



# **Debiasing Property Appraisal AVMs: Protecting Civil Rights & Advancing Tech Equity**

# Background: Key Points



- ***AI is a civil rights issue!*** The neutralizing language of *algorithmic fairness* focuses attention on the tech, but *civil rights* invokes the harm to human communities and a tradition of powerful change.
- Percentage magnitude of error higher in majority-Black neighborhoods.
- Appraisal can calcify past patterns of discrimination.
  - Closely tailoring comparables advantages sellers in majority-white neighborhoods.
- White purchasers benefit in majority-Black communities, not vice versa.
  - AVM lag in detecting property value increase due to gentrification.
- Below-market appraisals more common in Black and Latino markets.
- AVM bias < human bias.
- Collateral benefits of AVM-first approach: democratizing and diversifying appraisal industry.
- Both intent and impact are actionable; impact is more relevant to AVM challenges.

# Problem #1:

## Test an AVM for racially biased outcomes.

### Given:

- log-error data for 2016 CA home appraisals calculated by automated valuation model (AVM)
- census tract aggregate demographic data

### Analyze:

- Does the AVM generate error that disproportionately harms communities of color?
- Magnitude and direction of any detected bias with respect to protected classes

### Strategy:

- Data preprocessing
- Exploratory data analysis and statistical testing
- Build a classifier to mimic the AVM
- Predict the log errors within protected and control group for 2017 test data
- Evaluate classifier performance
- Rank importance and relative magnitude of model's input features

**Fair Housing Act 55th Anniversary Event**

Tech Equity Hackathon 2023

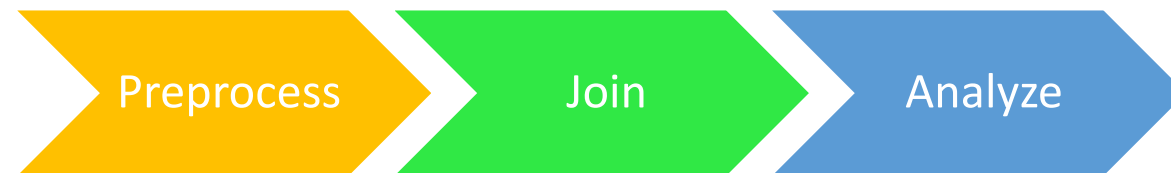
**NFHA** NATIONAL  
FAIR HOUSING  
ALLIANCE

**55<sup>th</sup>**  
ANNIVERSARY OF THE FAIR HOUSING ACT

# Preprocessing

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- Analysis of missingness
- Address null values
- Transform categorical variables
- Minimize cardinality
- Dimensionality reduction

