Musify- Music Composition using A.I.

By Abhijit Kumar

Music Composition

Music Composition is a process of creating a new piece of music

Composition means “putting together”. Thus, music composition is something where music notes are put together in such a way that it gives pleasant sensation to our ears

Parameters such as pitch interval, notes, chords, tempo etc. are used for composing short piece of music

About the Project

- The Project mainly focusses on music from **Piano** instrument
- Uses **Long Short Term Memory** (LSTM) , a type of Recurrent Neural Network (RNN)
- Platform: **Visual Studio Code / Jupyter Notebook**
- Language: **Python 3.8**
- Libraries Used: **Tensorflow, Music21, Keras, NumPy, Sklearn, tqdm**
- Dataset: Classical Music MIDI | Kaggle

Terminologies

- **Note**: This is a sound produced by a single key
- **Chords**: The combination of 2 or more notes is called a chord
- **Octave**: The distance between two notes is stated as an octave in a piano
  It is specifically the gap between the two notes that share the same letter name

- **Recurrent Neural Networks (RNN)**
  A recurrent neural network is a class of artificial neural networks that make use of sequential information. They are called recurrent because they perform the same function for every single element of a sequence, with the result being dependent on previous computations
- **Long Short Term Memory (LSTM)**
  - LSTMs are a type of Recurrent Neural Network that can efficiently learn via gradient descent
  - Using a gating mechanism, they are able to recognize and encode long-term patterns
  - Useful to solve problems where the network has to remember information for a long period of time
  - Applications: Music and text generation etc.
  - Limitation: It requires lots of resources and time to get trained for real world applications

Libraries

- **Music21**
  - Music21 is a Python toolkit used for computer-aided musicology
  - It allows us to teach the fundamentals of music theory, generate music examples and study music
  - The toolkit provides a simple interface to acquire the musical notation of MIDI files
  - Additionally, it allows us to create Note and Chord objects so that we can make our own MIDI files easily

- **Keras**
  - Keras is a high-level neural networks API that simplifies interactions with TensorFlow
  - It was developed with a focus on enabling fast experimentation

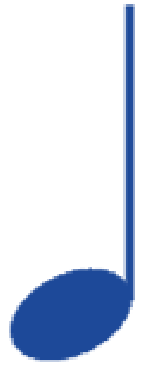
- **TensorFlow**
  - TensorFlow is a free and open-source software library for machine learning and artificial intelligence
  - It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks

- **NumPy**
  - NumPy is a Python library used for working with arrays
  - It also has functions for working in domain of linear algebra, Fourier transform, and matrices

- **tqdm**
  - *tqdm* is a library in *Python* which is used for creating Progress Meters or Progress Bars

Project Structure

- **All Midi Files/** : This is the dataset folder containing various midi files of different composers
- **code.ipynb** : In this file, we will build, train and test our model
- **MOD/** : This directory contains optimizer, metrics, and weights of our trained model
- **AI_composed_music.mid**: This is a music file of predicted notes



STEPS

(For developing Code from Scratch)

Import Libraries

- Import all the important Libraries

CODE SNIPPET

```
from music21 import *
import glob
from tqdm import tqdm
import numpy as np
import random
from tensorflow.keras.layers import LSTM,Dense,Input,Dropout
from tensorflow.keras.models import Sequential,Model,load_model
from sklearn.model_selection import train_test_split
```

STEP 2

Reading and Parsing the Midi File

- The midi file dataset has to be read using Music21 library
- “**Schubert**” composed files has been used. (You can use more or less depending on your system)
- For this project, the files that contain sequential streams of **Piano** data has only been worked on
- All files are separated by their instruments and **Piano** is used only
- Piano stream from the midi file contains many data like **Keys**, **Time Signature**, **Chord**, **Note** etc.
- We require only **Notes** and **Chords** to generate music
- Lastly, the arrays of notes and chords has to be returned

