

DataKind UK

Data science
and small charities

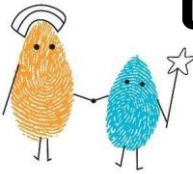
Giselle Cory, Executive Director

We're a charity that
builds **data science**
capacity in social
change organisations

NSPCC

CAFÉDIRECT
Producers' Foundation

ONE THE CAMPAIGN TO MAKE POVERTY HISTORY



Shooting Star Chase
Children's Hospice Care

centre point give homeless young people a future

American Red Cross

CONCERN
worldwide

AMNESTY INTERNATIONAL



STREETS OF LONDON

TACKLING HOMELESSNESS

the trussell trust
Stop UK Hunger



Oxfam

Ark

THEATRE FOR A CHANGE



Prince's Trust

NORTH EAST

Education • Awareness • Action

CHILD POVERTY COMMISSION

Shelter



WeFarm

HelpAge International
age helps



The Welcome Centre

love...

the key
YOUR POTENTIAL UNLOCKED

the audience agency

Oasis
Community Learning



Responding To Needs, Driving Change

mind
for better mental health



St Mungo's Broadway

Rebuilding lives, day by day

WE ARE MACMILLAN.
CANCER SUPPORT



Suas

Educational Development

NCO

Islington ageUK

BUTTLEuk
FOR CHILDREN & YOUNG PEOPLE

ANTHONY NOLAN
BE A MATCH, SAVE A LIFE



THE YOUNG FOUNDATION

(SHARED ASSETS)



ECOLOGICAL LAND CO-OPERATIVE



COFFEES OF CHARACTER

CAFÉDIRECT

MADE THE SMALL WAY



The Access Project

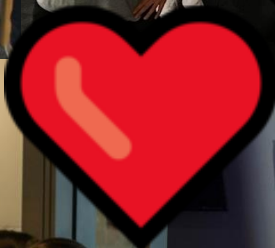


STREET LEAGUE



WOODLAND TRUST

one world



Use of AI in social sector is growing

Data Justice Lab

Over 50 local councils using predictive models and 14 police forces

See *Sky News* [report](#)

Guardian Research



Automating poverty

Digital dystopia: how algorithms punish the poor

In an exclusive global series, the Guardian lays bare the tech revolution transforming the welfare system worldwide - while penalising the most vulnerable
by [Ed Pilkington](#) in New York

All around the world, from small-town Illinois in the US to Rochdale in England, from Perth, Australia, to Dumka in northern [India](#), a revolution is under way in how governments treat the poor.

You can't see it happening, and may have heard nothing about it. It's being planned by engineers and coders behind closed doors, in secure government locations far from public view.

Only mathematicians and computer scientists fully understand the sea change, powered as it is by artificial intelligence (AI), predictive algorithms, risk modeling and biometrics. But if you are one of the millions of vulnerable people at the receiving end of the radical reshaping of welfare benefits, you know it is real and that its consequences can be serious - even deadly.

Using machine learning to identify food bank dependence early





Project Funding, a real enabler organisation

DKUK

Applying **data science** talent, tools and processes to achieve **social good**



Providing packs of food, essentials and support to people **in crisis** in Huddersfield and the surrounding area

MEETS

Both teams consisted of volunteers. All technical work completed 'out of hours'

Client Referral History

Status: Burst

Total Referrals: 29 in 15 episodes

Known for: 1910 days

Active: 12.2%, Inactive: 43.2%,

Dormant: 44.6%

Current Score: 7.7

Client Support Status

Status: Ongoing Support

Since: 31/01/2019

By: Cath

Future Score:

<https://vimeo.com/343034018>

Food bank use is on the rise...

Hungry for answers

The real reasons why food-bank use is soaring

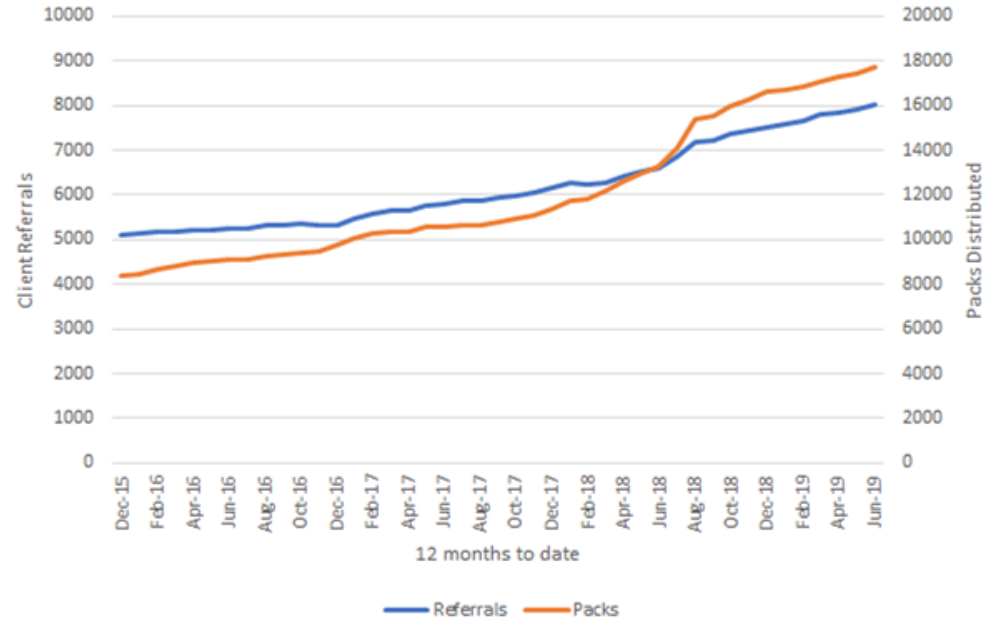
A shift in the nature of poverty, not its overall incidence, best explains their spread

Universal credit reform fails to satisfy food bank users

Slow payments and benefits freezes 'much bigger deal' than rise in work allowance



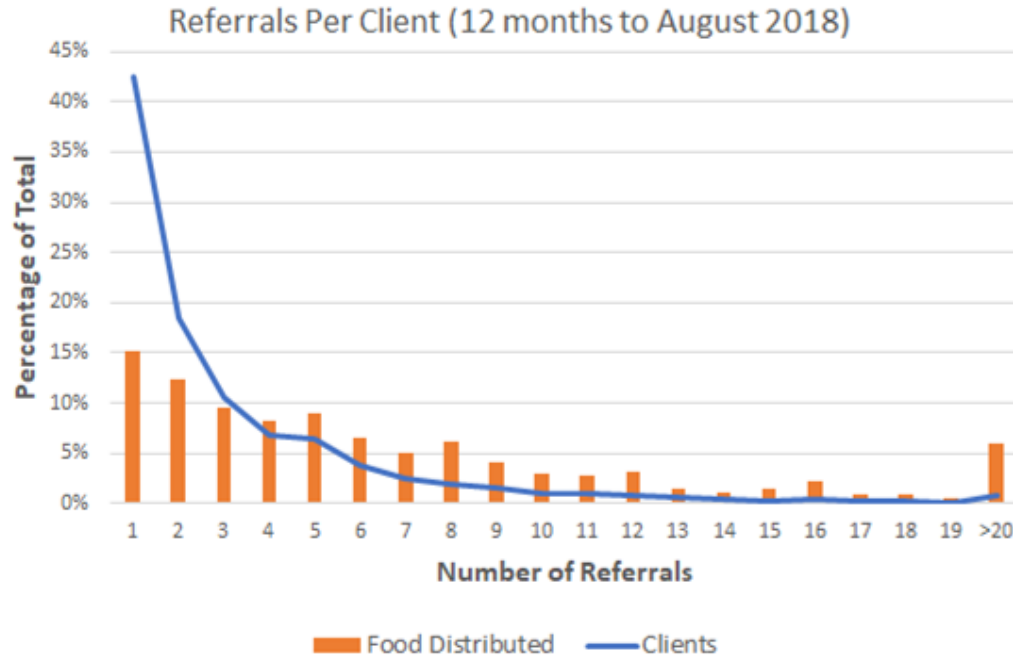
The Welcome Centre: Client Activity



Data from the Welcome Centre

The way they are being used is also changing...

