Welcome to JAYWING!

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SheffieldML Meetup

Feb 19th 2018

AI in Credit Scoring - Putting Fairness First

Housekeeping

- No fire drills are expected
- In the event of an emergency…
  - Please leave your belongings and exit via the route you came in
  - You will be guided to an Assembly Point in the car park across the street
- There is a designated smoking zone at the rear of the building
- Toilets are located just down the corridor
- We ask that you **please do not take any photos** while you're here (GDPR compliance)

SheffieldML MeetUp

Sponsors

RAZOR
The Technology Works

sheffield technology parks

Our Code of Conduct - https://sheffield.digital/events/meetup-code-of-conduct


JAYWING

Data Science-led.

An Agency & Consulting business with a marketing technology division and the beginnings of an international footprint.

Our locations

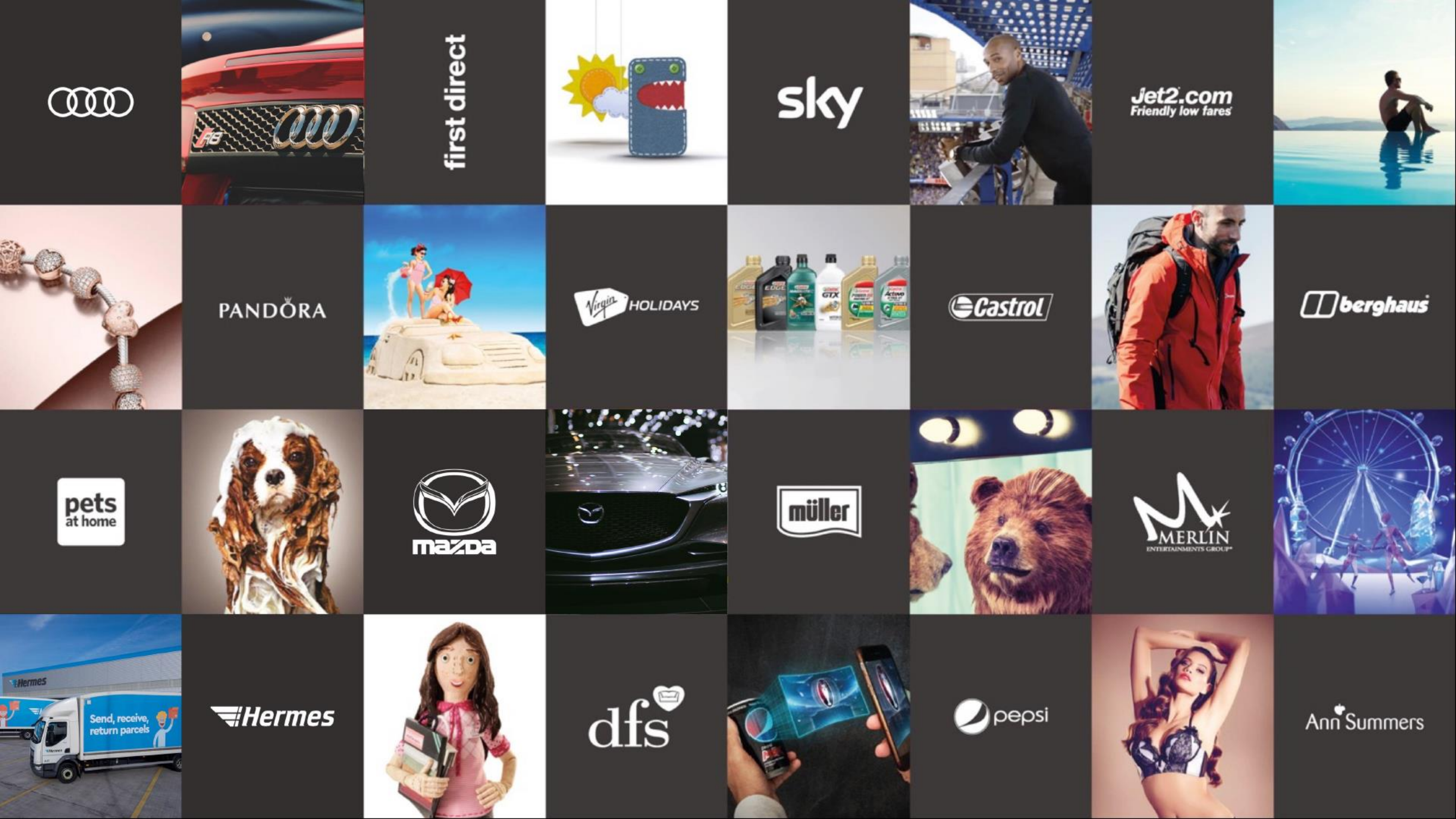
Our locations allow us to service clients across the UK, as well as in Australia's growing market.

