



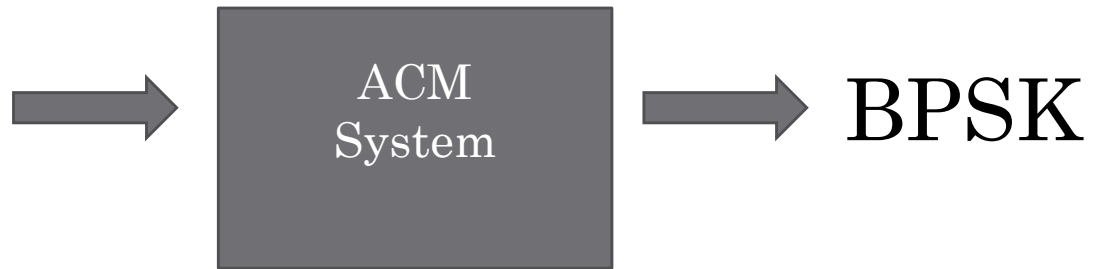
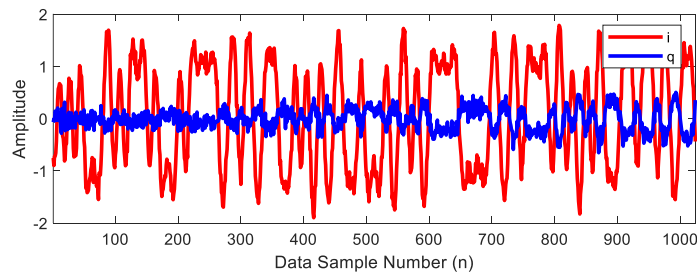
Design and Analysis of Convolutional Neural Network for RF Signal Modulation Classification for In-Orbit Deployment

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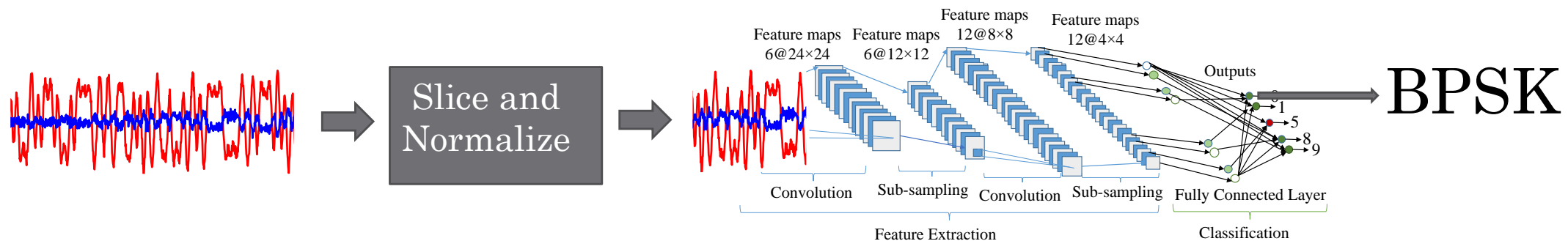
CNN for Automatic Modulation Classification

- Automatic signal modulation classification (AMC) is a major research direction of signal recognition.
- AMC is the automatic identification of the modulation format of the transmitted signals by observing the received data samples which are corrupted by the noise and fading channels.
- It is an intermediate operation between the signal detection and the data demodulation
- AMC plays an important role in civilian and military applications such as software-defined radio, cognitive radio, dynamic spectrum management, interference identification and electronic warfare.



