ECON 8310

Business Forecasting

Instructor:

Dustin White
Mammel Hall 332M

Office Hours:
TBA

Contact Info:
drwhite@unomaha.edu

Grade Details

Score	Grade	Score	Grade
>94%	A	62.5-69.9	D
90-93.9	A-	60-62.5	D-
87.5-89.9	B+	<60	F
82.5-87.4	B		
80-82.4	B-		
77.5-79.9	C+		
72.5-77.4	C		
70-72.4	C-		

Grade Details

Assignment	Percent of Grade
Lab Work	30%
Midterm Exam	10%
Final Exam	10%
Project 1	25%
Project 2	25%

My Expectations

- You will be expected to learn to program during this course if you do not already know how
- Plan on spending all of our time in lab working on projects and refining your predictions
- Take charge of your assignments; they will be open-ended

Expectations of Me

- I will work through examples of code in class
- I will be available during office hours to help you with assignments
- I will be revise the course material as needed to suit your interests

Day 1: Intro and OLS Review

What is Forecasting?

Forecast: "to predict or estimate (a future event or trend)" -- Google Dictionary

- Predict stock market movements
- Estimate the quantity of stock required during a certain time-span
- Determine the most likely outcome of a stochastic process based on previous events
- **Learn from patterns**

Quick Forecast

```python
import numpy as np
import matplotlib.pyplot as plt

x = np.linspace(-1, 1, 101)
y = 2 * (x + np.random.rand(101))

plt.plot(x, y)
plt.show()
```

What just happened??

```python
import numpy as np
import matplotlib.pyplot as plt
```

These are our import statements

- We import "libraries" into Python that enable us to do tons of cool things
- In this case, we import numeric functions and the ability to render plots

What just happened??

```
x = np.linspace(-1, 1, 101)
y = 2 * (x + np.random.rand(101))
```

Next, we generate all our x values, and our y values (a random process based on those x values)

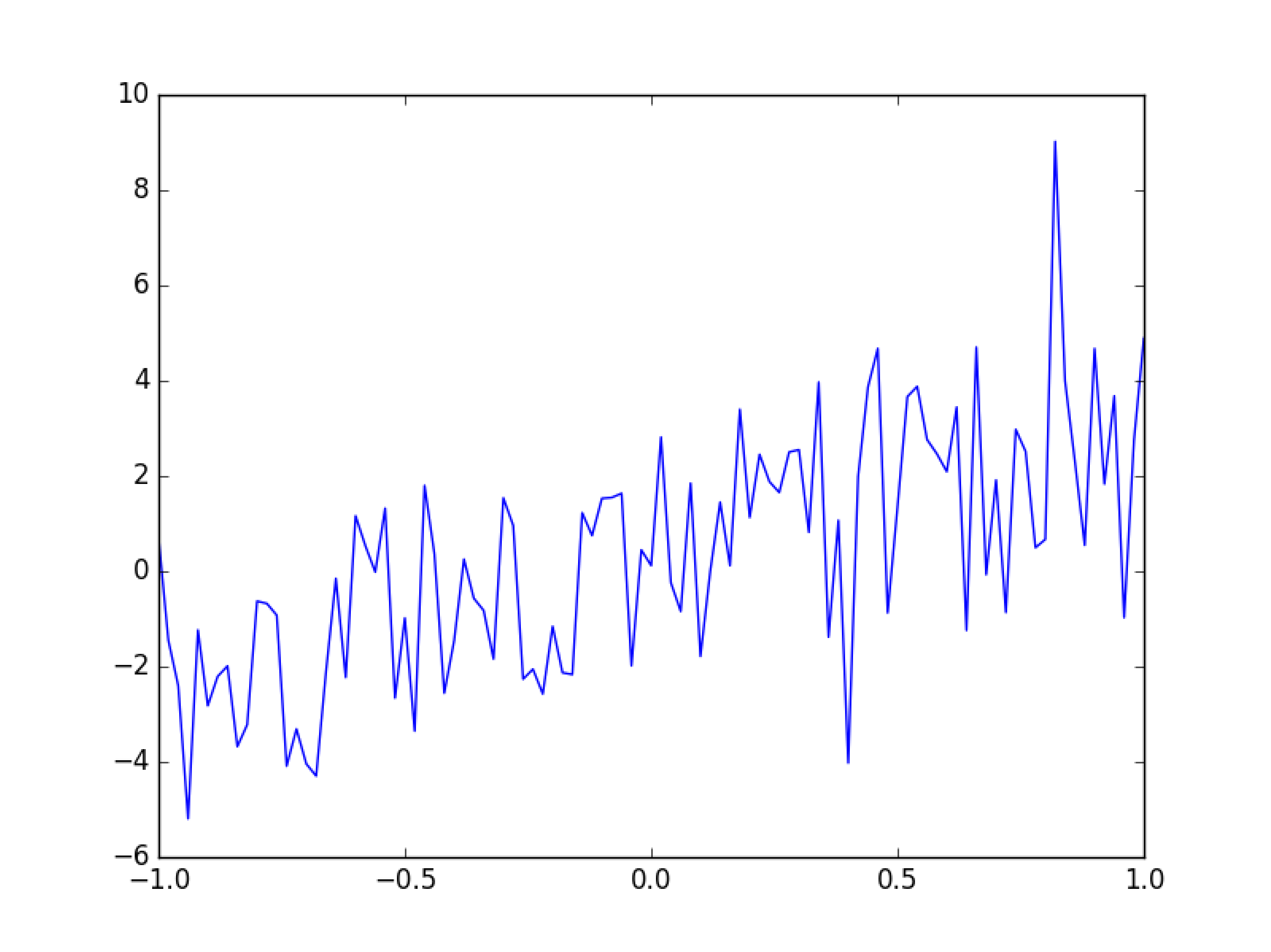
- There are 101 elements in both the x and y vectors

