



MIDI MUSIC GENERATOR



Group 15

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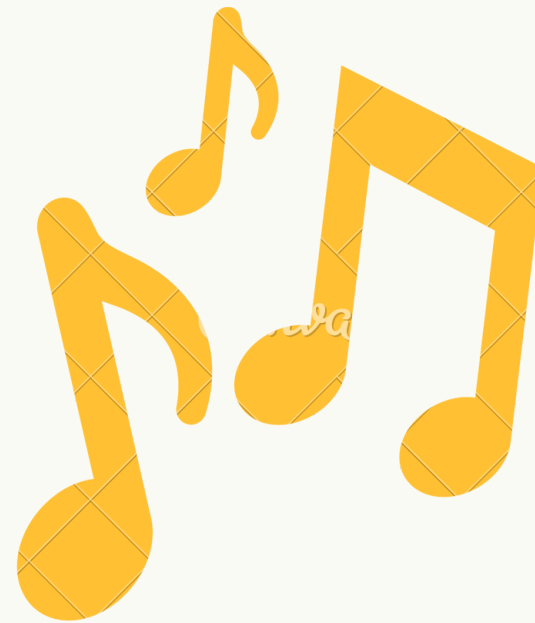
OUTLINE

Database Overview

Data Preprocessing

Math of Evaluation

Evaluation



DATABASE OVERVIEW⁺

Data: http://www.piano-midi.de/midi_files.htm

In the midi file, there contain three important element `note[24, 122]`, `velocity[0, 128)`, `time`.

DATA PREPROCESSING



The background is a vibrant pink color. It features decorative elements including yellow and blue wavy borders at the top and bottom corners, several yellow plus signs scattered throughout, and two yellow musical notes. Two white circles with a grid pattern and the word 'Canva' are also present. A large white oval in the center contains the title 'DATA PREPROCESSING' in bold yellow letters, with two horizontal yellow lines underneath it.



READING THE FILE

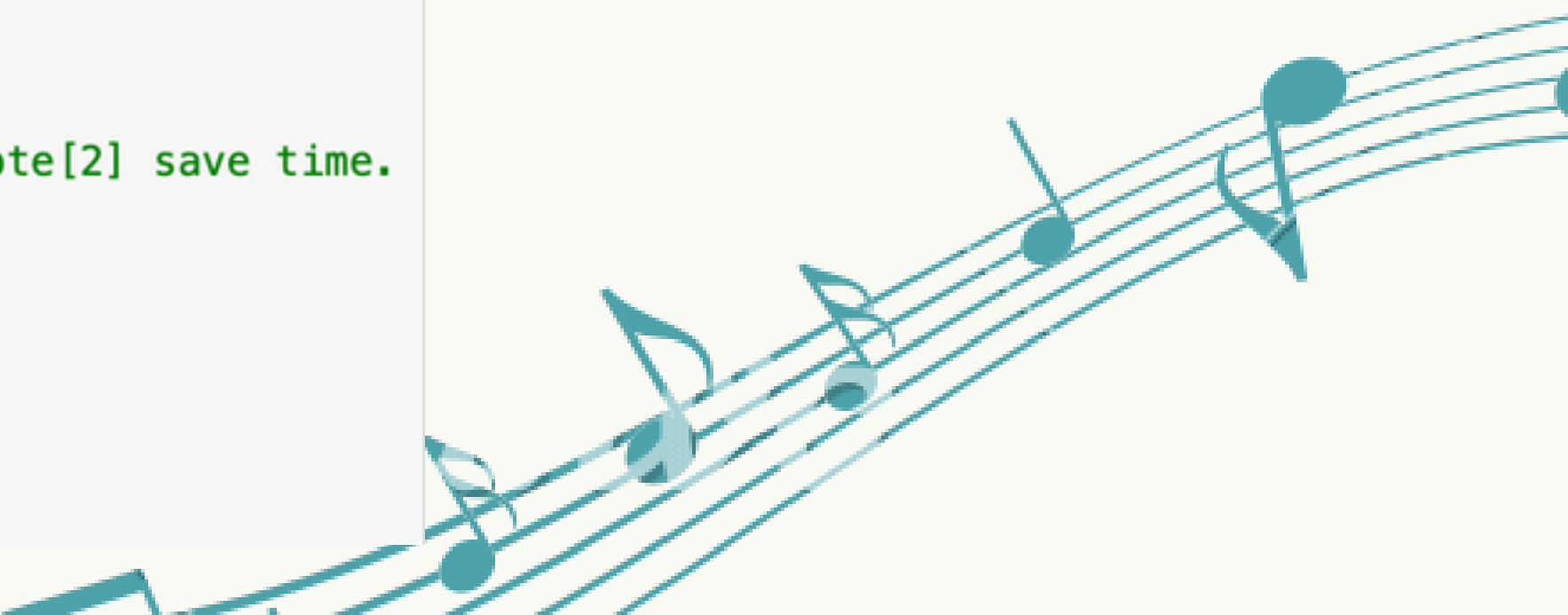
```
mid = MidiFile('./Sonata No. 16 C major Rondo Allegretto.mid')

notes = []
time = float(0)
prev = float(0)

original = []

for msg in mid:
    time += msg.time

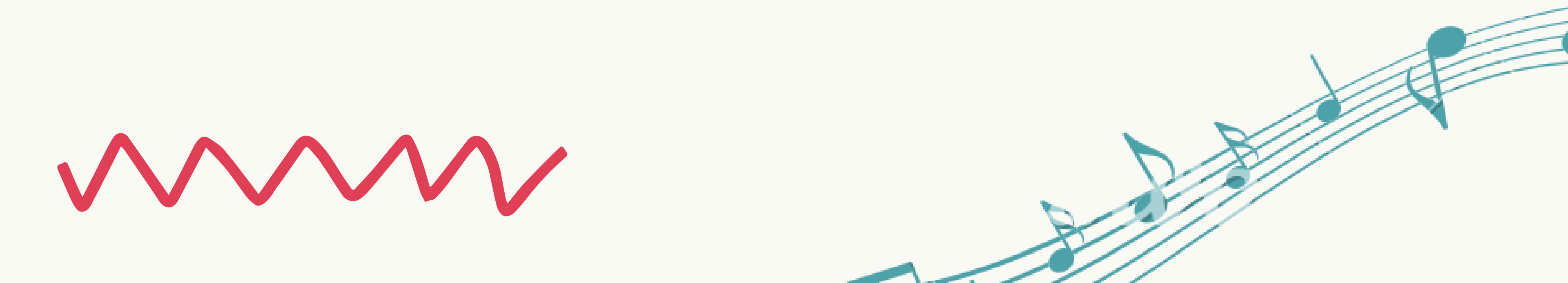
    if not msg.is_meta:
        if msg.channel == 0:
            if msg.type == 'note_on':
                # note[0] save pitch, note[1] save velocity, note[2] save time.
                note = msg.bytes()
                note = note[1:3]
                note.append(time - prev)
                prev = time
                notes.append(note)
                original.append([i for i in note])
```





