

Detecting circadian oscillations in lineage trajectories with Gaussian Processes



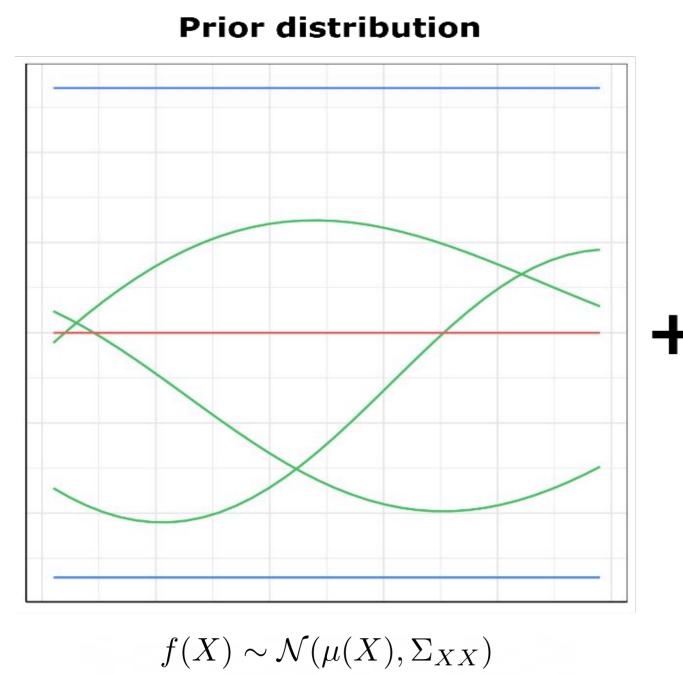
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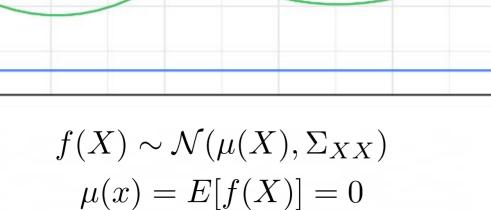
BACKGROUND

Quantitative inference of the presence of oscillations in time-series datasets is challenging, particularly the detection of circadian clock rhythms in dividing cells. In single cells, oscillations can be observed in lineage trajectories when the dividing cells contain reporters for circadian clock proteins. However, they have very low amplitude, are noisy, and non-stationary. Population level measurements like qPCR also exhibit these complex noisy patterns, making oscillation detection a difficult problem.

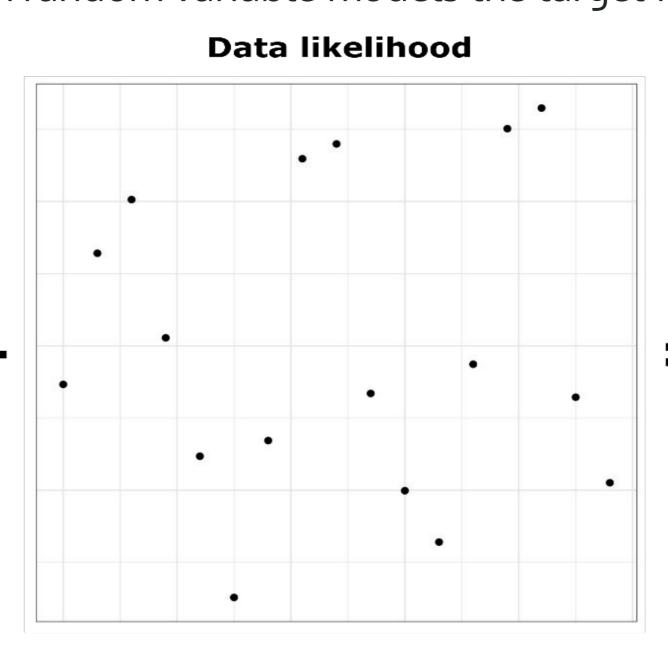
GAUSSIAN PROCESSES

A Gaussian Process (GP) is a set of random variables, any finite combination of which has a multivariate normal distribution. When fitting data, the *n*th random variable models the target function's value at *n*th domain point.

