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MANAGEMENT FORUM

Our Carbon Equation

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The Promises and Perils of Machine Learning in Infrastructure Asset Management

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RIMS
Roading Infrastructure Management Support

in association with
IDS
Infrastructure Decision Support

In this Presentation:

- Background to Machine Learning
- Promises of ML in Deterioration Modelling
- Perils of ML in Deterioration Modelling
- Concluding Thoughts

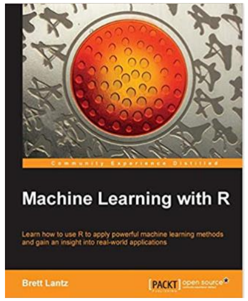
Historical Background

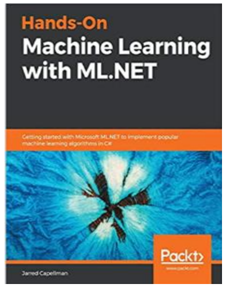
- "Machine Learning" is concerned with turning data into actionable intelligence
- The term "Machine Learning" was coined by Arthur Samuel in 1959

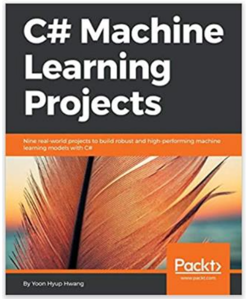
Machine Learning evolved in <u>two generally defined stages</u>:

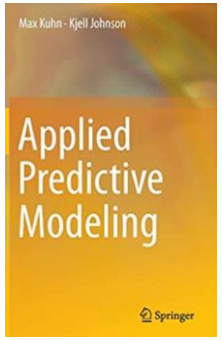
- Knowledge Based Systems – machine relies on rules (1970s)
- Machine Leaning by inference (1980's) – let machine learn by examples and infers "rules" by itself

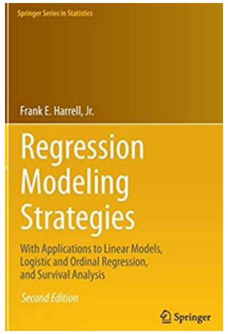
- A study estimated that in 2017 90% of the world's data was created in the preceding two years



