In [1]:
```
!pip install torchinfo
!pip install torchmetrics
```

```
Requirement already satisfied: torchinfo in /usr/local/lib/python3.10/dist-
packages (1.8.0)
Requirement already satisfied: torchmetrics in /usr/local/lib/python3.10/di
st-packages (1.3.1)
Requirement already satisfied: numpy>1.20.0 in /usr/local/lib/python3.10/di
st-packages (from torchmetrics) (1.25.2)
Requirement already satisfied: packaging>17.1 in /usr/local/lib/python3.10/
dist-packages (from torchmetrics) (23.2)
Requirement already satisfied: torch>=1.10.0 in /usr/local/lib/python3.10/d
ist-packages (from torchmetrics) (2.1.0+cu121)
Requirement already satisfied: lightning-utilities>=0.8.0 in /usr/local/li
b/python3.10/dist-packages (from torchmetrics) (0.10.1)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist
-packages (from lightning-utilities>=0.8.0->torchmetrics) (67.7.2)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.
10/dist-packages (from lightning-utilities>=0.8.0->torchmetrics) (4.10.0)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-p
ackages (from torch>=1.10.0->torchmetrics) (3.13.1)
Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-pack
ages (from torch>=1.10.0->torchmetrics) (1.12)
Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-p
ackages (from torch>=1.10.0->torchmetrics) (3.2.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-pac
kages (from torch>=1.10.0->torchmetrics) (3.1.3)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-pac
kages (from torch>=1.10.0->torchmetrics) (2023.6.0)
Requirement already satisfied: triton==2.1.0 in /usr/local/lib/python3.10/d
ist-packages (from torch>=1.10.0->torchmetrics) (2.1.0)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.1
0/dist-packages (from jinja2->torch>=1.10.0->torchmetrics) (2.1.5)
Requirement already satisfied: mpmath>=0.19 in /usr/local/lib/python3.10/di
st-packages (from sympy->torch>=1.10.0->torchmetrics) (1.3.0)
```

In [2]:
```
import pandas as pd
import joblib
from functools import partial
import ast
from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.model_selection import train_test_split
from collections import Counter
from torchtext.vocab import vocab
import torch
from torchinfo import summary
from torchmetrics import HammingDistance
```

In [3]:
```
df = joblib.load('/content/drive/MyDrive/df_multilabel_hw_cleaned.joblib')
df.head()
```

Out[3]:

	cleaned_text	Tags	Tag_Number
0	asp query stre dropdown webpage follow control...	c# asp.net	[0, 9]
1	run javascript code server java code want run ...	java javascript	[1, 3]
2	linq sql throw exception row find change hi li...	c# asp.net	[0, 9]
3	run python script php server run nginx web ser...	php python	[2, 7]
4	advice write function m try write function res...	javascript jquery	[3, 5]

In [4]:
```
df['Tag_Number_int'] = df['Tag_Number'].apply(ast.literal_eval)
df.head()
```

Out[4]:

	cleaned_text	Tags	Tag_Number	Tag_Number_int
0	asp query stre dropdown webpage follow control...	c# asp.net	[0, 9]	[0, 9]
1	run javascript code server java code want run ...	java javascript	[1, 3]	[1, 3]
2	linq sql throw exception row find change hi li...	c# asp.net	[0, 9]	[0, 9]
3	run python script php server run nginx web ser...	php python	[2, 7]	[2, 7]
4	advice write function m try write function res...	javascript jquery	[3, 5]	[3, 5]

In [5]:
```
mlb = MultiLabelBinarizer()
one_hot_encoded_tags = mlb.fit_transform(df['Tag_Number_int']).astype(float)
print("Classes:", mlb.classes_)
```

```
Classes: [0 1 2 3 4 5 6 7 8 9]
```

In [6]:
```
one_hot_encoded_tags
```

Out[6]:
```
array([[1., 0., 0., ..., 0., 0., 1.],
       [0., 1., 0., ..., 0., 0., 0.],
       [1., 0., 0., ..., 0., 0., 1.],
       ...,
       [0., 1., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 1.],
       [0., 0., 0., ..., 0., 0., 0.]])
```

In [7]:
```
X_temp, X_test, y_temp, y_test = train_test_split(df['cleaned_text'].values,
X_train, X_val, y_train, y_val = train_test_split(X_temp, y_temp, test_size=
```

