CS-E4895 Gaussian Processes
Lecture 9: Deep GPs

Markus Heinonen

Aalto University

Monday 27.3.2023

Roadmap for today

1. Introductions to Deep GPs
   - Limitations of standard GPs
   - Function Composition and Deep Learning

2. The Deep GP Model
   - Combining Layers of GPs
   - Deep GP Covariance
   - The Deep GP Posterior

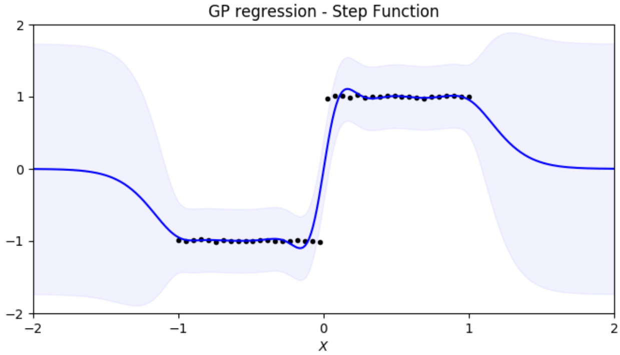
3. Inference in Deep GPs
   - Stochastic Variational Inference
   - Alternative Approaches
   - Performance and Issues

Section 1

Introductions to Deep GPs

Limitations of Standard GPs

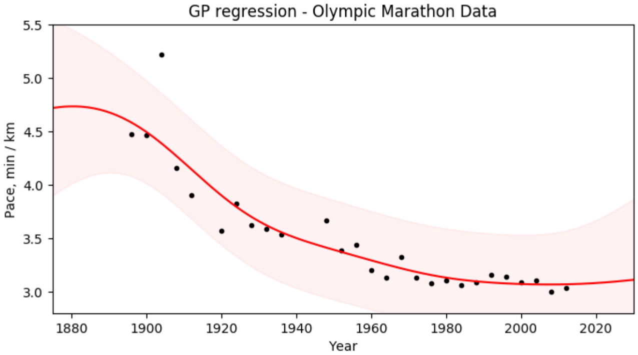
- **Discontinuities / jumps**



- A stationary GP fails to capture the sharp jump, and the variance is too large everywhere.

Limitations of Standard GPs

- **Discontinuities / jumps**
- **Outliers**



- The outlier has a *very* low probability under the model.
- To account for this, the model learns a likelihood variance that is too high for all other data points.

Limitations of Standard GPs

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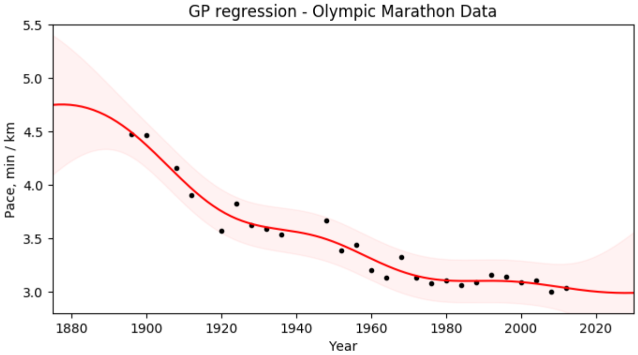
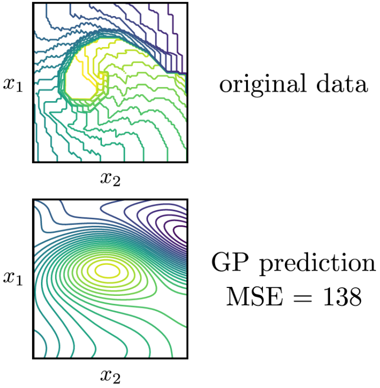


- Removing the outlier vastly improves the result. But we'd rather avoid such a manual intervention.

Limitations of Standard GPs

- **Discontinuities / jumps**
- **Outliers**
- **Non-stationarity**

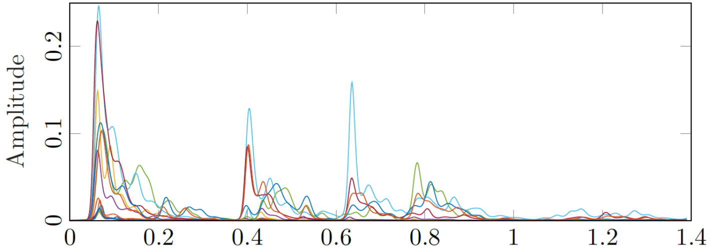
The previous two problems can be seen as issues arising due to a *stationary* model being applied to non-stationary data.



- Many real-world data sets do not have constant smoothness across the entire input space.

