

DESIGNING FOR DISCOVERY IN THE ERA OF DATA-INTENSIVE ASTRONOMY

Sarah Hegarty

with A/Prof Christopher Fluke, Dr Aidan Hotan (CSIRO), & Dr Amr Hassan (Monash)

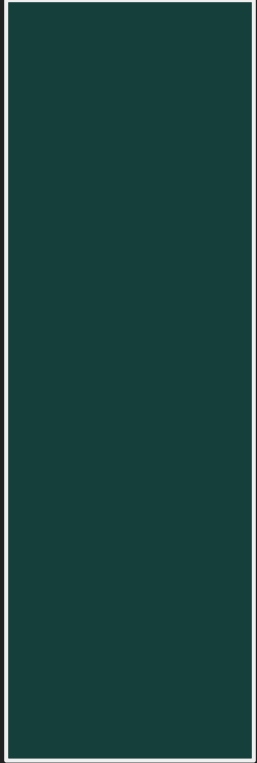
Melbourne University | August 29th, 2018

SWIN
BUR
NE

SWINBURNE
UNIVERSITY OF
TECHNOLOGY



Making Discoveries in Astronomy



Making Discoveries in Astronomy



Making Discoveries in Astronomy



+



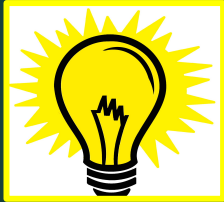
Making Discoveries in Astronomy



+



=



Making Discoveries in Astronomy



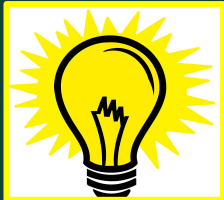
Making Discoveries in Astronomy



+



=



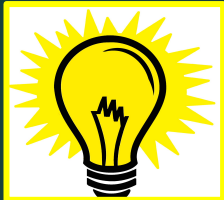
Making Discoveries in Astronomy



+



=



'Most astronomers will never go near a cutting-edge telescope.....

(Norris, 2016)

Making Discoveries in Data-Intensive Astronomy



~1TB/night



~20TB/night



~75PB/year

'Most astronomers will never go near a cutting-edge telescope.....

(Norris, 2016)

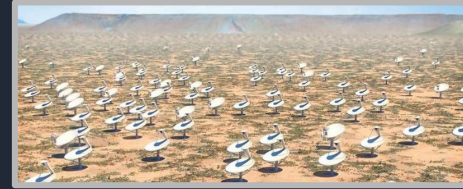
Making Discoveries in Data-Intensive Astronomy



~1TB/night



~20TB/night



~75PB/year

'Most astronomers will never go near a cutting-edge telescope.....

(Norris, 2016)

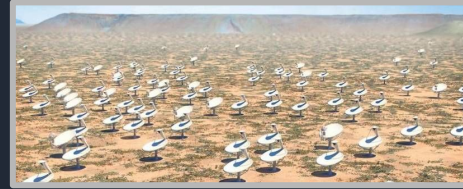
Making Discoveries in Data-Intensive Astronomy



~1TB/night



~20TB/night



~75PB/year

'Most astronomers will never go near a cutting-edge telescope.....'

(Norris, 2016)



Making Discoveries in Data-Intensive Astronomy



~1TB/night



~20TB/night



~75PB/year

'Most astronomers will never go near a cutting-edge telescope.....

(Norris, 2016)



Making Discoveries in Data-Intensive Astronomy



~1TB/night



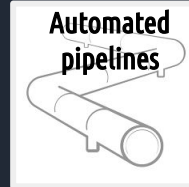
~20TB/night



~75PB/year

'Most astronomers will never go near a cutting-edge telescope.....'

(Norris, 2016)



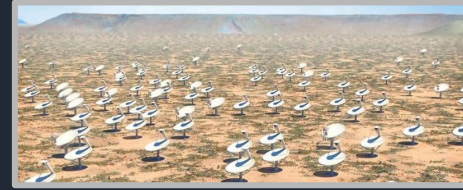
Making Discoveries in Data-Intensive Astronomy



~1TB/night



~20TB/night



~75PB/year

'Most astronomers will never go near a cutting-edge telescope.....
They will rarely analyse data, since all the leading-edge telescopes will have pipeline processors'
(Norris, 2016)



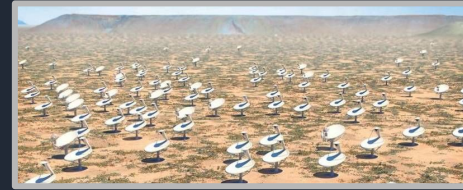
Making Discoveries in Data-Intensive Astronomy



~1TB/night



~20TB/night



~75PB/year

'Most astronomers will never go near a cutting-edge telescope.....
They will rarely analyse data, since all the leading-edge telescopes will have pipeline processors'
(Norris, 2016)



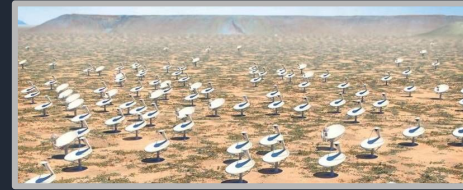
Making Discoveries in Data-Intensive Astronomy



~1TB/night



~20TB/night

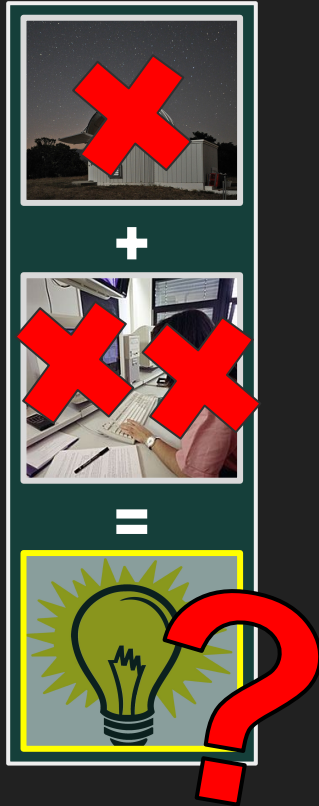


~75PB/year

'Most astronomers will never go near a cutting-edge telescope.....
They will rarely analyse data, since all the leading-edge telescopes will have pipeline processors'
(Norris, 2016)



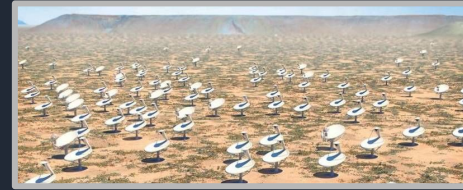
Making Discoveries in Data-Intensive Astronomy



~1TB/night



~20TB/night



~75PB/year

'Most astronomers will never go near a cutting-edge telescope.....
They will rarely analyse data, since all the leading-edge telescopes will have pipeline processors'
(Norris, 2016)



How can we capitalise on the discovery potential of data-intensive astronomy?

How can we capitalise on the discovery potential of data-intensive astronomy?

→ Understand how we make discoveries

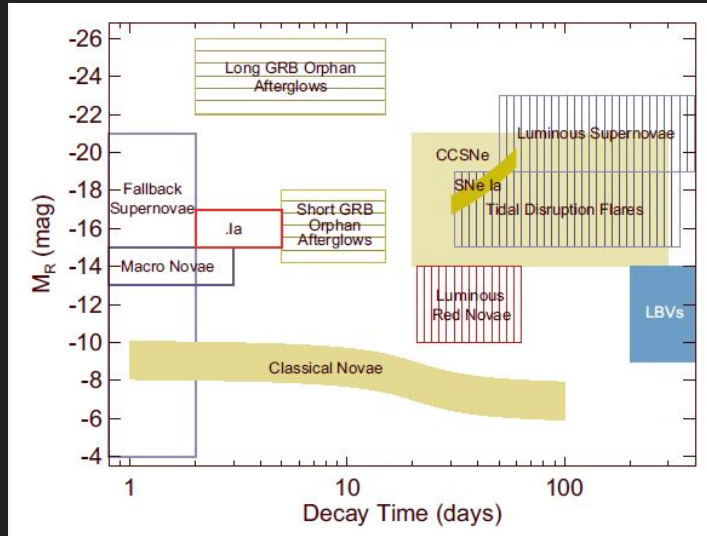
Technological Development

Technological Development

Astronomical discoveries tend to be made when new technology enables the construction of a new telescope or instrument that can make observations that were previously impossible.

Harwit (1981)

Technological Development

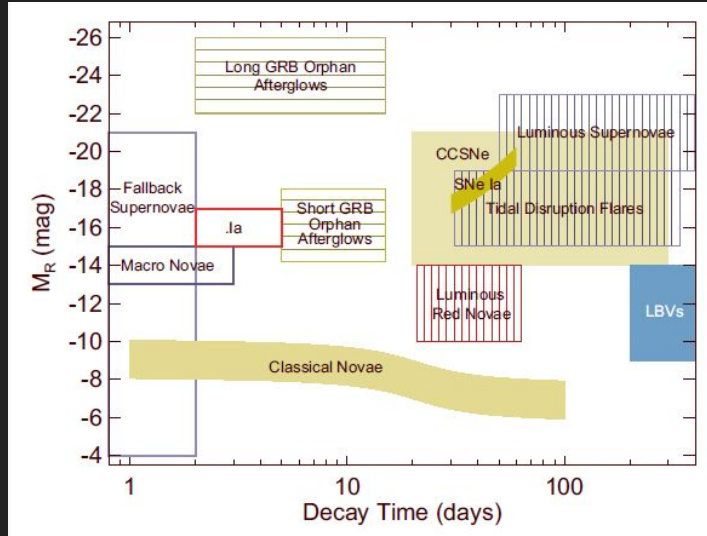


Rau+, 2009

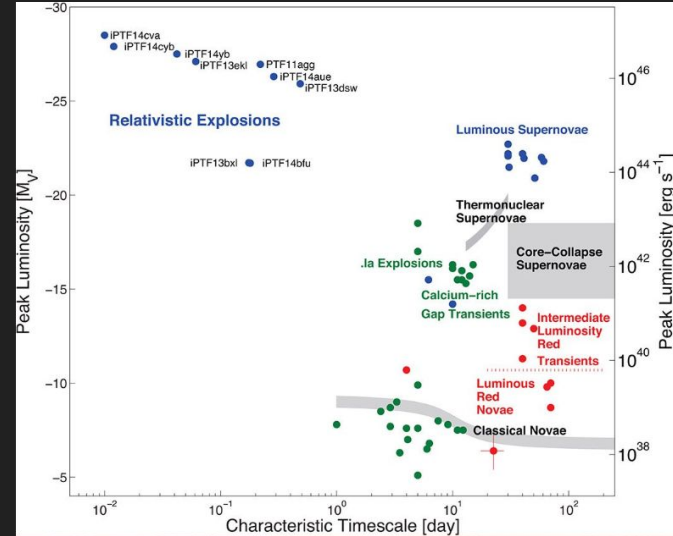
Astronomical discoveries tend to be made when new technology enables the construction of a new telescope or instrument that can make observations that were previously impossible.

Harwit (1981)

Technological Development



Rau+, 2009



Nugent, 2015

Astronomical discoveries tend to be made when new technology enables the construction of a new telescope or instrument that can make observations that were previously impossible.

Harwit (1981)

Planning vs Serendipity

Planning vs Serendipity

Project
Use cepheids to improve value of H_0
UV spectroscopy of ig medium
Medium-deep survey
Image quasar host galaxies
Measure SMBH masses
Exoplanet atmospheres
Planetary Nebulae
Discover Dark Energy
Comet Shoemaker-Levy
Deep fields (HDF, HDFS, GOODS, FF, etc)
Proplyds in Orion
GRB Hosts

Norris, 2016

Planning vs Serendipity

Project	Key Project?
Use cepheids to improve value of H_0	✓
UV spectroscopy of ig medium	✓
Medium-deep survey	✓
Image quasar host galaxies	
Measure SMBH masses	
Exoplanet atmospheres	
Planetary Nebulae	
Discover Dark Energy	
Comet Shoemaker-Levy	
Deep fields (HDF, HDFS, GOODS, FF, etc)	
Proplyds in Orion	
GRB Hosts	

Norris, 2016

Planning vs Serendipity

Project	Key Project?	Planned?	Nat Geo top ten?	Highly cited?	Nobel Prize?
Use cepheids to improve value of H_0	✓	✓	✓	✓	
UV spectroscopy of ig medium	✓	✓			
Medium-deep survey	✓	✓			
Image quasar host galaxies		✓	✓		
Measure SMBH masses		✓	✓		
Exoplanet atmospheres		✓	✓		
Planetary Nebulae		✓	✓		
Discover Dark Energy			✓	✓	✓
Comet Shoemaker-Levy			✓		
Deep fields (HDF, HDFS, GOODS, FF, etc)			✓	✓	
Proplyds in Orion			✓		
GRB Hosts			✓		

Norris, 2016

Planning vs Serendipity

Project	Key Project?	Planned?	Nat Geo top ten?	Highly cited?	Nobel Prize?
Use cepheids to improve value of H_0	✓	✓	✓	✓	
UV spectroscopy of ig medium	✓	✓			
Medium-deep survey	✓	✓			
Image quasar host galaxies		✓	✓		
Measure SMBH masses		✓	✓		
Exoplanet atmospheres		✓	✓		
Planetary Nebulae		✓	✓		
Discover Dark Energy			✓	✓	✓
Comet Shoemaker-Levy			✓		
Deep fields (HDF, HDFS, GOODS, FF, etc)			✓	✓	
Proplyds in Orion			✓		
GRB Hosts			✓		

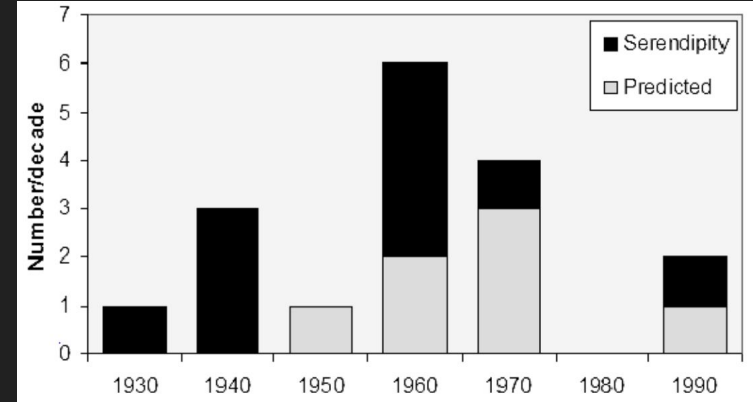
Norris, 2016

“Theoretical anticipation has usually had little to do with astronomical discovery”
(Wilkinson+, 2004)

Planning vs Serendipity

Project	Key Project?	Planned?	Nat Geo top ten?	Highly cited?	Nobel Prize?
Use cepheids to improve value of H_0	✓	✓	✓	✓	
UV spectroscopy of ig medium	✓	✓			
Medium-deep survey	✓	✓			
Image quasar host galaxies		✓	✓		
Measure SMBH masses		✓	✓		
Exoplanet atmospheres		✓	✓		
Planetary Nebulae		✓	✓		
Discover Dark Energy			✓	✓	✓
Comet Shoemaker-Levy			✓		
Deep fields (HDF, HDFS, GOODS, FF, etc)			✓	✓	
Proplyds in Orion			✓		
GRB Hosts			✓		

Norris, 2016



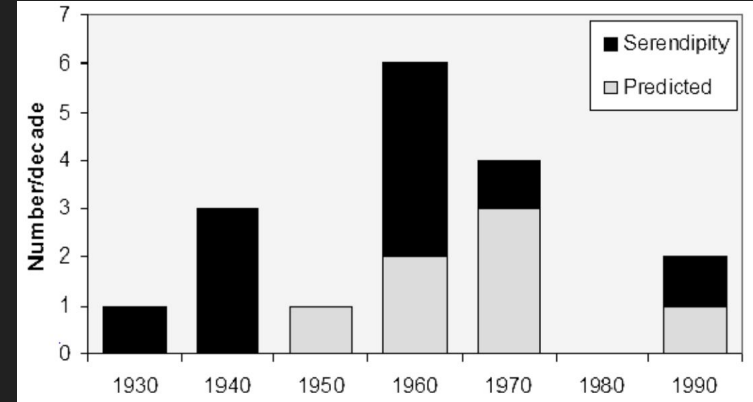
Ekers, 2009

“Theoretical anticipation has usually had little to do with astronomical discovery”
(Wilkinson+, 2004)

Planning vs Serendipity

Project	Key Project?	Planned?	Nat Geo top ten?	Highly cited?	Nobel Prize?
Use cepheids to improve value of H_0	✓	✓	✓	✓	
UV spectroscopy of ig medium	✓	✓			
Medium-deep survey	✓	✓			
Image quasar host galaxies		✓	✓		
Measure SMBH masses		✓	✓		
Exoplanet atmospheres		✓	✓		
Planetary Nebulae		✓	✓		
Discover Dark Energy			✓	✓	✓
Comet Shoemaker-Levy			✓		
Deep fields (HDF, HDFS, GOODS, FF, etc)			✓	✓	
Proplyds in Orion			✓		
GRB Hosts			✓		

Norris, 2016



Ekers, 2009

“Theoretical anticipation has usually had little to do with astronomical discovery”

