Imperial College London

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Uncertainty quantification(UQ) for offshore pile design

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Need for a general data-driven UQ framework

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Figure 1: Offshore piles from PISA project

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Figure 1: Offshore piles from PISA project

- Different **sources** of uncertainties from soil parameters and complex physics
- **Manual** back analysis to reduce the uncertainties is either **time-consuming** or **computationally expensive**
- Current UQ works require considerable resources and expertise to **deploy** and **maintenance**
- There exists a notable absence of **ML** for data-driven UQ for offshore piles

Problems, solutions and goals

Towards a scalable data-driven UQ framework for offshore piles

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- ! How to make UQ framework **adaptive** and **scalable**?

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- ! How to make UQ framework **adaptive** and **scalable**?

- ✓ By replacing the original model with a smipler **surrogate model**

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[a] Dimensionality reduction

[b] Probabilistic graphical model

Goals: Leverage cutting-edge methodologies in the fields of **surrogate modeling**, **UQ**, **PGM** and **control theory**, to deliver a robust UQ framework in offshore piles

Choice for the UQ method

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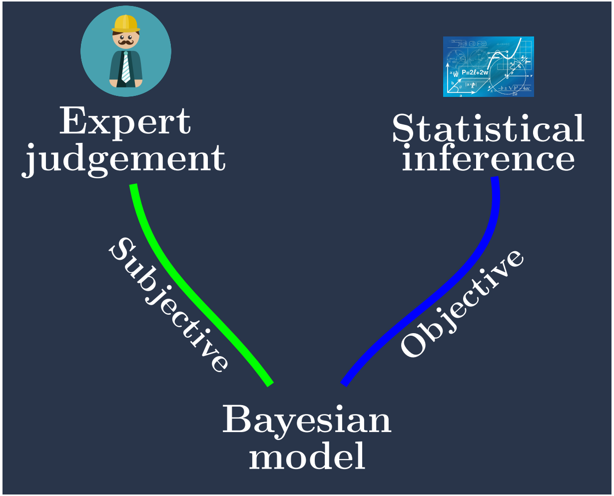
Choice for the UQ method is totally based on the **quantity** of accessible data:

- **Lack** or **no** data available, model can be solely based on expert judgement
- **Substantial** volume data available, model can fully use statistical inference (e.g., the methods of moments[1])
- **Combination** of two above: Bayesian methods

$$\pi(\boldsymbol{x}|\boldsymbol{y}) = \frac{\mathcal{L}(\boldsymbol{x}|\boldsymbol{y}) \cdot \pi(\boldsymbol{x})}{\pi(\boldsymbol{y})}$$



Sequential Bayesian inference for offshore piles

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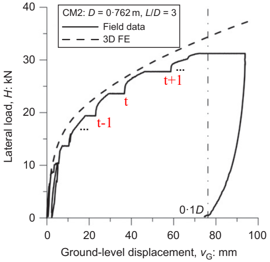
PISA pile loading[2]



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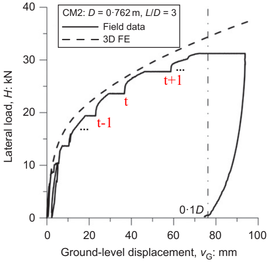
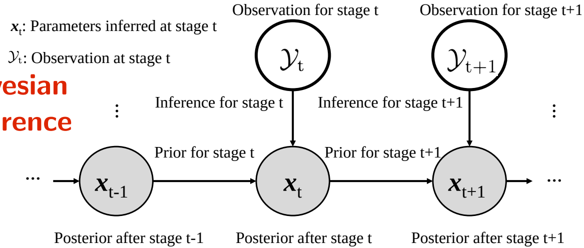


Bayesian inference



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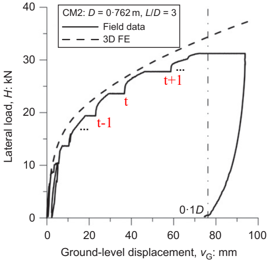

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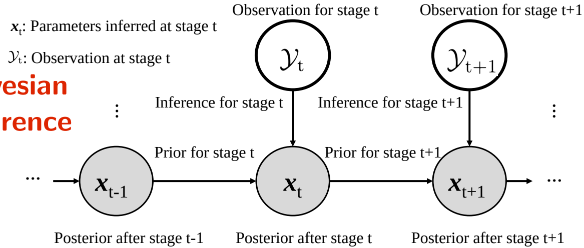

