



Department of
Agriculture and Food



Using NeuralTools to generate a pricing model for wool

Kimbal Curtis and John Stanton

Australian Wool Industry

- 70% of world trade in apparel wool is Australian wool
- Unlike other commodities
 - Each farm lot is fully measured
 - Each farm lot has an individual price
- About 450,000 farm lots sold each year in Australia
- Raw wool value of AUD3 billion annually

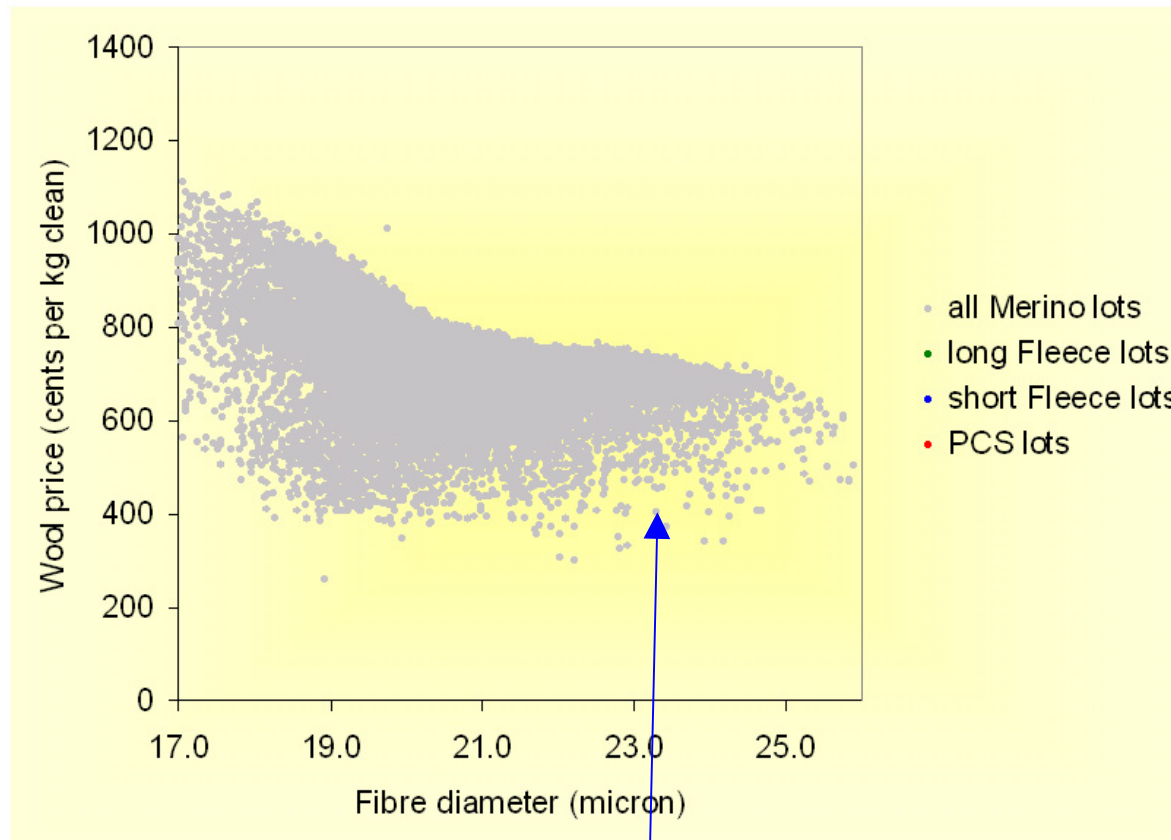
Wool prices & market reporting

- Estimates of auction price on individual lots needed by sellers (farmers)
- Forecast auction price on individual lots required by buyers for contracts
- Market reporting of price paid for different wool types

Neural nets & wool prices

- Neural nets attractive because
 - Number of records is large
 - Prices are dynamic
 - Price/attribute relationships are non-linear and interactive
 - Price/attribute relationships are dynamic over time
 - The data set is incomplete and imprecise

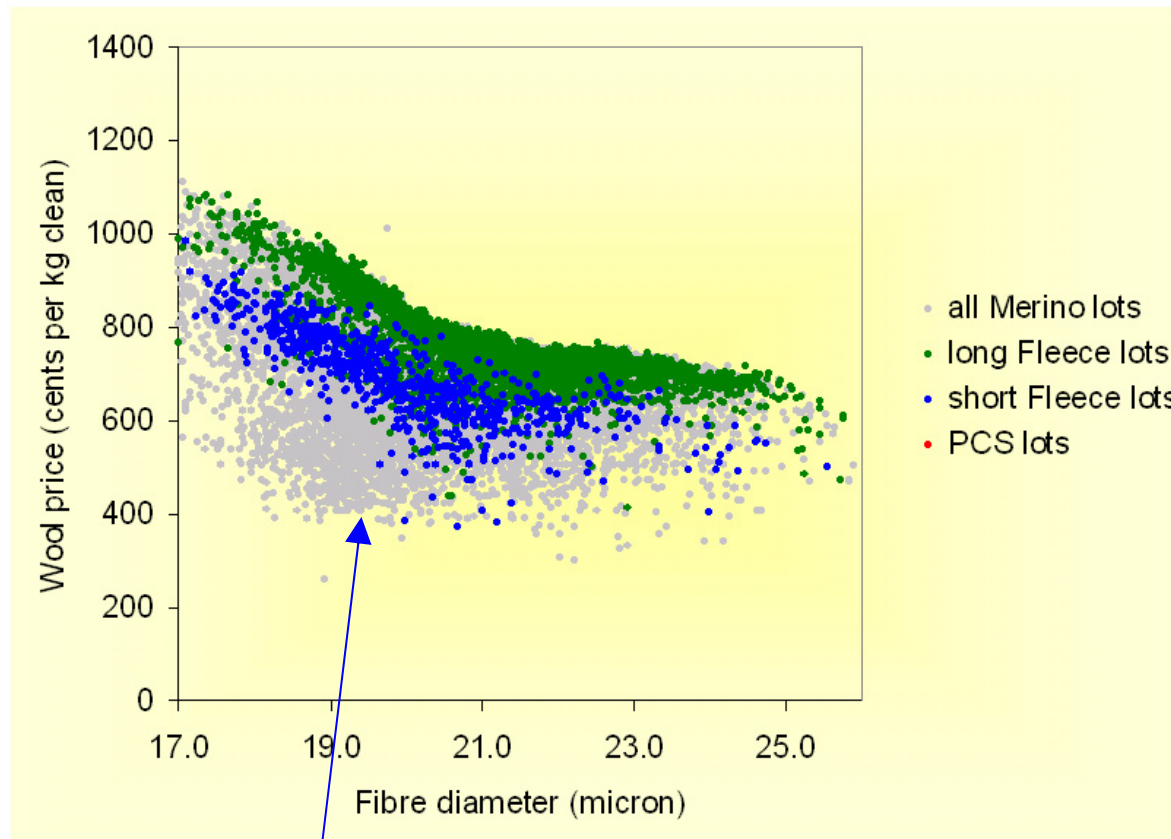
All Merino fleece lots



(Fremantle Jan-Mar 2006)

Each grey dot represents a parcel of wool sold at auction i.e. a 'case'

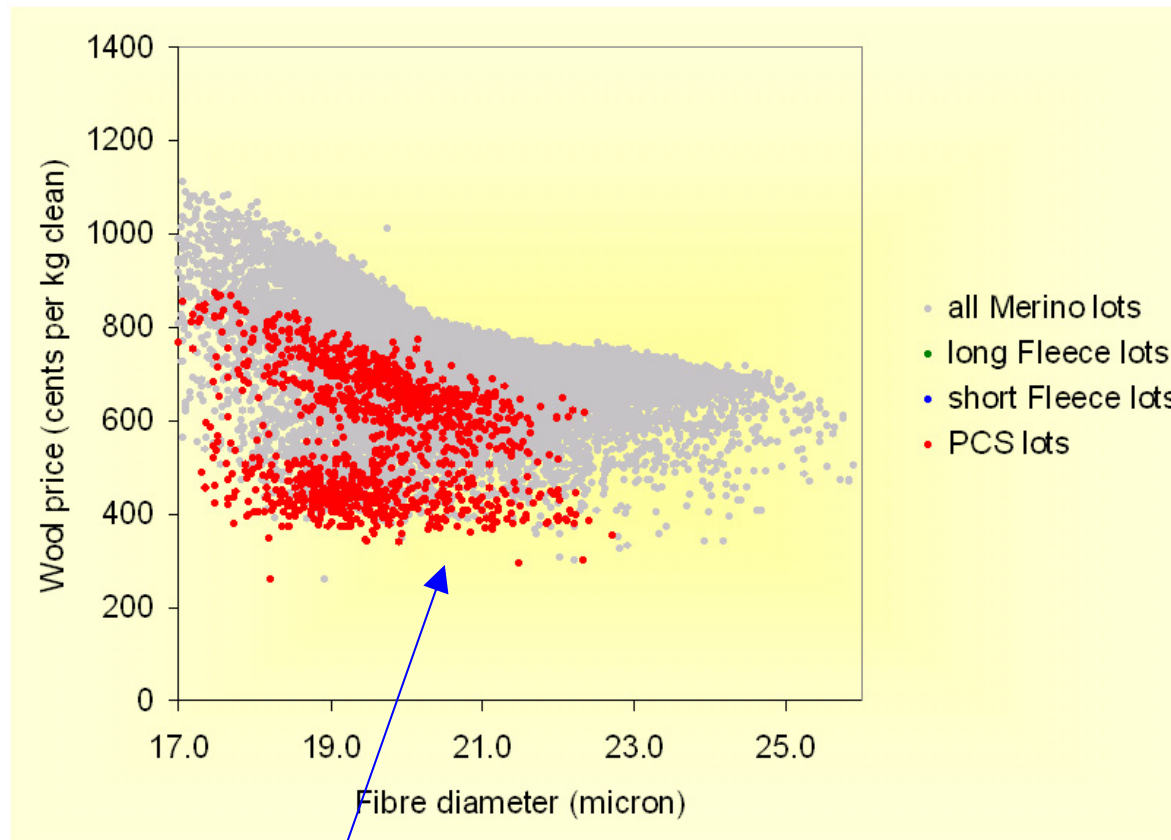
Long & short fleece lots



(Fremantle Jan-Mar 2006)