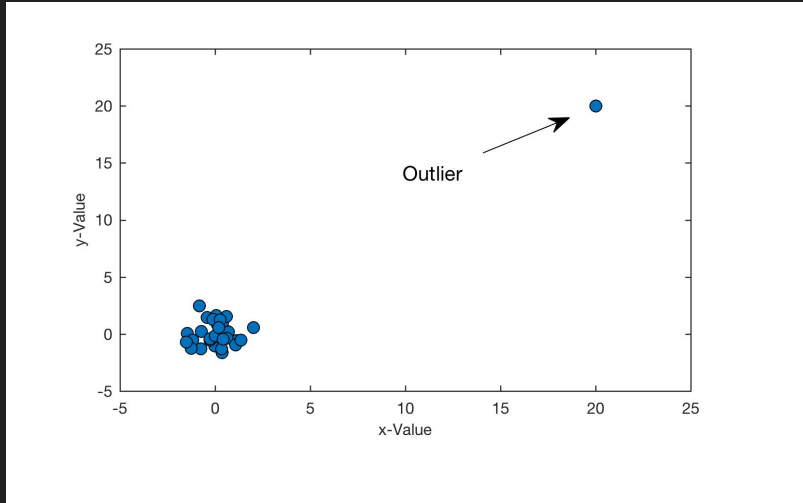
(Wilkinson+, 2004)

“Astronomy is powered by serendipitous observations”

(Fabian, 2009)

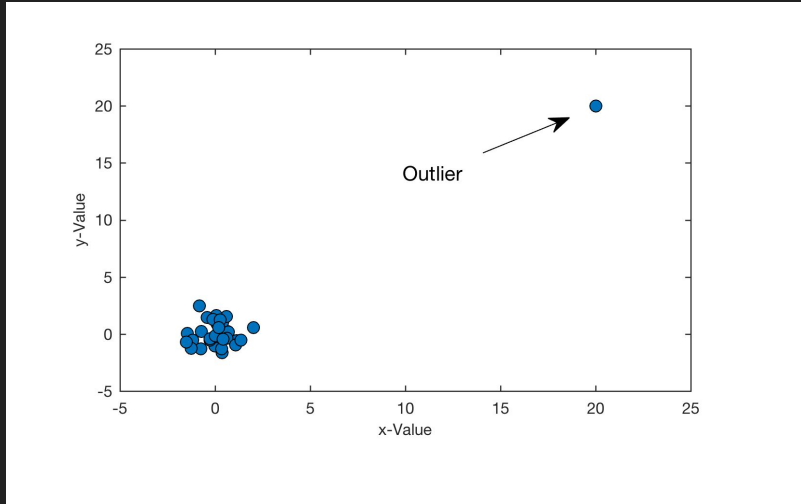
The Importance of Visualisation

The Importance of Visualisation

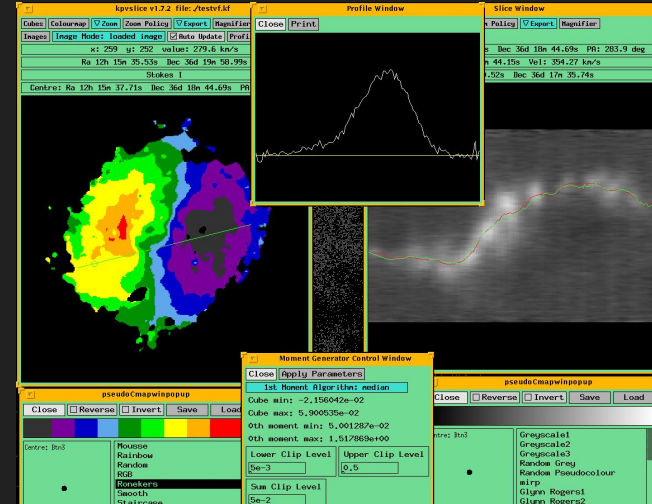


<http://mres.uni-potsdam.de/index.php/2017/02/14/outliers-and-correlation-coefficients/>

The Importance of Visualisation

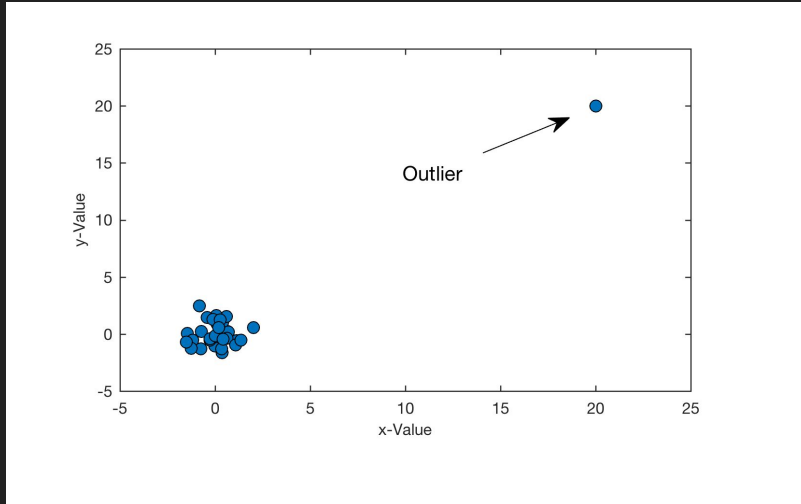


<http://mres.uni-potsdam.de/index.php/2017/02/14/outliers-and-correlation-coefficients/>

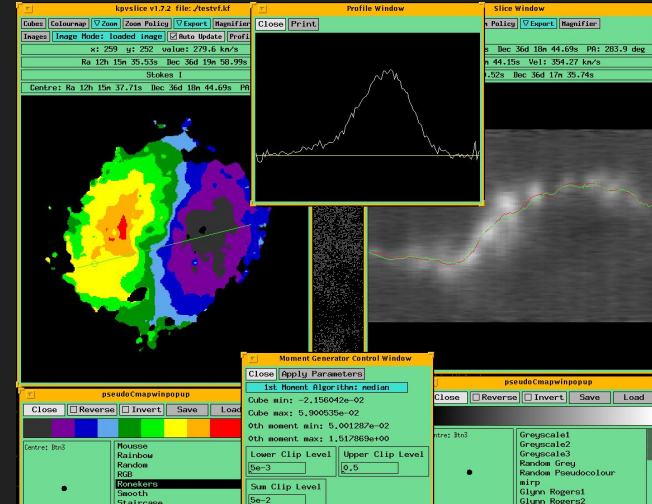


<https://www.atnf.csiro.au/computing/software/karma/>

The Importance of Visualisation



<http://mres.uni-potsdam.de/index.php/2017/02/14/outliers-and-correlation-coefficients/>



<https://www.atnf.csiro.au/computing/software/karma/>

‘Visualization is a crucial component of knowledge discovery in astronomy....at present, humans have pattern recognition and feature identification skills that exceed those of any existing automated approach.’
(Hassan & Fluke 2011)

Astronomical Expertise

Astronomical Expertise

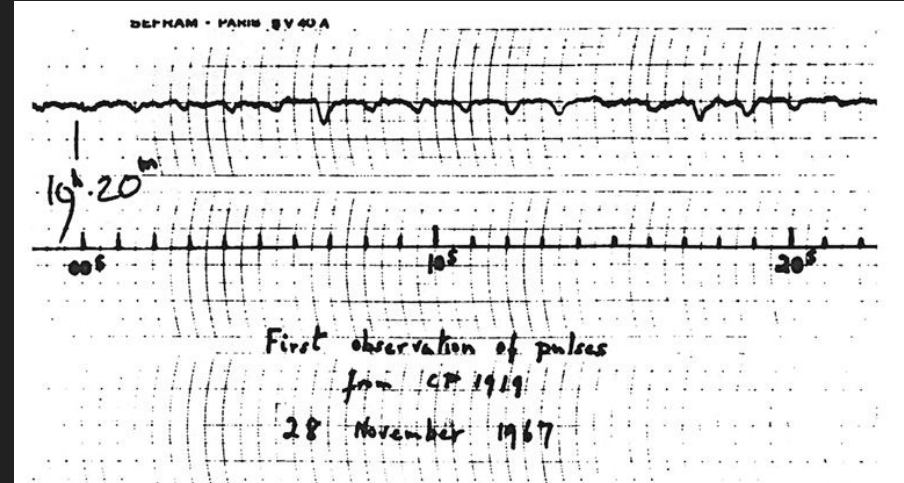


<https://www.newscientist.com/article/mg23531370-800>

Astronomical Expertise



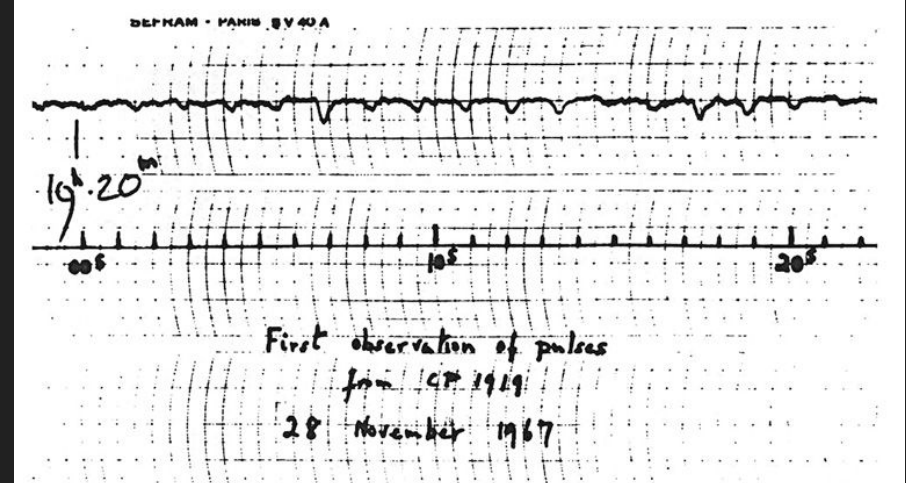
<https://www.newscientist.com/article/mg23531370-800>



Astronomical Expertise

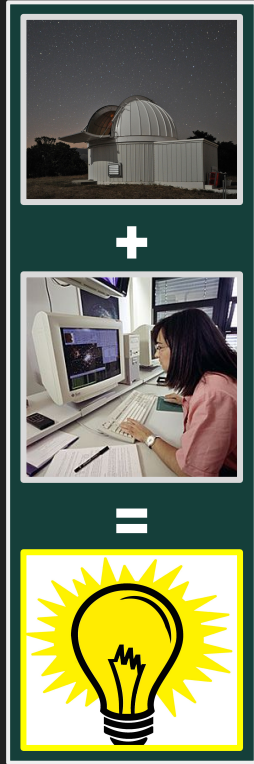


<https://www.newscientist.com/article/mg23531370-800>

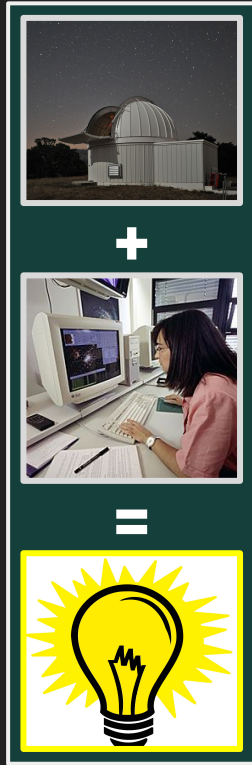


‘Discoveries invariably result from an individual becoming so familiar with the data, and hence the possible sources of error in them, that he/she can recognize an unexpected clue for what it is worth.’
(Wilkinson et al., 2004)

The Discovery Workflow



The Discovery Workflow



Telescopes

Data Reduction

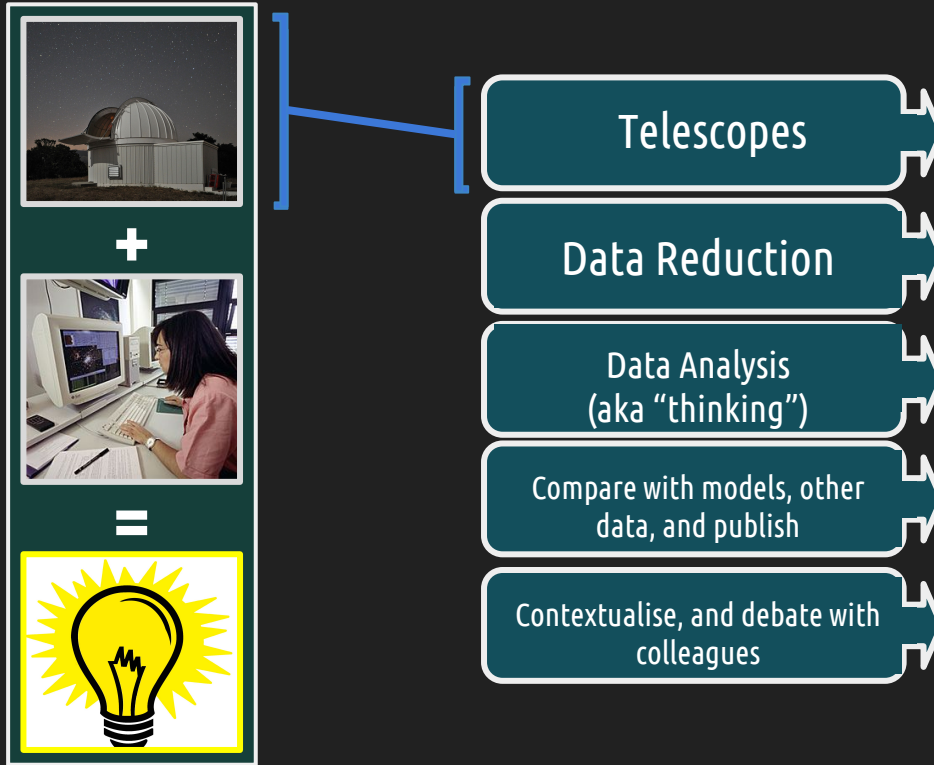
Data Analysis
(aka “thinking”)

Compare with models, other
data, and publish

Contextualise, and debate with
colleagues

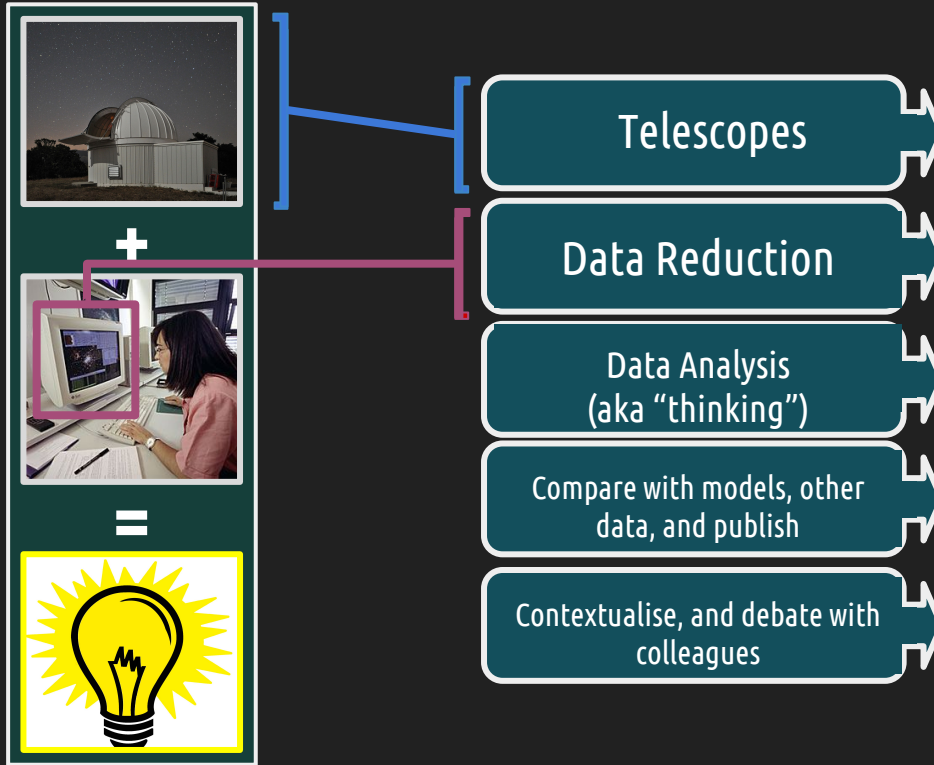
Adapted from Norris (2010)

