Inf2 – Foundations of Data Science
S2 Week 6: Project Q&A and Ethics of supervised learning

THE UNIVERSITY *of* EDINBURGH
informatics

FOUNDATIONS OF DATA SCIENCE

Agenda

- Project Q&A
- Ethics and law in supervised learning

RTM

- This session is an overview and opportunity for questions
- Full instructions, FAQ and Rubric are in Learn
- Please try reading them fully for details, before asking for clarification

Project admin information

- Project description available in **Assessment->Coursework 2: Project** in Learn
- This is a **marked** assignment which will count towards **40%** of your final grade for **Inf2-FDS**
- **Submission deadline:** Friday 28 March at 12:00 UK time
- This coursework uses the Informatics Late Submission of Coursework Rule 1: Extensions are permitted (3 days) and Extra Time Adjustments (ETA) are permitted and can be combined.

Project aim

- The goal of the project is to go through the complete data science process to answer a question. You will:
    - Acquire the data, explore and visualise it
    - Apply basic techniques from descriptive and inferential statistics and machine learning
    - Interpret and describe the output from your analysis
    - Communicate the results so that there is a clear story.

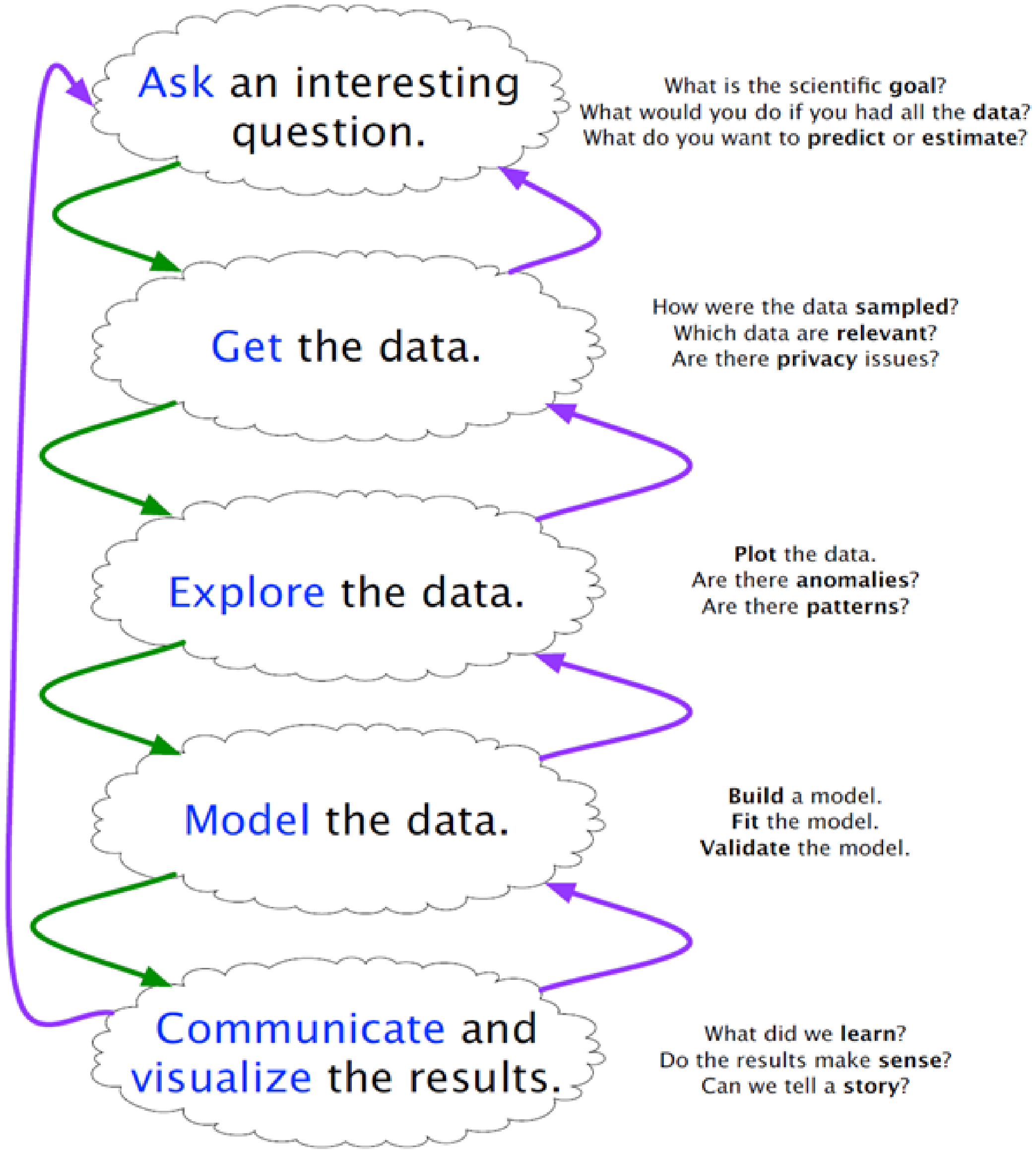


Image taken from Harvard CS109

Dataset options – more details and questions in instructions

- Heat and electric data from Appleton Tower since 2016
- Video game data from the Steam catalogue
- University of Edinburgh course data

Two **requirements** for submission

- A short report of your project written in LaTeX
  - Submitted using Gradescope and marked using rubric on Learn
- Jupyter notebooks and/or python files containing the code
  - Submitted as zip file to Learn, not marked, but used in cases of doubt

Optional, but encouraged:

- Project survey
- Feedback on your progress during the project period

Final Report Structure

- Overview
- Introduction
- Context and Motivation
- Objectives/questions
- Data Description
- Exploration and Analysis
- Discussion and Conclusion

- Page limit: 6 pages, excluding references, including visualisations and tables
- LaTeX template provided in Overleaf – take a copy of this template: https://www.overleaf.com/read/yzbyfvyvtyjg#0f70cd

PUT THE TITLE OF YOUR PROJECT HERE

PUT YOUR EXAM NUMBER HERE

24th February 2025

1 Overview

2 Introduction

Context and motivation

Previous work E.g. Recent surveys show that most students prefer final projects to final exams [3].

