



# Astronomical archives: Serving up the Universe

# 1. Science Archives

# Science Archives

## Rationale

- Archival research
- Multi-wavelength astronomy
- Proposing
- Reproducibility
- Time variability
- Support of developing countries
- Citizen-Science
- Outreach

# Science Archives

## Photons

**Position**

**Energy**

**Time**

**Polarisation**

# Science Archives

## 6D hypercubes

Pos1	Pos2	Energy	Time	Pol.	Quantity
1	1	N	1	1	1
1	1	1	N	1	1
N	N	1	1	1	N
N	N	N	1	N	1

Spectrum

Time-series

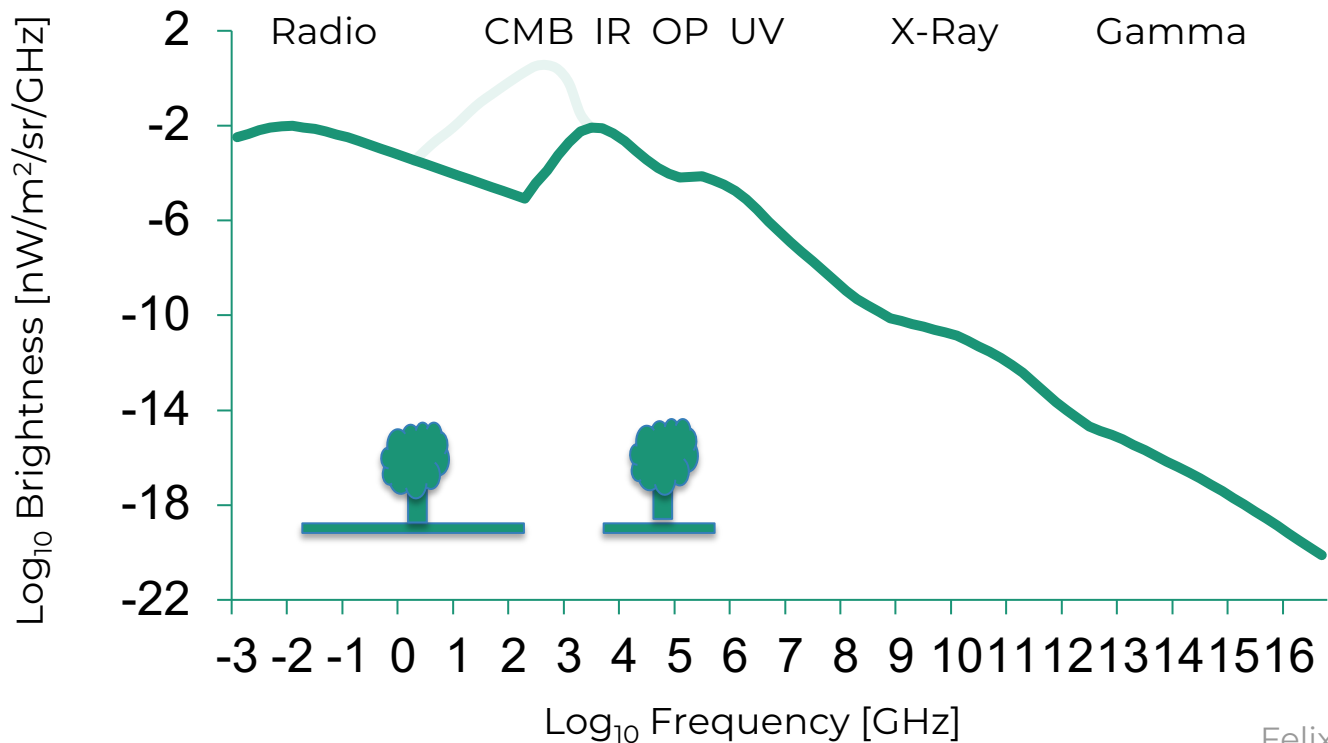
Image with error map

Data cube with polarisations

Quantity: flux, counts, errors, weights, ...