The Discovery Workflow



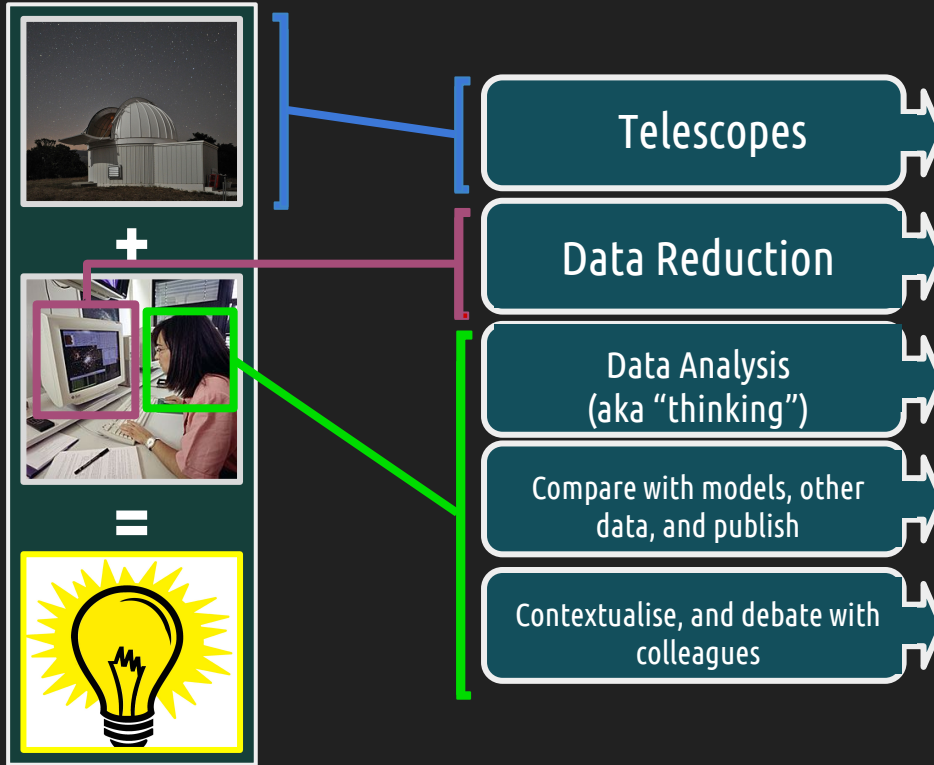
Adapted from Norris (2010)

The Discovery Workflow



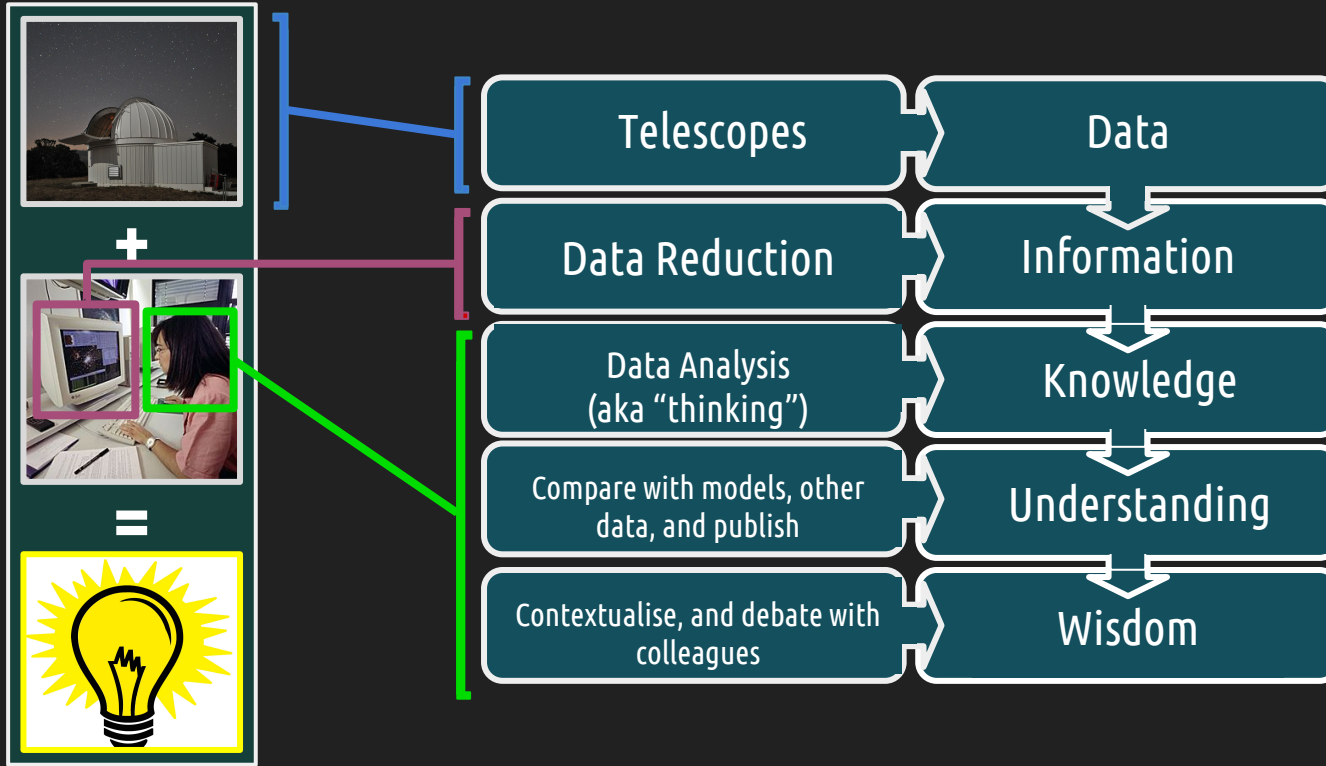
Adapted from Norris (2010)

The Discovery Workflow



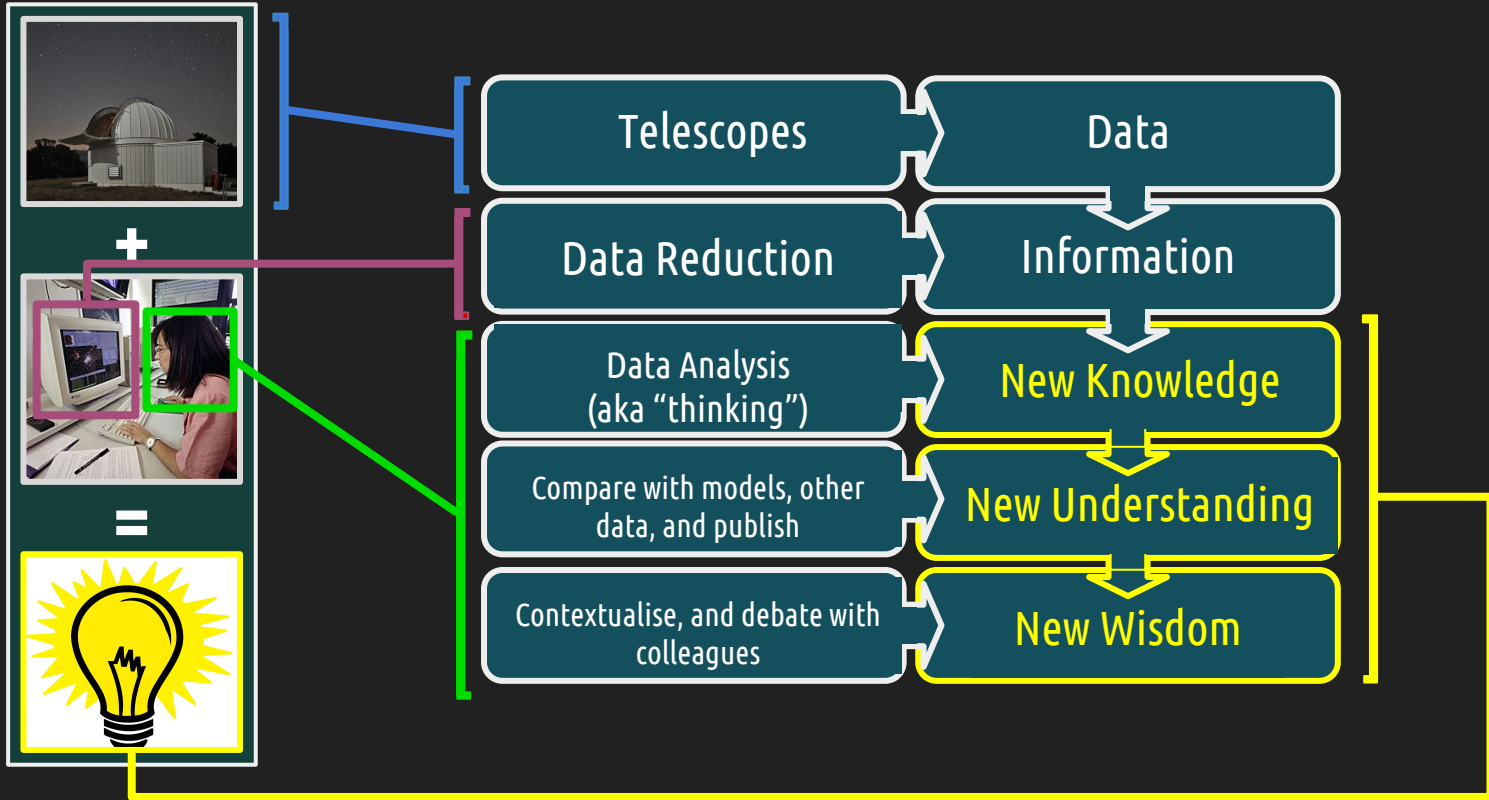
Adapted from Norris (2010)

The Discovery Workflow



Adapted from Norris (2010)

The Discovery Workflow



Adapted from Norris (2010)

What Do We Know About Making Discoveries in Astronomy?

What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space

What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous

What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable

What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new

What Do We Know About Making Discoveries in Astronomy?

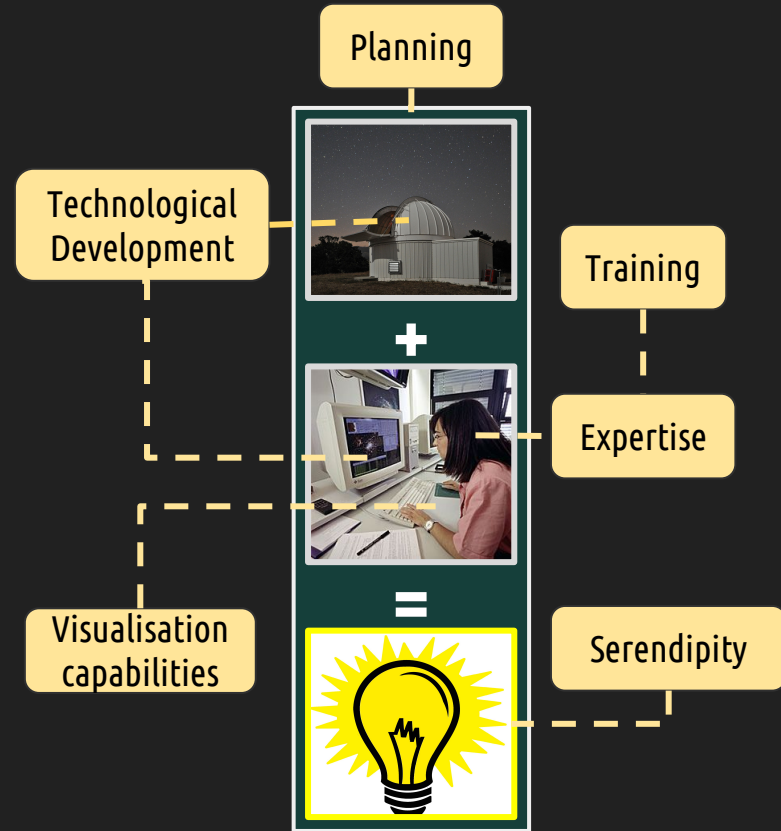
- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*

What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows

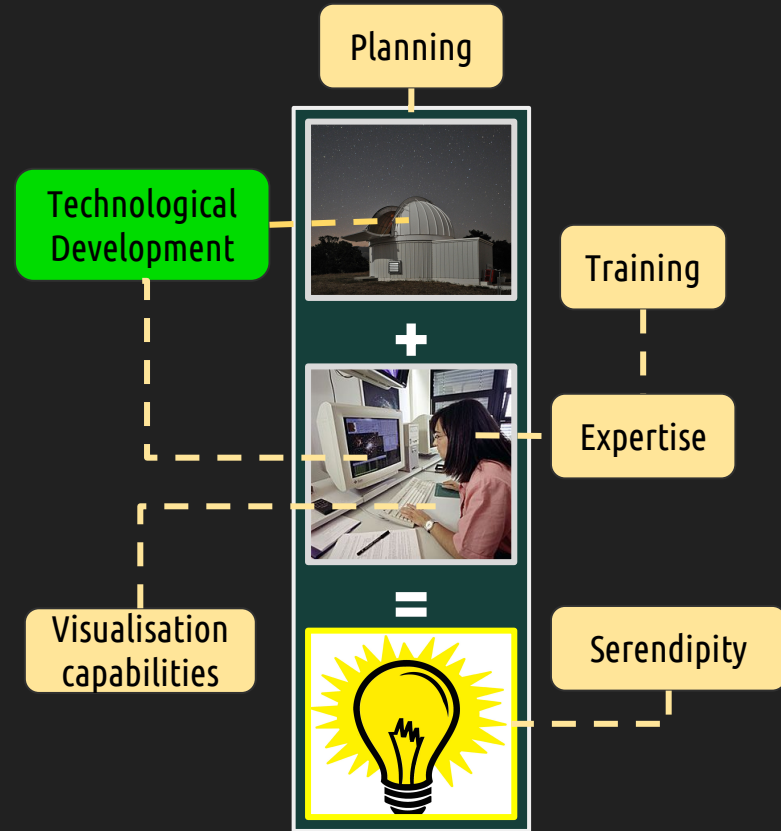
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



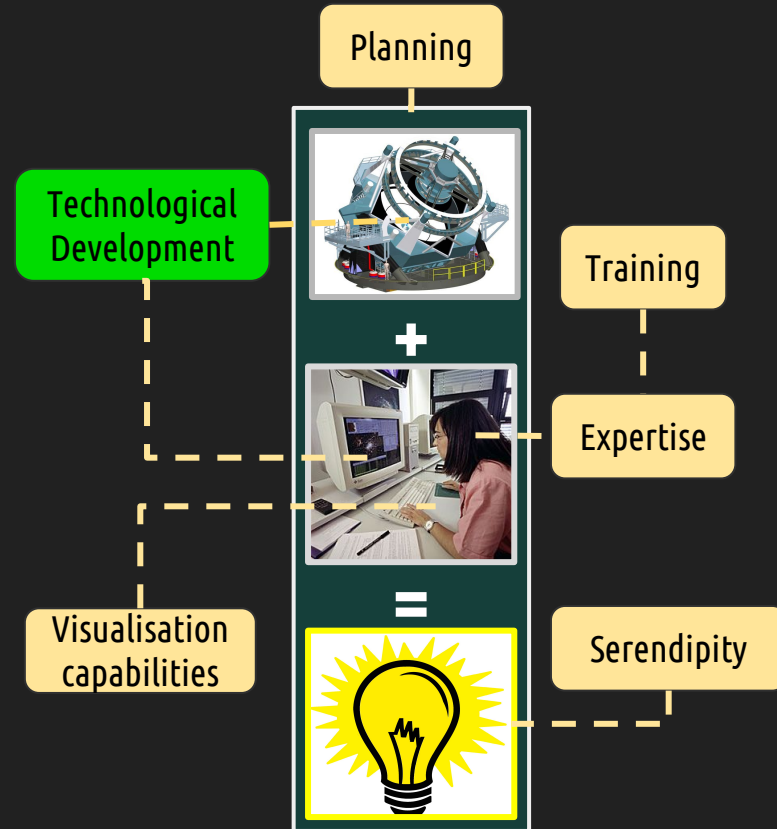
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



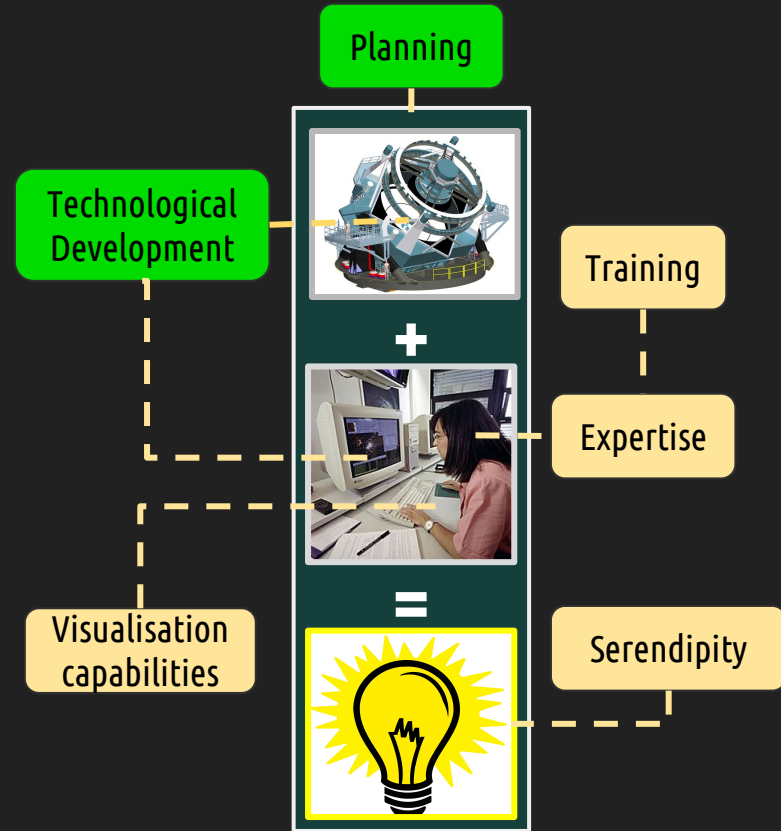
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



