

# Model-Data Weak Formulation (MDWF): Galerkin Approximation

Recapitulation

Unlimited-Observations Statement

Limited-Observations Statement

Experimentally Observable Spaces

Interpretation: Variational Data Assimilation

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## Abstraction

We consider a

physical system

and associated *true* state

*field*

$$u^{\text{true}} \in \mathcal{X},$$

which we assume is *deterministic* and stationary.

We wish to predict the field  $u^{\text{true}}$  based on

a best-knowledge mathematical model  $\{A, f\}$ , and

$M$  experimental observations,

within an integrated (variational) *weak formulation*.

## Model Bias ...

Given the true state of the physical system

$$\text{(field)} \quad u^{\text{true}} \in \mathcal{X} ,$$

define the model bias as

residual

$$g \equiv Au^{\text{true}} - f \in \mathcal{Y}' ,$$

such that

$$Au^{\text{true}} = f + g .$$

Recall  $Au^{\text{bk}} = f : u^{\text{bk}} = u^{\text{true}}$  if and only if  $g = 0$ .

## ... Model Bias

Given that

$$Au^{\text{true}} = f + g$$

we must *simultaneously* estimate

model bias:  $g \in \mathcal{Y}'$ , and

state:  $u^{\text{true}} \in \mathcal{X}$ ;

unique decomposition of  $f = Au^{\text{true}} - g$  in terms of

$g$  and  $u^{\text{true}}$

requires experimental observations.

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# Operators and Sesquilinear Forms

Recall

inner products  $(\cdot, \cdot)_{\mathcal{X}}$ ,  $(\cdot, \cdot)_{\mathcal{Y}}$ ,

duality pairings  $\langle \cdot, \cdot \rangle_{\mathcal{X}' \times \mathcal{X}}$ ,  $\langle \cdot, \cdot \rangle_{\mathcal{Y}' \times \mathcal{Y}}$ ,

representation operators  $X: \mathcal{X} \rightarrow \mathcal{X}'$ ,  $Y: \mathcal{X} \rightarrow \mathcal{Y}'$ ,

associated with our spaces  $\mathcal{X}(\Omega)$ ,  $\mathcal{Y}(\Omega)$ , and

operator  $A: \mathcal{X} \rightarrow \mathcal{Y}'$ , or equivalently

sesquilinear form  $a: \mathcal{X} \times \mathcal{Y} \rightarrow \mathbb{C}$ , and

source  $f \in \mathcal{Y}'$ ,

associated with our best-knowledge model.



## Model Bias

Recall the definition of model bias

$$g \equiv Au^{\text{true}} - f \in \mathcal{Y}'$$

in terms of best-knowledge model and true state.

Now introduce the  $\mathcal{Y}$ -representation of  $g$

$$q^{\text{mod}} \equiv Y^{-1}g \in \mathcal{Y};$$

we shall refer to both  $g$  and  $q^{\text{mod}}$  as model bias.

Recall that model bias can also represent error in  
the best-knowledge model  $\{A, f\}$ ,  $\{\delta A, \delta f\}$ .

## Observable Field (Assumption: Strong)

Recall the “true state” of the physical system,

$$u^{\text{true}} \in \mathcal{X},$$

which we assume is deterministic and stationary.

Now express the “observable” state as

$$u^{\text{obs}} \equiv u^{\text{true}} - q^{\text{obs}},$$

for  $q^{\text{obs}} \in \mathcal{X}$  deterministic and stationary:

- $q^{\text{obs}} = 0$  — perfect observations;
- $q^{\text{obs}} \neq 0$  — imperfect observations;
- $q^{\text{obs}} \rightarrow \infty$  — uninformative observations;

$q^{\text{obs}}$  represents a measurement-induced perturbation.

## Weighting Parameter

Introduce non-negative real parameter,

$$\nu \in \mathbb{R}_{+,0} ,$$

which can be interpreted (conceptually) as<sup>†</sup>  
trust in best-knowledge model  
trust in experimental observations

*A priori* theory shall suggest

$$\nu^{\text{opt}} \equiv \frac{\|\Delta q^{\text{obs}}\|_{\mathcal{Y}}}{\|q^{\text{mod}}\|_{\mathcal{Y}}}$$

as a guideline for choice of  $\nu$ .

Note as approach perfect observations,  $\nu \rightarrow 0$ ;

as approach uninformative observations,  $\nu \rightarrow \infty$ .

<sup>†</sup>We can view  $\nu^{-1}$  as the gain on the data “innovation”.

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## Statement

Given  $\nu \in \mathbb{R}_{+,0}$ , find  $(u, \psi) \in \mathcal{X} \times \mathcal{Y}$  such that

$$a(u, v) - (\psi, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$\begin{aligned} -a(u, \phi) - \nu(\psi, \phi)_{\mathcal{Y}} &= -a(u^{\text{true}}, \phi) \\ &\quad - \nu(q^{\text{mod}}, \phi)_{\mathcal{Y}}, \end{aligned} \quad \forall \phi \in \mathcal{Y},$$

or

$$a(u, v) - (\psi, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$\begin{aligned} -a(u, \phi) - \nu(\psi, \phi)_{\mathcal{Y}} &= -a(u^{\text{obs}}, \phi) - a(q^{\text{obs}}, \phi) \\ &\quad - \nu(q^{\text{mod}}, \phi)_{\mathcal{Y}}, \end{aligned} \quad \forall \phi \in \mathcal{Y},$$

since  $u^{\text{true}} = u^{\text{obs}} + q^{\text{obs}}$ .

## Solution (by Construction)

Proposition 1. The unique solution to our saddle problem is  $(u, \psi) = (u^{\text{true}}, q^{\text{mod}}) \in \mathcal{X} \times \mathcal{Y}$ .

Sketch of proof:

Satisfaction of second equation: trivial.

Satisfaction of first equation (also trivial):

$$a(u, v) - (\psi, v)_{\mathcal{Y}}$$

$$= \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}},$$

from definitions of  $q^{\text{mod}}$  and  $g$ .

