Python and OOI hydrophone data

Virtual Meeting, Fall 2024

Environment setup for this notebook

In this section of the notebook, I'll walk you through setting up a python environment for this notebook. It's not necessary to use this exact configuration. These instructions were written for a UNIX based system (Mac or Linux). Some of instructions are likely different for a windows system.

I use miniconda as my package manager. You can install it here

- creata a new miniconda environment

```
conda create -n ooi
```

- activate the new conda environment

```
conda activate ooi
```

- When the environment is activated, you should see the environment name in the console. It should look something like this:

  ```
  (ooi) John@<computer name> ~ %
  ```

- install python and the the packages that this notebook uses

```
conda install python numpy matplotlib scipy pandas seaborn hvplot
```

- install xarray. Xarray has several backends that aren't strict dependancies but increase the functionality of the python package. We'll use some of these later in the notebook. For more information about installing xarray, see the install section of xarray docs. I've added zarr to the default backends listed in the docs section, which we'll use later in notebook

```
conda install -c conda-forge xarray dask netCDF4 bottleneck zarr
```

- install ooipy

```
pip install ooipy
```

- install jupyter-lab to be able to open and edit the notebook.

```
conda install -c conda-forge jupyterlab
pip install dask-labextension
```

You should now have a conda environment named ooi, with all of the packages that we need for this notebook. You can double check that which packages you have installed with the command:

```
conda list
```

If you want to open the notebook on your own computer and run the code, you can run jupyter lab, which should open on your web browser

```
jupyter lab
```

Overview of ooipy

ooipy is a python package designed to help access hydrophone data from the Ocean Observatories Initiative (OOI) cabled ocean observatory. OOI hydrophone data is all open access, and is a great opportunity for educational exercises and conducting novel research.

ooipy is a community backed, open source python package that is a stand in for an API to access OOI hydrophone data.

In [1]:

```
import ooipy
from datetime import datetime
import numpy as np
import matplotlib.pyplot as plt
import xarray as xr
import pandas as pd
from IPython.display import Audio
import seaborn as sns
import hvplot.xarray

%config InlineBackend.figure_format='retina'
```

download hydrophone data within python environment

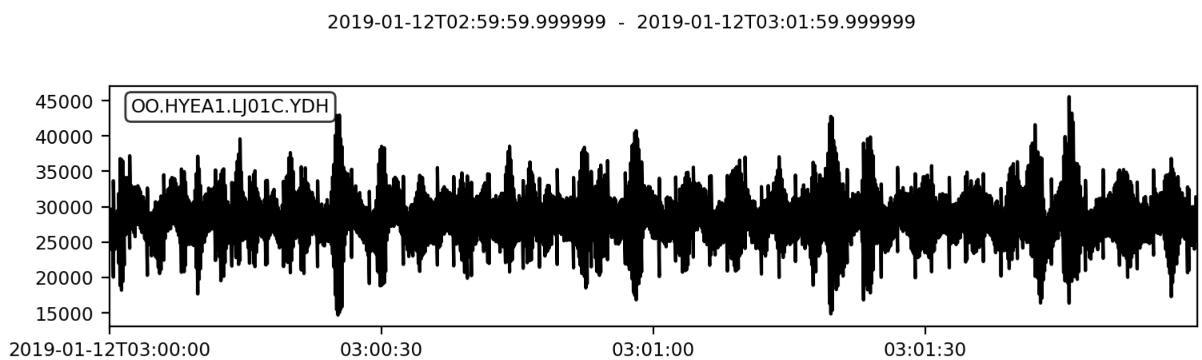
In [2]:

```
starttime=datetime(2019,1,12,3)
endtime=datetime(2019,1,12,3,2)
node = 'LJ01C'
```

```
hdata = ooipy.get_acoustic_data(starttime, endtime, node, verbose=True)
```

```
Fetching URLs...
Sorting valid URLs for Time Window...
Downloading mseed files...
100%|████████████████████████████████████████| 4/4 [00:07<00:00,  1.91
s/it]
Merging 4 Traces...
Data has Gaps
```

