
MATH6912
Final Project
Approved
Your bank uses AI to decide whether you get a mortgage.
But is it fair?
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Rishigesh Patgunarajah,
Vincent Sham, Zohaib Ahmed
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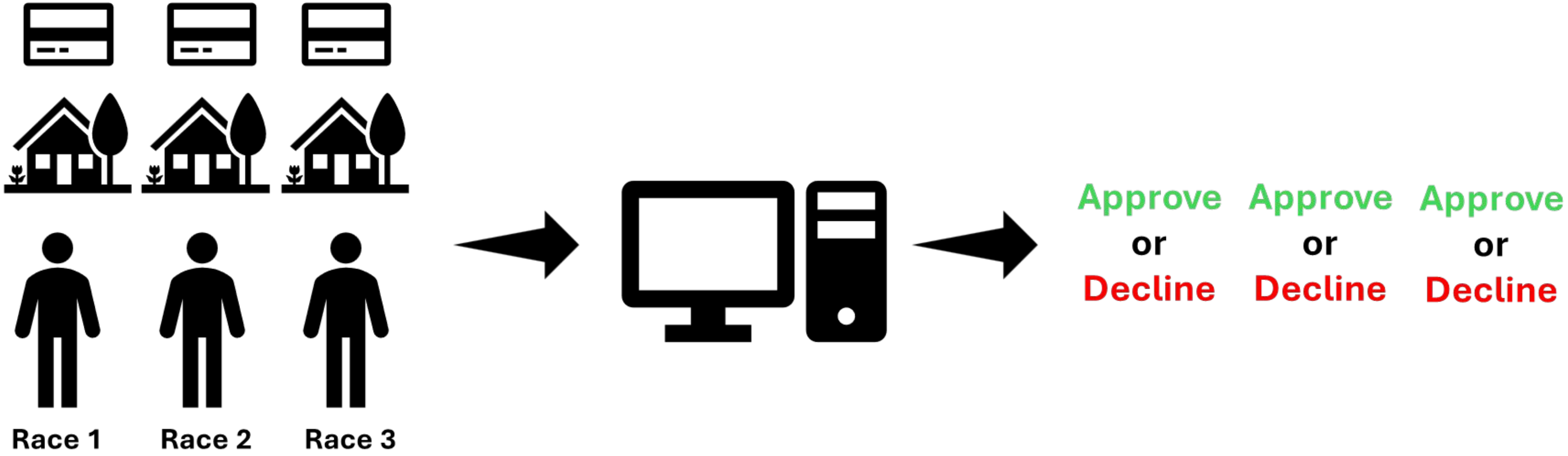
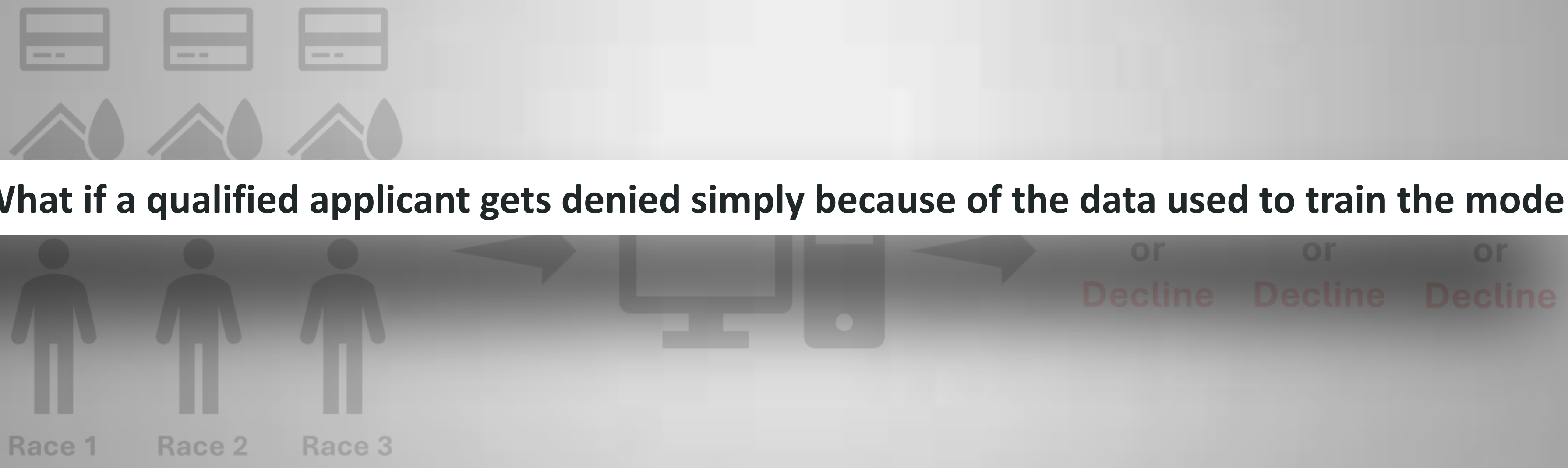
Can AI Make Fair Mortgage Decisions?

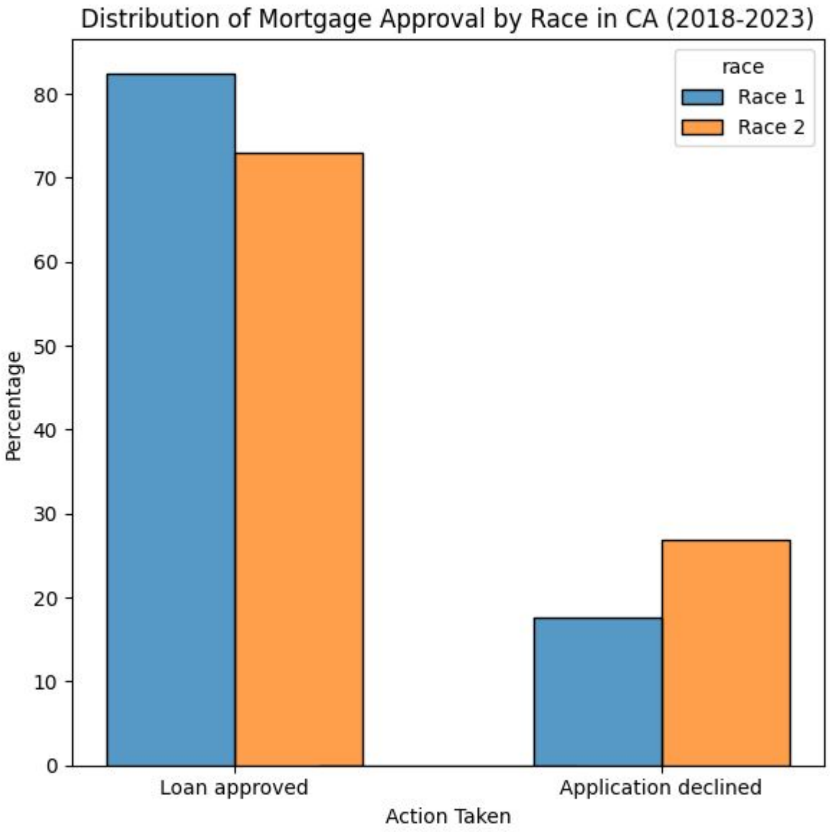


Can AI Make Fair Mortgage Decisions?



What if a qualified applicant gets denied simply because of the data used to train the model?

Bias by the Numbers



"Artificial Intelligence and its inherent bias seems to be an ongoing contributing factor ***in slowing minorities home loan approvals****... Specifically,* ***80% of Black applicants are more likely to be rejected****, along with* ***40% of Latino applicants****, and* ***70% of Native American applicants are likely to be denied****."*

Kori Hale (2021)

Reference: https://www.forbes.com/sites/korihale/2021/09/02/ai-bias-caused-80-of-black-mortgage-applicants-to-be-denied/

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Objective:
Accuracy without Bias

Accuracy without Bias

Develop a machine learning model for mortgage approvals that **minimizes bias** while **maintaining predictive accuracy**.

HMDA Data: Provided by FFIEC

The Home Mortgage Disclosure Act (HMDA):

A U.S. federal law that requires financial institutions to disclose data about their mortgage lending activities.

Data source:

- Federal Financial Institutions Examination Council (FFIEC)

Data coverage:

- California, USA
- 2018-2023

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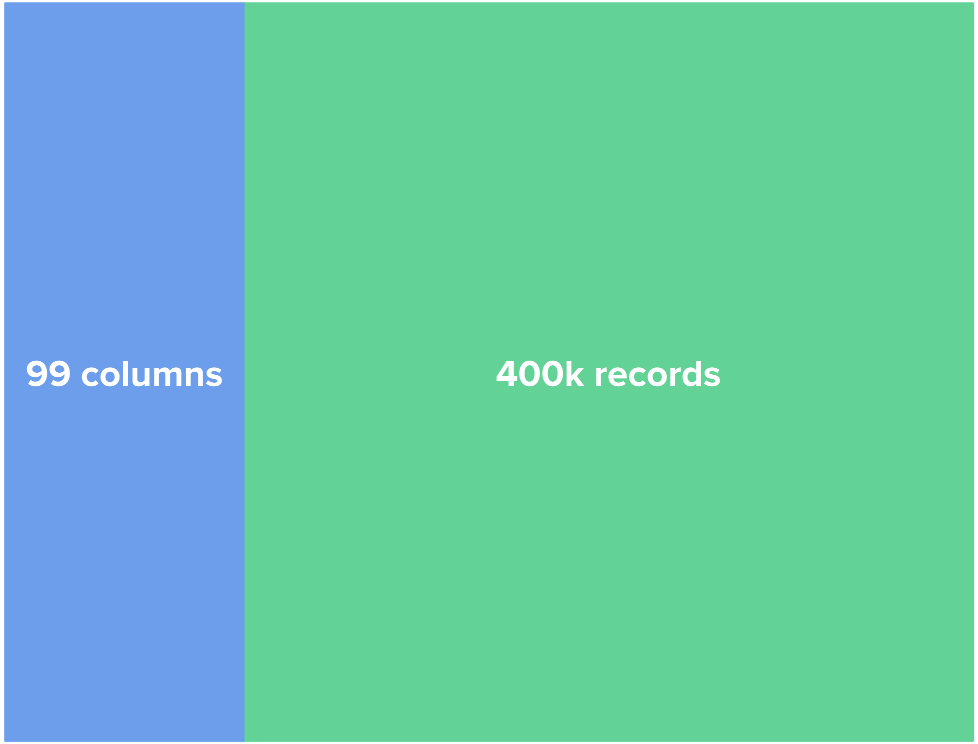
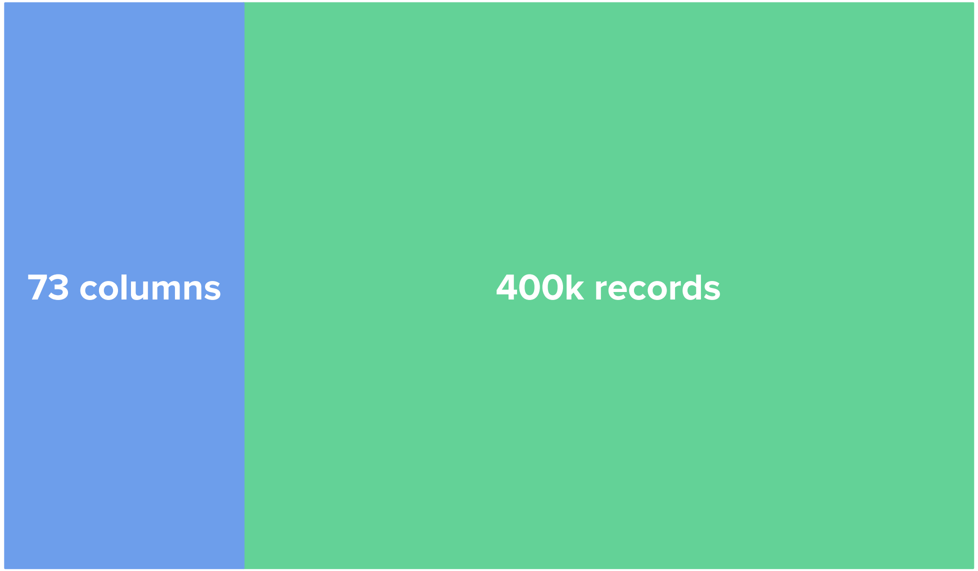
HMDA Data: Feature Selection

