## Multiple Stage Selection <br> Jack Dekkers

Multi-trait breeding goal:

$$
H=\mathrm{v}_{1} \mathrm{~g}_{1}+\mathrm{v}_{2} \mathrm{~g}_{2}+\mathrm{v}_{3} \mathrm{~g}_{3}+\ldots \ldots+\mathrm{v}_{\mathrm{n}} \mathrm{~g}_{\mathrm{n}}=\mathbf{v}^{\prime} \mathbf{g}
$$

Information sources:

$$
\mathrm{X}_{1}, \mathrm{X}_{2}, \mathrm{X}_{3}, \mathrm{X}_{4}, \ldots \ldots, \mathrm{X}_{\mathrm{m}}
$$

Multi-trait selection index: $\quad I=\mathrm{b}_{1} \mathrm{X}_{1}+\mathrm{b}_{2} \mathrm{X}_{2}+\mathrm{b}_{3} \mathrm{X}_{3}+\ldots \ldots+\mathrm{b}_{\mathrm{m}} \mathrm{X}_{\mathrm{m}}$
Optimal index weights:

$$
\mathbf{b}=\mathbf{P}^{-1} \mathbf{G} \mathbf{v}
$$

Selection on $I$ maximizes response to selection in $H$, but requires all animals to be measured for all traits.

## Multiple-stage selection:

Stage 1: select on $\quad I_{1}=\mathrm{b}_{1} \mathrm{X}_{1}+\mathrm{b}_{2} \mathrm{X}_{2}+\ldots+\mathrm{b}_{\mathrm{k}} \mathrm{X}_{\mathrm{k}} \quad=\mathbf{b}_{\mathbf{1}}{ }^{\prime} \mathbf{X}_{\mathbf{1}}$
Stage 2: select on $I_{2}=\mathrm{b}_{1} \mathrm{X}_{1}+\mathrm{b}_{2} \mathrm{X}_{2}+\ldots+\mathrm{b}_{\mathrm{k}} \mathrm{X}_{\mathrm{k}}+\mathrm{b}_{\mathrm{k}+1} \mathrm{X}_{\mathrm{k}+1}+\ldots+\mathrm{b}_{\mathrm{m}} \mathrm{X}_{\mathrm{m}}=\mathbf{b}_{\mathbf{2}}{ }^{\prime} \mathbf{X}$
Only animals that are selected in stage 1 have to be evaluated for $X_{k+1}, \ldots, X_{m}$
$\rightarrow$ Cost savings
$\rightarrow$ Opportunities to increase population size for early stages
Optimal index weights:

| Stage 1: | $I_{1}:$ | $\mathbf{b}_{\mathbf{1}}=\mathbf{P}_{11}{ }^{-1} \mathbf{G}_{1} \mathbf{v}$ |
| :--- | :--- | :--- |$\quad \mathbf{P}_{\mathbf{1 1}}=\operatorname{Var}\left(\mathbf{X}_{\mathbf{1}}\right) \quad \mathbf{G}_{\mathbf{1}}=\operatorname{Cov}\left(\mathbf{X}_{\mathbf{1}}, \mathbf{g}\right)$

Optimal weights for index $I_{2}$ are not affected by selection on $I_{1}$ in stage 1, provided all data included in $I_{1}$ is also included in $I_{2}$ (Cunningham 1975 Theor. Appl. Genet. 46:55)

But accuracy and response to selection on $I_{2}$ are affected by selection on $I_{1}$ :
Stage 1: accuracy of $I_{1:}: \quad r_{1}=\sqrt{\frac{\mathbf{b}^{\prime}{ }^{\prime} \mathbf{G}_{\mathbf{1}} \mathbf{v}}{\mathbf{v}^{\prime} \mathbf{C} \mathbf{v}}} \quad$ Trait response vector: $\boldsymbol{S}_{g, 1}=i_{1} \frac{\mathbf{b}_{\mathbf{1}}{ }^{\prime} \mathbf{G}_{1}}{\sqrt{\mathbf{b}_{1}{ }^{\prime} \mathbf{P}_{11} \mathbf{b}_{\mathbf{1}}}}$
Stage 2: accuracy of $I_{2:}: r_{2}=\sqrt{\frac{\mathbf{b}_{\mathbf{2}}{ }^{\prime} \mathbf{G}^{*} \mathbf{v}}{\mathbf{v}^{\prime} \mathbf{C}^{*} \mathbf{v}}}$ Trait response vector: $\boldsymbol{S}_{g, 2}=i_{2} \frac{\mathbf{b}_{\mathbf{2}}{ }^{\prime} \mathbf{G}^{*}}{\sqrt{\mathbf{b}_{\mathbf{2}}{ }^{\prime} \mathbf{P}^{*} \mathbf{b}_{\mathbf{2}}}}$
This assumes multi-variate normality of variables at stage 2 (despite stage 1 selection).
Total response vector across both stages: $\quad \boldsymbol{S}_{g}=\boldsymbol{S}_{g, 1}+\boldsymbol{S}_{g, 2}$
Matrices $\mathbf{P}^{*}, \mathbf{G}^{*}$, and $\mathbf{C}^{*}$ are $\mathbf{P}, \mathbf{G}$, and $\mathbf{C}$ matrices adjusted for selection on $I_{1}$

