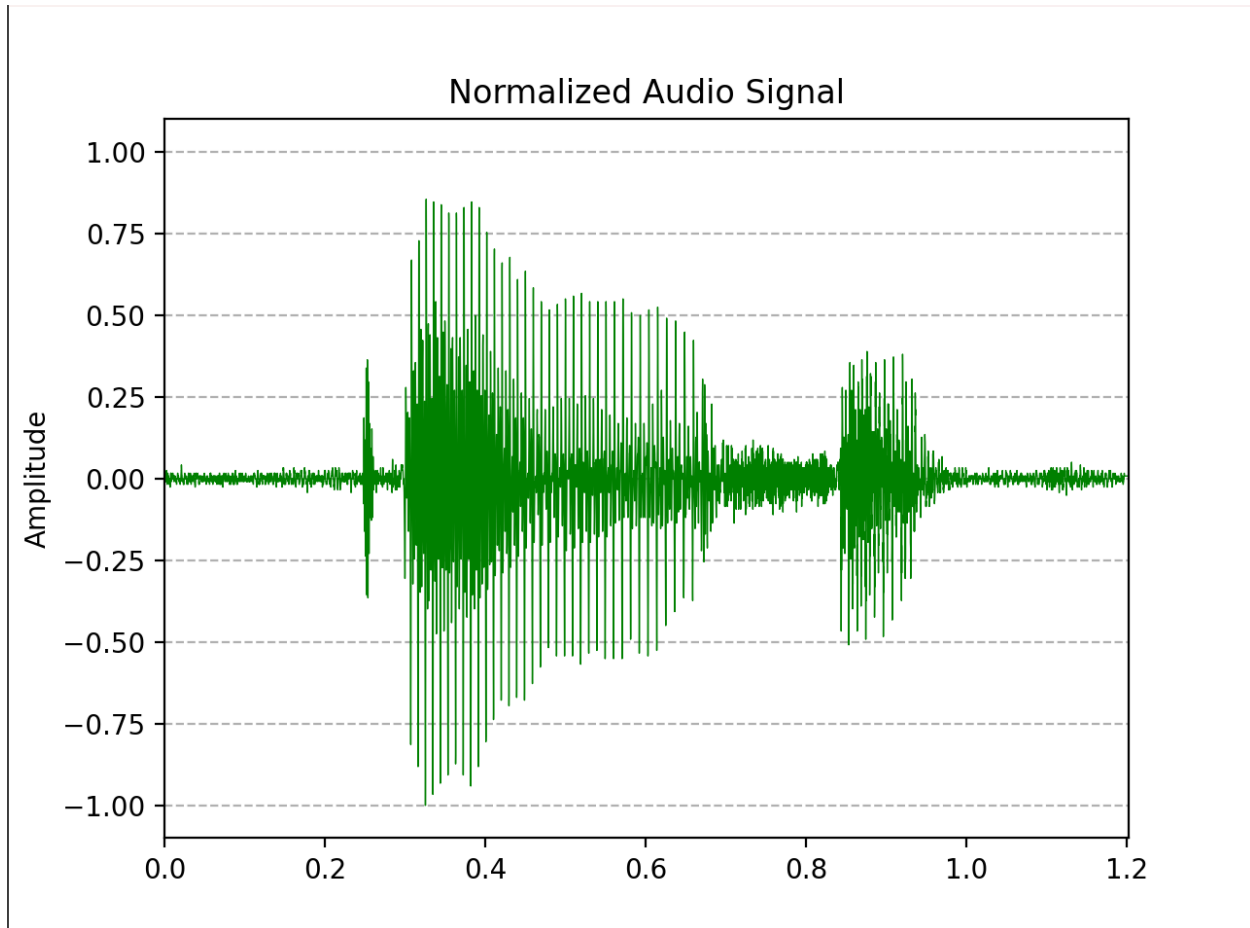


**Sentongo Hamza**  
**Master's in Data Science**

Question 1



I successfully removed the mean from this audio file, and I scaled successfully the amplitude between -1 and 1. The resulting waveform is centered around zero with normalized amplitude as shown in the above figure. The purpose of this is to standardize the amplitude for consistent processing.

