Appendix 1

Let us assume that the weights on sensitivity and specificity sum to one, i.e. k and (1-k), where $0 < k < 1$. If this is not the case, we can divide k by their sum and normalize.

We are interested in finding c that maximizes

$$k \Pr ob(X > c) + (1-k) \Pr ob(Y < c)$$

or equivalently

$$k(1 - G(c)) + (1-k)F(c)$$

where G and F are cumulative distribution functions.

This yields the solution

$$\frac{f(c)}{g(c)} = \frac{k}{(1-k)}$$

Since, multiple solutions may exist (i.e. when $\sigma^2_x \neq \sigma^2_y$), only the optimal cut-point c satisfies the condition that

$$f'(c) < \left(\frac{k}{(1-k)}\right) * g'(c).$$

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For equal weight (k = 0.5), the optimal cut-point is at the intersection between the two distributions ($f(c) = g(c)$) and is subject to $f'(c) < g'(c)$. which guaranties that J would be a global maximum.