


# Physical and Mathematical Interpretations of an Adjoint Model with Application to ROMS

Andy Moore  
University of Colorado  
Boulder

A stylized teal silhouette of a mountain range is located in the bottom right corner of the slide.

# Linearized Systems

- ◆ Consider a state-space (the ocean) with state vectors  $\Phi$
- ◆ Denote  $\Phi = (u, v, T, S, \zeta, N, P, Z, D, \dots)^T$
- ◆ ROMS is just a set of operators:

$$\partial\Phi/\partial t = M(\Phi) + F(t)$$

- ◆ In general  $M(\Phi)$  will be nonlinear.
- ◆ For many problems it is of considerable theoretical and practical interest to consider perturbations to  $\Phi$

◆ Let  $\Phi \rightarrow \Phi + \delta\Phi$      $F \rightarrow F+f$

◆ In which case:

$$\partial \delta\Phi / \partial t = \left( \partial M / \partial \Phi \right) \delta\Phi + M(\delta\Phi) + f(t)$$

◆ For many problems, it is sufficient to consider small perturbations:

$$|\delta\Phi^2| \ll |\delta\Phi| \text{ and } M(\delta\Phi) \text{ negligible}$$

◆ The Tangent Linear Equation (TLE):

$$\partial \delta\Phi / \partial t = \left( \partial M / \partial \Phi \right) \delta\Phi + f(t)$$

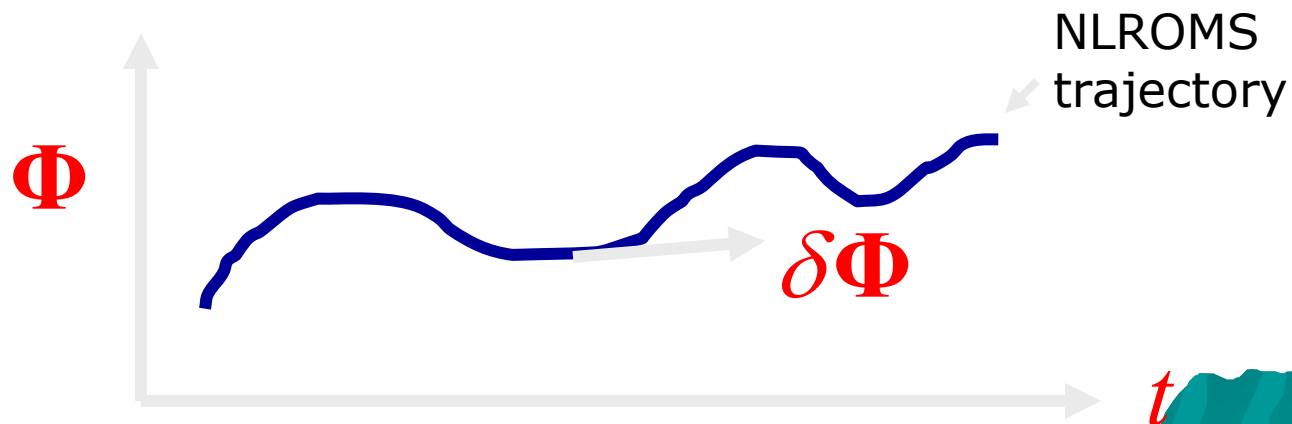
◆ TLE forms core of many analyses  
(e.g. normal modes, linear iteration  
of nonlinear problems (data assimil))

# Matrix-Vector Notation

- ◆ ROMS solves the primitive equations in discrete form:

$$\partial \mathbf{M} / \partial \Phi \equiv \mathbf{A}(t)$$

$$d \delta \Phi / dt = \mathbf{A}(t) \delta \Phi + \mathbf{f}(t)$$




# Important Questions

- ◆ Now that we have reduced the linearized ROMS (TLROMS) to a matrix, what would we like to know?
- ◆ We should perhaps ask of what value is  $\mathbf{A}(t)$  since in reality ROMS (and the real ocean) is nonlinear?



