

# Property Valuation and AI In Practice

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technologies

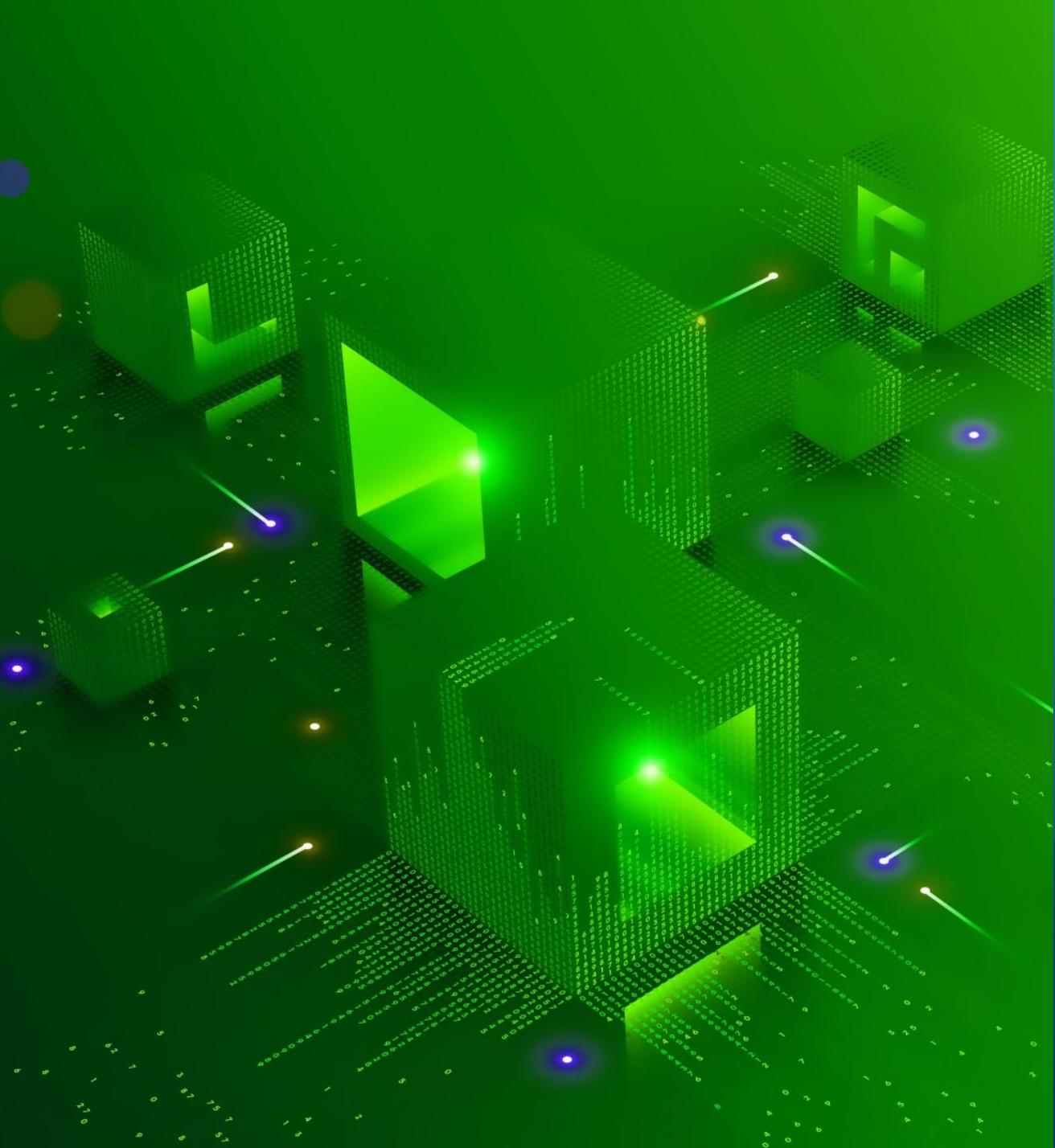


## **Daniel Fasteen, Ph.D.**

SENIOR RESEARCH SCIENTIST

SPECIAL PROJECTS



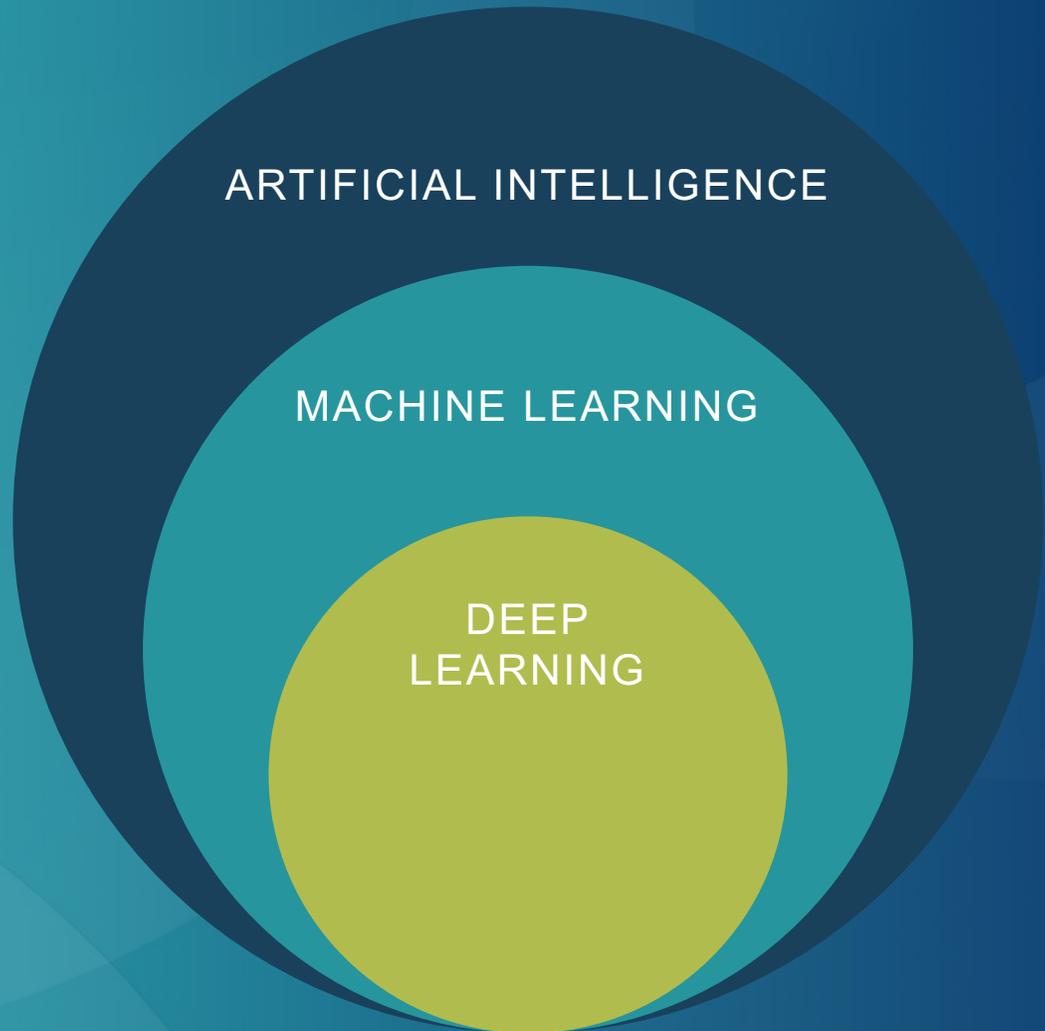


# What is Data Science?

Data Science is the discipline of extracting knowledge and insights from data using analytical, statistical, and computational methods

- Data Engineering
- Statistical Modeling
- Machine Learning & Algorithms
- Visualization & Communication

Data Science allows us to augment traditional appraisal methods with evidence-based, scalable tools which helps us improve efficiency, equity, and transparency in mass appraisal.