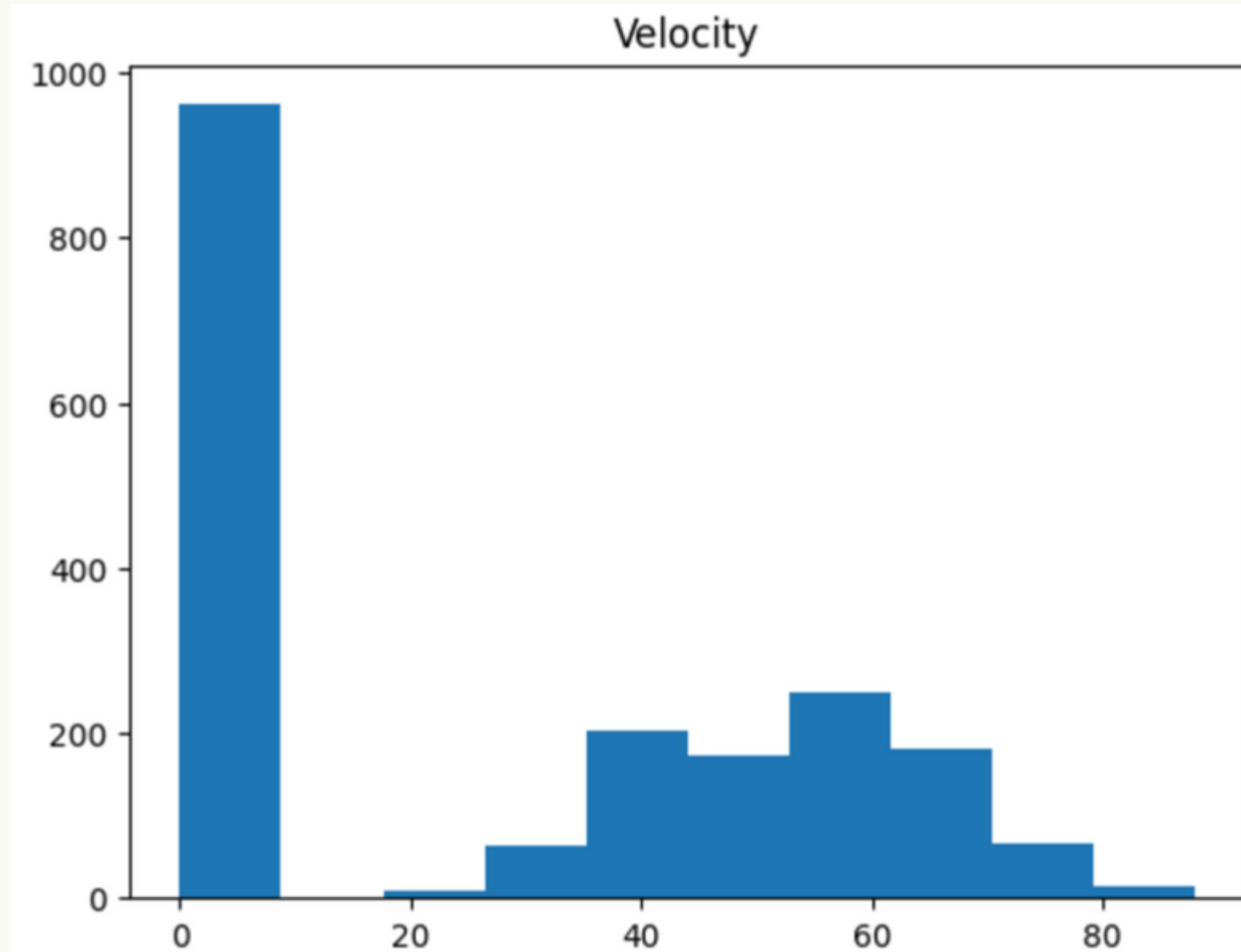
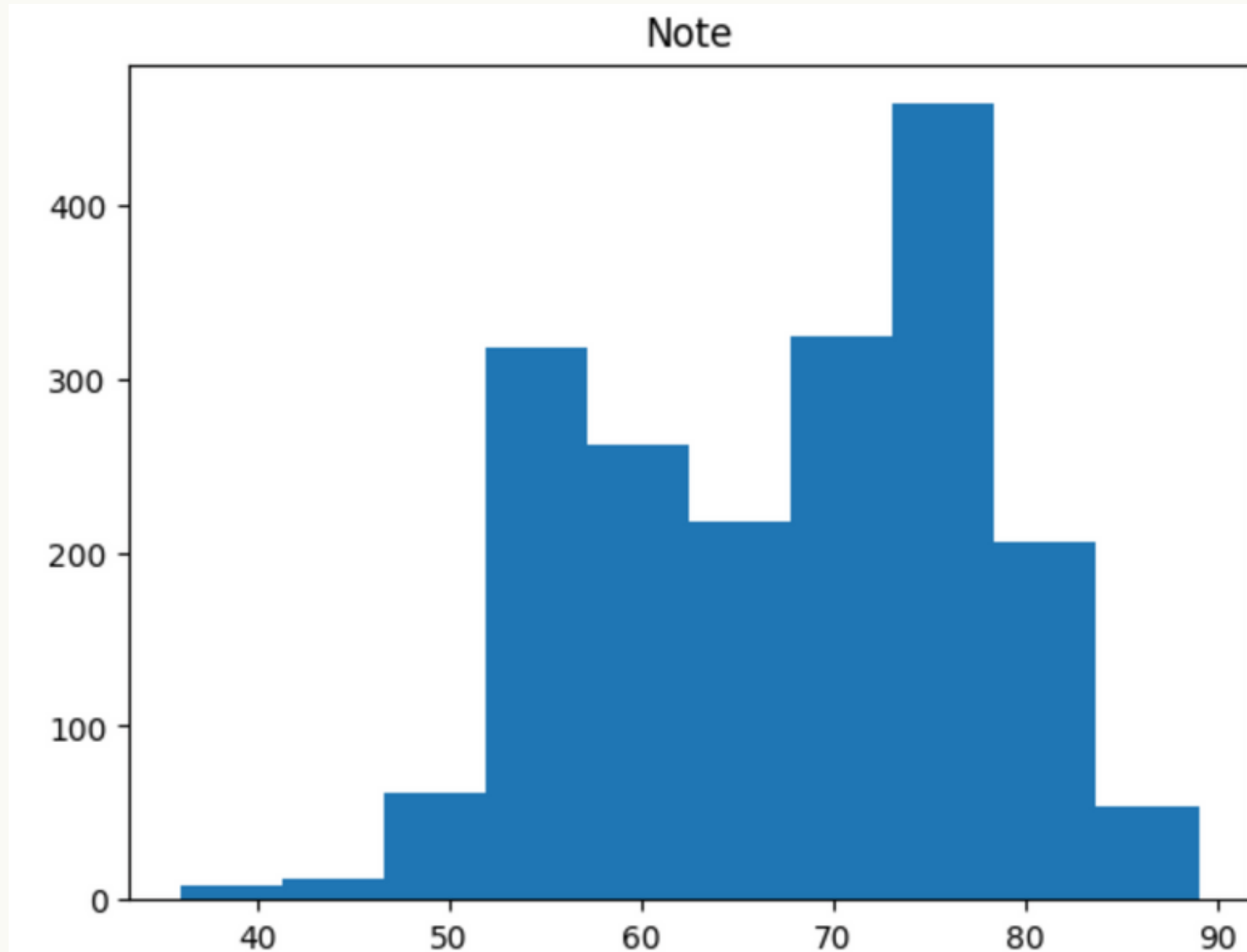
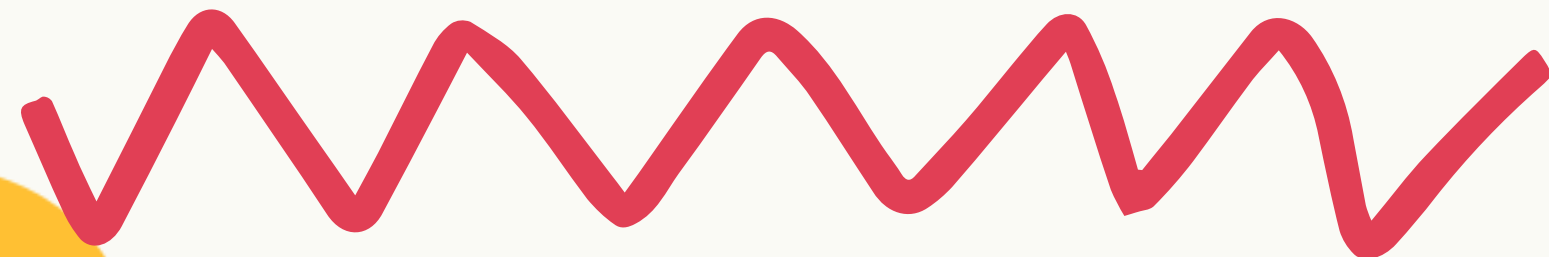
READING THE FILE

```
plt.figure()
plt.hist([i[0] for i in notes])
plt.title('Note')
plt.figure()
plt.hist([i[1] for i in notes])
plt.title('Velocity')
plt.figure()
plt.hist([i[2] for i in notes])
plt.title('Time')
```



