```python
import os
import pandas as pd
import numpy as np
import librosa
import random
import time
import pickle

from librosa.display import specshow, waveplot

from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelBinarizer

import IPython.display as ipd

import matplotlib
import matplotlib.pyplot as plt
%matplotlib inline
```

```python
from keras.models import Sequential
from keras.layers import Dense, MaxPooling2D, Conv2D, Flatten, Dropout, Input, BatchNor
from keras.models import Model, load_model
from keras.callbacks import Callback, EarlyStopping
from keras.metrics import top_k_categorical_accuracy
```

```
Using TensorFlow backend.
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.
We recommend you upgrade now or ensure your notebook will continue to use TensorFlow 1.x via the `%tensorflow_version 1.x` magic: more info.

```python
from google.colab import drive
drive.mount('/gdrive')
%cd /gdrive/My\ Drive/Colab\ Notebooks
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=9473189

Enter your authorization code:
··········
Mounted at /gdrive
/gdrive/My Drive/Colab Notebooks
```

Making Sense of Genres

The first step is seeing how many tracks per genre we have in our dataset, and potentially simplifiying the output of our neural net to include only the top 5. I ended up not doing this in this notebook, but was able to achieve a higher accuracy than before.

Previously, I attempted outputing its confidence for all 161 total genres, and only reached 20% accuracy while training. You can see that journey in my other notebook, training2_svc.

```
genres = pd.read_csv("genres.csv", index_col=0)
genres
```

	#tracks	parent	title	top_level
genre_id				
1	8693	38	Avant-Garde	38
2	5271	0	International	2
3	1752	0	Blues	3
4	4126	0	Jazz	4
5	4106	0	Classical	5
...	...	...	...	...
1032	60	102	Turkish	2
1060	30	46	Tango	2
1156	26	130	Fado	2
1193	72	763	Christmas	38
1235	14938	0	Instrumental	1235

163 rows × 4 columns

```
genres = genres.sort_values(by='#tracks', ascending=False)
genres.head(5)
```

	#tracks	parent	title	top_level
genre_id				
38	38154	0	Experimental	38
15	34413	0	Electronic	15
12	32923	0	Rock	12
1235	14938	0	Instrumental	1235
10	13845	0	Pop	10

Adding Echonest Attributes

Whoop, our top genres are: Experimental, Electronic, Rock, Instrumental, and Pop.

Next, since I want to use this classifier for my senior design project as well, I want to incorporate attributes from *echonest*.

Echnoest, now Spotify, includes numerical values for tracks for traits like dancebility, energy, speechiness, etc-- these will be very valuable when teaching a stick figure to dance. (my senior design)

```python
echonest = pd.read_csv("echonest.csv", header=[0, 2], skipinitialspace=True, index_col=
echonest.head()
```

	echonest						
	acousticness	danceability	energy	instrumentalness	liveness	speechiness	t
track_id							
2	0.416675	0.675894	0.634476	0.010628	0.177647	0.159310	1
3	0.374408	0.528643	0.817461	0.001851	0.105880	0.461818	1
5	0.043567	0.745566	0.701470	0.000697	0.373143	0.124595	1
10	0.951670	0.658179	0.924525	0.965427	0.115474	0.032985	1
134	0.452217	0.513238	0.560410	0.019443	0.096567	0.525519	1

5 rows × 249 columns

```python
for col in echonest:
    if col[0] == "metadata":
        echonest.drop(col, axis=1, inplace=True)
    elif col[0] == "ranks":
        echonest.drop(col, axis=1, inplace=True)
    elif col[0] == "social_features":
        echonest.drop(col, axis=1, inplace=True)
```

```python
echonest.columns = echonest.columns.droplevel(0)
```

```python
echonest_sub = echonest[['acousticness', 'danceability', 'energy', 'instrumentalness',
echonest_sub.head()
```

Adding Track Data

Now let's incorporating part of the track dataset.

