TorchSig: A GNU Radio Block and New Spectrogram Tools for Augmenting ML Training

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TORCHSIG

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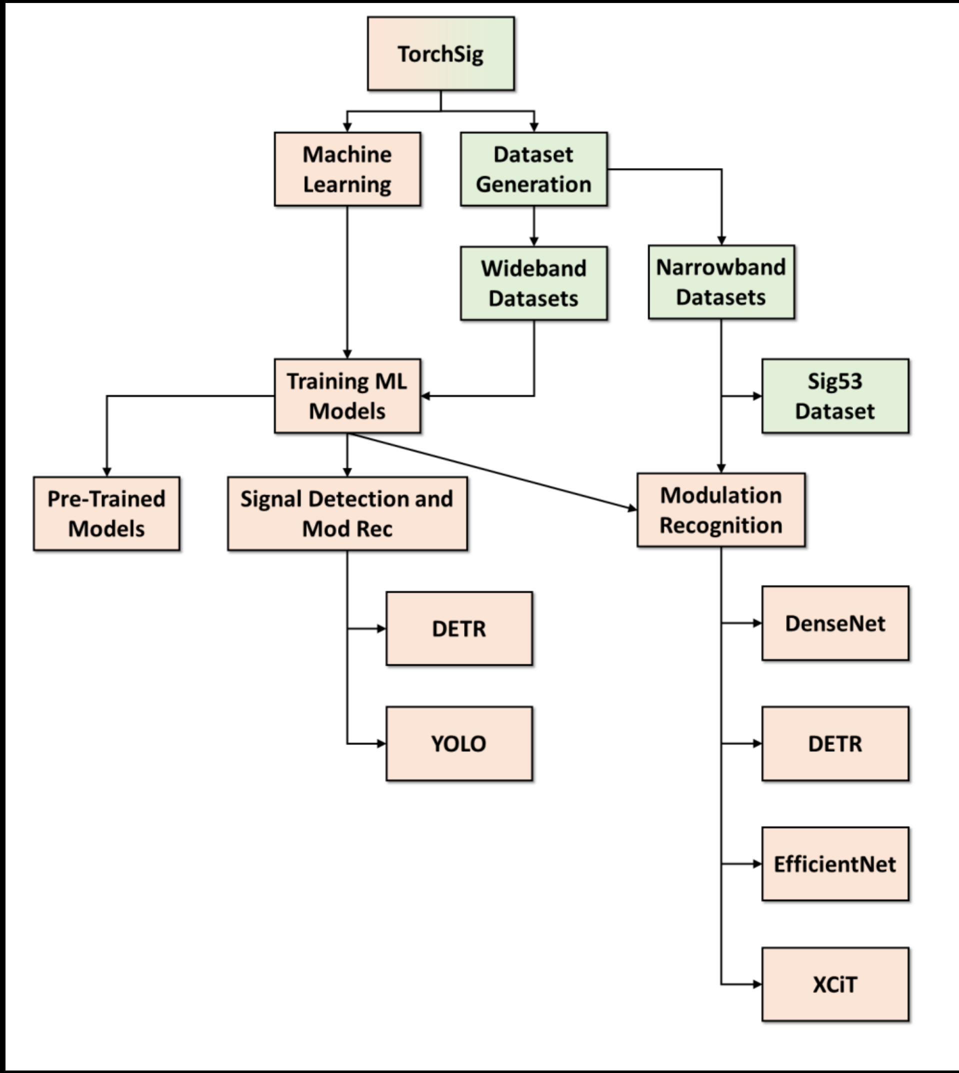
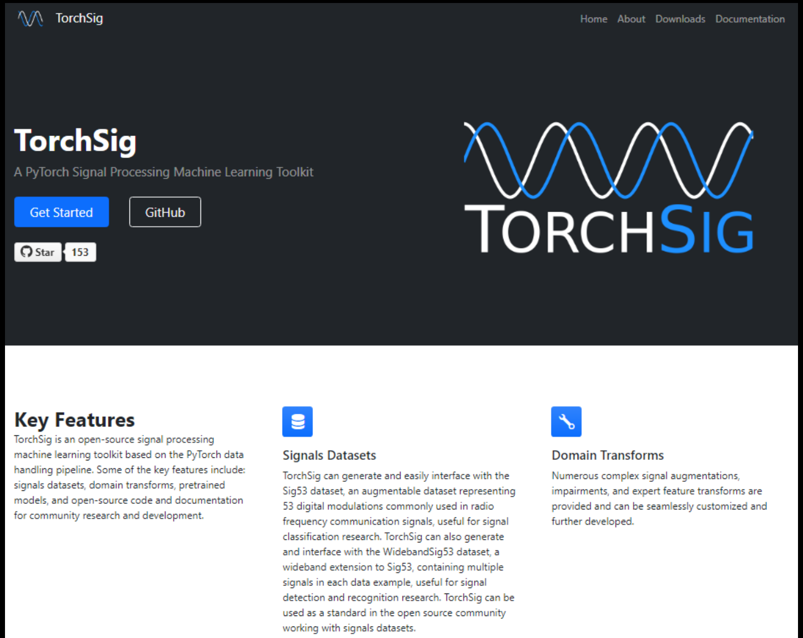
What is TorchSig?