CODE SNIPPET

Reading and Parsing the Midi File

```python
def read_files(file):
    notes=[]
    notes_to_parse=None
    #parse the midi file
    midi=converter.parse(file)
    #seperate all instruments from the file
    instrmt=instrument.partitionByInstrument(midi)

    for part in instrmt.parts:
        #fetch data only of Piano instrument
        if 'Piano' in str(part):
            notes_to_parse=part.recurse()

            #iterate over all the parts of sub stream elements
            #check if element's type is Note or chord
            #if it is chord split them into notes
            for element in notes_to_parse:
                if type(element)==note.Note:
                    notes.append(str(element.pitch))
                elif type(element)==chord.Chord:
                    notes.append('.'.join(str(n) for n in element.normalOrder))

    #return the list of notes
    return notes

#retrieve paths recursively from inside the directories/files
file_path=["schubert"]
all_files=glob.glob('All Midi Files/'+file_path[0]+'/*.mid',recursive=True)

#reading each midi file
notes_array = np.array([read_files(i) for i in tqdm(all_files,position=0,leave=True)])
```

STEP 3 Exploring the Dataset

- This is done to check the number of **unique notes** and their **distribution**
- **50** is used as a threshold frequency
- Only those notes which have frequencies more than **50** have been considered
- These parameters can be **changed** anytime
- **Two** dictionaries are created where one will have **notes index as a key and notes as value** and other will be the reverse of the first i.e. **key will be notes and value will be its respective index**
- These dictionaries will be used in the next steps

CODE SNIPPET

Exploring the Dataset

```
#unique notes
notess = sum(notes_array,[])
unique_notes = list(set(notess))
print("Unique Notes:",len(unique_notes))

#notes with their frequency
freq=dict(map(lambda x: (x,notess.count(x)),unique_notes))

#get the threshold frequency
print("\nFrequency notes")
for i in range(30,100,20):
    print(i,":",len(list(filter(lambda x:x[1]>=i,freq.items()))))

#filter notes greater than threshold i.e. 50
freq_notes=dict(filter(lambda x:x[1]>=50,freq.items()))

#create new notes using the frequent notes
new_notes=[[i for i in j if i in freq_notes] for j in notes_array]

#dictionary having key as note index and value as note
ind2note=dict(enumerate(freq_notes))

#dictionary having key as note and value as note index
note2ind=dict(map(reversed,ind2note.items()))
```

✓ 1.6s

```
Unique Notes: 345

Frequency notes
30 : 204
50 : 182
70 : 163
90 : 153
```

STEP 4 Input and Output Sequence for model

- **Input** and **output** sequences for our model are created
- A **timestep** of **50** has been used. So, if we traverse 50 notes of our input sequence then the **51st** note will be the output for that sequence
- **Example**:
  - While using 'SOC stands for Seasons of Code' sentence with a timestep of 2, we will have to provide 2 words at every input to get the output

(x)	**(y)**
SOC stands	for
Stands for	Seasons
for Seasons	of
Seasons of	Code

- As our model requires numeric data, all notes are converted to its respective index value using the "**note2ind**" (note to index) dictionary which has been created earlier

CODE SNIPPET

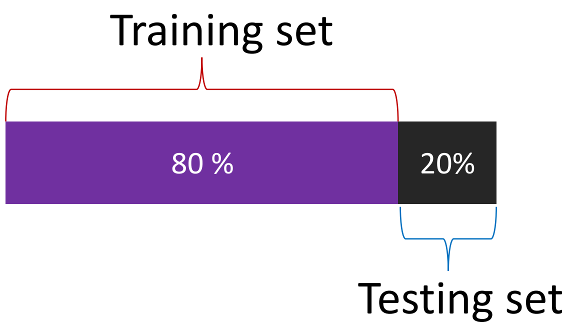
Input and Output Sequence for model

```
#timestep
timesteps=50

#store values of input and output
x=[] ; y=[]

for i in new_notes:
    for j in range(0,len(i)-timesteps):
        #input will be the current index + timestep
        #output will be the next index after timestep
        inp=i[j:j+timesteps] ; out=i[j+timesteps]

        #append the index value of respective notes
        x.append(list(map(lambda x:note2ind[x],inp)))
        y.append(note2ind[out])

x_new=np.array(x)
y_new=np.array(y)
```

STEP 5

Training and Testing sets

- Array for our model is re-shaped and the data is split into 80:20 ratio.



CODE SNIPPET

```
#reshape input and output for the model
x_new = np.reshape(x_new,(len(x_new),timesteps,1))
y_new = np.reshape(y_new,(-1,1))

#split the input and value into training and testing sets
#80% for training and 20% for testing sets
x_train,x_test,y_train,y_test = train_test_split(x_new,y_new,test_size=0.2,random_state=42)
```

STEP 6 Building the Model

- 2 stacked **LSTM** layers with a dropout rate of **0.2** are used
- A fully connected **Dense** layer has been used for output
- Output dimension of the Dense Layer is taken same as the length of our unique notes along with the '**softmax**' activation function (Used for multi-class classification problems)

Dropout refers to ignoring units (i.e. neurons) during the training phase of certain set of neurons which is chosen at random. It basically prevents overfitting while training the model, while it does not affect the inference model.

