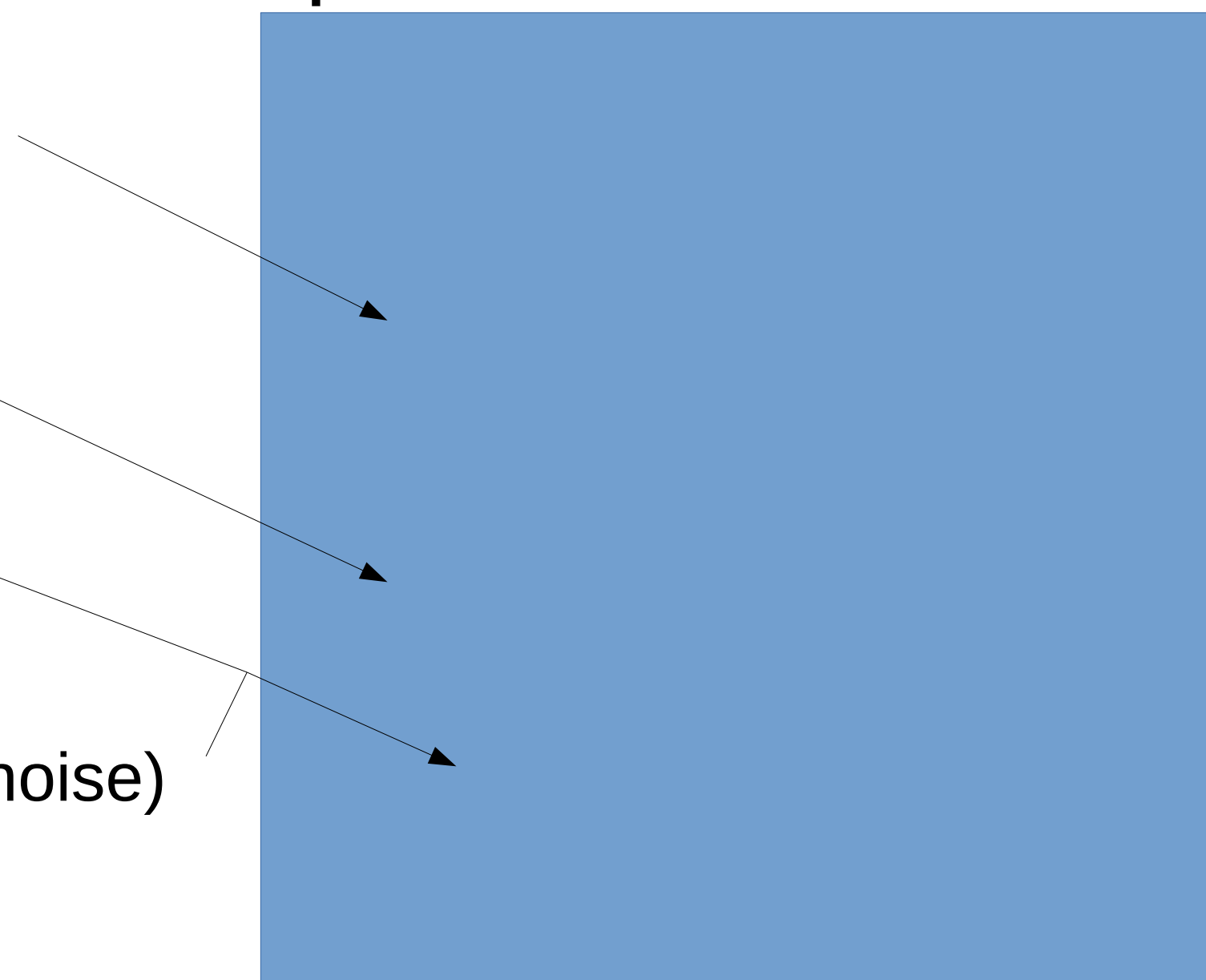


(Time) series

- Sequence of data points over some parameter
- Analysis methods can be applied to any data with some natural ordering
- Main topic: Separation of signal components
 - Main goal: Predicting the future (model)

Components

- Seasonal
 - Trend
 - Cyclic
 - Irregular (noise)
- 
- A large, solid blue rectangle occupies the right half of the slide. Four thin black arrows originate from the text labels on the left and point towards the left edge of the blue rectangle. The arrows for 'Seasonal' and 'Trend' point to the upper portion of the rectangle, while the arrows for 'Cyclic' and 'Irregular (noise)' point to the lower portion.

