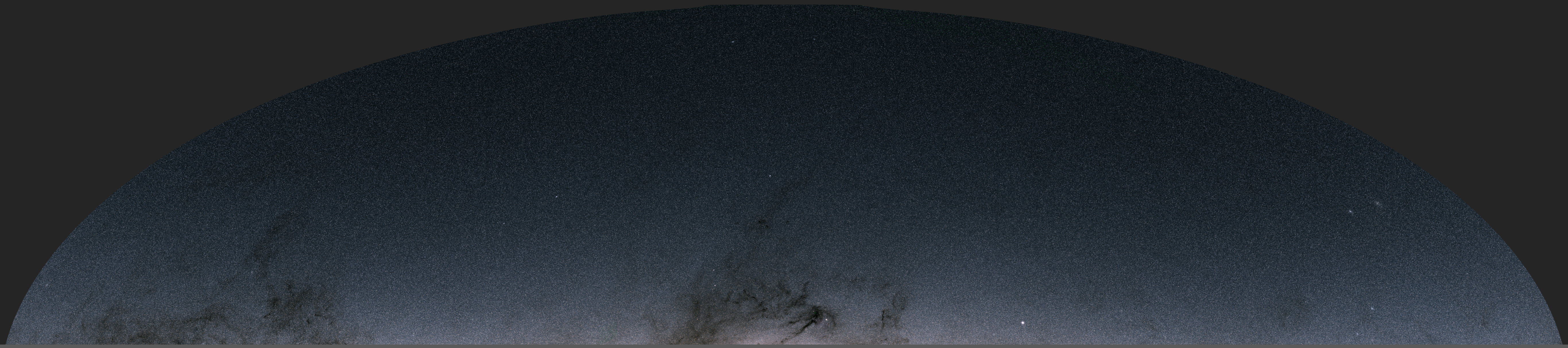
GRAL: IN SEARCH OF QUASAR GRAVITATIONAL LENSES FROM GAIA AND BEYOND

Alberto Krone-Martins, on behalf of Gaia GraL

Donald Bren School of Information and Computer Sciences

University of California, Irvine



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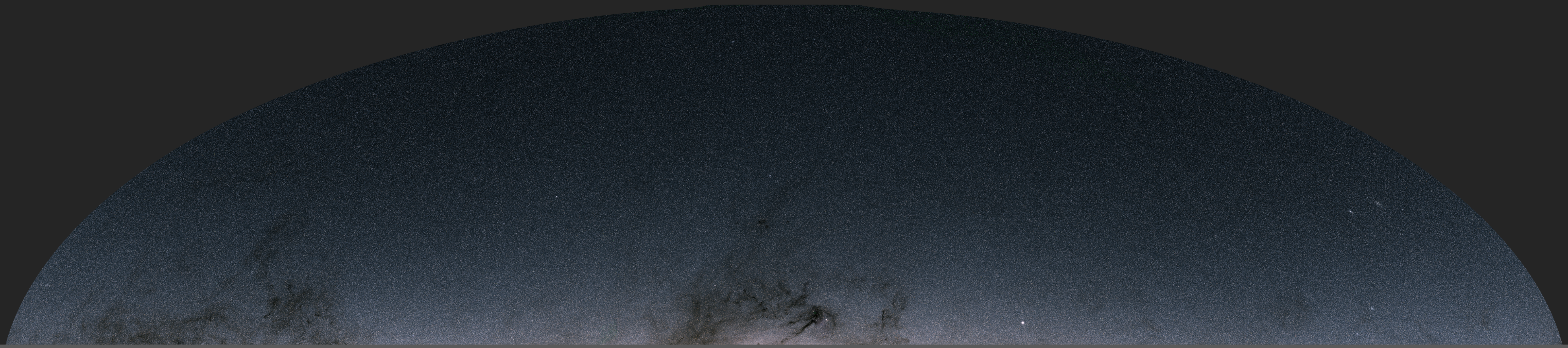

In this short talk…

Why?

How?

The future?

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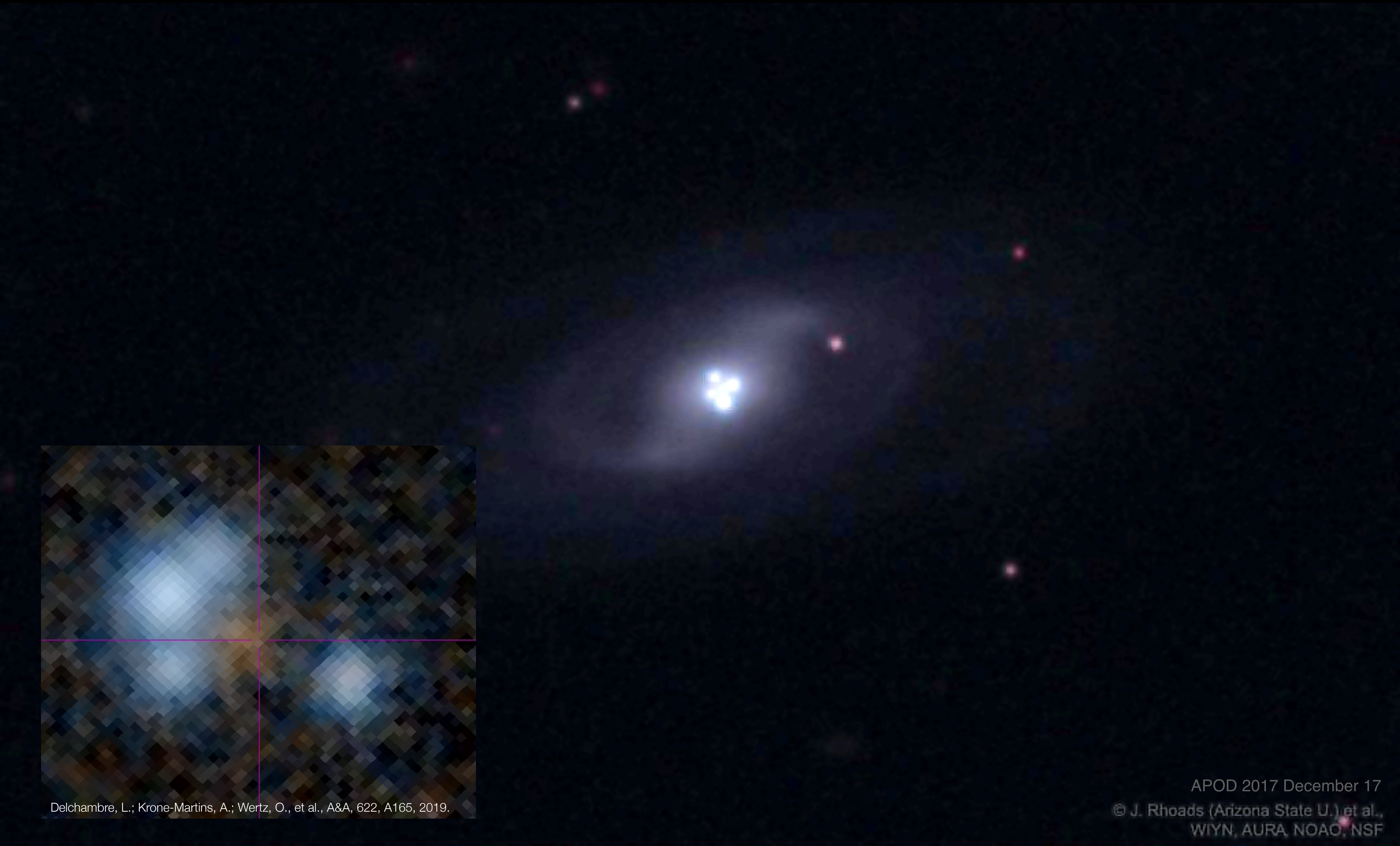
Why?

How?

The future?

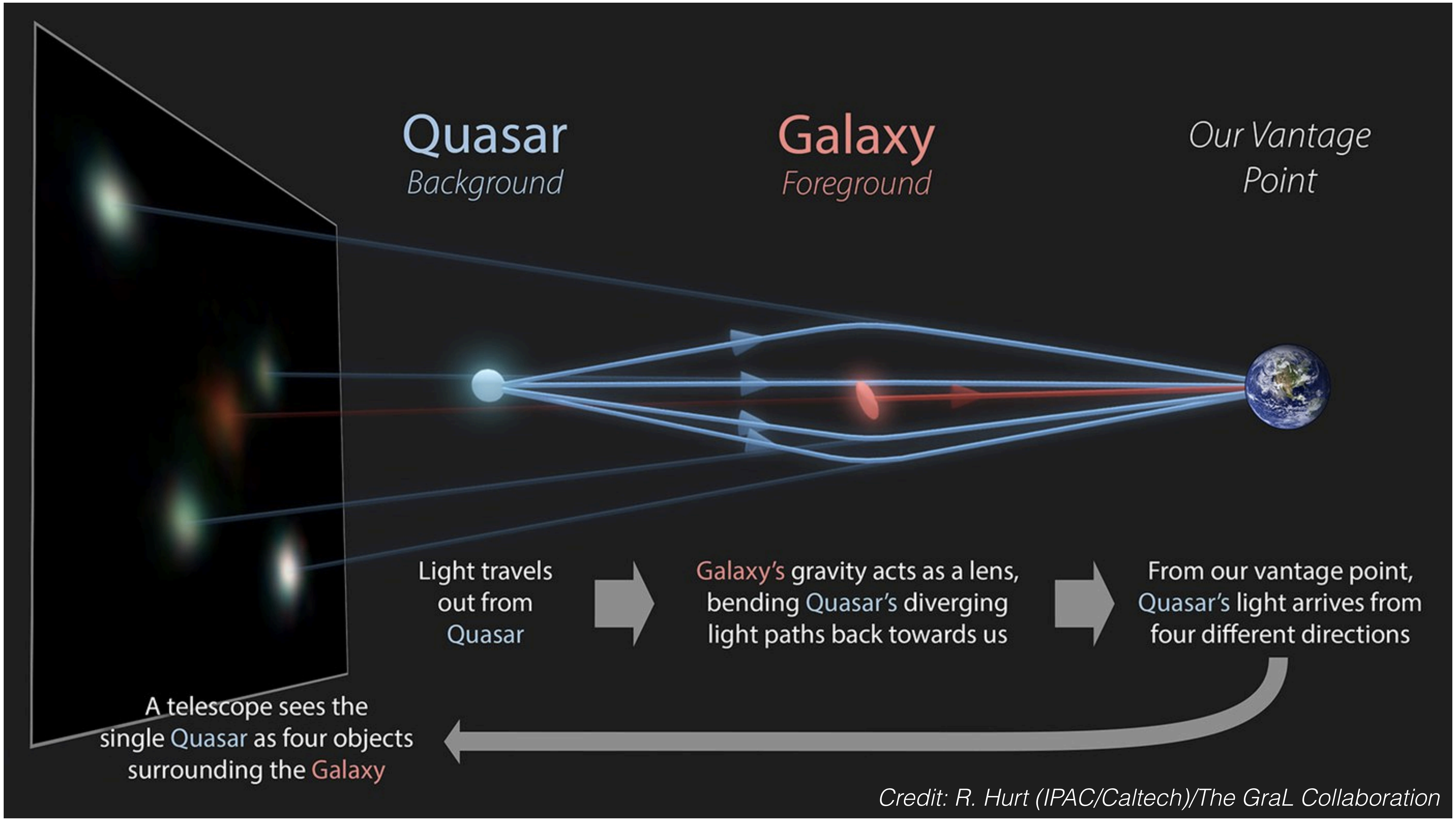
Why Strongly Lensed Quasars?

Why Strongly Lensed Quasars?



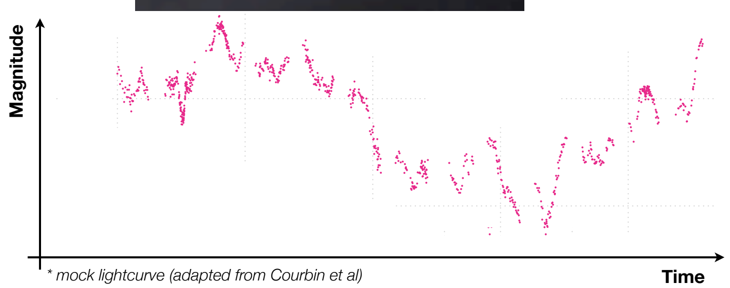
MULTIPLY-IMAGED QSOS

Among the most interesting and useful (and rare) extragalactic phenomena…

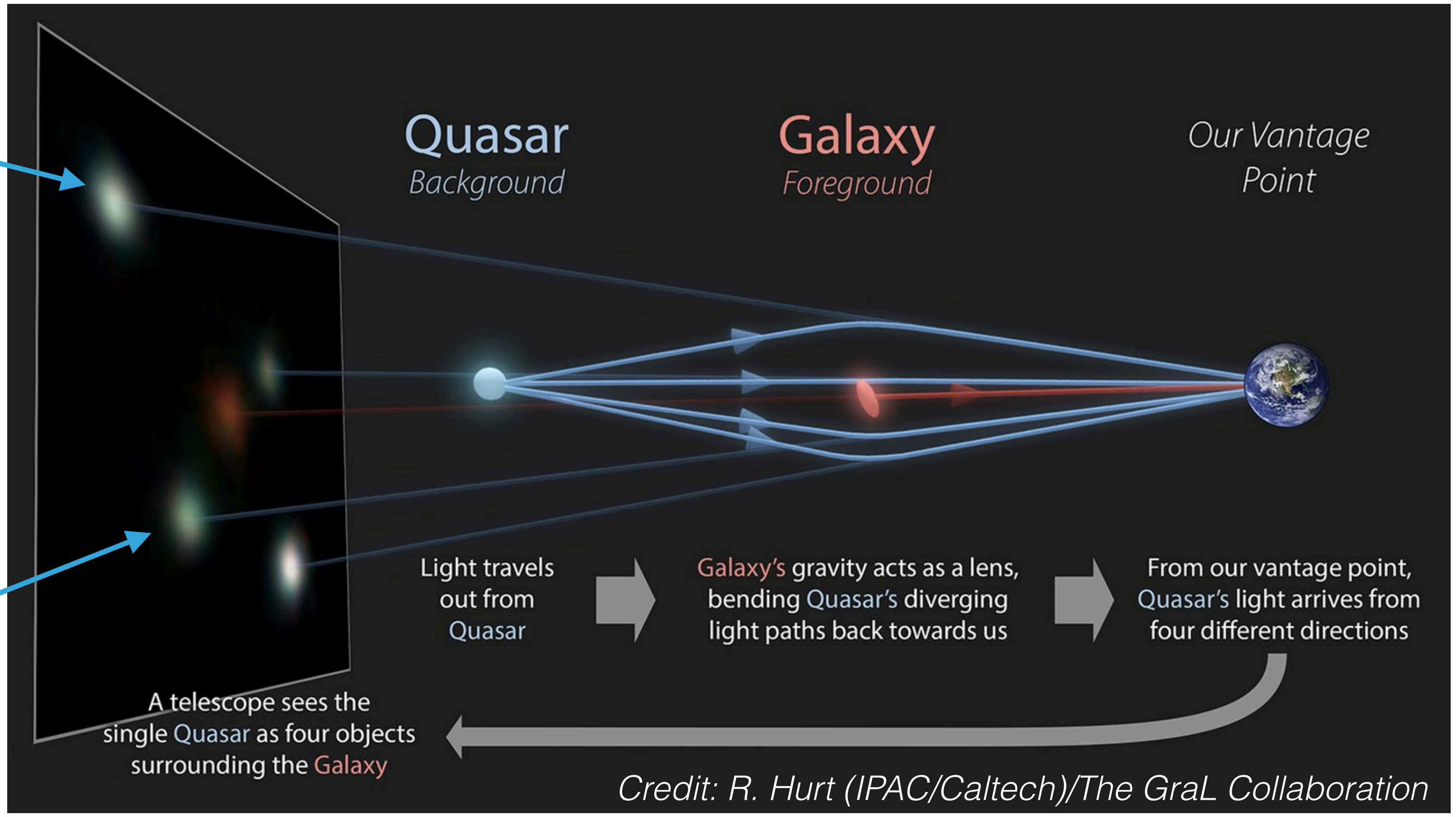


MULTIPLY-IMAGED QSOS

Quasars are variable sources…



Photometric time-series



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MULTIPLY-IMAGED QSOS

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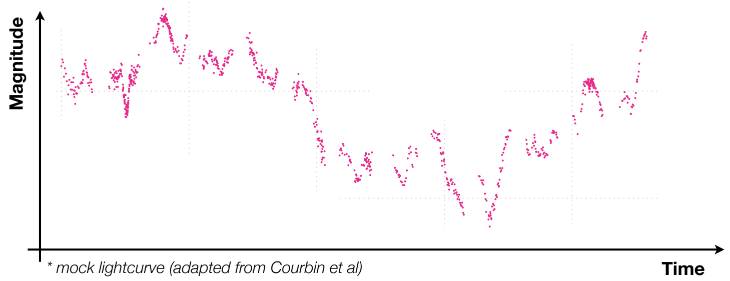

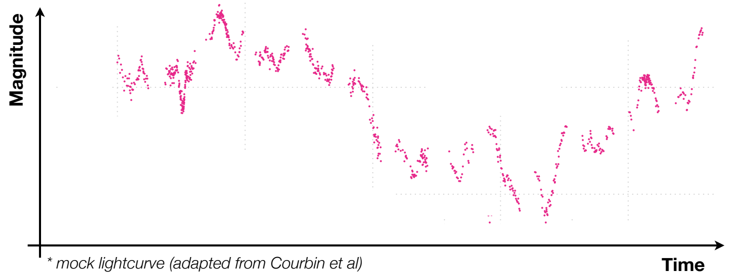

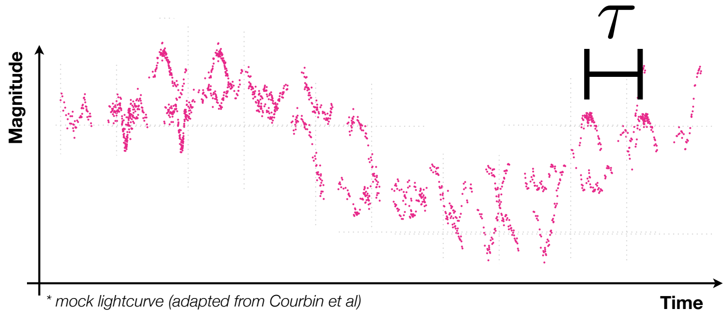

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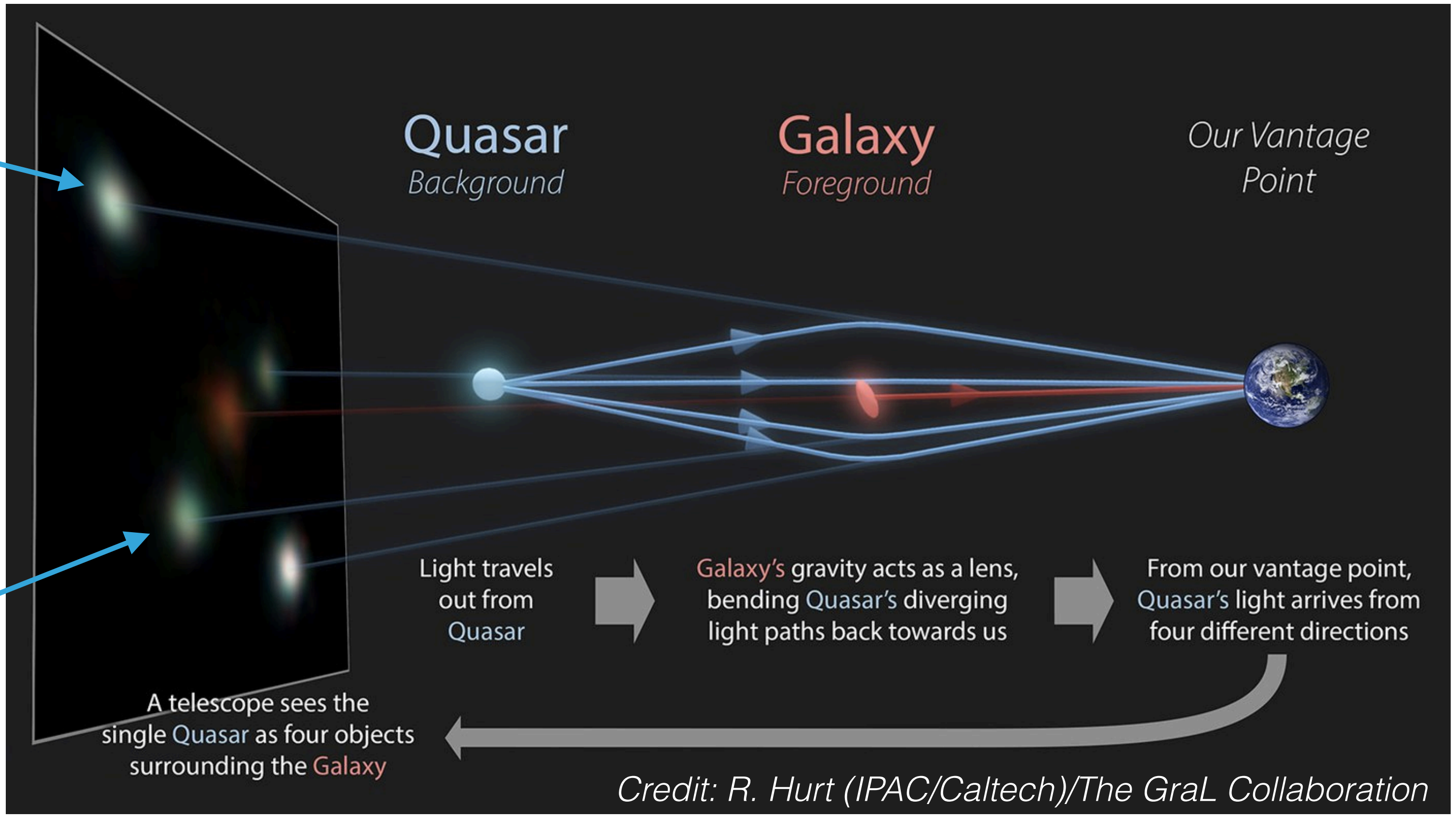

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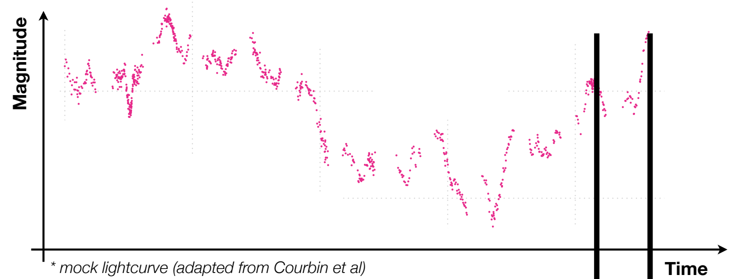

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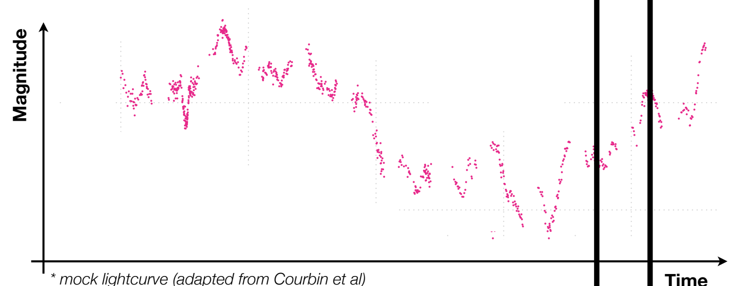
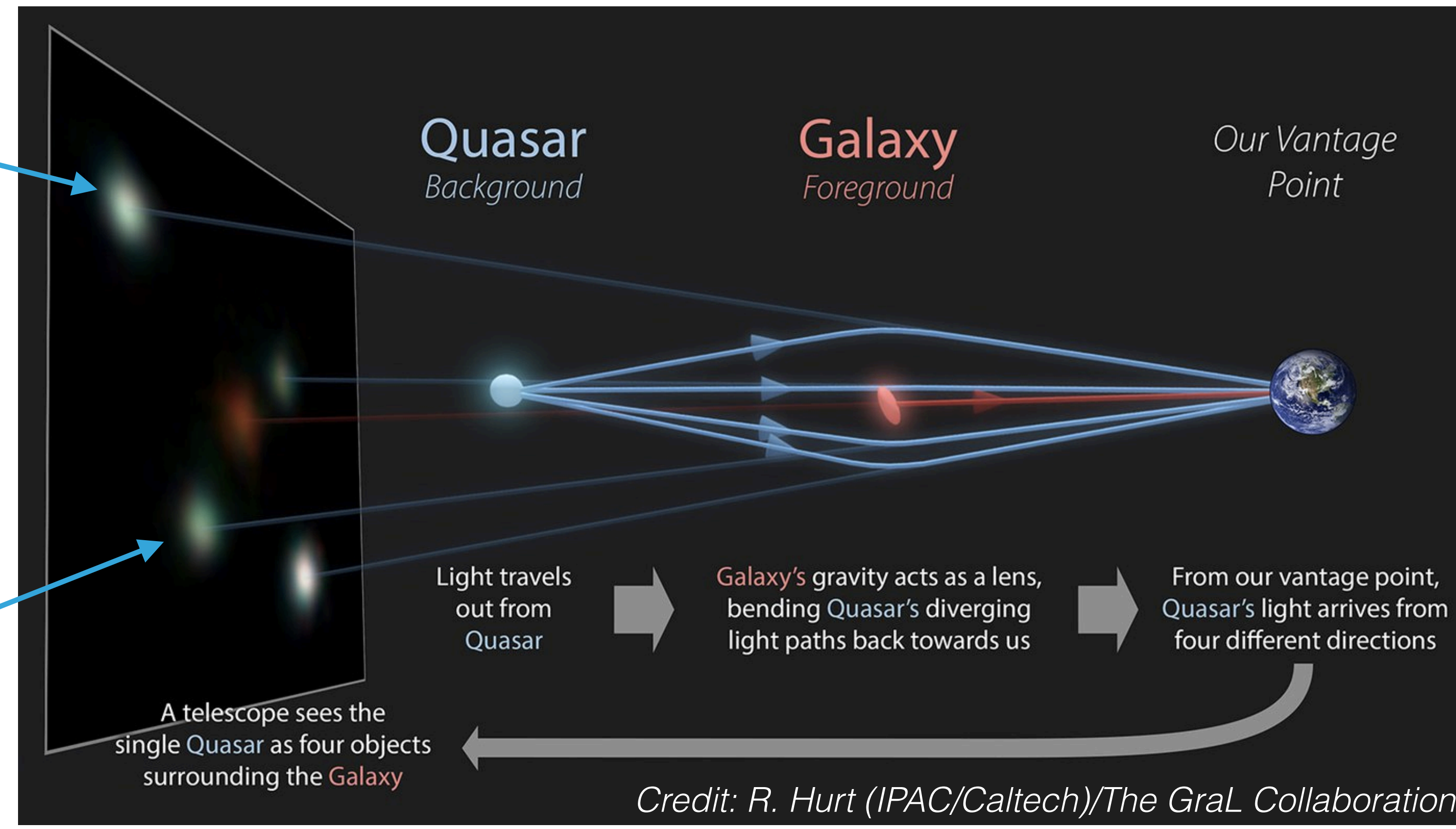