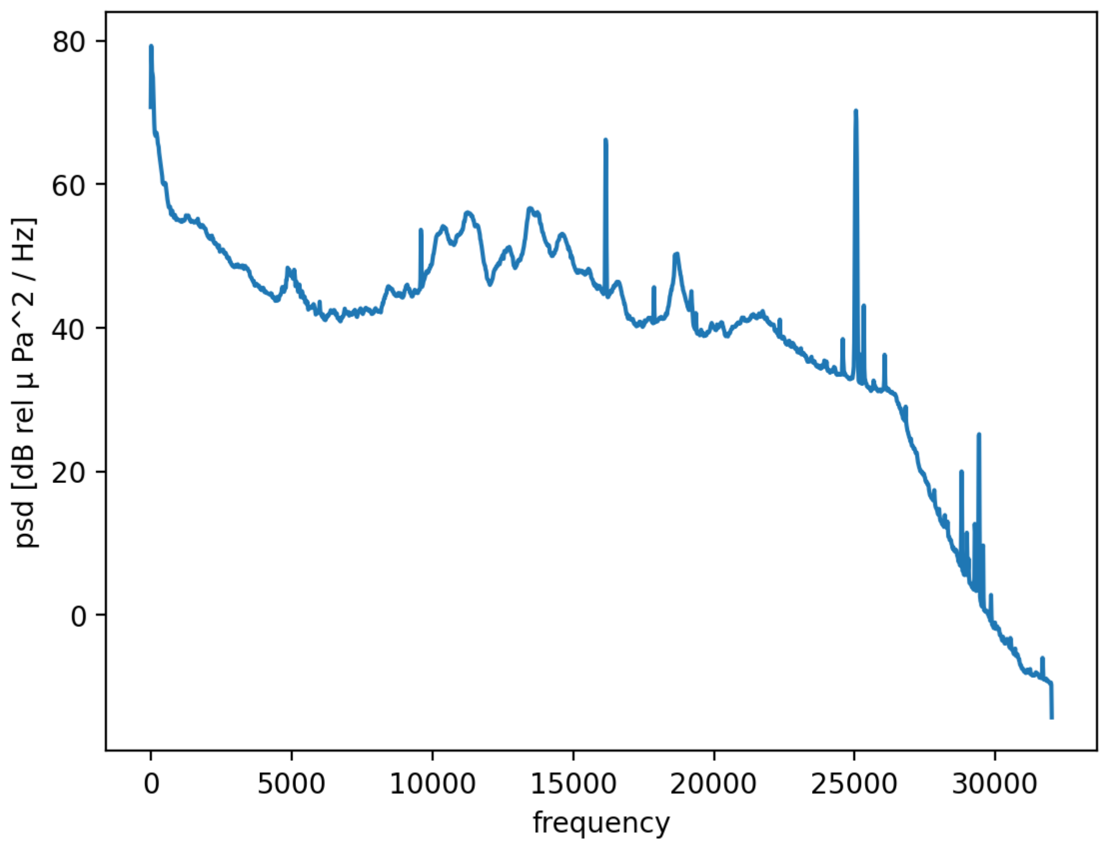
In [7]:
```
_ = hdata.plot()
```



In [8]:
```
psd = hdata.compute_psd_welch()
```

In [10]:
```
psd.plot()
```

Out[10]: `[<matplotlib.lines.Line2D at 0x30e28a8a0>]`



In [11]:
```
hdata_norm = (hdata.data - np.mean(hdata.data))
hdata_norm = hdata_norm / np.max(hdata_norm)
```

