Loan Algorithms

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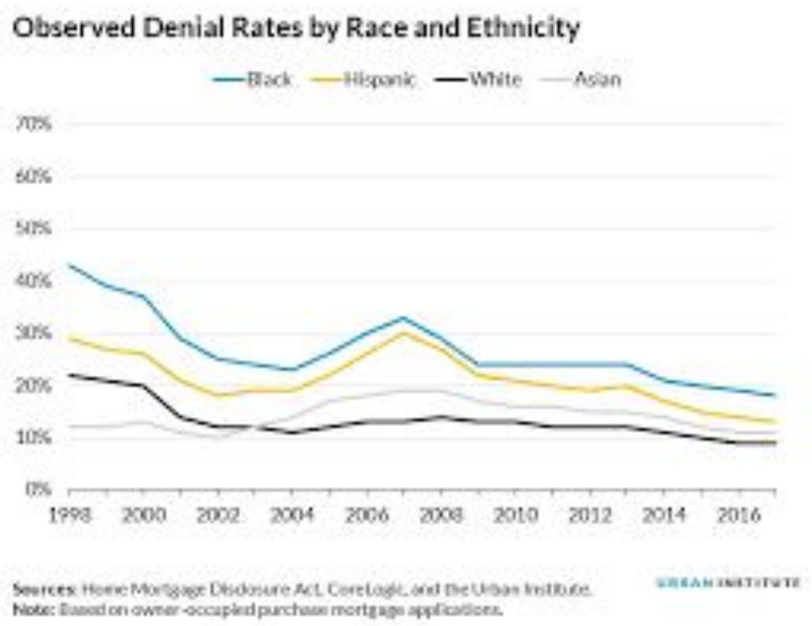
Overview/History

- Before FICO (Fair Isaac Corporation) scores, credit was determined based on the character of the consumer
  - church going, legal issues, employment and finances
    - minorities and women were locked out
- Today consumer credit is determined by
  - FICO scores
  - income and employment history
  - debt-to-income ratio
  - down payment
  - liquid assets
  - loan term
  - demographics
- Nonstandard data are
  - personal habits (shop at Target or Whole Foods, owning a Mac or a PC, and social media data)

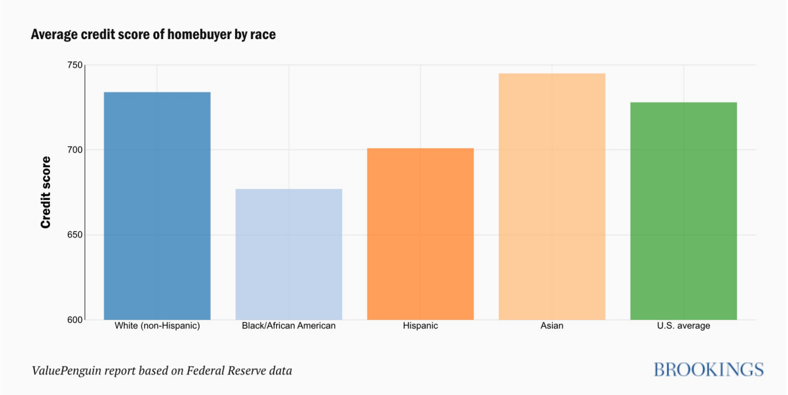
Why It Should Be Addressed

- Lenders are more likely to deny mortgage loans to people of color than to White people with comparable financial profiles.
  - 40% more likely to reject Latino applicants
  - 50% more likely to reject Asian and Pacific Islanders
  - 70% more likely to reject Native American applicants
  - 80% more likely to reject Black applicants



Why It Should Be Addressed

- Minorities already economically behind because of systemic racism (explicit exclusion from government benefits, jobs, criminal justice, healthcare, redlining)
- Depending on what algorithms are used no one including the algorithm's creators can easily explain why the model generated the results that it did
- Existing credit reporting system has many errors
    - 1 out of every 5 people may have material error on their credit report
        - Eg: loan servicer incorrectly reported 4.8 million Americans as being late on paying their student loans but the government had suspended payments as part of COVID-19 relief