Objectives

3 Data

Data provenance

Assessment criteria

- Rubric now available on **Project Instructions** page in Learn
- See **Assignment Brief** in Learn **Assessment** section for overview of how we mark
  - Note some details in Assignment brief, e.g. dates, have changed since it was written before the start of the Academic Year.

Rubric

Markers will mark your project according to this rubric. For more details on the marking procedure, see the FDS Assignment Brief in the Assessment section.

Name	Marks	Description	Absent	Inadequate	Poor	Fair	Good	Excellent
Overview	5	Clear and full overview section	No or very minimal overview section given. Omits description of problem, work carried out and overall results.	Minimal overview section that omits one or several of the following: description of problem, work carried out and/or overall results.	Overview section that contains a description of problem, work carried out and overall results, but there may be major problems (e.g. inaccuracies, or description has simply been copied from the project instructions).	Full overview section that contains an original description of problem, work carried out and overall results, but several minor problems may be present.	Clear and full overview section; no problems, but there may be some debatable / subjective points.	Very clear and full overview section; only very minor suggestions (if any) as to how the overview could be improved.
				Minimal introduction given. Aims or		Aims or motivation are	Aims and	Aims or motivation are

Assignment Brief 24-25

INF2-FDS 2024-25.pdf

Page 1 of 6

Course information from DRPS

Course acronym	INF2-FDS
Course code	INFR08830
Credits	20

Support

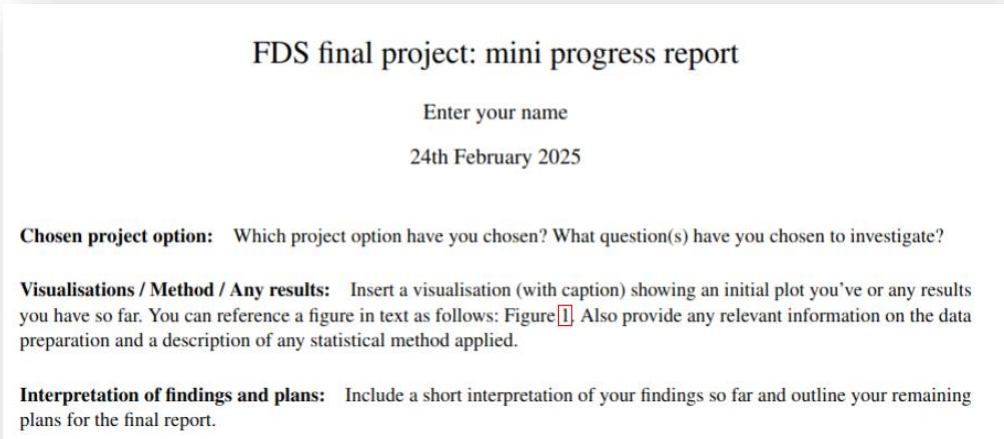
- Exemplars from previous years in Learn
- InfPALS have done LaTeX tutorials - and more info later
- Writing Q&A session in Week 8
- Look at the FAQ on Learn
- Feel free to ask questions on Piazza
  - If in doubt make them private
- Feedback via presentations or project update (last year's students appreciated them)
- Office hour: Now **Monday at 4pm after the lecture. This week we'll try downstairs in 40GS in the seating area beside LG07.**

Feedback via written update or presentations (not for credit)

By week 7 (Monday) say whether you will either:

- Be attending a week 8 or 10 workshop to present an update on your project
  - e.g. at least one visualisation

- Or submitting a written one-page document of your update to receive some written feedback on
  - Please use given latex template: https://www.overleaf.com/read/ktmrsbwgmwjn#9f6061
  - If doc goes on to two pages, it's OK



FDS final project: mini progress report

Enter your name

24th February 2025

Chosen project option: Which project option have you chosen? What question(s) have you chosen to investigate?

Visualisations / Method / Any results: Insert a visualisation (with caption) showing an initial plot you've or any results you have so far. You can reference a figure in text as follows: Figure 1. Also provide any relevant information on the data preparation and a description of any statistical method applied.

