AGN Selection and Characterization in Next-Generation (UV/Optical) Time-Domain Surveys

Weixiang Yu

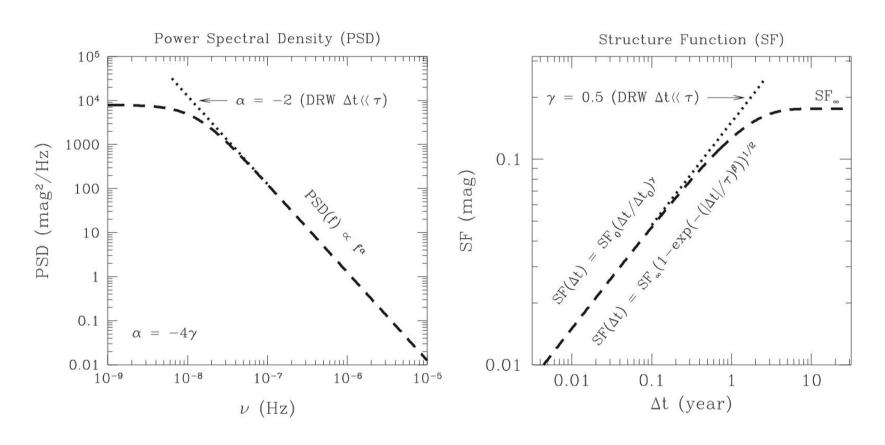
Drexel University => Bishop's University

Mentors/Collaborators: Gordon Richards, Michael Vogeley, Jackie Moreno, Matthew Graham, and the entire LSST AGN Science Collaboration

AGN UV/Optical Variability Characterization



Power Spectral Density & Structure Function



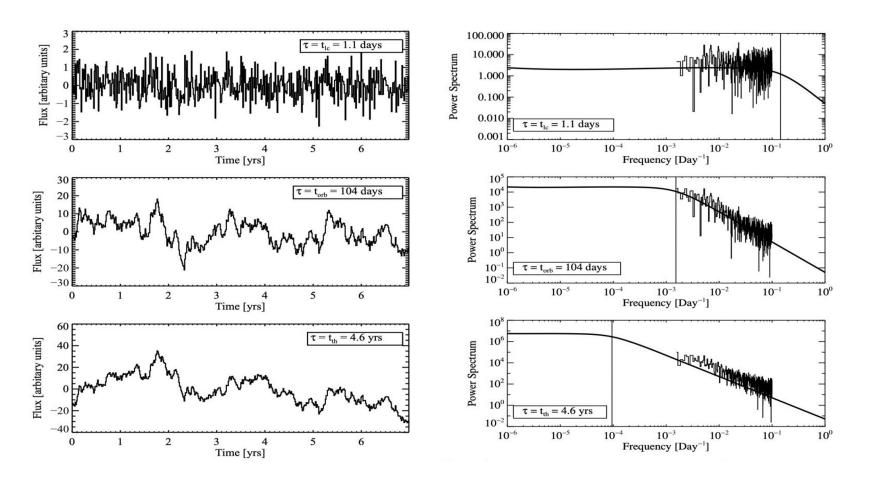
Kozlowski+16



The Damped Random Walk - A Generative Process

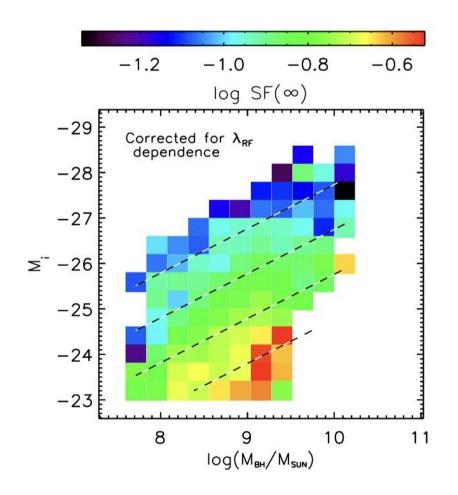
$$dX(t) = -\frac{1}{\tau}X(t)dt + \sigma\sqrt{dt}\epsilon(t) + b\ dt,$$