In [8]:
```
X_train.shape, X_val.shape, X_test.shape
```

Out[8]:
```
((28455,), (9486,), (9486,))
```

In [9]:
```
class CustomDataset(torch.utils.data.Dataset):
    def __init__(self, X, y):
        self.X = X
```

```
        self.y = y

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

    def __getitem__(self, idx):
        texts = self.X[idx]
        labels = self.y[idx]
        sample = (labels, texts)

        return sample
```

In [10]:
```
trainset = CustomDataset(X_train, y_train)
validset = CustomDataset(X_val, y_val)
testset = CustomDataset(X_test, y_test)
```

In [11]:
```
def get_vocab(dataset, min_freq=1):
    counter = Counter()
    for (label, text) in dataset:
        counter.update(text.split())
    my_vocab = vocab(counter, min_freq=min_freq)
    my_vocab.insert_token('<unk>', 0)
    my_vocab.set_default_index(0)

    return my_vocab
```

In [12]:
```
train_vocab = get_vocab(trainset, min_freq=2)
```

In [13]:
```
def tokenizer(x, vocab):
    return [vocab[token] for token in x.split()]
```

In [14]:
```
def collate_batch(batch, my_vocab):
    labels, texts = zip(*batch)
    labels = torch.tensor(labels, dtype=torch.long)
    list_of_list_of_indices = [tokenizer(text, my_vocab) for text in texts]
    indices = torch.cat([torch.tensor(i, dtype=torch.int64) for i in list_of
    offsets = [0] + [len(i) for i in list_of_list_of_indices]
    offsets = torch.tensor(offsets[:-1]).cumsum(dim=0)

    return (indices, offsets), labels
```

In [15]:
```
collate_partial = partial(collate_batch, my_vocab=train_vocab)
check_loader = torch.utils.data.DataLoader(dataset=trainset, batch_size=2,
                                           shuffle=True, collate_fn=collate_
```

In [16]:
```
for (indices, offset), label in check_loader:
    print(indices, offset, label)
    break
```

```
tensor([   98, 13383,   173,   985,    70,   488,   199,     0,  2224,    9
7,
           98,   241,   227,   252,   101,     0,  2224,  3225,    18,  322
5,
          816,    18,     0,   407,     0,     5,   989, 27651,   696,  282
5,
          309,  1241,   226,   987,   343,  1758,    17,  1086,  1821,   10
3,
          411,  1241,   681,    39,   197,  4471,   568,   293,  4015,  104
0,
          568,  6197,  1437,    70,  2412,   985,   496,   653,   197,  167
2,
          132,  2412,   252,  2025,   647,   567,   201,   907,   527,   52
8,
         4015,   568,   370,   723,  1355,   560,   568,  4294,   629,   56
7,
          342,   567,   619,   668,   560,    41,   641,   942,   943,   94
4,
         1781,   261,     0,    48,   261,     0,  1781,   919,   919,    4
8,
        60950,  1781,  2025, 68819,    48,  2025,     0,  1781,  2025,
0,
           48,  2025,     0,  1781,    64, 68820,    48,  1967,  4941,  318
6,
         1781,    64, 68821,    48,  1967,  4941,  4943,  1781,    64, 6882
2,
           48, 68823,  1781,    64, 68824,    48, 14737,     0,   558,   66
7,
          668,   560,    41,   669,   558, 68825, 68826,    48,    49,
0,
        68821, 68822, 68824, 68819, 68826, 68827,    64,  1672,    48,
0,
            0,   560,   568, 68825,  1665,   293,   615, 68828,    64, 6882
9,
           64, 68830,   615, 68831,  1668,    64, 68832, 15392,   790,   25
2,
           64, 10672,  2025, 68833,   252,   252,   919,  9877,  1781,    6
4,
            0,    48,   252,  9873,   560,     0, 68820,    64, 68821,    6
4,
        68822,    64, 68824,  2025,  7097, 35289,  1668,   293, 68828,    4
8,
        68820, 68829,    48, 68821, 68831,    48, 68824, 68830,    48, 6882
2,
        68833,    48,  7097,   410,  1468, 68834,   103,   560,    41, 6882
7,
        68835,  9877,    48, 68835,  1079,    49,   967,  2267,  2412,   96
7,
          967,    48,    49,     0,     0,  5561,  1400,   139,   199,   96
7,
        68836,     0, 68836,     0, 68836,     0, 68836,     0,  4268,  611
6,
        35614,  5075, 32017,    48,    49,  5075,   668,   560,    41,  509
4,
          919,   967,     0,   642,   642,    48,     0,     0,    48,
0,
```

```
        15392,   619,   252,     0,   252,    48,    49,     0, 17103,   61
9,
          252, 10672,    48,     0,     0,     0,   619,   252,   253,
0,
            0, 10672,  2026,  2800,  2035, 10672,  2026,  2800,     0,
0,
           63, 32017,    63,   567, 15932,    63,    63,   410,   103,  241
2,
          560,    64,     0,   173, 68832,   560,    64,     0,   173, 1067
2,
          410,   568]) tensor([ 0, 44]) tensor([[0, 0, 0, 1, 0, 1, 0, 0, 0,
0],
        [0, 1, 0, 0, 1, 0, 0, 0, 0, 0]])
```

```
<ipython-input-14-b523db7c5814>:3: UserWarning: Creating a tensor from a li
st of numpy.ndarrays is extremely slow. Please consider converting the list
to a single numpy.ndarray with numpy.array() before converting to a tensor.
(Triggered internally at ../torch/csrc/utils/tensor_new.cpp:261.)
  labels = torch.tensor(labels, dtype=torch.long)
```

