nnAudio Documentation

Release 0.3.1

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GETTING STARTED

Welcome to nnAudio 0.3.1. A big shout out to Miguel Pérez who made this new update possible. Please feel free to check out his github repositories too.

This new version restructured the coding style, making things more modular and pythonic. In terms of functionalities, everything remains the same. In the future releases, `nnAudio.Spectrogram` will be replaced by `nnAudio.features` (see also `features()`.)

`VQT()` is finally avaliable in version 0.3.1 thanks to Hao Hao Tan!

CHAPTER

ONE

QUICK START

```python
from nnAudio import features
from scipy.io import wavfile
import torch
sr, song = wavfile.read('./Bach.wav') # Loading your audio
x = song.mean(1) # Converting Stereo  to Mono
x = torch.tensor(x, device='cuda:0').float() # casting the array into a PyTorch Tensor

spec_layer = features.STFT(n_fft=2048, freq_bins=None, hop_length=512,
                              window='hann', freq_scale='linear', center=True, pad_mode=
↪'reflect',
                              fmin=50,fmax=11025, sr=sr) # Initializing the model

spec = spec_layer(x) # Feed-forward your waveform to get the spectrogram
```

nnAudio is an audio processing toolbox using PyTorch convolutional neural network as its backend. By doing so, spectrograms can be generated from audio on-the-fly during neural network training and the Fourier kernels (e.g. or CQT kernels) can be trained. Kapre has a similar concept in which they also use 1D convolutional neural network to extract spectrograms based on Keras.

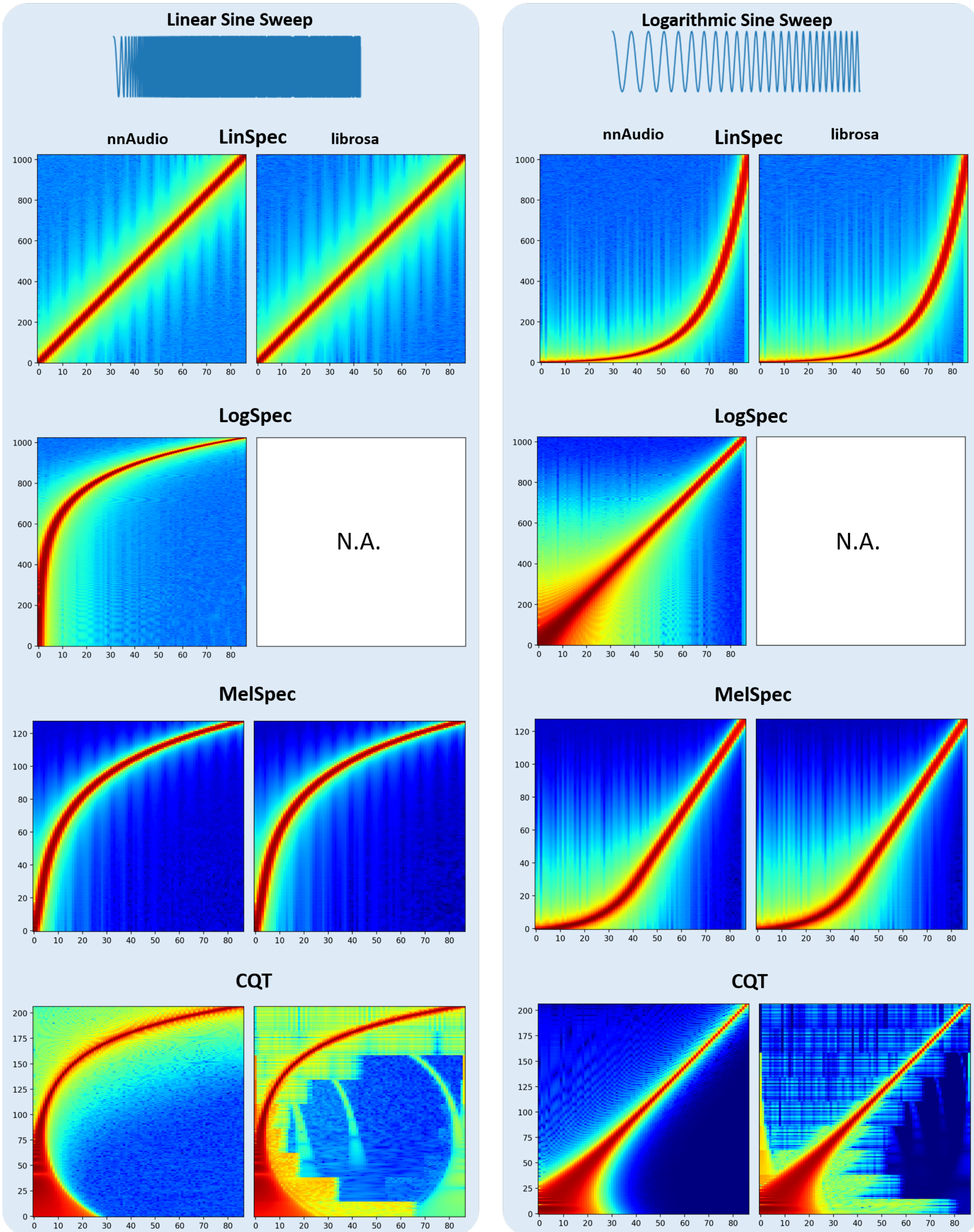
Other GPU audio processing tools are torchaudio and tf.signal. But they are not using the neural network approach, and hence the Fourier basis can not be trained. As of PyTorch 1.6.0, torchaudio is still very difficult to install under the Windows environment due to `sox`. nnAudio is a more compatible audio processing tool across different operating systems since it relies mostly on PyTorch convolutional neural network. The name of nnAudio comes from `torch.nn`.

