GENERAL ASSEMBLY

INTRODUCTION TO REGRESSION ANALYSIS

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INTRODUCTION TO REGRESSION ANALYSIS

PRE-WORK

PRE-WORK REVIEW

- Effectively show correlations between an independent variable x and a dependent variable y
    - What is collinearity and how do you detect it using pandas?
- Be familiar with the get_dummies function in pandas
    - What does it do?
- Understand the difference between vectors, matrices, Series, and DataFrames
- Be able to interpret p values and confidence intervals
    - What is the p-value and how does it related to confidence interval?

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.

OPENING

INTRODUCTION TO REGRESSION ANALYSIS

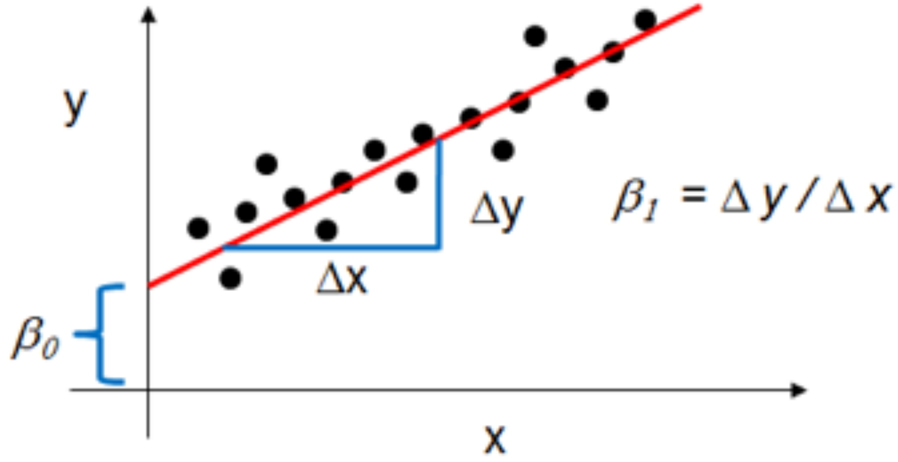
WHERE ARE WE IN THE DATA SCIENCE WORKFLOW?

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

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** the starting point **b** and the power in



