Description of example system of linear models.

We define M , the family of linear models as

$$
\{ \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon} | \beta_{i\cdots jv} \neq 0 \Rightarrow (\beta_i \neq 0, \cdots, \beta_v \neq 0, \cdots, \beta_{i\cdots j} \neq 0) \}.
$$

Here, y is $n \times 1$ vector of response variables, X is $n \times p$ matrix of predictor variables, β is $p \times 1$ vector of model parameters, and ϵ is $n \times 1$ vector of random errors satisfying the Gauss-Markov conditions $\mathbb{E}(\epsilon_i) = 0$, $\text{Var}(\epsilon_i) = \sigma^2$, and $Cov(\epsilon_i, \epsilon_j) = 0$ for all i, j. M contains L linear models with up to k factors subject to the constraint $\beta_{i\cdots j\nu}\neq 0 \Rightarrow (\beta_i \neq 0, \cdots, \beta_{i\cdots j}\neq 0)$ which guarantees that if a model contains a v–way ($v \leq k$) interaction term of v factors in the model, then all $(v - 1)$ –way, $(v - 2)$ –way, \dots , 2–way interactions of those factors and their main effects are included in the model. We include the predictor x_1 and the response variable y in all models reflecting our assumption that all scientists in the community focus on a research question that involves at least one common factor of interest and a common response variable. Let $M_i \in \mathcal{M}$ be a model with p_i parameters of which v_{ℓ_i} is the highest order interaction term with order ℓ_i denoting the order, $\#v_{\ell_i}$ is the cardinality of v_{ℓ_i} . Let $M_i \succ M_j$ denote that M_i is more complex than M_j . We define the *model complexity* as a partial ordering obeying three conditions:

- 1. If $p_i > p_j$ then $M_i \succ M_j$.
- 2. If $p_i = p_j$ and $\ell_i > \ell_j$, then $M_i \succ M_j$.
- 3. If $p_i = p_j$, $\ell_i = \ell_j$, and $\#v_{\ell_i} > \#v_{\ell_j}$, then $M_i \succ M_j$.

Otherwise, we say that complexities of M_i and M_j are indistinguishable.