Photometric time-series



modelling: astrometry + photometry + spectroscopy

measurement: photometry time-series

$$\tau = \frac{(1+z_L)}{?}\,\frac{d_L d_S}{d_{LS}}\left[\frac{1}{2}|\vec{\theta}-\vec{\beta}| - \psi_{2D}(\vec{\theta})\right]$$

MULTIPLY-IMAGED QSOS : H0

Lensed QSO variability is a key to H0 inference

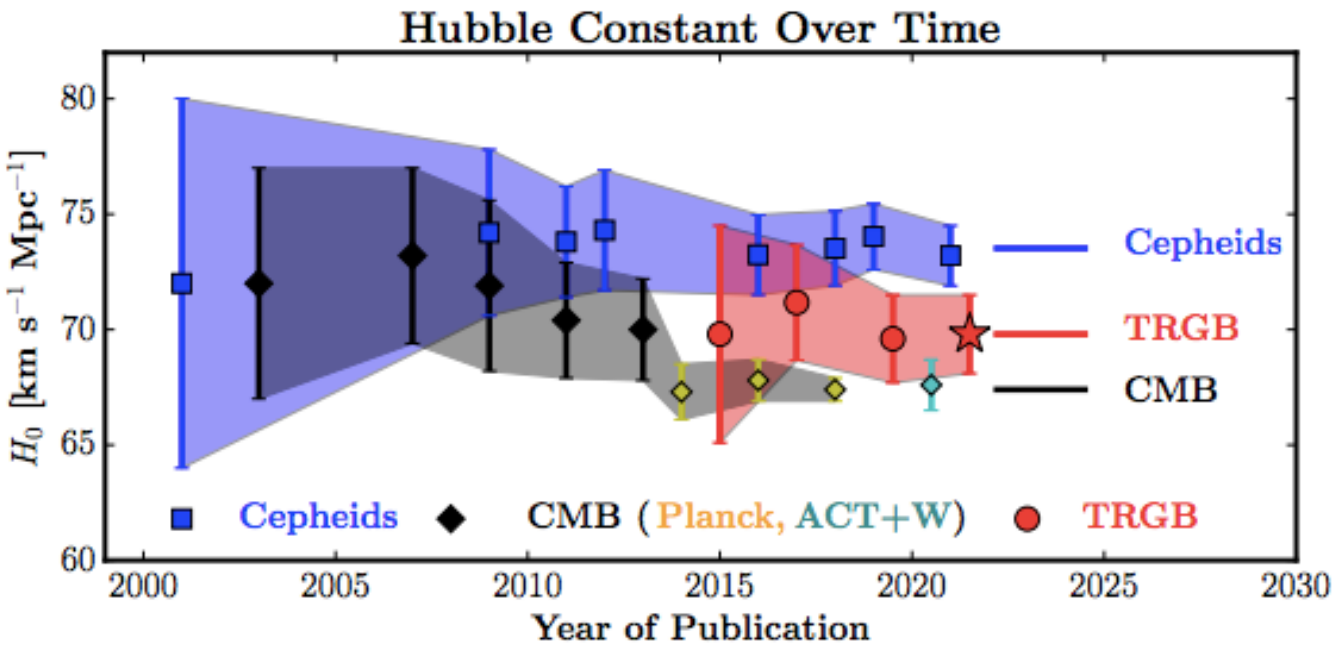
modelling: astrometry + photometry + spectroscopy

measurement: photometry time-series

$$\tau = \frac{(1+z_L)}{H_0}\frac{d_L d_S}{d_{LS}}\left[\frac{1}{2}|\vec{\theta}-\vec{\beta}| - \psi_{2D}(\vec{\theta})\right]$$

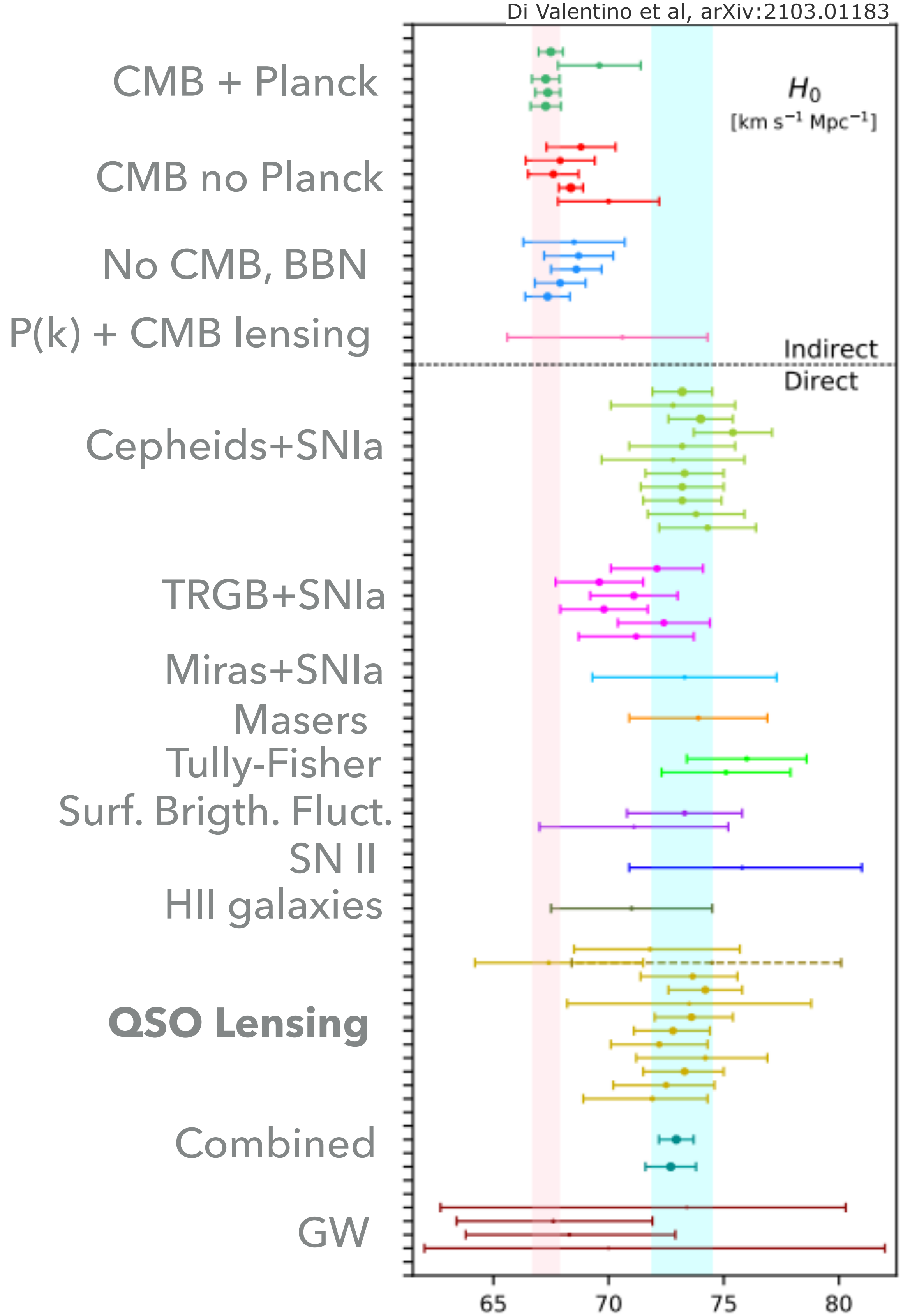

BBC

MULTIPLY-IMAGED QSOS : H0



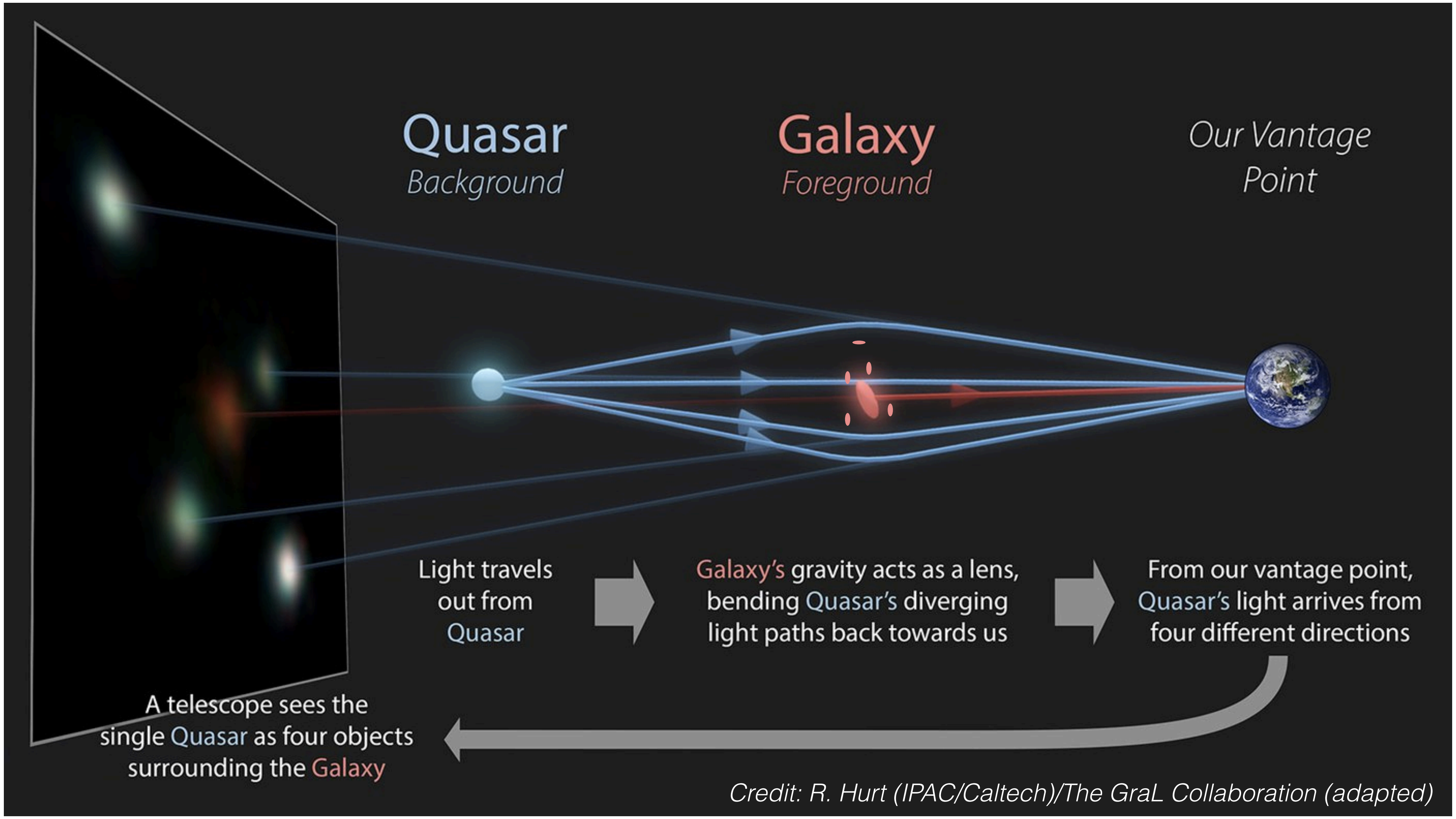
Freedman, W. arXiv:2106.15656v1

Di Valentino et al, arXiv:2103.01183



MULTIPLY-IMAGED QSOS : DARK MATTER

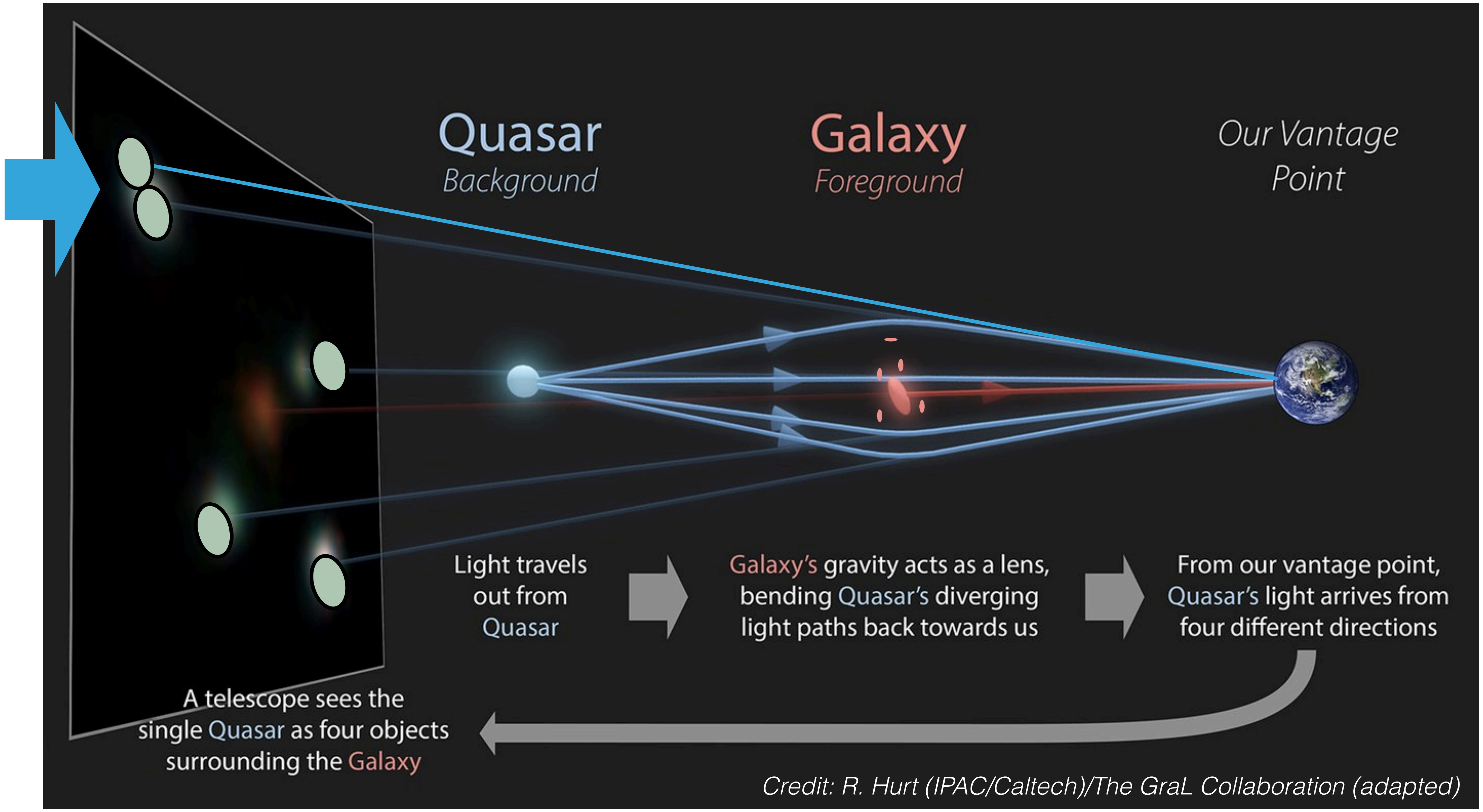
What would happen if you had more matter around the lensing galaxy?



MULTIPLY-IMAGED QSOS : DARK MATTER

Lensed QSOs are a probe of the dark matter clumpiness in the lens

Astrometric + photometric deviation from smooth potential prediction due to DM substructure



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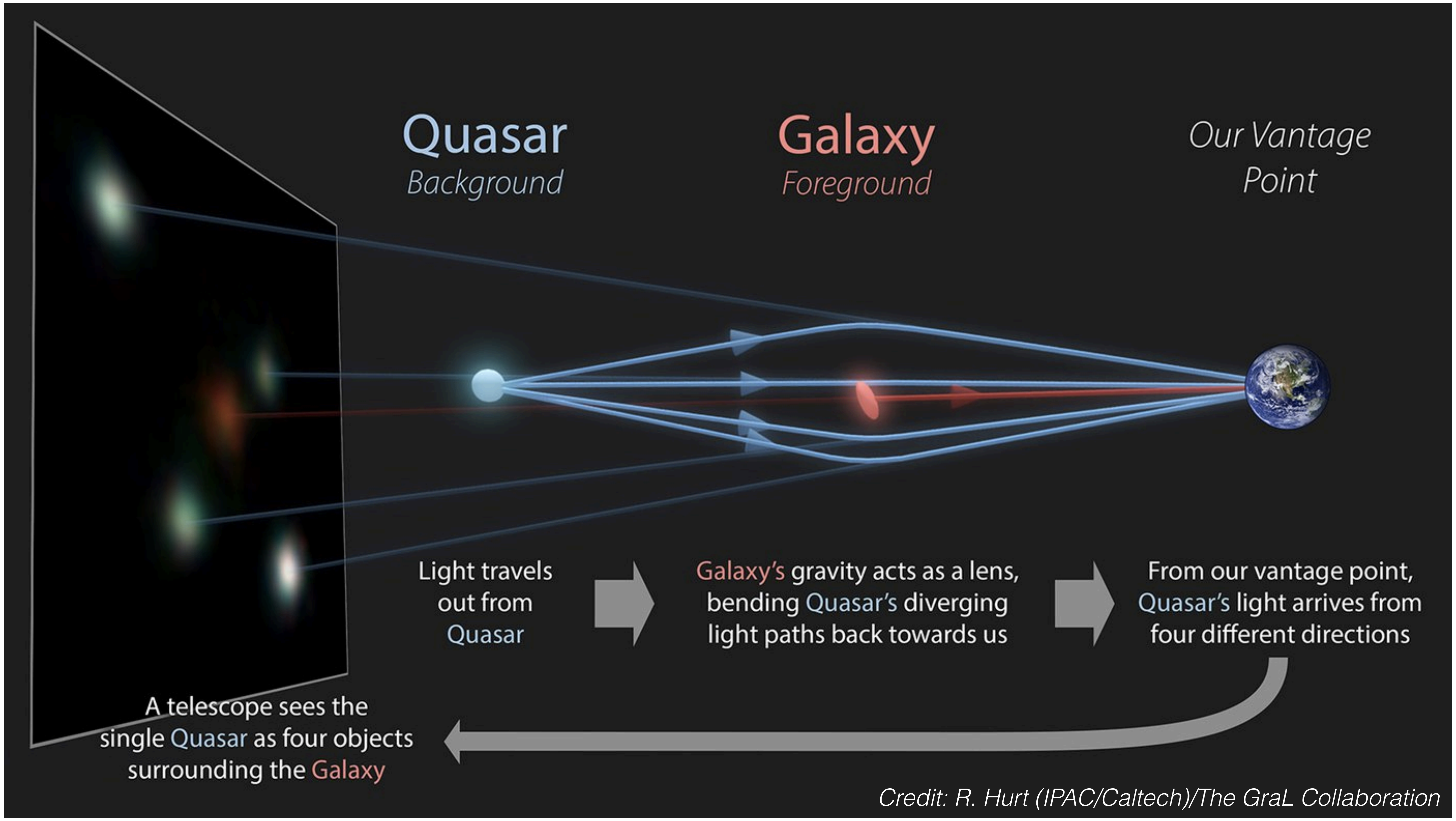
MULTIPLY-IMAGED QSOS

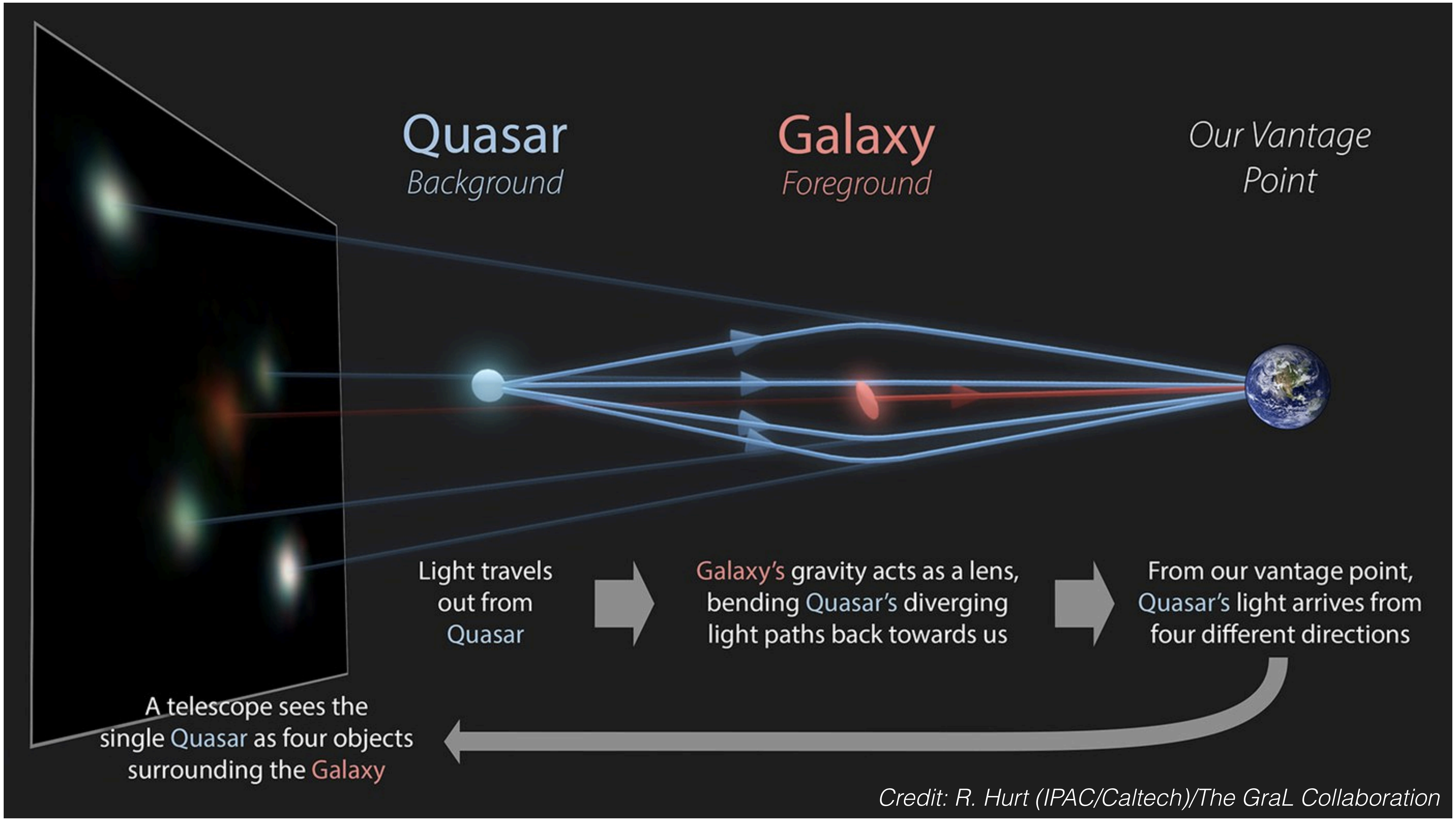
Among the most interesting and useful (and rare) extragalactic phenomena…



Credit: R. Hurt (IPAC/Caltech)/The GraL Collaboration

MULTIPLY-IMAGED QSOS

Among the most interesting and useful (and rare) extragalactic phenomena:
~2 x 10^3 among the ~2 x 10^9 Gaia sources



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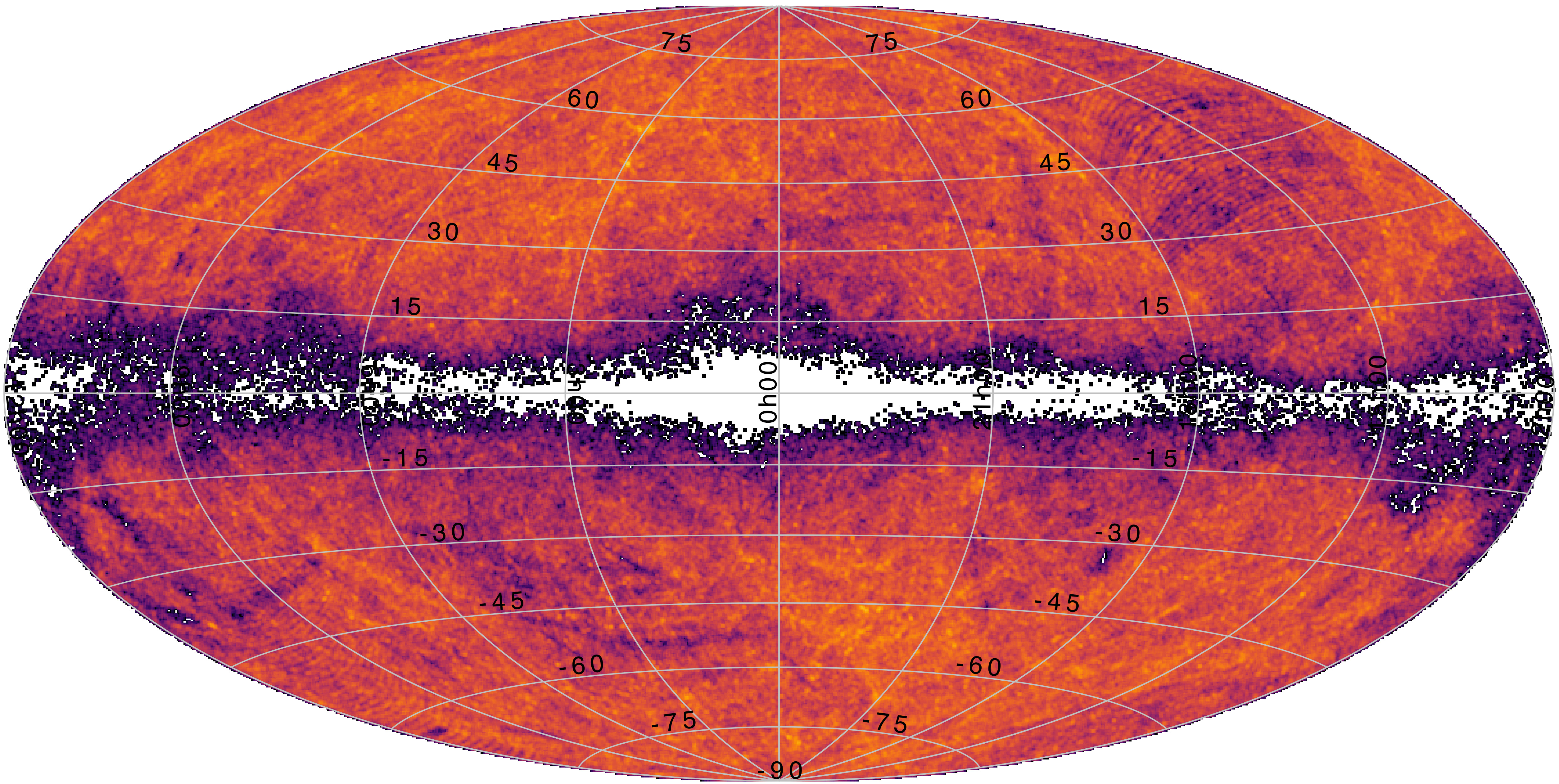
The future?

