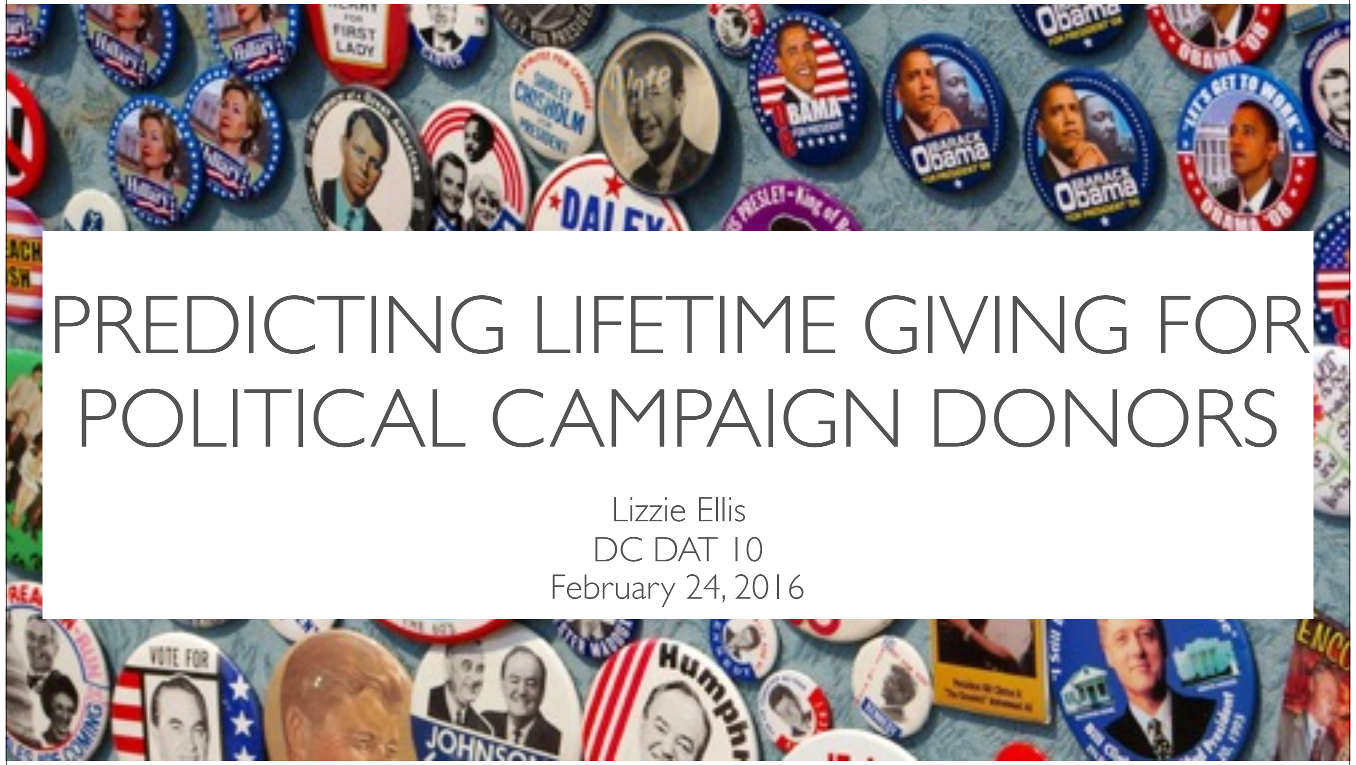

PREDICTING LIFETIME GIVING FOR POLITICAL CAMPAIGN DONORS

