I am excited to teach all of you again in the second year because:

1. I found the class to be very engaging and a pleasure to teach;
2. I want to design the complete scope and curricula of electronics for Design Engineers as an example to other similar courses;
3. I want to learn from this experience, and transfer as much of the new stuff as possible back to EEE, so that EEE can benefit from this experience.

This year, I am helped by Professor Bob Shorten, who has recent joined us from University College Dublin. He will be delivering some lectures on the days that I have to be away, and he will also help me, along a number of GTAs, run the Laboratory Session (similar to what David Boyd did last year in Electronics 1).
This year’s electronics module is not just about electronics. Instead, I will be covering THREE fundamental aspects of electrical engineering that ALL EEE UG students would learn. These are:

1. **Signals** – this is about how to process electrical signals in order to extract useful information from them, to eliminate noise, to compress information, and to transform them into a form that is more useful;

2. **Systems** – this is about the behaviour of electronic (or other non-electronic) systems as black-boxes, or as mathematical models, so that one can either predict its behaviour, or design circuits around such a system in order to obtain desirable behaviour;

3. **Control** – this is about using feedback as a technique to modify the overall behaviour of the system.
Again I will organise my course module with supporting Laboratory sessions, which are compulsory, formal lectures where I will provide the theoretical underpinning, tutorial problems to help you learn the subject, interactive tutorial for us to discuss any issues that the class find difficult or confusing, and a final group project to bring everything together.

Although I am not using the “flip classroom” model for my module, I have faithfully follow the principle that:

1. I first designed the final group project;
2. I then designed all the laboratory experiments which are necessary for you to learn what’s needed in order to do the project;
3. I finally constructed the lectures in a way that you will understand what you do in the laboratory sessions.

In other words, although I am not strictly doing “problem-based” learning, I am not too far from that model. Having said that, I am still a strong believer of the strict mathematical approach to signals, systems and control. I will not be “dumbing down” anything, except that what I teaching will be focused.

Remember, I want you to acquire CONFIDENCE in the subject, and know both what you know, as well as what you don’t know.

In summary, the structure of my course this year will be similar to that in your first year.
The first lecture is an introduction to signals from the time domain perspective. This lecture will be slightly longer than 50 minutes. The main focus is a revision of some of the materials covered last year, but I am taking a more mathematical modeling approach to signals with voltage expressed as a function of time.

In the next lecture, I will take an alternative view, where signals will be considered not as functions of time, but of frequency.
Here are three examples of signals that we often encounter, and require some form of “processing”. Firstly is the cardiac signal that your doctor may acquire. This is a **continuous time signal**, which is almost (but not exactly) periodic. The importance of this signal lies in the detail features appearing in the voltage vs time curve.

Another type of signal is actually NOT a real signal. For example, the plot of FTSE 100 index as it varies throughout the day is essentially numbers that are man-made, and it is **discrete** in nature, expressed as a sequence known as a time series. However, we often treat such a time series as a signal and apply the conventional processing techniques to perform prediction, analysis and the like!

Finally, shown here is a 2-dimensional MRI scan image of a brain. This is actually a function of intensity (of the image as pixels) in 2-D space. Therefore the independent variables are the x and y coordinate, and NOT time. However, signal processing techniques are applicable to such signals, not only as a function of distance (space), but also in 2 or more dimensions.
The first issue to consider when encountering a signal is to ask “how big is it?”

What is meant by “size” of a signal?

One useful measure of a signal size is its energy measure as defined here in the slide.

The square term (of voltage, say) ensures that the sign of the signal \( x(t) \) does not matter. (Otherwise, there is a danger that positive and negative parts of the signal cancel out each other.) The integration is over the duration of \( \pm \infty \).

To be more general, the signal \( x(t) \) could be complex (i.e. with real and imaginary parts). What does a complex value mean? It means that the signal not only have magnitude, but also has phase information. For example if you are dealing with a sinusoidal signal, then the magnitude determines the signal amplitude (or peak value), and the phase determines the starting position at time 0.

Since the definition of energy of a signal requires integral over infinite time, this measure is only useful if the energy is finite. That is, as \( |t| \to \infty \), the signal amplitude must \( \to 0 \).
What happens if the signal does not have finite energy? What does this mean anyway?

For example, if you are considering the signal of the power mains from your household power socket. For all intents and purposes, the mains signal (50 Hz at 230V RMS) is continuous (i.e. goes on forever). Therefore when we consider the size of such a signal, we don’t use energy – we use POWER instead as defined above.

In other words,

\[
\text{POWER} = \text{ENERGY} / \text{TIME},
\]

and

\[
\text{ENERGY} = \text{POWER} \times \text{TIME}
\]
When we consider signals as a function of time, there are a number of useful mathematical models that are being used very often.

Perhaps the most common is to express a signal with a certain time delay as shown above. Note that advancement in time is simply a delay of $-T$. 

- Signal may be delayed by time $T$:
  
  $$\phi (t + T) = x(t)$$

- or advanced by time $T$:
  
  $$\phi (t - T) = x(t)$$
Another mathematical model we often use is the stretching and compression of a signal in time.
The third common operation on a signal is time reversal. This may not appear practical. (Who would play a tape back to front?)

However, as you will find out later on the course when we consider a common signal processing operation known as “convolution”, time-reversal plays a very important part.

Time reversal is achieved by simply reversing the sign of the time variable.
Signals Classification (1)

- Signals may be classified into:
  1. Continuous-time and discrete-time signals
  2. Analogue and digital signals
  3. Periodic and aperiodic signals
  4. Energy and power signals
  5. Deterministic and probabilistic signals
  6. Causal and non-causal
  7. Even and Odd signals

Here is 7 separate classifications of signals. Often such classification does not appear that useful. However, they are actually very important in signal processing because each class of signal has its own unique set of properties, significance and implications.
We have already looked at continuous time signal such as the ECG signal, and discrete time signal such as the stock market or the UK growth rate in the last few years.

