Application of Supervised Machine Learning to the Classification of Variable Young Stars

Philip Carr

Mentor: Lynne Hillenbrand

SURF 2018

Outline

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- Introduction and Motivation
  - What’s this project about?
  - Project scope
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- Conclusions and Future Work
  - Evaluating current strategies and moving forward
  - Improvements and new research directions

Introduction: Looking Back in Time

https://en.wikipedia.org/wiki/Protoplanetary_disk#/media/File:HL_Tau_protoplanetary_disk.jpg

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- Young stars are a window into the recent past
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  - Can we classify young star variability?

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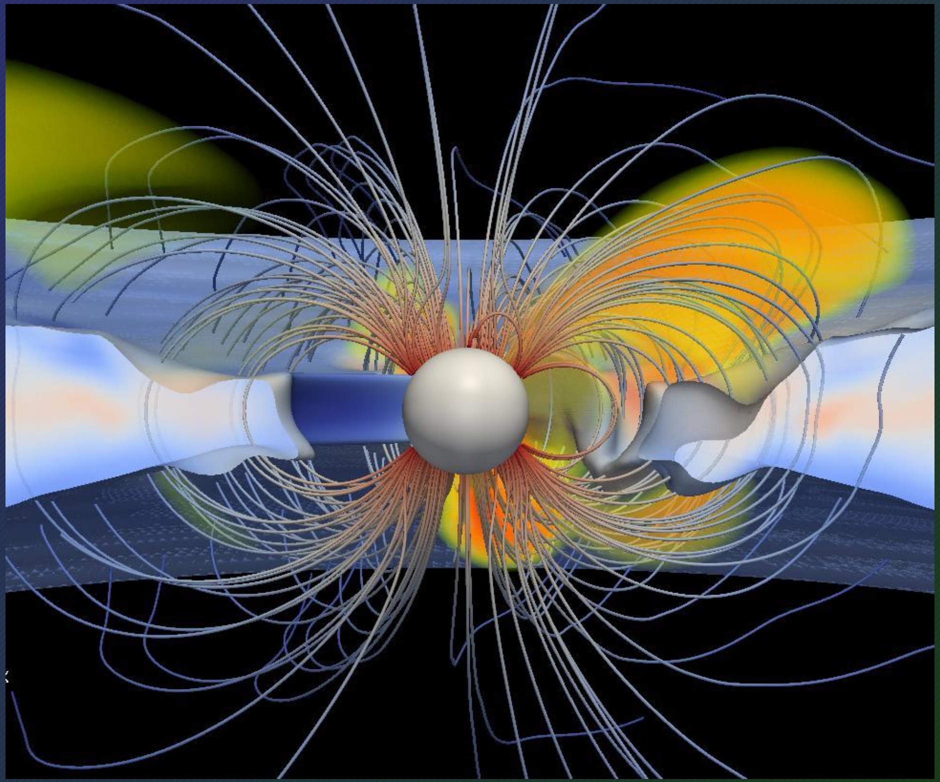
Motivation: Young Stars



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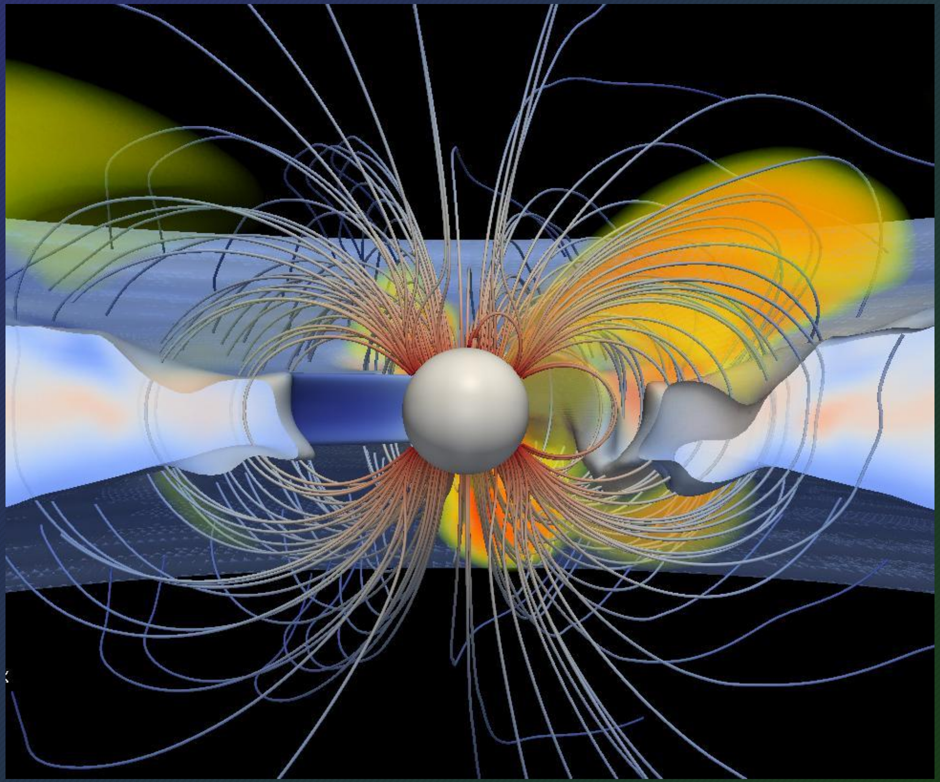

