

# Classification of variable stars observed in multiple filters with MeerLICHT and BlackGEM”

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# Outlines

1) MeerLICHT and BlackGEM

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2) Motivation

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3) Steps towards our goals

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4) Results

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5) Conclusion

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# MeerLICHT and BlackGEM

MeerLICHT



South Africa

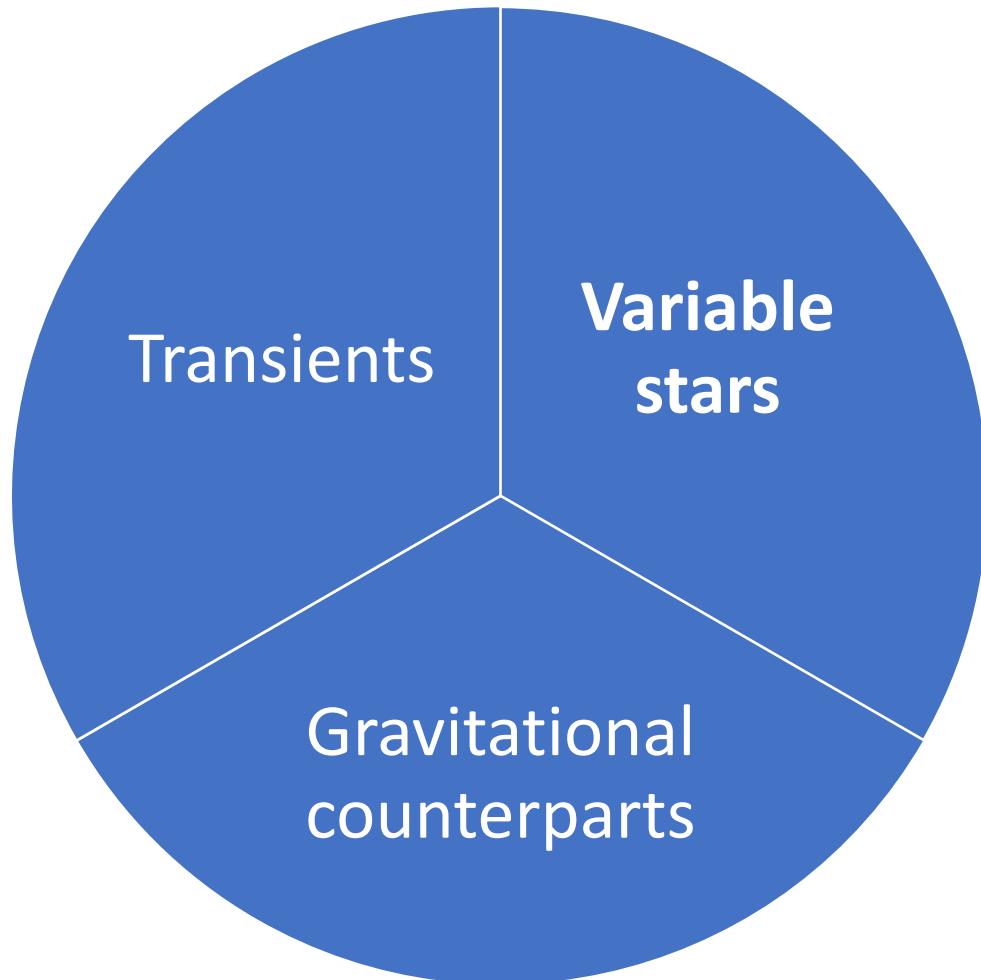
- Southern all-sky survey
- **fully robotic telescope**
- pixel scale: 0.56 arcsec/pixel.

BlackGEM



# MeerLICHT and BlackGEM

## Scientific goals



Filter	Wavelength range (nm)
$u$	350 – 410
$g$	410 – 550
$q$	440 – 720
$r$	563 – 690
$i$	690 – 840
$z$	840 – 990

# Classification of variable stars

## Motivation

- Multiband lightcurves
  - Characterise fainter object: ~23 mag
  - 60s integration
  - + 10s readout time
- 
- Better characterisation

# Classification of variable stars

## Motivation

- Multiband lightcurves
  - Observe fainter object: ~23 mag
  - 60s integration
  - + 10s readout time
- 
- More sources

# Classification of variable stars

## Motivation

- Multiband lightcurves
- Observe fainter object: ~23 mag
- 60s integration
- + 10s readout time



Detect high-frequency variables

# Problems we want to solve

Automatically ...



Given ...