Classical decomposition (~1920s)

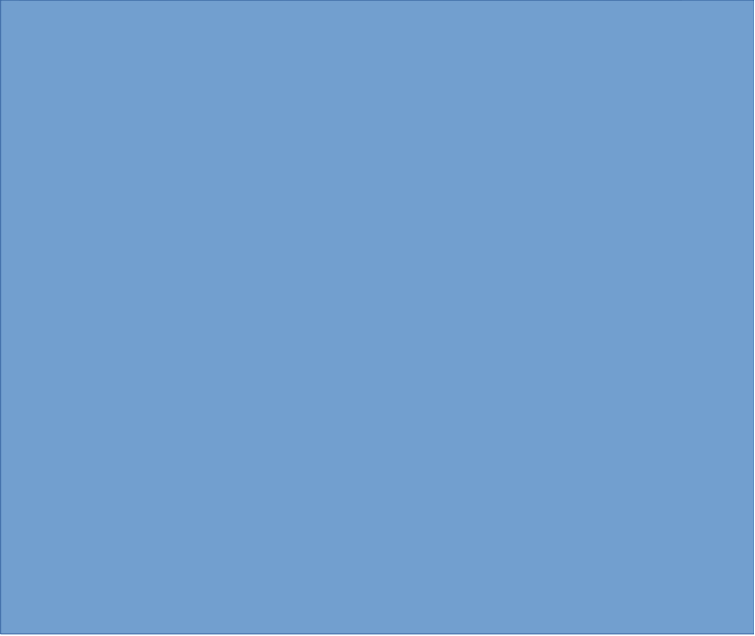
- Additive: $y = T + S + C + I$
- Multiplicative: $y = T \cdot S \cdot C \cdot I$
- Recipe:
 - Find trend T and detrend: $y' = y - T$ ($y' = y/T$)
 - Find seasonal comp.: $y'' = y' - S$ ($y'' = y'/S$)
 - Remainder consists of cyclic and irregular comp.
- We will focus on:
 - 2 detrending methods (moving avg. & fourier ana.)
 - A method for finding seasonal comp. (fourier ana.)
 - A method for finding cyclic comp. (autocorr.)

Detrending - Moving average

Average over a moving window of data

- Add weights if necessary:
$$\hat{T}_t = \frac{1}{m} \sum_{j=-k}^k y_{t+j}$$
 - Gaussian
 - Exponential
 - Triangle
 - Whatever you can think of
- Pro: Easy and robust
- Con: Will usually incorporate part of other comp. (median?)

Slime mould experiment

- Show: https://www.youtube.com/watch?v=GY_uMH8Xpy0
 - Mention visible “vibrations” (~scale minute[s])
 - What is a slime mould:
 - One cell, move stuff around inside
 - Contractions (almost periodic), pumping function
 - Microplasma does the same
 - Preparations (and data acquisition):
 - Remove slime in centrifuge
 - Resuspend in growth medium on petri dish
 - Remove liquid after spreading
 - Put under light microscope
 - Wait and take pictures
 - Analysis:
 - Do a lot of image processing to get a binary picture
 - Analyze boundary oscillations and analyze area oscillation
- 