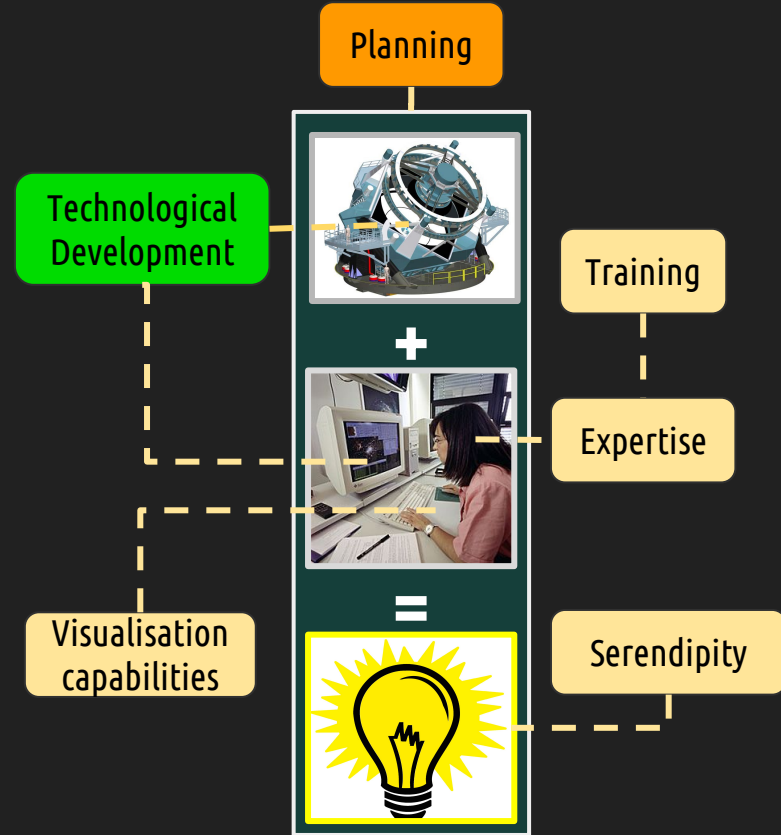
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



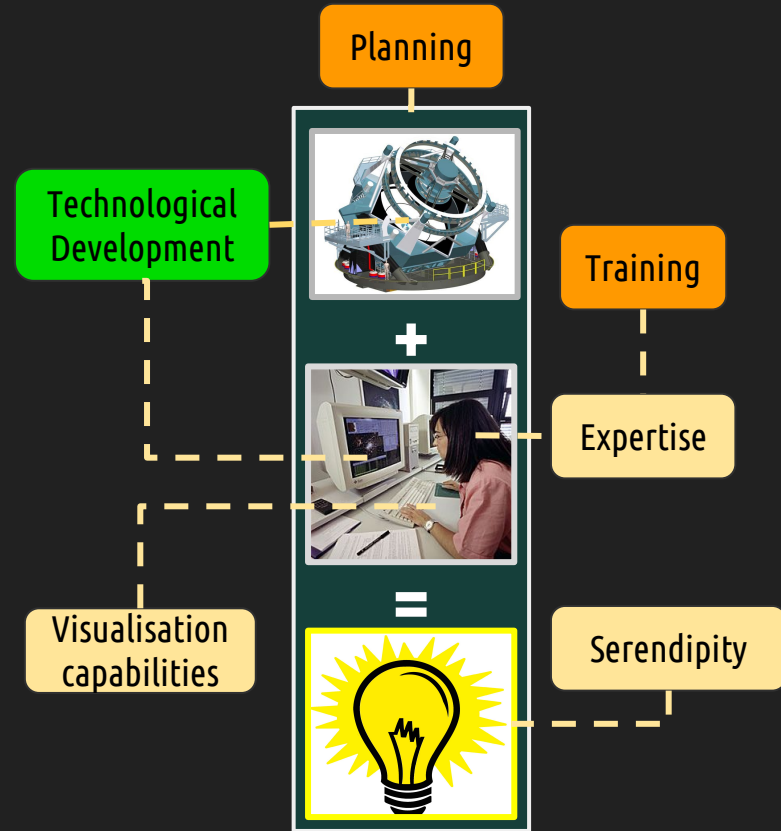
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



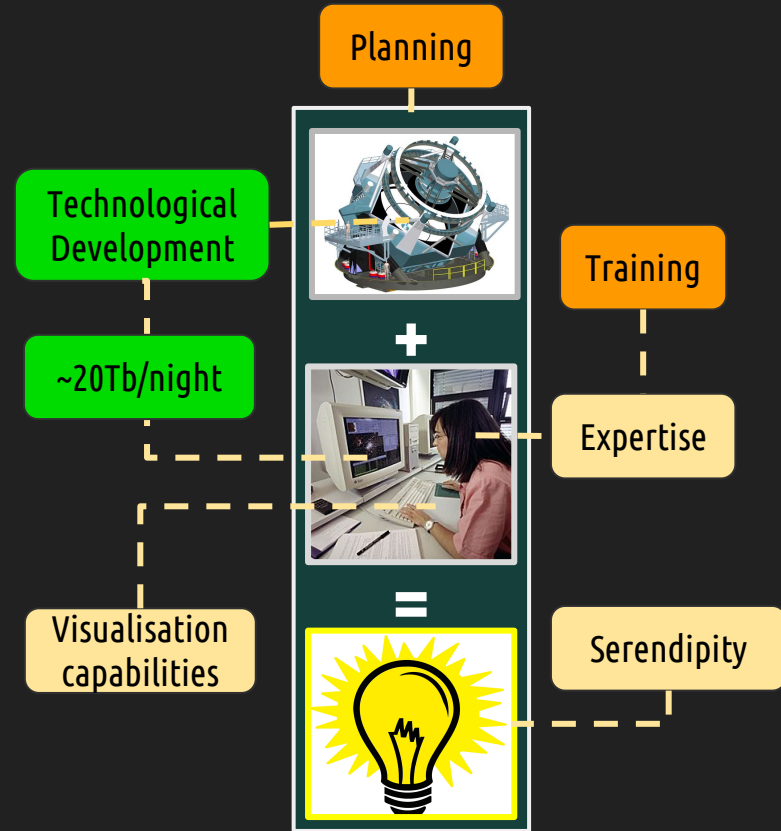
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



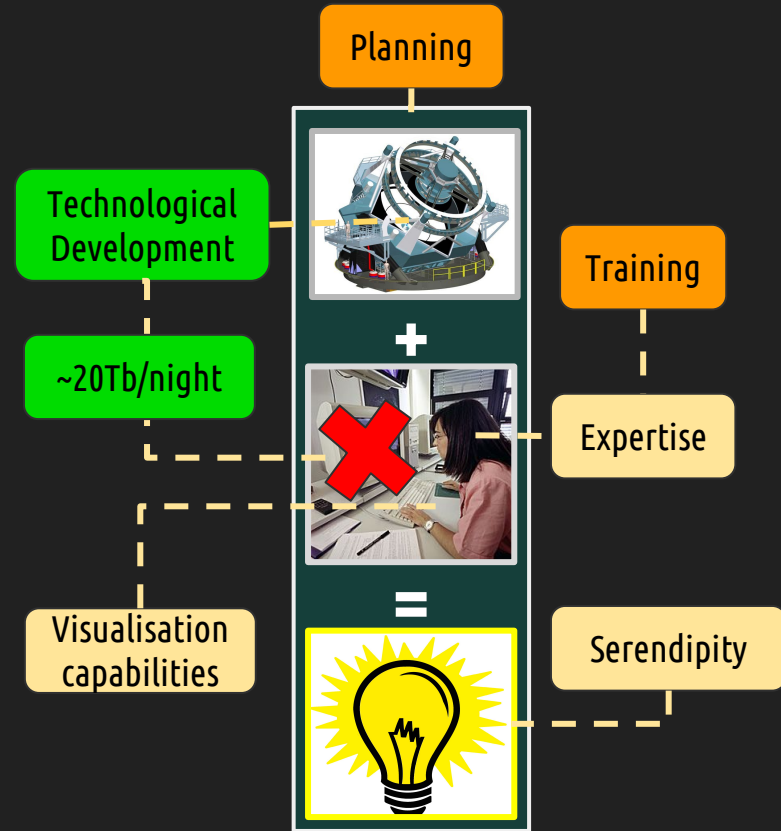
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



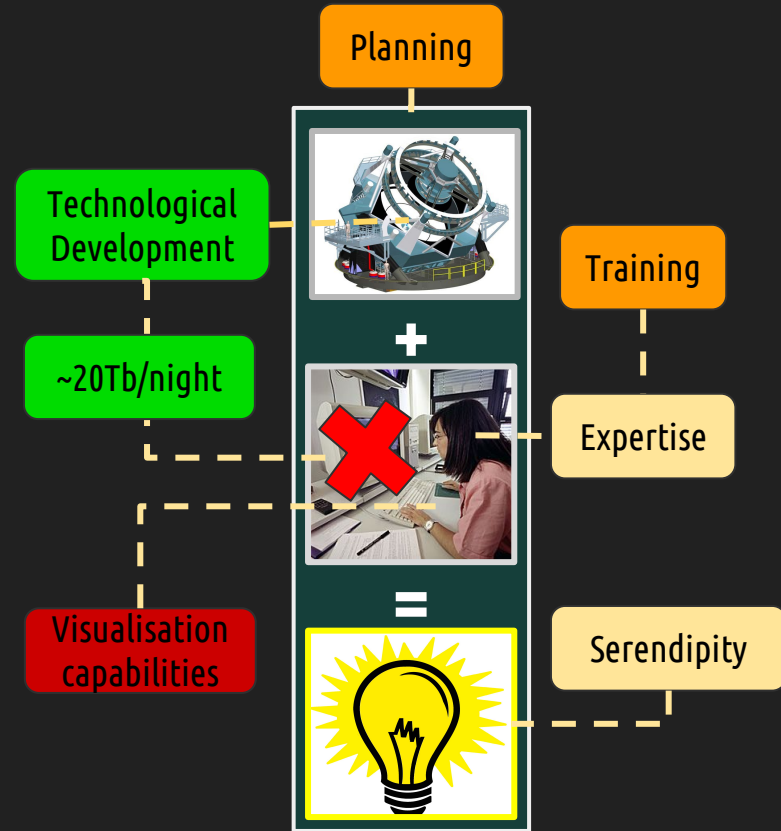
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



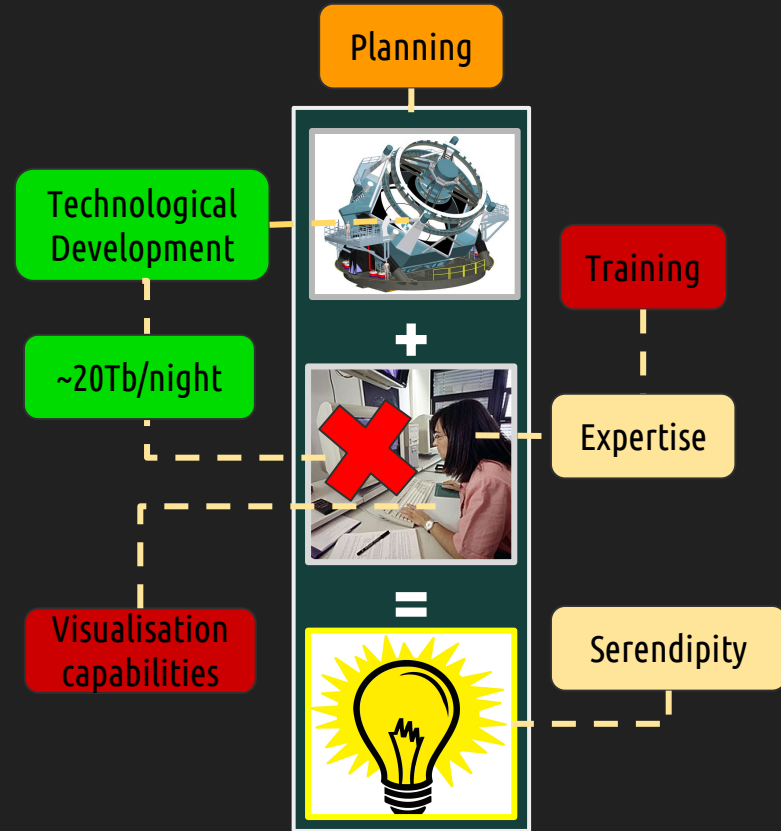
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



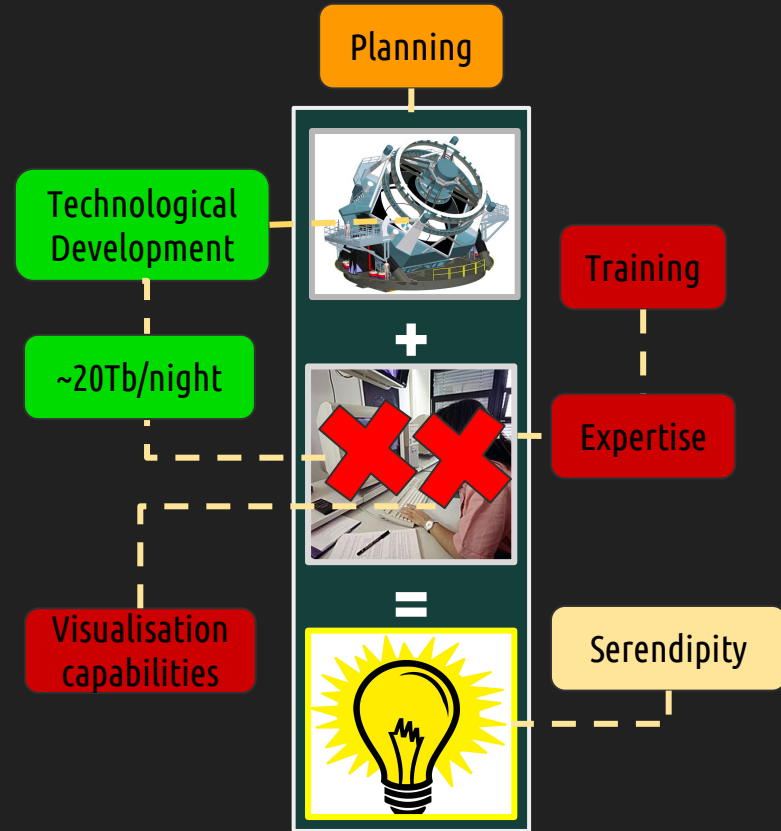
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



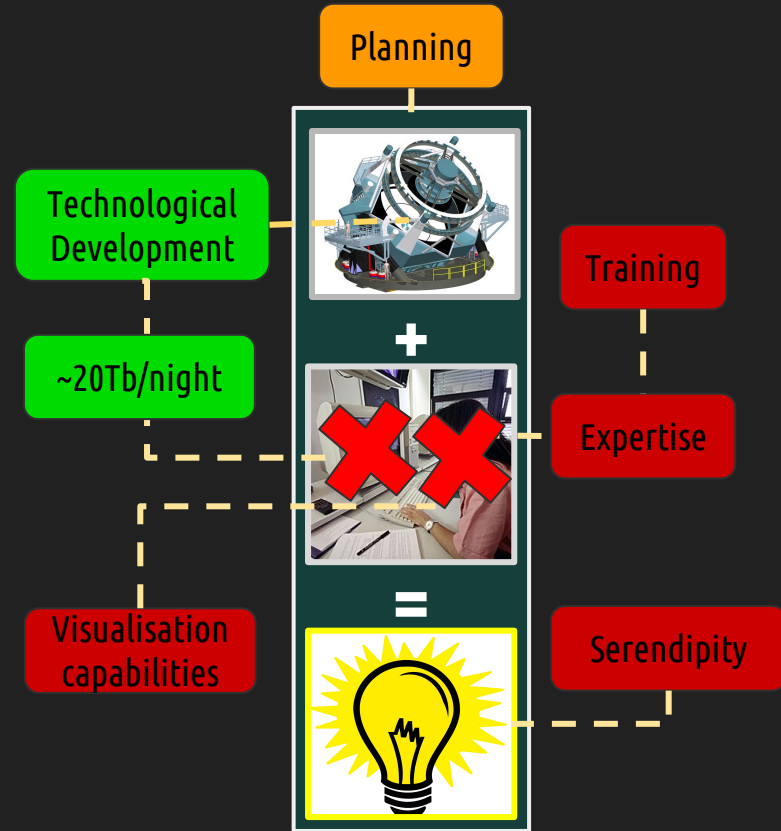
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



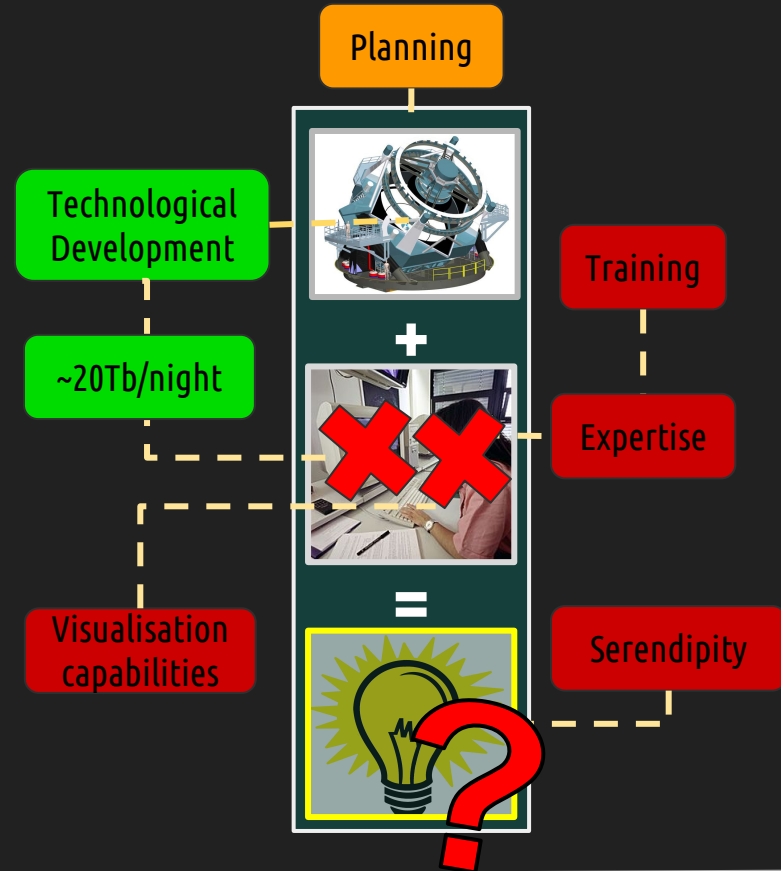
What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



What Do We Know About Making Discoveries in Astronomy?