- A system for RF machine learning
  - Training new ML models
  - Models for energy detection and mod rec
  - Narrowband and wideband dataset generation
  - Pretrained, downloadable models

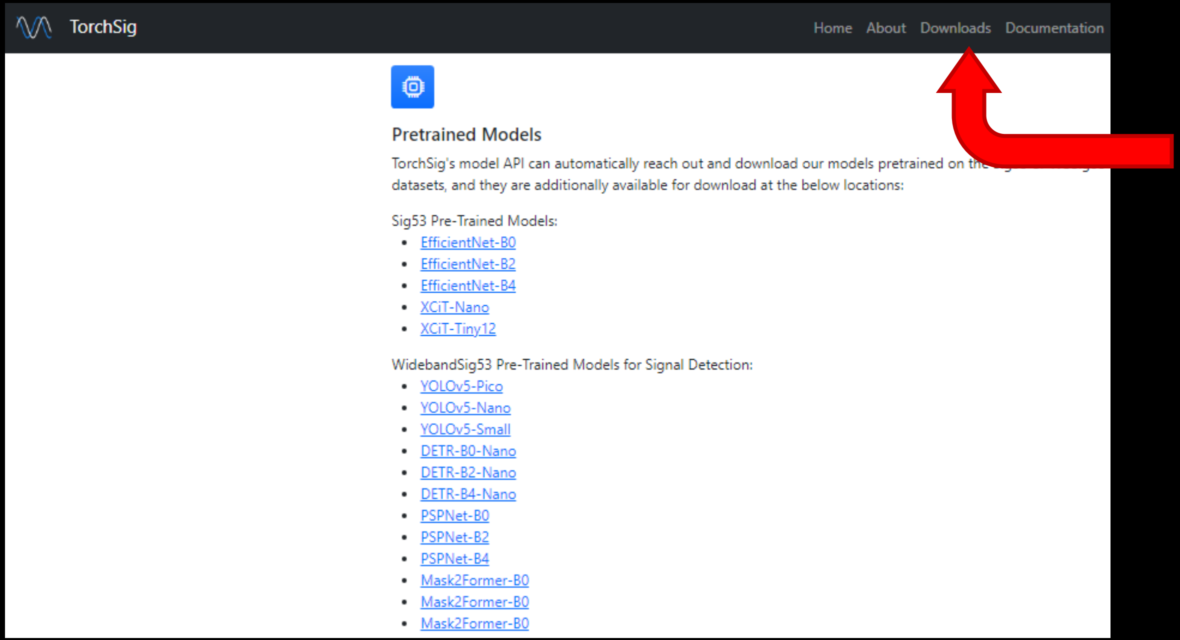


TorchSig.com

What is TorchSig? (cont.)



