The Discrete Fourier Transform

Lab Objective: The analysis of periodic functions has many applications in pure and applied mathematics, especially in settings dealing with sound waves. The Fourier transform provides a way to analyze such periodic functions. In this lab, we use Python to work with digital audio signals and implement the discrete Fourier transform. We use the Fourier transform to detect frequencies present in a given sound wave. We recommend this lab be done in a Jupyter Notebook.

Sound Waves

Sound is how vibrations are perceived in matter. These vibrations travel in waves. Sound waves have two important characteristics that determine what is heard, or whether or not it can be heard. The first characteristic is *frequency*, which is a measurement of the number of vibrations in a certain time period, and determines the pitch of the sound. Only certain frequencies are perceptible to the human ear. The second characteristic is *intensity* or *amplitude*, and determines the volume of the sound. Sound waves correspond physically to continuous functions, but computers can approximate sound waves using discrete measurements. Indeed, discrete measurements can be made indistinguishable to the human ear from a truly continuous wave. Usually, sound waves are of a sinusoidal nature (with some form of decay); the frequency is related to the wavelength, and the intensity to the wave amplitude.

Digital Audio Signals

Computer use *digital audio signals* to approximate sound waves. These signals have two key components that relate to the frequency and amplitude of sound waves: samples and sampling rate. A sample is a measurement of the amplitude of a sound wave at a specific instant in time. The sampling rate corresponds to the sound frequency.

To see why the sample rate is necessary, consider an array with samples from a sound wave. If how frequently those samples were collected is unknown, then the sound wave can be arbitrarily stretched or compressed to make a variety of sounds. See Figure ?? for an illustration of this principle.

However, if the rate at which a set of samples is taken is known, the wave can be reconstructed exactly as it was recorded. If the sample rate is unknown, then the frequencies will be unknown. In most applications, this sample rate will be measured in the number of samples taken per second,



Figure 6.1: The plots of the same set of samples from a sound wave with varying sample rates. The plot on the left is the plot of the samples with the original sample rate (in this case, 22050), while the sample rate of the plot on the right has been doubled, resulting in a compression of the actual sound when played back. The compressed sound will be shorter and have a higher pitch. Similarly, if this set of samples were played back with a lower sample rate will be stretched and have a lower pitch.

Hertz (Hz). The standard rate for high quality audio is 44100 equally spaced samples per second, or 44.1 kHz.

Wave File Format

One of the most common audio file formats across operating systems is the *wave* format, also called wav after its file extension. SciPy has built-in tools to read and create wav files. To read in a wav file, use SciPy's read() function that returns the file's sample rate and samples.

```
# Read from the sound file.
>>> from scipy.io import wavfile
>>> rate, wave = wavfile.read('tada.wav')
```

It is sometimes useful to visualize a sound wave by plotting time against the amplitude of the sound, as in Figure ??. This type of plotting plots in the *time domain*. The amplitude of the sound at a given time is just the value of the sample at that time. Note that since the sample rate is given in samples per second, the length of the sound wave in seconds is found by dividing the number of samples by the sample rate.

Problem 1. Make a class called **SoundWave** for storing digital audio signals. Write the constructor and have it accept a sample rate (integer) and an array of samples (NumPy array), which it stores as class attributes. Then, write a method called plot() that generates the graph of the sound wave. Use the sample rate to label the x-axis in terms of seconds. Finally, construct a **SoundWave** object using the data in tada.wav and display its plot. Your plot should look like Figure 6.1a.

Scaling

Writing a sound wave to a file is slightly more complicated than reading from a file. Use wavfile. write(), specifying the name of the new file, the sample rate, and the array of samples.

```
# Write a random signal sampled at a rate of 44100 Hz to my_sound.wav.
>>> wave = np.random.randint(-32767, 32767, 30000)
>>> samplerate = 44100
>>> wavfile.write('my_sound.wav', samplerate, wave)
```

