



MIR - HWo -Report

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cloud drive link:

<https://drive.google.com/drive/u/4/folders/1Di79YIJdo6KXicygmjk8l8uyP9Sbp3xn>



Agenda

- Task 1
- Task 2
- Task 3



Task 1

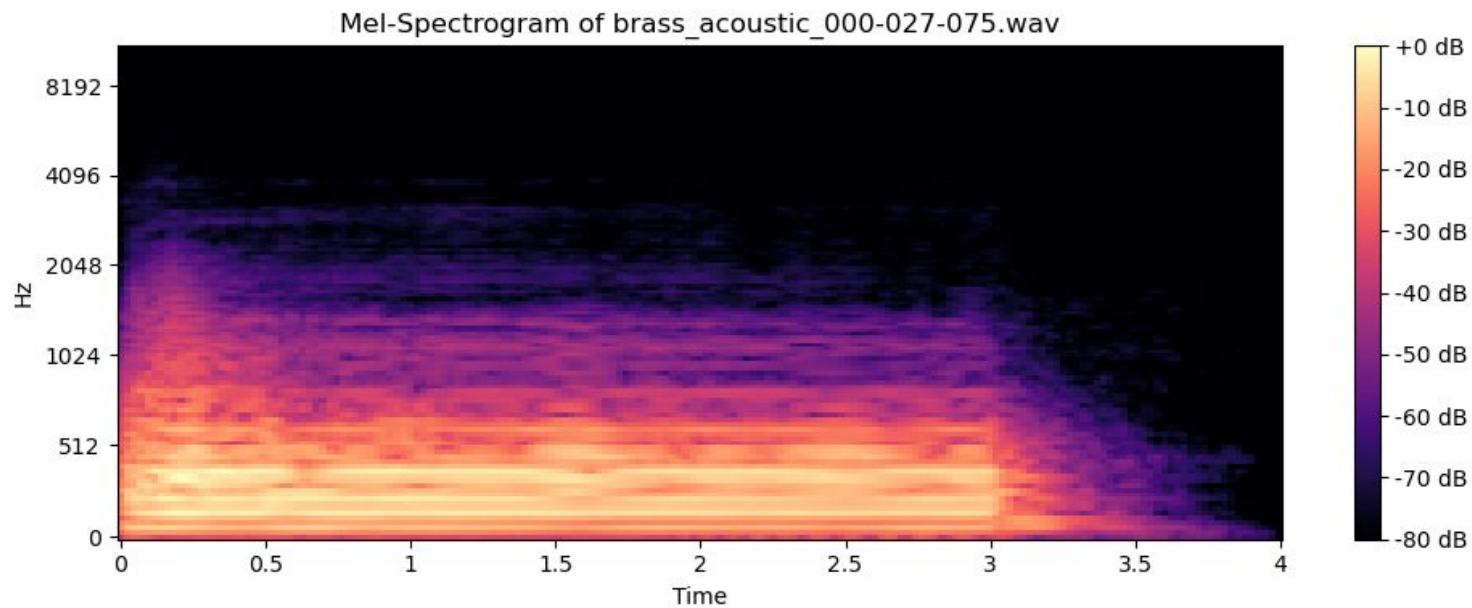
- Selected pitch: 27, 51, 23
- Selected instrument: brass, synth_lead, reed
- Selected .wav file:
 - brass_acoustic_000-027-075
 - synth_lead_synthetic_007-027-100
 - reed_acoustic_026-027-100
 - brass_acoustic_008-051-075
 - synth_lead_synthetic_005-051-050
 - reed_acoustic_059-051-025
 - brass_acoustic_030-023-050
 - synth_lead_synthetic_010-023-100
 - reed_acoustic_021-023-050



