Mining the Data: Algorithmic Bias in Housing Related Transactions

Thank you for participating. The event will begin shortly…

U.S. DEPARTMENT OF HOUSING AND URBAN DEVELOPMENT

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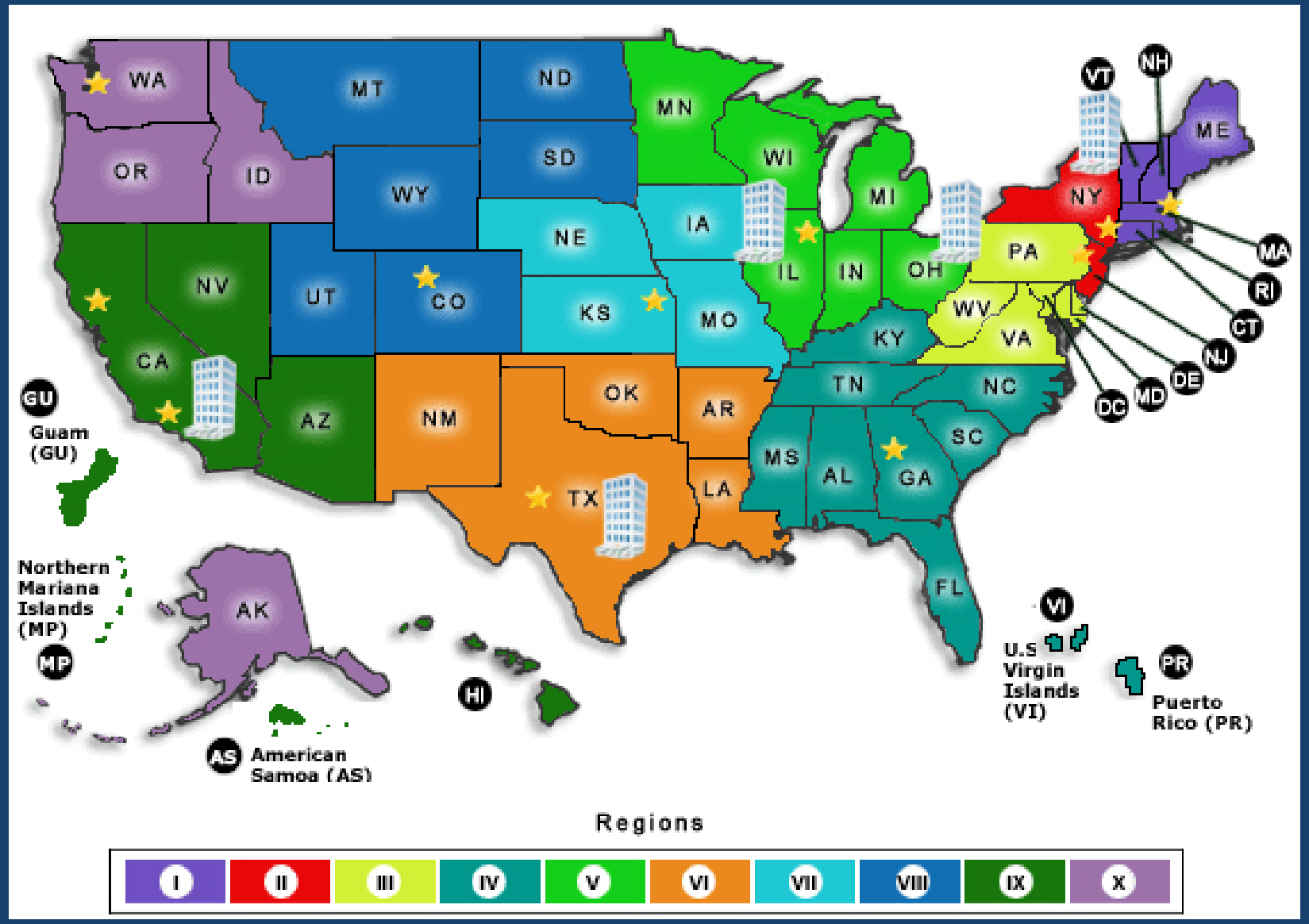
HUD Regional Map



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Mining the Data: Algorithmic Bias in Housing Related Transactions

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Technical Tips

- To access Closed Captioning, click the Live Transcript button, and then click "Show Subtitles" to view closed captioning.
- You can choose for your audio to come through your computer speakers or your phone.
- This event is being recorded. Materials will be posted on www.HUDExchange.info/NFHTA
- For technical difficulties:
  - Sign out, then sign back in
  - Request help in the Q&A box
  - Email NFHTA@cloudburstgroup.com for further assistance

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Learning Objectives

- ❑ Comprehend the basics of artificial intelligence and machine learning (AI/ML)
- ❑ Increase understanding of how data is used in the rental, sales, and lending housing sectors
- ❑ Know more about third party technology companies and services used by housing industry (rental, sales, lending)
- ❑ Ascertain solutions for eliminating bias in data and technology
- ❑ Describe the applicable sections of the Fair Housing Act and Regulations to other applicable laws
- ❑ Recognize features of key cases challenging tech bias in housing or that relate to housing transactions

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Reminders

- ❑ This event is being recorded.
- ❑ Materials, including the slide deck and event recording, will be posted on www.HUDExchange.info/NFHTA.
- ❑ Submit questions in the Q&A box at any time during today's event.

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FAIRNESS-AS-A-SERVICE

A Conceptual Introduction to Machine Learning

January 19, 2022

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What is Machine Learning?

Traditional Programming

Ingredients

+

Recipe

MAKES

=

Outcome

But what if you don’t have a recipe?

