Introduction to Finance for Data Scientists

Session 8: Scoring

Johan Hombert

HEC Paris, 2025

Scoring

- Credit markets

  mortgages, consumer loans, business loans

  $\Rightarrow$ lender must predict default

- Insurance markets

  health, property and casualty

  $\Rightarrow$ insurer must predict losses and damages

- Accurate prediction is key

  price too low $\Rightarrow$ lose money

  price too high $\Rightarrow$ lose market shares

Road Map

Mini-Case: Credit Scoring with Digital Footprints

- E-commerce company in Germany[1]
- The company conducted A/B testing
  - Randomized customers viewing an item on the website
  - Treatment group: Offered the option to pay within 15 days of receiving the purchased item
  - Control group: Option not offered
  - Both groups had the same item price
- Impact
  - Control group: 45% probability of purchasing the item
  - Treated group: 85% probability of purchasing the item
- What should the company's management do?

[1] Berg, Burg, Gombovic, Puri, 2019, "On the Rise of FinTechs: Credit Scoring Using Digital Footprints" *Review of Financial Studies* [pdf]

Credit Scoring with Digital Footprints

- Trade-off in offering payment facility: increased sales vs. default risk

$\Rightarrow$ Assess default risk and offer payment facility if default probability is low

- Phase 1: Purchase credit scores from a credit bureau
  - Scores based on credit history and sociodemographic data
- Phase 2: Use proprietary customer data
  - Digital footprints: OS, email, login information, etc.
  - Does this data improve default prediction?

Scoring Model

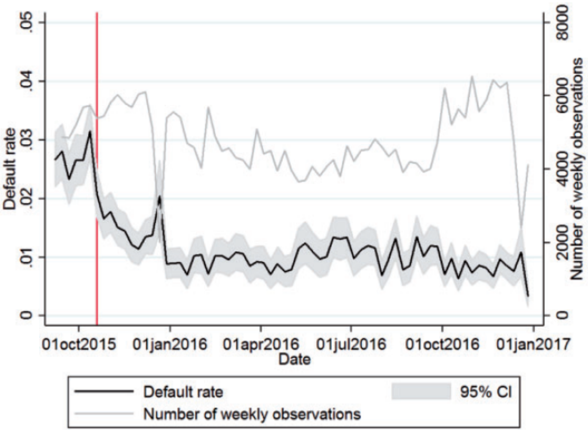
- Logistic regression to predict default
- Dependent variable: =1 if default
- Predictive variables
  (1) Credit bureau score
  (2) Digital footprints
  (3) Credit bureau score + digital footprints

Default regressions (scorable customers)

Variables	(1) Credit bureau score Coef.	(1) z-stat	(2) Digital footprint Coef.	(2) z-stat	(3) Credit bureau score & digital footprint Coef.	(3) z-stat
Credit bureau score	−0.17***	(−7.89)			−0.15***	(−6.67)
Device type & operating system[a]						
Desktop/Windows			Baseline		Baseline	
Desktop/Macintosh			−0.07	(−0.53)	−0.13	(−1.03)
Tablet/Android			0.29***	(3.19)	0.29***	(3.06)
Tablet/iOS			0.08	(1.05)	0.08	(0.97)
Mobile/Android			1.05***	(17.25)	0.95***	(15.34)
Mobile/iOS			0.72***	(9.07)	0.57***	(6.73)
E-mail Host[a]						
Gmx (partly paid)			Baseline		Baseline	
Web (partly paid)			0.00	(0.00)	−0.02	(−0.22)
T-Online (affluent customers)			−0.40***	(−3.90)	−0.35***	(−3.35)
Gmail (free)			0.34***	(3.81)	0.29***	(3.09)
Yahoo (free, older service)			0.75***	(9.19)	0.72***	(8.98)
Hotmail (free, older service)			0.35***	(3.70)	0.28***	(2.72)
Channel						
Paid			Baseline		Baseline	
Affiliate			−0.49***	(−5.35)	−0.54***	(−5.58)
Direct			−0.27***	(−4.25)	−0.28***	(−4.44)
Organic			−0.15*	(−1.79)	−0.15*	(−1.74)
Other			−0.47***	(−4.50)	−0.48***	(−4.36)
Checkout time						
Evening (6 p.m.-midnight)			Baseline		Baseline	
Morning (6 a.m.-noon)			0.28***	(4.50)	0.28***	(4.60)
Afternoon (noon-6 p.m.)			0.08	(1.42)	0.08	(1.47)
Night (midnight-6 a.m.)			0.79***	(7.73)	0.75***	(7.09)
Do-not-track setting			−0.02	(−0.25)	−0.07	(−0.91)
Name in e-mail			−0.28***	(−5.67)	−0.29***	(−5.70)
Number in e-mail			0.26***	(4.50)	0.23***	(3.91)
Is lowercase			0.76***	(13.10)	0.74***	(13.20)
E-mail error			1.66***	(20.00)	1.67***	(20.36)
Constant	12.42***	(5.76)	−4.92***	(−62.87)	9.97***	(4.48)
Control for *Age*, *Gender*, *Item category*, *Loan amount*, and month and region fixed effects	No		No		No	
Observations	254,819		254,819		254,819	
Pseudo R^2	**.0244**		**.0524**		**.0717**	
AUC	**0.683**		**0.696**		**0.736**	
(SE)	**(0.006)**		**(0.006)**		**(0.005)**	
Difference to AUC=50%	**0.183*****		**0.196*****		**0.236*****	
Difference AUC to (1)			**0.013***		**0.053*****	

