



# The Alan Turing Institute

Turing/UK-HDAN Workshop on Health Data Analytics

Friday 3<sup>rd</sup> November 2017

Workshop Session Output



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## ESPRC

Engineering and Physical Sciences  
Research Council

**Title:** Identifying Sub-groups

**Group:** Brown Group  
(Session One)

<b>Issues</b>	<b>Existing solutions/gaps</b>
<p><b>Headline:</b> - Re-identifying disease using unsupervised methods.</p> <p><b>Headline:</b> "Patients Like Me"</p>	<p>- Standard unsupervised clustering: distance based, model based etc. Lack of gold-standard validation.</p>
<p><b>Headline:</b> - Unsupervised clustering, inter/intra clustering</p> <p><b>Headline:</b> Uncertainty in clustering labelling</p>	<p>- Latent growth modelling for dynamic clustering</p> <p>Probabilistic inference</p> <p>- Hierarchical mixtures</p> <p>Fuzzy clustering</p> <p>Flexible clustering: hard vs. soft clustering</p>
<p><b>Headline:</b> Response-based clustering</p> <p>- to action for the most positive outcome</p> <p><b>Headline:</b> "Multi-objective" clustering</p>	<p>- Profile Regression</p> <p>-Integrative Clustering Methods</p>
<p><b>Headline:</b> Stratifying disease</p> <p><b>Headline:</b> Missing data within clustering</p>	<p>- Local modelling methods</p> <p>- Hierarchical: Global to Local</p> <p>- Multilevel Modelling</p>
<p><b>Headline:</b> Drugs</p> <p>- Identifying tissue cascades to develop drug targets.</p> <p>- Identifying groups with worse/better side effects</p>	<p>-Individualised treatment effect (causal inference)</p>
<p><b>Headline:</b> Identifying sub-populations in the context of clinical trials</p> <p><b>Headline:</b> Interpretation of clusters &amp; validation (Gap!)</p>	

<b>Contributors</b>	<b>Potential Contributors</b>
<p>Lydia Drumwright, Tingting Zhu, Andrey Kormitzlin, Shang-ming Zhou, Catalina Vallejos, Allan Tucker, Arianna Dagliati, Fotios Drenos, Hamza Javed, Joris Bucker, Jans Dattscher, Mihaela Van Der Schaar</p>	

**Title:** Identifying Sub-groups **Group colour/number:** Brown Group Session One

1: Describing, understanding & managing boundaries between clusters both within and across time.

2: Validation of methods for data driven approaches in sub-typing in the absence of a gold standard. Specifically those approaches that would be accepted by the medical community.

3: Methods/partnerships for interpreting subgroup profiles or identify globally accepted methods. Design across disciplines.

4: Partnership, cross training & common language development between HCW's & analysts. Training/Pilot Scheme?

5: Methods for managing the bias in the observational data.

6: Methods for multi-objective clustering.

Specific Use Case Examples:

A: Drug Development (See Headline #9 on main sheet).

B: Application to diseases with different time spans & progression over time (e.g Diabetes, IBD).

**Contributors**

**Potential Contributors**

**Title:** Linking & Integrating Heterogeneous Data

**Group:** Green Group  
(Session One)

Issues	Existing solutions/gaps
<p>Headline: Linking Across scale, time and space, format/modality.</p>	<p>- RB2; Data shield distributed frameworks, implementation, temporal data is challenging.</p>
<p>Headline: Analyse the linked data (prior to or post linkage).</p>	<p>- Distributed Learning, hierarchical models.</p>
<p>Headline: Statistical linkage and statistical disclosure and associated uncertainty.</p>	<p>- Data perturbation, differential privacy.</p>
<p>Headline: Handle Conflicting Data</p>	<p>- New Logics</p>
<p>Headline: Real-time inference on continuous data</p>	
<p>Headline: Life-cycle of research data particularly categorical.</p>	<p>- FAIR data principles</p>

Contributors	Potential Contributors
<p>Ann Gledson, Goran Nenadic, Arianna Daguati, Emily Jefferson, Hamed Haddadi, Marcos Barreto, Jens Rittecher, Jan Wildenhain, Nophar Geifmen</p>	