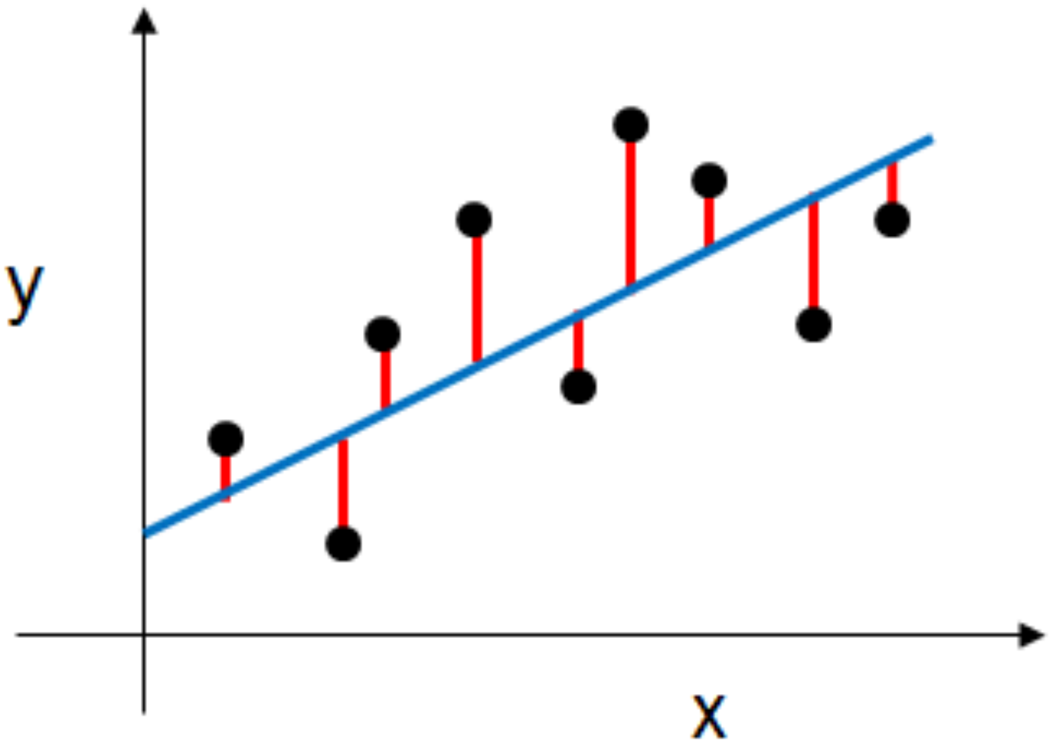
SIMPLE LINEAR REGRESSION

- However, linear regression uses linear algebra to explain the relationship between *multiple* x's and y.

- The more sophisticated version: y = beta * X + alpha (+ error)

- Explain the relationship between the matrix **X** and a dependent vector **y** using a y-intercept **alpha** and the relative coefficients **beta**.

