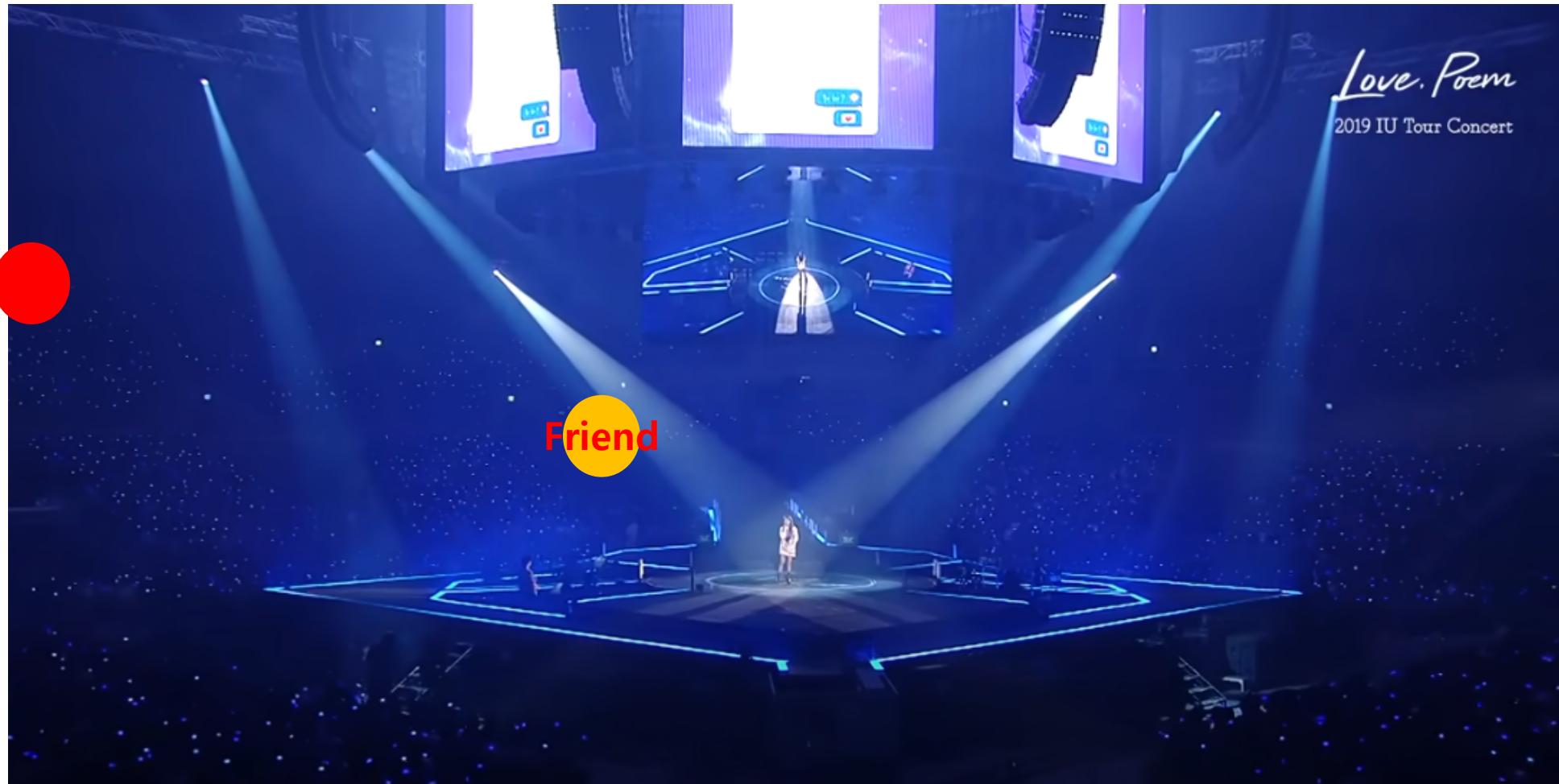


# **Neural process : Another way to merge NN and GP**

Jaehyoung Hong

# Can we predict scene of people in different positions?



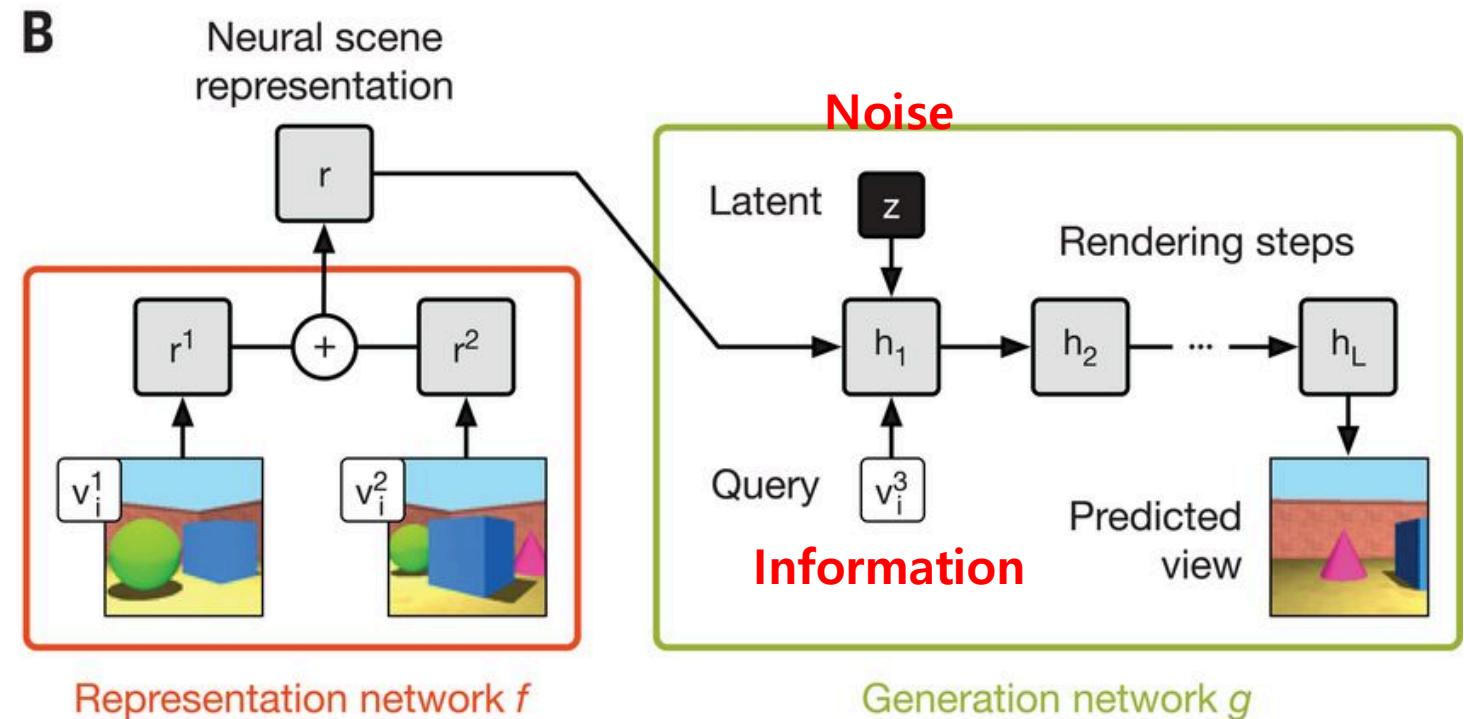
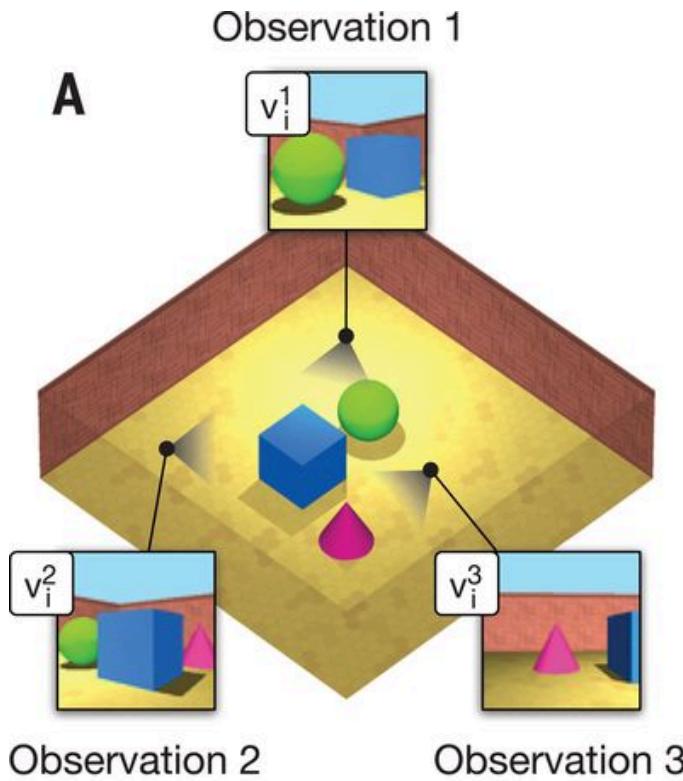
# For such purpose, we need more information



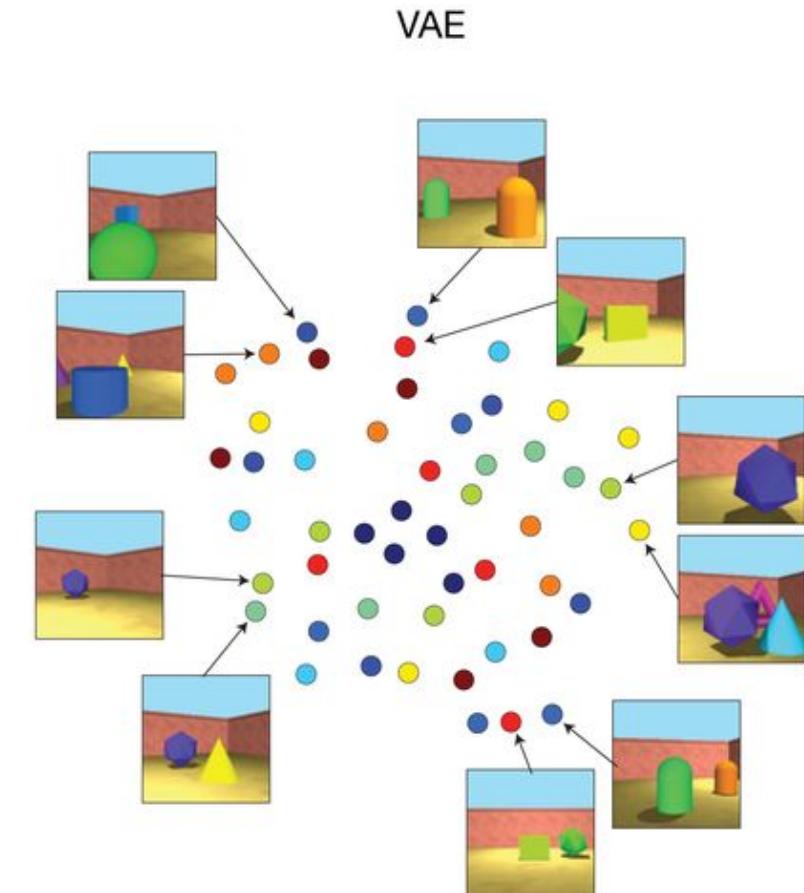
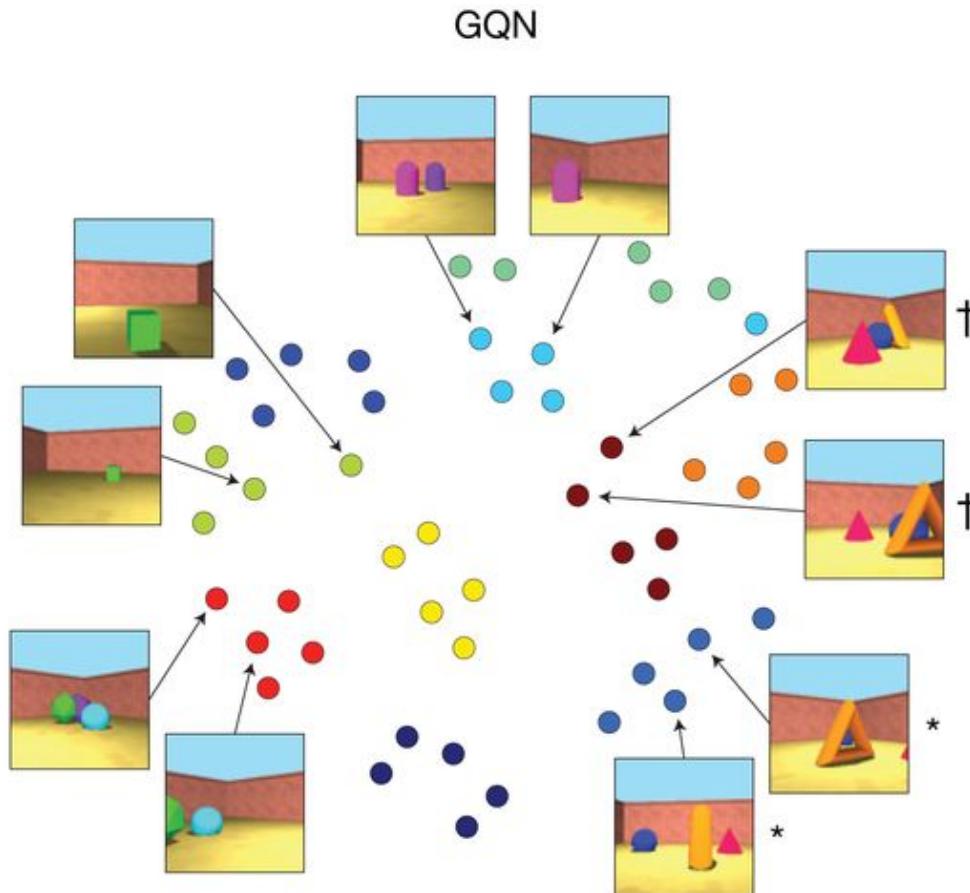
# For such purpose, we need more information



