





[illegible]



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[illegible]



[illegible]



Character Zero's "Down with Disease" lyrics, featuring a dense and repetitive list of names and phrases.



[illegible]

```
Bag"\n', 'Possu  
now"\n', 'Golgi  
'McGrupp and the
```

'Letter to Jimmy Page'\n', 'Alumni Blues'\n', 'Whipping Post'\n', 'E  
'Funky Bitch'\n', 'Sneakin\' Sally Through the Alley'\n', 'Take the \n'

'"Wilson"  
ds"\n', '  
of Curtis

ET 1"'\n', "Jump Monk"'\n', "McGrupp and the Watchful Hosemasters"'\n', "The Lizards"'\n', "Tela"'\n', "Wilso  
n"'\n', "AC/DC Bag"'\n', "Colonel Forbin's Ascent"'\n', "Fly Famous Mockingbird"'\n', "The Sloth"'\n', "Possu  
m"'\n', "Run Like an Antelope"'\n', "Suzy Greenberg"'\n', "Golgi Apparatus"'\n', "McGrupp and the Watchful Hosema  
sters"'\n', "Sneakin' Sally Through the Alley"'\n', "Divided Sky"'\n', "Boogie On Reggae Woman"'\n', "Timber (Je  
xuu The Mule)"'\n', "The Lizards"'\n', "USER 2"'\n', "Sire"'\n', "13/C DC Bag"'\n', "The Chase"'\n', "Pocahontas"

"Dinner and a Movie"\n,"I Didn't Know"\n,"Colonel Porbin's Ascend"\n,"Fly Famous Mockingbird"\n,"E ND"\n,"Set 1"\n,"Harpua"\n,"Wilson"\n,"Peaches en Regalia"\n,"Funky Bitch"\n,"Golgi Apparatu s"\n,"Suzzy Greenberg"\n,"You Enjoy Yourself"\n,"The Lizards"\n,"Good Times Bad Times"\n,"Happy BIRTh day to You"\n,"Colonel Porbin's Ascend"\n,"Inculus"\n,"Colonel Porbin's Ascend"\n,"Fly Famous Mock ingbird"\n,"A Good Read"\n,"I Didn't Know"\n,"Colo

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ngbird'\n', 'AC/DC Bag'\n', 'I Didn't Know'\n', 'Suzy Apparat'\n', 'Fee'\n', 'AC/DC Bag'\n', 'Fussy  
n'\n', 'Fluffhead Blue'\n', 'Alumni Blues'\n', 'The Lizards'\n', 'Colonel Forbin's Ascent'\n', 'Fly Fames Mocki  
ngbird'\n', 'Take the 'A' Train'\n', 'Fire'\n', 'You Enjoy Myself'\n', 'Wilson'\n', 'Fire'\n', 'Good Time  
s Bad Times'\n', 'I Didn't Know'\n', 'Goli Apparat'\n', 'The Lizards'\n', 'Fee'\n', 'Shaggy Dog'\n', 'B  
ig Black Furry Creature from Mars'\n', 'You Enjoy Myself'\n', 'Suzy Greenberg'\n', 'Ya Mac'\n', 'AC/DC Ba

[illegible]



[illegible]



[illegible]



[illegible]



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[illegible]



[illegible]



