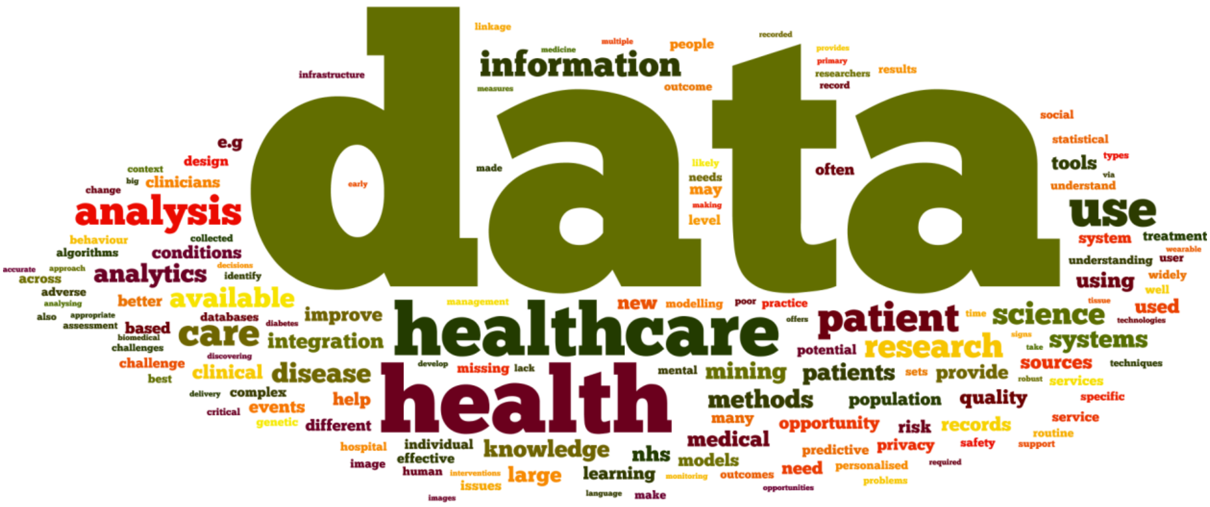
UK Health Data Analytics Network Inaugural Workshop

6th – 7th January 2016, Manchester



(Wordle Generated from all ideas submitted by attendees)

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Introduction

On the 6th and 7th of January, 2016 the UK Health Data Analytics Network held their inaugural workshop in Manchester. Before the meeting, all attendees were asked to submit a single answer to two different questions, using the Well Sorted meeting organisation tool. The answers to these questions were then clustered and discussed separately on the two days of the meeting.

Those questions were as follows:

6th (Healthcare Opportunities):
"Describe one important opportunity for data science to improve healthcare."

7th (Research Challenges):
"Describe one important data science research challenge posed by healthcare data and application."

In the rest of this document, the documentation generated by both Well Sorted and the attendees will be collated.

First, we present the information about the Healthcare Opportunities question (behind the first divider). Second, we present the information about the Research Challenges question (behind the second divider). Finally, we present general details from the meeting, such as the agenda and photos taken during the meeting.

UK Health Data Analytics Network Inaugural Workshop

Chancellors Hotel, Manchester

Our Speakers

Professor Ann Blandford, Director of UCL Institute of Digital Health, The Alan Turing Institute

Ann Blandford is Professor of Human–Computer Interaction at University College London and Director of the UCL Institute of Digital Health. With colleagues, she is organising an ATI workshop on "Opportunities and challenges for data-intensive healthcare". She serves on the Executive Committee for Farr London.

She is an expert on the design and use of interactive technology in healthcare, and on how people make sense of information. She has been Principal Investigator on grants investigating the design and use of interactive systems in healthcare from EPSRC, ESRC, MRC, NIHR, and the Royal Society.

Professor Chris Taylor, Associate Vice President for Research, The University of Manchester

Chris Taylor FREng, OBE, of the University of Manchester has been at the forefront of computer vision research for over 35 years, with some of the most highly cited publications in the field and a strong record in technology transfer. He founded one of the world's leading multidisciplinary research centres in computer vision and medical image analysis. Chris is a Distinguished Fellow of the British Machine Vision Association, International Association for Pattern Recognition and Medical Image Computing and Computer-Aided Intervention Society. He was elected a Fellow of the Royal Academy of Engineering in 2006.

Chris is currently Associate Vice President Research for the University and is the Director of Manchester Informatics (Mi) the University's strategic response to the opportunities and challenges of the digital revolution.

Professor Iain Buchan, Director, The Farr Institute for Health Informatics Research

Iain Buchan is a Professor in Public Health Informatics and leads the Centre for Health Informatics at the University of Manchester. Nationally, he is Director of the MRC Health eResearch Centre of the UK's Farr Institute for Health Informatics Research. He has over twenty years' experience in Health Informatics, with backgrounds in Clinical Medicine, Pharmacology, Biostatistics and Public Health. His research is focused on harnessing large-scale linked health data to build usefully complex models of health and care.

He leads a multi-disciplinary research team that is deep in statistical and software engineering methodology. He writes software (e.g. www.statsdirect.com) as well as working at higher levels of abstraction and leadership in advancing reproducible, larger scale health science. He is a Fellow of the American College of Medical Informatics, the top honour in the field.

In association with:

MANCHESTER 1824 The University of Manchester

EPSRC Engineering and Physical Sciences Research Council

Farr

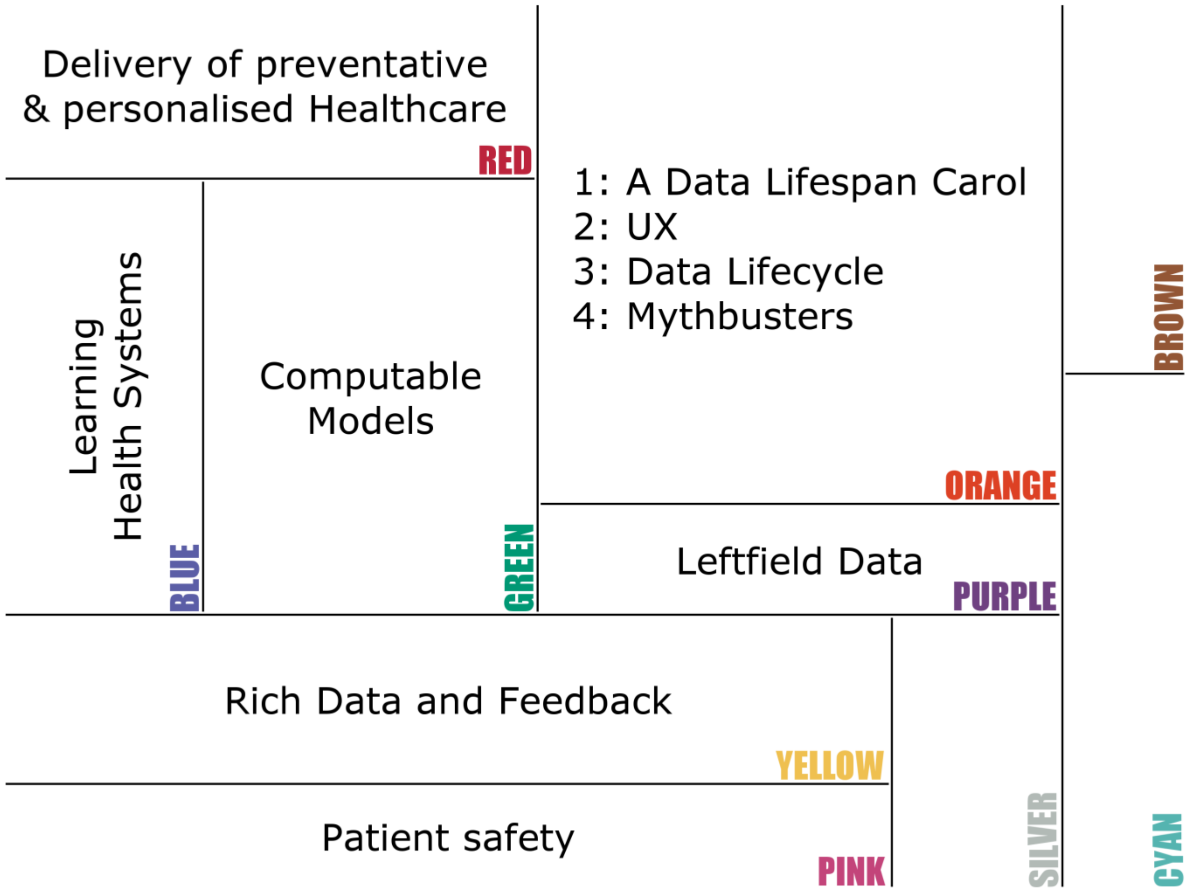
THE ALAN TURING INSTITUTE

@Man_Inf @EPSRC @herc_farr #UKHDAN

6th – Healthcare Opportunities

(Wordle Generated from ideas submitted by attendees for the Healthcare question)

Healthcare Opportunities Overview Tree Map



UK Health Data Analytics Workshop: Well Sorted Materials

6th January 2016

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For an online, interactive version of the visualisations in this document, go here:

www.well-sorted.org/output/UKHDANHealthcareOpportunities

Introduction

Dear participant,

Thank you for taking part in submitting and sorting your ideas.

This document contains several visualisations of your ideas, grouped by the average of your online sorts. They are:

Dendrogram - This tree shows each submitted idea and its similarity to the others. The lower two ideas 'join' the more people grouped those two ideas together. For example, if two ideas join at the bottom, every person grouped those two together.

Tree Map - This visualisation presents an 'average' grouping. It is calculated by 'cutting' the Dendrogram at the dashed line so that any items which join lower than that line are placed in the same group. In addition, rectangles which share a side of the same length are more similar to each other than their peers.

Heat Map - This visualisation shows a similarity matrix where each idea is given a colour at the intersection with another idea, showing how similar the two are. This is useful to see how well formed a group is. The more red there is in a group (shown by the black lines), the more similar the ideas inside it were judged to be.

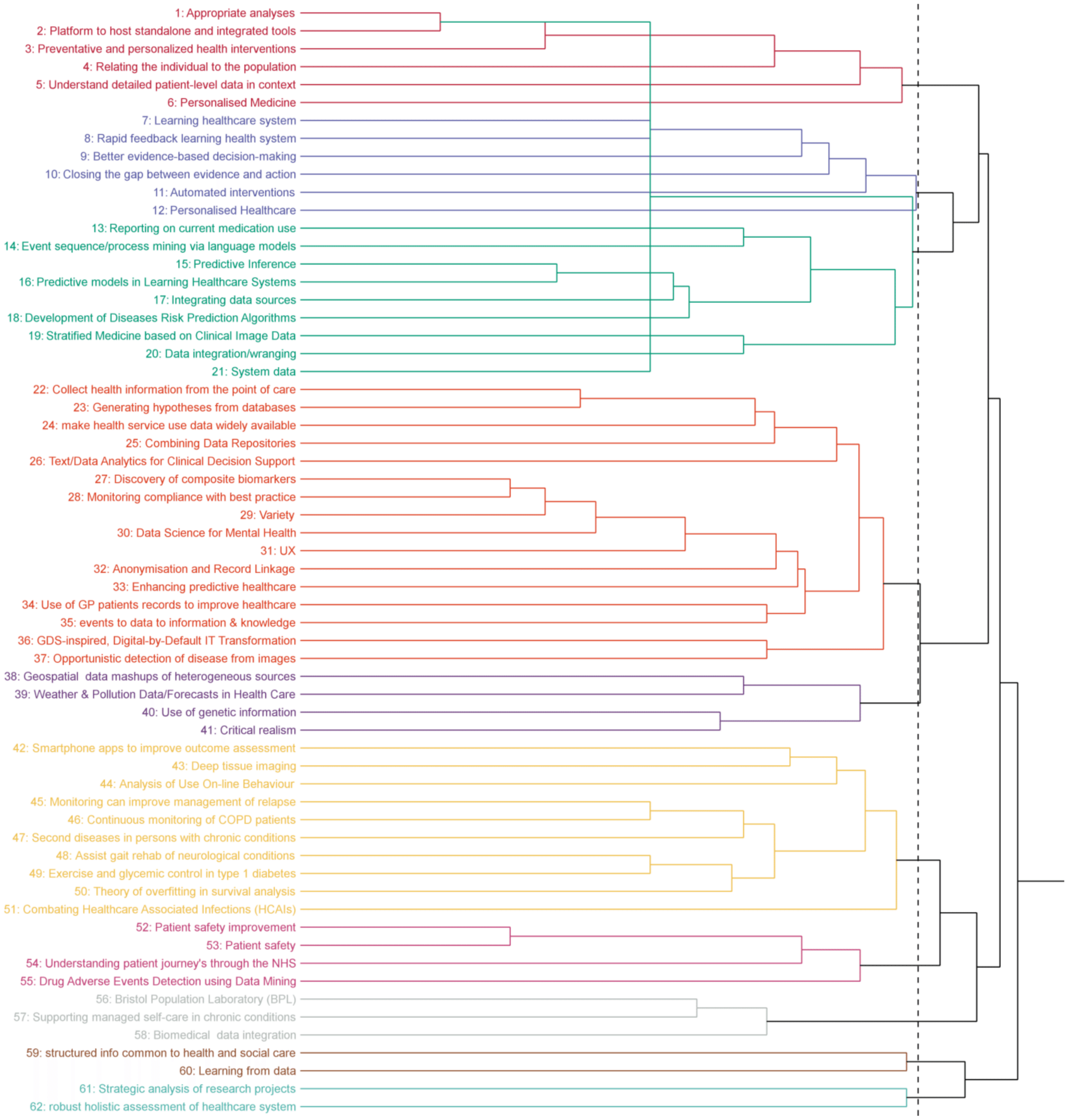
Raw Group Data - This table shows every submitted idea and its longer description. They are shown in the same order as the Dendrogram (so similar ideas are close to each other) and split into the coloured groups used in the Tree Map. In addition, each idea has been given a unique number so they are easier to find.

