Shaplet method to classify GRS1915+105 black hole signal anomalies

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Summary

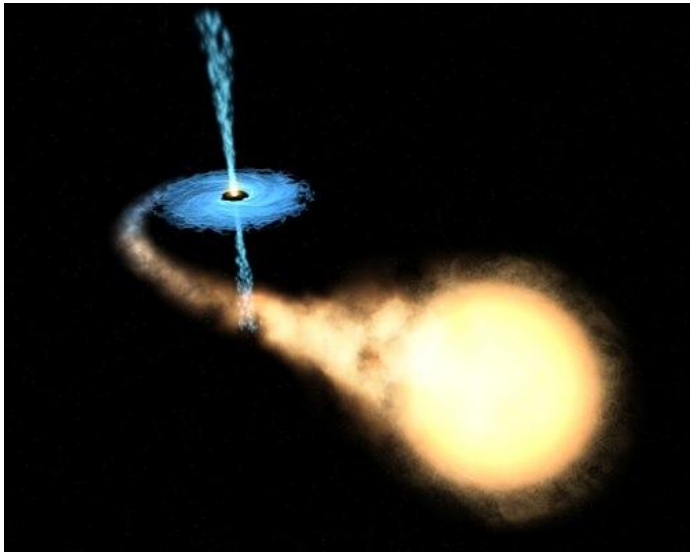
1. Introduction to GRS 1915+105
2. Shaplets in action
3. Library building and main results

1. Introduction to GRS 1915+105 : X ray binaries evolution

1. Evolution of binary system
2. Death of the primary star → compact remnant
3. Mass transfer begins: The second star radius

   exceeds Roche Lobe

4. Formation of accretion disk → X ray emission

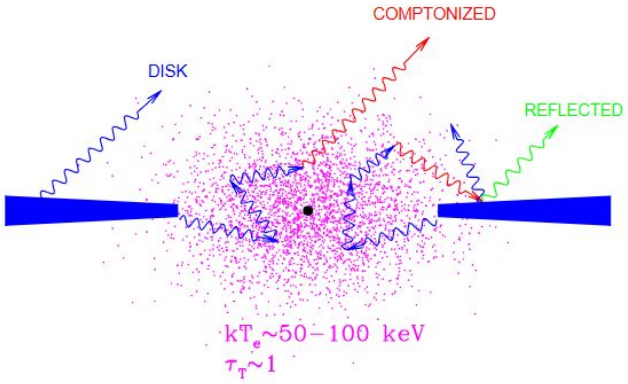


A special type of x binaries: Microquasars

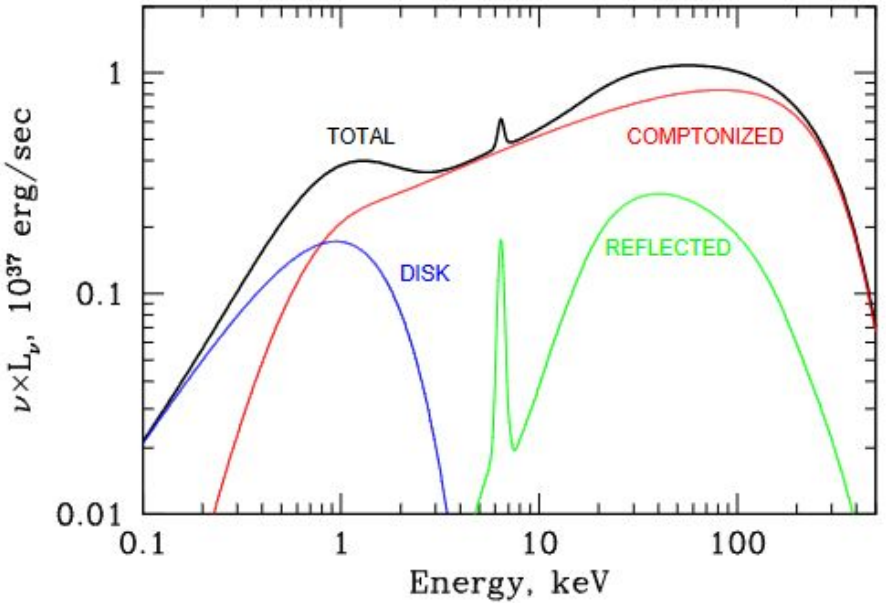
Stellar black hole

Emission of relativistic particles and generation of strong radio wave emission.

1. Introduction to GRS 1915+105 : X ray emission & Data

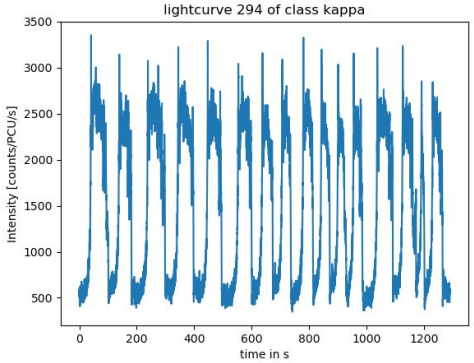


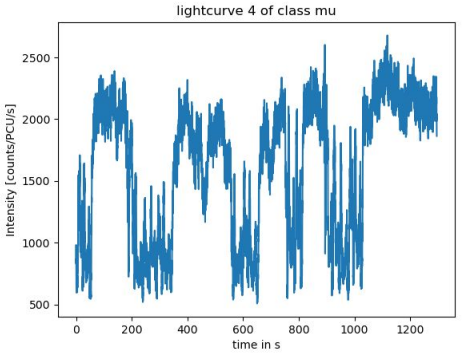
- RXTE observatory
- Use Crab Nebula for calibration
- light curves with 3 energy bands :
  - low: 2-5 keV
  - mid: 5-13 keV
  - high: 13-60keV

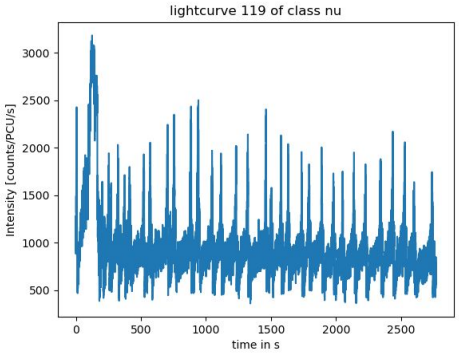


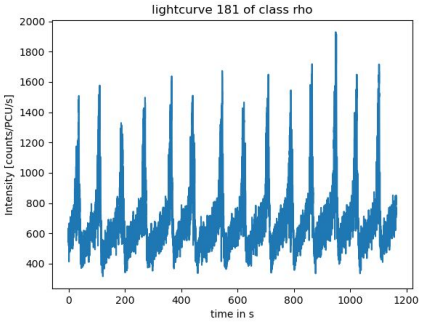
1. Introduction to GRS 1915+105 : GRS 1915+105

-14 modes of outburst compared to 3 for usual microquasars









-modes are indicate transition from accretion state to another

-Classifying the states and identifying them helps us understand the physics in the disk

How to address the variability?

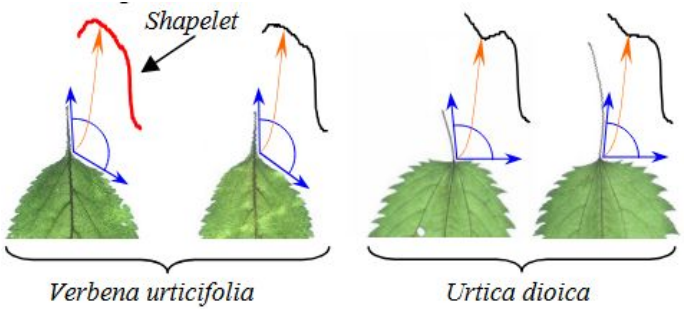
- Are there similar patterns?
- Classification questions? (human classification ?)
- Can we see transitions between classes?
- Are there anomalies ?

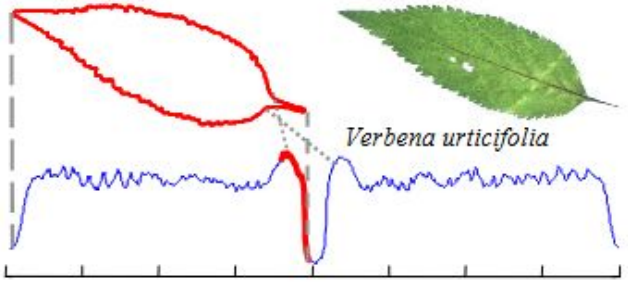
=> Exploration tool

Shapelet algorithm

Supervised learning technique to identify and classify time series

Use a maximally representative subsequence





Advantages:

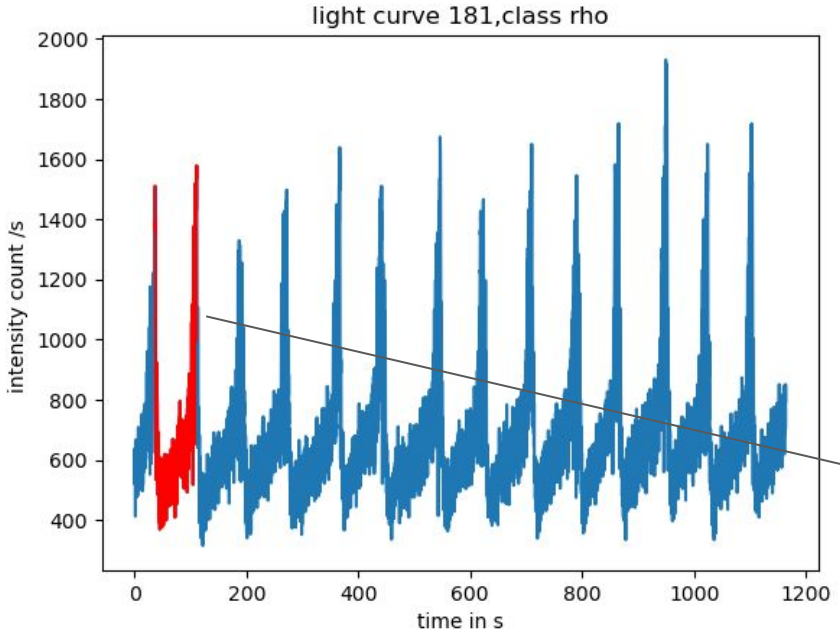
- Interpretability
- Robust: more resistant to artifacts
- Computational efficiency
- Translation invariant

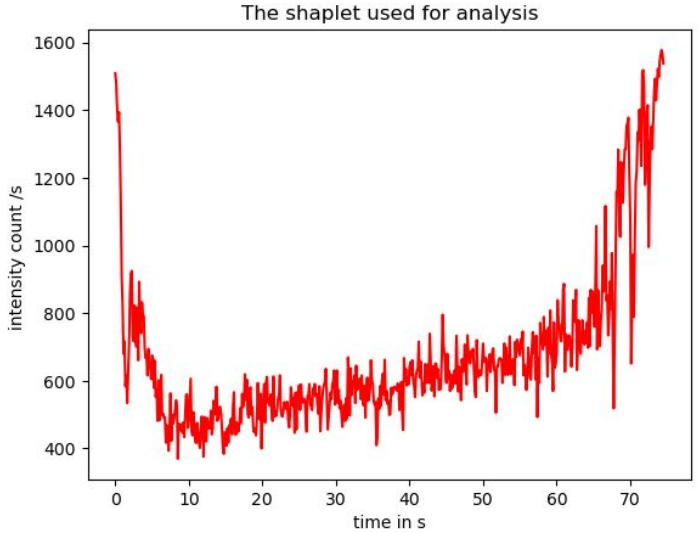
How to define similarity metric?
How to choose useful set of shaplets?

How to choose a shaplet

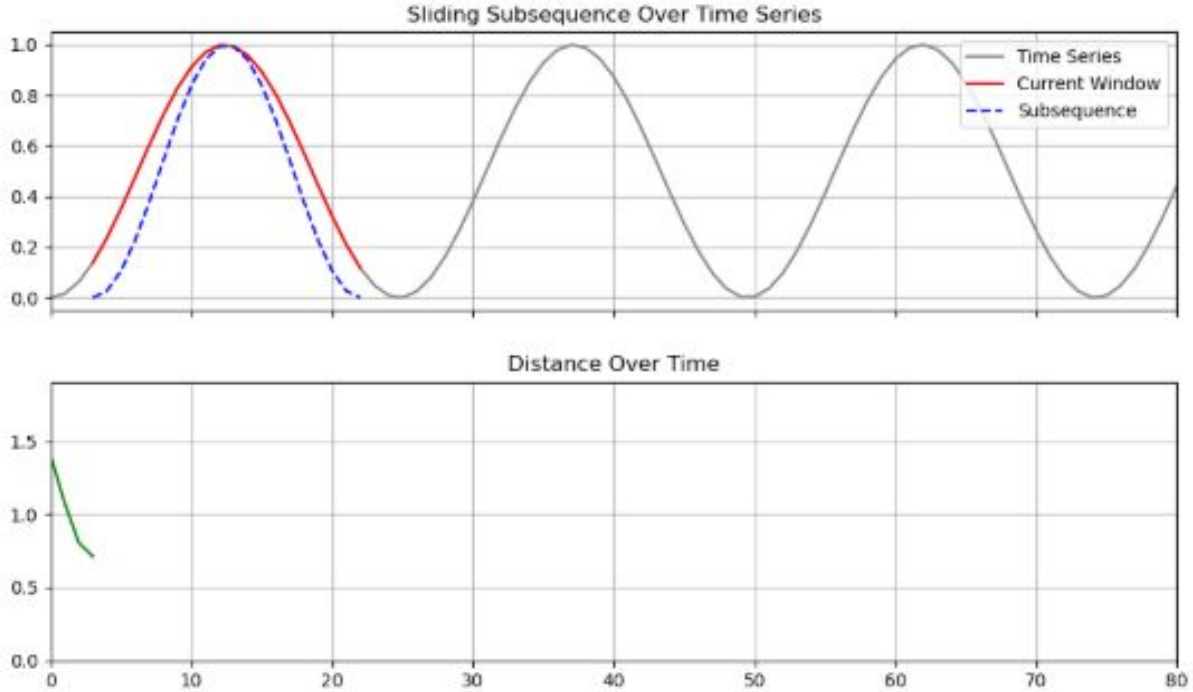
Rho class most periodic: easy to test
Windowing

Shaplet defined from a maxima to another:
the maximas are well defined whereas the minimas are ‘fuzzy’