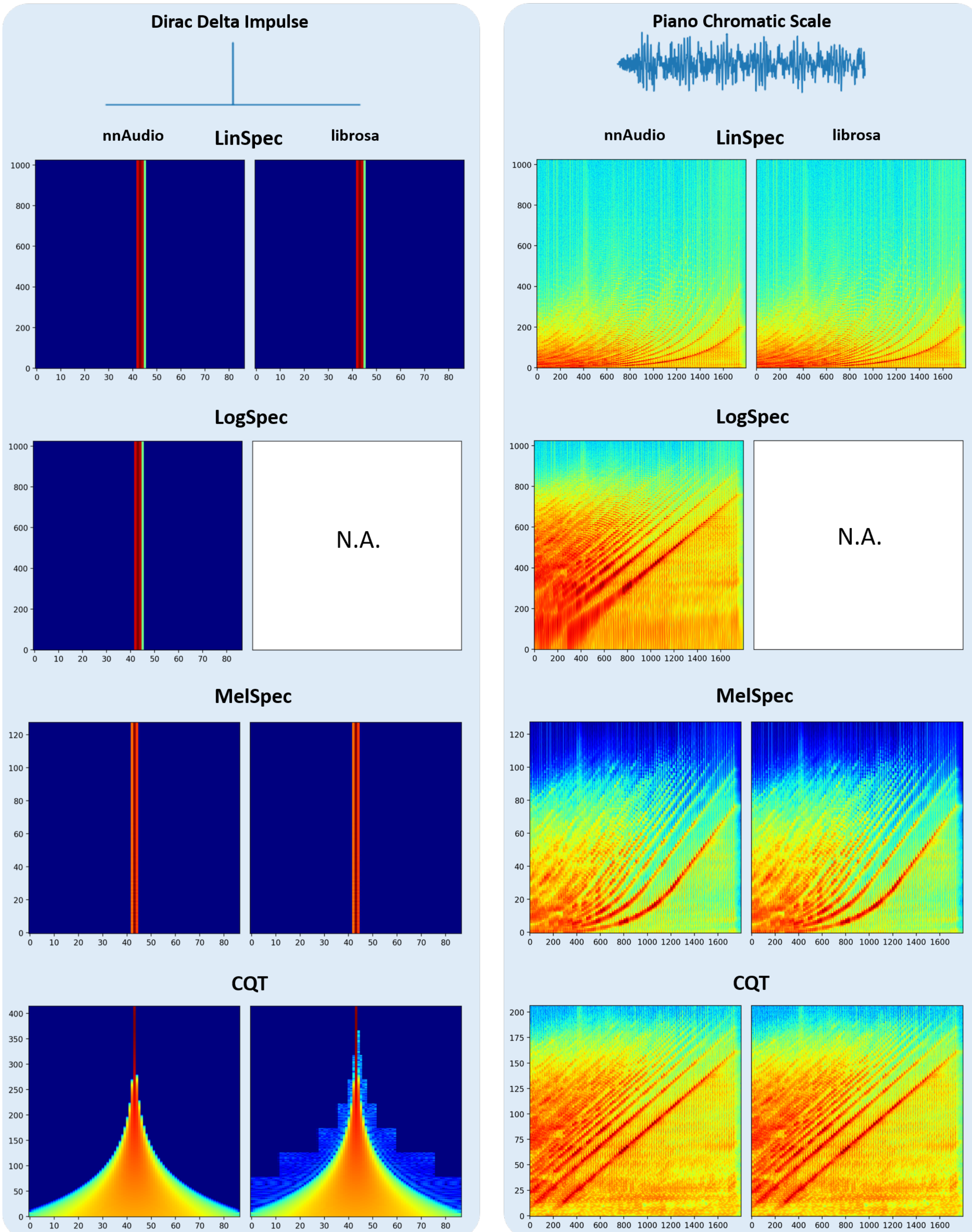
The implementation details for **nnAudio** have also been published in IEEE Access, people who are interested can read the paper.

