# Identifying cross-cutting capabilities to extract information from big geospatial datasets

Birds of a Feather - C3DIS 2021 Wednesday 7 July

Geospatial Capabilities Community of Practice

We acknowledge and celebrate the First Australians on whose traditional lands we meet, and we pay our respect to the elders past, present and emerging.

#### Geospatial Capabilities Community of Practice

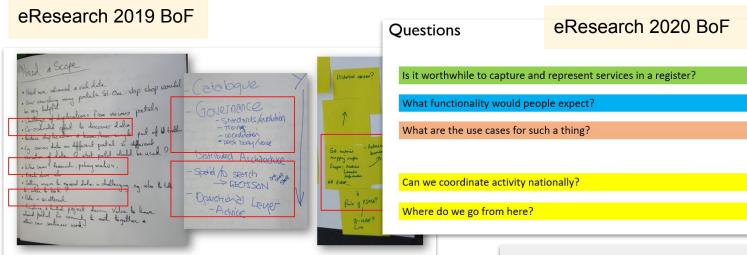
#### Established in September 2019

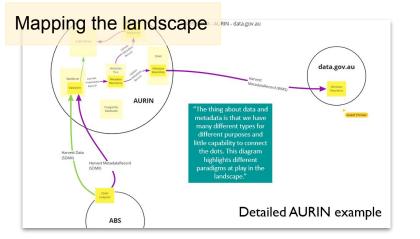
#### Purpose

- bring people together as a community who, in some capacity, work with geospatial data and make it available for broader use
- a forum for sharing knowledge and experiences with finding, accessing, transforming, using and making available geospatial data

https://sites.google.com/ardc.edu.au/geospatialcapcop

Meetings are held online and occur every couple of months.





Topics we've covered or discussed:

- ✓ Loc-I
- ✓ ANZ Metadata Working Group
- Elevation Information System (ELVIS)
- OSGeo Oceania community
- / GDA2020
- ✓ Geoprivacy
- Communicating the Value of Space and Spatial technologies

# Agenda for today

Introduction

#### Lightning talks: (3 x 5min)

- 1. Big Geospatial Data: challenges and opportunities (Sanjeev Srivastava)
- 2. Use of ML in geospatial data (Hassan Talebi)
- 3. Digital Twins Gemini principles (Michael Rigby)

#### Breakout Sessions (25min)

- 1. What are the key challenges with big geospatial data? (Sanjeev Srivastava)
- What are the key challenges in the use of AI in Geospatial Data? (Jens Klump)
- What are the key challenges to consider when incorporating built/natural environment and social data within Digital Twins? (Michael Rigby)

#### Report back plenary (3min for each group)

Wrap up and future directions

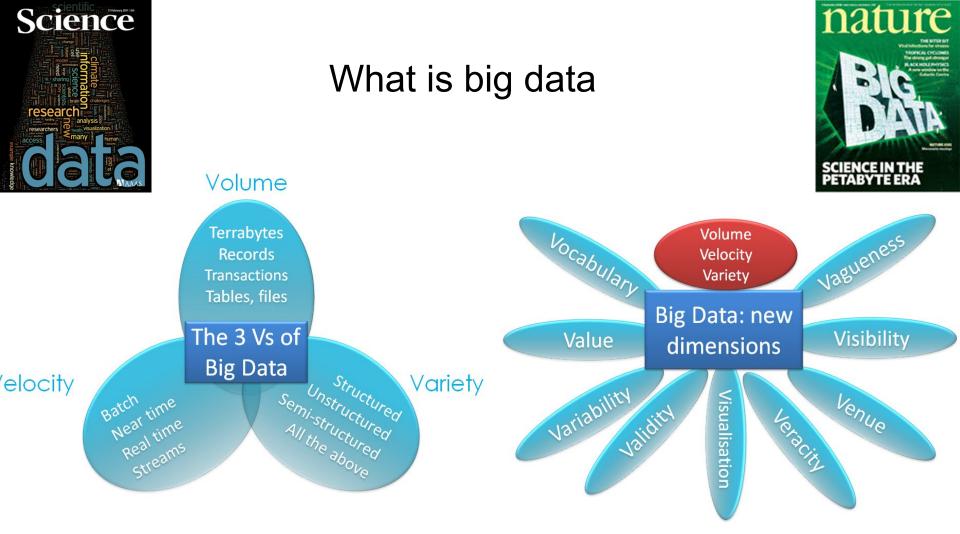
#### Session notes at https://bit.ly/C3DISGEO

