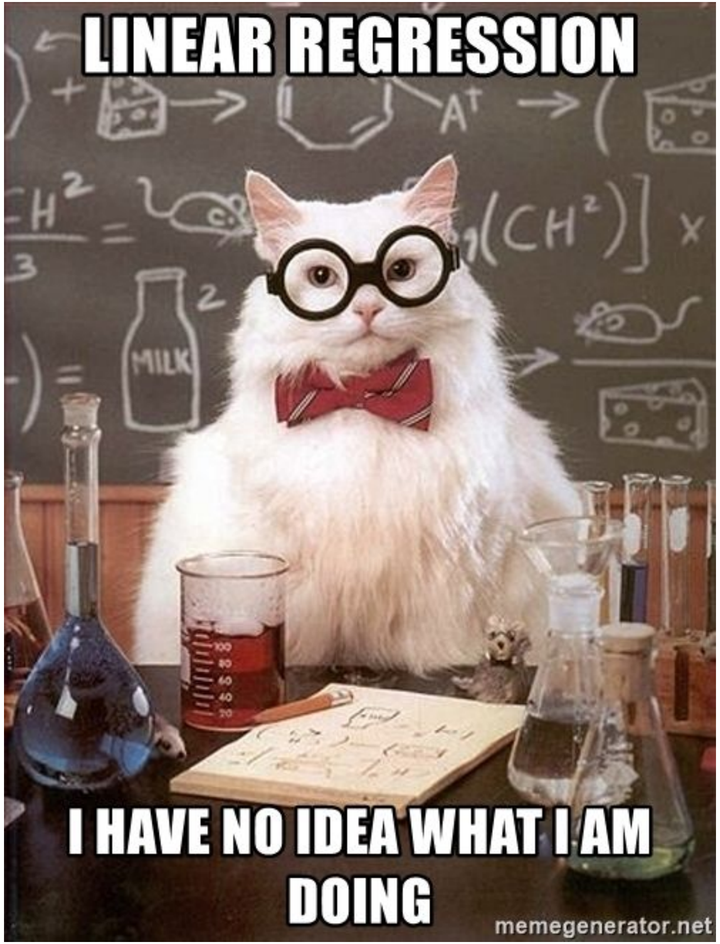

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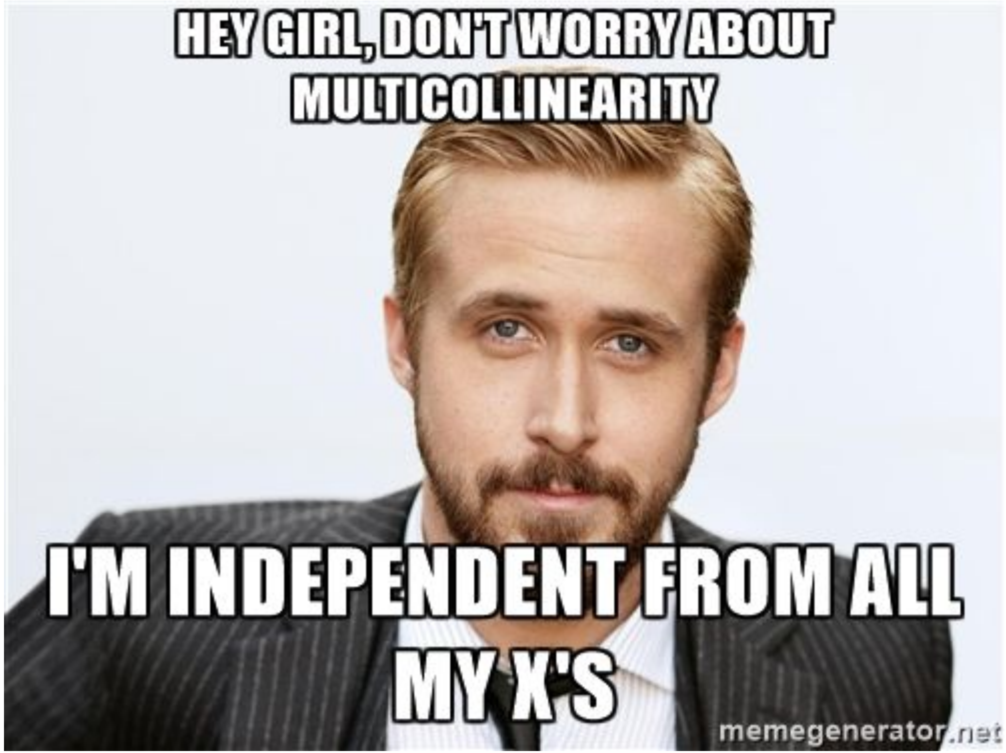

