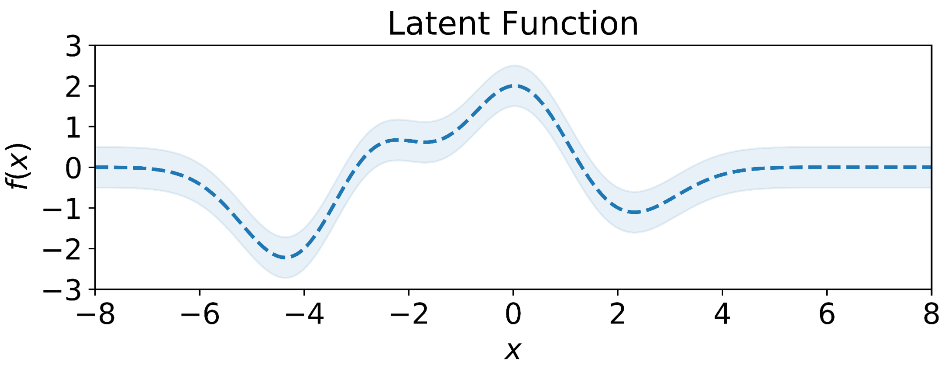
THE UNIVERSITY OF SYDNEY

Bayesian Deconditional Kernel Mean Embeddings

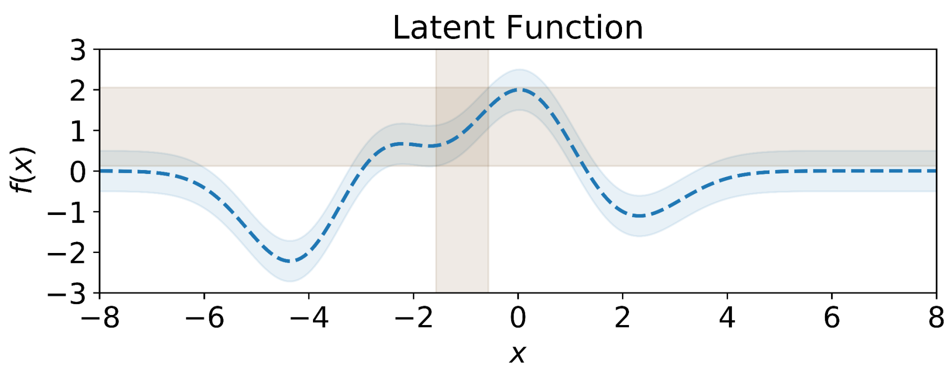
Kelvin Hsu and Fabio Ramos

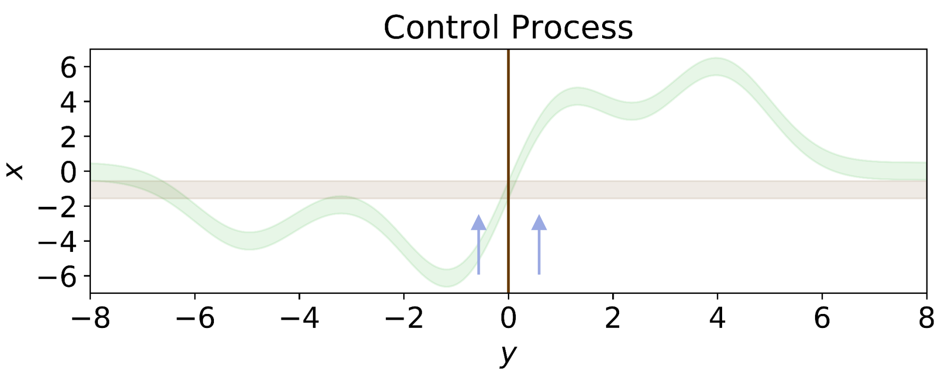
You want to model some latent phenomenon f