Limitations of Standard GPs

- **Discontinuities / jumps**
- **Outliers**
- **Non-stationarity**
- **Misalignment**



- Multiple misaligned data streams cannot be modelling with a standard (multi-output) GP.
- The data must be aligned via a pre-processing step.
- Ideally this step should be incorporated into the probabilistic model, so that its uncertainty can be incorporated.

Function Composition

- Function composition is at the heart of modern-day machine learning. Deep neural networks are made up of compositions of neural networks.
- Deep Gaussian processes work in an analogous way, whilst incorporating uncertainty and prior knowledge.

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Single GPs can model simple, stationary functions. The composition of multiple GPs,

$$f_3(f_2(f_1(\cdot))) = (f_3 \circ f_2 \circ f_1)(\cdot)$$

can model more complex, nonstationary functions.

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- We can view each "layer" as a warping of the inputs before feeding to the next layer.
- Function composition can be used to incorporate multiple layers of prior knowledge.

Section 2

The Deep GP Model

Deep GP Intuition

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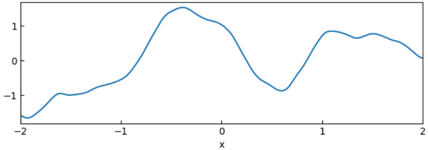
$$f_1(\boldsymbol{x}) \sim \mathcal{N}(\mu_1(\boldsymbol{x}), \kappa_1(\boldsymbol{x}, \boldsymbol{x}))$$

Draw a sample, $\tilde{\boldsymbol{y}}_1$, from this multivariate Gaussian:



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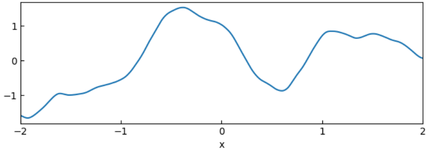
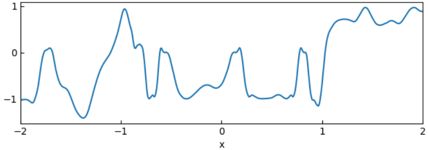


Treat this sample as the input to *another* GP, $f_2(\cdot) \sim \mathcal{GP}(\mu_2(\cdot), \kappa_2(\cdot, \cdot))$:

$$f_2(\tilde{\boldsymbol{y}}_1) \sim \mathcal{N}(\mu_2(\tilde{\boldsymbol{y}}_1), \kappa_2(\tilde{\boldsymbol{y}}_1, \tilde{\boldsymbol{y}}_1))$$

and draw a sample, $\tilde{\boldsymbol{y}}_2$.



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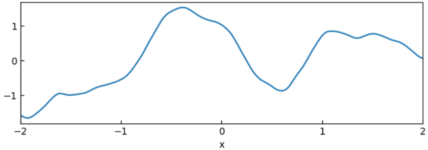

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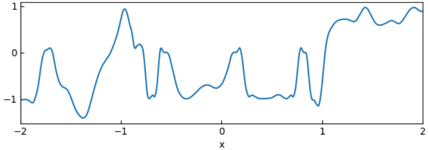

Repeat a third time for $f_3(\cdot) \sim \mathcal{GP}(\mu_3(\cdot), \kappa_3(\cdot, \cdot))$:

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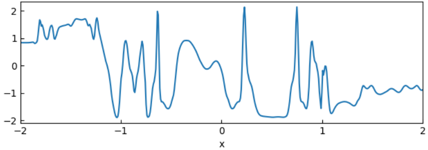
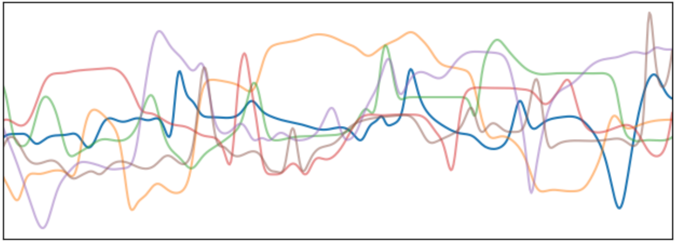
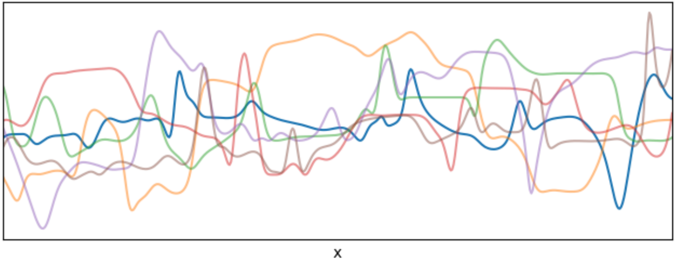


Deep GP Intuition



These are samples from a 3-layer deep GP.