Food bank users are coming back more regularly and becoming **dependent** on the support



- Most clients visit relatively few times
- But the few clients who visit regularly consume a high proportion of resources and are at risk of becoming dependent
- Hence need for support

Typical Journey



Client is referred
by phone



Volunteer puts
details in the
system

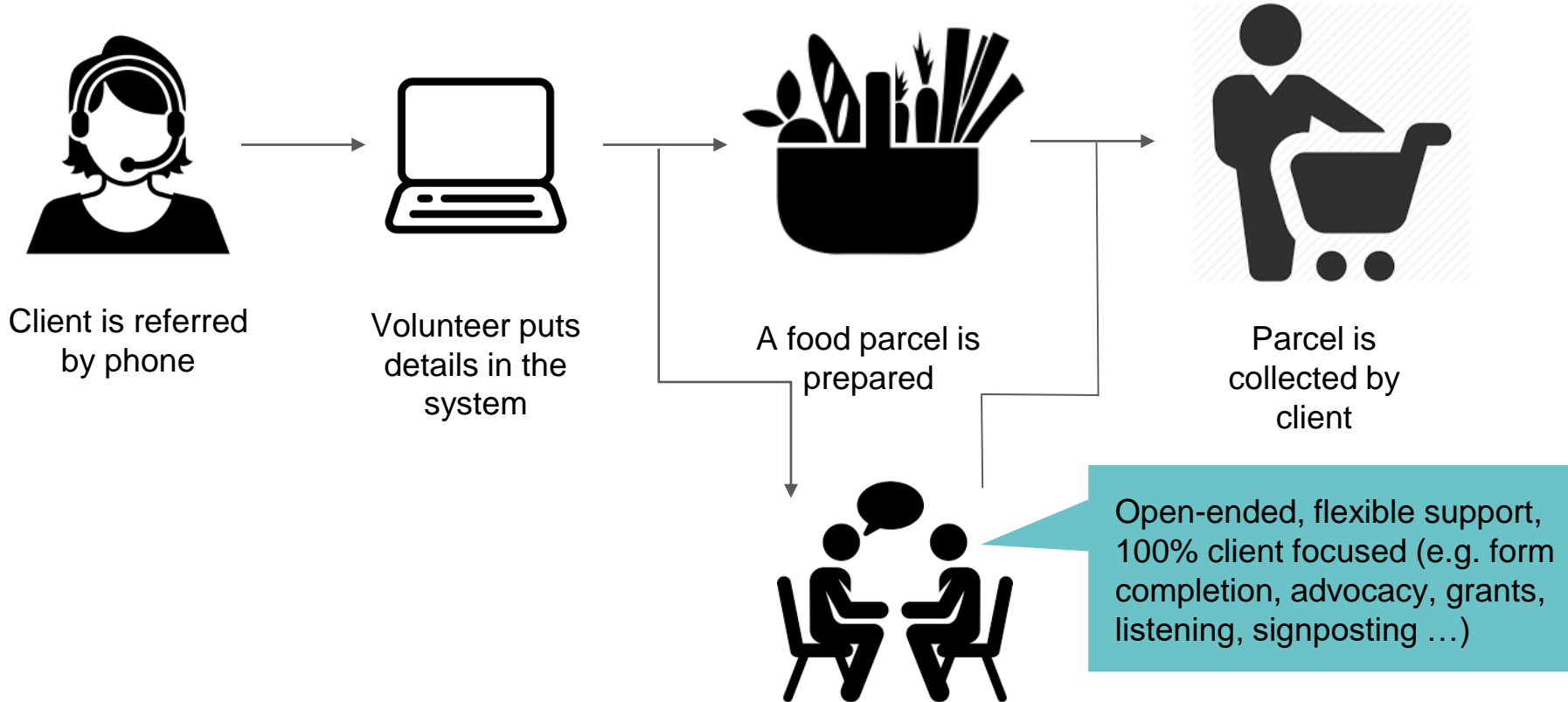


A food parcel is
prepared

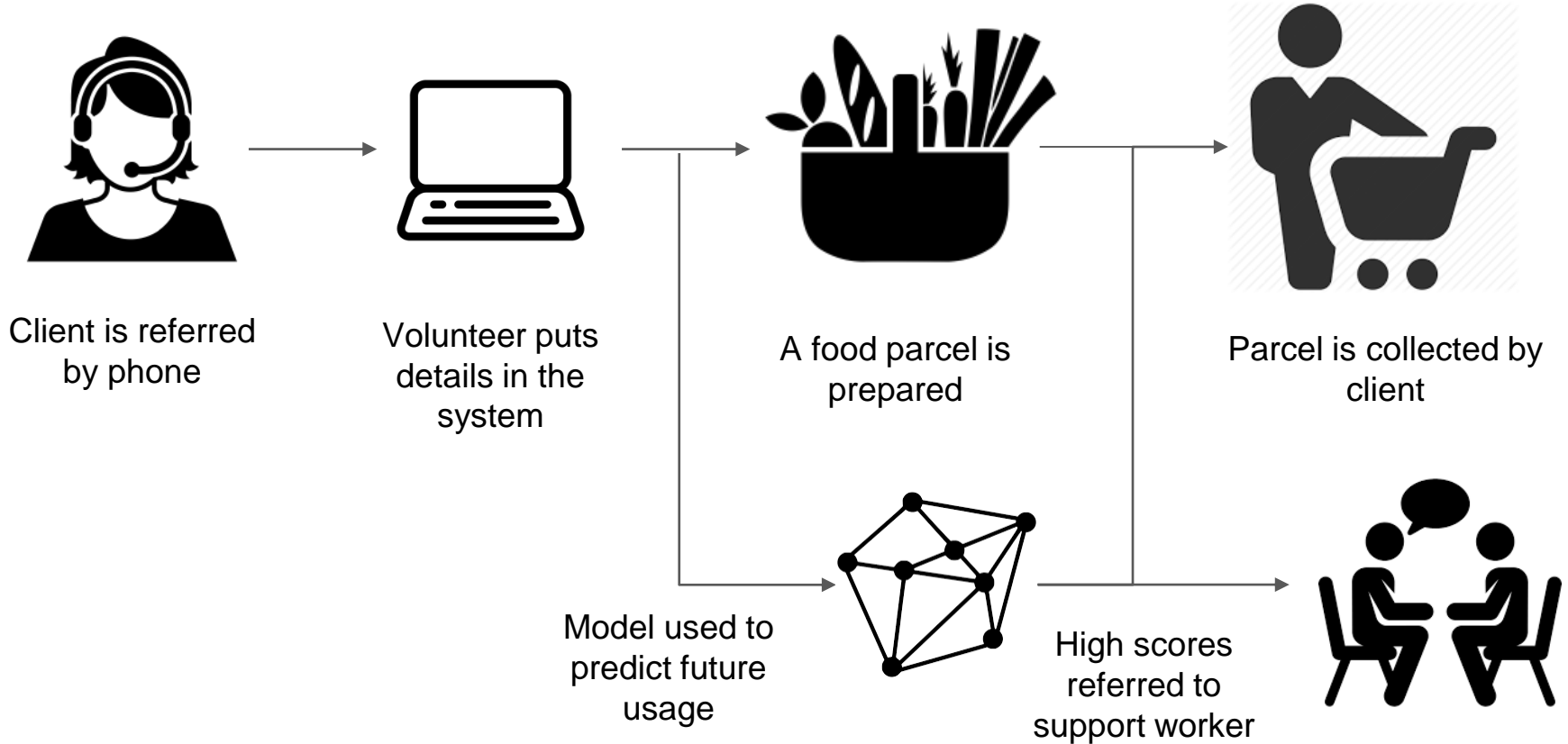


Parcel is
collected by
client

Supported Journey



Using Machine Learning to Triage



The Challenge

Integrate it into a system
written in **BASIC** on Windows
servers

Have it run with zero
maintenance and
low cost

Provide a way to retrain the
model

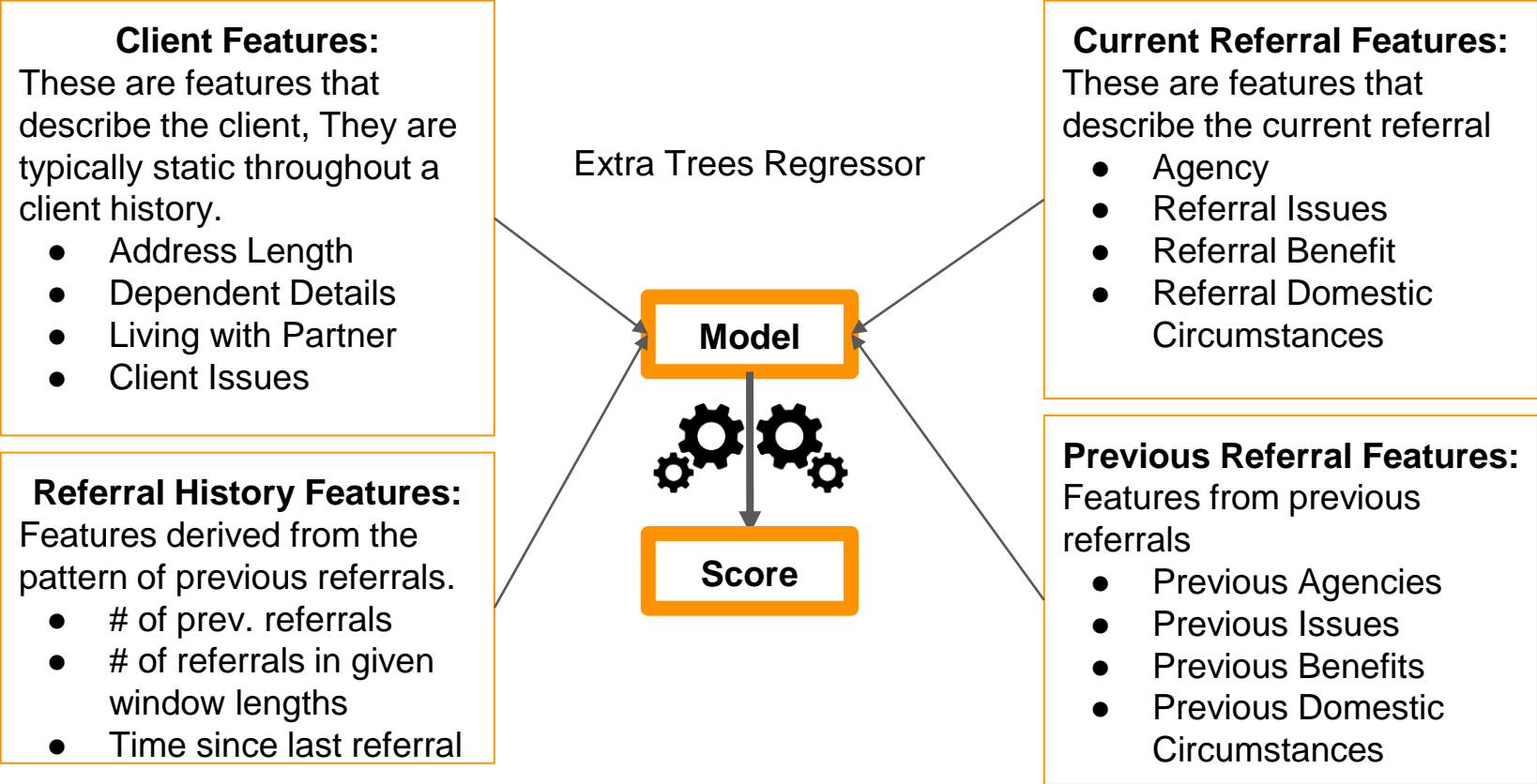
Build a production grade
model that predicts future
visits

