Error propagation: Three approaches

- H&H Functional Approach
- H&H Calculus Approach
- Monte Carlo simulation

```
In [33]: import scipy as sp
    from scipy import stats
    import sympy as sym # for symbolic differentiation
    from sympy.interactive import init_printing # provides LaTex formatted outpu
    sym.init_printing()
```

In PHYS 211 we did an experiment to determine "little g" from measurement of the length and period of a pendulum. The following cell defines a function giving g for known values of l and T; the next cell it gives typical data and associated uncertainties.

```
In [8]: def g(l,t):
    return 4*sp.pi**2*l/t**2
```

"Functional approach"

$$(\sigma_g)_L = g(L + \Delta L, T) - g(L, T)$$

$$(\sigma_g)_T = g(L, T + \Delta T) - g(L, T)$$

$$\sigma_g = \sqrt{(\sigma_g)_L^2 + (\sigma_g)_T^2}$$

```
In [10]: sigma_gl = g(mean_l+sigma_l,mean_t)-g(mean_l,mean_t)
sigma_gt = g(mean_l,mean_t+sigma_t)- g(mean_l,mean_t)
sigma_g = sp.sqrt(sigma_gl**2 + sigma_gt**2)
g(mean_l,mean_t),sigma_gl,sigma_gt,sigma_g
```

Result: $g = 9.87 \pm 0.06$

"Calculus approach"

$$(\sigma_g)_L = \frac{\partial g}{\partial L} \Big|_{\bar{L},\bar{T}} \sigma_L$$

$$(\sigma_g)_T = \frac{\partial g}{\partial T} \Big|_{\bar{L},\bar{T}} \sigma_T$$

$$\sigma_g = \sqrt{(\sigma_g)_L^2 + (\sigma_g)_T^2}$$

Redefine g(L,T) in terms of sympy floats so that we can do symbolic work. Will also use sym.sqrt() below.

NOTE: sympy floats != regular python floats See http://docs.sympy.org/dev/gotchas.html (http://docs.sympy.org/dev/gotchas.html) Either sym.sqrt(sym.pi), or sp.sqrt(float(sym.py)), or sym.sqrt(sym.syimpify(sp.pi))

In sympy you must declare symbolic variable explicitly.

The method below allows you to control assumptions, as in

n = sym.symbols('n',postive=True)

You can also import directly from a set of common symbols, e.g.,

from sympy.abc import w or sym.var('z')

see http://docs.sympy.org/latest/gotchas.html#symbols (http://docs.sympy.org/latest/gotchas.html#symbols)

In [37]:
$$sym.diff(g(l,t),t,1),sym.diff(g(l,t),l)$$

Out[37]:
$$\left(-\frac{8l}{t^3}\pi^2, \frac{4\pi^2}{t^2}\right)$$

Evaluate the symbolic expressions at the values \bar{l} and \bar{t} , and calculate the uncertainty.

Result: $g = 9.87 \pm 0.06$

This agrees with previous result.

Monte Carlo technique

Here we are going to get the uncertainty in a different way, using simulated data. Our propagation of uncertainty formulas assume that the uncertainties are standard deviations of normal distribution. We can "redo" the experient, with new simulated "measurements" sampled from the assumed distributions.

First we return to our definition of g(L, T) that returns a regular python float.

```
In [39]: def q(l,t):
             return 4*sp.pi**2*l/t**2
In [40]: nEx = 10000
                                                   # Number of simulated experiments
                                                   # Pick values of l from normal dis
         l = sp.random.normal(mean l,sigma l,nEx)
                                                   # Pick values of t from normal dis
         t = sp.random.normal(mean t,sigma t,nEx)
                                                   # Calculate nEx values of g using
         gg = g(l,t)
         gg
Out[40]: array([ 9.9317706 , 9.89335535, 9.87379594, ..., 9.79706201,
                 9.89475928, 9.93274119])
In [41]: | sp.mean(gg), sp.std(gg)
Out[41]: (9.86959434768,
                           0.0633946166306)
         Result: g = 9.87 \pm 0.06
In [42]: %load ext version information
         %version information numpy, sympy
```

Out[42]:

Software	Version
Python	3.5.1 64bit [GCC 4.4.7 20120313 (Red Hat 4.4.7-1)]
IPython	4.2.0
os	Linux 3.10.0 327.el7.x86_64 x86_64 with redhat 7.2 Maipo
numpy	1.11.0
sympy	1.0
Thu Sep 15 13:44:35 2016 EDT	

```
In [ ]:
```