Deep Learning Engines for LSST AGN photometric reverberation mapping

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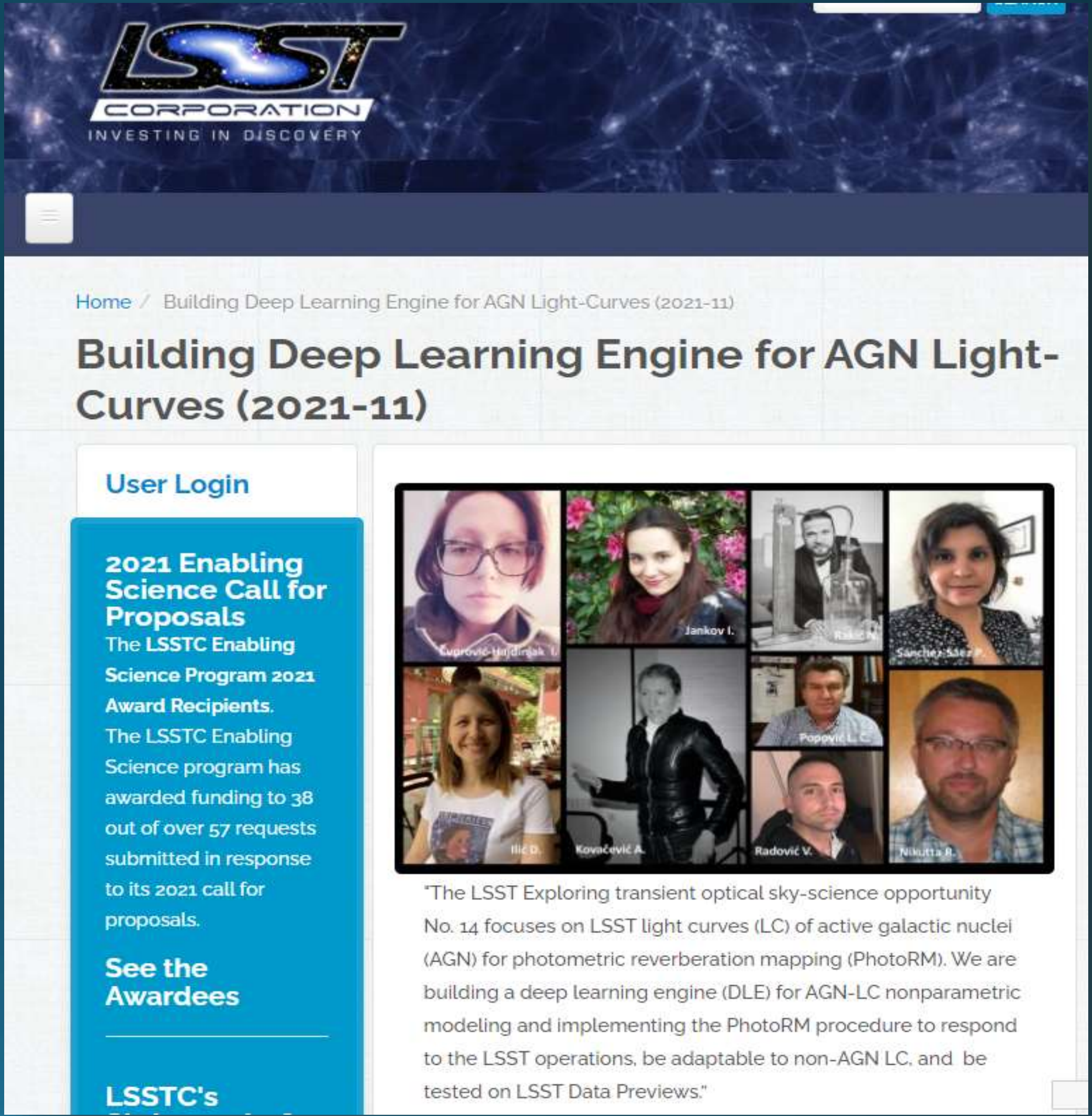
The 2021 Summer Meeting of the LSST
Active Galactic Nuclei Science Collaboration

Introduction

- Exploring transient optical sky (ETOS) is among four Rubin Observatory LSST key science drivers (Ivezić et al. 2019).

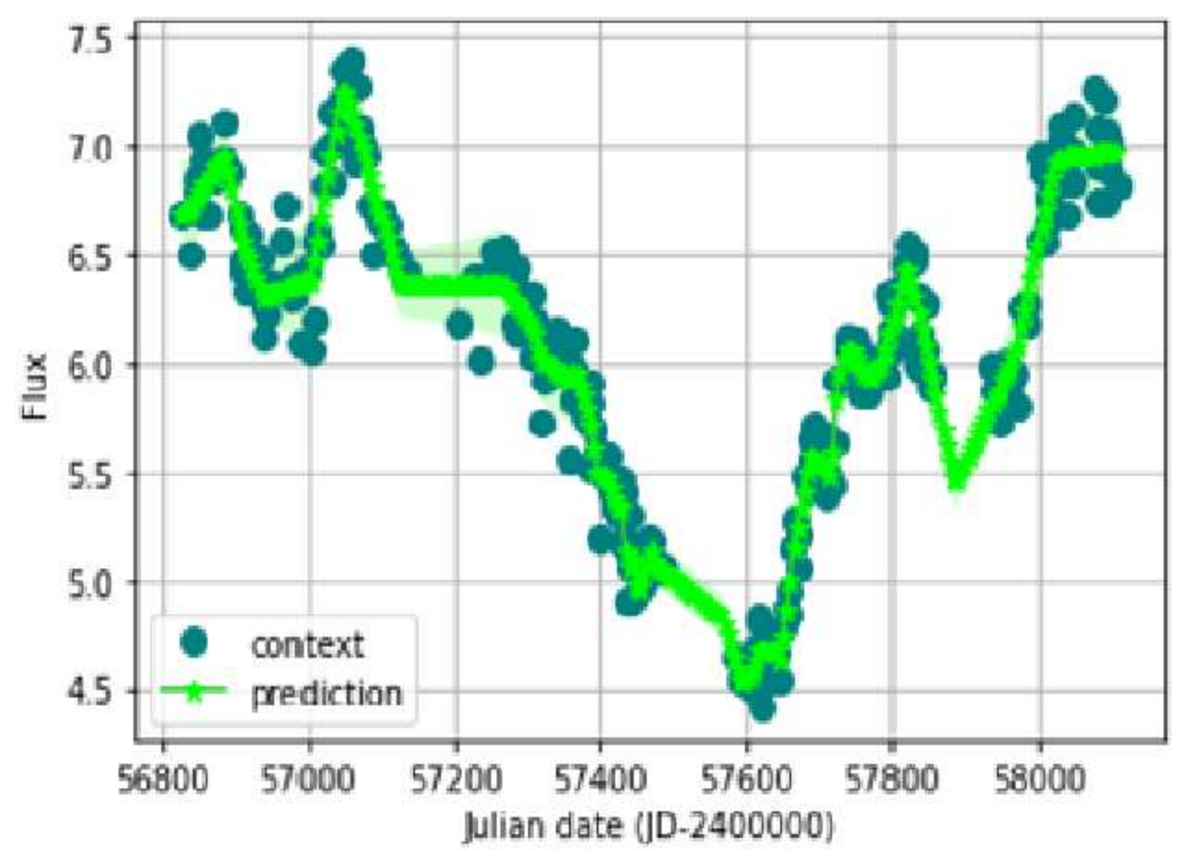
- **Our motivation:** the ETOS LSST science opportunity #14 (sec 4, Ivezić et al. 2019),

- **Our goal:** build a deep learning engine (DLE) for LC nonparametric modeling and implementation of the PhotoRM procedure to respond to the observing strategy of the LSST (Jones et al. 2020).