1) Characterise  
lightcurves

2) Classify variables

3) Detect new class of  
variables

a) Unevenly sampled multi-  
band lightcurves

b) Few labelled (in our)  
dataset

c) Imbalanced class dataset

# Related work

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## **ASAS-SN catalog of variable stars (Jayasinghe et al. 2018, 2019b, 2021)**

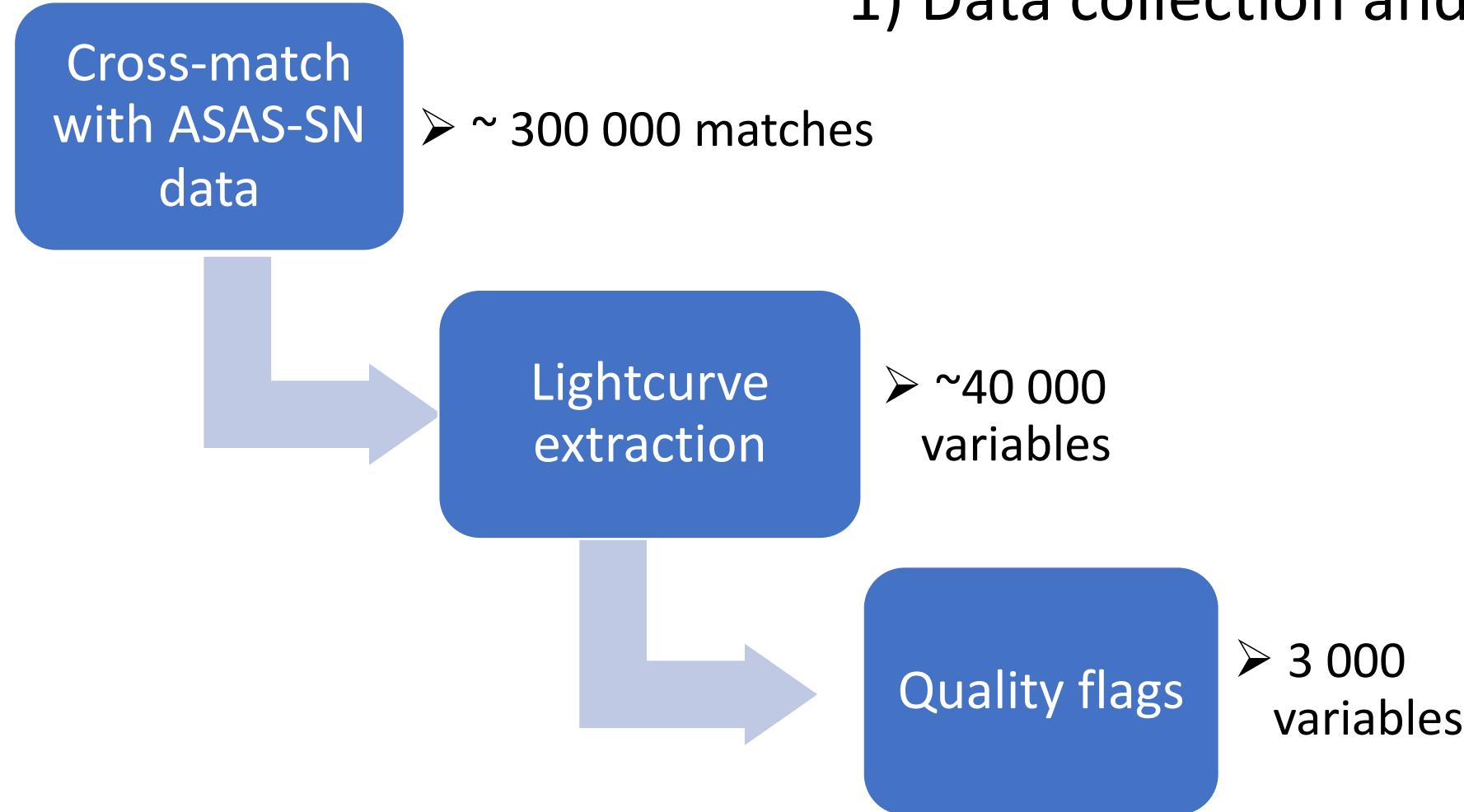
Labelled data from Variable Star Index (VSX),  
General Catalog of Variable Stars (GCVS),  
Upsilon (Kim & Bailer-Jones 2015)

