

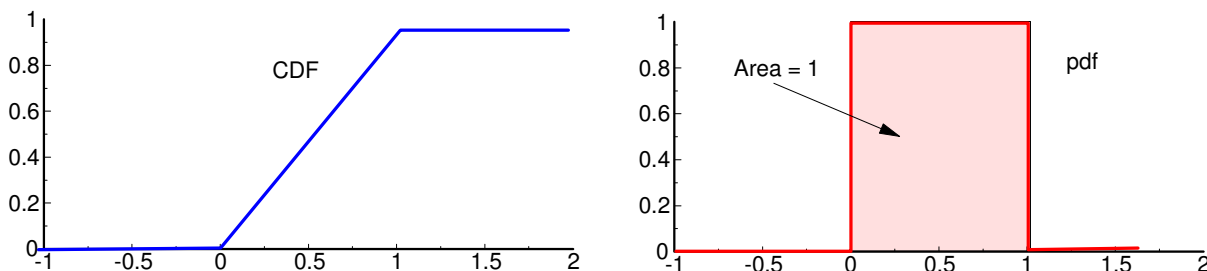
# Uniform Distribution

## Introduction:

A uniform distribution is one where the probability density function (pdf) is

- constant over a range (a, b), and
- zero otherwise.

For example, a variable X which has a uniform distribution function over the interval of (1, 2) is as follows:



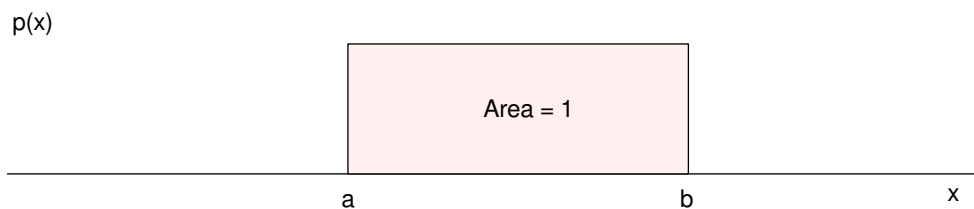
There are several situations where you encounter uniform distributions:

- A 1k resistor with a tolerance of 5% will have a value in the range of +/- 5%. This can be modeled as a uniform distribution over the range of  $950 < R < 1050$
- A 3904 transistor has a nominal gain of 200 with a variation of +/- 100. This can be modeled as a uniform distribution over the range of  $100 < gain < 300$

In general, if you know the limits but know nothing else about the distribution, a uniform distribution is a reasonable assumption to make about the random variable.

## Properties of Uniform Distributions:

Assume a uniform distribution over the interval (a, b)



Since the area must be 1.000, the height must be

$$\text{Area} = \text{width} * \text{height} = 1$$

$$p(x) = \left( \frac{1}{b-a} \right) \quad a < x < b$$

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**Mean:** The mean of the function (almost by inspection) is

$$\mu = \left( \frac{a+b}{2} \right)$$

**Variance:** The mean does not affect the variance. If you assume  $a = -b$ , then

$$\begin{aligned}\sigma^2 &= \int_{-b}^b p(x) (x - \bar{x})^2 dx \\ &= \int_{-b}^b \left( \frac{1}{2b} \right) (x)^2 dx \\ &= \left( \frac{1}{6b} \right) (x^3)_{-b}^b \\ &= \left( \frac{b^2}{3} \right)\end{aligned}$$

$b$  is 1/2 of the width ( $b-a$ ) in this case, so in general the variance is 1/12th of the width

$$\sigma^2 = \left( \frac{(b-a)^2}{12} \right)$$

**Moment Generating Function**

$$\Psi(s) = \left( \frac{1}{s} \right) (e^{-bs} - e^{-as})$$

## Combinations of Uniform Distributions

If you add two uniform distributions, the result is

- The convolution of their pdf's, or
- The product of their moment generating functions.

Example: Assume A and B are uniform distributions over the interval (0, 1). Find the pdf of the sum  $Y = A + B$ .