[illegible]

```

    "Als
    D"\n',
    ee"\n'
    wist"\
    o"\n',

```

```

C/D/2 Bag's"/, "5555"/, "666666"/, "Sample in a Jar"/, "Stash"/, "The Wedge"/, "Frost"/, "Gailly"/, "Haley"/, "Huh/Heves"/, "Lave Boy"/, "You Enjoy Yourself"/, "SET 2"/, "Zlana"/, "The Final H
urrah"/, "Wingsuit"/, "Golden Age"/, "I Always Wanted It This Way"/, "Prince Caspian"/, "IET I CO
d"/, "46 Days"/, "RENCOR"/, "Drift While You're Sleeping"/, "END"/, "SET 1"/, "The Curtain Mil
"/, "Fast Enough for You"/, "Buried Alive"/, "Cameo Walk"/, "Freak"/, "Sample in a Jar"/, "Fash
les and Marble"/, "Teia"/, "The Mango Song"/, "Driver"/, "David Bowie"/, "SET 2"/, "Mr. Compie
tely"/, "Twenty Years Later"/, "Big Black Party Creature from Mars"/, "Twelve"/, "Shade"/, "Host
Bov/Be About"/, "Waklupa Policemen"/, "Chalk Dust Torture"/, "Buz/ Greenberg"/, "Rush
B"/, "Punch You in the Eye"/, "What's the Use"/, "Julius"/, "END"/, "SET 1"/, "Cathy's Clow
n"/, "Twelve Reprise"/, "Carlin"/, "K/C/D/2 Bag's"/, "The Wom Dance"/, "Wenme From the Bottom"/,
"Beat"/, "Home"/, "Bathtub Gin"/, "Walls of the Cave"/, "SET 2"/, "Cool Amber and Mercury"/,
"Down With Disease"/, "Scents and Subtle Sounds"/, "Wistful"/, "Wilson"/, "Scent of a Mule"/, "Fuc
k"/, "Face"/, "Haley's Comet"/, "Harry Hood"/, "RENCOR"/, "Fae"/, "A Life Beyond the Dream"/,
"First Tube"/, "END"/, "SET 1"/, "Can't Always Listen"/, "Free"/, "No Men in No Man's Lan
d"/, "5555"/, "The End of the Train"/, "Rice"/, "Hear"/, "Four Heart"/, "Undermind"/, "Train Go
ng"/, "Wingsuit"/, "Blaze Boin"/, "SET 2"/, "Everything's Right"/, "Mercury"/, "Shade"/, "Lig
ht"/, "Party Time"/, "Sand"/, "What's the Use"/, "Harry Hood"/, "RENCOR"/, "Say It To Me S.A.
t.o.s."/, "END"/, "SET 1"/, "The Wom Dance"/, "The Final Hurrah"/, "Gumbo"/, "Access Me"/,
"Punky Bitch"/, "Ghost"/, "Tuber"/, "Mountains in the Mist"/, "Drift While You're Sleeping"/, "S
B"/, "Miles"/, "Hear"/, "The End of the Train"/, "Rice"/, "Hear"/, "Four Heart"/, "Undermind"/,
"Down With Disease"/, "H/C/D/2"/, "Bug"/, "The Wedge"/, "Slave to the Traffic Light"/, "RENCOR
B"/, "Brian and Robert"/, "Character Zero"/, "END"/, "SET 1"/, "Sigma Gasin"/, "Buried Ali
e"/, "Coush/ Backpump"/, "My Sweet One"/, "Everything is Hollow"/, "The Curtain Mil", "Wound"/,
"ian and Robert"/, "Crazy Sometimes"/, "Frost"/, "Breath and Burning"/, "Alumni Blues"/, "Letter t
Jimmy Page"/, "Alumni Blues"/, "It's Ice"/, "Walls of the Cave"/, "SET 2"/, "After Midnight"/,
"Waiting Time From the Pastry Plan"/, "Rever"/, "Soul Planet"/, "Wingsuit"/, "I Always Wanted It
This Way"/, "Petricor"/, "Boogie On Reggae Woman"/, "Rise/ Come Together"/, "RENCOR"/, "Fiebles a
B"/, "Hear"/, "Breath a Sea of Stars Part 1"/, "Frisella"/, "Chalk Dust Torture Reprise"/, "END"/,
"SET 1"/, "Evening Song"/, "No Men in No Man's Land"/, "Down With Disease"/, "20-20 Vision"/,
"Ghost"/, "Gumbo"/, "Rift"/, "Wag"/, "Boy Back Boy"/, "Twenty Years Later"/, "Tuber"/,
"Set It To Me S.A.t.o.s."/, "SET 2"/, "Everything's Right"/, "Beneath a Sea of Stars Part 1"/,
"Get Your Soul Free"/, "Gotta Zibbo"/, "Free"/, "Pipe"/, "Drowned"/, "Ass Hand"/, "Chalk
Dust Torture Reprise"/, "Character Zero"/, "RENCOR"/, "A Life Beyond the Dream"/, "Rocky Top"/,
"END"/]

```

## Model Parameters

Here is a list of parameters that can be useful to modify that will have impact on the speed and accuracy of the model.

```

In [90]: # The length of the song sequence that the model will look at to predict the next song.
         SEQ_LENGTH = 5

         # Number of nodes in the LSTM layer
         LSTM_NODES = 128

         # Number of epochs - how many times the layers are passed through (forward + backwards - 1 epoch)
         NUM_EPOCHS = 2

         # Learning Rate
         LR = 0.01

