# 9th-place-modeling-kernel

January 11, 2020

**This kernel is used for training our models. In the end, we went with an ensemble of 15 models similar to the one trained here.**

**Their CV are all above 0.86 and 5-folds LB varies between 0.71 and 0.72**

For our solution writeup, please check : https://www.kaggle.com/c/freesound-audio-tagging-2019/discussion/95409#latest-551352

## 1 Initialization

### 1.1 Imports

[1]:
```
import re
import gc
import os
import time
import pywt
import pickle
import random
import operator
import warnings
import numpy as np
import pandas as pd
import seaborn as sns
import tensorflow as tf
import IPython.display as ipd
import matplotlib.pyplot as plt

from PIL import Image
from sklearn.metrics import *
from collections import Counter
from sklearn.model_selection import *
from tqdm import tqdm_notebook as tqdm
from keras.utils import to_categorical
from multiprocessing import Pool, cpu_count
from collections import OrderedDict
```

```
import torch
import torch.nn as nn
import torch.utils.data
import torch.nn.functional as F
import torchvision.models as models
from torch.autograd import Variable
from torch.optim.lr_scheduler import *
from torchvision.transforms import transforms
from torch.utils.data import Dataset, DataLoader

import librosa
import librosa.display


begin = time.time()
sns.set_style('white')
warnings.simplefilter(action='ignore', category=FutureWarning)
warnings.simplefilter(action='ignore', category=UserWarning)
warnings.simplefilter(action='ignore', category=RuntimeWarning)

print("Number of available cpu cores: {}".format(cpu_count()))
```

```
Using TensorFlow backend.

Number of available cpu cores: 2
```

## 1.2 Seeding

[2]:
```
def seed_everything(seed):
    random.seed(seed)
    os.environ['PYTHONHASHSEED'] = str(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed(seed)
    torch.backends.cudnn.deterministic = True
    tf.set_random_seed(seed)
```

[3]:
```
seed = 2019
seed_everything(seed)
```

[4]:
```
N_JOBS = cpu_count()
os.environ['MKL_NUM_THREADS'] = str(N_JOBS)
os.environ['OMP_NUM_THREADS'] = str(N_JOBS)
DataLoader = partial(DataLoader, num_workers=N_JOBS)
```

### 1.3 Load Data

[5]:
```
DATA_PATH = '../input/freesound-audio-tagging-2019/'
TRAIN_CURATED_PATH = DATA_PATH + 'train_curated/'
TRAIN_NOISY_PATH = DATA_PATH + 'train_noisy/'
TEST_PATH = DATA_PATH + 'test/'
```

[6]:
```
df_train = pd.read_csv(DATA_PATH + 'train_curated.csv')
df_noisy = pd.read_csv(DATA_PATH + 'train_noisy.csv')
df_test = pd.read_csv(DATA_PATH + 'sample_submission.csv')

df_train.head()
```

[6]:

| | fname | labels |
|---|---|---|
| 0 | 0006ae4e.wav | Bark |
| 1 | 0019ef41.wav | Raindrop |
| 2 | 001ec0ad.wav | Finger_snapping |
| 3 | 0026c7cb.wav | Run |
| 4 | 0026f116.wav | Finger_snapping |

[7]:
```
labels = list(df_test.columns[1:])
num_classes = len(labels)

print("Number of classes :", num_classes)
```

```
Number of classes : 80
```

*Removing "corrupted" files*

[8]:
```
to_remove = ["f76181c4.wav", "77b925c2.wav", "6a1f682a.wav", "c7db12aa.wav",␣
↪"7752cc8a.wav", "1d44b0bd.wav"]

for i in df_train.copy().index:
    if df_train['fname'][i] in to_remove:
        df_train.drop(i, inplace=True)

df_train = df_train.reset_index(drop=True)
```

*Restraining noisy data to samples with only one label*

[9]:
```
df_noisy["nb_labels"] = df_noisy["labels"].apply(lambda x: len(x.split(',')))
df_noisy = df_noisy[df_noisy["nb_labels"] == 1].copy().reset_index(drop=True)
```

# 2 Signal Processing

## 2.1 Config

[10]:
```
class config:
    sampling_rate = 44100  # 44.1 kHz
    duration = 4 #2 # Minimum length for short samples (seconds)
    samples = sampling_rate * duration # Minimum sample size

    top_db = 60 # Noise filtering, default = 60

    # Frequencies kept in spectrograms
    fmin = 20
    fmax =  sampling_rate // 2  # Shannon theorem

    # Spectrogram parameters
    n_mels = 64 # = spec_height
    n_fft = n_mels * 30 # Size of fft window - smooths the spectrogram
    spec_min_width = 256 #128
    x_mean,x_std = -35.7, 21.6
    hop_length = duration * sampling_rate // spec_min_width + 1 # Number of␣
 ↪samples between each frame - impacts y size of spectrogram
```

## 2.2 Read Audio

[11]:
```
def read_audio(pathname, conf, trim_long_data):
    y, sr = librosa.load(pathname, sr=conf.sampling_rate)
    # trim silence
    if len(y) > 0: # workaround: 0 length causes error
        y, _ = librosa.effects.trim(y) # trim, top_db=default(60)
    # make it unified length to conf.samples
    if len(y) > conf.samples: # long enough
        if trim_long_data: y = y[0:0+conf.samples]
    else: # pad blank
        padding = conf.samples - len(y)    # add padding at both ends
        offset = padding // 2
        y = np.pad(y, (offset, conf.samples - len(y) - offset), 'constant')
    return y
```

## 2.3 MEL Spectrogram

The three chanel mode adds first and second or delta to the data. It did not improve the results.

[12]:
```
def audio_to_melspectrogram(audio, config, three_chanels=False):
    spectrogram = librosa.feature.melspectrogram(audio,
                                                 sr=config.sampling_rate,
                                                 n_mels=config.n_mels,
                                                 hop_length=config.hop_length,
                                                 n_fft=config.n_fft,
                                                 fmin=config.fmin,
                                                 fmax=config.fmax)
    logmel = librosa.power_to_db(spectrogram).astype(np.float32)

    if three_chanels:
        return np.array([logmel, librosa.feature.delta(logmel), librosa.feature.
 ↪delta(logmel, order=2)])
    else:
        return logmel
```

### 2.4 Normalize

We can either use individual image statistics or statistics computed on train data.

[13]:
```
def normalize(X, mean=None, std=None):
    mean = mean or X.mean()
    std = std or (X-X.mean()).std()
    return ((X - mean)/std).astype(np.float16)
```

## 3 Labels

[14]:
```
def get_labels(df, labels):
    mapping = {label:i for i, label in enumerate(labels)}
    y = np.zeros((len(df), len(labels)))
    all_labels = df['labels'].apply(lambda x: x.split(','))
    for i, label in enumerate(all_labels):
        for l in label:
            y[i, mapping[l]] = 1
    return y.astype(int)
```

[15]:
```
y_train = get_labels(df_train, labels)
```

### 3.1 Select best noisy samples

We load predictions that were computed using a model that was trained only on curated data. The idea is to keep the ones that were the most correctly predicted, using the log loss as metric. As some class were better predicted than others, we restrict the number of added samples to 50 per class.

[16]:
```
scores_noisy = np.load("../input/fat-cp/scores.npy")
y_noisy = get_labels(df_noisy, labels)
```

[17]:
```
def sort_by_loss(y_noisy, scores_noisy):
    losses_dic = {i : log_loss(y_noisy[i], scores_noisy[i]) for i in␣
 ↪range(scores_noisy.shape[0])}
    sorted_dic = sorted(losses_dic.items(), key=operator.itemgetter(1))
    return sorted_dic
```

[18]:
```
sorted_by_loss = sort_by_loss(y_noisy, scores_noisy)
```

[19]:
```
def select_noisy(sorted_by_loss, nb_noisy, max_per_class=50):
    selected = np.array(sorted_by_loss)[:nb_noisy, 0].astype(int)
    to_keep = []
    counts = {}
    for s in selected:
        l = df_noisy["labels"][s]
        try:
            counts[l] += 1
        except:
            counts[l] = 0
        if counts[l] < max_per_class:
            to_keep.append(s)


    return df_noisy.iloc[to_keep].reset_index(drop=True)

    df_noisy_selected
```

[20]:
```
nb_noisy = 5000
```

[21]:
```
df_noisy_selected = select_noisy(sorted_by_loss, nb_noisy, max_per_class=50)
y_noisy = get_labels(df_noisy_selected, labels)
```

### 3.2 Input data

[22]:
```
three_chanels = False
crop = False
```

[23]:
```
def process(df, path, config, crop=False, three_chanels=False):
    X = []
    for i in df.index:
        signal = read_audio(path + df['fname'][i], config, crop)
```

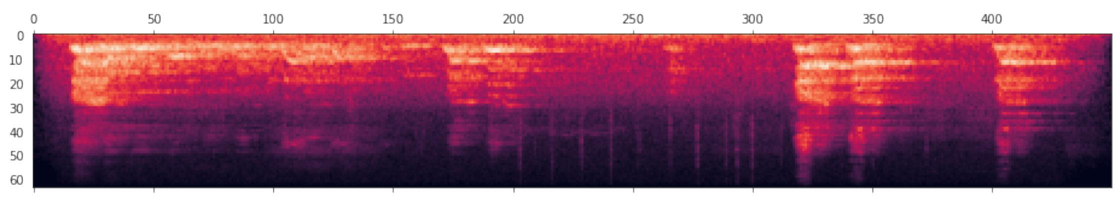
```
        X.append(normalize(audio_to_melspectrogram(signal, config), config.
↪x_mean, config.x_std)) #normalize based on global statistics
        #X.append(normalize(audio_to_melspectrogram(signal, config)))␣
↪#normalize based on individual statistics
    return X
```

[24]:
```
# df_train = df_train.head(100)
# df_test = df_test.head(100)
# df_noisy_selected = df_noisy_selected.head(100)
```

[25]:
```
%%time
X_train = process(df_train, TRAIN_CURATED_PATH, config, crop=crop,␣
↪three_chanels=three_chanels)
X_noisy = process(df_noisy_selected, TRAIN_NOISY_PATH, config, crop=crop,␣
↪three_chanels=three_chanels)
X_test = process(df_test, TEST_PATH, config, three_chanels=three_chanels)
```

```
CPU times: user 10min 3s, sys: 8min 7s, total: 18min 11s
Wall time: 9min 48s
```

[26]:
```
plt.matshow(X_train[0].astype(np.float32))
plt.show()
```




## 3.3 Datasets

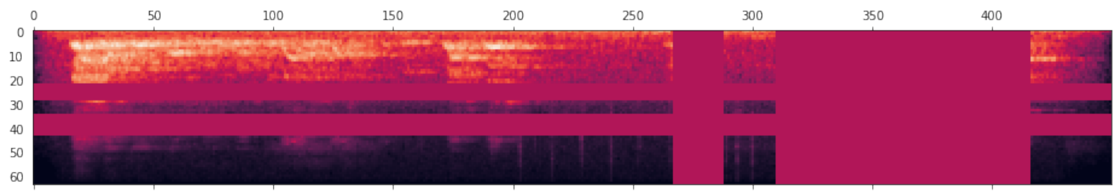
### 3.3.1 Augmentation

We augment spectrograms by hiding random time & frequency intervals

[27]:
```
def spec_augment(spec: np.ndarray, num_mask=2, freq_masking_max_percentage=0.
↪15, time_masking_max_percentage=0.3):
    spec = spec.copy()
    for i in range(num_mask):
        num_freqs, num_frames = spec.shape
        freq_percentage = random.uniform(0.0, freq_masking_max_percentage)
        time_percentage = random.uniform(0.0, time_masking_max_percentage)
```

```
        num_freqs_to_mask = int(freq_percentage * num_freqs)
        num_frames_to_mask = int(time_percentage * num_frames)

        t0 = int(np.random.uniform(low=0.0, high=num_frames -␣
↪num_frames_to_mask))
        f0 = int(np.random.uniform(low=0.0, high=num_freqs - num_freqs_to_mask))

        spec[:, t0:t0 + num_frames_to_mask] = 0
        spec[f0:f0 + num_freqs_to_mask, :] = 0

    return spec
```

[28]:
```
plt.matshow(spec_augment(X_train[0].astype(np.float32)))
plt.show()
```




### 3.3.2 Usual transforms

Only the conversion to tensor is kept, we also tried flipping and resized cropping.

[29]:
```
transforms_dict = {
    'train': transforms.Compose([
        transforms.ToTensor(),
    ]),
    'test': transforms.Compose([
        transforms.ToTensor(),
    ]),
    'viz': transforms.Compose([
    ]),
}
```

### 3.3.3 Train

[30]:
```
class FATDatasetTrain(Dataset):
    def __init__(self, mels, transforms, y, apply_spec_aug=False):
        super().__init__()
        self.mels = mels
```

```python
        self.labels = y
        self.transforms = transforms
        self.apply_spec_aug = apply_spec_aug

    def __len__(self):
        return len(self.mels)

    def __getitem__(self, idx):
        data = self.mels[idx].astype(np.float32)
        base_dim,time_dim = data.shape
        crop = random.randint(0, max(time_dim - config.spec_min_width,0))
        data = data[0:base_dim,crop:crop + config.spec_min_width]

        if self.apply_spec_aug:
            data = spec_augment(data)

        data = np.expand_dims(data, axis=2)
        data = self.transforms(data)

        label = self.labels[idx]
        label = torch.from_numpy(label).float()
        return data, label
```

### 3.3.4 Test + TTA

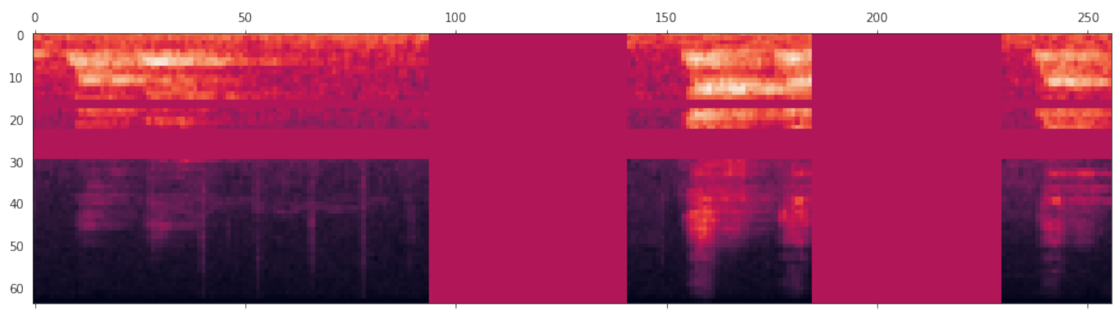
TTA helped to fight instability, it worked well for us.