Kelly+09

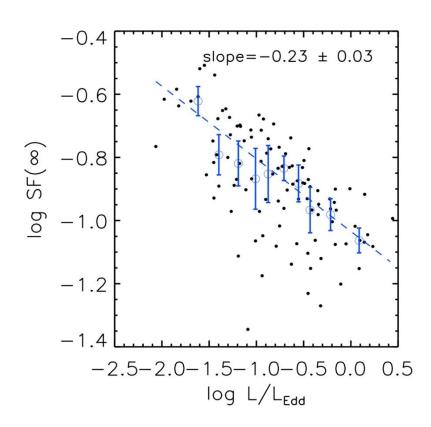




SF_∞-L/L_{Edd} Correlation



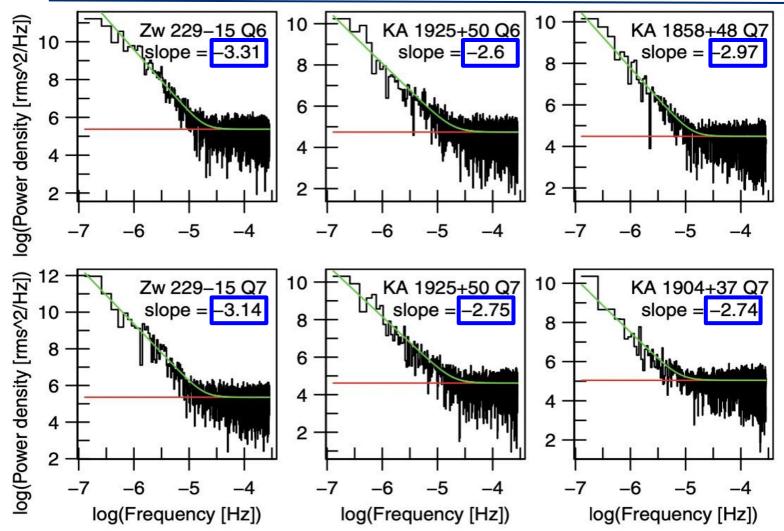
$$SF_{\infty} = \sqrt{2} * \sigma_{DRW}$$



MacLeod+10, Suberlak+21



Is DRW Enough?



Mushotzky+11; also Edelson+14, Kashiwal+15, Smith+18



Alternative Models?

Continuous-Time Autoregressive Moving-Average (CARMA)

$$\mathrm{d}^p X(t) + lpha_1 \mathrm{d}^{p-1} X(t) + \dots + lpha_p X(t) \ = eta_0 \epsilon(t) + eta_1 \mathrm{d}(\epsilon(t)) + \dots + eta_q \mathrm{d}^q (\epsilon(t))$$

Kelly+14, Kasliwal+17 Caplar+17, Goyal+18 Stone+22

CARMA(1,0) => Damped Random Walk (DRW)

$$\mathrm{d}X(t) + lpha_1 X(t) = eta_0 \epsilon(t)$$
 \Longrightarrow $\mathrm{d}X(t) + rac{1}{ au} X(t) = \sigma \, \epsilon(t)$

❖ CARMA(2,1) => Damped Harmonic Oscillator (DHO)

$$\mathrm{d}^2 X(t) + lpha_1 \mathrm{d} X(t) + lpha_2 X(t) = eta_0 \epsilon(t) + eta_1 \mathrm{d} (\epsilon(t))$$

Kasliwal+17, Moreno+19, Yu+22

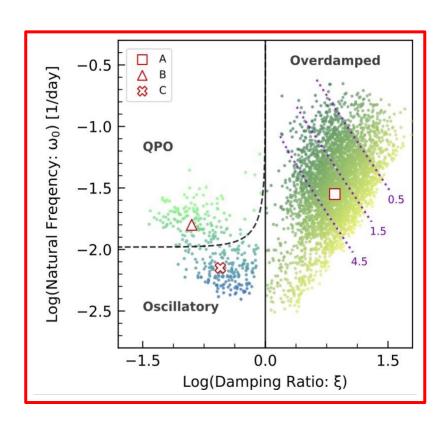
Deep Learning

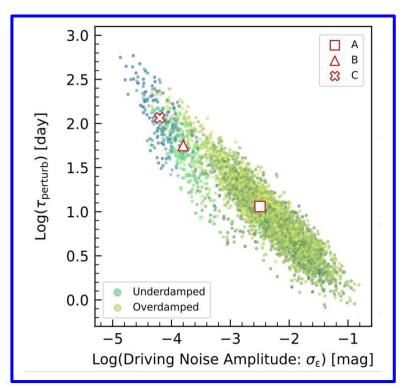
See Tachibana+20, Cvorovic-Hajdinjak+22, Sheng+22, Fagin+23