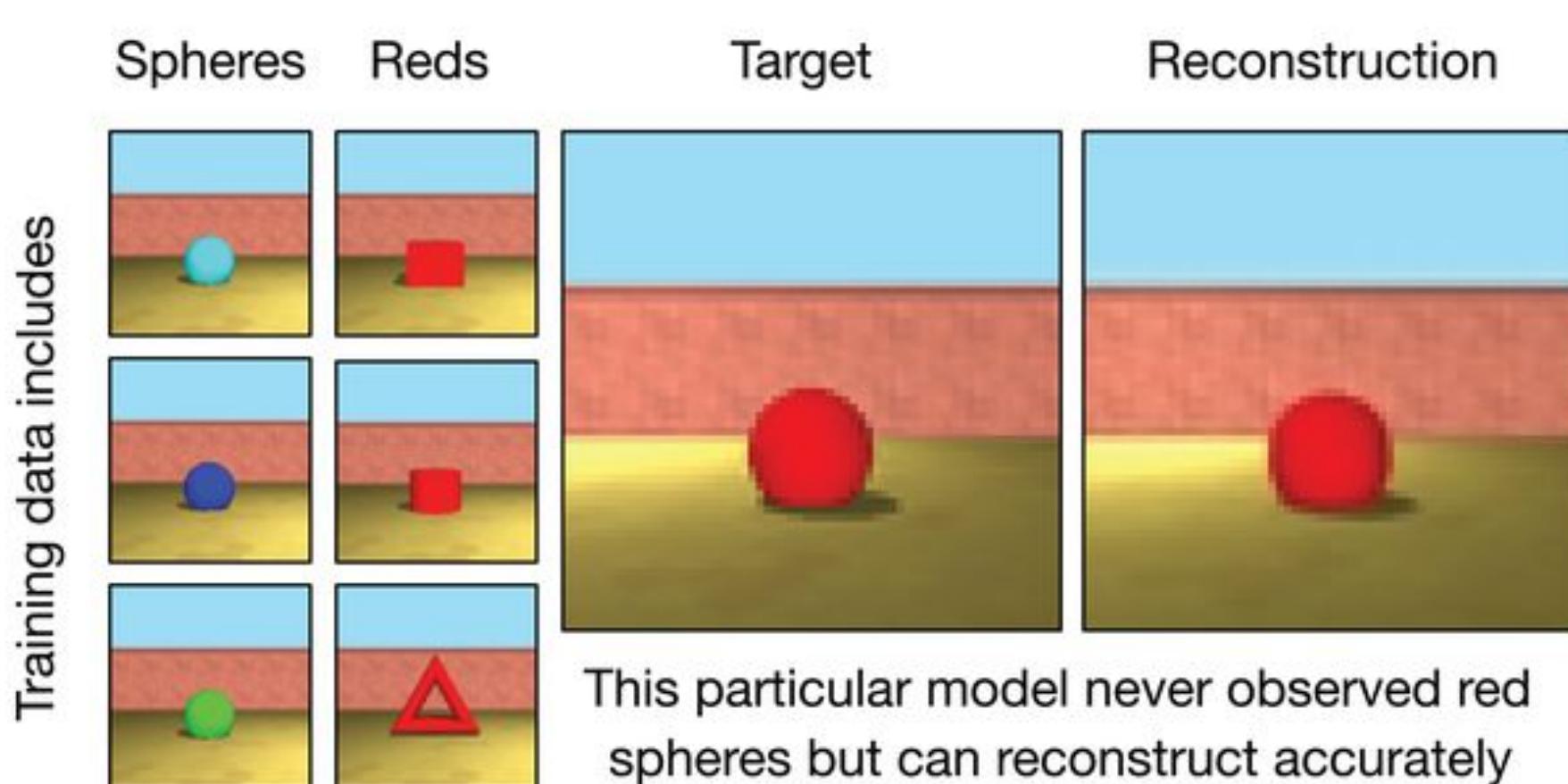
# Generative Query Network (GQN) can predict different scene



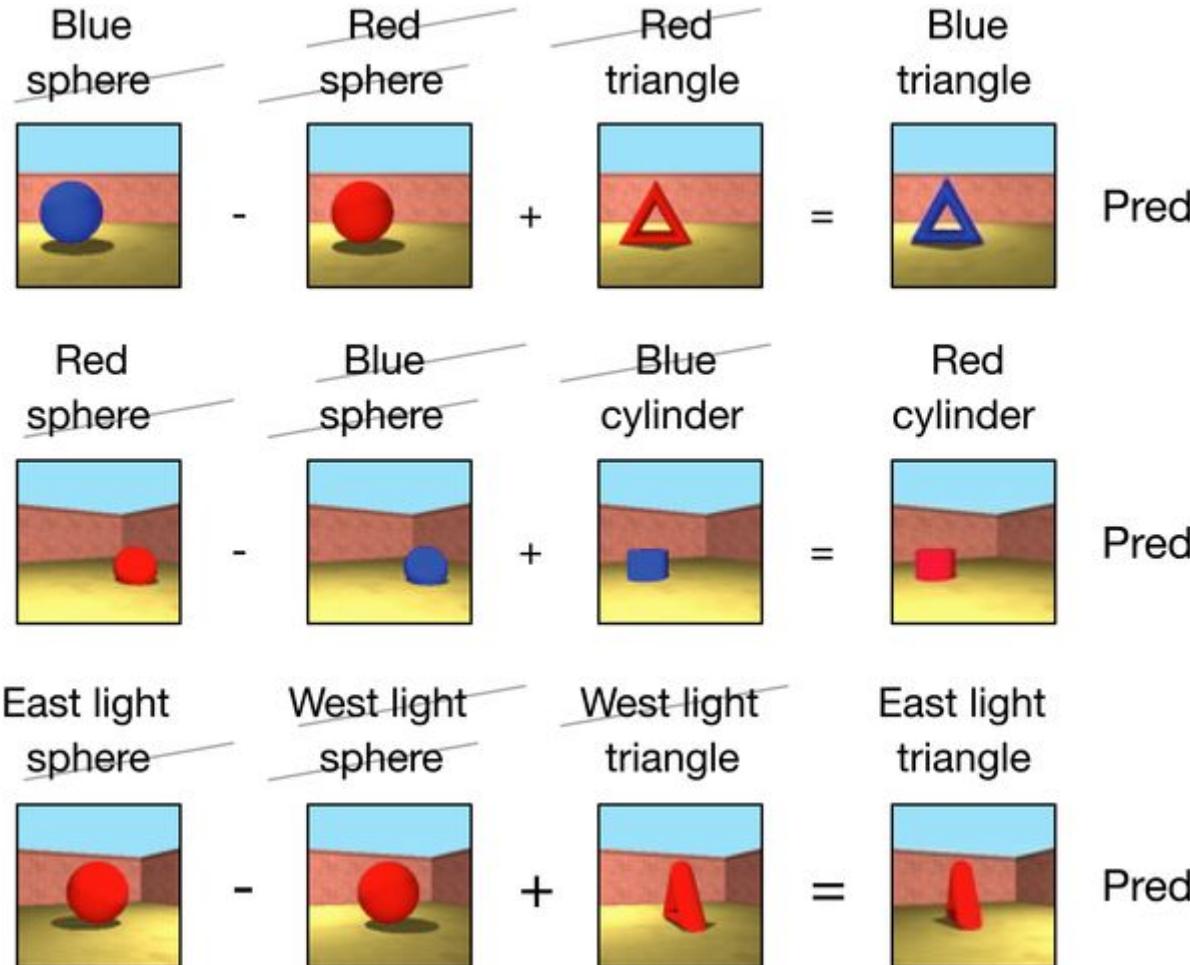
# GQN learns some information (latent variables) for scene latter than pixels



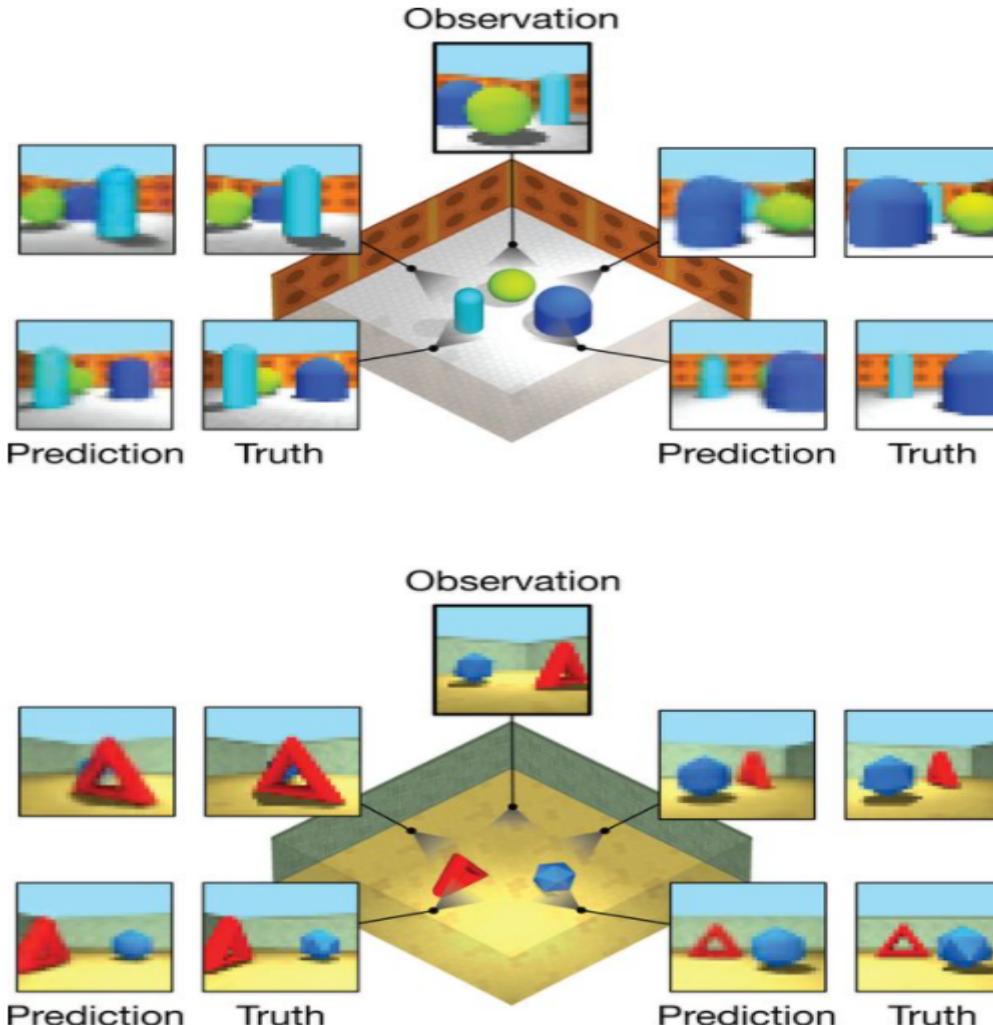
# GQN learns some information (latent variables) to predict unknown target : Flexibility



