FACULTAD DE CIENCIAS FÍSICAS Y MATEMÁTICAS
UNIVERSIDAD DE CHILE

INSTITUTO MILENIO DE ASTROFÍSICA

PONTIFICIA UNIVERSIDAD CATÓLICA DE CHILE

The QUEST-La Silla AGN Variability survey

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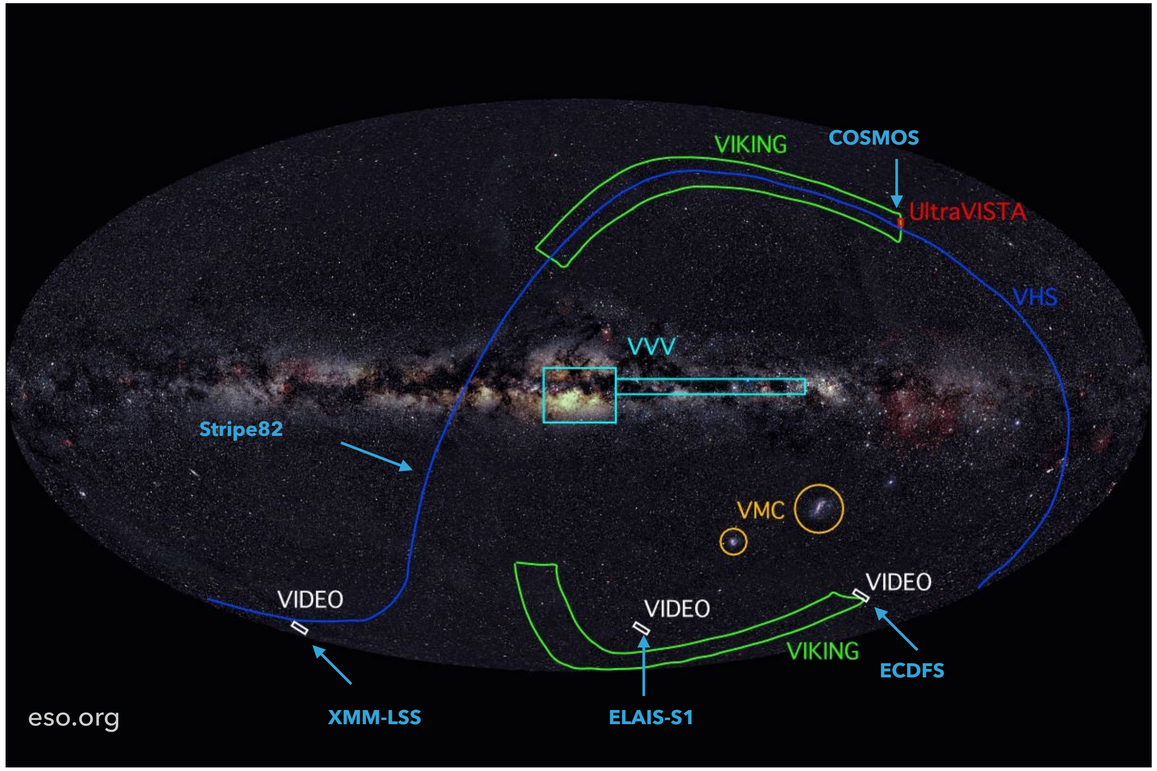
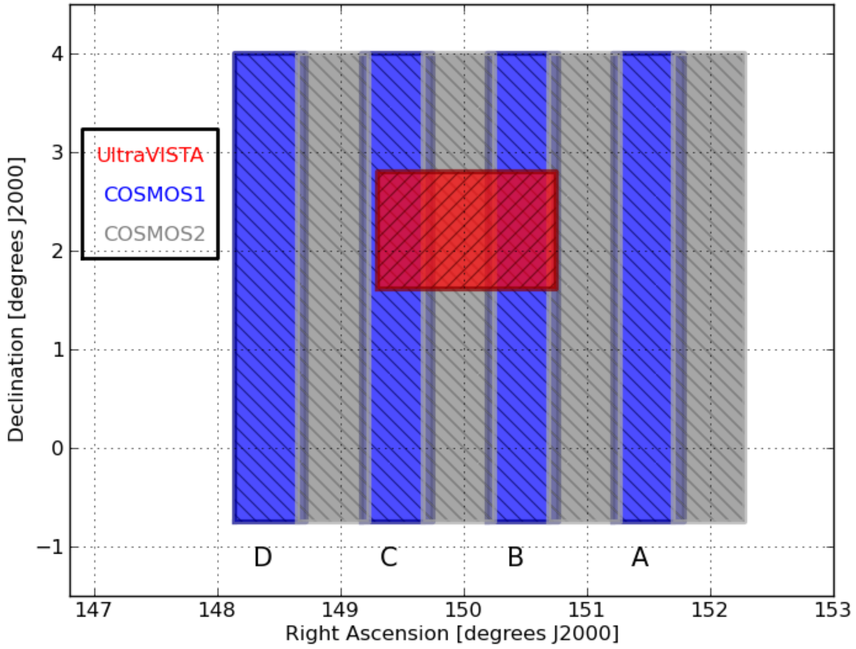
The QUEST-La Silla AGN Variability Survey

- Wide-field QUEST camera on the 1-meter ESO-Schmidt telescope at La Silla Observatory.
- Images of Stripe82, ECDFS, XMM-LSS, ELAIS-S1, and COSMOS fields, taken between 2011 and 2015.
- Q band ~ $(g + r)_{SDSS}$, total area ~94 deg^2, limiting magnitude r ≲ 21.





Details in Cartier et al. 2015.

The QUEST-La Silla AGN Variability Survey

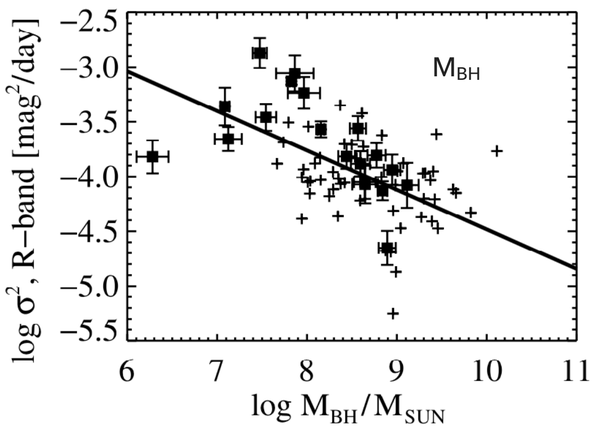
Main scientific questions:

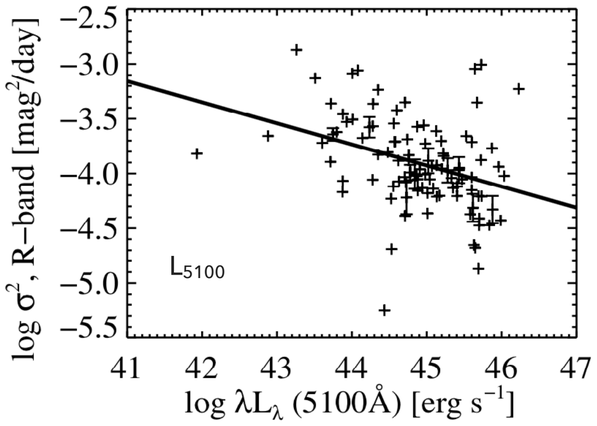
- Which is/are the mechanism/s responsible for AGN variability?
- What are the differences in the variability behavior of different AGN populations?
- **Is the variability related with the physical properties of AGN?**
- **Can we improve the selection of AGN candidates using variability-based techniques?**

Is the variability related with the physical properties of AGN?

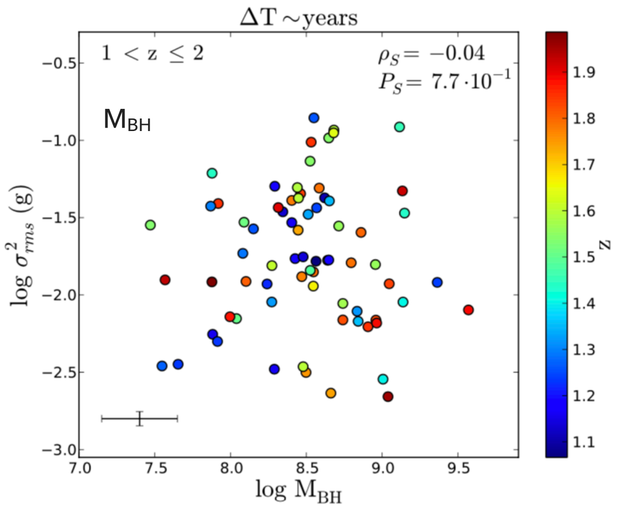
AGN Variability: what do we know?