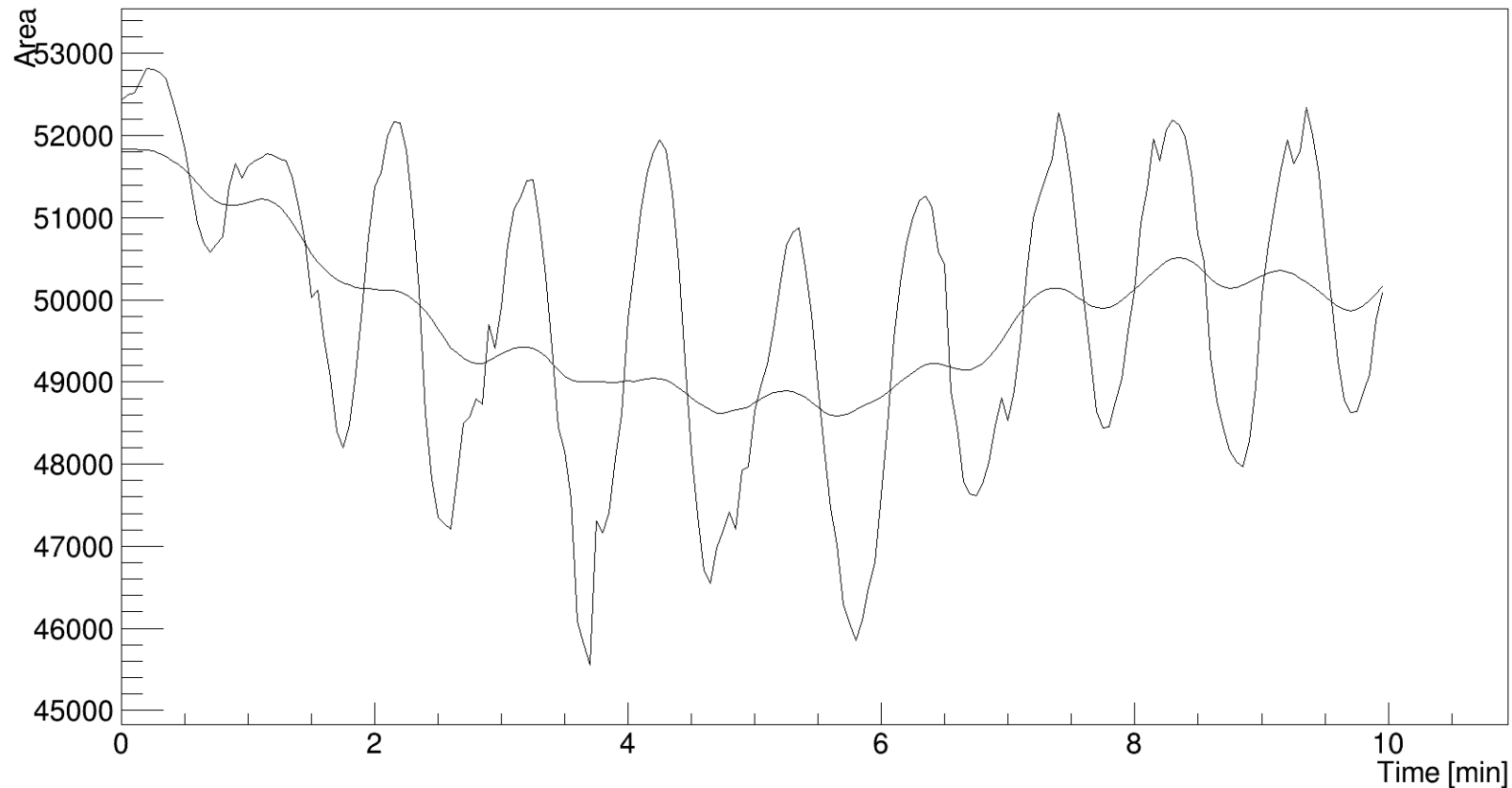
Exercise

- Download 3 files:
 - images.json.gz – data (explain data origin here!)
 - timeSeries.py – main program
 - timeSeries_functions.py – useful functions
- You will only write very short pieces of code
 - Don't write ROOT code (use DrawGraph, saves time)
 - Don't write your own functions (only fill in missing code)
 - Carefully read the comments on each function (save yourself a lot of time)
- All steps are explained in detail in the main program

Exercise

- Work on the exercise until you have a moving average of the cell area:

Cell cross-section



Fast fourier transform (FFT)

- Algorithm for DFT
 - Fast! (scales linearly)
- Requires same distance
 - Interpolate if necessary
- Returns spectrum of complex numbers over frequency
 - Represents amplitude & phase in one number
- I am assuming fourier transforms are familiar
 - Tell me if I am wrong
 - Do you have any questions regarding this (technical stuff?)