#### Please register your attendance

so we know who came

# Big geospatial data: challenges and opportunities

Sanjeev Srivastava



# Big geospatial data types

- Archived geographic information
- Geo-localised data
  - Collected as point
    - using GPS or GPS chip embedded in devices such as mobile phones
    - Using address geocoding
- Spatially grounded
  - location, shape, size, orientation and spatial relationships are integral to the data
    - Remote sensing images (lidar, radar, optical images from satellites and drones).

- Human-sourced
  - Volunteered GIS
    - www.openstreetmap.org
  - Social media
    - Twitter, Flickr
- Process-mediated
  - Government data
    - ABS, BOM
- Consumer data
  - Transactions, loyalty cards etc.
- Machine generated
  - Smart cities sensors (CCTV, traffic flow, etc.)

## Big geospatial data formats

Software specific raster/vector/tabular data

Geographic databases (geodatabase, OGC Geopackage)

Point cloud (las)

Web files

Complex scientific data (NetCDF, HDF, GRIB)

# **Application examples**

- Built environment
  - Smart cities
  - IoT
  - Mobility
  - Transport
- Natural resources
  - Forest inventory
  - Climatic change
  - Animal tracking

#### • Health and wellbeing

- Sentiment analysis
- Pandemic and endemic hot spots
- Migration

• Google's flu map

# Big geospatial data and geospatial concepts

- Place, space and time
  - Location
  - Context
  - Geographic extent
  - Temporal extent

#### Representation

- Data models
- Coordinate system
- Structured/unstructured
- Generalisation
- Scale
  - Spatial dependance

- Quality
  - Biasness
    - Sample and population
- Users and usability
  - Access
  - Ethics
  - Interaction
- Interoperability
  - Device
  - software/apps
  - Fusion
- Visualisation
  - 2d patterns
  - Digital twin
- Analytics
  - Patterns, coordinated view, user-centred



Australia's National Science Agency

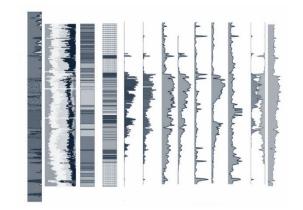
# Use of ML in geospatial data: Towards geostatistical learning

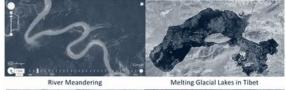
Hassan Talebi | July 2021

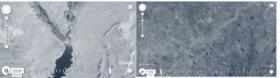
CSIRO Deep Earth Imaging FSP, Australia, <u>Hassan.Talebi@csiro.au</u> CSIRO Mineral Resources, Australia

#### The particularities of geosystems and geoscience data

- Big data
- Multi-source and mixed-type
- Multi-scale
- High-dimensionality
- Limited sample size
- Paucity of ground truth information
- Importance of extreme cases
- Spatial and temporal heterogeneity
- Auto- and cross-correlations







**Dam Construction** 

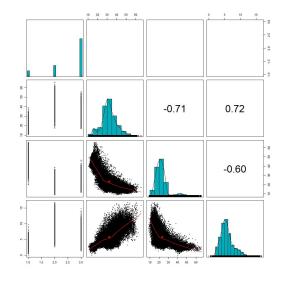
Shrinking Lake Mead



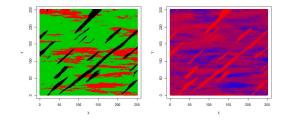


#### Statistical learning

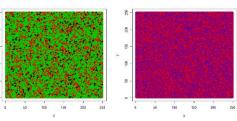
#### Nonspatial learners



RF#1 = RF#2 SVM#1 = SVM#2 LR#1 = LR#2... = ...