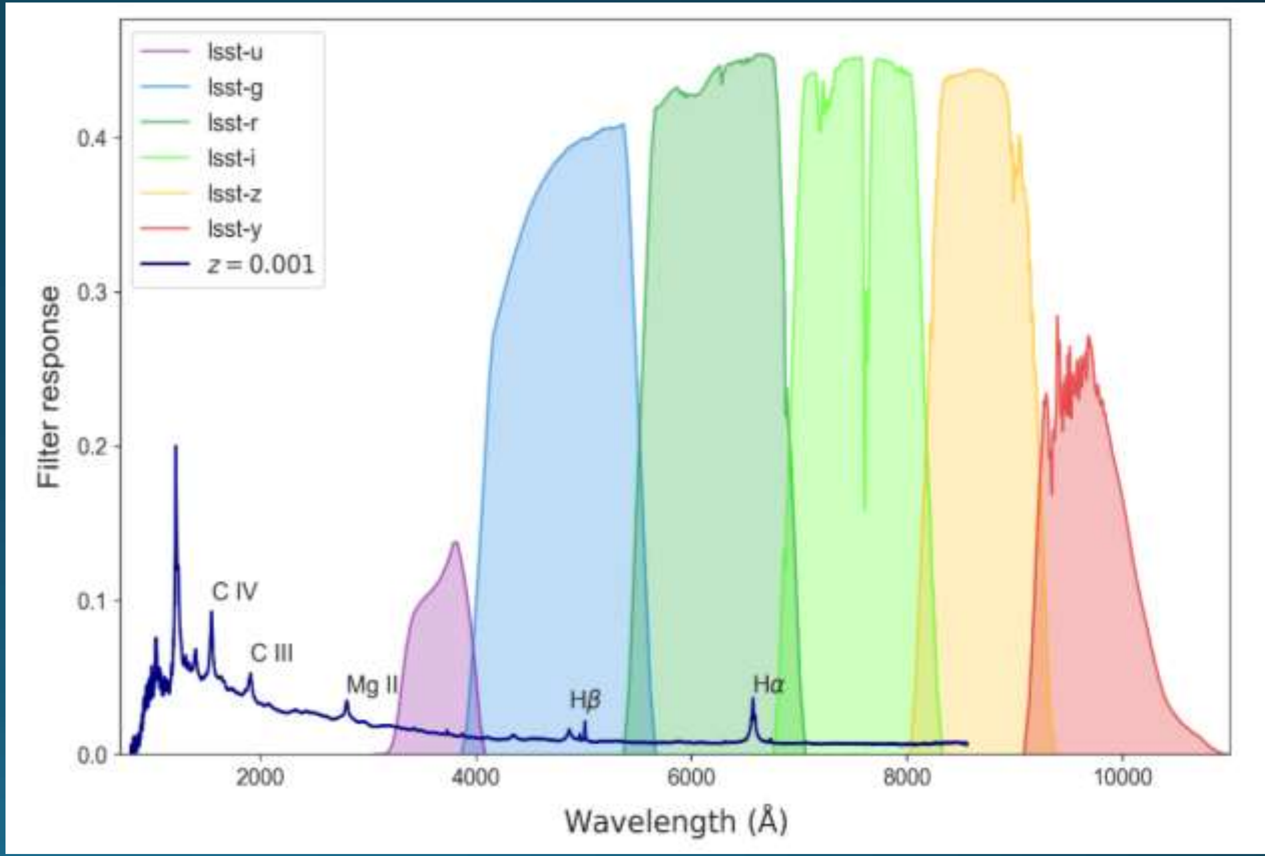
Subtasks

DLE subtask 1 (DLE1): LC nonparametric modeling (Conditional Neural Process)



Learned LC will enable us to improve time-lag determination as a goal of PhotoRM.

DLE subtask 2 (DLE2): photometric reverberation mapping (PhotoRM)



New tools for PhotoRM based on the formalism by Chelouche & Daniel (2012)

Deep Learning Engine (DLE1)

AGN light curves difficult to analyze

- sparse
- gaped
- irregular
- nonlinear
- stochastic

⇩

Modeling tools

- Damped Random Walk (*Kozlowski 2016, Kelly et al. 2009*)
- Gaussian Process with different kernels (*Shapovalova et al. 2001-2019, Kovačević et al. 2018*)
- Autoencoder neural network (*Tachibana et al. 2020*).

DLE1

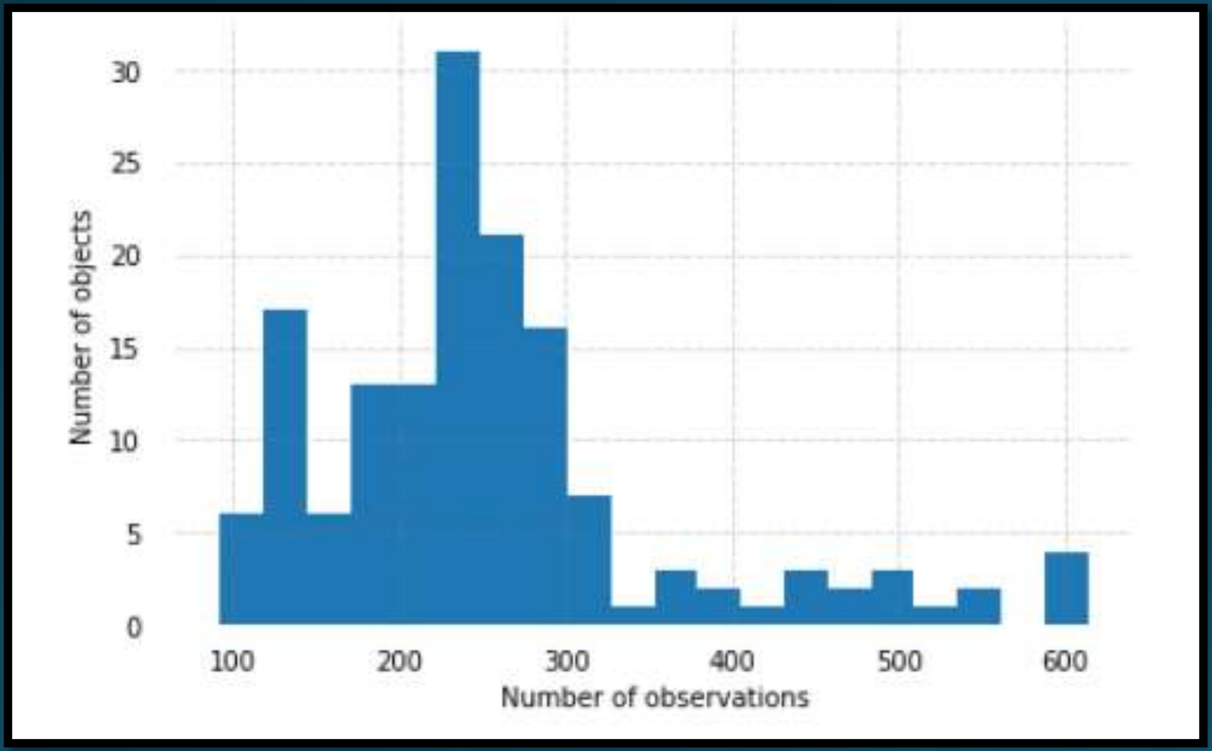
- applicable for modeling stochastic data
- incorporates ideas from GP into a neural network training regime (*Garinelo et al. 2018*)