Least Squares



Model Prediction

$$SS_{residuals} = \sum_{i=1}^{N} (\hat{y}_i - y_i)^2$$

Observed Result

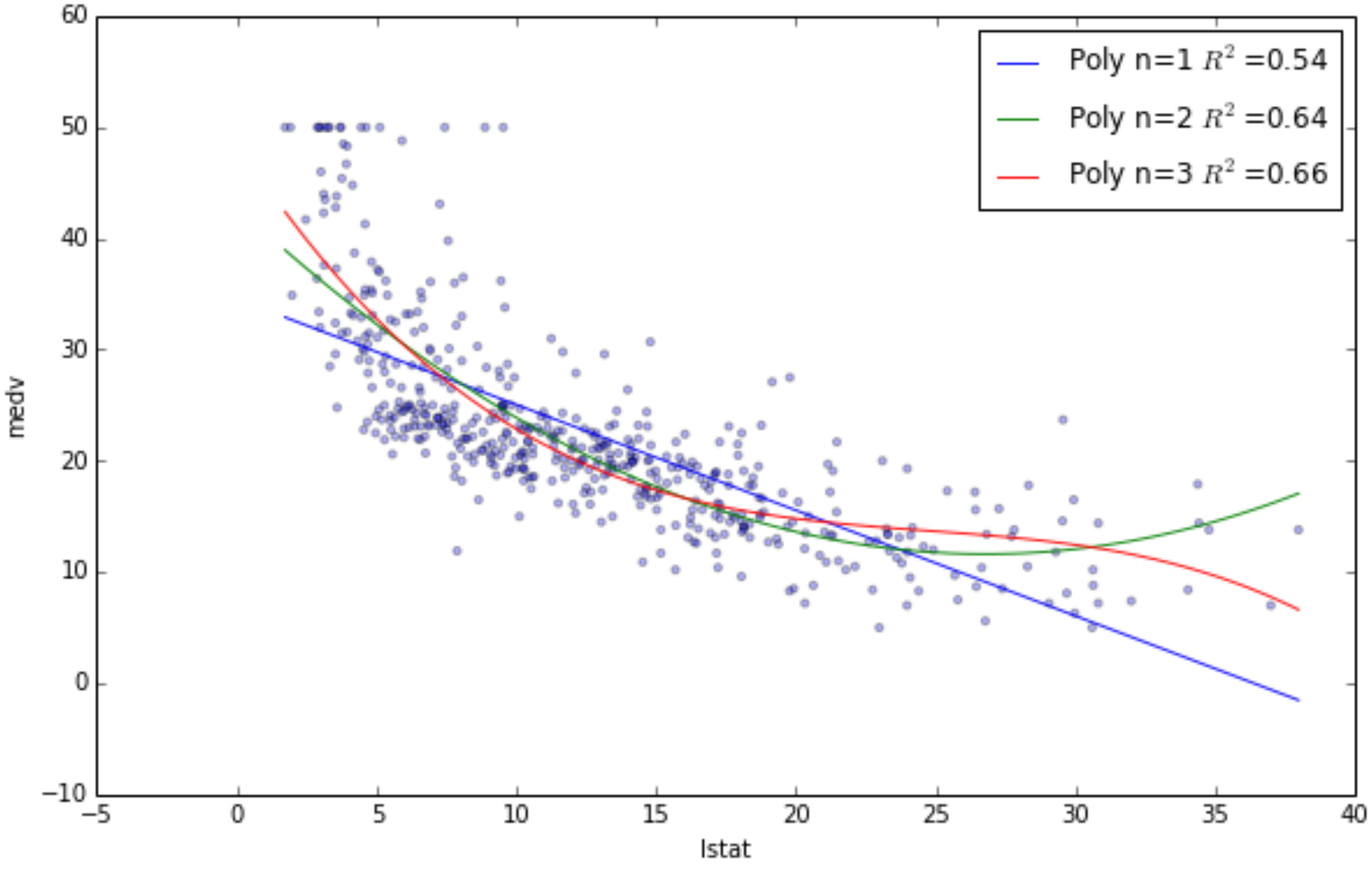
OPENING

R-SQUARES AND RESIDUALS

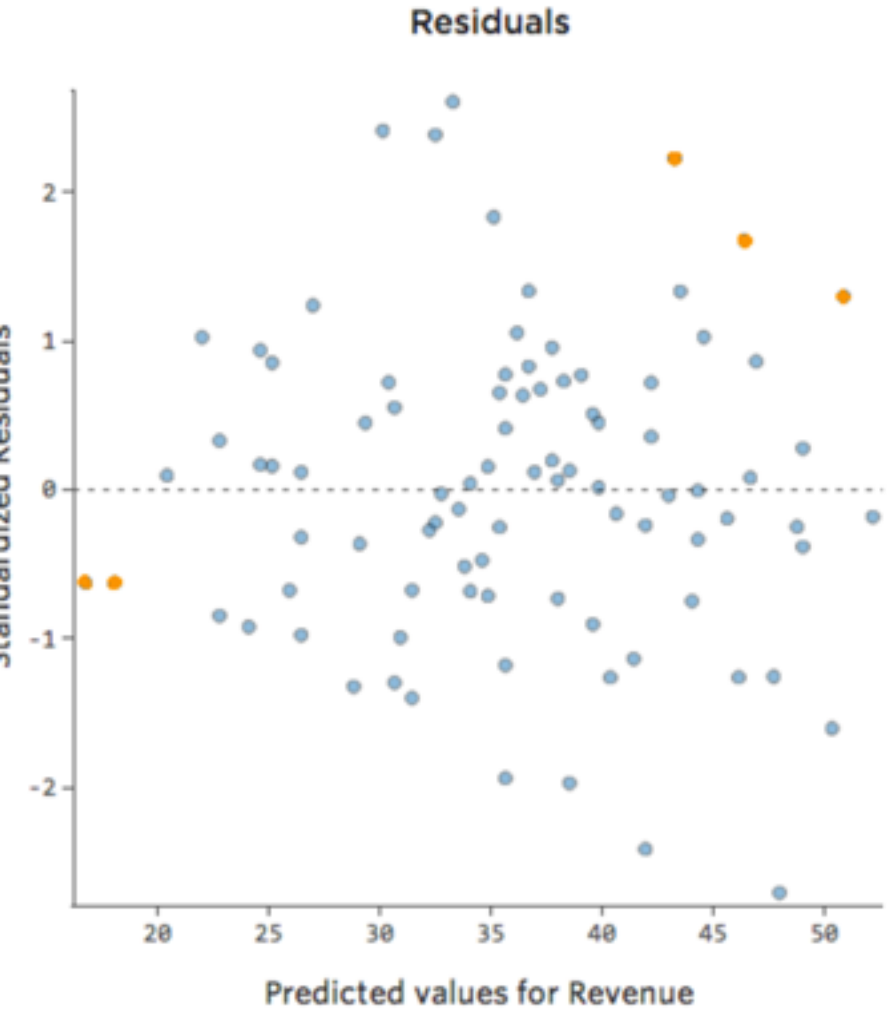
WHAT IS R-SQUARED? WHAT IS A RESIDUAL?

- R-squared, the central metric introduced for linear regression
- Which model performed better, one with an r-squared of 0.79 or 0.81?
- R-squared measures explained variance.
- But does it tell the magnitude or scale of error?
- We’ll explore loss functions and find ways to refine our model.