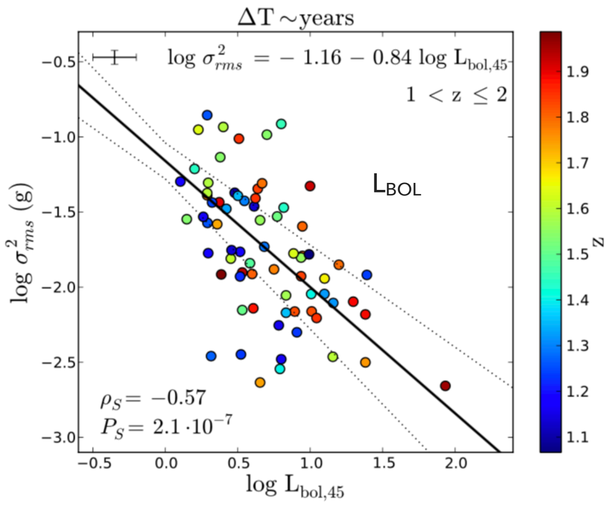
Connection between AGN variability and black hole physical properties?





Kelly et al. 2009 (**~100 sources**): the amplitude of short-timescale variations is significantly anti-correlated with black hole mass and luminosity





Simm et al. 2016 (**~90 sources**): the amplitude of the variability is strongly anti-correlated with bolometric luminosity, and there is no evidence of dependency with black hole mass.

See also MacLeod et al. 2010, Caplar et al. 2017

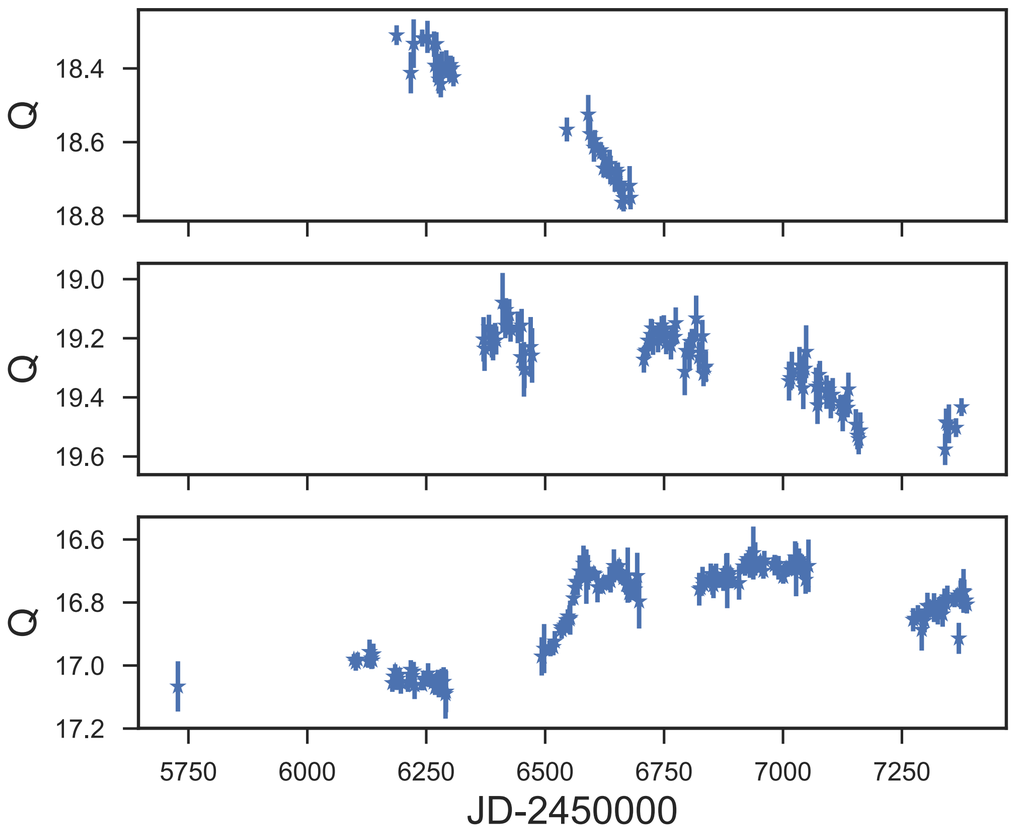
What is the connection between AGN variability and black hole physical properties?

We need a large sample of AGN with well sampled light curves!

We need careful estimations of the BH physical properties!

Connection between variability and physical properties of AGN

- AGN selected from SDSS Data Release 14 Quasar catalog (DR14Q, Pâris et al. 2017a). 1473 classified as quasars in DR14Q, with more than 40 epochs and rest frame coverage of 200 days or more in our survey.
- 1348/1473 variable sources (91,5%).



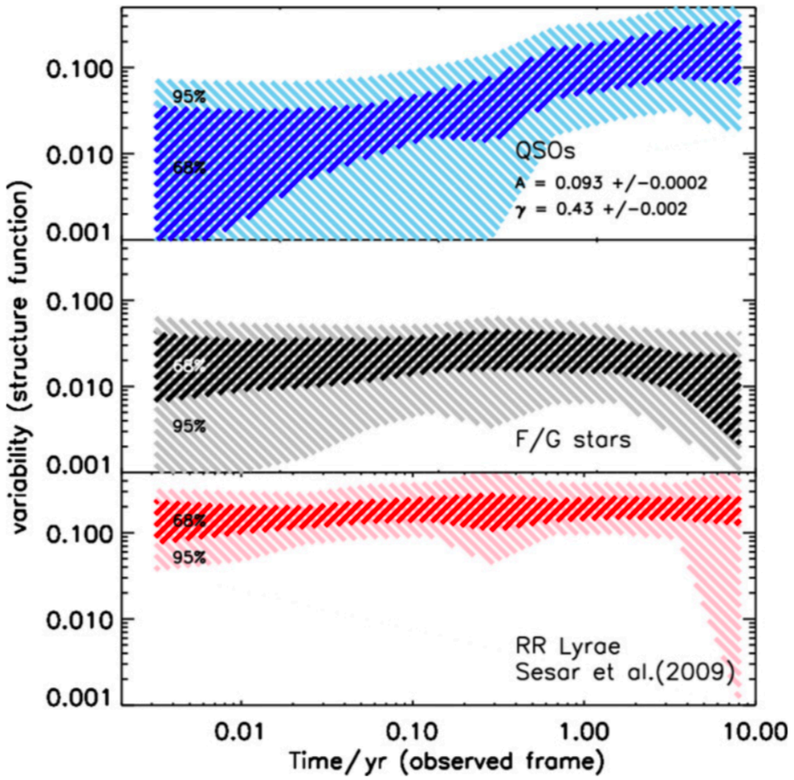
Sánchez-Sáez et al. (2018)

Connection between variability and physical properties of AGN

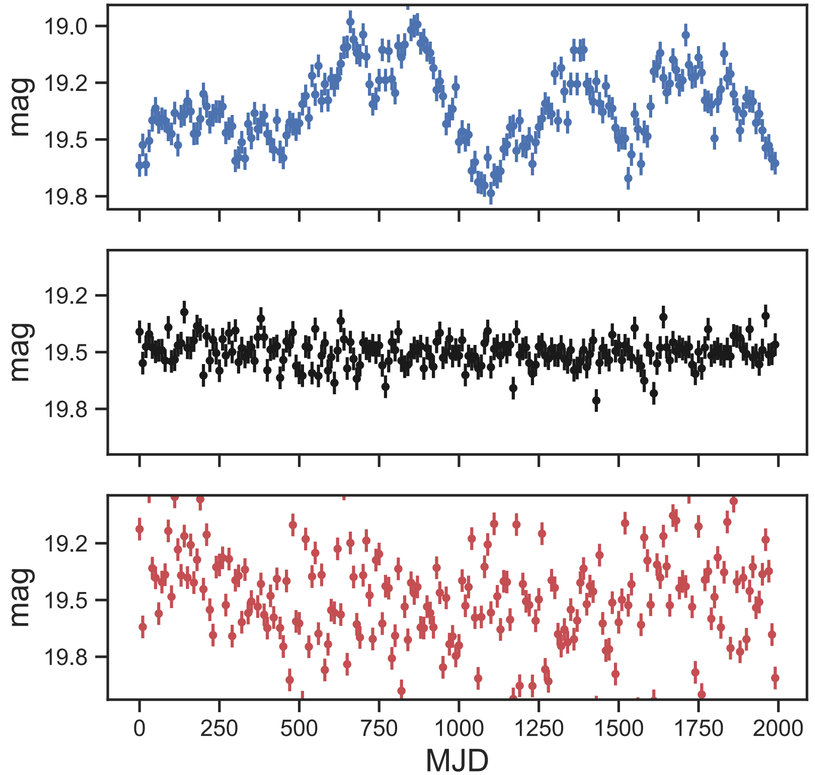
- Structure Function (SF)

$$SF(\Delta t) = \left\langle \sqrt{\frac{\pi}{2}} |\Delta m_{i,j} - \sqrt{\sigma_i^2 + \sigma_j^2} \right\rangle_{\Delta t}$$