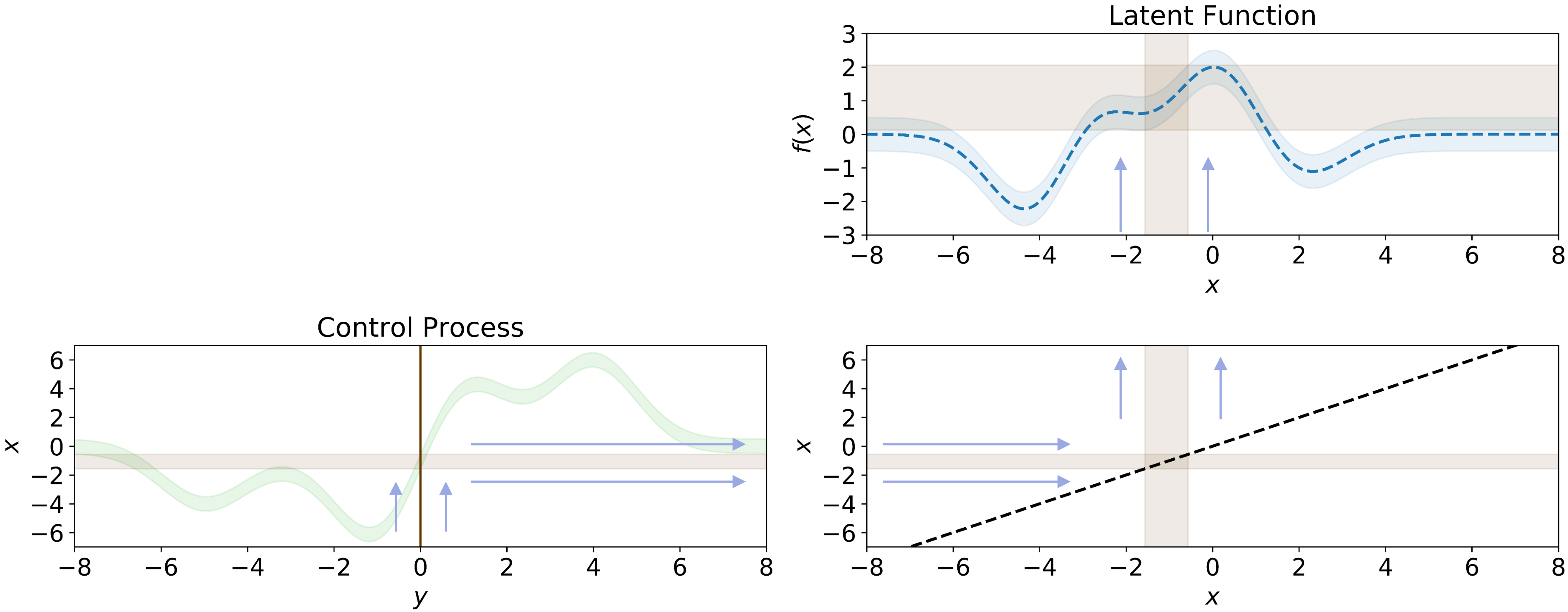
$$Z = f(x) + noise$$

But! When collecting observations, you don’t get to control x directly! You only get to control y!

