Lecture 16: Lingering Questions and A Basic Case Study

CS109A Introduction to Data Science

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Lecture Outline

- A Little Review: some lingering questions
- Some HW feedback
- The Data Science Process: A Basic Case Study

Some Lingering Questions

What's the deal with the Intercept?

We've seen many forms of parametric models: linear regression, LASSO and ridge regression, and now logistic regression:

$$\mu_Y = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p.$$

$$\ln\left(\frac{P(Y=1)}{P(Y=0)}\right) = \beta_0 + \beta_1 X_1 + \cdots + \beta_p X_p$$

What does β_0 represent? Why do we need it? When do we not need it?

Modeling specifics: you almost always (>99% of the time) want to have an intercept (sometimes called the bias term) in your model. Why?

sklearn specifics: linear and logistic regression include an intercept by default (yay!). Polynomial features creates the bias term by default (boo). You don't want both, and if you are regularizing, you don't want to shrink it!

What's the difference: Standardize vs. Normalize

What is the difference between Standardizing and Normalizing a variable?

- Normalizing means to bound your variable's observations between zero and one. Good when interpretations of "percentage of max value" makes sense.
- Standardizing means to re-center and re-scale your variable's observations to have mean zero and variance one. Good to put all of your variables on the same scale (have same weight) and to turn interpretations into "changes in terms of standard deviation."

Warning: the term "normalize" gets incorrectly used all the time (online, especially)!

To Standardize, or Not to Standardize, that is the question…

When should you do each?

- Normalizing is only for improving interpretation (and dealing with numerically very large or small measures). Does not improve algorithms otherwise.
- Standardizing can be used for improving interpretation and should be used for specific algorithms. Which ones? Regularization and *k*-NN (so far)!
- For best interpretations, do not change the scale from the original units.

*Note: you can standardize without assuming things to be [approximately] Normally distributed! It just makes the interpretation nice if they are Normally distributed.

(Train & Validation) & Test Splits

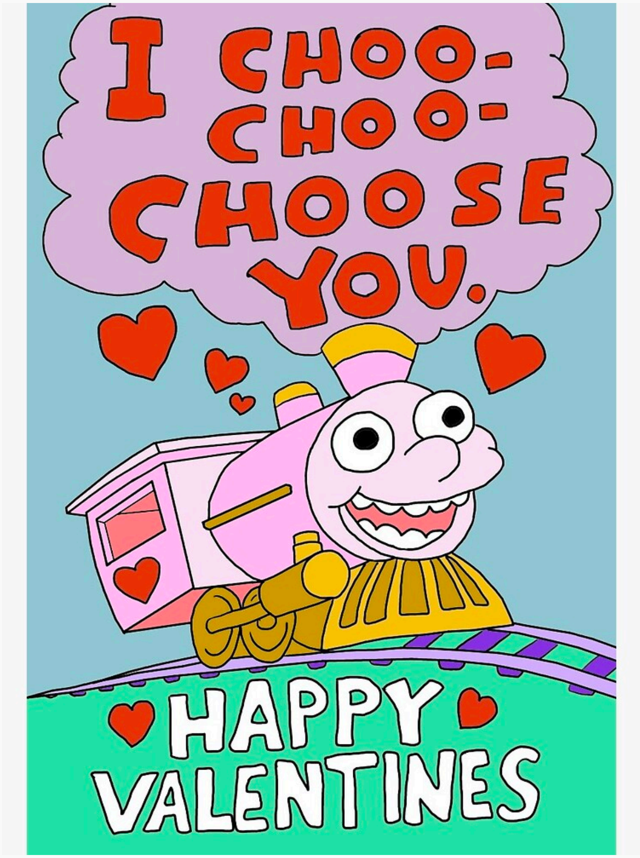
What is the proper use of Train, Validation, and Test Splits? What is the purpose?

<u>Purpose</u>: to select and evaluate a **predictive** model. Not needed for interpretative models.

- The **test** set is used only for evaluating the error of the model (and used just once).
- The (**train** & **validation**) sets are used to estimate/fit and select between models, respectively.
- Since it is so important to choose your best predictive model, we often perform cross validation so that a single random validation set does influence this decision.

Note: you should refit the model on the entire (Train & Validation) set after choosing the best model.

It’s funny, because it’s a train



A few other lingering thoughts:

What happens when multicollinearity is present? Why is multicollinearity bad? Why is it not always bad? How can this be handled?