 $\frac{1}{2} \int_{\frac{1}{2}} \frac{1}{2} \int_{\frac{1}{2}} \frac{1$ 



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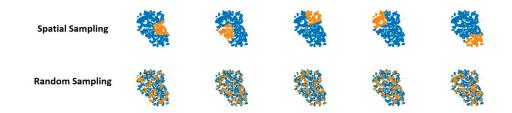


Case #1

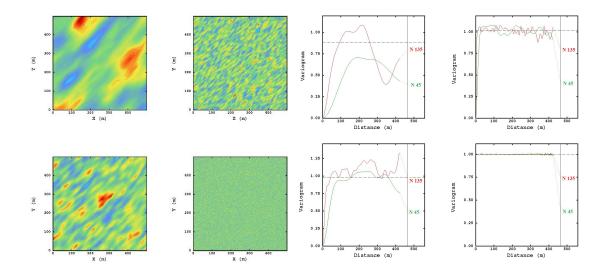


### **Statistical learning**

Nonspatial learners



- Independent and identically distributed random variables •
- Random sampling and overoptimistic learners •

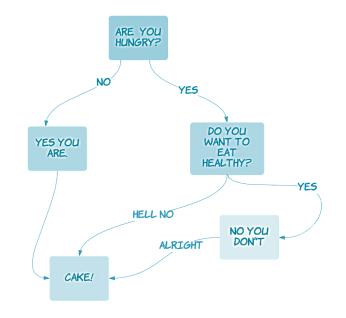




#### **Statistical learning**

Nonspatial learners

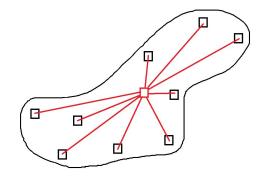
- Incorporating prior physical knowledge in the learning process
- Discovering the physics behind the geological phenomena by machine learning ٠



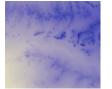


#### **Geostatistical Learning**

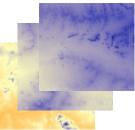
Improve spatial awareness using higher order spatial statistics



Continuous



Compositional



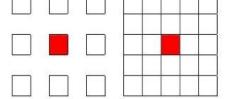


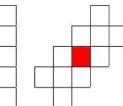
Categorical

















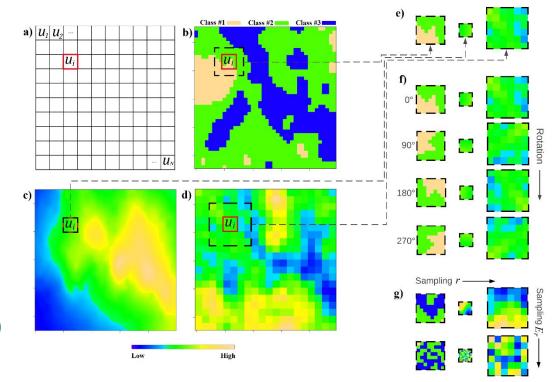
#### **Geostatistical Learning**

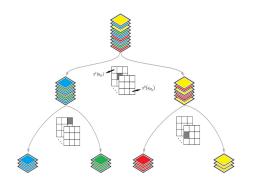
Spatial Random Forests

CSIRO

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- Multiresolution and mixed data
- Supervised and unsupervised learning