Sequential Bayesian inference setting in high dimensional space:

- Adaptive learning to enrich the experimental design
- DR-based surrogate to accelerate inversion
- Advanced MCMC sampler to obtain *QoI*

Abstraction for DR-based surrogate in Bayesian inference

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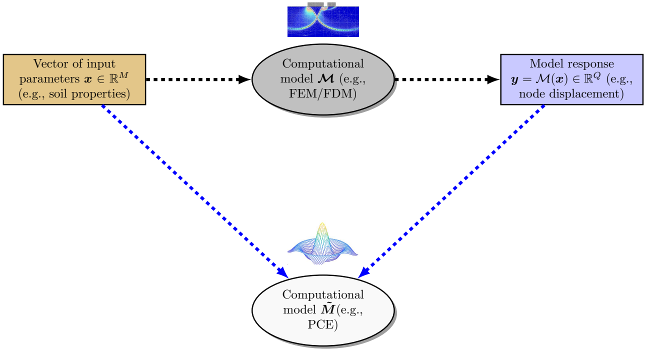

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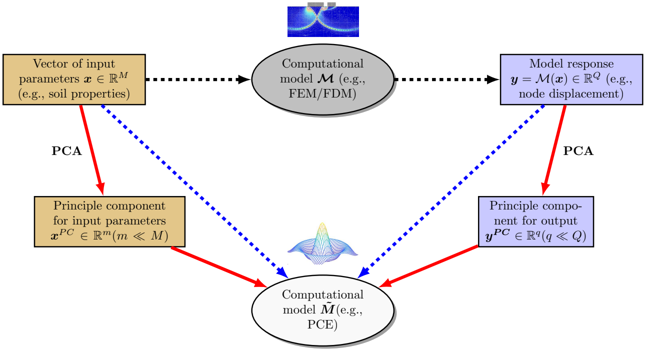

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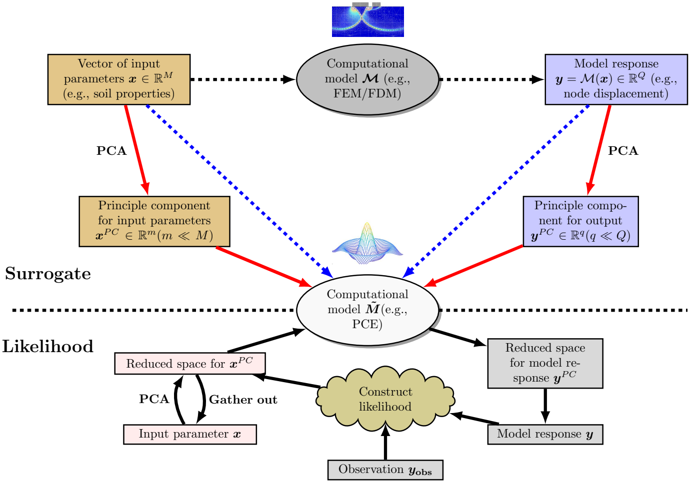

Why introduce DR-based surrogate to Bayesian inference

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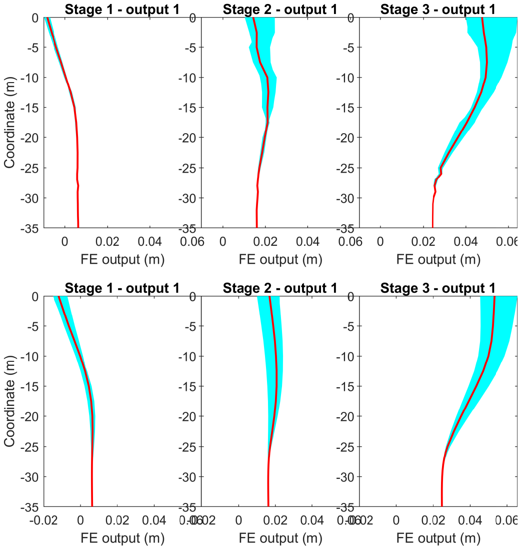
Surrogate-PCE