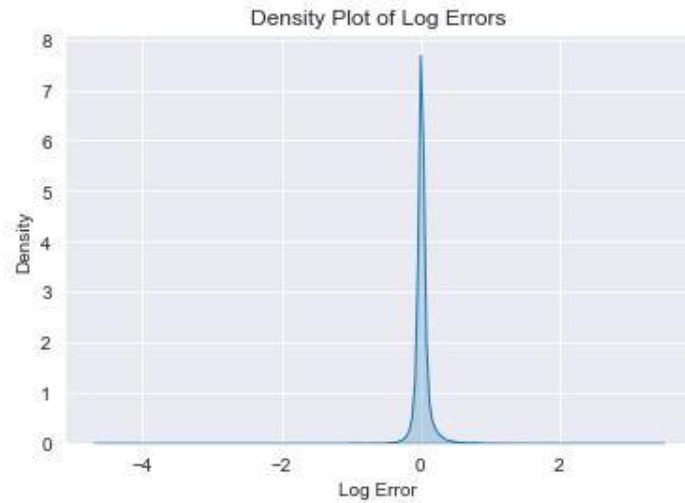


## Joining

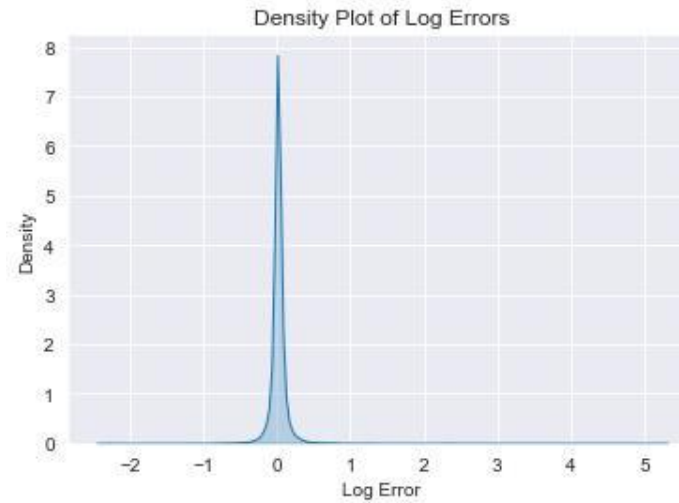
- Property specs with training and testing data
- Census demographics with preprocessed data