```

## Features

We create two features X, containing a sequence of given length songs, and Y, the subsequent song, or target value.

```

In [91]: prev_songs = []
         next_songs = []
         for i in range(len(training_set) - SEQ_LENGTH):
             prev_songs.append(training_set[i:i + SEQ_LENGTH])
             next_songs.append(training_set[i + SEQ_LENGTH])

         X = np.zeros((len(prev_songs), SEQ_LENGTH, len(unique_songs)), dtype = bool)
         Y = np.zeros((len(next_songs), len(unique_songs)), dtype = bool)

         for i, each_song in enumerate(prev_songs):
             for j, each_song in enumerate(each_song):
                 X[i, j, unique_song_index(each_song)] = 1

         Y[i, unique_song_index(next_songs[i])] = 1

```

## Model Creation

Our model is a single-layer LSTM model with a number of nodes that can be specified above, a dense-layer (layer of fully-connected nodes), and an activation layer using a softmax (generalized sigmoid) function.

```

In [92]: model = Sequential()
         model.add(LSTM(LSTM_NODES, input_shape=(SEQ_LENGTH, len(unique_songs))))
         model.add(Dense(len(unique_songs)))
         model.add(Activation('softmax'))

```

## Training the Model

Next, we train the model using an RMSprop optimizer, which is similar the gradient descent algorithm. Our learning rate is set by the LR parameter defined above.

```

In [93]: optimizer = RMSprop(LR)
         model.compile(loss=(categorical_crossentropy), optimizer=optimizer, metrics=['accuracy'])
         history = model.fit(X, Y, validation_split=0.05, batch_size=128, epochs=NUM_EPOCHS, shuffle = True, history

```

```

Epoch 1/2
246/246: ----- 11s 33ms/step - loss: 5.1117 - accuracy: 0.1126 - val_loss: 5.3407 - v
al_accuracy: 0.1598
Epoch 2/2
246/246: ----- 7s 29ms/step - loss: 4.0841 - accuracy: 0.2139 - val_loss: 5.3808 - va
l_accuracy: 0.1659

```

Lastly, we can save the model and its history (containing an evaluation of the model's loss and accuracy) for future retrieval using the following lines of code:

```

In [94]: model.save("keras_next_song_model.h5")
         pickle.dump(history, open("history.p", "wb"))

         model = load_model("keras_next_song_model.h5")
         history = pickle.load(open("history.p", "rb"))

```

## Using the Model to Generate Predictions

Now that we have a trained model, we can use it to generate song predictions based on a subsequence of the test set. First, we use the prepare\_input function to mark the indices corresponding to the songs contained in the sequence. Then, the sample function will select the

In [144]

```
def prepare_input(text, seq_length = SEQ_LENGTH):
    x = np.zeros((1, seq_length, len(unique_songs)))
    for t, song in enumerate(text):
        x[0, t, unique_song_index[song]] = 1
```



```
return x

def sample(preds, top_n = 3):
    preds = np.argsort(preds).astype("float64")
    preds = np.topk(preds)
    exp_preds = np.exp(preds)
    preds = exp_preds / np.sum(exp_preds)

    return heapq.nlargest(top_n, range(len(preds)), preds.take)

def predict_completions(text, n=3):
    x = prepare_input(text, n)
    preds = model.predict(x, verbose=0)[0]
    next_indices = sample(preds, n)
    return [unique_songs[idx] for idx in next_indices]
```

We can use this code to randomly predict songs in the test set.

```
In [111]: rand = np.random.randint(len(test_set))
q = test_set[rand+SEQ_LENGTH]
seq = q[0:len(q) - 1]
print("Sequence: ", seq)
print("Correct song: ", q[SEQ_LENGTH - 1])
print("Next possible songs: ", predict_completions(seq, SEQ_LENGTH))

Sequence: ['"Mike\'s Song"\n', '"The Horse"\n', '"Silent in the Morning"\n', '"Punch You in the Eye"\n']
Correct song: "McGrupp and the Matchful Hosemasters"

Next possible songs: ["Weekapaug Groove"\n', '"ENCORE"\n', '"SET 2"\n', '"Hold Your Head Up"\n', '"SET 3"\n']
```