Uniqueness follows from our assumptions on  $A$ .  $\square$

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$$\begin{aligned} a(u^{\text{true}}, v) - (q^{\text{mod}}, v)_{\mathcal{Y}} &= \langle Au^{\text{true}} - Yq^{\text{mod}}, v \rangle_{\mathcal{Y}' \times \mathcal{Y}} \\ &= \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \end{aligned}$$

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Uniqueness follows from our assumptions on  $A$ .  $\square$

## Interpretation

We interpret the first equation

$$a(u, v) - (\psi, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$\begin{aligned} -a(u, \phi) - \nu(\psi, \phi)_{\mathcal{Y}} &= -a(u^{\text{obs}}, \phi) - a(q^{\text{obs}}, \phi) \\ &\quad - \nu(q^{\text{mod}}, \phi)_{\mathcal{Y}}, \quad \forall \phi \in \mathcal{Y}, \end{aligned}$$

as the “model” equation: best-knowledge *plus* model bias.

We interpret the second equation

$$a(u, v) - (\psi, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$\begin{aligned} -a(u, \phi) - \nu(\psi, \phi)_{\mathcal{Y}} &= -a(u^{\text{obs}}, \phi) - a(q^{\text{obs}}, \phi) \\ &\quad - \nu(q^{\text{mod}}, \phi)_{\mathcal{Y}}, \quad \forall \phi \in \mathcal{Y}, \end{aligned}$$

as the “data” equation: model-observation connection. 75

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## Unlimited-Observations: Impractical

Our infinite-observations saddle

$$a(u, v) - (\psi, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$\begin{aligned} -a(u, \phi) - \nu(\psi, \phi)_{\mathcal{Y}} &= - \underbrace{a(u^{\text{obs}}, \phi)}_{(\mathbb{A}u^{\text{obs}}, \phi)_{\mathcal{Y}}} - \underbrace{a(q^{\text{obs}}, \phi)}_{(\mathbb{A}q^{\text{obs}}, \phi)_{\mathcal{Y}}} \\ &\quad - \nu(q^{\text{mod}}, \phi)_{\mathcal{Y}}, \quad \forall \phi \in \mathcal{Y}, \end{aligned}$$

is not actionable since we do not know

1. the observable field,  $u^{\text{obs}}$ , *everywhere*;
2. (precisely) the *observational imperfection*,  $q^{\text{obs}}$ ;
3. the *model bias*,  $q^{\text{mod}}$ .

We can not evaluate the “knowns” for the second equation. 77

## Limited-Observations: Discretization Procedure

To construct our *limited-observations* saddle we

- 1a. project  $\mathbb{A}u^{\text{obs}}$  over *appropriate* approximation space  $\mathcal{Y}_M \subset \mathcal{Y}$  of *finite* dimension  $M \geq 0$ ;
- 1b. search for  $\psi_{M,\nu} \approx \psi$  in  $\mathcal{Y}_M$  to ensure uniqueness of discrete solution  $(u_{M,\nu}, \psi_{M,\nu})$ ;
  2. assume that  $\|\mathbb{A}q^{\text{obs}}\|_{\mathcal{Y}}$  is negligibly small;
  3. assume that  $\nu\|q^{\text{mod}}\|_{\mathcal{Y}}$  is negligibly small.

The latter two assumptions reflect

the achievable accuracy (for  $\nu \approx \nu^{\text{opt}}$ ).

## Limited-Observations Saddle

Given  $\nu \in \mathbb{R}_{+,0}$ , find  $(u_{M,\nu}, \psi_{M,\nu}) \in \mathcal{X} \times \mathcal{Y}_M$  such that

$$\begin{aligned} a(u_{M,\nu}, v) - (\psi_{M,\nu}, v)_{\mathcal{Y}} &= \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y}, \\ -a(u_{M,\nu}, \phi) - \nu(\psi_{M,\nu}, \phi)_{\mathcal{Y}} &= -a(u^{\text{obs}}, \phi), \quad \forall \phi \in \mathcal{Y}_M; \end{aligned}$$

recall that  $u^{\text{obs}}$  is the experimentally observable field.

Note for  $M = 0$  ( $\mathcal{Y}_M \equiv 0$ ):  $\psi_{M,\nu} = 0$  and hence

$$u_{M,\nu} = u^{\text{bk}}$$

since

$$a(u^{\text{bk}}, v) = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y};$$

in absence of data, recover best-knowledge model.

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## Observation Functionals [F]

We introduce  $M_{\max}$  observation functionals

$$\ell_m^o \in \mathcal{X}', \quad m = 1, \dots, M_{\max},$$

which reflect

transducer position or focus, and

transducer filter characteristics,

associated with the data acquisition procedure.

We define a single observation as

$$m \in \{1, \dots, M_{\max}\} \rightarrow \ell_m^o(u^{\text{obs}}) \in \mathbb{C},$$

where recall  $u^{\text{obs}} = u^{\text{true}} - q^{\text{obs}}$  is the observable field.

## Example: Gaussian Observation Functionals

Consider  $\Omega \subset \mathbb{R}^d$ ,  $H_0^1(\Omega) \subset \mathcal{X} \subset H^1(\Omega)$ , and define

$$\ell_m^o(v) = \text{Gauss}(v; x_m^c, \sigma) \equiv \int_{\Omega} \frac{1}{(2\pi)^{d/2} \sigma^d} e^{-\frac{|x-x_m^c|^2}{2\sigma^2}} v(x) dx$$

for

observation *centers*  $x_m^c \in \Omega$ ,  $m = 1, \dots, M_{\max}$ ,

observation *filter width*  $\sigma \in \mathbb{R}_+$ ;

we apply corrections near the domain boundary  $\partial\Omega$ .

In theory, we may consider  $\sigma \rightarrow 0$  but only for  $d = 1$ ;

for *real* transducers,  $\sigma$  will be finite for any  $d$ .

