Loan Algorithms and Ethics

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The practice of borrowing and lending money goes back as far as 1,800 BC in Ancient Babylon, popularized by the Greeks and Romans in the 15th and 16th centuries, and has been a cornerstone of American society since its origin.

Like most American institutions, racism and discrimination have permeated the banking industry for as long as its existence. Although one could examine this topic in-depth from various angles, the scope of this paper will focus on the advent of modern Loan Algorithms -- from the motivation and rationale for automating systems that were once performed exclusively by banks and loan officers to the consequences and problems -- intentional and unintentional. The scope of the paper will assess the pros and cons of loan algorithms and provide a suggestion that as long as the loan algorithms close historical demographic gaps in loan approval then they should be implemented. The wealth that grows as a result of owning a home is substantial enough that new loan algorithms, risk assessments, and methods are necessary to approve more worthy people for home loans. The coding simulation will demonstrate the impact of home ownership on one's net worth for a person who would not be approved based on traditional loan standards.

Fair Housing Act:

In 1968, US Lawmakers passed the Fair Housing Act, which sought to eliminate discrimination perpetrated by the banking industry against marginalized communities and communities of color. Banks and other credit lenders often discriminated against these communities, denying them home and business loans in specific neighborhoods or outright. Banks and lenders provided foggy justifications to these persons seeking loans. Although discrimination was challenging to prove on a case-by-case basis, by zooming out and examining loan denials on a larger scale, lawmakers found patterns based on neighborhoods and ethnic enclaves. This practice became known as "Redlining,"; a term derived from the red line around individually denied loans in a neighborhood or area, where, once examined in aggregate on a large scale, reveals large-scale racial discrimination against communities of color.

The Fair Housing Act set specific guidelines for banks and financial institutions, explicitly protecting borrowers from discrimination based on race, color, religion, national origin, handicap, or gender.

FICO Credit Scores:

In the years following the passage of the Fair Housing Act, regulators and banking sought ways to standardize and mechanize the criteria for loan approval. Lenders used various metrics -- early algorithms -- that used specific criteria for loan approval. Although multiple methods of assessing credit existed before, modern credit scoring models began in 1958, when Bill Fair and Earl Isaac created the *Credit Application Scoring Algorithms*.

In 1989, the industry adopted the FICO credit score. The FICO credit score was adopted as a standard after Freddie Mac adopted it for all mortgage applications in 1995. The FICO credit score compiled consumer credit history and provided potential lenders with a score between 300 and 850. Financial industries pitched credit scores as an objective metric for assessing risk and granting loans.

The metrics used in the FICO Credit Score algorithm consider five components:

- Payment history (35%): Whether or not you've paid past credit accounts on time;
- Amounts owed (30%): The total amount of credit and loans you're currently using compared to your total credit limit;
- Length of credit history (15%): The length of time you've had credit;
- New credit (10%): How often do you apply for and open new accounts;
- Credit mix (10%): The variety of credit products you have, including credit cards, installment loans, finance company accounts, and mortgage loans

Algorithm implementation and unintended ethical consequences:

Removing or limiting the human element when approving or denying loan applications and putting decision-making into the hands of an algorithm is supposed to remove biases that may exist when dealing exclusively with human loan officers.

If implemented as intended, using credit scores is designed to democratize the process of applying for a loan. The premise is simple: banks use credit scores and algorithms to evaluate applicants equally based on the same financial criteria. There is no metric to consider ethnicity, neighborhoods, religion, or gender identity – all historically discriminatory fields – only the 3-digit number credit score that the algorithm devises -- technology solves a social issue.

However, the credit score algorithm and other newer and more complex loan screening algorithms do not manage to democratize the banking and lending industry. The algorithms codify the discrimination in the code itself.

For example, as of 2019, an estimated 22% or 63 million Americans are underbanked or unbanked – meaning they do not have a bank account or have limited access to financial institutions. This issue primarily affects historically marginalized communities. Persons in the most need of low-cost loans to secure housing and create businesses are the least able to receive them.

This exclusion of large swaths of the population from the modern banking industry creates various ethical dilemmas, including the advent of Pay Day loans and Guaranteed-approval loans. Both loan types are considered an "alternative" route for individuals and families who otherwise cannot borrow money based on their credit history. These loan "alternatives" have a high Annual Percentage Rate (APR) or interest and very unfavorable terms, often saddling borrowers with more debt and worsening their financial situation further. It locks borrowers into a vicious cycle perpetuated by automated banking systems, credit algorithms, and systemically biased systems.

Alternative Risk Assessment:

An AI System is able to develop an alternative risk assessment for borrowers. As noted above many US households are under banked. In fact about 20% of households have no traditional credit. 3/4s of those households were up to date on their bills and rent. An AI model would be able to gather more information on the applicant to better decide on their risk and whether to approve them or not. Classic models are riddled with historical and discriminatory bias and in order to make the necessary progress we need then we need new models to incorporate more people into home ownership.