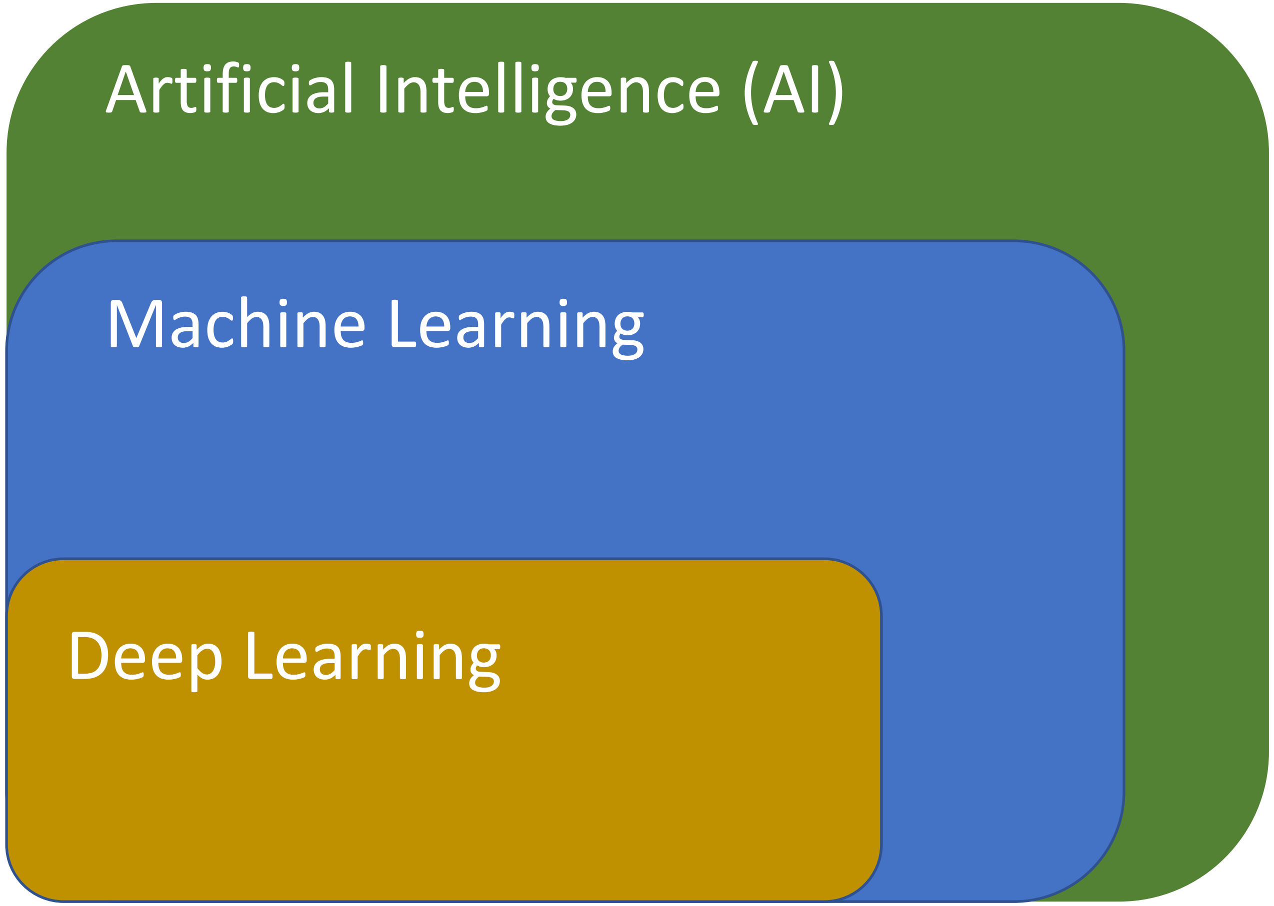








The Machine Learning Landscape



https://docs.microsoft.com/en-us/azure/machine-learning/concept-deep-learning-vs-machine-learning

Artificial Intelligence

Any technique that enables computers to <u>mimic</u> human intelligence

Machine Learning

- A subset of AI
- Techniques that enable machines to improve at tasks/predictions by learning from examples

Deep Learning

- A subset of ML
- Uses Artificial Neural Networks
- Needs more data
- Infers/creates the features by itself

