Machine Learning Applications in Astrophysics

Stefan Baar

Nishi-Harima Astronomical Observatory, University of Hyogo

Machine Learning Applications in Astrophysics

Introduction

- Nishi-Harima Observatory
- Telescopes and Research

Machine Learning Artificial Intelligence

Optical Astro

- Observations
- Astrometry

Radio Astro

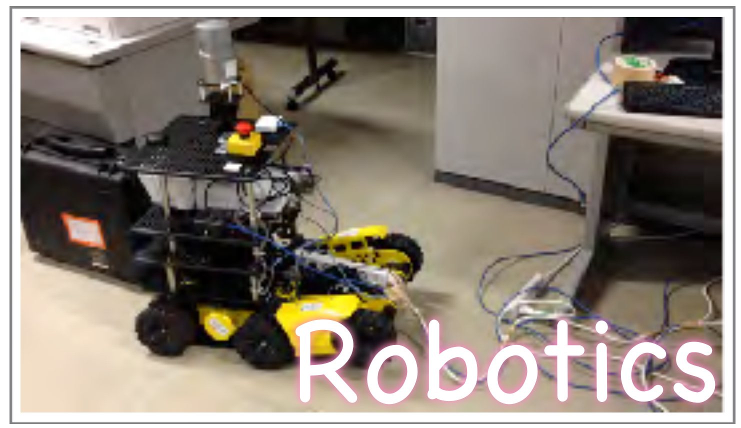
- Image Enhancement
  - Radio Interferometers
  - Blackholes
- Detection and Classification
  - Stars, Galaxies
  - Radio Relics, etc.

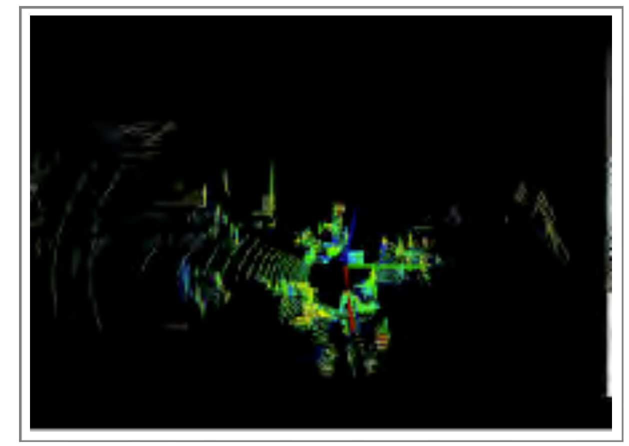
Cosmology

University of Jena

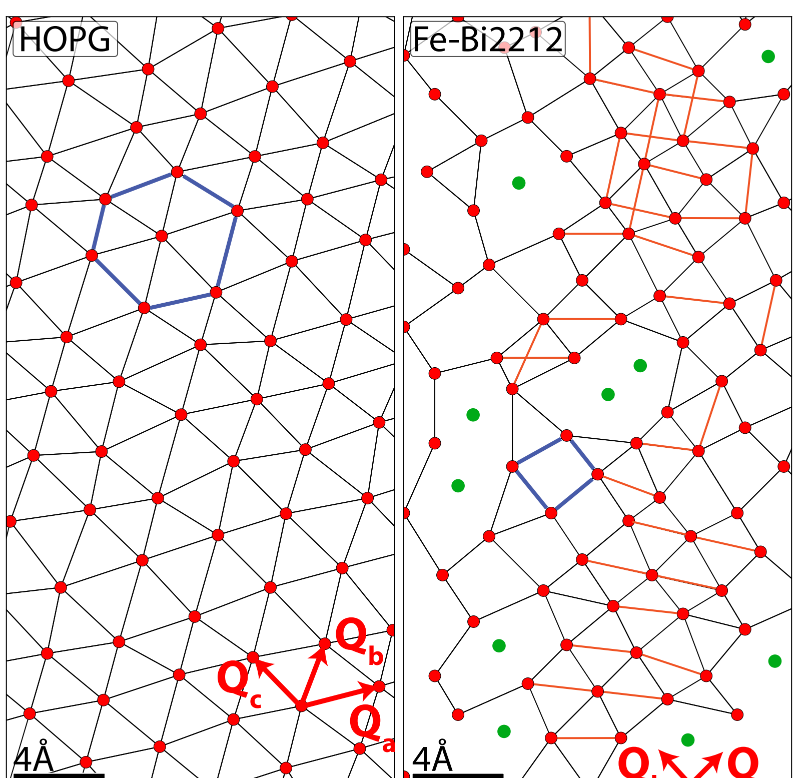
2008 - 2013

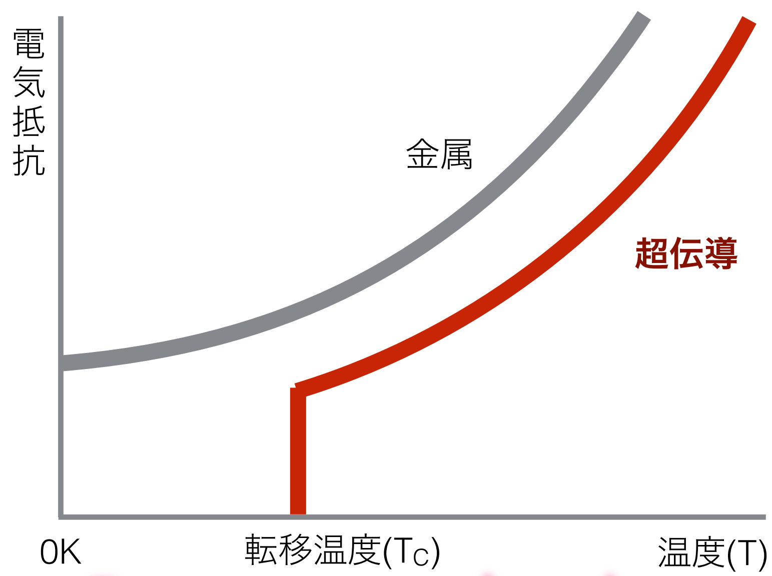
Muroran Institute of Technology



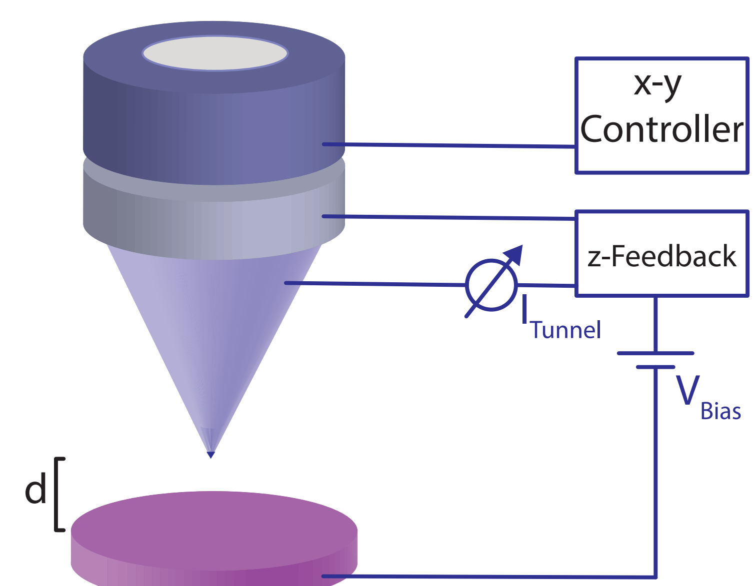


2013 - 2016





Superconductors

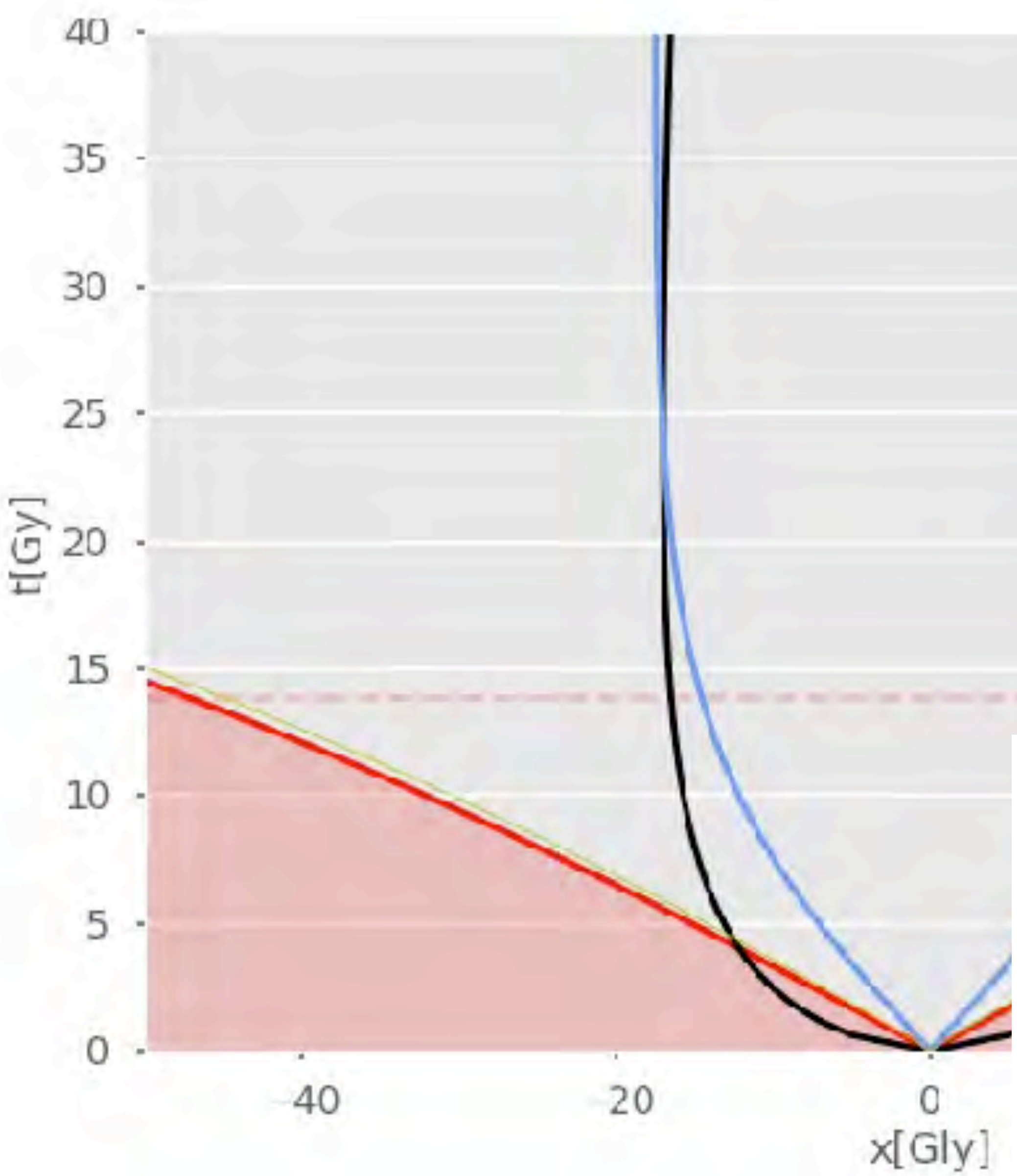


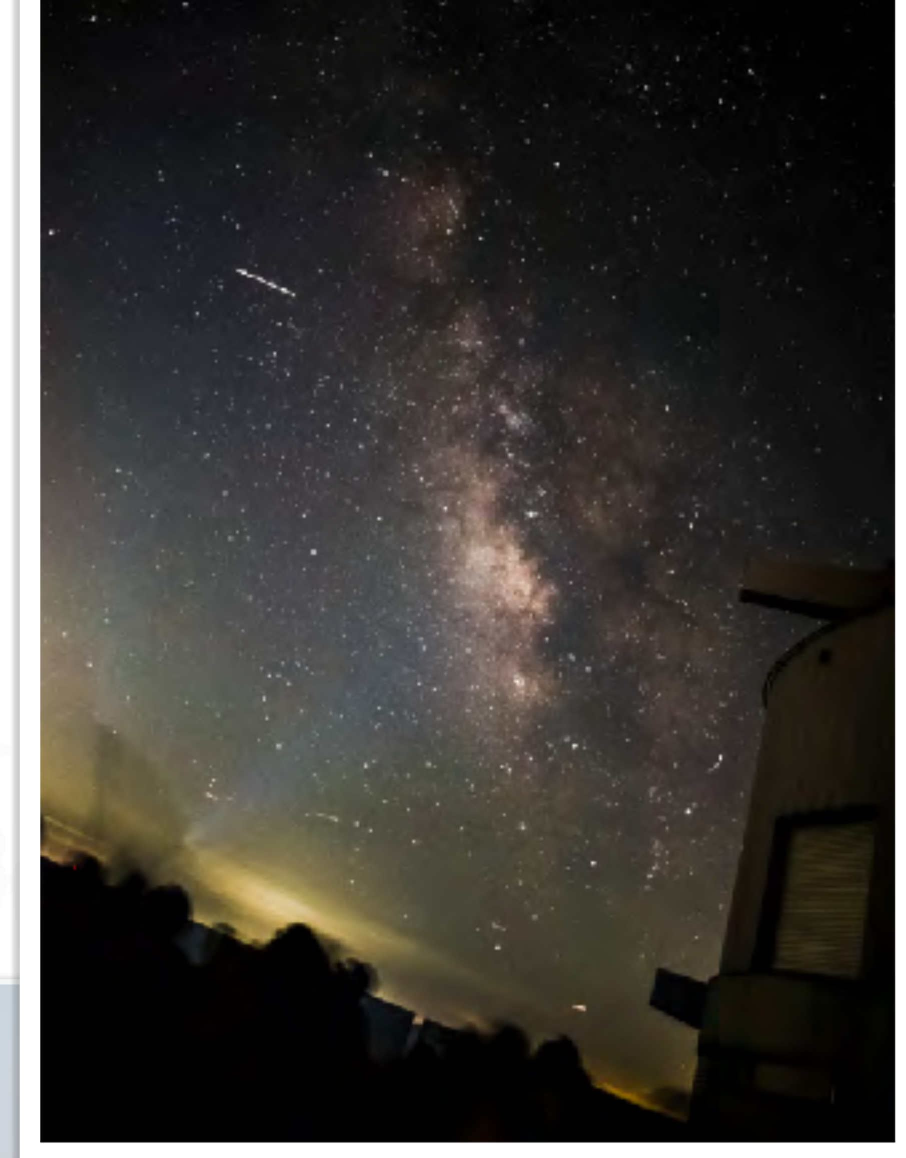
Interests

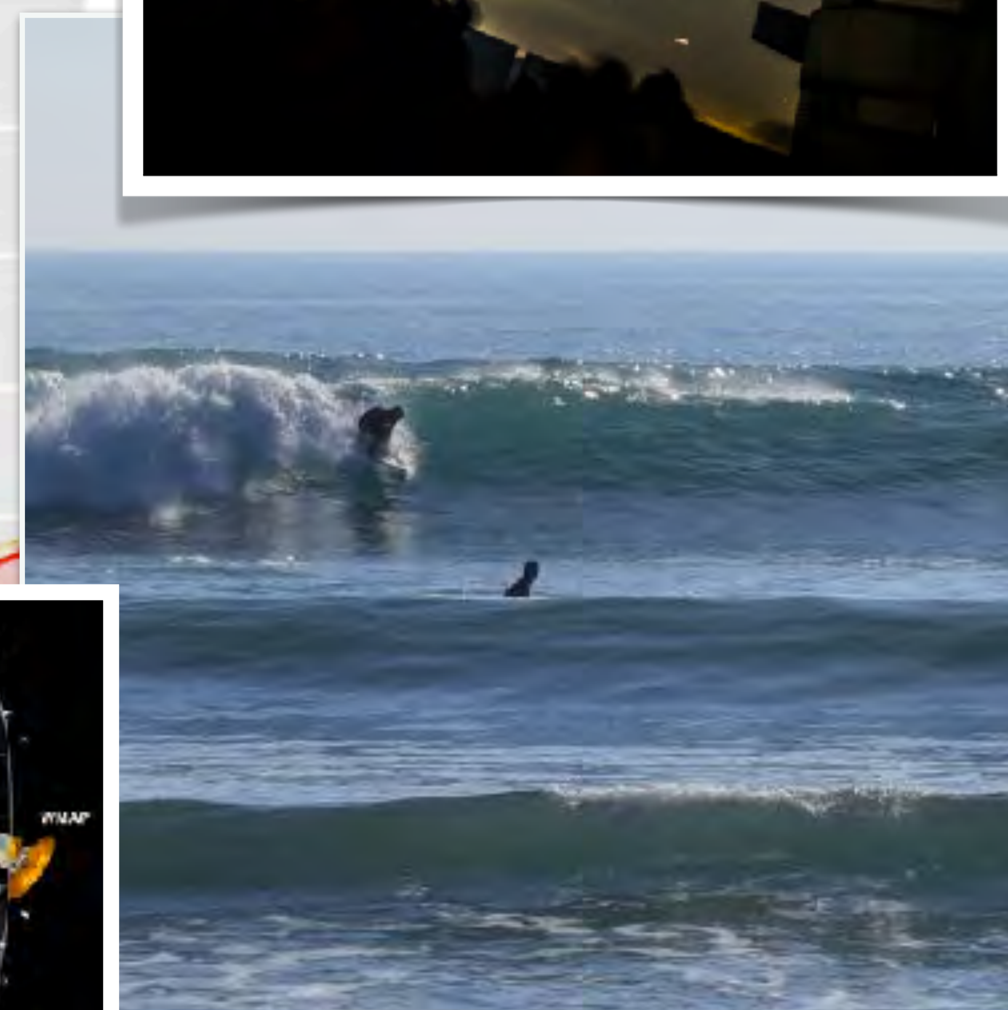
Website: http://www.nhao.jp/~sbaar

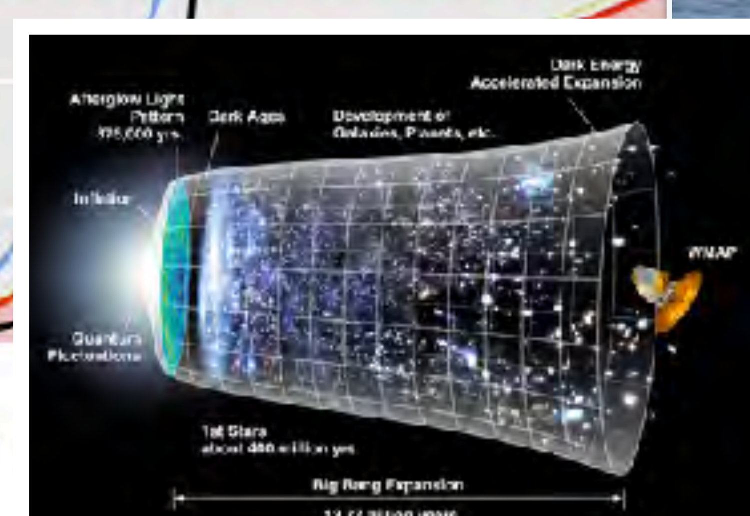
GitHub: https://github.com/StefanBaar

- Cosmology
- Photography
- Programming
- Deeplearning
- Robotics
- Surfing









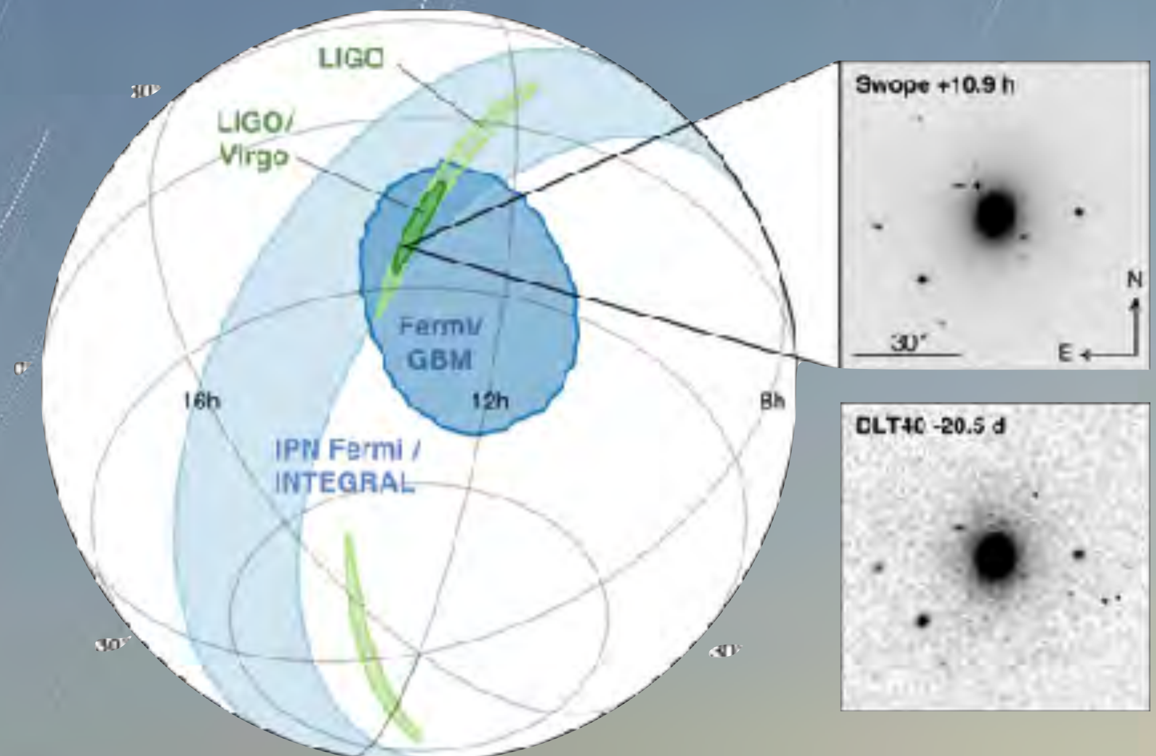
Nishi-Harima Astronomical Observatory

Personal:
- 4 Professors
- 10 researchers
- 2 instructors
- 12 students

Nishi-Harima Astronomical Observatory

Colaboration:
- LIGO/Virgo (GW)

Research:
- Minor Planets
- Variable Stars
- Exo-Planets
- Galaxies
- Quasars
- Cosmology



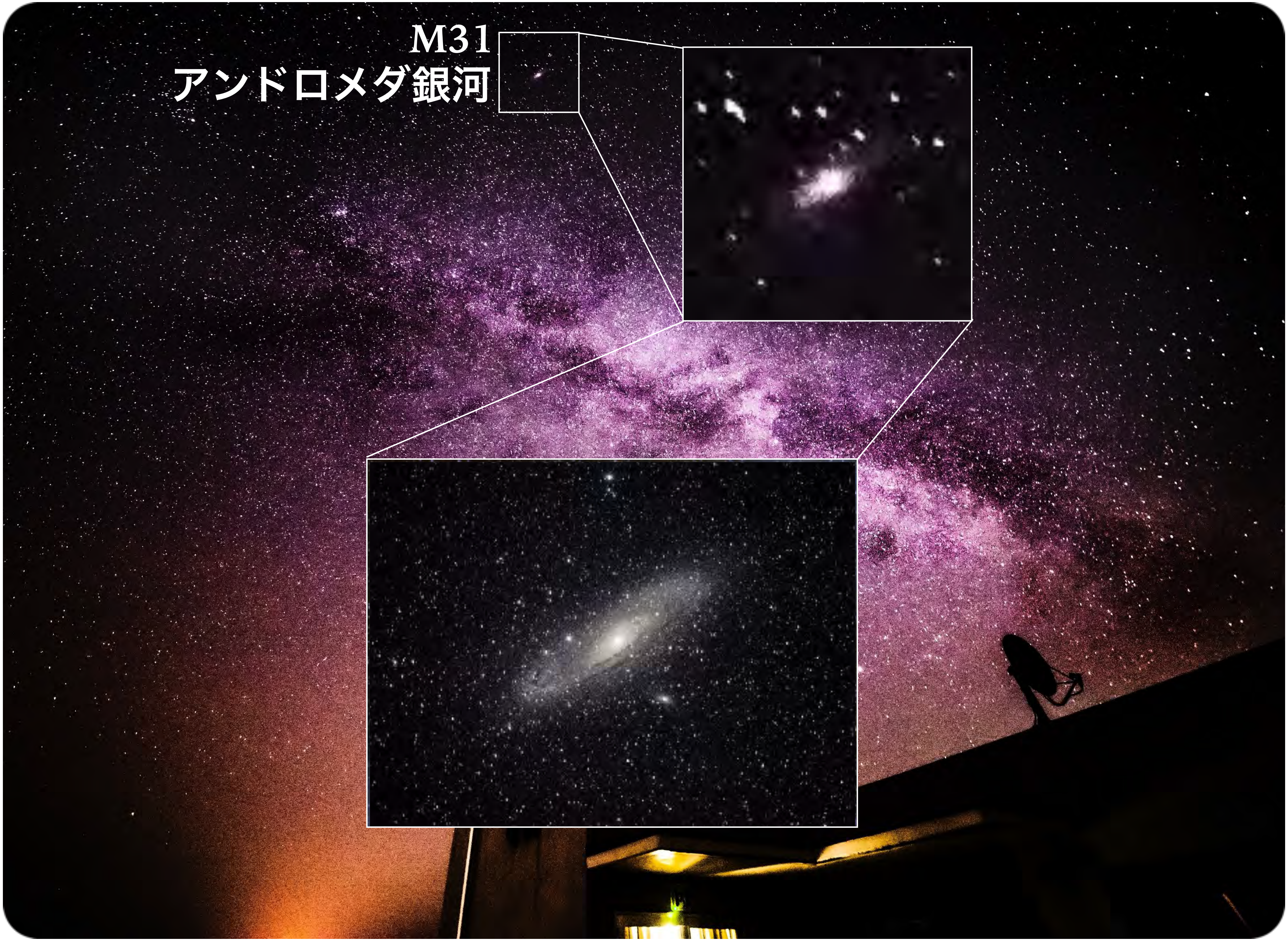
Events

StarDust

Candle Night

天の川


銀河系


M31
アンドロメダ銀河


アンドロメダ銀河
ミラク
さんかく座銀河

Nishi-Harima Astronomical Observatory

Stargazing

TELESCOPES

西はりま天文台

60cm望遠鏡

本天文台開設以来、公開天文台のパイオニアとして活躍してきた赤道儀式の望遠鏡。太陽や金星・水星の他、昼間の一等星の観測など、主に昼間の観測で活躍中。

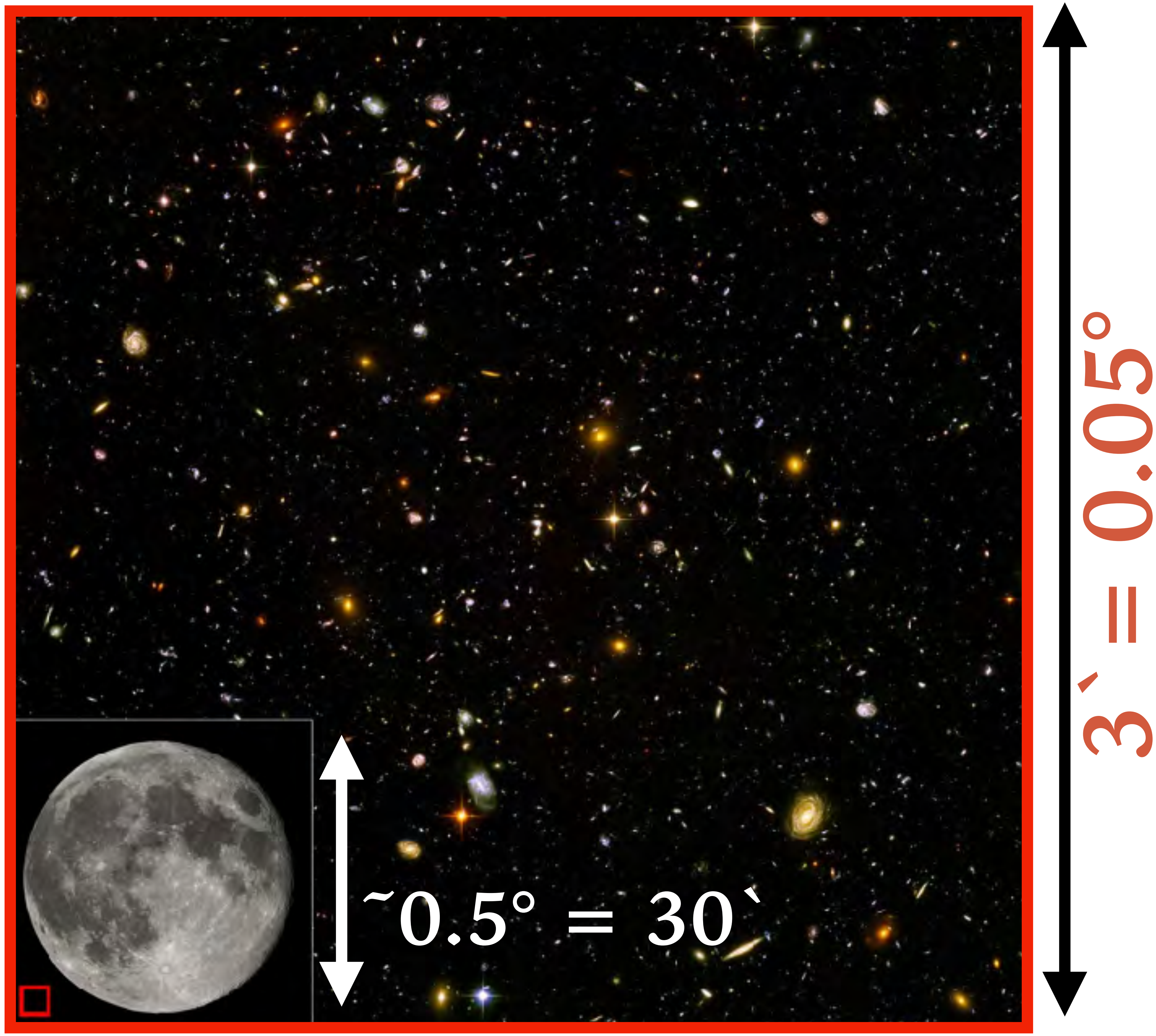
太陽望遠鏡

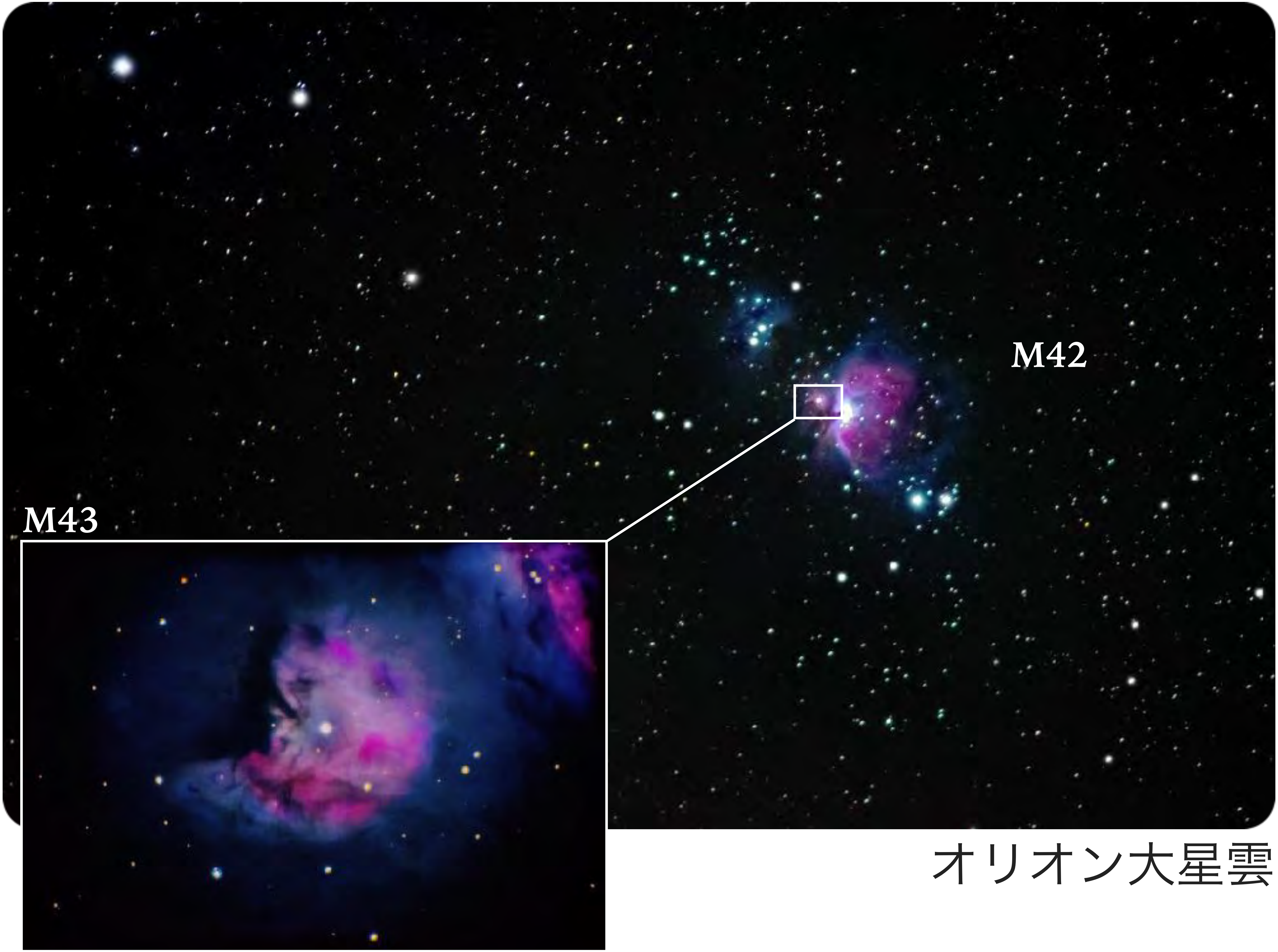
太陽モニター望遠鏡が見つけた動きにズームアップして太陽活動を詳しく観測する望遠鏡。「キラキラとんぼ」という名前は設置時に一般公募で付けていただいたも

太陽モニター望遠鏡

肉眼では眩しくて見ることのできない太陽を特殊な光で観測する望遠鏡。太陽の表面に現れる黒点やフレア（爆発）現象を見ることができます。

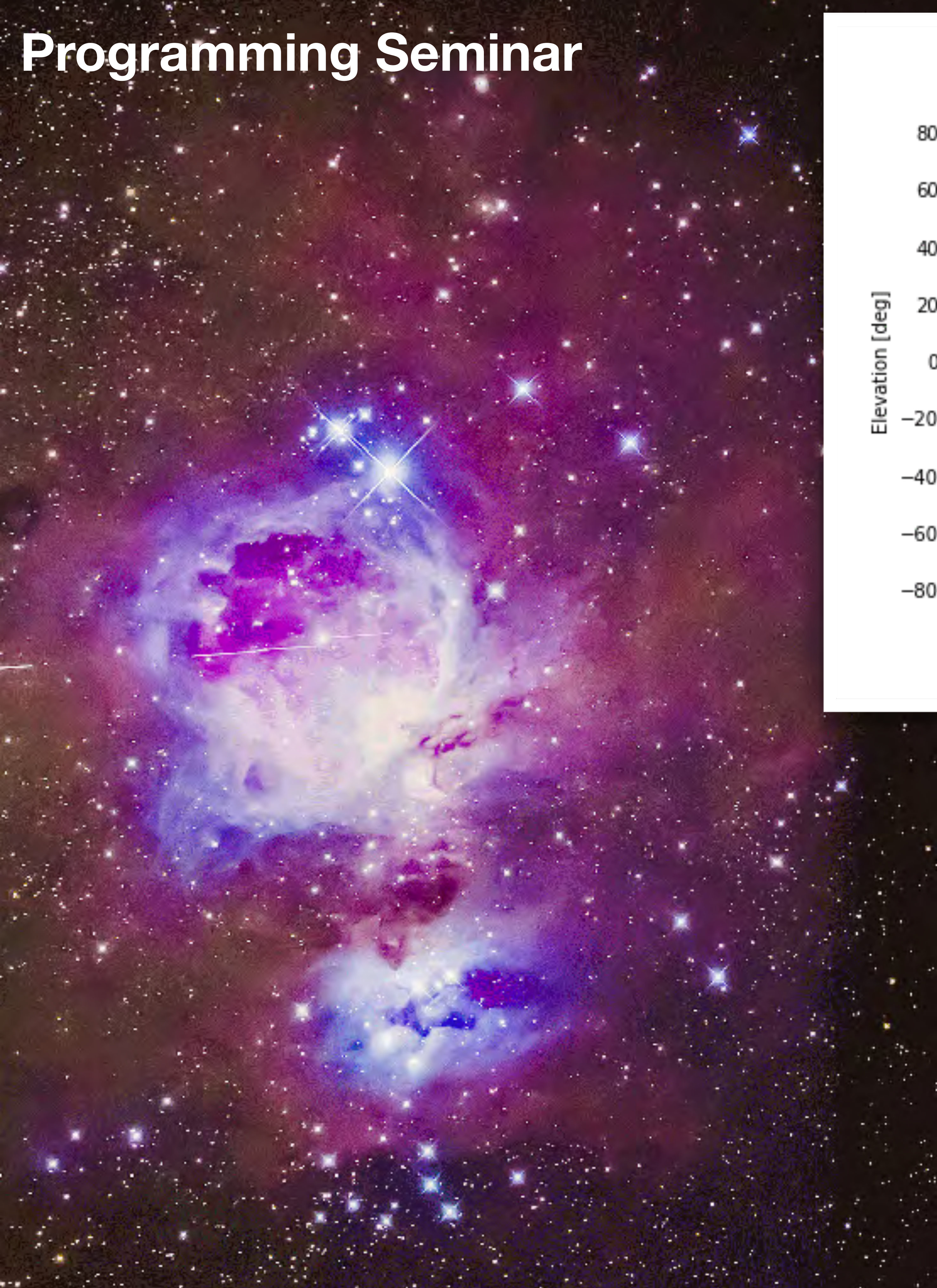
Nayuta Telescope

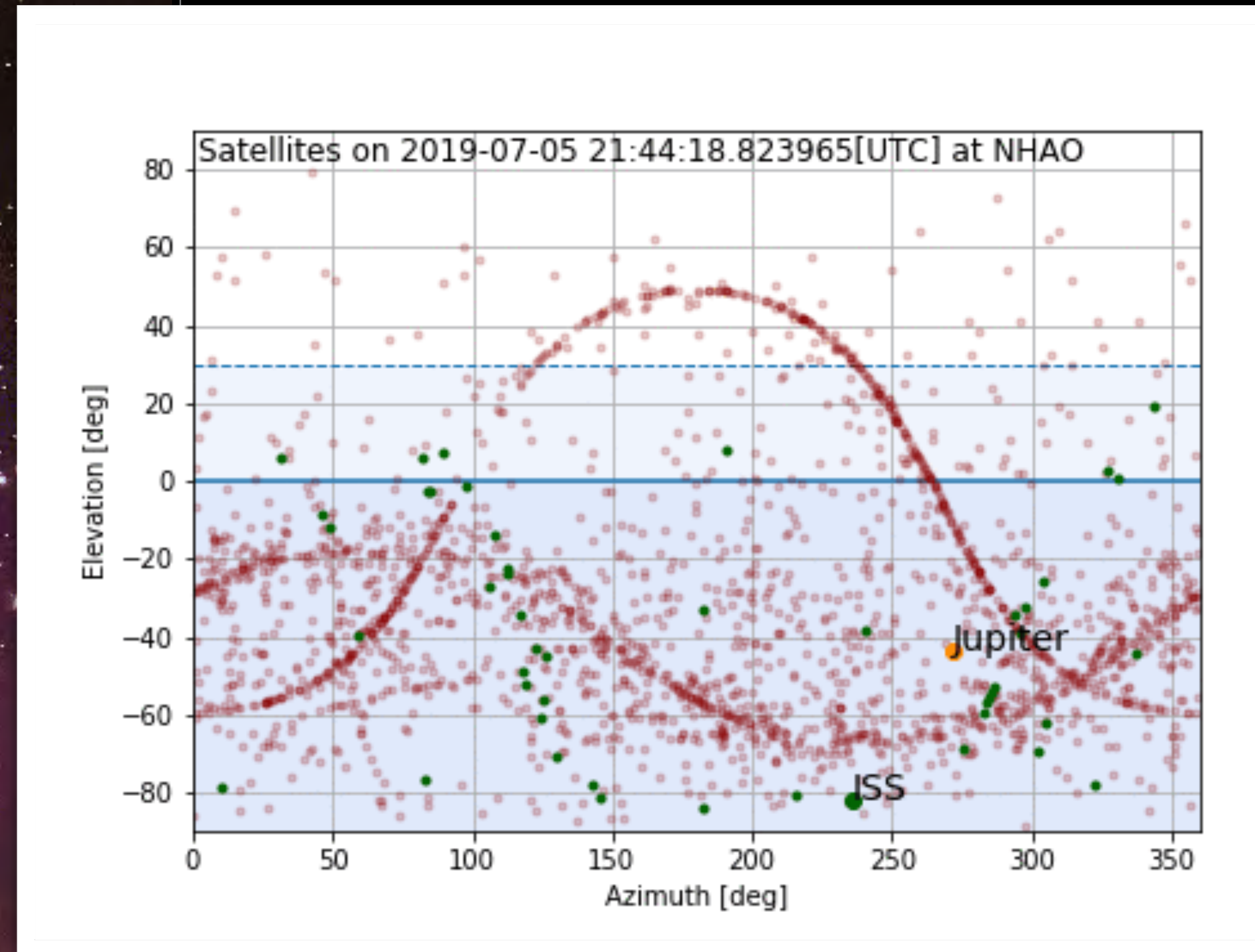




オリオン大星雲

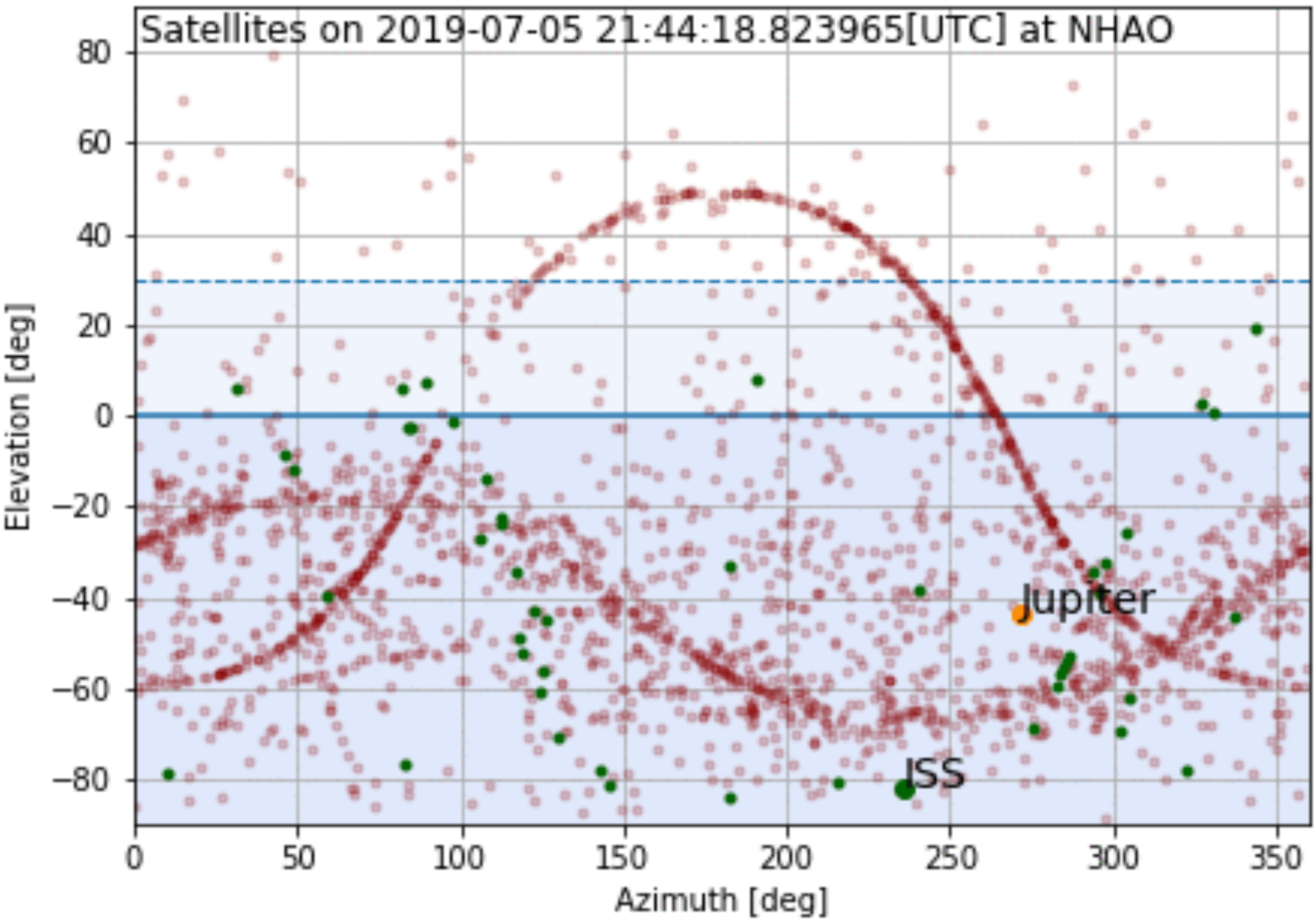
Programming Seminar





Contents
- Math
- Astrometry
- Image processing
- Observation planning
- Data visualization
- Simple ML

http://www.nhao.jp/~sbaar/seminar.html



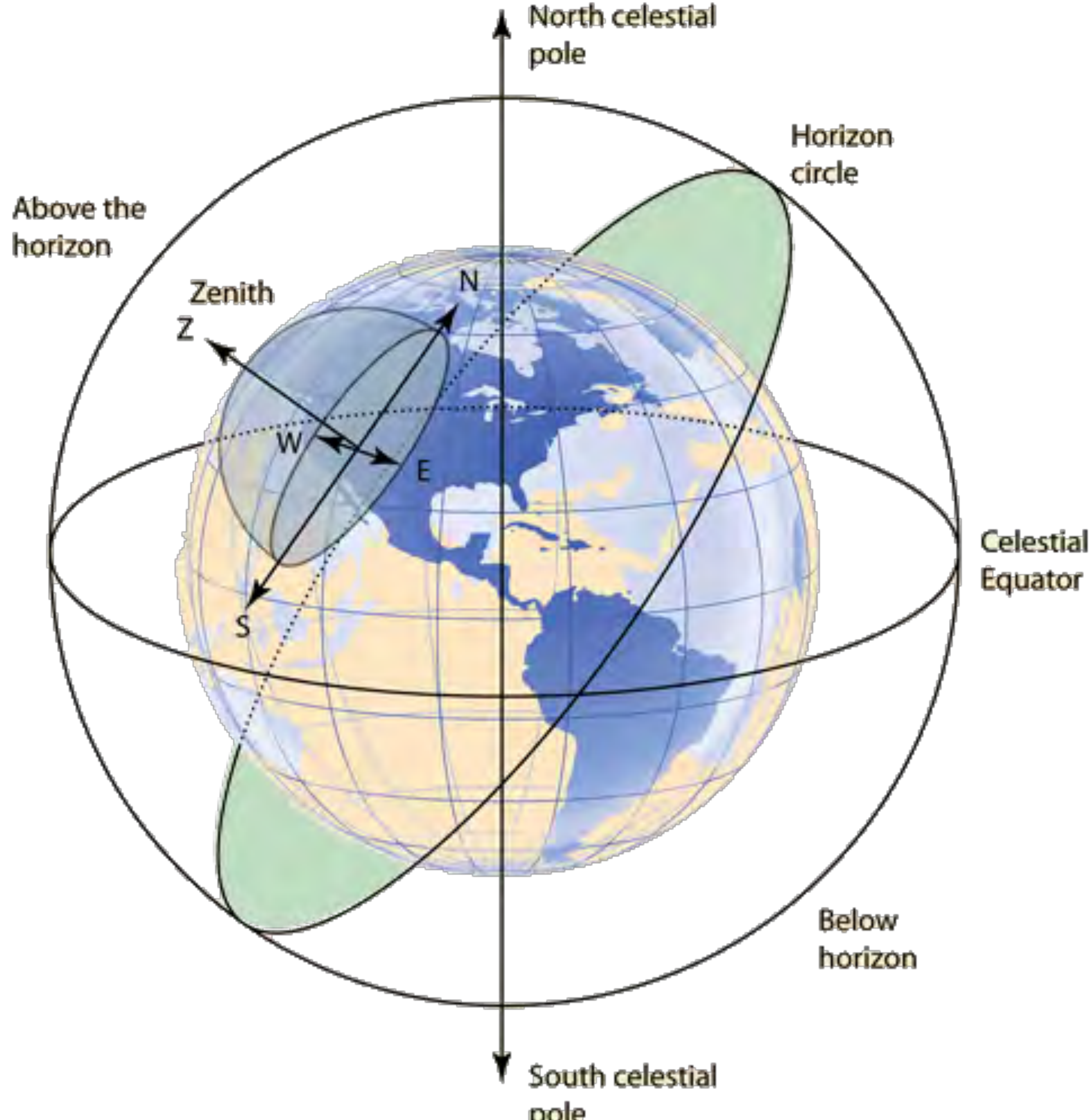
Satellites on 2019-07-05 21:44:18.823965[UTC] at NHAO
Jupiter
ISS
Elevation [deg]
Azimuth [deg]
80
60
40
20
0
−20
−40
−60
−80
0
50
100
150
200
250
300
350