Modern AI can work through significantly more data then people using traditional models can and we should be leveraging this technology to benefit as many people as possible. The government can also step in to codify in policy changes to the C.F.P.B. which would require lenders to adopt equitable AI based models. These models can account for numerous historical factors as well such as salary disparities that are a result of years of bias. These new systems are crucial for us to make real practical progress towards closing the wealth gap between white people and other minorities.

AI Loan Approval:

Financial institutions are implementing AI systems to approve or deny loan applications to combat biases in loan approvals. These systems are fully automated and remove human input from the decision-making process. Based on a 2018 study conducted at UC Berkley, AI loan systems' objectivity is better at objectively granting loans and assessing risk; however, the quality of data that these systems are culling still preserves the historic socioeconomic biases of marginalized communities. The demonstrated that AI-based systems reduced racial bias by 40% and show no discrimination in rejection rates. There needs to be a major urgency in implementing AI-based systems to take more equitable risk assessments. Even if the interest rates are higher for Black and Hispanic applicants in many AI systems the benefit of owning the home greatly outweighs renting. The additional bias can be accounted for with work.

Researchers believe the solution to these problems is explicitly addressing biases in data – lack of credit history, credit disparity based on gender or ethnicity, increased debt, etc. – before AI computes the information. By preemptively judging the pre-existing bias before any determination is reached, based on the norming of data and providing a "fairness" layer of computing, AI loan approval has the opportunity to correct deeply historical trends in lending.

Conclusion:

Correcting hundreds of years of economic discrimination in the financial industry is challenging. Although we may look to emerging technologies to assist in the effort, no real change will occur unless the system and the deeply interconnected conditions of poverty, racism, and sexism are addressed in society first.

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Home Loan Algorithm Project

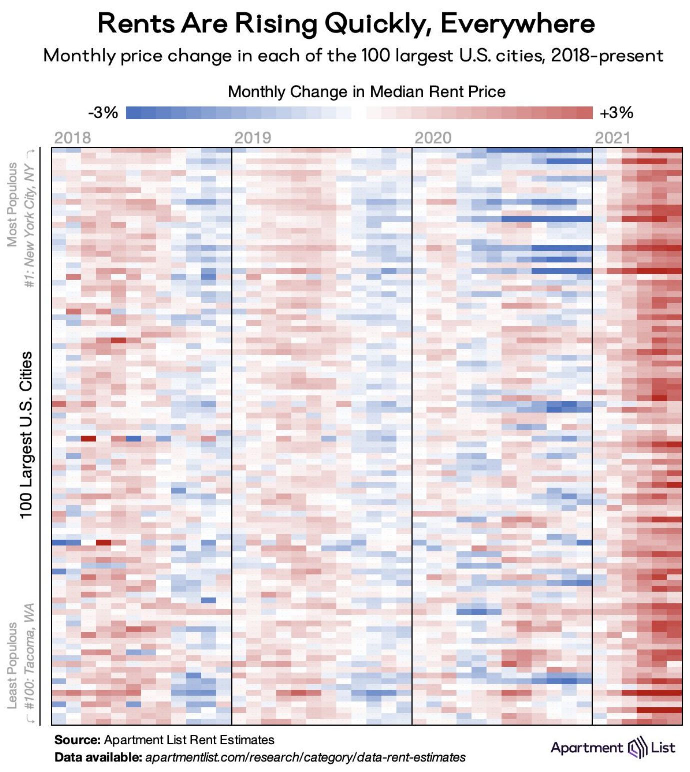
Why it is important that loan algorithms address discriminatory bias and offer an alternative risk assessment process in order to approve more people for life changing home loans.

Why Home Loans?

In most places in the US, there aren't strong renter protection laws, like rent stabilization or rent control (like exists in New York City and Los Angeles).

Home-ownership remains one way to stabilize housing costs.