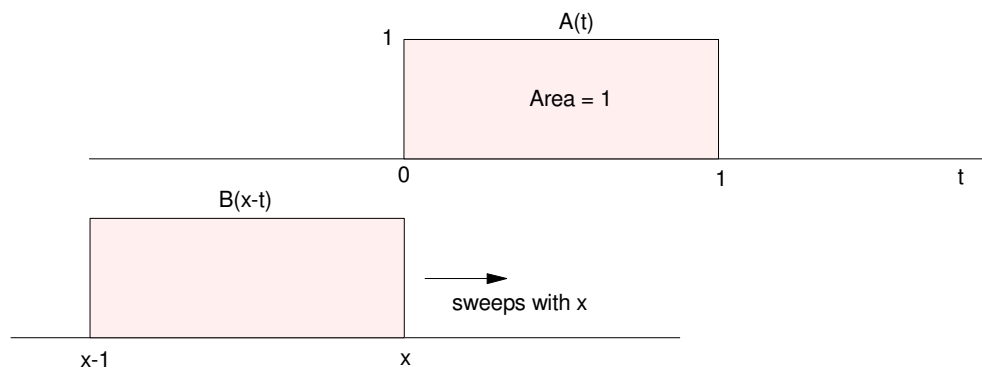
Solution using convolution:

$$A(x) = u(x) - u(x - 1)$$

$$B(x) = u(x) - u(x - 1)$$

$$Y(x) = A(x) * * B(x)$$

$$Y(x) = \int_{-\infty}^{\infty} A(t)B(x-t)dt$$



From the graph, this integral is

$$Y(x) =$$

- 0       $x < 0$
- x       $0 < x < 1$
- 1 - x     $1 < x < 2$
- 0       $2 < x$

This can be done with the functions as well

$$Y(x) = \int_{-\infty}^{\infty} A(t) B(x-t) dt$$

$$Y(x) = \int_{-\infty}^{\infty} (u(t-1) - u(t)) (u(x-t-1) - u(x-t)) dt$$

Note that  $B(x - t)$  is zero for

$$\begin{array}{ll} x - t < 0 & t > x \\ x - t > 1 & t < x - 1 \end{array}$$

This allows us to simplify the integral

is one in the range of  $(0, 1)$ , zero otherwise. This allows us to simplify:

$$Y(x) = \int_{x-1}^x (u(t) - u(t-1)) dt$$

Integrating each part

$$Y(x) = (t u(t))_{x-1}^x - ((t-1)u(t-1))_{x-1}^x$$

solving should give your the same answer...

**Solve using moment generating functions**

$$A(s) = \left(\frac{1}{s}\right) (1 - e^{-s})$$

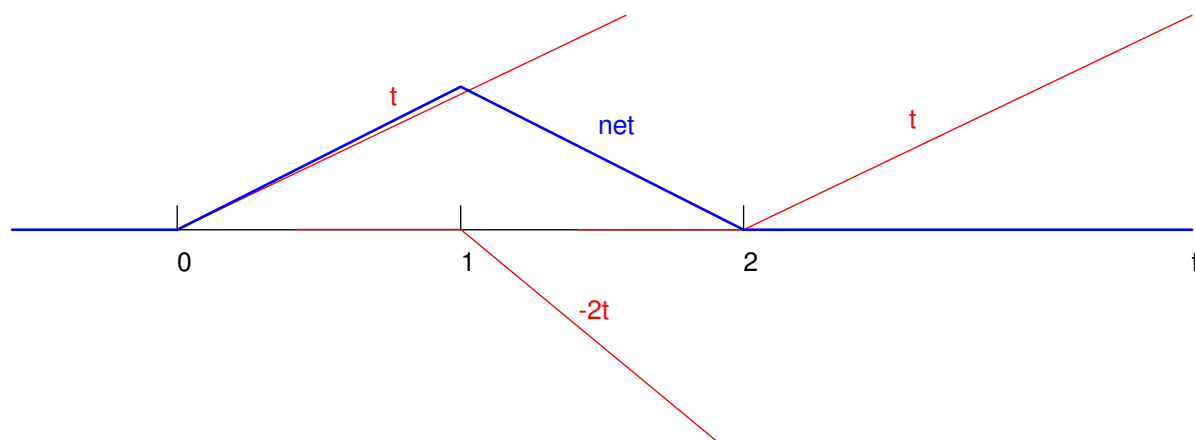
$$B(s) = \left(\frac{1}{s}\right) (1 - e^{-s})$$