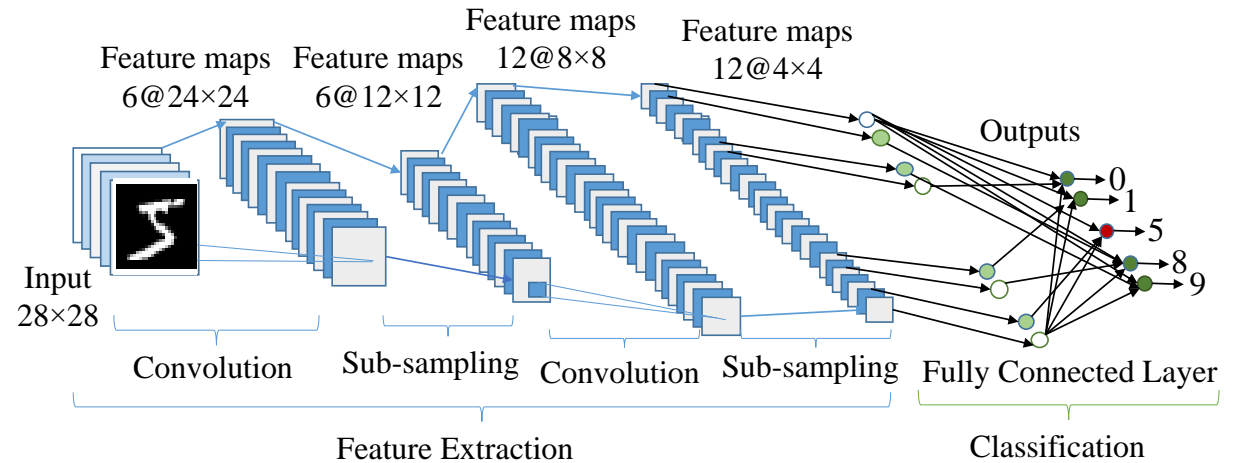
CNN for Automatic Modulation Classification

- Deep Learning (DL) has been described as a universal learning approach that is able to solve many types problems in different application domains.
- Our focus is on implementing a DL engine in space that would enable Automatic Modulation Classification (AMC) outside of Earth's atmosphere. Implementation of modulation recognition algorithm would allow for the deployment of real-time, high rate, low-power and useful neural network for RF communications.
- We explored a Convolutional Neural Network (CNN), and a Convolution Neural Network that Implements Transfer Learning (CNN-TL) for the successful classification of different modulation schemes for data transmission.
- The developed software was shown to successfully classify the modulation schemes using the open source Radio ML 2018 dataset.



CNN Algorithm

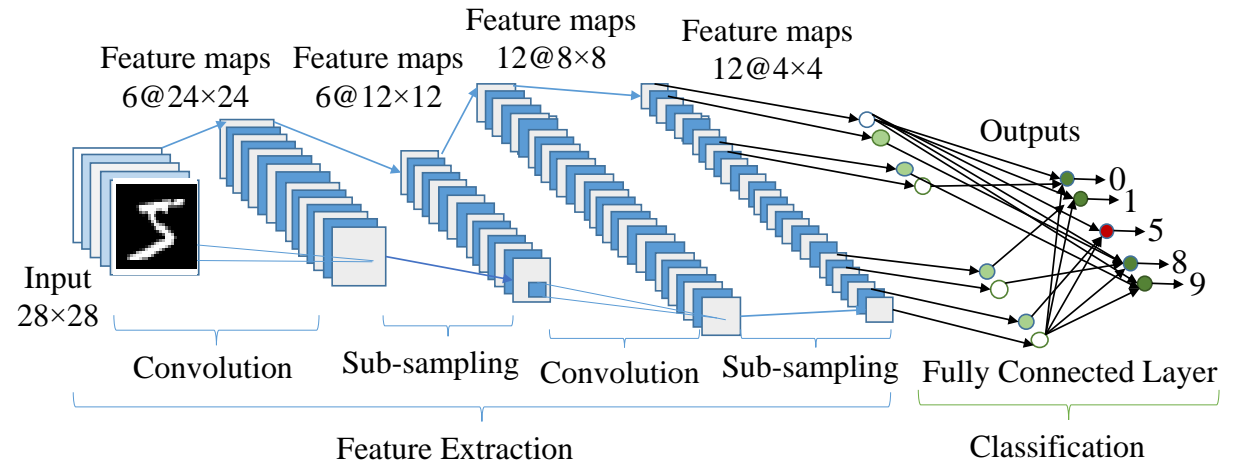
- Learns by extracting features from data samples using trainable convolution kernels (filters)
- Last layer is typical fully connected layer
- Very strong for image recognition and classification