Deep GP Intuition

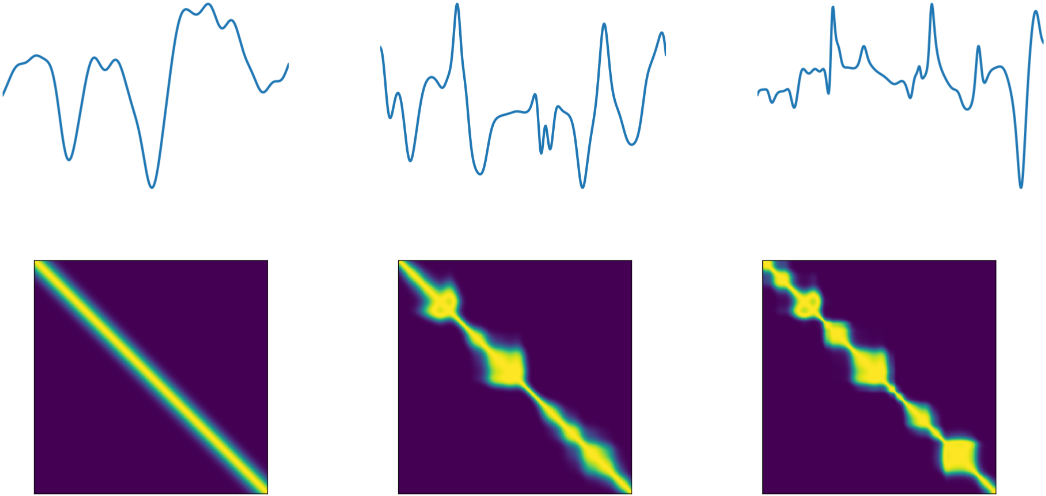


These are samples from a 3-layer deep GP.

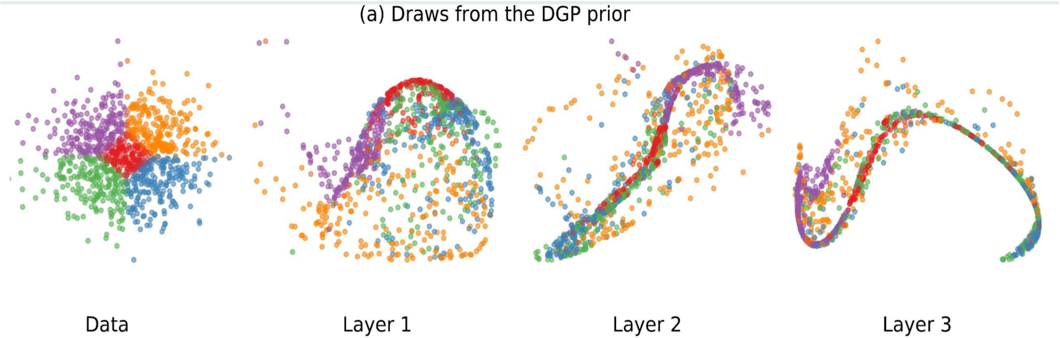
- sharp jumps / discontinuities.
- highly nonstationary smoothness.
- rich space of function, high capacity
- how to avoid overfitting?

Deep GP Covariance

As well as sampling, we can also plot the covariance matrix in each layer.
Initially we have uniform input, later more 'clumping'



Signal propagates through layers



- The color is only a visual aide
- In this example each layer maps $\mathbb{R}^2$ to $\mathbb{R}^2$
- The plot shows one sample path from the DGP
- Each sample path conserves neighborhoods to a degree
- No output layer shown

The Deep GP Model

Now let's write down the deep GP model and look at its properties. Inference will come later.

$$
\begin{aligned}
f_\ell(\cdot) &\sim \mathcal{GP}\left(\mu_\ell(\cdot), \kappa_\ell(\cdot,\cdot)\right), \qquad \ell = 1,\ldots,L \\
p(\tilde{\boldsymbol{y}}_\ell \mid f_\ell, \tilde{\boldsymbol{y}}_{\ell-1}) &= \prod_n \mathcal{N}(\tilde{y}_{\ell,n} \mid f_\ell(\tilde{y}_{\ell-1,n}), \sigma_\ell^2), \qquad \tilde{\boldsymbol{y}}_1 = \boldsymbol{x} \\
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- We denote layer by ℓ (not lengthscale!)
- L layers of Gaussian process priors.
- $\tilde{\boldsymbol{y}}_\ell$ are latent variables - treated as input to layer $\ell + 1$.
- Typically include Gaussian noise between layers.

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where $f_0 = \boldsymbol{x}$ and $f_{L,n} = f_L(f_{L-1}(\ldots(x_n)))$.