$$Y(s) = A(s)B(s)$$

$$Y(s) = \left(\frac{1}{s^2}\right) (e^{-2s} - 2e^{-s} + 1)$$

Take the inverse LaPlace transform

$$y(x) = (x-2) u(x-2) - 2(x-1) u(x-1) + x u(x)$$



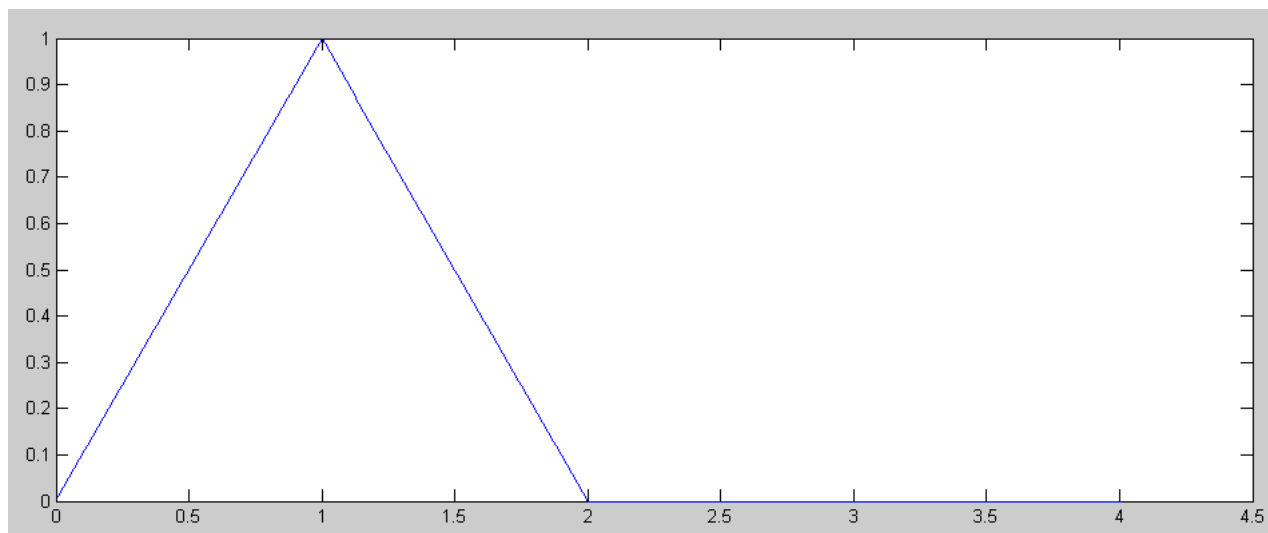
Solve using Matlab: Approximate a uniform distribution with 100 points over the interval (0, 1)

```
dx = 0.01;
x = [0:dx:2]';

A = 1*(x<1);
B = 1*(x<1);

Y = conv(A, B) * dx;

plot([1:length(Y)]*dx, Y)
```



pdf for the sum of two uniform distributions

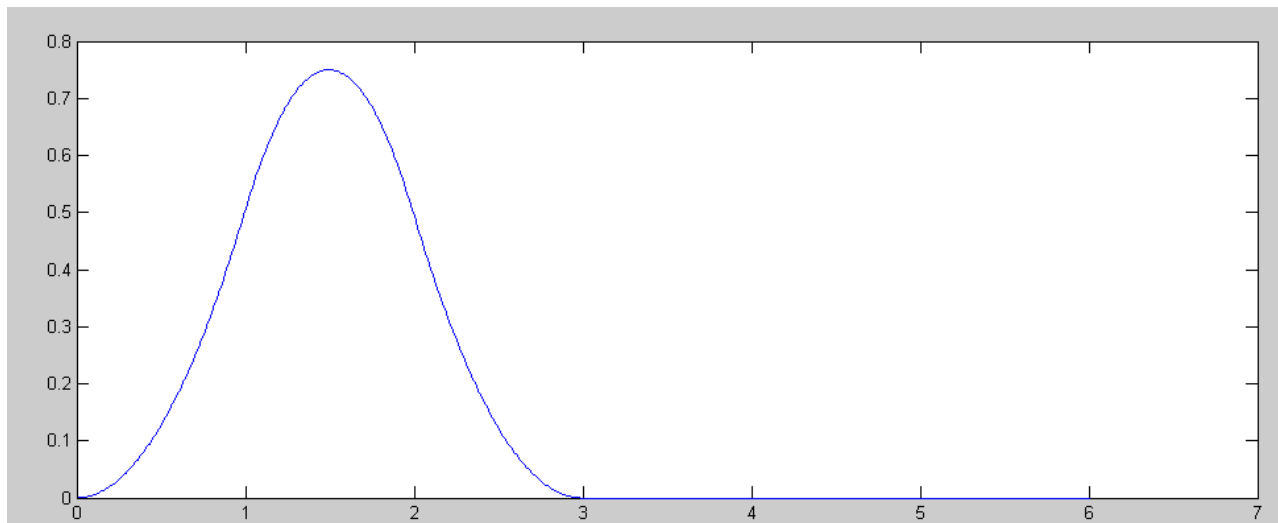
Example 2: Find the pdf of summing three uniform distributions