**Code**

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.io import wavfile
```

```
Fs, y_initial = wavfile.read('./Kuusi.wav')
```

```
y = y_initial.astype(np.float64)
```

```
y_mean_removed = y - np.mean(y)
```

```
y = y_mean_removed / np.max(np.abs(y_mean_removed))
```

```
duration = len(y) / Fs
```

```
time = np.linspace(0, duration, len(y))
```

```
plt.plot(time, y, label='Normalized Signal', color='green', linewidth=0.5)
```

```
plt.title('Normalized Audio Signal')
```

```
plt.ylabel('Amplitude')
```

```
plt.grid(axis='y', linestyle='--')
```

```
plt.ylim(-1.1, 1.1)
```

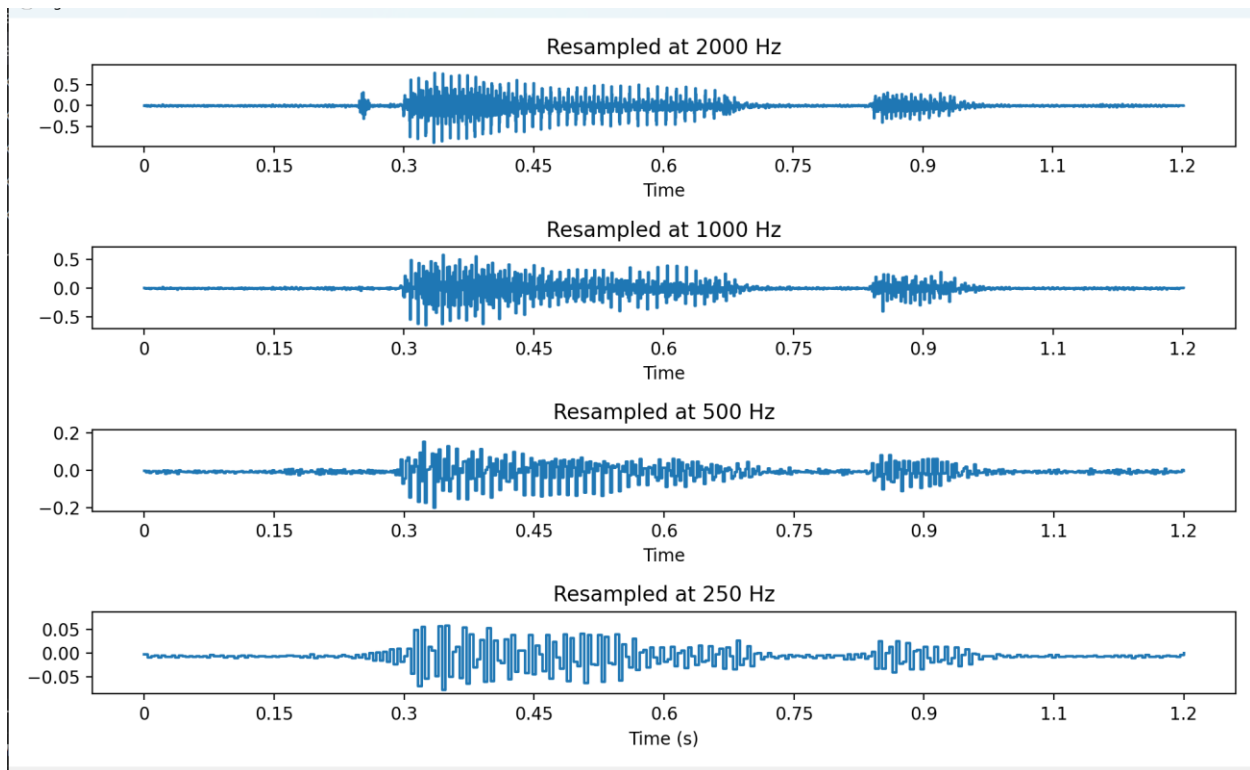
```
plt.xlim(0, duration)
```

```
plt.show()
```

## Question2

The message can still be understood when resampled down to **about 2000 Hz**

It becomes difficult to understand at **1000Hz, 500Hz and 250hz**



## Code

```
import librosa
import soundfile as sf
import matplotlib.pyplot as plt
import librosa.display

y, sr = librosa.load('Kuusi.wav', sr=8000)

y_2000 = librosa.resample(y, orig_sr=sr, target_sr=2000)
sf.write('Kuusi_2000Hz.wav', y_2000, 2000)

y_1000 = librosa.resample(y, orig_sr=sr, target_sr=1000)
sf.write('Kuusi_1000Hz.wav', y_1000, 1000)
```

```
y_500 = librosa.resample(y, orig_sr=sr, target_sr=500)
sf.write('Kuusi_500Hz.wav', y_500, 500)
```

```
y_250 = librosa.resample(y, orig_sr=sr, target_sr=250)
sf.write('Kuusi_250Hz.wav', y_250, 250)
```

