



# COMPARISON OF METHODS TO VALIDATE THE PREDICTION OF HAM AND BELLY COMPOSITION BY MAGNETIC INDUCTION SCANNER



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Statistical validation is an important stage in testing a technology, but there is no consensus on a method. The objective of this study was to compare the performance of five prediction methods of the composition of hams and bellies by magnetic induction. Magnetic induction, which principle takes advantage of the dielectric properties of tissues, was tested by Simoncini et al. (2012) on hams and by Daumas et al. (2019) on bellies and hams.

## Material and Methods

- Two samples: one of 100 hams and the other of 80 bellies
- Analyzed by a magnetic induction scanner (HAM-Inspector II), developed by Lenz Instruments S.L. (Barcelona, Spain) (Fig. 1)
- Measured by computed tomography (reference) (Fig. 2)



Fig. 1 – Magnetic induction scanner



Fig. 2 – CT Scanner (X-Ray)

- 4 response variables for each primal cut:
  - weight of muscle and weight of fat,
  - muscle content and fat content.
- Numerous collinear explanatory variables
- Calculation of  $R^2$  and prediction error in a 10-fold cross validation repeated 100 times with random division of the data into 10 segments.
- Comparison with R software of 5 linear regression methods:
  - OLS** : estimation by the usual ordinary least squares method;
  - Lasso** : minimization of the ordinary least squares criterion penalized by a term proportional to the sum of absolute values of regression coefficients, with choice of the penalization parameter by minimization of prediction error;
  - Ridge** : minimization of the ordinary least squares criterion penalized by a term proportional to the sum of squares of regression coefficients, with choice of the penalization parameter by minimization of prediction error;
  - PLS** : partial least squares, with choice of the number of components by minimization of prediction error;
  - Subset** : minimization of the Bayesian information criterion (BIC) on all possible sub-models.

## References

- Daumas, G., Monziols, M., Rodriguez, J. M., Álvarez-García, J., & Causeur, D. (2019). Estimation of the tissue composition of hams and bellies by magnetic induction. *Journées Rech. Porcine*, 51, 339-344.
- Simoncini, N., Virgili, R., Schivazappa, C., Pinna, A., Rossi, A., Alvarez, J., & Rodríguez, J. M. (2012). Assessment of fat and lean content in Italian heavy green hams by means of on-line non-invasive techniques. *Proceedings of the 58th ICoMST, Montréal, Canada, ID CARCASSP-12.*

## Conclusion

The differences in cross-validated  $R^2$  between the five statistical methods tested were found to be substantial. Of the five methods, none proved to be the best on both ham and belly samples. The ranking of methods based on their prediction performance depended on the cut. Subset, Ridge and Lasso seemed to show the most stable prediction performance results among the cuts and response variables, always being close or equal to the best performance.

## Results

### For Hams (Fig. 3):

- The highest difference of median  $R^2$  between methods was 0,14 (for muscle %);
- PLS was the best method and OLS the worst;
- PLS showed the lowest variability and OLS the highest.

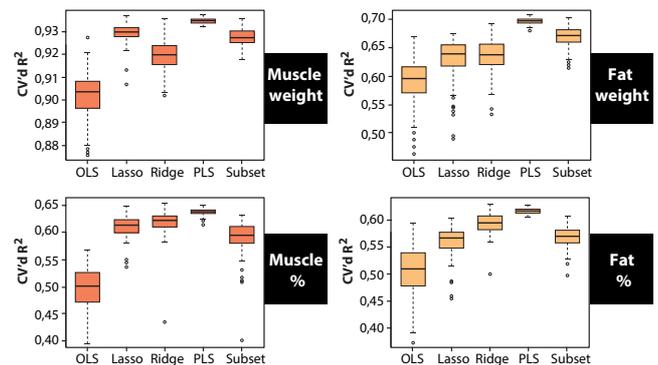


Fig. 3 – HAM: Distribution of cross-validated  $R^2$  by prediction method

### For Bellies (Fig. 4):

- The highest difference of median  $R^2$  between methods was 0,22 (for muscle weight)
- PLS was the worst method, Ridge the best, except for fat % (Subset the best);
- The lowest variability was with PLS for fat and muscle contents.

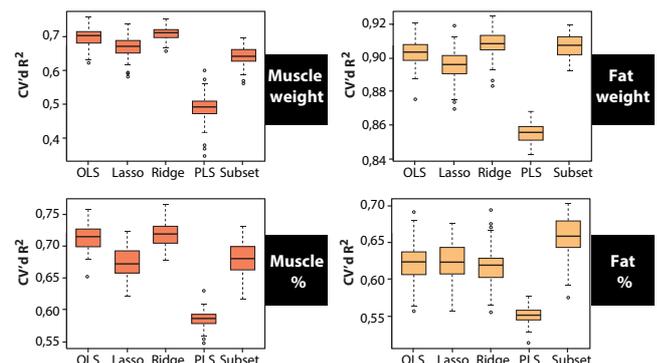


Fig. 4 – BELLY: Distribution of cross-validated  $R^2$  by prediction method