## CS/ECE/ME 532 Period 11

- Today: Unit 3 Low Rank Decompositions
- Low rank decompositions:
  - k-means
  - The singular value decomposition (SVD)
- Properties of the SVD
- Least squares and the SVD

 Next week: Unit 4 – Applications of the SVD

## Today – Properties of the SVD and LS+SVD

Low rank decompositions:

$$m{A} pprox m{U}m{W}^T = egin{bmatrix} u_{1,1} & u_{1,2} \ u_{2,1} & u_{2,2} \ u_{3,1} & u_{3,2} \ u_{4,1} & u_{4,2} \end{bmatrix} m{w}_{1,1} & \dots & w_{1,6} \ w_{2,1} & \dots & w_{2,6} \end{bmatrix}$$

basis vectors or patterns

We'd like decomposition with:

- 1. columns of  $oldsymbol{U}$  to be orthonormal:  $oldsymbol{U}^Toldsymbol{U}=oldsymbol{I}$
- 2. unique, meaningful ordering
  - find first basis vector that well aligned with columns of A:

large 
$$|\boldsymbol{u}^T\boldsymbol{a}_i|$$
  $\boldsymbol{u}_1 = \arg\max_{||\boldsymbol{u}||_2=1}||\boldsymbol{u}^T\boldsymbol{A}||_2$ 

Answer: these two requirements **define** the SVD!

$$A = \begin{bmatrix} A \\ N \times M \end{bmatrix} = \begin{bmatrix} U \\ O \\ N \times M \end{bmatrix} \begin{bmatrix} V^T \\ N \times M \end{bmatrix}$$

## SVD defines the 'best' rank r approximation (EY, 1936):

$$\min ||\boldsymbol{A} - \tilde{\boldsymbol{A}}||_F$$
over all matrices  $\tilde{\boldsymbol{A}}$  with rank  $\leq r$ 
given by  $\tilde{\boldsymbol{A}} = \sum_{i=1}^r \sigma_i \boldsymbol{u}_i \boldsymbol{v}_i^T$ 

## SVD for least squares:

$$\min_{oldsymbol{w}} ||oldsymbol{A}oldsymbol{w} - oldsymbol{y}||^2 \ oldsymbol{w}^* = (oldsymbol{A}^Toldsymbol{A})^{-1}oldsymbol{A}^Toldsymbol{y} \ oldsymbol{w}^* = oldsymbol{V}\Sigma^{-1}oldsymbol{U}^Toldsymbol{y} \ economy\ SVD$$

Problems when small singular values! Fix by dropping corresponding singular vectors.