Avoid any socio-
demographic bias

Ensure it's GDPR
compliant

Make sure the staff
understand it

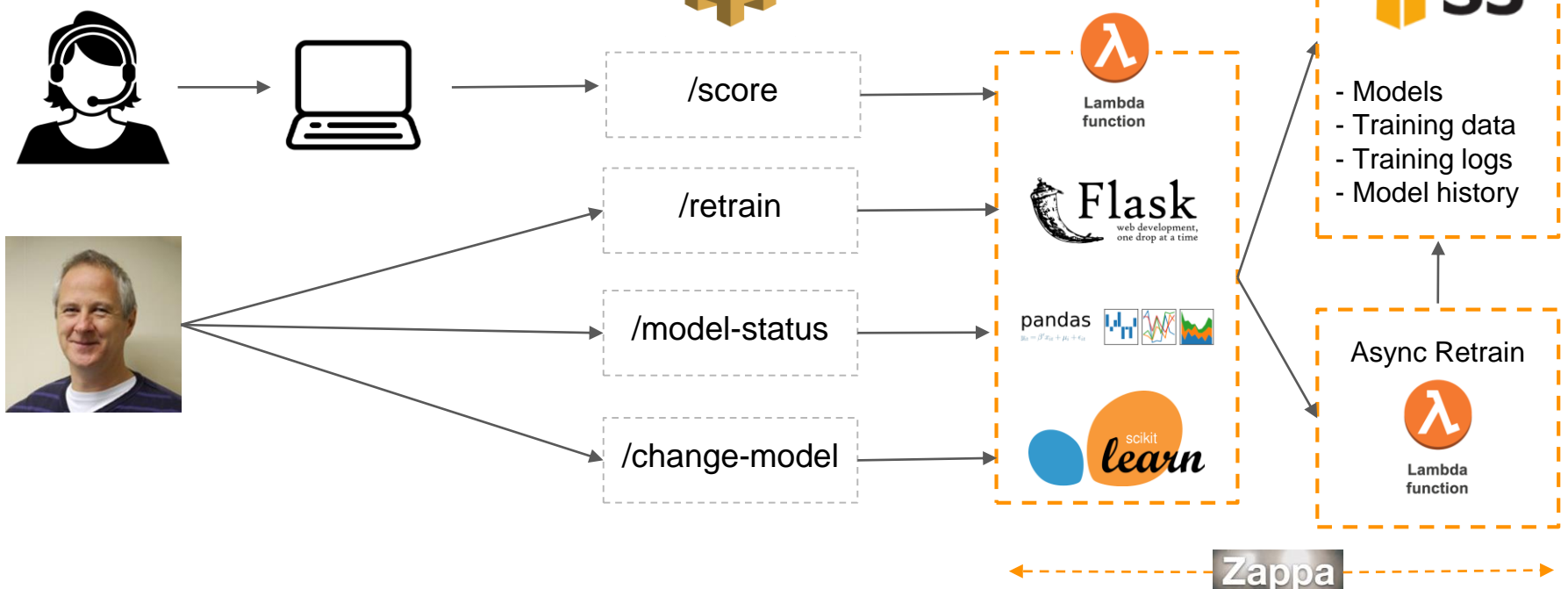
The Model



** we will not be using free text fields as these are very sensitive to the agent inputting the data

Advanced technology

API Gateway



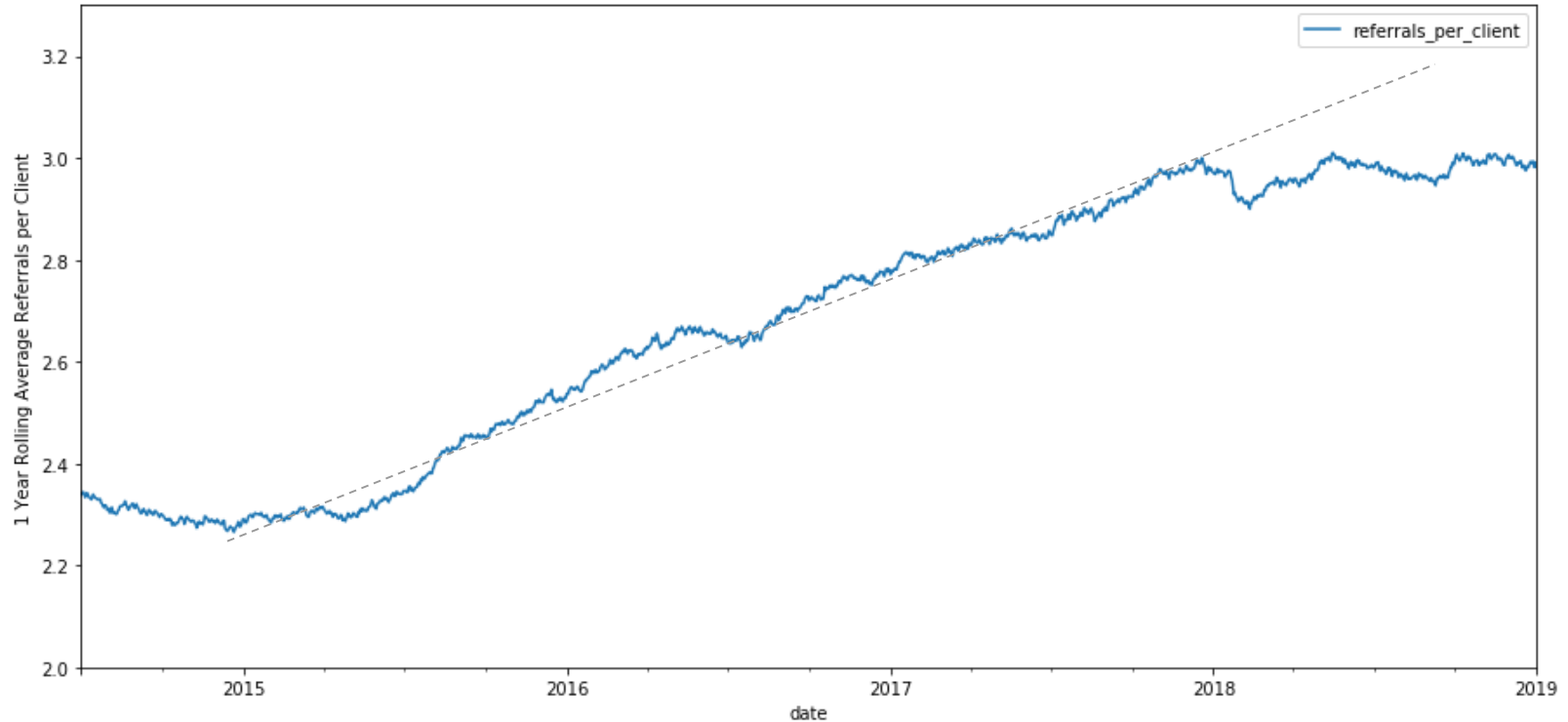
...at a low and sustainable cost

AWS server

£1.20 a month!