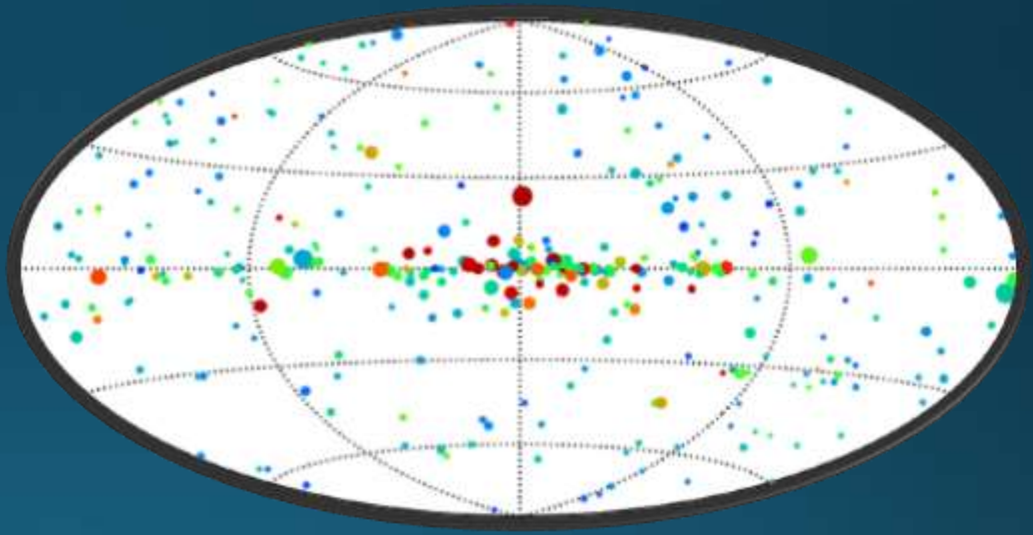
⇩

Learned AGN light curves

Data

- optical AGN light curves taken from ASAS-SN survey as a follow up for 153 AGNs detected in the first 9 months of all sky survey by BAT X-ray survey
- homogenous data which covers up to 5.5 years long period
- possible flares, quasi-periodic oscillations, gaps, irregular points density

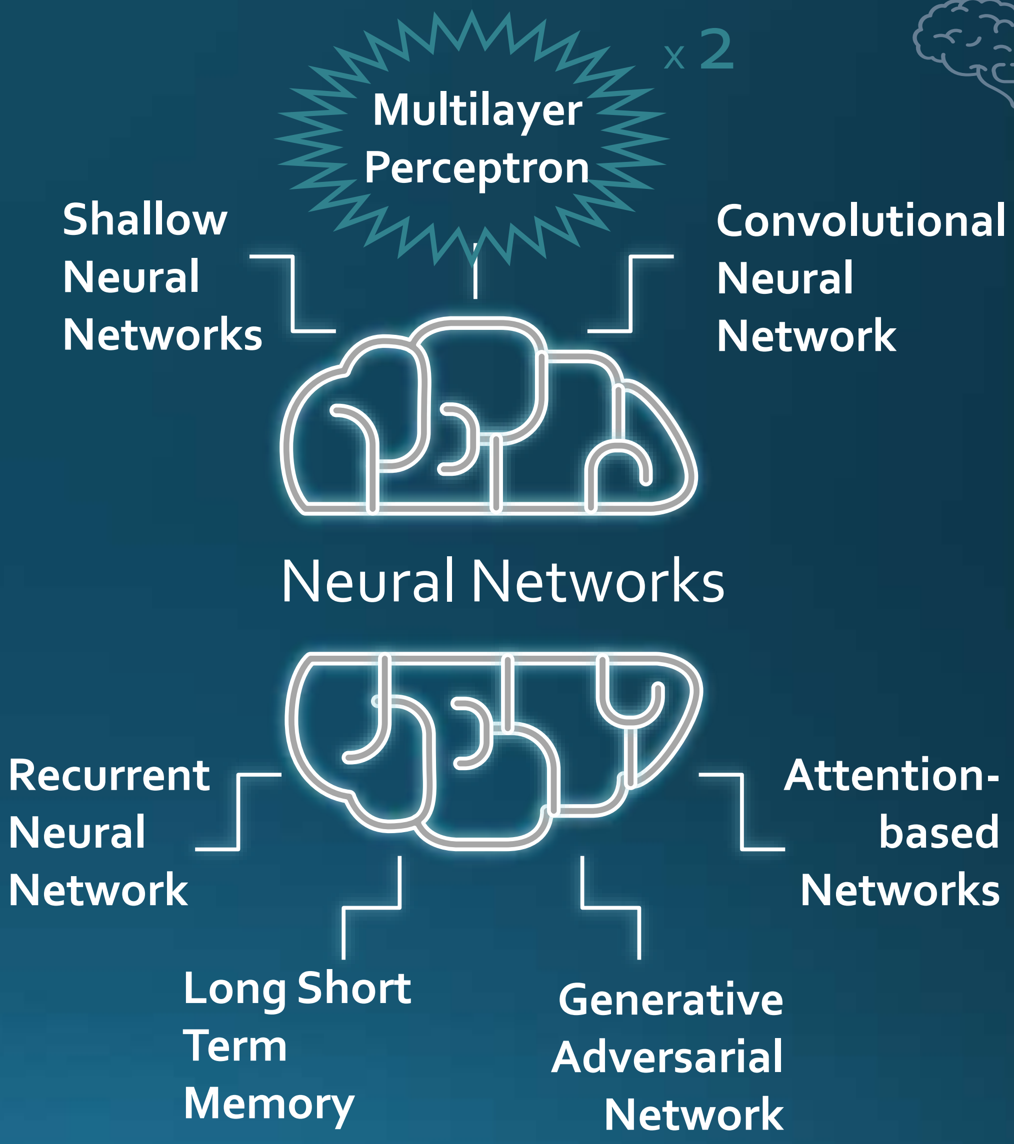




Red dots are soft sources, blue are hard sources, and the dot diameter is proportional to the source flux (taken from https://swift.gsfc.nasa.gov/results/bs9mon/).