# Artificial Intelligence

Computer systems/algorithms that can perform complex tasks by mimicking human like reasoning.

## Machine Learning

An algorithm with the ability to learn patterns without explicit programming

## Deep Learning

A type of machine learning that uses artificial neural networks constructed of multiple layers to process data and make predictions.

## Data Science

Provides the foundation with which we can explore and create intelligent systems.



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IAAO AI Taskforce Overview

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Research Areas

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Results by Area

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General Findings and Recommendations

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Research Outcomes and Future

# IAAO TASKFORCE OVERVIEW

- Comparative research on the performance of AI valuation models in different international contexts.
- Three Areas, Nine Valuation Models
- Also compared the use of Hyperparameter Tuning (not important)
- **Committee Members:** Luc Hermans (Chair), Paul Bidanset, Daniel Fasteen, PhD., Pim Hessing, Joshua Jorgenson, Luke Jorgenson, Annita Ng, Michael McCord, PhD., Russ Thimgan, John Valente, Joe Wehrli



# Why This Research Matters

Problems practitioners face

- Increased complexity in housing markets
- Equity Pressure (PRB, PRD, Etc)
- Shorter Revaluation Cycles
- Budget and Staffing Constraints

Key Question:

“ Do AI-Based AVMS meaningfully improve ratio study performance and equity compared to traditional regression?”



# Methodologies Tested



## TRADITIONAL METHODS

**Linear Additive**  
**Linear Multiplicative**

## AI METHODS

**Decision Trees**  
**Random Forest**  
**Gradient Boosting Machine (GBM)**  
**Light GBM**  
**Generalized Regression Neural Network (GRNN)**  
**Multi Layer Perceptron (MLP)**  
**Tensor Flow Dense NN**



# Research Study Areas



## Belfast Northern Ireland, UK

- Heterogeneous housing stock
- Many categorical variables
- 342,000 Inhabitants



## Adams County Colorado, USA

- Homogeneous housing stock
- Very large dataset
- 363,000 Inhabitants



## Eindhoven, Netherlands

- Mixed (homogeneous)
- High quality dataset
- 250,000 Inhabitants

# ADAMS COUNTY, COLORADO USA



Model	R squared	Racine R squared	Weighted Mean	COD	PRD	PRB	MAE	RMSE
Linear Regression	0.8251	0.8255	1.0035	9.2122	1.012	-0.0205	43672.88	66310.83
Multiplicative Regression	0.8291	0.8292	0.9949	9.2679	1.015	-0.0531	43592.07	65549.80
Decision Tree	0.8379	0.8423	1.0016	8.1374	1.009	-0.0164	38552.52	63834.62
Random Forest	0.8908	0.8908	1.0020	6.5923	1.010	-0.0368	31246.45	52398.09
Gradient Boosting	0.8860	0.8869	1.0019	6.4482	1.008	-0.0208	30504.07	53545.15
Light Gradient Boosting	0.9115	0.9117	1.0023	6.0197	1.007	-0.0259	28162.71	47167.87
Generalized Regression Neural Network	0.7981	0.7981	0.9989	9.6277	1.020	-0.0884	45691.83	71251.74
Multi Layer Perceptron	0.8600	0.8611	1.0081	7.8437	1.010	-0.0278	37038.51	59334.90
Tensor Flow Dense Neural Network	0.8846	0.8849	0.9995	6.8309	1.010	-0.0375	32268.81	53875.52

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Decision Tree	0.8487	0.8491	0.9986	7.8938	1.012	-0.0350	37425.18	61670.72
Random Forest	0.9015	0.9020	1.0014	6.2996	1.011	-0.0475	29775.83	49760.40
Gradient Boosting	0.9142	0.9145	1.0021	5.7832	1.007	-0.0210	27138.23	46434.53
Light Gradient Boosting	0.9118	0.9122	1.0026	5.8315	1.007	-0.0195	27366.06	47102.41
Generalized Regression Neural Network	0.7981	0.7981	0.9989	9.6277	1.020	-0.0884	45691.83	71251.74
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# EINDHOVEN, THE NETHERLANDS



