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): $(Y_i|U=u) \sim \text{indep.} f_{Y_i|U}(y_i|u) \text{ for } i \in \{1, 2, ..., n\}, \ U \sim f_U(u).$ $f_{Y_i|U}(y_i|u) = h(y_i) \exp\left(\langle T(y_i), \eta \rangle - A(\eta)\right),$ $\mu_i = \mathrm{E}(Y_i|U=u) = f(\eta),$ $q(\mu_i) = x_i^T \beta + z_i^T u.$ 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: $E(Y_i) = X\beta$, tuning parameter $\lambda \geq 0$, $E(Y_i) = X\beta$, 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: $E(Y_i) = X\beta, \text{ tuning parameters } \lambda \geq 0 \text{ and } \alpha \in [0, 1],$ $\hat{\beta} = \operatorname{argmin}_{b \in \mathbb{R}^p} \left\{ \frac{1}{2} \|y - Xb\|_2^2 + \lambda \left[\frac{1}{2} (1 - \alpha) \|b\|_2^2 + \alpha \|b\|_1 \right] \right\}.$