

# Autoregressive Conditional Neural Processes

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\*Equal contribution

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# Collaborators



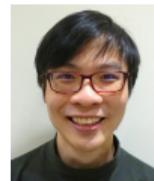
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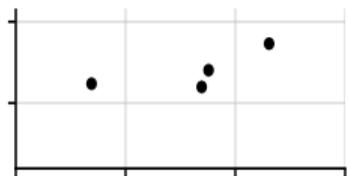
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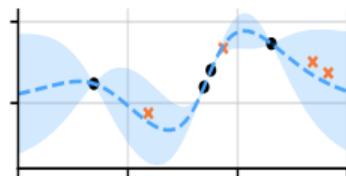
# Meta-Learning and Neural Processes

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$\pi$ : data sets  $\mathcal{D}$   $\rightarrow$  predictions  $\mathcal{P}$



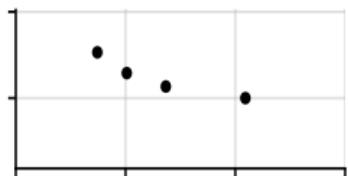
$\pi$



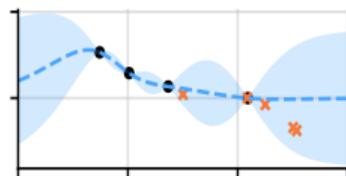
$\vdots$

neural process

$\vdots$



$\pi$

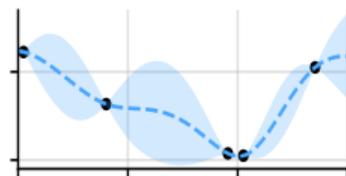


training

test



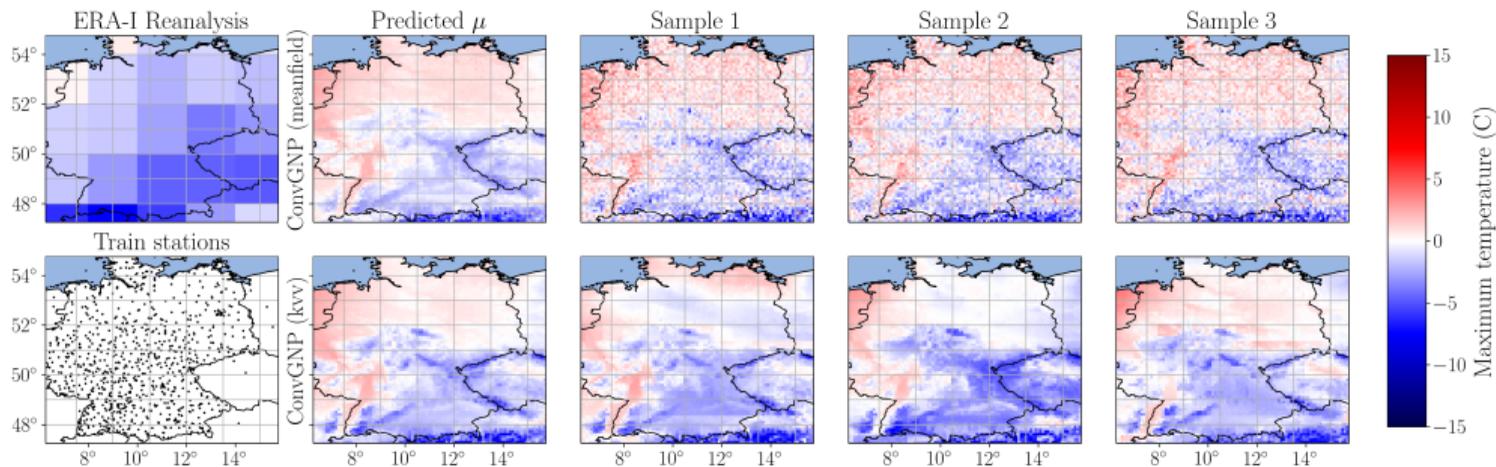
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# The Appeal of Neural Processes