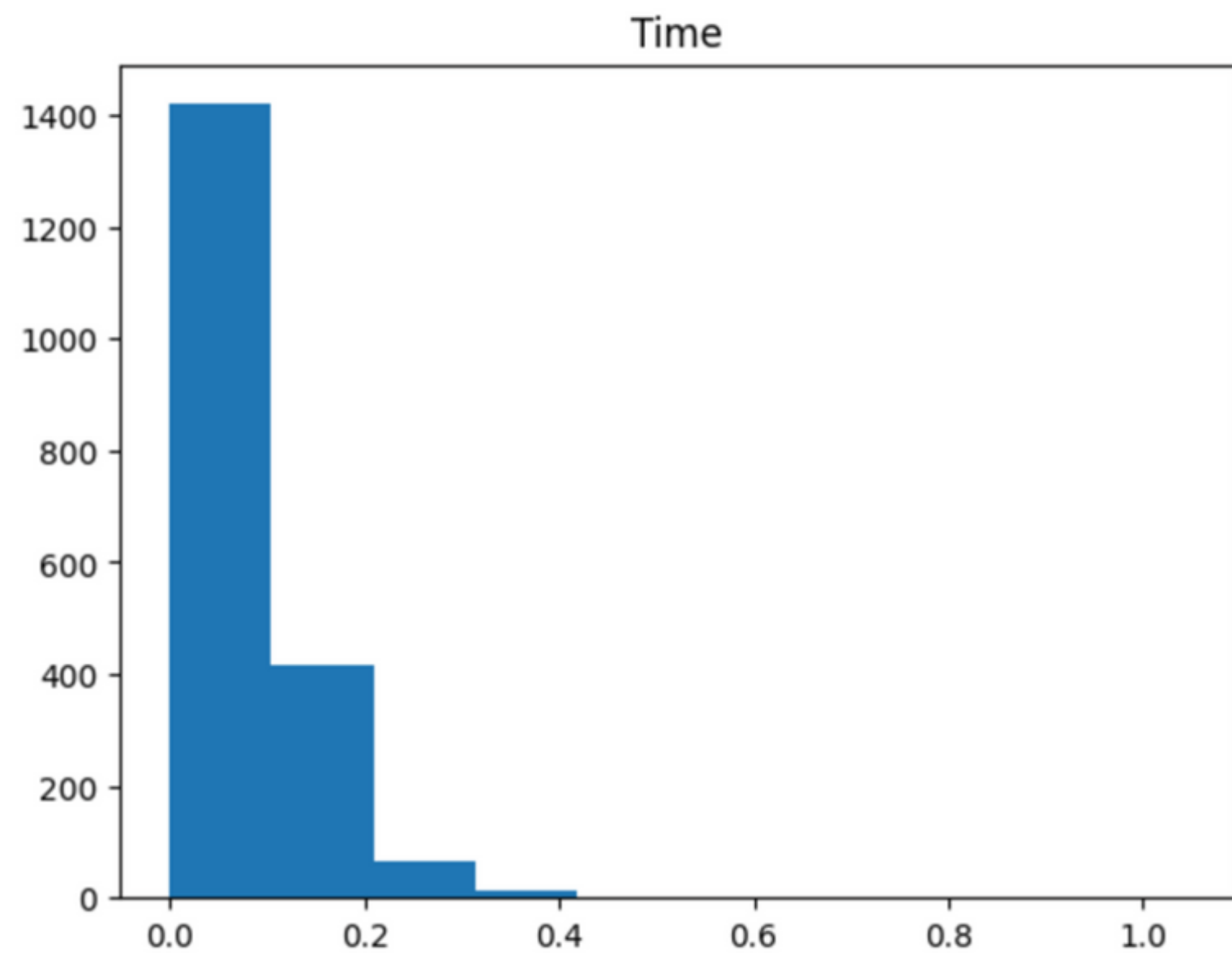


READING THE FILE





READING THE FILE



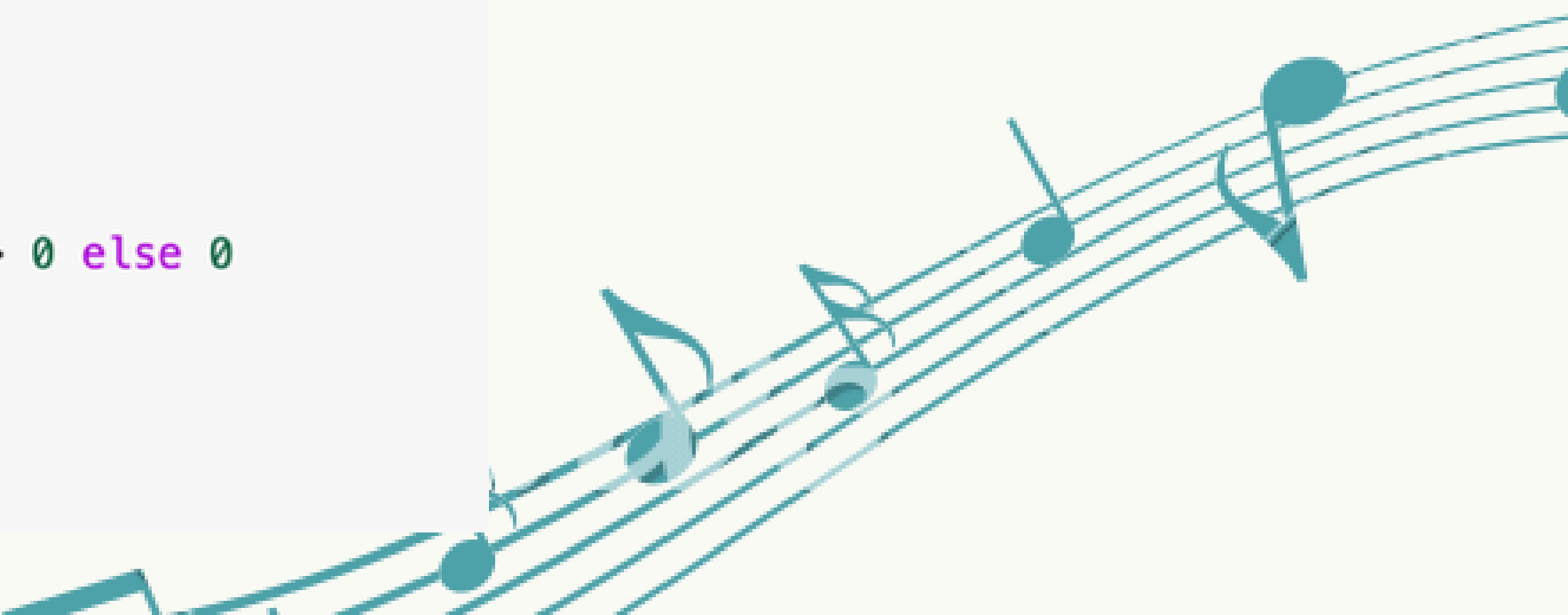


DATA PREPROCESSING

```
intervals = 10
values = np.array([i[2] for i in notes])
max_t = np.amax(values)
min_t = np.amin(values[values > 0])
interval = 1.0 * (max_t - min_t) / intervals

dataset = []
for note in notes:
    slot = np.zeros(229)

    # because note >= 24 and note <= 112, we first minus 24 to note.
    note[0] -= 24
    ind1 = note[0]
    # velocity >= 0 && velocity < 128
    ind2 = note[1]
    ind3 = int((note[2] - min_t) / interval + 1) if note[2] > 0 else 0
    slot[ind1] = 1