```
tracks = pd.read_csv("tracks.csv", header=[0, 1], skipinitialspace=True, index_col=0)
tracks.columns = tracks.columns.droplevel(0)
tracks.head()
```

	comments	date_created	date_released	engineer	favorites	id	information	li
track_id								
2	0	2008-11-26 01:44:45	2009-01-05 00:00:00	NaN	4	1	<p></p>	
3	0	2008-11-26 01:44:45	2009-01-05 00:00:00	NaN	4	1	<p></p>	
5	0	2008-11-26 01:44:45	2009-01-05 00:00:00	NaN	4	1	<p></p>	
10	0	2008-11-26 01:45:08	2008-02-06 00:00:00	NaN	4	6	NaN	
20	0	2008-11-26 01:45:05	2009-01-06 00:00:00	NaN	2	4	<p> "spiritual songs" from Nicky Cook</p>	

```
tracks_sub = tracks[['listens', 'name', 'duration', 'genre_top', 'genres', 'title']]
tracks_sub.head()
tracks_sub.columns = ['listens_album', 'listens_track', 'name', 'duration', 'genre_top'
```

```
tracks_sub.head()
```

track_id	listens_album	listens_track	name	duration	genre_top	genres	title_album
2	6073	1293	AWOL	168	Hip-Hop	[21]	AWOL - A Way Of Life
3	6073	514	AWOL	237	Hip-Hop	[21]	AWOL - A Way Of Life
5	6073	1151	AWOL	206	Hip-Hop	[21]	AWOL - A Way Of Life
10	47632	50135	Kurt Vile	161	Pop	[10]	Constant Hitmaker
20	2710	361	Nicky Cook	311	NaN	[76, 103]	Niris

Merging Tracks, Echonest, and Genres

oh boy

```
tracks_echo = pd.merge(tracks_sub, echonest_sub, how="inner", on="track_id")
```

```
tracks_echo.head()
```

track_id	listens_album	listens_track	name	duration	genre_top	genres	title_album
2	6073	1293	AWOL	168	Hip-Hop	[21]	AWOL - A Way Of Life
3	6073	514	AWOL	237	Hip-Hop	[21]	AWOL - A Way Of Life
5	6073	1151	AWOL	206	Hip-Hop	[21]	AWOL - A Way Of Life
10	47632	50135	Kurt Vile	161	Pop	[10]	Constant Hitmaker
134	6073	943	AWOL	207	Hip-Hop	[21]	AWOL - A Way Of Life

```
tracks_echo_genres = pd.merge(tracks_echo, genres, how="left", left_on="genre_top", rig
```

```python
tracks_echo_genres.head()
```

	listens_album	listens_track	name	duration	genre_top	genres	title_album
track_id							
2	6073	1293	AWOL	168	Hip-Hop	[21]	AWOL - A Way Of Life
3	6073	514	AWOL	237	Hip-Hop	[21]	AWOL - A Way Of Life
5	6073	1151	AWOL	206	Hip-Hop	[21]	AWOL - A Way Of Life
10	47632	50135	Kurt Vile	161	Pop	[10]	Constant Hitmaker
134	6073	943	AWOL	207	Hip-Hop	[21]	AWOL - A Way Of Life

```python
tracks_echo_genres.to_pickle("./tracks_echo_genres.pkl")
```

Adding Features

This is the final piece left to merge into our monster dataset. There are a lot of attributes here-- 518-- so I want to do some dimensionality reduction here. I will be using PCA post-merge.

```python
features = pd.read_csv("features.csv", header=[0, 1, 2], skipinitialspace=True, index_c
features.head()
```

feature	**chroma_cens**								
statistics	**kurtosis**								
number	**01**	**02**	**03**	**04**	**05**	**06**	**07**	**08**	**09**
track_id									
2	7.180653	5.230309	0.249321	1.347620	1.482478	0.531371	1.481593	2.691455	0.86
3	1.888963	0.760539	0.345297	2.295201	1.654031	0.067592	1.366848	1.054094	0.10
5	0.527563	-0.077654	-0.279610	0.685883	1.937570	0.880839	-0.923192	-0.927232	0.66
10	3.702245	-0.291193	2.196742	-0.234449	1.367364	0.998411	1.770694	1.604566	0.52
20	-0.193837	-0.198527	0.201546	0.258556	0.775204	0.084794	-0.289294	-0.816410	0.04

5 rows × 518 columns

```python
# MERGING!!!
monster = pd.merge(tracks_echo_genres, features, how="inner", on="track_id")
```

```
/usr/local/lib/python3.6/dist-packages/pandas/core/reshape/merge.py:617: UserWarning: me
  warnings.warn(msg, UserWarning)
```

```
monster.head()
```

.e_album	title_track	acousticness	danceability	energy	instrumentalness	liveness	spe
)L - A Way Of Life	Food	0.416675	0.675894	0.634476	0.010628	0.177647	
)L - A Way Of Life	Electric Ave	0.374408	0.528643	0.817461	0.001851	0.105880	
)L - A Way Of Life	This World	0.043567	0.745566	0.701470	0.000697	0.373143	
Constant Hitmaker	Freeway	0.951670	0.658179	0.924525	0.965427	0.115474	
)L - A Way Of Life	Street Music	0.452217	0.513238	0.560410	0.019443	0.096567	