Impact on Default Rate

- New credit scoring model put in production in October 2015
- Default rate divided by 3



Issues for Data Scientists

- Scoring with AI can be very powerful
- But also important pitfalls to avoid → today's lecture

Road Map

VC Game

- You manage a venture capital (VC) fund
  - A startup seeks financing
  - Potential deal: Receive an ownership stake in exchange for cash payment P
- Valuation
  - Cash-out value of ownership stake V is uncertain
  - Assume a zero discount rate
  - A priori estimate of present value: $E[V]$

VC Game

- Information
  - You analyze the company to estimate V
  - V is drawn from uniform distribution between 20 and 100
  - Your best estimate of V: check your private signal
  - Your best estimate is unbiased: Generated as the true V plus Gaussian noise (mean 0, s.d. 20)
- Competition
  - Compete with other VC funds (students) who also have their own estimate of V
  - Each VC makes an offer; the highest offer wins the deal

VC Game

- Profits
  - If you win the deal at price P and the true value is V, profit (or loss if negative) is $V - P$
  - If you don't win, profit is zero
- Submit your bid at https://forms.gle/seYd1YQAkhLLe3WN6

Winner's Curse

- Estimates are unbiased
  - Some above, some below; average is V
  - The highest estimate exceeds V
- If all bid their best estimate, the winning price is the highest estimate $\Rightarrow$ above V $\Rightarrow$ winner overpays
- This is the **winner's curse**
- The winner's curse is a form of **adverse selection**

Adverse Selection Everywhere

- Lending
  - Borrowers accept your loan offer when other lenders charge higher rates, indicating your credit risk estimate is too optimistic
- Insurance
  - Customers buy insurance from you when other insurers charge higher premiums, indicating your risk estimate is too optimistic
- Trading
  - Cf. Glosten-Milgrom model of market making studied with Jean-Edouard

Adverse Selection Everywhere

- Real estate

ZDNet

Zillow: Machine learning and data disrupt real estate

Learn how big data and the Zillow Zestimate changed and disrupted real estate. It's an important case study on the power of machine learning models and digital innovation.

Written by **Michael Krigsman**, Contributor
Posted in Beyond IT Failure on July 30, 2017

Interview with Zillow's Chief Analytics Officer Stan Humphries in 2017

ZD: How accurate is the Zestimate?

S.H.: Our models are trained such that half of the Earth will be positive and half will be negative; meaning that on any given day, half of [all] homes are going to transact above the Zestimate value and half are going to transact below.