Matrix equivalent of adjustment of (co-)variance for selection on variable w (used for Bulmer effect):

$$
\sigma_{\mathrm{xy}}^{*}=\sigma_{\mathrm{xy}}-k \frac{\sigma_{\mathrm{wx}} \sigma_{\mathrm{wy}}}{\sigma_{\mathrm{w}}^{2}} \quad k=i(i-t) \quad t=\text { truncation point }
$$

Consider vectors $\mathbf{w}, \mathbf{x}, \mathbf{y} \quad$ Select on index $\mathbf{b}^{\prime} \mathbf{w}$

$$
\begin{aligned}
\operatorname{Cov}(\mathbf{x}, \mathbf{y})^{*} & =\operatorname{Cov}(\mathbf{x}, \mathbf{y})-k \frac{\operatorname{Cov}\left(\mathbf{x}, \mathbf{b}^{\prime} \mathbf{w}\right) \operatorname{Cov}\left(\mathbf{b}^{\prime} \mathbf{w}, \mathbf{y}\right)}{\operatorname{Var}\left(\mathbf{b}^{\prime} \mathbf{w}\right)} \\
& =\operatorname{Cov}(\mathbf{x}, \mathbf{y})-k \frac{\operatorname{Cov}(\mathbf{x}, \mathbf{w}) \mathbf{b b}^{\prime} \operatorname{Cov}(\mathbf{w}, \mathbf{y})}{\mathbf{b}^{\prime} \operatorname{Var}(\mathbf{w}) \mathbf{b}}
\end{aligned}
$$

With stage 1 selection on $\mathbf{b}^{\mathbf{\prime}} \mathbf{w}=\mathbf{b}_{\mathbf{1}}{ }^{\prime} \mathbf{X}_{\mathbf{1}} \rightarrow$ Matrices to use in Stage 2:

$$
\begin{aligned}
& \mathbf{P}^{*}=\operatorname{Var}(\mathbf{X})^{*}=\operatorname{Cov}(\mathbf{X}, \mathbf{X})^{*}=\mathbf{P}-k \frac{\operatorname{Cov}\left(\underline{\mathbf{X}}, \underline{\mathbf{X}}_{1}\right) \underline{\mathbf{b}}_{1} \underline{\mathbf{b}}_{1}{ }^{\prime} \operatorname{Cov}\left(\underline{\mathbf{X}}_{1}, \underline{\mathbf{X}}\right)}{\left.\underline{\mathbf{b}}_{1} \operatorname{Var}^{\operatorname{Var}} \underline{\mathbf{X}}_{1}\right) \underline{\mathbf{b}}_{1}} \\
&\left.=\mathbf{P}-k \frac{\left[\begin{array}{l}
\underline{\mathbf{P}}_{11} \\
\underline{\mathbf{P}}_{21}
\end{array}\right] \underline{\mathbf{b}}_{1} \underline{\mathbf{b}}_{1}{ }^{\prime}\left[\underline{\mathbf{P}}_{11}\right.}{} \underline{\mathbf{P}}_{21}\right] \\
& \underline{\mathbf{b}}_{1}{ }^{\prime} \underline{\mathbf{P}}_{11} \underline{\mathbf{b}}_{1} \\
& \mathbf{G}^{*}=\operatorname{Cov}(\mathbf{X}, \mathbf{g})^{*} \quad \mathbf{G}-k \frac{\operatorname{Cov}\left(\underline{\mathbf{X}}, \underline{\mathbf{X}}_{1}\right) \underline{\mathbf{b}}_{1} \underline{\mathbf{b}}_{1}{ }^{\prime} \operatorname{Cov}\left(\underline{\mathbf{X}}_{1}, \mathbf{g}\right)}{\underline{\mathbf{b}}_{1}^{\prime} \operatorname{Var}\left(\underline{\mathbf{X}}_{1}\right) \underline{\mathbf{b}}_{1}} \\
&=\mathbf{G}-k \frac{\left[\begin{array}{l}
\underline{\mathbf{P}}_{11} \\
\underline{\mathbf{P}}_{21}
\end{array}\right] \underline{\mathbf{b}}_{1} \underline{\mathbf{b}}_{1}^{\prime} \underline{\mathbf{G}}_{1}}{\underline{\mathbf{b}}_{1} \underline{\mathbf{P}}_{11} \underline{\mathbf{b}}_{1}}
\end{aligned}
$$