```
plt.figure(figsize=(10, 6))
```

```
plt.subplot(4,1,1)
librosa.display.waveshow(y_2000, sr=2000)
plt.title('Resampled at 2000 Hz')
```

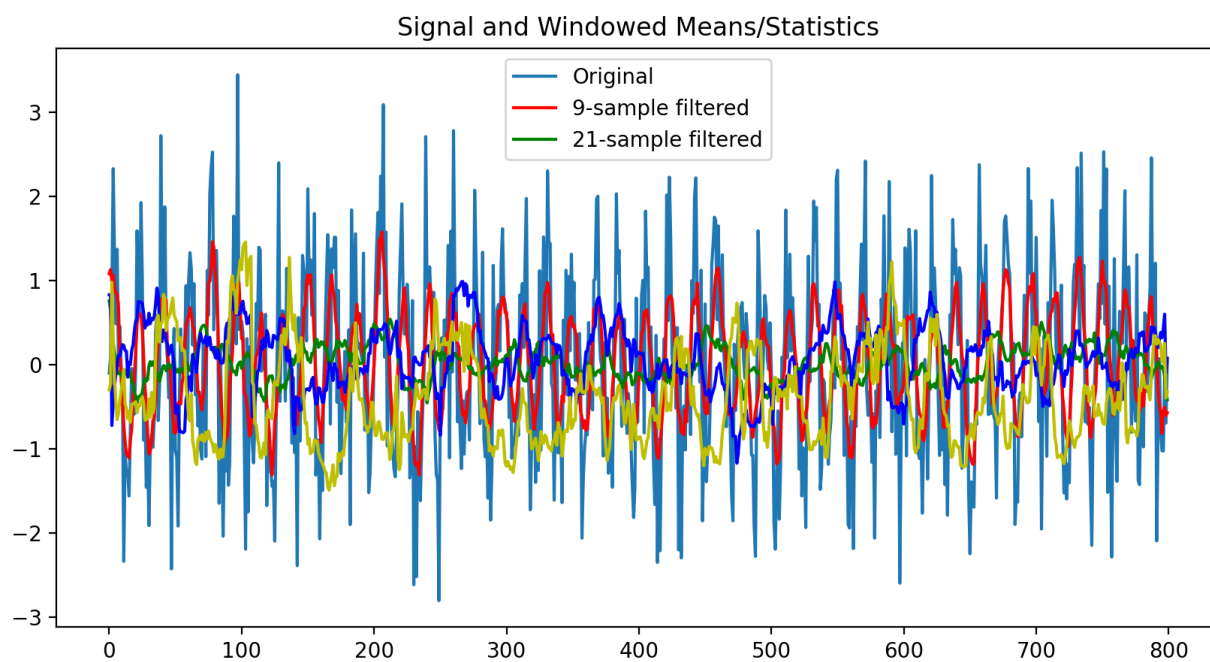
```
plt.subplot(4,1,2)
librosa.display.waveshow(y_1000, sr=1000)
plt.title('Resampled at 1000 Hz')
```

```
plt.subplot(4,1,3)
librosa.display.waveshow(y_500, sr=500)
plt.title('Resampled at 500 Hz')
```

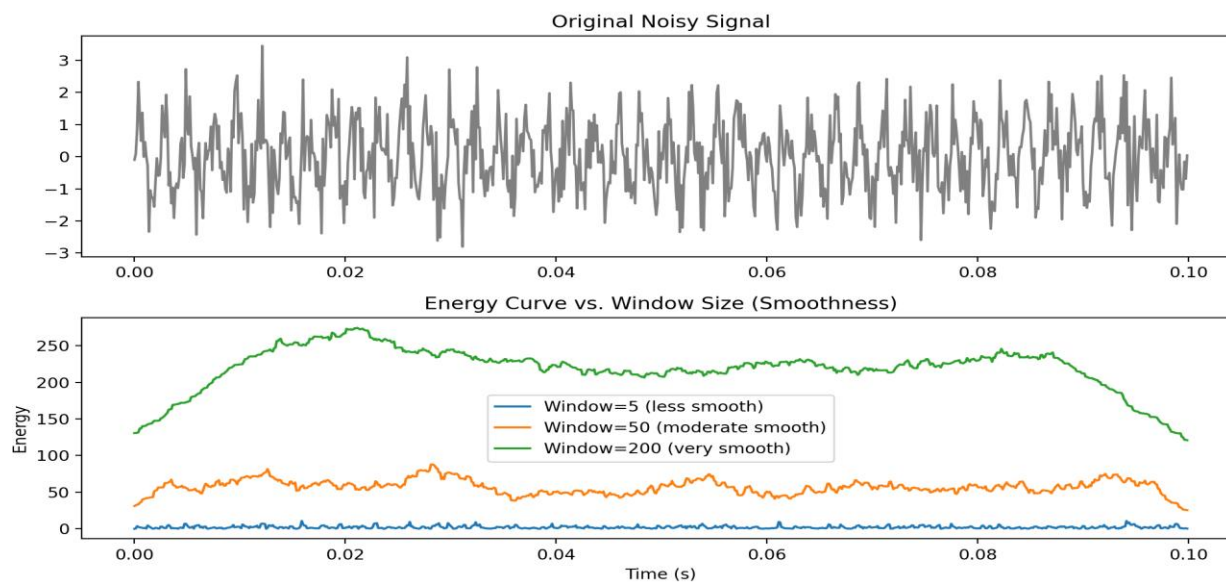
```
plt.subplot(4,1,4)
librosa.display.waveshow(y_250, sr=250)
plt.title('Resampled at 250 Hz')
plt.xlabel('Time (s)')
plt.tight_layout()
plt.show()
```

### Question 3

#### Part 1



#### Part 2



As the window size increases, the energy curve becomes smoother and less affected by short-term noise fluctuations. This makes the signal energy representation more stable and interpretable for machine processing instead of reacting to random noise spikes. As shown in the above figure

### Code