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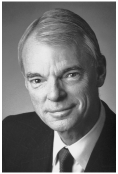
CHRIS STOKEL-WALKER BUSINESS NOV 11, 2021 :00 AM

WIRED

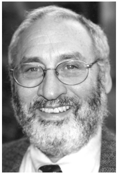
Why Zillow Couldn't Make Algorithmic House Pricing Work

Adverse Selection Everywhere

George A. Akerlof
Nobel Prize 2001

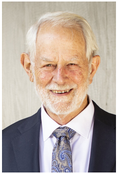


A. Michael Spence
Nobel Prize 2001



Joseph E. Stiglitz
Nobel Prize 2001

Paul R. Milgrom
Nobel Prize 2020



Robert B. Wilson
Nobel Prize 2020

Adverse Selection in Lending

- Let's study the statistical underpinnings of adverse selection in a lending context. Highly relevant for the group work!
- You run a fintech making loans to businesses
  - Receive loan applications
  - Info on loan applicants: vector X (financial info, online reviews, ...)
  - Offer interest rate R. Loan applicant may take the loan or not
  - If loan is taken, then cash flow is

    today: $-1 + R$

    at maturity: $\begin{cases} 1 \text{ if no default} \\ 0 \text{ if default} \end{cases} = 1 - D$ where $D \in \{0, 1\}$ is default indicator

    (Unimportant assumptions to simplify formulas: interest paid at issuance; loan size normalized to one; zero recovery rate; zero discount rate)

$\Rightarrow$ Profit $= 1\{\text{loan taken}\} \times (R - D)$

Adverse Selection in Lending

- Probability of default: PD $= f(X) + U$
  - X: observed characteristics
  - U: unobserved determinants of default, uncorrelated with X, $E[U] = 0$
- Applicant offered an interest rate R takes the loan iff $R < \overline{R} + PD$
  - Applicants take the loan if the interest rate is not too high
  - $\overline{R}$: maximum rate a risk-free applicant would accept
  - Riskier applicants are more likely to take the loan at a given R (because their chance to get a loan from another bank is lower)

Adverse Selection in Lending

- Predicting default

Step 1: Construct scoring model. You have data on past loans with info (X, D). You recover $f(.)$ using ML

Step 2: Score new applications. You have info X on new applications. Your best estimate of PD is $P[D|X] = f(X)$

- How to set the interest rate?

- Simple idea: take a margin over estimated PD: $R = f(X) + M$ with $M > 0$

Q. What is your expected profit per loan granted?

a. M b. more than M c. less than M d. it depends

Adverse Selection in Lending

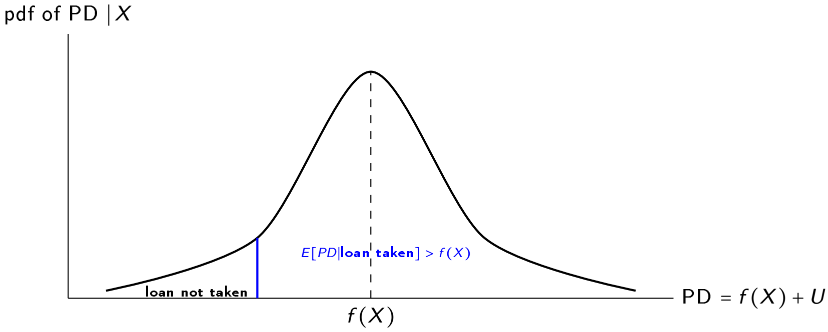
- Expected profit per loan granted (conditional on X)

$$
\begin{aligned}
&= E[R - D \mid \text{loan is taken}] \\
&= R - E[D \mid R < \overline{R} + PD] \\
&= f(X) + M - E[f(X) + U \mid f(X) + M < \overline{R} + f(X) + U] \\
&= M - E[U \mid U > M - \overline{R}] \quad < \quad M \quad \text{!!!}
\end{aligned}
$$

$\Rightarrow$ You earn less than M per loan. What happened?

