Statistical challenges for the red meat industry

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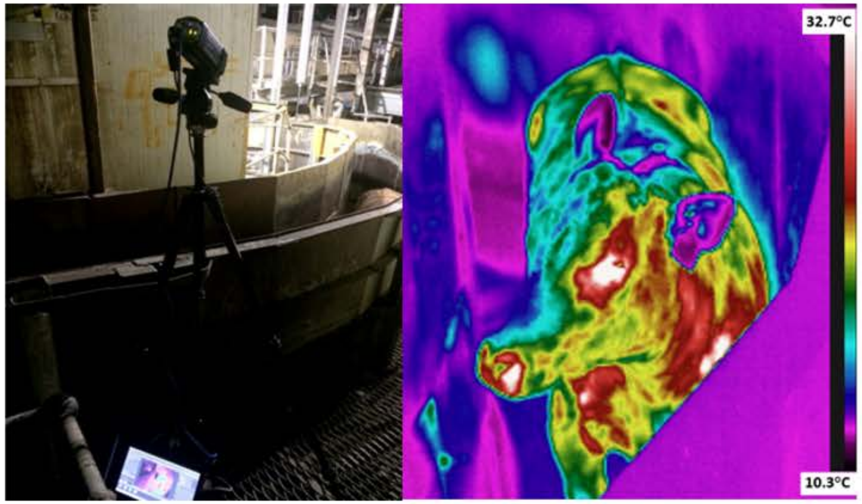
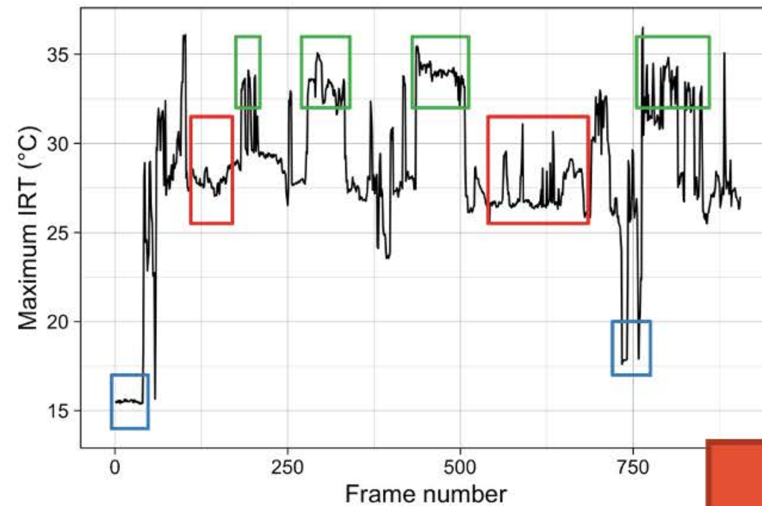
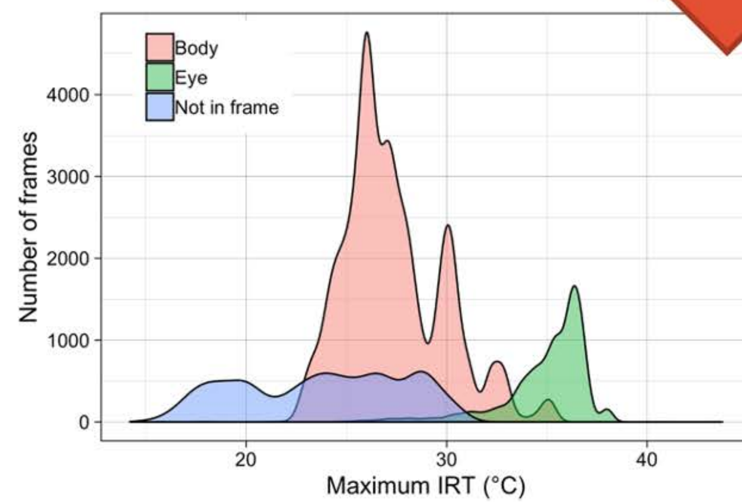
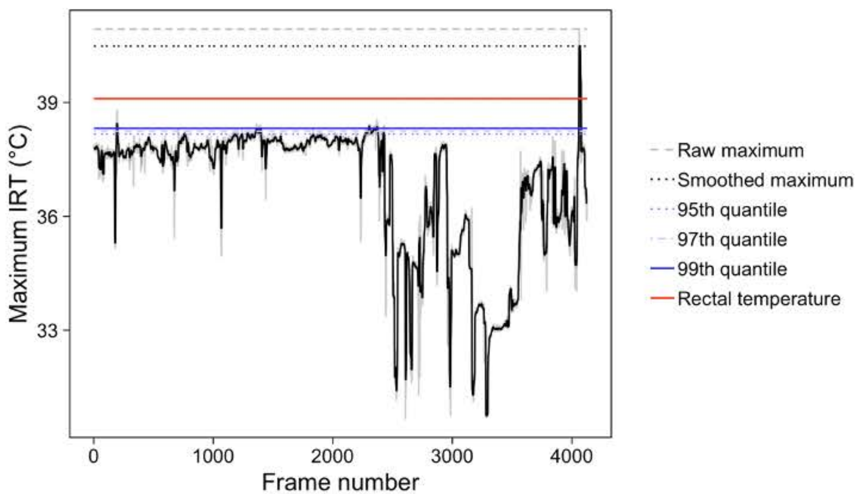
Animal welfare

