Notation:  $Y = (Y_1, Y_2, \dots, Y_n)^T \in \mathbb{R}^N$  and  $U = (U_1, U_2, \dots, U_q)^T \in \mathbb{R}^q$  are random vectors (response and random/mixed effects); their realizations are denoted  $y = (y_1, y_2, \dots, y_n)^T$  and  $u = (u_1, u_2, \dots, u_q)^T$ ;  $\beta \in \mathbb{R}^p$  is the vector of fixed effects;  $X \in \mathbb{R}^{n \times p}$  and  $Z \in \mathbb{R}^{n \times q}$  are model matrices, where  $x_i^T$  or  $z_i^T$  denote the *i*th row of X or Z respectively. Generalized linear mixed model (GLMM):  $(Y_i|U=u) \sim \text{indep.} f_{Y_i|U}(y_i|u) \text{ for } i \in \{1, 2, ..., n\}, \ U \sim f_U(u).$  $f_{Y_i|U}(y_i|u) = h(y_i) \exp\left(\langle T(y_i), \eta \rangle - A(\eta)\right),$  $\mu_i = \mathrm{E}(Y_i|U=u) = f(\eta),$  $g(\mu_i) = x_i^T \beta + z_i^T u.$ Normality Z = 0Linear mixed model (LMM): Generalized linear model (GLM):  $(Y|U=u) \sim \mathcal{N}(X\beta + Zu, \sigma^2 I),$  $Y_i \sim \text{indep.} f_{Y_i}(y_i) \text{ for } i \in \{1, 2, \dots, n\},\$  $U \sim \mathcal{N}(0, \Sigma(\theta)).$  $f_{Y_i}(y_i) = h(y_i) \exp(\langle T(y_i), \eta \rangle - A(\eta)),$ Solution:  $\mu_i = \mathrm{E}(Y_i) = f(\eta),$  $\hat{\beta}_{ML} = (X^T \hat{V}^{-1} X)^{-1} X^T \hat{V}^{-1} y$  is MLE, where  $g(\mu_i) = x_i^T \beta.$  $\hat{V} = Z \Sigma_{\hat{\theta}_{ML}} Z^T + \hat{\sigma}_{ML}^2 I$  is MLE of Var(Y). Normality Z = 0Linear model (LM):  $Y \sim \mathcal{N}(X\beta, \sigma^2 I)$ . Closed form solution:  $\hat{\beta} = (X^T X)^{-1} X^T y$  is MLE, UMVU and BLUE. Normality,  $\lambda = 0$ Normality,  $\lambda = 0$ Ridge regression: LASSO:  $E(Y) = X\beta$ , tuning parameter  $\lambda \ge 0$ ,  $E(Y) = X\beta$ , tuning parameter  $\lambda \geq 0$ ,  $\hat{\beta} = \operatorname{argmin}_{b \in \mathbb{R}^p} \left\{ \frac{1}{2n} \|y - Xb\|_2^2 + \lambda \|b\|_2^2 \right\}.$  $\hat{\beta} = \operatorname{argmin}_{b \in \mathbb{R}^p} \left\{ \frac{1}{2n} \|y - Xb\|_2^2 + \lambda \|b\|_1 \right\}.$ Closed form solution:  $\hat{\beta} = (X^T X + \lambda I)^{-1} X^T y.$ Elastic net:

 $E(Y) = X\beta$ , tuning parameters  $\lambda \ge 0$  and  $\alpha \in [0, 1]$ ,  $\hat{\beta} = \operatorname{argmin}_{b \in \mathbb{R}^p} \left\{ \frac{1}{2} \|y - Xb\|_2^2 + \lambda \left[ \frac{1}{2} (1 - \alpha) \|b\|_2^2 + \alpha \|b\|_1 \right] \right\}$ .