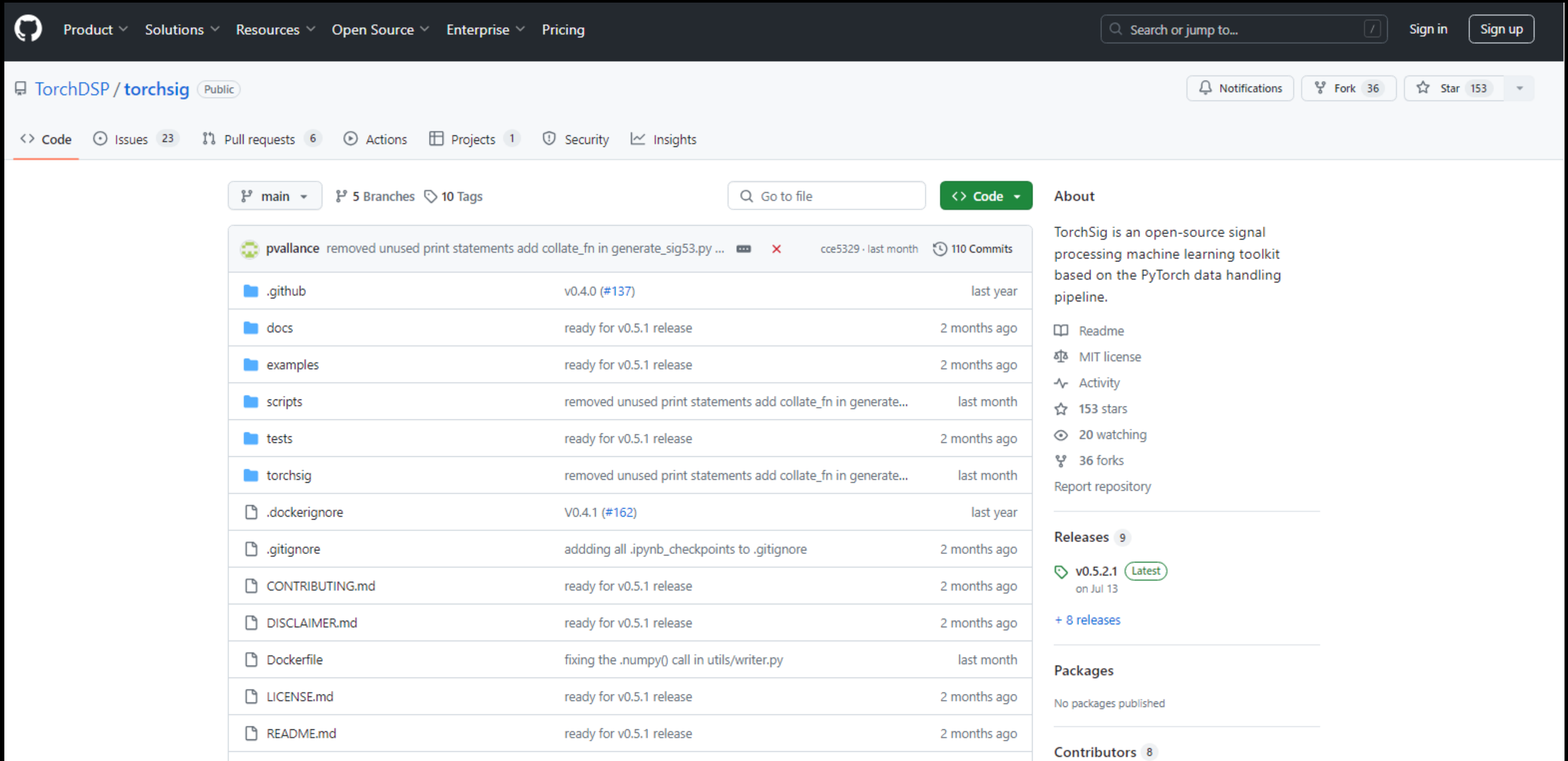
TorchSig.com



Papers & Pretrained Models (models under development and likely to be replaced & reworked soon)

What is TorchSig? (cont.)

- Code available github.com/torchdsp/torchsig



Machine Learning Models

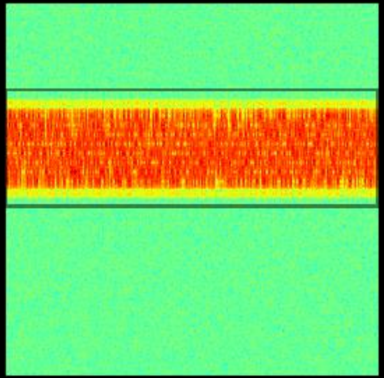
- TorchSig provides two types of models:
- “Narrowband” or modulation recognition model
  - Operates on IQ samples
  - Assumes signal is already channelized, basebanded and roughly time-aligned by an energy detector
- “Wideband” model
  - Operates on spectrograms
  - Able to locate multiple signals in time and frequency
  - Also has modulation recognition feature

Dataset Generation and Sig53

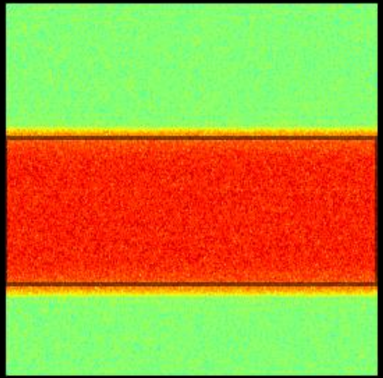
- Signal modulators:
  - Frequency Shift Keying (FSK and GFSK)
  - Minimum Shift Keying (MSK and GMSK)
  - Quadrature Amplitude Modulation (QAM)
  - Phase Shift Keying (PSK)
  - Pulse Amplitude Modulation (PAM)
  - On-Off Keying (OOK)
  - Orthogonal Frequency Division Multiplexing (OFDM)
- Narrowband datasets: single signal channelized and time-aligned at complex baseband
- Wideband datasets: multiple constant-wave (continuous) or bursty signals across a wide bandwidth

Dataset Generation and Sig53 (cont.)

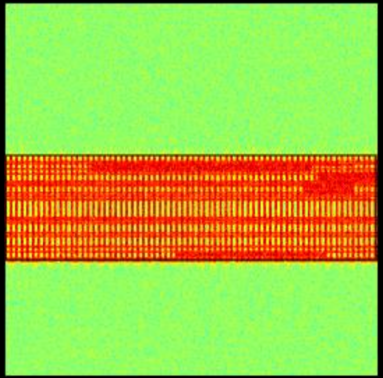
- Examples of wideband signals:



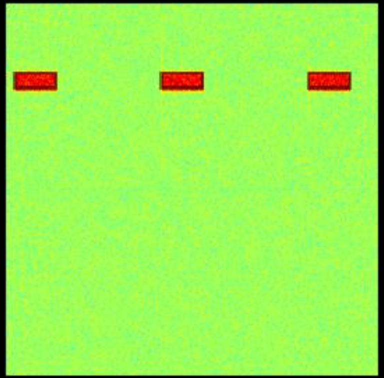
8-FSK



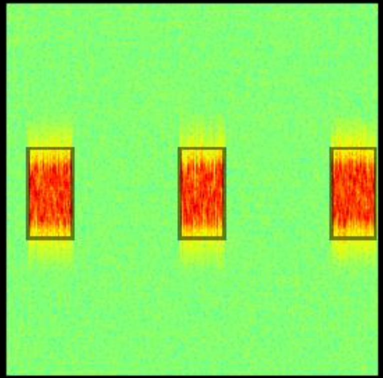
128-QAM



OFDM w/ 256 Subcarriers

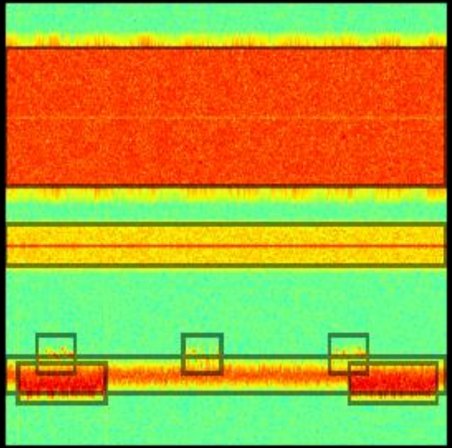


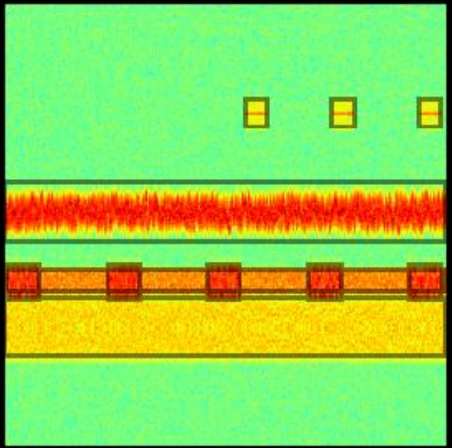
16-QAM



16-MSK

32-PAM, 2-GFSK, 4-GFSK, 16-GMSK, OFDM w/ 72 Subcarriers





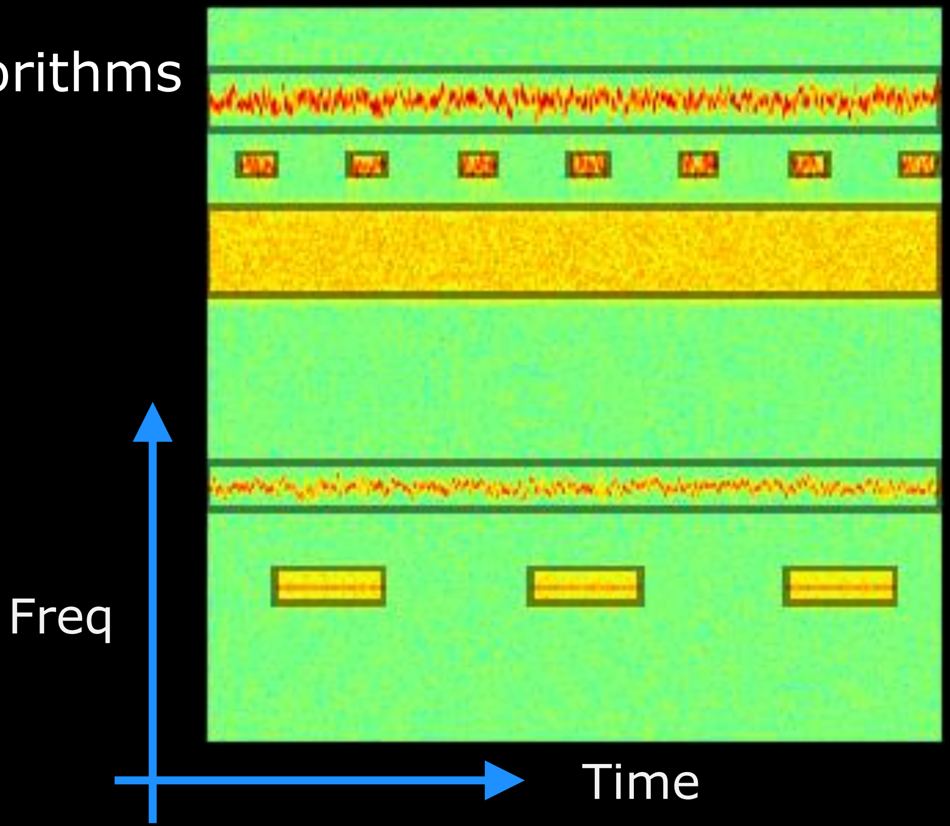
BPSK, 8-PAM, 32-QAM, 4-FSK, 4-GMSK

Recent Updates

- Three releases in 2024: 0.5.1, 0.5.2, 0.5.2.1, with more planned
- New features, improved DSP algorithms, faster speed, reduced memory, fixed bugs
  - Image-only spectrogram-based dataset tools: create, transform, extract
  - 10x speed improvement when using more than 32 workers
  - Reduced file size stored to disk by using different storage datatype
  - Improved randomization by fixing bug that caused some identical signals to be generated
  - Tighter bounding boxes for FSK and MSK
  - Reduced the sidelobes in resampling filters from -60 dB to -90 dB
  - Improved anti-aliasing filtering, minimize energy wrapping around the –fs/2 and +fs/2 boundary for multiple cases and transforms