Deep Neural Network

- Deep learning offers a way to model nonlinear behavior based on data-learnt representations and promises new insights into the underlying physical processes.
- In our work we have used CNP as supervised training via gradient descent in attempt to approximate function given a finite set of observations.
- This is the first attempt to examine applicability of CNP on AGN light curve modeling.



Conditional Neural Process

encoder: e

aggregator: a

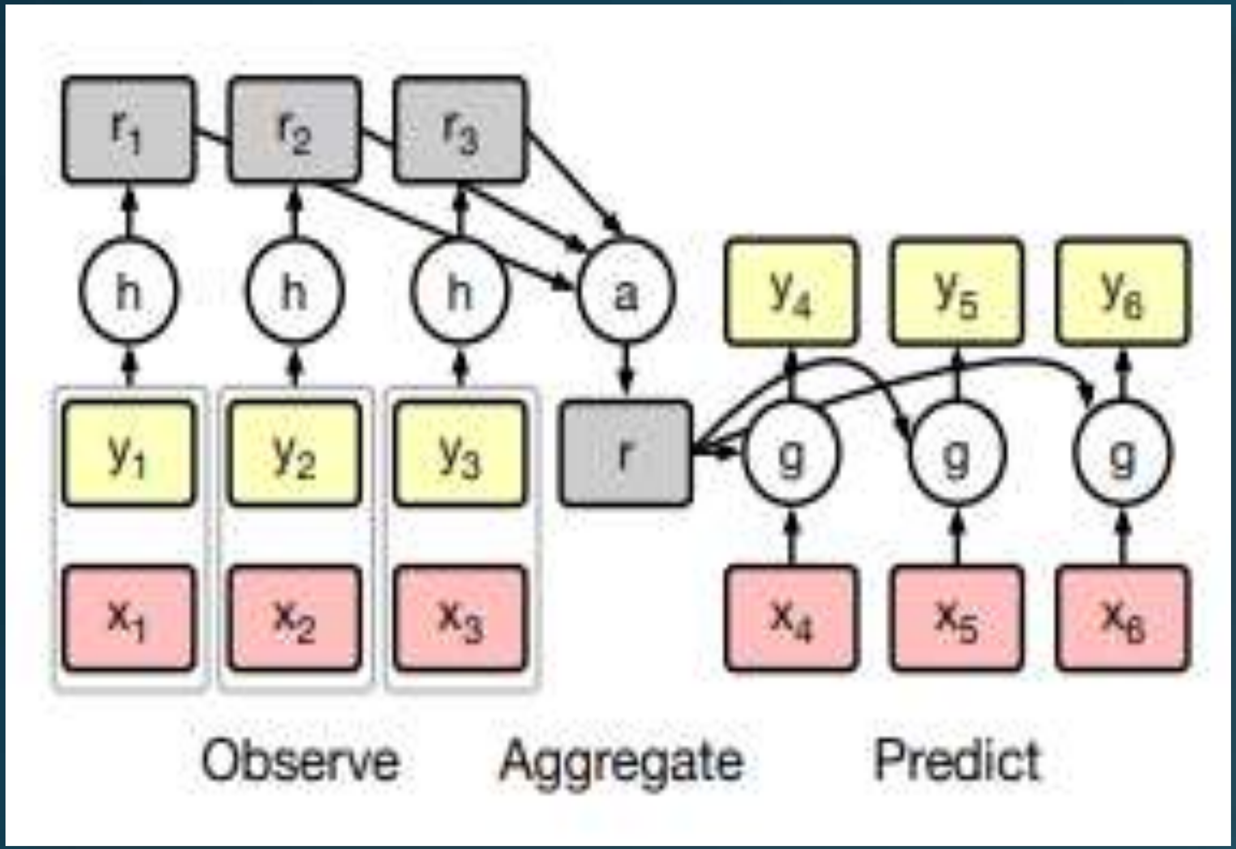
decoder: d

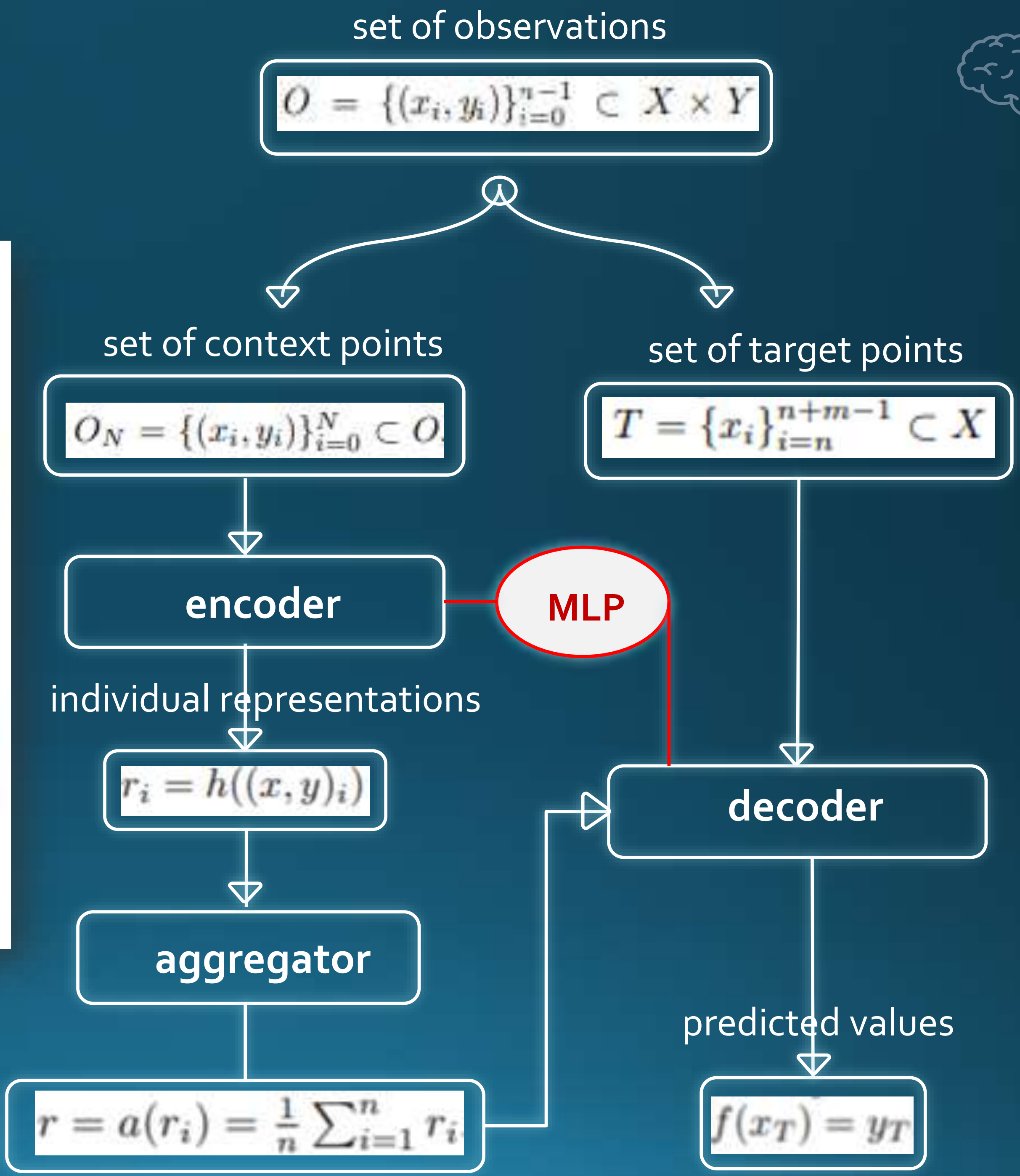
target values:
red dots

unknown function:
blue line

output:
mean and
variance

Calculation protocol





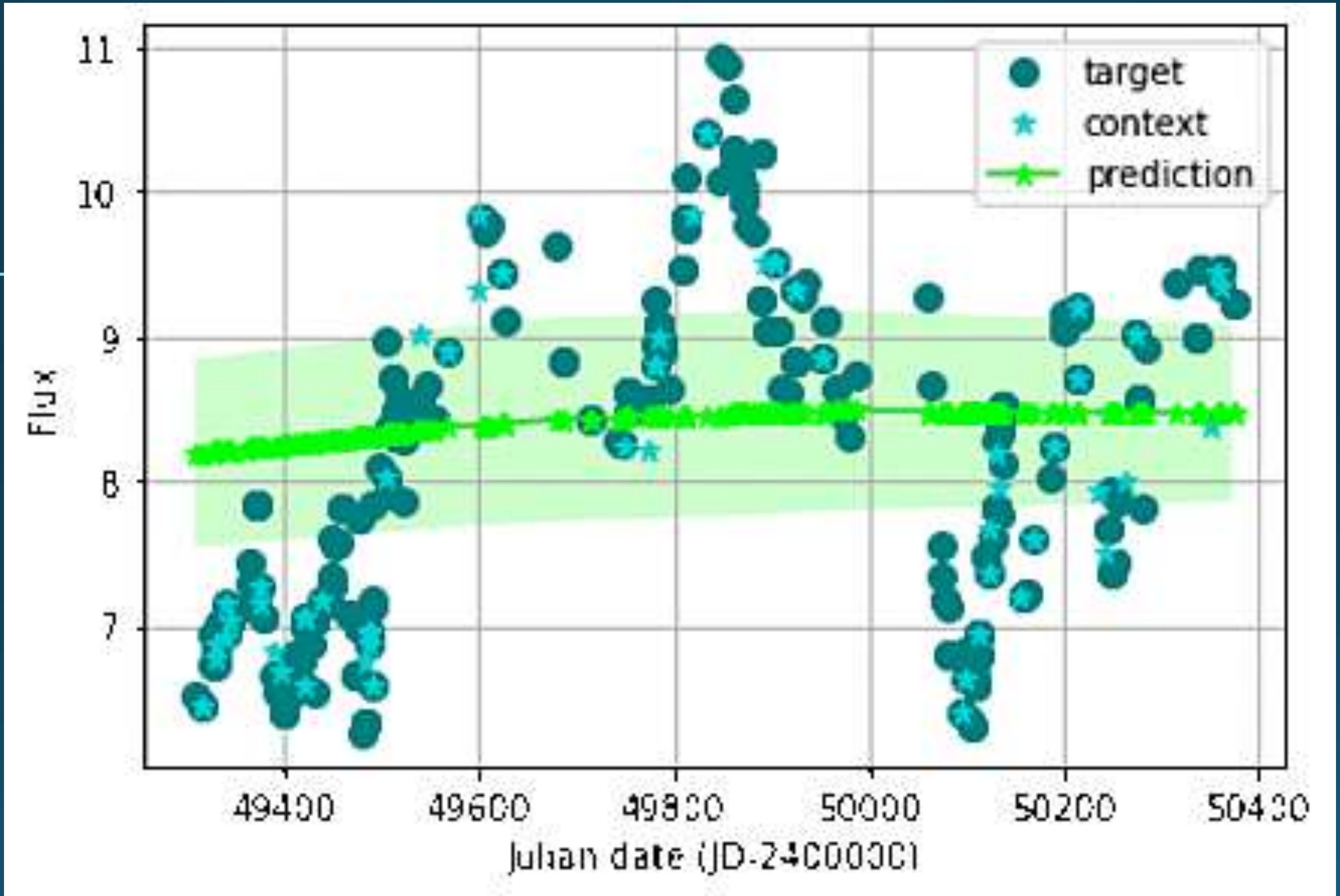
h is functional representation of encoder *e*
g is functional representation of decoder *d*
(*Garinelo et al. 2018*)