GAIA WAS CREATED FOR STARS, BUT IT ALSO OBSERVES GALAXIES!



Sky density of 1.8 million Gaia input galaxies selected by a fully unsupervised method (iterative HDBSCAN+SVM+Hausdorf metric over GaiaDR1+DR2+PS1DR2+AllWISE)

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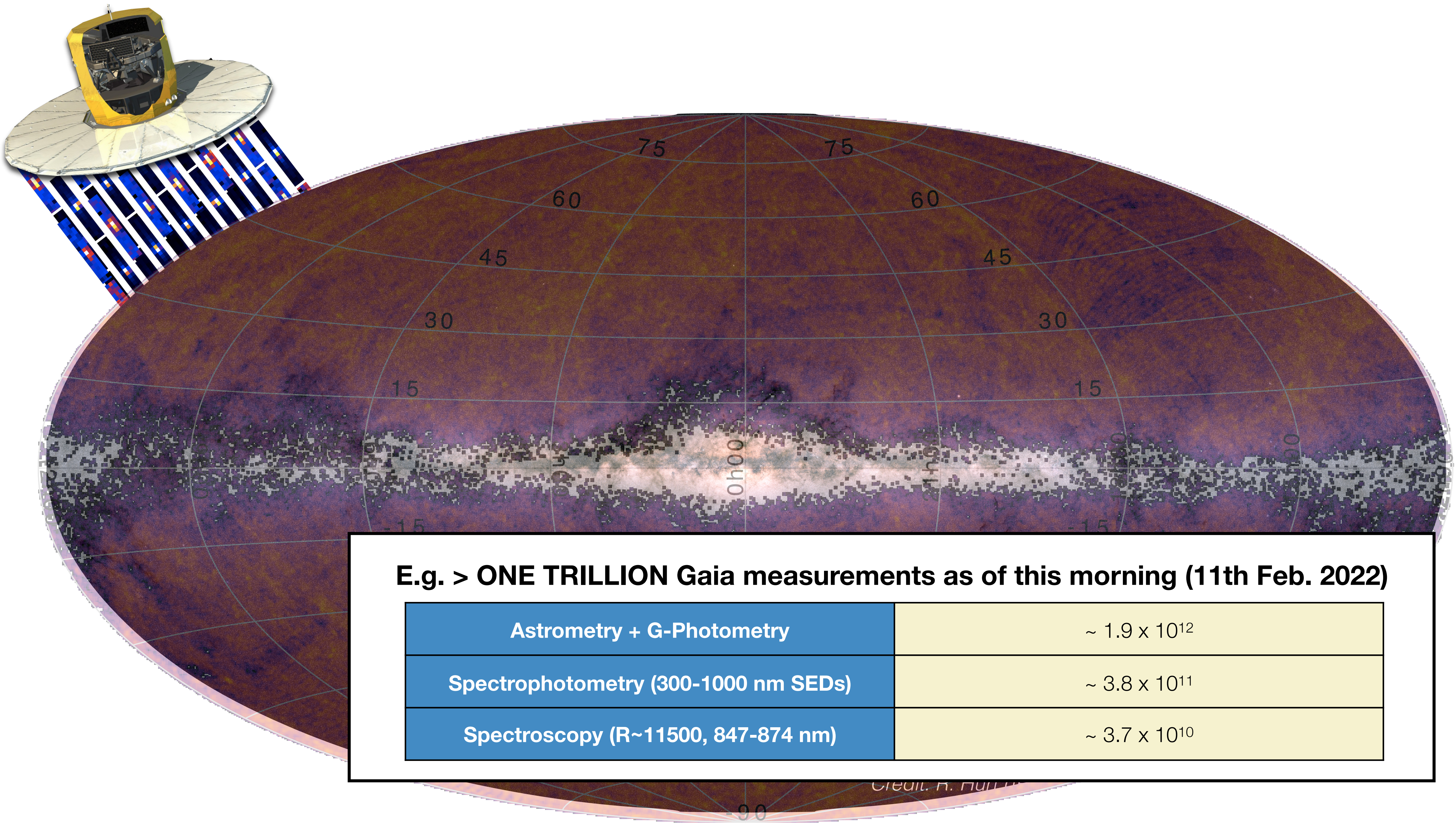
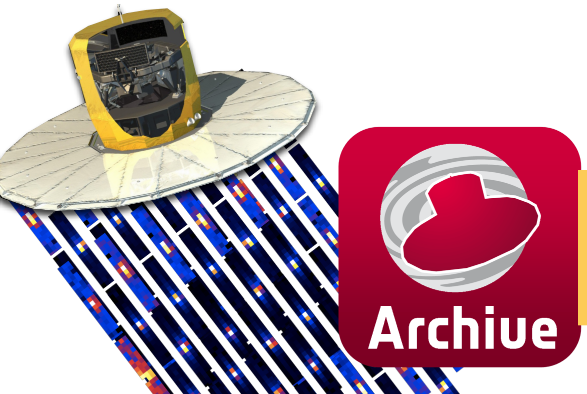
MULTIPLY-IMAGED QSOS



E.g. > ONE TRILLION Gaia measurements as of this morning (11th Feb. 2022)

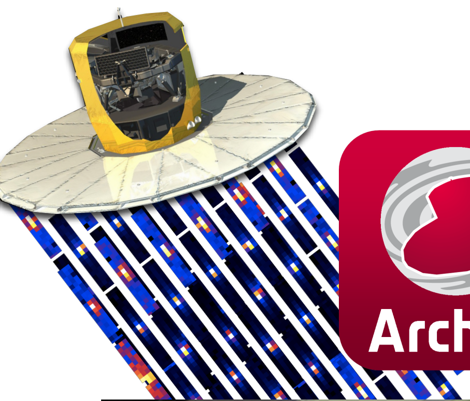
Astrometry + G-Photometry	~ 1.9×10^{12}
Spectrophotometry (300-1000 nm SEDs)	~ 3.8×10^{11}
Spectroscopy (R~11500, 847-874 nm)	~ 3.7×10^{10}

SEARCHING FOR GRAVITATIONAL LENSES



BULK DOWNLOAD
VIA ESA CDN

SEARCHING FOR GRAVITATIONAL LENSES



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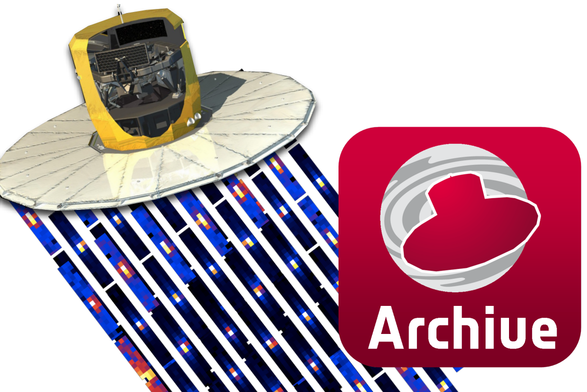
SEARCHING FOR GRAVITATIONAL LENSES



CRTS Catalina Real-Time Transient Survey

WISE

ZTF

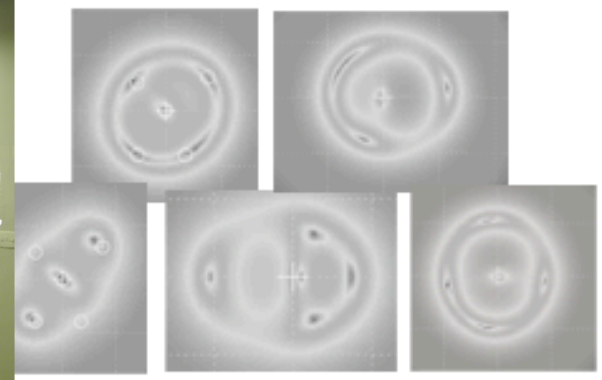
Pan-STARRS

IVOA

Lens candidate selection

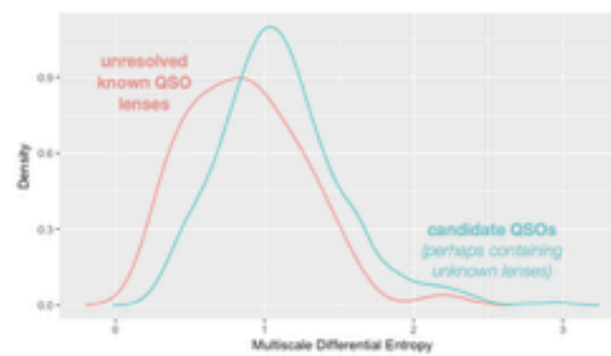
C

Astrometric + photometric patterns + ERTs



R, FORTAN,C

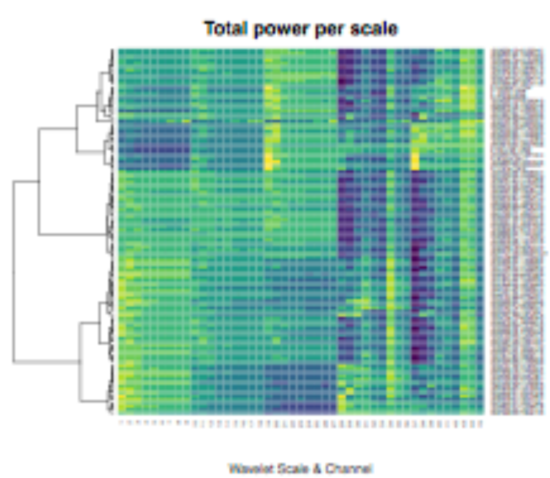
Astrometry + lower lightcurve entropy + SVM



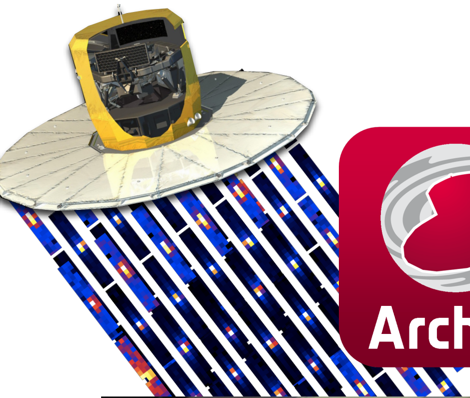
R, C, PERL, POSTGRESQL

Image wavelet power spectrum signatures + hierarchical clustering

+Astrometry



SEARCHING FOR GRAVITATIONAL LENSES



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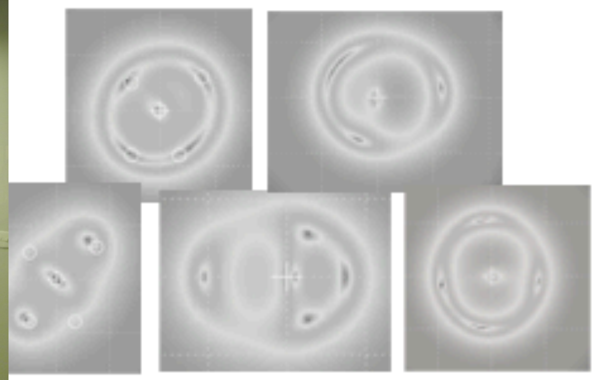
Lens candidate selection

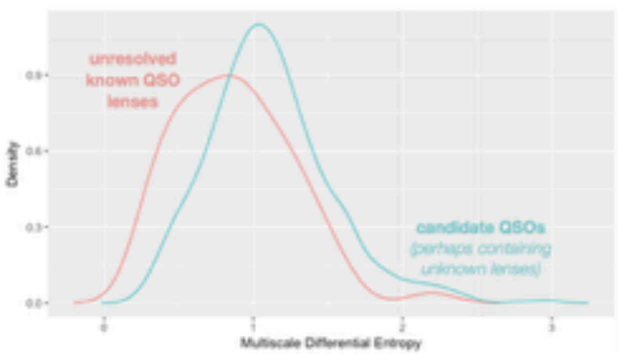
~1.8 BILLION INITIAL SOURCES

Astrometric + photometric patterns + ERTs



~20 MILLION INITIAL SOURCES

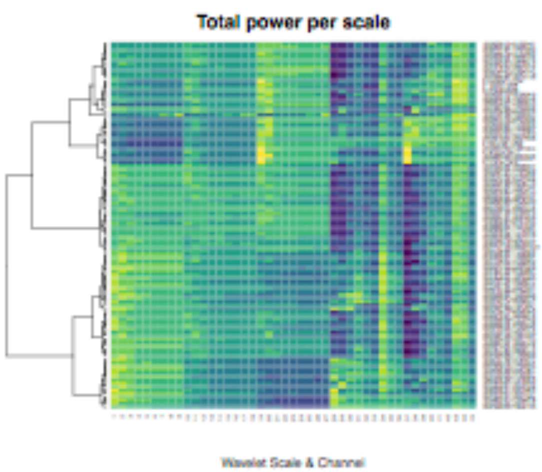
Astrometry + lower lightcurve entropy + SVM



~2 MILLION INITAL SOURCES

Image wavelet power spectrum signatures + hierarchical clustering

+Astrometry

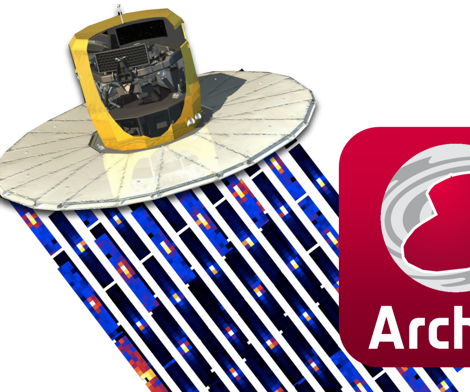


~1 THOUSAND CANDIDATES

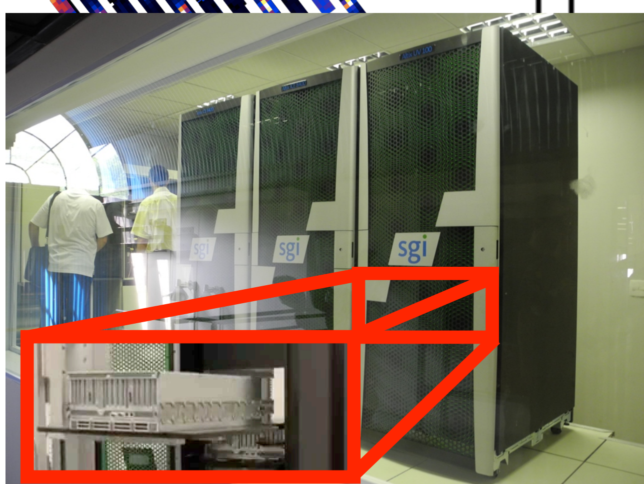
Human Vetoing Of Candidates

~100 CANDIDATES

SEARCHING FOR GRAVITATIONAL LENSES



Archive



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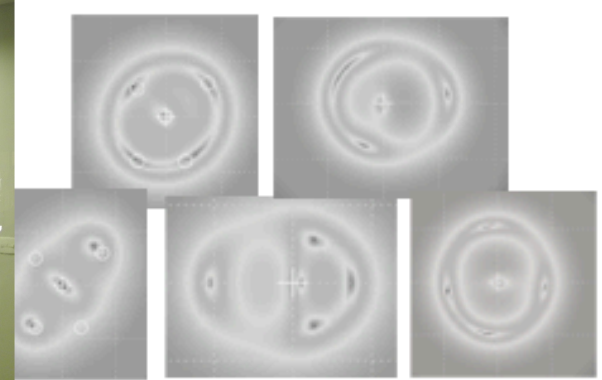

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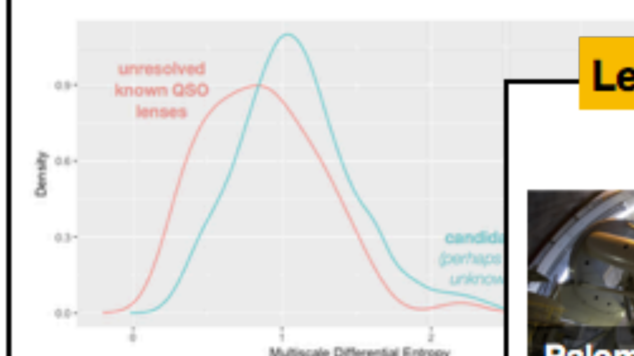

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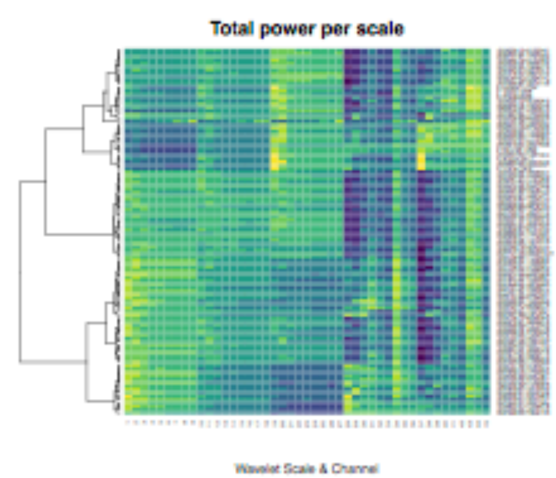

Human Vetoing Of Candidates

Lens spectroscopic confirmation

And more recently SOAR, DOT, BTA, VLT

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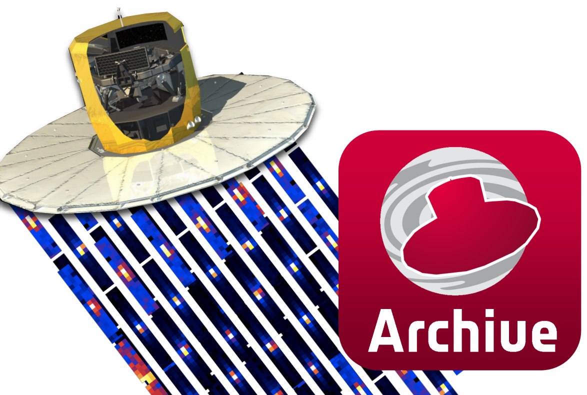
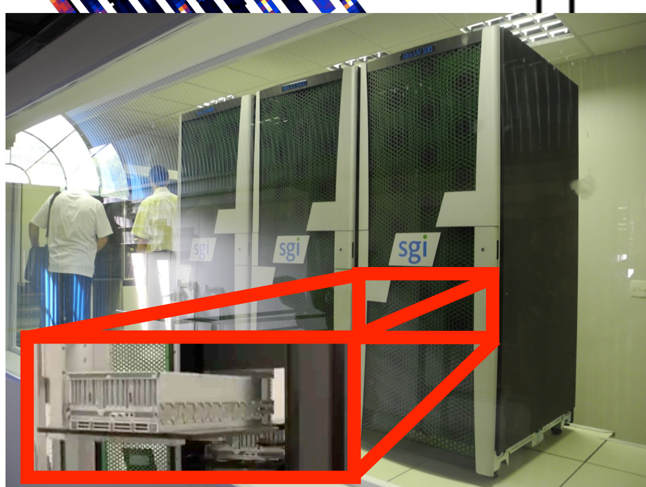
SEARCHING FOR GRAVITATIONAL LENSES





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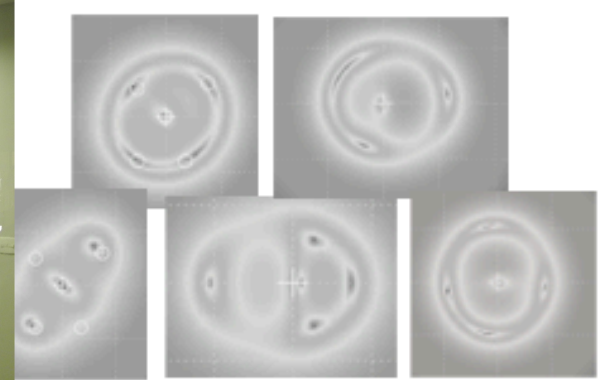

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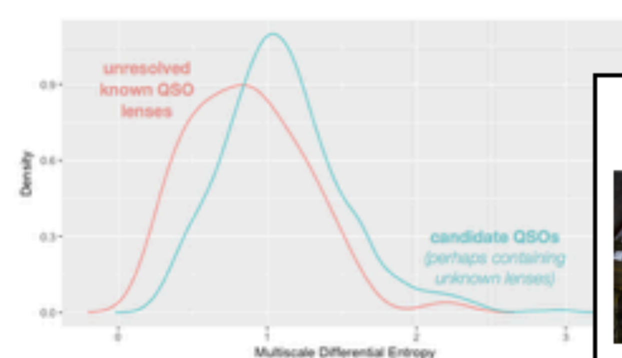

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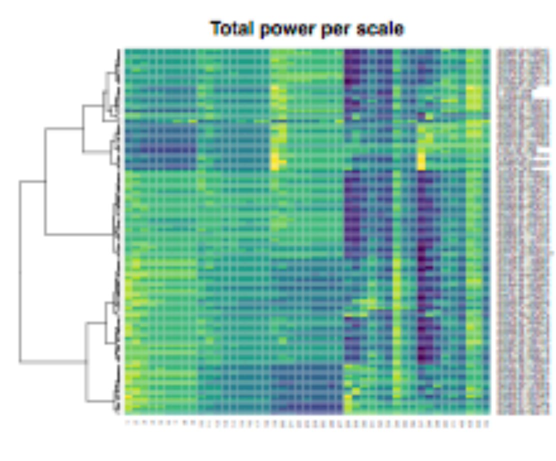


