PART 1: Logistic regression

Recall that Logistic Regression maximizes the conditional data likelihood as follows:

$$\ln P(\mathcal{D}_Y \mid \mathcal{D}_{\mathbf{X}}, \mathbf{w}) = \sum_{j=1}^{N} \ln P(y^j \mid \mathbf{x}^j, \mathbf{w})$$

$$= \sum_j y^j (w_0 + \sum_i^n w_i x_i^j) - \ln(1 + exp(w_0 + \sum_i^n w_i x_i^j))$$

This function is concave and can be optimized using the gradient ascent/descent algorithm.

For all the background in Logistic Regression read Tom Mitchell's online chapter: **http://www.cs.cmu.edu/~tom/mlbook/NBayesLogReg.pdf**. Note especially section **3.4**

PART 2: Music classification

Let us assume a scenario where we find a set of randomly named MP3 files on our hard disk, which are assumed to contain music. Your task is to sort them according to the music genre into different folders such as jazz, classical, country, pop, rock, and metal.

We will use the GTZAN dataset, which is frequently used to benchmark music genre classification tasks. It is organized into 10 distinct genres, of which we will use only six for the sake of simplicity: classical, jazz, country, pop, rock, and metal. The dataset contains the first 30 seconds of 100 songs per genre. You can download the dataset from UNM Learn. The tracks are recorded at 22,050 Hz (22,050 readings per second) mono in the WAV format.

One advantage of having all these music files in the WAV format is that it is directly readable by the SciPy toolkit:

```
sample_rate, X = scipy.io.wavfile.read( wave_filename)
```

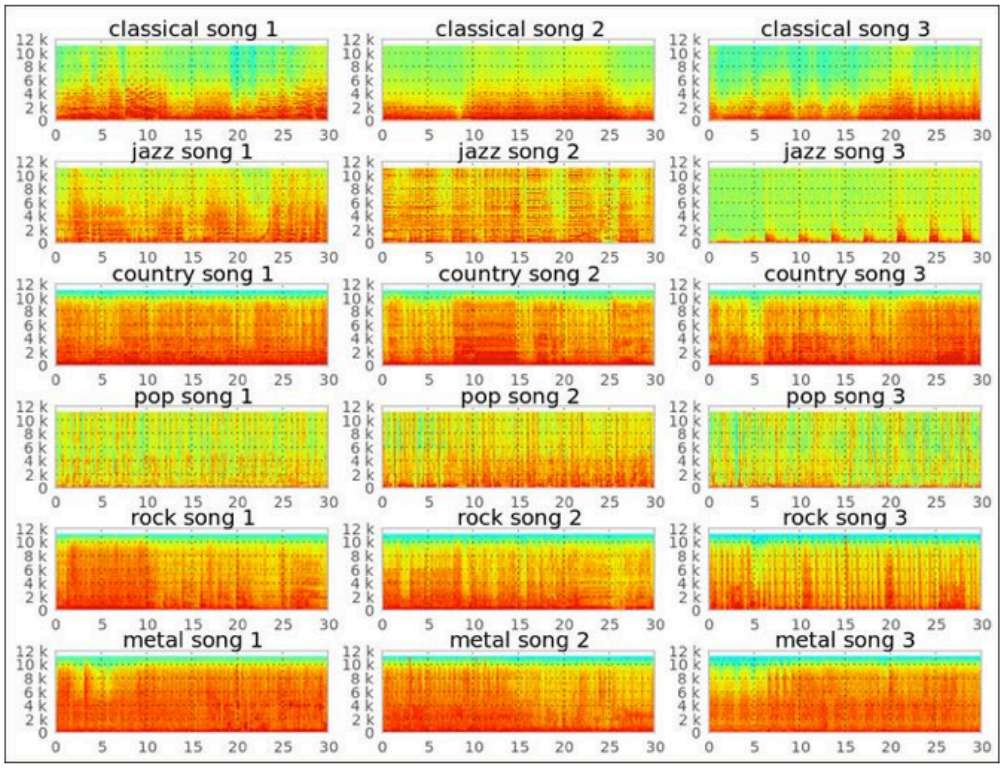
For MatLab implemenations look at the `audioread` function.