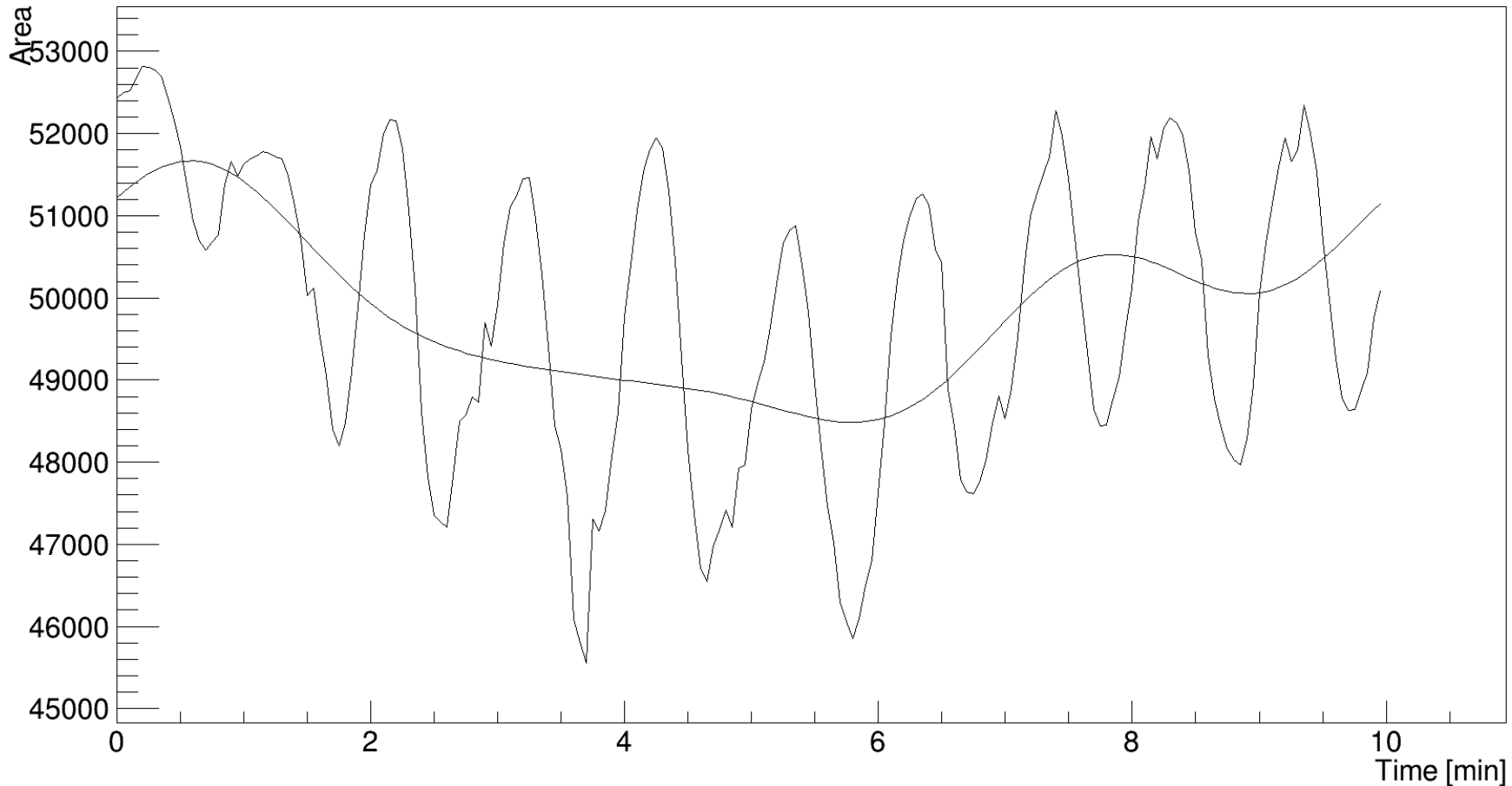
Uses of FFT

- Transform; modify spectrum; transform back
- Compression
 - Identify important frequencies, delete the rest
- Detrending (similar to compression)
 - Separate into high and low frequencies
 - Low frequencies are trend (Low-pass filter)
 - High frequencies are detrended data (High-pass filter)
- Seasonal components are peaks frequency domain
 - Separate seasonal component by isolating peaks
 - Peaks are seasonal component
 - Rest is deseasonalized data
- Carefull: Not usefull for cyclic components
 - Reason: Phase shift between cycles