Traditional / Programming

Ingredients

+

Recipe

MAKES

=

Final Product

Machine Learning Algorithm

Ingredients

+

Outcome

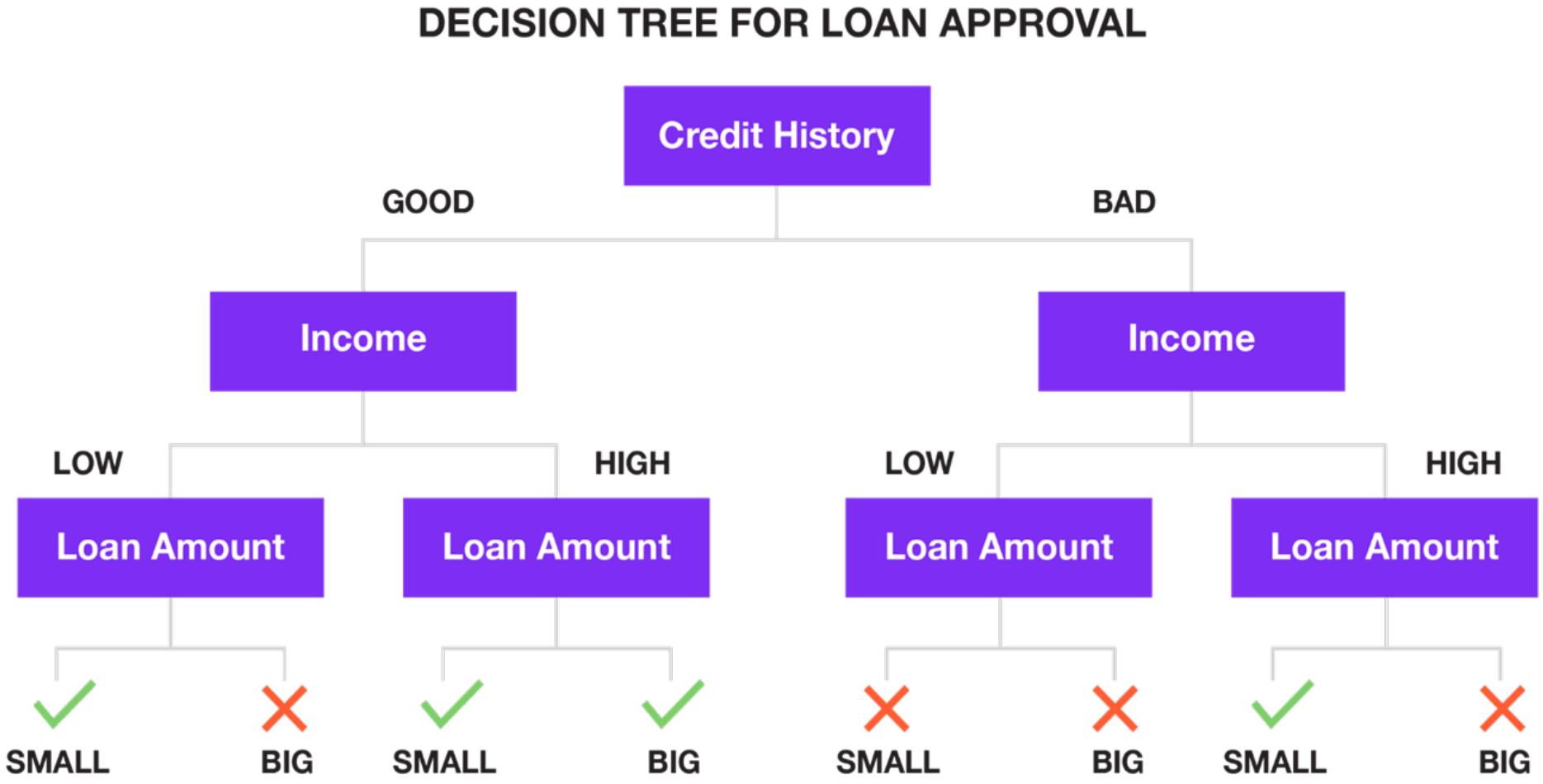
FIGURES OUT

Recipe

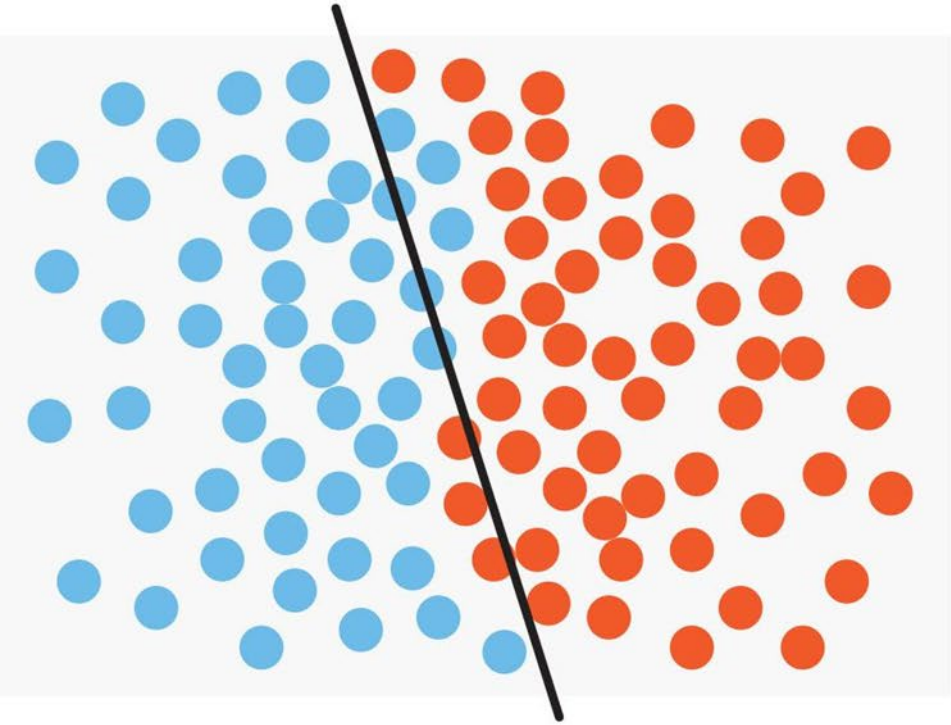
Lending decisions used to be made by humans who tried to assess an applicant's creditworthiness