[31]:
```python
class FATDatasetTest(Dataset):
    def __init__(self, mels, transforms, y=None, nb_tta=5):
        super().__init__()
        self.mels = mels
        self.transforms = transforms
        self.tta = nb_tta
        if y is None:
            self.y = np.zeros(len(self.mels))
        else:
            self.y = y

    def __len__(self):
        return len(self.mels) * self.tta

    def __getitem__(self, idx):
        new_idx = idx % len(self.mels)

        data = self.mels[new_idx].astype(np.float32)#/255.0
        base_dim,time_dim = data.shape
```

```
        crop = random.randint(0, max(time_dim - config.spec_min_width,0))
        data = data[0:base_dim,crop:crop + config.spec_min_width]
        data = np.expand_dims(data, axis=2)
        data = self.transforms(data)

        return data, self.y[new_idx]
```

[32]:
```
dataset = FATDatasetTrain(X_train[:10], transforms_dict['viz'], y_train[:10],␣
 ↪apply_spec_aug=True)
print('Input shape : ', dataset[0][0].squeeze().shape)
plt.matshow(dataset[0][0].squeeze())
plt.show()
```

```
Input shape :  (64, 256)
```




# 4 Modeling

## 4.1 Tools

### 4.1.1 Adaptative Pooling

[33]:
```
def adaptive_concat_pool2d(x, sz=(1,1)):
    out1 = F.adaptive_avg_pool2d(x, sz).view(x.size(0), -1)
    out2 = F.adaptive_max_pool2d(x, sz).view(x.size(0), -1)
    return torch.cat([out1, out2], 1)
```

### 4.1.2 ConvBlock

Adapted from https://www.kaggle.com/mhiro2/simple-2d-cnn-classifier-with-pytorch

[34]:
```
class ConvBlock(nn.Module):
    def __init__(self, in_channels, out_channels, kernel_size=3, pool=True):
```

```
        super().__init__()

        padding = kernel_size // 2
        self.pool = pool

        self.conv1 = nn.Sequential(
            nn.Conv2d(in_channels, out_channels, kernel_size=kernel_size,␣
↪stride=1, padding=padding),
            nn.BatchNorm2d(out_channels),
            nn.ReLU(),
        )
        self.conv2 = nn.Sequential(
            nn.Conv2d(out_channels + in_channels, out_channels,␣
↪kernel_size=kernel_size, stride=1, padding=padding),
            nn.BatchNorm2d(out_channels),
            nn.ReLU(),
        )

        self._init_weights()

    def _init_weights(self):
        for m in self.modules():
            if isinstance(m, nn.Conv2d):
                nn.init.kaiming_normal_(m.weight)
                if m.bias is not None:
                    nn.init.zeros_(m.bias)
            elif isinstance(m, nn.BatchNorm2d):
                nn.init.constant_(m.weight, 1)
                nn.init.zeros_(m.bias)

    def forward(self, x): # x.shape = [batch_size, in_channels, a, b]
        x1 = self.conv1(x)
        x = self.conv2(torch.cat([x, x1],1))
        if(self.pool): x = F.avg_pool2d(x, 2)
        return x    # x.shape = [batch_size, out_channels, a//2, b//2]
```

### 4.2 Models

[35]:
```
class Classifier_M1(nn.Module):
    def __init__(self, num_classes=num_classes):
        super().__init__()
        self.conv = nn.Sequential(
            ConvBlock(in_channels=1, out_channels=64),
            ConvBlock(in_channels=64, out_channels=128),
            ConvBlock(in_channels=128, out_channels=256),
            ConvBlock(in_channels=256, out_channels=512),
```

```
        )

        self.fc = nn.Sequential(
            nn.BatchNorm1d(512*2),
            nn.Linear(512*2, 128),
            nn.PReLU(),
            nn.BatchNorm1d(128),
            nn.Linear(128, num_classes),
        )

    def forward(self, x): # batch_size, 3, a, b
        x = self.conv(x)  # batch_size, 512, a//16, b//16
        x = self.fc(adaptive_concat_pool2d(x))
        return x
```

[36]:
```
class Classifier_M2(nn.Module):
    def __init__(self, num_classes=num_classes):
        super().__init__()
        self.conv1 = ConvBlock(1,64)
        self.conv2 = ConvBlock(64,128)
        self.conv3 = ConvBlock(128,256)
        self.conv4 = ConvBlock(256,512,pool=False)

        self.fc = nn.Sequential(
            nn.BatchNorm1d(1792),
            nn.Linear(1792, 256),
            nn.PReLU(),
            nn.BatchNorm1d(256),
            nn.Linear(256, num_classes),
        )

    def forward(self, x): # batch_size, 3, a, b
        x1 = self.conv1(x)
        x2 = self.conv2(x1)
        x3 = self.conv3(x2)
        x4 = self.conv4(x3)
        #pyramid pooling
        x = torch.cat([adaptive_concat_pool2d(x2), adaptive_concat_pool2d(x3),
                       adaptive_concat_pool2d(x4)], 1)
        x = self.fc(x)
        return x
```

[37]:
```
class Classifier_M3(nn.Module):
    def __init__(self, num_classes=num_classes):
        super().__init__()
        self.conv1 = ConvBlock(1,64)
        self.conv2 = ConvBlock(64,128)
```

```
        self.conv3 = ConvBlock(128,256)
        self.conv4 = ConvBlock(256,512)
        self.conv5 = ConvBlock(512,1024,pool=False)

        self.fc = nn.Sequential(
            nn.BatchNorm1d(3840),
            nn.Linear(3840, 256),
            nn.PReLU(),
            nn.BatchNorm1d(256),
            nn.Linear(256, num_classes),
        )

    def forward(self, x): # batch_size, 3, a, b
        x1 = self.conv1(x)
        x2 = self.conv2(x1)
        x3 = self.conv3(x2)
        x4 = self.conv4(x3)
        x5 = self.conv5(x4)
        #pyramid pooling
        x = torch.cat([adaptive_concat_pool2d(x2), adaptive_concat_pool2d(x3),
                       adaptive_concat_pool2d(x4),adaptive_concat_pool2d(x5)],␣
↪1)
        x = self.fc(x)
        return x
```

# 5 Tools

## 5.1 LwLRAP

[38]:
```
def _one_sample_positive_class_precisions(scores, truth):
    num_classes = scores.shape[0]
    pos_class_indices = np.flatnonzero(truth > 0)

    if not len(pos_class_indices):
        return pos_class_indices, np.zeros(0)

    retrieved_classes = np.argsort(scores)[::-1]

    class_rankings = np.zeros(num_classes, dtype=np.int)
    class_rankings[retrieved_classes] = range(num_classes)

    retrieved_class_true = np.zeros(num_classes, dtype=np.bool)
    retrieved_class_true[class_rankings[pos_class_indices]] = True

    retrieved_cumulative_hits = np.cumsum(retrieved_class_true)
```

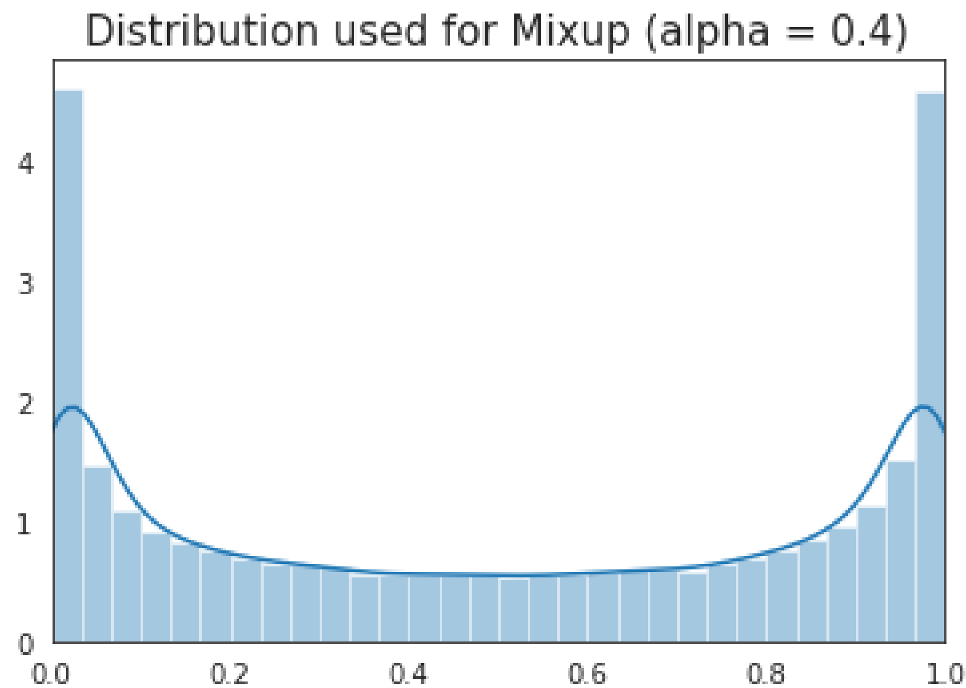
```python
    precision_at_hits = (
            retrieved_cumulative_hits[class_rankings[pos_class_indices]] /
            (1 + class_rankings[pos_class_indices].astype(np.float)))
    return pos_class_indices, precision_at_hits
```

[39]:
```python
def lwlrap(truth, scores):
    assert truth.shape == scores.shape
    num_samples, num_classes = scores.shape
    precisions_for_samples_by_classes = np.zeros((num_samples, num_classes))
    for sample_num in range(num_samples):
        pos_class_indices, precision_at_hits =␣
 ↪_one_sample_positive_class_precisions(scores[sample_num, :],␣
 ↪truth[sample_num, :])
        precisions_for_samples_by_classes[sample_num, pos_class_indices] =␣
 ↪precision_at_hits

    labels_per_class = np.sum(truth > 0, axis=0)
    weight_per_class = labels_per_class / float(np.sum(labels_per_class))

    per_class_lwlrap = (np.sum(precisions_for_samples_by_classes, axis=0) /
                        np.maximum(1, labels_per_class))
    return per_class_lwlrap, weight_per_class
```

### 5.2 Mixup

Facebook's implementation is used for Mixup. With its default parameters.

[40]:
```python
alpha_ = 0.4
sns.distplot(np.random.beta(alpha_, alpha_, 100000))
plt.xlim(0, 1)
plt.title(f'Distribution used for Mixup (alpha = {alpha_})', size=15)
plt.show()
```




[41]:
```
def mixup_data(x, y, alpha=alpha_, use_cuda=True):
    if alpha > 0:
        lam = np.random.beta(alpha, alpha)
    else:
        lam = 1

    batch_size = x.size()[0]
    if use_cuda:
        index = torch.randperm(batch_size).cuda()
    else:
        index = torch.randperm(batch_size)

    mixed_x = lam * x + (1 - lam) * x[index, :]
    y_a, y_b = y, y[index]
    return mixed_x, y_a, y_b, lam
```

[42]:
```
def mixup_criterion(criterion, pred, y_a, y_b, lam):
    return lam * criterion(pred.float().cuda(), y_a.float().cuda()) + (1 - lam)
 ↪* criterion(pred.float().cuda(), y_b.float().cuda())
```

### 5.3 Label Smoothing

We tried this as well, without any success. I do believe that clever use of label smoothing & noisy data can improve results

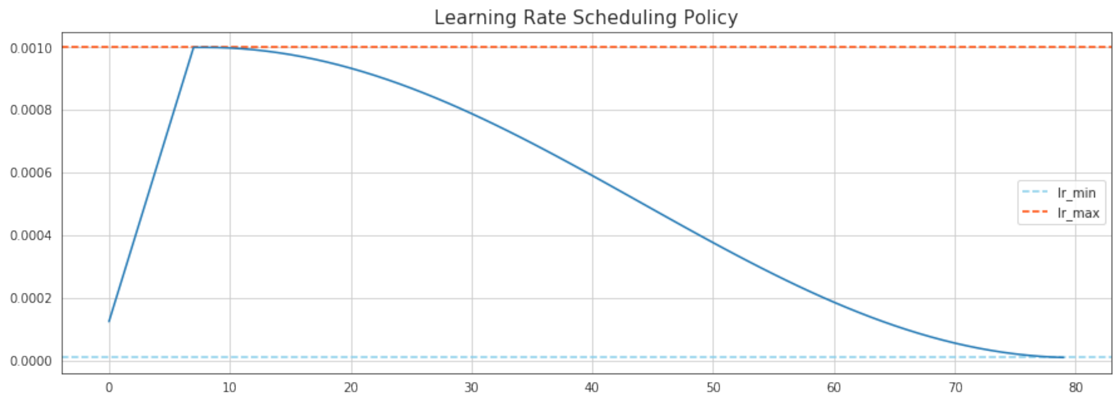
[43]:
```
def smooth(y, eps=0.4):
    a = 1 - eps * (1 + 1/y.shape[1])
    b = eps / y.shape[1]
    return a * y + b
```

### 5.4 Learning Rate

I reimplemented a custom Scheduler, that does Cosine Annealing and warmup. We found out that warmup played a quite important role