# Science Archives

## Photons in the Universe



Values: Hervé Dole

# Science Archives

## Best practices

- Physical quantities
- Unscoped search
- Observations, Proposals, Publications
- Target-list upload
- Previews
- Modern user-experience
- Programmatic access (VO)
- Metadata are public
- Result table + SkyView
- Science-grade products + PL
- Anonymous downloads
- Self-describing FITS files
- Parallel downloads
- Authors must cite data-use
- Frequent Reprocessing

# Science Archives Usage

**fraction cumulative Search Field**

26.9%	26.9%	Source Name (Resolver)
25.5%	52.4%	Project Code
11.4%	63.8%	Ra Dec
8.0%	71.8%	Source Name (ALMA)
7.8%	79.7%	PI Name
3.7%	83.4%	Band
3.7%	87.1%	Public Data
2.0%	89.1%	Frequency
1.4%	90.5%	Start Date
1.1%	91.6%	
1.1%	92.8%	Spatial Resolution
1.0%	93.7%	Project Abstract
0.9%	94.6%	Science Keyword
0.8%	95.4%	Project Title
0.8%	96.2%	Galactic
0.7%	96.9%	Targetlist

0.5%	97.4%	Proposal Authors
0.5%	97.9%	Spectral Resolution
0.4%	98.4%	Integration Time
0.2%	98.6%	Continuum Sensitivity
0.2%	98.8%	FOV
0.2%	99.0%	Polarisation Type
0.2%	99.1%	First Author
0.1%	99.3%	Water Vapour
0.1%	99.4%	Spatial Scale Max
0.1%	99.5%	Line Sensitivity
0.1%	99.6%	Authors
0.1%	99.7%	Publication Year
0.1%	99.7%	Publication Count
0.1%	99.8%	Publication Title
0.1%	99.9%	Publication Abstract
0.1%	100.0%	Bandwidth
0.0%	100.0%	Bibcode



