WORKING WEEK 2025 AND Locate25 THE NATIONAL GEOSPATIAL CONFERENCE

Collaboration, Innovation and Resilience: Championing a Digital Generation

FIG Geospatial Council of Australia

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The Future of Urban Planning: Blending Planning Expertise with AI Technology

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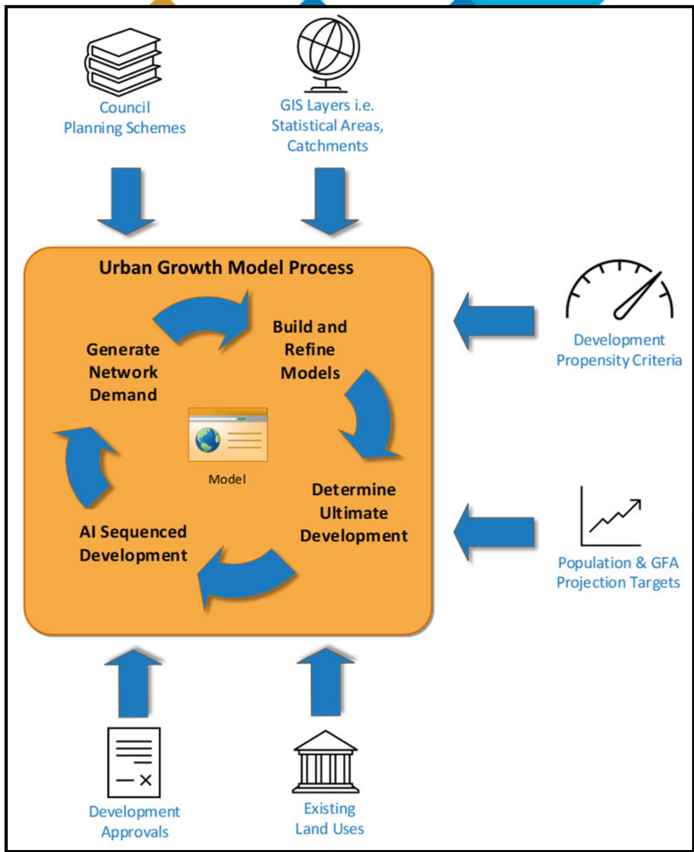
Urban Growth Modelling Challenges

- Modelling urban growth is complex
- Many inputs and many processes, as shown in this example
- Core requirement – method to determine the development propensity of properties
- Aligns to predicting the occurrence of Development Applications/Permits
- Why not use DA/Permits as input to Machine Learning Model to assist with determining propensity?



Limitations of Development Applications/Permits data

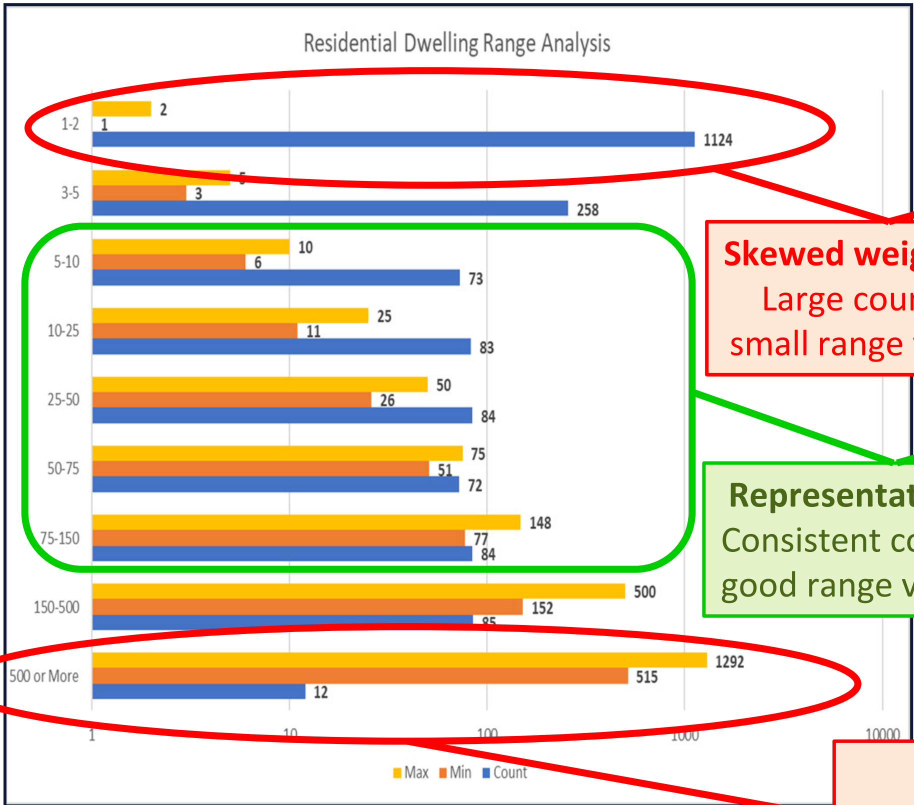
- Uneven mix of Residential DA/Permits vs Non-Residential DA/Permits