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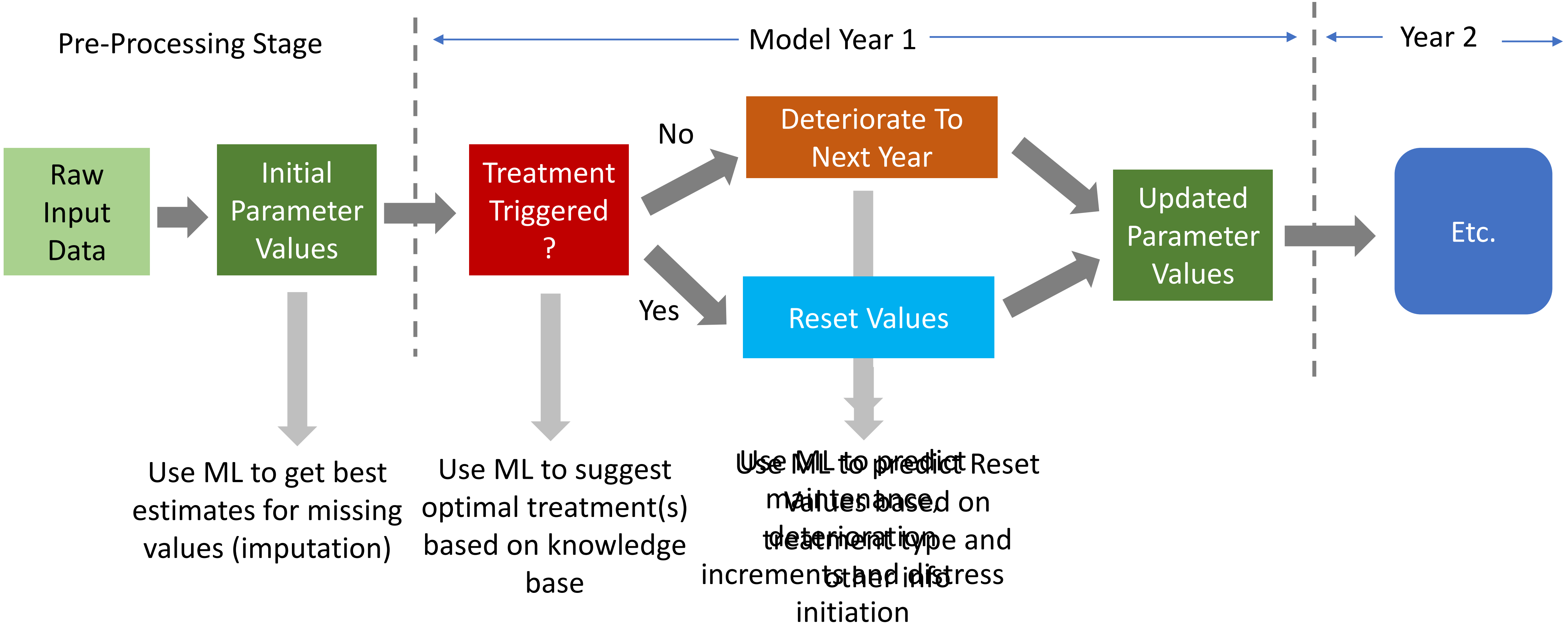
Where can we use ML in Deterioration Modelling?

What happens at the model element level?



A peek into the future

Data Stream 1 (HSD)

Data Stream 2
(AI Distress Inference)

Data Stream 3
Crash & Maintenance

Asset Management
System &
Database

Extract Training and
Testing Set

Train and Evaluate
Models

Review Performance
Metrics

Stored ML
Models

Deterioration
Models

Decision Support
(Virtual FIT, Mobile Apps)

- More accurate, evidence based decisions and forecasts
- Improved Risk-Cost-Benefit

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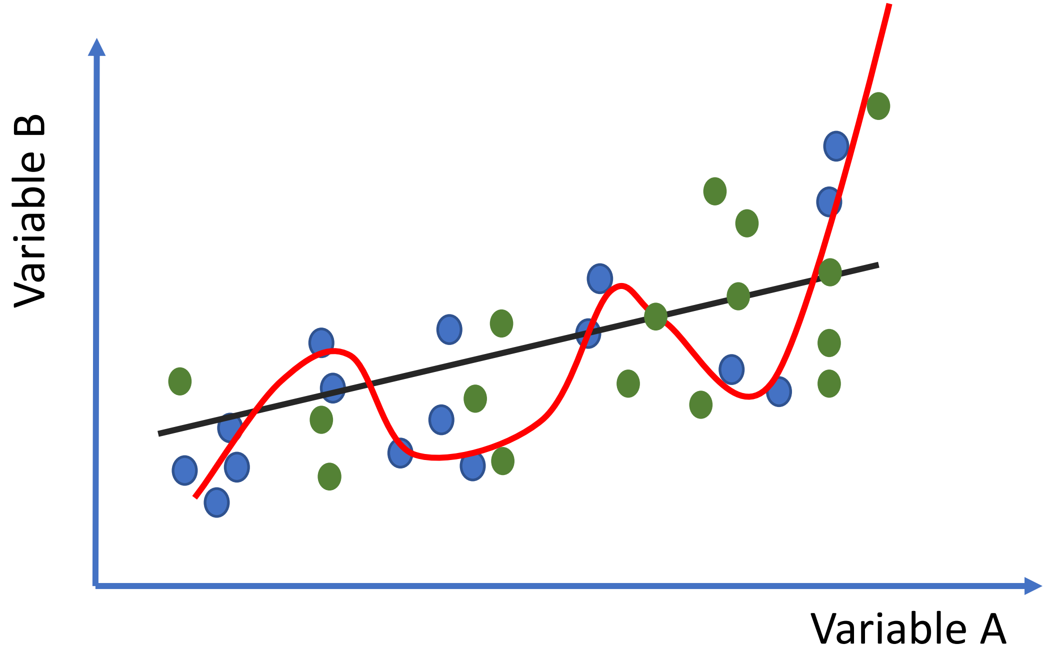
Challenges in Machine Learning:

1. Model Overfitting



Challenges in Machine Learning:

1. Model Overfitting – the solution?

Use Machine Learning best practices:

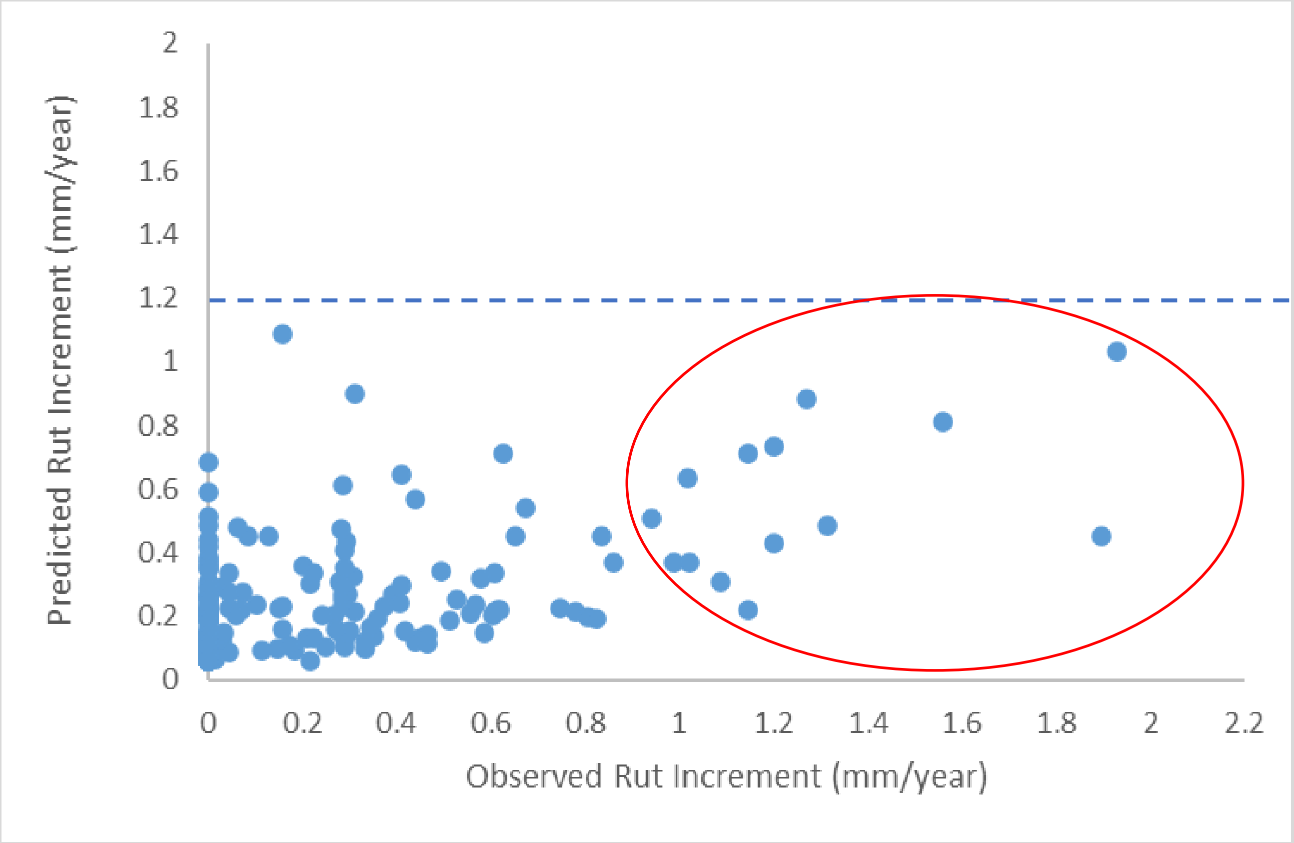
- Use a holdout set for testing (80% training data, 20% testing)
- Use k-fold Cross-Validation

