A Stochastic Structure Function for Light Curves

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Outline

• Light Curves
• Probabilistic Models
• Classification Results
• Structure Functions
• Conclusions
Light Curves: SN-I vs SN-II

Classifying LCs with adequate # of obs is ~ “easy”
Light Curves: SN-I vs SN-II

It's much harder yet more critical to classify them "early"
Light Curves: Blazar vs CV

Some are intrinsically hard no matter how many obs
Classifying LCs

\[ \{ \text{SN-Ia, CV, Blazar, ...} \} \]

Feature Extraction

\[
\begin{bmatrix}
  f_1 \\
  f_2 \\
  \vdots \\
  f_n
\end{bmatrix}
\]

Classifier

THE BLACK BOX
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“Gap Histograms” (SSF)

- Model distribution of “gaps” \((\Delta t, \Delta m)\) in LC
  \[
  \text{LC}(t, m) \rightarrow \{ (\Delta t, \Delta m) \} \rightarrow \text{density model}
  \]

- Causal gaps \((t_k - t_j, m_k - m_j)\) where \(t_k > t_j\)

- Key advantages:
  - No LC pre-processing (alignment) required
  - Minimal storage requirements for each LC
  - Fast classification: histogram likelihoods
  - Every object class is modeled \textit{in the same way}
  - Can incorporate “error bars” in magnitude obs
LC $\Rightarrow$ Gap Histogram

Gap histograms let you work with LC fragments and to also pool multiple LCs.

The underlying density model is invariant to absolute magnitude and time shifts (no alignment).

Gap histograms can model not just error bars but also bounded flux observations e.g. under poor seeing, we may only have bounds such as $m > 18$. 
Class Prototype Histograms

SN-Ia   (879 LCs)

SN-IIp  (282 LCs)

CV      (426 LCs)
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Decision Tree Classifier

Event

96% accuracy

SN

86% accuracy

SN - I

SN - II

Collapsing

CV/Blazar

93% accuracy

RR Lyr / Mira

CV

Blazar

RR Lyrae

Mira

Cataclysmic

Periodic
Decision Tree Nodes

• each node uses a gap histogram based classifier
  - currently independently optimized

• histogram density model for LC gaps ($\Delta t, \Delta m$) is built for the two classes being discriminated

• classify LCs based on standard inferential rules

\[
\text{Posterior odds} = (\text{Likelihood ratio}) \times (\text{Prior odds})
\]
DT Classifier Results (1)

LC Test Data

Class 0 : 1236 SN
(908 SN-Ia + 328 SN-II)

Class 1 : 932 “not SN”
(121 Blazars + 417 CVs
+ 29 Miras + 355 RR Lyrae)

Accuracy = 96 % (assuming equal priors)
DT Classifier Results (2)

LC Test Data

Class 0 : 908 SN Ia

Class 1 : 328 SN II

Accuracy = 86 % (assuming equal priors)
DT Classifier Results (3)

LC Test Data

Class 0: 417 CV + 121 Blazars

Class 1: 355 RR + 29 Miras

Accuracy = 93% (assuming equal priors)
Performance vs. $N_{\text{obs}}$
Marginal Distributions

$p(\Delta t, \Delta m)$

$\Delta m$

$\Delta t$
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Structure Functions

- “1st order” SF

\[
SF(\tau) = \frac{1}{N(\tau)} \sum_{i=1}^{N} w(t_i) w(t_i + \tau) [x(t_i + \tau) - x(t_i)]^2
\]

- “variance” of increments with time lag \( \Delta t \)

\[
SF(\Delta t) = \langle [m(t + \Delta t) - m(t)]^2 \rangle
\]

Structure Functions

Two Red Noise Sources

P. Arevalo
“Gap Histogram” = Stochastic SF

CV

Instead of a scalar $\text{var}(\Delta m)$ at each lag $\Delta t$, SSF gives a full pdf on $\Delta m$

SF

A standard SF can be trivially computed from the SSF
“Gap Histogram” = Stochastic SF

Instead of a scalar $\text{var}(\Delta m)$ at each lag $\Delta t$
SSF gives a full pdf on $\Delta m$

A standard SF can be trivially computed from the SSF
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Conclusions

- SSF is a fast, cheap, flexible, probabilistic method
- Handles LC fragments, error bars, bounds, etc.
- Optimal Binning of $\Delta t - \Delta m$ space (with Jeff Scargle)
- Can do full multi-class classification (not just binary)
- SSF can be informative for optimal sampling
- A standard SF can be easily derived from a SSF
The End

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