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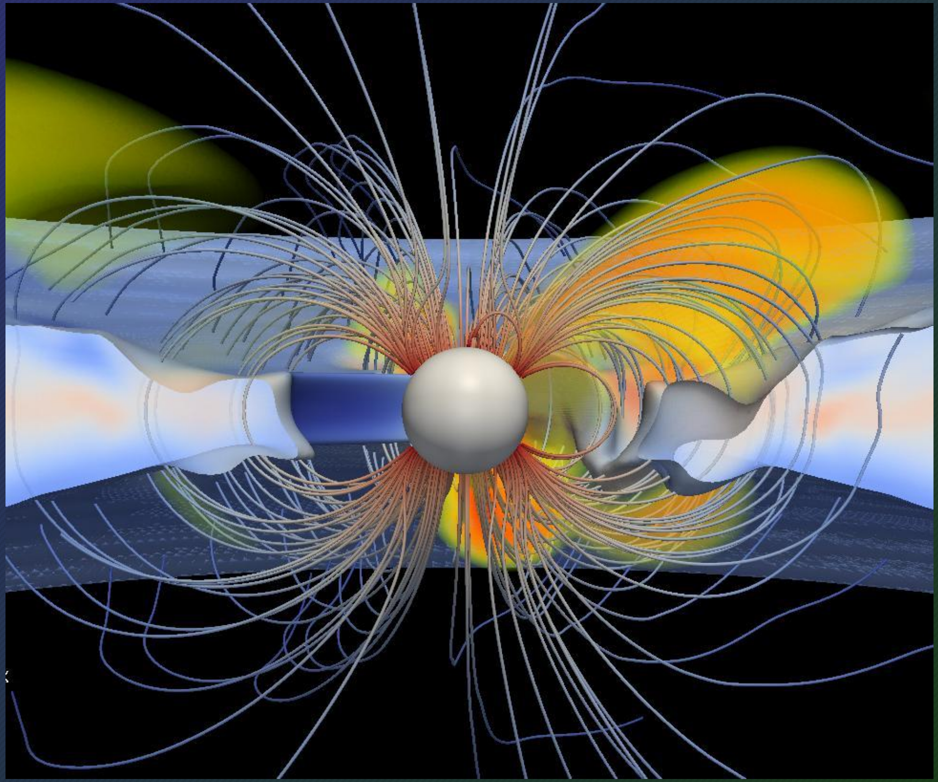

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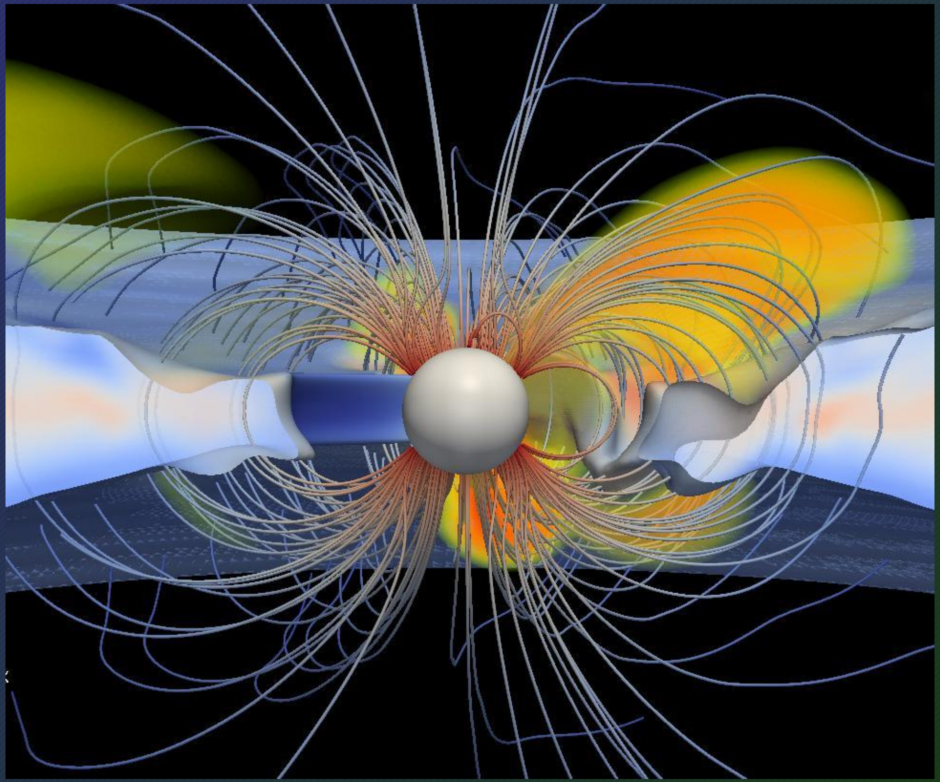
- Highly dynamic
  - Variable flux
  - Accretion disk interaction



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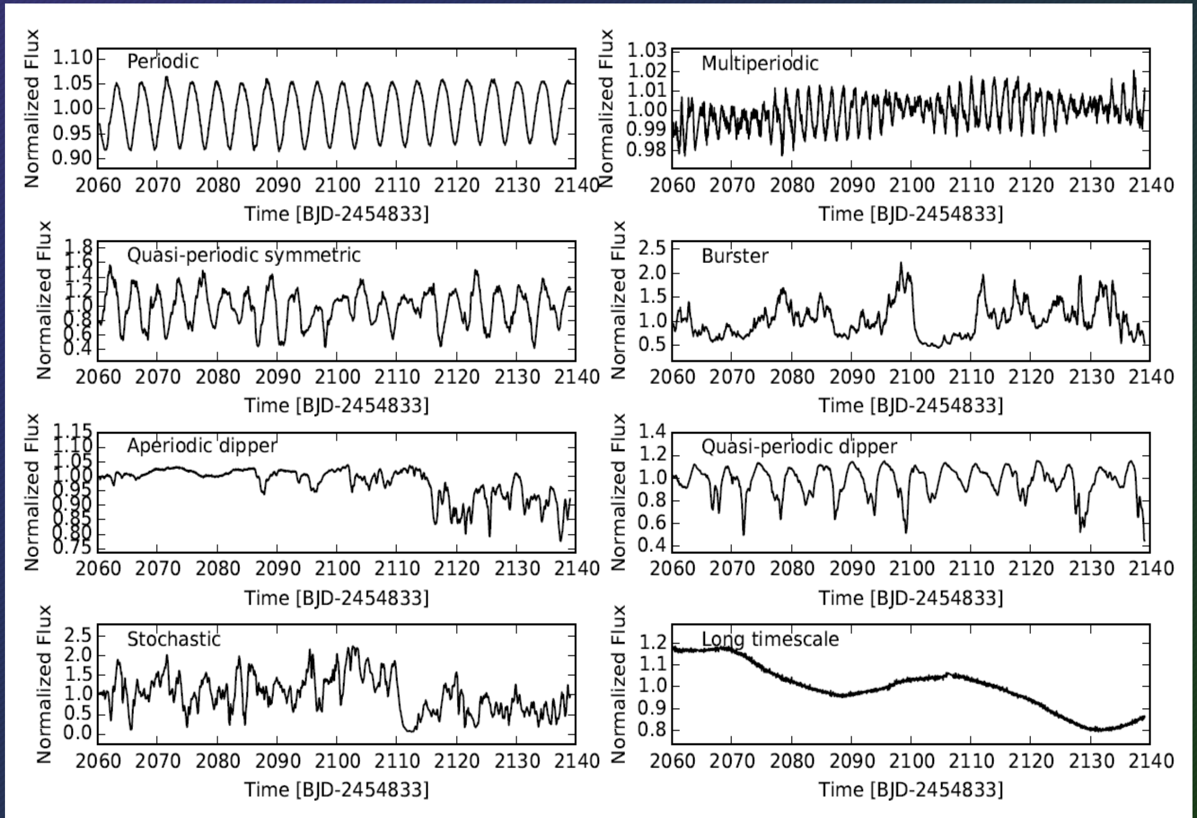
- Previous examples of machine learning applied in astronomy
  - Classifying other types of variable stars (Richards, J. W. et al. 2011)
  - Applying recurrent neural networks and feature engineering for prediction and classification of stellar properties (Hinners et al. 2018)