Basics

Azimuth (AZ)
Elevation (RA)

TIME

Right Ascension (RA)
Declination (DEC)

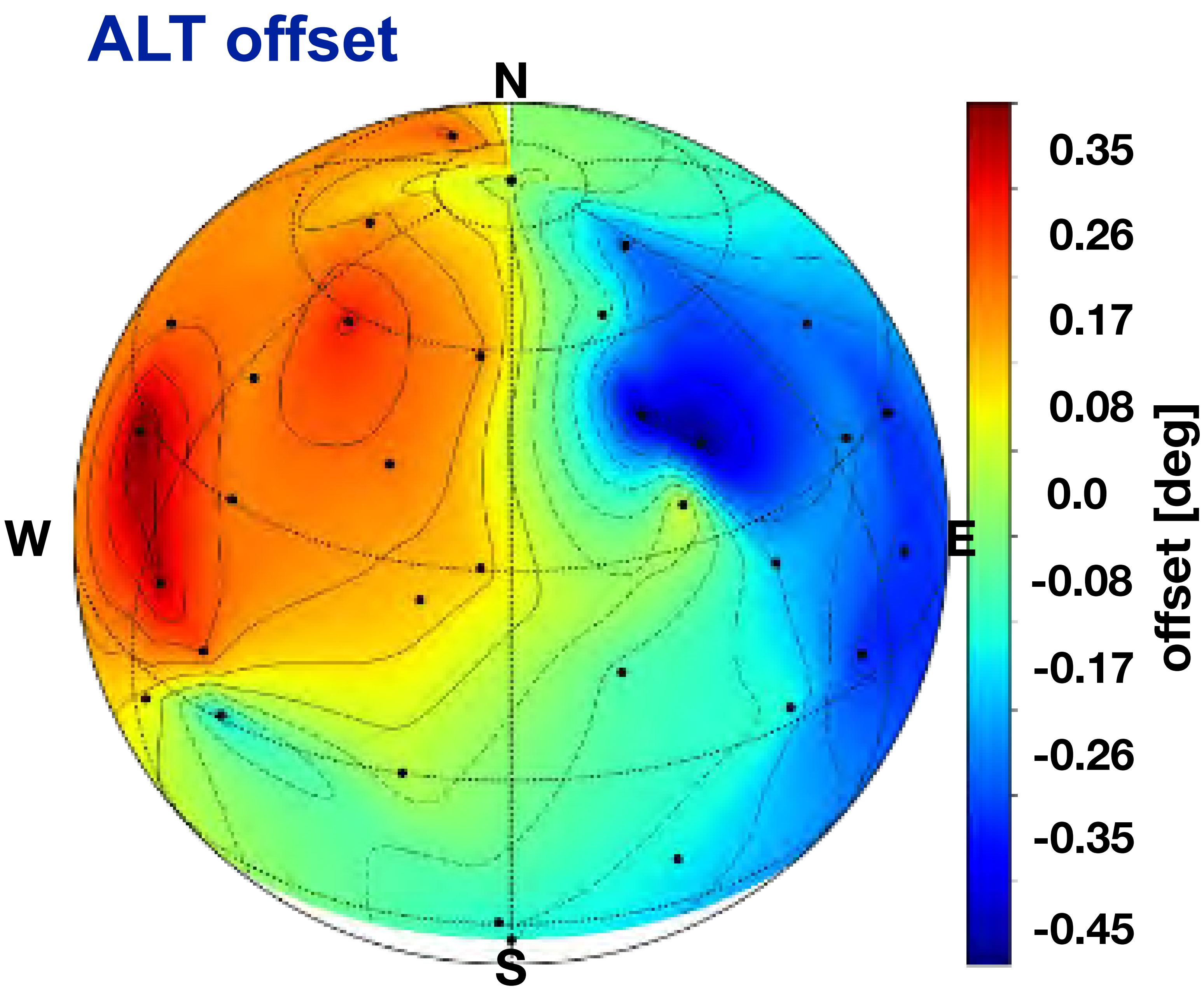


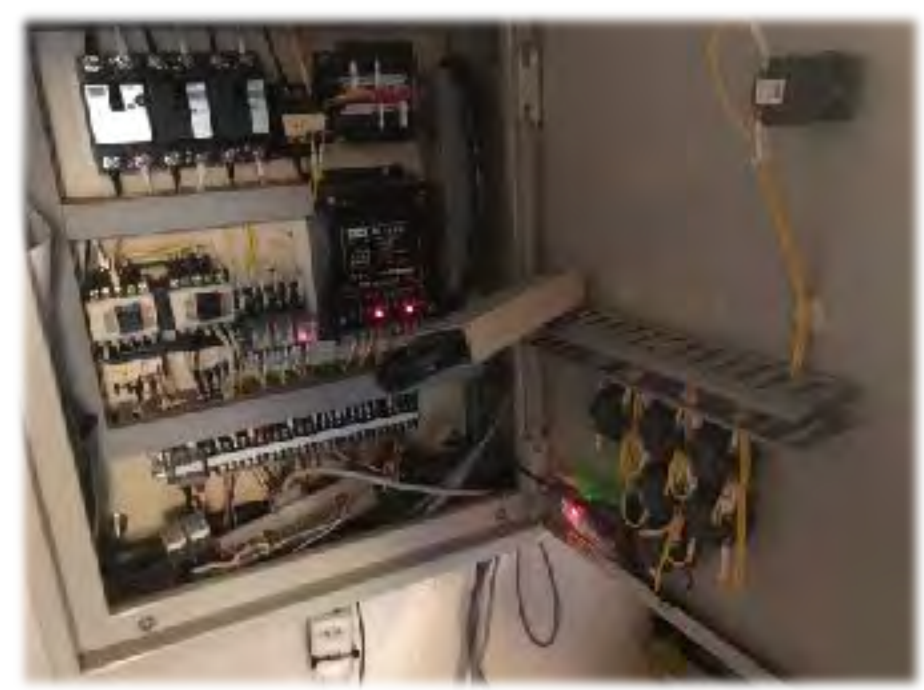
60cm Telescope

Build: 1989
Problems:

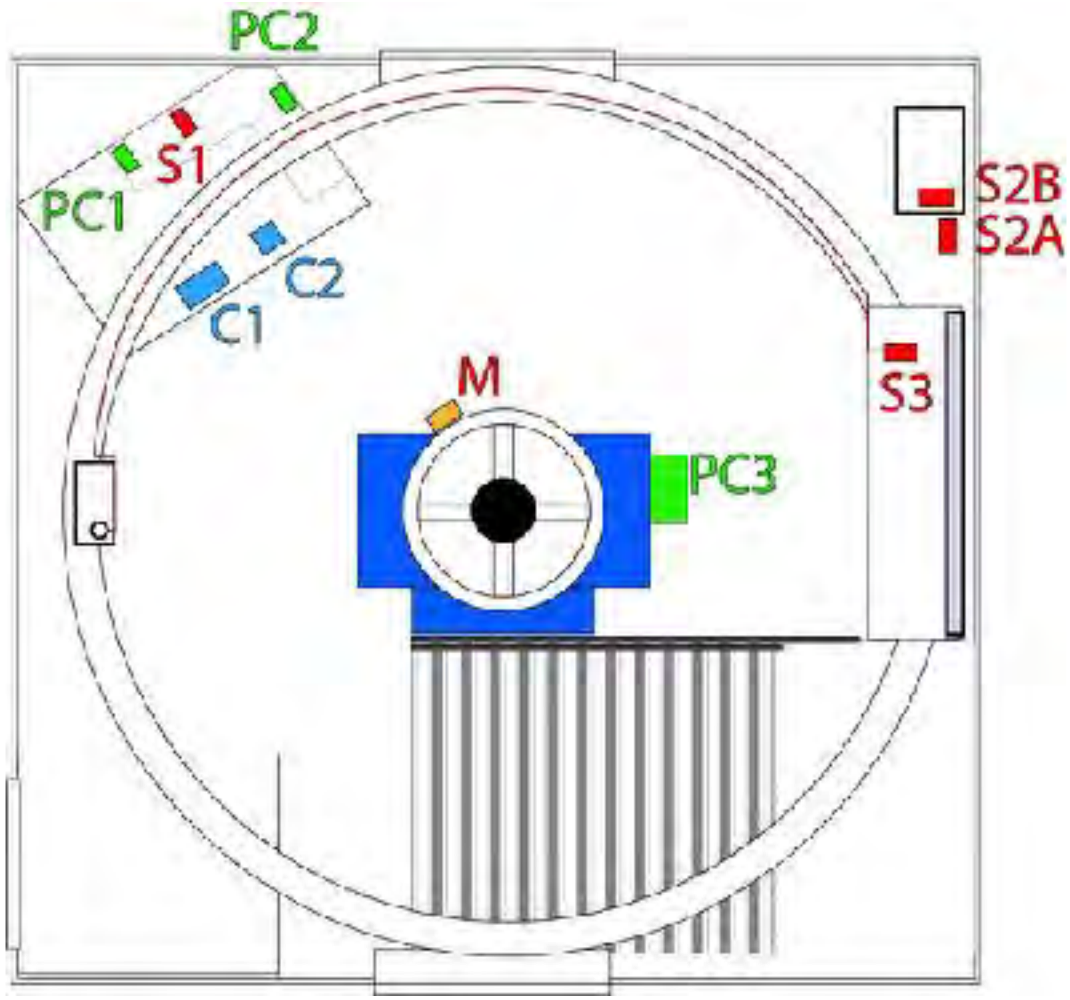
- Bad Pointing
- No Encoders for Slit and Dome
- Sometimes malfunctioning
- Most components are analog →

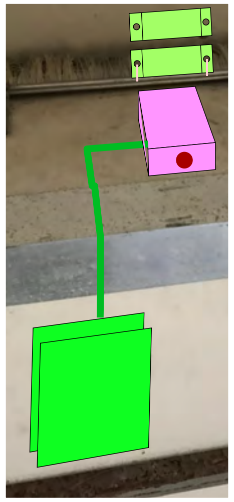
- Dome
- Slit
- Mirror Cover
- etc.





60cm Telescope



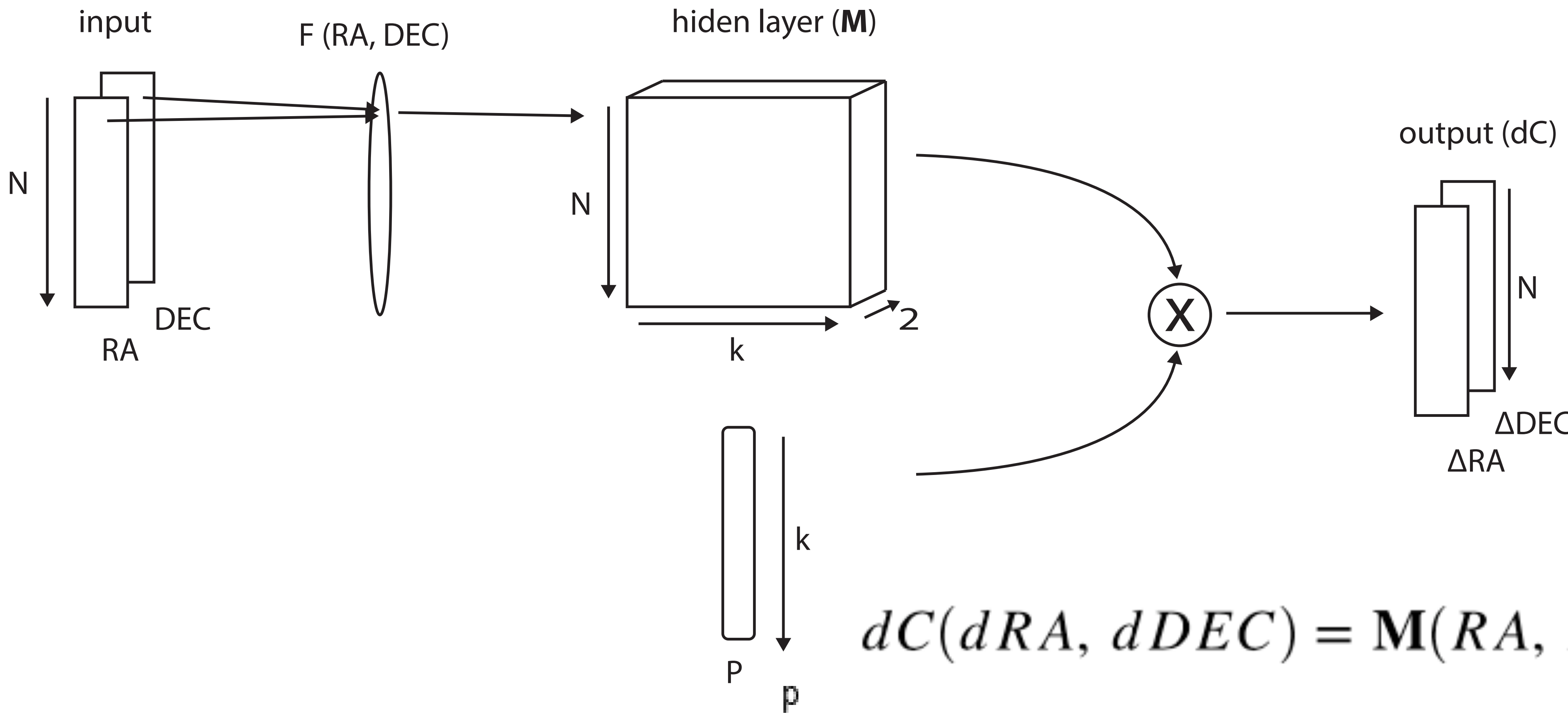


Computers

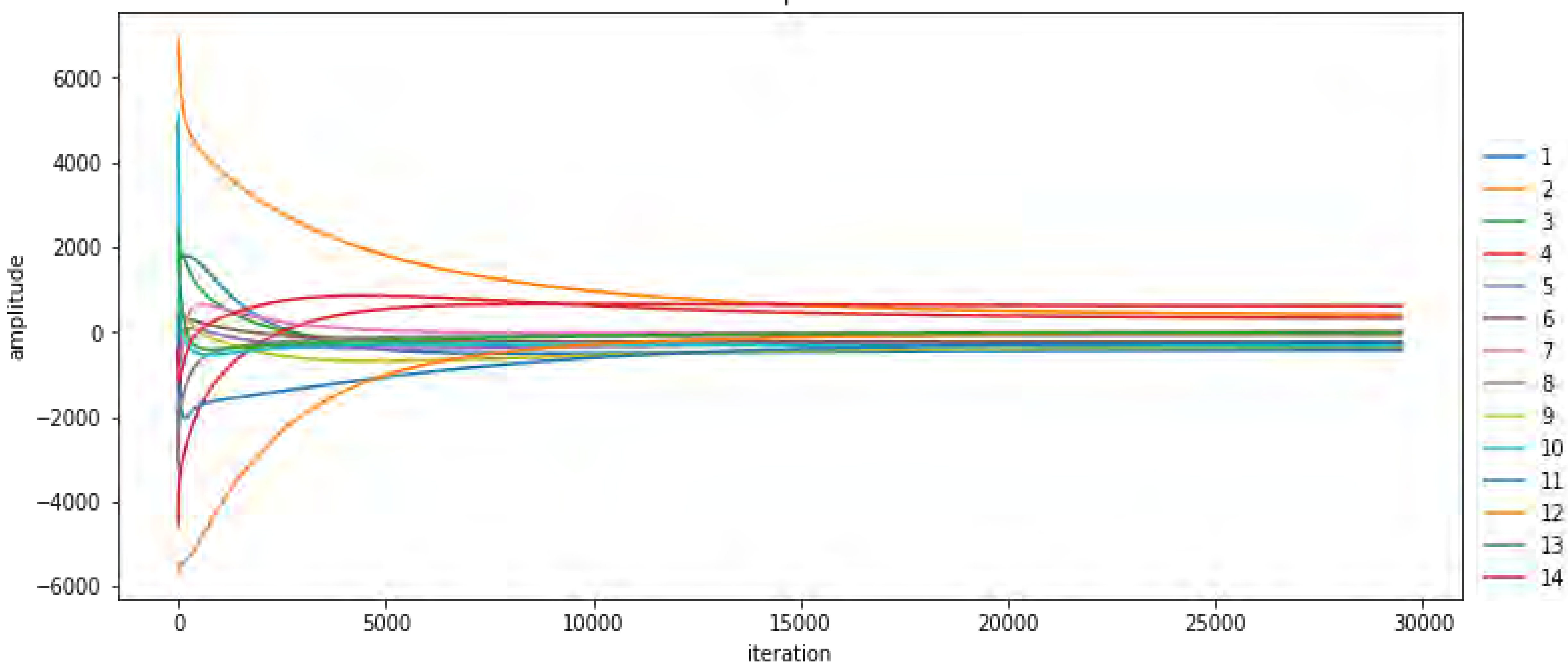
RaspberryPi /USB relay

Analog
- Dome
- Slit
- Mirror Cover
- etc.

Digital



$$dC(dRA,\, dDEC) = \mathbf{M}(RA,\, DEC) \times \mathbf{P}$$

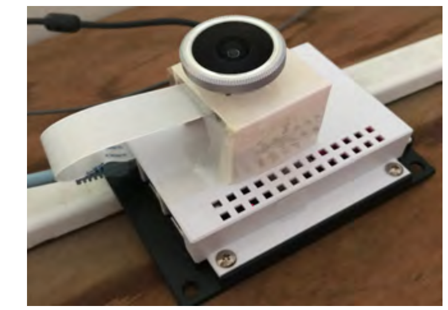


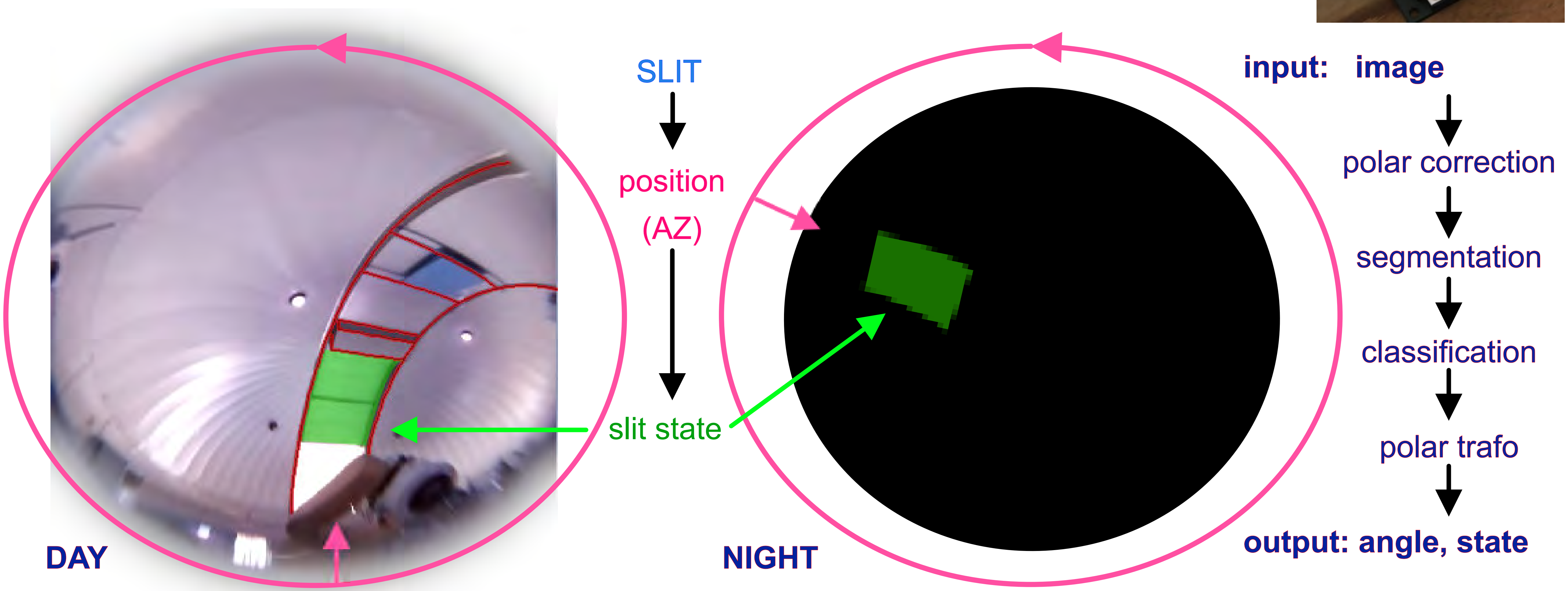
Enclosure / Slit Encoder

Since the motors driving the enclosure and slit have no readable encoders, we employ active object detection to locate the Az component of the slit position and whether it is open, closed or moving into either state.

motion tracking without encoder → optical encoder

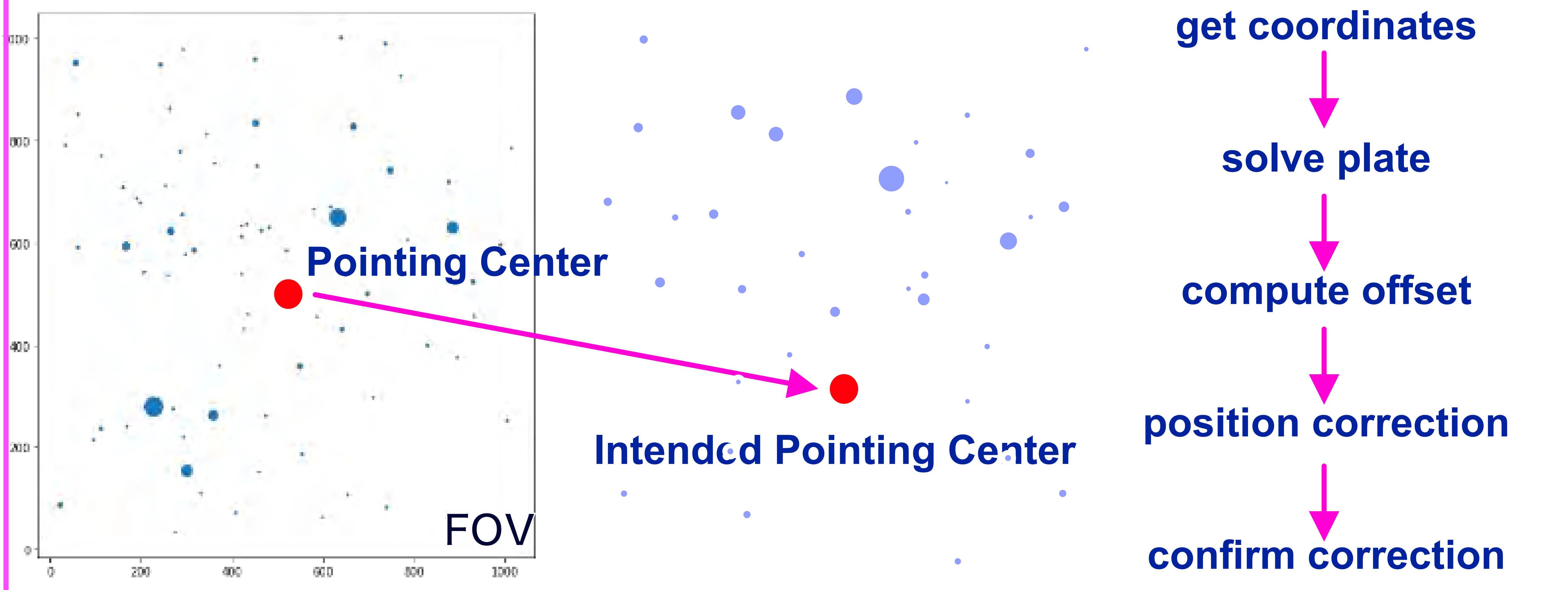
Raspberry Pi + IRcam + YOLO object detection





On-the-Fly Offset Correction and Tracking

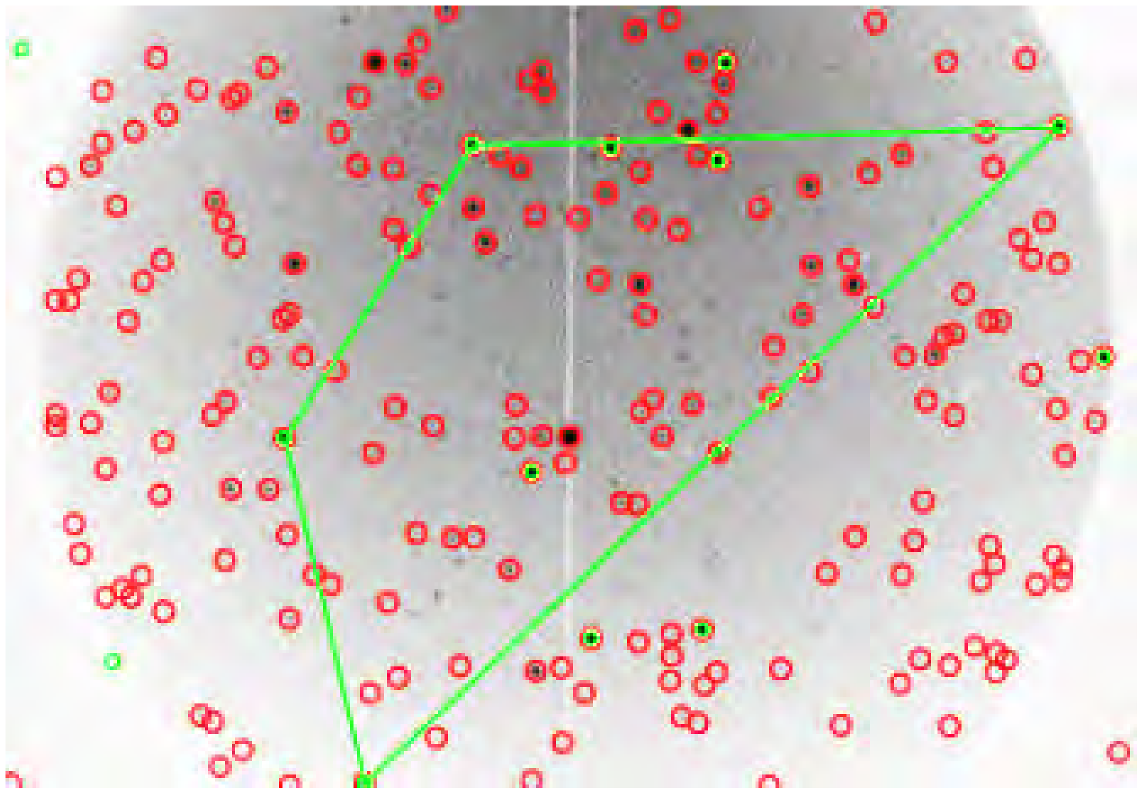
We use on the fly plate solving to ensure correct pointing of the telescope and correct the pointing when needed.



NAYUTA – 60CM –Synchronization

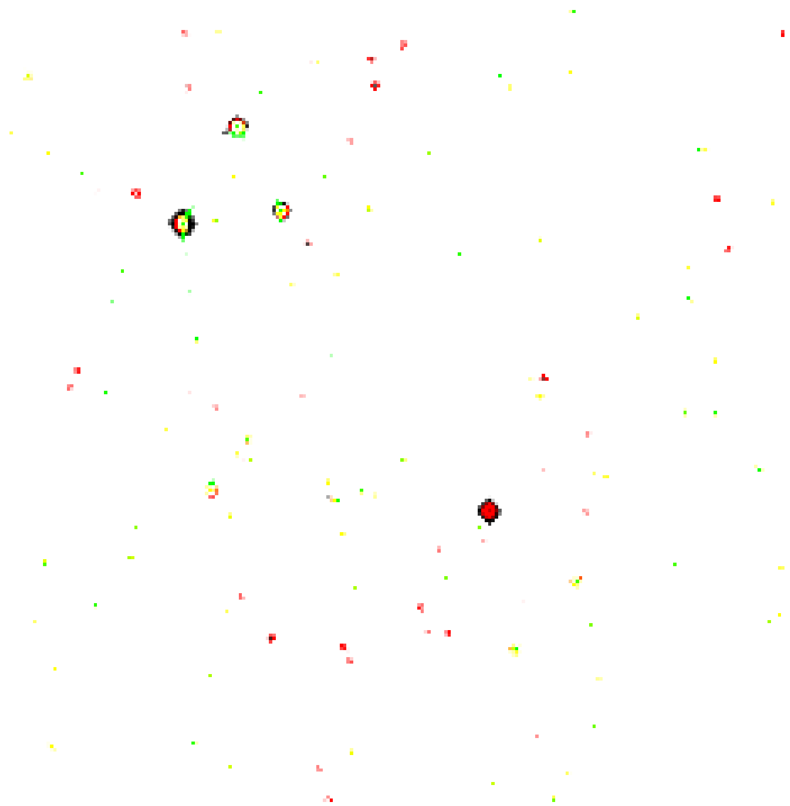
The telescope pointing can be synchronized to that of the Nayuta telescope by evaluating the MALLS FOV and determining position and and brightness of the currently observed object.

We evaluate the FOV of both malls and the 60cm CCD camera by computing a brightness level function, extracting sources and solving the source positions through pyplate and astrometry-net



NAYUTA MALLS FOV: 7' x 4'

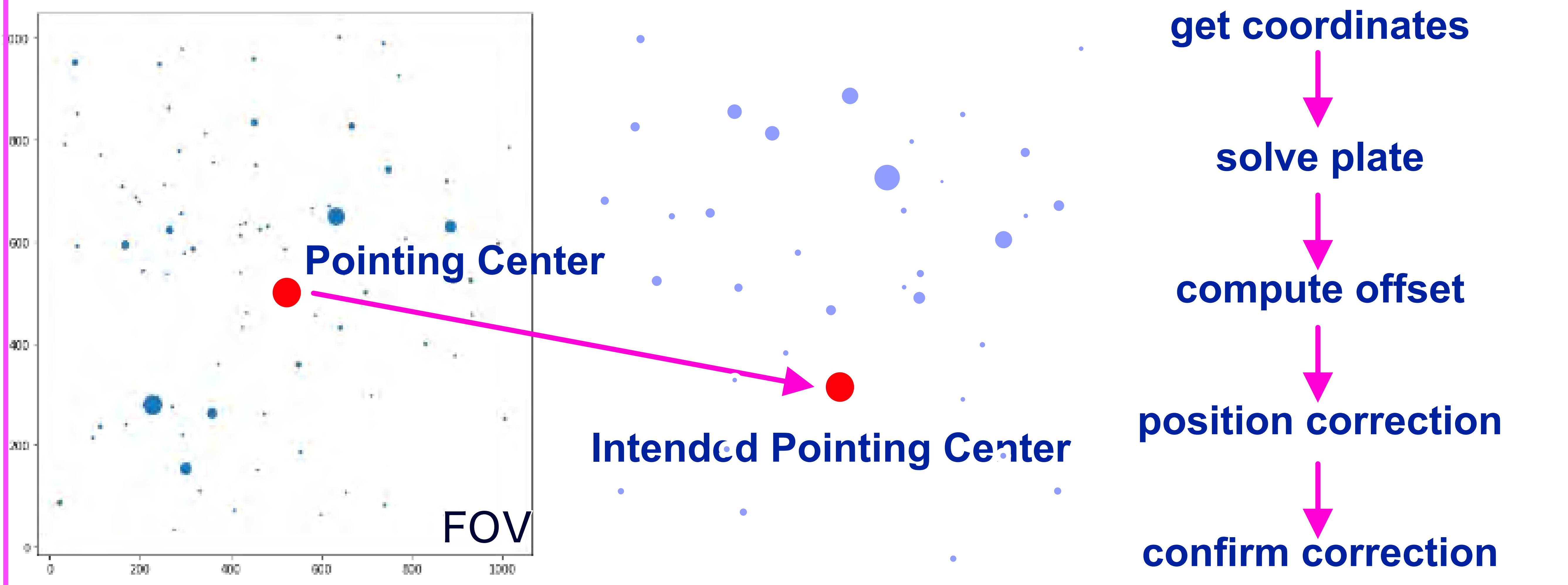
Sync. sky Position



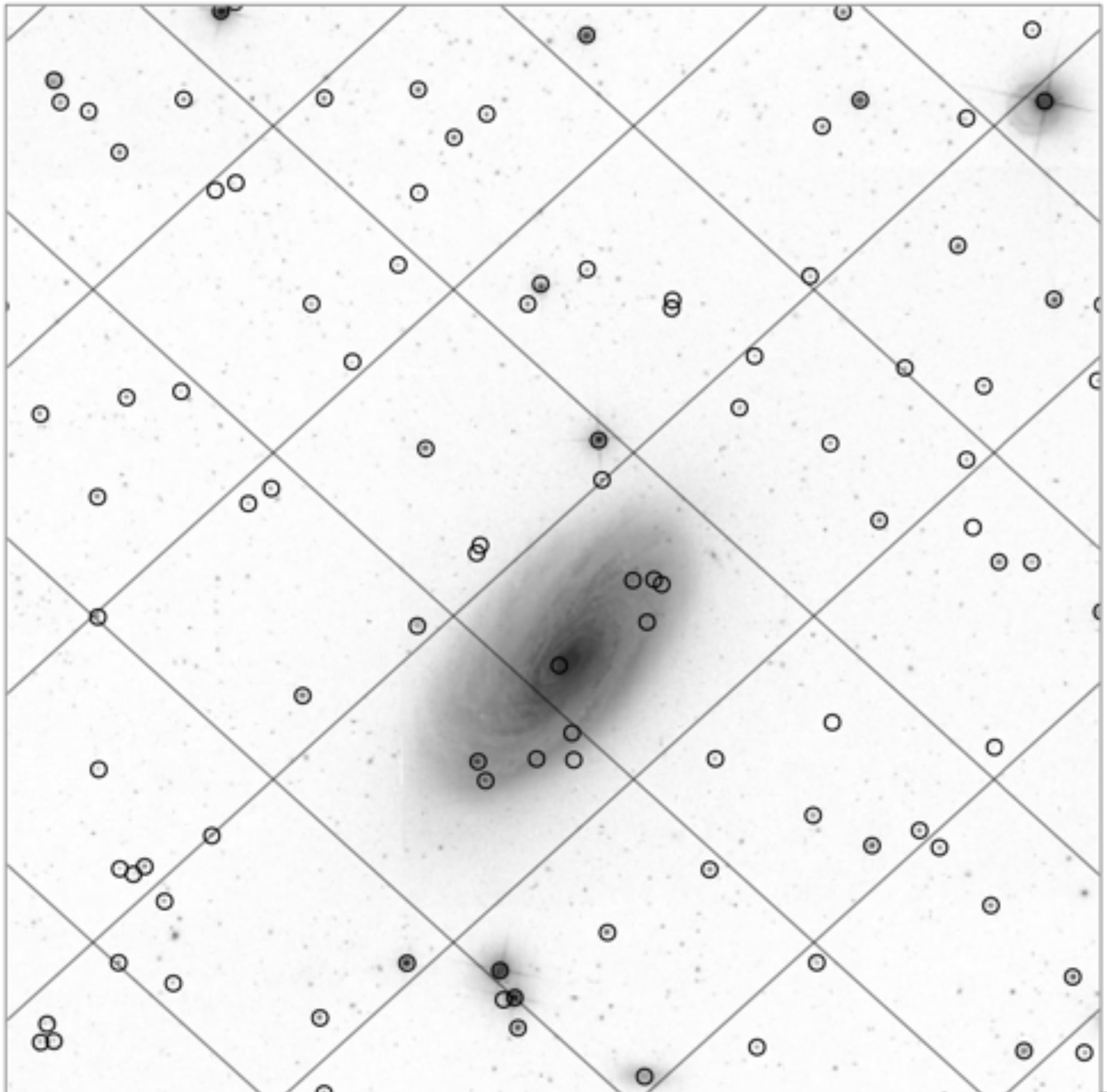
60CM STL FOV: 11' x 11'

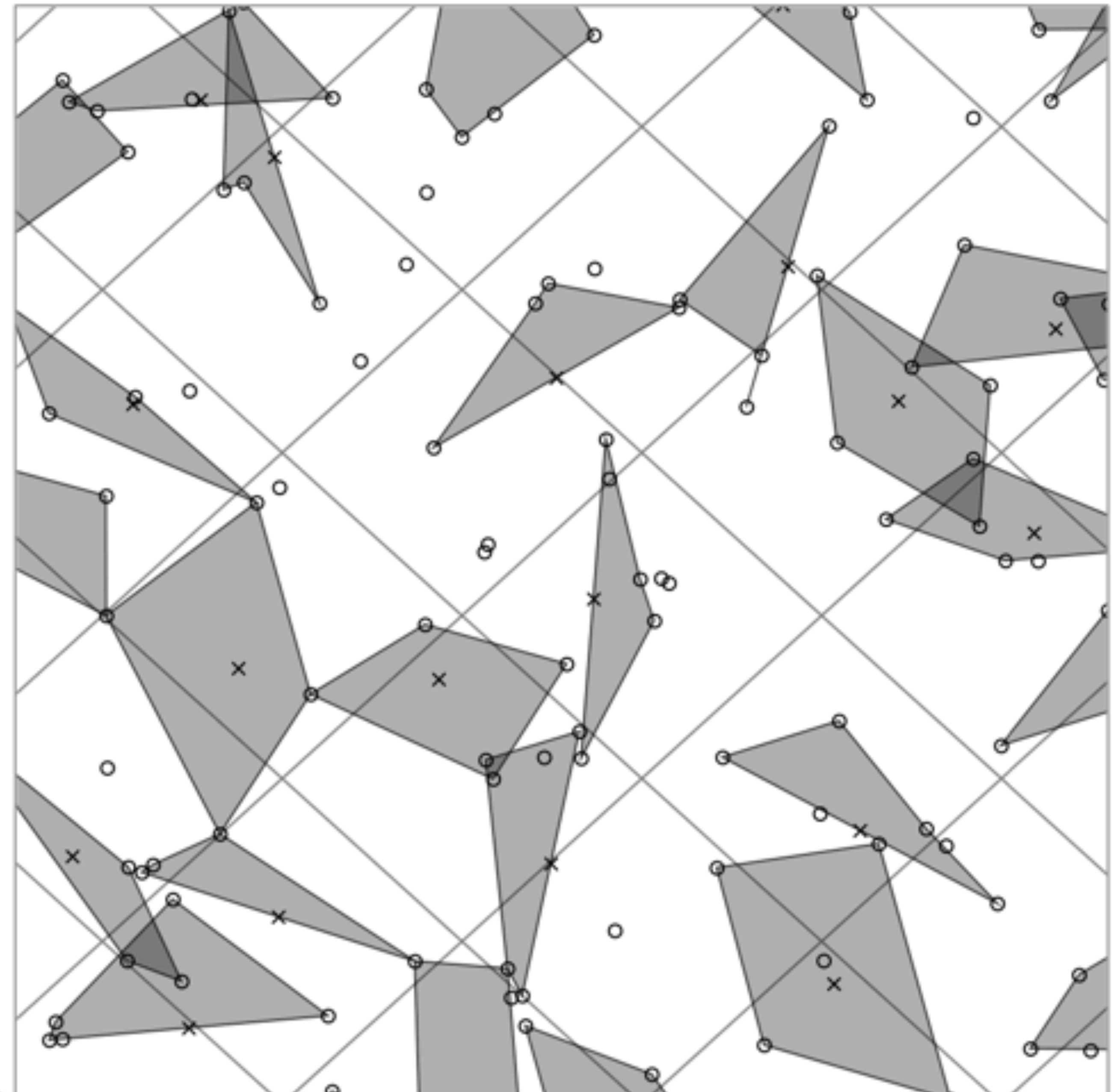
On-the-Fly Offset Correction and Tracking

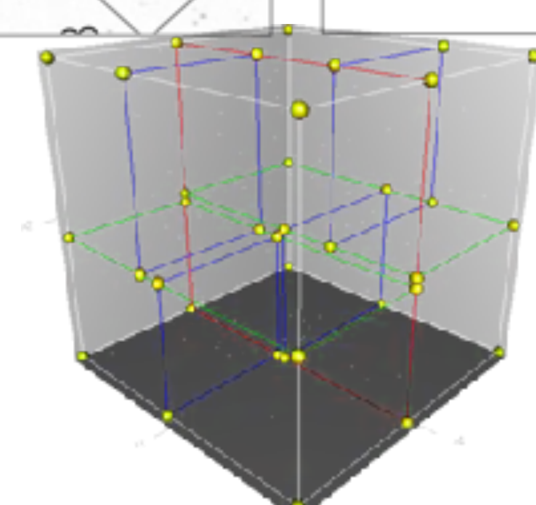
We use on the fly plate solving to ensure correct pointing of the telescope and correct the pointing when needed.