Spectrograms

- Spectrograms display time-varying frequency content
- Also referred as “waterfalls”
- Easy for signals to be identified visually
- Foundational tool for training TorchSig ML algorithms
- ML to locate in both time and frequency
- “Bounding boxes”

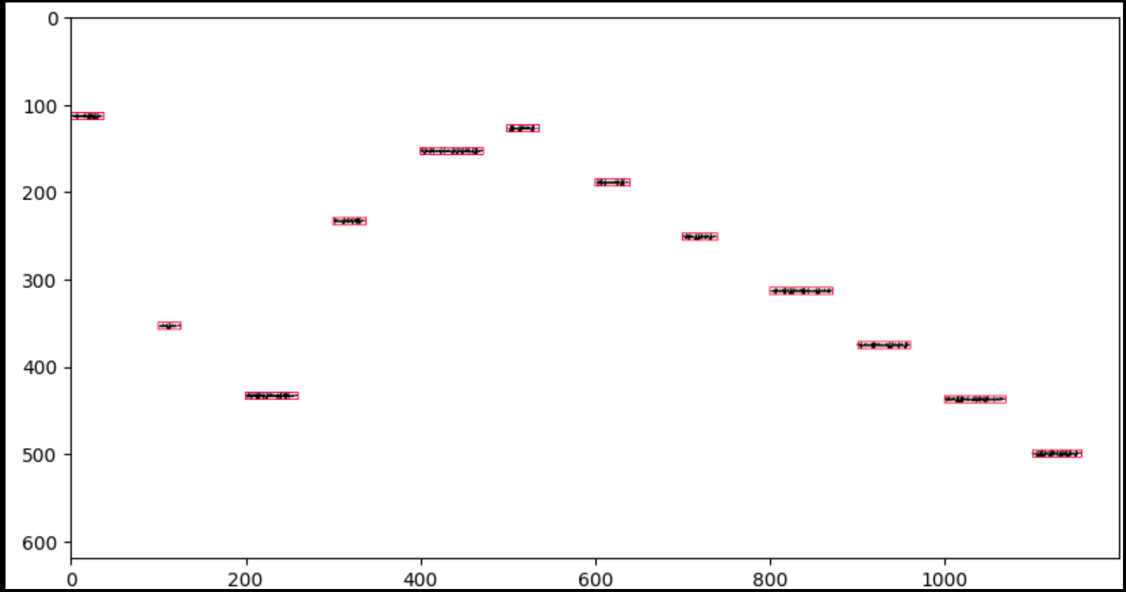


Synthetic Spectrograms

- Simulating spectrograms require large memory and computational effort
  - Creation and modulation of underlying signal(s)
  - Noise and channel impairments
  - Computation of spectrogram itself
- Can result in large databases (Many GBs, sometimes TBs)
- Slow to compute, therefore training must be done offline and in non-real time
- Synthetic Spectrograms are created directly, avoiding memory and computational burden
- Training can be done in near-real time, one spectrogram at a time
- Avoids large database problem

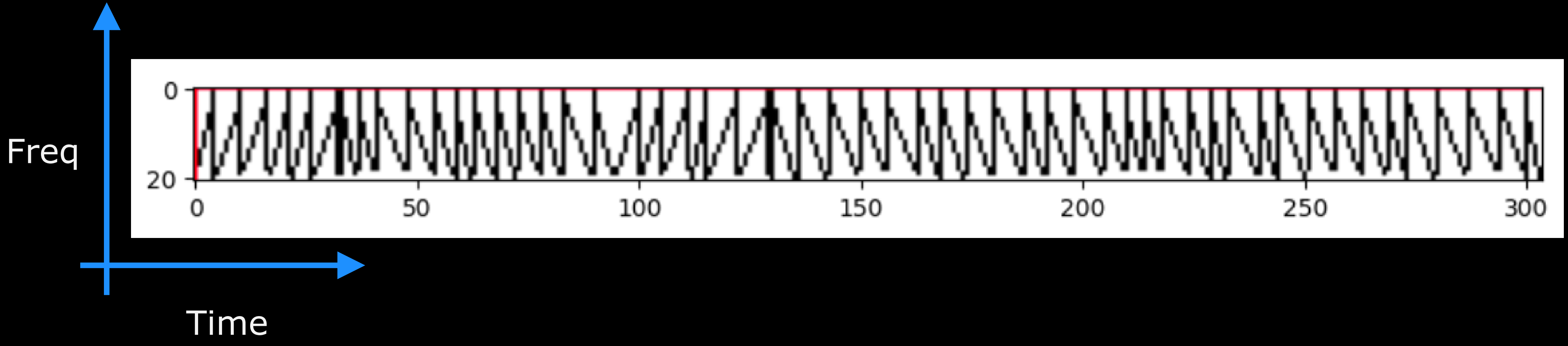
Recycling and Reusing Spectrograms

- When training ML models, more data is better
- But what if limited data is available?
- Few-shot ML techniques can be used to expand dataset
- Impairments and transforms on original data augment the dataset
- Example: "recycling" narrowband spectrograms and building a frequency hopper dataset



Direct Creation of Synthetic Spectrograms

- Some modulations allow for direct creation of synthetic spectrograms
- Chirp-based waveforms (LoRa-like) can be simulated this way
- A rising chirp and a falling chirp are defined and assembled



Direct Creation of Synthetic Spectrograms (cont.)