# Justification for TLROMS

- ◆ All perturbations begin in the linear regime.
  - ◆ Linear regime often continues to provide useful information long after nonlinearity becomes important.
  - ◆ Since the action of  $M(\delta\Phi)$  is to merely “scatter” energy, linear regime yields stochastic paradigms.
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# The Propagator


- ◆ It is more convenient to work in terms of the TLROMS propagator:

$$\delta\Phi(t_f) = \mathbf{R}(t_i, t_f)\delta\Phi(t_i)$$

- ◆ So, what would we like to know about  $\mathbf{R}$  ?



# Dimension

- ◆ The ocean is a very large and potentially very complicated place!
  - ◆ But just how complicated is it?
  - ◆ What is its effective dimension?
  - ◆ Low dimension described by just a few d.o.f? or high dimension?
  - ◆ Does dimension depend on where we look?
- 
- A decorative graphic at the bottom right of the slide, consisting of a jagged, teal-colored silhouette of a mountain range or coastline.



# R is BIG!!!

- ◆ R is a monster!  $\sim 10^{5-6} \times 10^{5-6}$

# R

- ◆ Can we reduce R to something more manageable?

# Enter the Adjoint!

- ◆ Eckart-Schmidt-Mirsky theorem: the most efficient representation of a matrix:

$$\mathbf{R} = \sum_{i=1}^K \mathbf{u}_i \lambda_i \mathbf{v}_i^T$$

where  $\mathbf{u}_i$  and  $\mathbf{v}_i$  are the orthonormal singular vectors of  $\mathbf{R}$

- ◆ Singular Value Decomposition (SVD).

◆ By definition:

$$\mathbf{R}\mathbf{v}_i = \lambda_i\mathbf{u}_i$$
$$\mathbf{R}^T\mathbf{u}_i = \lambda_i\mathbf{v}_i$$

where  $\lambda_i$  = singular values  
 $\mathbf{R}^T$  = transpose propagator or adjoint (wrt Euclidean norm)

◆ Clearly:


$$\mathbf{R}^T\mathbf{R}\mathbf{v}_i = \lambda_i^2\mathbf{v}_i$$
$$\mathbf{R}\mathbf{R}^T\mathbf{u}_i = \lambda_i^2\mathbf{u}_i$$

- ◆ Consider:

$$\langle \mathbf{R}\mathbf{R}^T \rangle \mathbf{u}_k = \lambda_k \mathbf{u}_k$$

- ◆ So  $\mathbf{u}$  looks like an EOF (i.e. something that we “observe”).

# The Question of Dimension

- ◆ The dimension of **R** is equal to the “range” of **R** (i.e. the set of singular vectors with  $\lambda_i \neq 0$  ).
  - ◆ Dimension=“rank”=maximal # of independent rows and columns of **R**
  - ◆ SVD is the most reliable method for determining numerically the rank of a matrix.
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# Hypothesis

- ◆ In the limit  $(\Delta x, \Delta y, \Delta z, \Delta t) \rightarrow 0$   
 $\mathbf{R} \rightarrow$  to its continuous counterpart.
- ◆ The rank of  $\mathbf{R}$  will provide fundamental information about the dimensionality of the real ocean circulation



# The Active and Null Space

◆  $\mathbf{R}\mathbf{v}_i = \lambda_i\mathbf{u}_i$  i.e.  $\mathbf{R}$  Transforms from  
Initial state  $\mathbf{v}_i$  to Final/Observed state  $\mathbf{u}_i$  v-space to u-space

◆ Suppose  $\mathbf{R}$  is an (N×N) matrix of rank P (i.e.  $\lambda_i \neq 0, i = 1, \dots, P$

$\lambda_i = 0, i = P + 1, \dots, N$ )  
◆ If  $\lambda_i = 0$ ,  $\mathbf{R}\mathbf{v}_i = 0$  (i.e. nothing is observed).