In [12]:
```
Audio(hdata_norm[64000*45:64000*60], rate=64000)
```

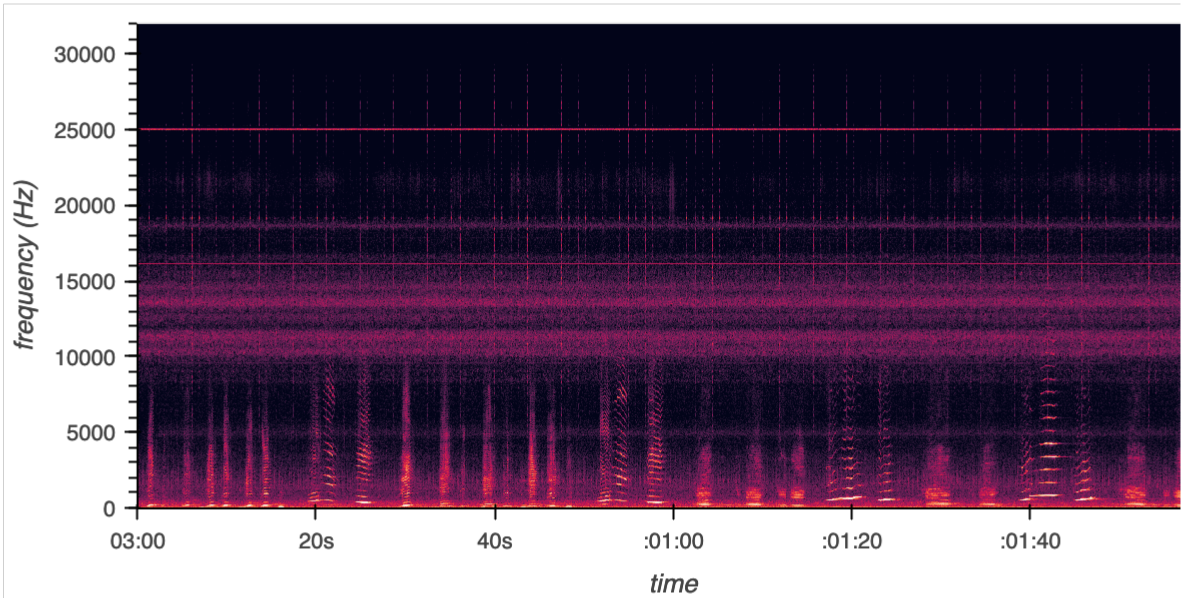
Out[12]:

0:00 / 0:15

In [13]:
```
spec = hdata.compute_spectrogram(avg_time=0.08, L=2048)
spec.frequency.attrs['units'] = 'Hz'
```

In [15]:
```
spec.hvplot.image(x='time', cmap='rocket',clim=(40,90))
```

Out[15]:



In [16]:
```
hdata.save('mat', 'humpback')
```

Batch downloading from terminal / command line

ooipy also comes with a program that can batch download data specified by a csv file. This would be useful if you want to use different software (other than python) to analyze your acoustic data.

Some of the features of this are still under development, but a simple working example is provided below. If you run into a use case that you would like that currently isn't working, I'd encourage you to submit an issue on GitHub and consider contributing as well.

- included in the repository is the file batch_download.csv
- In the terminal type

```
download_hydrophone_data -h
```

- this should give you the documentation of the program. Now in the command line, navigate to the directory that your csv file is saved and run the program with:

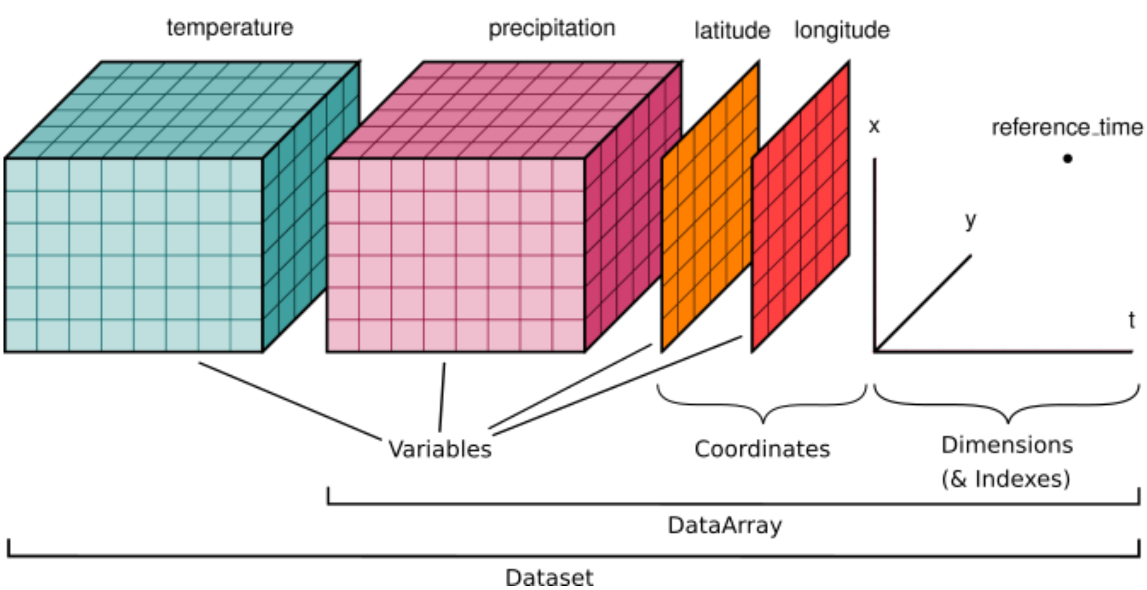
`download_hydrophone_data --csv batch_download.csv --output_path .`
This specifies the csv path and the path to download the files (`.` specifies to download the files in the current directory)