- Synthetic spectrograms assembled using Context Free Grammar (CFG)
- Establishes rules for how spectrograms are to be created and combined
- Example:
  - Multiple chirps = a data symbol
  - Header + multiple data symbols = data packet

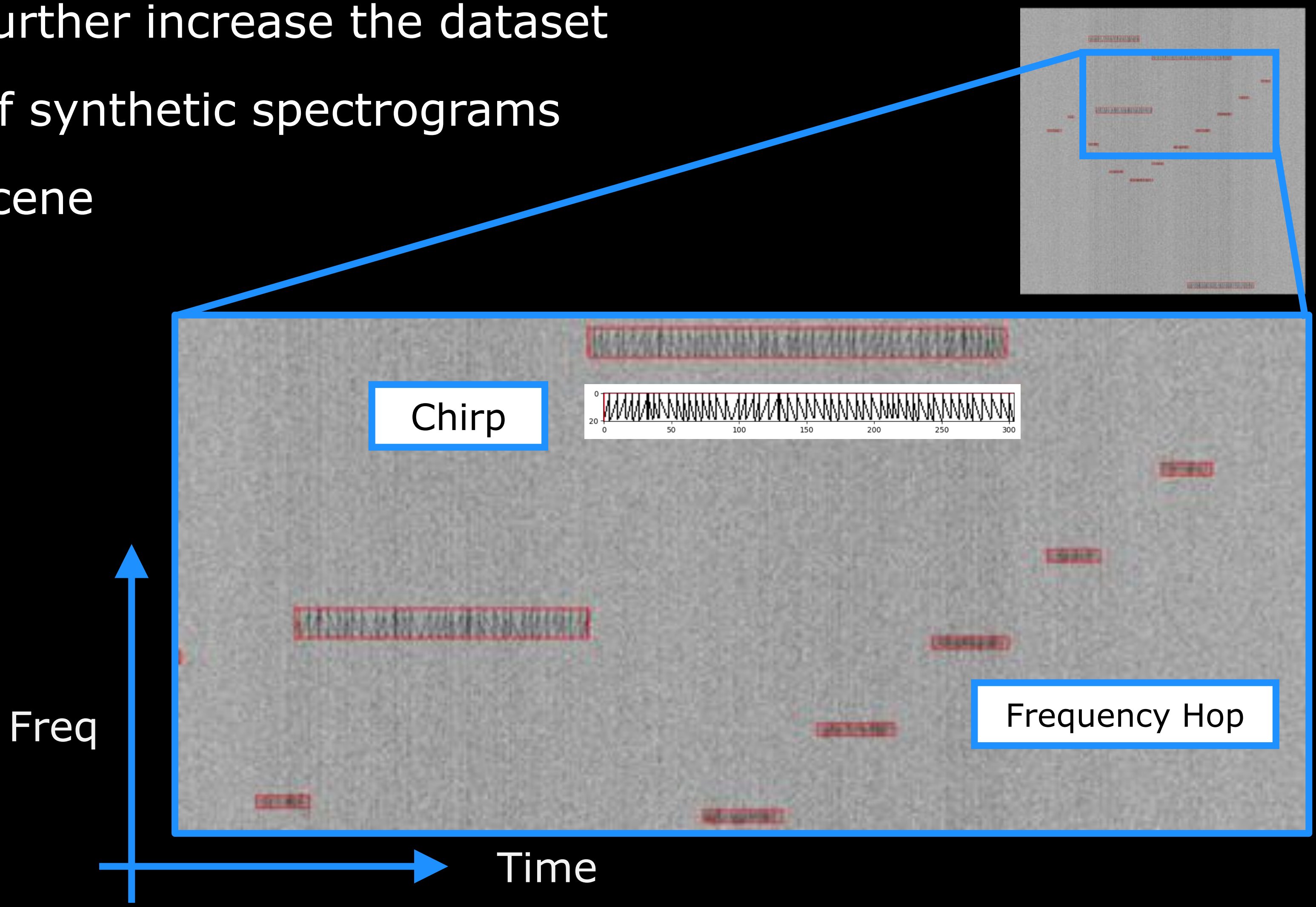
```
rising_chirp = GeneratorFunctionDataset(
    chirp_generator_function(1, 20, 4, random_height_scale = [0.9,1.1], random_width_scale = [1,2]),
    transforms=add_falling_edge)
falling_chirp = GeneratorFunctionDataset(
    chirp_generator_function(1, 20, 4, random_height_scale = [0.9,1.1], random_width_scale = [1,2]),
    transforms=[add_falling_edge, lambda x: x.flip(-1)])

chirp_stream_ds = CFGSignalProtocolDataset('cfg_signal')
chirp_stream_ds.add_rule('cfg_signal', ['rising_or_falling_stream'] + ['rising_falling_or_null']*12)
chirp_stream_ds.add_rule('rising_falling_or_null', 'rising_or_falling_stream', 1)
chirp_stream_ds.add_rule('rising_falling_or_null', 'null', 1)
chirp_stream_ds.add_rule('null', None)
chirp_stream_ds.add_rule('rising_or_falling_stream', 'rising_stream')
chirp_stream_ds.add_rule('rising_or_falling_stream', 'falling_stream')
chirp_stream_ds.add_rule('rising_stream', ['rising_segment'] + ['rising_segment_or_null']*2)
chirp_stream_ds.add_rule('rising_segment_or_null', 'rising_segment')
chirp_stream_ds.add_rule('rising_segment_or_null', 'null')
chirp_stream_ds.add_rule('rising_segment', ['rising_chirp']*3)
chirp_stream_ds.add_rule('rising_chirp', rising_chirp)
chirp_stream_ds.add_rule('falling_stream', ['falling_segment'] + ['falling_segment_or_null']*2)
chirp_stream_ds.add_rule('falling_segment_or_null', 'falling_segment')
chirp_stream_ds.add_rule('falling_segment_or_null', 'null')
chirp_stream_ds.add_rule('falling_segment', ['falling_chirp']*3)
chirp_stream_ds.add_rule('falling_chirp', falling_chirp)

yolo_chirp_stream_ds = YOLODatasetAdapter(chirp_stream_ds, class_id=0)
```