# Science Archives

## No time to talk about:

- FITS
- Code reuse
- Keeping data alive

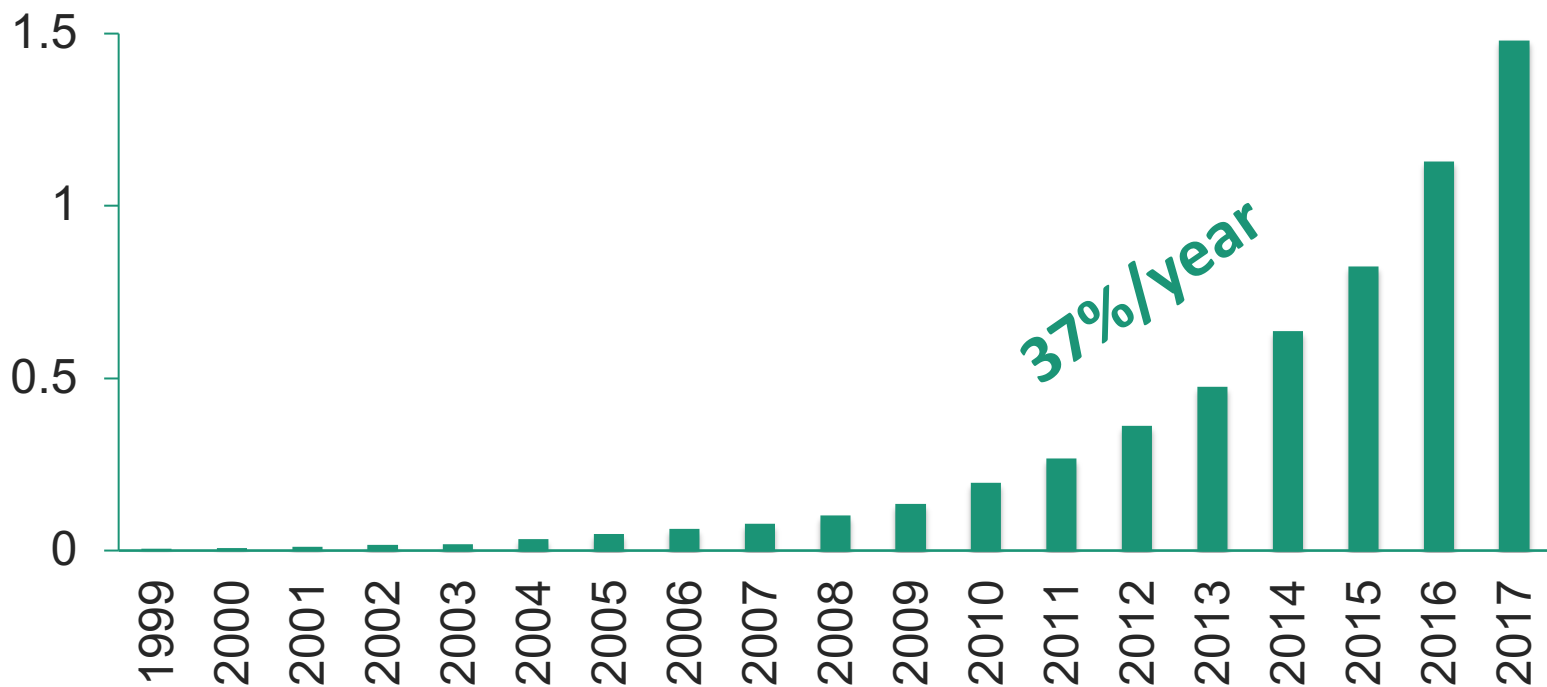
## | 2. Observatories

# Observatories

## Trends

- From experiments to observatories
- From single archives to data-portals
- Increased use of VO standards and protocols
- Science-grade data approach universally accepted
- Massive data-sets