**Long and short wool
differentiated on price**

Merino pieces lots

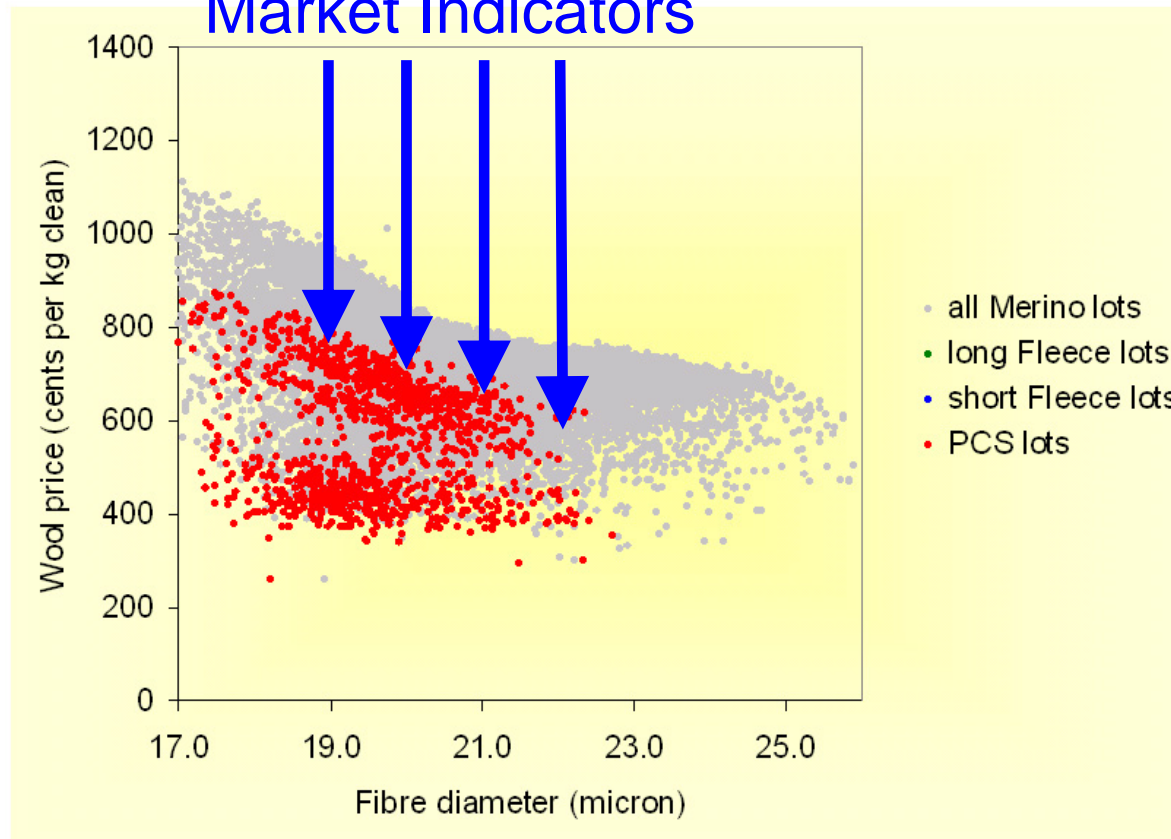


(Fremantle Jan-Mar 2006)

Pieces wool
(a subset of the wool clip)

The Challenge !

Market Indicators



(Fremantle Jan-Mar 2006)

Market indicators, like a stock market index, used to price wool

Model development (1)

- Assemble 6 month data set
 - Independent category and numeric variables
 - Dependent numeric variable (price)
 - Training, testing and prediction data
- Use *Best Net Search*
- Evaluate predictive capability
- Refine model



Excel Demo

Model development (2)

- Assemble a 6 month data set
- Use *Best Net Search*
 - GRN – proved best in most cases (generalised regression neural net)
 - MLFN – also tried with up to 5 nodes (multi layer feed-forward neural net)
- Evaluate predictive capability
- Refine model

Configuration summary

Net Information

| | |
|--|---|
| Name | Net Trained on Pieces wool sales, weeks 33 - 38, 2006 (3) |
| Configurations Included in Search | GRNN, MLFN 2 to 3 nodes |
| Best Configuration | GRNN Numeric Predictor |
| Location | Palisade Conf Curtis v6 BNS 6hrs.xls |
| Independent Category Variables | 8 (Sale centre, Sale week, Sale outcome, Style, Med Hard Cotts, Unscourable Colour, Jowls, Dark Stain) |
| Independent Numeric Variables | 8 (Staple Length, Staple Strength, Vegetable Matter, Diameter, CV Diameter, Mid Breaks, Yield, Hauteur) |
| Dependent Variable | Numeric Var. (Clean price) |

Model development (3)

- Assemble a 6 month data set
- Use *Best Net Search*
- Evaluate predictive capability
- Refine model

Model evaluation (1)

- NeuralTools outputs
 - Error measures
 - Actual versus Predicted, Residuals
 - Variable Impact Analysis
- Live Prediction
- Relationships between variables
- Compare to published market indicators

Model evaluation (1)

Training and Testing summary

Training

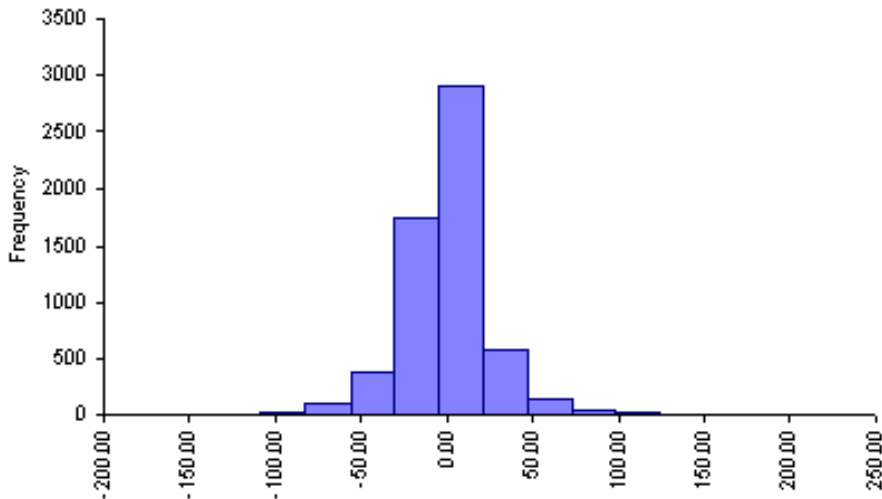
| | |
|----------------------------------|--------------|
| Number of Cases | 5910 |
| Training Time (h:min:sec) | 0:39:43 |
| Number of Trials | 104 |
| Reason Stopped | Auto-Stopped |
| % Bad Predictions (5% Tolerance) | 14.7377% |
| Root Mean Square Error | 24.72 |
| Mean Absolute Error | 16.42 |
| Std. Deviation of Abs. Error | 18.48 |

Testing

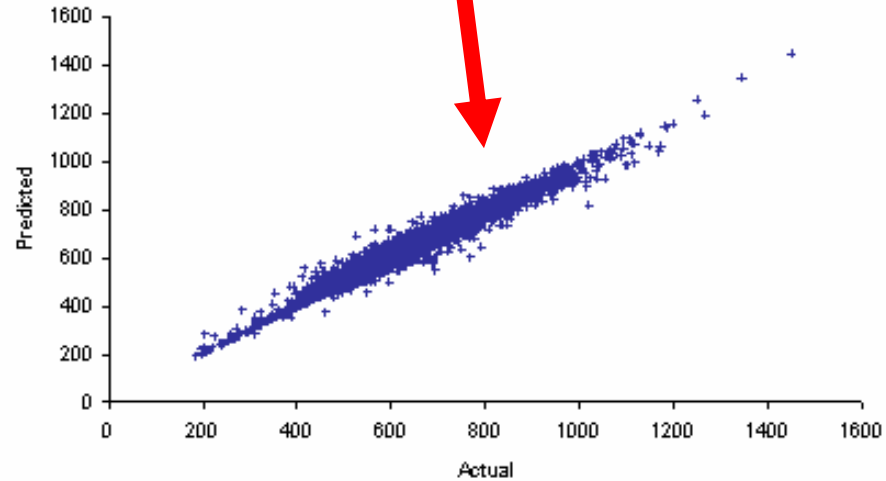
| | |
|----------------------------------|----------|
| Number of Cases | 1507 |
| % Bad Predictions (5% Tolerance) | 43.3975% |
| Root Mean Square Error | 53.18 |
| Mean Absolute Error | 36.99 |
| Std. Deviation of Abs. Error | 38.21 |

Model evaluation - Training data (mean absolute error 16 cents)

Histogram of Residuals (Training)

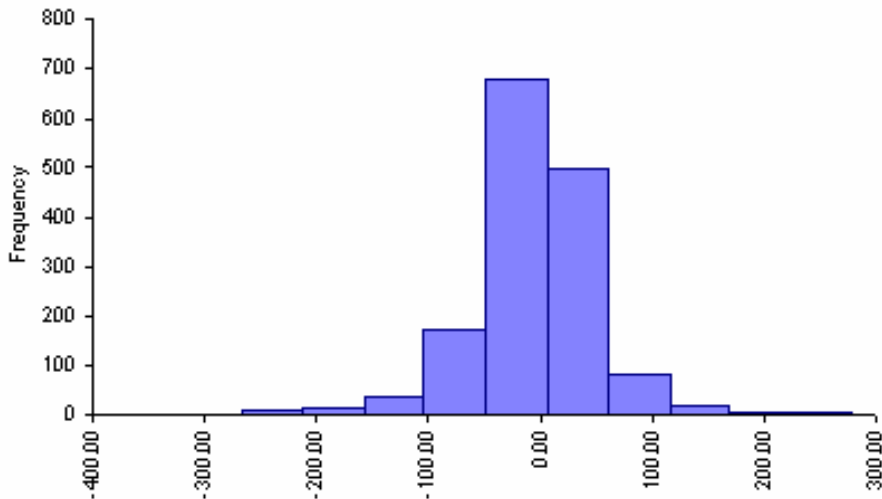


Predicted vs. Actual (Training)

