main_analysis

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In [1]:

```
import math
import matplotlib as mpl
# mpl.use('pgf')
import matplotlib.cm as cm
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd

from scipy import stats
from matplotlib import rc

%matplotlib inline

print plt.style.available
# plt.style.use('classic')
```

```
[u'seaborn-darkgrid', u'seaborn-notebook', u'classic', u'seaborn-
ticks', u'grayscale', u'bmh', u'seaborn-talk', u'dark_background',
u'ggplot', u'fivethirtyeight', u'seaborn-colorblind', u'seaborn-deep',
u'seaborn-whitegrid', u'seaborn-bright', u'seaborn-poster', u'seaborn-
muted', u'seaborn-paper', u'seaborn-white', u'seaborn-pastel', u
'seaborn-dark', u'seaborn-dark-palette']
```

In [2]:

```
## Change default plot style
def_style = 'ggplot'
plt.style.use(def_style)
# plt.style.use('grayscale')
fig_scl = 3
## set up latex output

def figsize(scale, height_ratio=(np.sqrt(5.0)-1.0)/2.0):
    # got after running \the\textwidth
    fig_width_pt = 345.000

    inches_per_pt = 1.0/72.0

    fig_width = fig_width_pt*inches_per_pt*scale
    fig_height = fig_width*height_ratio
    fig_size = (fig_width,fig_height)

    return fig_size

def setup_tex():
    """
    formats the plots for production with latex
    """
    pgf_with_latex = {                      # setup matplotlib to use latex for output
        "pgf.texsystem": "pdflatex",        # change this if using xetex or lautex
        "text.usetex": True,                # use LaTeX to write all text
        "font.family": "serif",
        "font.serif": ["palatino"],
```

```
        "font.sans-serif": [],
        "font.monospace": [],
        "axes.labelsize": 10,               # LaTeX default is 10pt font.
        "text.fontsize": 10,
        "legend.fontsize": 8,               # Make the legend/label fonts a little sma
        "xtick.labelsize": 8,
        "ytick.labelsize": 8,
        "figure.figsize": figsize(1)
    }
    mpl.rcParams.update(pgf_with_latex)

def savefig(filename):
    pass
#     plt.savefig('{}.pgf'.format(filename))
#     plt.savefig('{}.pdf'.format(filename))
#     plt.savefig('{}.eps'.format(filename))
```

In [3]:

```
## Load all required data
print "Loading data into pandas data frame..."
data_spring_coeff = pd.read_csv("p1_coeff.csv")
data_damped_motion = {k:pd.read_csv("DM" + str(k) + ".csv") for k in [2, 3, 4, 5]}
print "Done loading."
```

```
Loading data into pandas data frame...
Done loading.
```

In [4]:

```
def get_intercept(m, (x, y)):
    """
    returns the y-intercept of a line given a
    single point <(x, y)> and the corresponding
    slope <m>
    """
    return (y - m*x)

def get_slope((x1, y1), (x2, y2)):
    """
    returns the slope of the line connecting the
    points <(x1, y1)> and <(x2, y2)>.
    """
    return float(y2 - y1)/float(x2 - x1)
```

0.1 Part I: Calculation of spring constant

We use the force (F) and position (x) data collected in the first part of the experiment to get the line of best fit for the x-F graph.

The slope of this line $\left(m = \dfrac{\Delta F}{\Delta x}\right)$ will give us $-k$ (since the position sensor was located at the bottom and therefore records $-x$ instead of x).