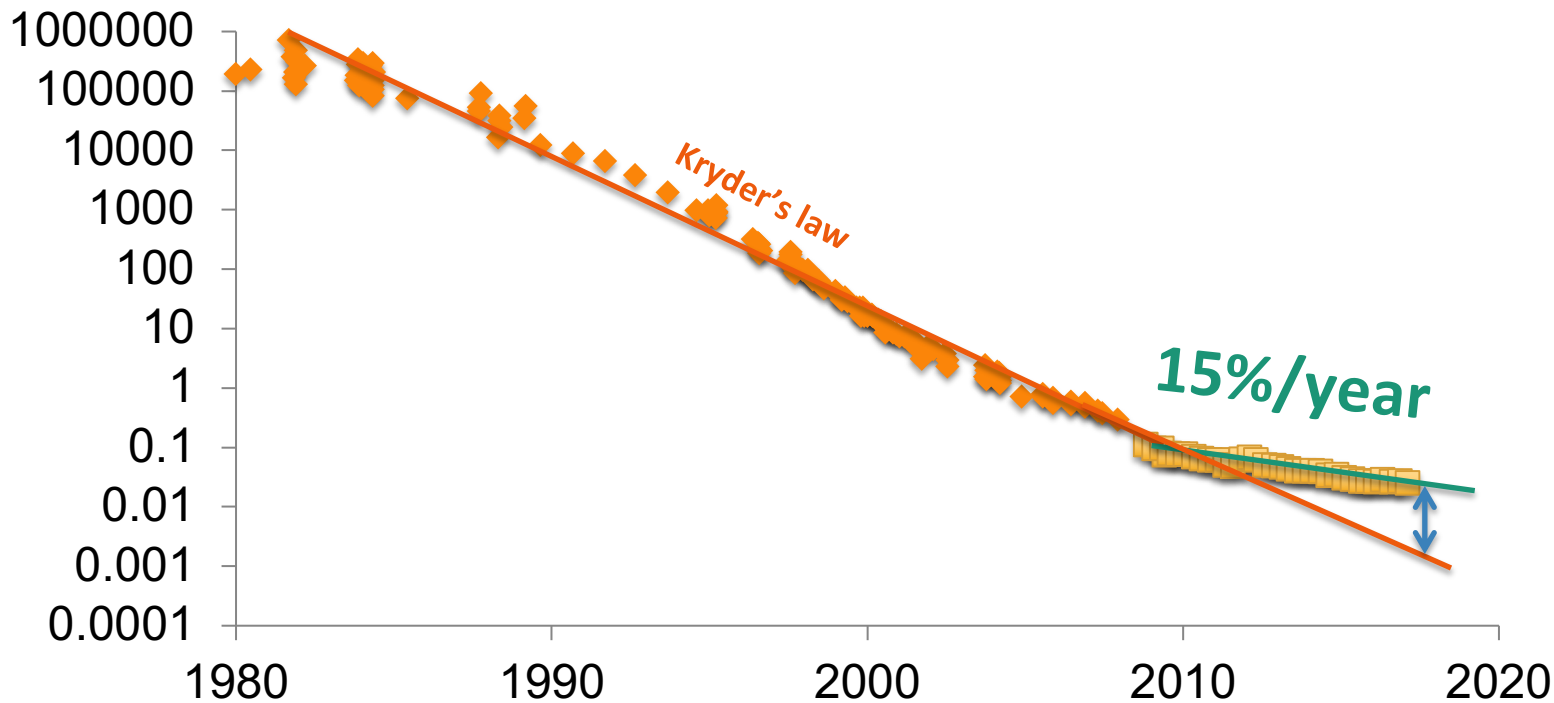
# Observatories Petabytes at ESO



values: Adam Dobrzynski

# Observatories

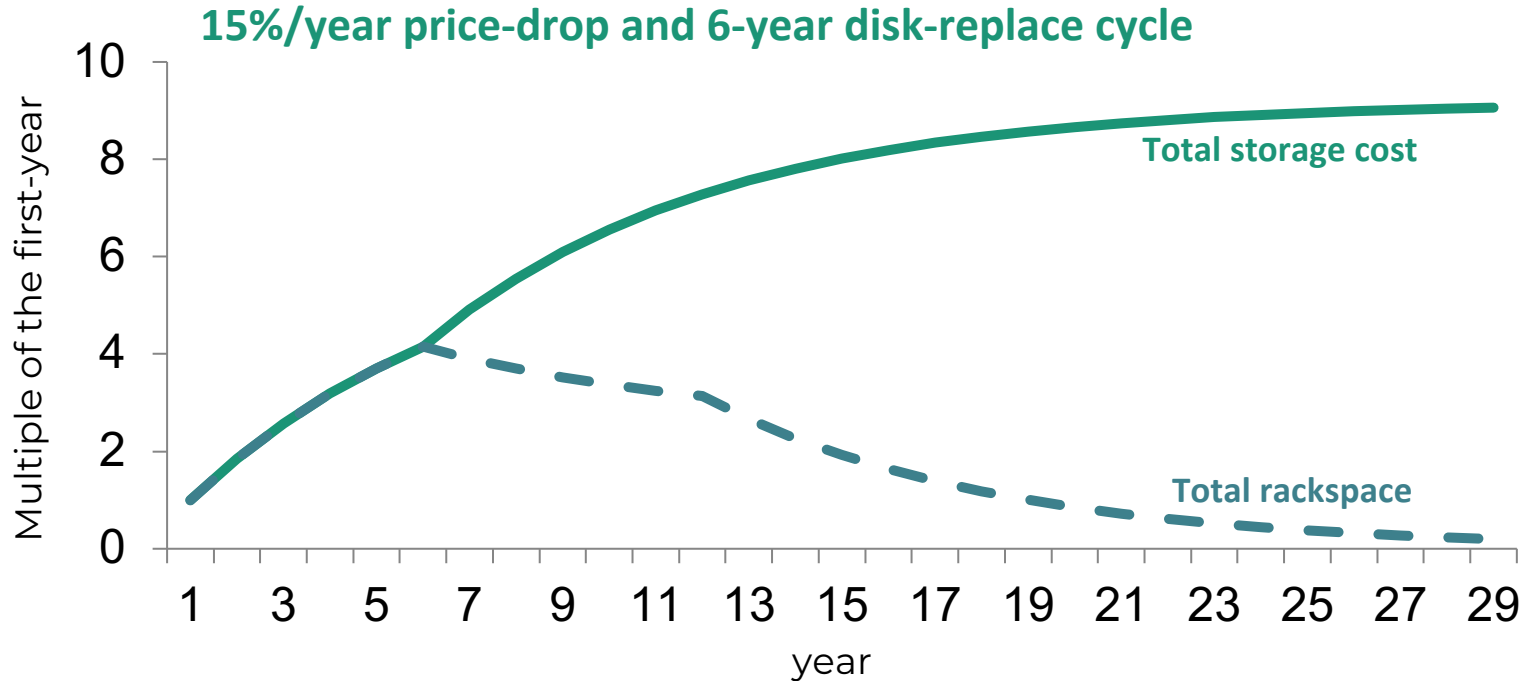
## Hard-disks: USD per Gigabyte



values: mkomo.com, blackblaze.com

# Observatories

## Linear data intake



# Observatories

## So much data

- Today
  - VLT + ALMA + Magic 70GB/year/astronomer