◆  $\lambda_i = 0$  is the Null Space of  $\mathbf{R}$

◆  $\lambda_i \neq 0$  is the Activated Space of  $\mathbf{R}$

Null Space

$$\mathbf{R}\delta\Phi = 0$$

$$\lambda_i = 0$$

$$\delta\Phi = \sum_{i=1}^N a_i \mathbf{v}_i$$

$$\mathbf{R}\delta\Phi = \sum_{i=1}^N a_i \mathbf{R}\mathbf{v}_i$$

$$\mathbf{R}\delta\Phi \neq 0$$

$$\lambda_i \neq 0$$

Activated Space





◆ Recall:

$$\mathbf{R}^T \mathbf{u}_i = \lambda_i \mathbf{v}_i$$

Observed State                      Initial State

- ◆  $\mathbf{R}^T$  transforms from “observed  $\mathbf{u}$ ” back to “activated  $\mathbf{v}$ -space”.
- ◆ So if we observe “ $\mathbf{u}$ ” the adjoint tells us from whence it came!  
(cf Green’s functions).

# Generating Vectors

- ◆ Let  $\mathbf{A}$  be an  $(N \times M)$  matrix, where  $N < M$ .
- ◆ SVD yields two fundamental spaces:  
N-space and M-space

$$\underset{(N \times M)(M \times 1)}{\mathbf{A} \mathbf{v}_i} = \underset{(N \times 1)}{\lambda_i \mathbf{u}_i}$$

M-space to N-space

$$\underset{(M \times N)(N \times 1)}{\mathbf{A}^T \mathbf{u}_i} = \underset{(M \times 1)}{\lambda_i \mathbf{v}_i}$$

N-space to M-space

- ◆ Consider the underdetermined system

$$\mathbf{Ax} = \mathbf{b}$$

$(N \times M)(M \times 1) \quad (N \times 1)$

$\mathbf{A}$  ,  $\mathbf{b}$  given;  $\mathbf{x}$  unknown.

- ◆ Unique solutions exist if:  $\mathbf{x} = \mathbf{A}^T \mathbf{y}$

- ◆ Then:

$$\mathbf{AA}^T \mathbf{y} = \mathbf{b}$$

$(N \times M)(M \times N)(N \times 1) \quad (N \times 1)$

- ◆  $\mathbf{y}$  is called the “generating vector”.
- ◆  $\mathbf{x}$  is called the “natural solution”.

- ◆ Suppose that  $\mathbf{A}$  has only  $P$  non-zero singular values:  $\lambda_i \neq 0, i = 1, \dots, P$

- ◆ SVD:  $\mathbf{A} = \mathbf{U}_p \mathbf{\Lambda}_p \mathbf{V}_p^T$

$$\mathbf{A}^T = \mathbf{V}_p \mathbf{\Lambda}_p \mathbf{U}_p^T$$

$$\mathbf{x} = \mathbf{A}^T \mathbf{y} = \mathbf{V}_p (\mathbf{\Lambda}_p \mathbf{U}_p^T \mathbf{y}) = \mathbf{V}_p \mathbf{q}$$

- ◆ So  $\mathbf{x}$  is ALWAYS in  $P$ -space (i.e. "activated space" identified by  $\mathbf{A}^T$ )

# A Familiar Example

- ◆ The QG barotropic vorticity equation:

$$\frac{\partial}{\partial t} (v_x - u_y) + \beta v = 0$$

- ◆ Solve for  $\mathbf{u} = u\mathbf{i} + v\mathbf{j}$  :  
underdetermined!

- ◆ Adjoint vorticity equation yields the generating (stream) function:

$$\mathbf{u} = -\partial\psi/\partial y \mathbf{i} + \partial\psi/\partial x \mathbf{j}$$

# Adjoint Applications

- ◆ Clearly the adjoint operator  $\mathbf{R}^T$  of ROMS yields information about the subspace or dimensions that are activated by  $\mathbf{R}$ .
- ◆ There are many applications that take advantage of this important property.



