# Predicting Home Improvement: Green Or Not?

**Amber Rivera**

*http://bit.ly/ee-upgrades*

# Predict whether a household will choose an energy efficient upgrade

Building characteristics

Census information

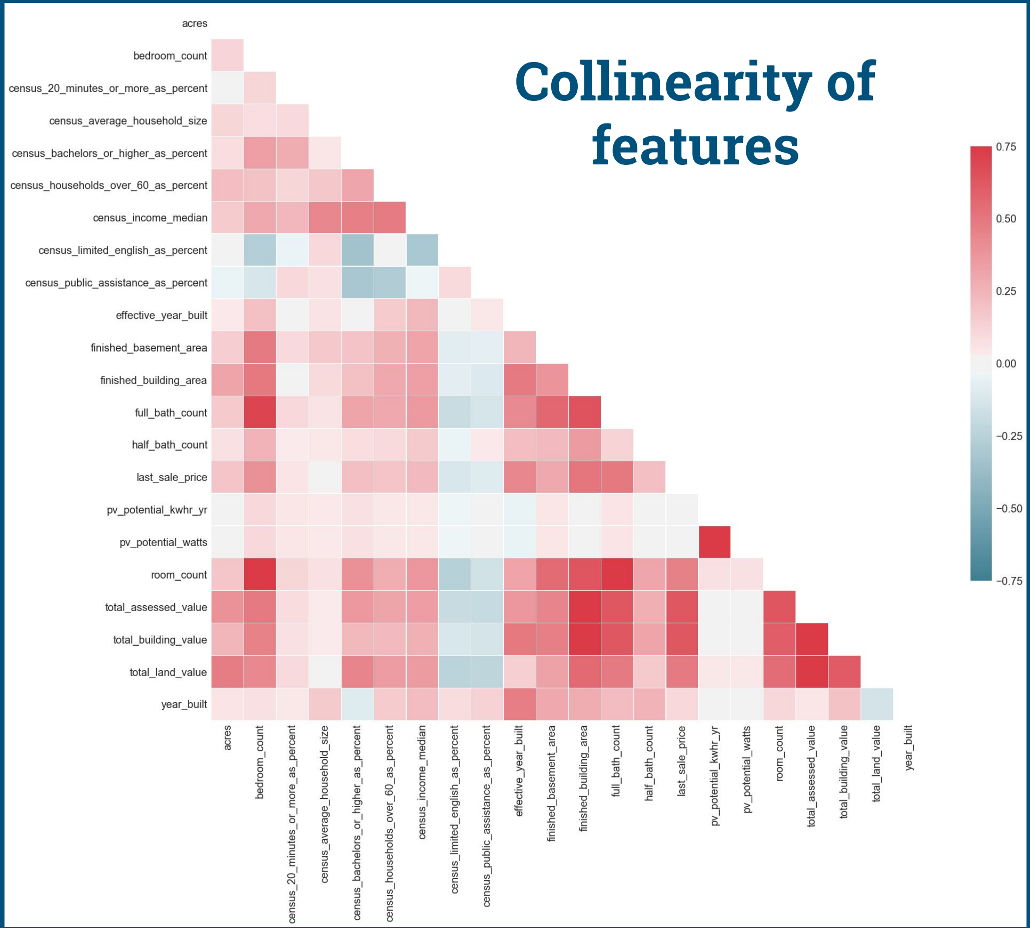
Simulated energy usage

# The Data

- 18,000 homes, 360 features
    - 30% numerical - Last Sale Price
    - 70% categorical - AC Type, Garage

- New features:
    - *# upgrades in neighborhood*
    - *# permits since purchase*

- Only 9% of homes in positive class
    - Tried upsampling minority class
        - Random Over Sampling
        - SMOTE
    - Downsampling to 50/50 generalized best!



# Finding The Best Model

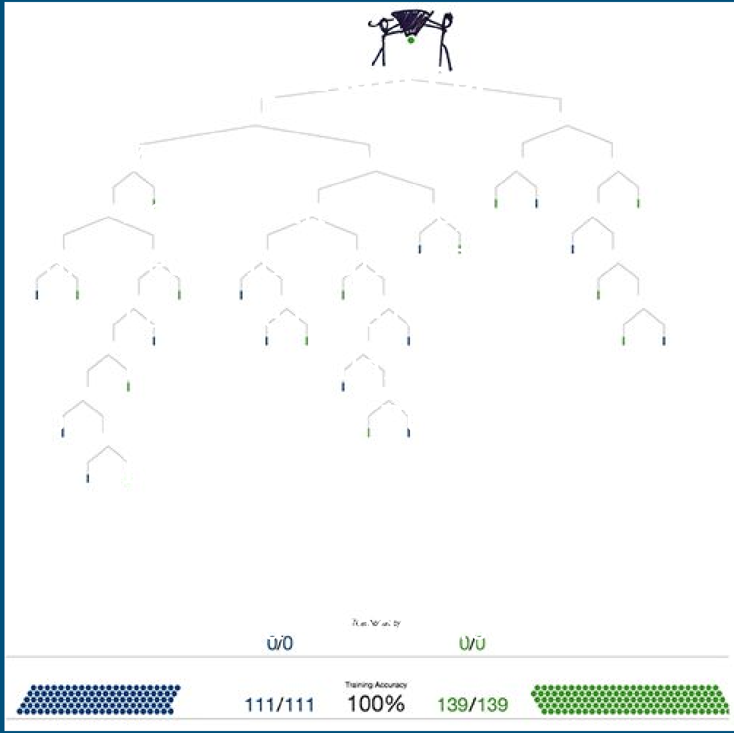
## Random Forest (200 trees)