What just happened??

```
plt.plot(x, y)
plt.show()
```

Finally, we generate a series on our plot space using the x and y vectors as coordinates, and tell Python to show us the plot

Should look like:



Quick Forecast

```
xs = np.concatenate((np.ones(101).reshape(101,1),
                     x.reshape(101,1)), axis=1)

beta = np.linalg.solve(np.dot(xs.T, xs), np.dot(xs.T, y))

yhat = beta[0] + beta[1]*x

plt.plot(x, yhat)
plt.plot(x, y)
plt.show()
```

Now What?

```
xs = np.concatenate((np.ones(101).reshape(101,1),
                     x.reshape(101,1)), axis=1)
```

We create a matrix with a column of ones (to generate an intercept), and our x values.

Now What?

```
beta = np.linalg.solve(np.dot(xs.T, xs), np.dot(xs.T, y))
```

Then we solve the equation

$$\hat{\beta} = (x'x)^{-1}x'y$$

- Note that we do NOT explicitly calculate the inverse of the $(x'x)$ matrix!

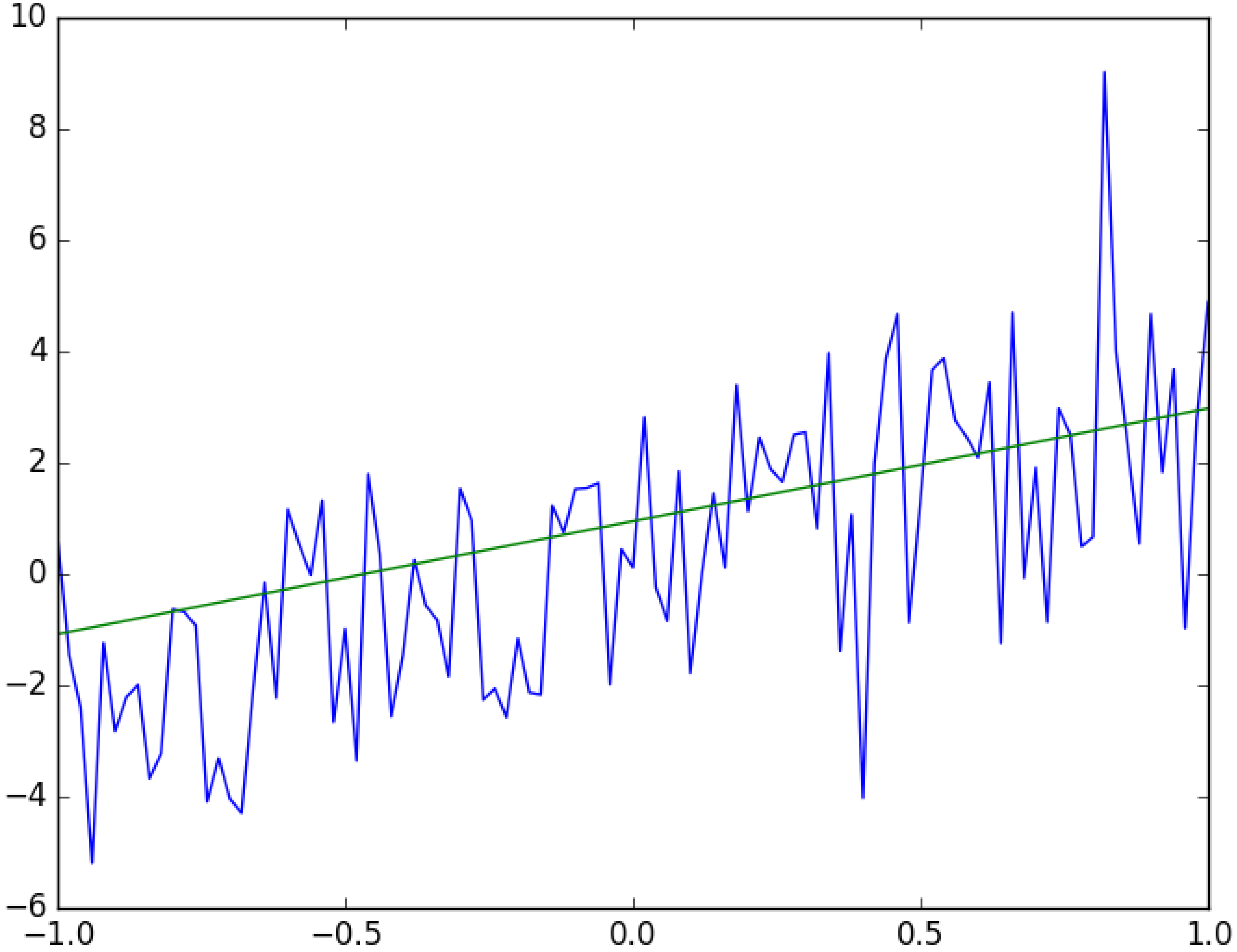
Now What?

```
yhat = beta[0] + beta[1]*x

plt.plot(x, yhat)
plt.plot(x, y)
plt.show()
```

And then we calculate our *estimate* of y using the first element (beta[0]) as an intercept, and the second element (beta[1]) as the slope of our function

Now we see...