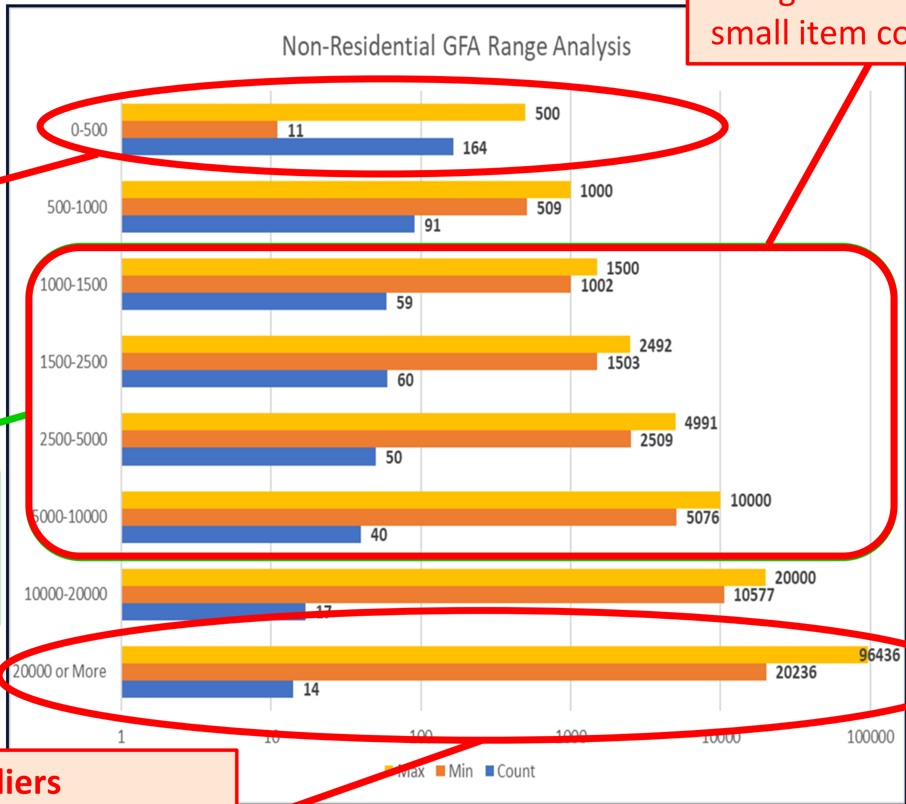
Typically 75% - 80% Residential Development

Typically 20% - 25% Non-Residential Development

- DA/Permits represent a small portion of all properties that can be developed
  - Typically 5% - 10% of developable properties
- Normally do not contain DA/Permits that were refused or did not proceed - Important data for ML analysis

