Model Selection Strategy for Bayesian Networks

A Case Study of New Zealand Viticulture

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NEW ZEALAND WINE PURE DISCOVERY · MINISTRY OF BUSINESS, INNOVATION & EMPLOYMENT HIKINA WHAKATUTUKI · Plant & Food RESEARCH RANGAHAU AHUMARA KAI · THE UNIVERSITY OF AUCKLAND NEW ZEALAND SCIENCE · BRAGATO RESEARCH INSTITUTE NEW ZEALAND GRAPE AND WINE RESEARCH RANGAHAU KAREPE, WĀINA O AOTEAROA

The vineyard as an ecosystem (VE) programme

- Wine is New Zealand's 6th largest export good; in Nov 2020, it was valued at NZ$2B [1].
- Challenge: pests and diseases diminish the grape quality, yield and threaten the sustainability of the wine industry [1].

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- Wine is New Zealand's 6th largest export good; in Nov 2020, it was valued at NZ$2B [1].
- Challenge: pests and diseases diminish the grape quality, yield and threaten the sustainability of the wine industry [1].
- Investigate the long-term impacts of two distinct **management practices** on the longevity and sustainability of vineyards.

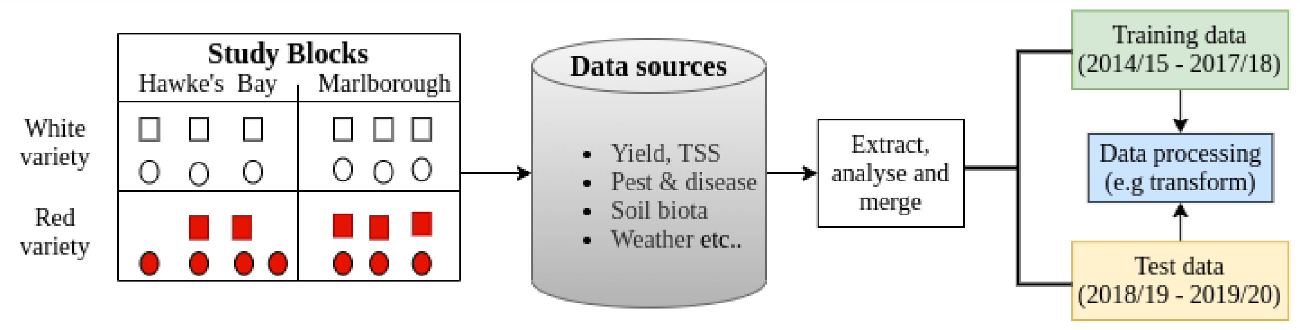
Contemporary: use synthetic sprays and herbicides to control under-vine weeds.

Future: use fewer synthetic sprays and cultivation to control weeds; can support biodiversity.

- Focus on identifying the factors influencing yield components, pests and diseases.

Data and data processing

- Study design:
  - 24 vineyard blocks in **Marlborough** (12) and Hawke's Bay (12).
  - Each group of 12 comprised 6 Sauvignon blanc blocks and 6 red varieties.
  - 11C and 13F managed blocks were monitored 1-3 times/season for 5 seasons.



- After data processing; n = 120, p = 131 variables representing the VE components.

Learning Bayesian networks (BNs)

- BNs express the conditional independence relationships among variables $\mathbf{X}$ via graphical separation [2].
  - Thus specifying the factorisation $\mathrm{P}(\mathbf{X}) = \prod \mathrm{P}(X_i \mid \Pi_{X_i}, \Theta_{X_i})$ [2].
- A BN is defined by a DAG $\mathcal{G} = (\mathbf{V}, A)$ and parameters Θ of $P(\mathbf{X})$ [2].

$$\underbrace{\mathrm{P}(\mathcal{G}, \Theta \mid \mathcal{D})}_{\text{learning}} = \underbrace{\mathrm{P}(\mathcal{G} \mid \mathcal{D})}_{\text{structure learning}} \cdot \underbrace{\mathrm{P}(\Theta \mid \mathcal{G}, \mathcal{D})}_{\text{parameter learning}}.$$

- Greedy search algorithm to learn $\mathrm{P}(\mathcal{G} \mid \mathcal{D})$ from 10k bootstrap samples [5, 6, 7].
- Searches over the space of DAGs for a structure that maximises a score [5].