Fold 1	Group 1	Group 2	Group 3	Group 4	Group 5	R2 = 0.45
Fold 2	Group 1	Group 2	Group 3	Group 4	Group 5	R2 = 0.67
Fold 3	Group 1	Group 2	Group 3	Group 4	Group 5	R2 = 0.55
Fold 4	Group 1	Group 2	Group 3	Group 4	Group 5	R2 = 0.8
Fold 5	Group 1	Group 2	Group 3	Group 4	Group 5	R2 = 0.46
						Mean R2 = 0.59

Training Data | Testing Data

Challenges in Machine Learning:

2. ML may distract us to Focus on Wrong Problem



R^2 = 0.36 on 10-fold Cross-Validation

<u>Variability may be a more serious challenge than Accuracy:</u>

- ML addresses mainly Accuracy
- Most cost comes from semi-outliers?
- More data types will help, but will be costly and may not solve the problem
- Need to move to probabilistic thinking and modelling

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Challenges in Machine Learning:

3. Human Resource Challenges

What do you mean? Won't machine learning put us all out of work?

The Paradox of Automation:
The more efficient an Automated system is, the more crucial the contribution of human operators. Efficient automation makes humans more important, not less

The Irony of Automation:
The more reliable an Automated system is, the less human operators have to do, so the less attention they pay to it. And so they are less likely to notice when things go wrong.

New human resources and cooperation models may be needed to handle these paradoxes

Some conclusions:

- Machine Learning is an exciting new tool in the Asset Manager’s toolbox
- It may lead to significant improvements in decision making
- It is not a silver bullet
- Critical challenges remain – particularly high variability in many road asset management problems
- Managers need to build internal and external human resources to maximise the ML wave
- Young engineers – your ability to control and focus your attention is your most valuable asset – guard and protect it!

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Thank You!

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References:

- Stages of Machine Learning, see:
  - Kubat, M: An Introduction to Machine Learning
- Proliferation of Data, see:
  - Cappelman, J: Machine Learning with ML.NET
- Machine Learning Landscape: see:
  - https://docs.microsoft.com/en-us/azure/machine-learning/concept-deep-learning-vs-machine-learning

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Machine Learning: Some Background