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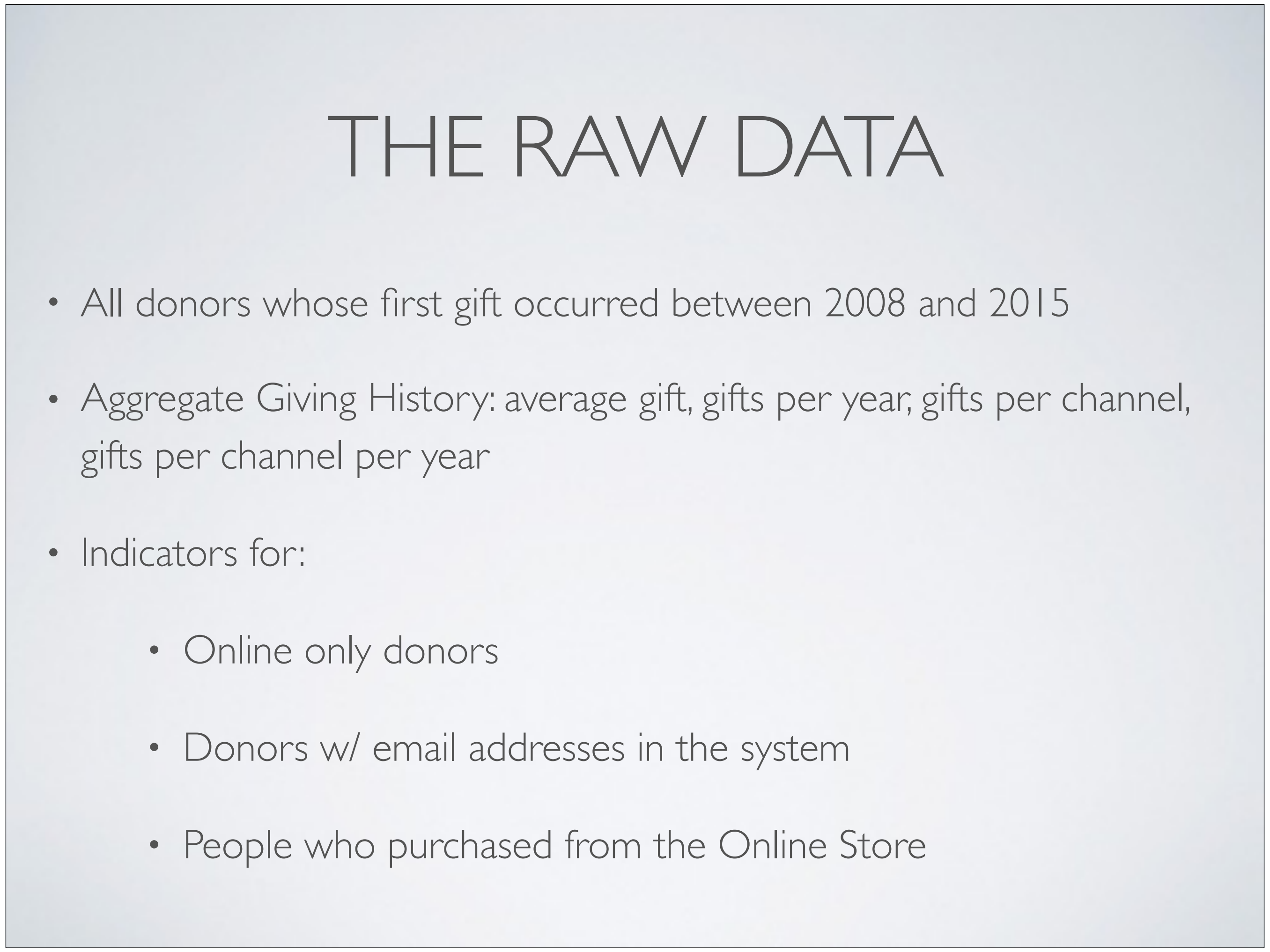
DC DAT 10
February 24, 2016

THE GOAL:

1. Can we predict how long a donor will continue to give to the organization?

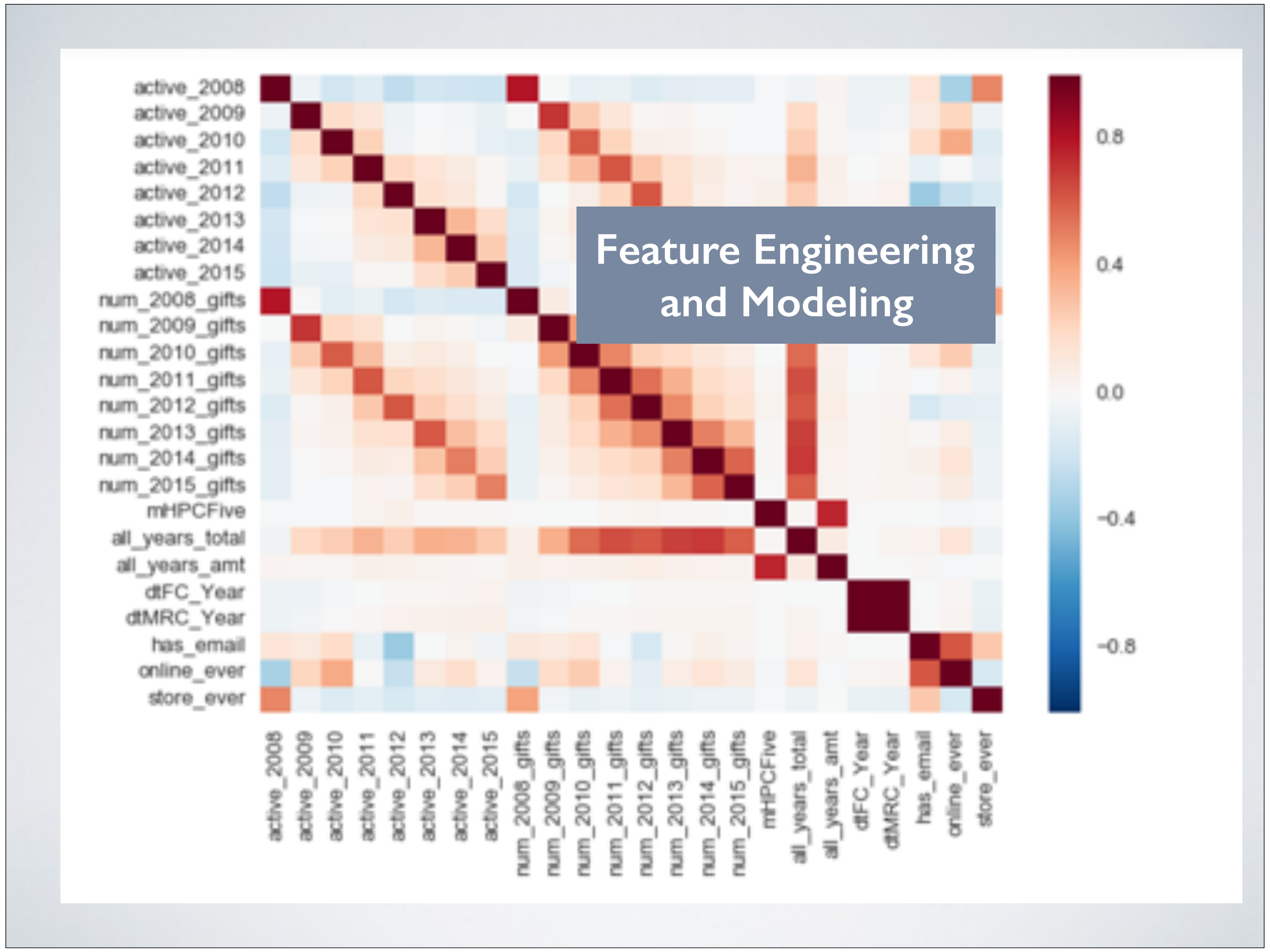
2. Are there certain characteristics that make someone more likely to give repeatedly over time?



THE RAW DATA

- All donors whose first gift occurred between 2008 and 2015
- Aggregate Giving History: average gift, gifts per year, gifts per channel, gifts per channel per year
- Indicators for:
    - Online only donors
    - Donors w/ email addresses in the system
    - People who purchased from the Online Store

Had to restrict universe to a managable size for the sake of time
Difficulty — what makes a donor “Active”? 1 gift in how many years? What do we actually care about when it comes to donors? Answer: active giving



Feature Engineering and Modeling

Many of the variables expected to be influential in the model — total # of gifts, date of first gift, date of most recent gift, highest $ amount in the last 5 years — are actually pretty correlated with each other

Raises the question of whether a more complex regression model would work better here?