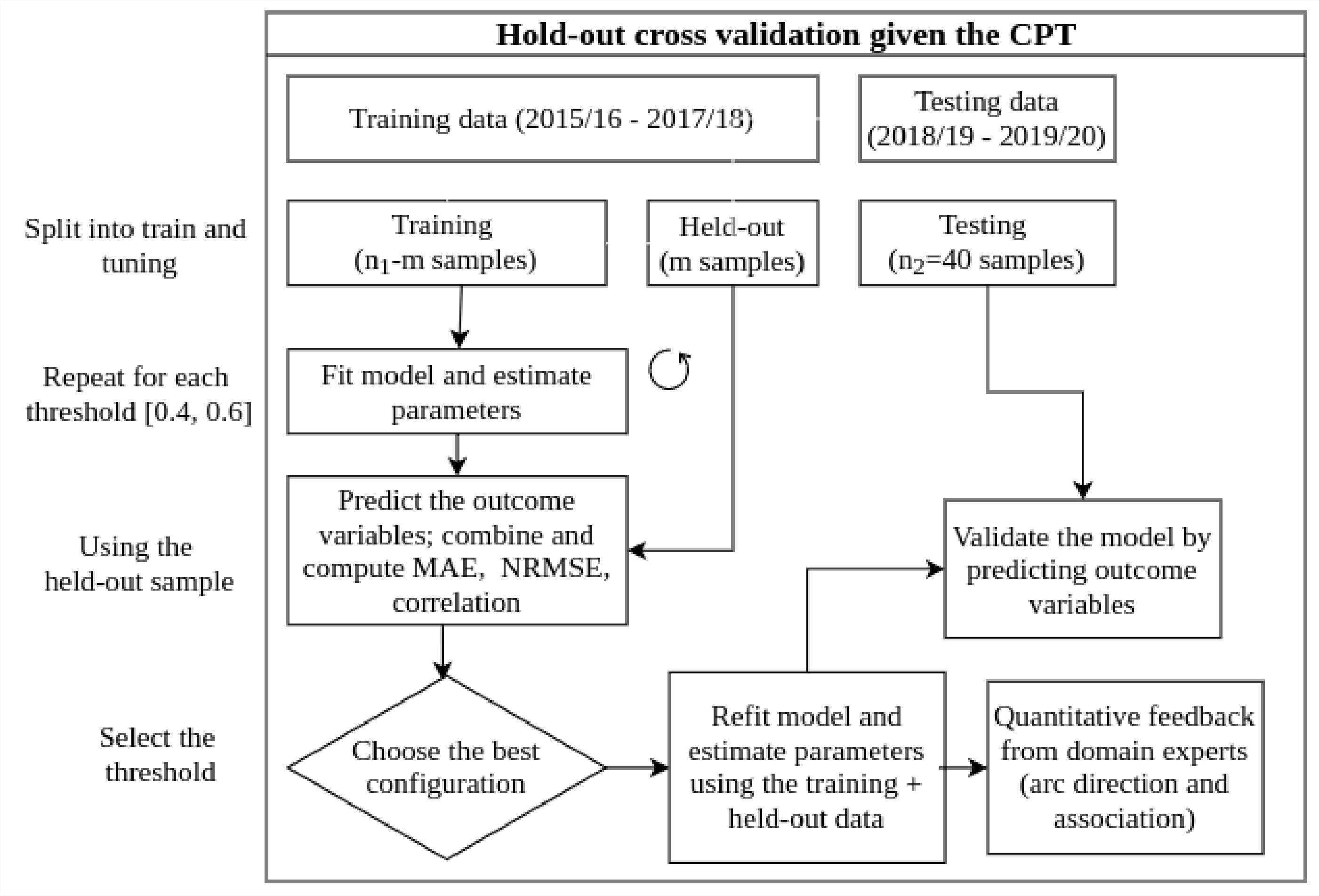
Motivation: Choice of threshold

- **Output**: CPT (17k arcs) contains the frequency and confidence in direction of each arc.

from	to	strength	direction
Syn_BotsFungicide	VI_H	0.65	0.85
MBCatch_InFl	MBCatch_BC	0.57	1.00
Management	TSS_H	0.48	1.00
Soft_PMFungicide	BunchPM_BC	0.44	0.67

- How can we choose the threshold to identify significant arcs when some variables are more important (yield, pests and diseases)?