Model	R squared	Racine R squared	Weighted Mean	COD	PRD	PRB	MAE	RMSE
Linear Regression	0.7428	0.7449	0.9912	13.1206	1.024	0.0	60863.18	116616.86
Multiplicative Regression	0.8160	0.8243	0.9823	11.7684	1.029	-0.0741	54901.51	98645.39
Decision Tree	0.7733	0.7765	1.0035	11.8983	1.017	0.0	57900.00	109482.94
Random Forest	0.8403	0.8404	1.0016	8.9390	1.017	-0.0357	44176.53	91887.05
Gradient Boosting	0.8819	0.8821	1.0006	7.5081	1.011	-0.0145	36898.66	79012.37
Light Gradient Boosting	0.8469	0.8478	1.0022	7.4761	1.010	-0.0126	37479.29	89966.50
Generalized Regression Neural Network	0.8000	0.8060	0.9845	9.8105	1.027	-0.0767	48204.75	102850.37
Multi Layer Perceptron	0.7083	0.7126	0.9871	10.5863	1.022	-0.0348	53740.80	124192.64
Tensor Flow Dense Neural Network	0.8722	0.8742	1.0047	8.9812	1.018	-0.0406	43941.32	82192.92

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Multiplicative Regression	0.8160	0.8243	0.9823	11.7684	1.029	-0.0741	54901.51	98645.39
Decision Tree	0.8118	0.8119	0.9970	11.0599	1.019	-0.0243	53599.63	99760.59
Random Forest	0.8624	0.8679	0.9988	8.5802	1.021	-0.0557	42027.78	85290.86
Gradient Boosting	0.8995	0.9099	0.9900	7.5999	1.017	-0.0393	36962.21	72908.54
Light Gradient Boosting	0.8951	0.8954	1.0003	7.3509	1.010	-0.0128	35727.51	74478.12
Generalized Regression Neural Network	0.8000	0.8060	0.9845	9.8105	1.027	-0.0767	48204.75	102850.37
Multi Layer Perceptron	0.7083	0.7126	0.9871	10.5863	1.022	-0.0348	53740.80	124192.64
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# BELFAST, NORTHERN IRELAND



Model	R squared	Racine R squared	Weighted Mean	COD	PRD	PRB	MAE	RMSE
Linear Regression	0.6830	0.6888	1.0116	24.6743	1.067	-0.0538	45597.16	64086.58
Multiplicative Regression	0.6990	0.7017	0.9703	23.0826	1.070	-0.1040	43840.29	62448.93
Decision Tree	0.6937	0.7200	1.0046	19.9726	1.038	0.0	38831.88	63001.20
Random Forest	0.8195	0.8196	1.0025	15.6552	1.044	-0.0587	30115.14	48365.08
Gradient Boosting	0.7822	0.7882	1.0041	16.3753	1.035	0.0	31681.45	53117.60
Light Gradient Boosting Machine	0.8373	0.8373	0.9985	14.7658	1.038	-0.0477	28432.45	45920.72
Generalized Regression Neural Network	0.8311	0.8312	0.9984	14.7327	1.038	-0.0560	28330.79	46782.71
Mult Layer Perceptron	0.6847	0.6928	1.0210	23.3764	1.067	-0.0814	44203.23	63913.60
Tensor Flow Dense Neural Network	0.8134	0.8136	0.9883	17.5650	1.043	-0.0533	33046.98	49165.46

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Multiplicative Regression	0.6990	0.7017	0.9703	23.0826	1.070	-0.1040	43840.29	62448.93
Decision Tree	0.7345	0.7386	0.9815	18.4385	1.046	-0.0360	35877.20	58646.84
Random Forest	0.8432	0.8483	0.9905	14.5257	1.047	-0.0812	28193.35	45075.88
Gradient Boosting	0.8561	0.8569	0.9876	13.5212	1.037	-0.0576	26356.79	43186.94
Light Gradient Boosting Machine	0.8487	0.8487	0.9980	14.9267	1.036	-0.0482	28021.28	44272.70
Generalized Regression Neural Network	0.8311	0.8312	0.9984	14.7327	1.038	-0.0560	28330.79	46782.71
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# Overall Results