    slot[89 + ind2] = 1
    slot[89 + 128 + ind3] = 1
    dataset.append(slot)
```





DATA PREPROCESSING

```
X = []
Y = []

n_prev = 10

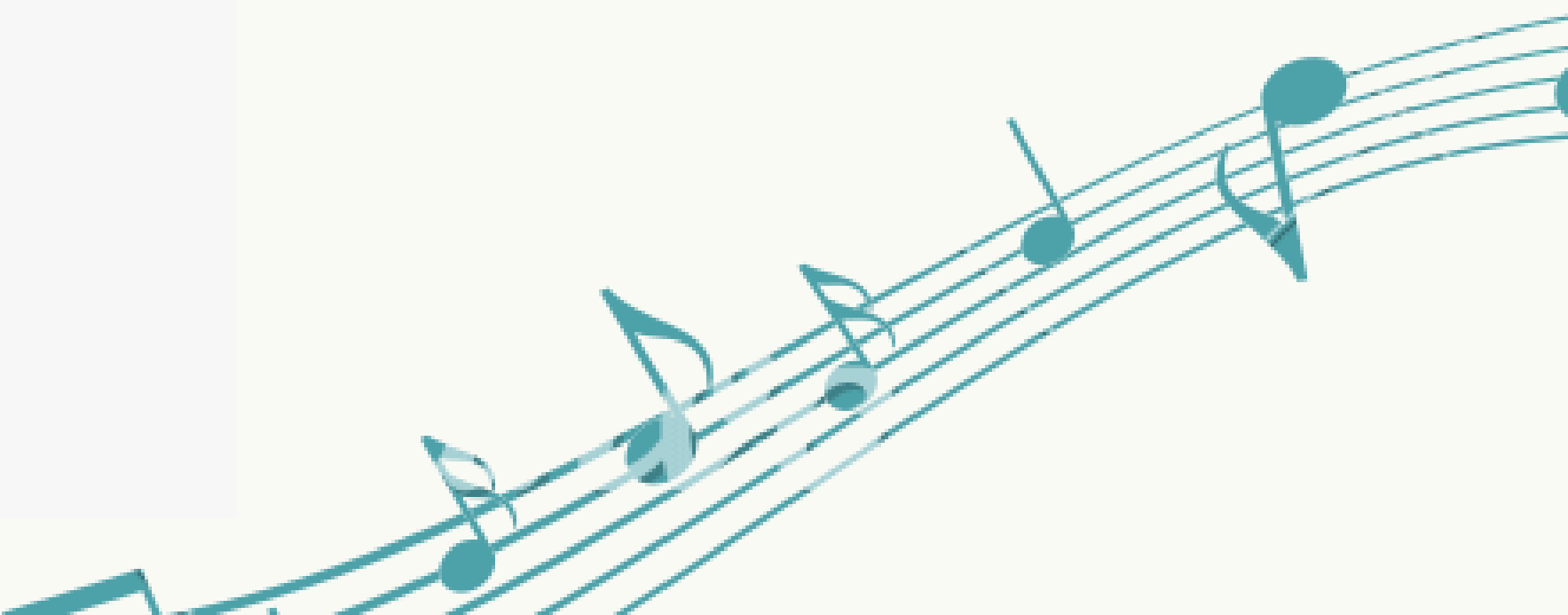
for i in range(len(dataset) - n_prev):
    x = dataset[i:i+n_prev]
    y = notes[i+n_prev]
    ind3 = int((y[2] - min_t) / interval + 1) if y[2] > 0 else 0
    y[2] = ind3

    X.append(x)
    Y.append(y)

seed = dataset[0:n_prev]

idx = np.random.permutation(range(len(X)))
X = [X[i] for i in idx]
Y = [Y[i] for i in idx]

validX = X[: len(X) // 10]
X = X[len(X) // 10 :]
validY = Y[: len(Y) // 10]
Y = Y[len(Y) // 10 :]
```