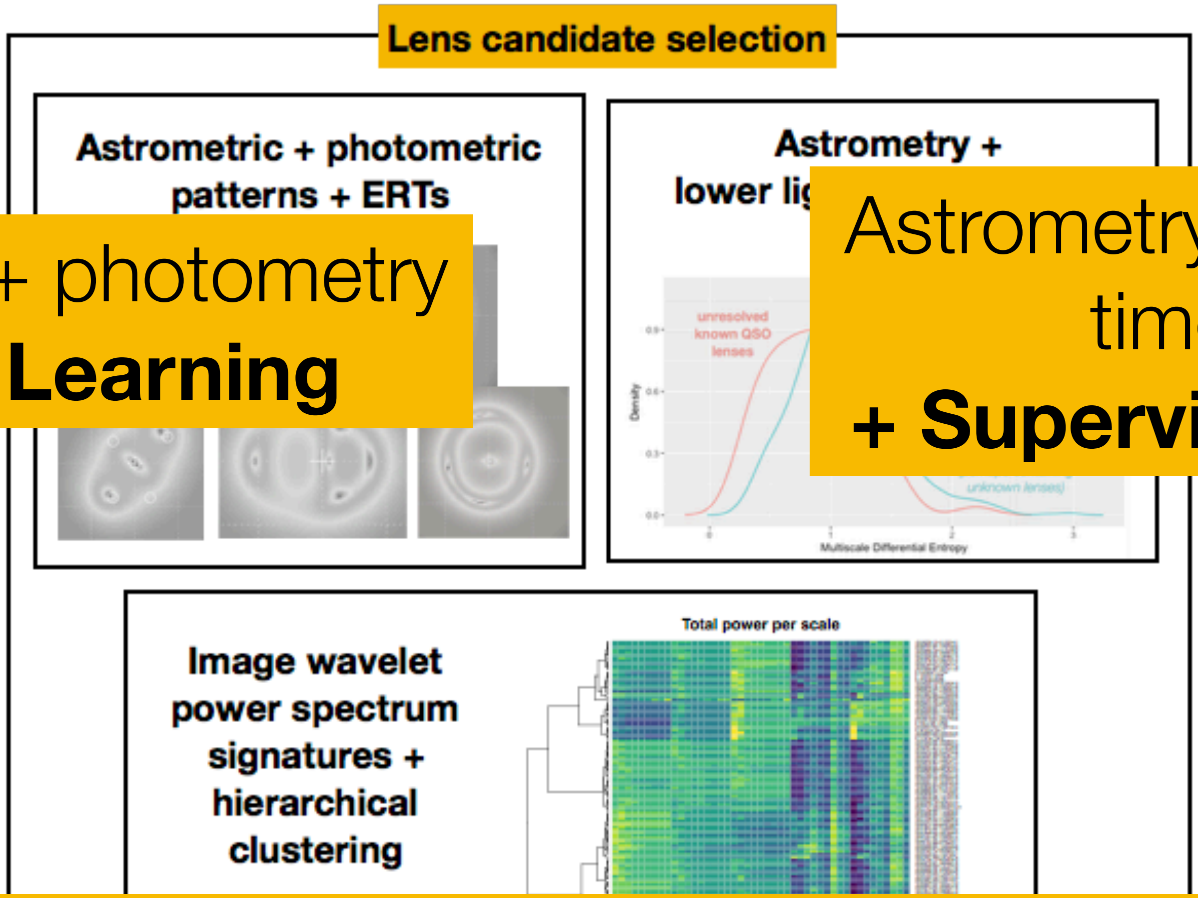
Human Vetoing Of Candidates

Lens spectroscopic confirmation

Results

A continuous learning loop, with continuously evolving training sets AND methods
AI as *Augmented* Intelligence, not as *Artificial* Intelligence

THREE MAJOR METHODOLOGICAL FAMILIES



Mean astrometry + photometry
+ Supervised Learning

Astrometry + Photometry time-series
+ Supervised Learning

Imaging data (including time-series)
+ Unsupervised and supervised learning

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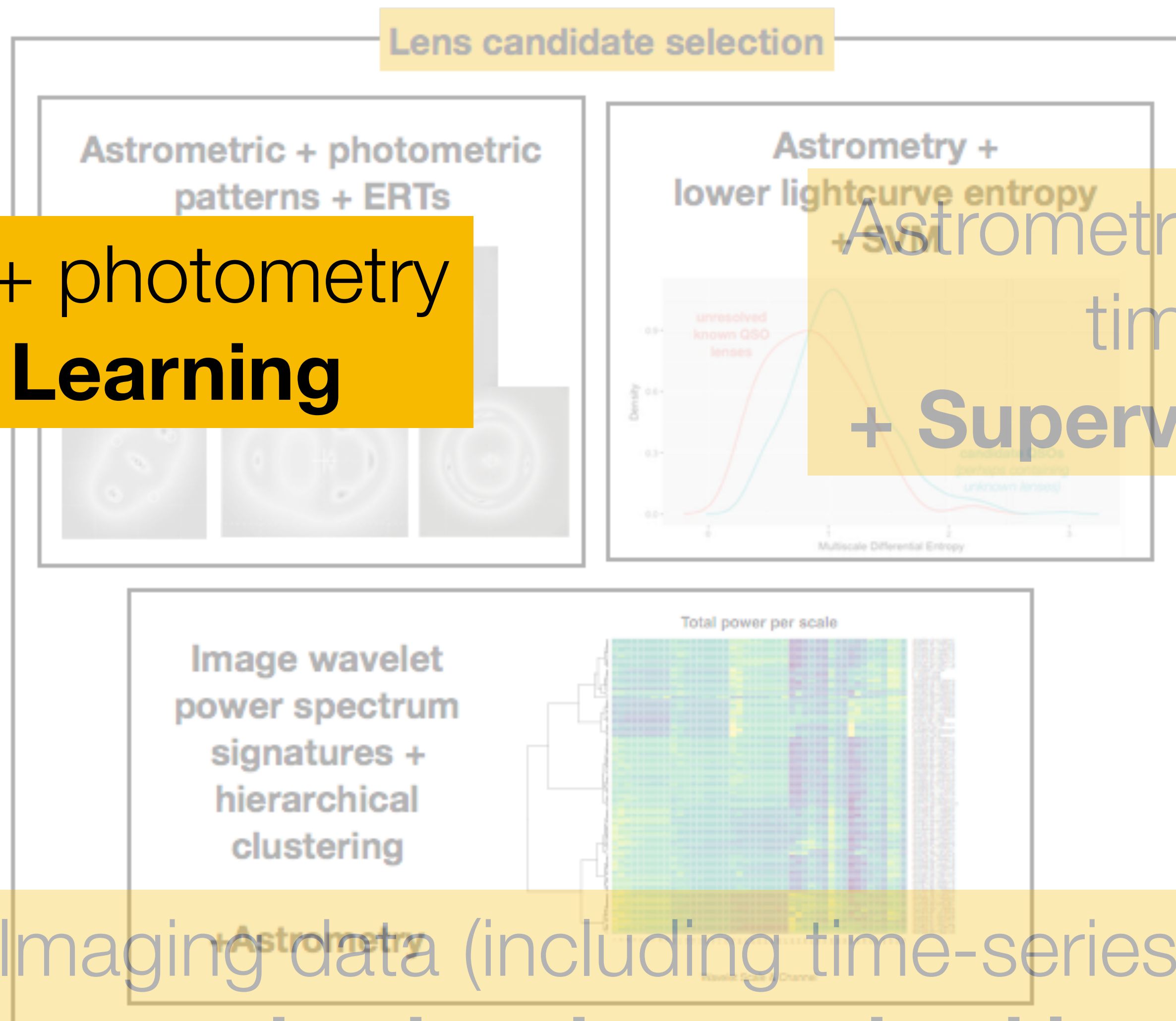

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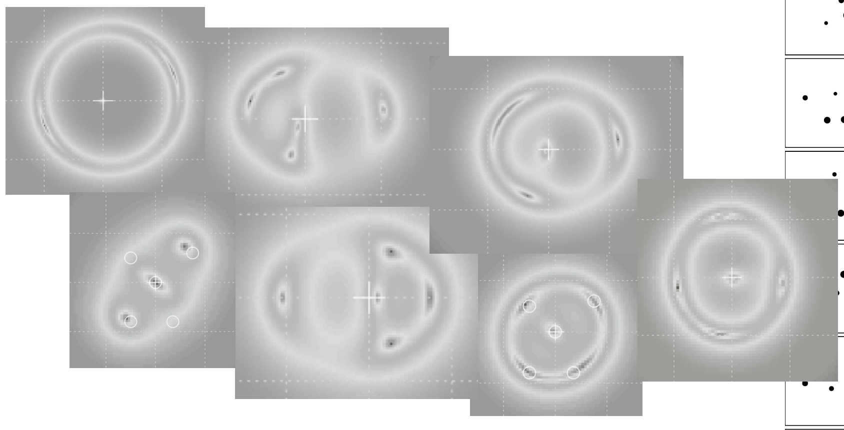
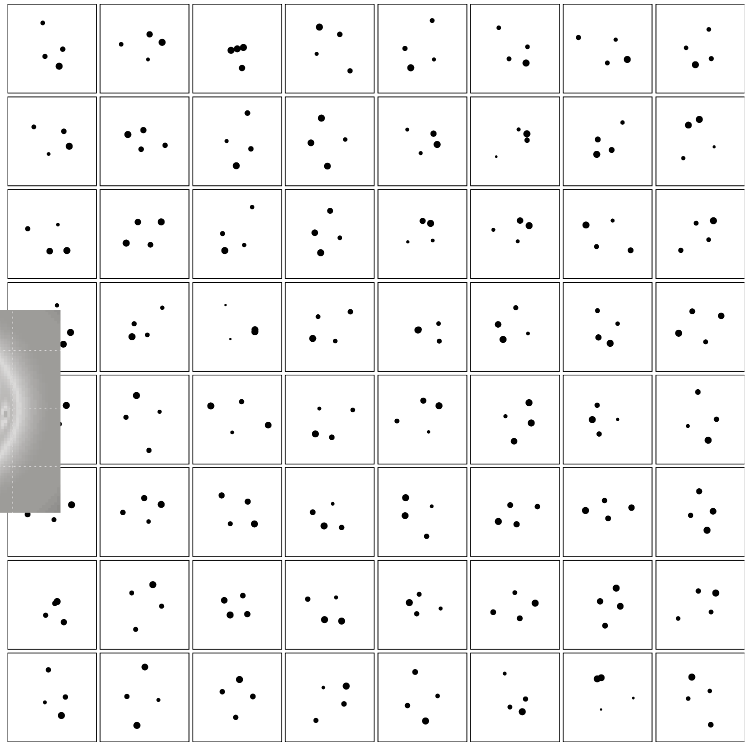
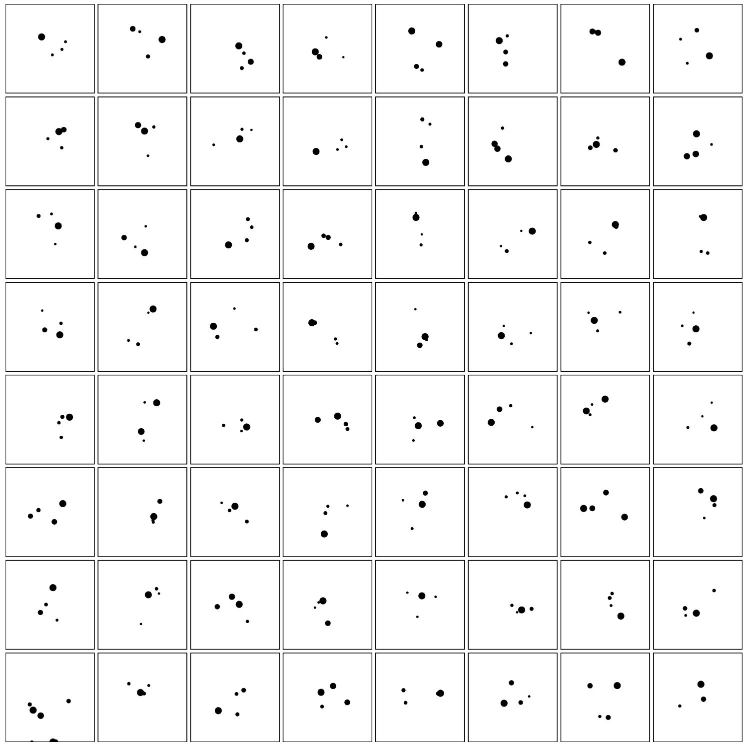
SEARCHING FOR GRAVITATIONAL LENSES: ERTS

The learning set of observations

- 10^8 simulated GLs composed of four components (ABCD)
- + all combinations of three components (ABC, ABD, ACD, BCD)
- 10^8 configurations of random fluxes/positions



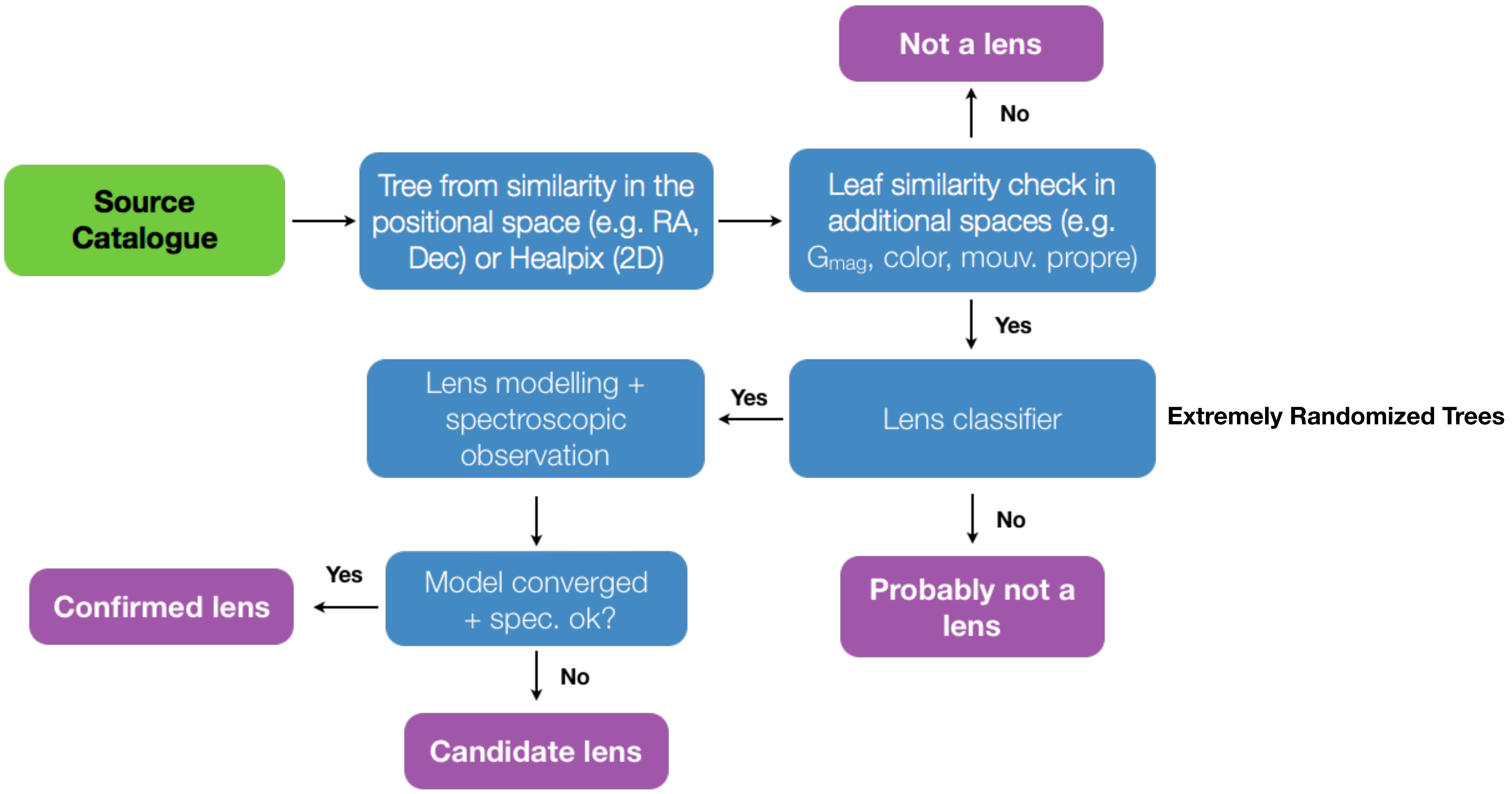




PRODUCE > 106 MILLION "GAIA SIMULATIONS"

INCLUDING GAIA DR2/EDR3 ERROR DISTRIBUTIONS (TRAIN WITH A BIASED SET!)

SEARCHING FOR GRAVITATIONAL LENSES: ERTS



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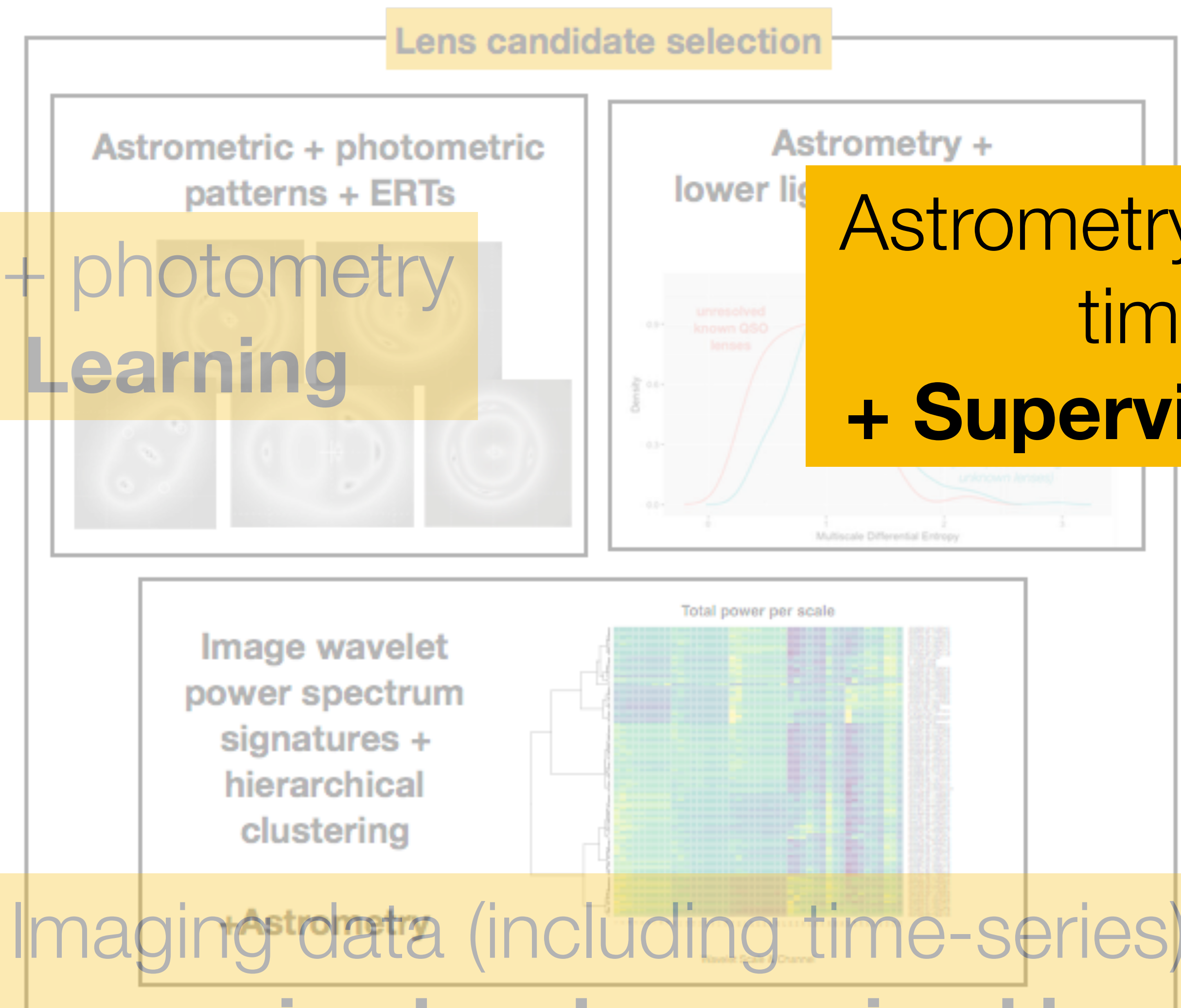


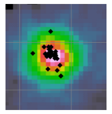
Mean astrometry + photometry
+ Supervised Learning

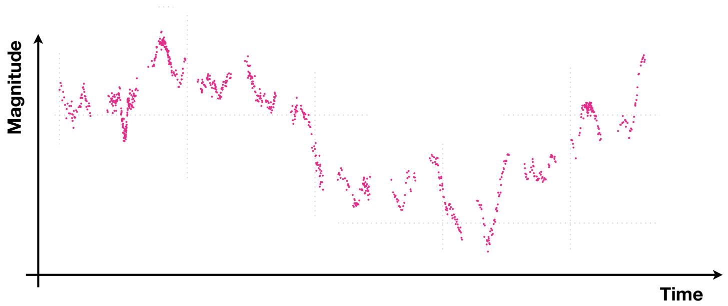
Astrometry + Photometry
time-series
+ Supervised Learning