FEATURE ENGINEERING

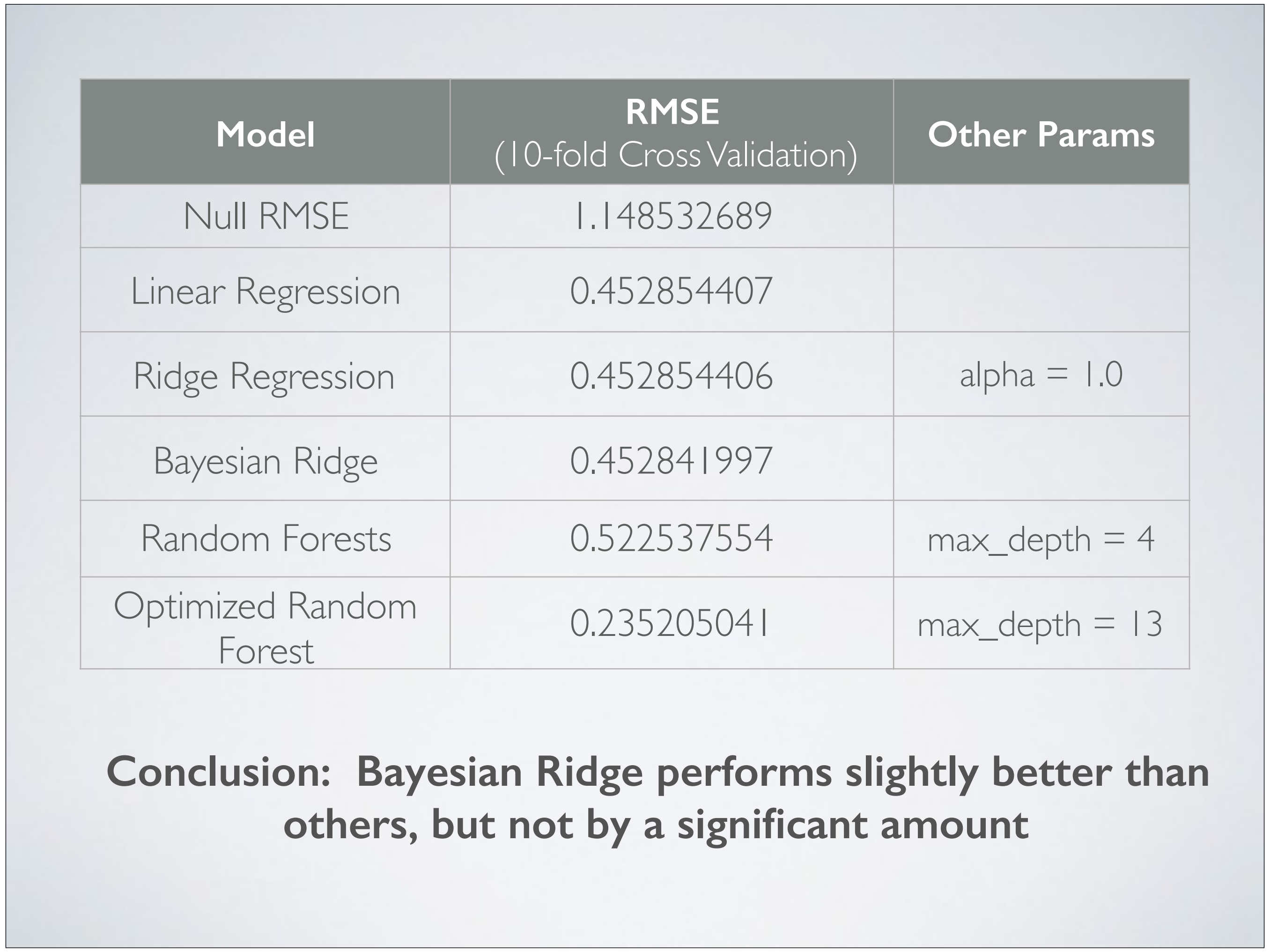
- **Aggregate giving over time, by donor and by channel**
- **Flags for election year only donors, online only donors, mail only donors**
- **Alternatives to Datetimes**
  - Created dummies for month of first gift and year of first gift
  - Calculated months since first gift using timedelta functions, convert to int
- **Zipcode:**
  - Can't treat as a float or int, really more a categorical
  - Created zip_region indicator off first digit of zip