HMDA Data: Feature Selection



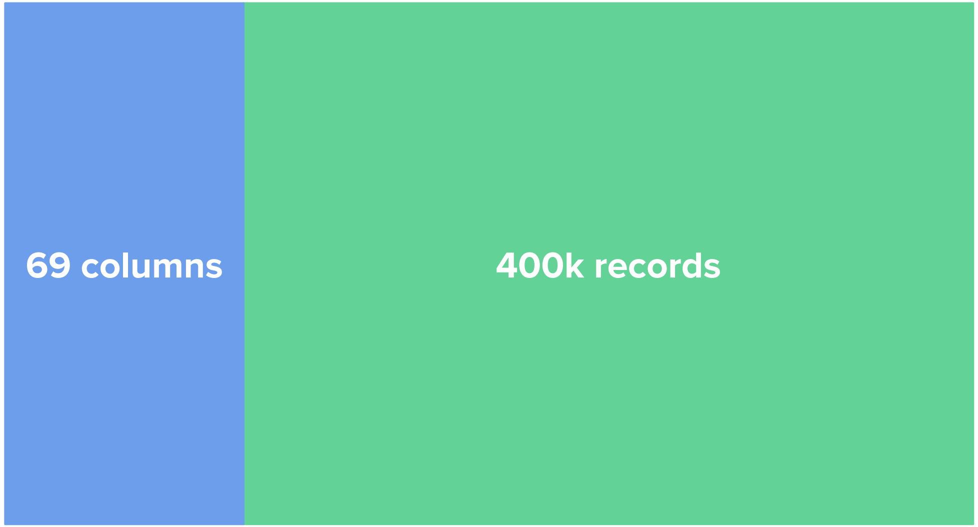
- Stratified Sampling (13M => 400k records)
    - Preserve **race population ratio**
    - Preserve **approval ratio for each race**

HMDA Data: Feature Selection



- Remove features with **90%+ missing values** (drop 26 features in total)

HMDA Data: Feature Selection



- Remove **geographic** features (drop 4 features in total)

HMDA Data: Feature Selection

- Remove features that have **potential data leakage** (drop 36 features in total)
  - denial reason
  - interest rate
  - rate spread
  - origination charges

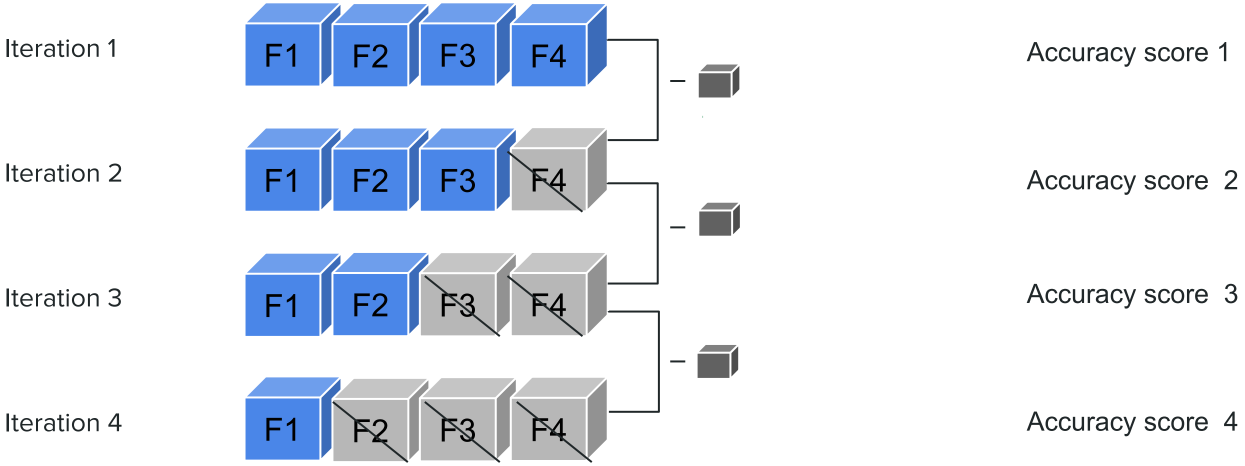
HMDA Data: Feature Selection

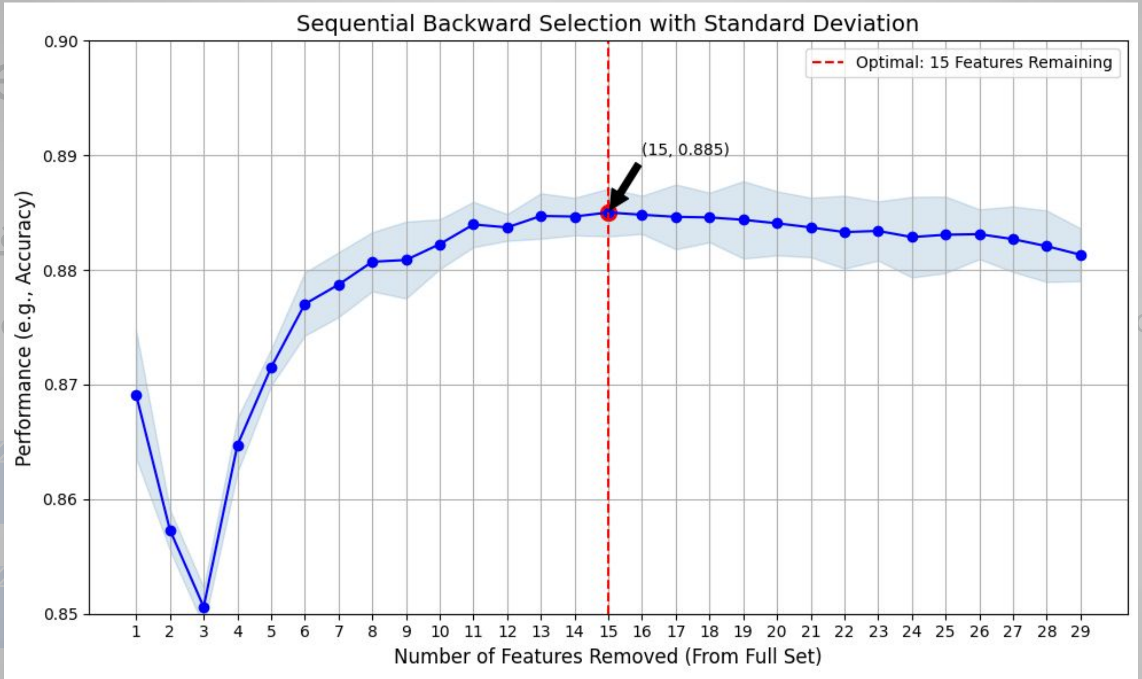
- **Key features**
  - Mortgage Amount & Type
  - Sex, Age
  - Race
  - Income
  - Debt to Income Ratio
  - Action Taken

Greedy Feature Selection

Backward:

Remove one feature in each iteration.





15 Greedy selected features:

1 - Income
2 - loan purpose
3 - loan amount
4 - loan term
5 - loan type
6 - loan to value ratio
7 - Debt to income ratio
8 - Race
9 - Sex
10 - Applicant age above 62
11 - Open end line of credit
12 - Tract median age of housing units
13 - Property value
14 - Total units
15 - Applicant credit score type

Performance Metric - Accuracy

- Overall Accuracy

- True Positive (**TP**) and False Positive (**FP**)

Fairness Metric - Equal Opportunities

- Good candidates should have **the same chance** to get approved **independent of their race**.

$$TPR(protected\, race) = TPR(unprotected\, race)$$

- Fairness Score

$$F = \frac{1}{1 + |TPR(protected\, race) - TPR(unprotected\, race)|}$$

Business Metric

$$
\begin{aligned}
B = {} & mortgage\ amount \times interest\ rate \times term \\
& + other\ charges \\
& - default\ rate \times mortgage\ amount
\end{aligned}
$$

- Assumptions
  - **TP** - Good default rate = 1.0%
  - **FP** - Bad default rate = 4.0%
  - Constant interest rate