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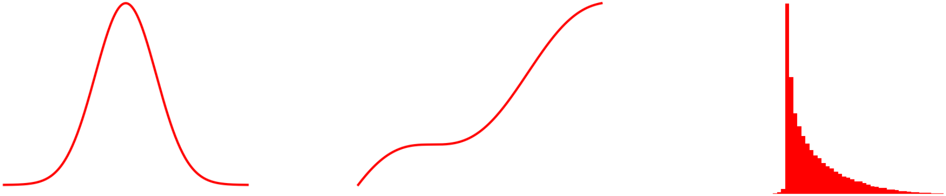
Using notation $\boldsymbol{f}_\ell = f(\boldsymbol{f}_{\ell-1})$, the full process has joint density

$$p(\boldsymbol{y},\, \{\boldsymbol{f}_\ell\}_{\ell=1}^L) = \underbrace{\prod_{n=1}^N p(y_n \mid \boldsymbol{f}_{L,n})}_{\text{Likelihood}} \underbrace{\prod_{\ell=1}^L p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1})}_{\text{Deep GP Prior}}$$
$$p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}) = \mathcal{N}(\boldsymbol{f}_\ell | \mu_{\ell-1}(\boldsymbol{f}_\ell), \mathbf{K}_\ell(\boldsymbol{f}_{\ell-1}, \boldsymbol{f}_{\ell-1}))$$

The $\boldsymbol{f}_\ell$ is of size (N, M_ℓ) where $M_0 = D$ and $M_L = size(y)$

The Deep GP Posterior

A Gaussian propagated through a nonlinearity is no longer Gaussian:

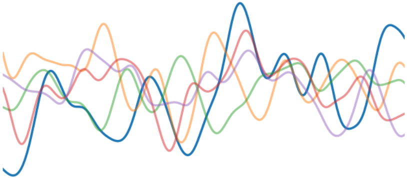


$x \sim \mathcal{N}(x \mid \cdot, \cdot)$ $\qquad f(\cdot)$ $\qquad f(x) \sim$ **???**

The Deep GP Posterior

Similarly, a Gaussian process propagated through a nonlinearity (e.g., another GP) is no longer a Gaussian process (in the original inputs $\boldsymbol{x}$).

$$f_1(\cdot) \sim \mathcal{GP}\left(\mu_1(\cdot), \kappa_1(\cdot, \cdot)\right)$$
$$f_2(\cdot) \sim \mathcal{GP}\left(\mu_2(\cdot), \kappa_2(\cdot, \cdot)\right)$$



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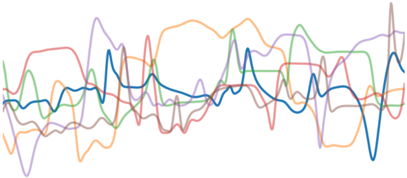
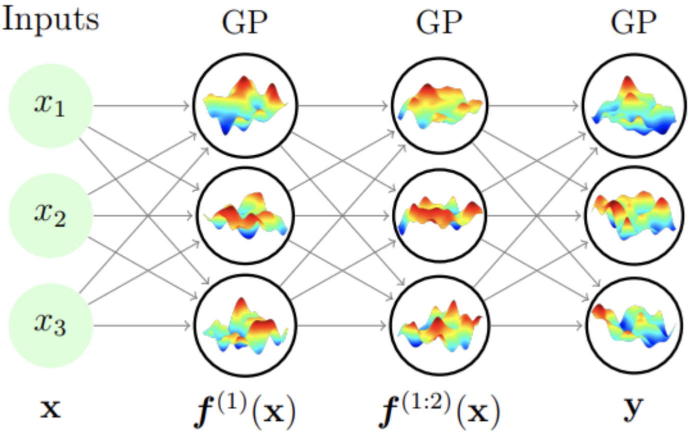


$f_2 \circ f_1(\boldsymbol{x}) = f_2(f_1(\boldsymbol{x})) \sim$ **???**

Deep GP illustration



- The size of each layer space can vary
- If observation y is a scalar, the final layer needs to map to scalar space

Section 3

Inference in Deep GPs

Inference in Deep GPs

Since the posterior is not Gaussian, it is clear that we must resort to approximate inference.

- Various schemes have been proposed: Variational Inference, Expectation Propagation, Hamiltonian Monte Carlo.
- We will focus on **sparse, stochastic variational inference**.

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- We will focus on **sparse, stochastic variational inference**.
- Recall our joint probability:

$$p(\boldsymbol{y}, \{\boldsymbol{f}_\ell\}_{\ell=1}^L) = \prod_{n=1}^N \underbrace{p(y_n \mid \boldsymbol{f}_{L,n})}_{\text{likelihood}} \prod_{\ell=1}^L \underbrace{p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1})}_{\text{DGP priors}}$$

  where $\boldsymbol{f}_0 = \boldsymbol{x}$.