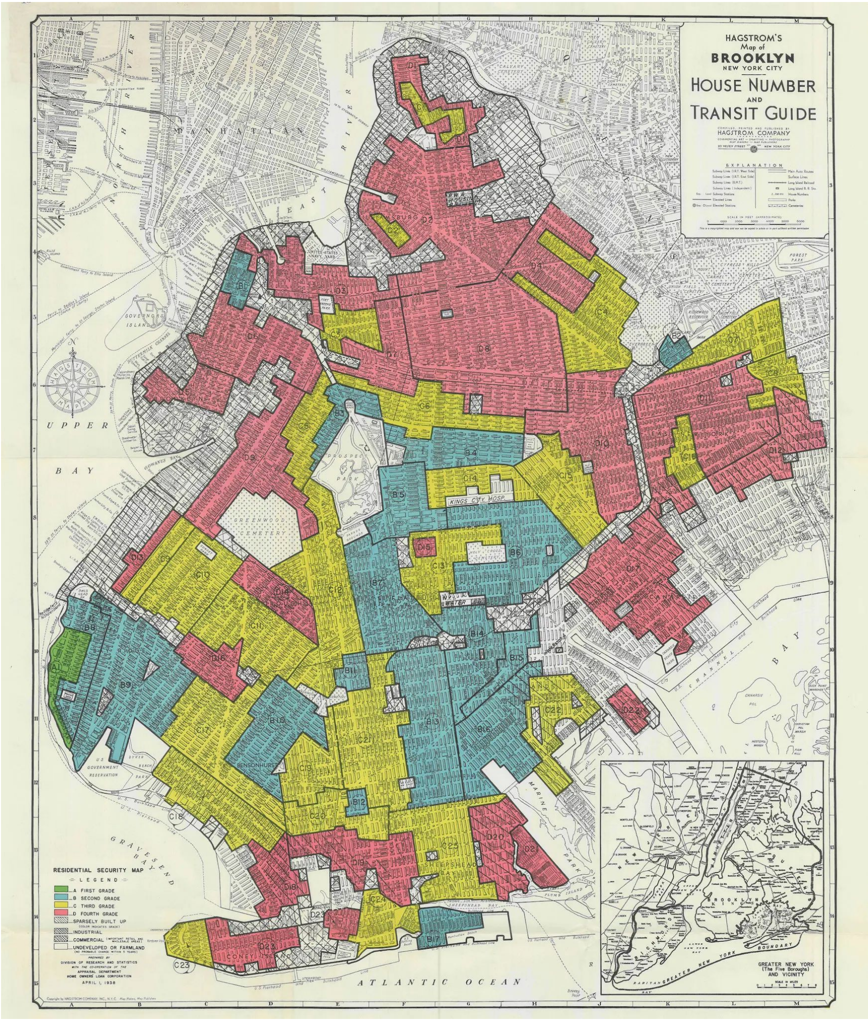
It is the biggest factor in the development of wealth, especially with rising rents



Redlining

Redlining is the practice of systematically discriminating against borrowing funds and opening lines of credit based on a neighborhoods ethnic makeup.

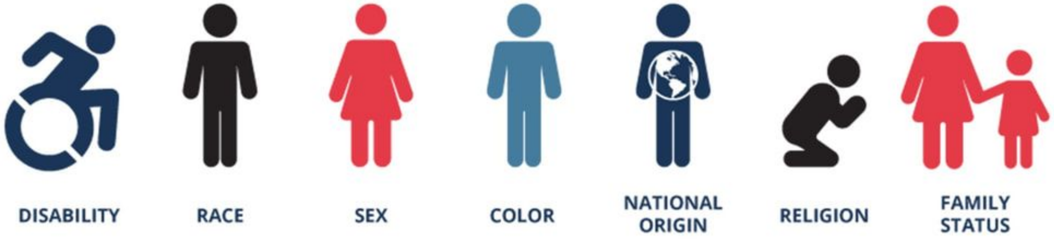
Banks would discriminate against individual families, making it difficult to prove a lager system, however, when examined in aggregate, clear patterns of “redlines” of denied loans, appeared.



Fair Housing Act

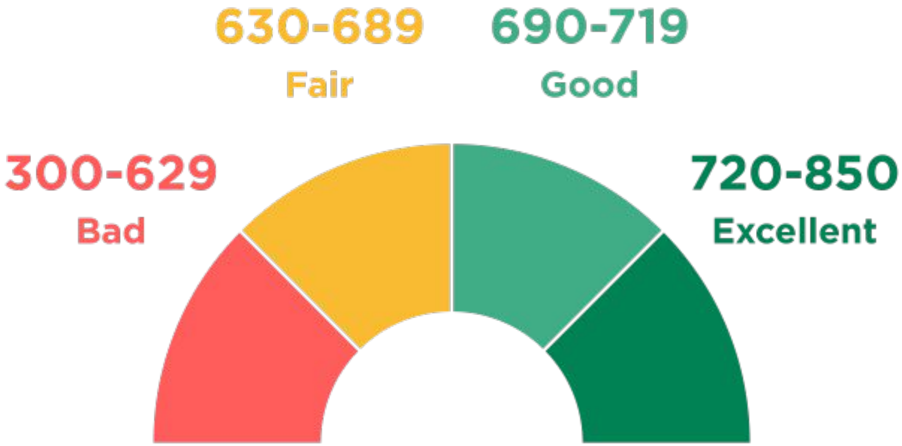
In 1968, after years of direct action from Housing and Social Justice Advocates, the Fair Housing Act was passed and signed into law. The Act made the practice of Redlining illegal, along with many other discriminatory practices.

