

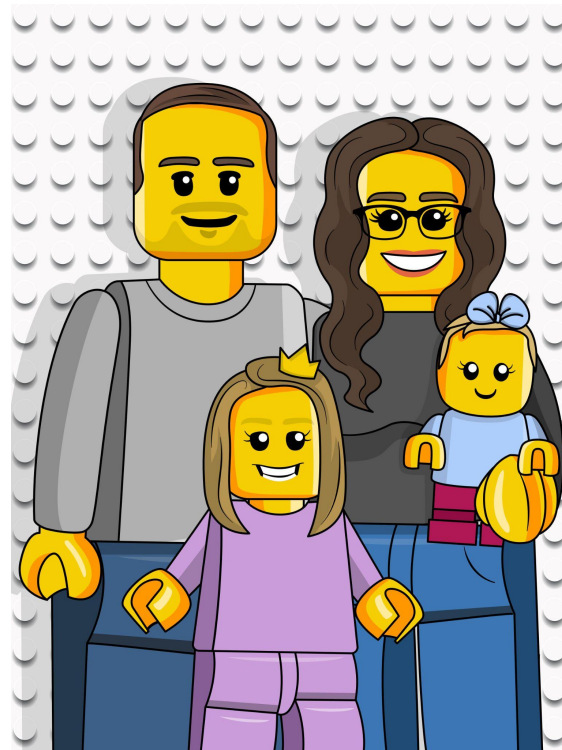
# Predictive Model for Utah Housing Values

By Josh Funderburk

A dark blue diagonal gradient bar that starts from the bottom left corner and extends towards the top right corner, covering the lower half of the slide.

# Intro to Josh

- Education
  - Bachelors of Science in Information Systems (2019) - University of Utah
  - Masters of Science in Data Analytics (current) - Western Governors University
- Employment
  - Included Health
    - Manager, Member Care Analytics (7/2024 - present)
    - Service Quality Analyst (8/2022 to 7/2024)
  - NexRep
    - Business Analyst Manager (1/2020 - 7/2022)
    - Workforce Management Analyst (12/2018 - 1/2020)
  - Upwell Health
    - Business Analyst (5/2017 - 12/2018)



# Problem Statement & Hypothesis

## Research Question:

Can property features such as square footage, lot size, and city predict Utah housing unit values?

## Hypothesis:

- Null ( $H_0$ ): Property features do not significantly predict housing prices
- Alternative ( $H_1$ ): Property features significantly predict housing price

## Why this matters:

- Utah ranks top 5 in population growth
- Need for accurate valuation method
- Traditional methods rely heavily on comparative analysis
- Data-driven approach could improve valuation accuracy and efficiency

# Data Analysis: Preparation

## 1. Initial Data Collection & Cleaning

- Utah Housing Unit Inventory: 688,270 records
- Filtered to single family homes
- Removed nulls
- Removed invalid values
  - i. Example: Total Value = \$0
- Applied outlier handling (IQR method)

## 2. Feature Engineering

- Encoded categorical variables (City, County, Subtype)
- Standardized numerical features

## 3. Model Setup

- Split in to Training and Test sets
- Training set (80%): 533,269 records
- Test set (20%): 198,017 records

# Data Analysis: Model Strategy

## 1. Algorithm Choice:

- Random Forest Regression
- Chosen for ability to handle mixed data types
- Strong with non-linear relationships

## 2. Evaluation Framework:

- R-squared: percentage of total value variation explained
- Mean Squared Error: average squared distance from predicted values
- Root Mean Squared Error: average error in dollars
- Mean Absolute Error: average magnitude of prediction errors

## 3. Optimization Strategy:

- Initial baseline model
- Hyperparameter tuning
- Final optimized model

# Data Analysis: Initial Model

## Core Metrics:

- R-squared: 84.2% variance explained
- Mean Absolute Error: ~\$56,000

## Key Insights:

- Model shows strong predictive power
- Error margin significant but reasonable for housing market
- Good foundation for optimization