Full CNN Training: All Layers are Optimized

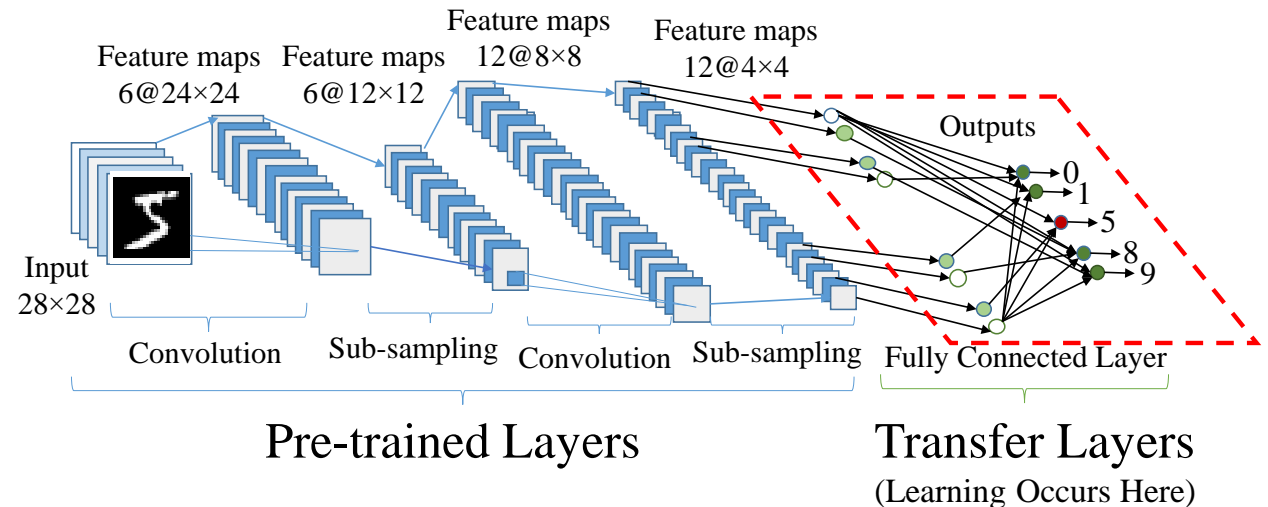
CNN for Transfer Learning

- Learns by extracting features from data samples using trainable convolution kernels (filters)
- Last layer is typical fully connected layer
- Very strong for image recognition and classification



Full CNN Training: All Layers are Optimized

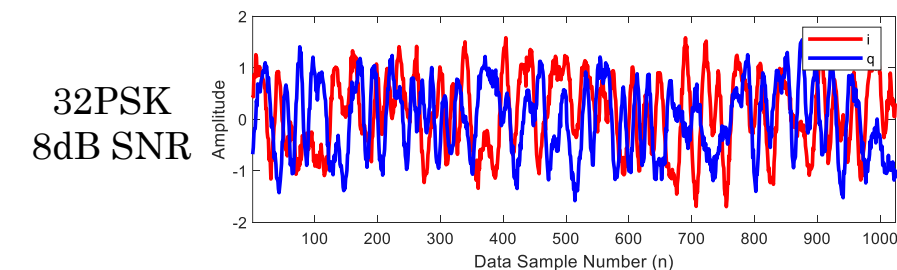
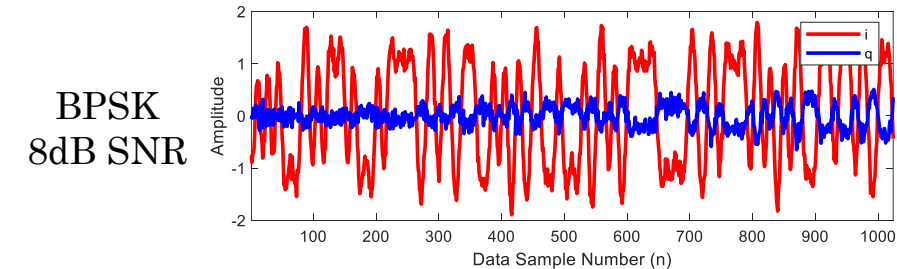
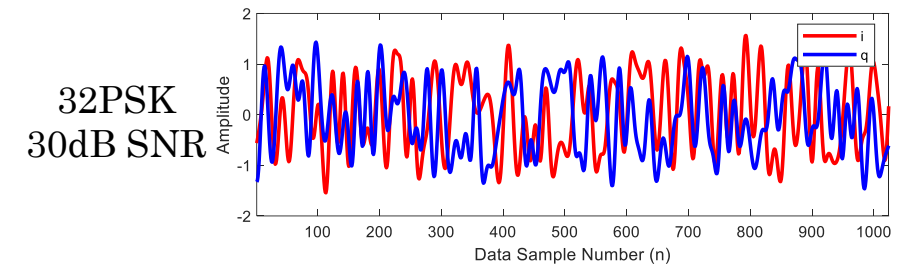
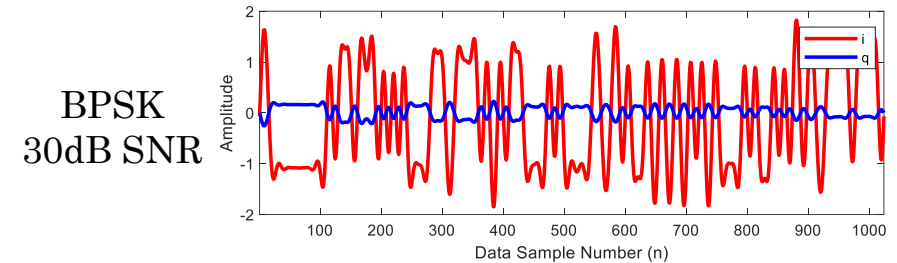
- **Transfer Learning**
 - Pre-train the convolution part of the network
 - Train only the fully connected layer with new data
 - Much simpler to implement in hardware