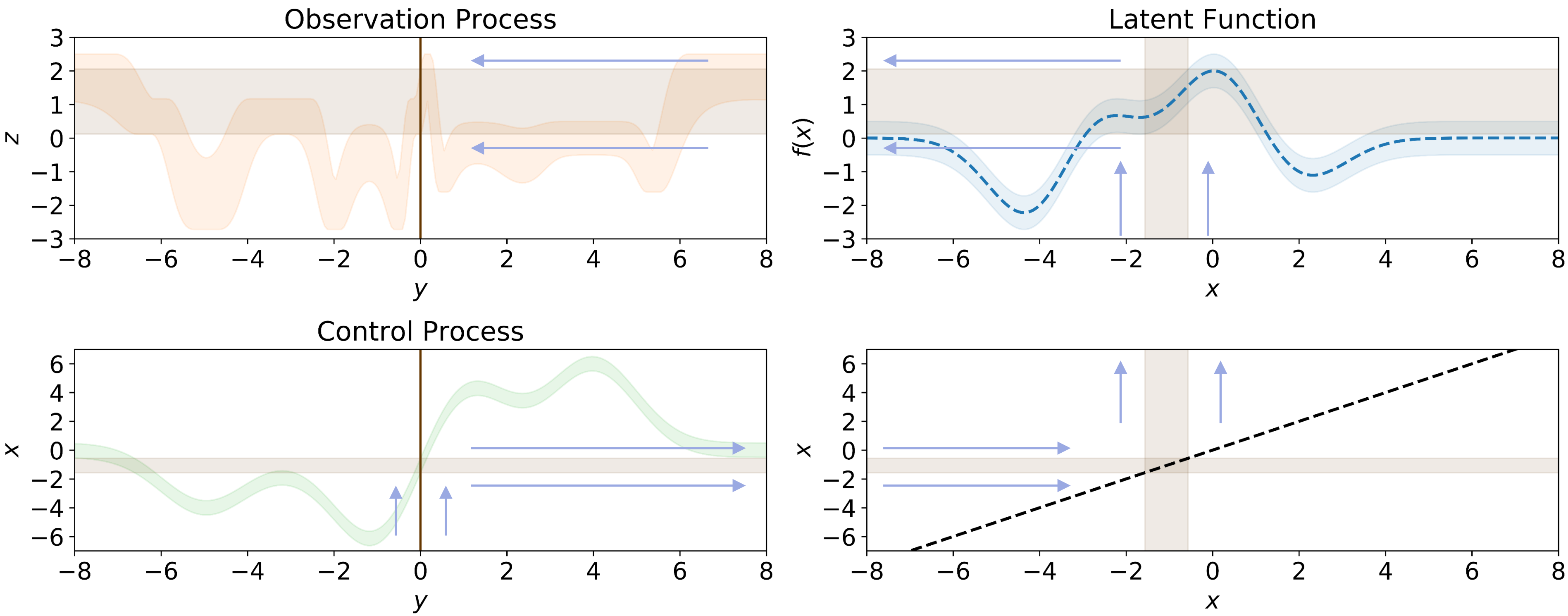




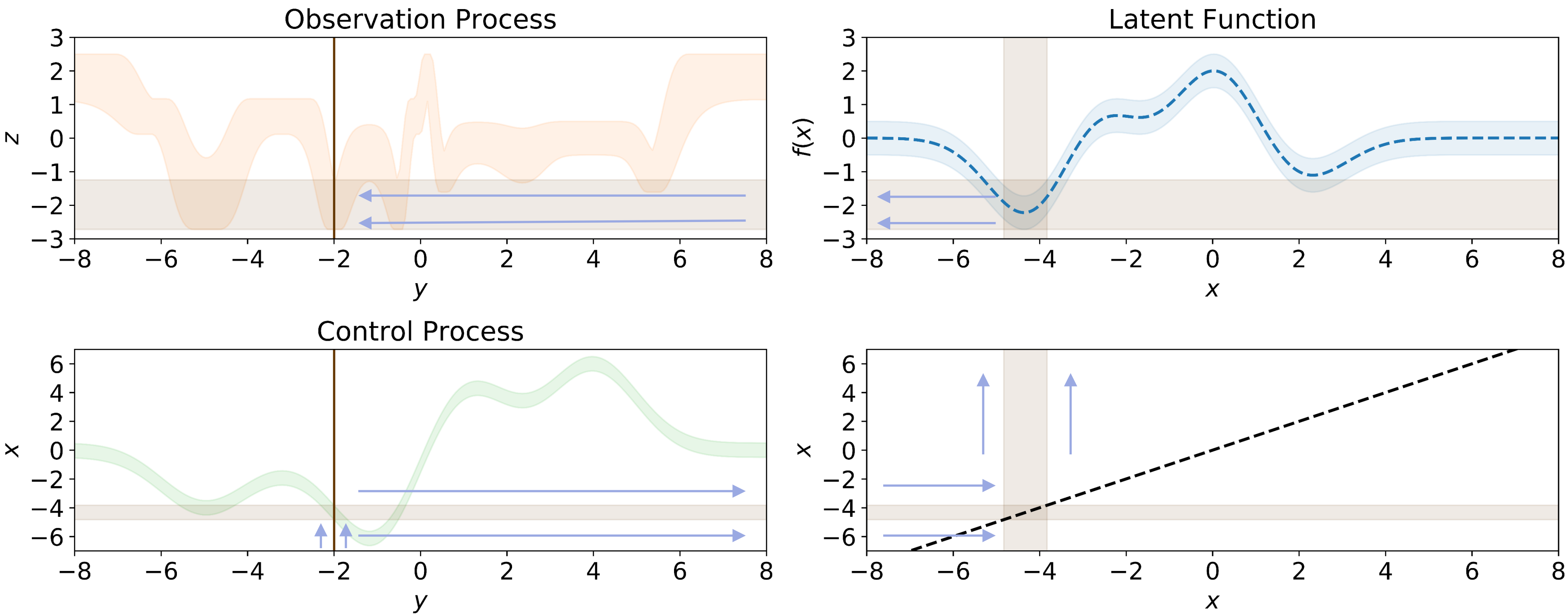
…which gives some x that goes into f



