

# Dynamic Mode Decomposition (DMD) Workshop on Data -Driven Modelling 2017

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#### Outline

Introduction

Eigen Values and Vectors

Singular Values and Vectors

Dynamic Mode Decomposition



## Dynamic Mode Decomposition (DMD)

- Dynamic systems: Measurements of nonlinear dynamical systems and/or complex systems.
- DMD: Integrating data with dynamical systems theory.
- Has deep connections with many recent innovations in compressed sensing and machine learning.
- Algorithm evolved with Eigen Values and Vectors.



## Eigen Values and Vectors

- Eigen Value  $(\lambda)$  = characteristic value
- Eigen Vector (v) = characteristic vector.

$$Av = \lambda v \tag{1}$$



#### Example

$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \tag{2}$$

$$Av = \lambda v \tag{3}$$

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = (1) \begin{bmatrix} 1 \\ 1 \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = (-1) \begin{bmatrix} -1 \\ 1 \end{bmatrix} \tag{5}$$

$$v1, v2 = (1, 1), (1, -1)$$
 (6)

$$\lambda 1, \lambda 2 = 1, -1 \tag{7}$$



### Visualizing an Example

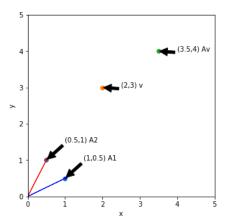


Figure: A is a matrix with A1, A2 column vectors, v is a Eigen vector, Magnitude of the green line is Eigen value



#### Eigen Spaces

$$A = \lambda v \tag{8}$$

$$Av = (\lambda I)v \tag{9}$$

$$(A - (\lambda I))v = 0 (10)$$

$$v \in N(A - \lambda I)$$
 is the nullspace of the matrix  $(A - \lambda I)$  (11)

$$N(A - \lambda I) \neq \{0\}$$
 is the eigenspace of A with  $\lambda$  (12)



## Singular Value Decomposition - SVD

· Generalization of the Eigen decomposition

$$U_{m \times m} \Sigma_{m \times n} V_{n \times n}^{T} = svd \left( A_{m \times n} \right)$$
 (13)

$$U_{m \times m} = eigen \ vector \left( A_{m \times n} A_{n \times m}^{T} \right)$$
 (14)

$$V_{n \times n} = eigen \ vector \left( A_{n \times m}^T A_{m \times n} \right) \tag{15}$$

$$\Sigma_{m \times n} = \sqrt{\text{eigen value}\left(A_{m \times n} \text{ or } A_{n \times m}^{T}\right)}$$
 (16)

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## Singular Value Decomposition - SVD

Full Matrix

$$U_{m\times m}\Sigma_{m\times n}V_{n\times n}^{T} = svd\left(A_{m\times n}\right) \tag{17}$$

Truncated Matrix

$$\tilde{A} \approx U_{m \times r} \Sigma_{r \times r} V_{r \times n}^{T} \tag{18}$$



#### Singular Value Decomposition - SVD

$$\begin{pmatrix} \hat{X} & U & S & V^{\mathsf{T}} \\ x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & \\ \vdots & \vdots & \ddots & \\ x_{m1} & & x_{mn} \end{pmatrix} \approx \begin{pmatrix} U & S & V^{\mathsf{T}} \\ u_{11} & \dots & u_{1r} \\ \vdots & \ddots & \\ u_{m1} & & u_{mr} \end{pmatrix} \begin{pmatrix} s_{11} & 0 & \dots \\ 0 & \ddots & \\ \vdots & & s_{rr} \end{pmatrix} \begin{pmatrix} v_{11} & \dots & v_{1n} \\ \vdots & \ddots & \\ v_{r1} & & v_{rn} \end{pmatrix}$$

Figure: Truncation of the matrix

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#### **DMD** Formulation

Observed Sequences = 
$$\begin{bmatrix} | & | & | & | & | \\ x_1 & x_2 & x_3 & \dots & x_n & x_{n+1} \\ | & | & | & | & | \end{bmatrix}$$
 (19)

$$X_{m \times n} = \begin{bmatrix} | & | & | & | & | \\ x_1 & x_2 & x_3 & \dots & x_{n-1} & x_n \\ | & | & | & | & | \end{bmatrix}$$
 (20)

$$Y_{m \times n} = \begin{bmatrix} | & | & | & | & | \\ x_2 & x_3 & x_4 & \dots & x_n & x_{n+1} \\ | & | & | & | & | \end{bmatrix}$$
 (21)