How does a multiple regression model for 2 predictors (one binary, the other quantitative) compare in interpretation when the interaction is included vs. not included in the model. How can we visualize this?

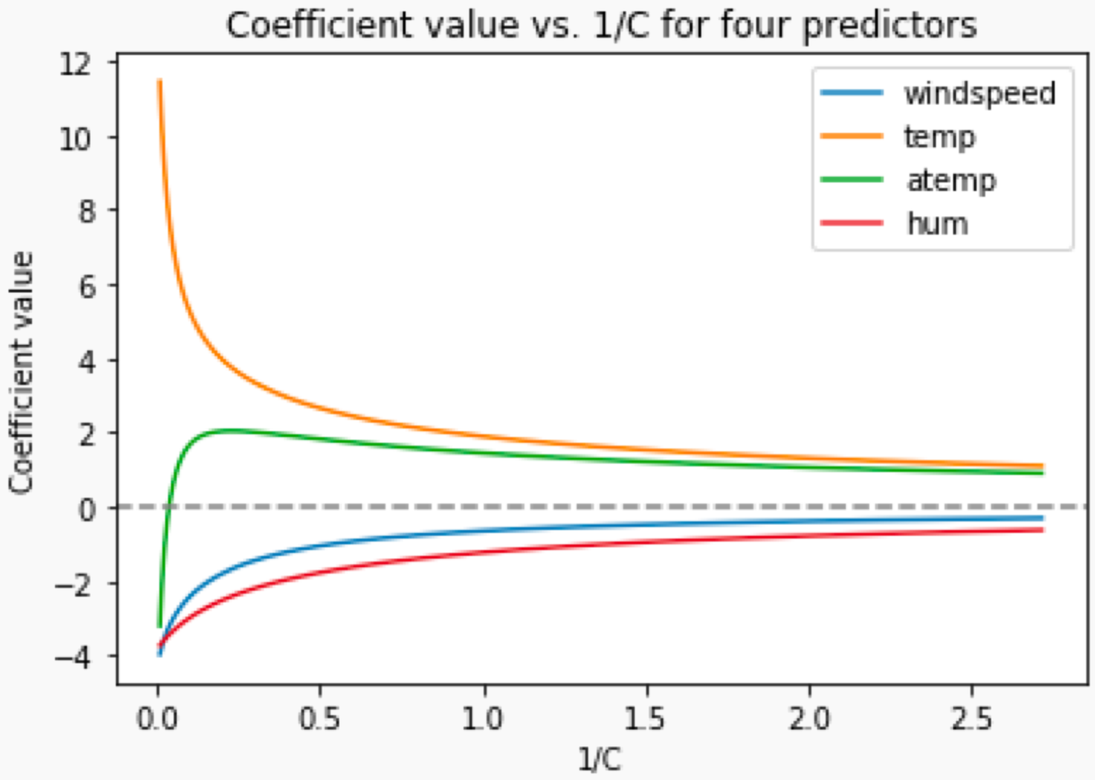
Why is one of the binary/dummy terms dropped out of the predictor set when modeling a categorical predictors?

Some Regularizing Details

Why is the intercept term not penalized in regularized methods? What if it was penalized?

When is LASSO preferred over Ridge? What about the other way around?

How do regularization methods affect multicollinearity?



Suggestions/Comments about HW

- Plotting your model's predictions (presumably on a scatterplot with real data) use np.linspace to create a "*dummy x*" and connect with lines and not points!
- Sorting data: don't do it! What could go wrong? Sorting results, do it!
- How do you "compare the performance" of several models (to select a best *k* in *k*-NN or λ in LASSO/Ridge?
- Bar plot vs. Histogram: what if we have integers?
- When bootstrapping (or simulating) to compare models/approaches: sample once and fit all models your comparing on this same sample (not a separate sample for each model). Why?
- Significant digits!!! Avoid extremes: 0.00001 and 9.2857104571934812 are not the best choices. We are not super critical, but 3-5 sigdigs are reasonable.
- Be sure to re-run the entire notebook and label your output (don't just print out numbers without reference): **we'll start taking off points in HW4.**

The Data Science Process: A ‘Case Study’

The Data Science Process

- Ask an interesting question
- Get the Data
- Explore the Data
- Model the Data
- Communicate/Visualize the Results

I started with some interesting questions. I wanted to address:

- **The wage gap**. There is actually lot of publicly available salary data out on the web. But the data do not include sex/gender/race/ethnicity, and are typically volunteered.
- **The effect of COVID-19 on various things: mental health, media consumption, etc.** Publicly available data is very spotty. Or not *raw* enough to be useful. Or very expensive (see, Nielsen cost).
- I browsed Kaggle Competitions for interesting questions they have. Nothing tickled my fancy.