```
monster.to_pickle("./monster.pkl")
```

PCA Shenanigans for Dimensionality Reduction

```
from sklearn.preprocessing import StandardScaler
feats = monster.columns

# Separating out the features
numerics = ['int16', 'int32', 'int64', 'float16', 'float32', 'float64']
x = monster.select_dtypes(include=numerics).values

# x = monster.loc[:, feats].values
# Separating out the target
y = monster.loc[:,['genre_top']].values

# Standardizing the features
X = StandardScaler().fit_transform(x)
```

```
X.shape
```

```
(13129, 532)
```

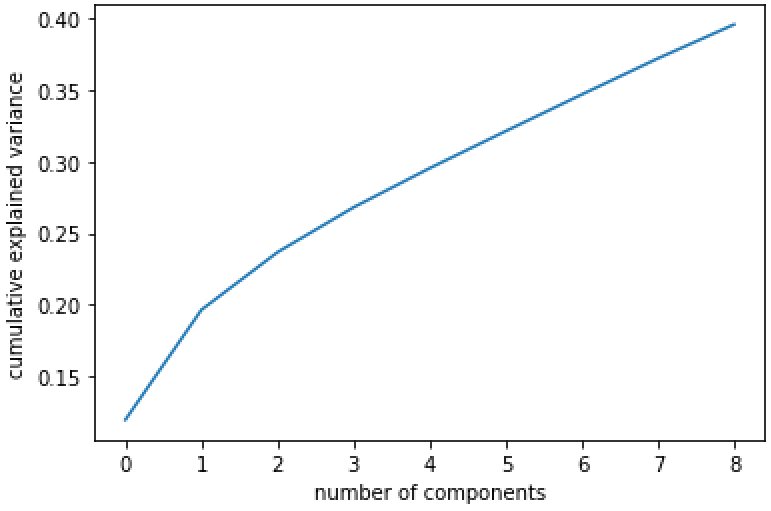
```
# no nan vals allowed!!!
```

```
from sklearn.impute import SimpleImputer

imputer = SimpleImputer(missing_values=np.nan, strategy='mean')
imputer = imputer.fit(X[:,1:532])
X[:,1:532] = imputer.transform(X[:,1:532])
```

```
from sklearn.decomposition import PCA

pca = PCA(n_components=9) # for number of big attributes?
principalComponents = pca.fit_transform(X)
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2', 'principal 
```

```
# SCREE PLOT
print(pca.explained_variance_ratio_)
print(np.cumsum(pca.explained_variance_ratio_))

#Explained variance
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('number of components')
plt.ylabel('cumulative explained variance')
plt.show()
```

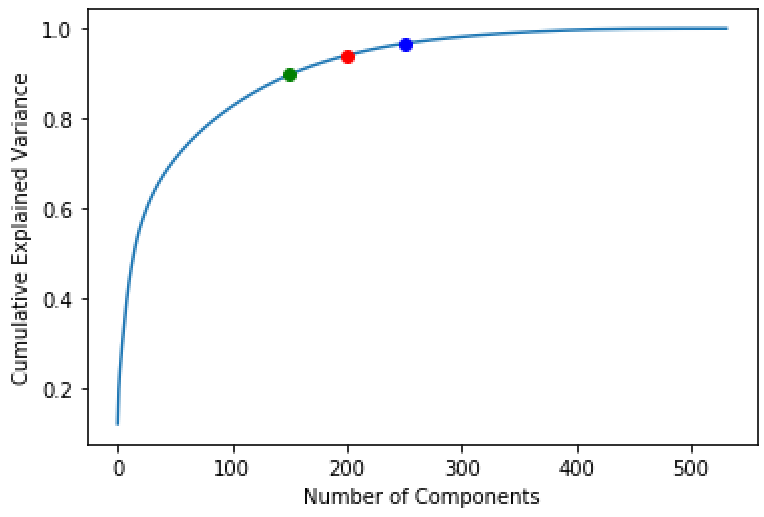
```
[0.11959576 0.07689131 0.04026169 0.03136196 0.02734066 0.0259367
 0.02560827 0.02520922 0.02367956]
[0.11959576 0.19648707 0.23674876 0.26811072 0.29545139 0.32138809
 0.34699636 0.37220558 0.39588514]
```



Ok!!!!!!!! So, this shows that with 9 components, it represents 40% of variance in the data.

Let's make a generic scree plot to see how many components might make more sense:

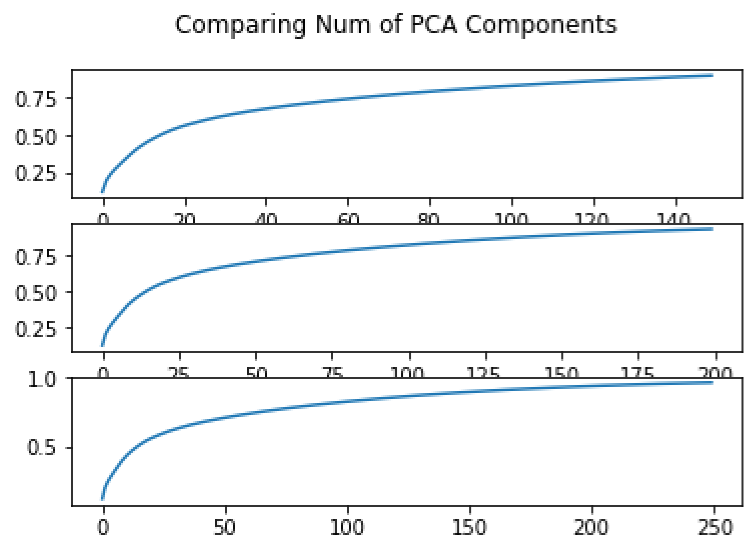
```
# SCREE PLOT