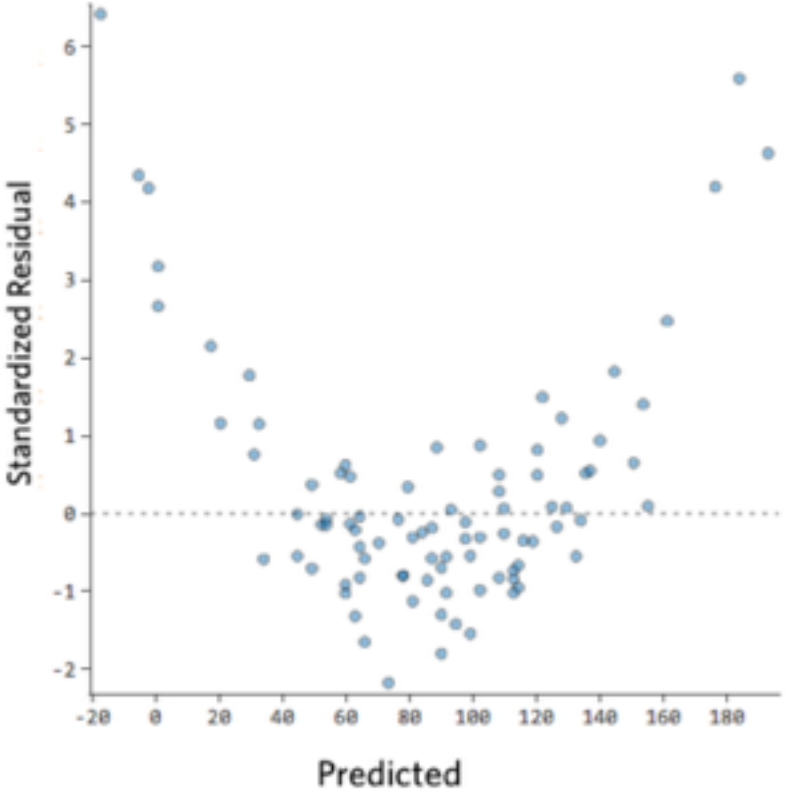
R^2's for Different Fits

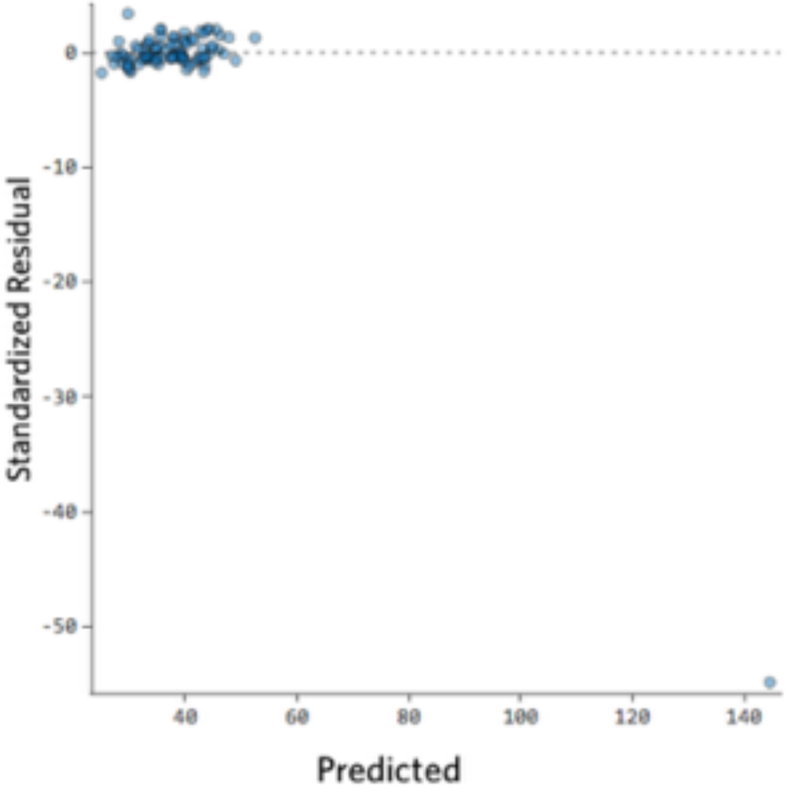


Residuals



Good





Bad

Checks

SIMPLE LINEAR REGRESSION ASSUMPTIONS

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)
    - Categorical variables must be represented in N-1 categories. (Dummy Variable Trap)
- If data is not normally distributed, we could introduce *bias*.