Machine Learning

- “Machine Learning” is concerned with turning data into actionable intelligence
- The term “Machine Learning” was coined by Arthur Samuel in 1959
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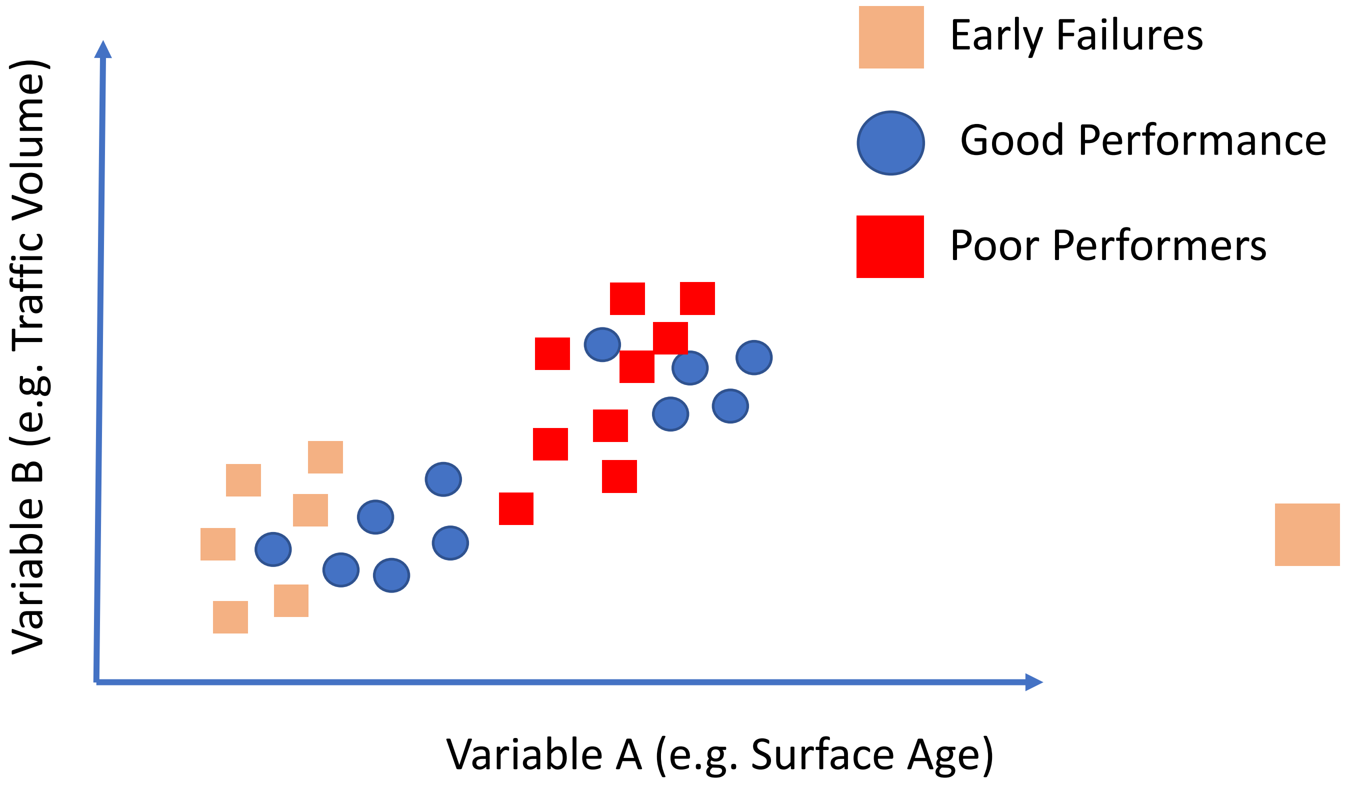
Promises of Machine Learning in IAM

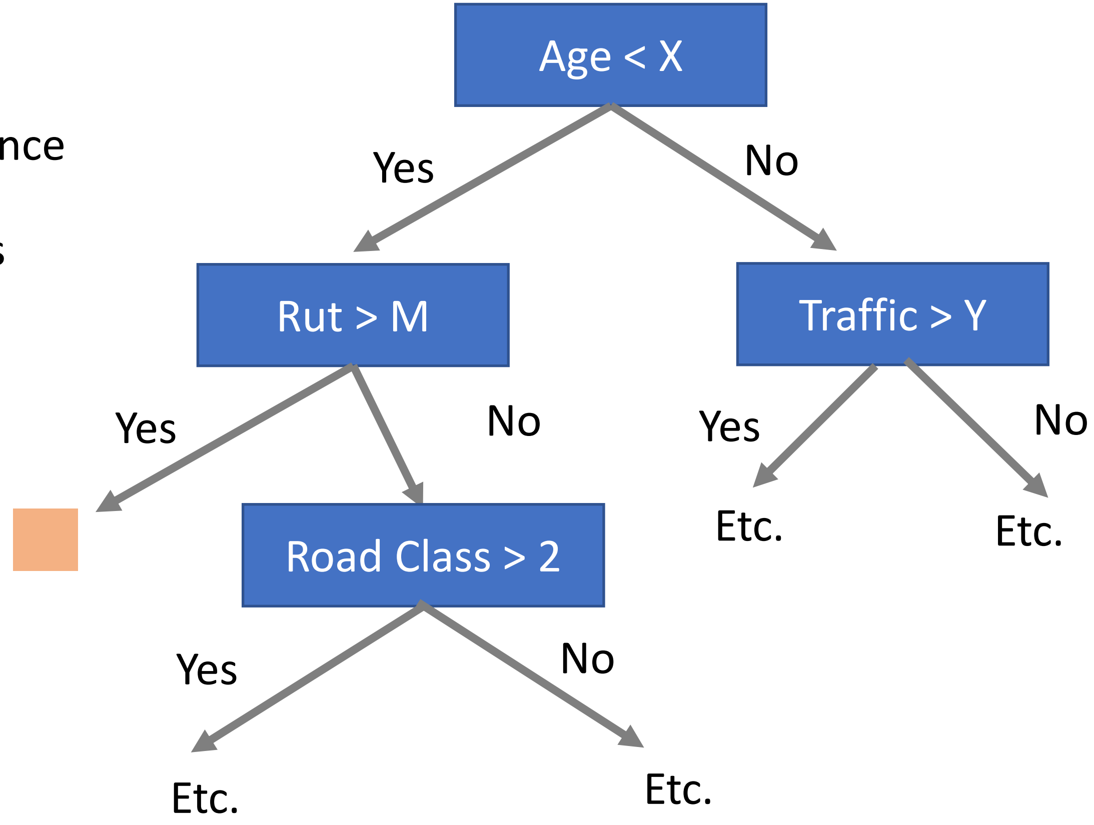
- Maximise value gained from available data
- Improved accuracy
- Potential for automation – models updated on demand
- Improved decision making, reduction in risk and cost