Imaging data (including time-series)
+ Unsupervised and supervised learning

THE ROLE OF TIME SERIES ENTROPY

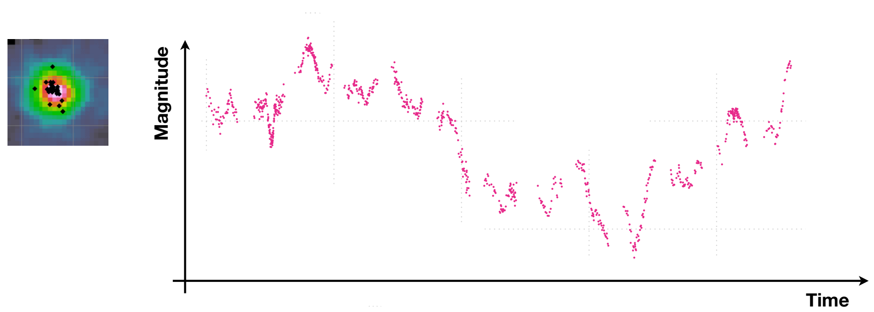
non-lensed QSO



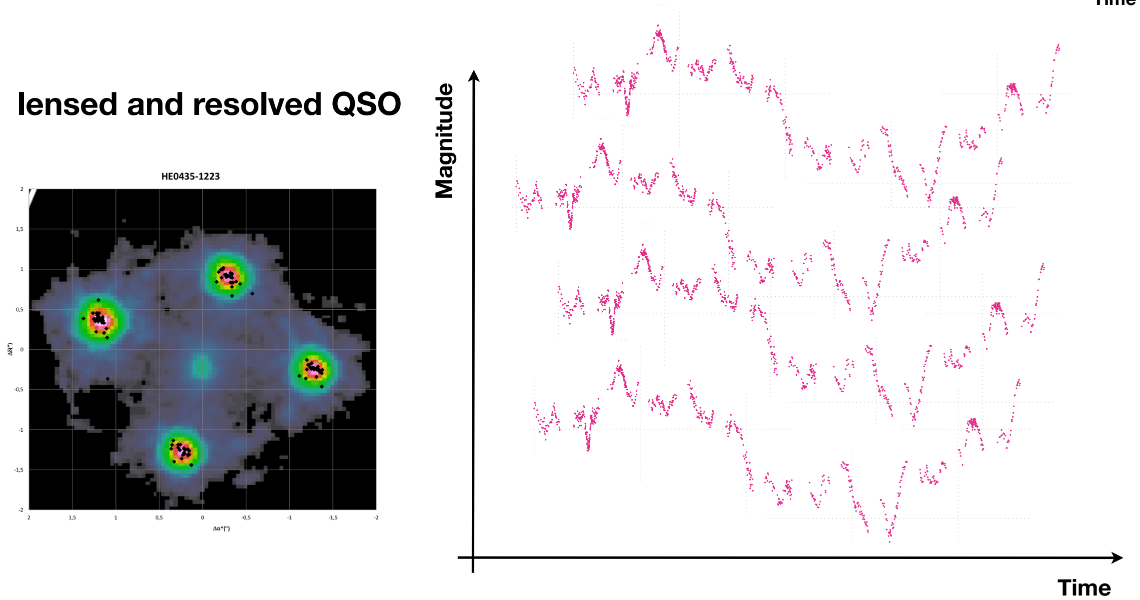


THE ROLE OF TIME SERIES ENTROPY

non-lensed QSO

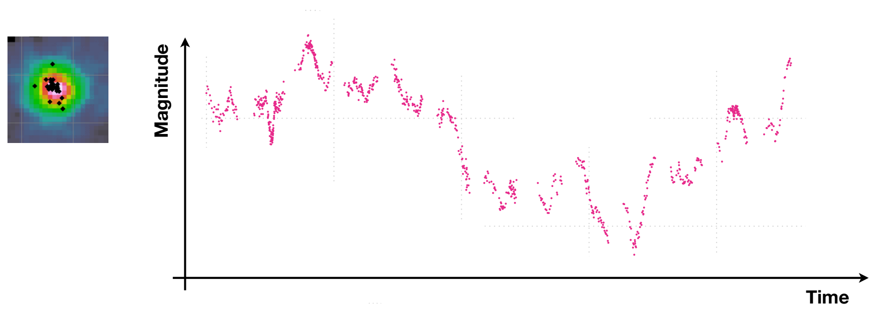


lensed and resolved QSO

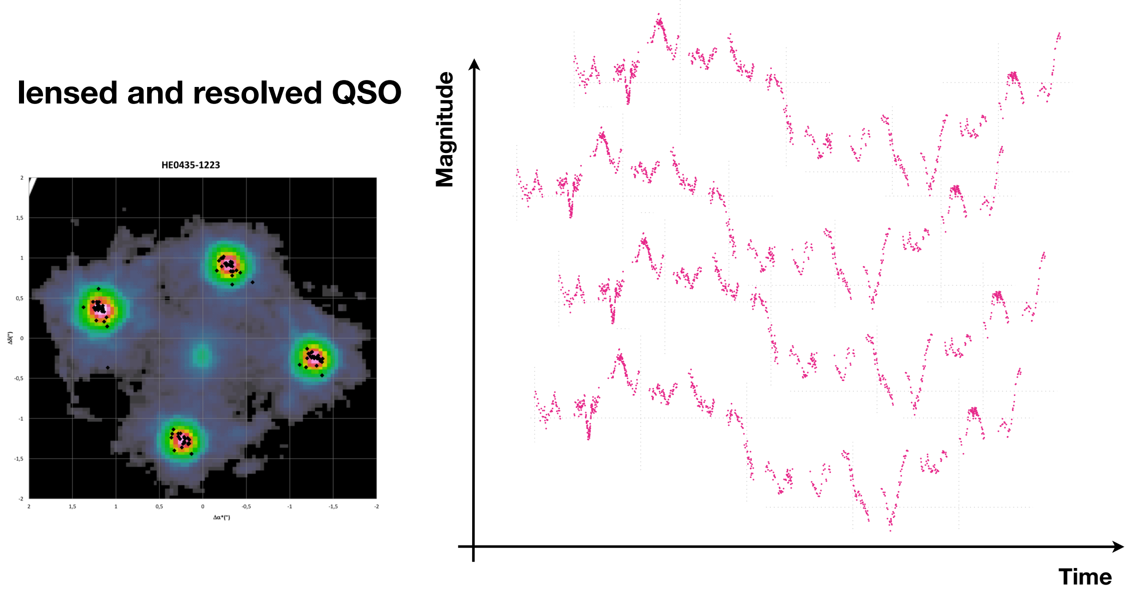


THE ROLE OF TIME SERIES ENTROPY

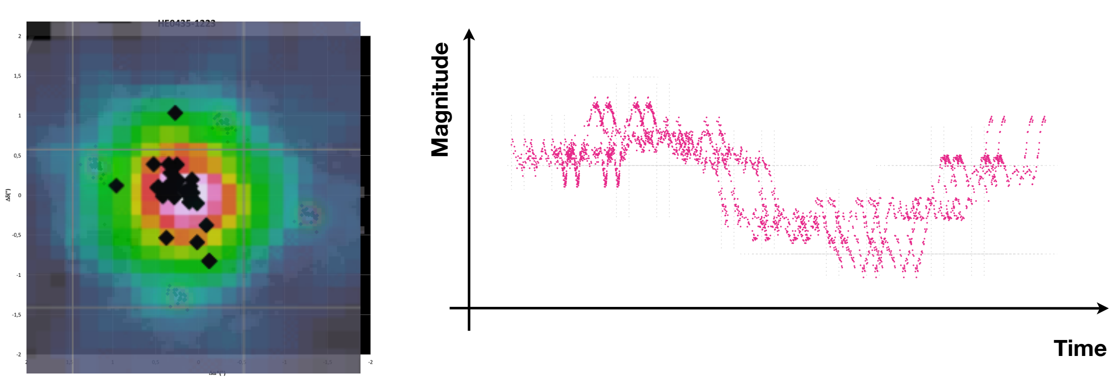
non-lensed QSO



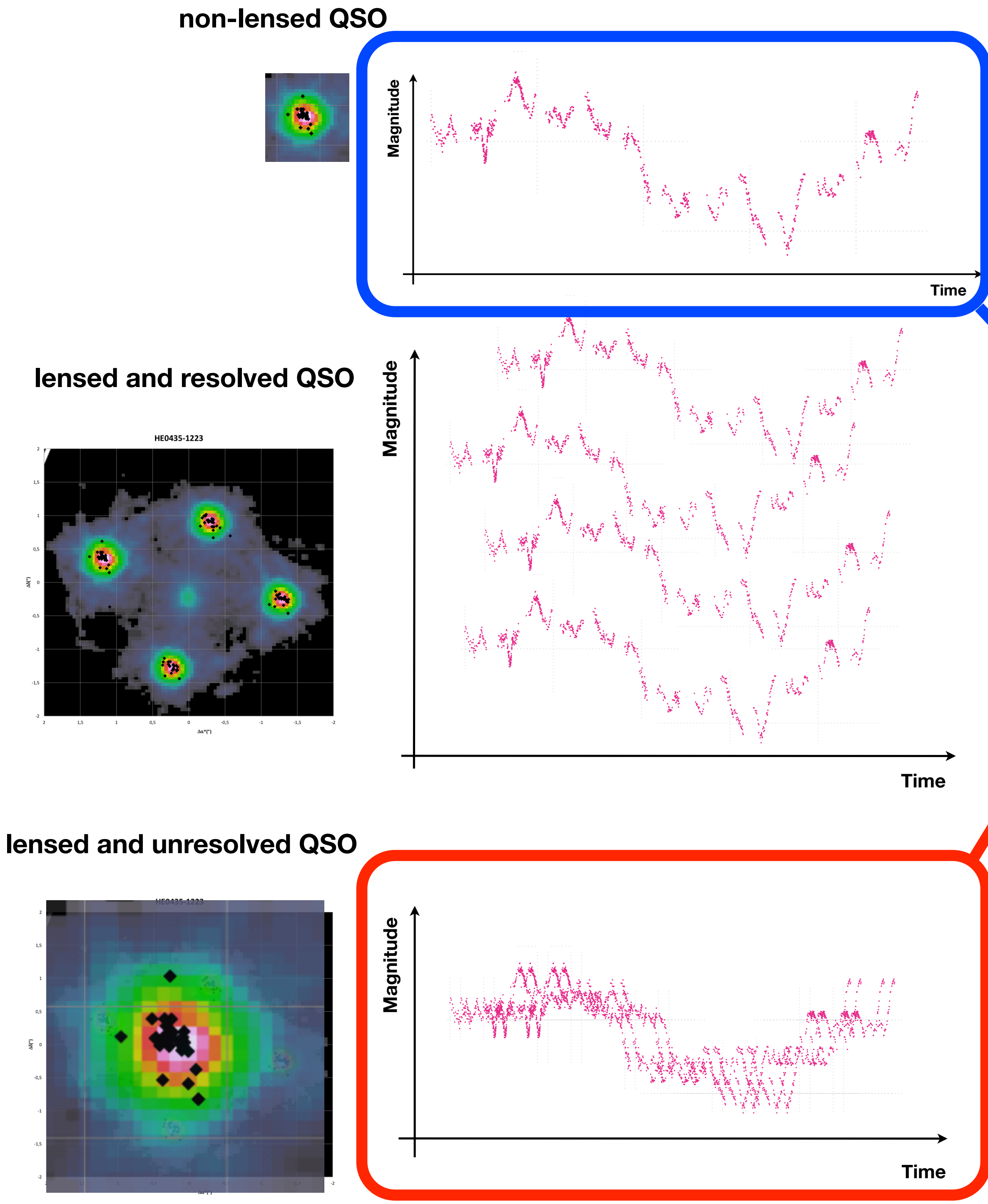
lensed and resolved QSO



lensed and unresolved QSO

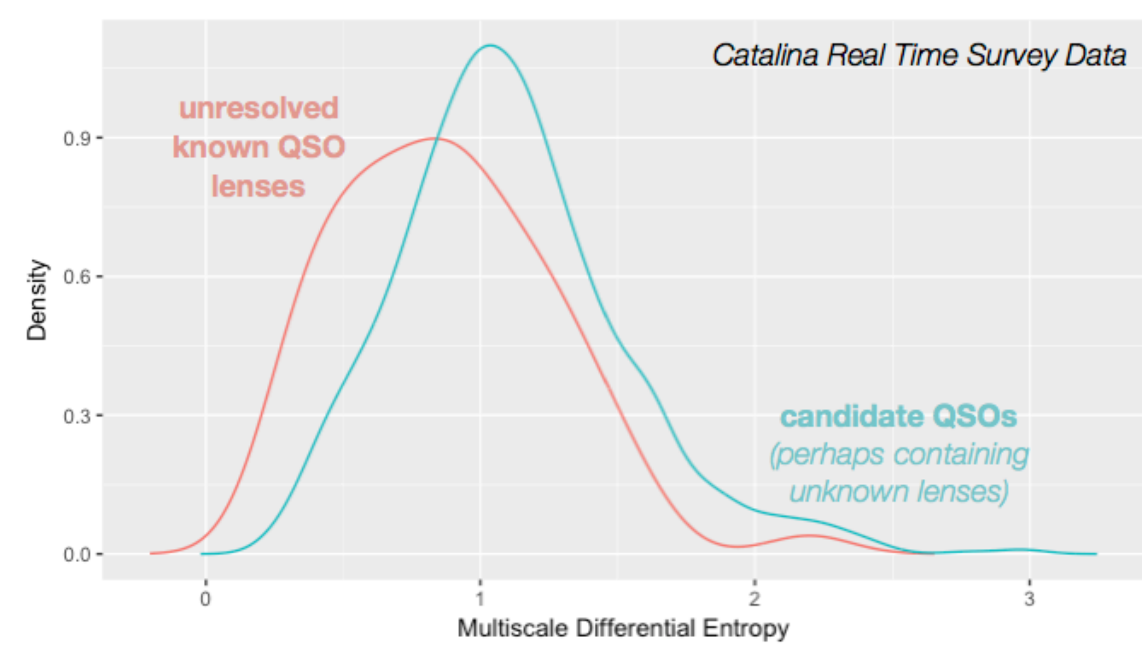


THE ROLE OF TIME SERIES ENTROPY



Principle

The stochasticity of non-lensed QSOs should be **higher** than the stochasticity of lensed, **but unresolved,** QSOs.



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DETECTION FROM TIME SERIES

DATA	ZTF PHOTOMETRIC TIMESERIES		ZTF ASTROMETRIC TIMESERIES
FEATURE EXTRACTION	ENTROPY FOURIER POWERSPECTRA	SLOPES OF SIGNIFICANT FREQUENCIES IN POWERSPECTRA (PVAL SELECTED)	CORRELATIONS BETWEEN PHOTOMETRIC AND ASTROMETRIC TIME SERIES

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DETECTION FROM TIME SERIES

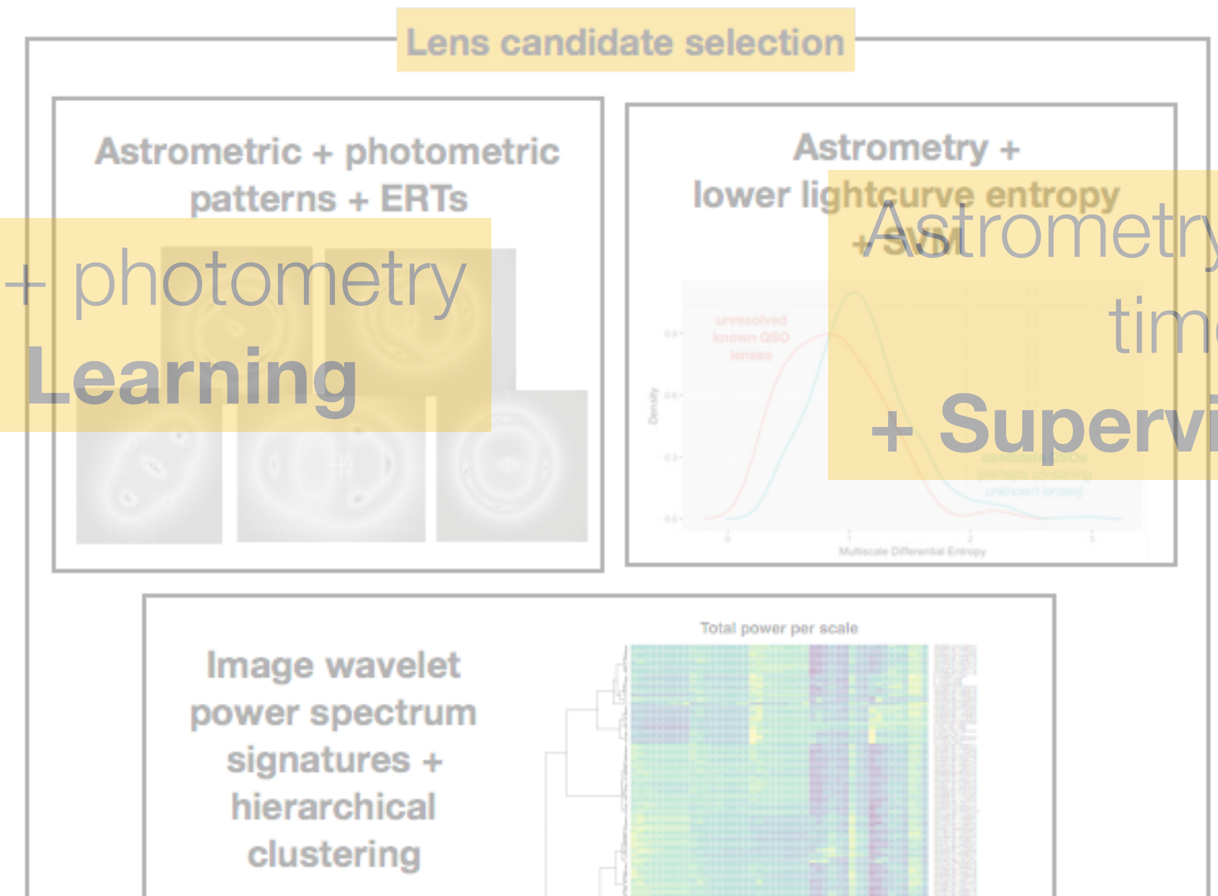
DATA	ZTF PHOTOMETRIC TIMESERIES		ZTF ASTROMETRIC TIMESERIES
FEATURE EXTRACTION	ENTROPY; FOURIER POWERSPECTRA	SLOPES OF SIGNIFICANT FREQUENCIES IN POWERSPECTRA (PVAL SELECTED)	CORRELATIONS BETWEEN PHOTOMETRIC AND ASTROMETRIC TIME SERIES
FEATURE TRANSFORMATION	PCA		
DIMENSION SELECTION	ANDERSON-DARLING TESTS BETWEEN ALL DIMENSIONS (USING KNOWN LENSES)		

PROBLEM: DIMENSIONALITY

DETECTION FROM TIME SERIES

DATA	ZTF PHOTOMETRIC TIMESERIES		ZTF ASTROMETRIC TIMESERIES
FEATURE EXTRACTION	ENTROPY FOURIER POWERSPECTRA	SLOPES OF SIGNIFICANT FREQUENCIES IN POWERSPECTRA (PVAL SELECTED)	CORRELATIONS BETWEEN PHOTOMETRIC AND ASTROMETRIC TIME SERIES
FEATURE TRANSFORMATION	PCA		
DIMENSION SELECTION	ANDERSON-DARLING TESTS BETWEEN ALL DIMENSIONS (USING KNOWN LENSES)		
ML MODEL TRAINING	ENSEMBLE RANDOM FOREST MODEL CREATED FROM THE RESULTS OF : RANDOM FORESTS, RECURSIVE PARTITIONS, SUPPORT VECTOR MACHINE WITH RBF, KNN, GRADIENT BOOSTED DECISION TREES, ROTATION FORESTS & SHRINKAGE DISCRIMINANT ANALYSIS		

THREE MAJOR METHODOLOGICAL FAMILIES



Mean astrometry + photometry
+ Supervised Learning

Astrometry + Photometry time-series
+ Supervised Learning

Imaging data (including time-series)
+ Unsupervised and supervised learning

DETECTION FROM IMAGES

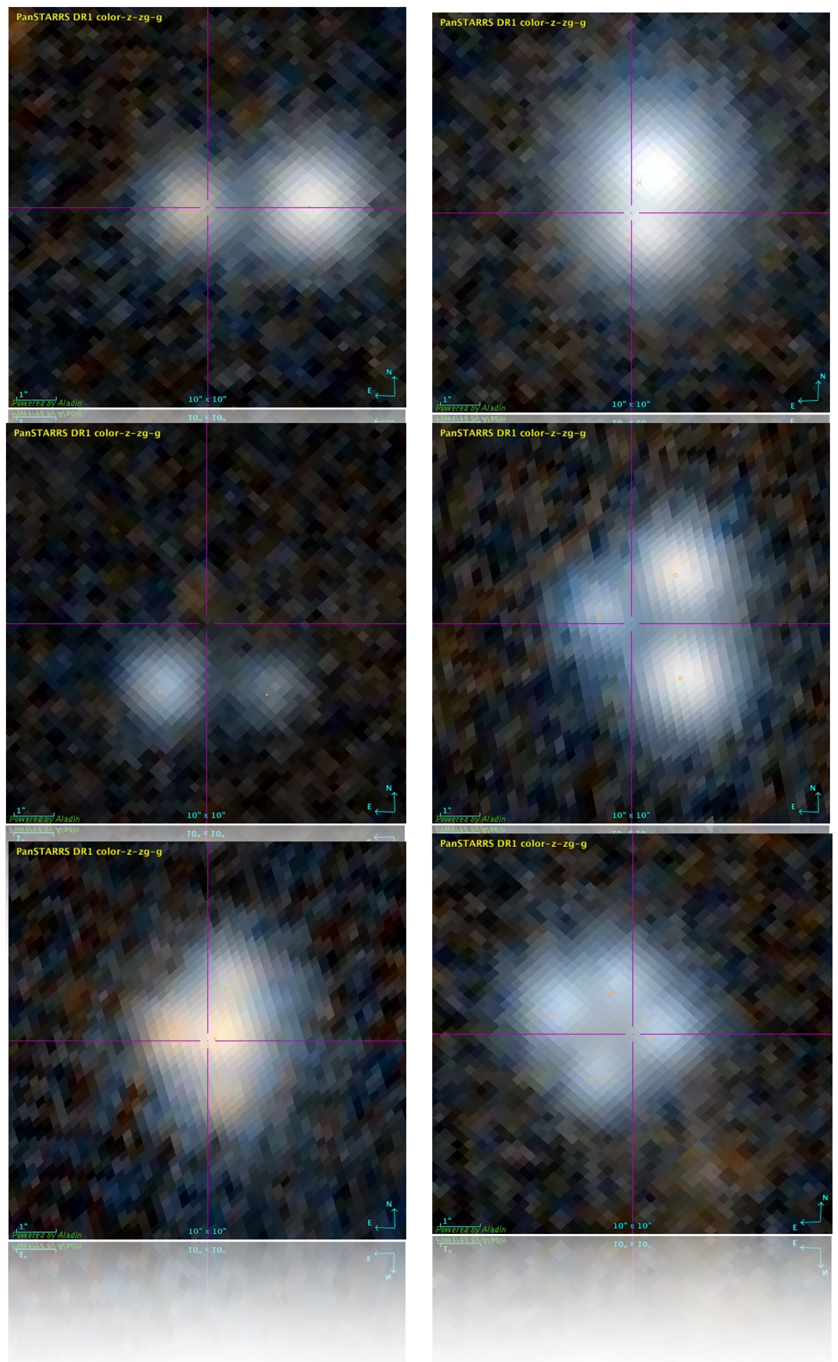
DATA	PS1 IMAGES (GRIZY)		
FEATURE EXTRACTION	WAVELET POWERSPECTRA OF G,R,I,Z,Y AND (G-R), (R-I), … IMAGES	FOURIER POWERSPECTRA OF G,R,I,Z,Y AND (G-R), (R-I), … IMAGES	WASSERSTEIN DISTANCES BETWEEN IMAGES

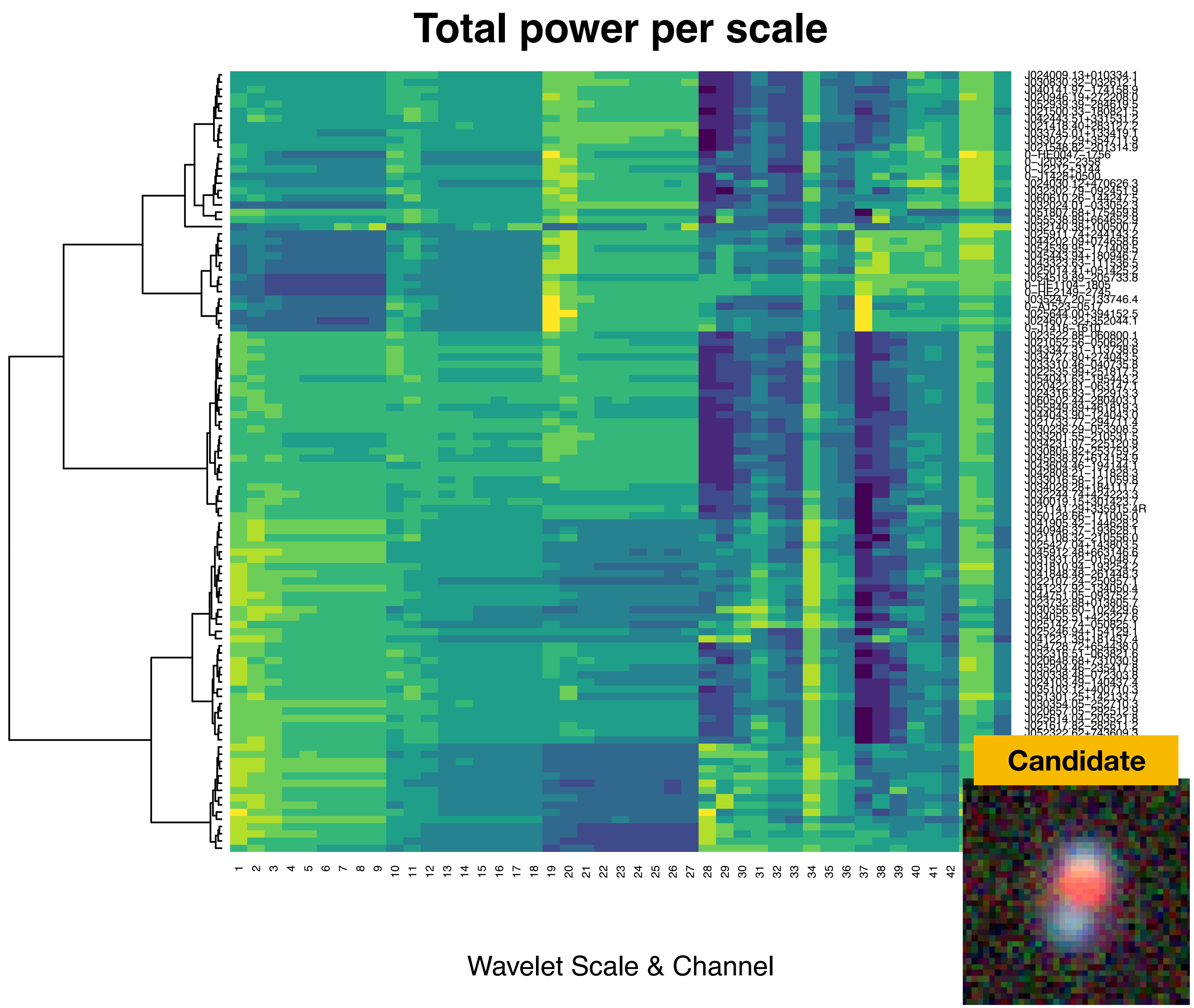
DETECTION FROM IMAGES

PROBLEM: DIMENSIONALITY

DATA	PS1 IMAGES (GRIZY)		
FEATURE EXTRACTION	WAVELET POWERSPECTRA OF G,R,I,Z,Y AND (G-R), (R-I), . . . IMAGES	FOURIER POWERSPECTRA OF G,R,I,Z,Y AND (G-R), (R-I), . . . IMAGES	WASSERSTEIN DISTANCES BETWEEN IMAGES
DIMENSION SELECTION		ANDERSON-DARLING TESTS BETWEEN ALL DIMENSIONS (USING KNOWN LENSES)	
ML MODEL TRAINING		SIMPLE HIERARCHICAL CLUSTERING MODEL (WAVELETS ONLY)	

DETECTION FROM IMAGES





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DETECTION FROM IMAGES

DATA	PS1 IMAGES (GRIZY)		
FEATURE EXTRACTION	WAVELET POWERSPECTRA OF G,R,I,Z,Y AND (G-R), (R-I), . . . IMAGES	FOURIER POWERSPECTRA OF G,R,I,Z,Y AND (G-R), (R-I), . . . IMAGES	WASSERSTEIN DISTANCES BETWEEN IMAGES
DIMENSION SELECTION		ANDERSON-DARLING TESTS BETWEEN ALL DIMENSIONS (USING KNOWN LENSES)	
ML MODEL TRAINING	XGBOOST MODEL	SIMPLE HIERARCHICAL CLUSTERING MODEL (WAVELETS ONLY)	

MORE ABOUT THE DIMENSIONALITY OF THIS CASE LATER IN THIS TALK!

