Supplement A. A heuristic procedure for score components weights assignment

To optimize the score components weights, we assume that a set of N various laboratory tests is available. Each test i produces result X_i which may be either \hat{D}_i in case of predicted death or \hat{S}_i when successful discharge is predicted. Let α_i and β_i be test i marginal false positive and false negative error rates correspondingly. To draw a final decision basing on all the tests results, the following a posteriori (AP) probability ratio may be written:

$$AP(X_{1}...X_{N}) = \frac{\Pr\{D \mid X_{1}...X_{N}\}}{\Pr\{S \mid X_{1}...X_{N}\}} = \frac{\Pr\{D\}\Pr\{X_{1}...X_{N} \mid D\}}{\Pr\{S\}\Pr\{X_{1}...X_{N} \mid S\}}$$
(A.1)

If a preliminary correlation analysis was performed and the given set of tests has a reasonably small mutual dependence, the following approximation of expression (A.1) may be proposed:

$$AP(X_1X_2...X_N) \approx \frac{\Pr\{D\} \prod_{i=1}^N \Pr\{X_i \mid D\}}{\Pr\{S\} \prod_{i=1}^S \Pr\{X_i \mid D\}}$$
(A.2)

Let's split the products in the nominator and the denominator in (A.2) into two sub-products depending on marginal decisions results:

$$\frac{\Pr\{D\}\prod_{i=1}^{N}\Pr\{X_{i}\mid D\}}{\Pr\{S\}\prod_{i=1}^{S}\Pr\{X_{i}\mid D\}} = \frac{\Pr\{D\}\prod_{X_{i}=\hat{D}_{i}}\Pr\{X_{i}\mid D\}\prod_{X_{i}=\hat{S}_{i}}\Pr\{X_{i}\mid D\}}{\Pr\{S\}\prod_{X_{i}=\hat{D}_{i}}\Pr\{X_{i}\mid S\}\prod_{X_{i}=\hat{S}_{i}}\Pr\{X_{i}\mid S\}} = \frac{\Pr\{D\}\prod_{X_{i}=\hat{D}_{i}}\Pr\{\hat{D}_{i}\mid D\}\prod_{X_{i}=\hat{S}_{i}}\Pr\{\hat{S}_{i}\mid D\}}{\Pr\{S\}\prod_{X_{i}=\hat{D}_{i}}\Pr\{\hat{D}_{i}\mid S\}\prod_{X_{i}=\hat{S}_{i}}\Pr\{\hat{S}_{i}\mid D\}}$$

$$= \frac{\Pr\{S\}\prod_{X_{i}=\hat{D}_{i}}\Pr\{\hat{D}_{i}\mid S\}\prod_{X_{i}=\hat{S}_{i}}\Pr\{\hat{S}_{i}\mid S\}}{\Pr\{S\}\prod_{X_{i}=\hat{S}_{i}}\Pr\{\hat{S}_{i}\mid S\}}$$

The substitution of α_i and β_i instead of conditional probabilities in (A.3) results in the following expression:

$$\frac{\Pr\{D\}\prod_{X_i=\hat{D}_i}\Pr\{\hat{D}_i\mid D\}\prod_{X_i=\hat{S}_i}\Pr\{\hat{S}_i\mid D\}}{\Pr\{S\}\prod_{X_i=\hat{D}_i}\Pr\{\hat{D}_i\mid S\}\prod_{X_i=\hat{S}_i}\Pr\{\hat{S}_i\mid S\}} = \frac{\Pr\{D\}\prod_{X_i=\hat{D}_i}(1-\beta_i)\prod_{X_i=\hat{S}_i}\beta_i}{\Pr\{S\}\prod_{X_i=\hat{D}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)} = \frac{\Pr\{D\}\prod_{X_i=\hat{D}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)}{\Pr\{S\}\prod_{X_i=\hat{D}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)} = \frac{\Pr\{D\}\prod_{X_i=\hat{D}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)}{\Pr\{S\}\prod_{X_i=\hat{D}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)} = \frac{\Pr\{D\}\prod_{X_i=\hat{D}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)}{\Pr\{S\}\prod_{X_i=\hat{S}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)} = \frac{\Pr\{D\}\prod_{X_i=\hat{D}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)}{\Pr\{S\}\prod_{X_i=\hat{S}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)} = \frac{\Pr\{D\}\prod_{X_i=\hat{S}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)}{\Pr\{S\}\prod_{X_i=\hat{S}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)} = \frac{\Pr\{D\}\prod_{X_i=\hat{S}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-\alpha_i)}{\Pr\{S\}\prod_{X_i=\hat{S}_i}\alpha_i\prod_{X_i=\hat{S}_i}(1-$$

The latter expression may be rewritten using indicator functions:

$$\begin{split} &\frac{\Pr\{D\}}{\Pr\{S\}} \prod_{X_i = \hat{D}_i} \left(\frac{1 - \beta_i}{\alpha_i}\right) \prod_{X_i = \hat{S}_i} \left(\frac{\beta_i}{1 - \alpha_i}\right) = \frac{\Pr\{D\}}{\Pr\{S\}} \prod_i \left(\frac{1 - \beta_i}{\alpha_i}\right)^{I\left\{X_i = \hat{D}_i\right\}} \left(\frac{\beta_i}{1 - \alpha_i}\right)^{I\left\{X_i = \hat{S}_i\right\}} = \\ &= \frac{\Pr\{D\}}{\Pr\{S\}} \prod_i \left(\frac{1 - \beta_i}{\alpha_i}\right)^{I\left\{X_i = \hat{D}_i\right\}} \left(\frac{\beta_i}{1 - \alpha_i}\right)^{I-I\left\{X_i = \hat{D}_i\right\}} = \frac{\Pr\{D\}}{\Pr\{S\}} \prod_i \left(\frac{\beta_i}{1 - \alpha_i}\right) \left[\left(\frac{1 - \beta_i}{\alpha_i}\right) \left(\frac{1 - \alpha_i}{\beta_i}\right)\right]^{I\left\{X_i = \hat{D}_i\right\}} \end{split}$$

Applying a logarithmic function to the AP ratio gives:

$$\log AP(X_1...X_N) = \log \frac{\Pr\{D\}}{\Pr\{S\}} + \sum_{i} \log \left(\frac{\beta_i}{1-\alpha_i}\right) + \sum_{i} I\{X_i = \hat{D}_i\} \log \left[\left(\frac{1-\beta_i}{\alpha_i}\right)\left(\frac{1-\alpha_i}{\beta_i}\right)\right]$$
(A.4)

A conventional classification approach consists in comparing $\log AP(X_1...X_N)$ with a threshold chosen according to a required sensitivity/specificity trade-off. As we can see, the first two components of the sum in (A.4) don't depend on values $X_1...X_N$. Thus, they may be omitted without loss of prediction efficiency. The resulting score function will be written then as follows:

$$Score = \sum_{i} I \left\{ X_{i} = \hat{D}_{i} \right\} \omega_{i}.$$

Here:

$$\omega_i = \left[\left(\frac{1 - \beta_i}{\alpha_i} \right) \left(\frac{1 - \alpha_i}{\beta_i} \right) \right]$$

In the above equation [.] denotes a rounding procedure.