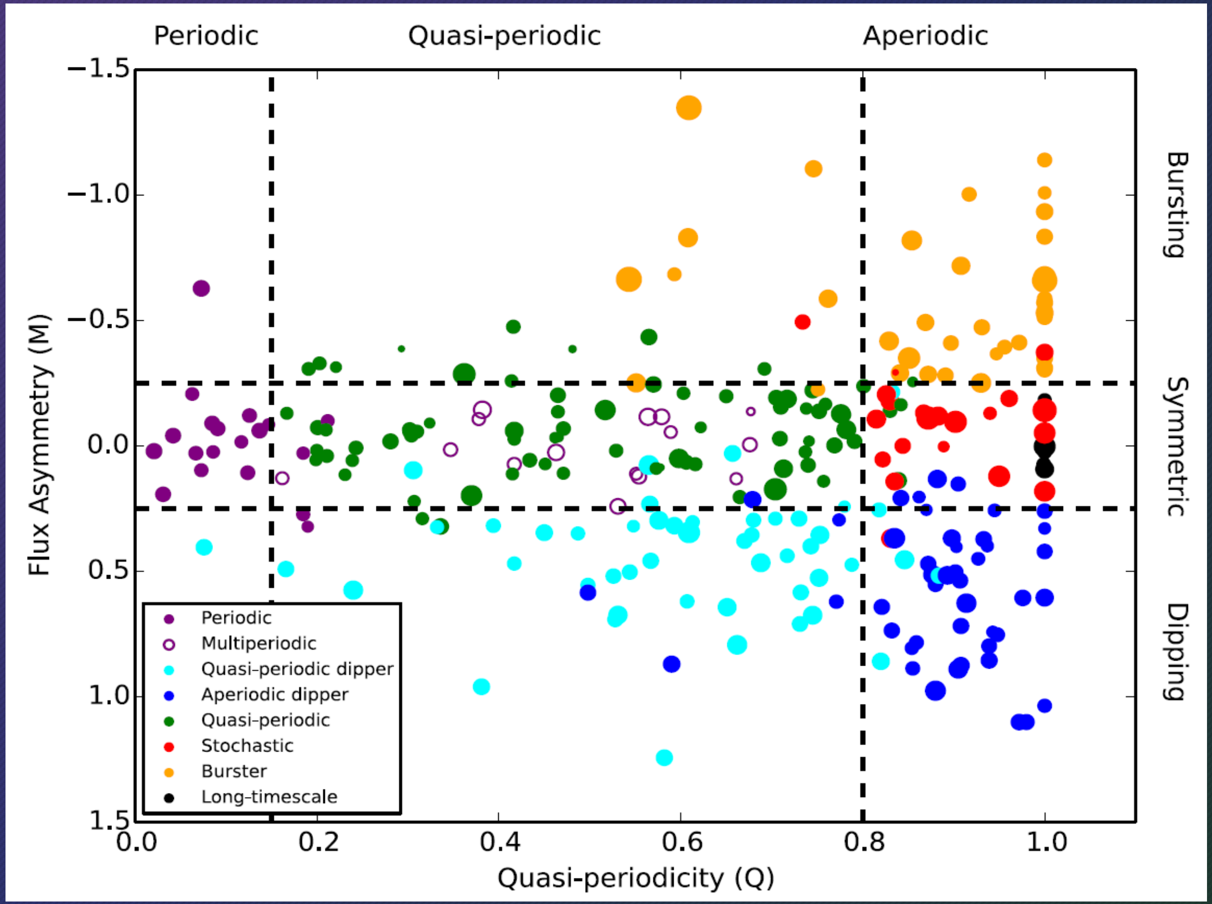
Machine Learning: Data Organization

- About the Data
  - Light curves
  - Obtained from Kepler K2 mission
  - Data were labelled (supervised learning)
  - 8 variability types (Cody & Hillenbrand 2018)
    - Periodicity
    - Flux Asymmetry



Adapted from Cody, A. M. & Hillenbrand, L. A. 2018

Motivation: Young Stars + Automation



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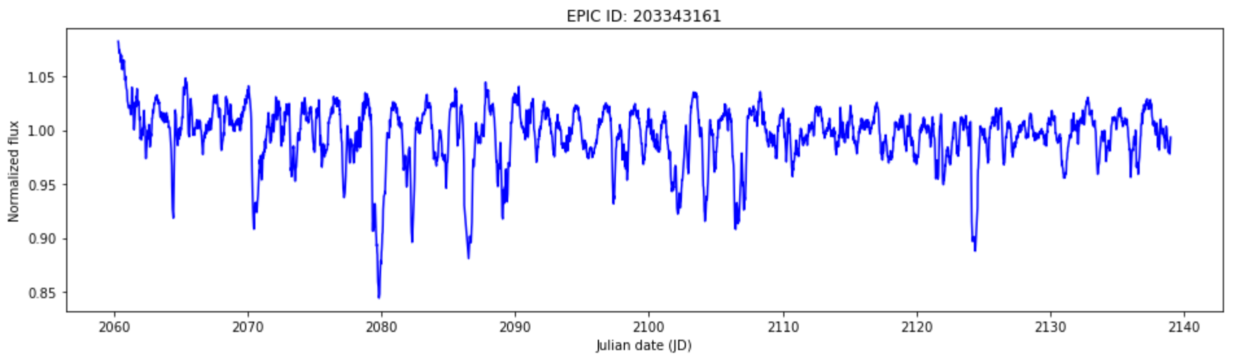
- Reading in Data
  - Data read in through Python
  - Option to remove first n days of observation from original light curve

Machine Learning: Feature Selection



Feature	Value
Normalized Flux Amplitude	0.0869
Timescale	0.237
Quasi-periodicity	0.771
Flux Asymmetry	0.621