Spectral Statistical Analysis using xarray

playing around with big(ish) data

xarray is a great tool for scientific data analysis that combines the concept of the n-dimensional array (like a numpy.array) and labeled coordinates the data. It came out of the earth / space science community, but is relevant to acoustic data though as well.

Learning all of the ins and outs of xarray is beyond the scope of this demo, but there exists some great resources to learn more about xarray. Specifically, this chapter of the book **Earth and Environmental Data Science** book link does a great job of going over some of the capabilities of xarray in more detail.



Downloading the data for this section The spectrograms that we use in this section are about 1.5 GB, and can be downloaded from zenodo. Follow the link below and download the zip file into the current directory. Then unzip the file. You should see a folder named `lf_specs.zarr` .

https://doi.org/10.5281/zenodo.14048118

- zarr files are a nice way to store large datasets that enable larger than memory calculations

- all of the details of utilizing zarr and dask arrays is beyond the scope of this presentation, but this chapter of the same book does a great job of explaining it.

In [17]:
```
import xarray as xr
from dask.distributed import LocalCluster, Client
import hvplot.xarray
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
```

In [18]:
```
client = Client()
client
```

Out[18]:

Client

Client-dd16cd80-9d25-11ef-813a-7ab3f75eed06

Connection method: Cluster object **Cluster type:** distributed.LocalCluster

Dashboard: http://127.0.0.1:8787/status

Launch dashboard in JupyterLab

▸ Cluster Info

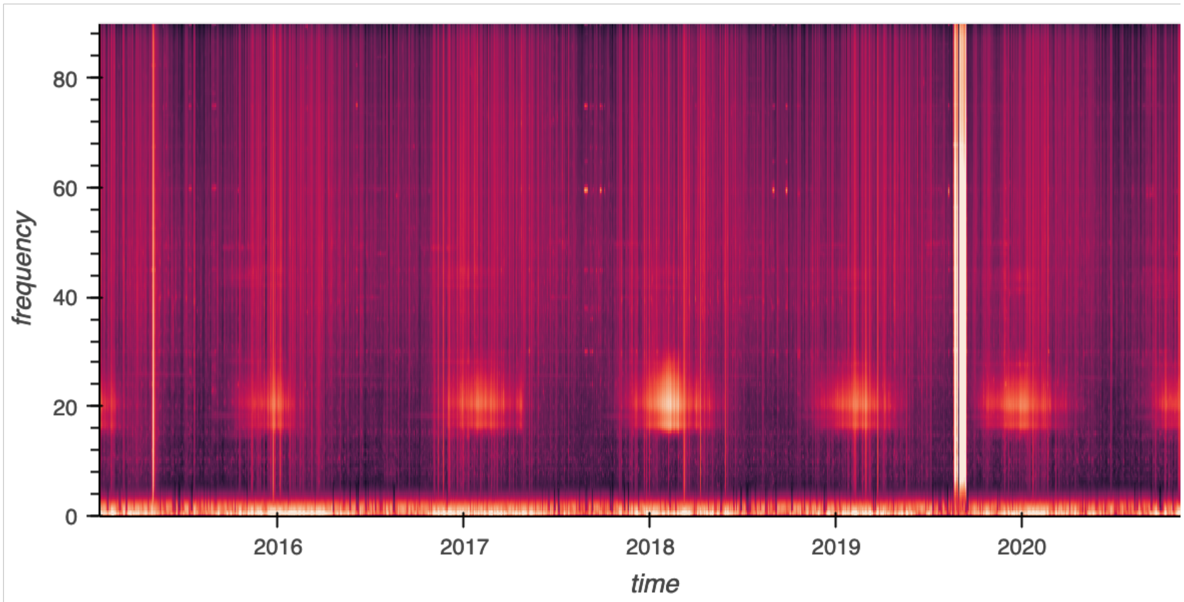
In [19]:
```
fn = 'lf_specs.zarr'
ds = xr.open_zarr(fn)
```