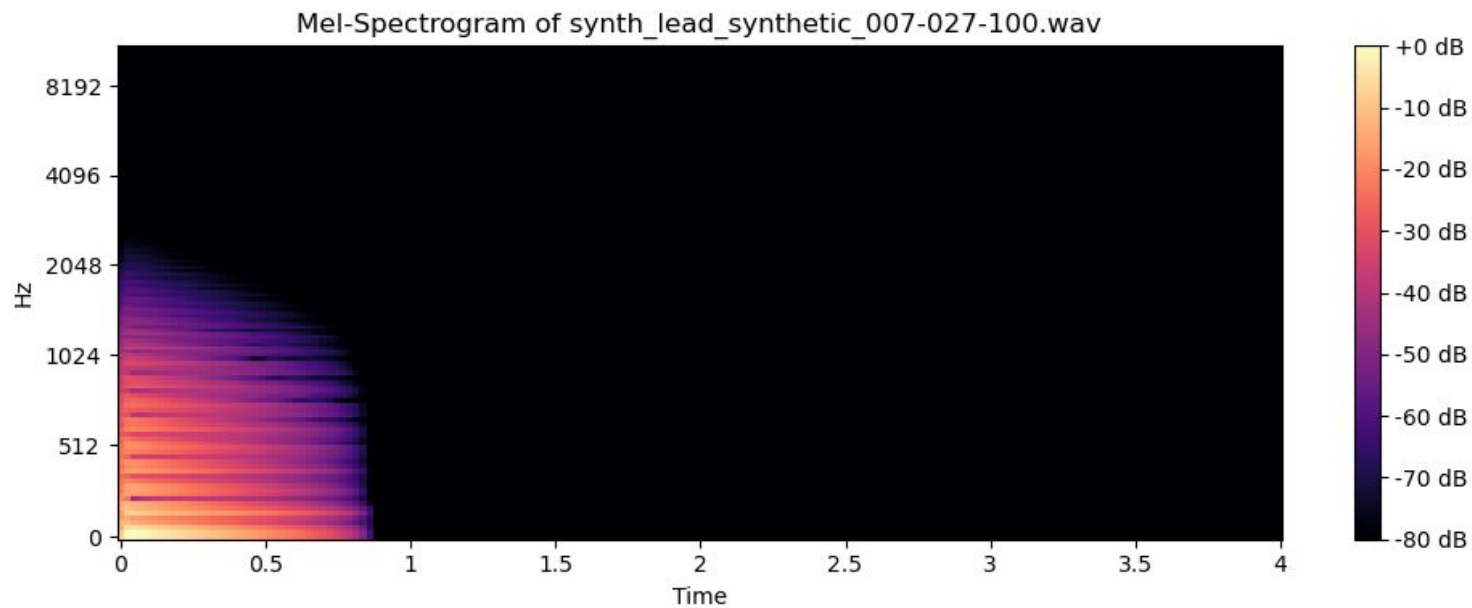
Task 1

- use *librosa.feature.melspectrogram* to generate Mel Spectrogram and use *matplotlib.pyplot* to plot it