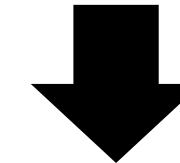
# GQN learns some information (latent variables) to predict unknown target : Flexibility



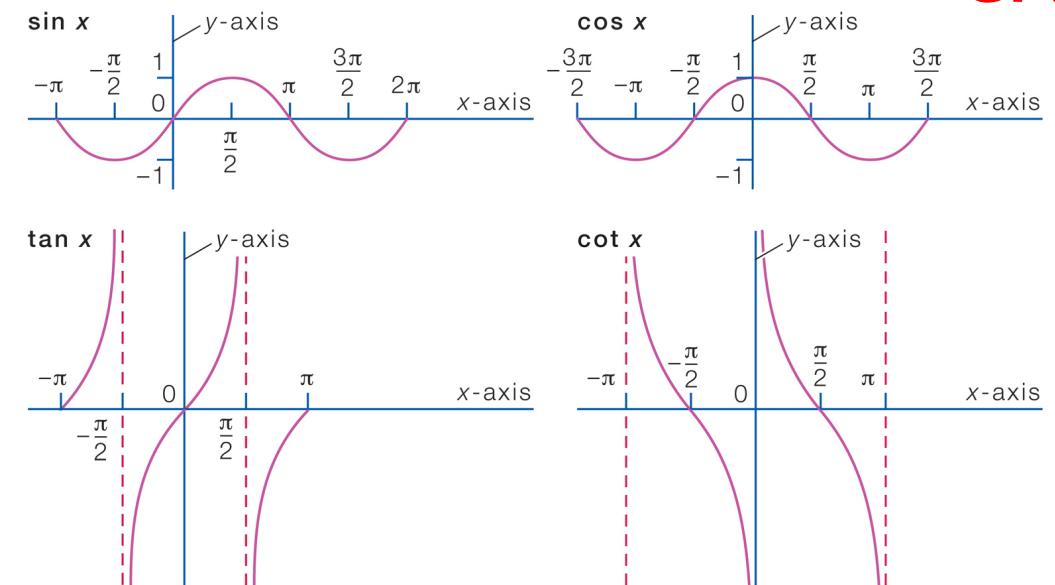
# GQN for function regression gives conditional neural process (CNP)



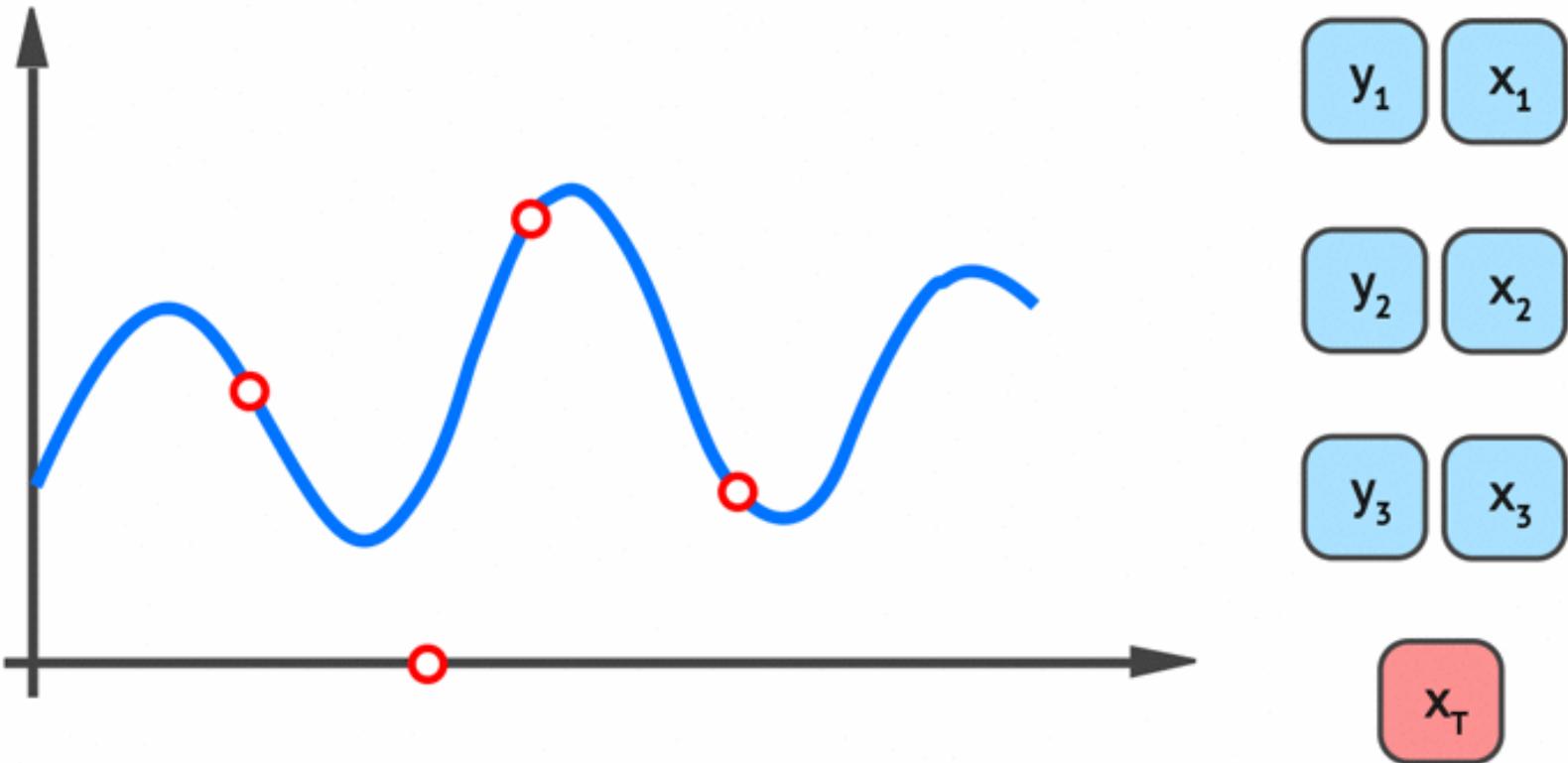
- GQN learns objects / position / light / color of the observation