Analysis of Development Applications/Permits data





Skewed weighting
Large count with small range variation

Representative Data
Consistent count with good range variation

Low num Items
Range variation has small item count <60

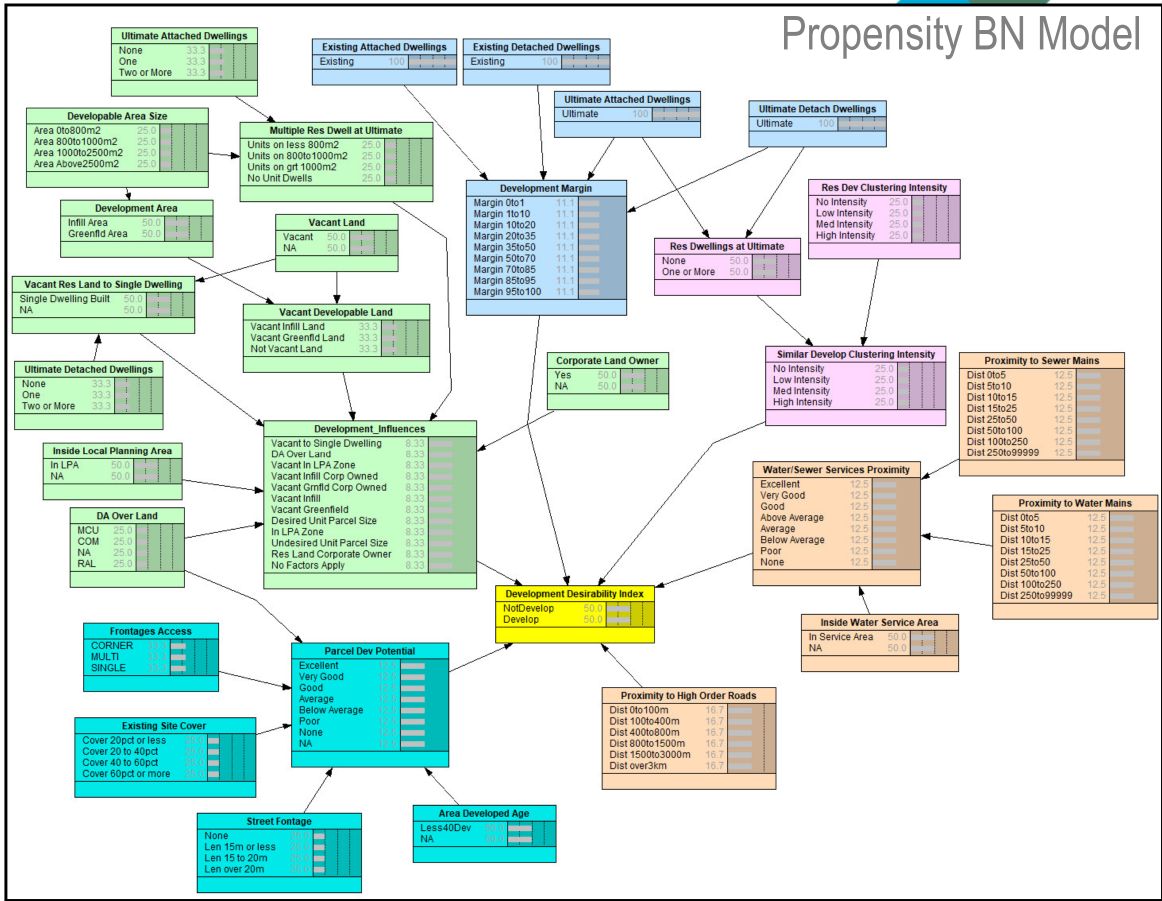
Outliers
Small count with large range variation >70,000 GFA

