

## DataMIX

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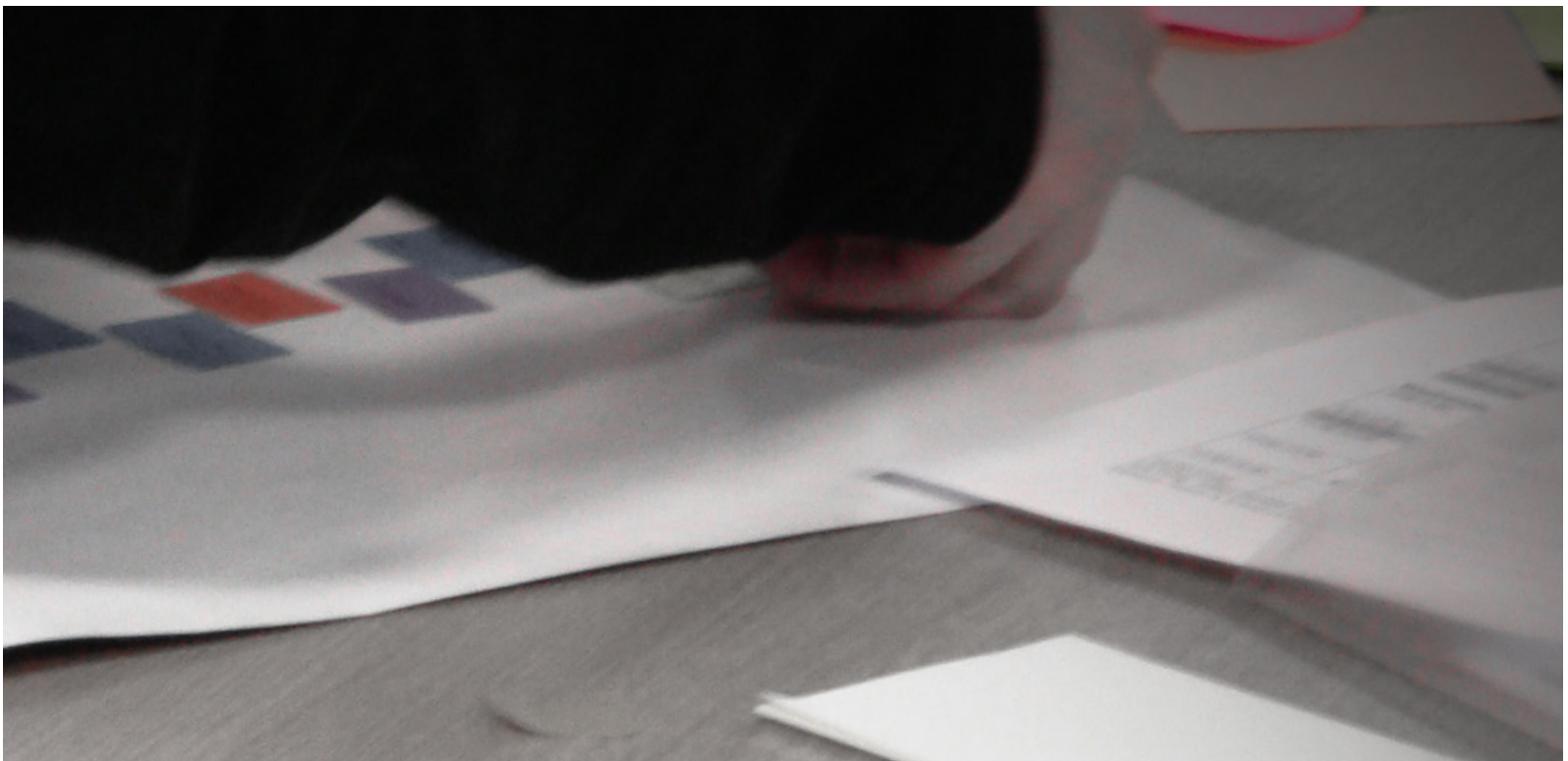
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# DOX<sup>T</sup>Amix

**A visual book about data visualisation.**

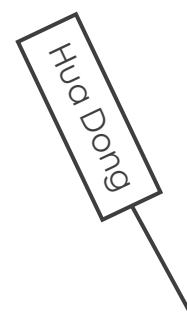
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## Graphic Design, Book layout, Illustration

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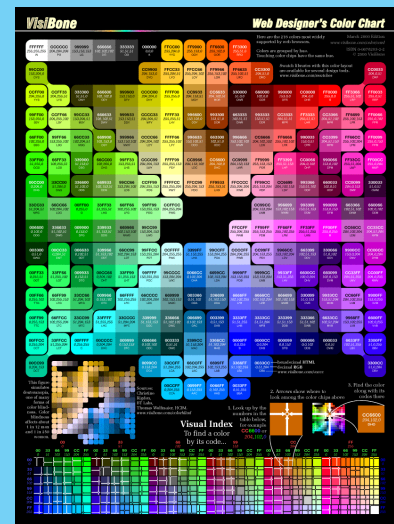
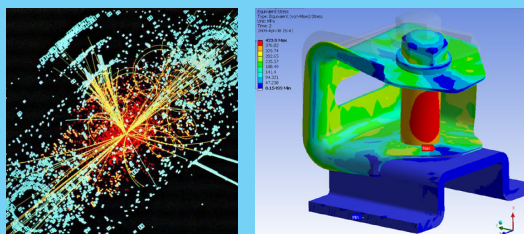
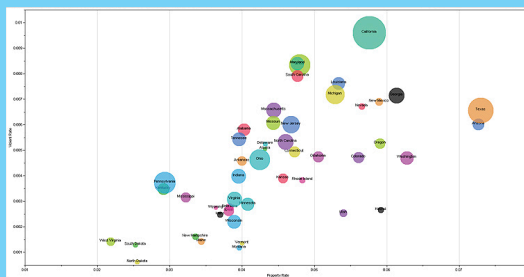
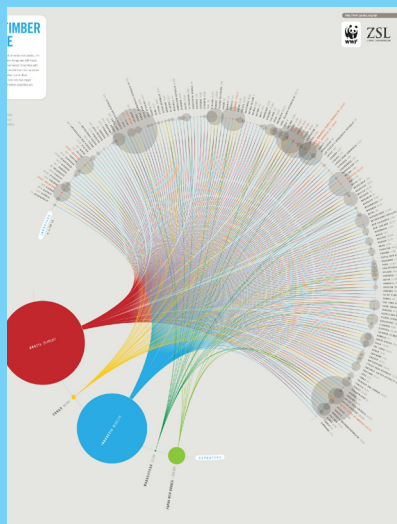
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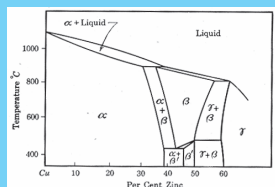
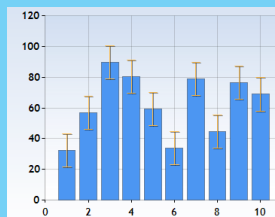
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# Executive Summary

## **The DataMIX project aimed to explore more inclusive means of communicating data.**

It was proposed by seven young researchers from different backgrounds who deal with a variety of data on a daily basis: some generate and analyse large volumes of data, some handle multi-dimensional data and some investigate data transformation.

Together we organised a series of workshops to discuss data format, methods of presenting data, and effective ways of communicating data. Experts from relevant fields and

people with various sensory capability losses were invited to the workshops.

The workshops took place at the University of Birmingham, Brunel University and the Open University during an 18-month period. The project aimed to enable the researchers to apply inclusive design thinking across different disciplines, and to evaluate how 'useful', 'usable' and 'inclusive' data from any experiment can be made.

The DataMIX Project was funded as part of NESTA's Crucible programme.