Results

25 000 iterations

loss: 0.19258184

flux units mJy



230 observed points

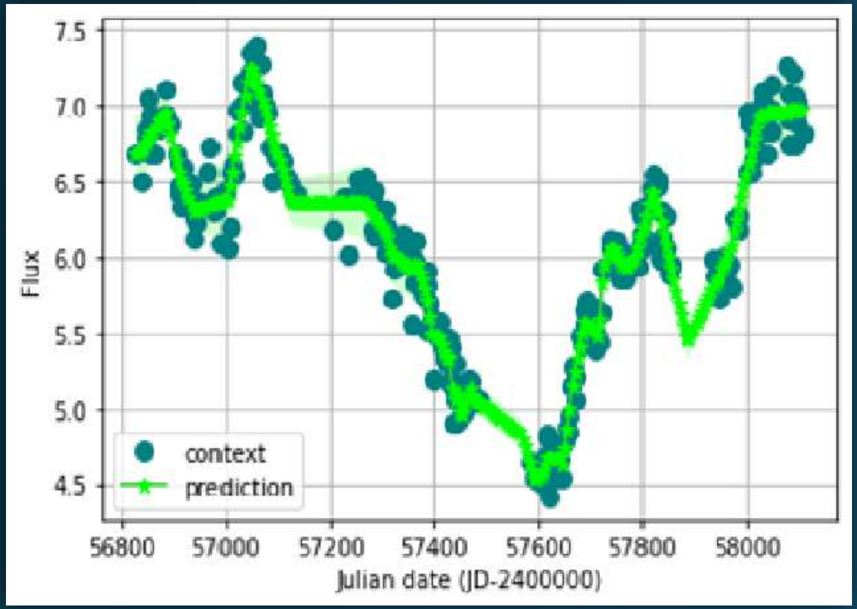
execution time: 19^m10^s

green shaded bend confidence interval

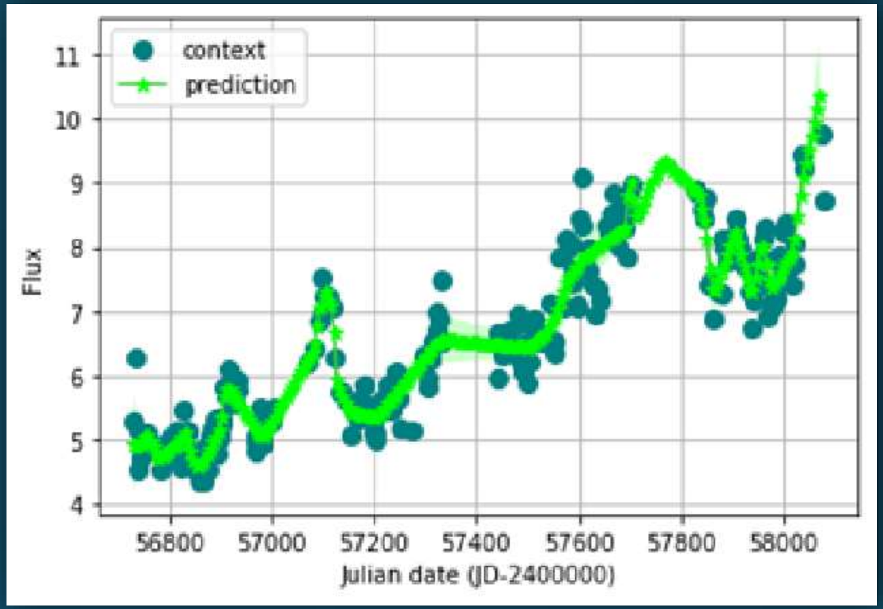
NGC 5548 H_β

Results

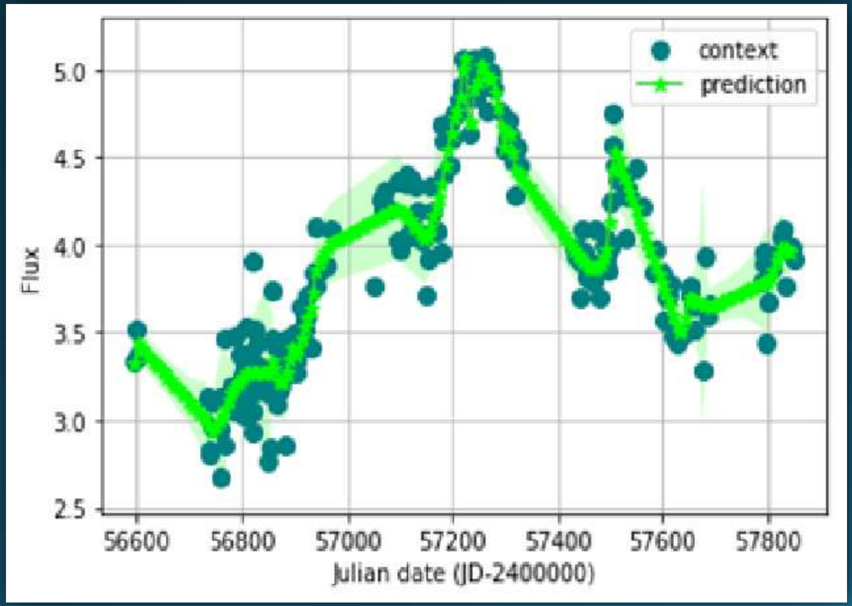
1H0419m577



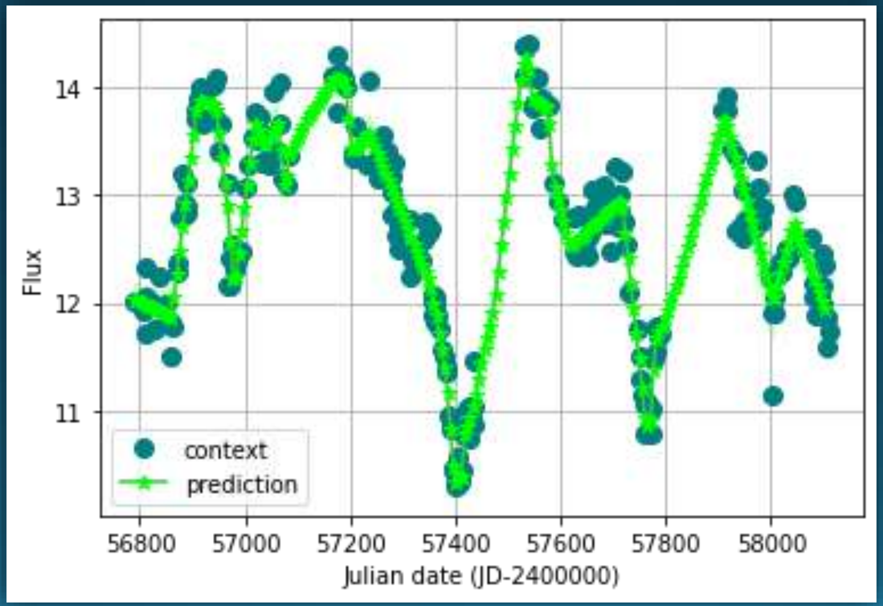
2MASXJ19595975p6508547



3C382



Fairall9



153 objects

150-600 points per source

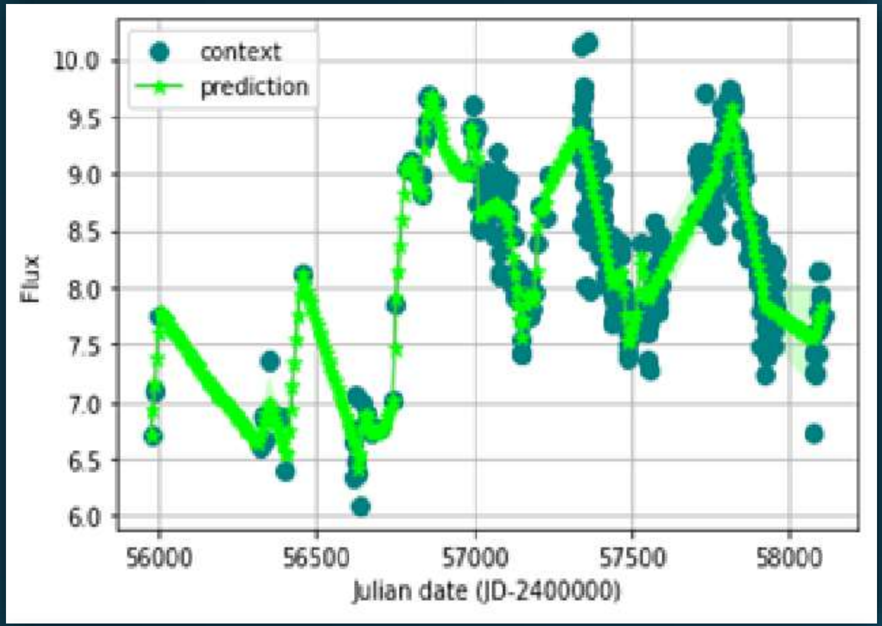
12-47 min execution time per curve