The source code for **nnAudio** can be found in GitHub.

1.1 Introduction

nnAudio is basically a GPU version of some of the librosa functions, with additional features such as differentiable and trainable. The figure below shows the spectrograms obtained by nnAudio and librosa using different input signals.


Linear Sine Sweep
Logarithmic Sine Sweep
nnAudio
LinSpec
librosa
LogSpec
N.A.
MelSpec
CQT


Dirac Delta Impulse
Piano Chromatic Scale
nnAudio
LinSpec
librosa
LogSpec
N.A.
MelSpec
CQT

1.2 Installation

1.2.1 Via PyPI

To install previous releases from pypi: `pip install nnAudio==x.x.x`, where `x.x.x` is the version number. The lastest version might not be always available in PyPI, in this case, please install the lastest version from github.

1.2.2 Via GitHub

To install the lastest version from github, you can do `pip install git+https://github.com/KinWaiCheuk/nnAudio.git#subdirectory=Installation`.

Alternatively, you can also install from the github manually by the following steps:

1. Clone the repository with git clone https://github.com/KinWaiCheuk/nnAudio.git <any path you want to save to>
2. `cd` into the `Installation` folder where the `setup.py` is located at
3. `python setup.py install`.

1.2.3 Requirement

Numpy >= 1.14.5

Scipy >= 1.2.0

PyTorch >= 1.6.0 (Griffin-Lim only available after 1.6.0)

Python >= 3.6

librosa = 0.7.0 (Theortically nnAudio depends on librosa. But we only need to use a single function mel from librosa.filters. To save users troubles from installing librosa for this single function, I just copy the chunk of functions corresponding to mel in my code so that nnAudio runs without the need to install librosa)

1.3 Usage

1.3.1 Standalone Usage

To use nnAudio, you need to define the spectrogram layer in the same way as a neural network layer. After that, you can pass a batch of waveform to that layer to obtain the spectrograms. The input shape should be *(batch, len_audio)*.

```
from nnAudio import features
from scipy.io import wavfile
import torch
sr, song = wavfile.read('./Bach.wav') # Loading your audio
x = song.mean(1) # Converting Stereo  to Mono
x = torch.tensor(x, device='cuda:0').float() # casting the array into a PyTorch Tensor

spec_layer = features.STFT(n_fft=2048, freq_bins=None, hop_length=512,
                            window='hann', freq_scale='linear', center=True, pad_mode=
↪'reflect',
                            fmin=50,fmax=11025, sr=sr) # Initializing the model
```

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```
spec = spec_layer(x) # Feed-forward your waveform to get the spectrogram
```

1.3.2 On-the-fly audio processing

By integrating nnAudio inside your neural network, it can be used as on-the-fly spectrogram extracting. Here is one example on how to put nnAudio inside your neural network (highlighted in yellow):

```
from nnAudio import features
import torch
import torch.nn as nn

class Model(torch.nn.Module):
    def __init__(self, n_fft, output_dim):
        super().__init__()
        self.epsilon=1e-10
        # Getting Mel Spectrogram on the fly
        self.spec_layer = features.STFT(n_fft=n_fft, freq_bins=None,
                                        hop_length=512, window='hann',
                                        freq_scale='no', center=True,
                                        pad_mode='reflect', fmin=50,
                                        fmax=6000, sr=22050, trainable=False,
                                        output_format='Magnitude')
        self.n_bins = n_fft//2