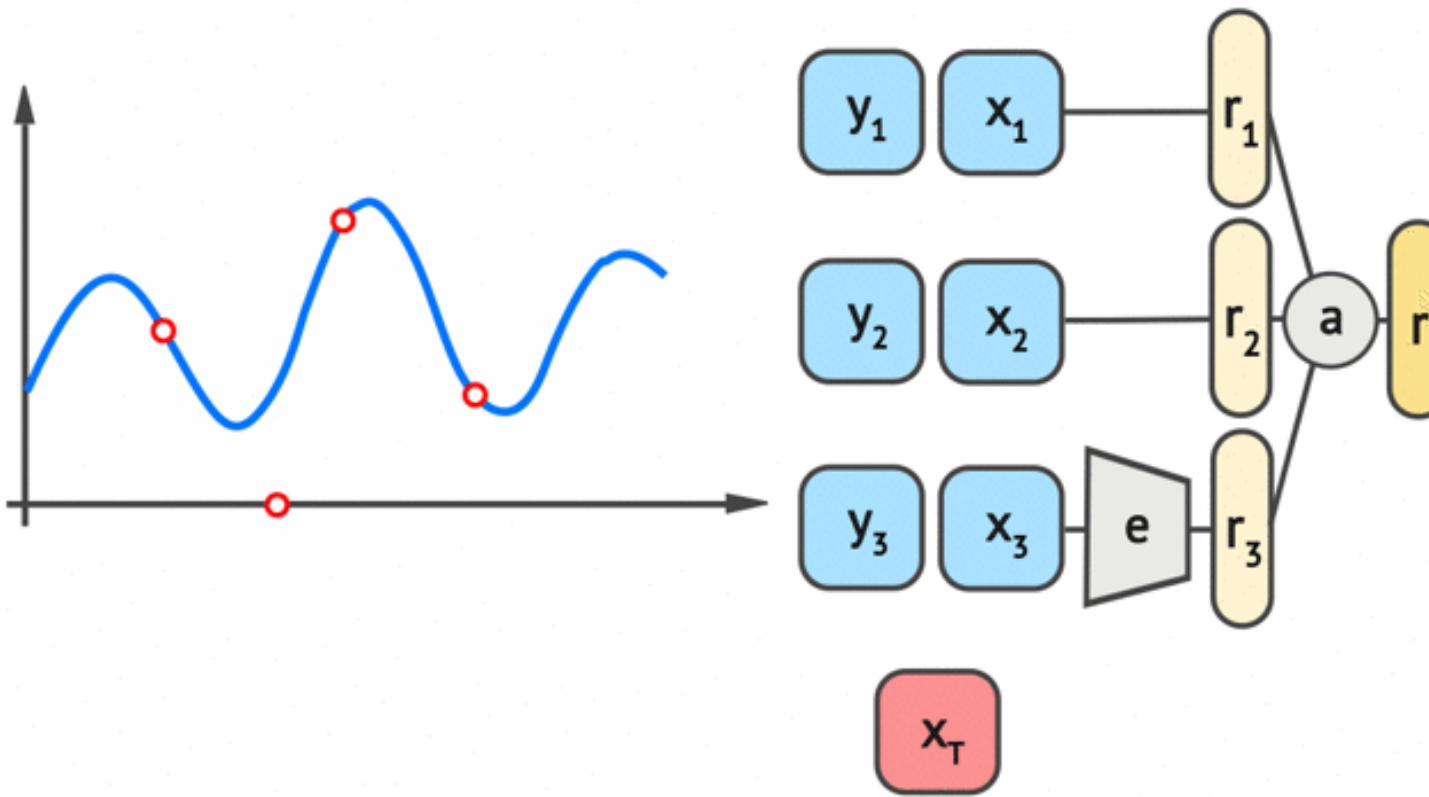
**GP!!**



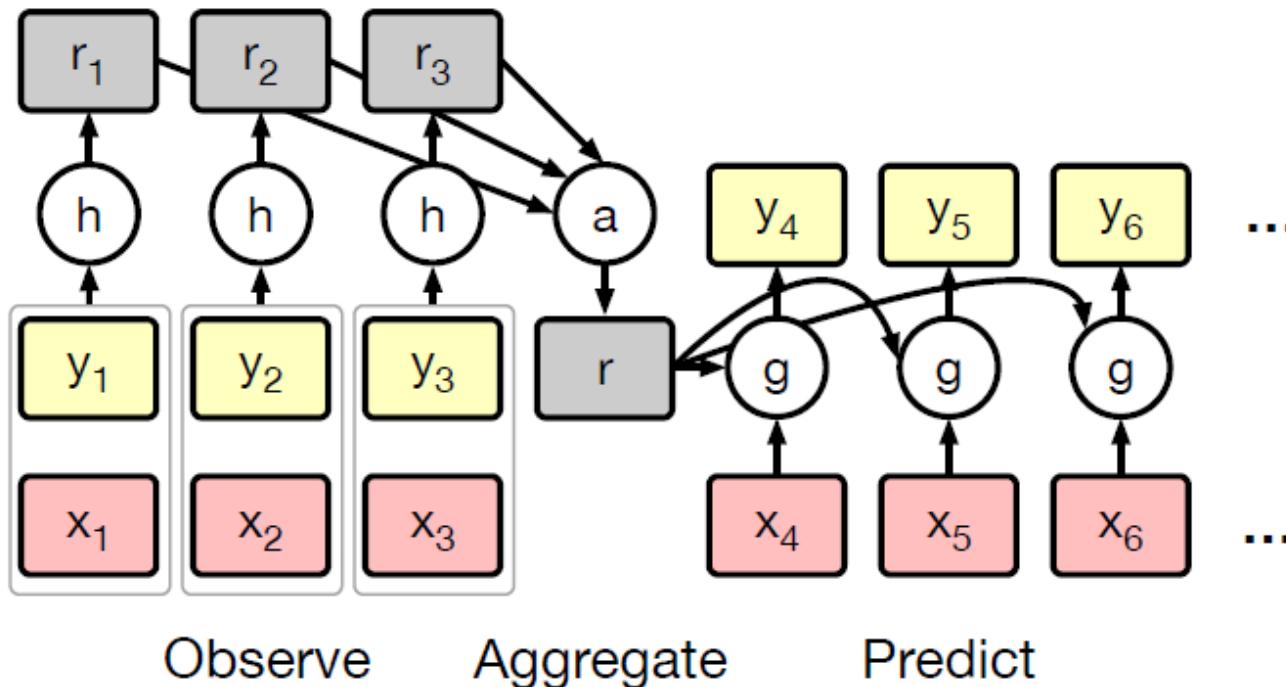
**CNP encodes training data (context) with encoder (NN) to find representation**



# CNP decodes representation at test time as mean and variance of Gaussian distribution



# Architecture of CNP ensures invariance to permutation of observation and target



Encoder (NN)

$$r_i = h_\theta(x_i, y_i) \quad \forall (x_i, y_i) \in O$$

$$r = r_1 \oplus r_2 \oplus \dots \oplus r_{n-1} \oplus r_n$$

Commutative operation (Mean)

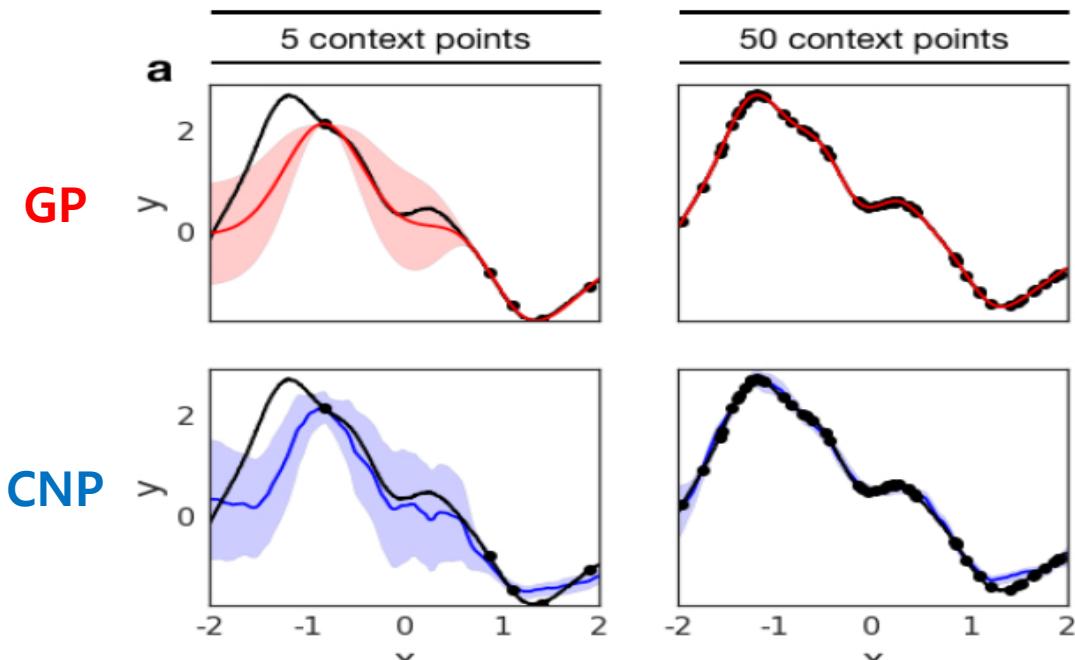
$$\phi_i = g_\theta(x_i, r) \quad \forall (x_i) \in T$$

Decoder ( $\phi_i = (\mu_i, \sigma_i^2)$  : Gaussian)

✓  $O(n + m)$  cost :  $n = \#obs, m = \#target$

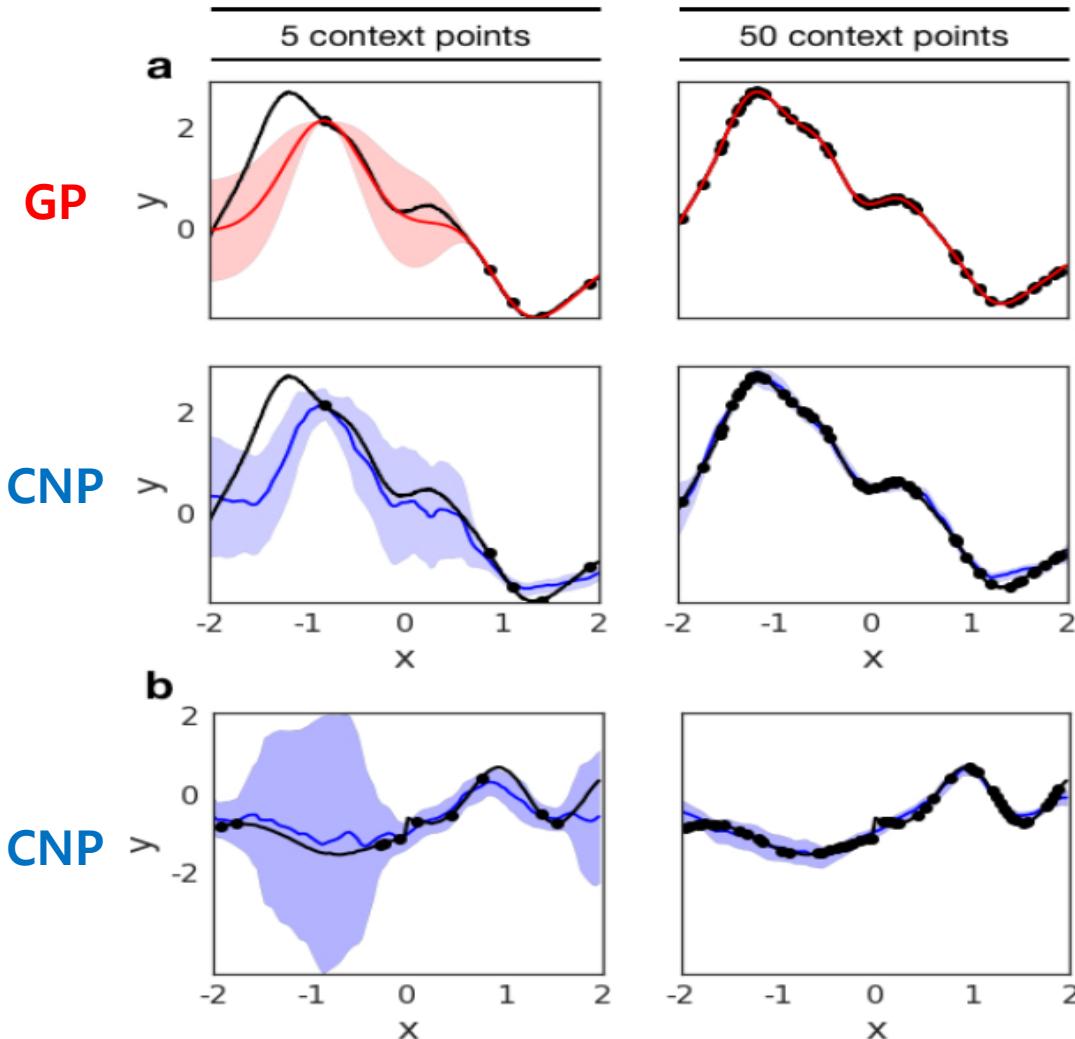
✓ Suitable for online learning ( $O(1)$  for calculate  $r$  from previous)

# Result for 1d-regression : Can achieve similar accuracy with GP



- Training : Sample a curve from the GP
- Context : We observe 5 / 50 points for new curve we want to fit
- GP is upper bound for accuracy

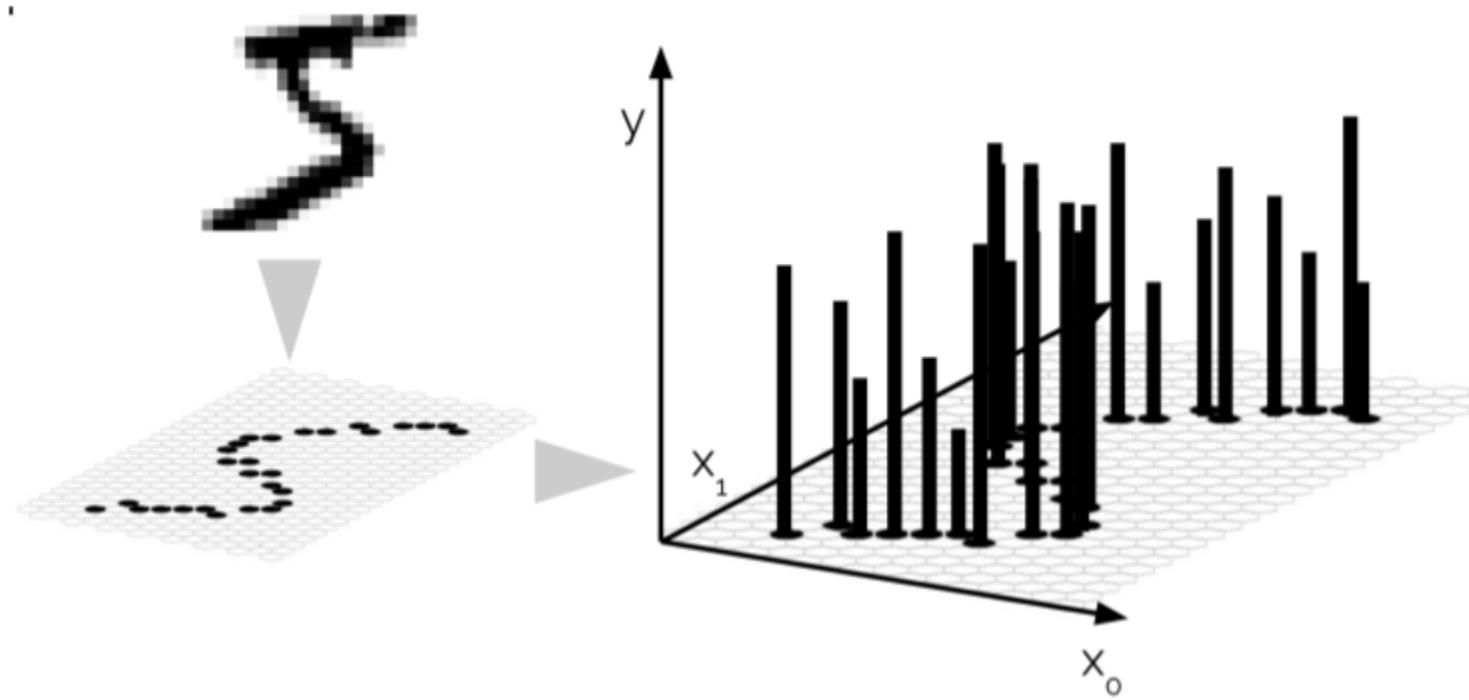
# Result for 1d-regression : Can predict curve from GPs having different kernels