Exercise

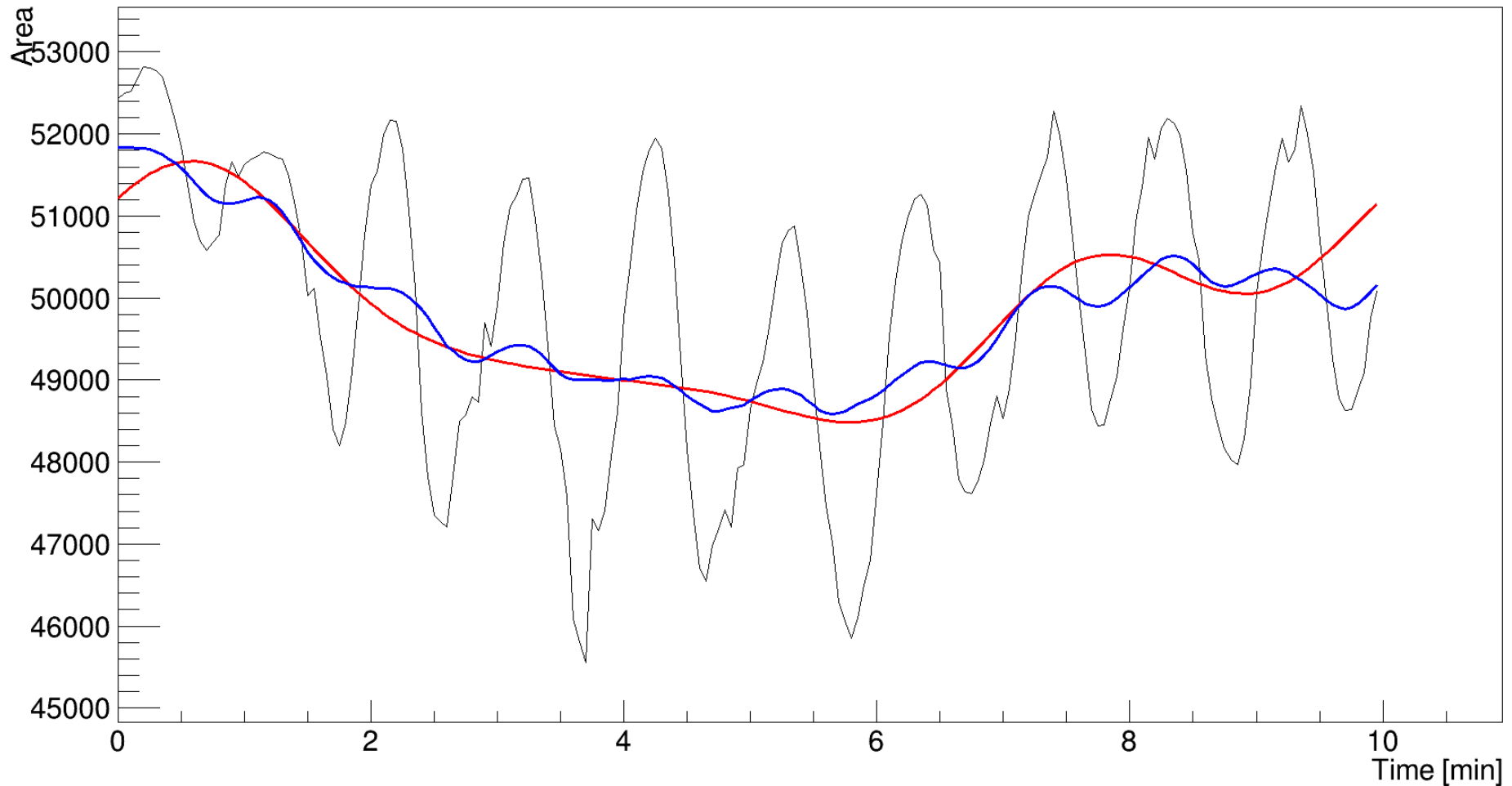
- Work on the exercise until you have applied a low pass filter to the cell area

Low Pass



What do you think?

Low Pass
VS Moving Average



Cyclic (& irregular) component

- Any correlation without exact timing
 - Oscillations with phase shifts
 - Feedback of past data on current data
 - Flights (Peak of return flights after peak in outgoing ones)
 - Random walk (maximum step size, questionable if cyclic)
 - Influenza (higher chance for epidemics after quiet times)
- Hard to model
 - Correct model depends on exact mechanism