DR-based Surrogate-(PCA-PCE)



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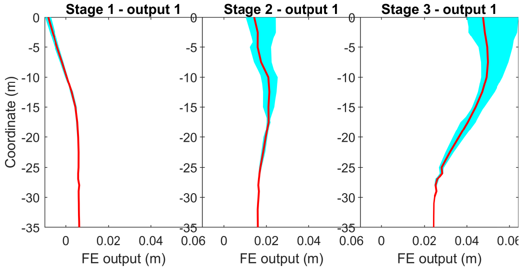
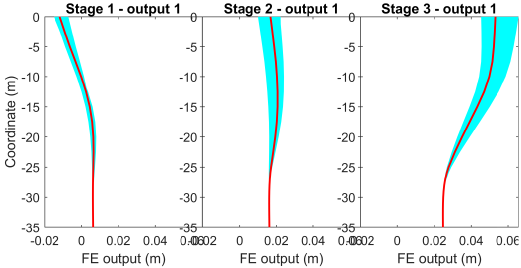


- **Reduce** the output size, and alleviate the burden on the surrogate construction

DR-based Surrogate-(PCA-PCE)



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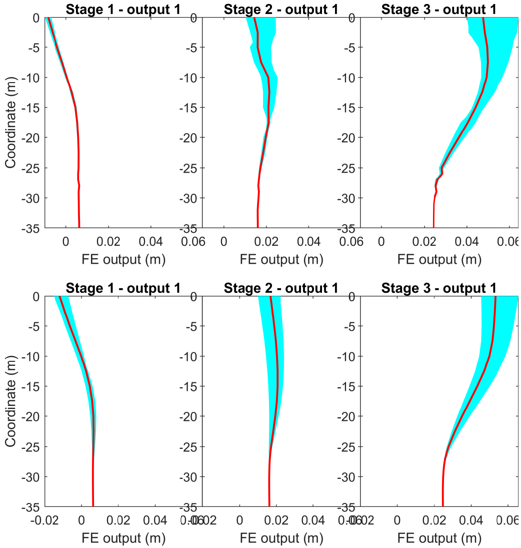
- **Reduce** the output size, and alleviate the burden on the surrogate construction
- Capture the **shape/covariance** matrix of the output



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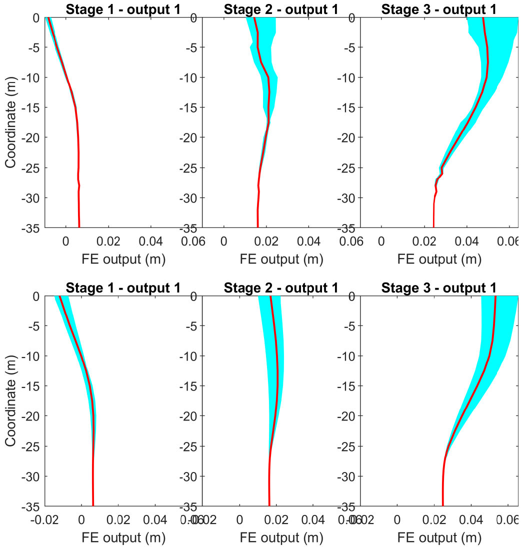
Why introduce DR-based surrogate to Bayesian inference

Surrogate-PCE

- **Reduce** the output size, and alleviate the burden on the surrogate construction
- Capture the **shape/covariance** matrix of the output
- Compared to scalar models (e.g., PCE, kriging), DR-based surrogate can consider the **multiple output predictions**

DR-based Surrogate-(PCA-PCE)



Next plan
Active learning for an efficient surrogate

In high dimensions, **experimental design** for a surrogate can be very **expensive**.

