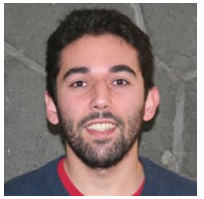
The astroinformatics Laboratory at CMM

Jaime San Martín
Professor
Ph.D. Mathematics

Eduardo Vera
Scientist
Ph.D. Physics

Guillermo Cabrera
Engineer
Ph.D. Comp. Sc.

Pablo Román
Postdoc
Ph.D. Systems Eng.



Francisco Förster
Scientist
Ph.D. Astronomy

J. Carlos Maureira
Scientist
Ph.D. Comp. Sc.

Santiago González-Gaitán
Postdoc
Ph. Astronomy

Pablo Huijse
Postdoc
Ph.D. Elec. Eng.

Pablo Estévez
Professor
Ph.D. Elec. Eng.

and many more collaborators...

CMM
Center for Mathematical Modeling

NLHPC
National Laboratory for High Performance Computing
Chile

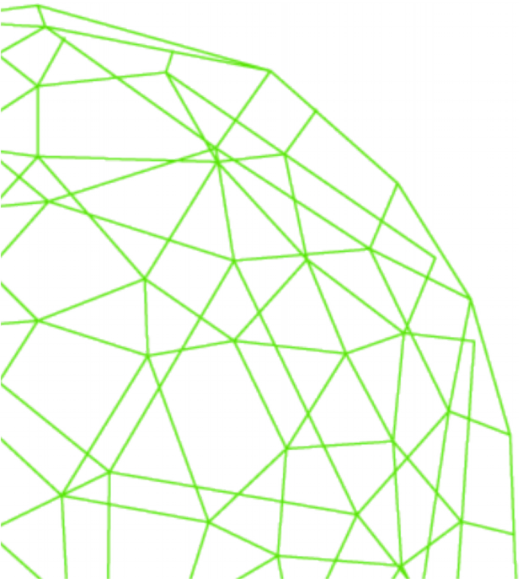
MILLENNIUM INSTITUTE OF ASTROPHYSICS

CONICYT
Ministerio de Educación
Gobierno de Chile

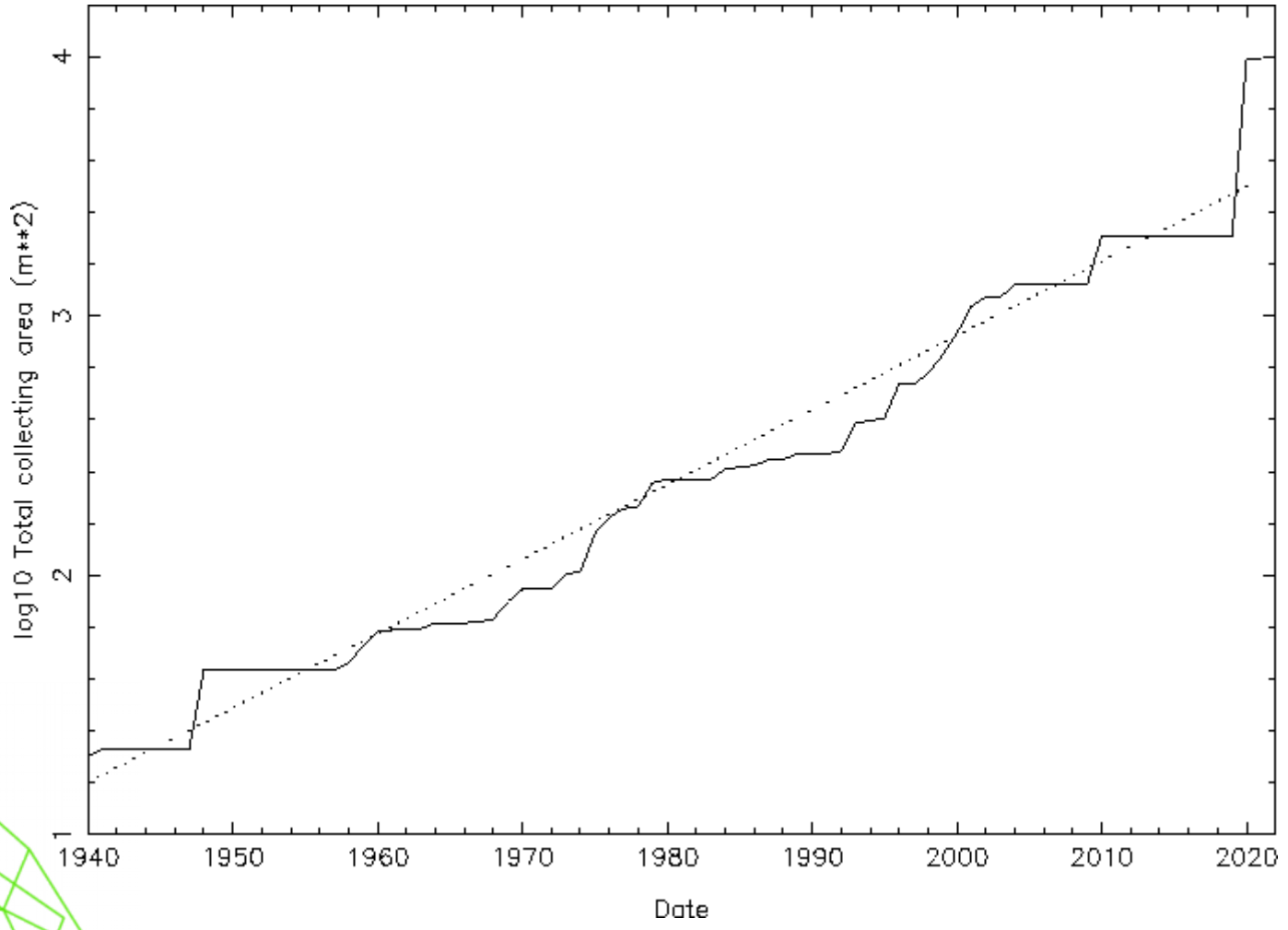
Astroinformatics Laboratory

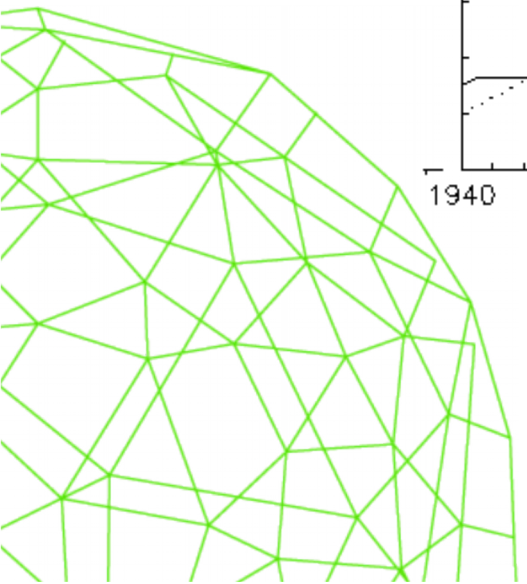
- Focus in astronomical problems that require the analysis of **large volumes of data.**
- Efficient algorithms, statistics, data handling methods, visualization, inverse problems, image processing, machine learning, high performance computing.
- **Interdisciplinary** focus gives **flexibility** to move into new developing areas of astronomy.
- Focus on **data−driven** and well defined problems.
- e.g. real−time, high−cadence survey for transient objects (**DECam**); automatic classification of galaxies (**LSST**), characterization of light curves (**DECam**, **LSST**) and image synthesis in interferometric observations (**ALMA**).

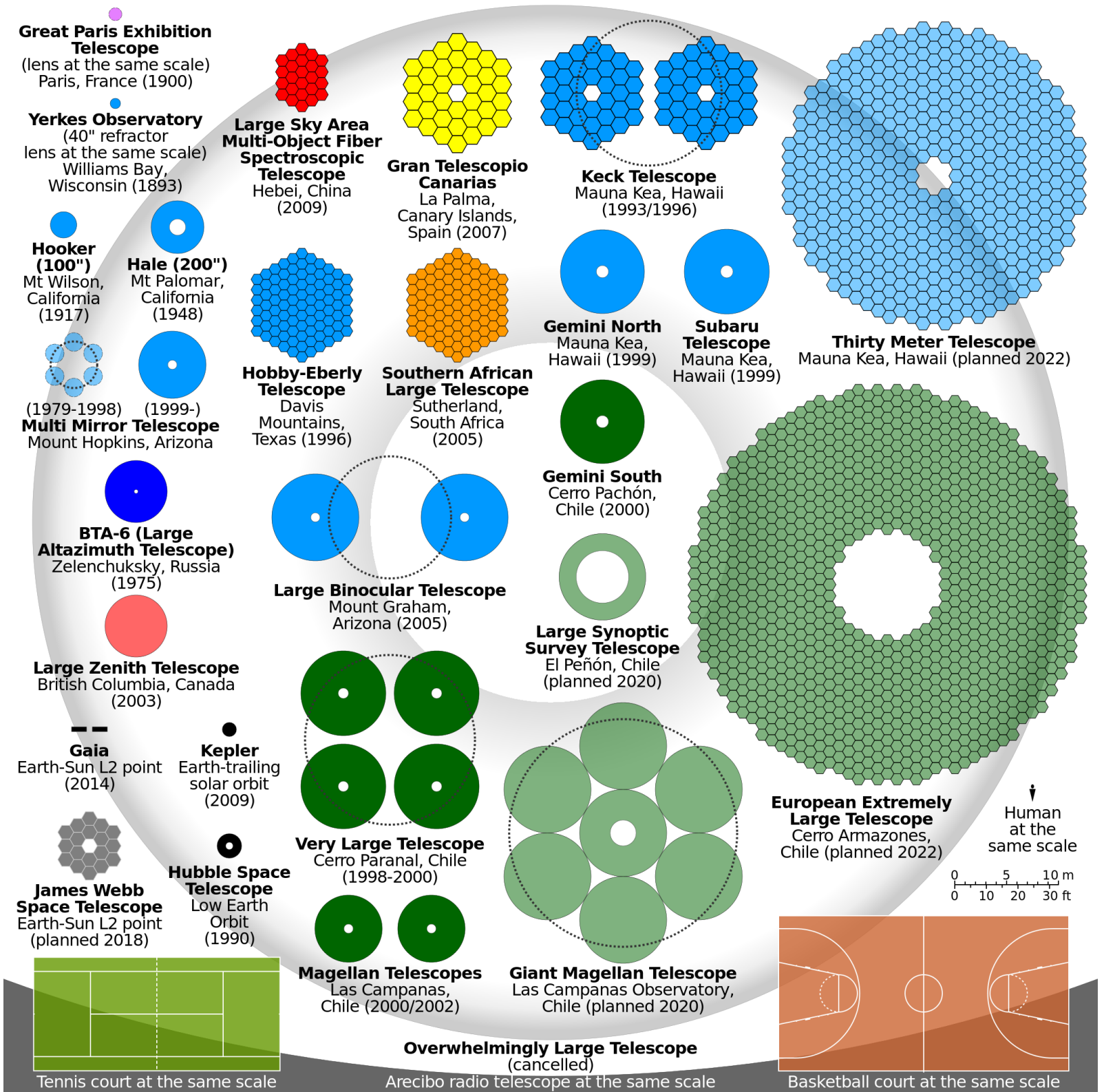
Astronomy in the next decade: Big Data & Big Telescopes



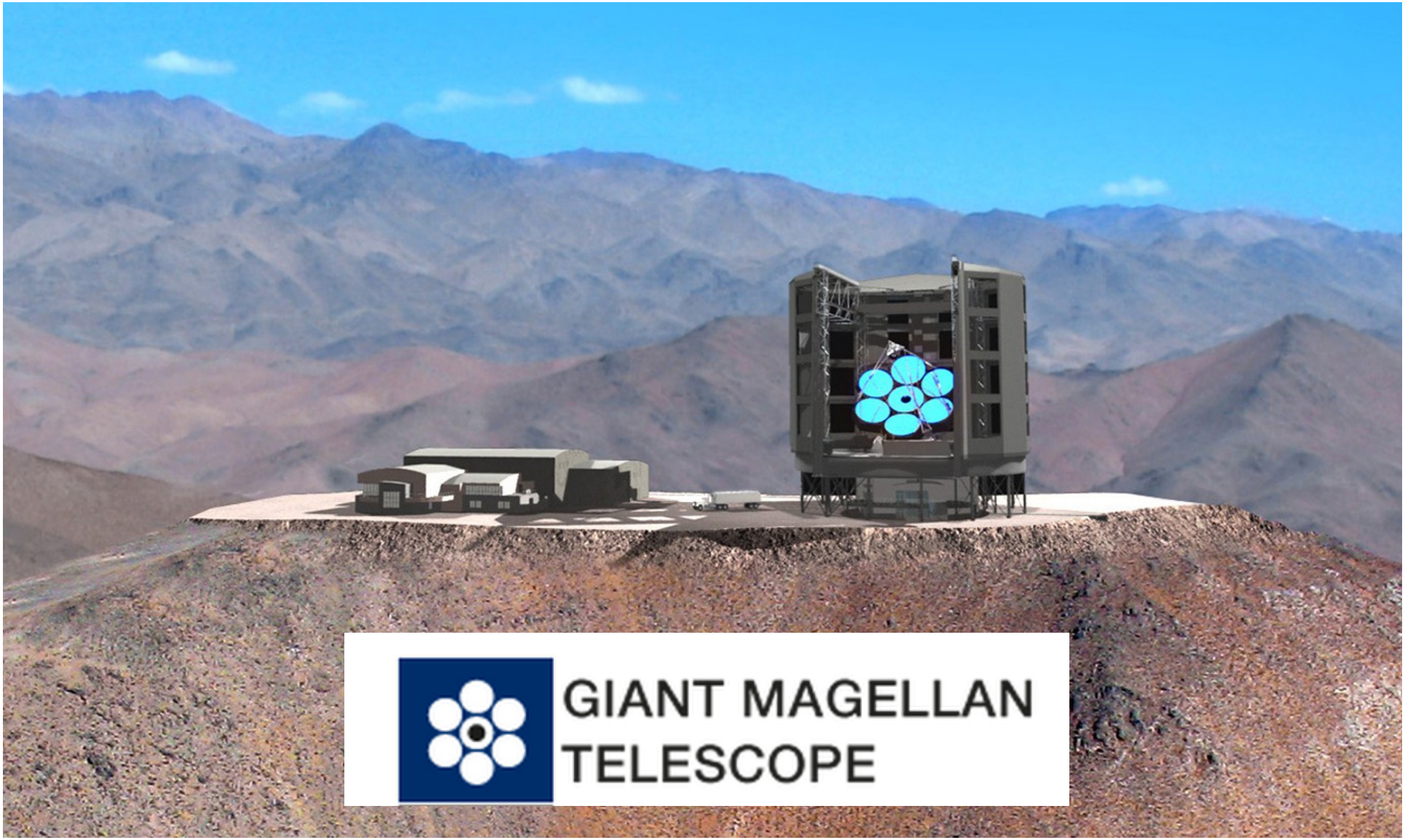
Big Telescopes

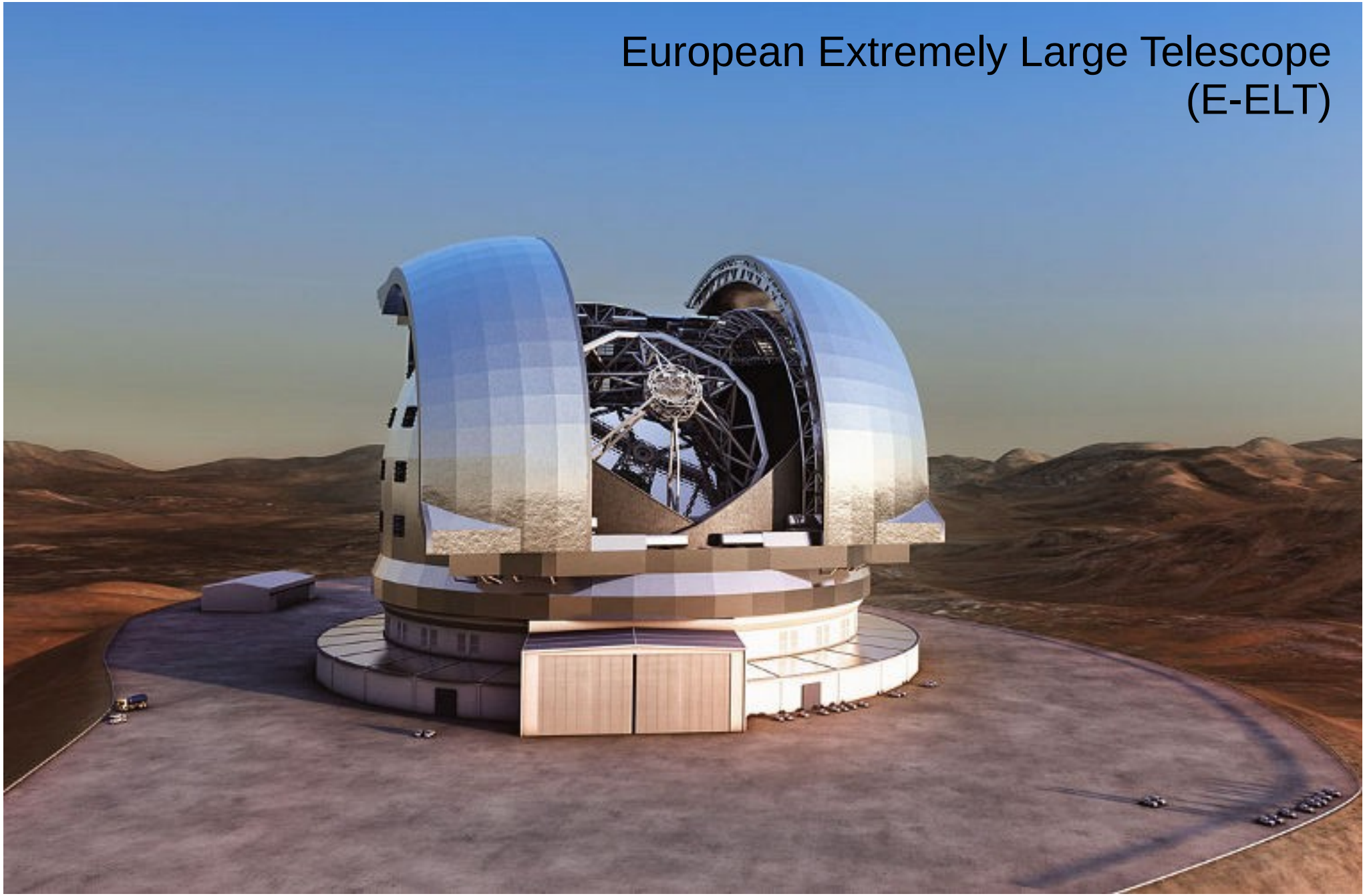




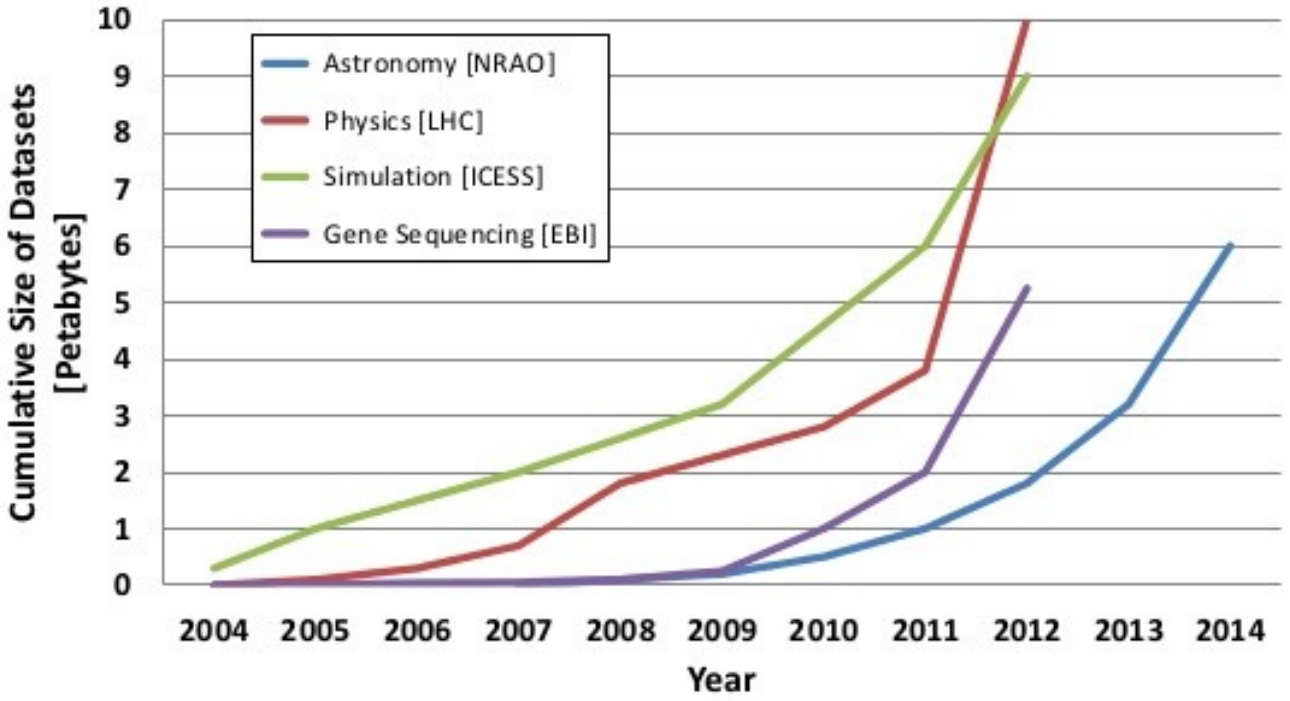

Great Paris Exhibition Telescope
(lens at the same scale)
Paris, France (1900)
Yerkes Observatory
(40" refractor
lens at the same scale)
Williams Bay,
Wisconsin (1893)
Large Sky Area Multi-Object Fiber Spectroscopic Telescope
Hebei, China
(2009)
Gran Telescopio Canarias
La Palma,
Canary Islands,
Spain (2007)
Keck Telescope
Mauna Kea, Hawaii
(1993/1996)
Thirty Meter Telescope
Mauna Kea, Hawaii (planned 2022)
Hooker (100")
Mt Wilson,
California
(1917)
Hale (200")
Mt Palomar,
California
(1948)
Hobby-Eberly Telescope
Davis
Mountains,
Texas (1996)
Southern African Large Telescope
Sutherland,
South Africa
(2005)
Gemini North
Mauna Kea,
Hawaii (1999)
Subaru Telescope
Mauna Kea,
Hawaii (1999)
(1979-1998)
(1999-)
Multi Mirror Telescope
Mount Hopkins, Arizona
Gemini South
Cerro Pachón,
Chile (2000)
BTA-6 (Large Altazimuth Telescope)
Zelenchuksky, Russia
(1975)
Large Binocular Telescope
Mount Graham,
Arizona (2005)
Large Synoptic Survey Telescope
El Peñón, Chile
(planned 2020)
Large Zenith Telescope
British Columbia, Canada
(2003)
European Extremely Large Telescope
Cerro Armazones,
Chile (planned 2022)
Human at the same scale
Gaia
Earth-Sun L2 point
(2014)
Kepler
Earth-trailing
solar orbit
(2009)
Very Large Telescope
Cerro Paranal, Chile
(1998-2000)
James Webb Space Telescope
Earth-Sun L2 point
(planned 2018)
Hubble Space Telescope
Low Earth
Orbit
(1990)
Magellan Telescopes
Las Campanas,
Chile (2000/2002)
Giant Magellan Telescope
Las Campanas Observatory,
Chile (planned 2020)
0 5 10 m
0 10 20 30 ft
Overwhelmingly Large Telescope
(cancelled)
Tennis court at the same scale
Arecibo radio telescope at the same scale
Basketball court at the same scale

Wikipedia


GIANT MAGELLAN
TELESCOPE


European Extremely Large Telescope
(E-ELT)

Big Data in astronomy

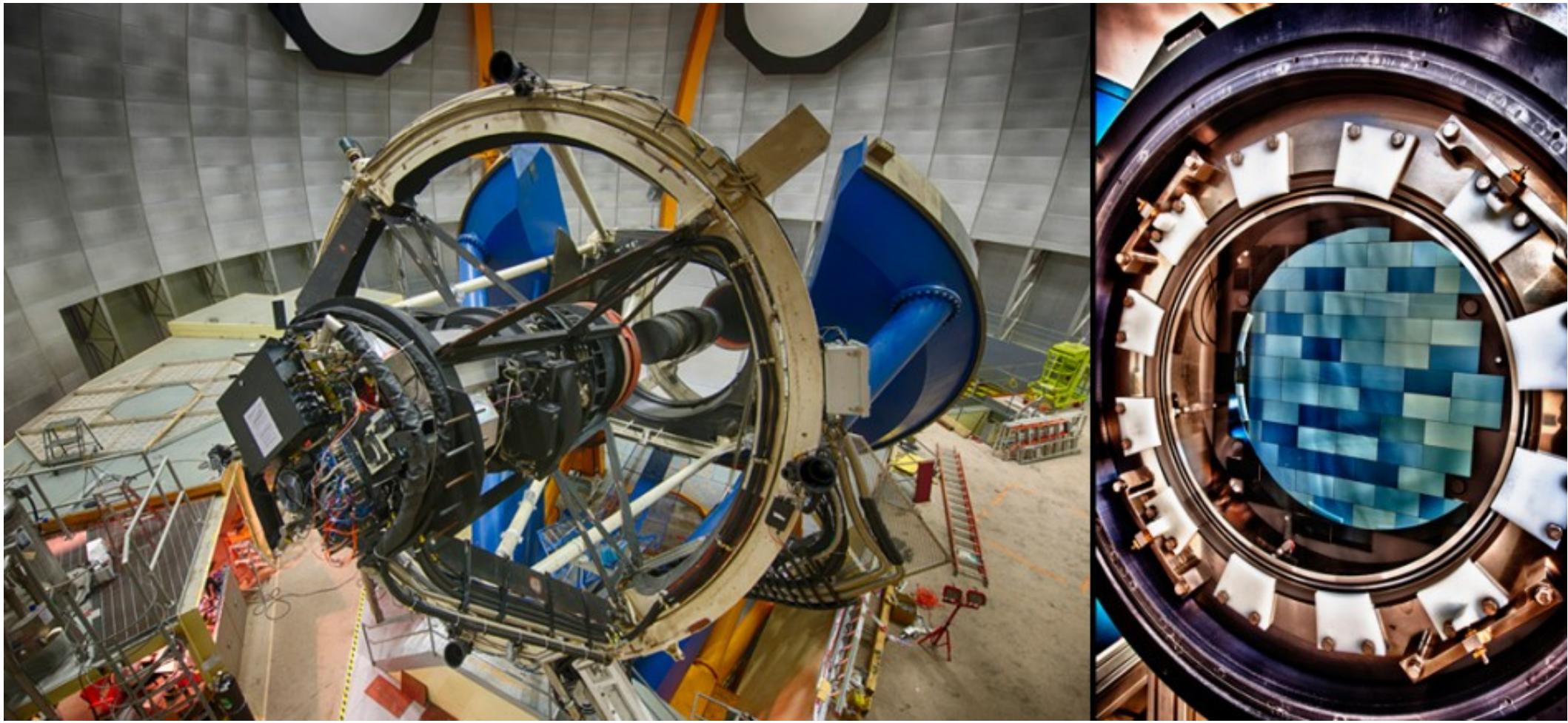


Scientific Data Grows Exponentially!