  - WMA 350GB/year/astronomer
- 2030
  - VLT + ELT + ALMA + CTA 1TB/year/astronomer
  - SKA 200TB/year/astronomer
- Astronomers don't scale: they will be the rare resource

# Observatories

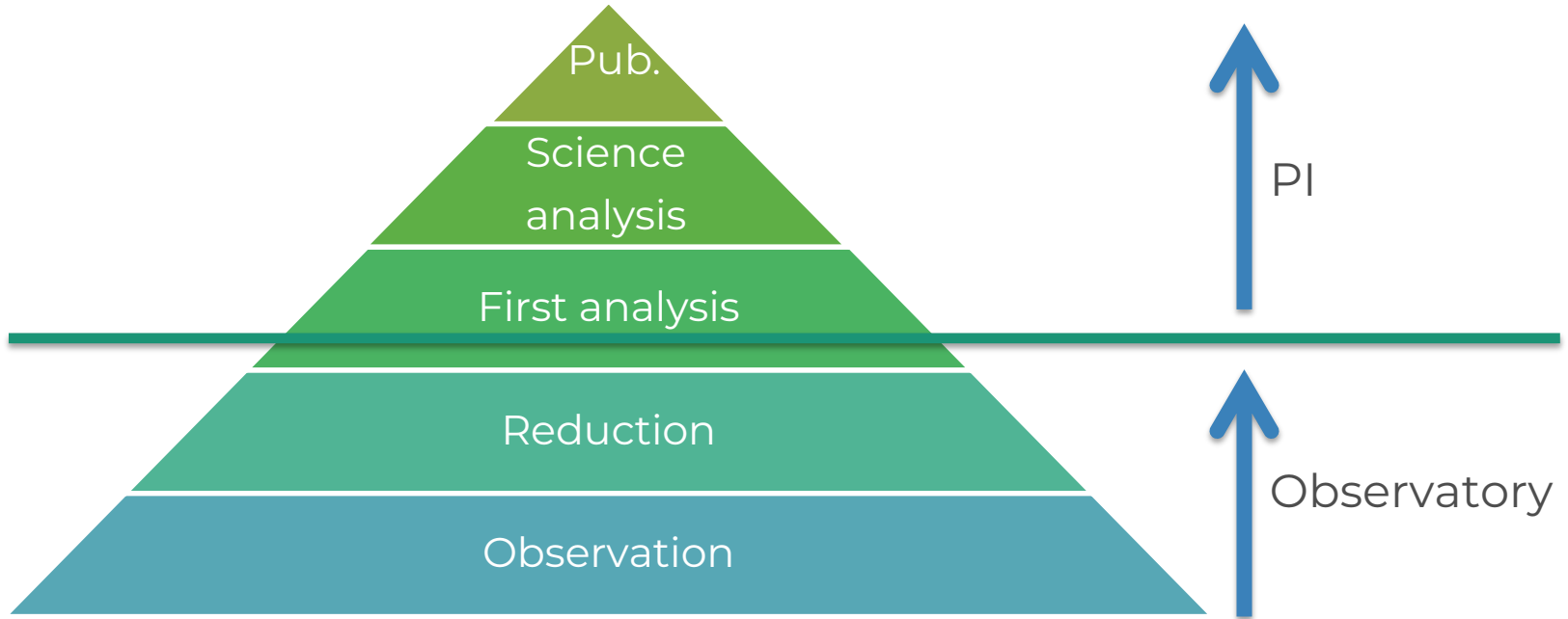
## So much data: solutions

- “Think of taking less data” (Alex Szalay)
- Process data to higher levels
- Machines do astronomy