Astrometric solving

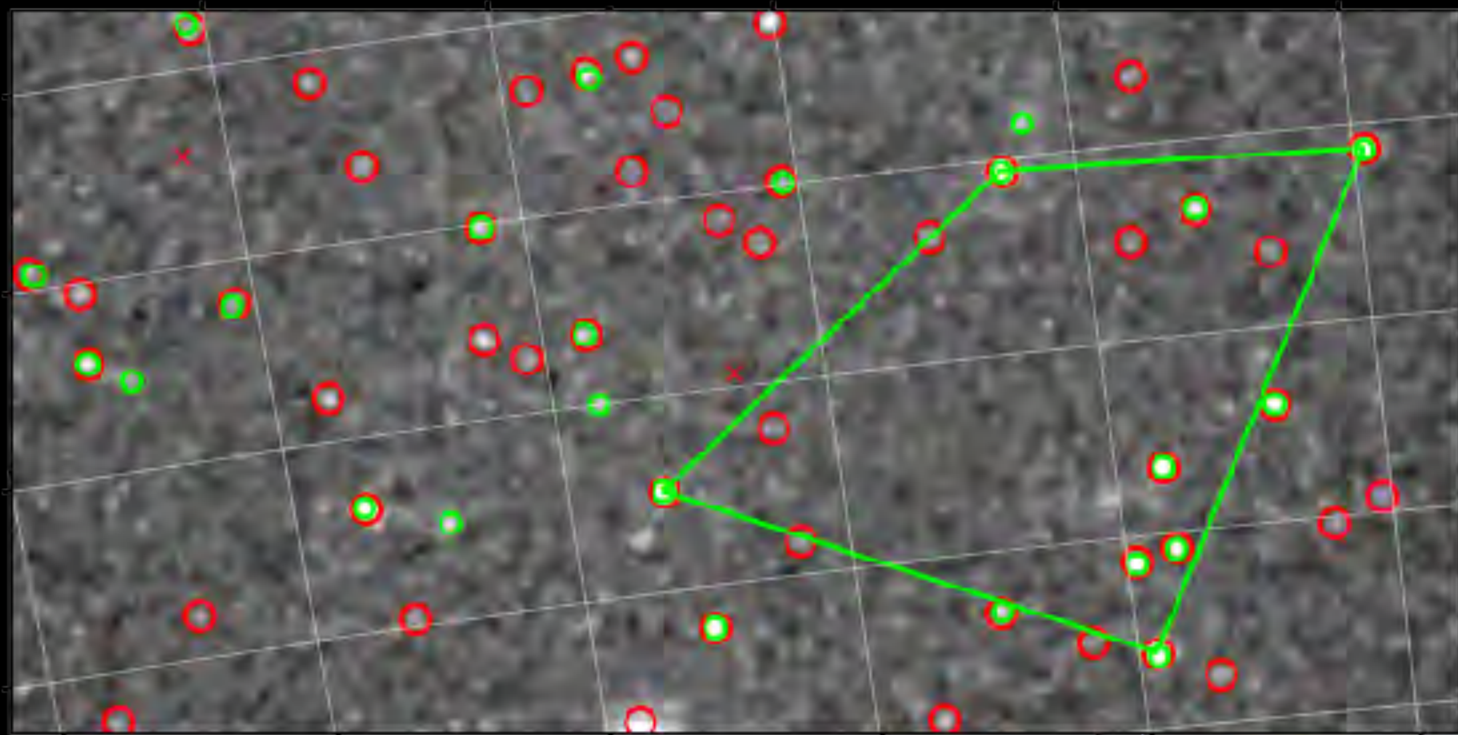


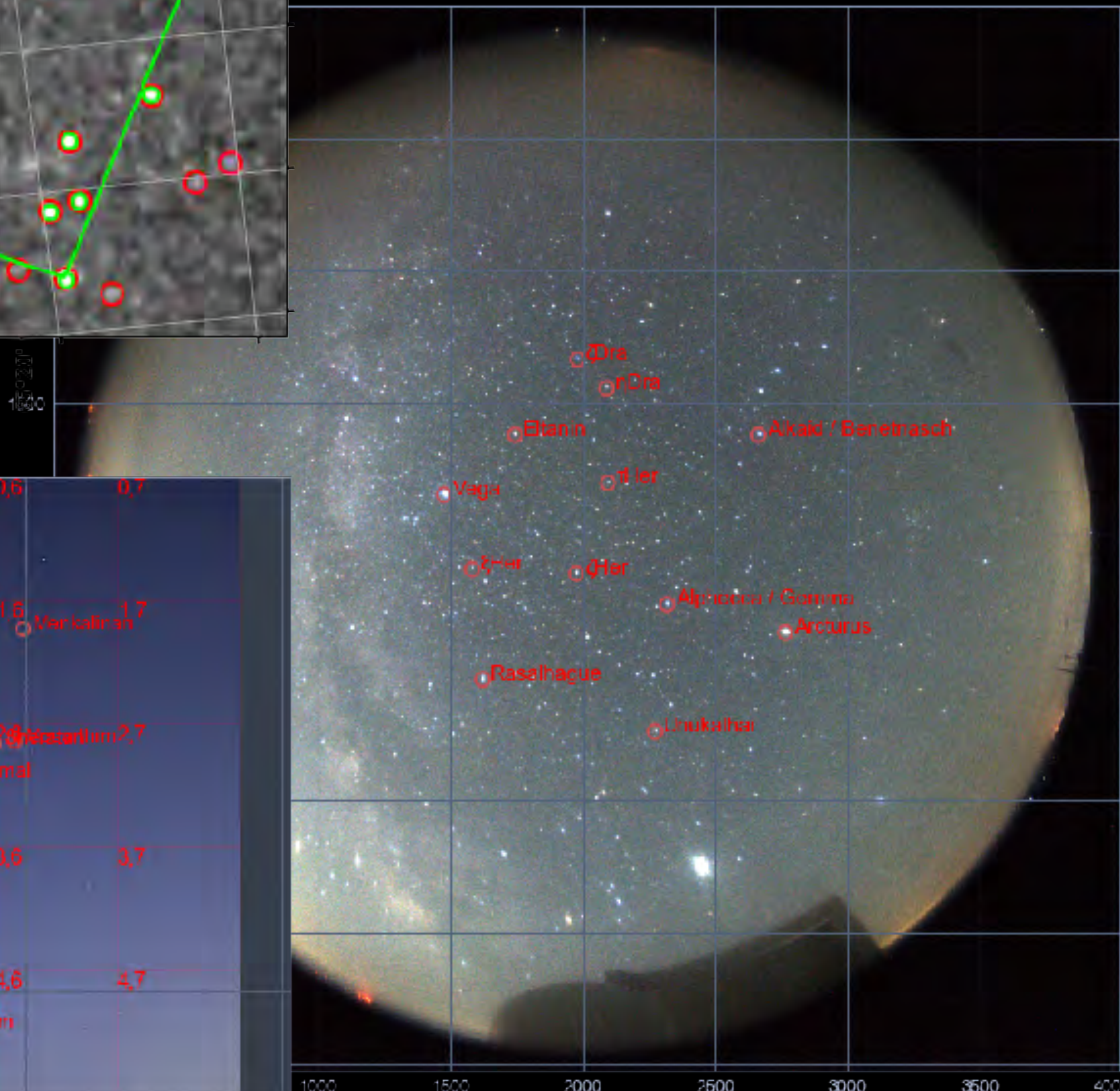


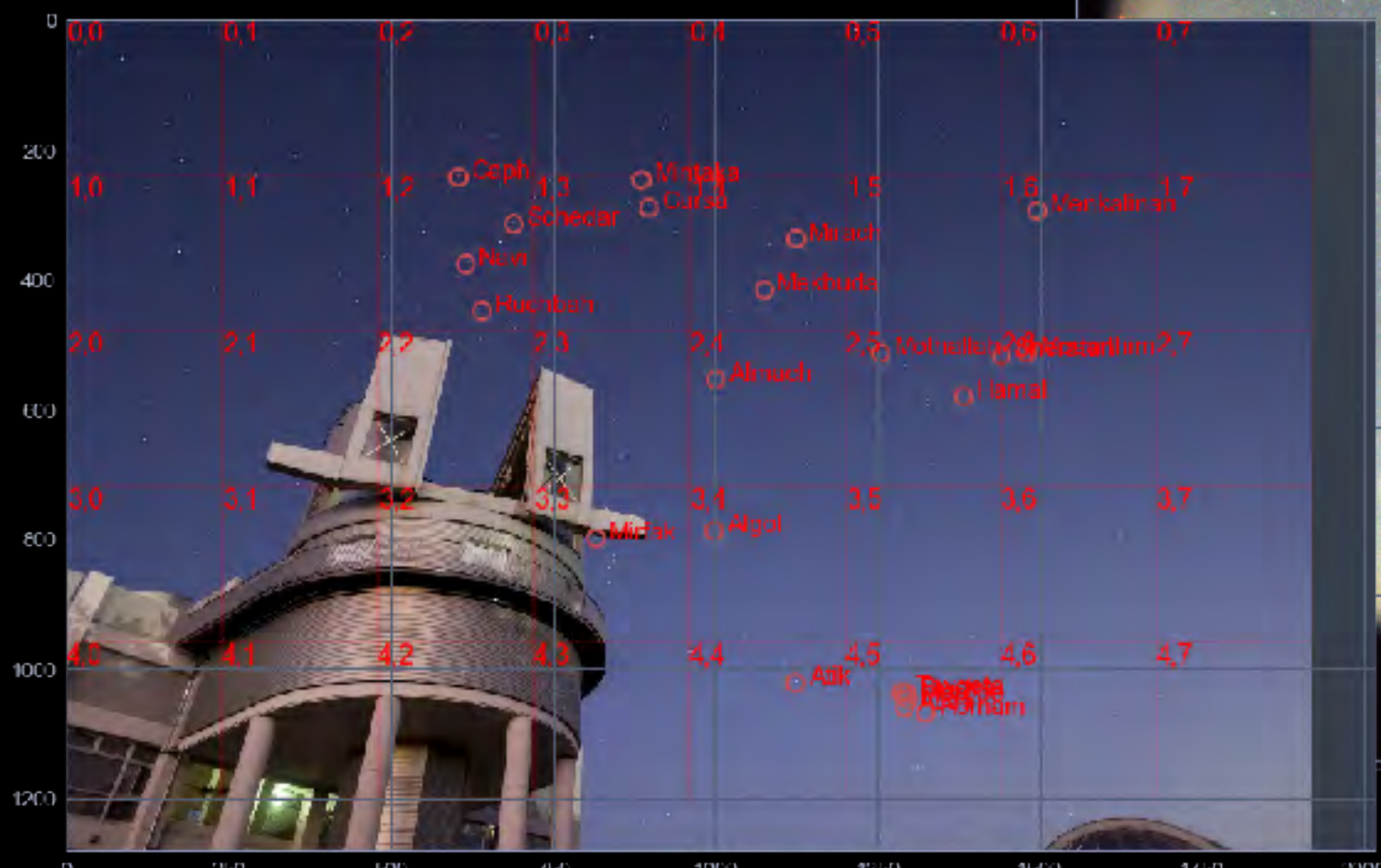


Astrometry-net

2019 Lang et. al

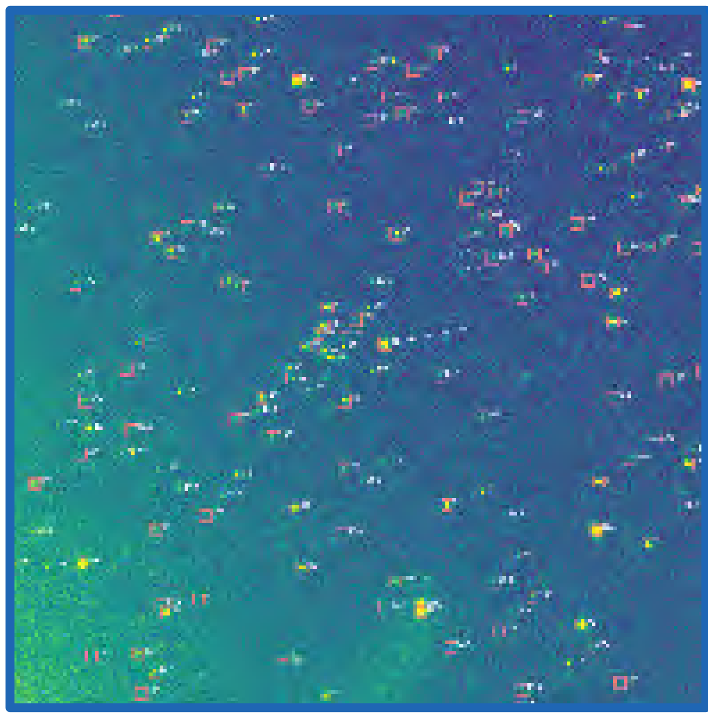



Eltanin
Alkaid / Benetnasch
Vega
Arcturus
Rasalhague
1000 1500 2000 2500 3000 3500 4000


Caph
Schedar
Mirach
Almach
Hamal
Mirfak
Algol
0 250 500 750 1000 1250 1500 1750 2000

Weather and Observation Conditions

relative Nr. of stars → **seeing**

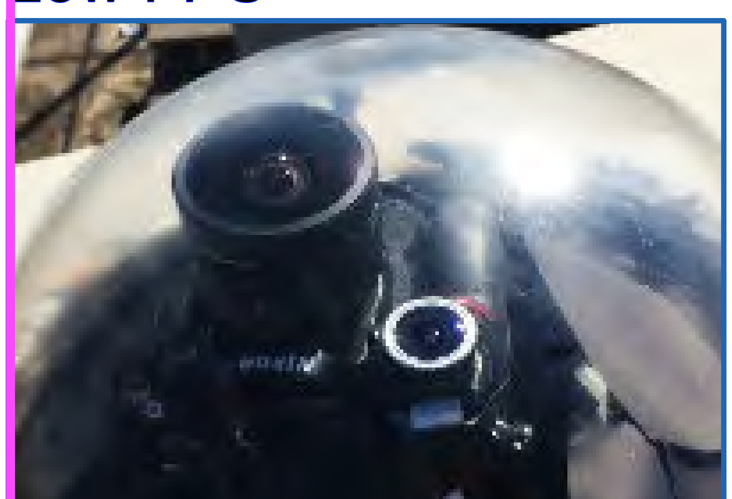


Semantic Segmentation

↓

cloud coverage estimation

Low FPS



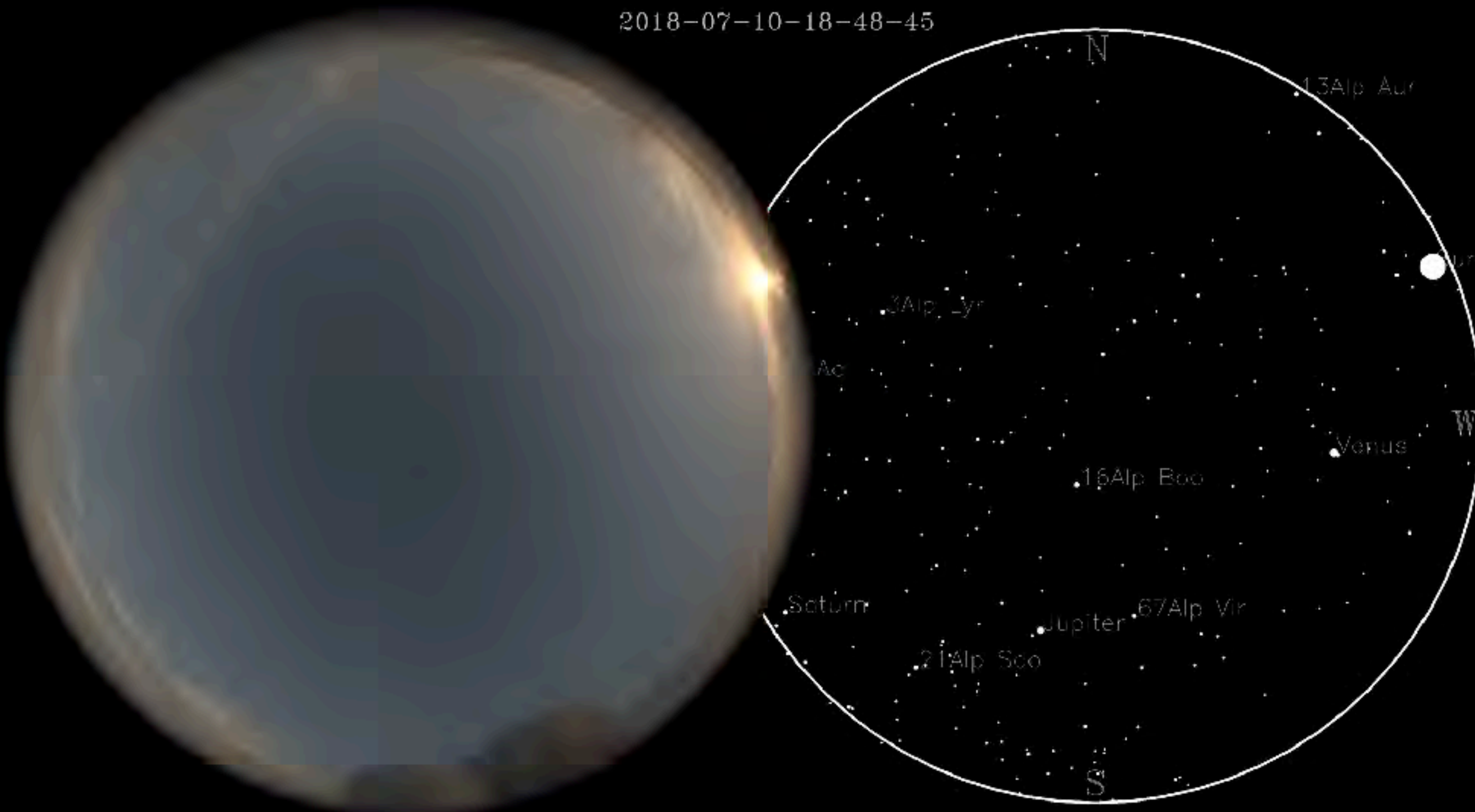
High FPS

seeing estimation (~30sec)

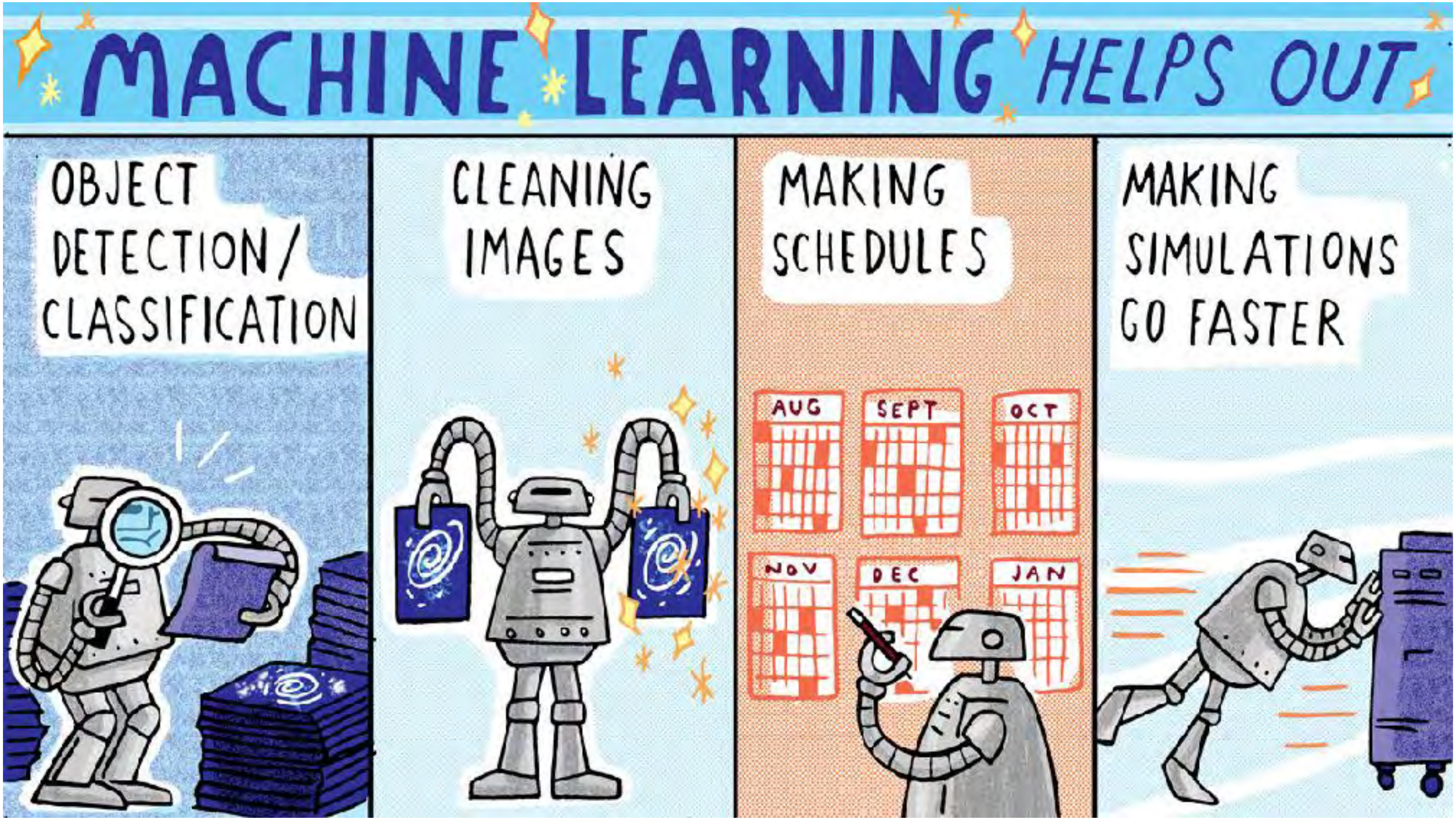
cloud coverage estimation (~2sec)

+ rain, snow, wind sensors

NHAO Skymonitor



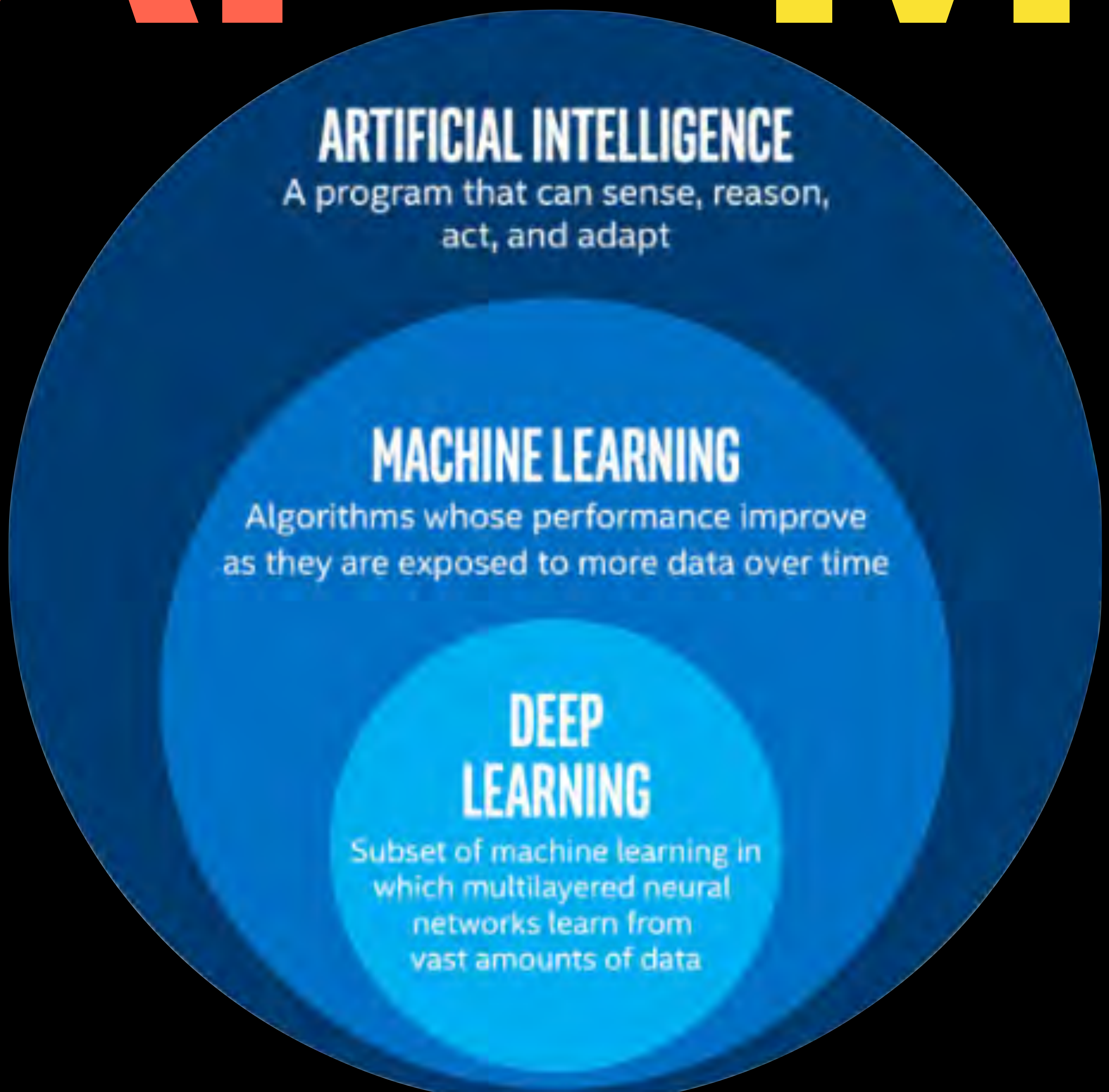
Youtube
http://www.nhao.jp/nhao/live/skymonitor.cgi



BUT: We need DATA !!!

https://www.symmetrymagazine.org/article/studying-the-stars-with-machine-learning

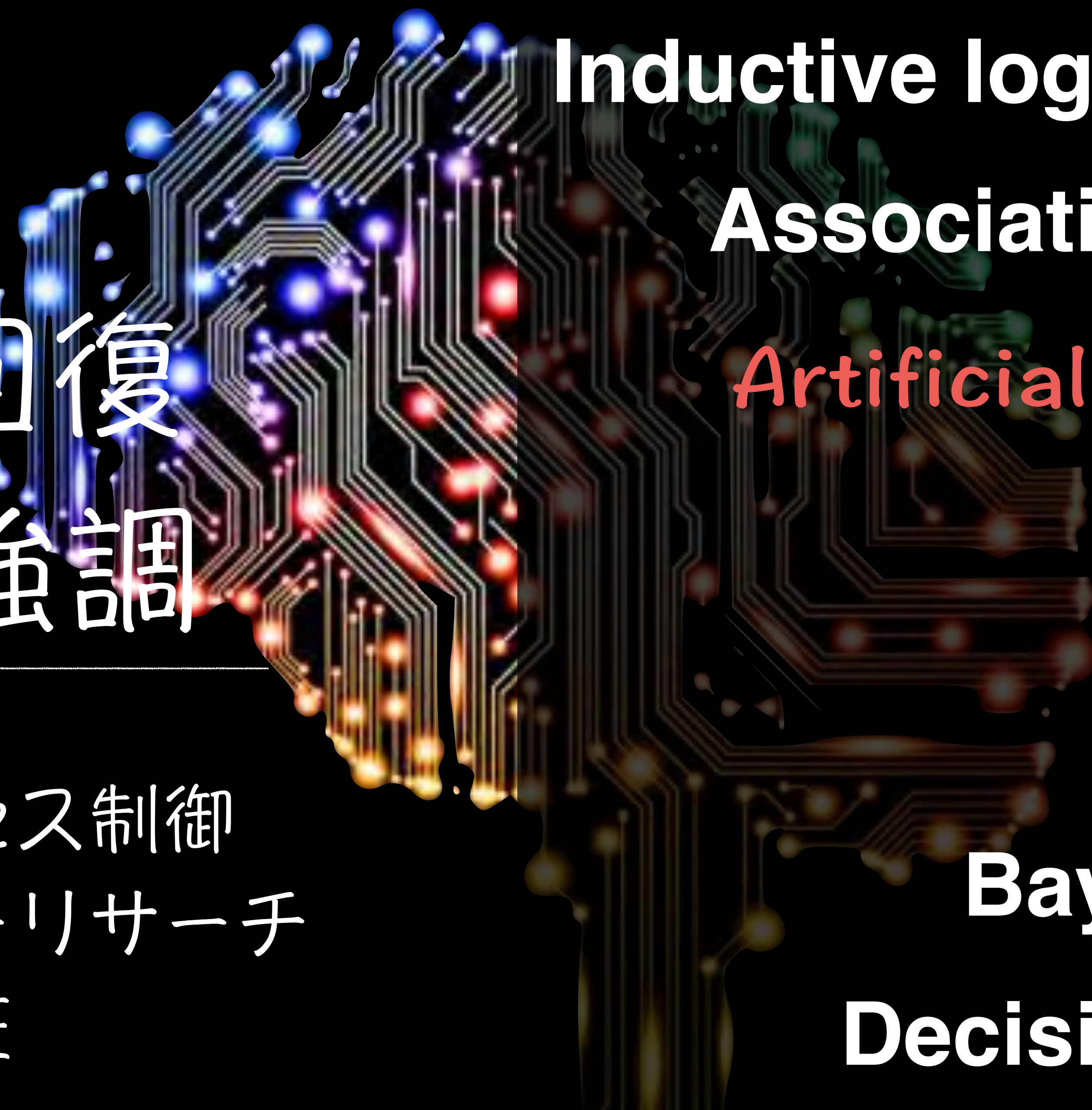
AI $\stackrel{?}{=}$ ML



応用

- 分類
- 画像回復
- 画像強調

- 売上予測
- 工業プロセス制御
- カスタマーリサーチ
- データ検証
- 危機管理
- ターゲットマーケティング



機械学習

Inductive logic programming

Association rule learning

Artificial neural networks

Deep learning

Clustering

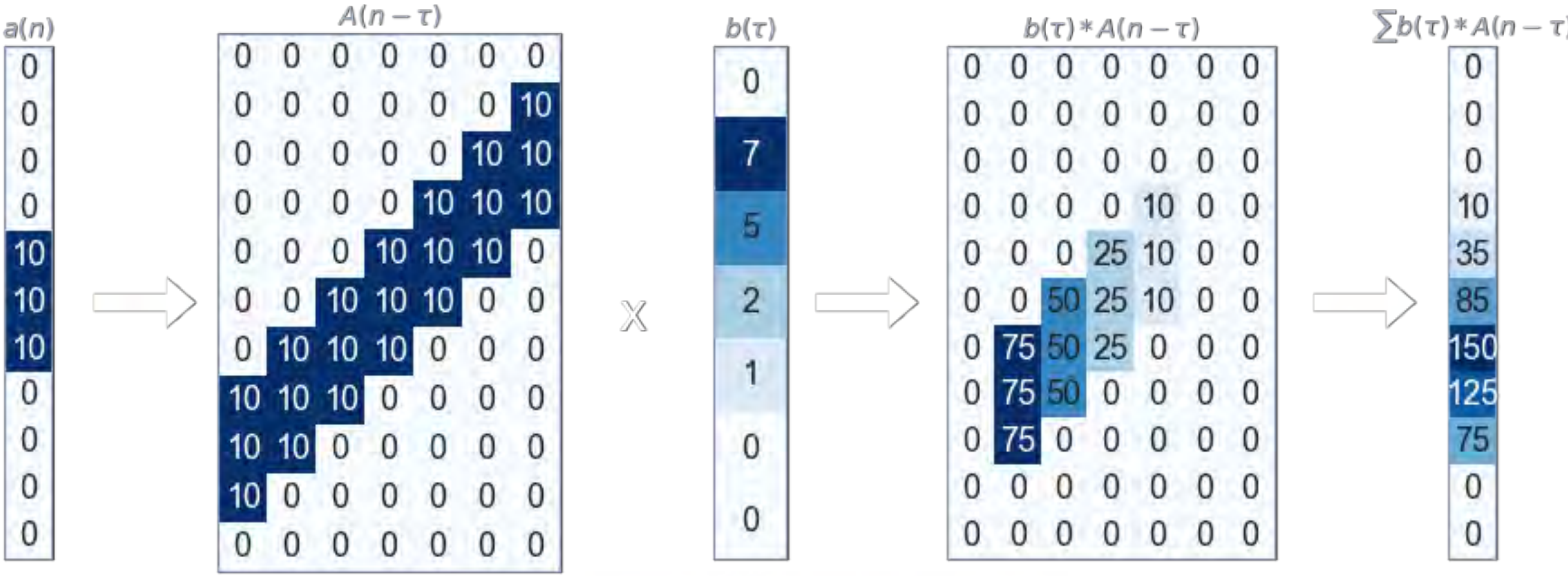
Bayesian networks

Decision tree learning

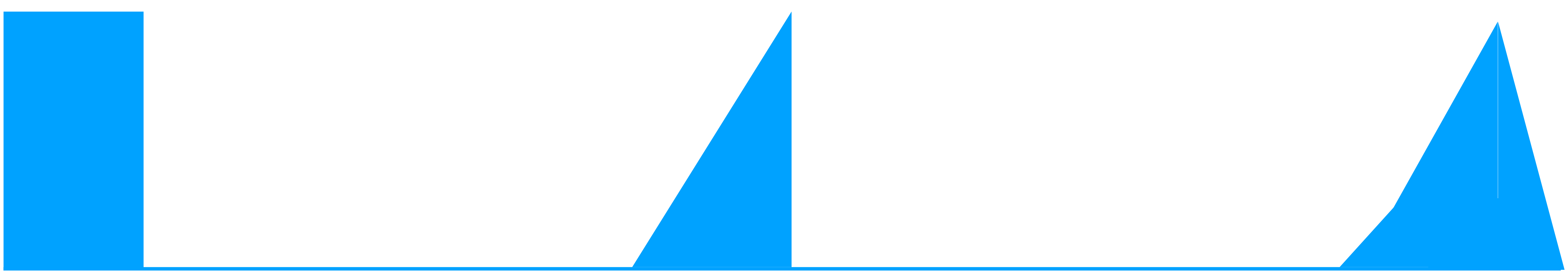
Reinforcement learning

Similarity and metric learning

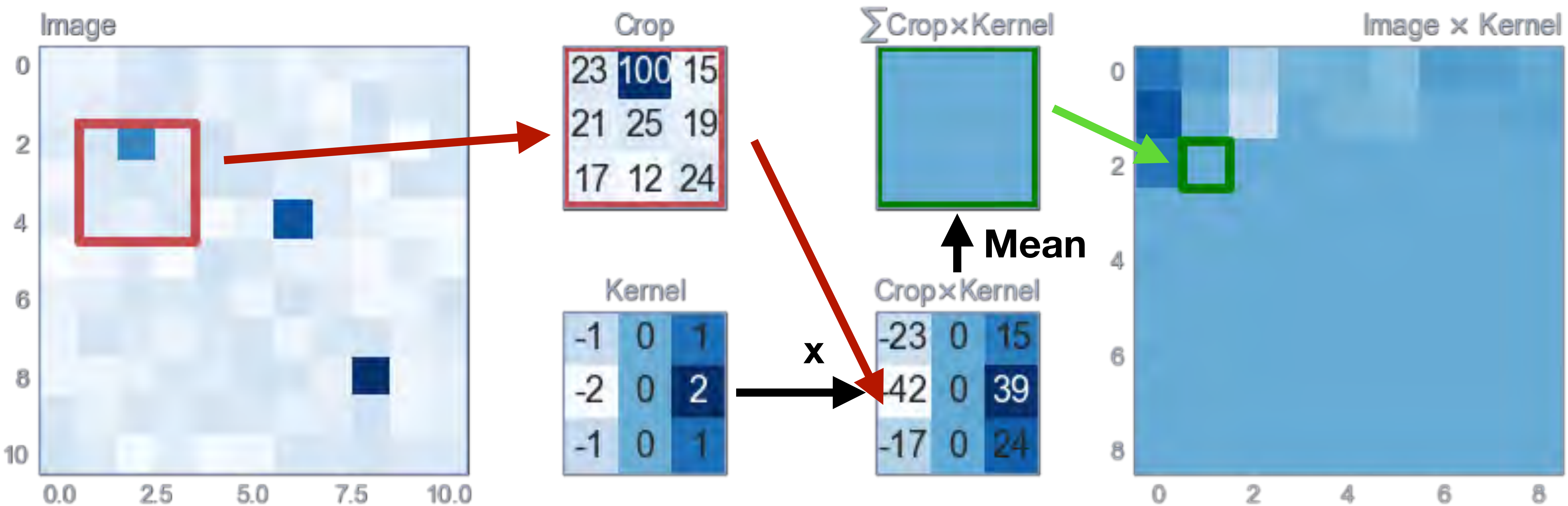
Convolution

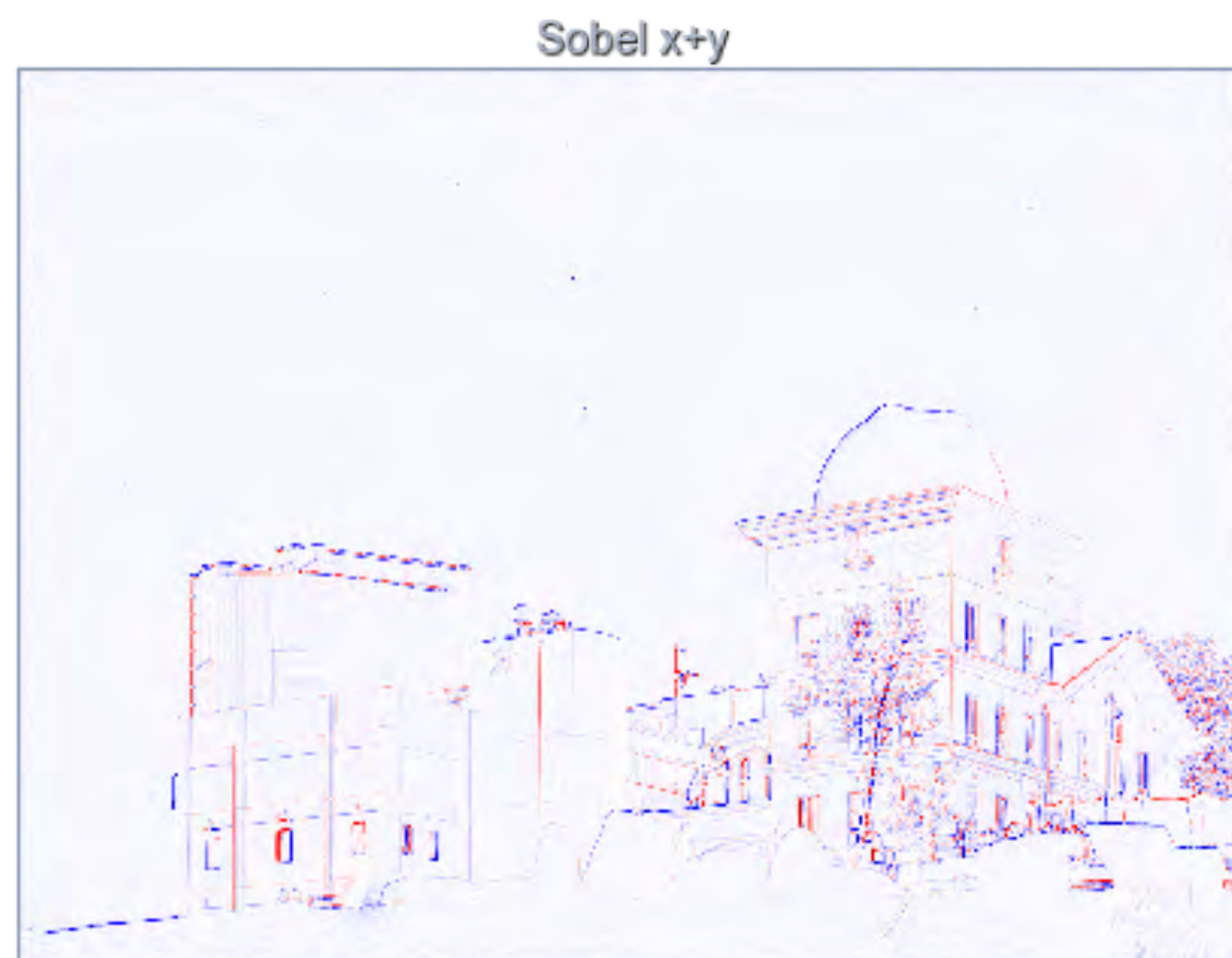


$$(a \times b)[n] = \sum_{m=-\infty}^{\infty} a[m]b[n-m]$$



http://www.nhao.jp/~sbaar/seminar/convolution.html

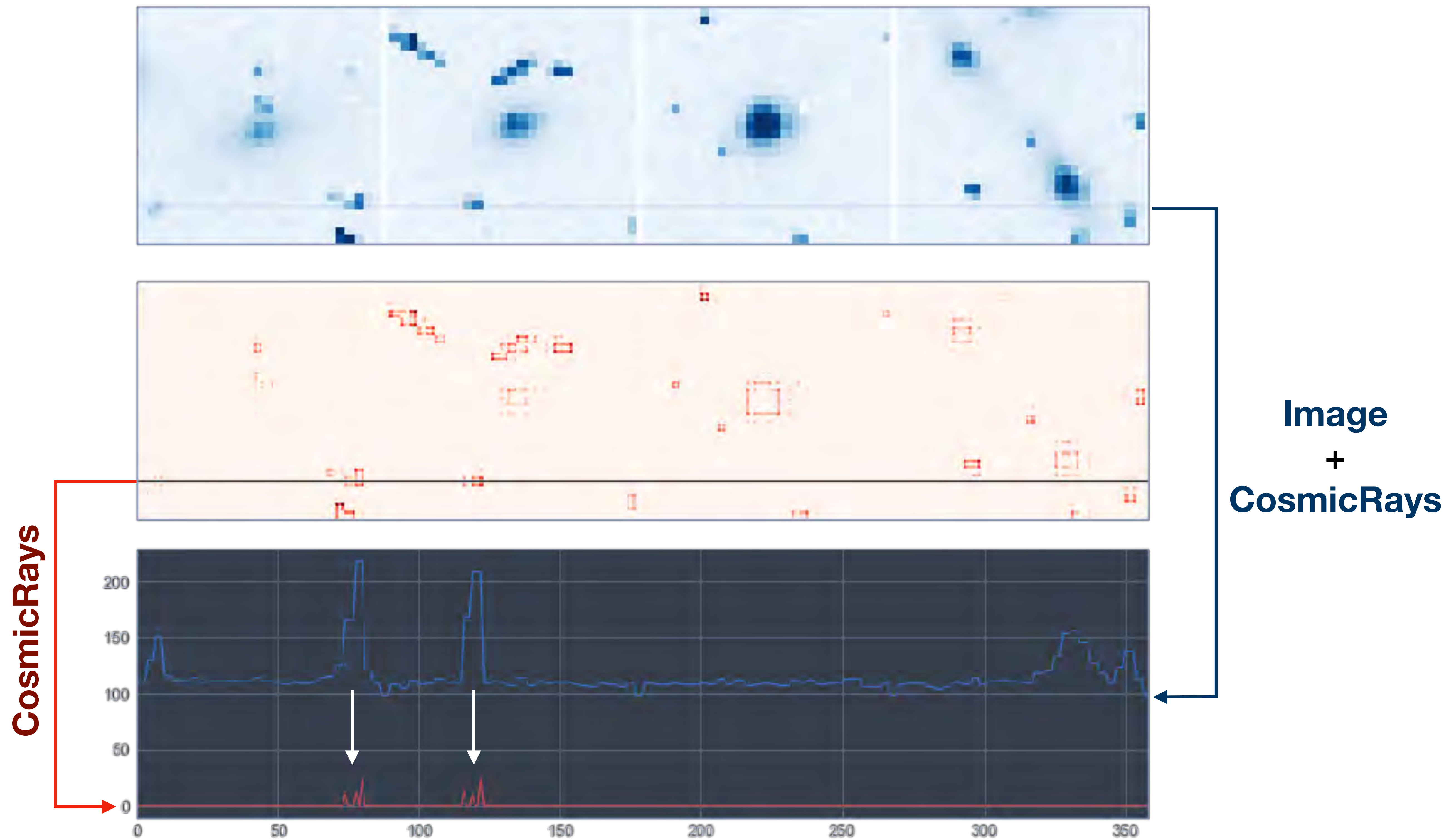




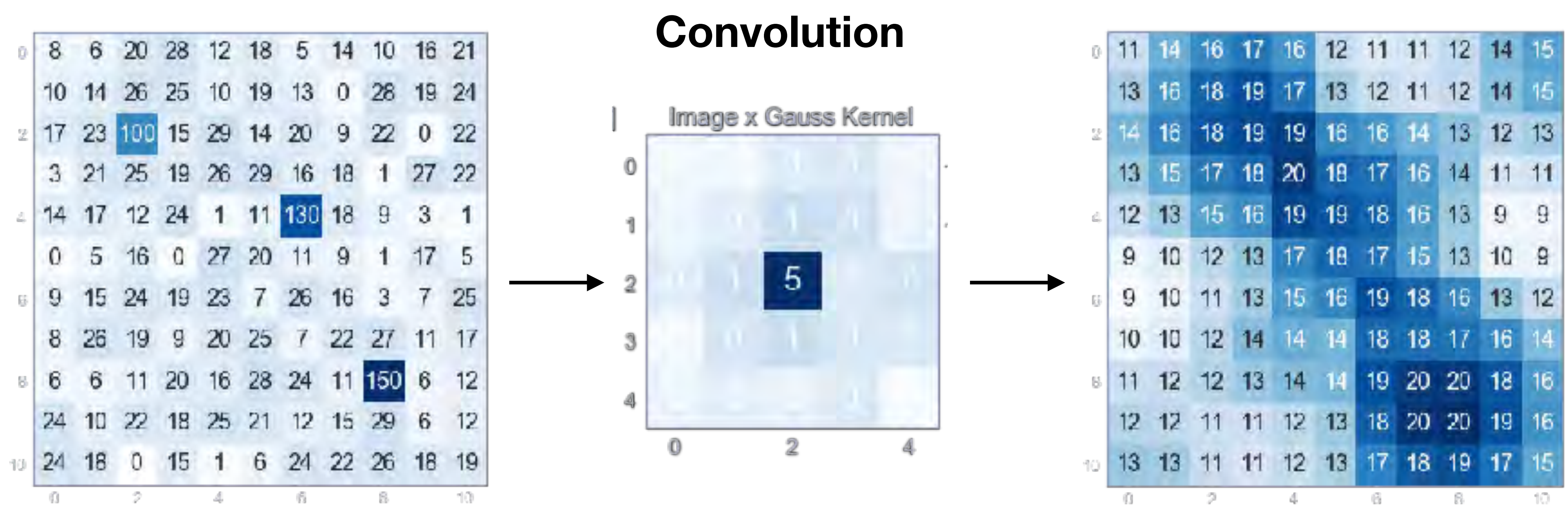
http://www.nhao.jp/~sbaar/seminar/convolution.html