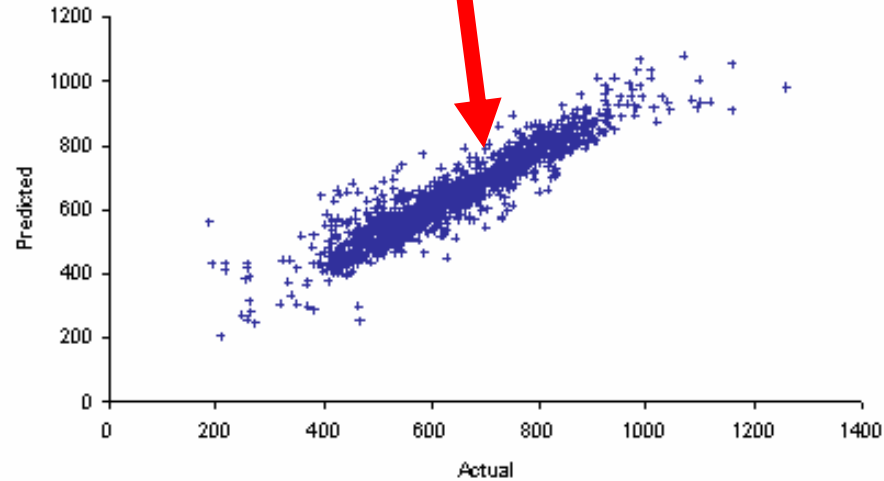


Model evaluation - Testing data (mean absolute error 37 cents)

Histogram of Residuals (Testing)



Predicted vs. Actual (Testing)

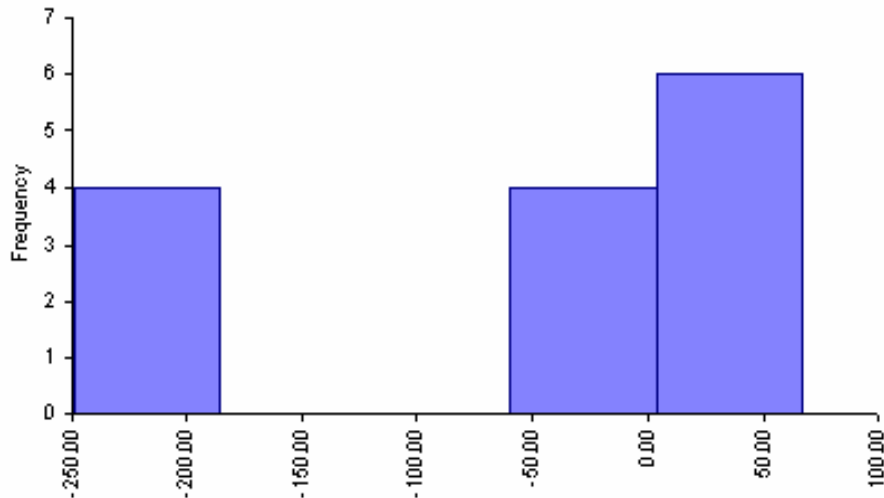


Model evaluation (1)

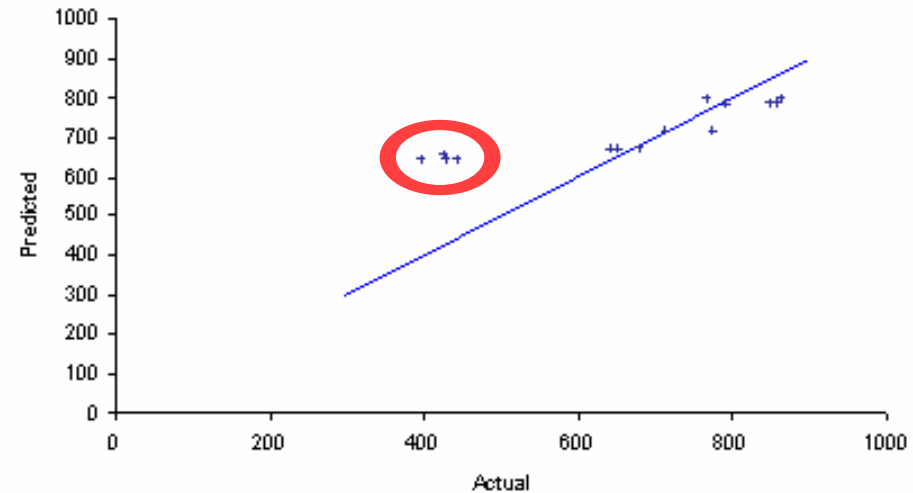
Testing data (indicators)

Observed versus predicted for the published Pieces Market indicators

Histogram of Residuals (Testing)



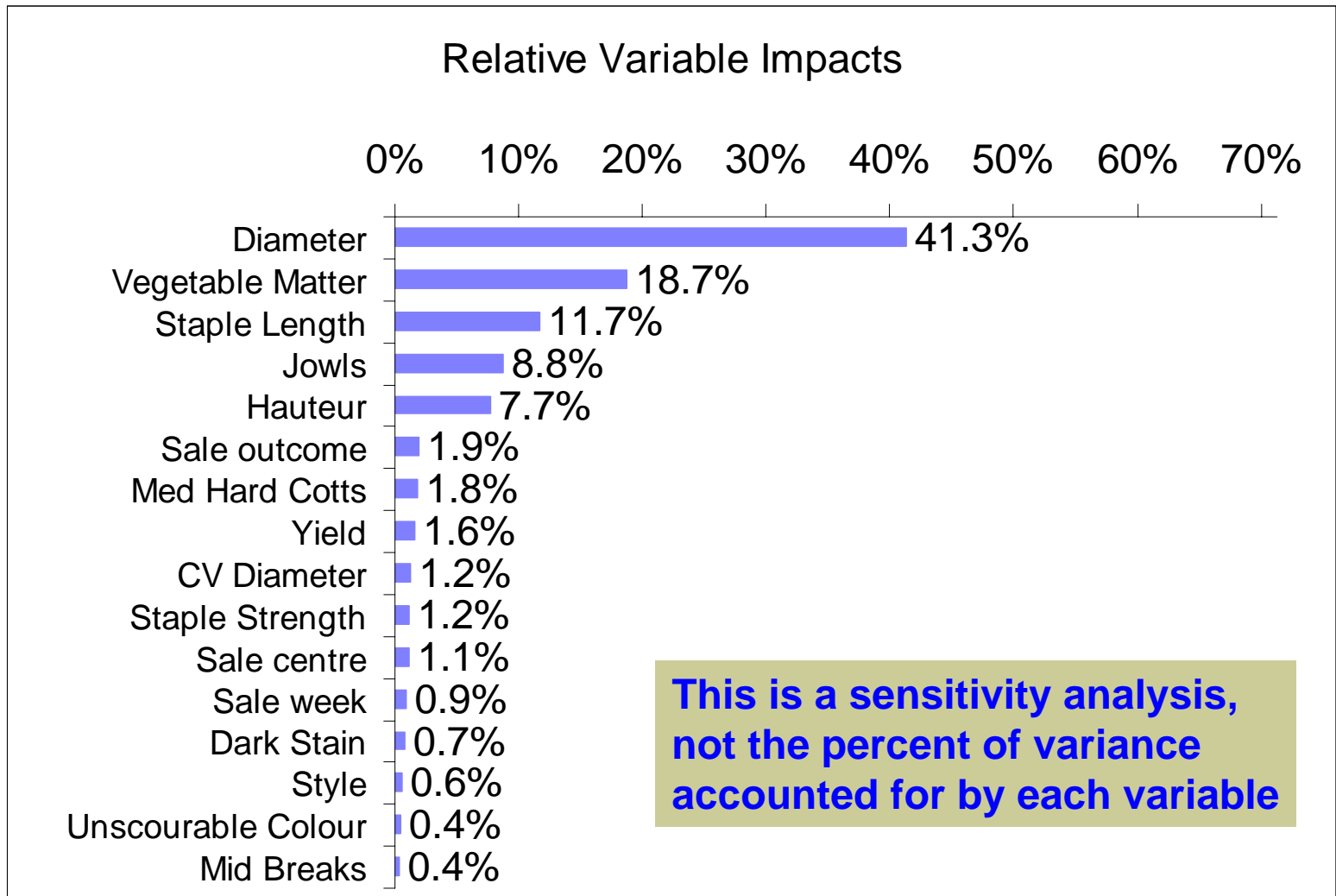
Predicted vs Actual (Testing)



Most points are on the 1:1 line, but a small group hover above i.e. they have higher predicted values than reported

Model evaluation (1)

Variable impact analysis



Model evaluation (2)

- NeuralTools outputs
 - Error measures
 - Actual versus Predicted, Residuals
 - Variable Impact Analysis
- **Live Prediction**
- Relationships between variables
- Compare to published market indicators

Model evaluation (2)

Live prediction

Simple spreadsheet pricing tool.