$$SF(\tau) = A \left(\frac{\tau}{1yr} \right)^{\gamma}$$



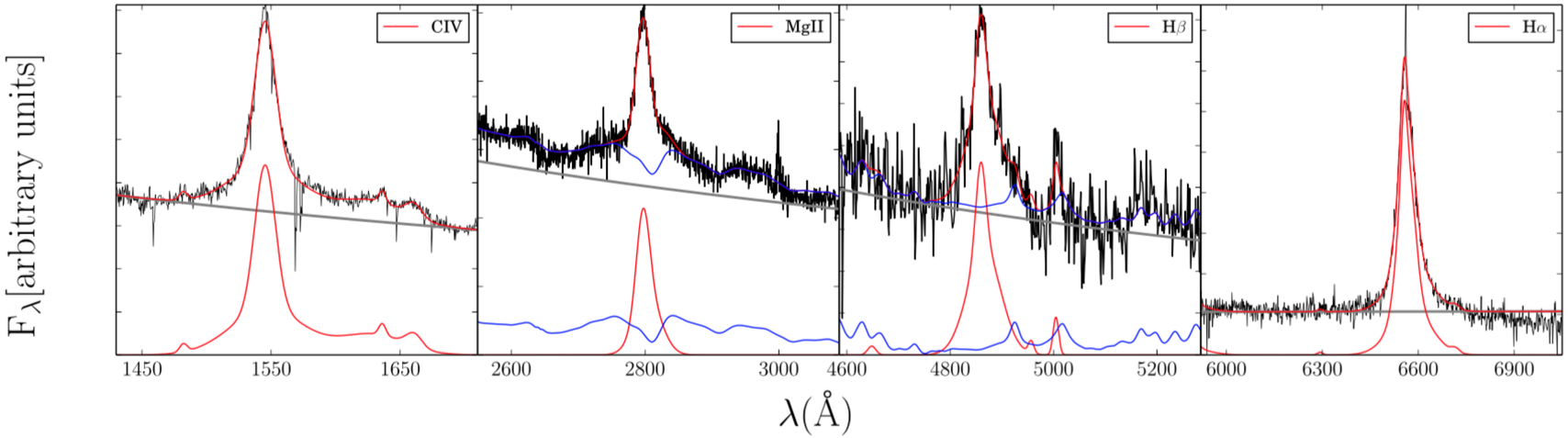
Schmidt et al. 2010



Sánchez-Sáez et al. (2018)

Connection between variability and physical properties of AGN

We used the procedure proposed by Mejía-Restrepo et al. (2016) to estimate the **black hole masses (M_{BH}), luminosities at 5100 Å (L_{5100}), accretion rates ($\dot{M}$), and the Eddington ratios (L/L_{Edd})** from SDSS spectra.



From Mejía-Restrepo et al. (2016)

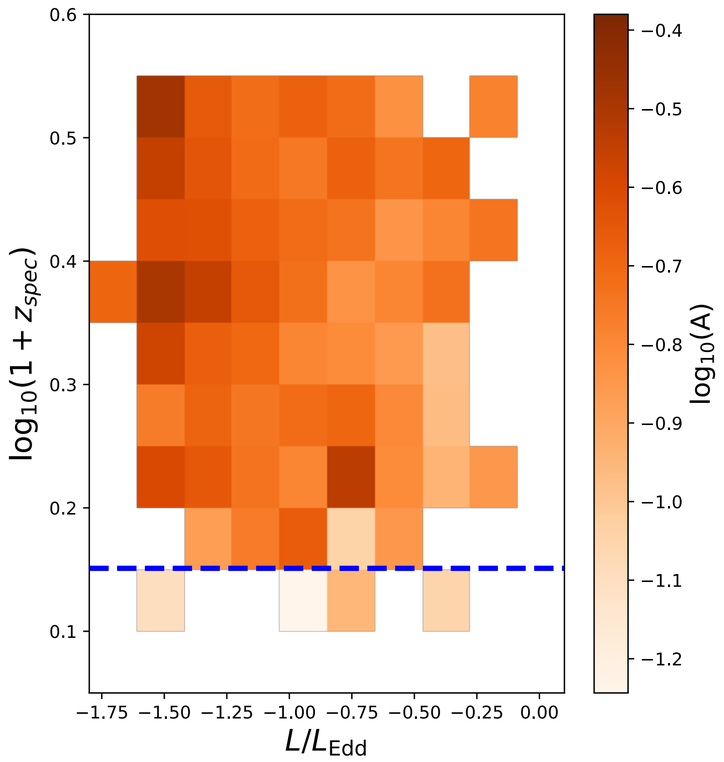
Sánchez-Sáez et al. (2018)

Connection between variability and physical properties of AGN

We found that **the amplitude of the variability (A) depends primarily on the rest frame emission wavelength and the Eddington ratio**, where A anti-correlates with both λ_{rest} and L/L_{Edd}.

Table 1. Linear Regression α, β and ϵ coefficients for A as the dependent variable (for the not − C IV sample). The columns headed by physical quantities refer to their slope in the regression model (β).

#	α	$\log_{10}(1+z_{spec})$	$\log_{10}(L_{5100}/10^{44})$	$\log_{10}(M_{BH}/10^{8})$	$\log_{10}(L/L_{Edd})$	$\log_{10}(\dot{M})$	ϵ
1	-0.88 ± 0.03	0.44 ± 0.08	X	X	X	X	0.26 ± 0.01
2	-0.74 ± 0.01	X	0.03 ± 0.02	X	X	X	0.26 ± 0.01
3	-0.77 ± 0.01	X	X	0.12 ± 0.02	X	X	0.25 ± 0.01
4	-0.93 ± 0.03	X	X	X	-0.19 ± 0.02	X	0.25 ± 0.01
5	-0.79 ± 0.01	X	X	X	X	-0.09 ± 0.02	0.26 ± 0.01
6	-0.87 ± 0.03	0.52 ± 0.11	-0.21 ± 0.03	0.18 ± 0.03	X	X	0.25 ± 0.01
7	-1.08 ± 0.04	0.50 ± 0.11	-0.02 ± 0.03	X	-0.18 ± 0.03	X	0.25 ± 0.01
8	-1.14 ± 0.06	0.57 ± 0.11	X	-0.04 ± 0.03	-0.22 ± 0.03	X	0.25 ± 0.01
9	-0.92 ± 0.03	0.72 ± 0.10	-0.10 ± 0.03	X	X	X	0.25 ± 0.01
10	-0.83 ± 0.03	0.18 ± 0.10	X	0.09 ± 0.02	X	X	0.25 ± 0.01
11	**-1.09 ± 0.04**	**0.45 ± 0.07**	**X**	**X**	**-0.19 ± 0.02**	**X**	**0.25 ± 0.01**



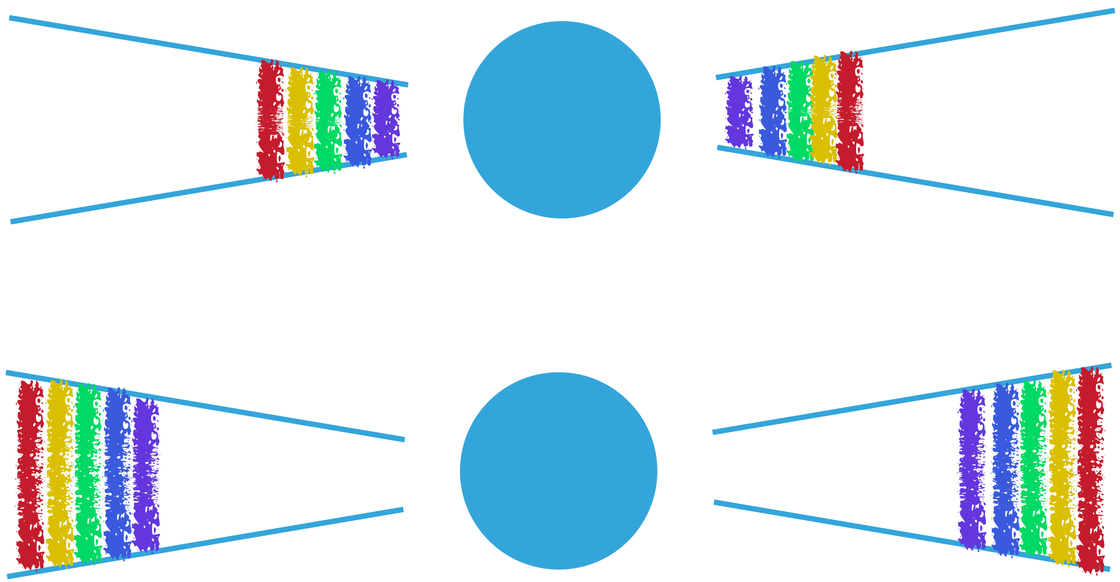
Correlation with z –> anti-correlation with λ_{rest}

Sánchez-Sáez et al. (2018)

L/L_{Edd} as the main driver of the amplitude of the variability

For lower accretion rates, the disk becomes cooler and the innermost, most variable region, will shift its emission from the UV to optical wavebands.