*... but beware data leakage!*

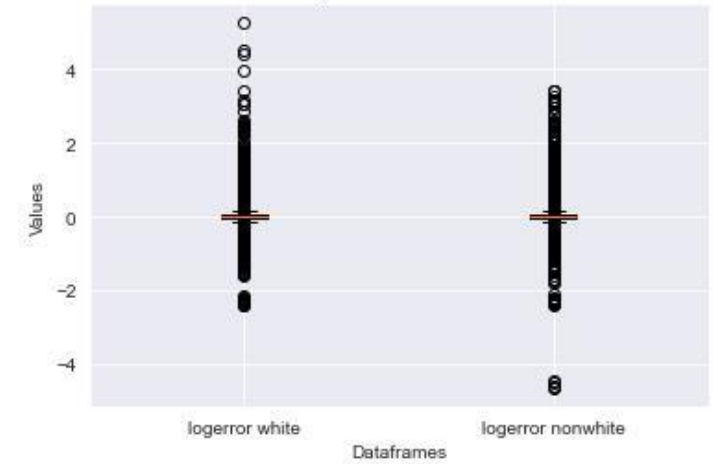
Properties in communities of color



Properties in majority-white communities



Comparison of Box Plots



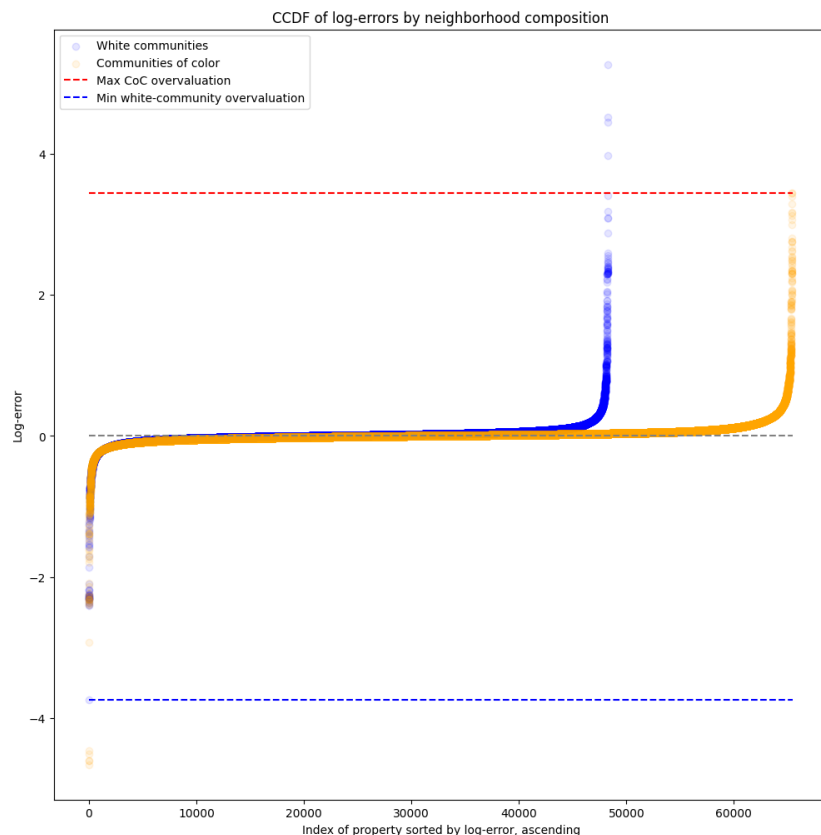
## Exploratory Data Analysis

- Skewness for majority-white: 4.774
- Skewness for communities of color: 1.364
- **Majority-white has much more extreme right-tailed distribution.** Values asymmetric about the mean with a higher proportion of scores above than below the mean.



# Problem #2: Quantify the size of the bias.

- Median log-error favors properties sold in white neighborhoods.

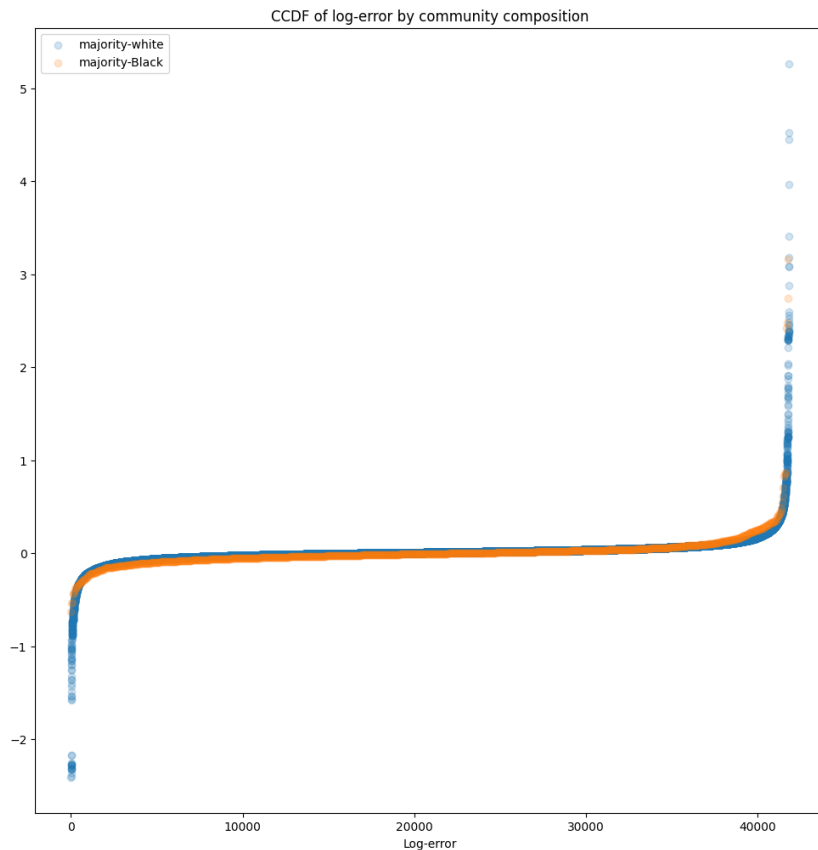


	Majority White	Communities of Color
Count	48264.0	65399.0
Mean	0.010618	0.014172
Standard Deviation	0.159759	0.154437
Minimum	-3.737018	-4.65542
25%	-0.0233	-0.0263
Median	0.007	0.004
75%	0.0392	0.0363
Maximum	5.262999	3.443

\*  $p$ -value = 0.00017 for  $H_0: \bar{x}_w = \bar{x}_{coc}$ , but fails independence test  
(but that's also the point!)

# Problem #2: Quantify the size of the bias.

- Median log-error favors properties sold in white neighborhoods.