In order for the wavfile.write() function to accurately write an array of samples to a file, the samples must be of an appropriate type. There are four types of sample values that the function will accept: 32-bit floating point, 32-bit integers, 16-bit integers, and 8-bit unsigned integers. If a different type of samples are passed into the function, it's possible that the function will write to a file, but the sound will likely be distorted in some way. This lab works with only 16-bit integer types, unless otherwise specified.

```
# The type of the elements of an array is stored in an attribute called dtype.
>>> x = np.array([1, 2, 3])
>>> y = np.array([1.0, 2.0, 3.0])
>>> print(x.dtype)
dtype('int64')
>>> print(y.dtype)
dtype('float64')
```

A 16-bit integer is an integer between -32767 and 32767. If an array of samples does not already have all of its elements as 16-bit integers, it will need to be scaled in such a way so that is does before it can be written to a file. In addition, it is ideal to scale the samples so that they cover as much of the 16-bit integer range as possible. This will ensure the most accurate representation of the sound.

```
# Generate random samples between -0.5 and 0.5.
>>> samples = np.random.random(30000)-.5
>>> print(samples.dtype)
dtype('float64')
# Scale the wave so that the samples are between -32767 and 32767.
>>> samples *= 32767*2
# Cast the samples as 16-bit integers.
>>> samples = np.int16(samples)
>>> print(samples.dtype)
dtype('int16')
```

In the above example, the original samples are all less than 0.5 in absolute value. Multiplying the original samples by 32767 and 2 scales the samples appropriately. In general, to get the scaled samples from the original, multiply by 32767 and divide by the greatest magnitude present in the original sample. Note also that for various reasons, samples may sometimes contain complex values. In this case, scale and export only the real part.

Problem 2. Add a method to the SoundWave class called export() that accepts a file name and generates a .wav file of that name from the sample rate and the array of samples. If the array of samples is not already in int16 format, scale it appropriately before writing to the output file. Use your method to create a differently named file that contains the same sound as tada.wav. Display the two sounds to make sure the method works correctly.

Note

To display a sound in a Jupyter Notebook, first import IPython, then use IPython. display.Audio(). This function can accept either the name of a .wav file present in the same directory, or the keyword arguments rate and data, which represent the sample rate and the array of samples, respectively. The function will generate a music player that can be played within the Jupyter Notebook.

Creating Sounds in Python

In order to generate a sound in Python, sample the corresponding sinusoidal wave. The example below generates a sound with a frequency of 500 Hertz for 10 seconds.

```
>>> samplerate = 44100
>>> frequency = 500.0
>>> duration = 10.0  # Length in seconds of the desired sound.
```

Recall the function sin(x) has a period of 2π . To create sounds, however, the desired period of a wave is 1, corresponding to 1 second. Thus, sample from the function

 $\sin(2\pi xk)$

where k is the desired frequency.

The lambda keyword is a shortcut for creating a one-line function.
>>> wave_function = lambda x: np.sin(2*np.pi*x*frequency)

To generate a sound wave, use the following three steps: First, generate the points at which to sample the wave. Next, sample the wave by passing the sample points into wave_function(). Then, use the SoundWave class to plot the sound wave or write it to a file.

```
# Calculate the sample points and the sample values.
>>> sample_points = np.linspace(0, duration, int(samplerate*duration))
>>> samples = wave_function(sample_points)
# Use the SoundWave class to write the sound to a file.
>>> sound = SoundWave(samplerate, samples)
>>> sound.export("example.wav")
```

Problem 3. Write a function that accepts a frequency and a duration. Follow the pattern above to generate and return an instance of the SoundWave class with the given frequency and duration. Use a sample rate of 44100.

The following table shows some frequencies that correspond to common notes. Octaves of these notes are obtained by doubling or halving these frequencies.

Note	Frequency
A	440
B	493.88
C	523.25
D	587.33
E	659.25
F	698.46
G	783.99
A	880

The "A" note occurs at a frequency of 440 Hertz. Use your function to generate and display an "A" note being played for 2 seconds.

Problem 4.

- 1. A chord is a conjunction of several notes played together. You can create a chord in Python by adding several sound waves together. Write the __add__() magic method in the SoundWave so that it adds together the samples of two SoundWave objects and returns the resulting SoundWave object. Note this is only valid if the two sample arrays are the same length. Raise a ValueError if the arrays are not the same length.
- 2. Generate and display a minor chord (made up of the "A", "C", and "E" notes).
- 3. Add a method called append() to the SoundWave class that accepts a SoundWave object and appends the additional samples from the new object to the end of the samples from the current object. Note this only makes sense if the sample rates of the two objects are the same. Raise a ValueError if the sample rates of the two objects are not equal.
- 4. Finally, generate and display a sound that changes over time.