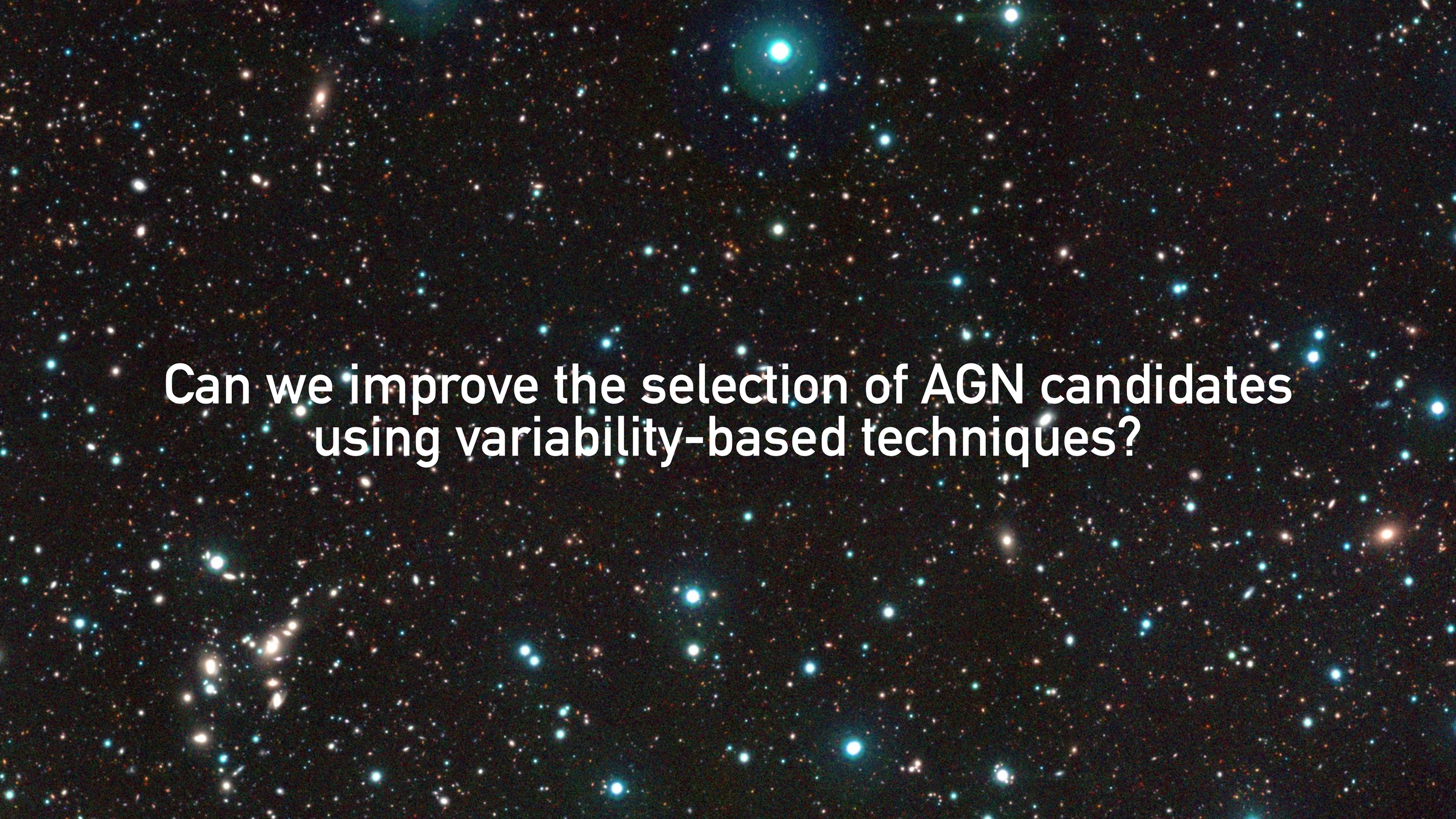
$$r_\lambda \propto M_{\rm BH}^{2/3}(L/L_{\rm Edd})^{1/3}\lambda^{4/3}$$



$\downarrow L/L_{\rm Edd}$

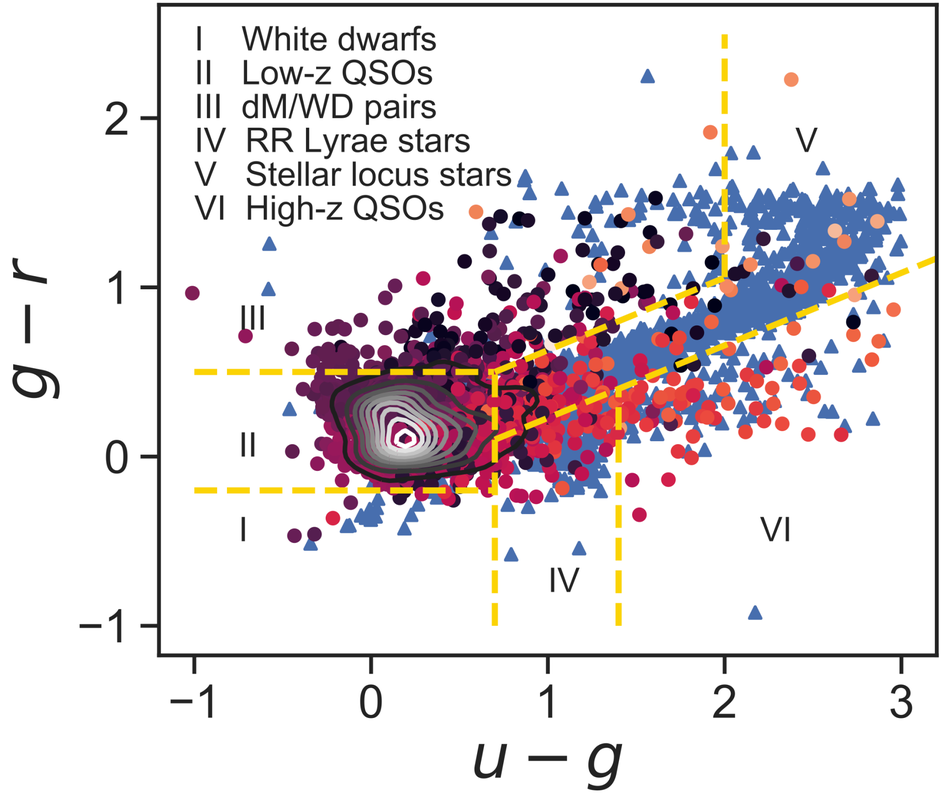
$\uparrow L/L_{\rm Edd}$

Sánchez-Sáez et al. (2018)


Can we improve the selection of AGN candidates
using variability-based techniques?

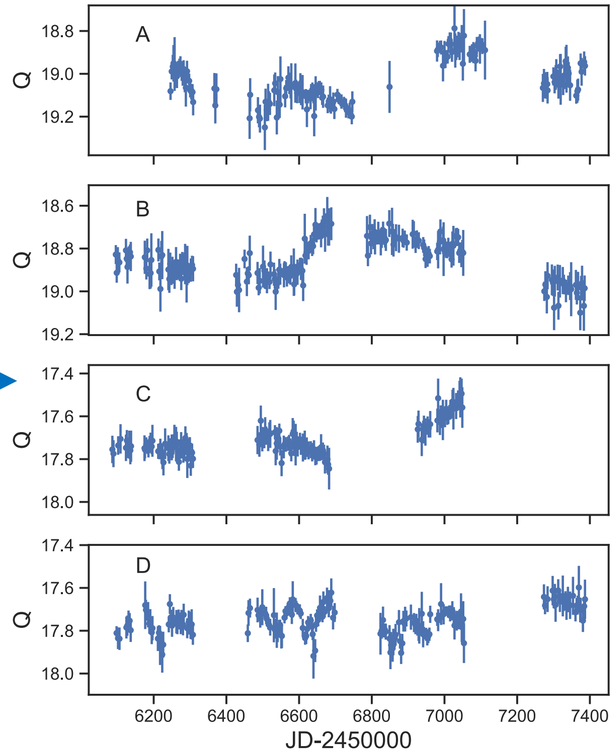
Selection of AGN candidates through optical variability

Traditionally, AGN selection follows the philosophy of finding regions in UV/optical/mid-IR color-color space in which **point-like AGN** can be cleanly separated from stars and galaxies.



Selection of AGN candidates through optical variability

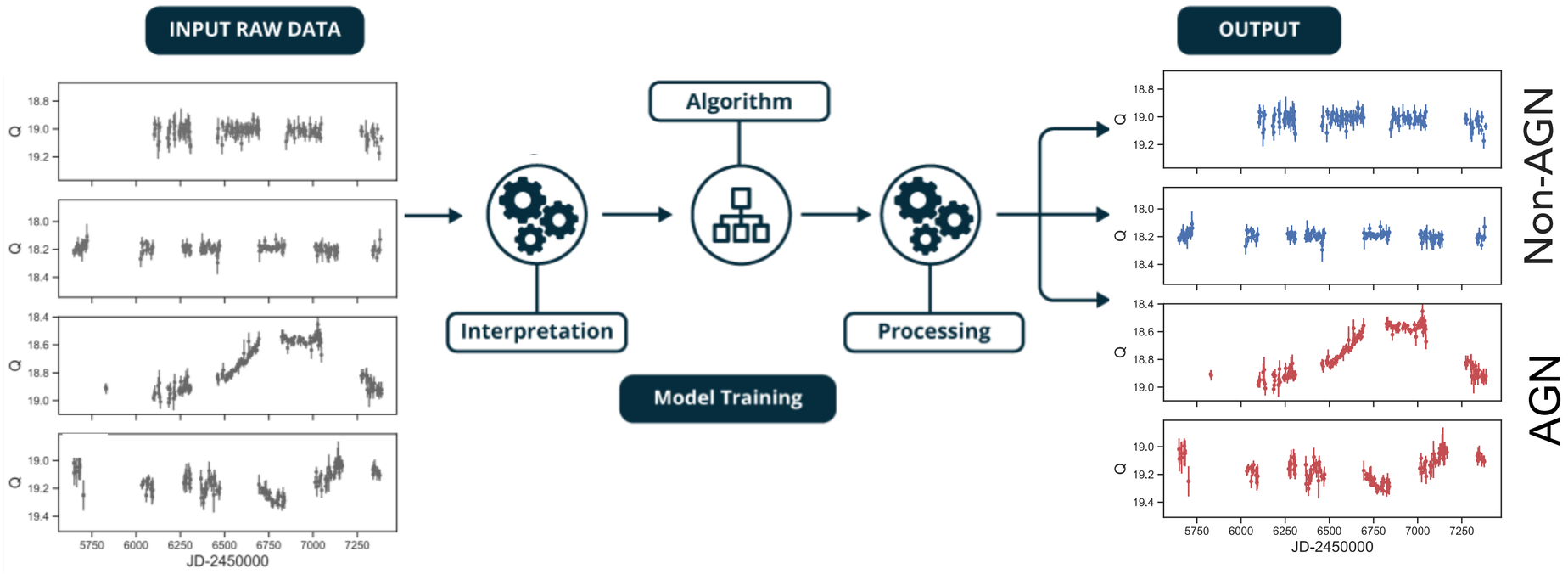
We used data from the **QUEST-La Silla AGN Variability Survey** to construct light curves for ~208.000 objects, located in the ECDFS, XMM-LSS, ELAIS-S1, and COSMOS fields. **We selected light curves with at least 40 epochs and a length > 200 days**.



