

FASTER GAUSSIAN PROCESS MODELING

TBD

ABSTRACT

Much faster solves using Cholesky solver.

Keywords: methods: data analysis — methods: statistical — asteroseismology — stars: rotation — planetary systems

1. INTRODUCTION

Gaussian Processes (GPs; Rasmussen & Williams 2006). We made this faster.

2. CHOLESKY METHOD

2.1. *Factorization*

Semi-separable

$$u_{n,j}^{(1)} = a_j e^{-c_j t_n} \cos(d_j t_n) + b_j e^{-c_j t_n} \sin(d_j t_n) \quad (1)$$

$$u_{n,j}^{(2)} = a_j e^{-c_j t_n} \sin(d_j t_n) - b_j e^{-c_j t_n} \cos(d_j t_n) \quad (2)$$

$$v_{m,j}^{(1)} = e^{c_j t_m} \cos(d_j t_n) \quad (3)$$

$$v_{m,j}^{(2)} = e^{c_j t_m} \sin(d_j t_n) \quad (4)$$

$$K = \text{diag}(\Sigma) + \text{tril}(U V^T) + \text{triu}(V U^T) \quad (5)$$

$$= L \text{diag}(D) L^T \quad (6)$$

where

$$L = I + \text{tril}(U X^T) \quad (7)$$

Pre-condition:

$$\phi_{n,j} = e^{-c_j (t_n - t_{n-1})} \quad (8)$$

and $\phi_{1,j} = 1$.

$$\tilde{u}_{1,n,j} = a_j \cos(d_j t_n) + b_j \sin(d_j t_n) \quad (9)$$

$$\tilde{u}_{2,n,j} = a_j \sin(d_j t_n) - b_j \cos(d_j t_n) \quad (10)$$

$$\tilde{v}_{1,m,j} = \cos(d_j t_n) \quad (11)$$

$$\tilde{v}_{2,m,j} = \sin(d_j t_n) \quad (12)$$

$$\tilde{X}_{k,n,j} = e^{-c_j t_n} X_{k,n,j} \quad (13)$$

Recursion:

$$S_n^{(j,k)} = \text{diag}(\phi_n) \left[S_{n-1}^{(j,k)} + D_{n-1} \tilde{X}_{j,n-1}^T \tilde{X}_{k,n-1} \right] \text{diag}(\phi_n) \quad (14)$$

$$D_n = \Sigma_n - \tilde{u}_{1,n} S_n^{(1,1)} \tilde{u}_{1,n}^T - 2 \tilde{u}_{1,n} S_n^{(1,2)} \tilde{u}_{2,n}^T - \tilde{u}_{2,n} S_n^{(2,2)} \tilde{u}_{2,n}^T \quad (15)$$

$$D_n \tilde{X}_{1,n} = \tilde{v}_{1,n} - \tilde{u}_{1,n} S_n^{(1,1)} - [S_n^{(1,2)} \tilde{u}_{2,n}^T]^T \quad (16)$$

$$D_n \tilde{X}_{2,n} = \tilde{v}_{2,n} - \tilde{u}_{2,n} S_n^{(2,2)} - \tilde{u}_{1,n} S_n^{(1,2)} \quad (17)$$

where the matrices $S_1^{(j,k)}$ are $J \times J$ matrices of zeros. The computational cost of this section is $\mathcal{O}(N J^2)$.

2.2. Solving

To solve $L \mathbf{z} = \mathbf{y}$,

$$f_{k,n} = \text{diag}(\phi_n) \left[f_{k,n-1} + \tilde{X}_{k,n-1}^T z_{n-1} \right] \quad (18)$$

$$z_n = y_n - [\tilde{u}_{1,n} f_{1,n} + \tilde{u}_{2,n} f_{2,n}] \quad (19)$$

where $f_{k,1} = 0$. Start from $n = 1$ and repeat. The computational cost of this section is $\mathcal{O}(N J)$.

To solve $L^T \mathbf{z} = \mathbf{y}$,

$$f_{k,n} = \text{diag}(\phi_{n+1}) \left[f_{k,n+1} + \tilde{u}_{k,n+1}^T z_{n+1} \right] \quad (20)$$

$$z_n = y_n - [\tilde{X}_{1,n} f_{1,n} + \tilde{X}_{2,n} f_{2,n}] \quad (21)$$

where $f_{k,N} = 0$. Start from $n = N$ and repeat. The computational cost of this section is $\mathcal{O}(N J)$.

2.3. Dot products

To compute the dot product $L^T \mathbf{z} = \mathbf{y}$,

$$f_{k,n} = \text{diag}(\phi_{n+1}) \left[f_{k,n+1} + \tilde{u}_{k,n+1}^T z_{n+1} \right] \quad (22)$$

$$y_n = z_n + [\tilde{X}_{1,n} f_{1,n} + \tilde{X}_{2,n} f_{2,n}] \quad (23)$$

where $f_{k,N} = 0$.

To compute the dot product $L \mathbf{z} = \mathbf{y}$

$$f_{k,n} = \text{diag}(\phi_n) \left[f_{k,n-1} + \tilde{X}_{k,n-1}^T z_{n-1} \right] \quad (24)$$

$$y_n = z_n + [\tilde{u}_{1,n} f_{1,n} + \tilde{u}_{2,n} f_{2,n}] \quad (25)$$

To compute the dot product $K \mathbf{z} = \mathbf{y}$, take two passes

$$f_{k,n} = \text{diag}(\phi_n) \left[f_{k,n-1} + \tilde{v}_{k,n-1}^T z_{n-1} \right] \quad (26)$$

$$y_n = \Sigma_n z_n + \tilde{u}_{1,n} f_{1,n} + \tilde{u}_{2,n} f_{2,n} \quad (27)$$

then

$$f_{k,n} = \text{diag}(\phi_{n+1}) [f_{k,n+1} + \tilde{u}_{k,n+1}^T z_{n+1}] \quad (28)$$

$$y_n = y_n + [\tilde{v}_{1,n} f_{1,n} + \tilde{v}_{2,n} f_{2,n}] \quad (29)$$

REFERENCES

Rasmussen, C. E., & Williams, K. I. 2006,
Gaussian Processes for Machine Learning
(MIT Press)