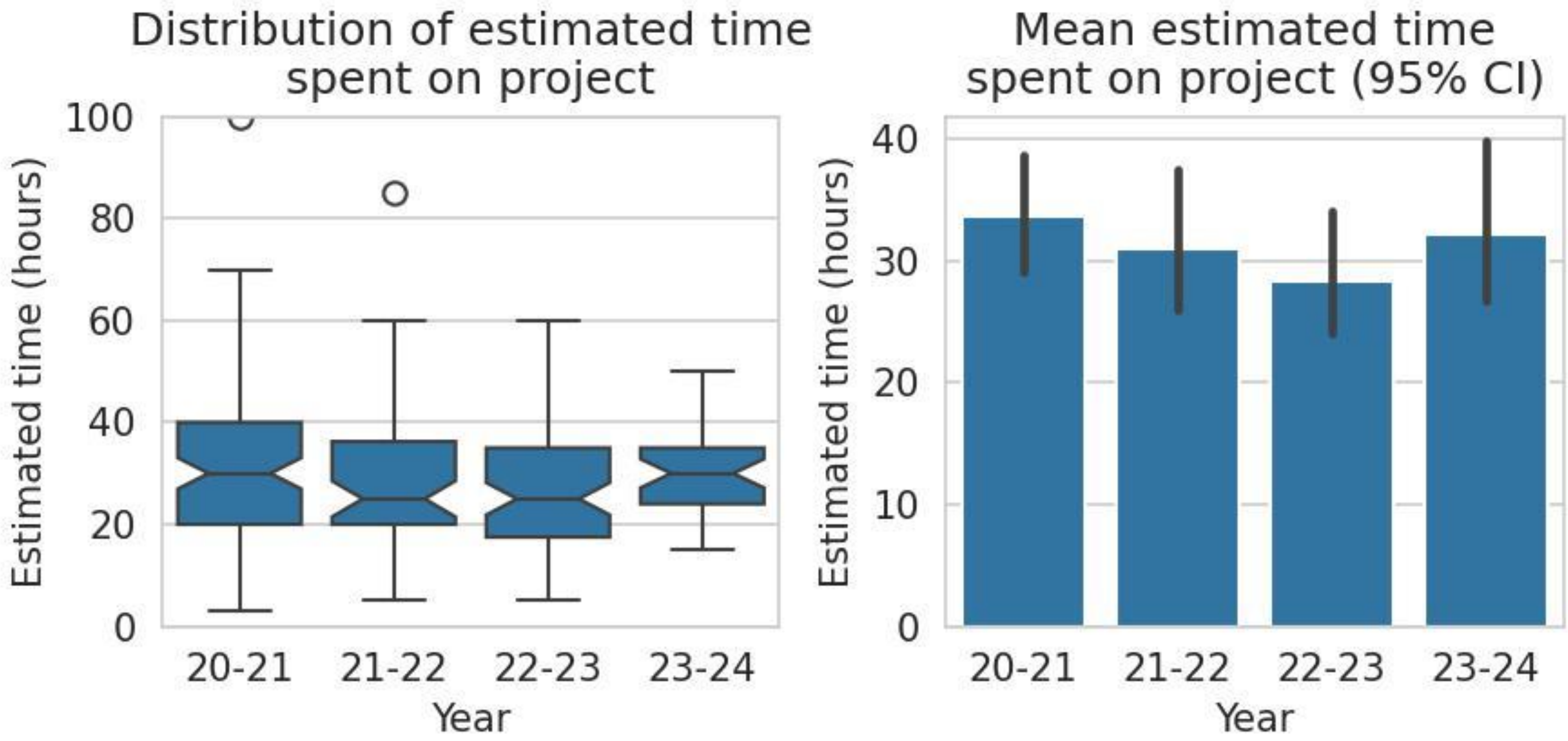
Interpretation of findings and plans: Include a short interpretation of your findings so far and outline your remaining plans for the final report.

If opting to present (not for credit)

- You will sign up to a presentation slot in week 8 or 10 that happen during usual workshop slots
  - Details to follow
- We'll split workshop into two rooms
- You'll give a *short* presentation to your group and tutor
- The presentation is intended:
  - to be low-stress
  - to help you reflect on your progress
  - to get feedback from your tutor and peers.

How long should you work?

- 6 hours a week for 5 weeks => about 30 hours, close to the median and mean times from previous years.

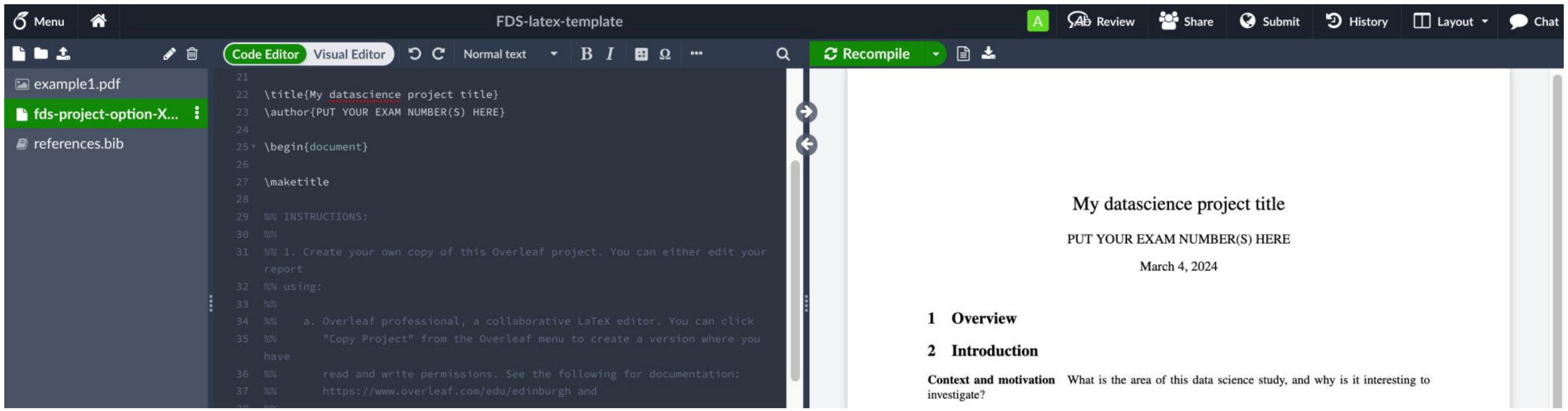


Some FAQs on Learn

- Do I have to answer the main question exactly as given on the project description sheet?
  - The main question can be addressed in a number of ways – it might help to reframe as a more precise question
- Do I need to use one technique from each of descriptive stats, inferential stats and ML?
  - You **do not,** but **do** use techniques that make sense make a convincing argument
- Yes, please feel free to look for extra data
  - but question how much it adds
- Yes, feel free to use extra libraries or techniques
  - But be careful about doing complicated things before simple things

Why LaTeX?