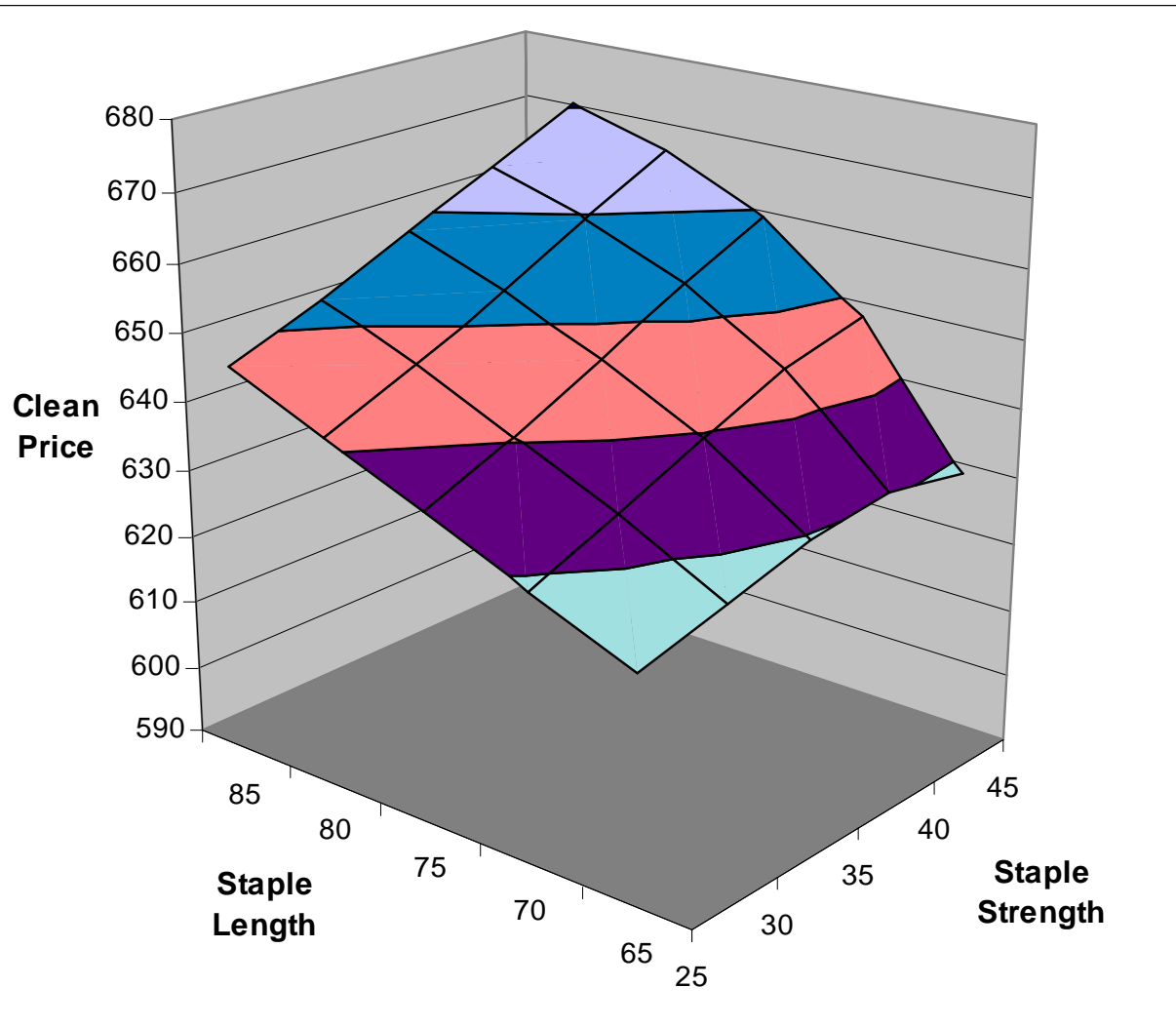
Change any of the values in the yellow cells, and '*Live prediction*' updates the clean price

| | |
|--------------------|------------|
| Sale centre | Fremantle |
| Sale week | W38 |
| Style | Average |
| Med Hard Cotts | C0 |
| Unscourable Colour | H0 |
| Jowls | J0 |
| Dark Stain | S0 |
| Diameter | 20.0 |
| Yield | 50.0 |
| Vegetable Matter | 2.5 |
| Staple Length | 80 |
| Staple Strength | 35 |
| Mid Breaks | 55 |
| Hauteur | 62 |
| Clean price | 664 |

Model evaluation (3)

- NeuralTools outputs
 - Error measures
 - Actual versus Predicted, Residuals
 - Variable Impact Analysis
- Live Prediction
- Relationships between variables
- Compare to published market indicators

Model evaluation (3) relationships between variables



Sydney
Week 38
21 micron
2% VM



Department of
Agriculture and Food



Model evaluation (3)

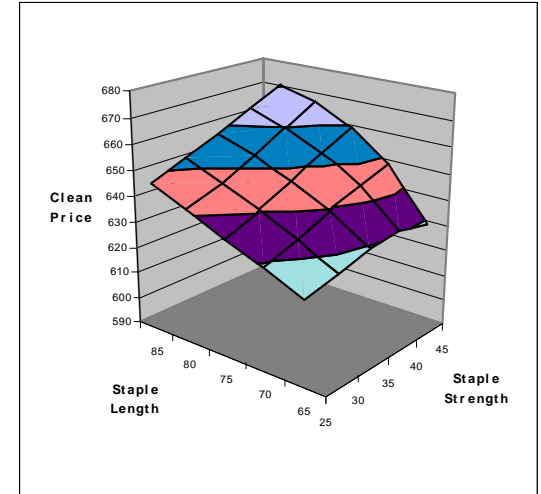
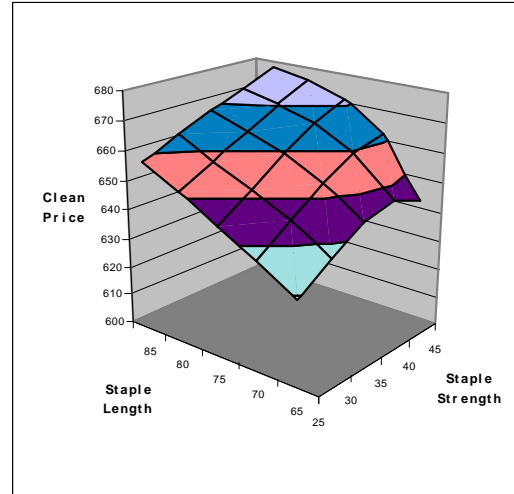
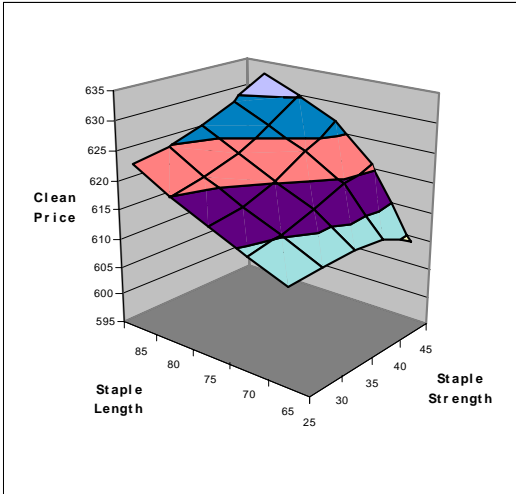
relationships between variables

Fremantle

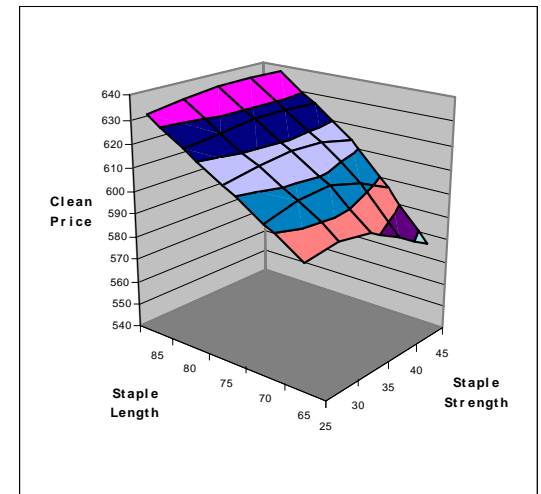
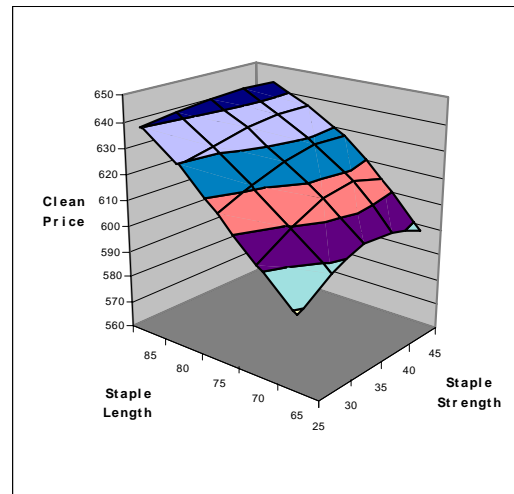
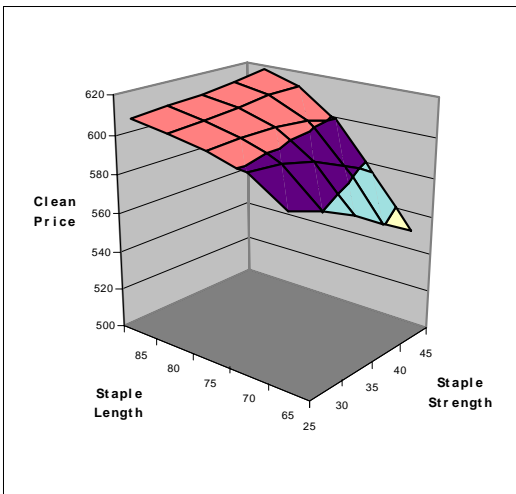
Melbourne

Sydney

21 micron



22 micron





Department of
Agriculture and Food



Model evaluation (3)

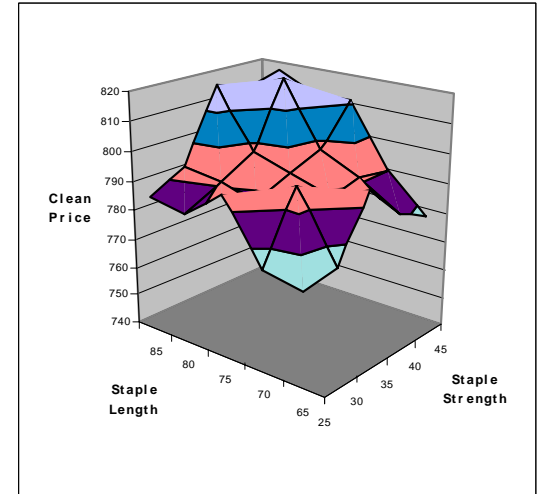
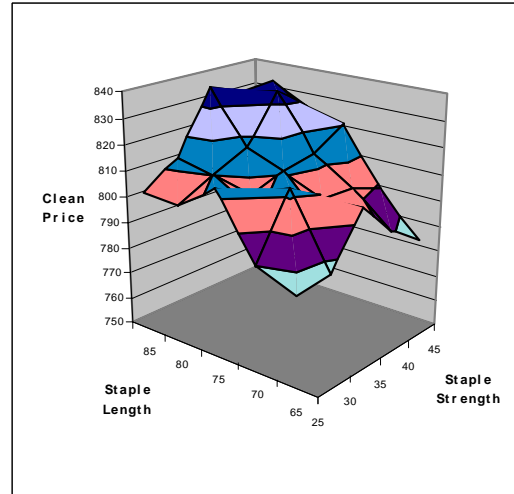
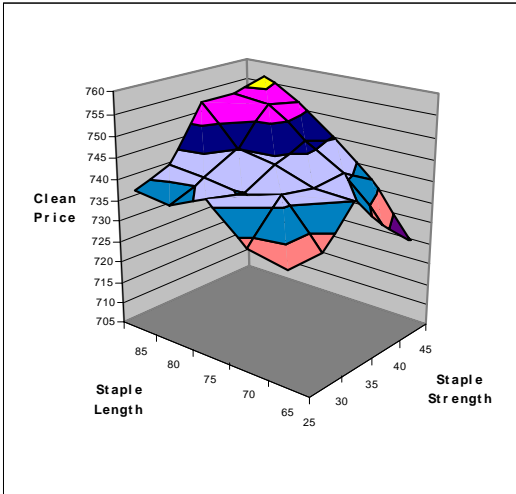
relationships between variables

