



# Algorithmic Credit Scoring

Katja Langenbucher

langenbucher@jur.uni-frankfurt.de



# Credit scoring – from intuition to statistics

- Historically, loan decisions were based on an (often intuitive) mix of qualitative and quantitative information
- Cognitive errors and implicit biases occurred frequently
- Fair Isaac & Co. introduced statistical probability



# Credit scoring – from statistics to artificial intelligence

- The FICO score relies on a fixed number of standardized input variables
- A.I. scoring vastly expands input variables by finding correlations from past data sets
- It thereby promises better access for borrowers who (for a variety of reasons) don't have the credit history to inform the traditional factors



# Credit scoring – A.I. and behavioral tracking

The EFL assessment captures more than 25 personality traits. The most relevant are locus of control, fluid intelligence, impulsiveness, confidence, delayed gratification and conscientiousness. These traits let us identify applicants who are likely to repay their loans.



- Further input variables include:
  - Education, area of study, SMS logs, GPS data, the time it takes to fill out an application, the amount of spelling mistakes in text messages, the frequency of charging your smartphone battery and more
- Many of these variables seem neutral, yet manifest implicit bias
  - Algorithms may incorporate variables that are proxies for protected classes (race, gender, religion, etc.), or create new proxies in the modelling process

# Data privacy – U.S. *v* EU

	Lender	Scoring Agency
U.S.	<p>Gramm-Leach-Bliley Act: personal data</p> <ul style="list-style-type: none"> <li>- Access, safeguard</li> <li>- Notification when sharing with non-affiliated parties</li> <li>- Opt out: sometimes</li> </ul> <p>FCRA: only applicable to credit report data (see right)</p>	<p>FCRA</p> <ul style="list-style-type: none"> <li>- „consumer reporting agency“</li> <li>- „consumer report“</li> <li>- Permissible purpose necessary (only) for <u>furnishing a report</u> to a third party (not for collecting)</li> <li>- Borrower rights to disclosure of score, rectification of incorrect data, fault-based claims for compensation for damages</li> </ul>
EU	<p>GDPR</p> <ul style="list-style-type: none"> <li>- Lender is considered a data processor</li> <li>- Legitimate reason for <u>any collection and processing</u> of data               <ul style="list-style-type: none"> <li>(i) „freely given consent“ (ii) Explicit consent for protected categories</li> </ul> </li> <li>- Strict rules on profiling</li> <li>- Strict rules on decisions based solely on automated processing</li> <li>- Rights of access, rectification, erasure, data portability, restrictions of processing, strict compensation for damages</li> </ul>	<p>GDPR</p> <ul style="list-style-type: none"> <li>- Scoring Agency is also a data processor (see left)</li> </ul>

# A.I. scoring & data privacy: Planet49

- Planet49 organised a promotional lottery on its website.
- Participants were redirected to a page with a pre-checked box, agreeing to have a web analytics service evaluate their behavior on websites of advertising partners
- European Court of Justice: „Art. 4, 6 GDPR must be interpreted as meaning that (...) consent (...) is not validly constituted (...) in the form of cookies (...) by way of a pre-checked checkbox which the user must deselect to refuse his or her consent“



Reports of Cases

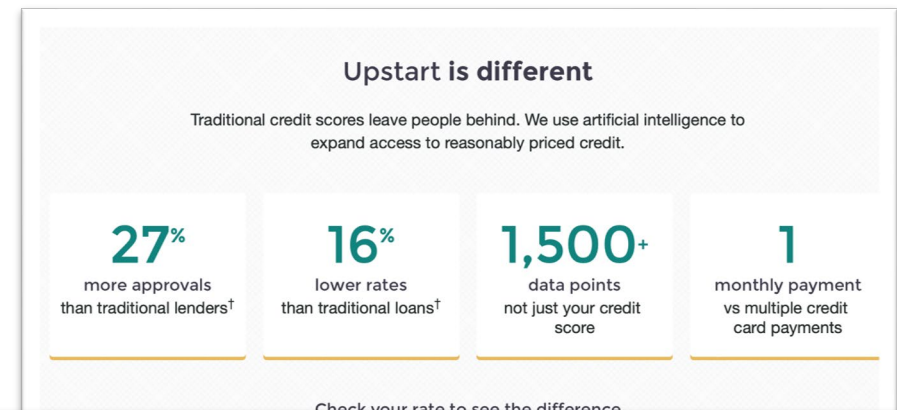
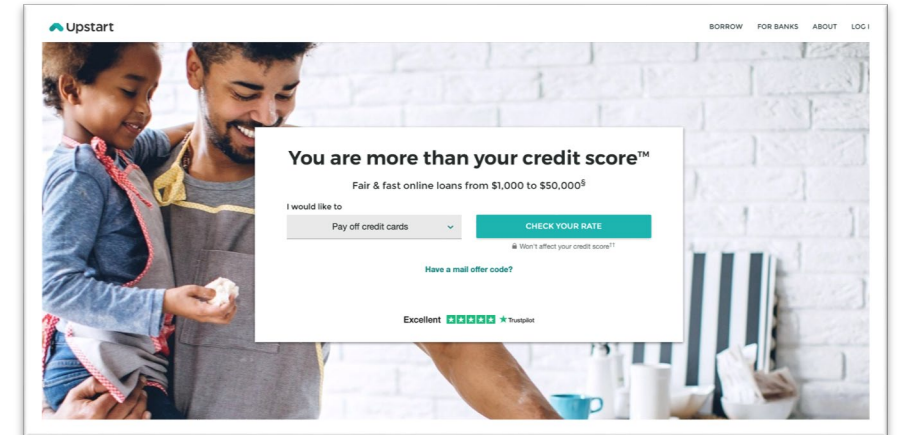
JUDGMENT OF THE COURT (Grand Chamber)