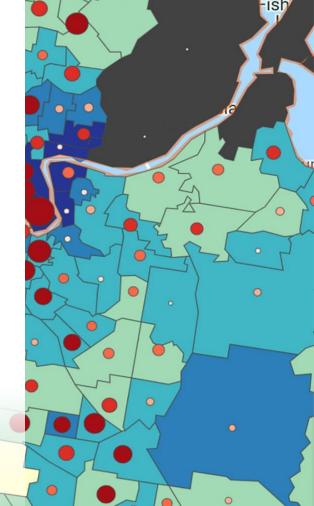
 $pat_{r}(u_{i}) = [x^{r}(u_{i1}), ..., x^{r}(u_{iE_{r}})]$   $pat(u_{i}) = [pat_{1}(u_{i}), ..., pat_{R}(u_{i})]$   $pat^{*}(u_{i}) = [pat_{1}^{*}(u_{i}), ..., pat_{R}^{*}(u_{i})]$   $\mathcal{D} = \{(pat(u_{1}), y(u_{1})), ..., (pat(u_{N}), y(u_{N}))\}$ 

# Digital Twins and Research Infrastructures in Australia

The Gemini Principles

Dr Michael Rigby Data Science Support Team Lead





Digital twins are digital representation of cities/towns that are connected to the physical world

Impacts are predicted across various social, economic and environmental dimensions

Given this breadth, a framework is required to guide the development of digital twins



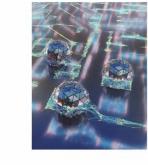
# Transformative

#### Next generation transformative technologies

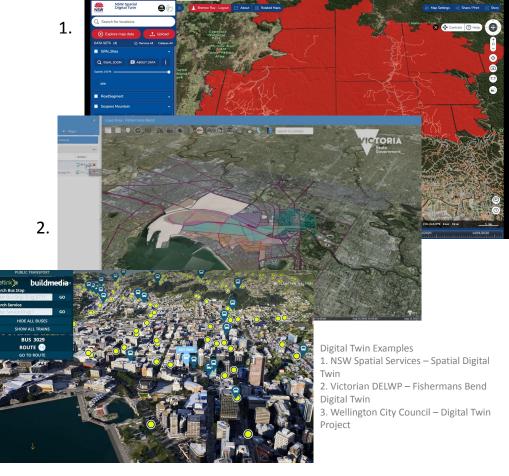
- Artificial Intelligence (AI)
- · Digital Twins
- Engineering Biology
- Quantum Computing
- Autonomous systems

UK Research and Innovation

Source: DAFNI 2 Launch Event, July 2021



3.



4. FrontierSI https://frontiersi.com.au/digital-twins/

# Information value chain

Oecision nating Rule-based automation Improved decisions Decision Machine support learning tools Optimisation algorithms Decreasing data volume, increasing data value Sense making -earning Improved Big data Data Middleware Analytics Modelling insight analysis mining Date management Data Data Data cleaning structure storage Customer Activity Asset data Cost data data data GPS Ticketing/ Social GIS Manufacturers' CCTV Control SCADA Customer Sensors Drone Satellite Scanned media & BIM data systems billing counting surveys surveys imagery images systems

Source: Bolton, A. et al. (2018) The Gemini Principles: Guiding values for the national digital twin and information management framework. DOI: https://doi.org/10.17863/CAM.32260



1. Purpose

<u>Real-time decision making</u> Dynamic model

#### <u>Strategic Planning</u> Static model

#### 2. Requirements

Representation must meet requirements that address the intended purpose

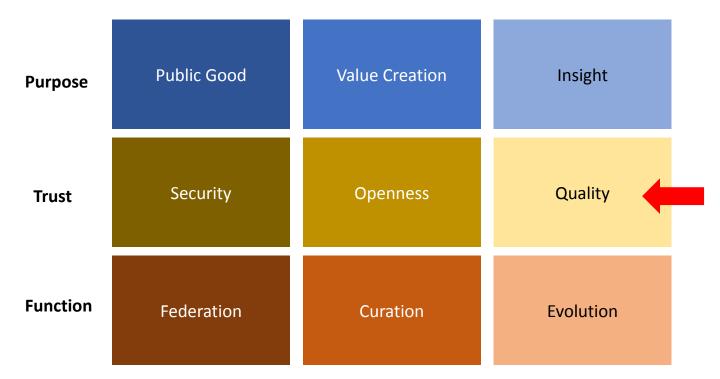
Data – quality (accuracy, scale, granularity, etc.)
Model – quality (parsimony → appropriateness of assumptions, algorithms, etc.)
Visualisation – quality (effective visual codings, etc.)