Some General Classes of ML Models

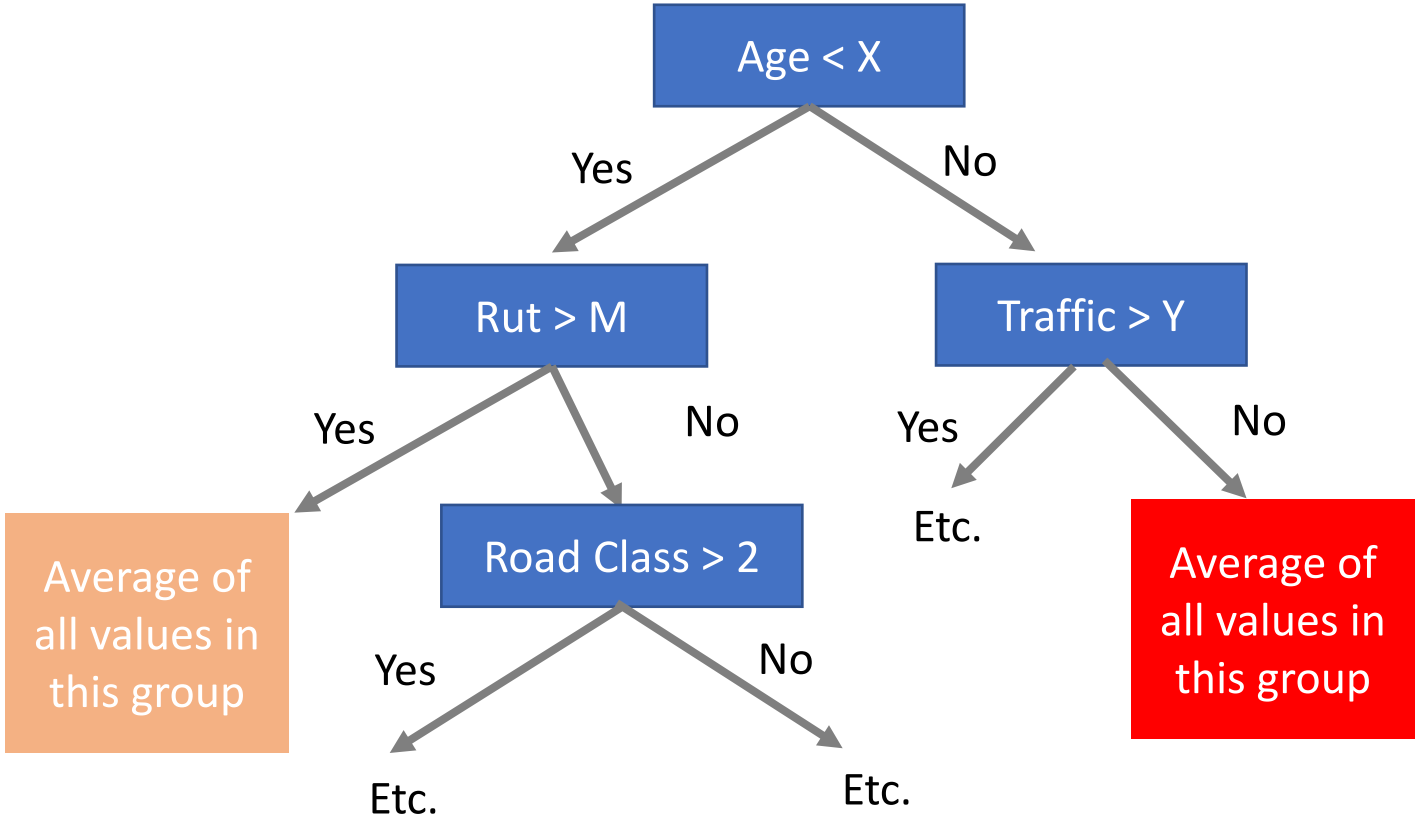
- Classification (two-class)
- Classification (multi-class)
- Regression
- Clustering
- Image Classification

