Highlights from NeurIPS 2019

Vancouver, Canada

Function-Space Distributions over Kernels

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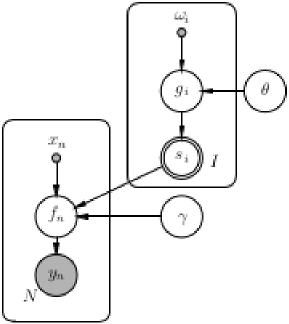
[1]Gregory Benton et al. “Function-Space Distributions over Kernels”. In: *Advances in Neural Information Processing Systems*. 2019, pp. 14939–14950.

Spectral Representation



Bochner's Theorem: Can represent a (positive definite) kernel as

$$k(\tau) = \int_{\mathbb{R}} e^{2\pi i \omega \tau} S(\omega) d\omega,$$

with $\tau = |x - x'|$, the distance between any two inputs, and some positive finite function $S(\omega)$. Only need to learn the (unnormalized) spectral density $S(\omega)$ to learn $k(\tau)$.

Model Specification

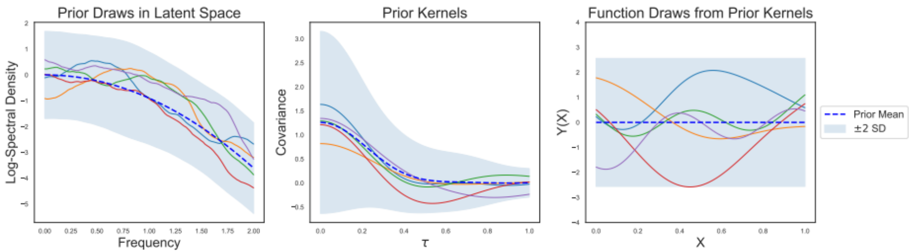
{Hyperprior} $\quad p(\boldsymbol{\phi}) = p(\theta, \gamma)$

{Latent GP} $\quad g(\omega)|\theta \sim \mathcal{GP}\left(\mu(\omega;\theta), k_g(\omega, \omega';\theta)\right)$

{Spectral Density} $\quad S(\omega) = \exp\{g(\omega)\}$

{Data GP} $\quad f(x_n)|S(\omega), \gamma \sim \mathcal{GP}(\gamma_0, k(\tau; S(\omega))).$

Forward sampling



[2]

[2]Gregory Benton et al. “Function-Space Distributions over Kernels”. In: *Advances in Neural Information Processing Systems*. 2019, pp. 14939–14950.

Inference & Prediction

Updating Hyper-Parameters: Considering the model specification in Eq. 4, we can define a loss as a function of $\phi = \{\theta, \gamma\}$ for an observation of the density, $\tilde{g}(\omega)$, and data observations $y(x)$. This loss corresponds to the entropy, marginal log-likelihood of the latent GP with fixed data GP, and the marginal log-likelihood of the data GP.

$$\mathcal{L}(\phi) = -\left(\log p(\phi) + \log p(\tilde{g}(\omega)|\theta, \omega) + \log p(y(x)|\tilde{g}(\omega), \gamma, x)\right). \tag{7}$$

Updating Latent Gaussian Process: With fixed hyper-parameters ϕ, the posterior of the latent GP is

$$p(g(\omega)|\phi, x, y(x), f(x)) \propto \mathcal{N}(\mu(\omega; \theta), k_g(\omega; \theta))p(f(x)|g(\omega), \gamma). \tag{9}$$