Cosmic Ray Detection (LAcosmic filter)

In this example we will take a look on how to locate sharp-edged objects in astronomic images using a Lagrangian Kernel as discribed in the paper of P.G. Dokkum. (http://www.astro.yale.edu/dokkum/lacosmic/cosmic.ps.gz)

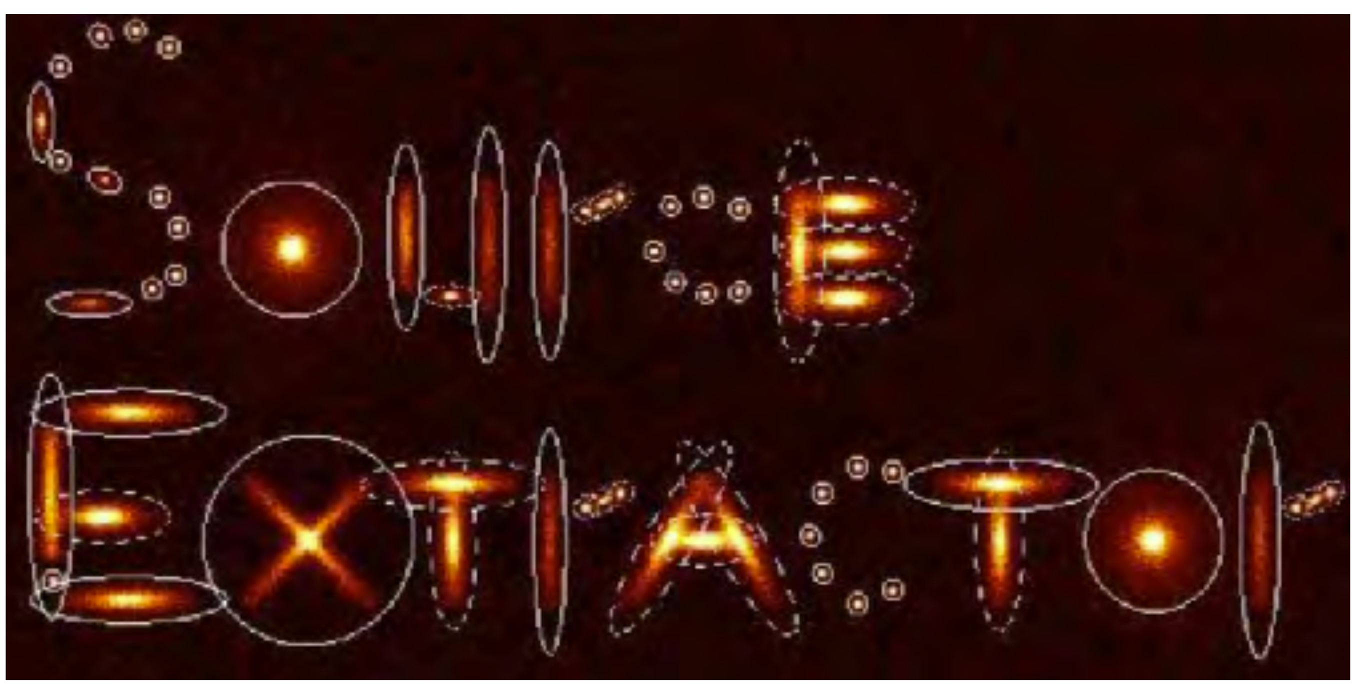


SEXTRACTOR



Regmax

Positions



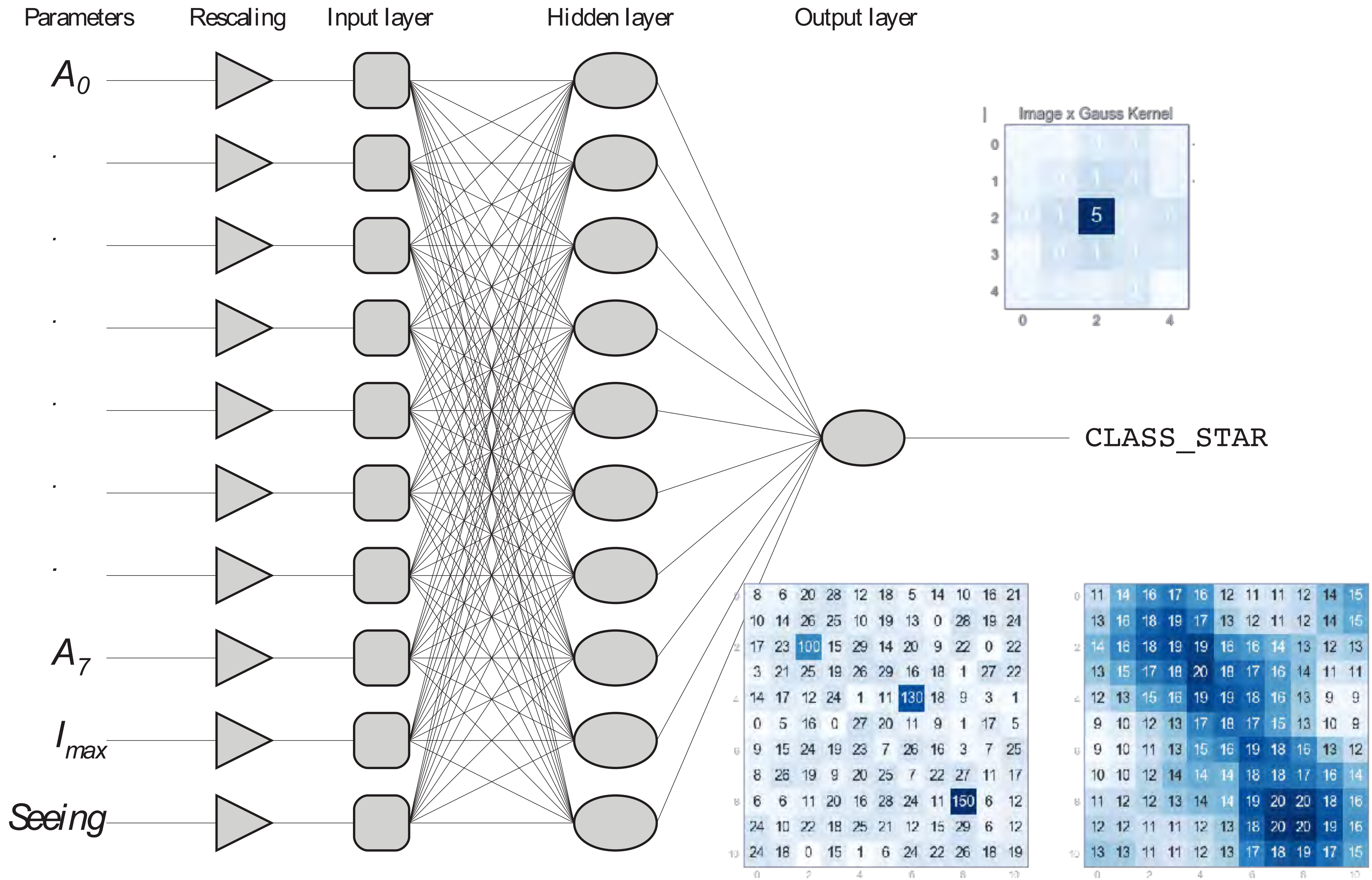
Additional Convolutions

↓

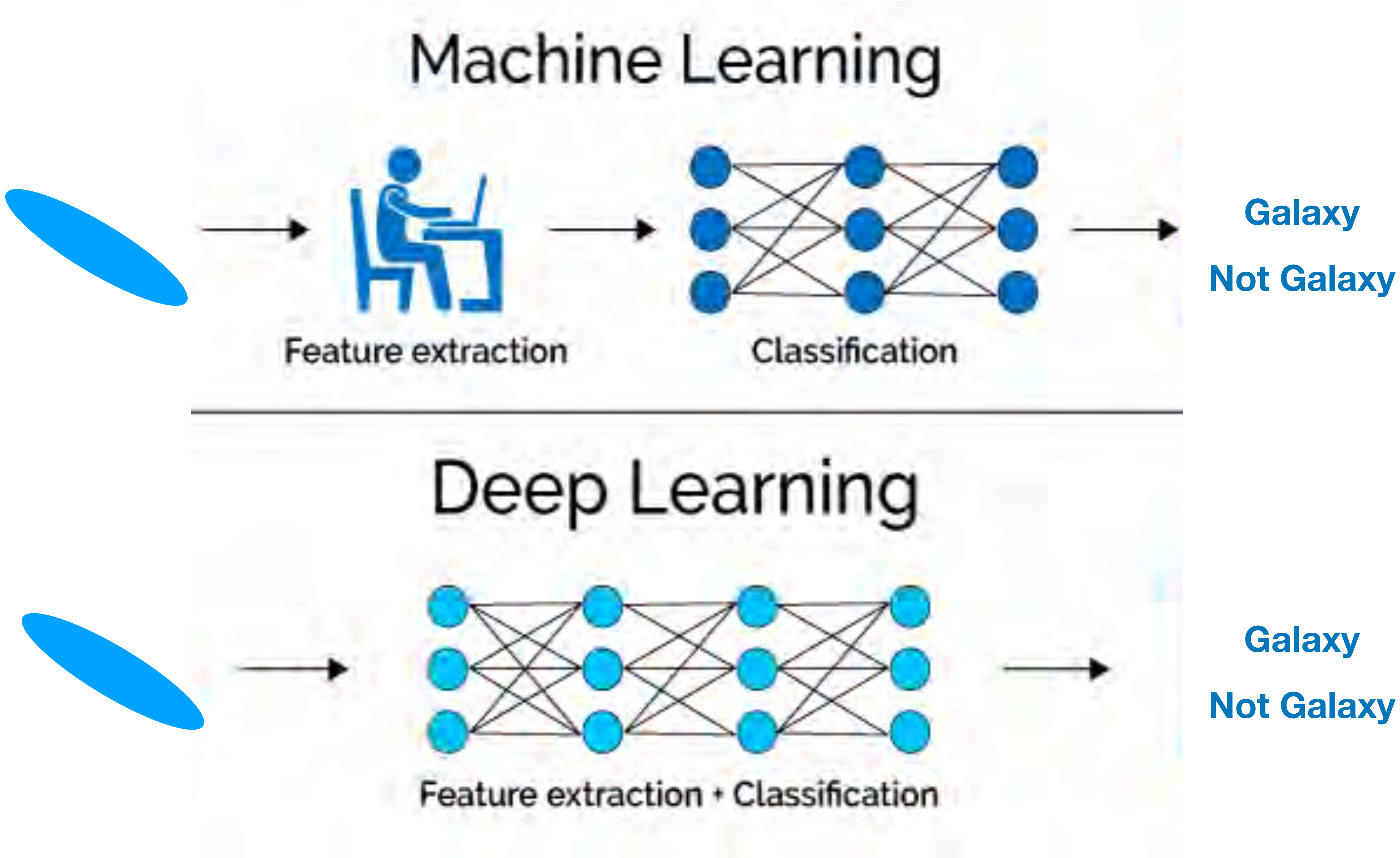
Parameters (shape, etc.)

https://sextractor.readthedocs.io/en/latest/ClassStar.html

SExtractor

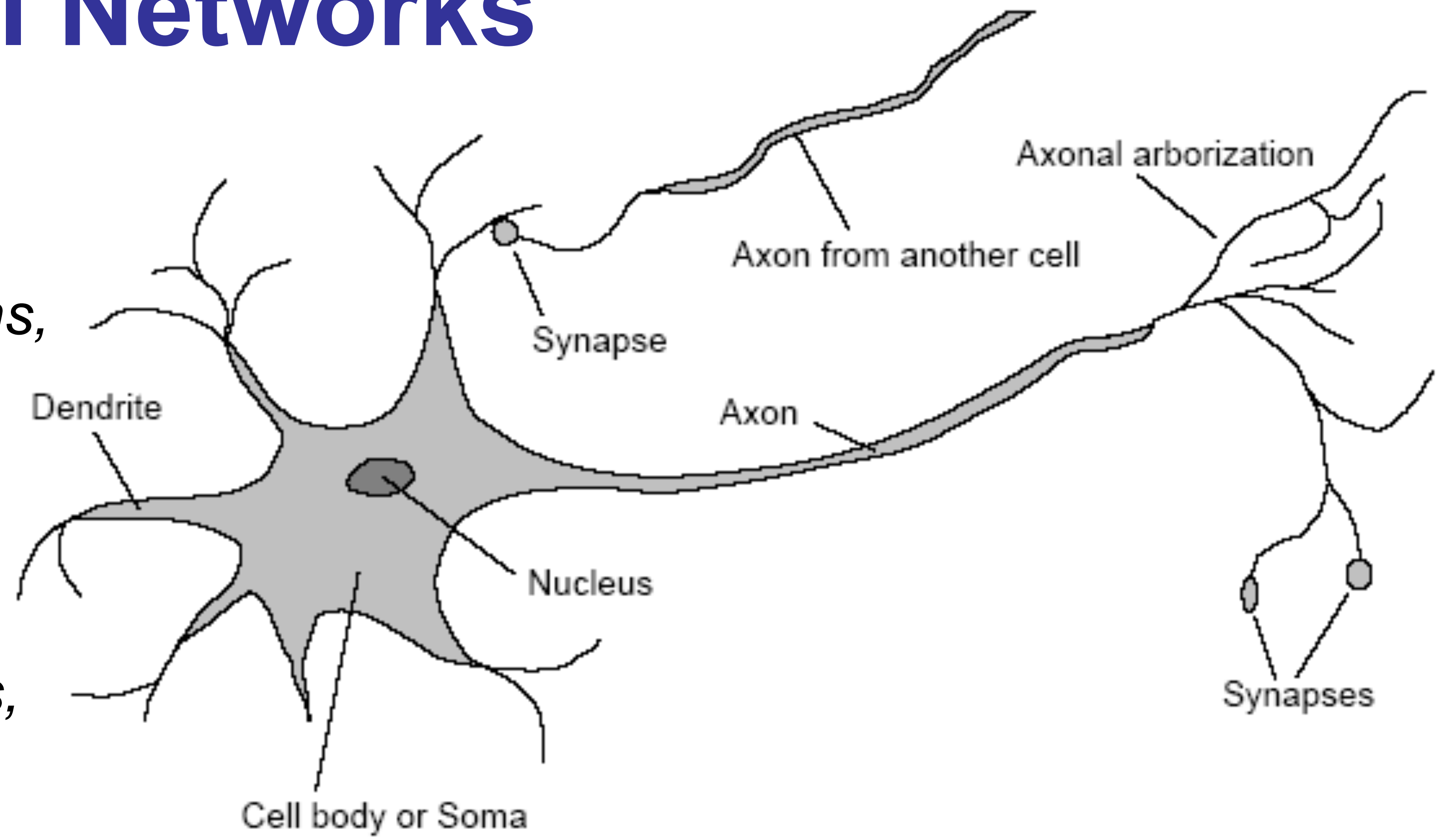


https://sextractor.readthedocs.io/en/latest/ClassStar.html


Machine Learning
Feature extraction
Classification
Galaxy
Not Galaxy
Deep Learning
Feature extraction + Classification
Galaxy
Not Galaxy

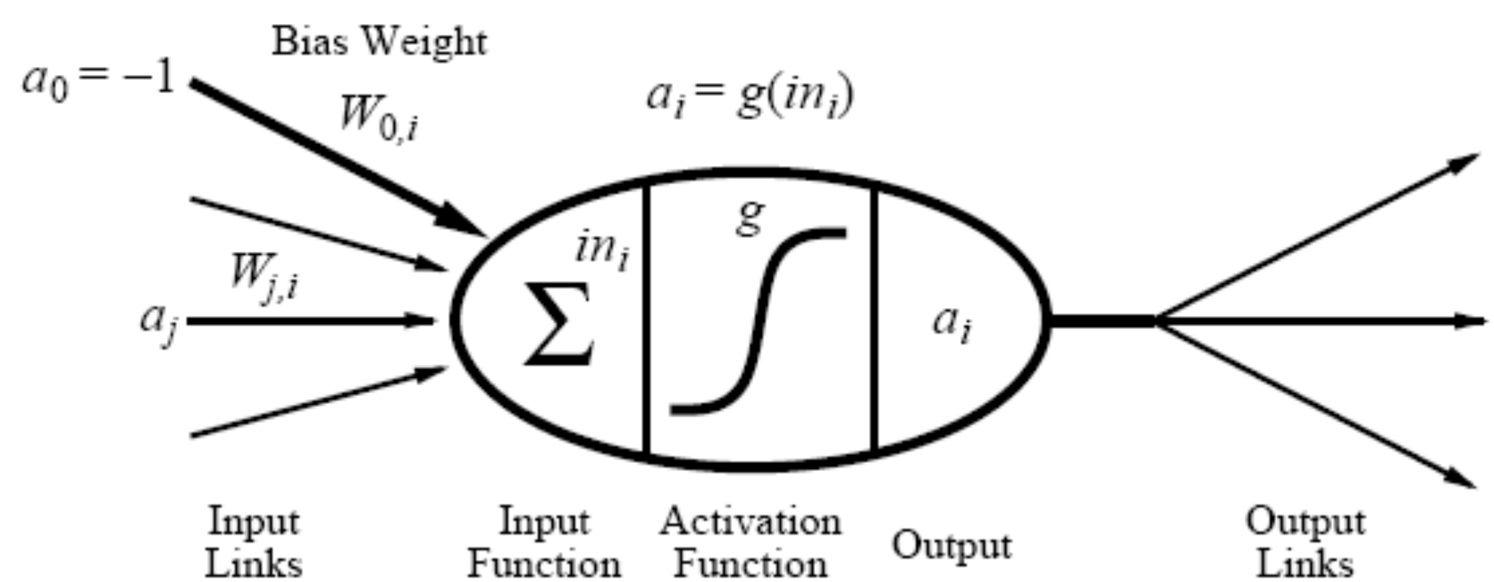
(Artificial) Neural Networks

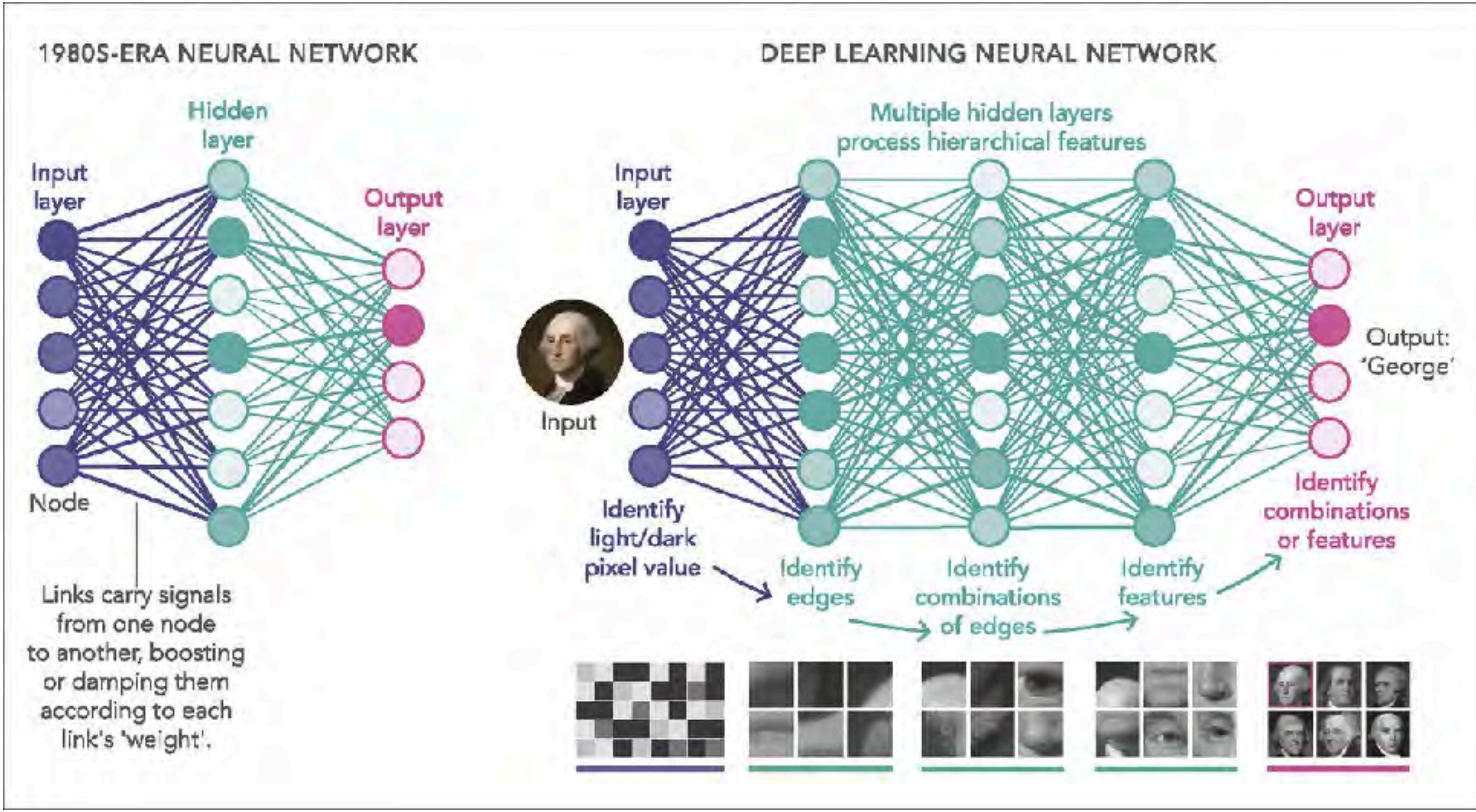
- Motivation: human brain
  - massively parallel (*10^{11} neurons, ~20 types*)
  - small computational units with simple low-bandwidth communication (*10^{14} synapses, 1-10ms cycle time*)



- Realization: neural network
  - *units* (≈ neurons) connected by *directed weighted links*
  - *activation function* from inputs to output

$$a_i \leftarrow g(in_i) = g\left(\Sigma_j W_{j,i} a_j\right)$$

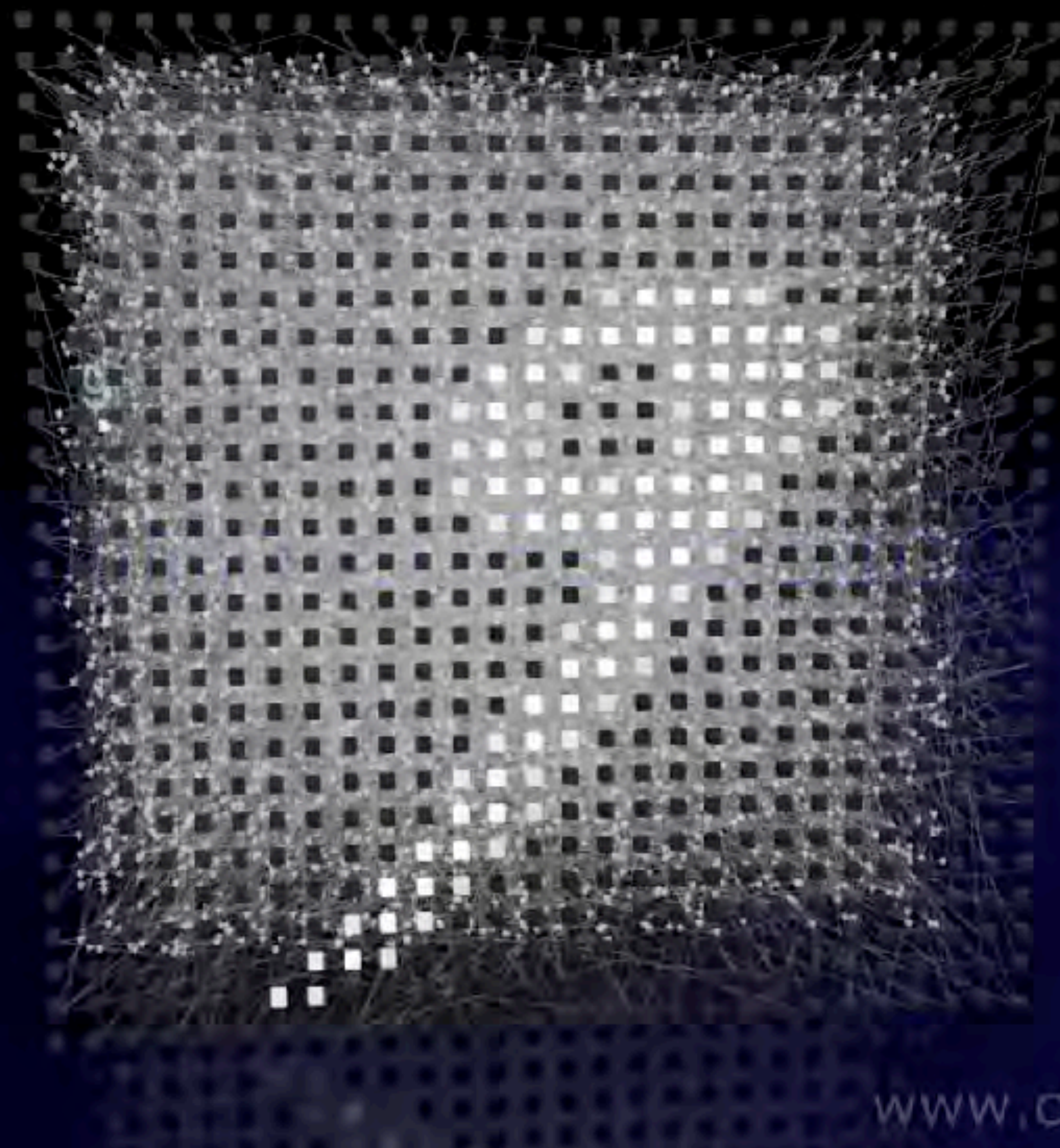




Benefits of neural networks:

- **Extract meaning from complicated data**
- **Detect trends and identify patterns too complex for humans to notice**
- **Learn by example**
- **Speed advantages**

https://www.deeplearning-academy.com/p/ai-wiki-machine-learning-vs-deep-learning

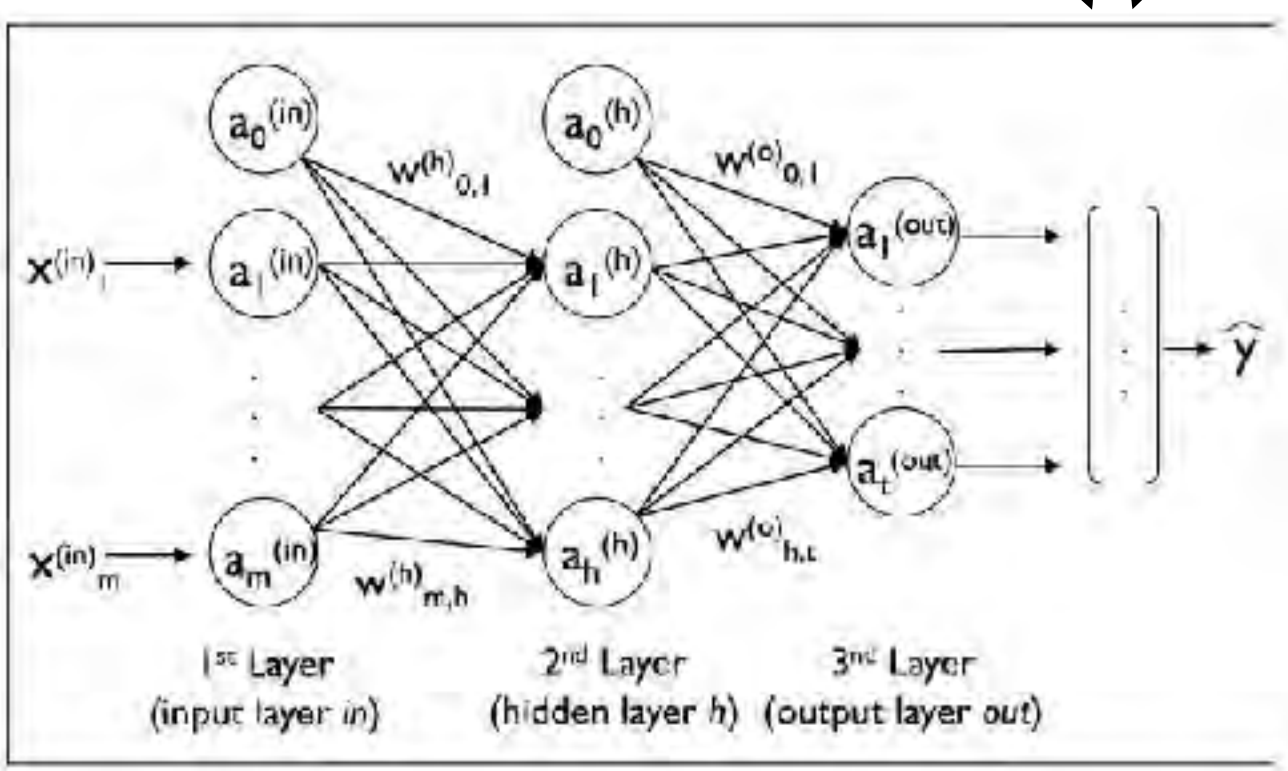


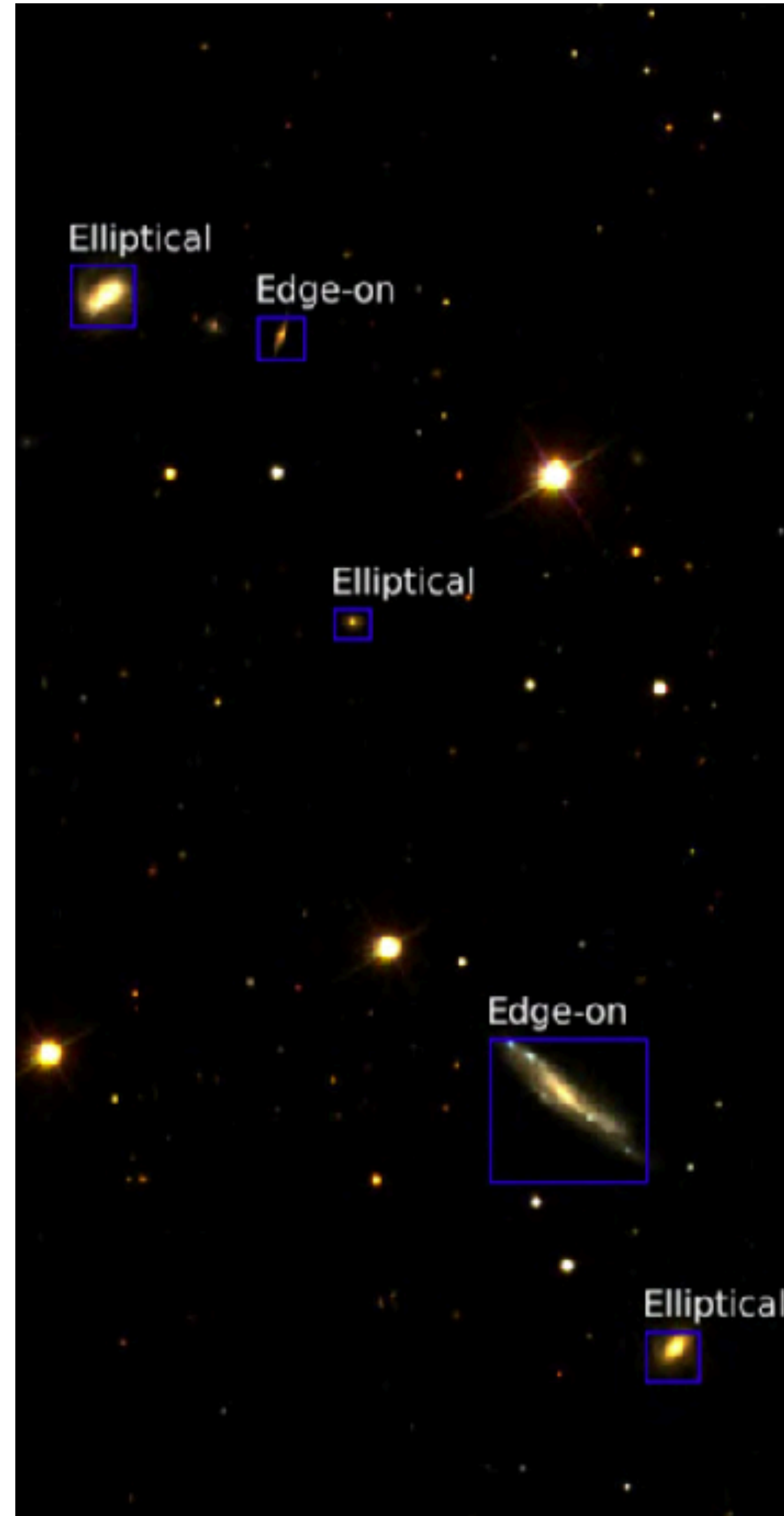
AstroCV

Image Data

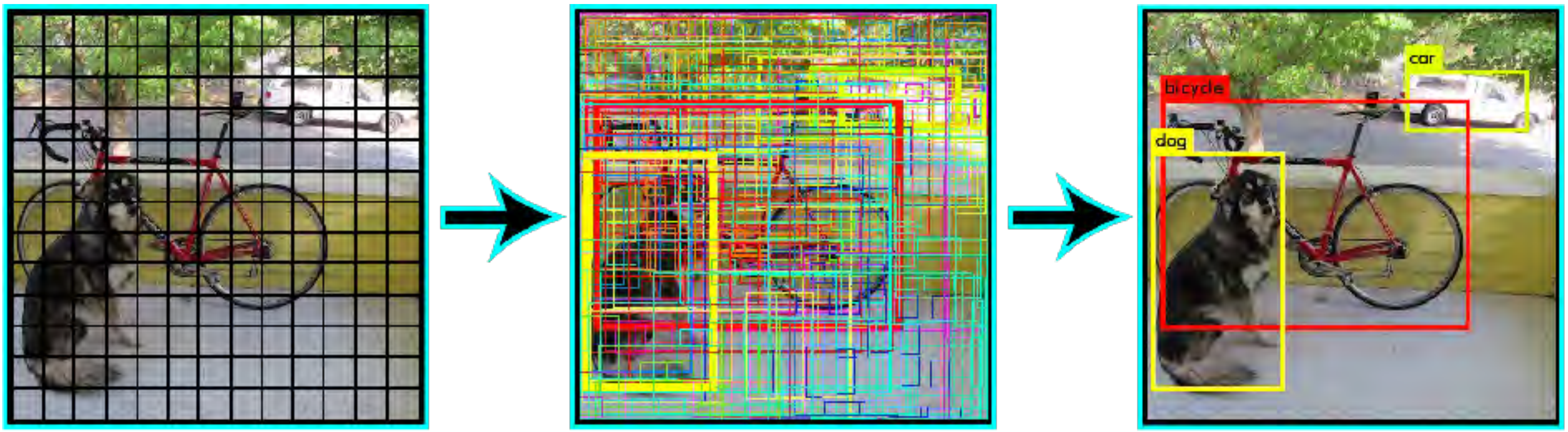
Source Catalog

Position **Type**



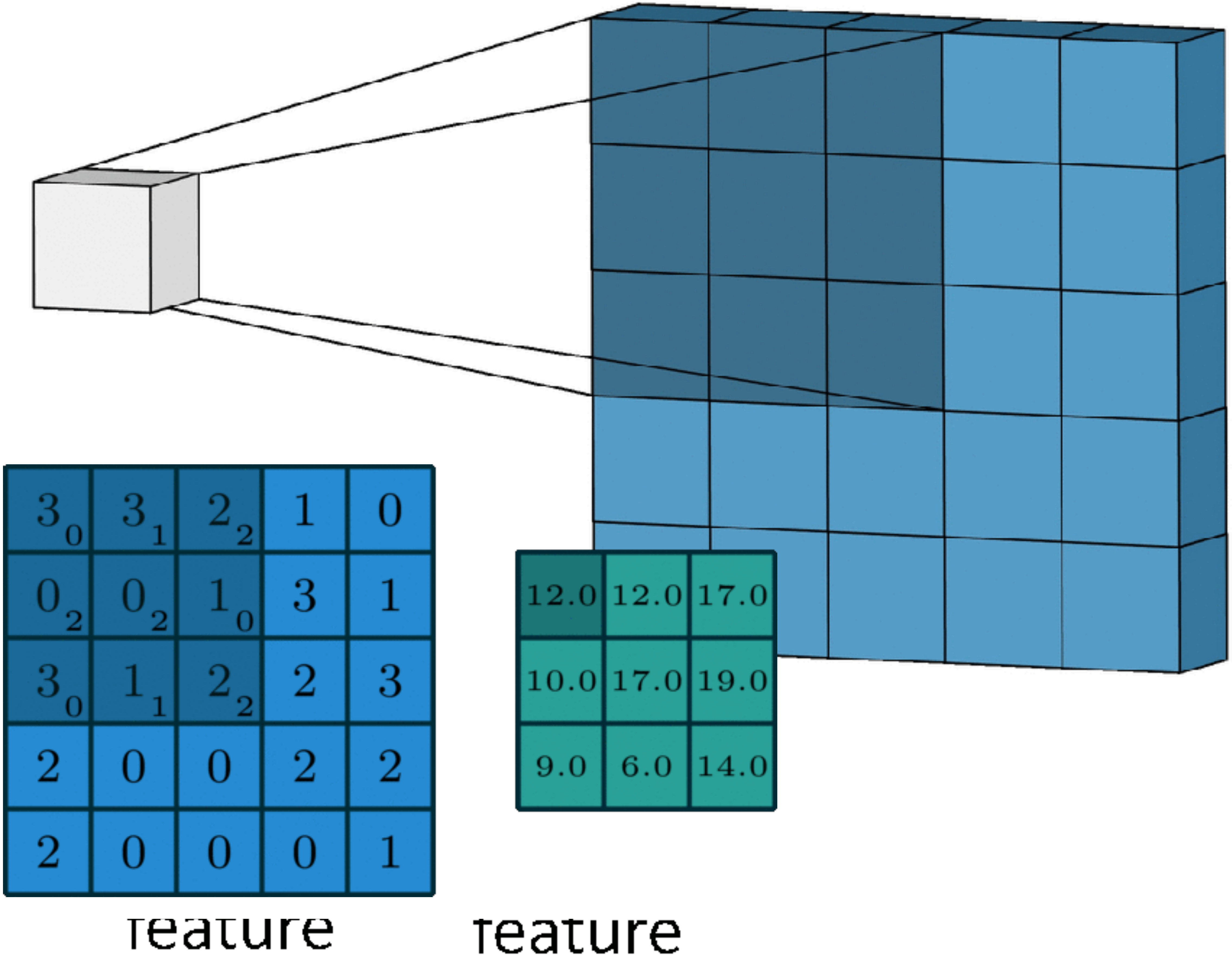


YOLO in real life

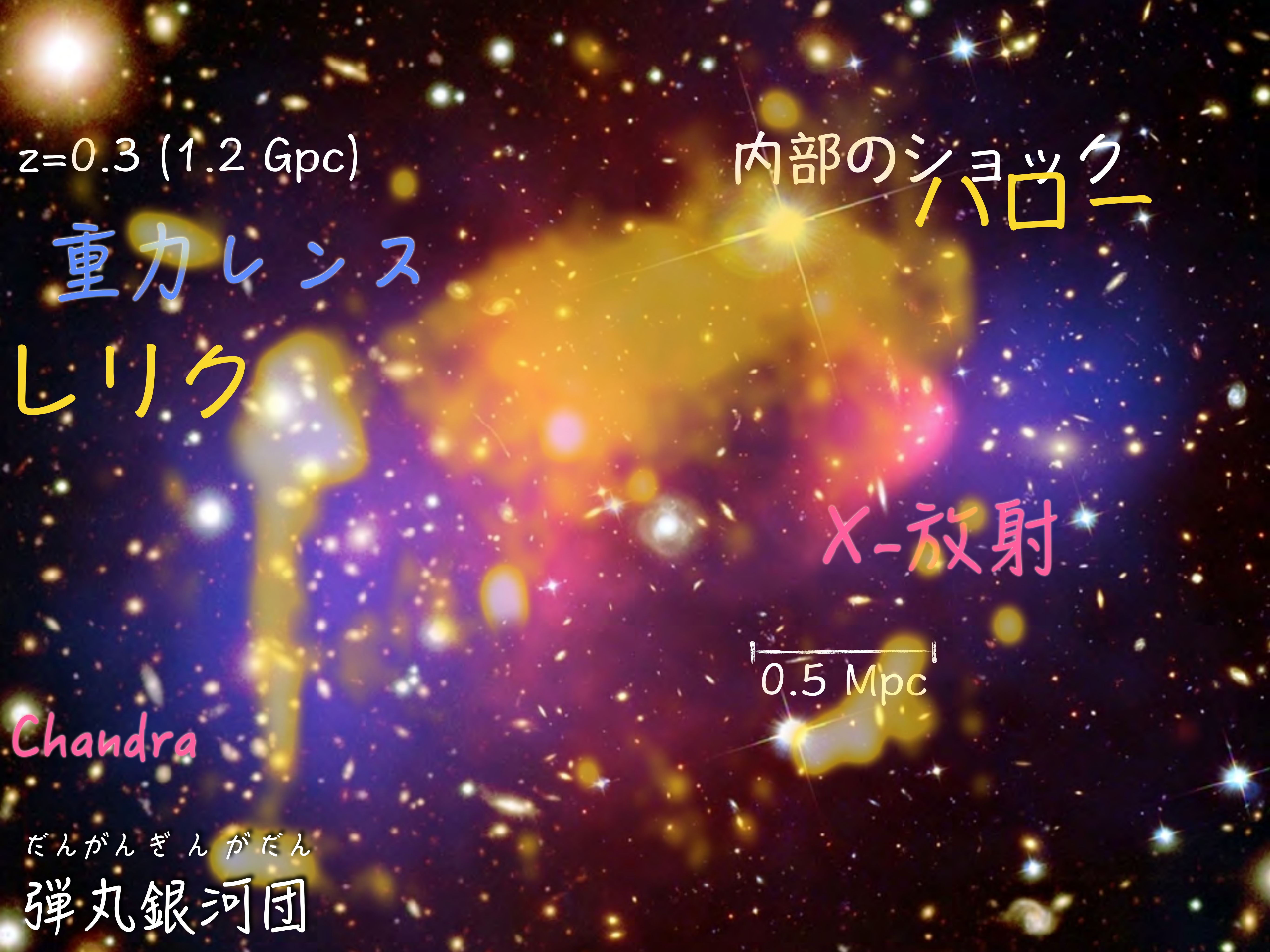


What's the Problem?

