EFT for ML (and flows)



L Del Debbio

Higgs Centre for Theoretical Physics University of Edinburgh based on paper [Roberts et al 21]

Bayesian inference

$$y_I = \int dx \, C_I(x) f(x)$$

Bayesian solution:

$$f_i = f(x_i) \longrightarrow p(f_1 \dots f_N | y, \mathcal{H}) = \frac{p(y|f, \mathcal{H})p(f|\mathcal{H})}{p(y|\mathcal{H})}$$

 \hookrightarrow dependence on the choice of the prior

Gaussian processes: $f \sim \mathcal{GP}(m,k)$

$$\mathbb{E}[f_i] = m(x_i), \quad \operatorname{Cov}[f_i, f_j] = k(x_i, x_j)$$

prior :
$$\mathcal{GP}(m,k) \implies \text{posterior} : \mathcal{GP}(\tilde{m},\tilde{k})$$

L Del Debbio

EFT4ML

NNPDF-like analysis

- generate $N_{\rm rep}$ replicas NN initialized from random distributions
- NNs at initialization provide the prior, $f_i = N(x_i; \theta)$
- train the NNs using data
- NNs after training provide the posterior



Neural Networks



MLP architecture

layers: $\ell = 1, \ldots, L$ neurons: $i = 1, \ldots, n_{\ell}$ weights $w_{ij}^{(\ell)}$, biases $b_i^{(\ell)}$ data: $(x_{\alpha}, y_{\alpha}), \alpha \in \mathcal{D}$

pre-activation functions



$$\phi_{i\alpha}^{(\ell+1)} = \sum_{j=1}^{n_{\ell}} w_{ij}^{(\ell+1)} \rho_{j\alpha}^{(\ell)} + b_i^{(\ell+1)}$$

statistical ensembles of NNs

initialize Gaussian weights and biases using Gaussians

$$\begin{split} \langle b_i^{(\ell)} \rangle &= 0 \,, \quad \langle b_{i_1}^{(\ell)} b_{i_2}^{(\ell)} \rangle = \delta_{i_1 i_2} C_b^{(\ell)} \\ \langle w_{i_j}^{(\ell)} \rangle &= 0 \,, \quad \langle w_{i_1 j_1}^{(\ell)} w_{i_2 j_2}^{(\ell)} \rangle = \delta_{i_1 i_2} \delta_{j_1 j_2} \frac{C_w^{(\ell)}}{n_{\ell-1}} \end{split}$$

parameters/functions duality

$$p(\phi^{(\ell)}|\mathcal{D}) = \int \left[dw \, p(w)\right] \left[db \, p(b)\right] \,\prod_{i,\alpha} \delta\left(\phi_{i\alpha}^{(\ell)} - \sum_{j} w_{ij}^{(\ell)} \rho\left(\phi_{j\alpha}^{(\ell-1)}\right) - b_{i}^{(\ell)}\right)$$

computing the integral

$$p(\phi^{(\ell+1)}|\mathcal{D}) = \int d\phi^{(\ell)} p(\phi^{(\ell+1)}|\phi^{(\ell)}) p(\phi^{(\ell)}|\mathcal{D})$$

$$p(\phi^{(\ell+1)}|\phi^{(\ell)}) = \int \left[dw^{(\ell+1)} p(w^{(\ell+1)}) \right] \left[db^{(\ell+1)} p(b^{(\ell+1)}) \right]$$

$$\times \prod_{i,\alpha} \delta(\phi_{i\alpha}^{(\ell+1)} - \sum_{j} w_{ij}^{(\ell+1)} \rho\left(\phi_{j\alpha}^{(\ell)}\right) - b_{i}^{(\ell+1)})$$

$$= \frac{1}{|2\pi \widehat{G}^{(\ell+1)}|^{n_{\ell}/2}} \exp\left[-\frac{1}{2} \widehat{G}_{\alpha_{1}\alpha_{2}}^{(\ell+1)} \phi_{\alpha_{1}}^{(\ell+1)} \cdot \phi_{\alpha_{2}}^{(\ell+1)} \right]$$

$$\langle \phi_{i_1\alpha_1}^{(\ell+1)} \dots \phi_{i_{2k}\alpha_{2k}}^{(\ell+1)} \rangle = \sum_{\text{pairs}} \delta_{i_{P_1}i_{P_2}} \dots \left\langle \left(\widehat{G}^{(\ell+1)}\right)_{\alpha_{P_1}\alpha_{P_2}}^{-1} \dots \right\rangle$$

propagators and all that

$$\widehat{G}_{\alpha_{1}\alpha_{2}}^{(\ell+1)} = C_{b}^{(\ell+1)} + \frac{C_{w}^{(\ell+1)}}{n_{\ell}} \vec{\rho}_{\alpha_{1}}^{(\ell)} \cdot \vec{\rho}_{\alpha_{2}}^{(\ell)}$$

