

Module – 4.1

# INTERLUDE

## AN ASSESSMENT AND A WAY FORWARD

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# LEAST SQUARES FORMULATIONS – A CLASSIFICATION

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- Linear vs nonlinear
- Ordinary vs weighted
- Orthogonal vs oblique projection
- Full rank vs rank deficient
- Over vs under determined
- Off-line vs on-line formulations

# PATHWAYS TO THE SOLUTION

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Two ways



- Directly minimize  $f(x)$
- Iterative minimization
- Module – 4.3

- Solve  $\nabla_x f(x) = 0$
- Check if  $\nabla_x^2 f(x)$  is SPD
- Matrix methods
- Module – 4.2

- These methods are useful throughout the course

# PATHWAYS TO SOLUTION – LINEAR CASE

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- Off-line, ordinary linear, full rank formulation: Module – 3.1  
 $(H^T H)x = H^T Z$ ,  $(H^T H) - \text{SPD}$ ,  $m > n$   
 $(H H^T)y = Z$  and  $x = H^T y$ ,  $(H H^T) - \text{SPD}$ ,  $m < n$
- Off-line, weighted, linear full rank formulation: Module – 3.1  
 $(H^T W H)x = H^T W Z$ ,  $(H^T W H) - \text{SPD}$ ,  $m > n$   
 $(H W H^T)y = Z$  and  $x = W H^T y$ ,  $(H W H^T) - \text{SPD}$ ,  $m < n$
- $W - \text{SPD}$

# PATH WAYS TO SOLUTION – LINEAR CASE

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- Off-line, ordinary linear, rank-deficient formulation: Module – 3.2

$$(H^T H + \alpha I)x = H^T Z, \quad (H^T H + \alpha I) - \text{SPD}, \quad \alpha > 0, \quad m > n$$

$$(H H^T + \alpha I)y = Z \text{ and } x = H^T y, \quad (H H^T + \alpha I) - \text{SPD}, \quad \alpha > 0, \quad m < n$$

- On-line, ordinary linear, full rank case: Module – 10

$$X^*(m+1) = X^*(m) + K_{m+1} h_{m+1} [z_{m+1} - h_{m+1}^T x^*(m)]$$

$$K_m^{-1} = H^T H$$

$$K_{m+1}^{-1} = K_m^{-1} + h_{m+1} h_{m+1}^T$$

- $K_{m+1}$  is obtained by Sherman-Morrison-Woodbury formula

# PATH WAYS TO SOLUTION – NONLINEAR CASE

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- Off-line, ordinary, nonlinear case: Module – 3.4
  - Solve a set of non-linear equations:

$$\nabla_x f(x) = D_x^T(h)[h(x) - Z] = 0$$

- On-line, ordinary, nonlinear case:
  - Use first-order approximation to  $h(x)$

$$[D_{x_c}^T(h)D_{x_c}(h)](x - x_c) = D_{x_c}^T(h)Z$$

$$x_c^{\text{new}} \leftarrow x_c + (x - x_c)$$

- Use second-order approximation to  $h(x)$

$$[D_{x_c}^T(h)D_{x_c}(h) - \sum_{i=1}^m g_i \nabla_x^2 h_i(x_c)](x - x_c) = D_{x_c}^T(h)Z$$

$$g = z - h(x_c), x_c^{\text{new}} \leftarrow x_c + (x - x_c)$$

# A WAY FORWARD – COMING ATTRACTIONS:

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- Method of normal equations
- At its core, need methods for solving

$$(H^T H)x = H^T Z \text{ or } (H H^T)y = Z$$

- These are linear systems of the form

$$Ax = b$$

with  $A$  as a symmetric positive definite (SPD) matrix

- A stand method to linear systems with SPD matrix is the Cholesky decomposition method – (Module 4.2)

# ALTERNATE DECOMPOSITION (QR AND SVD) METHODS

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- Instead of decomposing  $(H^T H)$  or  $(H H^T)$  using cholesky method, we can directly decompose  $H$  that will simplify the form of the least squares solution
- QR – decomposition – (Module 4.2)
- (SVD) – (Module 4.2)



# DIRECT MINIMIZATION OF $f(x)$

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- Use well known iterative methods to directly minimize  $f(x)$ : (Module 4.3):
  - Gradient method
  - Conjugate gradient method
  - Quasi-Newton methods

# REFERENCES

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- This Module is a summary of Chapters 5 -7 in LLD (2006)