Proposed model selection strategy for BNs



Results: choice of threshold

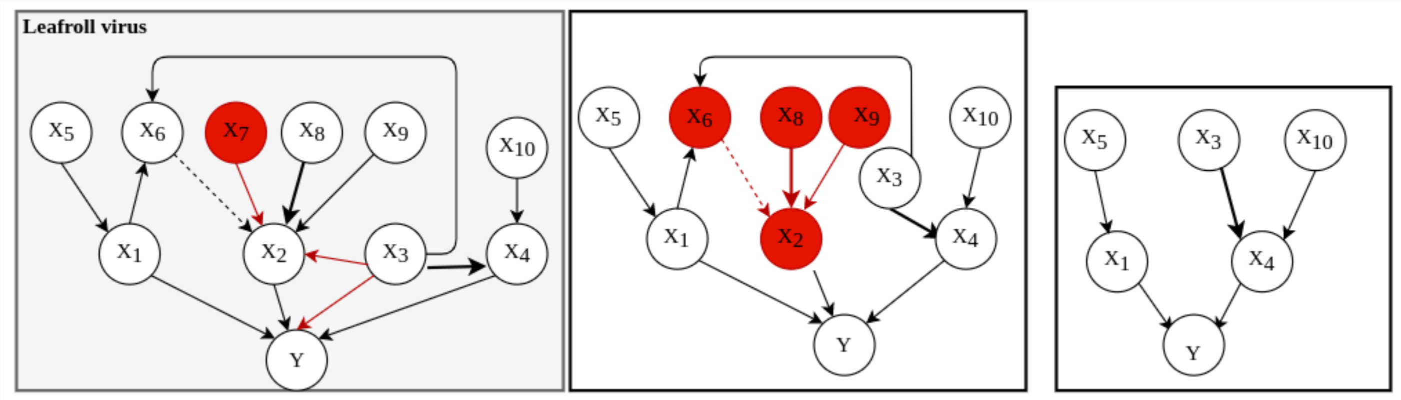


Diagram	**-**	**1**	**2**	**3**
Threshold	0.4	**0.47**	0.5	0.55
Average NRMSE (X_i = 12)	1.472	**0.772**	0.767	0.797
Average correlation (X_i = 12)	0.568	**0.578**	0.574	0.538
Directed arcs	471	**351**	303	250

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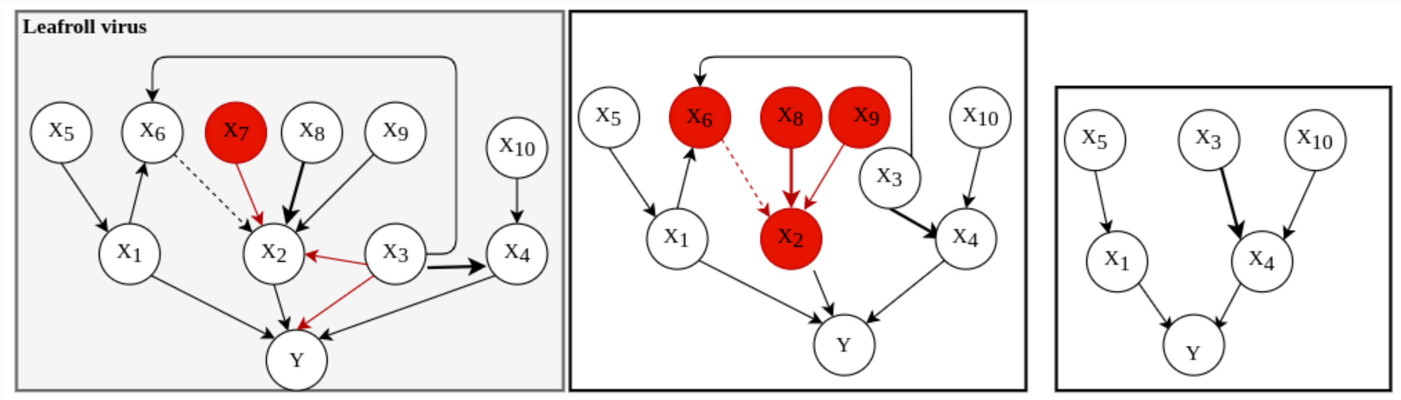

A threshold = 0.47 provided a sparse, interpretable model with better prediction performance.

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Conclusion

- Built a consensus model with arcs that appear more than 47% in the 10k structures (351 directed arcs).
- Model validation: prediction correlation was [0.11, 0.84] and NRMSE [0.49, 2.33].
- Pests and diseases were influenced by management, weather, soil and region/variety.

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Future work

- Perform what-if scenario analysis to predict the impact of climate change.
- Finalise the three-step framework for hypothesis generation, refinement and analysis.

Thank You

- Supervisors: Beatrix Jones, Sarah Knight and Kate Lee.
- Members past and present who have contributed to the vineyard ecosystem programme.
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