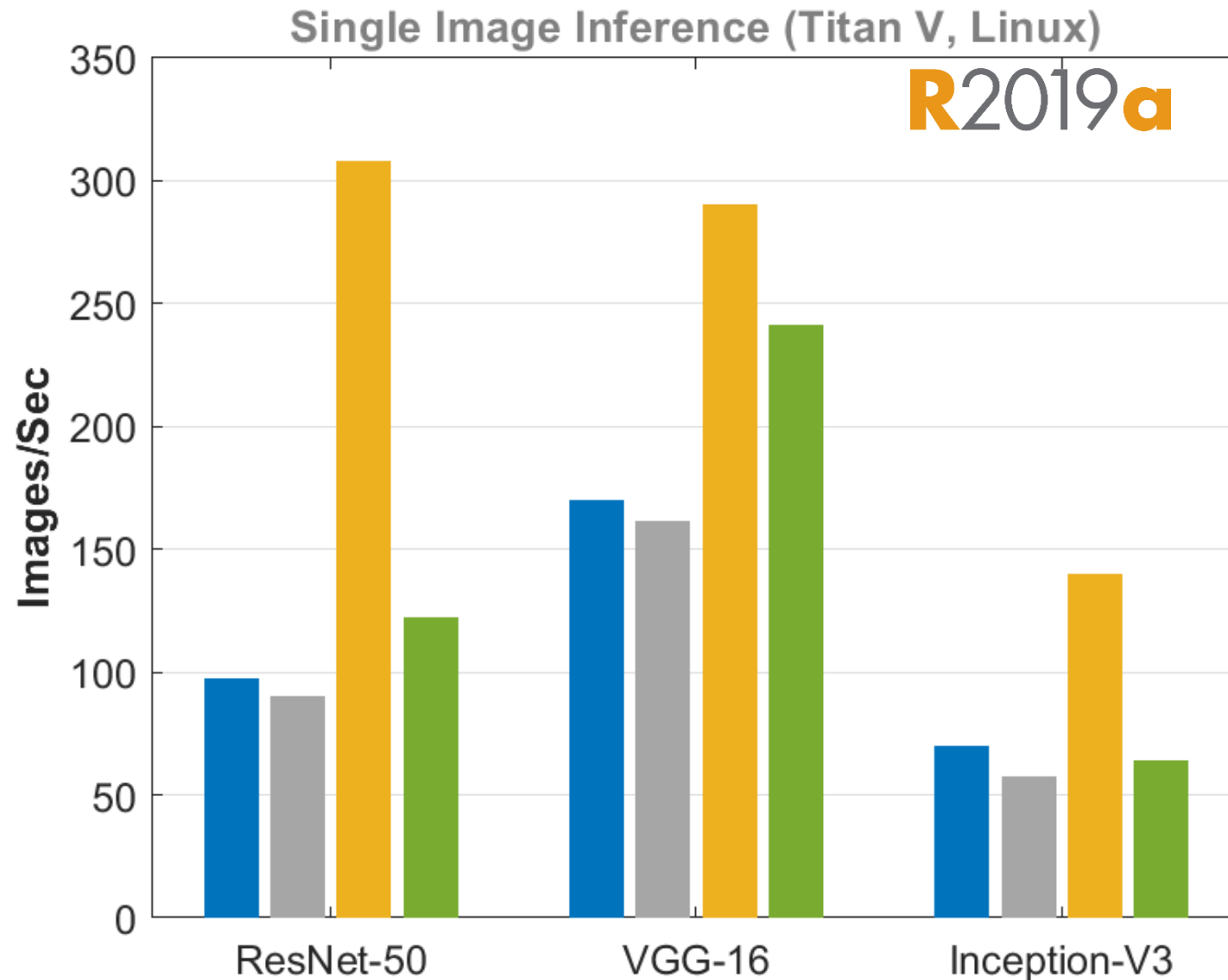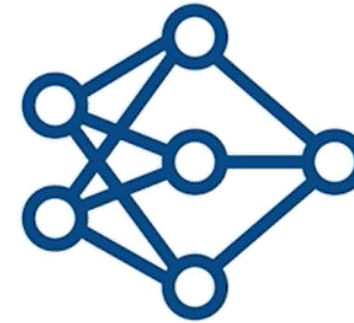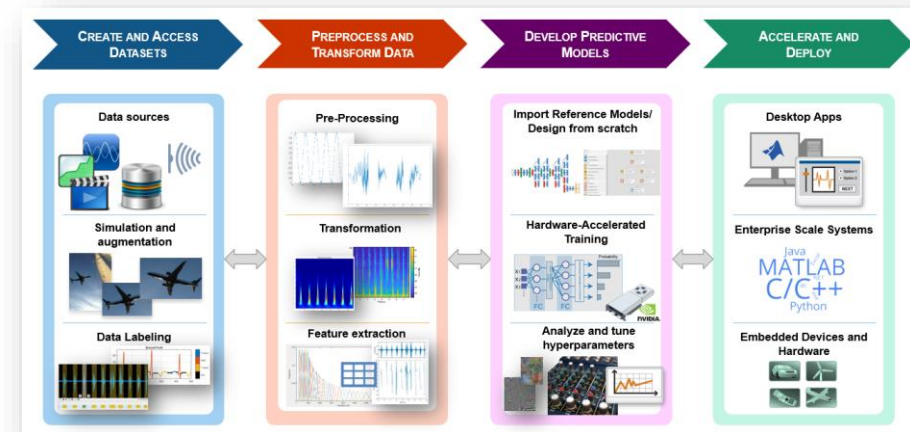 - Acceleration, prototyping, and deployment