# Hierarchical Spaces $\mathcal{E}_M^{\{\ell^o\}}$

Given choices of

observation functionals  $\ell_m^o$ ,  $m = 1, \dots, M_{\max}$ ,

define, for  $1 \leq M \leq M_{\max}$ ,  $\mathcal{E}_0^{\{\ell^o\}} \equiv 0$

$$\mathcal{E}_M^{\{\ell^o\}} \equiv \text{span}\{A^{-*}\ell_m^o, 1 \leq m \leq M\};$$

note spaces are hierarchical,  $\mathcal{E}_M^{\{\ell^o\}} \subset \mathcal{E}_{M+1}^{\{\ell^o\}}$ .

We say that  $\mathcal{E}_M^{\{\ell^o\}}$  is *experimentally observable*  
with respect to observation functionals  $\{\ell_m^o\}_{1 \leq m \leq M}$ .

## Projection of Observable Field

Recall that  $(u_{M,\nu}, \psi_{M,\nu}) \in \mathcal{X} \times \mathcal{Y}_M$  satisfies

$$a(u_{M,\nu}, v) - (\psi_{M,\nu}, v)_\mathcal{Y} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

projection of observable field:  $(\mathbb{A}u^{\text{obs}}, \phi)_\mathcal{Y}$

$$-a(u_{M,\nu}, \phi) - \nu(\psi_{M,\nu}, \phi)_\mathcal{Y} = -\overbrace{a(u^{\text{obs}}, \phi)}, \quad \forall \phi \in \mathcal{Y}_M.$$

We now require  $\mathcal{Y}_M = \mathcal{E}_M^{\{\ell^o\}}$ : then, for  $\phi \in \mathcal{Y}_M$ ,

$$\begin{aligned} \left( \mathbb{A}u^{\text{obs}}, \underbrace{\sum_{m=1}^M \alpha_m A^{-*} \ell_m^o}_{\phi \in \mathcal{Y}_M} \right)_\mathcal{Y} &= \left\langle A^* \sum_{m=1}^M \alpha_m A^{-*} \ell_m^o, u^{\text{obs}} \right\rangle_{\mathcal{X}' \times \mathcal{X}} \\ &= \sum_{m=1}^M \alpha_m \langle \ell_m^o, u^{\text{obs}} \rangle_{\mathcal{X}' \times \mathcal{X}} \end{aligned}$$

corresponds to  $M$  (realizable) single observations.

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# Regularization-Misfit Minimization [ZN] (restricted to Galerkin approximation)

The state  $u_{M,\nu} \in \mathcal{X}$  satisfies

$$u_{M,\nu} = \arg \min_{w \in \mathcal{X}} \left( \underbrace{\|f - Aw\|_{\mathcal{Y}'}^2}_{\text{regularization}} + \frac{1}{\nu} \underbrace{\|\Pi_M \mathbb{A}(u^{\text{obs}} - w)\|_{\mathcal{Y}}^2}_{\text{model-observation misfit}} \right),$$

where the projector  $\Pi_M: \mathcal{Y} \rightarrow \mathcal{Y}_M$  is given by

$$(\Pi_M w, v)_{\mathcal{Y}} = (w, v)_{\mathcal{Y}}, \quad \forall v \in \mathcal{Y}_M, \text{ for any } w \in \mathcal{Y}.$$

For *perfect observations* and  $\nu \rightarrow 0$  we recover  
a penalty formulation for *constrained estimation*.

Saddle: primal-dual Euler-Lagrange equations.<sup>†</sup>

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<sup>†</sup>The primal-only Euler-Lagrange equation constitutes a single-field formulation for  $u_{M,\nu} \in \mathcal{X}$  (not well-suited to computation).

## MDWF Galerkin: Analysis

A Priori Estimates

Stability Constant: Monotonic Improvement

Approximation Theory: Simple Example

Limit of Small Model Bias

# MDWF Galerkin: Analysis

## A Priori Estimates

Perfect Observations (P-O) [QV]

Imperfect Observations (I-O)

Stability Constant: Monotonic Improvement

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# MDWF Galerkin: Analysis

## A Priori Estimates

Perfect Observations (P-O) [QV]

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## Formulation Rappel (I-O) ...

Recall  $(u, \psi) \in \mathcal{X} \times \mathcal{Y}$  satisfies

$$a(u, v) - (\psi, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$\begin{aligned} -a(u, \phi) - \nu(\psi, \phi)_{\mathcal{Y}} &= -a(u^{\text{obs}}, \phi) - a(q^{\text{obs}}, \phi) \\ &\quad - \nu(q^{\text{mod}}, \phi)_{\mathcal{Y}}, \quad \forall \phi \in \mathcal{Y}, \end{aligned}$$

and  $(u_{M,\nu}, \psi_{M,\nu}) \in \mathcal{X} \times \mathcal{Y}_M$  satisfies

$$a(u_{M,\nu}, v) - (\psi_{M,\nu}, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$-a(u_{M,\nu}, \phi) - \nu(\psi_{M,\nu}, \phi)_{\mathcal{Y}} = -a(u^{\text{obs}}, \phi), \quad \forall \phi \in \mathcal{Y}_M.$$

Now recall (P-O)  $\equiv q^{\text{obs}} = 0 \Rightarrow$  choose  $\nu = 0$ .

## ... Formulation Rappel (P-O) ...

Then  $(u, \psi) \in \mathcal{X} \times \mathcal{Y}$  satisfies<sup>†</sup>

$$a(u, v) - (\psi, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$-a(u, \phi) = -a(u^{\text{obs}}, \phi) - a(q^{\text{obs}}, \phi), \quad \forall \phi \in \mathcal{Y},$$

and  $(u_{M,0}, \psi_{M,0}) \in \mathcal{X} \times \mathcal{Y}_M$  satisfies

$$a(u_{M,0}, v) - (\psi_{M,0}, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$-a(u_{M,0}, \phi) = -a(u^{\text{obs}}, \phi), \quad \forall \phi \in \mathcal{Y}_M.$$

We henceforth suppress the subscript  $\nu (= 0)$ .

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<sup>†</sup>This nonsymmetric saddle may be converted to a symmetric saddle.