Active learning hopes to construct the surrogate in an **adaptive** way

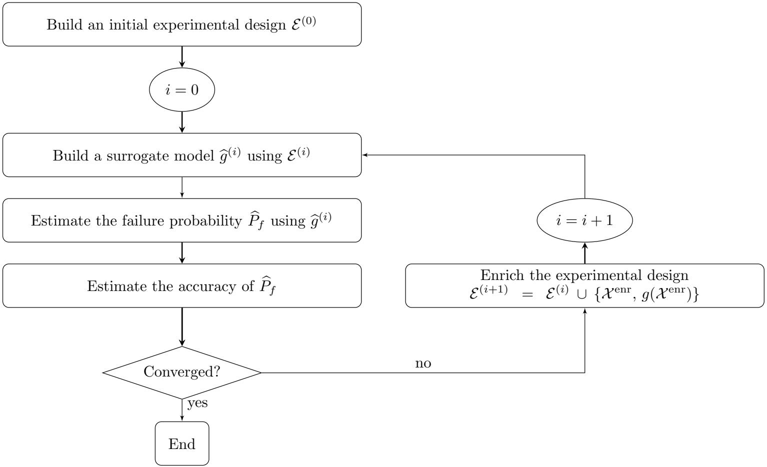
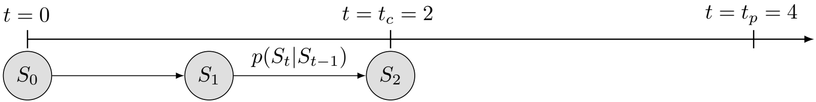


Figure 2: Active learning workflow[3]

Next plan

A unified and scalable digital twin for piles

- Visualize the sequential inversion calculation
- Bring in control theory naturally to make prompt actions
- Support the transition from custom defined model towards a unified and scalable digital twin



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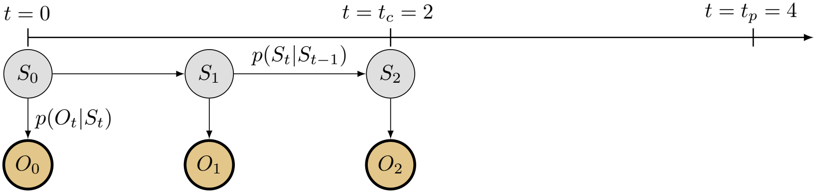

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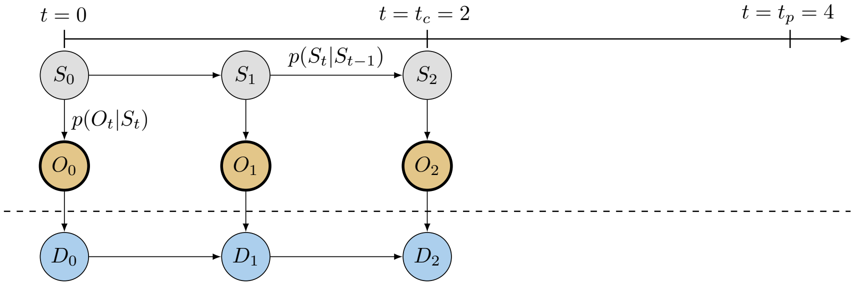

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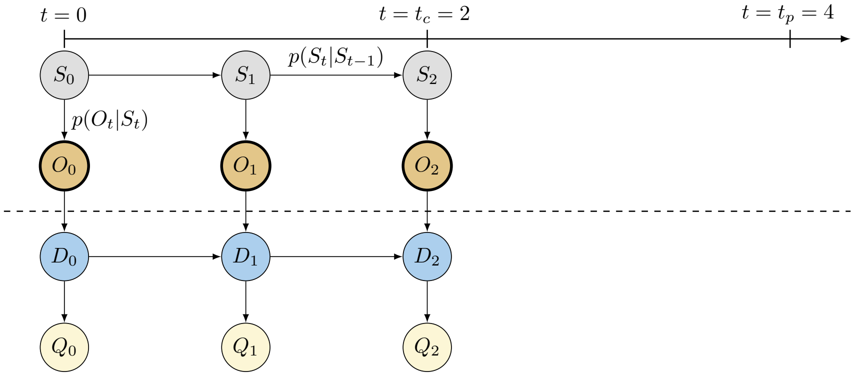