FAIR HOUSING ACT



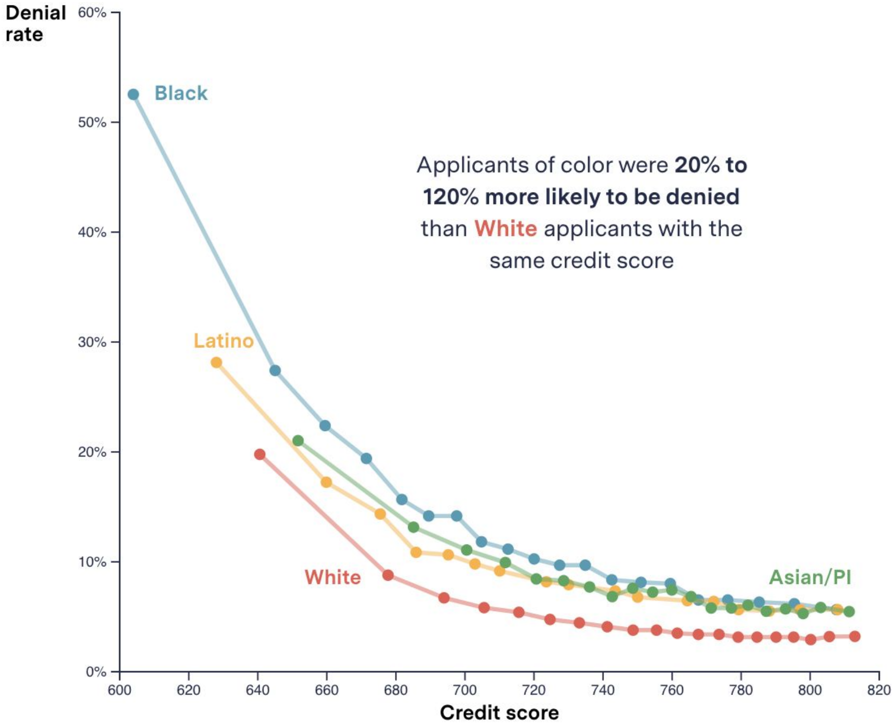
FICO Credit Score

FICO Credit Score



Credit Score Bias

Applicants of color were significantly more likely to be denied than White applicants with comparable credit scores



Alternative Risk Assessment

- Can provide tailored support to change one's risk profile
- Use other data sources to overcome the nearly 20% of U.S. households with no mainstream credit
    - ¾ of these homes remain up to date on bills and rent payments
- Disproportionately Black and Hispanic households
- This means under traditional models many of these households would be excluded from a home loan
- More equitable models and loan algorithms can use alternative data to make a more equitable and fair risk assessment

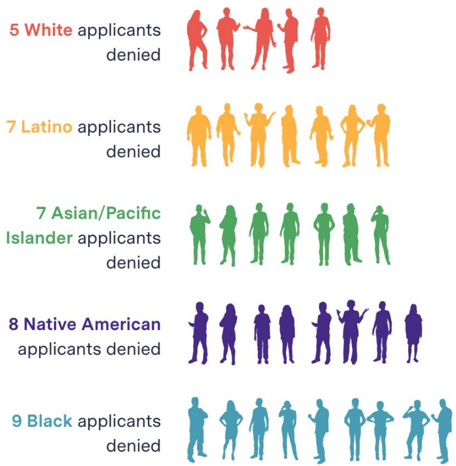
Costs

- Some may argue it would be too costly and a strain on resources, but in fact it benefits the bank to use an alternative method: “Companies have seen a decrease of 20 to 40 percent in their credit losses by using models that could more precisely determine customers’ likelihood to default.”
- This becomes crucial here to have oversight in the loan algorithm to make sure it is not perpetuating bias. The algorithm can remain private but the government can review results to ensure that the new model is actually closing the discriminatory gaps in lending.

Discriminatory Bias

Applicants of color denied at higher rates

To illustrate the odds of denial that our analysis revealed, we calculated how many people of each race/ethnic group would likely be denied if 100 similarly qualified applicants from each group applied for mortgages in **the United States**



Source: 2019 HMDA Data, illustrations from ProPublica. We applied the odds ratios from our regression to White applicants' actual denial rates to calculate the number of denials for each racial and ethnic group above. These numbers are not the actual denials or actual number of applications in each location, but rather have been standardized for comparison. We rounded to the nearest person.

Ben Tanen for The Markup

In 2019, African Americans were denied mortgages at a rate of 16 percent and Hispanics were denied at 11.6 percent, compared with just 7 percent for white Americans, according to data from the Consumer Finance Protection Bureau. An Iowa State University study published the same year found that L.G.B.T.Q. couples were 73 percent more likely to be denied a mortgage than heterosexual couples with comparable financial credentials.

AI Can perpetuate the Bias

A Berkeley study found that fintech lenders still charged higher interest to Black and Hispanic

Progress has been made and with more competition discrepancies should be eliminated.

U.S. government can step in to regulate interest based on race and review algorithms when bias is emerging along discriminatory and historical lines.

Companies like ZEST AI claim their software can pinpoint bias relationships and tune down infringing variables

AI can overcome bias

A recent study demonstrated that AI-based systems reduced racial bias by 40% and show no discrimination in rejection rates.

May not be perfect but it is a step in the right direction

Must be used to address major gap in wealth by approving more home ownership.