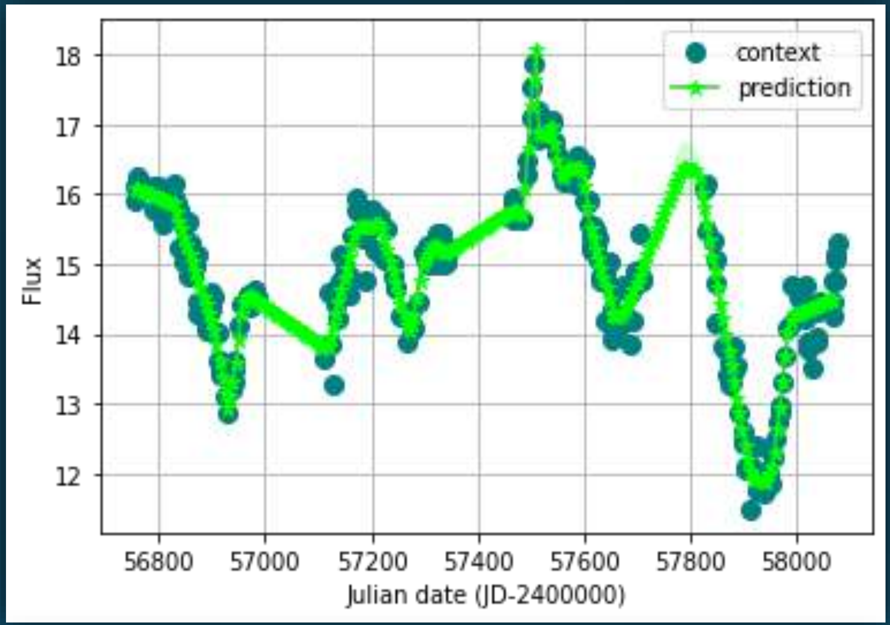
300 000 iterations per object

5.5 years long period

Results

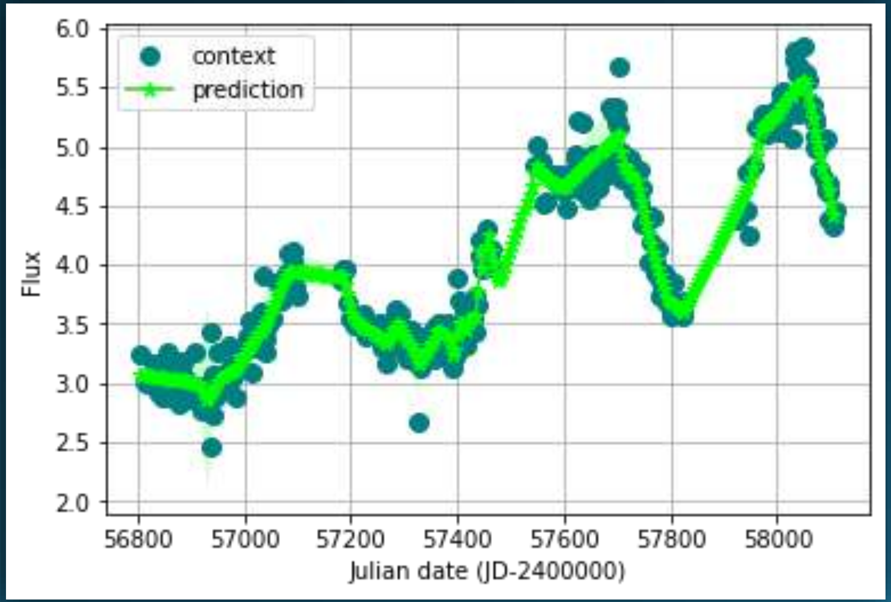
2MASXJ11454045m1827149

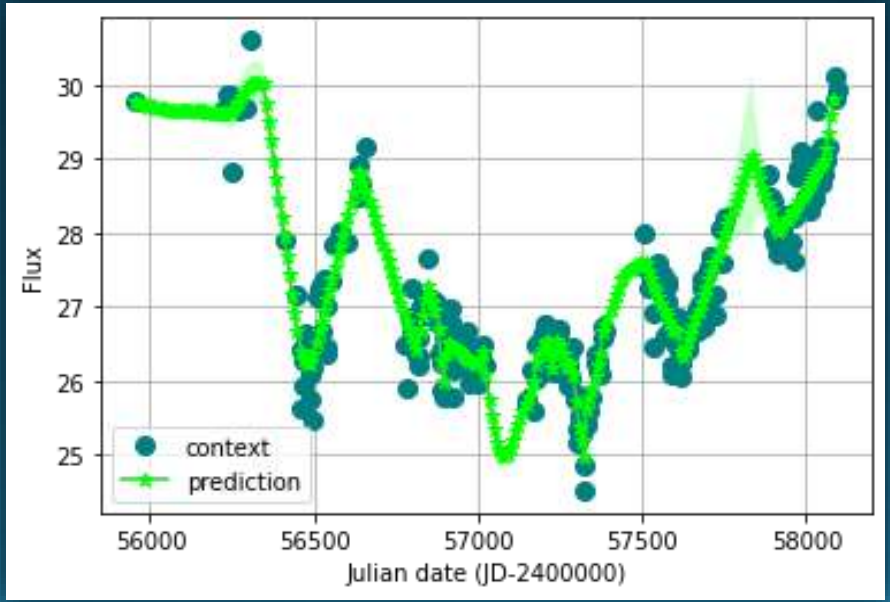




Mrk509

ESO198m024





NGC7469

flares & gapes

harder to learn - requires dividing data into subsets.

scattered data

harder to learn – requires additional iterations

processing time

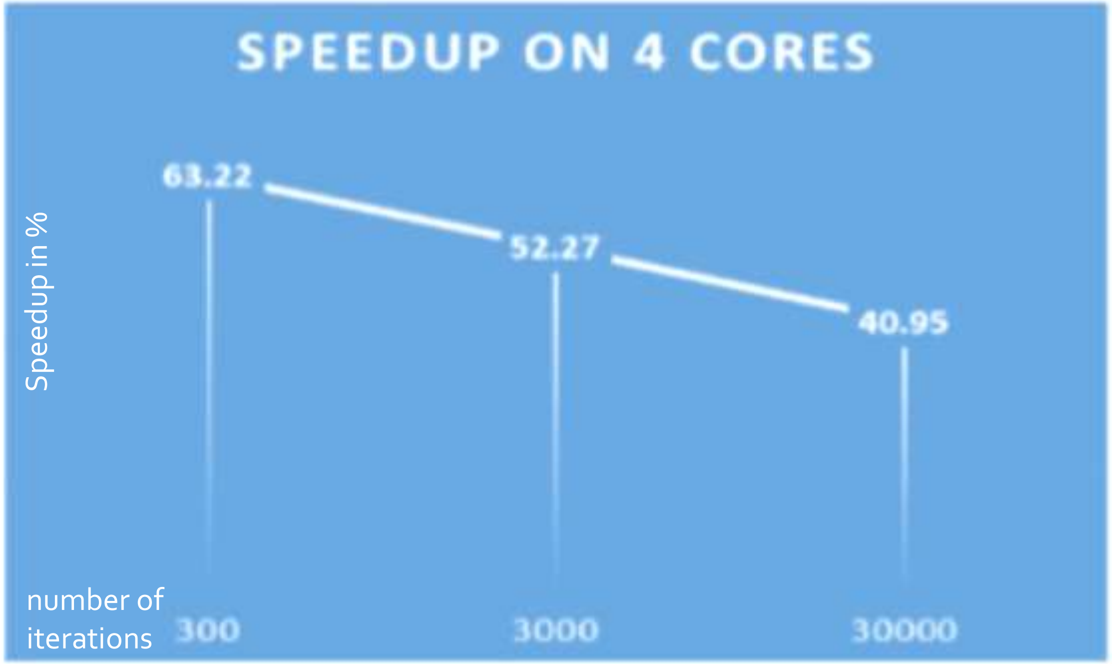
increases with Nº of iterations and data - requires optimization