## ... Formulation Rappel (P-O)

Equivalently,  $(u, \psi) \in \mathcal{X} \times \mathcal{Y}$  satisfies

$$\begin{aligned}(\mathbb{A}u, v)_{\mathcal{Y}} - (\psi, v)_{\mathcal{Y}} &= \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y}, \\ -(\mathbb{A}u, \phi)_{\mathcal{Y}} &= -(\mathbb{A}u^{\text{obs}}, \phi)_{\mathcal{Y}}, \quad \forall \phi \in \mathcal{Y},\end{aligned}$$

and  $(u_M, \psi_M) \in \mathcal{X} \times \mathcal{Y}_M$  satisfies

$$\begin{aligned}(\mathbb{A}u_M, v)_{\mathcal{Y}} - (\psi_M, v)_{\mathcal{Y}} &= \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y}, \\ -(\mathbb{A}u_M, \phi)_{\mathcal{Y}} &= -(\mathbb{A}u^{\text{obs}}, \phi)_{\mathcal{Y}}, \quad \forall \phi \in \mathcal{Y}_M.\end{aligned}$$

Recall  $\mathbb{A} = Y^{-1}A$  such that

$$a(w, v) = \langle Aw, v \rangle_{\mathcal{Y}' \times \mathcal{Y}} = (\mathbb{A}w, v)_{\mathcal{Y}},$$

for any  $w \in \mathcal{X}$ ,  $v \in \mathcal{Y}$ .

## A Priori Estimates (P-O): Definitions

Define observation-constrained spaces

$$\mathcal{Y}_M^\perp \equiv \{w \in \mathcal{Y} : (w, v)_\mathcal{Y} = 0, \forall v \in \mathcal{Y}_M\}$$

$$\mathcal{X}_M^\perp \equiv \{w \in \mathcal{X} : \underbrace{(\mathbb{A}w, v)_\mathcal{Y}}_{a(w,v)} = 0, \forall v \in \mathcal{Y}_M\}$$

and an associated inf-sup constant<sup>†</sup>  $\nu = 0$

$$\beta_{M,\nu=0} \equiv \inf_{w \in \mathcal{X}_M^\perp} \frac{\|\mathbb{A}w\|_\mathcal{Y}}{\|w\|_\mathcal{X}};$$

note

$$\beta_{M=0,\nu=0} = \beta_0 \equiv \inf_{w \in \mathcal{X}} \sup_{v \in \mathcal{Y}} \frac{\langle \mathbb{A}w, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}}{\|w\|_\mathcal{X} \|v\|_\mathcal{Y}} > 0.$$

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<sup>†</sup>The norm  $\|\cdot\|_\mathcal{X}$  can be replaced with a semi-norm  $|\cdot|_\mathcal{X}$ .

## A Priori Estimates (P-O)

Proposition 2: The error  $e \equiv u^{\text{true}} - u_M$  satisfies

$$\|\Delta e\|_{\mathcal{Y}} = \inf_{\phi \in \mathcal{Y}_M} \underbrace{\|q^{\text{mod}} - \phi\|_{\mathcal{Y}}}_{\text{model bias}}$$

or in  $\mathcal{X}$ -norm

$$\|e\|_{\mathcal{X}} \leq \frac{1}{\beta_{M, \nu=0}} \inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}};$$

furthermore

$$\|q^{\text{mod}} - \psi_M\|_{\mathcal{Y}} = \inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}}.$$

Recall  $\nu = \nu^{\text{opt}} = 0$  (for  $q^{\text{obs}} = 0$ ).

## Proof of Proposition 2 (P-O): Preliminaries

*Error Equation:* The error  $e \equiv u^{\text{true}} - u_M$  satisfies

$$(\mathbb{A}e, v)_{\mathcal{Y}} - (q^{\text{mod}} - \psi_M, v)_{\mathcal{Y}} = 0, \quad \forall v \in \mathcal{Y}, \quad \text{EQN1}$$

$$-(\mathbb{A}e, \phi)_{\mathcal{Y}} = 0, \quad \forall \phi \in \mathcal{Y}_M, \quad \text{EQN2}$$

since  $\psi = q^{\text{mod}}$ .

*Projection Operator:* Recall  $\Pi_M: \mathcal{Y} \rightarrow \mathcal{Y}_M (\equiv \mathcal{E}_M^{\{\ell^o\}})$

$$(\Pi_M w, v)_{\mathcal{Y}} = (w, v)_{\mathcal{Y}}, \quad \forall v \in \mathcal{Y}_M, \text{ for any } w \in \mathcal{Y}.$$

*Constrained Spaces:* Recall

$$\mathcal{Y}_M^{\perp} = \{w \in \mathcal{Y}: (w, v)_{\mathcal{Y}} = 0, \quad \forall v \in \mathcal{Y}_M\},$$

$$\mathcal{X}_M^{\perp} = \{w \in \mathcal{X}: \mathbb{A}w \in \mathcal{Y}_M^{\perp}\}.$$

## Proof of Proposition 2 (P-O) ...

To recover the first result

(a) from EQN2,  $\mathbb{A}e \in \mathcal{Y}_M^\perp$ ,  $e \in \mathcal{X}_M^\perp$ ;

(b) from EQN1 tested on  $v \in \mathcal{Y}_M^\perp \subset \mathcal{Y}$ ,  
 $(\mathbb{A}e, v)_\mathcal{Y} = (q^{\text{mod}}, v)_\mathcal{Y}$ ,  $\forall v \in \mathcal{Y}_M^\perp$ ;

