Fairness in Mortgage Approvals: an Optimization Approach

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The Problem

- Systemic bias in mortgage lending → racial wealth disparities in the US
- Fair Housing Act of 1968
  - tradeoffs between bias and profit in mortgage approvals
- Can we mimic mortgage approval models and improve them to correct bias against Black applicants?
- What financial impact will a fair model have on a bank?

The Data + Baseline Models

Home Mortgage Disclosure Act Data, Flagstar, 2019

Dropping rows & columns +
Creating minority feature +
undersampling +
normalization

Clean training set: 32k+ obs., 126 features

"Unfair" baseline models:
Logistic regression, SVM
including minority feature

"Fair" baseline models:
Logistic regression, SVM
not including minority feature

Predict classes: mortgage denied = 1, mortgage approved = -1

Method 1: Linear Optimization

Indirectly attack group disparities:
Increase scrutiny on majority borrowers

Minimize $\sum_{i=1}^{n} t_i$

Subject to:

$0 \leq t_i \; \forall i \in \{1, ..., n\}$

$1 - y_i * (\beta_0 + \beta_1 x_1 + ... + \beta_p x_p) \leq t_i \; \forall i \in \{1, ..., n\}$

$$\boxed{n * 1.5 * \sum_{i=1}^{n} majority_i * t_i \leq MajorityCount * \sum_{i=1}^{n} t_i}$$

1.5 * Share of Loss from Majority borrowers
is less than share of Majority Borrowers

5 minutes of solving: solves to optimality

Method 2: Mixed-Integer Optimization

Directly attack group disparities: equalize false positive rate across groups

Minimize $\sum_{i=1}^{n} t_i$

Subject to:

$$1 - y_i * (\beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p) \leq t_i \ \forall i \in \{1, \ldots, n\}$$

$$f_i \geq \frac{-y_i + (1/M)*(\beta_0 + \beta_1 x_2 + \ldots + \beta_p x_p) - 1}{2} \quad \forall i \in \{1, \ldots, n\}$$

$$f_i \leq y_i + 2 + (1/M) * (\beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p) \ \forall i \in \{1, \ldots, n\}$$

$$f_i \leq M * (1 - y_i) \quad \forall i \in \{1, \ldots, n\}$$

$f_i = 1$ when i is FP

$$\frac{1}{|H|} \sum_{i \in K} f_i - \epsilon \leq \frac{1}{|I|} \sum_{i \in J} f_i \leq \frac{1}{|H|} \sum_{i \in K} f_i + \epsilon$$

Minority FPR within ϵ of non-minority FPR

$$t_i \geq 0 \ \forall i \in \{1, \ldots, n\}$$

$$f_i \in \{0, 1\} \ \forall i \in \{1, \ldots, n\}$$

24 hrs of solving: 1% optimality gap

Out-of-sample Results

FP: qualified but rejected

FN: unqualified but approved

Model	AUC	Overall Neg. PV[1] (%)	FPR Gap (%) (min. - maj.)	FNR Gap (%) (min. - maj.)	Minority denial rate (%)
SVM Approval (MIP)	0.710	85.8	21.6	-11.9	43.8
Constrained SVM (LP)	0.705	85.4	8.0	0.6	31.1
Two Stage SVM (LP)	0.705	85.4	7.7	0.9	30.8
SVM FPR (MIP)	0.697	85.8	3.9	8.0	26.5
Fair baseline	0.710	85.7	10.6	-2.8	34.0

Outperforms baseline

- Model performance is not that much worse with fairness
- Different types of constraints give different results
- Linear methods give results comparable to MIP formulations

[1]True negatives/(True negatives + false negatives)

Impact and Conclusions

Model Impact - 2-Stage SVM

Bank profit = Good loan \$ - Bad loan \$

Profit from minorities goes up by 46% 💲
(15% better than fair baseline)

Overall profit goes down by 0.1%
(0.1% better than fair baseline)

With full data, results could be even better

Fairness does not severely affect performance/profit

Future Work: warm starts, robustification, sparsity; using a prescriptive lens; different types of discrimination; dealing with bias in the data itself

Thank you!