# Introduction





**Data are important sources of information and knowledge, and they take different forms, e.g. numbers, graphs, images, or texts. Data visualisation is the process of transforming data into sensory stimuli, usually visual images (Schroeder et al, 2003). Through effective visualisation, data can be rapidly understood by the user.**

*“The main goal of data visualisation is to communicate information clearly and effectively through graphical means.”*

*(Friendly, 2008)*

Good data graphs, as suggested by Edward Tufte (1992):

- ▲ Help the audience think about the important messages from the data, rather than about

methodology, or something else;

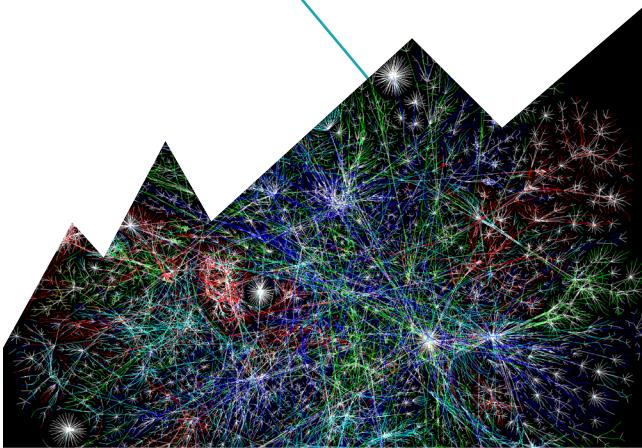
- ▲ Avoid distorting what the data have to say;
- ▲ Present many numbers in a small space – but also emphasise the important numbers;
- ▲ Make large data sets coherent, and encourage the audience to compare different pieces of data;
- ▲ Reveal the data at several levels of detail, from a broad overview to the fine structure.

Effective data visualisation does not only facilitate learning, but also enriches the process of scientific discovery and fosters profound (and sometimes unexpected) insights. A good example is the periodic table of the chemical elements. To extract new meaning from the sea of data, scientists have begun to embrace the tools of visualisation (Frankel and Reid, 2008). The Cambridge Engineering





## Internet mapping

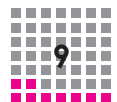


Selector (CES) for material selection is an excellent example that illustrates Tufte's aforementioned characteristics of good data graphs. By visualising hundreds and thousands of materials in a novel way, it opens a new path to understanding materials and a new approach to material selection (Ashby, 2005).

To help data originators communicate data more effectively, Harvard University has recently organised a series of workshops on Image and Meaning

(<http://www.imageandmeaning.org/>), aiming to "help scientists, writers and visual communicators develop and share improved methods of communicating scientific concepts and technical information through images and visual representations." The power to visualise and graphically represent results and ideas in multiple dimensions and to manipulate data has already been predicted as the next big revolution in technology.

To explore a more inclusive means of communicating data, seven UK university-based researchers started a multidisciplinary research collaboration project in May 2009. Their backgrounds include industrial design and engineering, architecture and civil engineering, chemistry, physics, biochemistry, computational linguistics and digital music. They all deal with a







variety of data on a daily basis, such as numbers, codes, symbols, spectra, text, diagrams, tables, images, sound, and animation, and they all shared an interest in exploring effective methods of distilling meaning from data.

The collaborative project has provided an opportunity for the researchers to apply inclusive design thinking across different disciplines, and to evaluate how 'useful', 'usable' and 'inclusive' data from any experiment can be made. The project aimed to:

**1** Identify data visualisation challenges in different disciplines and data communication criteria from the perspectives of both data developers and data users.

**2** Propose strategies in making data communication more inclusive for different target users.

**3** Develop a methodology for evaluating the effectiveness of data communication.

The multidisciplinary dialogue about data communication was conducted through a series of three workshops over a period of 18 months (the first two held in August 2009 and February 2010; the third workshop held in November 2010), involving the seven researchers, invited guests (e.g. from areas of Brain Scanning and MRI, Archaeology, Architecture, and the Semantic Web to Software Design), and different types of data users (e.g. layman users, knowledgeable professionals, people with disabilities).







# Workshop 1





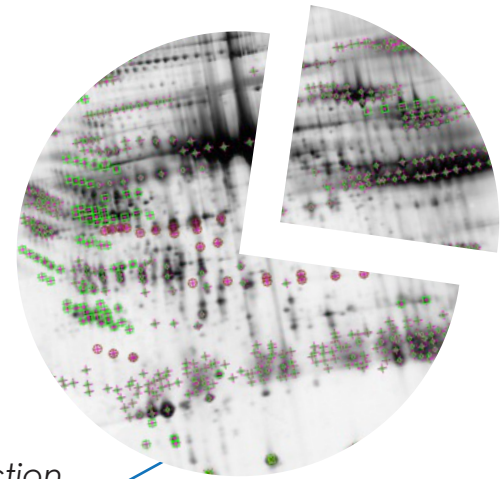
Workshop 1:

## Birmingham University in August, 2009.

**At the first workshop, each researcher presented a short talk in a Pecha Kucha style (20 slides with 20 seconds per slide) on what constitutes 'data' in each of their own disciplines. They also gave examples of the types of data and discipline-specific data communication methods and techniques. For example, in chemistry, data are often presented in 1D, 2D or 3D forms; while in architecture, they are typically displayed in 2D (layout), 3D (models) and 4D (animation).**

A number of data visualisation challenges were identified, including:

- Communicating data to different potential users (e.g. expert colleagues; knowledgeable professionals, layman clients and interested parties)
- Difficulties in choosing the right (or optimal) tool for complicated data sets
- Balancing clarity against economy (e.g. the amount of texts used)
- Different terminologies
- Dilemmas in applying novel data visualisation methodologies (graphic design, the technology of graphic production etc): they may help attract users' attention but may also distract users from focusing on important messages from the data
- A huge increase in the amount of data available because of technological facilitation, yet which corresponds in many cases only to electronic versions of standard practice



*Protein selection*

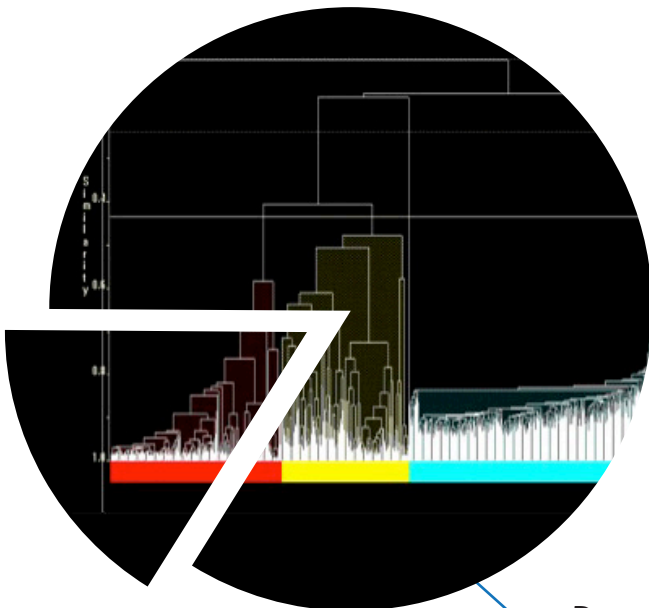


## Data Visualisation Processes

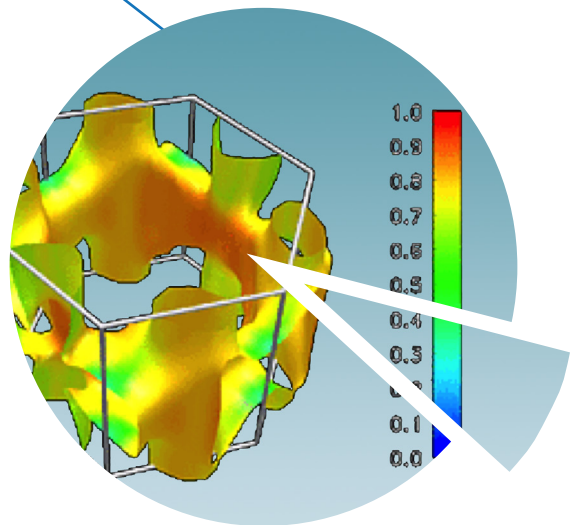
The first workshop also saw the researchers' engagement with a data visualisation exercise: an 'unknown' large dataset (numbers in a table format, with no context apart from names of countries and continents and the time period) had been selected from a publically available data source, and

each researcher was asked to analyse the dataset prior to the workshop, visualise the data and present a poster outlining the approach they had taken to analysing and presenting this unknown dataset. As a result, seven different versions of 'visualisation' of the same dataset were demonstrated at the workshop, ranging from typical

