Bryan Chen
bc2vf
CS 6316 Basit
HW 1

1.2
Import required packages:

In [463]:
```
%matplotlib inline

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

Generate 12 data samples (x, y) such that x is uniformly distributed in the interval [0,1], and y is normally distributed y ~ N(0, 0.5):

In [464]:
```
y = np.random.uniform(low=0, high=1, size=12)
x = np.random.normal(loc=0, scale=0.5, size=12)
```

Model this data as y = f(x) + noise, using polynomials of degree 1, 2 and 6, to estimate unknown f(x):

In [465]:
```
p1 = np.polyfit(x=x, y=y, deg=1)
p1 = np.poly1d(p1)
p2 = np.polyfit(x=x, y=y, deg=2)
p2 = np.poly1d(p2)
p3 = np.polyfit(x=x, y=y, deg=6)
p3 = np.poly1d(p3)

f1 = p1(x)
f2 = p2(x)
f3 = p3(x)
```

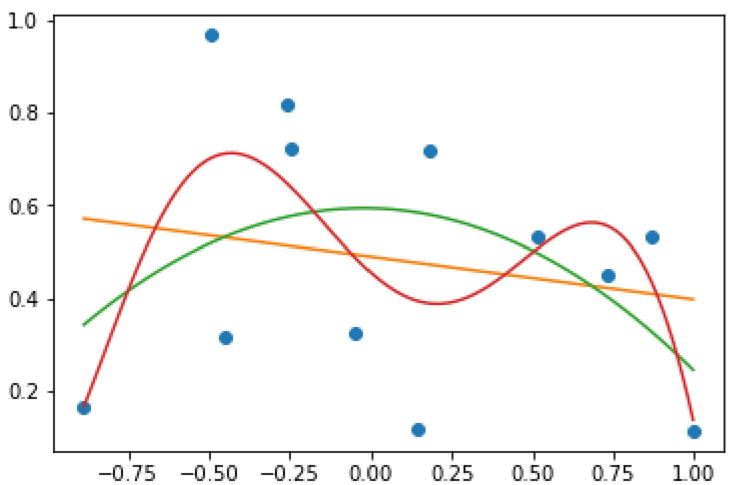
Report the fitting error (MSE) for each model:

In [466]:
```
def fitting_error(yhat, y, n):
    return sum(pow((yhat - y), 2)) / n

e1 = fitting_error(f1, y, 12)
e2 = fitting_error(f2, y, 12)
e3 = fitting_error(f3, y, 12)
print(e1)
print(e2)
print(e3)
```

```
0.0715851320077
0.0610380336032
0.0412958324612
```

Show the estimated regression model graphically along with the data samples:

In [467]:
```
x_new = np.linspace(min(x), max(x), 120)
y_new1 = p1(x_new)
y_new2 = p2(x_new)
y_new3 = p3(x_new)

plt.plot(x, y, 'o')
plt.plot(x_new, y_new1, '-')
plt.plot(x_new, y_new2, '-')
plt.plot(x_new, y_new3, '-')
plt.show()
```



The small fitting error can be used as a good indicator for small prediction error for such polynomial models.

1.7

Import the daily closing prices Z(t) of the S&P 500 stock index for each trading day throughout year 2006:

In [468]:
```
df = pd.DataFrame.from_csv("sp500.csv")
n = len(df)
df.index = np.arange(0, n)
close = df['Close']
```

The daily percentage price change of SP500 index is X(t), defined as:

In [ ]:
```
def price_change(z0, z1):
    return (z1 - z0) / z0 * 100
```

The daily percentage change of the 5-day moving average (MA) of the daily closing prices is Y(t), defined as:

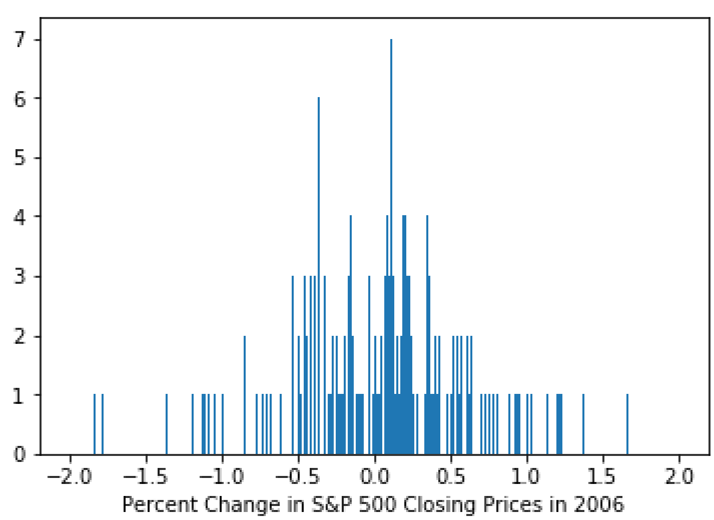
In [470]:
```
def five_day_ma(z0, z1, z2, z3, z4):
    return (z4 + z3 + z2 + z1 + z0) / 5