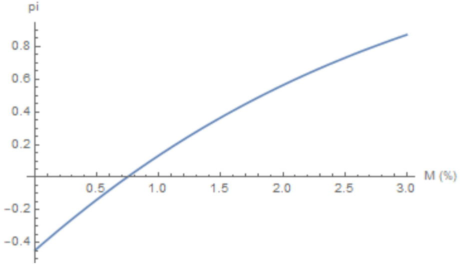
Adverse Selection in Lending

- Adverse selection: The pool of applicants who accept the loan offer are more risky than the overall pool of applicants (i.e., the pool of accepted offers is *adversely selected*)



Adverse Selection in Lending

- Expected profit per loan granted as function of M

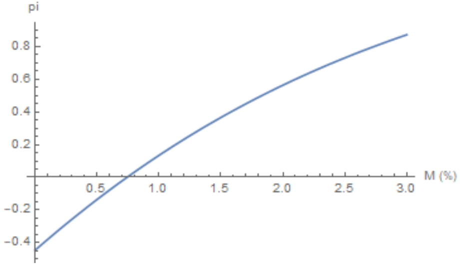


$\overline{R} = 2\%;\ U \sim \mathcal{N}(0, 1.8\%)$

- Adverse selection $\Rightarrow$ profit per loan less than M; can be negative even if $M > 0$

Adverse Selection in Lending

- Expected profit per loan granted as function of M



$\overline{R} = 2\%$; $U \sim \mathcal{N}(0, 1.8\%)$

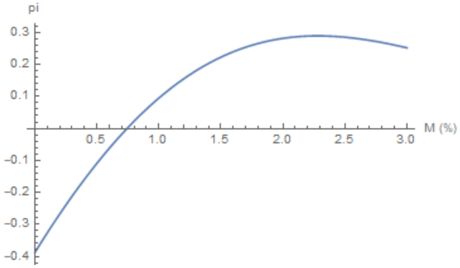
- Adverse selection $\Rightarrow$ profit per loan less than M; can be negative even if $M > 0$

- Next question: Which M maximizes expected profit?

Adverse Selection in Lending

- Expected profit

$$= E[(R-D)\times 1\{\text{loan taken}\}] = \underbrace{E[R-D\,|\,\text{loan taken}]}_{\uparrow M \text{ (previous graph)}} \times \underbrace{P[\text{loan taken}]}_{\downarrow M}$$



- Why hump-shaped? Higher $M \Rightarrow$ higher profit per loan granted but fewer loan offers are accepted

- Profit is maximized for $M \approx 2.2\%$

Adverse Selection: Summary

- If competitors or customers have info about default that you don't have, customers who take your offer are worse than average

Adverse Selection: What To Do?

- Ask yourself which information YOU DON'T HAVE and others have

  If that information is correlated with the variable to predict (e.g., default), you face an adverse selection problem

- Practical solutions

  1. Adjust your forecast (be more conservative)
  2. Structural modeling
  3. Backtest after putting in production

Backward-Looking AI

- Another AI limitation in VC: AI is backward-looking, while VC focuses on identifying novel ideas

- *"Data-Driven Investors"* [pdf] Maxime Bonelli (HEC PhD 2023)

  VC firms using AI to screen startups tend to select those that:

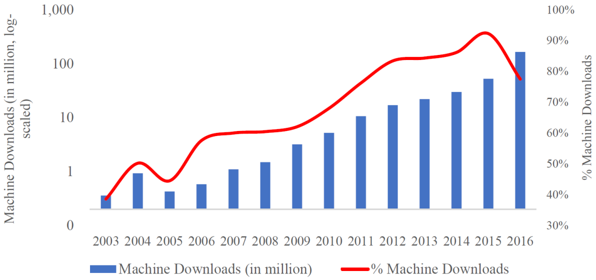
  1) Are more likely to survive and receive follow-up funding $\Rightarrow$ AI is good at avoiding mistakes

  2) Are less likely to file patents and IPO $\Rightarrow$ AI struggles to identify breakthrough ideas

Road Map

Goodhart's Law

- This figure shows machine downloads of companies' filings with the SEC[2]

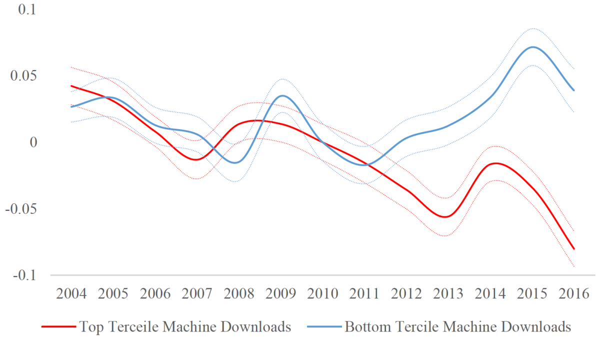


Q. What should companies do?

[2] Cao, Jiang, Yang, Zhang, 2023. "How to Talk When a Machine is Listening: Corporate Disclosure in the Age of AI" *Review of Financial Studies* [pdf]