*The Fermi surface*



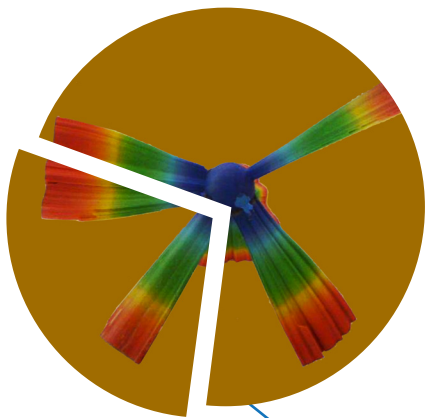
*Dendrogram*





EXCEL bar charts to sophisticated cluster analysis graphs (dendrogram), and the original data (i.e. numbers) were also transformed into different modalities: 3D models, sound, and spoken language.

Follow-up analyses of the processes of visualisation were conducted after the first workshop, and the pros and cons of each method were discussed at the second workshop.



*3D Model of population data*

Although the researchers from different disciplines used different techniques in visualising the given dataset, common patterns were identified. The common procedure was to **process data** based on the source (raw data), through **deducting noise** (“remove/select/filter/extract/distil”), **sorting** (“sort/cluster/remap/group/organise”) and **normalising** (“calculate/normalise/convert”). Sometimes new data were also created in the process. When visualising data, common methods adopted included 2D graphs, 3D plots, change of modalities (e.g. visual/auditory/dialogue), and adding new dimensions (e.g. colour, animation).

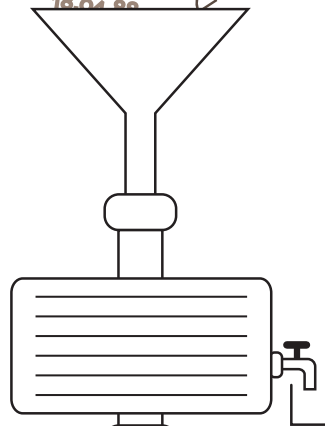




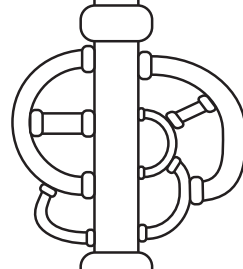
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Common pattern of the data visualisation process

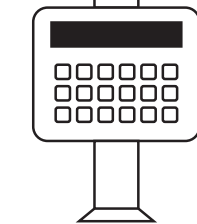
Raw Data



Deducting Noise



Sorting



Normalasing







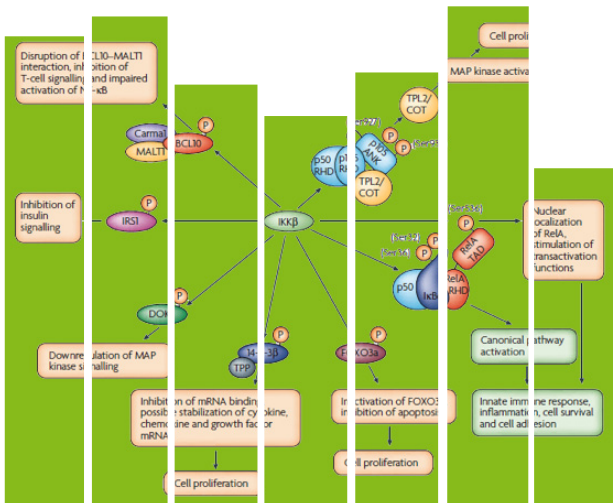
# Workshop 2



Workshop 2:

*Brunel University  
in February 2010.*

At the second workshop, each researcher presented good and bad data visualisation examples from their own field. The pictures below show an example from biochemistry. On the left is an example of good communication: colour and spatially divided items with distinct summaries of information;

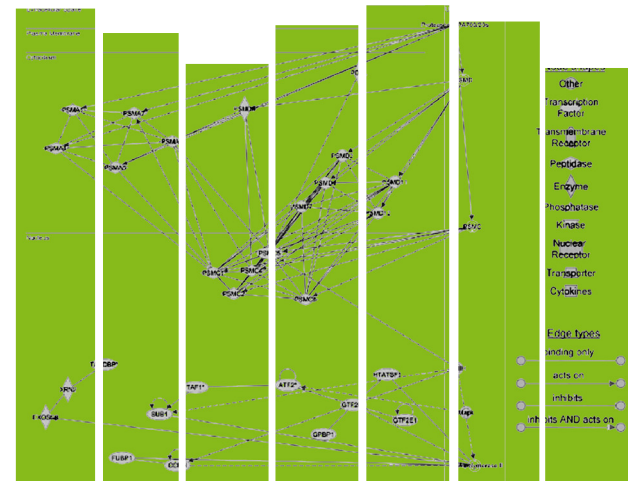


while the right hand side shows a bad communication: mono chrome and spatially confused items with indistinct actions.

A creative exhibition of live, general examples of data visualisation was also organised at the second workshop.

Based on the examples, a number of characteristics of good data visualisation were identified:

Clean presentation with clear labels



*Good and bad data visualisation examples in biochemistry*





3d access accuracy annotations attractiveness clarity colour  
 complexity context conventions data detail dimensions domain  
 easy explanation familiarity file flow fun image interactive labels layers  
 legibility level levels multiple navigation purpose raw  
 reference references relevance representativeness representatives retrieve size sound standard  
 structure symbology time trust understanding universal views visualisation

*Data visualisation criteria: researchers' viewpoint*

and use of standard conventions

- ▄ Showing contexts and details-on-demand
- ▄ Allowing inspection by giving access to the underlying data
- ▄ Appropriate scale with size of data set
- ▄ Concise explanation (annotation) with distinct summaries of information
- ▄ Highlighting important data
- ▄ Adding dimensions (e.g. colour)

to make data patterns clearer

Interactive features to enable multiple views and data references

- ▄ Showing the right level of information.

### Data Visualisation Criteria

An important aim of the research was to identify data communication criteria from different perspectives (e.g. expert





colleagues; knowledgeable professionals, and lay users). At the second workshop, the participants were asked to select up to 15 most important data communication criteria from a list compiled based on the issues mentioned at the first workshop. A 'tag cloud' tool (available from [www.manyeyes.com](http://www.manyeyes.com)) was used to illustrate the criteria in terms of their relevant importance. The relative size and

weight of the font for each criterion corresponds to the relative frequency of its mention by the participants.