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Welcome to Week 16, Lecture 02!

Diagnosing and Interpreting Linear Regression

06/15/22

Agenda

- Assignments
- Announcements

- Last Class:
    - Why Use Linear Regression?
    - How does Linear Regression work?
    - What are coefficients?
    - The 4 Assumptions of Linear Regression

- Today:
    - Demo: How to fit a linear regression with statsmodels.
    - Diagnosing a Regression model
    - Iterating on our model
    - 🤞Advanced approaches for multicollinearity
    - 🤞Coefficient Interpretation

Assignments

Only 1 required assignment:

- **Project 3 - Part 4(Core)**

Highly Recommended:

- Do Project 3 - Part 5 for your portfolio!!!

Week 3 assignment feedback added!

Final Assignment Deadline = Friday at 9 AM PST!

- All resubmissions from week 1 and 2 .
- All week 3 and 4 assignments turned in.
- **Grace Period for Week 3 Resubmits:**
  - If you are asked for resubmissions for week 3 assignments, the deadline for submitting those is Monday at 9 AM PST.

📣 Announcements/Reminders

- 🙏 **Please take a few minutes to fill out the End of Stack survey.** 🥺 **https://login.codingdojo.com/dashboard/end-stack-survey**

- 🏁**Graduation Requirements:**
  - 90% Core Assignment Completion
  - 80% Attendance
  - **Deadline: Friday 6/17 at 9 AM PST**

- 🎓 **Online DS Graduation!**
  - **Friday, July 01st @ 5 PM PST**
    - Our cohort + students from 12 week program.
    - In the same Zoom Room as lecture

Linear Regression Assumptions

Review

The 4 Assumptions of Linear Regression

The first 2 assumptions are about the **features:**

- **Linearity**
- **Independence of features** (AKA Little-to-No Multicollinearity)

The last 2 assumptions are about the **residuals (errors):**

- **Normality**
- **Homoscedasticity**

Fitting a Linear Regression with Statsmodels

Walkthrough: Linear Regression with statsmodels

Fitting a linear regression to predict movie revenue.

- Basically, the optional assignment: Project 3 - Part 5.
- Repo: https://github.com/coding-dojo-data-science/data-enrichment-linear-regression-with-movies

- Last Class:
    - Combining many csvs
    - Feature engineering
    - Preparing the data for a statsmodels OLS (add constant)

- Today:
    - Fitting an OLS model.
    - Interpreting the Model Summary and its coefficients.
    - Diagnosing the model
    - Better meeting the assumptions
    - Advanced approaches to dealing with multicollinearity

- BUT BEFORE WE DIVE BACK IN….

Linear Regression Modeling is Iterative

- Be prepared to try MANY versions of your model with changes to your features.