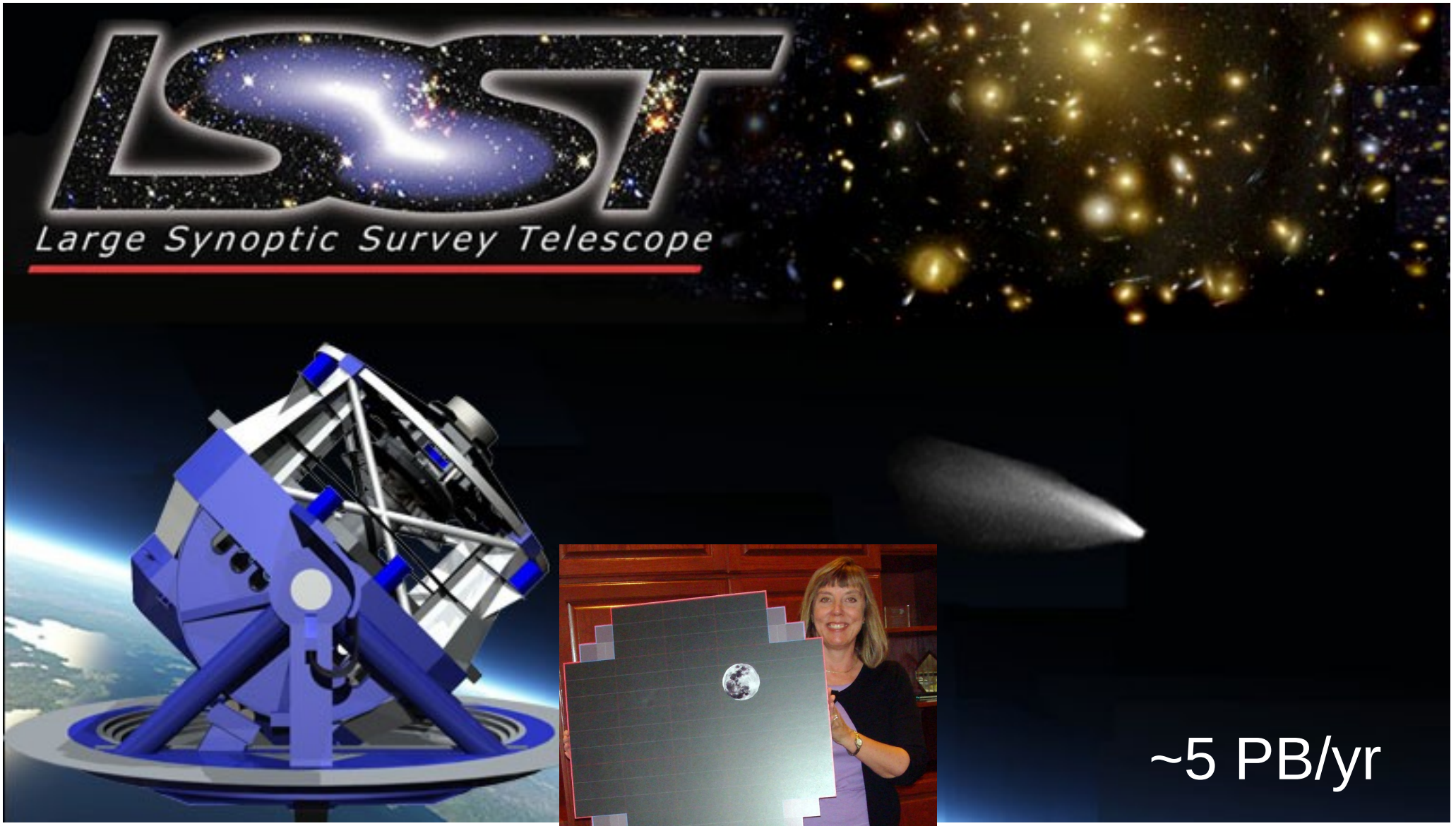
Thomas Heinis, Human Brain Project

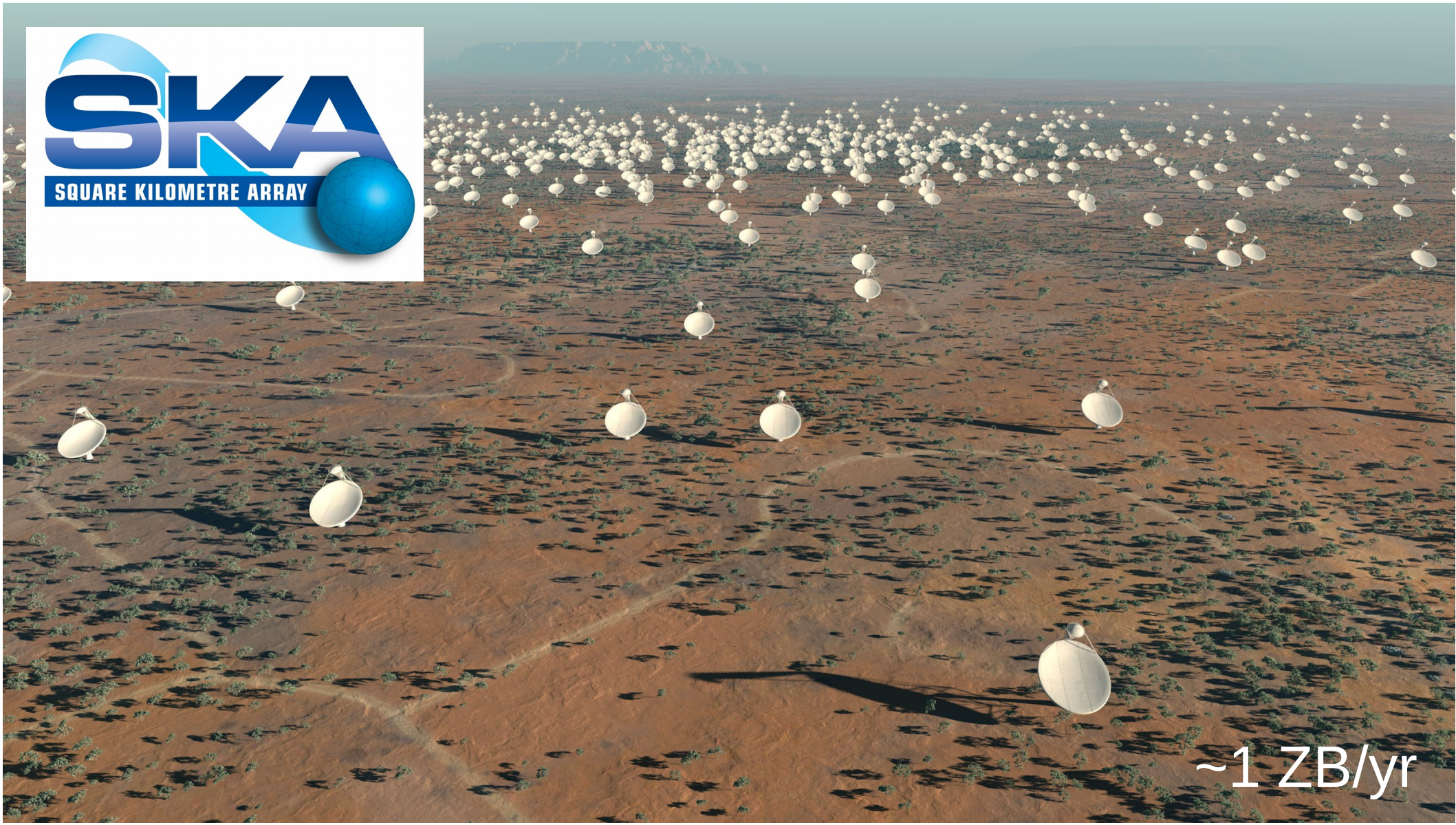

ALMA
~0.2 PB/yr

Dark Energy Camera (DECam)



~0.4 PB/yr


LSST
Large Synoptic Survey Telescope
~5 PB/yr

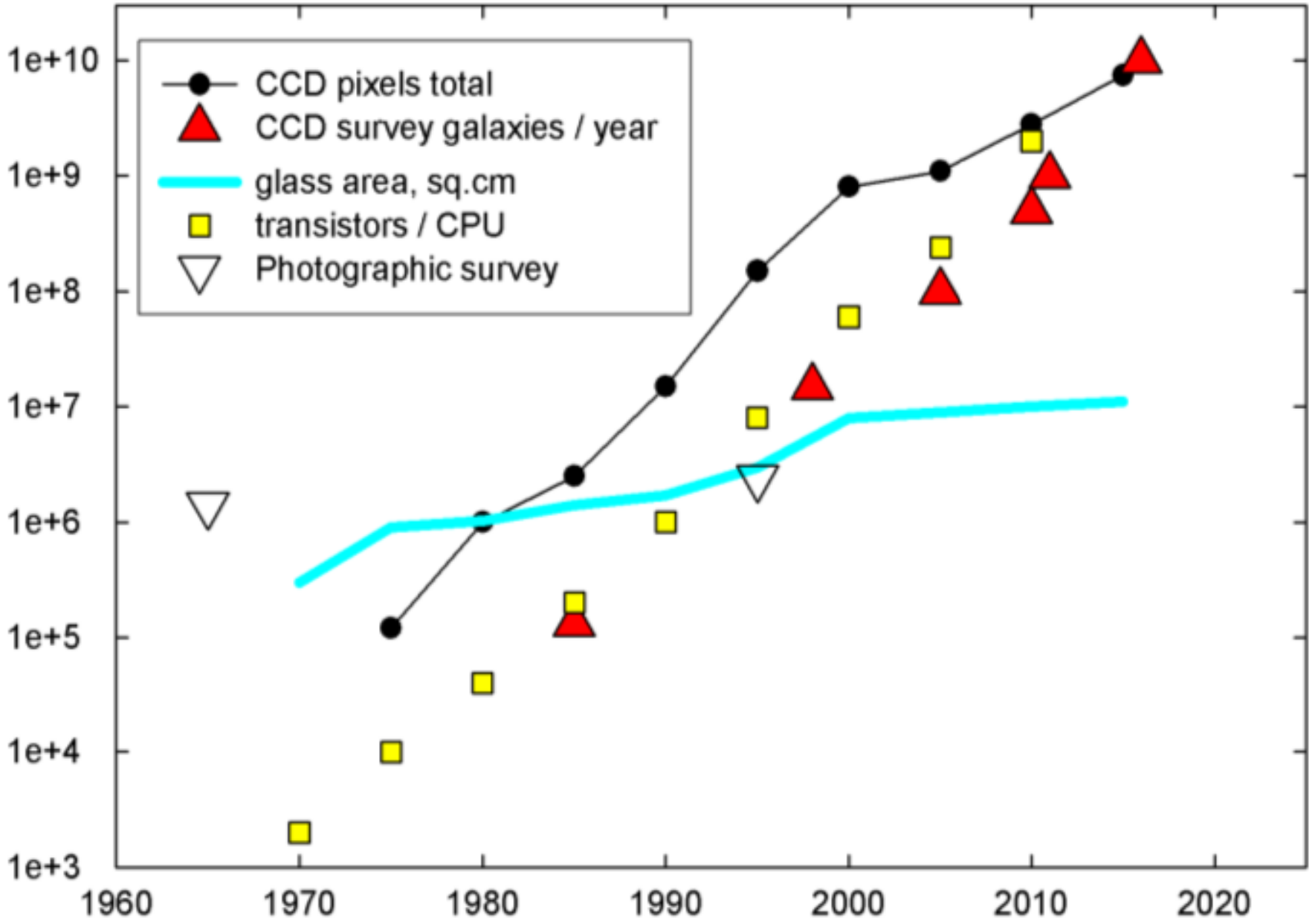


1 Zettabyte = 10^3 ExaBytes = 10^6 PB

SKA

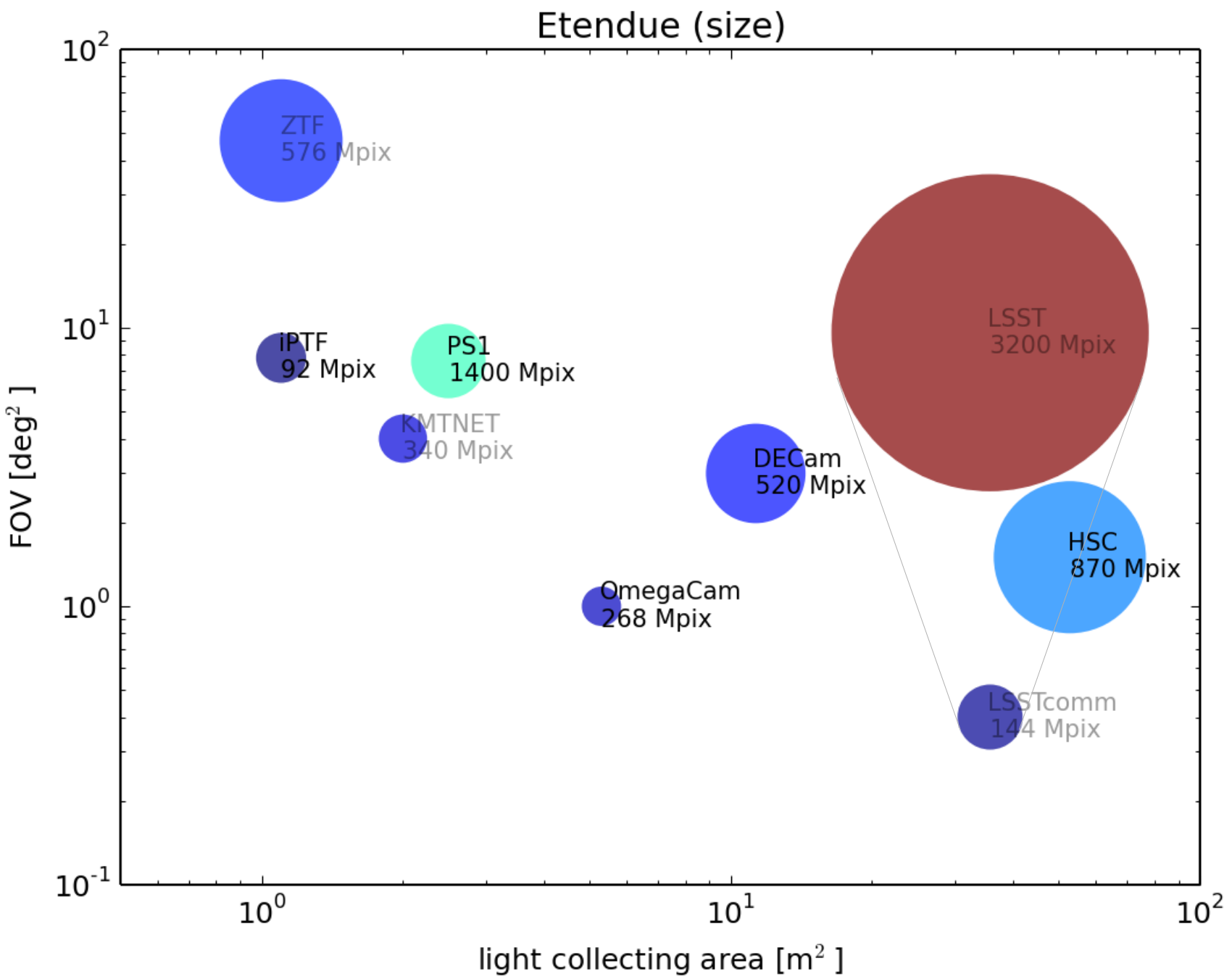
SQUARE KILOMETRE ARRAY

Data volume > telescope size



from T. Tyson, 2010

Etendue and number of pixels



The large Synoptic Survey Telescope (LSST)

Time domain science

- Nova, supernova, GRBs
- Source characterization
- Instantaneous discovery

Census of the Solar System

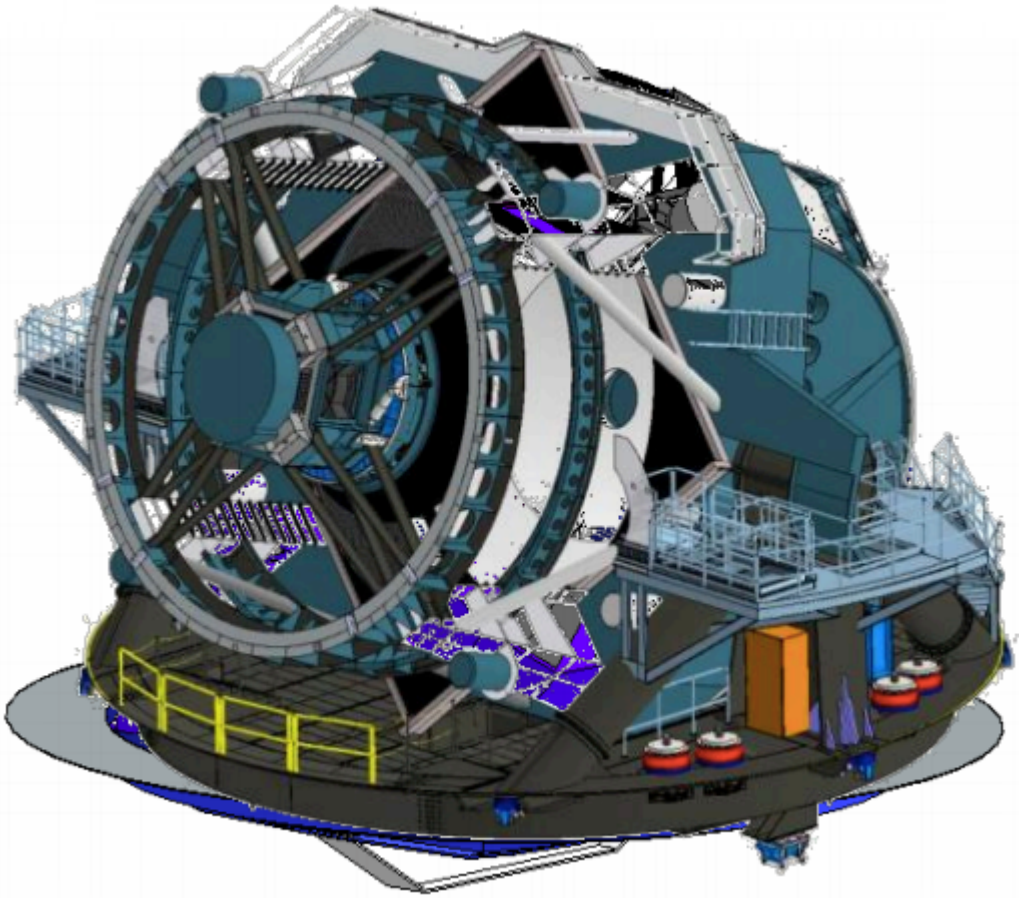
- NEOs, MBAs, Comets
- KBOs, Oort Cloud

Mapping the Milky Way

- Tidal streams
- Galactic structure

Dark energy and dark matter

- Strong Lensing
- Weak Lensing
- Constraining the nature of dark energy



The large Synoptic Survey Telescope (LSST)

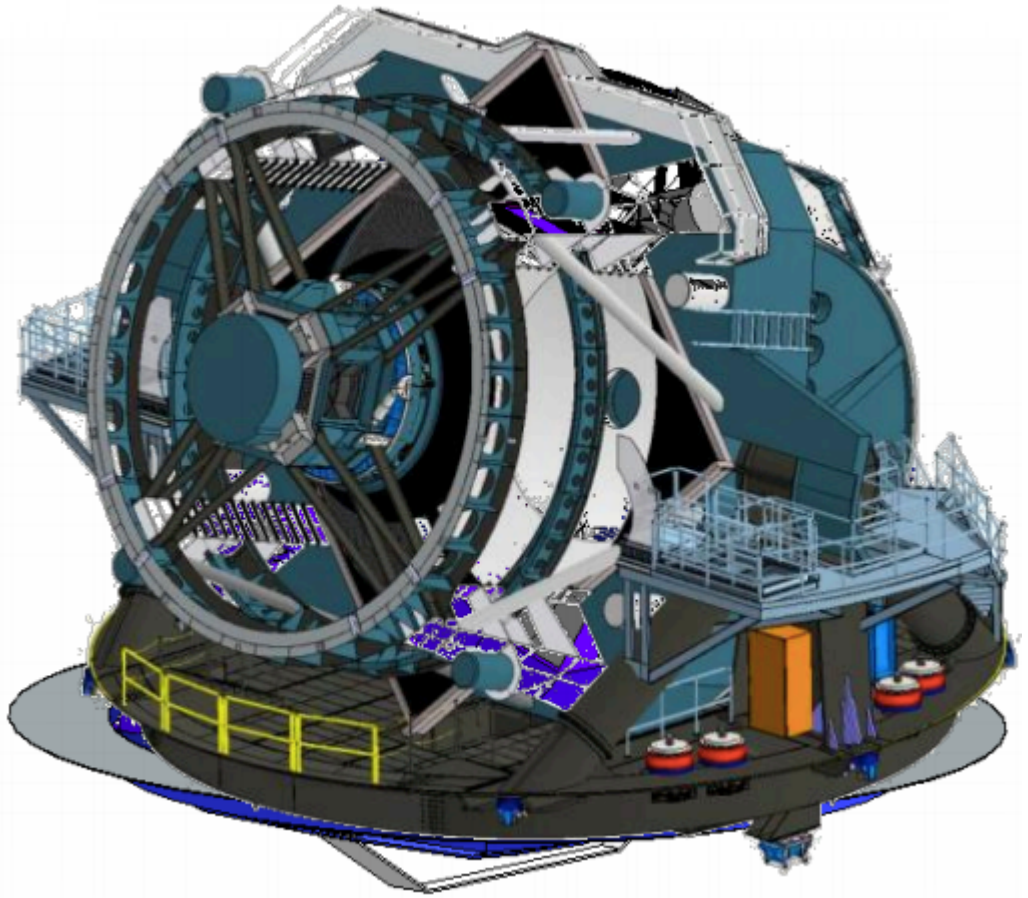
Traditional scientists

What data should I collect to test an hypothesis?