Radio ML Dataset

- Dataset used in this study
 - RadioML 2018
 - 24 Modulation Classes
 - SNR range: -20 to 30dB
- 4069 samples for each class in each SNR segment
- Sample size 2×1024 for CNN input
 - I channel
 - Q channel
- Little post processing within data
 - Cut sample lengths
 - Normalize to zero mean and unit variance

Class Number	Mod. Class
1	OOK
2	4ASK
3	8ASK
4	BPSK
5	QPSK
6	8PSK
7	16PSK
8	32PSK
9	16APSK
10	32APSK
11	64APSK
12	128APSK
13	16QAM
14	32QAM
15	64QAM
16	128QAM
17	256QAM
18	AM-SSB-WC
19	AM-SSB-SC
20	AM-DSB-WC
21	AM-DSB-SC
22	FM
23	GMSK
24	OQPSK



CNN Transfer Learning

- CNN used for transfer learning test
 - 2 convolution layers
 - 2 fully connected layers
- Dataset broken into two groups
 - Fully train on one set
 - Transfer learn the other set

```

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Layer (type)           Output Shape           Param #
-----
Conv2d-1               [-1, 32, 1024, 1]     1,632
ReLU-2                 [-1, 32, 1024, 1]     0
MaxPool2d-3            [-1, 32, 512, 1]      0
Conv2d-4               [-1, 64, 512, 1]      51,264
ReLU-5                 [-1, 64, 512, 1]      0
MaxPool2d-6            [-1, 64, 256, 1]      0
Dropout-7              [-1, 16384]            0
Linear-8               [-1, 1000]             16,385,000
Linear-9               [-1, 24]               24,024
-----
Total params: 16,461,920
Trainable params: 16,461,920
Non-trainable params: 0
-----
Input size (MB): 0.01
Forward/backward pass size (MB): 1.38
Params size (MB): 62.80
Estimated Total Size (MB): 64.19
-----
    
```

	Class Number	Mod. Class
Transfer Set A	1	OOK
	2	4ASK
	3	8ASK
	4	BPSK
	5	QPSK
	6	8PSK
	7	16PSK
	8	32PSK
	9	16APSK
	10	32APSK
	11	64APSK
	12	128APSK
Transfer Set B	13	16QAM
	14	32QAM
	15	64QAM
	16	128QAM
	17	256QAM
	18	AM-SSB-WC
	19	AM-SSB-SC
	20	AM-DSB-WC
	21	AM-DSB-SC
	22	FM
	23	GMSK
	24	OQPSK