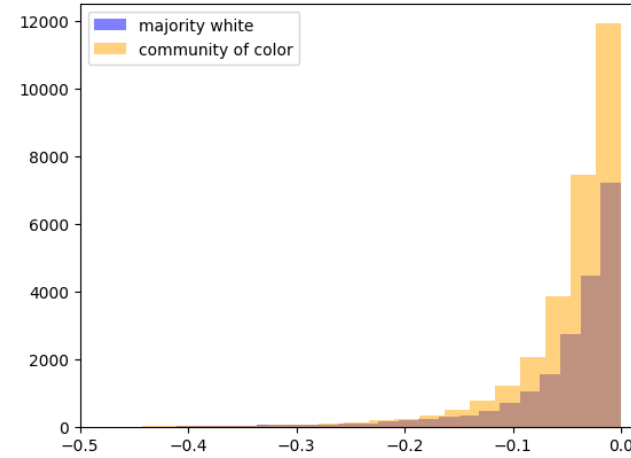
	Majority White	Majority Black
Count	41841.0	1176.0
Mean	0.011515	0.008474
Standard Deviation	0.157885	0.202334
Minimum	-2.406257	-0.62716
25%	-0.0243	-0.0513
Median	0.007	-0.007
75%	0.040278	0.0344
Maximum	5.262999	3.16

\*  $p\text{-value} = 0.609$  for  $H_0: \bar{x}_w = \bar{x}_{coc}$   
not statistically significant

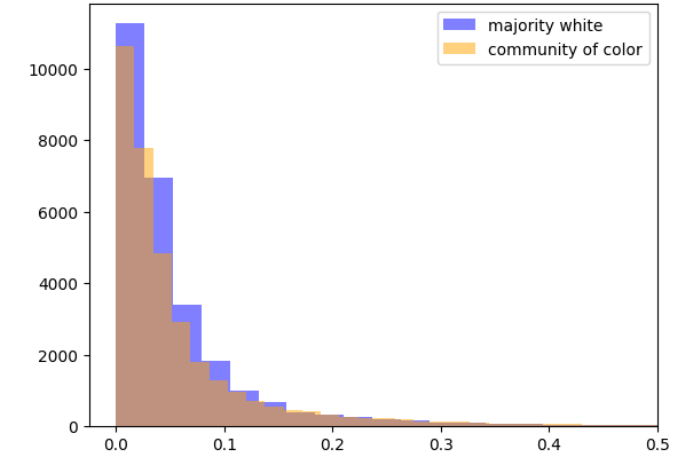
# What does bias look like?

- Median log-error greater for overappraised properties in majority-white neighborhoods, equal for undervalued properties.

Distribution of log errors by community demographic composition, Underestimations



Distribution of log errors by community demographic composition, Overestimations



	Overvalued Majority White	Overvalued Communities of Color	Undervalued Majority White	Undervalued Communities of Color
Count	27355.0	35361.0	20641.0	29645.0
Mean	0.06778	0.074075	-0.064998	-0.057093
Standard Deviation	0.153748	0.154276	0.135287	0.121922
Minimum	0.000003	0.000007	-3.737018	-4.65542
25%	0.0149	0.0139	-0.067242	-0.0619
Median	0.0334	0.032591	-0.0305	-0.0305
75%	0.0686	0.0714	-0.012563	-0.0131
Maximum	5.262999	3.443	-0.000002	-0.000007

\*  $p$ -value = 0.00000 for  $H_0: \bar{x}_w = \bar{x}_{coc}$  both for undervalued and overvalued



# Does appraisal differ by home size across communities?

- Dataset is noisy, so we segmented the market into quartiles by square footage.
- For the largest houses, median log-error overvalues properties in majority white houses more than in communities of color.
- For smallest houses, houses in communities of color are more undervalued.