# Sensitivity Analysis

- ◆ Consider a function  $J = G(\Phi)$
- ◆ Clearly  $\delta J = \delta\Phi^T (\partial G / \partial \Phi)$
- ◆ But  $\delta\Phi(t_f) = \mathbf{R}(t_i, t_f) \delta\Phi(t_i)$
- ◆ So  $\partial J / \partial \Phi = \mathbf{R}^T(t_f, t_i) (\partial G / \partial \Phi)$

Sensitivity



- ◆ Clearly the action of the adjoint restricts the sensitivity analysis to the subspace activated by  $\mathbf{R}^T$  (i.e. to the space occupied by “natural” solutions).






# Least-Squares Fitting and Data Assimilation

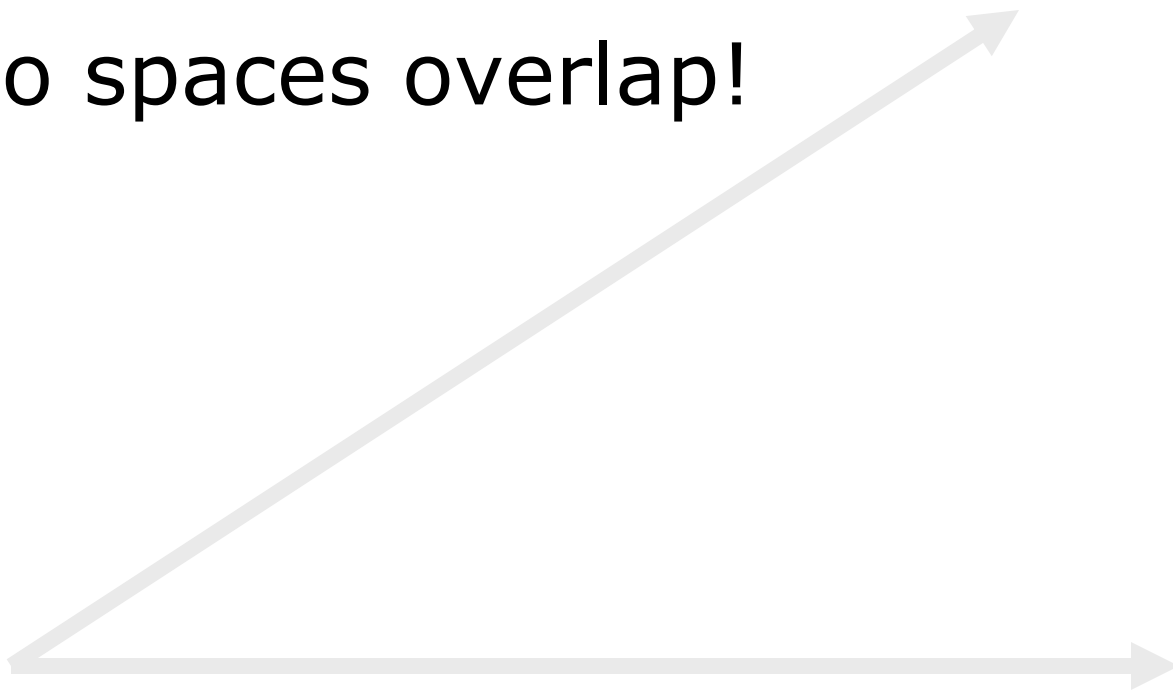
- ◆ If  $J = (\Phi - \Phi^{obs})^T X (\Phi - \Phi^{obs})$  then the gradient provided by  $R^T$  can be used to find  $\Phi(t_i)$  that minimizes  $J$ .
- ◆ This is the idea behind 4-dimensional variational data assimilation (4DVAR)
- ◆ Clearly the  $\Phi(t_i)$  that minimizes  $J$  lies within the active subspace of  $R$