A short questionnaire was taken to the 5th Cambridge Workshop on Universal Design and Assistive Technologies (CWUAAT'10) in March 2010 where data users' viewpoints on data visualisation criteria were collected. The CWUAAT workshop was selected as it had

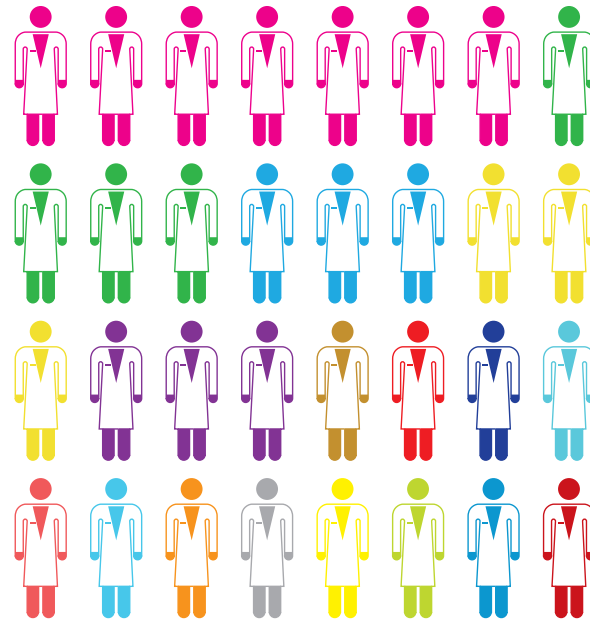


*Data visualisation criteria: users' viewpoint*



an audience who were aware of inclusive design. A short introduction to the research project was given at the CWUAAT workshop's user forum session, and then the audience was asked to write down their five most important criteria for data visualisation and three strategies for making data communication more inclusive. The results (based on 19 responses) of the criteria are shown on the left (Data visualisation criteria: users' wiewpoint).

Although intended for lay users' viewpoints, the backgrounds of the questionnaire respondents suggested that they were more "knowledgeable professionals" than layman users. Among the 19 respondents, six were "data developers/researchers", three were "data users", and nine were "both data developers and data users".



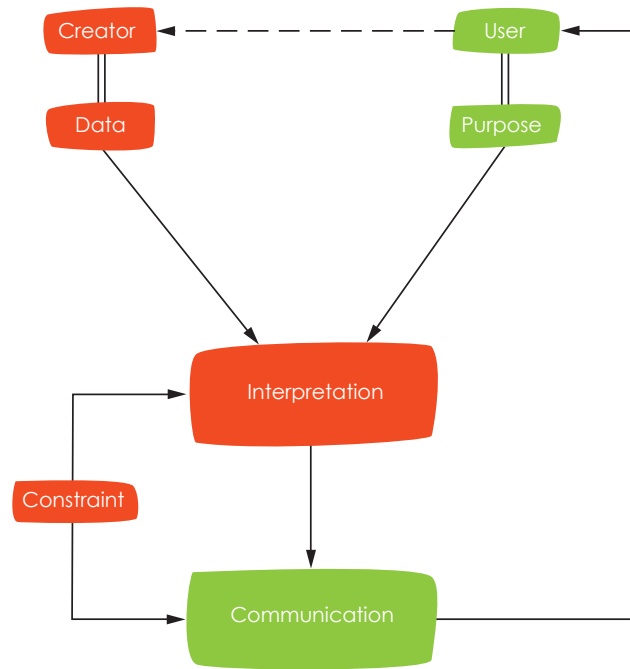
- multiple modalities, views, media 7
- multiple levels of detail, complexity, ability to drill down 4
- involve user 3
- interactive 3
- use of metadata/standards 3
- multilingual labelling 1
- use the 'real thing', rather than data 1
- protect privacy 1
- allow users to tailor visualisation 1
- portable tools for multimodality 1
- explain purpose clearly 1
- selecting appropriate tools 1
- understand user diversity 1
- least 'capability demand' 1
- extreme users 1
- accuracy 1

*Strategies proposed by experts*



- understand users 6
- avoid data overload/keep it simple 5
- multi-modal presentation/flexibility of visualisation 4
- font size must be adequate 4
- define objective and customise for purpose 4
- user involvement 4
- highlight salient points/emphasise important information 3
- accessibility 3
- inclusion of raw data/data source 2
- good contrast of text and background 2
- build up understanding /interpret what it means 2
- different levels of detail 2
- be more graphically illustrative 1
- the structure of the content presented is important 1
- 3D 1
- use simple diagram in support of text 1
- Interactive 1
- consider context 1
- possibility to navigate through contents (pick and mix) 1

*Strategies proposed by knowledgeable professionals*



*"Purrfect" Process*

## Data Visualisation Strategies

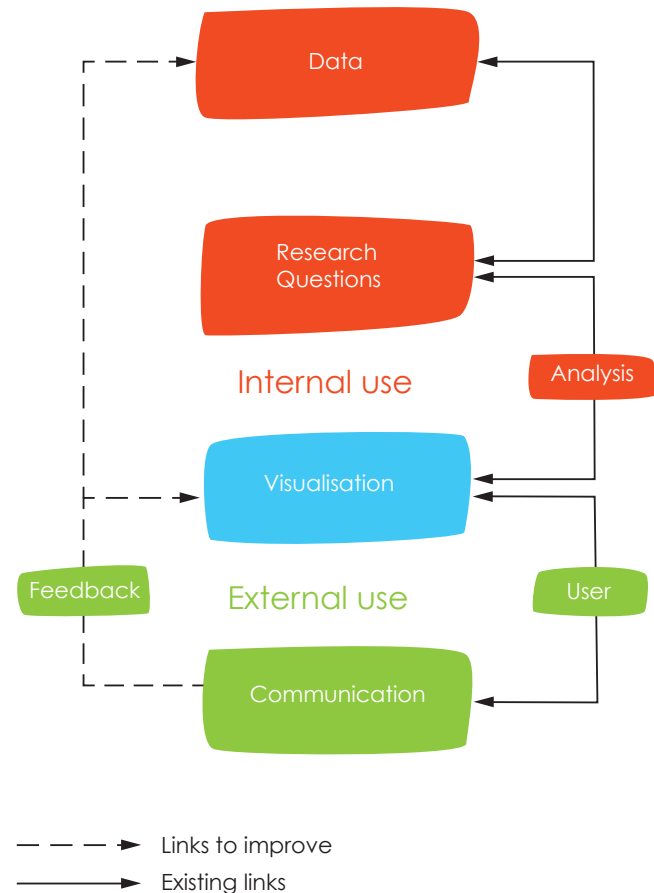
At the second workshop, the participants were each asked to propose **three strategies for making data visualisation more inclusive** to different groups of users. The CWUAAT participants were also asked to do the same task.

The results were summarised in two diagrams, i.e. strategies proposed by experts; strategy proposed by knowledgeable professionals.

## Data Visualisation Methodologies

The participants formed three groups during the second workshop to discuss the methodologies of data visualisation. The 'PURRFECT PROCESS' diagram suggests that data interpretation has to be connected to both the data and the user, and the efficiency of the communication has to be evaluated by the user. The methodology shown in the diagram on the right put data in a research project context, suggesting that data and research questions are interrelated. Data visualisation is for internal use (to help the researcher better understand the data), and data communication (for external use, i.e., to communicate research to all parties interested) should take all potential users into consideration. The links between data communication and the original data have to be strengthened, and user feedback should be used

to improve data visualisation, and consequently, data communication.



*Data visualisation methodologies*



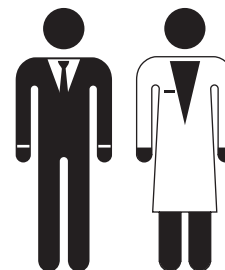
Another methodology framework started with a set of questions:

- ▄▄▄ What is the purpose of the visualisation?
- ▄▄▄ Who is the audience? (background: education; cultural; capabilities)
- ▄▄▄ Practical constraints (money, time: end users/developers, equipment)
- ▄▄▄ Is the visualisation transferable?
- ▄▄▄ Redundancy/inclusivity balance?

Therefore, to evaluate data visualisation, the following aspects should be considered:

- 1 Purpose (this will help define the level of detail to be communicated)
- 2 Audience (e.g. colleagues/peers, client/scientists, public, use of language)
- 3 Constraints (medium: visual, auditory, olfactory, taste, haptic; practicalities, convention)

The group believed that this research project would generate insights that will help with the transfer from raw data to effective communication.