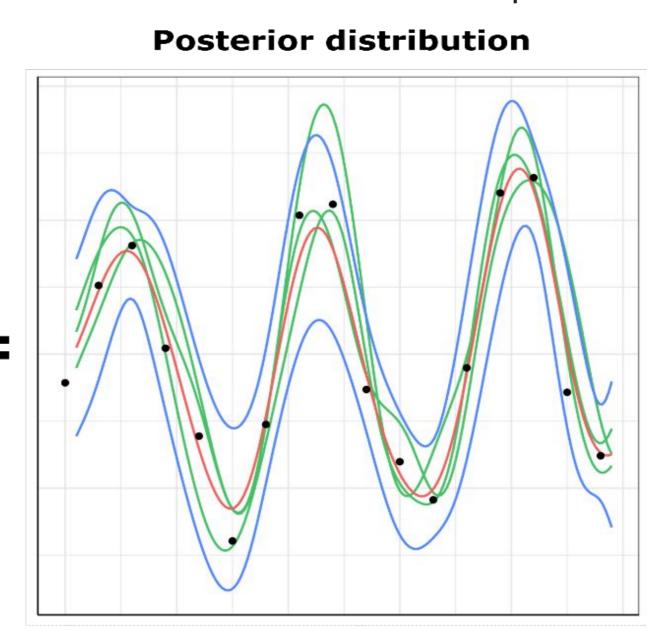




 $\Sigma_{ij} = Cov(f(x_i), f(x_j)) = k(x_i, x_j)$



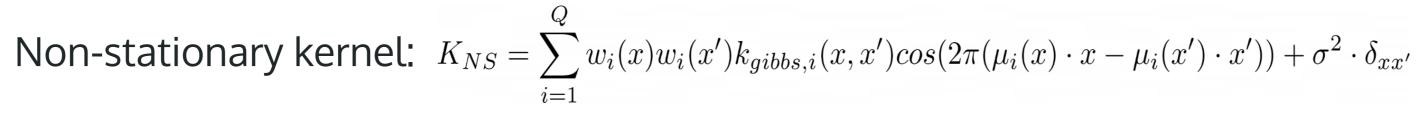
Data: y, measured at N points YMarginal Log Likelihood (MLL) = $\log(y|X,k)$ $= -\frac{1}{2}y^T K_{YY}^{-1} y - \frac{1}{2}\log|K_{YY}| - \frac{N}{2}\log(2\pi)$



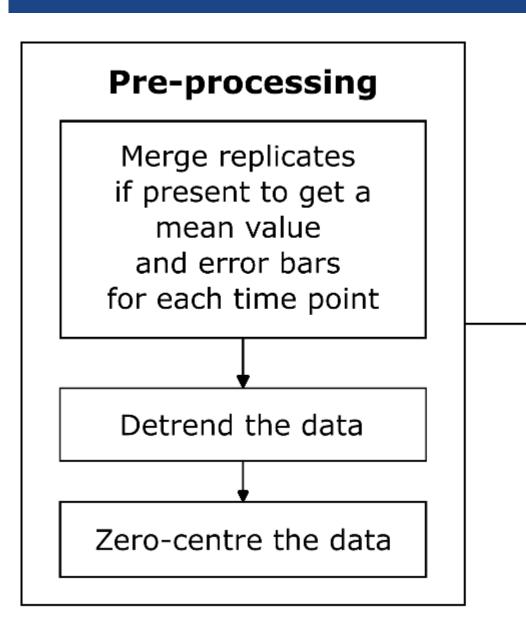
 $f(X|y) \sim \mathcal{N}(\mu^*(X), \Sigma_{XX}^*)$ $\mu^*(x) = \mu(x) + \sum_{XY} \sum_{YY}^{-1} (y - \mu(Y))$ $\Sigma_{XX}^* = \Sigma_{XX} - \Sigma_{XY} \Sigma_{YY}^{-1} \Sigma_{YX}$

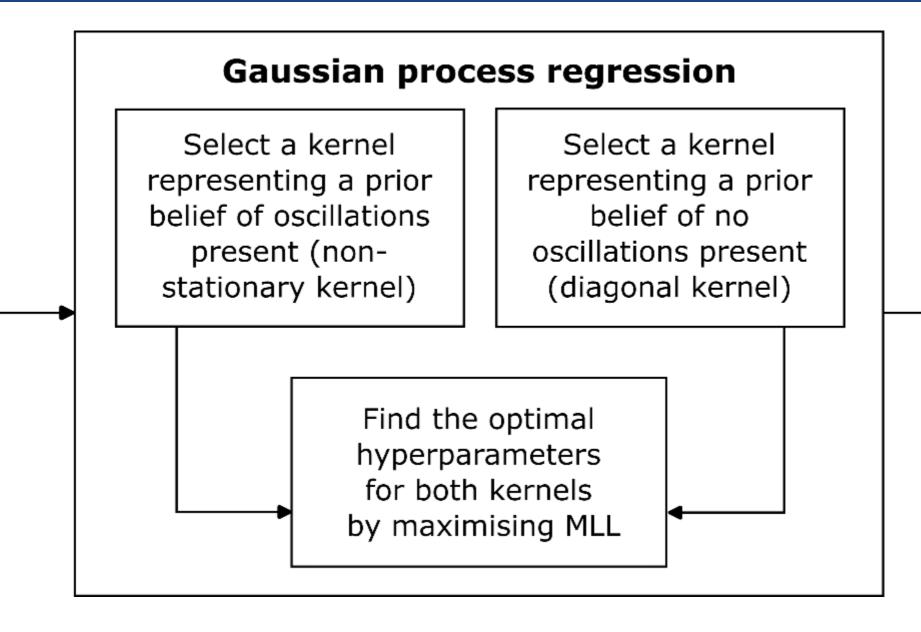
k describes the similarity between function values, and thus controls the shapes that a fitted function can adopt.