References

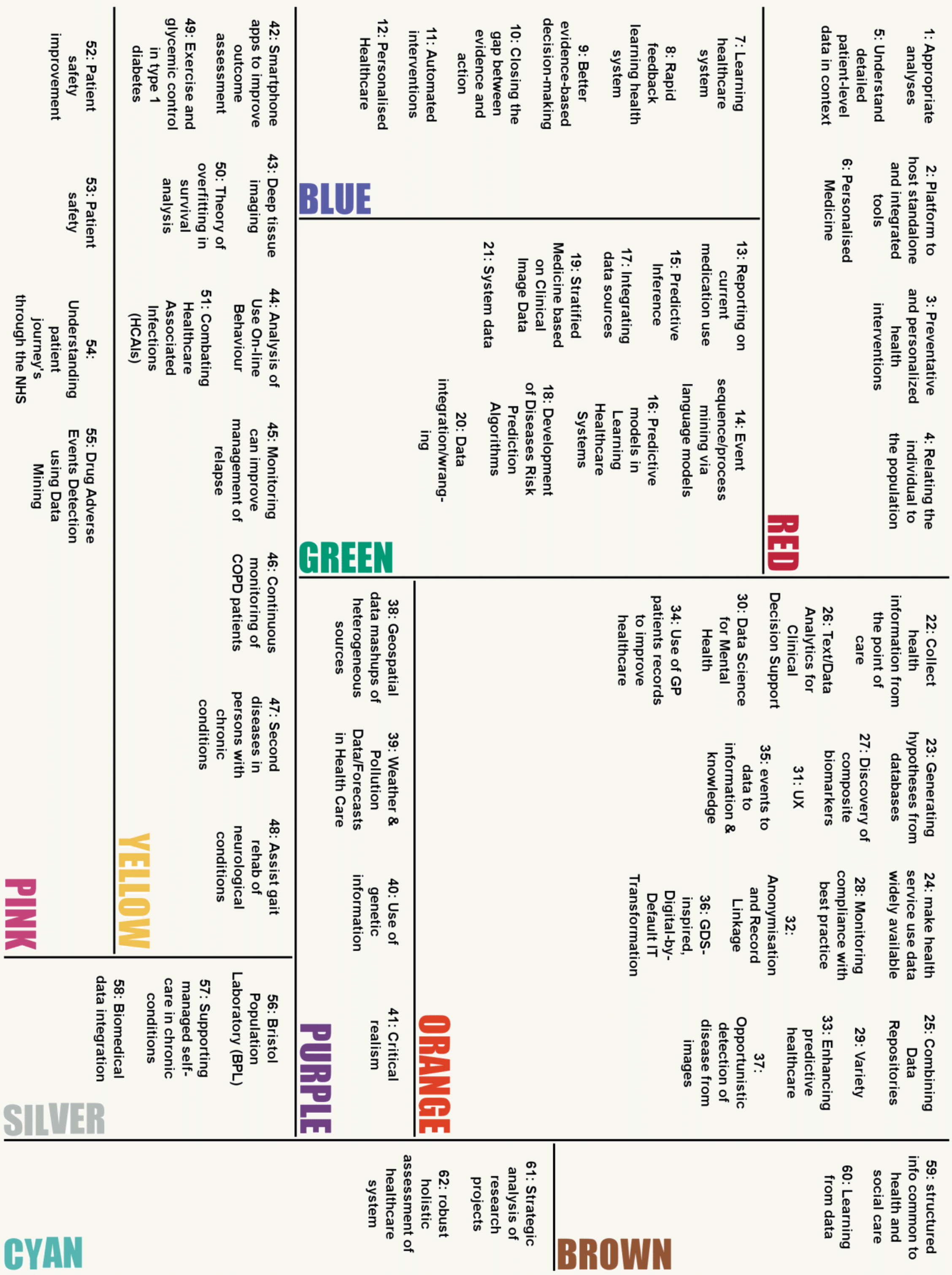
[1] Methven, T. S., Padilla, S., Corne, D. W., & Chantler, M. J. (2014, February). Research Strategy Generation: Avoiding Academic 'Animal Farm'. In Proceedings of the companion publication of the 17th ACM conference on Computer supported cooperative work & social computing (pp. 25-28). ACM. doi>10.1145/2556420.2556785

Well Sorted
Organising the World

Dendrogram


1: Appropriate analyses
2: Platform to host standalone and integrated tools
3: Preventative and personalized health interventions
4: Relating the individual to the population
5: Understand detailed patient-level data in context
6: Personalised Medicine
7: Learning healthcare system
8: Rapid feedback learning health system
9: Better evidence-based decision-making
10: Closing the gap between evidence and action
11: Automated interventions
12: Personalised Healthcare
13: Reporting on current medication use
14: Event sequence/process mining via language models
15: Predictive Inference
16: Predictive models in Learning Healthcare Systems
17: Integrating data sources
18: Development of Diseases Risk Prediction Algorithms
19: Stratified Medicine based on Clinical Image Data
20: Data integration/wranging
21: System data
22: Collect health information from the point of care
23: Generating hypotheses from databases
24: make health service use data widely available
25: Combining Data Repositories
26: Text/Data Analytics for Clinical Decision Support
27: Discovery of composite biomarkers
28: Monitoring compliance with best practice
29: Variety
30: Data Science for Mental Health
31: UX
32: Anonymisation and Record Linkage
33: Enhancing predictive healthcare
34: Use of GP patients records to improve healthcare
35: events to data to information & knowledge
36: GDS-inspired, Digital-by-Default IT Transformation
37: Opportunistic detection of disease from images
38: Geospatial data mashups of heterogeneous sources
39: Weather & Pollution Data/Forecasts in Health Care
40: Use of genetic information
41: Critical realism
42: Smartphone apps to improve outcome assessment
43: Deep tissue imaging
44: Analysis of Use On-line Behaviour
45: Monitoring can improve management of relapse
46: Continuous monitoring of COPD patients
47: Second diseases in persons with chronic conditions
48: Assist gait rehab of neurological conditions
49: Exercise and glycemic control in type 1 diabetes
50: Theory of overfitting in survival analysis
51: Combating Healthcare Associated Infections (HCAIs)
52: Patient safety improvement
53: Patient safety
54: Understanding patient journey's through the NHS
55: Drug Adverse Events Detection using Data Mining
56: Bristol Population Laboratory (BPL)
57: Supporting managed self-care in chronic conditions
58: Biomedical data integration
59: structured info common to health and social care
60: Learning from data
61: Strategic analysis of research projects
62: robust holistic assessment of healthcare system

Tree Map


RED
1: Appropriate analyses
2: Platform to host standalone and integrated tools
3: Preventative and personalized health interventions
4: Relating the individual to the population
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6: Personalised Medicine
BLUE
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12: Personalised Healthcare
GREEN
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ORANGE
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58: Biomedical data integration
PINK
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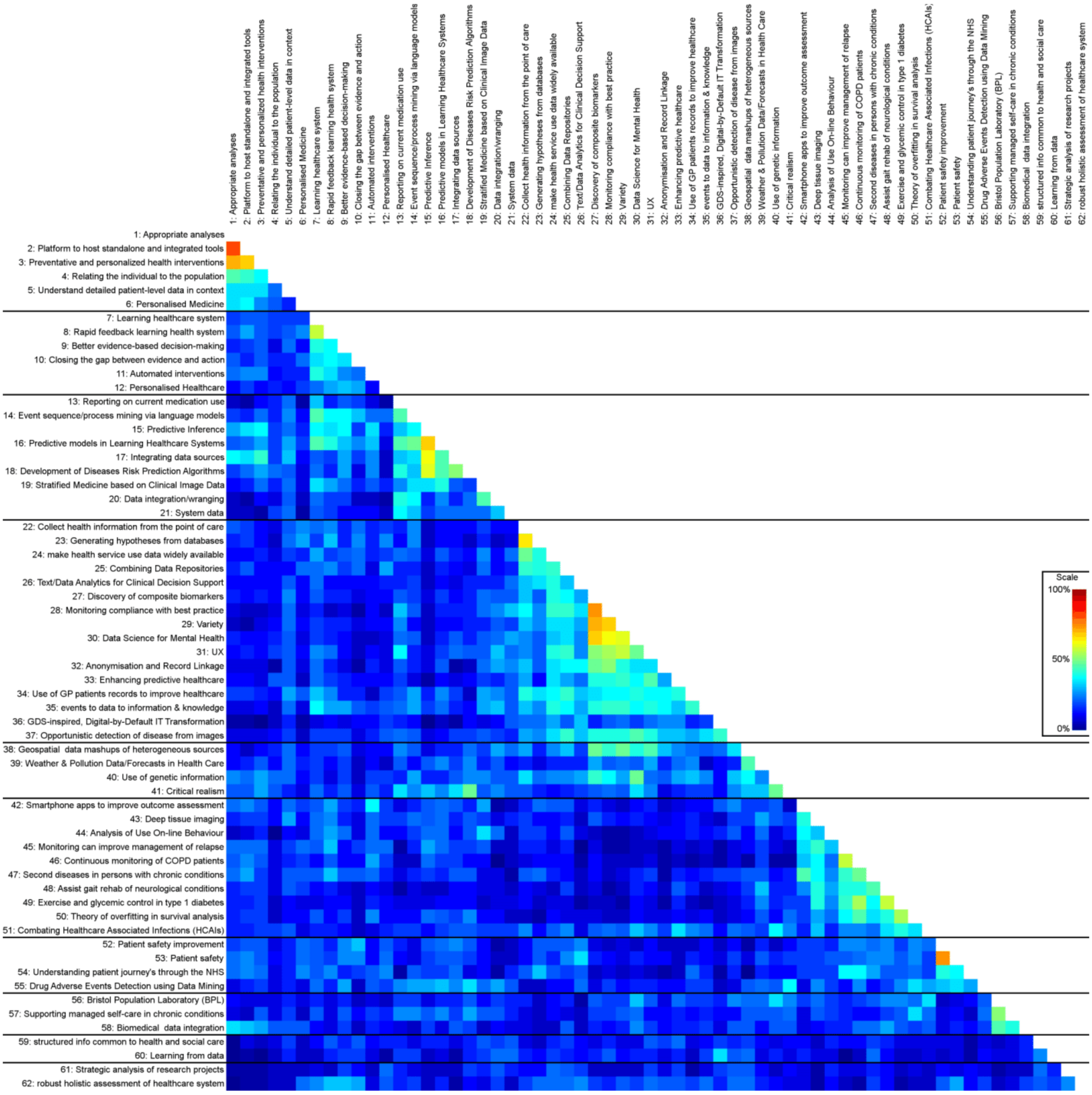
54: Understanding patient journey's through the NHS
55: Drug Adverse Events Detection using Data Mining
BROWN
59: structured info common to health and social care
60: Learning from data
61: Strategic analysis of research projects
62: robust holistic assessment of healthcare system
CYAN

Heat Map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Scale
100%
50%
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Raw Group Data

Colour	#	Title	Description
Red	1	Appropriate analyses	There will always be missing or incomplete data within healthcare records. Being able to apply the "best" analytical techniques to highlight the clinically relevant data would be of great benefit to the public and HCPs using/contributing data.
	2	Platform to host standalone and integrated tools	Provide an open reference platform having containers for versioned software with dependencies, easing the on ramp for less technical researchers to discover, reuse, integrate and repurpose open source tools for health research.
	3	Preventative and personalized health interventions	Large amounts of data are routinely captured for patients from interaction with health service that can be used by clinicians and medical professionals to drive preventative, personalised health interventions.
	4	Relating the individual to the population	When self-managing, people want to find "people like me". How to identify the key "fingerprints" in data for individual and population to facilitate clustering of people with similar conditions and experiences?
	5	Understand detailed patient-level data in context	Health questions often involve the analysis of large quantities of data that are of unknown quality. Visualization allows people to assess fine-grained, high-dimensional data in the context of underlying patterns.
	6	Personalised Medicine	The volume of genetic data available has vastly increased without a proportionate level of impact from the health research community. This is an opportunity to to build on huge amounts of data if we can establish the necessary research infrastructure.

Colour	#	Title	Description
Blue	7	Learning healthcare system	To distil relevant information from routinely collected data, feed that back to patients / clinicians and to test whether that makes a difference.
	8	Rapid feedback learning health system	Data is available to provide rapid feedback on many aspects of health care quality, safety and effectiveness, but we lack effective frameworks to ensure analysis, use and implementation of findings
	9	Better evidence-based decision-making	Access to well presented historical data / analysis will help health practicioners to make better informed decisions by exploring data from cohorts that are more widely sampled but also more specific to the diagnosis.
	10	Closing the gap between evidence and action	There is a cycle of data production to knowledge generation to action. How can we make sure the knowledge is produce in a timely fashion from the data and the knowledge delivered to the actor(s) who can take action?
	11	Automated interventions	Using sensing and real-time data analytics to detect when to trigger a treatment. e.g. to release a drug, not on a fixed timetable, but when the body is detected to be most receptive to it.
	12	Personalised Healthcare	Our digital presence, though inconsistent and varied, provides opportunities for traditional approaches to be improved and complemented towards a personalised, interactive and proactive approach.

Colour	#	Title	Description
Green	13	Reporting on current medication use	Creation of prescribing datasets provides a unique opportunity to report to clinicians and individuals on their current medication use. This would allow for more accurate reconciliation but could also provide a number of value added views of the data.
	14	Event sequence/process mining via language models	Standard data mining classifies and clusters unordered sets of data. health data has ordered sequences of events, more suited to language models from linguistics, e.g. n-gram taggers, Brill taggers and Chart parsers for tagging Part-of-Speech sequences.
	15	Predictive Inference	Most healthcare technologies are not predictive, and merely identify deterioration as it occurs; there is an opportunity to exploit fully-predictive systems for improving patient outcomes.
	16	Predictive models in Learning Healthcare Systems	Develop predictive models that respond to continuous feedback - i.e. coefficients that dynamically update based on secular trends, changing outcome distributions, changing coding practices.
	17	Integrating data sources	The use of multiple data sources and types to better model and understand health care problems and issues. I.e. using all available data regarding a patient to better diagnose and understand underlying conditions.
	18	Development of Diseases Risk Prediction Algorithms	Validated, applicable to clinical practice, predictive algorithms to calculate the risk of individuals for a specific disease to decide on lifestyle modifications and preventive medical treatments
	19	Stratified Medicine based on Clinical Image Data	Providing an integrated infrastructure across PACS and Life Sciences Image and related data sets offers novel tissue and organ-centric data analytics opportunities for clinical and translational sciences, including in stratified medicine.
	20	Data integration/wranging	Bringing together (disparate, large, multi-modal, sensitive) data sources is estimated to take 80% of the "analysis" process. It is critical to achieve effective heath data analytics to address this upstream activity to enable value-added analytics.
	21	System data	Errors in medical device use and EHR use cause harm, but we are not yet collecting use data, nor are logs accurate. We should use data to help design safer systems, and could mine it with patient outcomes. Currently we have no idea which things are safer.