In [17]:

```python
import torch
import torch.nn as nn
import torch.nn.functional as F

class SimpleMLP(nn.Module):
    def __init__(self, vocab_size, embedding_dim, hidden_dim1, hidden_dim2,
        super().__init__()
        self.embedding_bag = nn.EmbeddingBag(vocab_size, embedding_dim, mode
        self.fc1 = nn.Linear(embedding_dim, hidden_dim1)
        self.relu = nn.ReLU()
        self.dropout1 = nn.Dropout(drop_prob1)
        self.batchnorm1 = nn.BatchNorm1d(hidden_dim1)
        self.fc2 = nn.Linear(hidden_dim1, hidden_dim2)
        self.dropout2 = nn.Dropout(drop_prob2)
        self.batchnorm2 = nn.BatchNorm1d(hidden_dim2)
        self.fc3 = nn.Linear(hidden_dim2, num_outputs)

    def forward(self, input_tuple):
        indices, offsets = input_tuple
        x = self.embedding_bag(indices, offsets)
        x = self.fc1(x)
        x = self.relu(x)
        x = self.dropout1(x)
        x = self.batchnorm1(x)
        x = self.fc2(x)
        x = self.relu(x)
        x = self.dropout2(x)
        x = self.batchnorm2(x)
        output = self.fc3(x)

        return output
```

In [19]:

```python
device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
model = SimpleMLP(vocab_size=10 , embedding_dim=300, hidden_dim1=200, hidder
model = model.to(device)
```

```python
# Generate some dummy input data and offsets, and move them to the device
data = torch.tensor([1, 2, 4, 5, 4], dtype = torch.int32).to(device)
offsets = torch.tensor([0, 2, 4], dtype = torch.int32).to(device)

hamming_distance = HammingDistance(task="multilabel", num_labels=10).to(devi

summary(model, input_data=[(data, offsets)], device=device, depth=10, verbos
```

Out[19]:

```
===========================================================================
===============
Layer (type:depth-idx)                   Output Shape              Param #
===========================================================================
===============
SimpleMLP                                [3, 10]                   --
├─EmbeddingBag: 1-1                      [3, 300]                  3,000
├─Linear: 1-2                            [3, 200]                  60,200
├─ReLU: 1-3                              [3, 200]                  --
├─Dropout: 1-4                           [3, 200]                  --
├─BatchNorm1d: 1-5                       [3, 200]                  400
├─Linear: 1-6                            [3, 100]                  20,100
├─ReLU: 1-7                              [3, 100]                  --
├─Dropout: 1-8                           [3, 100]                  --
├─BatchNorm1d: 1-9                       [3, 100]                  200
├─Linear: 1-10                           [3, 10]                   1,010
===========================================================================
===============
Total params: 84,910
Trainable params: 84,910
Non-trainable params: 0
Total mult-adds (M): 0.25
===========================================================================
===============
Input size (MB): 0.00
Forward/backward pass size (MB): 0.02
Params size (MB): 0.34
Estimated Total Size (MB): 0.36
===========================================================================
===============
```