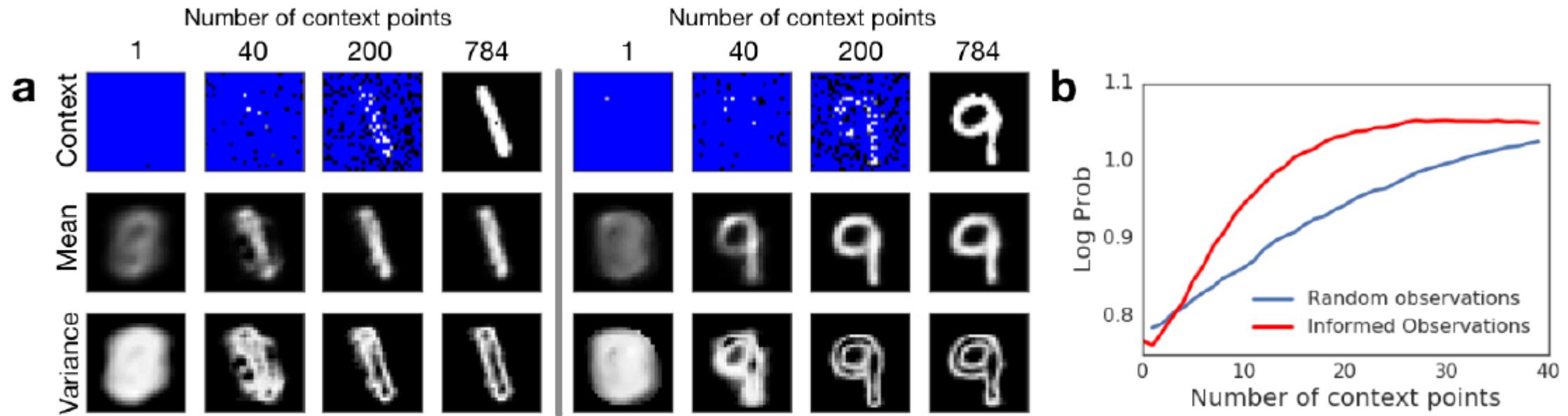
- Training : Sample a curve from the GP
- Context : We observe 5 / 50 points for new curve we want to fit
- GP is upper bound for accuracy

- Training : Sample point of curve with GPs having different kernel parameters
- Not trivial for GPs

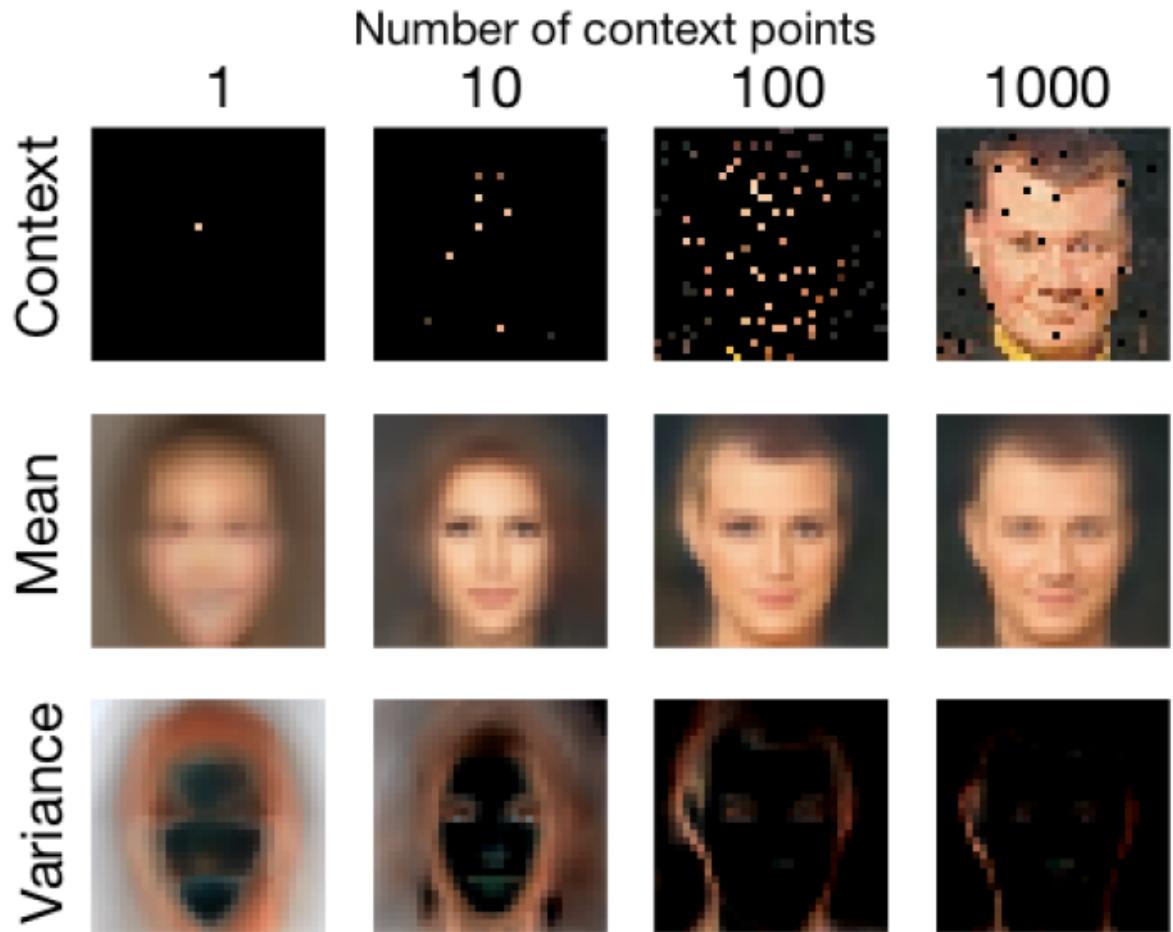
# Image completion : Regression for pixel



# Result for image completion : Good prediction of mean & variance



# Result for image completion : Good prediction of mean & variance



- ✓ Bad points : Too smooth  
(underfitting for lots of context)

# **Result for image completion : Flexible image completion (Recall permutation invariance)**



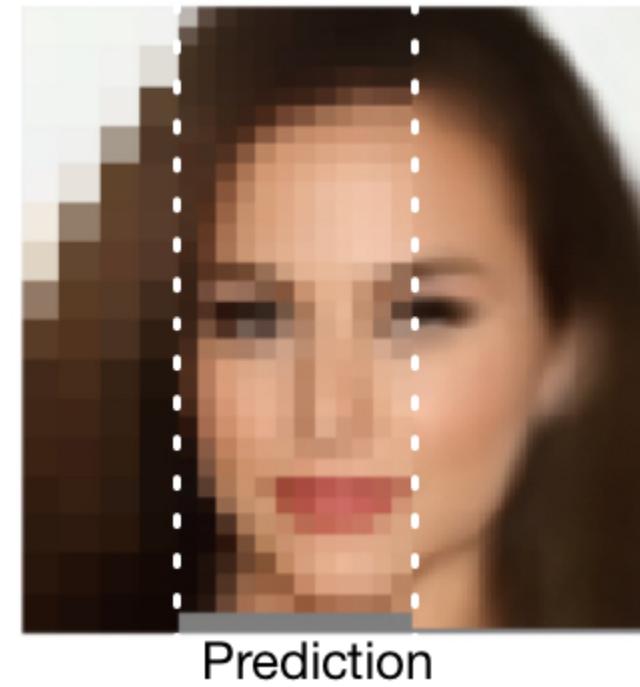
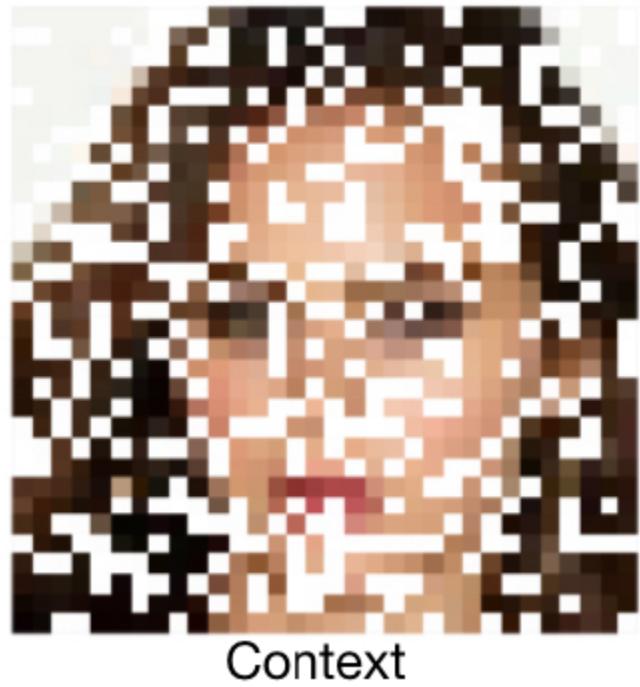
- ✓ Any position of context are given, CNP can predict other parts

# **Result for image completion : Flexible image completion (Recall permutation invariance)**



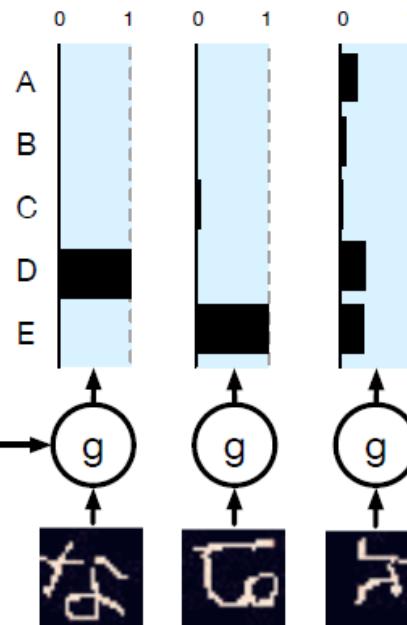
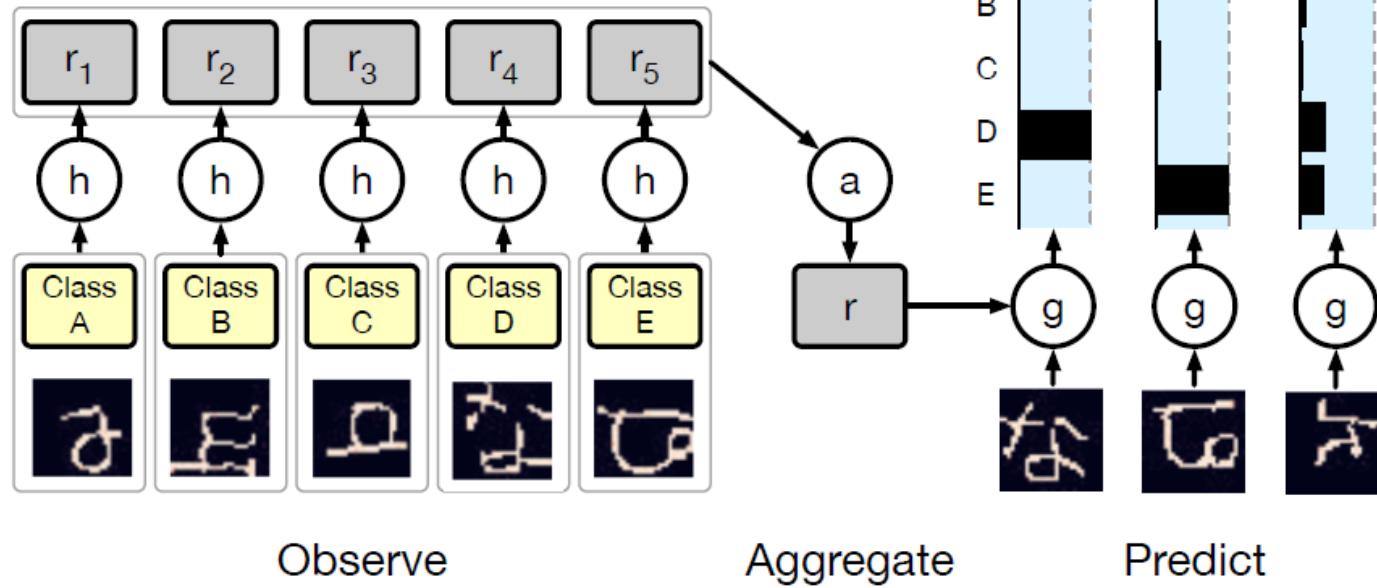
- ✓ Any position of context are given, CNP can predict other parts