(and no local support overhead for The Welcome Centre)

Support and the model is reducing dependency



How well is the model working? (Anecdotal)

- 40 referrals per day, around 50% from new clients.
- ~10 model-based support recommendations made per day, depending upon overall demand and the specific clients being referred
- Very few false positives

Anecdotal evidence

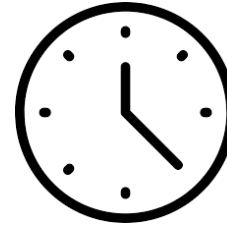
- The support worker 'trusts' the recommendations and no longer spends time on manual checking
- After 9 months the system is an integral part of TWC's business processes (not sitting on a shelf gathering dust)

Direct impacts of the Welcome Centre



Early intervention

Allows the Welcome Centre to realise the goal of meeting with clients at the beginning of their journey



Time Saving

The support worker has more time to spend in direct contact with clients and spends less time reviewing new client referrals



More effective client engagement

Provision of food packs becomes part of support management plan rather than being based on ad hoc referrals



New Ways of Working

Facilitates the move from a purely reactive to a more proactive way of engaging with clients

Wider impacts of the Welcome Centre



Funding bid

Funding bid for expanding the support service submitted. This will provide a second support worker, backed by volunteers. Use of the recommendations made by the model is central to this bid

(model threshold can be adjusted to match support capacity)



Enhanced strategy

Enabled more effective proactive approach of support service to become a 'core' function within TWC

Early intervention is vital



Data-driven organisation

Good data and data analysis is now regarded as a key tool for informing strategic decision making at board level



[Mary's story]



Strata Data Conference



Impact Aloud 2018 - Presentation

“Really inspiring and eye-opening about what could be achieved by a small organisation with this sort of help.”



Babbage: Data to the rescue


Babbage from Economist Radio



Finalist for *Best Use of Data to Achieve Social Impact*

Wider community impacts - further projects

DataKind



Huddersfield, UK
The Welcome Centre

Identifying Food Bank Dependency Early

June 2019

Objectives

- Build a machine learning model to predict which of The Welcome Centre's clients are likely to become dependant on the food bank's food and other packs
- Deploy the machine learning model within The Welcome Centre's existing system and flag those who are mostly likely to become dependant, enabling them to be prioritised for additional support from the food bank's support work

Question

The Welcome Centre (TWC) is a food bank based in Huddersfield, UK. They provide support to people in crisis, offering practical help in the form of food, toiletry, and household support packs. A support worker provides advice to those using the service to help address the underlying problems, and help them avoid becoming dependant on the food bank.

TWC has seen the number of people dependent on their packs grow over time, but identifying those most in need of support (who are most likely to become dependant) is challenging. Currently, such clients are identified manually by the support worker, based on the frequency and number of their referrals.

DataKind UK and TWC partnered to build a system that could identify a client's likelihood of needing additional or longer term support and to work jointly to implement this process. The aim was to create a probability score which could aid the support worker to decide, in conjunction with other information, whether a client is likely to need extra support. This would enable TWC to improve the accuracy and efficiency of the targeted work that the support worker undertakes, and make an earlier intervention before a crisis escalates.



DKUK Workshop

GREATER
LONDON
AUTHORITY



DKUK



2-year initiative to help small charities in London to improve their digital skills and analysis of data

TWC Client Journey - Mary

Refereed by Local Welfare and recommended for support by the DK model 47 year old Mary had never claimed benefits, she had worked all her life, brought up three children and was a part-time carer for her granddaughter. Sadly she had a breakdown and became very unwell. She was signed off work for three months, but soon realised that she needed to give up work to concentrate on her health and well being.

Mary made a Universal Credit claim on line with the help of her sister, but there were issues with her bank account and therefore payment was delayed. Cath saw Mary on a one 2 one basis and over the next few months, she helped Mary to do the following:

- Phone DWP to sort out the issue with her bank account.
- Complete a UC50 form – medical health form.
- Prepare for the medical assessment that she had to attend.
- Apply for PIP – personal independence payment.
- Apply for council tax reduction.
- Speak to the carers allowance team regarding a change in circumstance.
- Refer Mary for money advice via KNH money advice unit.

Mary now has her benefits in place, she has been found unfit for work and is entitled to higher rate benefit for 12 months, giving her the time she needs to attend counselling, so that she can get better. She was given seven food parcels during this time, five whilst her Universal Credit was processed (standard for all UC claimants) and two extra food parcels whilst the issue with her bank account was resolved.

What is AI

and Machine Learning?

→What is **AI**?

→What is **machine learning**?

→How could this be applied
to **your organisation**?

→ But first....

011100101110011110101101110010111001111010110111001011100111101
100011001010100101010110001100101010010101011000110010101001010
101011011010101101101110101101101010110110111010110110101011011
1110101110011111101101110101110011111101101110101110011111110
000101010010000101111100010101001000010111110001010100100001011
10010101010101010101010010010101010101010101010100100101010101010
111110011111101100100011111001111110110010001111100111111011001
11100111101011 0111001011100111101011 0111001011100111101011 01110
L11001011100111101011011100101110011110101101110010111001111010:
)00110010101001010101100011001010100101010110001100101010010101(
)101101101010110110111010110110101101101101110101101101010110110:
L101011100111111011011101011100111111011011101011100111111101:
)01010100100001011111000101010010000101111100010101001000010111:
)01010101010101010100100101010101010101010100100101010101010101(
L11100111111011001000111110011111101100100011111001111110110010(
L100111101011 0111001011100111101011 0111001011100111101011 011100:
L11001011100111101011011100101110011110101101110010111001111010:
)00110010101001010101100011001010100101010110001100101010010101(
)10110110101011011011101011011010101101101110101101101010110110:
L1010111001111111011011101011100111111011011101011100111111101:
)01010100100001011111000101010010000101111100010101001000010111:

011100101110011110101101110010111001111010110111001011100111101
100011001010100101010110001100101010010101011000110010101001010
101011011010101101101110101101101010110110111010110110101011011
1110101110011111101101110101110011111101101110101110011111110
00010101001000010111100010101001000010111110001010100100001011
100101010101010101010010010101010101010101001001010101010101010
1111100111111011001000111110011111011001000111110011111011001
11100111101011 011100101100111101011 011100101100111101011 01110
111001011100111101011011100101110011110101101110010111001111010:
)00110010101001010111000110010101001010110001100101010010101(
)0110110101011011011101011010110101101101110101101101010110110:
1101011100111111101101110101110011111101101110101110011111101:
)0101010010000101111000101010010000101111100010101001000010111:
)01010101010101010100100101010101010101010100100101010101010101(
11110011111101100100011111001111101100100011111001111110110010(
1100111101011 0111001011100111101011 0111001011100111101011 011100:
11001011100111101011011100101110011110101101110010111001111010:
)00110010101001010111000110010101001010110001100101010010101(
)0110110101011011011101011010110101101110101101101010110110:
1101011100111111101101110101110011111101101110101110011111101:
)01010100100001011111000101010010000101111100010101001000010111:



011100101110011110101101110010111001111010110111001011100111101
100011001010100101010110001100101010010101011000110010101001010
10101101101010110110111010110110101011011011011011011010101011011
111010111001111110101110101110011111101101110101110011111110
0001010100100001011110001010100100001011110001010100100001011
100101010101010101001001010101010101010010010101010101010101010
11111001111110110010001111100111110110010001111100111111011001
11100111101011 0111001011100111101011 0111001011100111101011 01110
111001011100111101011011100101110011110101101110010111001111010:
)00110010101001010101100011001010100101010110001100101010010101(
)01101010101011011011101011010101010110110110110110110101010110110:
1101011100111111011011101011100111111011011101011100111111101:
)010101001000010111100010101001000010111100010101001000010111:
)0101010101010101001001010101010101010100100101010101010101010101(
11110011111011001000111100111110110010001111001111110110010(
1100111101011 0111001011100111101011 0111001011100111101011 011100:
11100101110011110101101110010111001111001010101110010111001111010:
)00110010101001010101100011001010100101010110001100101010010101(
)01101010101011011011101011010101010110110110110110110101010110110:
1101011100111111011011101011100111111011011101011100111111101:
)010101001000010111100010101001000010111100010101001000010111:



What is AI?

→ **What is machine learning?**

→ **How could this be applied
to your organisation?**



A.I. is a fundamental risk to the existence of human civilization.

Artificial intelligence

Artificial intelligence

General intelligence

A machine capable of true learning

Narrow intelligence

A machines that is good at one task



Artificial intelligence

```
graph TD; AI[Artificial intelligence] --> VR[Virtual reality]; AI --> Robotics[Robotics]; AI --> ML[Machine learning]; AI --> CV[Computer vision];
```

Virtual
reality

Robotics

Machine
learning

Computer
vision

→What is AI?

What is machine learning?

→How could this be applied
to **your organisation?**

Machine learning

Supervised: We tell the model what we want to look out for

Unsupervised Learning: The model does its own thing

→What is AI?

→What is machine learning?