In [20]:

```python
output = model((data, offsets))
print(output)
```

```
tensor([[ 0.4241,  0.0916,  0.2717, -0.2661, -0.0904, -0.4252, -0.5955, -0.
2791,
          0.6692,  0.5841],
        [-0.2563, -0.5006, -0.3026, -0.2827,  0.4733, -0.2126,  0.0840, -0.
2129,
         -1.0135, -0.5543],
        [ 0.0122,  0.6028,  0.0529,  0.3907, -0.2295,  0.3974,  0.4681,  0.
2645,
          0.0876, -0.0246]], device='cuda:0', grad_fn=<AddmmBackward0>)
```

In [21]:

```python
def step(inputs, targets, model, device, loss_function=None, optimizer=None)
    model = model.to(device)
    inputs = tuple(input_tensor.to(device) for input_tensor in inputs)
    targets = targets.to(dtype=torch.float32)
```

```python
    targets = targets.to(device)

    outputs = model(inputs)

    if loss_function:
        loss = loss_function(outputs, targets)

    predicted = outputs.to(device)

    if optimizer:
        optimizer.zero_grad()
        loss.backward()
        torch.nn.utils.clip_grad_value_(model.parameters(), clip_value=10.0)
        optimizer.step()

    if loss_function:
        return loss, predicted
    else:
        return None, predicted
```

In [22]:
```python
def train_epoch(train_loader, model, device, loss_function, optimizer):
    train_hamming_distance = HammingDistance(task="multilabel", num_labels=1
    model.train()
    running_train_loss = 0.0

    for inputs, targets in train_loader:
        targets = targets.to(device)
        loss, predicted = step(inputs, targets, model, device, loss_functior
        running_train_loss += loss.item()
        train_hamming_distance.update(predicted, targets)

    train_loss = running_train_loss / len(train_loader)
    train_hamming_distance = train_hamming_distance.compute()

    return train_loss, train_hamming_distance
```

In [23]:
```python
def val_epoch(valid_loader, model, device, loss_function):
    val_hamming_distance = HammingDistance(task="multilabel", num_labels=10)
    model.train()
    running_val_loss = 0.0

    for inputs, targets in valid_loader:
        targets = targets.to(device)
        loss, predicted = step(inputs, targets, model, device, loss_functior
        running_val_loss += loss.item()
        val_hamming_distance.update(predicted, targets)

    val_loss = running_val_loss / len(valid_loader)
    val_hamming_distance = val_hamming_distance.compute()

    return val_loss, val_hamming_distance
```

In [24]:
```python
def train(train_loader, valid_loader, model, optimizer, loss_function, epoch
    train_loss_history = []
    valid_loss_history = []
```

```python
    train_hamm_history = []
    valid_hamm_history = []

    for epoch in range(epochs):
        train_loss, train_hamm = train_epoch(
            train_loader, model, device, loss_function, optimizer)

        valid_loss, valid_hamm = val_epoch(
            valid_loader, model, device, loss_function)

        train_loss_history.append(train_loss)
        train_hamm_history.append(train_hamm)
        valid_loss_history.append(valid_loss)
        valid_hamm_history.append(valid_hamm)

        print(f"Epoch {epoch+1}/{epochs}")
        print(f"Train Loss: {train_loss:.4f} | Train Hamming Loss: {train_ha
        print(f"Valid Loss: {valid_loss:.4f} | Valid Hamming Loss: {valid_ha
        print()

        if all(element == valid_loss_history[-1] for element in valid_loss_h
          break

    return train_loss_history, train_hamm_history, valid_loss_history, valic
```

In [25]:

```python
# model Parameters
EMBED_DIM=300
VOCAB_SIZE=len(train_vocab)
HIDDEN_DIM1=200
HIDDEN_DIM2=100
DROP_PROB1=0.5
DROP_PROB2=0.5
NUM_OUTPUTS=10
PATIENCE=5

# training
EPOCHS=5
BATCH_SIZE=128
LEARNING_RATE=0.001
WEIGHT_DECAY=0.0
```