CODE SNIPPET

Building the Model

```
#create the model
model = Sequential()
#create two stacked LSTM layer with the latent dimension of 256
model.add(LSTM(256,return_sequences=True,input_shape=(x_new.shape[1],x_new.shape[2])))
model.add(Dropout(0.2))
model.add(LSTM(256))
model.add(Dropout(0.2))
model.add(Dense(256,activation='relu'))

#fully connected layer for the output with softmax activation
model.add(Dense(len(note2ind),activation='softmax'))
model.summary()
```

✓ 0.7s

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 50, 256)           264192

 dropout (Dropout)           (None, 50, 256)           0

 lstm_1 (LSTM)               (None, 256)               525312

 dropout_1 (Dropout)         (None, 256)               0

 dense (Dense)               (None, 256)               65792

 dense_1 (Dense)             (None, 182)               46774

=================================================================
Total params: 902,070
Trainable params: 902,070
Non-trainable params: 0
_________________________________________________________________
```

STEP 7 Training the Model

- After building the model, it is trained on the input and output data
- For this, '**Adam**' optimizer is used on **batch size** of **128** and for total **80 epochs**
- After Training, model is **saved** for prediction

CODE SNIPPET

```
#compile the model using Adam optimizer
model.compile(loss='sparse_categorical_crossentropy', optimizer='adam',metrics=['accuracy'])

#train the model on training sets and validate on testing sets
model.fit(
    x_train,y_train,
    batch_size=128,epochs=80,
    validation_data=(x_test,y_test))
```

```
#save the model for predictions
model.save("MOD")
```

STEP 8

Inference Phase

- Using the trained model, the notes will be predicted
- A random integer(**index**) is generated for our testing input array which will be our testing input pattern
- Our array is then re-shaped and the output is predicted
- Using the ‘**np.argmax()**’ function, we get the data of the maximum probability value
- This predicted index is converted to notes using ‘**ind2note**’(index to note) dictionary
- Our next music pattern is one step ahead of the previous pattern
- This process is repeated till we generate **200** notes
- This parameter can be **changed** as per your requirements

CODE SNIPPET

Inference Phase

```
#load the model
model=load_model("MOD")
#generate random index
index = np.random.randint(0,len(x_test)-1)
#get the data of generated index from x_test
music_pattern = x_test[index]

out_pred=[] #it will store predicted notes

#iterate till 200 note is generated
for i in range(200):

  #reshape the music pattern
  music_pattern = music_pattern.reshape(1,len(music_pattern),1)

  #get the maximum probability value from the predicted output
  pred_index = np.argmax(model.predict(music_pattern))
  #get the note using predicted index and
  #append to the output prediction list
  out_pred.append(ind2note[pred_index])
  music_pattern = np.append(music_pattern,pred_index)

  #update the music pattern with one timestep ahead
  music_pattern = music_pattern[1:]
```

STEP 9 Saving the File

- The predicted output notes are saved into a MIDI File

CODE SNIPPET

```
output_notes = []
for offset,pattern in enumerate(out_pred):
  #if pattern is a chord instance
  if ('.' in pattern) or pattern.isdigit():
    #split notes from the chord
    notes_in_chord = pattern.split('.')
    notes = []
    for current_note in notes_in_chord:
        i_curr_note=int(current_note)
        #cast the current note to Note object and
        #append the current note
        new_note = note.Note(i_curr_note)
        new_note.storedInstrument = instrument.Piano()
        notes.append(new_note)

    #cast the current note to Chord object
    #offset will be 1 step ahead from the previous note
    #as it will prevent notes to stack up
    new_chord = chord.Chord(notes)
    new_chord.offset = offset
    output_notes.append(new_chord)

  else:
    #cast the pattern to Note object apply the offset and
    #append the note
    new_note = note.Note(pattern)
    new_note.offset = offset
    new_note.storedInstrument = instrument.Piano()
    output_notes.append(new_note)

#save the midi file
midi_stream = stream.Stream(output_notes)
midi_stream.write('midi', fp='AI_composed_music.mid')
```

MUSIFY

THANKS