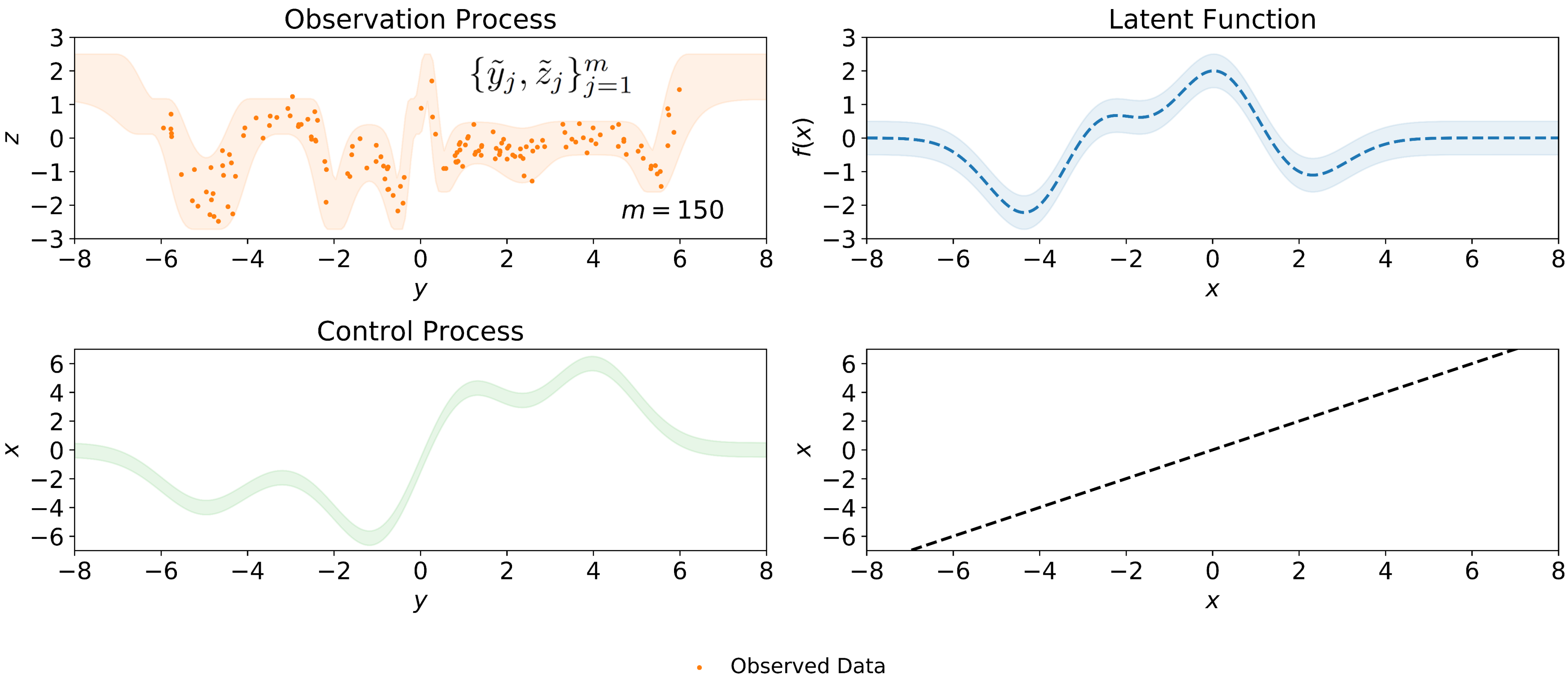
…which finally gives you observations z