Here, X contains the samples and sample_rate is the rate at which they were taken. Let us use this information to peek into some music files to get a first impression of what the data looks like. A very convenient way to get a quick impression of how the songs of the diverse genres "look" like is to draw a spectrogram for a set of songs of a genre. A spectrogram is a visual representation of the frequencies that occur in a song. It shows the intensity of the frequencies on the y axis in the specified time intervals on the x axis; that is, the darker the color, the stronger the frequency is in the particular time window of the song. Matplotlib provides the convenient function

specgram() that performs most of the under-the-hood calculation and plotting for us (look at the `spectrogram` function in MatLab)

```
>>> import scipy
>>> from matplotlib.pyplot import specgram
>>> sample_rate, X =
scipy.io.wavfile.read(wave_filename)
>>> print sample_rate, X.shape
22050, (661794,)
>>> specgram(X, Fs=sample_rate, xextent=(0,30))
```

If we now plot the spectrogram for these first 30 seconds of diverse wave files, we can see that there are commonalities between songs of the same genre:



Our plan is to extract individual frequency intensities from the raw sample readings (stored in X earlier) and feed them into a classifier. These frequency intensities can be extracted by applying the Fast Fourier Transform (FFT). *TIP: look at the scipy.fft() function in python or fft in matlab.* For the sake of complexity, and speed, you can fix the number of FFT components to the first 1000.

Another feature extraction technique that has been successfully applied in the Music Information Retrieval field deals with the Mel Frequency Cepstral Coefficients (MFCC). The Mel Frequency Cepstrum (MFC) encodes the power spectrum of a

sound. It is calculated as the Fourier transform of the logarithm of the signal's spectrum. MFC has been successfully used in speech and speaker recognition.

PART 3: Deliverables

Implement a multinomial logistic regression classifier that uses gradient descent to calculate its weights. (both algorithms should be coded by yourself, not downloaded from internet, obtained from a classmate – past or present – or used from external/built in libraries)

For each of the following tasks, use 10-fold cross validation to train and test your classifier. Be careful to not introduce additional bias by partitioning your data in a way that one or more genres could be underrepresented. Always report your accuracy using the confusion matrix.

A) Use the 1000 first FFT components as features. You can use for example:

```
sample_rate, X = scipy.io.wavfile.read(fn)
fft_features = abs(scipy.fft(X)[:1000])
```

B) Using your knowledge from the previous homework, design a method to rank the FFT components and select the best 20 per genre. Use the selected 200 features to classify the data set. Explain how this step affects your accuracy.

C) Extract the MFCC and use them as your data features. Feel free to use the python Talkbox SciKit. You can install it from https://pypi.python.org/pypi/scikits.talkbox. Afterwards, you can call the mfcc() function, which calculates the MFC coefficients as follows:

```
>>>from scikits.talkbox.features import mfcc
>>>sample_rate, X = scipy.io.wavfile.read(fn)
>>>ceps, mspec, spec = mfcc(X)
>>> print(ceps.shape)
(4135, 13)
```

The data we would want to feed into our classifier is stored in ceps, which contains 13 coefficients (the default value for the nceps parameter of the mfcc() function) for each of the 4135 frames for the song with the filename fn. Taking all of the data would overwhelm the classifier. What we could do instead is to do an averaging per coefficient over all the frames (i.e., your classifier will use only 13 features per song). Assuming that the start and end of each song are possibly less genre-specific than the middle part of it, we also ignore the first and last 10 percent:

```
x =
np.mean(ceps[int(num_ceps*1/10):int(num_ceps*9/10)]
, axis=0)
```

NOTE: Even though the code snippets provided in this document are in python, you can implement this assignment in any other programming language. You can use comparable libraries for FFTs and MFCC. However, the implementation of logistic regression and gradient descent must be yours.

Rubric:

Implement gradient descent (Code – 15 pts)

Implement multinomial logistic regression (Code – 15 pts)

Provide comments and README (Code & Documentation – 5 pts)

Use FFT components for classification (Code - 5 pts)

Use 10-fold cross validation for training and testing (Code - 5 pts)

Report accuracy with the confusion matrix (Report – 5 pts)

Describe results and provide an explanation for bias (Report - 5 pts)

Define a rank for FFT components and use 200 for classification (Code - 5 pts)

Use 10-fold cross validation for training and testing (Code - 5 pts)

Report accuracy with the confusion matrix (Report - 5 pts)

Describe results and provide an explanation for bias (Report - 5 pts)

Use MFCC components for classification (Code - 5 pts)

Use 10-fold cross validation for training and testing (Code - 5 pts)

Report accuracy with the confusion matrix (Report - 5 pts)

Describe results and provide an explanation for bias (Report - 5 pts)

Describe how could you improve further this classification task (Report - 5 pts)

Total 100 pts (This homework accounts for 10 points of your final grade)