DHO & SDSS Stripe 82 Quasars

$$\mathrm{d}^2 X(t) + 2 \xi \omega_0 \mathrm{d} X(t) + \omega_0^2 X(t) = \sigma_\epsilon \epsilon(t) + \sigma_\epsilon au_\mathrm{perturb} \ \mathrm{d}(\epsilon(t))$$



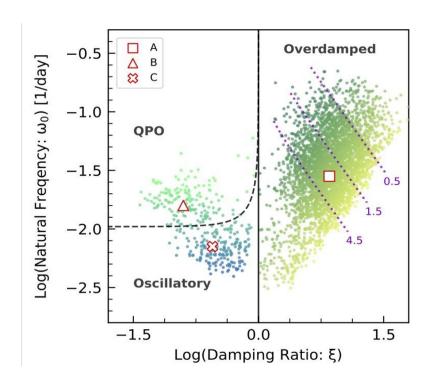


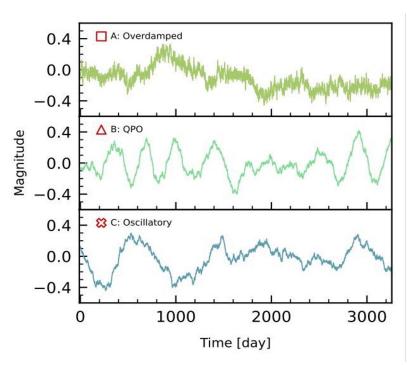
Yu+22 (ApJ, 936, 132)



AGN Stochastic Variability Captured By DHO

$$\mathrm{d}^2 X(t) + 2 \xi \omega_0 \mathrm{d} X(t) + \omega_0^2 X(t) = \sigma_\epsilon \epsilon(t) + \sigma_\epsilon au_\mathrm{perturb} \mathrm{d} (\epsilon(t))$$

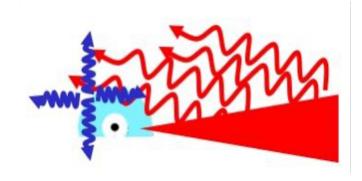


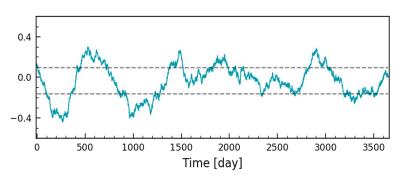




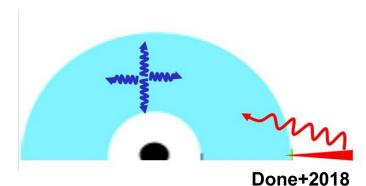
Variability & Accretion Flows

weak corona & strong disk => more disk variability





strong corona & weak disk => more X-ray variability



0.4 0.0 -0.4 0 500 1000 1500 2000 2500 3000 3500 Time [day]



DHO in a Perturbation-Response Framework

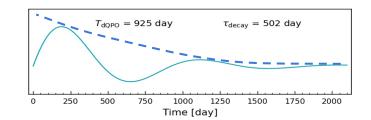
$$\mathrm{d}^2 X(t) + 2 \xi \omega_0 \mathrm{d} X(t) + \omega_0^2 X(t) = \sigma_\epsilon \epsilon(t) + \sigma_\epsilon au_\mathrm{perturb} \ \mathrm{d}(\epsilon(t))$$