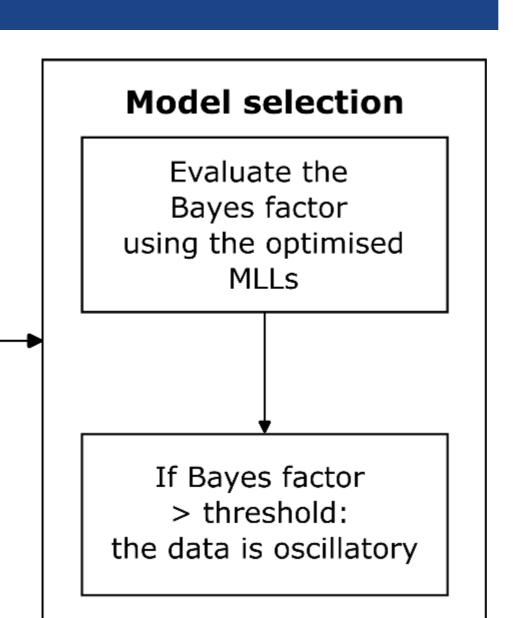
Diagonal kernel: $K_D = \sigma^2 \cdot \delta_{xx'}$



WORKFLOW OF THE METHOD



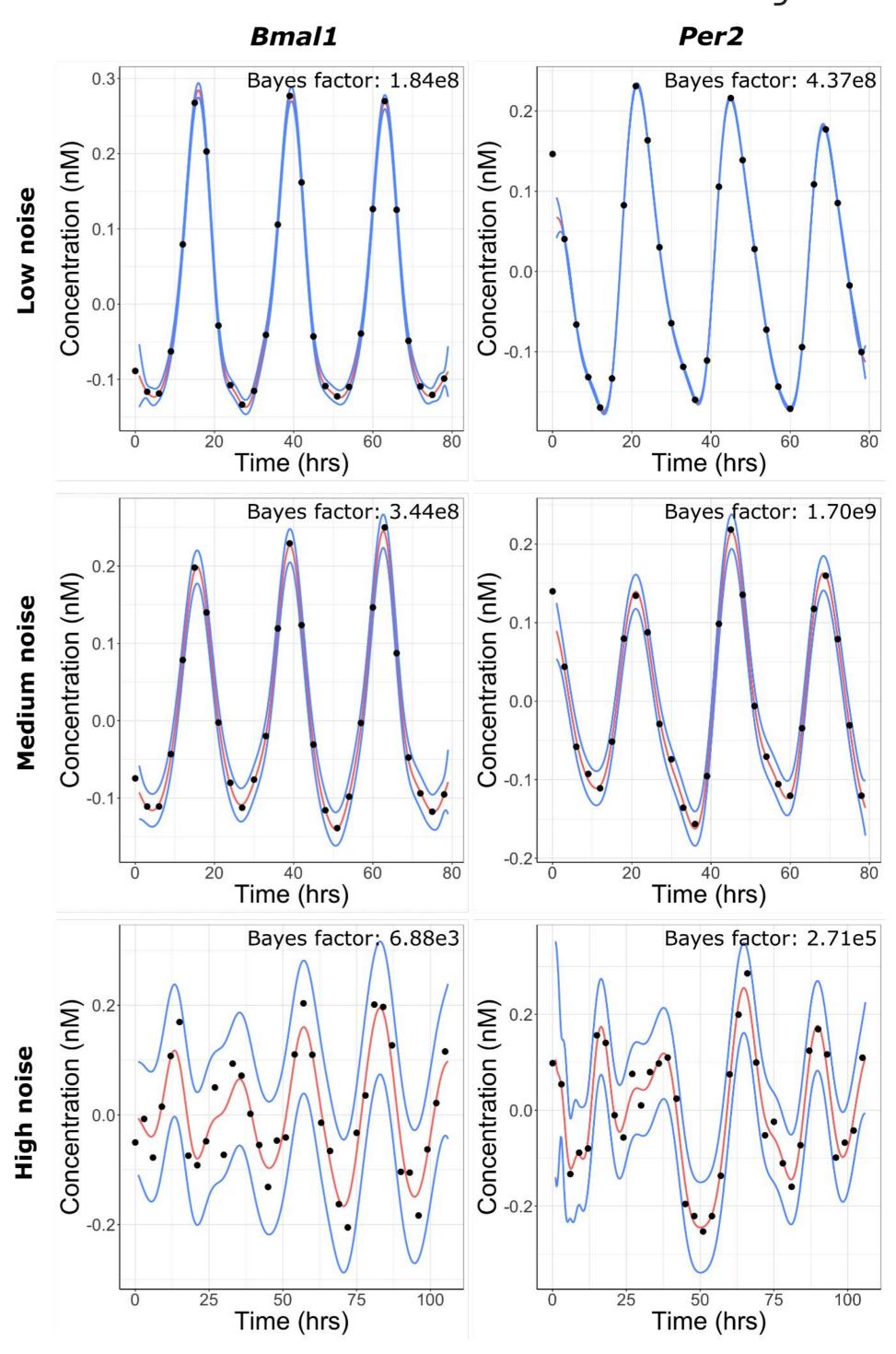




Times among worst 3

RESULTS: SIMULATED LINEAGES

A coupled circadian clock - cell cycle gene network was simulated with ODEs, and used to generate cell lineages. Concentration of clock gene products over time was extracted from individual lineages.

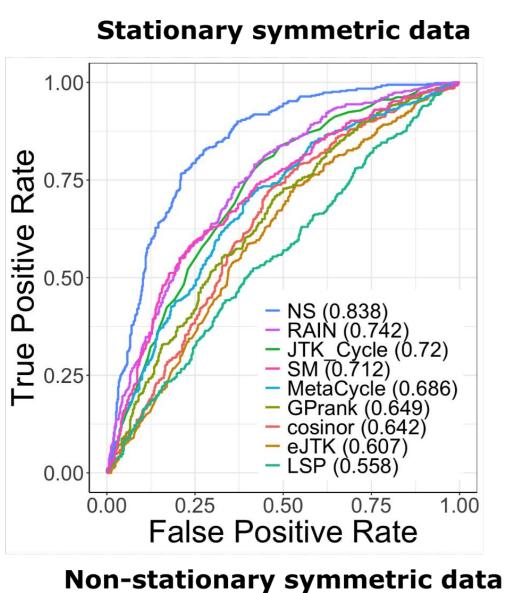