- Binary classification; 30% holdout
- Evaluated with Recall metric
- Seeking stability and interpretability

Final results:

Confusion Matrix
TP: 342
FP: 2193
FN: 148
TN: 2523

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 | 0.94 | 0.53 | 0.68 | 4716 |
| 1 | 0.13 | 0.70 | 0.23 | 490 |
| avg / total | 0.87 | 0.55 | 0.64 | 5206 |




Source: http://www.r2d3.us/visual-intro-to-machine-learning-part-1/

# Making Predictions

✔ TP: Has upgraded; Predicted ‘Yes’

✔ FP: Has not upgraded; Predicted ‘Yes’

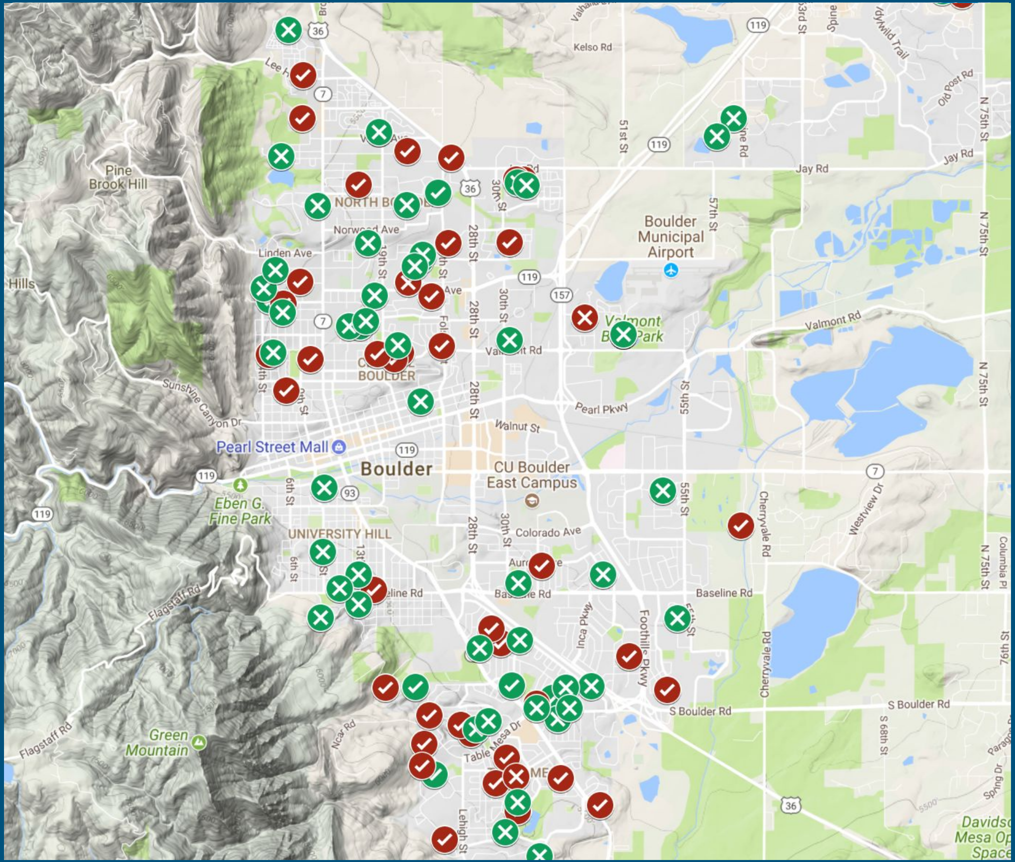
X TN: Has not upgraded; Predicted ‘No’

X FN: Has upgraded; Predicted ‘No’

Business Implications:

- Volume of 500 jobs per year
- TP: (111) * (revenue - cost)
- FP: (389) * (cost)

= **13% potential increase in profit**



# Next Iteration

- Supervised
    - Incorporate behavioral information
    - Develop more sophisticated handling of class imbalance
- Unsupervised
    - Clustering algorithms
    - Outlier detection algorithms

# More at: *http://bit.ly/ee-upgrades*

**Contact:** linkedin.com/in/amberjrivera

**Technologies Used:**

- Python, Pandas, NumPy for data analysis
- Matplotlib, Seaborn , Google for visualization
- Scikit-learn and imbalanced-learn for machine learning
    - Check out this gist I co-wrote on Sklearn's Pipeline constructor: ***http://bit.ly/Pipeline-gist***