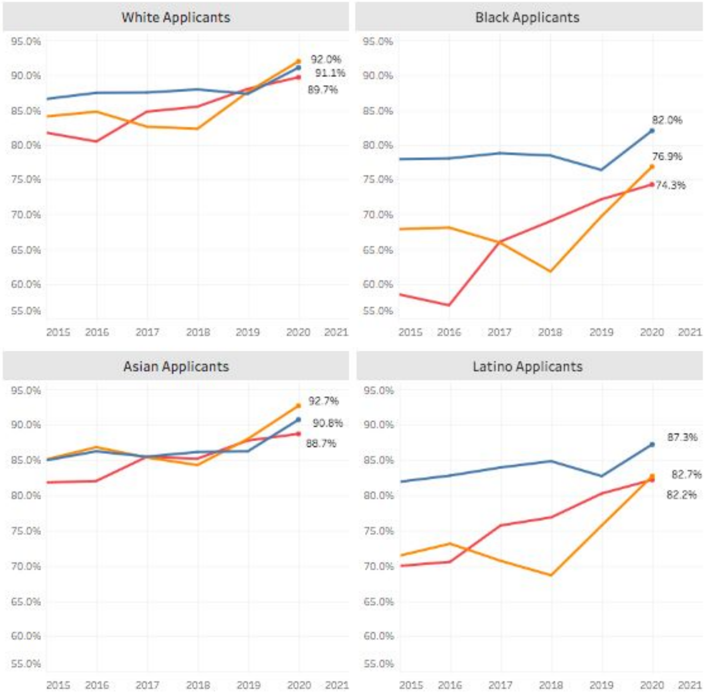
Why It Should Be Addressed

- Video: Mortgage Market Bias
    - Black man trying to refinance his mortgage
        - "I know that I am not the only one to go through this. I know I'm not the first. I know I won't be the last, but at least I want someone else out there to understand that this is not normal, that this is not right."
        - Akili Akridge had all the right stats: a steady six-figure salary, an 800 FICO credit score, and 20% equity in a home
        - He experienced firsthand the persistent racial discrimination in the housing market

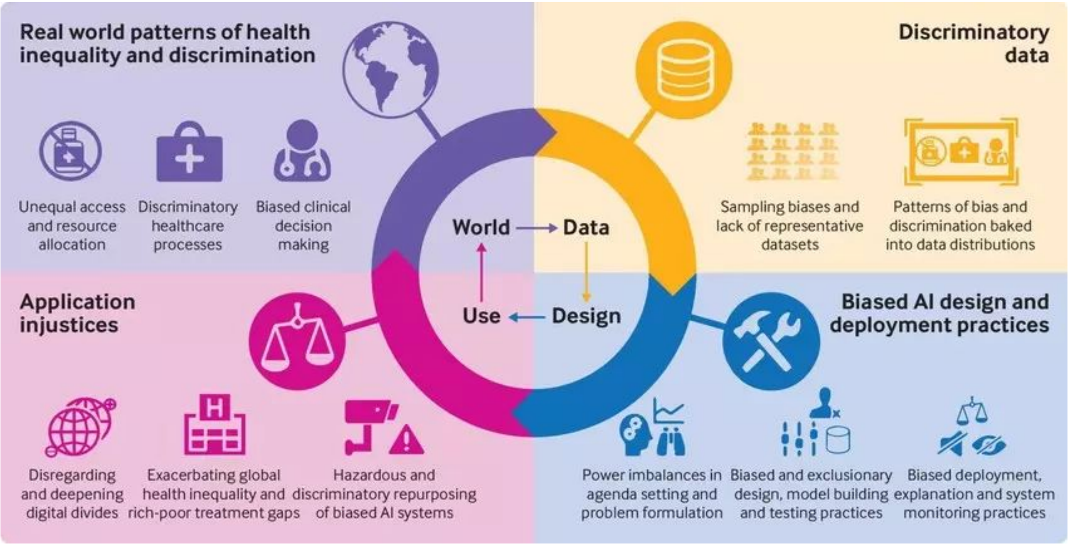
Program-Based Examples

- Secret Algorithm's Secret Decision
  - No one outside Fannie and Freddie knows exactly how the factors in their underwriting software are used or weighted

- Lending agencies claim that the Information on data methodology and definitions is on the dashboard BUT it is convoluted and you have to email Fair lending FairLending@fhfa.gov



Possible Solutions



1. Test the model in different environments
2. AI product designed with consideration for diverse groups such as race, class, and culture, etc.
3. Predict the impact the AI will have right now and over time

Possible Solutions

How do we prevent discrimination in loan algorithms?