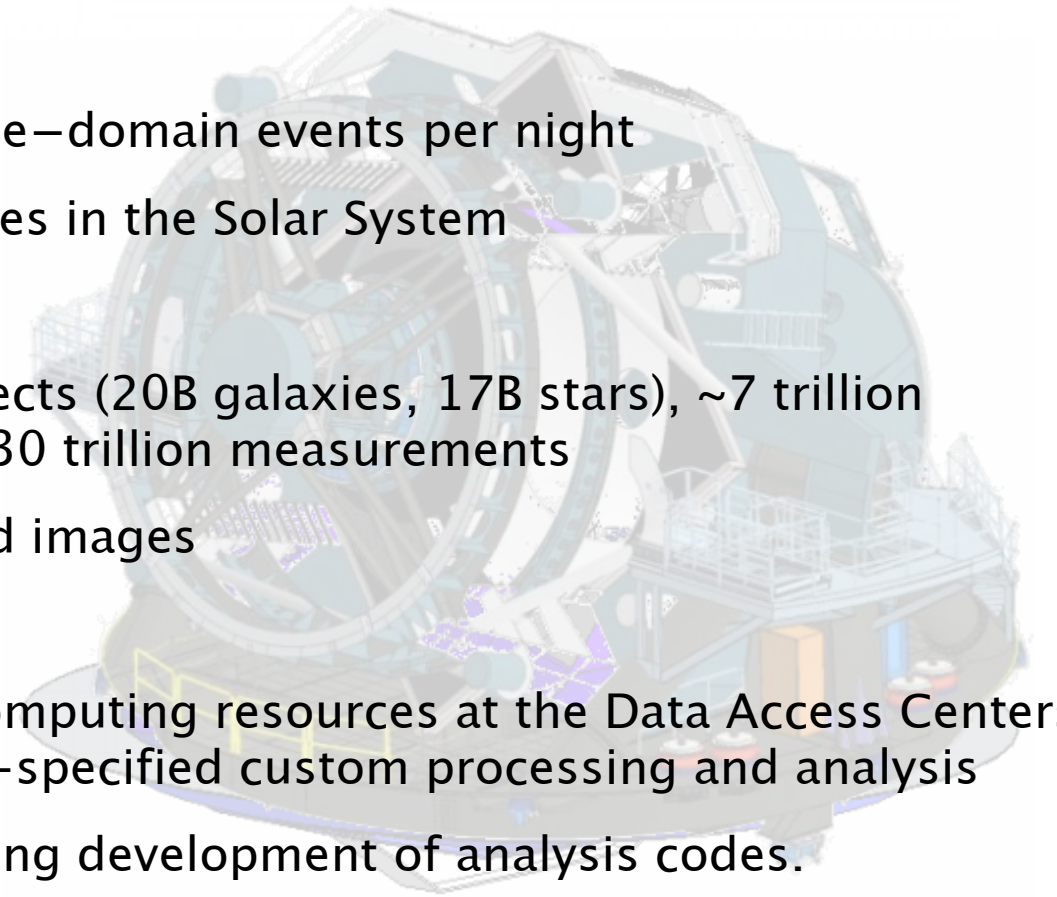
Data−driven scientist

What theories can I test given the data I already have?

Success in research will depend on the ability to mine knowledge from data.



The large Synoptic Survey Telescope (LSST)



LEVEL 1:
Nightly alerts

~10 million time−domain events per night

~6 million bodies in the Solar System

LEVEL 2:
Yearly data releases

~37 billion objects (20B galaxies, 17B stars), ~7 trillion sources, and ~30 trillion measurements

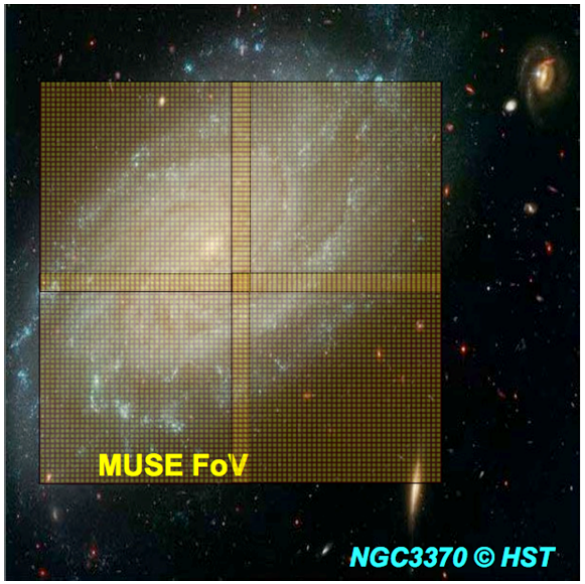
Deep co−added images

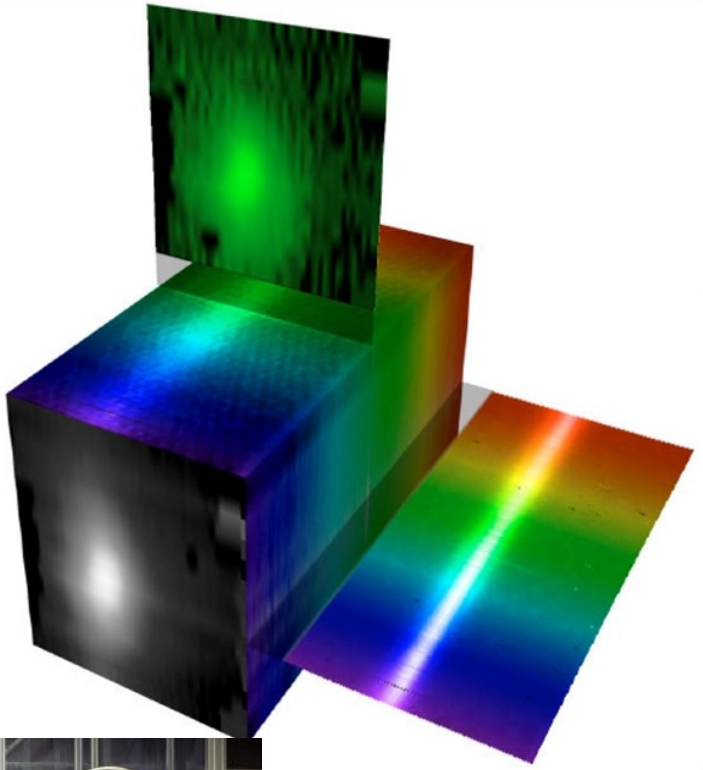
LEVEL 3:
Community projects

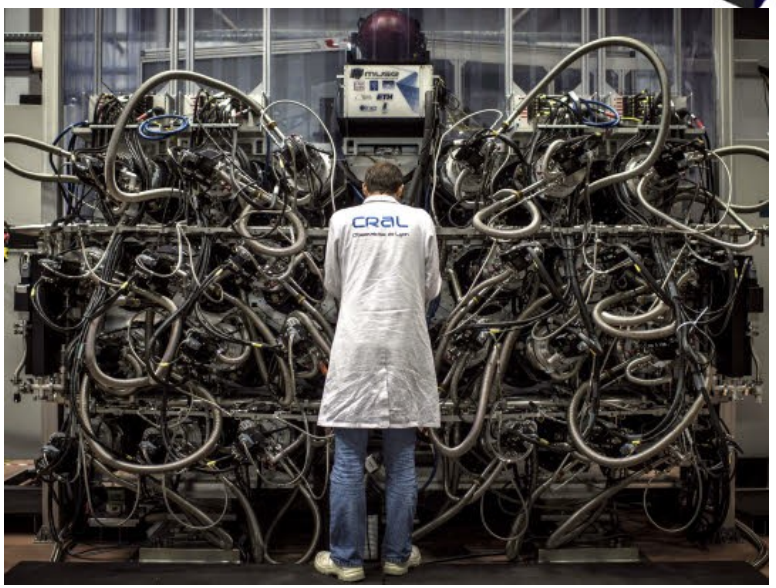
Services and computing resources at the Data Access Centers to enable user−specified custom processing and analysis

Software enabling development of analysis codes.

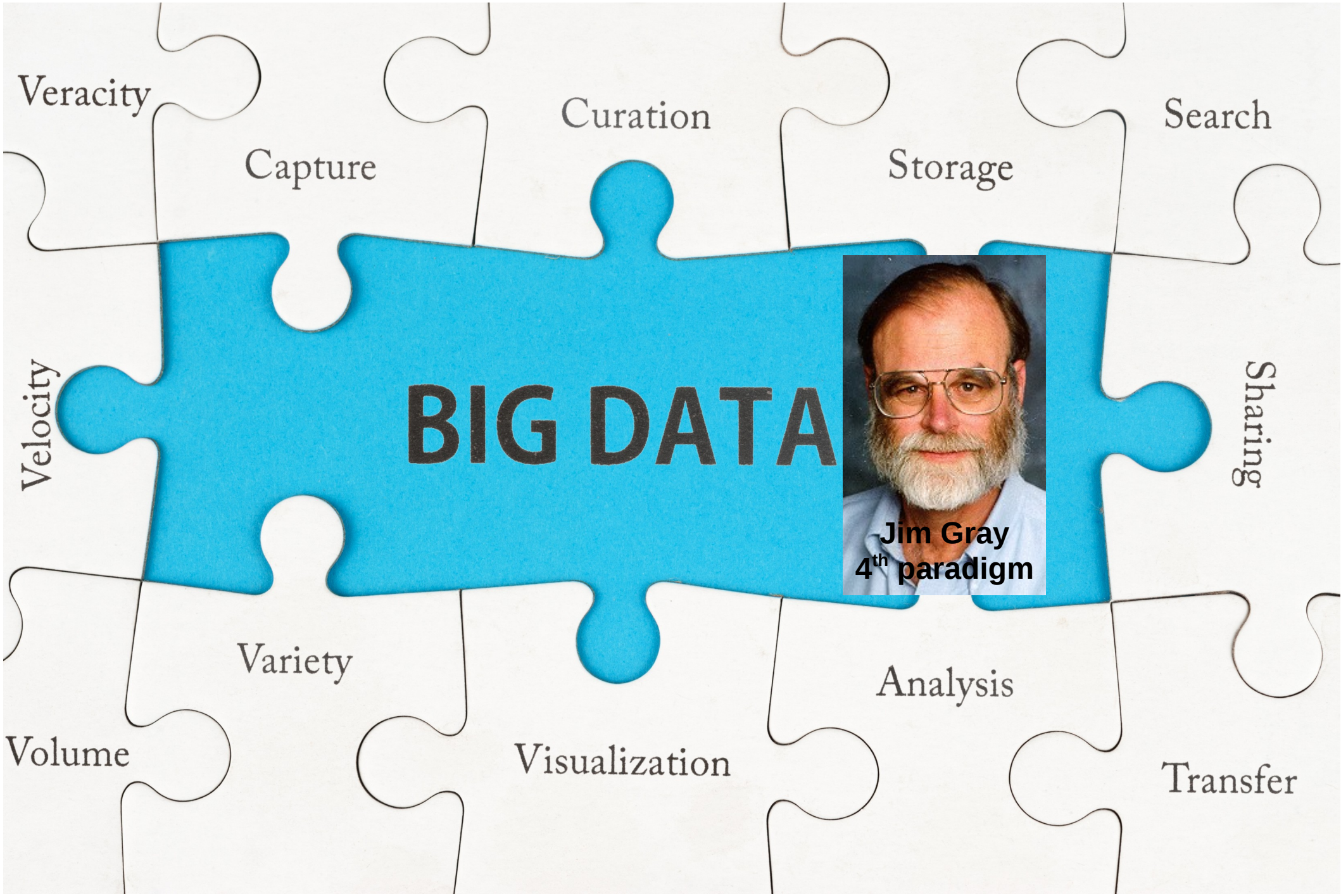
Integral Field Units, e.g. Multi-Unit Spectroscopic Explorer (MUSE)







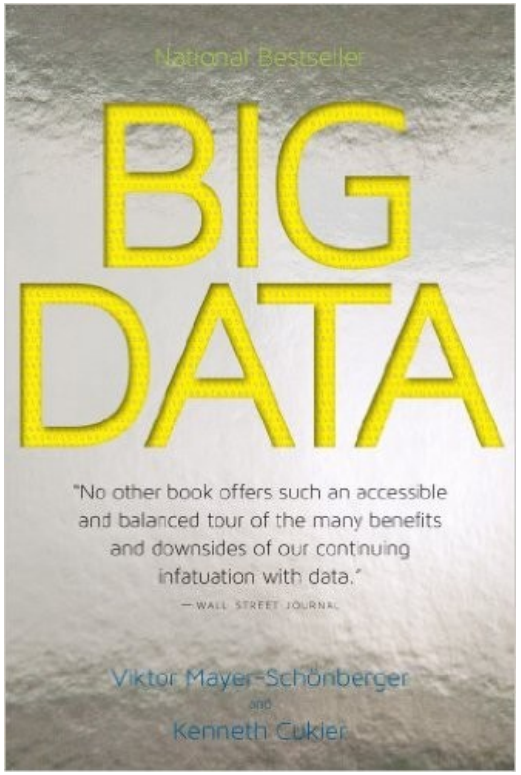
Internet submarine cables


Veracity
Capture
Curation
Storage
Search
Velocity
BIG DATA
Sharing
Jim Gray
4th paradigm
Variety
Analysis
Volume
Visualization
Transfer

Big data

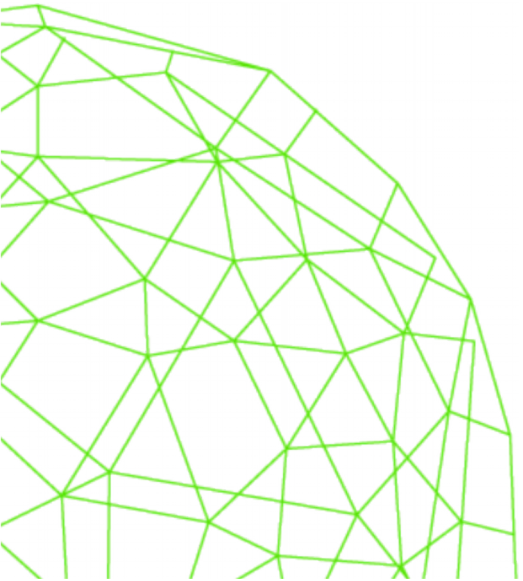
"Big Data is all about seeing and understanding the relations within and among pieces of information..."

"It is about three major shifts of mindset … the ability to analyze **vast amounts of data** about a topic … willingness to embrace **data's real-world messiness** … growing respect for **correlations** rather than a continuous quest for elusive **causality**."



"Simple models and a lot of data trump over more elaborate models on less data"

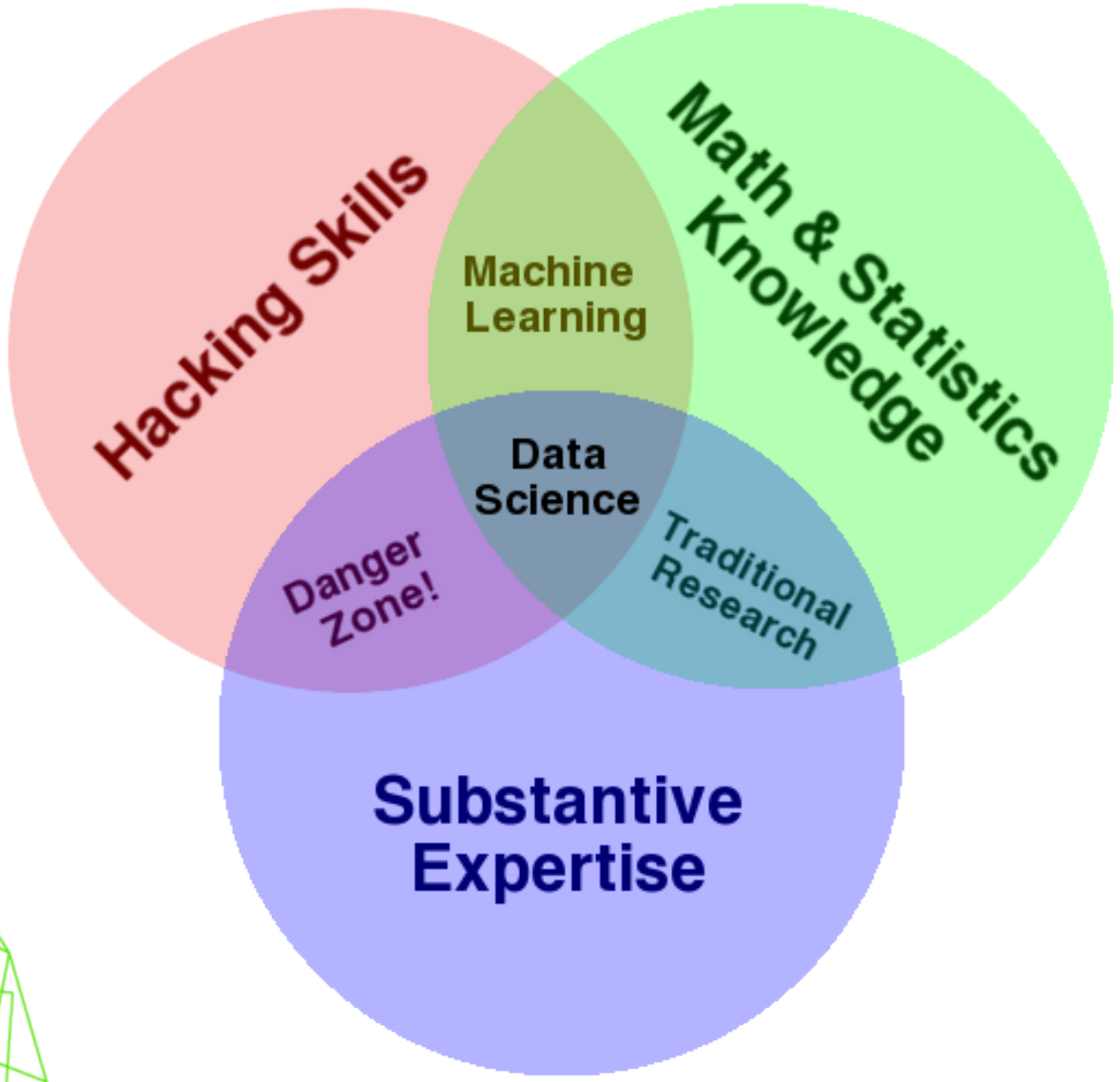
Peter Norvig, Google artificial intelligence.



"Big data is like teenage sex: everyone talks about it, nobody really knows how to do it, everyone thinks everyone else is doing it, so everyone claims they are doing it..."

Dan Ariely,
Duke University

Data science



Harvard Business Review
2012

DATA

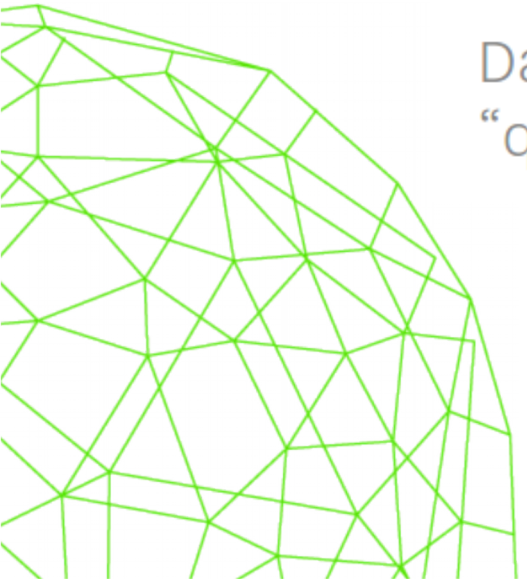
Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil

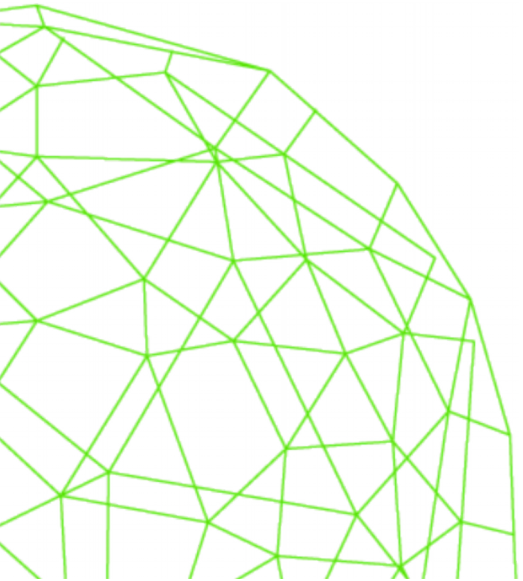
FROM THE OCTOBER 2012 ISSUE

The shortage of data scientists is becoming a serious constraint in some sectors.

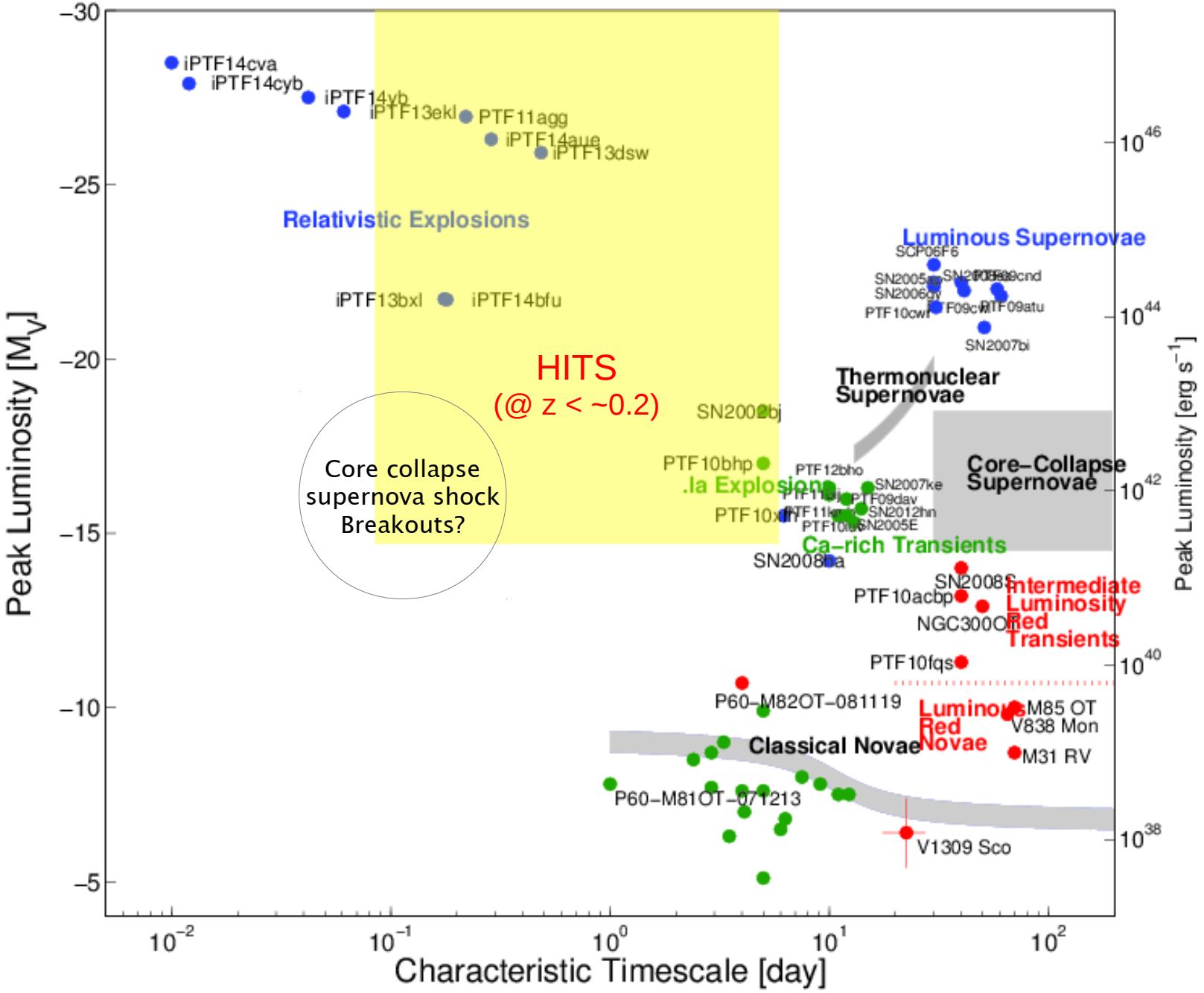
Data scientists today are akin to the Wall Street "quants" of the 1980s and 1990s.