DEMO

REGRESSING AND NORMAL DISTRIBUTIONS

LAB: REGRESSING AND NORMAL DISTRIBUTIONS

- Follow along with your starter code notebook while I walk through these examples.
- The first plot shows a relationship between two values, though not a linear solution.
- Note that lmplot() returns a straight line plot.
- However, we can transform the data, both log-log distributions to get a linear solution.

GUIDED PRACTICE

USING SEABORN TO GENERATE SIMPLE LINEAR MODEL PLOTS

ACTIVITY: GENERATE SINGLE VARIABLE LINEAR MODEL PLOTS

EXERCISE

DIRECTIONS (15 minutes)

1. Update and complete the code in the starter notebook to use **lmplot** and display correlations between body weight and two dependent variables: **sleep_rem** and **awake**.

DELIVERABLE

Two plots

DEMO

SIGNIFICANCE IS KEY

DEMO: SIGNIFICANCE IS KEY

- Follow along with your starter code notebook while I walk through these examples.

- What does the residual plot tell us?

- How can we use the linear assumption?

GUIDED PRACTICE

USING THE LINEAR REGRESSION OBJECT

ACTIVITY: USING THE LINEAR REGRESSION OBJECT

EXERCISE

DIRECTIONS (15 minutes)

1. With a partner, generate two more models using the log-transformed data to see how this transform changes the model's performance.

DELIVERABLE

Two new models

INTRODUCTION

MULTIPLE REGRESSION ANALYSIS

MULTIPLE REGRESSION ANALYSIS

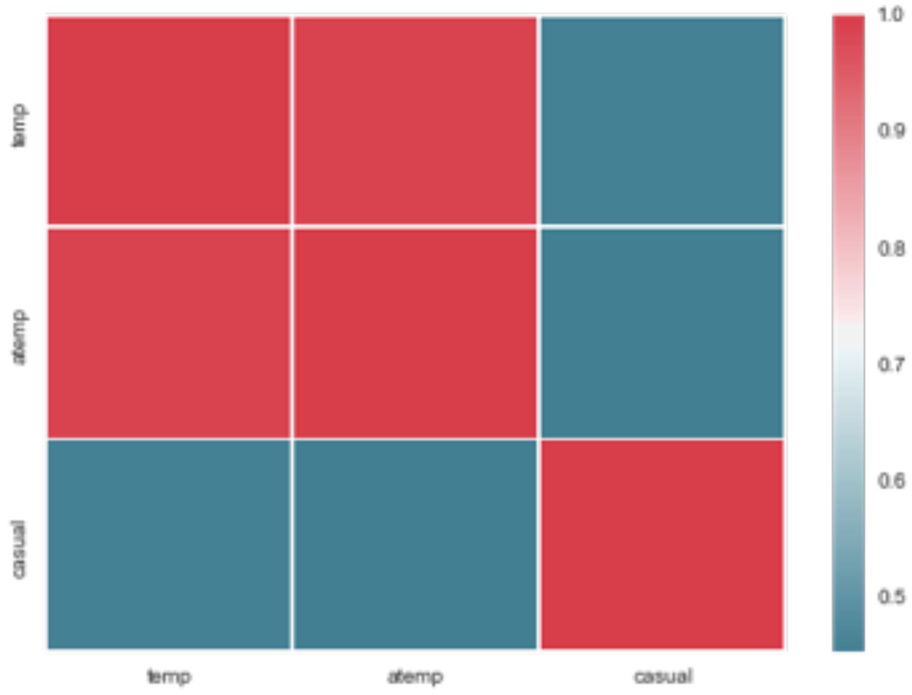
- Simple linear regression with one variable can explain some variance, but using multiple variables can be much more powerful.
- We want our multiple variables to be mostly independent to avoid multicollinearity.
- Multicollinearity, when two or more variables in a regression are highly correlated,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

BIKE DATA EXAMPLE

- Lets check Part 2 of the starter-code notebook - 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?