R-squared Score: 0.842

Mean Squared Error: 10186082188.194

Root Mean Squared Error: 100926.122

Mean Absolute Error: 55948.001

# Data Analysis: Tuning

- Hyperparameter tuning:
  - Number of trees
  - Maximum tree depth
  - Minimum samples required for node splitting
  - Minimum samples per leaf node
- Tuned on 5% sample of training data due to computational limitations (21,964 samples)
- Scoring metric: R-squared
- Best parameters R-squared = 0.799

# Data Analysis: Final Model

## Performance Metrics:

### 1. Explanatory Power:

- R-squared: 80.5%
- Slight decrease from initial model
- More robust and generalizable

R-squared Score: 0.805

### 2. Error Measures:

- Mean Absolute Error: \$62,548
- Root Mean Squared Error: \$111,984
- Context: ~12% of median home value (\$509,000)

Mean Squared Error: 12540528306.686

Root Mean Squared Error: 111984.500

### 3. Key Takeaway:

- Model shows strong predictive power
- Error margin suggests need for traditional methods
- Ready for production with proper safeguards

Mean Absolute Error: 62548.030



# Key Findings

## 1. Model Performance:

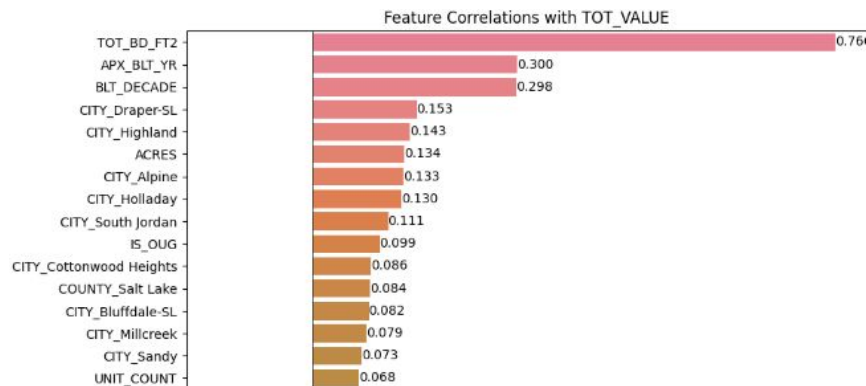
- Property features explain 80.5% of house price variation
- Total building square footage strongest predictor (correlation = 0.778)
- Building age shows meaningful influence (correlation = 0.198)

## 2. Location Impact:

- City and county significantly affect values
- Salt Lake County shows strongest location correlation
- Higher density areas generally show higher values

## 3. Practical Implementation:

- Average prediction deviation: \$62,548
- Context: 12% of median home value (\$509,000)
- Model suitable as supporting tool, not replacement



# Limitations

1. Prediction Accuracy Challenges:
  - \$62,548 average error on \$509,000 median home value (~12%)
  - Current margin limits use as standalone tool
2. Data Coverage Limitations:
  - Only 8 of 29 Utah counties represented
  - Missing critical features (bedrooms, bathrooms, garage)
  - Interior quality data not available
3. Technical Constraints:
  - Complex model reduces interpretability
  - Limited computing power for model tuning
  - Results harder to explain to stakeholders

# Proposed Actions

1. Use as baseline alongside traditional methods
  - Support, not replace, current valuation process
  - Provide objective starting points
2. Expand dataset coverage
  - Include remaining 21 Utah counties
  - Collect additional property features
  - Focus on key value indicators
3. Improve model performance
  - Focus on single-family homes initially
  - Enhance computational resources
  - Reduce prediction error margin

# Expected Benefits

1. For Appraisers & Assessors:
  - Data-driven starting points for valuations
  - Potential to reduce assessment time by 30-40%
  - Consistent baseline across properties
2. For Property Owners:
  - More objective, transparent valuations
  - Faster assessment processes
  - Better understanding of value drivers
3. For Real Estate Market:
  - Supporting Utah's top 5 population growth
  - Foundation for advanced valuation tools
  - More efficient market operations

Thank you!