Decision Tree Visualisation





Regression Tree Visualisation



Classification Model Types

Objective: Predict a Class given some information

- Decision Tree
- Decision Forest
- **Logistic regression**
- Boosted Decision Tree
- Neural Networks

Regression Model Types

Objective: Predict a numerical value given some information

- Fast Forest Quantile Regression (predicts a distribution)
- Poisson Regression (predicts counts)
- **OLS: Ordinary Least-Squares Regression (our old friend – use Excel!)**
- Bayesian Linear Regression (small data sets)
- Decision Forest Regression
- Neural network regression
- Boosted Decision Tree Regression

Ensemble Models

Approach: Build multiple models and average the result

Bagged Trees

- Randomly sample with replacement
- Build a model on each random sample set
- Average the predictions of each model

Boosting

1. Train a model
2. Identify where it makes errors
3. Build next model to improve on errors
4. Repeat Steps 1-3 many times
5. Average the predictions of all models

An example – pothole prediction:

Potholes one of the most difficult distresses to predict
Historically potholes observed on 12% of segments

Model 1: Randomly Assign Potholes on 12%

Potholes		Predicted	
		TRUE	FALSE
Observed	TRUE	48	354
	FALSE	354	2642

Accuracy = 79%

Sensitivity = 12% (of segments that did have potholes, what % correctly identified?)

Precision = 12% (what prop. of segments where potholes were predicted did actually have potholes?)

An example – pothole prediction:

Boosted Decision Tree – prediction on holdout test set
(Model based on ADT, HCV, Surface Type etc.)

<table>
<tr><th colspan="2" rowspan="2">Potholes</th><th colspan="2">Predicted</th></tr>
<tr><th>TRUE</th><th>FALSE</th></tr>
<tr><th rowspan="2">Observed</th><th>TRUE</th><td>18</td><td>50</td></tr>
<tr><th>FALSE</th><td>17</td><td>475</td></tr>
</table>

Accuracy = 88%

Sensitivity = 26% (of segments that did have potholes, what % correctly identified?)

Precision = 51% (what prop. of segments where potholes were predicted did actually have potholes?)

Longitudinal and Transverse Cracks

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Boosted Decision Tree – prediction on holdout test set
(Model based on ADT, HCV, Surface Type etc.)

Potholes		Predicted	
		TRUE	FALSE
Observed	TRUE	158	86
	FALSE	54	262

Accuracy = 75%

Sensitivity = 65% (of segments that did have L&T Cracks, what % correctly identified?)

Precision = 75% (what prop. of segments where L&T cracks were predicted did actually have cracks?)