Hence,

$$-k = \frac{\Delta F}{\Delta x}$$

In [5]:

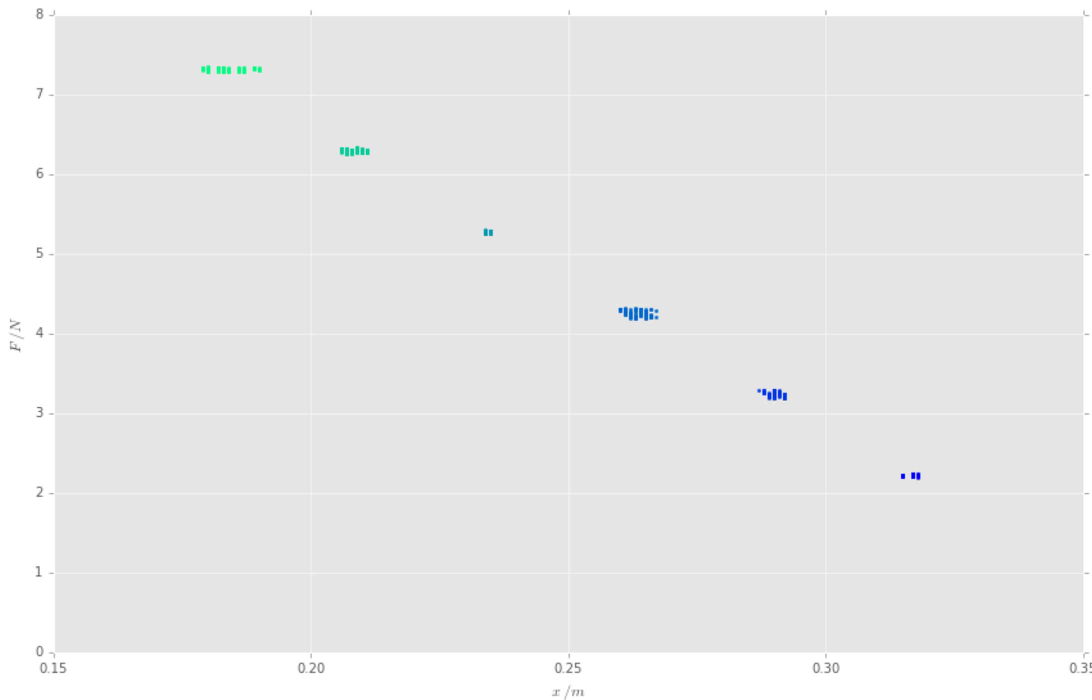
```
# store the Position (X) and Force (F) data in arrays
X_rw = np.array([data_spring_coeff['P M' + str(k)] for k in range(6)])
F_rw = np.array([data_spring_coeff['F M' + str(k)] for k in range(6)])

# calculate the mean value and related uncertainties (standard deviation)
X = [(x.mean(), x.std()) for x in X_rw]
F = [(f.mean(), f.std()) for f in F_rw]

print X
```

```
[(0.31733200000000006, 0.00073059975362711489), (0.29065999999999997,
0.0011799999999999983), (0.26306000000000002, 0.0017596590578859317),
(0.23413199999999995, 0.00033849076796864082), (0.20786000000000002,
0.0013741906709041499), (0.18293199999999998, 0.0025122452109617032)]
```

In [6]:

```
## Plot the raw data points
plt.clf()
plt.figure(figsize=figsize(fig_scl))

plt.xlim([0.15, 0.35])
plt.ylim([0.0, 8.00])

plt.xlabel('$x\; /m$')
plt.ylabel('$F\; /N$')

c = cm.winter(np.linspace(0, 1, len(X_rw)))

for (x_p, f_p, c) in zip(X_rw, F_rw, c):
    plt.scatter(x_p, f_p, marker='.', color=c)
savefig('pt1_x-F_raw_graph')
```