**Title:** Untitled

**Group:** Orange Group  
(Session One)

<b>Issues</b>	<b>Existing solutions/gaps</b>
<p>Headline: People</p>	<ul style="list-style-type: none"> <li>- Small Scale Efforts to engage patients but Gov/NHS pushing other way</li> <li>- Country does not work together</li> <li>- The infrastructure exists, but the formulation is not yet right</li> </ul>
<p>Headline: Policy/Law</p>	<p>Policy + Law not linked to norms Gap: interpretation by data controllers leadership Needs a long-term plan - 30 yr - but how to do this with a 5 yr Gov cycle and link long term research progress to Gov policy</p>
<p>Headline: Data Use</p> <p>Flexibility - Care is not the same as research but need links</p>	<ul style="list-style-type: none"> <li>- Making the NHS electronic and sharing between institutions</li> <li>- What is allowed and what is <u>believed to be</u> allowed?</li> <li>- Put the algorithm in the clinical space</li> </ul>
<p>Headline: Catastrophic Confounding - experimental design</p>	<p>Gap: aftercare linkage</p> <p>Policy for data linkage exists for point of care</p>
<p>Headline: Technical Solutions Synthetic Data Sets</p>	<ul style="list-style-type: none"> <li>- Multiple platforms exist but are not linked</li> <li>- Banks can do it! Medical records need translation to research</li> </ul>
<p>Headline:</p>	

<b>Contributors</b>	<b>Potential Contributors</b>
<p>John Parry, Nigel Birch, Rachel Furner, Lydia Drumwright</p>	

**Title:** Untitled

**Group colour/number:** Orange Group Session One

- De-identification: How to anonymise (remove data) whilst still retaining usefulness.
- What is the status of linkages between NHS datasets and what are the restrictions?
- The law makes assumptions about what people want which aren't necessarily correct. Disconnect between patient/ delivery of care and legal/policy.
- Conflict between use of data, data control officers and info commission
- Format of date
- Policy Issues
- People Issues (Data Owners)
- Data Use, research and care, what are the links?

**Contributors**

**Potential Contributors**

<b>Title:</b> U u )	<b>Group:</b> h Group (Session u )
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<b>Issues</b>	<b>Existing solutions/gaps</b>
Headline: - Irregular Sampling  - Purposive Sampling	- Sliding Windows - Data Imputation but MNAR and UNK links - PROMS & Experience Measures
Headline:  - Range of Time Scales	- Gaussian Process Models - Recurrent Neural Networks - Hidden Marker Models
Headline:  - Anonymisation by removing absolute time stamps. "Fuzzing"	- Privacy rather than anonymisation. Data behind firewall analysis
Headline: - Stratifying disease  Headline: - Missing data within clustering	- Local modelling methods - Hierarchical: Global to Local - Multilevel Modelling
Headline:  - Quality of Time Capture	-Individualised treatment effect (causal inference)
Headline: - Identifying sub-populations in the context of clinical trials  Headline: - Interpretation of clusters & validation (Gap!)	

<b>Contributors</b> Lydia Drumwright, Tingting Zhu, Andrey Kormitzlin, Shang-ming Zhou, Catalina Vallejos, Allan Tucker, Arianna Dagliati, Fotios Drenos, Hamza Javed, Joris Bucker, Jans Dattscher	<b>Potential Contributors</b>
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**Title:** Modelling Temporal Data

**Group colour/number:** Pink Group Session Two

How do we model/analyse longitudinal data.

Irregular sampling & purposeful sampling (consultation for a reason).

Range of time scales (Daily/seasonal/shorter)

Anonymisation by removing absolute time stamps (e.g for hour of the day, for month of the year).

Data Quality of date stamps - difference in linked data (e.g DoD)

System date does not equal event date and time stamps not right. Messy

Using the past to predict the future. Is this a reliable premise for (e.g training algorithms).

- Fast moving tech development
- Confounding context. Capture this richly.

Outlier patients (modelling without observing individuals).

- Similarity across patient pathways
- Modelling disease trajectories
- Trajectory clustering

Time Series:

Treat a time line as a sentence. Synatactic approach, borrow techniques from NLP community.

Using time to predict time. "Time to event" as an outcome.

Understanding human gaming of the systems.

Separating a path into "pathlets"

Understanding the drivers of timing of data recording.

It is easier to go from time-course data to action than build a model in between.

**Contributors**

**Potential Contributors**



**Title:** Effective Visualisation of Data

**Group:** Purple Group  
(Session One)

<b>Issues</b>	<b>Existing solutions/gaps</b>
<p>Headline: Actionable Visualisations, communicating what people need to know and useful discoveries</p>	<ul style="list-style-type: none"> <li>- Education, training, software tools</li> <li>- Expensive, few UIS Experts in the UK</li> </ul>
<p>Headline: Availability of technical expertise and understanding to make visualisations useful (not necessarily pretty). Linking to semantics.</p>	<ul style="list-style-type: none"> <li>- Education, training</li> <li>- Funding, lack of standards, data quality</li> </ul>
<p>Headline: Availability and enthusiasm of workforce to interpret and value data.  Multiple audiences - different understanding/ actions.</p>	<ul style="list-style-type: none"> <li>- Success stories curriculum.</li> <li>- Demonstrating value, medical safety and validation.</li> </ul>
<p>Headline: Interacting with high-dimensional data (geospatial, temporal, qualitative, quantitative, anatomical...)</p>	<ul style="list-style-type: none"> <li>- Cartographic Treemaps, research area.</li> <li>- Unsolved Technical Challenges.</li> </ul>
<p>Headline: Communicating Uncertainty &amp; Trends.</p>	<ul style="list-style-type: none"> <li>- Existing Software Tools.</li> <li>- Generic Tools are Challenging.</li> </ul>
<p>Headline: Overlaying individual and population data for contextual interpretation. Real-time Visualisation</p>	