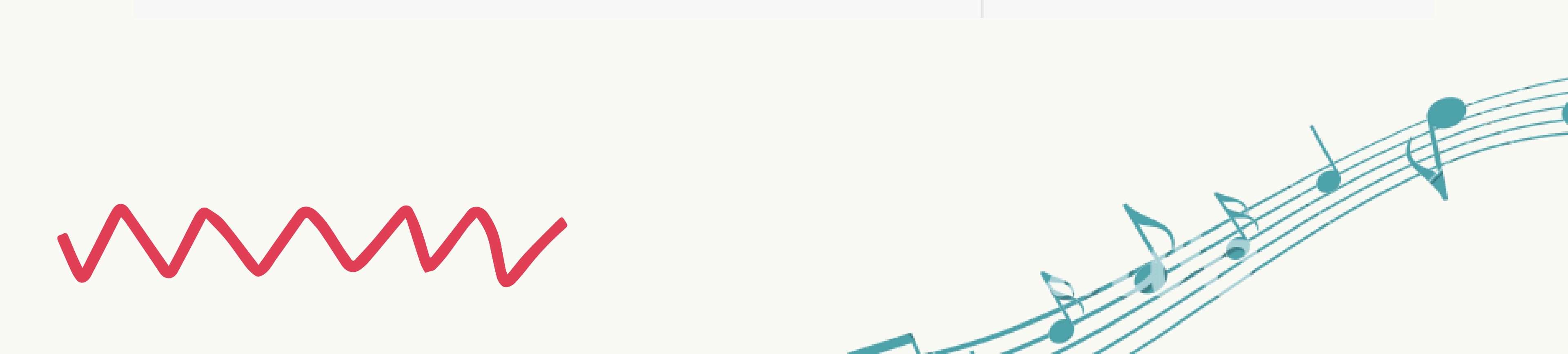


DATA PREPROCESSING

```
batch_size = 16

train_ds = DataSet.TensorDataset(torch.FloatTensor(np.array(X, dtype = float)), torch.LongTensor(np.array(Y)))
train_loader = DataSet.DataLoader(train_ds, batch_size = batch_size, shuffle = True, num_workers=4)

valid_ds = DataSet.TensorDataset(torch.FloatTensor(np.array(validX, dtype = float)), torch.LongTensor(np.array(validY)))
valid_loader = DataSet.DataLoader(valid_ds, batch_size = batch_size, shuffle = True, num_workers=4)
```





MATH EVALUATION

GRADIENT DESCENT

$$\theta_{\text{new}} = \theta_{\text{old}} - \eta \cdot \nabla \theta L$$

- θ : model parameters
- L : gradient of the loss function
- η : learning rate
- $\nabla \theta L$: gradient of the loss function with respect to the model parameters

BACKPROPAGATION

$$\partial L / \partial w$$

- L: loss function
- w: a weight in the network

Is used to update the weights in the direction that minimizes the loss.

LOSS FUNCTION (CROSSENTROPY)

$$L = -1/N * \sum \log(p_i)$$

- L: cross-entropy loss
- p_i : the predicted probability of the correct class for the i th sample

It penalizes predictions that are confident but wrong.