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$$Y_{m \times n} = A_{m \times m} X_{m \times n} \tag{22}$$

$$A_{m \times m} = Y_{m \times n} X_{n \times m}^{\dagger} \tag{23}$$

$$DMD\ Modes = eigen\ vector\left(A_{m \times m}\right) \tag{24}$$



Finding pseudo inverse of X

$$X^{\dagger} = (X^*X)^{-1} X^*$$

$$= (V\Sigma U^* U\Sigma V^*)^{-1} V\Sigma U^*$$

$$= (V\Sigma^2 V^*)^{-1} V\Sigma U^*$$

$$= (V^*)^{-1} \Sigma^{-2} V^{-1} V\Sigma U^*$$

$$= V\Sigma^{-2} \Sigma U^*$$

$$X^{\dagger} = V\Sigma^{-1} U^*$$

$$X^{\dagger}_{n \times m} = V_{n \times n} \Sigma_{n \times m}^{-1} U_{m \times m}^*$$
(25)

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Projection of the full matrix A onto U

$$Y_{m \times n} = A_{m \times m} X_{m \times n}$$
$$A_{m \times m} = Y_{m \times m} X_{n \times m}^{\dagger}$$

$$\tilde{A} = U^* A U = U^* Y X^{\dagger} U \tag{27}$$

$$\tilde{A} = UAU^* = U^*YV\Sigma^{-1}U^*U \tag{28}$$

$$\tilde{A} = U^* Y V \Sigma^{-1} \tag{29}$$

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• Reducing dimension to r (rank)

$$\tilde{A}_{m \times m} = U_{m \times m}^* Y_{m \times n} V_{n \times n} \Sigma_{n \times m}^{-1}$$

$$\tilde{A}_{r \times r} \approx U_{r \times m}^* Y_{m \times n} V_{n \times r} \Sigma_{r \times r}^{-1}$$
(30)



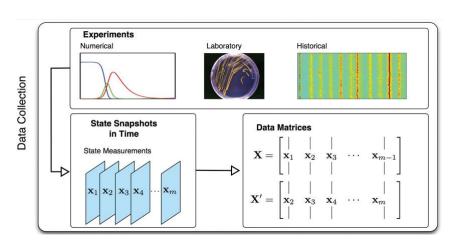
ullet Eigen Vectors of  $ilde{A}$ 

$$W_{r \times r} = eigen \ vector \left( \tilde{A}_{r \times r} \right)$$
 (31)

DMD Modes

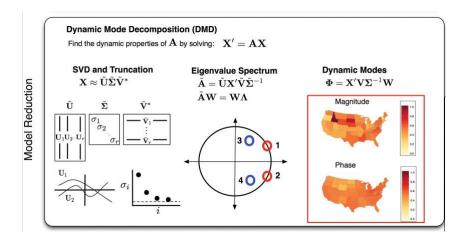
$$\phi_{m\times r} = Y_{m\times n} V_{n\times r} \Sigma_{r\times r} W_{r\times r}$$
 (32)





source: www.dmdbook.com

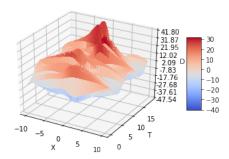




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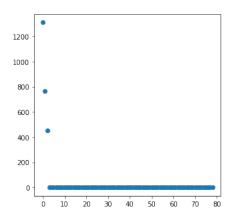


#### Dynamic System



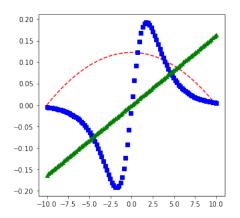


## Singular Values



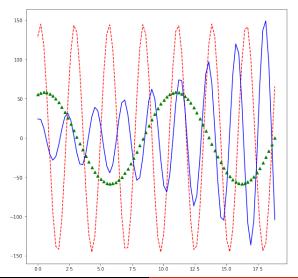


#### **DMD** Modes



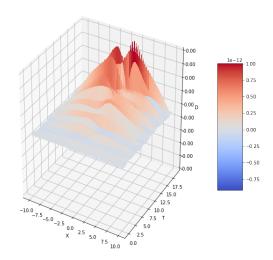


#### Time Evolution





#### Reconstructed Error





Thank You.

you can follow me through:

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