[44]:
```
class WarmupCosineAnnealingLR(CosineAnnealingLR):
    def __init__(self, optimizer, warmup_prop, T_max, eta_min=0, last_epoch=-1):
        self.warmup_prop = warmup_prop
        super(CosineAnnealingLR, self).__init__(optimizer, T_max, eta_min,␣
 ↪last_epoch)

    def get_lr(self):
        if self.last_epoch < T_max * warmup_prop:
            return [self.base_lrs * self.last_epoch/T_max
                    for base_lr, group in zip(self.base_lrs, self.optimizer.
 ↪param_groups)]
        else:
            return super(CosineAnnealingLR, self).step()
```

[45]:
```
lr_max = 0.001
lr_min = 1e-5
warmup_prop = 0.1
nb_epochs = 80
epochs = [i for i in range(nb_epochs)]
lrs_warmup = [lr_max * i / (warmup_prop * nb_epochs) for i in range(1,␣
 ↪int(warmup_prop * nb_epochs) + 1)]
lrs_scheduler = [lr_min + 0.5 * (lr_max - lr_min) * (1 + np.cos(np.pi * i / ((1␣
 ↪- warmup_prop) * nb_epochs))) for i in range(int((1 - warmup_prop) *␣
 ↪nb_epochs))]

plt.figure(figsize=(15, 5))
plt.axhline(lr_min, label='lr_min', c='skyblue', linestyle='--')
plt.axhline(lr_max, label='lr_max', c='orangered', linestyle='--')
plt.plot(epochs, lrs_warmup + lrs_scheduler[:len(epochs)])
plt.grid(True)
plt.legend()
plt.title('Learning Rate Scheduling Policy', size=15)
plt.show()
```




### 5.5 Sigmoid

[46]:
```
def sigmoid(x):
    return 1 / (1 + np.exp(-x))
```

### 5.6 Save & Load

[47]:
```
def save_model_weights(model, filename, verbose=1):
    if verbose:
        print(f'Saving weights to {filename}\n')
    torch.save(model.state_dict(), filename)
```

[48]:
```
def load_model_weights(model, filename, verbose=1):
    if verbose:
        print(f'Loading weights from {filename}\n')
    model.load_state_dict(torch.load(filename))
    return model
```

### 5.7 Predict

[49]:
```
def predict(dataset, model, batch_size=64):
    model.eval()
    y = np.array([[]] * num_classes).T
    loader = torch.utils.data.DataLoader(dataset, batch_size=batch_size,␣
↪shuffle=False)
    with torch.no_grad():
        for x, target in loader:
            y = np.concatenate((y, sigmoid(model(x.cuda()).view(-1,␣
↪num_classes).detach().cpu().numpy())))
```

```
    return y
```

### 5.8 Fit

Code is a bit ugly, you might not want to dive into it. It's PyTorch. Here are the main points :

- Weight decay (0.001)
- Gradient clipping (1)
- Binary Cross Entropy loss
- Adam is used here, Adabound was also tried
- Custom lr scheduler (see above), with a warmup proportion 0.1 usually.
- Apply mixup with a probability *mixup* (chosen at 1)
- Checkpointing is used

[50]:
```
def fit(model, train_dataset, val_dataset, epochs=50, batch_size=128, nb_tta=5,␣
↪mixup=False, warmup_prop=0.1,
        verbose=1, cp=False, model_name='model', lr=0.001):
    avg_val_loss = 1000
    best_score = 0
    clip_value = 1.0

    model.cuda()

    opt_params = [
        {'params': [p for n, p in list(model.named_parameters()) if not any(nd␣
↪in n for nd in ['bias', 'LayerNorm.bias', 'LayerNorm.weight'])],␣
↪'weight_decay': 0.01},
        {'params': [p for n, p in list(model.named_parameters()) if any(nd in n␣
↪for nd in ['bias', 'LayerNorm.bias', 'LayerNorm.weight'])], 'weight_decay':␣
↪0.0}
    ]

    for p in model.parameters():
        p.register_hook(lambda grad: torch.clamp(grad, -clip_value, clip_value))

    optimizer = torch.optim.Adam(opt_params, lr=lr)
    scheduler = CosineAnnealingLR(optimizer, T_max=epochs, eta_min=1e-7)
    loss_fn = nn.BCEWithLogitsLoss(reduction='sum')

    train_loader = torch.utils.data.DataLoader(train_dataset,␣
↪batch_size=batch_size, shuffle=True)
    val_loader = torch.utils.data.DataLoader(val_dataset,␣
↪batch_size=batch_size, shuffle=False)


    if warmup_prop >= 1:
```

```
        warmup_prop = warmup_prop / epochs

    for epoch in range(epochs):
        model.train()
        avg_loss = 0
        start_time = time.time()

        if epoch < epochs * warmup_prop:
            lr = 5e-5 + 0.001 * epoch / (epochs * warmup_prop)
            for param_group in optimizer.param_groups:
                param_group['lr'] = lr
        else:
            scheduler.step()
            lr = np.mean([param_group['lr'] for param_group in optimizer.
↪param_groups])

        for x, y_batch in train_loader:
            optimizer.zero_grad()

            dice = np.random.random() < mixup
            if dice:
                x, y_a, y_b, lam = mixup_data(x, y_batch.float())
                x, y_a, y_b = map(Variable, (x, y_a, y_b))


            y_pred = model(x.cuda()).view(-1, num_classes)
            if dice:
                loss = mixup_criterion(loss_fn, y_pred, y_a, y_b, lam)
            else:
                loss = loss_fn(y_pred.float(), y_batch.float().cuda())

            loss.backward()
            avg_loss += loss.item() / len(train_dataset)
            optimizer.step()

        model.eval()
        avg_val_loss = 0.
        pred_val = np.array([[]]*num_classes).T

        for x, y_batch in val_loader:
            y_pred = model(x.cuda()).view(-1, num_classes).detach()
            avg_val_loss += loss_fn(y_pred.float(), y_batch.float().cuda()).
↪item() / len(val_dataset)
            pred_val = np.concatenate((pred_val, sigmoid(y_pred.cpu().numpy())))

        pred_val = np.mean(pred_val.reshape((nb_tta, -1, num_classes,)), axis=0)
        score_class, weight = lwlrap(val_dataset.y, pred_val)
```

```
        score = (score_class * weight).sum()

        elapsed_time = time.time() - start_time

        if cp:
            if score > best_score:
                save_model_weights(model, f"{model_name}.pt", verbose=0)
                best_score = score

        if (epoch + 1) % verbose == 0:
            elapsed_time = elapsed_time * verbose
            print(f'Epoch {epoch+1}/{epochs}     lr={lr:.1e}     lwlrap={score:.
↪5f}     ', end='')
            print(f'loss={avg_loss:.2f}     val_loss={avg_val_loss:.2f}     ␣
↪t={elapsed_time:.0f}s')

    return best_score
```

### 5.9 Refit

- Same thing as the previous function, but:
- We change the scheduler to reduce_lr_on_plateau, starting from 0.001
- Used with curated data only

```
[51]: def refit(model, train_dataset, val_dataset, epochs=10, batch_size=128,␣
↪nb_tta=5, mixup=False,
             verbose=1, cp=False, model_name='model', best_score=0, lr=0.001):
    avg_val_loss = 1000
    clip_value = 1.0

    model.cuda()

    opt_params = [
        {'params': [p for n, p in list(model.named_parameters()) if not any(nd␣
↪in n for nd in ['bias', 'LayerNorm.bias', 'LayerNorm.weight'])],␣
↪'weight_decay': 0.01},
        {'params': [p for n, p in list(model.named_parameters()) if any(nd in n␣
↪for nd in ['bias', 'LayerNorm.bias', 'LayerNorm.weight'])], 'weight_decay':␣
↪0.0}
    ]

    for p in model.parameters():
        p.register_hook(lambda grad: torch.clamp(grad, -clip_value, clip_value))

    optimizer = torch.optim.Adam(opt_params, lr)
```

```
    scheduler = ReduceLROnPlateau(optimizer, mode='min', patience=3, factor=0.1, verbose=0)
    loss_fn = nn.BCEWithLogitsLoss(reduction='sum')

    train_loader = torch.utils.data.DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
    val_loader = torch.utils.data.DataLoader(val_dataset, batch_size=batch_size, shuffle=False)

    for epoch in range(epochs):
        model.train()
        avg_loss = 0
        start_time = time.time()

        scheduler.step(avg_val_loss)
        lr = np.mean([param_group['lr'] for param_group in optimizer.param_groups])

        for x, y_batch in train_loader:
            optimizer.zero_grad()

            dice = np.random.random() < mixup
            if dice:
                x, y_a, y_b, lam = mixup_data(x, y_batch.float())
                x, y_a, y_b = map(Variable, (x, y_a, y_b))


            y_pred = model(x.cuda()).view(-1, num_classes)
            if dice:
                loss = mixup_criterion(loss_fn, y_pred, y_a, y_b, lam)
            else:
                loss = loss_fn(y_pred.float(), y_batch.float().cuda())

            loss.backward()
            avg_loss += loss.item() / len(train_dataset)
            optimizer.step()

        model.eval()
        avg_val_loss = 0.
        pred_val = np.array([[]]*num_classes).T

        for x, y_batch in val_loader:
            y_pred = model(x.cuda()).view(-1, num_classes).detach()
            avg_val_loss += loss_fn(y_pred.float(), y_batch.float().cuda()).item() / len(val_dataset)
            pred_val = np.concatenate((pred_val, sigmoid(y_pred.cpu().numpy())))
```

```
        pred_val = np.mean(pred_val.reshape((nb_tta, -1, num_classes,)), axis=0)
        score_class, weight = lwlrap(val_dataset.y, pred_val)
        score = (score_class * weight).sum()

        elapsed_time = time.time() - start_time

        if cp:
            if score > best_score:
                save_model_weights(model, f"{model_name}.pt", verbose=0)
                best_score = score

        if (epoch + 1) % verbose == 0:
            elapsed_time = elapsed_time * verbose
            print(f'Epoch {epoch+1}/{epochs}     lr={lr:.1e}     lwlrap={score:.
↪5f}     ', end='')
            print(f'loss={avg_loss:.2f}     val_loss={avg_val_loss:.2f}    ␣
↪t={elapsed_time:.0f}s')

        if lr <= 1e-6:
            break
    return best_score
```

### 5.10 *k*-folds

- 5 folds Stratified, using one of the labels if there are more. Only curated data is kept.
- Fit for 65 (approx.) epochs on curated + selected noisy (optional)
- Refit twice for a few epochs on curated only

[52]:
```
def k_fold(model_class, X, y, X_test, transform_dic, X_noisy=[], y_noisy=np.
↪array([]),
           k=5, batch_size=32, epochs=5, seed=2019, nb_tta=5, tta_eval=25,␣
↪mixup=False,
           verbose=1, save=True, cp=False, warmup_prop=0.1, model_name="model",␣
↪pretrained_path=''):

    splits = list(StratifiedKFold(n_splits=k, shuffle=True, random_state=seed).
↪split(X, np.argmax(y, axis=1)))

    pred_test = np.zeros((len(X_test), num_classes))
    pred_oof = np.zeros((y.shape[0], num_classes))

    for i, (train_idx, val_idx) in enumerate(splits):
        print(f"-------------   Fold {i+1}  -------------")
        seed_everything(seed + i)
        start_time = time.time()
```

```
        model = model_class(num_classes=num_classes)

        if len(pretrained_path):
            load_model_weights(model, pretrained_path)

        train_dataset = FATDatasetTrain([X[i] for i in train_idx] + X_noisy, transforms=transform_dic['train'],
                                        y=np.concatenate((y[train_idx], y_noisy)),apply_spec_aug=True)
        val_dataset = FATDatasetTest([X[i] for i in val_idx], transforms=transform_dic['test'], y=y[val_idx], nb_tta=nb_tta)
        test_dataset = FATDatasetTest(X_test, transforms=transform_dic['test'], nb_tta=tta_eval)

        print('\n - Fitting \n')

        best_score = fit(model, train_dataset, val_dataset, epochs=epochs, batch_size=batch_size, nb_tta=nb_tta, mixup=mixup,
                         warmup_prop=warmup_prop, verbose=verbose, cp=cp, model_name=f'{model_name}_{i+1}', lr=1e-3)

        print('\n - Re-fitting with curated data only (1/2)\n')

        retrain_dataset = FATDatasetTrain([X[i] for i in train_idx], transforms=transform_dic['train'], y=y[train_idx])

        best_score = refit(model, retrain_dataset, val_dataset, epochs=epochs, batch_size=batch_size, nb_tta=nb_tta, mixup=mixup,
                           verbose=verbose, cp=cp, model_name=f'{model_name}_{i+1}', best_score=best_score, lr=1e-4)

        if cp:
            load_model_weights(model, f"{model_name}_{i+1}.pt", verbose=1)
        elif save:
            save_model_weights(model, f"{model_name}_{i+1}.pt", verbose=1)

        print('\n - Re-fitting with curated data only (2/2)\n')

        best_score = refit(model, retrain_dataset, val_dataset, epochs=epochs, batch_size=batch_size, nb_tta=nb_tta, mixup=mixup,
                           verbose=verbose, cp=cp, model_name=f'{model_name}_{i+1}', best_score=best_score, lr=1e-4)

        if cp:
            load_model_weights(model, f"{model_name}_{i+1}.pt", verbose=1)
        elif save:
```

```
            save_model_weights(model, f"{model_name}_{i+1}.pt", verbose=1)

        print(f'\n - Predicting with {tta_eval} TTA \n')

        val_dataset = FATDatasetTest([X[i] for i in val_idx],␣
↪transforms=transform_dic['test'], y=y[val_idx], nb_tta=tta_eval)
        pred_val = np.mean(predict(val_dataset, model).reshape((tta_eval, -1,␣
↪num_classes,)), axis=0)
        pred_oof[val_idx, :] = pred_val

        score_class, weight = lwlrap(y[val_idx], pred_val)
        score = (score_class * weight).sum()

        pred_test += np.mean(predict(test_dataset, model).reshape((tta_eval,␣
↪-1, num_classes,)), axis=0)


        print(f"\n lwlrap : Scored {score :.4f} on validation data")
        print(f"\n    Done in {(time.time() - start_time) / 60 :.1f} minutes␣
↪\n")

    return pred_test, pred_oof
```

# 6 Training

### 6.0.1 Parameters

[53]:
```
model_name = "model"
k = 5
epochs = 65
batch_size = 64
nb_tta = 5
mixup = 1
cp = True
warmup_prop = 0.1
```

[54]:
```
model = Classifier_M3
transforms_ = transforms_dict
```

### 6.0.2 Weights pretrained on noisy data

In case we want to use weights pretrained on noisy, we specify weights to load.