Colour	#	Title	Description
Orange	22	Collect health information from the point of care	... Using pre-existing transactional opportunities. One of the biggest challenges to front line clinicians as the population ages and hospital care becomes more expensive is seeing multi disciplinary,multi organizational care information at presentation.
	23	Generating hypotheses from databases	We need better statistical methods (possibly combined with expert systems) for examining large databases for e.g. genetics and disease. This should mean reducing false positives and allowing formation of, rather than just testing, hypotheses.
	24	make health service use data widely available	administrative records of patients' use of services and prescriptions should be firstly, recorded more accurately, and secondly, made widely available to researchers in order to assess what specific groups within the population may have unmet needs
	25	Combining Data Repositories	There are many growing data repositories associated with experiment/modelling. There is value in combining these with data derived from patient records etc. Centralising these in a regional data centre opens great opportunity for further analysis. Discuss
	26	Text/Data Analytics for Clinical Decision Support	Current text analytics technologies can provide the necessary tools to extract information from unstructured text sources. Such an approach can exploit exemplar cases to help the provision of the right intervention to the right patient at the right time.
	27	Discovery of composite biomarkers	Risk assessment (precursors, biomarkers) for high-prevalence disease based on data analysis with measures from genotype and phenotype info. What groups of 'measures' associate best with outcome (disease)?
	28	Monitoring compliance with best practice	Variance in service delivery has positive and negative clinical and cost implications. EHR data presents an opportunity to identify correlations between service delivery patterns and outcomes to monitor compliance with established best practice.
	29	Variety	Exploiting, joining, and synthesizing a large variety of medical, healthcare and many other types of social data which are originally disconnected. This has provided a great chance of discovery!
	30	Data Science for Mental Health	How to use wearable devices, ubiquitous sensing, data analytics to track markers of mental health issues and provide real-time recommendations to people with mental health problems as which coping strategies to use
	31	UX	Moving well-understood techniques in UX/HCI into the healthcare domain. Especially around data presentation, interaction, and user modelling.
	32	Anonymisation and Record Linkage	The release of health records is dependent on how well we can anonymise the data for research

Colour	#	Title	Description
			purposes. For this, we need state-of-the-art statistical disclosure control techniques. Record linkage and statistical matching can fuse sources of data.
	33	Enhancing predictive healthcare	Integration of multi-omic data along with the extensive patient phenotype data available facilitates predictive modelling of healthcare outcomes. This approach is also central for personalised prediction.
	34	Use of GP patients records to improve healthcare	Longitudinal data is available from patients visiting their GPs. Data mining methods can be used to extract useful information and to potentially identify new drug adverse reactions/symptoms.
	35	events to data to information & knowledge	the technical infrastructure 4 the appropriate distribution of information in the healthcare sector is improving, a lot of the information is still in paper format & not shared; organisational processes to convert events into data, information need help
	36	GDS-inspired, Digital-by-Default IT Transformation	Commercial systems have largely failed to engage with the needs of the end user in health care. Poor IT design has huge costs in primary, 2ndary & social care. GDS-led agile devt. would transform health sector efficiency & transform clinician-engagement.
	37	Opportunistic detection of disease from images	All clinical images are recorded in hospital databases. Though taken to help diagnose a particular disease, they may show signs of other (unsuspected) disease. Automatic analysis algorithms could scan all images and warn if they detect relevant signs.

Colour	**#**	**Title**	**Description**
Purple	**38**	Geospatial data mashups of heterogeneous sources	Data science by mining associations and relations in multiple variables related to a domain can help in discovering important facts that healthcare needs to work better. Visualising these geographically give rise to better analytics and decisions.
	39	Weather & Pollution Data/Forecasts in Health Care	Weather influences human health (e.g. the risk of heat exhaustion, falls on ice, respiratory illness during high pollution episodes, weather influences on arthritis). New data and forecasts being collected can help diagnoses and hospital staff management.
	40	Use of genetic information	Genetic data can be used to aid in diagnosis and refined care pathways.
	41	Critical realism	Critical realism offers exciting prospects in shifting attention toward the real problems that we face and their underlying causes, and away from a focus on data and methods of analysis. As such, it offers a robust framework for the use of a variety of me

Colour	#	Title	Description
Yellow	42	Smartphone apps to improve outcome assessment	Smartphones offer opportunities to collect data directly from patients regarding the symptoms of their disease, and the benefits and harms of treatment, with the potential to improve how the information is used during routine clinic visit.
	43	Deep tissue imaging	We are now in a position to map out tissues using advanced image analysis and machine learning methods. This provides the opportunity to link genomic and proteomic data with the tissue hence putting it into the spatial context of the tissue.
	44	Analysis of Use On-line Behaviour	Log and analyse user on line behaviour to detect early signs of mental health problems, dementia and other pathologies. Data mining of keystrokes, gesture, and mouse input combined with text from email and Internet activity
	45	Monitoring can improve management of relapse	Real time symptom monitoring has the potential to pick up on early warning signs of relapsing mental health problem such as psychosis and therefore result in earlier and more effective and efficient treatment management.
	46	Continuous monitoring of COPD patients	COPD is common, increasing, and not well treated. Ideally treatment should reflect infections-exacerbations and recovery; patient activity levels; and environmental variation. How do we track 24/7 cough and activity to personalise therapy?
	47	Second diseases in persons with chronic conditions	Persons with chronic conditions (e.g. diabetes) are at increased risk of second (often fatal) diseases (e.g. cancer). There is a need to better predict these taking account of age, disease severity, duration and treatment, to develop optimal surveillance.
	48	Assist gait rehab of neurological conditions	People suffering from neurological conditions often experience symptoms affecting their gait. Using wearables to monitor gait and provide assistance when needed in home-based or outdoor settings may help to reduce visits to the clinic and overall cost.
	49	Exercise and glycemic control in type 1 diabetes	The effect of exercise on glycemic control for type 1 diabetics is complex, is specific to the exercise undertaken and is specific to the individual. Data science has the potential to quantify correlations and improve patient quality of life.
	50	Theory of overfitting in survival analysis	Overfitting (many variables, too few samples) is an increasing problem in medical outcome prediction. There is no method yet for predicting required sample sizes for the main statistical method used in the analysis of time-to-event data, Cox regression.
	51	Combating Healthcare Associated Infections (HCAIs)	Recent years have seen rapidly evolving, next-generation whole-genome-sequence (WGS) technologies becoming widely available. There is an exciting opportunity for developing new principled methods to jointly analyse WGS and epidemiological

			data.

Colour	#	Title	Description
Pink	52	Patient safety improvement	Risk in healthcare is dynamic and needs to be assessed continuously as knowledge about patient conditions, treatments and environment increases. Data science would provide proactive/structured means for evolving our understanding of patient safety risks.
	53	Patient safety	Primary health care data has the potential to be used to provide more information on adverse events and long-term health complications for specific treatments.
	54	Understanding patient journey's through the NHS	At present in the NHS in England trying to understand the interaction with the full range of NHS services is difficult as not all services have the capacity to share data and different coding systems are used by different NHS contributors.
	55	Drug Adverse Events Detection using Data Mining	Some drugs can cause serious adverse events on patients. Discovering new adverse events of drugs is important for pharmaceutical companies. Data mining algorithms have been applied to discovering new adverse events of drugs from electronic health records.

Colour	#	Title	Description
Silver	56	Bristol Population Laboratory (BPL)	A range of data is relevant to understanding causes of health problems and to evaluate health interventions. BPL will enable different scales of data (at population macro level, individual level and molecular level) to be linked and worked across together
	57	Supporting managed self-care in chronic conditions	Using data from a range of sources, including home and wearable sensors, to provide personalised advice and feedback, and detect deterioration early enough to avoid unplanned hospital admission and long-term decline.
	58	Biomedical data integration	A big progress has been made in utilizing the genetics or imaging clinical data (histology, MRI) to support diagnostic. On the other hand the integration of multiple source of the information still remains a challenge.

Colour	#	Title	Description
Brown	59	structured info common to health and social care	An agreed representation for the information commonly shared between health and social care, for use in research and direct patient care where appropriate. This would simplify the asking of research questions and the effective use of research results
	60	Learning from data	Using appropriate tools to support evidence-based medicine

Colour	#	Title	Description
Cyan	61	Strategic analysis of research projects	Billions of dollars are spent by research directorates across the globe on healthcare. Yet there is no single uniform view that provides decision makers with an overview of this research or how, for instance, RCUK and NSF spend and trends compare.
	62	robust holistic assessment of healthcare system	some major issues in healthcare are knowledge sharing, establishment of multi-agency, provision of multidisciplinary services and early diagnosis by evidence-based assessment tools. A robust holistic analysis of healthcare data helps to improve them.

Learning Health Systems — BLUE

Healthcare Opportunity #1:

- An opportunity to make a paradigm shift from Evidence Based Medicine to Learning Health Systems

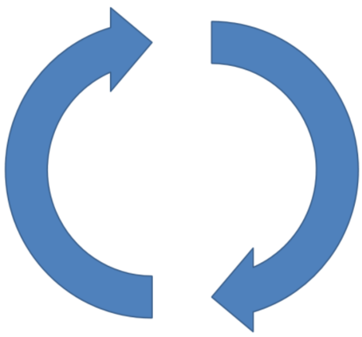
Healthcare Opportunity #2:

- Redefining organisational/professional/civic/ relationships to a more data-centric culture

Healthcare Opportunity #3:

- High resolution longitudinal data

If you wish, draw a diagram which represents your group's area, below:



Group Members:

Neils Peek	Allan Tucker
Ruth Norris	Pete Bower
John Ainsworth	Samhar Mahmoud
George Moulton	David Prieto-Merino
Alex Casson	Amitava Banerjee
Tjeerd Van Staa	Catherine Castillo
Ed Conely	

A Data Lifespan Carol — ORANGE A

Healthcare Opportunity #1: Ghost of data past

- Data reuse/repurpose
- Confidence/trust in meta-data
- Data decay/obsolescence
- Missing data

Healthcare Opportunity #2: Ghost of data present

- Harmonisation
- Availability

Healthcare Opportunity #3: Ghost of data future

- Standardisation – centrally pushed good standards/SOPs etc.
- Broad consent

If you wish, draw a diagram which represents your group's area, below:

Group Members:

Olly Butters	Emanuele Trucco
Becca Wilson	Jo Knight
Michael Stone	Andrew Dowsey

UX — ORANGE B

Healthcare Opportunity #1: Collecting, integrating & availability

- Across databases, from point of care
- Anonymise for linkage and research => publication
- Security; access; how to improve – scale

Ideas: 22, 24, 25, 29, 32, 34*

Healthcare Opportunity #2: Using and understanding data

- Enabling clinical decisions
- Analytics
- Knowledge discovery from databases
- "Right tool for the right job"

Ideas: 23, 26, 27, 35, 36

Healthcare Opportunity #3: Cross-talk/end-UX

- Taking collection and integration and understanding output to maximise output
- Stakeholders + end-user benefit experience (UX)

Ideas: 28, 30, 31, 33, 37

If you wish, draw a diagram which represents your group's area, below:	Group Members:
	Stephen Swift, Kayleigh Mason, Grant Thiltgen, Alison Noble, Sandra Bucci, Maarten De Vos, George Demetriou

Data Lifecycle — ORANGE C

Healthcare Opportunity #1: Collecting, integrating & availability

Data aggregation

- Hypothesis generation
- Methodological developments

Healthcare Opportunity #2: Using and understanding data

Data analysis methods and models

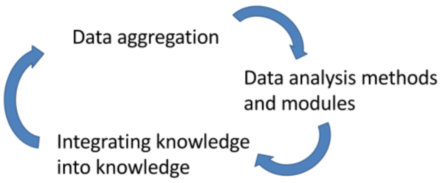
- Methodological developments
- Anomaly detection
- Decision support

Healthcare Opportunity #3: Cross-talk/end-UX

Integrating knowledge into practice

- Improved user experience
- Improved decision support to patients and healthcare professionals

If you wish, draw a diagram which represents your group's area, below:	Group Members:
	Chris Smith, Natalie Shlomo, Tarani Chandola, Duncan Appelbe, Para Vezyridis, Adele Marshall, Dai Evans



Mythbusters

ORANGE D

Healthcare Opportunity #1: Feedback on Data

Improve quality of data collection by rapid feedback

- Incentives to do it right/contribute
- E.g. proportion of patients with blood pressure measures (relative to others)

Healthcare Opportunity #2: Participatory design of the analytical workflow

- Use results/data to bring experts together
- Improve quality of results
- Avoid meaningless results/conclusions and thus wrong policy
- Improve acceptance of future results

Healthcare Opportunity #3: Better understanding/diagnosis using multi-modal data

- Bring together different data sources
- Different views on data
- Avoid inappropriate treatments
- Stratification

If you wish, draw a diagram which represents your group's area, below:

Good Data	Bad Data
☺	☹
Good Analysis	Bad Analysis

Group Members:

Tim Cootes	Carole Goble
Caroline Jay	Krysztof Poterlowicz
Roy Ruddle	Mike Pearson
Edwin Beggs	

Delivery of preventative & personalised Healthcare

RED

Healthcare Opportunity #1:

- Development of personalised medicine through engagement involvement & inter-disciplinary collaborations

Healthcare Opportunity #2:

- Development of analytical tools and guidance to facilitate #1

Healthcare Opportunity #3:

- Development of research infrastructures to share and manage #1 and #2

If you wish, draw a diagram which represents your group's area, below:

1 **2** **3|** **4|** **5** **6|**

Group Members:

Lydia Drumright	Samantha Crossfield
Alistair Sutcliffe	Ian Craddock
Philip Quinlan	Simon Harper
Daniele Soria	Daniel Neagu
Jane Sarginson	

Rich Data and Feedback — YELLOW

Healthcare Opportunity #1:

Richer better time-resolved data would enable:
Improved prediction and early intervention

- Preventing relapse
- Detecting need for therapy change
- Targeted further investigations
- Dynamic management of care intervention

Healthcare Opportunity #2:

Involving the individual

- Personalised feedback
- Influencing lifestyle
- Understanding individual needs
- ☹ this may increase inequality

Healthcare Opportunity #3:

Better decision making

- Objective rich real life data
- Joint decision-making
- Opportunity for better analysis of models
- Contexualisation

If you wish, draw a diagram which represents your group's area, below:

Group Members:

Jens Rittscher	Theodore Kypraios
Chris Taylor	Thomas Ploetz
Anthony Coolen	Theodoros Georgiou
Paula Williamson	Sacha Manson-Smith

Computable Models — GREEN

Healthcare Opportunity #1: Predictive Analytics

- Integration of text mining and time series

Healthcare Opportunity #2: Natural Language Processing

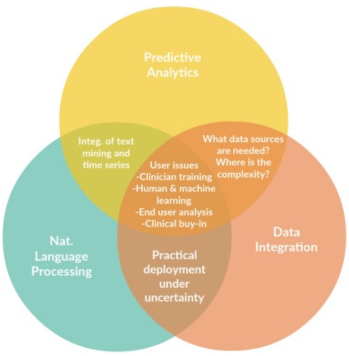
User issues

- Clinician training
- Human & machine learning
- End user analysis
- Clinician buy-in

Healthcare Opportunity #3: Data Integration

- What data sources are needed?
- Where's the complexity?
- Practice deployment under uncertainty

If you wish, draw a diagram which represents your group's area, below:



Group Members:

Owen Johnson	David Rew
John Keane	Arief Gusnanto
Robert Stevens	Albert Burger
Colin McCowan	David Clifton
Andrew Renehan	Emily Petherick
Alistair Willis	Jim Weatherall
Behzad Bordbar	Charlie McCay

Patient safety	**PINK**

Healthcare Opportunity #1:

Real-time monitoring and responses
- E.g. Intensive Care Unit
- Adverse drug reactions
- Patient pathway

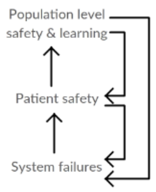
Healthcare Opportunity #2:

Learning from failures of safety critical systems & learning new analysis/learning systems
- Proof of correctness of patient pathway

Healthcare Opportunity #3:

Population-level learning for safety = 8-12%

If you wish, draw a diagram which represents your group's area, below:



Group Members:
Ibrahim Habli
David Tian
David Hogg
Ann Blanford

Leftfield Data	**PURPLE**

Healthcare Opportunity #1:

Geodata – location. Health in the community.
Need to understand what is going on in the community
- Twitter location data
- Ambulance service data
- Pollution
- Weather
- Smartphone/wearable tech
- Environment/people
- Part of forecasting process

Healthcare Opportunity #2:

- Genome data
- Diagnosis
- Treatment
- Engine of precision medicine
- Larger scale than ever
- Ability to link biology/medicine
- Variant have clinical significance
- Tools used – variant has consequences

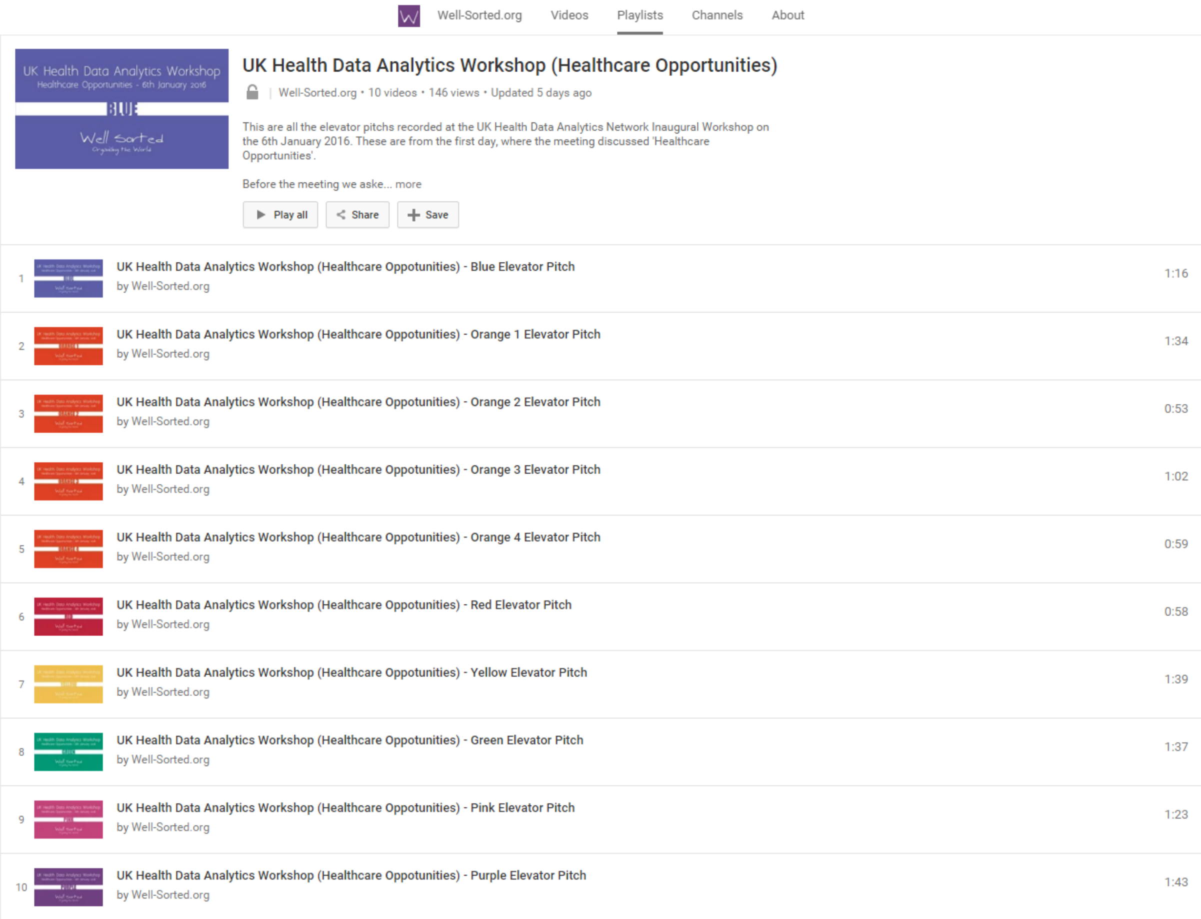
Healthcare Opportunity #3:

Combining Genotype and Phenotype data
Real data/real problems
How we capture phenotype correctly

If you wish, draw a diagram which represents your group's area, below:

Group Members:
Andy Brass
Yi Wang
Kieran O'Malley

Healthcare Opportunities Elevator Pitch Video Playlist


Well-Sorted.org Videos Playlists Channels About

UK Health Data Analytics Workshop (Healthcare Opportunities)

Well-Sorted.org • 10 videos • 146 views • Updated 5 days ago

This are all the elevator pitchs recorded at the UK Health Data Analytics Network Inaugural Workshop on the 6th January 2016. These are from the first day, where the meeting discussed 'Healthcare Opportunities'.

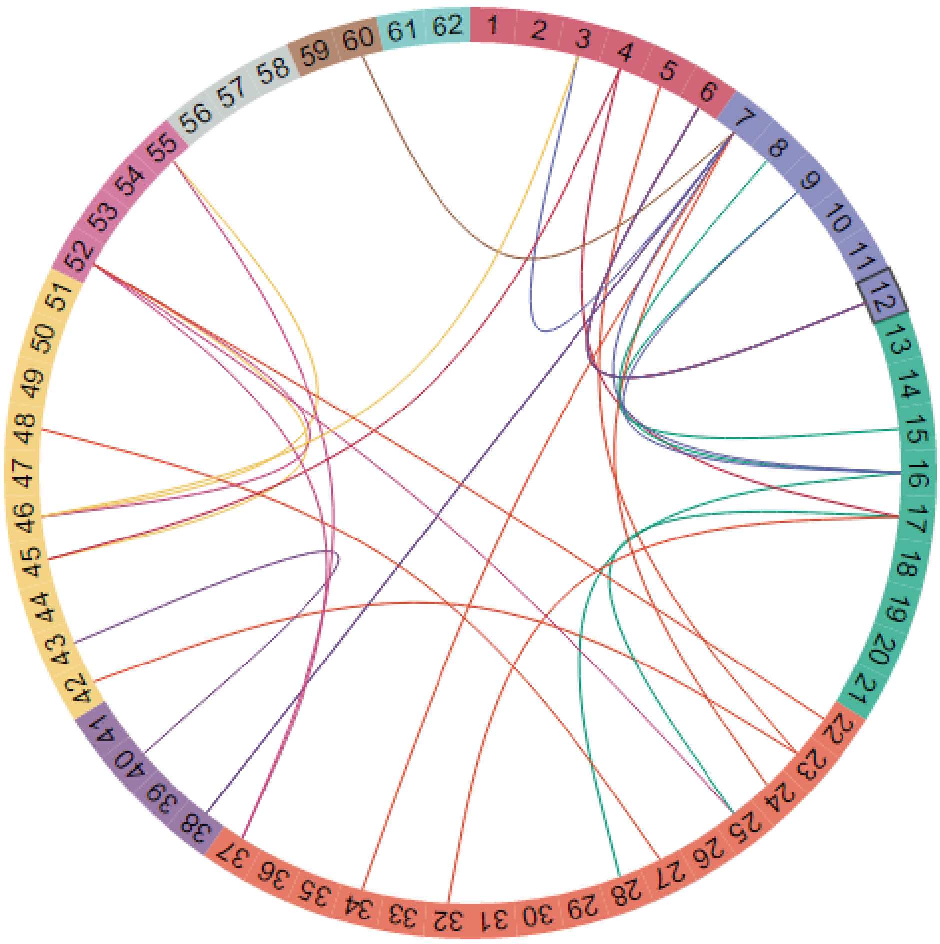
Before the meeting we aske... more

Play all Share Save

1	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Blue Elevator Pitch by Well-Sorted.org	1:16
2	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Orange 1 Elevator Pitch by Well-Sorted.org	1:34
3	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Orange 2 Elevator Pitch by Well-Sorted.org	0:53
4	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Orange 3 Elevator Pitch by Well-Sorted.org	1:02
5	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Orange 4 Elevator Pitch by Well-Sorted.org	0:59
6	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Red Elevator Pitch by Well-Sorted.org	0:58
7	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Yellow Elevator Pitch by Well-Sorted.org	1:39
8	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Green Elevator Pitch by Well-Sorted.org	1:37
9	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Pink Elevator Pitch by Well-Sorted.org	1:23
10	UK Health Data Analytics Workshop (Healthcare Oppotunities) - Purple Elevator Pitch by Well-Sorted.org	1:43

https://www.youtube.com/playlist?list=PLB-YaUclLgfPK2sceyM5StFmr6rwltf7T

Healthcare Opportunities Networking Visualisation



Idea A	Idea B	Comment	People
Generating hypotheses from databases	Understand detailed patient-level data in context	creating catalyst for engagement involving multiple disciplines to cover tra... more	Roy Ruddle, Philip Quinlas
Continuous monitoring of COPD patients	Drug Adverse Events Detection using Data Mining	Population-level leading to identifying key indicators of risk	Chris Taylor, Pink (3)
Learning healthcare system	Geospatial data mashups of heterogeneous sources	Use data in different. Embrace the learning health system	Kieran, Niels

Generating hypotheses from databases	Smartphone apps to improve outcome assessment	Tools to make aspects of database to become dynamic. If intervention change... more	Michael Stone, N/A
Personalised Medicine	Personalised Healthcare	infrastructure to enable personalised healthcare	Niels Peek, Simon Harper
Monitoring can improve management of relapse	Patient safety improvement	Continuous, real-time monitoring of critical health parametric and conditi... more	Thomas, Ibrahim
Predictive models in Learning Healthcare Systems	Monitoring compliance with best practice	Predictive Analytics to provide feedback to clinicians to create learning c... more	Owen J, Dan e Evans
Patient safety improvement	Combining Data Repositories	Standardisation of datasets, methodologies, hardware designs to aid in safe... more	David Hogg, Emanelle Trucco
Geospatial data mashups of heterogeneous sources	Learning healthcare system	Geotagging integrated with health data -> learning heath systems	Allan Tucker, Kieran O'Malley
Integrating data sources	Combining Data Repositories	Data integration to facilitate statistical modelling and epidemiological stu... more	Adele Marshall, Emily Petherick
Relating the individual to the population	Integrating data sources	Issue of accessible in safe and trustful way, effciently, data from clinica... more	Daniel, N/A
Use of genetic information	Deep tissue imaging	Refined gene panels for histological analysis	Andy, Jens
Personalised Medicine	Personalised Healthcare	Breaking down communications barriers and having different scientists, heal... more	Lydia, Peter B
Learning healthcare system	Preventative and personalized health interventions	Leaning health system - Continuously using routine data to improve health s... more	Ami, Sam