Given DA/Permits data limitations for machine learning…

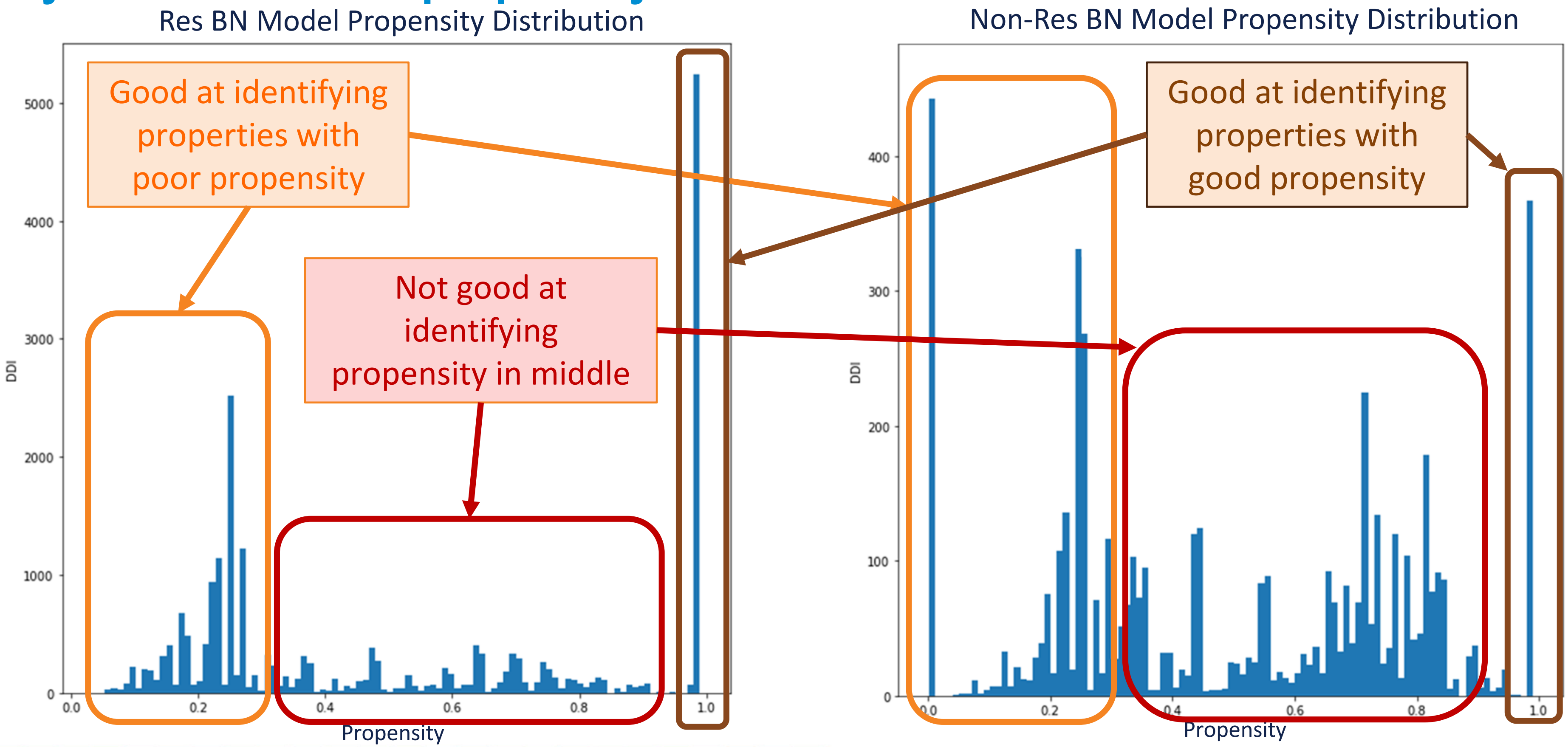
Can we utilise an urban planner's knowledge to assist with determining development propensity?

