FIG WORKING WEEK 2023
28 May - 1 June 2023 Orlando Florida USA
Protecting Our World, Conquering New Frontiers

Using Machine Learning to Create High Performing Models for Automated Valuation

May 29th, 2023

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Meet the Speakers

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Introduction

- Mass Appraisal is key to being able to quickly and fairly appraise large volumes of properties
  - One of the difficulties is ensuring equity and fairness of the Mass Appraisal values
- Linear/Logistic Regression has been the gold standard for creating Mass Appraisal models
  - Ability to learn from very large data sets and provide accurate and unbiased predictions
  - Model interpretability
- Machine Learning models have made great strides in the past decade
  - Machine learning models offer high levels of accuracy
  - Explainable AI allows for the interpretation

Linear Regression Models

- Use statistics to determine the contribution and effect of predictors to predict the value of a parcel
- Using coefficients (β), models illustrate the effect of a predictor on an outcome
  - Ex. For one unit increase in base area, the parcel's value increased by $10.02
- Regression models do have restrictions

$$y = \beta_1 x_1 + \beta_2 x_2 + \varepsilon$$

Machine Learning Models

- There has been significant advancements in the field of machine learning over the past decade
  - Consist of algorithms that try to learn latent patterns and relationships from data without hard coding fixed rules
  - Allows the models to capture non linearities in the data
  - Many ML algorithms can handle non independent features and even imbalanced data

Data For the Model

- All models were trained and tested on Market Area 02
  - Vast swathes of housing in Estero, FL and Bonita Springs, FL
- 10 years of sales
  - Totaling 24,556 sales

Lee County
Southwest Florida

Model Construction

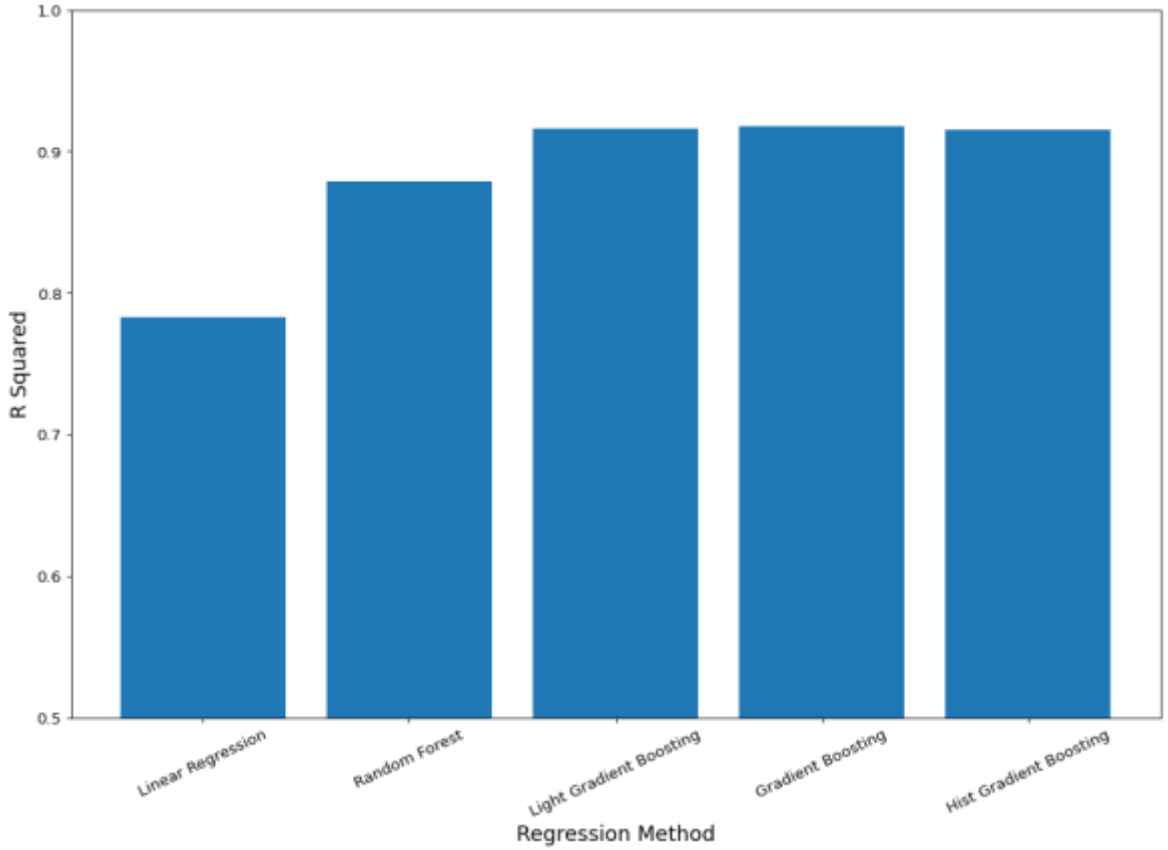
A model is considered high performing if it has a high level of accuracy and utilizes as few independent variables/predictors as possible