- + Manual selection
- + Random Forest

## **Supernova photometric classification (Ashley Villar et al., 2020)**

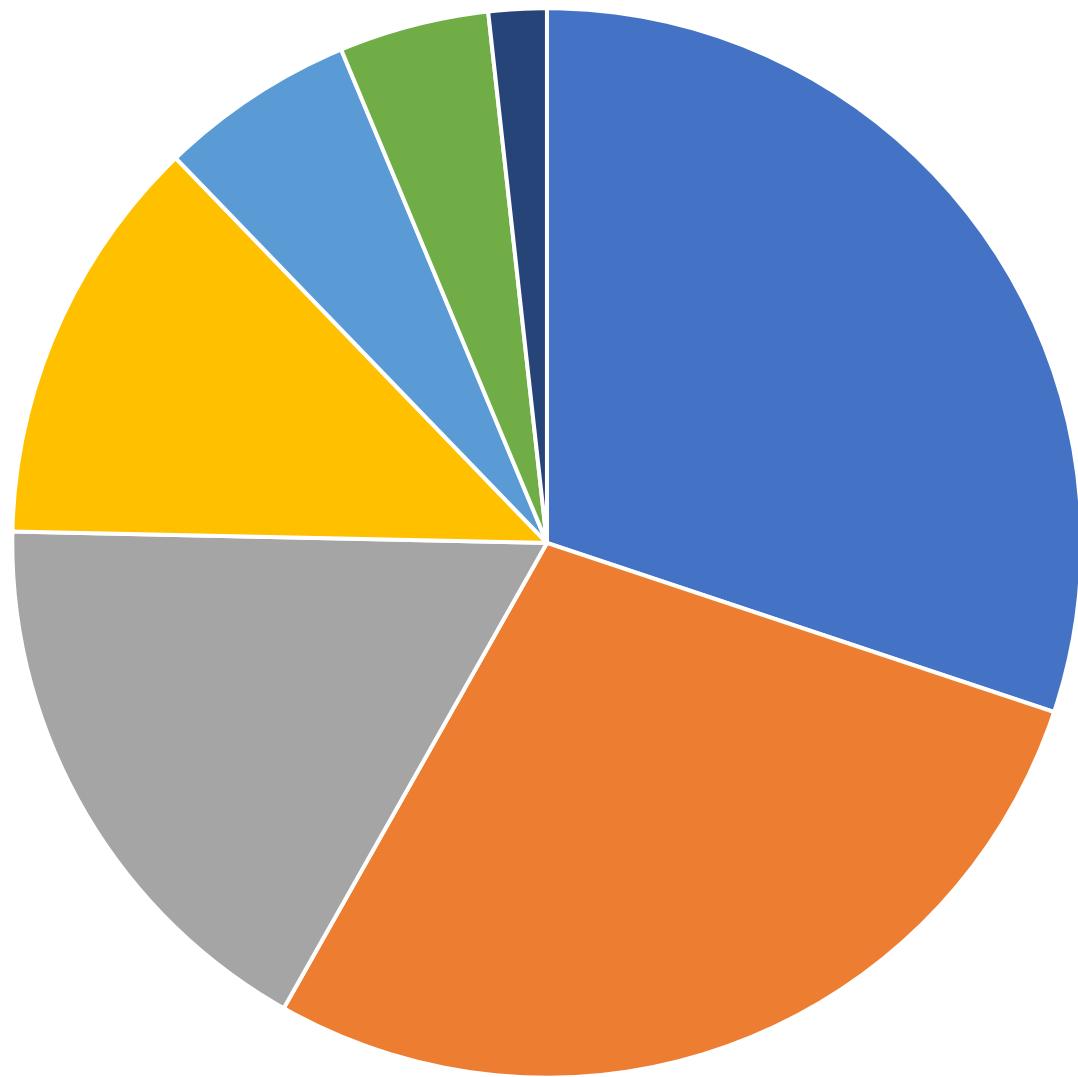
Gaussian Process  
+ Neural network  
+ Random Forest