visualize spectrogram

In [23]:
```
ds['central_caldera'].hvplot.image(x='time', rasterize=True, cmap='rocket',
```

```
WARNING:param.Image00336: Image dimension time is  not evenly sampled to rel
ative tolerance of 0.001. Please use the QuadMesh element for irregularly sa
mpled data or set a higher tolerance on hv.config.image_rtol or the rtol par
ameter in the Image constructor.
WARNING:param.Image00336: Image dimension time is  not evenly sampled to rel
ative tolerance of 0.001. Please use the QuadMesh element for irregularly sa
mpled data or set a higher tolerance on hv.config.image_rtol or the rtol par
ameter in the Image constructor.
```

Out[23]:



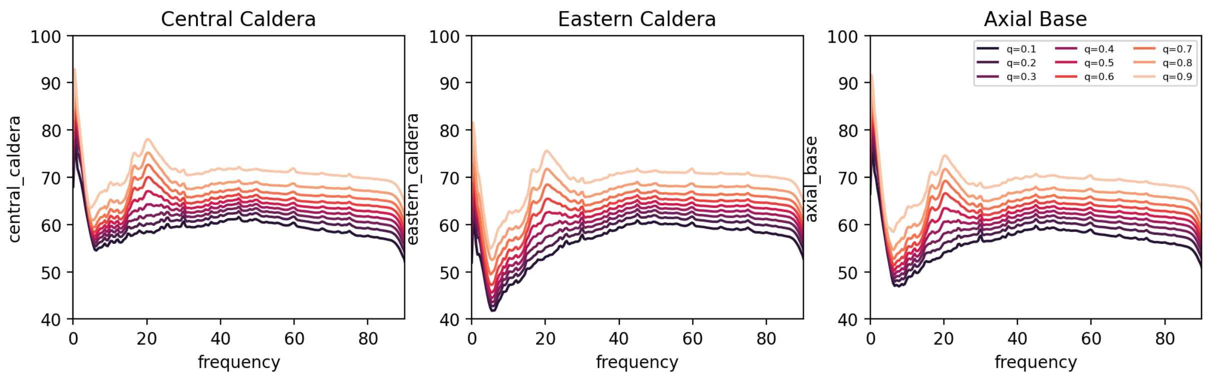
Spectral Quantiles

In [24]:
```
frequency_quantiles = ds.chunk({'time': -1}).quantile(np.arange(0.1,1,0.1),
```

In [26]:
```
frequency_quantiles = frequency_quantiles.compute()
```

In [27]:
```
sns.set_palette('rocket',9)

fig = plt.figure(figsize=(10,3))

plt.subplot(1,3,1)
# central Caldera
for k in range(9):
    frequency_quantiles['central_caldera'][k,:].plot(label=f'q={float(freque
#plt.legend(ncols=4)
plt.xlim(0,90)
plt.ylim([40,100])
plt.title('Central Caldera')

plt.subplot(1,3,2)
# Eastern Caldera
for k in range(9):
    frequency_quantiles['eastern_caldera'][k,:].plot(label=f'q={float(freque
plt.xlim(0,90)
plt.ylim([40,100])
plt.title('Eastern Caldera')

plt.subplot(1,3,3)
# Axial Base
for k in range(9):
    frequency_quantiles['axial_base'][k,:].plot(label=f'q={float(frequency_q
plt.xlim(0,90)
plt.ylim([40,100])
plt.title('Axial Base')
```

```
plt.legend(ncols=3, fontsize=6)
plt.tight_layout(pad=0)
```



Integrating over frequency band

In [28]:
```
f_band1 = (20*np.log10((10**(ds/20)).sel({'frequency':slice(15,25)}).integra
f_band2 = (20*np.log10((10**(ds/20)).sel({'frequency':slice(50,60)}).integra
```