(c) from (a) and (b)

$$\mathbb{A}e = q^{\text{mod}} - \Pi_M q^{\text{mod}};$$

(d) from definition of projection

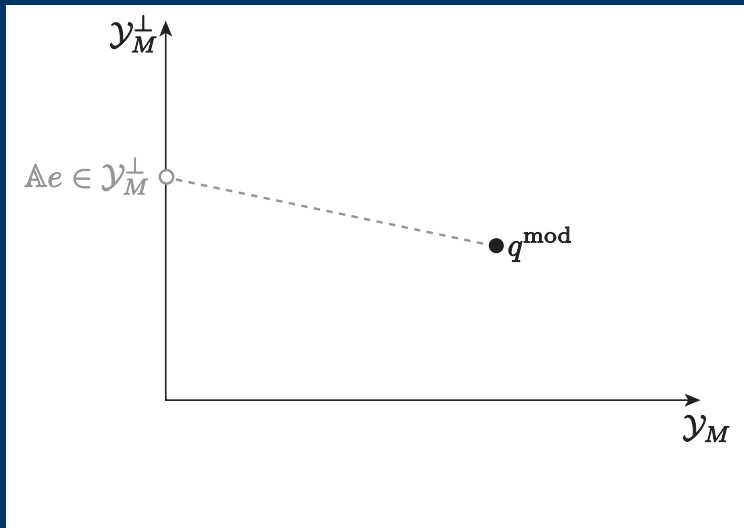
$$\|\mathbb{A}e\|_\mathcal{Y} = \inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_\mathcal{Y}.$$

Error in bias induces error in state.



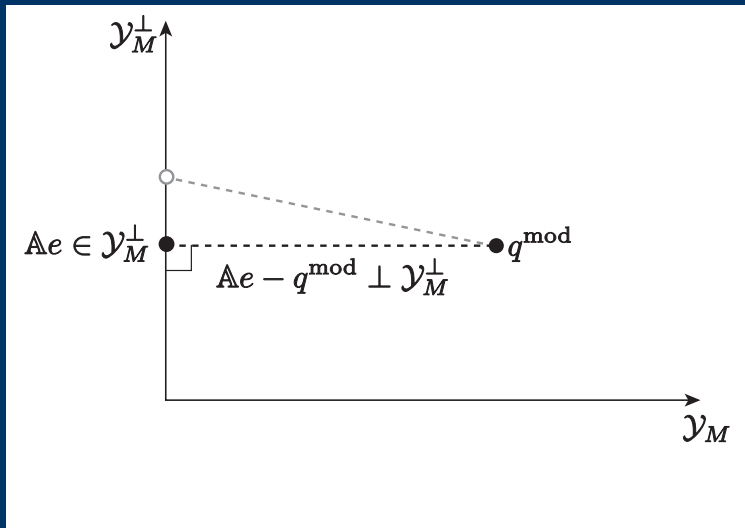
... Proof of Proposition 2 (P-O) ...

or, in a picture



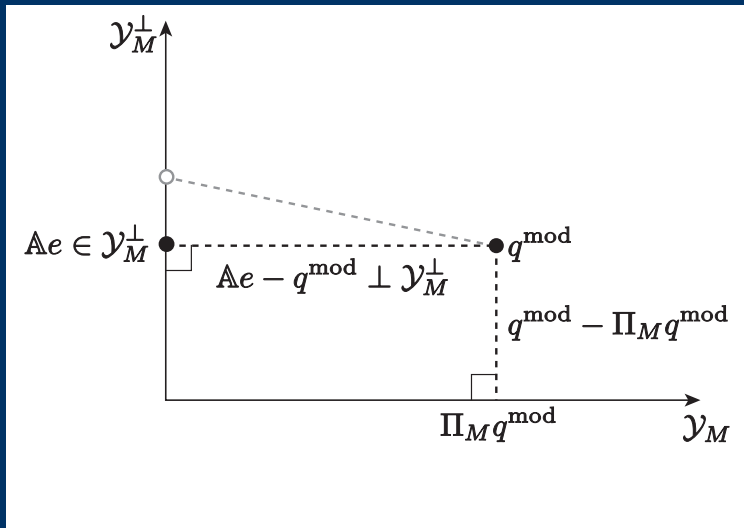
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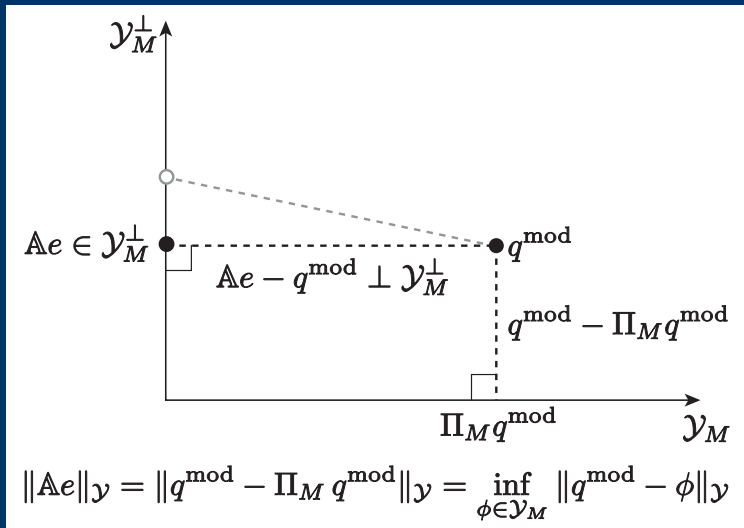
... Proof of Proposition 2 (P-O) ...

or, in a picture



... Proof of Proposition 2 (P-O) ...

or, in a picture



## ... Proof of Proposition 2 (P-O)

To recover the second result

(e) from (a), (d), and definition of stability constant<sup>†</sup>

$$\beta_{M,\nu=0} \equiv \inf_{w \in \mathcal{X}_M^\perp} \frac{\|\Delta w\|_{\mathcal{Y}}}{\|w\|_{\mathcal{X}}},$$

we obtain

$$\beta_{M,\nu=0} \|e\|_{\mathcal{X}} \leq \inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}}.$$

To recover the third result

(f) from EQN1 tested on  $v \in \mathcal{Y}$

$$q^{\text{mod}} - \psi_M = \Delta e;$$

(g) from (c),  $\psi_M = \Pi_M \psi$ .  $\square$

---

<sup>†</sup>We may replace  $\|w\|_{\mathcal{X}}$  with any desired semi-norm  $|w|_{\mathcal{X}}$ .