GUIDED PRACTICE

MULTICOLLINEARITY WITH DUMMY VARIABLES

ACTIVITY: MULTICOLLINEARITY WITH DUMMY VARIABLES

EXERCISE

DIRECTIONS (15 minutes)

1. Load the bike data.
2. Run through the code on the following slide.
3. What happens to the coefficients when you include all weather situations instead of just including all except one?

DELIVERABLE

Two models' output

ACTIVITY: MULTICOLLINEARITY WITH DUMMY VARIABLES

EXERCISE

DIRECTIONS (15 minutes)

```
lm = linear_model.LinearRegression()
weather = pd.get_dummies(bike_data.weathersit)
get_linear_model_metrics(weather[[1, 2, 3, 4]], y, lm)
print
# drop the least significant, weather situation  = 4
get_linear_model_metrics(weather[[1, 2, 3]], y, lm)
```

DELIVERABLE

Two models' output

GUIDED PRACTICE

COMBINING FEATURES INTO A BETTER MODEL

ACTIVITY: COMBINING FEATURES INTO A BETTER MODEL

EXERCISE

DIRECTIONS (15 minutes)

1. With a partner, complete the code on the following slide.
2. Visualize the correlations of all the numerical features built into the dataset.
3. Add the three significant weather situations into our current model.
4. Find two more features that are not correlated with the current features, but could be strong indicators for predicting guest riders.

DELIVERABLE

Visualization of correlations, new models

ACTIVITY: COMBINING FEATURES INTO A BETTER MODEL

EXERCISE

DIRECTIONS (15 minutes)

```
lm = linear_model.LinearRegression()
bikemodel_data = bike_data.join() # add in the three weather
situations

cmap = sns.diverging_palette(220, 10, as_cmap=True)
correlations = # what are we getting the correlations of?
print correlations
print sns.heatmap(correlations, cmap=cmap)

columns_to_keep = [] #[which_variables?]
final_feature_set = bikemodel_data[columns_to_keep]

get_linear_model_metrics(final_feature_set, y, lm)
```

DELIVERABLE

Visualization of correlations, new models

INDEPENDENT PRACTICE

BUILDING MODELS FOR OTHER Y VARIABLES

ACTIVITY: BUILDING MODELS FOR OTHER Y VARIABLES

EXERCISE

DIRECTIONS (25 minutes)

1. Build a new model using a new y variable: registered riders.
2. Pay attention to the following:
    a. the distribution of riders (should we rescale the data?)
    b. checking correlations between the variables and y variable
    c. choosing features to avoid multicollinearity
    d. model complexity vs. explanation of variance
    e. the linear assumption

BONUS

1. Which variables make sense to dummy?
2. What features might explain ridership but aren't included? Can you build these features with the included data and pandas?

DELIVERABLE

A new model and evaluation metrics

BONUS MATERIAL

SIMPLE REGRESSION ANALYSIS IN SKLEARN

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 **X**, either sparse or dense.
    - Supervised estimators also take a vector **y** (the response).
    - Estimators can be customized through setting the appropriate parameters.

SIMPLE LINEAR REGRESSION ANALYSIS IN SKLEARN

- General format for sklearn model classes and methods

```
# generate an instance of an estimator class
estimator = base_models.AnySKLearnObject()
# fit your data
estimator.fit(X, y)
# score it with the default scoring method (recommended to use the metrics module in the future)
estimator.score(X, y)
# predict a new set of data
estimator.predict(new_X)
# transform a new X if changes were made to the original X while fitting
estimator.transform(new_X)
```

- LinearRegression() doesn't have a transform function

- With this information, we can build a simple process for linear regression.

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?
    - How do you dummy a category variable?
    - How do you detect multi-colinearity?

UPCOMING WORK

UPCOMING WORK

- Project: Final Project, Deliverable 1

INTRODUCTION TO REGRESSION ANALYSIS

Q & A

INTRODUCTION TO REGRESSION ANALYSIS

EXIT TICKET

DON'T FORGET TO FILL OUT YOUR EXIT TICKET!