Fremantle

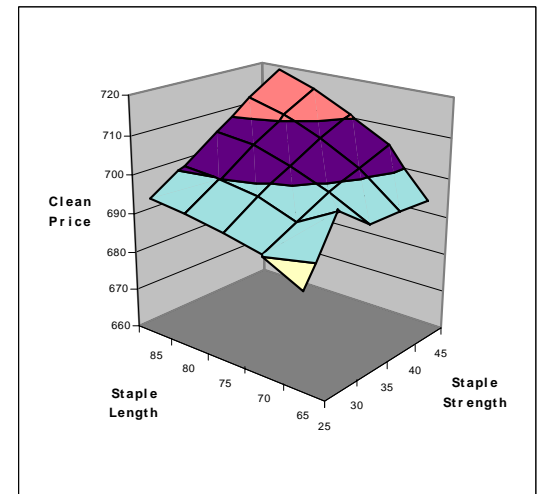
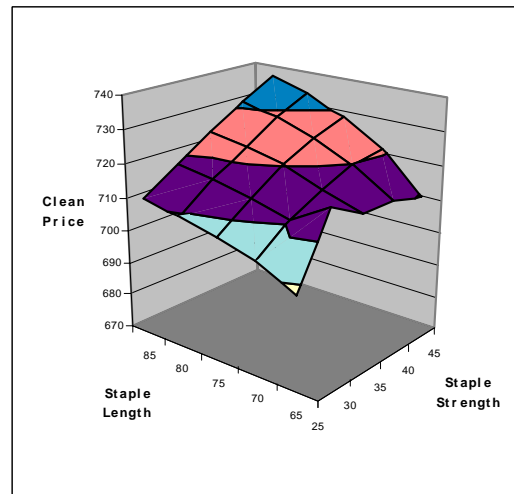
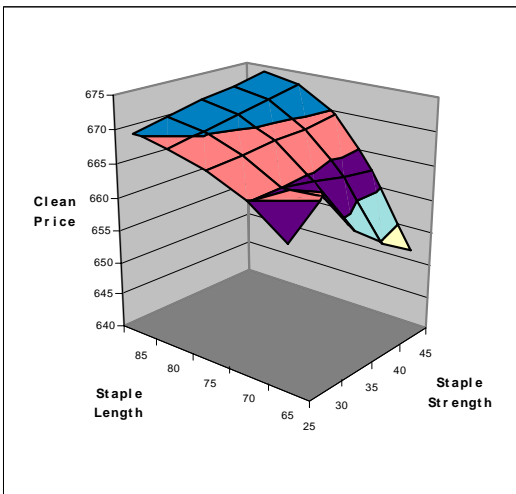
Melbourne