# Traditional Eigenmode Analysis

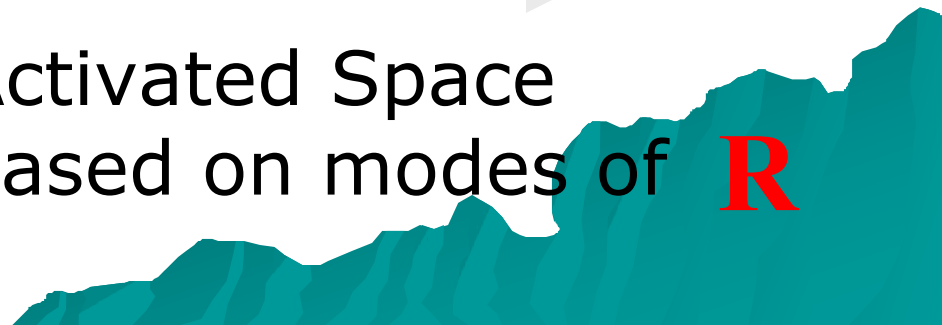
- ◆ We are often taught to use the eigenmodes of  $\mathbf{R}$  to explore properties and stability of ocean.
  - ◆ In general, the eigenmodes of  $\mathbf{R}$  are NOT orthogonal, meaning each mode has a non-zero projection on other modes.
  - ◆ What does this do to our notion of active and null space?
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Null Space based on modes of **R**

The two spaces overlap!



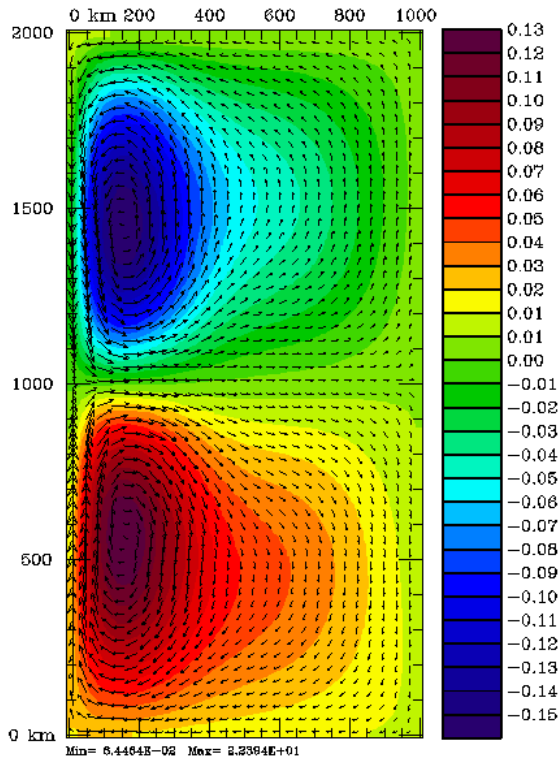
Activated Space based on modes of **R**



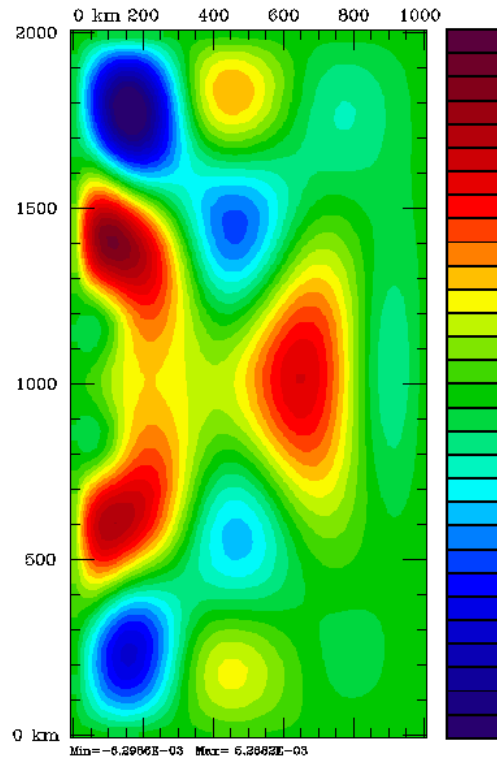
- ◆ The amplitude of a particular eigenmode of  $\mathbf{R}$  is determined by its projection on the active subspace (i.e. by its projection on the corresponding eigenmode of  $\mathbf{R}^T$ ).