Our people

At Jaywing, we employ over 450 people. One in six of them is an experienced data scientist, the rest are specialists in all of today's key data science, risk and marketing disciplines.

450+ people

1/6 data scientists



first direct
sky
Jet2.com
Friendly low fares
PANDORA
Virgin HOLIDAYS
Castrol
berghaus
pets at home
mazda
müller
MERLIN
ENTERTAINMENTS GROUP
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Hermes
dfs
pepsi
Ann Summers

AI CONSULTING

Applying Artificial Intelligence to real business challenges

Fairness and Bias in AI

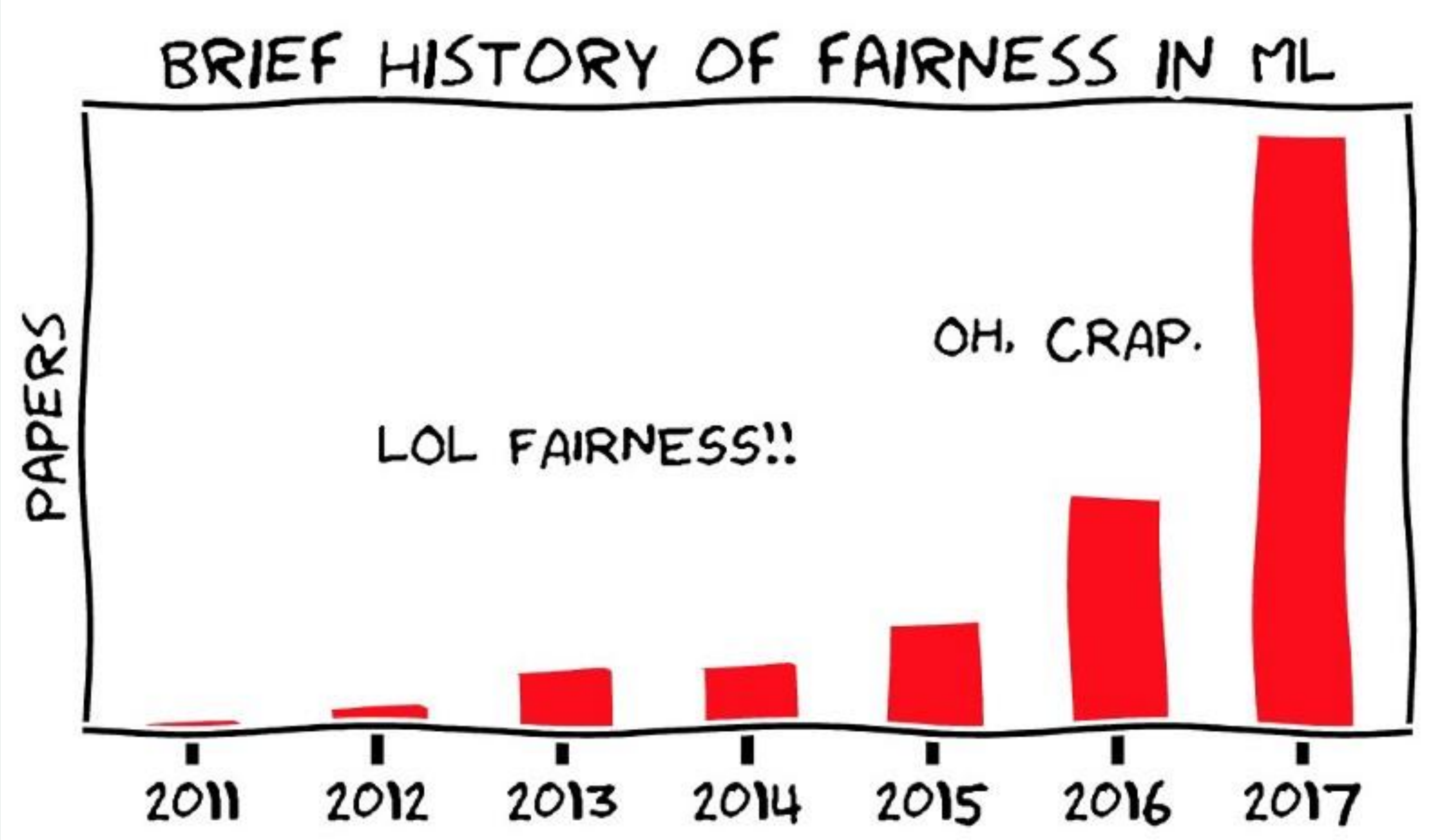