MODELING

- Data scaled before regression to offset impact of high dollar donors
- Feature set of 11 values, plus first gift month and account dummies

- Linear regression
- Ridge regression
- Baysean Ridge Regression
- Random Forest Regression

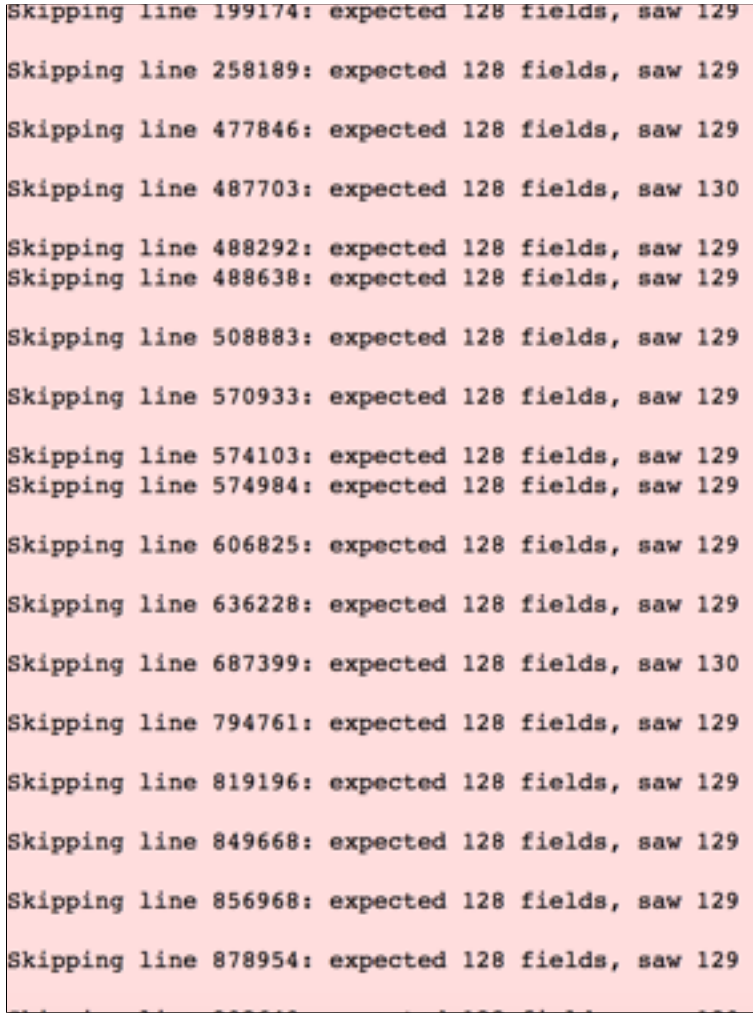
findings & lessons learned



Model	RMSE (10-fold Cross Validation)	Other Params
Null RMSE	1.148532689	
Linear Regression	0.452854407	
Ridge Regression	0.452854406	alpha = 1.0
Bayesian Ridge	0.452841997	
Random Forests	0.522537554	max_depth = 4
Optimized Random Forest	0.235205041	max_depth = 13

Conclusion: Bayesian Ridge performs slightly better than others, but not by a significant amount

Go back to title slide with correlation heat map and talk about initial findings and how correlation influenced next steps