# Basin Modes in a Mean Flow

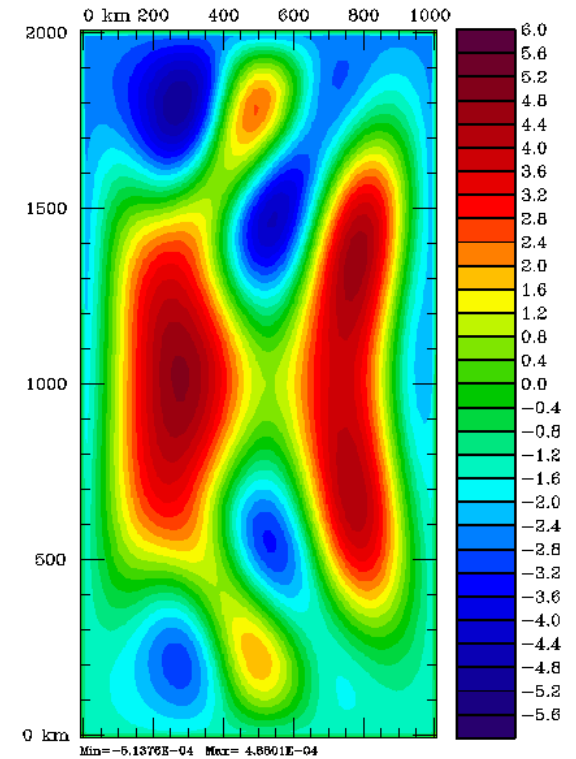


Basic State  
Circulation



FTE 12

Eigenmode #6



AFTE 12

Adjoint  
Eigenmode #6

# SVD and Generalized Stability Analysis

- ◆ Recall from SVD that:  $\mathbf{R}^T \mathbf{R} \mathbf{v}_i = \lambda_i^2 \mathbf{v}_i$
- ◆ Time evolved SV is  $\mathbf{R} \mathbf{v}_i$
- ◆ Ratio of final to initial “energy” is:

$$\frac{(\mathbf{R} \mathbf{v}_i)^T (\mathbf{R} \mathbf{v}_i)}{(\mathbf{v}_i^T \mathbf{v}_i)} = \frac{\mathbf{v}_i^T \mathbf{R}^T \mathbf{R} \mathbf{v}_i}{(\mathbf{v}_i^T \mathbf{v}_i)} = \lambda_i^2$$

- ◆ So of all perturbations,  $\mathbf{v}_1$  is the one that maximizes the growth of “energy” over the time interval  $[t_i, t_f]$ .

- ◆ Consider the forced TL equation:

$$\partial \delta \Phi / \partial t = (\partial \mathbf{M} / \partial \Phi) \delta \Phi + \mathbf{f}(t)$$

- ◆ If  $\mathbf{f}(t)$  is stochastic in time, more general forms of SVD are of interest.
- ◆ Assume unitary forcing:  $\langle \mathbf{f}(t) \mathbf{f}^T(t) \rangle = \mathbf{I}$
- ◆ Of particular interest are:

$$\mathbf{P} = \int \mathbf{R} \mathbf{R}^T dt \quad \leftarrow \quad \text{Controllability Grammian}$$

$$\mathbf{Q} = \int \mathbf{R}^T \mathbf{R} dt \quad \leftarrow \quad \text{Observability Grammian}$$

- ◆ Eigenvectors of  $\mathbf{P}$  are the EOFs.
- ◆ Eigenvectors of  $\mathbf{Q}$  are the Stochastic Optimals.
- ◆ Variance:  $Var = \text{tr}\{\mathbf{P}\} = \text{tr}\{\mathbf{Q}\}$
- ◆ Eigenvectors of  $\mathbf{P}^{1/2}\mathbf{Q}\mathbf{P}^{1/2}$  are balanced truncation vectors.
- ◆ All have considerable practical utility and applications that go far beyond traditional eigenmode analysis!