Image Credit: Moritz Hardt (https://fairmlclass.github.io)

Image Credit: Moritz Hardt (ht

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

Tolga Bolukb... Adam Kalai[2]

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$$\overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \approx \overrightarrow{\text{king}} - \overrightarrow{\text{queen}}$$

$$\overrightarrow{\text{man}} - \overrightarrow{\text{woman}} \approx \overrightarrow{\text{computer programmer}} - \overrightarrow{\text{homemaker}}.$$

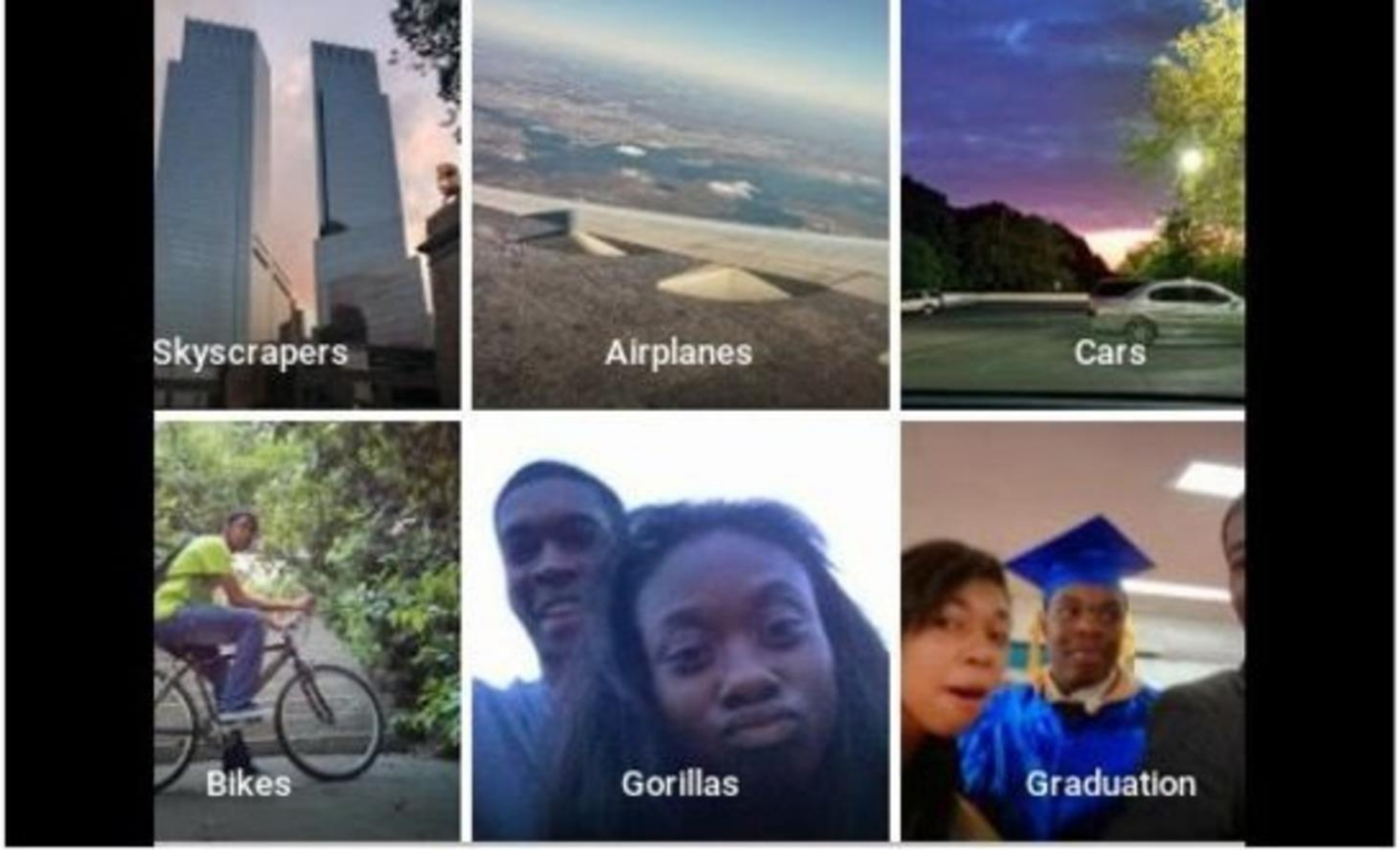
has been used in many machine learning and natural language processing tasks. We show that even

Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss



diri noir avec banan @jackyalcine · Jun 29

Google Photos, y'all [redacted] My friend's not a gorilla.

Bernard Parker, left, was rated high risk; Dylan Fugett was rated low risk. (Josh Ritchie for ProPublica)

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

On the (im)possibility of fairness*

Sorelle A. Friedler *Haverford College*[†]

Carlos Scheidegger *University of Arizona*[‡]

Suresh Venkatasubramanian *University of Utah*[§]

Abstract

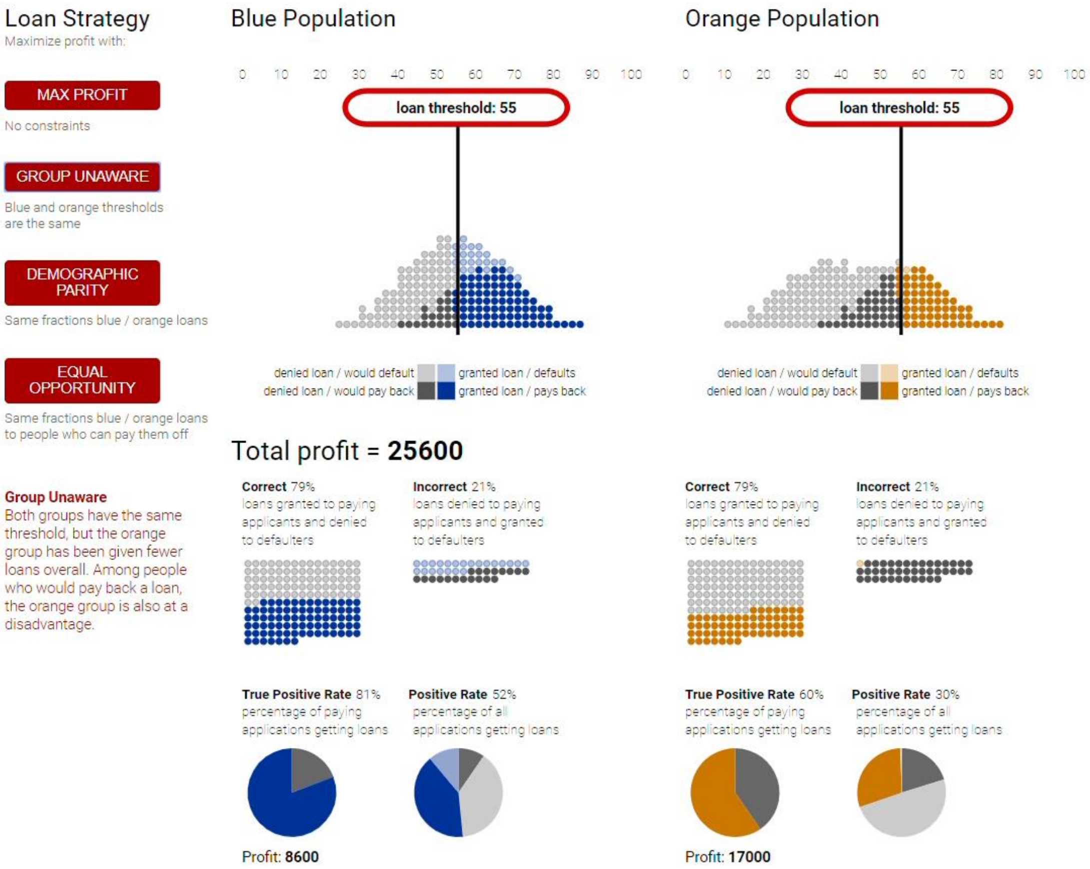
What does it mean for an algorithm to be fair? Different papers use different notions of algorithmic fairness, and although these appear internally consistent, they also seem mutually incompatible. We present a mathematical setting in which the distinctions in previous papers can be made formal. In addition to characterizing the spaces of inputs (the "observed" space) and outputs (the "decision" space), we introduce the notion of a *construct space*: a space that captures unobservable, but meaningful variables for the prediction. We show that in order to prove desirable properties of the entire decision-making process, different mechanisms for fairness require different assumptions about the nature of the mapping from construct space to decision space. The results in this paper imply that future treatments of algorithmic fairness should more explicitly state assumptions about the relationship between constructs and observations.