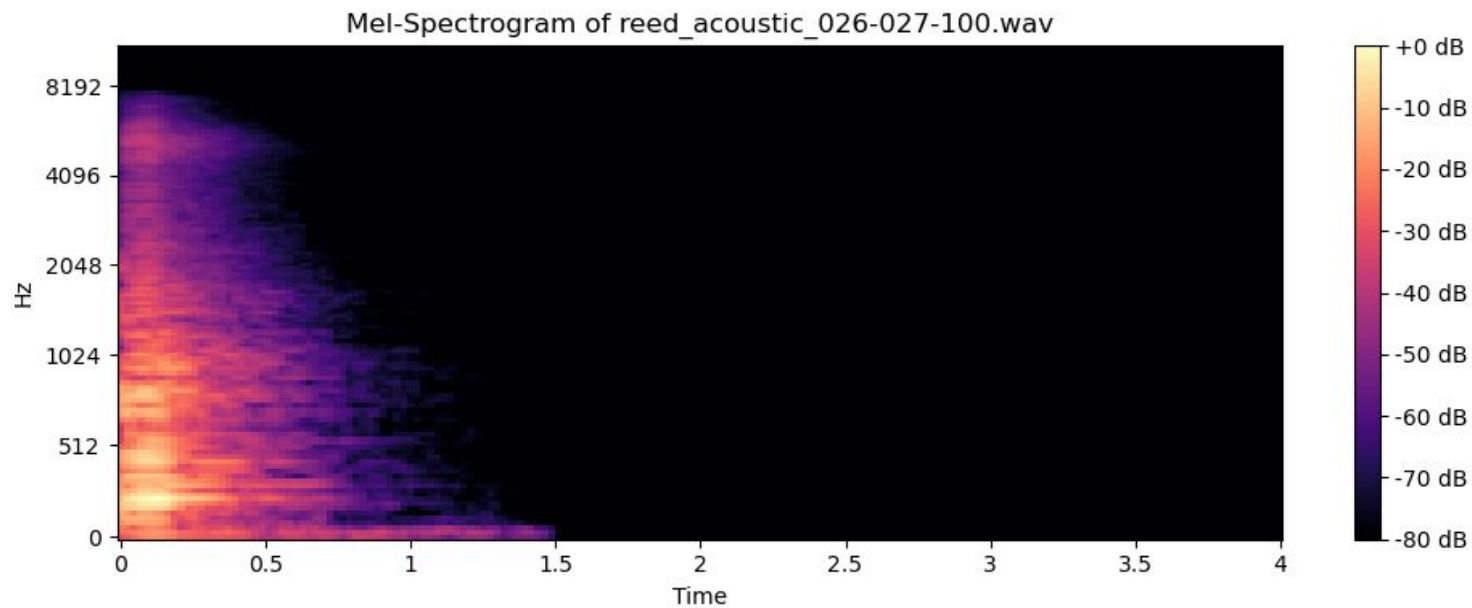
Task 1



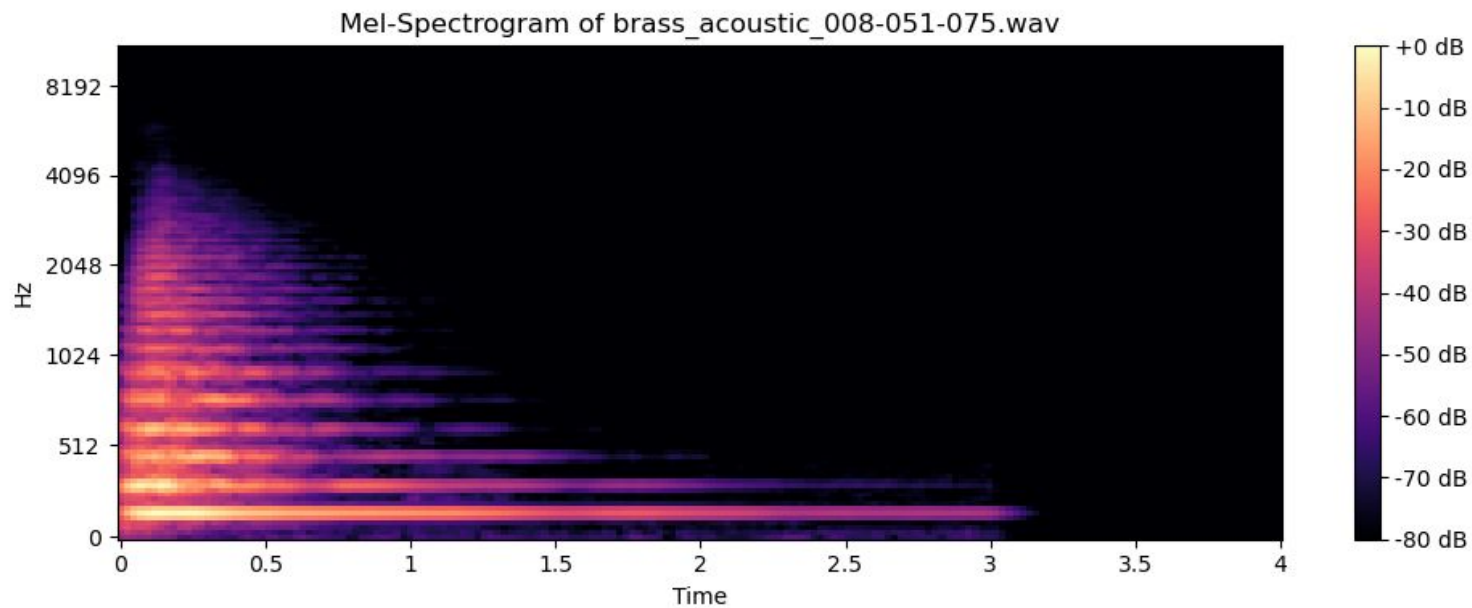
Task 1



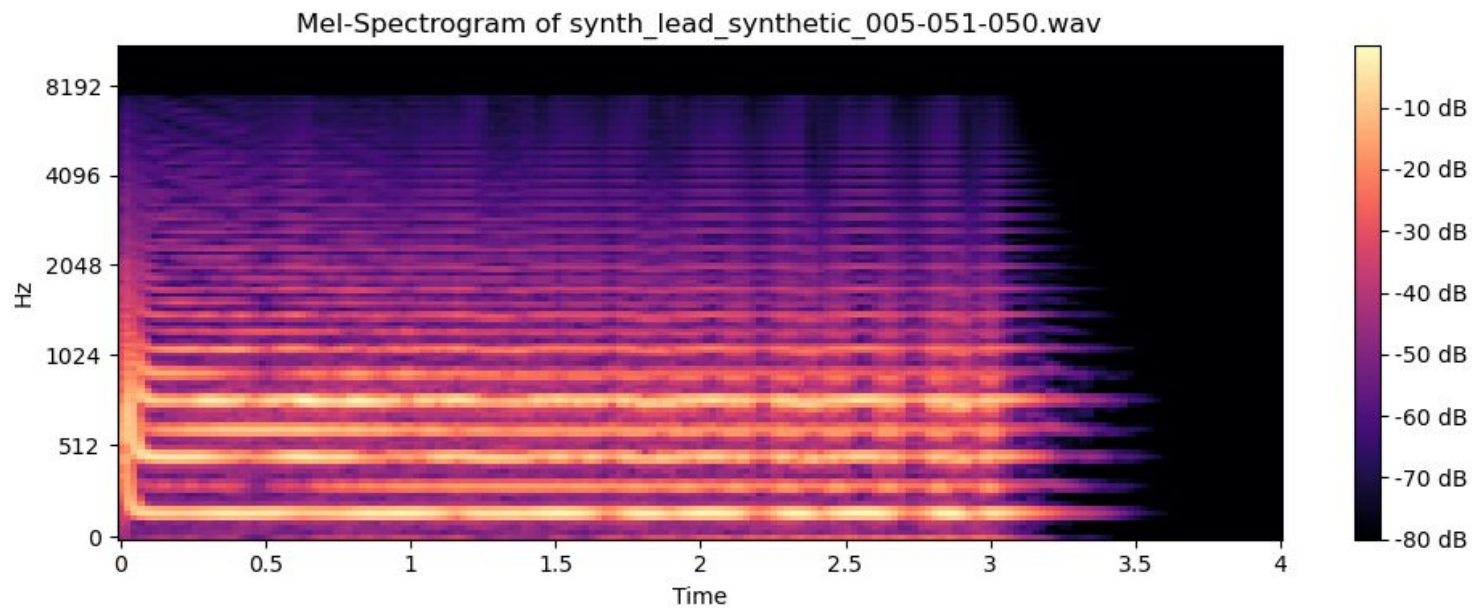
Task 1



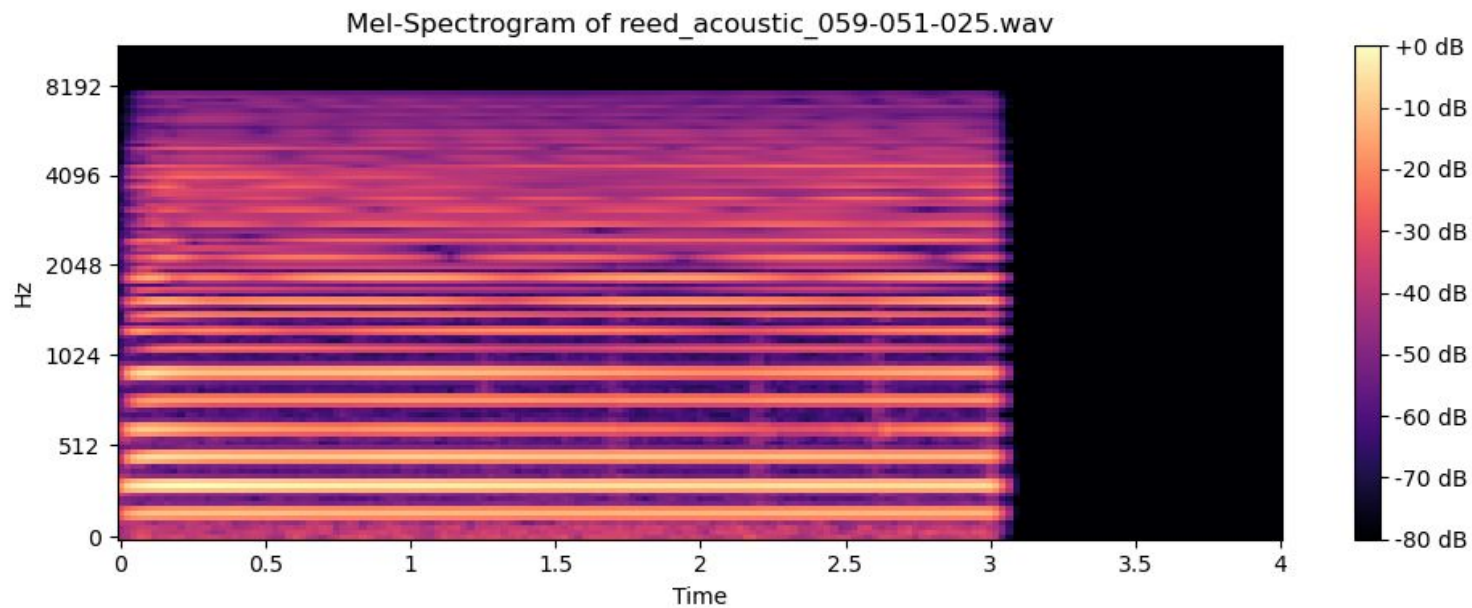
Task 1



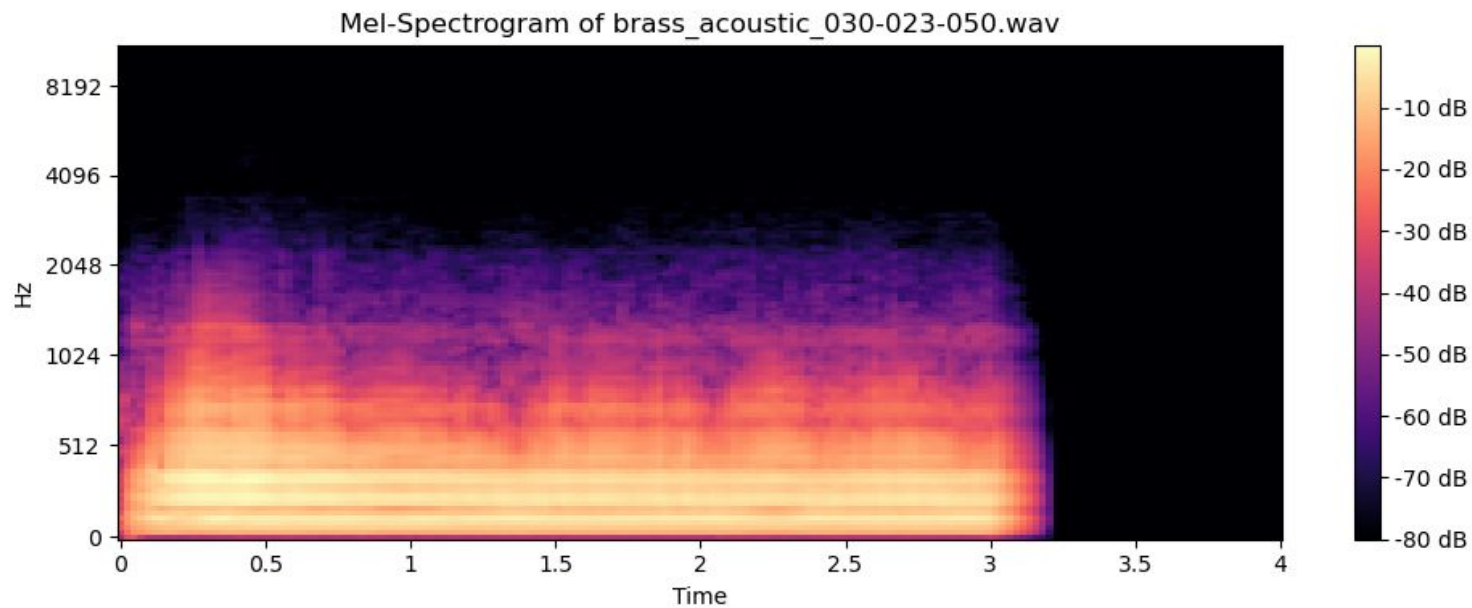
Task 1



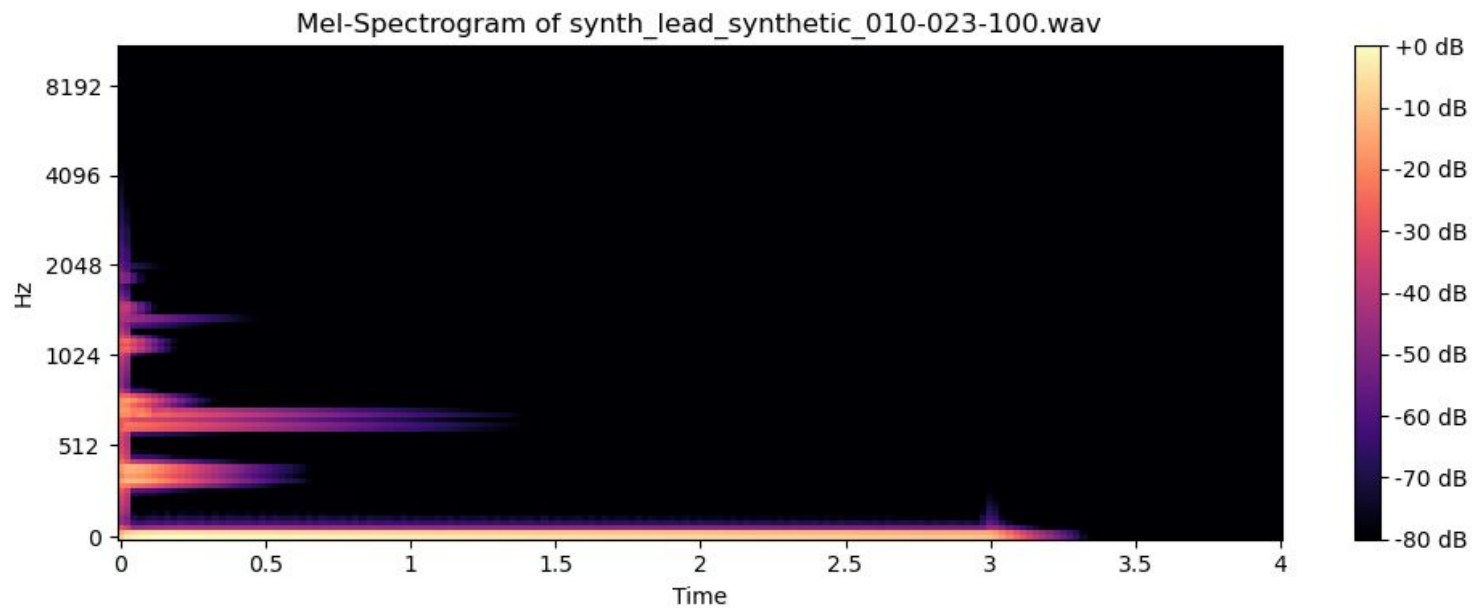
Task 1



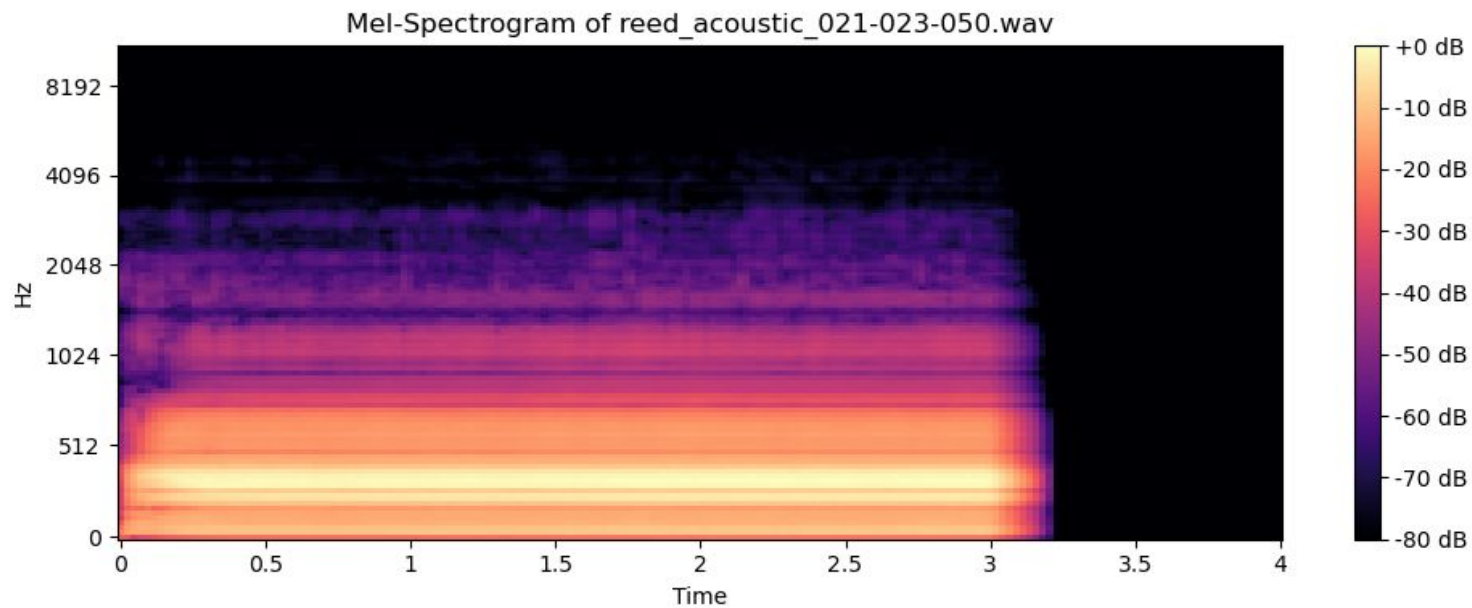
Task 1



Task 1



Task 1





Task 2

- Using *librosa.feature* to extract two features:
 - **Spectral_contrast**: It accentuate the frequency difference between each