Overall: Query a *y* and observe a *z*

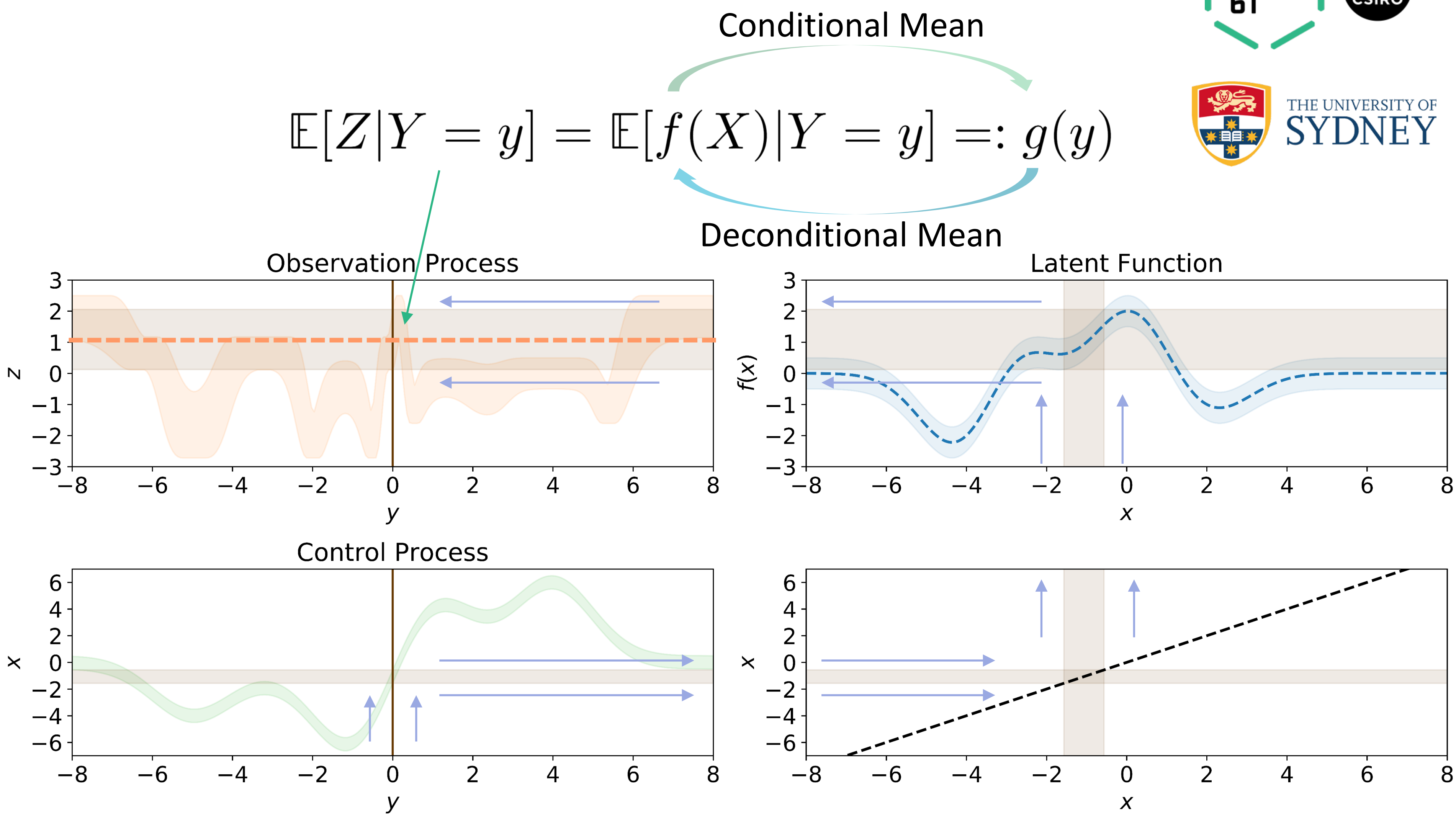


So, you end up with only pairs of (y, z)