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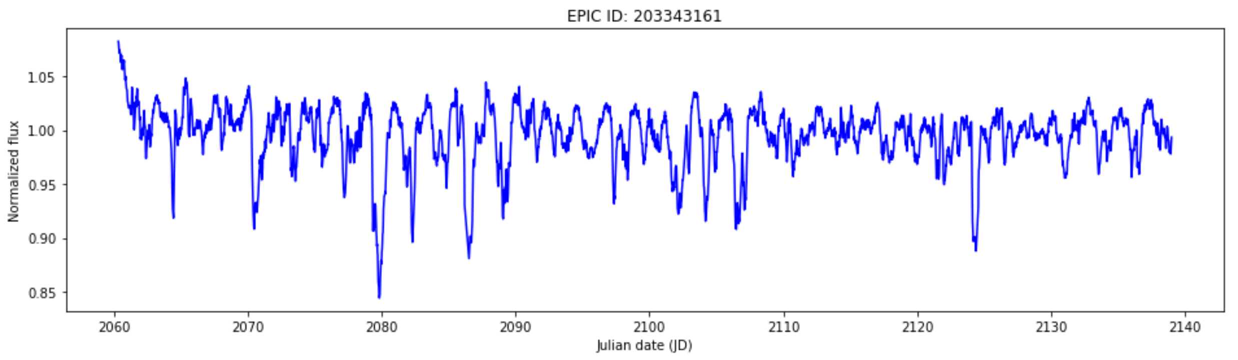
  - Supervised learning algorithm only sees feature data, not necessarily raw data



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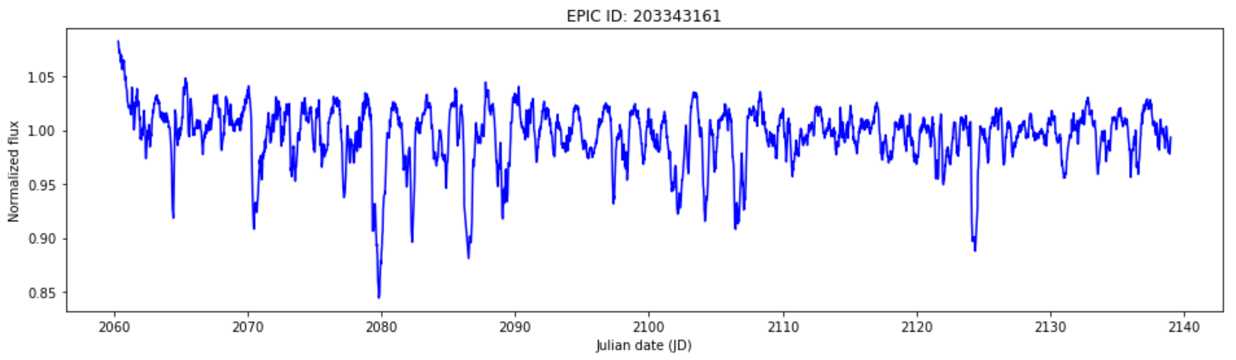
- Feature selection
  - Specialized features
    - Based largely off of classification system (including periodicity, flux asymmetry, timescale, flux amplitude, etc.)
  - Public feature libraries
    - FATS
    - feets



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- Once trained, classifier can make predictions based on how it learned from training data

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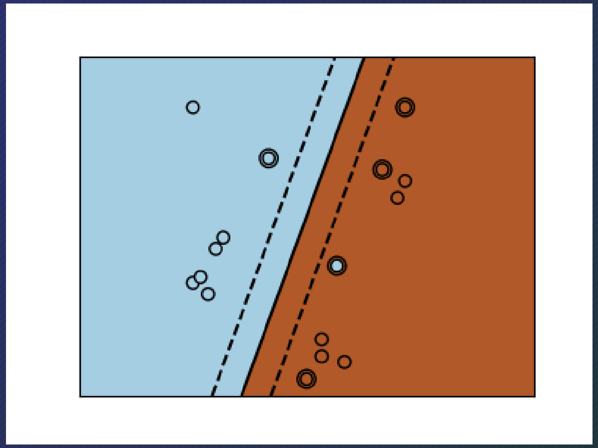

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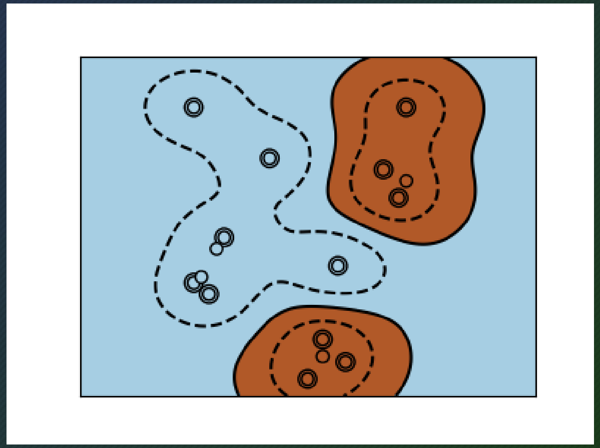

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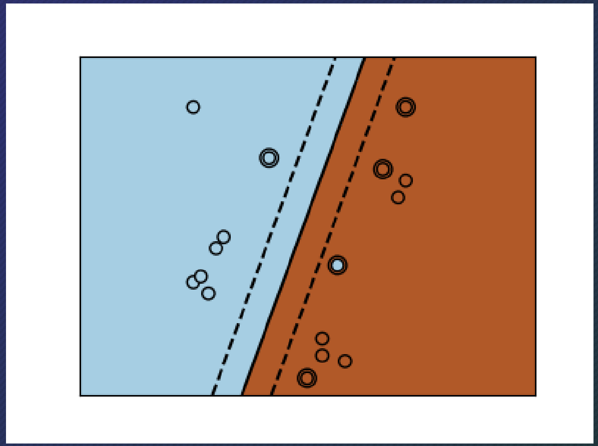
  - Parameters that modify different aspects of machine learning algorithm
  - Can have significant impact on how well classifier learns from data
  - Example:
    - Linear vs. RBF kernel



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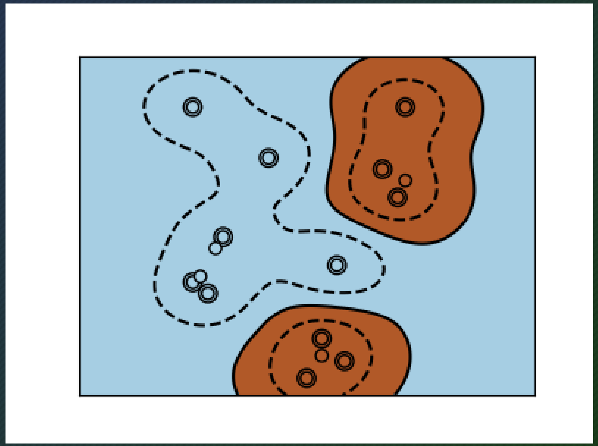