## Testing The Effect Various Parameters

Here, the code from above has been copied down to conveniently test the effects that changing various parameters has on the speed and accuracy of the model.

```
In [162]: def create_and_evaluate_model(seq_length, lstm_nodes, num_epochs, lr):
    prev_songs = []
    test_songs = []
    for i in range(len(training_set) - seq_length):
        prev_songs.append(training_set[i:i + seq_length])
        next_songs.append(training_set[i + seq_length])

    X = np.zeros((len(prev_songs), seq_length, len(unique_songs)), dtype = bool)
    Y = np.zeros((len(next_songs), len(unique_songs)), dtype = bool)

    for i, each_song in enumerate(prev_songs):
        for j, each_song in enumerate(each_song):
            X[i, j, unique_song_index(each_song)] = 1
            Y[i, unique_song_index(next_songs[i])] = 1

    model = Sequential()
    model.add(LSTM(lstm_nodes, input_shape=(seq_length, len(unique_songs))))
    model.add(Dense(len(unique_songs)))
    model.add(Activation("softmax"))

    optimizer = RMSprop(lr)
    model.compile(loss="categorical_crossentropy", optimizer=optimizer, metrics=["accuracy"])
    history = model.fit(X, Y, validation_split=0.05, batch_size=128, epochs = num_epochs, shuffle = True, history

    # summarize history for accuracy
    plt.plot(history['accuracy'])
    plt.plot(history['val_accuracy'])
    plt.title('model accuracy')
    plt.xlabel('epoch')
    plt.ylabel('accuracy')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()

    # summarize history for loss
    plt.plot(history['loss'])
    plt.plot(history['val_loss'])
    plt.title('model loss')
    plt.xlabel('epoch')
    plt.ylabel('loss')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()

    correct = 0
    for i in range(seq_length, len(test_set) - seq_length):