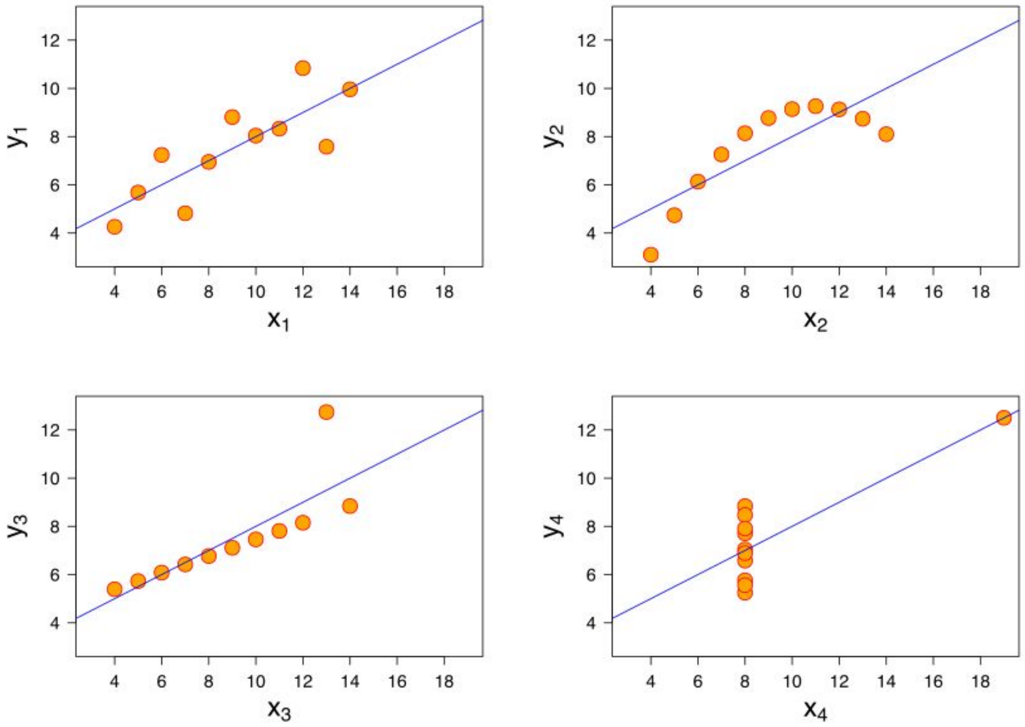
- Functionize your data prep and evaluation process for easy iteration.

- Keep your notebook organized with headers!
    - Add a header for each iteration of your model.

Diagnosing Linear Regression Models

& What to do if you violate the assumptions

Anscombe's quartet



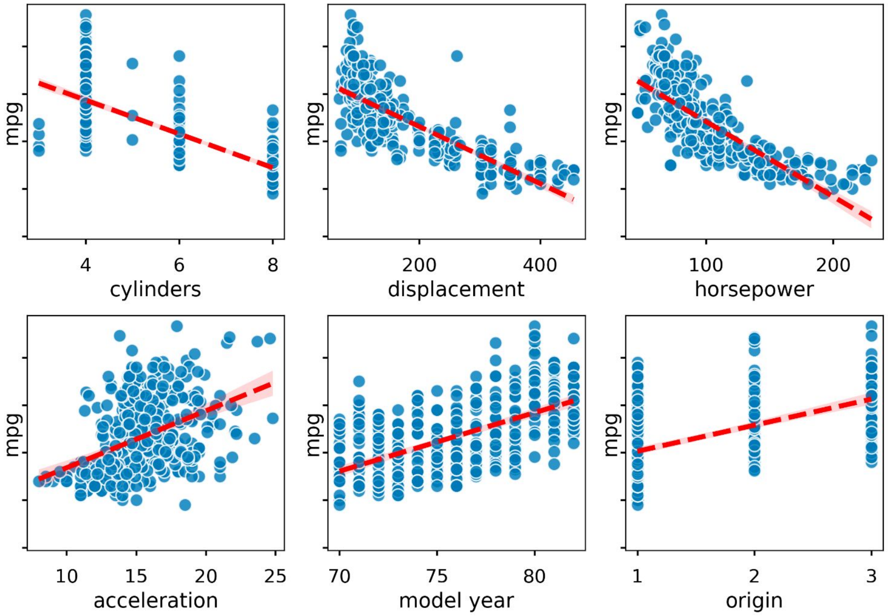
- All 4 of these regression lines have the SAME scores/metrics.
- Without looking at the data/errors, we CANNOT trust our R2 & RMSE alone!

Assumption of Linearity

Checking for Linearity

That the input features have a linear relationship with the target.

- To check:
  - Use visualizations!



If your features violate linearity

- Simplest solution:
  - Drop features that are not linearly correlated with target.