Utilise Bayesian Network Models

- Probabilistic graphical models with a clear schema, as shown in this example
- Commonly used for land use scenario modelling
- Studies show BN Models can produce good predictions from expert analysis
- “Codify” urban planner’s knowledge of factors that influence development
- Use BN models to describe the propensity for a property to develop



Analysis of BN Model propensity distribution



Given Urban Planner BN Model shortcomings…

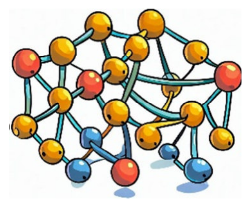
Could Machine Learning assist with determining a better propensity for the mid-section distribution?

What if we combine BN Model data with the DA/Permit data?

What does that look like…

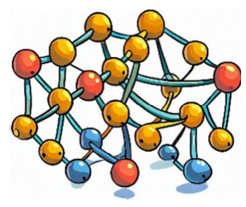
BN node data points
All other 30+ data points

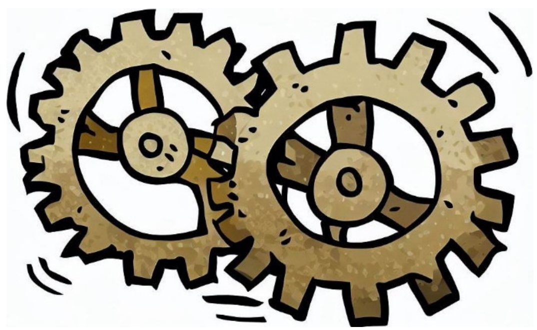
Property development with great propensity