<b>Contributors</b>	<b>Potential Contributors</b>
<p>Mahmood Adil, Ann Blandford, Bob Laramée, Gary Leeming</p>	



**Title:** Imperfect Data

**Group:** Red Group  
(Session One)

<b>Issues</b>	<b>Existing solutions/gaps</b>
<p>Headline: Messy Data</p> <p>Missingness (MNAR), artifacts, units of measurement unknown</p>	<ul style="list-style-type: none"> <li>- Exploratory data analysis with domain experts</li> <li>- Rich models of observation process (including prior domain knowledge)</li> </ul>
<p>Headline: Missing Context</p> <p>e.g linking temporal events e.g environmental information for patient</p>	<p>Capture Meta-data</p>
<p>Headline: Inaccessible Data</p> <p>e.g free-text (not available) e.g constraints in collections</p>	<ul style="list-style-type: none"> <li>- With regards to free-text, issue is governance.</li> <li>- Pushing of NLP processing behind firewall</li> </ul>
<p>Headline: Lack of gold Standard/ground truth, difficulty in validating results.</p>	<p>Systems design of data collection.</p>
<p>Headline: Catastrophic Confounding, experimental Design</p>	
<p>Headline:</p>	

**Contributors**

Magnus Rattray, Chris Williams, Sam Relton, Jian-Bo Yang, Hamza Javed, David Hogg, Kenan Direk, Liz Ford

**Potential Contributors**

**Title:** Imperfect Data **Group colour/number:** Red Group Session One

Expt. Design

**5** Complete Confounding (Experimental Design) for inference of causal effects.

Str. of observations process (studies vs. routine observational data) Variable measured for a reason.

**1** Missingness (not MAR), types of data (patient data vs. molecular).

**1** Artifacts (incorporation in analysis).

**4** Lack of gold standard (partially unlabelled).

**2** Linking Temporal Events.

Accessibility of Data:

- Info in free-text (but this may not be available).
- Constraints of data collection & availability (was data collected? is it available to researchers?).

Incomplete Data.

Missing contextual information for observations (different state of person).

Data preparation process (80-90% of time), reproducibility.

Biases in recording outcome (and knowledge about context).

Probabilistic Programming

Standard methods to map data - diagnosis

- Combining Data Sources
- Treat variables as noisy - use proxy variables/latent
- How to treat subjective variables (e.g; pain)
- Use of RL (reinforcement learning)

- Investigate variations of outcomes/variables

- Symptom development over time  
semi-supervised learning

Latent variable for MNAR

Class for study adherence

Changes in recording patterns over time (and locations) e.g QOF.

Variation in GP's coding some interaction

SLAM obtained free-text for NLP Processing

How to create synthetic missing data, density models, GAN's

**Contributors**

**Potential Contributors**

<b>Title:</b> Data & Knowledge Life Cycle	<b>Group:</b> Silver Group (Session One)
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<b>Issues</b>	<b>Existing solutions/gaps</b>
Headline: Applied Intelligence - "Active" Data Analytics & DSS - Spectrum of analytics	- Integrate with Social Care - Data analytics life cycle - Not only descriptive, but also predictive and prescriptive
Headline: Meta-Data - Data Models - discrete data - Best Practice	
Headline: Knowledge Engineering - Context - Executable Guidelines/Pathway Models - Data/Knowledge Provenance	
Headline: How Knowledge Changes?	- Maintenance
Headline: Bringing data science and knowledge engineering together.	-Bridging data & Knowledge
Headline:	

<b>Contributors</b> John Fox, Goran Nenadic, Emily Jefferson, Gary Leeming, Mahmood Adil	<b>Potential Contributors</b> Jian-Bo Yang
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<b>Title:</b> Data & Knowledge Life Cycle	<b>Group colour/number:</b> Silver Group Session One
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Visualisation Issues:

1: Actionable Visualisations

- Questions people know they want to know & useful discovery

2: Availability of expertise to make visualisations useful but not necessarily pretty. 3a:

Extracting knowledge from data.

3: Ability/enthusiasm at workforce to understand/interpret data and value it.

4: Ontologies, high dimensional data - geospatial temporal, qualitative, quantitative.  
Communicating uncertainty trends.