        # Creating CNN Layers
        self.CNN_freq_kernel_size=(128,1)
        self.CNN_freq_kernel_stride=(2,1)
        k_out = 128
        k2_out = 256
        self.CNN_freq = nn.Conv2d(1,k_out,
                                kernel_size=self.CNN_freq_kernel_size,stride=self.CNN_
↪freq_kernel_stride)
        self.CNN_time = nn.Conv2d(k_out,k2_out,
                                kernel_size=(1,3),stride=(1,1))

        self.region_v = 1 + (self.n_bins-self.CNN_freq_kernel_size[0])//self.CNN_freq_
↪kernel_stride[0]
        self.linear = torch.nn.Linear(k2_out*self.region_v, output_dim, bias=False)

    def forward(self,x):
        z = self.spec_layer(x)
        z = torch.log(z+self.epsilon)
        z2 = torch.relu(self.CNN_freq(z.unsqueeze(1)))
        z3 = torch.relu(self.CNN_time(z2)).mean(-1)
        y = self.linear(torch.relu(torch.flatten(z3,1)))
        return torch.sigmoid(y)
```

After that, your model can take waveforms directly as the input, and extract spectrograms on-the-fly during feedforward.

```
waveforms = torch.randn(4,44100)
model(waveforms) # automatically convert waveforms into spectrograms
```

1.3.3 Using GPU

If a GPU is available in your computer, you can use `.to(device)` method like any other PyTorch `nn.Modules` to transfer the spectrogram layer to any device you like.