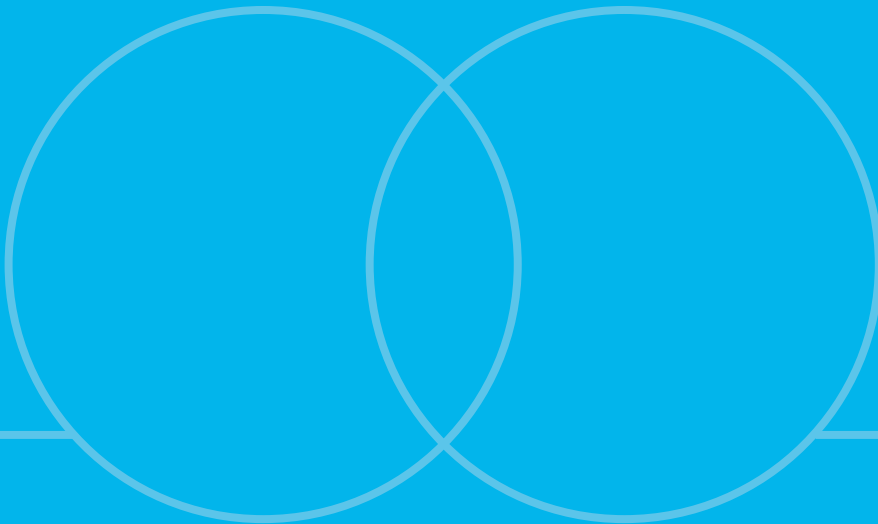


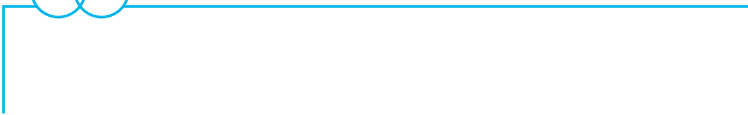






# Workshop 3





Workshop 3:

## *the Open University in November, 2010.*

Data users of different capabilities were invited to attend the workshop, including a visually-impaired user and representatives from the Papworth Trust (a wheelchair user with speech impairment, a carer and a researcher from the organisation). In addition, five guest speakers were invited to attend the workshop, including an information designer.

**At the workshop, a range of activities took place, including:**  
**Short presentations of data visualisation research projects:**  
**ErgoCES (contextualising numerical data for use in design) and CODA (from monologue to dialogue).**

Further exploration of the application of data visualisation tools:

- Visualising statistical data using Many Eyes
- Statistical data represented as speech and sound
- Visual and tactile 3D
- Sonification exercises
- Case study of visualising water footprint

The methodology developed in the second workshop was evaluated at the workshop and refined. The common methodology framework is illustrated on the opposite page.

The team members were asked to represent the framework in different formats to achieve the most inclusive communication effect.

An interesting format of the methodology is shown by a photo where the snow on

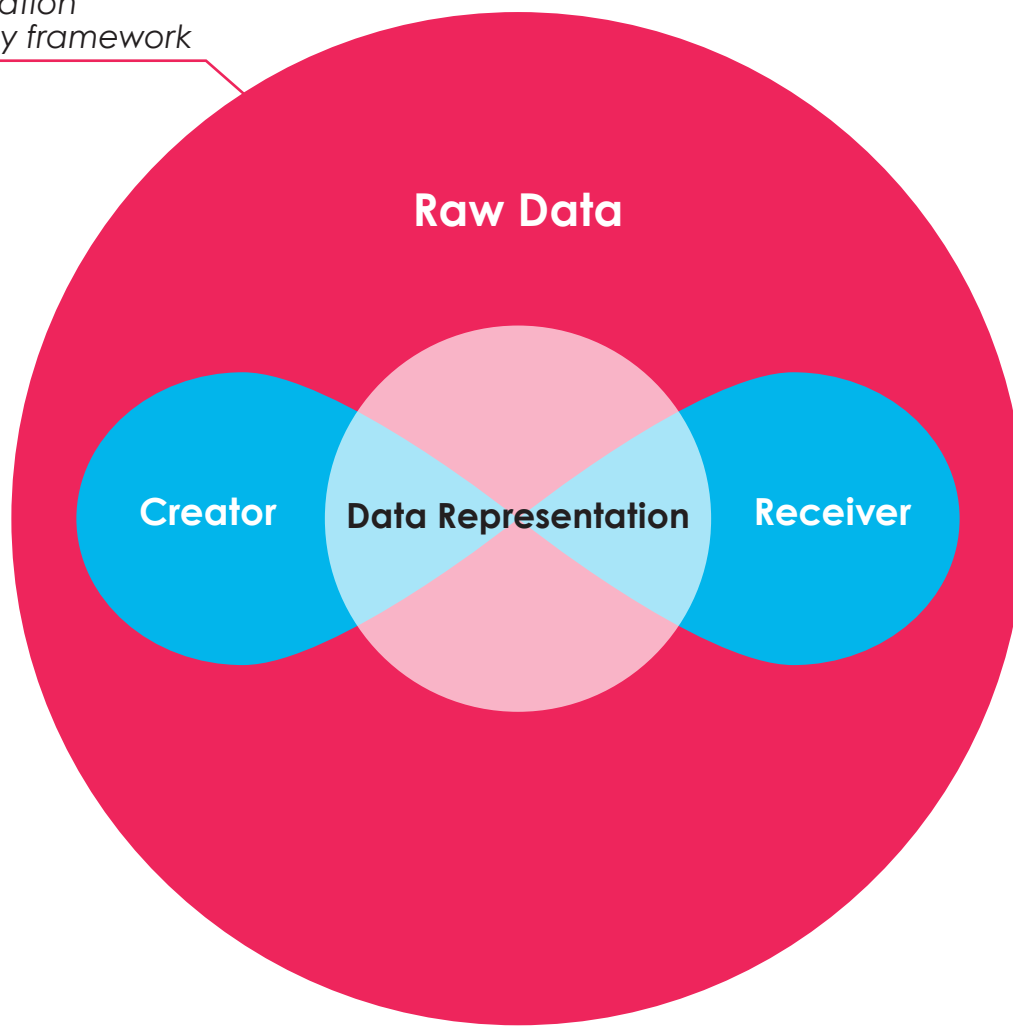


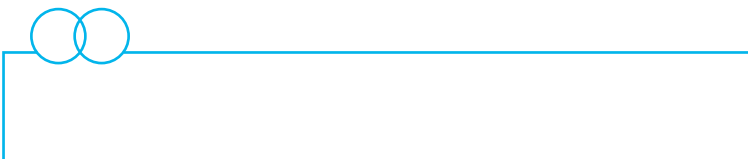


the ground represents “raw data”, and the snow ball “data representation”,

the two hands represent the “data creator” and the “data receiver”.