# **Result for image completion : Flexible image completion (Recall generalization)**



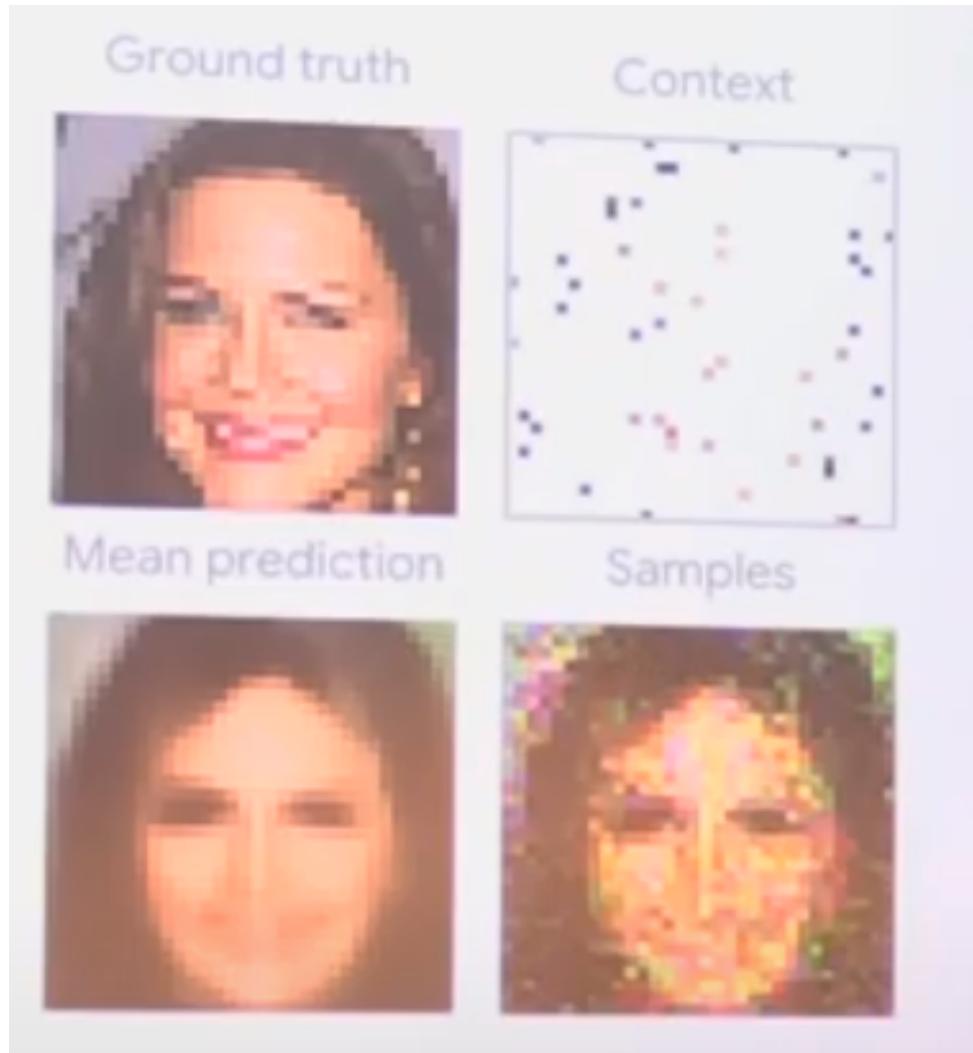
- ✓ Can predict different resolution which are not shown during training

# Image classification : Given image and label



	5-way Acc		20-way Acc		Runtime
	1-shot	5-shot	1-shot	5-shot	
MANN	82.8%	94.9%	-	-	$\mathcal{O}(nm)$
MN	<b>98.1%</b>	<b>98.9%</b>	<b>93.8%</b>	<b>98.5%</b>	$\mathcal{O}(nm)$
CNP	95.3%	98.5%	89.9%	96.8%	$\mathcal{O}(n + m)$

# Sampling is not adequate for CNP

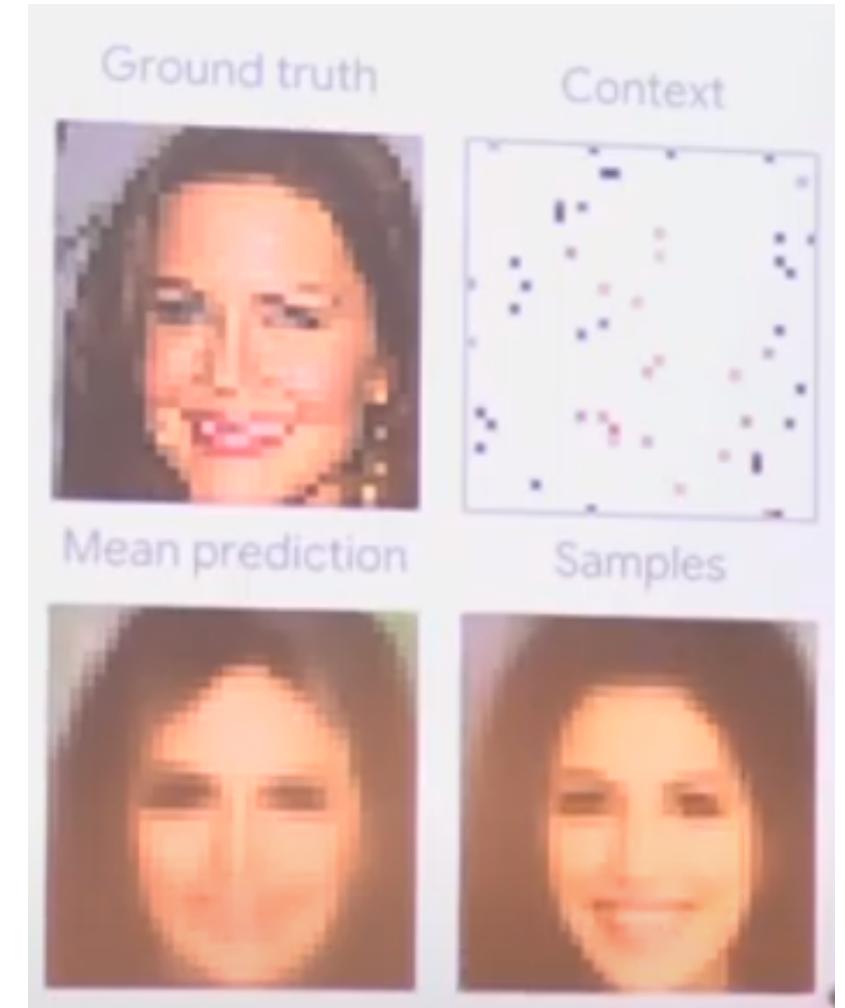
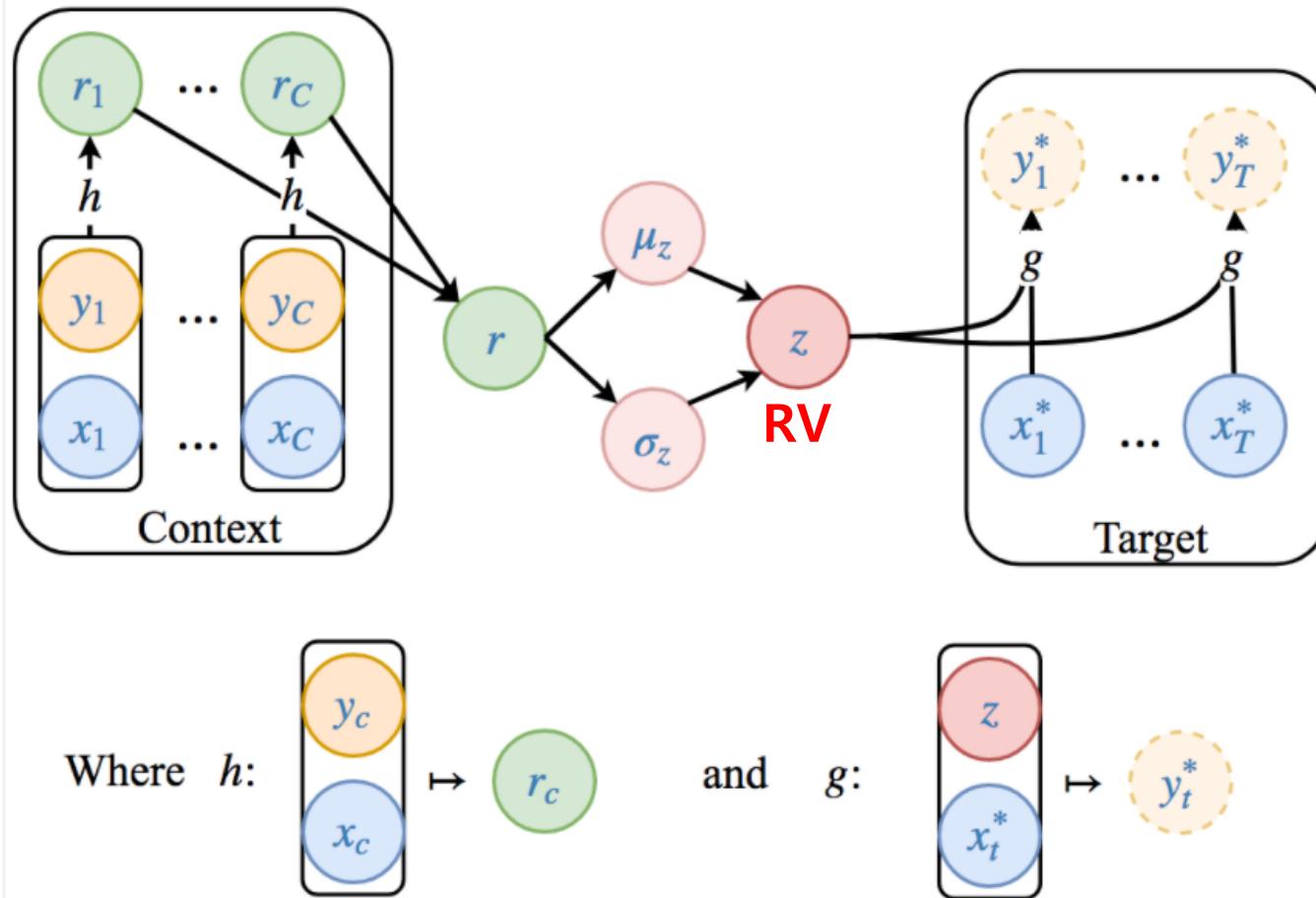


Sampling is done for each pixel  
(no trend finding in whole pixels)