- Consistent format, especially with margins and font sizes
- Used for academic papers in computer science
- Excellent for typesetting maths
- Used for the UG4 project
- Git can be used to track LaTeX code (also using Overleaf)



LaTeX resources

- *"Something that I would suggest for future years is to add a bit of course content about how to use Latex, since at least for me I had no experience whatsoever and I would have appreciated having some background on it."* - FDS Student in 2021/22
- InfPALS tutorials
- UoE Digital Skills training: https://edin.ac/3Qv8xdR
- https://www.overleaf.com/events/webinars

Writing your project report

- **Don't worry!** Writing is hard, but the more you do, the better you get.
- **Don’t wait.** Write. Poor writing is the enemy of great ideas!
- We'll have writing workshop in Week 8
- Advice from previous FDS student: *"Do work regularly, submit early, write a draft for report early."*

Questions & RTM

- Questions?
- Full instructions, FAQ & Rubric are in Learn
  - Please refer to them first ...
  - … then ask for clarifications

Inf2 – Foundations of Data Science
S2 Week 6: Ethical and legal issues in supervised learning

Overview

- Fairness in classification and protected attributes
- Credit scoring case study

Fairness in Classification

Advertising

Education

Financial aid

Banking

Health Care

Insurance

Taxation

many more…

Prediction = Judgement

Prediction = judgement. It affects the lives of real people.

- Recidivism prediction for granting bail
- Predicting credit worthiness to give loans
- Predicting success in school/job to decide on admission/hiring

Are people being treated as they deserve?

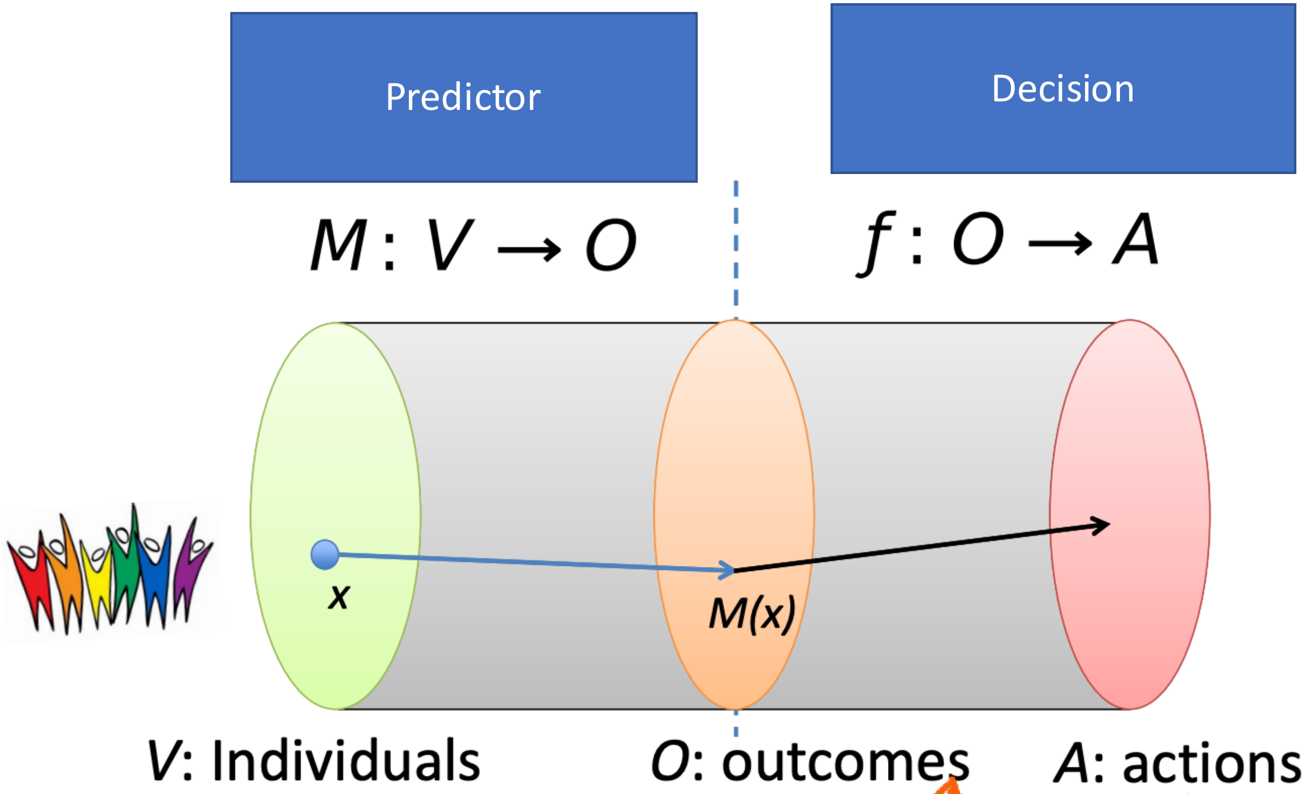
One concern

- Certain attributes should be irrelevant to decisions.
- Example: gender, sexual orientation, minority groups – ethnic, religious, medical, geographic, etc…
- Protected by law!
- Discrimination arises even without intent