- **UCI Machine Learning Repository (University of California, School of Information and Computer Science)**
- **https://archive.ics.uci.edu/ml/index.php**
- **Amazon Datasets**
- **Kaggle Datasets**
- **GOOGLE**



3 0
3 1
2 2
1
0
0 2
0 2
1 0
3
1
3 0
1 1
2 2
2
3
2
0
0
2
2
2
0
0
0
1
12.0
12.0
17.0
10.0
17.0
19.0
9.0
6.0
14.0
feature
feature

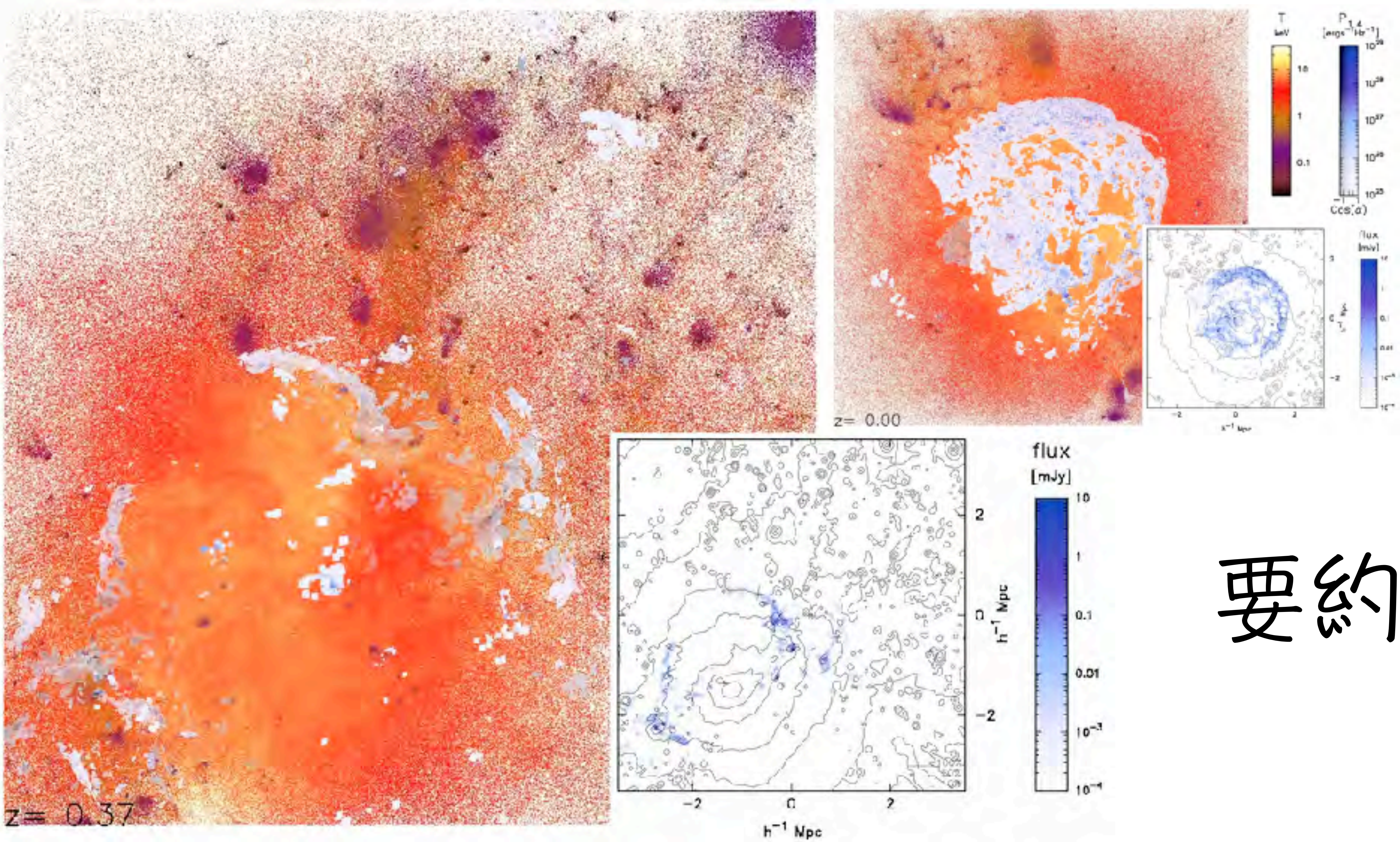


z=0.3 (1.2 Gpc)
内部のショック
ハロー
重力レンズ
レリク
X-放射
0.5 Mpc
Chandra
だんがんぎんがだん
弾丸銀河団

電波研究

電波レリック

- 拡張 (~1 Mpc)
- 銀河団の周辺(しゅうへん)の拡散(かくさん)放出(ほうしゅつ) (diffuse emission)
- 光学的(こうがくてき)カウンターパートない
- 不規則(ふきそく)な形態(けいたい)
- ~60 個遺物見つた

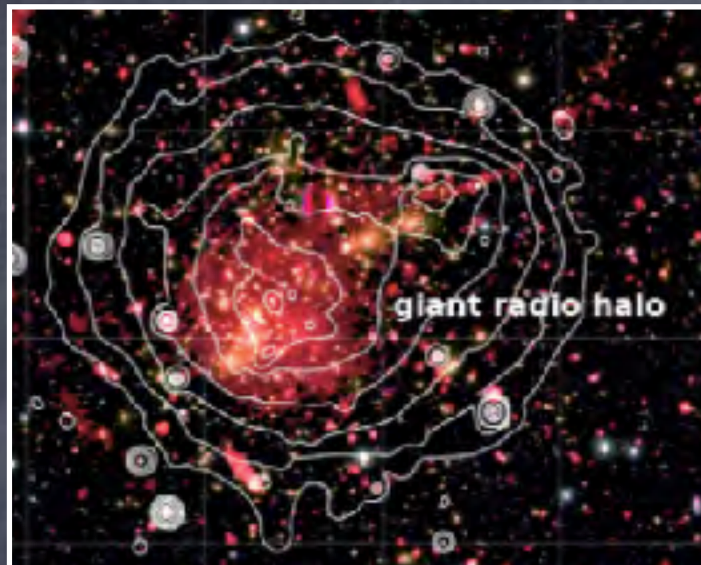


要約

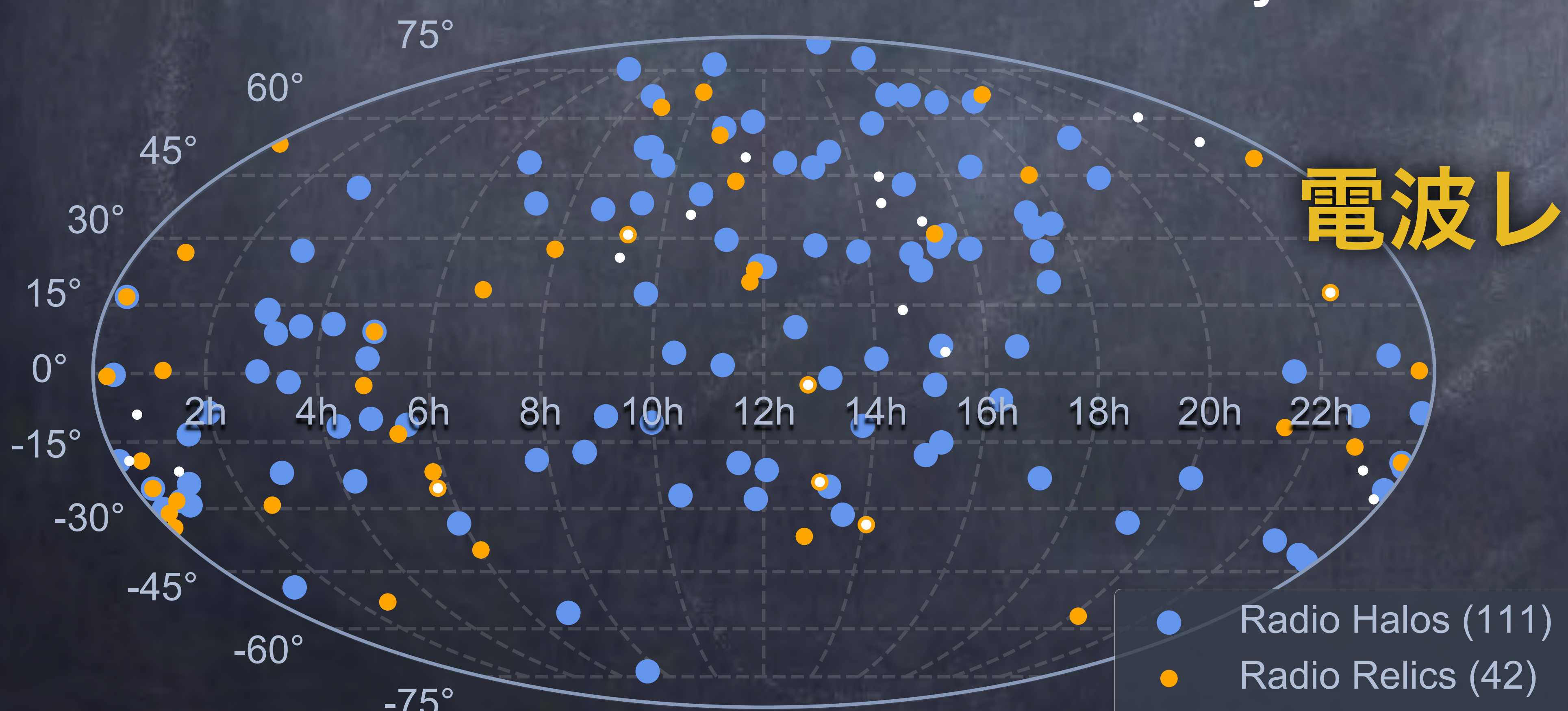
Hoeft et. al. 2011

Merging Galaxy Clusters

175個クラスター が 拡散電波放射含む (van Weeren 2019)



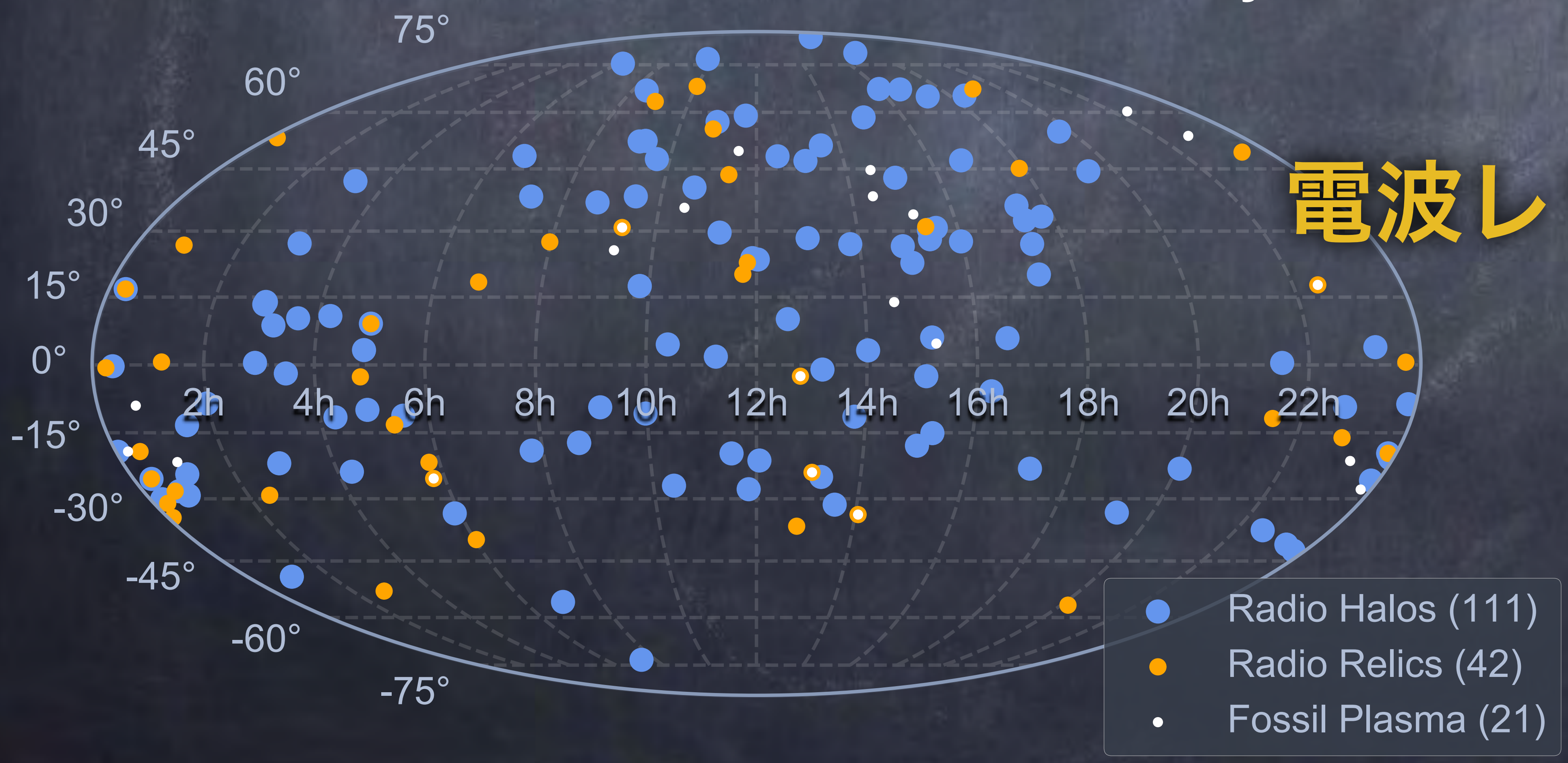
Z < 0.8: Galaxy Clusters > 13万個　Z.L.Wen et.al:



電波レリック< 100個

Merging Galaxy Clusters

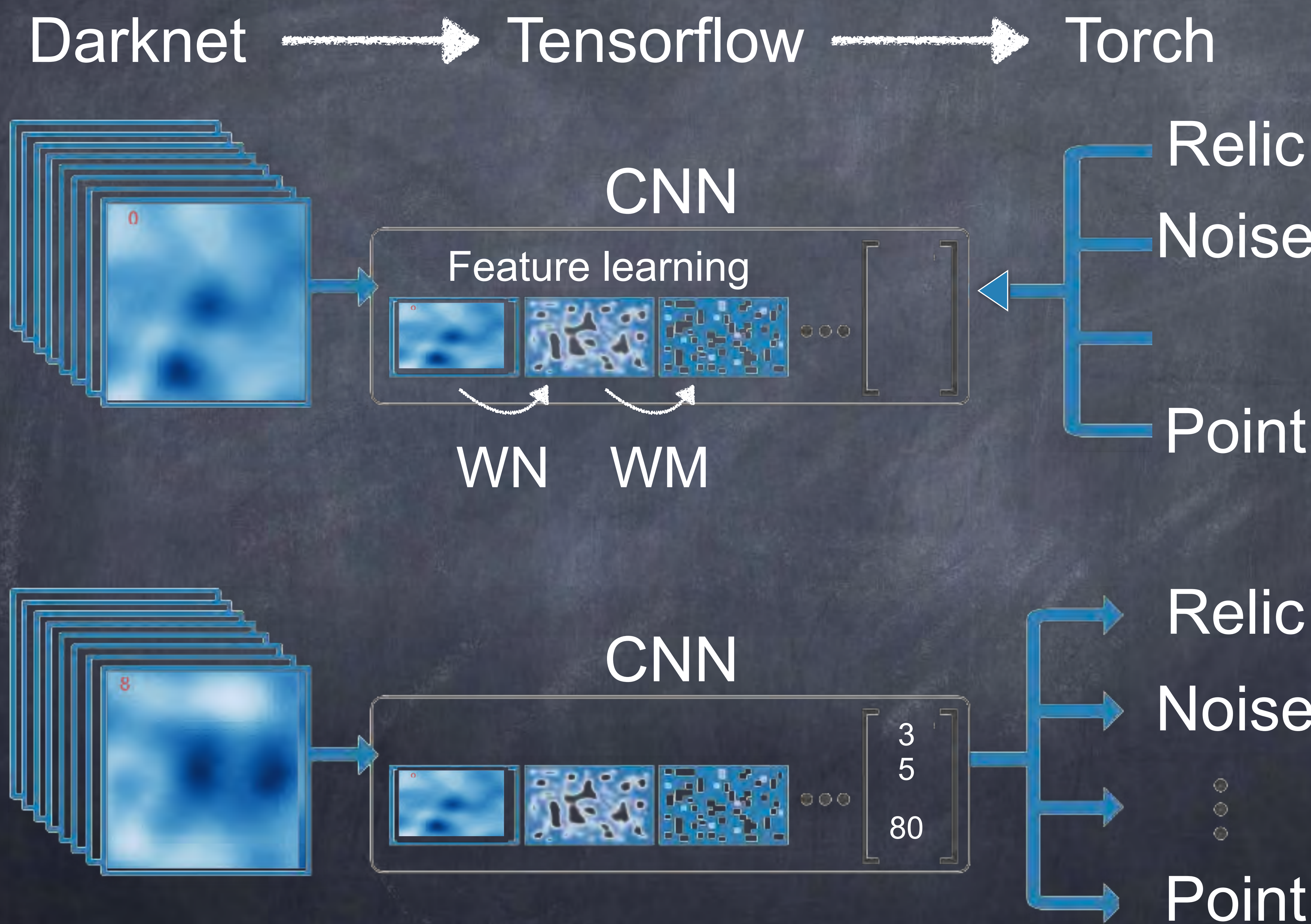
Z < 0.8: Galaxy Clusters > 13万個　Z.L.Wen et.al:



電波レリック< 100個

分類 (Redmon 2016)

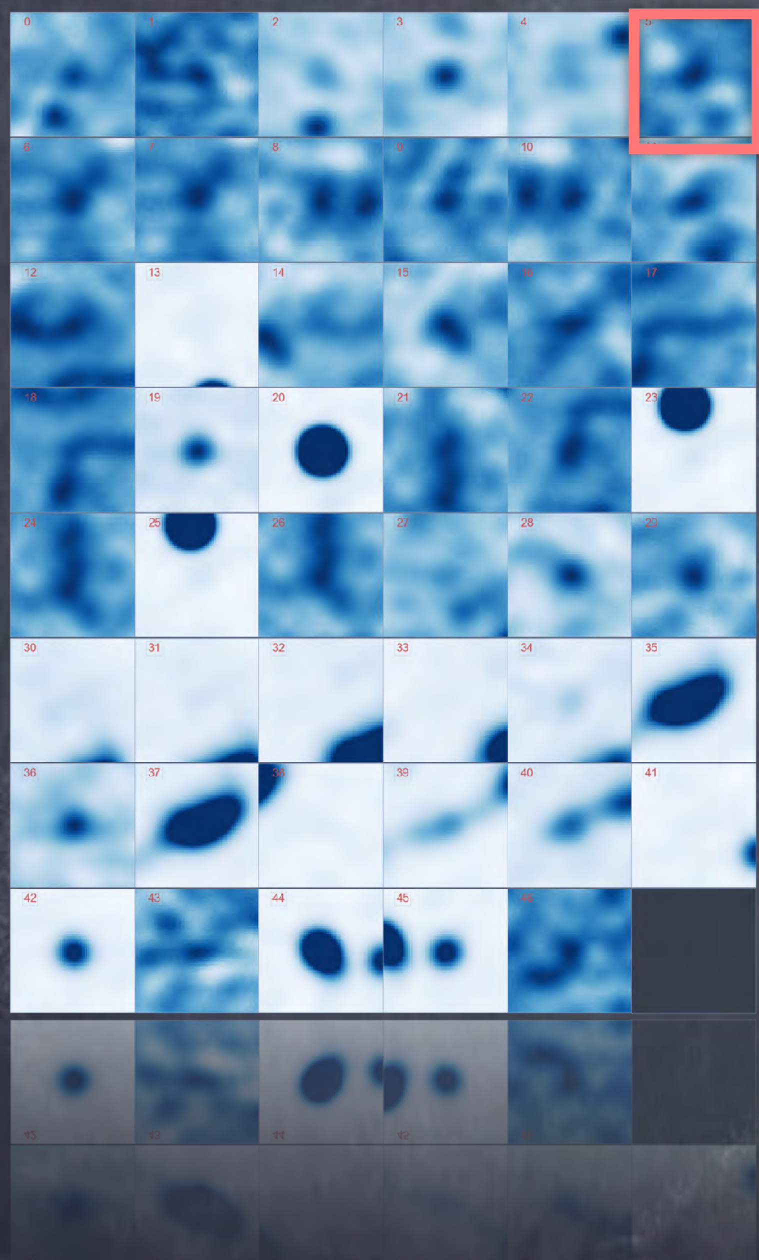
With SSD

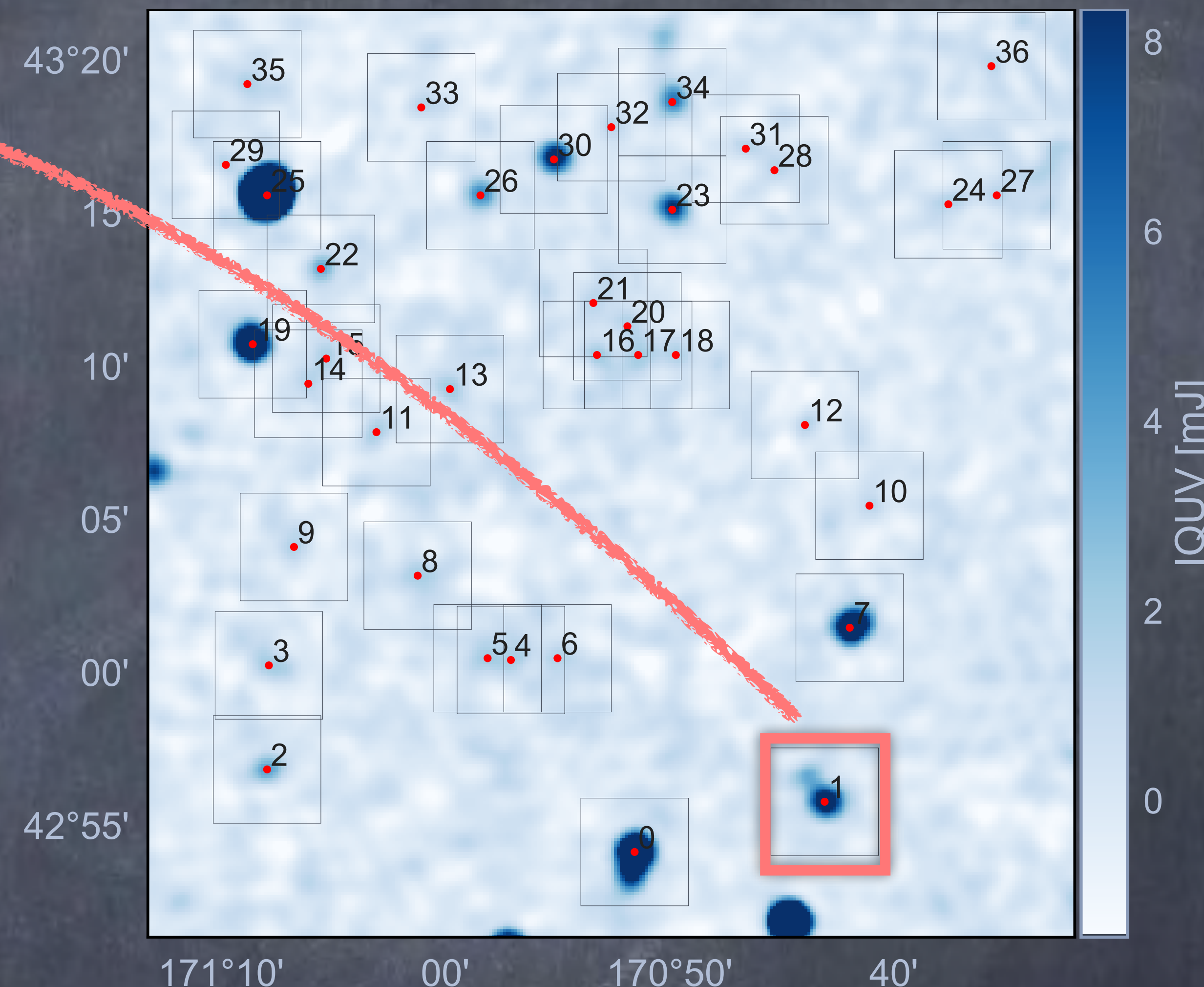


分類の準備

32

32





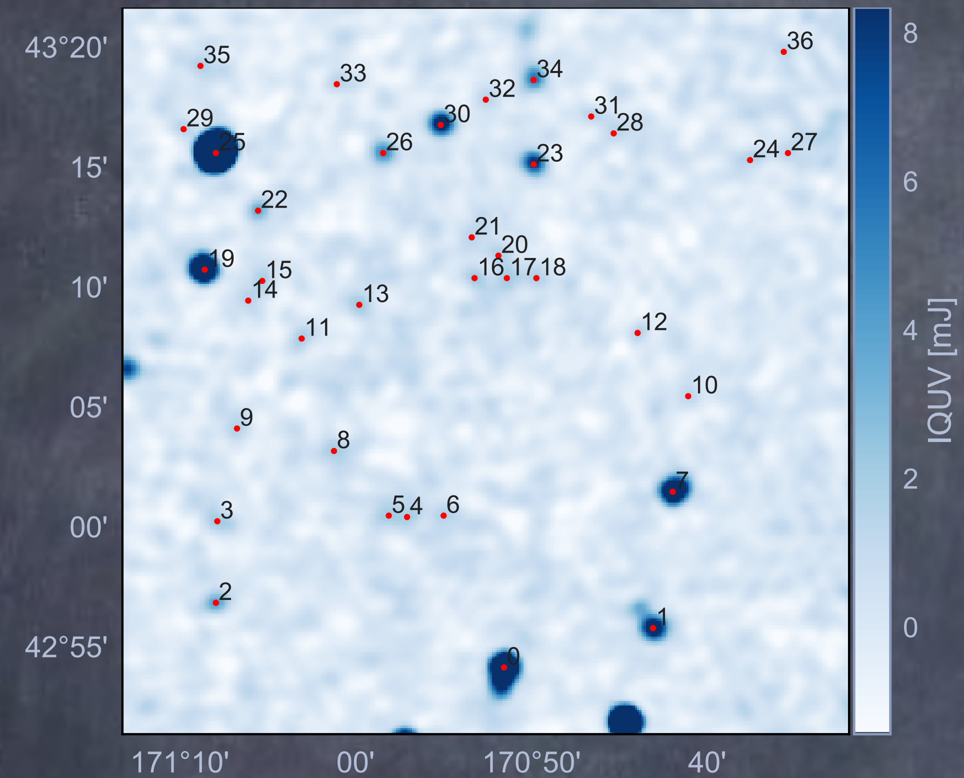
Iamge Synthesis

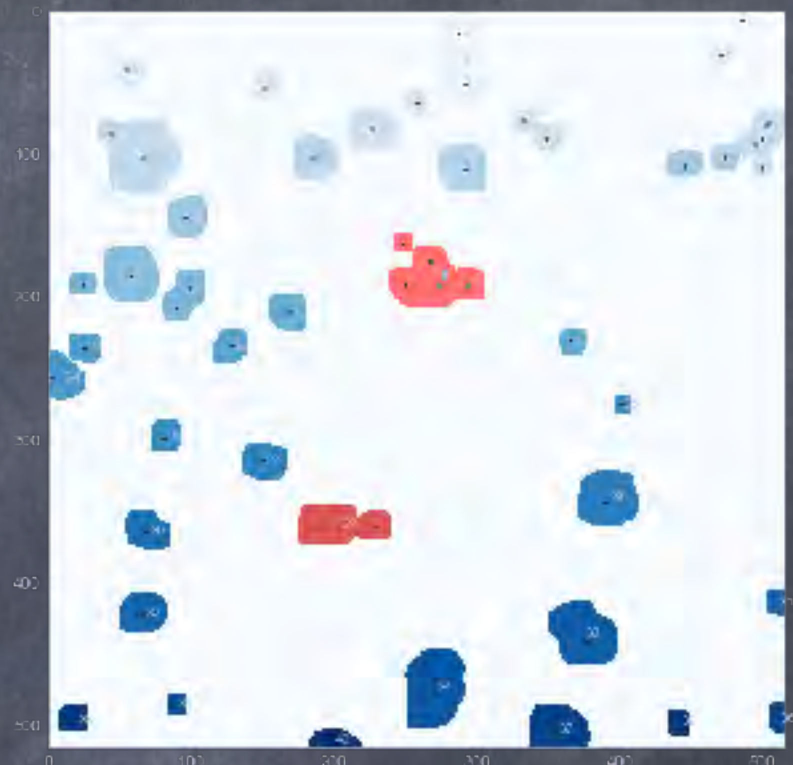
40クラスター

１万サンプル作

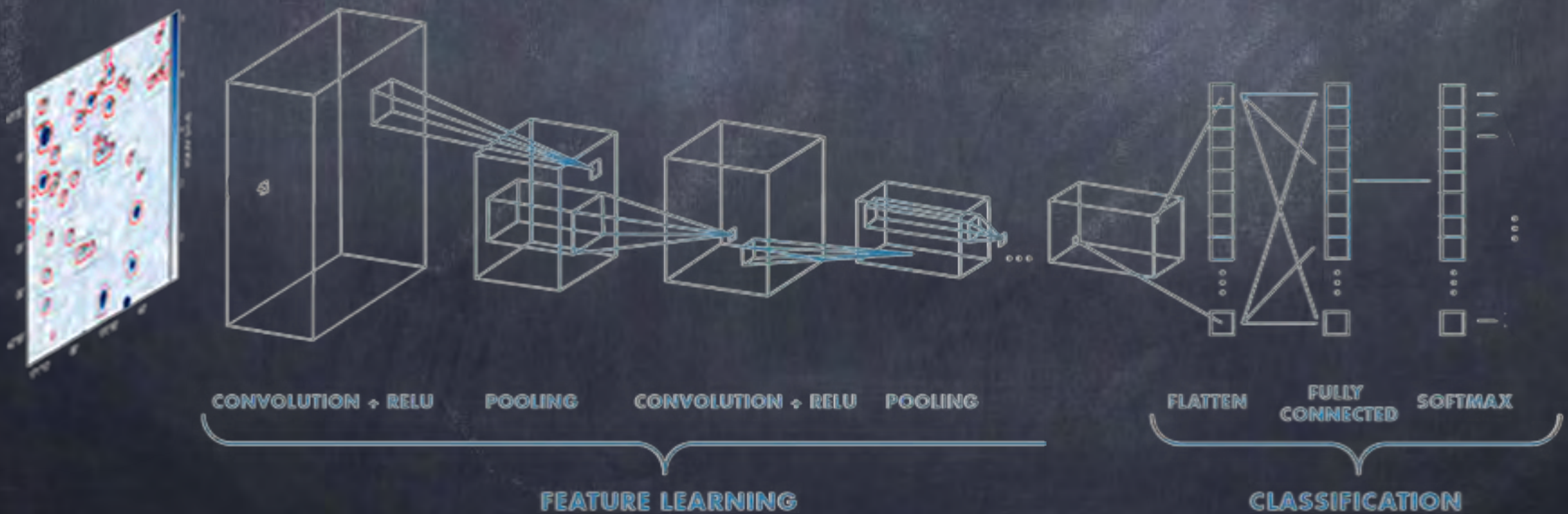
- Zoom
- Rotate
- Etc.

Costume NN based on YOLO (Redmon 2016)



