ECON 8310

Business Forecasting

Instructor:
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Office Hours:
Mondays (second half of semester), Thursdays from 4:45-5:45 PM

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Quick Note

You will be expected to program in class every week. If you haven't taken ECON 8320 (Tools for Data Analysis), this might mean that you need to spend some extra time outside of class:

- Udacity.com is an excellent learning resource
- Datacamp.com is another great resource to get you started
- Remember: if you need to, spend time outside class practicing (by time I mean hours)

Quick Note

Your ability to use code to solve problems will be the basis for your grade in this course, so if you cannot commit the time to practice coding, you are not likely to pass this class.

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	360 points
Reading Assignments	120 points
Midterm Exam	250 points
Final Exam	270 points

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 revise the course material as needed to suit your interests

Lecture 1: Intro and OLS Review

What is Forecasting?

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

- Predict commodity pricing
- 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

```
import numpy as np
from plotly.offline import iplot, init_notebook_mode
import plotly.graph_objs as go
init_notebook_mode(connected=True)

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

trace1 = go.Scatter(
    x = x,
    y = y,
    mode = "markers"
    )

data = go.Data([trace1])

iplot(data)
```

What just happened??

```
import numpy as np
from plotly.offline import iplot, init_notebook_mode
import plotly.graph_objs as go
```

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??

```
init_notebook_mode(connected=True)
```

This line tells our plotting library to render the figure inside of our notebook environment

NOTE: If you are not using Jupyter notebooks, you need to import `plot` instead of `iplot`, and do not need to keep this line in your code.

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??

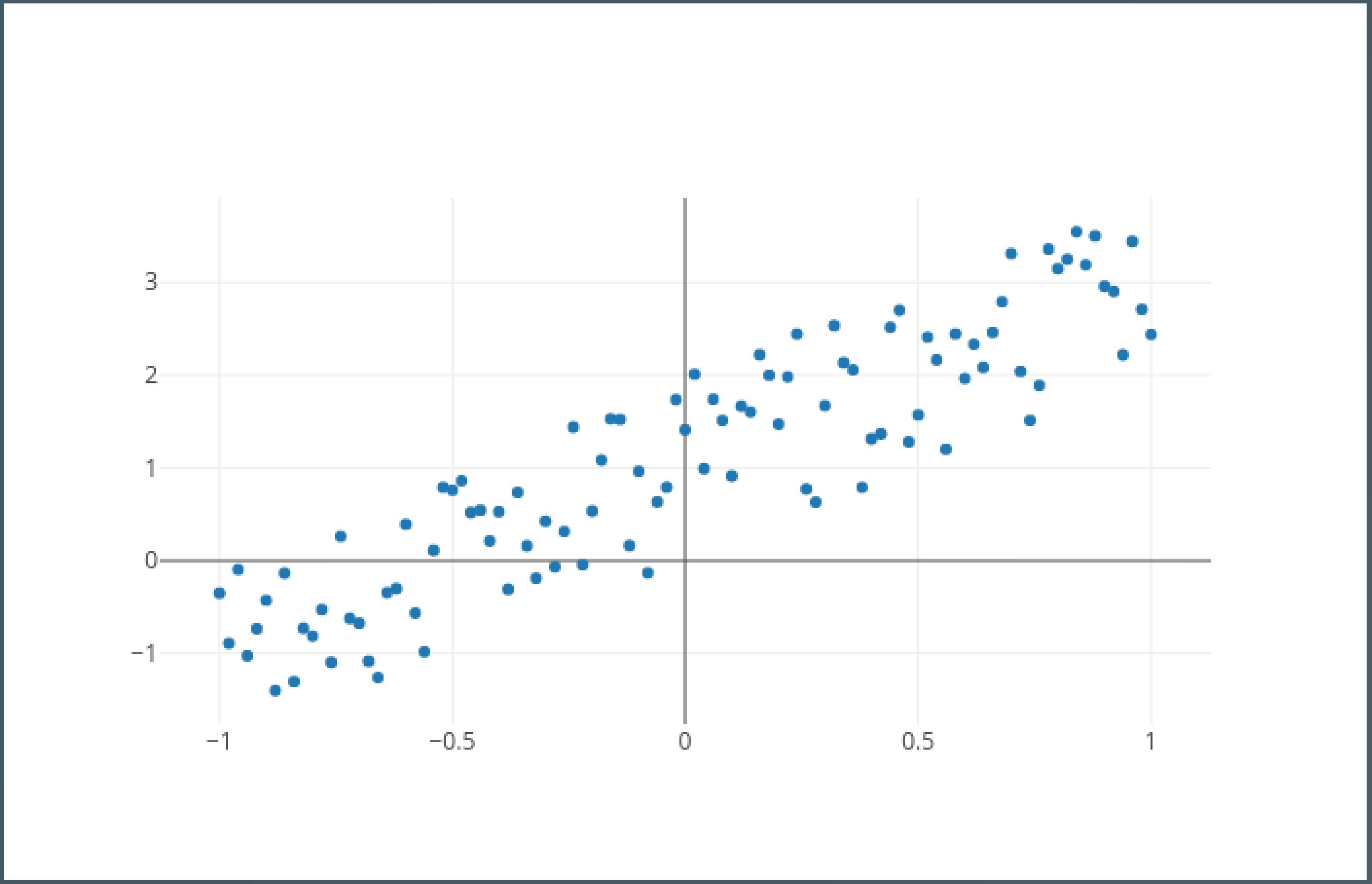
```
trace1 = go.Scatter(
    x = x,
    y = y,
    mode = "markers"
    )

data = go.Data([trace1])

plot(data)
```

Finally, we generate a plot 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

trace1 = go.Scatter(x = x, y = y,
    mode = "markers"
    )
trace2 = go.Scatter(x = x, y = yhat,
    mode = "lines"
    )

data = go.Data([trace1, trace2])
plot(data)
```

What was that??