#Explained variance
pca = PCA().fit(X)
plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')

plt.plot(250, np.cumsum(pca.explained_variance_ratio_)[250], "ob")
plt.plot(200, np.cumsum(pca.explained_variance_ratio_)[200], "or")
plt.plot(150, np.cumsum(pca.explained_variance_ratio_)[150], "og")

plt.show()
```



This plot shows us that around 150-250 components might be a better number to try. Let's try it:

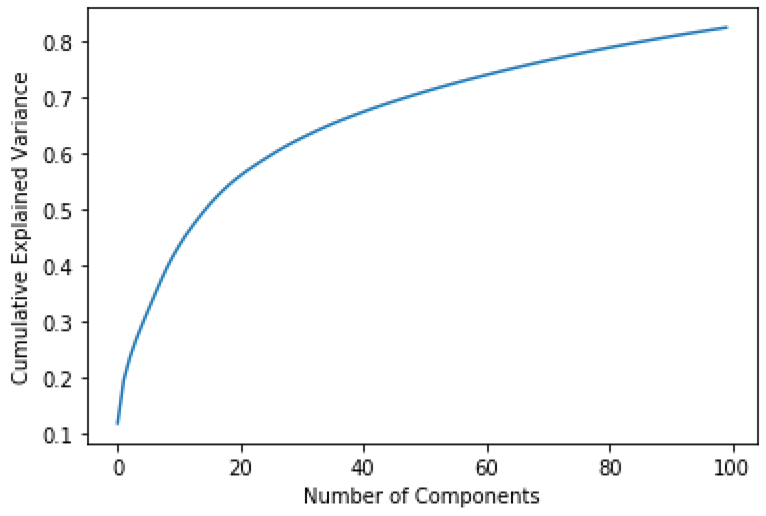
```
#Explained variance

fig, axs = plt.subplots(3)
fig.suptitle('Comparing Num of PCA Components')
# fig.xlabel('Number of Components')
# fig.ylabel('Cumulative Explained Variance')

# PLOT 1: 150 COMPONENTS
pca = PCA(n_components=150)
principalComponents = pca.fit_transform(X)
col_names = [("col_" + str(i)) for i in range(150)]
principalDf = pd.DataFrame(data = principalComponents
             , columns = col_names)
axs[0].plot(np.cumsum(pca.explained_variance_ratio_))

# PLOT 2: 200 COMPONENTS
pca = PCA(n_components=200)
principalComponents = pca.fit_transform(X)
col_names = [("col_" + str(i)) for i in range(200)]
principalDf = pd.DataFrame(data = principalComponents
             , columns = col_names)
axs[1].plot(np.cumsum(pca.explained_variance_ratio_))

# PLOT 3: 250 COMPONENTS
pca = PCA(n_components=250)
principalComponents = pca.fit_transform(X)
col_names = [("col_" + str(i)) for i in range(250)]
principalDf = pd.DataFrame(data = principalComponents
             , columns = col_names)
axs[2].plot(np.cumsum(pca.explained_variance_ratio_))
```

```
[<matplotlib.lines.Line2D at 0x7f5f3d5f8978>]
```



So.... they are looking basically the same! Let's see if we can go smaller than 150 components so that we can be faster while training