1 October 2019\*



# A.I. scoring & disparate impact: upstart.com

- Upstart operates an online lending platform, targeting attractive (!) borrowers with a „thin file“
- Borrowers are asked to provide their educational history, name colleges/graduate schools and degrees.



† As reported by the [Consumer Financial Protection Bureau](#), based on an internal Upstart study which compares outcomes from Upstart's underwriting and pricing model against outcomes from a hypothetical model that uses traditional application and credit file variables and does not employ machine learning (traditional lending model).

# A.I. scoring & disparate impact: upstart.com

- Upstart obtained a No-Action Letter with respect to the ECOA's prohibition of discriminatory lending practices
- Disparate impact requires...
  - Understand the relevant proxy – „educational redlining“
  - Define the groups to be compared – do only the „similarly situated“ count?
  - Decide on the level of acceptable outcome disparity – when do we see „significantly different effects“?
  - Understand defenses – „legitimate aims“, „business necessity“ and banking supervisory concerns



1700 G Street NW, Washington, DC 20552

September 14, 2017

Thomas P. Brown  
Paul Hastings, LLP  
55 Second Street, 24<sup>th</sup> Floor  
San Francisco, CA 94105

Dear Mr. Brown

This letter is in response to a Request for a No-Action Letter ("Request"), filed with the Consumer Financial Protection Bureau ("Bureau") by Upstart Network, Inc. ("Upstart"). Bureau staff has considered and grants Upstart's Request, and accordingly issues this No-Action Letter ("No-Action Letter") pursuant to the Bureau's Policy on No-Action Letters.<sup>1</sup>

Staff has no present intention to recommend initiation of an enforcement or supervisory action against Upstart with regard to application of the Equal Credit Opportunity Act (ECOA)<sup>2</sup> and its implementing regulation, Regulation B,<sup>3</sup> to Upstart's automated model for underwriting applicants for unsecured non-revolving credit, as that model is described in the Request and confidential Model Risk Management & Compliance Plan ("Compliance Plan"). This staff intention is subject to the statements and commitments set forth in the Request, the Compliance Plan, and Appendix A to this No-Action Letter.

## ML models that increase access to capital for all can still adversely impact protected classes

Lenders rely on "legitimate business necessity" to continue using less powerful models

	Old Model Approval Rate	New Model Approval Rate	Approval Impact Ratio
Overall	50%	60%	
White, Non-Hispanic	55%	65%	
African American	40%	50%	77%
Hispanic	45%	55%	85%
Asian	49%	58%	89%
Other	49%	58%	89%



# Discrimination – U.S. *v* EU

	Direct discrimination/ Disparate treatment	Indirect discrimination/ Disparate impact	Defenses
U.S.	ECOA <ul style="list-style-type: none"> <li>• Discriminatory treatment</li> <li>• Requires notification/ explanation why loan request is denied</li> <li>• Civil liability</li> </ul>	<ul style="list-style-type: none"> <li>• SCt.: disparate impact only in housing &amp; employment law</li> <li>• CFPB/some courts: suggest application as to ECOA</li> </ul>	<ul style="list-style-type: none"> <li>• No alternative practice with less discriminatory results</li> <li>• Manifest business necessity</li> </ul>
EU	<ul style="list-style-type: none"> <li>• Anti-discrimination Directives</li> <li>• Fundamental Human Rights</li> <li>• Liability: Member States</li> </ul>	Accepted general principle	<ul style="list-style-type: none"> <li>• Legitimate aim</li> <li>• appropriate and</li> <li>• necessary means</li> </ul>

# Going forward

## ➤ Data privacy

- Consent & Scoring
- Scoring and enforcement

## ➤ Anti-discrimination

- Detecting variables
- Protecting trade secrets
- Weighing discrimination against financial stability