- Less than 20 features were used to predict the parcel values
  - Same predictors were used to train and test each model
  - Features included base area, age, improvement code, quality, land square footage, etc.

- Models were compared based on the performance metrics of R-squared, price related differential, and coefficient of dispersion
  - Allowed for gauging performance as well as fairness and equity of the models

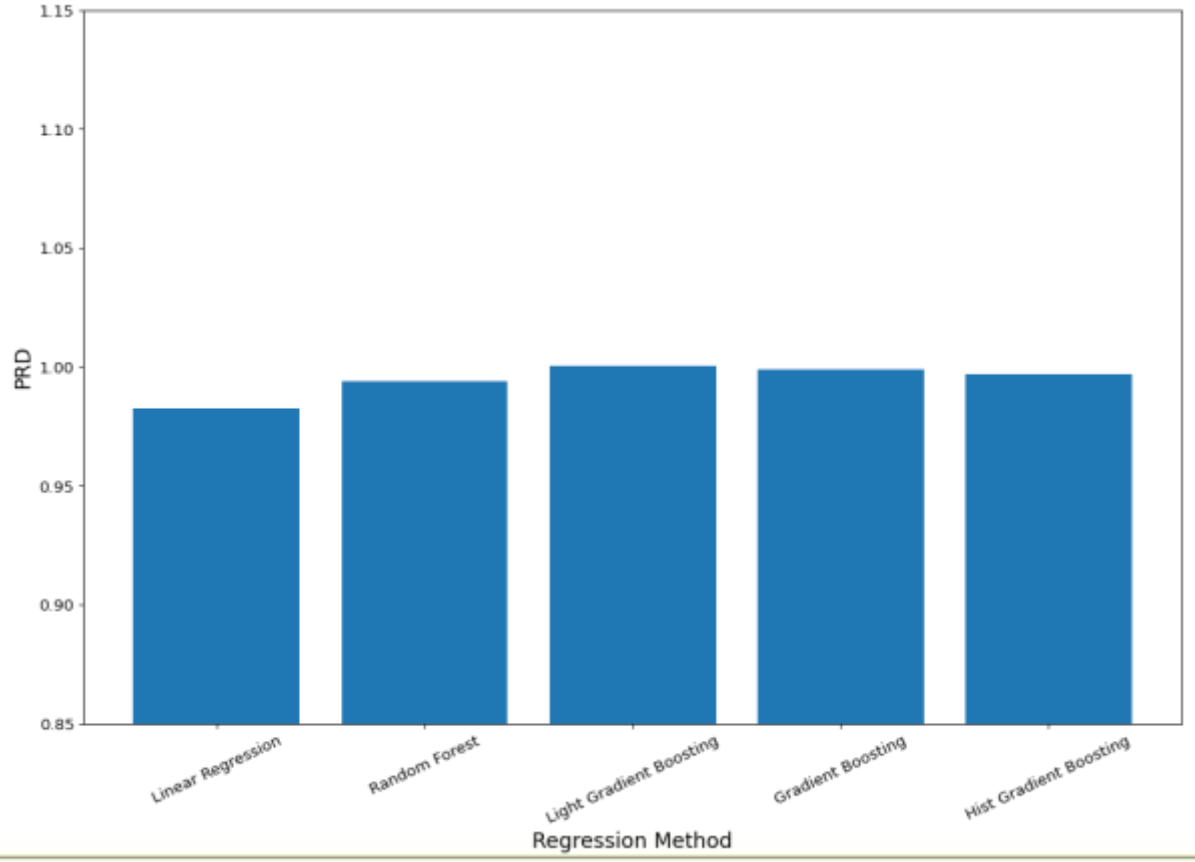
R Squared

- ✓ Linear Regression: 0.783
- ✓ Random Forest: 0.879
- ✓ Light Gradient Boosting: 0.916
- ✓ Gradient Boosting: 0.918
- ✓ Histogram Gradient Boosting: 0.916