## 1. Linear Regression is no longer the Standard

- Its interpretable, familiar, stable
- Not the most equitable for non-linear data

## 2. ML Models Consistently Outperformed Traditional

- $R^2$ , COD, PRD, PRB, MAE, RMSE
- Even with ~10 predictor variables only

## 3. Tree based models are sweet spot

- **Random Forest, GBM, LightGBM**
  - Handle nonlinearity
  - Reduces Overfitting
  - Improve COD and PRD
  - Scale well

# The Blackbox Concern

- Key Clarification:
  - These are supervised models in a control environment.
  - Not GenAI or ChatGPT
- Modelers choose the data, features and control the training.
  - Still Garbage in = Garbage Out
- Transparency should focus on what variables are used, why they are used, and model governance.

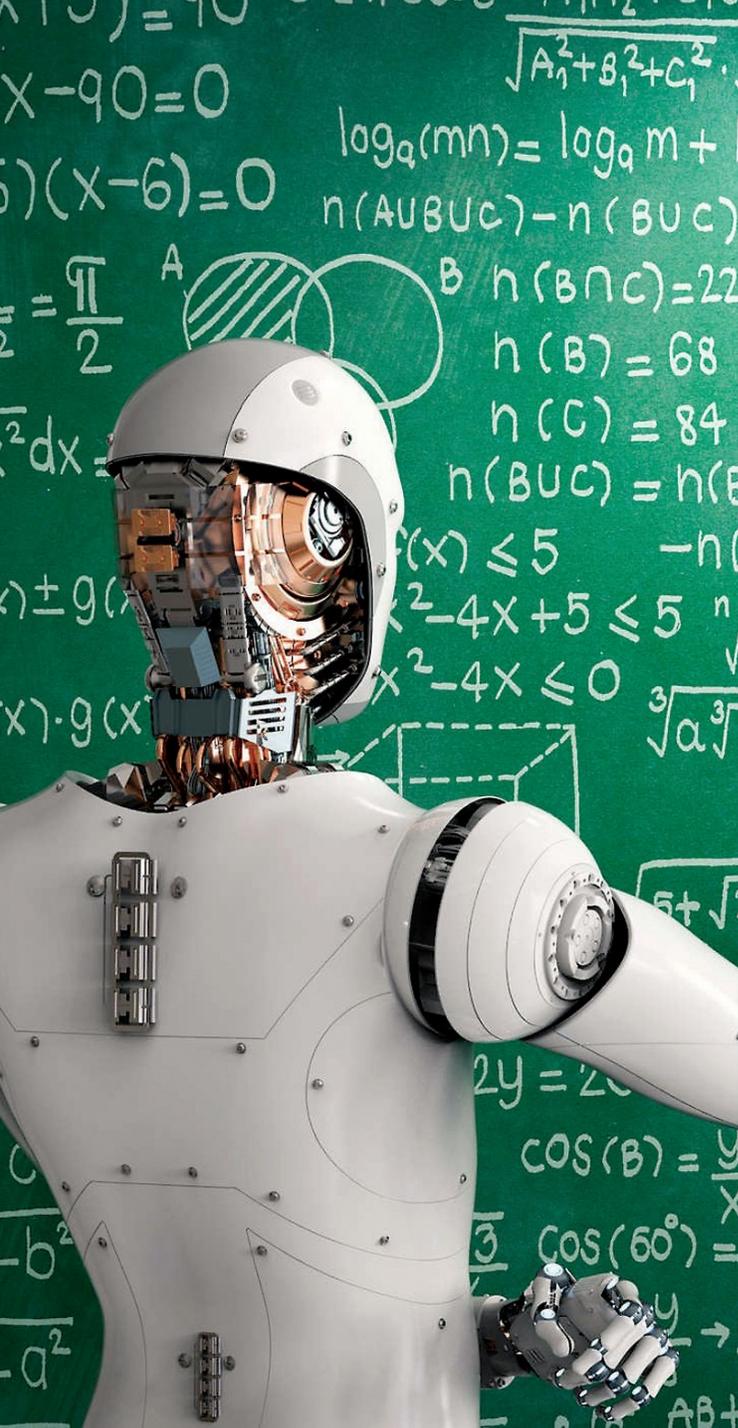
# Takeaways

- **AI Based AVMS are no longer experimental**
- **They Work in Large, medium and small areas with adequate data.**
  - Especially used in nonparametric data
- **They improve Accuracy, Precision, Equity**
- **Mainly used for reconciliation against other models for accuracy.**

## Consider ML Models when:

- COD is consistently above 15
- Urban heterogeneity is present
- Spatial Clustering Patterns
- Evidence of vertical inequity
- Nonlinear relationships

# AI Use Cases in Property Valuation



# #1 AI POWERED ASSESSMENT ROLL (PVSC)

First Canadian jurisdiction to publish an AI-based roll.

- Used ML for residential Assessment
- Ran traditional roll and ML roll in parallel

## Scope

- 33% Residential Improved
- 30% Condominiums

## Oversight

- Full Ratio Study Validation
- External Audit Review
- Assessor Review before deployment



# Operational Impacts

AI POWERED ASSESSMENT ROLL CONT..

## Impacts – What Changed

- 85% fewer person – hours for reassessment
- Completed in less than 3 months vs. 12 months
- Minimal inquiry/appeal impact

## What did not Change

- Ratio Study Standards
- Assessor Oversight
- Defensibility Expectations

**AI Only Reallocated the time – It did not replace assessors**

## #2 NETHERLANDS ML RESIDENTIAL PILOT

Evaluate whether ML is a viable tool for mass appraisal

- Single Model vs. Multiple market area models.