Goodhart's Law

- This figure plots the use of words scored negatively by the Loughran-McDonald dictionary (which was widely used by quant funds) by companies analyzed by machines (red) versus companies less analyzed by machines (blue)



⇒ Incentives to use language evaluated positively by algorithms

Goodhart's Law — Implications

1. Beware scoring on behavior that can be strategically modified

   $\Rightarrow$ Ask yourself if data is exogenous or the result of a strategic choice

2. **Goodhart's law:** A good predictor when not used, can become a poor predictor once used

   $\Rightarrow$ Check if the predictive power changes after data is used

Goodhart's Law — Implications

3. More data can make everyone worse off
   - Users being scored try to game the algorithm ⇒ Costly for users
   - The predictive power of the algorithm decreases ⇒ Costly fintechs
4. Commitment <u>not to</u> use data can sometimes create value
   - Example: *"The Value of Privacy: Evidence from Online Borrowers"* [pdf] Huan Tang (HEC PhD 2020)

     Using A/B testing, a lending platform found out that customers are more likely to apply for a loan if there are asked to provide less information

     ⇒ Tradeoff between privacy and adverse selection
   - More on the privacy paradox at https://johanhombert.github.io/blog/20210418-privacy-paradox

Road Map

Information in Insurance

- Suppose we discover how to predict perfectly who will get sick, but this foreknowledge does not help to prevent or cure diseases

- Insurers use this information to price health insurance

Q1. Will this make people better or less-well insured?

a. better insured b. less-well insured

Q2. Will this make insurers more or less profitable?

a. more profitable b. less profitable

Information in Insurance

- What will happen?
  - No insurers accept to insure people predicted to be sick
  - People predicted to be healthy don't need insurance

$\Rightarrow$ The health insurance market breaks down

  - People are worse off: they can't get insurance
  - Insurers are worse off: they can't sell insurance

- **Hirshleifer effect:** Information can destroy insurance

How to Overcome the Hirshleifer Effect?

- Suppose an insurer announces it will not use the information and the promise is credible

Q3. Does this overcome the Hirshleifer effect and allow the insurer to sell insurance?

a. yes b. no

How to Overcome the Hirshleifer Effect?

- Suppose an insurer announces it will not use the information and the promise is credible

Q3. Does this overcome the Hirshleifer effect and allow the insurer to sell insurance?

a. yes   b. no

- No, because of adverse selection
  - People predicted to be healthy are offered cheap insurance from other insurers, or they don't even buy insurance
  - The insurer only gets people who will be sick, so it cannot insure them

- See practice problem 2

How To Overcome the Hirshleifer Effect?

- Solution 1: Ensure no insurer uses the information
  - Industry self-regulation
  - Regulation (insurers are not allowed to use DNA testing)
- Solution 2: Insure before information is revealed
  - Long-term insurance
  - Government-provided insurance

Short-Term Insurance and Repricing

- Short-term insurance contracts are exposed to the risk of information arrival and repricing

What happens to insurance premiums after the LA wildfires?

Longstanding insurance issues in the Golden State are sure to be exacerbated by the fires roaring through the LA area

January 8, 2025, 3:55 pm *By Sarah Wolak*

Road Map

Discrimination

- Legal and conceptual distinction between:
  - Direct discrimination
  - Indirect discrimination

Direct Discrimination

- Treatment is based on a protected characteristic such as sex, ethnicity, social origin
- May happen for two reasons:
  1. Outright prejudice

     Example: Job opening for white men only

  2. Statistical discrimination: the protected characteristic is a predictor of risk

     Example: Cheaper car insurance for women because women have fewer accidents
- Illegal in both cases in EU and US

Indirect Discrimination

- Treatment is not based on protected characteristics but ends up being different for people with a protected characteristic
- Happens when treatment is based on variables correlated with protected characteristics

  Example: Interest rate based on borrower's job occupation may end up different for people with different ethnicities
- May be legal or illegal (legal for "business necessity" in US)