Parallelization

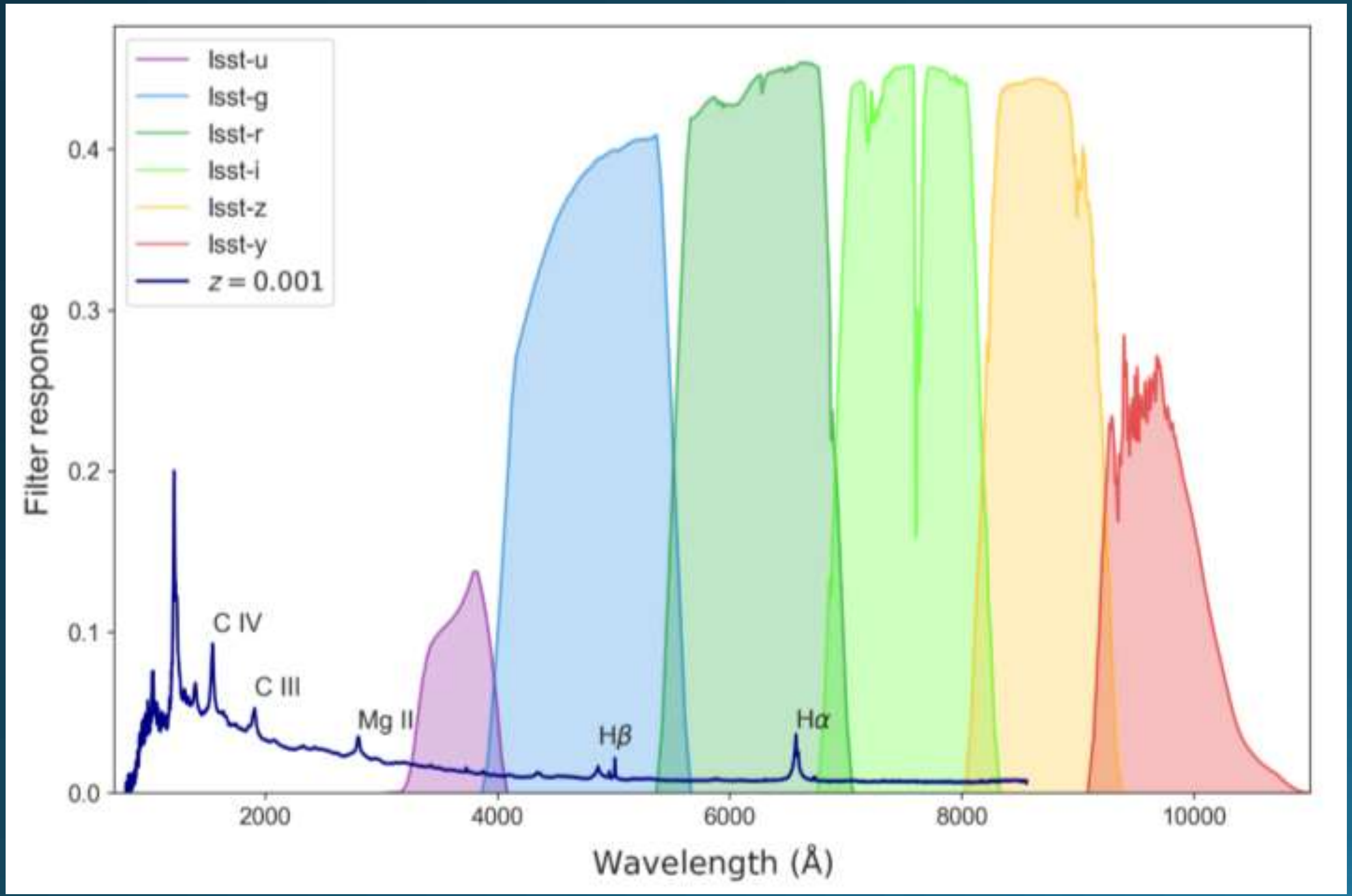
object	number of points	batch size	number of iterations	execution time (mm:ss.ms)
1H0419m577	272	30	25000	12:50.7
1H0419m577	272	15	25000	07:39.5
1H0419m577	272	3	25000	03:21.0
1H0419m577	272	3	200000	14:21.0

- We have detected speedup up to 63%
- Speedup depends on number of iterations
- Execution time decreeases upto 4 cores.

Amdahl's law ?



Deep Learning Engine 2 (DLE-PhotoRM)



- PhotoRM – method for BLR radius estimation using broadband photometric filters.
- Photometric light curves track both continuum and emission line variability together.
- Example ($z = 0.001$):
  - continuum: i-band
  - Hα + continuum: r-band
  - Hβ + continuum : g –band
- To obtain time-lag we use formalism by Chelouche & Daniel (2012) and Edri et al. (2012).

$$\boxed{CCF(\tau) = CCF_{XY}(\tau) - ACF_X\,(\tau)}$$

X – band: continuum **Y – band:** continuum + line

Data

- NGC 4395 light curves in g, r and i – bands obtained during the monitoring period of 9 nights (Edri et al. 2012).

- Expected time lag: $\sim$ few hours

- Confirmed with spectroscopic RM using HST data (C IV time lag ~1 hr)

Jupyter Notebook – reproduces the results from Edri et al. (2012) in order to demonstrate our implementation of PhotoRM.

Future

- Since our tools are non-parametric, they are also applicable to other astronomical objects, so we plan to utilize different light curve datasets (e.g., PLAsTiCC, DP0);
- Try different methods for cross-correlation function calculation;
- Use developed methods to test our simulated light curves for different LSST OpSim strategies;
- We are working on this for the next 10 months, as described in our LSST Enabling Science Project Proposal;
- Every input & feedback is more than welcome!

Thank you!

Visit our github: https: //github.com/LSST-sersag/dle

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This project is graciously supported by a grant from the 2021 LSST Corporation Enabling Science Call for Proposals (https://github.com/LSST-sersag/dle):