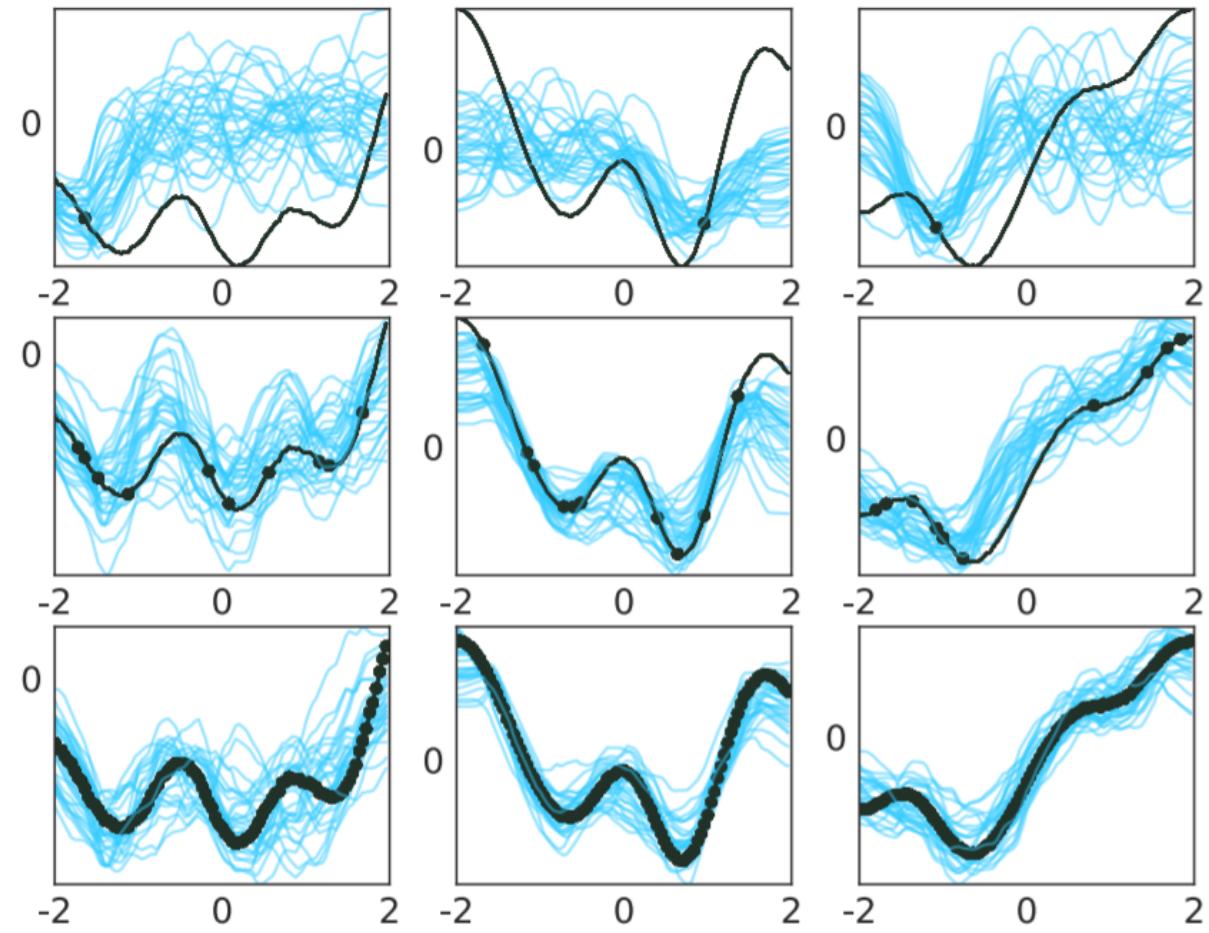
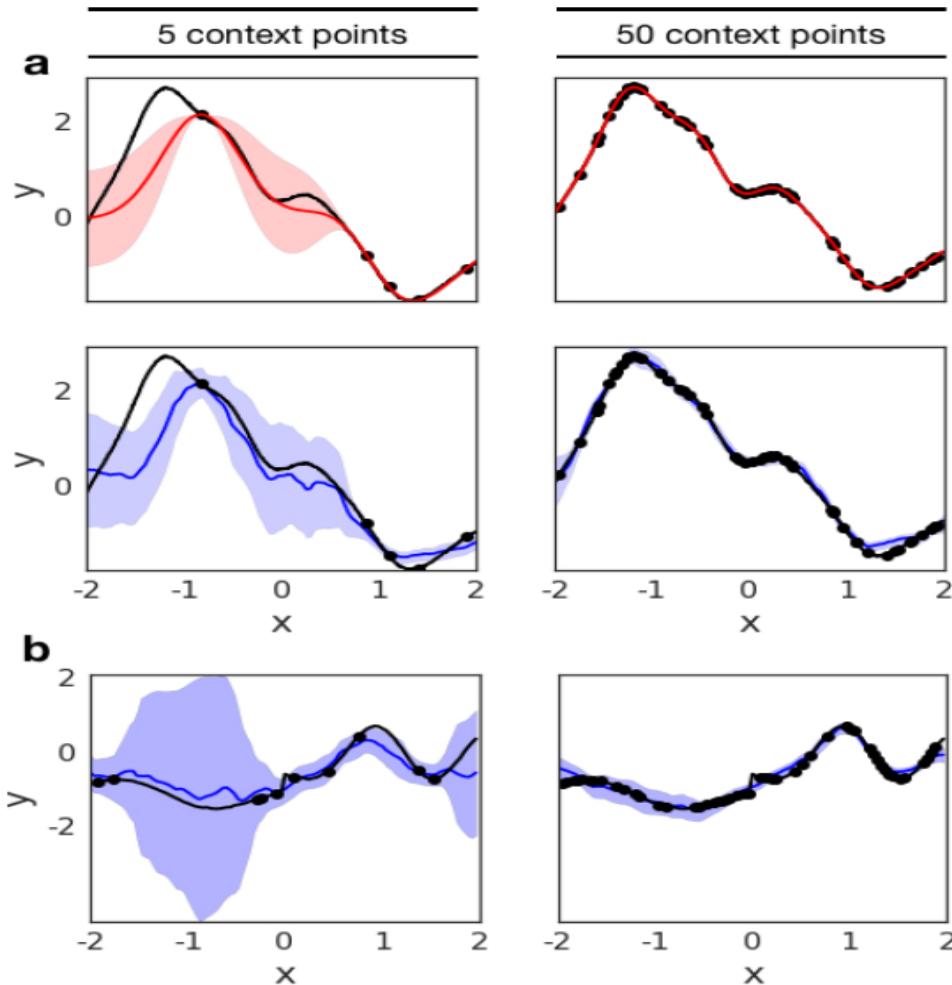
- ✓ Deterministic process (No random variable)

# Neural process (NP) use latent variables to enable sampling and to give global consistency

Generative model of the Neural Process



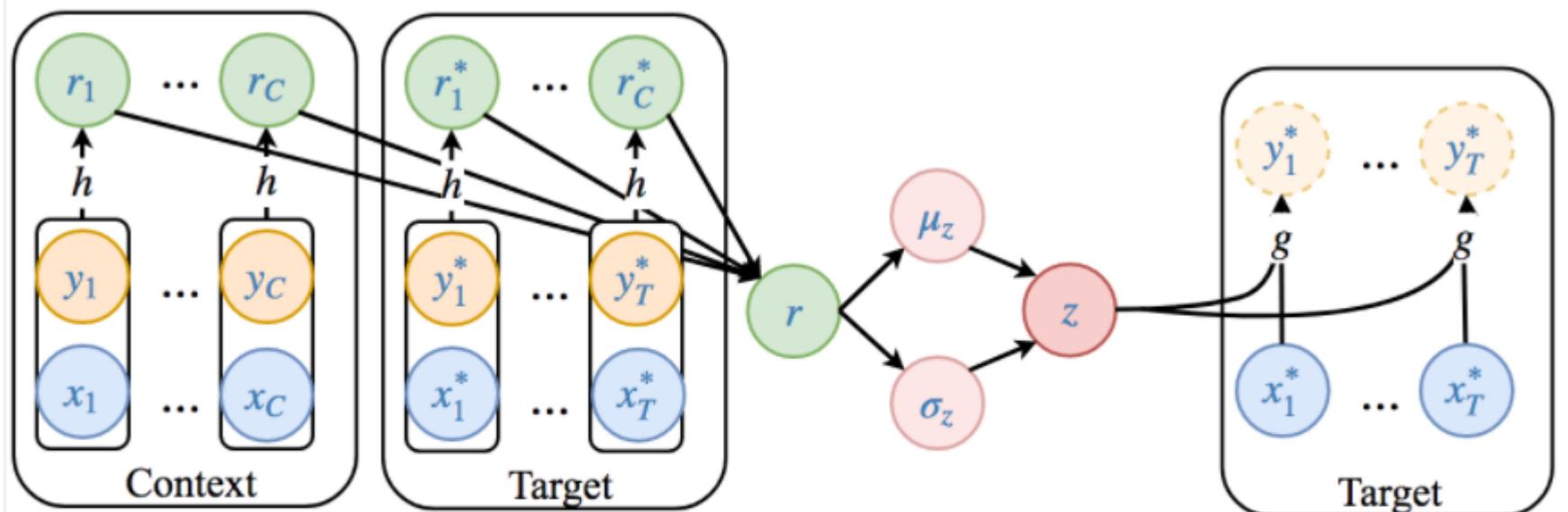
Rather than one mean & variance in CNP,  
NP provides samples



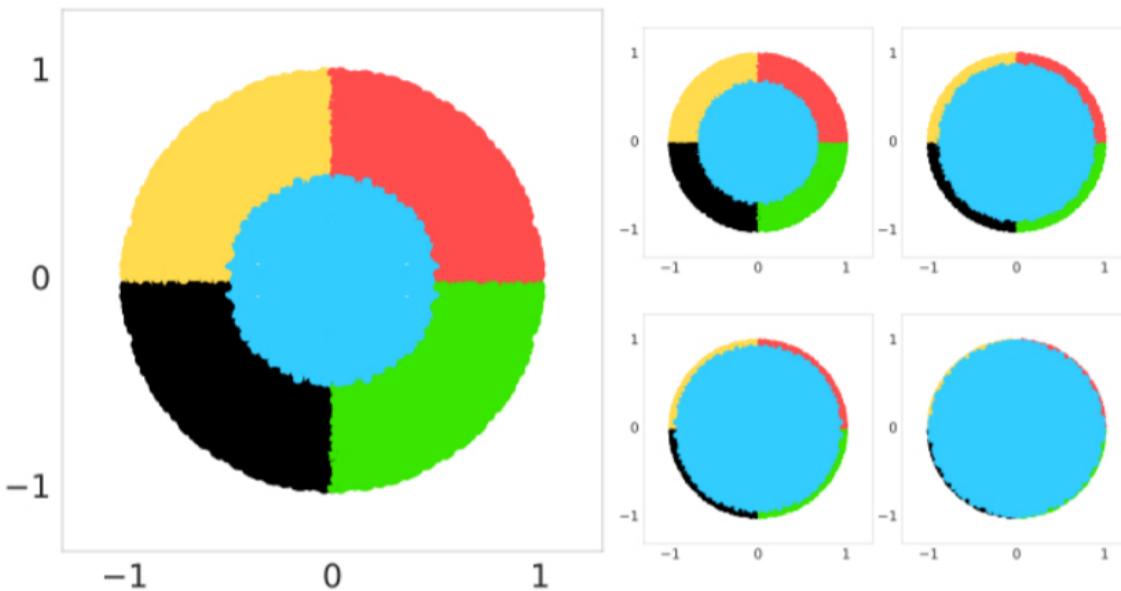
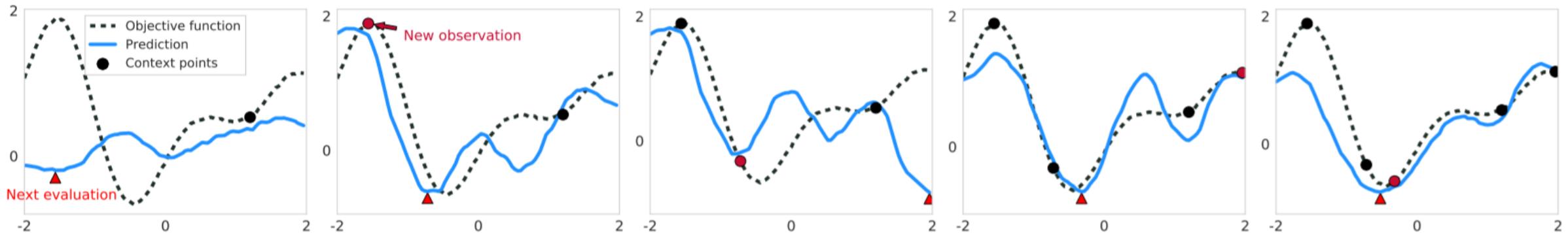
# Inference of NP