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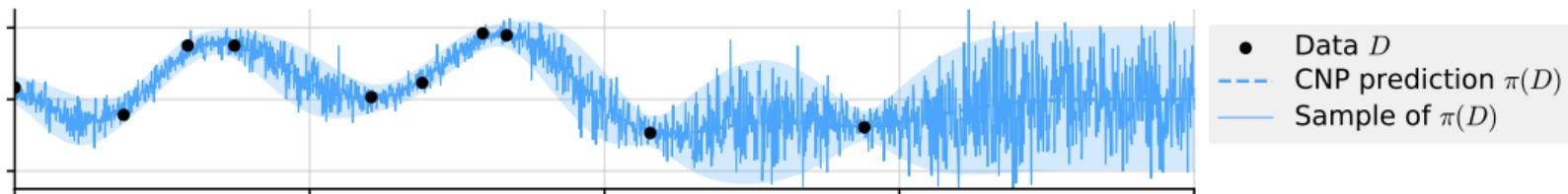
- ✓ Extremely versatile and flexible
  - ✓ Fast, probabilistic predictions
  - ✓ Simple to train
  - ✓ Work well in practice
- Climate model downscaling (Markou et al., 2022):



## But Neural Processes Are Not Without Challenges...

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- Conditional neural process (CNP; Garnelo, Rosenbaum, et al., 2018):



	Correlated predictions	Non-Gaussian predictions	Exact training	Consistent predictions
CNPs (Garnelo, Rosenbaum, et al., 2018)	✗	✓	✓	✓
Gaussian NPs (Markou et al., 2022)	✓	✗	✓	✓
Latent-variable NPs (Garnelo, Schwarz, et al., 2018)	✓	✓	✗	✓
Autoregressive CNPs (AR CNPs; this work!)	✓	✓	✓	✗

- **Idea:** feed output of CNP back into the model in an autoregressive fashion:

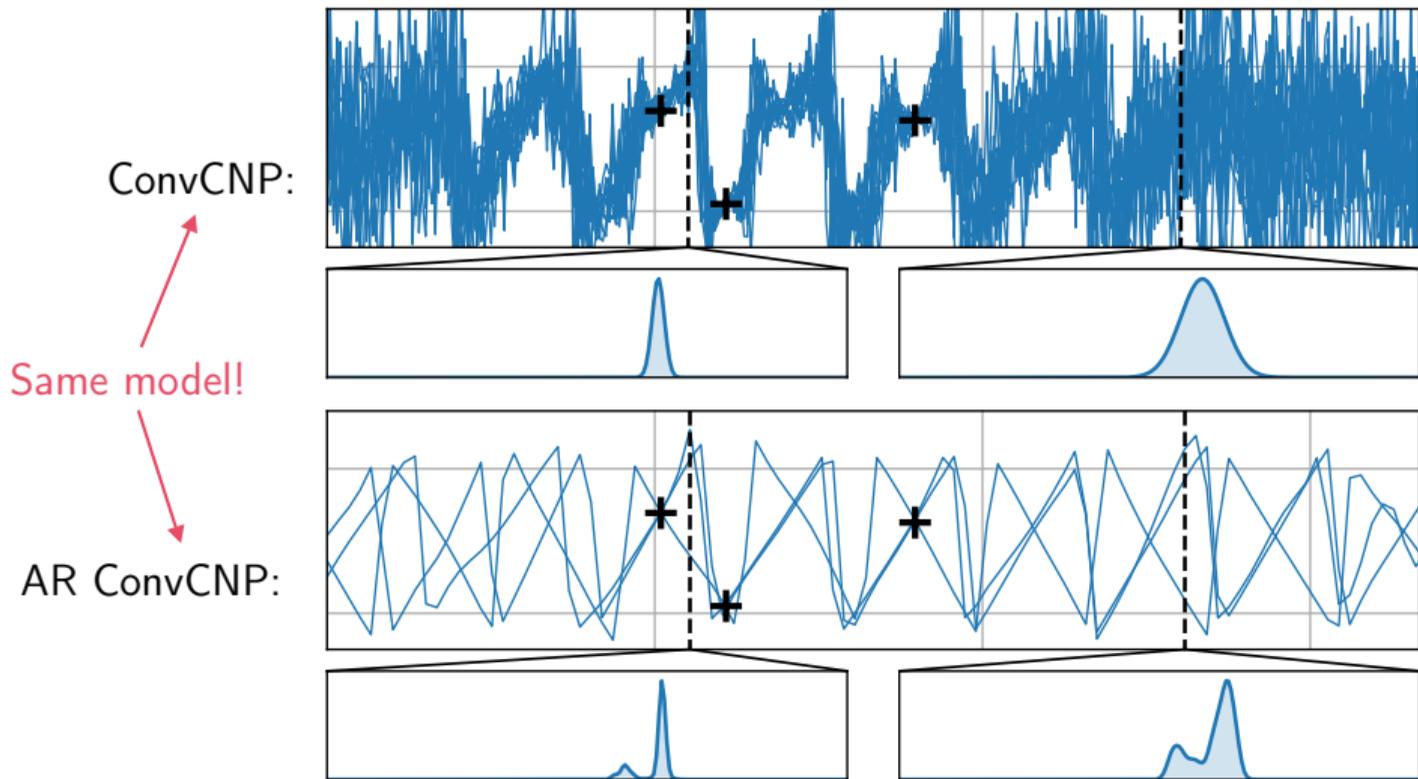
$$q^{(\text{AR CNP})}(\mathbf{y}_{1:3} | D) = q(y_1 | D)q(y_2 | y_1, D)q(y_3 | y_1, y_2, D).$$