MODEL

```
class LSTMNetwork(nn.Module):
    def __init__(self, input_size, hidden_size, out_size, n_layers=1):
        super(LSTMNetwork, self).__init__()
        self.n_layers = n_layers
        self.hidden_size = hidden_size
        self.out_size = out_size
        self.lstm = nn.LSTM(input_size, hidden_size, n_layers, batch_first = True)
        self.dropout = nn.Dropout(0.2)
        self.fc = nn.Linear(hidden_size, out_size)
        self.softmax = nn.LogSoftmax(dim = 1)

    def forward(self, input, hidden=None):
        hhh1 = hidden[0]
        output, hhh1 = self.lstm(input, hhh1)
        output = self.dropout(output)
        output = output[:, -1, ...]
        out = self.fc(output)

        x = self.softmax(out[:, :89])
        y = self.softmax(out[:, 89: 89 + 128])
        z = self.softmax(out[:, 89 + 128:])
        return (x,y,z)
```


MODEL

```
def initHidden(self, batch_size):  
    out = []  
    hidden1=torch.zeros(1, batch_size, self.hidden_size)  
    cell1=torch.zeros(1, batch_size, self.hidden_size)  
    out.append((hidden1, cell1))  
    return out
```

DEFINE CRITERION AND RIGHTNESS

```
def criterion(outputs, target):  
    x, y, z = outputs  
    loss_f = nn.NLLLoss()  
    loss1 = loss_f(x, target[:, 0])  
    loss2 = loss_f(y, target[:, 1])  
    loss3 = loss_f(z, target[:, 2])  
    return loss1 + loss2 + loss3  
  
def rightness(predictions, labels):  
    pred = torch.max(predictions.data, 1)[1]  
    rights = pred.eq(labels.data).sum()  
    return rights, len(labels)
```

TRAIN

```
lstm = LSTMNetwork(229, 64, 229)
optimizer = optim.SGD(lstm.parameters(), lr=1e-1, momentum=0.9)
num_epochs = 100
train_losses = []
valid_losses = []
records = []
```

TRAIN

```
for epoch in range(num_epochs):
    train_loss = []
    for batch, data in enumerate(train_loader):
        lstm.train()
        init_hidden = lstm.initHidden(len(data[0]))
        optimizer.zero_grad()
        x, y = data[0].clone().detach().requires_grad_(True), data[1].clone().detach()
        outputs = lstm(x, init_hidden)
        loss = criterion(outputs, y)
        train_loss.append(loss.data.numpy())
        loss.backward()
        optimizer.step()
```

TRAIN

```
valid_loss = []
lstm.eval()
rights = []
for batch, data in enumerate(valid_loader):
    init_hidden = lstm.initHidden(len(data[0]))
    x, y = data[0].clone().detach().requires_grad_(True), data[1].clone().detach()
    outputs = lstm(x, init_hidden)
    loss = criterion(outputs, y)
    valid_loss.append(loss.data.numpy())
    right1 = rightness(outputs[0], y[:, 0])
    right2 = rightness(outputs[1], y[:, 1])
    right3 = rightness(outputs[2], y[:, 2])
    rights.append((right1[0] + right2[0] + right3[0]).numpy() * 1.0 / (right1[1] + right2[1] + right3[1]))
```

TRAIN

```
Epoch 86/100, trainingg loss:1.37, validation loss:4.78, accuracy:72.47%
Epoch 87/100, trainingg loss:1.24, validation loss:4.87, accuracy:72.29%
Epoch 88/100, trainingg loss:1.21, validation loss:4.70, accuracy:70.72%
Epoch 89/100, trainingg loss:1.10, validation loss:4.64, accuracy:71.93%
Epoch 90/100, trainingg loss:1.05, validation loss:4.74, accuracy:71.90%
Epoch 91/100, trainingg loss:1.12, validation loss:4.66, accuracy:72.47%
Epoch 92/100, trainingg loss:1.04, validation loss:4.67, accuracy:73.08%
Epoch 93/100, trainingg loss:1.04, validation loss:4.95, accuracy:72.95%
Epoch 94/100, trainingg loss:1.01, validation loss:4.77, accuracy:72.62%
Epoch 95/100, trainingg loss:0.84, validation loss:4.76, accuracy:73.29%
Epoch 96/100, trainingg loss:0.74, validation loss:4.83, accuracy:74.57%
Epoch 97/100, trainingg loss:0.70, validation loss:4.79, accuracy:73.76%
Epoch 98/100, trainingg loss:0.70, validation loss:4.84, accuracy:73.14%
Epoch 99/100, trainingg loss:0.71, validation loss:4.92, accuracy:74.07%
Epoch100/100, trainingg loss:0.65, validation loss:4.94, accuracy:73.53%
```