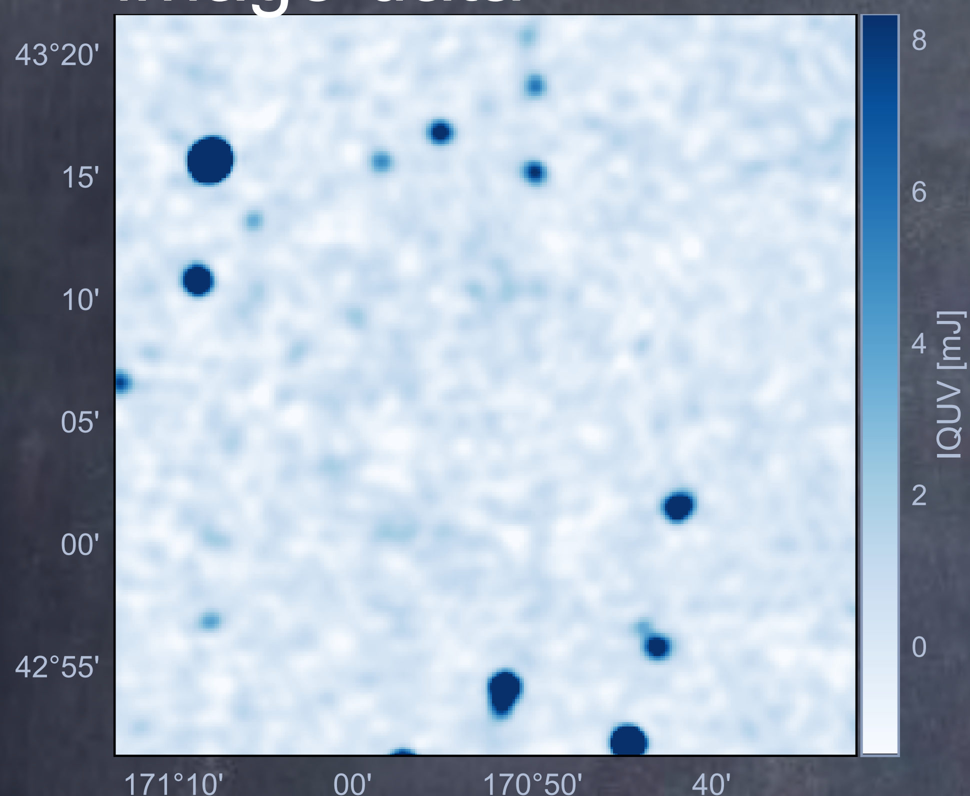


A1240



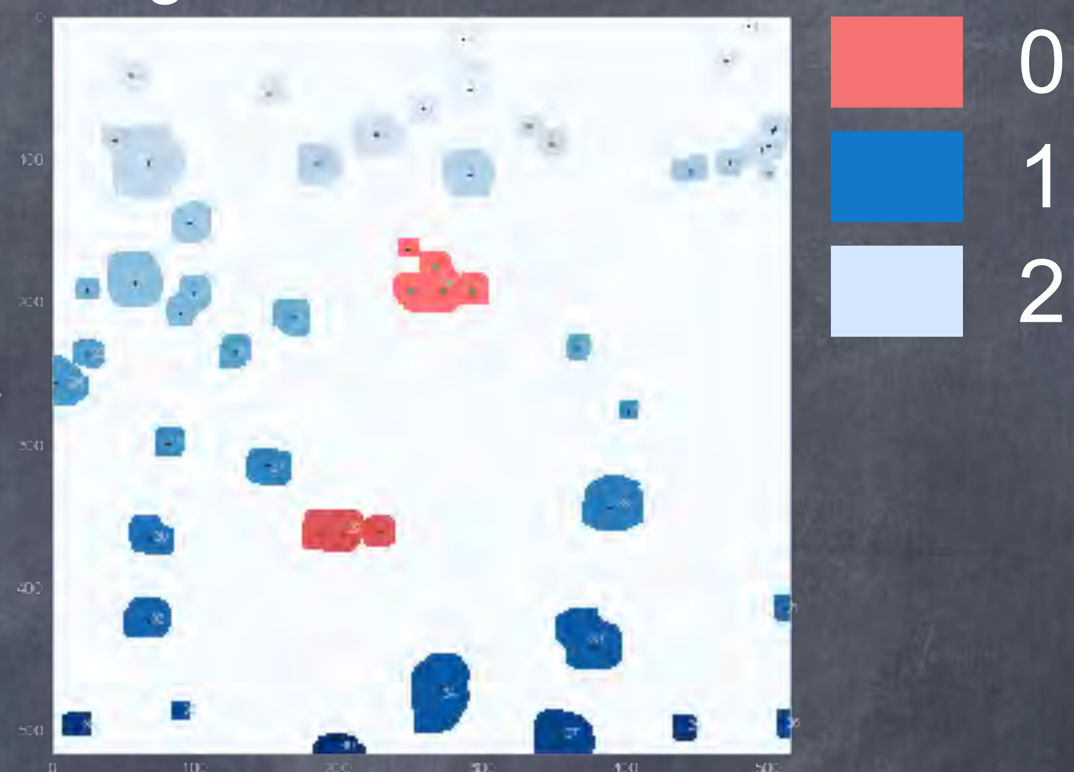
semantic segmentation data preparation

image data

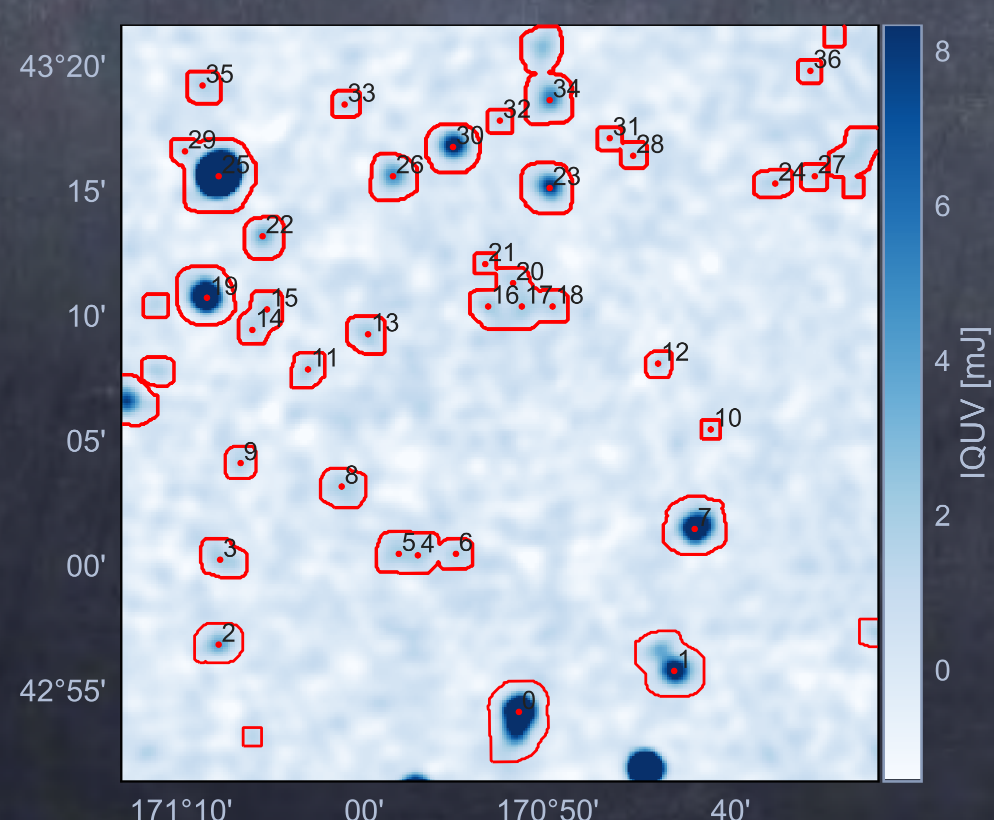


Input

Segmentation mask

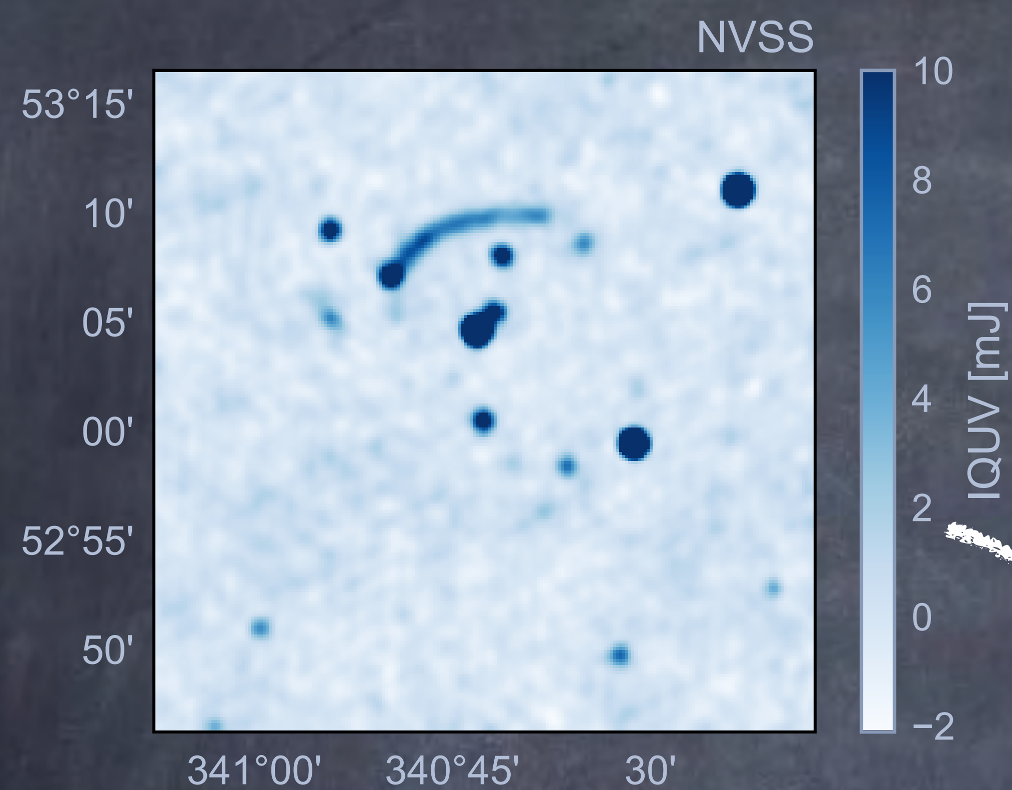


Localization

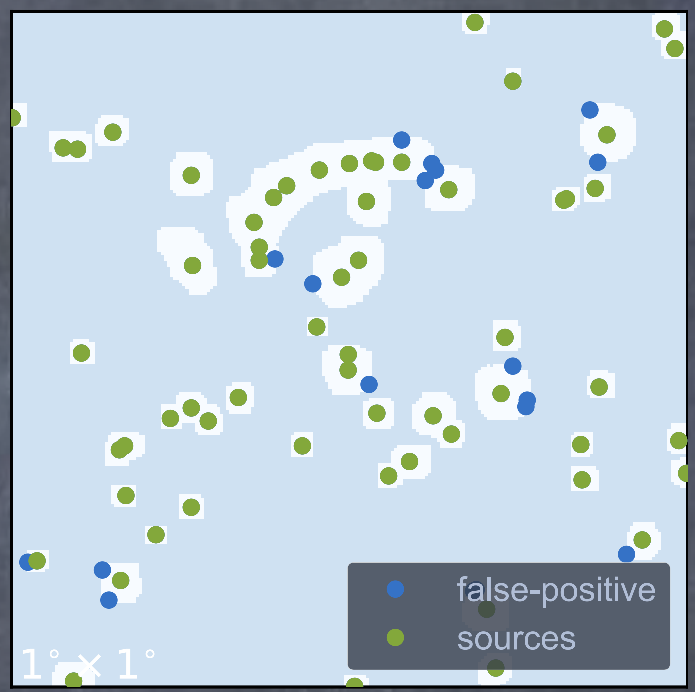


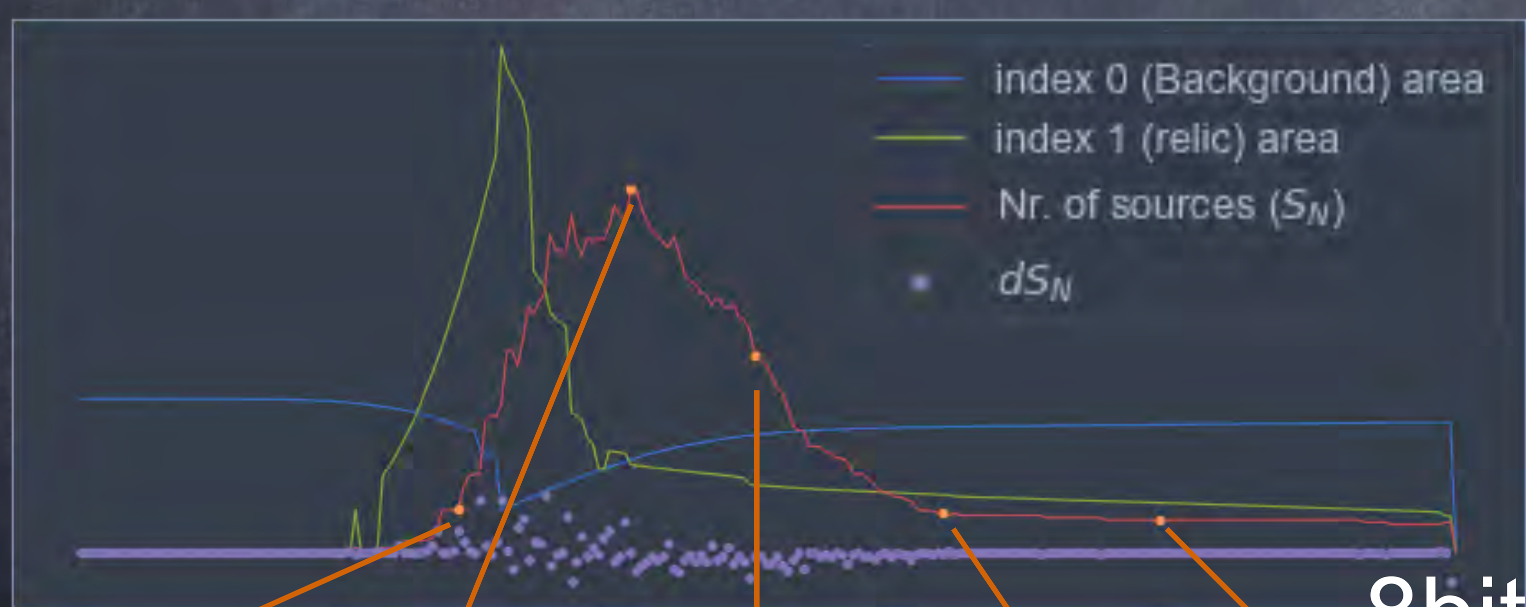
Classification

Detecting Point source and Islands

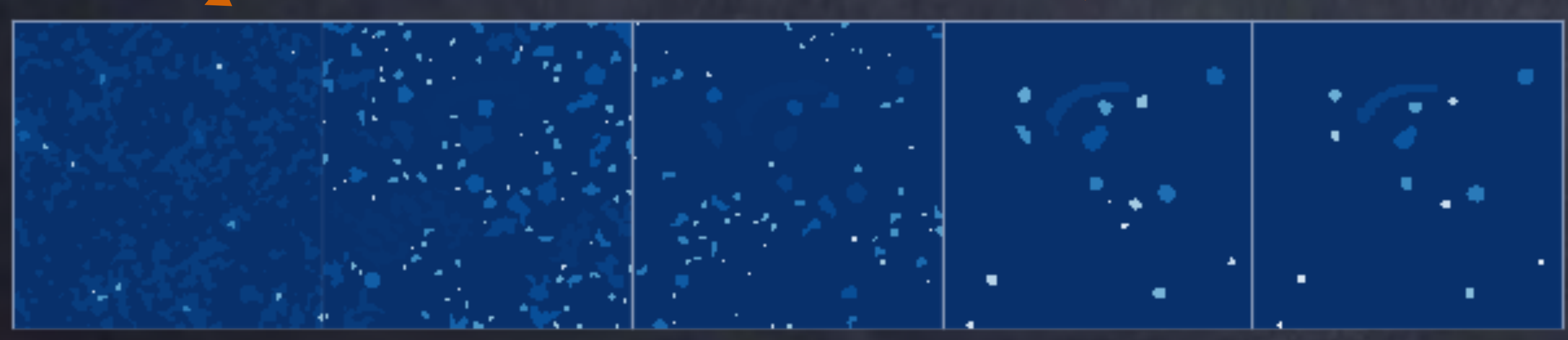


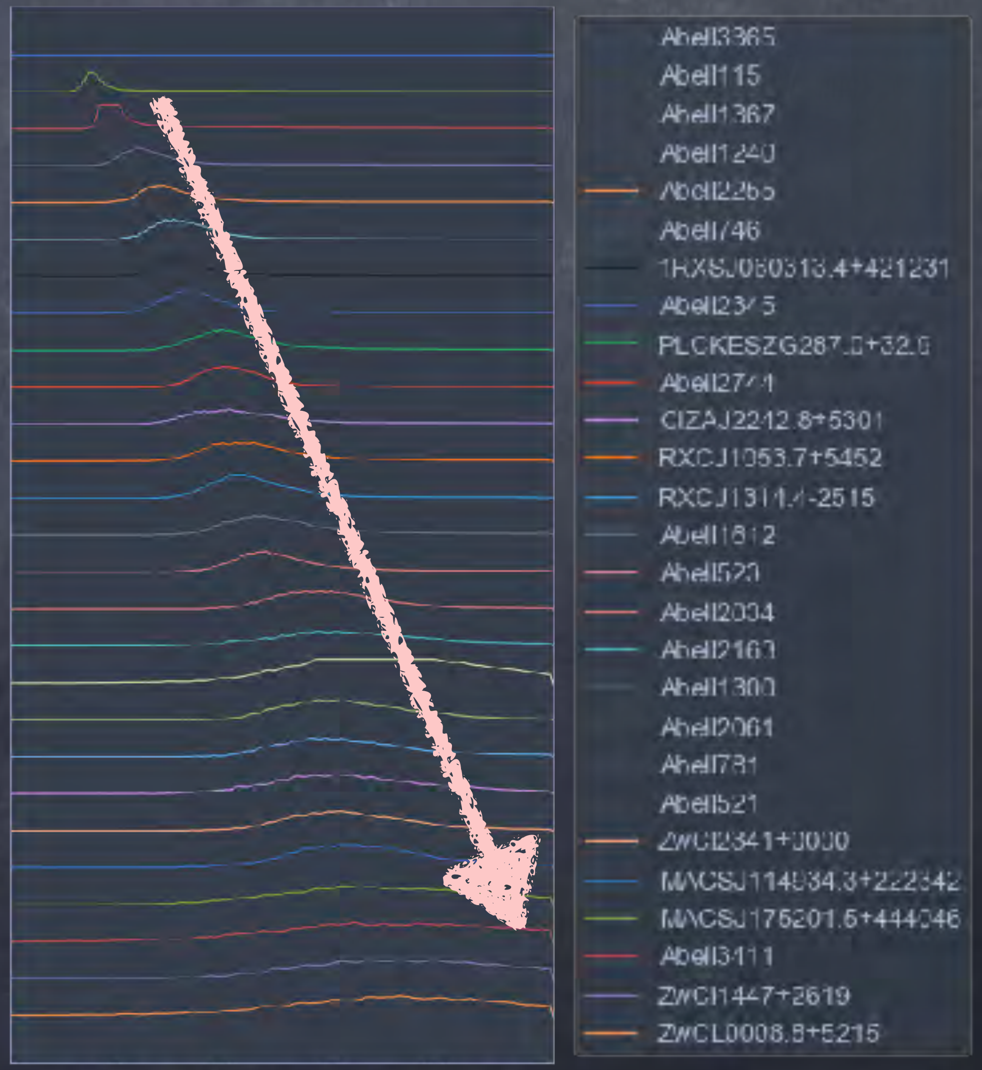
- F/std(F,sig=N)
- Agglomerative Clustering



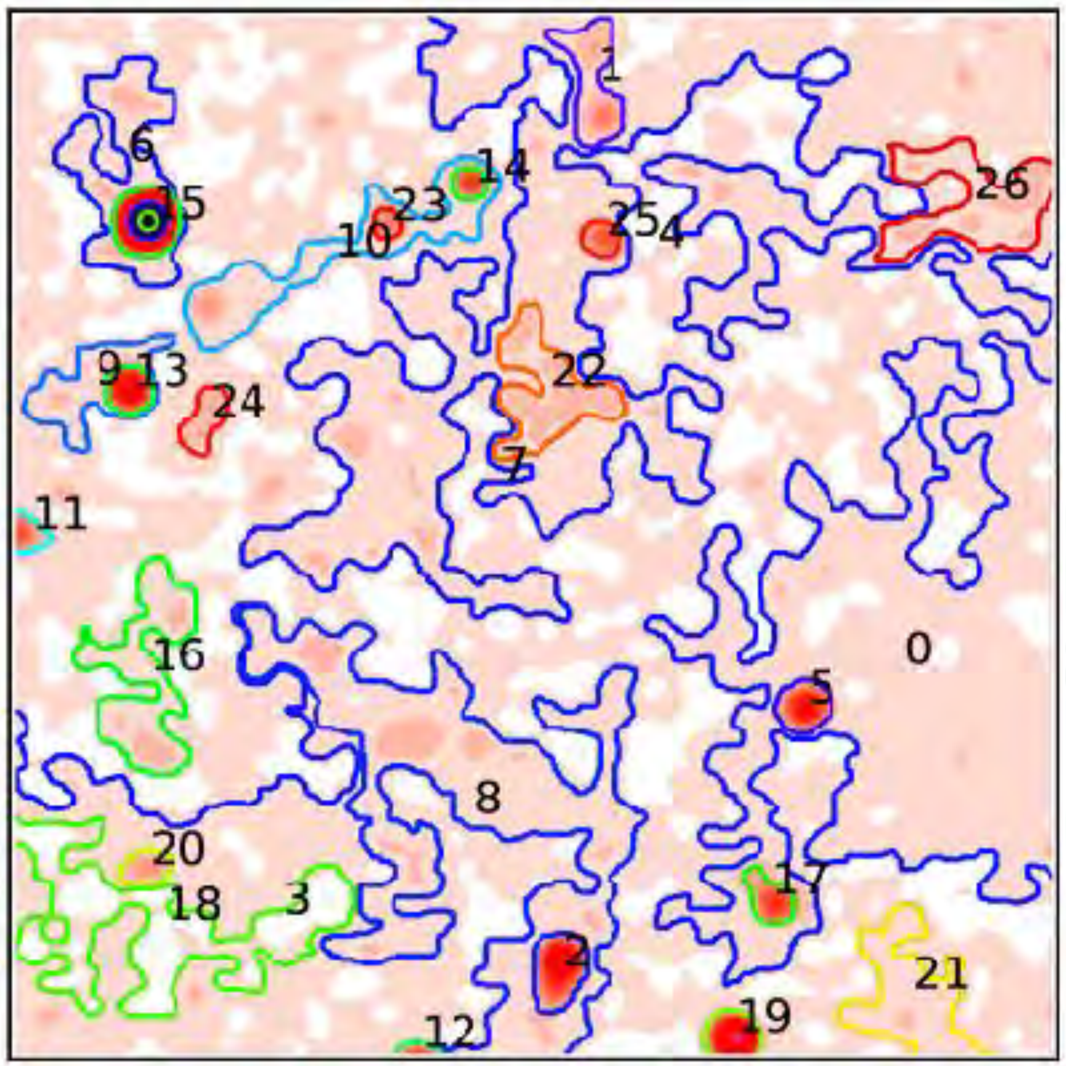


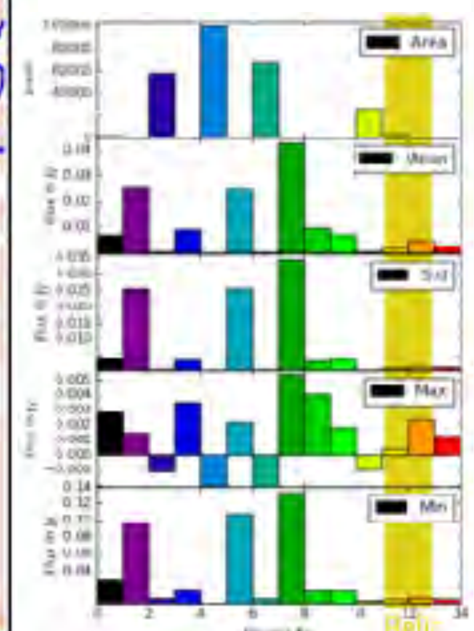
8bit





nD Attribute space



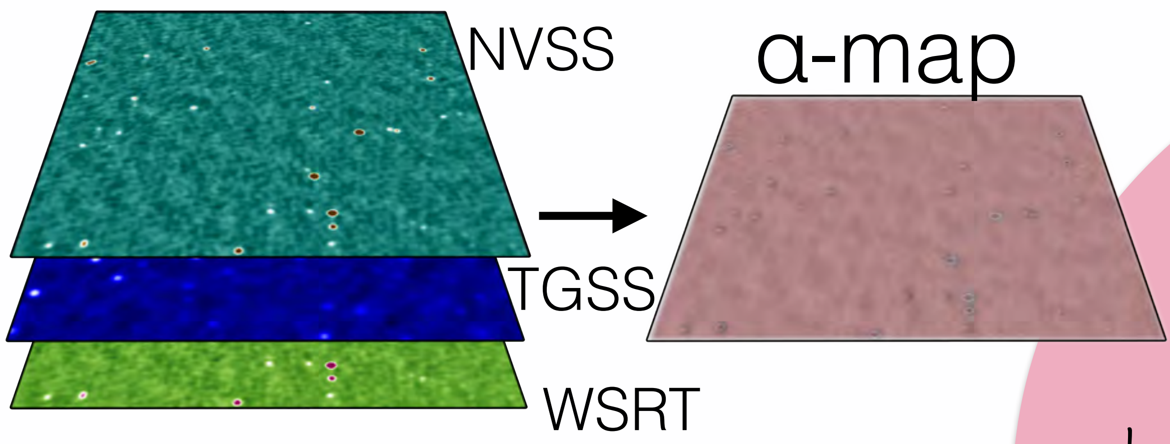


.

.

.

- spectral index mapping

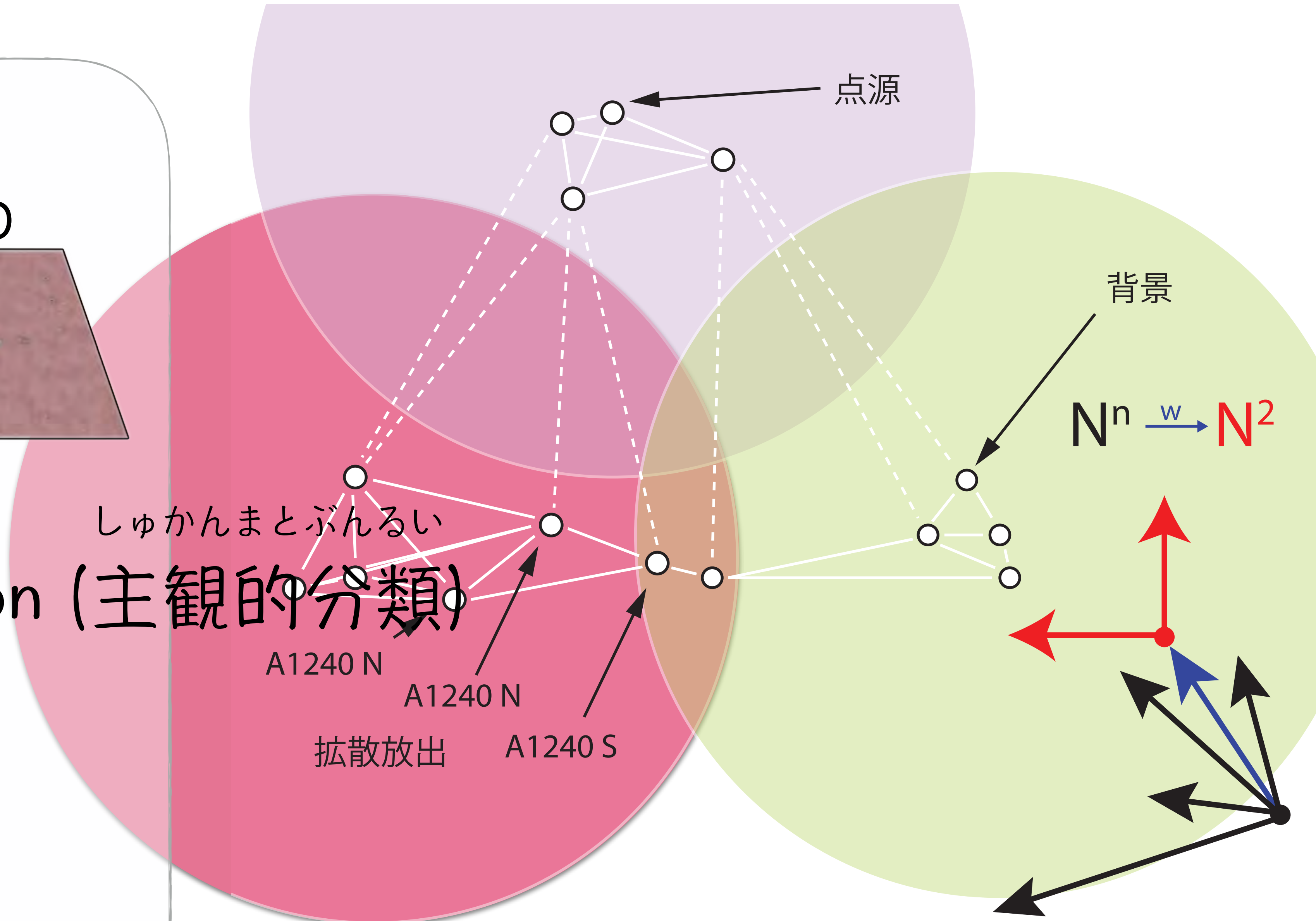


しゅかんまとぶんるい

Subjective Categorisation (主観的分類)

- 3 Groups
  - Background
  - Extended
  - Compact
- eigen solving
- Linear data embedding

説明：http://scikit-learn.org/stable/modules/manifol



manifold embedding algorithm

Work in progress… まとめ

- **Training NN to detect and classify diffuse emission**
- **Testing and classifying 1000 random 1deg x1deg fields**
- **Confirming new found Emission structures**

Future…

- **Survey Image enhancement by training on deep observations (based on Chen 2016)**
- **Application in future Deep surveys (Lofar, SKA, etc…)**

1RXS J0603.3+4214

K. Rajpurohit et al

銀河団の衝突 → 宇宙論

ΛCDM MUSIC-2
シミュレーション

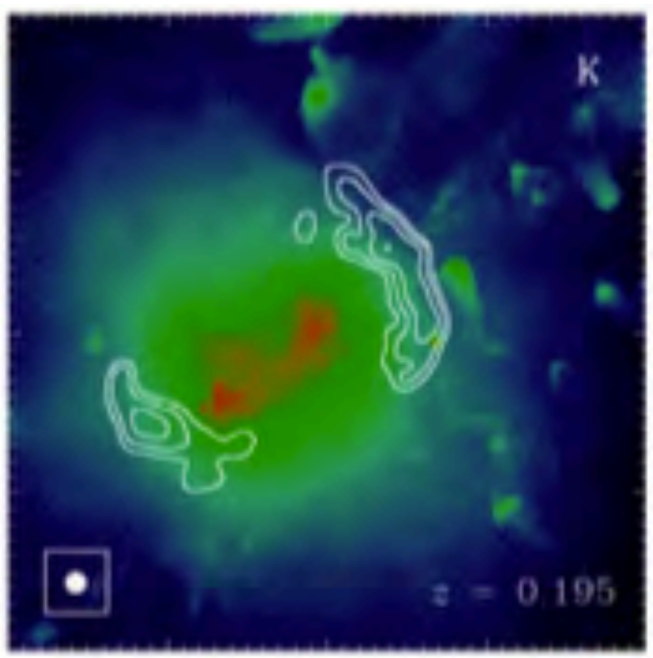
電波観測
NVSS

GMRT
LOFAR
ALMA
未来

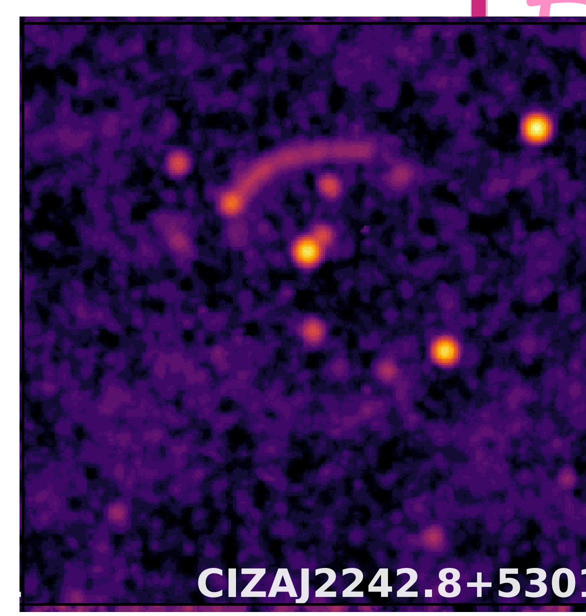
比較

電波レリック

数、形、....

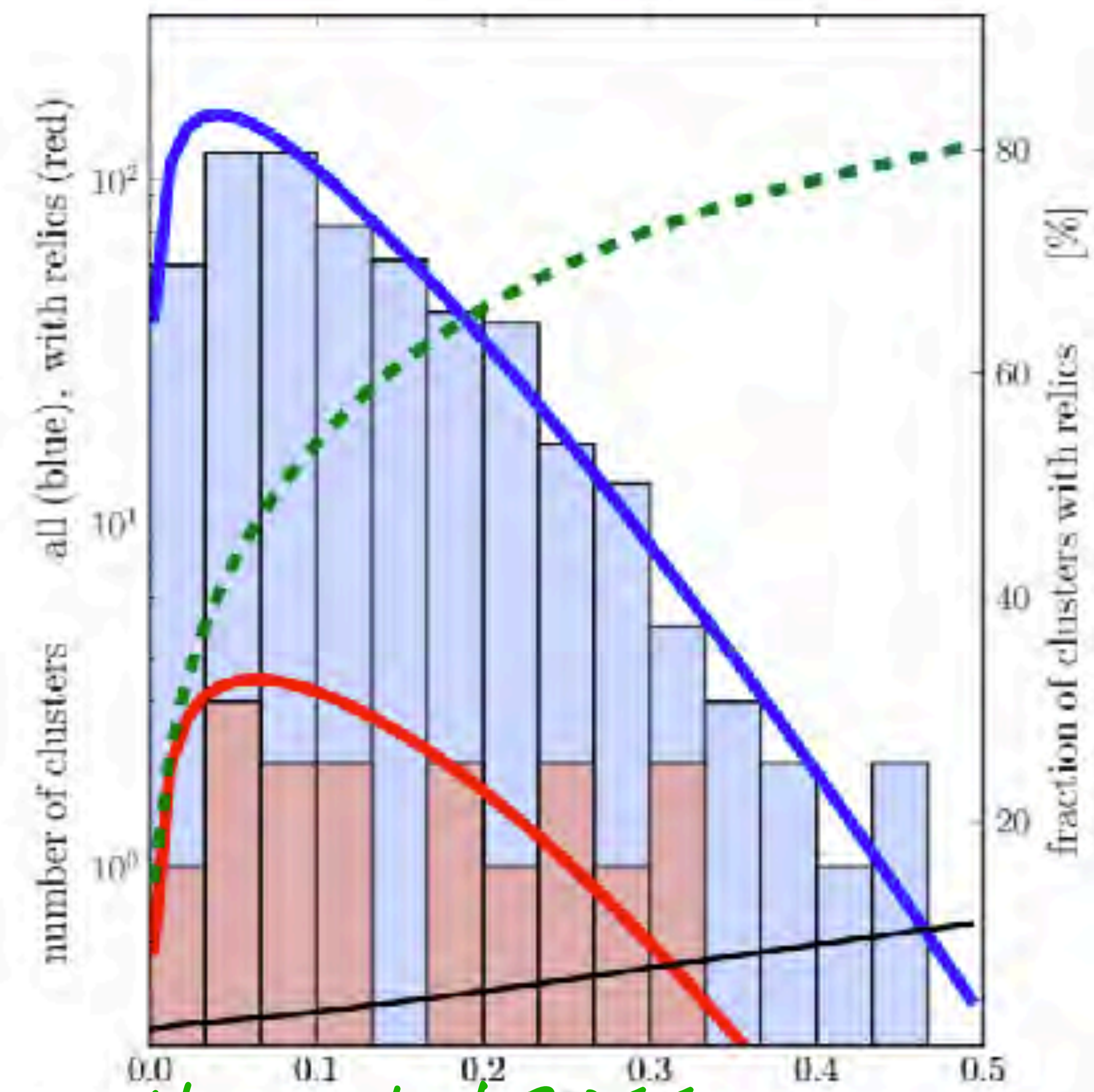


あっしゅくけいすう
圧縮係数（compression factor)
ショックのマッハ数

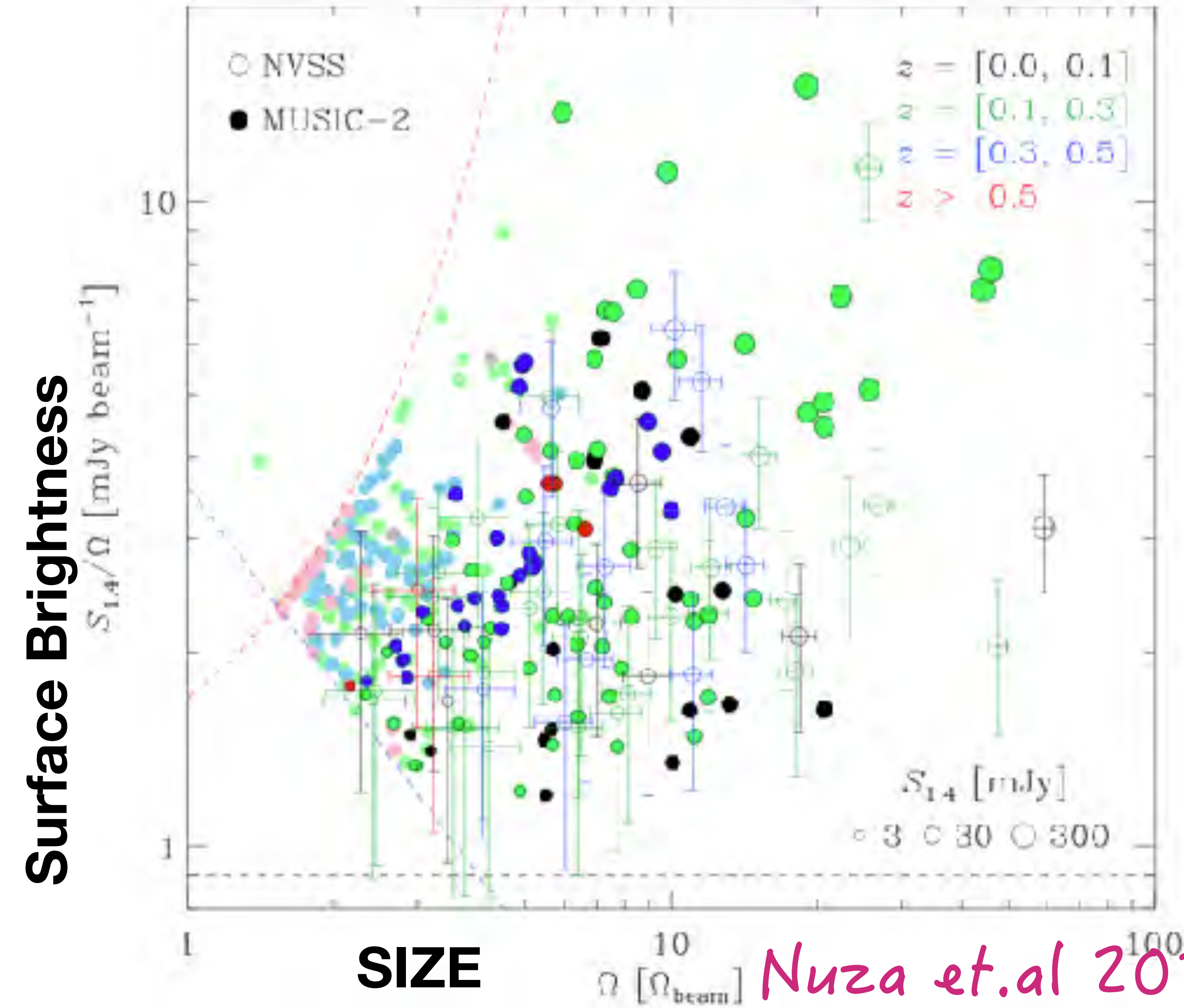


z=0.1883

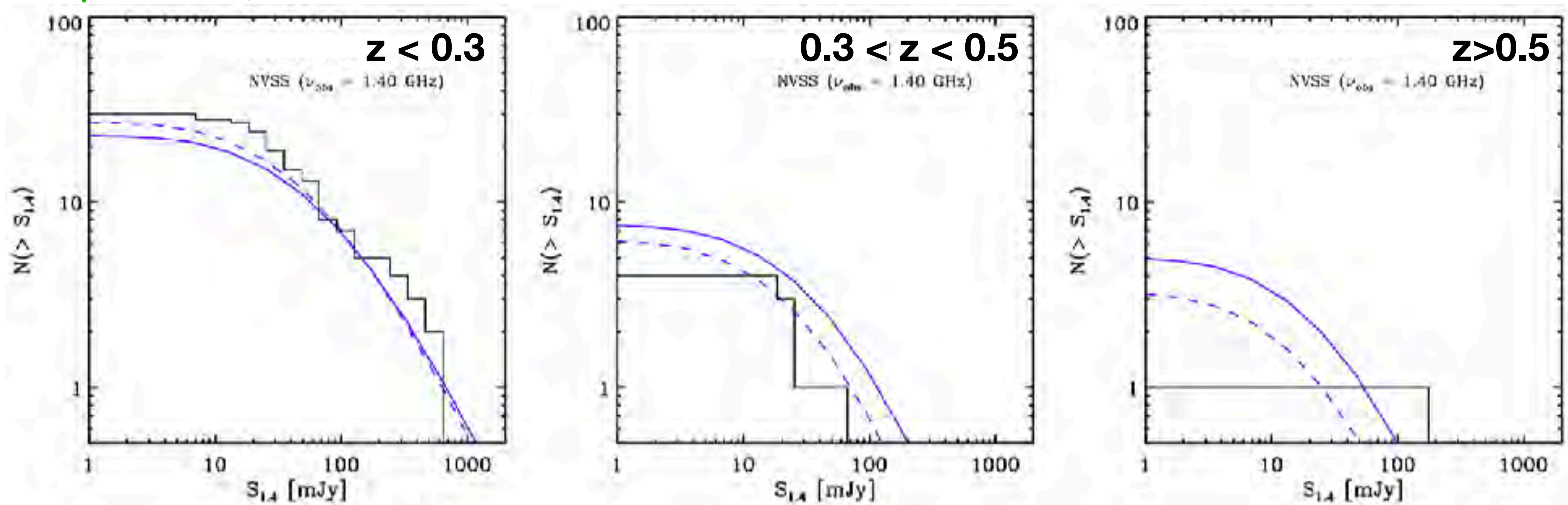
宇宙論的パラメータを制限

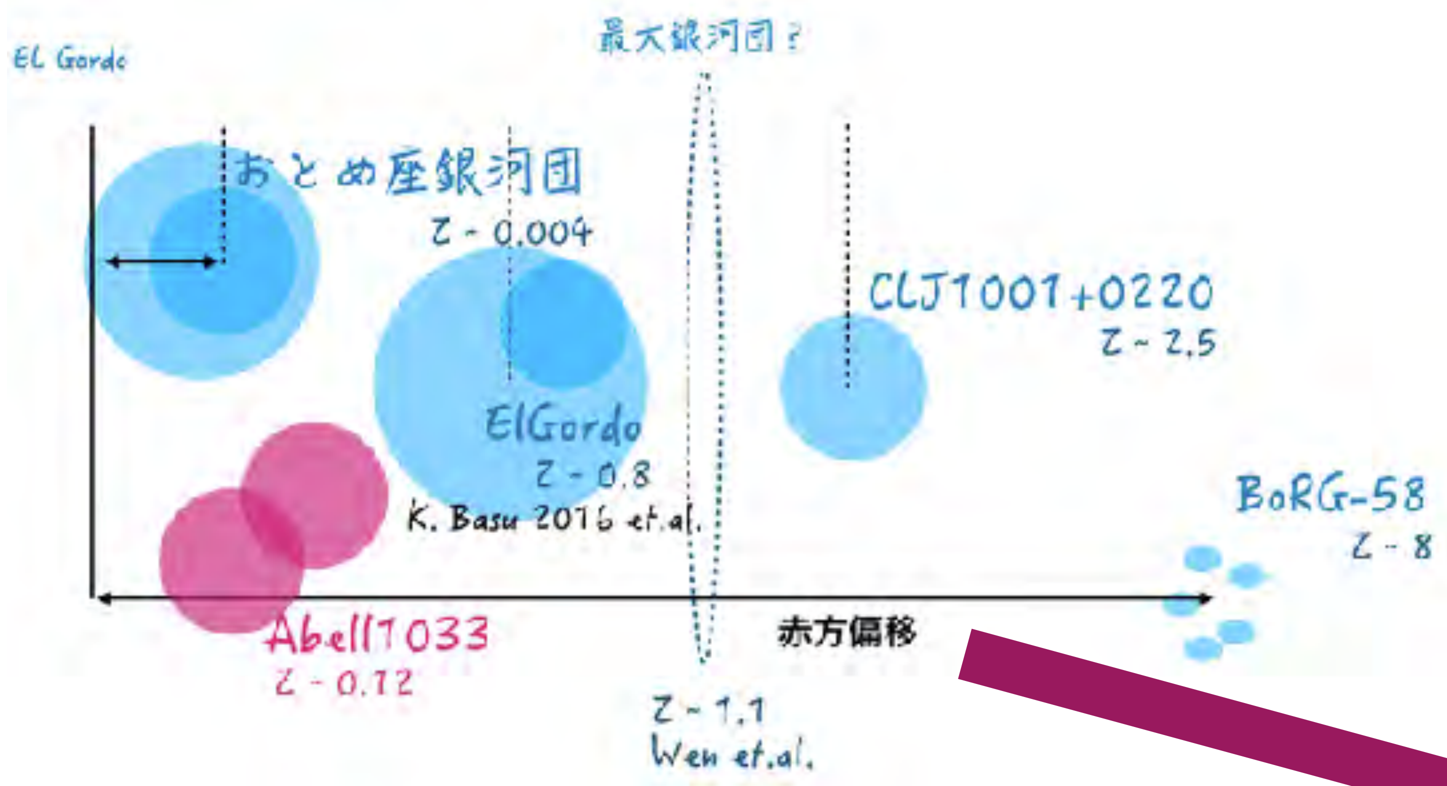


Nuza et.al 2011



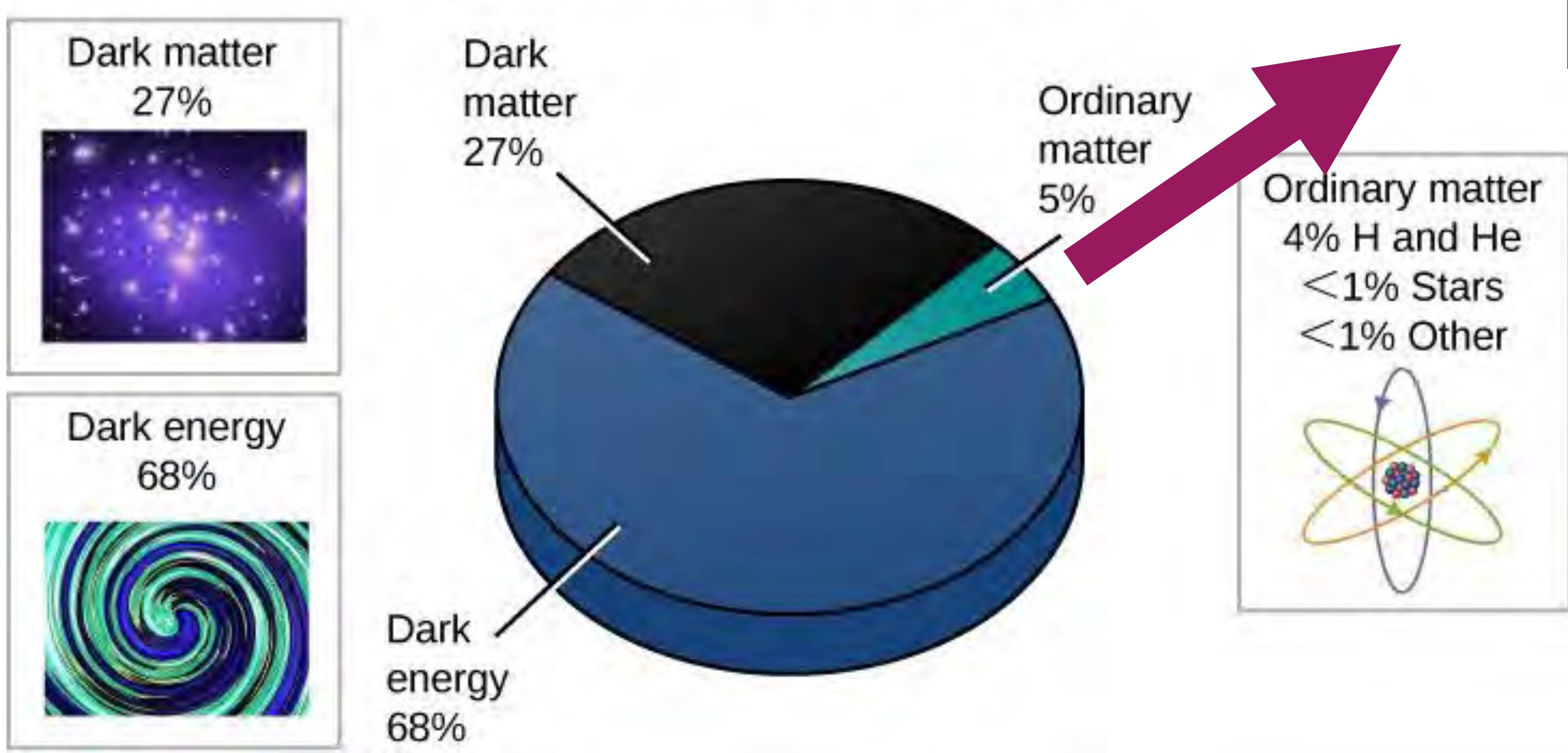
Nuza et.al 2017




El Gordo
最大銀河団？
おとめ座銀河団
z ~ 0.004
CLJ1001+0220
z ~ 2.5
ElGordo
z ~ 0.8
K. Basu 2016 et.al.
BoRG-58
z ~ 8
赤方偏移
Abell1033
z ~ 0.12
z ~ 1.1
Wen et.al.

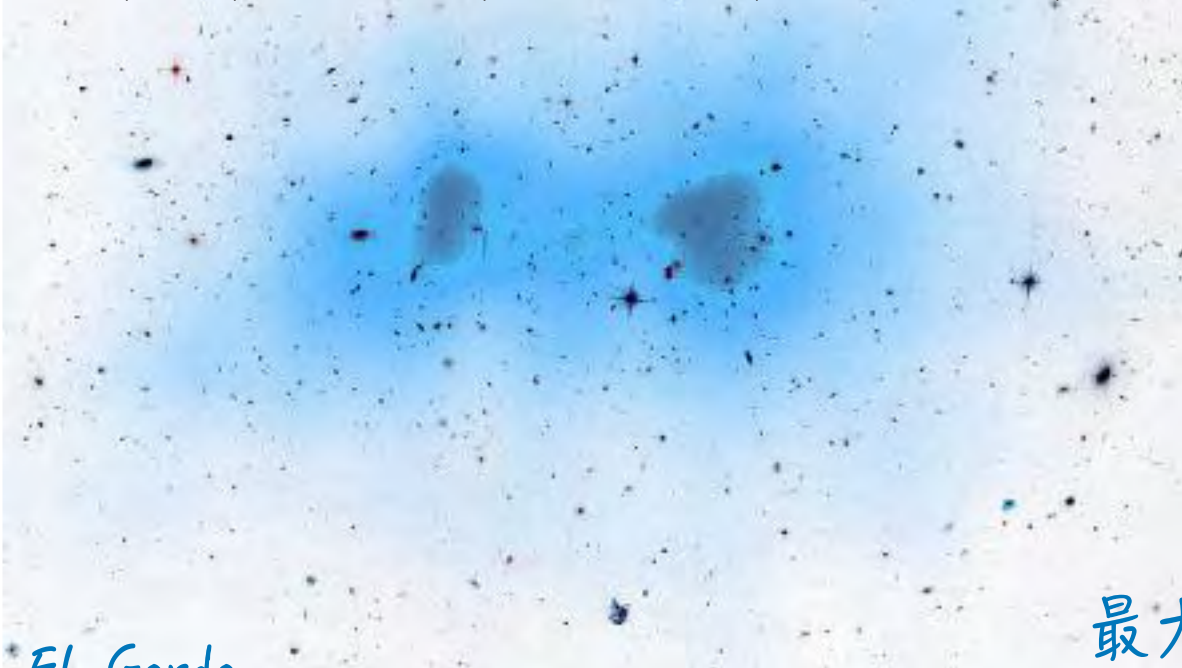
MODEL

?