RESULTS: EXPERIMENTAL DATA

Time lapse microscopy was carried out over 72 hours on live U2OS (osteosarcoma) cells containing a reporter for circadian protein Rev-Erba. The corresponding channel intensity was extracted from all possible lineages via image analysis. (Data courtesy Granada Lab at Charité.)

COMPARISON AGAINST EXISTING METHODS

Method



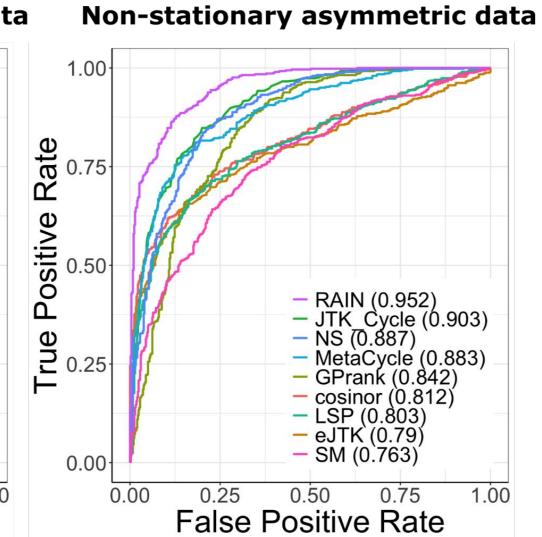
JTK_Cycle (0.689)

MetaCycle (0.679) RAIN (0.634)