- **Conclusions**

Deep Learning Workflow Challenges – Signals and Time Series

Data-labeling Apps and Examples

Augmentation and simulation algorithms

Deployment and Scaling to various platforms

Deep learning models only as good as training data

CREATE AND ACCESS DATASETS

PREPROCESS AND TRANSFORM DATA

DEVELOP PREDICTIVE MODELS

ACCELERATE AND DEPLOY

Application-specific algorithms and tools

Collaboration in the AI ecosystem
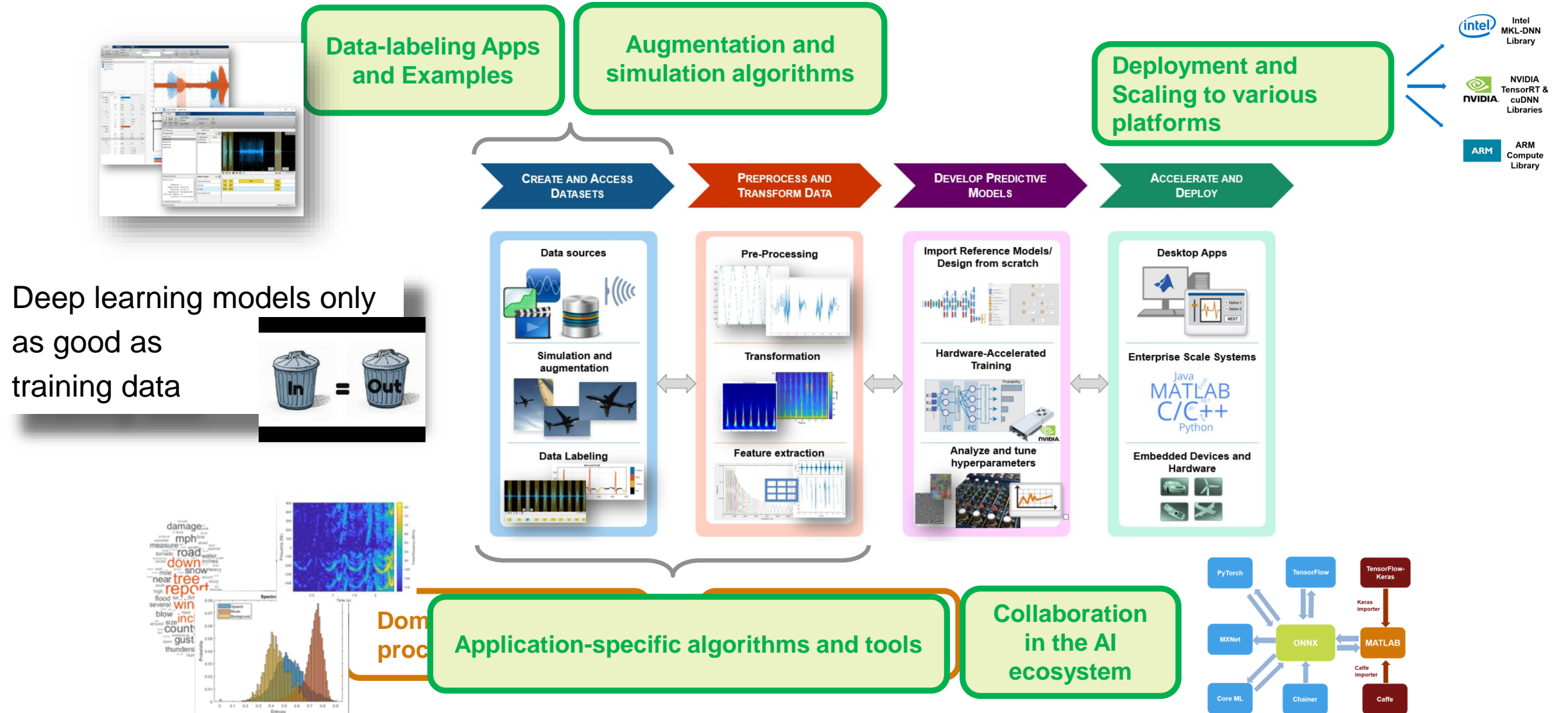
Domain-Specific Features and Transformations – Examples

Audio
Speech Command Recognition
Voice Activity Detection in Noise
Denoise Speech
Classify Gender

Time-Series and Text
Classify Time Series Using Wavelet Analysis
Sequence-to-Sequence Classification
Classify Text Data Using LSTMs
Classify Text Data Using CNNs

Signal
Music Genre Classification
Human Activity Recognition
ECG Signal Classification
Waveform Segmentation