Dark matter
27%
Dark energy
68%
Dark matter
27%
Ordinary matter
5%
Dark energy
68%
Ordinary matter
4% H and He
<1% Stars
<1% Other

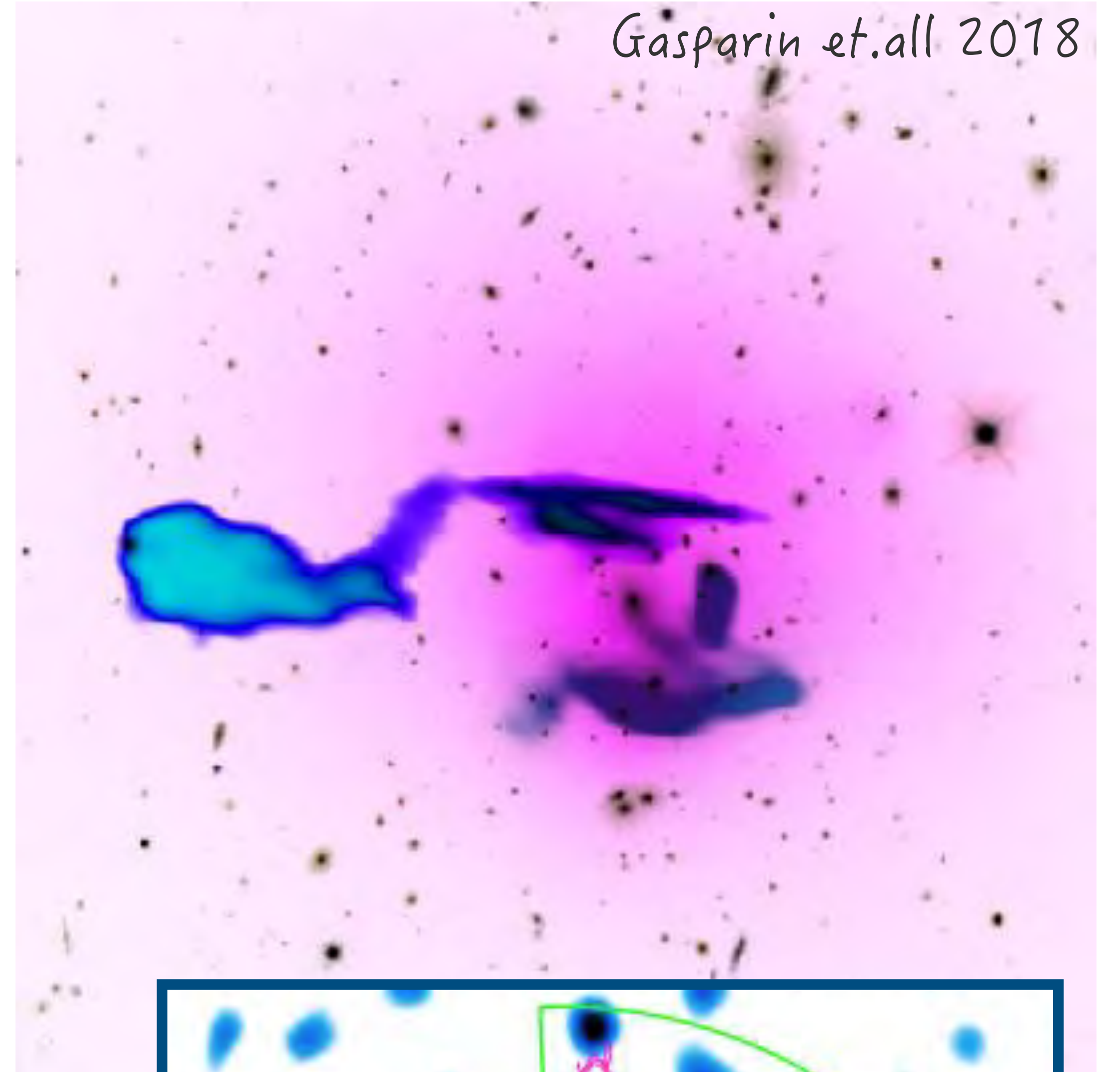
概要

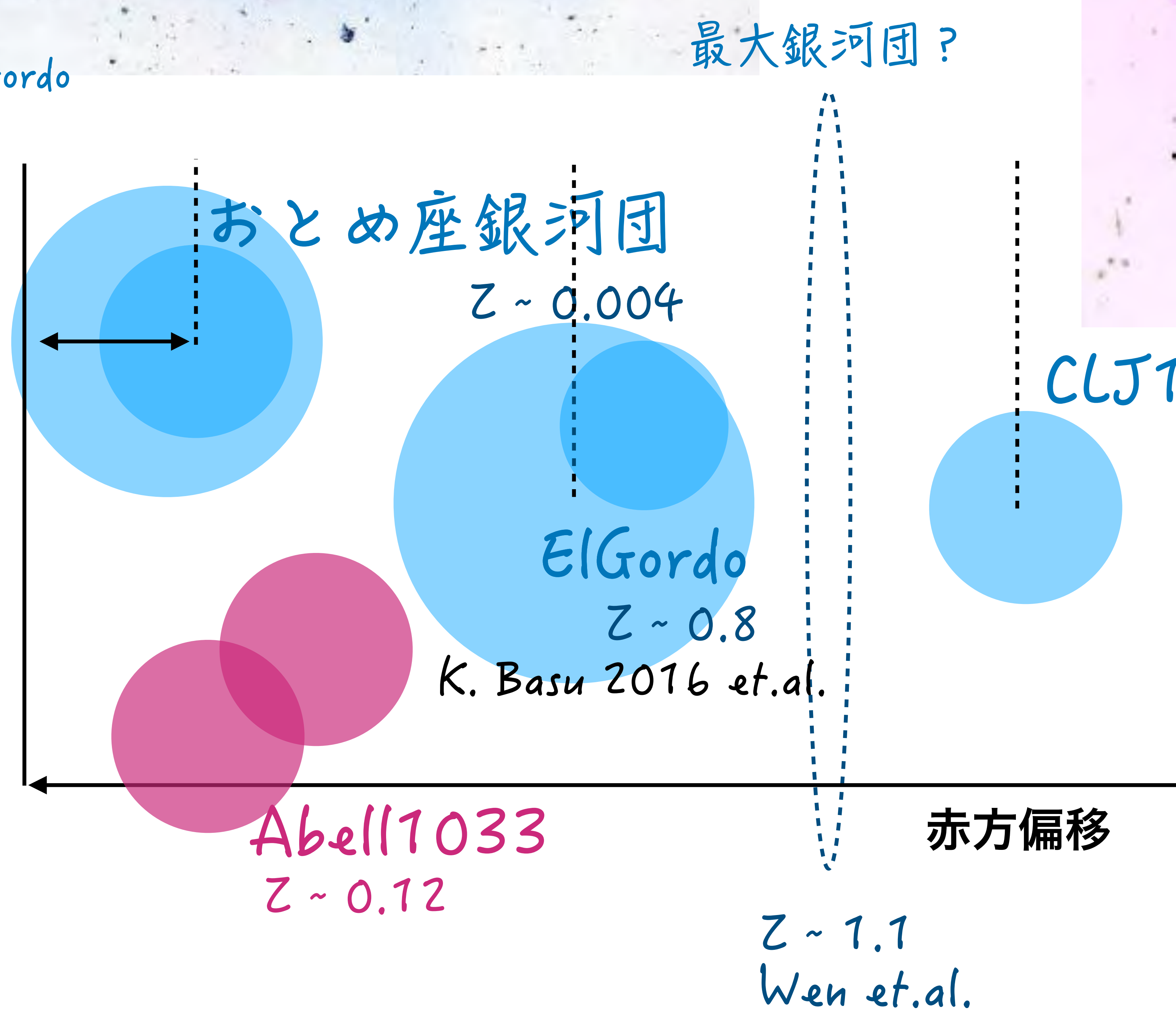
NASA, ESA, and J. Lotz, M. Mountain, A. Koekemoer, and the HFF Team (STScI).

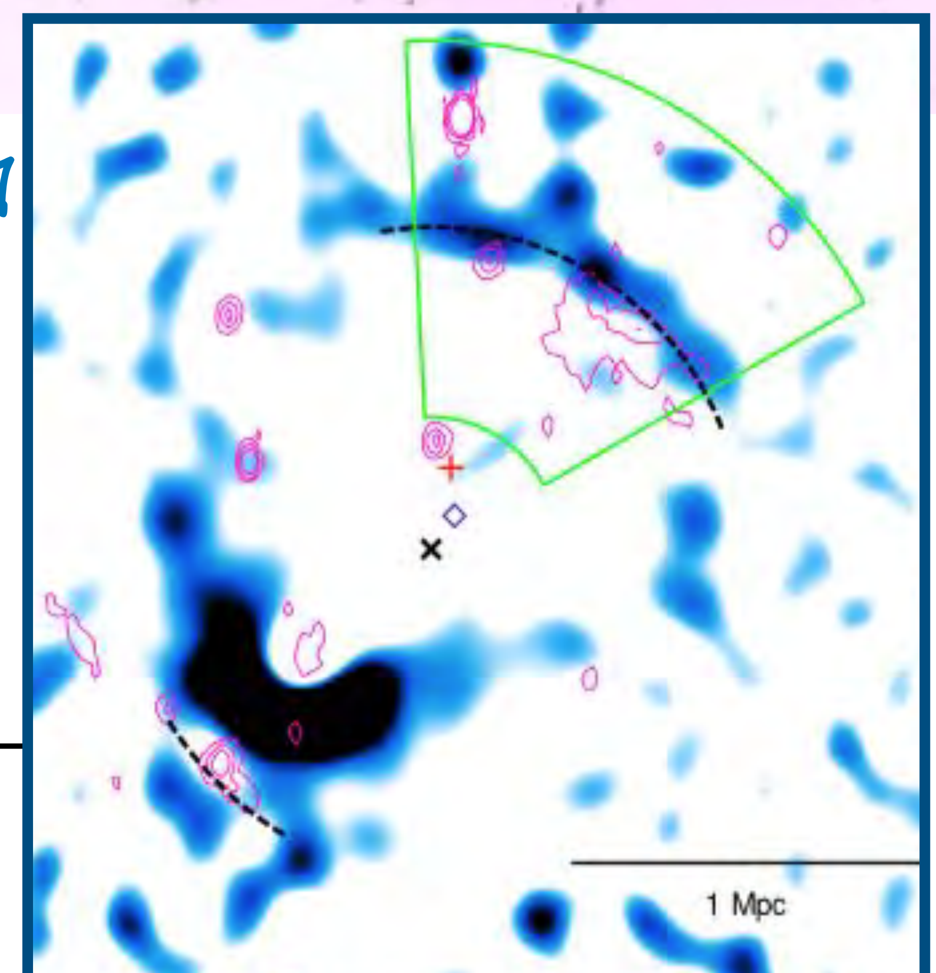


EL Gordo

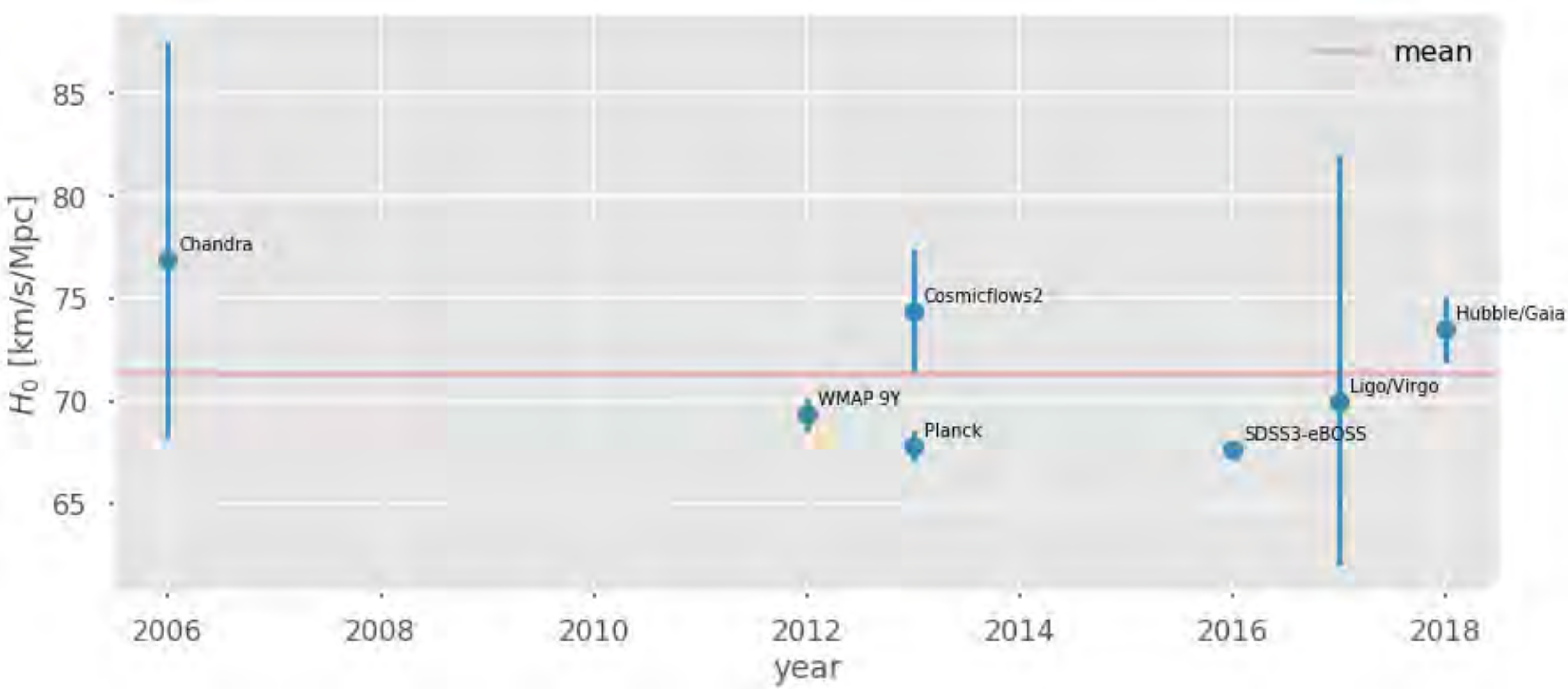
Gasparin et.all 2018



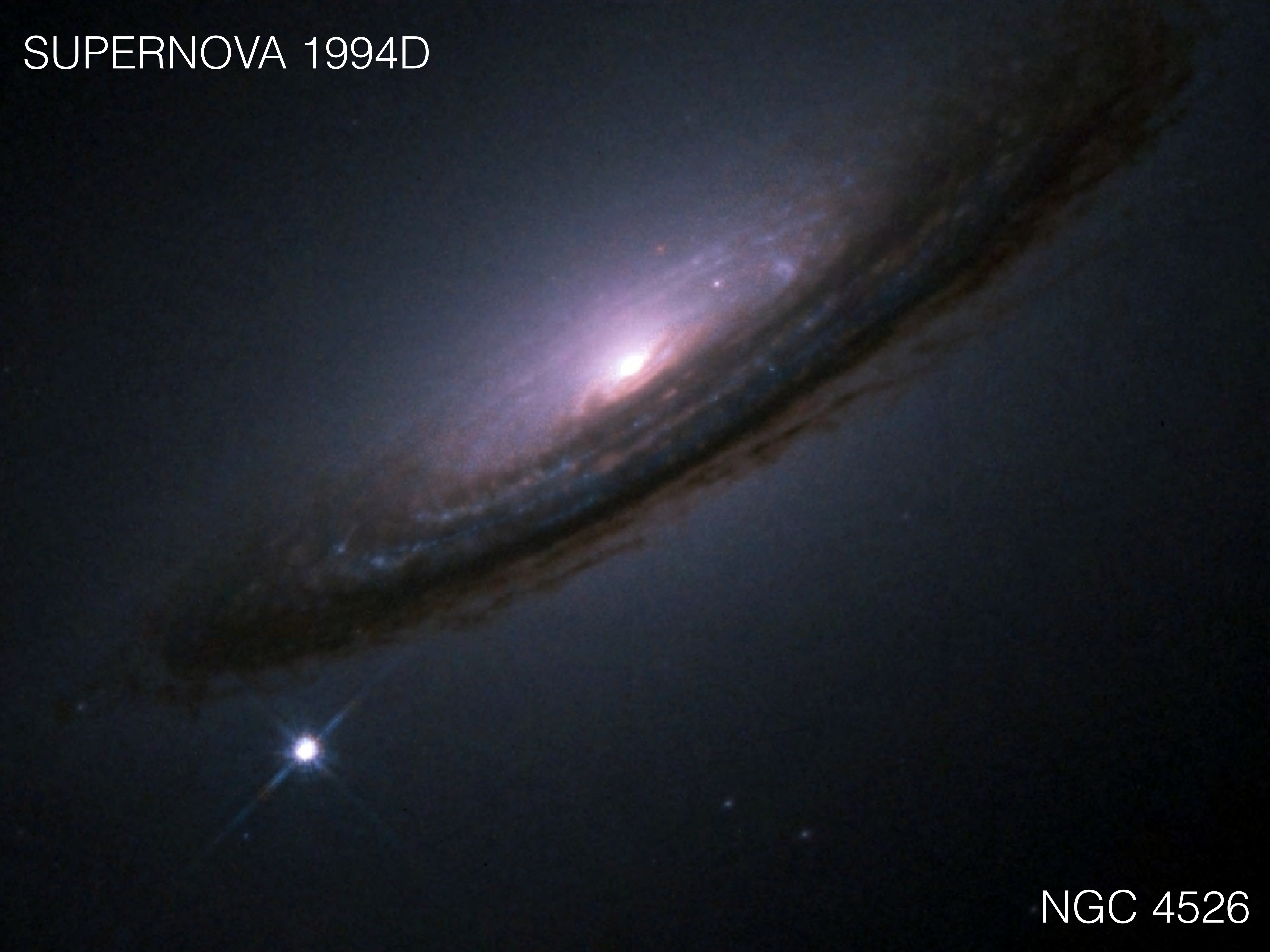


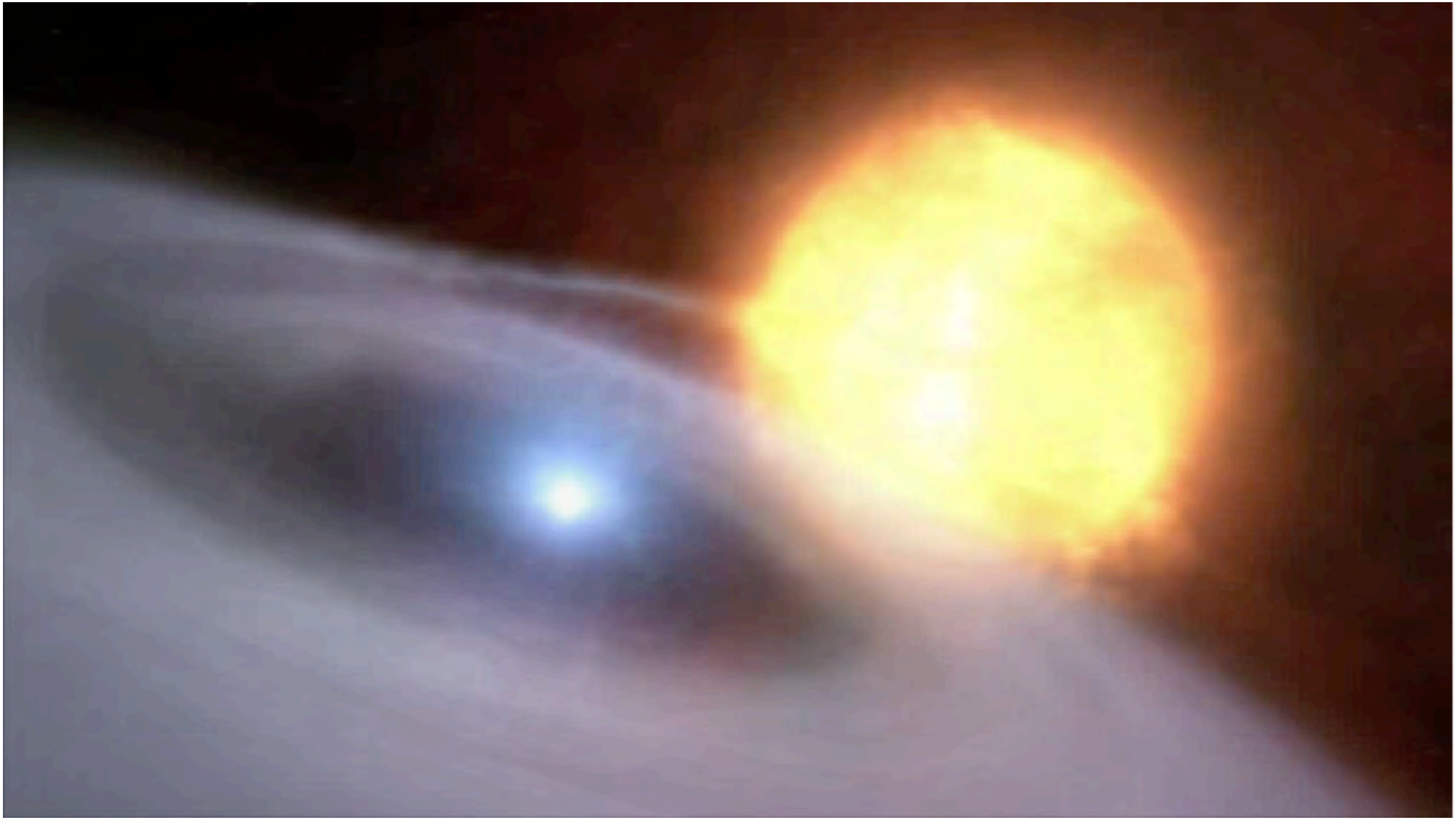


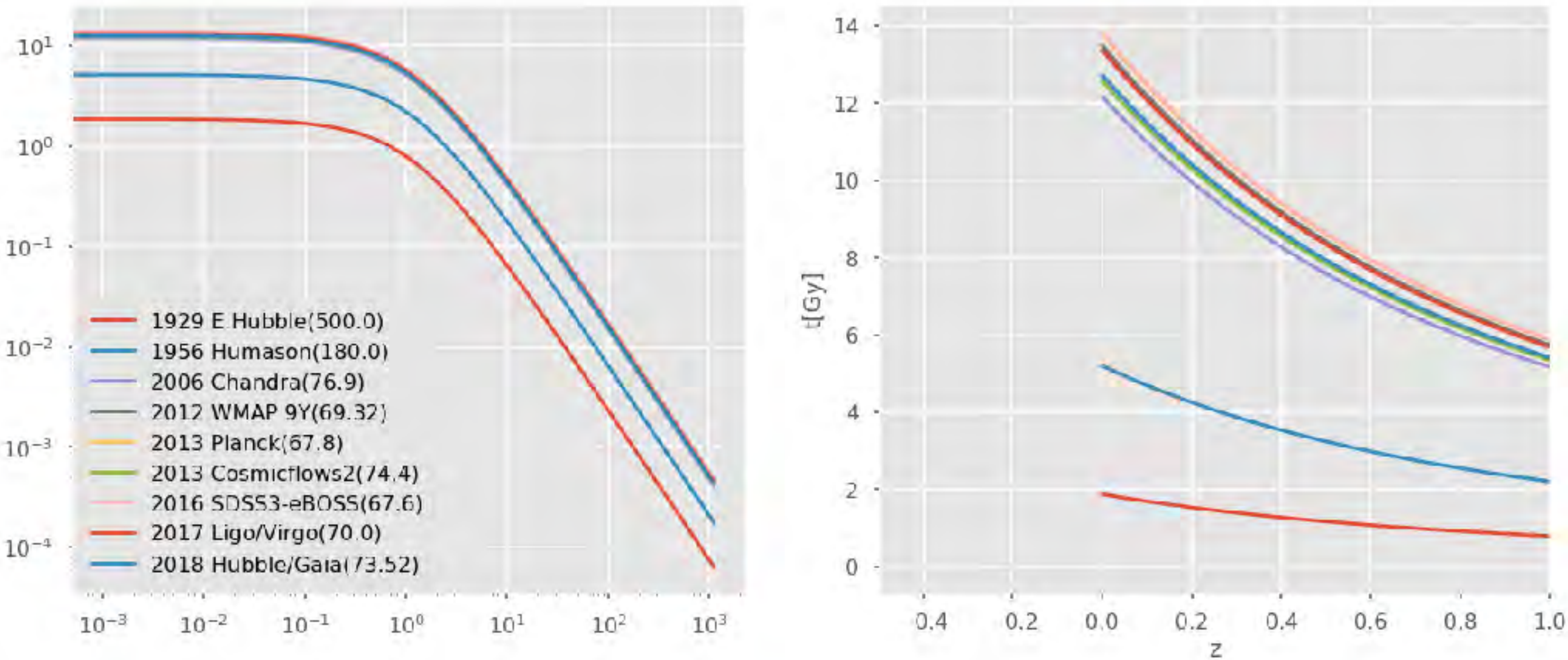
Appendix



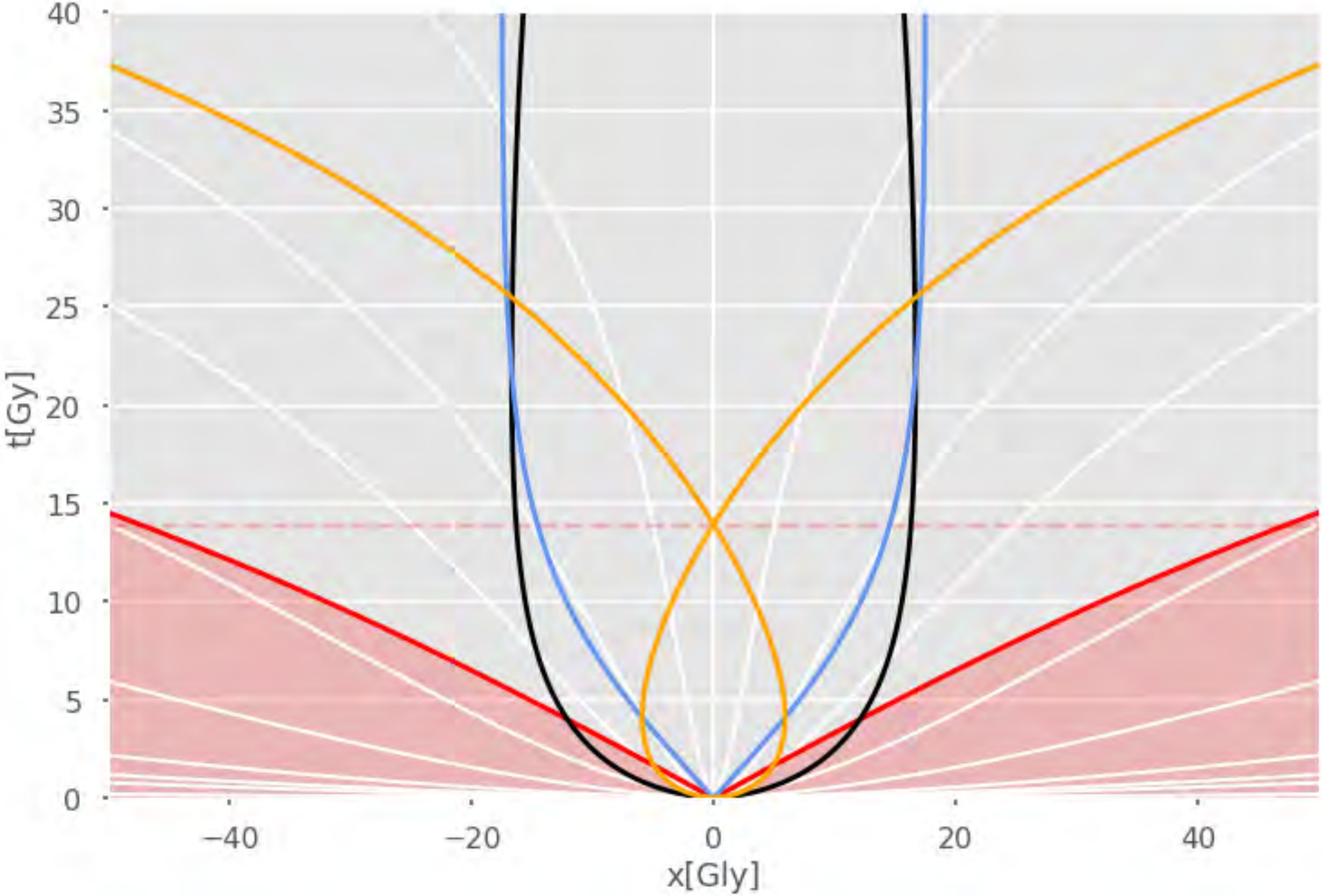
mean
85
80
75
70
65
H_0 [km/s/Mpc]
Chandra
Cosmicflows2
Hubble/Gaia
WMAP 9Y
Planck
Ligo/Virgo
SDSS3-eBOSS
2006
2008
2010
2012
2014
2016
2018
year


SUPERNOVA 1994D
NGC 4526

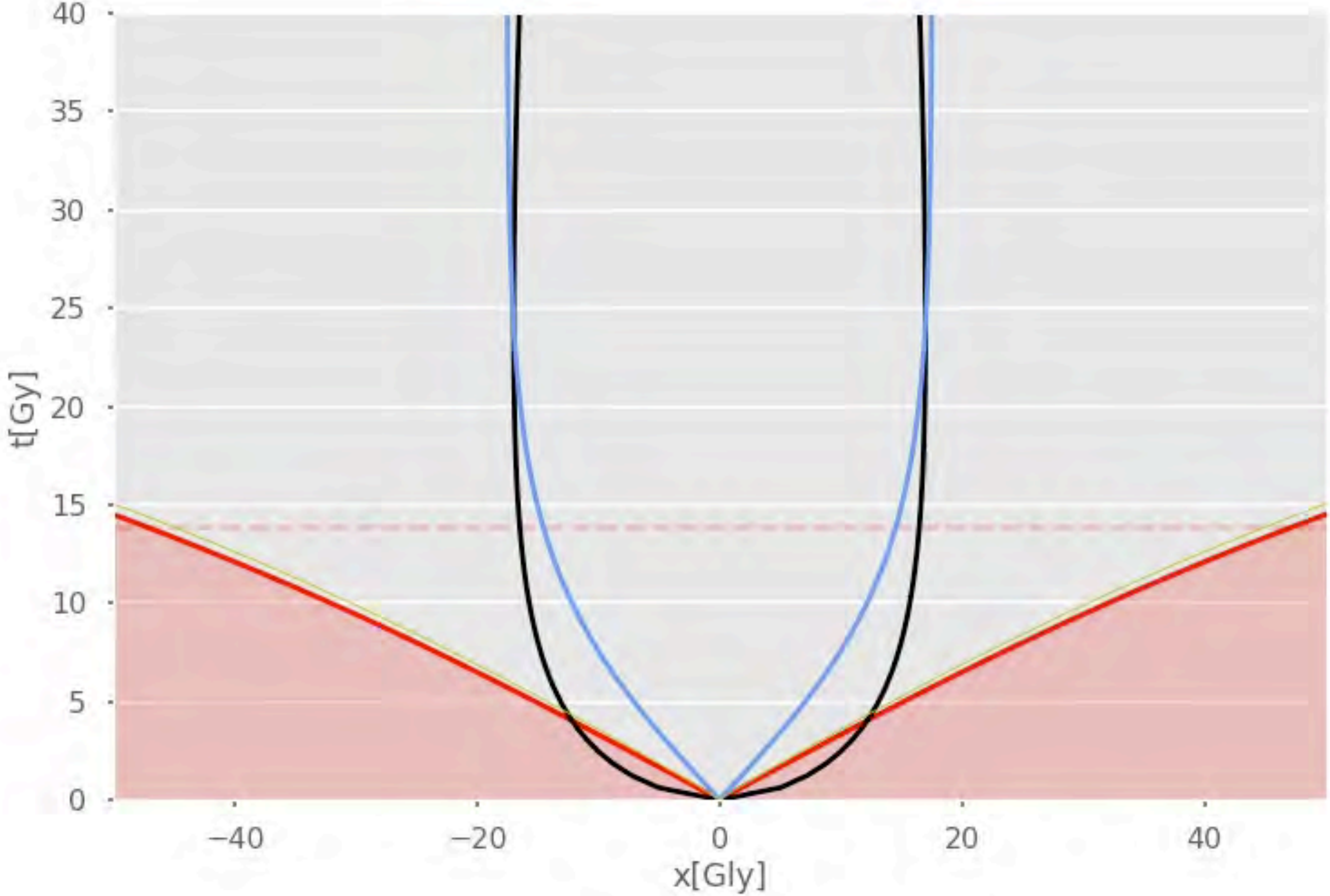




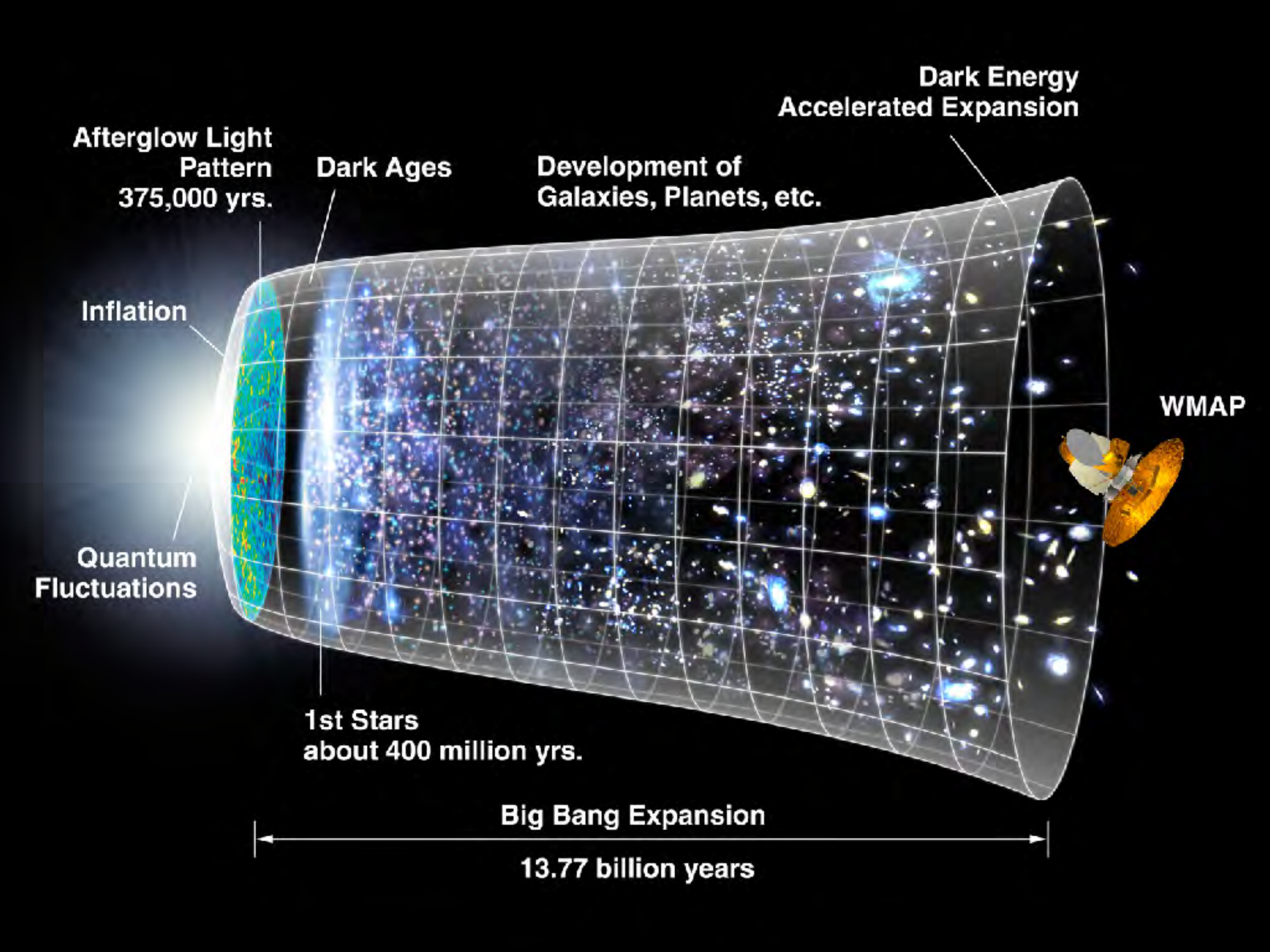
1929 E.Hubble(500.0)
1956 Humason(180.0)
2006 Chandra(76.9)
2012 WMAP 9Y(69.32)
2013 Planck(67.8)
2013 Cosmicflows2(74.4)
2016 SDSS3-eBOSS(67.6)
2017 Ligo/Virgo(70.0)
2018 Hubble/Gaia(73.52)
t[Gy]
z



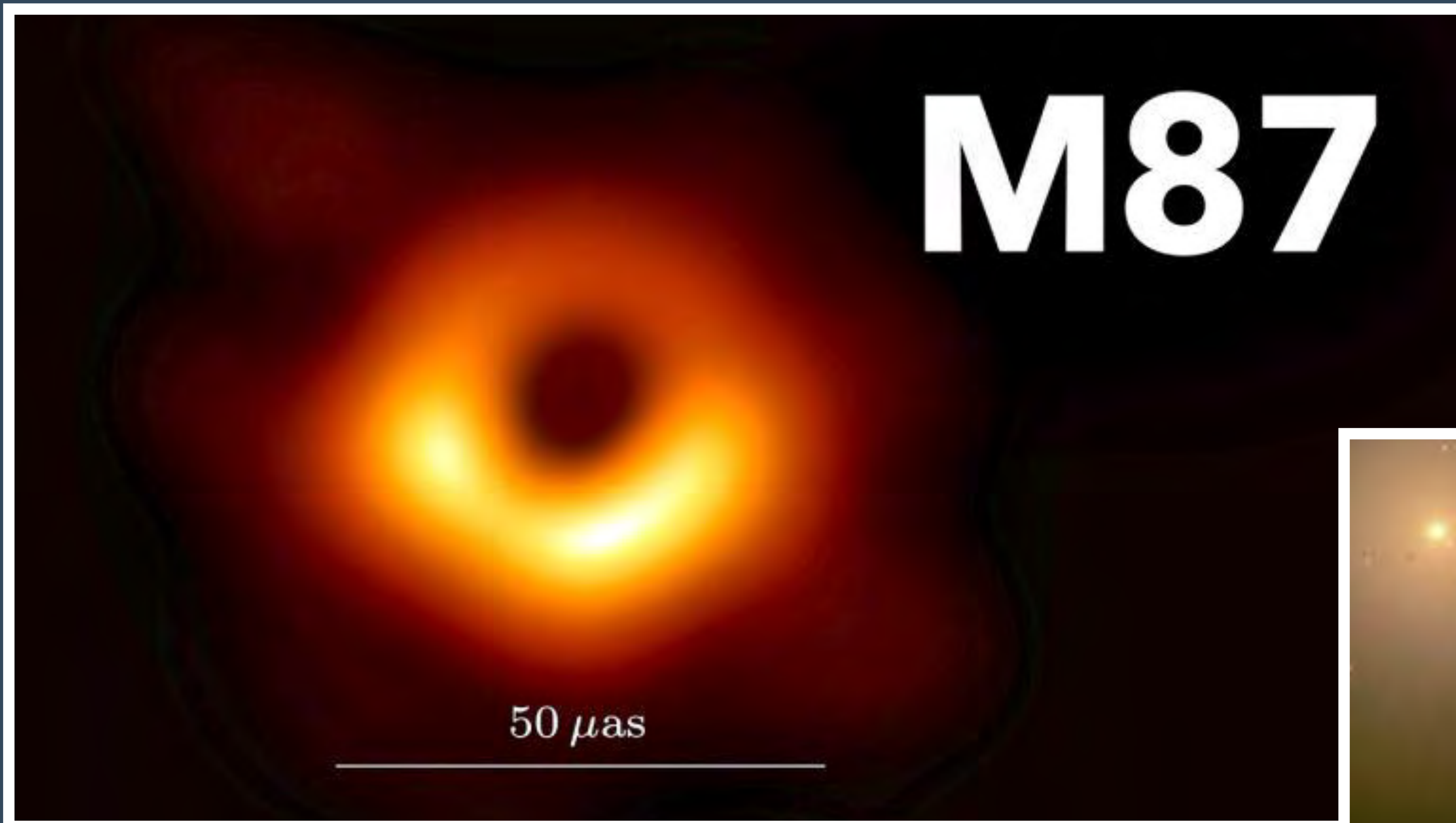
t[Gy]
x[Gly]
0
5
10
15
20
25
30
35
40
−40
−20
0
20
40

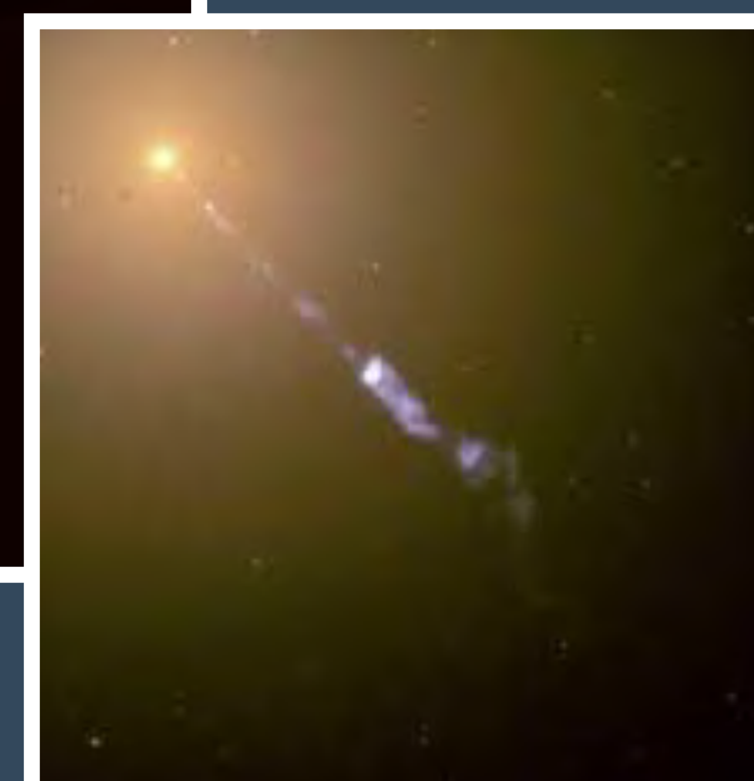


t[Gy]
x[Gly]
40
35
30
25
20
15
10
5
0
−40
−20
0
20
40


Dark Energy
Accelerated Expansion
Afterglow Light
Pattern
375,000 yrs.
Dark Ages
Development of
Galaxies, Planets, etc.
Inflation
WMAP
Quantum
Fluctuations
1st Stars
about 400 million yrs.
Big Bang Expansion
13.77 billion years

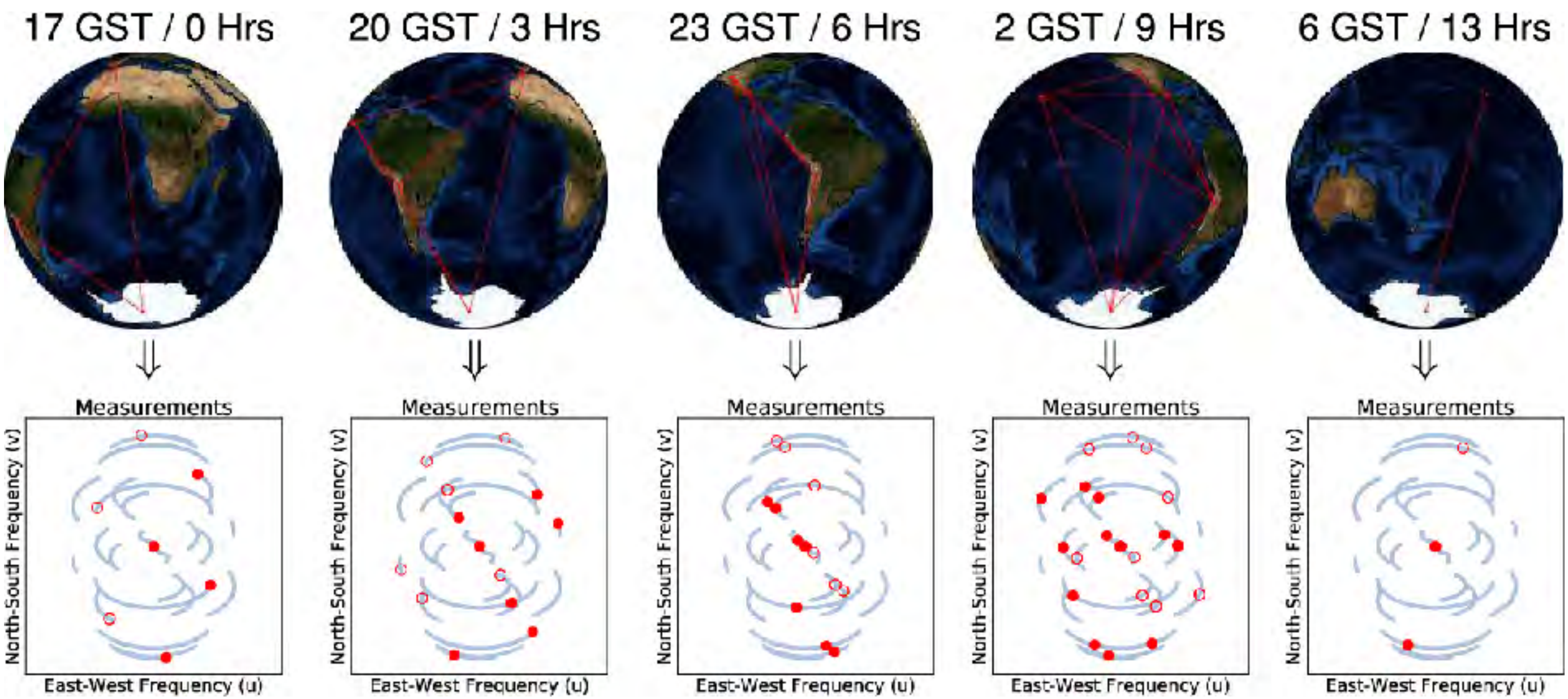
How Imaging A Blackhole Gives Us One More Reason To Embrace Python For Larger Datasets