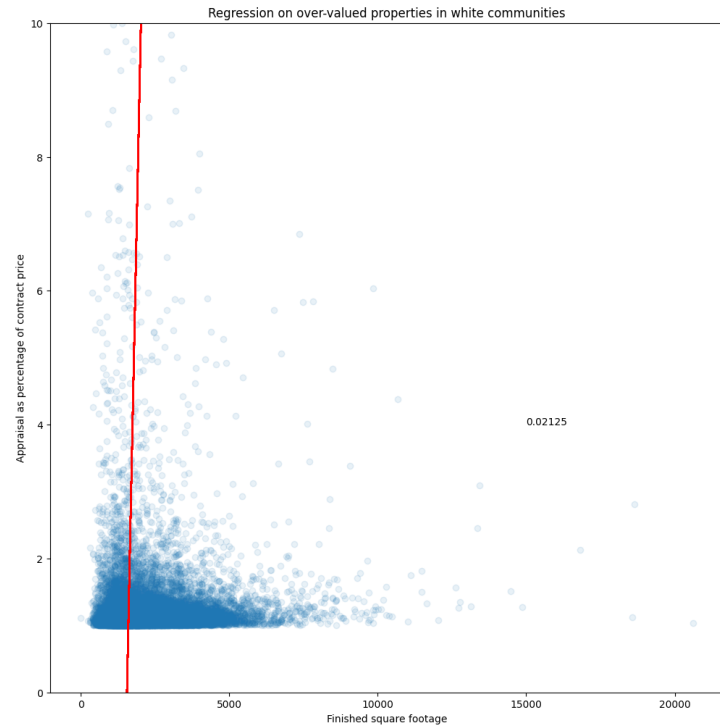
... see caveats: sample size sensitivity,  
lack of data on buyer/seller rate

Top percentile

	Majority White	Communities of Color
Count	30511.0	26265.0
Mean	0.012893	0.020559
Standard Deviation	0.163023	0.149315
Minimum	-3.737018	-4.605
25%	-0.021831	-0.019843
Median	0.009	0.008
75%	0.0431	0.04013
Maximum	5.262999	3.443

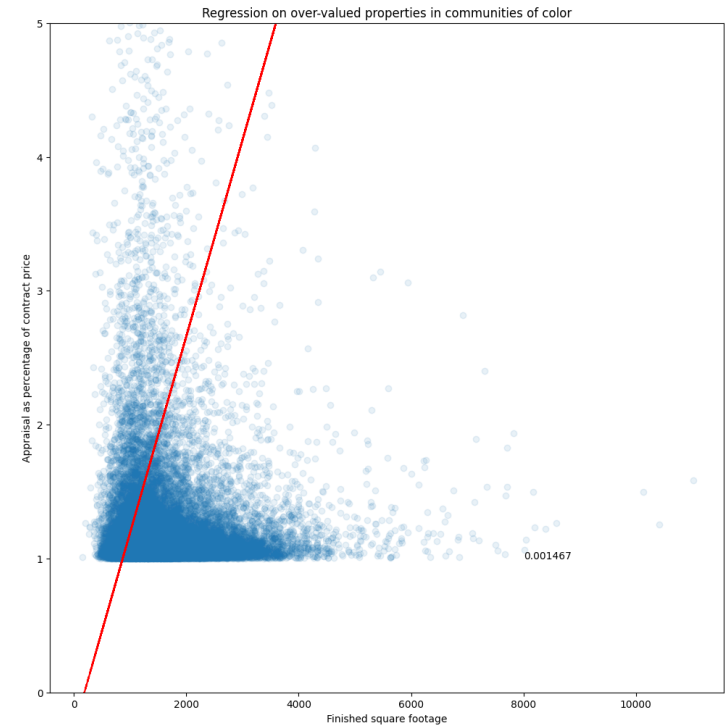
Bottom percentile

	Majority White	Communities of Color
Count	8130.0	20224.0
Mean	0.007297	0.010192
Standard Deviation	0.159965	0.158988
Minimum	-2.323	-4.605
25%	-0.0263	-0.032266
Median	0.004	0.002
75%	0.032983	0.0354
Maximum	2.56	3.123634



$$10^{\log \frac{\text{appraisal}}{\text{contract}}}$$

$$= \frac{\text{appraisal}}{\text{contract}}$$



## Error Scaling

- Exponentiated the appraisal error score to get a measure of appraisal as a proportion of contract price.
- + 2.1% increase in appraisal as percent of contract price per finished square foot for overvalued white communities.
- + 0.15% increase in appraisal as percent of contract price per finished square foot for overvalued communities of color.