Discrete Fourier Transform

Under the right conditions, a continuous periodic function may be represented as a sum of sine waves:

$$f(x) = \sum_{k=-\infty}^{\infty} c_k \sin kx$$

where the constants c_k are called the *Fourier coefficients*.

Such a transform also exists for discrete periodic functions. Whereas the frequencies present in the continuous case are multiples of a sine wave with a period of 1, the discrete case is somewhat different. The Fourier coefficients in the discrete case represent the amplitudes of sine waves whose periods are multiples of a "fundamental frequency". The fundamental frequency is a sine wave with a period length equal to the amount of time of the sound wave.

The k^{th} coefficient of a sound wave $\{x_0, ..., x_{N-1}\}$ is calculated with the following formula:

$$c_k = \sum_{n=0}^{N-1} x_n e^{\frac{-2\pi i k n}{N}}$$
(6.1)

where i is the square root of -1. This process is done for each k from 0 to N - 1, where N is the number of sample points. Thus, there are just as many Fourier coefficients as samples from the original signal. The discrete Fourier transform (DFT) is particularly useful when dealing with sound waves. The applications will be discussed further later on in the lab.

Problem 5. Write a function called **naive_DFT()** that accepts a NumPy array and computes the discrete Fourier transform of the array using Equation 6.1. Return the array of calculated coefficients.

SciPy has several methods for calculating the DFT of an array. Use scipy.fft() or scipy.fftpack.fft() to check your implementation by using your method and the SciPy method to calculate the DFT and comparing the results using np.allclose(). The naive method is significantly slower than SciPy's implementation, so test your function only on small arrays. When you have your method working, try to optimize it so that you can calculate each coefficient c_k in just one line of code.

Fast Fourier Transform

Calculating the DFT of a large set of samples using only (6.1) can be incredibly slow. Fortunately, when the size of the samples is a power of 2, the DFT can be implemented as a recursive algorithm by separating the computation of the DFT into its even and odd indices. This method of calculating the DFT is called the *Fast Fourier Transform* (FFT) due to its remarkably improved run time. The following algorithm is a simple implementation of the FFT.

Algorithm 6.1

-		
1:	procedure $FFT(x)$	
2:	$N \leftarrow \operatorname{size}(x)$	
3:	if $N = 1$ then	
4:	$\mathbf{return} \ \mathrm{DFT}(x)$	\triangleright Use the DFT function you wrote for Problem 5.
5:	else	
6:	$even \leftarrow \text{FFT}(x_{::2})$	
7:	$odd \leftarrow FFT(x_{1::2})$	
8:	$k \leftarrow arange(N)$	⊳ Use np.arange.
9:	$factor \leftarrow exp(-2\pi ik/N)$	
10:		\triangleright Note $*$ is component-wise multiplication.
11:	return $concatenate((even + f))$	$actor_{:N/2} * odd, even + factor_{N/2:} * odd))$

This algorithm performs significantly better than the naive implementation using only (6.1). However, this simplified version will only work if the size of the input samples is exactly a power of 2.



Figure 6.2: Plots of the DFT (with and without symmetries). Notice that the x-axis of the symmetrical plot goes up to 44100, or the sample rate of the sound wave being plotted, while the x-axis of the other plot goes up to half of that. Also notice that the spikes occur at 440.0 Hz and 43660.0 Hz (which is 44100.0 - 440.0).

SciPy's FFT functions manage to get around this by padding the sample array with zeros until the size is a power of 2, then executing the remainder of the algorithm from there. In addition, SciPy's functions use various other tricks to speed up the algorithm even further.

Problem 6. Write a function that accepts a NumPy array and computes the discrete Fourier transform of the array using Algorithm 6.1. Return the array of calculated coefficients.