- More Advanced Solutions (not covered today):
  - Transform your non-linear features into PolynomialFeatures.
    - Towards Data Science: Polynomial Regression
    - Machine Learning Mastery: Polynomial Feature Transformations

- When all else fails:
  - Try a different type of regression!

Assumption of Independence

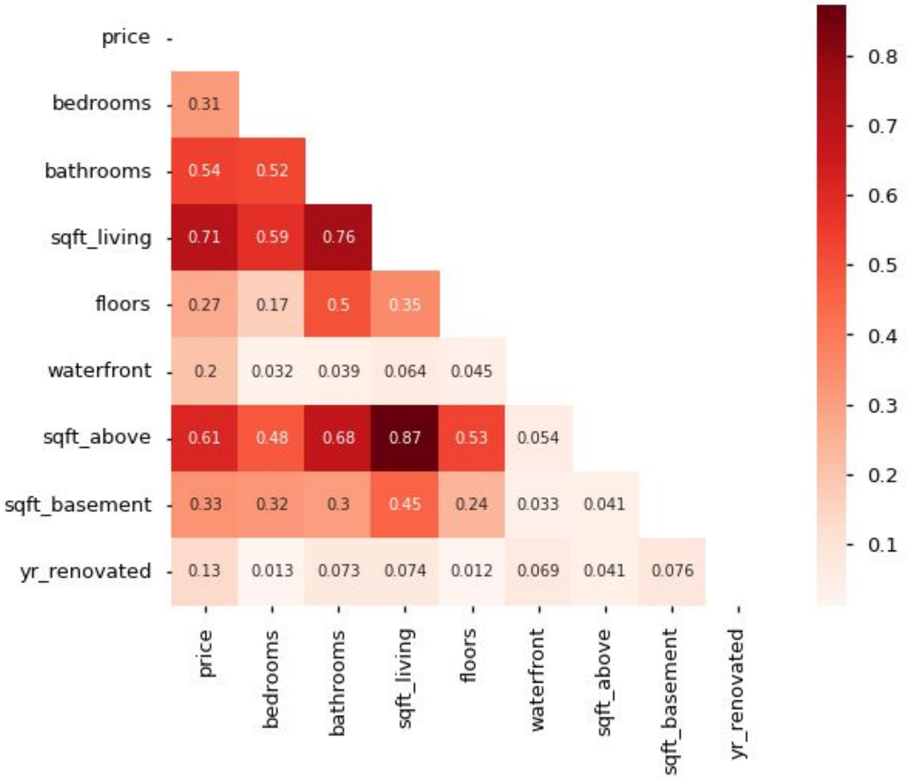
Checking for multicollinearity

(AKA Little-to-No Multicollinearity)

That the features are not strongly related to other features.

To Check:

- Use correlation heatmaps!
- Use Variance Inflation Factor (VIF).
- Look for condition number warning on model.summary()



If your features have multicollinearity:

- Change argument for your OneHotEncoder:
  - Add drop='first"
  - But can't use handle_unknown='ignore'

- Use Variance Inflation Factor! (will demonstrate today)
  - Get VIF Values for your features.
    - Examples:
      - https://www.geeksforgeeks.org/detecting-multicollinearity-with-vif-python/
      - Drop features with a score > ~5