- Discoveries strongly follow technological developments that open up new parameter space
- Many of the most exciting discoveries are serendipitous
- Visual inspection of the data can be invaluable
- Individual expertise, and familiarity with the data and the instrument, are crucial in recognising something new
 - *Developing this expertise through training is key*
- Discoveries are the end result of effective workflows



How can we capitalise on the discovery potential of data-intensive astronomy?

→ Understand how we make discoveries

How can we capitalise on the discovery potential of data-intensive astronomy?

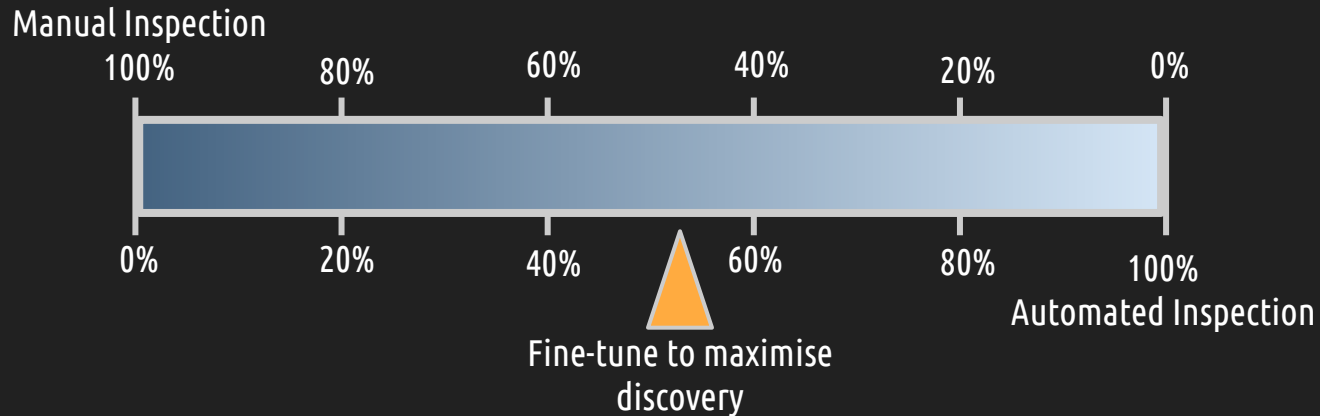
→ Understand how we make discoveries

→ Use this understanding to “design in” discovery when we build data-intensive workflows

Designing Effective Discovery Workflows


Automated pipelines and machine-learning approaches are **essential** for data-intensive astronomy
but

We must **integrate** a role for the human astronomer **alongside** automated methods to maintain discovery mechanisms that we know to be important




Adapted from Fluke *et al.* (2016)

Responding to the Data-Intensive Discovery Challenge



Director:
A/Prof Christopher Fluke



Advanced Visualisation Lab

Data visualisation uses a combination of hardware and software to explore patterns and relationships in research data, giving researchers greater understanding of their projects and potential outcomes.

swinburne.edu.au/90/advanced-visualisation-lab

**Centre for Astrophysics & Supercomputing
PhD Students**

- **Dr Dany Vohl**
- Ms Sarah Hegarty
- **Dr Bernard Meade**



External Collaborators

- A/Prof David Barnes (Monash)
- **Dr Amr Hassan (Monash)**


Swinburne Colleagues

- Dr Clare MacMahon (Skilled Performance)
- Prof Virginia Kilborn
- A/Prof Jeff Cooke

Responding to the Data-Intensive Discovery Challenge



Director:
A/Prof Christopher Fluke



Advanced Visualisation Lab

Data visualisation uses a combination of hardware and software to explore patterns and relationships in research data, giving researchers greater understanding of their projects and potential outcomes.

swinburne.edu.au/90/advanced-visualisation-lab

Centre for Astrophysics & Supercomputing PhD Students

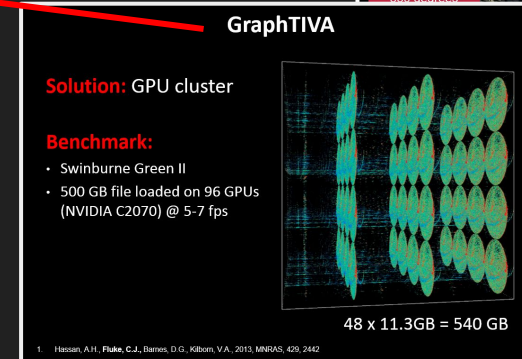
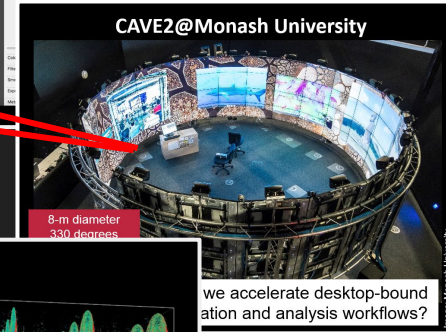
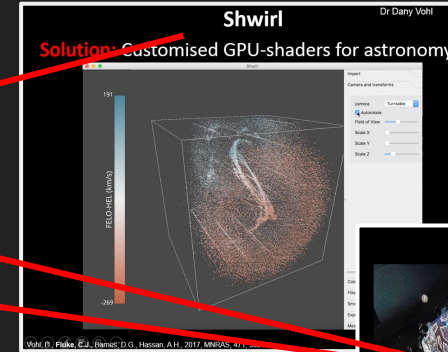
- Dr Dany Vohl
- Ms Sarah Hegarty
- Dr Bernard Meade

External Collaborators

- A/Prof David Barnes (Monash)
- Dr Amr Hassan (Monash)

Swinburne Colleagues

- Dr Clare MacMahon (Skilled Performance)
- Prof Virginia Kilborn
- A/Prof Jeff Cooke



Responding to the Data-Intensive Discovery Challenge



**Centre for Astrophysics & Supercomputing
PhD Students**

- Dr Dany Vahl
- Ms Sarah Hegarty
- Dr Bernard Meade

Responding to the Data-Intensive Discovery Challenge

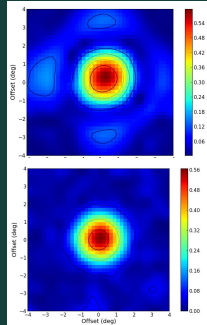


Centre for Astrophysics & Supercomputing
PhD Students

- Dr Dany Vohl
- Ms Sarah Hegarty
- Dr Bernard Menze

Designing Out Data Artefacts:

Better Beamforming for ASKAP



Responding to the Data-Intensive Discovery Challenge

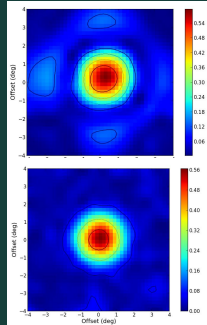


Centre for Astrophysics & Supercomputing
PhD Students

- Dr Dany Vohl
- Ms Sarah Hegarty
- Dr Bernard Menze

Designing Out Data Artefacts:

Better Beamforming for ASKAP



Building eResearch Workflows:

Theoretical Astrophysical Observatory



and: Deeper, Wider, Faster



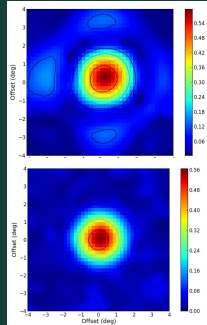
Responding to the Data-Intensive Discovery Challenge



Centre for Astrophysics & Supercomputing
PhD Students

- Dr Dany Vohl
- Ms Sarah Hegarty
- Dr Bernard Morde

Designing Out Data Artefacts: Better Beamforming for ASKAP



Building eResearch Workflows: Theoretical Astrophysical Observatory

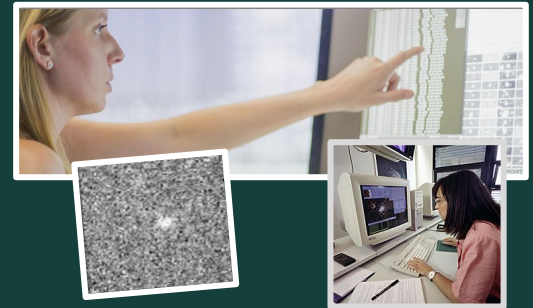


and: Deeper, Wider, Faster



Understanding the Astronomer's Role:

PerSieve

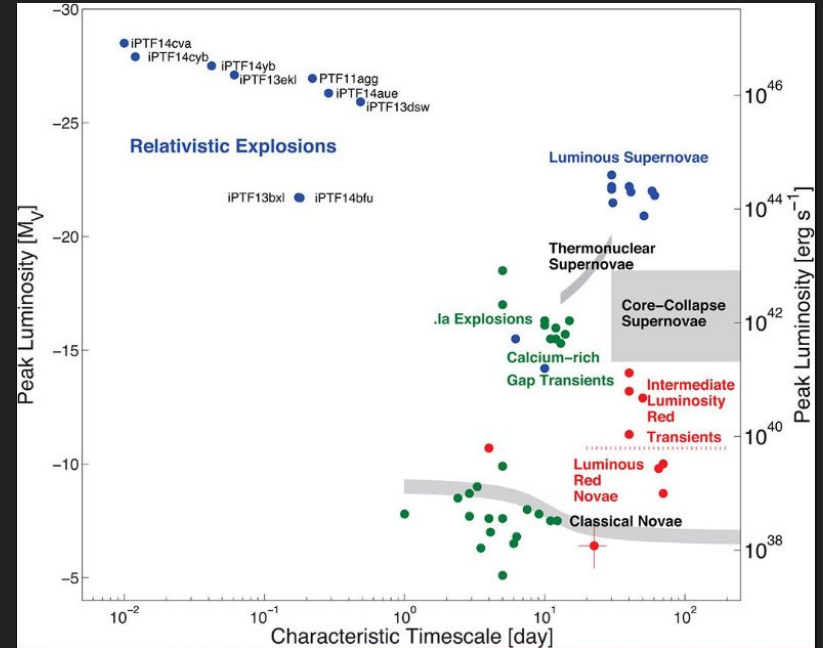


A Case Study: *Deeper, Wider, Faster*

A detection and follow-up program for
fast transients (Cooke+, in prep.)

A Case Study: *Deeper, Wider, Faster*

A detection and follow-up program for
fast transients (Cooke+, in prep.)

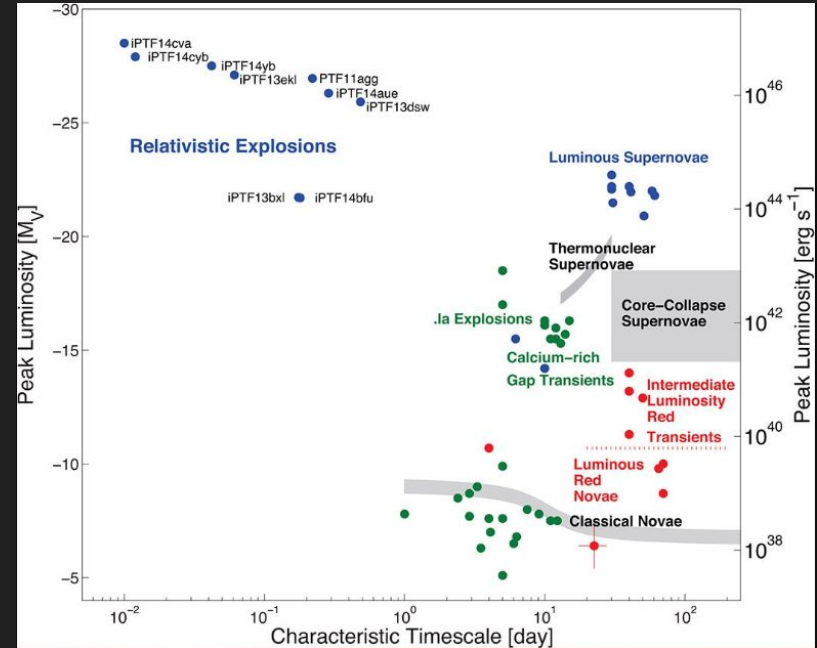


Nugent, 2015

A Case Study: *Deeper, Wider, Faster*

A detection and follow-up program for
fast transients (Cooke+, in prep.)

- Targets transients on timescales from hours down to seconds

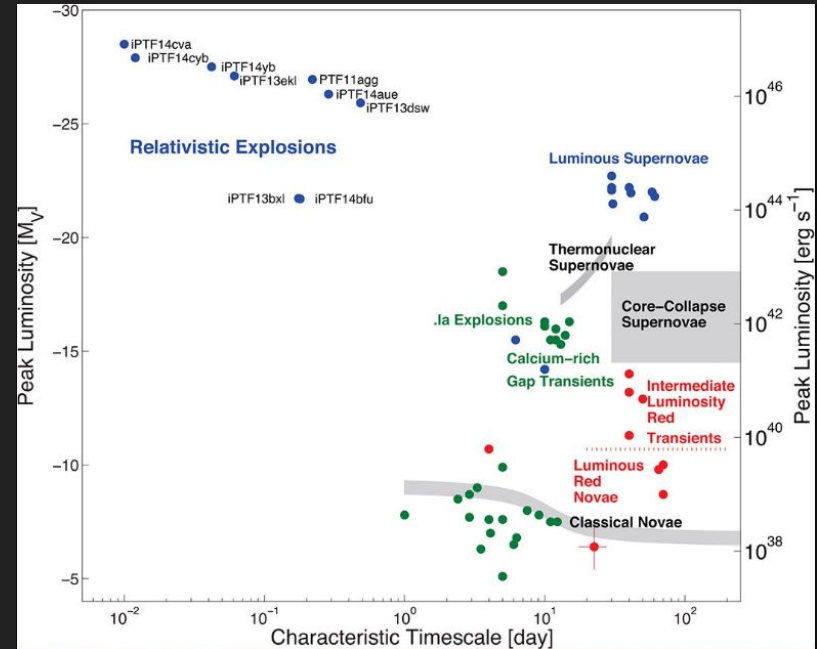


Nugent, 2015

A Case Study: *Deeper, Wider, Faster*

A detection and follow-up program for
fast transients (Cooke+, in prep.)

- Targets transients on timescales from hours down to seconds
- Aims to achieve real-time, multiwavelength observations, and rapid multiwavelength follow up

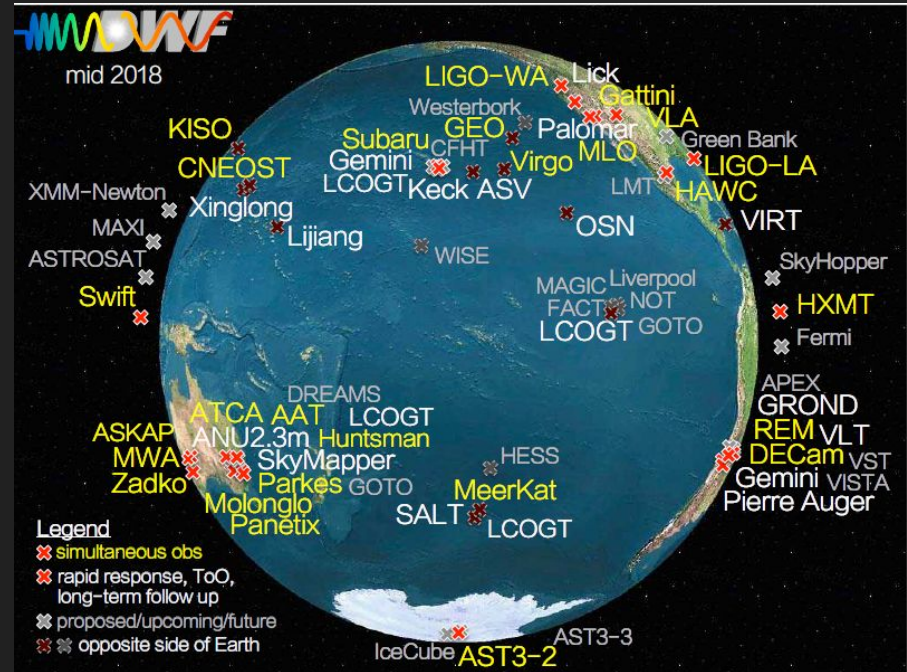


Nugent, 2015

A Case Study: *Deeper, Wider, Faster*

A detection and follow-up program for
fast transients (Cooke+, in prep.)