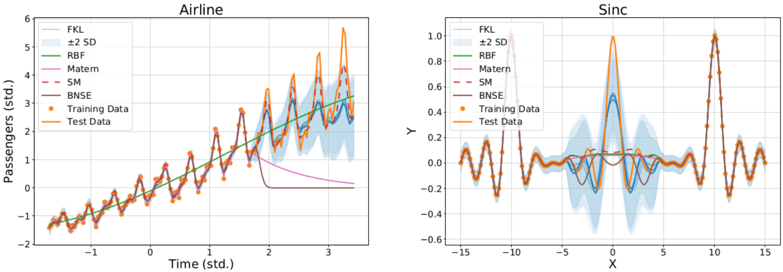
Prediction: The predictive distribution for any test input x^* is given by

$$p(f^*|x^*, x, y, \phi) = \int p(f^*|x^*, x, y, \phi, k)p(k|x^*, x, y, \phi)dk$$

$$p(f^*|x^*, x, y, \phi) \approx \frac{1}{J}\sum_{j=1}^{J} p(f^*|x^*, x, y, \phi, k_j), \quad k_j \sim p(k|x^*, x, y, \phi).$$ [3]

[3] Gregory Benton et al. “Function-Space Distributions over Kernels”. In: *Advances in Neural Information Processing Systems*. 2019, pp. 14939–14950.

Extrapolation and Interpolation



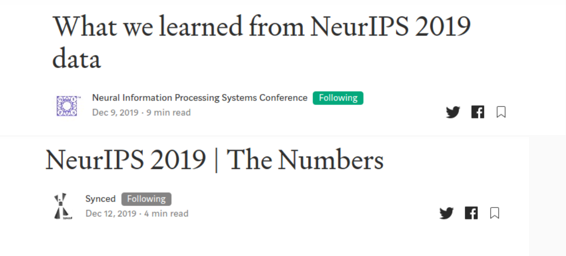
[4]

[4] Gregory Benton et al. “Function-Space Distributions over Kernels”. In: *Advances in Neural Information Processing Systems*. 2019, pp. 14939–14950.

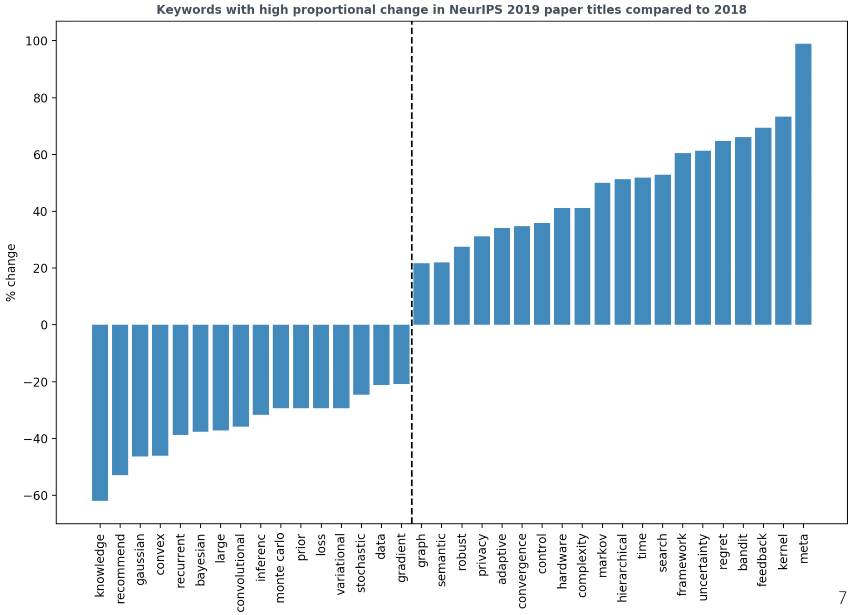
1. Matthew D Hoffman and Yian Ma. “Langevin Dynamics as Nonparametric Variational Inference”. In: *2nd Symposium on Advances in Approximate Bayesian Inference* (2019) ”Best Industry paper”

2. Yoshua Bengio Keynote on **”Going from System 1 to System 2 Deep learning”**

3. NeurIPS Summaries (on Medium):



Trivia



Keywords with high proportional change in NeurIPS 2019 paper titles compared to 2018
% change
100
80
60
40
20
0
−20
−40
−60
knowledge
recommend
gaussian
convex
recurrent
bayesian
large
convolutional
inferenc
monte carlo
prior
loss
variational
stochastic
data
gradient
graph
semantic
robust
privacy
adaptive
convergence
control
hardware
complexity
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time
search
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