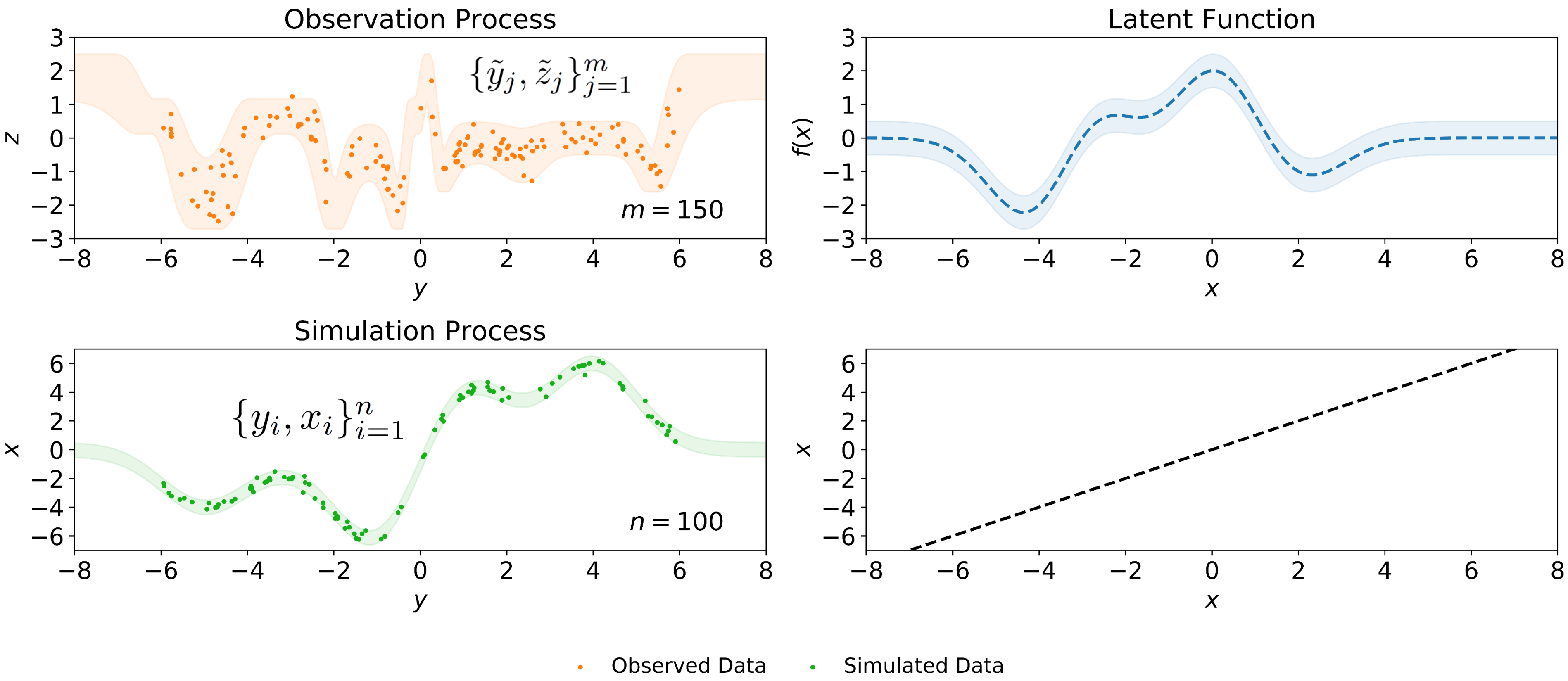


Conditional mean of targets Z given y

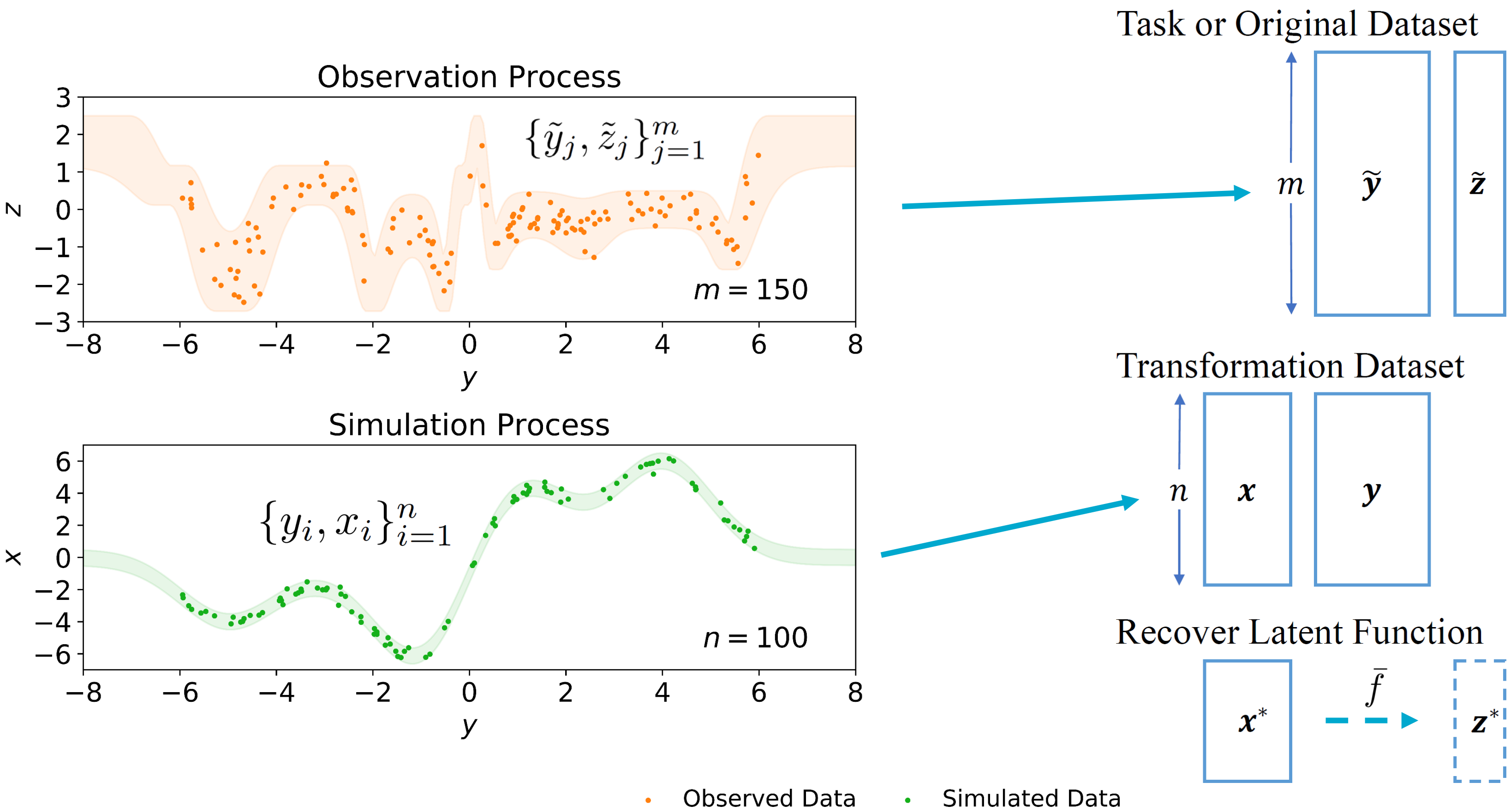
$$\mathbb{E}[Z|Y = y] = \mathbb{E}[f(X)|Y = y] =: g(y)$$