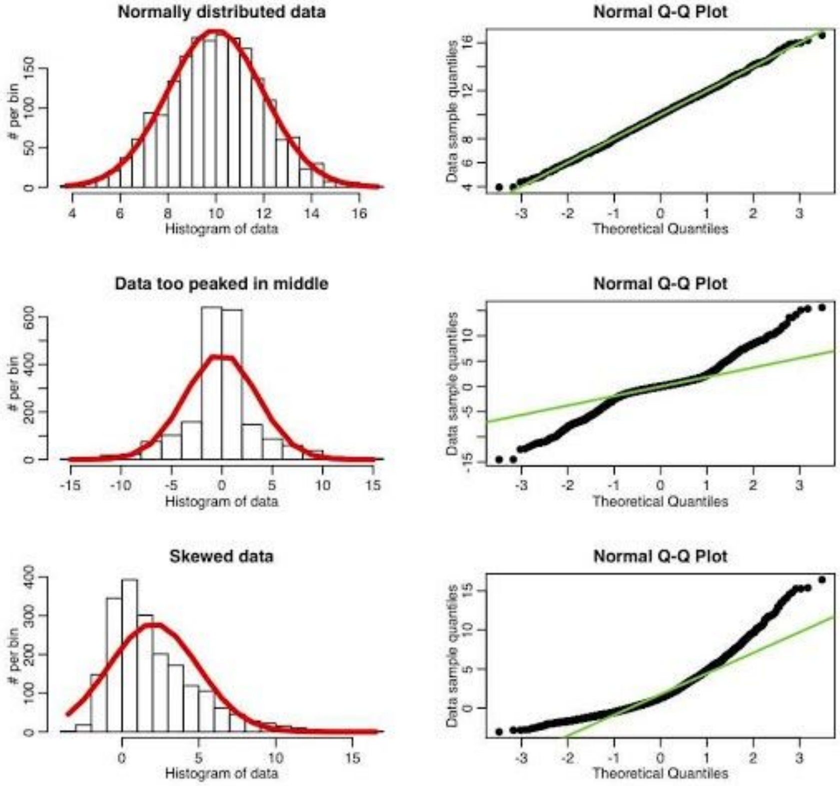
- Try creating "interaction" features to combine 2 features that are highly correlated. Chris Albon Article on Interactions

Assumption of Normality

Checking for Normality (of residuals)

The model's residuals are approximately normally distributed.

- To Check:
  - Use a Quantile-Quantile (Q-Q) Plot!
- Resource:
  - https://towardsdatascience.com/q-q-plots-explained-5aa8495426c0



Source: Sherrytowers Q-Q plot [examples]()

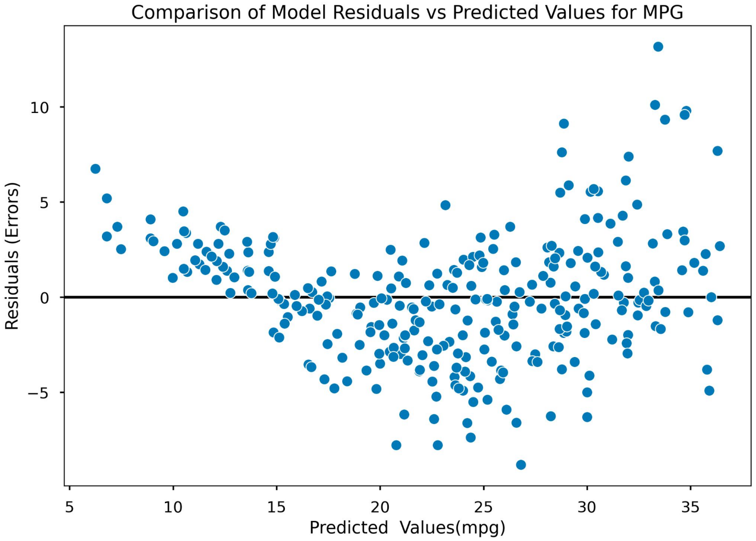
Assumption of Homoscedasticity

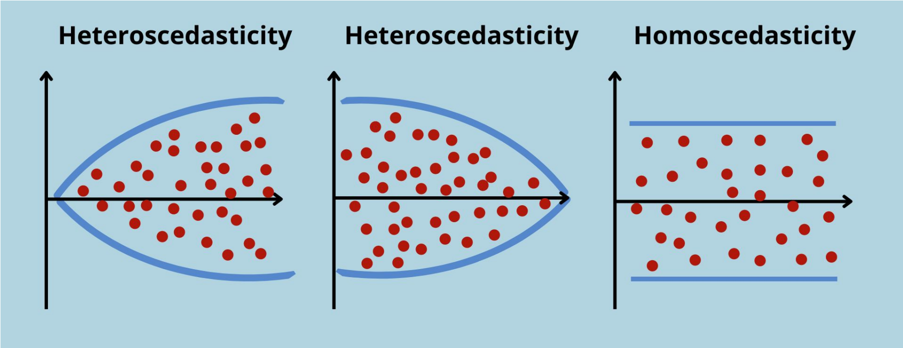
(Equal Variance)

Checking for Homoscedasticity

The model residuals have equal variance across all predictions.