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  where $\boldsymbol{f}_0 = \boldsymbol{x}$.
- We introduce inducing inputs $\boldsymbol{z}_\ell$ and outputs $\boldsymbol{u}_\ell = f_\ell(\boldsymbol{z}_\ell)$ in each layer:

$$p(\boldsymbol{y}, \{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) = \prod_{n=1}^N p(y_n \mid \boldsymbol{f}_{L,n}) \prod_{\ell=1}^L p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}, \boldsymbol{u}_\ell) p(\boldsymbol{u}_\ell)$$

  where

$$p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}, \boldsymbol{u}_\ell) = \mathcal{N}(\mathbf{f}_\ell | \mathbf{K}(\mathbf{f}_{\ell-1}, \mathbf{z}_\ell)\mathbf{K}(\mathbf{z}_\ell, \mathbf{z}_\ell)^{-1}\mathbf{u}_\ell, \mathbf{K}(\mathbf{f}_{\ell-1}, \mathbf{f}_{\ell-1}) - \mathbf{K}(\mathbf{f}_{\ell-1}, \mathbf{z}_\ell)\mathbf{K}(\mathbf{z}_\ell, \mathbf{z}_\ell)^{-1}\mathbf{K}(\mathbf{z}_\ell, \mathbf{f}_{\ell-1}))$$

Stochastic VI for Sparse Deep GPs

True joint distribution

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- To construct a variational lower bound for the deep GP, we must first define an **approximate posterior**:

$$q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) = \prod_{\ell=1}^L \underbrace{p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}, \boldsymbol{u}_\ell)}_{\text{Gaussian conditional}} q(\boldsymbol{u}_\ell)$$

where $q(\boldsymbol{u}_\ell) = \mathcal{N}(\boldsymbol{u}_\ell \mid \boldsymbol{m}_\ell, \boldsymbol{S}_\ell)$ are free-form Gaussians whose parameters are to be optimised. We also optimise inducing inputs $\mathbf{z}_\ell$ as variational parameters.

Stochastic VI for Sparse Deep GPs

- Recall the sparse variational bound for a single GP derived in previous lectures:

$$
\begin{aligned}
\ln p(\boldsymbol{y}) &\geq \sum_{n=1}^{N} \int q(f_n) \ln p(y_n|f_n)\, \mathsf{d} f_n - \mathbb{D}\left[q(\boldsymbol{u})||p(\boldsymbol{u})\right] \\
&= \mathbb{E}_{q(\boldsymbol{f},\boldsymbol{u})}\left[\ln p(\boldsymbol{y}|\boldsymbol{f})\right] + \mathbb{E}_{q(\boldsymbol{f},\boldsymbol{u})}\left[\ln p(\boldsymbol{f},\boldsymbol{u})\right] - \mathbb{E}_{q(\boldsymbol{f},\boldsymbol{u})}\left[\ln q(\boldsymbol{f},\boldsymbol{u})\right] \\
&= \mathbb{E}_{q(\boldsymbol{f},\boldsymbol{u})}\left[\ln \frac{p(\boldsymbol{y},\boldsymbol{f},\boldsymbol{u})}{q(\boldsymbol{f},\boldsymbol{u})}\right]
\end{aligned}
$$

where

$$
\begin{aligned}
q(\mathbf{f}) &= \int p(\mathbf{f}|\mathbf{u}) q(\mathbf{u}) d\mathbf{u} \\
&= \mathcal{N}(\mathbf{f}|\mathbf{A}\mathbf{m}, \mathbf{K}_{\mathbf{xx}} + \mathbf{A}(\mathbf{S} - \mathbf{K}_{\mathbf{zz}})^{-1}\mathbf{A}^T) \\
\mathbf{A} &= \mathbf{K}_{\mathbf{xz}}\mathbf{K}_{\mathbf{zz}}^{-1}
\end{aligned}
$$

- We will now derive a similar bound for the deep GP.