```
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.

What was that??

```
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!

What was that??

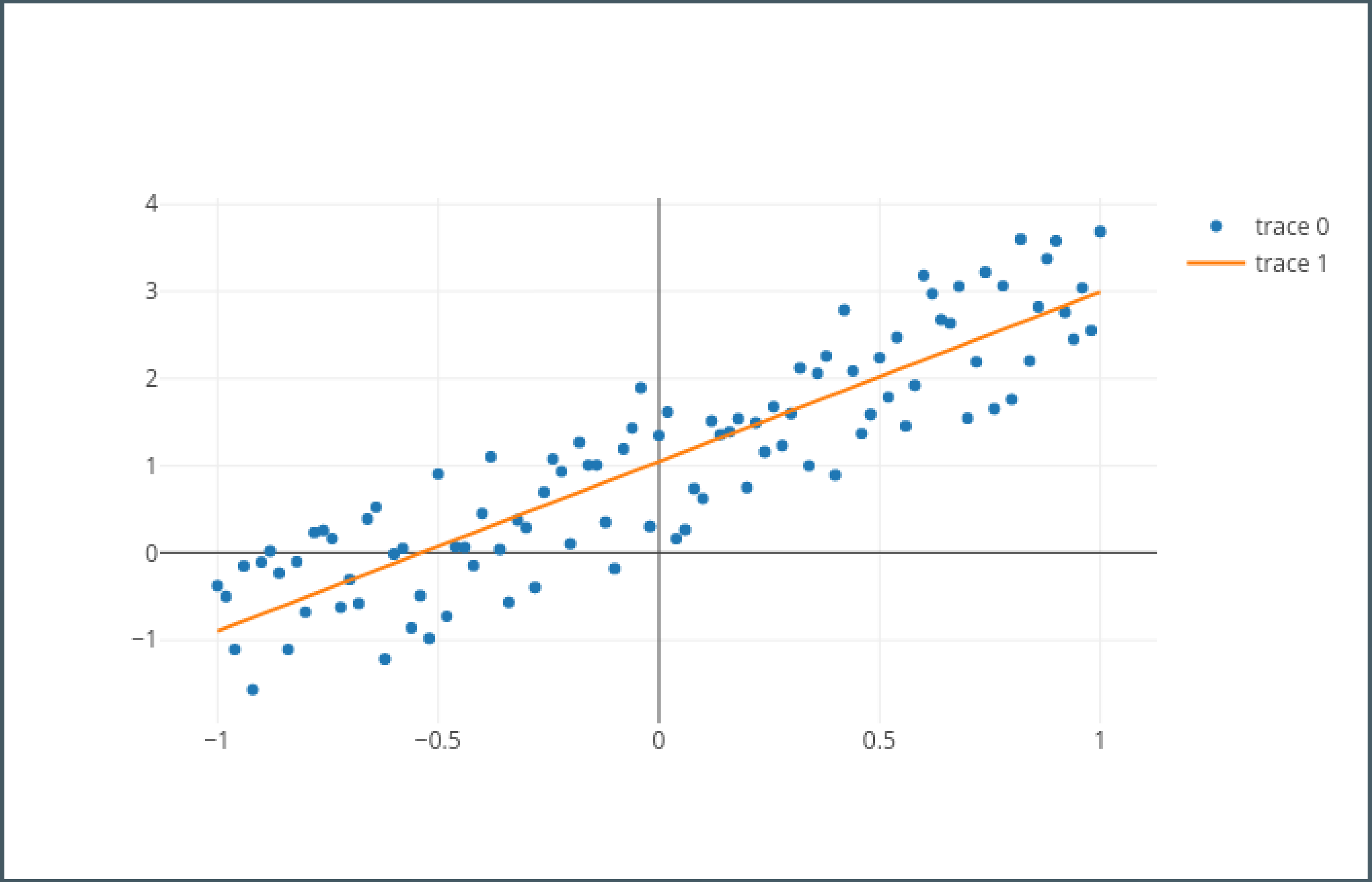
```
yhat = beta[0] + beta[1]*x

trace1 = go.Scatter(x = x, y = y,
    mode = "markers")
trace2 = go.Scatter(x = x, y = yhat,
    mode = "lines")
data = go.Data([trace1, trace2])
plot(data)
```

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.

Then we plot both the output variable (`y`) and our prediction (`yhat`).

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
- Probability 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

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

$$\Downarrow$$

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

$$\Downarrow$$

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

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

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

Note: The main diagonal of the covariance matrix is the variance of each $\hat{\beta}$ coefficient.

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 square root of the j-th element on 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

```
from scipy.stats import t

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

We use the `sf` (denoting *survival function*) 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

```python
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

Using `patsy` allows us to easily replicate our formatting from one dataset to another (more on this next week)

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.

OLS in Statsmodels

```
import statsmodels as sm
# Declare the model, and create an instance of the OLS
#  class
model = sm.OLS(endog = y, exog = x)
# Fit the model, optionally using specific parameters
modelFit = model.fit()
```

We can easily use just a couple lines to implement an Ordinary Least Squares regression model. We simply declare the model, then fit it.

We can also use the `.summary()` and `.predict()` methods on fitted models to view regression tables or to make predictions with new observations.

Bonus Exercise

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):
    ...
```

Links: [t-stats in Scipy]

Next week, we will start using pre-built libraries