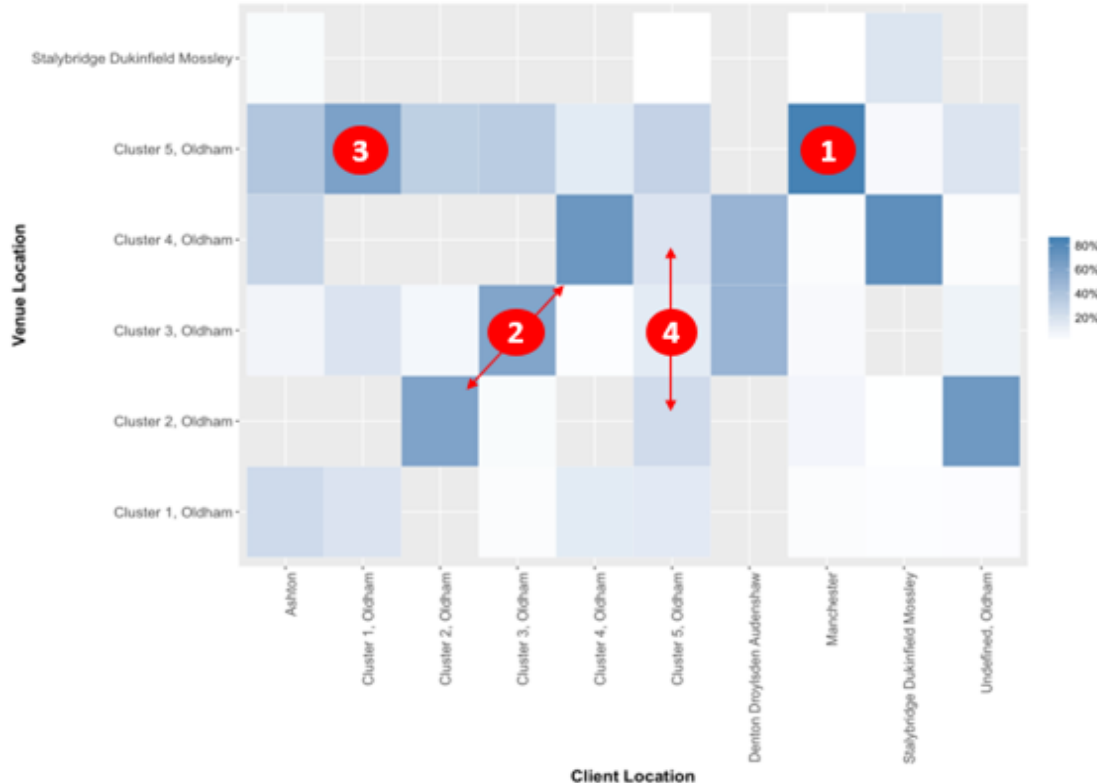
How could this be applied

to **your organisation?**

To provide additional insight or challenge/confirm existing assumptions to enable humans to deliver better services

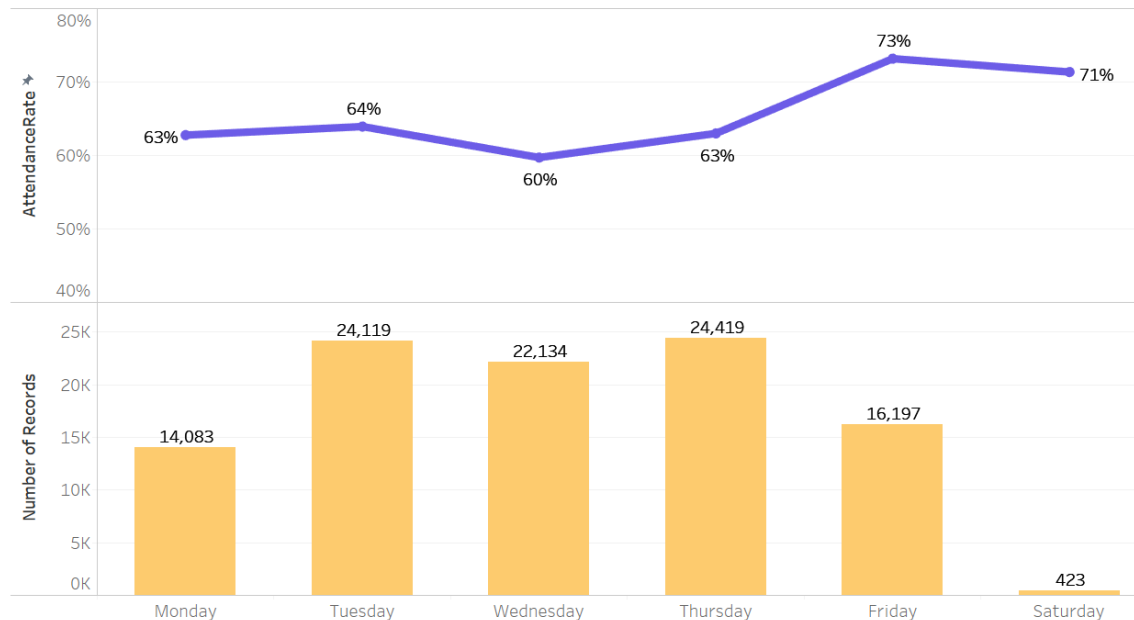
- Understand need and demand
- Effective campaigning
- Understand the people we work with
- Evaluate services
- Improve operational efficiency

Q. Who accesses our services and where?



- 1 Clients who live in Manchester are much more likely to visit venues in Cluster 5 – this is the closest cluster to central Manchester
- 2 We would expect to see a pattern of clients visiting venues where they live – this trend is not evident for clients who live in cluster 1 or 5.
- 3 Clients who live in cluster 1 are more likely to visit cluster 5 venues
- 4 Clients who live in Cluster 5 are visiting venues in all clusters, with no pronounced preference