1 Introduction

Machine learning has embedded itself deep in
driven by humans. Whether it's resume filterin
or all components of the criminal justice pipeline, automated tools are being used to find patterns, make predictions, and assist in decisions that have significant impact on our lives.

The "rise of the machines" has raised concerns about the fairness of these processes. Indeed, while one of the rationales for introducing automated decision making was to replace subjective human decisions

Also:
Fair prediction with disparate impact: A study of bias in recidivism prediction instruments.
A. Chouldechova (2016)



https://research.google.com/bigpicture

Intro to Credit Scoring

Credit Scoring

Payment history	35%
Amounts owed	30%
Length of credit history	15%
New credit	10%
Types of credit used	10%

An example credit scorecard

Gross Annual Income	Points
<£15k	-20
£15k-£25k	0
£25k-£50k	+10
>£50k	+15

Employment Status	Points
Unemployed	-50
Self-employed	0
Employed part-time	+20
Employed full-time	+30

Worst Current Payment Status	Points
0 missed payments	0
1 missed payments	-25
2+ missed payments	-75
⋮	⋮

The points that are assigned to each attribute are optimised via **logistic regression**

The model parameters are estimated on a set of historic loan applications which have been labelled as “good” or “bad” based on whether or not the applicant failed to make payments

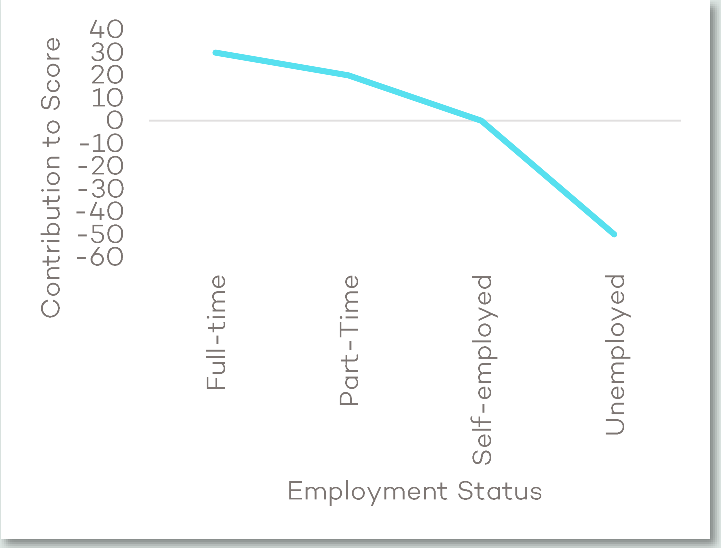
Points for every variable are summed to generate a total score

Credit scores typically contain 15-20 variables

Care is taken to ensure that model parameters follow intuitive patterns

Increasing salary should always mean increasing score

Being in full-time employment should always produce a higher score than being unemployed



Ensuring intuitive behaviours for each variable ensures that decisions are always fair and defensible