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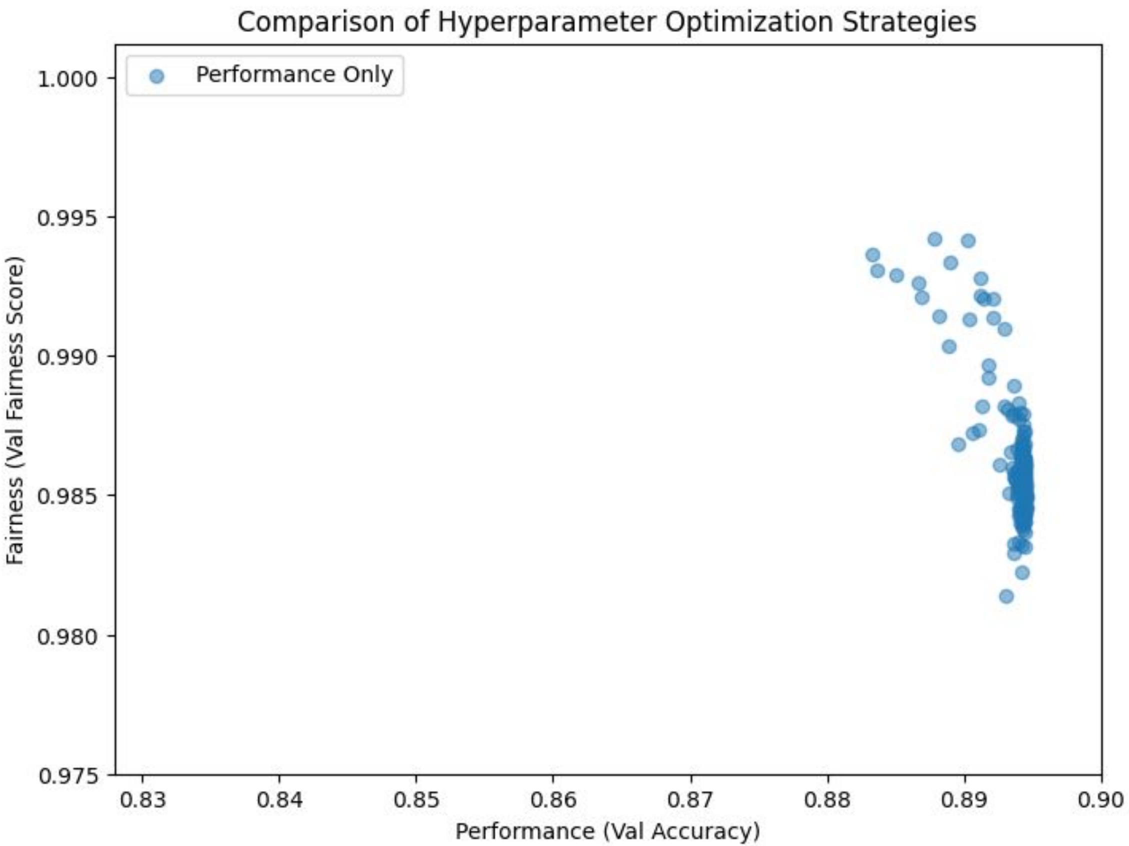
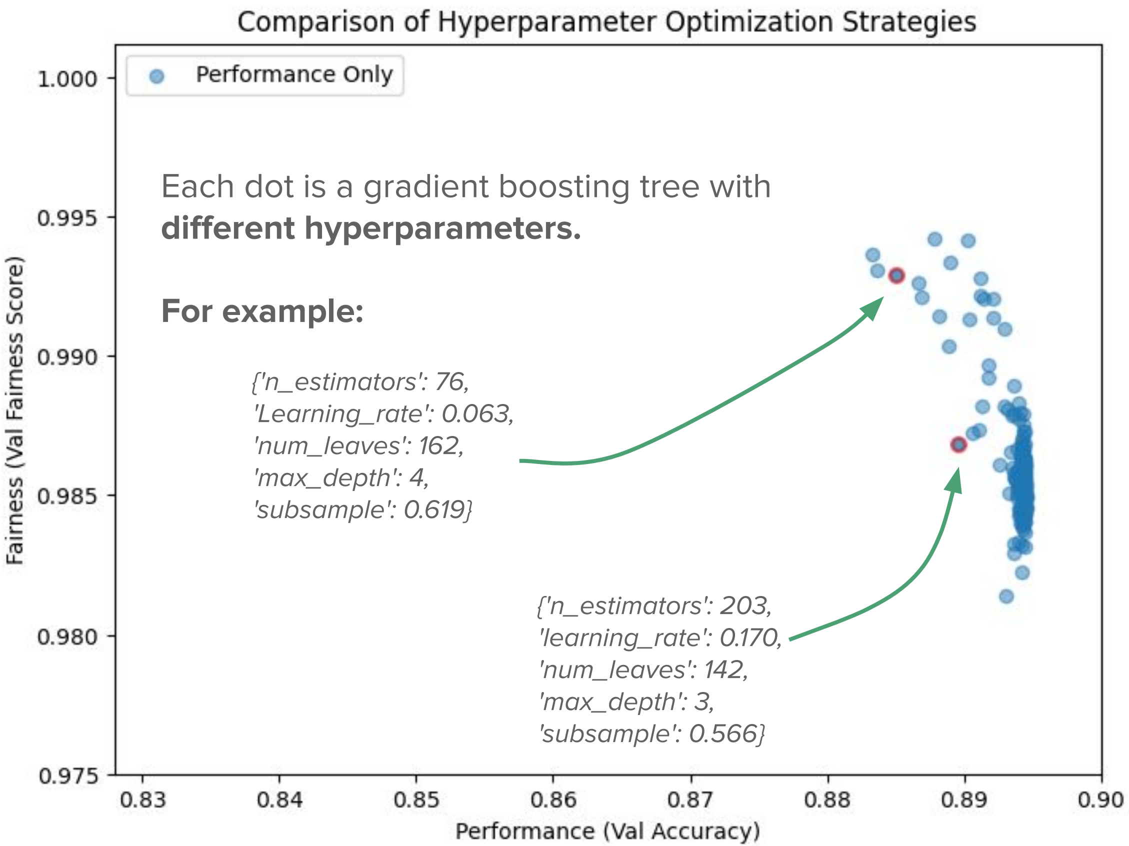
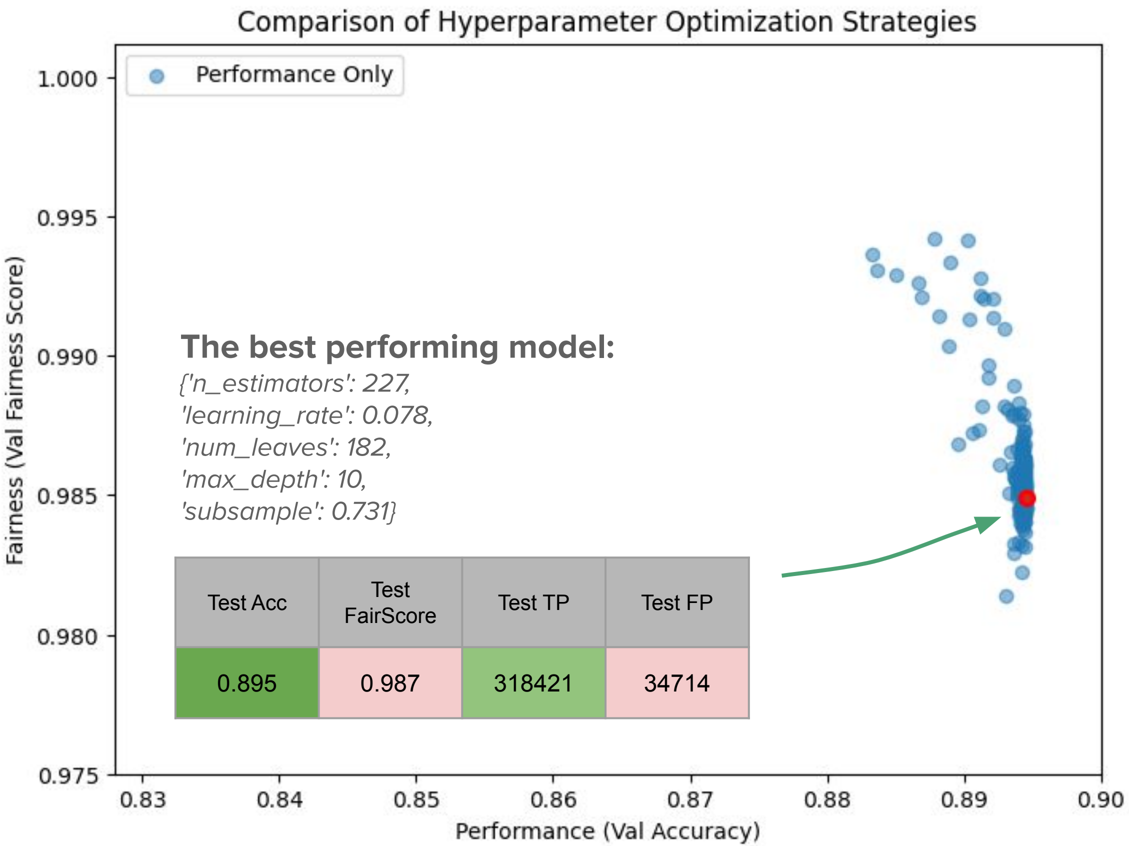
Hyperparameter Optimizations



Hyperparameter Optimizations



Hyperparameter Optimizations

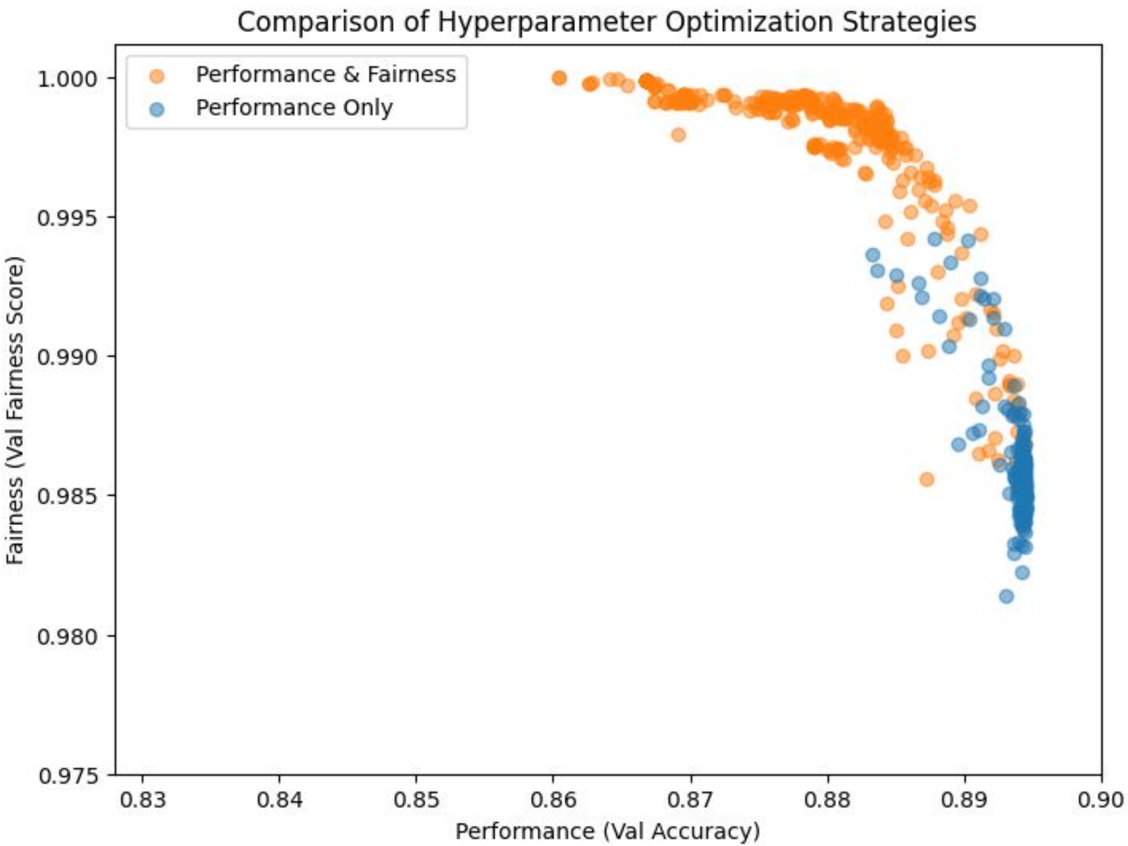


The best performing model:

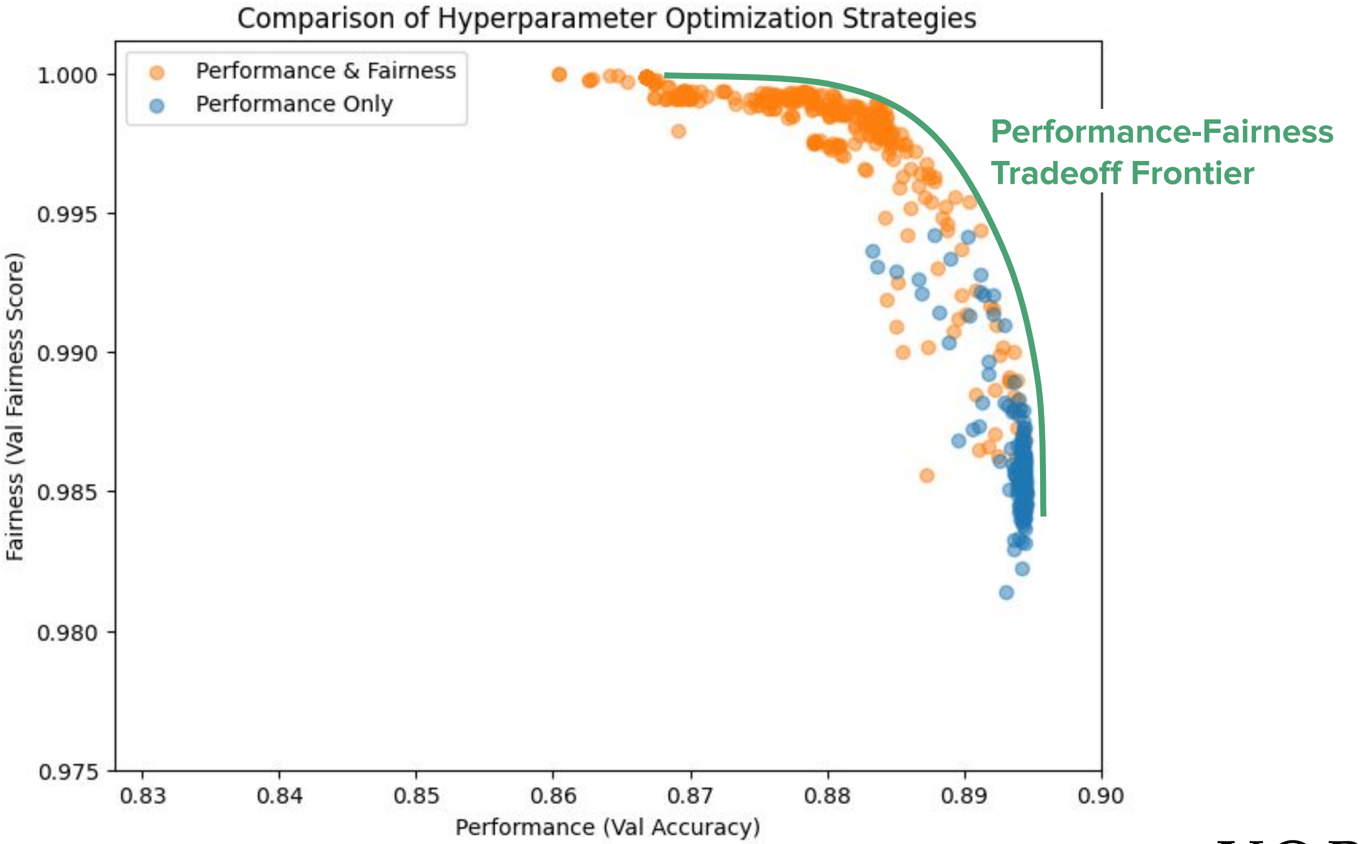
{'n_estimators': 227,
'learning_rate': 0.078,
'num_leaves': 182,
'max_depth': 10,
'subsample': 0.731}

Test Acc	Test FairScore	Test TP	Test FP
0.895	0.987	318421	34714

Hyperparameter Optimizations



Hyperparameter Optimizations



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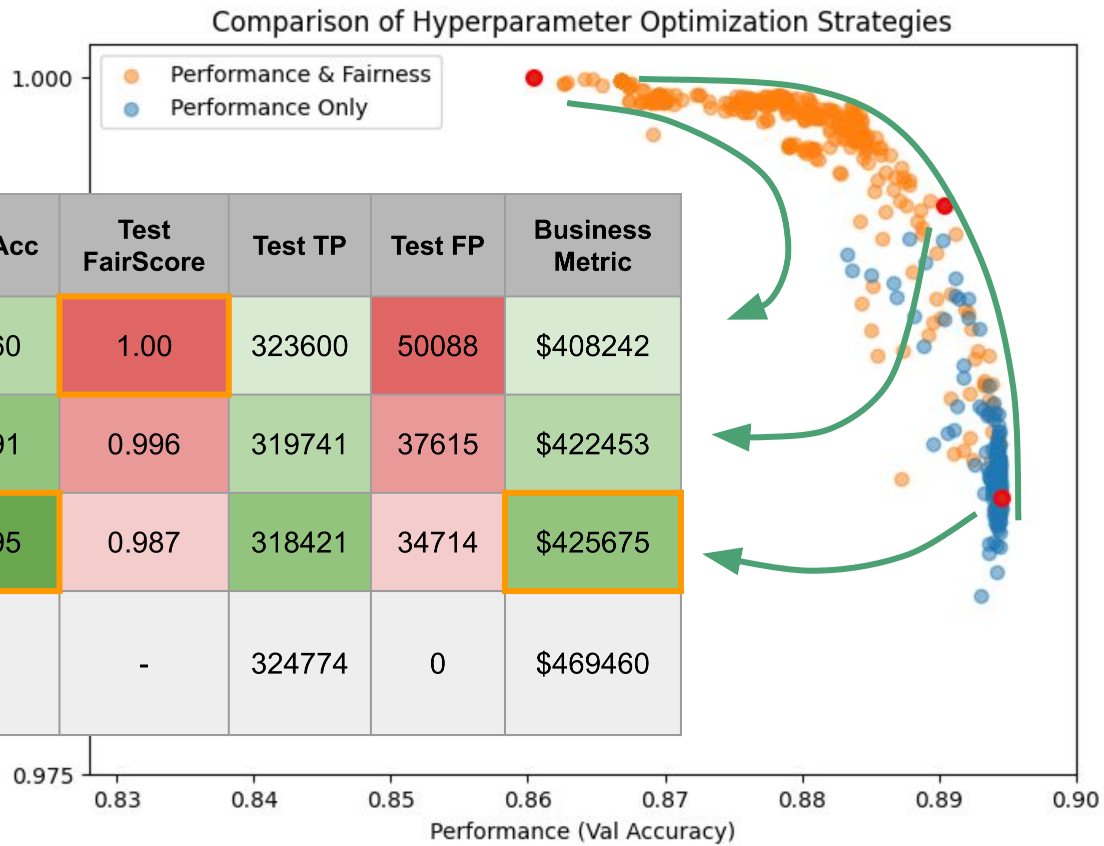
Hyperparameter Optimizations



Models	Test Acc	Test FairScore	Test TP	Test FP	Business Metric
Fair	0.860	1.00	323600	50088	$408242
Balance	0.891	0.996	319741	37615	$422453
Performance	0.895	0.987	318421	34714	$425675
Ground Truth (Perfect Prediction)	-	-	324774	0	$469460

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Our Observations

	Unprotected Race	Protected Race
Population	93.8%	6.2%
Approval Rate	82.4%	73.1%

VS

Our Observations

	Unprotected Race	Protected Race
Population	93.8%	6.2%
Approval Rate	82.4%	73.1%

VS

- Resample the dataset to make it **balanced** and **fair**
  - Hurt the performance

- We propose a **generic resampling method** to build our gradient boosting tree.

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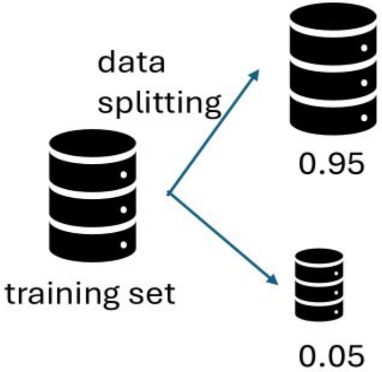
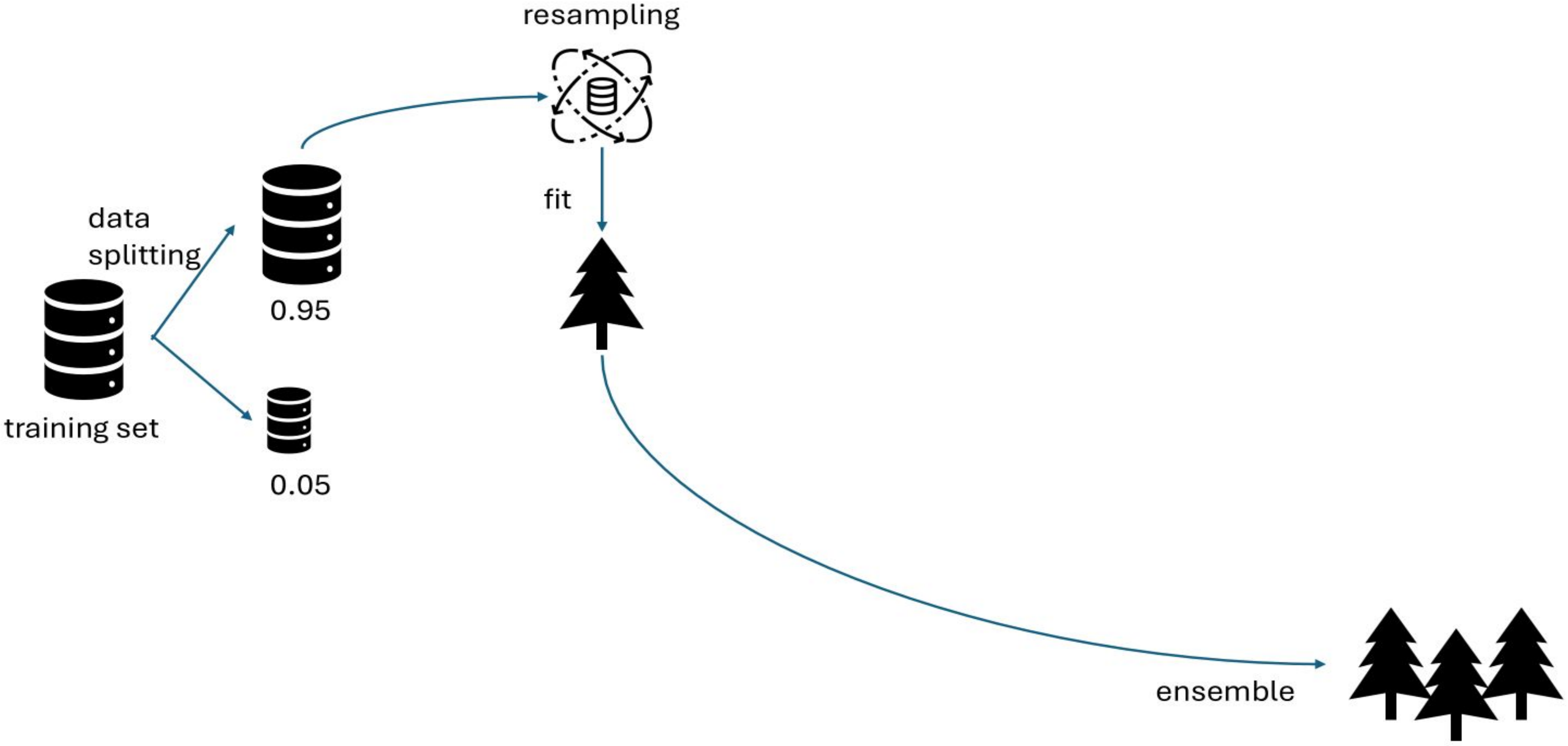
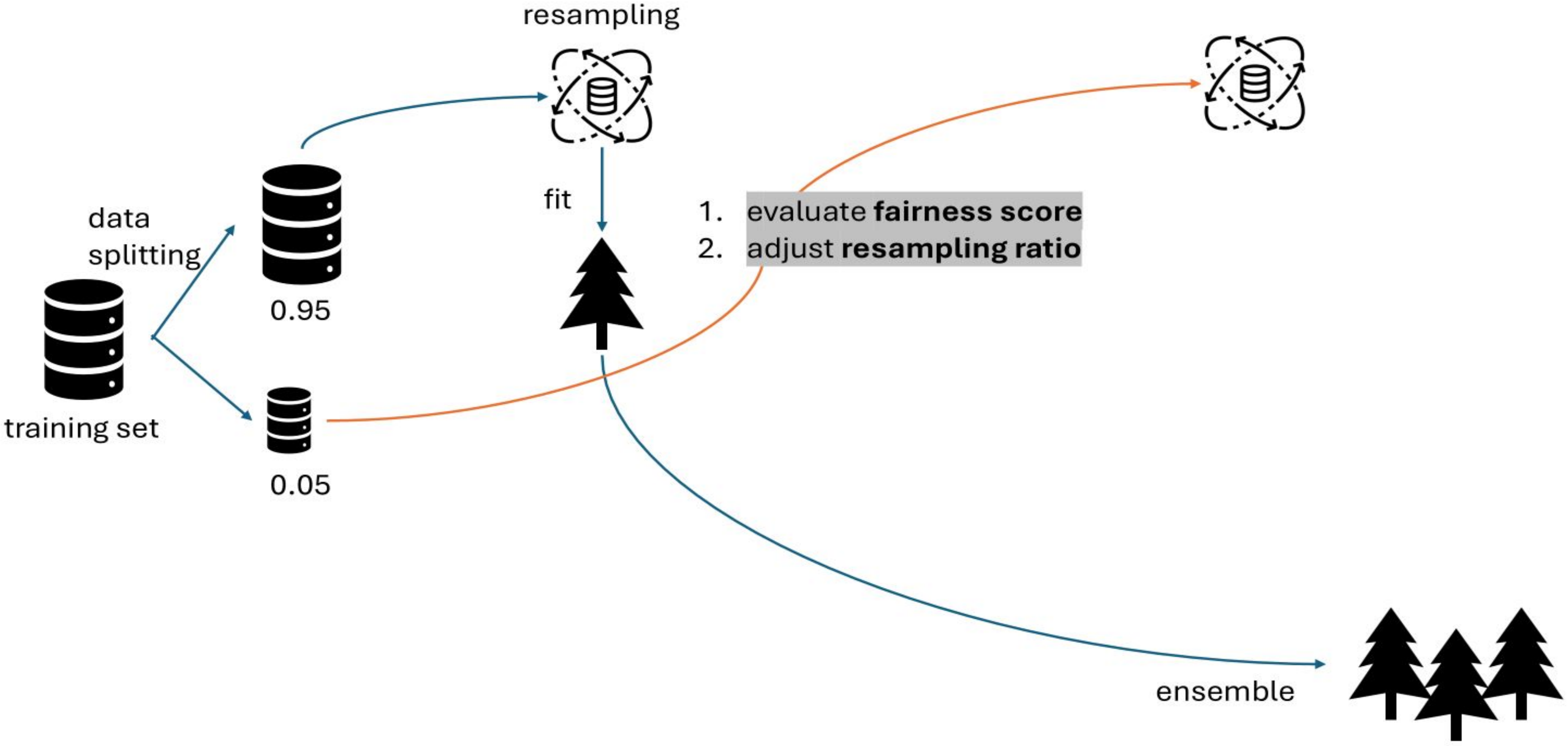
Our Method