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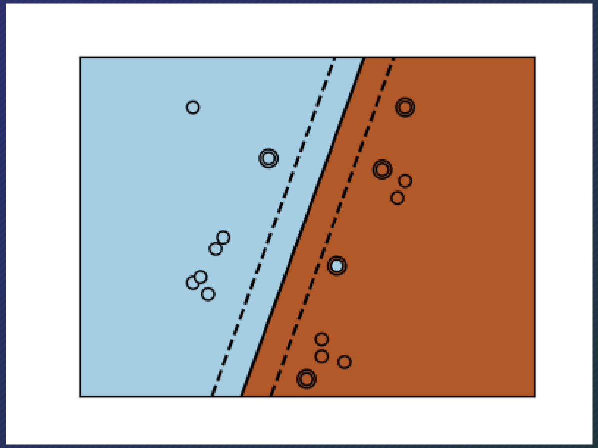
- Sklearn implements two optimization methods
  - Randomized Search
  - Grid Search



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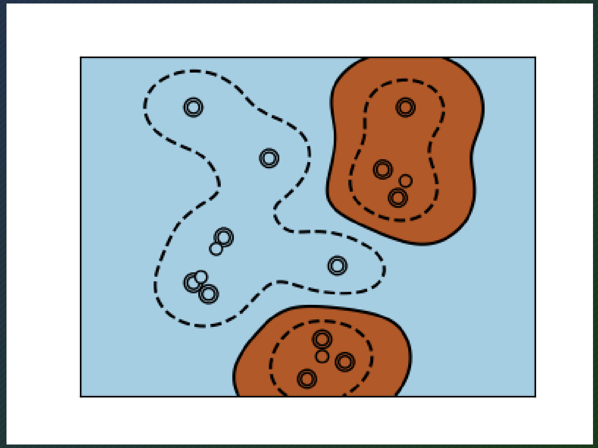

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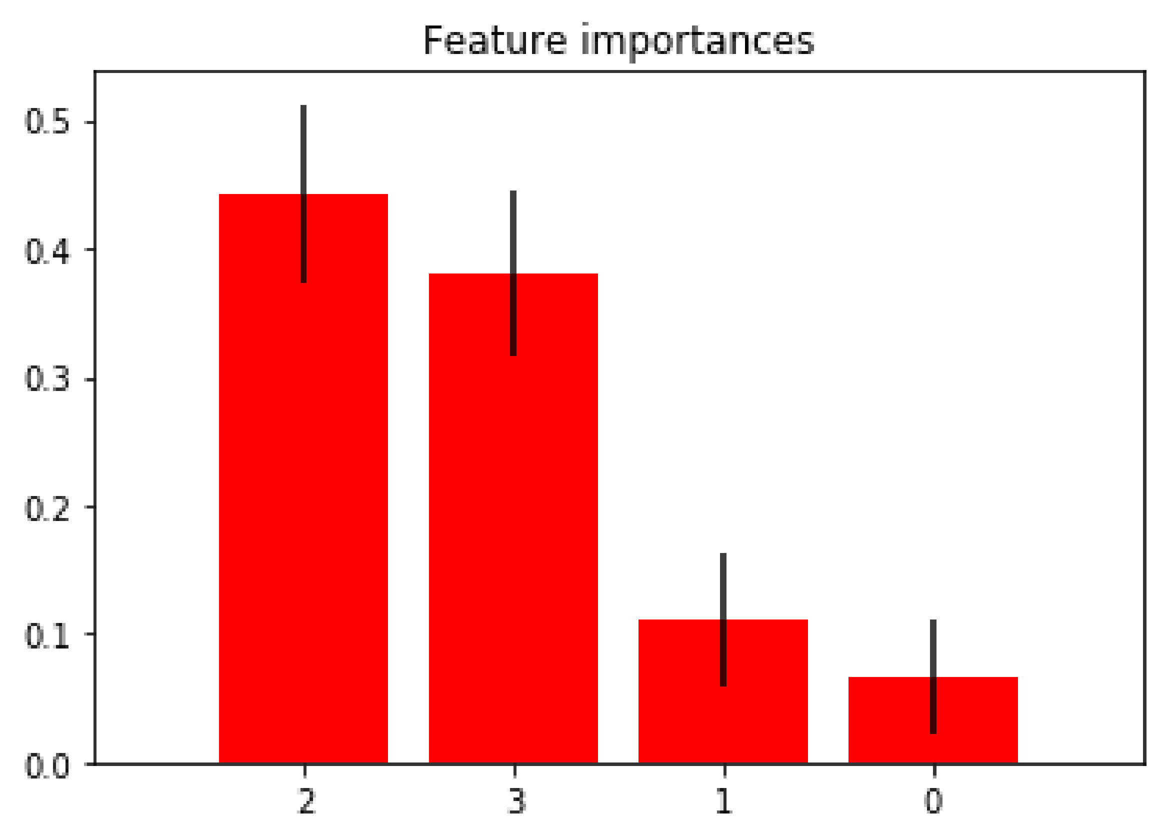
- Confusion matrices
  - Show detailed information about how well objects are classified
  - Show ways in which classifier confuses different objects in prediction

Results: Feature Importances



Feature Number	Value
0	Normalized Flux Amplitude
1	Timescale
2	Quasi-periodicity
3	Flux Asymmetry