Tim

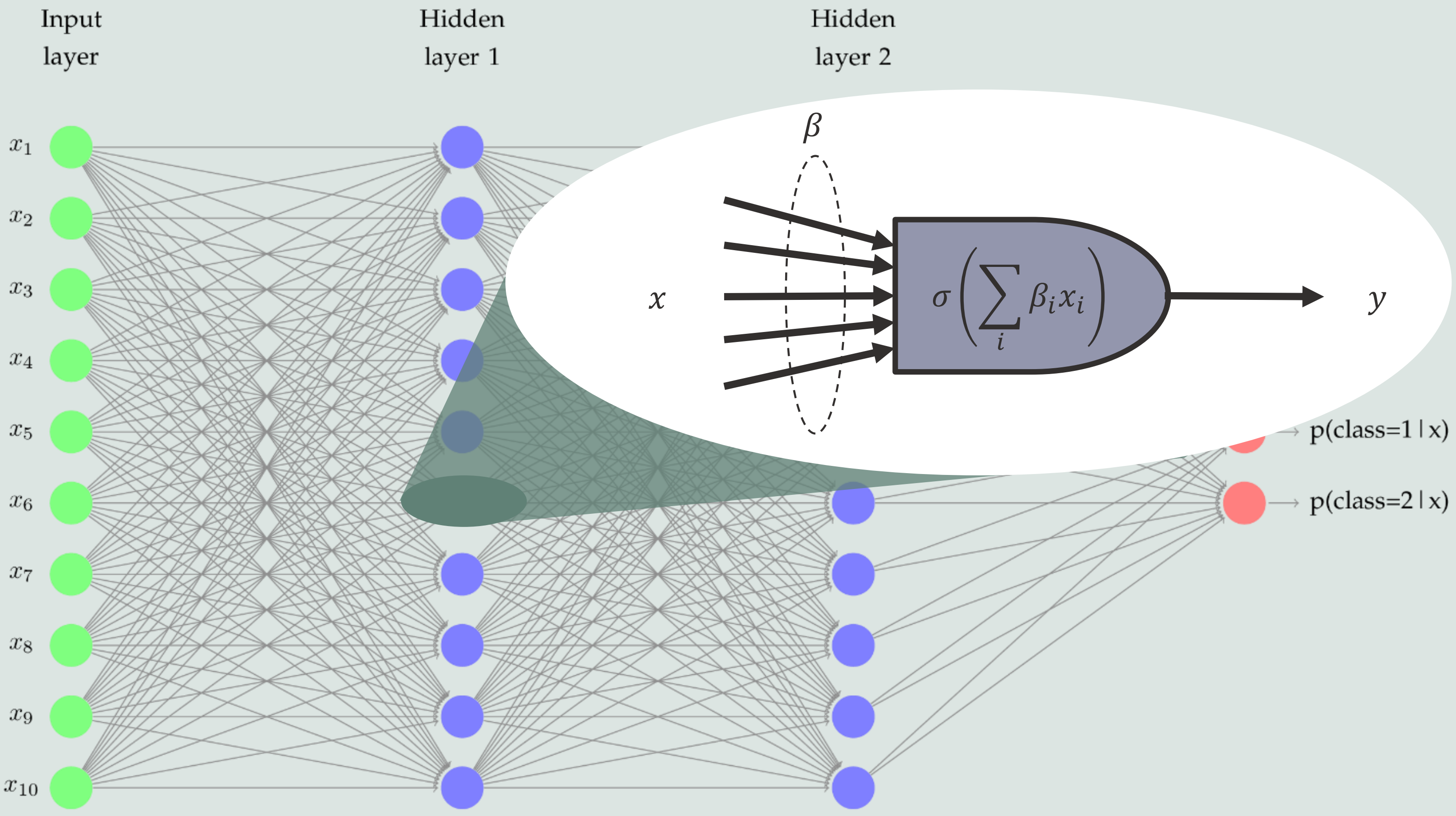
Age	28
Employment Status	Full-time
Annual Income	£30k
Number of Dependants	1
Prior County Court Judgements	2

Tom

Age	28
Employment Status	Full-time
Annual Income	£30k
Number of Dependants	1
Prior County Court Judgements	0

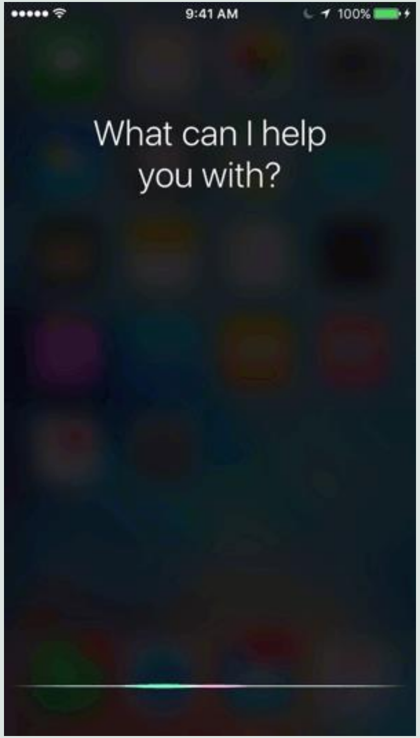

COMPUTER SAYS NO

Applying Deep Learning to Credit Scoring


Input
layer
Hidden
layer 1
Hidden
layer 2
x_1
x_2
x_3
x_4
x_5
x_6
x_7
x_8
x_9
x_{10}
β
x
$\sigma\left(\sum_i \beta_i x_i\right)$
y
p(class=1 | x)
p(class=2 | x)

Self-driving cars

Personal Assistants



...Tumor detection, machine translation, recommender systems, and more!...