## A Priori Estimates (P-O): Contributions

(Recall) Proposition 2:

$$\|u^{\text{true}} - u_M\|_{\mathcal{X}} \leq \frac{1}{\beta_{M,\nu=0}} \inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}} .$$

The state error depends on

$$\mathcal{Y}_M \subset \mathcal{Y}_{M+1}$$

1. the stability constant:

$$\beta_{M,\nu=0} (\uparrow) \text{ as } M (\uparrow);$$

2. the model-bias best-fit error:

$$\inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}} (\downarrow) \text{ as } M (\uparrow).$$

Note implicit dependence on regularity of  $q^{\text{mod}}$ .

## Output Error Estimation (P-O)

Proposition 3: for any  $\ell^{\text{out}} \in \mathcal{X}$ ,

$$|\ell^{\text{out}}(e)| \leq \inf_{\zeta \in \mathcal{Y}_M} \|A^{-*} \ell^{\text{out}} - \zeta\|_{\mathcal{Y}} \inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}}.$$

The output error depends on

1. the model-bias best-fit error:

$$\inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}} \quad (\downarrow) \text{ as } M \quad (\uparrow);$$

2. the adjoint best-fit error:

$$\inf_{\zeta \in \mathcal{Y}_M} \|A^{-*} \ell^{\text{out}} - \zeta\|_{\mathcal{Y}} \quad (\downarrow) \text{ as } M \quad (\uparrow).$$

Note for  $\ell^{\text{out}} = \ell^{\circ}$ ,  $|\ell^{\text{out}}(e)| = 0$ .

# MDWF Galerkin: Analysis

## A Priori Estimates

Perfect Observations (P-O) [QV]

Imperfect Observations (I-O)

Stability Constant: Monotonic Improvement

Approximation Theory: Simple Example

Limit of Small Model Bias



## Energy Norm (I-O)

Define an energy norm

$$\Pi_M: \mathcal{Y} \rightarrow \mathcal{Y}_M$$

$$|||w|||_{M,\nu} \equiv (\|\mathbb{A}w\|_{\mathcal{Y}}^2 + \nu^{-1}\|\Pi_M\mathbb{A}w\|_{\mathcal{Y}}^2)^{1/2}$$

and a stability constant

or semi-norm  $|w|_{\mathcal{X}}$

$$\beta_{M,\nu} \equiv \inf_{w \in \mathcal{X}} \frac{|||w|||_{M,\nu}}{\|w\|_{\mathcal{X}}};$$

note consistency in the  $\nu \rightarrow 0$  limit,

$$\beta_{M,\nu \rightarrow 0} = \inf_{w \in \mathcal{X}} \frac{|||w|||_{M,\nu \rightarrow 0}}{\|w\|_{\mathcal{X}}} \rightarrow \inf_{w \in \mathcal{X}_M^\perp} \frac{\|\mathbb{A}w\|_{\mathcal{Y}}}{\|w\|_{\mathcal{X}}} \equiv \beta_{M,\nu=0}$$

since  $\|\Pi_M\mathbb{A}w\|_{\mathcal{Y}}$  is penalized by  $\nu^{-1} \rightarrow \infty$ .

## A Priori Estimate (I-O): Contributions

Proposition 4: The state estimate satisfies  $\nu = \nu^{\text{opt}}$

$$\|u^{\text{true}} - u_{M,\nu}\|_{\mathcal{X}} \leq \frac{1}{\beta_{M,\nu^{\text{opt}}}} \left( \inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}}^2 + \underbrace{4\|q^{\text{mod}}\|_{\mathcal{Y}}\|\Delta q^{\text{obs}}\|_{\mathcal{Y}}}_{\text{dictates error as } M \rightarrow \infty} \right)^{\frac{1}{2}}.$$

The state error depends on

1. the stability constant:  $\beta_{M,\nu^{\text{opt}}} (\uparrow)$  as  $M (\uparrow)$ ;

2. the model-bias best-fit error:

$$\inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}} (\downarrow) \text{ as } M (\uparrow);$$

3. the observation imperfection:  $\|\Delta q^{\text{obs}}\|_{\mathcal{Y}}$ .

Note  $\|\Delta q^{\text{mod}}\|_{\mathcal{Y}}$  does not depend on  $M$ .

## A Priori Estimate (I-O): Observations $\rightarrow$ Perfect

As  $\|\Delta q^{\text{obs}}\|_{\mathcal{Y}} / \|q^{\text{mod}}\|_{\mathcal{Y}} \rightarrow 0$  (and  $\nu^{\text{opt}} \rightarrow 0$ ),

$$\|u^{\text{true}} - u_{M,\nu=0}\|_{\mathcal{X}} \leq \frac{1}{\beta_{M,\nu=0}} \inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}};$$

if  $\inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}} \rightarrow 0$  as  $M \rightarrow \infty$  then

$$\|u^{\text{true}} - u_{M,\nu=0}\|_{\mathcal{X}} \rightarrow 0 \text{ as } M \rightarrow \infty.$$

Note  $\{A, f\}^{\text{bk}}$  will still play role in convergence:

inf-sup constant,  $\beta_{M,\nu=0}$ ;

magnitude and regularity of  $q^{\text{mod}}$ ;

experimentally observable spaces  $\mathcal{Y}_M$ .

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## Stabilization (P-O)

Proposition 5. The inf-sup constant

$$\beta_{M,0} \equiv \inf_{w \in \mathcal{X}_M^\perp} \frac{\|\Delta w\|_{\mathcal{Y}}}{\|w\|_{\mathcal{X}}}$$

is a *non-decreasing* function of  $M$ .

*Proof.* We note that

$$\mathcal{Y}_{M+1} \supset \mathcal{Y}_M \Rightarrow \mathcal{X}_{M+1}^\perp \subset \mathcal{X}_M^\perp;$$

more data implies greater stability.  $\square$

## Improvement in Stability: Ideal Case ...

Consider a generalized SVD of  $A \in \mathcal{L}(\mathcal{X}, \mathcal{Y}')$ ,

$$(\mathbb{A}\xi_j, \mathbb{A}v)_{\mathcal{Y}} = \sigma_j^2(\xi_j, v)_{\mathcal{X}}, \quad \forall v \in \mathcal{X},$$

$$\eta_j = \frac{1}{\sigma_j} \mathbb{A}\xi_j,$$

for

singular values in  $\mathbb{R}^+$ :  $\sigma_1 \leq \sigma_2 \leq \dots$ ;

trial singular functions in  $\mathcal{X}$ :  $(\xi_m, \xi_n)_{\mathcal{X}} = \delta_{mn}$ ;

test singular functions in  $\mathcal{Y}$ :  $(\eta_m, \eta_n)_{\mathcal{Y}} = \delta_{mn}$ .