Underdamped:

$$- (2\xi\omega_0)^2 - 4*\omega_0^4 < 0$$

- T_{dqpo} , au_{decay} from LHS



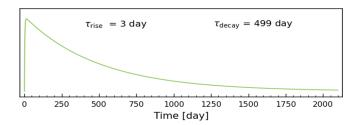


Overdamped:

$$-(2\xi\omega_0)^2-4*\omega_0^4>0$$

- τ_{rise} , τ_{decay} from LHS

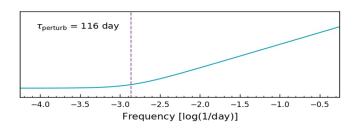




Underdamped & Overdamped

 σ_{ϵ} , $au_{ ext{perturb}}$ from RHS







Underdamped DHOs

$$\mathrm{d}^2 X(t) + 2 \xi \omega_0 \mathrm{d} X(t) + \omega_0^2 X(t) = \sigma_\epsilon \epsilon(t) + \sigma_\epsilon au_\mathrm{perturb} \ \mathrm{d}(\epsilon(t))$$

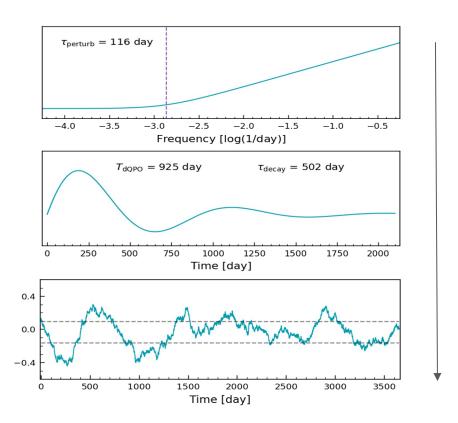
$$(2\xi\omega_0)^2-4*\omega_0^4=\xi^2-1<0$$

- σ_{ϵ} , $au_{perturb}$ from RHS
- T_{dqpo} , τ_{decay} from LHS

$$\sigma_{ ext{DHO}} = \sigma_{\epsilon} \sqrt{rac{\omega_0^2 au_{ ext{perturb}}^2 + 1}{2 \xi \omega_0^3}}$$

weak corona & strong disk







Overdamped DHOs

$$\mathrm{d}^2 X(t) + 2 \xi \omega_0 \mathrm{d} X(t) + \omega_0^2 X(t) = \sigma_\epsilon \epsilon(t) + \sigma_\epsilon au_\mathrm{perturb} \ \mathrm{d}(\epsilon(t))$$

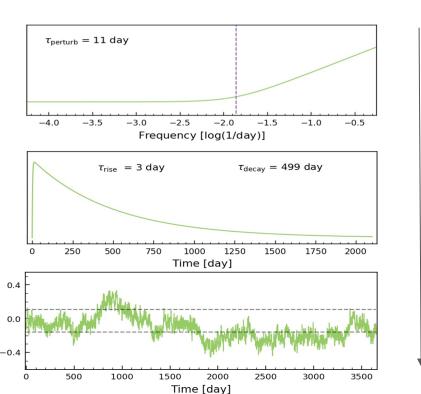
$$(2\xi\omega_0)^2-4*\omega_0^4=\xi^2-1>0$$

- σ_{ϵ} , τ_{perturb} from RHS
- τ_{rise} , τ_{decay} from LHS

$$\sigma_{ ext{DHO}} = \sigma_{\epsilon} \sqrt{rac{\omega_0^2 au_{ ext{perturb}}^2 + 1}{2 \xi \omega_0^3}}$$

strong corona & weak disk







Sanity Check: Are the Fits Robust?

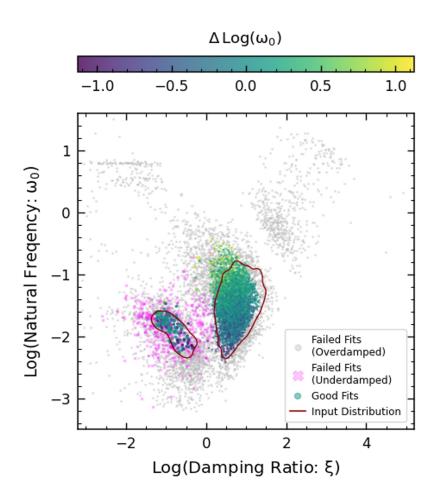


Table 1. DHO Classification Purity (Recall)