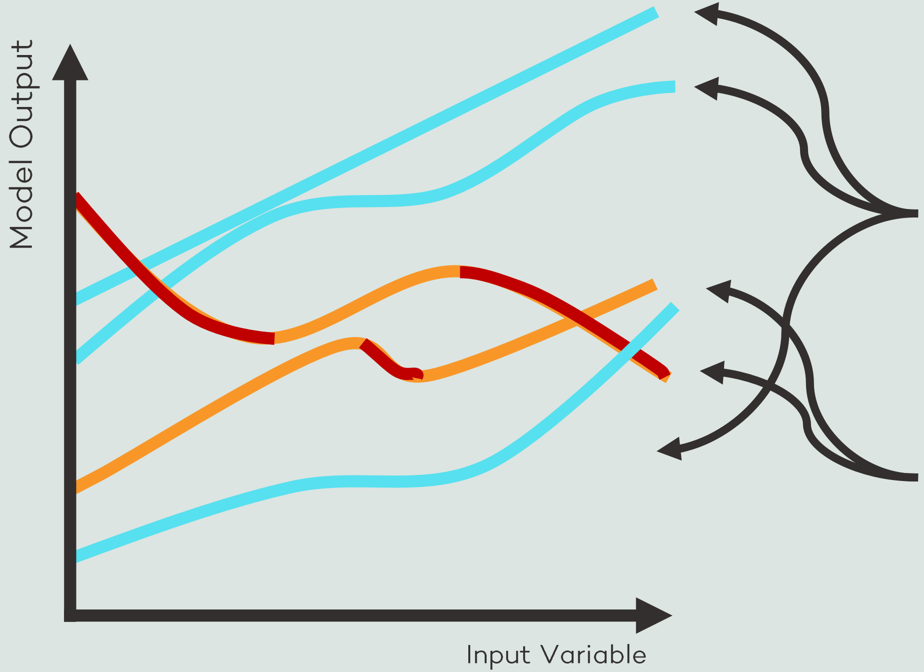
Investigations into use of Neural Networks for credit scoring in the 90s and 00s generated relatively little success