Analysis of infrared video thermography



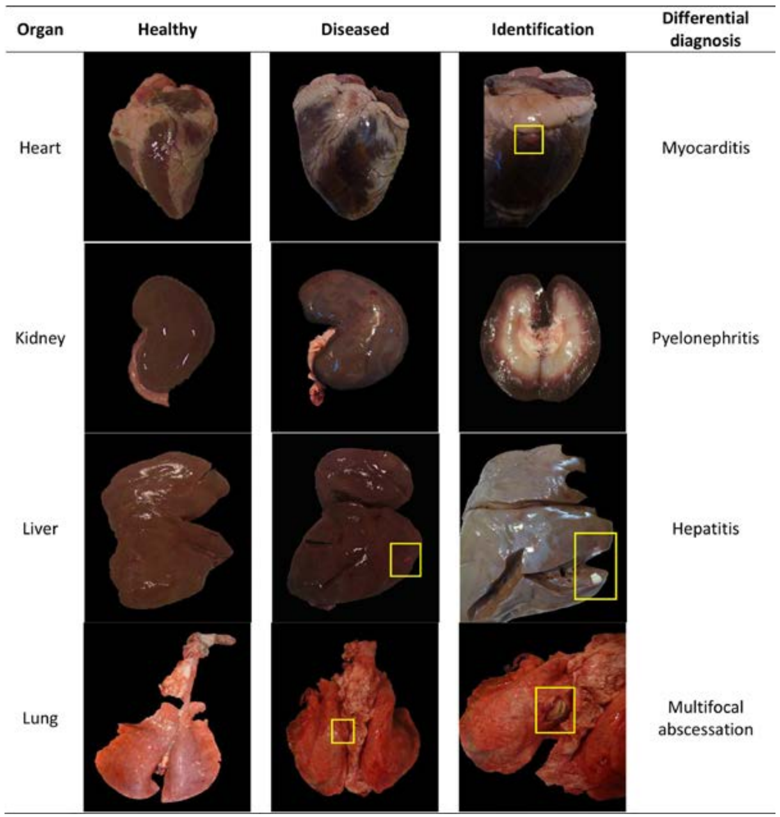


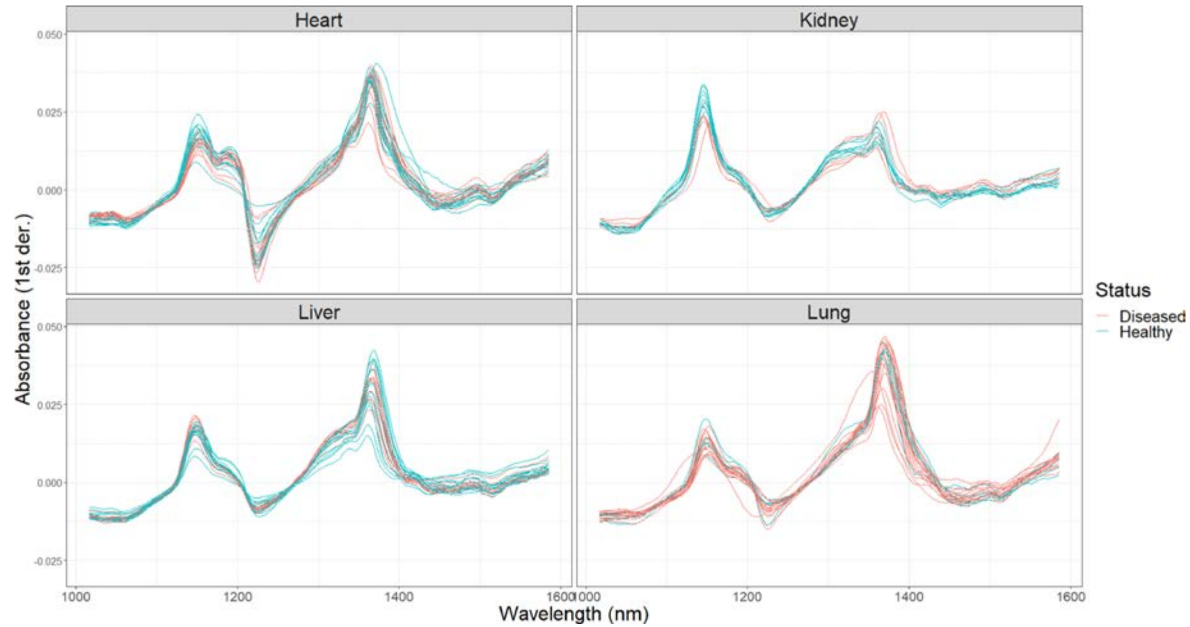




Cuthbertson et al. (2019)

Automatic detection of diseased organs using hyperspectral imaging sensors



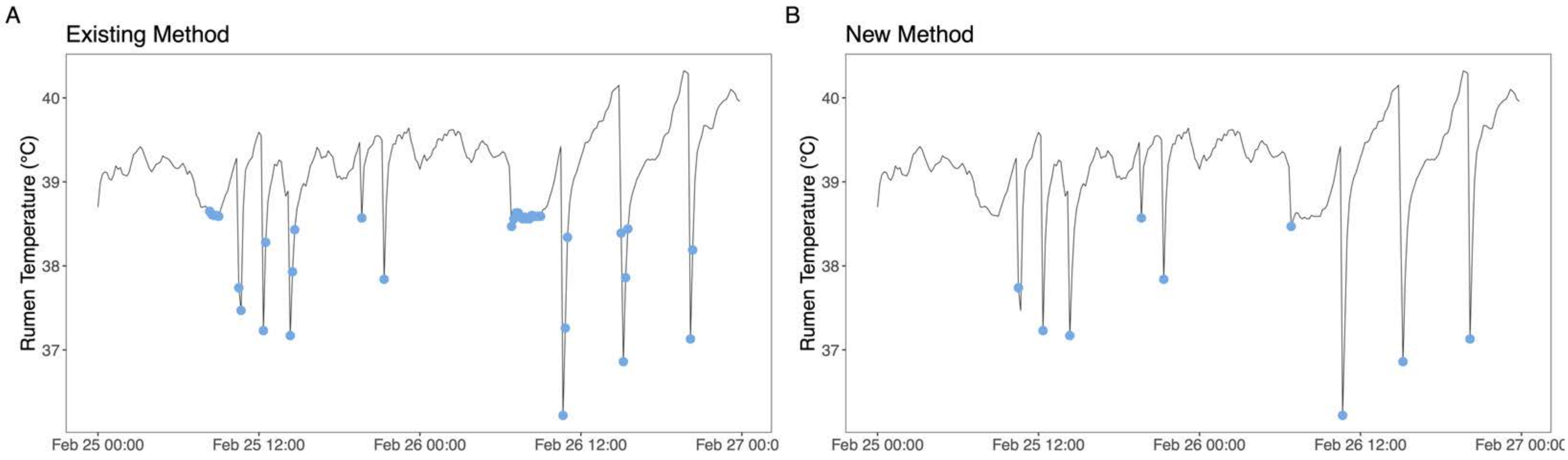


Coombs et al. (2023)

Evaluation of shade and shelter solutions

Evaluation of shade and shelter solutions

- Standard component: differences in outcomes between treatment groups
- Exciting component: boluses in 90 or 180 animals giving 10 minute internal temperature measurements for 100 days.
  - Creating synthetic data to “fill in” missingness
  - Using robust methods to improve drinking event detection (with Rajan Shankar)



Health and welfare data

A lot of information…

- ailments
- treatments/medication
- outcomes

Challenges

- data quality and linkage
- presence only data
- rare events

Eating quality

Meat Standards Australia eating quality model

> **Aim**
>
> Predict the **consumer experience** based on what is observable at the farm/abattoir.