# Steps towards our goals



# Steps towards our goals

Distribution of variables



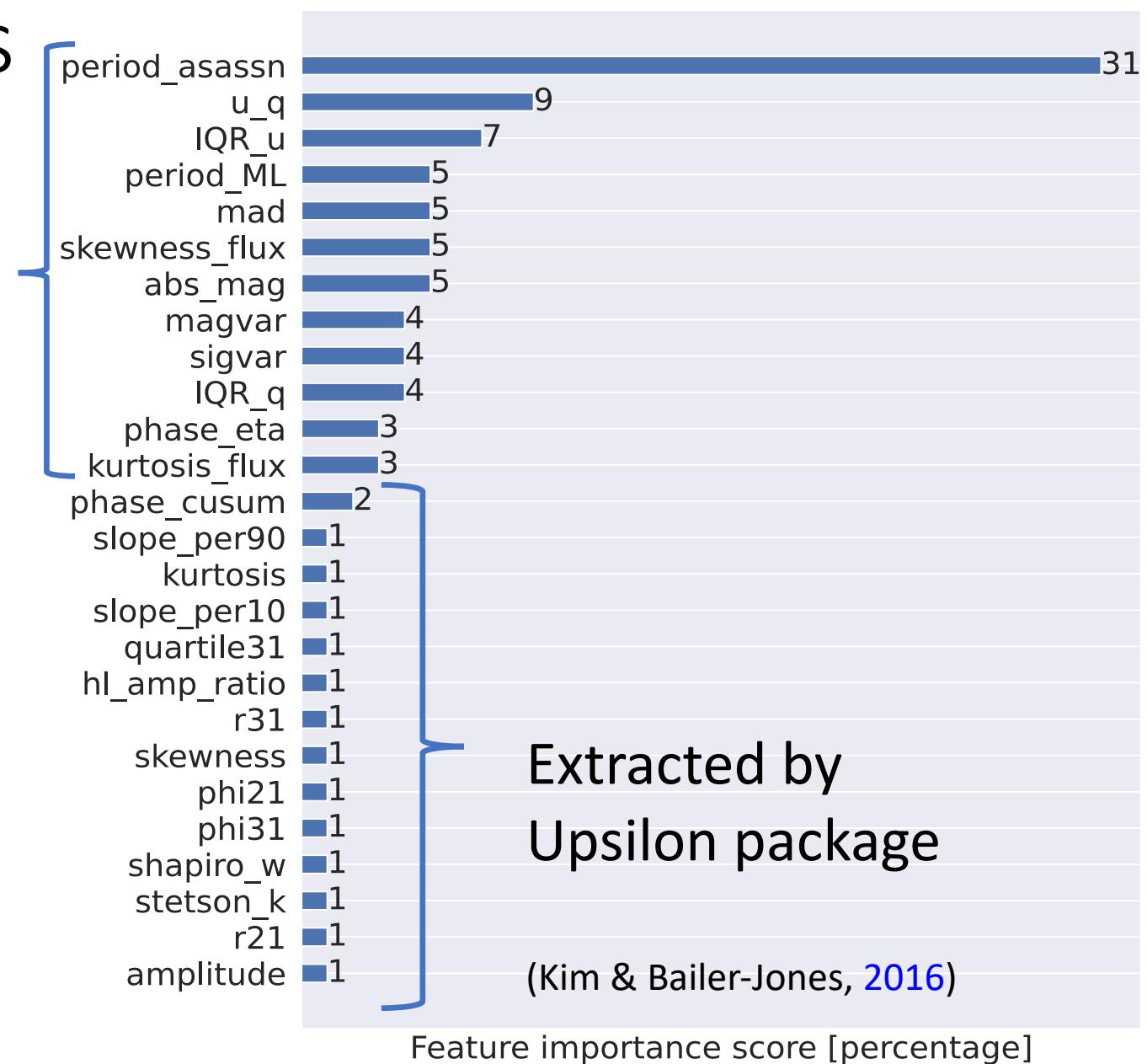
■ E ■ SR ■ RRAB ■ EW ■ RRC ■ EA ■ M