So I called an audible…

Do you like…stuff?

Ask an interesting question

Get the Data

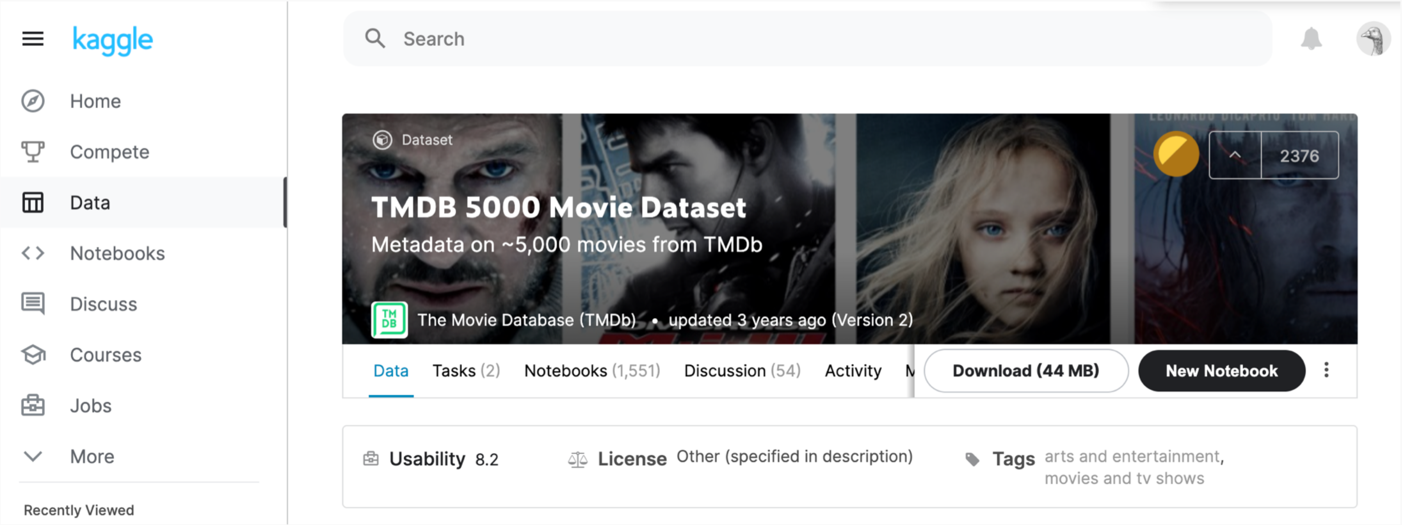
Explore the Data

Model the Data

Communicate/Visualize the Results

I like movies. Let’s start our process by considering a data set from Kaggle:

https://www.kaggle.com/tmdb/tmdb-movie-metadata



What should we do first?

First Glimpse at the Data

Explore the Data

```python
print(movies.dtypes)
```

```
budget                   int64
genres                  object
homepage                object
id                       int64
keywords                object
original_language       object
original_title          object
overview                object
popularity             float64
production_companies    object
production_countries    object
release_date            object
revenue                  int64
runtime                float64
spoken_languages        object
status                  object
tagline                 object
title                   object
vote_average           float64
vote_count               int64
dtype: object
```

```python
movies = pd.read_csv('data/tmdb_5000_movies.csv')
credits = pd.read_csv('data/tmdb_5000_credits.csv')

movies.head()
```

	budget	genres	homepage	id	keywords	original_language	original_title	overview	popularity	production_co
0	237000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam...	http://www.avatarmovie.com/	19995	[{"id": 1463, "name": "culture clash"}, {"id":...	en	Avatar	In the 22nd century, a paraplegic Marine is di...	150.437577	[{"name": "I Film Partne
1	300000000	[{"id": 12, "name": "Adventure"}, {"id": 14, "...	http://disney.go.com/disneypictures/pirates/	285	[{"id": 270, "name": "ocean"}, {"id": 726, "na...	en	Pirates of the Caribbean: At World's End	Captain Barbossa, long believed to be dead, ha...	139.082615	[{"name": "Wa Pictures", "id
2	245000000	[{"id": 28, "name": "Action"}, {"id": 12, "nam...	http://www.sonypictures.com/movies/spectre/	206647	[{"id": 470, "name": "spy"}, {"id": 818, "name...	en	Spectre	A cryptic message from Bond's past sends him o...	107.376788	[{"name": "(Pictures"