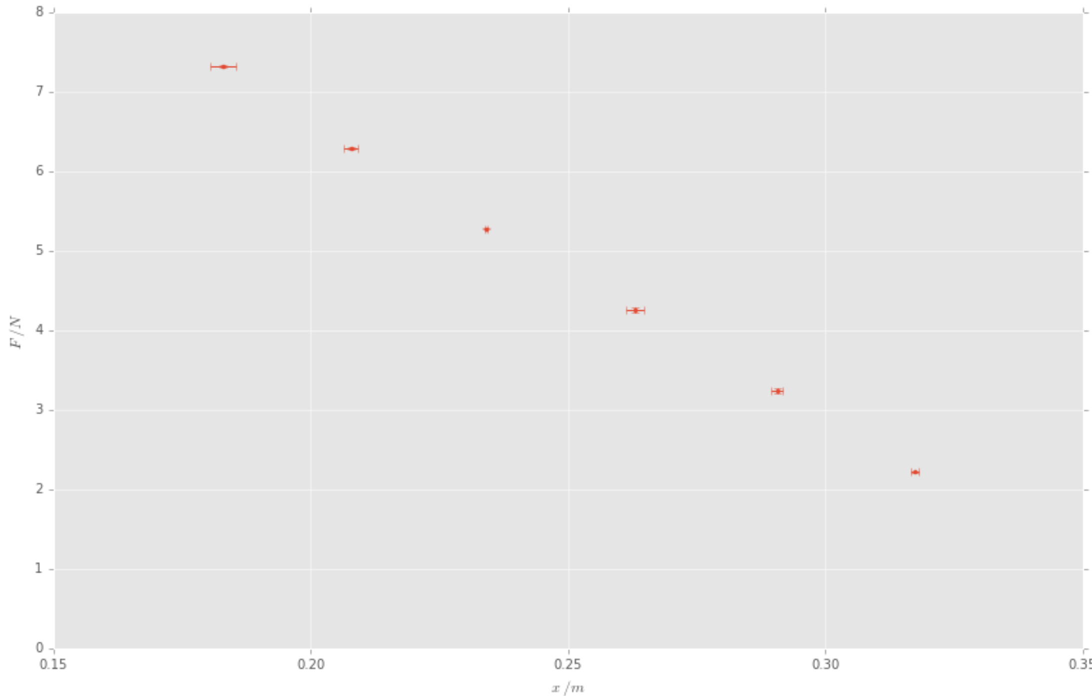
```
<matplotlib.figure.Figure at 0x7f6c99e64190>
```



In [12]:

```
# Plot the x-F graph with error bars.
# Also, save the file with a proper name.
plt.clf()
plt.figure(figsize=figsize(fig_scl))

plt.xlim([0.15, 0.35])
plt.ylim([0.0, 8.00])

plt.xlabel('$x\; /m$')
plt.ylabel('$F\; /N$')

plt.errorbar([x[0] for x in X], [f[0] for f in F],
             xerr=[x[1] for x in X], yerr=[f[1] for f in F],
             fmt='--.', linestyle="None")

savefig('pt1_x-F_graph')
```

```
<matplotlib.figure.Figure at 0x7f6c99c77350>
```



In [8]:

```
## Get the line of best fit for the x-F graph
m, b = np.polyfit(X_rw.flatten(), F_rw.flatten(), 1)

## Get the other bounding lines for the main line
m_1 = get_slope((X[0][0]-X[0][1], F[0][0]-F[0][1]), (X[-1][0]+X[-1][1], F[-1][0]+F[-1]
b_1 = get_intercept(m_1, (X[0][0]-X[0][1], F[0][0]-F[0][1]))
m_2 = get_slope((X[0][0]+X[0][1], F[0][0]+F[0][1]), (X[-1][0]-X[-1][1], F[-1][0]-F[-1]
b_2 = get_intercept(m_2, (X[0][0]+X[0][1], F[0][0]+F[0][1]))

# print "Points:\nP1: ({}, {})".format(X[0][0]-X[0][1], F[0][0]+F[0][1])
# print "P2: ({}, {})".format(X[-1][0]+X[-1][1], F[-1][0]-F[-1][1])

## Print out the values
print "Line of best fit:"
print "y = {}x + {}".format(m, b)
print ""
print "Lines of min/max slope:"
print "* y = {}x + {}".format(m_1, b_1)
print "* y = {}x + {}".format(m_2, b_2)
```