*Data visualisation methodology framework*

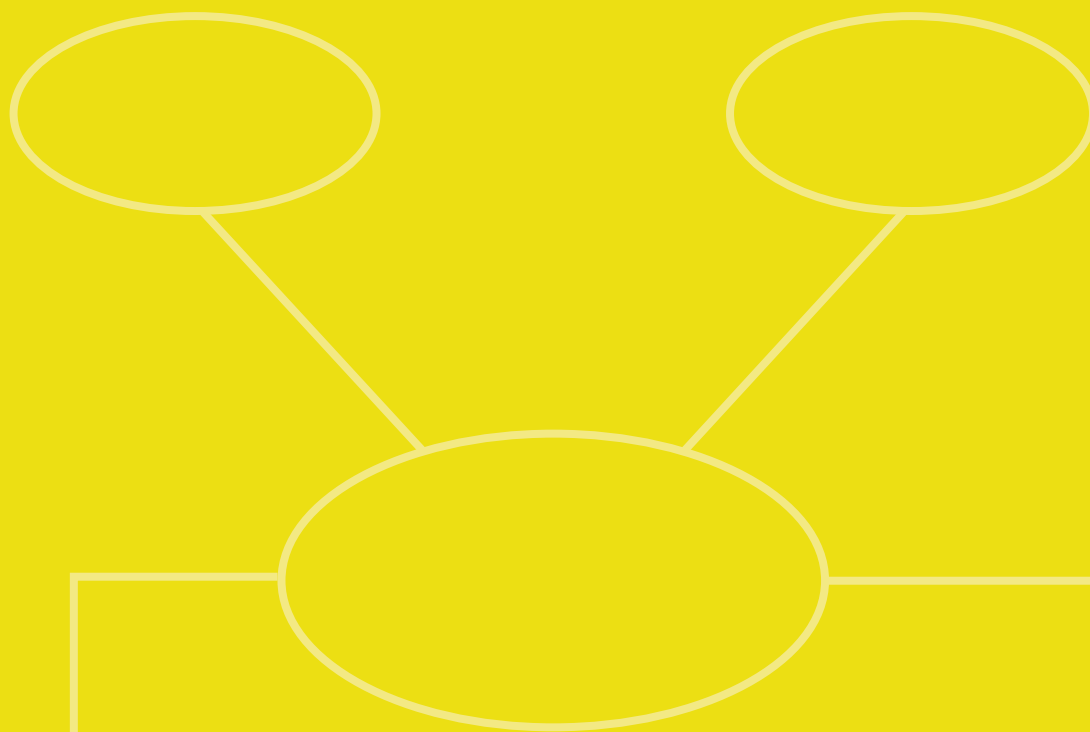




*Data visualisation  
methodology representation*



# Discussion





**This multidisciplinary project has helped identify a number of data visualisation challenges. Our primary point is that there is currently a great lack of inclusivity in data visualisation. Even within narrow expert communities (e.g. biochemistry), data visualisation can be exclusive/difficult to understand without expending significant effort.**

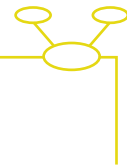
The researchers and the knowledgeable professionals share some common strategies for making data visualisation more inclusive to different groups of users, for example,

“multi-modal presentation”; “involving users” and “use of accessibility standards/guidelines”. The researchers frequently mentioned the strategy of providing “multiple levels of detail” and making the data visualisation “interactive”; while the knowledgeable professionals think “understanding users” is of paramount importance; and they frequently mentioned the strategy of avoiding “data overload” and keeping the information “simple”.

This was in interesting contrast to the comments by the researchers which mentioned ‘complexity’ as a point of interest, expressing the desire to communicate complex information successfully. We suggest that, here, ‘complexity’ and ‘simplicity’ represent the same ideal: complex interpretation, rendered accessible for the end user.

The most important data visualisation criteria, as suggested by the researchers, were concerned with “clarity”, “(level of) complexity”, “context”, “explanation”, “multiple (views)”, “purpose”, “relevance” and “trust”; while the knowledgeable professionals at the CWUAAT workshop





suggested that the most important criteria included “clarity”, “detail”, “ease of use (easy to understand/remember/identify/compare)” “simplicity” and “structure”.

Although people from different disciplines use different techniques in visualising data, common patterns and procedures were identified. One common theme was the addition of extra dimensions to assist understanding. This can be done through a variety of means:

- Physical objects
- Time
- Colour
- Sound

All of these possibilities have advantages and disadvantages. For example, colour can help make data patterns clearer, and provides an easy way to delineate between differing data streams.

However, it may introduce unintended exclusion, e.g. for the colour blind, or for those without access to colour printers. In some cases, this can be resolved by application of alternative markers (e.g. spatial separation).

The researchers participating in the project all emphasised the importance of having access to raw data; this may be because many of them not only use data but also generate new data (and visualisation) based on combining datasets.









Conclusion





**There is a lack of inclusivity in data visualisation, but not much research on this topic.** This research project has taken a multidisciplinary approach to explore data visualisation from the 'inclusion' viewpoint. "Clarity" has been identified as the most important, and commonly agreed, criterion for data visualisation. While data developers think it is very important to provide

"different levels of complexity", "multi-views" and the "context" of data; data users are more concerned with the "ease of use", "simplicity", "detail" and "structure". Communicating data using multiple modalities (visual, auditory, haptic...) and understanding users were regarded as most important strategies for making data communication more inclusive for different target users.





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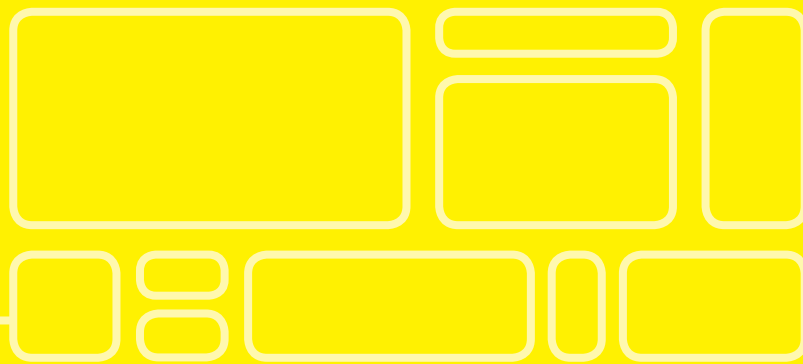
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# Acknow- ledgements





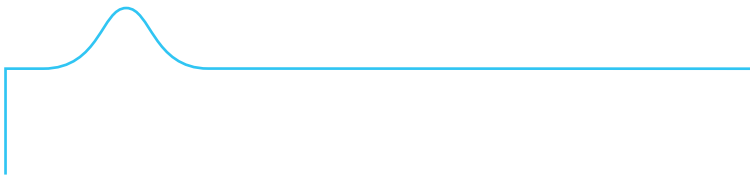
This research project has received support from the UK's National Endowment for Science, Technology and Arts (NESTA), an independent body with a mission to make the UK more innovative. The authors would also like to thank the following people for their input to the project: Professor **Ann Heylighen** from K.U.Leuven, Belgium; Professor **Yong Zhang** from Tsinghua University, China; Dr **Michel Wermelinger** and Dr **Svetlana Stoyanchev** from the Open University, UK; Ms **Farnaz Nickpour**, Mr **Chris McGinley** and Mr **Abdusselam Selami Cifter** from Brunel University, UK; Ms. **Angela Moreli** from Central St. Martins; and the CWUAAT workshop **participants** who took time to answer the questionnaires.



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# Appendix





## The proposal

**DataMIX mixes seven researchers from different backgrounds who deal with a variety of data on a daily basis: numbers, codes, symbols, spectra, text, diagrams, tables, images, sound, animation ... we all share an interest in exploring effective methods of distilling meaning from data. This project gives us an opportunity to apply inclusive design thinking across different disciplines, and to evaluate how 'useful', 'usable' and 'inclusive' data from any experiment can be made.**

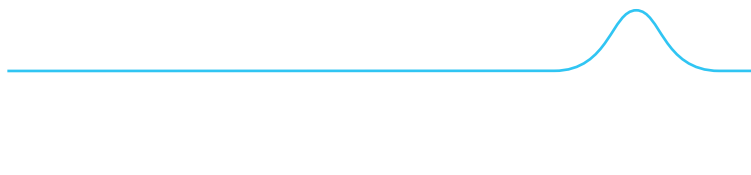
Effective data communication does not only facilitate learning, but also provides clues for new discovery. A good example is the periodic table of the chemical elements. To extract new meaning from the sea of data, scientists have begun to embrace the tools of visualization<sup>1</sup>. The Cambridge Engineering Selector (CES) software is a good example. By visualizing hundreds and thousands of materials in a novel way, it opens a new path to understanding materials and a new approach to material selection. To help data originators communicate data more effectively, Harvard

University has recently organized a series of workshops on Image and Meaning, aiming to "help scientists, writers and visual communicators develop and share improved methods of communicating scientific concepts and technical information through images and visual representations."