Autocorrelation

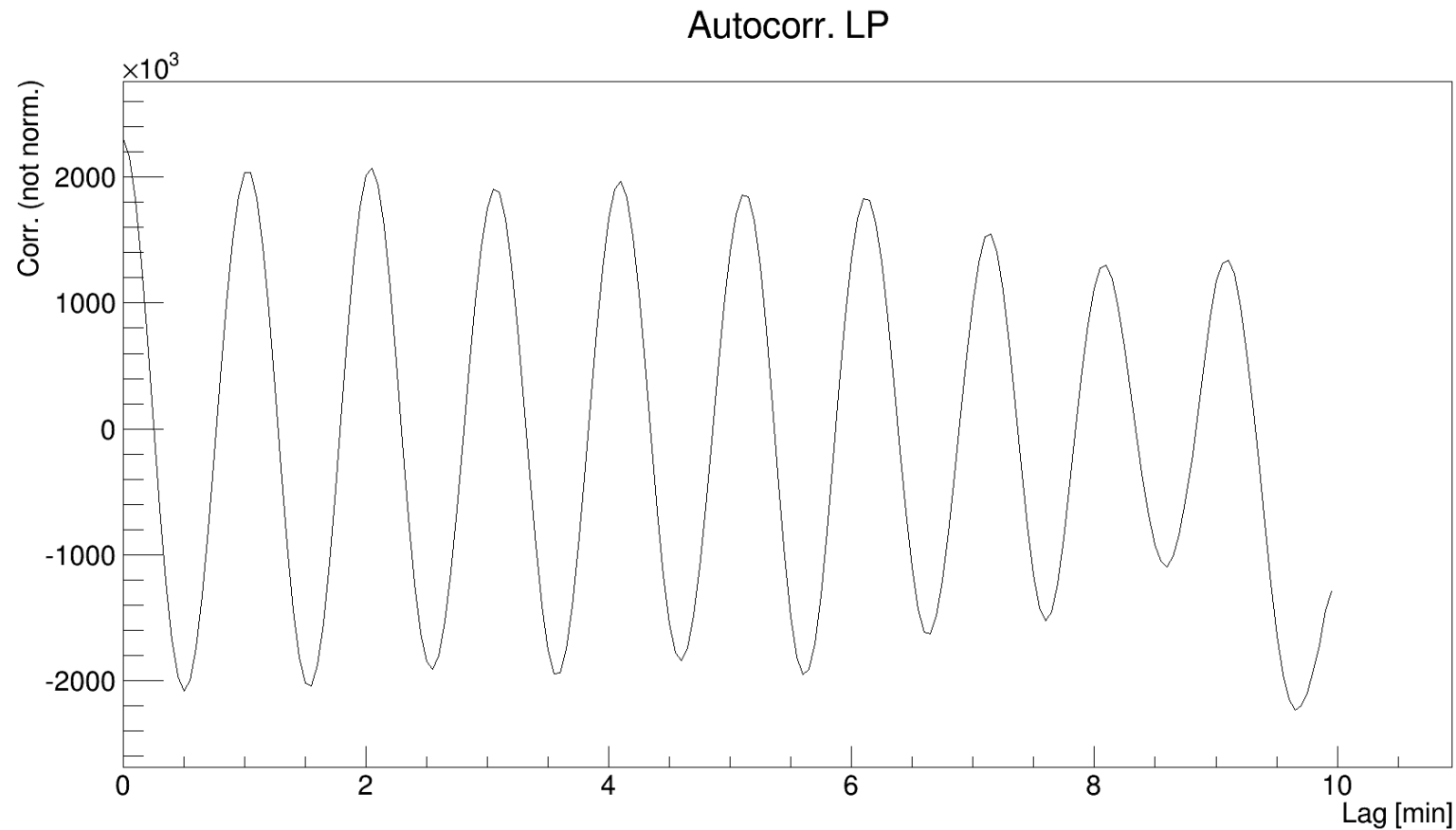
- Relationship between observations of the same variable at different times:

$$R(\tau) = \frac{\frac{1}{N-\tau} \sum_{t=1}^{N-\tau} (X_t - \mu)(X_{t+\tau} - \mu)}{\sigma^2}$$

- Confidence interval: $CI = \frac{\pm 2}{\sqrt{N-\tau}}$

Exercise

- Continue with the exercise until you computed the autocorrelation and the contraction frequency



Autoregressive model

- Suppose you found significant autocorrelation
- Assume random process with linear dependence on last few timesteps

$$X_t = c + \sum_{i=1}^p \varphi_i X_{t-i} + \epsilon_t$$

$\varphi_1, \dots, \varphi_p$: model parameters
 ϵ_t : noise term

- Fit using the appropriate method for your noise term (least-squares for gaussian)
- Now that you have a model, you can use it to extrapolate (while propagating errors in each step)
- Combine this with other components by fitting their residuals