CNN Transfer Learning

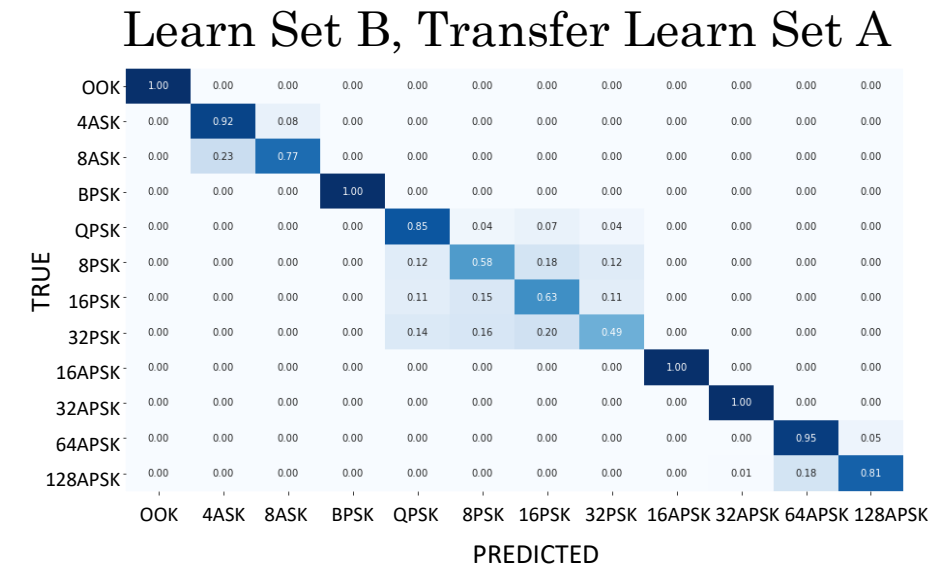
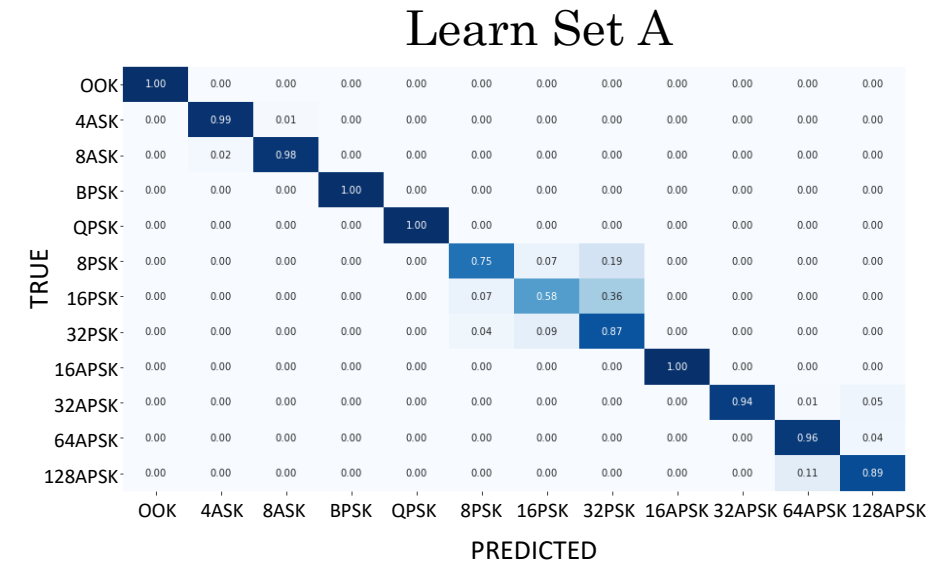