Update Policy

Current C.F.P.B criteria can be updated in order to promote and accept more equitable model

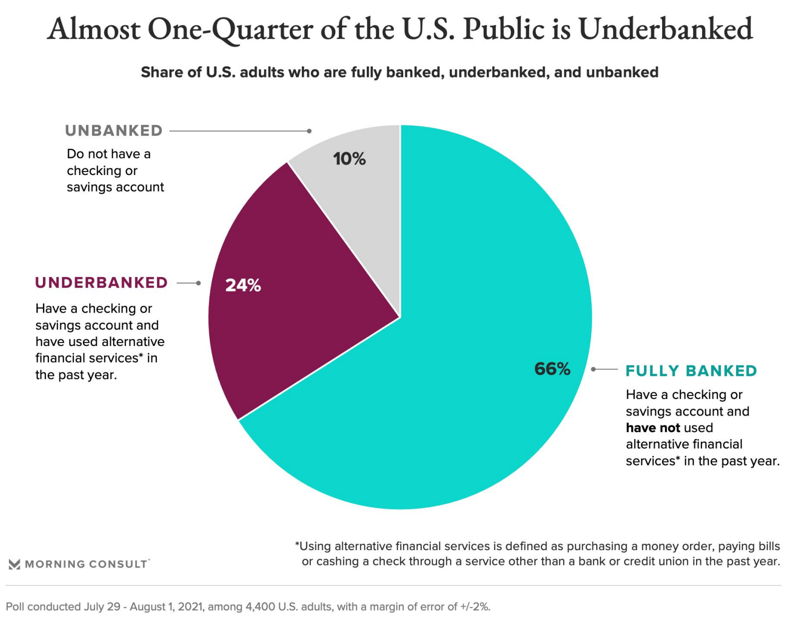
Will allow for discriminatory bias to be addressed and government regulation of modern lending assessments

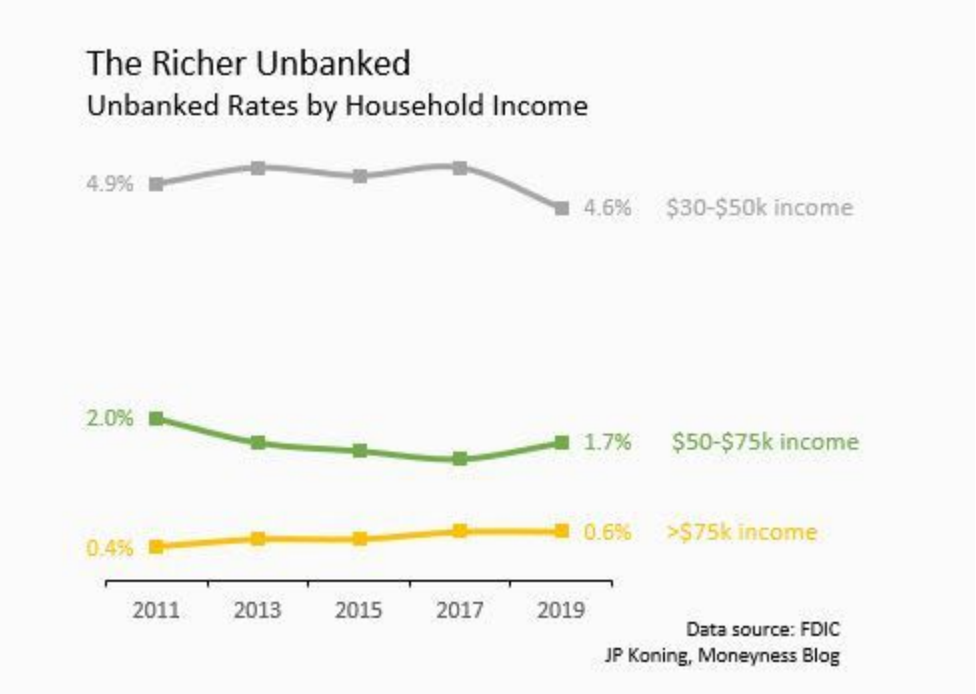
Wealth gap between white and black families is already large and widening. Government policy can make sure more black families receive a home loan based on a more equitable model

Home ownership is one of biggest factors in developing wealth quickly–Imperative loan algorithms are adopted so that more people, excluded from traditional credit, can begin to build generational wealth