False Positive Rate

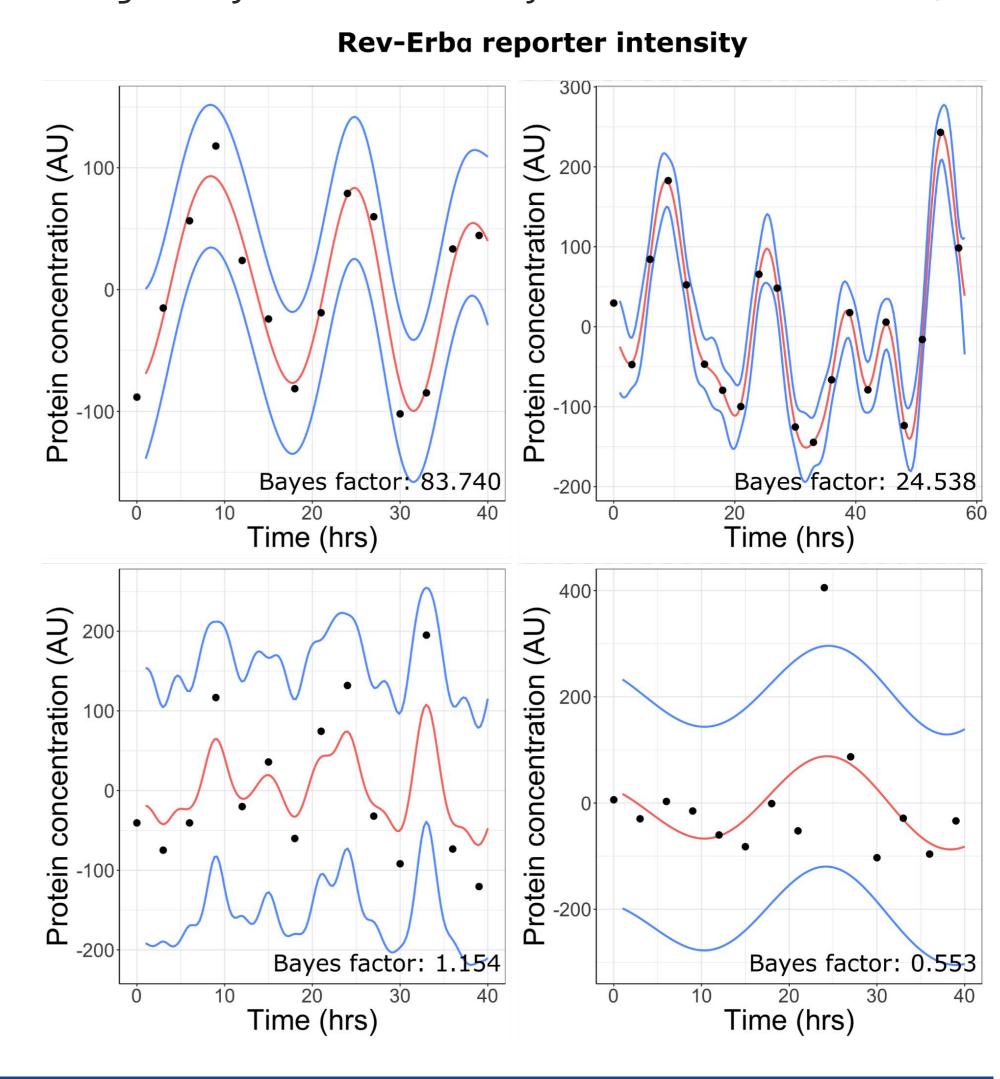
ROC curves were constructed for each method over multiple types of simulated oscillatory data to compare performance.

Our method is the consistent best performer across all simulated symmetric datasets. In asymmetric datasets, RAIN most often has the best AUC, and our method maintains an above-average performance.



Stationary symmetric datasets (Total: 9)	
9	0
5	3
5	3
Non-stationary symmetric datasets (Total: 15)	
15	0
9	2
7	4
Stationary asymmetric datasets (Total: 8)	
7	0
3	0
2	1
Non-stationary asymmetric datasets (Total: 12)	
10	0
8	0
5	0
	9 5 ationary symmetric dat 15 9 7 onary asymmetric dat 7 3 2 ationary asymmetric d 10 8

Times among best 3



CONCLUSIONS

Our method demonstrates the power and flexibility of GPs in modelling of noisy non-stationary time-series data, and provides a way of classifying oscillatory versus non-oscillatory datasets without using p-values. It outperforms existing methods for oscillatory/non-oscillatory classification of simulated symmetric data. It can effectively detect oscillations in noisy circadian clock protein time-series datasets extracted from both simulated and experimentally generated lineage trajectories.

REFERENCES