Sánchez-Sáez et al. (2019)

Selection of AGN candidates through optical variability

We implemented a **Random Forest** algorithm to classify our objects as either AGN or non-AGN according to their variability features and optical colors, excluding morphology cuts.



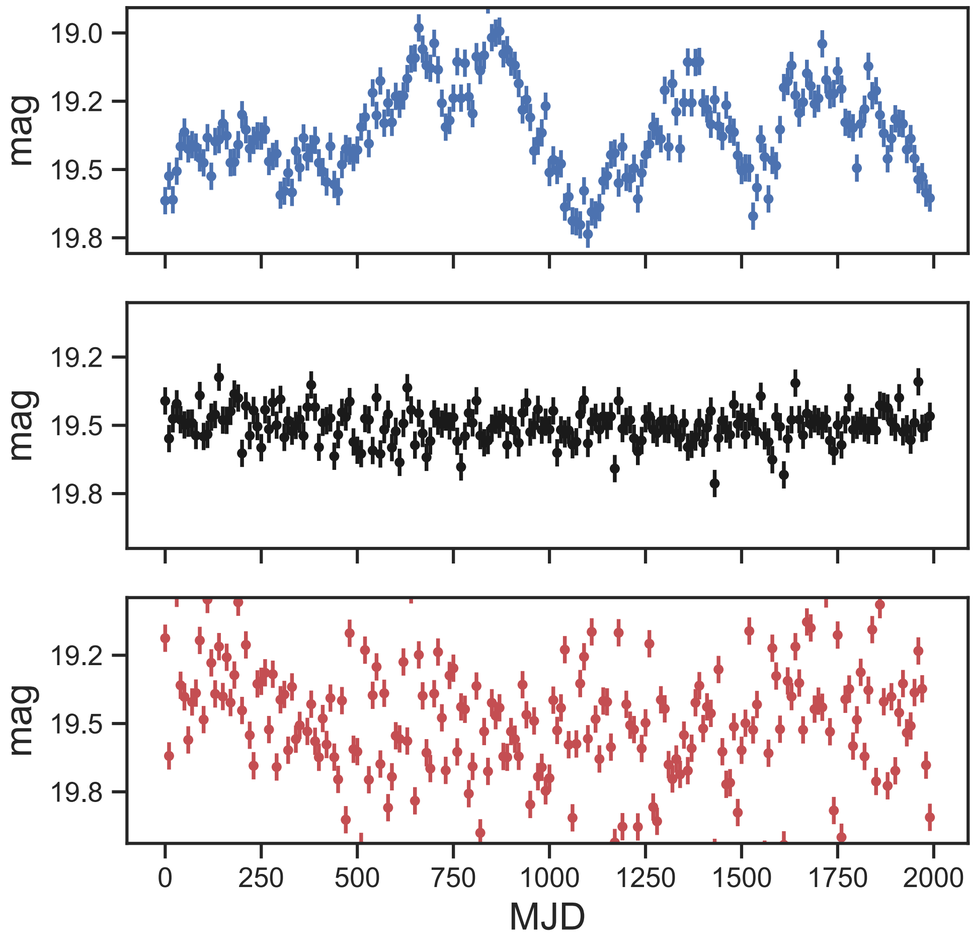
Sánchez-Sáez et al. (2019)

Selection of AGN candidates through optical variability

Variability Features: how can we separate AGN and non-AGN?

Feature	Description	Reference
P_{var}	Probability that the source is intrinsically variable	McLaughlin et al. (1996)
$\sigma_{\rm rms}$	Measure of the intrinsic variability amplitude.	Allevato et al. (2013)
$A_{\rm SF}$	Amplitude of the variability at 1 year, derived from the SF	Schmidt et al. (2010)
$\gamma_{\rm SF}$	Logarithmic gradient of the change in magnitude, derived from the SF	Schmidt et al. (2010)
Std*	Standard deviation of the light curve (σ_{LC})	Nun et al. (2015)
Meanvariance*	Ratio of the standard deviation to the mean magnitude ($\sigma_{LC}/\overline{m}$)	Nun et al. (2015)
MedianBRP*	Fraction of photometric points within amplitude/10 of the median magnitude	Richards et al. (2011)
Autocor–length*	Lag value where the auto–correlation becomes smaller than e^{-1}	Kim et al. (2011)
StetsonK*	A robust kurtosis measure	Kim et al. (2011)
η^e*	Ratio of the mean of the square of successive differences to the variance of data points	Kim et al. (2014)
PercentAmp*	Largest percentage difference between either the max or min magnitude and the median	Richards et al. (2011)
Con*	number of three consecutive data points that are brighter or fainter than $2\sigma_{LC}$	Kim et al. (2011)
LinearTrend*	Slope of a linear fit to the light curve	Richards et al. (2011)
Beyond1Std*	Percentage of points beyond one σ_{LC} from the mean	Richards et al. (2011)
Q31*	Difference between the third quartile and the first quartile of a light curve	Kim et al. (2014)
PeriodLS	Period from the Lomb–Scargle periodogram	VanderPlas (2018)

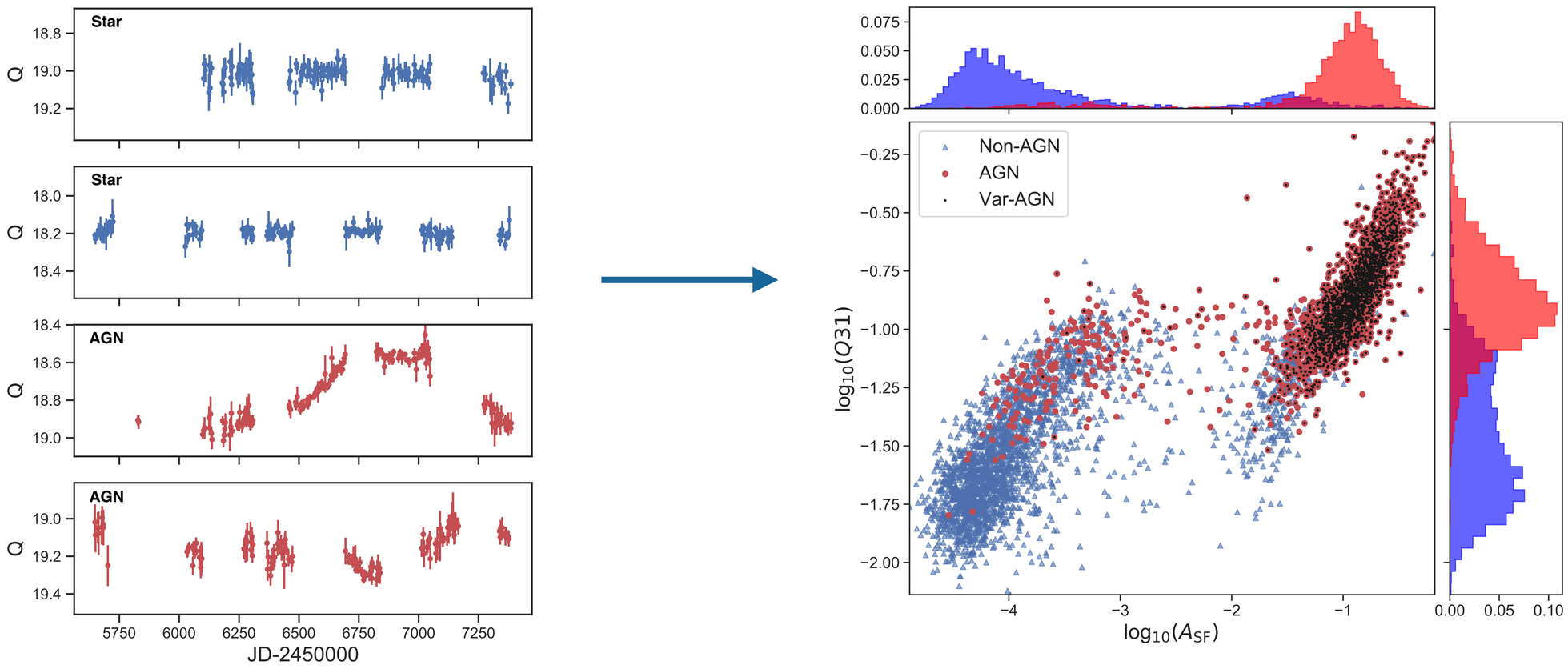
Note. (*) Features from FATS



Sánchez-Sáez et al. (2019)