"Active" Data Analysis

- Suitable representation of data models.
- Scale-up knowledge
- "Technology is not an issue"
- Managing Data Provenance
- Research is part of NHS landscape
- Health and Social Care Intelligence

"Applied" Data Analysis

- Meta-data is important? Interoperable?
- Two streams: Care & Research
- "Executable guidelines", modelling practice/pathways

<b>Contributors</b>	<b>Potential Contributors</b>

**Title:** Predictive Modelling & Actionability

**Group:** Yellow Group  
(Session One)

<b>Issues</b>	<b>Existing solutions/gaps</b>
<p>Headline: Missing Data</p> <ul style="list-style-type: none"> <li>- Informative Missingness</li> <li>- Informative Censoring</li> <li>- Missing Context / Clinical Knowledge</li> </ul>	<ul style="list-style-type: none"> <li>- Knowledge Based Systems</li> <li>- MLI Stats Methods (Patterns and prior knowledge)</li> <li>- Causal Interference</li> </ul>
<p>Headline:</p> <ul style="list-style-type: none"> <li>- Prediction with observational Data</li> <li>- Optimal Treatment Prediction</li> <li>- Treatment Effect on Prediction</li> </ul>	<ul style="list-style-type: none"> <li>- Causal Inference (Propensity Scoring)</li> <li>- Mendelian Randomise</li> <li>- Machine Learning methods for individualised treatment effects</li> </ul>
<p>Headline: Imbalanced Data</p> <ul style="list-style-type: none"> <li>- Specially in the context of longitudinal data</li> </ul>	<ul style="list-style-type: none"> <li>- Prior Knowledge</li> <li>- Boosting Methods</li> <li>- Re-Weighting Methods</li> <li>- Synthetic Data</li> <li>- Transfer Data</li> </ul>
<p>Headline: Pre symptomatic prediction - Early Prediction</p>	<ul style="list-style-type: none"> <li>- Transfer Learning</li> <li>- Knowledge Engineering</li> <li>- Disease/Risk Trajectory</li> <li>- Wearables</li> <li>- State-space models</li> </ul>
<p>Headline: Dealing with Drifts or changes in practice</p>	<ul style="list-style-type: none"> <li>- Scoring Methods</li> <li>- Change Point Analysis</li> <li>- Unsupervised Learning</li> <li>- State Space Models</li> </ul>
<p>Headline: Action upon Predictive Models &amp; Feedback</p>	<ul style="list-style-type: none"> <li>- Clinical Decision Support Systems</li> <li>- Causal Inference</li> <li>- Online Learning &amp; Re-Calibration</li> </ul>

<b>Contributors</b>	<b>Potential Contributors</b>
<p>Catalina Vallejas, Mihaela Van Der Schaar, Tingting Zhu, Fotios Drenos, Lisa Koeppel, Joris Buckler, Robert Goudie, Shang-Ming Zhou, Allan Tucker, Andrey Kormilitzin, Maxine Mackintosh</p>	

**Title:** Predictive Modelling & Accountability      **Group colour/number:** Yellow Group Session One

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|--|---|
| 0: Bridging the gap between medical knowledge and modelling. 1:                  | John  |
| Dealing with gradual shifts  | Rob   |
| - Changing Features in the context of changing points                            |   |
| - State-Space representations (latent models)                                    |   |
| 2: Interpretability vs predictive ability  | Shang-Ming                                    |
| - Interaction between MLI stats approaches                                       |   |
| - Increases interpretability in ML settings                                      |   |
| - Clinical relevance vs prediction   |   |
| 3: Features selection in high-dimensional spaces                                 | Michaela                                      |
| 4: Dealing with outliers & rare events on/off line                               | Cata  |
| 5: Rare Diseases & Unknown Features  | Fotios  |
| 6: Co morbidities - how to incorporate them in predictive models & poli pharmacy | Mihaela, Catalina<br>Shang-Ming &<br>Tingting |
| 7: Multiple pathways of care that interact (treatments, interventions)           | Tingting                                      |

**Contributors**

**Potential Contributors**



<b>Title:</b> Predictive Modelling	<b>Group:</b> Yellow Group (Session Two)
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<b>Issues</b>	<b>Existing solutions/gaps</b>
Headline:  Trust Issues. Performance vs explainability trade-off	- Actionability
Headline:  - Predicting the effects of interventions. "What if?"	- Causal Inference Methods - Control Engineering - Complexity? - Smart Cities?
Headline:  - Predict Outcome (decision) of consultation	
Headline:  - Holistic biology & behaviour. Predict health state based on corporate history.	
Headline:  - Online vs. batch learning	- Trust/certification
Headline:	

<b>Contributors</b>  Niels Peek, Jian-Bo Yang, Jan Wildenhain, Chris Williams	<b>Potential Contributors</b>
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