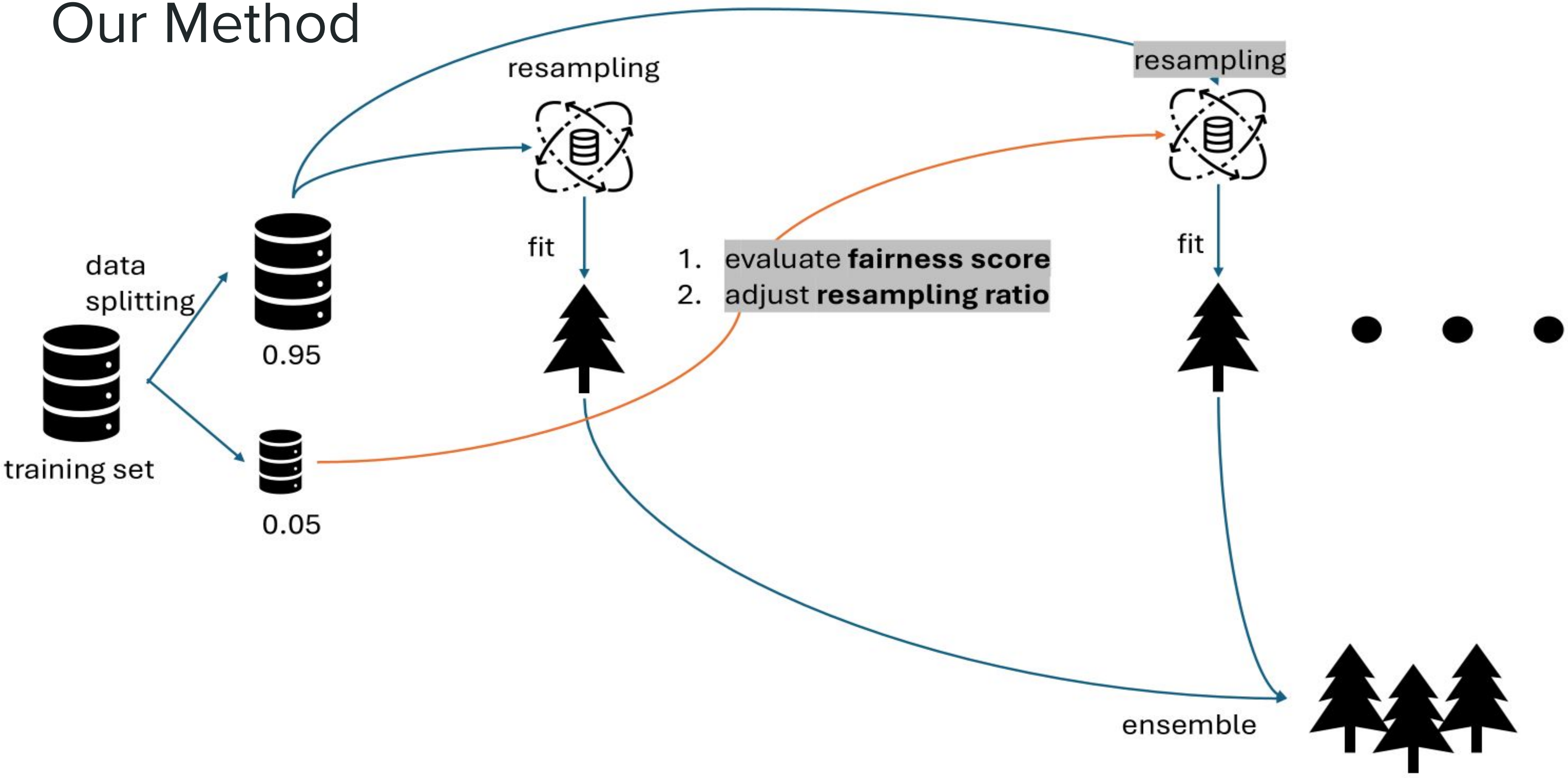
Our Method


resampling
fit
data
splitting
0.95
training set
0.05
ensemble

Our Method


resampling
data
splitting
0.95
fit
1. evaluate **fairness score**
2. adjust **resampling ratio**
training set
0.05
ensemble

Our Method



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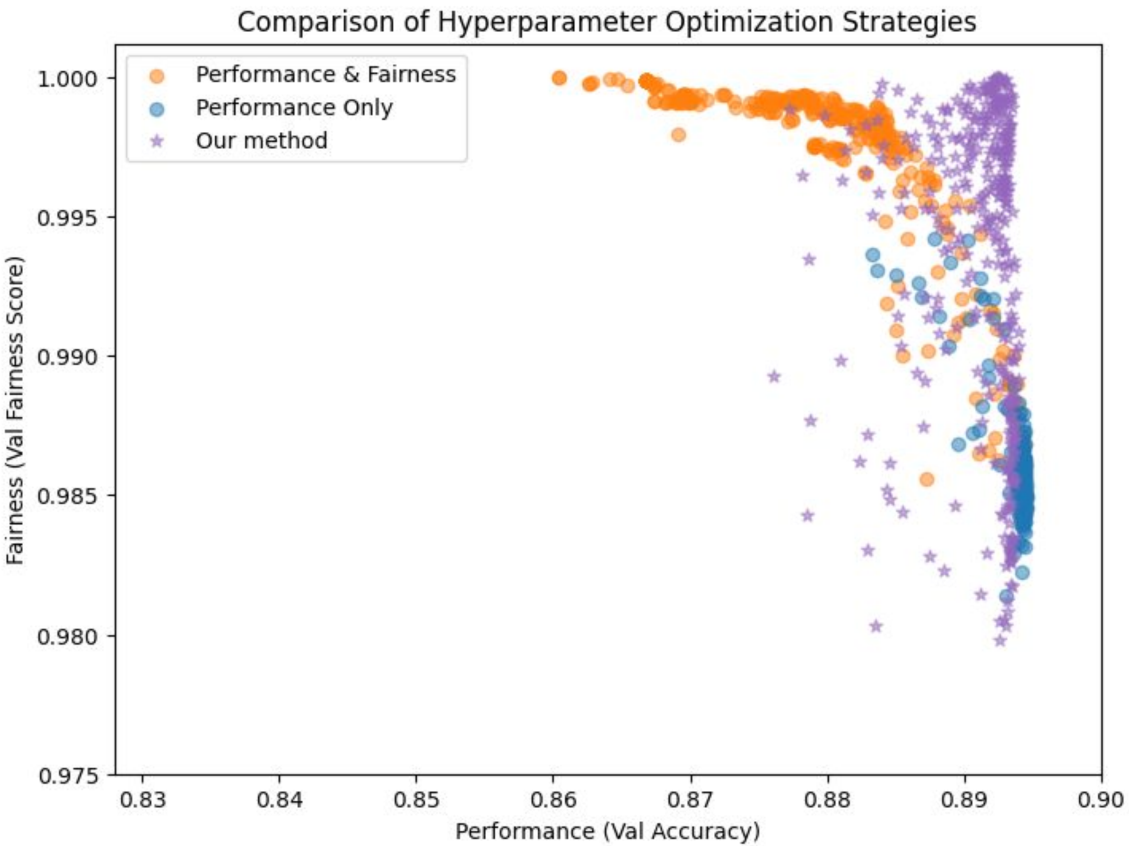
Hyperparameter Optimizations