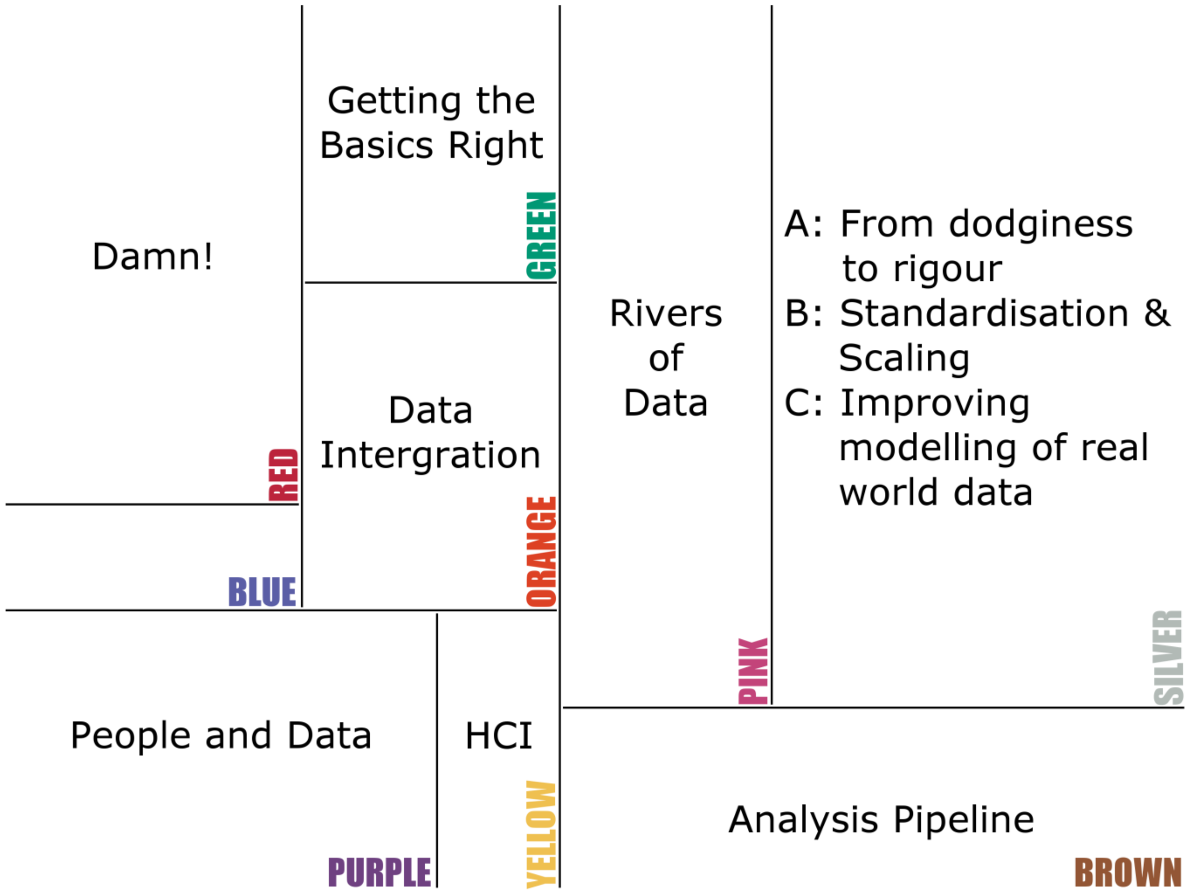
Discovery of composite biomarkers	Assist gait rehab of neurological conditions	The speaker (for Yellow) talked of integrating data of different types, e.g... more	Emanuele, Yellow group speaker
Patient safety improvement	Continuous monitoring of COPD patients	Continuous monitoring of patients can lead to earlier interventions and imp... more	Sacha Manson-Smith, Ibrahim Mabli
Anonymisation and Record Linkage	Integrating data sources	Data linkage and wrongly and collection (Connection from 22,24,25,32,34,35 ... more	Dai, Owen
Drug Adverse Events Detection using Data Mining	Opportunistic detection of disease from images	Use EHR to improve patient safety (Connection from 52 + 55 TO 22 + 37	David Tian, Steve Swift
Predictive Inference	Better evidence-based decision-making	Improving outcome prediction is an important input in evidence-based decisi... more	David, Colin
Relating the individual to the population	Monitoring can improve management of relapse	Individuals - not just patients but clinicians as recipients of feedback (C... more	Carole Goble,
Patient safety improvement	Opportunistic detection of disease from images	Strong link between pink and orange no2 (Connection from 52 + 55 TO 22 + 37... more	Steve Swift, David Tan
Learning from data	Learning healthcare system	Learning from data is a key component to LHS	Ruth/George, Brown
Use of GP patients records to improve healthcare	Learning healthcare system	Information from GP practices can input into a learning health system	Ruth,
make health service use data widely available	Learning healthcare system	From accurately / easy to use real time real world data gathering and analy... more	Alison Noble, Catherine Castillo
Predictive models in Learning Healthcare	Rapid feedback learning health system	Create new ways of using continuous data feeds to create predictive real-ti... more	David/Ruth/George, Colin

Systems			
Continuous monitoring of COPD patients	Preventative and personalized health interventions	Connecting primary care data with continuous experimental data by improving... more	Ian, Jane
Collect health information from the point of care	Patient safety improvement	Collecting healthcare data @ poc	n/a, n/a
Learning healthcare system	Predictive models in Learning Healthcare Systems	Socio-technical aspects of learning and outcome improvement	E S Cowley, Charlie McCoy
Better evidence-based decision-making	Predictive models in Learning Healthcare Systems	Dealing with output of statistical analysis (Connection from Purple group T... more	Yi, Arief
Personalised Healthcare	Personalised Medicine	Infrastructure to enable Personalised health care and Personalised medicine	Simon Harper, Niels Peek

7th – Research Challenges

(Wordle Generated from ideas submitted by attendees for the Healthcare question)

Research Challenges Overview Tree Map



UK Health Data Analytics Workshop: Well Sorted Materials

7th January 2016

Contents

Introduction	**1**
Dendrogram	**2**
Tree Map	**3**
Heat Map	**4**
Raw Group Data	**5**

For an online, interactive version of the visualisations in this document, go here:

www.well-sorted.org/output/UKHDANTechnologyChallenges

Introduction

Dear participant,

Thank you for taking part in submitting and sorting your ideas.

This document contains several visualisations of your ideas, grouped by the average of your online sorts. They are:

Dendrogram - This tree shows each submitted idea and its similarity to the others. The lower two ideas 'join' the more people grouped those two ideas together. For example, if two ideas join at the bottom, every person grouped those two together.

Tree Map - This visualisation presents an 'average' grouping. It is calculated by 'cutting' the Dendrogram at the dashed line so that any items which join lower than that line are placed in the same group. In addition, rectangles which share a side of the same length are more similar to each other than their peers.

Heat Map - This visualisation shows a similarity matrix where each idea is given a colour at the intersection with another idea, showing how similar the two are. This is useful to see how well formed a group is. The more red there is in a group (shown by the black lines), the more similar the ideas inside it were judged to be.

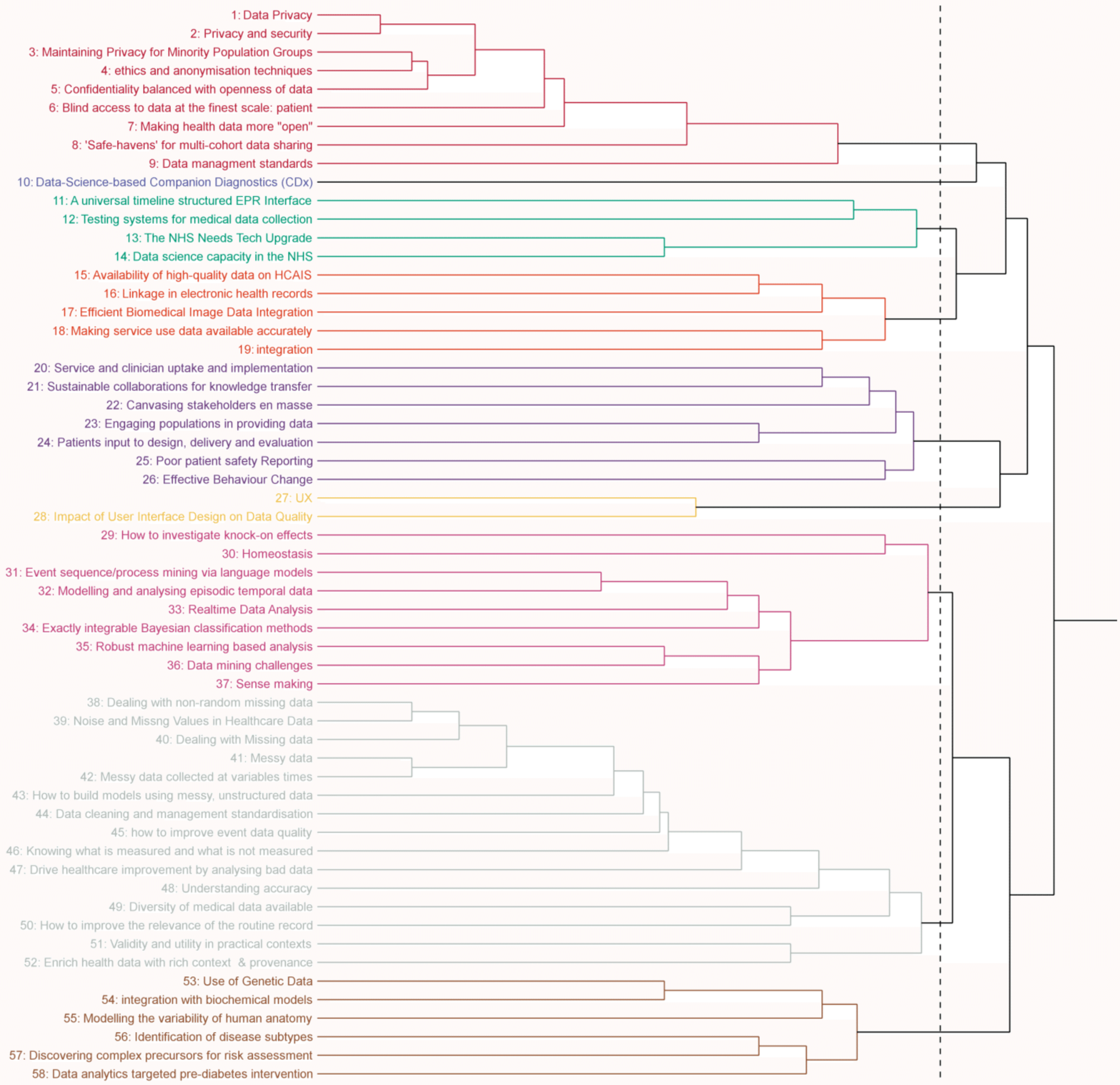
Raw Group Data - This table shows every submitted idea and its longer description. They are shown in the same order as the Dendrogram (so similar ideas are close to each other) and split into the coloured groups used in the Tree Map. In addition, each idea has been given a unique number so they are easier to find.

References

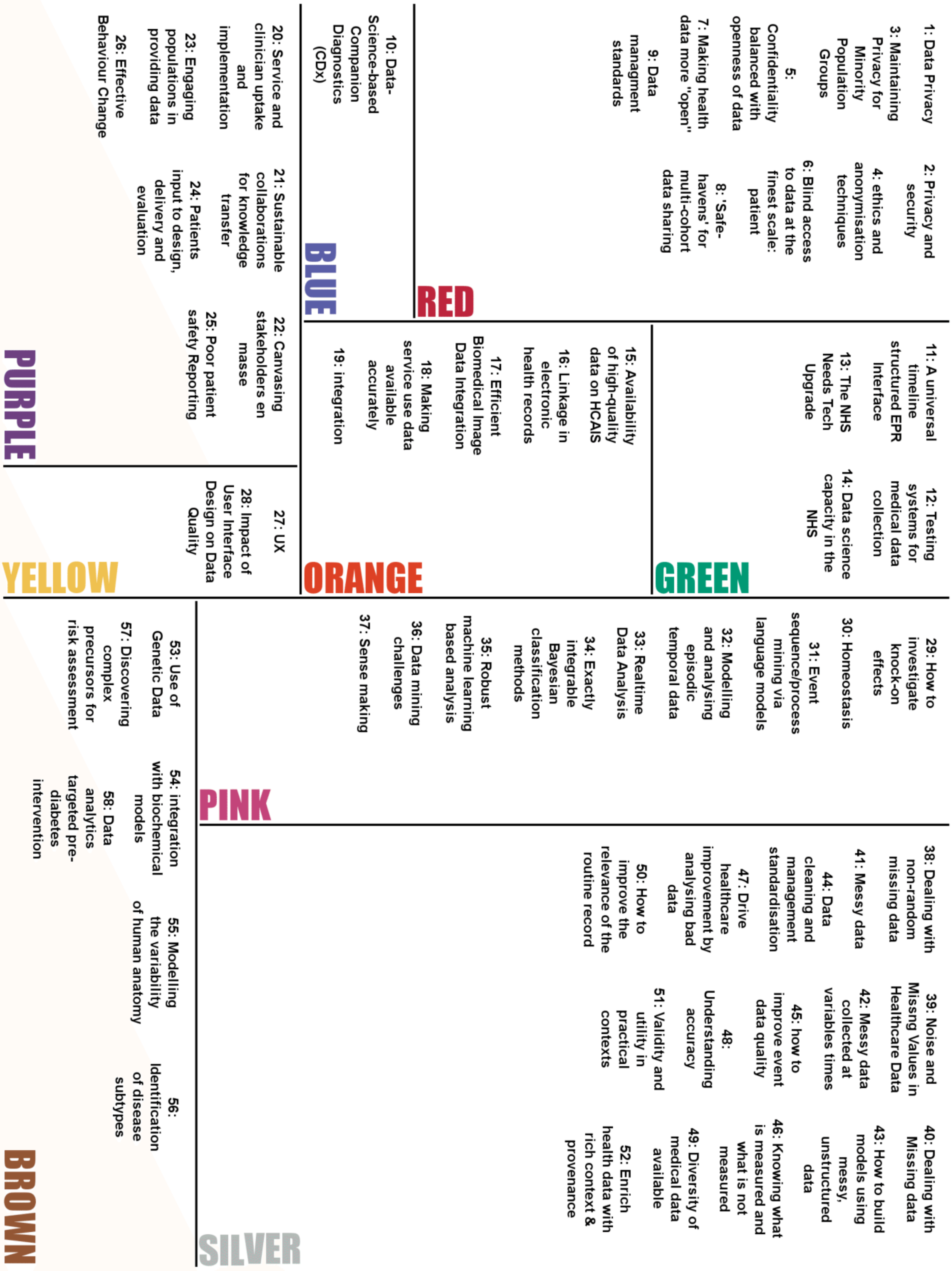
[1] Methven, T. S., Padilla, S., Corne, D. W., & Chantler, M. J. (2014, February). Research Strategy Generation: Avoiding Academic 'Animal Farm'. In Proceedings of the companion publication of the 17th ACM conference on Computer supported cooperative work & social computing (pp. 25-28). ACM. doi>10.1145/2556420.2556785