Beef

- 3k trials each with 60 consumers
- 180k consumers who each tasted 7 samples
- 1.2m samples eaten

Sheep

- 594 trials each with 60 consumers
- 594 x 60 = 35,640 consumers who each tasted 7 samples
- 35,640 x 7 = **249,480** samples eaten

Why?

Meat Standards Australia deliv... ×

mla.com.au/news-and-events/industry-news/meat-standards-australia-delivers-another-record-year-for-producers/

Meat Standards Australia delivers another record year for producers

13 October 2022

Australia's world-leading eating quality grading program, Meat Standards Australia (MSA), continues to deliver significant benefits and value to the red meat industry, from the farm gate through to the consumer's plate, according to Meat & Livestock Australia (MLA).

In financial year 2021–2022, the MSA program delivered a record $204 million in estimated additional farm gate returns to MSA beef producers, a significant increase from the estimated $157m delivered in 2020–2021, and more than the previous record high of $198 million in 2018–2019.

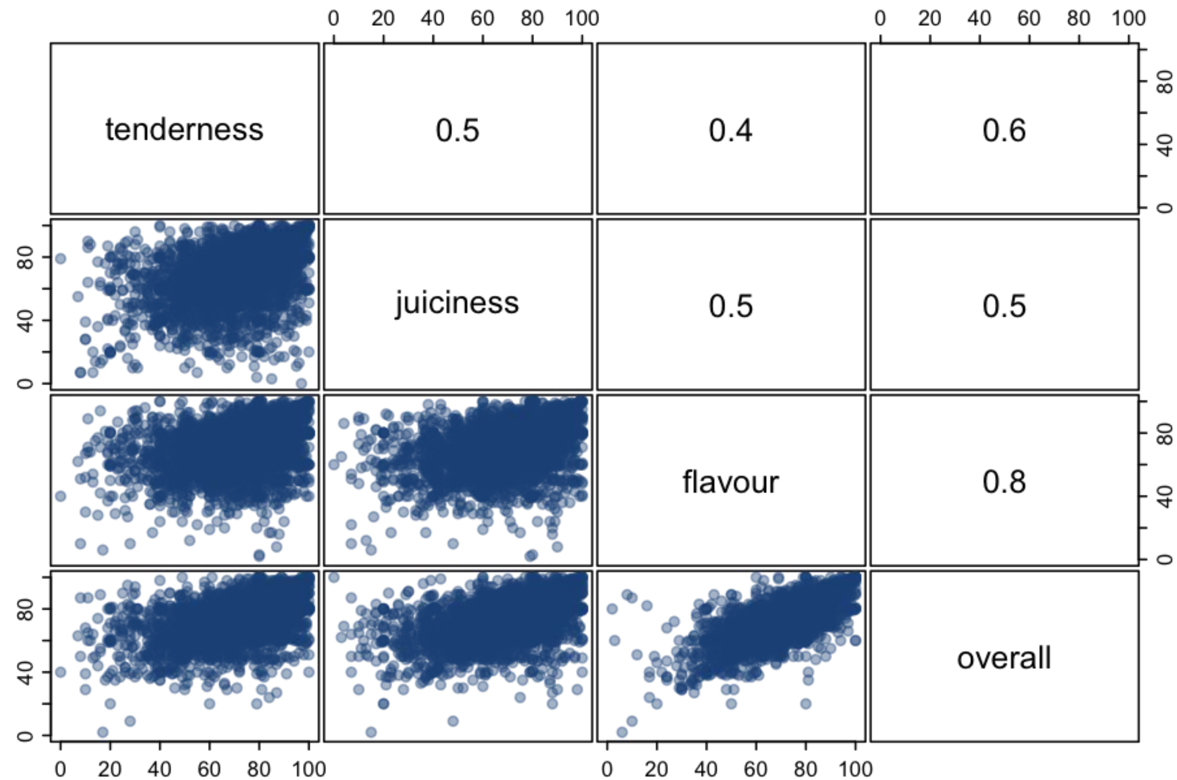
MSA graded cattle continue to represent more than half of the national adult cattle slaughter at another record of 55% in 2021–2022, up from 53% in 2020–2021. More than 3.25 million cattle were MSA graded through 39 Australian beef processors in 2021–2022, with an equal highest national MSA compliance of 95.5%.

FEEDBACK

How?

Target variable: eating quality

- 10 untrained consumers eat each sample (muscle) cooked to a certain protocol
- Consumers rate the sample on a scale from 0-100 on:
    - Tenderness
    - Juiciness
    - Flavour liking
    - Overall liking