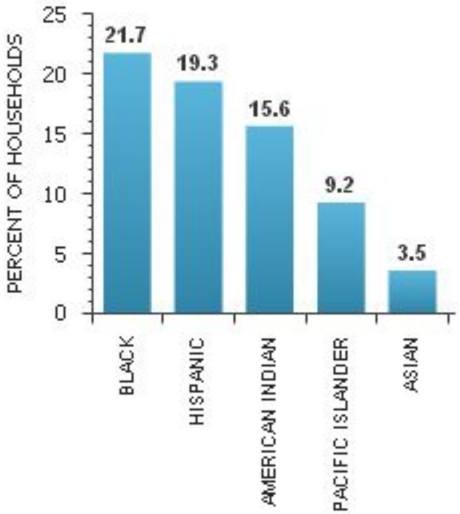
Payday Loans

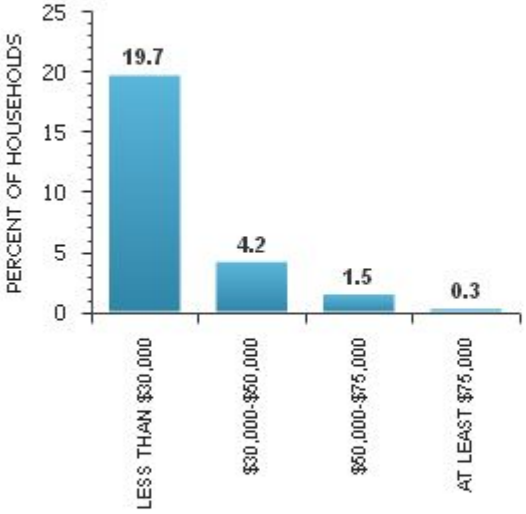
Unbanked or Underbanked





Net worth by race or ethnicity (Thousands of Dollars)	White, non- Hispanic	Black, non- Hispanic	Hispanic	Other
1989	$ 143.56	$ 8.55	$ 9.94	$ 72.00
1992	$ 124.60	$ 17.70	$ 12.14	$ 66.41
1995	$ 128.20	$ 18.23	$ 20.87	$ 51.88
1998	$ 150.96	$ 24.38	$ 15.46	$ 60.40
2001	$ 177.50	$ 27.87	$ 16.90	$ 75.82
2004	$ 191.11	$ 27.66	$ 20.80	$ 96.12
2007	$ 211.73	$ 25.92	$ 26.05	$ 75.18
2010	$ 152.88	$ 18.73	$ 19.50	$ 50.31
2013	$ 155.83	$ 14.36	$ 15.15	$ 44.98
2016	$ 181.87	$ 18.24	$ 22.04	$ 68.73
2019	$ 189.10	$ 24.10	$ 36.05	$ 74.50


PERCENT OF HOUSEHOLDS
25
20
15
10
5
0
21.7
19.3
15.6
9.2
3.5
BLACK
HISPANIC
AMERICAN INDIAN
PACIFIC ISLANDER
ASIAN

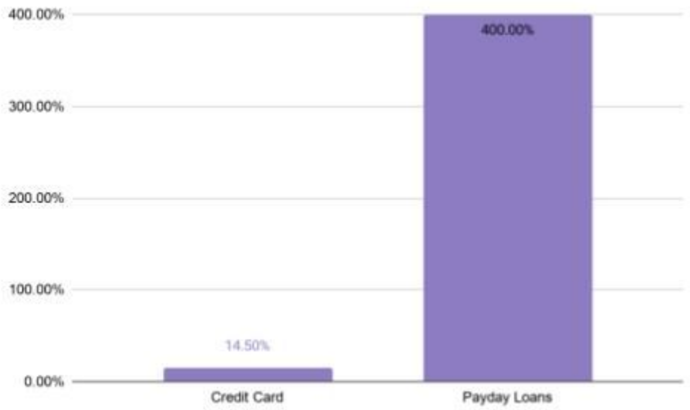

PERCENT OF HOUSEHOLDS
25
20
15
10
5
0
19.7
4.2
1.5
0.3
LESS THAN $30,000
$30,000-$50,000
$50,000-$75,000
AT LEAST $75,000