Astroinformatics Laboratory Projects

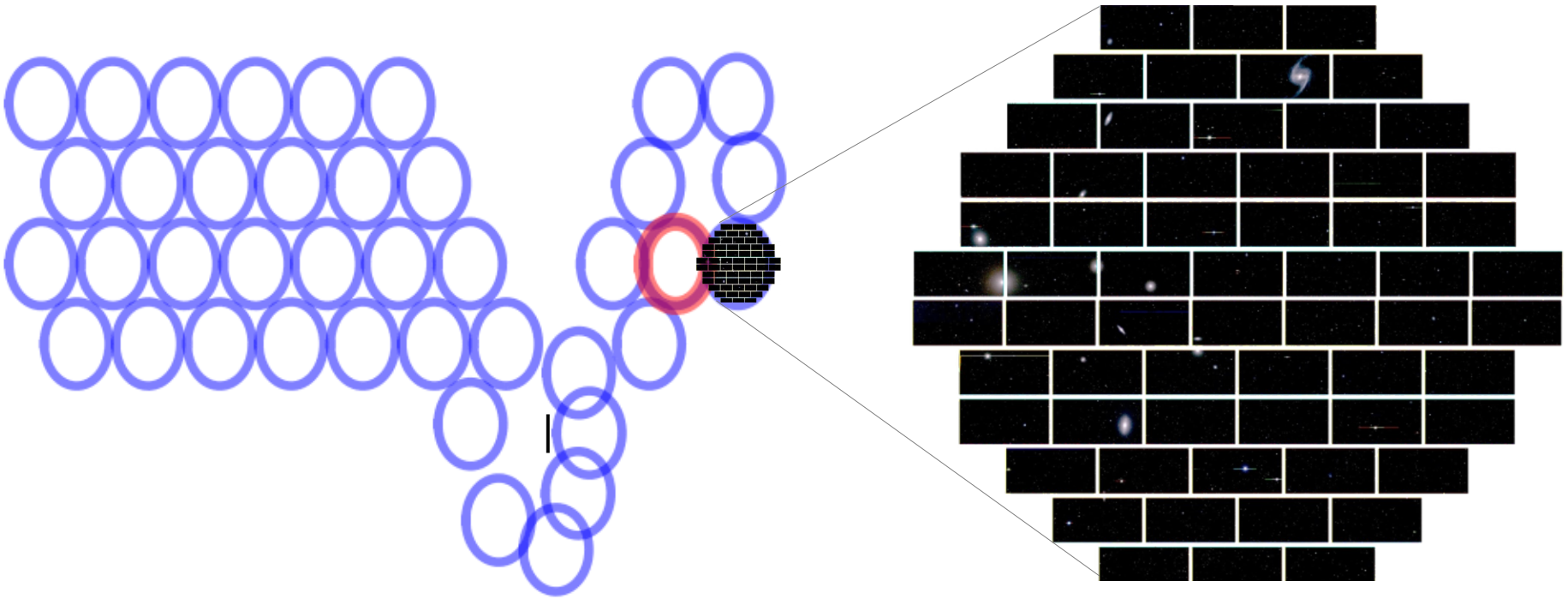


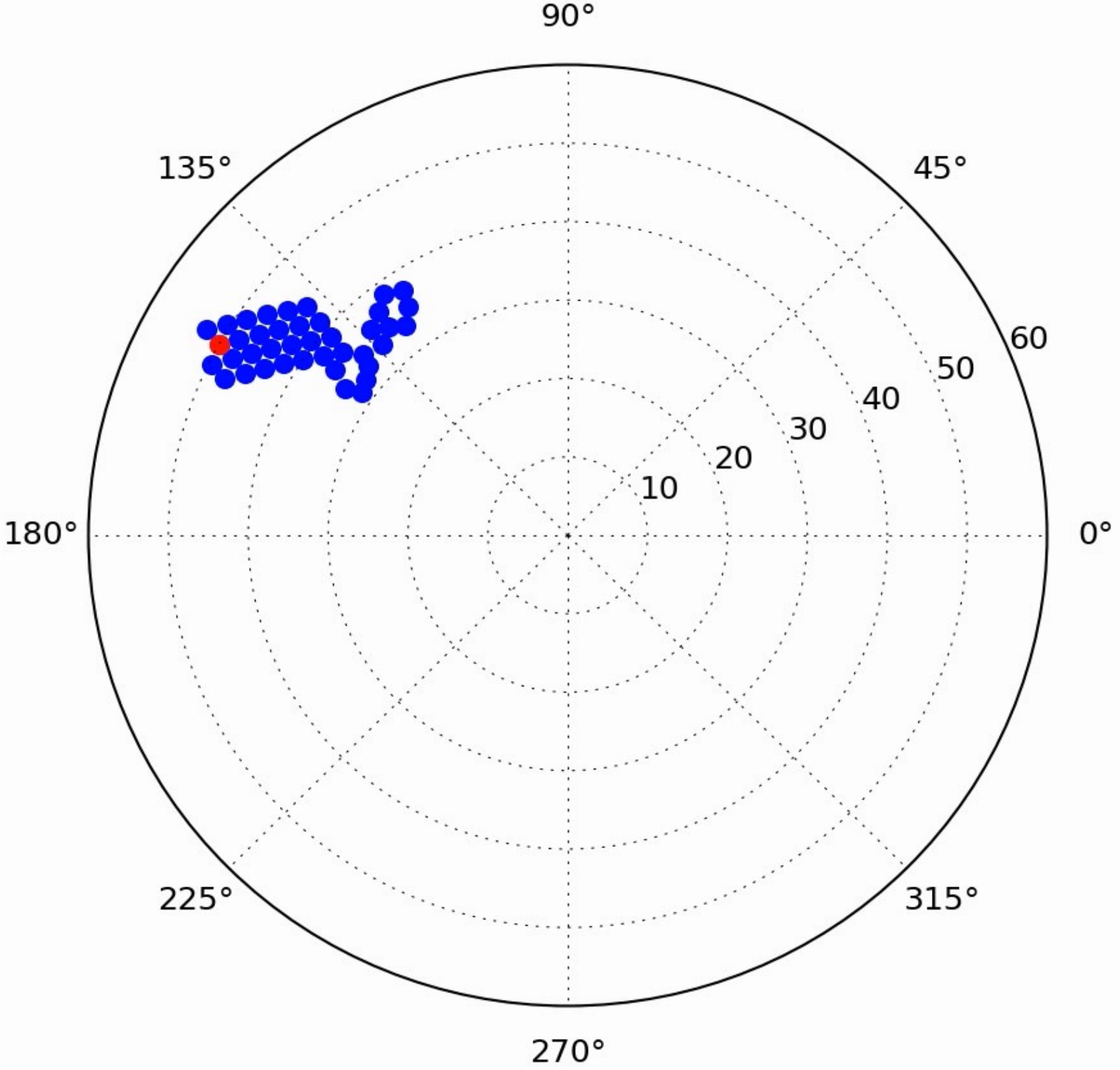
Transient sky

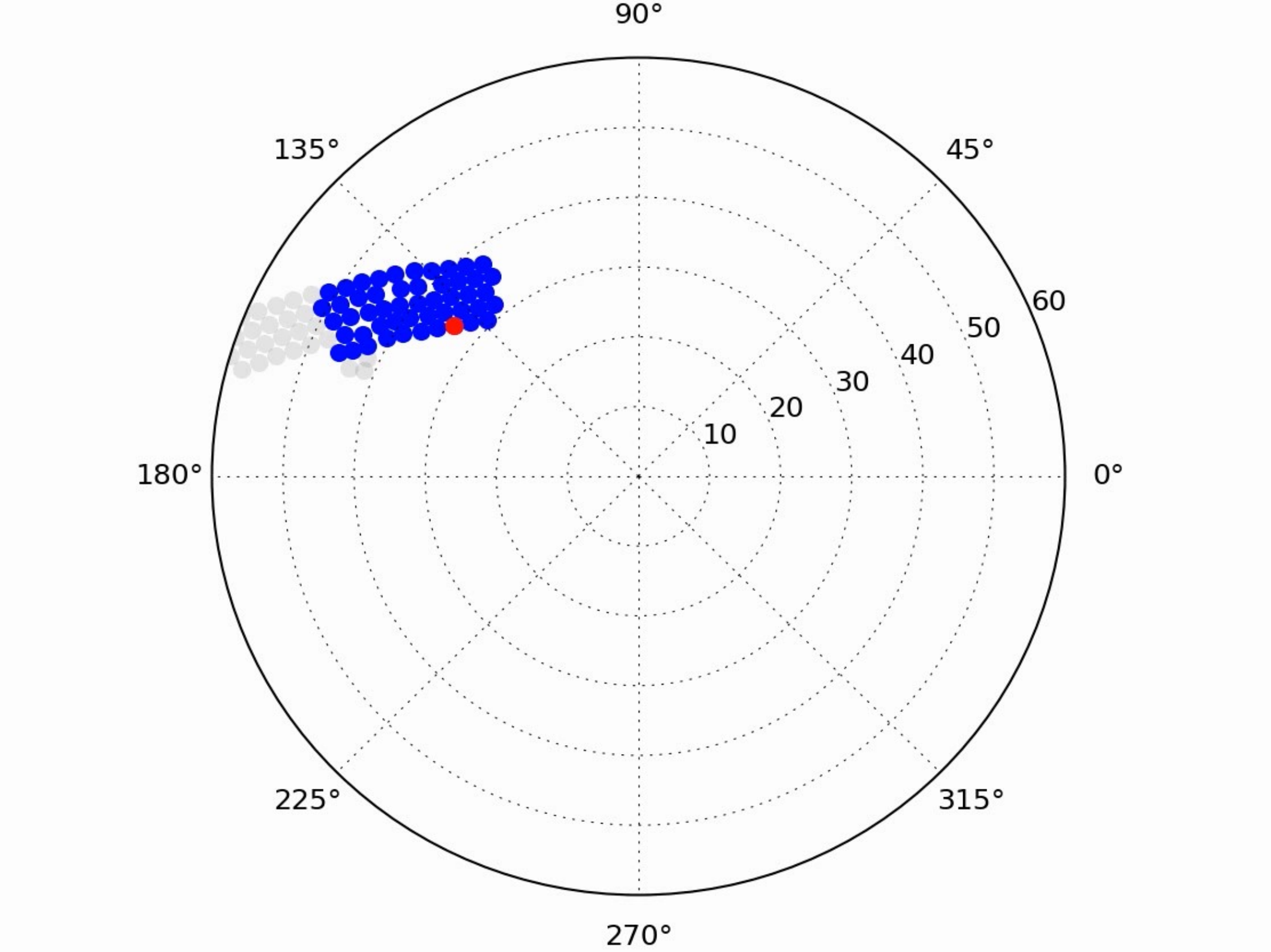


Mansi Kasliwal

HiTS: searching for shock breakouts in the optical




90°
135°
45°
60
50
40
30
20
10
180°
0°
225°
315°
270°


90°
135°
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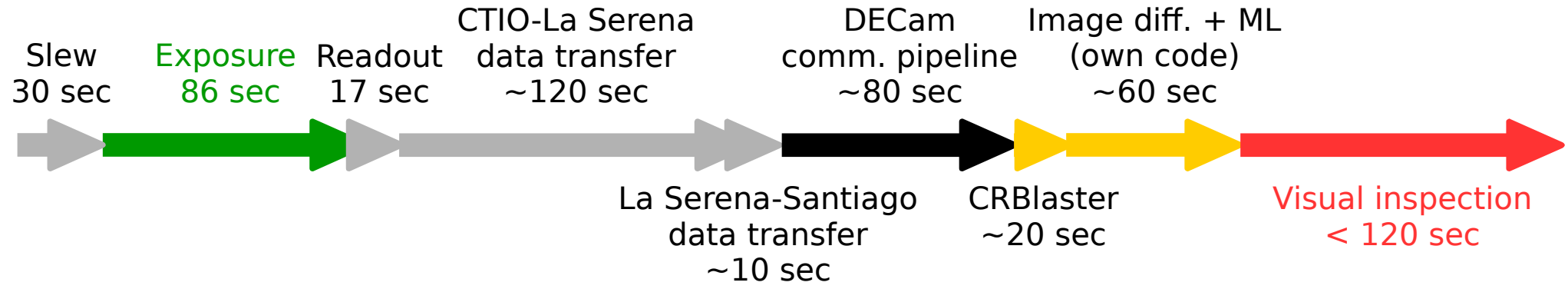
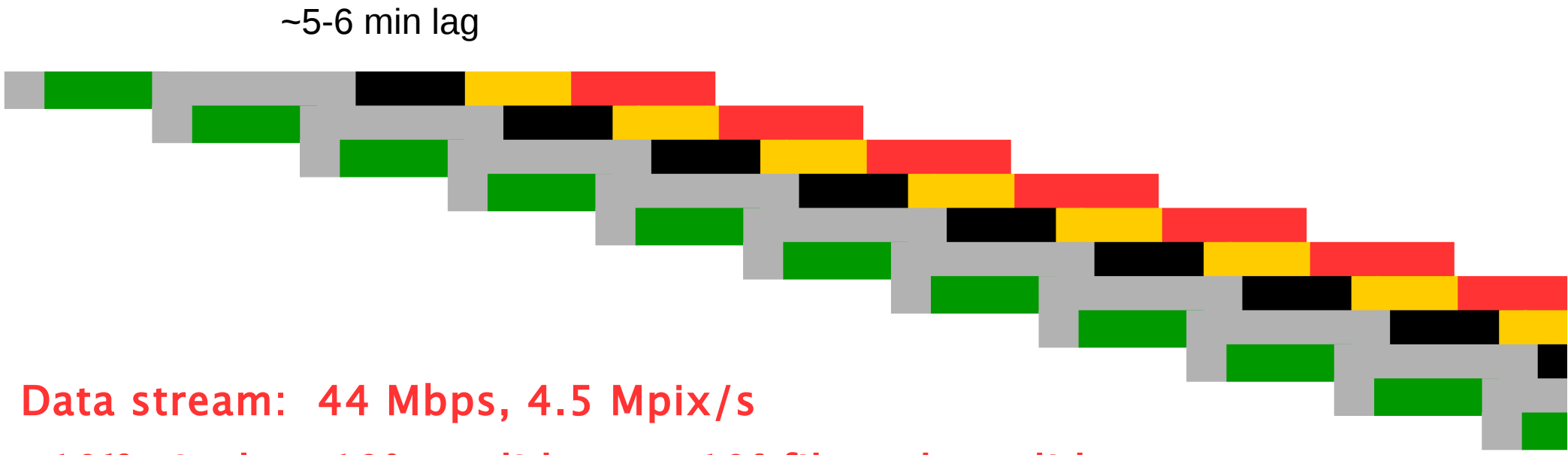
315°
270°

Pipeline flow outline

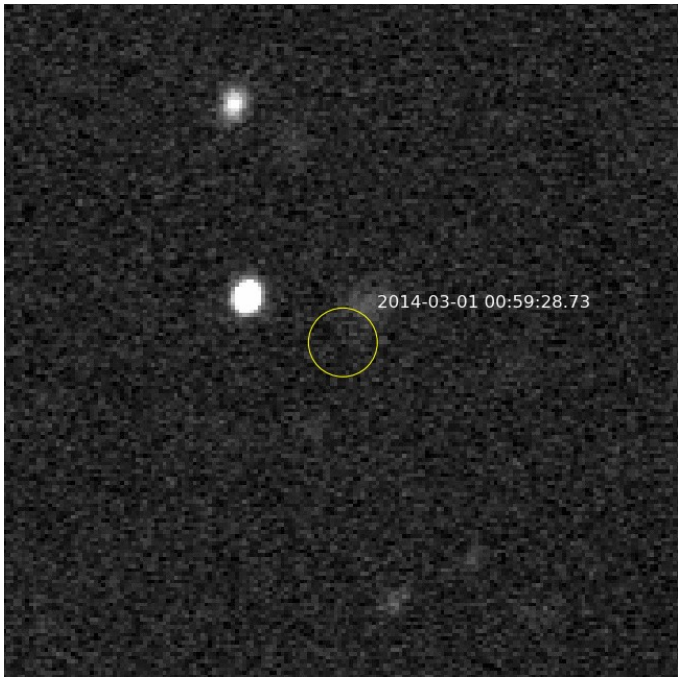


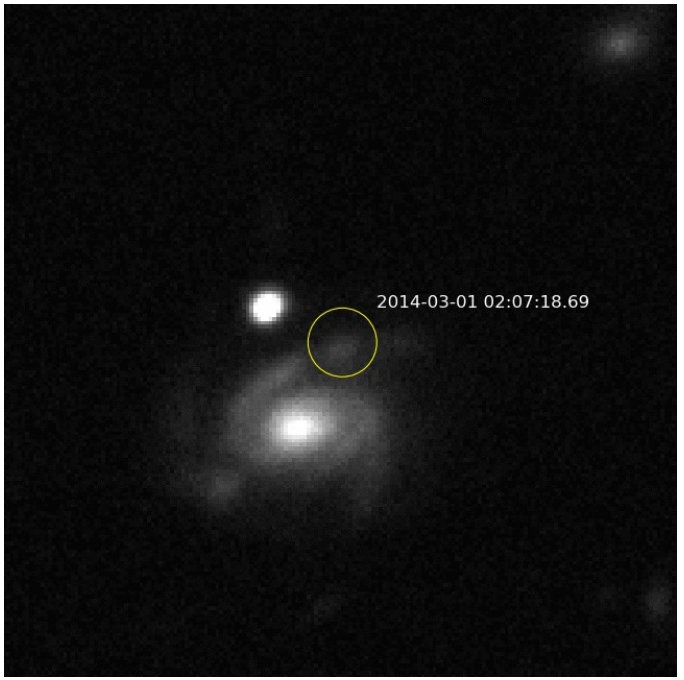


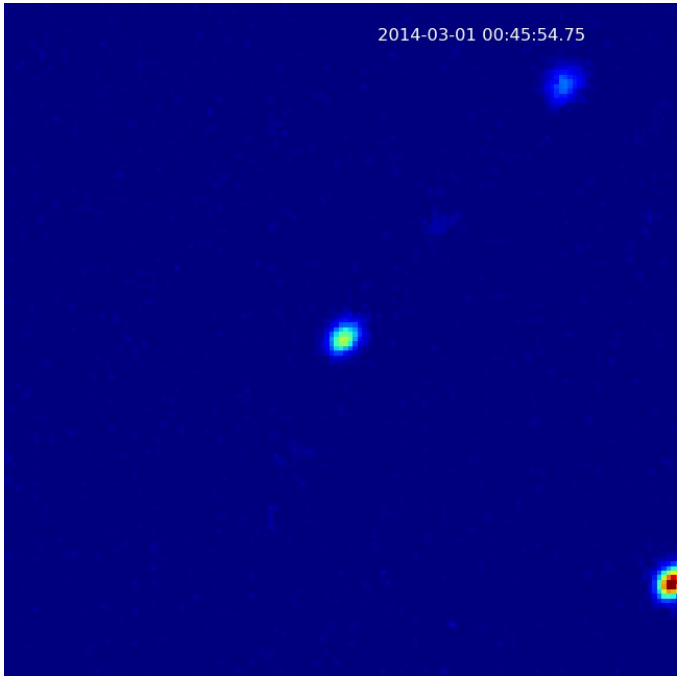
Data stream: 44 Mbps, 4.5 Mpix/s

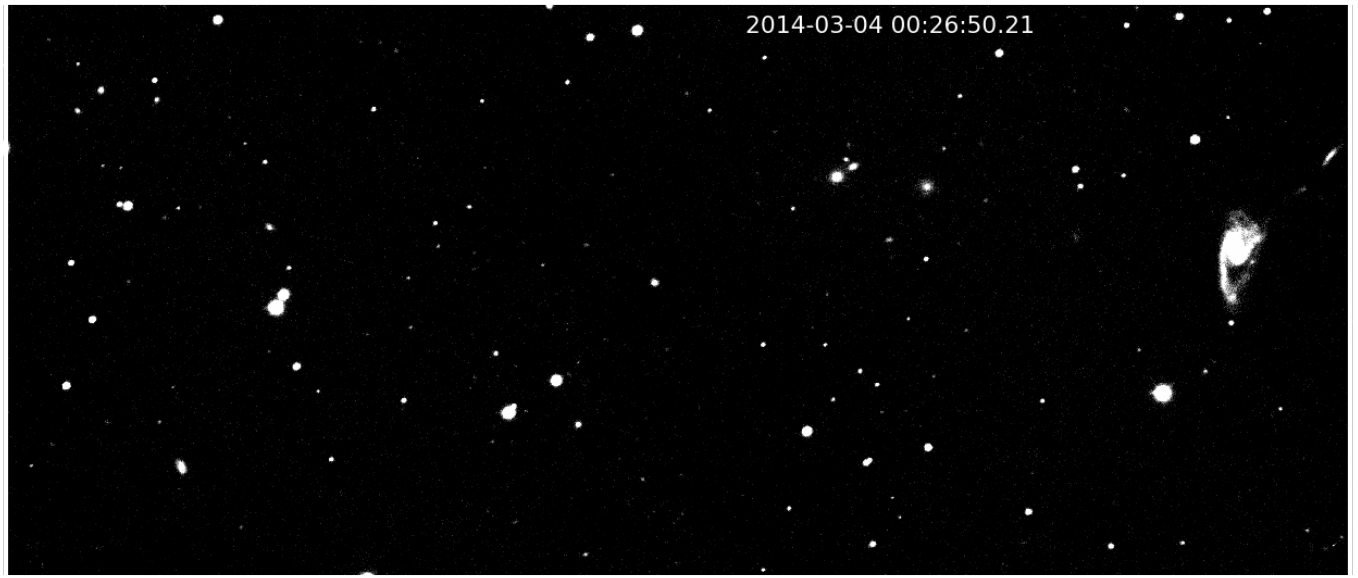
~10^{12} pixels, ~10^{8} candidates, ~10^{6} filtered candidates

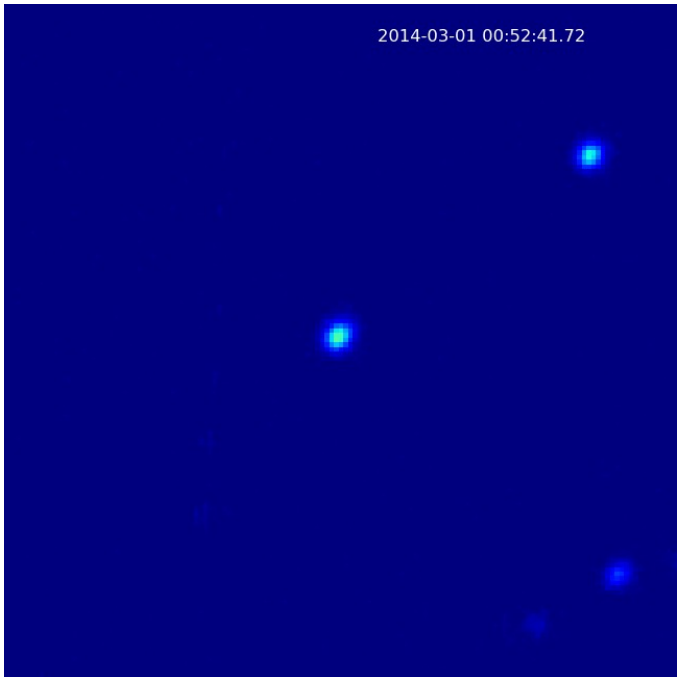
~10^{4} visual inspections, 125 SNe







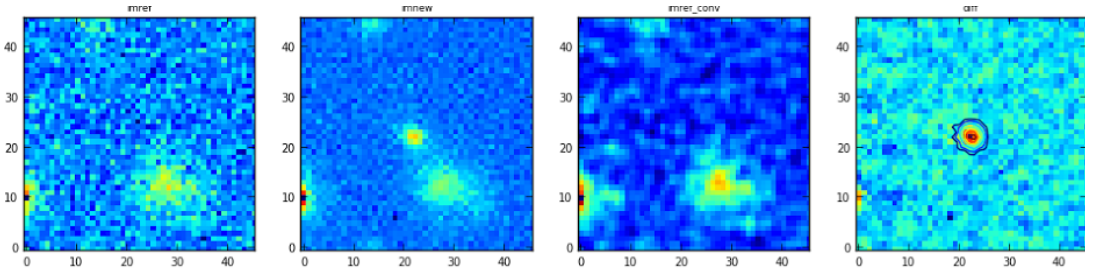




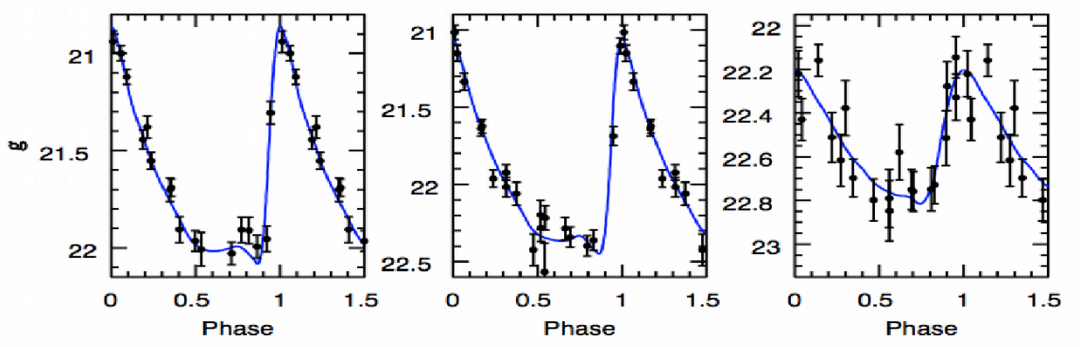
ATEL 5949, 5956

http://www.das.uchile.cl/~fforster/ATEL/summary_das.html

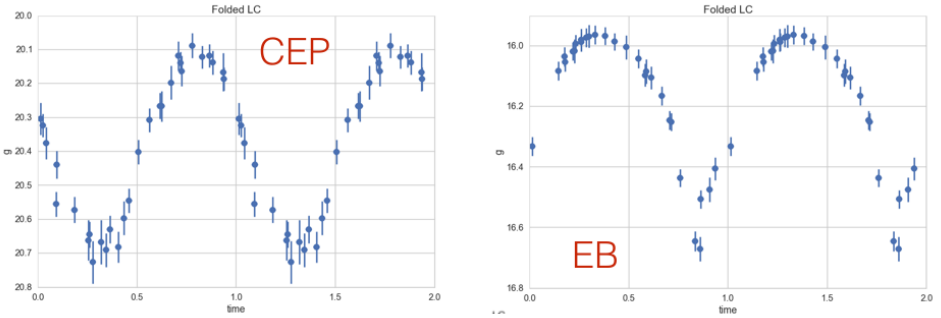
Other science



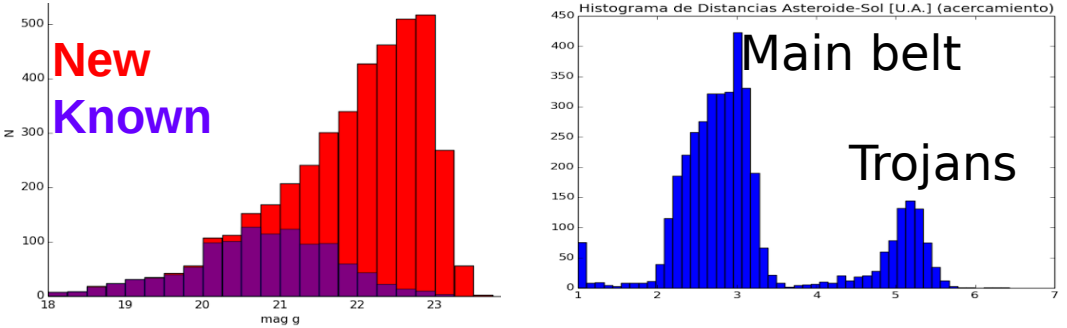
Alessandro Razza:
Combining Decam with other telescopes