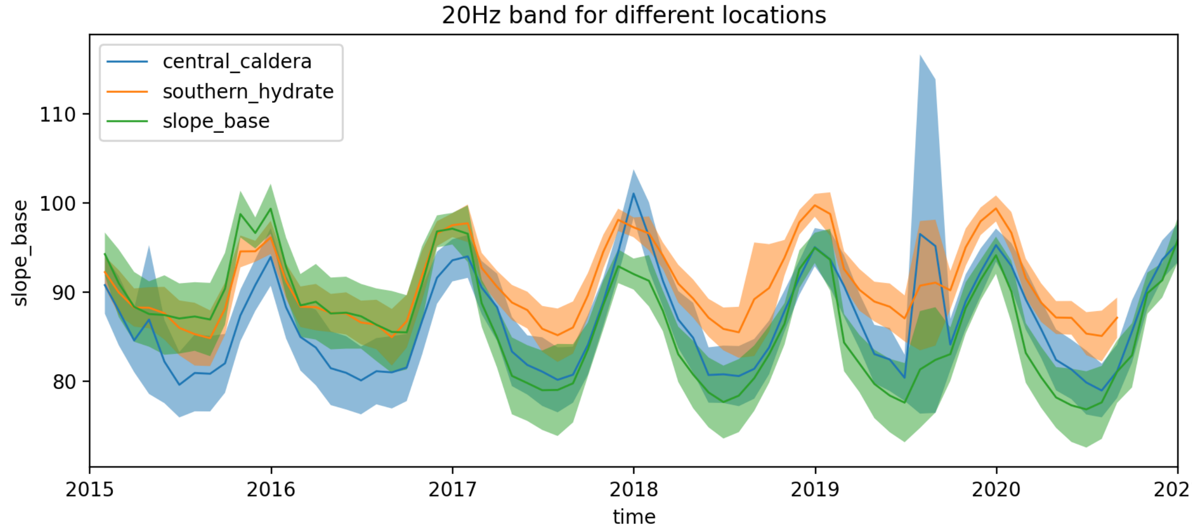
In [32]:
```
f_band1_month = f_band1.resample({'time':'ME'})
f_band2_month = f_band2.resample({'time':'ME'})

#f_band1_month = f_band1.resample({'time':'d'})
#f_band2_month = f_band2.resample({'time':'d'})
```

In [33]:
```
f_band1_mean = f_band1_month.mean().compute()
f_band1_std = f_band1_month.std().compute()

f_band2_mean = f_band2_month.mean().compute()
f_band2_std = f_band2_month.std().compute()
```

```
/opt/miniconda3/envs/ooi/lib/python3.12/site-packages/dask/array/numpy_compa
t.py:57: RuntimeWarning: invalid value encountered in divide
  x = np.divide(x1, x2, out)
/opt/miniconda3/envs/ooi/lib/python3.12/site-packages/dask/array/numpy_compa
t.py:57: RuntimeWarning: invalid value encountered in divide
  x = np.divide(x1, x2, out)
```

In [34]:
```
fig = plt.figure(figsize=(10,4))

sns.set_palette('tab10',3)

nodes = ['central_caldera', 'southern_hydrate', 'slope_base']

for node in nodes:
    f_band1_mean[node].plot(lw=1, label=node)
    plt.fill_between(f_band1_mean[node].time, f_band1_mean[node] + f_band1_s

plt.legend()
plt.xlim([pd.Timestamp('2015-01-01'), pd.Timestamp('2021-01-01')])
plt.title('20Hz band for different locations')
```

Out[34]:
```
Text(0.5, 1.0, '20Hz band for different locations')
```



In [35]:

```
fig = plt.figure(figsize=(10,4))

sns.set_palette('tab10',3)

node = 'central_caldera'

f_band1_mean[node].plot(lw=1, label='20Hz band')
plt.fill_between(f_band1_mean[node].time, f_band1_mean[node] + f_band1_std[n

f_band2_mean[node].plot(lw=1, label='50Hz band')
plt.fill_between(f_band2_mean[node].time, f_band2_mean[node] + f_band2_std[n

plt.legend()
plt.xlim([pd.Timestamp('2015-01-01'), pd.Timestamp('2021-01-01')])
plt.title('20Hz and 50Hz bands for Central Caldera')
```

Out[35]: `Text(0.5, 1.0, '20Hz and 50Hz bands for Central Caldera')`