Afterwards, you obtain pairs of (x, y) from a separate process or simulation



Your Goal: Recover f without observing direct pairs of (x, z)



Deconditional Mean Embeddings

First View: Reversing Conditional Means of Functions

$$(C_{X|Y})^T f = g$$

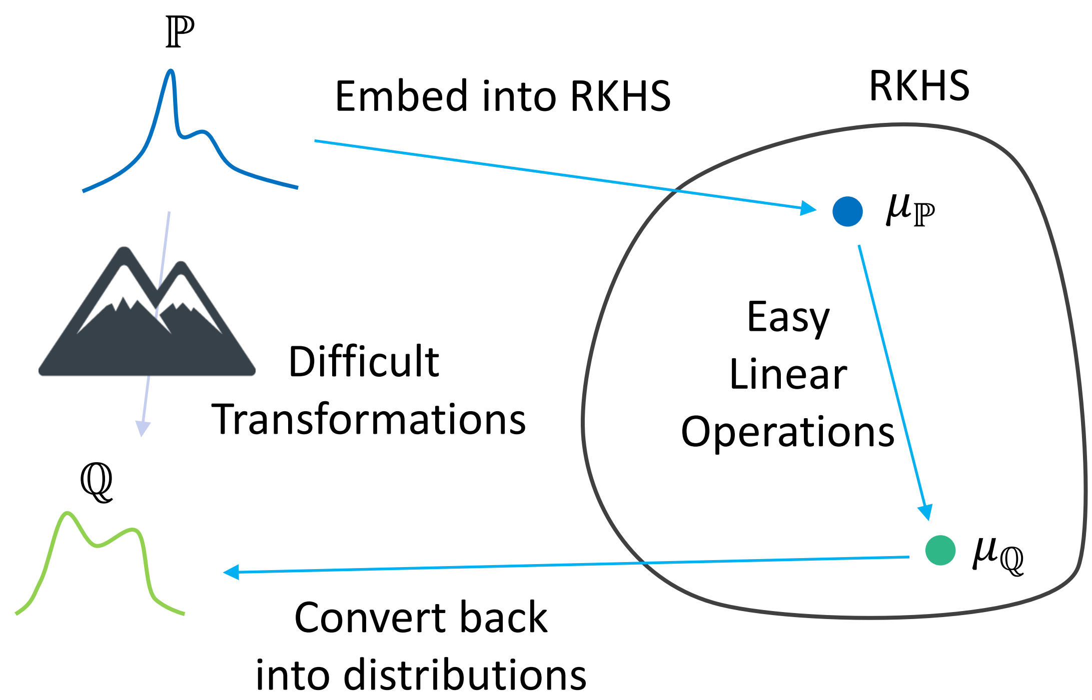
Conditional Mean Operator

$$\mathbb{E}[f(X)|Y = y] =: g(y)$$

Deconditional Mean Operator

$$(C'_{X|Y})^T g = f$$

Kernel Mean Embeddings



$$C'_{X|Y} = (C_{X|Y} C_{YY})^T (C_{X|Y} C_{YY} (C_{X|Y})^T)^{-1}$$

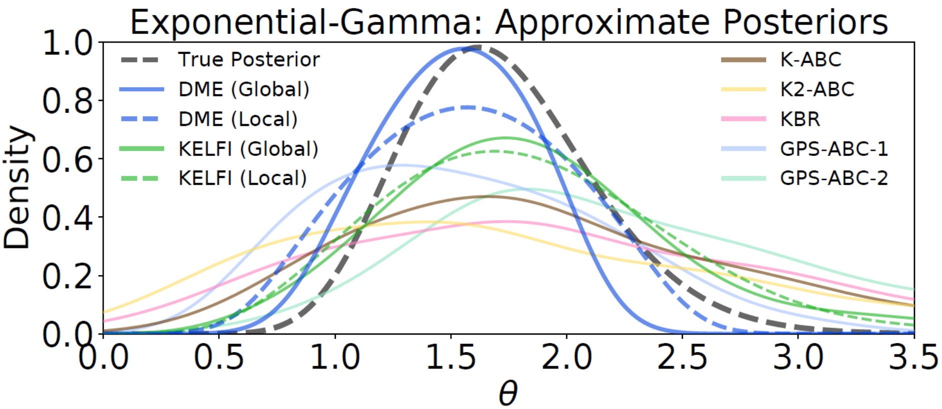
Nonparametric Bayes' Rule

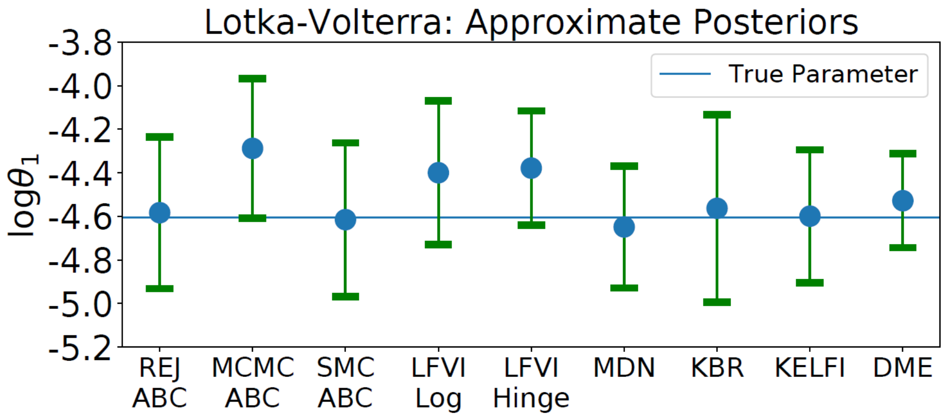
$\mathbb{P}_{Y|X}$? $\mathbb{P}_{X|Y}$ $\mathbb{P}_Y$

$$C'_{X|Y} = (C_{X|Y} C_{YY})^T (C_{X|Y} C_{YY} (C_{X|Y})^T)^{-1}$$

If $\mathbb{P}_{X|Y}$ and $\mathbb{P}_Y$ play the roles of likelihood and prior respectively, then when is $C'_{X|Y}$ the same as $C_{Y|X}$, which encodes the corresponding posterior $\mathbb{P}_{Y|X}$?