# Steps towards our goals

- 1) Data collection and labelling
- 2) Feature extraction/selection
- 3) Model selection

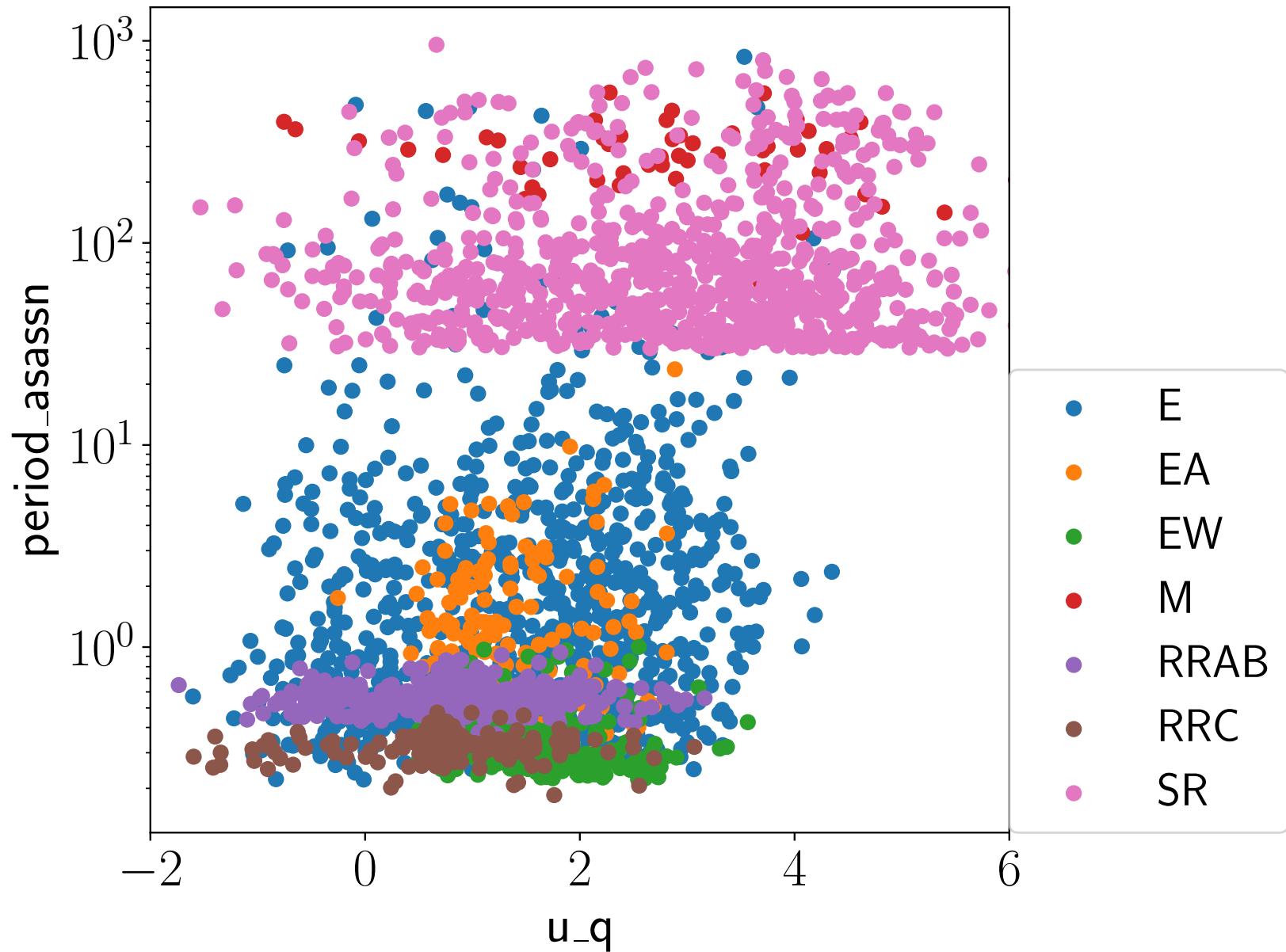
Descriptive statistics

Random Forest (RF)