# Model selection

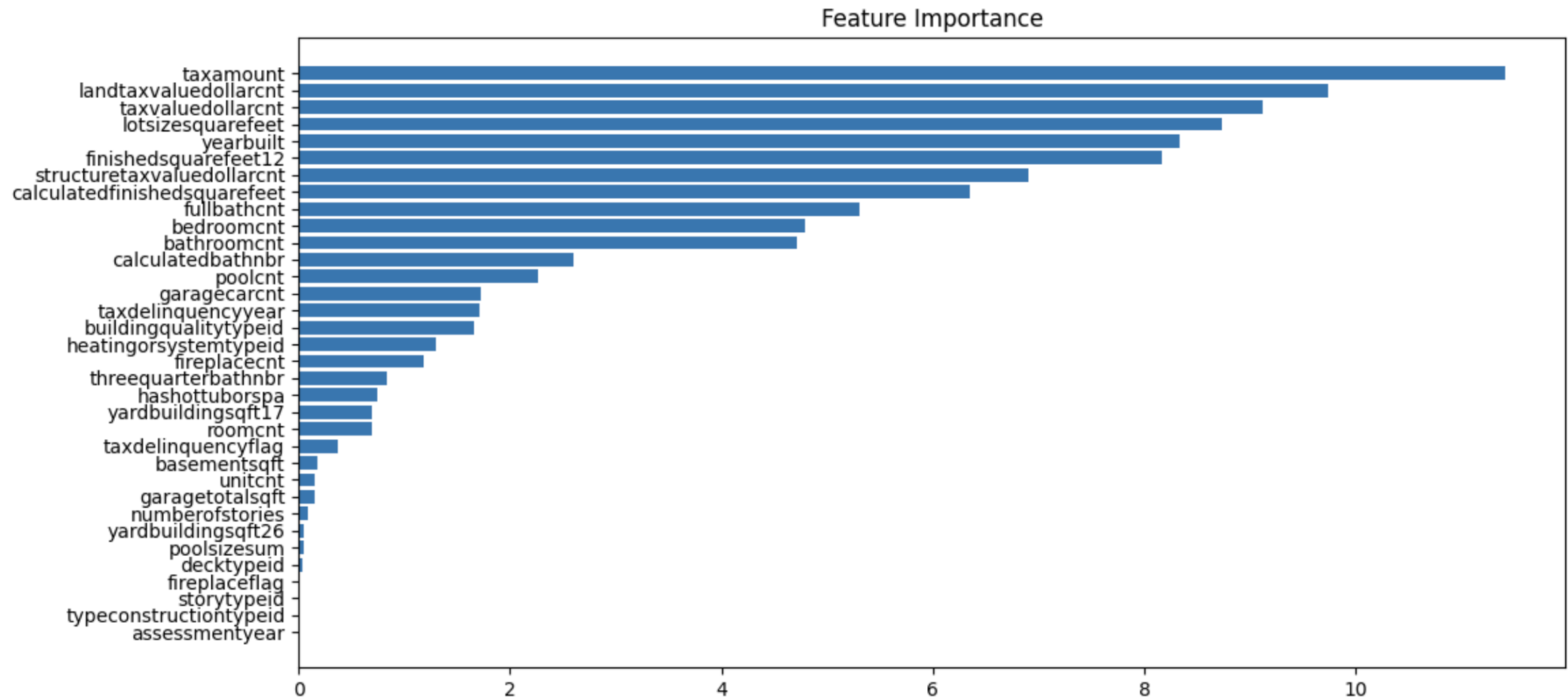


- CatBoost – Open Source Gradient Boosting
  - Gradient Boosting combines weak models with strong ones for competitive modelling
  - applies target encoding with random permutation to handle categorical features
  - very efficient for high cardinality columns creates just a new feature to account for the category encoding
  - Uses ordered boosting, a permutation-driven approach to train the model on a subset of data while calculating residuals on another subset prevents target leakage and overfitting

