Factorized Diffusion Policies for Conditional Action Diffusion

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$$\mathrm{p}(\mathrm{x}|y_1, y_2 \ldots y_M)$$

Full conditional learned by **Diffusion Policy (DP)**
- Sensitive to distribution shifts in observations
- Lacks sample efficiency

FDP →

Train with loss $\mathcal{L}^t(\theta)$

$$\mathrm{p}(\mathrm{x}|y_1 \ldots y_k) * \mathrm{p}(\mathrm{y}_{k+1} \ldots y_M | x, y_1 \ldots y_k)$$

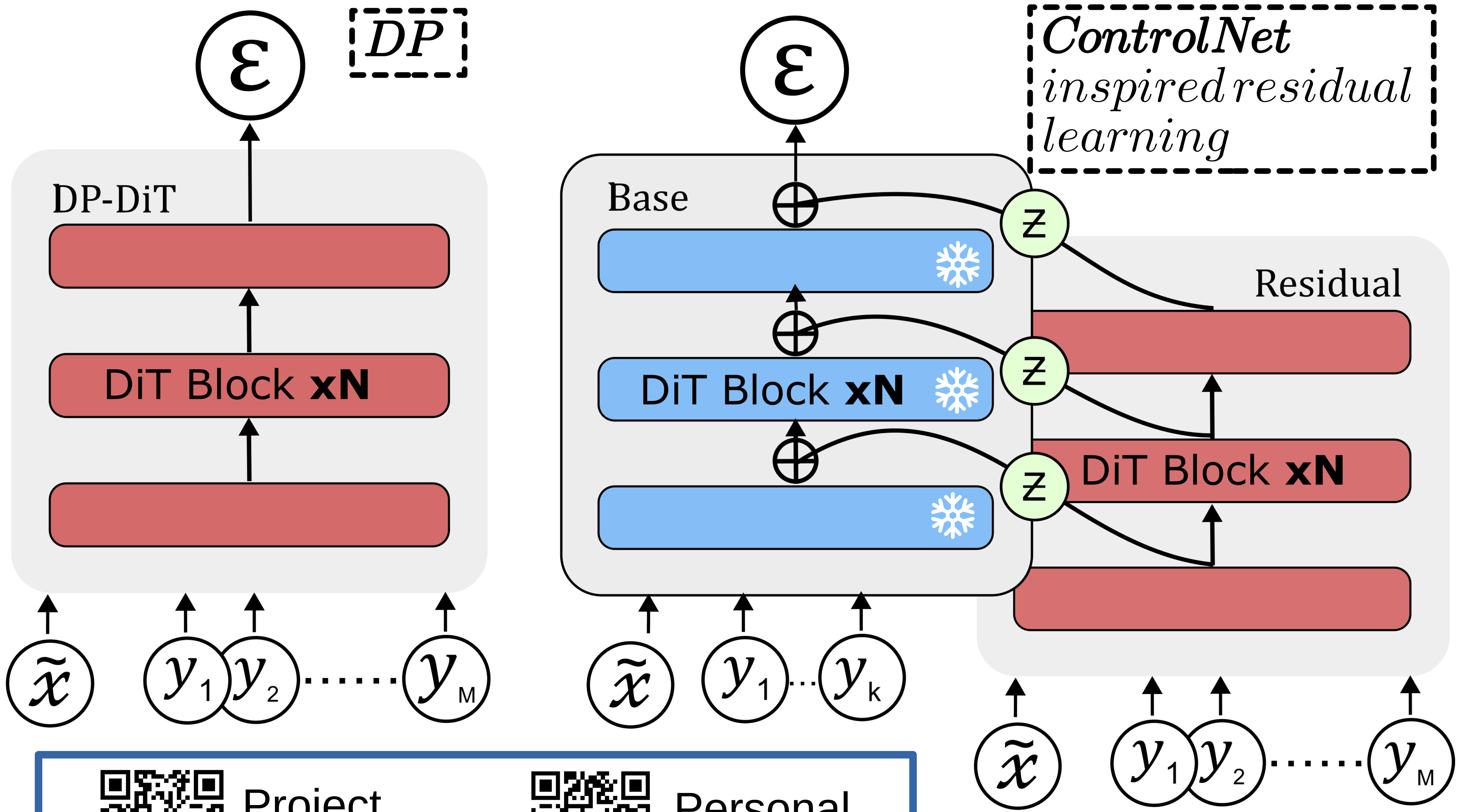
Learn **base model** π_{base} for prioritized modalities $y_1 \ldots y_k$
- Sample efficient

Learn a **residual model** π_{res} for "classification" of other modalities
- Robust to distribution shifts in $y_{k+1} \ldots y_M$
- But y is high dimensional? **Use FDP Loss!**

Train with loss $\mathcal{L}^t_{res}(\phi)$

$$\mathcal{L}^t(\theta) = \mathbb{E}_{p(\mathbf{x}_0, \mathbf{y}^{1:M})} \mathbb{E}_{\boldsymbol{\epsilon}_0 \sim \mathcal{N}(0,\mathcal{I})} \left[\frac{1}{2} \left\| \boldsymbol{\epsilon}_0 - \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, \mathbf{y}^{1:M}, t) \right\|^2 \right]$$

$$\mathcal{L}^t_{res}(\phi) = \mathbb{E}_{p_\tau(\mathbf{x}_0, \mathbf{y}^{1:M}, \tilde{\mathbf{y}}^{1:M})} \mathbb{E}_{\boldsymbol{\epsilon}_0 \sim \mathcal{N}(0,\mathcal{I})} \left[\frac{1}{2} \left\| \boldsymbol{\epsilon}_0 - \boldsymbol{\epsilon}_\theta(\mathbf{x}_t, \tilde{\mathbf{y}}^{1:k}, t) - \hat{\boldsymbol{\epsilon}}_\phi(\mathbf{x}_t, \tilde{\mathbf{y}}^{1:M}, t) \right\|^2 \right]$$



Z: Zero layer

Project Website

Personal Webpage