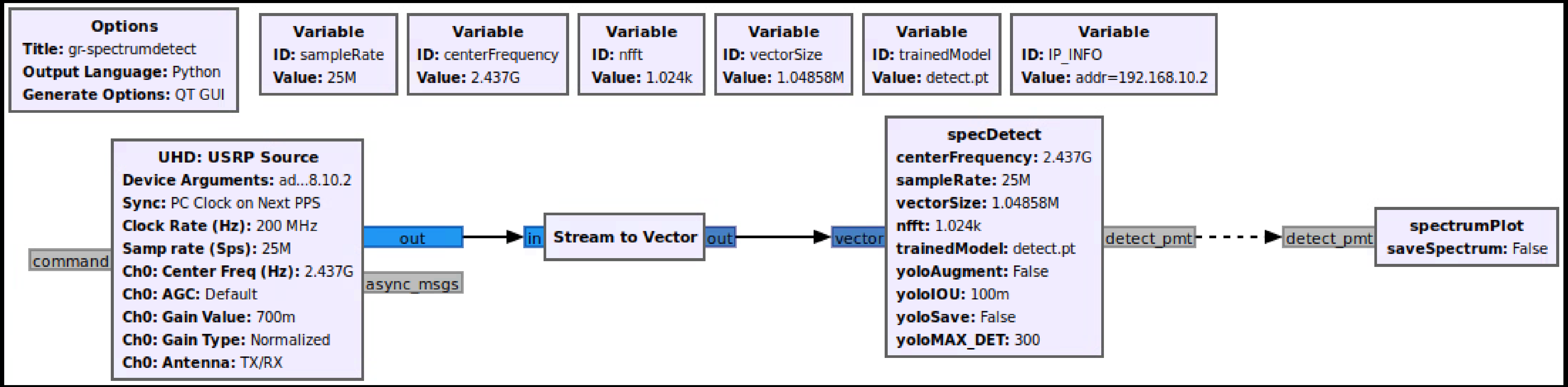
Composite Spectrograms

- Composite spectrograms further increase the dataset
- Combines multiple types of synthetic spectrograms
- Creates a more complex scene