- CNN used for transfer learning test
 - 2 convolution layers
 - 2 fully connected layers
- Dataset broken into two groups
 - Fully train on one set
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Layer (type)	Output Shape	Param #
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ReLU-5	[-1, 64, 512, 1]	0
MaxPool2d-6	[-1, 64, 256, 1]	0
Dropout-7	[-1, 16384]	0
Linear-8	[-1, 1000]	16,385,000
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Total params: 16,461,920
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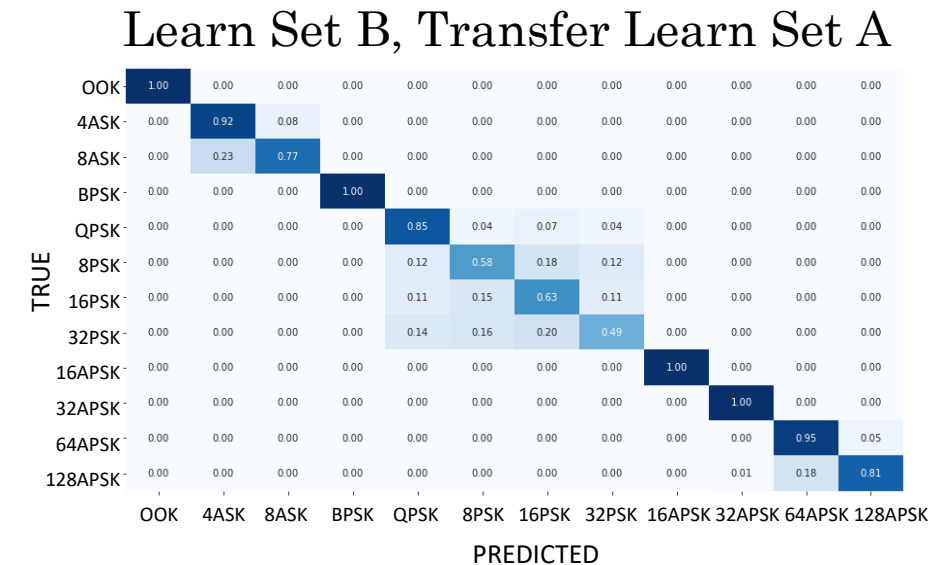
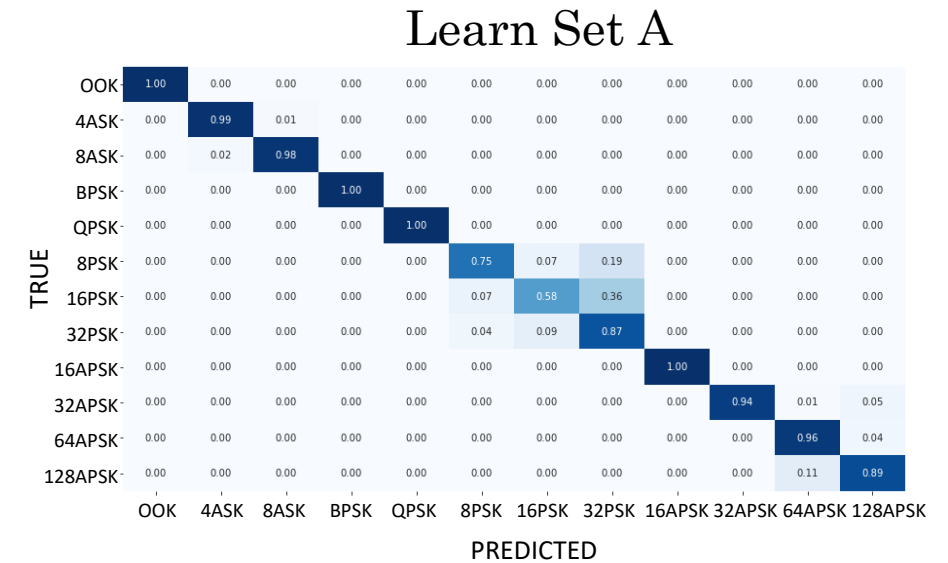
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CNN Transfer Learning



- CNN used for transfer learning test
 - 2 convolution layers
 - 2 fully connected layers
- Dataset broken into two groups
 - Fully train on one set
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Metric	Train A (40 Epochs)	Train B (40 Epochs)	Train A Transfer B (40 + 40 Epochs)	Train B Transfer A (40 + 40 Epochs)
Accuracy	91.15%	80.40%	78.32%	83.34%

CNN Optimization



- Deeper CNN

- More convolution layers
- More fully connected layers
- Fewer parameters
- Experiment is learning all 24 classes and testing using unique untrained data samples

Convolution Layers	Filter Size	FC Layers	Epochs	Parameters	Training Accuracy (%)	Testing Accuracy (%)
2→16→16→16	1 by 5	2048→250→24	40	521,042	82.0	74.8
	1 by 3		40	519,954	78.9	71.7
2→16→16→16→16→16	1 by 3	512→250→24	40	137,522	77.4	75.9
		512→128→24	40	72,008	71.4	70.28
2→16→16→16→16→16→16	1 by 3	256→128→24	40	40,024	76.7	75.6
			80	40,024	82.7	81.4
2→12→12→12→12→12→12	1 by 3	192→128→24	40	30,104	66.3	65.2
			80	30,104	75.7	74.8
2→12→12→12→12→12→12	1 by 3	192→64→24	80	16,216	77.8	76.5
			160	16,216	78.2	77.4
2→8→8→8→8→8→8	1 by 3	128→64→24	80	10,872	68.3	67.4
			160	10,872	72.5	71.7
2→8→8→8→8→8→8	1 by 3	128→24	160	4,152	54.6	54.06

CNN Optimization



- Range of CNN designs were evaluated to find tradeoff between number of parameters and accuracy
 - Two bold networks show strong accuracy vs. throughput results