Slow to Train

Underwhelming Performance

Black Box

The black box problem

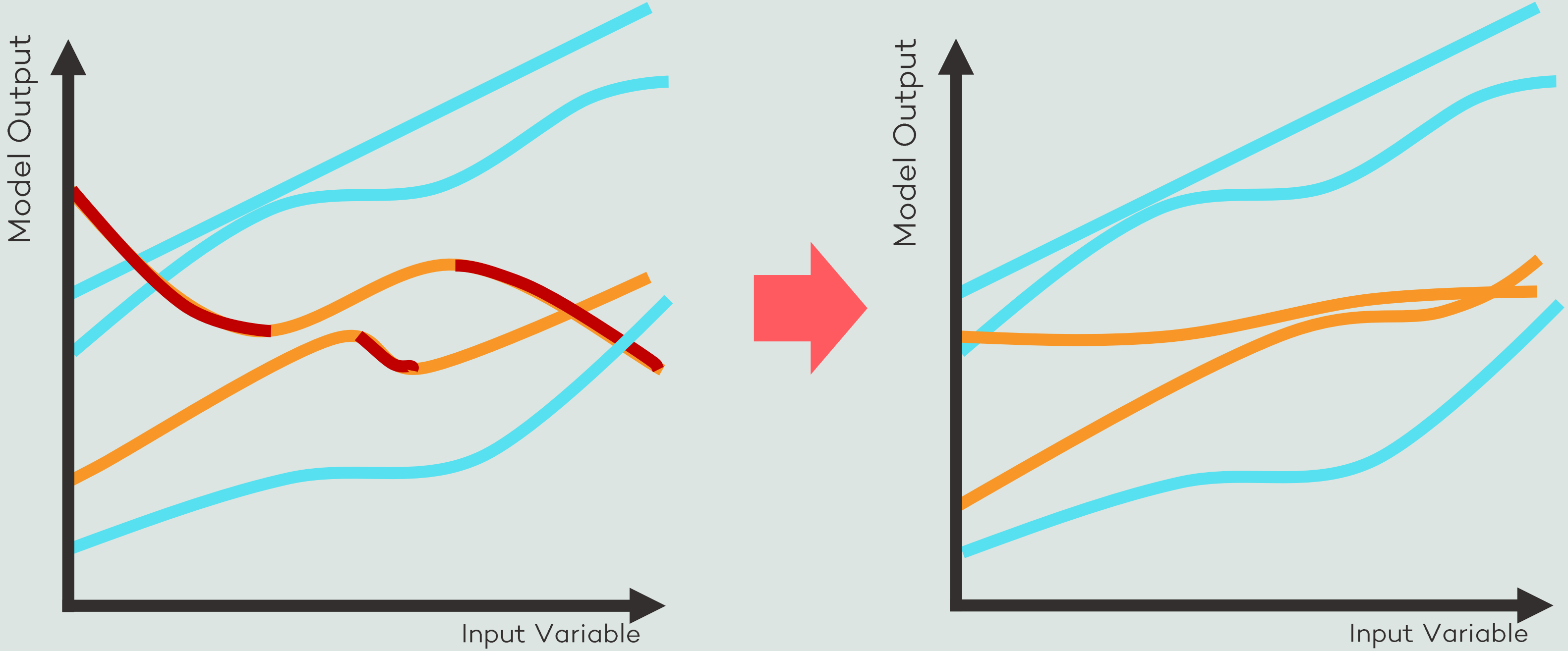


In non-linear models, the way the model responds to changes in an input variable can change from case to case.

The response can even invert, across the whole range of the variable or just a portion of it.

This is highly problematic from the perspective of being able to justify decisions.

We'd like to ensure that desired relationships exist for all conceivable input data



We developed an approach to training neural networks that ensures that specified dependencies are met.

E.g.

- As income increases, score should always increase,
- A homeowner should receive a higher score than a tenant
- etc…

This is a mathematical guarantee that the specified relationships always hold, providing confidence that the scores assigned are justifiable in all cases.

Archetype

The Artificial Intelligence-based
modelling suite from Jaywing

Archetype ← All Projects

A Demo Project

Martin Benson Help Admin

- Project Definition
- Identify Key Fields
- Metadata
- Variable Selection
- Variable Specification
- Model Creation

Project Definition

Name

A Demo Project

Project Description

Model Data Set

Upload a .CSV file

Browse Files

Update

Next: Identify Key Fields

JAYWING

Jaywing plc is registered in England and Wales. Albert Works, 71 Sidney Street, Sheffield S1 4RG. Company number 05935923.

Improving application credit scores through Archetype

Demonstrating remarkable Gini uplifts of 7% & 11% on personal retail loan portfolios

HITACHI
Inspire the Next

Newcastle
Building Society

Archetype enhances application credit scores within secured portfolios

Demonstrating impressive Gini uplifts of 4.6% on Residential mortgages and 18.6% on Buy To Let

Supporting Secure Trust over a 3-Year engagement to revolutionise their credit scoring models using Archetype

Questions?

https://risk.jaywing.com/specialisms/artificial-intelligence/archetype/

Coming up...

sheffield.digital

18/2 Sheffield Digital Leadership Meetup & Code First: Girls
19/2 AWS Sheffield Meetup & SheffieldML - AI in Credit Scoring with Jaywing
20/2 #SheffDataForGood
21/2 Cooper Sessions Lunch & Learn, Immerse Sheffield & ShefTest & BCS South Yorkshire
26/2 Cyber Republic
27/2 G Suite User Group
28/2 Front End Sheffield: Andy Carter and Amanda Cookson
5/3 Cooper Sessions Fireside Chat & dotnetsheff
7/3 GoSheffield
9/3 #SheffDataForGood & Dark Peak Data Co-Operative
11/3 Sheffield Ruby User Group
12/3 (def shef) Advent of Code

… plus Geek Brekky from 9am every Friday at Tamper Sellers Wheel

sheffield.digital/events