# Covariance Functions and Representers

- ◆ The “controllability” Grammmiam  $\mathbf{P}$  is nothing more than a covariance matrix.

- ◆ Note that  $\mathbf{b} = \mathbf{P}\mathbf{y} = \left( \int \mathbf{R}\mathbf{R}^T dt \right) \mathbf{y}$  looks a lot like:

$$\mathbf{A}\mathbf{A}^T \mathbf{y} = \mathbf{b}$$

which yields the “natural solution”.

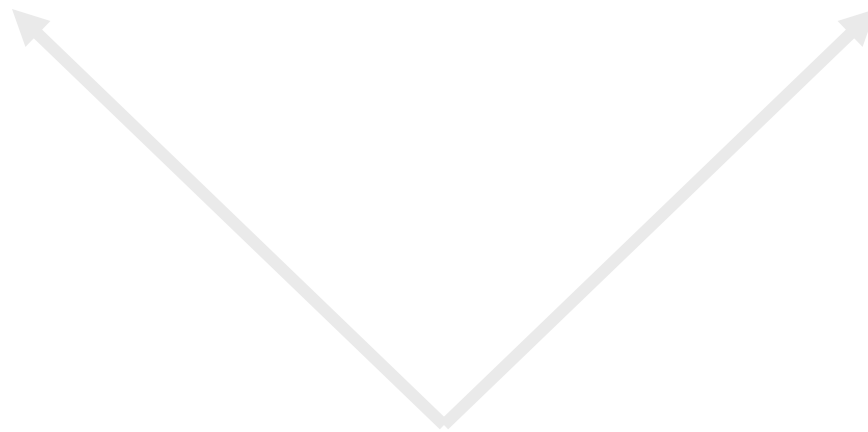
- ◆ Operations involving  $\mathbf{P}$  yield only natural solutions related to “Representer Functions”.

# Norm Dependence

- ◆ The adjoint  $\mathbf{R}^\dagger$  is norm dependent.
- ◆ For the Euclidean norm,  $\mathbf{R}^\dagger = \mathbf{R}^T$
- ◆ Changing norms is simply equivalent to a rotation and/or change in metric

Null Space

Activated Subspace



# Summary

Null Space

The adjoint identifies the bits of state-space that actually do something!

Activated Space



The Adjoint of ROMS  
is a Wonderful Thing!



# The Cast of Characters

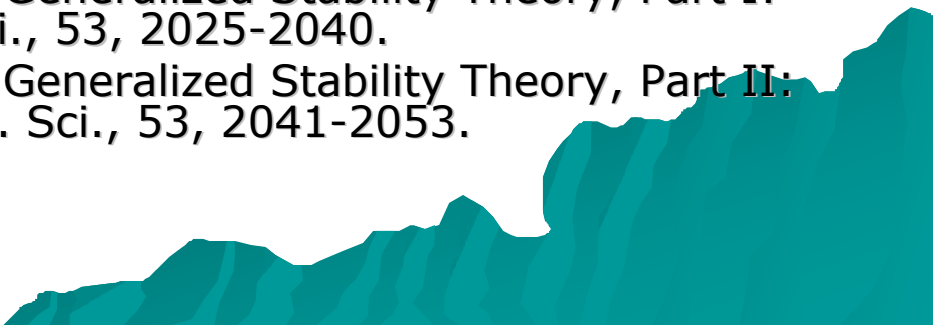
$M(\Phi)$  - played by NLROMS

$R$  - played by TLROMS

$R^T$  - played by ADROMS



# Acknowledgements

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- ◆ Can we reduce R to something more manageable?