- Targets transients on timescales from hours down to seconds
- Aims to achieve real-time, multiwavelength observations, and rapid multiwavelength follow up



Courtesy J. Cooke

A Case Study: *Deeper, Wider, Faster*

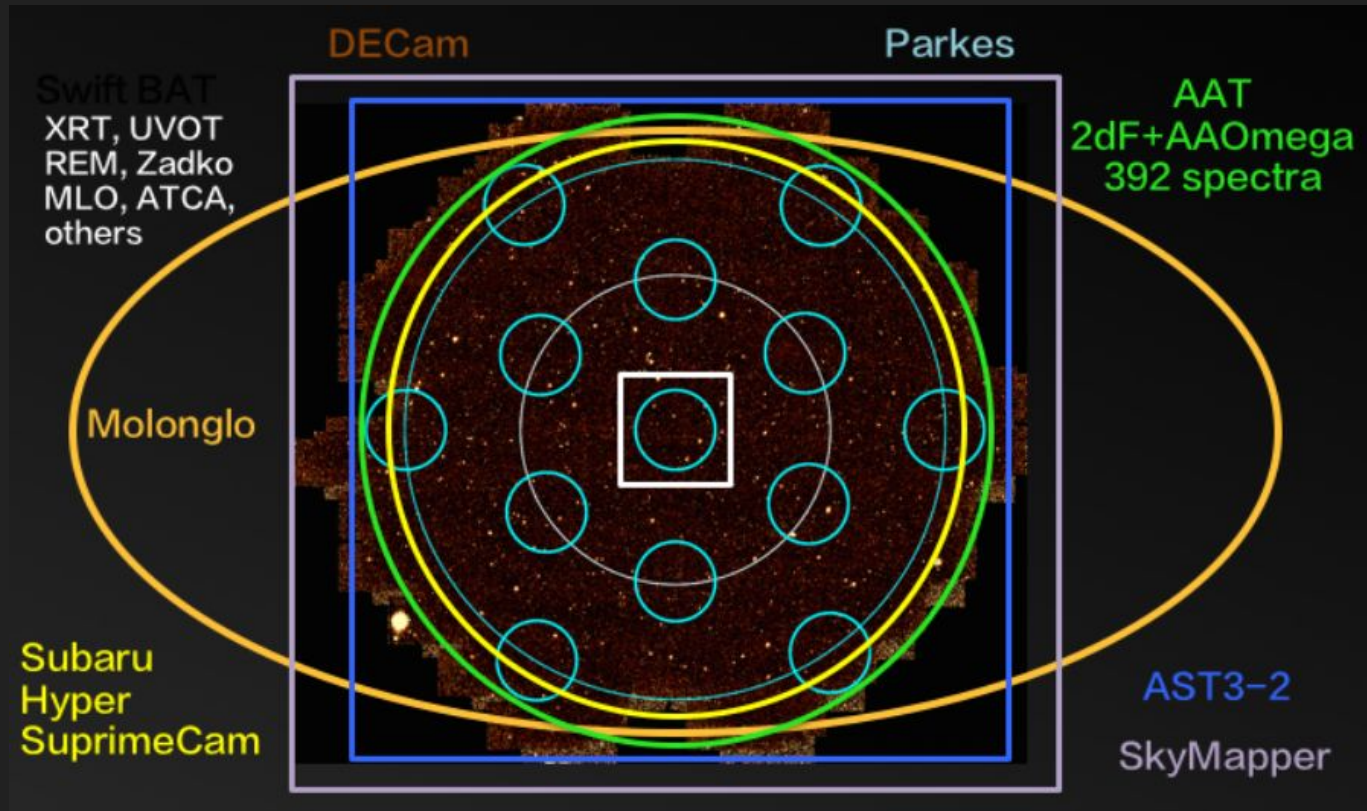
A detection and follow-up program for fast transients (Cooke+, in prep.)

- Targets transients on timescales from hours down to seconds
- Aims to achieve real-time, multiwavelength observations, and rapid multiwavelength follow up

PI: Jeff Cooke¹ **Co-I:** Igor Andreoni¹
Radio: Emily Petroff², Evan Keane³ and the Parkes team, Chris Flynn¹, Manisha Caleb^{1,4}, Shivani Bhandari¹, Fabian Jankowski¹, Vivek Venkatraman Krishnan¹, Themiyi Nanayakkara¹, Aditya Parthasarathy¹, Wael Farah¹ and the Molonglo team, Martin Bell⁵, Keith Bannister⁵, Adam Deller¹, Stuart Ryder⁶ and the ATCA team, Gemma Anderson⁷ and the MWA team, Sarah Burke-Spolaor⁸, Casey Law⁸ and the VLA team
Infrared: Sergio Campana⁹, Paolo D'Avanzo⁹ and the REM team, Janet Chen¹⁰ and the GROND team
Optical: Tyler Pritchard¹, Chris Curtin¹, Tim Abbott¹², and the CTIO DECam team, Masaomi Tanaka¹³, Takashi Moriya¹³, Nozomu Tominaga¹³ and the Subaru HSC team, Mansi Kasliwal¹⁴ and the Gemini-South team, Michael Shara¹⁵ and SALT team, Stephanie Bernard¹⁶, Chuck Horst¹⁷ and the AAT AAOmega team, Anais Möller⁴ and the SkyMapper team, David Coward⁷ and the Zadko team, Jeremy Mould⁴, Shuvo Uddin¹⁸ and the ANU 2.3m team, Chuck Horst¹⁷ and the MLO team, Lifan Wang^{18,19} and the AST3-2 Antarctica team
UV/x-ray/gamma-ray: Tyler Pritchard¹, Igor Andreoni¹, Amy Lien²⁰, Neil Gehrels^{21*} and the Swift team
Multi-messenger: The LIGO / Virgo consortium, the IceCube and AMON
Real-time processing: Igor Andreoni¹, Tyler Pritchard¹, Armin Rest^{20,22}, Alex Codoreanu¹, Phil Cowperthwaite²², Chuck Horst¹⁷, Jarrod Hurley¹, Robin Humble¹, and the Swinburne High Performance Computing team
Data Science: Dany Vohl¹, Colin Jacobs¹, Jarrod Hurley¹, Robin Humble¹, Frank Valdes¹², Vincent Morello²³
Data visualization: Bernard Meade¹⁶, Chris Fluke¹, Dany Vohl¹, Sarah Hegarty¹
Real-time data inspection and Analysis: Uros Mestric¹, Chuck Horst¹⁷, Garry Foran¹, Rebecca Allen¹, Michael Murphy¹, Srdan Kotus¹, Albany Asher¹, Shivani Bhandari¹, Chris Curtin¹, Wael Farah¹, Sarah Hegarty¹, Vivek Venkatraman Krishnan¹, Aditya Parthasarathy¹, Geoff Bryan¹, Frederic Robert¹, Themiyi Nanayakkara¹, Dany Vohl¹, Colin Jacobs¹, Stefan Osowski¹, Fabian Jankowski¹, Kathryn Plant^{1,14}, Renee Spiewak¹, Morgan O'Neill¹, SAO students¹, Pamela Bain, Stephanie Bernard¹⁶, Katie Mack¹⁶, Bernard Meade¹⁶, Tristan Reynolds¹⁶, Cameron van der Velden¹⁶, Faruq Rumokoy¹⁶, Eric Howell⁷, Regina Jorgenson²⁴ and the Maria Mitchell Observatory students, Luciana Sinpetru²⁵, Ibnul Hussaini²⁶, Merv McKibben²⁶, Riley Hodgson¹, Sophia Hodgson¹, Jade Devlin¹, Michelle Ko¹, Blanka White¹, Chuck Horst¹⁷ and the San Diego State University students

Courtesy J. Cooke

A Case Study: *Deeper, Wider, Faster*



Andreoni & Cooke, 2018

A Case Study: *Deeper, Wider, Faster*

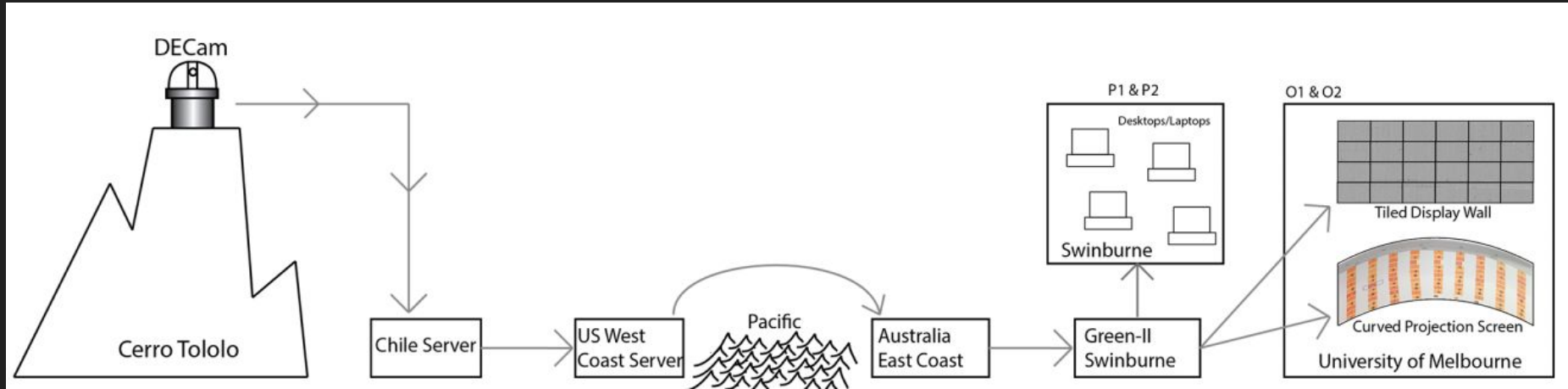
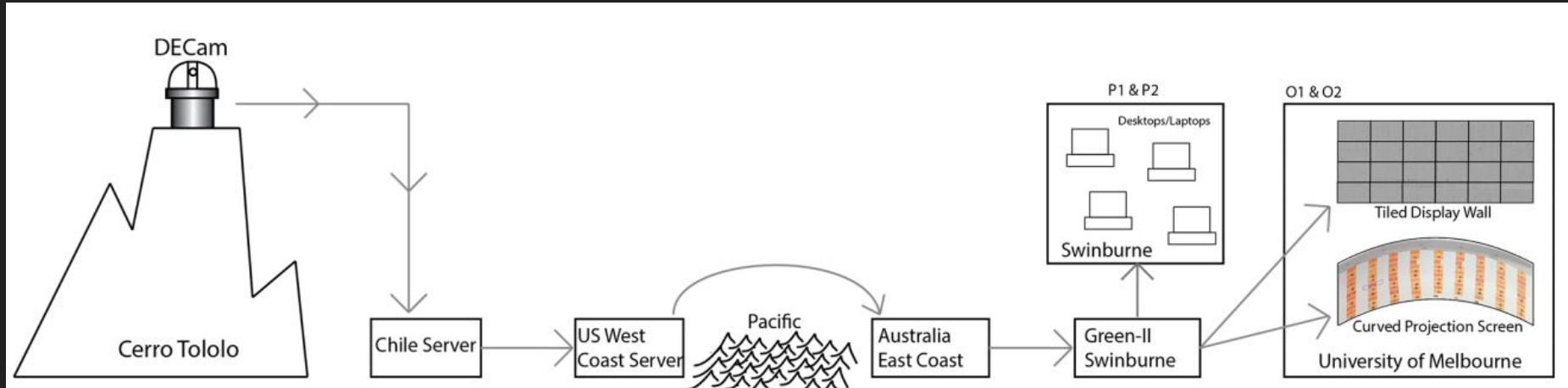


Figure: Meade+, 2017

A Case Study: *Deeper, Wider, Faster*

3 square degree FOV

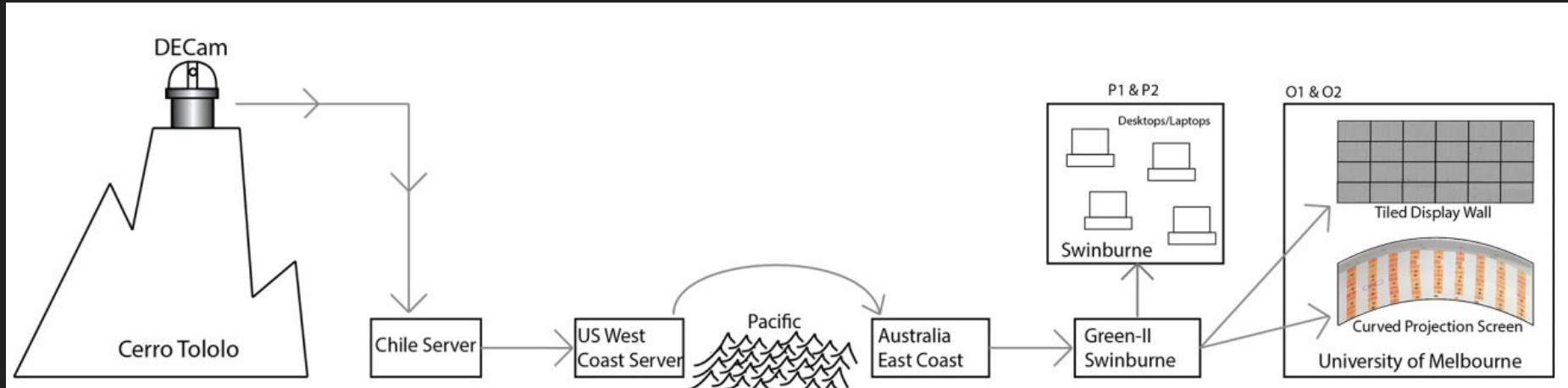


~60 CCD images / 40 seconds
2048 x 4096 pixels each

Figure: Meade+, 2017

A Case Study: *Deeper, Wider, Faster*

3 square degree FOV



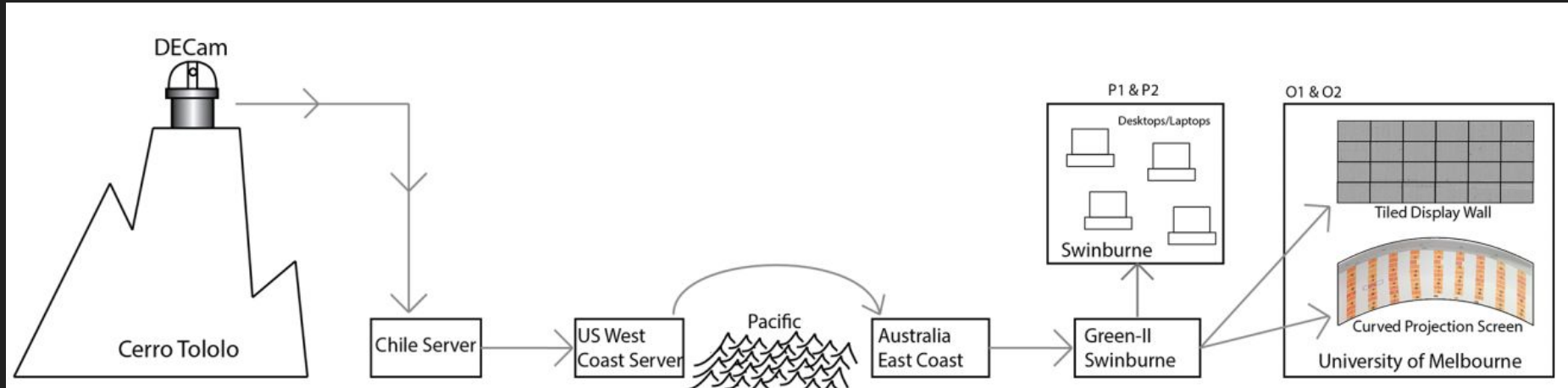
~60 CCD images / 40 seconds
2048 x 4096 pixels each

JPEG2000 data compression
(Vohl+, 2017)