- Time trended sales vs. time as a variable.
- More years of sales vs. limited sales window.

### Method

- Training/holdout test split
- Ratio study validation (IAAO standards)
- Variance analysis vs. traditional values.



# What Did They Learn?

NETHERLANDS ML PILOT

## Findings

- ML is viable for residential improved properties
- No significant difference between
  - Time Trending vs. Time Variable
  - One model vs. market area models
  - Expanded vs. limited sales windows

## Practical Implication

- A single well-structured ML model handled the full population effectively.
- Simplification without sacrificing accuracy or equity.
- Validate with ratio studies.

### Testing AI in a difficult market segment

- Small Universe of Properties (~80,000 properties)
- Limited Sales (~20,000 over 5 years)
- High price variability
- Hard to model reliably

### Traditional Challenges

- Too few sales per market set
- Difficult to automate cost factor calibration
- Geographic effects hard to model using MRA

### Pilot Approach

- Gradient Boosting Model (GBM)
- Parallel testing vs. appraiser-derived values.



# Results and Implications

MANUFACTURED HOMES (BC ASSESSMENT)

## Model Performance

- ML values comparable to appraiser-driven values
- Ratio studies on holdout sales confirm stability

**AI can stabilize small sale segments, but integration drives adoption**

## Critical Success Factors

- Shared dashboards with appraisers.
- Side-by-side value comparison
- Integrated ML into existing CAMA workflow.
- Used ML to inform cost factors – not replace the system

## Automating Land Classification

- The Problem
  - Outdated or incomplete land-use data
  - Wetlands and restricted land misclassified
  - Manual field verification is expensive.
- AI and GIS Approach
  - High resolution imagery (false color imagery)
  - Elevation and slope data
  - Supervised machine learning (e.g., Random Forest, SVM, Neural Networks)
- Goal
  - Automatically classify land use (e.g., wetlands, vs. developable land)



## GEOSPATIAL AI-LAND USE DETECTION

### Operational Impact

- Flags parcels for review
- Identifies undevelopable or restricted land
- Improves classification consistency.