fluctuations of \widehat{G}

$$\begin{split} \widehat{\Delta G}_{\alpha_1 \alpha_2}^{(\ell+1)} &= \widehat{G}_{\alpha_1 \alpha_2}^{(\ell+1)} - \langle \widehat{G}_{\alpha_1 \alpha_2}^{(\ell+1)} \rangle \\ \langle \widehat{\Delta G}_{\alpha_1 \alpha_2}^{(\ell+1)} \widehat{\Delta G}_{\alpha_3 \alpha_4}^{(\ell+1)} \rangle &= \frac{1}{n_\ell} V_{\alpha_1 \alpha_2, \alpha_3 \alpha_4}^{(\ell+1)} \end{split}$$

correlators

$$\langle \phi_{i_1\alpha_1}^{(\ell+1)} \phi_{i_2\alpha_2}^{(\ell+1)} \rangle = \delta_{i_1i_2} \langle \widehat{G}_{\alpha_1\alpha_2}^{(\ell+1)} \rangle = \delta_{i_1i_2} G_{\alpha_1\alpha_2}^{(\ell+1)} \\ \langle \phi_{i_1\alpha_1}^{(\ell+1)} \phi_{i_2\alpha_2}^{(\ell+1)} \phi_{i_3\alpha_3}^{(\ell+1)} \phi_{i_4\alpha_4}^{(\ell+1)} \rangle_c = \frac{1}{n_\ell} \left[\delta_{i_1i_2} \delta_{i_3i_4} V_{\alpha_1\alpha_2,\alpha_3\alpha_4}^{(\ell+1)} + \dots \right]$$

1/n expansion

correlators can be expanded in 1/n

$$G_{\alpha_{1}\alpha_{2}}^{(\ell)} = K_{\alpha_{1}\alpha_{2}}^{(\ell)} + \frac{1}{n_{\ell-1}} G_{\alpha_{1}\alpha_{2}}^{\{1\}(\ell)} + \frac{1}{n_{\ell-1}^{2}} G_{\alpha_{1}\alpha_{2}}^{\{2\}(\ell)} + O(\frac{1}{n_{\ell-1}^{3}})$$
$$V_{\alpha_{1}\alpha_{2},\alpha_{3}\alpha_{4}}^{(\ell)} = V_{\alpha_{1}\alpha_{2},\alpha_{3}\alpha_{4}}^{\{0\}(\ell)} + \frac{1}{n_{\ell-1}} V_{\alpha_{1}\alpha_{2},\alpha_{3}\alpha_{4}}^{\{1\}(\ell)} + O(\frac{1}{n_{\ell-1}^{2}})$$

therefore

$$\langle \phi_{i_1\alpha_1}^{(\ell+1)} \phi_{i_2\alpha_2}^{(\ell+1)} \rangle = \delta_{i_1i_2} K_{\alpha_1\alpha_2}^{(\ell+1)} + O(1/n)$$

$$\langle \phi_{i_1\alpha_1}^{(\ell+1)} \phi_{i_2\alpha_2}^{(\ell+1)} \phi_{i_3\alpha_3}^{(\ell+1)} \phi_{i_4\alpha_4}^{(\ell+1)} \rangle_c = \frac{1}{n_\ell} \left[\delta_{i_1i_2} \delta_{i_3i_4} V_{\alpha_1\alpha_2,\alpha_3\alpha_4}^{\{0\}(\ell+1)} + \dots \right] + O(1/n^2)$$

EFT

probability described by an effective action

$$p(\phi|\mathcal{D}) = \frac{e^{-S(\phi)}}{Z}$$

$$S(\phi) = \frac{1}{2}\gamma^{(2)}_{\alpha_1\alpha_2}\vec{\phi}_{\alpha_1} \cdot \vec{\phi}_{\alpha_2} + \frac{1}{8}\gamma^{(4)}_{\alpha_1\alpha_2,\alpha_3\alpha_4}\vec{\phi}_{\alpha_1} \cdot \vec{\phi}_{\alpha_2}\vec{\phi}_{\alpha_3} \cdot \vec{\phi}_{\alpha_4} + \dots$$

couplings fixed by matching correlators in 1/n expansion

$$\langle \phi_{i_1\alpha_1}^{(\ell+1)} \phi_{i_2\alpha_2}^{(\ell+1)} \rangle = \delta_{i_1i_2} K_{\alpha_1\alpha_2}^{(\ell+1)} + O(1/n)$$

= $\delta_{i_1i_2} (\gamma^{(2,(\ell+1))})_{\alpha_1\alpha_2}^{-1} + O(\gamma^{(4,(\ell+1))})$

$$\langle \phi_{i_1\alpha_1}^{(\ell+1)} \phi_{i_2\alpha_2}^{(\ell+1)} \phi_{i_3\alpha_3}^{(\ell+1)} \phi_{i_4\alpha_4}^{(\ell+1)} \rangle_c = \delta_{i_1i_2} \delta_{i_3i_4} \frac{1}{n_\ell} V_{\alpha_1\alpha_2,\alpha_3\alpha_4}^{\{0\}(\ell+1)} + \dots$$