Although real physical signals (such as ECG) are generally continuous in nature, we almost always process such as signal using computers. Therefore, in practice, signal processing are usually perform in the discrete time domain. The process of turning a continuous time signal to a discrete time signal is known as sampling. We will consider the mathematics relating to sampling in a later lecture.
Signals can be analogue or digital. Again most real signals are analogue in nature, but digital computers need to process this as numbers with discrete levels. The process of turning an analogue signal to a digital signal is through A-to-D converters.

It is important to note that digitising an analogue signal introduces error (or distortion) and therefore it inherently a “corrupting” process. Digitizing a signal introduce quantization noise. In contrast, the process of sampling, done properly, will not corrupt the signal. We can always recover the original continuous time signal from the discrete time version perfectly. (At least this is theoretically possible).
Signals can be periodic or not. ECG is approximately periodic, and speech signal is definitely NOT periodic.

If a signal is periodic with period $T_0$, then it has a fundamental frequency $1/T_0$. An example of this is the note from a tuning fork – which is almost a perfect sinewave of a known frequency.
A signal can be **deterministic** or **random**.

Real signals are generally not completely deterministic, but many signals can be approximated by the sum of a deterministic component with random noise added. Often, the deterministic part of the signal is what you want to retain, and the random part is what you want to get rid of.
**Causal** and **non-causal** simply refers to whether the signal has zero amplitude at time $t \leq 0$. If a signal $x(t) = 0$ for all $t \leq 0$, it is known as causal. Otherwise, it is non-causal.

All real physical signals has a definite start and therefore it is causal. However, with the help of digital circuits and delay components, we actually can now processing signals and “pretend” that they are non-causal. We will see more of this later on in the course.
Next let us consider a number of important time domain signals that will be used throughout this course.

Most important is the step function as shown here. Step signal is common – an instruction to a robot arm moving from A to B can be model as a step signal. As will be seen later on this course, the response of a system to a step signal input (known as the “step response”) will characterise the entire system.

We often use the step function $u(t)$ in modelling a causal signal. Here is a decay exponential that is causal. We simply multiply the exponential function with the step function!

$$e^{-at}u(t)$$
Pulse signals are obvious. Less obvious is how to model this as the sum of two step functions with two different delays, one by 2 time units, and another by 4 time units:

\[ x(t) = u(t - 2) - u(t - 4) \]
Impulse function is one of the most important functions in signal processing. It is sometimes known as the Dirac function, after the mathematician Paul Dirac.

It is also known as the delta function and is written as $\delta(t)$.

Unit impulse is a spike at $t=0$, and that its area is exactly $= 1$.

An impulse function can take on many other forms. For example, it can also be a pulse with with $\pm \varepsilon/2$, and the amplitude of the pulse is $1/\varepsilon$. It is centred at $t = 0$, and the area of the pulse (i.e. under the curve) is again exactly 1.
If we have a time domain function $\phi(t)$ and multiply this with the impulse $\delta(t)$, we basically extract or sample the signal $\phi(t)$ at $t = 0$.

Therefore if we now delay the impulse function by $T$, then what we get is the value of $\phi(t)$ at $t = T$. In otherwise, we are sampling the function $\phi(t)$ at $T$. Therefore impulse function has a SAMPLING property.
Let us consider what happens when we multiply the unit impulse \( \delta(t) \) by a function \( \phi(t) \) that is continues at \( t = 0 \). Since the impulse has nonzero value only at \( t=0 \), and the value of \( \phi(t) \) at \( t=0 \) is \( \phi(0) \), we obtain:

\[
\phi(t)\delta(t) = \phi(0)\delta(t)
\]

In order words, multiplying a continuous function \( \phi(t) \) with a unit impulse at \( t = 0 \) results in an impulse, also located at \( t=0 \) and has strength of \( \phi(0) \).

We can now generalise this results by time-shifting the impulse function by delaying it by \( T \). If you multiple \( \phi(t) \delta(t - T) \), which is an impulse located at \( t=T \), we get:

\[
\int_{-\infty}^{\infty} \phi(t)\delta(t - T)dt = \phi(T)
\]

This result means that the area under the product of a function with an impulse \( \delta(t) \) is equal to the value of that function at the instant at which the unit impulse is located. This property is known as the sampling property of the unit impulse.
Another important function in the area of signals and systems is the exponential signal $e^{st}$, where $s$ is complex in general, given by:

$$s = \sigma + j\omega$$

Substituting this provides the following important equation:

$$e^{st} = e^{(\sigma + j\omega)t} = e^{\sigma t}e^{j\omega t} = e^{\sigma t}(\cos\omega t + j\sin\omega t)$$

We can compare this exponential function $e^{st}$ to the of the Euler’s formula:

$$e^{j\omega t} = (\cos\omega t + j\sin\omega t)$$

Here the frequency variable $j\omega$ is generalized to a complex variable $s = \sigma + j\omega$. For this reason, we designate the variable $s$ as the complex frequency.
This function is a very important. If $\sigma = 0$, then $e^{st}$ is a sinusoidal function. It is used to represent steady state signal with a frequency $\omega$.

If $\sigma \neq 0$, then the signal either grows or decay exponentially.

Laplace and Fourier transform, which we will study in later lectures, are based on this exponential function.
This four plots shows the four different possible signals represented by such an exponential function.
Finally, one can express the value $s$ (which is also known as “complex frequency”, in a complex plane as shown here. We call this the s-plane. The location of the complex frequency of a signal will then take on the four different forms depending where $s$ lies.