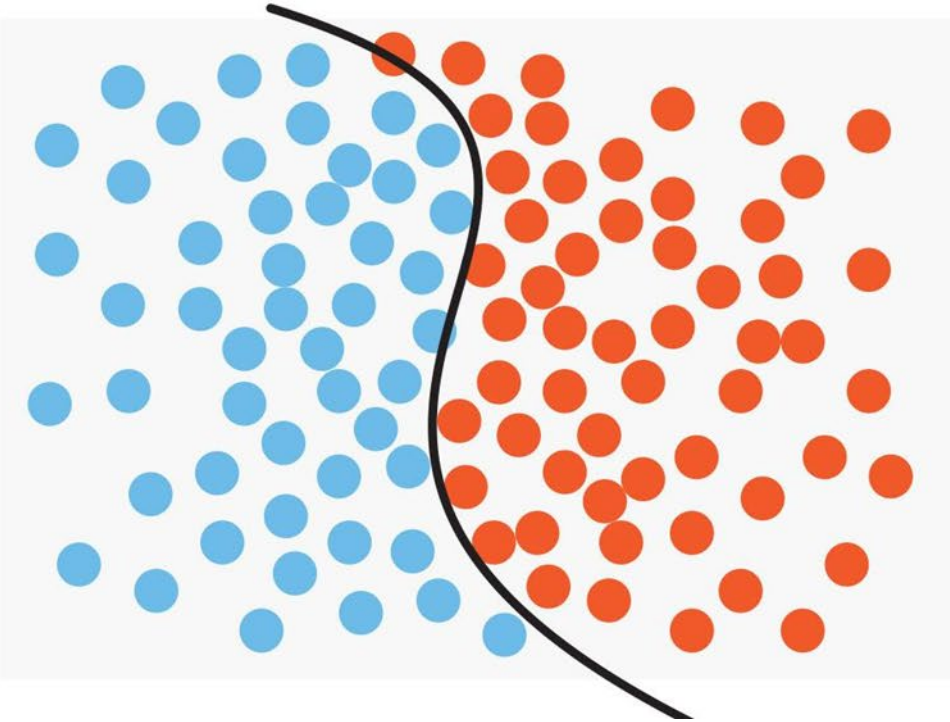
LOAN OFFICER

In the 1980s started using math instead of humans to make lending decisions - it was seemingly more “neutral” and “objective”



Old math assumes relationships between ingredients (variables) are straight-forward, but the world is actually complex and nonlinear





Imagine we tried to build a model that predicts gender

CAN WE DETERMINE GENDER USING HEIGHT?

+ Men, on average, are taller than women.

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Height is somewhat but not perfectly predictive of gender

CAN WE DETERMINE GENDER USING HEIGHT?

- Men, on average, are taller than women.
- But there are tall women and short men, and many people that are the same height.
- ***Using height alone isn't very accurate.***

Including weight adds predictive power, but the model still isn't perfect

CAN WE DETERMINE GENDER USING HEIGHT + WEIGHT?

- Because men are, on average, heavier than women of the same height, accuracy would improve.

Using height and weight to predict gender causes kids to be classified as women

CAN WE DETERMINE GENDER USING HEIGHT + WEIGHT?

- Because men are, on average, heavier than women of the same height, accuracy would improve.
- ***But children would mostly be misclassified as women.***

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Is birthdate predictive of gender?

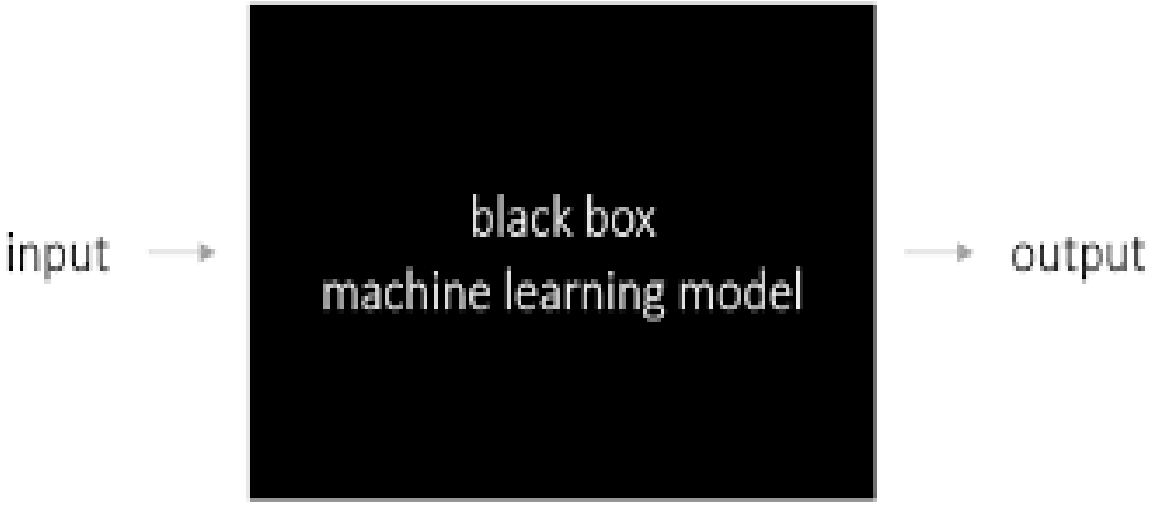
CAN WE DETERMINE GENDER USING HEIGHT + WEIGHT + BIRTHDATE?

+ Knowing people's age eliminates the misclassification of children, and improves the model's accuracy of determining gender across all age groups.

+ ***But the idea that birthdate can help determine gender is not obvious***

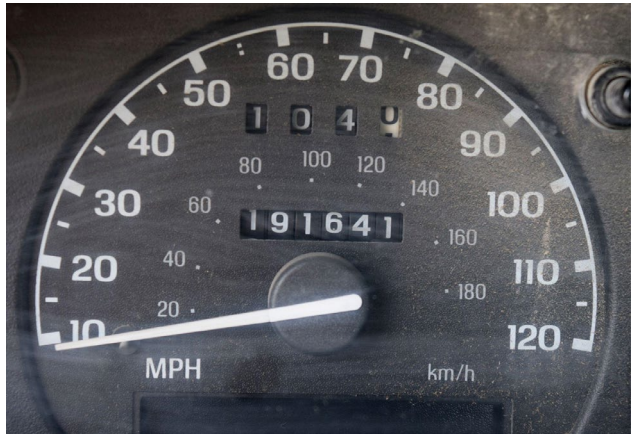
When there are a lot variables, the recipe connecting them to an outcome can be so complex no one can understand it:

When there are a lot variables, the recipe connecting them to an outcome can be so complex no one can understand it:



The problem with the black box is the risk it will be biased in ways we don’t understand.