DETECTION FROM IMAGES

DATA	PS1 IMAGES (GRIZY)
FEATURE EXTRACTION	WAVELET POWERSPECTRA OF G,R,I,Z,Y AND (G−R), (R−I), . . . IMAGES
ML MODEL TRAINING	VARIATIONAL AUTOENCODER : VARIABLE TRANSFORMATION
	RANDOM FOREST + SIMPLE NNETS

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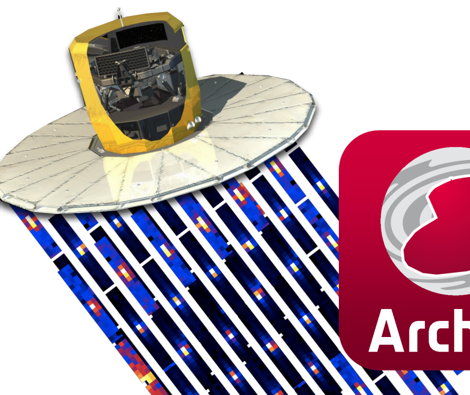
SEARCHING FOR GRAVITATIONAL LENSES



Archive

CRTS Catalina Real-Time Transient Survey

WISE

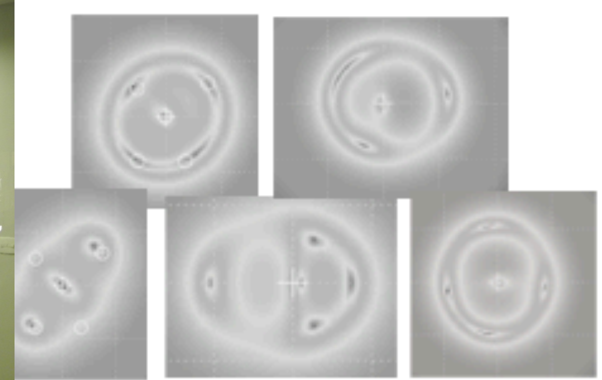
ZTF

Pan-STARRS

IVOA

Lens candidate selection

Astrometric + photometric patterns + ERTs



Astrometry + lower lightcurve entropy + SVM

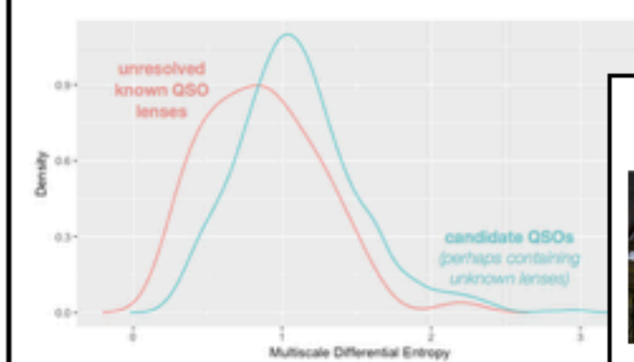
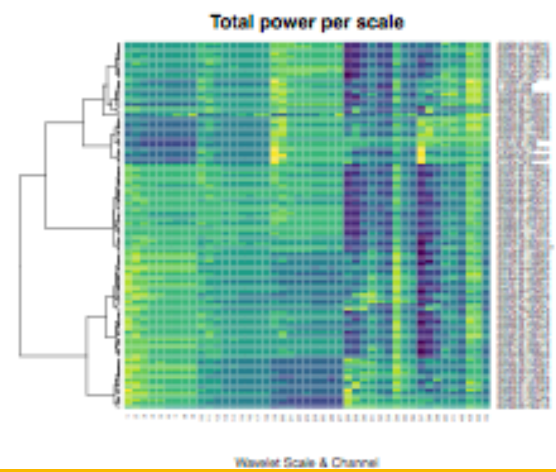


Image wavelet power spectrum signatures + hierarchical clustering

+Astrometry



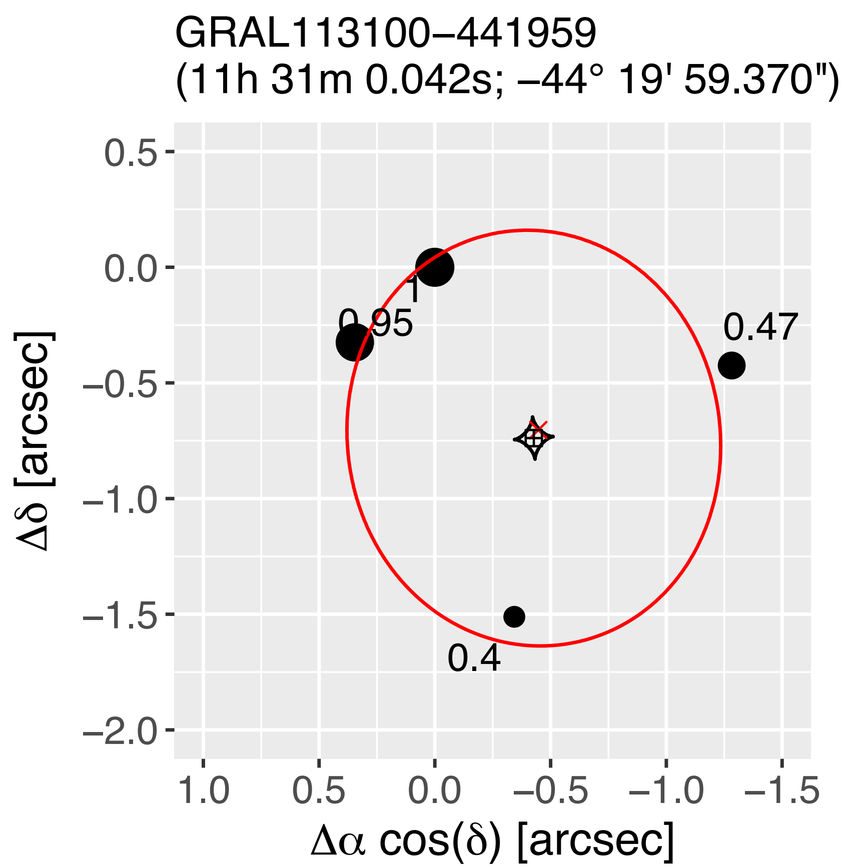
Human Vetoing Of Candidates

Lens spectroscopic confirmation

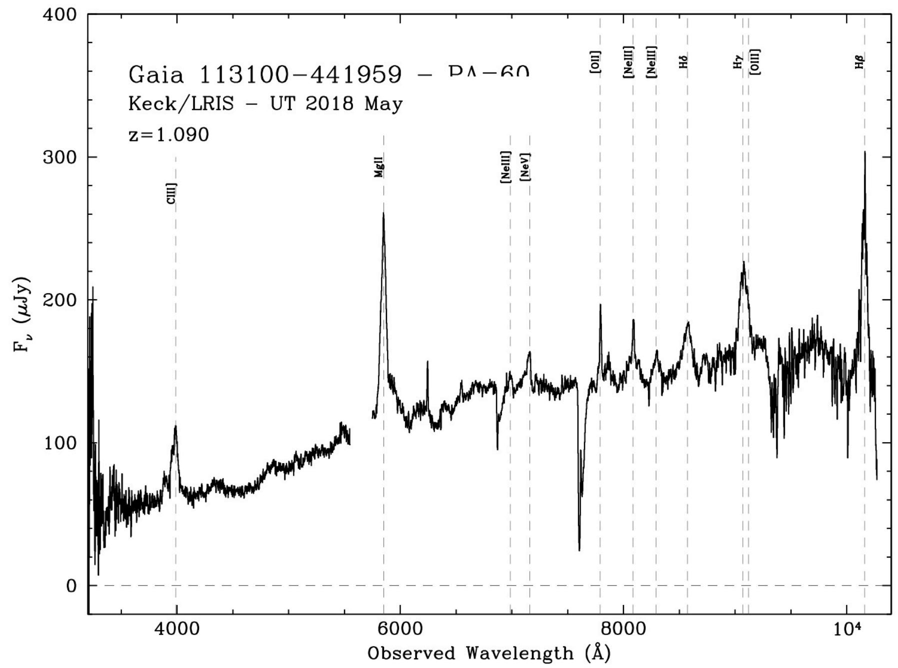
Results

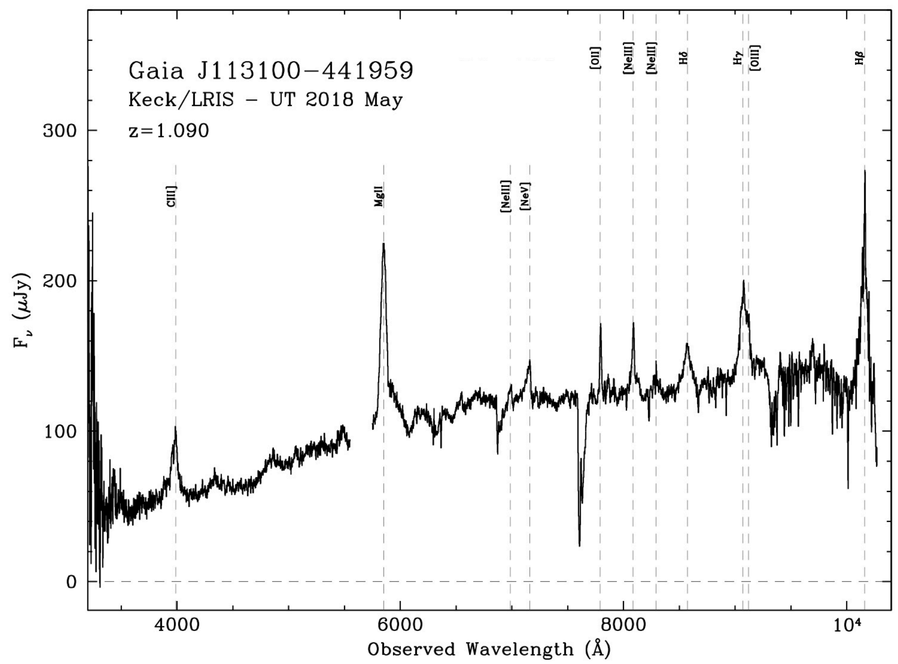
A continuous learning loop, with continuously evolving training sets AND methods
AI as *Augmented* Intelligence, not as *Artificial* Intelligence

THE FIRST LENSED QSO DISCOVERED FROM ASTROMETRY



Krone-Martins, A.; Delchambre, L.; Wertz, O. et al., A&A, 616, L11, 2018





Wertz, O.; Stern, D.; Krone-Martins, A. et al., A&A, 628, A17, 2019

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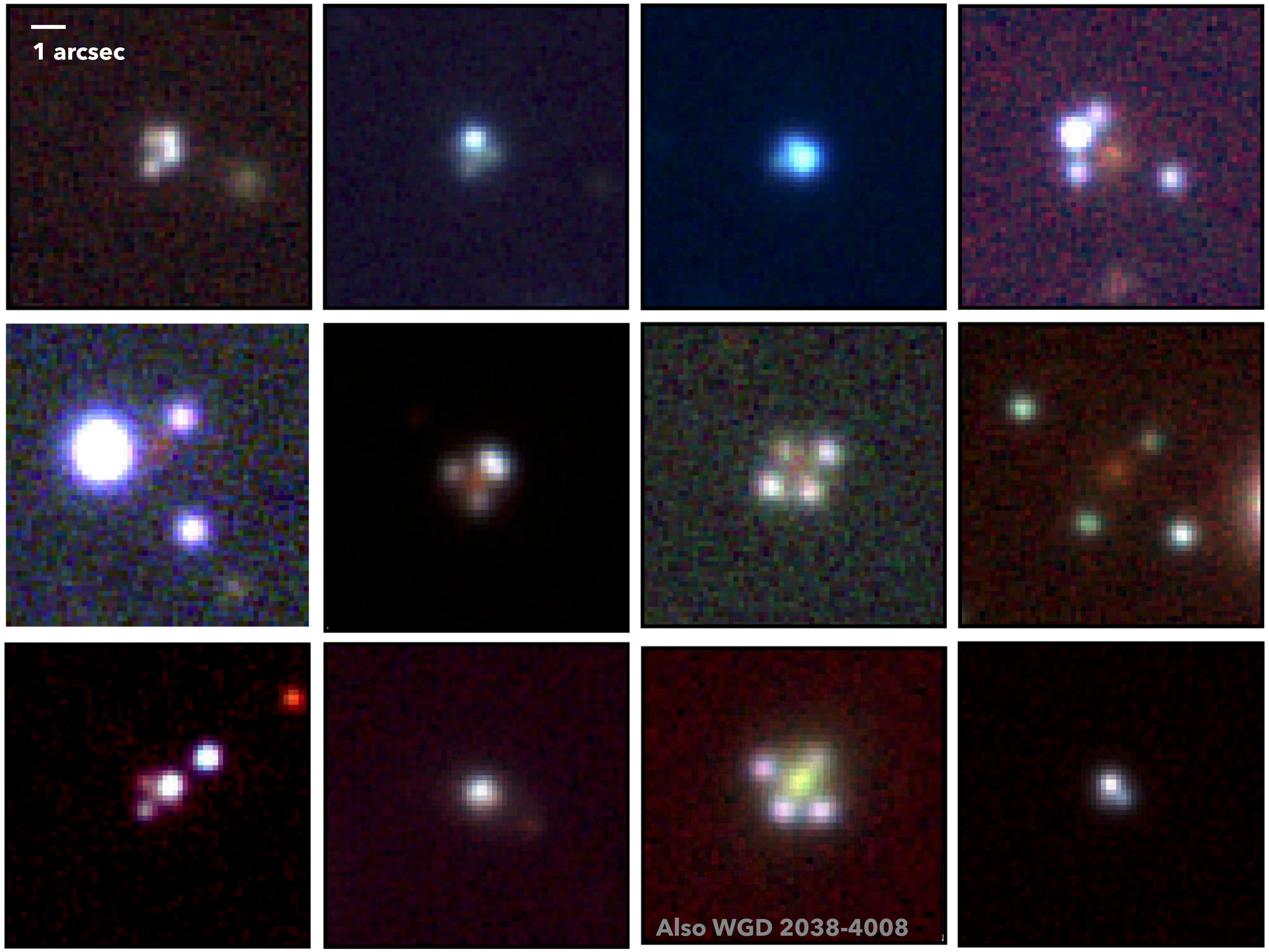
GRAL: SEEING QUADRUPLE…



+ ~3 quadruply imaged, exact number still waiting higher SNR spectra **(EDR3)**

+ ~31 doubly imaged (DR2+EDR3)

Connor, T., Stern, D., Krone-Martins, A., arXiv:2109.14103
Stern, D. Djorgovski, S. G., Krone-Martins, A., et al., arXiv:2012.10051
Krone-Martins, A., Graham, M..; Stern D, et al., arXiv:1912.08977
Wertz, O.; Stern, D.; Krone-Martins, A. et al., A&A, 628, A17, 2019
Delchambre, L.; Krone-Martins, A.; Wertz, O., et al., A&A, 622, A165, 2019
Ducourant, C.; Wertz, O.; Krone-Martins, A., et al., A&A, 618, A56, 2018
Krone-Martins, A.; Delchambre, L.; Wertz, O. et al., A&A, 616, L11, 2018

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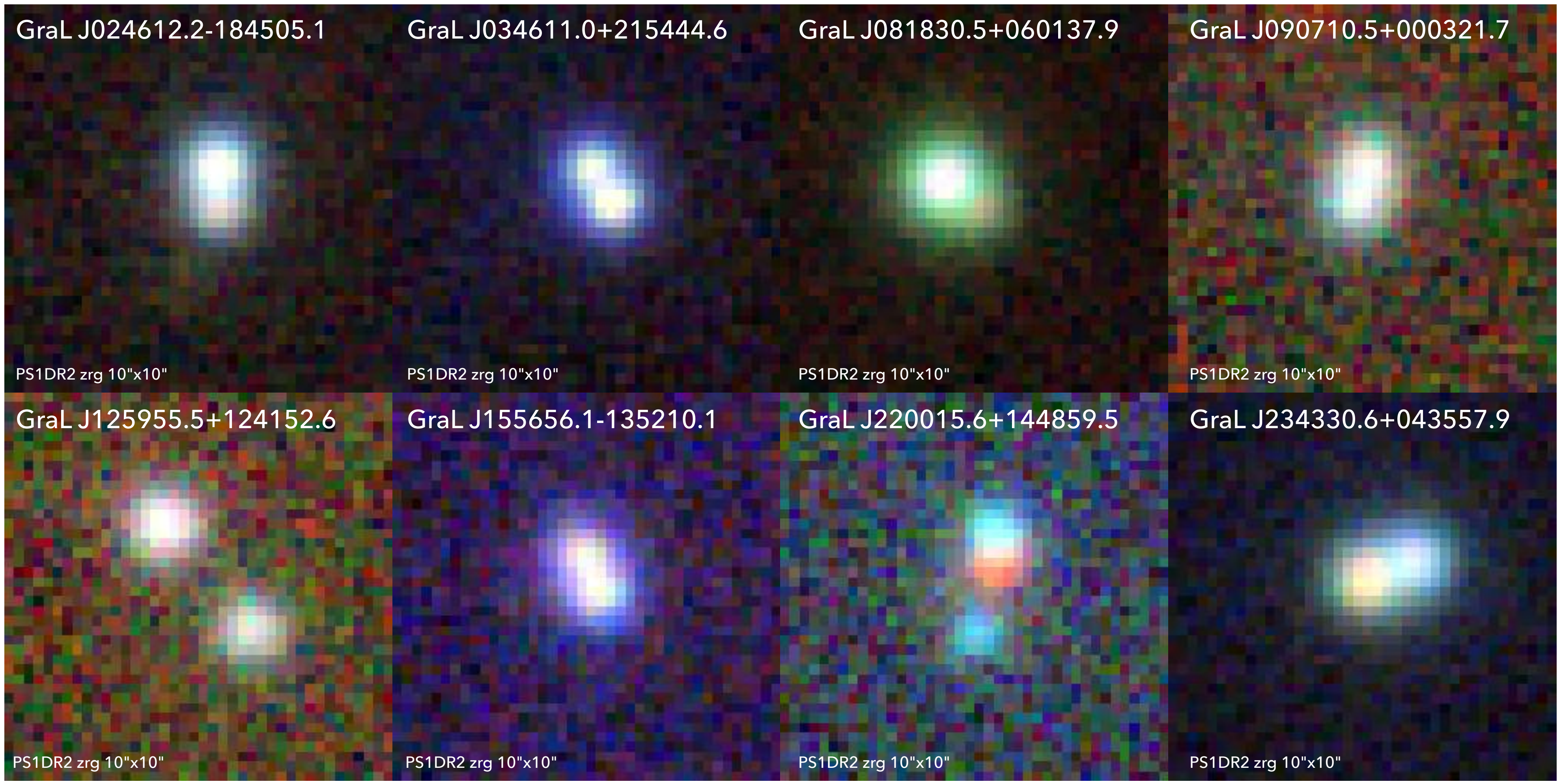
GRAL: SEEING DOUBLE…



+ ~15 quadruply imaged, exact number still waiting higher SNR spectra **(EDR3)**

+ ~23 doubly imaged (DR2+EDR3)

Connor, T., Stern, D., Krone-Martins, A., arXiv:2109.14103
Stern, D. Djorgovski, S. G., Krone-Martins, A., et al., arXiv:2012.10051
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Wertz, O.; Stern, D.; Krone-Martins, A. et al., A&A, 628, A17, 2019
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Krone-Martins, A.; Delchambre, L.; Wertz, O. et al., A&A, 616, L11, 2018

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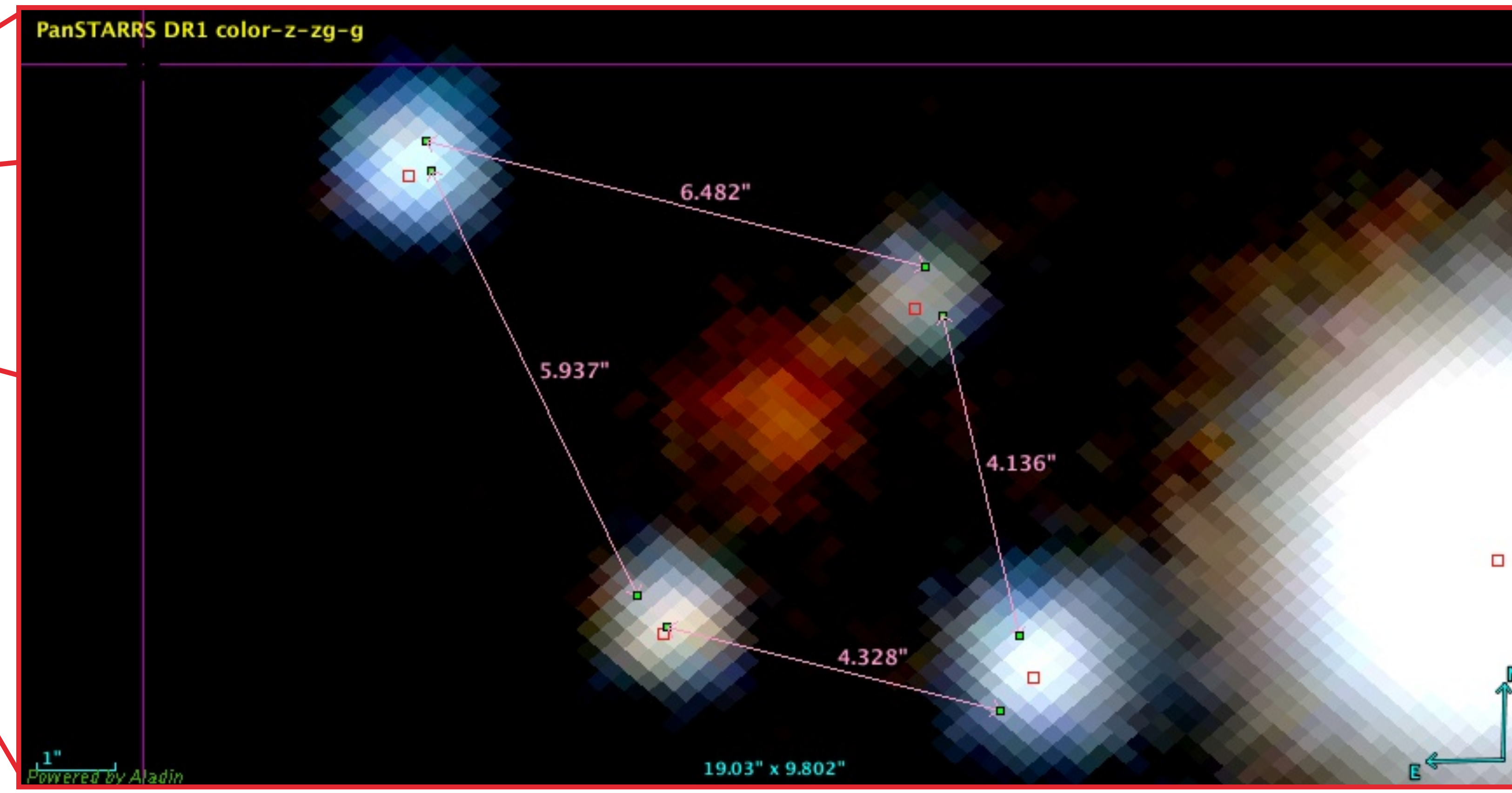
A CURIOUS CASE… THE DRAGONS' KITE

GRALJ165105371-041724936

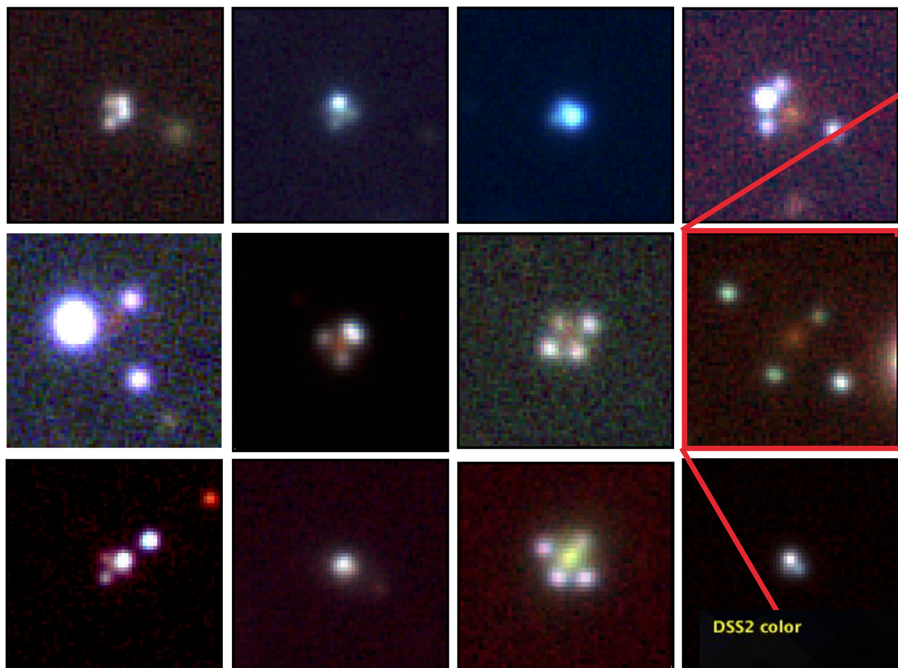


+ ~3 quadruply imaged, **TBC!** (EDR3)

+ ~31 doubly imaged (DR2+EDR3)

Connor, T., Stern, D., Krone-Martins, A., arXiv:2109.14103
Stern, D. Djorgovski, S. G., Krone-Martins, A., et al., arXiv:2012.10051
Krone-Martins, A., Graham, M..; Stern D, et al., arXiv:1912.08977
Wertz, O.; Stern, D.; Krone-Martins, A. et al., A&A, 628, A17, 2019
Delchambre, L.; Krone-Martins, A.; Wertz, O., et al., A&A, 622, A165, 2019
Ducourant, C.; Wertz, O.; Krone-Martins, A., et al., A&A, 618, A56, 2018
Krone-Martins, A.; Delchambre, L.; Wertz, O. et al., A&A, 616, L11, 2018