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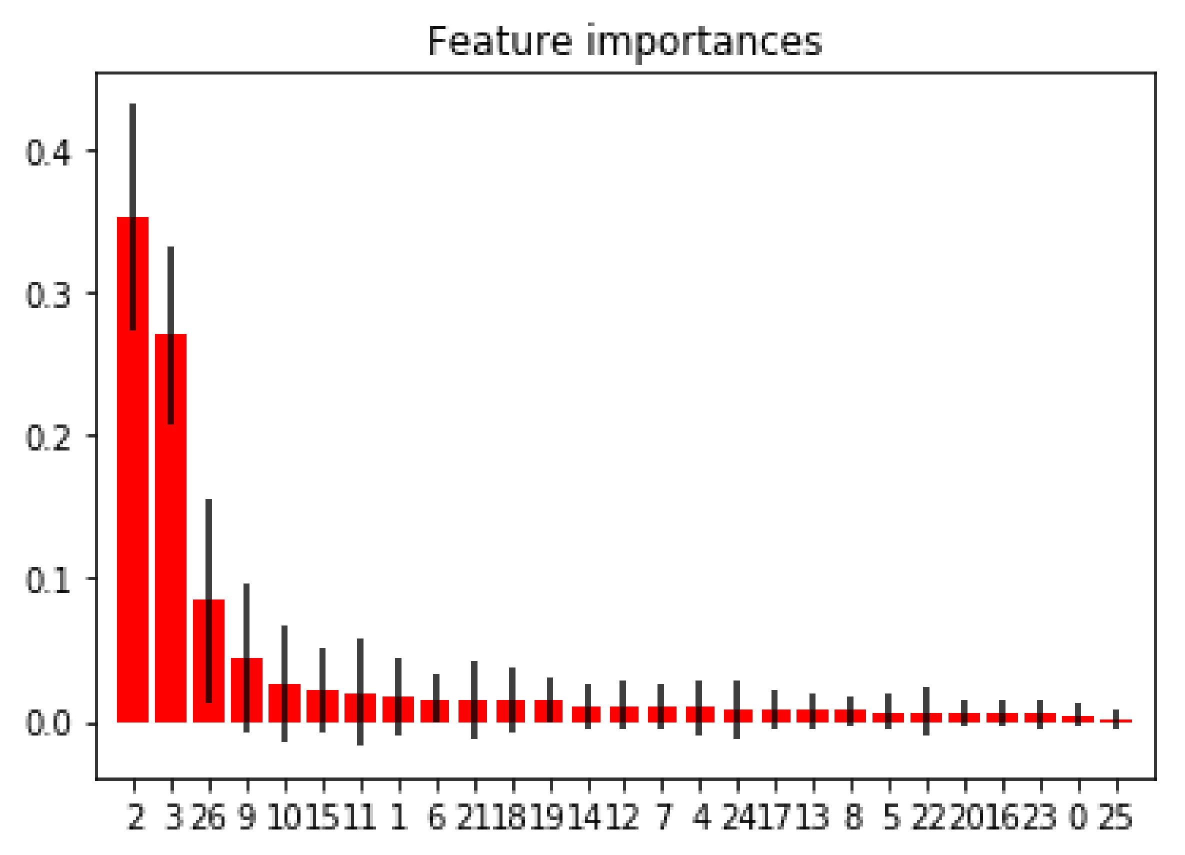
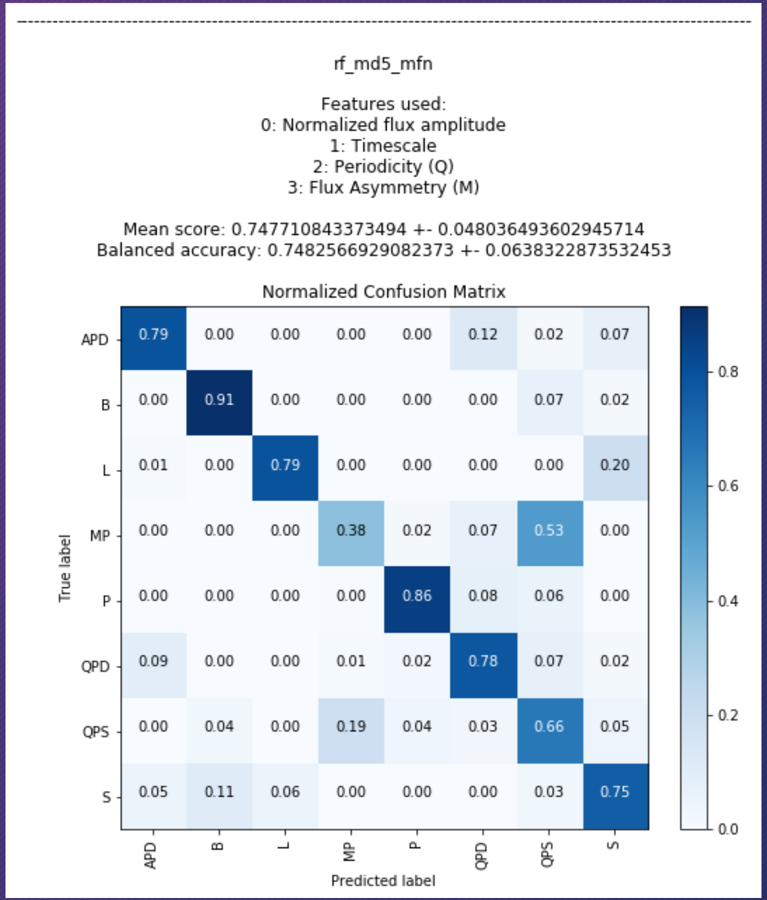
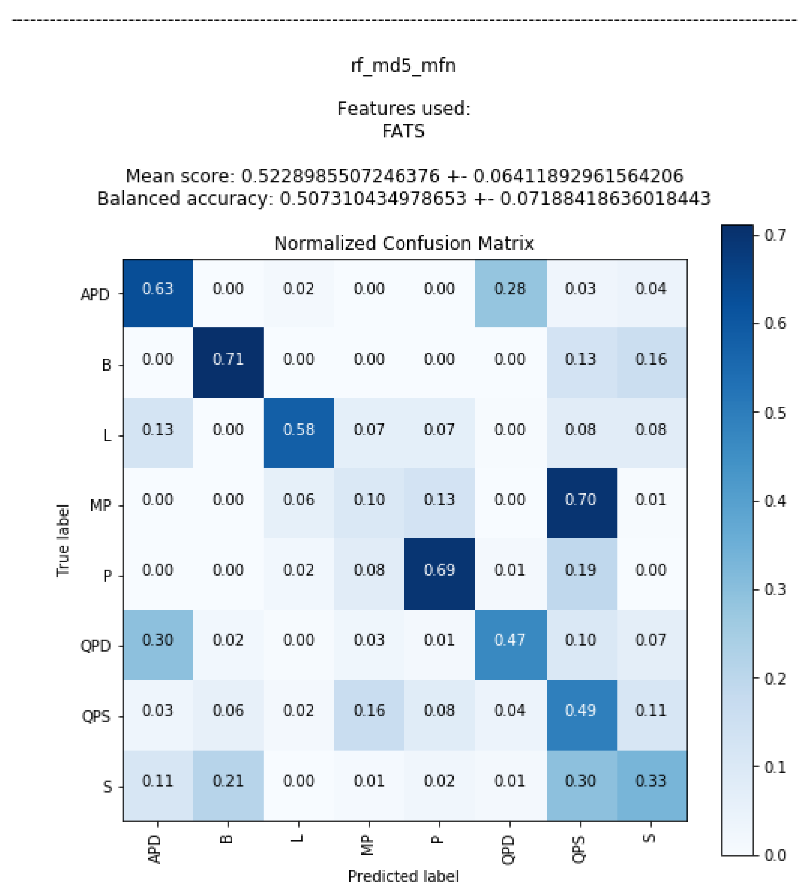
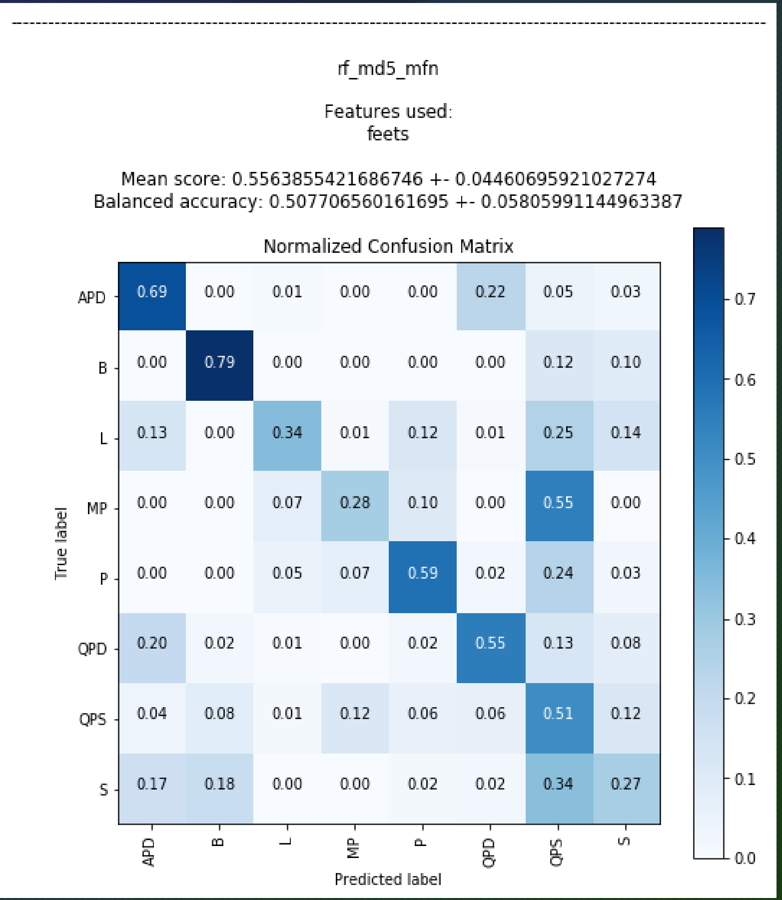


