

Variational Gaussian Process Models without Matrix Inverses

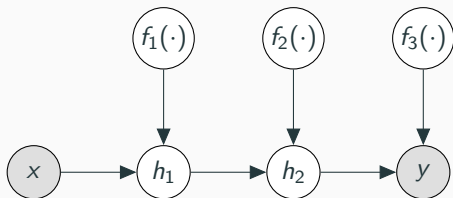
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Gaussian processes as building blocks

Q: Can Gaussian processes be building blocks for Bayesian deep learning?



Variational inference is **general** and **actually works** in GP models:

- the ELBO is tight enough for **hyperparameter selection**.
- the variational posterior predicts with **non-parametric error bars**.

Scalability

Cost of minibatch iteration: $\mathcal{O}(BM^2 + M^3)$

for batch size B and model capacity M .

$$\mathcal{L} = \sum_{n=1}^N \mathbb{E}_{q(f(\mathbf{x}_n))} [\log p(y_n | f(\mathbf{x}_n))] - \text{KL}[q(f(\cdot)) || p(f(\cdot))]$$

$$q(f(\mathbf{x}_n)) = \mathcal{N}\left(\mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{m}, k_{f_n f_n} - \underbrace{\mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{k}_{\mathbf{u}f_n}}_{\text{difficult}} + \mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{S} \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{k}_{\mathbf{u}f_n}\right)$$

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A: As long as they need a matrix inverse...
probably not.

Inverse-free Gaussian Processes

1. New variational posterior:

Hensman et al [2013] posterior:

$$\mathcal{N}(\mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{m}, k_{f_n f_n} - \mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{k}_{\mathbf{u}f_n} + \mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{S} \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{k}_{\mathbf{u}f_n})$$

Our posterior:

$$\mathcal{N}(\mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{m}, k_{f_n f_n} + \mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{T} \mathbf{K}_{\mathbf{u}\mathbf{u}} \mathbf{T} \mathbf{k}_{\mathbf{u}f_n} - 2 \mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{T} \mathbf{k}_{\mathbf{u}f_n} + \mathbf{k}_{\mathbf{u}f_n}^\top \mathbf{S}' \mathbf{k}_{\mathbf{u}f_n})$$

Inverse-free Gaussian Processes

1. New variational posterior:

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$$\mathcal{N}(\mathbf{k}_{\mathbf{u}f_n}^T \mathbf{m}, k_{f_n f_n} - \mathbf{k}_{\mathbf{u}f_n}^T \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{k}_{\mathbf{u}f_n} + \mathbf{k}_{\mathbf{u}f_n}^T \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{S} \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1} \mathbf{k}_{\mathbf{u}f_n})$$

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2. New variational bound also a function of \mathbf{T} , with property:

$$\mathbf{T}^* = \underset{\mathbf{T}}{\operatorname{argmax}} \mathcal{L}(\dots, \mathbf{T}) = \mathbf{K}_{\mathbf{u}\mathbf{u}}^{-1}$$

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3. Stochastic estimate of bound costs $\mathcal{O}(BM^2)$

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See more at our poster #49!