Modify and publicize the criteria lenders use when assessing loan applications

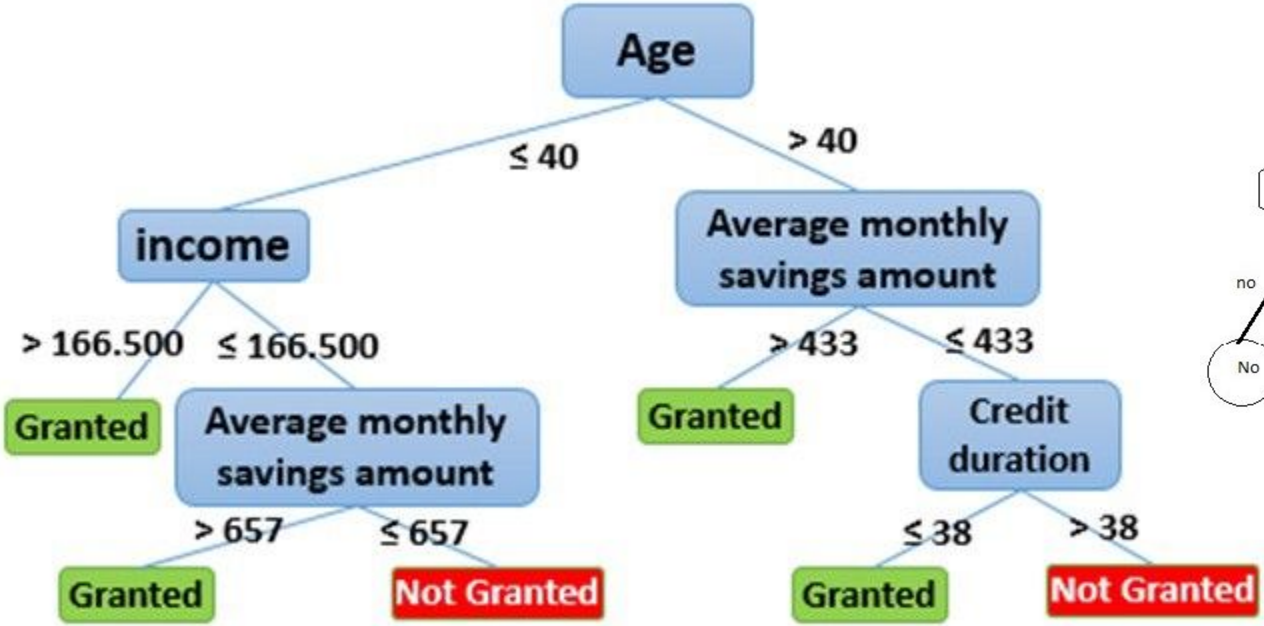
1. ~~The type of borrower you are (age, race/ethnicity, zip code, etc)~~
2. ~~Credit scores~~
3. Deposit/down payment (weighted adjustment)
4. Employment/Income (weighted adjustment)
5. Savings (weighted adjustment)
6. Expenses (weighted adjustment)
7. Assets and liabilities (weighted adjustment)
8. Amount to borrow

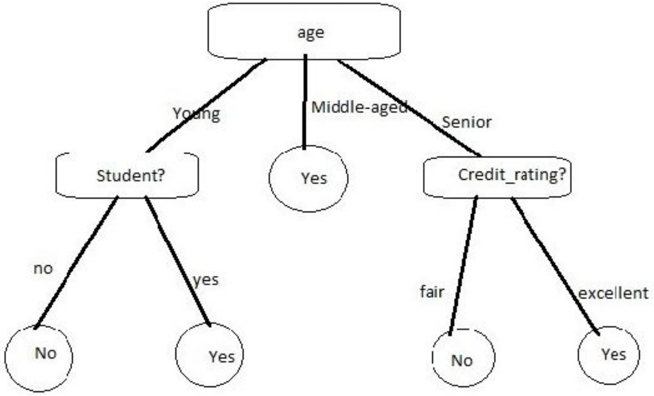
Possible Solutions

- Difficult and honest conversations in technology and government about
    - how much bias we are willing to tolerate
    - the impact of biased algorithms on vulnerable populations
    - uniform rules and clear frameworks for loan algorithms
- Work on the fractured regulatory systems
    - financial products
    - government policies

Something classmates can incorporate into their own praxis

TASK: Ask students to create a decision tree to predict who will or will not qualify for a loan





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Ethics Classroom Discussion/Activity

Question: Do we want a society where if you get sick, or if a computer algorithm thinks you are ill, that your terms of credit decrease? How would you deal with this situation?