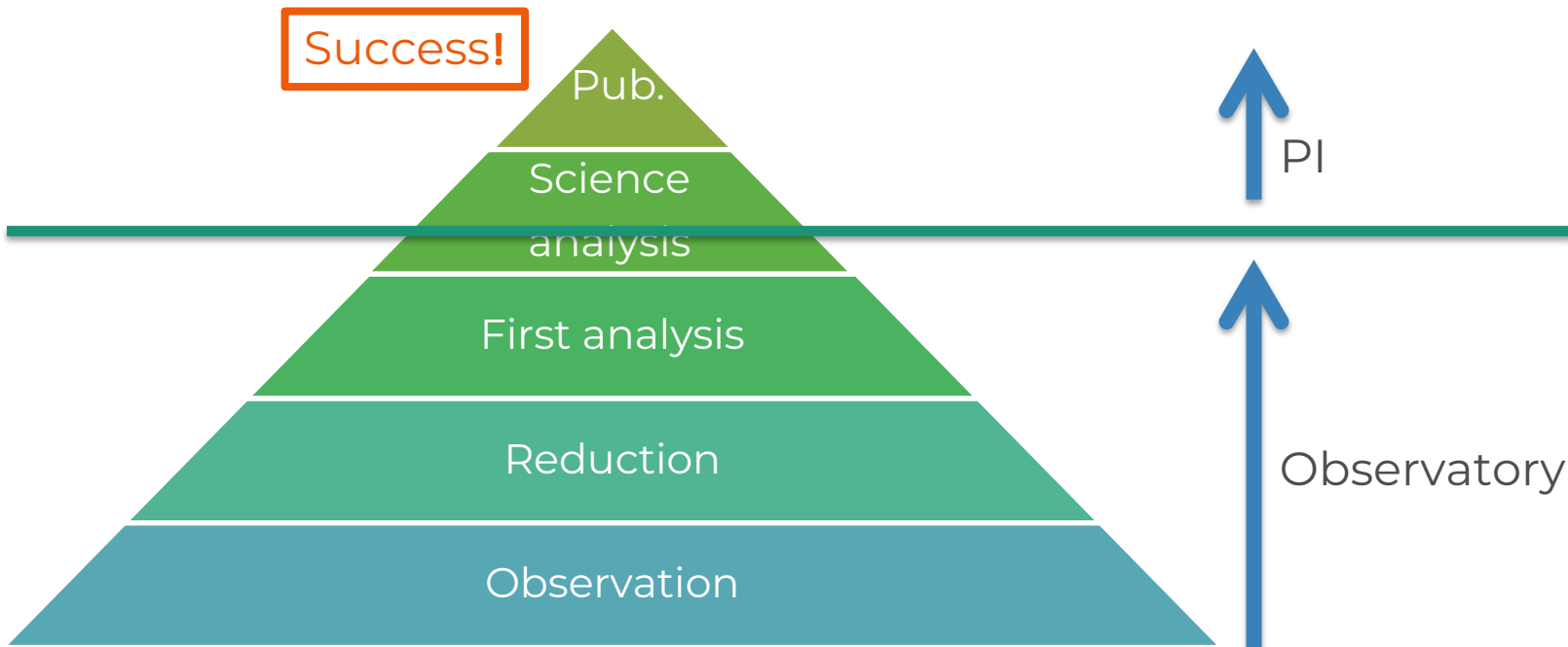
# Observatories

## More responsibility



# Observatories

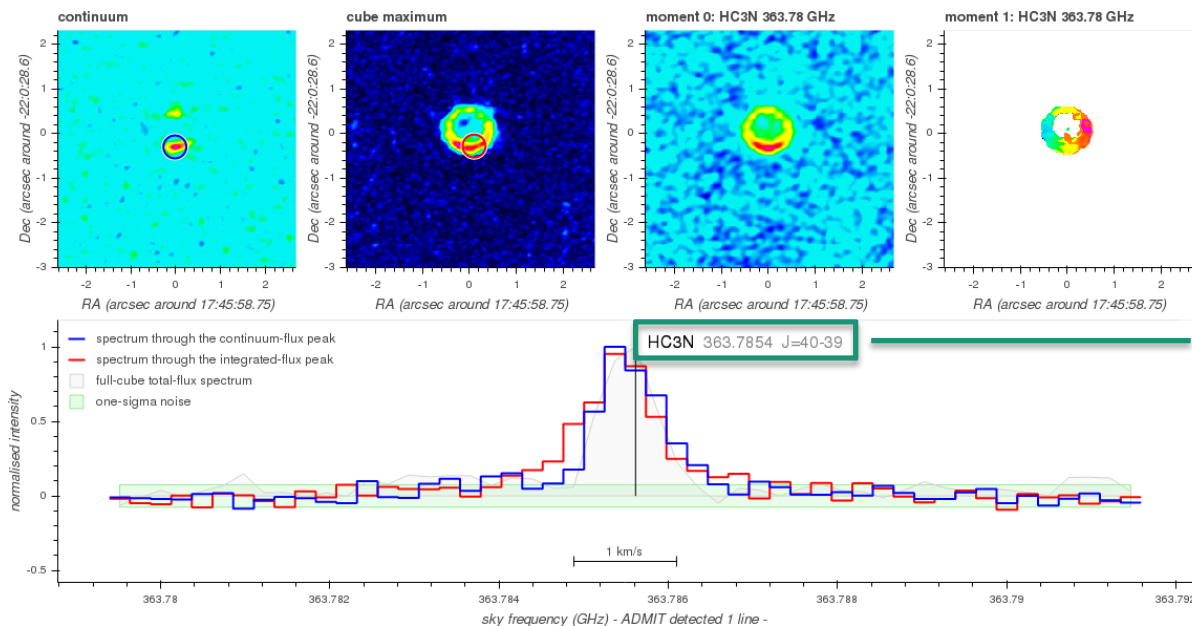
## More responsibility



# Observatories

## First analysis

Titan.pbcor.fits



ALMA Data Mining  
Toolkit (ADMIT)

# Observatories

## 3D

- ESO: VLT (MUSE, KMOS, SINFONI), ELT (HARMONI)
- ALMA
- SKA
- LOFAR
- WMA
- ATHENA
- Keck (ESI)
- JWST (MIRI, NIRSpec)
- ...

# | 3. Machine Learning

# Machine Learning Will be needed

- in data processing
- in quality control
- in source-extraction
- in source-classification

**Relevant for  
Science Archives**

# Machine Learning explosion

- 1810.07857: Multiband galaxy morphologies for CLASH: a convolutional neural network transferred from CANDELS
- 1810.07703: A Deep Learning Approach to Galaxy Cluster X-ray Masses
- 1810.01483: DeepCMB: Lensing Reconstruction of the Cosmic Microwave Background with Deep Neural Networks
- 1810.00592: Extracting gamma-ray information from images with convolutional neural network methods on simulated Cherenkov Telescope Array data
- 1810.07888: Classifying Lensed Gravitational Waves in the Geometrical Optics Limit with Machine Learning
- 1809.09622: Convolutional Neural Networks for Spectroscopic Redshift Estimation on Euclid Data
- 1809.05748: Segmentation of coronal holes in solar disk images with a convolutional neural network
- 1809.03043: Fast Radio Burst 121102 Pulse Detection and Periodicity: A Machine Learning Approach
- 1809.03315: Deep Learning Based Detection of Cosmological Diffuse Radio Source
- 1809.09722: TSARDI: a Machine Learning data rejection algorithm for transiting exoplanet light curves
- 1809.02154: From FATS to feets: Further improvements to an astronomical feature extraction tool based on machine learning
- 1809.01934: Towards online triggering for the radio detection of air showers using deep neural networks
- 1809.01691: Galaxy detection and identification using deep learning and data augmentation

# Machine Learning explosion

1808.09955: QuasarNET: Human-level spectral classification and redshifting with Deep Neural Networks