Gustavo Medina:
Most distant RR Lyrae in the galaxy



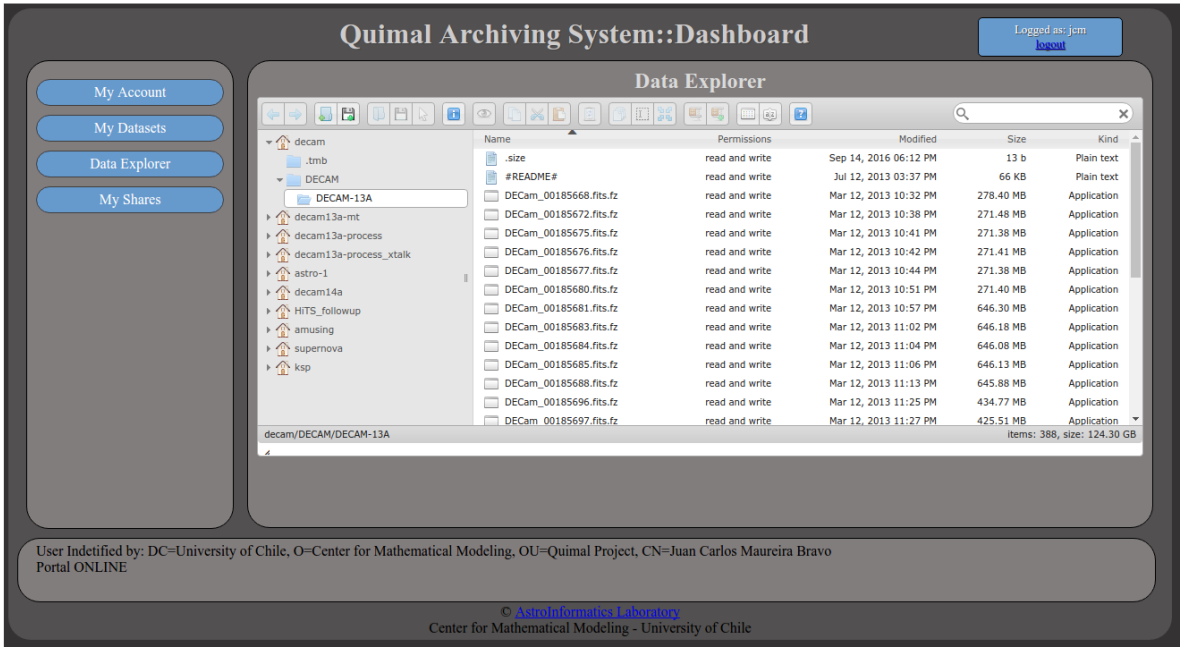
Jorge Martínez:
Classifying every transient object, astroinformatics

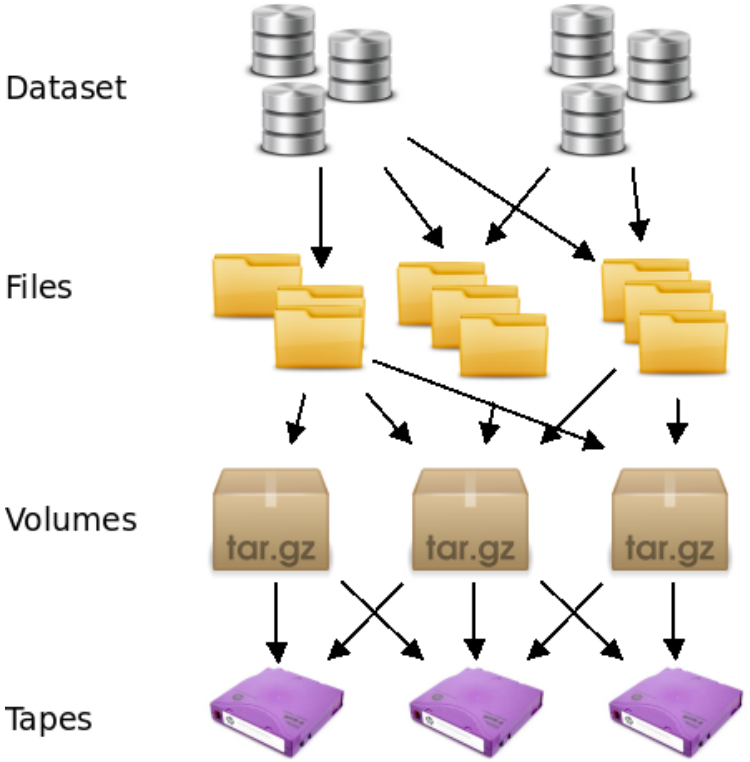


José Peña
Detecting and characterizing asteroids

Quimal archiving system

Juan Carlos Maureira





LTO6 – 2.5 TB raw, 6.25 TB 2:5:1 compression
LTFS – Linear Tape File system
PKI – Public Key Infrastructure

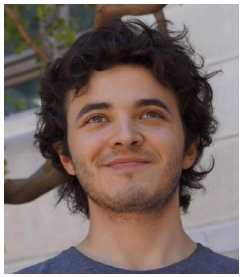
National Laboratory for High Perforamance Computing (NLHPC)

Fastest computer in Chile, 2nd in Latin America (LARTop50)
- 2640 cores (44 TFlops)
- Infiniband (FDR 56 Gbps)
- Lustre storage (DDN)

Services for:
- Academia
- Public sector
- Industry

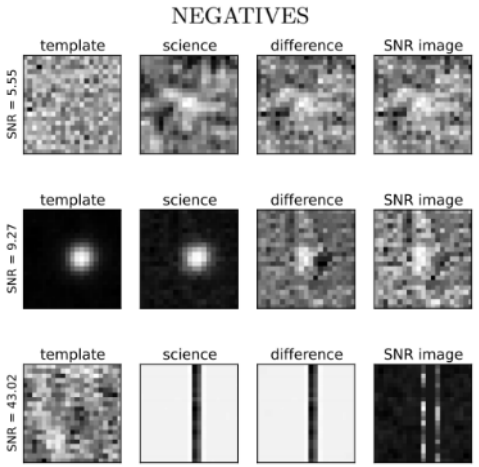
Team of HPC experts

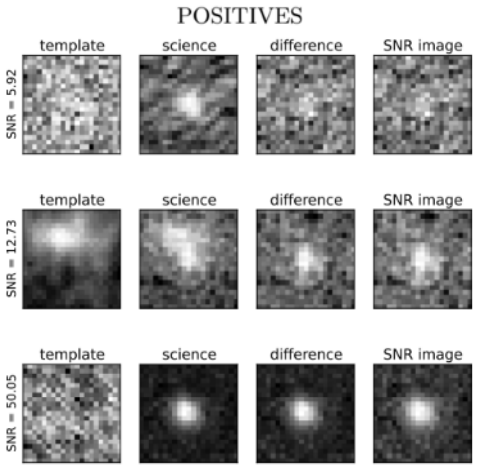
Deep learning for real bogus separation

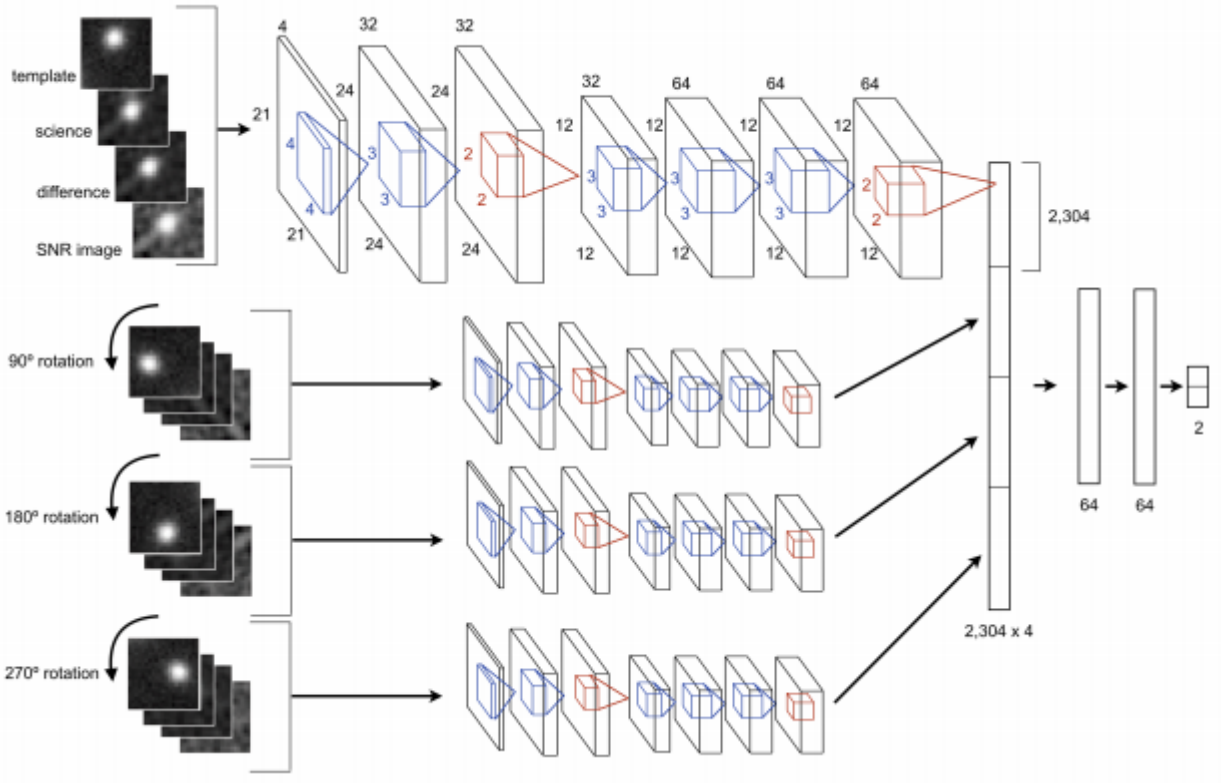


Ignacio Reyes
DIE

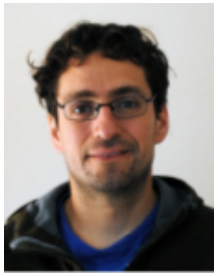
Guillermo Cabrera
CMM, U. Chile







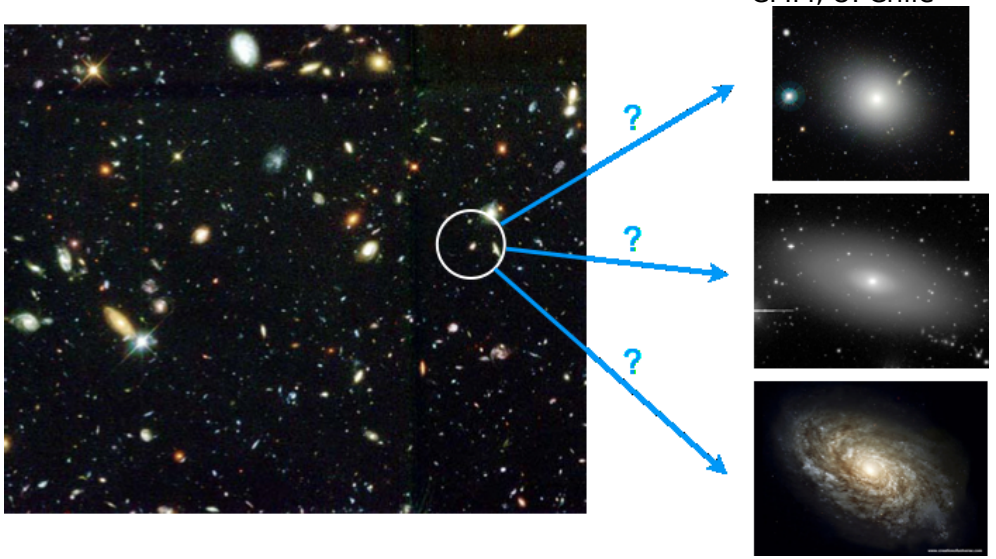
Un-biased Supervised Learning



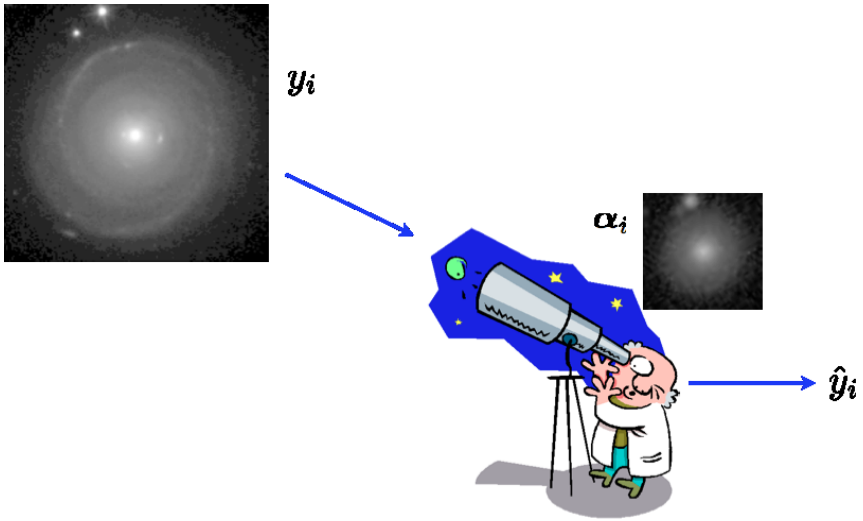
Guillermo Cabrera
CMM, U. Chile

Chris Miller
Astronomy, U. Michigan

Jeff Schneider
Robotics Institute, CMU



- Biased labels due to observable parameters
- Quantify the labeling bias.
- De-bias the labels.

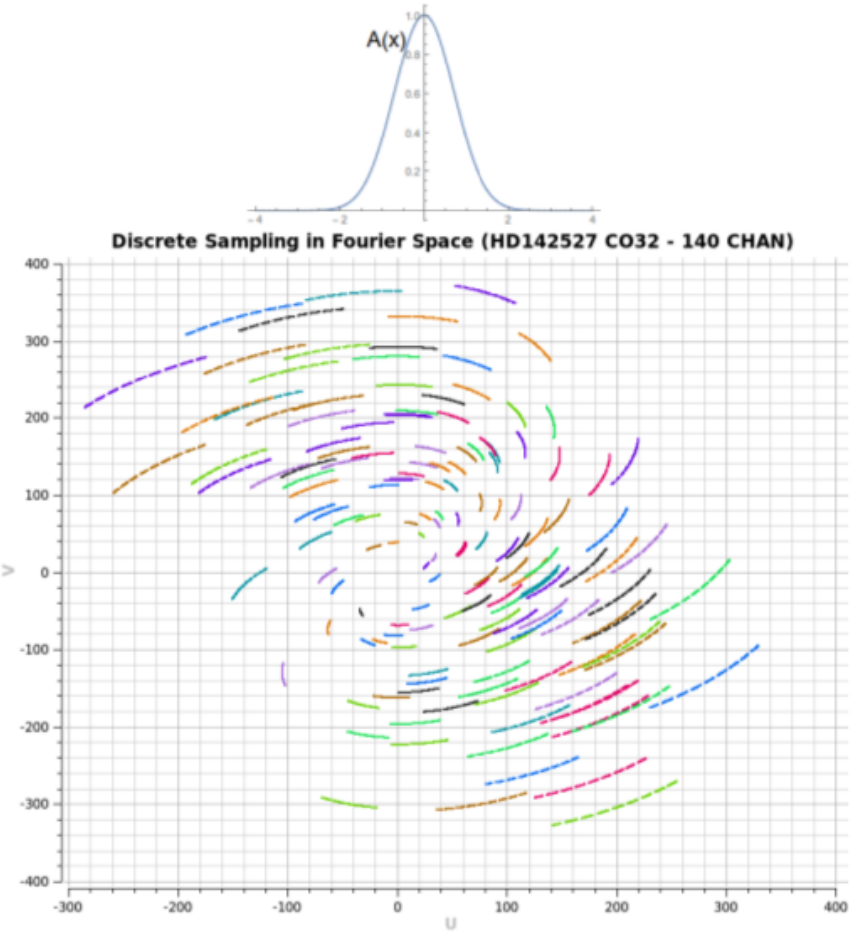


Interferometric Image Reconstruction

Pablo Román
Postdoc
Ph.D. Systems Eng.

Simón Casassus
Professor
Ph.D. Astrophysics

1. $V(u,v) = \mathcal{F}[\mathcal{A} \cdot I](u,v)$
2. V **function is a random variable**: is a Random Field.
3. **We want**: estimation for $E(I)$.
4. **We want**: estimation for $E(I^2)$.
5. **Our data**: (Simplified version)
   - Sampling points $\{z_k = (u_k, v_k)\}_{k=1}^{N}$, $N \sim 10^4 - 10^6$
   - Sampled function values at those points $\{V_k^o\}_{k=1}^{N}$
   - Variance estimation of measurement $\{\sigma_k\}_{k=1}^{N}$



Interferometric Image Reconstruction

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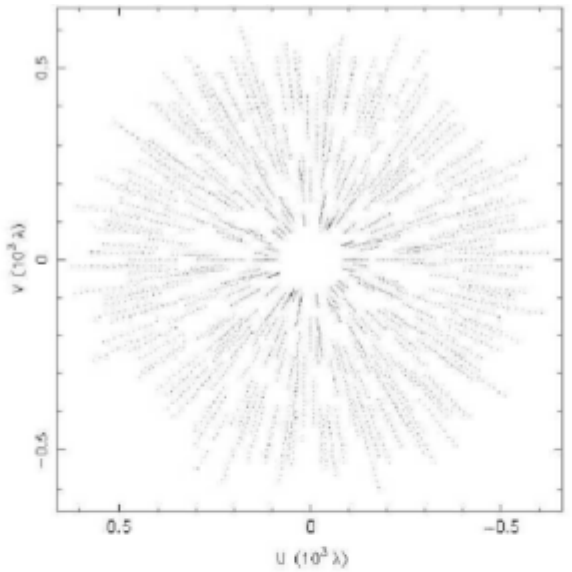
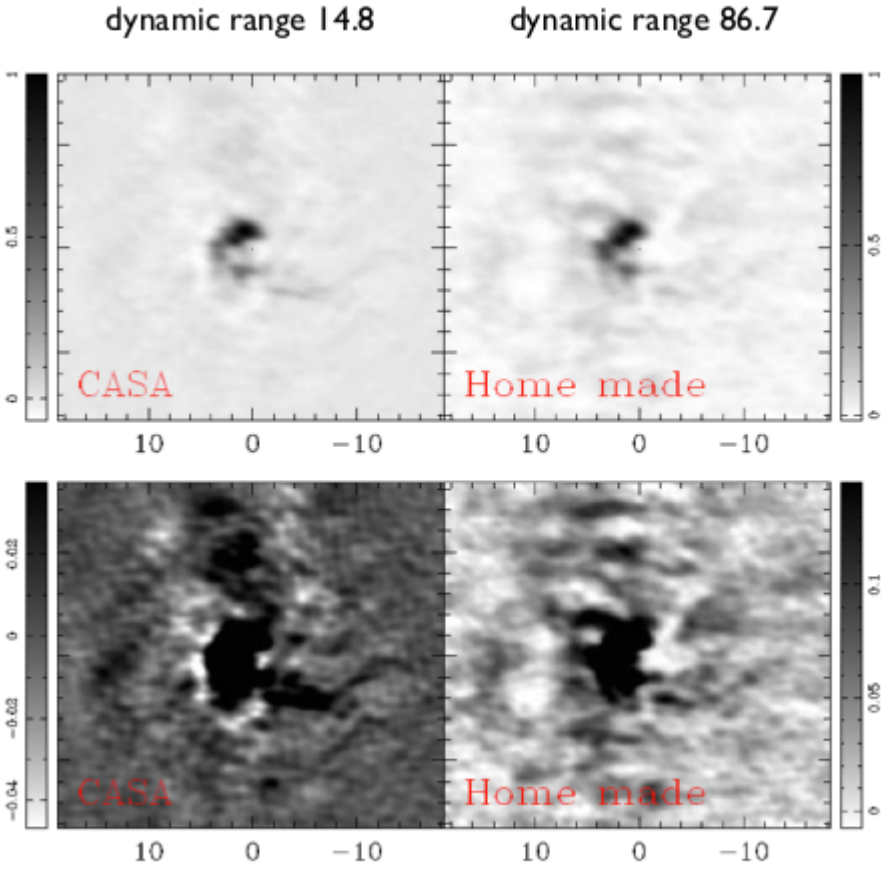


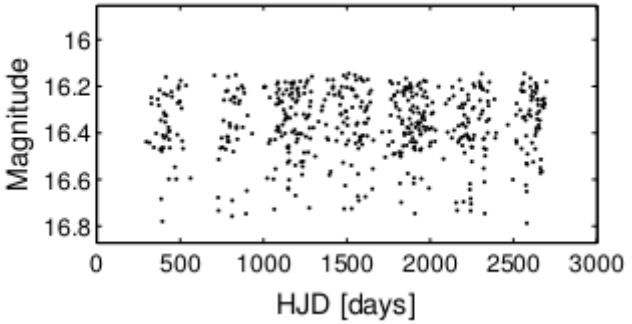


dynamic range: the ratio of the peak signal over the norm of the most negative artifact.

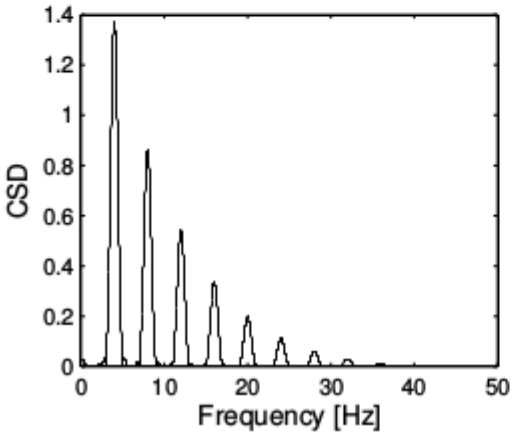
Correntropy Non-negative Matrix Factorization (NMF) Spectrum

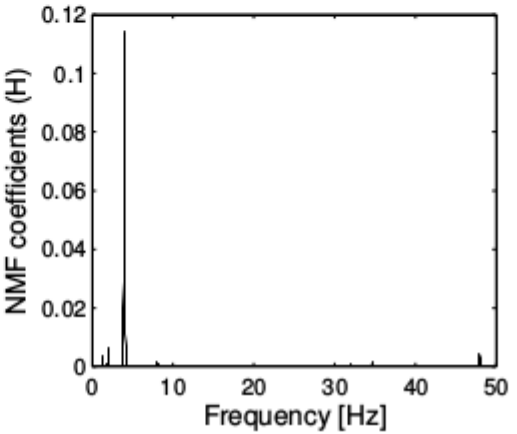
Pablo Huijse
Postdoc
Ph.D. Elec. Eng.