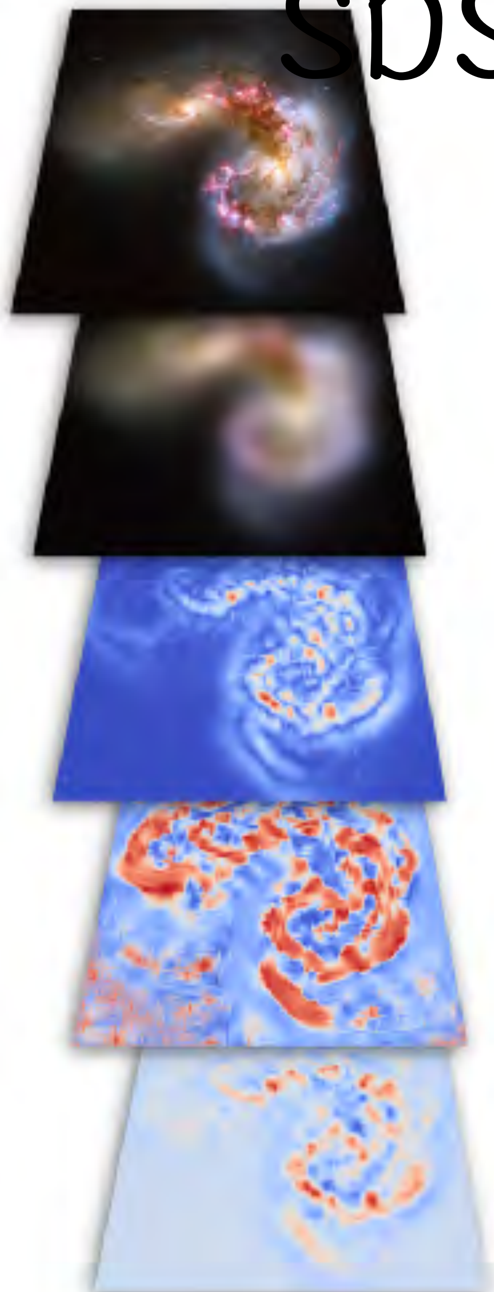
https://www.analyticsindiamag.com/how-imaging-a-blackhole-gives-us-one-more-reason-to-embrace-python-for-larger-datasets/

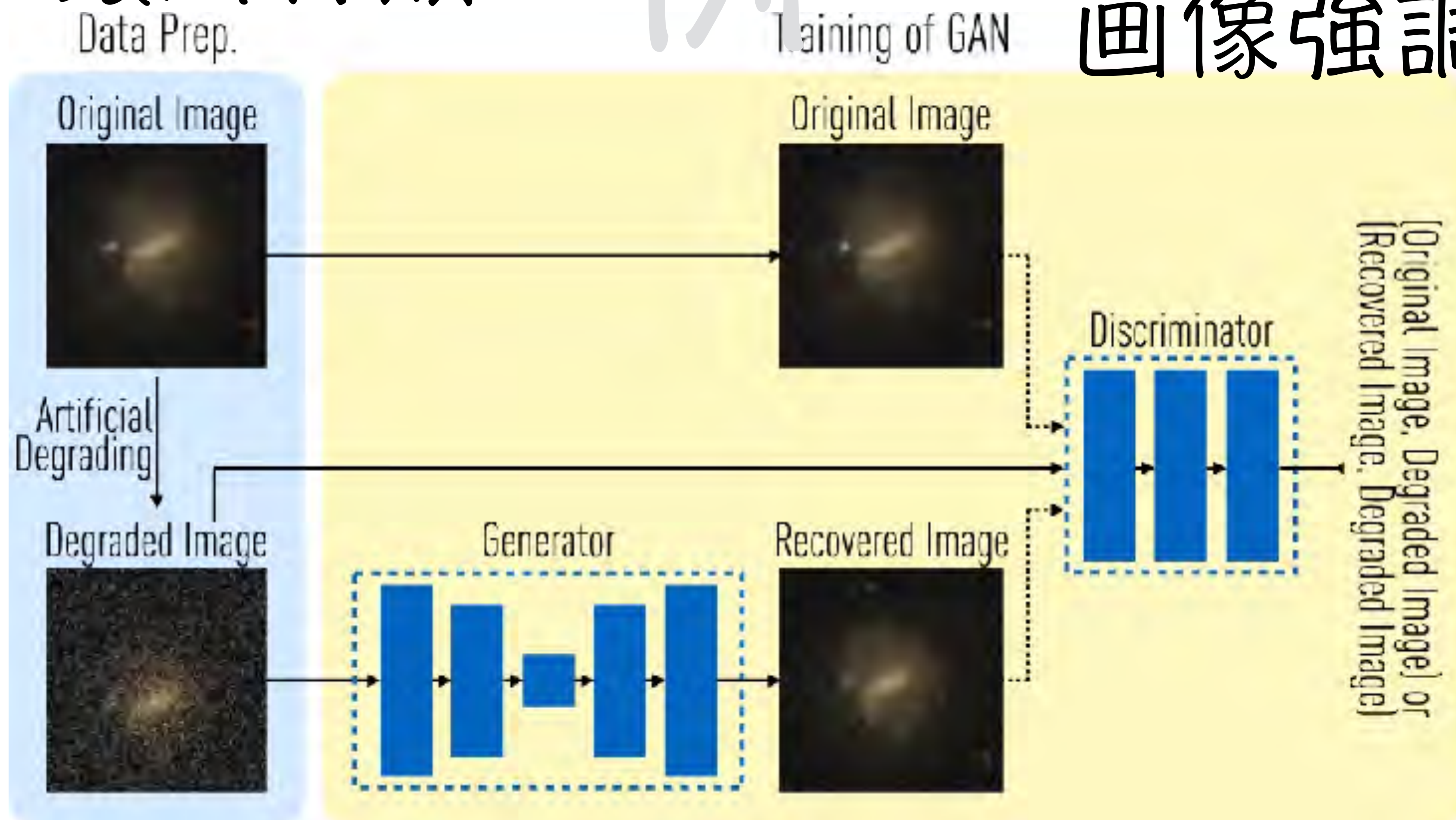
EHT


17 GST / 0 Hrs
20 GST / 3 Hrs
23 GST / 6 Hrs
2 GST / 9 Hrs
6 GST / 13 Hrs
Measurements
North-South Frequency (v)
East-West Frequency (u)

SDSS 銀河分類　例

画像強調



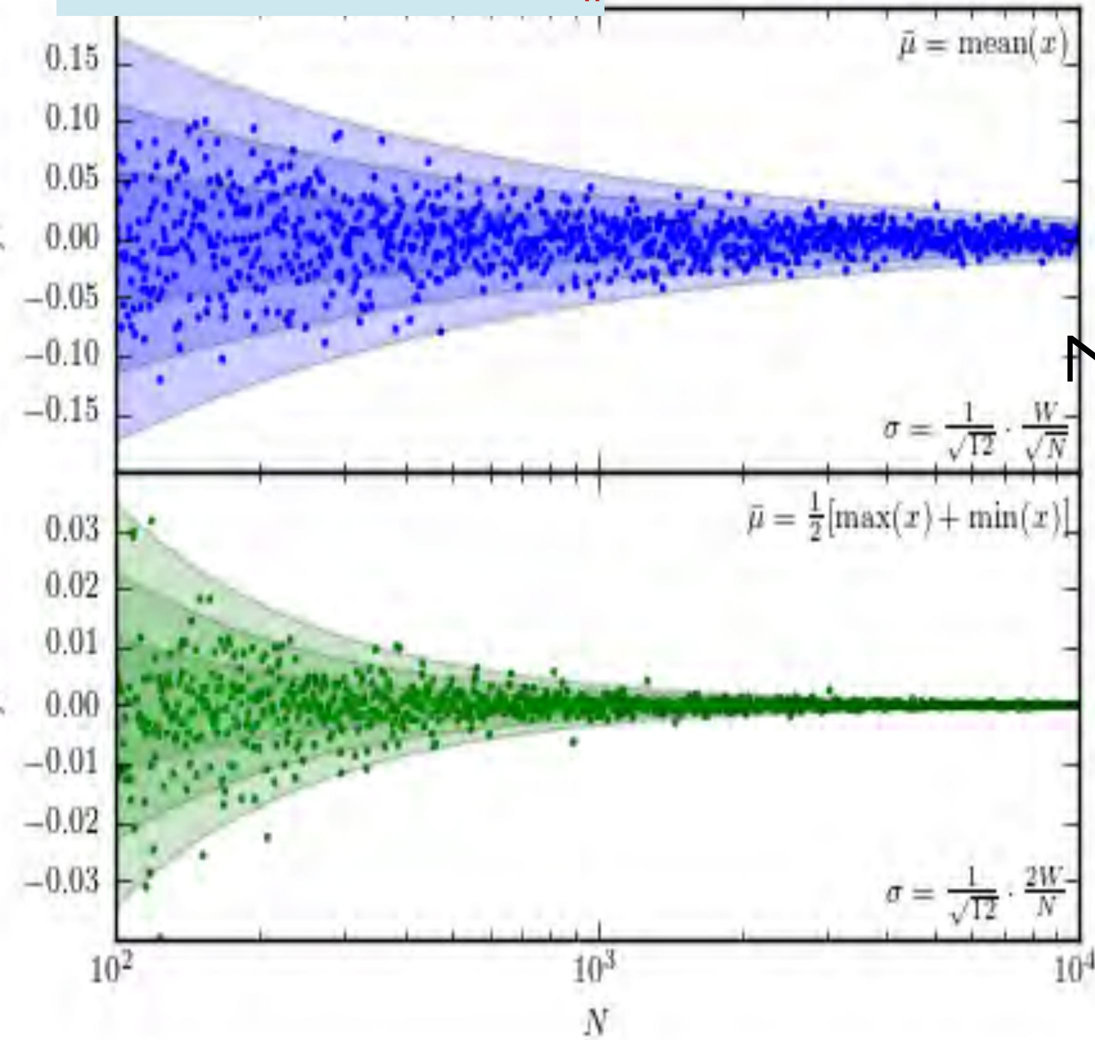


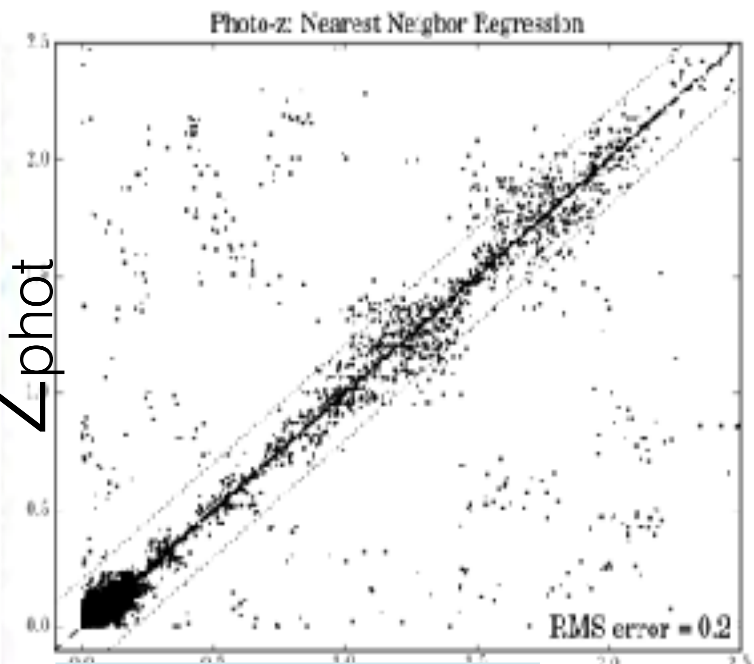
Zhang et. al. 2017

https://demo.ds3.ethz.ch/zarastro/

Kremer et. al. 2017

Convergence of mean for uniformly distributed values¶



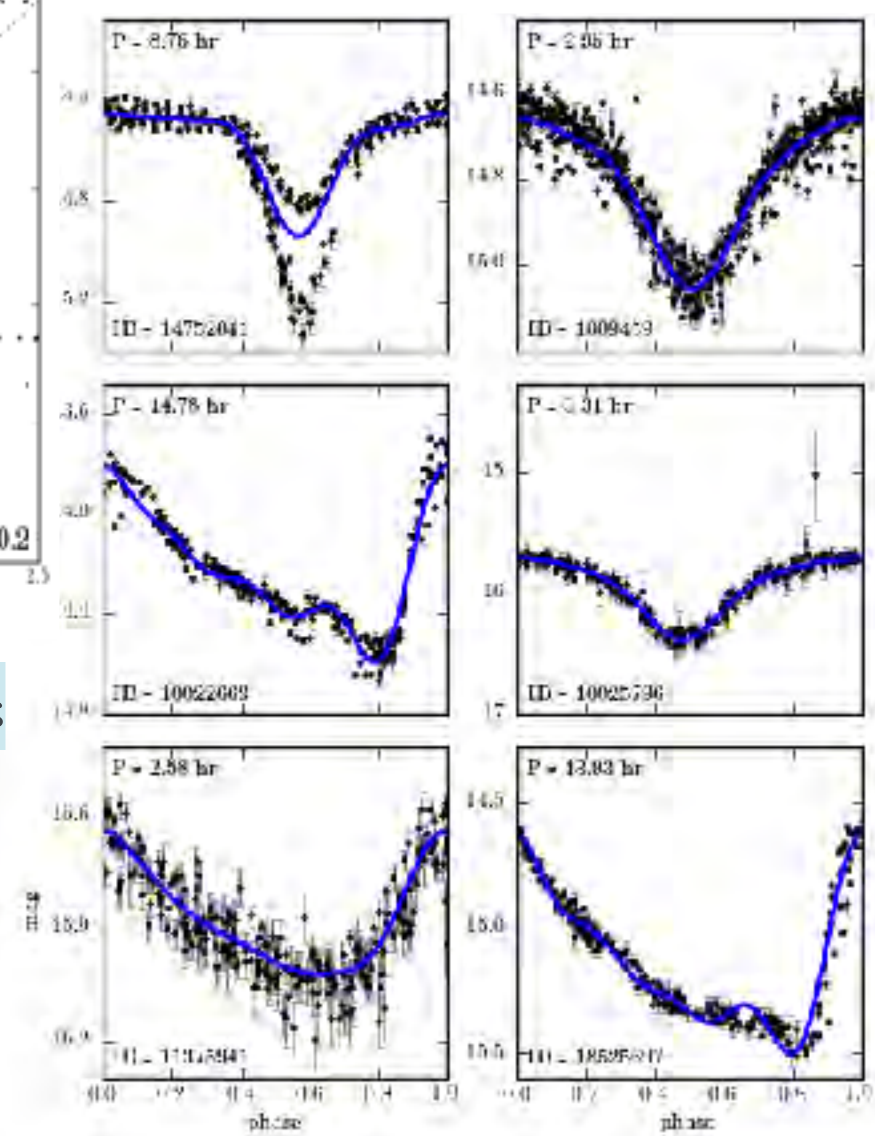


K-Neighbors for Z_{spec}

Photometric Redshifts

赤方偏移

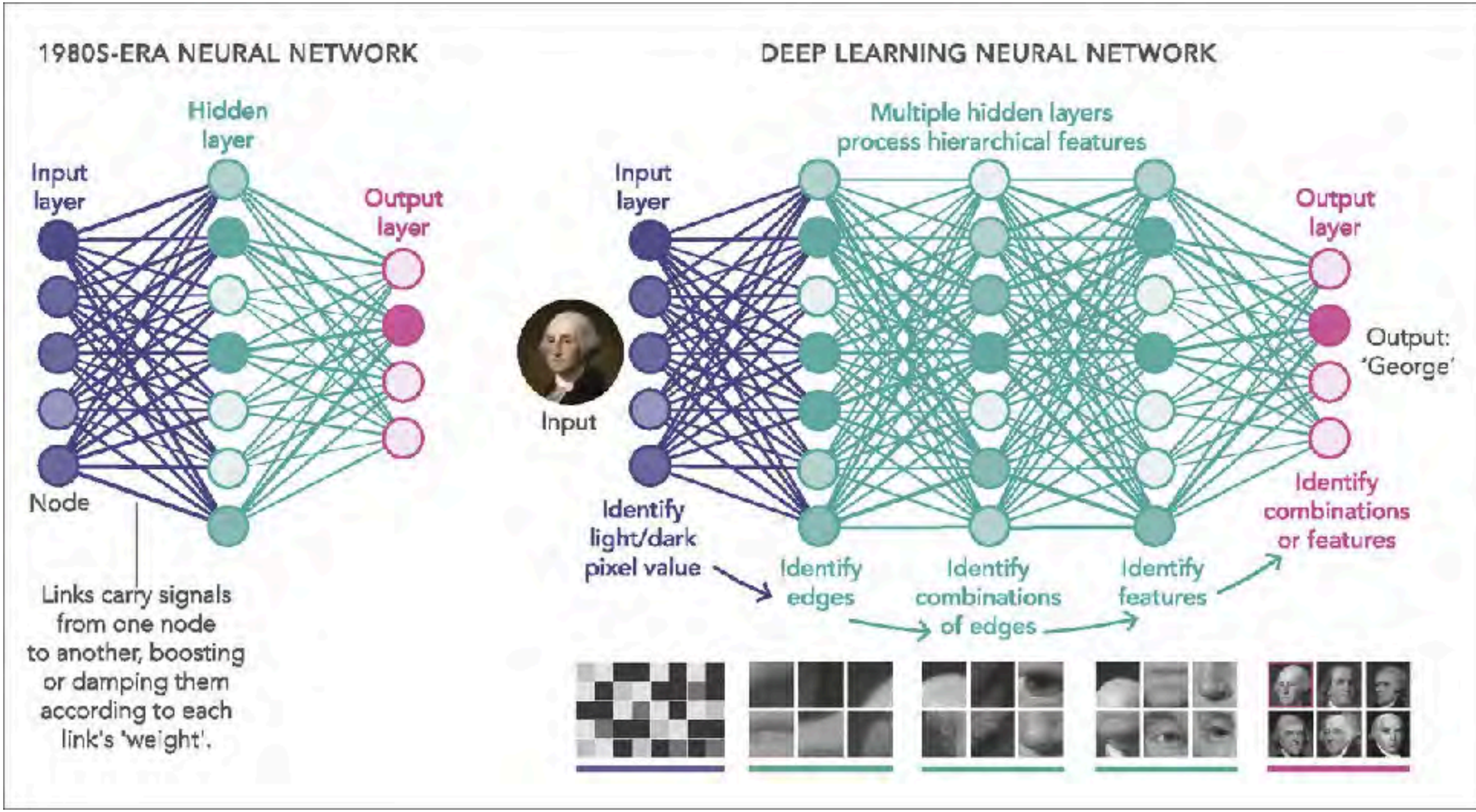
Phased LINEAR Light Curve



astroML

Machine Learning Applications in Astrophysics

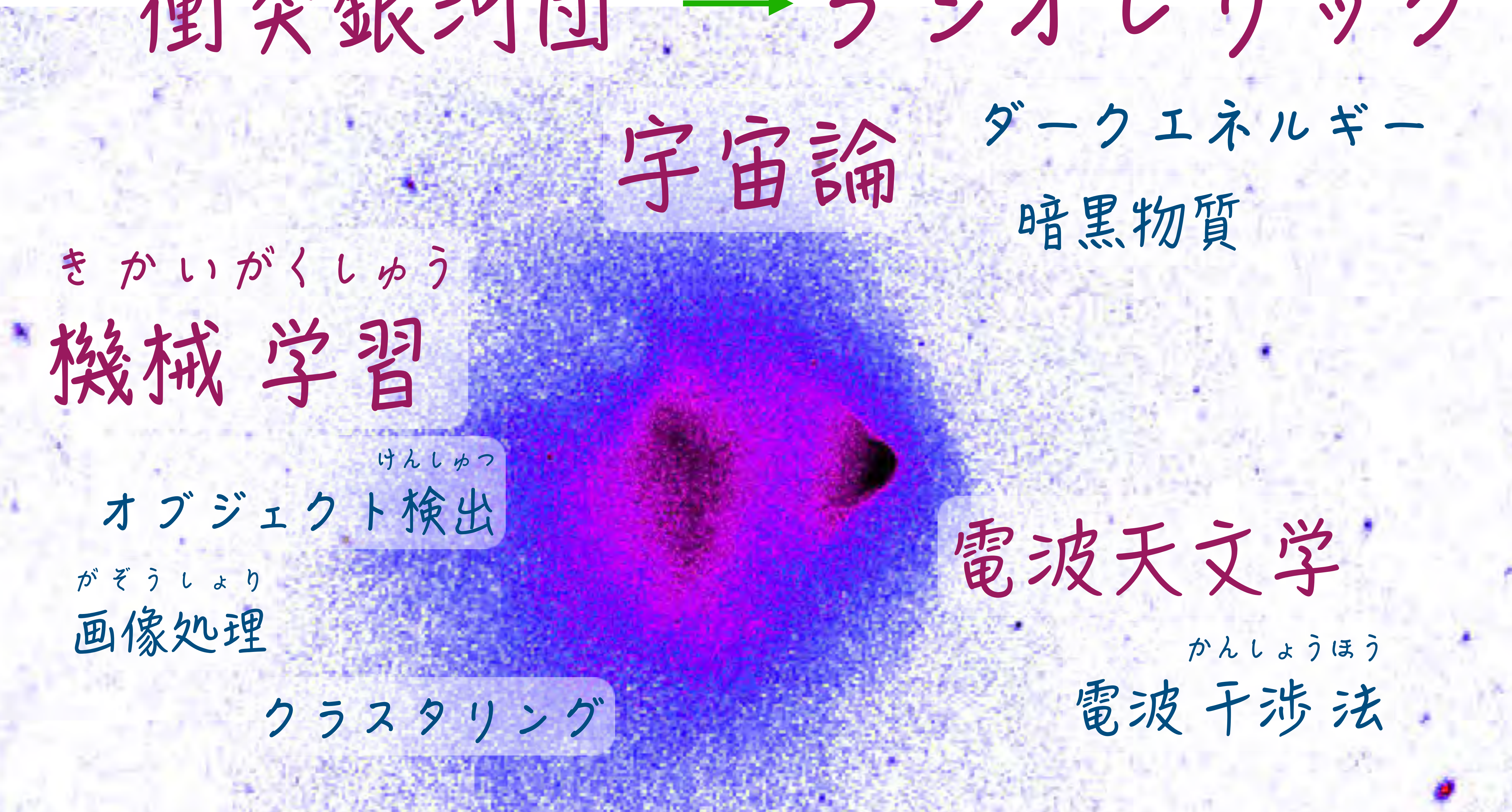
Summary


1980S-ERA NEURAL NETWORK
Hidden layer
Input layer
Output layer
Node
Links carry signals from one node to another, boosting or damping them according to each link's 'weight'.
DEEP LEARNING NEURAL NETWORK
Multiple hidden layers process hierarchical features
Input layer
Output layer
Input
Output: 'George'
Identify light/dark pixel value
Identify edges
Identify combinations of edges
Identify features
Identify combinations or features

紹介

興味（きょうみ）

Merging Galaxy Clusters



衝突銀河団 → ラジオレリック

宇宙論

ダークエネルギー

暗黒物質

機械学習（きかいがくしゅう）

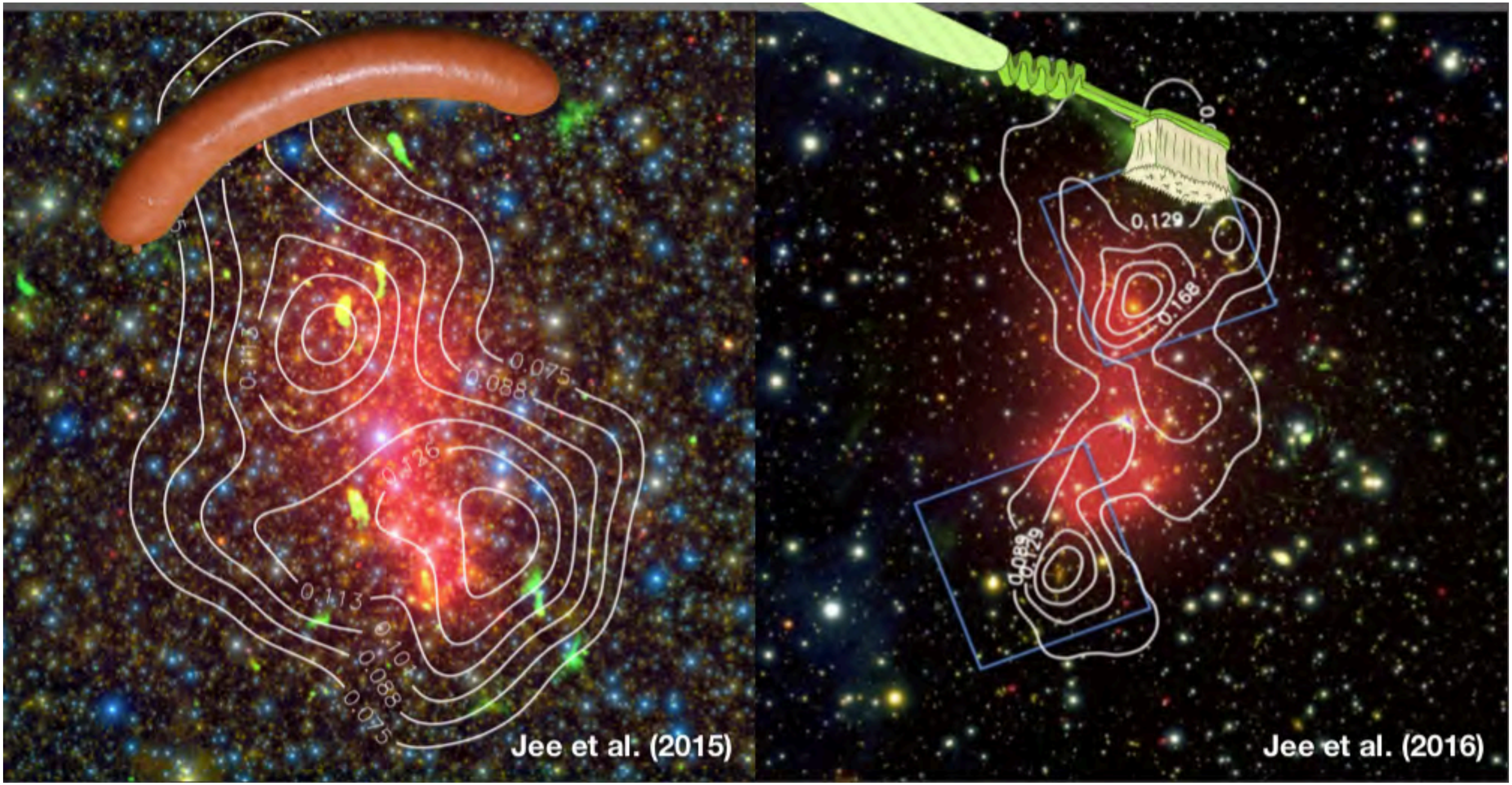
オブジェクト検出（けんしゅつ）

画像処理（がぞうしょり）

クラスタリング

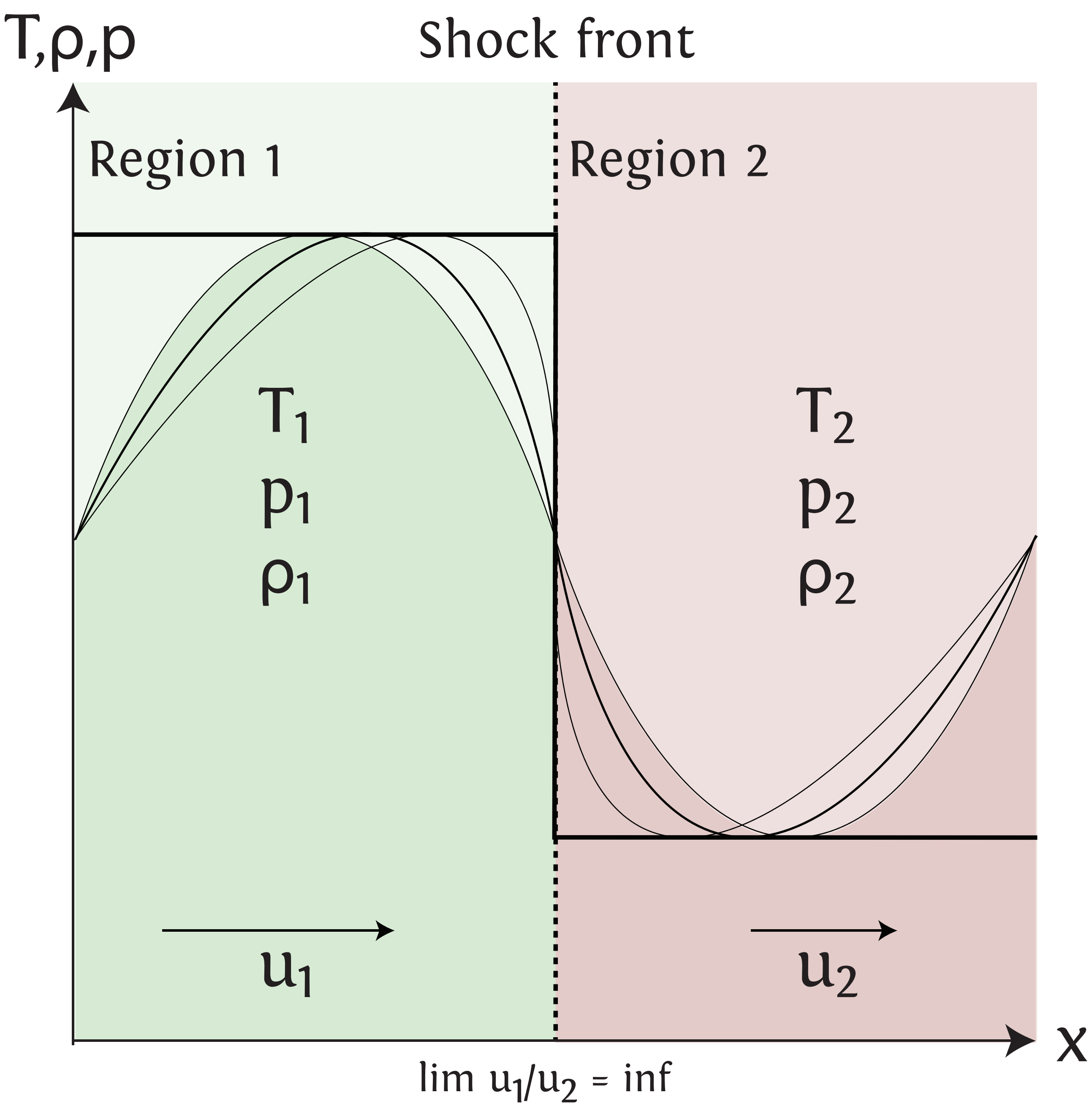
電波天文学

電波干渉法（かんしょうほう）

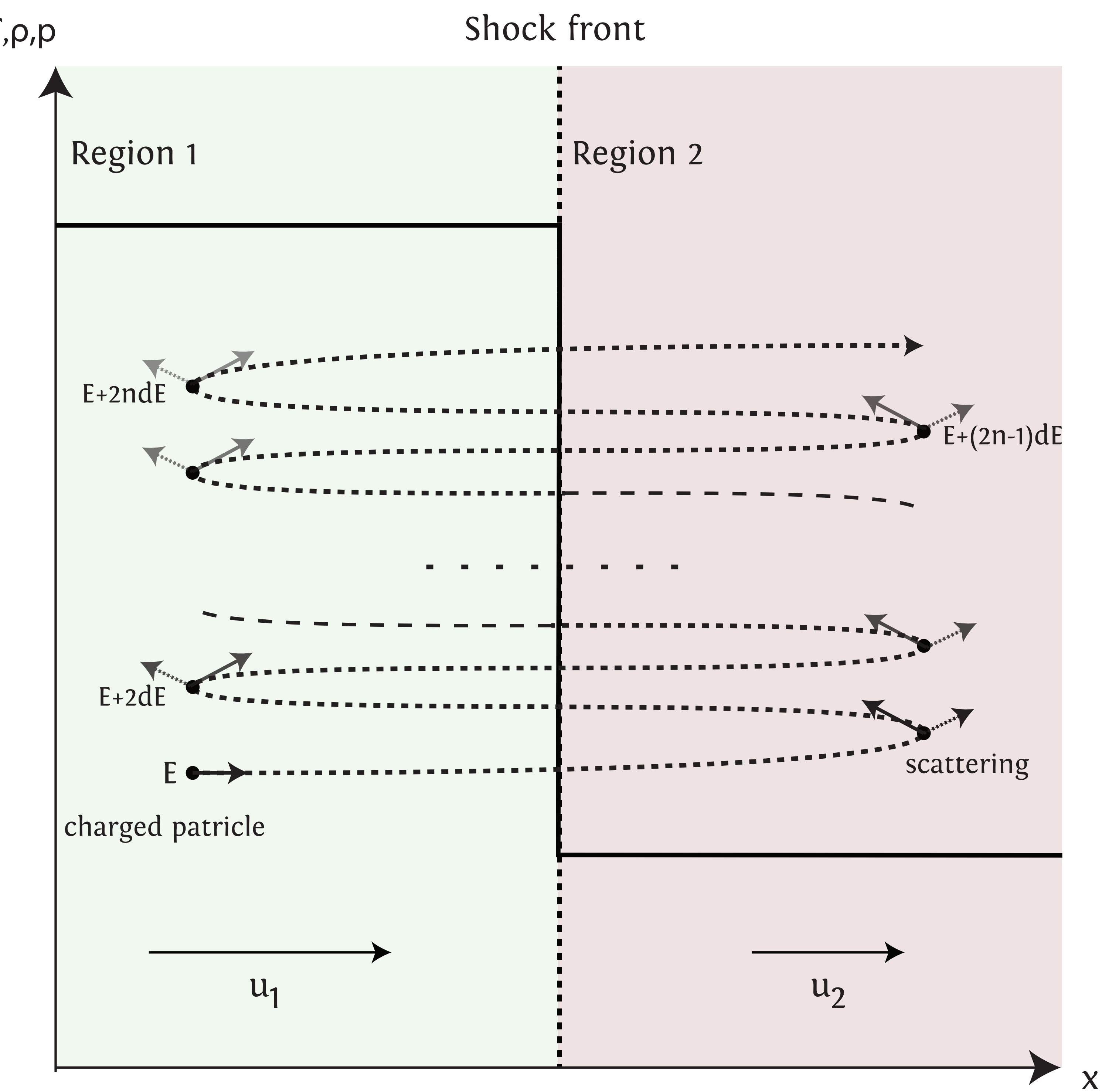


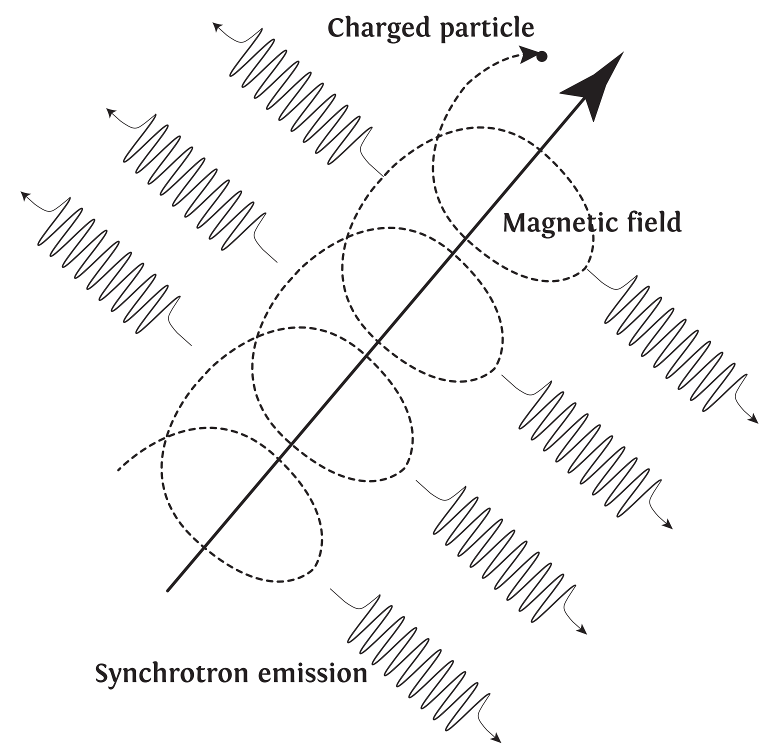
0.113
0.075
0.088
0.126
0.113
0.101
0.088
0.075
Jee et al. (2015)
0.129
0.168
0.089
0.129
Jee et al. (2016)

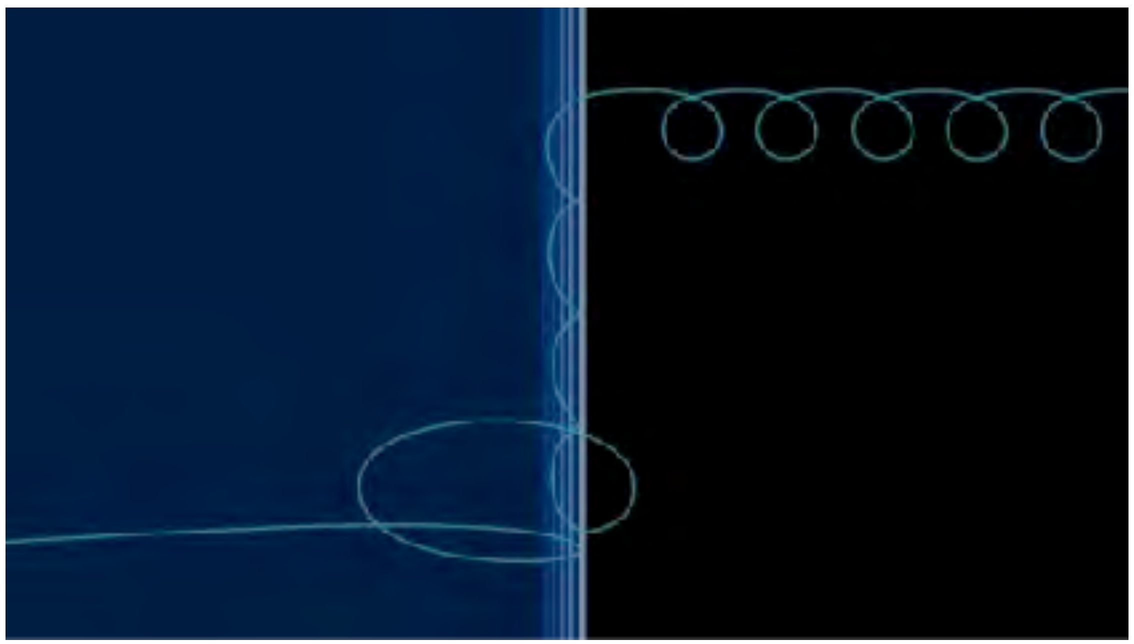
ラジオレリックの起源


T,ρ,p
Shock front
Region 1
Region 2
T1
p1
ρ1
T2
p2
ρ2
u1
u2
x
lim u1/u2 = inf

ラジオレリックの起源







Zhang et.al. 2019

Abell Catalogue:

4073 rich galaxy clusters (z <= 0.2)

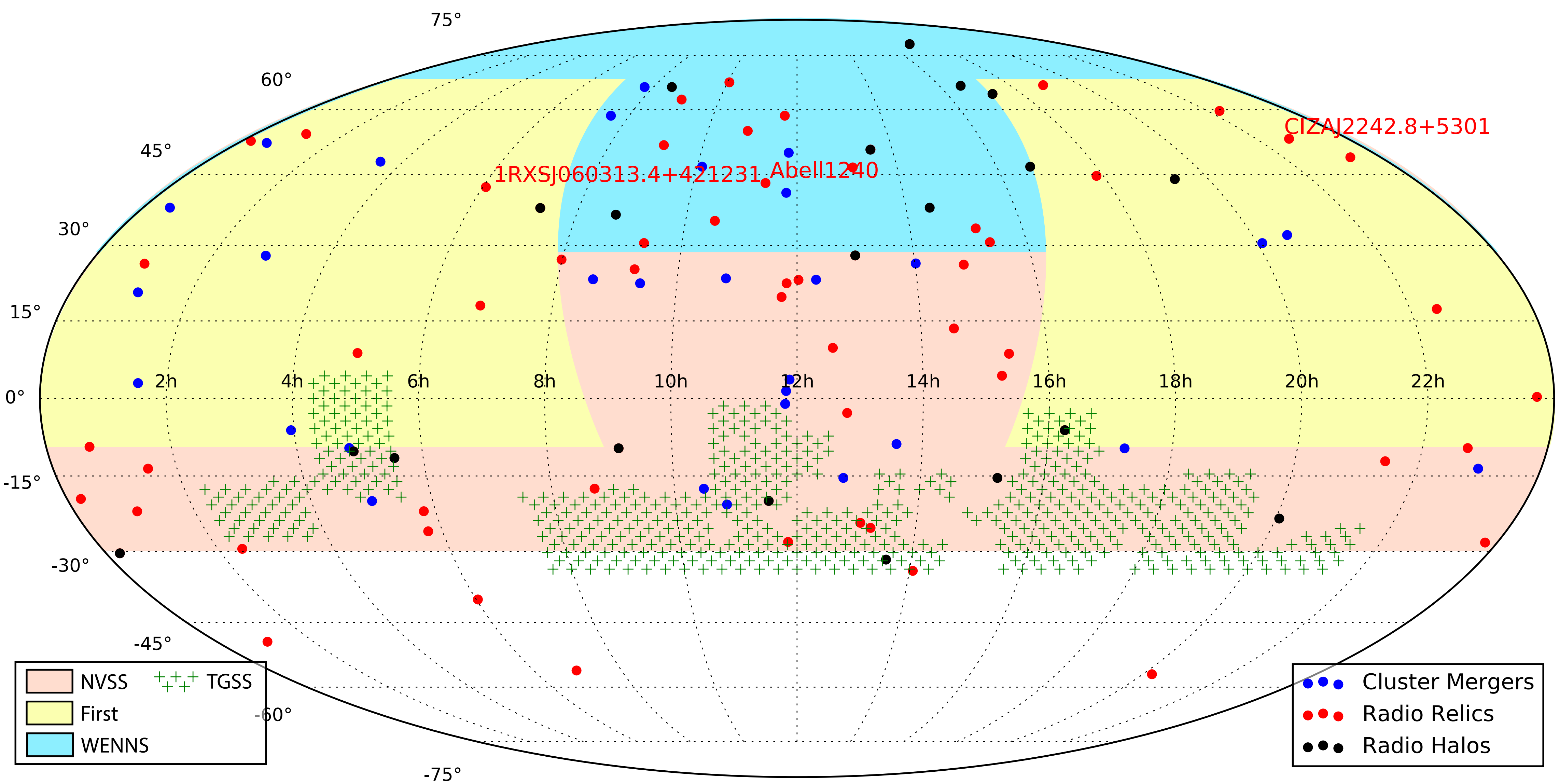
Z.L.Wen et.al:

Z < 0.8: Galaxy Clusters > 13万個

Radio Relics < 100個

Nuza et.al 2017

Merging Clusters: 現在 ~ 200個 : 0.01< z < 0.8



もくひょう
目標

- 新しい電波レリックを見つける
- どこ？：

NVSS - GMRT - LOFAR - ALMA(多分)

surveys

- どうやって？：

きかいがくしゅう

プログラミング + 機械学習 + magic

Deadline: ７月まで -> 論文