1808.09739: Detecting Radio Frequency Interference in radio-antenna arrays with the Recurrent Neural Network algorithm

1808.08371: Protostellar classification using supervised machine learning algorithms

1808.07491: Weak lensing shear estimation beyond the shape-noise limit: a machine learning approach

1808.06977: Searching for Sub-Second Stellar Variability with Wide-Field Star Trails and Deep Learning

1808.05728: Machine Learning Classification of Gaia Data Release 2

1808.04728: CosmoFlow: Using Deep Learning to Learn the Universe at Scale

1808.04428: Deep learning of multi-element abundances from high-resolution spectroscopic data

1808.03626: Enhanced Rotational Invariant Convolutional Neural Network for Supernovae Detection

1808.00011: Analyzing interferometric observations of strong gravitational lenses with recurrent and convolutional neural networks



# Machine Learning

## Explainable AI

- Dan Jacobsen (ORNL)
- 2.36 Exaops (17 million GPU cores)
- Explainable AI (iterative Random Forests)

# Machine Learning

## Catalogue of the Universe

- AI combines and cross-matches all surveys and catalogues
- AI goes through all science-grade data of all observatories
- Use SIMBAD + NED for learning
- Hierarchical

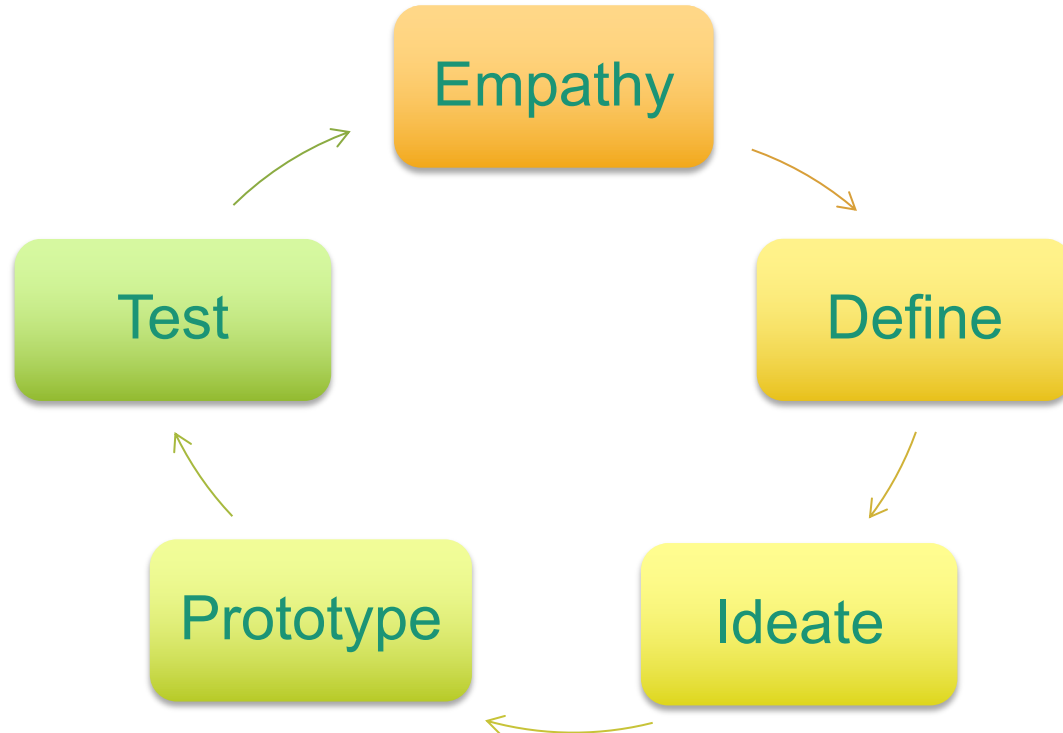
# | 4. User Experience

# User-experience 2007



“ *User-experience is how it feels* ”

# User-experience Design Thinking



# | 5. Conclusions

# Conclusions

## Summary

- Photons are simple
  - Science Archive best practices have emerged
  - Huge challenges ahead for observatories (and Archives)
  - AI comes to the rescue
  - Embrace user-centric design
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