Sydney

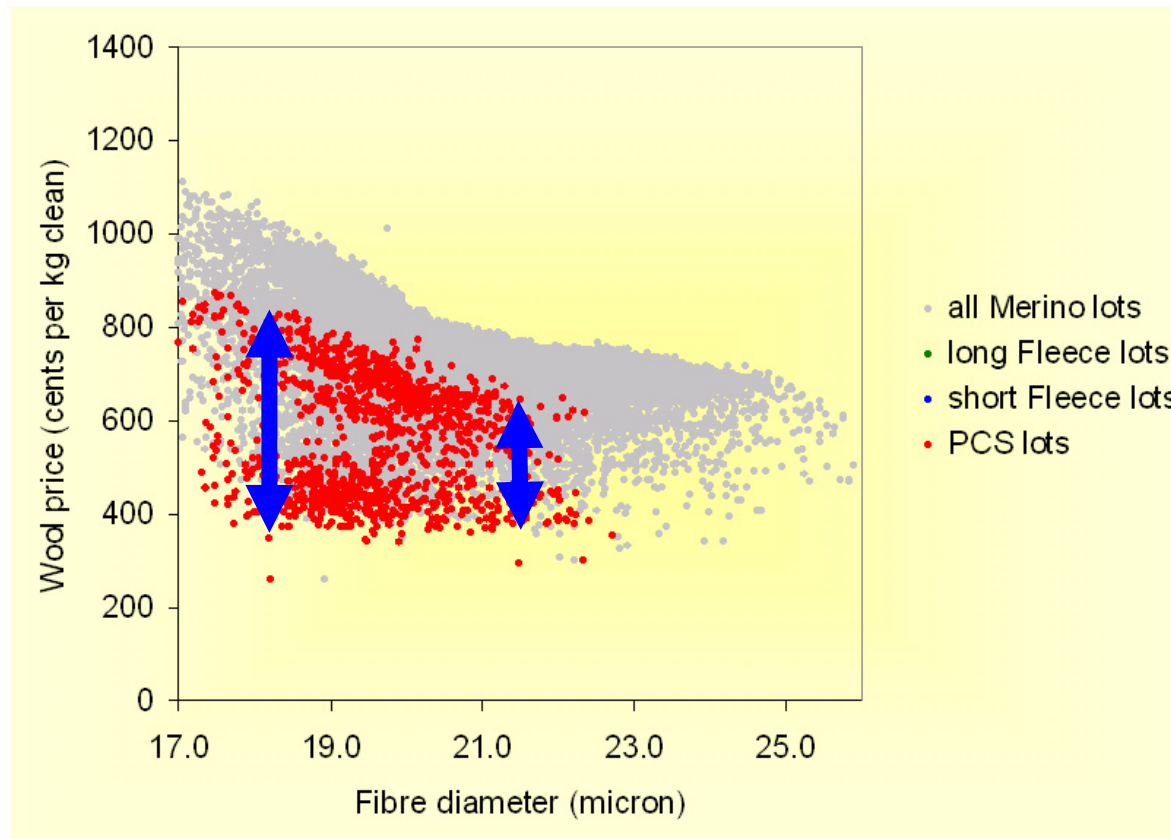
19 micron



20 micron



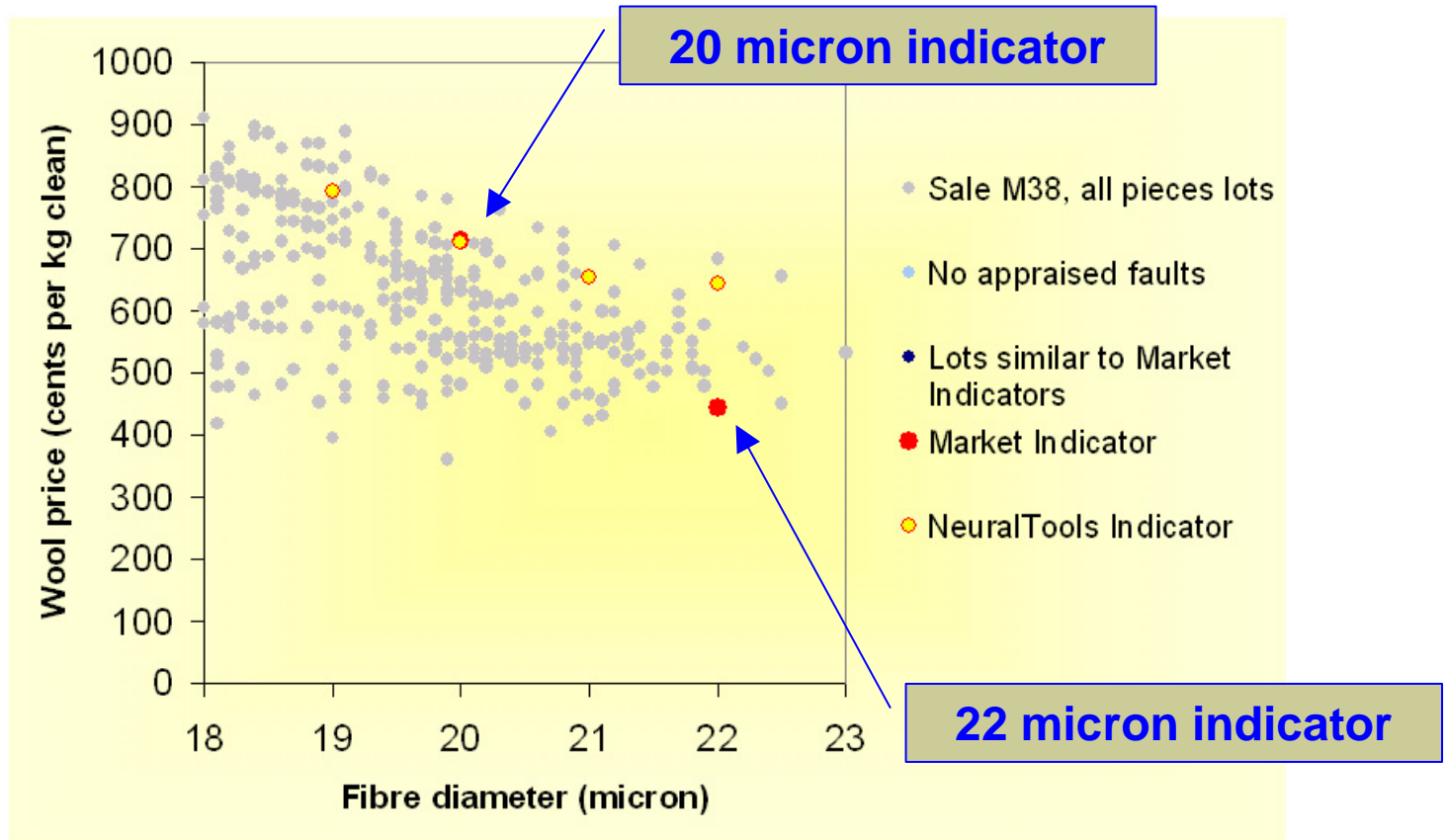
Price spread variation



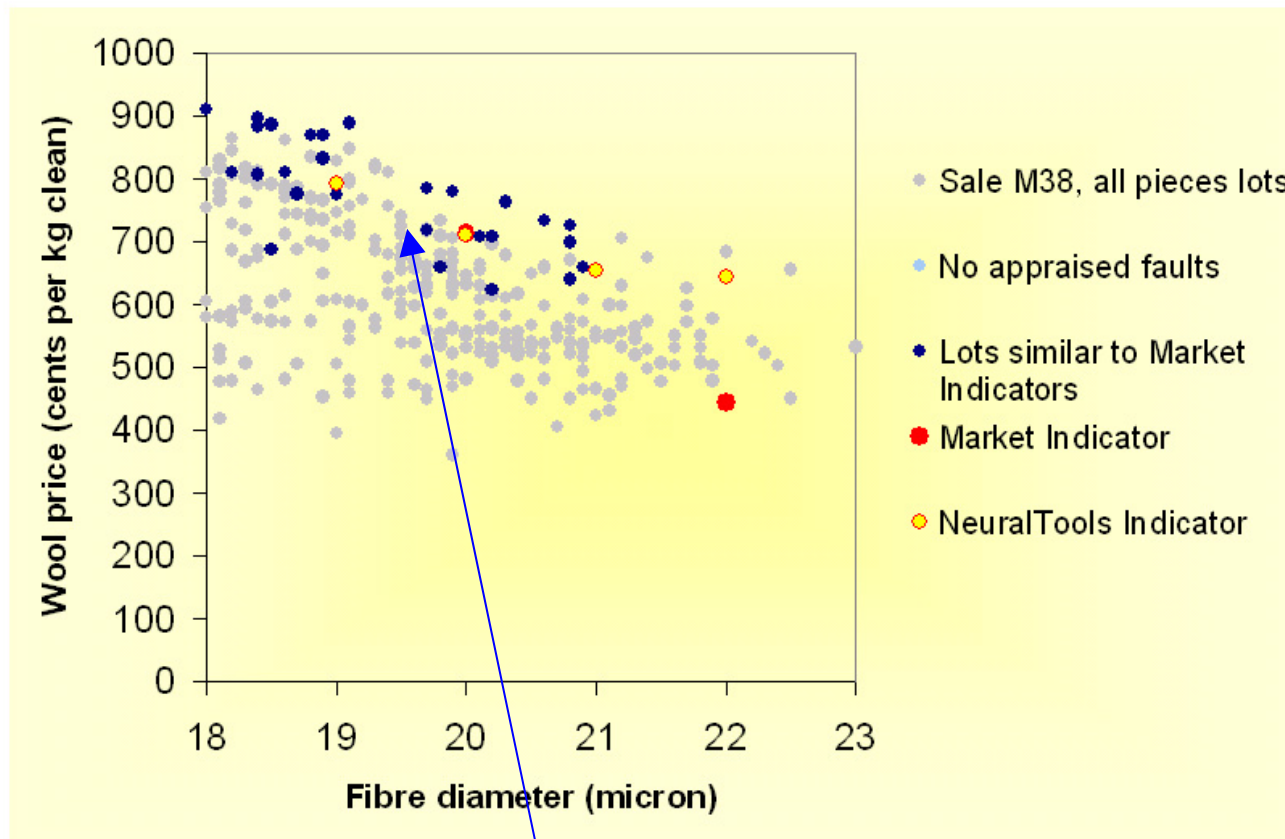
Model evaluation (4)

- NeuralTools outputs
 - Error measures
 - Actual versus Predicted, Residuals
 - Variable Impact Analysis
- Live Prediction
- Relationships between variables
- Compare to published market indicators

Model evaluation (4) predictive capability



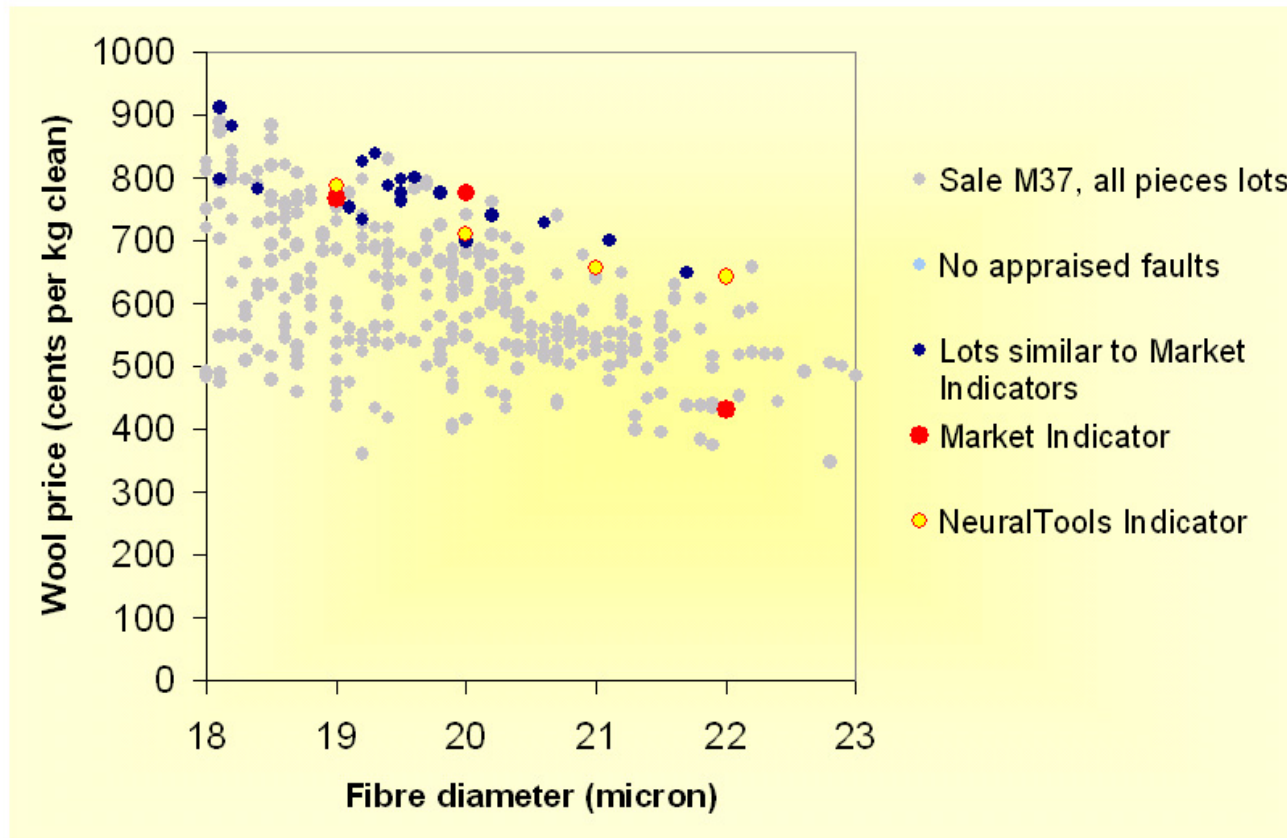
Model evaluation (4) predictive capability



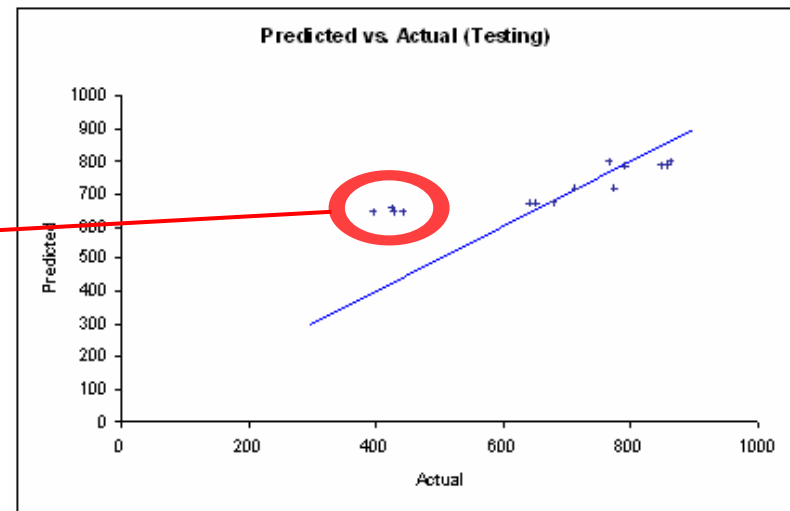
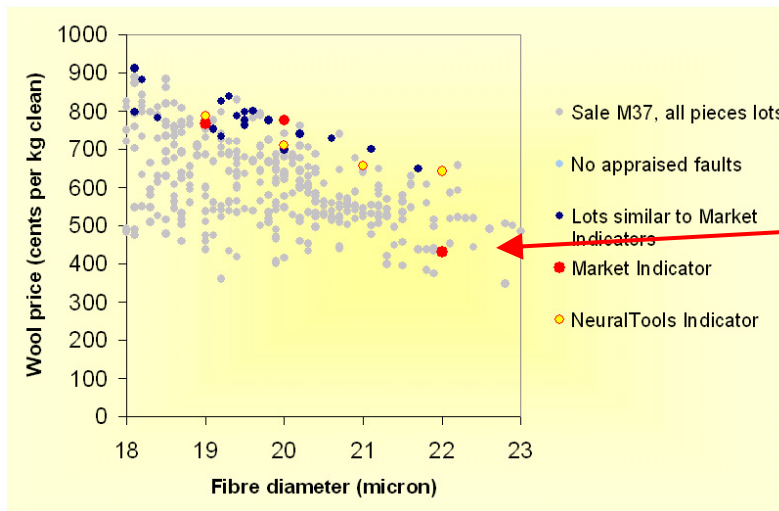
Melbourne
Week 38