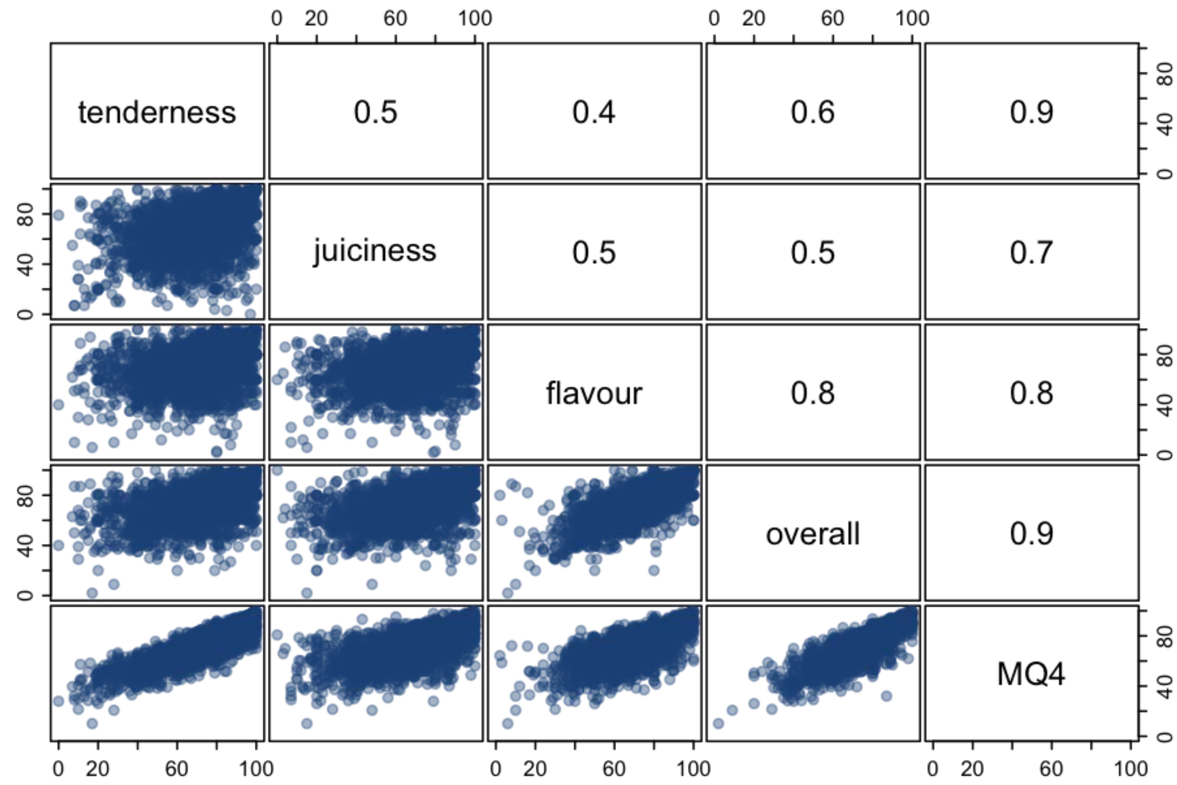


Clearly some outliers present!

Target variable: eating quality

A weighted average is calculated to get an overall MQ4 score.

> ! Predicting eating quality ≈ predicting MQ4 score



Model scope

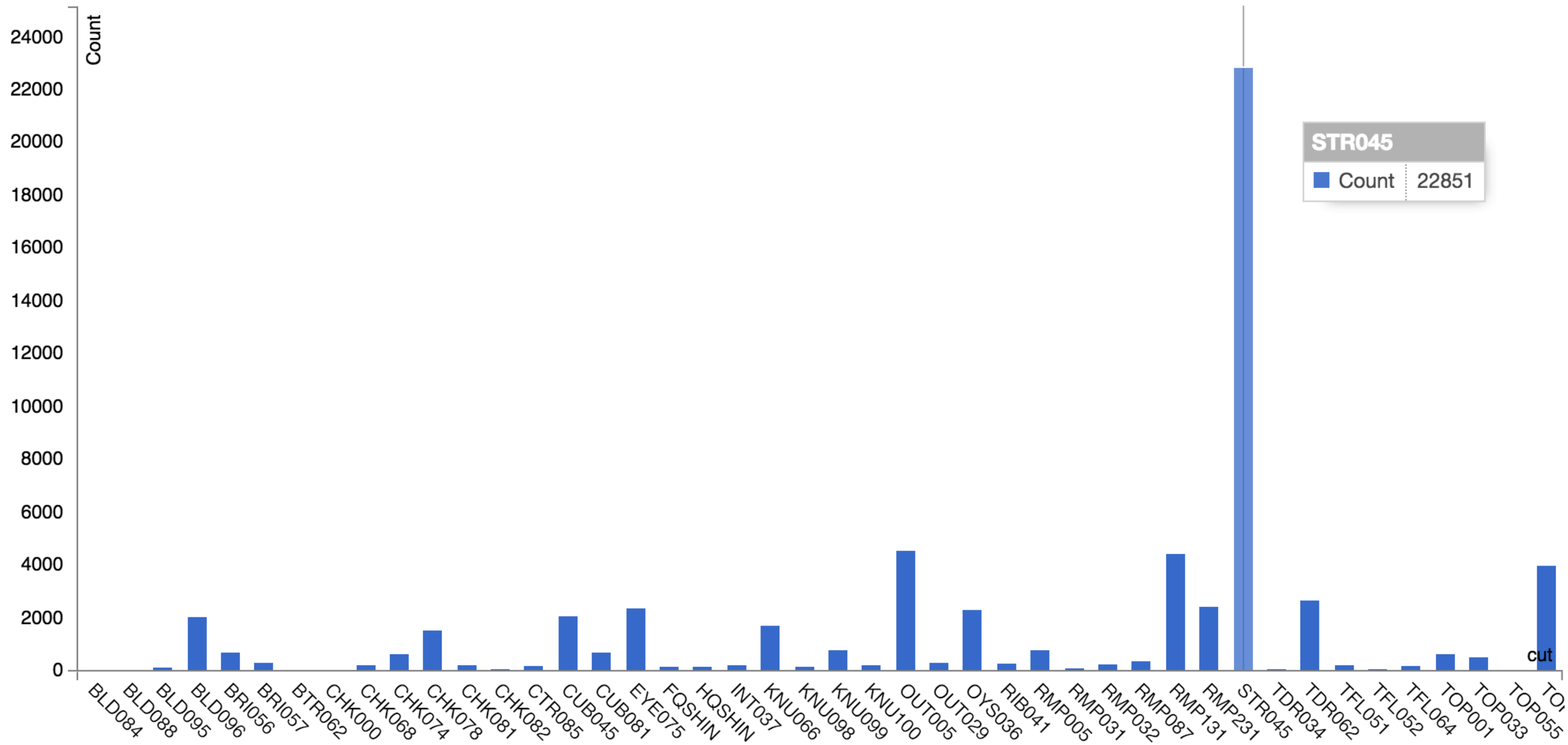
- A "separate" model for each muscle by cook combination
  - 70+ distinct muscles
  - 8+ cooking protocols
    - Grill, roast, slow cook, stir fry, shabu shabu, yakiniku, sous vide...
- 300+ models in total

Models take the form:

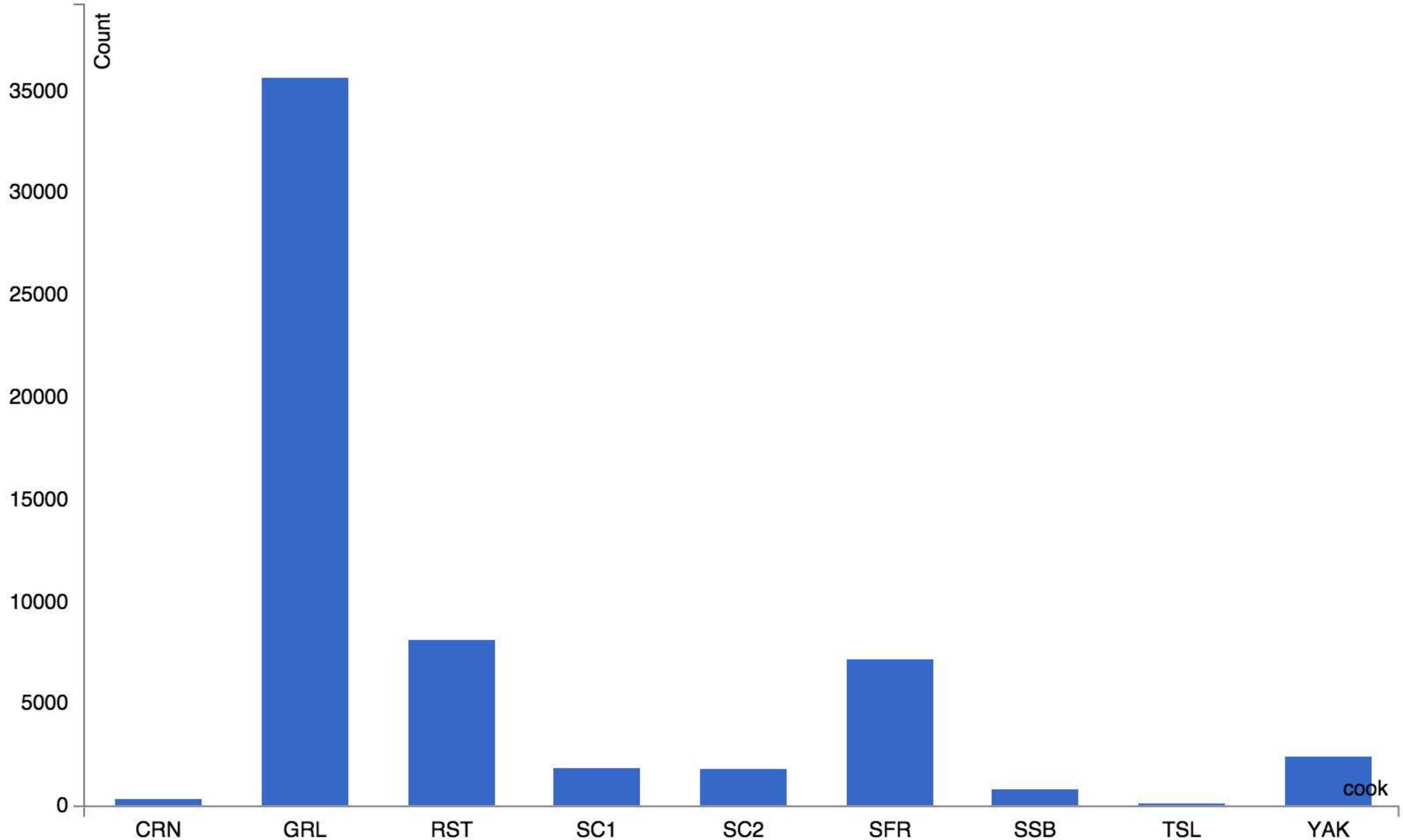
$$\begin{aligned}\text{predicted MQ score } = \text{MQ}_0 + f(&\text{marbling, sex, pH, feed type,}\\ &\text{HGP, hump height, maturity,}\\ &\text{carcase weight, hang method, days aged})\end{aligned}$$

Seems straightforward enough...

Challenge 1: unbalanced data across muscles



Challenge 2: unbalanced data across cooks



Challenge 3: unbalanced covariates

$$\begin{aligned}\text{predicted MQ score } = \mathrm{MQ}_0 + f(&\text{marbling, sex, pH, feed type,}\\ &\text{HGP, hump height, maturity,}\\ &\text{carcase weight, hang method, days aged})\end{aligned}$$

- Vast majority of hangs are of one type (Achilles hang)
- Missing & unbalanced hormone growth promotant (HGP) data
- Don't always have adequate variation in the other covariates
- Opportunistically collected data over 20 years

A standard modelling process won't work

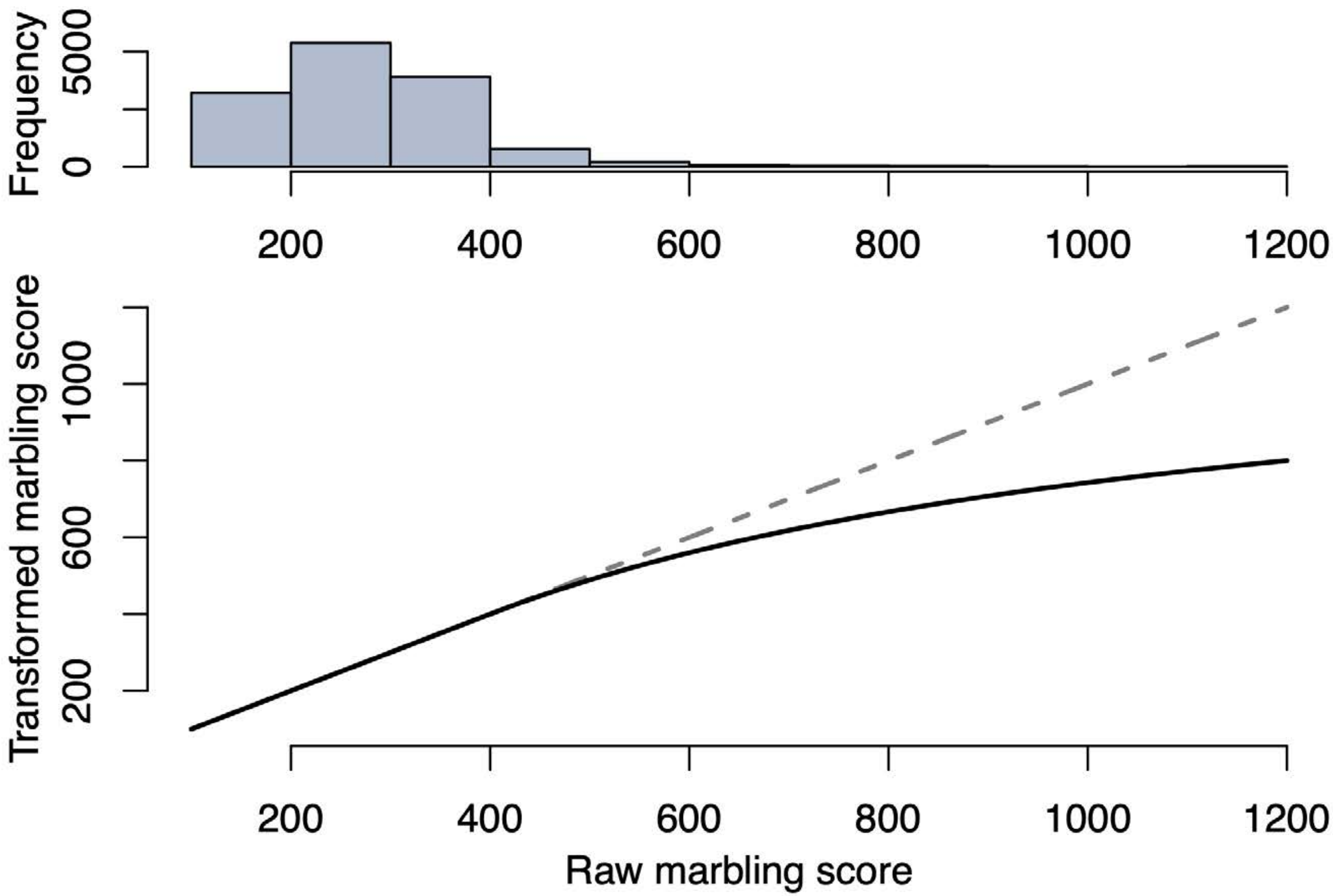
Core principle 1: borrow strength from similar cooks and muscles