Pablo Estévez
Professor
Ph.D. Elec. Eng.



- Decompose correntropy into a frequency dictionary
- The NMF coefficients are the spectral ordinates of the periodogram
- Overcomplete dictionary + optimization procedure: sparse and high-res periodogram
- Adapt the kernel size of the atoms to further increase resolution





Correntropy NMF Spectrum

Pablo Huijse
Postdoc
Ph.D. Elec. Eng.

Pablo Estévez
Professor
Ph.D. Elec. Eng.

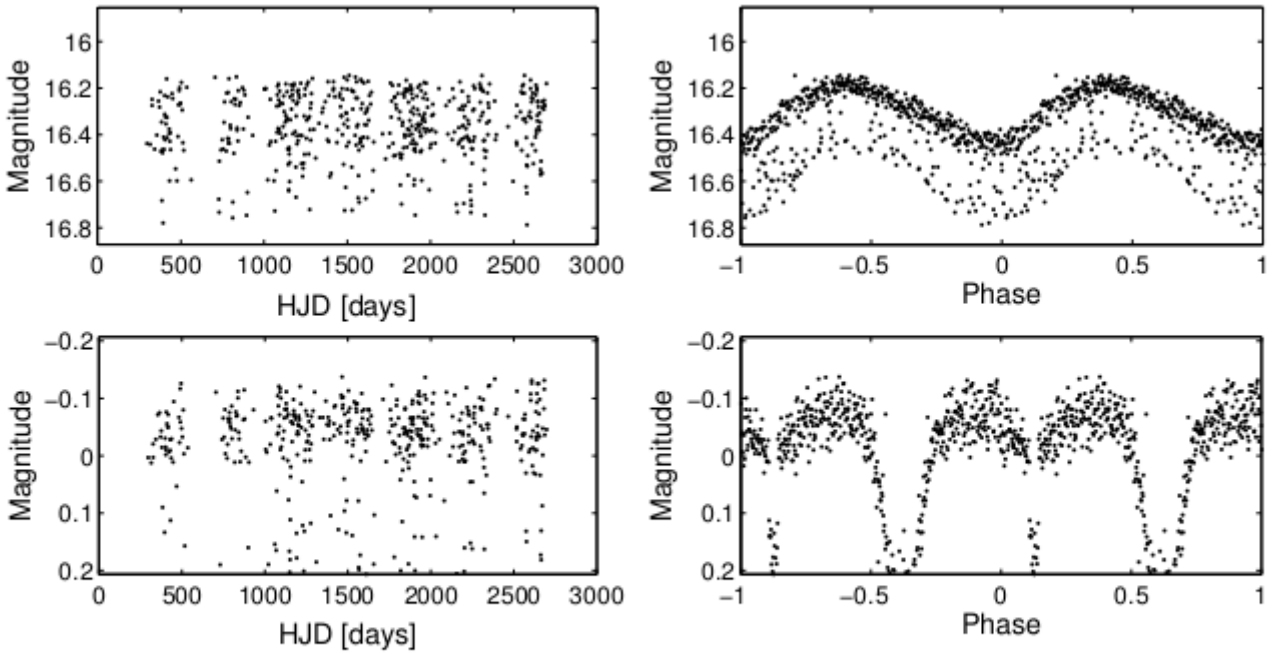
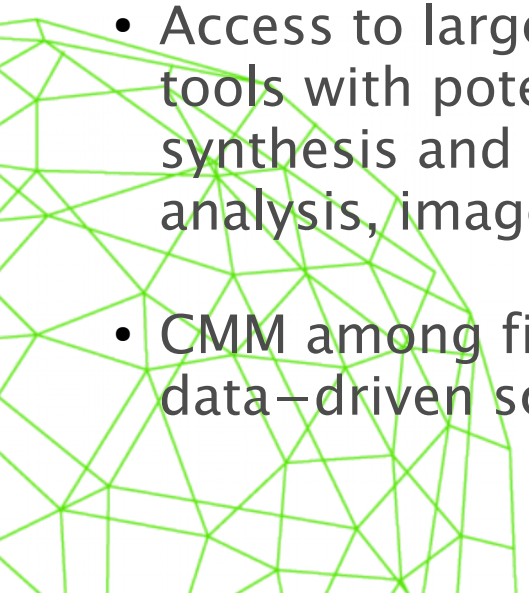


Figure: Pulsating with a 3.6 days periods plus EB with 68 days period.

The future

- Big opportunities ahead for Chilean astronomy, but bigger challenges for traditional astronomy → growth of astroinformatics
- Data−driven, interdisciplinary **teams** needed.
- Access to the National Laboratory for High Performance Computing a unique opportunity
- Astroinformatics must tackle real astrophysical questions and work closely with astronomers to be relevant
- Access to large volumes of data is a test bed for new data analysis tools with potential applications in other fields (e.g. ALMA image synthesis and medical imaging, LSST for real−time data stream analysis, image processing, machine learning)
- CMM among first truly interdisciplinary centers in the world, pioneered data−driven science in Chile. **Focus on technology transfer.**

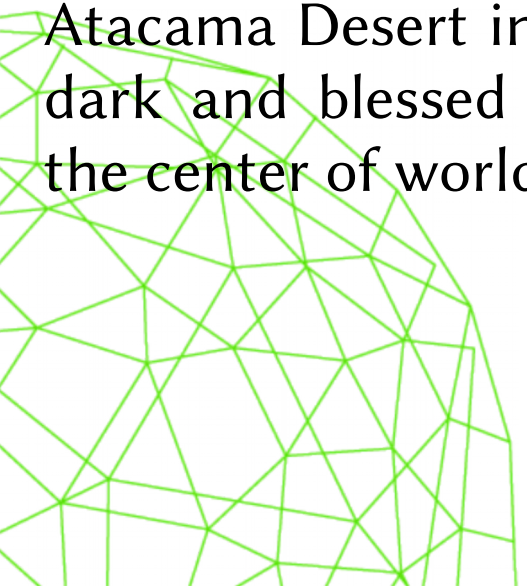


New York Times

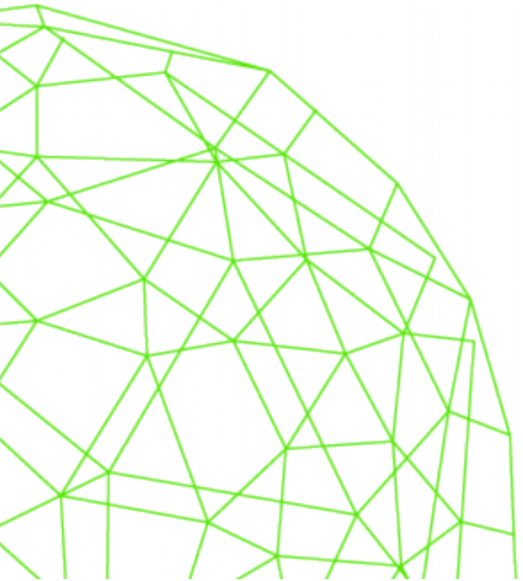
"More Eyes on the Skies", July 2014

"If it all plays out as expected and budgeted, astronomers of the 2020s will be swimming in petabytes of data streaming from space and the ground"

"The inauguration of these new telescopes, early in the next decade, will further enshrine the Atacama Desert in Chile, which is bone-dry, high, dark and blessed with remarkably steady air, as the center of world astronomy"



THANKS!



The astroinformatics Laboratory at CMM

Jaime San Martín
Professor
Ph.D. Mathematics

Eduardo Vera
Scientist
Ph.D. Physics

Guillermo Cabrera
Engineer
Ph.D. Comp. Sc.

Pablo Román
Postdoc
Ph.D. Systems Eng.

Francisco Förster
Scientist
Ph.D. Astronomy

J. Carlos Maureira
Scientist
Ph.D. Comp. Sc.

Santiago González-Gaitán
Postdoc
Ph. Astronomy

Pablo Huijse
Postdoc
Ph.D. Elec. Eng.

Pablo Estévez
Professor
Ph.D. Elec. Eng.

and many more collaborators...

CMM
Center for Mathematical Modeling

NLHPC
National Laboratory for High Performance Computing
Chile

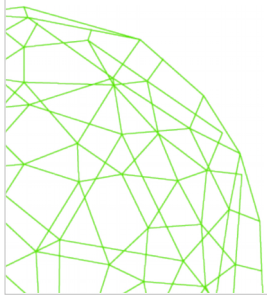
MILLENNIUM INSTITUTE OF ASTROPHYSICS

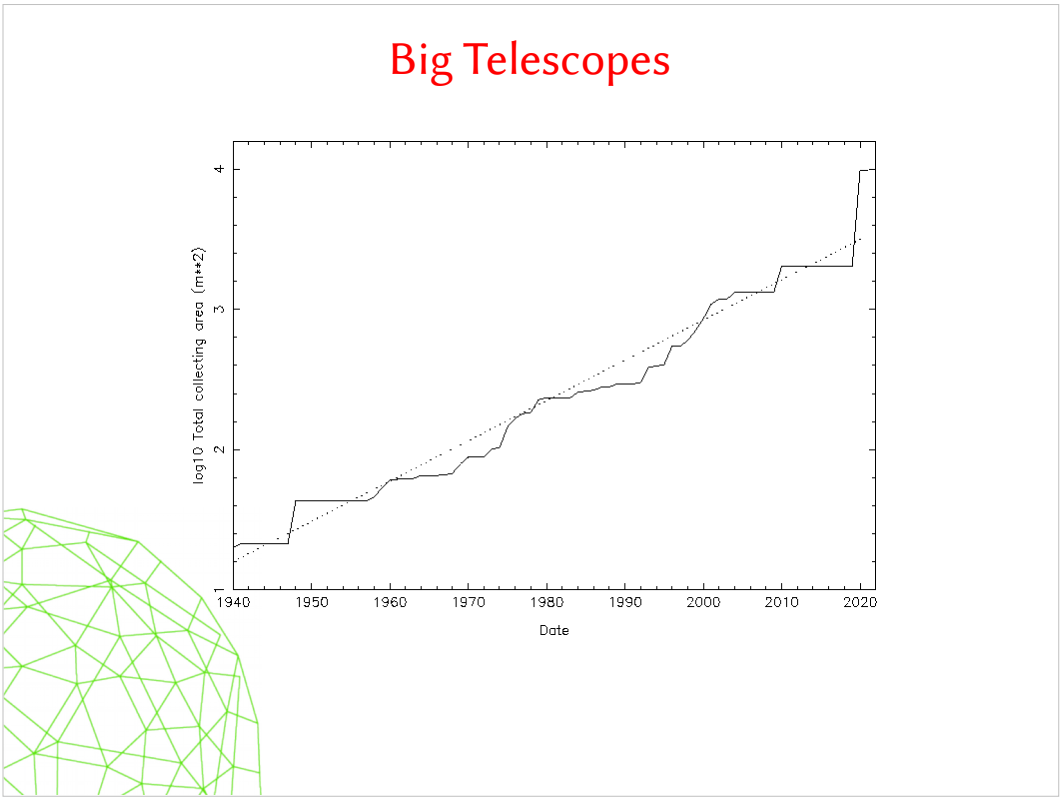
CONICYT
Ministerio de Educación
Gobierno de Chile

Astroinformatics Laboratory

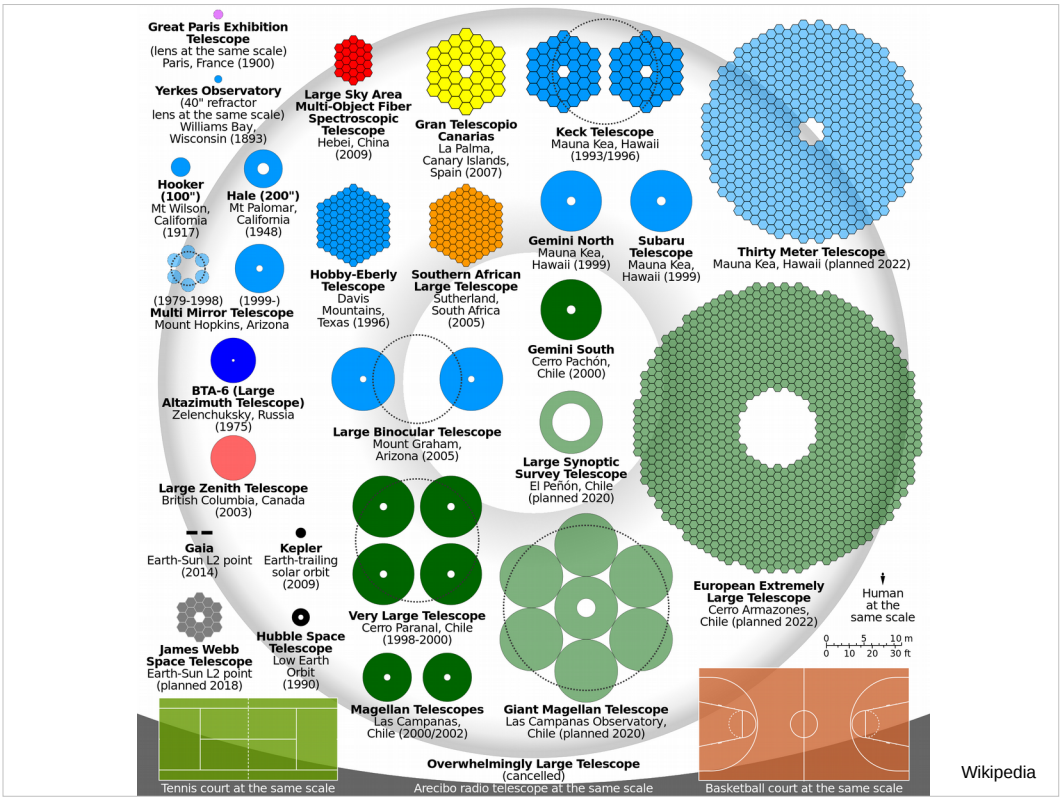
- Focus in astronomical problems that require the analysis of **large volumes of data.**
- Efficient algorithms, statistics, data handling methods, visualization, inverse problems, image processing, machine learning, high performance computing.
- **Interdisciplinary** focus gives **flexibility** to move into new developing areas of astronomy.
- Focus on **data−driven** and well defined problems.
- e.g. real−time, high−cadence survey for transient objects (**DECam**); automatic classification of galaxies (**LSST**), characterization of light curves (**DECam**, **LSST**) and image synthesis in interferometric observations (**ALMA**).

Astronomy in the next decade:
Big Data & Big Telescopes

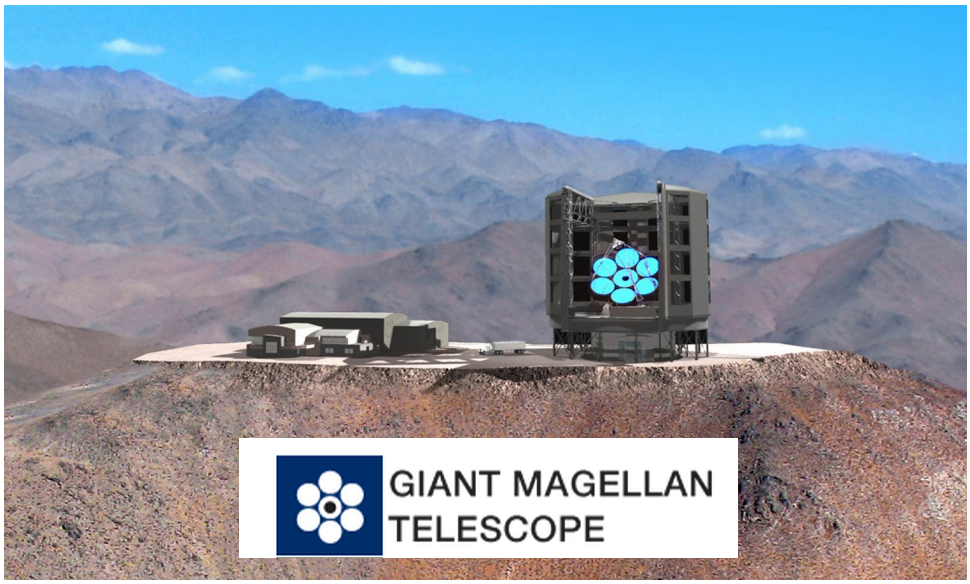


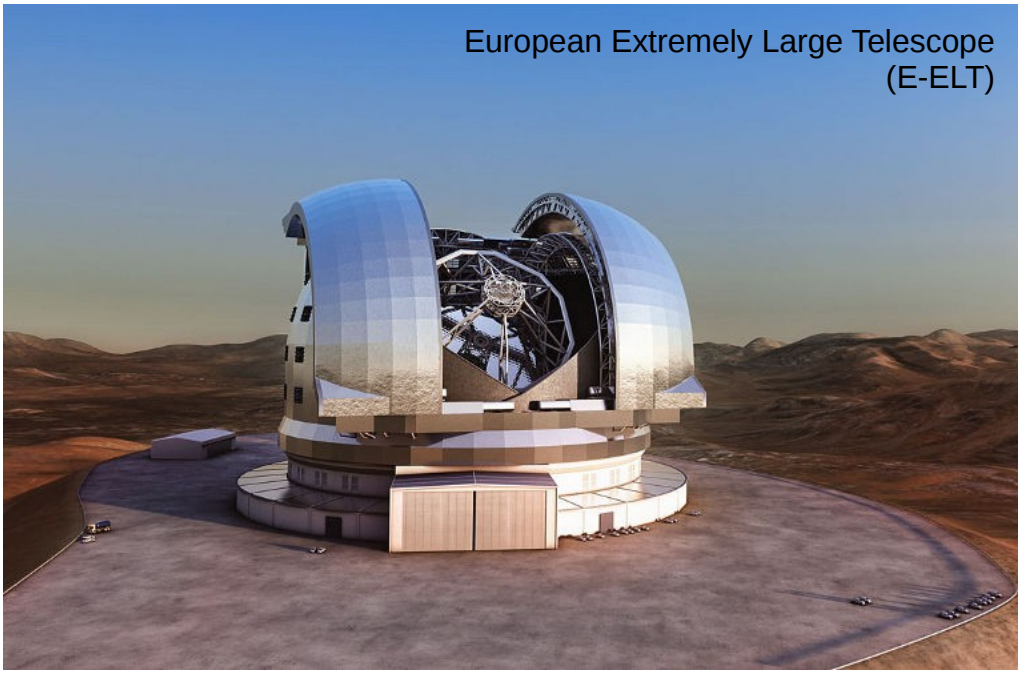


1era revolución en astronomía: evolución exponencial del área colectora de los telescopios

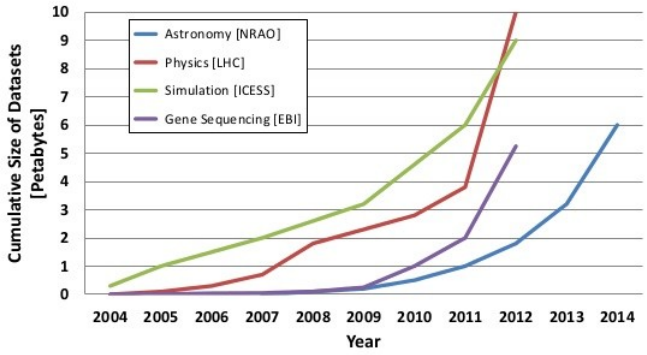


Tamaños de telescopios. En verde son telescopios instalados o a instalarse (verde claro) en Chile.


GIANT MAGELLAN
TELESCOPE


European Extremely Large Telescope
(E-ELT)

Big Data in astronomy



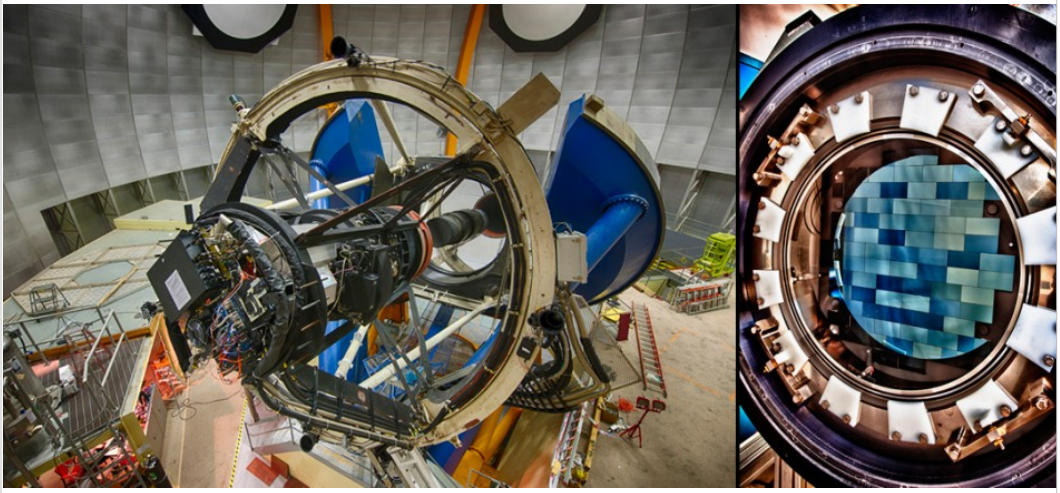
Scientific Data Grows Exponentially!