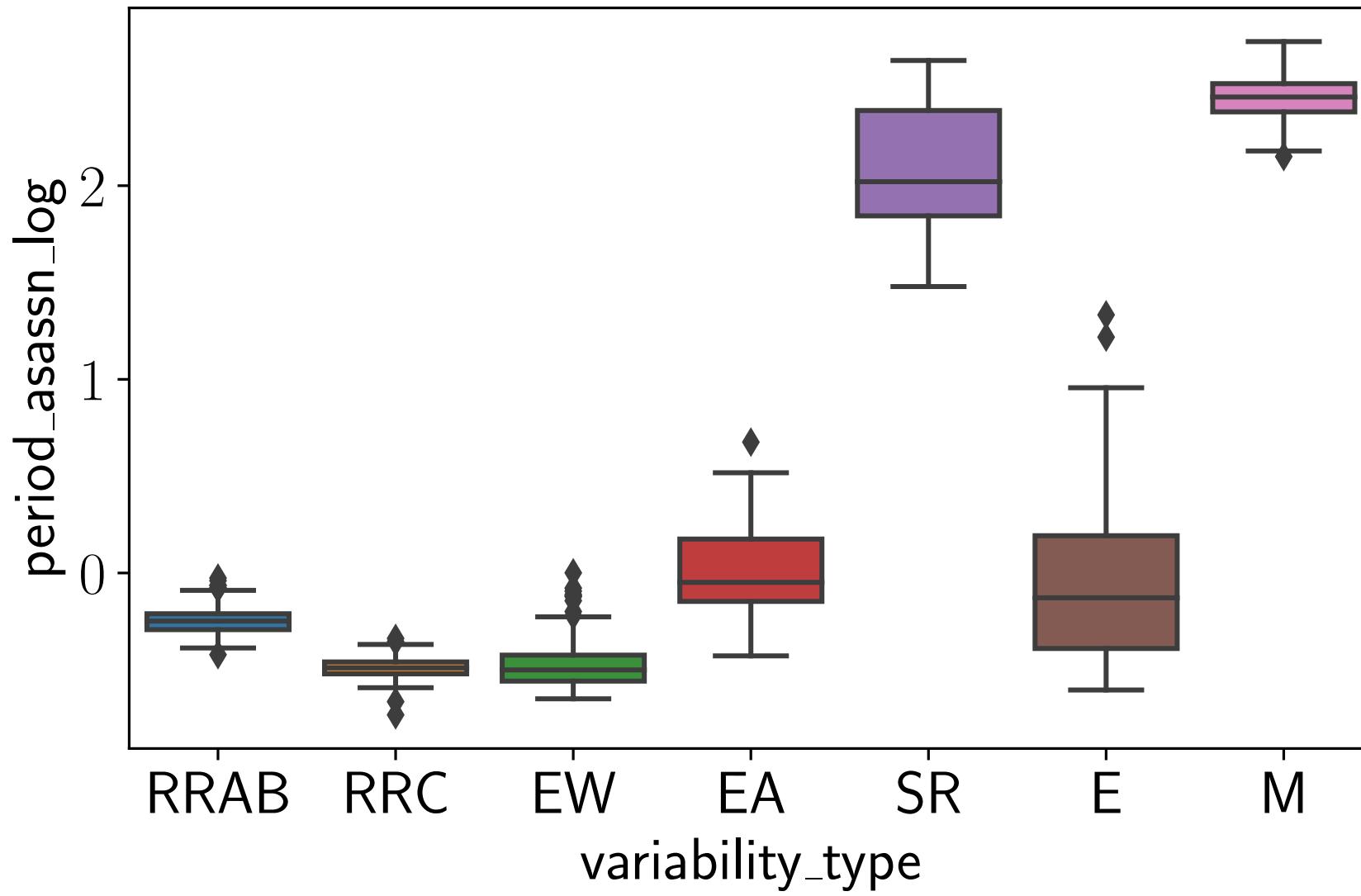


# Steps towards our goals

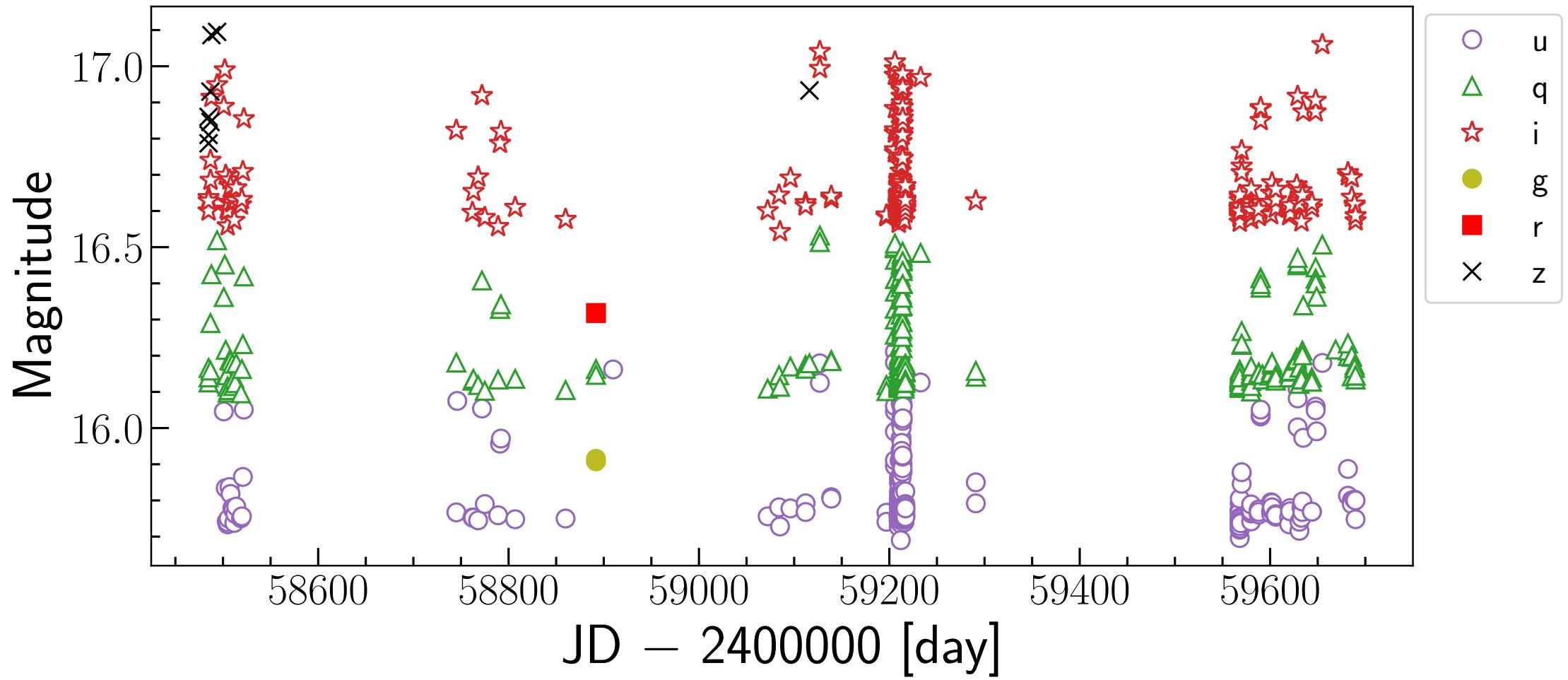
2-D feature space