↑ CNP pred. of  $y_3$   
given  $y_1, y_2$ , and  $D$

- AR modelling certainly not new, but not yet explored for NPs.
- ✓ Correlated and non-Gaussian predictions!
- ✓ No modifications to model or training procedure!
- ✗ Predictions depend on number and order of data (predictions no longer consistent)
- ✗ Requires multiple forward passes of CNP (Prop. 2.2 offers a partial remedy!)

# Example: ConvCNP (Gordon et al., 2020) Trained on Sawtooth Data

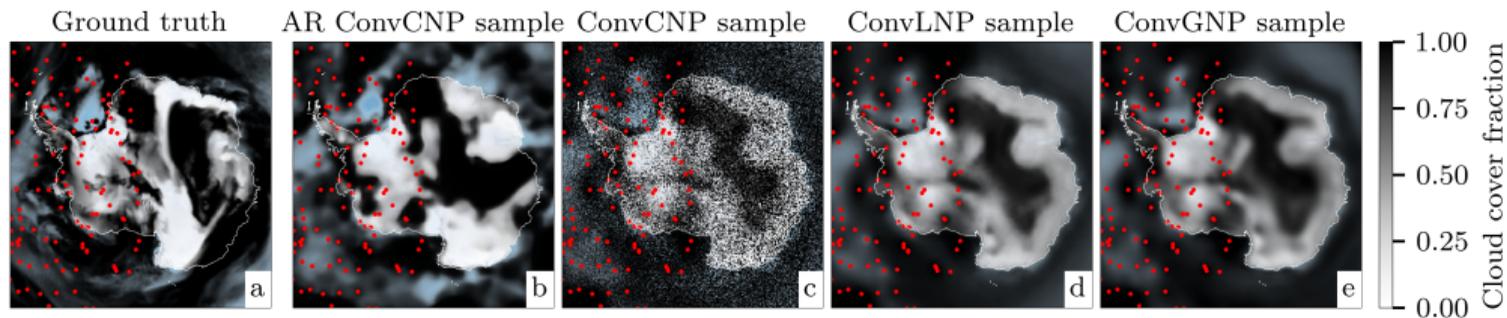
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## So What Else Is in the Paper?

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- **Prop. 2.1:** In an idealised case, AR CNPs are guaranteed to perform better than GNPs.
- A detailed comparison of AR CNPs and neural density estimators (NDEs).
- Exceptional performance of the **AR ConvCNP** (Gordon et al., 2020) in 60 synthetic scenarios.
- A variety of real-world experiments, including a challenging **cloud cover experiment**:



Code: <https://github.com/wesselb/neuralprocesses>

Please come see us at the poster, or contact us at [wbruinsma@microsoft.com](mailto:wbruinsma@microsoft.com)! :)