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Exploiting Inferential Structure in Neural Processes

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Main Takeaway

- **Problem:** Neural processes (NPs) perform fast-adaptation to new tasks at test-time but their training procedure is data-inefficient requiring a wide range of datasets to generalize well.
- **Main contribution:** We propose to incorporate a structured-inference network (SIN) [1]
- **Technical contributions:**
  - i. priors can be naturally incorporated
  - ii. leads to aggregation strategies in which context points are appropriately weighted
  - iii. interpretability of datapoint-wise encodings as neural sufficient statistics

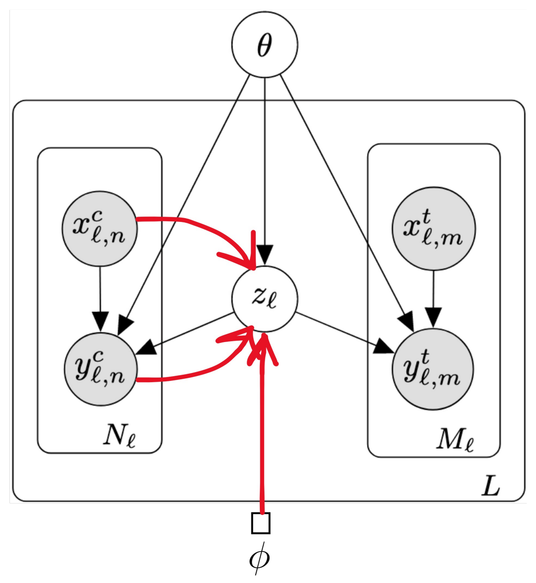
Background: Meta-Learning

- **Meta-learning**: NPs generalize between multiple, related tasks by modelling task-relatedness using hierarchical Bayes [2]
- **Train-time:**

$$\max \sum_{l=1}^{L} \log p_\theta\left(\mathcal{D}_l^t | \mathcal{D}_l^c\right)$$

$$= \sum_{l=1}^{L} \log \int p_\theta\left(\mathcal{D}_l^t | z_l\right) p_\theta\left(z_l | \mathcal{D}_l^c\right) dz_l$$

$$\gtrapprox \sum_{l=1}^{L} \mathbb{E}_{q_\phi(z|\mathcal{D}_l)}\left[\log p_\theta\left(\mathcal{D}_l^t | z\right)\right] - \mathrm{D}_{\mathrm{KL}}\left[q_\phi\left(z|\mathcal{D}_l^t \cup \mathcal{D}_l^c\right) \| q_\phi\left(z|\mathcal{D}_l^c\right)\right]$$



