

INTRODUCTION TO REGRESSION ANALYSIS

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DAT₂

INTRODUCTION TO REGRESSION ANALYSIS

LEARNING OBJECTIVES

- ▶ Define data modeling and simple linear regression
- ▶ Build a linear regression model using a dataset that meets the linearity assumption using the sci-kit learn library
- ▶ Understand and identify multicollinearity in a multiple regression

PRE-WORK REVIEW

- Effectively show correlations between an independent variable x and a dependent variable y
- Be familiar with the `get_dummies` function in pandas
- Understand the difference between vectors, matrices, Series, and DataFrames
- Understand the concepts of outliers and distance.
- Be able to interpret p values and confidence intervals

WHERE ARE WE IN THE DATA SCIENCE WORKFLOW?

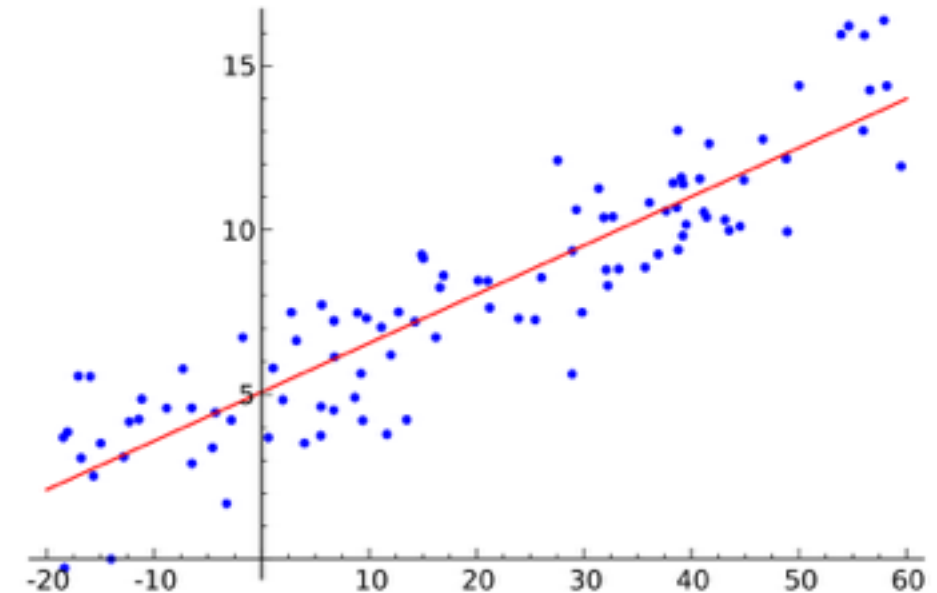
- ▶ Data has been **acquired** and **parsed**.
- ▶ Today we'll **refine** the data and **build** models.
- ▶ We'll also use plots to **represent** the results.

INTRODUCTION

SIMPLE LINEAR REGRESSION

SIMPLE LINEAR REGRESSION

- ▶ Def: Explanation of a continuous variable given a series of independent variables
- ▶ The simplest version is just a line of best fit:
 $y = mx + b$
- ▶ Explain the relationship between **x** and **y** using the starting point **b** and the power in explanation **m**.



SIMPLE LINEAR REGRESSION

- ▶ However, linear regression uses linear algebra to explain the relationship between *multiple* x's and y.
- ▶ The more sophisticated version: $y = \text{beta} * X + \text{alpha} (+ \text{error})$
- ▶ Explain the relationship between the matrix **X** and a dependent vector **y** using a y-intercept **alpha** and the relative coefficients **beta**.

SIMPLE LINEAR REGRESSION

- ▶ Linear regression works **best** when:
 - ▶ The data is normally distributed (but doesn't have to be)
 - ▶ X's significantly explain y (have low p-values)
 - ▶ X's are independent of each other (low multicollinearity)
 - ▶ Resulting values pass linear assumption (depends upon problem)
- ▶ If data is not normally distributed, we could introduce *bias*.

SIMPLE LINEAR REGRESSION ANALYSIS IN SKLEARN

- ▶ Sklearn defines models as *objects* (in the OOP sense).
- ▶ You can use the following principles:
 - ▶ All sklearn modeling classes are based on the [base estimator](#). This means all models take a similar form.
 - ▶ All estimators take a matrix \mathbf{X} , either sparse or dense.
 - ▶ Supervised estimators also take a vector \mathbf{y} (the response).
 - ▶ Estimators can be customized through setting the appropriate parameters.