```
#Jari Turunen, TUNI

import numpy as np

from numpy import cos, sin, pi, absolute, arange, mean

from matplotlib import pyplot as plt

from scipy.stats import skew, kurtosis


fs = 8000

freq = 440

end_time = 0.1

time = np.arange(0, end_time, 1/fs)

print(len(time))


y = sin(2*pi*freq*time) + np.random.normal(loc=0.0, scale=0.8, size=[1, len(time)])

y = y.squeeze()

print(y.shape)


len1 = 4

len2 = 10

x = y.copy()*0

x2 = y.copy()*0

x3 = y.copy()*0

x4 = y.copy()*0
```

```

for i in range(len(y)):
    print("%d / %d\n" % (i, len(y)))
    start = i - len1
    if start < 1:
        start = 1
    start2 = i - len2
    if start2 < 1:
        start2 = 1

    ending = i + len1
    if ending > len(y):
        ending = len(y)
    ending2 = i + len2
    if ending2 > len(y):
        ending2 = len(y)

    if len(y[start:ending]) < 2:
        x[i] = 0
    else:
        x[i] = np.mean(y[start:ending])
    if len(y[start2:ending2]) < 2:
        x2[i] = 0
    else:
        x2[i] = np.mean(y[start2:ending2])
        x3[i] = skew(y[start2:ending2], axis=0, bias=True)

```

```
x4[i] = kurtosis(y[start2:ending2], axis=0, bias=True)
```

```
plt.figure(figsize=(10,5))
```

```
plt.plot(y)
```

```
plt.plot(x, 'r')
```

```
plt.plot(x2, 'g')
```

```
plt.plot(x3, 'b')
```

```
plt.plot(x4, 'y')
```

```
plt.legend(['Original', str(len1*2+1)+'-sample filtered', str(len2*2+1)+'-sample filtered'])
```

```
plt.title("Signal and Windowed Means/Statistics")
```

```
plt.show()
```

```
def energy_curve(signal, window):
```

```
    en = np.zeros(len(signal))
```

```
    half_win = window // 2
```

```
    for i in range(len(signal)):
```

```
        start = max(0, i - half_win)
```

```
        end = min(len(signal), i + half_win)
```

```
        segment = signal[start:end]
```

```
        en[i] = np.sum((segment - np.mean(segment))**2)
```

```
    return en
```

```
E1 = energy_curve(y, 5)
```

```
E2 = energy_curve(y, 50)
```

```
E3 = energy_curve(y, 200)
```



```
plt.figure(figsize=(10,6))  
plt.subplot(2,1,1)  
plt.plot(time, y, color='gray')  
plt.title("Original Noisy Signal")
```