        q = test_set[i:seq_length + 1]
        seq = q[0:len(q)-1]
        predicted_songs = predict_completions(seq, seq_length)
        if q[len(q)-1] in predicted_songs:
            correct += 1
    print("Guessed", correct, "correct out of", len(test_set) - seq_length)
```

```
In [161]: # The length of the song sequence that the model will look at to predict the next song.
SEQ_LENGTH = 5

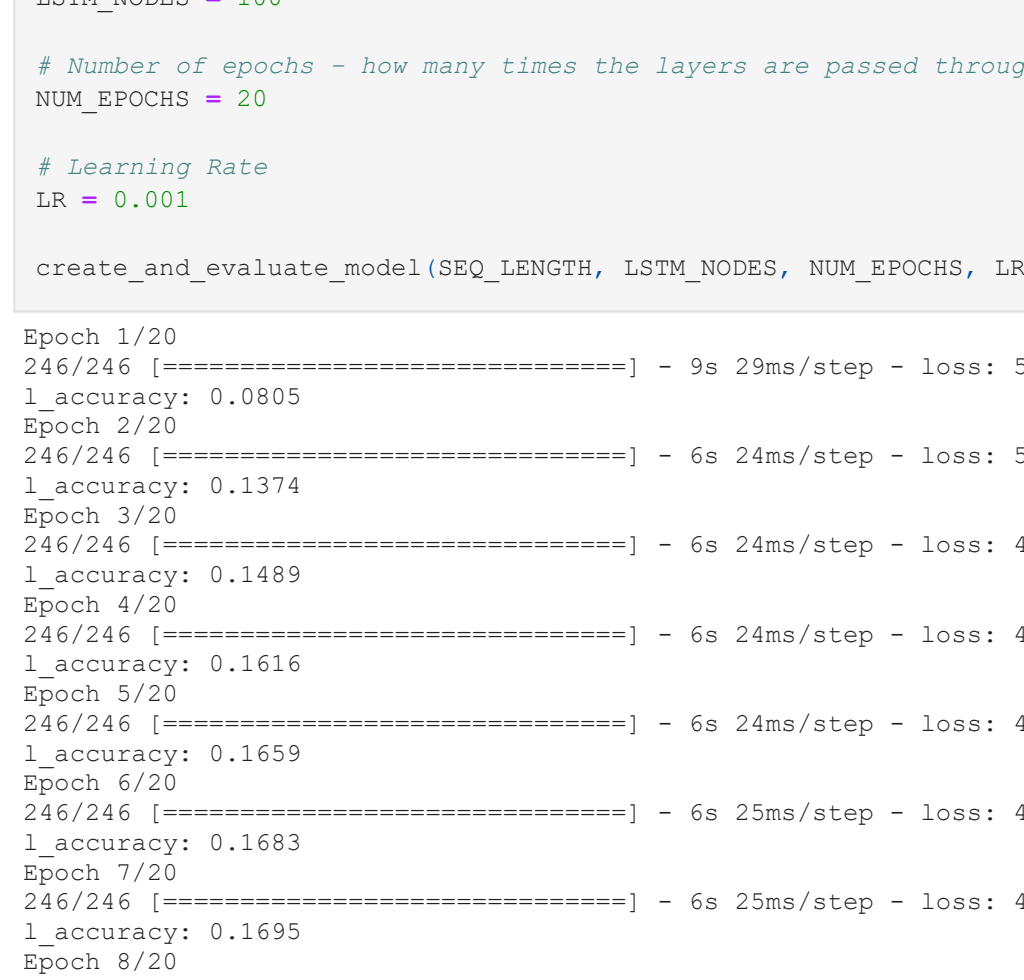
# Number of nodes in the LSTM layer
LSTM_NODES = 128

# Number of epochs - how many times the layers are passed through (forward + backwards = 1 epoch)
NUM_EPOCHS = 2

# Learning Rate
LR = 0.01

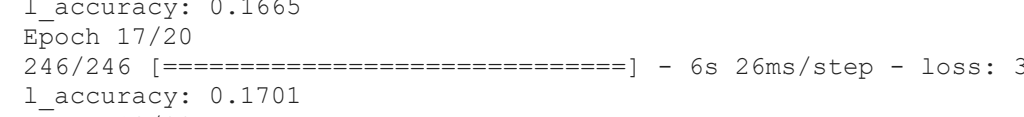
# Testing various values:
print("1. Default values:")
create_and_evaluate_model(SEQ_LENGTH, LSTM_NODES, NUM_EPOCHS, LR)
print("2. SEQ_LENGTH = 10:")
create_and_evaluate_model(10, LSTM_NODES, NUM_EPOCHS, LR)
print("3. SEQ_LENGTH = 20:")
create_and_evaluate_model(20, LSTM_NODES, NUM_EPOCHS, LR)
print("4. LSTM_NODES = 50:")
create_and_evaluate_model(SEQ_LENGTH, 50, NUM_EPOCHS, LR)
print("5. LSTM_NODES = 150:")
create_and_evaluate_model(SEQ_LENGTH, 150, NUM_EPOCHS, LR)
print("6. NUM_EPOCHS = 5:")
create_and_evaluate_model(SEQ_LENGTH, LSTM_NODES, 5, LR)
print("7. NUM_EPOCHS = 10:")
create_and_evaluate_model(SEQ_LENGTH, LSTM_NODES, 10, LR)
print("8. NUM_EPOCHS = 20:")
create_and_evaluate_model(SEQ_LENGTH, LSTM_NODES, 20, LR)
print("9. LR = 0.1:")
create_and_evaluate_model(SEQ_LENGTH, LSTM_NODES, NUM_EPOCHS, 0.1)
print("10. LR = 0.001:")
create_and_evaluate_model(SEQ_LENGTH, LSTM_NODES, NUM_EPOCHS, 0.001)
```

```
10. LR = 0.001:
246/246 [=====] - 10s 32ms/step - loss: 5.6307 - accuracy: 0.0489 - val_loss: 6.0575 - v
l_accuracy: 0.0981
Epoch 2/2:
246/246 [=====] - 7s 29ms/step - loss: 5.0534 - accuracy: 0.1043 - val_loss: 5.9492 - va
l_accuracy: 0.1386
```