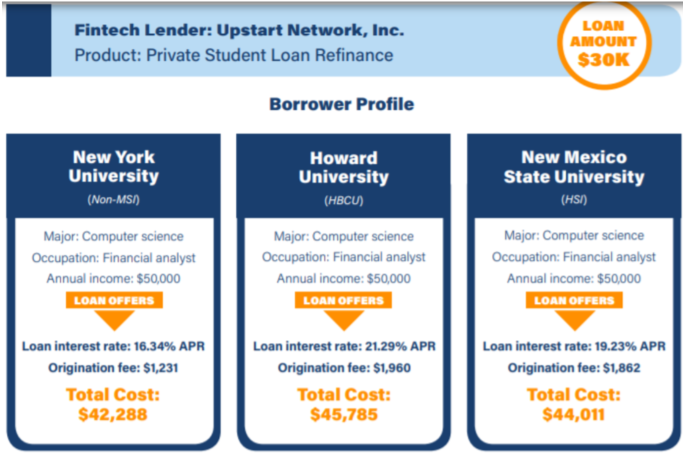
AI and Discrimination

Wells Fargo, Upstart criticized after study finds loan disparities

Published Feb. 6, 2020 • Updated Feb. 14, 2020

The request comes a week after the nonprofit Student Borrower Protection Center found that an Upstart borrower who attended historically black Howard University would pay thousands of dollars more on average for a five-year loan than a borrower with an identical credit profile who studied at New York University.

AI and Discrimination



Q. What may explain the discrimination?

Invisible Primes: Fintech Lending with Alternative Data*

Marco Di Maggio† Dimuthu Ratnadiwakara‡

January 4, 2024

Abstract

We use anonymized data and an underwriting algorithm that incorporates alternative data from a major platform to study how alternative data affects credit access and borrower outcomes. Comparing actual outcomes of the fintech platform's model to counterfactual outcomes based on a "traditional model" used for regulatory reporting purposes, we find that the fintech platform's model approves 15-30% of low credit score applicants rejected by the traditional model and offers substantial reductions in interest rates. The borrowers most positively affected are the "invisible primes"—borrowers with low credit scores and short credit histories, but also a low propensity to default. Some high credit score borrowers are instead rejected by the platform. About two-thirds of the effects are due to the inclusion of additional data, while the remainder is due to a more sophisticated underwriting model. Leveraging exogenous variations in credit access, we show that funding loans to invisible primes leads to better economic outcomes for borrowers.

6th CFPB Research Conference, 5th Annual IMF Macro-Financial Research Conference, Eighth ECB Annual Research Conference 2023, and 4th Future of Financial Information Conference for helpful comments. We thank Upstart Network, Inc. for providing access to its data. Special thanks to Don Carmichael for his assistance in setting up access to the data infrastructure on the cloud and for his assistance in navigating

Redistributive Effects of AI

Q. How can AI lead at the same time to better credit access for "invisible primes"

. . . and to worst credit access for people who went to minority-attended colleges?

⇒ More data create winners and losers

"winners:" those whose data reveal good things

"losers:" those whose data reveal bad things

AI and Discrimination

Q. How can AI lead to (indirect) discrimination even though algorithms do not use protected characteristics?

$\Rightarrow$ Screening on variables correlated with protected characteristics may unintendedly screen on protected characteristics

- e.g., college attended correlates with race

- A solution: algorithm interpretability

Group Work: Lending Game

- 3 fintech lenders (=3 teams of students) compete to make loans
- Data on past loans: predictors + default
- New loan applications
- All teams have data on the same past loans and receive the same new loan applications, but each team has different predictors
- The game (detailed guidelines on Slack)

Stage 0: NOW Form teams of 4±1 persons and email your team's composition by the end of the class today to hombert@hec.fr

Stage 1: Each team makes an offer to every loan applicant → offers due on October 16 (October 15 afternoon is free)

Each loan applicant chooses which team's loan offer to take. Applicants repay or default → profits and losses for each team

Stage 2: Each team improves its strategy based on the experience of stage 1 and play the same game again → offers + report due on October 26 (October 20 morning is free)

Until Tomorrow

- Email me the composition of your team for the lending game

- Complete the practice problems on market efficiency

See you tomorrow!

😉