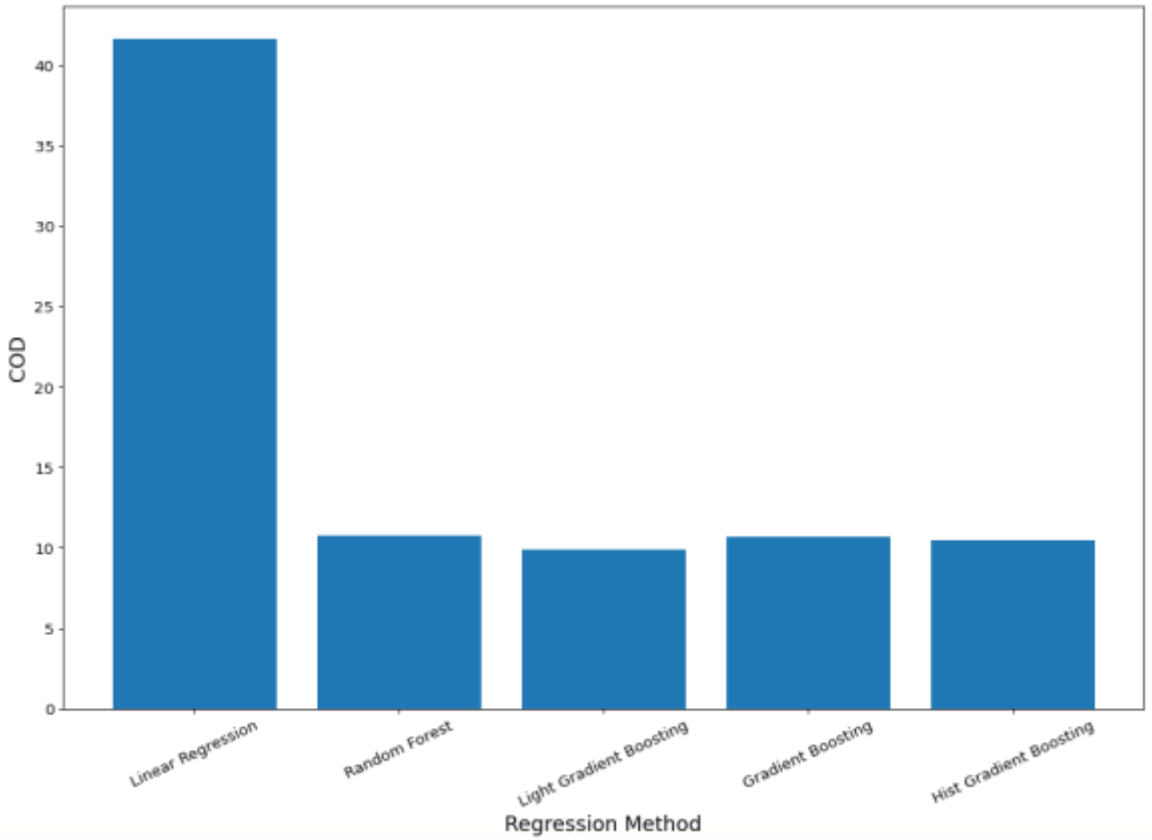
Price Related Differential

- ✓ Linear Regression: 0.983
- ✓ Random Forest: 0.994
- ✓ Light Gradient Boosting: 1.00
- ✓ Gradient Boosting: 0.999
- ✓ Histogram Gradient Boosting: 0.997



Coefficient of Dispersion

- ✓ Linear Regression: 41.62
- ✓ Random Forest: 10.75
- ✓ Light Gradient Boosting: 9.90
- ✓ Gradient Boosting: 10.65
- ✓ Histogram Gradient Boosting: 10.49



Hyperparameter Tuning

- Parameters are what the "model" uses to make predictions

- Hyperparameters are what a machine learning model learns
  - Come with default hyperparameters, they might not be optimal for your given process
  - Models can consist of a multitude of hyperparameters
  - Some of the hyperparameters can take on an infinite number of values

- Optuna is an automatic hyperparameter optimization software framework
  - Uses Bayesian Statistics to crawl through a custom search space of hyperparameters to optimize performance
  - Control metrics to increase performance