Selection of AGN candidates through optical variability

Labeled set: 2405 type 1 AGN and 2608 stars from SDSS



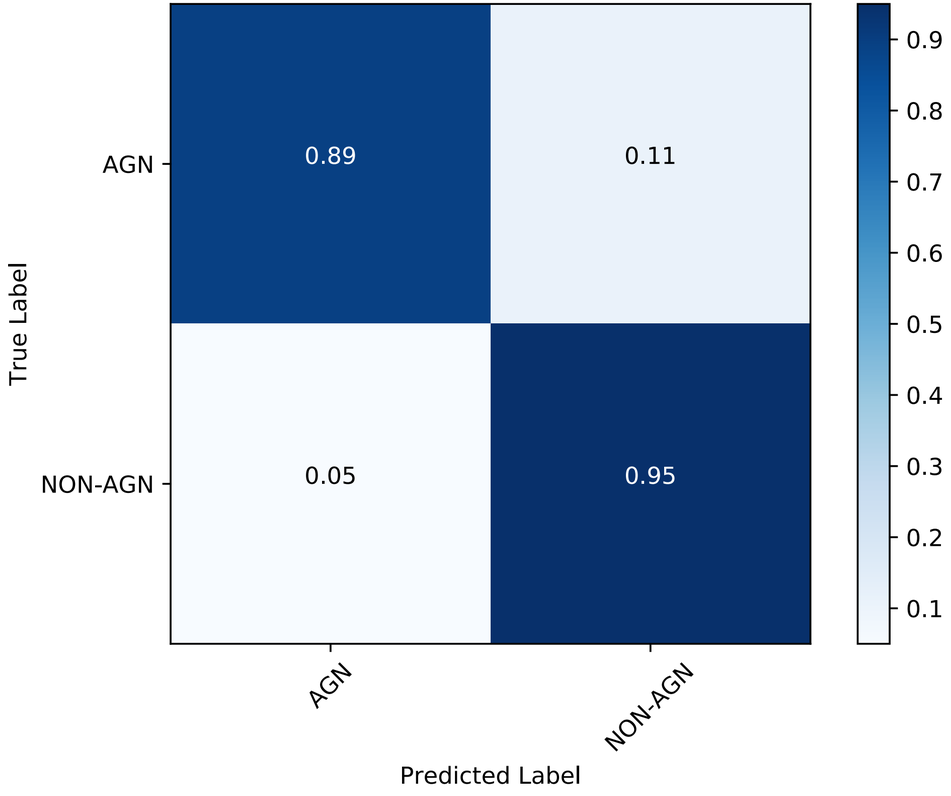
Sánchez-Sáez et al. (2019)

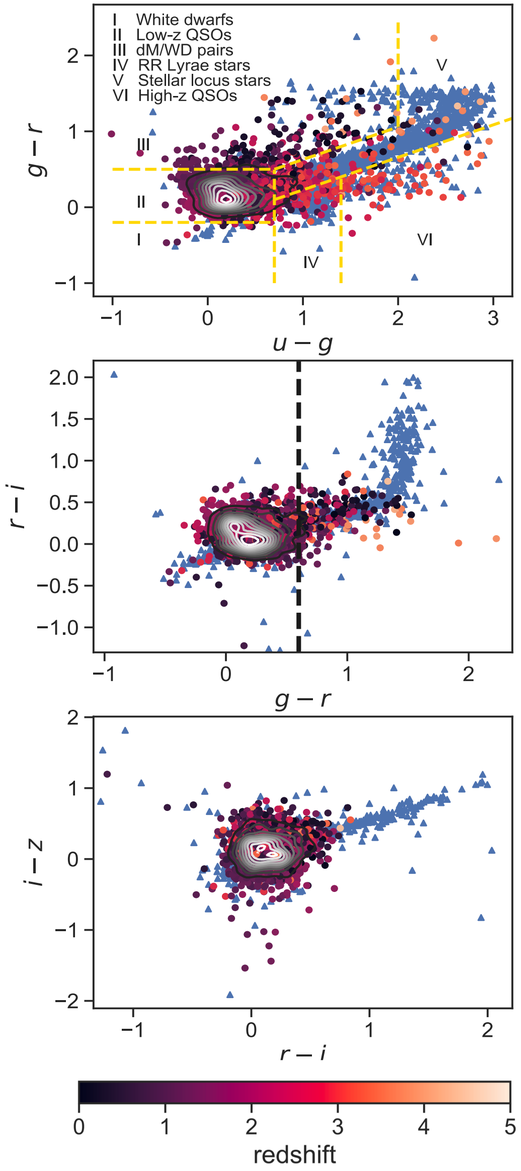
Selection of AGN candidates through optical variability

- RF2: variability features + (*r-i*) + (*i-z*)

Table 4. Feature importance

RF2	
Feature	Rank
$A_{\rm SF}$	0.209
$\sigma_{\rm rms}$	0.149
Q31	0.102
P_{var}	0.093
Std	0.088
Meanvariance	0.086
PercentAmp	0.045
Autocor–length	0.035
$\gamma_{\rm SF}$	0.031
$r-i$	0.028
MedianBRP	0.021
PeriodLS	0.020
η^e	0.019
Beyond1Std	0.019
LinearTrend	0.019
$i-z$	0.019
StetsonK	0.014
Con	0.002

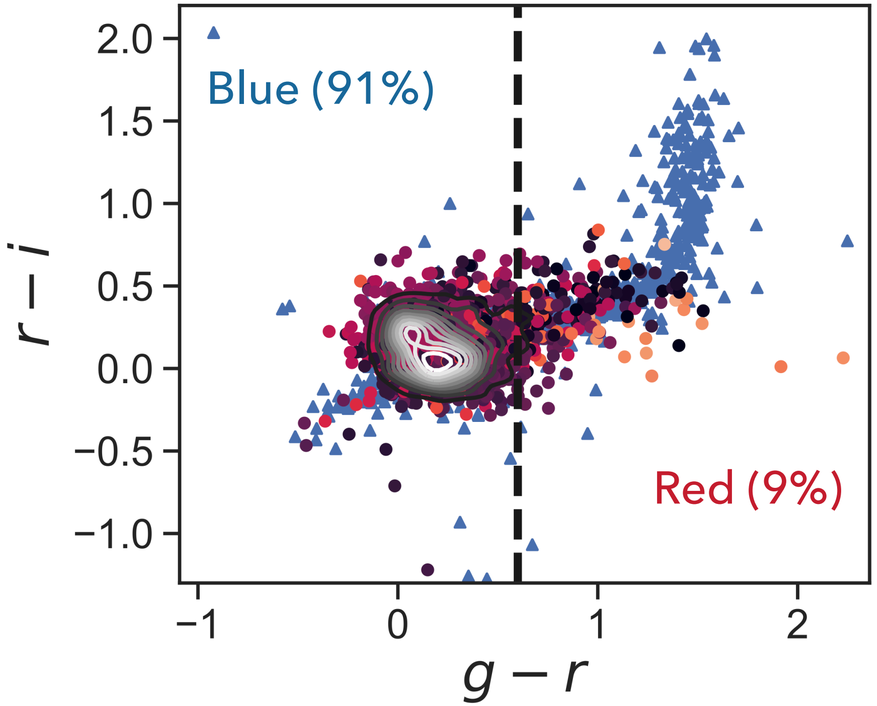




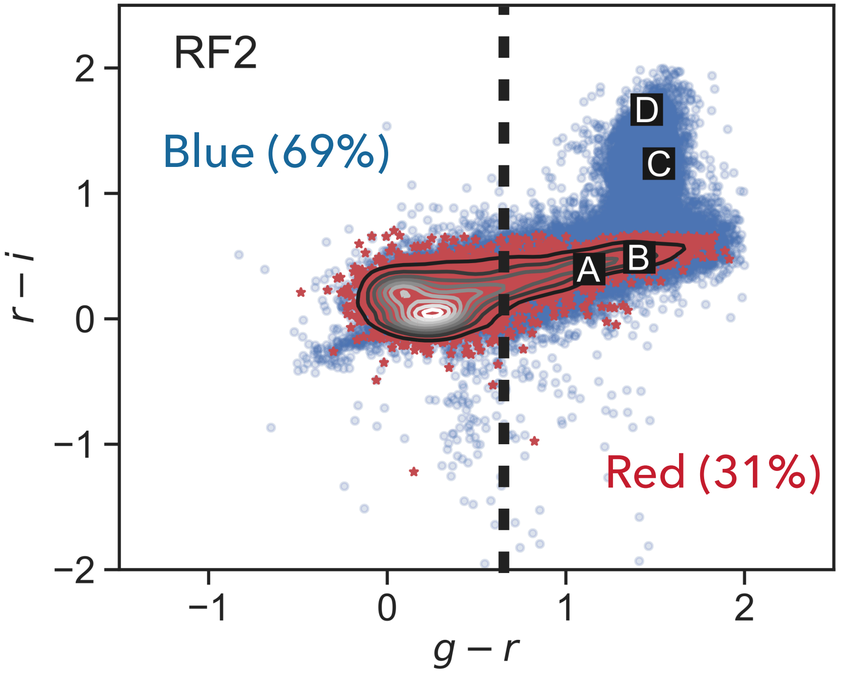
Sánchez-Sáez et al. (2019)

AGN candidates

- We obtained a sample of **5252** high probability candidates applying RF2 to the unlabeled light curves.
- We divided the candidates sample according to their $g - r$ colors, defining blue ($g - r \leq 0.6$) and red sub-samples ($g - r > 0.6$). **31%** of the RF2 candidates are in the **red sub-sample**.