Property development of DA/Permits

Property development with poor propensity





Machine Learning Model

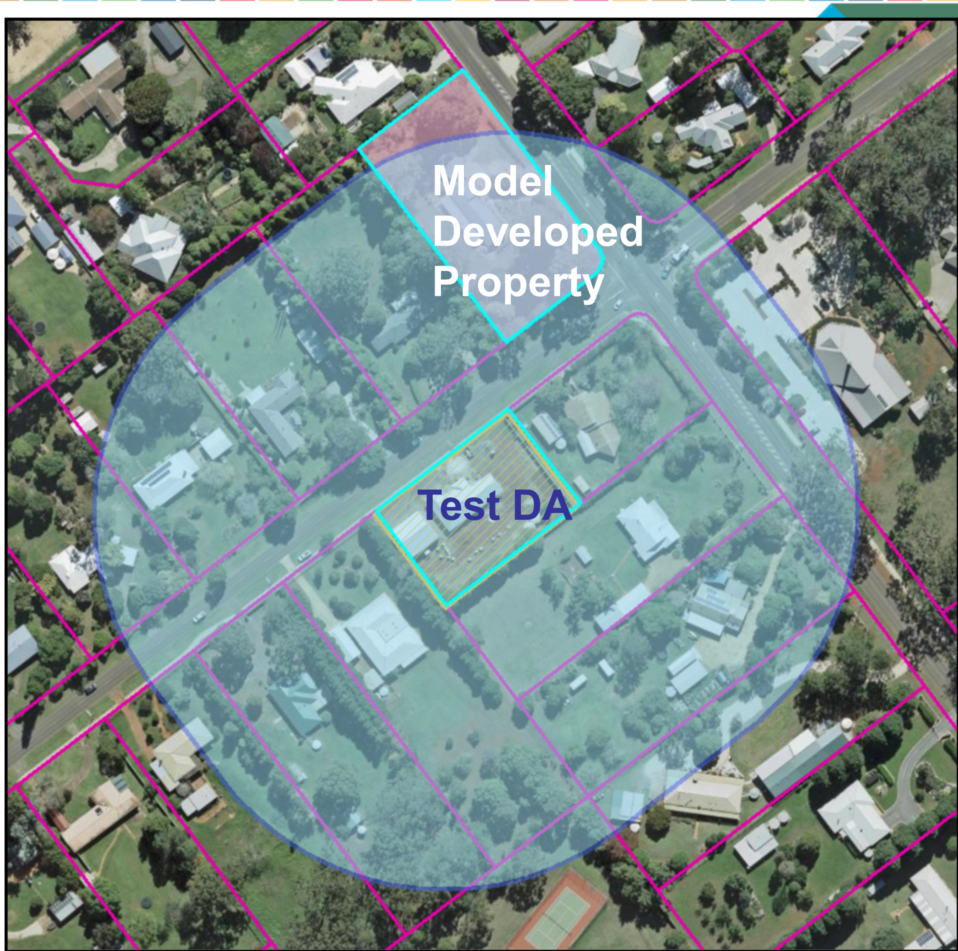
Can it inference a realist propensity

Testing the ML Model Prediction Performance

- Randomly remove 30% of the DA/Permits from the model – **Test DAs**
- Test if the model developed a property nearby to a **Test DA** using ML propensity
- Property nearby must satisfy the following criteria:
  - Must be developable
  - Cannot be a property it was trained on
  - Must not be a DA/Permit
  - Must be within a certain distance of the removed **Test DA**
  - Must have a residential/non-residential land use that matches the land use of the removed **Test DA**

Nearby Developed Property Example

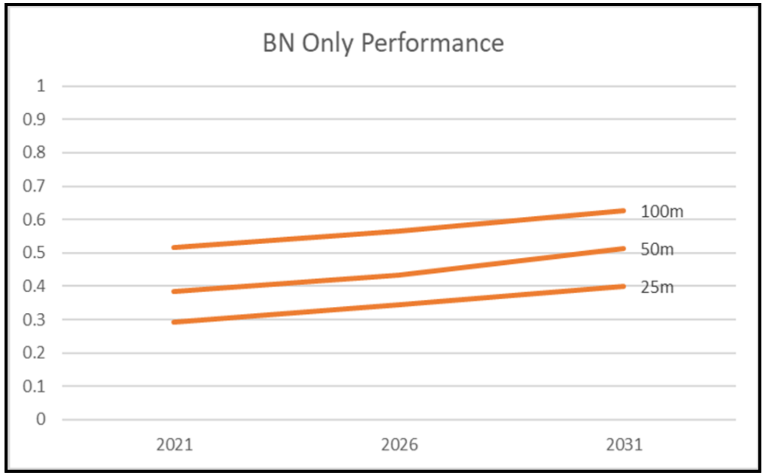
- The property developed by the model is within 100m of the **Test DA** (removed from model)
- Treated as a successful prediction

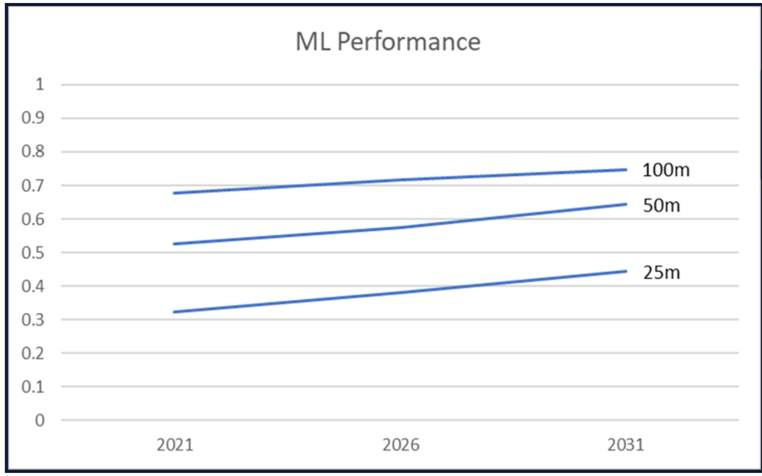


Non-Residential Testing Performance

BN Only Performance			
Projection Year from 2019	25	50m	100m
2021	29.29%	38.38%	51.52%
2026	34.51%	43.36%	56.64%
2031	40.00%	51.30%	**62.61%**