Improvements on Machine Learning Models from Optuna

LightGBM

Metric	Value
R Squared	0.916
PRD	1.00
COD	9.90

Metric	Value
R Squared	0.924
PRD	0.999
COD	9.19

Gradient Boosting

Metric	Value
R Squared	0.918
PRD	0.999
COD	10.65

Metric	Value
R Squared	0.919
PRD	1.00
COD	9.88

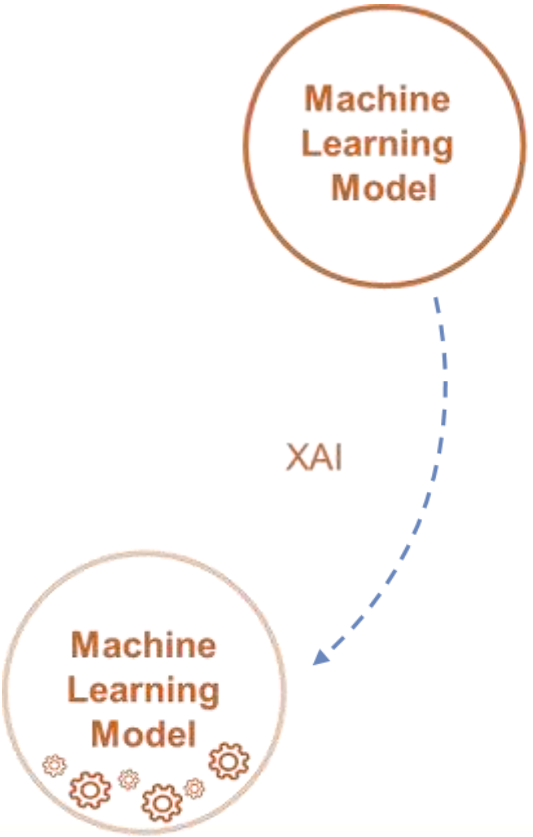
What stops some people from adopting Machine Learning?

- The strength of using algorithms without hard coding fixed rules also creates a weakness
  - Explaining how these models work always poses its own set of challenges
  - They change dynamically depending on what data point you are predicting; making them harder to explain
- Many individuals think of Machine Learning models as a black box
  - In turn, people do not trust the predictions provided by the model

How do you overcome this obstacle?

- Explainable AI (XAI) helps us to understand how a model is making its predictions
  - Ex. What features are positively or negatively impacting the outcome of a prediction?

- With Explainable AI, we can answer the following questions:
  - Why does the model predict that result?
  - What are the reasons for this prediction?
  - What are the strongest contributors to the prediction?
  - How does the model work?