```
spec_layer = features.STFT().to(device)
```

Alternatively, if your `features` module is used inside your PyTorch model as in the *on-the-fly processing section*, then you just need to simply do `net.to(device)`, where `net = Model()`.

1.4 Speed

The speed test is conducted using three different machines, and it shows that nnAudio running on GPU is faster than most of the existing libraries.

- Machine A: Windows Desktop with CPU: Intel Core i7-8700 @ 3.20GHz and GeForce GTX 1070 Ti 8Gb GPU
- Machine B: Linux Desktop with CPU: AMD Ryzen 7 PRO 3700 and 1 GeForce RTX 2080 Ti 11Gb GPU
- Machine C: DGX station with CPU: Intel Xeon E5-2698 v4 @ 2.20GHz and Tesla v100 32Gb GPU

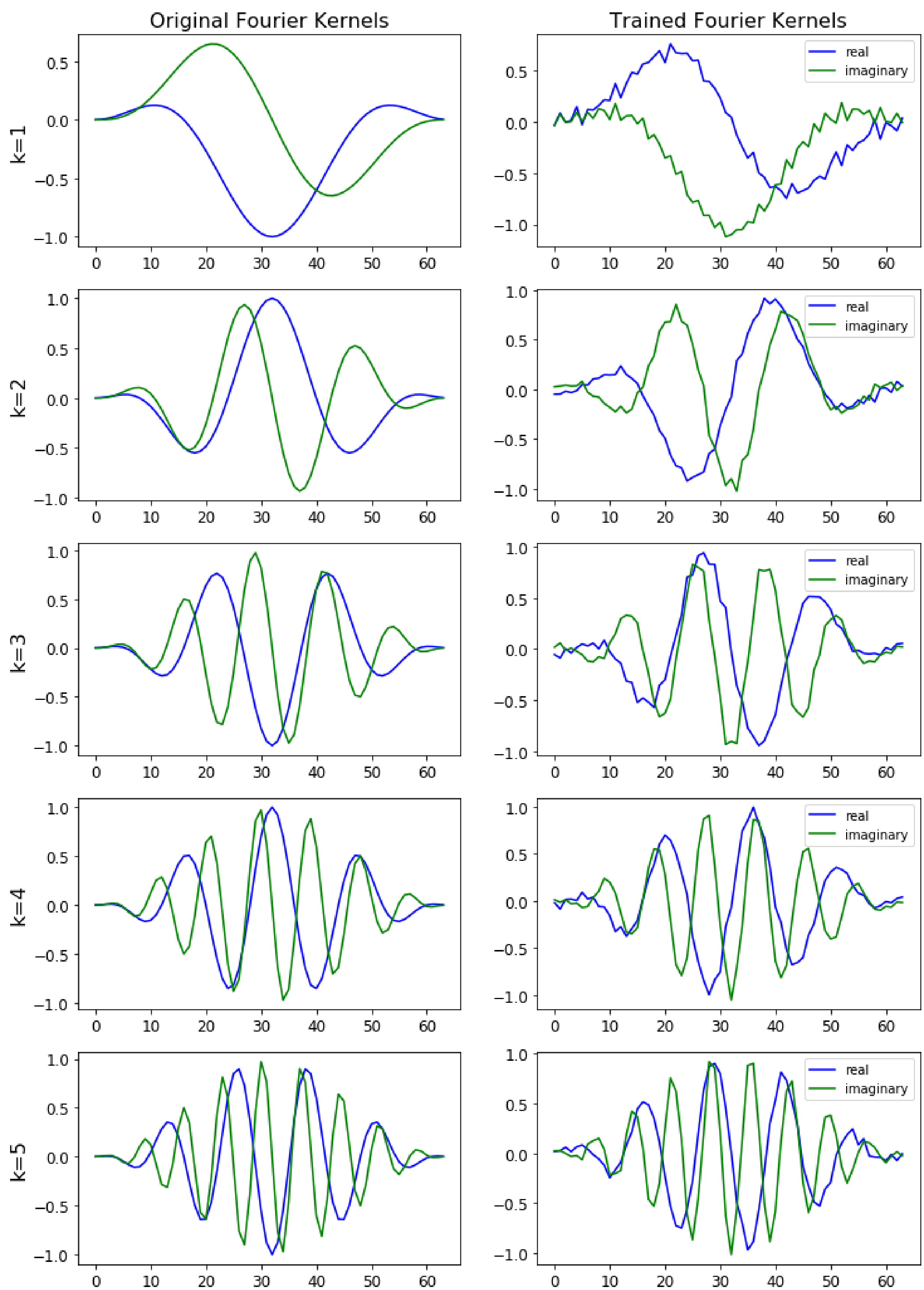
1.5 Trainable kernals

Fourier basis in `STFT()` can be set trainable by using `trainable=True` argument. Fourier basis in `MelSpectrogram()` can be also set trainable by using *trainable_STFT=True*, and Mel filter banks can be set trainable using `trainable_mel=False` argument. The same goes for `CQT()`.

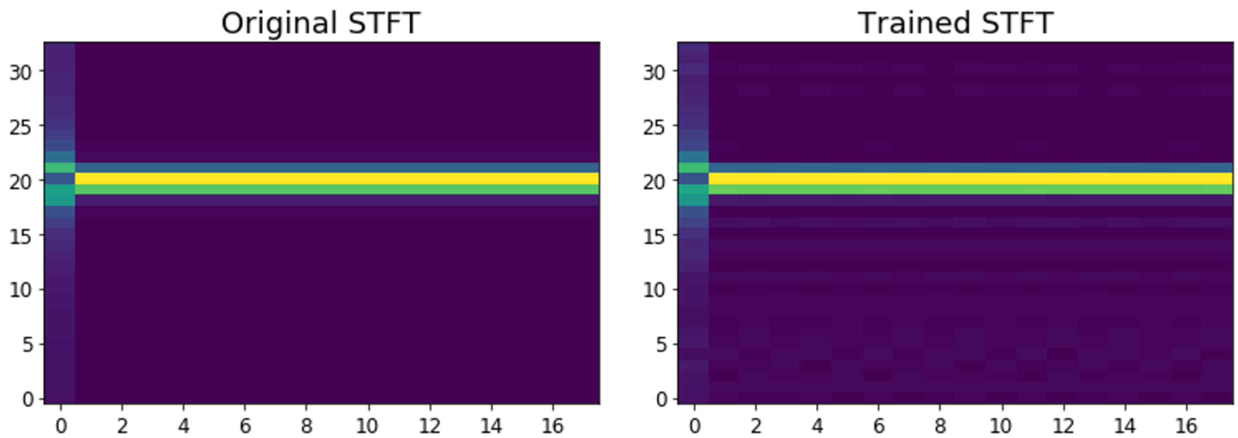
The follow demonstrations are avaliable on Google colab.

- Trainable STFT Kernel
- Trainable Mel Kernel
- Trainable CQT Kernel

The figure below shows the STFT basis before and after training.


Original Fourier Kernels
Trained Fourier Kernels
k=1
k=2
k=3
k=4
k=5
real
imaginary

The figure below shows how is the STFT output affected by the changes in STFT basis. Notice the subtle signal in the background for the trained STFT.



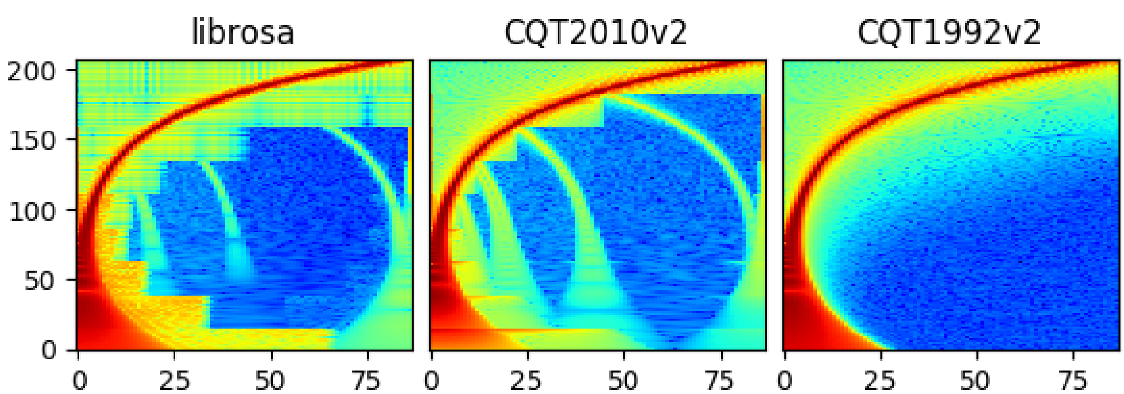
1.6 Different CQT versions

The result for `CQT1992` is smoother than `CQT2010` and librosa. Since librosa and `CQT2010` are using the same algorithm (downsampling approach as mentioned in this paper), you can see similar artifacts as a result of downsampling.

For `CQT1992v2` and `CQT2010v2`, the CQT is computed directly in the time domain without the need of transforming both input waveforms and the CQT kernels to the frequency domain. making it faster than the original CQT proposed in 1992.

The default CQT in nnAudio is the `CQT1992v2` version. For more detail, please refer to our paper

All versions of CQT are available for users to choose. To explicitly choose which CQT to use, you can refer to the CQT API section.