Dark blue lots have SL, SS and VM
“similar” to market indicator definition

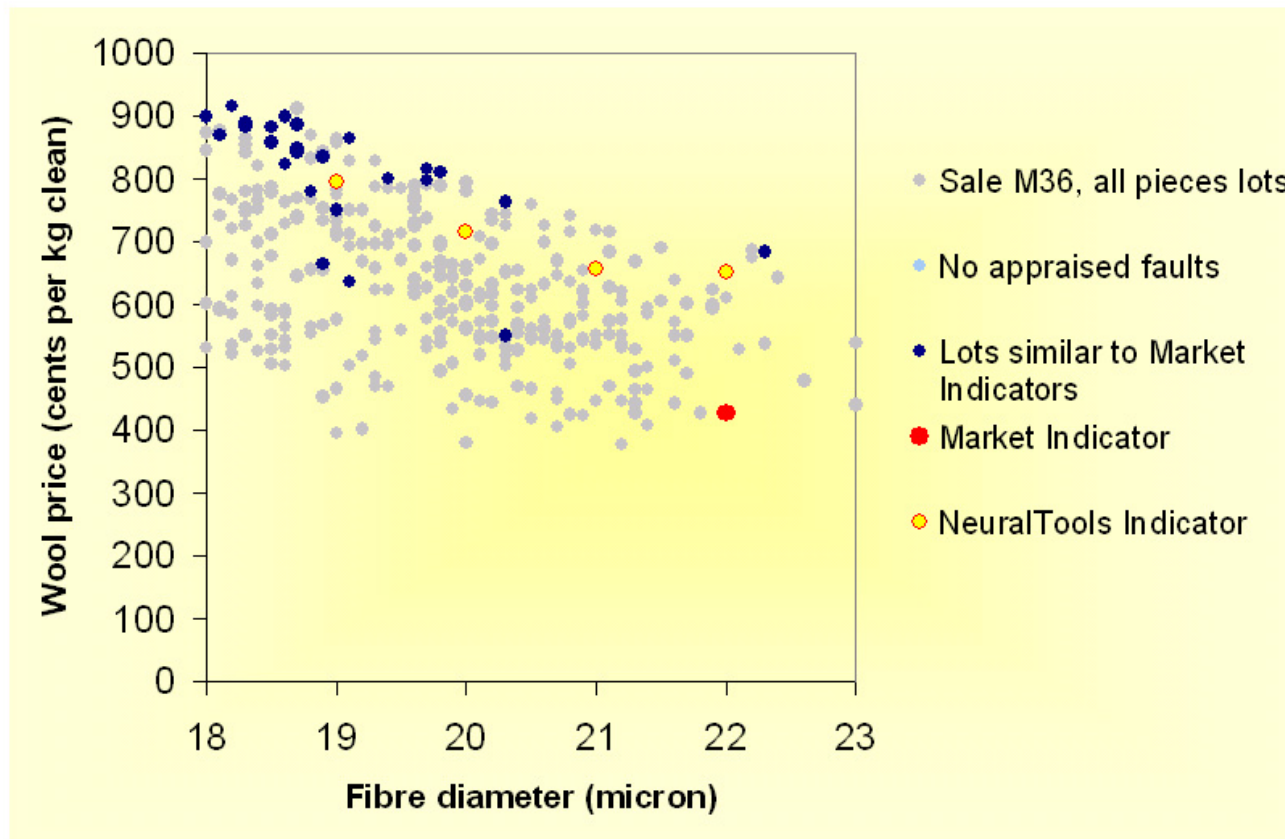
Model evaluation (4) predictive capability



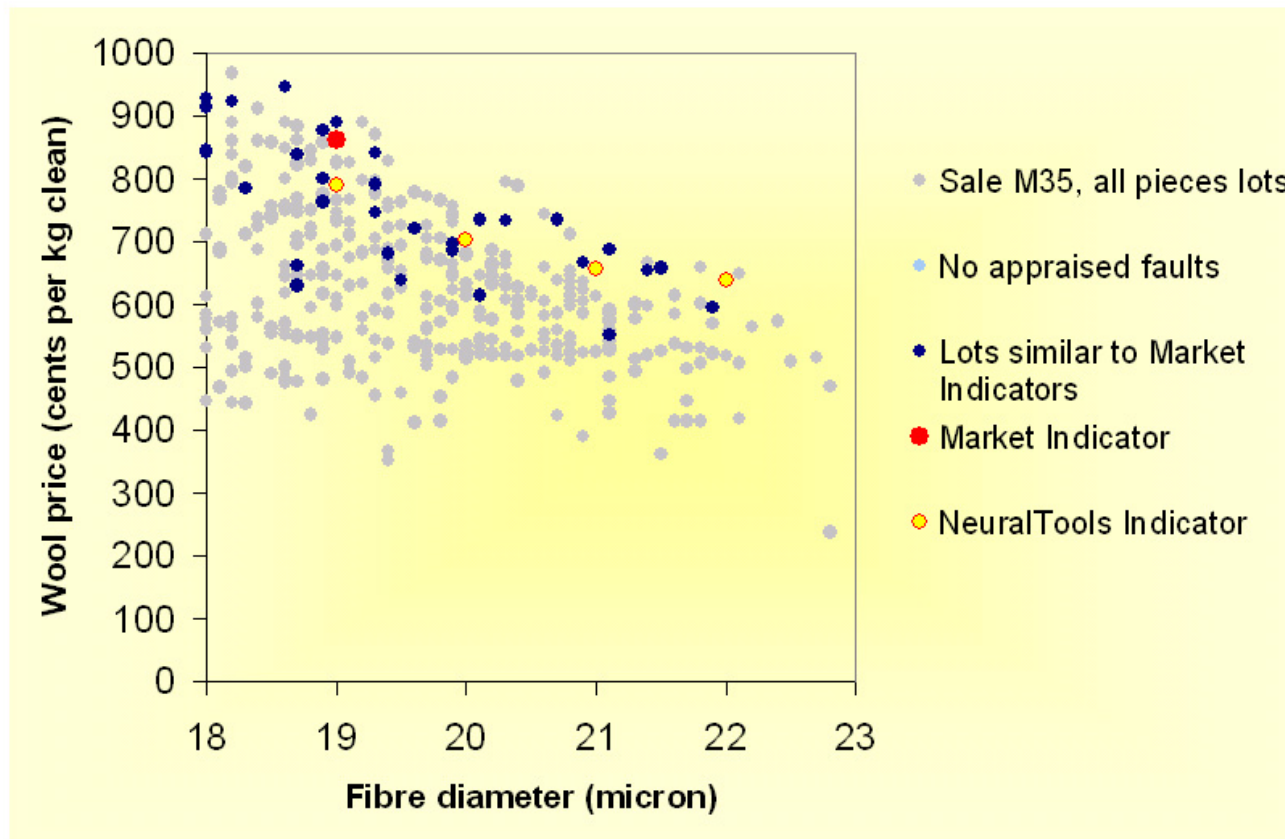
Model evaluation (4) predictive capability



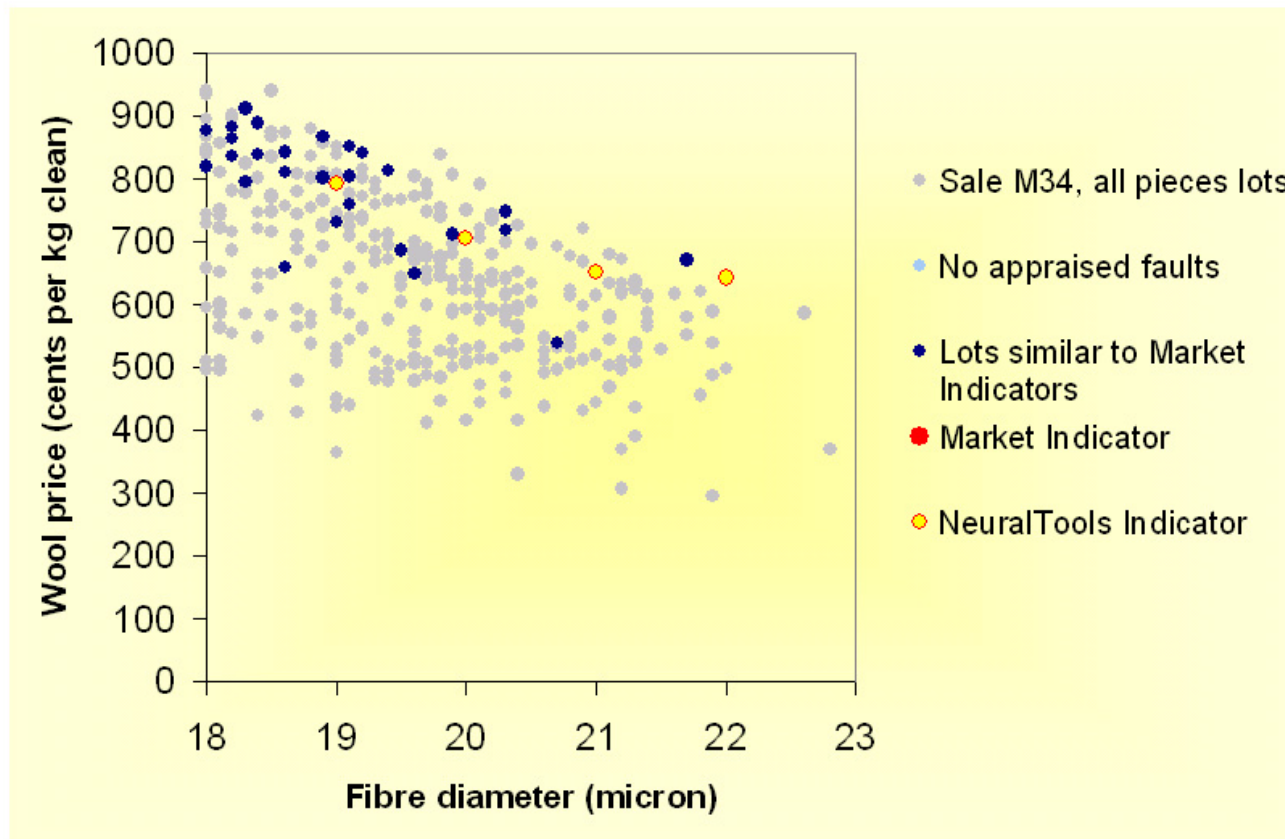
Model evaluation (4) predictive capability