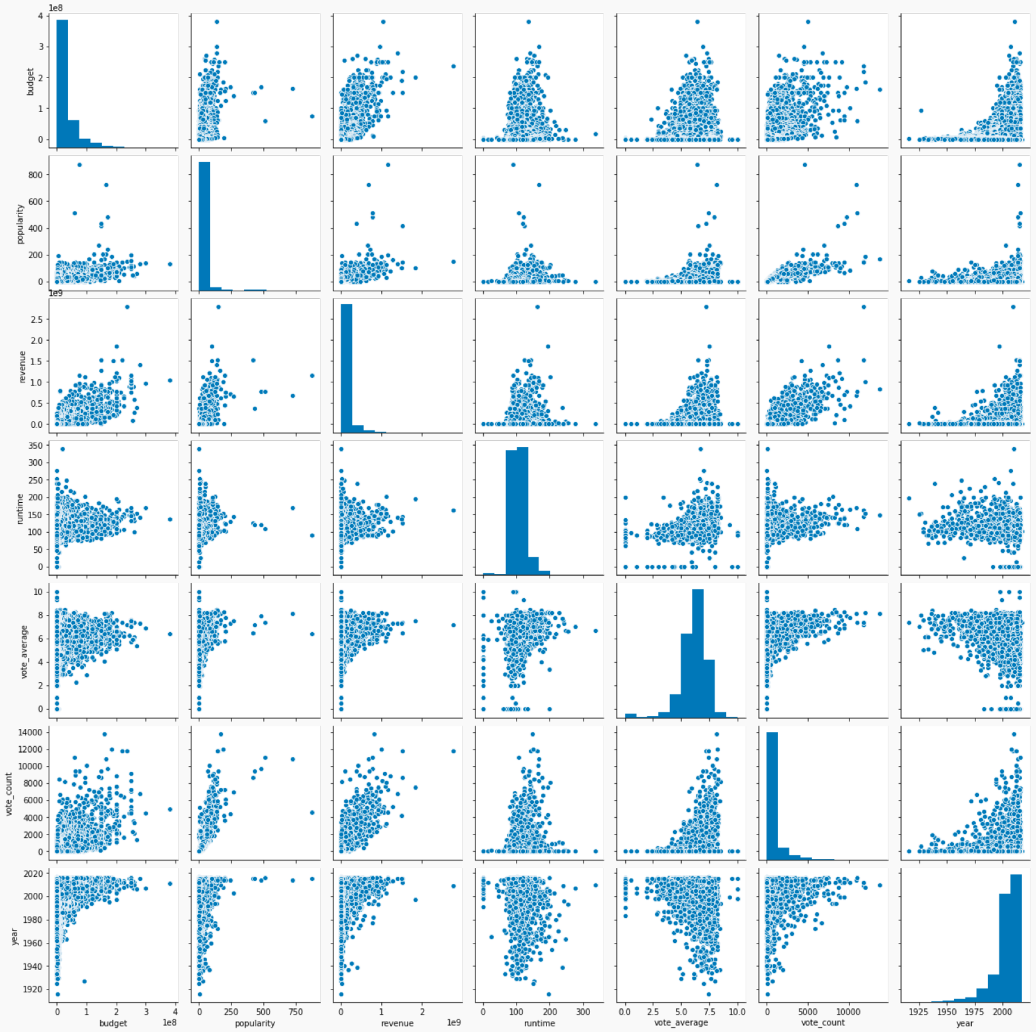
```python
credits.head()
```

	movie_id	title	cast	crew
0	19995	Avatar	[{"cast_id": 242, "character": "Jake Sully", "...	[{"credit_id": "52fe48009251416c750aca23", "de...
1	285	Pirates of the Caribbean: At World's End	[{"cast_id": 4, "character": "Captain Jack Spa...	[{"credit_id": "52fe4232c3a36847f800b579", "de...
2	206647	Spectre	[{"cast_id": 1, "character": "James Bond", "cr...	[{"credit_id": "54805967c3a36829b5002c41", "de...
3	49026	The Dark Knight Rises	[{"cast_id": 2, "character": "Bruce Wayne / Ba...	[{"credit_id": "52fe4781c3a36847f81398c3", "de...
4	49529	John Carter	[{"cast_id": 5, "character": "John Carter", "c...	[{"credit_id": "52fe479ac3a36847f813eaa3", "de...