Figure: Meade+, 2017

A Case Study: *Deeper, Wider, Faster*

3 square degree FOV



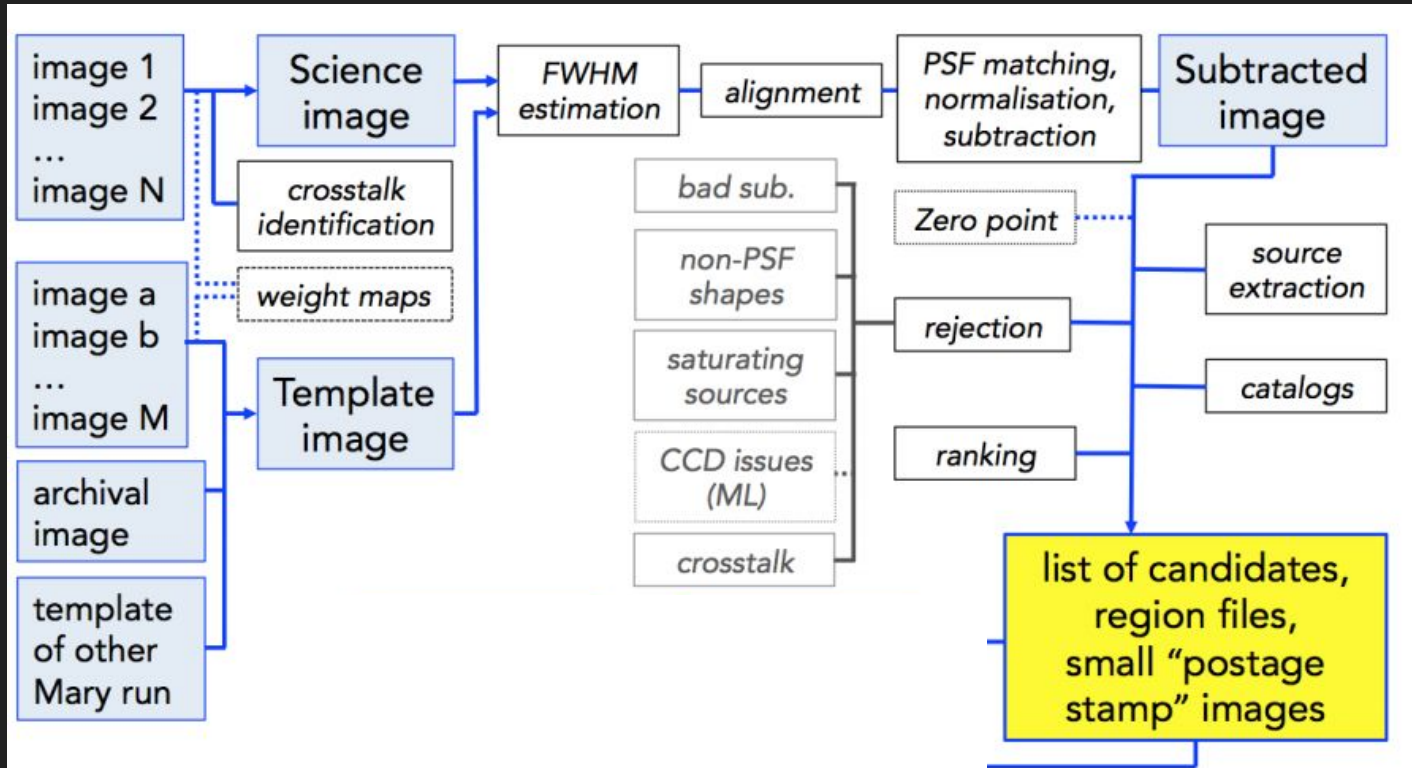
~60 CCD images / 40 seconds
2048 x 4096 pixels each

JPEG2000 data compression
(Vohl+, 2017)

'Mary' data reduction
pipeline (Andreoni+, 2017)

Figure: Meade+, 2017

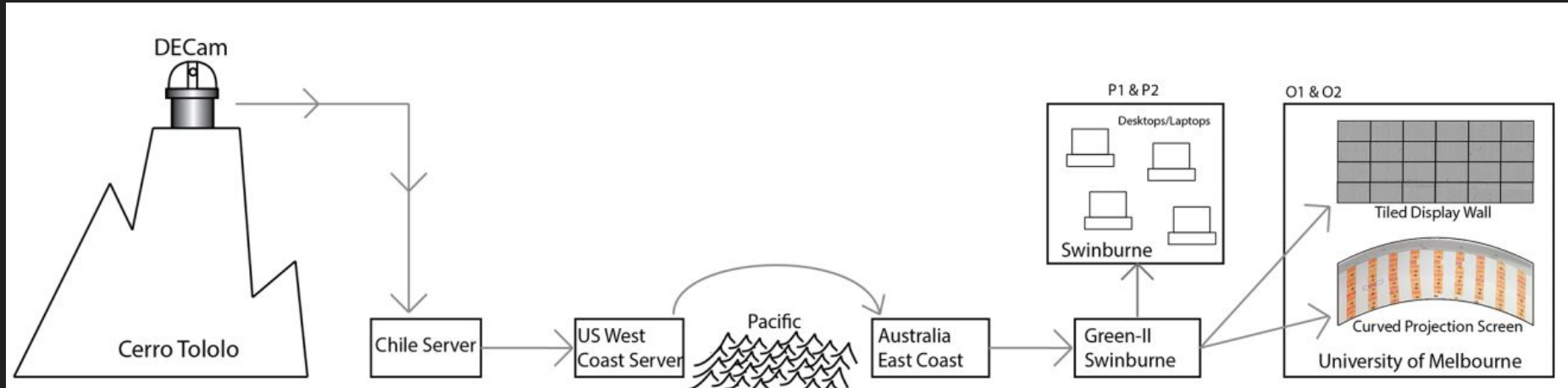
A Case Study: *Deeper, Wider, Faster*



A Case Study: *Deeper, Wider, Faster*

3 square degree FOV

Visual inspection by
volunteer astronomers



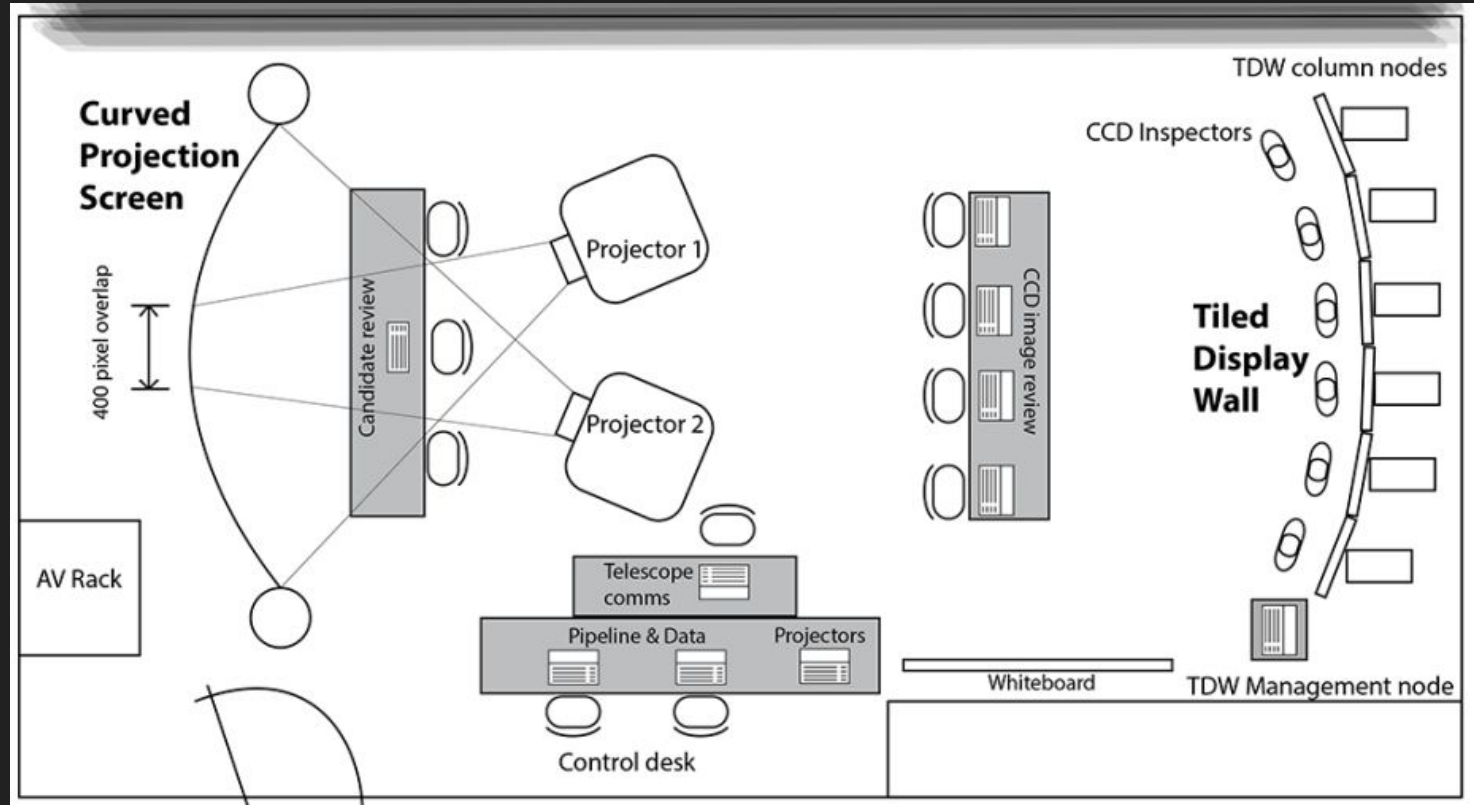
~60 CCD images / 40 seconds
2048 x 4096 pixels each

JPEG2000 data compression
(Vohl+, 2017)

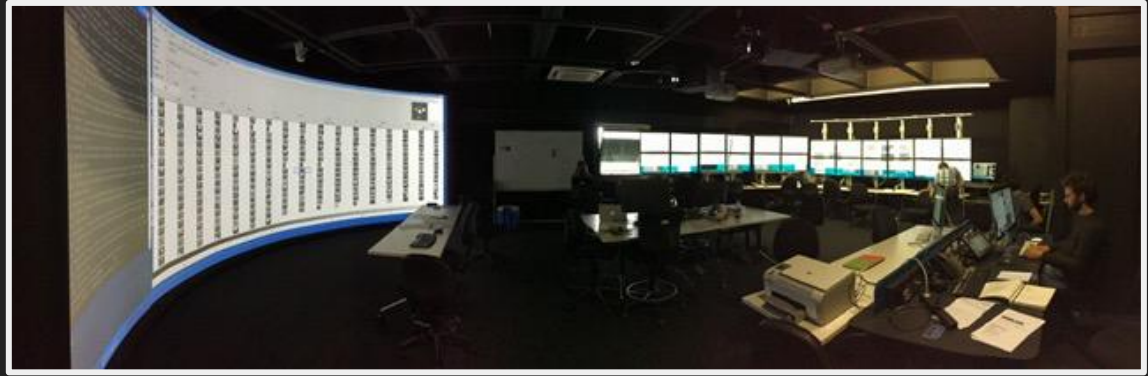
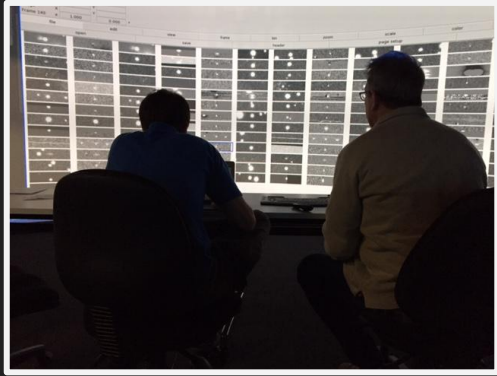
'Mary' data reduction
pipeline (Andreoni+, 2017)

Figure: Meade+, 2017

A Case Study: *Deeper, Wider, Faster*



A Case Study: *Deeper, Wider, Faster*



Photos courtesy B. Meade

A Case Study: *Deeper, Wider, Faster*



Integrating the visualisation, analysis and assessment work of volunteer astronomers as **part of** the DWF workflow would allow us to:

Photos courtesy B. Meade

A Case Study: *Deeper, Wider, Faster*

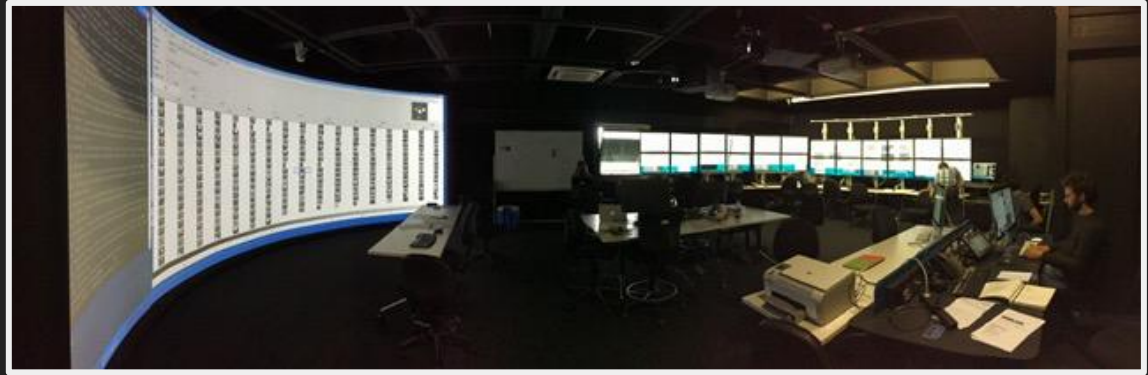


Integrating the visualisation, analysis and assessment work of volunteer astronomers **as part of** the DWF workflow would allow us to:

- ❑ Continue capitalising on the expertise and crucial discovery skills of these astronomers

Photos courtesy B. Meade

A Case Study: *Deeper, Wider, Faster*



Integrating the visualisation, analysis and assessment work of volunteer astronomers **as part of** the DWF workflow would allow us to:

- ❑ Continue capitalising on the expertise and crucial discovery skills of these astronomers
- ❑ Simplify and streamline the discovery workflow, and remove margin for error

Photos courtesy B. Meade

A Case Study: *Deeper, Wider, Faster*

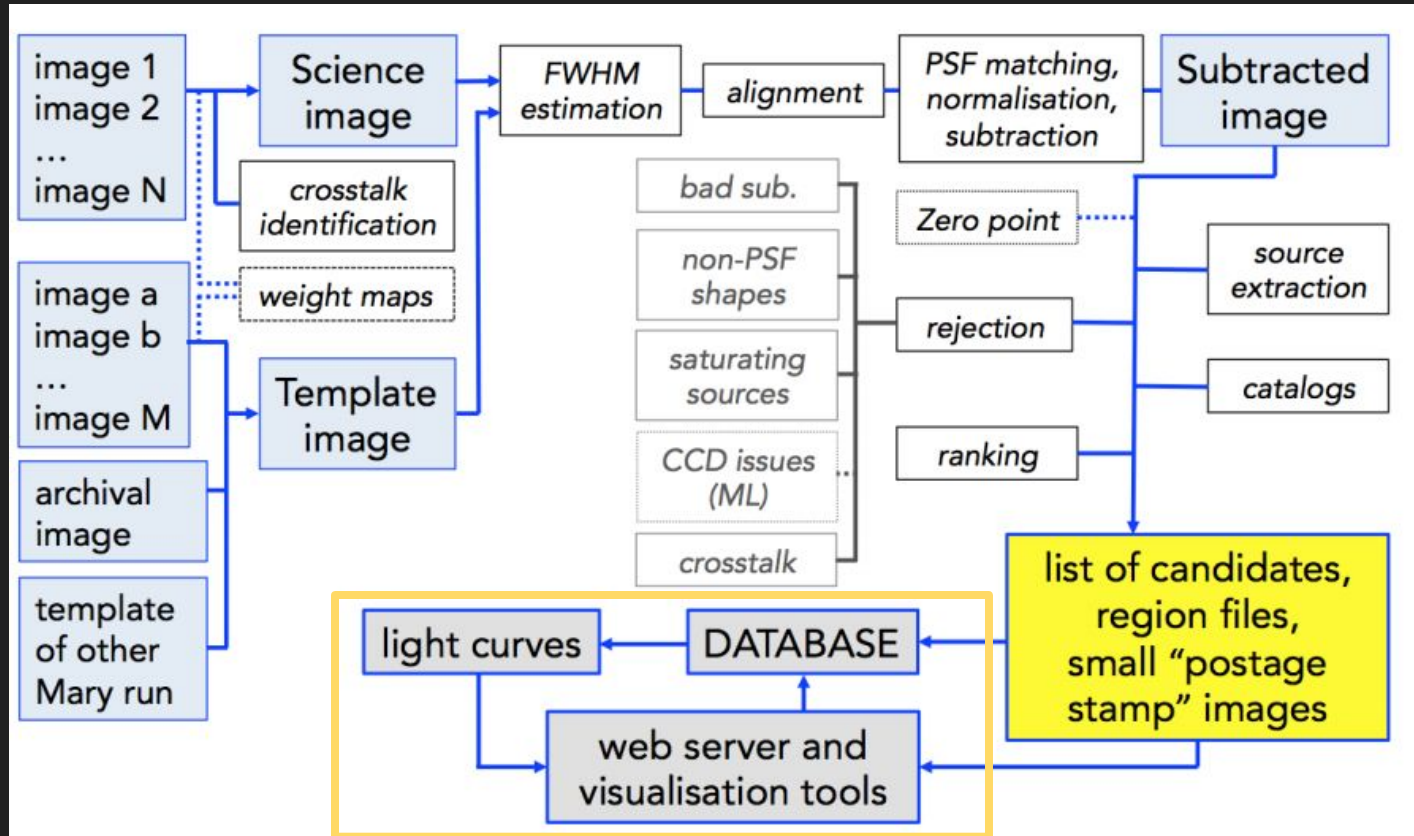


Integrating the visualisation, analysis and assessment work of volunteer astronomers **as part of** the DWF workflow would allow us to:

- ❑ Continue capitalising on the expertise and crucial discovery skills of these astronomers
- ❑ Simplify and streamline the discovery workflow, and remove margin for error
- ❑ Better understand the discovery process itself