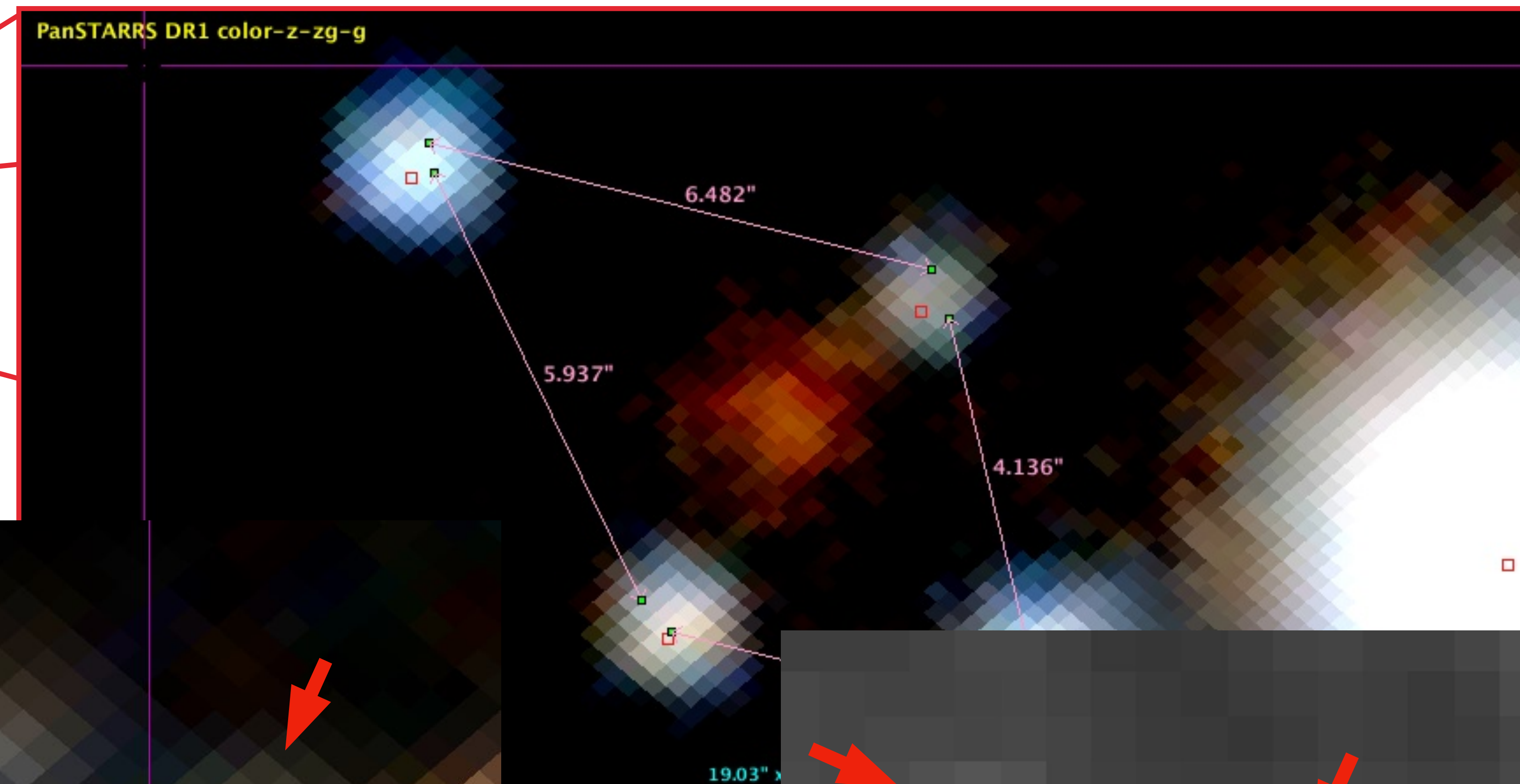
A CURIOUS CASE… THE DRAGONS' KITE

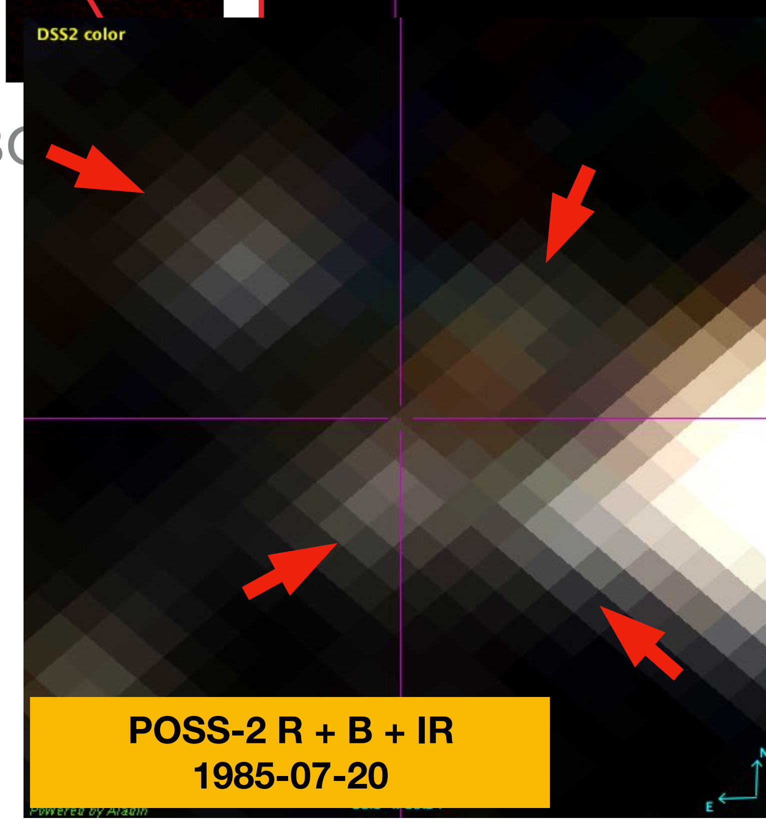


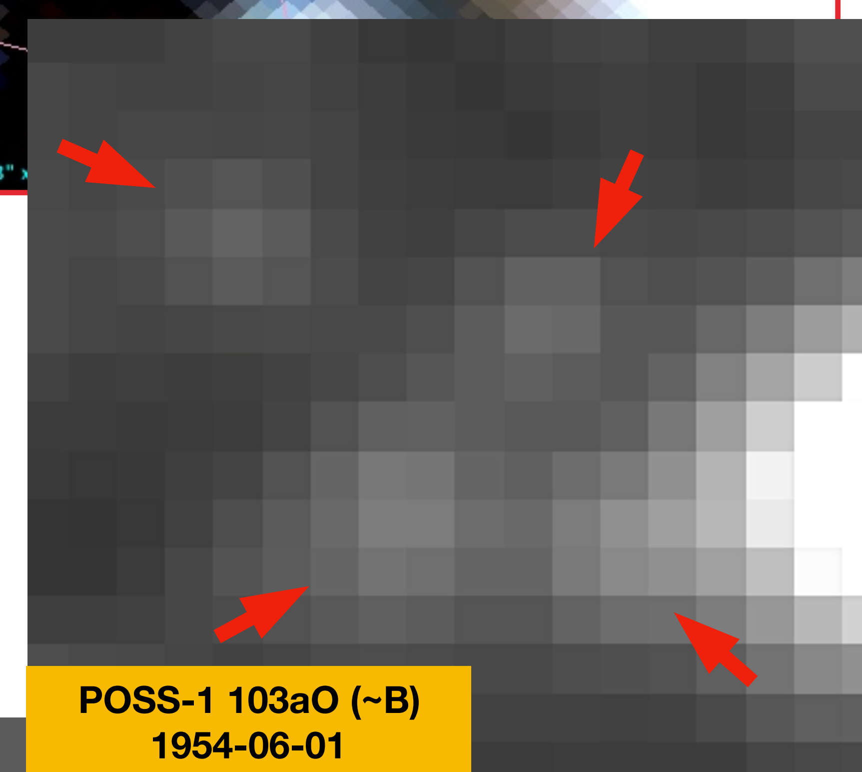
+ ~3 quadruply imaged, TBC (EDR3)

+ ~31 doubly imaged (DR2+EDR3)

GRALJ165105371-041724936







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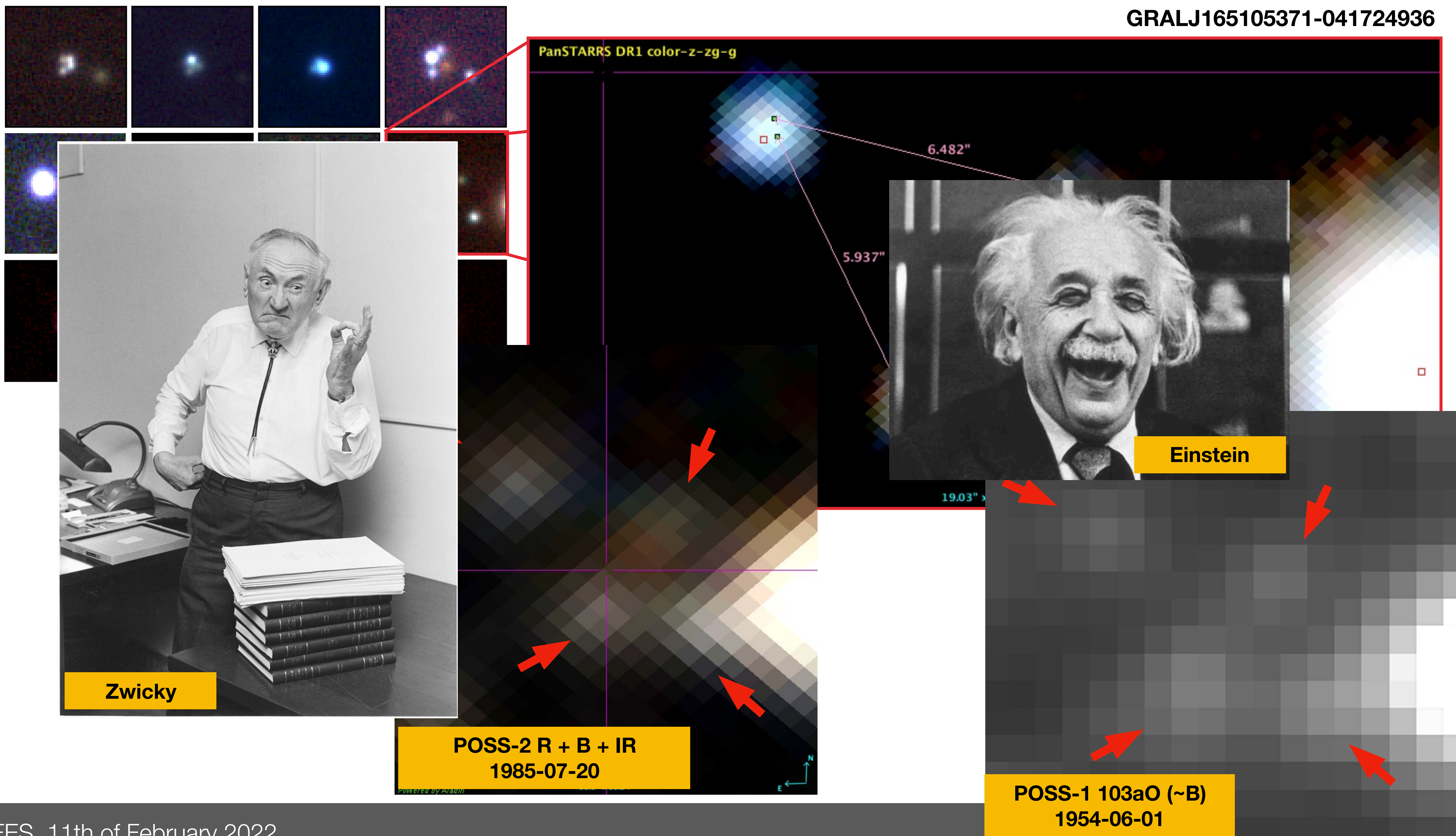
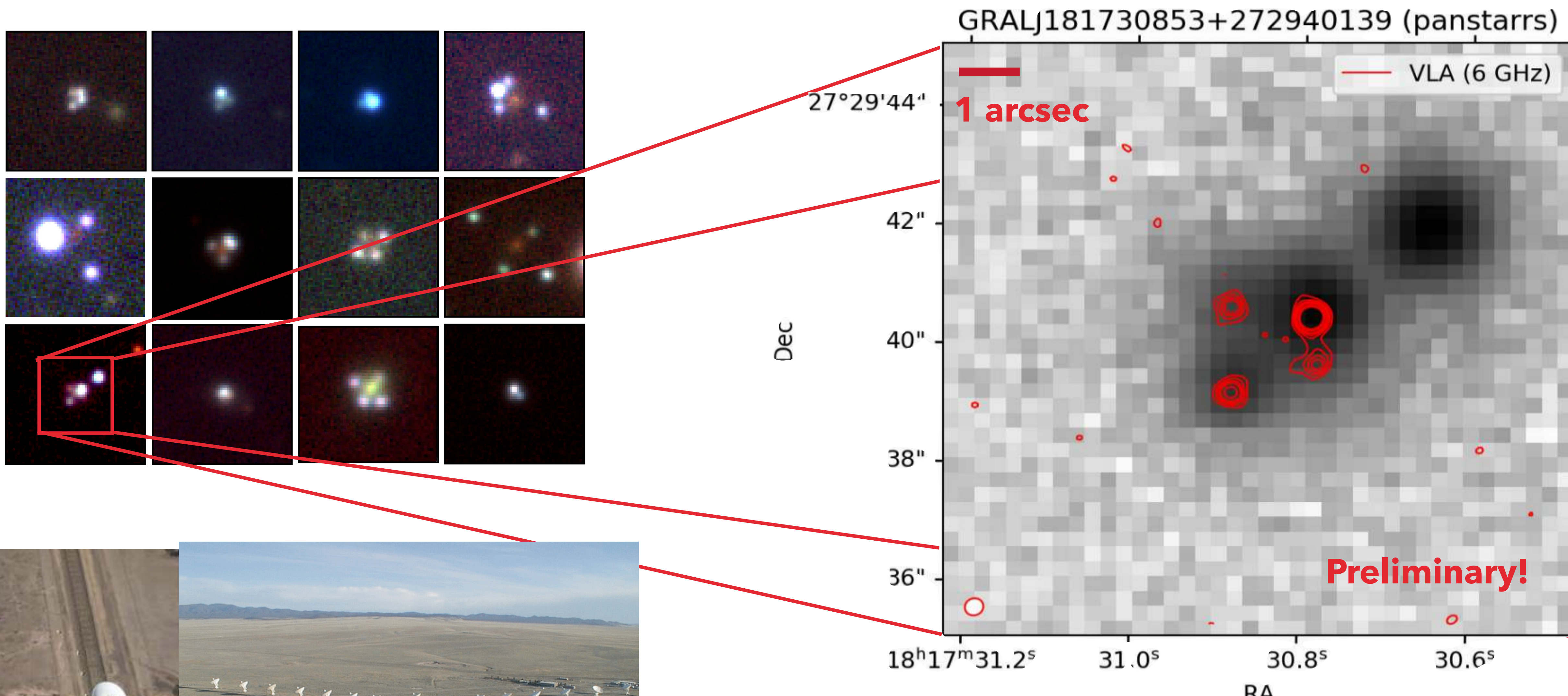


FOLLOW UPS FOR H0 + DM



ATCA

VLA/Jansky

Current:

Radio: ATCA/Australia + Jansky-VLA/USA

Optical: Keck/OSIRIS + Gemini/GMOS + VLT/MUSE (AO+IFU)

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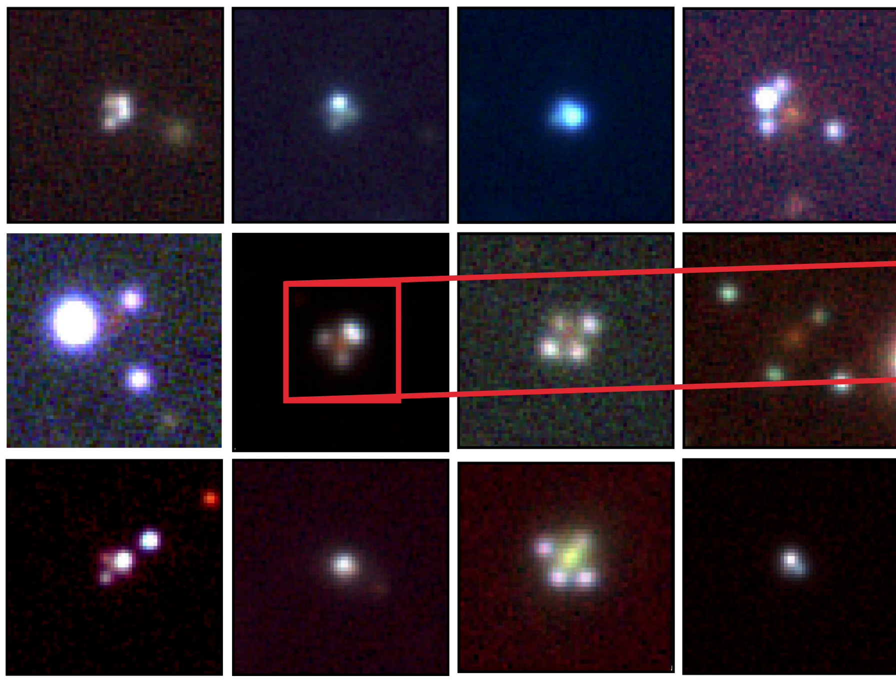
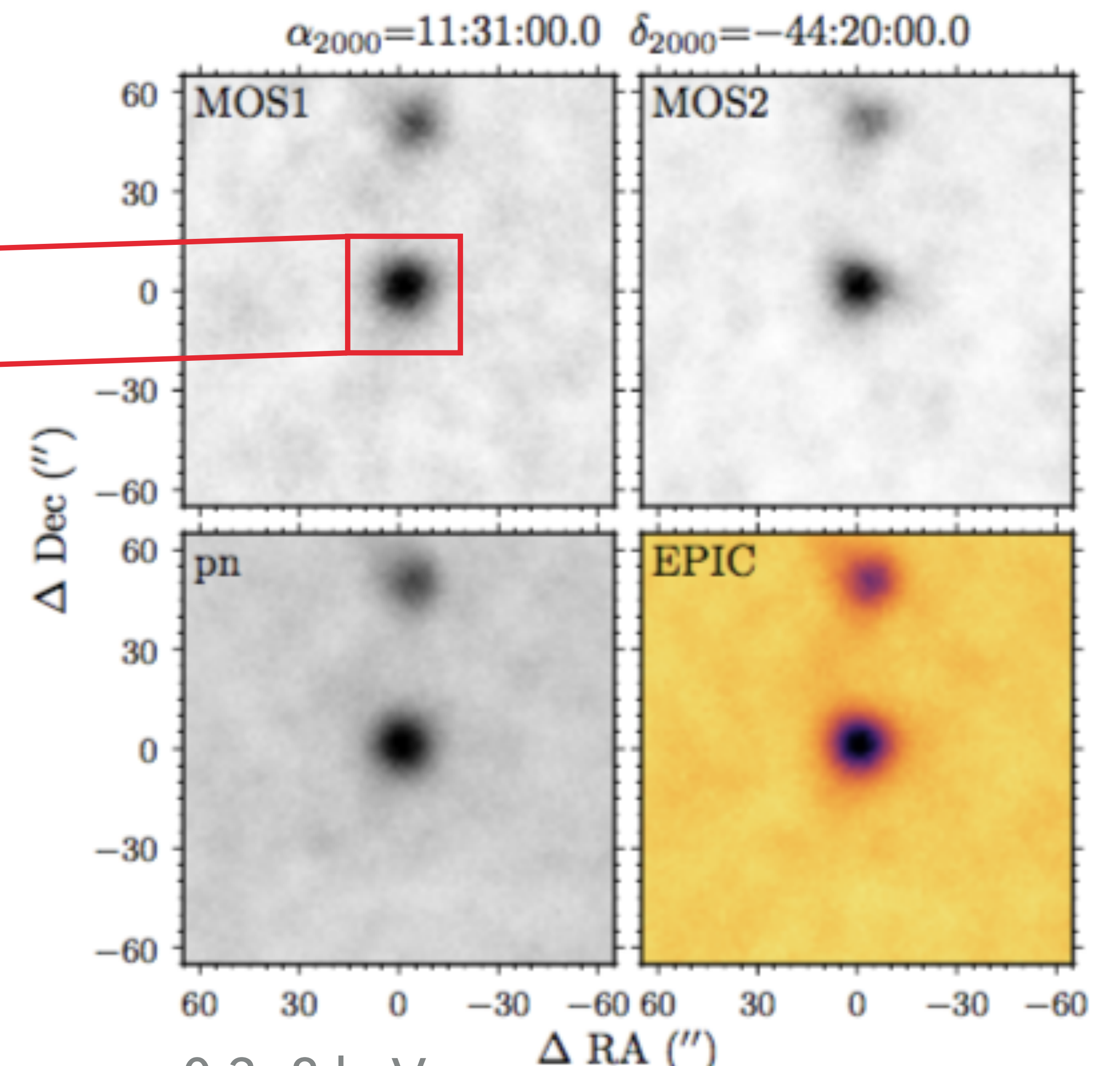
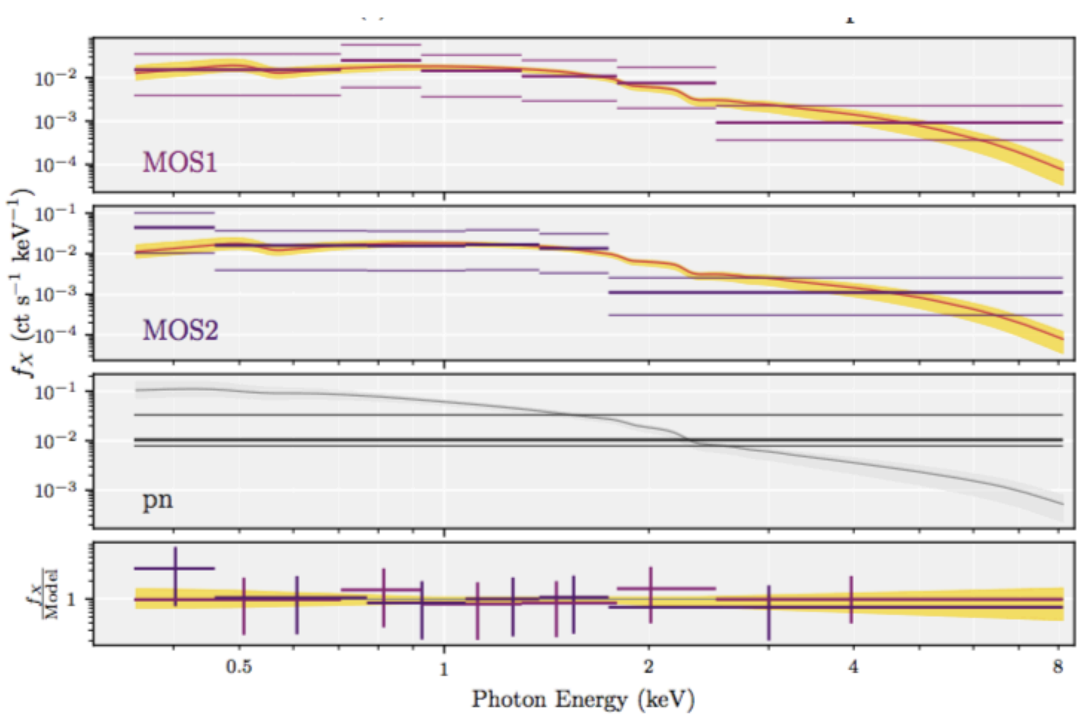
HIGH ENERGY FOLLOW UPS: BLACK HOLE PROPERTIES

ROSAT data ALSO!
Highly variable!
major microlensing?





0.3 -8 keV



Current:
XMM Newton EPIC

XMM

In this short talk…

Why?

How?

The future?

