Uncertainty in Decision Systems

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Sources of Uncertainty

- Geographical errors -- weather station is not located at farm of interest
- Representational errors -- weather station has different crop environment from weather station
- Prediction model itself is not completely accurate
Possible Solutions

- Models for interpolation
- Models for crop canopy
- Additional uncertainty from models
Pest Processes

- Non-linear systems
- *Phytophthora infestans*
  - water requirements
  - temperature requirements
  - population changes
- *Sclerotinia sclerotiorum*
  - apothecia and ascospore production
Measurement of Predictor Accuracy

- How often system predicts pest and pest is actually present
- How often system predicts absence of pest and pest is actually absent
### True and False Positive

<table>
<thead>
<tr>
<th></th>
<th>Pest Occurs</th>
<th>Pest Absent</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predict Pest</td>
<td>A</td>
<td>B</td>
</tr>
<tr>
<td>Predict No Pest</td>
<td>C</td>
<td>D</td>
</tr>
<tr>
<td>(\frac{A}{A+C})</td>
<td>True Positive Sensitivity</td>
<td>False Positive Specificity</td>
</tr>
<tr>
<td>(\frac{B}{B+D})</td>
<td>D</td>
<td>B/(B+D)</td>
</tr>
<tr>
<td>(\frac{B}{B+D})</td>
<td>D/(B+D)</td>
<td></td>
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</table>
**Numerical Example**

<table>
<thead>
<tr>
<th></th>
<th>Pest Occurs</th>
<th>Pest Absent</th>
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</thead>
<tbody>
<tr>
<td>Predict Pest</td>
<td>27</td>
<td>4</td>
</tr>
<tr>
<td>Predict No Pest</td>
<td>3</td>
<td>16</td>
</tr>
<tr>
<td>27/30</td>
<td>False Positive</td>
<td>4/20</td>
</tr>
<tr>
<td>True Positive</td>
<td>4/20</td>
<td>False Positive</td>
</tr>
<tr>
<td>Sensitivity</td>
<td>16/20</td>
<td>Specificity</td>
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Desirable Properties of Predictors

- High sensitivity
- High specificity -- low false positive rate
Continuous Predictor Variable

- Pest prediction systems often have a continuous variable derived from a number of other variables
- BLITECAST
- Sclerotinia predictor based on weather, cropping history and other variables
- Decision threshold
Effect of decision threshold on sensitivity and specificity

- Lower thresholds will increase the sensitivity of our predictive system but will also increase the false positive rate (decrease specificity).
- Higher thresholds can reduce the false positive rate (increase specificity) at the expense of decreased sensitivity.
What is a ROC curve?

- A graph of the true positive rate as a function of the false positive rate at varying decision thresholds is called a Receiver Operating Characteristic curve (ROC curve).
- An alternative used by some authors is a graph of the sensitivity as a function of specificity.
ROC curve example
Comparing Predictors with ROC curves
Assumptions

• Single control measure (often fungicide application)
• Single time point when the decision has to be made.
• Time point often determined by crop development stage (flowering in oilseed rape example)
Evaluation of Predictors

- Probability of pest occurrence before predictor
- What is the probability of the pest occurring after the predictor?
- Use of Baye’s Theorem
Bayes’ Theorem

$$Pr(A|B) = \frac{Pr(B|A)Pr(A)}{Pr(B|A)Pr(A) + Pr(B|\overline{A})Pr(\overline{A})}$$
Bayes’ Theorem

- Probability of pest presence if predictor is positive
- Sensitivity * prior prob of pest present
- divided by sum of sens * prob pest present and false positive and prob pest not present
More on Bayes’ Theorem

- Use odds instead of probabilities
- use sensitivity and specificity in likelihood ratios
- LR for positive test is sens/(1-spec)
- LR for negative test is (1-sens)/spec
- New odds = old odds * LR
Numerical Example

- Sensitivity is 80%
- Specificity 75%
- LR for positive prediction $0.80/(1-.75)$ or 3.2
- LR for negative prediction $(1-0.80)/0.75$ or 0.267
Numerical Example

- If old (prior) odds is 1 to 10 (1 year of 11)
- After positive prediction, posterior odds is 
  \[0.1 \times 3.2 = 0.32\] or about 24%
- After negative prediction, posterior odds is 
  \[0.1 \times 0.267 = 0.0267\]
Sclerotinia predictor
Increases in probability after a positive prediction

<table>
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<tr>
<th></th>
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<th>prior</th>
<th>prior</th>
<th>prior</th>
<th>prior</th>
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<tbody>
<tr>
<td>35</td>
<td>3.9</td>
<td>0.75</td>
<td>6.12</td>
<td>1.17</td>
<td>6.96</td>
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<tr>
<td>40</td>
<td>4.8</td>
<td>0.92</td>
<td>7.53</td>
<td>1.44</td>
<td>8.56</td>
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<tr>
<td>50</td>
<td>7</td>
<td>1.33</td>
<td>10.95</td>
<td>2.09</td>
<td>12.44</td>
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Decreases in probability after a negative prediction

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<th>prior</th>
<th>prior</th>
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</thead>
<tbody>
<tr>
<td>0.19</td>
<td>1.56</td>
<td>0.30</td>
<td>1.78</td>
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<tr>
<td>0.130</td>
<td>0.02</td>
<td>0.20</td>
<td>0.04</td>
<td>0.23</td>
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<tr>
<td>0.274</td>
<td>0.05</td>
<td>0.43</td>
<td>0.08</td>
<td>0.49</td>
</tr>
<tr>
<td>0.684</td>
<td>0.13</td>
<td>1.07</td>
<td>0.20</td>
<td>1.22</td>
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  YEAR = {1991},
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