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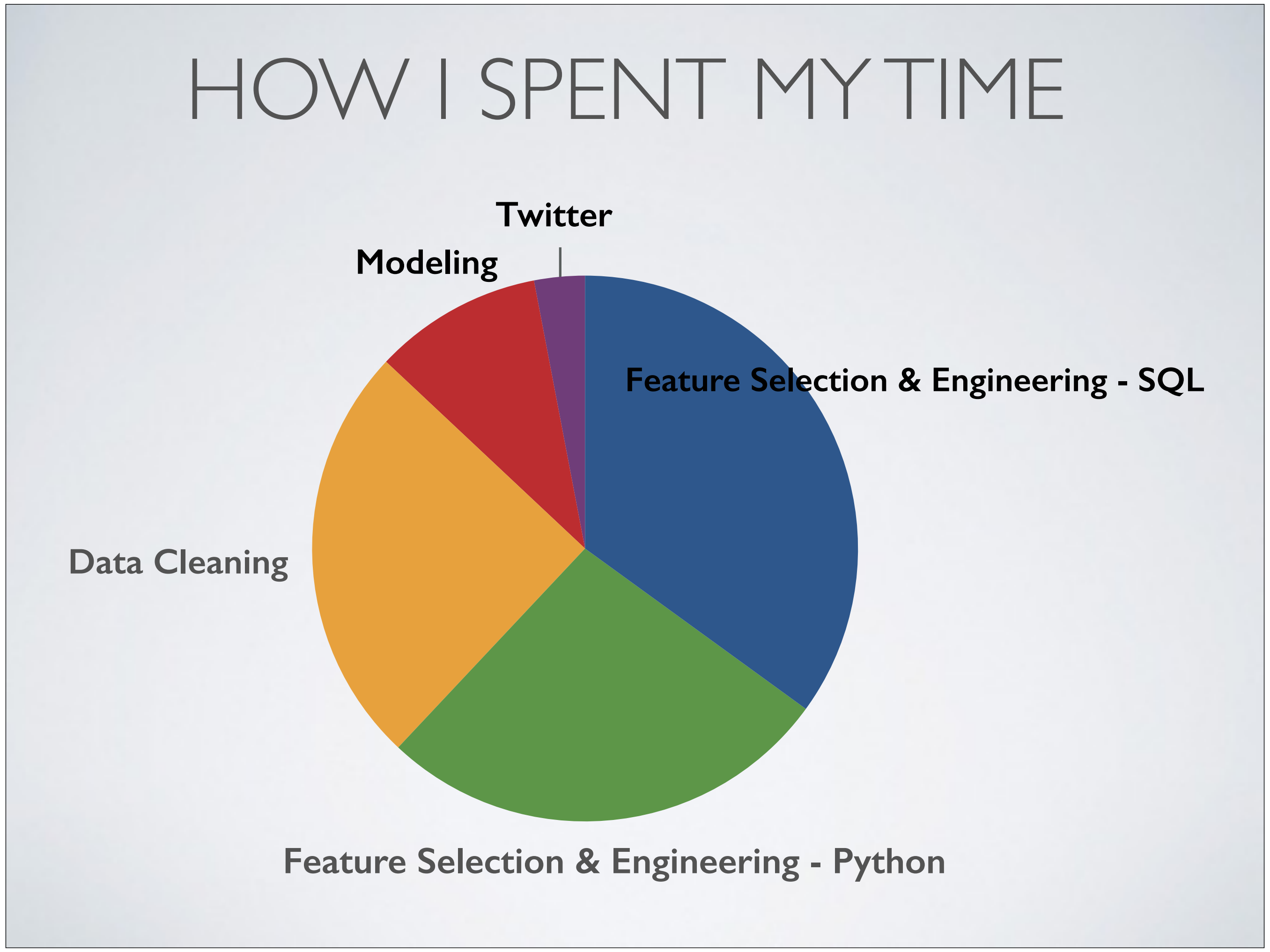
Challenges

Constantly losing lines w/ bad data
Import challenges led to bad rows — lots of find/replace
Many of the variables I wanted to include were non-numeric and couldn’t be included in regression
    (hard to come up with 500 employment categories)
Converting dates to something usable in the model was difficult
Scale of data was hard to determine patterns through visualization — can’t just drop high dollar or high frequency outliers because their giving patterns are equally important to our outcome



HOW I SPENT MY TIME

Majority of this project was spent on the initial data and feature selection — had to go back several times to re-pull raw data because of size, bad delimiters, goal redefinition, etc.

Once data was finally locked (had to draw the line somewhere)

NEXT STEPS

- Gradient Boosting Regression
- Increased tuning of models
- More feature selection analysis
- Include Telemarketing data
- Include Consumer/demographic data
- Look at coefficients on features

LESSONS LEARNED

Data Cleaning is …

…Frustrating

Beware the Feature Selection Quagmire

Datetime variables are extra tricky

Leave more time than you think you need

Answering the question is only part of the problem