[55]:
```
# cp_path = "../input/fat-cp/new_default_65.pt"
cp_path = ''
```

### 6.0.3 Fitting

[56]:
```
pred_test, pred_oof = k_fold(model, X_train, y_train, X_test, transforms_,
                             X_noisy=X_noisy, y_noisy=y_noisy,
                             k=k, batch_size=batch_size, epochs=epochs,
                             nb_tta=nb_tta, cp=cp, warmup_prop=warmup_prop,
                             mixup=mixup, seed=seed,
                             model_name=model_name, pretrained_path=cp_path)
```

```
-------------   Fold 1  -------------

 - Fitting

Epoch 1/65     lr=5.0e-05     lwlrap=0.26018     loss=55.27     val_loss=55.02
t=51s
Epoch 2/65     lr=2.0e-04     lwlrap=0.32222     loss=52.35     val_loss=47.70
t=51s
Epoch 3/65     lr=3.6e-04     lwlrap=0.26679     loss=34.57     val_loss=20.81
t=50s
Epoch 4/65     lr=5.1e-04     lwlrap=0.31297     loss=10.67     val_loss=5.44
t=50s
Epoch 5/65     lr=6.7e-04     lwlrap=0.36285     loss=5.08     val_loss=5.00
t=50s
Epoch 6/65     lr=8.2e-04     lwlrap=0.37723     loss=4.69     val_loss=4.69
t=50s
Epoch 7/65     lr=9.7e-04     lwlrap=0.43856     loss=4.48     val_loss=4.38
t=50s
Epoch 8/65     lr=1.0e-03     lwlrap=0.54052     loss=4.26     val_loss=3.80
t=50s
Epoch 9/65     lr=1.0e-03     lwlrap=0.60203     loss=4.01     val_loss=3.60
t=50s
Epoch 10/65     lr=1.0e-03     lwlrap=0.50895     loss=3.93     val_loss=4.25
t=50s
Epoch 11/65     lr=9.9e-04     lwlrap=0.61065     loss=3.86     val_loss=3.43
t=50s
Epoch 12/65     lr=9.9e-04     lwlrap=0.68352     loss=3.68     val_loss=3.00
t=51s
Epoch 13/65     lr=9.9e-04     lwlrap=0.66243     loss=3.74     val_loss=3.14
t=51s
Epoch 14/65     lr=9.8e-04     lwlrap=0.66513     loss=3.65     val_loss=3.08
t=50s
Epoch 15/65     lr=9.7e-04     lwlrap=0.69114     loss=3.68     val_loss=2.97
t=50s
```

```
Epoch 16/65     lr=9.6e-04     lwlrap=0.67038     loss=3.59     val_loss=3.05
t=51s
Epoch 17/65     lr=9.5e-04     lwlrap=0.74167     loss=3.55     val_loss=2.65
t=50s
Epoch 18/65     lr=9.4e-04     lwlrap=0.73690     loss=3.45     val_loss=2.61
t=51s
Epoch 19/65     lr=9.3e-04     lwlrap=0.73952     loss=3.38     val_loss=2.56
t=51s
Epoch 20/65     lr=9.2e-04     lwlrap=0.76187     loss=3.31     val_loss=2.55
t=50s
Epoch 21/65     lr=9.0e-04     lwlrap=0.73961     loss=3.37     val_loss=2.65
t=51s
Epoch 22/65     lr=8.9e-04     lwlrap=0.75324     loss=3.26     val_loss=2.45
t=50s
Epoch 23/65     lr=8.7e-04     lwlrap=0.75069     loss=3.30     val_loss=2.48
t=51s
Epoch 24/65     lr=8.6e-04     lwlrap=0.69725     loss=3.04     val_loss=2.94
t=50s
Epoch 25/65     lr=8.4e-04     lwlrap=0.76349     loss=3.24     val_loss=2.56
t=51s
Epoch 26/65     lr=8.2e-04     lwlrap=0.78099     loss=3.13     val_loss=2.32
t=51s
Epoch 27/65     lr=8.0e-04     lwlrap=0.76385     loss=3.30     val_loss=2.36
t=51s
Epoch 28/65     lr=7.8e-04     lwlrap=0.77796     loss=3.14     val_loss=2.37
t=51s
Epoch 29/65     lr=7.6e-04     lwlrap=0.78999     loss=3.08     val_loss=2.23
t=50s
Epoch 30/65     lr=7.4e-04     lwlrap=0.77614     loss=3.11     val_loss=2.27
t=50s
Epoch 31/65     lr=7.2e-04     lwlrap=0.79385     loss=2.93     val_loss=2.14
t=50s
Epoch 32/65     lr=7.0e-04     lwlrap=0.80254     loss=2.91     val_loss=2.08
t=51s
Epoch 33/65     lr=6.8e-04     lwlrap=0.82031     loss=2.95     val_loss=2.03
t=51s
Epoch 34/65     lr=6.5e-04     lwlrap=0.81929     loss=2.93     val_loss=2.02
t=51s
Epoch 35/65     lr=6.3e-04     lwlrap=0.82256     loss=2.82     val_loss=2.01
t=50s
Epoch 36/65     lr=6.1e-04     lwlrap=0.82071     loss=2.86     val_loss=1.95
t=50s
Epoch 37/65     lr=5.8e-04     lwlrap=0.82696     loss=2.78     val_loss=1.86
t=51s
Epoch 38/65     lr=5.6e-04     lwlrap=0.83216     loss=2.59     val_loss=1.93
t=51s
Epoch 39/65     lr=5.4e-04     lwlrap=0.83329     loss=2.78     val_loss=1.89
t=50s
```

```
Epoch 40/65     lr=5.1e-04     lwlrap=0.82690     loss=2.74     val_loss=1.91
t=51s
Epoch 41/65     lr=4.9e-04     lwlrap=0.82497     loss=2.55     val_loss=1.96
t=50s
Epoch 42/65     lr=4.6e-04     lwlrap=0.81964     loss=2.60     val_loss=1.95
t=50s
Epoch 43/65     lr=4.4e-04     lwlrap=0.82881     loss=2.66     val_loss=1.94
t=50s
Epoch 44/65     lr=4.2e-04     lwlrap=0.84151     loss=2.56     val_loss=1.82
t=51s
Epoch 45/65     lr=3.9e-04     lwlrap=0.83742     loss=2.42     val_loss=1.82
t=50s
Epoch 46/65     lr=3.7e-04     lwlrap=0.85139     loss=2.27     val_loss=1.72
t=50s
Epoch 47/65     lr=3.5e-04     lwlrap=0.83361     loss=2.42     val_loss=1.89
t=50s
Epoch 48/65     lr=3.2e-04     lwlrap=0.84908     loss=2.34     val_loss=1.76
t=50s
Epoch 49/65     lr=3.0e-04     lwlrap=0.85275     loss=2.42     val_loss=1.72
t=50s
Epoch 50/65     lr=2.8e-04     lwlrap=0.84569     loss=2.29     val_loss=1.75
t=51s
Epoch 51/65     lr=2.6e-04     lwlrap=0.85379     loss=2.30     val_loss=1.72
t=50s
Epoch 52/65     lr=2.4e-04     lwlrap=0.85505     loss=2.17     val_loss=1.66
t=50s
Epoch 53/65     lr=2.2e-04     lwlrap=0.85766     loss=2.19     val_loss=1.72
t=50s
Epoch 54/65     lr=2.0e-04     lwlrap=0.85389     loss=2.11     val_loss=1.71
t=50s
Epoch 55/65     lr=1.8e-04     lwlrap=0.86408     loss=2.08     val_loss=1.64
t=50s
Epoch 56/65     lr=1.6e-04     lwlrap=0.85847     loss=2.11     val_loss=1.68
t=50s
Epoch 57/65     lr=1.4e-04     lwlrap=0.86186     loss=2.16     val_loss=1.64
t=50s
Epoch 58/65     lr=1.3e-04     lwlrap=0.85690     loss=2.12     val_loss=1.71
t=50s
Epoch 59/65     lr=1.1e-04     lwlrap=0.86328     loss=2.12     val_loss=1.62
t=50s
Epoch 60/65     lr=9.6e-05     lwlrap=0.86328     loss=2.15     val_loss=1.64
t=50s
Epoch 61/65     lr=8.2e-05     lwlrap=0.85629     loss=2.10     val_loss=1.72
t=50s
Epoch 62/65     lr=6.9e-05     lwlrap=0.86327     loss=2.09     val_loss=1.63
t=50s
Epoch 63/65     lr=5.7e-05     lwlrap=0.86837     loss=1.95     val_loss=1.61
t=50s
```

```
Epoch 64/65     lr=4.7e-05     lwlrap=0.86044     loss=1.99     val_loss=1.64
t=50s
Epoch 65/65     lr=3.7e-05     lwlrap=0.86022     loss=2.02     val_loss=1.63
t=50s

 - Re-fitting with curated data only (1/2)

Epoch 1/65     lr=1.0e-04     lwlrap=0.86119     loss=1.81     val_loss=1.66
t=34s
Epoch 2/65     lr=1.0e-04     lwlrap=0.87080     loss=1.71     val_loss=1.63
t=34s
Epoch 3/65     lr=1.0e-04     lwlrap=0.86493     loss=1.70     val_loss=1.60
t=34s
Epoch 4/65     lr=1.0e-04     lwlrap=0.87125     loss=1.57     val_loss=1.61
t=34s
Epoch 5/65     lr=1.0e-04     lwlrap=0.86143     loss=1.68     val_loss=1.66
t=34s
Epoch 6/65     lr=1.0e-04     lwlrap=0.86141     loss=1.56     val_loss=1.67
t=34s
Epoch 7/65     lr=1.0e-04     lwlrap=0.86181     loss=1.64     val_loss=1.68
t=34s
Epoch 8/65     lr=1.0e-05     lwlrap=0.86455     loss=1.71     val_loss=1.66
t=34s
Epoch 9/65     lr=1.0e-05     lwlrap=0.86781     loss=1.69     val_loss=1.65
t=34s
Epoch 10/65     lr=1.0e-05     lwlrap=0.86688     loss=1.64     val_loss=1.66
t=34s
Epoch 11/65     lr=1.0e-05     lwlrap=0.86353     loss=1.54     val_loss=1.67
t=34s
Epoch 12/65     lr=1.0e-06     lwlrap=0.86722     loss=1.54     val_loss=1.65
t=34s
Epoch 13/65     lr=1.0e-06     lwlrap=0.86256     loss=1.68     val_loss=1.66
t=34s
Epoch 14/65     lr=1.0e-06     lwlrap=0.86433     loss=1.69     val_loss=1.64
t=34s
Epoch 15/65     lr=1.0e-06     lwlrap=0.87051     loss=1.69     val_loss=1.60
t=34s
Epoch 16/65     lr=1.0e-07     lwlrap=0.86571     loss=1.89     val_loss=1.64
t=34s
Loading weights from model_1.pt


 - Re-fitting with curated data only (2/2)

Epoch 1/65     lr=1.0e-04     lwlrap=0.86580     loss=1.79     val_loss=1.63
t=34s
Epoch 2/65     lr=1.0e-04     lwlrap=0.85720     loss=1.90     val_loss=1.68
t=34s
```

```
Epoch 3/65     lr=1.0e-04     lwlrap=0.86975     loss=1.65     val_loss=1.63
t=34s
Epoch 4/65     lr=1.0e-04     lwlrap=0.86020     loss=1.85     val_loss=1.69
t=34s
Epoch 5/65     lr=1.0e-04     lwlrap=0.85750     loss=1.50     val_loss=1.66
t=34s
Epoch 6/65     lr=1.0e-04     lwlrap=0.86362     loss=1.67     val_loss=1.64
t=34s
Epoch 7/65     lr=1.0e-04     lwlrap=0.87108     loss=1.37     val_loss=1.58
t=34s
Epoch 8/65     lr=1.0e-04     lwlrap=0.87157     loss=1.63     val_loss=1.63
t=34s
Epoch 9/65     lr=1.0e-04     lwlrap=0.86306     loss=1.86     val_loss=1.70
t=34s
Epoch 10/65     lr=1.0e-04     lwlrap=0.86813     loss=1.57     val_loss=1.68
t=34s
Epoch 11/65     lr=1.0e-04     lwlrap=0.85985     loss=1.70     val_loss=1.66
t=34s
Epoch 12/65     lr=1.0e-05     lwlrap=0.86882     loss=1.59     val_loss=1.63
t=34s
Epoch 13/65     lr=1.0e-05     lwlrap=0.86365     loss=1.61     val_loss=1.64
t=34s
Epoch 14/65     lr=1.0e-05     lwlrap=0.86310     loss=1.55     val_loss=1.66
t=34s
Epoch 15/65     lr=1.0e-05     lwlrap=0.86480     loss=1.73     val_loss=1.66
t=34s
Epoch 16/65     lr=1.0e-06     lwlrap=0.85833     loss=1.82     val_loss=1.69
t=34s
Epoch 17/65     lr=1.0e-06     lwlrap=0.87328     loss=1.50     val_loss=1.62
t=34s
Epoch 18/65     lr=1.0e-06     lwlrap=0.86849     loss=1.57     val_loss=1.64
t=34s
Epoch 19/65     lr=1.0e-06     lwlrap=0.86565     loss=1.51     val_loss=1.66
t=34s
Epoch 20/65     lr=1.0e-07     lwlrap=0.86396     loss=1.62     val_loss=1.67
t=34s
Loading weights from model_1.pt


 - Predicting with 25 TTA


 lwlrap : Scored 0.8720 on validation data

    Done in 79.2 minutes

-------------   Fold 2  -------------
```

```
 - Fitting

Epoch 1/65     lr=5.0e-05     lwlrap=0.25902     loss=55.37     val_loss=55.17
t=50s
Epoch 2/65     lr=2.0e-04     lwlrap=0.32307     loss=52.38     val_loss=48.82
t=50s
Epoch 3/65     lr=3.6e-04     lwlrap=0.25209     loss=34.42     val_loss=18.35
t=50s
Epoch 4/65     lr=5.1e-04     lwlrap=0.33309     loss=10.60     val_loss=6.06
t=50s
Epoch 5/65     lr=6.7e-04     lwlrap=0.40691     loss=5.06     val_loss=4.67
t=50s
Epoch 6/65     lr=8.2e-04     lwlrap=0.38906     loss=4.66     val_loss=4.56
t=50s
Epoch 7/65     lr=9.7e-04     lwlrap=0.48700     loss=4.38     val_loss=4.36
t=50s
Epoch 8/65     lr=1.0e-03     lwlrap=0.52742     loss=4.40     val_loss=3.99
t=50s
Epoch 9/65     lr=1.0e-03     lwlrap=0.62530     loss=4.10     val_loss=3.44
t=50s
Epoch 10/65     lr=1.0e-03     lwlrap=0.64406     loss=4.03     val_loss=3.24
t=50s
Epoch 11/65     lr=9.9e-04     lwlrap=0.65728     loss=3.90     val_loss=3.18
t=50s
Epoch 12/65     lr=9.9e-04     lwlrap=0.64846     loss=3.93     val_loss=3.13
t=50s
Epoch 13/65     lr=9.9e-04     lwlrap=0.68736     loss=3.70     val_loss=2.98
t=50s
Epoch 14/65     lr=9.8e-04     lwlrap=0.66574     loss=3.65     val_loss=3.13
t=50s
Epoch 15/65     lr=9.7e-04     lwlrap=0.71426     loss=3.61     val_loss=2.76
t=50s
Epoch 16/65     lr=9.6e-04     lwlrap=0.68025     loss=3.63     val_loss=2.97
t=50s
Epoch 17/65     lr=9.5e-04     lwlrap=0.71947     loss=3.52     val_loss=2.78
t=50s
Epoch 18/65     lr=9.4e-04     lwlrap=0.74868     loss=3.42     val_loss=2.53
t=50s
Epoch 19/65     lr=9.3e-04     lwlrap=0.71231     loss=3.41     val_loss=2.79
t=50s
Epoch 20/65     lr=9.2e-04     lwlrap=0.73408     loss=3.55     val_loss=2.73
t=50s
Epoch 21/65     lr=9.0e-04     lwlrap=0.73509     loss=3.31     val_loss=2.62