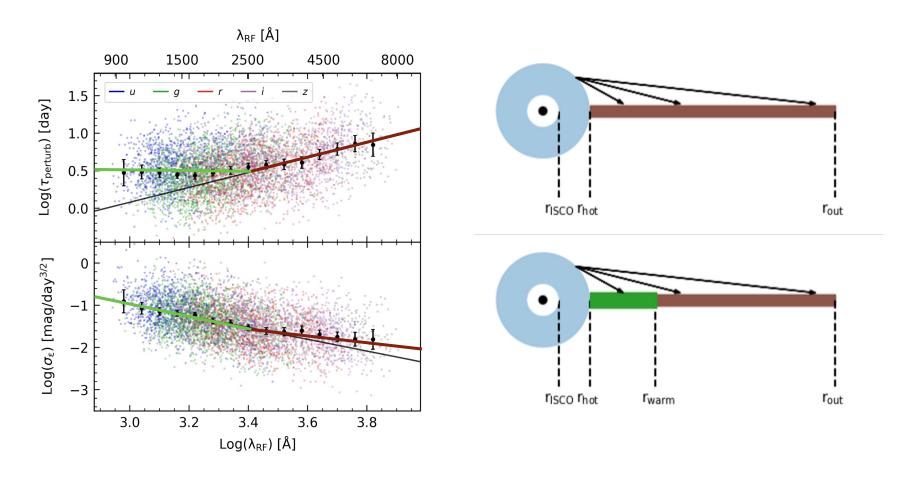
band	Underdamped DHO		Overdamped DHO	
u		(100.00)		(90.65)
g		(100.00)		(97.56)
r		(92.68)	99.93	(97.90)
i	24.16	(100.00)	100.00	(96.58)
\mathbf{z}	9.18	(100.00)	100.00	(87.85)

$$\operatorname{Purity}(\operatorname{Over}) = rac{\#\operatorname{True}\operatorname{Overdamped}}{\#\operatorname{Best-fit}\operatorname{Overdamped}}$$

$$Recall(Over) = \frac{\# Best-fit Overdamped}{\# Simulated Overdamped}$$



Probing Accretion Flow Geometry

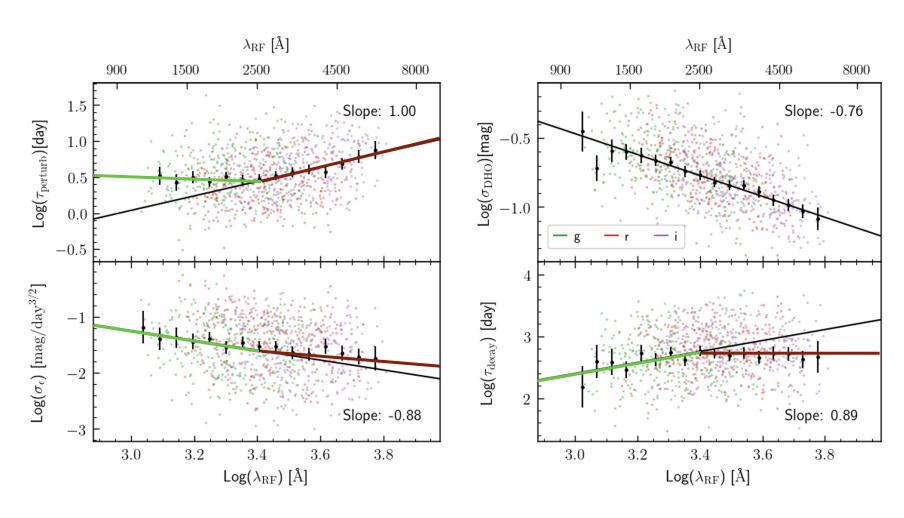


Yu+22 (ApJ, 936, 132)