Example

- Google+ tries to classify real vs fake names
- Fairness problem:
  - Most training examples standard white American names: John, Jennifer, Peter, Jacob, ...
- Ethnic names often unique, much fewer training examples Likely
- Outcome: Prediction accuracy worse on ethnic names

From Invididuals to decisions and another concern



Human in the loop

Human in the loop

GDPR

The data subject should have the **right not to be subject to a decision**, which may include a measure, evaluating personal aspects relating to him or her which is **based solely on automated processing and which produces legal effects concerning him or her** or similarly significantly affects him or her, such as automatic refusal of an online credit application or e-recruiting practices without any human intervention.

...

In any case, **such processing should be subject to suitable safeguards,** which should include specific information to the data subject and the right to obtain human intervention, to express his or her point of view, to obtain an explanation of the decision reached after such assessment and to challenge the decision.

Fairness in Algorithmic Decision Making

1. Why fairness is important
2. Credit scoring as an example
3. Overview of equality legislation
4. Case study: Andreeva G, Matuszyk A (2019) 'The Law of Equal Opportunities or Unintended Consequences: the impact of unisex risk assessment in consumer credit', *Journal of Royal Statistical Society, Series A*, https://rss.onlinelibrary.wiley.com/doi/10.1111/rssa.12494

Credit scoring

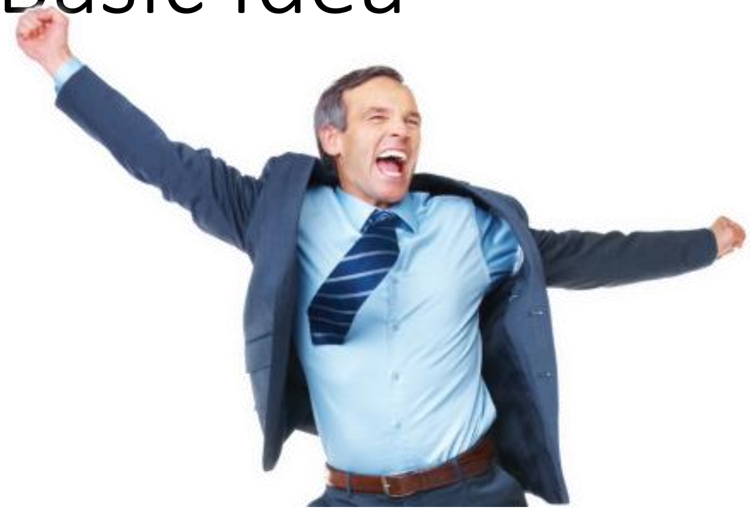
What is credit scoring?

- Decision support systems used in consumer credit
- Aims at risk assessment of:
  - potential borrowers (application scoring)
  - existing borrowers (behavioural scoring)
- Risk/creditworthiness is usually measured by **Probability of Default (PD)**
  - Larger value means higher risk
- PD is predicted from potential borrower's characteristics on the basis of the analysis of known performance of previous customers
  - Cf the lectures on Logistic Regression

Example of a scoring table

Time at current address	**Less than 6 months**	**6m – 2 years**	**2 – 6 years**	**6 - 10 years**	**10 + years**	**Unknown**	
	0	3	6	13	25	0	
Residential Status	**Owner**	**Tenant**	**With parents**	**Unknown**			
	15	5	2	0			
Banking	**Current account**	**Saving account**	**Current and saving**	**No account**	**Unknown**		
	5	10	14	0	0		
Occupation	**Retired**	**Full-time**	**Part-time**	**Self-employed**	**Student**	**Other**	**Un-known**
	21	16	7	6	5	10	0
Age	**18-25**	**26-31**	**32-40**	**41-54**	**55+**	**Unknown**	
	5	10	15	20	25	0	