t=50s
Epoch 22/65     lr=8.9e-04     lwlrap=0.75465     loss=3.25     val_loss=2.52
t=50s
Epoch 23/65     lr=8.7e-04     lwlrap=0.74000     loss=3.39     val_loss=2.49
t=50s
```

```
Epoch 24/65     lr=8.6e-04     lwlrap=0.75720     loss=3.28     val_loss=2.49
t=50s
Epoch 25/65     lr=8.4e-04     lwlrap=0.80292     loss=3.23     val_loss=2.22
t=50s
Epoch 26/65     lr=8.2e-04     lwlrap=0.77969     loss=3.08     val_loss=2.29
t=50s
Epoch 27/65     lr=8.0e-04     lwlrap=0.80895     loss=3.03     val_loss=2.17
t=50s
Epoch 28/65     lr=7.8e-04     lwlrap=0.76786     loss=3.14     val_loss=2.39
t=50s
Epoch 29/65     lr=7.6e-04     lwlrap=0.79010     loss=3.04     val_loss=2.28
t=50s
Epoch 30/65     lr=7.4e-04     lwlrap=0.79507     loss=3.06     val_loss=2.26
t=50s
Epoch 31/65     lr=7.2e-04     lwlrap=0.81043     loss=2.89     val_loss=2.05
t=50s
Epoch 32/65     lr=7.0e-04     lwlrap=0.79879     loss=3.04     val_loss=2.18
t=50s
Epoch 33/65     lr=6.8e-04     lwlrap=0.82446     loss=2.90     val_loss=1.98
t=50s
Epoch 34/65     lr=6.5e-04     lwlrap=0.81679     loss=2.73     val_loss=1.97
t=50s
Epoch 35/65     lr=6.3e-04     lwlrap=0.81098     loss=2.80     val_loss=2.14
t=50s
Epoch 36/65     lr=6.1e-04     lwlrap=0.83682     loss=2.79     val_loss=1.92
t=50s
Epoch 37/65     lr=5.8e-04     lwlrap=0.83089     loss=2.77     val_loss=1.87
t=50s
Epoch 38/65     lr=5.6e-04     lwlrap=0.82411     loss=2.64     val_loss=1.92
t=50s
Epoch 39/65     lr=5.4e-04     lwlrap=0.82888     loss=2.62     val_loss=1.90
t=50s
Epoch 40/65     lr=5.1e-04     lwlrap=0.83106     loss=2.65     val_loss=1.89
t=50s
Epoch 41/65     lr=4.9e-04     lwlrap=0.82978     loss=2.68     val_loss=1.87
t=50s
Epoch 42/65     lr=4.6e-04     lwlrap=0.83332     loss=2.75     val_loss=1.85
t=50s
Epoch 43/65     lr=4.4e-04     lwlrap=0.82566     loss=2.55     val_loss=1.94
t=50s
Epoch 44/65     lr=4.2e-04     lwlrap=0.85103     loss=2.45     val_loss=1.74
t=50s
Epoch 45/65     lr=3.9e-04     lwlrap=0.85199     loss=2.39     val_loss=1.71
t=50s
Epoch 46/65     lr=3.7e-04     lwlrap=0.83055     loss=2.42     val_loss=1.83
t=50s
Epoch 47/65     lr=3.5e-04     lwlrap=0.84993     loss=2.41     val_loss=1.72
t=50s
```

```
Epoch 48/65     lr=3.2e-04     lwlrap=0.85309     loss=2.16     val_loss=1.68
t=50s
Epoch 49/65     lr=3.0e-04     lwlrap=0.83150     loss=2.35     val_loss=1.90
t=50s
Epoch 50/65     lr=2.8e-04     lwlrap=0.84976     loss=2.37     val_loss=1.74
t=50s
Epoch 51/65     lr=2.6e-04     lwlrap=0.85226     loss=2.23     val_loss=1.69
t=50s
Epoch 52/65     lr=2.4e-04     lwlrap=0.85748     loss=2.32     val_loss=1.64
t=50s
Epoch 53/65     lr=2.2e-04     lwlrap=0.86178     loss=2.19     val_loss=1.63
t=50s
Epoch 54/65     lr=2.0e-04     lwlrap=0.85680     loss=2.24     val_loss=1.66
t=50s
Epoch 55/65     lr=1.8e-04     lwlrap=0.86760     loss=2.22     val_loss=1.58
t=50s
Epoch 56/65     lr=1.6e-04     lwlrap=0.86286     loss=2.23     val_loss=1.59
t=50s
Epoch 57/65     lr=1.4e-04     lwlrap=0.86606     loss=1.92     val_loss=1.60
t=50s
Epoch 58/65     lr=1.3e-04     lwlrap=0.86971     loss=2.10     val_loss=1.57
t=50s
Epoch 59/65     lr=1.1e-04     lwlrap=0.86235     loss=2.11     val_loss=1.60
t=50s
Epoch 60/65     lr=9.6e-05     lwlrap=0.86598     loss=2.01     val_loss=1.57
t=50s
Epoch 61/65     lr=8.2e-05     lwlrap=0.86078     loss=1.91     val_loss=1.59
t=50s
Epoch 62/65     lr=6.9e-05     lwlrap=0.86622     loss=2.07     val_loss=1.59
t=50s
Epoch 63/65     lr=5.7e-05     lwlrap=0.86156     loss=2.20     val_loss=1.58
t=50s
Epoch 64/65     lr=4.7e-05     lwlrap=0.86164     loss=2.06     val_loss=1.59
t=50s
Epoch 65/65     lr=3.7e-05     lwlrap=0.87069     loss=2.04     val_loss=1.55
t=50s

 - Re-fitting with curated data only (1/2)

Epoch 1/65     lr=1.0e-04     lwlrap=0.86663     loss=1.89     val_loss=1.66
t=34s
Epoch 2/65     lr=1.0e-04     lwlrap=0.86828     loss=1.80     val_loss=1.63
t=34s
Epoch 3/65     lr=1.0e-04     lwlrap=0.86489     loss=1.68     val_loss=1.62
t=34s
Epoch 4/65     lr=1.0e-04     lwlrap=0.86348     loss=1.61     val_loss=1.62
t=34s
Epoch 5/65     lr=1.0e-04     lwlrap=0.86184     loss=1.66     val_loss=1.66
```

```
t=34s
Epoch 6/65     lr=1.0e-04     lwlrap=0.86053     loss=1.73     val_loss=1.63
t=34s
Epoch 7/65     lr=1.0e-04     lwlrap=0.86825     loss=1.82     val_loss=1.64
t=34s
Epoch 8/65     lr=1.0e-04     lwlrap=0.86474     loss=1.60     val_loss=1.58
t=34s
Epoch 9/65     lr=1.0e-04     lwlrap=0.85932     loss=2.03     val_loss=1.69
t=34s
Epoch 10/65     lr=1.0e-04     lwlrap=0.86314     loss=1.70     val_loss=1.66
t=34s
Epoch 11/65     lr=1.0e-04     lwlrap=0.86507     loss=1.48     val_loss=1.63
t=34s
Epoch 12/65     lr=1.0e-04     lwlrap=0.85898     loss=1.68     val_loss=1.60
t=34s
Epoch 13/65     lr=1.0e-05     lwlrap=0.86231     loss=1.74     val_loss=1.63
t=34s
Epoch 14/65     lr=1.0e-05     lwlrap=0.86461     loss=1.56     val_loss=1.60
t=34s
Epoch 15/65     lr=1.0e-05     lwlrap=0.86098     loss=1.62     val_loss=1.64
t=34s
Epoch 16/65     lr=1.0e-05     lwlrap=0.86423     loss=1.71     val_loss=1.62
t=34s
Epoch 17/65     lr=1.0e-06     lwlrap=0.86734     loss=1.71     val_loss=1.60
t=34s
Epoch 18/65     lr=1.0e-06     lwlrap=0.86453     loss=1.60     val_loss=1.63
t=34s
Epoch 19/65     lr=1.0e-06     lwlrap=0.86644     loss=1.60     val_loss=1.60
t=34s
Epoch 20/65     lr=1.0e-06     lwlrap=0.86256     loss=1.87     val_loss=1.62
t=34s
Epoch 21/65     lr=1.0e-07     lwlrap=0.86764     loss=1.49     val_loss=1.60
t=34s
Loading weights from model_2.pt


 - Re-fitting with curated data only (2/2)

Epoch 1/65     lr=1.0e-04     lwlrap=0.86222     loss=1.44     val_loss=1.60
t=34s
Epoch 2/65     lr=1.0e-04     lwlrap=0.85909     loss=1.77     val_loss=1.65
t=34s
Epoch 3/65     lr=1.0e-04     lwlrap=0.85946     loss=1.73     val_loss=1.70
t=34s
Epoch 4/65     lr=1.0e-04     lwlrap=0.86801     loss=1.85     val_loss=1.60
t=34s
Epoch 5/65     lr=1.0e-04     lwlrap=0.86079     loss=1.68     val_loss=1.63
t=34s
```

```
Epoch 6/65     lr=1.0e-05     lwlrap=0.85941     loss=1.58     val_loss=1.65
t=34s
Epoch 7/65     lr=1.0e-05     lwlrap=0.86306     loss=1.48     val_loss=1.59
t=34s
Epoch 8/65     lr=1.0e-05     lwlrap=0.86403     loss=1.71     val_loss=1.62
t=34s
Epoch 9/65     lr=1.0e-05     lwlrap=0.86150     loss=1.60     val_loss=1.62
t=34s
Epoch 10/65     lr=1.0e-05     lwlrap=0.86144     loss=1.48     val_loss=1.59
t=34s
Epoch 11/65     lr=1.0e-05     lwlrap=0.86447     loss=1.66     val_loss=1.63
t=34s
Epoch 12/65     lr=1.0e-05     lwlrap=0.86403     loss=1.72     val_loss=1.63
t=34s
Epoch 13/65     lr=1.0e-05     lwlrap=0.86341     loss=1.71     val_loss=1.64
t=34s
Epoch 14/65     lr=1.0e-05     lwlrap=0.86714     loss=1.67     val_loss=1.60
t=34s
Epoch 15/65     lr=1.0e-06     lwlrap=0.86530     loss=1.47     val_loss=1.60
t=34s
Epoch 16/65     lr=1.0e-06     lwlrap=0.86637     loss=1.69     val_loss=1.62
t=34s
Epoch 17/65     lr=1.0e-06     lwlrap=0.86267     loss=1.68     val_loss=1.65
t=34s
Epoch 18/65     lr=1.0e-06     lwlrap=0.86653     loss=1.80     val_loss=1.62
t=34s
Epoch 19/65     lr=1.0e-07     lwlrap=0.86404     loss=1.66     val_loss=1.62
t=34s
Loading weights from model_2.pt


 - Predicting with 25 TTA


 lwlrap : Scored 0.8733 on validation data

    Done in 81.1 minutes

-------------   Fold 3  -------------

 - Fitting

Epoch 1/65     lr=5.0e-05     lwlrap=0.24414     loss=55.44     val_loss=55.32
t=50s
Epoch 2/65     lr=2.0e-04     lwlrap=0.30122     loss=52.45     val_loss=47.40
t=50s
Epoch 3/65     lr=3.6e-04     lwlrap=0.27746     loss=34.35     val_loss=21.69
t=50s
```

```
Epoch 4/65     lr=5.1e-04     lwlrap=0.35608     loss=10.50     val_loss=5.62
t=50s
Epoch 5/65     lr=6.7e-04     lwlrap=0.36117     loss=5.11     val_loss=5.15
t=50s
Epoch 6/65     lr=8.2e-04     lwlrap=0.42873     loss=4.66     val_loss=4.71
t=50s
Epoch 7/65     lr=9.7e-04     lwlrap=0.53984     loss=4.51     val_loss=3.84
t=50s
Epoch 8/65     lr=1.0e-03     lwlrap=0.46399     loss=4.30     val_loss=4.12
t=50s
Epoch 9/65     lr=1.0e-03     lwlrap=0.57711     loss=4.20     val_loss=3.63
t=50s
Epoch 10/65     lr=1.0e-03     lwlrap=0.53918     loss=3.95     val_loss=3.81
t=50s
Epoch 11/65     lr=9.9e-04     lwlrap=0.61374     loss=4.00     val_loss=3.40
t=50s
Epoch 12/65     lr=9.9e-04     lwlrap=0.56248     loss=3.86     val_loss=3.63
t=50s
Epoch 13/65     lr=9.9e-04     lwlrap=0.69307     loss=3.69     val_loss=2.90
t=50s
Epoch 14/65     lr=9.8e-04     lwlrap=0.72925     loss=3.73     val_loss=2.77
t=50s
Epoch 15/65     lr=9.7e-04     lwlrap=0.69479     loss=3.73     val_loss=2.92
t=50s
Epoch 16/65     lr=9.6e-04     lwlrap=0.69144     loss=3.63     val_loss=2.95
t=50s
Epoch 17/65     lr=9.5e-04     lwlrap=0.66020     loss=3.49     val_loss=3.14
t=50s
Epoch 18/65     lr=9.4e-04     lwlrap=0.71340     loss=3.61     val_loss=2.81
t=50s
Epoch 19/65     lr=9.3e-04     lwlrap=0.72814     loss=3.39     val_loss=2.66
t=50s
Epoch 20/65     lr=9.2e-04     lwlrap=0.71464     loss=3.40     val_loss=2.79
t=50s
Epoch 21/65     lr=9.0e-04     lwlrap=0.73708     loss=3.38     val_loss=2.64
t=50s
Epoch 22/65     lr=8.9e-04     lwlrap=0.78120     loss=3.20     val_loss=2.41
t=50s
Epoch 23/65     lr=8.7e-04     lwlrap=0.74806     loss=3.23     val_loss=2.52
t=50s
Epoch 24/65     lr=8.6e-04     lwlrap=0.75222     loss=3.29     val_loss=2.50
t=50s
Epoch 25/65     lr=8.4e-04     lwlrap=0.73320     loss=3.18     val_loss=2.63
t=50s
Epoch 26/65     lr=8.2e-04     lwlrap=0.77417     loss=3.21     val_loss=2.33
t=50s
Epoch 27/65     lr=8.0e-04     lwlrap=0.79568     loss=3.09     val_loss=2.23
t=50s
```

```
Epoch 28/65     lr=7.8e-04     lwlrap=0.74394     loss=3.08     val_loss=2.56
t=50s
Epoch 29/65     lr=7.6e-04     lwlrap=0.80027     loss=3.17     val_loss=2.15
t=50s
Epoch 30/65     lr=7.4e-04     lwlrap=0.79424     loss=2.97     val_loss=2.22
t=50s
Epoch 31/65     lr=7.2e-04     lwlrap=0.80583     loss=2.95     val_loss=2.13
t=50s
Epoch 32/65     lr=7.0e-04     lwlrap=0.79787     loss=3.06     val_loss=2.25
t=50s
Epoch 33/65     lr=6.8e-04     lwlrap=0.80842     loss=2.92     val_loss=2.12
t=50s
Epoch 34/65     lr=6.5e-04     lwlrap=0.79978     loss=2.72     val_loss=2.19
t=50s
Epoch 35/65     lr=6.3e-04     lwlrap=0.80208     loss=2.93     val_loss=2.15
t=50s
Epoch 36/65     lr=6.1e-04     lwlrap=0.80972     loss=2.73     val_loss=2.07
t=50s
Epoch 37/65     lr=5.8e-04     lwlrap=0.82559     loss=2.95     val_loss=1.99
t=50s
Epoch 38/65     lr=5.6e-04     lwlrap=0.82783     loss=2.75     val_loss=1.90
t=50s
Epoch 39/65     lr=5.4e-04     lwlrap=0.82657     loss=2.79     val_loss=1.94
t=50s
Epoch 40/65     lr=5.1e-04     lwlrap=0.83205     loss=2.69     val_loss=1.91
t=50s
Epoch 41/65     lr=4.9e-04     lwlrap=0.83138     loss=2.64     val_loss=1.92
t=50s
Epoch 42/65     lr=4.6e-04     lwlrap=0.83177     loss=2.48     val_loss=1.95
t=50s
Epoch 43/65     lr=4.4e-04     lwlrap=0.83187     loss=2.53     val_loss=1.90
t=50s
Epoch 44/65     lr=4.2e-04     lwlrap=0.84055     loss=2.56     val_loss=1.81
t=50s