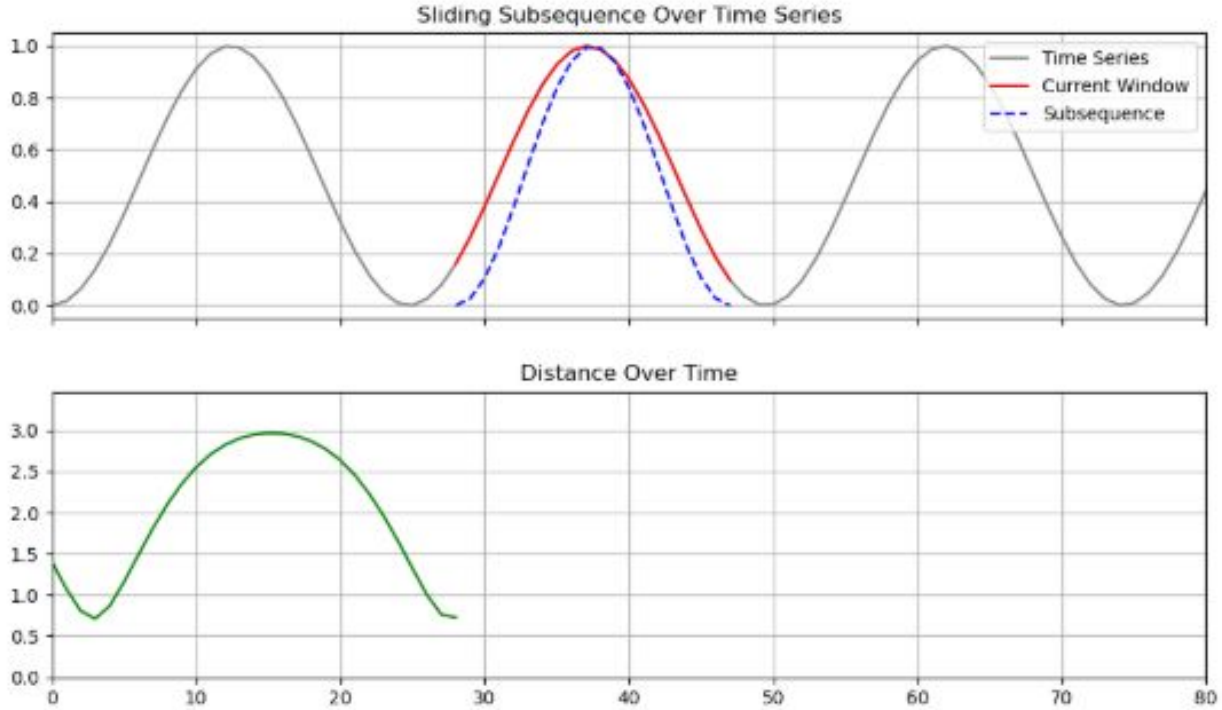




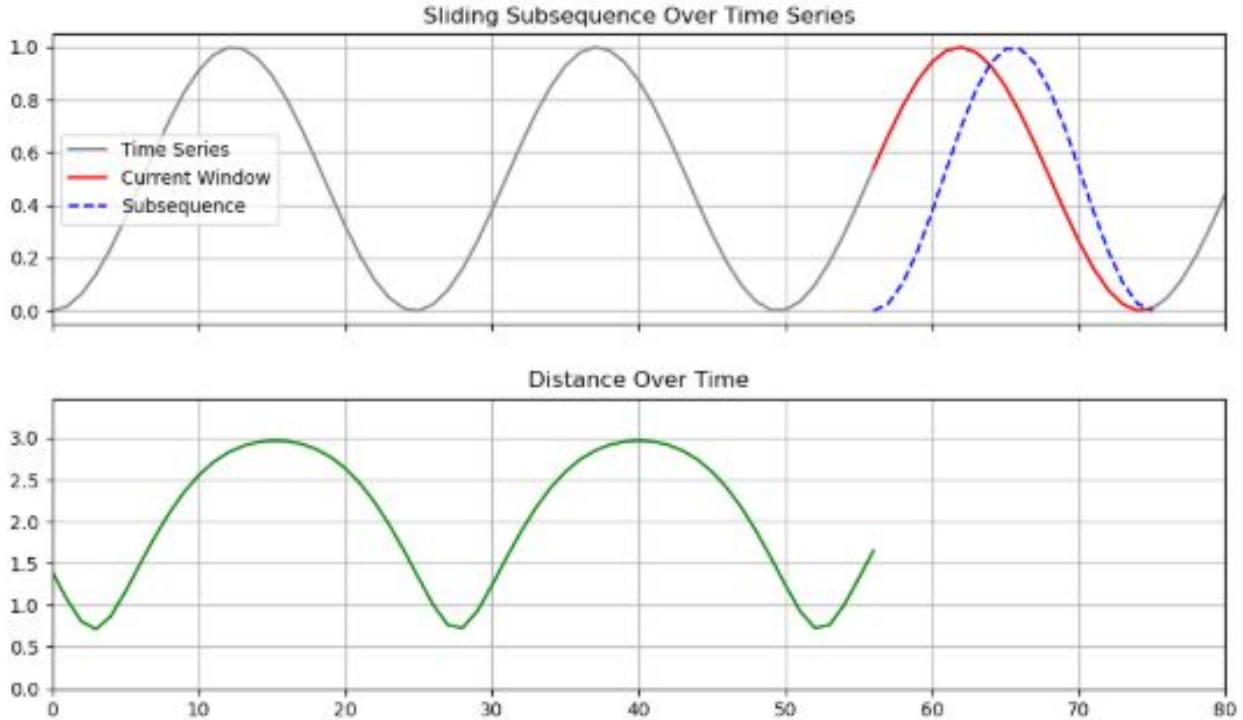
Windowing


Sliding Subsequence Over Time Series
Time Series
Current Window
Subsequence
1.0
0.8
0.6
0.4
0.2
0.0
Distance Over Time
1.5
1.0
0.5
0.0
0
10
20
30
40
50
60
70
80

Windowing


Sliding Subsequence Over Time Series
Time Series
Current Window
Subsequence
1.0
0.8
0.6
0.4
0.2
0.0
Distance Over Time
3.0
2.5
2.0
1.5
1.0
0.5
0.0
0
10
20
30
40
50
60
70
80

Windowing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2.5
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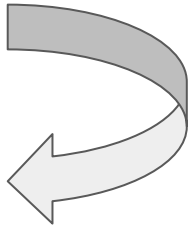
1.5
1.0
0.5
0.0
0
10
20
30
40
50
60
70
80

chi^2 test

$$\chi^2 = \sum_{i=0}^{\text{len(signal)}-\text{len(shaplet)}} \frac{(\text{signal} - \text{shaplet})^2}{\sigma^2_{\text{signal}} + \sigma^2_{\text{shaplet}}}$$



Will help us use an optimized method to compute sum (signal - shaplet)

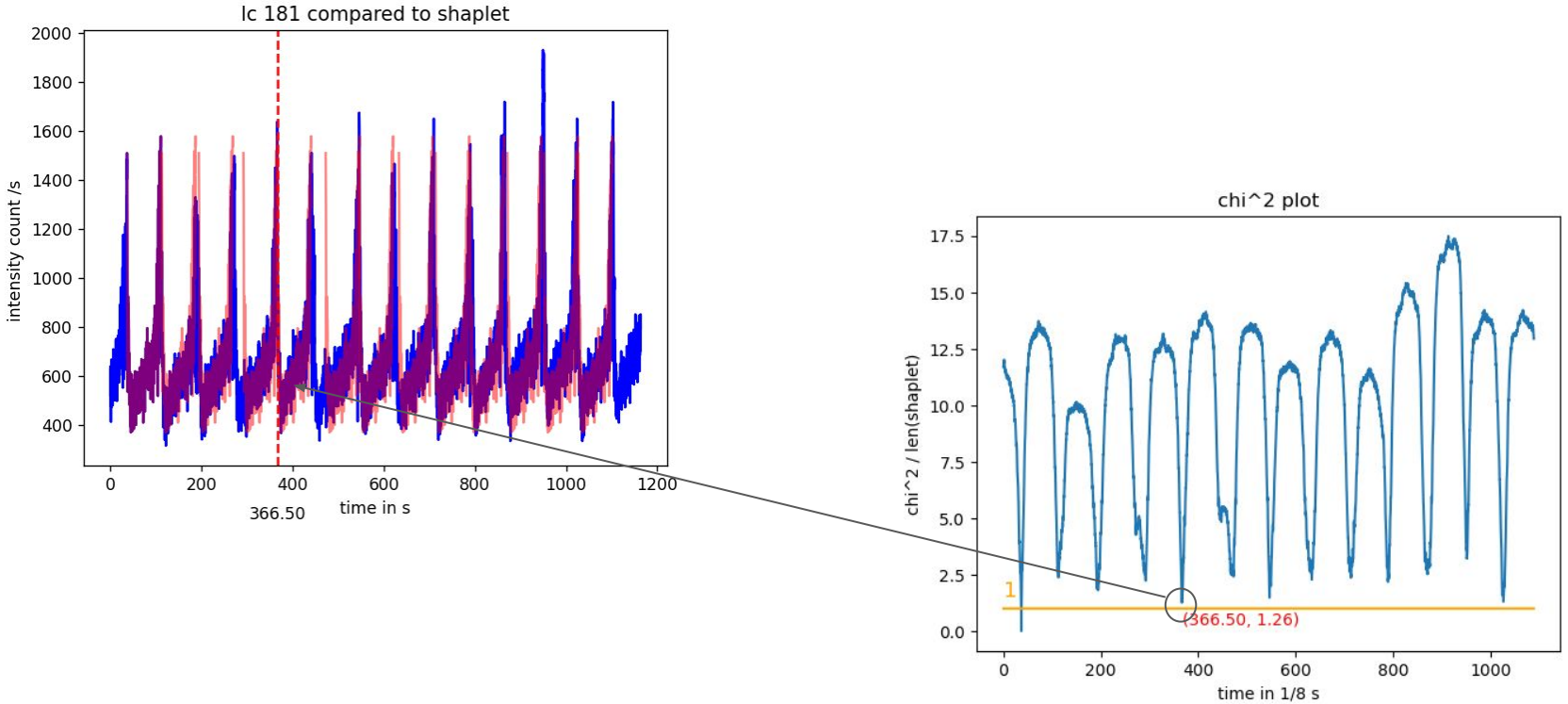
$$\chi^2 = \sum_{i=0}^{\text{len(signal)}-\text{len(shaplet)}} \frac{(\text{signal} - \text{shaplet})^2}{2\langle \text{shaplet} \rangle}$$

For a invariant chi^2 test with respect to the length of the shaplet we divide by the ndf

Ndf in our case is len(shaplet)

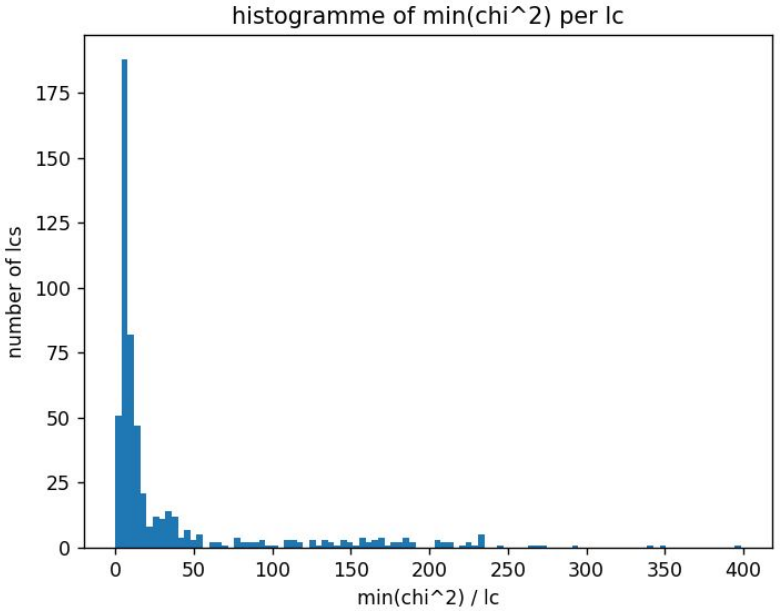
We expect an average value of 1 for the good matches

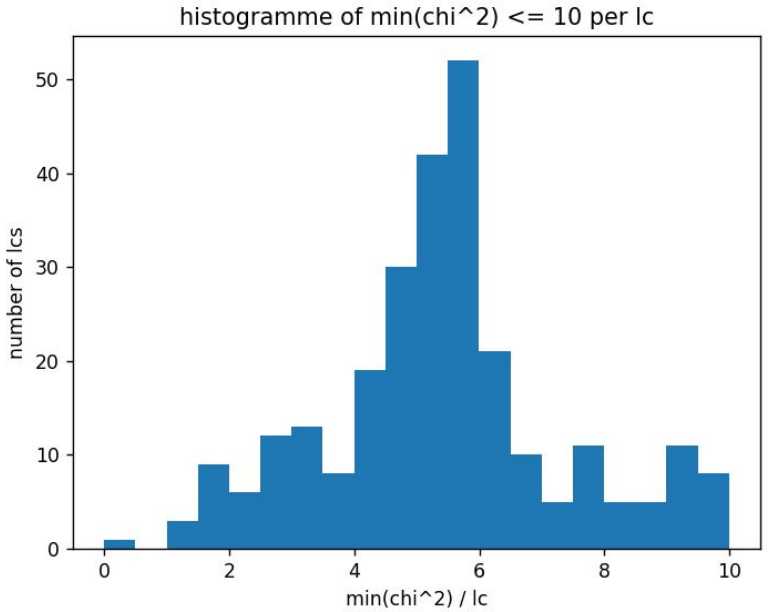
Chi^2 on lc181 example



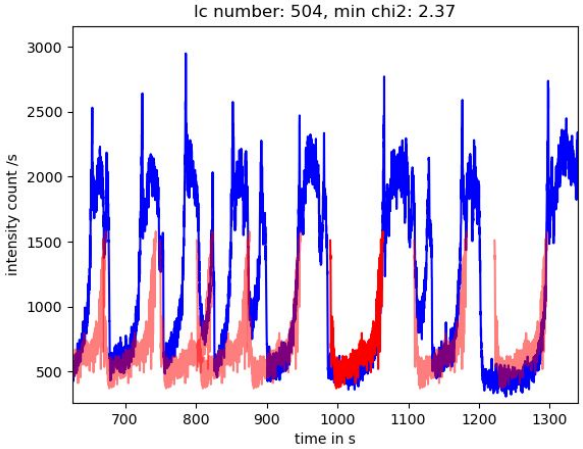
Metric used for a light curve,and a first overview