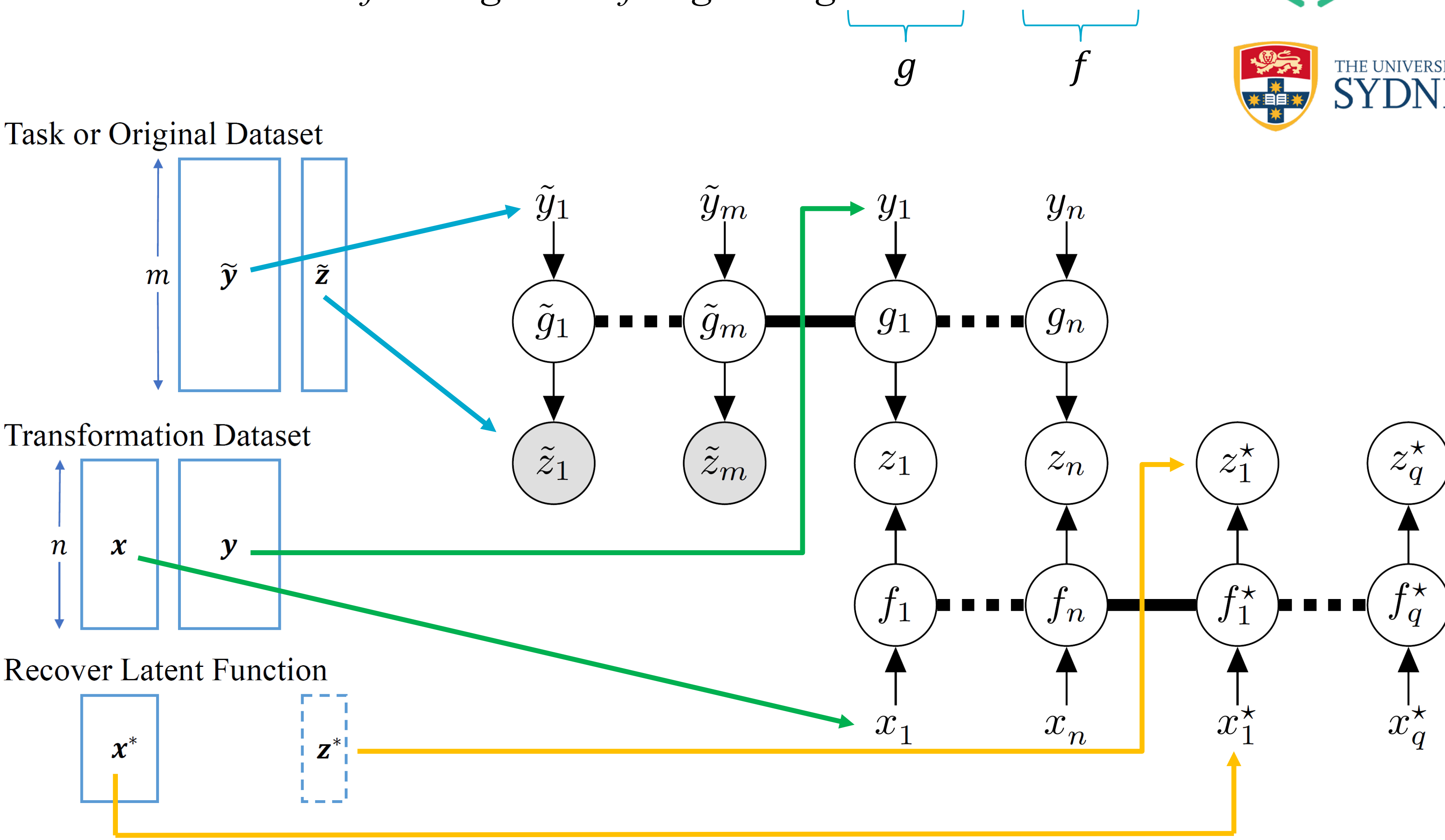
Likelihood-Free Inference





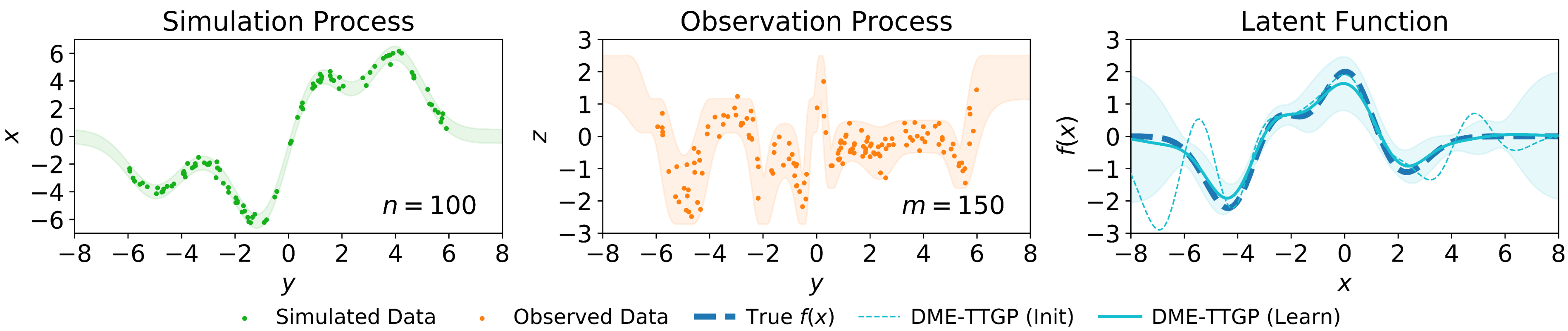
Task Transformed Gaussian Processes

Second View: Transforming Task of Regressing Z on Y to Z on X

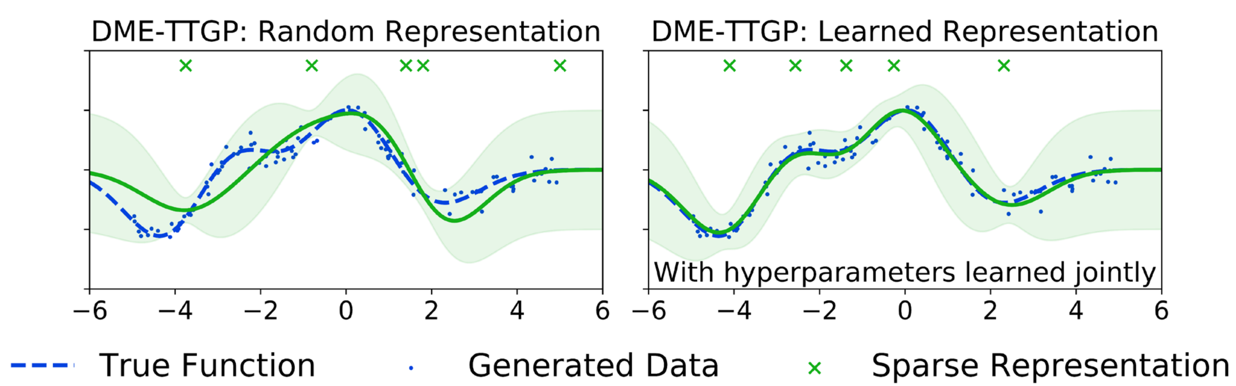


Uncertainty Propagation and Hyperparameter Learning

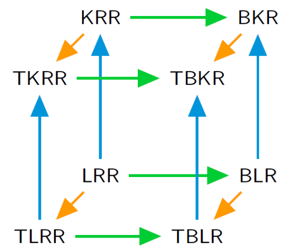
Task Transformed Regression



Sparse Representation Learning



Thank You!



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to find out more interesting connections
between the two views and more

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