What are some EDAs we should perform?

First EDA of the Data

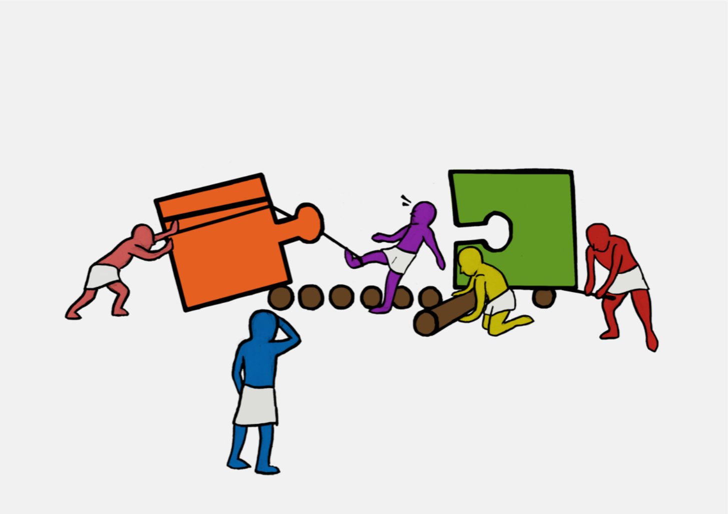
Explore the Data

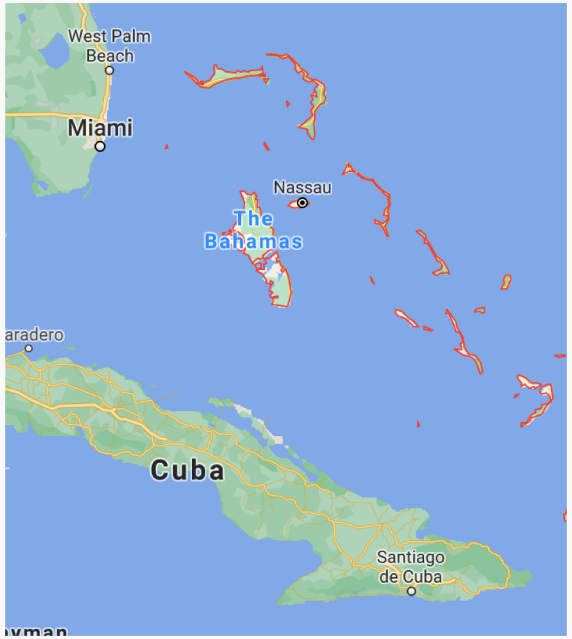


0	budget
1	popularity
2	revenue
3	runtime
4	vote_average
5	vote_count
6	year

What are some necessary cleaning and wrangling tasks?

What other EDAs we should perform?





Breakout #1 Tasks (15-20min):

1. Someone share (the person who resides closest to the Bahamas…thanks Columbus). Someone different will share in the next breakout.
2. Explore the data (some of that is done with you with code). Please do a little more exploration.
3. Come up with an interesting question or two you can answer with this data set. Come up with a question or two that can be answered with **supplemental data**:
    - start with ideal, and then get more practical based on what is likely available.

Any interesting questions?

Ask an interesting question

Get the Data

Explore the Data

Model the Data

Communicate/Visualize the Results

What are some interesting questions you came up with for this data set?

What are some interesting questions using supplemental data?

My questions:

Ask an interesting question

Get the Data

Explore the Data

Model the Data

Communicate/Visualize the Results

I came up with simple questions (and pretty straight-forward one for now):

#1: How is revenue associated with budget?

#2: How has this evolved over time?

#3: What other factors relate to revenue of a movie?