Small training sets: an important challenge

- Supervised learning: only a small number of known lenses to learn…
  - Creating training sets from **simulations always introduce biases**
- Semi-supervised learning and Unsupervised learning are very hard in **high-dimensional spaces**

Small training sets: an important challenge

- Supervised learning: only a small number of known lenses to learn…
  - Creating training sets from **simulations always introduce biases**
- Semi-supervised learning and Unsupervised learning are very hard in **high-dimensional spaces**
- **How to find the best subspace to solve a classification problem?**

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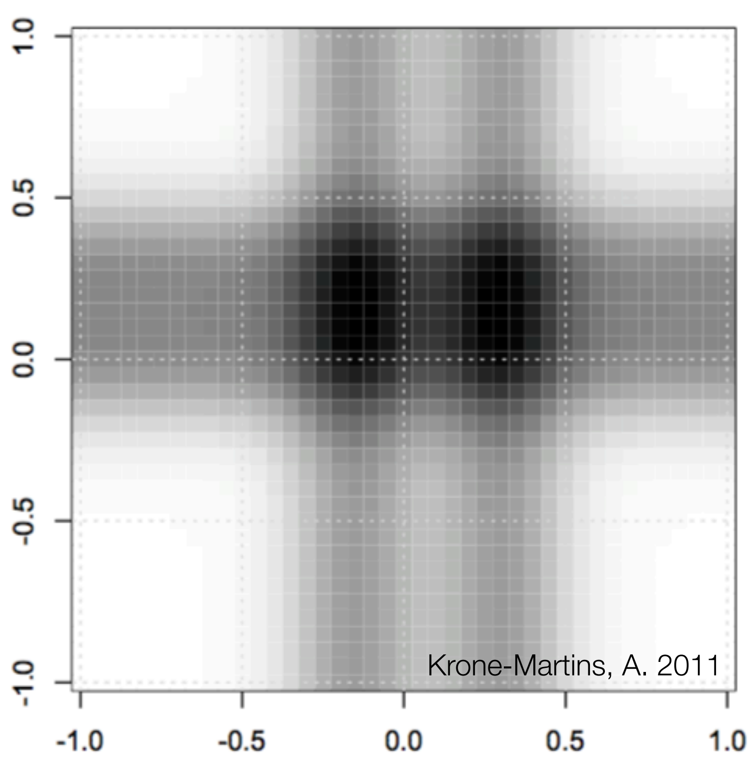
Small training sets: an important challenge

- How to find the best subspace to solve a classification problem?
  - This is equivalent to find the subspace for which the distance between your classes is maximal.
  - Example:



Small training sets: an important challenge

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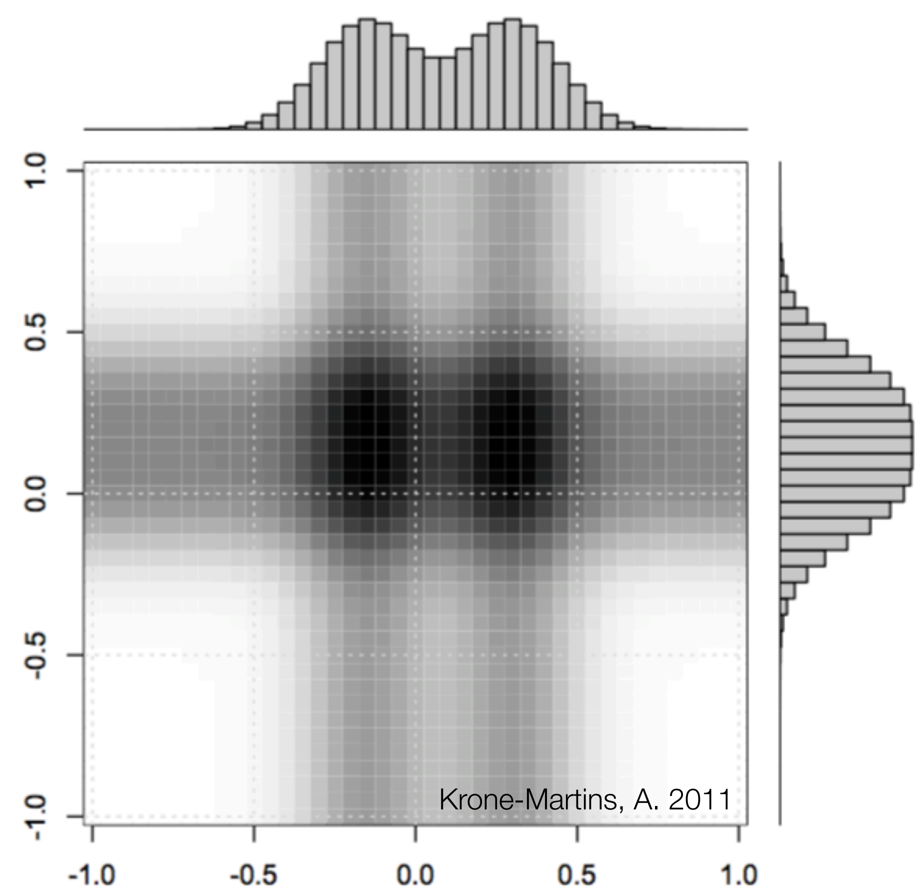
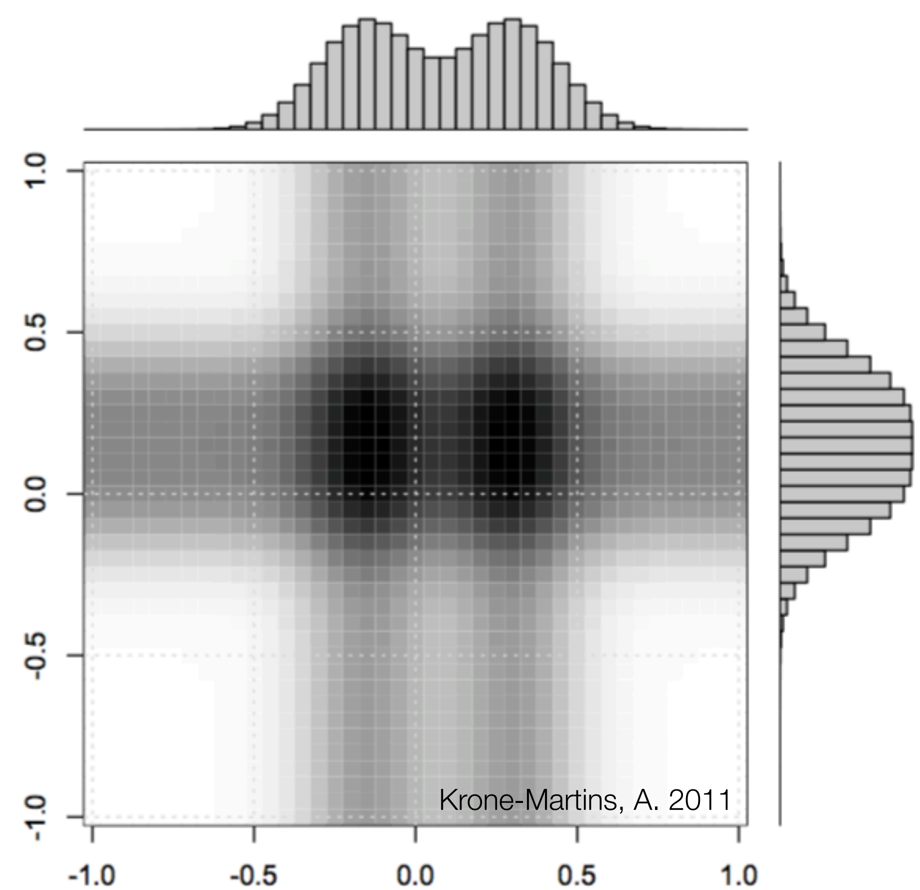


Small training sets: an important challenge

- How to find the best subspace to solve a classification problem?
  - This is equivalent to find the subspace for which the distance between your classes is maximal.
  - Example:
  - Select dimensions using maximal **Wasserstein distances**



Small training sets: an important challenge

- How to find the best subspace to solve a classification problem?
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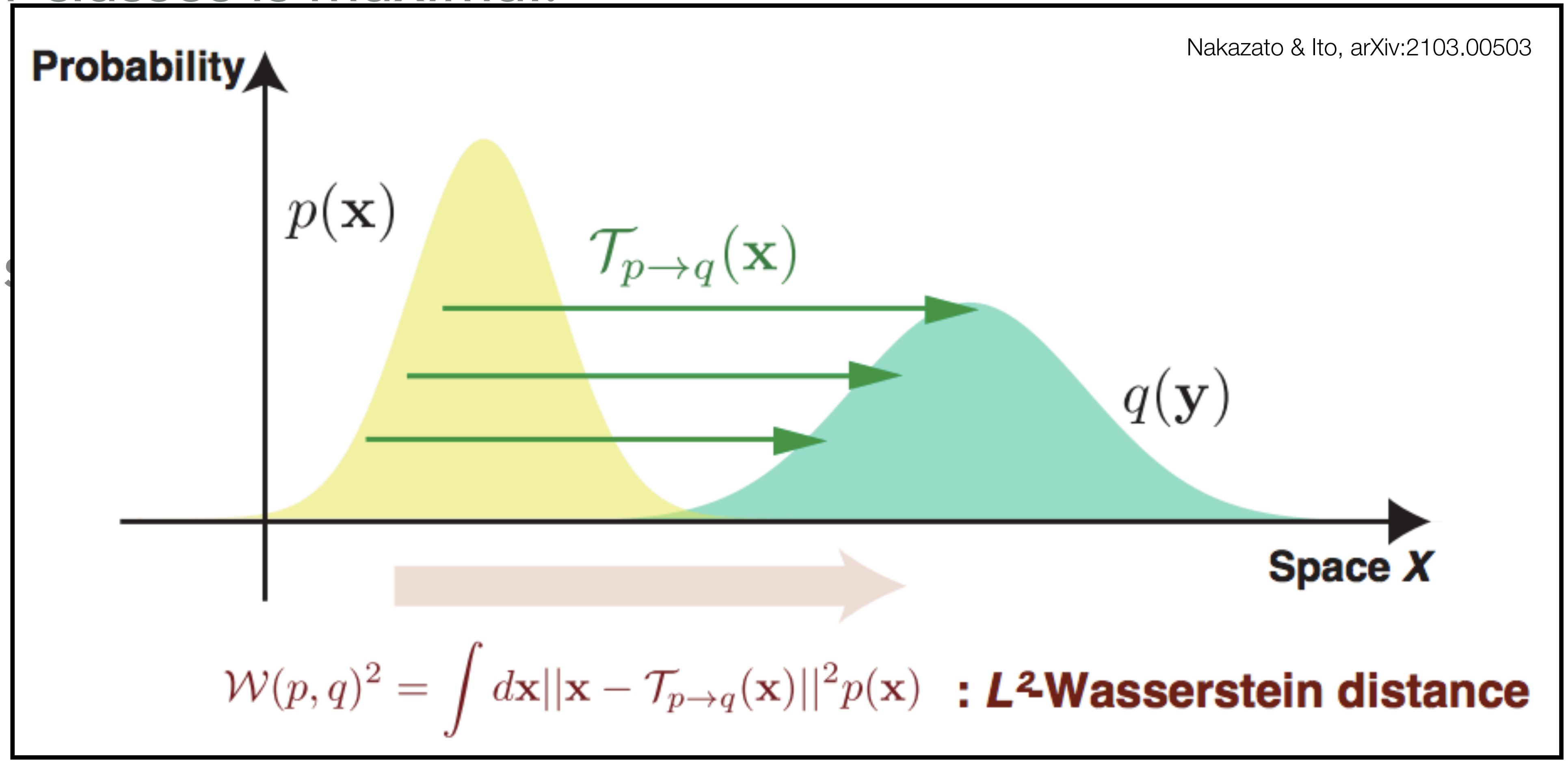
  - Example:
  - Select dimens
    Wasserstein



Small training sets: an important challenge

- How to find the best subspace to solve a classification problem?
  - This is equivalent to find the subspace for which the distance between your classes is maximal.
  - **Select dimensions by using Wasserstein distances**

Small training sets: an important challenge

- How to find the best subspace to solve a classification problem?
  - This is equivalent to find the subspace for which the distance between your classes is maximal.
  - Select dimensions by using Wasserstein distances
  - **Combine multiple dimensions by solving a QUBO problem**

$$\min_{x\in\{0,1\}^n} f_Q(x)$$

$$f_Q(x) = \sum_{i=1} q_{ii}x_i + \sum_{i<j} q_{ij}x_i x_j$$

Use $q_{i,j}$ to encode the Wasserstein distance between the p.d.f. of lenses and no-lenses, projected on the (i, j) dimensions.

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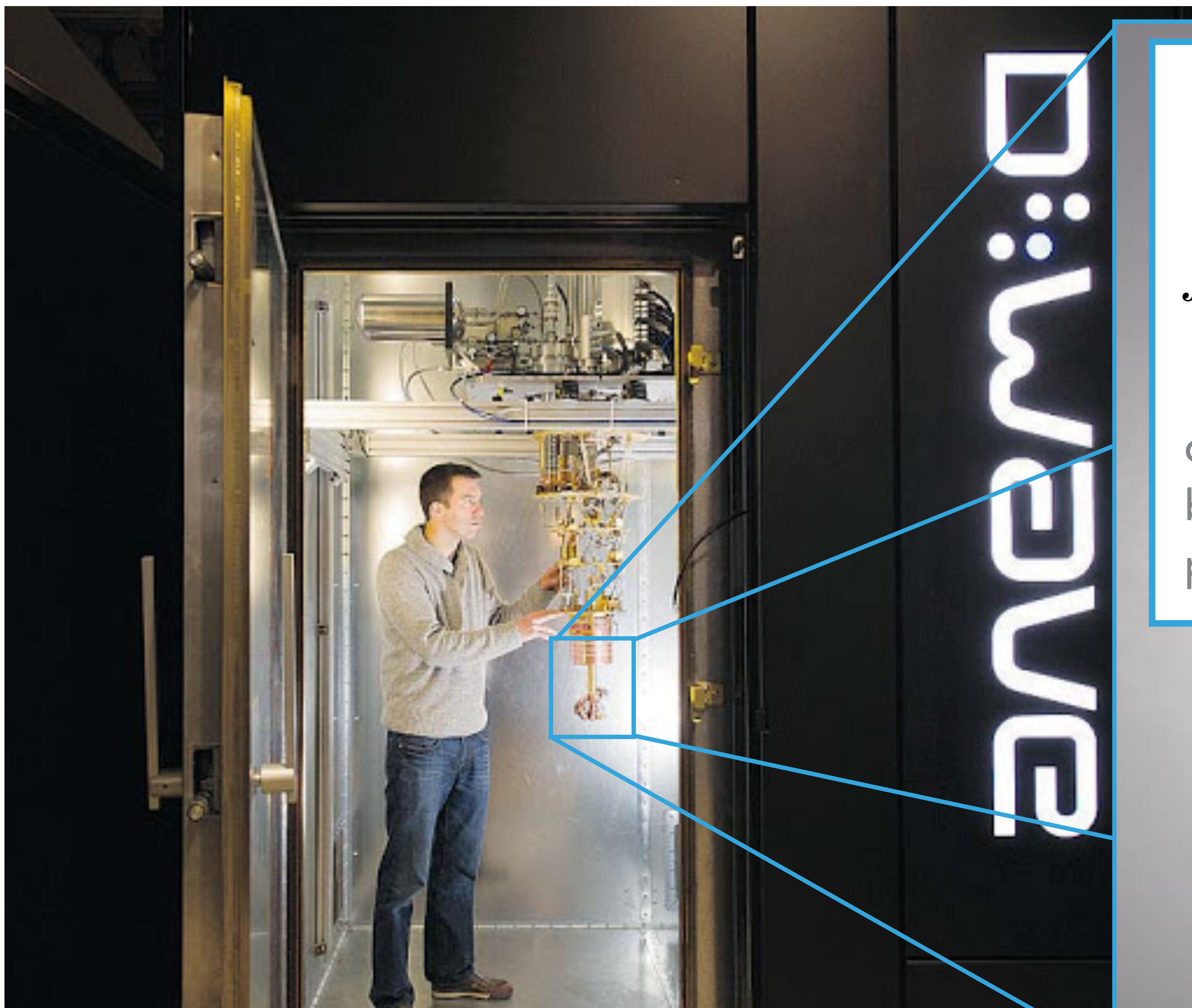
VARIABLE SELECTION VIA QUANTUM ANNEALING

- Heuristic to find good candidate solutions to certain optimization problems using **superposition and entanglement of qubits**



$$\min_{x \in \{0,1\}^n} f_Q(x)$$

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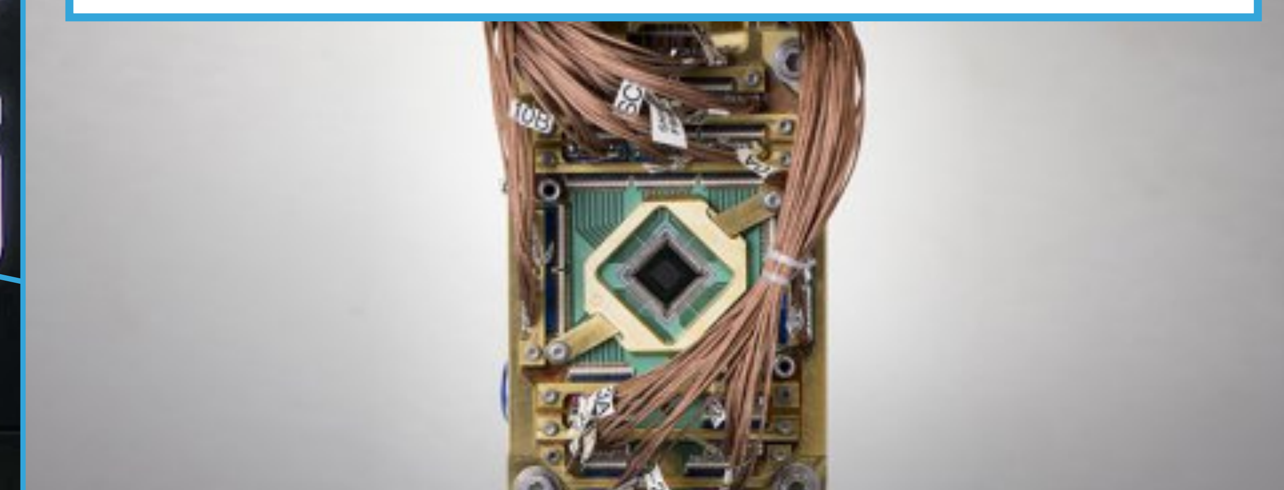


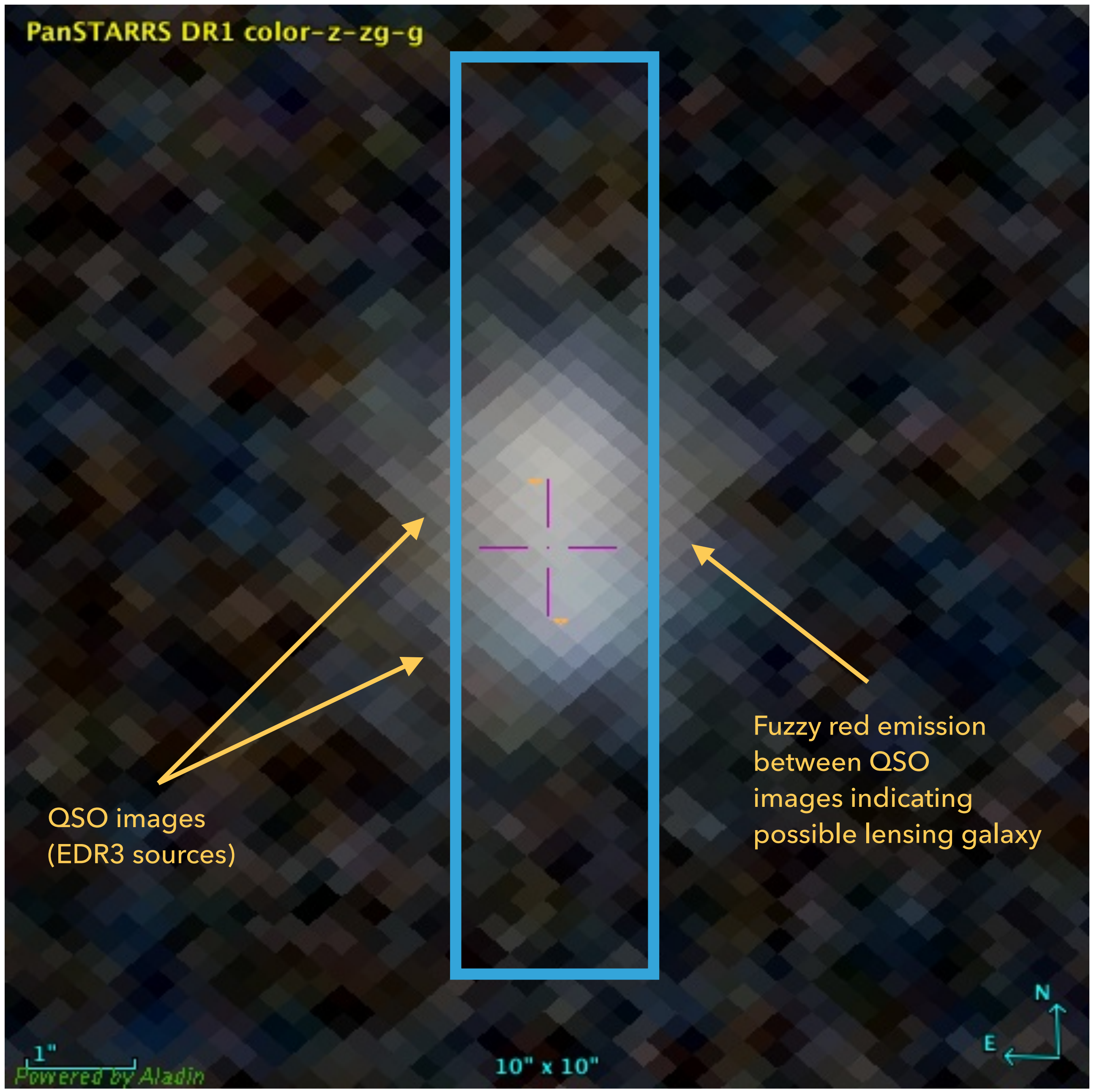
DOUBLE CANDIDATES FOR KECK, 2021-11-01 UT

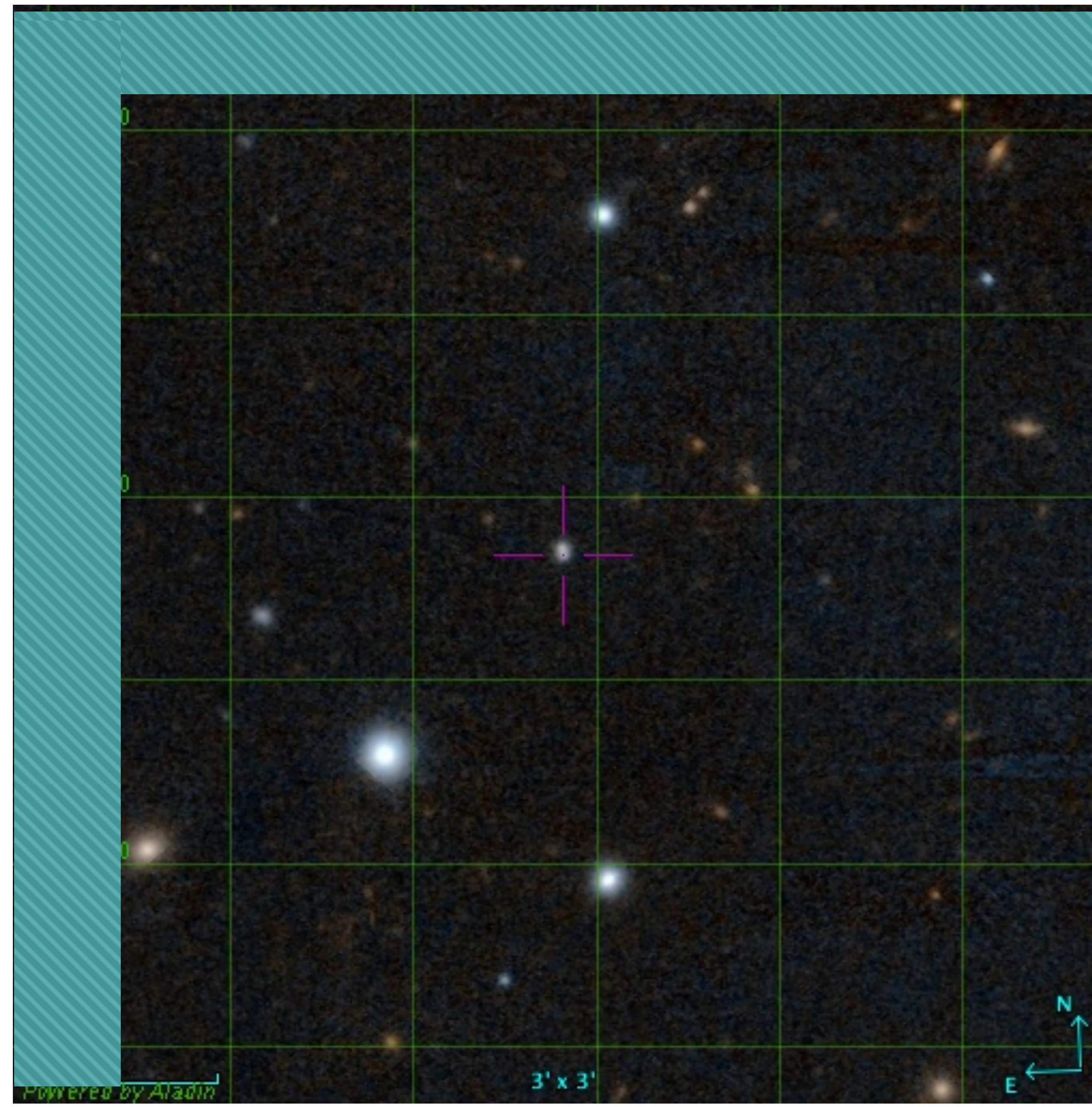
LENS!

Slit PA ~ 0º

(indicated by the blue rectangle)

HIGH PRIORITY OBSERVATION

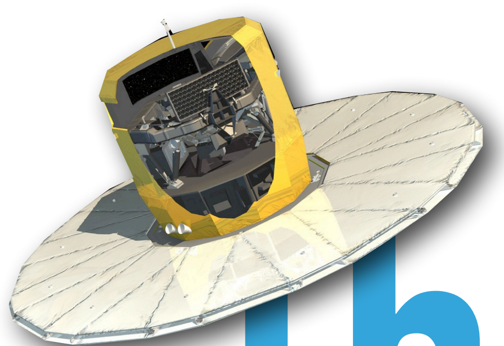




(XGBOOST + QUANTUM ANNEALING CANDIDATE SELECTION USING EDR3 + WISE + PANSTARRS CATALOGUE AND IMAGE DATA)

Current Members: A. Krone-Martins (U. California, Irvine); C. Ducourant, J. F. Le Campion (U. Bordeaux); L. Delchambre, J. Surdej, D. Sluse (U. Liège); D. Stern (JPL/Caltech), S. G. Djorgovski, M. J. Graham, A. Drake, A. Mahabal (Caltech); R. Teixeira, C. Spindola-Duarte (U. São Paulo); L. Galluccio, F. Mignard, E. Slezak, (Observatoire de la Côte d'Azur), S. Scarano (U. Sergipe), J. Kluter (Louisiana), A. Nierenberg (U. California, Merced), P. Jalan (Aryabhatta), D. Dobie, T. Murphy, C. Boehm (U. Sydney), J. Wambsganss (U. Heidelberg), S. Klioner (U. Dresden)

Past Members:
O. Wertz (Argelander/Bonn)
U. Bastian (ARI/Heidelberg)



Thank you!

Partially supported by: