



Approximate full solution: Derivation

- In prior lesson, you learned new AWTLS cost function

$$\chi_{\text{AWTLS}}^2 = \sum_{i=1}^N \frac{(y_i - \hat{Q}x_i)^2}{(1 + \hat{Q}^2)^2} \left(\frac{\hat{Q}^2}{\sigma_{x_i}^2} + \frac{1}{\sigma_{y_i}^2} \right)$$

- Jacobian of AWTLS cost function can be found to be

$$\begin{aligned} \frac{\partial \chi_{\text{AWTLS}}^2}{\partial \hat{Q}} &= \frac{2}{(\hat{Q}^2 + 1)^3} \sum_{i=1}^N \hat{Q}^4 \left(\frac{x_i y_i}{\sigma_{x_i}^2} \right) + \hat{Q}^3 \left(\frac{2x_i^2}{\sigma_{x_i}^2} - \frac{x_i^2}{\sigma_{y_i}^2} - \frac{y_i^2}{\sigma_{x_i}^2} \right) \\ &+ \hat{Q}^2 \left(\frac{3x_i y_i}{\sigma_{y_i}^2} - \frac{3x_i y_i}{\sigma_{x_i}^2} \right) + \hat{Q} \left(\frac{x_i^2 - 2y_i^2}{\sigma_{y_i}^2} + \frac{y_i^2}{\sigma_{x_i}^2} \right) + \left(\frac{-x_i y_i}{\sigma_{y_i}^2} \right) \end{aligned}$$



Recursive solution

- Can be rewritten in terms of recursive summations

$$\begin{aligned} \frac{\partial \chi_{\text{AWTLS}}^2}{\partial \hat{Q}} &= \frac{2}{(\hat{Q}^2 + 1)^3} \left(c_5 \hat{Q}^4 + (2c_4 - c_1 - c_6) \hat{Q}^3 \right. \\ &\quad \left. + (3c_2 - 3c_5) \hat{Q}^2 + (c_1 - 2c_3 + c_6) \hat{Q} - c_2 \right) \end{aligned}$$

where

$$\begin{aligned} c_{1,n} &= c_{1,n-1} + x_n^2 / \sigma_{y_n}^2; & c_{3,n} &= c_{3,n-1} + y_n^2 / \sigma_{y_n}^2; & c_{5,n} &= c_{5,n-1} + x_n y_n / \sigma_{x_n}^2 \\ c_{2,n} &= c_{2,n-1} + x_n y_n / \sigma_{y_n}^2; & c_{4,n} &= c_{4,n-1} + x_n^2 / \sigma_{x_n}^2; & c_{6,n} &= c_{6,n-1} + y_n^2 / \sigma_{x_n}^2 \end{aligned}$$

- Roots of the quartic equation, below, are candidate solutions for \hat{Q}

$$c_5 \hat{Q}^4 + (2c_4 - c_1 - c_6) \hat{Q}^3 + (3c_2 - 3c_5) \hat{Q}^2 + (c_1 - 2c_3 + c_6) \hat{Q} - c_2 = 0$$



Initializing recursive solution

- Initialized by setting

$$x_0 = 1 \text{ and } y_0 = Q_{\text{nom}}$$

$$\sigma_{y_0}^2 = \text{uncertainty in } Q_{\text{nom}} \text{ versus } Q$$

- We assume that $\sigma_{x_0} = \sigma_{y_0}$ to be compatible with TLS for $k = 1$ (will generalize for different k later in code)
- Therefore,

$$\begin{aligned} c_{1,0} &= 1 / \sigma_{y_0}^2; & c_{3,0} &= Q_{\text{nom}}^2 / \sigma_{y_0}^2; & c_{5,0} &= Q_{\text{nom}} / \sigma_{y_0}^2 \\ c_{2,0} &= Q_{\text{nom}} / \sigma_{y_0}^2; & c_{4,0} &= 1 / \sigma_{y_0}^2; & c_{6,0} &= Q_{\text{nom}}^2 / \sigma_{y_0}^2 \end{aligned}$$



Selecting solution

- Any root the quartic equation found earlier is a possible solution for the \hat{Q} that optimizes the cost function
 - Roots may be found using closed-form Ferrari method
 - Roots may also be found via eigenvalues of a “companion matrix”
- However, of the four roots only one is optimal, and no method to decide *a priori* which to solve for
- In my experience, with some sets of data all roots are real, but with other sets of data some can be complex, and some can be negative
- Only foolproof method to determine optimizing root is to evaluate χ^2_{AWTLS} at each of the four candidate solutions, retain the one that gives lowest value (skip for negative and complex roots)



Efficiently computing cost function, Hessian

- Computing the cost function may be very readily done if we rewrite it in terms of the running summations

$$\chi^2_{\text{AWTLS}} = \frac{1}{(\hat{Q}^2 + 1)^2} (c_4 \hat{Q}^4 - 2c_5 \hat{Q}^3 + (c_1 + c_6) \hat{Q}^2 - 2c_2 \hat{Q} + c_3)$$

- When the assumptions made in deriving AWTLS are approximately true, the Hessian yields a good value for the error bounds on the total capacity estimate
- After some straightforward but messy mathematics, we can find the Hessian to be

$$\frac{\partial^2 \chi^2_{\text{AWTLS}}}{\partial Q^2} = \frac{2}{(Q^2 + 1)^4} \left(-2c_5 Q^5 + (3c_1 - 6c_4 + 3c_6) Q^4 + (-12c_2 + 16c_5) Q^3 + (-8c_1 + 10c_3 + 6c_4 - 8c_6) Q^2 + (12c_2 - 6c_5) Q + (c_1 - 2c_3 + c_6) \right)$$



Summary

- Have now found solution to AWTLS cost function
- Optimizing \hat{Q} is root of a quartic equation
 - Can be found via Ferrari method or eigenvalue method
- Must substitute solutions into cost function to choose best one
- Made efficient via recursive summations
- Hessian can also be computed using recursive sums to provide confidence bounds