Situation: Medical problems are a strong indicator of future financial distress. Consider an AI that is able, with a good degree of accuracy, to detect a decline in a person's health with the data points:

- spending patterns (doctor's co-pays)
- internet searches (cancer treatment)
- joining new Facebook groups (living with cancer)

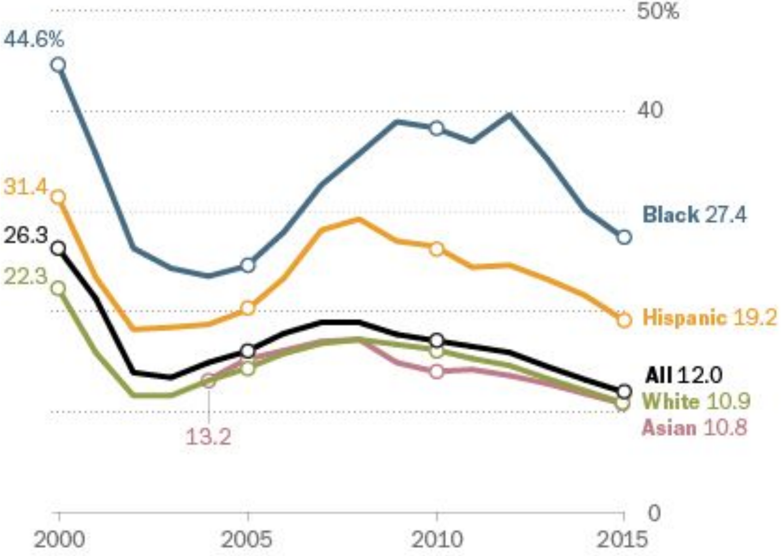
Something classmates can incorporate into their own praxis

Ask students to analyze graphs that show inequalities in society and ask them to discuss the questions:

1. What do you notice?
2. What do you wonder?
3. What impact does this have on you and your community?
4. What should be done about this situation (algorithm/model)?

Despite recent improvements, blacks and Hispanics still have harder time getting mortgages

Denial rates



Note: Data based on applications for conventional loans for one-to-four-family home purchases, including manufactured homes. Data on Asians were not broken out separately until 2004. Hispanics may be of any race.
Source: Pew Research Center analysis of Home Mortgage Disclosure Act data

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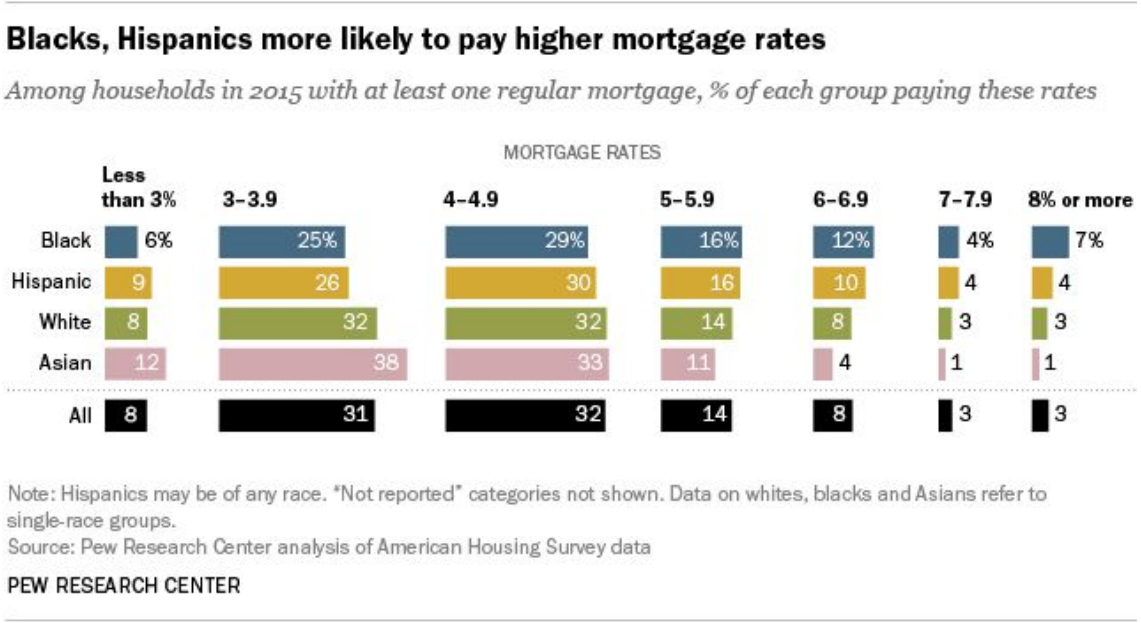

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