```
#Explained variance
pca = PCA(n_components=100) # for number of big attributes?
principalComponents = pca.fit_transform(X)
col_names = [("col_" + str(i)) for i in range(100)]
principalDf = pd.DataFrame(data = principalComponents
              , columns = col_names)

plt.plot(np.cumsum(pca.explained_variance_ratio_))
plt.xlabel('Number of Components')
plt.ylabel('Cumulative Explained Variance')
plt.show()

print(100, np.cumsum(pca.explained_variance_ratio_)[99])
```



```
100 0.8235167577314023
```

```
def compare_n_comp(n):
  pca = PCA(n_components=n)
  principalComponents = pca.fit_transform(X)
  print(n, str((np.cumsum(pca.explained_variance_ratio_)[n-1])*100), str('%'))

compare_n_comp(150)
compare_n_comp(175)
compare_n_comp(200)
```

```
150 89.51656816113069 %
175 91.96887994360743 %
200 93.89739765751429 %
```

Alright let's just go with 200 components. That'll be a 62% reduction!

```
#Explained variance
pca = PCA(n_components=200)
principalComponents = pca.fit_transform(X)
col_names = [("col_" + str(i)) for i in range(200)]
principalDf = pd.DataFrame(data = principalComponents
             , columns = col_names)
```

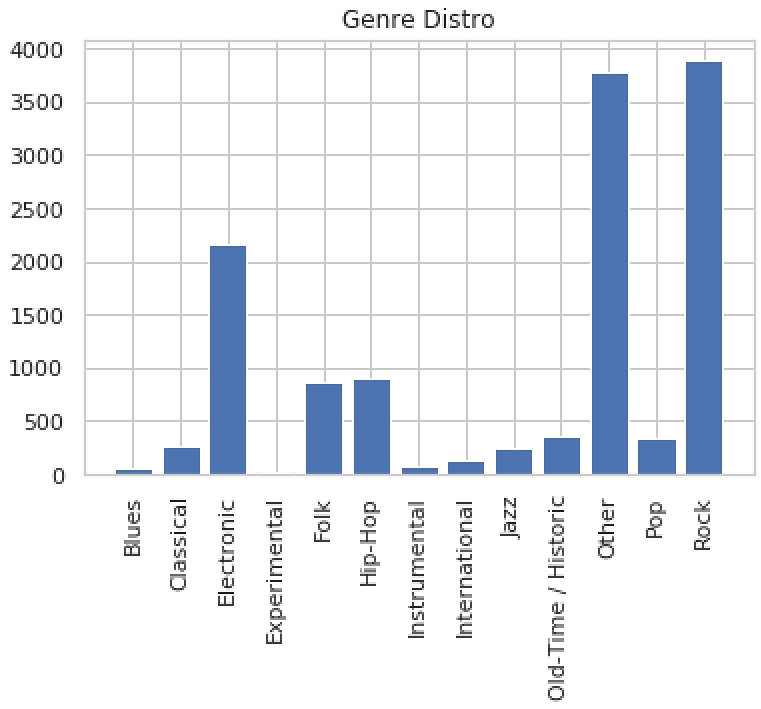
```
print(principalDf.shape)
print(y.shape)
```

```
(13129, 200)
(13129, 1)
```

I want to visualize the data I'm going to train with in some way... let's try taking the mean of all the numerical values in our PCA components and map them to their respective genre.

```
y_df = pd.DataFrame(y)
y_df = y_df.replace(np.nan, 'Other', regex=True)
y_map = dict(zip(*np.unique(y_df, return_counts=True)))
plt.bar(y_map.keys(), y_map.values())
plt.xticks(rotation='vertical')
plt.title("Genre Distro")

print(y_map)
```

```
{'Blues': 66, 'Classical': 265, 'Electronic': 2170, 'Experimental': 17, 'Folk': 874, 'Hi
```



Time to Train!

```
m sklearn.model_selection import train_test_split
ncipalDf = principalDf.replace(np.nan, 0, regex=True)

a = principalDf[:300]
els = y_df[:300]

a_train, data_test, label_train, label_test = train_test_split(data, labels, test_size=
```

```
scaler = StandardScaler()

# Fit on training set only.
scaler.fit(data_train)

# Apply transform to both the training set and the test set.
data_train = scaler.transform(data_train)
data_test = scaler.transform(data_test)
```

```
pca = PCA(.93) # this is about 200 components as we saw earlier
pca.fit(data_train)
```