Convolution Layers	Filter Size	FC Layers	Epochs	Parameters	Training Accuracy (%)	Testing Accuracy (%)
2→16→16→16	1 by 5	2048→250→24	40	521,042	82.0	74.8
	1 by 3		40	519,954	78.9	71.7
2→16→16→16→16→16	1 by 3	512→250→24	40	137,522	77.4	75.9
		512→128→24	40	72,008	71.4	70.28
2→16→16→16→16→16→16	1 by 3	256→128→24	40	40,024	76.7	75.6
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2→12→12→12→12→12→12	1 by 3	192→128→24	40	30,104	66.3	65.2
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			160	16,216	78.2	77.4
2→8→8→8→8→8→8	1 by 3	128→64→24	80	10,872	68.3	67.4
			160	10,872	72.5	71.7
2→8→8→8→8→8→8	1 by 3	128→24	160	4,152	54.6	54.06

CNN Optimization



- Deeper CNN

- 6 convolution layers
- 2 fully connected layers
- More layers and fewer parameters

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 12, 1024, 1]	72
ReLU-2	[-1, 12, 1024, 1]	0
MaxPool2d-3	[-1, 12, 512, 1]	0
Conv2d-4	[-1, 12, 512, 1]	432
ReLU-5	[-1, 12, 512, 1]	0
MaxPool2d-6	[-1, 12, 256, 1]	0
Conv2d-7	[-1, 12, 256, 1]	432
ReLU-8	[-1, 12, 256, 1]	0
MaxPool2d-9	[-1, 12, 128, 1]	0
Conv2d-10	[-1, 12, 128, 1]	432
ReLU-11	[-1, 12, 128, 1]	0
MaxPool2d-12	[-1, 12, 64, 1]	0
Conv2d-13	[-1, 12, 64, 1]	432
ReLU-14	[-1, 12, 64, 1]	0
MaxPool2d-15	[-1, 12, 32, 1]	0
Conv2d-16	[-1, 12, 32, 1]	432
ReLU-17	[-1, 12, 32, 1]	0
MaxPool2d-18	[-1, 12, 16, 1]	0
Dropout-19	[-1, 192]	0
Linear-20	[-1, 64]	12,288
Linear-21	[-1, 12]	768

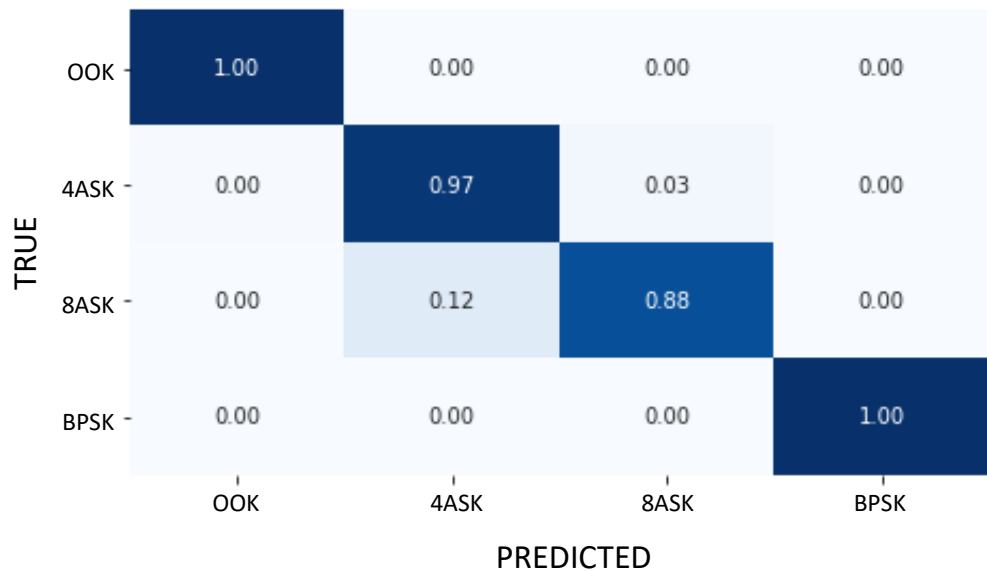
=====
Total params: 15,288
Trainable params: 15,288
Non-trainable params: 0

Input size (MB): 0.01
Forward/backward pass size (MB): 0.46
Params size (MB): 0.06
Estimated Total Size (MB): 0.53

Optimized CNN Transfer Learning



- Transfer Learning to Add Class
 - Step 1: Train CNN to learn 4 modulation types



Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 12, 1024, 1]	72
ReLU-2	[-1, 12, 1024, 1]	0
MaxPool2d-3	[-1, 12, 512, 1]	0
Conv2d-4	[-1, 12, 512, 1]	432
ReLU-5	[-1, 12, 512, 1]	0
MaxPool2d-6	[-1, 12, 256, 1]	0
Conv2d-7	[-1, 12, 256, 1]	432
ReLU-8	[-1, 12, 256, 1]	0
MaxPool2d-9	[-1, 12, 128, 1]	0
Conv2d-10	[-1, 12, 128, 1]	432
ReLU-11	[-1, 12, 128, 1]	0
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Conv2d-13	[-1, 12, 64, 1]	432
ReLU-14	[-1, 12, 64, 1]	0
MaxPool2d-15	[-1, 12, 32, 1]	0
Conv2d-16	[-1, 12, 32, 1]	432
ReLU-17	[-1, 12, 32, 1]	0
MaxPool2d-18	[-1, 12, 16, 1]	0
Dropout-19	[-1, 192]	0
Linear-20	[-1, 64]	12,288
Linear-21	[-1, 12]	768

Total params: 15,288
 Trainable params: 15,288
 Non-trainable params: 0

Input size (MB): 0.01
 Forward/backward pass size (MB): 0.46
 Params size (MB): 0.06
 Estimated Total Size (MB): 0.53

Optimized CNN Transfer Learning



- Transfer Learning to Add Class
 - Step 2: Test with 4 learned modulations in addition to a new unlearned class



Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 12, 1024, 1]	72
ReLU-2	[-1, 12, 1024, 1]	0
MaxPool2d-3	[-1, 12, 512, 1]	0
Conv2d-4	[-1, 12, 512, 1]	432
ReLU-5	[-1, 12, 512, 1]	0
MaxPool2d-6	[-1, 12, 256, 1]	0
Conv2d-7	[-1, 12, 256, 1]	432
ReLU-8	[-1, 12, 256, 1]	0
MaxPool2d-9	[-1, 12, 128, 1]	0
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Conv2d-13	[-1, 12, 64, 1]	432
ReLU-14	[-1, 12, 64, 1]	0
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Conv2d-16	[-1, 12, 32, 1]	432
ReLU-17	[-1, 12, 32, 1]	0
MaxPool2d-18	[-1, 12, 16, 1]	0
Dropout-19	[-1, 192]	0
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Total params: 15,288
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Optimized CNN Transfer Learning



- Transfer Learning to Add Class
 - Step 3: Use transfer learning to train only the fully connected layers
 - Step 4: Test if the network is able to learn all 5 modulations



Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 12, 1024, 1]	72
ReLU-2	[-1, 12, 1024, 1]	0
MaxPool2d-3	[-1, 12, 512, 1]	0
Conv2d-4	[-1, 12, 512, 1]	432
ReLU-5	[-1, 12, 512, 1]	0
MaxPool2d-6	[-1, 12, 256, 1]	0
Conv2d-7	[-1, 12, 256, 1]	432
ReLU-8	[-1, 12, 256, 1]	0
MaxPool2d-9	[-1, 12, 128, 1]	0
Conv2d-10	[-1, 12, 128, 1]	432
ReLU-11	[-1, 12, 128, 1]	0
MaxPool2d-12	[-1, 12, 64, 1]	0
Conv2d-13	[-1, 12, 64, 1]	432
ReLU-14	[-1, 12, 64, 1]	0
MaxPool2d-15	[-1, 12, 32, 1]	0
Conv2d-16	[-1, 12, 32, 1]	432
ReLU-17	[-1, 12, 32, 1]	0
MaxPool2d-18	[-1, 12, 16, 1]	0
Dropout-19	[-1, 192]	0
Linear-20	[-1, 64]	12,288
Linear-21	[-1, 12]	768

Training Here

Total params: 15,288
 Trainable params: 15,288
 Non-trainable params: 0

Input size (MB): 0.01
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Conclusion and Future Work



- Summary
 - CNN for AMC
 - Low power deployment of signal modulation classification
 - Through CNN optimization
 - Transfer learning makes system adaptable
 - Also reduces complexity of training if deployed on custom hardware
- Future Work
 - Hardware Survey
 - Best options for low SWaP deployment
 - Algorithm refinement
 - Optimize throughput and classification accuracy
 - Dataset improvement
 - Generate custom dataset using SDR for real world examination