Kubota+18

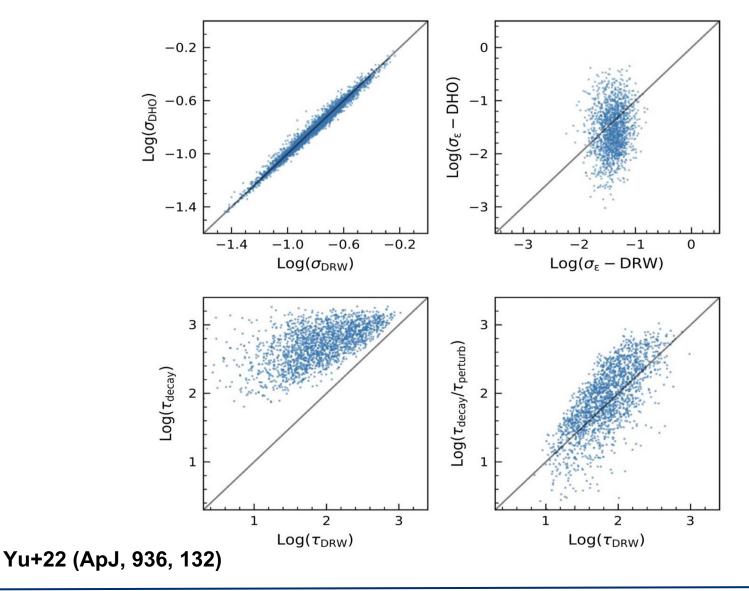


SDSS-PS1 (Preliminary)



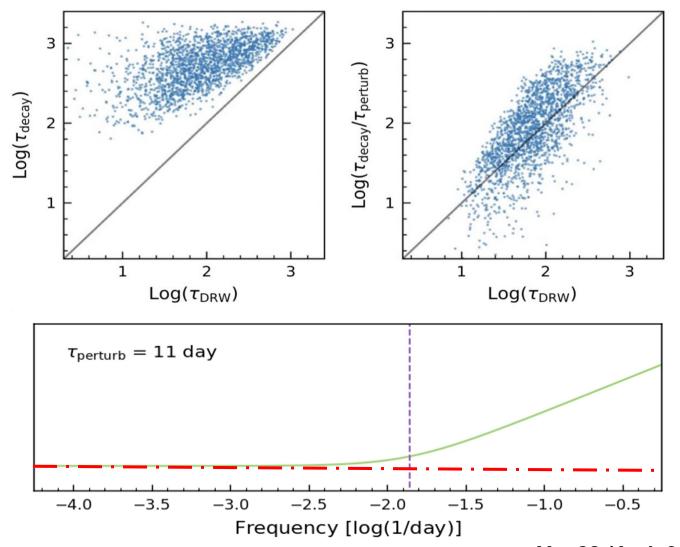
Yu+23 (in prep)