Stochastic VI for Sparse Deep GPs

joint: $$p(\boldsymbol{y}, \{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) = \prod_{n=1}^N p(y_n \mid \boldsymbol{f}_{L,n}) \prod_{\ell=1}^L p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}, \boldsymbol{u}_\ell) p(\boldsymbol{u}_\ell)$$

approx. posterior: $$q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) = \prod_{\ell=1}^L p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}, \boldsymbol{u}_\ell) q(\boldsymbol{u}_\ell)$$

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$$= \int \int q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) \ln \left(\frac{p(\boldsymbol{y}, \{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L)}{q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L)} \right) \mathrm{d}\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L$$

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\ln p(\boldsymbol{y}) \geq \mathcal{L}_{DGP} &= \mathbb{E}_{q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L)} \left[\ln \frac{p(\boldsymbol{y}, \{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L)}{q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L)} \right] \\
&= \int\int q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) \ln \left(\frac{p(\boldsymbol{y}, \{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L)}{q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L)} \right) \mathrm{d}\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L \\
&= \int\int q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) \ln \left(\frac{\prod_{n=1}^N p(y_n \mid \boldsymbol{f}_{L,n}) \prod_{\ell=1}^L p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}, \boldsymbol{u}_\ell) p(\boldsymbol{u}_\ell)}{\prod_{\ell=1}^L p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}, \boldsymbol{u}_\ell) q(\boldsymbol{u}_\ell)} \right) \mathrm{d}\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L
\end{aligned}$$

Stochastic VI for Sparse Deep GPs

$$\textbf{joint:} \quad p(\boldsymbol{y}, \{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) = \prod_{n=1}^N p(y_n \mid \boldsymbol{f}_{L,n}) \prod_{\ell=1}^L p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}, \boldsymbol{u}_\ell) p(\boldsymbol{u}_\ell)$$

$$\textbf{approx. posterior:} \quad q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) = \prod_{\ell=1}^L p(\boldsymbol{f}_\ell \mid \boldsymbol{f}_{\ell-1}, \boldsymbol{u}_\ell) q(\boldsymbol{u}_\ell)$$

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\end{aligned}$$

Stochastic VI for Sparse Deep GPs

- Simplifying further:

$$\mathcal{L}_{DGP} = \int\int q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) \ln\left(\frac{\prod_{n=1}^N p(y_n \mid \boldsymbol{f}_{L,n}) \prod_{\ell=1}^L p(\boldsymbol{u}_\ell)}{\prod_{\ell=1}^L q(\boldsymbol{u}_\ell)}\right) \mathrm{d}\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L$$

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$$+ \int\int q(\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L) \ln\left(\frac{\prod_{\ell=1}^L p(\boldsymbol{u}_\ell)}{\prod_{\ell=1}^L q(\boldsymbol{u}_\ell)}\right) \mathrm{d}\{\boldsymbol{f}_\ell, \boldsymbol{u}_\ell\}_{\ell=1}^L$$

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- The likelihood (first term) only depends on $\boldsymbol{f}_L$, and the second term does not depend on $\boldsymbol{f}_\ell$. So finally, the bound reduces to:

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Stochastic VI for Sparse Deep GPs

- The single GP bound:

$$\ln p(\boldsymbol{y}) \geq \sum_{n=1}^{N} \int q(f_n) \ln p(y_n | f_n) \mathsf{d} f_n - \mathbb{D}\left[q(\boldsymbol{u}) || p(\boldsymbol{u})\right]$$

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$$q(\boldsymbol{f}_{\ell,n}) = \int q(\boldsymbol{f}_{\ell,n} \mid \boldsymbol{u}_\ell) q(\boldsymbol{u}_\ell) \, \mathrm{d}\boldsymbol{u}_\ell = \mathcal{N}(\boldsymbol{f}_\ell \mid \cdot, \cdot)$$

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- This mean that sampling from $q(\boldsymbol{f}_{\ell,n})$ is cheap, and does not involve sampling from the full GP at each layer (in fact, it only requires sampling from univariate Gaussians).

Optimising the Deep GP Bound

$$\ln p(\boldsymbol{y}) \geq \mathcal{L}_{DGP} = \sum_{n=1}^{N} \int q(f_{L,n}) \ln p(y_n | f_{L,n}) \, \mathsf{d} f_{L,n} - \sum_{\ell=1}^{L} \mathbb{D}\left[q(\boldsymbol{u}_\ell) || p(\boldsymbol{u}_\ell)\right]$$

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$$\sum_{n=1}^{N} \int q(f_{L,n}) \ln p(y_n | f_{L,n}) \, \mathrm{d} f_{L,n} \approx \frac{1}{S} \frac{N}{N_*} \sum_{s=1}^{S} \sum_{n=1}^{N_*} \int \mathcal{N}(f_{L,n} \mid m_{L,n,s}, C_{L,n,s}) \ln p(y_n | f_{L,n}) \, \mathrm{d} f_{L,n}$$

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- For the second term, compute the KL divergence between $q(\boldsymbol{u}_\ell)$ and $p(\boldsymbol{u}_\ell)$ in each layer separately (this is available in closed form since both terms are Gaussian).

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- For the second term, compute the KL divergence between $q(\boldsymbol{u}_\ell)$ and $p(\boldsymbol{u}_\ell)$ in each layer separately (this is available in closed form since both terms are Gaussian).
- This inference technique is called **doubly stochastic VI**, due to the two sources of stochasticity.