```
PCA(copy=True, iterated_power='auto', n_components=0.93, random_state=None,
    svd_solver='auto', tol=0.0, whiten=False)
```

Bad

↳ *4 cells hidden*

So there's a problem here: I'm trying to use string values as labels for my dataset, which is not allowed. I decided to try this route (without thinking it all the way through) because the numerical genre values, genre_ids, were stored as a string of a list of a list, and I wanted to try to avoid dealing with that mess. Looks like it's unavoidable so let's...

Deal with the genre Label Mess

```
with open("genre_labels.pkl", "rb") as handle:
  genre_labels = pickle.load(handle)

genrelabels = pd.DataFrame.from_dict(genre_labels)
genrelabels.head()
```

	genre_id	genre_title
0	1	Avant-Garde
1	2	International
2	3	Blues
3	4	Jazz
4	5	Classical

```
abel_train2 = pd.merge(label_train, genrelabels, how="left", left_on=0, right_on="genre
```

```
label_train2.head()
```

	0	genre_id	genre_title
0	Other	NaN	NaN
1	Other	NaN	NaN
2	Rock	12.0	Rock
3	Rock	12.0	Rock
4	Other	NaN	NaN

```
label_test2 = pd.merge(label_test, genrelabels, how="left", left_on=0, right_on="genre_
label_test2.head()
```

	0	genre_id	genre_title
0	Other	NaN	NaN
1	Other	NaN	NaN
2	Rock	12.0	Rock
3	Other	NaN	NaN
4	Other	NaN	NaN

```
label_test = label_test2["genre_id"]
label_train = label_train2["genre_id"]
label_test = label_test.replace(np.nan, 0, regex=True)
label_train = label_train.replace(np.nan, 0, regex=True)

label_test, label_train
```

```
(0        0.0
 1        0.0
 2       12.0
 3        0.0
 4        0.0
         ...
 4328    12.0
 4329    15.0
 4330    12.0
 4331    12.0
 4332     4.0
 Name: genre_id, Length: 4333, dtype: float64, 0      12.0
 1      17.0
 2      12.0
 3      17.0
 4      17.0
        ...
 196    12.0
 197    12.0
 198    12.0
 199    21.0
 200    12.0
 Name: genre_id, Length: 201, dtype: float64)
```

OK! let's try to train again..

```
one_hot_train_labels = to_categorical(label_train.values)
one_hot_test_labels = to_categorical(label_test.values)

one_hot_train_labels.shape, one_hot_train_labels.shape
```

```
((201, 22), (201, 22))
```

```
from keras.models import Sequential
from keras.layers import Dense, Activation
```

```
model = Sequential()
model.add(Dense(32, activation='relu', input_shape=(200, )))
model.add(Dense(64, activation='relu'))
model.add(Dense(128, activation='relu'))
model.add(Dense(64, activation='relu'))
model.add(Dense(32, activation='tanh'))

model.add(Dense(161, activation='softmax'))

output = 164
model.add(Dense(output, activation='sigmoid')) # all genres

model.compile(optimizer='rmsprop', loss='sparse_categorical_crossentropy', metrics=['ac
model.summary()
```

```
Model: "sequential_60"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_296 (Dense)            (None, 32)                6432
_________________________________________________________________
dense_297 (Dense)            (None, 64)                2112
_________________________________________________________________
dense_298 (Dense)            (None, 128)               8320
_________________________________________________________________
dense_299 (Dense)            (None, 64)                8256
_________________________________________________________________
dense_300 (Dense)            (None, 32)                2080
_________________________________________________________________
dense_301 (Dense)            (None, 161)               5313
_________________________________________________________________
dense_302 (Dense)            (None, 164)               26568
=================================================================
Total params: 59,081
Trainable params: 59,081
Non-trainable params: 0
_________________________________________________________________
```