If you're buying a high mileage car in Nevada there’s a big probability you’re a person of color

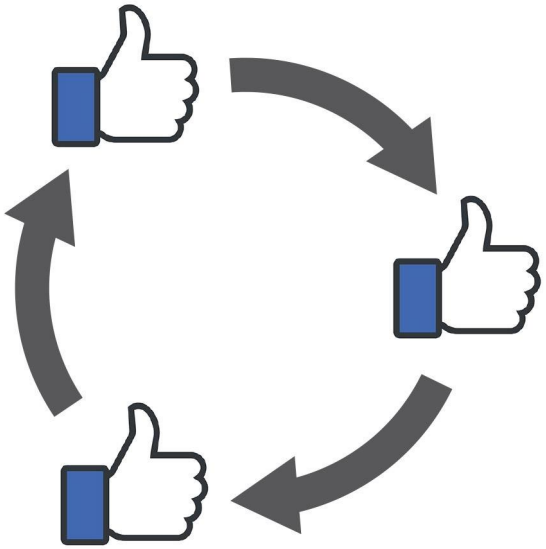


ML algorithms relentlessly refine their “recipe” to achieve the best outcome (aka they adjust to better accomplish their target or objective)

Every algorithm must be given a target

Social media algorithms seek to maximize their target: engagement

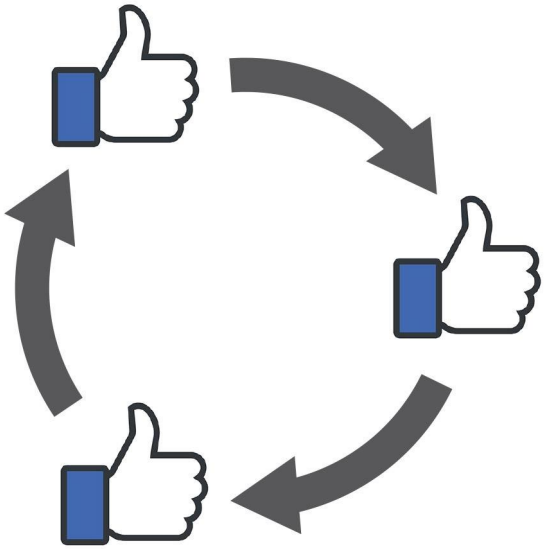
Every algorithm must be given a target



Social media target: Maximize engagement

The algorithm single mindedly focuses on engagement regardless of whether it’s good for your health or good for society

Every algorithm must be given a target



Social media target: Maximize engagement

Without regard for societal harm

Giving an algorithm one target is problematic: imagine a self-driving car whose only target was to get you from point (a) to point (b)

Target: Get from point (a) to point (b)

Self-driving cars have a second target: Safety

Target: Get from point (a) to point (b)

Second Target: Safety (obey traffic laws; avoid accidents with cars, pedestrians, cyclists, etc)

We can do this in financial services: Target a low risk of default . . .

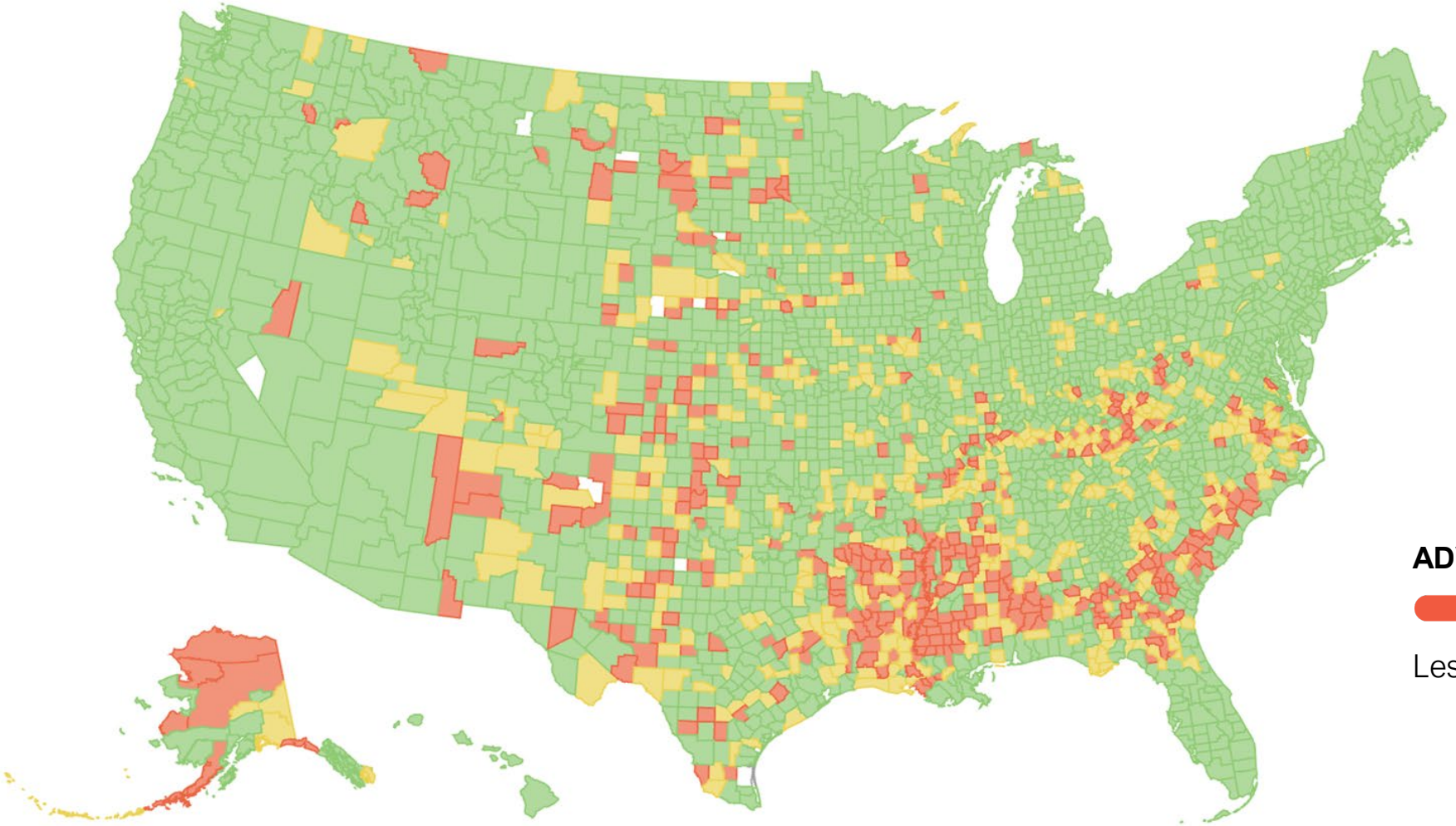
Target: Low risk of default

We can do this in financial services: Target a low risk of default . . . while also targeting fairness