$$
\mathbf{C}^{*}=\operatorname{Var}(\mathbf{g})^{*}=\operatorname{Cov}(\mathbf{g}, \mathbf{g})^{*}=\mathbf{C}-k \frac{\operatorname{Cov}\left(\underline{\mathbf{g}}, \underline{\mathbf{X}}_{1}\right) \underline{\mathbf{b}}_{1} \underline{\mathbf{b}}_{1}{ }^{\prime} \operatorname{Cov}\left(\underline{\mathbf{X}}_{1}, \underline{\mathbf{g}}\right)}{\left.\underline{\mathbf{b}}_{1} \operatorname{Var}^{(\underline{\mathbf{X}}} \underline{\mathbf{X}}_{1}\right) \underline{\mathbf{b}}_{1}}
$$

$$
=\mathbf{C}-k \frac{\underline{\mathbf{G}}_{1}^{\prime} \underline{\mathbf{b}}_{1} \underline{\mathbf{b}}_{1} \underline{\mathbf{G}}_{1} \underline{\mathbf{G}}_{1}}{\underline{b}_{1}^{\prime} \underline{\mathbf{P}}_{11} \underline{\mathbf{b}}_{1}}
$$

See 2-stage selection example.xls

## Multi-stage selection with availability of multi-trait EBV:

EBV for all $m$ traits available at every stage (but with different accuracies)

- select on complete index at every stage with weights $=$ economic values

$$
I=\mathbf{v}_{1} \hat{\mathbf{g}}_{1}+\mathbf{v}_{2} \hat{\mathbf{g}}_{2}+\ldots .+\mathbf{v}_{\mathbf{n}} \hat{\mathbf{g}}_{\mathbf{n}}
$$

## Optimization of proportions selected at each stage

Total proportion selected over $s$ stages $=\mathrm{P}$
Proportion selected at stage $\mathrm{i}=\mathrm{p}_{\mathrm{i}}$

$$
\} \quad P=\prod_{i=1}^{s} \mathbf{p}_{\mathbf{i}}
$$

$\mathbf{a}_{\mathbf{i}}=$ cost of traits measured at stage i

$$
\text { Total cost }=\mathrm{TC}=\mathbf{a}_{1}+\sum_{\mathrm{i}=2}^{\mathbf{s}} \mathbf{a}_{\mathbf{i}} \prod_{\mathrm{j}=\mathbf{1}}^{\mathrm{i}-1} \mathbf{p}_{\mathbf{j}}
$$

Proportions selected and measured at each stage can then be optimized based on an overall objective function (e.g. profit) and associated responses to selection.
$\begin{gathered}\text { Selection response in stage } \mathbf{2} \text { predicted by } \\ \text { assumes multivariate normality }\end{gathered} \quad \boldsymbol{S}_{g, 2}=i_{2} \frac{\mathbf{b}_{2} \mathbf{}^{\prime} \mathbf{G}^{*}}{\sqrt{\mathbf{b}_{2}{ }^{\prime} \mathbf{P}^{*} \mathbf{b}_{\mathbf{2}}}}$
But, selection in stage 1 not only reduces variances but also introduces skewness, depending on the correlation between $I_{1}$ and $I_{2}$.

Accounting for skewness requires integration of multivariate normal distributions, or Monte Carlo simulation.

See Ducroq and Colleau (1986 GSE 18:447)
Jopson et al. (2004, Proc. New Zealand Soc. Anim. Prod. 64: 217)
This has been implemented in SelAction

## References:

Cunningham (1975), Theor. Appl. Genet. 46:55
Ducrocq and Colleau (1989) Genet. Sel. Evol. 21:185
Xu and Muir (1991) Genetics 129:963
Xu and Muir (1992) Theor. Appl. Genet. 83:451
Xu, Martin, and Muir (1995) J. Anim. Sci. 73:699