In [26]:

```python
import random
import numpy as np

SEED = 1103
random.seed(SEED)
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed(SEED)
torch.backends.cudnn.deterministic = True

collate_fn = partial(collate_batch, my_vocab=train_vocab)

train_loader = torch.utils.data.DataLoader(trainset, batch_size = BATCH_SIZE
                                           collate_fn=collate_fn, num_worker
```

```
valid_loader = torch.utils.data.DataLoader(validset, batch_size=BATCH_SIZE,
                                            collate_fn=collate_fn, num_worker
test_loader = torch.utils.data.DataLoader(testset, batch_size=BATCH_SIZE, sh
                                           collate_fn=collate_fn, num_workers

loss_function = nn.BCEWithLogitsLoss()

model_facebook = SimpleMLP(vocab_size=VOCAB_SIZE,
                           embedding_dim=EMBED_DIM,
                           hidden_dim1=HIDDEN_DIM1,
                           hidden_dim2=HIDDEN_DIM2,
                           drop_prob1=DROP_PROB1,
                           drop_prob2=DROP_PROB2,
                           num_outputs=NUM_OUTPUTS)

optimizer = torch.optim.AdamW(model_facebook.parameters(), lr=LEARNING_RATE)
device = torch.device('cuda:0' if torch.cuda.is_available() else 'cpu')
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557:
UserWarning: This DataLoader will create 4 worker processes in total. Our s
uggested max number of worker in current system is 2, which is smaller than
what this DataLoader is going to create. Please be aware that excessive wor
ker creation might get DataLoader running slow or even freeze, lower the wo
rker number to avoid potential slowness/freeze if necessary.
  warnings.warn(_create_warning_msg(
```

In [27]:

```
for inputs, targets in train_loader:
    inputs = tuple(input_tensor.to(device) for input_tensor in inputs)
    targets = targets.to(dtype=torch.float32, copy=False).to(device)
    model_facebook = model_facebook.to(device)
    model_facebook.eval()

    with torch.no_grad():
        output = model_facebook(inputs)
        loss = loss_function(output, targets)
        print(f'Actual loss: {loss.item()}')
    break

print(f'Expected Theoretical loss: {np.log(2)}')
```

```
/usr/local/lib/python3.10/dist-packages/torch/utils/data/dataloader.py:557:
UserWarning: This DataLoader will create 4 worker processes in total. Our s
uggested max number of worker in current system is 2, which is smaller than
what this DataLoader is going to create. Please be aware that excessive wor
ker creation might get DataLoader running slow or even freeze, lower the wo
rker number to avoid potential slowness/freeze if necessary.
  warnings.warn(_create_warning_msg(
Actual loss: 0.6975612044334412
Expected Theoretical loss: 0.6931471805599453
```

In [28]:

```
%%time
train_losses, train_hamm, valid_losses, valid_hamm = train(
    train_loader, valid_loader, model_facebook, optimizer, loss_function, EP
```

```
Epoch 1/5
Train Loss: 0.3963 | Train Hamming Loss: 0.17122822999954224
Valid Loss: 0.2056 | Valid Hamming Loss: 0.07180052995681763

Epoch 2/5
Train Loss: 0.1678 | Train Hamming Loss: 0.05844312906265259
Valid Loss: 0.1660 | Valid Hamming Loss: 0.060046374797821045

Epoch 3/5
Train Loss: 0.1351 | Train Hamming Loss: 0.04784047603607178
Valid Loss: 0.1549 | Valid Hamming Loss: 0.055703163146972656

Epoch 4/5
Train Loss: 0.1168 | Train Hamming Loss: 0.04193991422653198
Valid Loss: 0.1454 | Valid Hamming Loss: 0.050748467445373535

Epoch 5/5
Train Loss: 0.1029 | Train Hamming Loss: 0.03718852996826172
Valid Loss: 0.1406 | Valid Hamming Loss: 0.04868227243423462

CPU times: user 18.9 s, sys: 1.66 s, total: 20.5 s
Wall time: 29.6 s
```