Guessed 18 correct out of 8217

```
In [161]: epoch_num = [1, 3, 5, 7, 9, 11, 13, 15, 17, 19]
epoch_time = [9, 21, 33, 45, 57, 69, 81, 93, 105, 117]
plt.plot(epoch_num, epoch_time)
plt.title('Time to Train Model')
plt.xlabel('Time (s)')
plt.ylabel('epoch')
plt.show()
```



Additionally, we can see from this graph above that the time to train the model increases linearly with the number of passes completed through the neural network.

Now, we are going to use the following values for our parameters:

```
In [164]: # The length of the song sequence that the model will look at to predict the next song.
SEQ_LENGTH = 5

# Number of nodes in the LSTM layer
LSTM_NODES = 100

# Number of epochs - how many times the layers are passed through (forward + backwards = 1 epoch)
NUM_EPOCHS = 20

# Learning Rate
LR = 0.001

create_and_evaluate_model(SEQ_LENGTH, LSTM_NODES, NUM_EPOCHS, LR)

Epoch 1/20
246/246 [=====] - 9s 29ms/step - loss: 5.6793 - accuracy: 0.0502 - val_loss: 5.9622 - va
l_accuracy: 0.0905
Epoch 2/20
246/246 [=====] - 6s 24ms/step - loss: 5.0932 - accuracy: 0.0865 - val_loss: 5.8209 - va
l_accuracy: 0.1374
Epoch 3/20
246/246 [=====] - 6s 24ms/step - loss: 4.7624 - accuracy: 0.1386 - val_loss: 5.6149 - va
l_accuracy: 0.1489
Epoch 4/20
246/246 [=====] - 6s 24ms/step - loss: 4.5648 - accuracy: 0.1598 - val_loss: 5.4905 - va
l_accuracy: 0.1616
Epoch 5/20
246/246 [=====] - 6s 24ms/step - loss: 4.3991 - accuracy: 0.1777 - val_loss: 5.4596 - va
l_accuracy: 0.1659
Epoch 6/20
246/246 [=====] - 6s 25ms/step - loss: 4.3095 - accuracy: 0.1835 - val_loss: 5.4483 - va
l_accuracy: 0.1683
Epoch 7/20
246/246 [=====] - 6s 25ms/step - loss: 4.2147 - accuracy: 0.2032 - val_loss: 5.4339 - va
l_accuracy: 0.1695
Epoch 8/20
246/246 [=====] - 6s 24ms/step - loss: 4.1575 - accuracy: 0.1963 - val_loss: 5.3296 - va
l_accuracy: 0.1659
Epoch 9/20
246/246 [=====] - 6s 24ms/step - loss: 4.0994 - accuracy: 0.2032 - val_loss: 5.2890 - va
l_accuracy: 0.1713
Epoch 10/20
246/246 [=====] - 6s 25ms/step - loss: 4.0777 - accuracy: 0.2118 - val_loss: 5.3262 - va
l_accuracy: 0.1713
Epoch 11/20
246/246 [=====] - 6s 26ms/step - loss: 4.0116 - accuracy: 0.2118 - val_loss: 5.3706 - va
l_accuracy: 0.1713
Epoch 12/20
246/246 [=====] - 6s 24ms/step - loss: 3.9403 - accuracy: 0.2242 - val_loss: 5.2758 - va
l_accuracy: 0.1659
Epoch 13/20
246/246 [=====] - 6s 26ms/step - loss: 3.9106 - accuracy: 0.2234 - val_loss: 5.4240 - va
l_accuracy: 0.1701
Epoch 14/20
246/246 [=====] - 6s 25ms/step - loss: 3.8898 - accuracy: 0.2271 - val_loss: 5.3879 - va
l_accuracy: 0.1737
Epoch 15/20
246/246 [=====] - 6s 26ms/step - loss: 3.8363 - accuracy: 0.2341 - val_loss: 5.3596 - va
l_accuracy: 0.1725
Epoch 16/20
246/246 [=====] - 6s 25ms/step - loss: 3.7861 - accuracy: 0.2424 - val_loss: 5.4190 - va
l_accuracy: 0.1665
Epoch 17/20
246/246 [=====] - 6s 26ms/step - loss: 3.7663 - accuracy: 0.2414 - val_loss: 5.4677 - va
l_accuracy: 0.1701
Epoch 18/20
246/246 [=====] - 6s 25ms/step - loss: 3.7258 - accuracy: 0.2465 - val_loss: 5.4435 - va
l_accuracy: 0.1634
Epoch 19/20
246/246 [=====] - 6s 25ms/step - loss: 3.6957 - accuracy: 0.2490 - val_loss: 5.4430 - va
l_accuracy: 0.1580
Epoch 20/20
246/246 [=====] - 6s 25ms/step - loss: 3.6553 - accuracy: 0.2594 - val_loss: 5.5645 - va
l_accuracy: 0.1665
```



Guessed 2956 correct out of 8217

When looking at the model's performance on the test set, we see that it always has a high loss and accuracy does not seem to be affected by the various parameters we modified. When running the model on the test set, we see that the prediction contained the actual next song 2856 out of 8217 times, for a test accuracy of ~35%.