To verify your method works, generate an array of random samples of a size that is a power of 2 (preferably size 1024 or larger) and use np.allclose() as in the previous problem to make sure the outputs are the same. Then, compare the runtimes of your DFT method, your FFT method, and one of the SciPy methods and print the results.

Hint: Concatenating vectors can be done with np.concatenate.

Plotting the DFT

The graph of the Fourier transform of a sound file is useful in a variety of applications. While the graph of the sound in the time domain gives information about the amplitude of a sound wave at a given time, the graph of the discrete Fourier transform shows which frequencies are present in the signal. Plotting a sound's DFT is referred to as plotting in the *frequency domain*. Often, this information is of greater importance.

Frequencies present in the sound have non-zero coefficients. The magnitude of these coefficients corresponds to how influential the frequency is in the signal. For example, in the case of the "A" note in Problem 3 the sound contained only one frequency. The graph of the DFT of this sound is Figure 6.2a. Note that in this plot, there are two spikes, despite there being only one frequency present in the sound. This is due to symmetries inherent in the DFT. For the purposes of this lab, ignore the second half of the plot. From now on, show plots of only the first half of the DFT, as in Figure 6.2b.

On the other hand, the DFT of a more complicated sound wave will have many frequencies present. Some of these frequencies correspond to the different tones present in the signal. See Figure 6.3 for an example.



Figure 6.3: The discrete Fourier transform of tada.wav. Each spike in the graph corresponds to a frequency present in the signal. Since the sample rate of tada.wav is only 22050 instead of the usual 44100, the plot of its DFT without symmetries will only go up to 11025, half of its sample rate.

Fixing the x-axis

Plotting the DFT of a signal without any other considerations results in an x-axis that corresponds to the index of the coefficients in the DFT, not their frequencies. As mentioned earlier, the "fundamental frequency" for the DFT corresponds to a sine wave whose period is the same as the length of the signal. Thus, if unchanged, the x-axis gives the number of times a particular sine wave cycles throughout the whole signal. To label the x-axis with the frequencies measured in Hertz, or cycles per second, the units must be converted. Fortunately, the bitrate is measured in samples per second. Therefore, dividing the frequency (given by the index) by the number of samples and multiplying by the sample rate, results in cycles per second, or Hertz.

 $\frac{\text{cycles}}{\text{samples}} \times \frac{\text{samples}}{\text{second}} = \frac{\text{cycles}}{\text{second}}$

Calculate the DFT and the x-values that correspond to the coefficients. Then
convert the x-values so that they measure frequencies in Hertz.
>>> dft = abs(sp.fft(samples)) # Ignore the complex part.
>>> N = dft.shape[0]
>>> x_vals = np.linspace(1, N, N)
>>> x_vals = x_vals * samplerate / N # Convert x_vals to frequencies

Problem 7. Write a method in the SoundWave class called plot_dft() that plots the frequencies present in a sound wave on the x-axis and the magnitude of those frequencies on the y-axis. Only display the first half of the plot (as in Figure 6.2b). Use one of SciPy's FFT implementations to calculate the DFT.

Display the DFT plots of the 'A' note and of the minor chord.



Figure 6.4: The DFT of the minor chord.

Conclusion

If the frequencies present in a sound are already known before plotting its DFT, the plot may be interesting, but little new information is actually revealed. Thus, the main applications of the DFT involve sounds in which the frequencies present are unknown. One application in particular is sound filtering, which has many uses, and will be explored in greater detail in a subsequent lab. The first step in filtering a sound is determining the frequencies present in that sound by taking its DFT.

Consider the minor chord as an example. The plot of its DFT looks like Figure 6.4. This graph shows that there are three main frequencies present in the sound. It remains to determine what exactly those frequencies are. There are many valid ways to do this. One possibility is to determine which indices of the array of DFT coefficients have the largest values, then scale these indices the same as the x-axis of the plot to determine to which frequencies these values correspond. This task is explored further in the next problem. **Problem 8.** The file mystery_sound.wav contains an unknown chord. Use what you have learned about the DFT to determine the individual notes present in the sound.

Hints: The function np.argmax() may be useful. Also, remember that the DFT is symmetric, meaning the last half of the array of DFT coefficients will need to be ignored.