Photos courtesy B. Meade

A Case Study: *Deeper, Wider, Faster*



Andreoni+, 2017

PerSieve

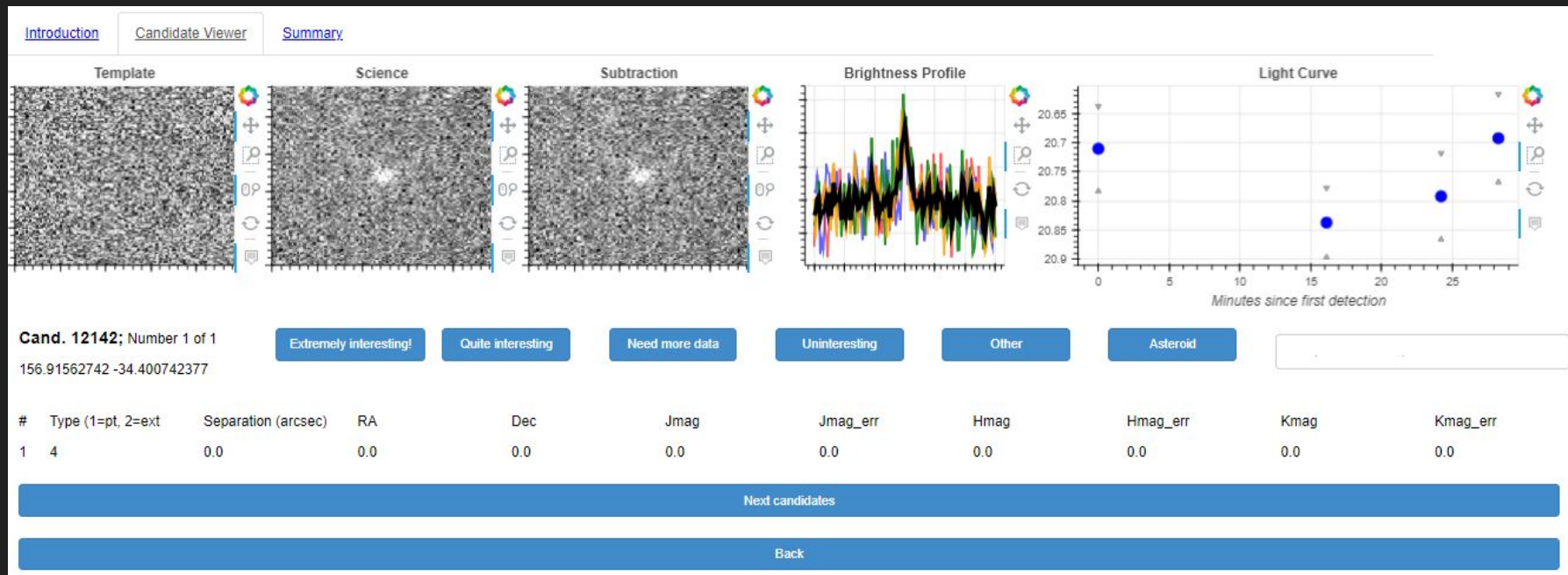
- ❏ **An application for interactive visualisation and assessment - in real time, in the browser**

PerSieve

- ❏ **An application for interactive visualisation and assessment - in real time, in the browser**
- ❏ Integrates visualisation and the human astronomer into DWF's automated pipeline

PerSieve

- ❑ An application for interactive visualisation and assessment - in real time, in the browser
- ❑ Integrates visualisation and the human astronomer into DWF's automated pipeline



February 2018 DWF Observing Campaign

- ❑ During a four-night, Subaru-led DWF observing campaign, PerSieve was used successfully as the primary visualisation and analysis tool

February 2018 DWF Observing Campaign

- ❑ During a four-night, Subaru-led DWF observing campaign, PerSieve was used successfully as the primary visualisation and analysis tool
- ❑ Over 30 astronomers participated on-site



February 2018 DWF Observing Campaign

- ❑ During a four-night, Subaru-led DWF observing campaign, PerSieve was used successfully as the primary visualisation and analysis tool
- ❑ Over 30 astronomers participated on-site
- ❑ Over 20 astronomers used PerSieve to participate remotely



February 2018 DWF Observing Campaign

- ❑ During a four-night, Subaru-led DWF observing campaign, PerSieve was used successfully as the primary visualisation and analysis tool
- ❑ Over 30 astronomers participated on-site
- ❑ Over 20 astronomers used PerSieve to participate remotely



Studying the February 2018 DWF Observing Campaign

Studying the February 2018 DWF Observing Campaign

I also captured detailed analytics of the volunteers' work and decision making processes*

*With the approval of the Swinburne Human Research Ethics Committee, and the informed consent of all participants

Studying the February 2018 DWF Observing Campaign

I also captured detailed analytics of the volunteers' work and decision making processes*

- What do they look at?
- How do they look at it?
- What evaluations do they make?

*With the approval of the Swinburne Human Research Ethics Committee, and the informed consent of all participants

Studying the February 2018 DWF Observing Campaign

I also captured detailed analytics of the volunteers' work and decision making processes*

→ What do they look at?

→ How do they look at it?

→ What evaluations do they make?

→ **What does an “effective” discovery workflow look like?**

*With the approval of the Swinburne Human Research Ethics Committee, and the informed consent of all participants

Studying the February 2018 DWF Observing Campaign

I also captured detailed analytics of the volunteers' work and decision making processes*

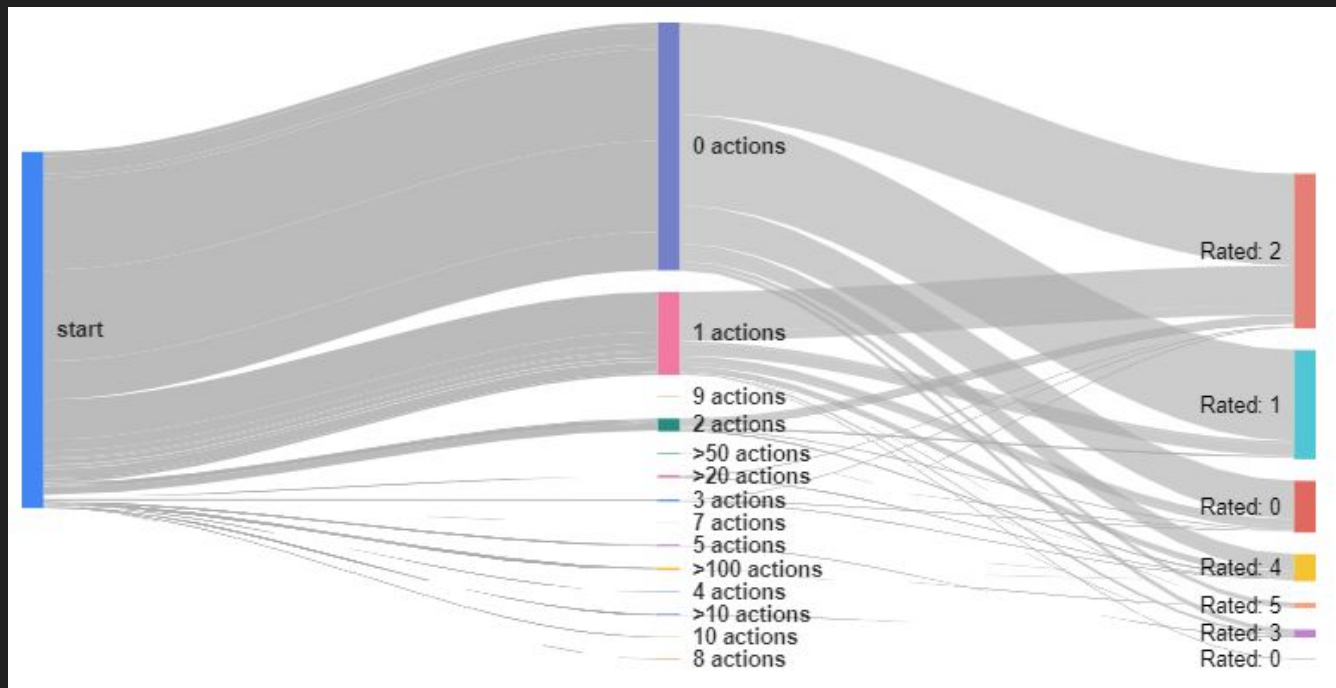
- What do they look at?
- How do they look at it?
- What evaluations do they make?
- **What does an “effective” discovery workflow look like?**
- **What can we learn about expertise?**

*With the approval of the Swinburne Human Research Ethics Committee, and the informed consent of all participants

STUDYING THE FEBRUARY 2018 DWF OBSERVING CAMPAIGN

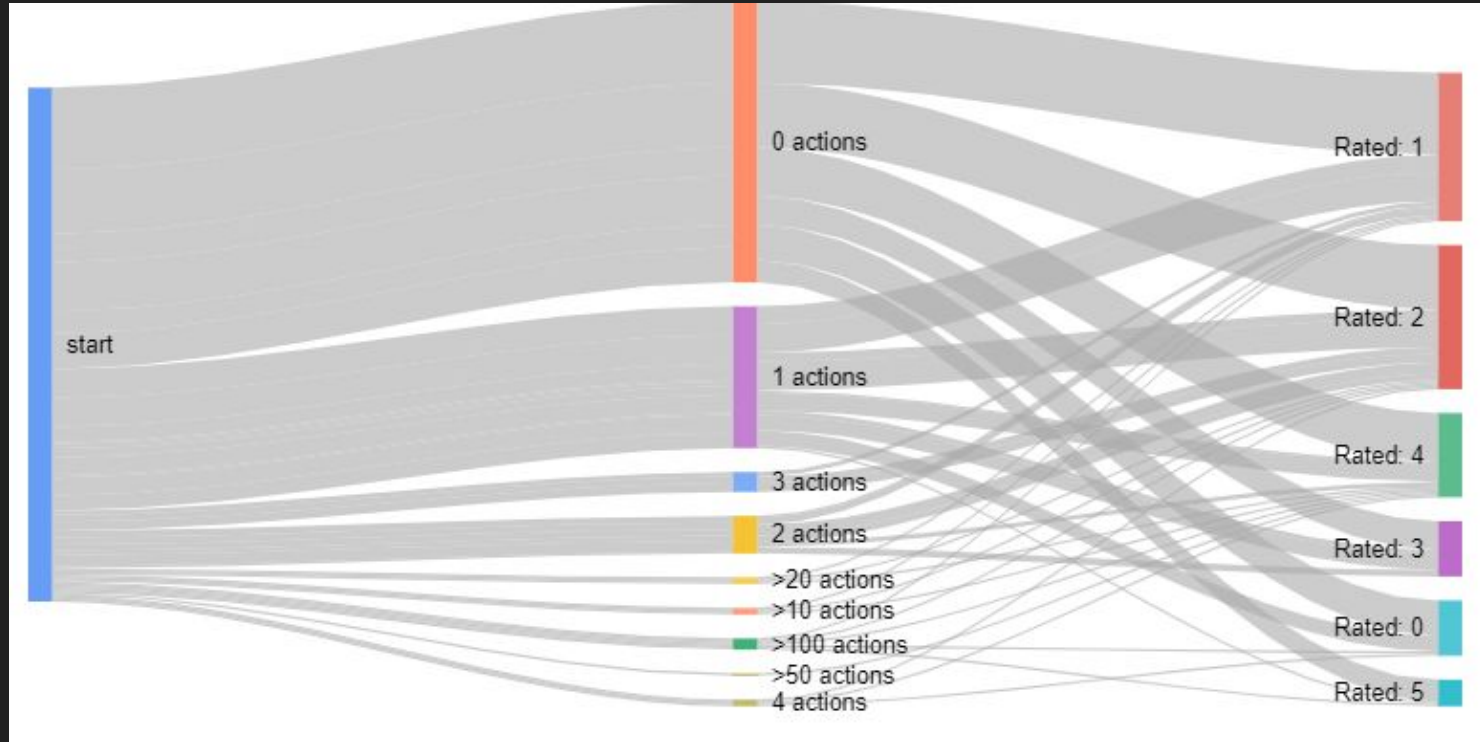
- ❑ Each interaction with the data, and the web framework, was tracked in detail
- ❑ Volunteers self-rated their astronomical expertise: Novice/Intermediate/Expert
 - Almost 19,000 total 'decision workflows' were captured
 - 21 'novices' assessed ~3700 transient candidates between them
 - 8 'intermediates' assessed ~630 transient candidates between them
 - 3 'experts' assessed ~3700 transient candidates between them

Studying the February 2018 DWF Observing Campaign



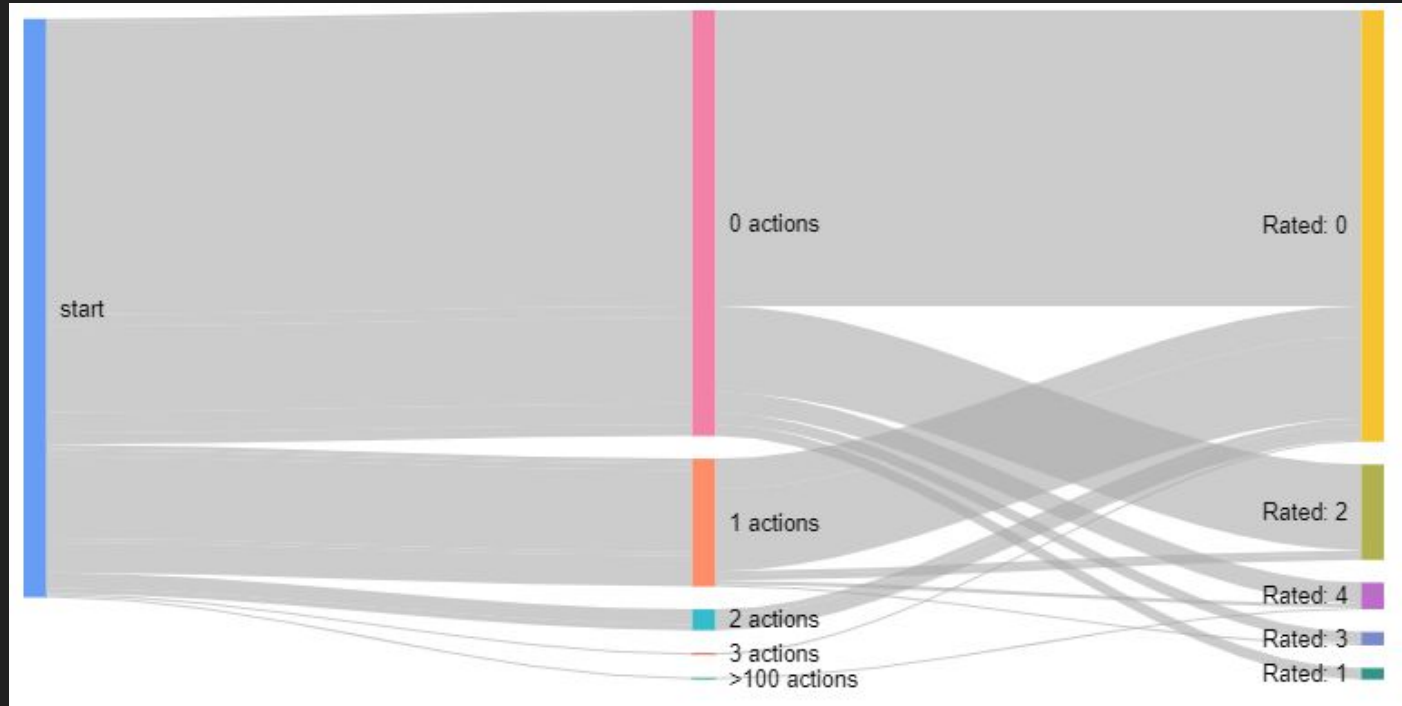
Flow diagram of 'Novice' workflows: interactions made with the data and final object ratings from 0 (least interesting) to 5 (most interesting)

Studying the February 2018 DWF Observing Campaign



Flow diagram of 'Intermediate' workflows: interactions made with the data and final object ratings from 0 (least interesting) to 5 (most interesting)

Studying the February 2018 DWF Observing Campaign



Flow diagram of Expert workflows: interactions made with the data and final object ratings from 0 (least interesting) to 5 (most interesting)

STUDYING THE FEBRUARY 2018 DWF OBSERVING CAMPAIGN

- ❑ Each interaction with the data, and the web framework, was tracked in detail
- ❑ Volunteers self-rated their astronomical expertise: Novice/Intermediate/Expert
 - Almost 19,000 total 'decision workflows' were captured
 - 21 'novices' assessed ~3700 transient candidates between them
 - 8 'intermediates' assessed ~630 transient candidates between them
 - 3 'experts' assessed ~3700 transient candidates between them
- ❑ This data is enabling a range of different analyses of how human astronomers make discoveries
- ❑ We can use this knowledge to help build the human factor into other workflows
- ❑ Outside astronomy, this project is also guiding research into data-driven decision making (collaboration with Dr Clare MacMahon, Dr Lisa Wise, and teams)

Summary

- The data intensive era will offer us unprecedented discovery potential: but it will also challenge our existing ways of making discoveries
- We need to “design in” discovery capabilities as we develop our workflows for the era of data-intensive astronomy
- Keeping the astronomer “in the loop” is a valuable way to make this happen, as we have demonstrated using PerSieve within the *Deeper, Wider, Faster* project
- We are using this platform to study the astronomer *in situ*, and learn even more about how they work and make decisions
- What we learn will help us build tools to capitalise on our discovery potential

Summary

- The data intensive era will offer us unprecedented discovery potential: but it will also challenge our existing ways of making discoveries
- We need to “design in” discovery capabilities as we develop our workflows for the era of data-intensive astronomy
- Keeping the astronomer “in the loop” is a valuable way to make this happen, as we have demonstrated using PerSieve within the *Deeper, Wider, Faster* project
- We are using this platform to study the astronomer *in situ*, and learn even more about how they work and make decisions
- What we learn will help us build tools to capitalise on our discovery potential