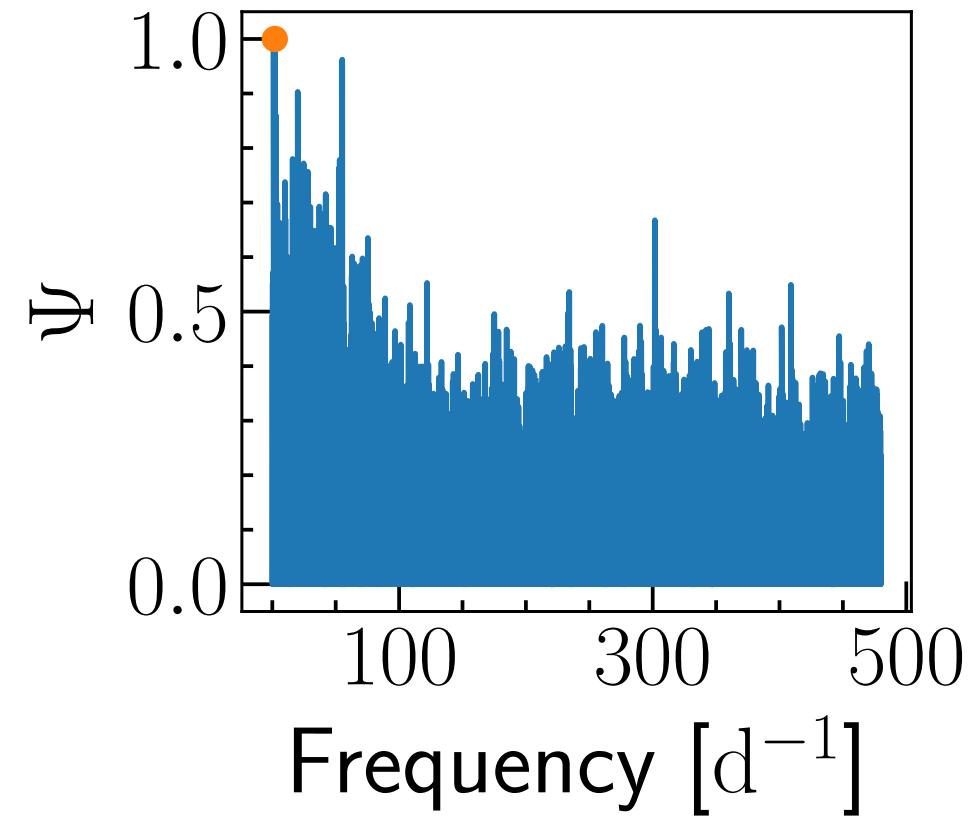
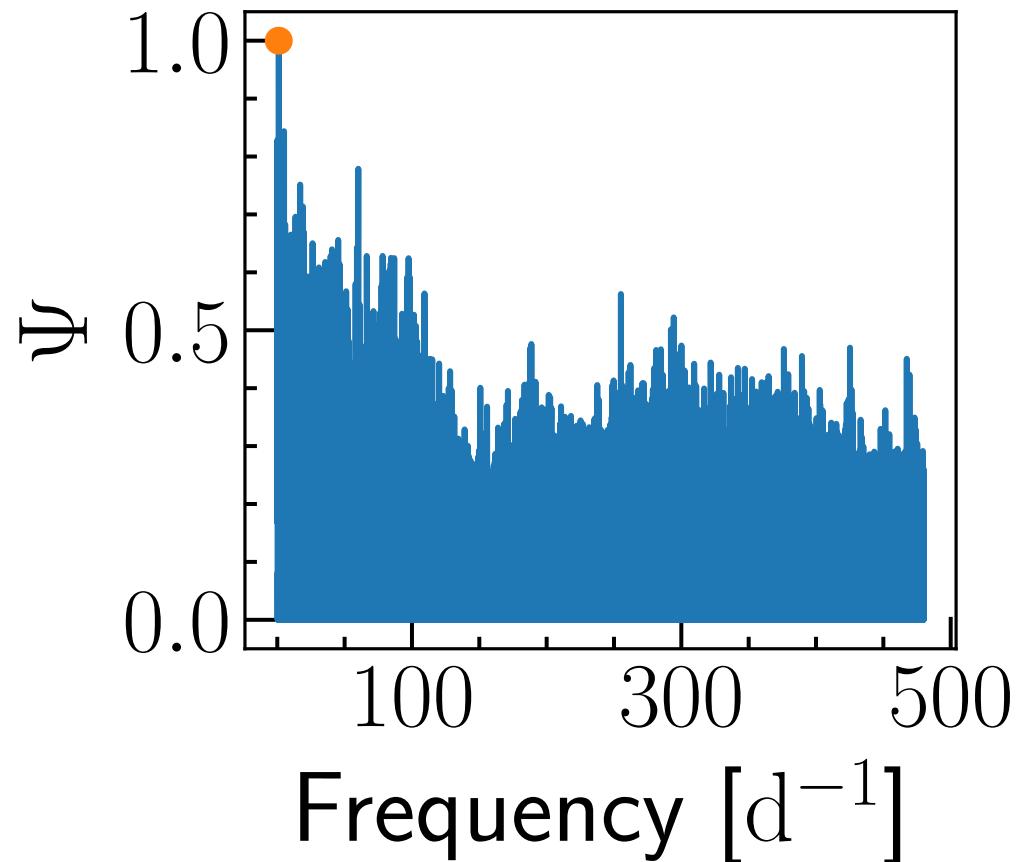
# The period and variability type