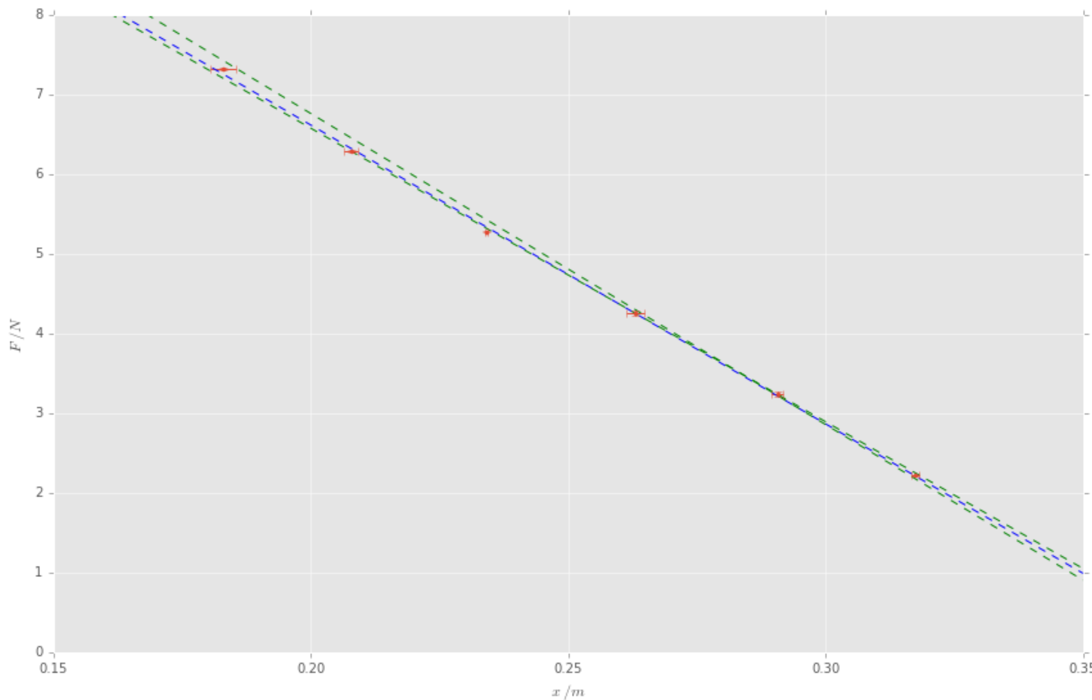
```
Line of best fit:
y = -37.5365286233x + 14.1271896573

Lines of min/max slope:
* y = -39.0690034548x + 14.5782117522
* y = -36.8643692166x + 13.9526105591
```

In [21]:

```
# Plot the lines of best and worst fit.
plt.clf()
plt.figure(figsize=figsize(fig_scl))

plt.xlim([0.15, 0.35])
plt.ylim([0.0, 8.00])

plt.xlabel('$x\; /m$')
plt.ylabel('$F\; /N$')
```

```
xs = np.linspace(0.15, 0.35, 10)

plt.plot(xs, m*xs+b, 'b--')
plt.plot(xs, m_1*xs+b_1, 'g--')
plt.plot(xs, m_2*xs+b_2, 'g--')

plt.errorbar([x[0] for x in X], [f[0] for f in F],
             xerr=[x[1] for x in X], yerr=[f[1] for f in F],
             fmt='--.', linestyle="None")

savefig('pt1_x-F_graph_fit_lines')
```

```
<matplotlib.figure.Figure at 0x7f6c99633cd0>
```



In [23]:

```
## Calculation of coefficient of friction and the related
## uncertainties
k = -m
k_1 = -m_1
k_2 = -m_2

k_err = (k_1 - k_2)/2.0

spring_coeff = k
spring_coeff_err = k_err

print "Spring coeff."
print "Best:\t{} N/m".format(round(k, 3))
print "Max:\t{} N/m".format(round(k_1, 3))
print "Min:\t{} N/m".format(round(k_2, 3))
print "A. Err:\t{} N/m".format(round(k_err, 2))
print "P. Err:\t{}%".format(round((k_err/k)*100, 2))
```

```
Spring coeff.
Best:   37.537 N/m
Max:    39.069 N/m
Min:    36.864 N/m
A. Err: 1.1 N/m
```

```
P. Err: 2.94%
```