= $\delta_{i_1i_2} \delta_{i_3i_4} \left[G_{\alpha_1\beta_1}^{(\ell+1)} G_{\alpha_2\beta_2}^{(\ell+1)} G_{\alpha_3\beta_3}^{(\ell+1)} G_{\alpha_4\beta_4}^{(\ell+1)} \right] \gamma_{\beta_1\beta_2,\beta_3\beta_4}^{\{4,(\ell+1))} + \dots$

recursion relations

two-pt function at leading order

$$\begin{split} K_{\alpha_{1}\alpha_{2}}^{(\ell+1)} &= C_{b}^{(\ell+1)} + C_{w}^{(\ell+1)} \frac{1}{n_{\ell}} \langle \vec{\rho}_{\alpha_{1}}^{(\ell)} \cdot \vec{\rho}_{\alpha_{2}}^{(\ell)} \rangle \bigg|_{O(1)} \\ &= C_{b}^{(\ell+1)} + C_{w}^{(\ell+1)} \frac{1}{n_{\ell}} \langle \vec{\rho}_{\alpha_{1}}^{(\ell)} \cdot \vec{\rho}_{\alpha_{2}}^{(\ell)} \rangle_{K^{(\ell)}} \end{split}$$

solving the recursion for $K_{\alpha\alpha}$

$$g(K) = \int d\phi \, \frac{1}{\sqrt{2\pi K}} \exp\left(-\frac{1}{2K}\phi^2\right) \rho(\phi)^2$$

fixed point: $K^* = C_b + C_w g(K^*)$ $K_{\alpha\alpha} = K^* + \Delta K_{\alpha\alpha} \Longrightarrow \Delta K_{\alpha\alpha}^{(\ell+1)} = \chi_{\parallel}(K^*) \Delta K_{\alpha\alpha}^{(\ell)}$

RG-style evolution as we go deep in the Neural Network

training

gradient descent

$$\frac{d}{dt}\theta_{\mu}(t) = -\lambda_{\mu\nu}\frac{\partial}{\partial\theta_{\mu}}\mathcal{L}_{A}$$

evolution of ${\cal O}(\phi)$

$$\frac{d}{dt}O(t) = -\frac{\partial O}{\partial \phi_{i\delta}} \frac{\partial \phi_{i\delta}}{\partial \theta_{\mu}} \lambda_{\mu\nu} \frac{\partial \mathcal{L}_A}{\partial \phi_{j\alpha}} \frac{\partial \phi_{j\alpha}}{\partial \theta_{\nu}} \\ = -\frac{\partial O}{\partial \phi_{i\delta}} \bigg|_{\phi(t)} H_{i\delta,j\alpha}(t) \varepsilon_{j\alpha}(t)$$

in particular

$$\frac{d}{dt}\phi_{i\delta}(t) = -H_{i\delta,j\alpha}(t)\varepsilon_{j\alpha}(t)$$

EFT again

introduce an auxiliary field $L_{i\alpha}(t)$

$$p(\varphi, L|\mathcal{D}) = \frac{1}{Z} \exp\left(-S(\phi) - \int dt \, L_{i\alpha}(t) \left(\frac{d}{dt}\varphi_{i\delta}(t) + H_{i\delta,j\alpha}(t)\varepsilon_{j\alpha}(t)\right)\right)$$

with $\varphi_{i\alpha}(0)=\phi_{i\alpha}$

use this theory to compute correlators during training

 $\langle L_{i_1\alpha_1}(t)\varphi_{i_2\alpha_2}(t')
angle$: propagator

interactions depend on the loss

exact solution quadratic loss

$$\mathcal{L}_A = \sum_{\alpha \in A} (y_\alpha - \phi_\alpha)^2$$

leading order in 1/n

$$\frac{d}{dt}H = 0 \implies \frac{d}{dt}\phi_{i\delta}(t) = 2H_{i\delta;j\alpha}(y_{j\alpha} - \phi_{j\alpha})$$

discrete integration

$$\phi(n+1) = \phi(n) - \eta H(\phi(n) - y)$$
$$\implies \phi(n) = \phi - Ha(n)$$

$$a(n) = \eta \frac{1 - (1 - \eta \hat{H})^n}{1 - (1 - \eta \hat{H})} (\phi - y)$$

conclusions

- EFT description of NN at initialization
- 1/n expansion is important to have a hierarchy of couplings
- training is a flow in functions space
- NTK dictates the properties of the flow
- understand 1/n corrections to GP
- maybe useful for trivializing maps?
- work in progress