# Period finding



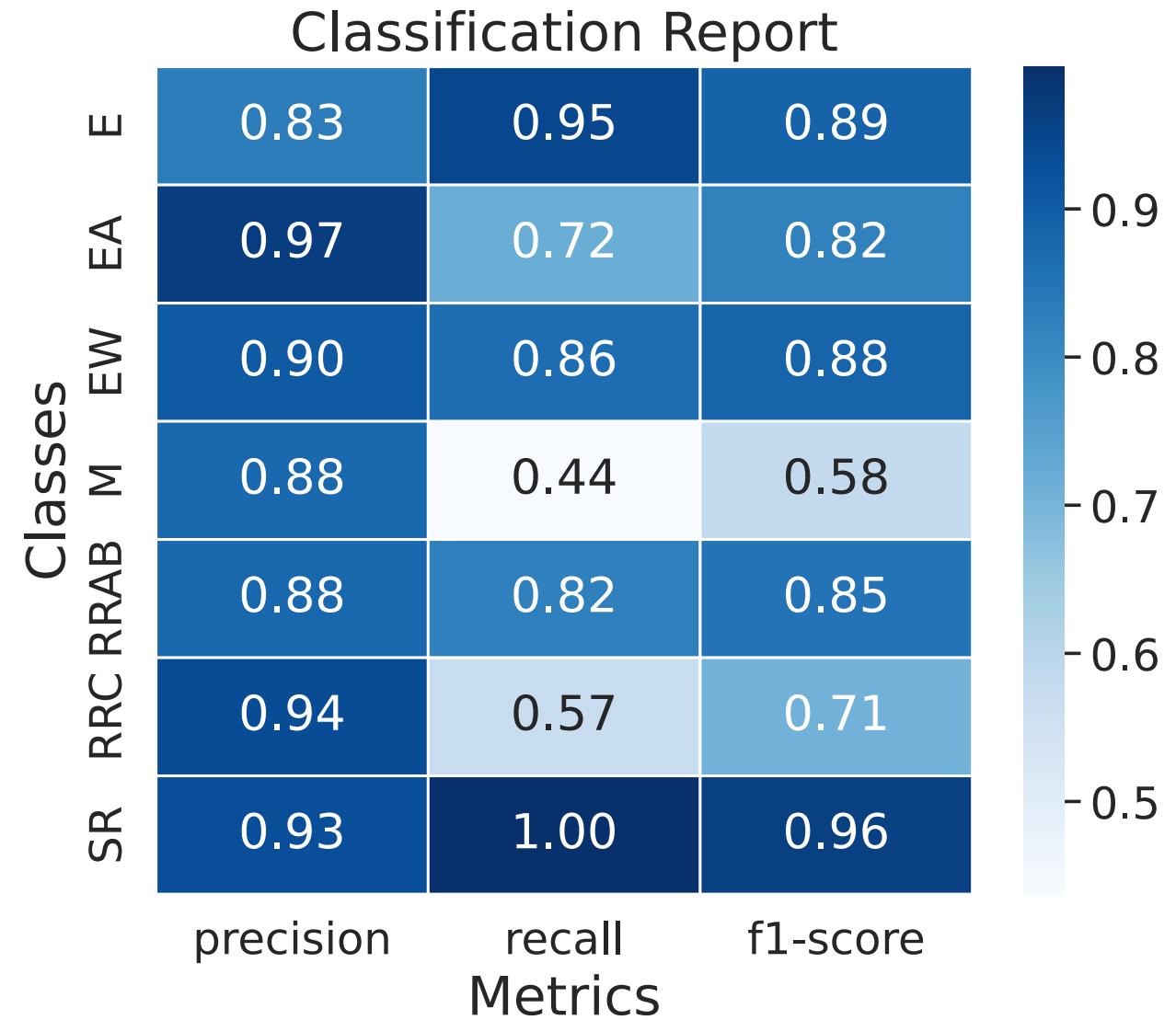
# Periodograms



# Steps towards our goals

## Random Forest performance

- 1) Data collection and labelling
- 2) Feature extraction/selection
- 3) Model selection
- 4) Model evaluation**



# Steps towards our goals

## Random Forest performance

1) Data collection and labelling

2) Feature extraction/selection

3) Model selection

**4) Model evaluation**

True labels

## Confusion matrix

Predicted labels

	E	EA	EW	M	RRAB	RRC	SR
E	235	0	1	0	3	0	9
EA	6	28	2	0	3	0	0
EW	3	1	95	0	9	2	0
M	0	0	0	7	0	0	9
RRAB	25	0	1	0	122	0	0
RRC	14	0	6	0	2	29	0
SR	0	0	0	1	0	0	245

# Next steps ...

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Re-evaluate class labels

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	E	EA
E	235	0
EA	6	28

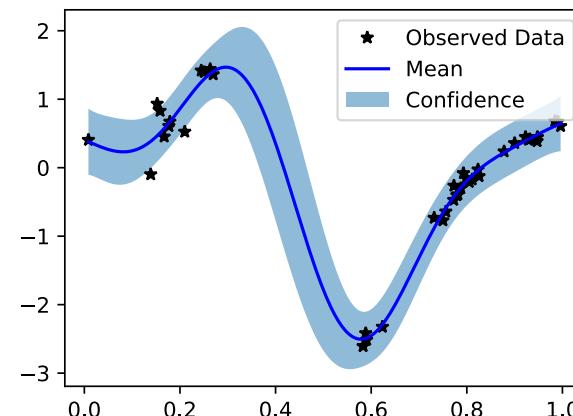
Data augmentation

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Ensemble learning

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Lightcurve modelling with GP

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# Conclusion

We have seen that

- The period is the most important feature, followed by descriptive statistics.
- Period finding are extremely challenging for unevenly sampled data
- Class imbalance leads to low performance for overlapping classes
- MeerLICHT and BlackGEM have great potential in studying stellar variability

# Thank you

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**Astronomy  
&  
Astrophysics**

## Identifying and characterising the population of hot sub-luminous stars with multi-colour MeerLICHT data<sup>★</sup>

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### ABSTRACT

*Context.* Colour-magnitude diagrams reveal a population of blue (hot) sub-luminous objects with respect to the main sequence. These hot sub-luminous stars are the result of evolutionary processes that require stars to expel their obscuring, hydrogen-rich envelopes to reveal the hot helium core. As such, these objects offer a direct window into the hearts of stars that are otherwise inaccessible to direct observation.

