



TLDR: We introduce a scalable Conditional Neural Process model which models statistical dependencies and has an analytically tractable log-likelihood.

Modelling Statistical Dependencies

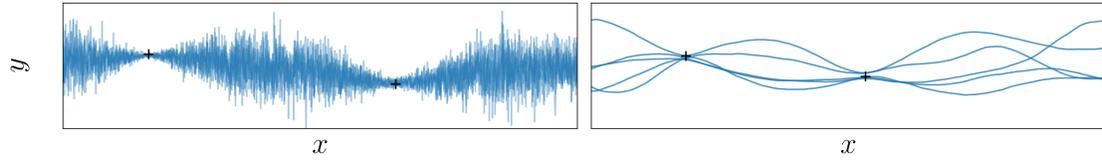


Figure 1: Samples from the predictives of a ConvCNP (left) and a ConvGNP (right).

Directly learn predictive mean \mathbf{m} and covariance \mathbf{K} as function of context \mathbf{x}_c and target \mathbf{x}_t

$$\mathbf{m}_i = f(x_{t,i}, \mathbf{r}), \quad \mathbf{K}_{ij} = k(g(x_{t,i}, \mathbf{r}), g(x_{t,j}, \mathbf{r})) \quad (1)$$

where $\mathbf{r} = r(\mathbf{x}_c, \mathbf{x}_t)$, f and g are neural networks, k is positive-definite.

	Conditional NP	Latent NP	Gaussian NP
Exact Likelihood	✓	✗	✓
Joint Dependencies	✗	✓	✓

Applicable to arbitrary architectures, e.g. translation equivariant networks.

Experiments with Real Data

Straightforward handling of multi-output regression

$$\mathbf{m}_{ia} = f_a(x_{t,i}, \mathbf{r}), \quad \mathbf{K}_{ijab} = k(g_a(x_{t,i}, \mathbf{r}), g_b(x_{t,j}, \mathbf{r})). \quad (2)$$

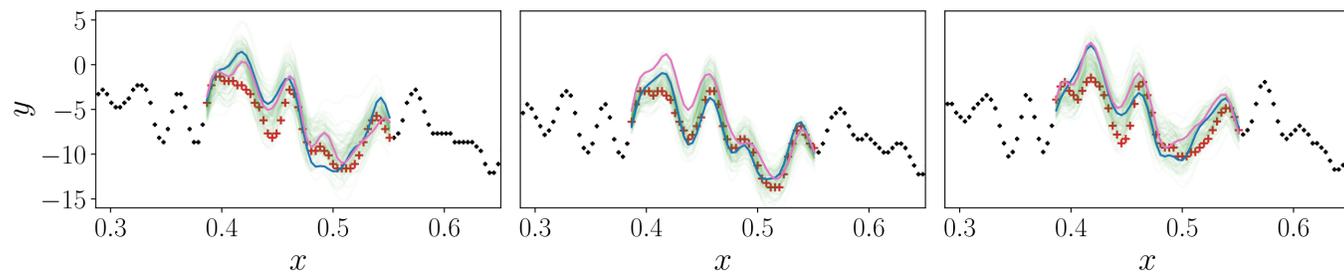


Figure 4: ConvGNP marginals and samples on multi-output regression task with EEG data.

	MOGP	ConvGNP	ConvNP	ConvGNP
Log Lik.	-12.7 ± 0.42	-5.27 ± 0.01	-3.96 ± 0.01	-1.24 ± 0.00

Table 1: Log-likelihoods on multi-output regression with EEG data.