Amortised inference network

- **Test-time**

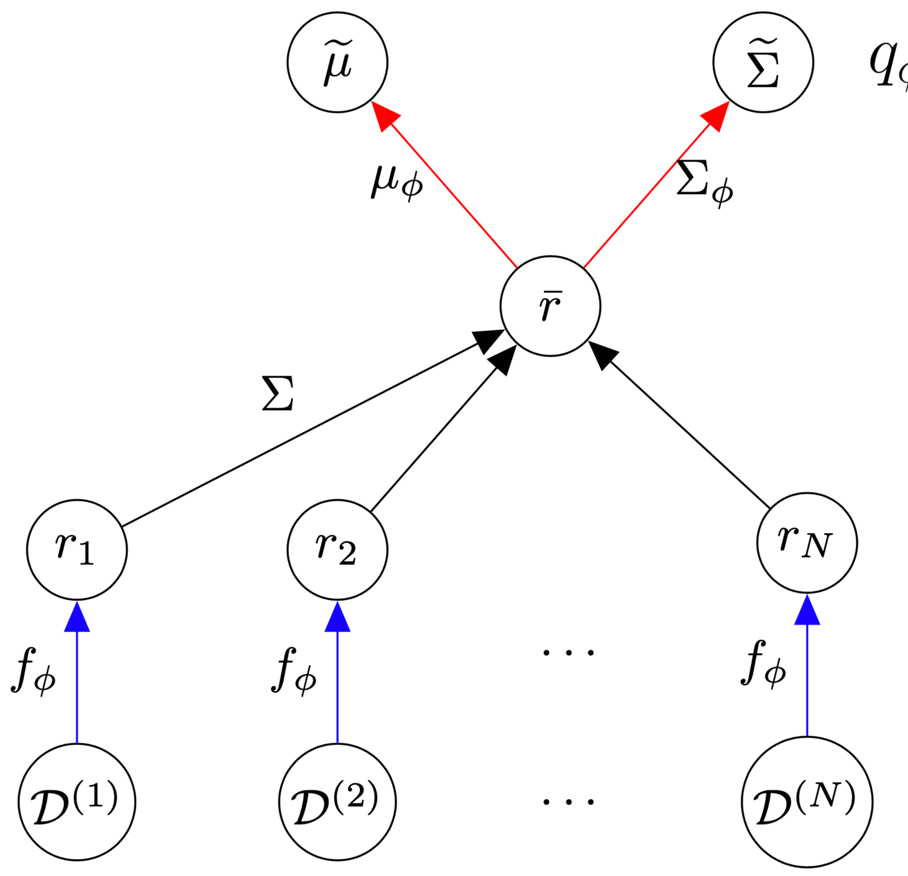
$$\mathbb{E}_{z \sim q_\phi(z|\mathcal{D}_*^c)}\left[\prod_{(x,y)\in\mathcal{D}_*^t} p_\theta(y|x,z)\right]$$

Background: Sum-Decomposition Network

Amortised inference network needs to:

- process datasets of variable-size
- permutation-invariant to the ordering of datapoints [3]

$$q_\phi(z|\mathcal{D}) = \mathbb{N}\left(\mu_\phi(\bar{\mathbf{r}}), \Sigma_\phi(\bar{\mathbf{r}})\right)$$



Aggregation:

$$\bar{\mathbf{r}} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{r}_i$$

Datapoint-wise encodings:

$$\mathbf{r}_i = f_\phi(\mathcal{D}^{(i)})$$

Structured-Inference Network

Conjugate-exponential family

$$p(z|\mathcal{D}) = \frac{1}{p(\mathcal{D})}\prod_{i=1}^{N} p(y_i|z)\, p(z)$$

$$\propto h(z)\exp\left[\left\langle T(z), \sum_{i=1}^{N} \eta_i(y_i) + \eta_0 \right\rangle\right]$$

Sufficient statistics of likelihood

Natural parameters of prior

Combine recognition networks with conjugate-computations:

$$q_\phi(z|\mathcal{D}) = h(z)\exp\left[\left\langle T(z), \sum_{i=1}^{N} f_\phi(\mathcal{D}^{(i)}) + \eta_0 \right\rangle\right]$$

Neural Sufficient Statistics

Bayesian Aggregation

Given an exp-family prior, aggregation strategy naturally arises from the choice of parameterisation

For example, Gaussian prior & moment parameterisation recovers a recently proposed weighted aggregation strategy [4]

$$\{\boldsymbol{\mu}_0, \boldsymbol{\Sigma}_0\} \leftrightarrow \eta_0$$

$$\boldsymbol{\Sigma}^{-1} = \sum_{i=1}^{N} \mathbf{V}_i^{-1} + \boldsymbol{\Sigma}_0^{-1}$$

$$\boldsymbol{\mu} = \boldsymbol{\Sigma}\left(\sum_{i=1}^{N} \mathbf{V}_i^{-1}\mathbf{m}_i + \boldsymbol{\Sigma}_0^{-1}\boldsymbol{\mu}_0\right)$$

$$\mathbf{m}_i, \mathbf{V}_i = f_\phi(\mathcal{D}^{(i)})$$

Extension to structured priors such as mixture of Gaussian and Student's T via minimal conditional-EF form [5]

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