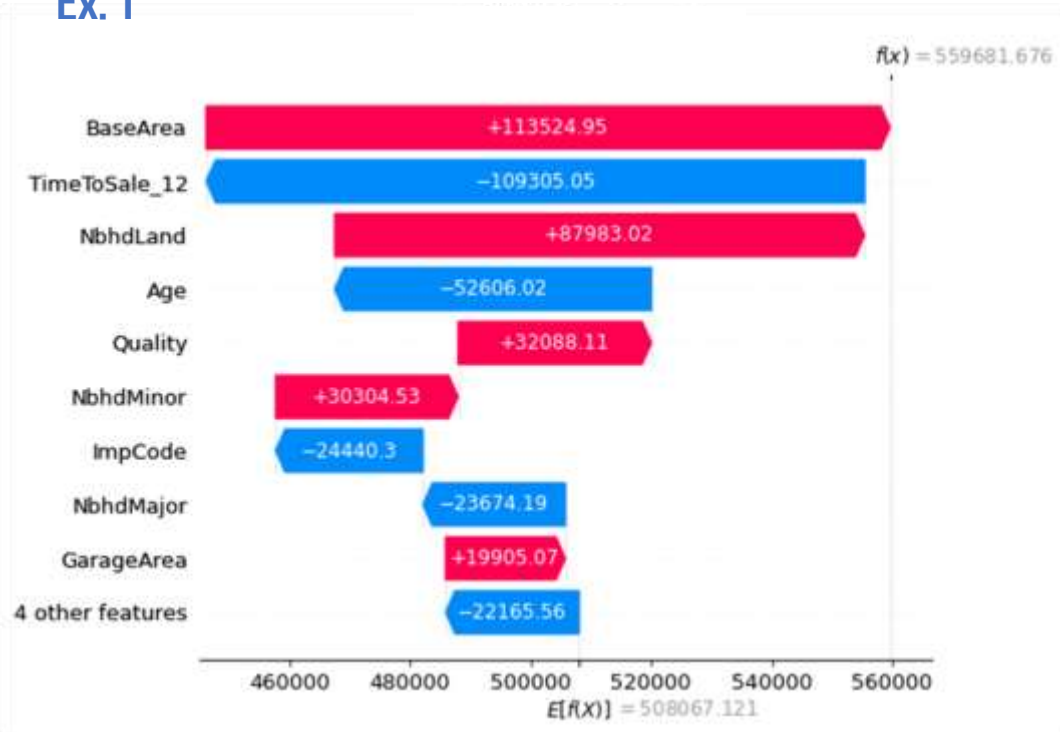


SHAP

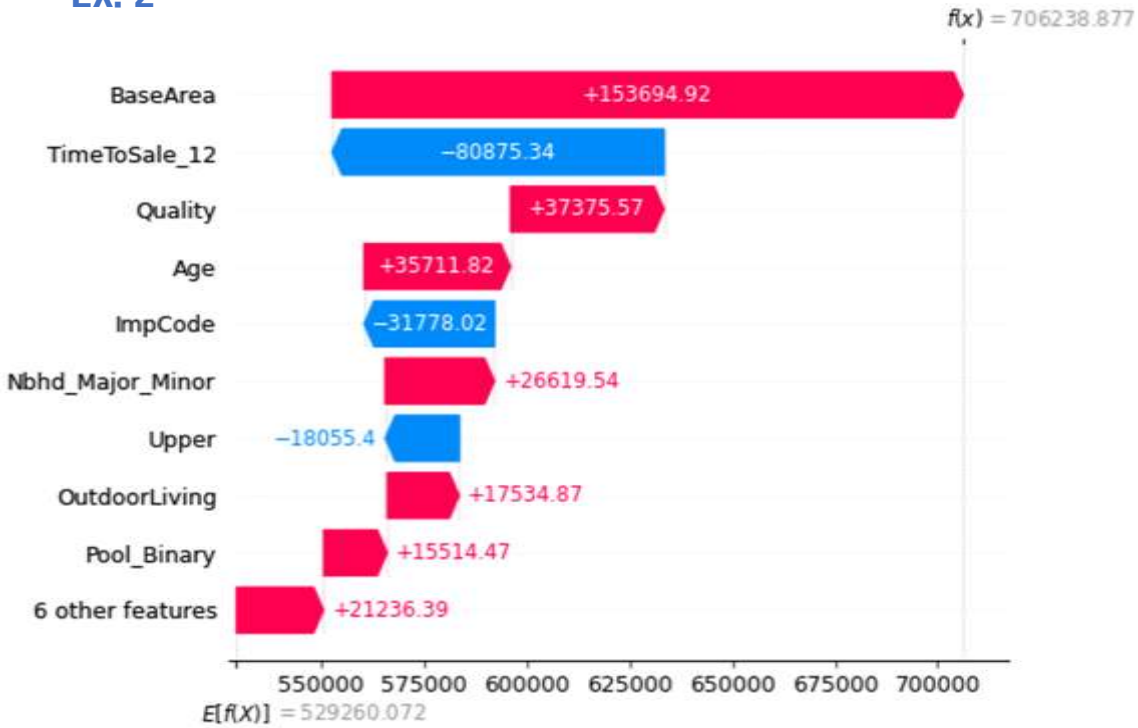
- SHAP stands for **SH**apley **A**dditive ex**P**lanations
- SHAP is a method for explaining Machine Learning by using concepts of game theory to reverse engineer the output of any predictive model
- SHAP is quantifying the contribution that each feature brings to the prediction made by the model
  - By using the outcome of each possible combination of features it determines the importance of a single feature
- SHAP offers unified global and local model interpretability