Experiments with Synthetic Data

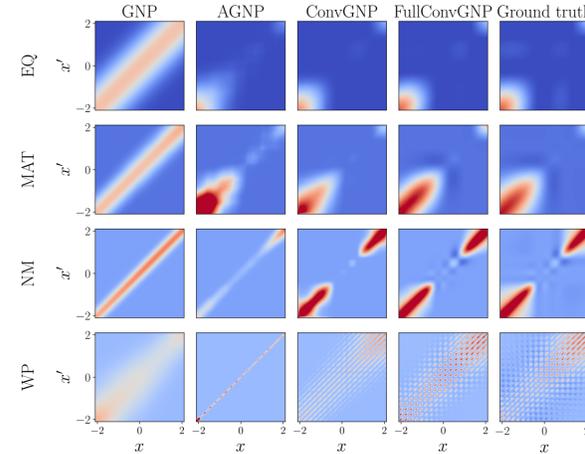


Figure 2: Model predictive covariances on synthetic GP data.

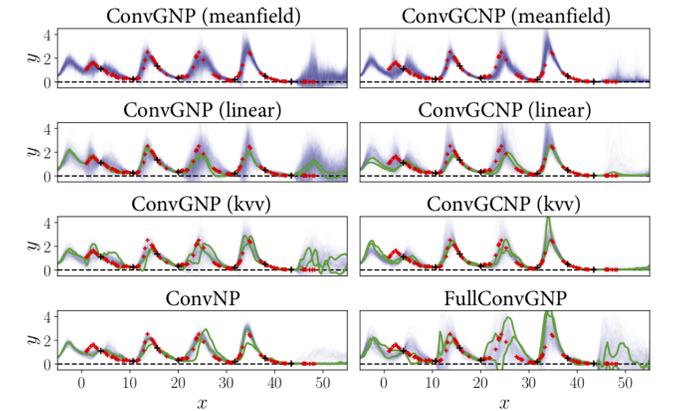


Figure 3: Model marginals and samples on synthetic predator-prey data.

Competitive performance in climate down-scaling. Modelling dependencies:

- ✓ Improves predictive log-likelihood.
- ✓ Enables sampling coherent temperature fields for downstream estimation.

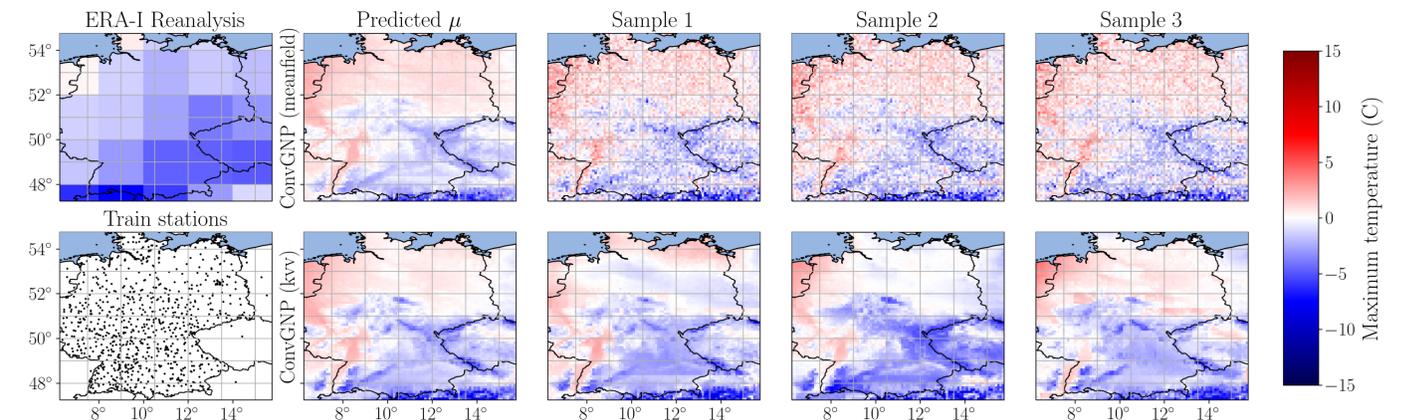


Figure 5: ConvCNP (top) and ConvGNP (bottom) on a larger scale climate down-scaling task.