```
history = model.fit(data_train, label_train, epochs=50, batch_size=512, validation_spli
Epoch 22/50
180/180 [==============================] - 0s 72us/step - loss: 5.0201 - acc: 0.6444 - v
Epoch 23/50
180/180 [==============================] - 0s 82us/step - loss: 5.0175 - acc: 0.6500 - v
Epoch 24/50
180/180 [==============================] - 0s 75us/step - loss: 5.0148 - acc: 0.6500 - v
Epoch 25/50
180/180 [==============================] - 0s 90us/step - loss: 5.0121 - acc: 0.6500 - v
Epoch 26/50
180/180 [==============================] - 0s 74us/step - loss: 5.0094 - acc: 0.6500 - v
Epoch 27/50
180/180 [==============================] - 0s 73us/step - loss: 5.0068 - acc: 0.6500 - v
Epoch 28/50
180/180 [==============================] - 0s 70us/step - loss: 5.0042 - acc: 0.6500 - v
Epoch 29/50
180/180 [==============================] - 0s 81us/step - loss: 5.0017 - acc: 0.6500 - v
Epoch 30/50
180/180 [==============================] - 0s 77us/step - loss: 4.9991 - acc: 0.6556 - v
Epoch 31/50
180/180 [==============================] - 0s 76us/step - loss: 4.9966 - acc: 0.6556 - v
Epoch 32/50
180/180 [==============================] - 0s 76us/step - loss: 4.9941 - acc: 0.6556 - v
Epoch 33/50
180/180 [==============================] - 0s 79us/step - loss: 4.9916 - acc: 0.6556 - v
Epoch 34/50
180/180 [==============================] - 0s 73us/step - loss: 4.9891 - acc: 0.6556 - v
Epoch 35/50
180/180 [==============================] - 0s 77us/step - loss: 4.9866 - acc: 0.6556 - v
Epoch 36/50
180/180 [==============================] - 0s 63us/step - loss: 4.9841 - acc: 0.6556 - v
Epoch 37/50
180/180 [==============================] - 0s 81us/step - loss: 4.9817 - acc: 0.6556 - v
Epoch 38/50
180/180 [==============================] - 0s 61us/step - loss: 4.9792 - acc: 0.6556 - v
Epoch 39/50
180/180 [==============================] - 0s 61us/step - loss: 4.9768 - acc: 0.6556 - v
Epoch 40/50
180/180 [==============================] - 0s 101us/step - loss: 4.9744 - acc: 0.6556 -
Epoch 41/50
180/180 [==============================] - 0s 71us/step - loss: 4.9720 - acc: 0.6556 - v
Epoch 42/50
180/180 [==============================] - 0s 57us/step - loss: 4.9697 - acc: 0.6556 - v
Epoch 43/50
180/180 [==============================] - 0s 85us/step - loss: 4.9673 - acc: 0.6556 - v
Epoch 44/50
180/180 [==============================] - 0s 73us/step - loss: 4.9650 - acc: 0.6556 - v
Epoch 45/50
180/180 [==============================] - 0s 81us/step - loss: 4.9626 - acc: 0.6556 - v
Epoch 46/50
180/180 [==============================] - 0s 74us/step - loss: 4.9603 - acc: 0.6556 - v
Epoch 47/50
180/180 [==============================] - 0s 74us/step - loss: 4.9580 - acc: 0.6556 - v
Epoch 48/50
180/180 [==============================] - 0s 76us/step - loss: 4.9557 - acc: 0.6556 - v
Epoch 49/50
180/180 [==============================] - 0s 79us/step - loss: 4.9534 - acc: 0.6556 - v
Epoch 50/50
180/180 [==============================] - 0s 74us/step - loss: 4.9511 - acc: 0.6556 - v
```

```
# serialize model to JSON
model_json = model.to_json()
with open("model_2.json", "w") as json_file:
    json_file.write(model_json)
# serialize weights to HDF5
model.save_weights("model_2.h5")
print("Saved model to disk")
```

```
Saved model to disk
```

```
results_test = model.evaluate(data_test, label_test[:99])
print("results_test:", results_test)

results_train = model.evaluate(data_train, label_train)
print("results_train:", results_train)
```