Epoch 45/65     lr=3.9e-04     lwlrap=0.83422     loss=2.58     val_loss=1.88
t=50s
Epoch 46/65     lr=3.7e-04     lwlrap=0.84742     loss=2.46     val_loss=1.77
t=50s
Epoch 47/65     lr=3.5e-04     lwlrap=0.84145     loss=2.29     val_loss=1.80
t=50s
Epoch 48/65     lr=3.2e-04     lwlrap=0.85495     loss=2.43     val_loss=1.70
t=50s
Epoch 49/65     lr=3.0e-04     lwlrap=0.84674     loss=2.39     val_loss=1.75
t=50s
Epoch 50/65     lr=2.8e-04     lwlrap=0.85250     loss=2.14     val_loss=1.67
t=50s
Epoch 51/65     lr=2.6e-04     lwlrap=0.84839     loss=2.42     val_loss=1.70
t=50s
```

```
Epoch 52/65     lr=2.4e-04     lwlrap=0.84246     loss=2.26     val_loss=1.72
t=50s
Epoch 53/65     lr=2.2e-04     lwlrap=0.84758     loss=2.17     val_loss=1.73
t=50s
Epoch 54/65     lr=2.0e-04     lwlrap=0.85836     loss=2.10     val_loss=1.68
t=50s
Epoch 55/65     lr=1.8e-04     lwlrap=0.85988     loss=2.25     val_loss=1.62
t=50s
Epoch 56/65     lr=1.6e-04     lwlrap=0.86222     loss=2.20     val_loss=1.66
t=50s
Epoch 57/65     lr=1.4e-04     lwlrap=0.86285     loss=2.17     val_loss=1.64
t=50s
Epoch 58/65     lr=1.3e-04     lwlrap=0.85746     loss=2.18     val_loss=1.63
t=50s
Epoch 59/65     lr=1.1e-04     lwlrap=0.86874     loss=1.87     val_loss=1.59
t=50s
Epoch 60/65     lr=9.6e-05     lwlrap=0.86401     loss=2.15     val_loss=1.59
t=50s
Epoch 61/65     lr=8.2e-05     lwlrap=0.86070     loss=2.03     val_loss=1.61
t=50s
Epoch 62/65     lr=6.9e-05     lwlrap=0.85960     loss=2.10     val_loss=1.64
t=50s
Epoch 63/65     lr=5.7e-05     lwlrap=0.86222     loss=2.00     val_loss=1.60
t=50s
Epoch 64/65     lr=4.7e-05     lwlrap=0.86746     loss=1.96     val_loss=1.56
t=50s
Epoch 65/65     lr=3.7e-05     lwlrap=0.86102     loss=2.04     val_loss=1.65
t=50s

 - Re-fitting with curated data only (1/2)

Epoch 1/65     lr=1.0e-04     lwlrap=0.85773     loss=1.65     val_loss=1.70
t=34s
Epoch 2/65     lr=1.0e-04     lwlrap=0.86105     loss=1.70     val_loss=1.66
t=34s
Epoch 3/65     lr=1.0e-04     lwlrap=0.86759     loss=1.65     val_loss=1.62
t=34s
Epoch 4/65     lr=1.0e-04     lwlrap=0.86566     loss=1.71     val_loss=1.61
t=34s
Epoch 5/65     lr=1.0e-04     lwlrap=0.86776     loss=1.70     val_loss=1.61
t=34s
Epoch 6/65     lr=1.0e-04     lwlrap=0.86389     loss=1.62     val_loss=1.66
t=34s
Epoch 7/65     lr=1.0e-04     lwlrap=0.86537     loss=1.59     val_loss=1.63
t=34s
Epoch 8/65     lr=1.0e-04     lwlrap=0.85872     loss=2.01     val_loss=1.62
t=34s
Epoch 9/65     lr=1.0e-04     lwlrap=0.86514     loss=1.93     val_loss=1.67
```

```
t=34s
Epoch 10/65    lr=1.0e-05    lwlrap=0.86215    loss=1.88    val_loss=1.70
t=34s
Epoch 11/65    lr=1.0e-05    lwlrap=0.86664    loss=1.60    val_loss=1.61
t=34s
Epoch 12/65    lr=1.0e-05    lwlrap=0.86899    loss=1.58    val_loss=1.62
t=34s
Epoch 13/65    lr=1.0e-05    lwlrap=0.86687    loss=1.68    val_loss=1.63
t=34s
Epoch 14/65    lr=1.0e-06    lwlrap=0.86990    loss=1.61    val_loss=1.59
t=34s
Epoch 15/65    lr=1.0e-06    lwlrap=0.86878    loss=1.60    val_loss=1.61
t=34s
Epoch 16/65    lr=1.0e-06    lwlrap=0.86478    loss=1.40    val_loss=1.60
t=34s
Epoch 17/65    lr=1.0e-06    lwlrap=0.86378    loss=1.35    val_loss=1.59
t=34s
Epoch 18/65    lr=1.0e-06    lwlrap=0.86469    loss=1.50    val_loss=1.63
t=34s
Epoch 19/65    lr=1.0e-07    lwlrap=0.87557    loss=1.50    val_loss=1.58
t=34s
Loading weights from model_3.pt


 - Re-fitting with curated data only (2/2)

Epoch 1/65    lr=1.0e-04    lwlrap=0.86746    loss=1.58    val_loss=1.58
t=34s
Epoch 2/65    lr=1.0e-04    lwlrap=0.86260    loss=1.87    val_loss=1.64
t=34s
Epoch 3/65    lr=1.0e-04    lwlrap=0.86753    loss=1.76    val_loss=1.62
t=34s
Epoch 4/65    lr=1.0e-04    lwlrap=0.85922    loss=1.76    val_loss=1.72
t=34s
Epoch 5/65    lr=1.0e-04    lwlrap=0.86343    loss=1.67    val_loss=1.63
t=34s
Epoch 6/65    lr=1.0e-05    lwlrap=0.86529    loss=1.55    val_loss=1.63
t=34s
Epoch 7/65    lr=1.0e-05    lwlrap=0.87115    loss=1.62    val_loss=1.56
t=34s
Epoch 8/65    lr=1.0e-05    lwlrap=0.86554    loss=1.43    val_loss=1.64
t=34s
Epoch 9/65    lr=1.0e-05    lwlrap=0.86417    loss=1.53    val_loss=1.61
t=34s
Epoch 10/65    lr=1.0e-05    lwlrap=0.86943    loss=1.85    val_loss=1.64
t=34s
Epoch 11/65    lr=1.0e-05    lwlrap=0.87077    loss=1.56    val_loss=1.60
t=34s
```

```
Epoch 12/65     lr=1.0e-06     lwlrap=0.86846     loss=1.49     val_loss=1.61
t=34s
Epoch 13/65     lr=1.0e-06     lwlrap=0.86334     loss=1.58     val_loss=1.64
t=34s
Epoch 14/65     lr=1.0e-06     lwlrap=0.86422     loss=1.68     val_loss=1.62
t=34s
Epoch 15/65     lr=1.0e-06     lwlrap=0.86728     loss=1.60     val_loss=1.63
t=34s
Epoch 16/65     lr=1.0e-07     lwlrap=0.86321     loss=1.45     val_loss=1.64
t=34s
Loading weights from model_3.pt


 - Predicting with 25 TTA


 lwlrap : Scored 0.8722 on validation data

    Done in 78.0 minutes

-------------   Fold 4  -------------

 - Fitting

Epoch 1/65     lr=5.0e-05     lwlrap=0.29778     loss=55.13     val_loss=54.73
t=50s
Epoch 2/65     lr=2.0e-04     lwlrap=0.31540     loss=52.07     val_loss=47.28
t=50s
Epoch 3/65     lr=3.6e-04     lwlrap=0.34737     loss=33.77     val_loss=19.99
t=50s
Epoch 4/65     lr=5.1e-04     lwlrap=0.35495     loss=10.24     val_loss=5.97
t=50s
Epoch 5/65     lr=6.7e-04     lwlrap=0.42731     loss=5.06     val_loss=4.36
t=50s
Epoch 6/65     lr=8.2e-04     lwlrap=0.40044     loss=4.62     val_loss=4.49
t=50s
Epoch 7/65     lr=9.7e-04     lwlrap=0.52729     loss=4.48     val_loss=3.93
t=50s
Epoch 8/65     lr=1.0e-03     lwlrap=0.55094     loss=4.28     val_loss=3.75
t=50s
Epoch 9/65     lr=1.0e-03     lwlrap=0.50160     loss=4.12     val_loss=4.12
t=50s
Epoch 10/65     lr=1.0e-03     lwlrap=0.64308     loss=3.95     val_loss=3.25
t=50s
Epoch 11/65     lr=9.9e-04     lwlrap=0.61630     loss=3.76     val_loss=3.34
t=50s
Epoch 12/65     lr=9.9e-04     lwlrap=0.64073     loss=3.78     val_loss=3.21
t=50s
```

```
Epoch 13/65     lr=9.9e-04     lwlrap=0.67801     loss=3.68     val_loss=2.93
t=50s
Epoch 14/65     lr=9.8e-04     lwlrap=0.69722     loss=3.62     val_loss=2.85
t=50s
Epoch 15/65     lr=9.7e-04     lwlrap=0.73045     loss=3.52     val_loss=2.69
t=50s
Epoch 16/65     lr=9.6e-04     lwlrap=0.70490     loss=3.63     val_loss=2.77
t=50s
Epoch 17/65     lr=9.5e-04     lwlrap=0.75872     loss=3.37     val_loss=2.47
t=50s
Epoch 18/65     lr=9.4e-04     lwlrap=0.72439     loss=3.49     val_loss=2.72
t=50s
Epoch 19/65     lr=9.3e-04     lwlrap=0.76779     loss=3.50     val_loss=2.47
t=50s
Epoch 20/65     lr=9.2e-04     lwlrap=0.74829     loss=3.34     val_loss=2.57
t=50s
Epoch 21/65     lr=9.0e-04     lwlrap=0.73985     loss=3.43     val_loss=2.63
t=50s
Epoch 22/65     lr=8.9e-04     lwlrap=0.77689     loss=3.30     val_loss=2.33
t=50s
Epoch 23/65     lr=8.7e-04     lwlrap=0.78717     loss=3.30     val_loss=2.31
t=50s
Epoch 24/65     lr=8.6e-04     lwlrap=0.75625     loss=3.15     val_loss=2.49
t=50s
Epoch 25/65     lr=8.4e-04     lwlrap=0.76155     loss=3.25     val_loss=2.47
t=50s
Epoch 26/65     lr=8.2e-04     lwlrap=0.76212     loss=3.10     val_loss=2.34
t=50s
Epoch 27/65     lr=8.0e-04     lwlrap=0.80013     loss=3.08     val_loss=2.14
t=50s
Epoch 28/65     lr=7.8e-04     lwlrap=0.78997     loss=3.10     val_loss=2.26
t=50s
Epoch 29/65     lr=7.6e-04     lwlrap=0.80464     loss=3.08     val_loss=2.15
t=50s
Epoch 30/65     lr=7.4e-04     lwlrap=0.77194     loss=3.07     val_loss=2.36
t=50s
Epoch 31/65     lr=7.2e-04     lwlrap=0.81336     loss=3.07     val_loss=2.11
t=50s
Epoch 32/65     lr=7.0e-04     lwlrap=0.80988     loss=2.96     val_loss=2.05
t=50s
Epoch 33/65     lr=6.8e-04     lwlrap=0.82385     loss=2.99     val_loss=2.00
t=50s
Epoch 34/65     lr=6.5e-04     lwlrap=0.80126     loss=2.86     val_loss=2.12
t=50s
Epoch 35/65     lr=6.3e-04     lwlrap=0.80687     loss=2.74     val_loss=2.12
t=50s
Epoch 36/65     lr=6.1e-04     lwlrap=0.81401     loss=2.74     val_loss=2.10
t=50s
```

```
Epoch 37/65     lr=5.8e-04     lwlrap=0.81070     loss=2.61     val_loss=2.06
t=50s
Epoch 38/65     lr=5.6e-04     lwlrap=0.82920     loss=2.83     val_loss=1.90
t=50s
Epoch 39/65     lr=5.4e-04     lwlrap=0.82754     loss=2.71     val_loss=1.91
t=50s
Epoch 40/65     lr=5.1e-04     lwlrap=0.84746     loss=2.67     val_loss=1.73
t=50s
Epoch 41/65     lr=4.9e-04     lwlrap=0.83863     loss=2.54     val_loss=1.81
t=50s
Epoch 42/65     lr=4.6e-04     lwlrap=0.84833     loss=2.69     val_loss=1.79
t=50s
Epoch 43/65     lr=4.4e-04     lwlrap=0.84437     loss=2.55     val_loss=1.77
t=50s
Epoch 44/65     lr=4.2e-04     lwlrap=0.84532     loss=2.72     val_loss=1.76
t=50s
Epoch 45/65     lr=3.9e-04     lwlrap=0.82494     loss=2.59     val_loss=1.96
t=50s
Epoch 46/65     lr=3.7e-04     lwlrap=0.85755     loss=2.41     val_loss=1.74
t=50s
Epoch 47/65     lr=3.5e-04     lwlrap=0.85326     loss=2.56     val_loss=1.71
t=50s
Epoch 48/65     lr=3.2e-04     lwlrap=0.85765     loss=2.30     val_loss=1.67
t=50s
Epoch 49/65     lr=3.0e-04     lwlrap=0.85991     loss=2.40     val_loss=1.67
t=50s
Epoch 50/65     lr=2.8e-04     lwlrap=0.85265     loss=2.56     val_loss=1.67
t=50s
Epoch 51/65     lr=2.6e-04     lwlrap=0.85622     loss=2.28     val_loss=1.68
t=50s
Epoch 52/65     lr=2.4e-04     lwlrap=0.85404     loss=2.36     val_loss=1.70
t=50s
Epoch 53/65     lr=2.2e-04     lwlrap=0.87021     loss=2.22     val_loss=1.60
t=50s
Epoch 54/65     lr=2.0e-04     lwlrap=0.86594     loss=2.19     val_loss=1.62
t=50s
Epoch 55/65     lr=1.8e-04     lwlrap=0.86740     loss=2.14     val_loss=1.56
t=50s
Epoch 56/65     lr=1.6e-04     lwlrap=0.86882     loss=2.16     val_loss=1.56
t=50s
Epoch 57/65     lr=1.4e-04     lwlrap=0.86947     loss=2.00     val_loss=1.55
t=50s
Epoch 58/65     lr=1.3e-04     lwlrap=0.86948     loss=2.19     val_loss=1.56
t=50s
Epoch 59/65     lr=1.1e-04     lwlrap=0.87085     loss=2.00     val_loss=1.55
t=50s
Epoch 60/65     lr=9.6e-05     lwlrap=0.87223     loss=2.21     val_loss=1.56
t=50s
```

```
Epoch 61/65     lr=8.2e-05     lwlrap=0.87082     loss=2.07     val_loss=1.55
t=50s
Epoch 62/65     lr=6.9e-05     lwlrap=0.86583     loss=2.05     val_loss=1.54
t=50s
Epoch 63/65     lr=5.7e-05     lwlrap=0.86745     loss=2.05     val_loss=1.59
t=50s
Epoch 64/65     lr=4.7e-05     lwlrap=0.86983     loss=2.00     val_loss=1.54
t=50s
Epoch 65/65     lr=3.7e-05     lwlrap=0.86802     loss=2.05     val_loss=1.60
t=50s

 - Re-fitting with curated data only (1/2)

Epoch 1/65     lr=1.0e-04     lwlrap=0.87000     loss=1.69     val_loss=1.58
t=34s
Epoch 2/65     lr=1.0e-04     lwlrap=0.86720     loss=1.75     val_loss=1.60
t=34s
Epoch 3/65     lr=1.0e-04     lwlrap=0.86865     loss=1.63     val_loss=1.58
t=34s
Epoch 4/65     lr=1.0e-04     lwlrap=0.86356     loss=1.75     val_loss=1.64
t=34s
Epoch 5/65     lr=1.0e-04     lwlrap=0.86371     loss=1.85     val_loss=1.61
t=34s
Epoch 6/65     lr=1.0e-05     lwlrap=0.86565     loss=1.59     val_loss=1.60
t=34s
Epoch 7/65     lr=1.0e-05     lwlrap=0.86302     loss=1.68     val_loss=1.61
t=34s
Epoch 8/65     lr=1.0e-05     lwlrap=0.87480     loss=1.79     val_loss=1.56
t=34s