References

https://www.cbsnews.com/news/redlining-what-is-history-mike-bloomberg-comments/

https://shiftprocessing.com/credit-score/

https://www.consumerfinance.gov/about-us/newsroom/ffiec-announces-availability-2019-data-mortgage-lending/

https://github.com/cfpb/hmda-platform/blob/master/docs/v2/spec/markdown/modified_lar/2019_Modified_LAR_Data_Dictionary.md

https://orwh.od.nih.gov/toolkit/other-relevant-federal-policies/OMB-standards

Appendix

Two Stage SVM

Minimize $\sum_{i=1}^{n} majority_i * t_i$

Subject to:

$0 \leq t_i \; \forall \, i \in \{1, \ldots, n\}$

$1 - y_i * (\beta_0 + \beta_1 x_1 + \ldots + \beta_p x_p) \leq t_i \; \forall \, i \in \{1, \ldots, n\}$

$\sum_{i=1}^{n} t_i \leq 1.5 * PreviousLoss$

SVM - Approval Rate Constraint

$$\text{Minimize } \sum_{i=1}^{n} t_i$$

Subject to:

$$1 - y_i * (\beta_0 + \beta_1 x_1 + \dots + \beta_p x_p) \leq t_i \; \forall\, i \in \{1, \dots, n\}$$

$$t_i \geq 0 \; \forall\, i \in \{1, \dots, n\}$$

$$(\beta_0 + \beta_1 x_1 + \dots + \beta_p x_p) \leq M * (1 - z_i) \quad \forall\, i \in \{1, \dots, n\}$$

$$(\beta_0 + \beta_1 x_1 + \dots + \beta_p x_p) \geq -M * z_i \; \forall\, i \in \{1, \dots, n\}$$

$$\frac{1}{|K|} \sum_{i \in K} z_i - \epsilon \leq \frac{1}{|J|} \sum_{i \in J} z_i \leq \frac{1}{|K|} \sum_{i \in K} z_i + \epsilon$$

$$z_i \in \{0, 1\} \; \forall\, i \in \{1, \dots, n\}$$

Results: Baseline Models

Method	AUC	Overall NPV (%)	FPR (%)			FNR (%)			Minority Denial Rate (%)
			Min.	Maj.	Diff.	Min.	Maj.	Diff.	
SVM w/ Minority Feature, IS	0.710	58.2	38.0	8.9	29.1	41.2	66.7	-25.5	51.3
SVM w/ Minority Feature, OOS	0.713	86.0	84.9	13.9	71.0	7.3	59.0	-51.7	87.4
Logistic w/ Minority Feature, IS	0.715	58.3	35.9	8.9	27.0	43.0	66.4	-23.4	49.4
Logistic w/ Minority Feature, OOS	0.717	86.0	54.2	15.4	38.8	29.1	56.6	-27.5	59.6
SVM No Minority Feature - IS	0.709	58.1	21.7	10.0	11.7	60.7	65.0	-4.2	32.9
SVM No Minority Feature - OOS	0.710	85.7	27.7	17.1	10.6	52.7	55.5	-2.8	34.0
Logistic No Minority Feature - IS	0.714	58.2	22.1	9.7	12.4	57.1	65.1	-8.0	35.4
Logistic No Minority Feature - OOS	0.714	85.9	33.1	16.6	16.5	50.3	54.9	-4.6	38.4

Features (126)

Loan amount (numeric)	State (50 categories)	Manufactured Home Secured Property Type (2 categories)
Income (numeric)	Lien status (2 categories)	Manufactured Home Land Property Interest (2 categories)
Combined loan-to-value ratio (numeric)	Borrower credit score type (6 categories)	Total units (4 categories)
Property value (numeric)	Coborrower credit score type (7 categories)	Submission type (2 categories)
Loan type (4 categories)	Debt-to-income ratio (19 buckets)	Open-End Line of Credit (2 categories)
Loan purpose (6 categories)	Loan term (3 buckets)	Business purpose (2 categories)
Construction method (2 categories)	Interest-only payments (2 categories)	Minority (binary, generated from race/ethnicity features)
Occupancy (3 categories)	Other non-amortizing features (2 categories)	Denied (binary, the response variable we are trying to predict)

Training set: 32,028 rows, Testing set: 20,072 rows

Visualizations