Note  $\sigma_1 = \beta_0 > 0$  (by assumption).

## ... Improvement in Stability: Ideal Case

Proposition 6: For P-O  $\Rightarrow \nu = 0$ ,

the choice<sup>†</sup>  $\ell_m^o = X\xi_m$ ,  $1 \leq m \leq M$ ,

yields

$$\beta_{M,\nu=0} = \sigma_{M+1} :$$

the first  $M$  singular functions are “deflated.”

*Proof.* Express inf-sup as Rayleigh quotient. □

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<sup>†</sup>Note this choice yields non-experimentally observable spaces  $\mathcal{Y}_M$ , however an SVD Anti-Node computational heuristic will be extracted.



# MDWF Galerkin: Analysis

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## Monotonicity: Statement (P-O,I-O)

Proposition 7: For any  $\nu \in \mathbb{R}_0^+$ , *hierarchical*  $\mathcal{Y}_M$

$$\beta_{M',\nu} \geq \beta_{M'-1,\nu}, \quad M' = 1, \dots, M;$$

and in particular

$$\beta_{M',\nu} \geq \beta_{M=0,\nu} = \beta_0, \quad M' = 1, \dots, M,$$

where (recall)

$$\beta_0 \equiv \inf_{w \in \mathcal{X}} \sup_{v \in \mathcal{Y}} \frac{\langle Aw, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}}{\|w\|_{\mathcal{X}} \|v\|_{\mathcal{Y}}}$$

is the “no-data” inf-sup of the best knowledge model.

## Proposition 5: Proof Sketch

Define the minimizer

*fixed*  $\nu$

$$\chi_M \equiv \arg \min_{w \in \mathcal{X}} \frac{\|\mathbb{A}w\|_y^2}{\|w\|_{\mathcal{X}}^2};$$

for any  $w \in \mathcal{X}$ ,  $\|\mathbb{A}w\|_y^2 \geq \|\mathbb{A}\chi_M\|_y^2$ , and hence

$$\begin{aligned} \beta_{M'}^2 &\equiv \frac{\|\chi_{M'}\|_{M'}^2}{\|\chi_{M'}\|_{\mathcal{X}}^2} = \frac{\|\mathbb{A}\chi_{M'}\|_y^2 + \nu^{-1}\|\mathbb{A}\chi_{M'}\|_y^2}{\|\chi_{M'}\|_{\mathcal{X}}^2} \\ &\geq \frac{\|\mathbb{A}\chi_{M'}\|_y^2 + \nu^{-1}\|\mathbb{A}\chi_{M'}\|_y^2}{\|\chi_{M'}\|_{\mathcal{X}}^2} = \frac{\|\chi_{M'}\|_{M'-1}^2}{\|\chi_{M'}\|_{\mathcal{X}}^2} \\ &\geq \frac{\|\chi_{M'-1}\|_{M'-1}^2}{\|\chi_{M'-1}\|_{\mathcal{X}}^2} \equiv \beta_{M'-1}^2. \quad \square \end{aligned}$$

## MDWF Galerkin: Analysis

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## One Space Dimension: Definitions

Consider

$$\Omega = ]0, 1[ ;$$

$$\mathcal{X} = \mathcal{Y} = H_0^1(\Omega) ;$$

$$\| \cdot \|_{\mathcal{X}} = \| \cdot \|_{\mathcal{Y}} = | \cdot |_{H^1(\Omega)} ;$$

$$A = Y ;$$

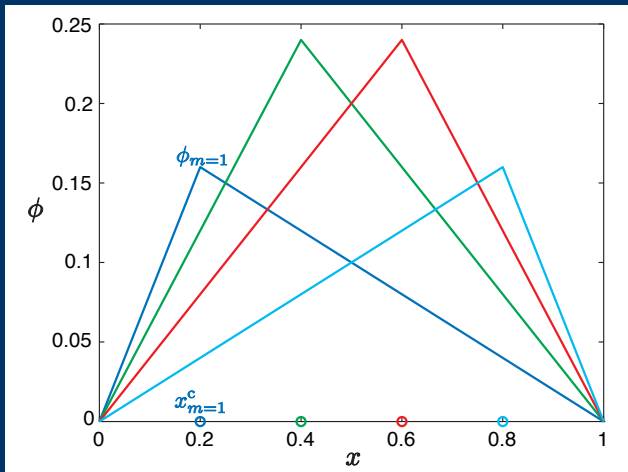
point-wise observation functionals ;

$$\ell_m^o \equiv \delta(\cdot; x_m^c), \quad m = 1, \dots, M ;$$

uniformly spaced observation centers  $\{x_m^c\}_{m=1}^M$  .

Note  $\ell_m^o$  bounded for  $\Omega \subset \mathbb{R}^1$ .

# One Space Dimension: Experimentally Observable Spaces $\mathcal{Y}_M$



Native basis functions for  $\mathcal{Y}_M$ :  $\phi_m = A^{-*} \ell_m^o$ ,  $1 \leq m \leq M$ .

# One Space Dimension: Model Bias Approximation

Proposition 8: For

$$q^{\text{mod}} \in H^2(\Omega),$$

we obtain

$$\inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}} \leq CM^{-1} \|q^{\text{mod}}\|_{H^2(\Omega)}$$

for  $C$  independent of  $M$  and  $q^{\text{mod}}$ .