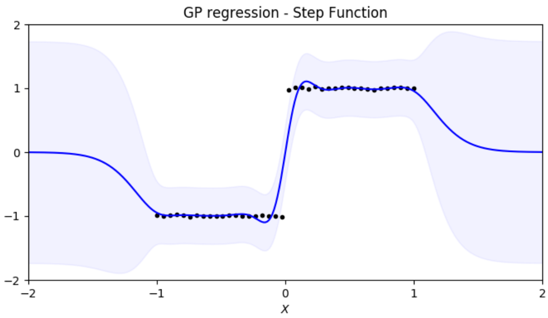
Alternative Approaches

Other approaches to deep GP inference exist, but we won't go over them here:

- **Deep GP Expectation Propagation** - similar to the above, but using EP for inference, and replacing the sampling procedure with Gaussian projections to approximate the marginals.
- **Importance-weighted VI with latent variables** - introduces additional latent variables which allow the model to represent non-Gaussian posteriors.
- **Hamiltonian Monte Carlo** - uses a sophisticated sampling approach to represent non-Gaussian posteriors.

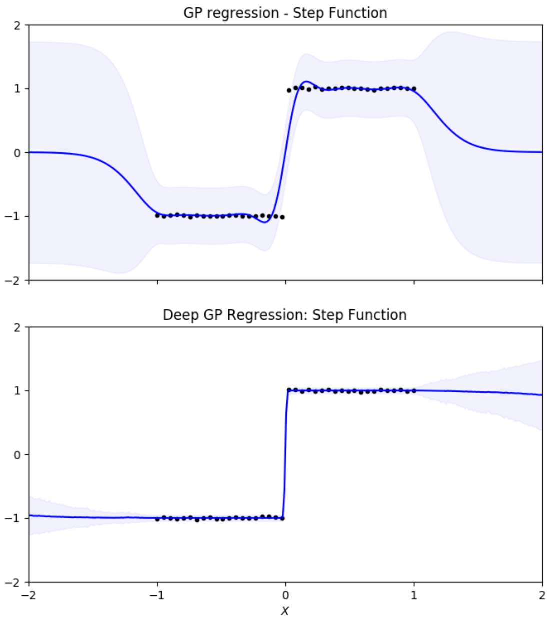
Deep GP Performance

- **Discontinuities / jumps:**



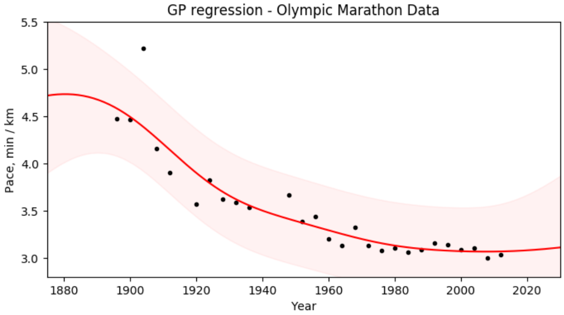
Deep GP Performance

- **Discontinuities / jumps:**
- The deep GP captures the jump, whilst the variance elsewhere remains low.
- However, we would prefer that the variances increases in the region of the discontinuity.
- In the exercises, you will examine what happens in each layer.



Deep GP Performance

- **Outliers:**



Deep GP Performance

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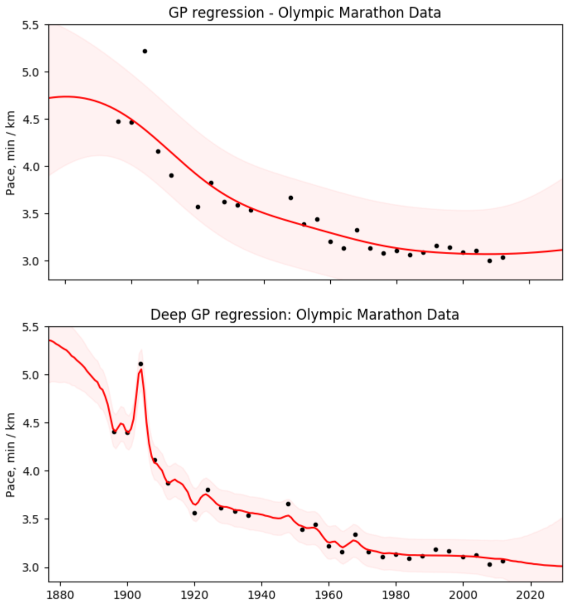
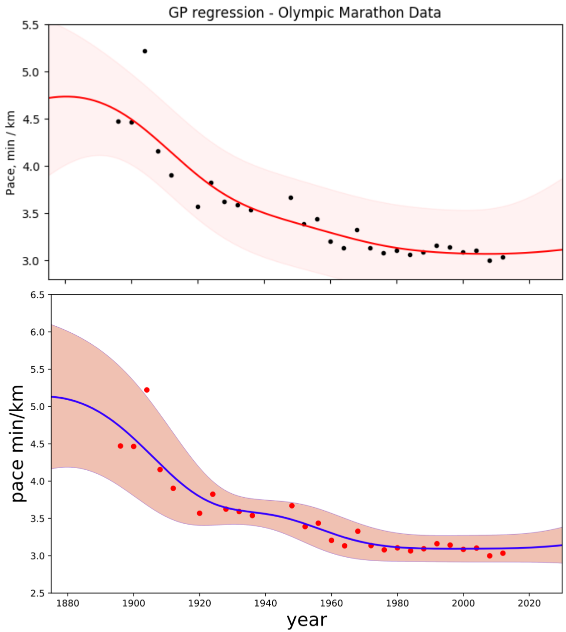
- The deep GP seems to overfit the outlier.