1.7 PyTorch Template for Audio projects

I am building a pytorch template which allows audio related projects to be quick setup. This template uses nnAudio to extract spectrograms on-the-fly.

1.8 Source Code

The source code for nnAudio is available at github.

1.9 Call for Contribution

nnAudio is a fast-growing package. With the increasing number of feature requests, we welcome anyone who is familiar with digital signal processing and neural network to contribute to nnAudio. The current list of pending features includes:

1. Invertible Constant Q Transform (CQT)
2. CQT with filter scale factor (see issue #54)
3. Variable Q Transform see VQT)
4. Speed and Performance improvements for Griffin-Lim (see issue #41)
5. Data Augmentation (see issue #49)

(Quick tips for unit test: *cd* inside Installation folder, then type *pytest*. You need at least 1931 MiB GPU memory to pass all the unit tests)

Alternatively, you may also contribute by:

1. Refactoring the code structure (Now all functions are within the same file, but with the increasing number of features, I think we need to break it down into smaller modules)
2. Making a better demonstration code or tutorial

People who are interested in contributing to nnAudio can visit the github page or contact me via kinwai<underscore>cheuk<at>mymail.sutd.edu.sg.

1.10 Citing nnAudio

If you use nnAudio in your research, please feel free to cite our work.

1.10.1 Plain Text

K. W. Cheuk, H. Anderson, K. Agres and D. Herremans, “nnAudio: An on-the-Fly GPU Audio to Spectrogram Conversion Toolbox Using 1D Convolutional Neural Networks,” in IEEE Access, vol. 8, pp. 161981-162003, 2020, doi: 10.1109/ACCESS.2020.3019084.

1.10.2 BibTex

```
@ARTICLE{9174990,
author={K. W. {Cheuk} and H. {Anderson} and K. {Agres} and D. {Herremans}},
journal={IEEE Access},
title={nnAudio: An on-the-Fly GPU Audio to Spectrogram Conversion Toolbox Using 1D␣
↪Convolutional Neural Networks},
year={2020},
volume={8},
number={},
pages={161981-162003},
doi={10.1109/ACCESS.2020.3019084}}
```

1.10.3 Link to the paper

The paper for nnAudio is avaliable on IEEE Access

1.11 Indices and tables

- genindex
- modindex