Payday Loans

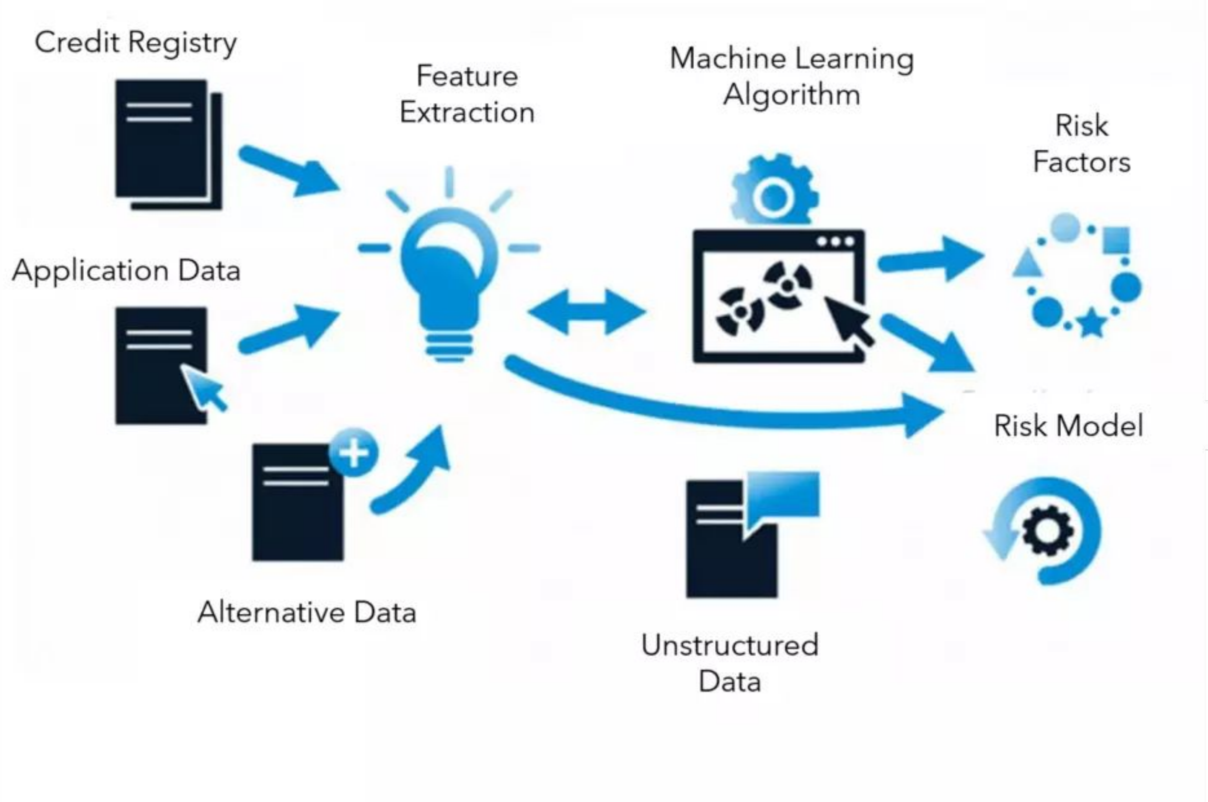
pheabs

The average APR for a payday loan is around 400%.

By contrast, an average credit card APR is around 14.5%.

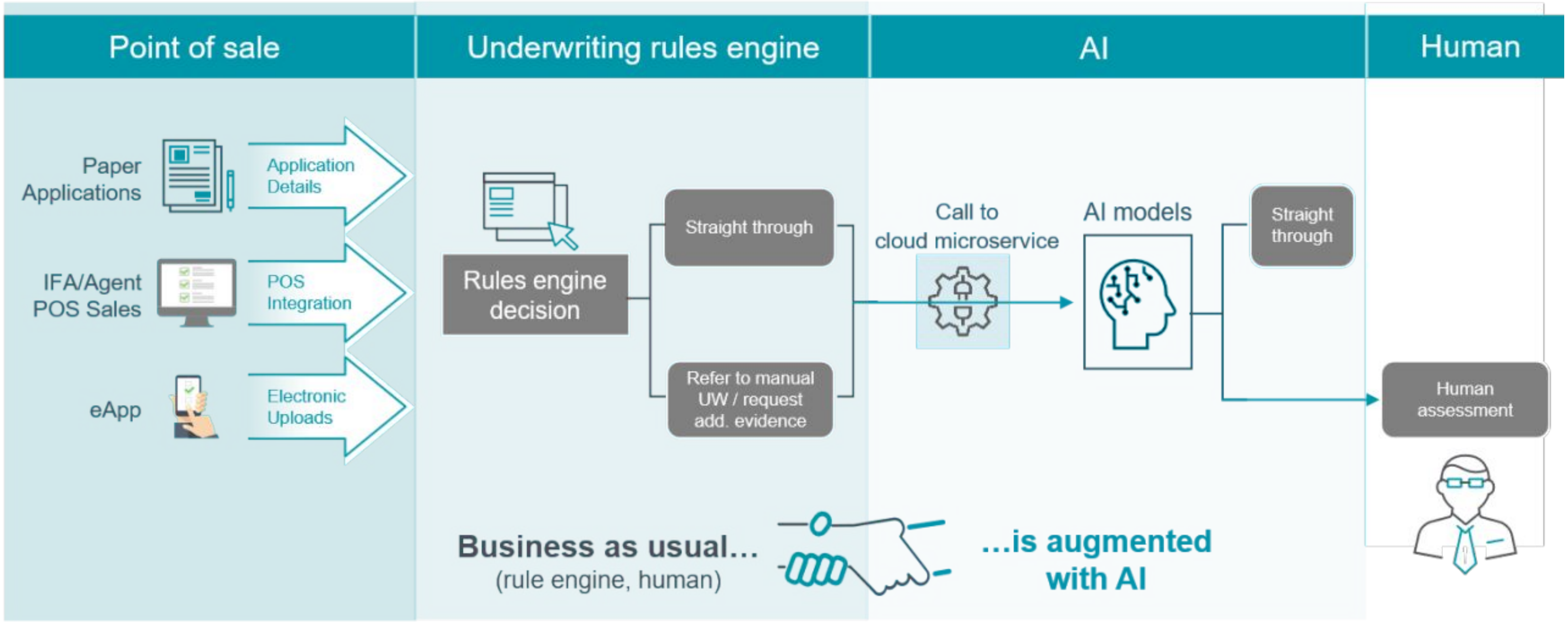



LOANS
ACCEPTED
REJECTED


Credit Registry
Feature Extraction
Machine Learning Algorithm
Risk Factors
Application Data
Risk Model
Alternative Data
Unstructured Data

