## Reduced Order Model for PDE Eigenvalue Problems

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## Introduction

Eigenvalue problems (EVPs) occurs naturally for modeling physical phenomena. The PDE eigenvalue problems arising from fluid dynamics, structural mechanics etc.

## Challanges

* Not straight forward form source problem
* Multiple Eigenmodes
* Medium size device may exhaust
* May Depend on parameters
* Parameters can be deterministic or stochastic.


## Strategies

* Design \& Analyze Reduced Order Models * Study in Three Category
I. EVPs without any parameter but introduce a fictitious parameter
II. EVPs with deterministic parameter
III. EVPs with stochastic parameter

Eigenvalue Problems with no parametric dependence

In spirit of [1], consider the Laplace eigenvalue problem with zero Dirichlet boundary condition. Introducing variable t

$$
\begin{equation*}
u_{t}-\Delta u(x, t)=\lambda(t, u) u(x, t) \tag{1}
\end{equation*}
$$

Where formula for $\lambda$ is

$$
\begin{equation*}
\lambda(t, u)=\frac{\int \nabla u \cdot n d s}{\int u d x} \tag{2}
\end{equation*}
$$

Applying the FEM we will get matrix vector form

$$
A u^{k+1}=\left(\lambda^{k}+\frac{1}{\Delta t}\right) M u^{k}
$$

Let $K$ be the matrix of $n_{s}$ snapshots. $K_{i, j}=K_{i, j}-\phi_{i}$ where $\phi_{i}=1 / n_{s} \sum_{j} K_{-}\{i, j\}$.

Write $K=U \Sigma V^{t}$, the first $n_{p}$ columns are of $U$ are POD basis. The solution of (1) can be written as

$$
u^{k}=\phi+U \psi^{k}
$$

The
$U^{t} A U \psi^{k+1}=-U^{t} \phi$

$$
+\left(\lambda^{k}+\frac{1}{\Delta t}\right)\left(U^{t} M \phi+U^{t} M U \psi^{k}\right)
$$

Rewrite the formula (2) in terms of $\psi^{k}$.

## Eigenvalue Problems with

Deterministic Parameter (approach)

* Design Efficient acheme and convergence analysis
* Selection of parameters to draw snapshots
* Determination of which eigenpairs have to compute in offline stage
* Optimize offline stage using technique of machine learning and data science


## Eigenvalue Problems With Stochastic Parameter (approach)

* Self-adjoint PDES with random data
* Use stochastic Galerkin Approach
* Use synthetic data driven algorithm to determine snapshots following [2]


## References

[1] A.G. Buchan, C.C. Pain, F. Fang, and I.M. Navon, A POD reduced-order model for eigenvalue problems with application to reactor physics. Int. J. Numer. Meth. Engng, 95: 10111032, 2013.
[2] M. Guo, J.S. Hesthaven, Data-driven reduced order modelling for time depedent problems, Compt. Mathods Appl. Mech. Engrg. 345(2019).