Feature Number	Value
2	Quasi-periodicity
3	Flux Asymmetry
26	smoothed light curve polynomial fit rms error
9	Stetson k index
10	half-magnitude amplitude ratio

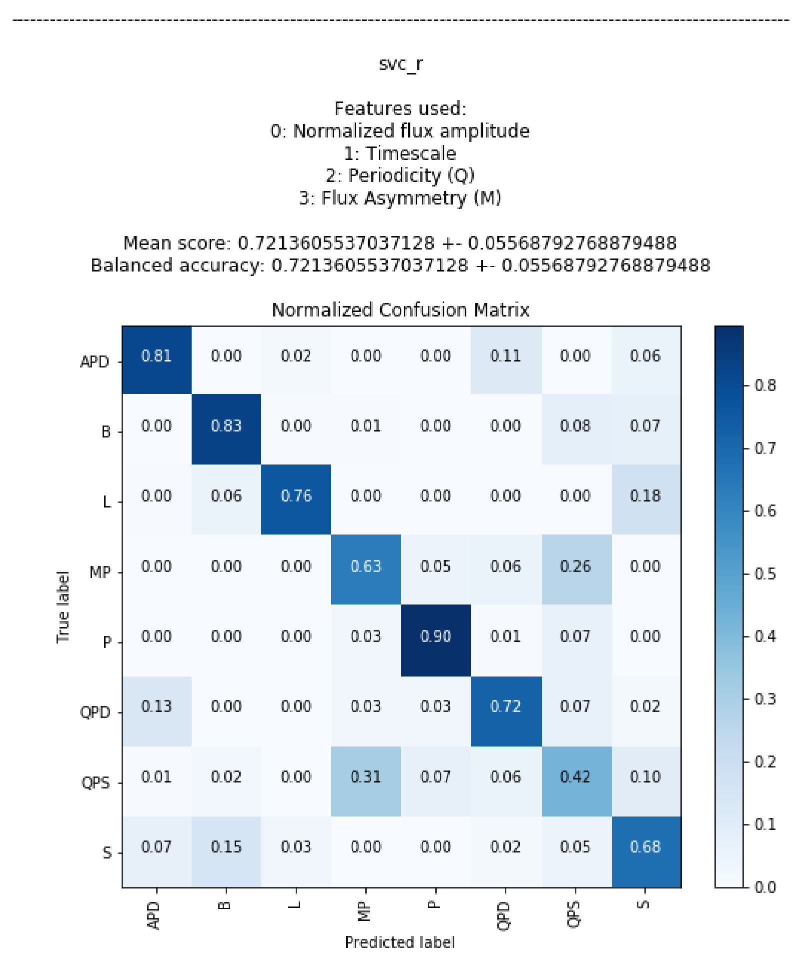
Results: Specialized vs. FATS vs. feets Features