Epoch 9/65     lr=1.0e-05     lwlrap=0.86982     loss=1.48     val_loss=1.57
t=34s
Epoch 10/65     lr=1.0e-05     lwlrap=0.86446     loss=1.49     val_loss=1.60
t=34s
Epoch 11/65     lr=1.0e-05     lwlrap=0.86673     loss=1.79     val_loss=1.64
t=34s
Epoch 12/65     lr=1.0e-05     lwlrap=0.86619     loss=1.62     val_loss=1.60
t=34s
Epoch 13/65     lr=1.0e-06     lwlrap=0.86983     loss=1.47     val_loss=1.56
t=34s
Epoch 14/65     lr=1.0e-06     lwlrap=0.86619     loss=1.64     val_loss=1.60
t=34s
Epoch 15/65     lr=1.0e-06     lwlrap=0.86529     loss=1.96     val_loss=1.65
t=34s
Epoch 16/65     lr=1.0e-06     lwlrap=0.86539     loss=1.48     val_loss=1.58
t=34s
Epoch 17/65     lr=1.0e-06     lwlrap=0.85853     loss=1.97     val_loss=1.66
t=34s
Epoch 18/65     lr=1.0e-07     lwlrap=0.86285     loss=1.57     val_loss=1.62
```

```
t=34s
Loading weights from model_4.pt


 - Re-fitting with curated data only (2/2)

Epoch 1/65     lr=1.0e-04     lwlrap=0.86174     loss=1.67     val_loss=1.63
t=34s
Epoch 2/65     lr=1.0e-04     lwlrap=0.87102     loss=1.48     val_loss=1.59
t=34s
Epoch 3/65     lr=1.0e-04     lwlrap=0.87003     loss=1.57     val_loss=1.60
t=34s
Epoch 4/65     lr=1.0e-04     lwlrap=0.86408     loss=1.66     val_loss=1.66
t=34s
Epoch 5/65     lr=1.0e-04     lwlrap=0.86615     loss=1.71     val_loss=1.65
t=34s
Epoch 6/65     lr=1.0e-04     lwlrap=0.87117     loss=1.73     val_loss=1.63
t=34s
Epoch 7/65     lr=1.0e-05     lwlrap=0.87320     loss=1.60     val_loss=1.60
t=34s
Epoch 8/65     lr=1.0e-05     lwlrap=0.86905     loss=1.50     val_loss=1.65
t=34s
Epoch 9/65     lr=1.0e-05     lwlrap=0.86685     loss=1.75     val_loss=1.66
t=34s
Epoch 10/65     lr=1.0e-05     lwlrap=0.87011     loss=1.52     val_loss=1.61
t=34s
Epoch 11/65     lr=1.0e-06     lwlrap=0.87083     loss=1.52     val_loss=1.62
t=34s
Epoch 12/65     lr=1.0e-06     lwlrap=0.87009     loss=1.67     val_loss=1.64
t=34s
Epoch 13/65     lr=1.0e-06     lwlrap=0.87265     loss=1.39     val_loss=1.57
t=34s
Epoch 14/65     lr=1.0e-06     lwlrap=0.86978     loss=1.36     val_loss=1.58
t=34s
Epoch 15/65     lr=1.0e-06     lwlrap=0.86828     loss=1.52     val_loss=1.64
t=34s
Epoch 16/65     lr=1.0e-06     lwlrap=0.87776     loss=1.54     val_loss=1.58
t=34s
Epoch 17/65     lr=1.0e-06     lwlrap=0.86879     loss=1.66     val_loss=1.62
t=34s
Epoch 18/65     lr=1.0e-07     lwlrap=0.87019     loss=1.40     val_loss=1.60
t=34s
Loading weights from model_4.pt


 - Predicting with 25 TTA
```

```
lwlrap : Scored 0.8784 on validation data

   Done in 78.8 minutes

-------------   Fold 5  -------------

 - Fitting

Epoch 1/65     lr=5.0e-05     lwlrap=0.25448     loss=55.14     val_loss=54.92
t=50s
Epoch 2/65     lr=2.0e-04     lwlrap=0.30980     loss=52.22     val_loss=47.82
t=50s
Epoch 3/65     lr=3.6e-04     lwlrap=0.27796     loss=34.42     val_loss=21.34
t=50s
Epoch 4/65     lr=5.1e-04     lwlrap=0.32000     loss=10.62     val_loss=5.56
t=50s
Epoch 5/65     lr=6.7e-04     lwlrap=0.33746     loss=5.05     val_loss=4.93
t=50s
Epoch 6/65     lr=8.2e-04     lwlrap=0.47756     loss=4.68     val_loss=4.30
t=50s
Epoch 7/65     lr=9.7e-04     lwlrap=0.51861     loss=4.43     val_loss=4.03
t=50s
Epoch 8/65     lr=1.0e-03     lwlrap=0.44956     loss=4.23     val_loss=4.27
t=50s
Epoch 9/65     lr=1.0e-03     lwlrap=0.45506     loss=4.16     val_loss=4.38
t=50s
Epoch 10/65     lr=1.0e-03     lwlrap=0.56731     loss=4.08     val_loss=3.59
t=50s
Epoch 11/65     lr=9.9e-04     lwlrap=0.60904     loss=3.86     val_loss=3.40
t=50s
Epoch 12/65     lr=9.9e-04     lwlrap=0.65139     loss=3.75     val_loss=3.13
t=50s
Epoch 13/65     lr=9.9e-04     lwlrap=0.64167     loss=3.78     val_loss=3.19
t=50s
Epoch 14/65     lr=9.8e-04     lwlrap=0.65755     loss=3.65     val_loss=3.10
t=50s
Epoch 15/65     lr=9.7e-04     lwlrap=0.68737     loss=3.68     val_loss=2.89
t=50s
Epoch 16/65     lr=9.6e-04     lwlrap=0.64564     loss=3.56     val_loss=3.13
t=50s
Epoch 17/65     lr=9.5e-04     lwlrap=0.70171     loss=3.48     val_loss=2.76
t=50s
Epoch 18/65     lr=9.4e-04     lwlrap=0.71702     loss=3.48     val_loss=2.74
t=50s
Epoch 19/65     lr=9.3e-04     lwlrap=0.67062     loss=3.49     val_loss=2.92
t=50s
Epoch 20/65     lr=9.2e-04     lwlrap=0.71658     loss=3.40     val_loss=2.69
t=50s
```

```
Epoch 21/65     lr=9.0e-04     lwlrap=0.73064     loss=3.35     val_loss=2.58
t=50s
Epoch 22/65     lr=8.9e-04     lwlrap=0.73799     loss=3.29     val_loss=2.51
t=50s
Epoch 23/65     lr=8.7e-04     lwlrap=0.75789     loss=3.28     val_loss=2.38
t=50s
Epoch 24/65     lr=8.6e-04     lwlrap=0.75757     loss=3.21     val_loss=2.42
t=50s
Epoch 25/65     lr=8.4e-04     lwlrap=0.73907     loss=3.42     val_loss=2.47
t=50s
Epoch 26/65     lr=8.2e-04     lwlrap=0.73268     loss=3.13     val_loss=2.57
t=50s
Epoch 27/65     lr=8.0e-04     lwlrap=0.77122     loss=3.05     val_loss=2.35
t=50s
Epoch 28/65     lr=7.8e-04     lwlrap=0.72806     loss=3.04     val_loss=2.52
t=50s
Epoch 29/65     lr=7.6e-04     lwlrap=0.77886     loss=3.11     val_loss=2.30
t=50s
Epoch 30/65     lr=7.4e-04     lwlrap=0.79369     loss=2.93     val_loss=2.17
t=50s
Epoch 31/65     lr=7.2e-04     lwlrap=0.78362     loss=2.85     val_loss=2.18
t=50s
Epoch 32/65     lr=7.0e-04     lwlrap=0.77815     loss=2.88     val_loss=2.25
t=50s
Epoch 33/65     lr=6.8e-04     lwlrap=0.79891     loss=2.84     val_loss=2.10
t=50s
Epoch 34/65     lr=6.5e-04     lwlrap=0.79023     loss=2.80     val_loss=2.20
t=50s
Epoch 35/65     lr=6.3e-04     lwlrap=0.78654     loss=3.01     val_loss=2.22
t=50s
Epoch 36/65     lr=6.1e-04     lwlrap=0.79897     loss=2.84     val_loss=2.11
t=50s
Epoch 37/65     lr=5.8e-04     lwlrap=0.78560     loss=2.74     val_loss=2.18
t=50s
Epoch 38/65     lr=5.6e-04     lwlrap=0.80790     loss=2.81     val_loss=2.01
t=50s
Epoch 39/65     lr=5.4e-04     lwlrap=0.81328     loss=2.71     val_loss=2.01
t=50s
Epoch 40/65     lr=5.1e-04     lwlrap=0.82248     loss=2.67     val_loss=1.92
t=50s
Epoch 41/65     lr=4.9e-04     lwlrap=0.81284     loss=2.42     val_loss=1.93
t=50s
Epoch 42/65     lr=4.6e-04     lwlrap=0.81495     loss=2.60     val_loss=2.05
t=50s
Epoch 43/65     lr=4.4e-04     lwlrap=0.82048     loss=2.53     val_loss=1.89
t=50s
Epoch 44/65     lr=4.2e-04     lwlrap=0.80833     loss=2.43     val_loss=2.02
t=50s
```

```
Epoch 45/65     lr=3.9e-04     lwlrap=0.81206     loss=2.49     val_loss=1.96
t=50s
Epoch 46/65     lr=3.7e-04     lwlrap=0.82150     loss=2.51     val_loss=1.90
t=50s
Epoch 47/65     lr=3.5e-04     lwlrap=0.81518     loss=2.43     val_loss=1.90
t=50s
Epoch 48/65     lr=3.2e-04     lwlrap=0.83123     loss=2.30     val_loss=1.84
t=50s
Epoch 49/65     lr=3.0e-04     lwlrap=0.82540     loss=2.54     val_loss=1.85
t=50s
Epoch 50/65     lr=2.8e-04     lwlrap=0.83077     loss=2.26     val_loss=1.77
t=50s
Epoch 51/65     lr=2.6e-04     lwlrap=0.84408     loss=2.06     val_loss=1.71
t=50s
Epoch 52/65     lr=2.4e-04     lwlrap=0.83360     loss=2.19     val_loss=1.78
t=50s
Epoch 53/65     lr=2.2e-04     lwlrap=0.83359     loss=2.28     val_loss=1.79
t=50s
Epoch 54/65     lr=2.0e-04     lwlrap=0.84448     loss=2.12     val_loss=1.71
t=50s
Epoch 55/65     lr=1.8e-04     lwlrap=0.84334     loss=2.15     val_loss=1.70
t=50s
Epoch 56/65     lr=1.6e-04     lwlrap=0.83961     loss=2.07     val_loss=1.74
t=50s
Epoch 57/65     lr=1.4e-04     lwlrap=0.85070     loss=2.09     val_loss=1.70
t=50s
Epoch 58/65     lr=1.3e-04     lwlrap=0.84274     loss=2.07     val_loss=1.71
t=50s
Epoch 59/65     lr=1.1e-04     lwlrap=0.84327     loss=1.93     val_loss=1.71
t=50s
Epoch 60/65     lr=9.6e-05     lwlrap=0.85504     loss=1.73     val_loss=1.65
t=50s
Epoch 61/65     lr=8.2e-05     lwlrap=0.84435     loss=2.03     val_loss=1.71
t=50s
Epoch 62/65     lr=6.9e-05     lwlrap=0.84088     loss=1.98     val_loss=1.74
t=50s
Epoch 63/65     lr=5.7e-05     lwlrap=0.84461     loss=1.99     val_loss=1.71
t=50s
Epoch 64/65     lr=4.7e-05     lwlrap=0.84903     loss=2.02     val_loss=1.67
t=50s
Epoch 65/65     lr=3.7e-05     lwlrap=0.84859     loss=2.06     val_loss=1.68
t=50s

 - Re-fitting with curated data only (1/2)

Epoch 1/65     lr=1.0e-04     lwlrap=0.84777     loss=1.78     val_loss=1.70
t=34s
Epoch 2/65     lr=1.0e-04     lwlrap=0.85251     loss=1.99     val_loss=1.73
```

```
t=34s
Epoch 3/65     lr=1.0e-04     lwlrap=0.85258     loss=1.79     val_loss=1.69
t=34s
Epoch 4/65     lr=1.0e-04     lwlrap=0.85211     loss=2.04     val_loss=1.74
t=34s
Epoch 5/65     lr=1.0e-04     lwlrap=0.83904     loss=1.69     val_loss=1.77
t=34s
Epoch 6/65     lr=1.0e-04     lwlrap=0.84374     loss=1.56     val_loss=1.74
t=34s
Epoch 7/65     lr=1.0e-04     lwlrap=0.84986     loss=1.58     val_loss=1.71
t=34s
Epoch 8/65     lr=1.0e-05     lwlrap=0.84990     loss=1.73     val_loss=1.72
t=34s
Epoch 9/65     lr=1.0e-05     lwlrap=0.85124     loss=1.52     val_loss=1.70
t=34s
Epoch 10/65     lr=1.0e-05     lwlrap=0.84645     loss=1.55     val_loss=1.74
t=34s
Epoch 11/65     lr=1.0e-05     lwlrap=0.84482     loss=1.75     val_loss=1.75
t=34s
Epoch 12/65     lr=1.0e-06     lwlrap=0.85043     loss=1.58     val_loss=1.72
t=34s
Epoch 13/65     lr=1.0e-06     lwlrap=0.85628     loss=1.75     val_loss=1.69
t=34s
Epoch 14/65     lr=1.0e-06     lwlrap=0.84924     loss=1.58     val_loss=1.74
t=34s
Epoch 15/65     lr=1.0e-06     lwlrap=0.84901     loss=1.70     val_loss=1.72
t=34s
Epoch 16/65     lr=1.0e-06     lwlrap=0.84862     loss=1.74     val_loss=1.76
t=34s
Epoch 17/65     lr=1.0e-06     lwlrap=0.85307     loss=1.77     val_loss=1.71
t=34s
Epoch 18/65     lr=1.0e-07     lwlrap=0.85125     loss=1.55     val_loss=1.71
t=34s
Loading weights from model_5.pt


 - Re-fitting with curated data only (2/2)

Epoch 1/65     lr=1.0e-04     lwlrap=0.85309     loss=1.68     val_loss=1.71
t=34s
Epoch 2/65     lr=1.0e-04     lwlrap=0.85129     loss=1.68     val_loss=1.72
t=34s
Epoch 3/65     lr=1.0e-04     lwlrap=0.84475     loss=1.66     val_loss=1.73
t=34s
Epoch 4/65     lr=1.0e-04     lwlrap=0.84503     loss=1.63     val_loss=1.73
t=34s
Epoch 5/65     lr=1.0e-04     lwlrap=0.84878     loss=1.65     val_loss=1.75
t=34s
```

```
Epoch 6/65     lr=1.0e-05     lwlrap=0.85322     loss=1.42     val_loss=1.68
t=34s
Epoch 7/65     lr=1.0e-05     lwlrap=0.85235     loss=1.69     val_loss=1.73
t=34s
Epoch 8/65     lr=1.0e-05     lwlrap=0.85302     loss=1.27     val_loss=1.69
t=34s
Epoch 9/65     lr=1.0e-05     lwlrap=0.85209     loss=1.89     val_loss=1.72
t=34s
Epoch 10/65     lr=1.0e-05     lwlrap=0.85469     loss=1.89     val_loss=1.72
t=34s
Epoch 11/65     lr=1.0e-06     lwlrap=0.84940     loss=1.72     val_loss=1.73
t=34s
Epoch 12/65     lr=1.0e-06     lwlrap=0.84937     loss=1.53     val_loss=1.74
t=34s
Epoch 13/65     lr=1.0e-06     lwlrap=0.85159     loss=1.41     val_loss=1.70
t=34s
Epoch 14/65     lr=1.0e-06     lwlrap=0.84585     loss=1.57     val_loss=1.73
t=34s
Epoch 15/65     lr=1.0e-07     lwlrap=0.85115     loss=1.66     val_loss=1.69
t=34s
Loading weights from model_5.pt


 - Predicting with 25 TTA


 lwlrap : Scored 0.8551 on validation data

    Done in 76.9 minutes
```