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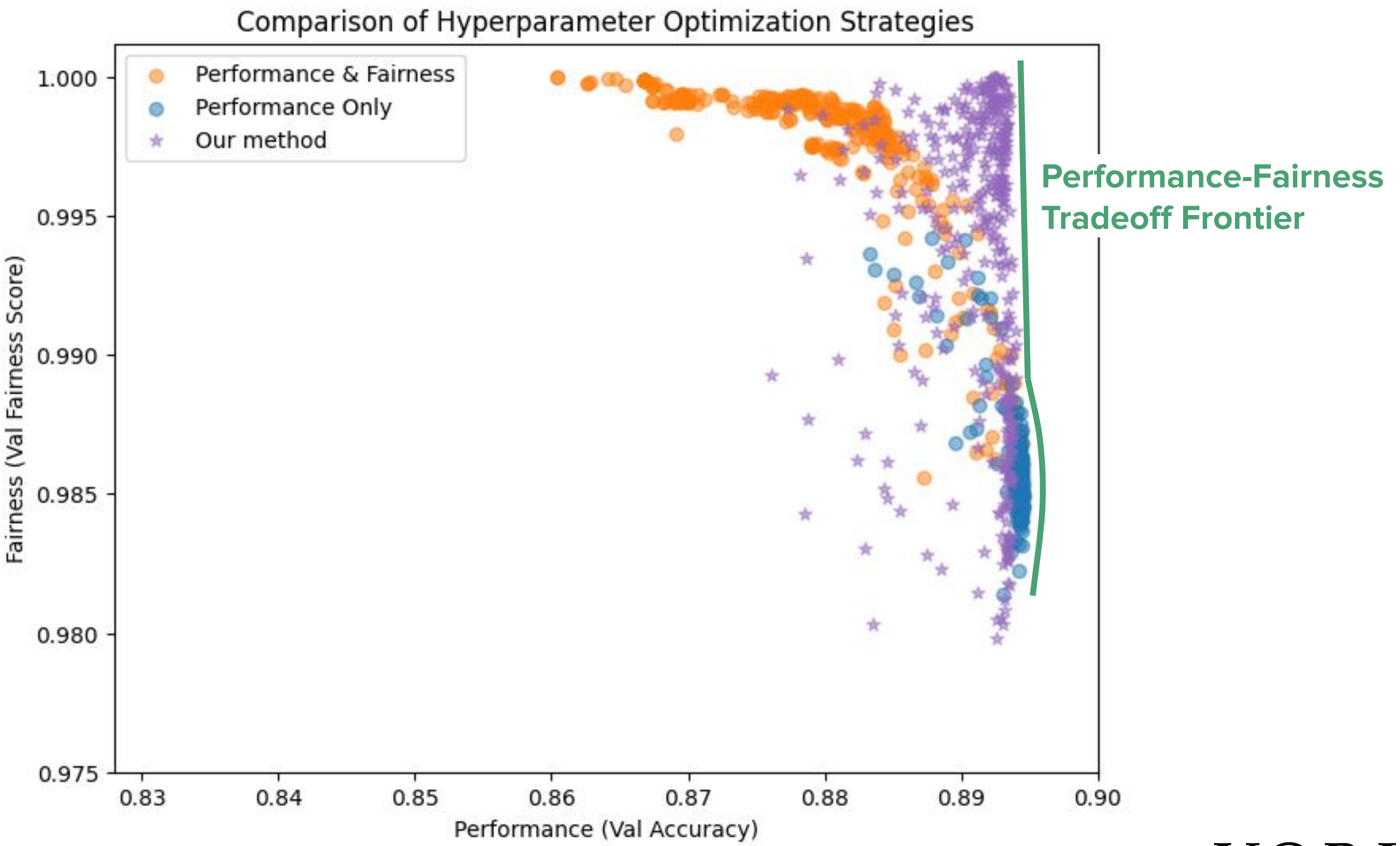

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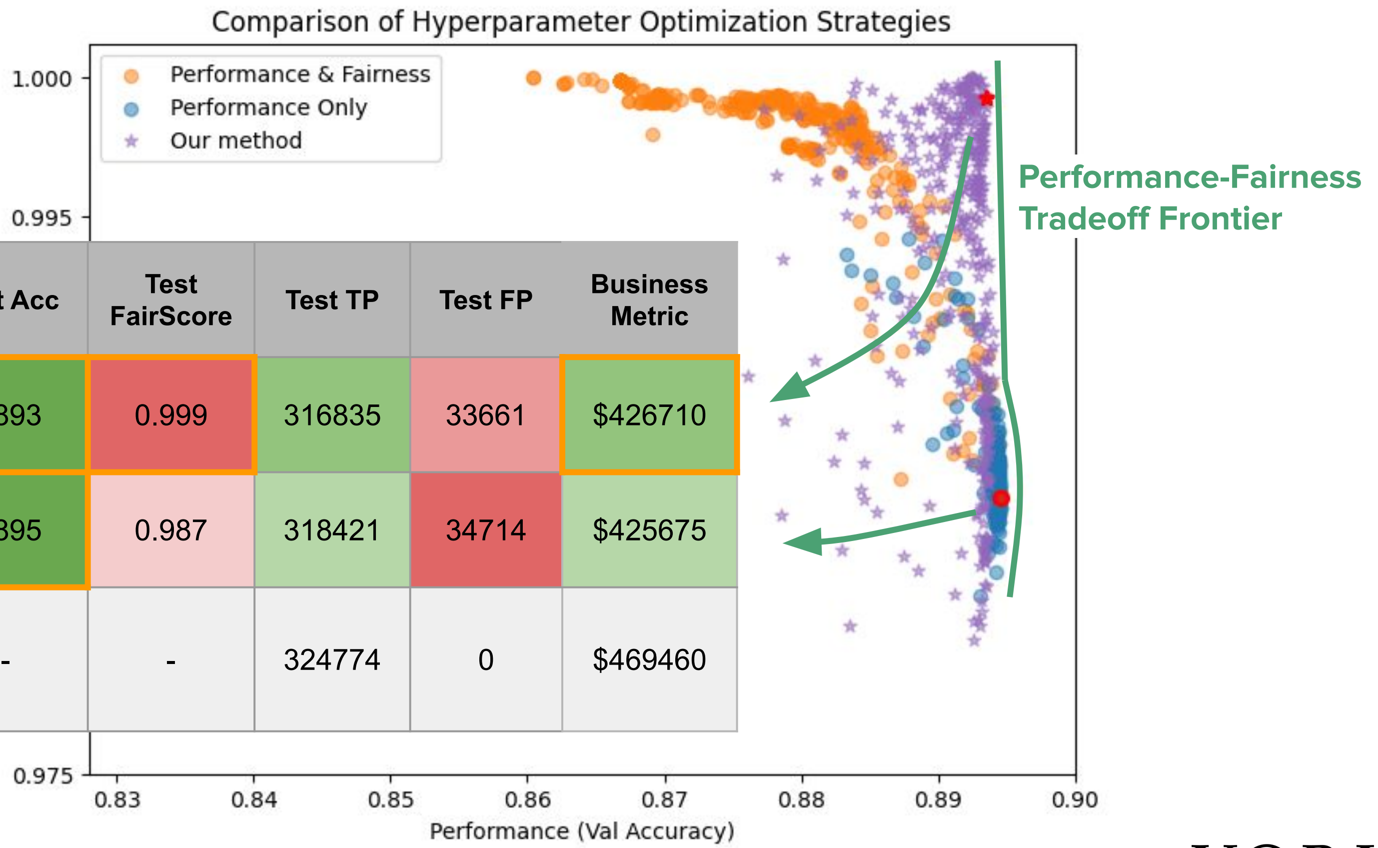


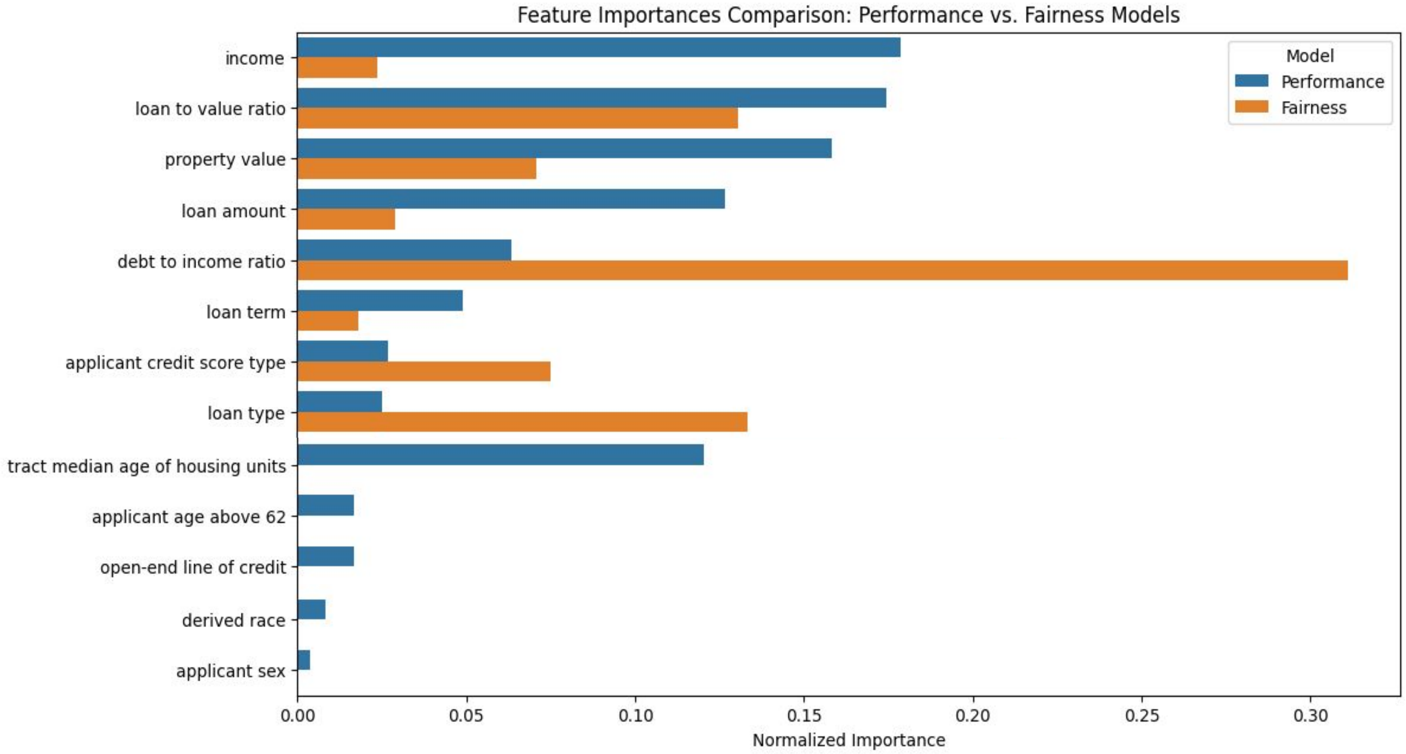
Models	Test Acc	Test FairScore	Test TP	Test FP	Business Metric
Our method	0.893	0.999	316835	33661	$426710
Performance	0.895	0.987	318421	34714	$425675
Ground Truth (Perfect Prediction)	-	-	324774	0	$469460

Model Analysis

1. **Feature Importance**
   - Ranks features by their overall impact on the tree model.

2. **SHAP (SHapley Additive exPlanations)**
   - Determines each feature's contribution to an individual prediction.