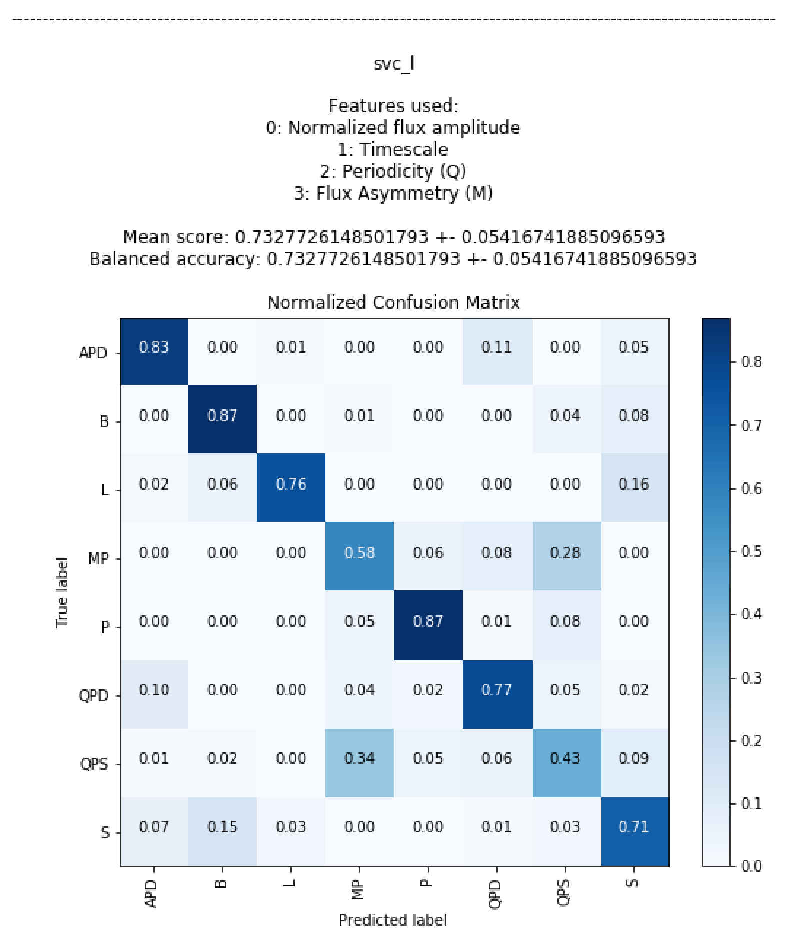




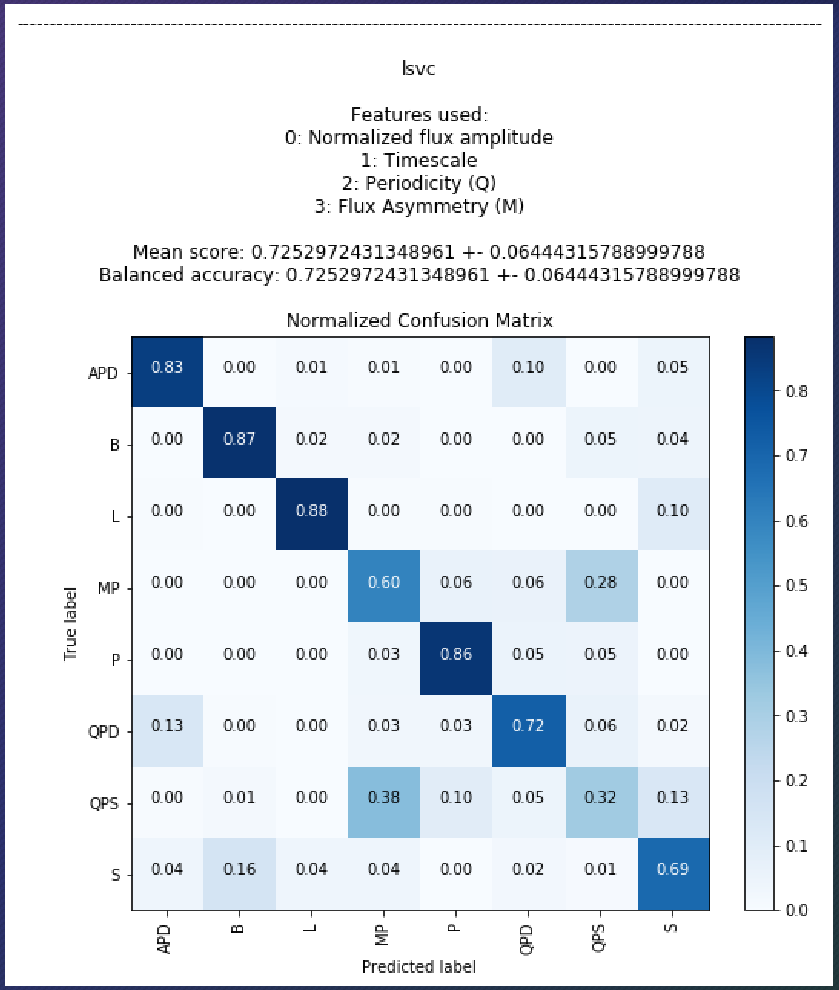


Results: Classification Performance Highlights (SVC)





Results: Classification Performance Highlights (LinearSVC)



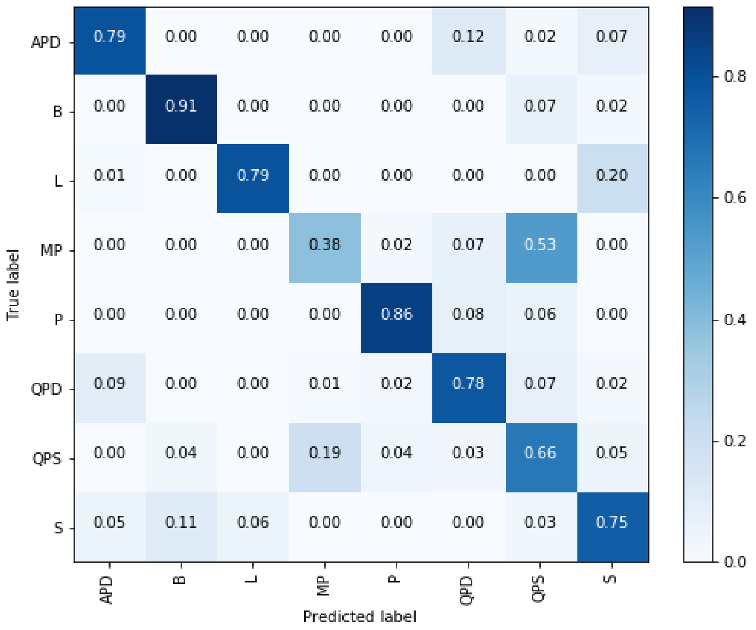
Results: Classification Performance Highlights (Random Forest)

rf_md5_mfn

Features used:
0: Normalized flux amplitude
1: Timescale
2: Periodicity (Q)
3: Flux Asymmetry (M)

Mean score: 0.747710843373494 +- 0.048036493602945714
Balanced accuracy: 0.7482566929082373 +- 0.0638322873532453

Normalized Confusion Matrix



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  - Best classification results capped at ~75% weighted, balanced accuracies
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  - Classifiers struggle with MP vs. QPS, APD vs. QPD, S in general

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- Supervised learning has great potential for automated variable young star classification!

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- Unsupervised Learning
  - clustering algorithms
  - re-evaluating variable type classifications, focusing on different light curve properties

Acknowledgements

- Mentor: Dr. Lynne Hillenbrand
- ZTF Summer School
- Dr. Ann Marie Cody
- scikit-learn documentation
- Flintridge Foundation

References

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