Well Sorted
Organising the World

Dendrogram


1: Data Privacy
2: Privacy and security
3: Maintaining Privacy for Minority Population Groups
4: ethics and anonymisation techniques
5: Confidentiality balanced with openness of data
6: Blind access to data at the finest scale: patient
7: Making health data more "open"
8: 'Safe-havens' for multi-cohort data sharing
9: Data managment standards
10: Data-Science-based Companion Diagnostics (CDx)
11: A universal timeline structured EPR Interface
12: Testing systems for medical data collection
13: The NHS Needs Tech Upgrade
14: Data science capacity in the NHS
15: Availability of high-quality data on HCAIS
16: Linkage in electronic health records
17: Efficient Biomedical Image Data Integration
18: Making service use data available accurately
19: integration
20: Service and clinician uptake and implementation
21: Sustainable collaborations for knowledge transfer
22: Canvasing stakeholders en masse
23: Engaging populations in providing data
24: Patients input to design, delivery and evaluation
25: Poor patient safety Reporting
26: Effective Behaviour Change
27: UX
28: Impact of User Interface Design on Data Quality
29: How to investigate knock-on effects
30: Homeostasis
31: Event sequence/process mining via language models
32: Modelling and analysing episodic temporal data
33: Realtime Data Analysis
34: Exactly integrable Bayesian classification methods
35: Robust machine learning based analysis
36: Data mining challenges
37: Sense making
38: Dealing with non-random missing data
39: Noise and Missng Values in Healthcare Data
40: Dealing with Missing data
41: Messy data
42: Messy data collected at variables times
43: How to build models using messy, unstructured data
44: Data cleaning and management standardisation
45: how to improve event data quality
46: Knowing what is measured and what is not measured
47: Drive healthcare improvement by analysing bad data
48: Understanding accuracy
49: Diversity of medical data available
50: How to improve the relevance of the routine record
51: Validity and utility in practical contexts
52: Enrich health data with rich context & provenance
53: Use of Genetic Data
54: integration with biochemical models
55: Modelling the variability of human anatomy
56: Identification of disease subtypes
57: Discovering complex precursors for risk assessment
58: Data analytics targeted pre-diabetes intervention

Tree Map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RED
10: Data-Science-based Companion Diagnostics (CDx)
BLUE
11: A universal timeline structured EPR Interface
13: The NHS Needs Tech Upgrade
12: Testing systems for medical data collection
14: Data science capacity in the NHS
GREEN
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16: Linkage in electronic health records
17: Efficient Biomedical Image Data Integration
18: Making service use data available accurately
19: integration
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SILVER
53: Use of Genetic Data
57: Discovering complex precursors for risk assessment
54: integration with biochemical models
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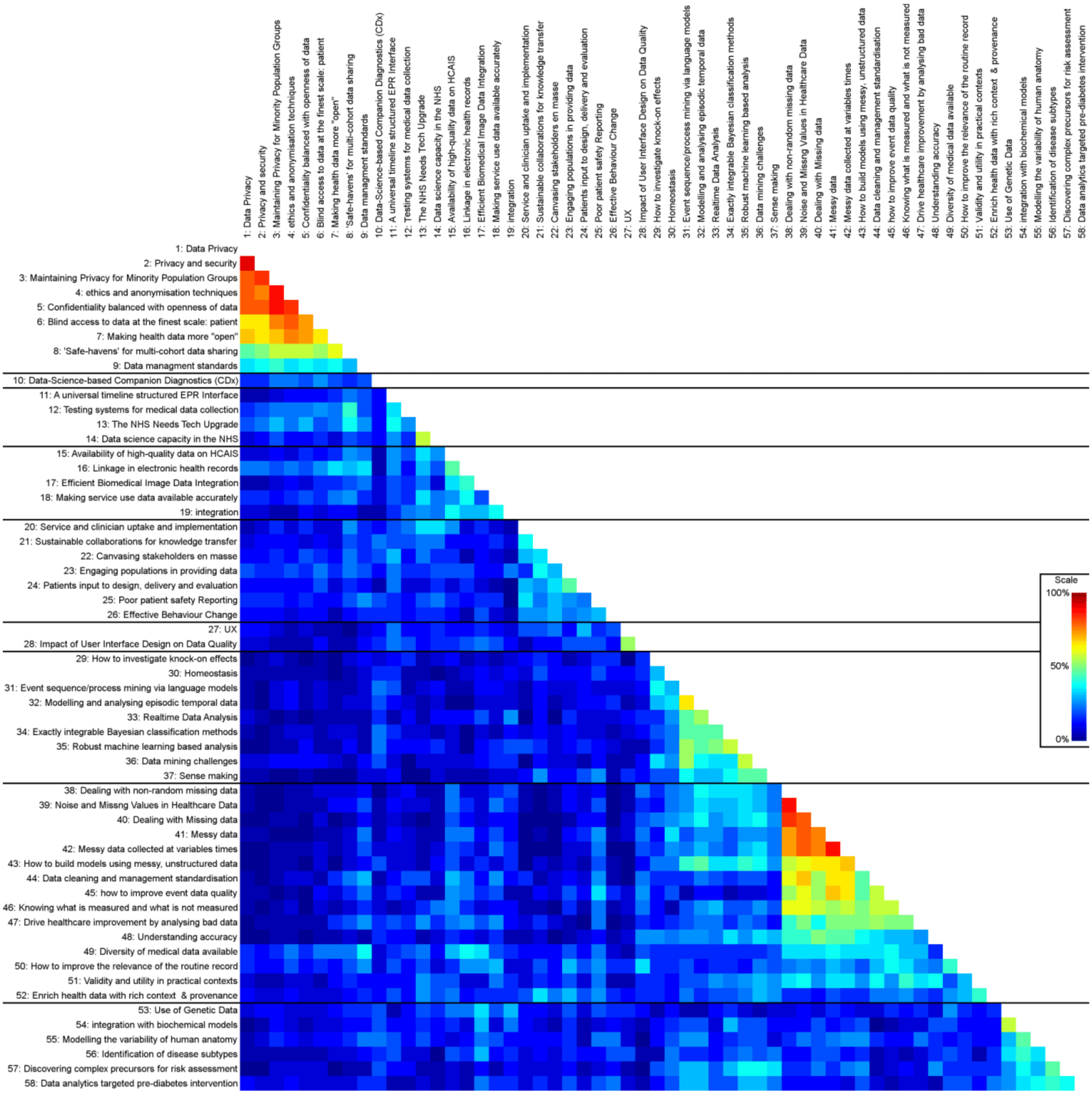
55: Modelling the variability of human anatomy
56: Identification of disease subtypes
BROWN

Heat Map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Scale
100%
50%
0%

Raw Group Data

Colour	#	Title	Description
Red	1	Data Privacy	Healthcare has particularly critical privacy requirements. How can data privacy be guaranteed, monitored and tracked through a data science ecosystem in a way that is personalized to a user?
	2	Privacy and security	Availability, ownership and usage of data for healthcare purposes come with both challenges of protecting privacy and assuring cyber security functionalities.
	3	Maintaining Privacy for Minority Population Groups	Analysing a large healthcare data set may not pose considerable risk of re-identification for individual research subjects, but for small minority groups and isolated communities, with a particularly rare disease, maintaining privacy is more challenging
	4	ethics and anonymisation techniques	It is very challenging to anonymise identities and have consent from individuals in the healthcare system. In my opinion, the qualitative data should always support the quantitative ones, and this makes the ethics considerations more complex.
	5	Confidentiality balanced with openness of data	For data science to fully exploit the potential of health data, the integration of many types of data is required. The problem with data integration is that it poses risks of confidentiality as more types of hetergenous data are combined.
	6	Blind access to data at the finest scale: patient	Due to privacy and security getting data at individual or household level is not possible. Nonetheless secure servers architecture with interoperability may allow computations at this level and render results at a higher geographical scale.
	7	Making health data more "open"	We are plagued by data sharing barriers: governance/disclosure restrictions, intellectual property issues or unsustainable to move large datasets. Requires an ethical-legal-social-technical solution to make biomedical data more accessible and reusable.
	8	'Safe-havens' for multi-cohort data sharing	There are a plethora of existing healthcare and social data in the UK but the single biggest barrier to effective linkage is governance. A pragmatic solution is the use of data safe-havens (e.g. Farr Institutes).
	9	Data managment standards	As a researcher involved in the experimental biomedical data management and analysis (RCUK grants) I found a lack of well characterized standards as one of the obstacle that effect my work.

Colour	#	Title	Description
Blue	10	Data-Science-based Companion Diagnostics (CDx)	Data Science can personalise healthcare. Drug regulators (FDA/EMA) may approve CDx to limit treatment only to those likely to benefit or not be harmed. Data-Science-based CDx must be strictly validated, available everywhere, and unchanged for years.

Colour	#	Title	Description
Green	11	A universal timeline structured EPR Interface	The timeline layered graphically rich EPR (cf UHS-Lifelines) offers a universal data structure for the integration & presentation of primary, 2ndary & social care records. The challenge is to implement this powerful NHS IT tool at local & national level.
	12	Testing systems for medical data collection	Although the miniaturisation of technology opens new possibilities of collecting healthcare data via wearable devices, testing prototype devices with participants suffering from neurological conditions often involves a lot of paperwork, delaying research.
	13	The NHS Needs Tech Upgrade	The NHS should take advantage of recent technological advancements in record keeping and real-time data collection as an opportunity to collaborate with researchers in utilising this info to help patients. Issues: confidentiality? Cost?
	14	Data science capacity in the NHS	Developing the skills across the NHS to understand what data science is and why it matters

Colour	#	Title	Description
Orange	15	Availability of high-quality data on HCAIS	It has been shown that integrating different hospital data sources can yield enhanced information for surveillance of a wide range of threats and this illustrates the need for integration of healthcare data from all sources.
	16	Linkage in electronic health records	The lack of direct linkage between some primary and secondary care databases can lead to difficulties in successfully tracking patients across centres. However, implementing a fully integrated system in the UK across all healthcare sites is problematic.
	17	Efficient Biomedical Image Data Integration	What kind of infrastructure enables data analytics involving very large, distributed clinical (PACS) and Life Science image data repositories, combining cloud computing, image compression and semantic web technologies? A multi-disciplinary challenge.
	18	Making service use data available accurately	Data on usage and access of health services is not properly recorded, nor widely available for researchers. Proposals to link health service use data to survey data have been made but how these will be carried out has not been forthcoming
	19	integration	how to integrate data from wearable sensors with information from traditional healthcare systems.

Colour	#	Title	Description
Purple	20	Service and clinician uptake and implementation	Clinicians often act as gatekeepers of mental health services. Therefore, clinicians views and attitudes effect type of healthcare received. Issues about how services manage complexities of real time, in-the-moment data collection.
	21	Sustainable collaborations for knowledge transfer	Sustainable collaboration and effective knowledge transfer will require the development of infrastructures and the formation of teams that share a common understanding of the potential benefits of data science for health care as well as its limitations.
	22	Canvasing stakeholders en masse	Extending tools like Well-Sorted and open innovation systems to harness the power of massed stakeholders to provide input on for instance, best practice patient support.
	23	Engaging populations in providing data	Much health care data is routine data on utilisation and costs, and lacks the other critical aspect for cost-effectiveness - quality of life and patient experience. How do we develop methods to collect patient reported data at scale?
	24	Patients input to design, delivery and evaluation	Need to make the data science tools accessible so that patients, professionals, managers, and policy folk can engage in the design, delivery and evaluation of healthcare. Research anticipated benefits and risks - and also to discover unintended outcomes.
	25	Poor patient safety Reporting	When it comes to patient safety data and incidents, there is a culture of poor and under reporting. Decisions made based on existing data tend to lack credibility due to poor confidence in the available data.
	26	Effective Behaviour Change	Using on line technology to change people's behaviour to improve wellbeing, follow treatment plans, and change lifestyle. Linking data analytic outcomes to low cost (ICT mediated) behaviour change.

Colour	#	Title	Description
Yellow	27	UX	Understanding the user-facing aspects required to convey complex information to multiple stakeholders.
	28	Impact of User Interface Design on Data Quality	Data quality issues resulting from variations in user interface design are non random and can act as a confounding factor on data science based on routine data. The causal relationship is evident but poorly understood.

Colour	#	Title	Description
Pink	29	How to investigate knock-on effects	Health data is often analysed in a series of discrete pipeline stages, but users rarely investigate the sensitivity of findings to decisions made earlier on during analysis. How can data science increase rigour by joining together this 'broken' workflow?
	30	Homeostasis	A characteristic of healthcare data is the fact that the time-series arise from a system with strong homeostasis - it is an individual that is actively attempting to restore itself to normality - this is a unique constraint for data science applications.
	31	Event sequence/process mining via language models	Standard data mining classifies and clusters unordered sets of data. health data has ordered sequences of events, more suited to language models from linguistics, e.g. n-gram taggers, Brill taggers and Chart parsers for tagging Part-of-Speech sequences.
	32	Modelling and analysing episodic temporal data	Consider recognising significant change in an individual's behaviour from wearable/IoT data. Since every day is different the challenge is how to go beyond crude averages (eg time spent sleeping, walking etc) to learn what is normal for that person.
	33	Realtime Data Analysis	There are many frameworks available for processing streaming realtime data (from medical sensors). Are these widely used? Can they be adapted to work with the tools that researchers currently use? Discuss.
	34	Exactly integrable Bayesian classification methods	Extracting clinically predictions from genomic data is presently done via so-called `gene signatures', which are poor man's alternatives to proper regression. One would prefer Bayesian methods, but in high dimensions they pose prohibitive CPU demands.
	35	Robust machine learning based analysis	The integration of machine learning approaches with traditional statistics is essential to deal with non-linearity and related variables within big data. A major associated challenge is the education of healthcare professionals in this approach.
	36	Data mining challenges	Data mining can unintentionally be misused, and can then produce results which appear to be significant; but which do not actually predict future behavior and cannot be reproduced on a new sample of data and bear little use.
	37	Sense making	Connecting analytical results with domain knowledge!

Colour	#	Title	Description
Silver	38	Dealing with non-random missing data	Data can sometimes be included or excluded due to it's relavence to an outcome, such as GP's being more likely to update or record smoking or BMI data if they think it is likely to become a health issue. This can make account for these measures difficult
	39	Noise and Missng Values in Healthcare Data	Healthcare data may have noise and missing values. If these are not handled appropriately, the results of the analysis may not be accurate. Human knowledge and data pre-processing methods can be used to clean noise and handle missing values in data.
	40	Dealing with Missing data	Missing data can be informative and hence need state-of-the-art modelling techniques to overcome this problem.
	41	Messy data	Dealing with missing and low quality data - managing uncertainty and interpolating between data points. Identifying which points are more likely to be accurate.
	42	Messy data collected at variables times	Routinely collected are messy (not systematically recorded) and collected at different points in time
	43	How to build models using messy, unstructured data	Statistical modelling is based on samples of complete data arising from a designed experiment. But healthcare data has a complex data generating process, missingness and lack of structure.
	44	Data cleaning and management standardisation	Analysing data for health care research normally requires a stage of cleaning and subsequent manipulation before analysis can be undertaken. This stage is often done by the researcher rather than at data source introducing repetition and inconsistency.
	45	how to improve event data quality	how do we improve the quality of the data to underpin information and knowledge in delivering healthcare
	46	Knowing what is measured and what is not measured	One of the biggest challenges of using routine health data is knowing what gets measured, when, by whom and to what standard. Routine NHS systems are not often equipped for the purposes of large scale data extraction which limits research potential.
	47	Drive healthcare improvement by analysing bad data	NHS IT systems are a mess. Operational data is a mess, and many patient records have major errors. Many systems use proprietary "standards". Data can take weeks to flow end to end (even if it gets there) ... the mess needs exposing and critiquing!
	48	Understanding accuracy	We're all familiar with papers where the algorithm performance results are optimistic (to put it politely). Is this just bad practice or do we need new tools to understand the performance of algorithms when working with Big Data?
	49	Diversity of medical data available	Medical records fall in the category of 'big data'. However, healthcare data is also multi-modal and extremely complex and noisy. A huge data science research challenge is to find methods to incorporate data of different types and from different sources.

	50	How to improve the relevance of the routine record	Methods are needed to address the inadequate attention paid to outcome measurement in clinical care, research, and consumer health applications, in order to reduce avoidable waste in health data analytics.
	51	Validity and utility in practical contexts	Tools and methods developed must have validity and utility for clinicians and medical professionals in practical contexts. Factors such as technical infrastructure, required expertise, data quality and usage context must be considered in their design.
	52	Enrich health data with rich context & provenance	Representation of data at the point of care is disappointing. For trrue Learning Health systems clinicians need rich context/provenance, as well as the ability to synthesise new best practice through system learning. Secondary use data isn't sufficient.

Colour	#	Title	Description
Brown	**53**	Use of Genetic Data	New methods are needed to store, access and interpret genetic data and its impact on human health.
	54	integration with biochemical models	Making genetic or protein databases with more knowledge of function in the cell, of facilitate hypothesis formation and reduce false positives on data mining.
	55	Modelling the variability of human anatomy	There are millions of images of parts of human bodies in hospital databases. It should be possible to use them to build statistical models of how human anatomy varies across the population. However, the data is very variable and only weakly annotated.
	56	Identification of disease subtypes	Large data sets if linked data sets allow us to identify disease subtypes that are currently not captures by existing disease categories (e.g. Cancer grade). The identification of these and the associated statistics pose significant challenges.
	57	Discovering complex precursors for risk assessment	Opportunity: simultaneous emergence of large clinical bioresources (eg UKBB), distr'd powerful computing platforms, analytics algorithms, & medical signal/img analysis. Challenge: discover complex, heterogeneous sets of 'measures' predicting disease risk.
	58	Data analytics targeted pre-diabetes intervention	Data analytics can be used to predict which people are more likely to develop diabetes, based on various lifestyle markers, and anti-diabetic medication can be prescribed to this population. This is a goal of the Diabetes Prevention Programme.

Data Integration — ORANGE

Research Challenge #1:

- Linkage of multi-stakeholder data sources
- Silo'd information (e.g. patient collected data vs. EHR data vs. HCP points of care)
- CDIM

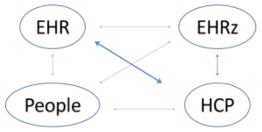
Research Challenge #2:

- Identifying relevant data to particular caregiving scenarios & personalised views of such data
- HCL - visualisation

Research Challenge #3:

- Clinical image data integration
- Semantics of images
- Data analytics over PACS systems

If you wish, draw a diagram which represents your group's area, below:



Silo'd information

Problem

Group Members:
Albert Burger
Sheldon Steed
Samhar Mahmoud

Damn! — RED

Research Challenge #1: Barriers

- Information governance: confidentiality and privacy (Caldicott report expected in Jan)
- Social: fear
- Organisational: bureaucracy & individuals (dog in manager, conspiracy/mess up, technical blocks – don't understand the coal face)
- Technical: open pseudonymiser
- Solution – locality warehouses

Research Challenge #2: Open-ness & Transparency

- Fear: professional/patient – dispel – publish data held & what used
- Data sets : patient level = few. Aggregate – anonymised – publish "CDC – Wonder"
- Build trust

Research Challenge #3: Infrastructure & funding

- Data Quality a problem (technical, coding, architecture, standards)
- Connecting silos
- Best practice
- SNOMED-CT is coming! Primary Care

If you wish, draw a diagram which represents your group's area, below:

Group Members:
Dai Evans
Duncan Appelbe
Allan Tucker
Para Vezyridis
Dave Robertson
Natalie Schlomo
Chris Smith
Lydia Drumright
Grant Thiltgen
Becca Wilson
Olly Butters

HCI	YELLOW
Research Challenge #1:	
• How to design interfaces to better effect behavioural change • Encourages data collection – non litigious • Applies to both patients/healthcare professionals • There is a reason/benefit for more data	
Research Challenge #2:	
• How information is presented • Universal platform/more personalised • Talking into account all stakeholders/users	
Research Challenge #3:	
• High quality data – minimum effort • How do we support data collection to minimise noise?	
If you wish, draw a diagram which represent your group's area, below:	Group Members: **Caroline Jay** Simon Harper Ruth Norris Kieran O'Malley

Getting the Basics Right	GREEN
Research Challenge #1: End user engagement	
• Sterling end user (health professional) engagement • Paper – paperless transition • Optimising – interfaces/systems • Out of which – better data capture	
Research Challenge #2: Agile by-product of Normal Clinical Activity	
• Early engagement of health informatics community in system design • Agile – iterative • "Natural by-product of activity" • Designing "values" & "ethics" into software systems	
Research Challenge #3: Education	
• Workforce education – digital transformation (understanding). Skills upgrade + gaps • Capacity issues • Dilemma agile vs. "enterprise hardening"	• Universities • Schools • Nat Comp Curriculum • Post-grad institutions • e.g. Farr institute, NHS
If you wish, draw a diagram which represents your group's area, below:	Group Members: **David Rew** Theodoros Georghiou George Moulton Jon Whittle

<table>
<tr><th colspan="3">Rivers of Data</th><th>PINK</th></tr>
<tr><td colspan="4">Research Challenge #1: Marriage of Human & Machine</td></tr>
<tr><td colspan="4">Interpretability
Role of expert
Personal responsibility
Co-development of models</td></tr>
<tr><td colspan="4">Research Challenge #2: Characterising complex temporal structure</td></tr>
<tr><td colspan="4">High dimensionality vs low-N diversity
“N of 1” models powered by population models
Temporal model evolution
Exploiting system characteristics (e.g. homeostasis)</td></tr>
<tr><td colspan="4">Research Challenge #3: Guaranteeing robustness (of models)</td></tr>
<tr><td colspan="4">Calibration drift
Quantifying/managing uncertainty
Characterising generalisability (or predicting it?!)
Verification</td></tr>
<tr><td>If you wish, draw a diagram which represents your group’s area, below:</td><td>Group Members:
Jim Weatherall
Chris Taylor
David Hogg
John Keane
Alistair Willis
Adele Marshall</td><td>
Thomas Ploetz
Joe Mellor
Stephen Swift
Anthony Coolen
Maarten De Vos
Owen Johnson</td><td>
Theo Kypraios
David Prieto-Merino
David Clifton
Arief Gusnanto</td></tr>
</table>

<table>
<tr><th colspan="2">People and Data</th><th>PURPLE</th></tr>
<tr><td colspan="3">Research Challenge #1:</td></tr>
<tr><td colspan="3">One size doesn’t fit all when people want to view/interact/share/collect their data</td></tr>
<tr><td colspan="3">Research Challenge #2:</td></tr>
<tr><td colspan="3">Communication: advancing clinical decision-making/for improving patient outcomes/health</td></tr>
<tr><td colspan="3">Research Challenge #3:</td></tr>
<tr><td colspan="3">How do we use data to change patient behaviour?</td></tr>
<tr><td>If you wish, draw a diagram which represents your group’s area, below:</td><td colspan="2">Group Members:
Amitara Banerjee
Alistair Sutcliffe
Ann Blanford
Peter Bower
Ibrahim Habli
David Schultz</td></tr>
</table>

Analysis Pipeline — BROWN

Research Challenge #1: Data Integration

- Bring together data from different groups/sources
- How to encourage collaboration, data sharing and common standards

Research Challenge #2: Learning Structure from Data

- Finding useful features + explanation
- Need new algorithms for huge data sets
- Effective use of prior info/models

Research Challenge #3: Stratification & disease subtypes

- Find disease subtypes
- Early diagnosis
- Personalise treatment

If you wish, draw a diagram which represents your group's area, below:	Group Members: **Tim Cootes** Robert Stevens Sacha Manson-Smith Jens Rittscher Jo Knight Edwin Beggs

From dodginess to rigour — SILVER A

Research Challenge #1: Understanding dodginess in all its guises

- Provenance recorded
- Assessing data quality
- Statistics, visualization, automation
- The human factor
- Understand data "fingerprint"

Research Challenge #2: Reduce preparation cost to <u>only</u> 30%

- Re-use by remote 3 parties
- Assimilation/data integration
- Data standards/formats/interchange

Research Challenge #3: Allow low-effort rigorous analysis that is holistic

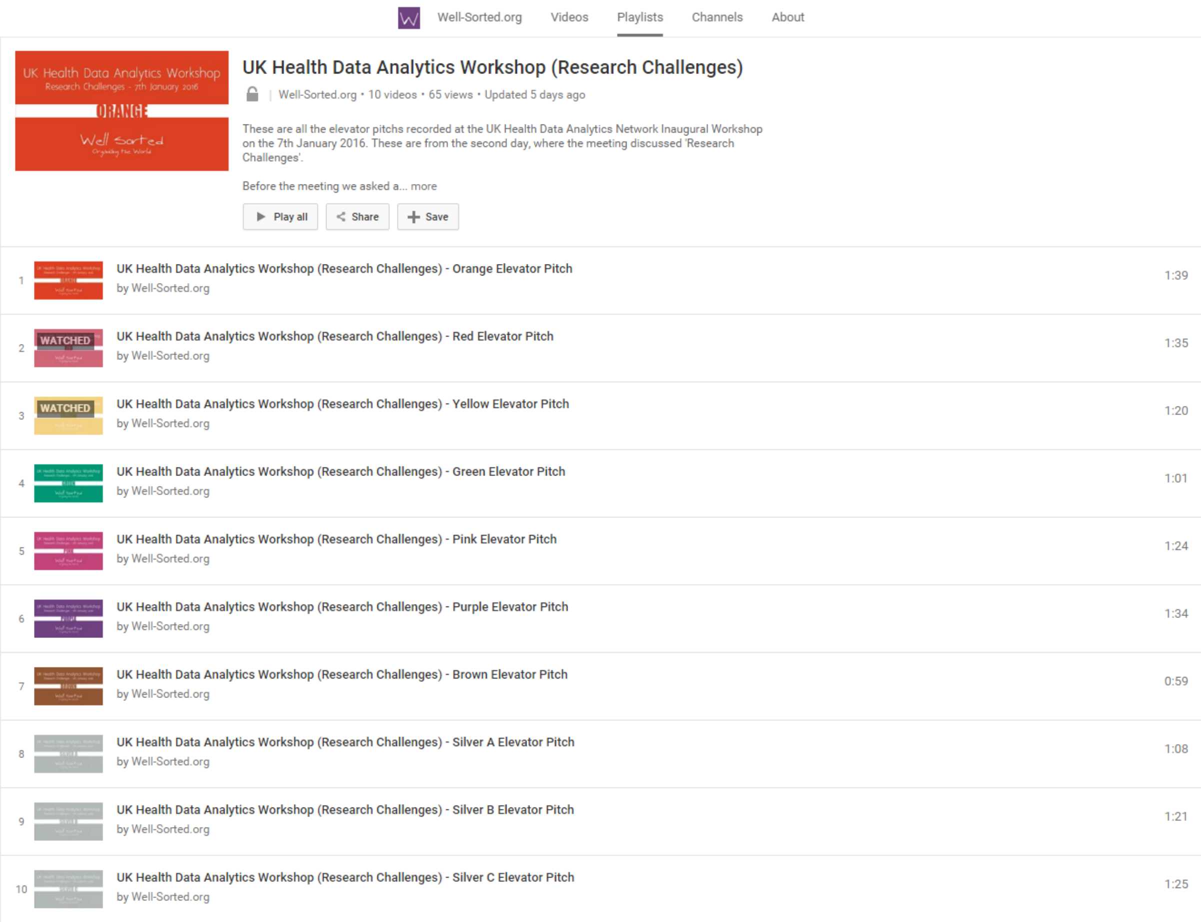
- Linked to resources & established knowledge about the data
- Sensitivity, uncertainty due to data and processing
- Propagation of confidence intervals across analysis workflow
- Validate assumptions made during analysis, at each stage of the processing pipeline

If you wish, draw a diagram which represents your group's area, below:	Group Members: **Roy Ruddle** Kayleigh Mason Daniel Neagu Niels Peek Jane Sargison Michael Stone Alex Casson