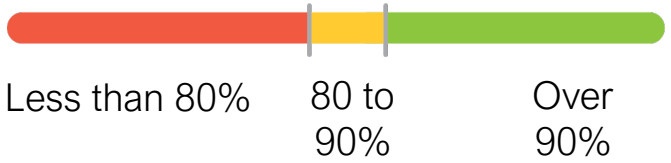
Target: Low risk of default

Second Target: Fairness

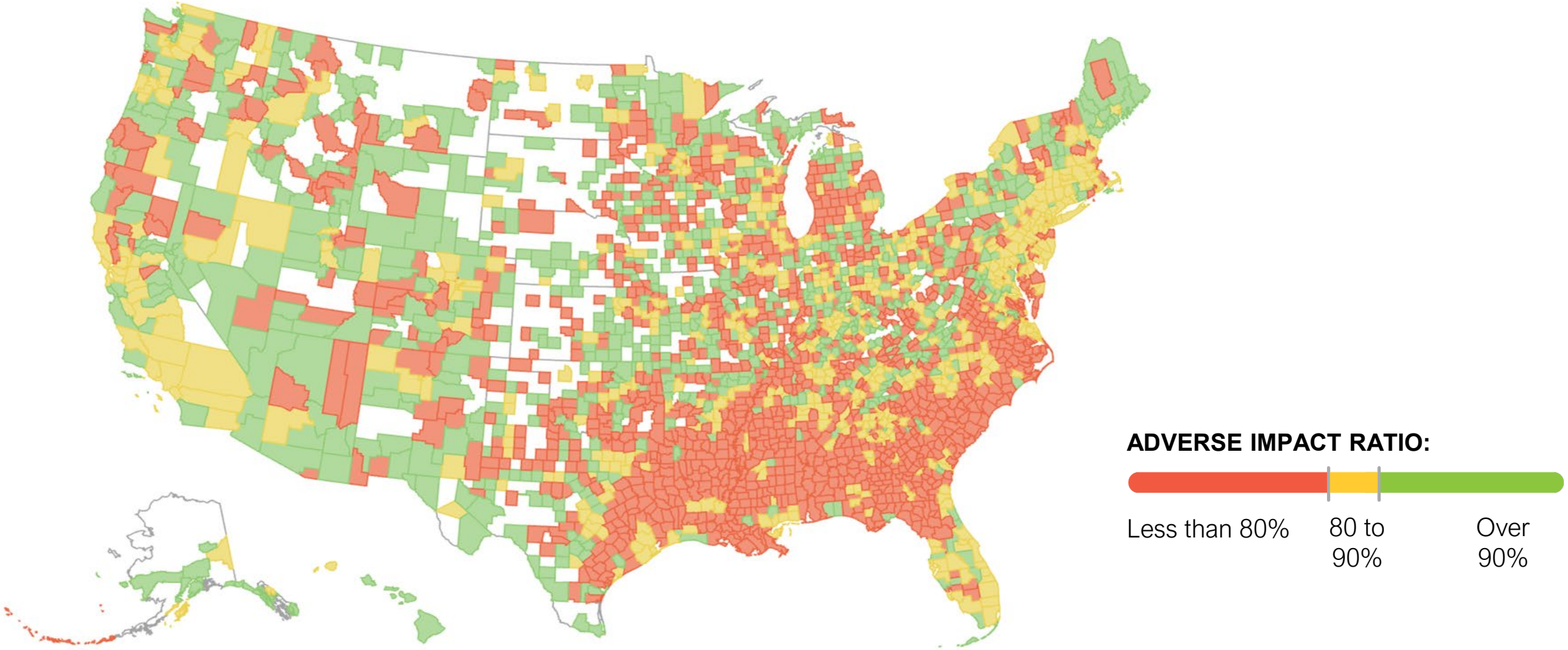
U.S. Mortgage Fairness in 2020: Female



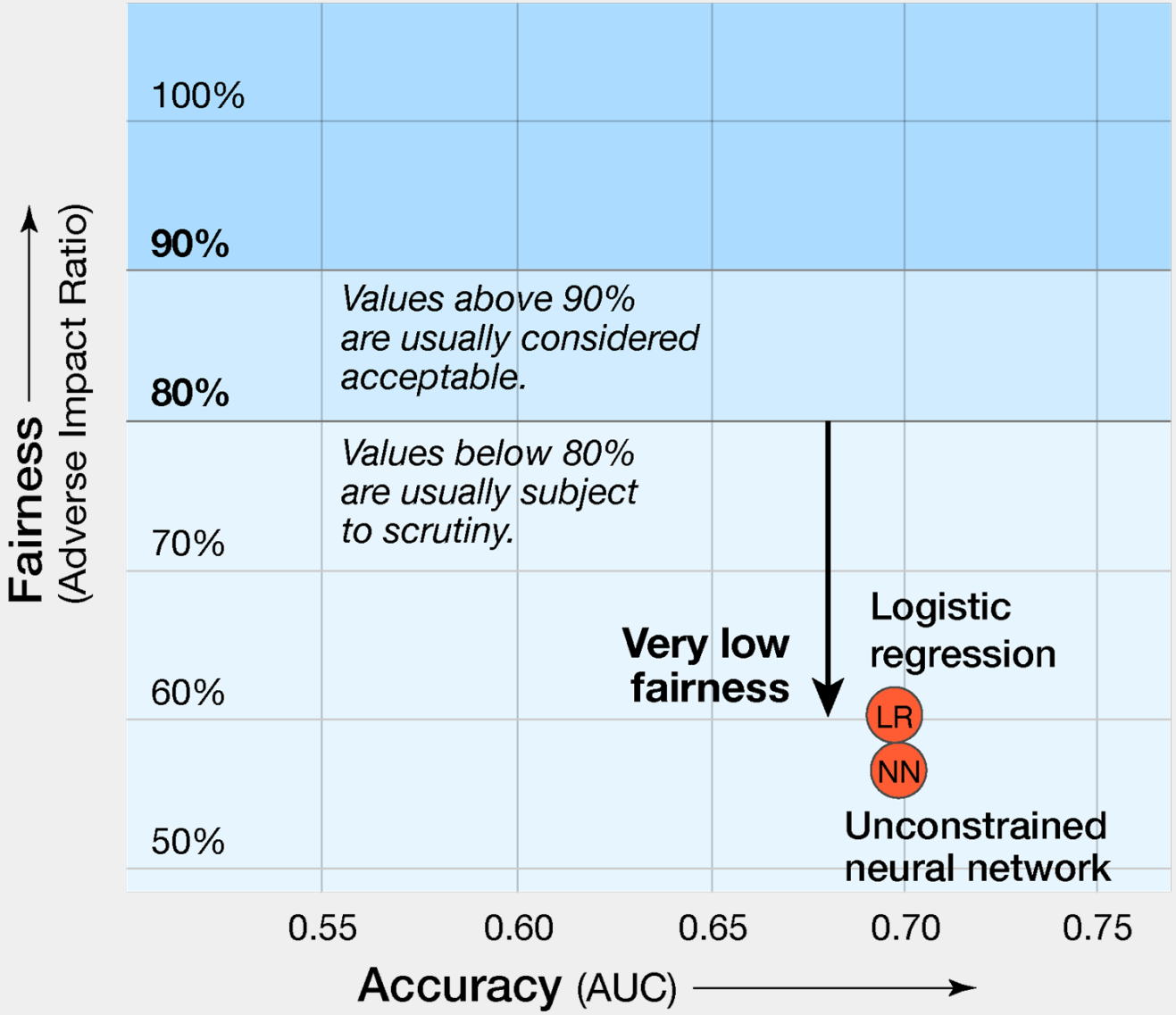
ADVERSE IMPACT RATIO:



U.S. Mortgage Fairness in 2020: Black



A fairness-optimized neural network can produce very accurate and considerably fairer mortgage outcomes than a logistic regression or unconstrained neural network



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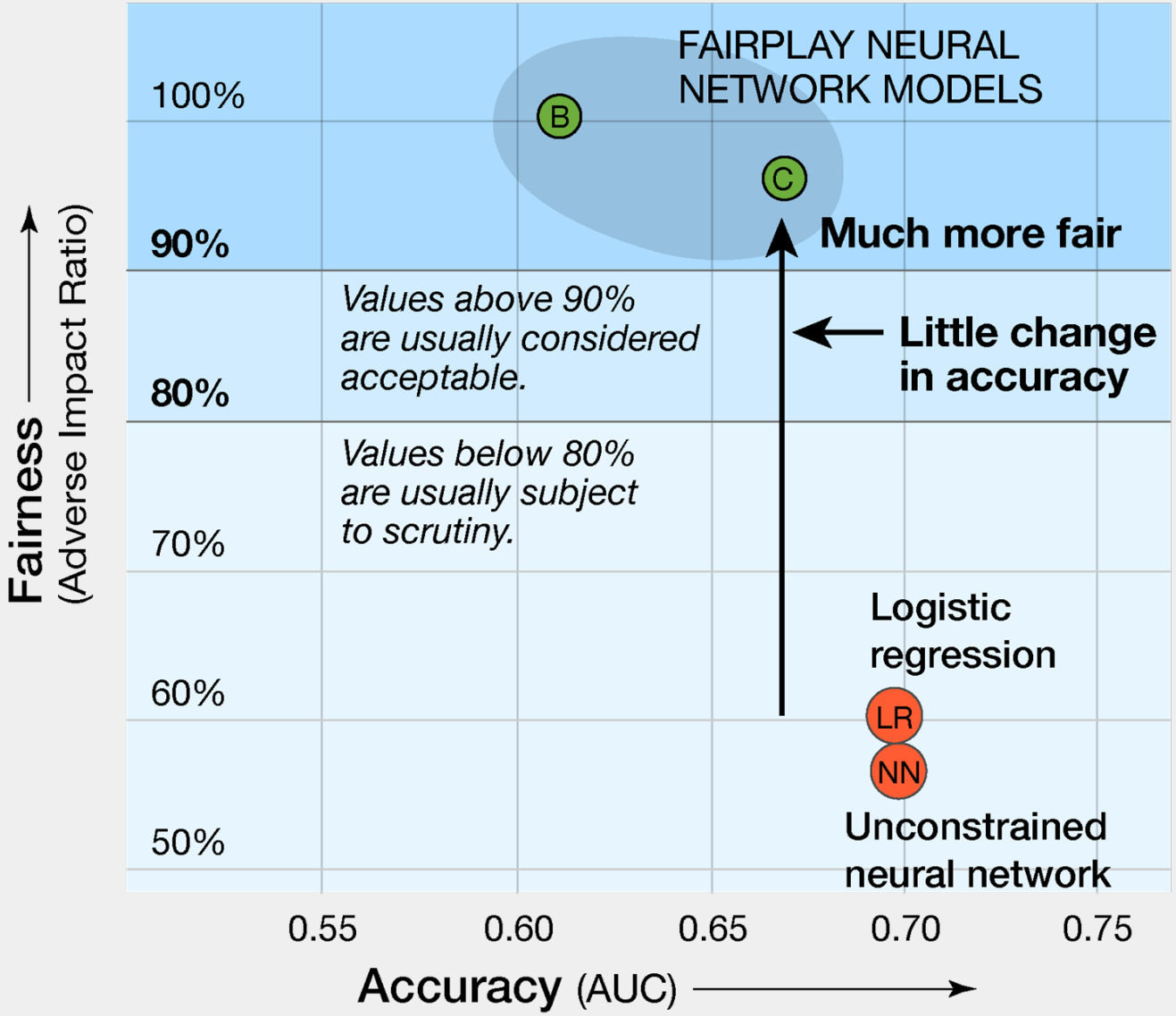
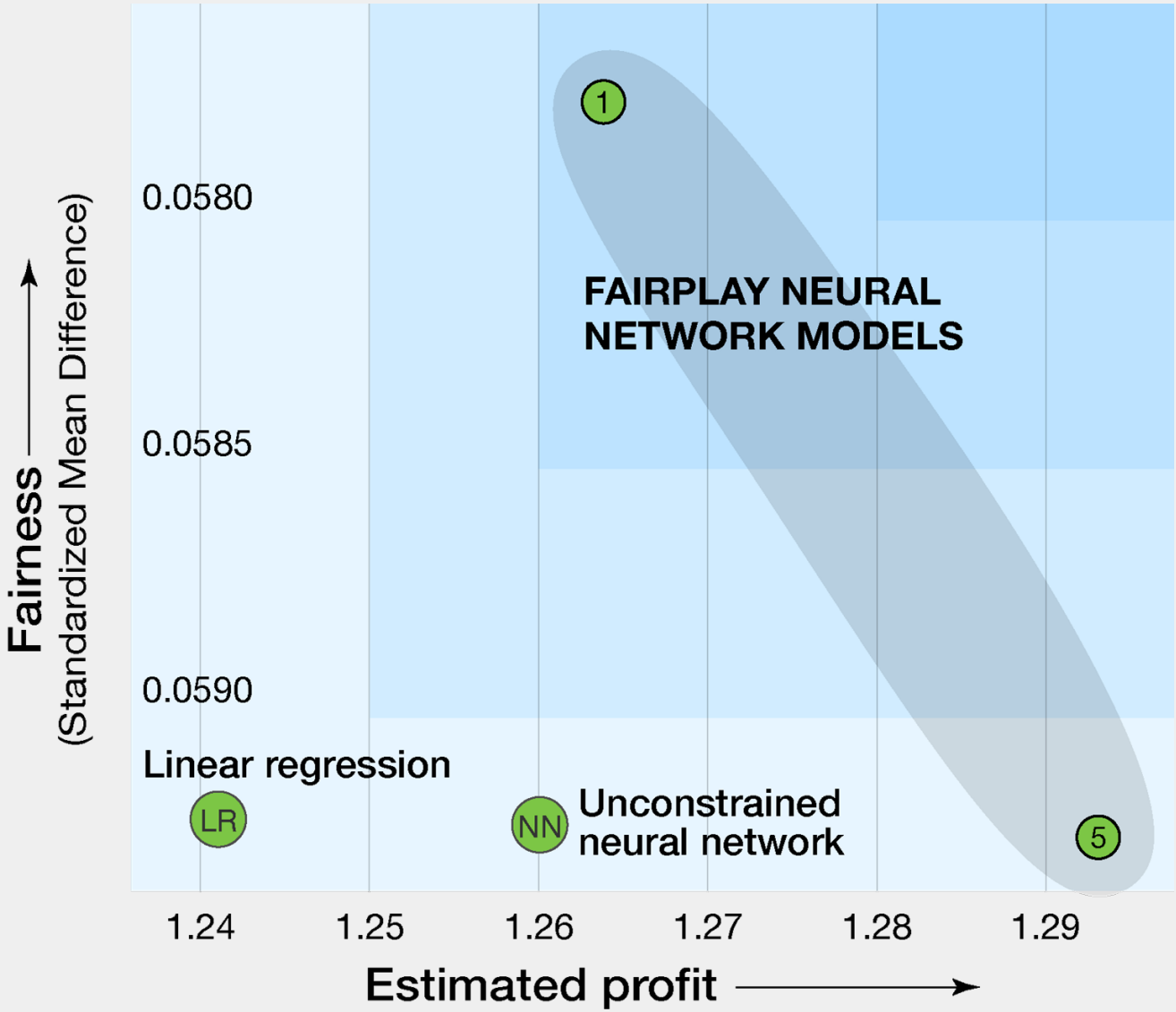