Back to exploring:

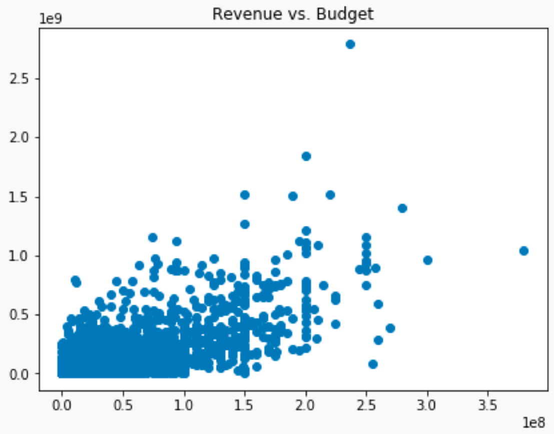
Ask an interesting question

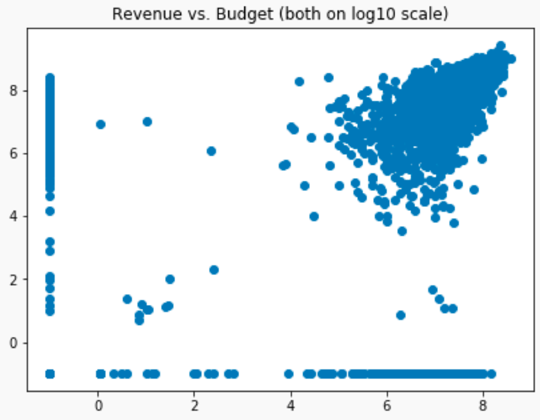
Get the Data

Explore the Data

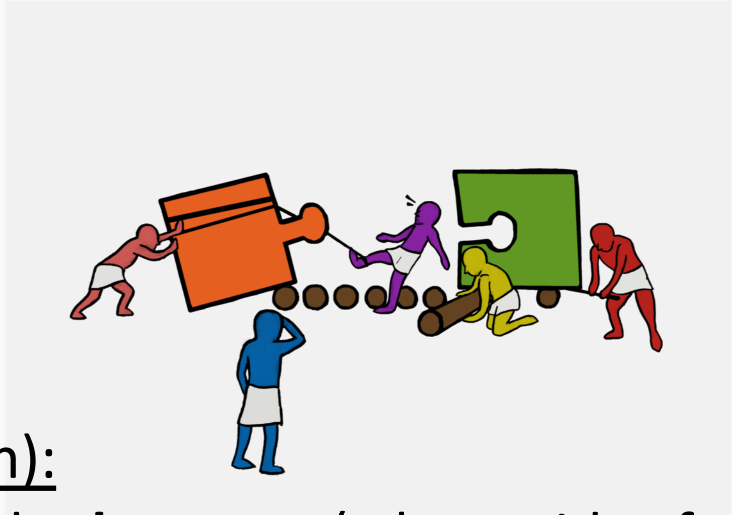
Model the Data

Communicate/Visualize the Results





Which is more appropriate for linear modeling (or any regression modeling, really)? What issues arise? What should we do about it?



Breakout #2 Tasks (20+min):

1. Someone else share and **take notes** (who resides furthest from the Bahamas)
2. Solidify your question(s) of interest.
3. Determine the next tasks:
   - What other data do you need? How will this data be collected and combined?
   - What data cleaning and wrangling tasks are needed?
   - What other EDA is necessary? What visuals should be included?
   - What is a goal for a first baseline model (Key: should be interpretable)?
     Be sure to include the class of model and the variables involved.
   - What is a reasonable goal for a final model and product?
4. Determine how long each task should take.
5. Assign next tasks to group members. Do not actual perform these tasks!

Scoping and Redefining the Problem

How did that go?

What is the biggest concern you have at this point for your questions?

Can these data answer your questions?

What supplemental data would be required?

What idealistic questions did you shy away from?

What models are you considering?

Scoping and Redefining your Project

This lecture is relevant for your group project:

Milestone 2 (due next week on Friday) is to scope and redefine your project.

You should converse with your group members to:

(a) **Redefine the problem**, if appropriate

- For example: maybe you want to not use the Boston Crime data set, but instead use the FBI's data for white collar crime).

(b) **Scope your project**

- What are the next tasks? Who will perform what ?
- What is a reasonable goal for a baseline model?
- What are both ideal and reasonable goals for a final model and product?)

*feel free to consult with your assigned TF in a message or two.

My question:

Ask an interesting question

Get the Data

Explore the Data

Model the Data

Communicate/Visualize the Results

What models should be considered for these questions?

#1: How is revenue associated with budget?

#2: How has this evolved over time?

#3: What other factors relate to revenue of a movie?

How could these models be communicated?