- $A = \text{uniform}(0, 1)$
- $B = \text{uniform}(0, 1)$
- $C = \text{uniform}(0, 1)$
- $Y = A + B + C$

In matlab:

```
x = [0:dx:2]';
A = 1*(x<1);
B = 1*(x<1);
C = 1*(x<1);

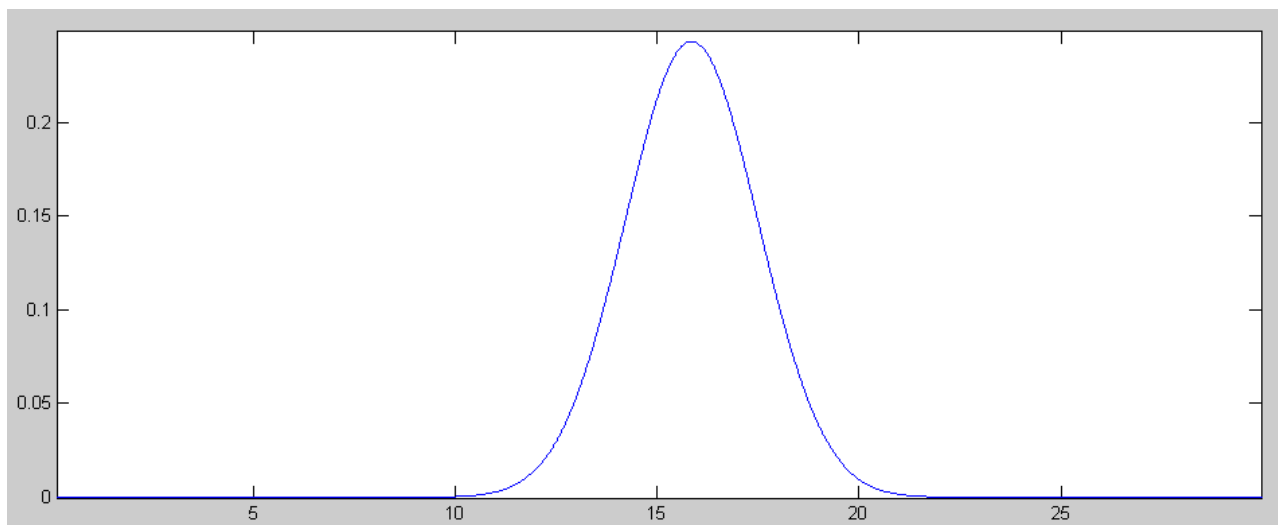
Y = conv(A, B) * dx;
Y = conv(Y, C) * dx;
plot([1:length(Y)]*dx, Y)
```



pdf for the sum of three uniform distributions

Example 3: Find the pdf for the sum of 32 uniform distributions:

```
x = [0:dx:2]';  
A = 1*(x<1);  
  
Y2 = conv(A, A) * dx;  
Y4 = conv(Y2, Y2) * dx;  
Y8 = conv(Y4, Y4) * dx;  
Y16 = conv(Y8, Y8) * dx;  
Y32 = conv(Y16, Y16) * dx;  
plot([1:length(Y32)]*dx, Y32)
```



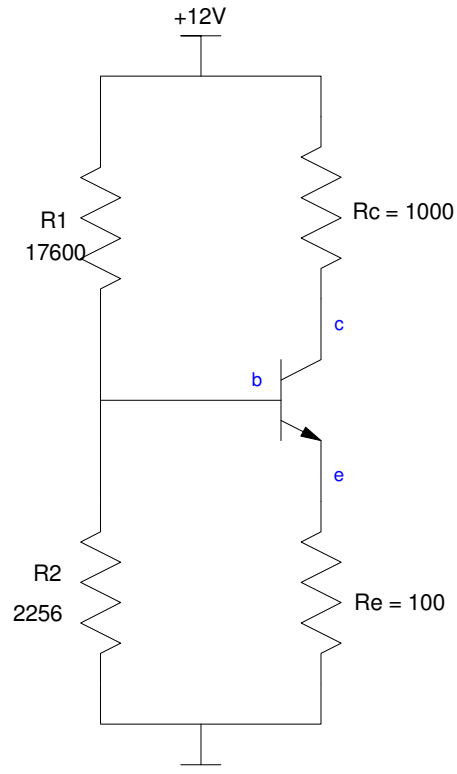
pdf for the sum of 32 uniform distributions

Note that the central limit theorem is evident here: the distribution is approaching a normal distribution.