instrument, I think it's a great way to differentiate between different instruments
 - **MFCC**: According to Wikipedia, it approximates the human auditory system's response more closely
- After extract the two features, they're normalized using *StandardScaler()*. After that, I flatten them and concat them, creating a [1, 4671] vector for each .wav file. For validation data and test data, the same pre-processing is applied

Task 2

- Model: using *knn*, with $k = 3$
- **Top 1 accuracy: 0.626953125**
- **Top 3 accuracy: Null**
 - It runs for 25 minutes but still not finished
 - It is likely because KNN is a lazy learner, and predicting the test data takes a long time, especially for labels that are far from the true label

Confusion Matrix

True label \ Predicted label	bass	brass	flute	guitar	keyboard	mallet	organ	reed	string	synth_lead	vocal
bass	558	2	14	71	95	46	15	1	7	9	25
brass	55	208	2	0	1	0	0	1	2	0	0
flute	6	5	135	0	0	0	15	14	0	0	5
guitar	97	0	6	256	181	57	44	4	3	4	0
keyboard	52	19	6	84	517	20	4	1	16	46	1
mallet	19	5	0	26	17	125	1	2	6	0	1
organ	9	10	37	24	10	14	282	0	9	64	43
reed	5	91	2	27	7	0	0	97	6	0	0
string	2	8	0	3	1	1	0	1	290	0	0
synth_lead	0	0	0	0	0	0	0	0	0	0	0
vocal	21	0	1	3	0	0	4	1	0	11	100



Task 2

- What I found:
 - The model can distinguish vocals and guitar from other instruments very well
- Improvements that can be done:
 - Try different model, such as SVM and random forest
 - Try larger *k* value in *knn*, to whether it perform better or not



Task 3

- use *librosa.feature.melspectrogram* to extract Mel Spectrogram feature and use *librosa.power_to_db* to extract feature with log scaling
- Encode the *.wav* file into integer encoding, label from 0 to 10, imply different instruments
- Reference the suggested Short Chunk CNN model([Here](#)), and modify some parts
 - Change the loss function from binary cross entropy loss to cross entropy loss
 - Modify the input, calculate the mel-spectrogram beforehand, instead of calculating in the the model



Task 3

- Improvements that can be done:
 - Implement the model **properly**