3

Thomas Heinis, Human Brain Project

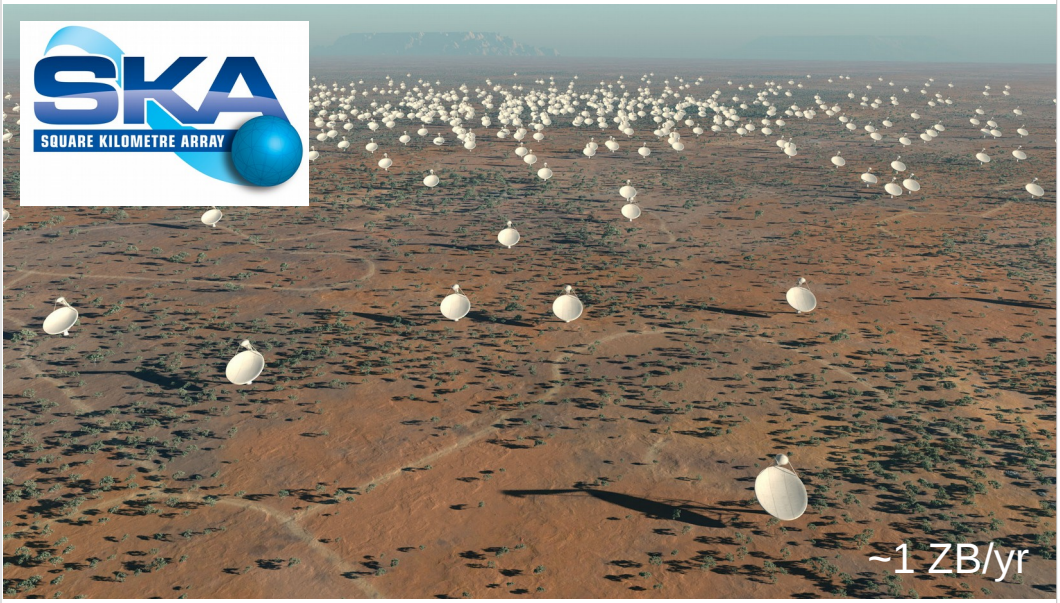

ALMA
~0.2 PB/yr

Dark Energy Camera (DECam)



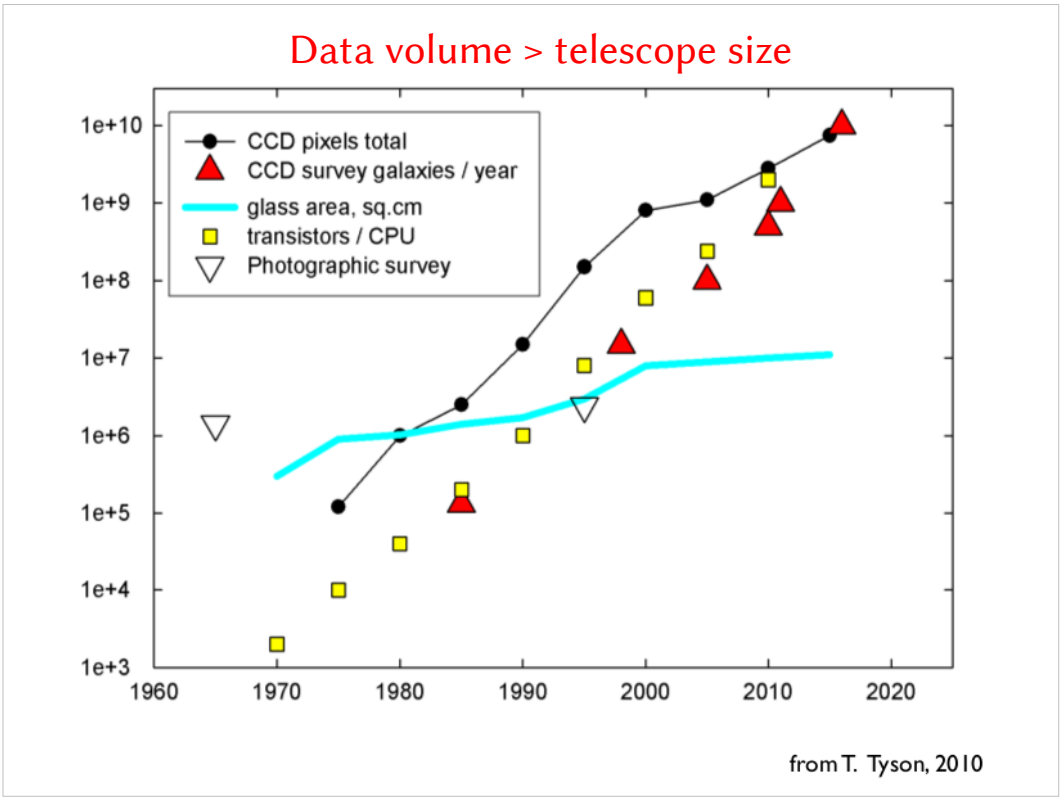
~0.4 PB/yr


LSST
Large Synoptic Survey Telescope
~5 PB/yr

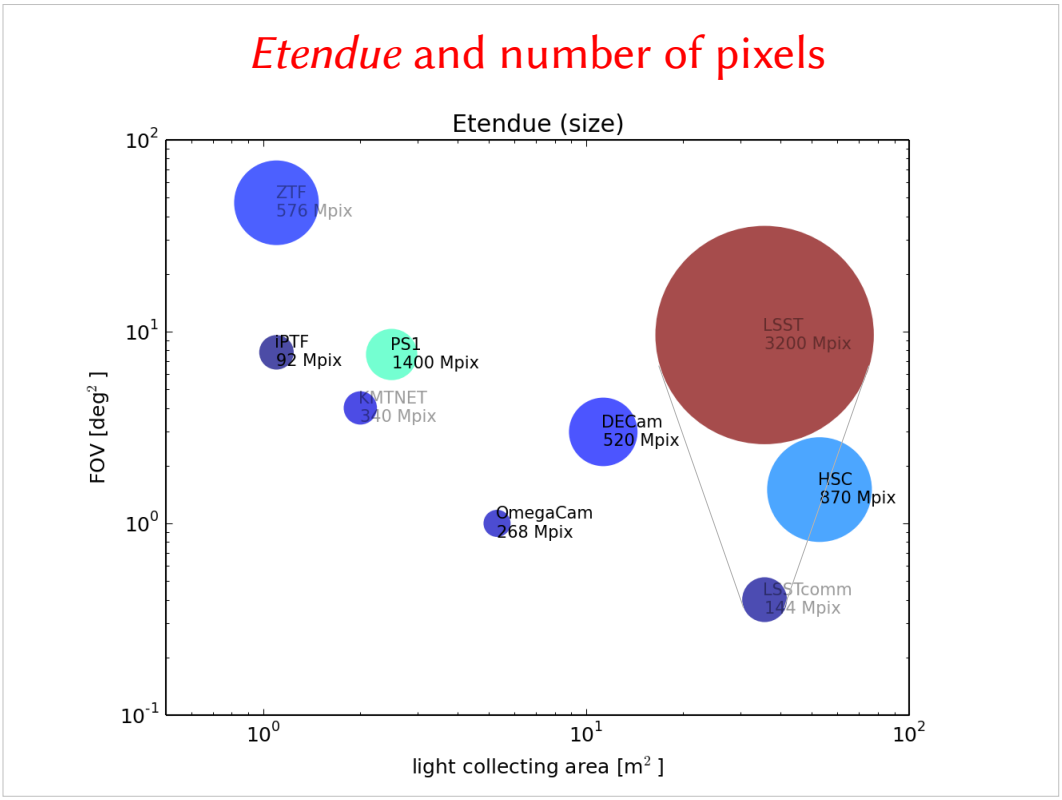


1 Zettabyte = 10^3 ExaBytes = 10^6 PB

El problema de cómo almacenar los datos de SKA no está resuelto. Hacerlo en la nube es muy caro, la solución probablemente sea distribuida



2da revolución en astronomía: ley de Moore se ve reflejada en el número de galaxias observadas



Área en el cielo vs área del espejo primario de diferentes telescopios. Producto de ambos se conoce como etendue y da cuenta de la capacidad de observar un mayor volumen del universo en una sola toma.

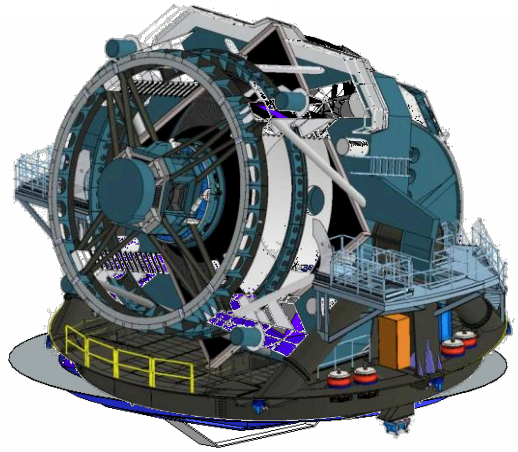
The large Synoptic Survey Telescope (LSST)

Time domain science
- Nova, supernova, GRBs
- Source characterization
- Instantaneous discovery

Census of the Solar System
- NEOs, MBAs, Comets
- KBOs, Oort Cloud

Mapping the Milky Way
- Tidal streams
- Galactic structure

Dark energy and dark matter
- Strong Lensing
- Weak Lensing
- Constraining the nature of dark energy



The large Synoptic Survey Telescope (LSST)

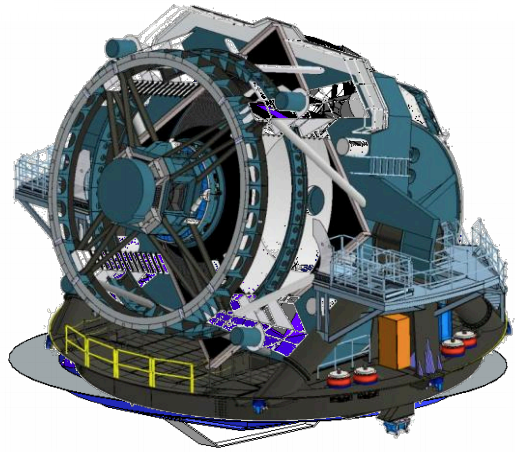
Traditional scientists

What data should I collect to test an hypothesis?

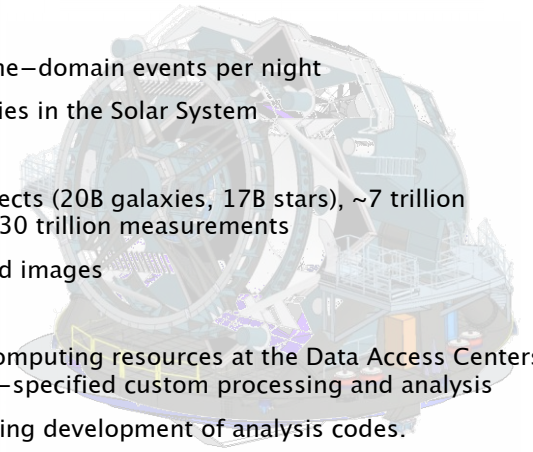
Data–driven scientist

What theories can I test given the data I already have?

Success in research will depend on the ability to mine knowledge from data.

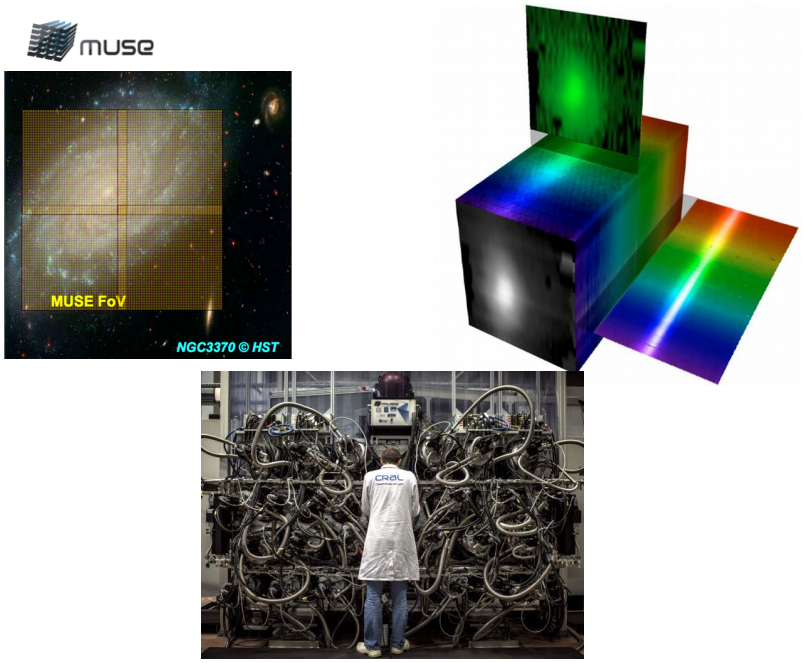


The large Synoptic Survey Telescope (LSST)



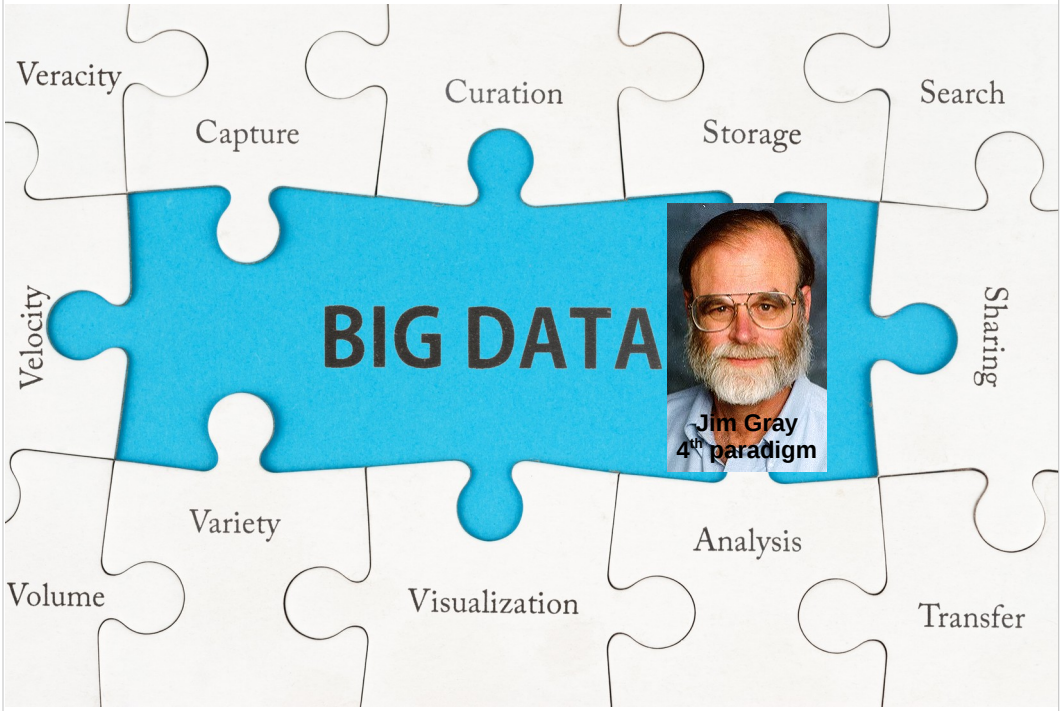
LEVEL 1: Nightly alerts	~10 million time−domain events per night ~6 million bodies in the Solar System
LEVEL 2: Yearly data releases	~37 billion objects (20B galaxies, 17B stars), ~7 trillion sources, and ~30 trillion measurements Deep co−added images
LEVEL 3: Community projects	Services and computing resources at the Data Access Centers to enable user−specified custom processing and analysis Software enabling development of analysis codes.

Integral Field Units, e.g. Multi-Unit Spectroscopic Explorer (MUSE)



MUSE es un intergral field unit telescope, que produce cubos de datos de 10 mil espectros en el óptico con excelente resoluciónn espectral y espacial

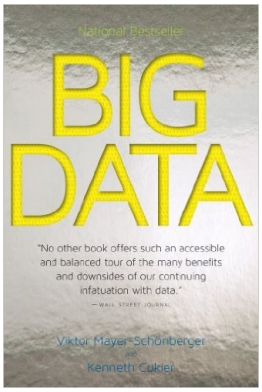
Internet submarine cables


Veracity
Capture
Curation
Storage
Search
Velocity
BIG DATA
Sharing
Jim Gray
4th paradigm
Variety
Analysis
Volume
Visualization
Transfer

Big data

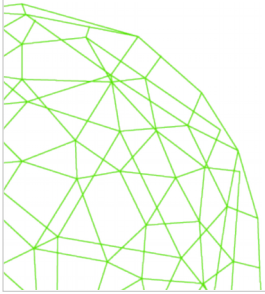
"Big Data is all about seeing and understanding the relations within and among pieces of information..."

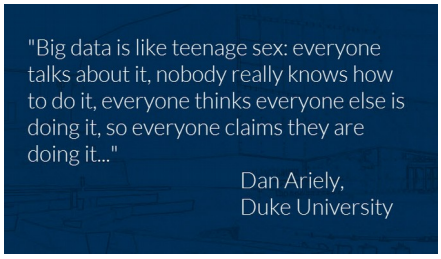
"It is about three major shifts of mindset … the ability to analyze **vast amounts of data** about a topic … willingness to embrace **data's real−world messiness** … growing respect for **correlations** rather than a continuous quest for elusive **causality**."



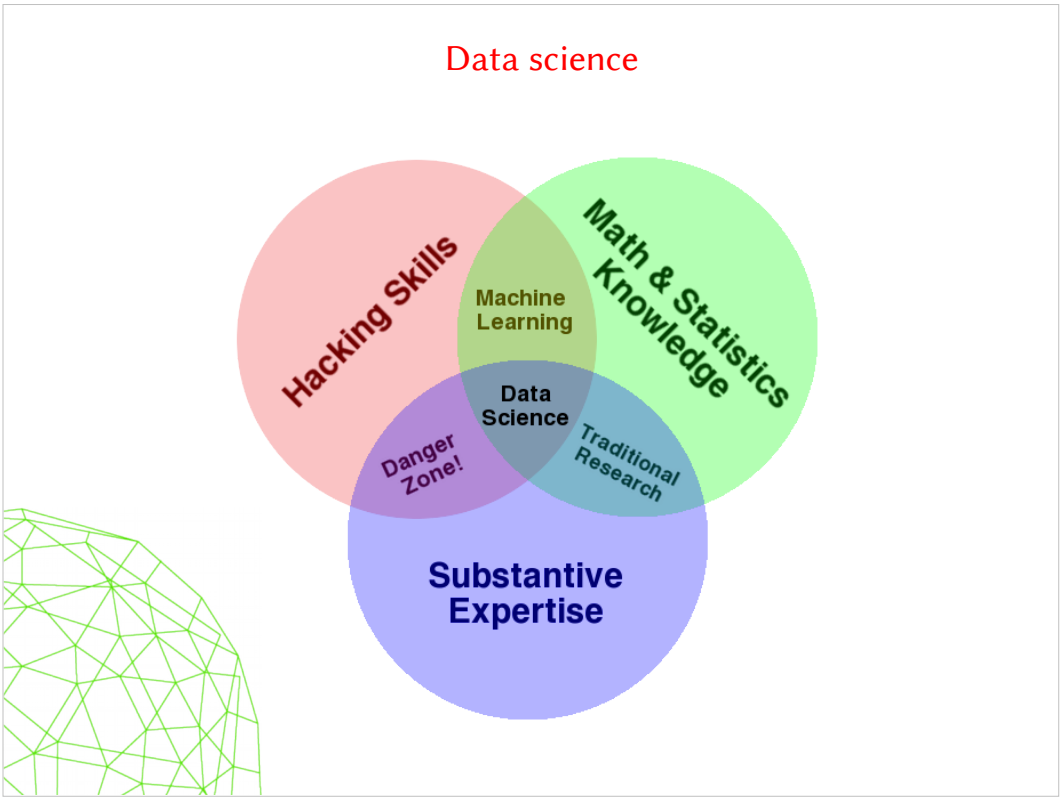
"Simple models and a lot of data trump over more elaborate models on less data"

Peter Norvig, Google artificial intelligence.





Data science



Harvard Business Review
2012

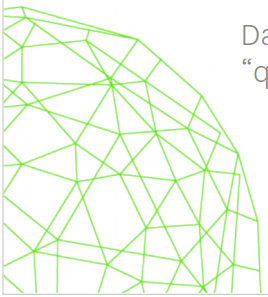
DATA

Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil

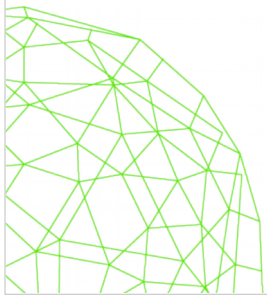
FROM THE OCTOBER 2012 ISSUE

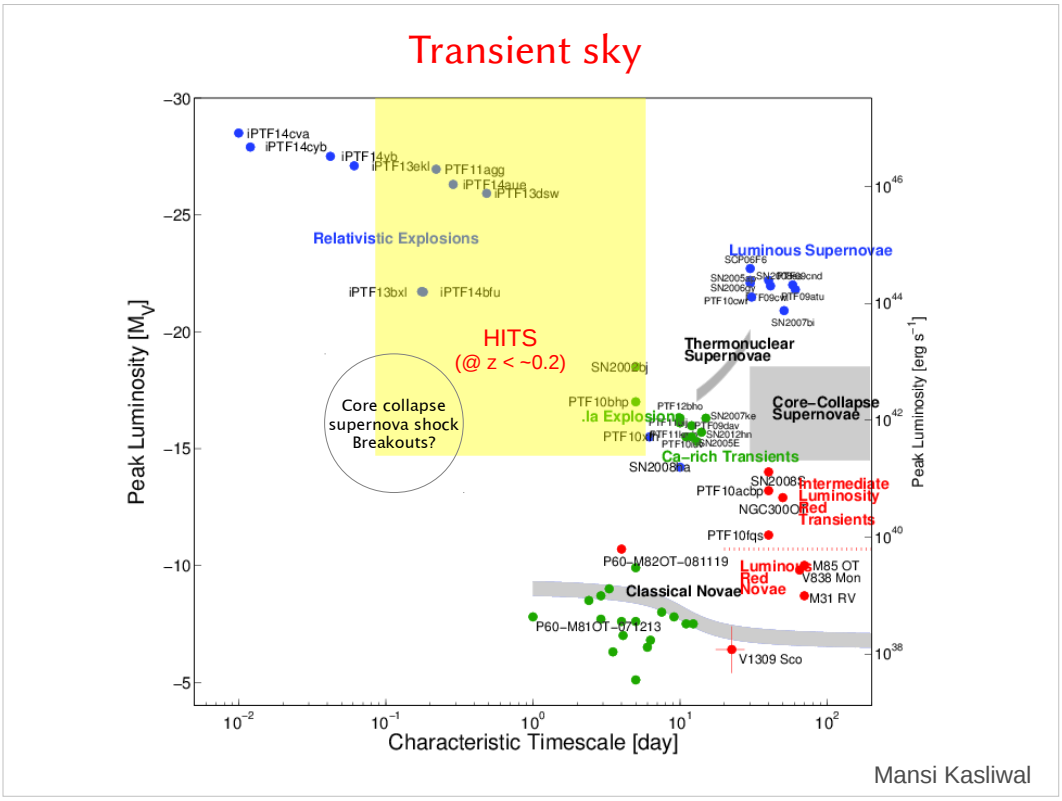
The shortage of data scientists is becoming a serious constraint in some sectors.



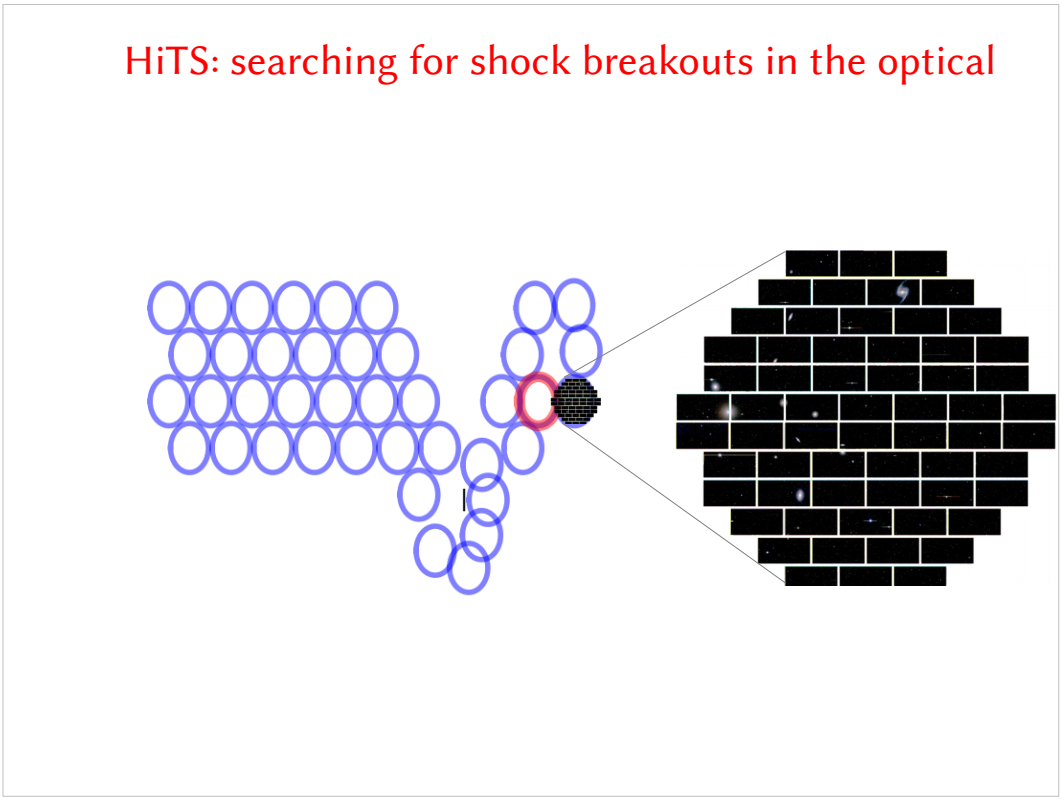
Data scientists today are akin to the Wall Street "quants" of the 1980s and 1990s.