**AI improves land-use equity by detecting Patterns humans can't see at scale.**

### Governance Component

- Uses known training samples (“ground truth”)
- Validated through confusion matrix and QA review.
- Iterative improvement process

# #5 LIDAR FOR BUILDING CHANGE DETECTION

- Finding additions without field visits
  - Unreported additions
  - Square footage drives value
  - Manual inspections are expensive
- The Data
  - LiDAR collected at two time periods
  - Millions of elevation points
  - Highly accurate 3D measurements
- The Goal
  - Identify parcels where building volume increased



## L I D A R   F O R   B U I L D I N G   C H A N G E   D E T E C T I O N

### How the Detection Works

- Step 1: Create two surfaces:
  - DEM -> Ground elevation
  - DSM -> Roof and structure elevation
- Step 2: Subtract Surfaces
  - Calculate building height & volume
- Step 3: Compare Time 1 vs. Time 2
  - Flag volume increases

### Operational Impact

- Flags likely additions
- Targets inspections
- Improves equity and efficiency

# #6 CNN FOR BUILDING FEATURE DETECTION

## Identifying Physical Features from Images

- Problem
  - Certain features are underreported or not feasibly obtained.
  - e.g., exterior stairways indicating possible basement use.
- AI Approach
  - Convolutional Neural Network (CNN)
  - Trained on labeled building façade images
  - Detects presence or absence of specific features.
- Pilot Result
  - ~90% accuracy identifying exterior stairs.





## C N N F O R B U I L D I N G F E A T U R E D E T E C T I O N

### What CNN Does

- Screens large image libraries
- Flags likely feature presence
- Reduces random field visits.

### What it does not do

- Automatically change records
- Eliminate assessor review
- Remove due process

**AI helps target inspections thereby improving efficiency and equity.**

### Can AI build the Model for you?

- How does automated machine learning compare to:
  - CAMA Market Comp Sales
  - CAMA MRA (analyst-built)
- The Experiment
  - Same NBHD dataset
  - AutoML applied to raw and engineered data
  - Compared using ratio study metrics
- What AutoML does
  - Selects model type automatically
  - Tunes hyperparameters
  - Engineers features
  - Optimizes via search algorithm's



## SEARCH OPTIMIZATION USING AUTOML

### Findings

- AutoML produced ratio metrics comparable to
  - CAMA Market Comp Sales
  - Analyst built-MRA models
- Even when using only raw data
- Required less manual feature engineering.

### Implication

- AI Search methods can match expert calibration in certain settings.

**Still requires validation, oversight, and ratio study review.**



# Common Patterns Across All Use Cases

## Targeting Not Replacing

Flags properties for review  
Assessors make the final decisions

## Data Driven Optimization

Models absorb complexity (time, location, segmentation) directly from the data

## Validation before Deployment

Successful Case Studies used:  
Ratio Studies, Holdout samples,  
Parallel testing, QA Review

## Integration into Existing Workflows

AI was embedded into CAMA using dashboards, GIS, or other form of assistance, not replacing it.

# *A Review of the Methods, Applications, and Challenges of Adopting Artificial Intelligence in the Property Assessment Office*

BY THE IAAO ARTIFICIAL INTELLIGENCE TASK FORCE

## Summary

In early 2020, IAAO President Amy Rasmussen created the Artificial Intelligence Task Force with the goal of developing a white paper describing the impact and uses of artificial intelligence (AI) in government valuation offices.

The COVID-19 pandemic in early 2020 forced government valuation offices to adapt overnight. Many jurisdictions rapidly virtualized tasks and duties, which accelerated ongoing efforts to utilize office automation and implement intelligent software solutions. More and more, workflows incorporating digital information and multiple sources of data are processed and analyzed using software and integrated applications. The fully integrated workflows facilitate the increased usage of AI in operations, assessment, and valuation.