Q. What are the best times to offer services?

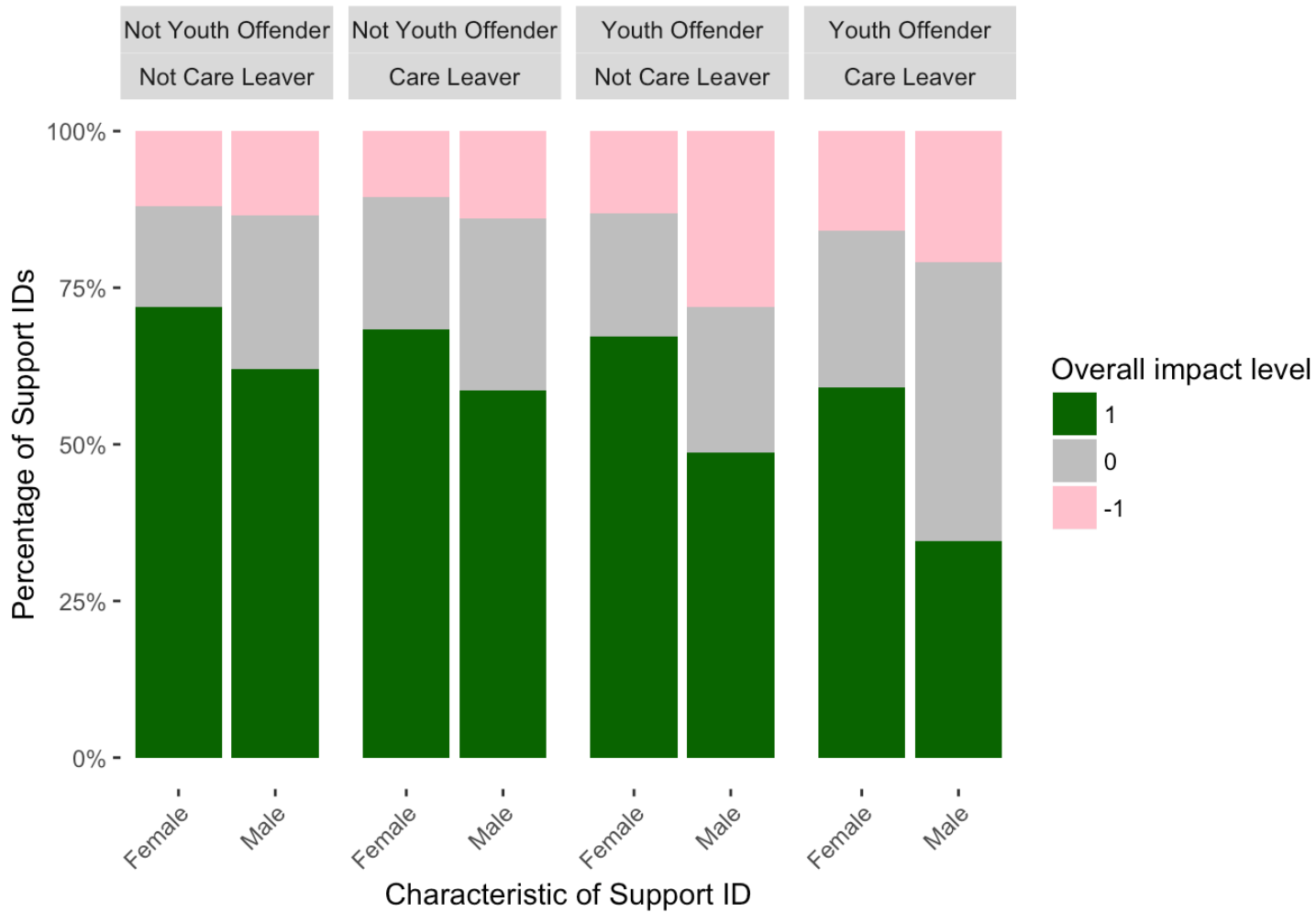


Challenges assumption
that weekend classes
are less attended



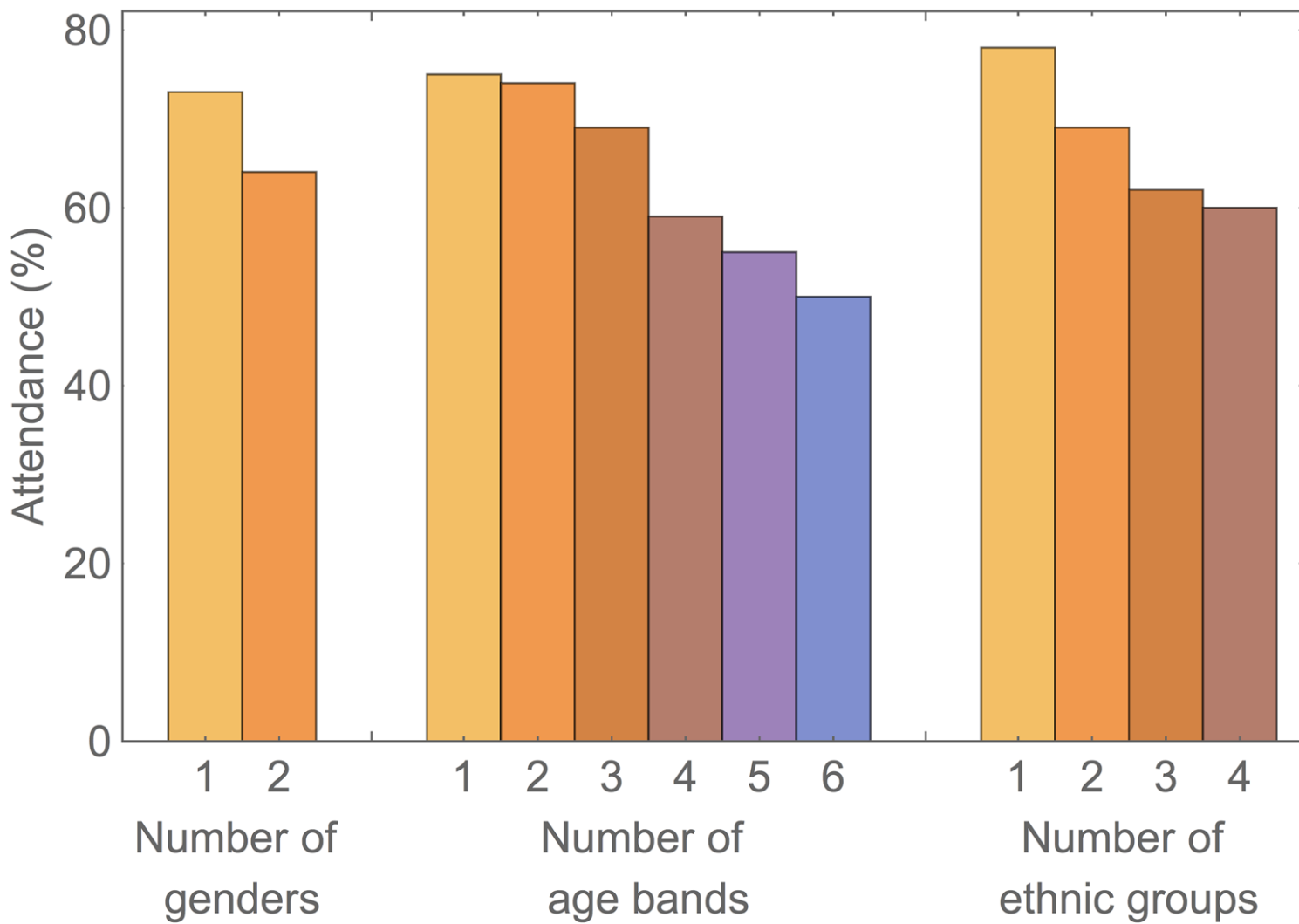


Impact by Segment: Youth Offenders By Gender

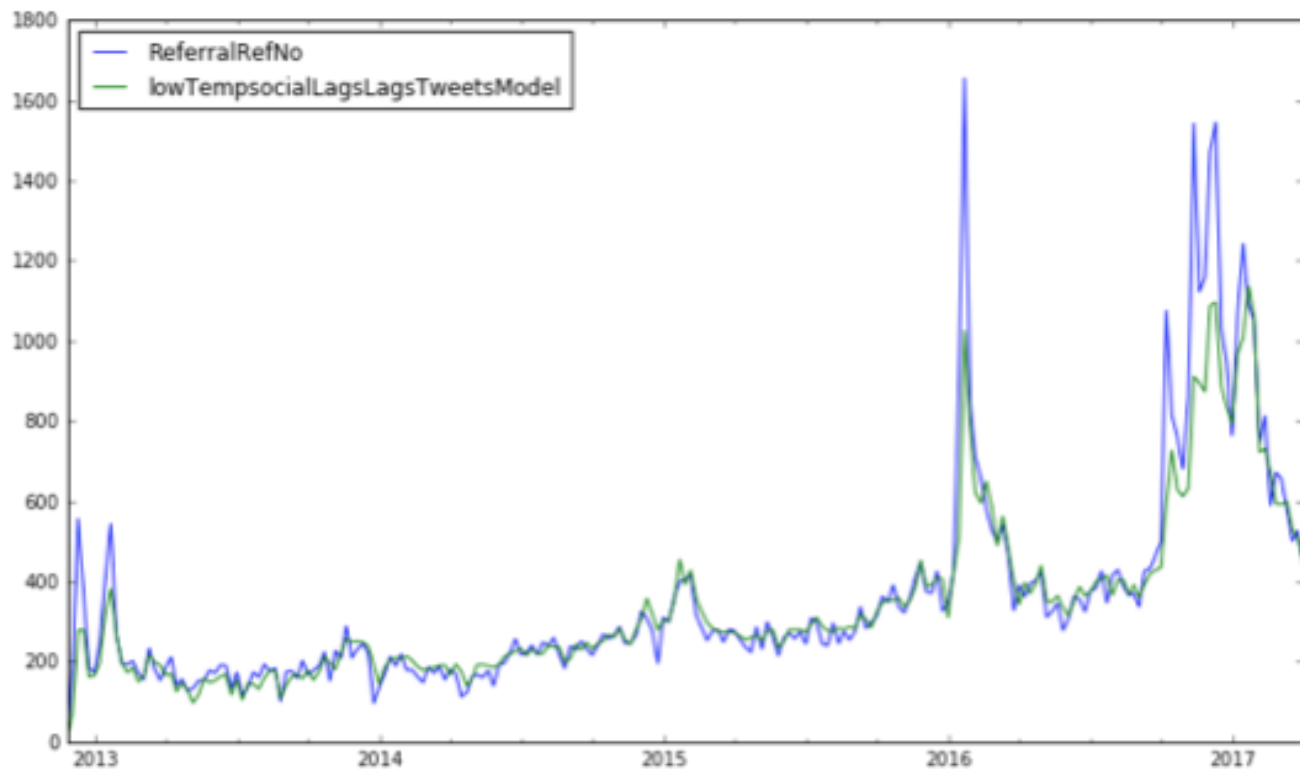




in the City,
Hackney and
Waltham Forest



Street Link



Data maturity



The Themes of Data Maturity

CULTURE

Team approach, self-questioning, openness and sharing, governance.

DATA

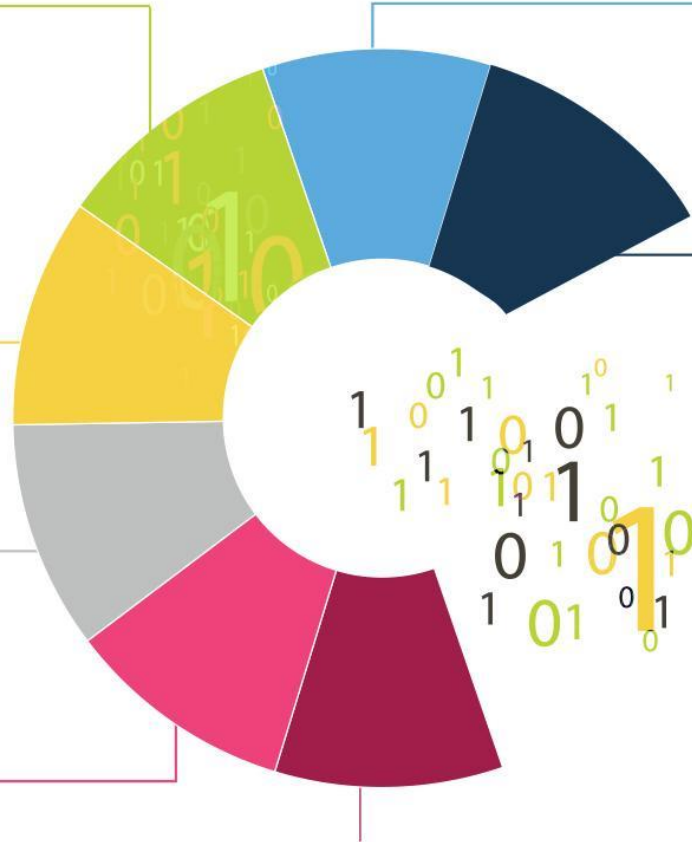
Assets, Collection, sources, quality.