In [29]:

```python
import matplotlib.pyplot as plt
def plot_history(train_losses, train_metrics, val_losses=None, val_metrics=N
    epochs = range(1, len(train_losses) + 1)
    plt.figure()
    plt.plot(epochs, train_losses, label="Train")
    if val_losses:
        plt.plot(epochs, val_losses, label="Validation")
    plt.xlabel("Epochs")
    plt.ylabel("Loss")
    plt.legend()
    plt.show()

    if train_metrics[0] is not None:
        plt.figure()
        plt.plot(epochs, train_metrics, label="Train")
        if val_metrics:
            plt.plot(epochs, val_metrics, label="Validation")
        plt.xlabel("Epochs")
        plt.ylabel("Metric (Hamming loss)")
        plt.legend()
        plt.show()
```

In [30]:

```python
train_hamm[0].item()
```

Out[30]:

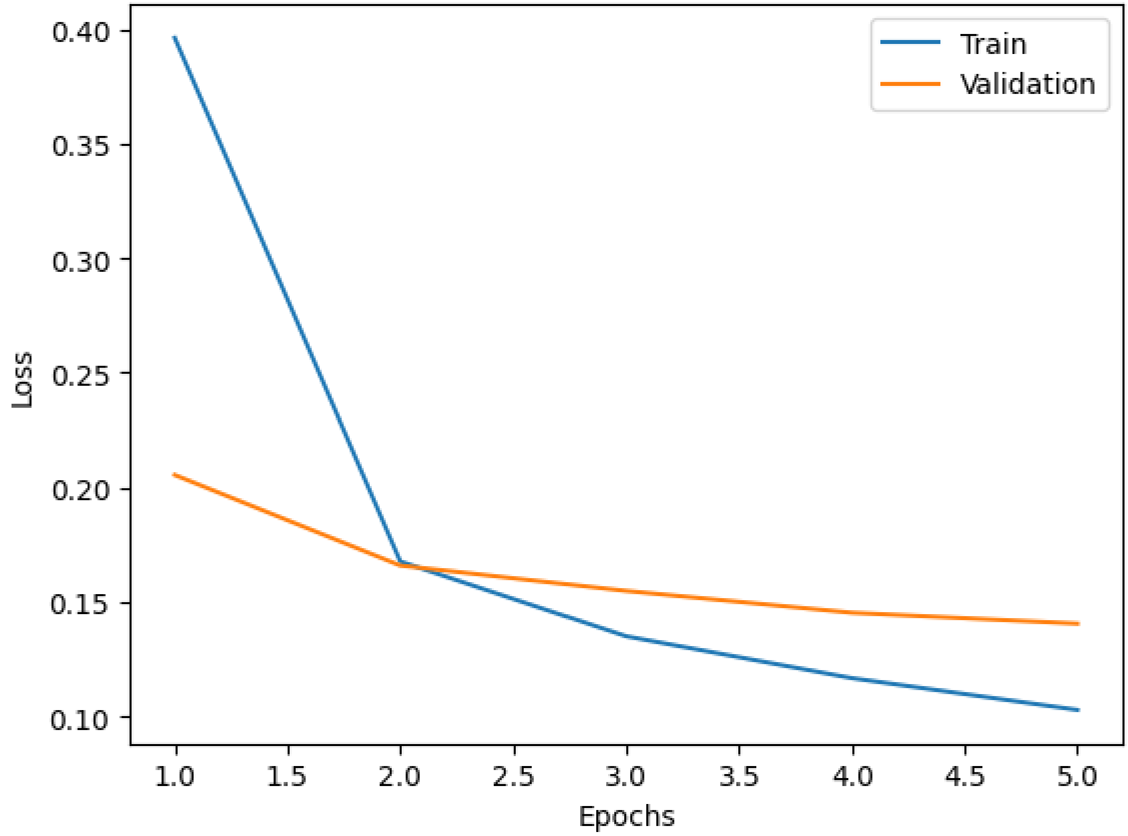
```
0.17122822999954224
```

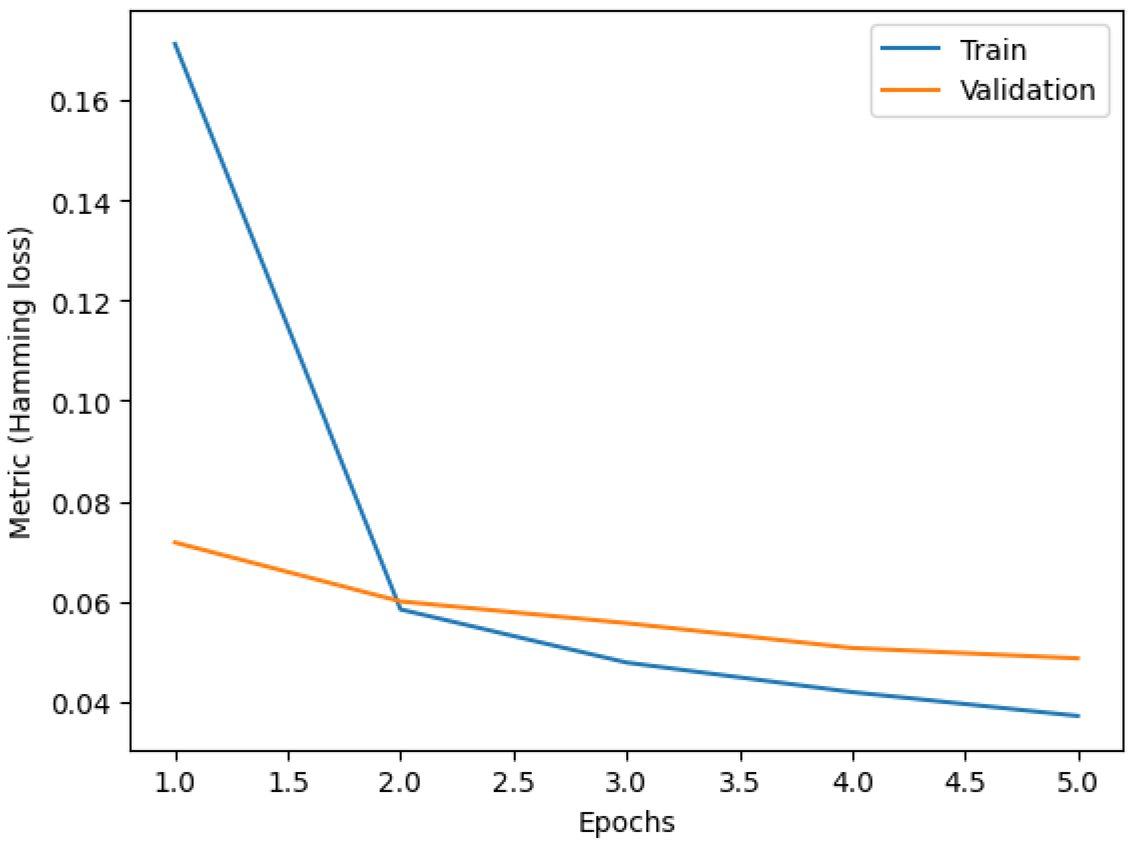
In [31]:

```python
train_hamm = [i.item() for i in train_hamm]
valid_hamm = [i.item() for i in valid_hamm]
```

In [32]:

```python
plot_history(train_losses, train_hamm, valid_losses, valid_hamm)
```





In [33]:

```
def get_acc_pred(data_loader, model, device):
    val_hamming_distance = HammingDistance(task="multilabel", num_labels=10)
    model = model.to(device)
    model.eval()
```

```
    predictions = torch.Tensor().to(device)
    y = torch.Tensor().to(device)
    running_correct = 0
    with torch.no_grad():
        for inputs, targets in data_loader:
            targets = targets.to(device)
            _, predicted = step(inputs, targets, model,
                                device, loss_function=None, optimizer=None)

            predictions = torch.cat((predictions, predicted))
            y = torch.cat((y, targets))
            val_hamming_distance.update(predicted, targets)

    val_hamming_distance = val_hamming_distance.compute()

    return predictions, y, val_hamming_distance.item()
```

In [34]:
```
predictions_test, labels_test, hamming_distance_test = get_acc_pred(test_loa
predictions_train, labels_train, hamming_distance_train = get_acc_pred(trair
predictions_val, labels_val, hamming_distance_val = get_acc_pred(valid_loade
```

In [35]:
```
# Print Test Accuracy
print('Test hamming distance:', hamming_distance_test)
```

```
Test hamming distance: 0.04128187894821167
```