Training set



Candidates

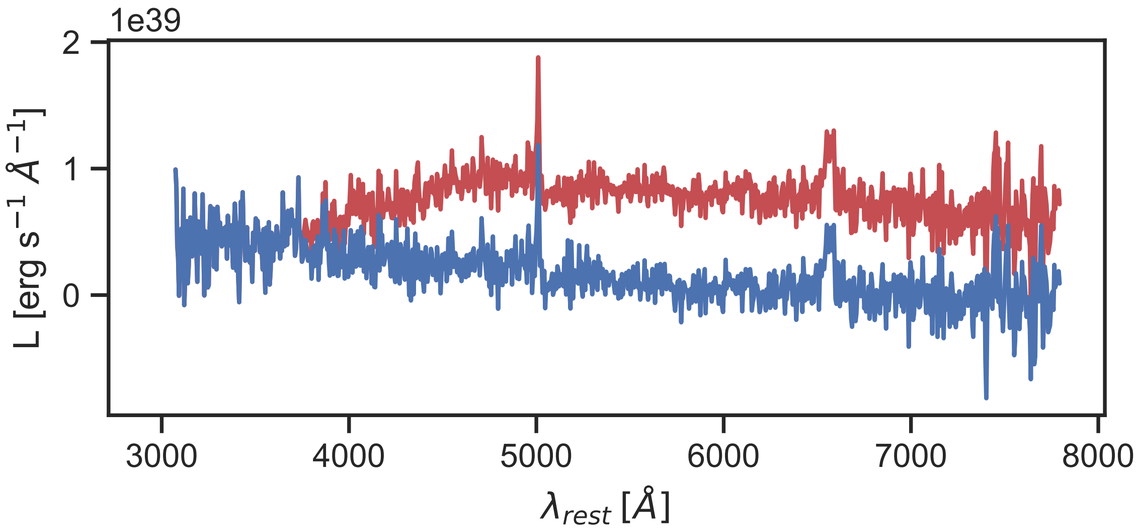
Sánchez-Sáez et al. (2019)

Confirmation of AGN candidates: follow-up

In order to test the efficiency of our technique we performed spectroscopic follow-up (with EFOCS2/NTT and GOODMAN/SOAR), **confirming the AGN nature of 43 among 50 observed candidates** (70% in the red sub-sample) from RF2 (**86%** of total efficiency).

Blue sub-sample: 100% efficiency. Red sub-sample: 79% efficiency.

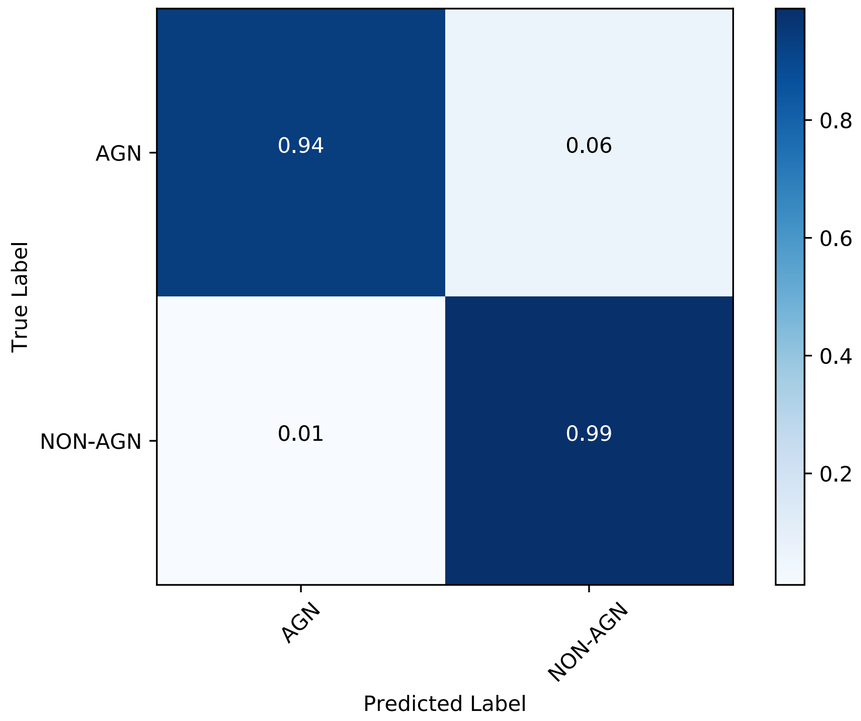
BAL-QSO	LLAGN	Z > 2.5
4	8	7



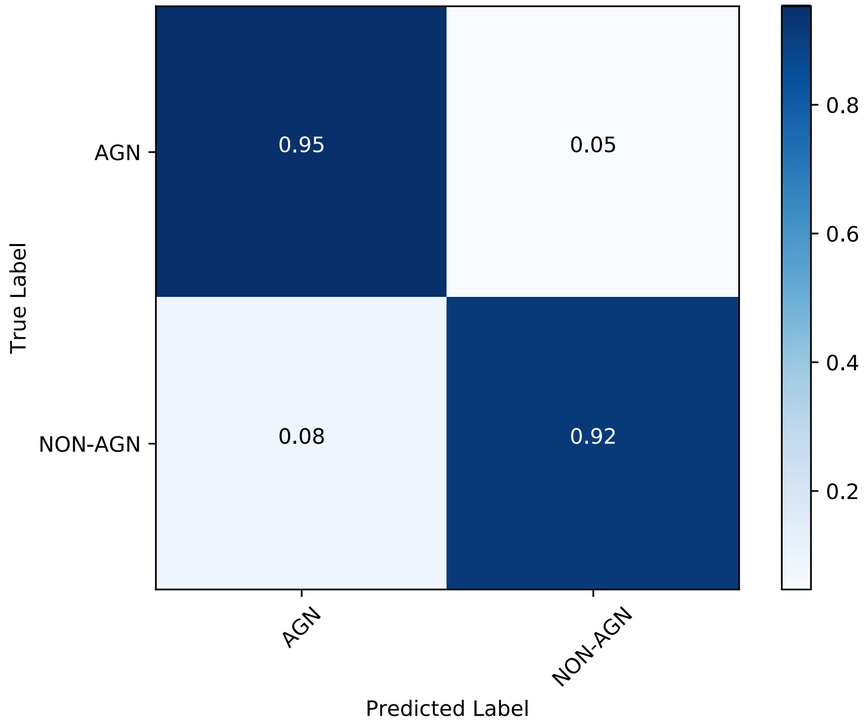
Sánchez-Sáez et al. (2019)

Applying this selection technique in other data sets **Preliminary!!!**

Optical range: VST survey of the COSMOS field (De Cicco et al. 2015, 2019)
r < 23.5



NIR: UltraVISTA survey (McCracken et al. 2012, Sánchez et al. 2017)
Y < 23.3



ALeRCE
Automatic Learning for the Rapid Classification of Events

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ZTF → LSST

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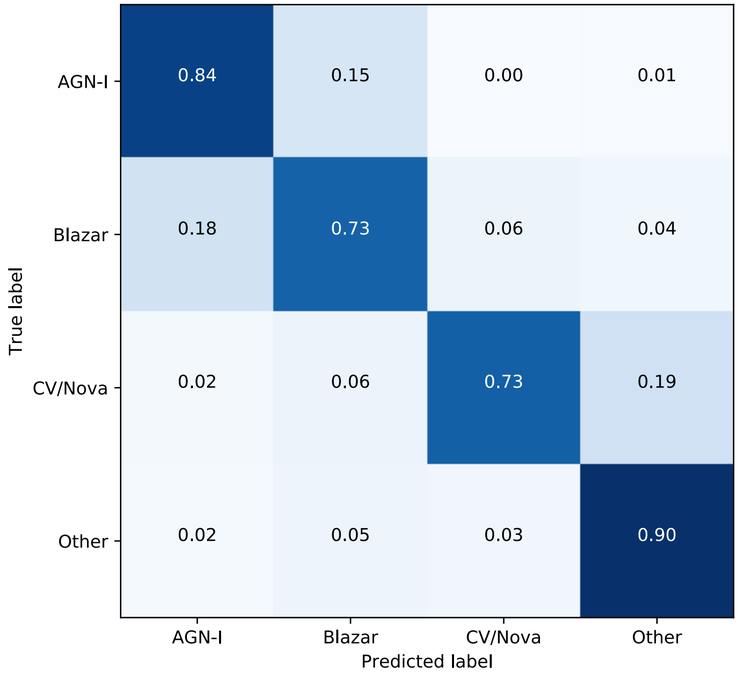
ZTF



Preliminary!!!