TOOLS

Storage, type and quality of tools and infrastructure.

USES

Range and extent of reasons for collecting and analysing data, and benefits and rewards reaped.



SKILLS

Internal capacity, roles and skill levels, access to external knowledge and expertise.

LEADERSHIP

Attitude, investment, plans for data development, alignment to business plans, capability.

ANALYSIS

Type of data analysed, techniques, presenting and communicating.



Leadership



Culture



Skills



Tools



Data



Uses



Analysis





Leadership



Culture



Skills



Tools



Data



Uses



Analysis

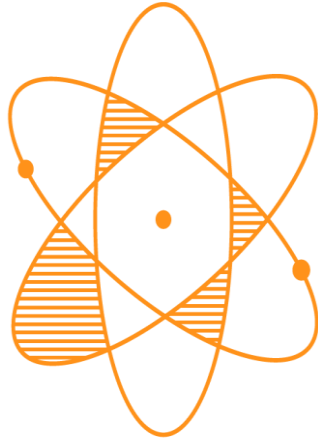


Machine learning **problem framing**

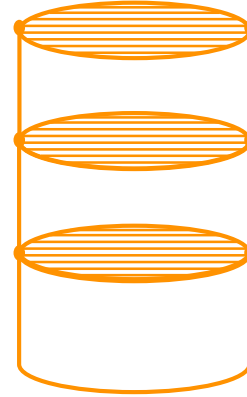
Ideal data for good projects have ...



+



+



+



Well-framed
Problem

Simple
(enough)
Solution

Relevant &
Responsible
Data

Social actor
Partner

What is the problem?

- What are some of the barriers you are facing?
- Does it align with a strategic priority?

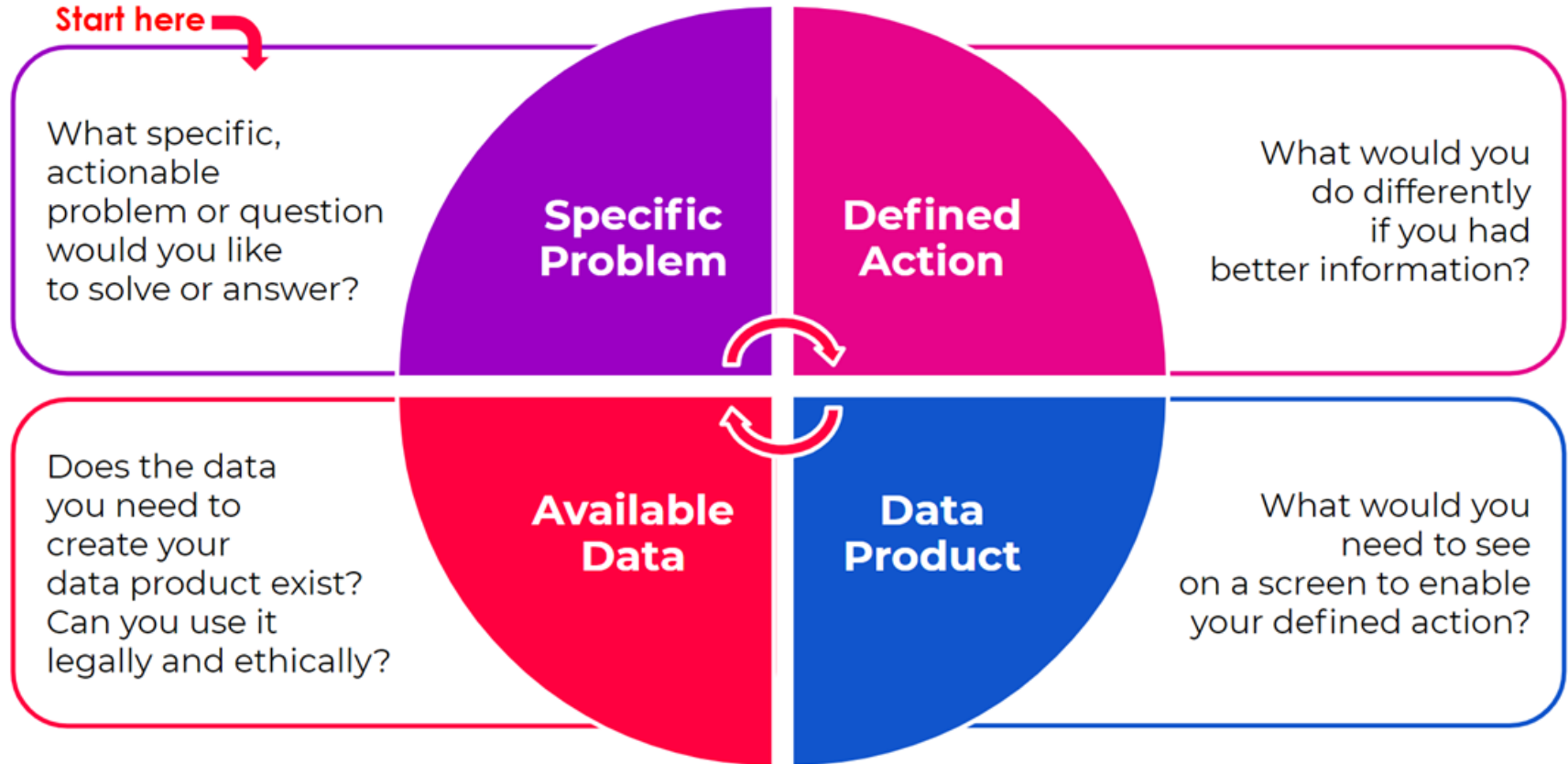


Two helpful resources:

1. Blog from Eddie Copeland [A four step step approach to collaborative data projects](#)
2. Google: [Introduction to Machine Learning Problem Framing](#) part of Google [AI for Social Good Guide](#)

Eddie Copeland: [A four step approach to collaborative data projects](#)

Can I address this problem / answer this question with data?



Google's Introduction to Machine Learning Problem Framing Exercise

1. What would you like the machine learning model to do?
2. What is the ideal outcome?
3. How will you know if it is successful?
4. What is the output of the model?
5. When do you need the output and how will it be used?
6. If you didn't use ML, what would you use?

1. Is there a clear problem that is suitable for ML/AI techniques?

> *Look at applied cases e.g [DataKind UK](#), [Google](#)*

1. Is there a clear problem that is suitable for ML/AI techniques?

2. Is there sufficient data?

> **Size** - *The more data you have, more precise the estimate. More complicated ML models require hundreds of thousands of 'rows'*

> **Quality** - *dodgy data in = dodgy results out*

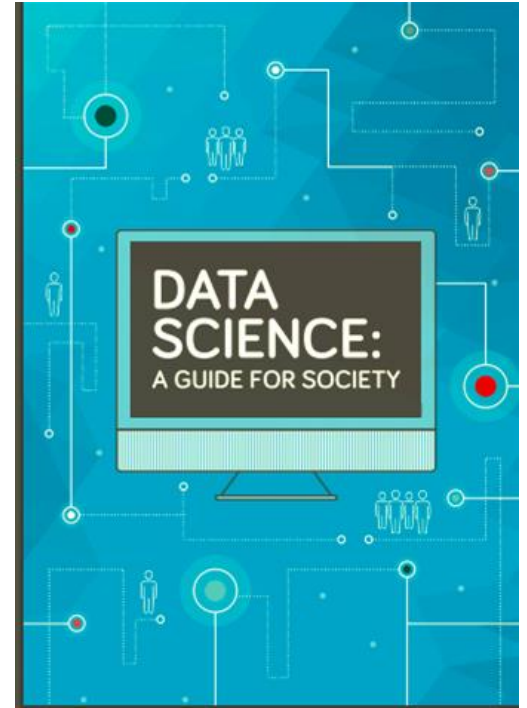
-
1. Is there a clear problem that is suitable for ML/AI techniques?
 2. Is there sufficient data?
 3. Are there assumptions that can be tested?

-
1. Is there a clear problem that is suitable for ML/AI techniques?
 2. Is there sufficient data?
 3. Are there assumptions that can be tested?
 4. Will the resulting ML/AI be used for an action?

Doing it right

1. Where does the data come from?
2. What assumptions are being made?
3. Can it bear the weight being put on it?

From [Sense About Science](#)



Data Science

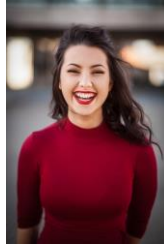
Step	Example
1. Set the research goal.	I want to predict how heavy traffic will be on a given day.
2. Make a hypothesis.	I think the weather forecast is an informative signal.
3. Collect the data.	Collect historical traffic data and weather on each day.
4. Test your hypothesis.	Train a model using this data.
5. Analyze your results.	Is this model better than existing systems?
6. Reach a conclusion.	I should (not) use this model to make predictions, because of X, Y, and Z.
7. Refine hypothesis and repeat.	Time of year could be a helpful signal.