The Basic Idea



5 years at current address + 6

Home Owner + 15

Current and Saving Account + 14

Full Time Work + 16

40 years old + 15

Score 66

6 months at current address + 3

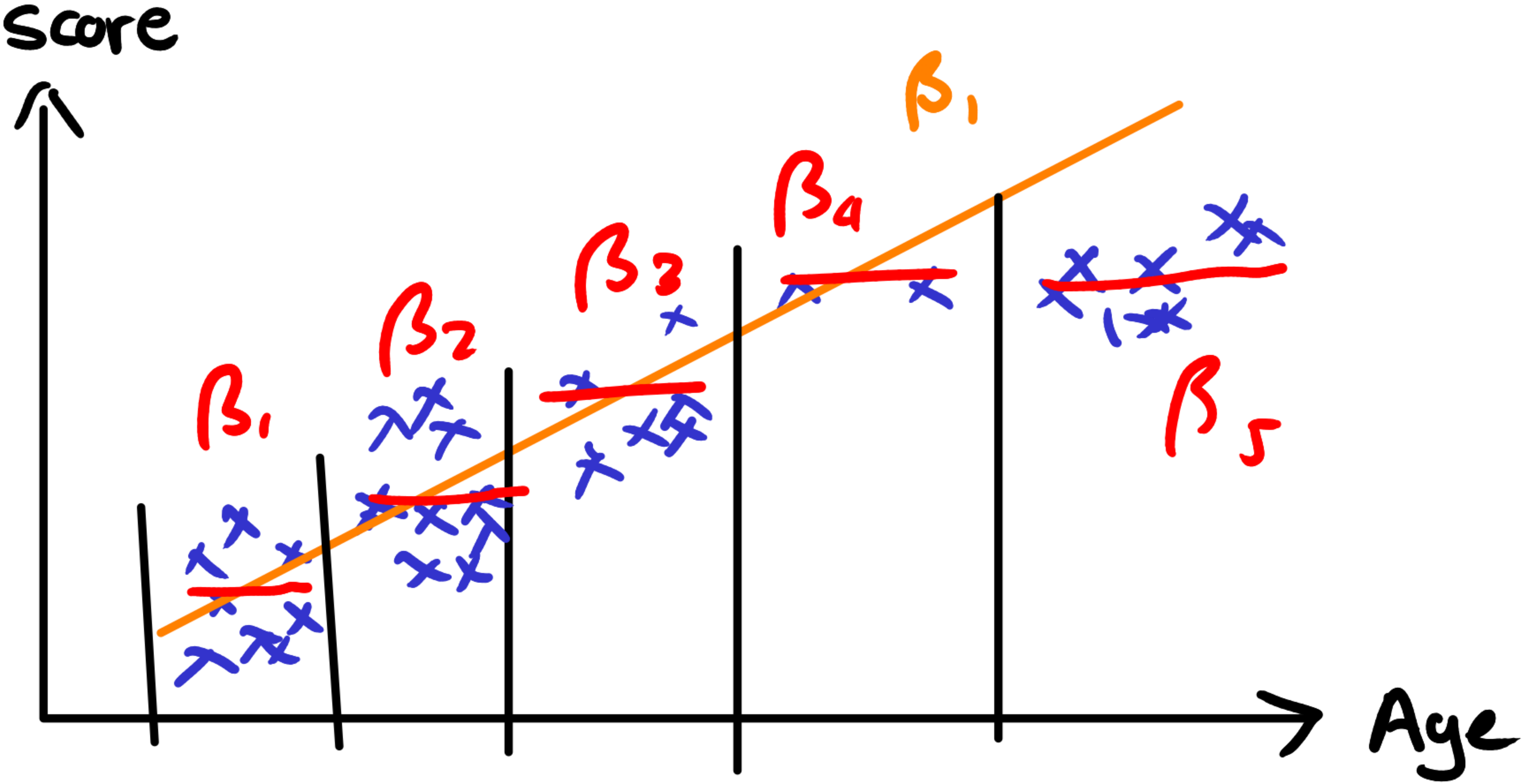
Tenant + 5

Current Account + 5

Self-Employed + 6

20 years old + 5

Score 24



Score
Age
β_1
β_1
β_2
β_3
β_4
β_5

Equality legislation

Equality/Anti-Discrimination Legislation

USA

Equal Credit Opportunity Act (ECOA, 1974) prohibits characteristics from being used in credit scoring (race, colour, national origin, gender, marital status, religion, receipt of public assistance, or exercise of consumer protection rights). Age has a special status.

EU

Articles 8, 19 of the Treaty of the Functioning of European Union (TFEU);

Gender Directive - Council Directive 2004/113/EC of 13 December 2004

Proposal for a Council Directive on implementing **the principle of equal treatment** between persons irrespective of religion or belief, disability, age or sexual orientation, COM(2008) 426 final.

UK

Equality Act (2010)

Protected characteristics under UK Equality act

- Age - unless good reason (‘objective justification’) can be shown for the differential treatment
- disability
- gender reassignment
- marriage and civil partnership
- pregnancy and maternity
- race
- religion or belief
- sex
- sexual orientation

Data description

- Portfolio of auto loans from a major bank in an EU country from 2003-2010
- Default definition is defaulting on the loan for 2 months (65 days)
- 80% (training) and 20% (test)

	Training			Test		
	Good	Bad	Total	Good	Bad	Total
Female	16746 98.70%	220 1.30%	16966 26.71%	4186 98.70%	55 1.30%	4241 26.71%
Male	45696 98.18%	847 1.82%	46543 73.29%	11424 98.18%	212 1.82%	11636 73.29%
Total	62442 98.32%	1067 1.68%	63509	15610 98.32%	267 1.68%	15877

Research design

- Four Logistic regression models to predict Probability of Default:
    1. Model with *Gender* (training sample comprising both men and women)
    2. Model without *Gender*
    3. Model trained and tested only on men
    4. Model trained and tested only on women
- The models are compared from the points of view of
    1. how they affect the chances of men/women being offered credit
    2. predictive accuracy

Relevant variables

There are 11 final variables selected by significance and predictive accuracy

- Marital status
- # kids
- Income
- Time in employment
- Profession
- Phone given
- Gender
- Loan duration
- Downpayment
- Car price
- Car age

Table 2. Parameter estimates (with standard errors are in parentheses) and model fit statistics for four logistic regression models to predict the PD†