0.2 Part 2: Calculation of Damping coeff.

In a damped simple harmonic motion, the location x of the particle is given by:

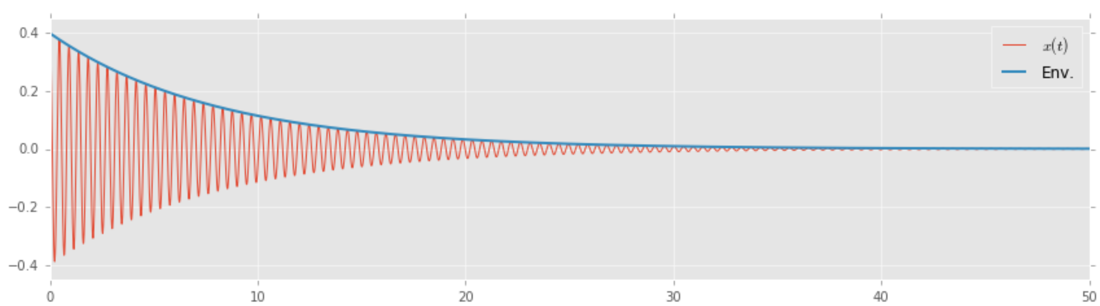
$x(t) = Ae^{\frac{-bt}{2m}}\cos{(\omega' t + \phi)}$

Where * A is the initial aplitude * m is the mass of the body * b is the damping coeff. * $\omega' = \sqrt{\omega^2 - \gamma^2} = \sqrt{\frac{k}{m} - \frac{b^2}{4m^2}}$

In [90]:

```
## Damped simple harmonic motion: EXAMPLE
def ex_damped_shm(A, m, b, k, ph = 0):
    t = np.linspace(0, 50, 5000)
    gamma = float(b)/float(2*m)
    omega = math.sqrt(float(k)/float(m))
    omega_prime = math.sqrt(omega**2 - gamma**2)
    x = []
    for T in t:
        x.append(A*(math.e**((-1*T*float(b))/float(2*m)))*(math.cos(omega_prime*T + ph
    x_e = A*(math.e**((-1*t*float(b))/float(2*m)))
#     plt.plot(t, [0*i for i in range(len(t))], linewidth=2.0)
    plt.plot(t, x, label="$x(t)$")
    plt.plot(t, x_e, label="Env.", linewidth=2)
    plt.legend()

plt.clf()
plt.figure(figsize=figsize(fig_scl, height_ratio=(1.0/4.0)))
plt.xlim([0, 50])
plt.ylim([-0.45, 0.45])
ex_damped_shm(0.4, 0.2, 0.05, 37)
```

```
<matplotlib.figure.Figure at 0x7f6c9975a210>
```



In [11]:

```
# dm5 = data_damped_motion[5]
# dm5 = dm5[(np.abs(stats.zscore(dm5)) < 10).all(axis=1)]
M5P1 = dm5['M5 P1']
# M5P2 = dm5['M5 P2']
# M5P3 = dm5['M5 P3']
# M5P4 = dm5['M5 P4']
# M5P5 = dm5['M5 P5']
# M5T = dm5['T']
# plt.figure(figsize=(12, 5))
# # plt.plot(M5P2[:25*2], M5V2[:25*2])
# plt.xlim([0, 150])
# # plt.ylim([-0.15, 0.15])
# k = (M5P1.mean() + M5P2.mean() + M5P3.mean() + M5P4.mean() + M5P5.mean())/5.0
# # print k
# plt.plot(M5T, M5P1-k)
# plt.plot(M5T, M5P2-k)
# plt.plot(M5T, M5P3-k)
# plt.plot(M5T, M5P4-k)
```

```
# plt.plot(M5T, M5P5-k)
# # plt.plot(M5T, M5P)
# # plt.legend()
```