```
plt.subplot(2,1,2)  
plt.plot(time, E1, label="Window=5 (less smooth)")  
plt.plot(time, E2, label="Window=50 (moderate smooth)")  
plt.plot(time, E3, label="Window=200 (very smooth)")  
plt.xlabel("Time (s)")  
plt.ylabel("Energy")  
plt.title("Energy Curve vs. Window Size (Smoothness)")  
plt.legend()  
plt.tight_layout()  
plt.show()
```

### Part 3

The function `skew()` measures the *asymmetry* of the data distribution.

The function `kurtosis()` measures how *peaked* or *flat* the distribution is compared to a normal distribution.

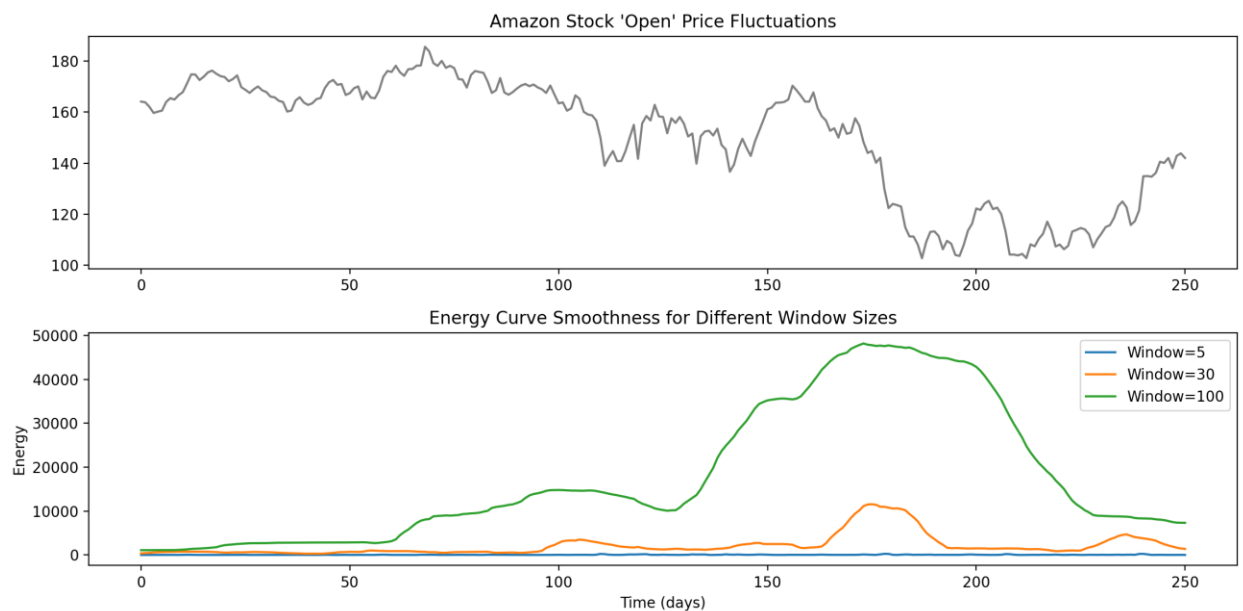
The energy function measures the total signal power within a window.

The python `moment()` function provides statistical features like variance, mean and it tells us how the values of a signal are distributed around the mean.

## Part 4

When using the Amazon stock data, the energy curve becomes smoother as the window size increases. A window size of 100 samples gives a visually smooth and meaningful energy curve that represents the general trend of fluctuations without being distorted by daily noise.

A smaller window (e.g., 5) captures too much short-term insights, making the energy curve irregular and less useful for machine-based pattern analysis.



## Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

data = pd.read_pickle("AMZN.pkl")
print(data.head())
y = data['Open'].values
time = np.arange(len(y))
```

```
def energy_curve(signal, window):  
    en = np.zeros(len(signal))  
    half_win = window // 2  
    for i in range(len(signal)):  
        start = max(0, i - half_win)  
        end = min(len(signal), i + half_win)  
        segment = signal[start:end]  
        en[i] = np.sum((segment - np.mean(segment))**2)  
    return en
```

```
E_small = energy_curve(y, 5)
```

```
E_medium = energy_curve(y, 30)
```

```
E_large = energy_curve(y, 100)
```

```
plt.figure(figsize=(12,6))
```

```
plt.subplot(2,1,1)
```

```
plt.plot(time, y, color='gray')
```

```
plt.title("Amazon Stock 'Open' Price Fluctuations")
```

```
plt.subplot(2,1,2)
```

```
plt.plot(time, E_small, label='Window=5')
```

```
plt.plot(time, E_medium, label='Window=30')
```

```
plt.plot(time, E_large, label='Window=100')
```

```
plt.xlabel("Time (days)")
```

```
plt.ylabel("Energy")
```

```
plt.title("Energy Curve Smoothness for Different Window Sizes")  
plt.legend()  
plt.tight_layout()  
plt.show()
```

#### Question 4

**Machine learning** is a field in technology which uses scientific methods to automate machines and make them learn and perform actions with minimal error.

**Neural networks** have been developed over the years but the basic principle of them being able to minimize error in their predictions with respect to what the actual outcome would be.

**Different architectures** have been developed to solve different problems, for example image processing, signal processing, Natural language processing and others.

I think these architectures have only been decided through making research and experiments in order to come up with an architecture that fits a specific problem