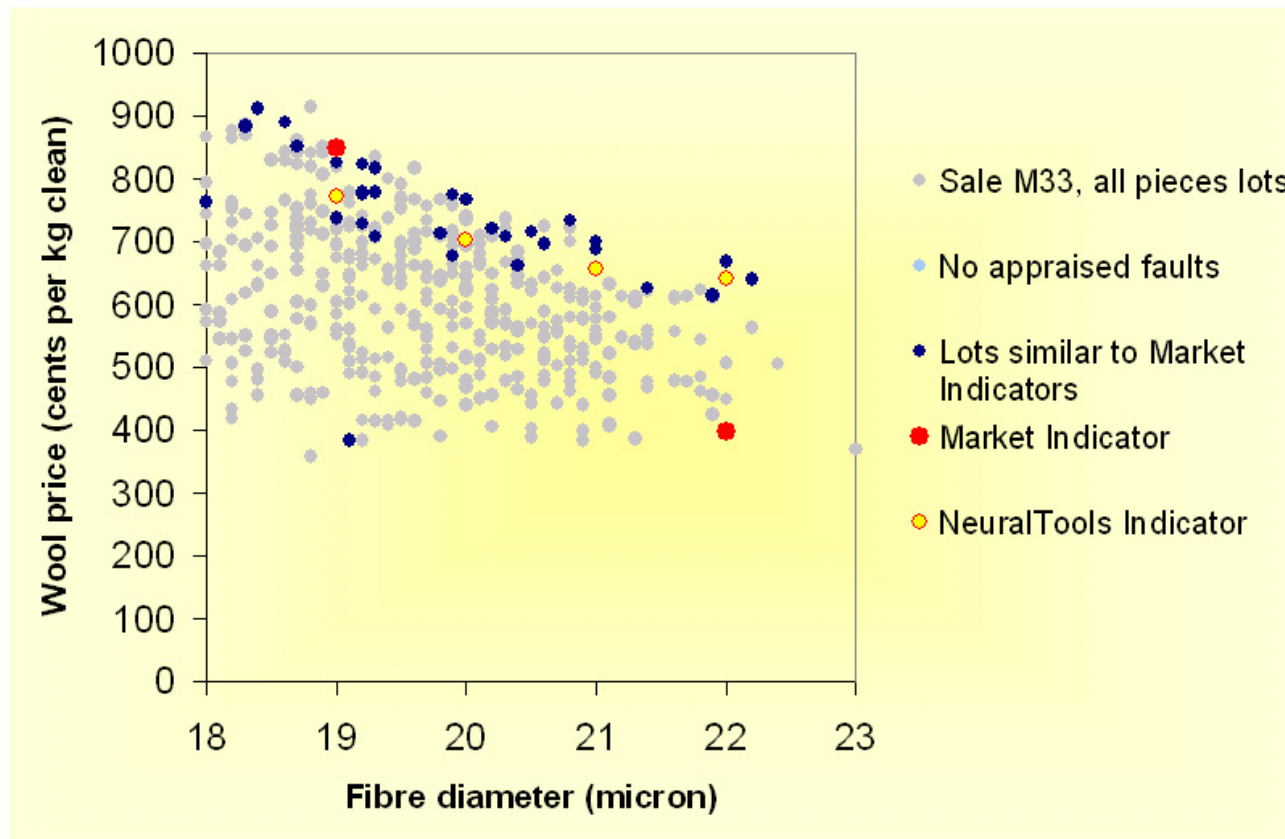
Model evaluation (4) predictive capability



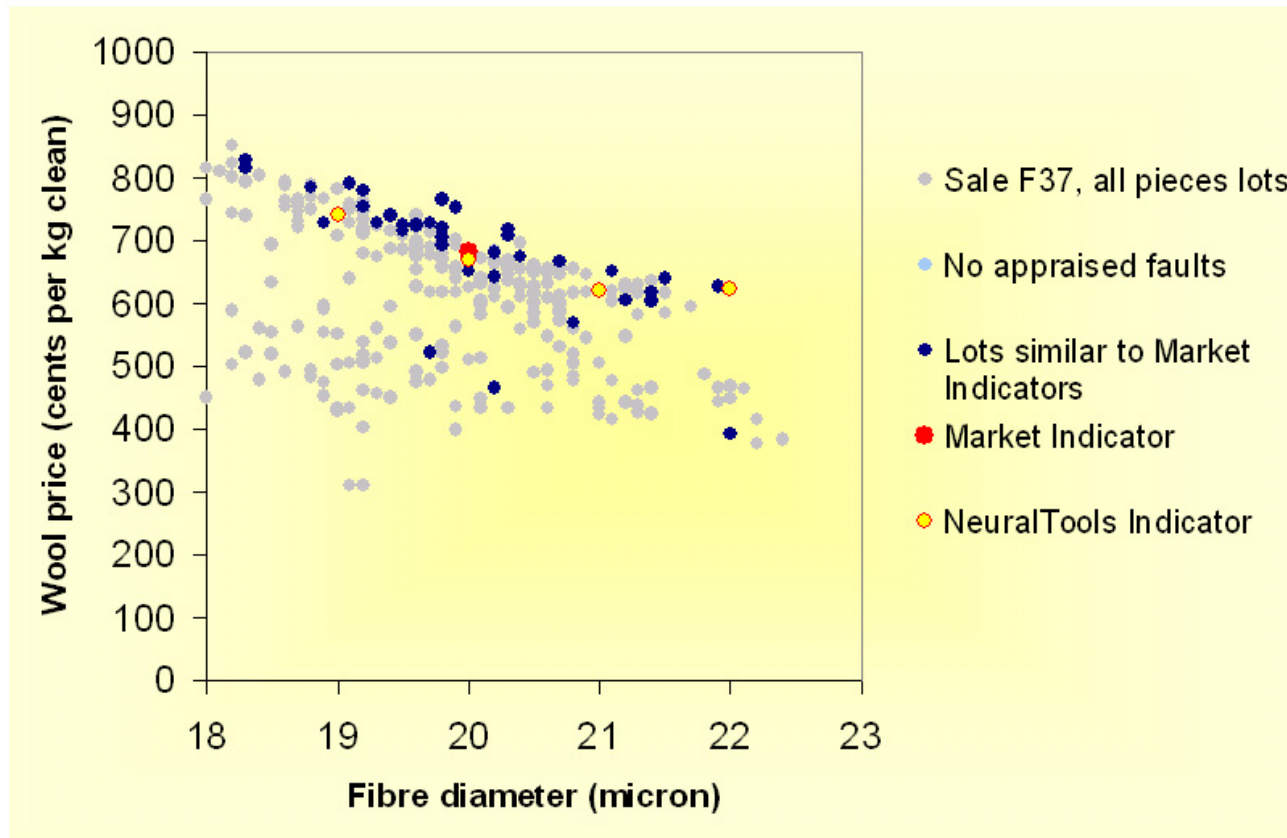
Model evaluation (4) predictive capability



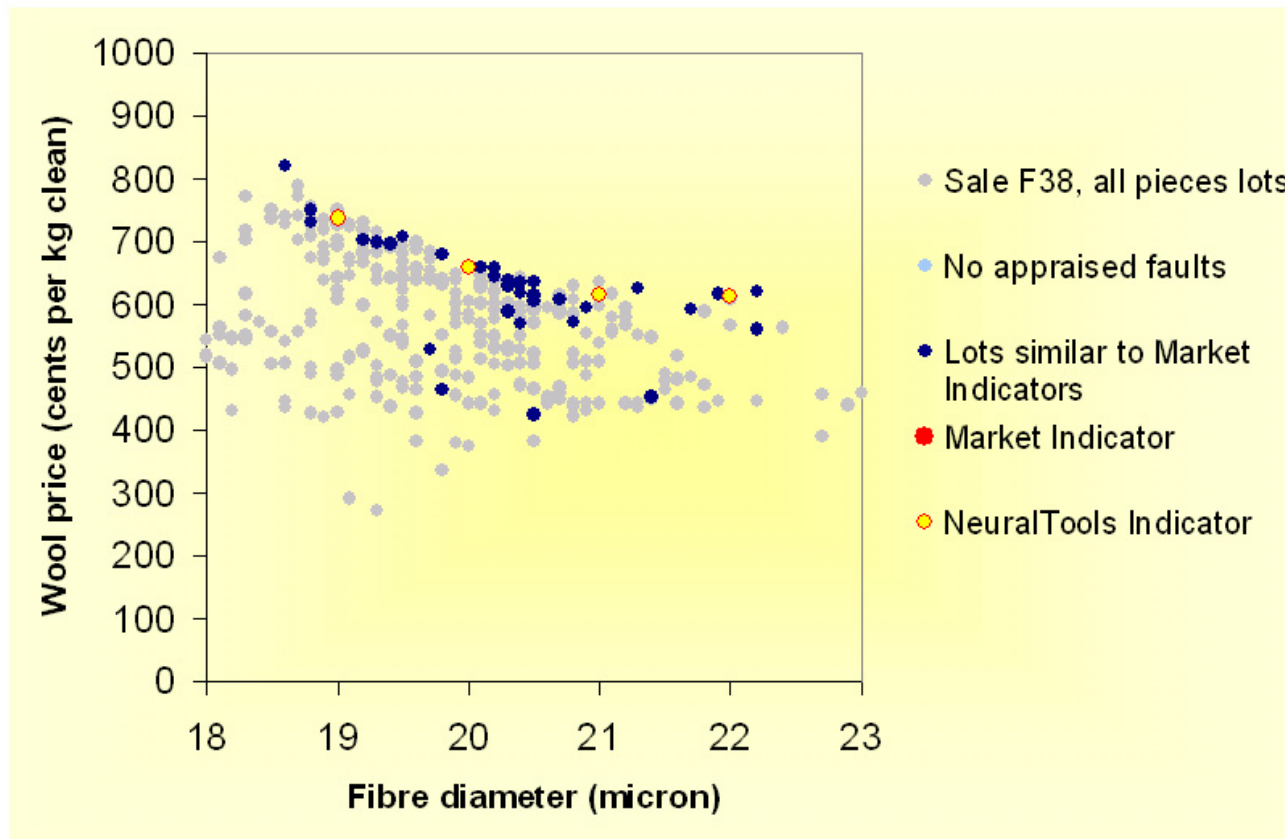
Model evaluation (4) predictive capability



Model evaluation (4) predictive capability



Model evaluation (4) predictive capability



Model development (4)

- Assemble a 6 month data set
- Use *Best Net Search*
- Evaluate predictive capability
- Refine model
 - Reduce variables
 - Combine selling centres
 - Sale week - category variable

Some Neural Net applications

- Market reporting
- Price predictor
- Validation check for other estimates
- Missing sale problem
- Generate price matrices
 - Using *Live Prediction* and *@Risk*

Summary

- Data rich application with characteristics that looked ideal for NeuralTools
- Solutions generated which can support industry analysis and generation of indicators