Astroinformatics Laboratory Projects

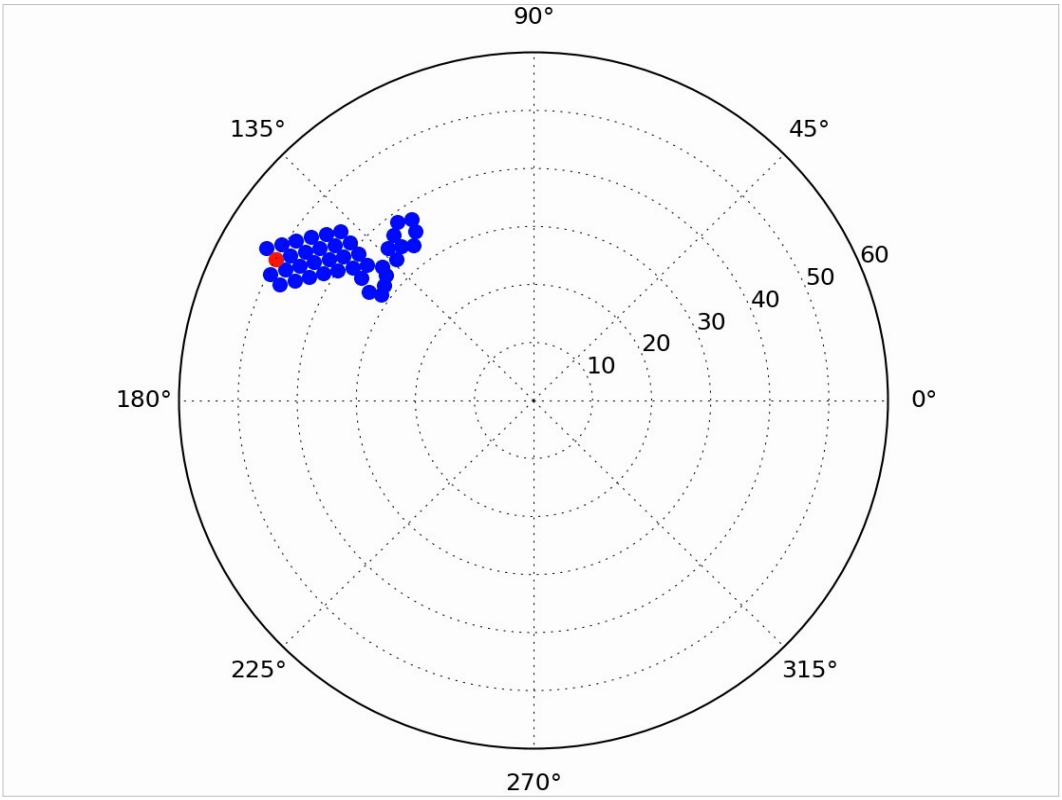




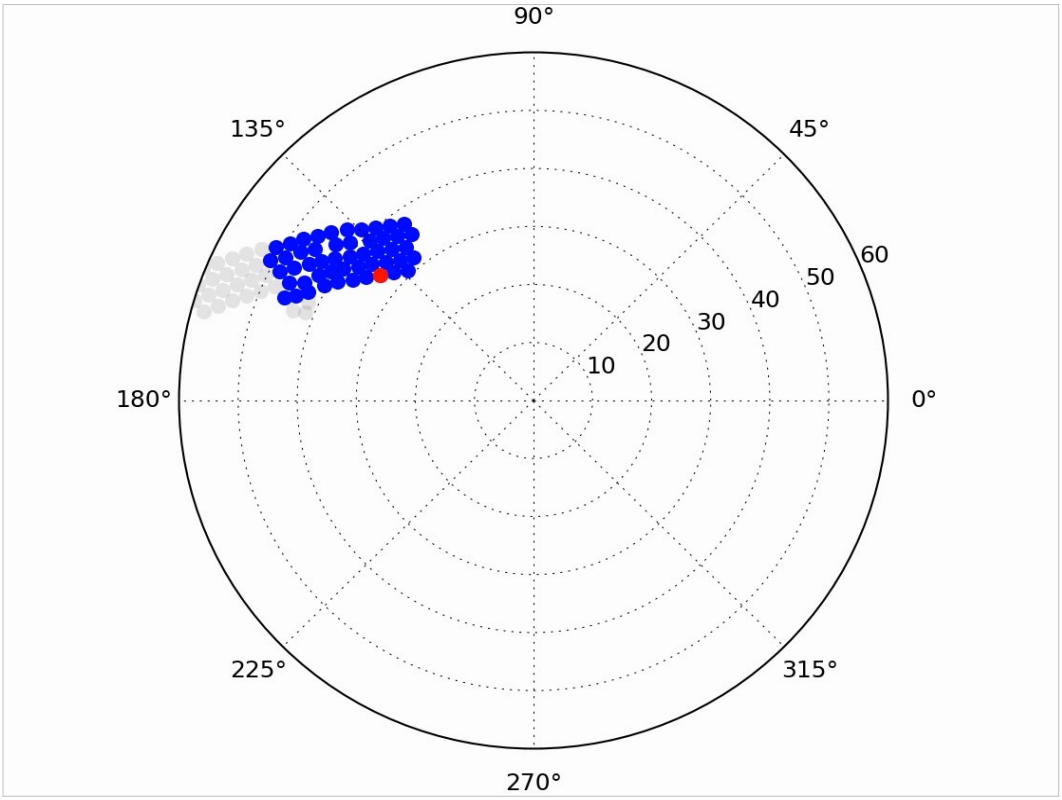
Brillo absoluto vs escala de tiempo característica de diferentes clases de transientes. Región de arriba a la izquierda corresponde a afterglows ópticos de gamma ray bursts (formación de agujeros negros), región de abajo a la derecha corresponde a explosiones estelares de la mayoría de la estrella (supernovas) o parciales (novas). Región de abajo a la izquierda del diagrama está despoblada por la dificultad técnica de las observaciones y es la zona que queremos estudiar con HiTS.



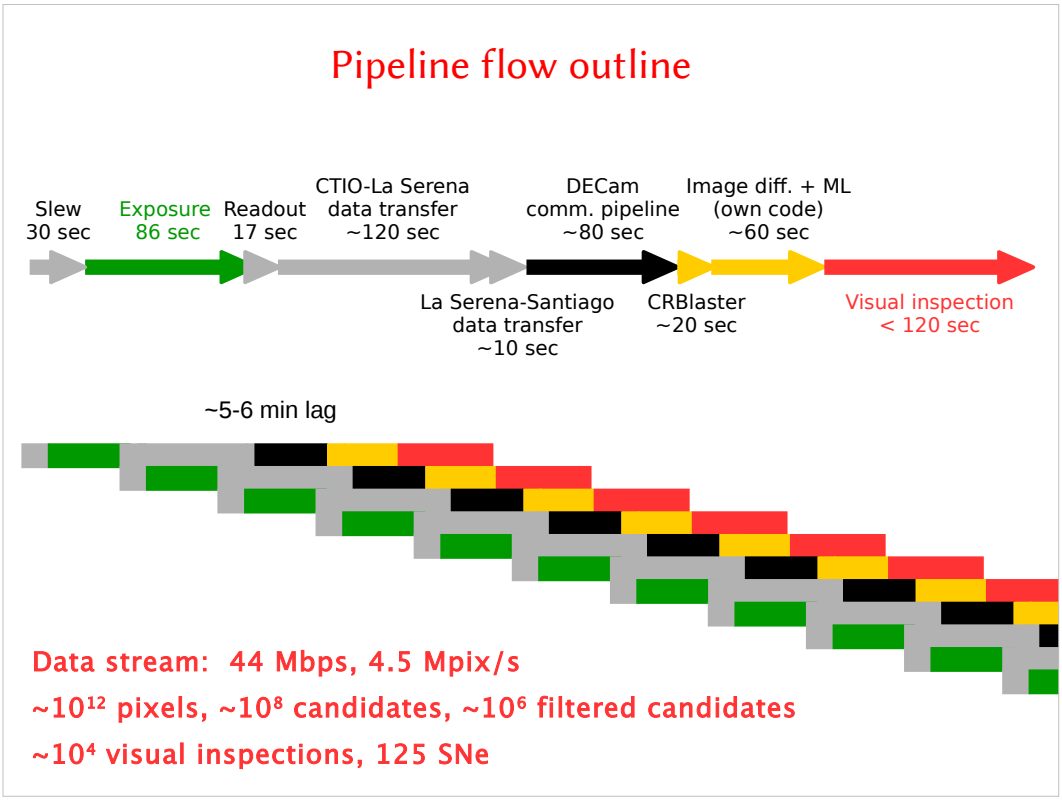
Mapa de la zona del cielo estudiada por HiTS. Cada región es observada con un pointing de DECam y contiene 520 Mpix. Cada observación toma aprox. 1.5 min. Se vuelve a la misma región 5 veces por noche.



Movimiento aparente de los campos debido a la rotación de la Tierra (de izquierda a derecha). La idea es que el telescopio permanezca en aprox. la misma posición en relación al horizonte local en cada una de las 5 épocas, i.e. que el telescopio no se mueva en cada época, sino que dejar que el cielo se mueva. Esto minimiza tiempos de movimiento del telescopio.



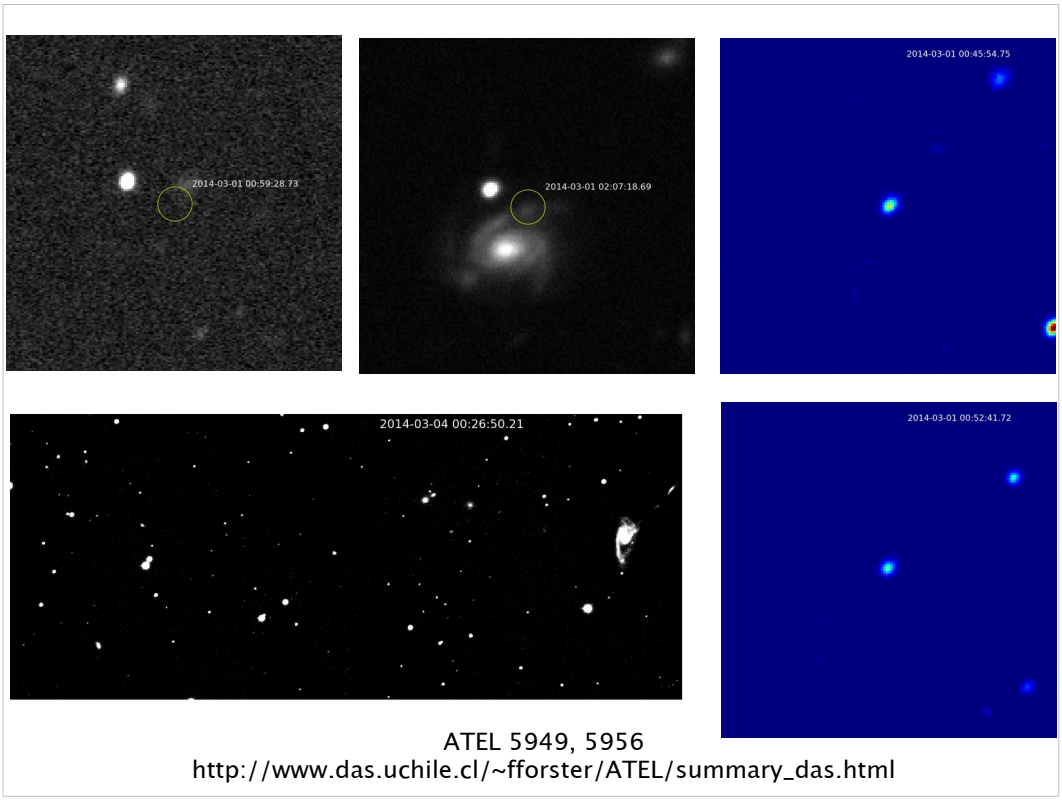
Igual que en slide anterior



Estructura de la pipeline

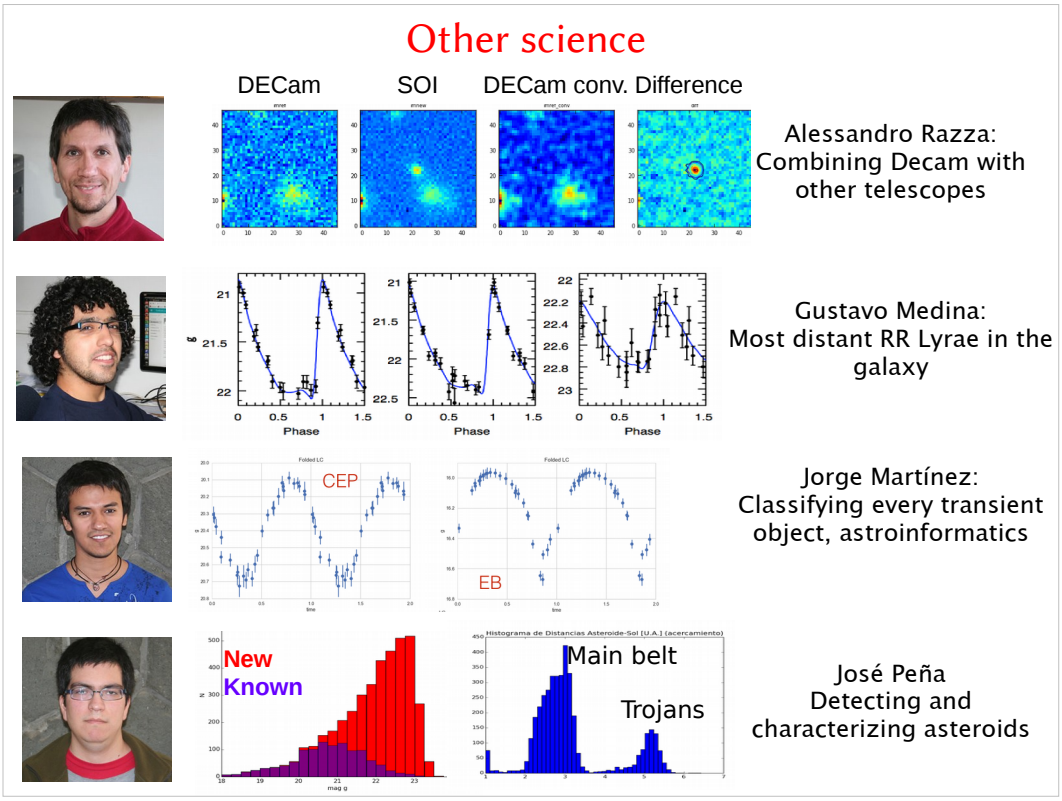
1. movimiento del telescopio (30 s)
2. tiempo de exposición (86 s)
3. tiempo de lectura (17 s)
4. transferencia por antena microondas (120 s)
5. transferencia por fibra óptica (10 s)
6. Preprocesamiento de datos en NLHPC (80 s)
7. Remoción de rayos cósmicos en NLHPC (20 s)
8. Algoritmo de alineación, convolución, diferencia, fotometría y filtrado vía señal a ruido y machine learning (nuestro algoritmo) en NLHPC (60 s)
9. Inspección visual

1e12 pix → 1e8 cand → 1e6 cand. ML → 1e4 cand repetidos en la misma posición (insp. Visual) → 125 SNe



ATEL 5949, 5956
http://www.das.uchile.cl/~fforster/ATEL/summary_das.html

Ejemplos de arriba a la izquierda en dirección de punnteros del reloj: supernova, supernova, estrella eclipsante, estrella pulsante RR Lyrae, asteroide

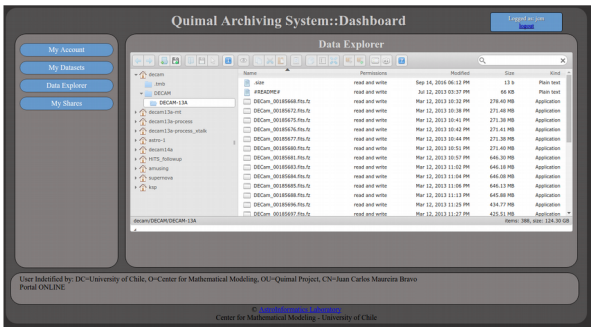


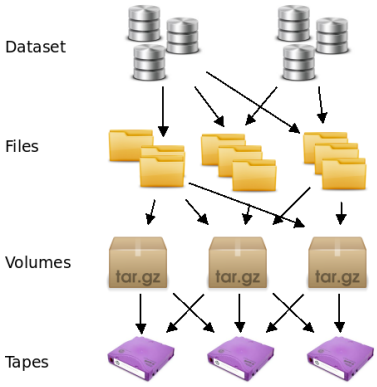
Ciencia relacionada:

1. combinación de datos DECam y otros telescopios
2. Estudio de RR Lyrae en las regiones externas de nuestra galaxia. Permite medir distancias y medir perfil de densidad de la galaxia, medir distancias a galaxias más cercanas
3. Clasificación de todas las estrellas variables usando machine learning
4. Descubrimiento y caracterización de miles de nuevos asteroides en el cinturón de asteroides y telescopios trojanos en la órbita de Júpiter

Quimal archiving system

Juan Carlos Maureira





LTO6 – 2.5 TB raw, 6.25 TB 2:5:1 compression
LTFS – Linear Tape File system
PKI – Public Key Infrastructure

Sistema jerárquico de almacenamiento basado en robot de cintas y discos duros con partes móviles y de estado sólido

National Laboratory for High Performamance Computing (NLHPC)

Fastest computer in Chile, 2nd in Latin America (LARTop50)
- 2640 cores (44 TFlops)
- Infiniband (FDR 56 Gbps)
- Lustre storage (DDN)

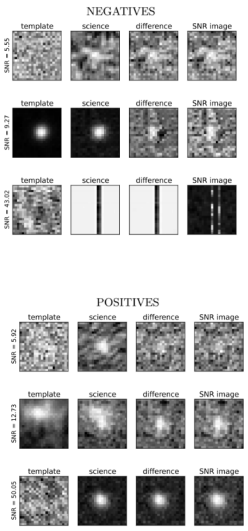
Services for:
- Academia
- Public sector
- Industry

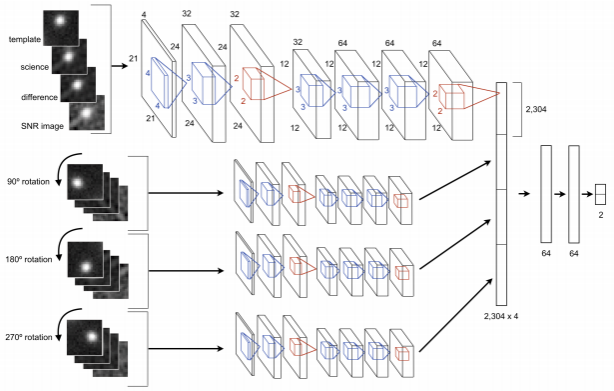
Team of HPC experts

Deep learning for real bogus separation


Ignacio Reyes
DIE


Guillermo Cabrera
CMM, U. Chile





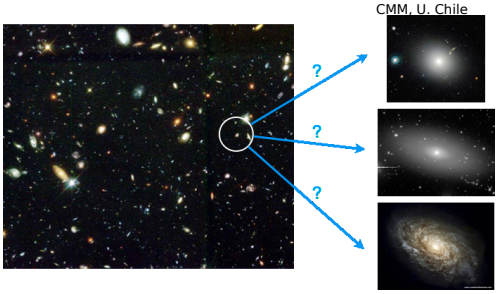
Red neuronal convolucional profunda usada para clasificar candidatos reales vs falsos. Al entrenar esta red se definen automáticamente los features que diseñamos manualmente en una primera iteración usando random forest classifiers. La gran ventaja de esta red es que es más sensible en bajas señales a ruido, donde un humano no es capaz de desarrollar features apropiados para una buena clasificación.

Un-biased Supervised Learning

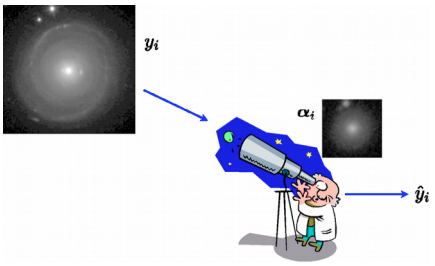

Guillermo Cabrera
CMM, U. Chile


Chris Miller
Astronomy, U. Michigan


Jeff Schneider
Robotics Institute, CMU



- Biased labels due to observable parameters
- Quantify the labeling bias.
- De-bias the labels.



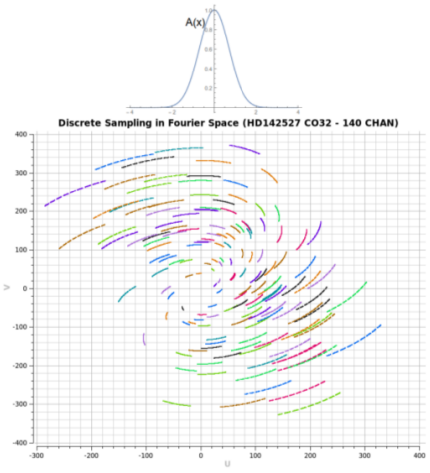
Estudio de bias en los set de entrenamiento y método para corregirlo.

Interferometric Image Reconstruction

Pablo Román
Postdoc
Ph.D. Systems Eng.

Simón Casassus
Professor
Ph.D. Astrophysics

1. $V(u,v) = \mathcal{F}[\mathcal{A} \cdot I](u,v)$
2. V **function is a random variable**: is a Random Field.
3. **We want**: estimation for $E(I)$.
4. **We want**: estimation for $E(I^2)$.
5. **Our data**: (Simplified version)
   - Sampling points $\{z_k = (u_k, v_k)\}_{k=1}^N$, $N \sim 10^4 - 10^6$
   - Sampled function values at those points $\{V_k^o\}_{k=1}^N$
   - Variance estimation of measurement $\{\sigma_k\}_{k=1}^N$



Síntesis de imágenes de ALMA usando maximum entropy algorithms

Interferometric Image Reconstruction

Pablo Román
Postdoc
Ph.D. Systems Eng.

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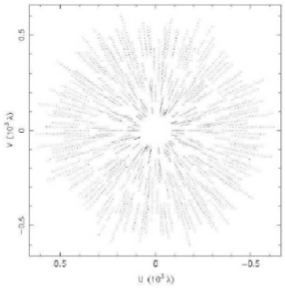
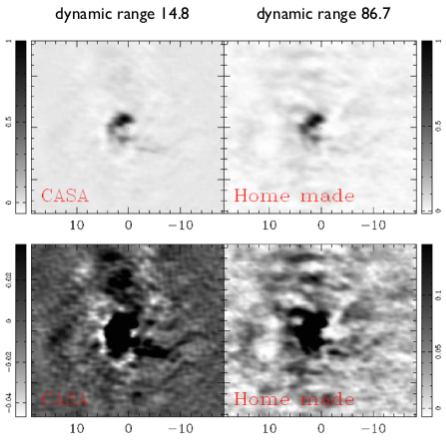
Professor
Ph.D. Astrophysics





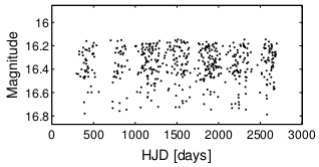
dynamic range: the ratio of the peak signal over the norm of the most negative artifact.

Lo mismo que slide anterior, notar mayor rango dinámico en imágenes usando máxima entropía

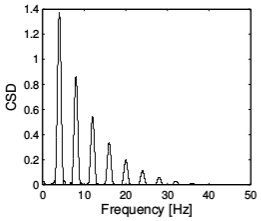
Correntropy Non-negative Matrix Factorization (NMF) Spectrum

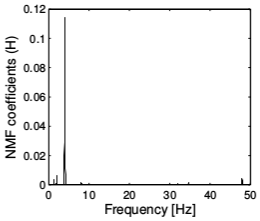
Pablo Huijse
Postdoc
Ph.D. Elec. Eng.

Pablo Estévez
Professor
Ph.D. Elec. Eng.



- Decompose correntropy into a frequency dictionary
- The NMF coefficients are the spectral ordinates of the periodogram
- Overcomplete dictionary + optimization procedure: sparse and high-res periodogram
- Adapt the kernel size of the atoms to further increase resolution





Método para detectar períodos usando non negative matrix factorization como regularizador de espectro de potencia de períodos.

Correntropy NMF Spectrum

Pablo Huijse
Postdoc
Ph.D. Elec. Eng.

Pablo Estévez
Professor
Ph.D. Elec. Eng.

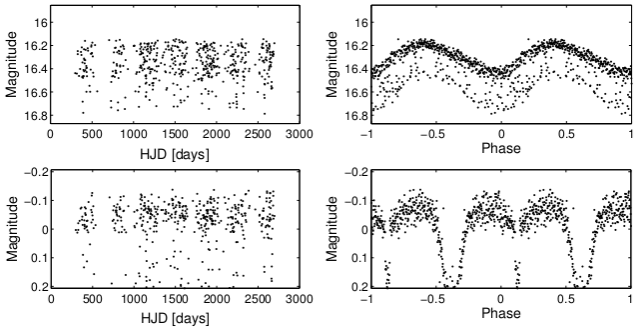
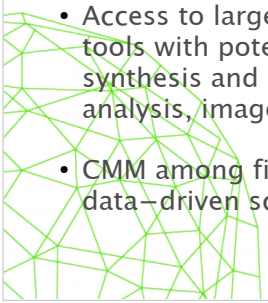


Figure: Pulsating with a 3.6 days periods plus EB with 68 days period.

Igual que slide anterior

The future

- Big opportunities ahead for Chilean astronomy, but bigger challenges for traditional astronomy → growth of astroinformatics
- Data−driven, interdisciplinary **teams** needed.
- Access to the National Laboratory for High Performance Computing a unique opportunity
- Astroinformatics must tackle real astrophysical questions and work closely with astronomers to be relevant
- Access to large volumes of data is a test bed for new data analysis tools with potential applications in other fields (e.g. ALMA image synthesis and medical imaging, LSST for real−time data stream analysis, image processing, machine learning)
- CMM among first truly interdisciplinary centers in the world, pioneered data−driven science in Chile. **Focus on technology transfer.**



New York Times

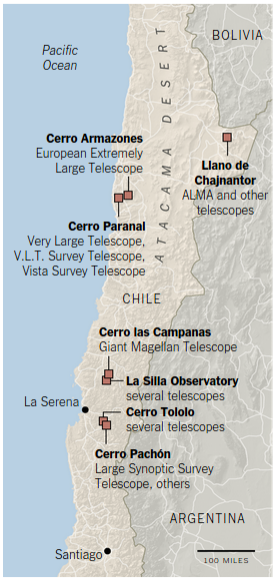
"More Eyes on the Skies", July 2014

"If it all plays out as expected and budgeted, astronomers of the 2020s will be swimming in petabytes of data streaming from space and the ground"

"The inauguration of these new telescopes, early in the next decade, will further enshrine the Atacama Desert in Chile, which is bone-dry, high, dark and blessed with remarkably steady air, as the center of world astronomy"

Looking Up

Northern Chile is dry and high, with little light pollution. The area already bristles with telescopes, and more are under construction.



Source: European Southern Observatory

By The New York Times

THANKS!