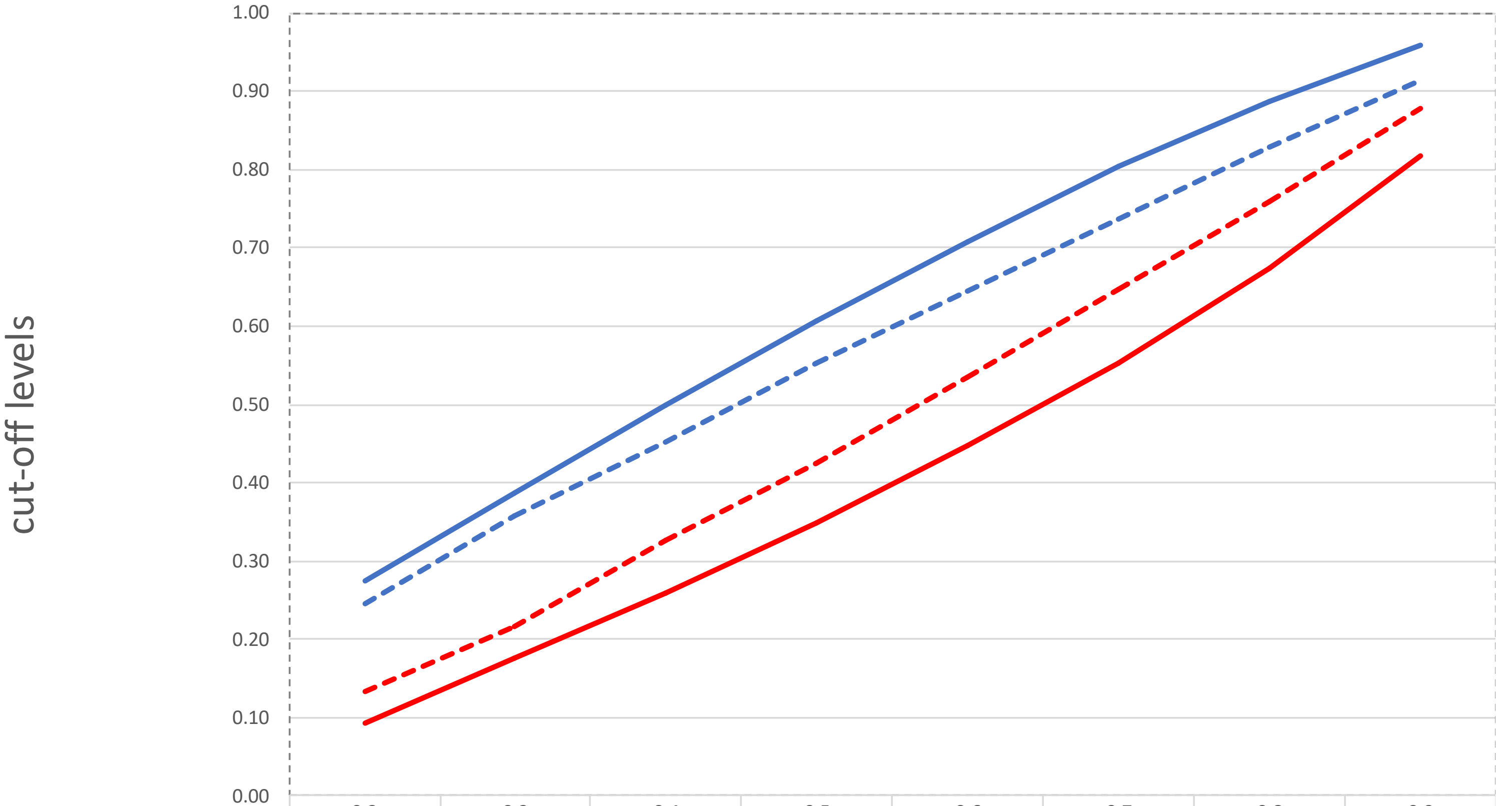
Variable	*Attribute or category*	*% in category*	*Results for model with gender (model 1)*	*Results for model without gender (model 2)*	*Results for model for men only (model 3)*	*Results for model for women only (model 4)*
Intercept			−7.3942‡ (0.1722)	−7.5207‡ (0.1708)	−7.6844‡ (0.2073)	−7.0066‡ (0.3135)
Gender	Female	26.71	−0.457‡ (0.0867)			
Number of children (reference: no kids)	1 kid	23.26	0.19 (0.1009)	0.1525 (0.1000)	0.267§§ (0.1219)	0.1248 (0.1874)
	2 kids	15.04	0.1918 (0.1302)	0.1763 (0.1298)		
	3+ kids	3.12	0.3553 (0.2313)	0.3494 (0.2310)		
	Missing information	10.87	−0.6816‡ (0.1254)	−0.6944‡ (0.1251)		
Car price (reference: medium price lower)	Cheap	5.28	−1.0987‡ (0.1326)	−1.1048‡ (0.1322)		
	Medium price higher	59.58	0.426§ (0.1099)	0.4406‡ (0.1095)		
	Expensive	15.87	1.1813‡ (0.1116)	1.1955‡ (0.1112)		
Down payment, % (reference: (35%, 50%])	⩽25%	16.87	1.2702‡ (0.1087)	1.2603‡ (0.1085)		
	(25%, 35%]	8.65	0.7133‡ (0.1248)	0.7096‡ (0.1246)		
	>51%	34.49	−1.2147‡ (0.1940)	−1.2075‡ (0.1941)		
Car age, years (reference: [0, 2))	2	1.56	1.311‡ (0.1454)	1.3197‡ (0.1448)		
	[3,4)	3.25	1.8426‡ (0.1196)	1.8691‡ (0.1191)		
	>4	3.31	2.5302‡ (0.1348)	2.5635‡ (0.1343)		

Questions

1. In the model with gender, is gender significant?
2. Does being female make the probability of default greater or smaller?
3. And by how much?
4. What factors increase and decrease the probability of default the most?

‡ p-value < 0.0001.
§ p-value < 0.005.
§§ p-value < 0.05.

Rejection rates by Gender for all unmarried customers



	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
female (M2 no gender)	0.13	0.22	0.33	0.43	0.54	0.65	0.76	0.88
male (M2 no gender)	0.25	0.36	0.45	0.55	0.65	0.74	0.83	0.91
female (M1 with gender)	0.09	0.18	0.26	0.35	0.45	0.55	0.67	0.82
male (M1 with gender)	0.28	0.39	0.50	0.61	0.71	0.80	0.89	0.96

$\text{logit}(p) = \beta_0 + \Sigma\beta_i x_i$

Reject if
p > cut-off probability

E.g. with cut-off of 0.6:

- 45% of women will be rejected
- 71% of men will be rejected

Courtesy of Galina Andreeva

What can we conclude?

- Women benefit from the model with gender
  - Women have had lower default rates in the past
- When gender is removed in the sample studied chances of being accepted for credit decrease for women, but increase for men
- Women in the group sampled still benefit when gender is not included in the model
- Thus **equal treatment of individuals** by ignoring a protected characteristic does not lead to **equal outcome at the group level**
- Why is there still an effect?

Proxies

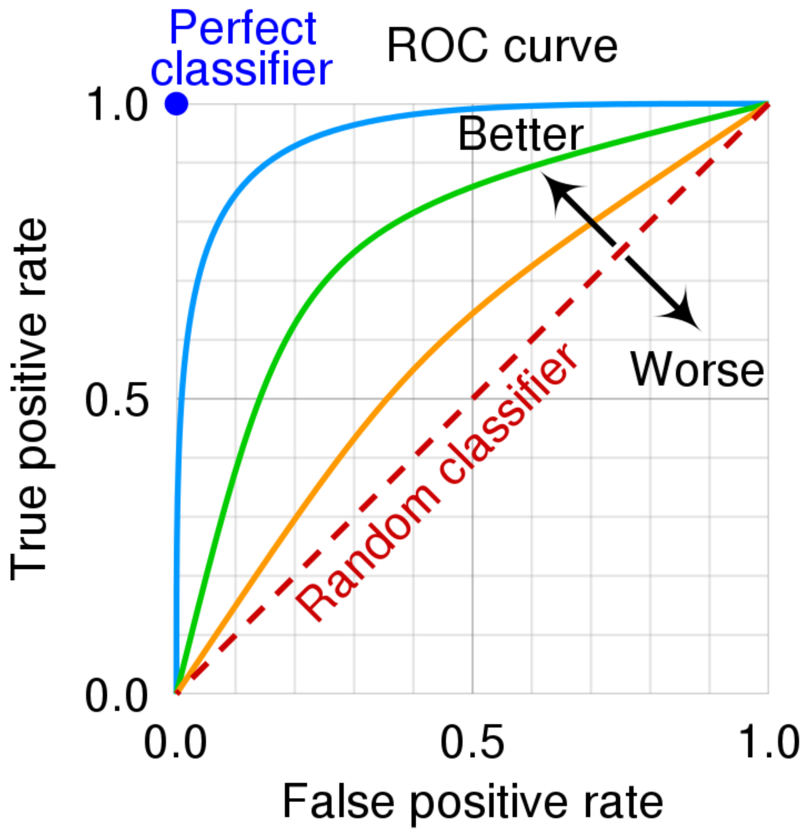
Table 2 (*continued*)

Variable	*Attribute or category*	*% in category*	*Results for model with gender (model 1)*	*Results for model without gender (model 2)*	*Results for model for men only (model 3)*	*Results for model for women only (model 4)*
Profession or occupation (reference: gender neutral)	Female profession	5.89	−0.5111§§ (0.1938)	−0.6108§ (0.1928)	−0.7843§§ (0.2827)	−0.2068 (0.2653)
	Male profession	13.08	−0.2709§§ (0.1134)	−0.224§§ (0.1129)	−0.2832§§ (0.1246)	−0.2767 (0.3003)
Model fit statistics						
Intercept AIC			10838.202	10838.202	8467.386	2351.084
Intercept and covariates AIC			6976.242	7003.602	5117.254	1833.609
Cox and Snell pseudo-R^2		0.0600	0.0600	0.0595	0.0707	0.0337
Nagelkerke pseudo-R^2		0.3823	0.3823	0.3796	0.4253	0.2606

†The reference category is given in parentheses under the corresponding variable name.
‡ p-value < 0.0001.
§ p-value < 0.005.
§§ p-value < 0.05.

Is the model without gender as accurate as the one with gender?

- To measure accuracy, use the metric of **Area Under the Curve (AUC)**
- To understand AUC, first understand the **Receiver Operator Characteristic** (ROC)



CMG Lee, Wikimedia Commons, CC BY-SA 4.0

[Demo at https://arogozhnikov.github.io/2015/10/05/roc-curve.html](https://arogozhnikov.github.io/2015/10/05/roc-curve.html)

Predictive accuracy, AUC

	Total sample		Men only		Women only	
	Model 1 with Gender	Model 2 without Gender	Model 1 with Gender	Model 2 without Gender	Model 1 with Gender	Model 2 without Gender
Train	0.9207	0.9211	0.9334	0.9331	0.8730	0.8739
Test	0.8901	0.8898	0.9147	0.9139	0.7965	0.7943

- Models with and without gender have near-equal prediction accuracy
- Prediction accuracy is lower for the group less represented in the training data

Discussion

- Equal treatment does not translate into equal outcomes
- Minority segments are dominated by majority ones
- It is not possible to completely remove the effect of a protected characteristic without deleting all correlated characteristics
- Conclusion in the paper: the existing law is not effective in promoting equality when it comes to algorithms
- What do we think?