## The Setlist Generator

We will use the final model with the parameters above to create the setlist generator. We start the setlist as every set should start - by annotating the beginning of the first set. The generator uses the last LENGTH songs from the setlist (or the entire setlist if it is smaller than LENGTH, and will select songs randomly from the set of predicted songs to append to the setlist. The generator will continue to generate values until it reaches a random limit (15-25, the range of an average Phish setlist), or "END", marking the end of the show.

```
In [178]: def generate_setlist():
    setlist = []
    rand = np.random.randint(len(songs))
    setlist.append("SET 1\n")
    idx = 1
    go = True
    limit = np.random.randint(15) + 10
    while(go and idx < limit):
        rand = np.random.randint(SEQ_LENGTH)
        if(idx < SEQ_LENGTH):
            new_songs = predict_completions(setlist[idx], SEQ_LENGTH)
            new_song = new_songs[rand]
            setlist.append(new_song)
            if new_song == "END\n":
                go = False
            idx += 1
    return setlist

print(generate_setlist())

["SET 1\n", '"Divided Sky"\n', '"Strash"\n', '"Sparkle"\n', '"I Didn\'t Know"\n', '"Split Open and Melt"\n', '"T
he Lizards"\n', '"Run Like an Antelope"\n', '"SET 2"\n', '"Wilson"\n', '"Mike\'s Song"\n', '"Simple"\n', '"Simpl
e"\n', '"Mike\'s Song"\n', '"Weekapaug Groove"\n', '"SET 2"\n', '"Mike\'s Song"\n', '"I Am Hydrogen"\n']

In [182]: for i in range(10):
    print(generate_setlist())

["SET 1\n", '"Water in the Sky"\n', '"Taste"\n', '"Scent of a Mule"\n', '"Stash"\n', '"Fee"\n', '"Maze"\n', '"S
trange Design"\n', '"Run Like an Antelope"\n', '"Goigi Apparatus"\n', '"SET 3"\n', '"Also Sprach Zarathustra"\n',
'"Mike\'s Song"\n', '"Mike\'s Song"\n', '"Simple"\n', '"I Am Hydrogen"\n', '"Weekapaug Groov
e"\n']
["SET 1\n", '"Divided Sky"\n', '"Strash"\n', '"Stash"\n', '"Maze"\n', '"I Didn\'t Know"\n', '"Run Like an Antelo
pe"\n', '"SET 2"\n', '"Also Sprach Zarathustra"\n', '"Mike\'s Song"\n', '"I Am Hydrogen"\n']
["SET 1\n", '"Funky Bitch"\n', '"David Bowie"\n', '"Alumni Blues"\n', '"Alumni Blues"\n', '"Run Like an Antelo
pe"\n', '"SET 3"\n', '"Alumni Blues"\n', '"Alumni Blues"\n', '"The Lizards"\n', '"Mike\'s Song"\n', '"Alumni Blues"\n',
'"Letter to Jimmy Page"\n', '"END"\n']
["SET 1\n", '"Water in the Sky"\n', '"Scent of a Mule"\n', '"Taste"\n', '"Strange Design"\n', '"Taste"\n', '"EN
CORE"\n', '"Stay Greenberg"\n', '"Body Top"\n', '"Weezer Reprise"\n', '"ENCORE 2"\n', '"Bouncing Around the Roo
m"\n', '"Poor Heart"\n']
["SET 1\n", '"Divided Sky"\n', '"Body Top"\n', '"Weezer Reprise"\n', '"ENCORE 2"\n', '"Bouncing Around the Roo
m"\n', '"Poor Heart"\n']
["SET 1\n", '"McGrupp and the Matchful Hosemasters"\n', '"David Bowie"\n', '"SET 2"\n', '"AC/DC Bag"\n', '"B
Divided Sky"\n', '"McGrupp and the Matchful Hosemasters"\n', '"David Bowie"\n', '"ENCORE"\n', '"Peaches en Regalia"\n', '"B
ND"\n']
["SET 1\n", '"Fee"\n', '"Fee"\n', '"I Didn\'t Know"\n', '"David Bowie"\n', '"SET 2"\n', '"AC/DC Bag"\n', '"The
Lizards"\n', '"Mike\'s Song"\n', '"Mike\'s Song"\n', '"McGrupp and the Matchful Hosemasters"\n', '"I Am Hydroge
n"\n', '"Mike\'s Song"\n']
["SET 1\n", '"Fee"\n', '"The Lizards"\n', '"I Didn\'t Know"\n', '"McGrupp and the Matchful Hosemasters"\n', '"D
avid Bowie"\n', '"Goigi Apparatus"\n', '"SET 3"\n', '"Wilson"\n', '"Peaches en Regalia"\n', '"You Enjoy Myse
lf"\n']
["SET 1\n", '"Divided Sky"\n', '"Split Open and Melt"\n', '"Maze"\n', '"Sparkle"\n', '"Stash"\n', '"SET 2"\n',
'"Maze"\n', '"Bouncing Around the Room"\n', '"Rite"\n', '"Free"\n', '"Prince Caspian"\n', '"David Bowie"\n', '"SE
T 2"\n', '"Down with Disease"\n', '"Free"\n', '"GulfStream"\n', '"Weezer"\n', '"The Sango Song"\n', '"Mike\'s Son
g"\n']
["SET 1\n", '"You Enjoy Myself"\n', '"AC/DC Bag"\n', '"Divided Sky"\n', '"You Enjoy Myself"\n', '"Fee"\n', '"Yo
u Enjoy Myself"\n', '"ENCORE"\n', '"Fize"\n', '"SET 2"\n', '"END"\n']
["SET 1\n", '"Water in the Sky"\n', '"Bogga"\n', '"Wolfman\'s Brother"\n', '"Limb By Limb"\n', '"Wolfman\'s Br
other"\n', '"SET 2"\n', '"Down with Disease"\n', '"Fize"\n', '"Fize"\n', '"Prince Caspian"\n', '"You Enjoy Myse
lf"\n']
["SET 1\n", '"Weezer Reprise"\n', '"END"\n']
```