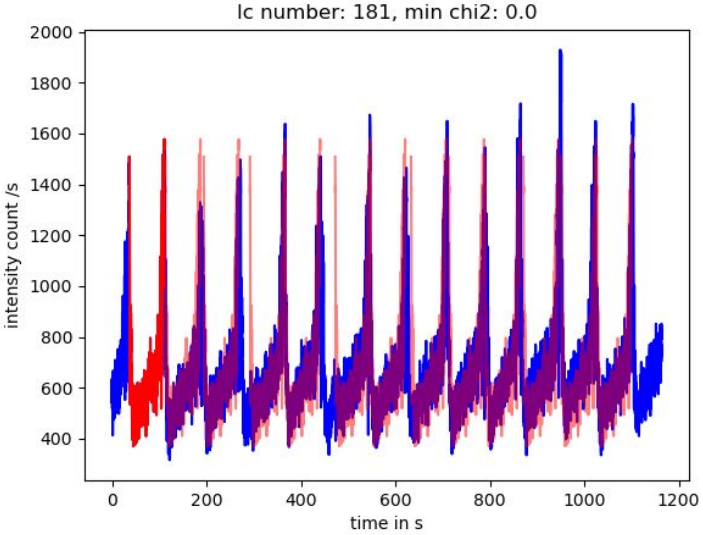
We used “min(chi^2)” as a metric to define difference (Shaplet , light curve)

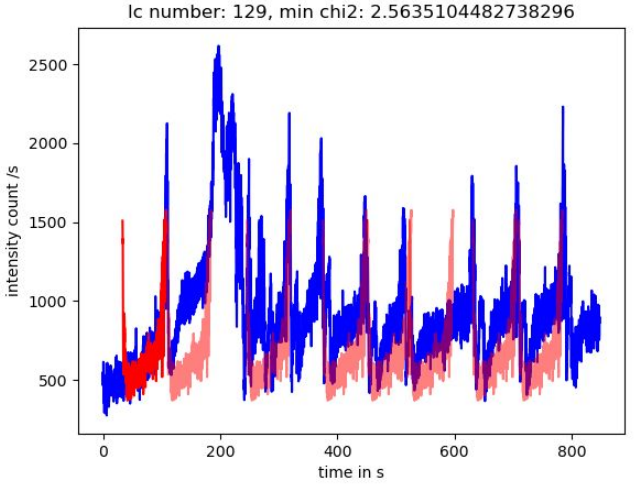




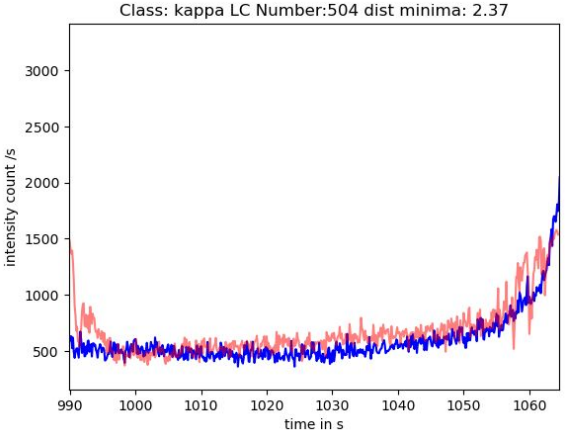
Lc examples

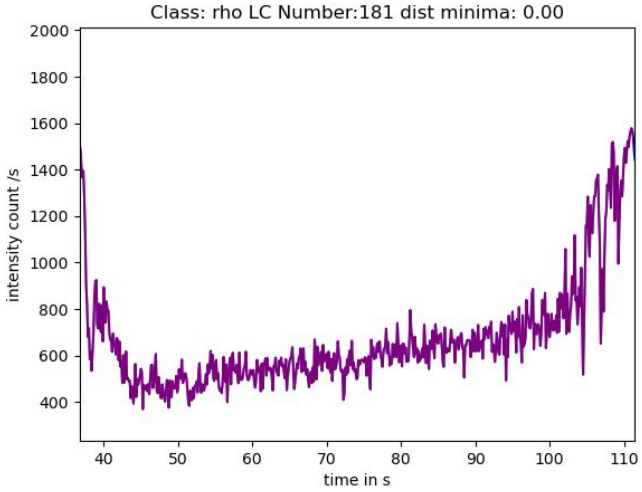

lc number: 504, min chi2: 2.37
intensity count /s
time in s


lc number: 181, min chi2: 0.0
intensity count /s
time in s

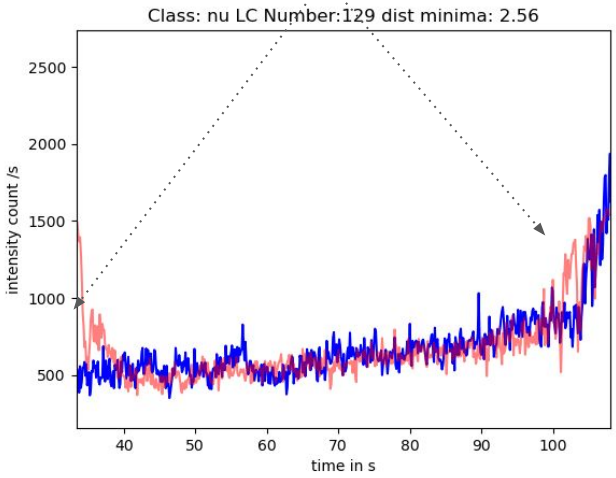

lc number: 129, min chi2: 2.5635104482738296
intensity count /s
time in s

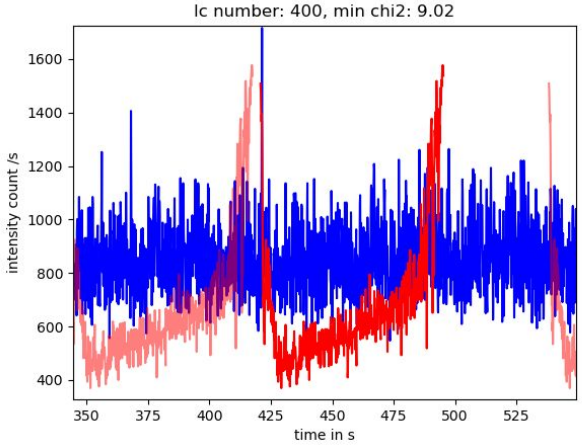
Same Lcs but plotted at high resemblance only:

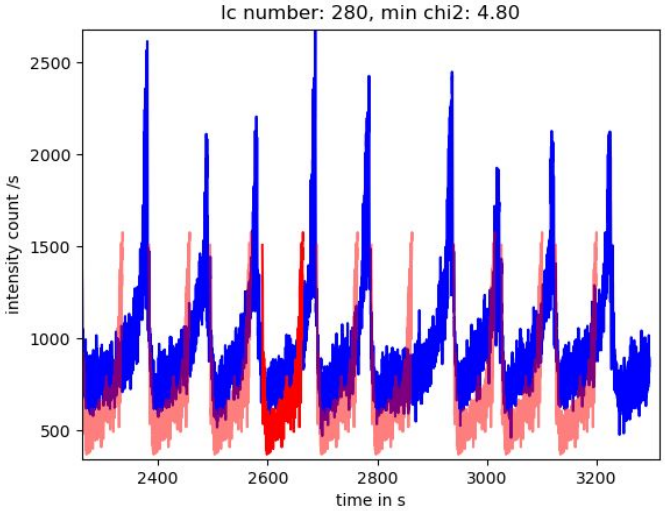


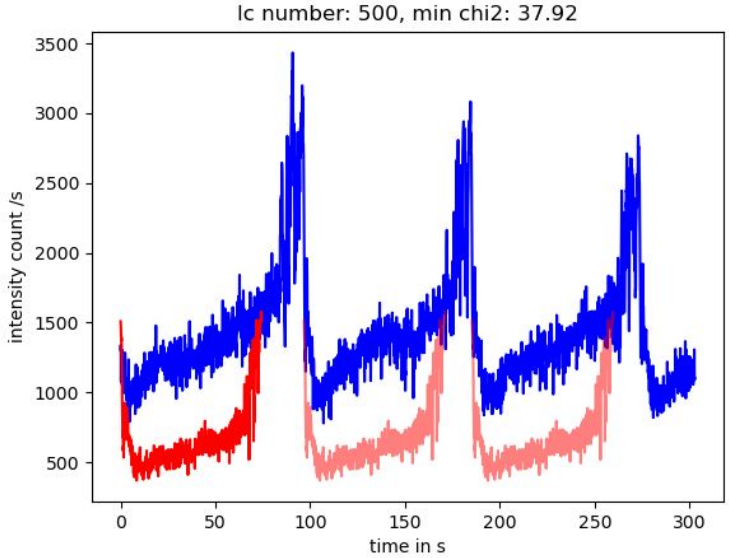


Partial match is considered a good match,'overall' the matching is close (try a shaplet of smaller length)