Human-centred: ISO 9241-210:2019

# **The Gemini Principles**

Guide the development of the framework and digital twin across three key areas:



Source: Bolton, A. et al. (2018) The Gemini Principles: Guiding values for the national digital twin and information management framework. DOI: https://doi.org/10.17863/CAM.32260

# Quality

Relates to the appropriateness of the data in relation to requirements

Must be transparent, defined and measured

A minimum standard of quality will be needed, e.g. functionality, security

Success of the digital twin judged of quality of decisions to enables

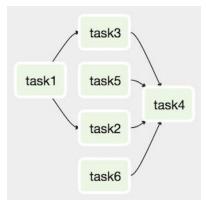


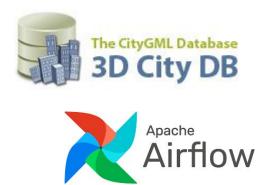
# **Data integration**

Data management to enable the integration of data

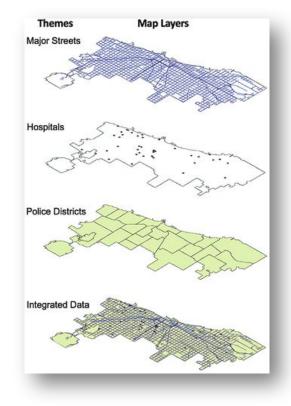
Methods vary dependent on dynamic or static model

Quality needs to be mapped throughout





#### Simplistic view



Balasubramani and Cruz (2018)

Harenslak (2019) godatadriven.com

# **Breakout Topics**

- 1. What are the key challenges with big geospatial data? (Sanjeev Srivastava)
- 1. What are the key challenges in the use of AI in Geospatial Data? (Jens Klump)
- 1. What are the key challenges to consider when incorporating built/natural environment and social data within Digital Twins? (Michael Rigby)

For use during breakout discussion: https://miro.com/app/board/o9J\_I8Yp5Dc=/

Report back: **Breakout 1** - What are the key challenges with big geospatial data?

- 1. Heterogeneity, size & scale, errors, methods and techniques for processing.
- 2. Completeness of coverage, biases in the data (how do you identify them?)



Report back: Breakout 2 What are the key challenges in the use of AI in Geospatial Data?

- 1. Need for developing proper spatial machine learning methods
- 2. How to extrapolate from machine learning? Needed in geological exploration
- 3. Need for explainable ML to help understand processes
- 4. Are there suitable methods for dimensionality reduction? (Min/Max Autocorrelation Factors)
- 5. Can we extrapolate to higher dimensions? e.g. from 1D to 2D/3D
- 6. Take into account physical laws (sanity checks)
- 7. Tracking features across scenes/frames

**Report back: Breakout 3** What are the key challenges of incorporating built/natural environment and social data within Digital Twins?

- Experience using geospatial data and performing data integration Similarities between geology vs urban research and associated models
- Challenges integrating and establishing built environment data Terrain, roads, buildings
- 1. Social data challenges
  - a. Spatial/temporal (patchiness and handling over time)
  - b. Connecting these to the built environment
  - c. Data availability
  - d. Secure/sensitive data ....

### Next steps

# Geospatial Capabilities Community of Practice

#### ABOUT

The intent of the Geospatial Capabilities Community of Practice is to bring people together as a community who, in some capacity, work with geospatial data and make it available for broader use. The group is intended as a forum for sharing knowledge and experiences with finding, accessing, transforming, using and making available geospatial data.

Terms of Reference - Geospatial Capabilities Community of Practice

#### OVERVIEW

Geospatial data creation and use, and related capabilities

https://sites.google.com/ardc.edu.au/geospatialcapcop/join