- Assume that the effects of the covariates are similar within blocks of muscle x cook cells.
- Reflects similarities in muscle type, position, …
- In the current process, the effect of each predictor is (manually) adjusted to ensure internal consistency of the model.

Core principle 2: underpinned by scientific research

- The model must reflect scientific truths and empirical observations.
- **Scientific truths:**
  - maturity ⬆️ $\implies$ eating quality ⬇️
  - marbling ⬆️ $\implies$ eating quality ⬆️
  - days aged ⬆️ $\implies$ eating quality ⬆️
- **Empirical observations:**
  - hormone growth promotant used $\implies$ eating quality ⬇️

Transformations



Goal

- Avoid a manual and tedious process of model building
- A data driven way to “borrow strength” from similar classes
- Maintain the assumption that effects of covariates are similar within classes
- Let domain experts contribute their wisdom

Regularised learning

Multiclass model

Consider the following multi-class multiple linear regression model for M classes

$$y_i^{(m)} = \mathbf{x}_i^{(m)\top} \boldsymbol{\beta}^{(m)} + \varepsilon_i^{(m)} \quad \text{for } m = 1 \ldots, M.$$

The parameter vector, $\boldsymbol{\beta}^{(m)}$, contains all p regression coefficients for the mth class. Define the multiclass regression parameter vector,

$$\boldsymbol{\beta} = (\boldsymbol{\beta}^{(1)\top}, \ldots, \boldsymbol{\beta}^{(M)\top})^\top.$$

We define its estimator as

$$\widehat{\boldsymbol{\beta}}_\lambda = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \; \frac{1}{2} \sum_{m=1}^{M} \sum_{i=1}^{n_m} (y_i^{(m)} - \mathbf{x}_i^{(m)\top} \boldsymbol{\beta}^{(m)})^2 + \lambda \sum_{m<m'}^{M} \sum_{j=1}^{p} w_j^{(m,m')} |\beta_j^{(m)} - \beta_j^{(m')}$$

Where $\lambda > 0$ is a regularisation parameter and $w_j^{(m,m')}$ are weights for each pair of muscle$\times$cook combinations m and m'.