Feature Importance - Performance vs Fairness Models



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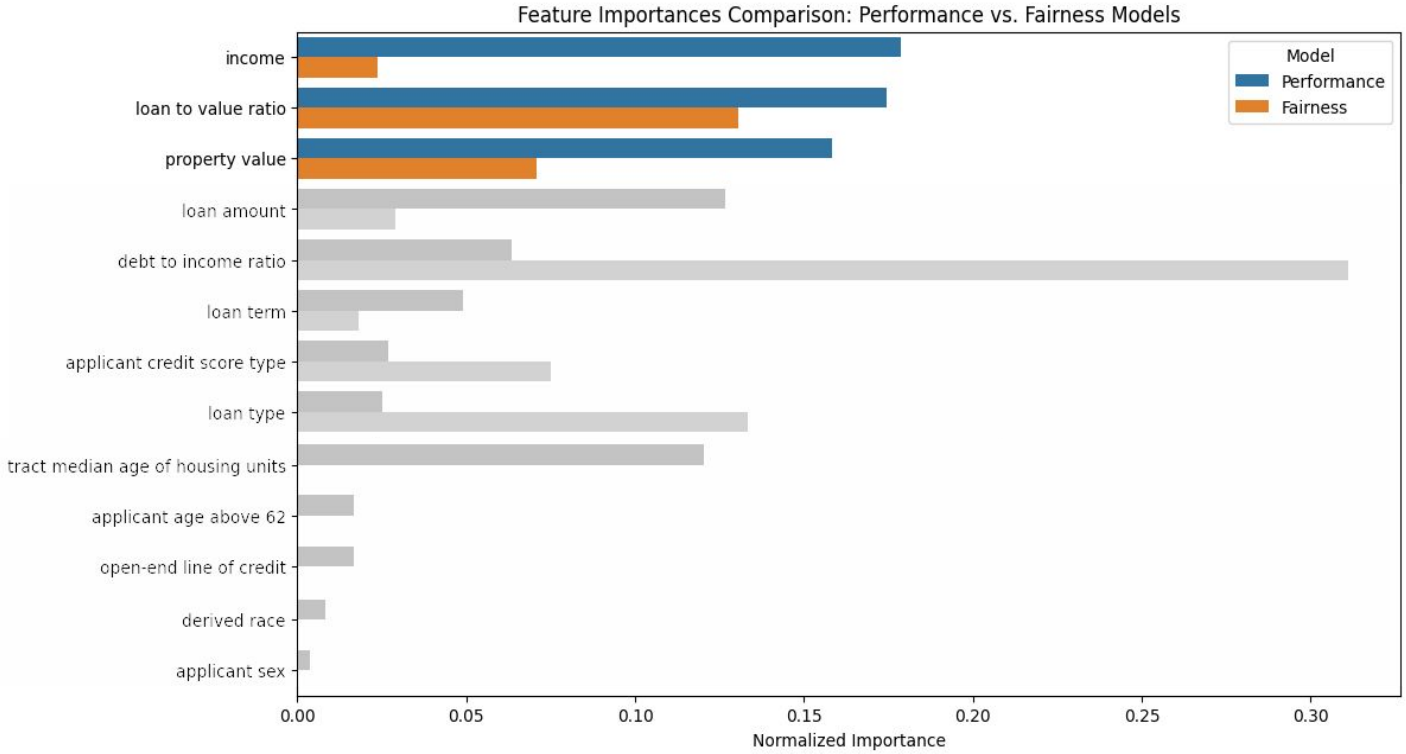

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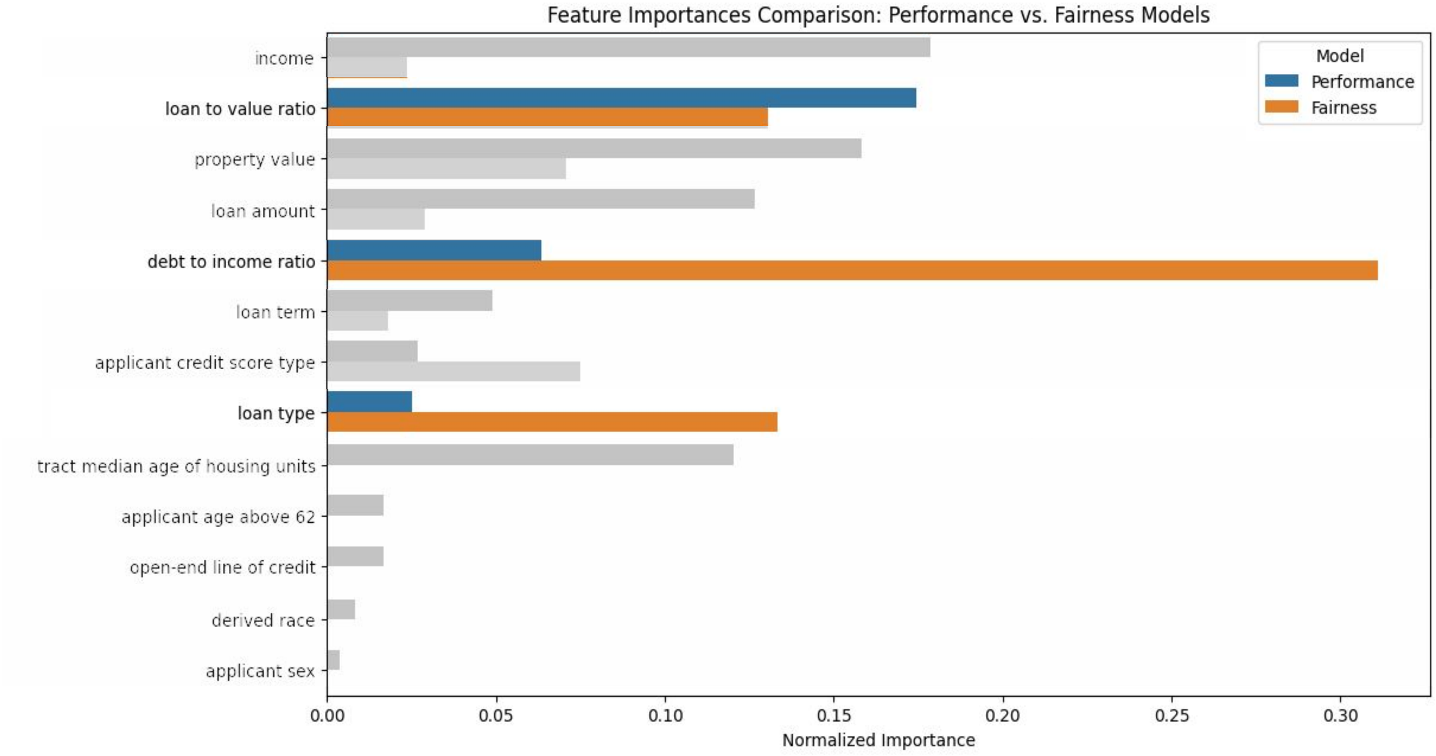
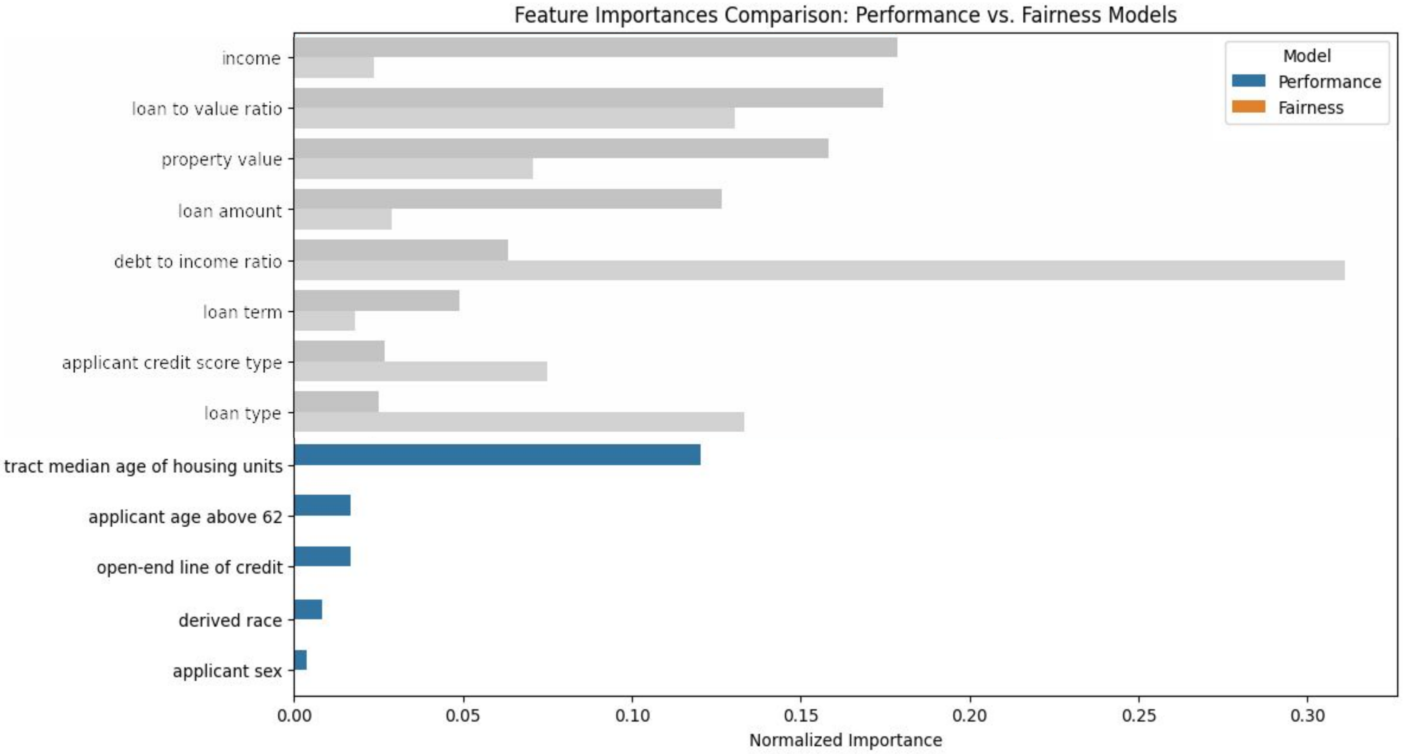
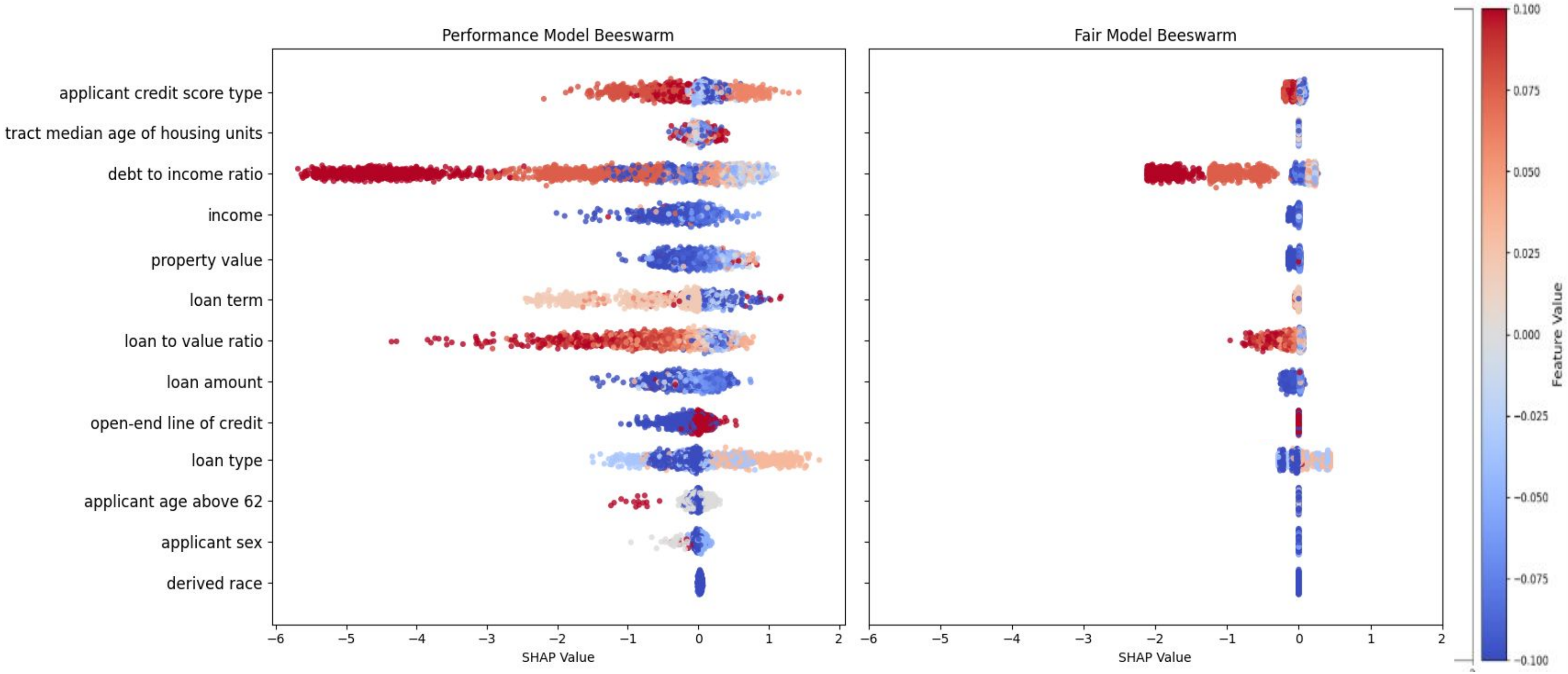