A fairness-optimized neural network can produce fairer mortgage pricing than a linear regression or unconstrained neural network

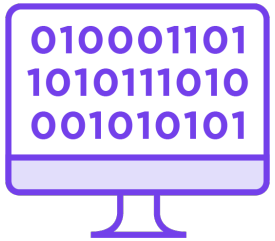
SMD values less than 0.2 are generally considered acceptable; all of the models shown here are well within that range.



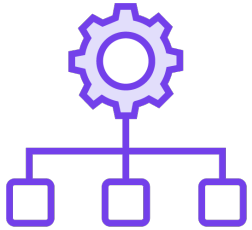
The fairness constrained neural network generates fairer results using the same variables

	Logistic Regression	Unconstrained Neural Network	Fair Neural Network
ADVERSE IMPACT RATIO	60% (90%)	56% (90%)	96% (90%)
RANK	REASON	REASON	REASON
1	Borrower's score Previous December	Borrower's score Previous December	Borrower's score Previous December
2	Borrower's score Previous September	Borrower's score Previous September	Borrower's score Previous June
3	Borrower's score Previous June	Borrower's score Previous June	Co-borrower's score Previous December
4	Borrower's score Previous March	Borrower's score Previous March	Co-borrower's score At origination
5	Is this the borrower's first mortgage?	Co-borrower's score Previous December	Loan-to-value

Catalysts driving AI's takeover of high stakes decisions



Data



Advanced Algorithms

Cloud Computing

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NFHA NATIONAL FAIR HOUSING ALLIANCE

Mining the Data

Algorithmic Bias in Housing Related Transactions

January 19, 2022

Michael Akinwumi, Chief Tech Equity Officer, NFHA

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Outline

- How data and AI/ML are used in rental, sales, and lending housing sectors
- Third party technology companies and services used by housing industry
- Solutions for eliminating bias in data and AI/ML

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Data & AI/ML in Housing: Why it Matters

- As of 2018, the U.S. Census Bureau show the median net worth for African American families is $9,000 and $12,000 for Latino families compared with $132,000 for a white family.

- In the United States, “wealth and financial stability are inextricably linked to housing opportunity and homeownership,” according to Lisa Rice, President & CEO, National Fair Housing Alliance.

- Attention to roles data, algorithms, and tech companies play in impeding people of color’s access to housing opportunities. And solutions for removing the data-driven and algorithm-powered impediments.

Source: Sam Ward/Reveal in https://tinyurl.com/2p8kmycw

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How data and AI/ML are used in rental, sales, and lending housing sectors

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Data & AI/ML in Rental

- Rent Listing: Base Rent vs. Concessions Rate
- Online Screening
- Maintenance Service Request

Source: Evanto Elements/AnnaStills

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Data & AI/ML in Sales

- Predicting Housing Prices
- Automated Valuation Models
- Real Estate Farming

Source: Evanto Elements/poungsaed_eco

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Data & AI/ML in Lending

- Advertising, Lead Generation and Outreach
- Pre-application Inquiries
- Loan Underwriting and Pricing
- Loan Administration

Source: Evanto **Elements**/LightFieldStudios

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Third party technology companies and services used by housing industry

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Third Party Technology Companies in Housing Transactions

Data Aggregation

- CoreLogic
- Zillow
- Optimal Blue
- ATTOM
- Credit Reporting Agencies
- Startups: HouseCanary, Reonomy, CoStar, Real Capital Analytics

Statistical or AI/ML Modeling

- FICO
- Vantage Score
- Upstart Network, Compass, and other similar startups

Algorithmic Fairness Servicing

- ZestAI, FairPlayAI, SolasAI
- Arthur, Weights & Biases
- Arize

Loan Servicing

- Capacity
- Elium
- Bloomfire
- Solvvy

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Solutions for eliminating bias in data and AI/ML