[57]:

```python
score_class, weight = lwlrap(y_train, pred_oof)
score = (score_class * weight).sum()
```

[58]:

```python
print(f'Local CV score is : {score:.4f}')
```

```
Local CV score is : 0.8703
```

[59]:

```python
score_df = pd.DataFrame(np.array([labels, np.round(score_class, 5), np.
 ↪round(weight, 5)]).T, columns=['Label', 'Score', 'Weight']).
 ↪set_index('Label').sort_values('Score')
score_df
```

[59]:

| | Score | Weight |
|---|---|---|
| Label | | |
| Walk_and_footsteps | 0.61816 | 0.01305 |
| Squeak | 0.66539 | 0.01305 |

| | | |
|---|---|---|
| Fill_(with_liquid) | 0.685 | 0.0087 |
| Buzz | 0.7367 | 0.00975 |
| Yell | 0.73886 | 0.01305 |
| Sink_(filling_or_washing) | 0.74065 | 0.01305 |
| Traffic_noise_and_roadway_noise | 0.74117 | 0.01305 |
| Water_tap_and_faucet | 0.74604 | 0.01305 |
| Mechanical_fan | 0.76589 | 0.00853 |
| Hiss | 0.76768 | 0.01305 |
| Tap | 0.77258 | 0.01305 |
| Cutlery_and_silverware | 0.77369 | 0.01305 |
| Microwave_oven | 0.77416 | 0.01305 |
| Bus | 0.78029 | 0.01305 |
| Motorcycle | 0.7861 | 0.01305 |
| Trickle_and_dribble | 0.79233 | 0.00922 |
| Gasp | 0.79252 | 0.00835 |
| Chink_and_clink | 0.80138 | 0.01305 |
| Dishes_and_pots_and_pans | 0.81386 | 0.01305 |
| Bathtub_(filling_or_washing) | 0.81556 | 0.01305 |
| Drip | 0.81887 | 0.01305 |
| Cupboard_open_or_close | 0.82087 | 0.01305 |
| Frying_(food) | 0.82089 | 0.01096 |
| Accelerating_and_revving_and_vroom | 0.82391 | 0.01305 |
| Run | 0.82789 | 0.01305 |
| Slam | 0.83424 | 0.01305 |
| Stream | 0.83956 | 0.01288 |
| Chewing_and_mastication | 0.84337 | 0.01305 |
| Crowd | 0.85428 | 0.01305 |
| Printer | 0.86122 | 0.01305 |
| … | … | … |
| Raindrop | 0.90862 | 0.01305 |
| Toilet_flush | 0.90946 | 0.01305 |
| Keys_jangling | 0.91089 | 0.01305 |
| Child_speech_and_kid_speaking | 0.9148 | 0.01305 |
| Shatter | 0.91578 | 0.01305 |
| Race_car_and_auto_racing | 0.91667 | 0.00975 |
| Writing | 0.91689 | 0.01305 |
| Gong | 0.91689 | 0.01305 |
| Zipper_(clothing) | 0.91949 | 0.01305 |
| Meow | 0.92131 | 0.01305 |
| Church_bell | 0.92703 | 0.01305 |
| Screaming | 0.92722 | 0.01305 |
| Sigh | 0.93567 | 0.00992 |
| Acoustic_guitar | 0.94529 | 0.01305 |
| Bark | 0.94714 | 0.01305 |
| Bass_drum | 0.94768 | 0.01305 |
| Fart | 0.952 | 0.01305 |
| Whispering | 0.95833 | 0.01288 |

```
Harmonica                              0.96003  0.01305
Accordion                              0.96099  0.00818
Glockenspiel                           0.96429  0.00975
Burping_and_eructation                 0.96468  0.01305
Bass_guitar                            0.96487  0.01305
Purr                                   0.97692  0.01131
Bicycle_bell                           0.97811  0.01166
Finger_snapping                        0.98444  0.01305
Hi-hat                                 0.98444  0.01305
Marimba_and_xylophone                  0.98444  0.01305
Skateboard                             0.98444  0.01305
Strum                                  0.99556  0.01305

[80 rows x 2 columns]
```

# 7 Submission

[60]:
```python
df_test[df_test.columns[1:]] = pred_test
```

[61]:
```python
df_test.to_csv('submission.csv', index=False)
```