## Conclusion

After testing the final model against the test set, we found that the correct subsequent song was present in the list of length 5 about 35% of the time, which is significantly greater than if 5 songs were to be chosen at random from the 950 songs that are in Phish's live catalogue. However, when looking at the actual accuracy of the model on the test set, the results became less impressive, as the accuracy falls to 26%.

When looking at the setlists generated by the final function, some of them appear to be very passable as legitimate Phish setlists. However, some quirks in other entries become immediately apparent: the duplicate entries (songs are allowed to appear on a setlist two or more times (with anything greater than three being an extreme rarity), however a song will never appear twice consecutively) and the seemingly random placement of the set-indicators (causing severe inequality between sets: set 1 may contain 80% of the songs while set 2 may only have a couple of songs; not all sets made equal and some sets may have significantly more songs than another set at the same show, but never to this extreme). The model's accuracy value and as well as looking at the randomly generated setlists myself has led me to this conclusion: the model is competent at recognizing certain patterns in setlist and set construction (certain songs always following each other- "I Am Hydrogen">"Weekapaug Groove", an encore will usually have one or two songs before show END). But, when looking at the dataset as a whole - 'setlist entries are an order or perhaps the dataset is not large enough to come to any reliable predictor of the bands setlists.

If I were to complete this project again, I would try to factor location and date of shows into the likelihood that a certain song will be played. As it stands now, the model is only looking for patterns in sequencing, but adding location and date data could be immensely helpful in clustering songs. Location would be useful for songs like "Fluffhead", which is performed more often at shows in New York City/State due to the lyric "Fluff Came To New York" provoking a cheer from the audience. For date, there are certain songs that were performed often in the past but infrequently now, or vice-versa (a song they may have just written, for example). These were all factors that I considered when originally brainstorming ideas for this project, however I unfortunately had to cut those aspects in order for this project to fit in a realistic time window and exist at a level of complexity that I was comfortable working on. This is a project and a topic that has inspired me, and I hope to return and improve upon it once I have more experience in the field of machine learning. Until then, only Phish can create Phish setlists.