ML Performance			
Projection Year from 2019	25m	50m	100m
2021	32.32%	52.53%	67.68%
2026	38.05%	57.52%	71.68%
2031	44.35%	64.35%	**74.78%**

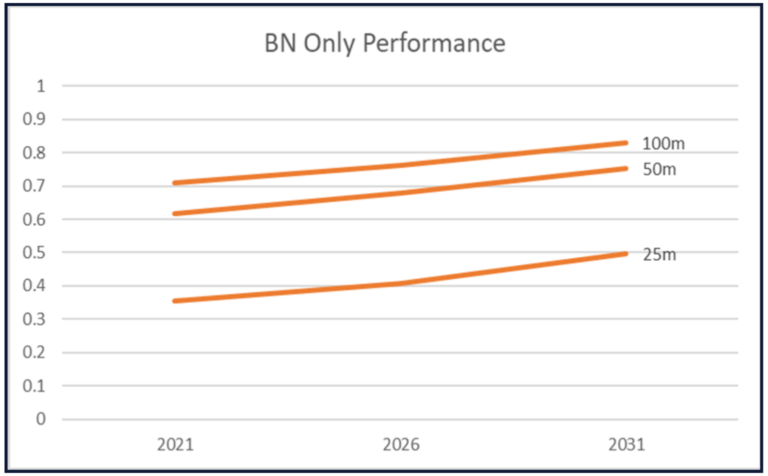


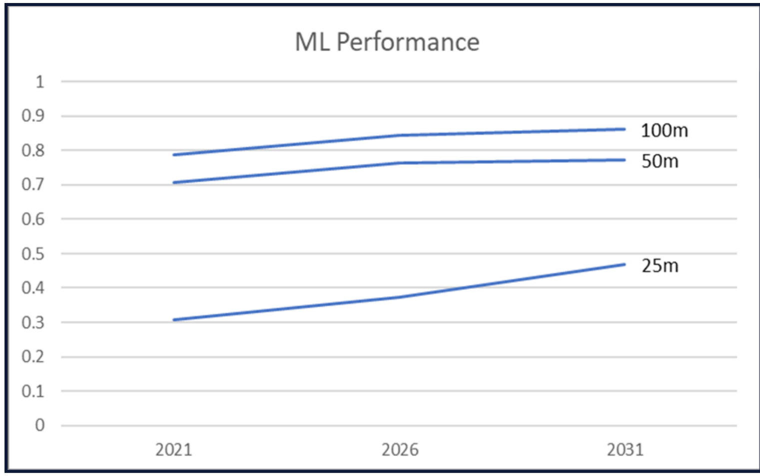


Residential Testing Performance

BN Only Performance			
Projection Year from 2019	25m	50m	100m
2021	35.63%	61.78%	70.98%
2026	40.71%	67.94%	76.08%
2031	49.77%	75.34%	**82.88%**

ML Performance			
Projection Year from 2019	25m	50m	100m
2021	30.67%	70.67%	78.67%
2026	37.25%	76.47%	84.31%
2031	46.90%	77.24%	**86.21%**





Conclusion

- Codifying Urban Planner's knowledge into BN Model produces good predictive performance for models
- Combining the BN Model with Machine Learning gives up to 10%-15% performance lift above the BN Model
- Good improvement in Non-Residential development predictions – 63% to 75%

Thank you

The most relevant SDGs related to the presentation and theme of this session

9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
1st relevant SDG

11 SUSTAINABLE CITIES AND COMMUNITIES
2nd relevant SDG

10 REDUCED INEQUALITIES
3rd relevant SDG

SUSTAINABLE DEVELOPMENT GOALS | International Federation of Surveyors supports the Sustainable Development Goals