- $\log(y_T|x_T, x_C, y_C) \geq E_{q(z|x_T, y_T)}[\sum_{target} \log p(y_i|z, x_i) + \log(\frac{p(z|x_T, y_T)}{q(z|x_T, y_T, x_C, y_C)})]$

## Inference for the Neural Process



# Result for problem need sampling



$\delta$	0.5	0.7	0.9	0.95	0.99
<i>Cumulative regret</i>					
Uniform	$100.00 \pm 0.08$	$100.00 \pm 0.09$	$100.00 \pm 0.25$	$100.00 \pm 0.37$	$100.00 \pm 0.78$
LinGreedy ( $\epsilon = 0.0$ )	$65.89 \pm 4.90$	$71.71 \pm 4.31$	$108.86 \pm 3.10$	$102.80 \pm 3.06$	$104.80 \pm 0.91$
Dropout	$7.89 \pm 1.51$	$9.03 \pm 2.58$	$36.58 \pm 3.62$	$63.12 \pm 4.26$	$98.68 \pm 1.59$
LinGreedy ( $\epsilon = 0.05$ )	$7.86 \pm 0.27$	$9.58 \pm 0.35$	$19.42 \pm 0.78$	$33.06 \pm 2.06$	$74.17 \pm 1.63$
Bayes by Backprob (Blundell et al., 2015)	$1.37 \pm 0.07$	$3.32 \pm 0.80$	$34.42 \pm 5.50$	$59.04 \pm 5.59$	$97.38 \pm 2.66$
NeuralLinear	<b><math>0.95 \pm 0.02</math></b>	<b><math>1.60 \pm 0.03</math></b>	$4.65 \pm 0.18$	$9.56 \pm 0.36$	$49.63 \pm 2.41$
MAML (Finn et al., 2017)	$2.95 \pm 0.12$	$3.11 \pm 0.16$	$4.84 \pm 0.22$	$7.01 \pm 0.33$	$22.93 \pm 1.57$
Neural Processes	$1.60 \pm 0.06$	$1.75 \pm 0.05$	<b><math>3.31 \pm 0.10</math></b>	<b><math>5.71 \pm 0.24</math></b>	<b><math>22.13 \pm 1.23</math></b>

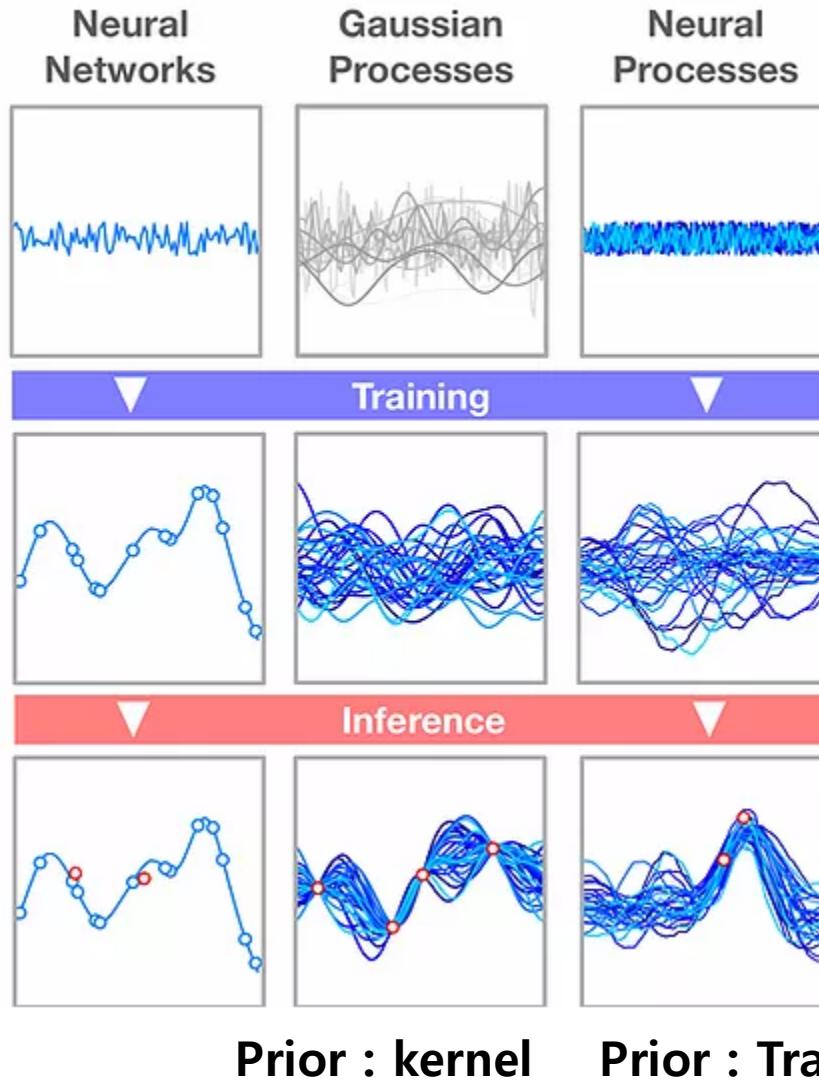
# Comparison between NN, GP and NP

## Neural Networks

Can learn the right parameters from data directly

Large number of parameters can regress complex functions

Quick predictions at test time



## Gaussian processes

Model distribution over functions and updates belief about underlying ground truth based on observations at test time

Has a measure of the uncertainty over its predictions given the observations

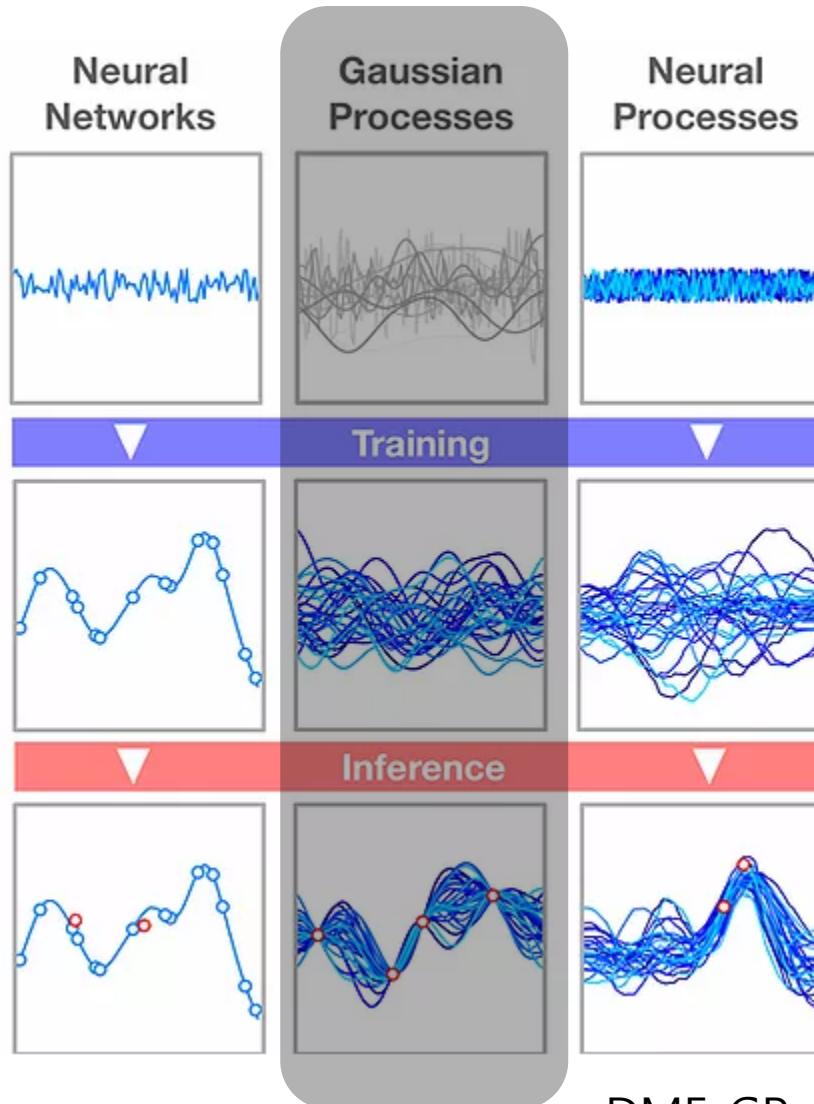
# What about DME-GP?

## Neural Networks

Can learn the right parameters from data directly

Large number of parameters can regress complex functions

Quick predictions at test time

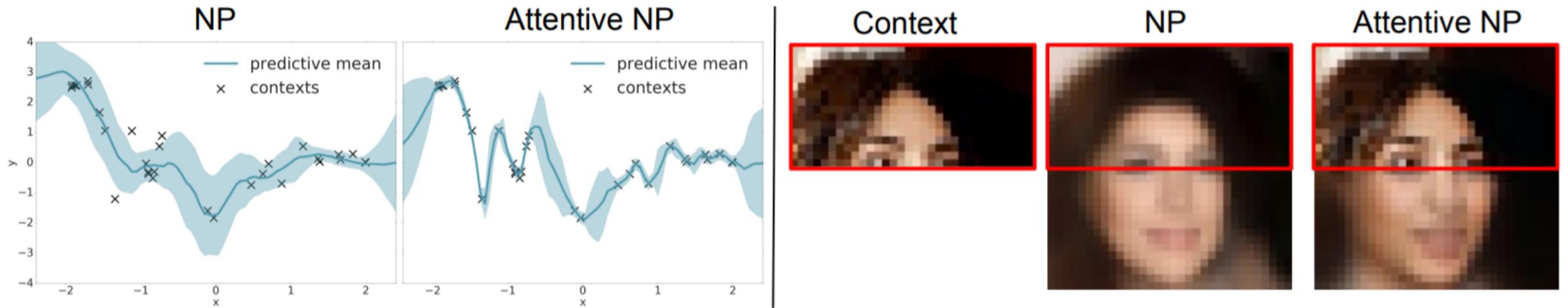


## Gaussian processes

Model distribution over functions and updates belief about underlying ground truth based on observations at test time

Has a measure of the uncertainty over its predictions given the observations

**Although NP has lower cost than DME-GP, to get high accuracy for given contexts it NP also needs same cost**



- ✓ Attentive NP have almost same cost with DME-GP

# Reference

- Eslami, SM Ali, et al. "Neural scene representation and rendering." *Science* 360.6394 (2018): 1204-1210.
- Garnelo, Marta, et al. "Conditional neural processes." *arXiv preprint arXiv:1807.01613* (2018).
- Garnelo, Marta, et al. "Neural processes." *arXiv preprint arXiv:1807.01622* (2018).
- Kim, Hyunjik, et al. "Attentive neural processes." *arXiv preprint arXiv:1901.05761* (2019).



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- <https://kasparmartens.rbind.io/post/np/>