CLASSES AND OBJECTS IN OOP

- ▶ **Classes** are an abstraction for a complex set of ideas, e.g. *human*.
- ▶ Specific **instances** of classes can be created as **objects**.
 - ▶ *john_smith = human()*
- ▶ Objects have **properties**. These are attributes or other information.
 - ▶ *john_smith.age*
 - ▶ *john_smith.gender*
- ▶ Objects have **methods**. These are procedures associated with a class/object.
 - ▶ *john_smith.breathe()*
 - ▶ *john_smith.walk()*

DEMO: REGRESSING AND NORMAL DISTRIBUTIONS

- ▶ Work through `/starter-code-6.ipynb` in pairs.
- ▶ The first plot shows a relationship between two values, though not a linear solution.
- ▶ Note that `lmplo()` returns a straight line plot.
- ▶ However, we can transform the data, both log-log distributions to get a linear solution.

INTRODUCTION

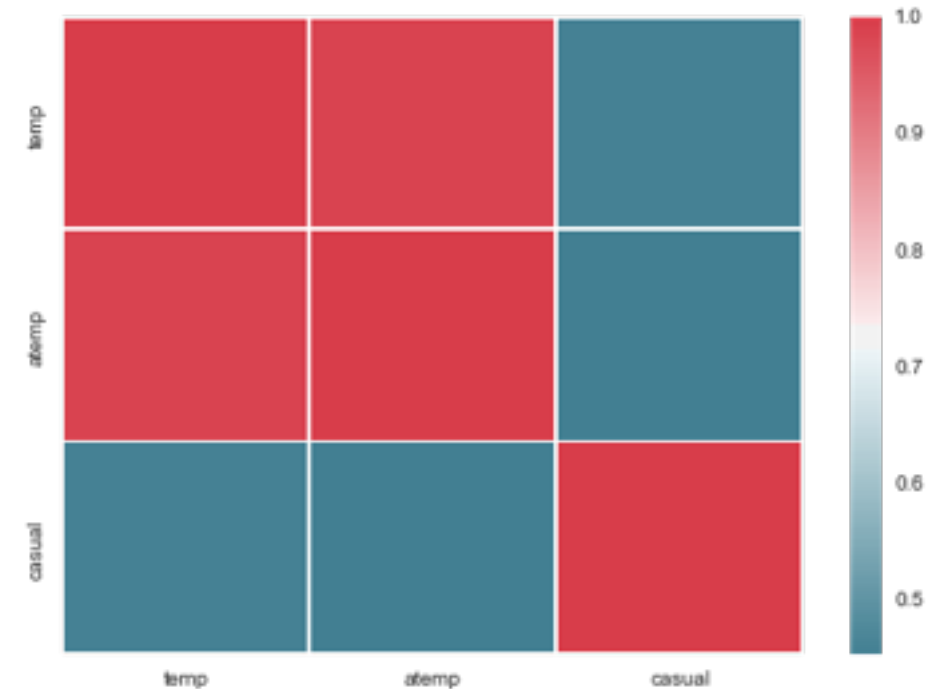
MULTIPLE REGRESSION ANALYSIS

MULTIPLE REGRESSION ANALYSIS

- ▶ Simple linear regression with one variable can explain some variance, but using multiple variables can be much more powerful.
- ▶ We want our multiple variables to be mostly independent to avoid multicollinearity.
- ▶ Multicollinearity, when two or more variables in a regression are highly correlated, can cause problems with the model.

BIKE DATA EXAMPLE

- ▶ We can look at a correlation matrix of our bike data.
- ▶ Even if adding correlated variables to the model improves overall variance, it can introduce problems when explaining the output of your model.
- ▶ What happens if we use a second variable that isn't highly correlated with temperature?



CONCLUSION

TOPIC REVIEW

CONCLUSION

- ▶ You should now be able to answer the following questions:
 - ▶ What is simple linear regression?
 - ▶ What makes multi-variable regressions more useful?
 - ▶ What challenges do they introduce?
 - ▶ How do you dummy a category variable?
 - ▶ How do you avoid a singular matrix?

WEEK 3 : LESSON 6

UPCOMING WORK

Final Project: Part 1
due L8

INTRODUCTION TO REGRESSION ANALYSIS

Q & A

INTRODUCTION TO REGRESSION ANALYSIS

EXIT TICKET

**DON'T FORGET TO FILL OUT YOUR EXIT
TICKET!**