Our Goal

In this course, we want to learn how to predict outcomes based on the information that we already possess.

Forecasting

- Time Series forecasts
- Probility models
- Forecasting using machine learning
- Using ensemble methods to strengthen our understanding
- Choosing the best tool for the job

Remembering OLS...

- Ordinary Least Squares (OLS) is the foundation of regression analysis, and an excellent starting point for this course
- Estimates the expected outcome ($\hat{y}$) given the inputs (x)

Remembering OLS...

- Ordinary Least Squares (OLS) is the foundation of regression analysis, and an excellent starting point for this course
- Estimates the expected outcome ($\hat{y}$) given the inputs (x)
- Calculating coefficient standard errors informs us about the level of noise in the data
- R^2 and Adjusted R^2 tell us how much of the total variation our model accounts for

Calculating the Least Squares Estimator

$$y = x\beta + \epsilon$$

$$\Downarrow$$

$$\epsilon = y - x\beta$$

So that we seek to minimize the squared error

$$min\ (y - x\beta)'(y - x\beta)$$

Calculating the Least Squares Estimator

$$min_{\hat{\beta}}\ (y - x\beta)'(y - x\beta)$$

$$\Downarrow$$

$$x'y = x'x\hat{\beta}$$

$$\Downarrow$$

$$\hat{\beta} = (x'x)^{-1}x'y$$

Variance Estimators

Our unbiased estimate of the variance matrix is $\hat{s}^2$:

$$\hat{s}^2 = \frac{(y - x\hat{\beta})'(y - x\hat{\beta})}{(n-k)}$$

or

$$\hat{s}^2 = \frac{y'y - y'x(x'x)^{-1}x'y}{(n-k)}$$

Covariance of $\hat{\beta}$

Under standard assumptions (specifically with normally distributed errors),

$$\hat{\beta} \sim N(\beta, \sigma^2(x'x)^{-1})$$

Therefore, our estimate of the covariance of $\hat{\beta}$ is

$$Cov(\hat{\beta}) = \hat{s}^2(x'x)^{-1}$$

Calculating t-statistics and significance

The t-statistic of an OLS regression coefficient can be calculated as

$$t_j = \frac{\hat{\beta}_j}{\hat{\sigma}_j}$$

Where $\hat{\sigma}_j$ is the j-th element of the main diagonal of $Cov(\hat{\beta})$.

Generating an OLS Results Table

We now have enough information to create a results table after performing OLS estimation:

Coefficient	Std. Error	t-stat	P-value
$\hat{\beta}_j$	$\hat{\sigma}_j$	t_j	$P(\mid \hat{\beta}_j \mid > 0 \mid t_j)$
...	...	...	...

Python and Distribution Functions

```
import scipy.stats.t as tdist

pval = tdist.sf(tstat, df)
```

We use the sf method of the t-distribution object to return 1-CDF of the t-distribution given our calculated t-statistic and our degrees of freedom $(n - k)$.

Functions in Python

Sometimes, we want to make a prepackaged function to repeatedly generate results of a certain kind.

```
def myFunction(input1, input2, ...):
    line1
    line2
    ...
    return results # can be one object, or a list of them
```

Functions in Python

A simple example:

```
def sayHello(n):
    for i in list(range(n_times)):
        print("Hello!")

    return None
```

Will print "Hello!" n times.

Import Data

```
import pandas as pd

# Read data from excel files
data = pd.read_excel("filename.xlsx")

# Read data from csv files
data = pd.read_csv("filename.csv")
```

We use the pandas library to import a table of data that we can use for calculations.

Break apart Data

```
import patsy as pt

# Create x and y matrices from a Data Frame

y, x = pt.dmatrices("y ~ x1 + x2 + ...", data=data)
```

We use the patsy library to generate the x and y matrices that are necessary for OLS estimation

Size of the Data

We can go back to numpy to find the shape of our data (important for degrees of freedom calculations):

```
import numpy as np

np.shape(data) # Returns (number_rows, number_columns)
```

Getting Help

```
help(pd.read_excel)
```

We use the help function to get information about an object or function.

```
dir(pd.read_excel)
```

The dir function will allow you to view all methods associated with a given object or function.

For lab today

Form a group (of 3-4 people). Work together to write a function that can take an arbitrary Data Frame (imported via pandas), and print an OLS Regression table.

hint:

```
def myOLS(data, regression_equation):
    ...
```