Augmenting underwriting with AI

Vision of the future: hybrid of AI, rules, human assessment



```
import random
import math

#for our model the location will not matter as much as we are running numbers based off max suggestions for budgeting.  It is impossible to ignore the impact of ones living location on their cost of living, their salary, and relative housing prices, but for our model we are only looking at the overall wealth of individuals based on approval for their first home.
#we are assuming a 10% down payment as people with high credit scores can get approved via FHA loans with 3% down. Also assuming 30 year fixed rate at an APR of 6.53%
#to keep things simple savings are in a high yeilds saving account growing at 3% a year and no stocks or investment outside 401K retirement fund which we are not tracking.  We are only focusing on how home ownership will directly impact wealth so we are trying to keep all other factors minimal and standard based on budgetary suggestions.

#print("They do not have traditional credit, but otherwise have very strong financial management and pay their rent on time and all other bills.  There are two possibilities in our simulation.  Both are random and highlight the disparities in traditional loan approvals.  If a loan algorithm can address these biases then the impact will be huge for those individuals who should have been approved and our society as a whole.  Simulation A is a person whose demographic, espcially their lack of credit, would likely not get approved or approved with a higher rate than someone with a similar demographic, but with some traditional credit. Simulation B is a member of a minority community who are approved at siginificantly lower rates than their white counterparts even with comparable financial profiles.  Our model assumes that a more progressive algorithm will approve our applicant for a loan verse a traditional approvah that would deny them.  Our model will trace each person's financial health and growth overtime.  Then we can compare the impact home laon approval has on possible overall outcomes.")

#steps to code:
#set up our profile and demographic data of applicant--one of two options--1-solid financial management, but no traditional credit--2-member of a minority community that is discriminated against in terms of loan approval

#setup the applicant's profile and overall networth

#our model does not look at utilities and other possible expenses.  We are simulating with perfect savings numbers of 20% and will track payments on the loan ammount for overall networth tracking.  So although per month is less there are other costs to owning a home which may balance out the per month costs, but we are specifically
```

looking at savings and networth which will grow consistently.

```
#set up initial net worth tracker for each -- post home purchase
class Applicant:
  applicantName = "Dave"
  applicantRacePossible = ["black", "hispanic", "asian", "middle
eastern"]
  applicantRace = random.choice(applicantRacePossible)
  applicantLGBTQ = random.randint(0, 1)
  applicantAge = random.randint(22, 30)
  applicantSalary = random.randint(45000, 150000)
  applicantRent = round((applicantSalary * .25) / 12, 2)
  print(applicantRent)
  homeCost = applicantSalary * 3.0
  homeValue = homeCost
  downPayment = homeCost * .10
  homeMortgage = round(homeCost - downPayment, 2)
  x = (1.0 + .0054)**360.0
  currentMortgageAmount = homeMortgage
  applicantMortgage = round((homeMortgage * (.0054 * x) / (x - 1)), 2)
  #assumed to have 6 + emergency fund and current savings.  Other net
worth is in the downpayment.
  currentSavings = applicantRent * random.randint(3, 9)
  print(currentSavings)
  #netWorth = downPayment + int(currentSavings)
  print(applicantName + " is " + str(applicantAge) +
        " years old.  They earn $" + str(applicantSalary) + " per
year.")
  print("They are applying for a $" + str('%.2f' % homeMortgage) +
        " mortgage.")
  print(
    "If purchasing the home their monthly payments on their mortgage
will be $ "
    + str(applicantMortgage) +
    ".  If they are renting their monthly payments will be 25% of
their current salary, which is currently $"
    + str(applicantRent))
  approvedNetWorth = round(currentSavings + homeCost - homeMortgage,
2)
  print("When approved Dave starts with net worth of $" +
        str(approvedNetWorth))
  deniedNetWorth = round(currentSavings + downPayment, 2)
  deniedCurrentSavings = deniedNetWorth
  print("When not approved Dave starts with net worth of $" +
        str(deniedNetWorth))
  count = 0
  homeAppreciation = 0
  while count < 5:
    count += 1
```

```
    homeAppreciation = homeAppreciation + round(homeValue * .10, 2)
    savingsNew = applicantSalary * .20
    applicantSalary = applicantSalary + (applicantSalary* .03)
    savingsGrowth = currentSavings * .03
    currentSavings = currentSavings + savingsGrowth
    currentMortgageAmount = currentMortgageAmount -
applicantMortgage*12
    approvedUpdatednetWorth = (homeValue + homeAppreciation) +
savingsNew + currentSavings - currentMortgageAmount
    print("After " + str(count) + " years, Dave's new Approved
networth is: " +
          str('%.2f' % approvedUpdatednetWorth))

    savingsNew = applicantSalary * .20
    applicantSalary = applicantSalary + (applicantSalary * .03)
    deniedSavingsGrowth = deniedCurrentSavings * .03
    deniedCurrentSavings = deniedCurrentSavings + deniedSavingsGrowth
    deniedUpdatednetWorth = deniedCurrentSavings + savingsNew
    print("After " + str(count) + " years, Dave's new Denied networth
is: " +
          str('%.2f' % deniedUpdatednetWorth))

  print(
    "If Dave is approved for a home his final net worth will be $" +
str('%.2f' % approvedUpdatednetWorth) + ". If Dave is denied for a
home his final net worth will be $" + str('%.2f' %
deniedUpdatednetWorth) +".")
  netWorthdifference = round(approvedUpdatednetWorth -
deniedUpdatednetWorth,2)
  print("The difference is $" + str(netWorthdifference) + ".  There
are many different factors that can be at play but just in terms of
wealth being built via homeownership and its associated appreciation
and equity outcomes could not be more staggering.")
  currentSavings = currentSavings + savingsNew
  deniedCurrentSavings = deniedCurrentSavings + savingsNew
```