Comms and Radar
Radar Waveform Classification
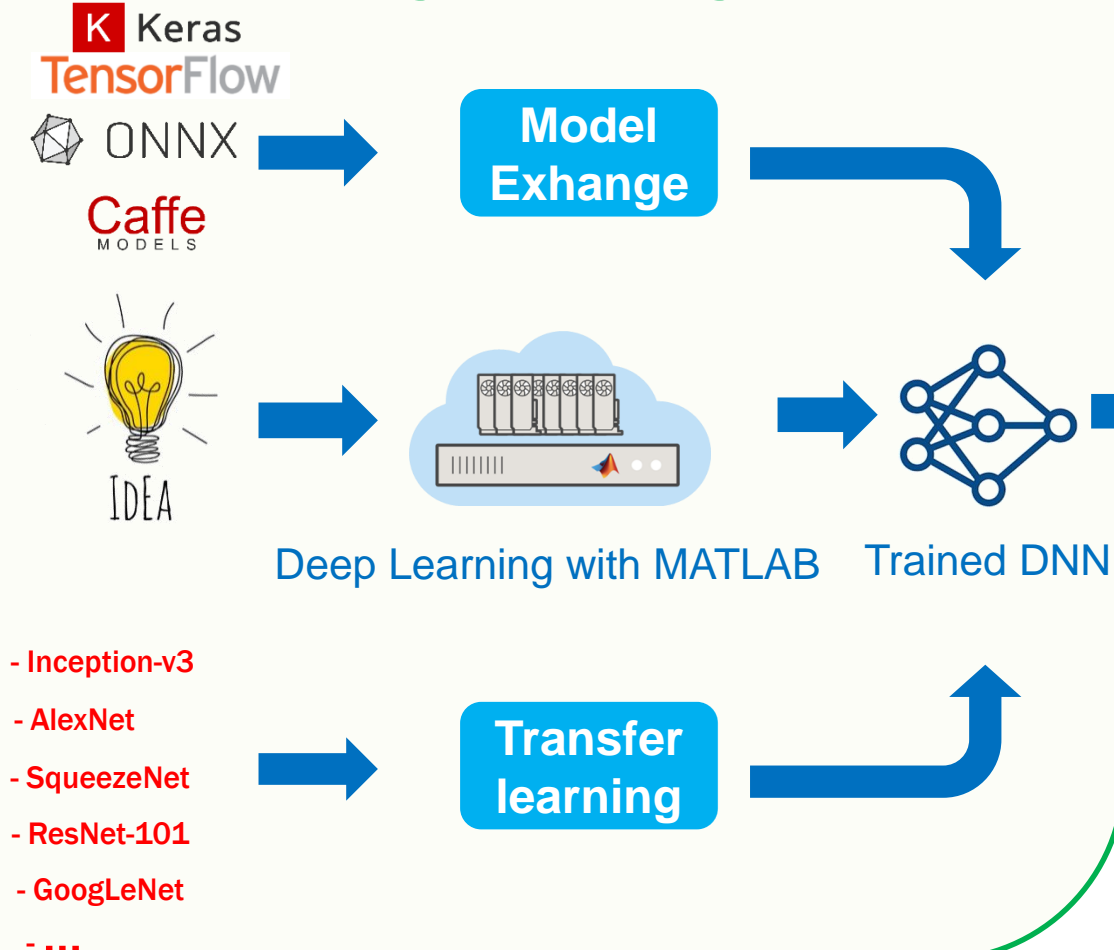Modulation Classification

Call to Action - to be edited by the local team

- Visit the booth
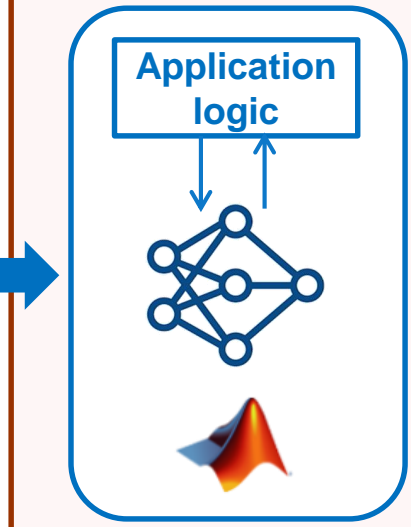**- Attend the talk on** Deep Learning and Reinforcement Learning Workflows in A.I.

Back up

Summary - Deep learning workflow in MATLAB

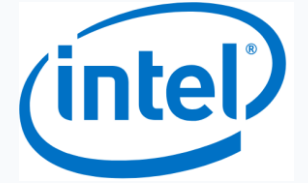**Deep Neural Network Design + Training**

Keras
TensorFlow
ONNX
Caffe MODELS

IDEA

Model Exhange

Deep Learning with MATLAB

Trained DNN

- Inception-v3
- AlexNet
- SqueezeNet
- ResNet-101
- GoogLeNet
- ...

Transfer learning

Application design

Application logic

Standalone Deployment

intel

Intel MKL-DNN Library

Coders

NVIDIA

NVIDIA TensorRT cuDNN Libraries

ARM NEON™

ARM Compute Library