Local Explanations

Ex. 1

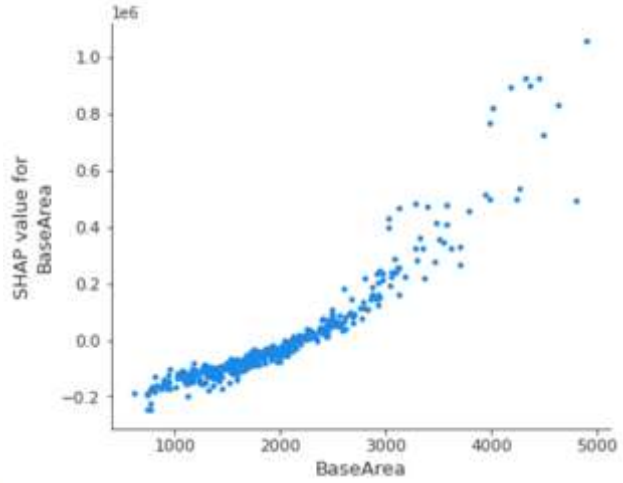


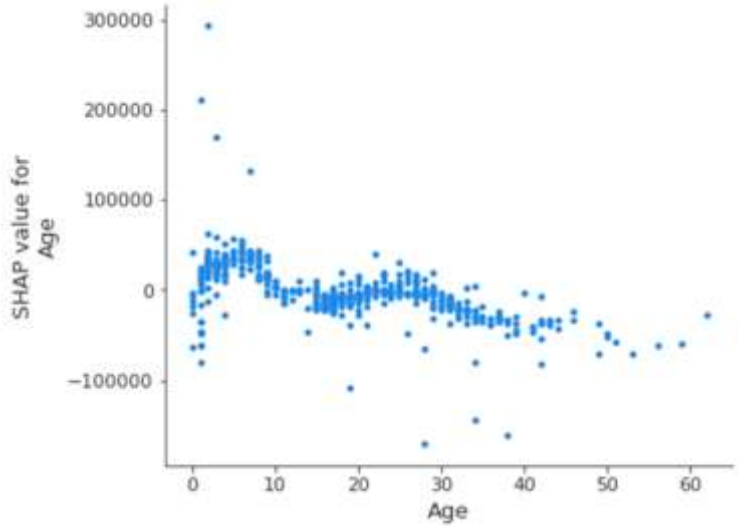
Ex. 2



Global Explanation

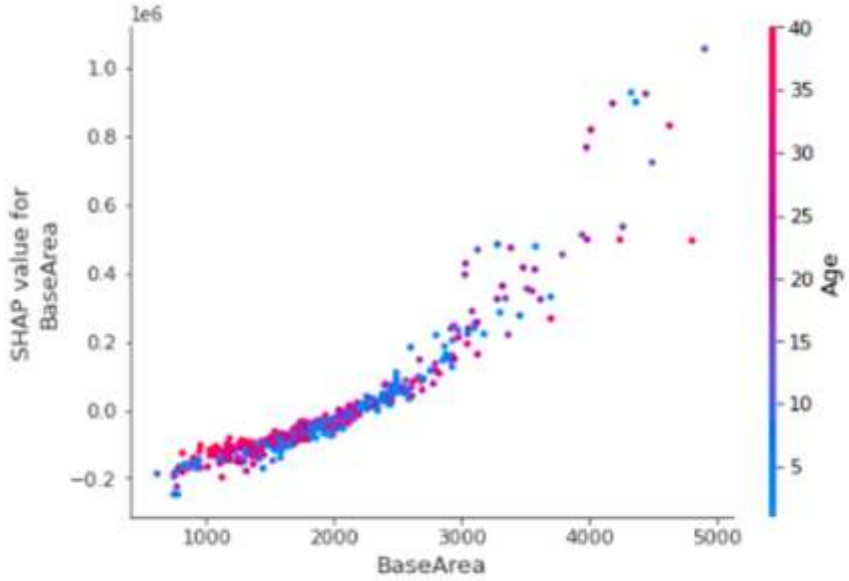
- SHAP can also visually represent the impact any predictor is making on the model for the entire range of values for that predictor
  - Allows for discussion with appraisers
  - Extraction of rate curves





Interaction of Features at a Global Level

- Many times, features can impact one another
  - Interaction plots let us see the importance of one feature to the model
  - Visually shows its relationship to another feature



Takeaways and Questions

- Employing machine learning models addresses many of the limitations of linear regression models
- Machine learning models have not only outperformed the linear regression models, but they also maintained appraisal vertical and horizontal equity where the linear model failed to do so
- Explainable AI techniques such as SHAP were applied to the model in order to provide a high level of "explainability" to the outcomes that capture nonlinearities and other nuances

Thank You!

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