Sánchez-Sáez et al. (in prep)

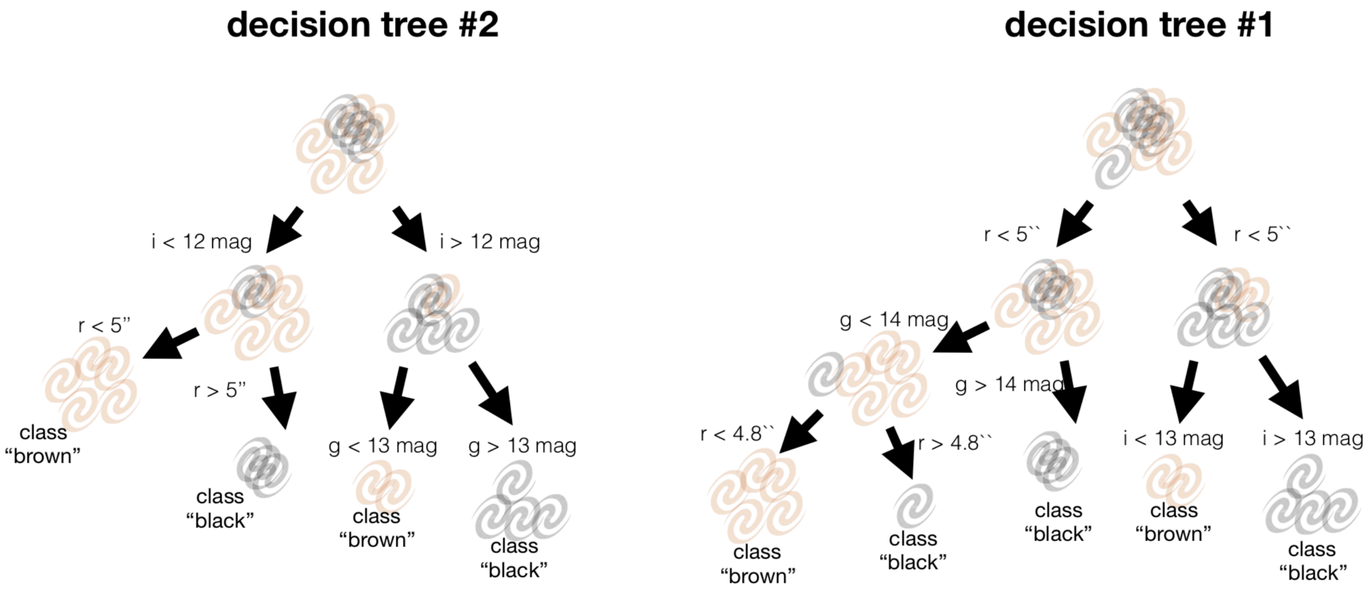
Summary

- The amplitude of the variability (A) depends primarily on the rest frame emission wavelength and the Eddington ratio, where A anti-correlates with both λ_{rest} and L/L_{Edd}.
- We can use AGN variability to improve the selection of AGN candidates, particularly, for the case of targets with extended shapes, targets whose colors are dominated by the host galaxy, high redshift sources, and BAL-QSO.
- The the optimal classifier includes variability features, like the structure function, and the the r-i and i-z optical colors.
- We can apply our variability-based technique in other data sets (e.g. optical and NIR data)
- We are working on a variability-based classifier that can separate Blazars and AGN.

Selection of AGN candidates through optical variability

We implemented a **Random Forest** algorithm to classify our objects as either AGN or non-AGN according to their variability features and optical colors, excluding morphology cuts.

Random Forest is an ensemble of decision trees



Sánchez-Sáez et al. (2019)

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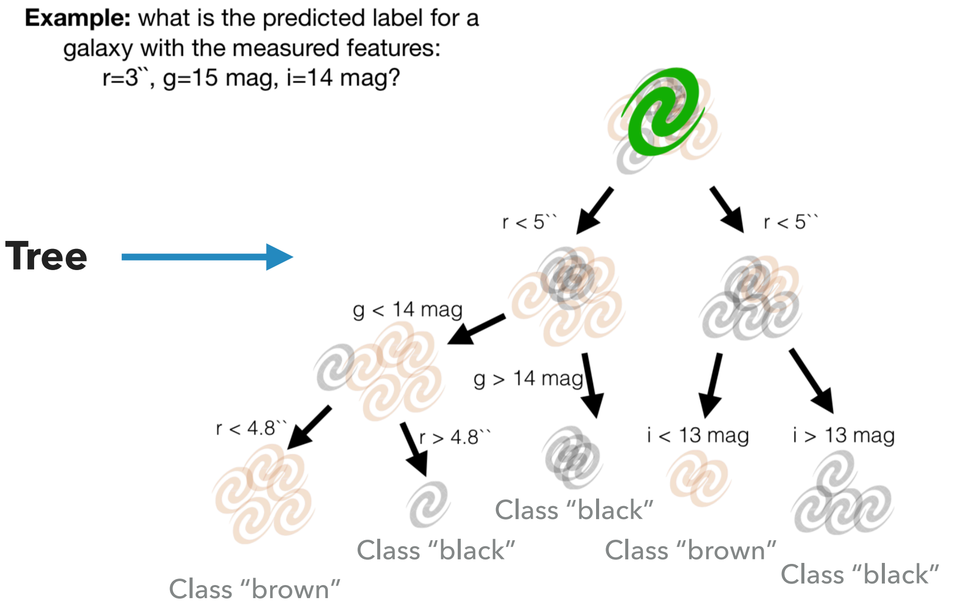
Decision Tree



Credits: Dalya Baron (Tel Aviv University)

Sánchez-Sáez et al. (2019)

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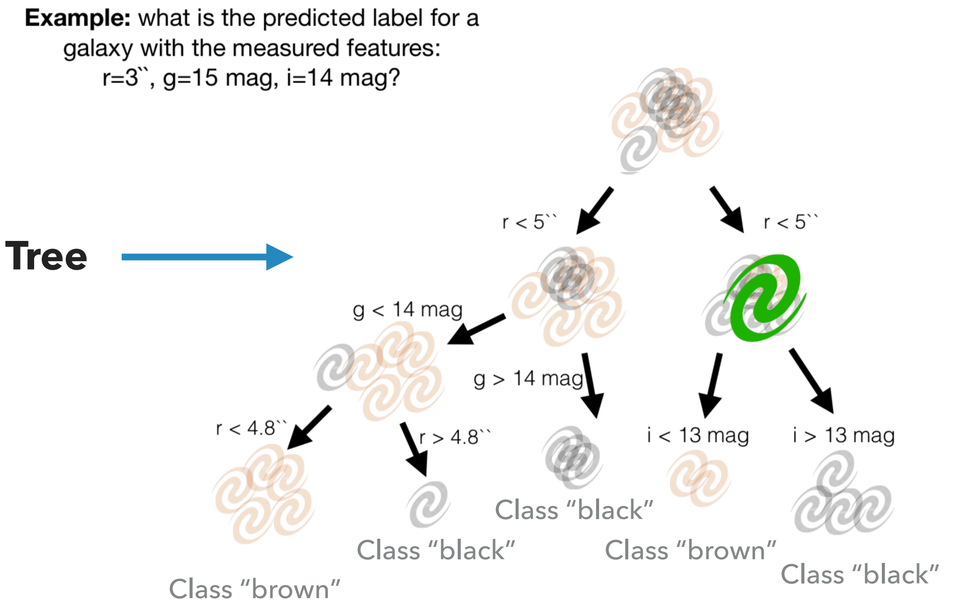

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Selection of AGN candidates through optical variability

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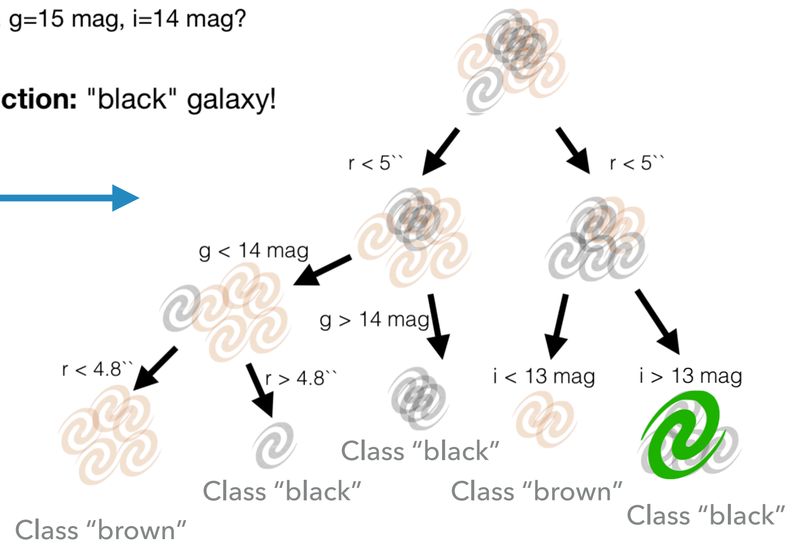
Random Forest is an ensemble of decision trees

Example: what is the predicted label for a galaxy with the measured features: r=3``, g=15 mag, i=14 mag?

Prediction: "black" galaxy!

Decision Tree



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Sánchez-Sáez et al. (2019)