Reference: Google: Introduction to Machine Learning Problem Framing <https://developers.google.com/machine-learning/problem-framing/big-questions>

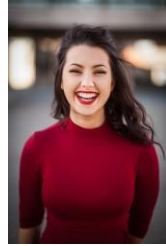
Tips for low
resource settings

People

- Invest in people before platforms

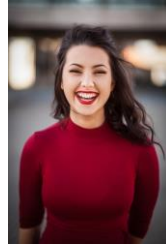


- Invest in people before platforms



- Upskill staff

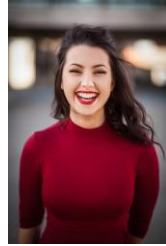
- Invest in people before platforms



- Upskill staff



- Invest in people before platforms



- Upskill staff

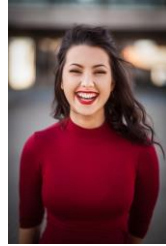
- Add an apprentice



python™



- Invest in people before platforms



- Upskill staff

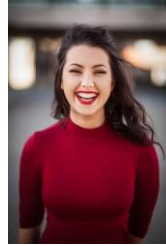
- Add an apprentice



python™



- Invest in people before platforms



- Upskill staff

- Add an apprentice

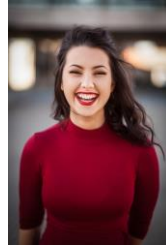
- Use support networks



python™



- Invest in people before platforms



- Upskill staff

- Add an apprentice

- Use support networks



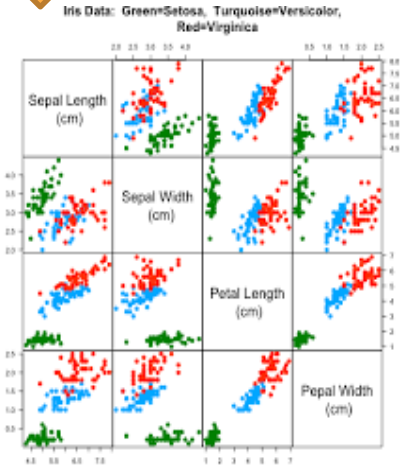
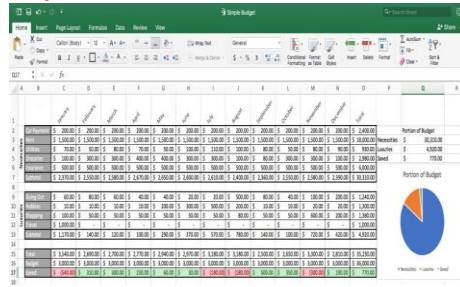
Social Data Society

Responsible Data

Leading the way from best intentions to best practice.













Tools

Everyone is on a digital/data journey!



Get there
without code

Get there
without code

	FRI, 31 JAN 13:30 Data essentials Waterloo Action Centre, London
FREE	#CharitiesCauses #Course  
	WED, 26 FEB 14:00 Data science for social impact: small charity workshop TBC - London
FREE	#CharitiesCauses #Course  
	TUE, 24 MAR 10:00 Excel for reporting and visualising your non-profit's data The Foundry (A Place for Chnage), London
£48 - £96	#CharitiesCauses #Course  
	WED, 25 MAR 10:00 Putting your data on the map Canada Water Theatre (Library), London
£30 - £54	#CharitiesCauses #Course  

Make maps
without code

Make maps
without code



 MapIt UK

The logo for MapIt UK, consisting of a white location pin icon on a blue background, followed by the text "MapIt UK" in white.

 Microsoft | Power BI

The Microsoft logo, a four-colored square (red, green, blue, yellow), followed by the text "Microsoft" and a vertical line, then "Power BI".

 tableau

The Tableau logo, featuring a cluster of colorful plus signs followed by the word "tableau" in a blue sans-serif font.

CARTO

The CARTO logo, with the word "CARTO" in white capital letters on a red background, followed by a white circle.

LONDON DATASTORE

The logo for London Datastore, with "LONDON" in bold black and "DATASTORE" in grey, both in a sans-serif font.

Get coding!

Get coding!



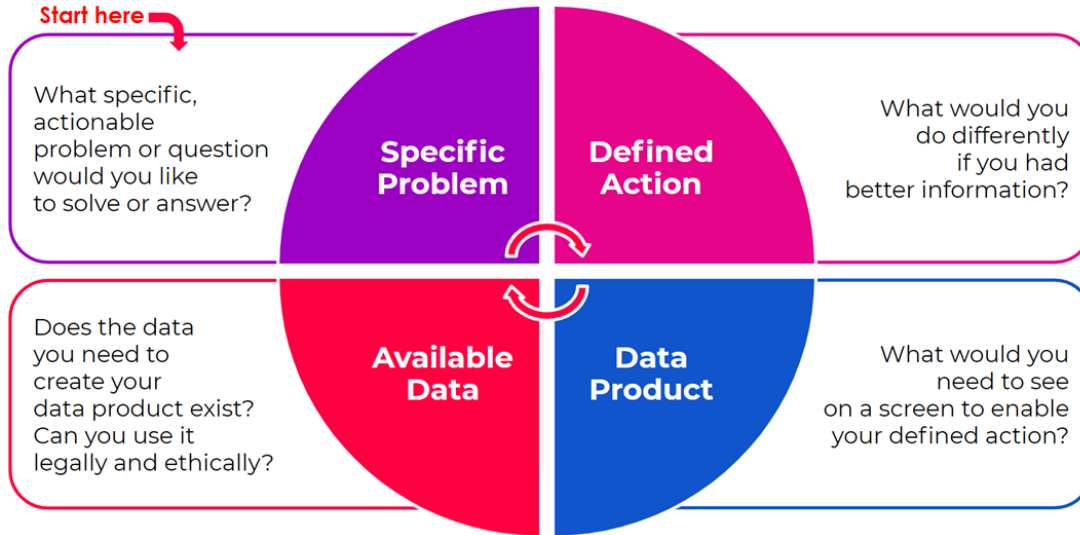
Approach

What is the problem?



What's the problem?

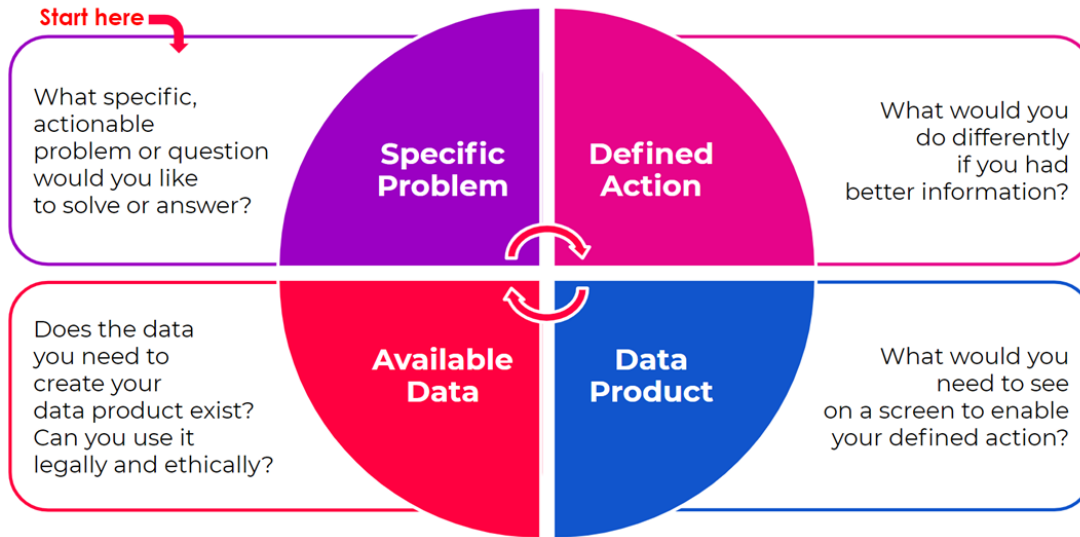
Can I address this problem / answer this question with data?



Eddie Copeland: [A four step approach to collaborative data projects](#)

What's the problem?

Can I address this problem / answer this question with data?



**INSPIRING
IMPACT**

COALITION
— FOR EFFICIENCY —

Eddie Copeland: [A four step approach to collaborative data projects](#)

Ethics and law

From *Sense About Science*

1. Where does the data come from?
2. What assumptions are being made?
3. Can it bear the weight being put on it?



Make the case

- Show, don't tell
 - Start with one thing
 - Don't worry about the tech
 - Educate your funders!

- Show, don't tell
- Use pro-bono support

- Show, don't tell

- Use pro-bono support



DataKindUK

COALITION
— FOR EFFICIENCY —

 Government
Statistical Service

Statisticians for Society



PRO BONO
OPERATIONAL
RESEARCH

PRO BONO ECONOMICS



About us

What does DataKind UK do?

- Data therapy
- DataDives
- DataCorps



DataKind **UK**

@DataKindUK

giselle@datakind.org.uk