## Building the model

- Separate out categorical features vs. Numerical
- Select parameters: 150 iterations (max trees), RMSE (training metric), 6 tree depth, .21 learning rate (default .1)
- Grid Search for parameter optimization, results by feature importance
- Evaluation using RMSE, best performing model performed had a RMSE of ~0.15

# Problem #3: Identify feature importance.



... recall that feature importance cannot be considered independently of model performance.

# Problem #4: Describe potential societal harm.



- Disparity in wealth generation through home sales due to disparate impact of property tax reform
- Legacy effect of discriminatory zoning
- Impact on appraisal of older home ownership by Black communities



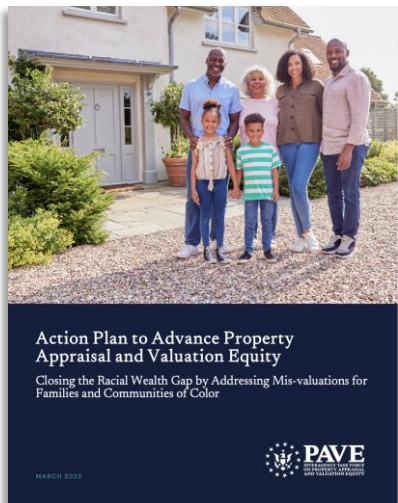
# Problem #5: Mitigate bias, retain AVM performance.

- Disentangle property appraisal from tax assessments
- Tune AVM to increase reliance on construction, size, and other features of value to homeowners
- Incentivize more complete data collection and reporting to drive appraisals based on a fuller picture, stronger multivariate analysis
- Build stronger real-time detection algorithm to boost sales price for sellers in gentrifying majority-Black neighborhoods
- Annual audit of semi-random sample of AVM appraisals of homes reflecting community demographics
  - Overseen by multidisciplinary Advisory Committee: community members, human appraisers, industry experts



# Broader Policy Recommendations

- Nonprofit, nonpartisan industry oversight, accreditation, and arbitration partnerships to provide alternatives to costly litigation before an underinformed judiciary
- More project-based learning and community-building events to support the BIPOC tech/AI community
- Public education campaigns to raise awareness of AVM risk and available remedies
- Make public funding available to increase risk tolerance for lenders to counterbalance AVM bias
- Fund small community businesses, especially in property rehab, to minimize default and distressed-property sales



Fair Housing Act 55th Anniversary Event

Tech Equity Hackathon 2023



SEP 21, 2022

## Announcing the winners of Zillow's HBCU hackathon

Zillow awards top prizes to students who innovate technology that helps break down housing barriers

### Community Impact

Zillow's HBCU Hackathon returned this year, encouraging students attending Historically Black Colleges and Universities (HBCUs) to develop and pitch a tech solution that supports Zillow's mission to make finding a home easier and more accessible for everyone. The weeklong event, produced in partnership with the United Negro College Fund (UNCF) and Amplify 4 Good, involved 219 students this year, representing 20 HBCUs.

Six teams advanced to the final round, during which each team had five minutes to present their ideas virtually to a panel of judges made up of Zillow and tech industry leaders. Three of those teams were awarded top prizes for their work. First place included a cash prize of \$20,000 shared amongst team members and a donation of \$25,000 to their university. Second- and third-place teams received a cash prize of \$12,000 and \$6,000 respectively. In addition, the students received a \$500 textbook gift card, a new laptop and a new wireless mouse.

