Accreditation of new technologies for predicting meat quality

Combining Bayesian models and industry rules for transparent decisions

Professor Graham Gardner & Dr Clair Alston-Knox

7th February 2024
Meat Standards Australia: Industry Problem

- Consumers want consistency in product
- Intramuscular fat is a key determinant of eating quality
- Used as an input into the Meat Standards Australia cuts-based eating quality prediction model
- Measurement of IMF% is undertaken by laboratory
- Cannot use in abattoirs as destructive and slow
- Technologies being developed using sensors capable of predicting this trait AND are fast
- Need accreditation by the Australian Meat Industry Language and Standards
Device estimates of IMF% must be at least of the standard;

- 67% of device estimates within $\pm 1$ IMF%
- 95% of device estimates within $\pm 2$ IMF%
- No need for disparities to be symmetric
Additional Requirements

- Sampling is very expensive
- Cost of accreditation needs to reflect the potential market

Decision

- Device can seek accreditation over a limited range of IMF%
- Sample coverage of this range must be reasonable
- Developer decide the thickness of their laboratory sample

Further Requirements

- Divide sample range into quarters for accreditation
- Requirement on samples in each IMF unit range
Comparison of Laboratory Device Measurements

Ranges of quarter partitions and number of samples

<table>
<thead>
<tr>
<th></th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range</td>
<td>1.35 - 3.11</td>
<td>3.11 - 4.87</td>
<td>4.87 - 6.63</td>
<td>6.63 - 8.38</td>
</tr>
<tr>
<td>Count</td>
<td>397</td>
<td>478</td>
<td>98</td>
<td>9</td>
</tr>
</tbody>
</table>

Number of laboratory samples in each IMF range. Minimum required in each range for accreditation is 20.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Count</td>
<td>39</td>
<td>314</td>
<td>361</td>
<td>182</td>
<td>65</td>
<td>14</td>
<td>6</td>
<td>1</td>
</tr>
</tbody>
</table>
Simulation Study of Rules Based Approach

- Committee believed Device B would pass accreditation
- Device C passing would not be earth shattering
Small Samples vs Rules Based Approach

- Samples are too small to rely on Normal distribution
- Hard thresholds result in many devices failing
- Visualisation helps in industry setting - “Is this your intent?”
Bayesian Regression Approach

- $\text{IMF}\%_{\text{Lab}} - \text{IMF}\%_{\text{Device}} = \beta_0 + \beta_{Q_2,3,4} + \epsilon$
- Idea is to use predictive posterior to “increase” sample size
- $p(\beta|\sigma^2, X) \sim N \left( \tilde{\beta}, \sigma^2 M^{-1} \right), \tilde{\beta} = 0 \& M = g(X^T X)^{-1}$
- $p(\sigma^2|X) \sim IG(\alpha, \delta), \alpha, \delta > 0.$
- Predictive posterior: $p(\tilde{y}|y, X, \tilde{X}) \sim T_m \left( n + 2\alpha, \hat{\theta}, \hat{\tau} \right)$

- Use what industry know to make prior distributions active
  - $\hat{\theta} = \tilde{X} \left( gX^T X + X^T X \right)^{-1} \left( X^T X \tilde{\beta} + gX^T \tilde{\beta} \right)^0 = \frac{\tilde{X}\tilde{\beta}}{(1+g)}$
  - $\hat{\tau} = \frac{2\delta + s^2 + (\hat{\beta} - \tilde{\beta})((gX^T X)^{-1} + (X^T X)^{-1})^{-1}(\hat{\beta} - \tilde{\beta})^0}{n + 2\alpha} \left( I_m + \tilde{X} (gX^T X + X^T X)^{-1} \right)$
Priors for $\sigma^2$  

- $\alpha$ & $\delta$ too small $\rightarrow$ predictive posterior = data driven  
- Sheep intramuscular fat exists over a limited range 0.5 - 8%  
- Unlikely to see devices that are highly inaccurate
Bayesian Regression Outcomes

- \textbf{0.95 IMF\% Device} rules based pass 40\% sample 200
- \textbf{0.80 IMF\% Device} rules based pass 100\% sample 100
- Min quarter sample (n) 30, default $\alpha = 0.25n$
Enabling Industry Use: R Shiny

Device Accreditation Analysis – IMF% Sheep Meat


Comparison of Laboratory Device Measurements

Ranges of quarter partitions and number of samples

<table>
<thead>
<tr>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.52 - 2.77</td>
<td>2.77 - 5.01</td>
<td>5.01 - 7.25</td>
<td>7.25 - 9.5</td>
</tr>
<tr>
<td>Count</td>
<td>202</td>
<td>199</td>
<td>199</td>
</tr>
</tbody>
</table>

Number of laboratory samples in each IMF range. Minimum required in each range for accreditation is 20.

<table>
<thead>
<tr>
<th>IMF range</th>
<th>Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 - 0.99</td>
<td>45</td>
</tr>
<tr>
<td>1 - 1.99</td>
<td>97</td>
</tr>
<tr>
<td>2 - 2.99</td>
<td>79</td>
</tr>
<tr>
<td>3 - 3.99</td>
<td>101</td>
</tr>
<tr>
<td>4 - 4.99</td>
<td>78</td>
</tr>
<tr>
<td>5 - 5.99</td>
<td>92</td>
</tr>
<tr>
<td>6 - 6.99</td>
<td>88</td>
</tr>
<tr>
<td>7 - 7.99</td>
<td>88</td>
</tr>
<tr>
<td>8 - 8.99</td>
<td>82</td>
</tr>
<tr>
<td>9 - 10</td>
<td>50</td>
</tr>
</tbody>
</table>

Selected Prior Distributions

Plausible values of coefficients

Plausible values of sigma
Conclusions

- Bayesian regression with informative priors was useful in this industry problem.
- Sample size in this scenario will always be hindered by expense, availability, and coverage.
- Industry knowledge can form the basis of an informative prior.
- Discussing the trade-off between data and prior is necessary for transparency of the solution and for industry partners to be comfortable with the process.
- Visualisations essential for navigating towards a transparent solution.