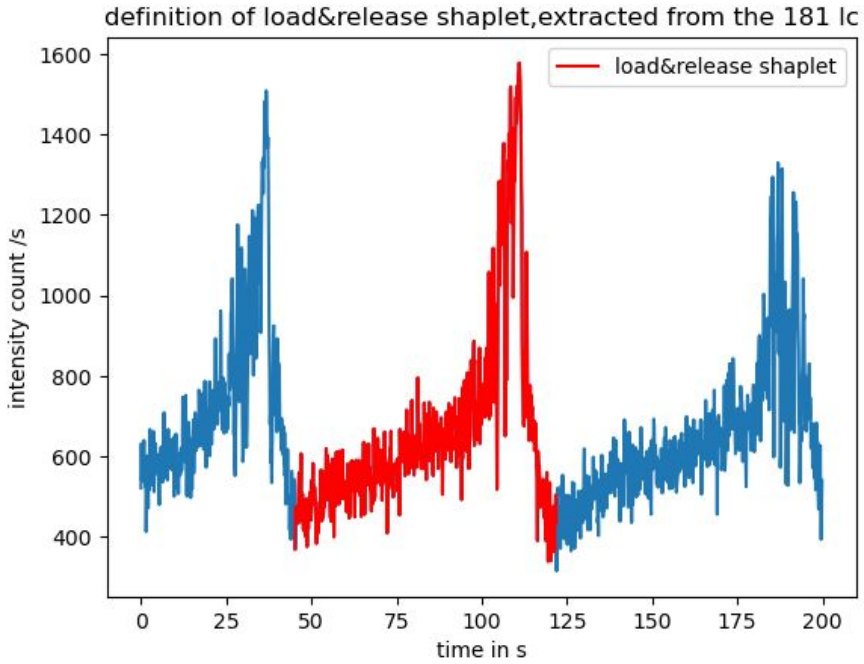

lc number: 400, min chi2: 9.02
intensity count /s
time in s


lc number: 280, min chi2: 4.80
intensity count /s
time in s

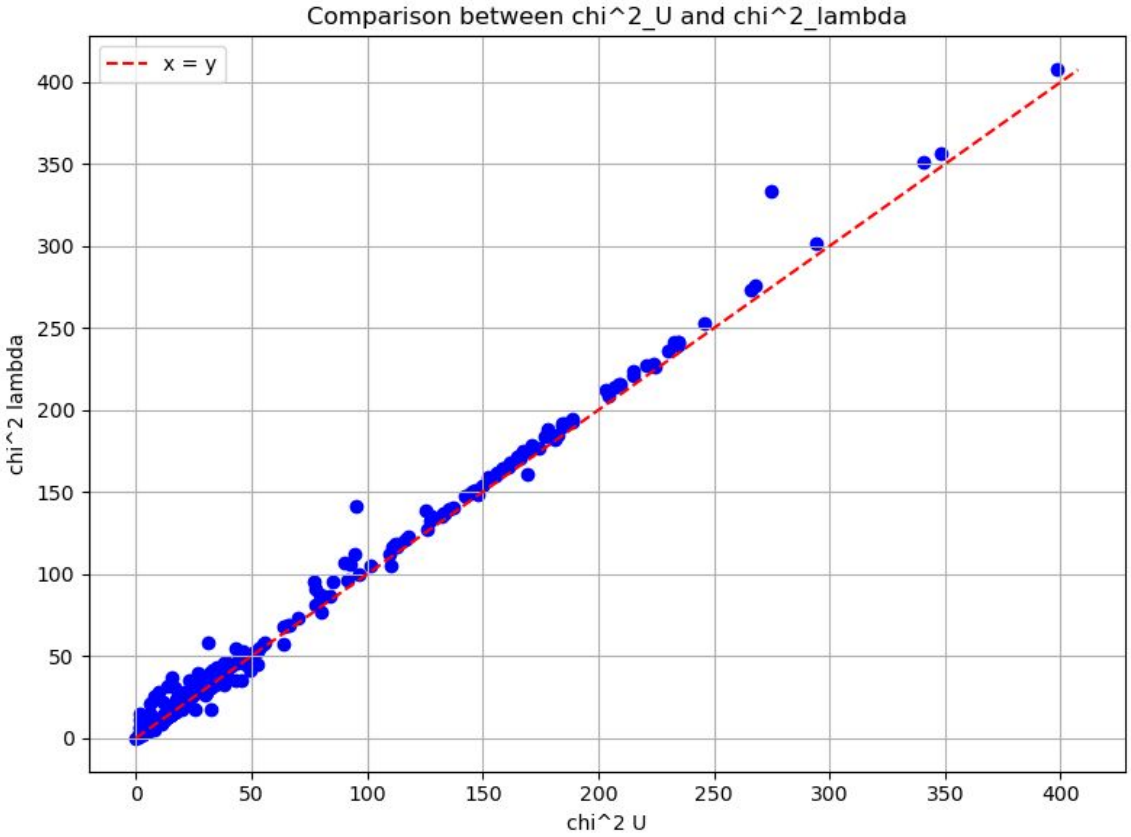

lc number: 500, min chi2: 37.92
intensity count /s
time in s

Robustness Testing

We take a new shaplet:

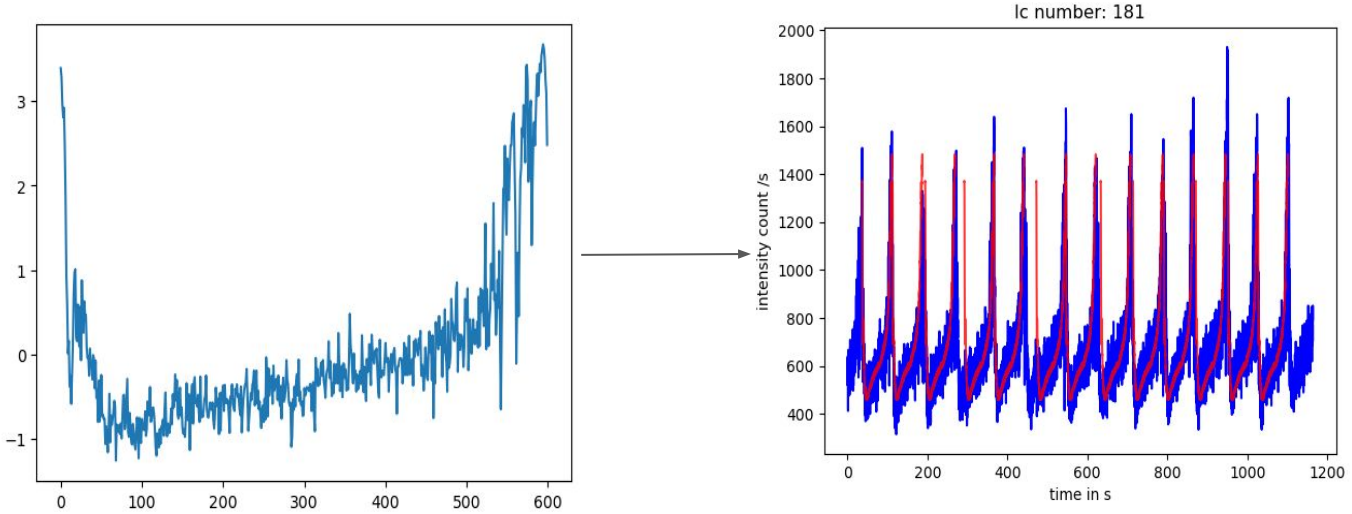


Chi^2 results comparison replace with chi^2U vs chi^lambda schema

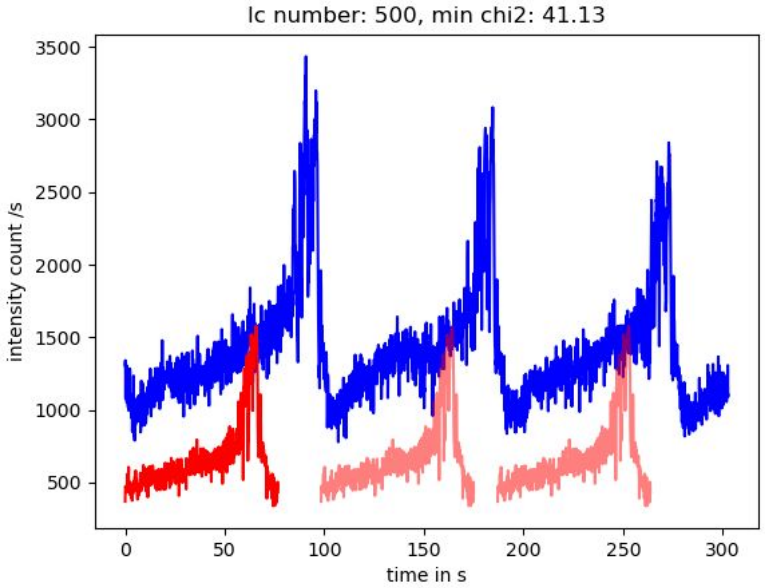


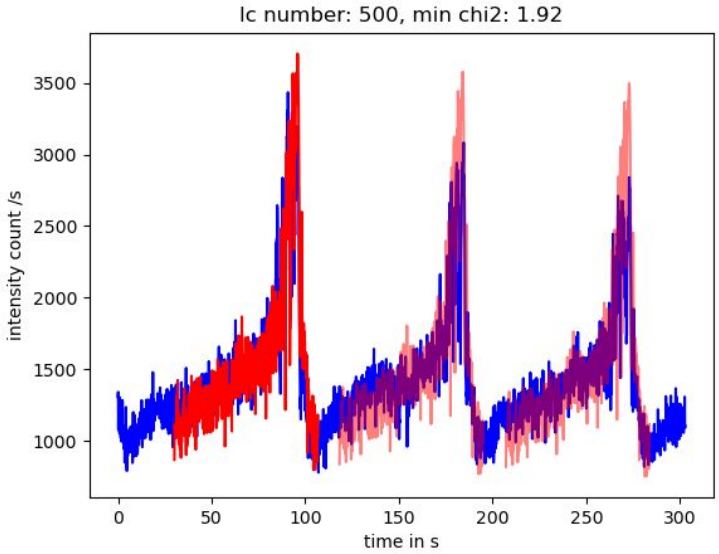
Averaging

$$\left\langle shaplet, \left\{ S \subseteq L \,\middle|\, \chi^2_{res}(S, shaplet) < 2 \right\} \right\rangle$$



Scaling





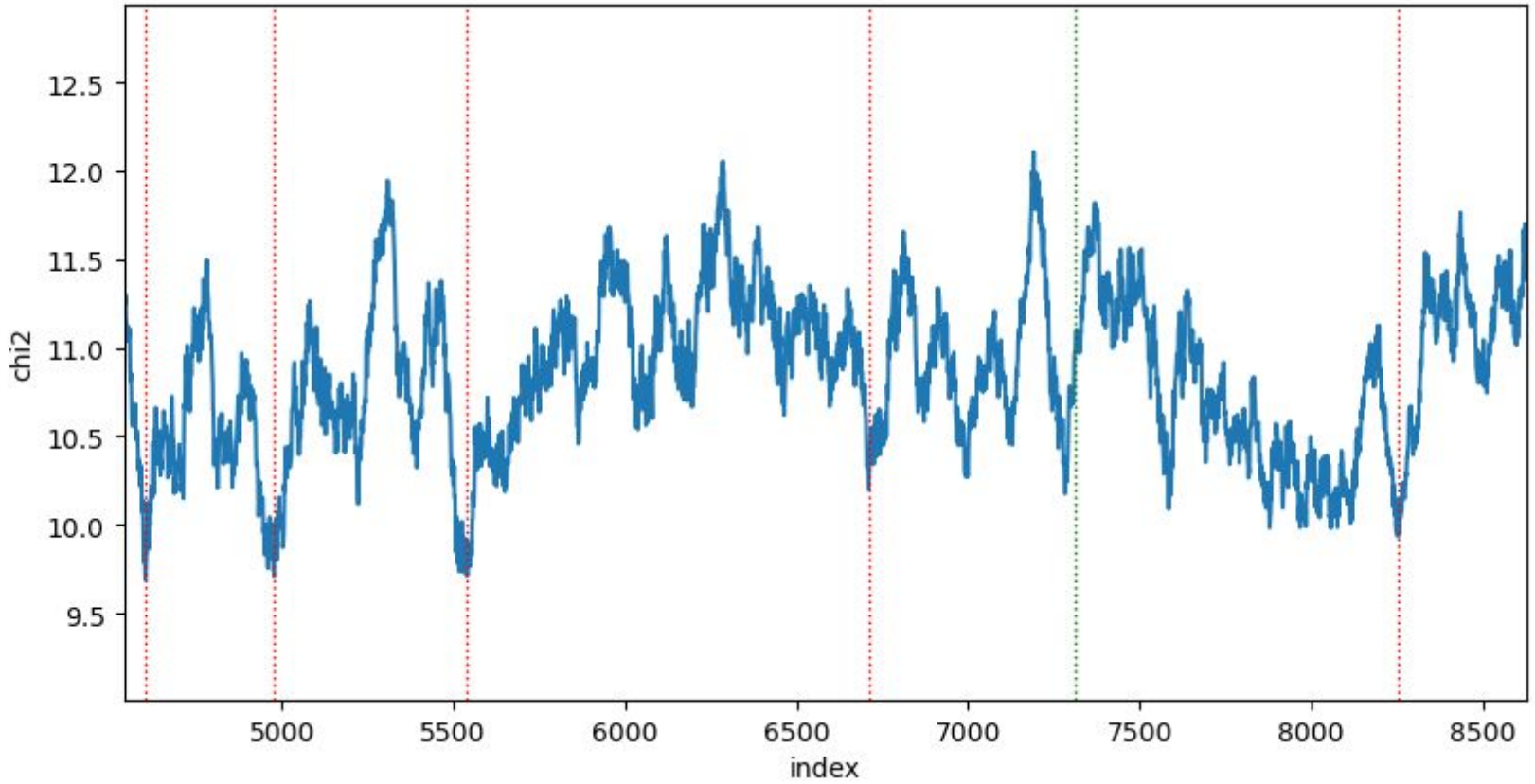
Observation:

Scaling: Affine transformation,not coherent with averaging process

Normalisation: Process in the normalized space

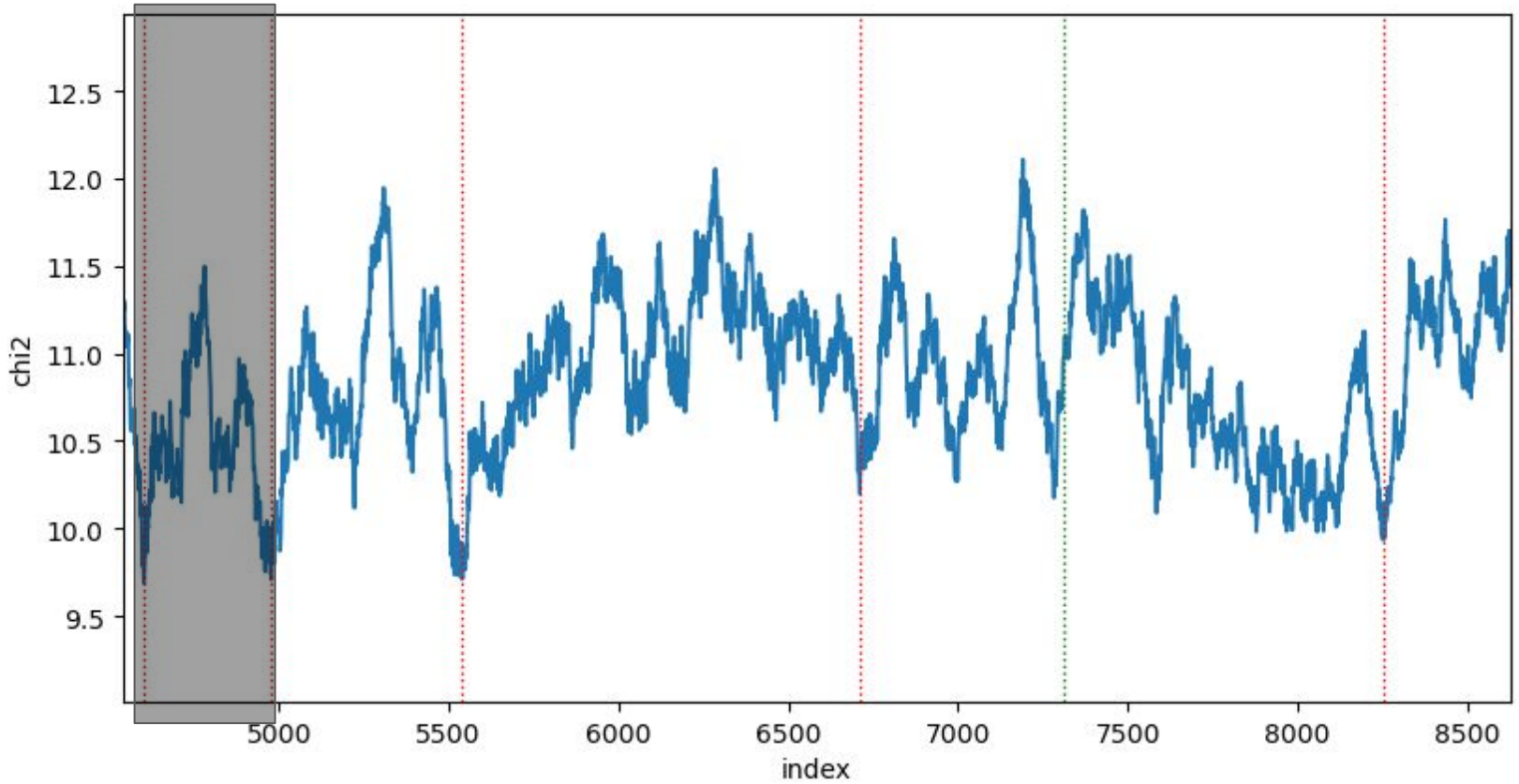
Building the dictionary:

Lightcurve 400, shaplet lambda



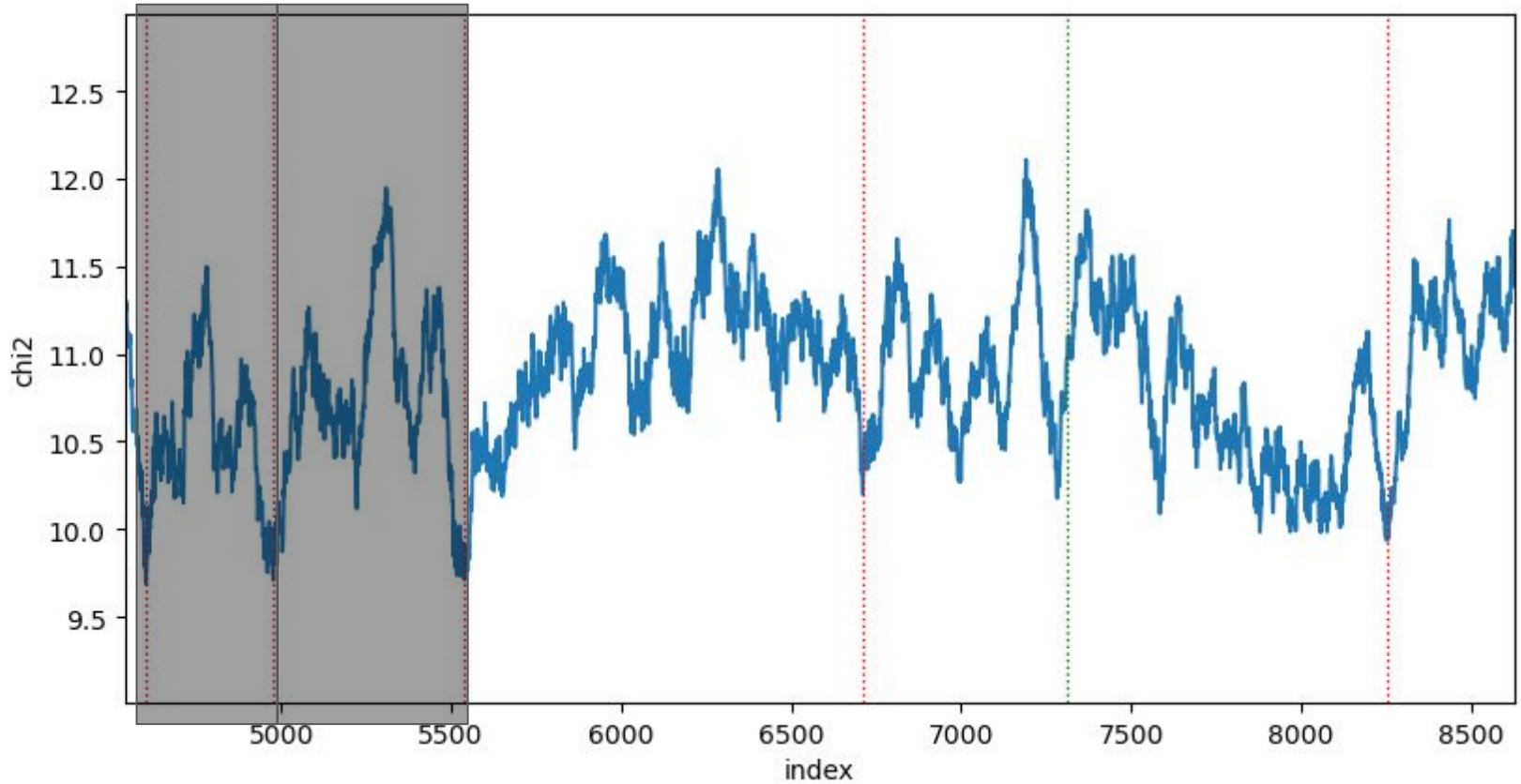
Building the dictionary:

Lightcurve 400, shaplet lambda



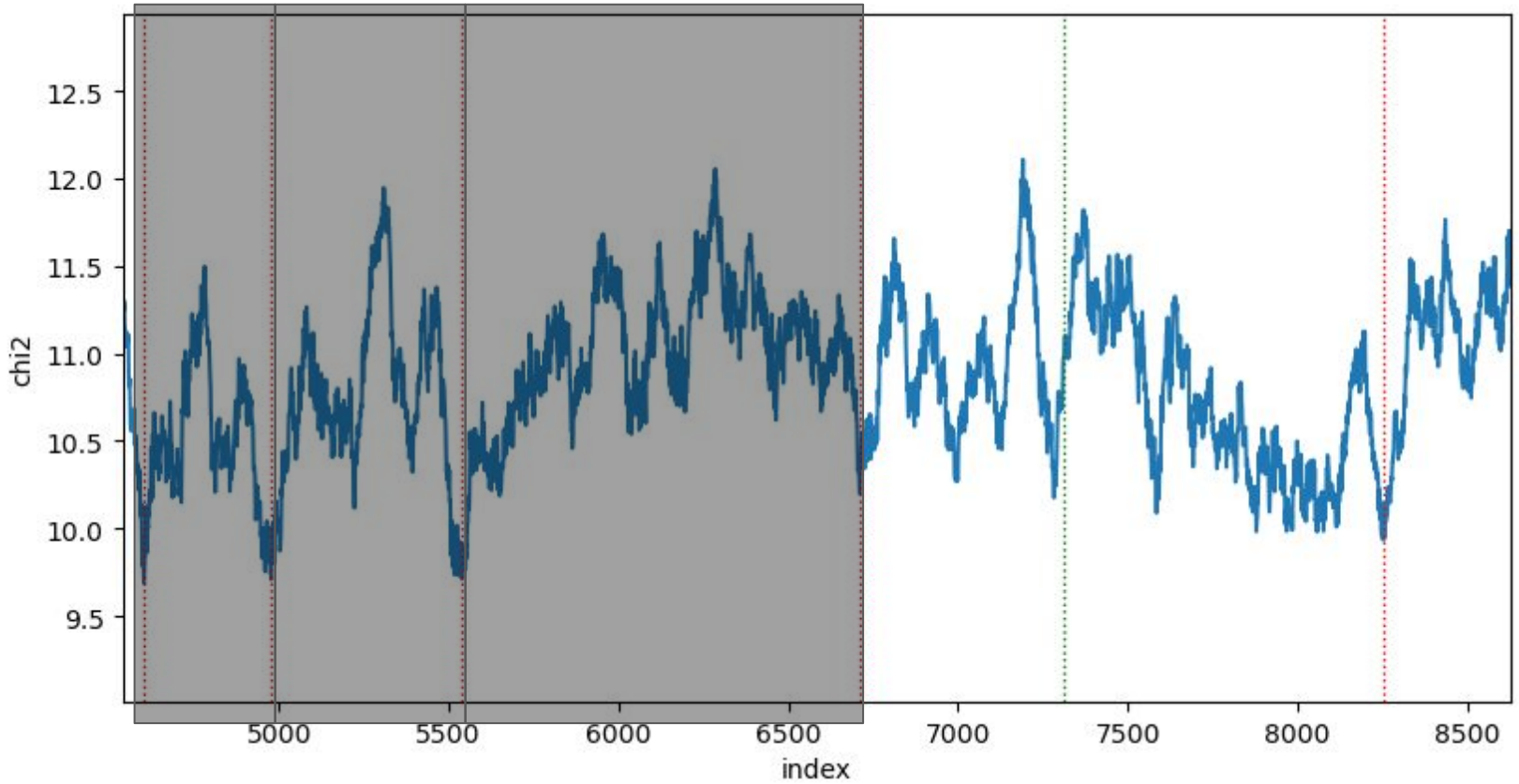
Building the dictionary:

Lightcurve 400, shaplet lambda



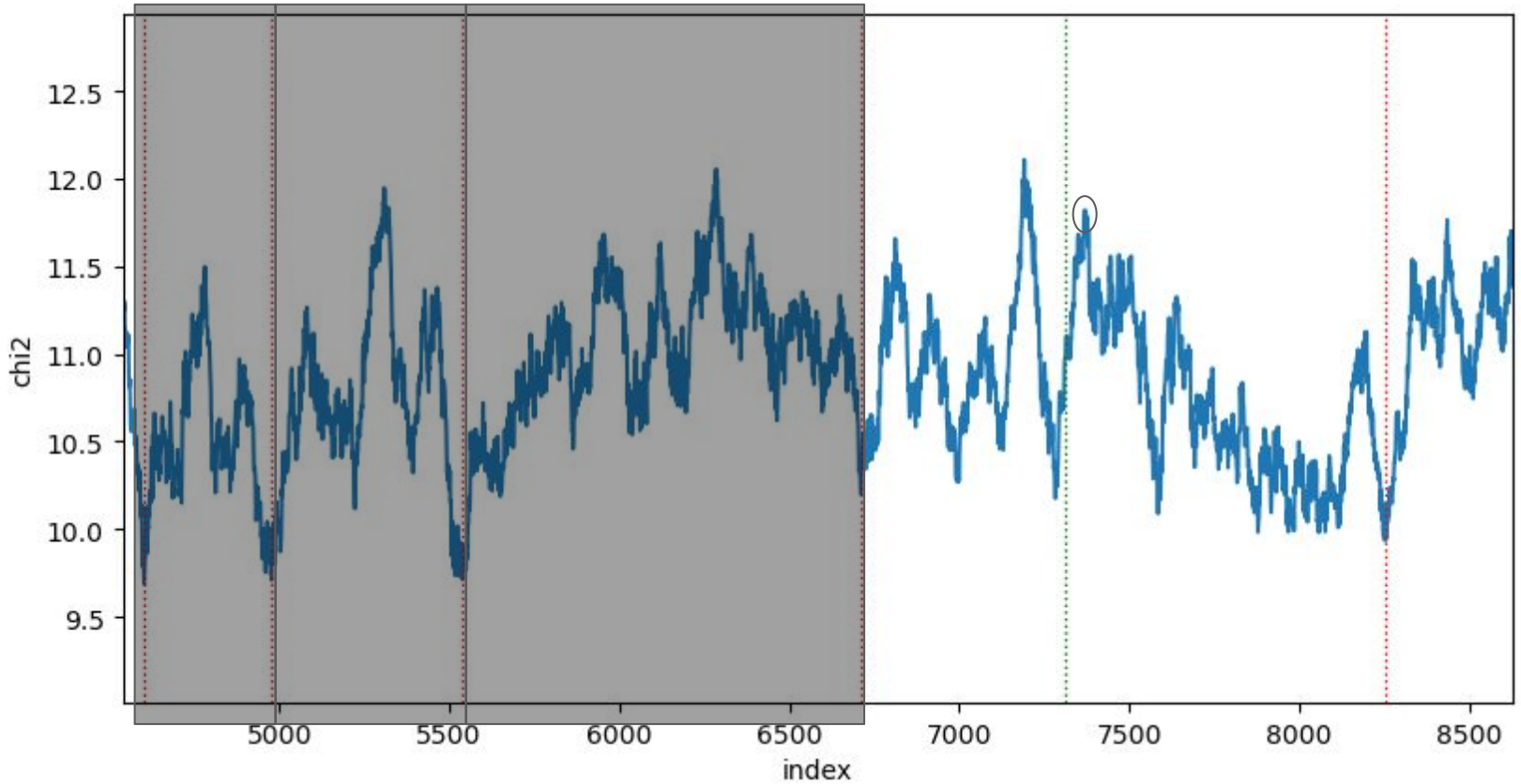
Building the dictionary:

Lightcurve 400, shaplet lambda



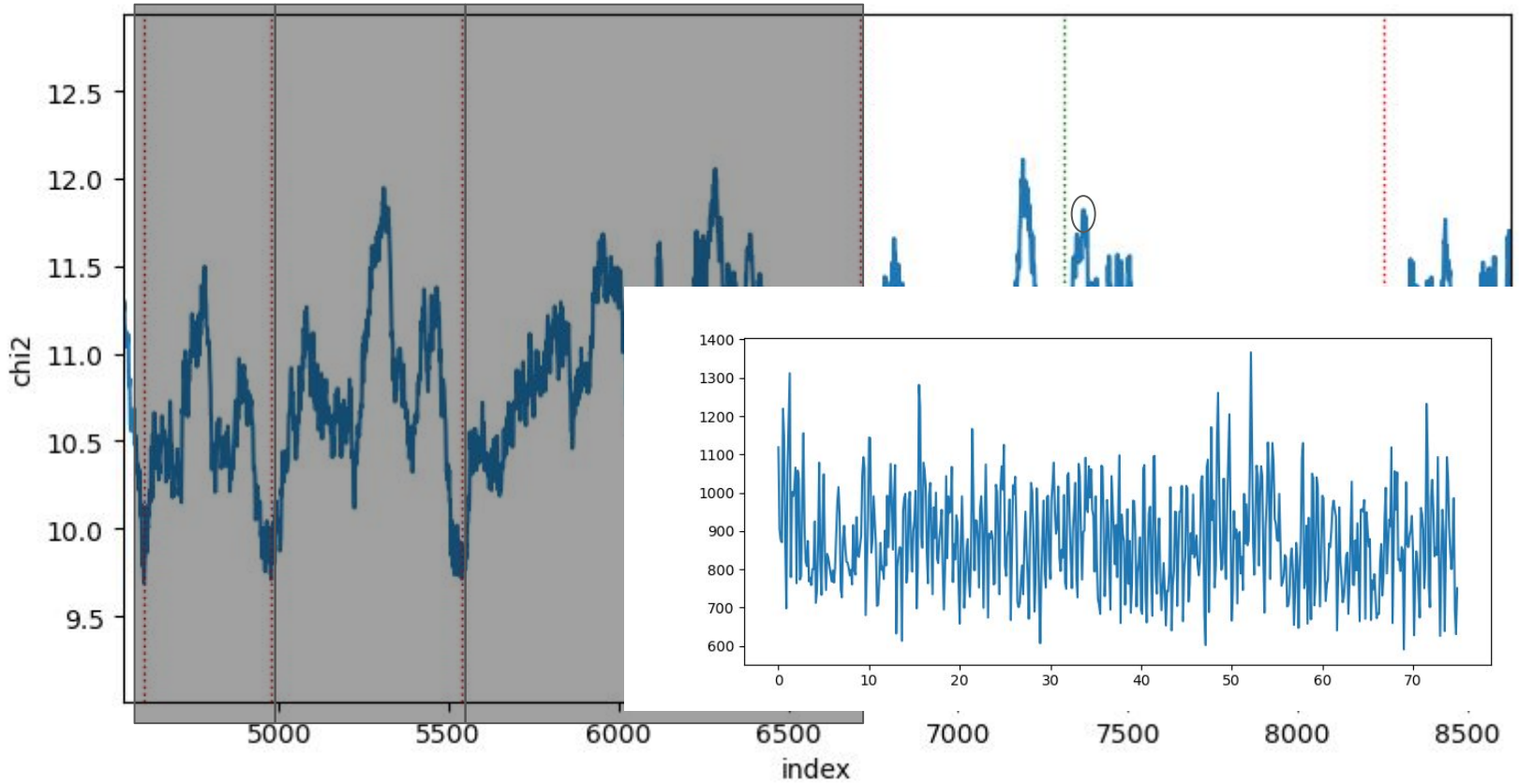
Building the dictionary:

Lightcurve 400, shaplet lambda

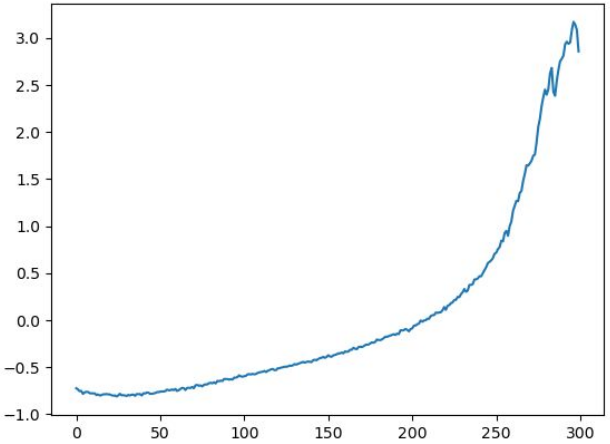


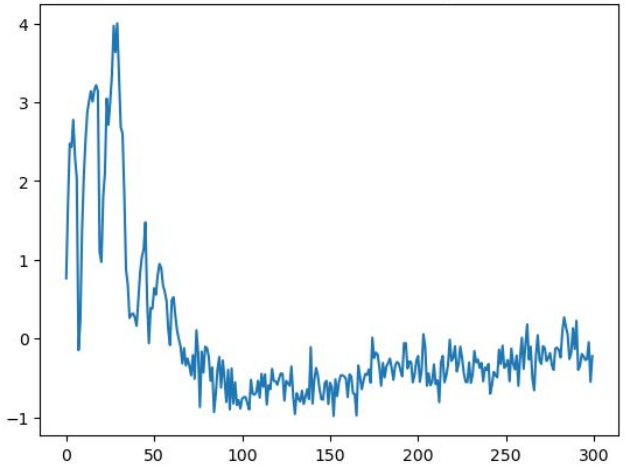
Building the dictionary:

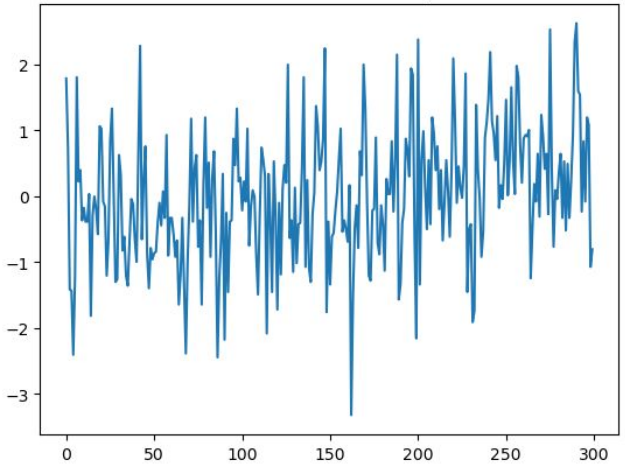
Lightcurve 400, shaplet lambda



Resulting shaplets







future work:

- Developed a dictionary encoding for **all** lightcurves using sequences of discrete shapelets -> facilitates effective anomaly detection by analyzing patterns and deviations in the shapelet sequences
- Use shapelets to generalize feature analysis.