Standardisation & Scaling		SILVER B
Research Challenge #1:		
• Appropriate standards (data collection) • Appropriate data/metadata		
Research Challenge #2:		
• Understanding the barriers to implementing standardisation		
Research Challenge #3:		
• • Building on the best of the past • Boosting at scale		
If you wish, draw a diagram which represents your group's area, below:	Group Members: **Charlie McCay** Emanuele Trucco Matthew Sperrin Daniele Soria	 Emily Petherick Tim Croudace Paula Williamson Tarani Chandola

Improving modelling of real world data		SILVER C
Research Challenge #1:		
• Machine learning to provide robust models for working with real world data in a variety of applications		
Research Challenge #2:		
• Develop methodologies to improve current practice and lack of consensus in decision making: efforts to improve underlying data to get closer to "perfect" data against using methods to report on uncertainty of results based on complexity of data		
Research Challenge #3:		
Can we better understand and improve the transparency of domain specific knowledge: • Accuracy of results • Provenance of data items • Steps/assumptions made • Human/clinician/computer interactions		
If you wish, draw a diagram which represents your group's area, below:	Group Members: **Colin McCowan** Ian Craddock George Demetriou Andrew Dowsey	 David Tian Samantha Crossfield Tjeerd Van Staa Alison Noble

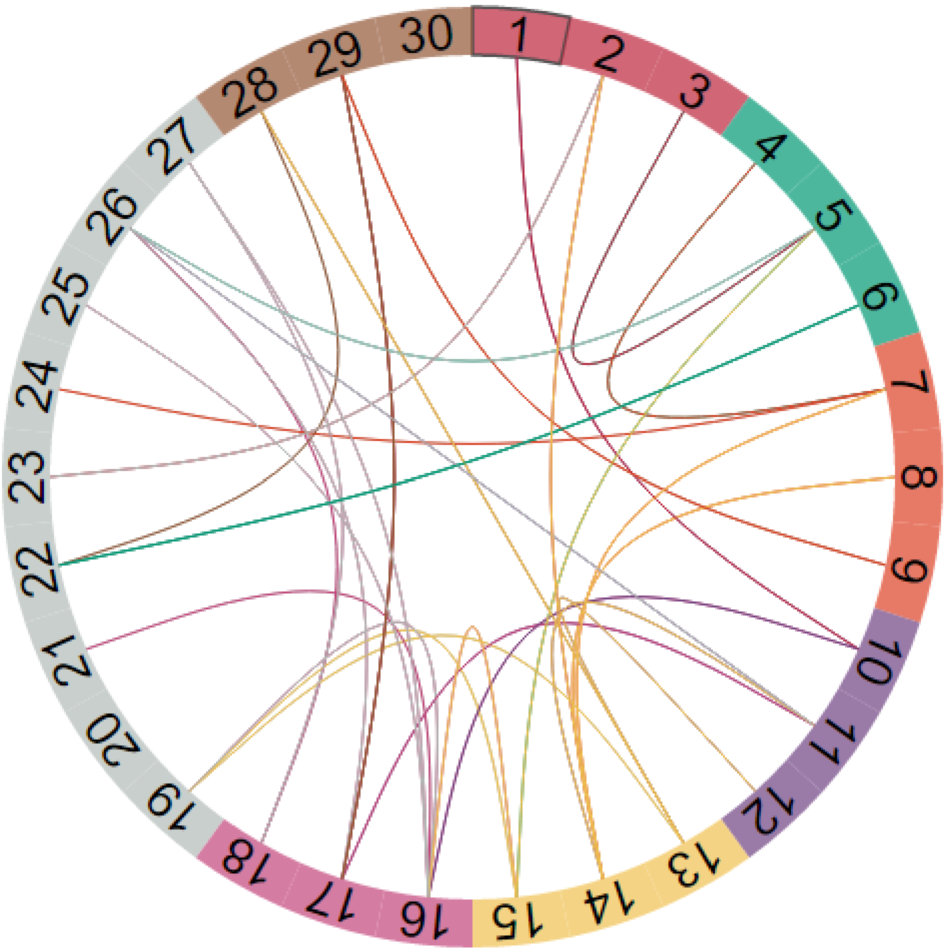
Research Challenges Elevator Pitch Video Playlist



https://www.youtube.com/playlist?list=PLB-YaUclLgfN99TpsTsSwgnLpslkvxdAX

Research Challenges Networking Visualisation

The ideas presented in this visualisation are from the 3 consolidated challenges presented by each breakout group



Idea Description A	Idea Description B	Comment	People
Develop methodologies to improve current practice and lack of consensus in ... more	Guaranteeing robustness (of models):- Calibration drift; Quantifying/managi... more	Understanding how to get benefit from data/machine leaving outputs. Even wh... more	Colin McCowan, Alistair Willis
Understanding dodginess in all its guises:- Provenance recorded; Assessing ... more	How to design interfaces to better effect behavioural change; Encourages da... more	Yellow: Data quality + being "trustworthy" Brown: How data captured + impro... more	Kayleigh, Ruth Norris
Understanding dodginess in all its guises:- Provenance recorded; Assessing ... more	High quality data Â– minimum effort; How do we support data collection to m... more	Data production - analytics pipeline/ data quality issues/ human factors	Niels Peek, Caroline Jay
Building on the best of the past; Boosting at scale	Linkage of multi-stakeholder data sources; SiloÂ'd information (e.g. patien... more	Building on tools developed in TRANSFORM Project. Workshop on Standards nee... more	Charlie McCoy, Samhar Mahmoud
Appropriate standards (data	Data Integration:- Bring	Lack of standards and importance	Daniele Soria, Tim

collection); Appropriate data/metadata	together data from different groups/sources; How t... more	of having standards so that large meaningf... more	Cootes
Characterising complex temporal structure:- High dimensionality vs low-N di... more	Develop methodologies to improve current practice and lack of consensus in ... more	Methods for improved clinical decision making.	Anthony Coolen,
Allow low-effort rigorous analysis that is holistic:- Linked to resources &... more	Marriage of Human & Machine:- Interpretability; Role of expert; Persona... more	Data processing includes many assumptions (parameters; model; domain-based)... more	Roy Ruddle, Thomas Ploetz
Guaranteeing robustness (of models):- Calibration drift; Quantifying/managi... more	Can we better understand and improve the transparency of domain specific kn... more	Focus on System failure through data provenance etc.	David Hogg,
Marriage of Human & Machine:- Interpretability; Role of expert; Persona... more	Understanding dodginess in all its guises:- Provenance recorded; Assessing ... more	Heterogeneity and Quality	Daniel Neagu,
Appropriate standards (data collection); Appropriate data/metadata	Education:- Workforce education Â– digital transformation (understanding) S... more	Digital health - educating the workforce on options and potentials. Accumul... more	Tim Croudace, David Rew
Identifying relevant data to particular caregiving scenarios & personal... more	How information is presented; Universal platform/more personalised; Talking... more	High Quality data. Modifying data. River more effective. (Connection from O... more	Caroline, Kieran
Communication: advancing clinical decision-making/for improving patient out... more	Characterising complex temporal structure:- High dimensionality vs low-N di... more	'Marriage of Human and Machine'. Discussed how much to trust output from ma... more	Dave, Anthony
Characterising complex temporal structure:- High dimensionality vs low-N di... more	Learning Structure from Data:- Finding useful features + explanation; Need ... more	The use of healthcare and omics data for prediction of disease subtypes by ... more	Arief Gusnanto,
Characterising complex temporal structure:- High dimensionality vs low-N di... more	Learning Structure from Data:- Finding useful features + explanation; Need ... more	Rivers of data. Characterising complete temporal structures (e.g. homeostas... more	Owen,
One size doesnÂ't fit all when people want to view/interact/share/collect t... more	Barriers:- Information governance: confidentiality and privacy (Caldicott r... more	The use of data all the way through its heath care life cycle is dependent ... more	Ami Banerjee, Dai Evans
Marriage of Human & Machine:- Interpretability; Role of expert; Persona... more	One size doesn't fit all when people want to view/interact/share/collect t... more	Focus on human/machine relationships. The context for Pink 1 is 'Rivers of ... more	David Hogg,
Learning Structure from Data:- Finding useful	Clinical image data integration; Semantics of images; Data	Extracting structured information/features from images	Tim Cootes, Albert Burger

features + explanation; Need ... more	analytics over P... more	to enable further an... more	
Agile by-product of Normal Clinical Activity:- Early engagement of health i... more	Infrastructure & funding:- Data Quality a problem (technical, coding, a... more	To connect silos and share best practice to overcome barriers (Red#3) throu... more	Dai (and Red Team), George
End user engagement:- Sterling end user (health professional) engagement; Pa... more	Linkage of multi-stakeholder data sources; Silo’d information (e.g. patien... more	The development of advanced timeline structured EPRs in the Southampton Cli... more	David Rew, Orange Team originator of Idea16
How do we use data to change patient behaviour?	How to design interfaces to better effect behavioural change; Encourages da... more	Both behaviour change, understanding people and the ways they/we engage wit... more	Ann B., Simon Harper
Data Integration:- Bring together data from different groups/sources; How t... more	How to design interfaces to better effect behavioural change; Encourages da... more	Effecting behaviour change by integrating disparate data sources and provid... more	Sacha, Caroline
Marriage of Human & Machine:- Interpretability; Role of expert; Persona... more	High quality data Â– minimum effort; How do we support data collection to m... more	Including people in the loop and using that to ensure collection of better/... more	Chris Taylor, Kieran
Marriage of Human & Machine:- Interpretability; Role of expert; Persona... more	Can we better understand and improve the transparency of domain specific kn... more	Improve understanding, reporting and use of uncertainty in data.	,
Communication: advancing clinical decision-making/for improving patient out... more	How information is presented; Universal platform/more personalised; Talking... more	The 'people' factor in presenting, collecting and using data. (Connection f... more	Caroline, People and Data group (Purple)
Linkage of multi-stakeholder data sources; SiloÂ’d information (e.g. patien... more	How information is presented; Universal platform/more personalised; Talking... more		Caroline, Niels Peek grp - Ruth
Agile by-product of Normal Clinical Activity:- Early engagement of health i... more	High quality data Â– minimum effort; How do we support data collection to m... more	.. (Connection from Green group to Yellow 3)	Caroline (Yellow), Green - Ruth
Agile by-product of Normal Clinical Activity:- Early engagement of health i... more	Develop methodologies to improve current practice and lack of consensus in ... more	Platform for showing best practice and knowledge. (Connection from Silver C... more	Tjeerd, George
Marriage of Human & Machine:- Interpretability; Role of expert; Persona... more	Machine learning to provide robust models for working with real world data ... more	Challenge 3 vs. 3. (Connection from Pink to Silver C)	Steve Swift, Colin McGowan
Communication: advancing	Develop methodologies to	Use of data mining to analyse	David Tian,

clinical decision-making/for improving patient out... more	improve current practice and lack of consensus in ... more	incident reports which are lacking in terms o... more	Ibrahim Habli
Appropriate standards (data collection); Appropriate data/metadata	Education:- Workforce education Â– digital transformation (understanding) S... more	Human factors of data and metadata collection. - Making it easier for clini... more	Jon, Tarani
Open-ness & Transparency:- Fear: professional/patient Â– dispel Â– publ... more	Understanding the barriers to implementing standardisation	Longitudinal data. (Groups omitted. So these were inferred from the names g... more	Allan Tucker, Matthew Sperrin
Open-ness & Transparency:- Fear: professional/patient Â– dispel Â– publ... more	How information is presented; Universal platform/more personalised; Talking... more	RC1 RC 2 (Connection from Challenge no. 27 to Challenge no.16)	Sheldon, Caroline

Miscellaneous Meeting Details

UK Health Data Analytics Network Inaugural Workshop

Wednesday 6 January 2016, 1530 - 2100
Thursday 7 January 2016, 0900 - 1600
Chancellors Hotel, Manchester

Agenda

Wifi: Eduroam & The Cloud

#UKHDAN

Wednesday 6 January

1530 - 1600	**Registration**	
1600 - 1615	Welcome & Introduction	Chris Taylor - Associate Vice President for Research, The University of Manchester
1615 - 1700	Farr: Epidemiologic Adventures for Data Scientists (Open Floor Q&A)	Iain Buchan - Director, Farr Institute for Health Informatics Research
1700 - 1800	Breakout: Healthcare Opportunities	All
1800 - 1830	Healthcare Opportunities Feedback Session	All
1830 - 1900	Finding Healthcare Opportunities Connections	All
1900 - 2100	**Dinner**	

Thursday 7 January

0900 - 0945	The Alan Turing Institute and challenges for big data in healthcare (Open Floor Q&A)	Ann Blandford - Director, UCL Institute of Digital Health, The Alan Turing Institute
0945 - 1100	Breakout: Research Challenges	All
1100 -1130	Research Challenges Feedback Session	All

In association with:

MANCHESTER 1824 The University of Manchester

EPSRC Engineering and Physical Sciences Research Council

Farr

THE ALAN TURING INSTITUTE

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1130 - 1200	Finding Research Challenge Connections	All
1200 - 1230	Research Landscape Presentation	Chris Taylor
1230 - 1330	**Lunch**	
1330 - 1430	Breakout: Research Landscape	All
1430 - 1500	Research Landscape Feedback Session	All
1500 - 1530	Next Steps- Future plans for the UK Health Data Analytics Network	Ann Blandford & Chris Taylor
	Close	

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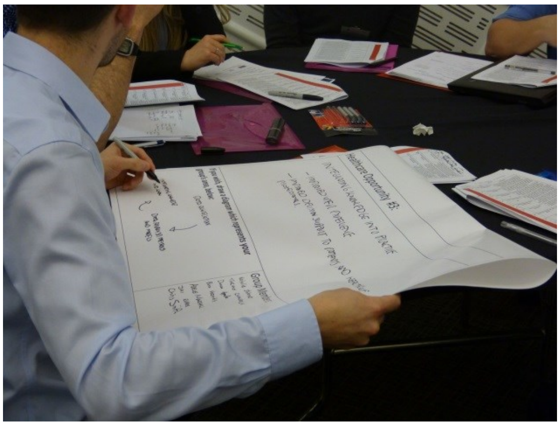






RED
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