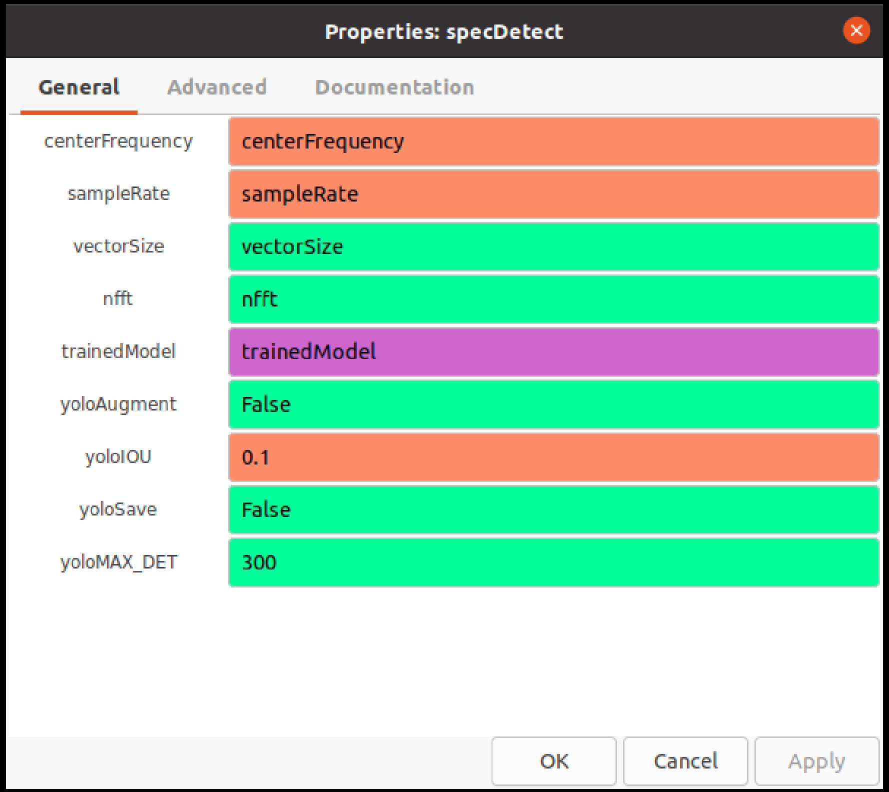
GNU Radio Block for Energy Detection

- OOT block gr-spectrumdetect performs energy detection with ML model
- Pretrained detect.pt YOLOv8x model against ISM band
- Uses a 1024x1024 spectrogram images
- specDetect block detects energy, spectrumPlot labels & displays spectrogram
- example.grc flowgraph:



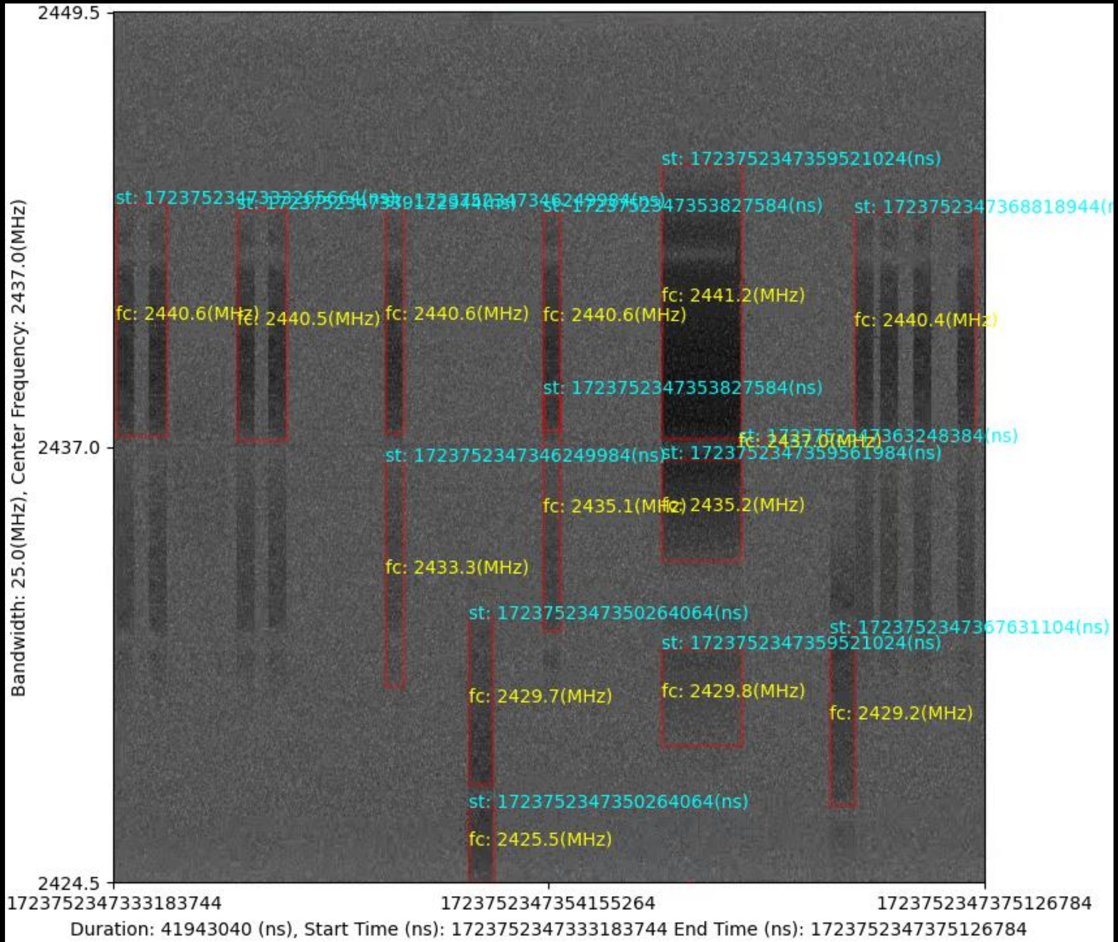
GNU Radio Block for Energy Detection (cont.)

- specDetect parameters must match those the model is trained for
- It's parametrizable, but not every feature is reconfigurable



GNU Radio Block for Energy Detection (cont.)

- spectrumPlot displays bounding boxes for detected energy



Future Work

- New tools and methods for integrating and labeling custom data sets, use of Label Studio
- Added support for HuggingFace and PyTorch, enable broader use and accessibility of TorchSig models
- Expansion of synthetic spectrogram generation feature, direct texturing and impairments to spectrograms
- Rework and expansion of analog modulations (AM, FM) and their variants (SSB, DSB, etc.)

Questions?

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