def five_day_ma_change(ma0, ma1):
    return (ma1 - ma0) / ma0 * 100
```

Obtain observations of random variable X:

In [471]:
```
x_data = []
for i in range(1, n):
    z0 = close[i-1]
    z1 = close[i]
    x = price_change(z0, z1)
    x_data.append(x)
```

Find the empirical distribution histogram, sample mean, standard deviation, and normal pdf of X:

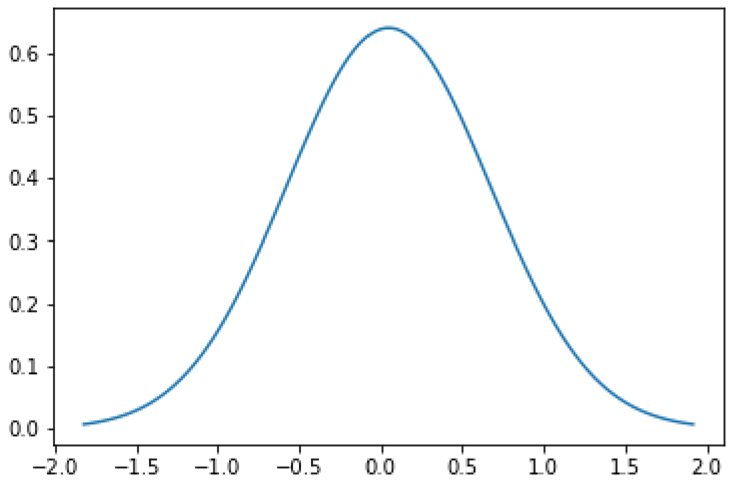
In [472]:
```
num, bins, _ = plt.hist(x_data, bins=500, range=[-2,2])
plt.xlabel("Percent Change in S&P 500 Closing Prices in 2006")
plt.show()
```



In [473]:
```
xbar = np.mean(x_data)
xsig = np.std(x_data)
print(xbar)
print(xsig)
```

```
0.046506680399
0.623438842809
```

In [474]:
```
x_normal = np.linspace(xbar - 3*xsig, xbar + 3*xsig, 120)
plt.plot(x_normal, mlab.normpdf(x_normal, xbar, xsig))
plt.show()
```

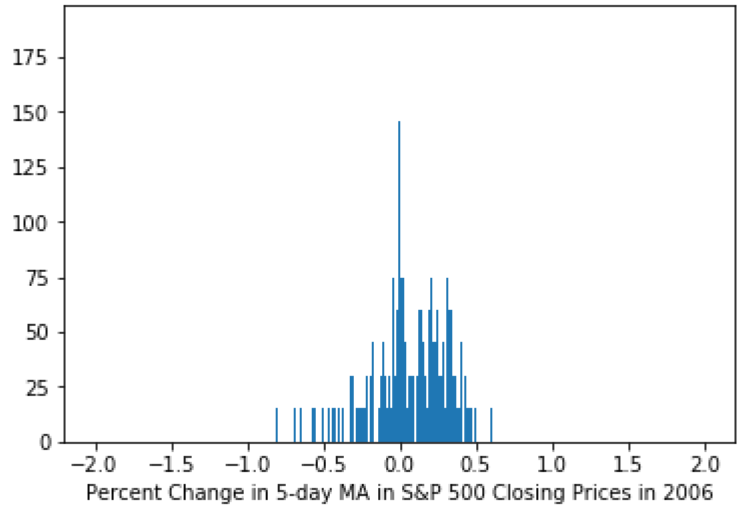


Obtain observations of random variable Y:

In [475]:
```
z0 = close[0]
z1 = close[1]
z2 = close[2]
z3 = close[3]
z4 = close[4]
ma0 = five_day_ma(z0, z1, z2, z3, z4)

for i in range(5, n):
    z0 = close[i-4]
    z1 = close[i-3]
    z2 = close[i-2]
    z3 = close[i-1]
    z4 = close[i]
    ma1 = five_day_ma(z0, z1, z2, z3, z4)
    y = five_day_ma_change(ma0, ma1)
    y_data.append(y)
    ma0 = ma1
```

Find the empirical distribution histogram, sample mean, and standard deviation of Y:

In [476]:
```
num, bins, _ = plt.hist(y_data, bins=500, range=[-2,2])
plt.xlabel("Percent Change in 5-day MA in S&P 500 Closing Prices in 2006")
plt.show()
```



In [477]:
```
ybar = np.mean(y_data)
ysig = np.std(y_data)
print(ybar)
print(ysig)
```

```
0.0402822792075
0.247863933673
```

Bryan Chen bc2vf

1.3

a) There are 10 beer choices for each person, so $10^{10} = 10000000000$

b) There are 10 beer choices for all 10 people, so $P_{10}^{10} = \frac{10!}{(10-10)!} = 10! = 3628800$

1.4

$P[R^c] = 1 - 0.004 = 0.996.$

$P[R_1^c \cap R_2^c \cap \dots R_{250}^c] = 0.996^{250} = 0.367$

$P[(R_1^c \cap R_2^c \cap \dots R_{250}^c)^c] = 1 - 0.367 = 0.633$

1.13

These theories represent pseudoscience beliefs. For example, the Mayan 260-day calendar was heavily based on the Maya Sacred Round. Each calendar round date is a date that has both the Haab' and the Tzolk'in, which translate into the Mayan concept called the year Bearers. These were not based on scientific research or empirical data, hence they represent pseudoscience.