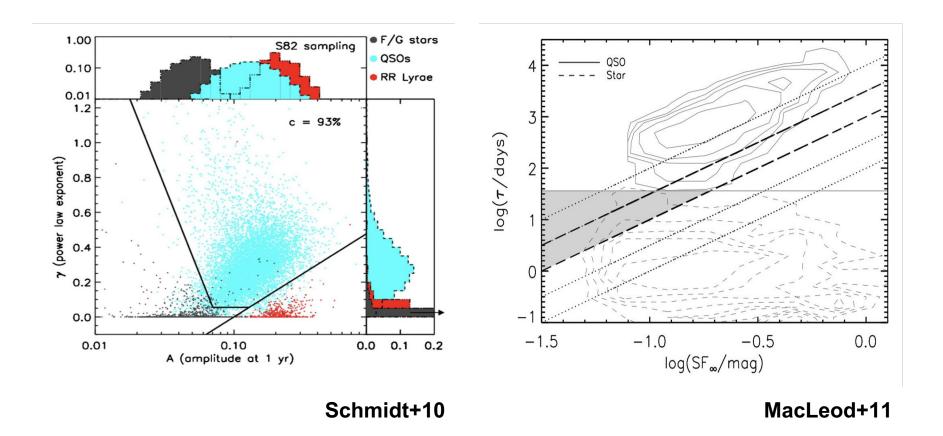


DHO vs DRW



AGN Selection via UV/Optical Variability

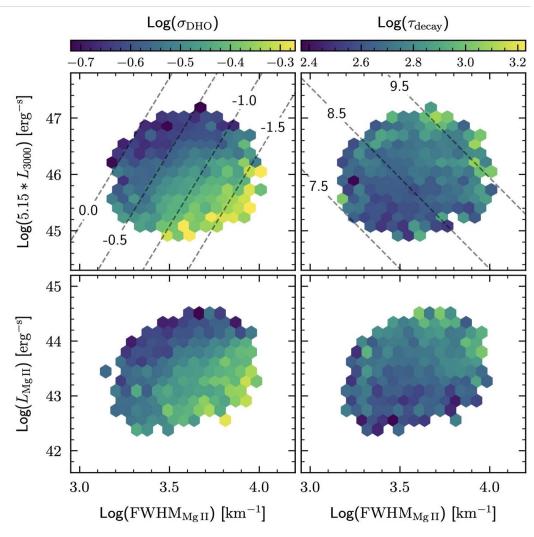




Also see Bulter & Bloom+11, Palanque-Delabrouille+11, Choi+14, Graham+14, Peters+15, Zinn+17, De Cicco+19.



AGN Sub-Classification



See poster from Priscilla Behar

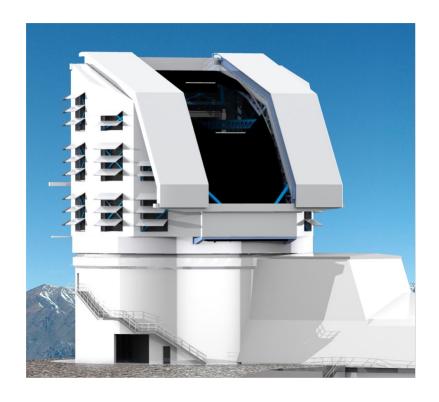
See talks from
Paula Sanchez Saez
Robbie Webbe
Summer McLaughlin

Yu+23 (in prep)

AGN Selection and Characterization in Next-Generation (UV/Optical) Time-Domain Surveys



Rubin Observatory LSST



- 18,000 square degrees
- 40 billion sources
- > 100 million AGNs

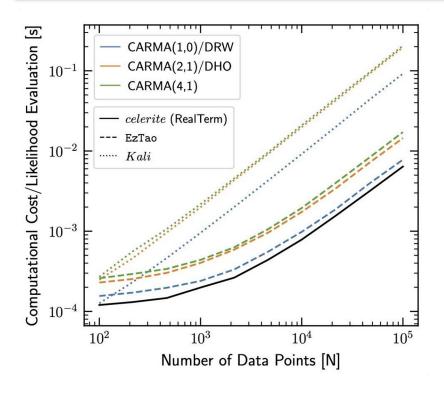
- 825 vistis over 10 years
- ugrizY bands
- 1% photometric accuracy





♂EzTao (易道)

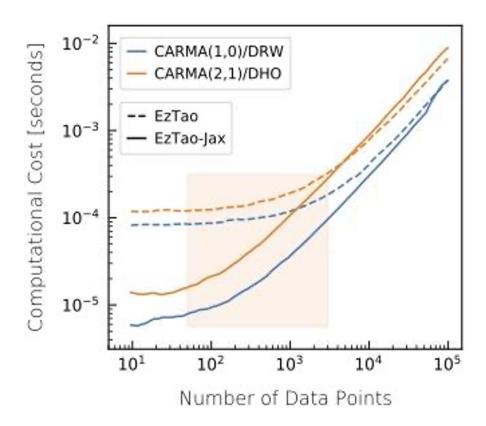
EzTao is a toolkit for conducting AGN time-series/variability analysis, mainly utilizing the continuous-time autoregressive moving average model (CARMA)



- A factor of 10 speed up for inference
- Fast light curve simulation
- Pip installable
- Custom optimizer
- Custom MCMC
- Unit-tested
- Documentation + tutorials



EzTao-Jax (work in progress)



- Utilizing JAX from Google
- Just-in-time (JIT) compilation
- Automatic differentiation
- A factor 5 to 10 speedup for LSST-like light curves
- Allows simultaneous fitting of CARMA and other GP kernels
- Multi-band fitting
- Integration with major DL frameworks
- ...



Main Takeaways

- Direct light curve modeling is useful for AGN characterization and selection, **but** extra care should be taken when quoting the best-fit parameters obtained with maximum likelihood (a posteriori).
- Given the superior light curves from future time-domain surveys, we can and should go beyond the simple DRW, such as, higher-order CARMA models or deep neural networks.
- We are entering a new regime of AGN sub-classification, and more robust variability modeling will help achieve that.
- Future algorithm/tool development needs to put more weight on scalability and integrability.



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