Clearly, visual thinking plays an important role in data communication. However, not all data recipients are visual thinkers, so images may not always be the best







way of communicating data. Natural languages, music, or physical forms may convey meaning more effectively.

We would like to explore data communication using a more inclusive approach, i.e., considering the different nature and contexts of data, and the diversity of the recipients. We are privileged to adopt this unique approach because we all have relevant experience of working on data-focussed research projects and have a good insight into the key issues associated with data communication in our own discipline.

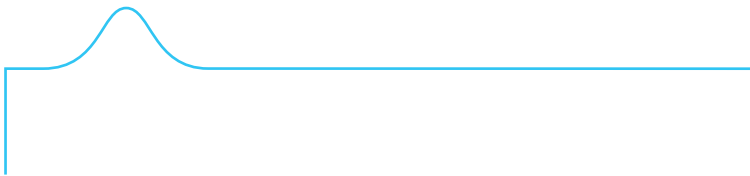
Some of us generate and analyse **large volumes of data**: for example, Melissa Grant generates large data sets during biomarker discovery that need evaluation for the best indicators for particular states of health and

disease. Gordon Barr specialises in the development of methods and software that applies cluster analysis and other statistics to problems in crystallography and chemistry, trying to make interpreting and handling large volumes of data easier.

Some of us handle **multi-dimensional data**: Paul Shepherd uses two- and three-dimensional visualisation and feedback techniques to help design large complex-shaped buildings. Elizabeth Blackburn handles multi-dimensional neutron scattering data sets requiring rapid analysis and visualisation techniques to pick out salient features.

Some of us investigate **data transformation**: Paul Piwek has worked on methods for automatically transforming information from one medium into





another one (including mapping databases to text and monologue to dialogue). Nick Collins has investigated new sound synthesis algorithms, and new methods of analyzing audio, which can feed into both sonification (translating data to sound) and feature extraction (translating from sound to numerical data). Hua Dong has worked on communicating scientific numeric data (e.g. anthropometrics) to industrial designers who prefer images to numbers.

We are keen to share:

- ▲ What we have learned from our own discipline regarding data communication
- ▲ Techniques we use in communicating data to different types of users
- ▲ Relevant examples (good and bad, in our own discipline and in general)
- ▲ Methods of evaluating data communication

Through this project, we shall explore:

- ▲ The characteristics of good data communication and poor data communication;
- ▲ 'Universal principles' of effective data communication
- ▲ Methods and techniques to communicate data more inclusively (i.e. addressing the needs of the widest possible audience)

We aim to develop a methodology of evaluating the effectiveness of data communication, and propose strategies in making data communication more inclusive for different target users.

The research could potentially broaden the horizon of all the researchers involved, making us think about the wider context and unfamiliar scenarios of data communication. The methodology and strategies to be proposed would





benefit all data originators (e.g. scientists) and data communicators (e.g. information designers).

1. Frankel F and Reid R (2008) "Big data: Distilling meaning from data", *Nature* 455, 30

## Objectives

We aim to develop a methodology of evaluating the effectiveness of data communication, and to propose strategies in making data communication more inclusive for different target users.

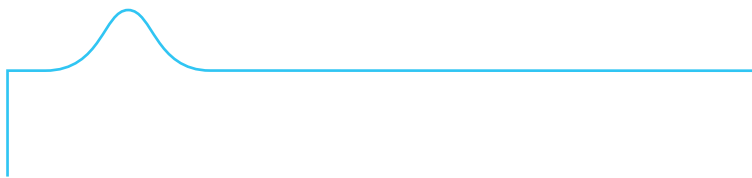
We believe that a truly successful interdisciplinary project recognises the unique perspective each discipline involved brings, and maximises the value of interaction. Since workshops are good at facilitating interaction, we shall organise a series of workshops, each aiming to fulfil one or two of the objectives listed below.

**Objective 1.** To build common ground and understand the state-of-the-art.

**Task 1a.** To comprehend 'data' in a broader context  
When talking about 'data', we may mean different things. So the first task is to clarify what we mean by 'data' in our disciplines, and develop a comprehensive definition of 'data' (based on a literature review spanning different disciplines and our own knowledge)

**Task 1b.** To learn the state-of-the-art in the field  
We shall each introduce our own, relevant research to the team, and draw a list of key references to start with. We shall construct a resource website to facilitate this investigation.





**Task 1c.** To ‘interpret’ a selected set of data using our own method and then share the outcome with all (through a small exhibition within the workshop). This will provide a very interesting, and meaningful, focal point of discussion.

**Objective 2.** To synthesise the best practice of data communication in different disciplines.

**Task 2a.** To analyse examples of data communication  
Each of us will provide case studies of good and bad examples of data communication in our own disciplines (and in general), and explain why they are good or bad. We shall analyse these examples and see whether we can extract from them a catalogue of common characteristics of good data communication and bad data communication. In so doing, we shall also

make explicit what criteria are used in evaluating the effectiveness of different methods of data communication.

**Task 2b.** “Toolstorming”

The data visualisation techniques we use range from Excel spreadsheet, interactive computer simulations and renderings to physical 3D rapid-prototype techniques and virtual-reality type game engines. We tend to use certain types of techniques in our own field, but in this project we shall brainstorm new ways of applying familiar techniques to unfamiliar contexts and vice versa, and borrowing ideas from other disciplines.

**Objective 3.** To develop a methodology of evaluating the effectiveness of data communication.

**Task 3a.** To develop a general methodology framework that can be





widely applied to evaluating different type of data communication.

**Task 3b.** To create a range of presentation modes for the methodology (e.g. text description, image, models) in order to share it with the widest possible research community.

**Objective 4.** To propose strategies for making data communication more inclusive for different groups of users.

**Task 4a.** To discuss how we can make data communication effective for different types of users. We shall tackle the question of how to gain knowledge of different types of users and their requirements.

**Task 4b.** To propose strategies that could potentially address the needs of the widest possible audience.

**Task 4c.** To invite potential users to evaluate the strategies.

In addition to the seven researchers involved and the guest speakers, we shall invite a diverse group of potential users to participate in the evaluation workshop.

### Interdisciplinarity

This proposal is clearly interdisciplinary in that the project team come from a very diverse range of fields. We are researchers with **different expertise, relevant experience, and a shared interest**. This makes us the perfect team for this proposed research.

By generalising the applicability of the project, and by allowing the multi-disciplinary team to bring our expertise to bear on the issues raised, it is expected that the resulting methodology will help researchers in all disciplines (especially quantitative disciplines). Moreover,





there are expected to be extra benefits to future interdisciplinary research from introducing a common framework for data communication through both methodology and language.

The proposed project involves an unusual collaboration between seven disciplines. We might have collaborated with one or two other disciplines, but not six. In multidisciplinary projects, people often struggle with understanding other's languages. But languages are the focus of this project, and we have to consciously make our own language comprehensible to others in this project. This makes the project highly challenging and extremely interesting. In the mean time, with a shared interest in data communication, and an ultimate goal of identifying "universal principles" and common frameworks, the project is feasible.

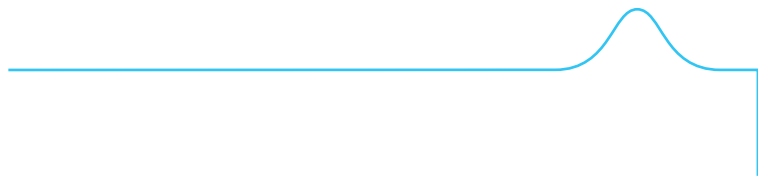
## Innovativeness

The approach has the potential to lead to new scientific insights regarding data communication through synthesising case studies and methodologies from different disciplines. This will impact on practitioners, including the UK's media industry and research communities, by providing a rich and practice-oriented methodology for optimizing data communication.