## Uniform Distribution in Circuit Analysis:

Determine the pdf for  $V_{ce}$ . Assume

- Resistors have a 5% tolerance
- The transistor has a gain in the range of 100 to 300



The equations for this circuit (from ECE 321)

$$V_{th} = \left( \frac{R_2}{R_2 + R_1} \right) 12V$$

$$R_{th} = \left( \frac{R_1 R_2}{R_1 + R_2} \right)$$

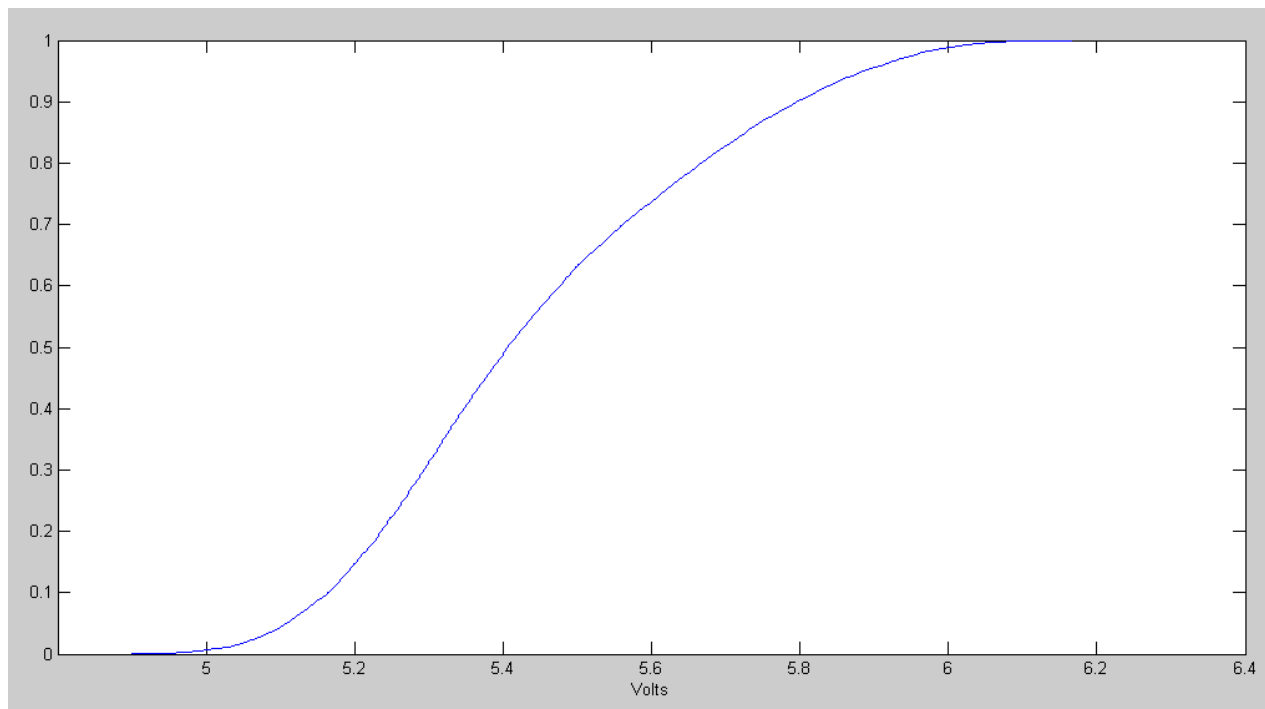
$$I_b = \left( \frac{V_{th} - 0.7}{R_{th} + (1 + \beta)R_e} \right)$$

$$I_c = \beta I_b$$

$$V_{ce} = 12 - R_c I_c - R_e (I_b + I_c)$$

Using a Monte-Carlo simulation

```
DATA = [];  
  
for i=1:1000  
    R1 = 17600 * (1 + (rand()*2-1)*0.01);  
    R2 = 2256 * (1 + (rand()*2-1)*0.01);  
    Rc = 1000 * (1 + (rand()*2-1)*0.01);  
    Re = 100 * (1 + (rand()*2-1)*0.01);  
    Beta = 200 + 100*(rand()*2-1);  
    Vb = 12*(R2 / (R1+R2));  
    Rb = 1/(1/R1 + 1/R2);  
    Ib = (Vb-0.7) / (Rb + (1+Beta)*Re);  
    Ic = Beta*Ib;  
    Vce = 12 - Rc*Ic - Re*(Ic+Ib);  
    DATA = [DATA; Vce];  
end  
  
p = [1:length(DATA)]' / length(DATA);  
plot(DATA, p)
```



Resulting distribution of Vce from a Monte Carlo simulation

Note that when you sort the data, the resulting plot is the cdf. The pdf is the derivative of this graph