**Methods**

I used extreme gradient boosted models (XGBMs) to identify important predictors, particularly interaction predictors, of tarsus length and weight at day 14. XGBMs are a decision tree based machine learning technique, where variable importance is determined by how often that variable is used as a branching criterion across many distinct trees. Despite being a black box algorithm, XGBMs produce metrics that tell the user how important individual variables, and even interactions, are.

I scaled all variables in the dataset and split the scaled dataset into training and testing halves, which allowed me to explore what models might fit best in the training set, and then test the final models in the testing set. I trained separate XGBMs for tarsus length and weight as outcomes. Hyperparameter tuning for each model was carried out sequentially, as written in the analytic code. Once the hyperparameters that yielded the lowest cross valid error in the training sample were determined, the resultant XGBM for each outcome was examined. The key output of the models was variable importance. Informed by variable importance, I built separate LMMs of the most important main effects, two way, and three way interactions. Since the influence by competition with siblings was a key component of the research question, I particularly investigated interactions that included the variables “net\_rearing\_manipulation” and “rear\_Cs\_at\_start\_of\_rearing”. If an effect was significant in the basic LMMs, it was included (along with main effects in the case of interactions) in comprehensive linear mixed multiple regression models that included all significant effects, one model for each outcome. These models were reduced by eliminating variables that were no longer significant, and refit. These reduced models were refit in the test subset, and the contribution of significant effects were evaluated on this basis.