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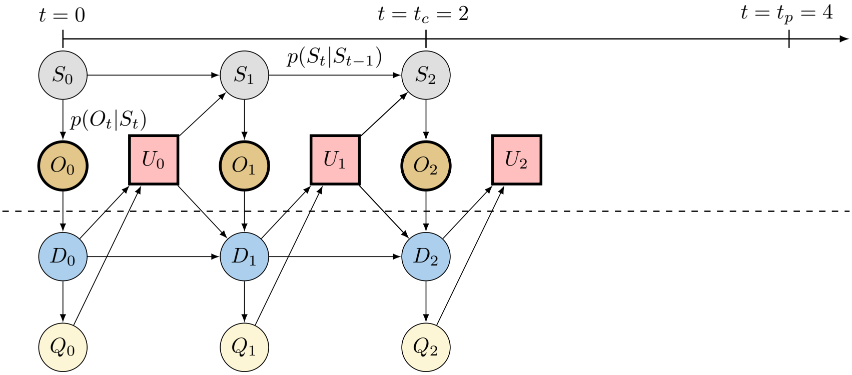

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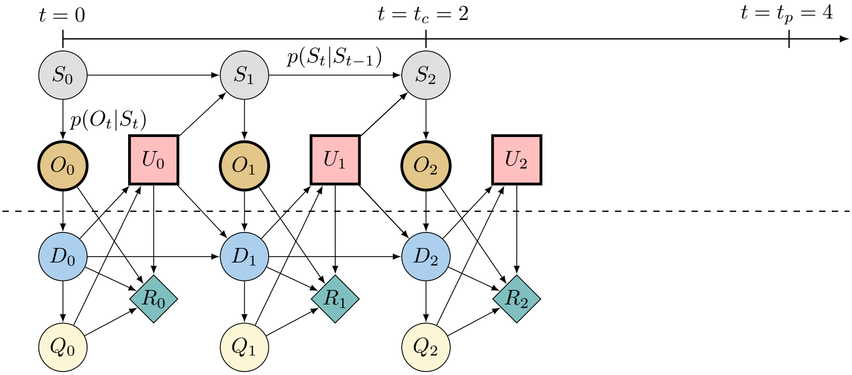

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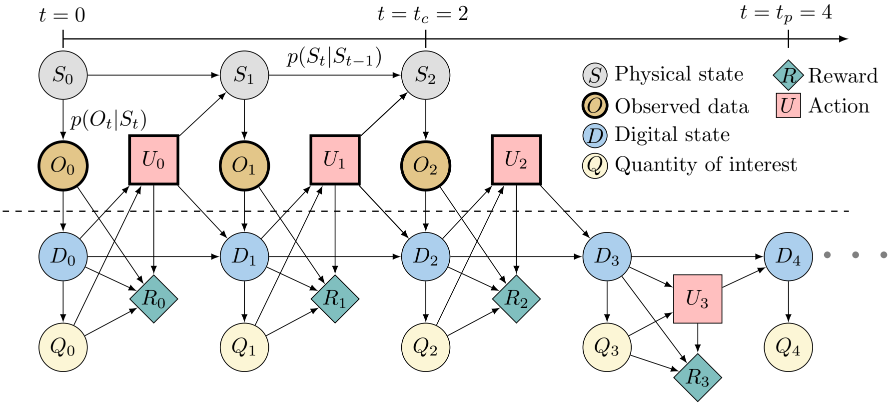

Time plan

Table 1: PhD timeline

month	0	3	6	9	12	15	18	21	24	27	30	33	36	39	42	45	48
Literature review	✓	✓	✓														
Numerical modelling		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓						
Implementing a data-driven approach (POMDP)		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Writing PGM in MATLAB or Python		✓	✓	✓													
Constructing the digital twin						✓	✓	✓									
Develop a methodology for calibrating a digital twin prediction									✓	✓	✓	✓					
Develop an approach for data assimilation based on Bayesian inference framework												✓	✓	✓			
Thesis writing															✓	✓	✓
Journal/Conference								✓				✓					✓

Reference

[1] P-R Wagner et al. "Bayesian calibration and sensitivity analysis of heat transfer models for fire insulation panels". In: *Engineering structures* 205 (2020), p. 110063.

[2] Lidija Zdravković et al. "Ground characterisation for PISA pile testing and analysis". In: *Géotechnique* 70.11 (2020), pp. 945–960.

[3] Maliki Moustapha, Stefano Marelli and Bruno Sudret. "Active learning for structural reliability: Survey, general framework and benchmark". In: *Structural Safety* 96 (2022), p. 102174.