*Proof.* Note  $\mathcal{Y}_M \equiv \text{span}\{A^{-*} \ell_m^o\}_{m=1}^M$  is equivalent to

{piecewise linear polynomials over nodes  $\{x_m^c\}_{m=1}^M$ };

now apply standard approximation theory.<sup>†</sup> □

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<sup>†</sup>Note that  $q^{\text{mod}} = \mathcal{Y}^{-1}g$  vanishes at end points of  $\Omega$ .

## MDWF Galerkin: Analysis

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## Strategy: Stabilization

Recall *a priori* estimate:

$$\|u^{\text{true}} - u_{M,\nu}\|_{\mathcal{X}} \leq \frac{1}{\beta_{M,\nu^{\text{opt}}}} \left( \inf_{\phi \in \mathcal{Y}_M} \|q^{\text{mod}} - \phi\|_{\mathcal{Y}}^2 + \underbrace{4\|q^{\text{mod}}\|_{\mathcal{Y}}\|\Delta q^{\text{obs}}\|_{\mathcal{Y}}}_{\text{dictates error as } M \rightarrow \infty} \right)^{\frac{1}{2}};$$

if  $\|q^{\text{mod}}\|_{\mathcal{Y}} \ll \|u^{\text{true}}\|_{\mathcal{X}}$ ,  $\|\Delta q^{\text{obs}}\|_{\mathcal{Y}} \ll \|u^{\text{true}}\|_{\mathcal{X}}$ ,

we can control the state error

(solely) by improvements in  $\beta_{M,\nu^{\text{opt}}}$ .

Best conditions: few small singular values.

## “Optimal” Spaces for Stabilization (P-O)

Goal: deflate dangerous modes (E-optimality [FM]),  
but remain experimentally observable.

*Algorithm* SVD Anti-Node: compute

$$w_{\min} \equiv \arg \inf_{w \in \mathcal{X}_M^\perp} \frac{\|Aw\|_{\mathcal{Y}}}{\|w\|_{\mathcal{X}}};$$

locate the most sensitive observation point

$$x_{M+1}^c = \arg \sup_{x \in \Omega} |w_{\min}(x)|;$$

and set

$$\mathcal{Y}_{M+1} = \mathcal{Y}_M \oplus (A^{-*} \text{Gauss}(\cdot; x_{M+1}^c, \sigma));$$

observe least stable mode.

## “Optimal” Spaces for Stabilization (I-O)

Goal: deflate dangerous modes (E-optimality [FM]),  
but remain experimentally observable.

*Algorithm* SVD Anti-Node: compute

$$w_{\min} \equiv \arg \inf_{w \in \mathcal{X}} \frac{\|w\|_{M,\nu}}{\|w\|_{\mathcal{X}}};$$

locate the most sensitive observation point

$$x_{M+1}^c = \arg \sup_{x \in \Omega} |w_{\min}(x)|;$$

and set

$$\mathcal{Y}_{M+1} = \mathcal{Y}_M \oplus (A^{-*} \text{Gauss}(\cdot; x_{M+1}^c, \sigma));$$

observe least stable mode.

# MDWF: Petrov-Galerkin Approach (in brief)

Motivation

Formulation

Analysis

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## Conundrum

For *MDWF formulation*, in data equation

projection of observable field:  $(\mathbb{A}u^{\text{obs}}, \phi)_{\mathcal{Y}}$

$$-a(u_{M,\nu}, \phi) - \nu(\psi_{M,\nu}, \phi)_{\mathcal{Y}} = -\overbrace{a(u^{\text{obs}}, \phi)}^{\text{projection of observable field}}, \quad \forall \phi \in \mathcal{Y}_M,$$

we need  $\mathcal{Y}_M \equiv \mathcal{E}_M^{\{\ell^o\}}$  — *experimentally observable*.

For *Galerkin*, in model equation

$$a(u_{M,\nu}, v) - (\psi_{M,\nu}, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

we need  $\psi_{M,\nu} \in \mathcal{Y}_M^{\text{trial}=\text{test}} = \mathcal{Y}_M = \mathcal{E}_M^{\{\ell^o\}}$ .

Unfortunately,  $\mathcal{Y}_M = \mathcal{E}_M^{\{\ell^o\}}$  provides

good stability: small model bias ✓,

but *poor* approximation: large model bias ✗.

# MDWF: Petrov-Galerkin Approach (in brief)

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## Unlimited Observations

Given  $\nu \in \mathbb{R}_{+,0}$ , find  $(u, \psi) \in \mathcal{X} \times \mathcal{Y}$  such that

$$a(u, v) - (\psi, v)_{\mathcal{Y}} = \langle f, v \rangle_{\mathcal{Y}' \times \mathcal{Y}}, \quad \forall v \in \mathcal{Y},$$

$$\begin{aligned} -a(u, \phi) - \nu(\psi, \phi)_{\mathcal{Y}} &= -a(u^{\text{obs}}, \phi) - a(q^{\text{obs}}, \phi) \\ &\quad - \nu(q^{\text{mod}}, \phi)_{\mathcal{Y}}, \quad \forall \phi \in \mathcal{Y}. \end{aligned}$$

The unlimited-observations formulation is unchanged from the case of Galerkin approximation.



## Limited Observations

Given  $\nu \in \mathbb{R}_{+,0}$ , find  $(u_{M,\nu}, \psi_{M,\nu}) \in \mathcal{X} \times \mathcal{Y}_M^{\text{trial}}$

$$a(u_{M,\nu}, v) - (\psi_{M,\nu}, v)_Y = \langle f, v \rangle_{Y' \times Y}, \quad \forall v \in \mathcal{Y},$$

$$-a(u_{M,\nu}, \phi) - \nu(\psi_{M,\nu}, \phi)_Y = -a(u^{\text{obs}}, \phi), \quad \forall \phi \in \mathcal{Y}_M^{\text{test}};$$

for

$\mathcal{Y}_M^{\text{test}} \equiv \mathcal{E}_M^{\{\ell^o\}}$  experimentally observable

but

$\mathcal{Y}_M^{\text{trial}}$  informed only by approximation considerations.

Strategy [DG,DPW]: choose  $\{\ell^o\}$  to maximize stability from SVD anti-node considerations.