Feature Importance - Performance vs Fairness Models



SHAP Analysis - Performance vs Fairness Models



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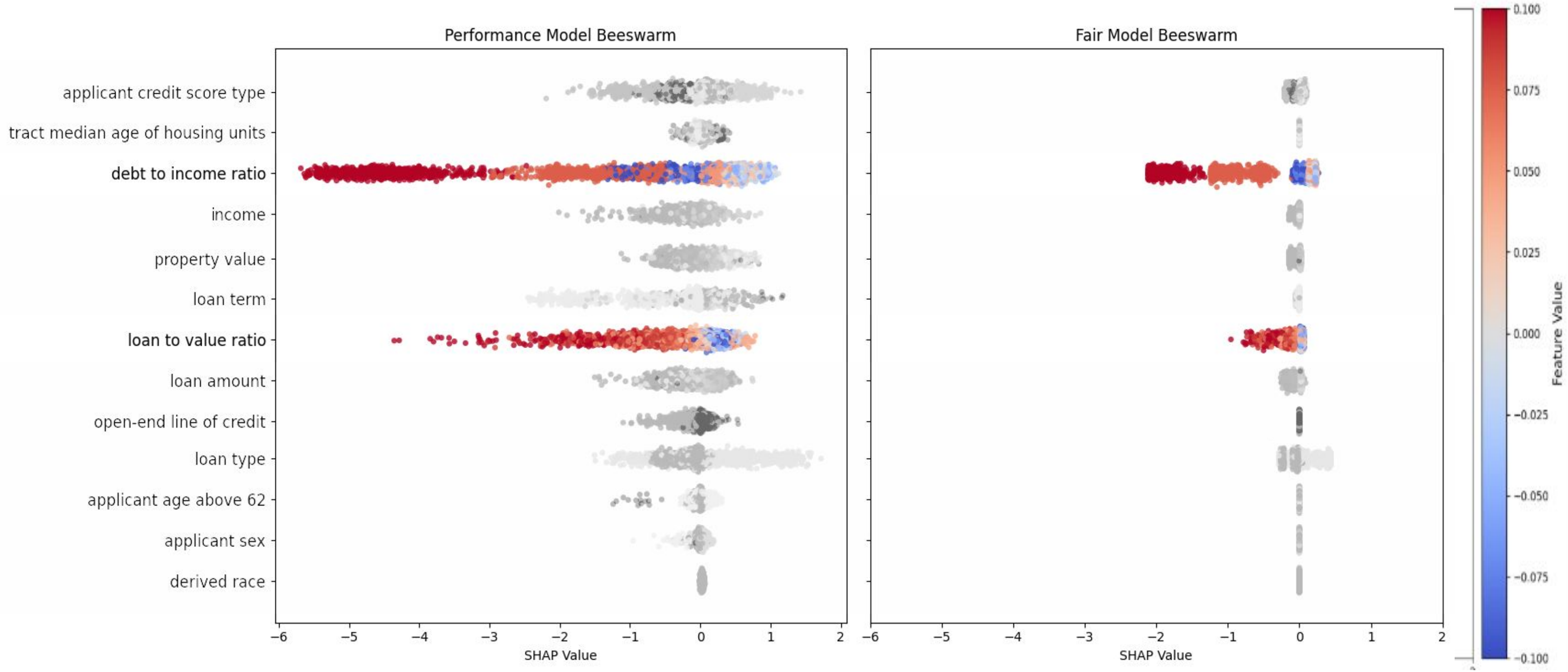

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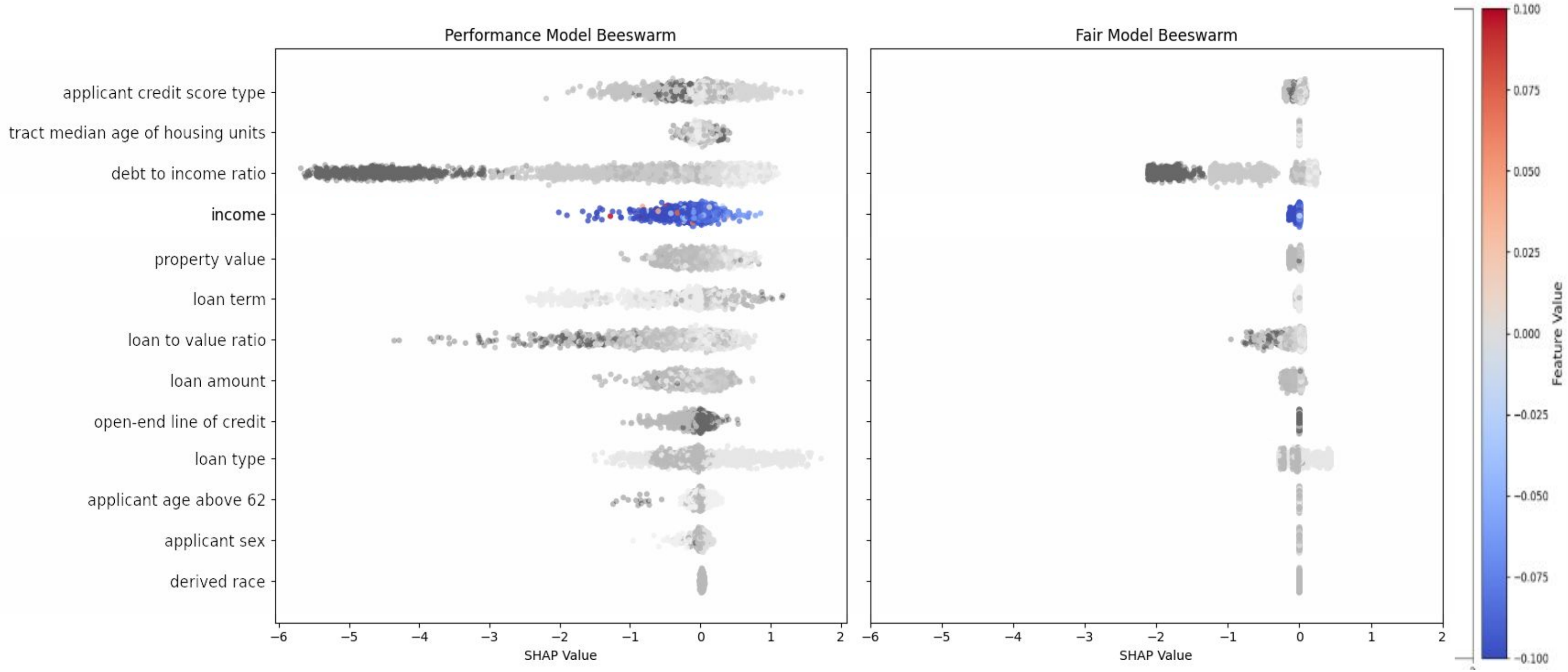

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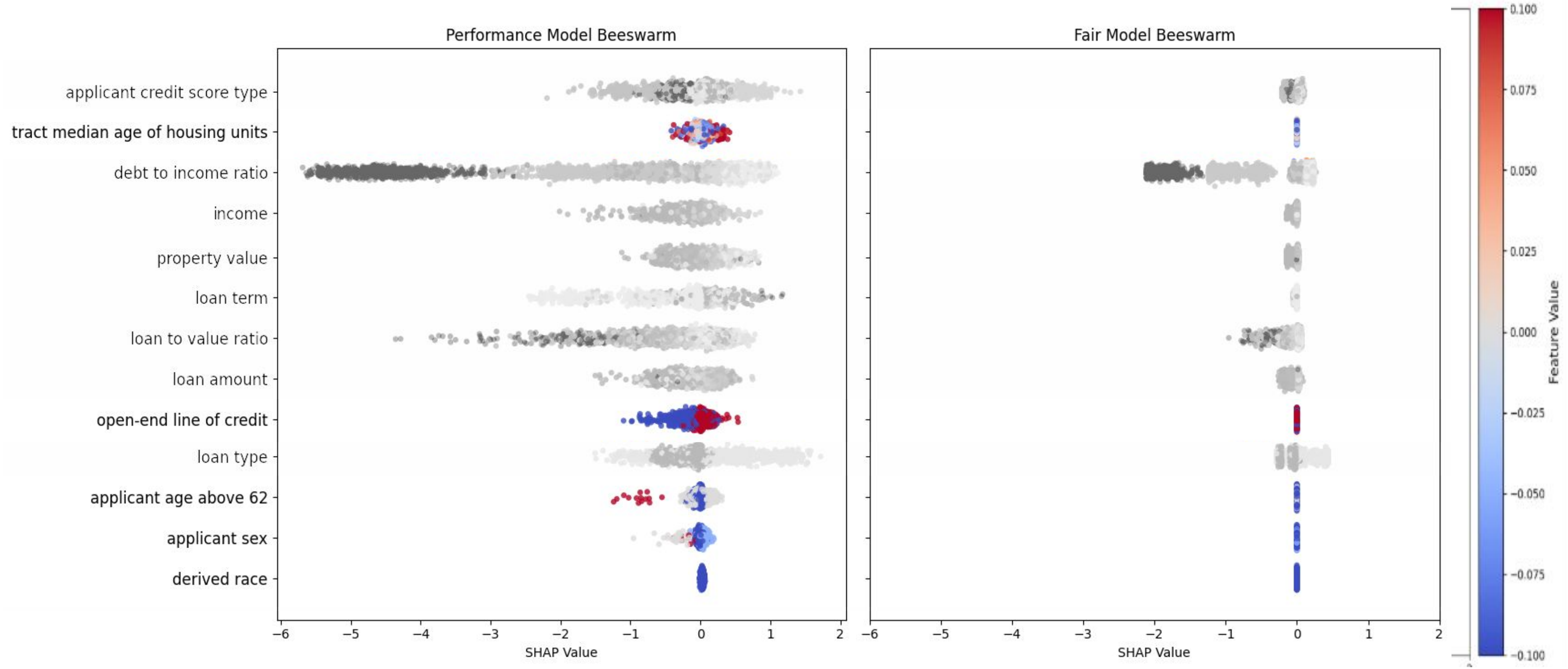
SHAP Analysis - Performance vs Fairness Models



Conclusions

- Demonstrate ML models achieving the **performance-fairness tradeoff** on California’s home mortgage approval

- Propose a new ML method with **generic resampling** on gradient boosting tree
    - **minimizes bias** while **maintaining predictive accuracy**

References

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4. Fairness and Bias in Artificial Intelligence: A brief survey of Sources, Impacts, and Mitigation Strategies https://arxiv.org/pdf/2304.07683#:~:text=Bias%20can%20arise%20due%20to,against%20any%20group%20or%20individual
5. A.I. Bias Caused 80% Of Black Mortgage Applicants To Be Denied https://www.forbes.com/sites/korihale/2021/09/02/ai-bias-caused-80-of-black-mortgage-applicants-to-be-denied/

Thank-you!