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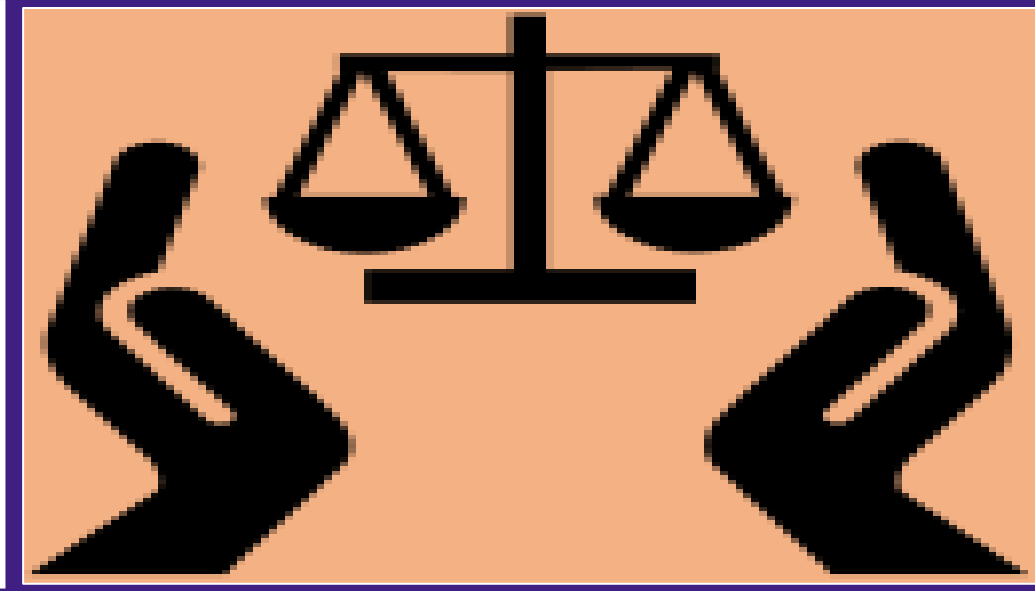
Tech Solutions for Eliminating Bias in Data & AI/ML

- Preprocessing techniques: taking poison out of the ingredients
- In-processing techniques: finding a recipe that does not produce poisonous food
- Post-processing techniques: dressing the food after it comes out of the kitchen
- Hybrid techniques: incorporating consumers' feedback and feedback of their advocates



Source: https://adioma.com/icons/equitable

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Algorithmic Bias: Legal Considerations

Sacha Markano-Stark
Relman Colfax

NFHTA Forum - January 19, 2022

Agenda

1. Statutes and Rules
2. Types of Discrimination
3. HUD DI Rulemaking
4. Case Features

Key Statutes

Key Statutes

- Fair Housing Act
- Equal Credit Opportunity Act
- Unfair, Deceptive, Abusive Acts & Practices
- State Public Accommodations Laws
- State AI-Specific Legislation
- Procedural Due Process

Key Statutes

FHA

- Applies to selling, renting, negotiating for housing
- Not limited to credit
- Covers disability, familial status

ECOA

- Applies to any aspect of a credit transaction
- Not limited to housing; *must be* related to credit
- Covers age, marital status, income from public assistance

State AI Legislation

- Some states are introducing AI/ML-specific anti-discrimination legislation
- California: AB 13 (pending), AB 2269 (failed)
- Washington DC: Stop Discrimination by Algorithms Act of 2021

Types of Discrimination

Types of Discrimination: DT

Disparate Treatment:

Intentional Discrimination

- Can be obviously overt/explicit ("we intend to treat Black people differently") or based on proxy
- Need not have negative animus
- Can be proved through direct or circumstantial evidence

Types of Discrimination: DI

Disparate Impact:

Discrimination Based on Results

- Facially neutral policy, practice, or model disproportionately results in negative outcomes for a protected group
- The policy/practice/model either does not advance a legitimate business interest, or if it does, there is a less discriminatory alternative
- Burden-shifting analysis

DI/DT and Models

DT

- Including a protected class as a variable

DT

- Including a proxy for protected class as a variable

DI

- Some variables are likely to lead to DI – criminal background, local geography, language preferences

Alternatives

- With sufficient information about a model, often possible to find less discriminatory version
- May be difficult to do externally without transparency into model/variables used

HUD DI Rulemaking

HUD DI Rule-Making - FHA

1974-2007

- All federal Courts of Appeals adopt the position that DI claims are cognizable under the FHA (except D.C. Cir., which hadn't ruled)

2013

- HUD issues rule confirming that FHA encompasses DI claims, setting standards for proof of DI

2015

- SCOTUS decides *Inclusive Communities*, 576 U.S. 519: confirms DI claims are cognizable under FHA

2020

- Sept.: HUD issues revised rule re: DI, ostensibly in order to follow *Inclusive Communities*. Effectively would make it difficult to bring cases.
- Oct.: Rule stayed; court determined that rule was arbitrary and capricious

2021

- HUD proposes to reinstate its 2013 rule (which remains in effect given the 2020 stay); reads *Inclusive Communities* as consistent with 2013 rule
- Still awaiting new codification

HUD Guidance - FHA

Rule

- 2013 Rule sets out a three-pronged, burden shifting framework that is substantially the same as what was discussed above

1

- A policy, even one that is neutral on its face, has a discriminatory effect when it actually or predictably results in disparate impact on a group of persons or creates, increases, reinforces, or perpetuates segregated housing patterns because of race, color, religion, sex, handicap, familial status, or national origin, ***unless***

2

- The policy is necessary to achieve one or more substantial, legitimate, nondiscriminatory interests ***and***

3

- Those interests could not be served by another practice that has a less discriminatory effect

Case Features

Case Features

CFHC v. CoreLogic	*NFHA v. Facebook* (settled)	*Opiotennione v. Bozzuto* (on appeal)	*NFHA v. Redfin* (pending)
Application for rental housing denied based on automated criminal history report	Plaintiffs alleged FB's advertising platform allowed advertisers to exclude groups based on protected class/adverse impact	55-year-old prospective tenant sued property management companies over alleged age-based exclusions for housing ads	Plaintiffs alleged that Redfin offered real estate services and discounts in white neighborhoods at a higher rate
Key claim: FHA disparate impact claim based on race	Key provision: illegal to make, print, publish, or cause . . . notice, statement, or ad that limits housing based on protected class	MTD granted (standing), in part because information about housing opportunities was otherwise available to the plaintiff	Some restrictions due to "minimum home price policy," which had case-by-case exceptions
Case relied on data showing disproportionate arrests by race that are applicable in CT/def's markets	Settlement required FB to create separate ad portal for HEC ads that limited targeting options	Currently on appeal to the Fourth Circuit COA	Alleged discrimination in brokerage services; discrimination in terms/conditions of sale; discrimination in sale

QUESTION & ANSWER

Enter questions into the Q&A box

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