This white paper delivers an introduction and overview of AI through case and pilot studies and review of relevant analytic methods while touching on possible organizational impacts. The paper looks at the changing role of valuers and assessment administrators and the evolution of valuation offices where AI will be used to improve operations, value estimates, and administration. It provides illustrative examples of AI use in the conduct of tax assessment, including the administrative aspects not directly involved in valuation. While there is substantial fanfare around valuation with AI, many of the benefits to be

## Acknowledgments

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Stay tuned for  
the 2025  
Paper on AI  
Coming in a  
JPTAA soon!

## A Comparative Study on Artificial Intelligence Based Automated Valuation Models

IAAO Taskforce on Artificial Intelligence 2025<sup>1</sup>

### Abstract

This paper presents a comparative study of traditional linear regression approaches, and a range of artificial intelligence (AI) based automated valuation models (AVMs) in the context of mass appraisal valuation. Using datasets from Adams County (USA), Belfast (UK), and Eindhoven (Netherlands), the research evaluates model performance across a diverse range of market structures and data characteristics. A suite of models including Decision Tree, Random Forest, Gradient Boosting, Light Gradient Boosting, Generalized Regression Neural Network, Multi-Layer Perceptron, and Dense Neural Network were developed and tested against standardised ratio study metrics from the International Association of Assessing Officers (IAAO), along with other statistical measures for evaluating model performance. The findings reveal that ensemble machine learning models consistently outperform traditional regression methods across all the jurisdictions examined, exhibiting superior accuracy, precision, and equity even with limited predictor datasets. Furthermore, the application of hyperparameter tuning was observed to enhance model performance, particularly for boosting based algorithms. The study highlights the adaptability of AI-based AVMs to heterogeneous and non-linear property markets, whilst emphasising the continued need for transparency in variable selection and communication around the variables used within automated valuation models. The findings underscore the transformative potential of AI in advancing equitable and accurate property assessment practices, and for the development of industry guidance on the ethical and transparent integration of AI and generative AI technologies within valuation frameworks and assessment practices.

**Keywords:** Automated Valuation Models, Artificial Intelligence, Mass Appraisal, Model Performance, Machine Learning, Hyperparameter tuning

### Introduction

Mass appraisal, the systematic valuation of groups of properties as of a given date using standardized procedures and statistical testing, forms the foundation of equitable property taxation and public revenue systems worldwide. Unlike single-property valuation, which relies on individualized inspection and appraisal judgment, mass appraisal employs model-based approaches to estimate market values efficiently across large datasets. The accuracy, consistency, and equity of these valuation models are essential to ensure public trust and compliance with statutory standards of fairness in taxation.

Traditionally, the assessment industry has relied heavily on traditional linear regression methods, and specifically ordinary least squares (OLS) models to explain the variation in property prices through structural, locational, and socio-economic and demographic characteristics. Whilst these approaches offer interpretability and established statistical explanation, they are often scrutinised as they are constrained by assumptions of linearity, independence, and homoscedasticity. As a consequence of these limitations, this often reduces their ability to capture the complex, non-linear relationships that characterise heterogeneous housing markets, particularly within and across urban environments.

<sup>1</sup>The IAAO Task Force on Artificial Intelligence comprises Luc D. Hermans (Chair), and members Paul Bidanset, Daniel Faesteen, Pim Hensing, Joshua Jorgensen, Luke Jorgensen, Anita Ng, Michael McCord, Russ Thimman, John Valente and Joe Wehrli, and Shaun York served as IAAO staff liaison.

# AI Methods & Assessment Practice

WHAT KIND OF AI TOOLS ARE BEING USED?

## Supervised Learning

- Regression – Value Prediction
- Classification – feature type and detection.
  - Decision Trees
  - Random Forest
  - Gradient Boosting

## Unsupervised Learning (Pattern Discovery)

- Clustering
  - Market Segmentation
- Outlier Detection
- Identifying hidden structure in data

## Deep Learning Image & Feature Detection

- Convolutional Neural Networks (CNN)
- Used for
  - Image Classification
  - Feature Detection
  - Feature Extraction

## Search & Optimization

- AutoML
- Hyperparameter Tuning
- Model calibration automation

# Questions

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