It is a novel idea to applying inclusive design thinking to data communication across different disciplines and engaging a diverse range of data originators, communicators and potential users in the process.

We plan to submit an article to 'Nature' about this project.





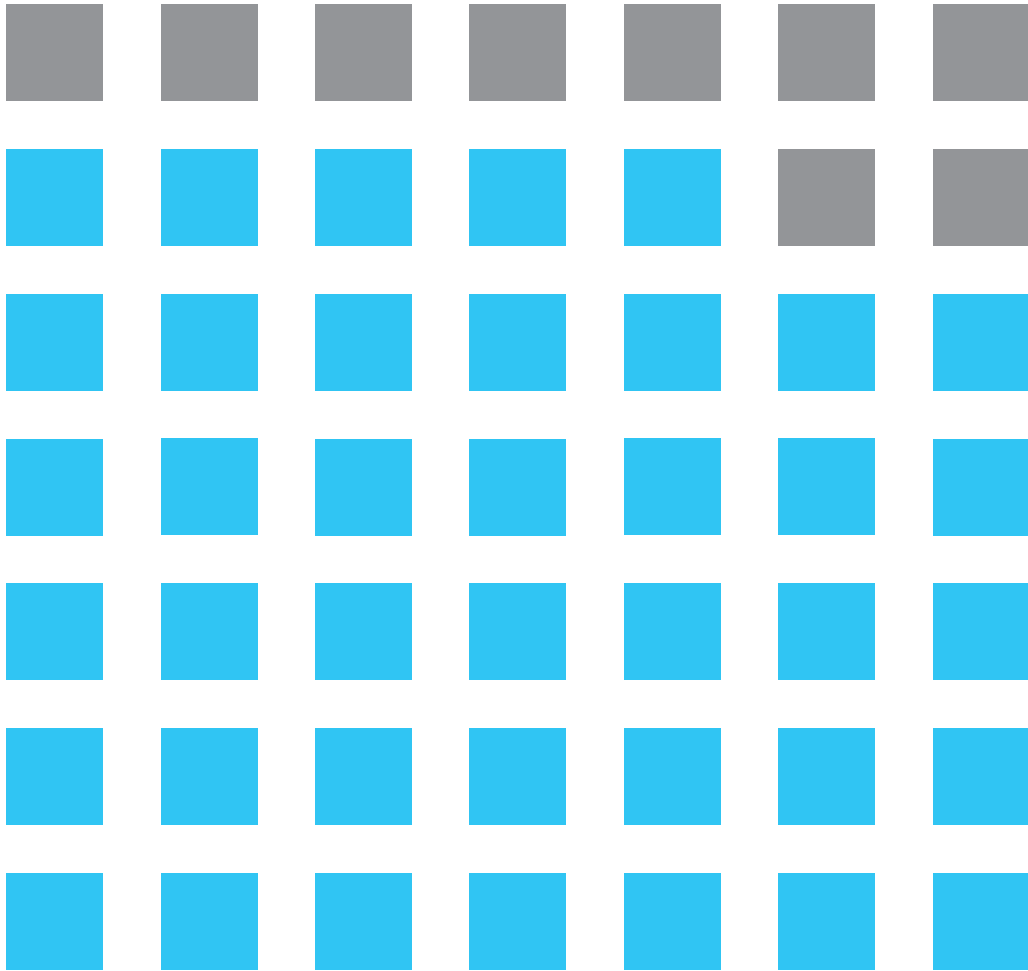
## Sustainability

We have a long-term plan for the project. We shall develop a web site as a research platform, which could later become a public engagement platform.

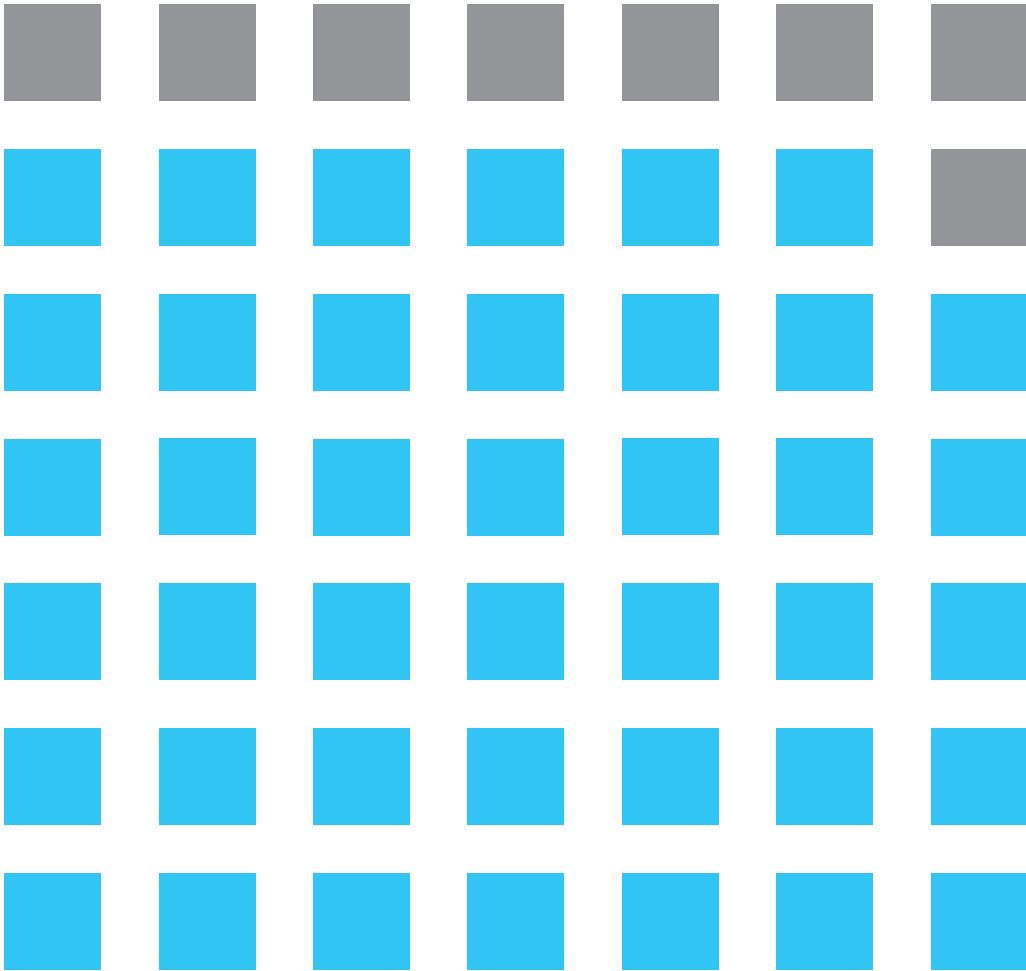
The series of workshops would provide opportunities for the researchers to familiarise ourselves with each other and with invited guest speakers, thus starting to build long-term research collaboration relationships. During and after the project, the researchers involved will discuss the possibility of submitting joint proposals (e.g. The EPSRC 'Design for the Digital Economy' call; The EU FP7 ICT call)

We shall also identify unconventional routes to continue our collaboration in this fascinating area, i.e. using the NESTA Ning tool to build a special interest group, and initiate an international network of data communication.













Data are important sources of information and knowledge. To explore a more inclusive means of communicating data, a team composed of seven researchers in the UK from different disciplines conducted a series of workshops: the first to share state-of-the-art data visualisation techniques in various disciplines and to identify data visualisation challenges; the second to extract universal principles from good examples of data communication, to identify data visualisation criteria, and to develop a set of strategies for inclusive data communication. The third workshop focused on developing and evaluating a methodology for more inclusive data communication with different groups of users.