Deep GP Performance

- **Outliers:**
- The deep GP seems to overfit the outlier.
- Whereas the originally proposed deep GP methods claim to solve these tasks well.
- But doubly stochastic VI reports superior performance on many machine learning tasks, potentially because it scales to large data.



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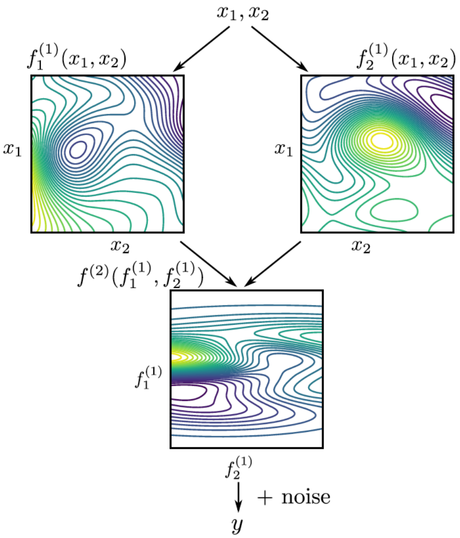

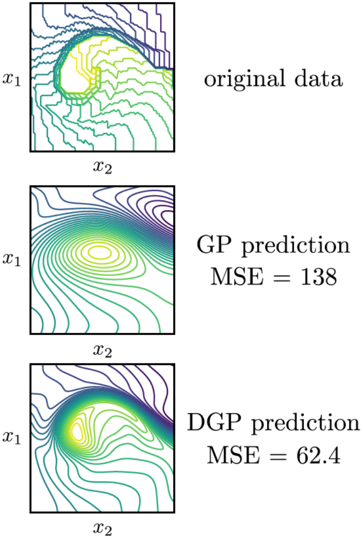

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- **Training can be slow**: we trade off the number of samples with accuracy.
- **Training is more prone to getting stuck in local minima** since there are many more parameters to optimise.
- **Current approaches to VI tend to "turn off" layers**, or reduce their variance to near-zero (such that they behave like deterministic mappings).

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- They have been combined with convolutional kernels (as presented in the previous lecture) to produce state-of-the-art results on image classification.
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- They have been combined with convolutional kernels (as presented in the previous lecture) to produce state-of-the-art results on image classification.
- Performance matches *e.g.*, deep CNNs, but improves uncertainty quantification in predictions, *i.e.*, **the model is more aware when it is wrong.**
- So deep GPs have great potential. But, as we have seen, there is still much work to be done.

References

- Salimbeni and Deisenroth. Doubly Stochastic Variational Inference for Deep Gaussian Processes, NIPS 2017
  - Today's lecture followed the ds-DGP
- Duvenaud, Rippel, Adams, Ghahramani. Avoiding pathologies in very deep networks. AISTATS 2014
  - Interesting discussion of DGP risks of *rank collapse*

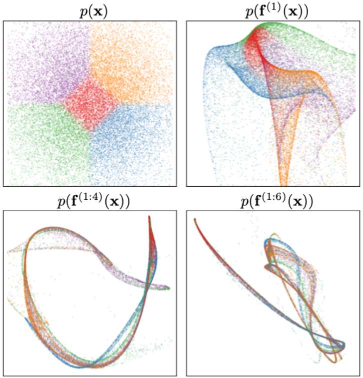

Figure 5: Visualization of draws from a deep GP. A 2-dimensional Gaussian distribution (top left) is warped by successive functions drawn from a GP prior. As the number of layers increases, the density concentrates along one-dimensional filaments.

End of Today's Lecture

- Next time: I will give a lecture on latent models with GPs.