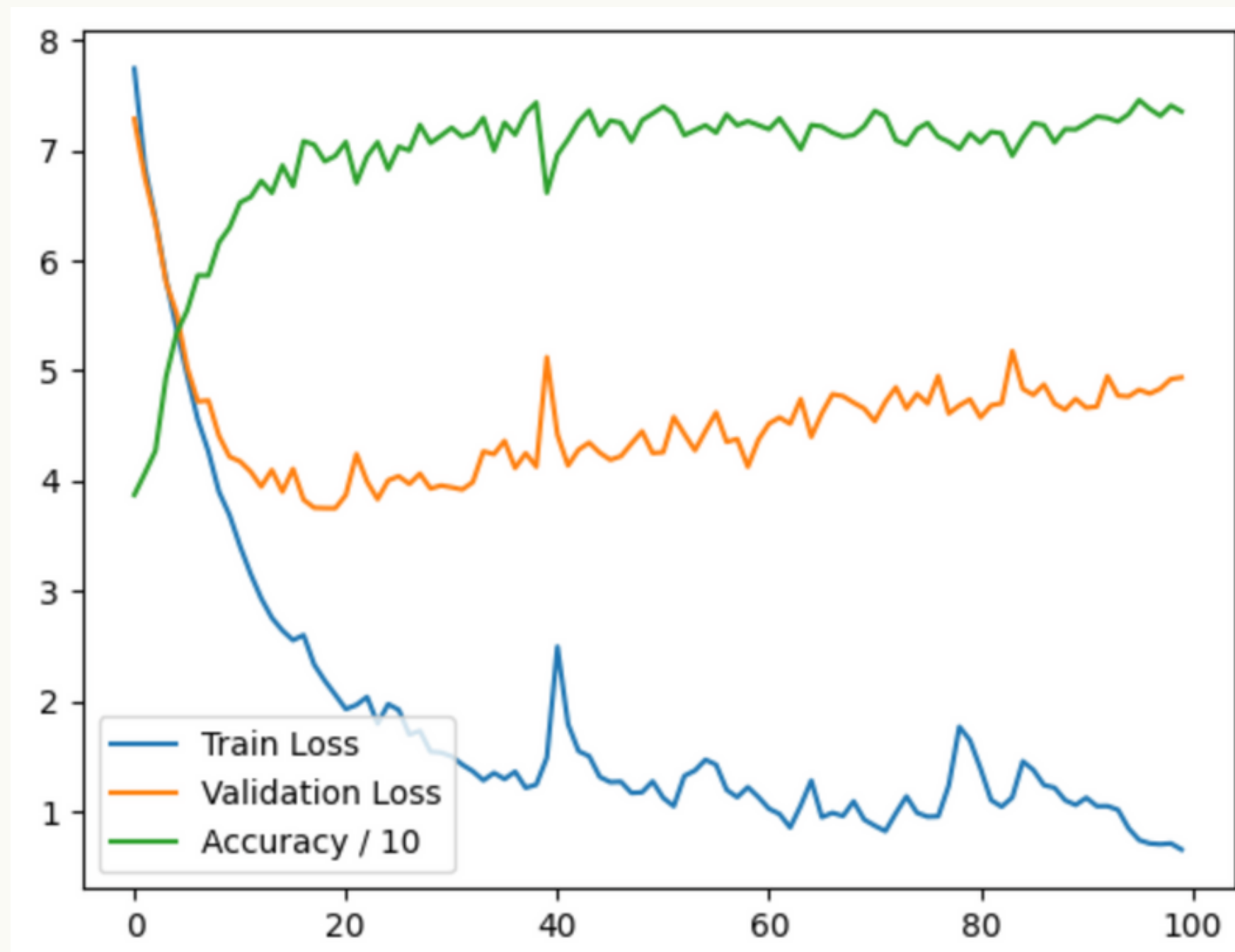


EVALUATION

PLOT THE LOSS AND ACCURACY

```
a = [i[0] for i in records]
b = [i[1] for i in records]
c = [i[2] * 10 for i in records]
plt.plot(a, '-', label = 'Train Loss')
plt.plot(b, '-', label = 'Validation Loss')
plt.plot(c, '-', label = 'Accuracy / 10')
plt.legend()
```


PLOT THE LOSS AND ACCURACY



CREATE MUSIC

```
predict_steps = 3000

x = seed
x = np.expand_dims(x, axis = 0)

lstm.eval()
init_i = lstm.initHidden(1)
predictions = []
for i in range(predict_steps):
    xx = torch.tensor(np.array(x, dtype = float), dtype = torch.float, requires_grad = True)
    preds = lstm(xx, init_i)
    a,b,c = preds

    ind1 = torch.multinomial(a.view(-1).exp(), num_samples = 1)
    ind2 = torch.multinomial(b.view(-1).exp(), num_samples = 1)
    ind3 = torch.multinomial(c.view(-1).exp(), num_samples = 1)

    ind1 = ind1.data.numpy()[0]
    ind2 = ind2.data.numpy()[0]
    ind3 = ind3.data.numpy()[0]
```

CREATE MUSIC

```
note = [ind1 + 24, ind2, 0 if ind3 == 0 else ind3 * interval + min_t]  
predictions.append(note)
```

```
slot = np.zeros(89 + 128 + 12, dtype = int)  
slot[ind1] = 1  
slot[89 + ind2] = 1  
slot[89 + 128 + ind3] = 1  
slot1 = np.expand_dims(slot, axis = 0)  
slot1 = np.expand_dims(slot1, axis = 0)
```

```
x = np.concatenate((x, slot1), 1)  
x = x[:, 1:, :]
```

LOAD CREATE MUSIC

```
mid = MidiFile()
track = MidiTrack()
mid.tracks.append(track)

for i, note in enumerate(predictions):
    note = np.insert(note, 0, 147)
    bytes = note.astype(int)
    msg = Message.from_bytes(bytes[0:3])
    time = int(note[3]/0.001025)
    msg.time = time
    track.append(msg)

mid.save('./new_song.mid')
```



DEMO



**THANK YOU FOR
LISTENING!**