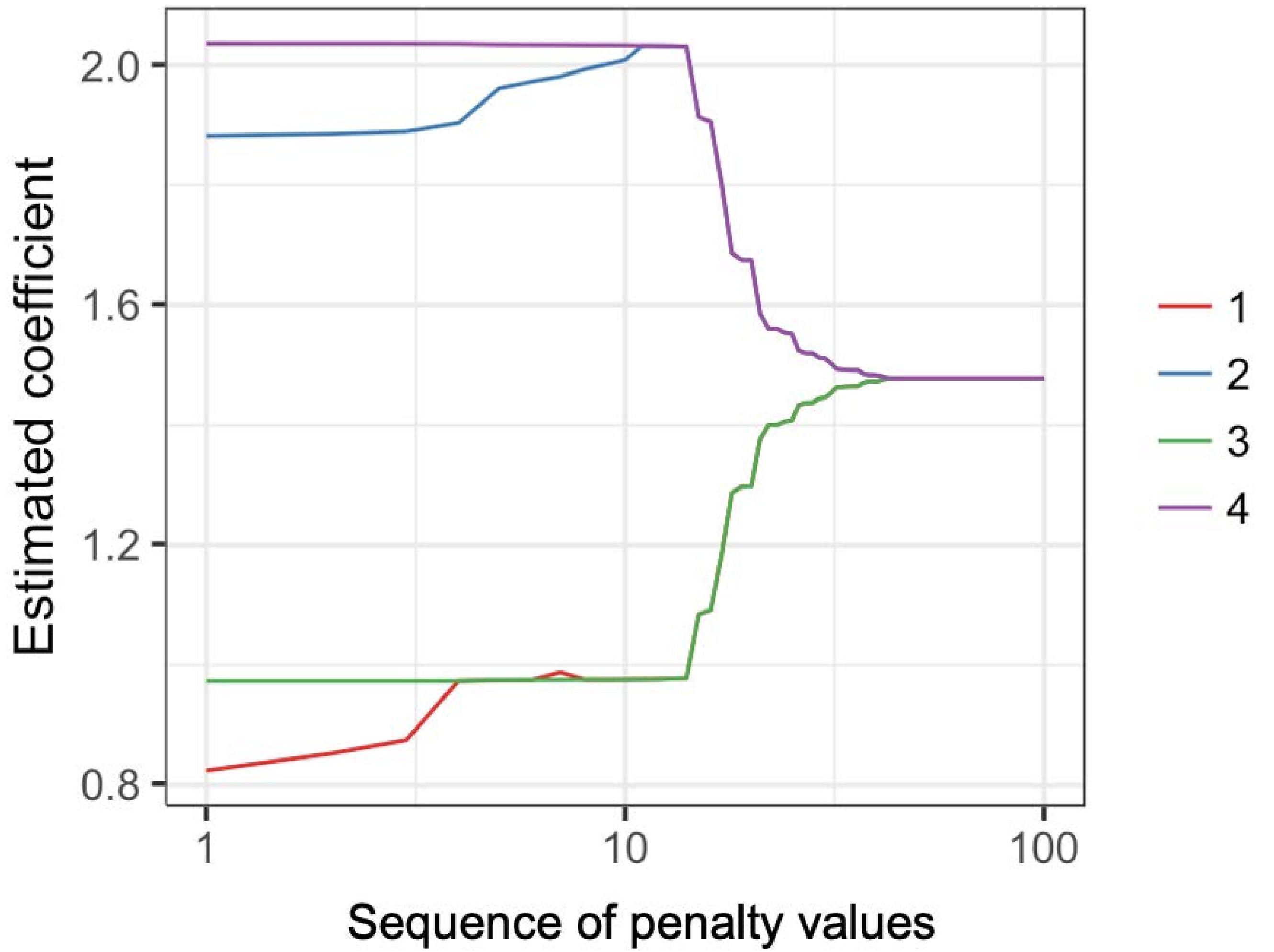
Regularisation to the rescue

$$\widehat{\boldsymbol{\beta}}_\lambda = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \ \frac{1}{2}\sum_{m=1}^{M}\sum_{i=1}^{n_m}(y_i^{(m)} - \mathbf{x}_i^{(m)\top}\boldsymbol{\beta}^{(m)})^2 + \lambda \sum_{m<m'}^{M}\sum_{j=1}^{p} w_j^{(m,m')}|\beta_j^{(m)} - \beta_j^{(m')}$$

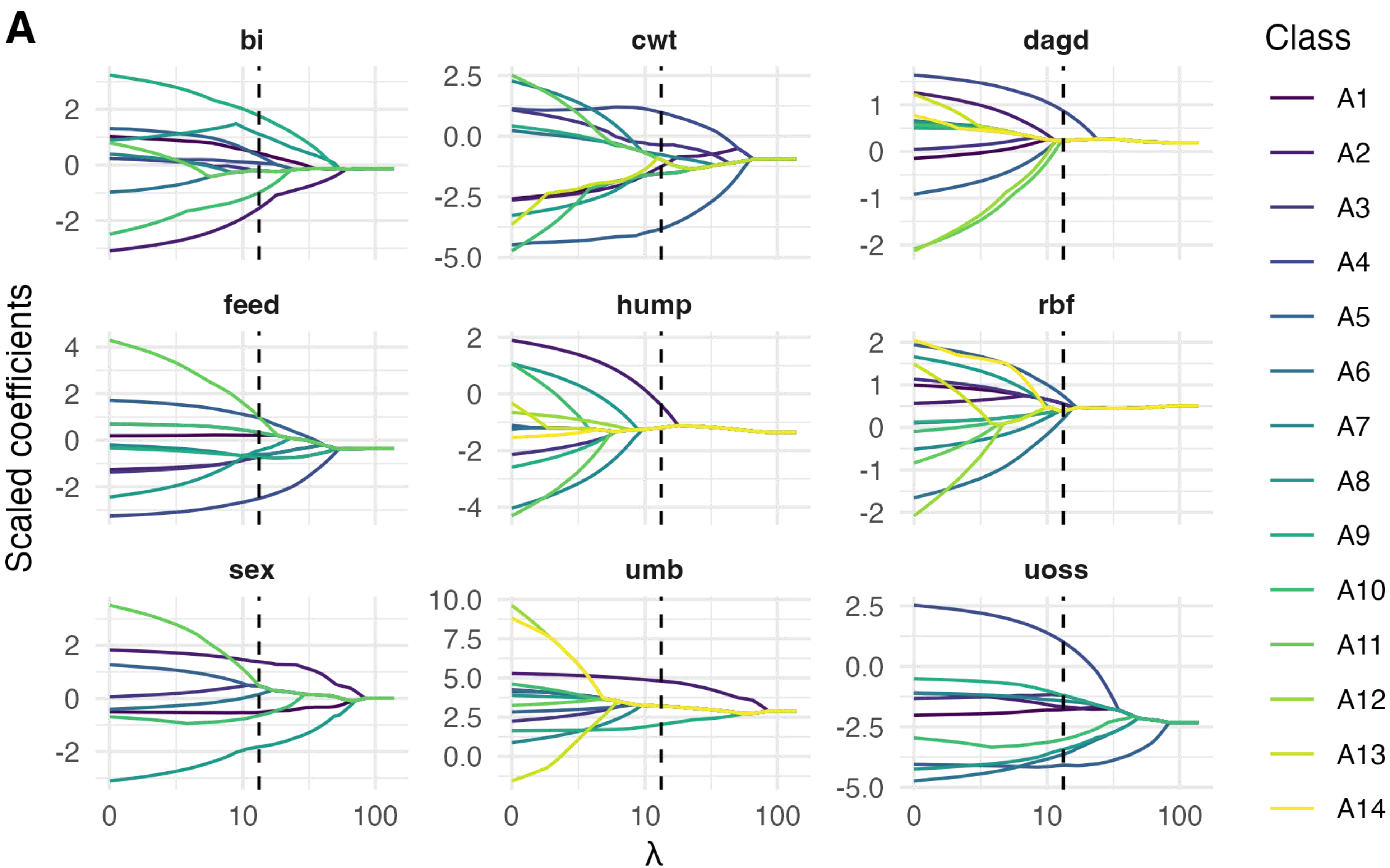
- Similarity across classes is induced via a fused-lasso type penalty, i.e. absolute value of the differences of corresponding regression parameters (Tibshirani et al., 2005).
- The larger the value of λ, the greater the pressure of zero differences between corresponding regression coefficients
  - For $\lambda = 0 \implies$ separate least squares estimator
  - As $\lambda \to \infty \implies$ pooled least squares estimator

Example coefficient paths

- Classes 1 and 3 have the same data generating process
- Classes 2 and 4 have the same data generating process
- Different values of the penalty encourage different levels of similarity



Eating quality example



Tarr & Wilms (2022)