```
99/99 [==============================] - 0s 242us/step
results_test: [nan, 0.25252525252525254]
201/201 [==============================] - 0s 117us/step
```

Another training attempt w another optimizer (worse)

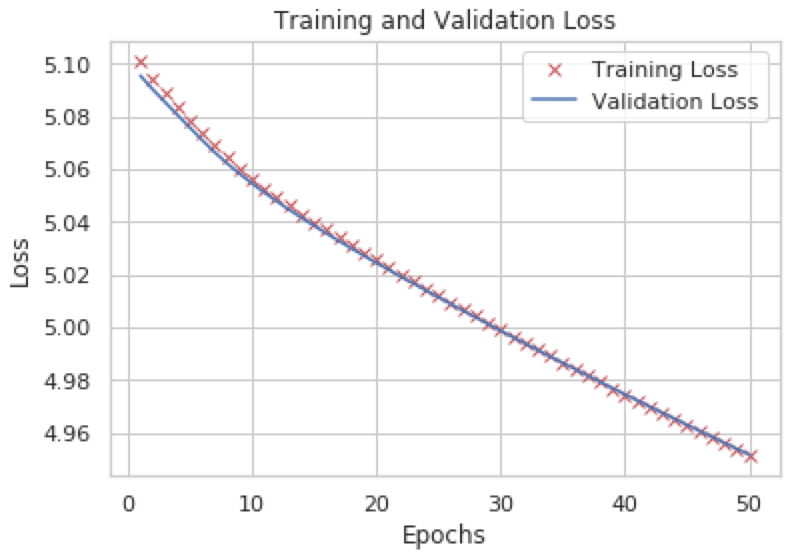
Not bad, we got to 76% (model_1) which is much better than the 21% we were getting before!

Let's play with a different regularizer to see if we can do better..

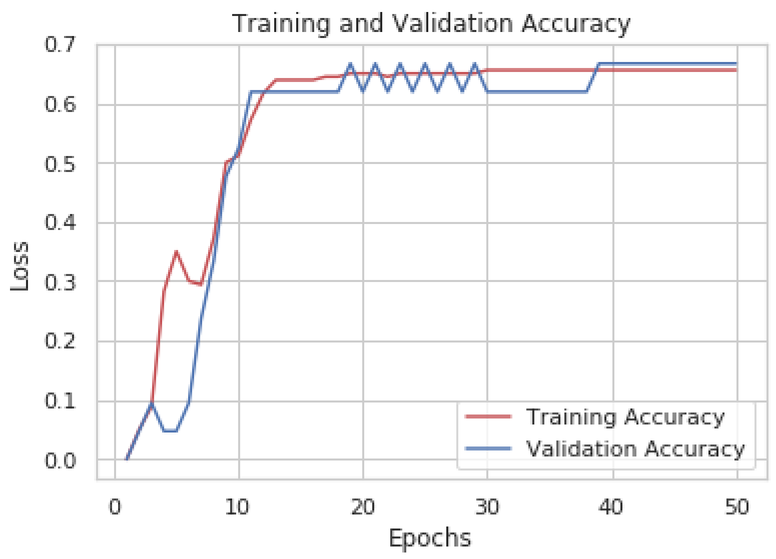
↳ *4 cells hidden*

Plotting Training and Validation Loss + Acc

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(loss) + 1)

plt.plot(epochs, loss, 'rx', label="Training Loss")
plt.plot(epochs, val_loss, 'b', label="Validation Loss")
plt.title("Training and Validation Loss")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.show()
```



```
plt.clf()

acc = history.history['acc']
val_acc = history.history['val_acc']
# epochs = range(1, len(loss) + 1)

plt.plot(epochs, acc, 'r', label="Training Accuracy")
plt.plot(epochs, val_acc, 'b', label="Validation Accuracy")
plt.title("Training and Validation Accuracy")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.legend()

plt.show()
```



Comparing to a Random Baseline

```
import copy
np.random.seed(4242)

test_labels_copy = copy.copy(label_test)
np.random.shuffle(test_labels_copy)
hits_array = np.array(label_test) == np.array(test_labels_copy)
float(np.sum(hits_array)) / len(label_test)
```

```
0.21832448649896147
```

Our test accuracy of 25% is slightly better than this random baseline of 21%. Certainly there is more room for improvement, but it is a good place to start. Exploring recurrent neural networks or CNNs with spectrogram data as an input instead of the .mp3 attributes may yield more accurate predictions.

Predictions on New Data

```
predictions = model.predict(data_test)
predictions[2].shape
```

```
(164,)
```

That's good! This is what's expected-- our 164 possible genres.

```
np.argmax(predictions[2])
```

```
17
```

```
genre_labels["genre_title"][17]
```

```
'Soundtrack'
```

```
genre_labels["genre_title"][int(label_test[2])]
```

```
'Easy Listening'
```

```
for i in range(0, 50):
  p_idx = np.argmax(predictions[i])
  p_genre = genre_labels["genre_title"][p_idx]
  a_genre = genre_labels["genre_title"][int(label_test[i])]
  print(i, '\t', p_genre, '\n\t', a_genre, '\n')
```

		Easy Listening
25	Soundtrack	Blues
26	Easy Listening	Avant-Garde
27	Soundtrack	Soundtrack
28	Soundtrack	Easy Listening
29	Easy Listening	Easy Listening
30	Easy Listening	Avant-Garde
31	Easy Listening	Easy Listening
32	Soundtrack	Sound Effects
33	Easy Listening	Easy Listening
34	Easy Listening	Classical
35	Easy Listening	Audio Collage
36	Easy Listening	Audio Collage
37	Easy Listening	Avant-Garde
38	Soundtrack	Soundtrack
39	Easy Listening	Country
40	Easy Listening	Avant-Garde
41	Easy Listening	Easy Listening
42	Easy Listening	Avant-Garde
43	Easy Listening	Audio Collage
44	Easy Listening	Avant-Garde