- To Check:
  - Plot a residual scatter plot!
    - X-axis: Predicted Y-Values
    - Y-axis: Residuals (y-y_pred)





If you violate assumption of homoscedasticity or normality…

If you violate normality OR homoscedasticity:

- **Check for outliers in your target and your numeric features.**
  - 1) Try the Z-score rule for outliers first.

  - 2) If still violating residual assumptions, try using the IQR outlier rule
    - We will demonstrate in activity
  - Perform on the ORIGINAL data, not the z-score outlier-removed data.

- **Revisit your numeric features and check for nonlinear features**
  - If so, remove it.

  - Note: Remember to tell your stakeholders what range of your target was used in the model.
    - "My model was designed to predict homes with a value < $2million"

More extreme solutions:

- **Forcing your numeric features to be more normally distributed using log-transformation.**
    - Convert raw column to a log-transformed column (np.log())
        - Warning: changes meaning of coefficients from the effect of increasing the value of a feature by 1 to:
            - Then effect of a change of 1 PERCENT of a log-transformed feature.

- **Use a special transformer from sklearn:**
    - Quantile Transformer: Documentation
    - Visual Comparison of Transformers
    - Warning: will also change the interpretation of that features coefficients and I have no idea how to explain it to non-technical stakeholder!

Workflow/Summary

Model Diagnostics: After Each OLS Model

- **Display the model.summary()**
  - Check R-Squared/Adj R-Squared
- **Get predictions and calculate residuals.**

- **Plot Diagnostic Visualizations:**
  - QQ-Plot of the residuals (normality)
  - Residual Scatter Plot (homoscedasticity)

- **Check the P-Values of your coefficients.**
  - Drop any that are not significant.
  - OHE Columns are dropped All-or-None.
    - If the majority of the column's coefficient are significant, keep them all.
    - If the majority are not significant, drop them ALL.

Remember…

- We like linear regression for its simplicity and interpretability!
- I recommend:
  - using linear regression for explanations moreso than predictions.
  - avoiding transforming your features as much as possible
  - This includes avoiding scaling numeric features
    - (unless trying to use regularization like LassoRegression)

- ***“Perfect is the enemy of good” -*** *Voltaire*
  - We want a better QQ-Plot, not a perfectly flat one.
  - We want a no obvious cone shape to our residual plots, but a blob is ok!

End of Final Lecture

Image Source

Final Thoughts/Advice/Reminders

Discord:

- Send friend requests on Discord to your instructors and cohort mates.
    - Easier to stay in touch!

- Make sure to save any links or conversations you want to keep from the discord channel!

Post-Graduation

- 🤩 Check Out the [Post-Graduation Resources!!!]
    - Save the Data Enrichment = notes repo: https://github.com/sensei-jirving/05.16.22-Data-Enrichment-Notes
    - Save our YouTube Playlist: https://youtube.com/playlist?list=PLmeeqPbYmMC36RCmLS2NiMr777HppUb3R

- DON'T STOP CODING AND DOING PROJECTS!
    - Re-do your first project from scratch in a new repo!

- Continue to practice SQL for job interviews!

APPENDIX

🕹️ Alternate CodeAlong/Activity

- **In lieu of continuing our Linear Regression with Movies - Part 2,** we are going to pivot back to our Linear Regression for House Prices example.
  - Here is a recording of Part 2 of Linear Regression with Movies from last cohort:
    - https://youtu.be/5UGE_HWxePA
- 📓 Colab Notebook:
  - https://colab.research.google.com/drive/1vrbweCAik4-CzW9Y8pwON97Ymgu7l_GZ?usp=sharing
  - Continue iterating on the first model in the notebook.
  - Solution Notebook (WIP): https://colab.research.google.com/drive/1fZerWju-rec6x-jOSz8p3EJb3d-sL4AE?usp=sharing