Pros and cons

Advantages of a multi-class approach

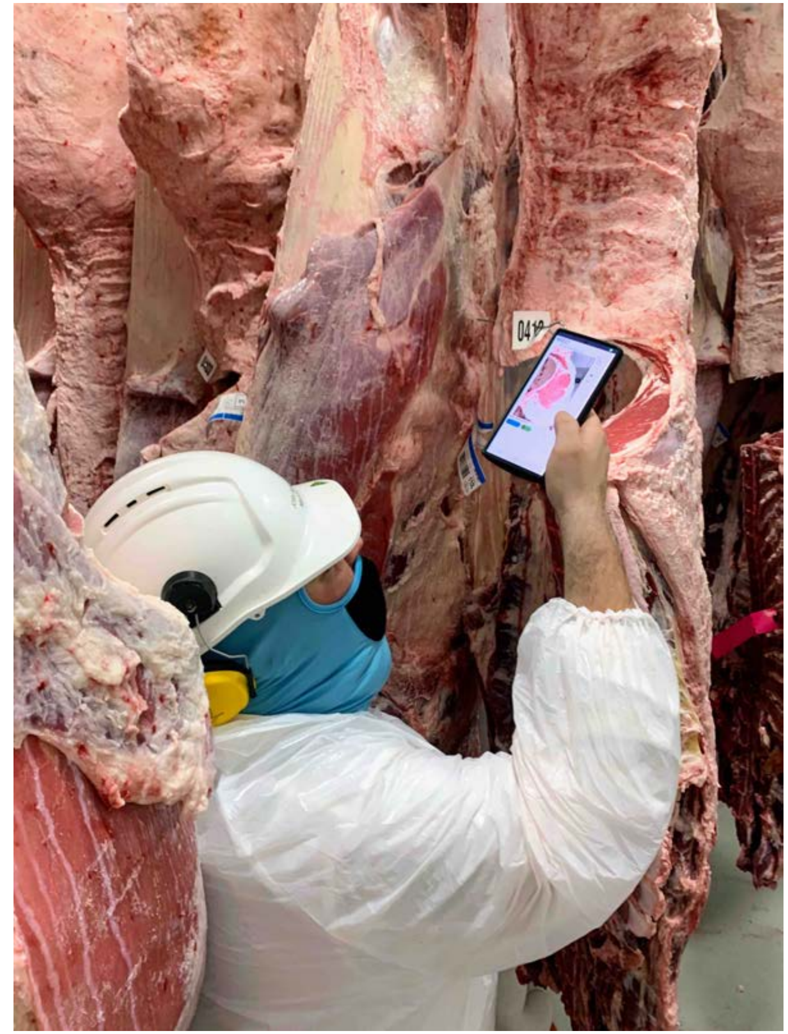
- Data driven approach to modelling a very complex scenario
- Perform at least as good as the current approach (pooled or separate, manually adjusted)

Limitations of a multi-class approach

- Signal to noise ratio
- Slow for large number of classes
- Modelling with too many disparate classes leads to the null model

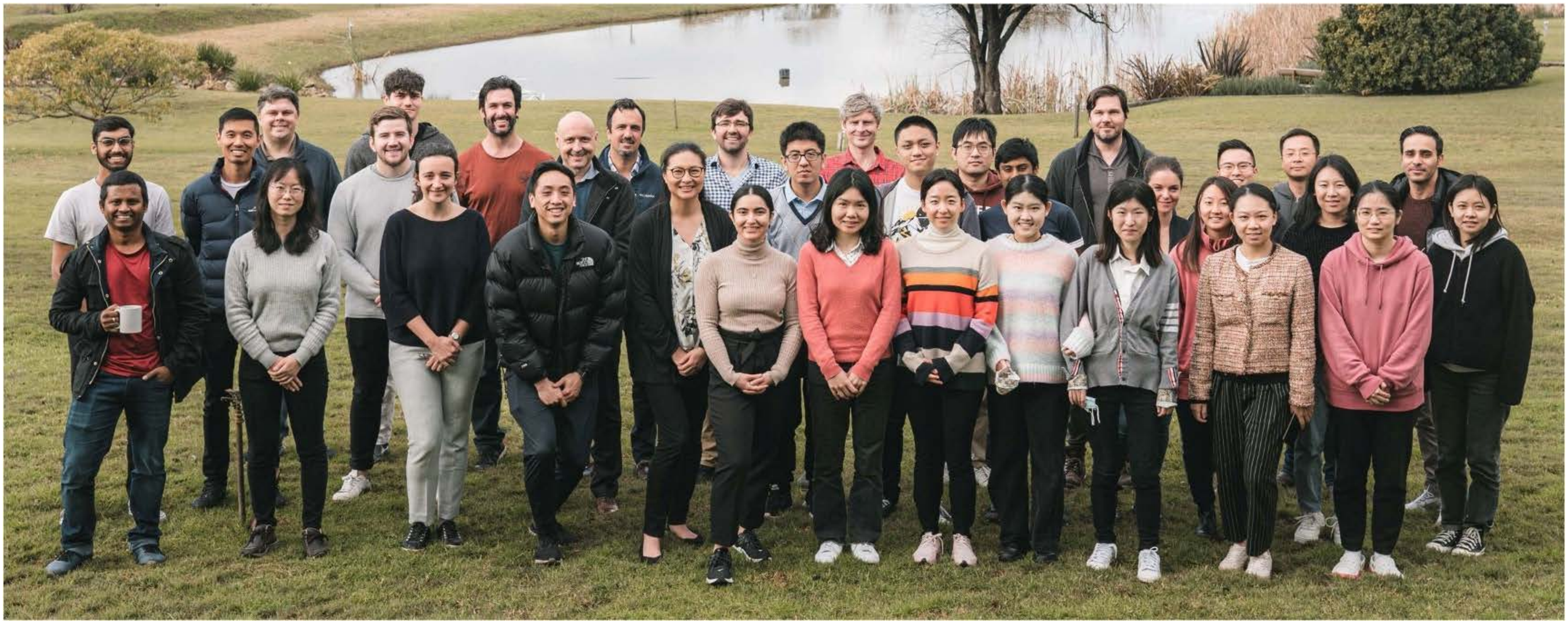
Where to next?

- Detecting outlying "classes"
- **Stable feature selection** for genetic data
- **Lamb model**: similar structure with fewer cuts and cooks
- New carcass grading technologies
  - Cameras and probes
  - Dual X-ray or CT scanning
  - Gene markers
- Outlier robust linear mixed models vs robust aggregation
- Importance of **"link" samples**
- Develop a detailed understanding of sources of idiosyncratic variation at each level (consumer, pick, animal, pen, supplier, kill date, …)



Sydney Precision Data Science Centre

We share an interest in developing statistical and computational methodologies that facilitates data decision making in the areas of health and wellbeing, food sciences, conservation, and biomedicine.



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