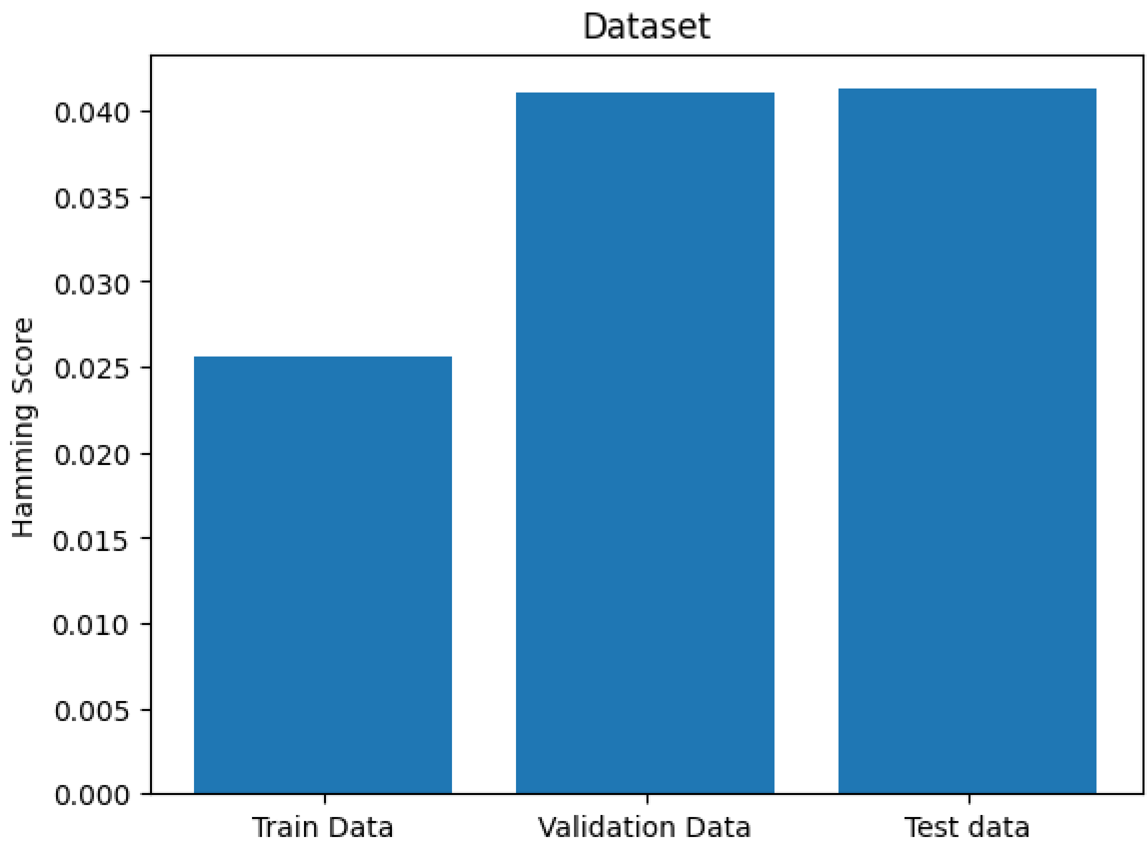
In [37]:
```
hamming_distance_train, hamming_distance_val, hamming_distance_test
```

Out[37]:
```
(0.025605320930480957, 0.04106050729751587, 0.04128187894821167)
```

In [36]:
```
import matplotlib.pyplot as plt

# Scalar values
values = [hamming_distance_train, hamming_distance_val, hamming_distance_tes
labels = ['Train Data', 'Validation Data', 'Test data']

# Plotting
plt.bar(labels, values)
plt.ylabel('Hamming Score')
plt.title('Dataset')
plt.show()
```



The model demonstrates good generalization capabilities, as evidenced by the minimal increase in Hamming distance when moving from the training set to the validation and test sets. This minor uptick is typical when models encounter new data, indicating that the model is not overly fitted to the training data and retains its predictive accuracy on unseen data.

The similarity in Hamming distances between the validation and test sets underscores the model's consistent performance across various unseen data sets. This consistency underscores the model’s dependability and stability.

Considering the low Hamming distances observed across the board, it's evident that the model achieves a high level of accuracy in its predictions for this multi-label classification task, with incorrect predictions being as low as approximately 0.025 for the training set and around 0.041 and 0.041 for the validation and test sets respectively.

```
In [ ]:
```